Language, Culture & Computation:
the adaptive systems approach to the
Evolution of language

Simon Kirby

Language Evolution & Computation Research Unit
University of Edinburgh
www.lel.ed.ac.uk/lec
Language Evolution

• I’m an evolutionary linguist
Language Evolution

• I’m an evolutionary linguist
• How is this even possible?
I’m an evolutionary linguist

How is this even possible?

A story about one attempt to find a way...

- Starts with the use of computational models
- Ends with a way of thinking about culture in the real world as a computational process
First things first...
First things first...

- What are evolutionary linguists interested in?
First things first...

- What are evolutionary linguists interested in?
- An origins story for humans that involves language
First things first...

• What are evolutionary linguists interested in?
  • An origins story for humans that involves language
  • Explaining the structure of language
First things first...

- What are evolutionary linguists interested in?
  - An origins story for humans that involves language
  - Explaining the structure of language
First things first...

• What are evolutionary linguists interested in?
  • An origins story for humans that involves language
  • Explaining the structure of language

• An evolutionary approach:
  • The universal properties of language arise from the fact that it is one of the most complex adaptive systems in nature
Why is language the way it is?
The orthodox Chomskyan view
Why is language the way it is?
The orthodox Chomskyan view
Why is language the way it is?
The orthodox Chomskyan view
Why is language the way it is?
The orthodox Chomskyan view

• Language structure is explained by innate constraints on a biological faculty for acquiring language
Why is language the way it is?
The orthodox Chomskyan view

• Very powerful and successful approach for linguistics
Why is language the way it is?
The orthodox Chomskyan view

• Very powerful and successful approach for linguistics

• Suggests:
  • We can infer human nature from human behaviour
  • We can move from description to explanation
Why is language the way it is?
The orthodox Chomskyan view

- Very powerful and successful approach for linguistics
- Suggests:
  - We can infer human nature from human behaviour
  - We can move from description to explanation
- Led to interesting relationship between theoretical linguistics and machine learning
Is there something missing?

- Seemed to a lot of people that this approach is explanatorily unsatisfying
- Where do these innate constraints on the language faculty come from?
Is there something missing?

- Seemed to a lot of people that this approach is explanatorily unsatisfying.
- Where do these innate constraints on the language faculty come from?
- Could we look to biology to help us explain why the language faculty is the way it is?
Why is language the way it is? 
Pinker & Bloom’s (1990) view

• Assumptions:
  • We have domain-specific machinery to allow us to learn language
  • This is a useful skill (i.e. it’s adaptive)
  • The machinery is complex
Why is language the way it is?
Pinker & Bloom’s (1990) view

- Assumptions:
  - We have domain-specific machinery to allow us to learn language
  - This is a useful skill (i.e. it’s adaptive)
  - The machinery is complex

- Claim:
  - We have only one explanation for explaining adaptive complexity in nature... *natural selection*
Why is language the way it is?
Pinker & Bloom’s (1990) view
Why is language the way it is?

Pinker & Bloom's (1990) view
Why is language the way it is?
Pinker & Bloom’s (1990) view

BIOLOGICAL EVOLUTION BY NATURAL SELECTION

INDIVIDUAL COGNITIVE MACHINERY

UNIVERSAL PROPERTIES OF LINGUISTIC STRUCTURE
Why is language the way it is?
Pinker & Bloom’s (1990) view

- Language structure is explained by innate constraints that have adapted through natural selection for communicative function
Opening the floodgates...
Opening the floodgates...

• After Pinker & Bloom, enormous increase in speculation about language evolution
Opening the floodgates...

- After Pinker & Bloom, enormous increase in speculation about language evolution
- Things seem simple, but actually very complicated!
- Two interacting *adaptive systems* at play:
  - Individual learning
  - Biological evolution of learning mechanisms
- Can we be confident in our intuitions?
The rise of computer simulation

• Don’t rely on verbal argument or intuition
  • Use computer simulation to model evolution of language learners
• First paper, Hurford (1989), led to “Edinburgh approach”
• At the same time, Artificial Life in general started looking at evolution and learning
  • Use multi-agent modelling, machine learning, evolutionary computation
e.g., The Baldwin Effect

- Chomskyan approach suggests a mix of learned features and innate constraints
- Where do the constraints come from?
e.g., The Baldwin Effect

• Chomskyan approach suggests a mix of learned features and innate constraints

• Where do the constraints come from?

• Baldwin (1896) suggests that learned behaviours can become innate
e.g., The Baldwin Effect

- Chomskyan approach suggests a mix of learned features and innate constraints
- Where do the constraints come from?
- Baldwin (1896) suggests that learned behaviours can become innate
- Various models test this for language acquisition (e.g. Turkel, Briscoe, Yamauchi, Batali...)
- Depends on learning cost, rate of change etc.
Something odd...
Something odd...

- Computational models of language learning
- Build model of learning; test on language problem
Something odd...

- Computational models of language learning
  - Build model of learning; test on language problem

- Computational models of language evolution
  - Build model of population of language learners; use language problem as selection pressure
Something odd...

