The Cultural Evolution of Language: From computation to experimentation (and back again?)

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Language Evolution

- I'm an evolutionary linguist

Language Evolution

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

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- 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...

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- What are evolutionary linguists interested in?

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- 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

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The orthodox Chomskyan view

UNIVERSAL PROPERTIES OF LINGUISTIC STRUCTURE

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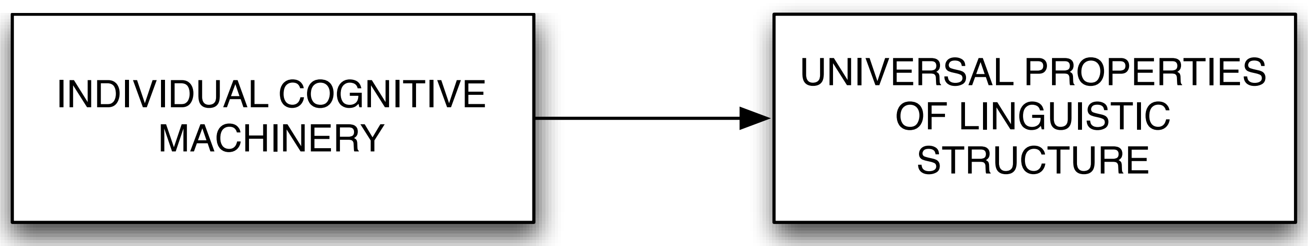

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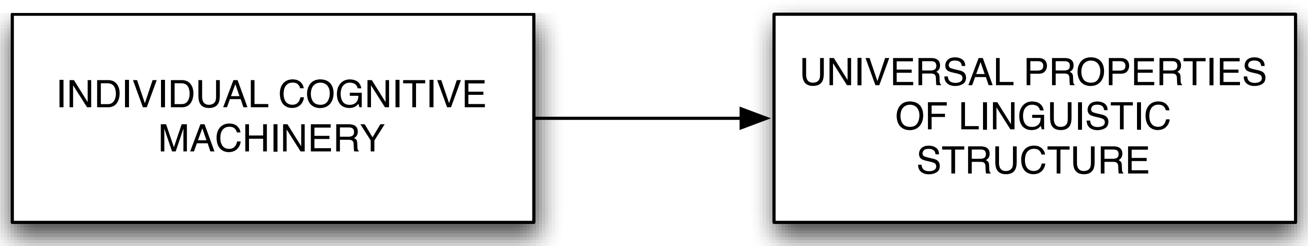

- Language structure is explained by innate constraints on a biological faculty for acquiring language

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- 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?

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- 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

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  - 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*

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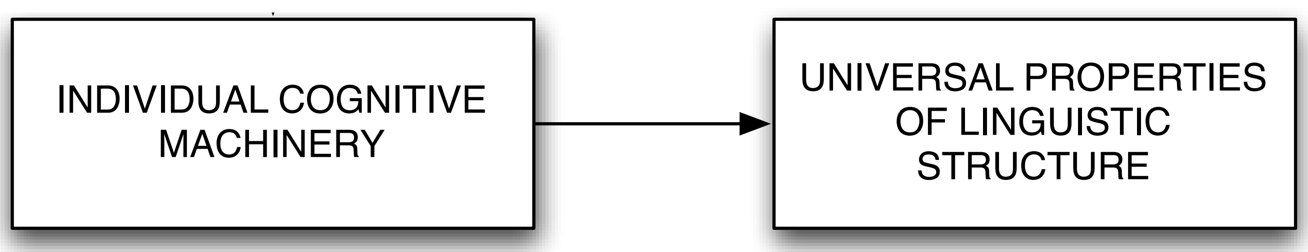

