



Review

Modelling language evolution: Examples and predictions

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Abstract

We survey recent computer modelling research of language evolution, focusing on a rule-based model simulating the lexicon–syntax coevolution and an equation-based model quantifying the language competition dynamics. We discuss four predictions of these models: (a) correlation between domain-general abilities (e.g. sequential learning) and language-specific mechanisms (e.g. word order processing); (b) coevolution of language and relevant competences (e.g. joint attention); (c) effects of cultural transmission and social structure on linguistic understandability; and (d) commonalities between linguistic, biological, and physical phenomena. All these contribute significantly to our understanding of the evolutions of language structures, individual learning mechanisms, and relevant biological and socio-cultural factors. We conclude the survey by highlighting three future directions of modelling studies of language evolution: (a) adopting experimental approaches for model evaluation; (b) consolidating empirical foundations of models; and (c) multi-disciplinary collaboration among modelling, linguistics, and other relevant disciplines.

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1. Computer modelling in evolutionary linguistics

“A basic task of science is to build models – simplified and abstracted descriptions – of natural phenomena” [1, p. 432]. Throughout the history of science, thought experiments have served as the “modelling” approach helping researchers conceive an abstract or poorly-understood domain in terms of a more familiar one [2–4]. Computer modelling dated back to John von Neumann’s universal constructor demonstrating that machines could self-reproduce just like living organisms [5]. As an efficient means to articulate sophisticated theories and address complex phenomena [6], computer modelling has now become pervasive in most traditional as well as newly-founded disciplines [7,8].

Abbreviations: *S*, subject; *V*, verb; *O*, object; *RC*, reliability of cue; *RE*, rule expressivity; *RE_{holist}*, RE of holistic rules; *RE_{comp}*, RE of compositional rules; *UR*, understanding rate; *UR_{GloOrd}*, *UR* of a global order; *UR_{LocOrd}*, *UR* of a local order; *UR_{con}*, *UR* become consecutive generations; *UR_{ini}*, *UR* between the first and later generations; *JA*, joint attention; *CS*, communicative success; *CCrate*, rate of child–child transmission; *ACrate*, rate of adult–child transmission; *PCrate*, rate of parent–child transmission.

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Evolutionary linguistics [9] did not escape the invasion of computer modelling. This resurgent linguistic subfield [10] aims to identify when, where, and how human language originates, changes, and dies out [11]. It studies (a) *origin* (the transition from a pre-linguistic communication system to a communication system with the sort of languages we use today), (b) *change* (the process whereby phonetic, semantic, or syntactic features of one or a group of languages are modified), and (c) *acquisition* (the course while a pre-language infant or an individual who already uses a language acquires a new one exposed to him/her in a socio-ecological environment [12]) of language. These topics address not only particular language(s) but also human *language faculty* (the set of capacities to master and use natural languages [13]) [14].

After more than half a century of modern research in evolutionary linguistics, there remain two issues that still lack decisive answers: (a) how human cognition enables language processing, more precisely, whether language processing abilities are formed by language-specific modules [15,16] or derived from *domain-general* (not language-specific or human-unique) abilities [17–20]; and (b) how biological or socio-cultural factors influence *language universals* (principles of structure or use that hold in most but not necessarily all languages [21]) [22,23] in a socio-ecological environment [22,23].

There exist bifurcating views regarding these issues. For instance, stressing the dissociation of language from other cognitive domains, the nativist view states that humans must have a language faculty that evolved from either a single mutation [24,25] or a series of natural selection [26,27]. In contrast, advocating the intrinsic connections between language and other cognitive functions, the connectionist or emergentist view [9,19,28] states that: (a) language resulted from elaboration of domain-general abilities into language activities and reconfiguration of ancestral systems in evolutionarily novel ways [29–32]; and (b) language processing relies upon not only general systems for expressing objects, actions and their relations, but also socio-cognitive constraints spanning from social interactions, pragmatics, memory, and other processing [33,34]. As for the driving force behind language evolution, the nativist view highlights the roles of biological evolution in forming linguistic abilities [25,35–38], whereas the emergentist view emphasizes the effects of socio-cultural factors on recruiting cognitive mechanisms and shaping language structures [22,23,30,39–43].

Due to the fact that linguistic behaviours are hard to preserve in fossils [19,44], research in evolutionary linguistics, especially on language origin, remains exploratory to a certain extent, which actually makes it suitable for computer modelling [45,46]. In evolutionary linguistics, *computer modelling* can be viewed as “operational” hypotheses or theories that are expressed by computer programs rather than verbal statements [47]. By running these programs, the simulation results obtained become the empirical predictions derived from the incorporated hypotheses or theories [48]. Unlike the definitions in other academic fields (e.g. psychology or neuroscience), we emphasize modelling as a scientific method to evaluate available theories, suggest new perspectives, and address questions more focused than what theoretical linguists can conceive of [49]. All these aspects help transform evolutionary linguistics from a speculative topic into a scientific domain [50].

According to how components of the target linguistic phenomenon are realised mathematically, available models of language evolution can be classified as rule-based and equation-based models (see [51,52] for other ways of classification). *Rule-based models* define concrete or abstract rules to describe or manipulate linguistic components and relevant behaviours. Correlation of these rules leads to acquisition of language within individuals and socio-cultural evolution of it among individuals. Such models often encode specific language structures and knowledge, simulate interested processing mechanisms, and analyse stochastically effects of these mechanisms on developing those structures or triggering new ones as attested in world languages. In contrast, *equation-based models* tend to transform linguistic and relevant behaviours into mathematical equations. Mathematical analyses on these equations and experimental or empirical confirmations allow equation-based models to reasonably approximate the history of language evolution or predict its future.

Ever since James Hurford designed his rule-based model demonstrating the origin of a coordinated signalling system via iterated communications, many computer models have been proposed to challenge the nativist view that minimizes the role of communication in language evolution [25] (see recent anthologies [47,53–62] and proceedings of the biennial conferences on language evolution [63–68]). For instance, some models ascribe the distributions of phonetic elements (e.g. vowels) to *self-organization* (the process whereby a global pattern of a system emerges from local interactions of its components [69]) during communications [70,71]. Others show that language universals arise naturally via *cultural transmission* (the process whereby information is passed among individuals via social learning

such as imitation or language [72]) [39,73] or *language games* (interacting protocols for individuals to develop shared conventions to exchange information) [58,59,74,75].

To avoid a tedious review, we focus on one rule-based and one equation-based model (see [46,76] for reviews of other models). The rule-based model is the lexicon–syntax coevolution model [77,78]. It adopts a *multi-agent system* [79] consisting of a population of interacting agents, and simulates some general learning abilities, a communication scenario, and a socio-cultural environment. It traces a coevolutionary origin of lexical items and simple word orders among agents. The equation-based model is the language competition model [80]. It assigns explicit linguistic meanings to parameters and uses these concrete parameters to address fundamental socio-cultural constraints on language competition. It adapts a biological competition model into the language competition model, and derives a series of mathematical principles from physics, biology, and population dynamics to estimate parameter values in actual cases of language competition.

After briefly describing these models, we discuss their primary contributions. The rule-based model demonstrates the domain-generality of language-specific processing mechanisms for lexical items and simple word orders [77,78]. By incorporating natural and cultural selections, it provides a coevolutionary explanation to the degree differences in language-related mechanisms between humans and non-human primates [81]. By simulating forms of cultural transmission and social structure, it also reveals the effect of cultural transmission on triggering and maintaining a communal language across generations of individuals [82,83] and the correlation between social structure and linguistic understandability within a group of individuals [84].

The equation-based model calculates parameter values from empirical data of population surveys and linguistic questionnaires, which allows reliably replicating and reasonably predicting the dynamics of language competition, especially in cases that lack sufficient competition data. In addition, the model itself and those mathematical principles are derived from well-attested principles in linguistics, biology, physics, and population dynamics, which reveal the intrinsic commonalities among linguistic, physical, and biological phenomena [80]. All these have significantly improved the robustness, applicability, and explanatory power of the language competition model.

We conclude the survey by pointing out three directions for future modelling research in evolutionary linguistics, including designing psycholinguistic experiments to evaluate simulation results concerning human behaviours, referring to language databases to consolidate the empirical bases of computer models, and conducting multi-disciplinary collaborations among relevant disciplines.

2. Behavioural model and its predictions

2.1. Lexicon–syntax coevolution model

This model aims to evaluate the “formulaic” theory of language origin [85,86]. This theory states that: modern languages originated from a holistic protolanguage using holophrastic utterances to encode integrated meanings; and by general learning mechanisms, early hominins segmented holistic expressions to acquire lexical items and relevant grammar. In the model, we simulate a communication system using a holistic protolanguage, define both holistic and compositional linguistic rules, and equip agents with general learning mechanisms to see whether these mechanisms can sufficiently trigger a compositional communal language.

2.1.1. Individuals, artificial language, and linguistic knowledge

In the model, language users are simulated as artificial agents, and the artificial language created and used by them is denoted by *meaning-utterance mappings*. Agents share a semantic space containing a number of *integrated meanings*, such as “run(fox)” (“a fox is running”) or “chase(lion, goat)” (“a lion is chasing a goat”). These meanings can be encoded by utterances (sentences), each being a string of syllables from a signalling space. An utterance encoding an integrated meaning can be segmented into subparts mapping semantic constituents, and subparts can also combine to encode an integrated meaning.

Agents’ linguistic knowledge is denoted by linguistic rules (see [77,78] for examples). For instance, “chase(wolf, bear)” ↔ /abcde/ is a *lexical rule* denoting that the meaning “chase(wolf, bear)” can be encoded by the utterance /abcde/; and /abcde/ can also be interpreted as “chase(wolf, bear)”. This is a *holistic* rule, mapping an integrated meaning onto a sentence. A lexical rule can also be *compositional*, mapping semantic constituent(s) onto a subpart of a sentence (e.g. “wolf” ↔ /cd/).

When forming sentences using compositional rules, their utterances in sentences are regulated by order rules. An *order rule*, e.g. “Category 1 \ll Category 2”, denotes that the utterances of lexical rules from Category 1 (see below) lie before (not necessarily immediately before) those from Category 2. One order rule helps form utterances encoding intransitive meanings like “run(wolf)”, and two or three help construct utterances encoding transitive meanings like “chase(wolf, bear)”.

A *category* contains a number of lexical and order rules. The lexical rules encode constituents having identical *thematic roles* (actions, action instigators, or entities undergoing actions) in integrated meanings, and the order rules specify the orders between the utterances of these lexical rules and the utterances of other lexical rules from other categories. For the sake of simplicity, categories of lexical rules encoding action instigators are also called S(ubject) categories, because without passive voice, action instigators are often subjects in sentences. Similarly, categories of entities undergoing actions are O(bject) categories, and categories of actions V(erb) categories. An order rule between two categories can also be denoted using the *syntactic roles* (S, V, or O) of these categories, e.g. S \ll V, or simply SV. Via categorisation, order rules acquired from some lexical items can be applied productively to others having identical thematic roles.

Each lexical or order rule is assigned a *strength* (within [0.0 1.0]), indicating how often this rule has been applied successfully during communications. A compositional rule also has *association weights* to categories that contain it, indicating how often the order rules in those categories are applied successfully on this rule during communications. Rule strength and association weight enable a strength-based competition in communications and a gradual forgetting of linguistic knowledge.

Using predicate-argument structures to represent semantics, syllables to form utterances, and lexical and grammatical rules to denote linguistic knowledge has been widely adopted in computer models of language evolution (e.g. [39, 71]), though semantic structures of integrated meanings, syntactic structures of exchanged utterances, and linguistic rules remain distinct among models focusing on different aspects of language evolution.

2.1.2. Domain-general learning mechanisms

Agents are equipped with general learning mechanisms to acquire linguistic rules (see [77,78] for details of these mechanisms). Lexical rules are acquired from constituent(s) and syllable(s) that appear repetitively in two or more meaning-utterance mapping. Agents store *previous experiences* (meaning-utterance mappings acquired in previous communications). New mappings, before being stored, are compared with those already existing. For instance, by comparing “hop(fox)” \leftrightarrow /ab/ and “run(fox)” \leftrightarrow /acd/, an agent can detect the recurrent pattern “fox” and /a/. If the agent has no rule recording this pattern, it will create a lexical rule “fox” \leftrightarrow /a/ for future use.

Categories and order rules are acquired based on thematic roles of lexical rules and sequential relations of their utterances in meaning-utterance mappings. If an agent notices that in some previous experiences, the utterances of two or more lexical rules having the same thematic role are consistently before (or after) the utterance of another lexical rule (or the utterances of another set of lexical rules all having identical thematic roles), the agent can associate these lexical rules into a category having the corresponding syntactic role, create an order rule to record the local order with respect to the other lexical rule(s), and put this order rule to the same category. In this way, the agent can gradually form categories associating different lexical rules and local orders among them.

These item-based learning mechanisms have been traced in language acquisition studies [87]. The categorization process resembles the verb-island hypothesis [30,88]. This hypothesis states that children’s early grammar consists of sets of lexically-specific predicate structures (i.e. verb-islands). For instance, a child can use any object that he/she knows has performed kicking as the antecedent to “kick”. Then, due to overlap of these object items, the child gradually merges verb-islands surrounding distinct verbs and forms a complete verb category. Until then, the verb-general marking can occur. Such islands are also formed around lexical items other than verbs [89].

2.1.3. Communication scenario

A linguistic communication involves two agents (a speaker and a listener), who perform a number of *sentence exchange*, each proceeding as follows.

In production, the speaker (hereafter as “she”) first selects randomly an integrated meaning from the semantic space to produce. She then activates her lexical, order, and category rules to form candidate sets for production, each offering a sentence to encode the meaning. For each set, she calculates the combined strength (see [77,78] for calculation equations), which is the average strength of the lexical rules in this set plus the average product of the

association weights of the lexical rules to the categories and the strengths of the order rules in these categories used for regulating the lexical rules. After calculation, she chooses the set having the highest combined strength, builds up the sentence accordingly, and transmits the sentence to the listener. If lacking enough rules to encode the meaning, she occasionally creates a holistic rule to encode the whole meaning and sends the utterance of this rule to the listener. In other words, before sufficient compositional knowledge is available, agents stick to holistic knowledge, which is in line with the “formulaic” theory.

In comprehension, the listener (hereafter as “he”) receives the sentence from the speaker and an *environmental cue*. The cue, as non-linguistic information, contains an integrated meaning plus a *cue strength*. Incorporating non-linguistic information into linguistic communications allows evaluating the correlation between the evolutions of language and non-language-specific abilities.

Cues are unreliable (not always containing the speaker’s intended meaning), which avoids *explicit meaning transfer* [90] (explicitly transferring meanings encoded in exchanged sentences via non-linguistic cues, thus making linguistic communication unnecessary) as in previous models (e.g. [39,91]). We define *reliability of cue (RC)* to denote how often the listener obtains a correct cue in an utterance exchange; otherwise, he receives a wrong cue. The correct cue contains the speaker’s intended meaning, whereas the wrong one contains an integrated meaning randomly chosen from the semantic space and distinct from the speaker’s intended meaning.

The listener activates his lexical, order and category rules that can interpret the heard sentence as integrated meaning(s). He then compares the cue’s meaning with the one(s) comprehended by linguistic rules, and sets up candidate sets for comprehension. If the cue’s meaning completely or particularly matches the one interpreted by some linguistic rules, the cue and those rules form a candidate set. Otherwise, the cue itself forms a candidate set. If some linguistic rules can also offer a complete interpretation, they form another set as well.

The listener calculates the combined strength of each set. For a set without a cue, its combined strength is calculated exactly the same as that in production. For a set having a cue, the cue strength is added to the combined strength. After calculation, he chooses the set having the highest combined strength for comprehension. If this combined strength exceeds a confidence threshold, the sentence exchange is deemed successful. In this situation, the listener stores the perceived meaning-utterance mapping as a previous experience, and then, both speaker and listener reward their rules in their chosen sets by adding a fixed amount to their strengths and association weights, and penalize competing ones in other sets by deducting the same amount from their strengths and association weights. Otherwise, the sentence exchange is failed. In this situation, the listener discards the perceived mapping, and both speaker and listener only penalize their rules in their chosen sets.

During a sentence exchange, non-linguistic information assists linguistic comprehension, by clarifying unspecified constituent(s) and enhancing rules that can lead to a similar interpretation to this information. The cue strength equals to the confidence threshold, so that linguistic and non-linguistic information are treated equally. Such multi-information coordination has its neural basis in the human brain [92]. In addition, throughout the sentence exchange, there is no check whether the speaker’s encoded meaning matches the listener’s decoded one, which allows the model to address whether unreliable cues help trigger fundamental linguistic knowledge. Furthermore, the strength adjustment mechanism leads to conventionalization of linguistic knowledge. Such linear inhabitation mechanism has been used in many rule-based models (e.g. [60,61]), with distinct details.

2.2. Correlation of domain-general abilities and language-specific mechanisms

The learning mechanisms adopted by agents are domain-general. Pattern extraction is to detect or encode isolated or combined items that appear repetitively in linguistic or other types of instances [93]; sequential learning is to detect or encode the sequential orders of discrete elements occurring in a temporal sequence [21]; and categorization is to apply available knowledge in novel, similar conditions [30]. Usage-based and functional linguists [94–96] group these mechanisms as general pattern-finding skills [30].

The model can simulate either a holistic language (via holistic rules) or a compositional one (via compositional, order, and category rules). To evaluate the “formulaic” theory, we test whether agents can develop, via those general mechanisms and iterated communications, a compositional language out of a holistic one. *Linguistic compositionality* refers to the principle on how the meaning of a complex expression is built from its subparts via regulating rules [97]. We divide it into *compositionality* (agents use compositional rules to build sentences encoding integrated meanings) and *regularity* (agents use consistent orders to regulate lexical items in sentences).

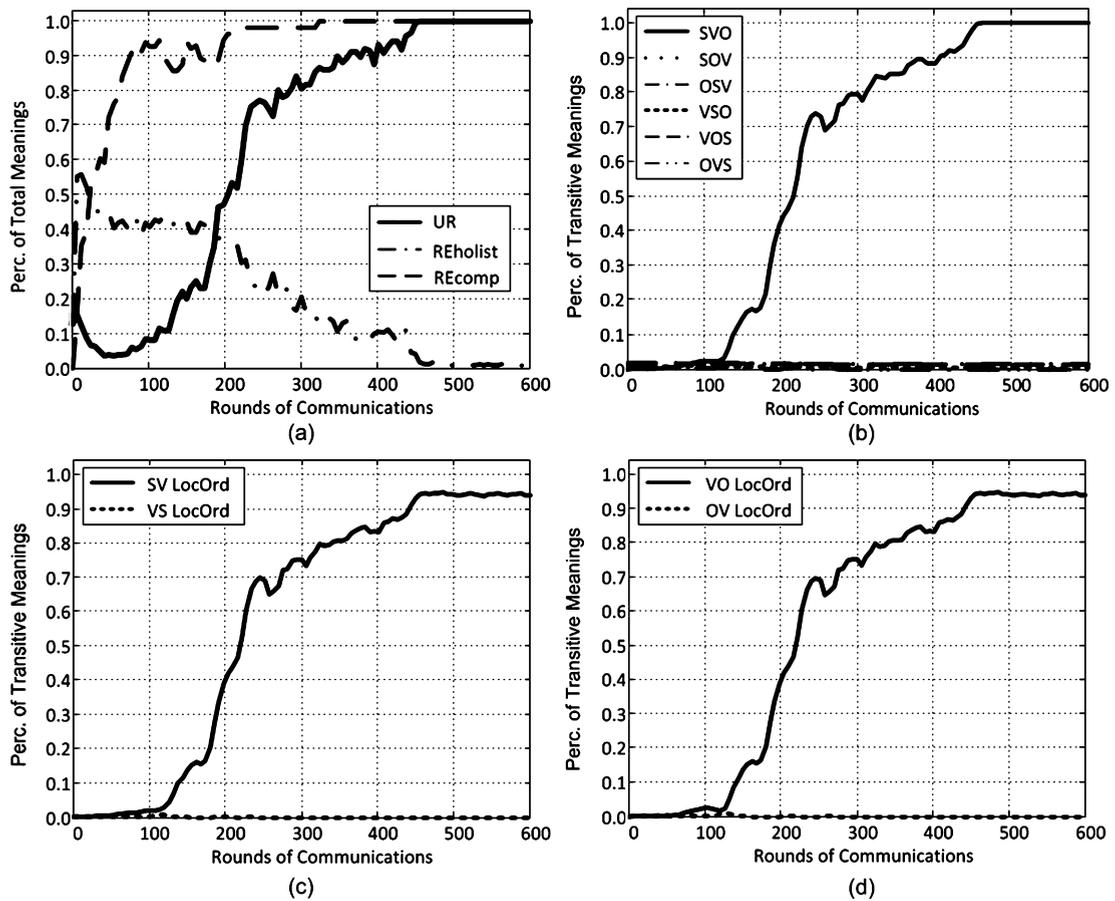


Fig. 1. These figures (adapted from [78]) illustrate that agents gradually develop a common set of compositional rules (high UR_{comp} in (a)) and order rules (high UR_{LocOrd} of SV and VO in (c) and (d)) leading to a consistent global order (high UR_{GloOrd} of SVO in (b)). These rules comprise a communal language capable of accurately exchanging most integrated meanings (high UR in (a)).