- Computational models of language learning
  - Build model of learning; test on language problem

- Computational models of language evolution
  - Build model of population of language learners; use language problem as selection pressure

- But where do these language problems come from?
Is there something else missing?
Is there something else missing?

- The Problem of Linkage
  - Language does not straightforwardly emerge from the idealised individual speaker/hearer
Is there something else missing?

• The Problem of Linkage
  • Language does not straightforwardly emerge from the idealised individual speaker/hearer

• It is the result of a socio/cultural process
  • Language structure emerges from the interaction of individuals (albeit ones with particular biases)
Why is language the way it is?
Our view
Why is language the way it is?
Our view

BIOLOGICAL EVOLUTION BY NATURAL SELECTION

INDIVIDUAL COGNITIVE MACHINERY
Why is language the way it is?
Our view

- Biological Evolution by Natural Selection
- Individual Cognitive Machinery
- Social Interaction & Cultural Evolution
- Universal Properties of Linguistic Structure
Why is language the way it is?  
Our view

• Now a potentially very complex picture – 3 interacting adaptive systems!

BIOLOGICAL EVOLUTION BY NATURAL SELECTION

INDIVIDUAL COGNITIVE MACHINERY

SOCIAL INTERACTION & CULTURAL EVOLUTION

UNIVERSAL PROPERTIES OF LINGUISTIC STRUCTURE
Why is language the way it is?

Our view

- Now a potentially very complex picture – 3 interacting adaptive systems!
- We need to understand cultural evolution, and we need computational modelling to help us
The Iterated Learning Model

- Around the late 90s several groups started looking at this problem
  - e.g. Batali at UCSD, Steels in Paris/Brussels using robotic models
The Iterated Learning Model

• Around the late 90s several groups started looking at this problem
  • e.g. Batali at UCSD, Steels in Paris/Brussels using robotic models

• In Edinburgh, the Iterated Learning Model
  • e.g. Brighton, Smith, Zuidema, Dowman, Hurford
  • an explicit model of cultural transmission of language
The iterated learning model.

The first agent has knowledge of language represented by a hypothesis $h_1$. This hypothesis itself represents a language $L_{h_1}$. Some subset of this mapping, $L'_{h_1}$, is externalized as linguistic performance for the next agent to learn from. The process of learning results in a hypothesis $h_2$. The process is then repeated, generation after generation.

3.2. The language model

Before proceeding to a fully-specified Iterated Learning Model we must introduce our language model. The particular model we introduce will figure in both models featured later in the paper. The discussion surrounding the language model will also allow us to define the feature of language we will be investigating throughout this article. This is a property of language—a linguistic universal—termed compositionality.

A model of language needs to capture the fact that all language is a particular relationship between sounds and meaning. The level of abstraction we will aim for captures the property that language is mapping from a "characteristic kind of semantic or pragmatic function onto a characteristic kind of symbol sequence" [73, p. 713]. When we refer to a model of language, we will be referring to a set of possible relationships between, on the one hand, entities representing meanings, and on the other, entities representing signals. Throughout this article we will consider meanings as multi-dimensional feature structures, and signals as sequences of symbols. Meanings are defined as feature vectors representing points in a meaning space. Meaning spaces will be defined by two parameters, $F$ and $V$. The parameter $F$ defines the dimensionality of the meaning space.
The Iterated Learning Model

- What we find:
  - Languages do not simply mirror learning constraints
  - Cultural evolution has explanatory role
The Iterated Learning Model

- What we find:
  - Languages do not simply mirror learning constraints
  - Cultural evolution has explanatory role
- The more difficult the learning task is, the more structured the languages become
  - Cultural evolution is another *adaptive system*
An example: the evolution of compositionality

- Languages involve non-random mappings between meanings and signals

- When signals are strings, this is manifested as compositionality
An example: the evolution of compositionality

- Many variants of this approach depending on model of meanings and model of learning
- Examples from Brighton (2003) using simple feature vectors and FST induction
- Initial state: unstructured, random, inexpressive
Fig. 12. Languages arising during linguistic evolution driven by MDL induction and intelligent invention. In (a), structure is evident as certain paths merge. In (b), an intermediate stage is shown where significant compression is evident but generalization is not possible. In (c), (d), further compression is possible, and no meanings can be expressed.
Typical evolution

Fig. 12. Languages a rising during linguistic evolution driven by MLD induction and intelligent invention. In (a), structure is identical as certain paths merge. In (b), an intermediate stage is shown where significant compression is evident but generalization is not possible. In (c), further compression is possible, and no meanings can be expressed.
Languages a rising during linguistic evolution driven by MDL induction and intelligent invention.

In (a), structure is identical as certain paths merge. In (b), an intermediate stage is shown where significant compression is evident but generalization is not possible. In (c), (d) further compression is possible, and no meanings can be expressed.
• Stable end state: compositional, expressive

• BUT: this only happens when there is a bottleneck on transmission
What’s going on?

- Hurford: “social transmission favours linguistic generalisation”
What's going on?

- Hurford: “social transmission favours linguistic generalisation”
- Generalisations are better replicators through iterated learning
What's going on?

- Hurford: “social transmission favours linguistic generalisation”
- Generalisations are better replicators through iterated learning
- As long as training data is a scarce resource, there will be differential success of regularity
What’s going on?