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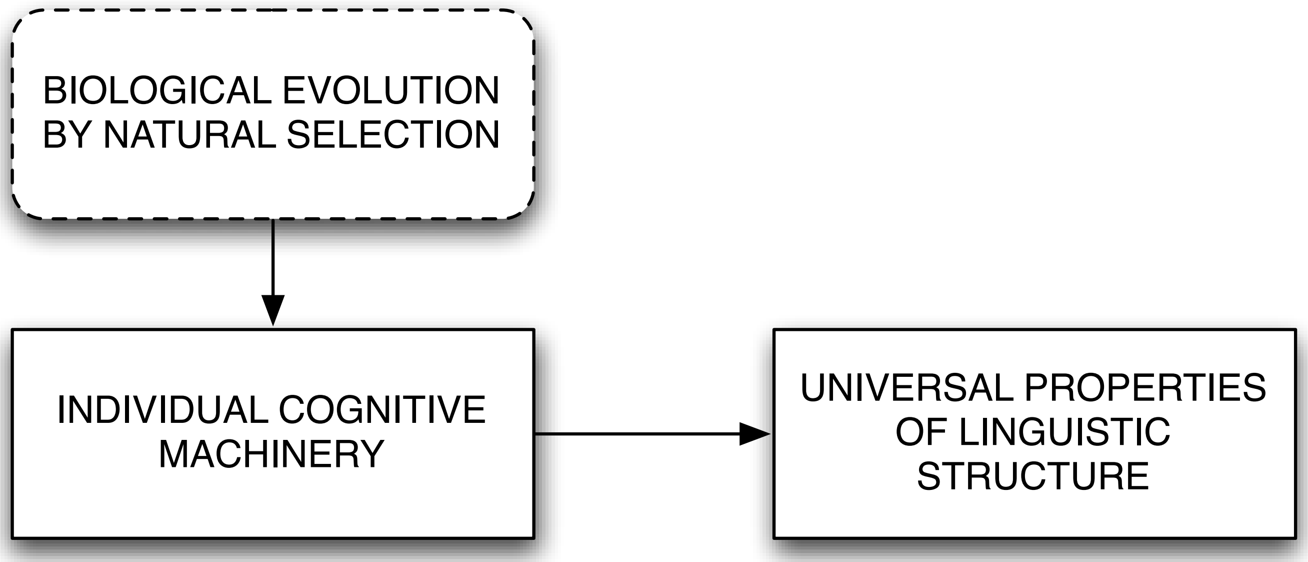

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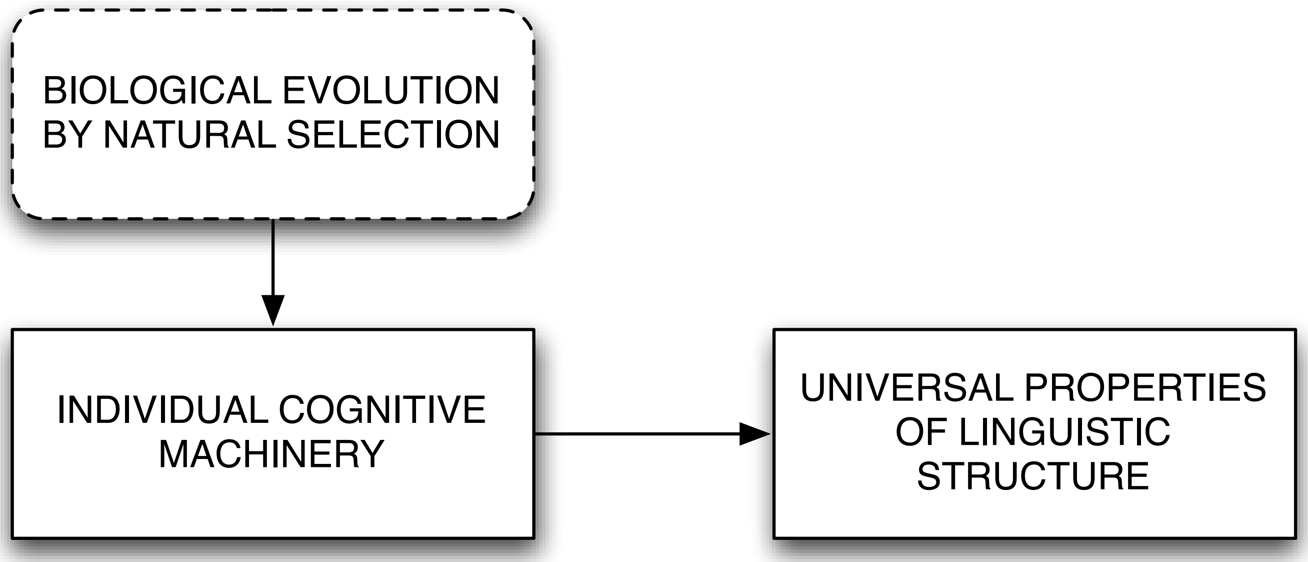