We define four indices to evaluate simulation results (see [78] for how to calculate them): (a) *rule expressivity* (RE), the average percentage of integrated meanings that all agents can produce; (b) *understanding rate* (UR), the average percentage of integrated meanings understandable to each pair of agents based on their linguistic knowledge, which evaluates whether the acquired linguistic knowledge helps agents efficiently produce and accurately comprehend integrated meanings; (c) *UR of a local order* (UR_{LocOrd}), the average percentage of transitive meanings understandable using agents' lexical knowledge and a particular local order (SV, VS, SO, OS, VO, or OV); and (d) *UR of a global order* (UR_{GloOrd}), the average percentage of transitive meanings understandable using agents' lexical knowledge and a particular global order (SVO, SOV, OSV, OVS, VSO, or VOS), here, a global order is the combined order of local orders (e.g. local orders SV and VO lead to a global order SVO).

Fig. 1 shows the result of a typical simulation run (under the settings in [78]). In this run, agents initially share only a small number of holistic rules, indicating a holistic language with limited expressivity. Fig. 1(a) traces RE of holistic rules (RE_{holist}), RE of compositional rules (RE_{comp}), and UR . As for RE , RE_{holist} first increases slightly, indicating that exchanged sentences are primarily formed by holistic rules. Given more linguistic experiences, recurrent patterns start to appear and get acquired as compositional rules, and a competition occurs between compositional and holistic rules. The combinatorial advantage (a compositional rule, due to combination, can express many meanings involving its encoded constituent(s), whereas a holistic rule only expresses one integrated meaning) makes compositional rules gradually win the competition. With more compositional rules being shared, RE_{holist} drops and RE_{comp} increases and approaches 1.0.

As for UR , it first increases with RE_{holist} , indicating that comprehension at this stage relies on holistic rules. With the origin of compositional rules, an explicit drop of UR is seen, reflecting the competition between holistic and

compositional rules. After compositional rules win the competition, UR starts to increase sharply, because sharing one more compositional rule enables agents to accurately exchange many more integrated meanings. With more compositional rules being shared, UR approaches 1.0, along with RE_{comp} . The high RE_{comp} and UR illustrate the origin of compositionality: agents share a common set of compositional rules to accurately exchange most integrated meanings.

Fig. 1(b) illustrates that along with the origin of compositional rules, UR_{GloOrd} of SVO increases. Figs. 1(c) and 1(d) illustrate that most agents in this run develop SV and VO to interpret transitive meanings, thus leading to SVO. Since V categories associate lexical rules encoding both transitive and intransitive actions, SV also regulates intransitive meanings (see [98] for discussions on relations between semantic structure, emergent global orders, and general learning mechanisms).

Fig. 1 illustrates a coevolutionary origin of compositionality and regularity; the sharp increase in UR synchronizes temporarily with that in UR_{GloOrd} or UR_{LocOrd} of the prevalent order(s). The driving forces for this process include mutual understanding, semantic similarity (integrated meanings share constituents having identical thematic roles), and non-linguistic cues (aiding comprehension when linguistic knowledge is insufficient).

These results illustrate the roles of domain-general mechanisms in acquiring lexical items and simple syntax, demonstrate the “formulaic” theory, match the general patterns of language acquisition [12,93,99], and reveal the inseparability of lexicon and syntax in language processing and development [100]. These results also trace a “bottom-up” syntactic development (consistent global order of multiple lexical items results from combination of local orders each between two items), which can trigger reconsideration on the nativist view on syntax and relevant mechanisms. An insightful future work here is to check whether complex syntactic hierarchy can also be triggered in such a “bottom-up” manner.

2.3. Coevolution between language and relevant abilities

Although the above simulation and previous studies (e.g. [19]) illustrate that domain-general mechanisms shared by humans and other animals can contribute to the acquisition and development of language, there are degree-differences in these mechanisms between humans and non-human primates [101]. One such mechanism is *joint attention* (JA) (establishing common ground in general interactive activities by means of socio-cognitive abilities [102]; e.g. one individual alerts another to an object or event by means of eye-gazing, pointing, or other verbal or non-verbal indications). There is a positive correlation between mother-child JA and child’s word learning efficiency [103,104], whereas wild or captive non-human primates of different ages exhibit a significantly lower JA level than humans [105].

This comparative evidence hints that a fully-formed high JA level in humans seems to be a prerequisite for language and communication [101,106–108], but the brain-language/gene-culture coevolution theory [109–111] also suggests that such difference could result from a *coevolution* (a reciprocal or competitive influence between two or more natural species or system components [112]) with language. According to the coevolution theory, early hominins borrowed JA from general interactions into linguistic communications to form mutual understanding and acquire basic linguistic knowledge, and once the JA level became correlated with linguistic comprehension, *communicative success* (CS) could enhance reciprocally the JA levels in language users. In other words, the initial JA level in early hominins need not be very high.

The rule-based model helps evaluate this coevolutionary scenario. First, the communication in the model involves non-linguistic cues to aid linguistic comprehension, and RC reflects the ability of establishing common grounds during communications (obtaining correct cues containing speakers’ intended meanings). If we simplify JA as availability of topics from non-linguistic information, RC can quantify the JA level. Second, CS of an agent can be reflected by the UR of this agent when others talk to it.

We implement a transmission framework that involves both genetic transmission (transmitting JA level (RC) from adults to offspring during reproduction) and cultural transmission (adult–adult and adult–offspring communications). During reproduction, half of the adults are chosen as parents, each producing two offspring (to keep the population size stable) who initially have no linguistic knowledge but inherit their parents’ RC with occasional mutation (increasing or decreasing copied RC value with a fixed amount). Then, these offspring learn from their parents or other adults as listeners in adult–offspring communications. After that, they become adults, replacing all adults in the previous generation, and conduct adult–adult communications with each other. Then, the next round of reproduction occurs.

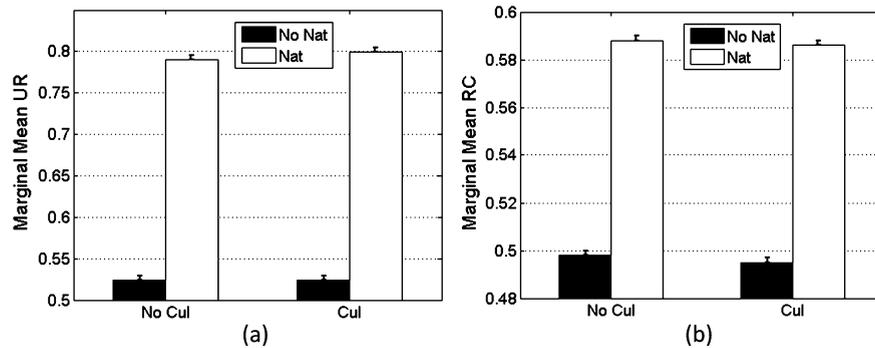


Fig. 2. These figures (adapted from [81]) illustrate the coevolution between language (UR) (a) and JA level (RC) (b) after 1000 rounds of reproduction. Results are obtained from 50 simulation runs in each condition.

Both natural and cultural selections can take effect in this framework. The former selects adults who understand others better (having higher CS) as parents to reproduce, and the latter chooses adults having higher CS as teachers talking to offspring in adult–offspring communications. We set up four sets of simulation to manipulate these selections. In the sets without natural or cultural selection, parents or teachers are randomly chosen in each generation. In these sets, RC values in the first generation are chosen from Gaussian distributions having fixed standard deviations but different means. According to these means, we set up nine RC conditions in each of the four sets.

Fig. 2 shows the simulation results (under the settings in [81]). In these simulations, agents initial use a holistic language with limited expressivity. As shown in Fig. 2(a), the mean UR (over all RC conditions of all simulations) in the sets with natural selection is significantly higher than that in the sets without, whereas the mean UR in the sets with cultural selection is similar to that in the sets without. Fig. 2(b) shows a similar effect on the mean RC . These results indicate that it is natural selection, rather than cultural selection, that drives the origin of a communal language with good understandability (UR) and enhances a low JA level (RC). Although the coevolution is mainly via natural selection, cultural transmission is inevitable, which serves as a medium for individuals to form their distinct CS to be selected by natural selection.

These results illustrate that culturally constituted aspects (e.g. CS) can drive the natural selection of predisposed cognitive features (e.g. JA) [113], and that genetic assimilation in the context of language evolution helps retain and expand communicatively effective features [33,114]. JA exists prior to language and takes effect during general interactive activities. However, once borrowed to aid linguistic comprehension, it could piggyback on language, having its level increased along with language evolution. Apart from JA , this coevolutionary scenario may help explain the degree-difference in other language-related competences (e.g. memory capacity or other socio-cognitive abilities), which paves the future work in this line of research.

2.4. Socio-cultural constraints on language evolution

Cultural transmission and social structure determine how individuals communicate with each other. In this way, these two aspects can cast their influence on language evolution. We conduct two studies based on the rule-based model to explore the effects of cultural transmission and social structure on linguistic understandability.

2.4.1. Cultural transmission and language evolution

This study examines the roles of cultural transmission in language origin and change [115]. Three forms of transmissions between two consecutive generations of individuals are considered: (a) *horizontal transmission*, communications between members of the same generation; (b) *vertical transmission*, a member of one generation talks to a biologically-related member of the next; and (c) *oblique transmission*, a member of one generation talks to a biologically-unrelated member of the next.

We implement an acquisition framework. During reproduction, half of the adults are randomly chosen as parents, each producing an offspring (child) who have no linguistic knowledge. Then, these children participate in child–child (horizontal), adult–child (oblique), or parent–child (vertical) transmissions (in each notion, the first part denotes speaker, and the second part listener) to acquire their idiolects. After that, they become adults, replacing their parents,

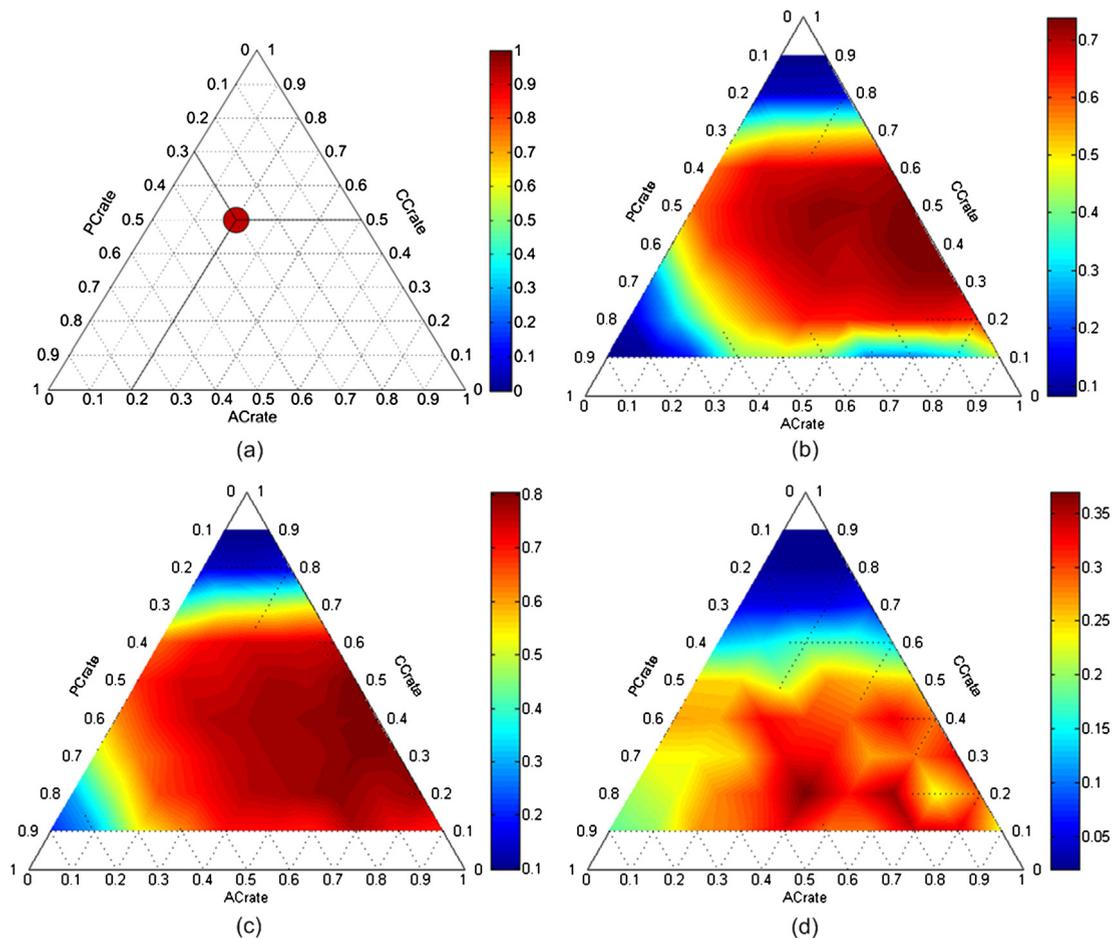


Fig. 3. These figures (adapted from [83]) illustrate that maximum linguistic understandability (UR_{con} in the origin simulations (b), UR_{con} in the change simulations (c), UR_{mil} in the change simulations (d)) can be achieved under non-zero $ACrate$, $CCrate$ and $PCrate$. Results are obtained after 100 rounds of reproduction, and averaged over 20 simulations runs in each case. In (a), the patch marks the case $CCrate = 0.5$, $PCrate = 0.3$, $ACrate = 0.2$, and the colour map clarifies the value obtained in this case.

and the next round of reproduction occurs. At children's acquisition stage, all three forms of transmissions are interwoven randomly, whose rates in the total transmissions are denoted respectively by $CCrate$, $ACrate$ and $PCrate$, the sum of which is 1.0.

We conduct *origin simulations*, in which adults in the first generation share only a small number of holistic rules, and *change simulations*, in which adults in the first generation share a compositional language capable of expressing all integrated meanings in the semantic space. The purpose of designing change simulations is to test whether the initial communal language can be sufficiently transmitted across generations under different combinations of the three forms of transmissions. However, in reality, individuals may not have such complete linguistic knowledge.

Fig. 3 shows the simulation results (under the setting in [83]). We evaluate UR between adults in consecutive generation (i and $i + 1$) (UR_{con}) and UR between the first and later generations (UR_{mil}). In the origin simulations, too many horizontal transmissions (top angle in Fig. 3(b)) or too many vertical transmissions (left angle in Fig. 3(b)) fail to trigger a communal language with high UR ; instead, a combination of all three forms of transmissions can efficiently trigger and largely maintain a communal language with high UR across consecutive generations (central area in Fig. 3(b)). In the change simulations, non-zero $CCrate$, $ACrate$ and $PCrate$ can largely preserve a communal language across consecutive (Fig. 3(c)) and many generations (Fig. 3(d)) (see [83] for discussions of respective and collective roles of these transmissions).

Figs. 3(c) and 3(d) also show that although a high UR_{con} is maintained in certain cases, after many generations, UR_{mil} drops inevitably in those cases. This reflects the dynamics of language change: although agents from consecutive

generations understand each other very well, the communal language changes inevitably in the long run (see [83] for discussions).

Apart from these forms, the acquisition framework can incorporate transmissions spanning three consecutive generations (e.g. grandparent–child, parent/adult–child, and child–child transmissions). Examining their roles in linguistic understandability serves as a future work for this line of research [116].

2.4.2. Social structure and language evolution

Agents in the previous simulations have uniform probabilities to take part in communications. In reality, social structures can break down such uniformity by allowing individuals of various social ranks to participate in more or fewer communications. Social rank is subject to many factors (e.g. economic condition, friendship, political influence, etc.).

One way to describe social structures is via network, treating each individual in the community as a *node*, and communications or connections among them as *edges* linking nodes. The number of edges a node has is its *degree*, and the probability distribution of these degrees over the network is the *degree distribution*. Using the network approach, empirical studies [117] have discovered that many social structures formed by language-related activities tend to exhibit a *power-law* degree distribution, and its λ value (quantifying the power relation between the two quantities in the distribution) is usually around 2.0 [118]. For instance, in the telephone call network, the ranks of phone numbers and the numbers of calls made or received via these phone numbers have a power relation, whose λ is 2.1. In the email network, the ranks of email addresses and the numbers of emails exchanged via these addresses have a power relation, whose λ is 2.0.

It is worth exploring whether this particular social organization can facilitate language evolution, in terms of triggering or preserving a communal language with high *UR*. We define a power-law *social popularity* (the probability for an agent to communicate with others) (Eq. (1), where r denotes agent's rank from 1 to N (population size) (the agent having the highest probability to communicate with others has rank 1, the one having the second highest probability has rank 2, and so on), $p(r)$ calculates the social probability for an agent of rank r to communicate with others, and c is a normalizing factor ensuring the sum of all probabilities as 1.0):

$$p(r) = cr^{-\lambda} \quad (1)$$

Defining social popularity allows us to manipulate (via λ) communications among agents at the population level, without specifying actual connections among agents. If we assume that the rank of an agent (node) is reversely accumulative with the number of agents that have more edges than this one (i.e. if the rank of a node is r , it means that there are $N - r$ nodes having equal or smaller degrees than this node), then, the λ in power-law social popularity is mathematically related to the λ' (to distinguish it from λ in power-law social popularity) in power-law degree distribution (Eq. (2), see [119] for proof), which enables a quantitative comparison between simulation results obtained under different λ and empirical data classified by λ' .

$$\lambda' = 1 + \frac{1}{\lambda} \quad (2)$$

Via the origin and change simulations (similar to those in the study of cultural transmission, but without reproduction) under various N (50, 100, 150, 200, 300, 400, and 500) and λ (0.0 (the case of random communication), 0.5, 1.0, 1.5, 2.0, 2.5, and 3.0), we study the effect of social popularity on *UR*.

Fig. 4 shows the simulation results. In the origin simulations (Fig. 4(a)), only if λ is 0.0 (solid lines), 0.5 (dash lines) or 1.0 (dot lines) can *UR* reach a high value after 600 rounds of communications in all populations. When λ is 1.0, the increase in *UR* from its initially-low value occurs the earliest among all λ values, and the shapes of *UR* curves do not change much across populations. In the change simulations (Fig. 4(b)), if λ is smaller than 1.0, a high *UR* is preserved in all populations, whereas for other λ values, *UR* drops with the increase in N .

These findings are not limited to the rule-based model [119]. They reveal an *optimal* λ value (1.0) of power-law social popularity: under it, emergent conventions can diffuse to preserve a high *UR*, even in bigger populations; whereas below or above it, with the increase in population size, language origin becomes less efficient.