- Hurford: “social transmission favours linguistic generalisation”
- Generalisations are better replicators through iterated learning
- As long as training data is a scarce resource, there will be differential success of regularity
- Cultural evolution leads to compressible representational systems
Cultural evolution and language

- Cultural evolution has a profound effect
- Properties of bottleneck shape language structure
- We don’t need natural selection
Cultural evolution and language

- Cultural evolution has a profound effect
  - Properties of bottleneck shape language structure
  - We don’t need natural selection

- Recent Bayesian generalisation of ILM shows:
  - We do not need strongly constraining innateness (Kirby, Dowman & Griffiths 2007)
  - Co-evolutionary results suggest reverse Baldwin effect (Smith & Kirby in prep)
Beyond models...

• Computational models show adaptation to bottleneck and emergence of generalisations
• Seems to reflect real language structure
• But hard to observe evolution through iterated learning “in the wild”
• Can we be sure this works in humans?
Cultural evolution in the lab
(Kirby, Cornish, Smith forthcoming)
Cultural evolution in the lab
(Kirby, Cornish, Smith forthcoming)

- Participants exposed to artificial language made up of picture/string pairs (initially random)
Cultural evolution in the lab
(Kirby, Cornish, Smith forthcoming)

- Participants exposed to artificial language made up of picture/string pairs (initially random)
- Try and learn this kunige
Cultural evolution in the lab
(Kirby, Cornish, Smith forthcoming)

• Participants exposed to artificial language made up of picture/string pairs (initially random)
• Try and learn this
• Tested on full set of “meanings”
Cultural evolution in the lab
(Kirby, Cornish, Smith forthcoming)

- Participants exposed to artificial language made up of picture/string pairs (initially random)
- Try and learn this
- Tested on full set of “meanings”
- Sample of output on test used as input language for next participant
### Example initial language

<table>
<thead>
<tr>
<th>Lumonamo</th>
<th>Kinahune</th>
<th>Lahupine</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nelu</td>
<td>Kanehu</td>
<td>Namopihu</td>
</tr>
<tr>
<td>Kapihu</td>
<td>Humo</td>
<td>Lahupiki</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Moki</th>
<th>Luneki</th>
<th>Lanepi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kalu</td>
<td>Mola</td>
<td>Pihukimo</td>
</tr>
<tr>
<td>Nane</td>
<td>Kalakihu</td>
<td>Mokihuna</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Kilamo</th>
<th>Kahuki</th>
<th>Neluka</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pilu</td>
<td>Neki</td>
<td>Pinemohu</td>
</tr>
<tr>
<td>Luki</td>
<td>Namola</td>
<td>Lumoka</td>
</tr>
</tbody>
</table>
### Example final language
(10 “generations” later)

<table>
<thead>
<tr>
<th>n-ere-ki</th>
<th>l-ere-ki</th>
<th>renana</th>
</tr>
</thead>
<tbody>
<tr>
<td>n-ehe-ki</td>
<td>l-aho-ki</td>
<td>r-ene-ki</td>
</tr>
<tr>
<td>n-eke-ki</td>
<td>l-ake-ki</td>
<td>r-ahe-ki</td>
</tr>
<tr>
<td>n-ere-plo</td>
<td>l-ane-plo</td>
<td>r-e-plo</td>
</tr>
<tr>
<td>n-eho-plo</td>
<td>l-aho-plo</td>
<td>r-eho-plo</td>
</tr>
<tr>
<td>n-eki-plo</td>
<td>l-aki-plo</td>
<td>r-ahe-plo</td>
</tr>
<tr>
<td>n-e-pilu</td>
<td>l-ane-pilu</td>
<td>r-e-pilu</td>
</tr>
<tr>
<td>n-eho-pilu</td>
<td>l-aho-pilu</td>
<td>r-eho-pilu</td>
</tr>
<tr>
<td>n-eki-pilu</td>
<td>l-aki-pilu</td>
<td>r-ahe-pilu</td>
</tr>
</tbody>
</table>
Experimental results

• Very similar to predictions from computational models
Experimental results

• Very similar to predictions from computational models
• Compressible, compositional languages emerge
  • Dependent on bottleneck
Experimental results

• Very similar to predictions from computational models
• Compressible, compositional languages emerge
  • Dependent on bottleneck
• Adaptation driven by cultural evolution not intentional design by participants
• Likely to be true for real language too
Conclusions
Conclusions

• Computational thinking opened the door to new ways of studying language evolution using simulation
Conclusions

• Computational thinking opened the door to new ways of studying language evolution using simulation

• Revealed problems with previous fundamentals of linguistic explanation
Conclusions

• Computational thinking opened the door to new ways of studying language evolution using simulation

• Revealed problems with previous fundamentals of linguistic explanation

• Suggests a way of thinking of culture itself as a computational system
Conclusions

• Computational thinking opened the door to new ways of studying language evolution using simulation

• Revealed problems with previous fundamentals of linguistic explanation

• Suggests a way of thinking of culture itself as a computational system

• Future research question: how general/powerful is cultural computation?