- Language structure is explained by innate constraints that have adapted through natural selection for communicative function

Opening the floodgates...

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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

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- Chomskyan approach suggests a mix of learned features and innate constraints
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- 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.

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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?

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  - Language does not straightforwardly emerge from the idealised individual speaker/hearer

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- 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)

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Our view

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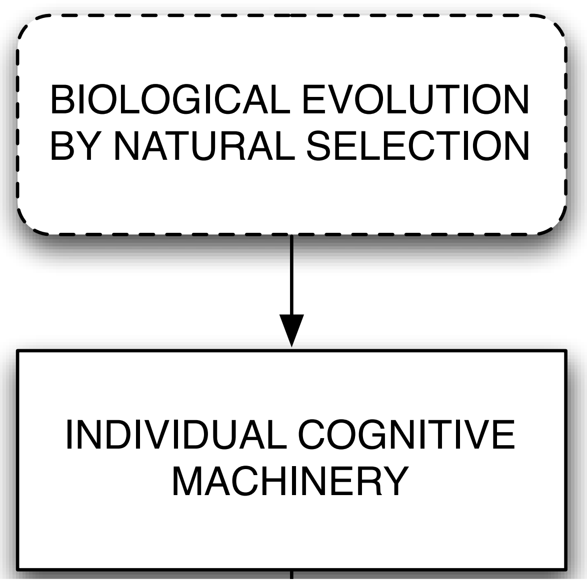