The change simulations seem exceptional to this general tendency. In these simulations, agents initially share a set of linguistic knowledge. When λ is smaller than 1.0, every agent has sufficient chances to communicate with others, so that their shared knowledge is frequently used. However, individuals in reality may not share all linguistic knowledge,

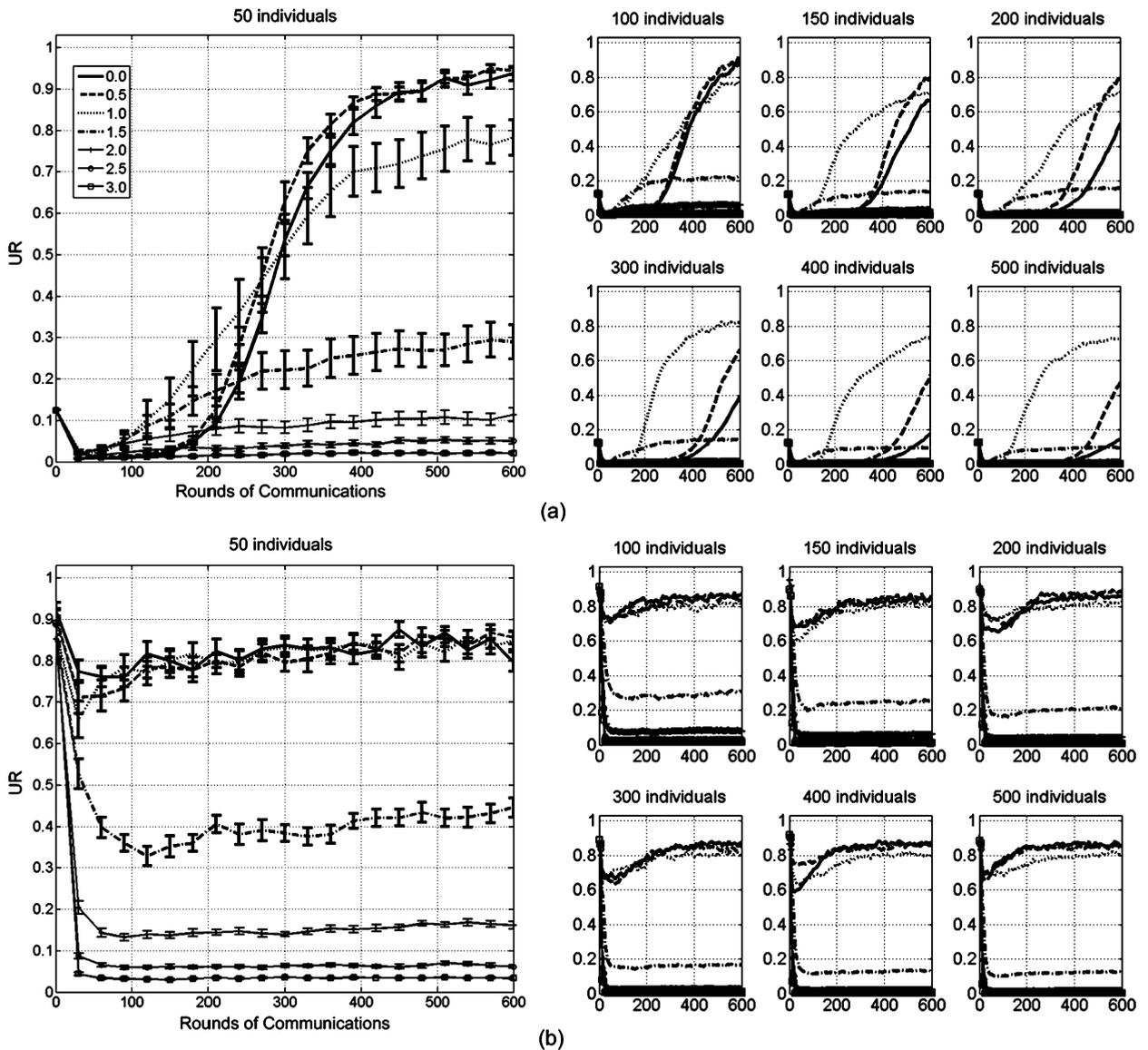


Fig. 4. These figures (adapted from [119]) illustrate that particular social popularity ($\lambda = 1.0$) can efficiently trigger and largely preserve a high UR in different populations in both the origin (a) and change (b) simulations. Each line shows the average UR over 20 simulation runs under a particular λ value. Error bars denote standard errors.

and shared knowledge has to be gradually developed during language origin. Therefore, even though λ as 0.0, 0.5 or 1.0 may have similar effects on maintaining common knowledge, as for development of common knowledge, only the power-law social popularity with λ as 1.0 has the best performance.

Following Eq. (2), the optimal λ (1.0) in power-law social popularity equals to the frequently-observed λ' (2.0) in power-law degree distribution of social structures formed by language-related activities. This offers the empirical support for the simulation results. These results not only reflect a close correlation between language and social structure in the human group, but also indicate that a human group tends to organize in such a way to efficiently trigger a communal language with a high UR . In other words, language is an *emergent group-level trait* [120,121], whose evolution not only concerns individual behaviours, but also helps shape and gets shaped by group structures. Apart from this structure, modelling studies have touched upon many other structures within and/or across groups [122–124].

The two studies on cultural transmission and social structure reveal the effects of socio-cultural constraints on developing and maintaining communal languages with good understandability. Other theoretical and empirical studies [22,23,39,58,59] advocate that the socio-cultural evolution of language is a much more powerful process than the genetic evolution of language in shaping particular language structures. More studied by means of computer modelling or other approaches are needed to better understand the effects of socio-cultural factors on language evolution.

3. Equation-based model and its predictions

3.1. The language competition model

3.1.1. The AS model

The most influential model studying the dynamics of competition between two languages (say, X and Y) is the AS model, proposed by Abrams and Strogatz [125]. It transforms the population conversation from using X to using Y and vice versa into differential equations (Eq. (3), the other equation can be obtained by swapping relevant components):

$$\frac{dx}{dt} = (1-x)P_{YX} - xP_{XY}, \quad \text{where } P_{YX} = cx^\lambda s \text{ and } P_{XY} = c(1-x)^\lambda(1-s) \quad (3)$$

Seen from Eq. (3), the transition in the proportion of speakers of X in the population per unit time is calculated as the proportion of speakers who convert from speaking Y to speaking X minus the proportion of speakers who convert from X to Y . These two values are calculated as the proportions of $Y(1-x)$ and $X(x)$ at time t multiplying the conversion rates P_{YX} and P_{XY} . P_{YX} (conversion rate from Y to X) is determined by the proportion of $X(x)$ (having a power relation; λ is claimed fixed across cultures) and the prestige of $X(s)$ with respect to Y . Mathematically speaking, Eq. (3) has two stable fixed points ($x = 0$ and $x = 1$), indicating that one language will eventually drive the other to extinction. Later extensions, also adopting the parameter of prestige, have incorporated additional elements into the model, such as the bilingual state and socio-cultural factors [126–129].

The beauty of the AS model and its extensions is that the competition dynamics (e.g. who will become the extinct language and how fast the extinction will proceed) is solely determined by prestige. The *prestige* of a language can be defined as the socio-economic status of the speakers of this language. Rather than explicitly estimating prestige from socio-economic factors, the AS model directly uses empirical data to tune its values in different cases. Under tuned prestige, the AS model reports well-fitted transition curves of proportions of speakers of competing languages to the historical data of English–Welsh, English–Gaelic, and other competitions.

Despite these good results, the parameter of prestige has an obscure link with actual socio-cultural conditions; prestige alone fails to address many fundamental factors that can affect language competition (e.g. population sizes of competing languages and distributions of speakers of different languages in the competing region [130–133]). Lacking such empirical foundations makes curve-fitting the only option to estimate prestige in reality, which makes these models dependent on the empirical data to be studied and restricts them from studying cases that lack sufficient data for parameter tuning. All these significantly reduce the explanatory power of these models. A more powerful model should define concrete parameters to directly address socio-cultural constraints on language competition, and use specific principles to estimate parameter values in actual cases of language competition.

3.1.2. Our language competition model

Considering the limitations of the AS model and its extensions, we propose two concrete parameters to address those socio-cultural constraints.

The first parameter is the *impact* of a language (σ), reflecting the influence of other language(s) on it (or vice versa) after it diffuses into the competing region. People are language carriers and language diffuses along with population diffusion from the centre of a language to elsewhere. Accordingly, the impact of a language is proportional to the population size of this language in the competing region.

The second parameter is the *inheritance rate* of a language (r), indicating its inheriting capacity during acquisition. In a mixed language population, a language with a high inheritance rate tends to be largely learned and used by people, whereas one with a low r is less preferred. The distribution of monolingual or bilingual speakers of different languages in the competing region affects the inheritance rate of a language.

Language competition can be viewed as a process whereby competing languages plunder speakers, which resembles species competition in biology. Language inheritance also resembles biological reproduction. Therefore, we adapt

the well-attested Lotka–Volterra competition model [134,135] in evolutionary biology to define our language competition model. This biological model also involves similar parameters of impacts and inheritance rates of competing species.

The transition functions in our language competition model are derived from the differential equations in the Lotka–Volterra competition model (Eq. (4), where n_X and n_Y are the numbers of speakers of X and Y in a region and at time t , r_X is the inheritance rate of X , N_X is the maximum monolingual population of X in this region, N_Y is the maximum monolingual population of Y , σ_X is the impact of Y on X ; the other equation can be obtained by swapping relevant components):

$$\frac{dn_X}{dt} = r_X n_X \left(1 - \frac{n_X}{N_X} - \sigma_X \frac{n_Y}{N_Y} \right) \quad (4)$$

Seen from Eq. (4), the transition in the number of speakers of X per unit time is determined by three factors: (a) $r_X n_X$, the potential number of local people who newly inherit X ; (b) $(1 - \frac{n_X}{N_X})$, the retarding effect casted by speakers of X , if a large proportion of local people already speak X , it would be hard to further increase speakers of X ; and (c) $(-\sigma_X \frac{n_Y}{N_Y})$, the retarding effect casted by speakers of Y , which concerns both the ratio of available speakers of Y among local people and the impact of Y on X (σ_X).

The competition dynamics in our model is determined by both impacts and inheritance rates of competing languages. We propose three principles to estimate the values of these critical parameters in actual cases of language competition.

We propose *the population diffusion principle* to calculate the impact of a language by estimating its population in the competing region. Generally speaking, the centre of a language has the maximum population density of this language, and this density drops along with the increase in the distance to the centre. Without geographical, social, or political constraints, people may diffuse in all directions at similar rates, and such diffusion resembles heat conduction in physics, though with distinct rates.

Noting these, the population diffusion principle adopts the Fourier's law of heat conduction to estimate population diffusion (Eq. (5), where d is the Euclidean distance between the population centre $(0, 0)$ and the competing region (x, y) , Q is the population at $(0, 0)$, and C calculates the population ratio between (x, y) and $(0, 0)$) (see [80] for derivation), and calculates the impacts of competing languages as the ratios between their populations in the competing region (Eq. (6), where d_X is the distance from (x, y) to the centre of X , d_Y is the distance from (x, y) to the centre of Y ; σ_Y is calculated by swapping relevant components).

$$C(d, t) = \frac{Q}{(4\pi)^{\frac{3}{2}}} e^{-\frac{d^2}{4}} \quad (5)$$

$$\sigma_X = \frac{Q_Y}{Q_X} e^{\frac{d_X^2 - d_Y^2}{4}} \quad (6)$$

Noting the similarity between language inheritance and biological reproduction, we adapt the Hardy–Weinberg genetic inheritance principle [136] (i.e. without disturbing influences, both allele and genotype frequencies in a population remain constant across generations) into *the language inheritance principle I*. Our language inheritance principle states that: populations speaking different languages remain constant across consecutive generations, if these populations are sufficiently large, people in the new generation sample these languages randomly, and there is no sudden change of language or selective pressure for or against any of these languages (see [80] for derivation).

Following this principle, we can estimate the occurring probabilities of competing languages from empirical questionnaires of language choices (Eq. (7), where n_X , n_{XY} , and n_Y are numbers of monolingual speakers of X , bilingual speakers, and monolingual speakers of Y , respectively, $p(XX)$, $p(XY)$, and $p(YY)$ calculate the type frequencies of X , bilinguals, and Y , respectively), and use these probabilities to calculate the inheritance rates (Eq. (8)).

$$p(XX) = \frac{n_X}{n_X + n_{XY} + n_Y}, \quad p(XY) = \frac{n_{XY}}{n_X + n_{XY} + n_Y}, \quad p(YY) = \frac{n_Y}{n_X + n_{XY} + n_Y} \quad (7)$$

$$r_X = p(X) = p(XX) + 0.5p(XY), \quad r_Y = p(Y) = p(YY) + 0.5p(XY) \quad (8)$$

As for cases lacking sufficient data of language choice, we propose *the language inheritance principle II* to estimate inheritance rate. It is inspired by the lexical diffusion dynamics [137,138], where the logistic function [139] is adopted

to describe change in population using one of the two lexical forms. As for language competition, inheritance rates of competing languages resemble the fractions of population using two lexical forms. Accordingly, we borrow the logistic function in the lexical diffusion dynamics to estimate inheritance rate (Eq. (9), where α adjusts the competition speed, since population size affects competition, we use Eq. (5) to estimate α). Then, suppose that competing languages were brought to the competing region at $t = 0$, their inheritance rates can be estimated as in Eq. (10), where ε is set to 0.1.

$$r(t) = \frac{\varepsilon e^{\alpha t}}{1 + \varepsilon(e^{\alpha t} - 1)} \quad \text{and} \quad \alpha = C = \frac{Q}{(4\pi)^{\frac{3}{2}}} e^{-\frac{d^2}{4}} \quad (9)$$

$$r_1 = r_A(1) = \frac{\varepsilon e^{\alpha_A}}{1 + \varepsilon(e^{\alpha_A} - 1)} \quad \text{and} \quad r_2 = r_B(1) = \frac{\varepsilon e^{\alpha_B}}{1 + \varepsilon(e^{\alpha_B} - 1)} \quad (10)$$

3.2. Applicability, robustness, and explanatory power of the model

We use two cases to test our model whose parameters are estimated from the three principles.

The first case is the English–Welsh competition that happened around the 20th century in Wales, UK [140]. This case, also referred to by the AS model, contains sufficient data of monolingual and bilingual populations of English and Welsh from 1901 to 2001 [141]. Following the population diffusion principle and the language inheritance principle I, we can explicitly calculate the impacts and inheritance rates of English and Welsh in 1901, and let the model predict the monolingual populations at later time points (see [80] for details). Fig. 5(a) shows that the predicted data of the model reliably replicate the historical data.

Apart from year 1901, if we choose other years as the initial time points of the model, calculate the parameters according to the data at those time points, and let the model predict the monolingual populations at later time points, we can still obtain a good match between the predicted data and the historical data (see [80] for details).

We can also use the language inheritance principle II to estimate inheritance rates. Fig. 5(b) shows that the predicted data under thus-obtained inheritance rates also reliably match the historical data. The inheritance rates calculated by these two inheritance principles are not the same, because the rates calculated by the language inheritance principle II may not match exactly the data at a particular time point. Nonetheless, the fact that the model under either set of inheritance rates can replicate the historical data reflects the consistency of these two inheritance principles.

The second case is the Mandarin–Malay competition in Singapore. There are only four data points tracing this on-going competition [142]. Both Mandarin and Malay were brought to Singapore by immigrants. When calculating their impacts, we have to consider the distance between Singapore and the centre of Mandarin and that between Singapore and the centre of Malay. We also need the population data in those centres. These data are also required in calculation of inheritance rates using the language inheritance principle II. We can obtain this relevant information from other reliable sources than this limited set of historical data, and still explicitly calculate the parameter values in this case (see [80] for details). Fig. 5(c) shows that the predicted data of our model with thus-estimated parameters still match this limited set of historical data.

If we apply the AS model to this case, several uncertainties are involved. For instance, the calculation of this model is restricted to this limited set of historical data, which cannot reflect the migration history of different speakers in Singapore. Apart from the Mandarin–Malay competition, other competitions are on-going in Singapore (e.g. English–Mandarin competition, see [80] for the study of this competition based on our model), but the AS model assumes that the whole population consists of only monolinguals of two languages. Moreover, a large proportion of Singapore people are bilingual or even trilingual and these people play important roles in language competition, but the AS model cannot address these roles. Although some extensions (e.g. [126,128]) of the AS model incorporate the bilingual state, due to the limited set of historical data, the tuned prestige values of monolinguals and bilinguals remain less reliable.

These two cases illustrate that our equation-based model has a wide scope of applicability, not limited to cases with sufficient competition data. The model is also robust, less dependent on initial conditions. Moreover, the three mathematical principles assign explicit meanings to the critical parameters of this model, make the model independent of the empirical data to be studied, and allow reasonably estimating their values in various cases of language competition. All these give the model a much better explanatory power than the AS model and its extensions.

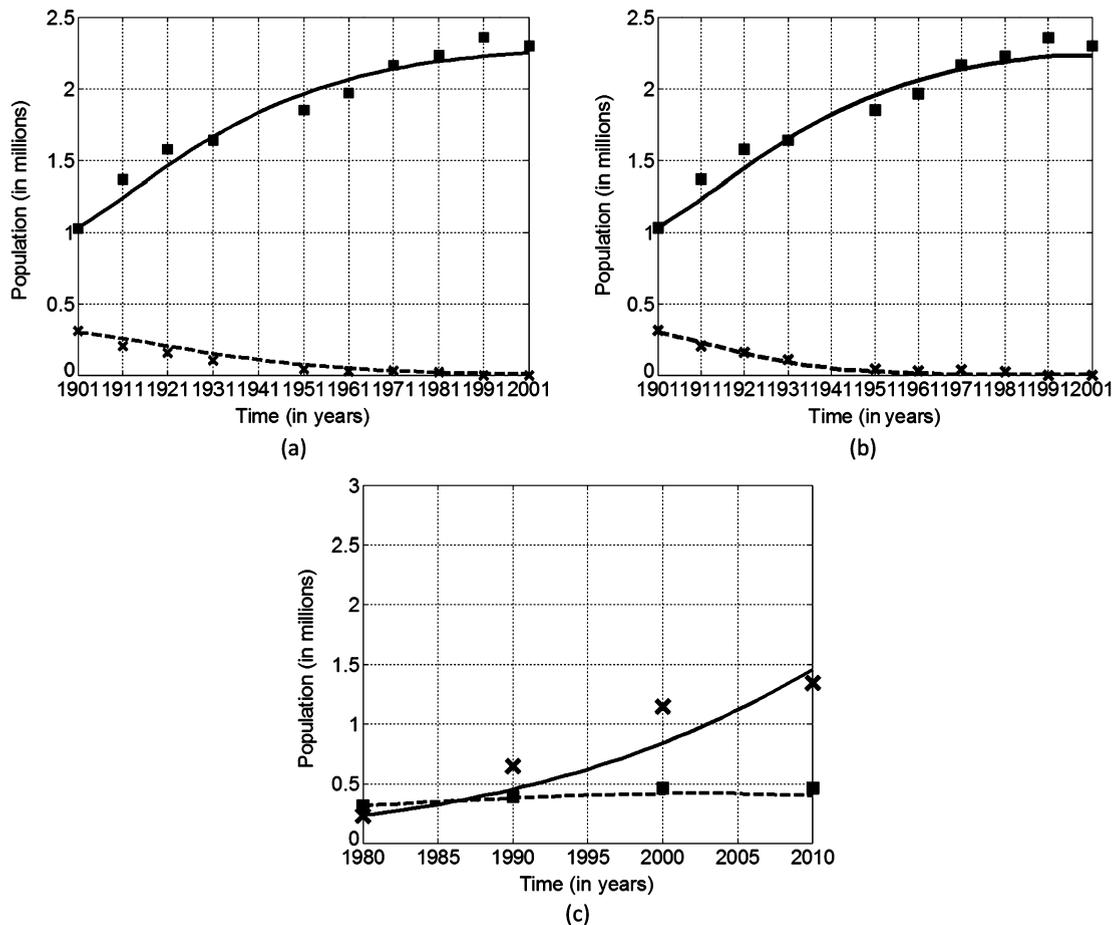


Fig. 5. These figures ((a) and (c) are extracted from [80]) illustrate that the predicted data of our language competition model match the historical data of English–Welsh (a) (b) and Mandarin–Malay (c) competitions. Predicted data are shown in solid (English or Mandarin) or dash (Welsh or Malay) lines, and historical data are shown in dots (English or Malay) or crossings (Welsh or Mandarin). Predicted data in (a) are obtained based on the inheritance rates calculated by the language inheritance principle I, and those in (b) are obtained based on the inheritance rates calculated by the language inheritance principle II.

3.3. Similarities and differences among linguistic, biological, and physical phenomena

The equation-based model and its underlying principles reveal intrinsic commonalities between language competition and biological or physical phenomena. First, competition among species resembles competition among languages (e.g. both are shown by changes in population sizes, and both proceed via plundering resources, such as members of a species or speakers of a language). Factors affecting biological dynamics also have their linguistic correspondences (e.g. inheritance rate of a species during reproduction corresponds to preference for a language during learning) and cast similar effects on linguistic dynamics.

Second, lexical diffusion and language inheritance also resemble each other (e.g. speaking a language is similar to using one type of lexical forms). Both dynamics are subject to similar constraints (e.g. the exponential factor adjusts the changing rates of lexical items and the inheritance rates of languages). The language inheritance principle II also uses the general logistic curve, also adopted in lexical diffusion dynamics and population dynamics, to estimate inheritance rate.