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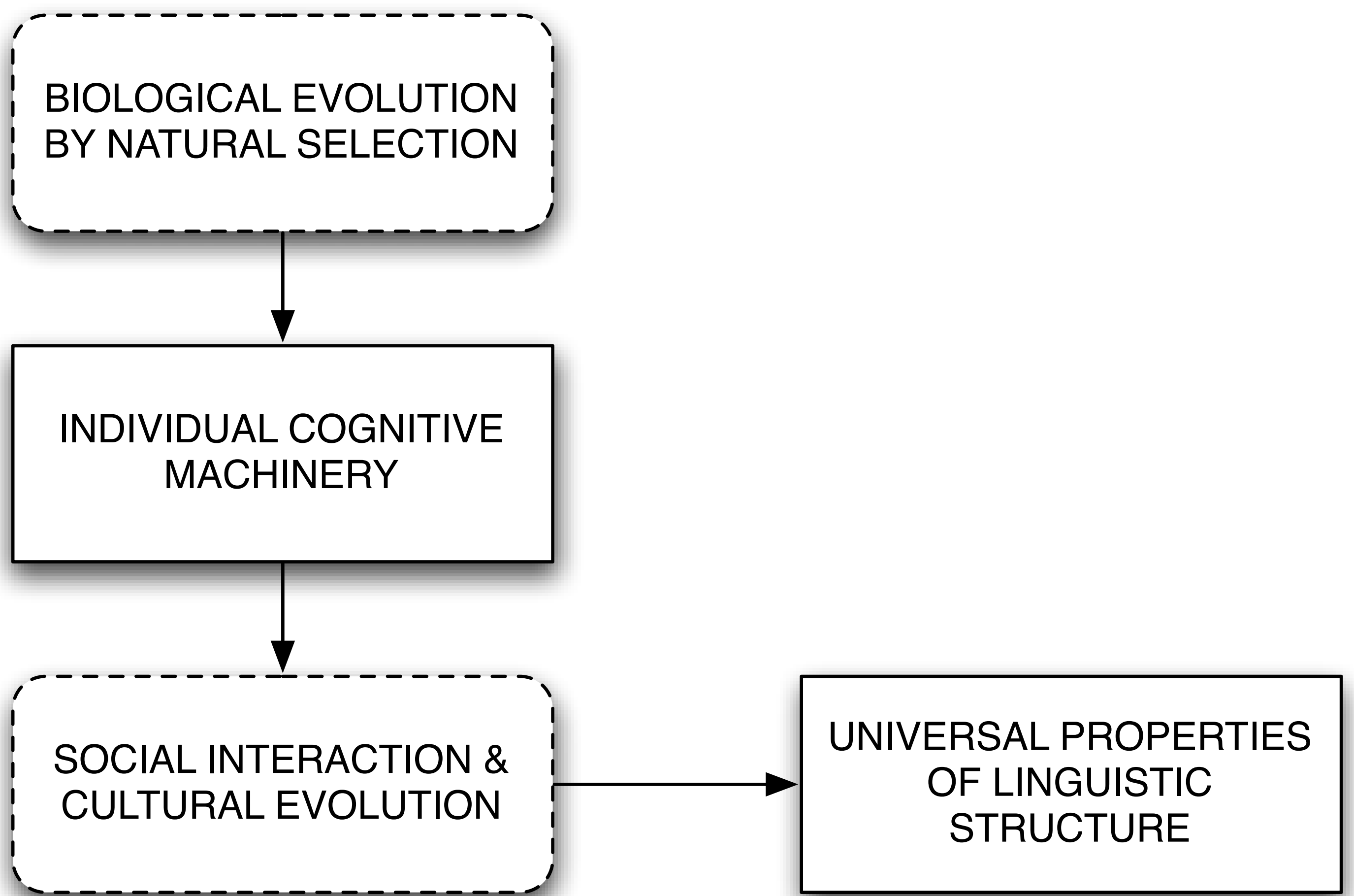