Third, the language diffusion principle adopts heat conduction equations to calculate population diffusion, which reveals the commonalities between molecule diffusion and population diffusion.

Apart from these cross-domain similarities, the proposed principles also highlight particular factors in language competition. For instance, the language inheritance principle I incorporates bilinguals into the calculation of language

impacts. Only in this way can the model successfully replicate the English–Welsh competition, because bilinguals in this case used to take up a sufficiently large proportion in the total population. In addition, both the population diffusion principle and the language inheritance principle II take into account the geographical distance, whose roles in language competition have been recently discovered and analysed in empirical and simulation studies [143–145].

These intrinsic similarities and critical aspects can shed important lights on our understanding of language competition and the design of future models of language competition as well as other linguistic or socio-cultural phenomena.

4. Future directions of computer modelling of language evolution

Recent theoretical and empirical research in evolutionary and general linguistics suggests that language is a *complex adaptive system* (CAS) [146,147]. For instance, language structures are formed by partially-separable components that are organized in a hierarchical way and interact closely during language processing [101]. Linguistic behaviours and language contact outcome are subject to many competing factors from individual perceptual mechanisms, linguistic experiences, and socio-cultural aspects [147].

Computer modelling serves as an efficient means to address such a CAS as language. For instance, by equipping agents with concrete mechanisms, our rule-based model evaluates whether and how these domain-general mechanisms can shape linguistic structures and affect language evolution. By quantifying correlations between language and socio-cultural factors, our equation-based model quantifies the effect of these factors on language competition. By adjusting simulated behaviours and parameter settings, our rule-based model conducts a thorough search in a much larger hypothesis space than what laboratory experiments can cover, which illustrates the possible coevolution between language and other abilities and the collective effect of cultural transmission on language evolution.

Despite these significant contributions, computer models tend to concentrate on particular aspects of language evolution and disregard other linguistic, processing, or environmental factors. For instance, our rule-based model focuses on word order regularity and neglects other grammatical structures. With the emphasis on socio-cultural factors, our equation-based model treats competing languages as monolithic wholes and ignores the components of these languages and the possible effects of these components on language competition. Such simplicity and specificity [46] make computer models only show what could happen, not necessarily what must have happened [114]. In other words, what models simulate or illustrate may not reliably reflect the reality. Therefore, additional evaluations on models are necessary, which lead to three immediate needs for future modelling studies of language evolution.

4.1. Incorporating additional experimental approaches for model evaluation

Two experimental approaches in psychology or psycholinguistics can be recruited to further evaluate simulated human behaviours and their outcomes.

The first approach is *experimental semiotics*, investigating experimentally the novel forms of human communication system [148,149]. Assuming that the origin of novel communication systems in a laboratory does not differ greatly from that in a more natural context, this approach recruits human participants and puts them in a situation where no communication systems are in place or available linguistic communications are disallowed. Then, it observes whether these participants can develop a communication system from scratch via some forms of intentional interactions [150]. By tracing the emerging process and analysing the characteristics of the emergent system, experimental semiotics can replicate the trajectory of language origin to a certain extent, and bring forth knowledge about: (a) what are the universal structural features in general communication systems; (b) how these features originate via human interactions; and (c) what are the roles of individual behaviours and socio-cultural settings in the evolution of such systems. These questions are in line with those in computer modelling studies.

Some experimental semiotics studies [151–153] show that signals in an emergent communication system must be arbitrary, easy to distinguish, and tolerable to variations. Linguistic signals possess all these characteristics. In line with explorations using computer models, some experimental studies [154,155] set up a similar iterated learning framework as in previous models [39,91], and trace the origin of compositionality in a chain of human participants. By adjusting interactions among participants, other studies discuss the effects of cultural transmission on the origin of compositionality [156]. Different socio-cultural settings in these studies can also guide the design of relevant frameworks in computer models. Apart from these studies that focus on language-like communications, another study

[157] explores how humans handle non-linguistic signals (e.g. colours or movements of items) and recruit a set of novel signals (e.g. movement patterns of items) for communicative purpose.

The second approach is *artificial language learning* [158]. It assumes that certain mechanisms are manifest in both artificial and natural language processing [159]. In a typical study, during the training phase, human participants are exposed to training utterances formed by arbitrary sounds or syllables and following specific structures as in natural languages. Then, during the subsequent testing phase, participants are asked to judge whether exposed testing utterances have the same underlying structures as in training utterances [160]. Some testing utterances are identical to the training ones, but others are novel, in terms of surface syllables and/or underlying structures.

Artificial language learning experiments have several advantages over natural language learning studies. For instance, using artificial languages allows precisely controlling the initial familiarity for exposed items [161] and generating a sufficiently large number of possible utterances to test participants' generalising ability beyond the limited input [160]. In addition, these experiments can test hypotheses on linguistic or language-like properties or structures that are hard to examine in a naturalistic condition, and help identify common properties in mechanisms that process structural regularities in linguistic and non-linguistic tasks [162–165].

By studying word segmentation [166], sequencing regularities [167], nonadjacent dependencies [168], and recursive structures [169], artificial language learning and relevant non-linguistic experiments have revitalized the research on language processing, acquisition, and evolution [158,159]. These experiments resemble rule-based models of language acquisition, though these experiments deal with real humans. Findings in these experiments are also informative to models studying specific mechanisms for particular language structures. For instance, a mismatch between the results and dynamics shown in these experiments and those shown in computer models may direct us to incorporate additional behaviours into models.

4.2. *Consolidating the empirical foundations for modelling studies of language evolution*

Comparing simulation results with empirical data is the most direct way of evaluating a computer model of language evolution. The empirical data are not limited to linguistic data, but extendable to non-linguistic data (e.g. population surveys or geographical distances), especially for discussing the effects of population, ecological or socio-cultural factors on language evolution. In addition, the available diachronic data covering a few years or centuries and synchronic data of world language characteristics also help propose general theories of language evolution and evaluate models that incorporate these theories. For instance, based on the diachronic data of language competition, our equation-based model illustrates the effects of population size and geographical distance on language competition. Based on the synchronic data of social networks, our rule-based model illustrate that the common structure formed by language-related activities can facilitate language evolution.

Modelling studies can also make use of well-established, large-scale databases in historical linguistics, typology, and psychology, such as Ethnologue [170], World Atlas of Language Structures (WALS) [171], World Colour Survey (WCS) [172], and Child Language Data Exchange Systems (CHILDES, childes.psy.cmu.edu). The abundant information contained in these databases can serve as inputs to models of language evolution or empirical observations for verifying their incorporated theories. For instance, based on Ethnologue and WALS, some models examine the effect of cultural transmission on word order bias [43] and the monogenesis of languages out of Africa [173]. Based on WCS, some models reveal the correlation between human perceptual constraint and universal colour categorization patterns in world languages [174–176]. Based on CHILDES, some models examine how children form basic linguistic categories in different languages (e.g. [177]).

4.3. *Collaboration between modelling, linguistics, and other disciplines*

Due to simplicity and specificity, computer models may not accurately predict the time spans of different evolutionary stages, reconstruct the full socio-ecological environment of early hominins, or reveal the whole story of the evolutions of different language faculty components. For instance, our rule-based model says nothing about when those domain-general mechanisms were first recruited for language processing and how long it takes for the degrees of relevant socio-cognitive abilities to reach stable levels.

Research in animal behaviours, anthropology, archaeology, neuroscience, genetics, sociology, and statistical physics helps clarify these issues. For instance, animal behaviour studies can provide knowledge about the character-

istics of animal communication systems and mechanisms involved (e.g. [18,19,101]). Archaeology and anthropology research can discover evidence about the time span of language origin (e.g. [178]) and the presence or absence of certain abilities in early hominins (e.g. [101,179,180]). Neuroscience experiments can reveal the neural bases of language-related abilities and illustrate the activation patterns between humans and other animals in linguistic and non-linguistic tasks (e.g. [181–183]). Genetic evidence can provide hints on the possibility of genetically encoding language components (e.g. [184–186]). Sociology research can collect rich information about the characteristics of social structures formed by human behaviours and the distinct ratios of cultural transmissions in different communities (e.g. [117,187]). As evident in our equation-based model and other studies (e.g. [188]), adopting well-attested theories or methods from statistical physics, evolutionary biology, population genetics, and bioinformatics into linguistics research is an efficient way to obtain better understanding of linguistic phenomena.

Just like computer models, these approaches from other disciplines also have their limitations and difficulties [14, 45,189]. For instance, uncertainty is inevitable when interpreting motivations and details of animal behaviours based on our own thoughts. Deficiency in archaeological or anthropological evidence often results in contradictory theories. Complex mappings between behaviours and genes or neural activities add difficulties in locating the genetic or neural bases of relevant behaviours behind language processing.

Noting these, we have to bring these numerous approaches together to tackle problems of language evolution. Only in this way can we obtain a biologically plausible, computationally feasible, and behaviourally adequate understanding of language evolution [45,57]. This multi-disciplinary perspective toward evolutionary linguistics has been advocated in many recent monographs (e.g. [19,101,190]). To modellers, this perspective requires paying sufficient attention to findings or approaches in other disciplines that help evaluate their models and results. To interested scholars in other fields, this perspective encourages them to contribute to evolutionary linguistics based on their expertise. To traditional linguists, this perspective appeals to exchange not only between linguists from different persuasions but also among scholars from a number of disciplines [45].

5. Conclusion

Base on two computer models of language evolution, we discuss: (a) what insights we can gain from these models and their simulation results on the evolutions of language structures, individual learning mechanisms, and relevant socio-ecological environment; and (b) how other approaches and empirical data help verify computer models and their incorporated theories of language evolution. All these call for a multi-disciplinary collaboration among modellers, linguists, and scholars from relevant disciplines, which can not only enhance the empirical foundations of computer models, but also continuously bring forth significant contributions to evolutionary linguistics.

References

- [1] Belew RK, Mitchell M, Ackley DH. Computation and the natural sciences. In: Belew RK, Mitchell M, editors. *Adaptive individuals in evolving populations: models and algorithms*. Reading, MA: Addison-Wesley Publishing; 1996. p. 431–46.
- [2] Nersessian NJ. A cognitive-historical approach to meaning in scientific theories. In: Nersessian NJ, editor. *The process of science: contemporary philosophical approaches to understanding scientific practice*. Dordrecht, the Netherlands: Martinus Nijhoff Publishers; 1987. p. 161–77.
- [3] Thagard P. Explanatory coherence. *Behav Brain Sci* 1989;12(3):435–502.
- [4] Gentner GD. Structure-mapping: a theoretical framework for analogy. *Cogn Sci* 1983;7(2):155–70.
- [5] Von Neumann J. *The theory of self-reproducing automata*. Urbana: University of Illinois Press; 1966 [edited and completed by Burks AW].
- [6] Jones M, Love BC. Bayesian fundamentalism or enlightenment? On the explanatory status and theoretical contributions of Bayesian models of cognition. *Behav Brain Sci* 2011;34(1):169–231.
- [7] Huang CR, Lenders W, editors. *Computational linguistics and beyond: perspectives at the beginning of the 21st century*. Taipei: Institute of Linguistics, Academia Sinica; 2004.
- [8] Feldman JA. *From molecule to metaphor: a neural theory of language*. Cambridge, MA: The MIT Press; 2006.
- [9] MacWhinney B, editor. *The emergence of language*. Mahwah, NJ: Lawrence Erlbaum Associates; 1999.
- [10] Stam JH. *Inquiries into the origin of language: the fate of a question*. New York: Harper & Row; 1976.
- [11] Ke JY, Holland JH. Language origin from an emergentist perspective. *Appl Linguist* 2006;27(4):691–716.
- [12] Clark EV. *First language acquisition*. Cambridge, New York: Cambridge University Press; 2003.
- [13] Hauser MD, Chomsky N, Fitch WT. The faculty of language: what is it, who has it, and how did it evolve?. *Science* 2002;298:1569–79.
- [14] Gong T, Shuai L, Wu Y. Multidisciplinary approaches in evolutionary linguistics. *Lang Sci* 2013;37:1–13.
- [15] Moscovitch M, Umiltà C. Modularity and neuropsychology: modules and central processes in attention and memory. In: Schwartz M, editor. *Modular deficits in Alzheimer-type dementia*. Cambridge, MA: The MIT Press; 1990. p. 1–59.

- [16] Fodor J. *The mind doesn't work that way: the scope and limits of computational psychology*. Cambridge, MA: The MIT Press; 2000.
- [17] Goldberg AE. *Constructions at work: the nature of generalization in language*. Oxford: Oxford University Press; 2006.
- [18] Yip MJ. The search for phonology in other species. *Trends Cogn Sci* 2006;10(10):442–6.
- [19] Hurford JR. *The origins of meaning*. Oxford: Oxford University Press; 2007.
- [20] MacNeilage PF. *The origin of speech*. Oxford: Oxford University Press; 2008.
- [21] Christiansen MH, Kirby S. Language evolution: consensus and controversies. *Trends Cogn Sci* 2003;7(7):300–7.
- [22] Steels L. The emergence and evolution of linguistic structure: from lexical to grammatical communication systems. *Connect Sci* 2005;17(3–4):213–30.
- [23] Steels L. Modelling the cultural evolution of language. *Phys Life Rev* 2011;8(4):339–56.
- [24] Chomsky N. *Knowledge of language: its nature, origin and use*. New York: Praeger; 1986.
- [25] Chomsky N. *The science of language: interviews with James McGilvray*. Cambridge: Cambridge University Press; 2012.
- [26] Pinker S, Bloom P. Natural language and natural selection. *Behav Brain Sci* 1990;13(4):707–84.
- [27] Clark A, Lappin S. *Linguistic nativism and the poverty of the stimulus*. Malden, MA: Wiley–Blackwell; 2011.
- [28] Elman J, Bates E, Johnson MH, Karmiloff-Smith A, Parisi D, Plunkett K. *Rethinking innateness: a connectionist perspective on development*. Cambridge, MA: The MIT Press; 1996.
- [29] Bates E, MacWhinney B. A functionalist approach to the acquisition of grammar. In: Ochs E, editor. *Developmental pragmatics*. New York: Academic Press; 1979. p. 167–209.
- [30] Tomasello M. *Constructing a language: a usage-based theory of language acquisition*. Cambridge, MA: Harvard University Press; 2003.
- [31] Fisher SE, Marcus GF. The eloquent ape: genes, brains and the evolution language. *Nat Rev Genet* 2005;7(1):9–19.
- [32] Wang WSY. *Explorations in language evolution*. In: Wang WSY, editor. *Explorations in language*. Seattle, WA: Pyramid Press; 1982. p. 105–31.
- [33] Christiansen MH, Chater N. Language as shaped by the brain. *Behav Brain Sci* 2008;31(5):489–509.
- [34] Frank SL, Bod R, Christiansen MH. How hierarchical is language use?. *Proc R Soc Lond B, Biol Sci* 2012;279:4522–31.
- [35] Bickerton D. *Language and species*. Chicago, IL: University of Chicago Press; 1990.
- [36] Nowak MA, Krakauer DC. The evolution of language. *Proc Natl Acad Sci* 1999;96(14):8028–33.
- [37] Niyogi P. *The computational nature of language learning and evolution*. Cambridge, MA: The MIT Press; 2006.
- [38] Dediu D, Ladd R. Linguistic tone is related to the population frequency of the adaptive haplogroups of two brain size genes, ASPM and Microcephalin. *Proc Natl Acad Sci* 2007;104(26):10944–6.
- [39] Kirby S. Function selection and innateness: the emergence of language universals. Oxford: Oxford University Press; 1999.
- [40] Croft W. Evolutionary linguistics. *Annu Rev Anthropol* 2008;37(1):219–34.
- [41] Mufwene SS. *The ecology of language evolution*. Cambridge: Cambridge University Press; 2001.
- [42] Evans N, Levinson SC. The myth of language universals: language diversity and its importance for cognitive science. *Behav Brain Sci* 2008;32(5):429–92.
- [43] Dunn M, Greenhill SJ, Levinson SC, Gray RD. Evolved structure of language shows lineage-specific trends in word-order universals. *Nature* 2011;473:79–82.
- [44] Lieberman P. *Toward an evolutionary biology of language*. Cambridge, MA: Belknap Press of Harvard University Press; 2006.
- [45] Gong T, Yang R, Zhang C, Ansaldo U. Review of the summer institute in cognitive sciences 2010: the origins of language. *Biolinguistics* 2010;4(4):385–402.
- [46] Gong T, Shuai L. Computer simulation as a scientific approach in evolutionary linguistics. *Lang Sci* 2013;40:12–23.
- [47] Cangelosi A, Parisi D, editors. *Simulating the evolution of language*. London: Springer-Verlag; 2002.
- [48] Parisi D, Mirolli M. The emergence of language: how to simulate it. In: Lyon C, Nehaniv CL, Cangelosi A, editors. *Emergence of communication and language*. London: Springer-Verlag; 2007. p. 269–85.
- [49] Jaeger H, Steels L, Baronchelli A, Briscoe T, Christiansen MH, Griffiths TL, et al. What can mathematical, computational and robotic models tell us about the origins of syntax?. In: Bickerton D, Szathmáry E, editors. *Biological foundations and origins of syntax*. Cambridge, MA: The MIT Press; 2009. p. 385–410.
- [50] Mareschal D, Thomas MSC. How computational models help explain the origins of reasoning. *IEEE Comput Intell Mag* 2006;1(3):32–40.
- [51] Wagner K, Reggia JA, Uriagereka J, Wilkinson GS. Progress in the simulation of emergent communication and language. *Adapt Behav* 2003;11(1):37–69.
- [52] Holland JH. Language acquisition as a complex adaptive system. In: Minett JW, Wang WSY, editors. *Language acquisition, change and emergence: essays in evolutionary linguistics*. Hong Kong: City University of Hong Kong Press; 2005. p. 411–36.
- [53] Briscoe T, editor. *Linguistic evolution through language acquisition: formal and computational models*. Cambridge: Cambridge University Press; 2002.
- [54] Wray A, editor. *The transition to language*. Oxford: Oxford University Press; 2002.
- [55] Christiansen MH, Kirby S, editors. *Language evolution*. Oxford: Oxford University Press; 2003.
- [56] Minett JW, Wang WSY, editors. *Language acquisition, change and emergence: essays in evolutionary linguistics*. Hong Kong: City University of Hong Kong Press; 2005.
- [57] Tallerman M, editor. *Language origins: perspectives on evolution*. Oxford: Oxford University Press; 2005.
- [58] Lyon C, Nehaniv CL, Cangelosi A, editors. *Emergence of communication and language*. London: Springer-Verlag; 2007.
- [59] Bickerton D, Szathmáry E, editors. *Biological foundations and origin of syntax*. Cambridge, MA: The MIT Press; 2009.
- [60] Steels L, editor. *Experiments in cultural language evolution*. Amsterdam: John Benjamins; 2012.
- [61] Steels L, Hild M, editors. *Language grounding in robots*. London: Springer-Verlag; 2012.
- [62] Tallerman M, Gibson KR, editors. *The Oxford handbook of language evolution*. Oxford: Oxford University Press; 2012.

- [63] Hurford JR, Studdert-Kennedy M, Knight C, editors. *Approaches to the evolution of language: social and cognitive bases*. Cambridge: Cambridge University Press; 1998.
- [64] Knight C, Studdert-Kennedy M, Hurford JR, editors. *The evolutionary emergence of language: social function and the origins of linguistic form*. Cambridge: Cambridge University Press; 2000.
- [65] Cangelosi A, Smith ADM, Smith K, editors. *The evolution of language: proceedings of the 6th international conference*. Singapore: World Scientific; 2006.
- [66] Smith ADM, Ferrer K, Cancho RS, editors. *The evolution of language: proceedings of the 7th international conference*. Singapore: World Scientific; 2008.
- [67] Smith ADM, Schouwstra M, de Boer B, Smith K, editors. *The evolution of language: proceedings of the 8th international conference*. Singapore: World Scientific; 2010.
- [68] Scott-Phillips TC, Cartmill EA, Hurford JR, editors. *The evolution of language: proceedings of the 9th international conference*. Singapore: World Scientific; 2012.
- [69] Camazine S, Deneubourg JL, Franks NR, Sneyd J, Theraulaz G, Bonabeau E, editors. *Self-organization in biological systems*. Princeton, NJ: Princeton University Press; 2001.
- [70] De Boer B. *The origins of vowel systems*. Oxford: Oxford University Press; 2001.
- [71] Oudeyer PY. *Self-organisation in the evolution of speech*. Oxford: Oxford University Press; 2006 [translated by Hurford JR].
- [72] Mesoudi A, Whiten A. The multiple roles of cultural transmission experiments in understanding human cultural evolution. *Philos Trans R Soc B* 2008;363:3489–501.
- [73] Vogt P. On the acquisition and evolution of compositional languages: sparse input and productive creativity of children. *Adapt Behav* 2005;13(4):325–46.
- [74] Baronchelli A, Felici M, Loreto V, Caglioti E, Steels L. Sharp transition towards shared vocabularies in multi-agent systems. *J Stat Mech* 2006. P06014.
- [75] Puglisi A, Baronchelli A, Loreto V. Cultural route to the emergence of linguistic categories. *Proc Natl Acad Sci* 2008;105(23):7936–40.
- [76] Perfors A. Simulated evolution of language: a review of the field. *J Artif Soc Soc Simul* 2002;5(2). Available: <http://jasss.soc.surrey.ac.uk/5/2/4.html>.
- [77] Gong T. *Computational simulation in evolutionary linguistics: a study on language emergence*. Taipei: Institute of Linguistics, Academia Sinica; 2009.
- [78] Gong T. Simulating the coevolution of compositionality and word order regularity. *Interact Stud* 2011;12(1):63–106.
- [79] Ferber J. *Multi-agent systems: an introduction to distributed artificial intelligence*. Harlow, UK: Addison-Wesley Publishing; 1998.
- [80] Zhang M, Gong T. Principles of parametric estimation in modelling language competition. *Proc Natl Acad Sci* 2013;110(24):9698–703.
- [81] Gong T, Shuai L. Modelling the coevolution of joint attention and language. *Proc R Soc Lond B, Biol Sci* 2012;279(1747):4643–51.
- [82] Gong T, Minett JW, Wang WSY. A simulation study exploring the role of cultural transmission in language evolution. *Connect Sci* 2010;22(1):69–85.
- [83] Gong T. Exploring the roles of horizontal, vertical, and oblique transmissions in language evolution. *Adapt Behav* 2010;18(3–4):356–76.
- [84] Gong T, Baronchelli A, Puglisi A, Loreto V. Exploring the roles of complex networks in linguistic categorization. *Artif Life* 2012;18(1):107–21.
- [85] Wray A. *Formulaic language and the lexicon*. New York: Cambridge University Press; 2002.
- [86] Arbib M. Holophrasis and the protolanguage spectrum. *Interact Stud* 2008;9(1):154–68.
- [87] Mellow JD. The emergence of complex syntax: a longitudinal case study of the ESL development of dependency resolution. *Lingua* 2008;118(4):499–521.
- [88] Tomasello M. *First verbs: a case study of early grammatical development*. Cambridge: Cambridge University Press; 1992.
- [89] Pine JM, Lieven EVM, Rowland CF. Comparing different models of the development of the English verb category. *Linguistics* 1998;36:807–30.
- [90] Smith ADM. Establishing communication systems without explicit meaning transference. In: Kelemen J, Sosik P, editors. *Advances in artificial life. Lecture notes in artificial intelligence*, vol. 2159. London: Springer-Verlag; 2001. p. 381–90.
- [91] Smith K, Kirby S, Brighton H. Iterative learning: a framework for the emergence of language. *Artif Life* 2003;9(4):371–86.
- [92] Esterman M, Chiu YC, Tamber-Rosenau BJ, Yantis S. Decoding cognitive control in human parietal cortex. *Proc Natl Acad Sci* 2009;106(42):17974–9.
- [93] Fillmore LW. Individual differences in second language acquisition. In: Fillmore CJ, Kempler D, Wang WSY, editors. *Individual differences in language ability and language behaviour*. New York: Academic Press; 1979. p. 203–28.
- [94] Langacker RW. *Foundations of cognitive grammar*. Stanford, CA: Stanford University Press; 1987.
- [95] Croft W. *Radical construction grammar: syntactic theory in typological perspective*. Oxford: Oxford University Press; 2001.
- [96] Givón T. *Functionalism and grammar*. Amsterdam: Benjamins; 1995.
- [97] Krifka M. Compositionality. In: Wilson RA, Keil FC, editors. *The MIT encyclopaedia of the cognitive sciences*. Cambridge, MA: The MIT Press; 2001. p. 152–7.
- [98] Gong T, Minett JW, Wang WSY. A simulation study on word order bias. *Interact Stud* 2009;10(1):51–76.
- [99] Rumelhart DE, McClelland JL. Learning the past tenses of English verbs: implicit rules or parallel distributed processing. In: MacWhinney B, editor. *Mechanisms of language acquisition*. Hillsdale, NJ: Lawrence Erlbaum Associates; 1987. p. 195–248.
- [100] Bates E, Goodman JC. On the inseparability of grammar and the lexicon: evidence from acquisition, aphasia and real-time processing. *Lang Cogn Processes* 1997;12(5–6):507–84.
- [101] Fitch WT. *The evolution of language*. Cambridge: Cambridge University Press; 2010.
- [102] Tomasello M, Carpenter M, Call J, Behne J, Moll H. Understanding and sharing intentions: the origins of cultural cognition. *Behav Brain Sci* 2005;28(5):675–91.

- [103] Mundy P, Block J, Delgado C, Pomares Y, van Hecke VA, Parlade MV. Individual differences and the development of joint attention in infancy. *Child Dev* 2007;78(3):938–54.
- [104] Bruinsma Y, Koegel RL, Koegel LK. Joint attention and children with autism: a review of the literature. *Ment Retard Dev Disabl Res Rev* 2004;10(3):169–75.
- [105] Tomasello M. Human culture in evolutionary perspective. In: Gelfand M, editor. *Advances in culture and psychology*. Oxford: Oxford University Press; 2011. p. 5–52.
- [106] Tomasello M. *Origins of human communication*. Harvard, MA: The MIT Press; 2008.
- [107] Goldin-Meadow S. What modern-day gesture can tell us about language evolution. In: Tallerman M, Gibson KR, editors. *The Oxford handbook of language evolution*. Oxford: Oxford University Press; 2012. p. 545–57.
- [108] Corballis MC. *From hand to mouth: the origins of language*. Princeton, NJ: Princeton University Press; 2002.
- [109] Deacon WT. *The symbolic species: the coevolution of language and the brain*. New York: W. W. Norton; 1997.
- [110] Laland KN, Odlin-Smee J, Myles S. How culture shaped the human genome: bring genetics and the human sciences together. *Nat Rev Genet* 2010;11:793–808.
- [111] Számádó S, Szathmáry E. Evolutionary biological foundations of the origin of language: the coevolution of language and brain. In: Tallerman M, Gibson KR, editors. *The Oxford handbook of language evolution*. Oxford: Oxford University Press; 2012. p. 157–67.
- [112] Thompson JN. *The coevolutionary process*. Chicago, IL: University of Chicago Press; 1994.
- [113] Hurford JR. *The origins of grammar*. Oxford: Oxford University Press; 2012.
- [114] Christiansen MH, Reali F, Chater N. Biological adaptations for functional features of language in the face of cultural evolution. *Hum Biol* 2011;83(2):247–59.
- [115] Cavalli-Sforza LL, Feldman M. *Cultural transmission and evolution: a quantitative approach*. Princeton, NJ: Princeton University Press; 1981.
- [116] Gong T, Shuai L. Simulating the effects of cross-generational cultural transmission on language change. In: Mehler A, Blanchard P, Job B, Banisch S, editors. *Towards a theoretical framework for analysing complex linguistic networks*. London: Springer; 2013 [in press].
- [117] Newman MEJ. The structure and function of complex networks. *SIAM Rev* 2003;45:167–256.
- [118] Barabási AL. Mean-field theory for scale-free. *Physica A* 1999;2(72):172–82.
- [119] Gong T, Shuai L. Exploring the effect of power-law social popularity on language evolution. *Artif Life* 2013 [in press].
- [120] Smaldino PE. The cultural evolution of emergent group-level traits. *Behav Brain Sci* 2013 [in press].
- [121] Shuai L, Gong T. Language as an emergent group-level trait – Commentary on Paul E. Smaldino, The cultural evolution of emergent group-level traits. *Behav Brain Sci* 2013 [in press].
- [122] Ke JY, Gong T, Wang WSY. Language change and social networks. *Commun Comput Phys* 2008;3(4):935–49.
- [123] Gong T, Minett JW, Wang WSY. Exploring social structure effect on language evolution based on a computational model. *Connect Sci* 2008;20(2–3):135–53.
- [124] Gong T, Baronchelli A, Puglisi A, Loreto V. Exploring the roles of complex networks in linguistic categorization. *Artif Life* 2012;18(1):107–21.
- [125] Abrams DM, Strogatz SH. Modelling the dynamics of language death. *Nature* 2003;424:900.
- [126] Mira J, Paredes A. Interlinguistic similarity and language death dynamics. *Europhys Lett* 2005;69:1031–4.
- [127] Stauffer D, Schulze C. Microscopic and macroscopic simulation of competition between languages. *Phys Life Rev* 2005;2:89–116.
- [128] Minett JW, Wang WSY. Modelling endangered languages: the effects of bilingualism and social structure. *Lingua* 2008;118:19–45.
- [129] Patriarca M, Castelló X, Uriarte JR, Eguíluz VM, San Miguel S. Modelling two-language competition dynamics. *Adv Complex Syst* 2012;15(3–4):1250048.
- [130] Labov W. *Principles of linguistic change: social factors*. Oxford: Basil Blackwell; 2001.
- [131] Kandler A. Demography and language competition. *Hum Biol* 2009;81(2–3):181–210.
- [132] Patriarca M, Heinsalu E. Influence of geography on language competition. *Physica A* 2009;388(2–3):174–86.
- [133] Manrubia SC, Axelsen JB, Zanette DH. Role of demographic dynamics and conflict in the population-area relationship for human languages. *PLoS ONE* 2012;7(7):e40137.
- [134] Gilpin ME, Ayala FJ. Global models of growth and competition. *Proc Natl Acad Sci* 1973;70(12):3590–3.
- [135] Lotka AJ. Contribution to the theory of periodic reaction. *J Phys Chem* 1910;14:271–4.
- [136] Hardy GH. Mendelian proportions in a mixed population. *Science* 1908;28(706):49–50.
- [137] Shen ZW. *Exploring the dynamic aspect of sound change*. Berkeley, CA: University of California Press; 1997.
- [138] Wang WSY, Minett JW. The invasion of language: emergence, change and death. *Trends Ecol Evol* 2005;20(5):263–9.
- [139] Kingsland SE. *Modelling nature: episodes in the history of population ecology*. Chicago, IL: University of Chicago Press; 1995.
- [140] Aitchison JW, Carter H. *Language, economy, and society: the changing fortunes of the Welsh language in the twentieth century*. Cardiff, UK: University of Wales Press; 2000.
- [141] Kandler A, Unger R, Steele J. Language shift, bilingualism and the future of Britain’s Celtic languages. *Philos Trans R Soc Lond B, Biol Sci* 2010;365:3855–64.
- [142] Leow BG. *Census of population 2000: education, language and religion*. Singapore: Department of Statistics; 2000.
- [143] Patriarca M, Heinsalu E. Influence of geography on language competition. *Physica A* 2009;388(2–3):174–86.
- [144] Holman EW, Schulze C, Stauffer D, Wichmann S. On the relation between structural diversity and geographical distance among languages: observations and computer simulations. *Linguist Typol* 2007;11(2):393–421.
- [145] Schulze C, Stauffer D. Competition of languages in the presence of a barrier. *Physica A* 2007;379(2):661.
- [146] Steels L. Language as a complex adaptive system. In: Schoenauer M, Deb K, Rudolph G, Yao X, Lutton E, editors. *Proceedings of the 6th international conference on parallel problem solving from nature*. Berlin: Springer-Verlag; 2000. p. 17–26.

- [147] Beckner C, Blythe R, Bybee J, Christiansen MH, Croft W, Ellis NC, et al. Language is a complex adaptive system: Position paper. *Lang Learn* 2009;59(suppl 1):1–26.
- [148] Galantucci B. Experimental semiotics: a new approach for studying communication as a form of joint action. *Top Cogn Sci* 2009;1(2):393–410.
- [149] Galantucci B, Garrod S. Experimental semiotics: a review. *Front Human Neurosci* 2012;5:article 1.
- [150] Cornish H. Investigating how cultural transmission leads to the appearance of design without a designer in human communication systems. *Interact Stud* 2010;11(1):112–37.
- [151] Galantucci B. An experimental study of the emergence of human communication systems. *Cogn Sci* 2005;29(5):737–67.
- [152] Selten R, Warglien M. The emergence of simple languages in an experimental coordination game. *Proc Natl Acad Sci* 2007;104(18):7361–6.
- [153] Healey PIU, Swoboda N, Umata I, King J. Graphical language games: interactional constraints on representational form. *Cogn Sci* 2007;31(2):285–309.
- [154] Smith K, Kirby S. Cultural evolution: implications for understanding the human language faculty and its evolution. *Philos Trans R Soc Lond B, Biol Sci* 2008;363:3591–603.
- [155] Kirby S, Cornish H, Smith K. Cumulative cultural evolution in the laboratory: an experimental approach to the origins of structure in human language. *Proc Natl Acad Sci* 2009;105(31):10681–6.
- [156] Tamariz M, Cornish H, Roberts S, Kirby S. How generation turnover and interlocutor negotiation affect language evolution. In: Scott-Phillips T, Tamariz M, Cartmill E, editors. *The evolution of language: proceedings of the 9th international conference on the evolution of language*. Singapore: World Scientific; 2012. p. 553–4.
- [157] Scott-Phillips T, Kirby S, Ritchie GRS. Signalling signalhood and the emergence of communication. *Cognition* 2010;113:226–33.
- [158] Folia V, Uddén J, de Vries M, Forkstam C, Petersson KM. Artificial language learning in adults and children. *Lang Learn* 2010;60(suppl 2):188–220.
- [159] Gómez RL, Gerken L. Infant artificial language learning and language acquisition. *Trends Cogn Sci* 2000;4(5):178–86.
- [160] Onnis L. Artificial language learning. In: Robinson P, editor. *Routledge encyclopedia of second language acquisition*. New York: Routledge; 2012. p. 35–9.
- [161] Magnuson JS. Nondeterminism, pleiotropy, and single word reading: Theoretical and practical concerns. In: Gregorenko EL, Naples AJ, editors. *Single word reading: behavioural and biological perspectives*. Mahwah, NJ: Lawrence Erlbaum Associates; 2008. p. 377–404.
- [162] Berwick R, Pietroski P, Yankama B, Chomsky N. Poverty of the stimulus revisited. *Cogn Sci* 2011;35:1207–42.
- [163] Saffran JR, Hauser MD, Seibel RL, Kapfhamer J, Tsao F, Cushman F. Grammatical pattern learning by human infants and cotton-top tamarin monkeys. *Cognition* 2008;107:479–500.
- [164] Christiansen MH, Conway CM, Onnis L. Similar neural correlates for language and sequential learning: evidence from event-related brain potentials. *Lang Cogn Processes* 2012;27(2):231–56.
- [165] Onnis L, Thiessen E. Language experience changes subsequent learning. *Cognition* 2013;126:268–84.
- [166] Pelucchi B, Hay JF, Saffran JR. Statistical learning in a natural language by 8-month-old infants. *Child Dev* 2009;80(3):674–85.
- [167] Saffran JR, Pollak SD, Seibel RL, Shkolnik A. Dog is a dog is a dog: infant rule learning is not specific to language. *Cognition* 2007;105:669–80.
- [168] Newport EL, Aslin RN. Learning at a distance: I. Statistical learning of non-adjacent dependencies. *Cogn Psychol* 2004;48:127–62.
- [169] Uddén J, Araujo S, Forkstam C, Ingvar M, Hagoort P, Petersson KM. A matter of time: implicit acquisition of recursive sequence structures. In: Taatgen NA, van Rijn H, editors. *Proceedings of the 31st annual conference of the cognitive science society*. Austin, TX: Cognitive Science Society; 2009. p. 444–9.
- [170] Grimes BF. *Ethnologue: languages of the world*. 14th edition. Dallas, TX: Summer Institute of Linguistics; 2000.
- [171] Dryer MS, Haspelmath M, editors. *The world atlas of language structures online*. Munich: Max Planck Digital Library; 2011.
- [172] Key P, Berlin B, Maffi L, Merrifield WR, Cook R. *The world colour survey*. Stanford: CSLI; 2009.
- [173] Atkinson QD. Phonemic diversity supports a serial founder effect model of language expansion from Africa. *Science* 2011;332:346–9.
- [174] Steels L, Belpaeme T. Coordinating perceptually grounded categories through language: a case study for colour. *Behav Brain Sci* 2005;28(4):469–89.
- [175] Baronchelli A, Gong T, Puglisi A, Loreto V. Modelling the emergence of universality in colour naming patterns. *Proc Natl Acad Sci* 2010;107(6):2403–7.
- [176] Loreto V, Mukherjee A, Tria F. On the origin of the hierarchy of colour names. *Proc Natl Acad Sci* 2012;109(18):6819–24.
- [177] Li P, Zhao X, MacWhinney B. Dynamic self-organization and early lexical development in children. *Cogn Sci* 2007;31:581–612.
- [178] White TD, Asfaw B, Degusta D, Gilbert H, Richards GD, Suwa G, et al. Pleistocene *Homo sapiens* from Middle Awash, Ethiopia. *Nature* 2003;423:742–7.
- [179] Clegg M. The evolution of the human vocal tract: specialized for speech?. In: Bannan N, editor. *Music, language and human evolution*. Oxford: Oxford University Press; 2012. p. 58–80.
- [180] Schoenemann PT. Syntax as an emergent characteristic of the evolution of semantic complexity. *Minds Mach* 1999;9:309–46.
- [181] Fedorenko E, Behr MK, Kanwisher N. Functional specificity for high-level linguistic processing in the human brain. *Proc Natl Acad Sci* 2011;108(39):16428–33.
- [182] Levitin DJ, Menon V. Musical structure is processed in “language” areas of the brain: a possible role for Brodmann Area 47 in temporal coherence. *NeuroImage* 2003;20(4):2142–52.
- [183] Novick JM, Trueswell JC, Thompson-Schill SL. Cognitive control and parsing: reexamining the role of Broca’s area in sentence comprehension. *Cogn Affect Behav Neurosci* 2005;5(3):263–81.
- [184] Enard W, Przeworski M, Fisher SE, Lai CS, Wiebe V, Kitano T, et al. Molecular evolution of FOXP2, a gene involved in speech and language. *Nature* 2002;418:869–72.

- [185] Dediu D, Ladd DR. Linguistic tone is related to the population frequency of the adaptive haplogroups of two brain size genes, ASPM and Microcephalin. *Proc Natl Acad Sci* 2007;104(26):10944–6.
- [186] Stromswold K. Genetics and the evolution of language: what genetic studies reveal about the evolution of language. In: Larson RK, Déprez V, Yamakido H, editors. *The evolution of human language: biolinguistic perspective*. Cambridge: Cambridge University Press; 2009. p. 176–90.
- [187] Maughan B, Golding J. Which children receive grandparental care and what effect does it have?. *J Child Psychol Psychiatry* 2008;49(2):161–9.
- [188] Levinson SC, Gray RD. Tools from evolutionary biology shed new light on the diversification of languages. *Trends Cogn Sci* 2012;16(3):167–73.
- [189] Logothetis NK. What we can do and what we cannot do with fMRI. *Nature* 2008;453:869–78.
- [190] Arbib MA. *How the brain got language: the mirror system hypothesis*. New York: Oxford University Press; 2012.



Comment

The challenges of language dynamics
Comment on “Modelling language evolution: Examples and
predictions” by Gong, Shuai, and Zhang

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The concept *language dynamics* is gaining currency and has been recognized as a field of study in its own right. There are review articles describing recent research in this domain [1–3] and even a journal dedicated to it, called *Language Dynamics and Change* (published since 2011 with Brill). Nevertheless, it is not easy to find a good definition of what exactly is covered by ‘language dynamics’. I will attempt to provide such a definition here: *The study, through observations, reconstructions or simulations, and, whenever possible, quantitative methods, of processes of emergence, change and interaction of languages at any time scale, possibly in relation to processes within or among human agents, who may pertain to specific environments.* This definition captures diverse popular areas of inquiry, such as, for instance, the interdisciplinary study of the evolution of language, historical-typological linguistics as carried out by professional linguists, and language competition—a topic most often addressed by statistical physicists. Providing such an overarching definition of a wide range of research foci contains a challenge: can they be combined?