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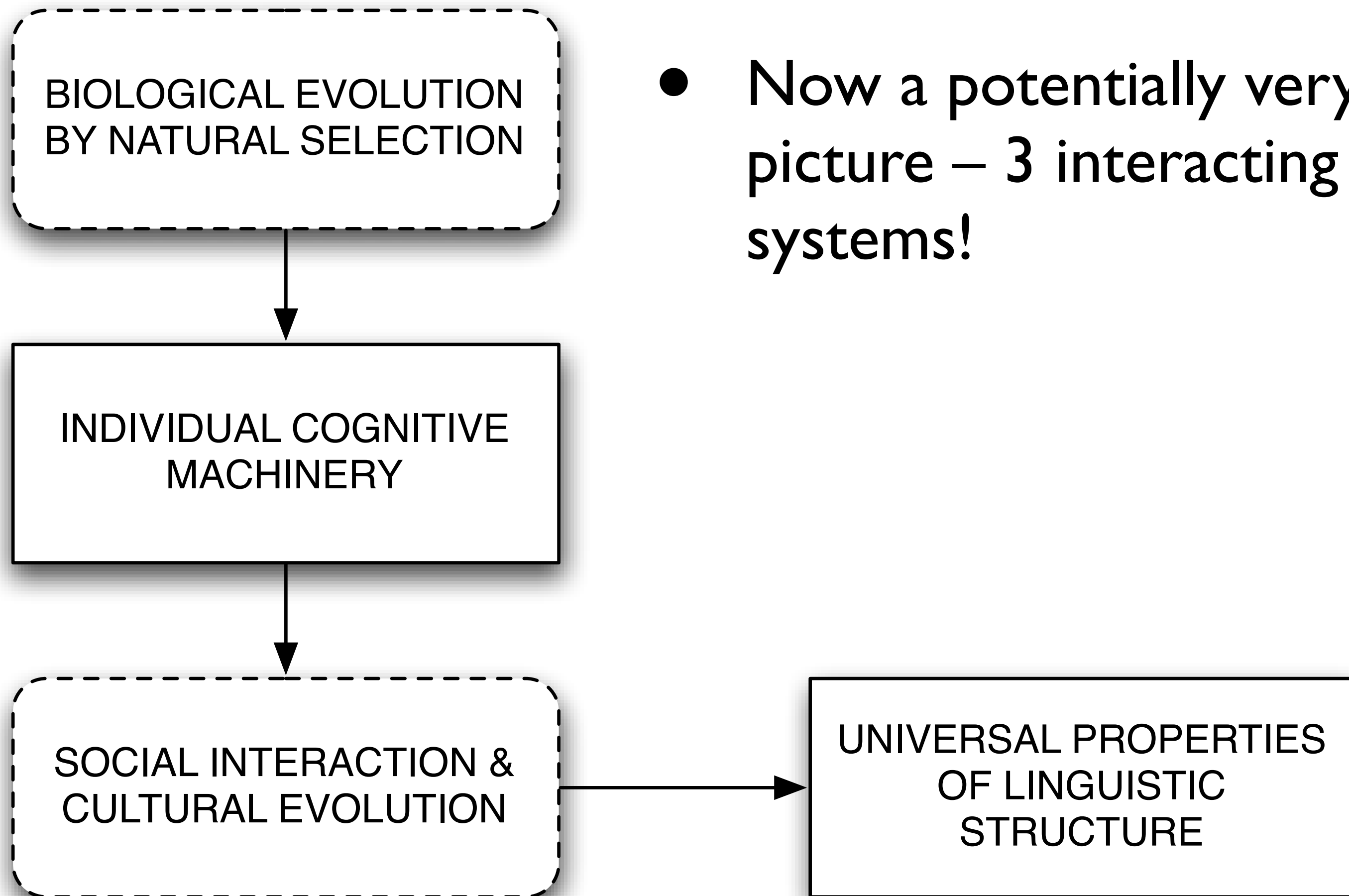

- Now a potentially very complex picture – 3 interacting adaptive systems!