To illustrate what this challenge means, we can take the example of preferred word orders in languages. For half a century it has been known that languages usually prefer a certain order of subject (S), verb (V), and object (O), and that, as far as the two first are concerned, there is a very strong preference for S to precede V [4]. Through the painstaking descriptive work on thousands of languages we can nowadays observe [5] that 47.1% of (a sample of) the world’s languages prefer SOV and 41.2% prefer SVO, with other orders ranging from uncommon to marginal. The preference for SOV comes out even stronger from the point of view of language families. Thus, SOV is found in 56.1% of families and SVO only in 21.7% [5]. Although more data would be needed to confirm this, it looks like SVO may be the preferred order from the point of view of the number of speakers: based on data available for 798 languages we can observe 1.8 billion SVO language speakers (365 languages, median number of speakers = 42,250) and 1.3 billion SOV language speakers (433 languages, median number of speakers = 7240). Clearly, word order falls under the purview of language dynamics. When a language evolves from scratch there must be mechanisms by which speakers converge on a certain preferred word order. But there must also be mechanisms by which SOV vs. SVO emerge as competing contenders for the dominant pattern *across* languages (with the other logically possible orders being attested but more infrequent to various degrees). Finally, models of language competition should contain

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a window on what goes on inside languages such that they can yield realistic worldwide distributions of typological features—e.g., word order—as well as predict changes in those distributions, instead of just treating speakers and languages as atomic entities.

The review paper of Tao Gong et al. [6] summarizes much of their own work. What is particularly exciting about this work is that the same author(s) try their hands at a range of topics which are within the purview of language dynamics as defined above. In other words, there is some promise here of more unification of approaches across the field—from the modelling of the first origins of language to the study and modelling of interaction among the thousands languages presently attested. My comments will concentrate on the extent to which this work exhibits tendencies towards the desired integration of approaches.

By choosing to discuss both what they call rule-based and equation-based models the authors already signal that quite different approaches can be found in different domains.

Various rule-based models have been used, among other things, to account for the emergence of language through language games, where speakers converge on a lexicon and some grammatical rules. An example from the authors' own work is the modelling of a particular word order preference through the interaction of speakers. (In their approach it is not clear why one particular order, namely SVO, tends to win, so there seems to be some way to go before results that approach the reality of the world's current languages with respect to word order preference as described above).

Equation-based models have been popular among some students of language competition since the early work of Abrams and Strogatz [7]. Although the authors' own model [8] represents a significant achievement in this area, incorporating interpretable parameters (unlike the vague 'prestige' parameter of [7], for instance) and achieving a good fit with empirical data, it still suffers from the inherent limitations of any equation-based model: it cannot be coupled with the kinds of agent-based model (a broadly encompassing term which also covers 'rule-based') that are used in the modelling of language evolution and transmission. In order to study language dynamics in its entirety, a consistency of models is desirable. For instance, just like an equation-based model, an agent-based one can describe and predict competition between languages and their outcome in terms of shifting numbers of speakers. But the latter can do much more than this. For instance, language shift is not always a 'clean affair' whereby speakers of A shift allegiance to B. In this process, especially when speakers are adult, they may retain general features of A—e.g., word order—that subsequently get adopted by B [9], which is one of the processes leading to the tendency for languages to exhibit greater similarity as the geographical distance between them decreases [10]. This kind of process has many similarities to language evolution, the main difference being that speakers do not create a language from scratch, but instead play a game involving two existing languages where one is usually a clear winner that, nevertheless, may concede some features to the loser. Such a phenomenon is most aptly described by an agent-based model, not an equation-based one.

The greatest current challenge for the study of language dynamics is a consistent approach which can provide realistic simulations of all stages of the evolution of language, from the first negotiations over form-meaning pairings as language was created, to the complex interaction among thousands of languages which we witness today.

References

- [1] Loreto V, Baronchelli A, Mukherjee A, Puglisi A, Tria F. Statistical physics of language dynamics. *J Stat Mech Theory Exp* 2011;P04006. <http://dx.doi.org/10.1088/1742-5468/2011/04/P04006>.
- [2] Wichmann S. The emerging field of language dynamics. *Lang Linguist Compass* 2008;2(3):442–55.
- [3] Schulze C, Stauffer D, Wichmann S. Birth, survival and death of languages by Monte Carlo simulation. *Commun Comput Phys* 2008;3(2):271–94.
- [4] Greenberg JH. Some universals of grammar with particular reference to the order of meaningful elements. In: Greenberg J, editor. *Universals of human language*. Cambridge, MA: MIT Press; 1963. p. 73–113.
- [5] Dryer MS. Order of subject, object, and verb. In: Haspelmath M, Dryer MS, Gil D, Comrie B, editors. *The world atlas of language structures*. Oxford: Oxford University Press; 2005. p. 330–3.
- [6] Gong T, Shuai L, Zhang M. Modelling language evolution: examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [7] Abrams DM, Strogatz SH. Modelling the dynamics of language death. *Nature* 2003;424:900.
- [8] Zhang M, Gong T. Principles of parametric estimation in modelling language competition. *Proc Natl Acad Sci USA* 2013;110(24):9698–703.
- [9] Thomason SG, Kaufman T. *Language contact, creolization, and genetic linguistics*. Berkeley: University of California Press; 1988.
- [10] Holman EW, Schulze C, Stauffer D, Wichmann S. On the relation between structural diversity and geographical distance among languages: observations and computer simulations. *Linguist Typol* 2007;11(2):395–423.



Comment

Understanding the origins of language: An interactive stance
Comment on “Modelling language evolution: Examples and
predictions” by Gong, Shuai and Zhang

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It is no exaggeration to say that “The story of language evolution underlies every other story that has ever existed and every story that ever will” [7]. Thanks to the rapid developments in computational powers and significant contributions from many other related disciplines, modern scientific research has been witnessing a surge of interest in the study of the origins of language. Evolutionary linguistics attempts to tackle many unresolved yet related questions, such as how world languages possess their distinct forms, why language is the way it is, and why only the human species possess a rich system of regularities, rules and patterns (see [2,5]).

Given that language mainly exists in two aspects, namely, in the form of idiolects and communal languages and in the form of the biological capacity for language [8], evolutionary linguistics is accordingly conducted in two lines, examining respectively both the evolution of language itself and the evolution of the biological capacity for language. What is particularly interesting about recent works in this area, as shown in Gong, Shuai and Zhang’s [3] review, is that researchers have been able to build computational models capable of capturing the dynamic process of the lexicon–syntax coevolution (a rule-based model) as well as the dynamic process of language competition (an equation-based model, e.g., [9]). More interestingly, these computer simulations enable researchers to make some predictions, such as coevolution of linguistic and nonlinguistic abilities, correlation between domain-general abilities and language-specific mechanisms, common grounds between linguistic, physical and biological phenomena, as well as social–cultural effects on language origin and change.

Computational modeling of language evolution would doubtless shed light on some highly controversial issues in modern linguistics and cognitive sciences. That said, these simulation studies are not without problems. First, researchers cannot possibly make a direct comparison between computer simulation results and existing empirical data, due to lack of direct evidence and quantitative evaluation mechanisms [4]. Hence, simulation works may merely show some possible evolutionary routes [6]. Second, since a model tends to represent restricted features in the authentic phenomenon, all simulation studies presumably capture only some of the complexities in linguistic structures, semantic–pragmatic contexts involving language users and sociocultural environments. For example, models of syntactic evolution tend to focus on a particular type of structure without considering the semantic as well as pragmatic motivations behind it. Considering that language is a communicative system, we should like to see more research

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that takes an interactive stance, that is, some simulation work should be done to characterize the subtle, complex interactions between structural, lexical and pragmatic information.

Given that language is such a complex adaptive system, the study of the origins of language is a hugely complex project, which is supposed to be carried out by interdisciplinary collaboration. This calls for more interactions between scholars in various disciplines. To get a holistic picture of how language emerges and evolves, researchers should pool knowledge from diverse disciplines to reconcile seemingly contradictory positions. Seen from this perspective, we still have a long way to go, if we want to gain a computationally feasible, biologically plausible, and behaviorally adequate understanding of language and its evolution [1,4].

References

- [1] Bickerton D, Szathmáry E, editors. *Biological foundations and origin of syntax*. Cambridge, MA: MIT Press; 2009.
- [2] Fitch WT. *The evolution of language*. Cambridge: Cambridge University Press; 2010.
- [3] Gong T, Shuai L, Zhang M. Modelling language evolution: Examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [4] Gong T, Shuai L, Wu Y. Multidisciplinary approaches in evolutionary linguistics. *Lang Sci* 2013;37:1–13.
- [5] Hauser MD, Barner D, O'Donnell T. Evolutionary linguistics: A new look at an old landscape. *Lang Learn Dev* 2007;3(2):101–32.
- [6] Hurford J. *The origins of grammar*. Oxford: Oxford University Press; 2012.
- [7] Kenneally C. *The first word: The search for the origins of language*. New York: Viking; 2007.
- [8] Steels L. The emergence and evolution of linguistic structure: From lexical to grammatical communication systems. *Connect Sci* 2005;17:213–30.
- [9] Zhang M, Gong T. Principles of parametric estimation in modeling language competition. *Proc Natl Acad Sci* 2013;110(24):9698–703.



Comment

Towards a methodology of language evolution modelling
Comment on “Modelling language evolution: Examples and
predictions” by Gong, Shuai and Zhang

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Gong et al. [1] present examples of agent- and equation-based models for investigating questions related to evolution of language. They demonstrate how to connect their models with real data: by comparing the agent-based model with real social networks and by comparing the equation-based model with real historic language data. Among other suggestions to improve computer models for language evolution, they discuss the importance of using real data to test models of language evolution.

Their work is a good example of how models can be successfully combined with real data, but the idea that it is important to combine models with real data in studying language evolution is hardly new [2,3]. The problem remains how to evaluate *how well* models fit the real data. However, there appear to be no standard methods for doing this, and in much work on language evolution (including my own older work [4]) results are evaluated by the criterion that they appear similar to the real data.

In order to make real progress in using computer models of language evolution, we do indeed need more interdisciplinary cooperation as Gong et al. argue, but we also need good methods for designing and evaluating modelling research. Foremost, we need a method that quantifies how well a prediction (made by an equation- or agent-based model) fits the real data. Some way of calculating the likelihood (using a number of assumptions about how the real data is distributed) is needed. It is an important issue *how* to calculate the likelihood, but the precise details are probably less important than the fact that we calculate the likelihood in the same way for all different models we compare.

Related to this is that we should avoid simplistic Fisher-like testing of null-hypotheses. After all, as we have built the computer system we are studying ourselves we *know* that it is different from the null-hypothesis, so running it sufficiently often with different random seeds will always result in a rejection of the null-hypothesis. Rather, we should strive for comparison of hypotheses along the lines of the Neyman–Pearson approach (e.g. [5]). In this approach we calculate the likelihood of two competing models to see which one best explains the data. This method was successfully applied to language evolution by Gray and Atkinson to compare two theories of Indo-European origins [6]. However, the method can also be used to compare a proposed model to a simple base-line model (for instance a polynomial fit with the same number of parameters). Such an approach would help quantify how “exceptional” the model’s fit to the data is.

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A good way of calculating likelihood also helps to address the problem of fine-tuning of parameters. Fine-tuning means that the data is only explained for a small range of parameter values. This will be reflected in a sharply peaked likelihood as a function of the parameters. When there is no sharp peak, it is clear that the fit is not due to fine-tuning. Of course it is possible that fine-tuning is necessary, as it may reflect fine-tuning in the real system (e.g. the human brain). In that case, it is essential to show how the parameter value is supported by real data.

Having systematic methods to quantify and evaluate model results will help make modelling results more convincing to other scientific disciplines. Improvements in methodology should therefore be the fourth future direction of modelling research, in addition to the three directions Gong et al. [1] propose.

References

- [1] Gong T, Shuai L, Zhang M. Modelling language evolution: Examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [2] Zuidema W, de Boer B. Models of language evolution: Does the math add up?. ILLC preprint series (PP-2009-49). University of Amsterdam; 2009.
- [3] de Boer B. Modelling and language evolution: Beyond fact-free science. In: McCrohon L, et al., editors. *Five approaches to language evolution*. Kyoto: Evolang Organizing Committee; 2012. p. 83–92.
- [4] de Boer B. Self organization in vowel systems. *J Phon* 2000;28:441–65.
- [5] Lehmann EL. The Fisher, Neyman–Pearson theories of testing hypotheses: one theory or two?. *J Am Stat Assoc* 1993;88:1242–9.
- [6] Gray RD, Atkinson QD. Language-tree divergence times support the Anatolian theory of Indo-European origin. *Nature* 2003;426:435–9.



Comment

Language is more a human-driven system than a semiotic system
Comment on “Modelling language evolution: Examples and
predictions” by Tao Gong, Shuai Lan, Menghan Zhang

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As the most fundamental means of human communication, language is the result of the long-term interactions between bio-cognitive, ecological, and socio-cultural factors [1,13]. The complexity of these factors and their interaction makes inquiry into language evolution an extremely difficult undertaking. As available evidence (such as historical records) is not sufficient to reconstruct a complete and continuous picture of language evolution, there is no clear knowledge regarding when and how these factors contributed to the emergence and change of language during the long history of language evolution. In recent years, computer modeling has made it possible to better understand the roles of these factors in language evolution. Computer modeling of language evolution helps to shed light on some unsolved or controversial linguistic issues and meanwhile poses new questions and challenges for traditional linguistic research [5]. The work of Gong et al. [6] is a comprehensive survey and elaboration of how to use computer modeling to deal with issues including how linguistic structure patterns are established, how human cognitive abilities and linguistic abilities coevolve, and how socio-cultural factors affect the origin and change of language.

From the point of view of modern linguistics, language is a semiotic system. However, language is a system whose evolution is human-driven rather than simply an abstract semiotic system. This requires that computer modeling of language evolution should, as far as possible, take into account human factors, especially the constraints of human cognitive abilities on the emergence and change of linguistic structure patterns. The Lexicon-Syntax Coevolution Model introduced in Gong et al. [6] simulates how particular dominant word orders of human language arise. This simulation process underlines the view of language as shaped by communication and deepens our understanding of the dominant word orders of human language. This also gives us good reasons to believe that language is a result of the equilibrium reached by the speaker's and the listener's cognitive effort during the achievement of successful information exchange [8,12]. In other words, dominant word orders may also reflect the constraints of human cognitive mechanisms on word orders [2–4]. Considering the human language parser's preference for minimal average dependency distance of sentences [9,10], the SVO word order, with the minimal dependency distance, is more likely to become a dominant word order of human language from the perspective of human cognition. However, it is insufficient to merely consider the principle of minimal dependency distance. For instance, this principle alone can not explain why few languages use the OVS word order. So why is SVO instead of OVS a dominant word order of human language? If computer modeling can better incorporate relevant findings in cognitive science and linguistics, does that

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mean that we can not only learn the specific process of language evolution but also obtain a deeper understanding of the underlying mechanisms?

As language is also a complex adaptive system, in constructing computer modeling systems we need to consider not only the individual elements but also their synergetic relations [8,11,12]. For instance, in constructing a syntax-related computer modeling system, with the minimization or equilibrium of the speaker's and the listener's cognitive effort as a basic prerequisite, we need to consider the relations and interactions between such factors as frequency, length, complexity, valency, position, depth of embedding, and information of syntactic constructions, the inventory of syntactic constructions, the inventory of syntactic functions, and the inventory of syntactic categories [8,11]. In the same way, when dealing with language competition [6], we also need to consider more factors. This is because the evolution of a language also needs to be investigated in its ecological environment, whereby the deliberate human effort to change its course of evolution is a factor that especially needs our attention [7].

We notice that Gong et al. [6] also outlines the future directions of computer modeling of language evolution: evaluation of simulation results with experiments, consolidation of the empirical foundations for modeling studies of language evolution, and enhancement of collaboration with relevant disciplines. We suggest that computer modeling of language evolution, based on its current achievements, treat language as a human-driven system by incorporating human factors (e.g., human cognition) and meanwhile consider the synergetic relations between the parameters selected for the modeling. With these improvements, this new approach will make a more substantial contribution to language evolution research.

References

- [1] Arbib MA. *How the brain got language: the mirror system hypothesis*. New York: Oxford University Press; 2012.
- [2] Ferrer-i-Cancho R. Some word order biases from limited brain resources. *A mathematical approach*. *Adv Complex Syst* 2008;11(3):393–414.
- [3] Ferrer-i-Cancho R. The placement of the head that minimizes online memory: a complex systems approach. <http://arxiv.org/abs/1309.1939>, 2013.
- [4] Gibson E, Pearlmutter NJ. Constraints on sentence comprehension. *Trends Cogn Sci* 1998;2:262–8.
- [5] Gong T. *Computational simulation in evolutionary linguistics: a study on language emergence*. Taipei: Institute of Linguistics, Academia Sinica; 2009.
- [6] Gong T, Shuai L, Zhang M. Modelling language evolution: Examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [7] Kaplan RB, Baldauf RB. *Language planning from practice to theory*. Clevedon: Multilingual Matters Ltd; 1997.
- [8] Köhler R. *Quantitative syntax analysis*. Berlin & Boston: Mouton de Gruyter; 2012.
- [9] Liu H. Probability distribution of dependency distance. *Glottometrics* 2007;15:1–12.
- [10] Liu H. Dependency distance as a metric of language comprehension difficulty. *J Cogn Sci* 2008;9(2):159–91.
- [11] Liu H. Quantitative properties of English verb valency. *J Quant Linguist* 2011;18(3):207–33.
- [12] Liu H, Huang W. Quantitative linguistics: state of the art, theories and methods. *J Zhejiang Univ (Humanit Social Sci)* 2012;43(2):178–92.
- [13] Steels L. Modeling the cultural evolution of language. *Phys Life Rev* 2011;8(4):339–56.



Comment

Language games: Comment on “Modelling language evolution: Examples and predictions” by Tao Gong, Lan Shuai, Menghan Zhang

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The debate on language origin and evolution has benefited from a largely interdisciplinary effort, involving linguists, anthropologists, sociologists as well as physicists, mathematicians and computer scientists. A fundamental question is whether a shared communication system can emerge from repeated interactions among individuals, not relying on any a priori or innate language-specific structure. Modeling, and in particular language games, proved to be a powerful tool to gain insight on this beautiful mystery. In particular, fruitful investigations have been done concerning the possibility for a population of individuals to exploit local communication acts to build up a shared vocabulary [1] or a system of linguistic categories reproducing the universality and the hierarchies observed in anthropological data [2–4]. A particular effort has been also devoted to the origin of the complex organization of syntax in hierarchical structures, one of the core design features of human language. As Gong and coauthors highlighted in this review [5], a combinatorial and compositional structure can emerge out of a holistic language due to communication purposes, and explaining how this could possibly happen still represents an intriguing challenge [6–11]. It is important to remark how theoretical investigations should be, and are more and more, paralleled by a growing attention to a careful comparison with data on language formation. Different kind of data can be exploited to shed light on different questions. Diachronic and historical data related to migration patterns have been used for instance to study the timescales of language evolution. Anthropological studies on pre-industrialized populations [12,13] have been crucial in the understanding language universals. At the same times, experiments in cognitive science helped in shading light on the mechanisms emerging when individuals are called to perform communicative tasks [14]. It is worth mentioning in this perspective how advances in information and communication technologies allow nowadays the realization of focused experiments also in the framework of the emergence of linguistic structures exploiting the huge basin of web users. In particular, a general trend is emerging for the adoption of web-games as a very interesting laboratory to run experiments in the social-sciences and whenever the contribution of human beings is crucially required for research purposes. This is opening tremendous opportunities to monitor the emergence of specific linguistic features and their co-evolution with the structure of our conceptual spaces.