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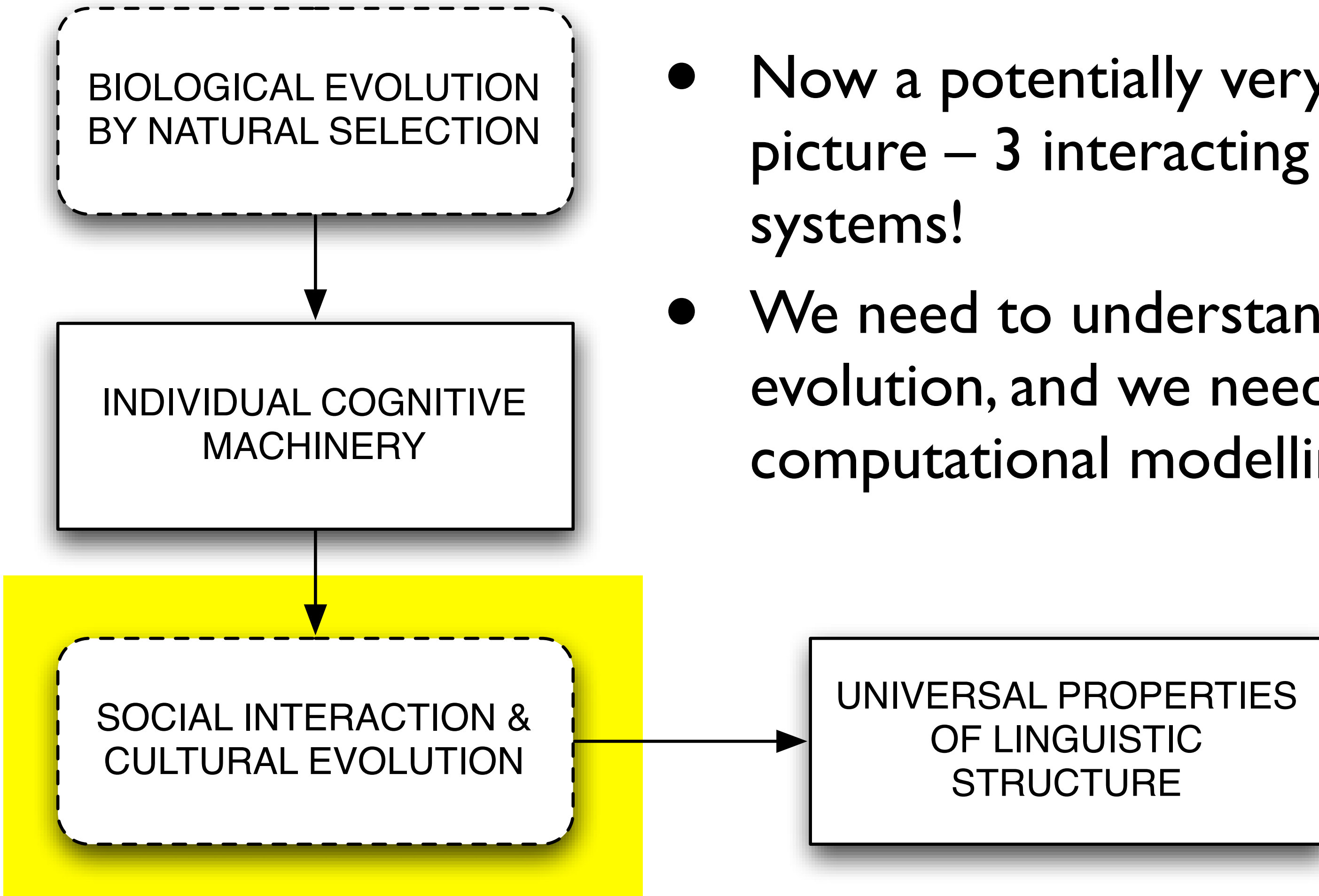

- Now a potentially very complex picture – 3 interacting adaptive systems!
- We need to understand cultural evolution, and we need computational modelling to help us

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

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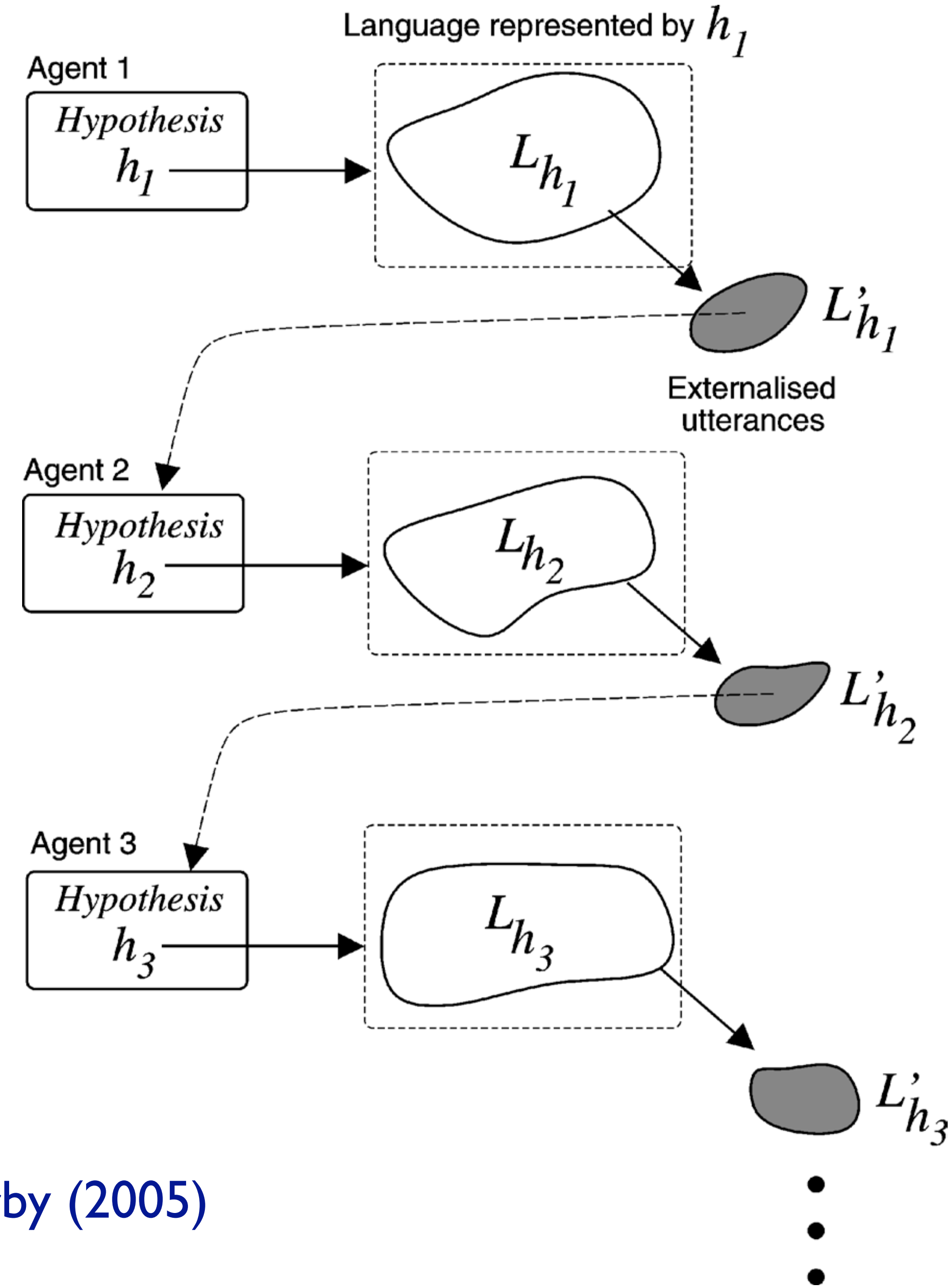
- In Edinburgh, the *Iterated Learning Model*
  - e.g. Brighton, Smith, Zuidema, Dowman, Hurford
  - an explicit model of cultural transmission of language



Brighton, Smith, Kirby (2005)

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  - Languages do not simply mirror learning constraints
  - Cultural evolution has explanatory role