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References

- [1] Baronchelli A, Felici M, Loreto V, Caglioti E, Steels L. Sharp transition towards shared vocabularies in multi-agent systems. *J Stat Mech Theory Exp* 2006;2006(06):P06014.
- [2] Puglisi A, Baronchelli A, Loreto V. Cultural route to the emergence of linguistic categories. *Proc Natl Acad Sci USA* 2008;105(23):7936.
- [3] Baronchelli A, Gong T, Puglisi A, Loreto V. Modeling the emergence of universality in color naming patterns. *Proc Natl Acad Sci USA* 2010;107(6):2403.
- [4] Loreto V, Mukherjee A, Tria F. On the origin of the hierarchy of color names. *Proc Natl Acad Sci USA* 2012;109(18):6819–24.
- [5] Gong T, Shuai L, Zhang M. Modelling language evolution: Examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [6] Brighton H. Compositional syntax from cultural transmission. *Artif Life* 2002;8(1):25–54.
- [7] Smith K, Brighton H, Kirby S. Complex systems in language evolution: the cultural emergence of compositional structure. *Adv Complex Syst* 2003;6(4):537–58.
- [8] Vogt P. The emergence of compositional structures in perceptually grounded language games. *Artif Intell* 2005;167(1–2):206–42.
- [9] Beule JD, Bergen BK. On the emergence of compositionality. In: *Proceedings of the 6th international conference on the evolution of language*. 2006. p. 35–42.
- [10] Gong T, Minett JW, Wang WS-Y. Computational simulation on the co-evolution of compositionality and regularity. In: *Proceedings of the 6th international conference on the evolution of language*. 2006. p. 99–106.
- [11] Tria F, Galantucci B, V L. Naming a structured world: a cultural route to duality of patterning. *PLoS ONE* 2012;7(6):e37744. <http://dx.doi.org/10.1371/journal.pone.0037744>.
- [12] Berlin B, Kay P. *Basic color terms*. Berkeley: University of California Press; 1969.
- [13] Cook R, Kay P, Regier T. *The World Color Survey database: history and use*. In: *Handbook of categorisation in the cognitive sciences*. Amsterdam and London: Elsevier; 2005.
- [14] Galantucci B, Kroos C, Rhodes T. The effects of rapidity of fading on communication systems. *Interact Stud* 2010;11(1):100–11.



Comment

Grounding models in empirical data of language socialisation
Comment on “Modelling language evolution:
Examples and predictions” by Gong, Shuai and Zhang

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Increasingly more support is found for viewing language as a complex dynamical adaptive system, not only from modelling work, but also from other disciplines such as linguistics [4]. The studies reviewed by Gong, Shuai and Zhang [1] provide prominent examples of models to investigate the validity of this view. These models yield interesting predictions, but the challenge remains how to verify predictions generated by models of language evolution.

Some predictions may be ‘verified’ using experiments [3], but experiments merely yield new predictions that require further verification in natural observations. A more effective approach would be to compare the predictions directly to empirical data of such observations, as suggested by Gong et al. [1]. However, the dynamics of models strongly depend on the setting of parameters, such as the ability to use joint attention, the population size, social network structure, or mode of transmission. A comparison with empirical data would therefore only be reliable if such parameters are grounded in empirical data [7].

When modelling the origins of language, it is not only important to ground the model in empirical data, but also to select these data with care. It is attractive to use data obtained from studies carried out among Western middle-class communities, because these are most readily available. However, Western middle-class communities have emerged only recently in evolutionary history, bringing about novel practices in children’s language socialisation [2], which could have a strong impact on the ways languages are evolving.

When looking at children’s language socialisation in a non-Western rural society, such as Mozambique, one can observe children growing up in large extended families, where they are raised by multiple caregivers (including siblings) who focus more on stimulating the development of communal responsibilities and action autonomy than language development [5]. These cultural practices may, for instance, weaken the importance of joint attention in language evolution and may yield a different transmission dynamics. Therefore, future models of language evolution should be grounded in naturally observed phenomena, such as the Nicaraguan Sign Language case [6] or using corpora like those being developed concerning natural observations of language socialisation from various cultures, including non-Western cultures [7].

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References

- [1] Gong T, Shuai L, Zhang M. Modelling language evolution: Examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [2] Greenfield PM. Linking social change and developmental change: shifting pathways of human development. *Dev Psychol* 2009;45(2):401.
- [3] Kirby S, Cornish H, Smith K. Cumulative cultural evolution in the laboratory: An experimental approach to the origins of structure in human language. *Proc Natl Acad Sci USA* 2008;105(31):10681–6.
- [4] Lupyán G, Dale R. Language structure is partly determined by social structure. *PLoS ONE* 2010;5(1):e8559.
- [5] Mastin JD., Vogt P. Exploring correlations between infant engagement levels and vocabulary development: An observational study of Mozambican infants from 1:1 to 2:1, 2014. Forthcoming.
- [6] Richie R, Yang C, Coppola M. Modeling the emergence of lexicons in homesign systems. In: *Proceedings of the 35th annual Cognitive Science Society conference*. Berlin, Germany. 2013.
- [7] Vogt P, Douglas Mastin J. Anchoring social symbol grounding in children’s interactions. *Künstl Intell* 2013;27:145–51.



Comment

Models – simple but not simpler
Comment on “Modelling language evolution: Examples and
predictions” by Tao Gong et al.

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Einstein famously said: “Make things as simple as possible, *but not simpler.*” Knowing exactly where to stop along the path of simplification, however, is a fundamental challenge in doing good science. The idiom: “The devil is in the detail” puts the emphasis at the other end of the path. The challenge is especially acute for the modeler, whose basic strategy is to strip away as much detail as possible in the hope of finding some answers to a complex issue in the virtual world of computer simulation. Language evolution in the real world is certainly as complex an issue as there is in science.

In an illuminating paper on evolution [3], Nobel Laureate François Jacob wrote that, “*Living organisms are historical structures, literally creations of history. They represent not a perfect product of engineering, but a patchwork of odd sets pieced together when and where opportunities arose.*” Languages, too, are historical structures, constantly changing their patchwork of odd sets, be they speech sounds, words, or constructions, as these odd sets get learned anew from generation to generation, and as they are transmitted from one language to another.

However, tracing back to Ferdinand de Saussure, and especially since Chomsky [1], there has been a serious misperception that language is like a perfect product of engineering, a homogeneous whole that is hermetically sealed from the surrounding biological and cultural worlds. Such a sterile outlook crossed the line that Einstein cautioned us against. Lieberman [4] and Wang [5], among many others, have provided trenchant critiques of this misperception.

In recent years, however, the tide has changed, and linguistic inquiry has replanted itself in the rich soil of biological and cultural co-evolution. As can be seen in this valuable overview by Gong et al. [2], modelers are now centrally concerned with how language interacts with general cognitive abilities on the one hand, and how social forces may channel the dynamics of how languages structure and change.

One may disagree with the authors on some points, such as the typology they propose for models, i.e., rule-based versus equation-based. This distinction seems more like one of granularity rather than of type; quantitative changes may become qualitative ones; e.g., a sound change is quantitative when it is diffusing across applicable words and becomes qualitative when it has completed its course of diffusion; see Wang et al. [6].

Nonetheless, their presentation of the landscape of language evolution models is balanced and fair. The examples they chose for illustration – on how global syntax may emerge from local constructions, and on modeling language

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competition (with a new case of Mandarin and Malay) – are well chosen and instructive. All in all, the review gives a good picture of how one leading edge of modern linguistics is advancing.

References

- [1] Chomsky N. Three models for the description of language. *IRE Trans Inf Theory* 1956;2:113–24.
- [2] Gong T, Shuai L, Zhang M. Modelling language evolution: examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [3] Jacob F. Evolution and tinkering. *Science* 1977;196:1161–6.
- [4] Lieberman P. The pied piper of Cambridge. *Linguist Rev* 2005;22:289–301.
- [5] Wang WSY. Phase transitions in language evolution. *Journal of Chinese linguistics monographs*, vol. 26. 2014.
- [6] Wang WSY, Ke JY, Minett JW. Computational studies of language evolution. In: Huang CR, Lenders W, editors. *Computational linguistics and beyond*. Taipei: Academia Sinica, Institute of Linguistics; 2004. p. 65–108.



Comment

Modeling is a tool, and data are crucial
A comment on “Modelling language evolution: Examples and
predictions” by Tao Gong et al.

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“Evolutionary linguistics did not escape the invasion of computer modeling” Tao, Lan and Zhang affirm correctly. In fact, examples are today so numerous that they prefer to offer a detailed analysis of two models rather than a systematic review of the vast literature – a very reasonable approach to illustrate the predictive power of modeling, be it based on equations or multi-agent systems (even though in some lucky case the latter can be understood analytically, too).

A first merit of the paper by Tao and coworkers consists in stressing that modeling is a tool for, and not a subfield of, Language Evolution. Indeed, the subfield misinterpretation has longly plagued research on the origins of language, denouncing a suspect towards the power of models that other disciplines abandoned a long time ago (in this respect, see for instance the “Modeling” session at the “Evolution of Language” – Evolang conferences). Modeling helps to verify hypotheses, showing for example which minimal ingredients are sufficient to account for the emergence of certain language properties. In this respect, simple models have provided important insights into such problems as the emergence of compositionality [1], the possible genetic basis for human language [2,3], and the categorization of color [4]. However, models can also inform new experiments by identifying possible mechanisms or features responsible for the observed phenomena. Thus, for example, the possible biological responsible for the universality observed in color naming patterns across cultures, namely the Just Noticeable Difference relative to hue perception in humans, has been pointed out by computer simulations [5] and lately indirectly confirmed in experiments on the influence of the two cone-opponent channels in the retinogeniculate pathway [6]. Of course, this evidence does not close the debate on color naming universals, but it helps to substantiate the debate around the role of a concrete biological source of universality that, together with the randomness introduced by cultural evolution, provides a quantitative interpretation to the existing data [7].

The second interesting point raised by the paper is the need for (comparisons with) data. Models certainly help identify which points of a theory are superfluous, or test whether proposed mechanisms are viable, but where they radically change the game is in their ability to interpret existing data in a compact way, and to predict new phenomena. Such approaches as experimental semiotics on the one hand and the analyses of existing databases on the other are certainly fundamental in substantiating models (and henceforth theories) of language evolution, and models contribute by raising new questions and suggesting new directions for data production or collection. Here examples are still

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limited (see the above mentioned case of color naming universals, as an example), but their number is growing and in the future the dialogue between modelers and experimentalists (or data collectors) will certainly become routinary.

References

- [1] Smith K, Brighton H, Kirby S. Complex systems in language evolution: the cultural emergence of compositional structure. *Adv Complex Syst* 2003;6:537.
- [2] Chater N, Reali F, Christiansen MH. Restrictions on biological adaptation in language evolution. *Proc Natl Acad Sci USA* 2009;106:1015.
- [3] Baronchelli A, Chater N, Pastor-Satorras R, Christiansen MH. The biological origin of linguistic diversity. *PLoS ONE* 2012;7:e48029.
- [4] Puglisi A, Baronchelli A, Loreto V. Cultural route to the emergence of linguistic categories. *Proc Natl Acad Sci USA* 2008;105:7936.
- [5] Baronchelli A, Gong T, Puglisi A, Loreto V. Modeling the emergence of universality in color naming patterns. *Proc Natl Acad Sci USA* 2010;107:2403.
- [6] Xiao Y, Kavanau C, Bertin L. The biological basis of a universal constraint on color naming: cone contrasts and the two-way categorization of colors. *PLoS ONE* 2011;6:e24994.
- [7] Baronchelli A, Loreto V, Puglisi A. Cognitive biases and language universals. Preprint, arXiv:1310.7782, 2013.



Comment

Power law, is it a fundamental law of cultural organization?
Comment on “Modelling language evolution: Examples and
predictions” by Tao Gong, Lan Shuai, Menghan Zhang

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In the target article [1] T. Gong and co-authors have noticed that a successful evolution of languages requires a condition of power-law distribution of agent's popularity or influence in a society (the probability for an agent of rank r to communicate with other agents is proportional to $r^{-\lambda}$). It might be more accurate to call the power law a self-organizing property. Possibly every successfully emerging and growing system exhibits power law. For example, connectivity of WWW sites follows power law [2] (power law is equivalent to a scale free property: at every scale the same pattern of connectivity is reproduced). I would emphasize that WWW emerged in recent decades, it grows fast, and its power-law property is self-organized.

The power-law distribution holds in many situations. Often it is called Zipf's law [3]. G.K. Zipf noticed that frequency of the word usage in many languages follows the power law. The power law also applies to many cultural objects, e.g. distribution of city populations [4]. Recent studies reviewing more than 500 estimates indicated that the power law widely holds [5,6]. A review of ubiquity of power laws can be found in [7]. One theoretical way to explain power law is to consider new entities emerging by splitting from older entities [8], which is a natural case for WWW cites, words in languages, and cities. Power law distribution of WWW connectivity [2] is explained by a closely related rule of preferential attachment, or “rich get richer.”

I would ask if successfully evolving social systems and possibly all human values to remain valuable and evolving must be distributed according to power law. In other words, evolving systems must be power-law hierarchical. Let me mention two examples: successfully evolving languages (languages increasing in the number of words) exhibit power law (Zipf's) in their word ranks. On the opposite, shrinking systems, such as diversity of human languages do not follow power law. The plot of language rank vs. the number of its speakers exhibit a sudden drop of languages from the power-law line below a certain number of language speakers [9].

In this comment I would like to emphasize that the target article possibly has indicated a new social law: successful evolution requires a power law.

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References

- [1] Gong T, Shuai L, Zhang M. Modelling language evolution: examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [2] Barabási A-L, Albert R. Emergence of scaling in random networks. *Science* 1999;286(543):509–12.
- [3] Zipf GK. *The psychobiology of language*. Boston (MA): Houghton–Mifflin; 1935.
- [4] Auerbach F. Das Gesetz der Bevolkerungskonzentration. *Petermanns Geogr Mitt* 1913;59(1):74–6.
- [5] Volker N. Zipf zipped. *Economics* 2004;2004(6).
- [6] Soo KT. Zipf’s law for cities: a cross country investigation. London School of Economics paper 641. [http://eprints.lse.ac.uk/19947/1/Zipf’s_Law_for_Cities_A_Cross_Country_Investigation.pdf](http://eprints.lse.ac.uk/19947/1/Zipf%27s_Law_for_Cities_A_Cross_Country_Investigation.pdf).
- [7] Newman MEJ. Power laws, Pareto distributions and Zipf’s law. *Contemp Phys* 2005;46(5):323–51.
- [8] Levitin LB, Schapiro B, Perlovsky LI. Zipf’s law revisited: evolutionary model of emergent multiresolution classification. In: *Proceedings of the conference on intelligent systems and semiotics ’96*, vol. 1. Gaithersburg (MD). 1996. p. 65–70.
- [9] Tuncay Ç. The physics of randomness and regularities for languages in terms of random matrices. *Europhys Lett* 2008;82(2). <http://dx.doi.org/10.1209/0295-5075/82/20004>.



Comment

On the expressiveness, validity and reproducibility of models of language evolution

Comment on “Modelling language evolution: Examples and predictions” by Tao Gong, Shuai Lan, and Menghan Zhang

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1. Introduction

Simulation models of language evolution (SMoLE) as reviewed by Gong et al. [1] span a very promising field of research. They contribute substantially to a paradigmatic shift from synchronic to diachronic linguistics. Computer simulations also give access to systems whose dynamics is otherwise non-accessible or for which empirical data is out of reach. Simulation modelling may further help to bridge the gap between yet unrelated, though equally promising fields of research such as *experimental semiotics* [2], *robotic experiments* [3] and *theories of grounding* [4]. All of this is excellently reviewed and exemplified by Gong et al. [1]. In spite of this and related success stories, simulation models raise questions about their expressiveness, validity and reproducibility whose answers may foster future research in this area.

2. Complexity

A general objection against SMoLEs is that what they learn (e.g., a context-free grammar), is determined by what they are endowed with by the modeller. Obviously, a more expressive SMoLE is one in which what is endowed (i.e., its input) is of a lower complexity than what emerges from running the simulation (i.e., its output). *But how big is the gap between input and output exactly and how to qualify this gap in terms of which notion of complexity?* For simplicity reasons, we may use the Chomsky hierarchy to assess this complexity – of course, semantics and pragmatics require more elaborated notions of complexity. From this point of view, we may question, for example, the expressiveness of a SMoLE that is endowed with a type-2 grammar (of predicate–argument structures) to observe the emergence of a homomorphism that provides compositionality by mapping to a second type-2 grammar (of syntactic structures). Further, we may ask about the exact increase in complexity if the SMoLE additionally starts from a probabilistic

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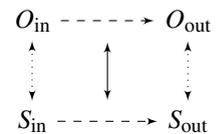
variant of the input grammar or considers optimality-theoretic elements. Answering questions of this sort – *about what can be learnt by a given SMoLE* – should always be part of the specification of a SMoLE – by analogy to proofing the time and space complexity as an integral part of algorithmic specifications. In my view, we lack a formal foundation that allows for systematically assessing what is learnable by a SMoLE in this sense. If this is true, SMoLEs are to date hardly comparable in terms of their complexity.

3. From compositionality to contextuality

Gong et al. [1] describe simulations of an emergent compositional semantics. This is a hot topic in research on language evolution [5] as it bypasses descriptive approaches, which dominated linguistics a long time. However, it also reflects a limited view on natural language semantics. The reason is that it neglects borderline cases of compositionality [6] and especially semantic contextuality as exemplified by metaphors [7]. Generally speaking, the meaning of a complex term is said to be *compositional*, if can be modelled as “a function of the meaning of its parts and of the syntactic rule by which they are combined” [8, p. 427]. Conversely, we speak of a *contextual semantics*, if the meaning of a term cannot be reduced in the latter sense but has to be modelled as a *relation* of its linguistic meaning and the contexts of its use [9]. Although compositionality is truly a core principle of semantics [8], it is questionable that it covers the majority of natural language predicates [10]. Once more, we need a *complexity hierarchy* along which the semantic expressiveness of a simulation model can be assessed to make it fully comparable – see Lücking and Mehler [11] for a proposal of such a hierarchy. Finally, we need to think about simulations of semantic *contextuality* embedded into experiments with artificial dialogue companions [12] in order to reach a full-fledged discourse semantics comprising compositionality *and* contextuality.

4. On the validity of SMoLEs

Insofar the states (S_{out}) entered by a SMoLE when running as a simulation can be related to what is independently known about the simulated system, explanatory power may be ascribed to it abductively. As a consequence of this abduction, by systematically varying the input (S_{in}) of the SMoLE one may be tempted to interpret its output as predicting/retrodicting states (O_{out}) of the simulated system. This reasoning – which seems to be common to many simulation models – assumes a sort of commuting diagram that relates both input and output of the simulating and the simulated system



in the sense that the simulative mapping $S_{in} \mapsto S_{out}$ is seen as a model of the mapping $O_{in} \mapsto O_{out}$. Obviously, this implies a triadic representational function of input, output and their procedural relation modelled by the SMoLE so that we get at least three reference points of its validity – each of which needs to be carefully considered in order to provide overall validity. It is a merit of Gong et al. [1] that they hint at this problem, which is somehow connected to the problem of spurious correlations as recently stated by Roberts and Winters [13] in a related context. In terms of simulation modelling: by observing a correlation between the output states of a SMoLE and some states of the simulated system, we cannot be sure about the validity of the above abduction. In order to tackle problems of this sort, we need to implement SMoLEs rather as *procedural* measurement devices subject to a theory of their validity that clarifies this triadic representational function. Doing this may help raising the acceptability of simulation modelling even in linguistics – seemingly, this is still a big issue. Once more, I doubt that such a theory of the validity of SMoLEs already exists. If this is true, we shall hesitate before believing in the explanatory power of SMoLEs with respect to the dynamics of linguistic systems.

5. Reproducible research

Gong et al. [1] plead for consolidating the empirical basis of SMoLEs to master problems of data sparseness and systematicity. I believe that we shall foster this discussion in the context of *reproducible research* [14]. That is, as a *computational science*, research on language evolution should provide both data *and* code to make its findings fully reproducible. To date, we lack a requirements analysis that reflects the specifics of the reproducibility of this research (e.g., concerning the sparsity of longitudinal historical data, parameter sets concerning social networks, etc.).

However, providing reproducibility may help raising the acceptability of this research among computational scientists and linguists, by providing sharable testbeds for testing the validity of SMOLEs.

6. Summary

SMOLEs still raise serious questions about their expressiveness, validity and reproducibility. Answering these questions will have a great impact on establishing SMOLEs as a paradigm in linguistics from a methodological point of view.

References

- [1] Gong T, Shuai L, Zhang M. Modelling language evolution: examples and predictions. *Phys Life Rev* 2014;11(2):280–302 [in this issue].
- [2] Galantucci B, Garrod S. Experimental semiotics: a review. *Front Human Neurosci* 2011;5:1–15.
- [3] Steels L. Modeling the cultural evolution of language. *Phys Life Rev* 2011;8(4):339–56. <http://dx.doi.org/10.1016/j.plrev.2011.10.014>.
- [4] Ziemke T. Rethinking grounding. In: Riegler A, Peschl M, Stein A, editors. *Understanding representation in the cognitive sciences*. 2000. p. 177–90.
- [5] Vogt P. The emergence of compositional structures in perceptually grounded language games. *Artif Intell* 2005;167(1–2):206–42.
- [6] Kamp H, Partee B. Prototype theory and compositionality. *Cognition* 1995;57(2):129–91.
- [7] Lakoff G. *Women, fire, and dangerous things: what categories reveal about the mind*. Chicago: University of Chicago Press; 1987.
- [8] Janssen TMV. Compositionality [with an appendix by Barbara H. Partee]. In: van Benthem J, ter Meulen A, editors. *Handbook of logic and language*. Amsterdam: Elsevier; 1997. p. 417–73.
- [9] Barwise J, Perry J. *Situations and attitudes*. Cambridge: MIT Press; 1983.
- [10] Lücking A, Mehler A. What's the score of the naming game? Constraints on semantic categorization. In: *Proceedings of Evolang IX*. Kyoto, Japan. 2012. p. 196–203.
- [11] Lücking A, Mehler A. A model of complexity levels of meaning constitution in simulation models of language evolution. *Int J Signs Semiot Syst* 2011;1(1):18–38.
- [12] Lücking A, Mehler A. On three notions of grounding of artificial dialog companions. *Sci Technol Innov Stud* 2013;10(1):31–6.
- [13] Roberts S, Winters J. Linguistic diversity and traffic accidents: lessons from statistical studies of cultural traits. *PLoS ONE* 2013;8(8):1–13.
- [14] Stodden V, Donoho D, Formel S, Friedlander MP, Gerstein M, LeVeque R, et al. Reproducible research: addressing the need for data and code sharing in computational science. *Comput Sci Eng* 2010;12(5):8–13. <http://dx.doi.org/10.1109/MCSE.2010.113>.

Reply to comment

Key issues for the prosperity of modelling research of language evolution

Reply to comments on “Modelling language evolution: Examples and predictions”

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Keywords: Evolutionary linguistics; Computer modelling; Complex adaptive system

We are grateful to all commentators for their thought-provoking commentaries from a diversity of expertise spanning from linguistics, psychology, statistical physics, and computer science. In this reply, based on the commentaries and our research experiences, we would like to stress several key issues on computer modelling of language evolution in socio-cultural communities:

- (a) Design principles of language evolution models;
- (b) Interdisciplinary components that may potentially influence language evolution;
- (c) Systematic comparison of simulation results with empirical data;
- (d) Modelling neural connectivity underlying linguistic and general cognitive functions;
- (e) Cross-fertilization of mathematical theorems and available models.

We elucidate each of these issues in the following sections.

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(a) *Design principles of language evolution models.* Designing a computer model of a real-world phenomenon requires a certain degree of simplification and abstraction [1]. Wang [2] underscores that a suitable degree of simplification is critical for designing and analyzing evolutionary models, and doubts our classification of available computer models into rule- and equation-based models.

This classification relies mainly on research foci and adopted approaches in modelling studies. For example, both rule- and equation-based models can simulate the same linguistic phenomena such as lexical diffusion [3,4]. By simulating specific rules about individual behaviors during production and perception, rule-based models often focus on elaborating the necessary individual learning mechanisms and the conventionalization process of lexical items via local interactions [5], whereas by transforming these behaviors into mathematical principles, equation-based models usually concentrate on how to quantify the diffusion dynamics at a population level [6].

In addition, without sufficient abstraction and simplification, it is difficult to develop a detailed equation-based model to address the dynamics of a complex adaptive system such as human language. Human language involves not only numerous components (e.g., language users, individual linguistic knowledge, and relevant cognitive behaviors) but also intrinsic connections among these components. Rule-based models are more straightforward in addressing particularly-interesting factors and illustrate their potential effects on language evolution.

Furthermore, rule- and equation-based models are mutually beneficial. On the one hand, equation-based models offer theoretical and mathematical support for rule-based models of similar phenomena. For example, equation-based models prove the S-shape dynamics of communicative conventions [7], which is also traced by rule-based models [5,8] and adopted to describe cross-generation changes in linguistic behaviors [9,10]. On the other hand, rule-based models can specify relevant mechanisms that cause the system to exhibit certain dynamics as quantified by equation-based models. For example, the rule-based model [11] illustrates the effect of three distinct mechanisms (i.e., genetic transmission, shared learning mechanisms, and language games) on the formation of common color categories among individuals. Each of these mechanisms renders a similar S-shape dynamics.

Along with Wichmann [12], we agree that both equation- and rule-based models need to couple together to form a consistent approach to study language dynamics at different stages. There have been preliminary attempts to achieve this goal. For example, our rule-based model [13] reveals that processing constraints and semantic structures collectively lead to the bias toward SVO or OVS, which also echoes the principles of efficiency and predictability in the equation-based model [14]. In addition, both models hint that the bias for SVO over OVS in world languages could result from nonlinguistic constraints that are not considered in these models.

(b) *Aspects that potentially influence language evolution.* Computer models only capture some facets of complexities in language structure and use. Many commentators advocate incorporating a variety of factors that could influence language evolution. These factors cover both individual and socio-cultural aspects of language evolution, such as: the discourse semantics that comprises compositionality and semantic contextuality [15]; interactions of structural, lexical, and pragmatic information during exchange of linguistic materials [16]; constraints from physiological or cognitive abilities, and synergic relations between multiple factors that affect the construction and function of syntactic elements [17]; various forms of cultural practices that involve extended families and multiple generations [18]; and the ecological environment and deliberate human effort during language change or competition [19]. All these enrich the purview of modelling research of language evolution, and traditional linguistics research has started to notice the potential effect of some of these aspects on language evolution.

Recent advancements in informatics, artificial intelligence, and complex systems have enabled us to incorporate some of these aspects in computer models. For example, informatics techniques help reveal the effects and constraints of human cognitive and physiological abilities on language processing and evolution [20], such as the Just Noticeable Difference of human eyes mentioned by Baronchelli [19,21]. By defining individuals as nodes and socio-cultural interactions between individuals as edges linking those nodes, the network approach can efficiently model linguistic diffusion, change, or competition in the same or different groups or generations of individuals [22,23].

Among the socio-cultural factors, Perlovsky [24] emphasizes that almost every successfully emerging and growing system exhibits a power-law hierarchy, which echoes recent empirical surveys [25,26], and that the successful evolution of language (as well as other biological or socio-cultural systems) must require a power law. This conjecture certainly deserves additional research, and our simulation studies on the lexical, categorical, and syntactic aspects of language evolution have already provided partial support on this claim [27]. In addition, since both the power-law hierarchy and human language exhibit self-organizing properties, we suggest that language and social structure could coevolve [28]; certain forms of social structure could assist language evolution, and success in language com-

munications could also reciprocally shape those forms of social structure [29]. Furthermore, such language-involved coevolution is not limited to socio-cultural factors. As shown in theoretical, empirical, and simulation studies (e.g., [30–33]), communicative success in the human cultural niche is an important driving force for the coevolution of idiolects or communal language, relevant socio-cognitive abilities in humans, and socio-cultural characteristics in communities. Considering that available comparative evidence between modern humans and other animals only reflects the outcome of evolution, rather than initial or intermediate stages, we advocate that computer modelling serves as an efficient means to evaluate Perlovsky's conjecture and the coevolutionary hypotheses on human cognition, language, and communities, thus contributing to relevant theoretical discussions and empirical research in evolutionary linguistics, biology, psychology, and sociology.

(c) *Comparison of simulation results with empirical data.* As uniformly agreed among commentators, how to validate simulation results depends crucially on how to ground computer models in empirical data.

Apart from directly comparing simulation results with empirical data, Mehler [15] points out that the gap between the inputs and outputs of a computer model greatly affects the expressiveness of the model. He also discusses the triadic representational function of input, output, and their procedural relation, and suggests using these reference points to verify a model [34]. De Boer [35] advocates using the Newman–Pearson approach [36] to test competing hypotheses of the same phenomena and tuning relevant model parameters to fit particular empirical data. Vogt [18] suggests cautiously selecting empirical data and avoiding biases toward Western middle-class communities [37]. Such communities, compared with non-Western rural societies, came into being only recently in evolutionary history. Apart from the traditional (e.g., questionnaires, field works, and typological databases) and new (e.g., experimental semiotics) sources of empirical data, Loreto and Tria [38] recommend the Internet as an additional, rich source of empirical data about the origins and spread of linguistic structures via web-based language games [39]. All these thoughtful suggestions have extended our visions on gathering empirical data and provided practical guidelines for comparing simulation results with empirical data.

(d) *Modelling neural connectivity underlying linguistic and general cognitive functions.* Available models of language evolution have been largely restricted at the behavioural or community level. For example, various forms of rules or artificial neural networks can be used to denote and simulate individual linguistic knowledge and language-related behaviors. Alternatively, mathematical principles can be designed to govern the dynamics of language communications. Owing to recent breakthroughs in non-invasive neuroimaging technology, we have gathered ample understandings of how individual or groups of neurons in the human brain interact with each other to perform different linguistic or general cognitive functions [40,41]. Along this trend, it is time to adopt a network perspective to describe and examine the structural and functional connectivity of the human brain [42–44], and to understand the neural foundations of language-related mechanisms.

Apart from descriptive work, computer models of neural activities and dynamics could join the endeavour to understand the neural foundations of language-related mechanisms. Such models can shed light on how the human brain is organized and how structural or functional connectivity of the human brain gives rise to specific dynamics of language processing. Similar to other models of language evolution, neural models can be either equation- or rule-based. For example, mathematical equations from complex network theorems help pinpoint critical clusters of neurons in the neural network underlying linguistic behaviors, or trace information diffusion within and across neural networks. Alternatively, simulating largely-homogeneous behaviors of individual neurons help trace the gradual formation of particular structural or functional connectivity during the ontogeny and phylogeny of language and the human brain. These simulation studies will clarify knowledge about similarities and differences between language processing mechanisms and domain-general cognitive abilities. They will also illustrate the development of domain-specific mechanisms from domain-general competences.

(e) *Cross-fertilization of computer models and mathematical theorems.* Knowledge and approaches from one scientific community can be accessible to researchers in other disciplines. A computational framework involving explicit assumptions and having quantified parameters can be borrowed directly to address a number of similar phenomena in other disciplines. Results of this framework can be exported from one field to another in a comprehensible manner [45,46].

This cross-fertilization property of computer models [47] allows us to obtain inspiring results about language evolution based on mathematical theorems and available models developed in other related disciplines. For example, the intrinsic similarities between language competition and species competition have inspired the language competition model [48] from the equation-based, species competition model [49]. The game theory derived from economic studies

have been borrowed to address the origin of altruistic language communications and to reveal the effect of pragmatic information in this process [50]. The rapid development in complex network research [51,52] have stimulated research on network effects in language evolution [23,53]. Tools from evolutionary biology have been successfully utilized to study the origins and diversification of world languages [54,55].

This short reply adumbrates the prosperous future of modelling research of language evolution. The above-mentioned aspects will significantly contribute, from an interdisciplinary perspective, to the prosperity of modern research in evolutionary linguistics [46,56].

References

- [1] Gong T, Shuai L. Computer simulation as a scientific approach in evolutionary linguistics. *Lang Sci* 2013;40:12–23.
- [2] Wang WSY. Models – simple but not simpler: Comment on “Modelling language evolution: examples and predictions” by Tao Gong et al. *Phys Life Rev* 2014;11(2):315–6 [in this issue].
- [3] Wang WSY. Competing changes as a cause of residue. *Language* 1969;45:9–25.
- [4] Shen ZW. Exploring the dynamic aspect of sound change. *J Chin Linguist* 1997;11. Berkeley: Project on Linguistic Analysis, University of California.
- [5] Ke JY, Minett JW, Au CP, Wang WSY. Self-organization and selection in the emergence of vocabulary. *Complexity* 2002;7(3):41–54.
- [6] Wang WSY, Ke JY, Minett JW. Computational studies of language evolution. In: Huang CR, Lenders W, editors. *Computational linguistics and beyond*. Taipei: Institute of Linguistics, Academia Sinica; 2004. p. 65–108.
- [7] Baronchelli A, Felici M, Loreto V, Caglioti E, Steels L. Sharp transition towards shared vocabularies in multi-agent systems. *J Stat Mech* 2006:P06014.
- [8] Steels L. A self-organizing spatial vocabulary. *Artif Life* 1995;2(3):319–32.
- [9] Weinreich U, Labov W, Herzog MI. Empirical foundations for a theory of language change. In: Lehmann WP, Malkiel Y, editors. *Direction for historical linguistics*. Austin: University of Texas Press; 1968. p. 97–195.
- [10] Bailey CJ. *Variation and linguistic theory*. Washington: Center for Applied Linguistics; 1973.
- [11] Steels L, Belpaeme T. Coordinating perceptually grounded categories through language: a case study for colour. *Behav Brain Sci* 2005;28(4):469–89.
- [12] Wichmann S. The challenges of language dynamics: Comment on “Modelling language evolution: examples and predictions” by Gong, Shuai & Zhang. *Phys Life Rev* 2014;11(2):303–4 [in this issue].
- [13] Gong T, Minett JW, Wang WSY. A simulation study on word order bias. *Interact Stud* 2009;10(1):51–76.
- [14] Ferrer-i-Cancho R. Some word order biases from limited brain resources: a mathematical approach. *Adv Complex Syst* 2008;11(3):393–414.
- [15] Mehler A. On the expressiveness, validity and reproducibility of models of language evolution: Comment on “Modelling language evolution: examples and predictions” by Tao Gong, Shuai Lan, and Menghan Zhang. *Phys Life Rev* 2014;11(2):321–3 [in this issue].
- [16] Wu Y. Understanding the origins of language: an interactive stance: Comment on “Modelling language evolution: examples and predictions” by Gong, Shuai and Zhang. *Phys Life Rev* 2014;11(2):305–6 [in this issue].
- [17] Liu H. Language is more a human-driven system than a semiotic system: Comment on “Modelling language evolution: examples and predictions” by Tao Gong, Shuai Lan, Menghan Zhang. *Phys Life Rev* 2014;11(2):309–10 [in this issue].
- [18] Vogt P. Grounding models in empirical data of language socialisation: Comment on “Modelling language evolution: examples and predictions” by Gong, Shuai and Zhang. *Phys Life Rev* 2014;11(2):313–4 [in this issue].
- [19] Baronchelli A. Modelling is a tool, and data are crucial: Comment on “Modelling language evolution: examples and predictions” by Tao Gong et al. *Phys Life Rev* 2014;11(2):317–8 [in this issue].
- [20] Nowak MA, Plotkin JB, Krakauer DC. The evolutionary language game. *J Theor Biol* 1999;200(2):147–62.
- [21] Baronchelli A, Gong T, Puglisi A, Loreto V. Modelling the emergence of universality in colour naming patterns. *Proc Natl Acad Sci USA* 2010;107(6):2403–7.
- [22] Ke JY, Gong T, Wang WSY. Language change and social networks. *Commun Comput Phys* 2008;3(4):935–49.
- [23] Gong T, Baronchelli A, Puglisi A, Loreto V. Exploring the roles of complex networks in linguistic categorization. *Artif Life* 2012;18(1):107–21.
- [24] Perlovsky L. Power law, is it a fundamental law of cultural organization? Comment on “Modelling language evolution: examples and predictions” by Tao Gong, Lan Shuai, Menghan Zhang. *Phys Life Rev* 2014;11(2):319–20 [in this issue].
- [25] Wang X, Chen G. Complex networks: small-world, scale-free and beyond. *IEEE Circuits Syst* 2003;3(1):6–20.
- [26] Kello CT, Brown GDA, Ferrer-i-Cancho R, Holden JG, Linkenkaer-Hansen K, Rhodes T, et al. Scaling laws in cognitive sciences. *Trends Cogn Sci* 2010;14:223–32.
- [27] Gong T, Shuai L. Exploring the effect of power-law social popularity on language evolution. *Artif Life* 2004;20(3).
- [28] Thompson JN. *The coevolutionary process*. Chicago, IL: University of Chicago Press; 2012.
- [29] Kendal J, Tehrani JJ, Odling-Smee FJ. Human niche construction in interdisciplinary focus. *Philos Trans R Soc B Biol Sci* 2011;366:785–93.
- [30] Deacon WT. *The symbolic species: the coevolution of language and the brain*. New York, NY: WW Norton; 1997.
- [31] Feldman MW, Laland KN. Gene-culture coevolutionary theory. *Trends Ecol Evol* 1996;11:453–7.
- [32] Gong T, Shuai L. Modelling the coevolution of joint attention and language. *Proc R Soc Lond B, Biol Sci* 2012;279(1747):4643–51.
- [33] Levinson SJ, Dedi D. The interplay of genetic and cultural factors in ongoing language evolution. In: Richerson PJ, Christiansen MH, editors. *Cultural evolution: society, technology, language, and religions*. Cambridge, MA: MIT Press; 2013. p. 219–32.

- [34] Lücking A, Mehler A. On three notions of grounding of artificial dialog companions. *Sci Technol Innov Stud* 2013;10(1):31–6.
- [35] De Boer B. Towards a methodology of language evolution modelling: Comment on “Modelling language evolution: examples and predictions” by Gong, Shuai and Zhang. *Phys Life Rev* 2014;11(2):307–8 [in this issue].
- [36] Lehmann EL. The Fisher, Neyman–Pearson theories of testing hypotheses: one theory or two? *J Am Stat Assoc* 1993;88:1242–9.
- [37] Henrich J, Heine SJ, Norenzayan A. The weirdest people in the world? *Behav Brain Sci* 2010;33:61–135.
- [38] Loreto V, Tria F. Language games: Comment on “Modelling language evolution: examples and predictions” by Tao Gong, Lan Shuai, Menghan Zhang. *Phys Life Rev* 2014;11(2):311–2 [in this issue].
- [39] Tria F, Galantucci B, Loreto V. Naming a structured world: a cultural route to duality of patterning. *PLoS ONE* 2012;7(6):e37744.
- [40] Brown CM, Hagoort P. *The neurocognition of language*. Oxford: Oxford University Press; 1999.
- [41] Arbib M, editor. *Language, music and the brain*. Cambridge, MA: MIT Press; 2013.
- [42] Sporns O. *Networks of the brain*. Cambridge, MA: MIT Press; 2011.
- [43] Sporns O. *Discovering the human connectome*. Cambridge, MA: MIT Press; 2012.
- [44] Seung, Connectome S. *How the brain’s wiring makes us who we are*. Harcourt: Houghton Mifflin; 2012.
- [45] Belew RK, Mitchell M, Ackley DH. *Computation and the natural sciences*. In: Belew RK, Mitchell M, editors. *Adaptive individuals in evolving populations: models and algorithms*. Reading, MA: Addison-Wesley Publishing; 1996. p. 431–46.
- [46] Ke JY. *Self-organization and language evolution: system, population and individual*. PhD dissertation. Hong Kong: City University of Hong Kong; 2004.
- [47] Gong T, Shuai L. Computer simulation as a scientific approach in evolutionary linguistics. *Lang Sci* 2013;40:12–23.
- [48] Zhang M, Gong T. Principles of parametric estimation in modelling language competition. *Proc Natl Acad Sci USA* 2013;110(24):9698–703.
- [49] Gilpin ME, Ayala FJ. Global models of growth and competition. *Proc Natl Acad Sci USA* 1973;70(12):3590–3.
- [50] Noble J. Cooperation, competition and the evolution of prelinguistic communication. In: Knight C, Studdert-Kennedy M, Hurford JR, editors. *The evolutionary emergence of language: social function and the origins of linguistic form*. Cambridge: Cambridge University Press; 2000. p. 40–61.
- [51] Barabasi AL, Albert R. Emergence of scaling in random networks. *Science* 1999;286:509–12.
- [52] Watts DJ, Strogatz SH. Collective dynamics of small-world networks. *Nature* 1998;393:440–2.
- [53] Gong T, Shuai L, Tamariz M, Jöger G. Studying language change using price equation and Pólya-urn dynamics. *PLoS ONE* 2012;7(3):e33171.
- [54] Levinson SC, Gray RD. Tools from evolutionary biology shed new light on the diversification of languages. *Trends Cogn Sci* 2012;16(3):167–73.
- [55] Gray RD, Greenhill SJ, Atkinson QD. Phylogenetic models of language change: three new questions. In: Richerson PJ, Christiansen MH, editors. *Cultural evolution: society, technology, language, and religions*. Cambridge, MA: MIT Press; 2013. p. 285–300.
- [56] Gong T, Shuai L, Wu Y. Multidisciplinary approaches in evolutionary linguistics. *Lang Sci* 2013;37:1–13.