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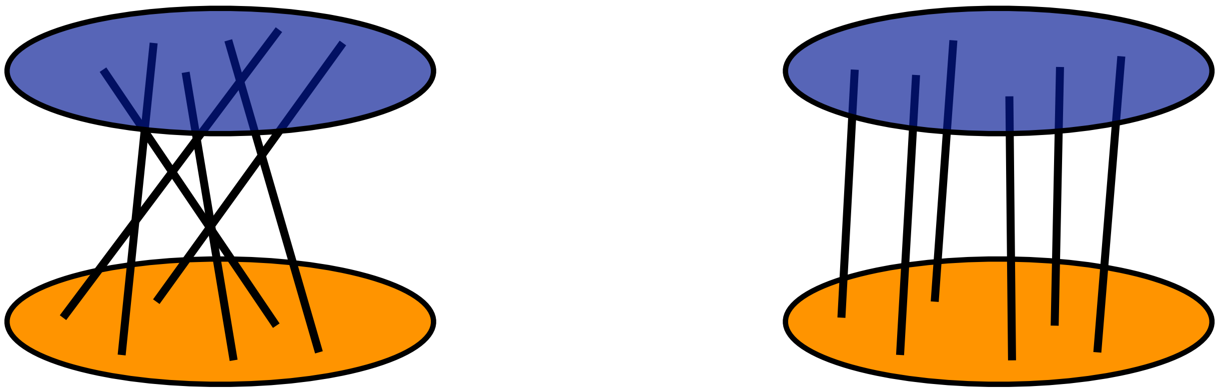
- What we find:
  - Languages do not simply mirror learning constraints
  - Cultural evolution has explanatory role
- The more difficult the learning task is, the more structured the languages become
  - Cultural evolution is another *adaptive system*

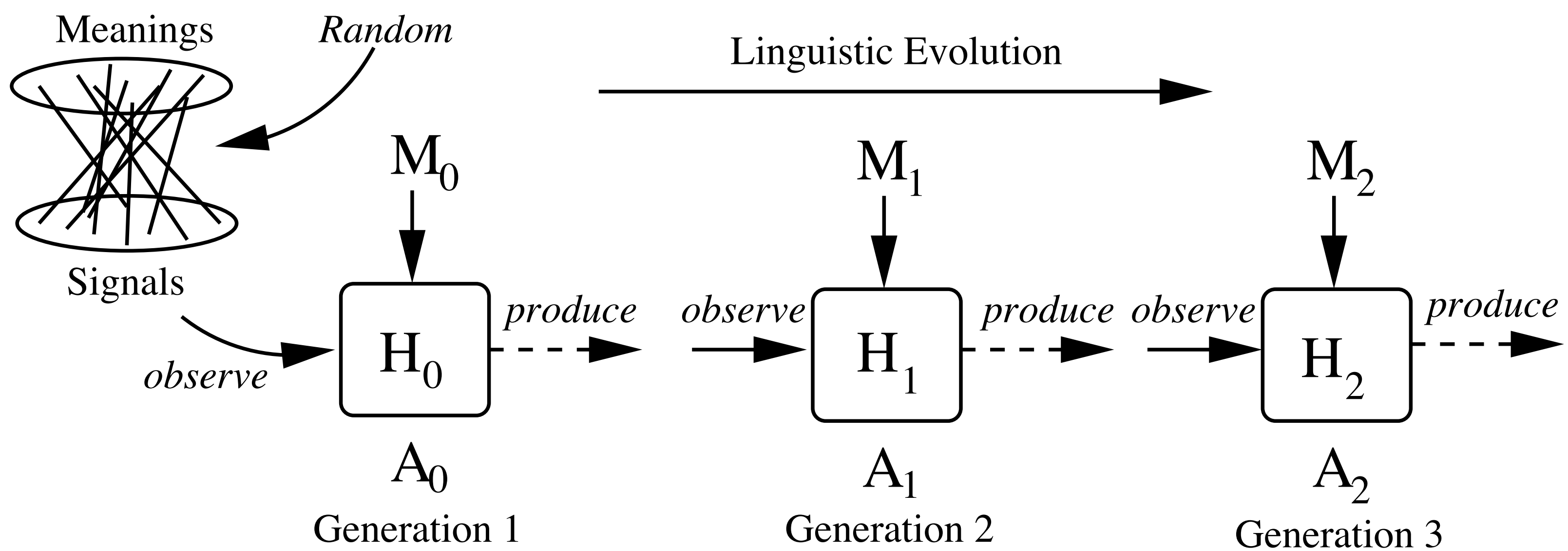
An example: the evolution of compositionality

- Languages involve non-random mappings between meanings and signals



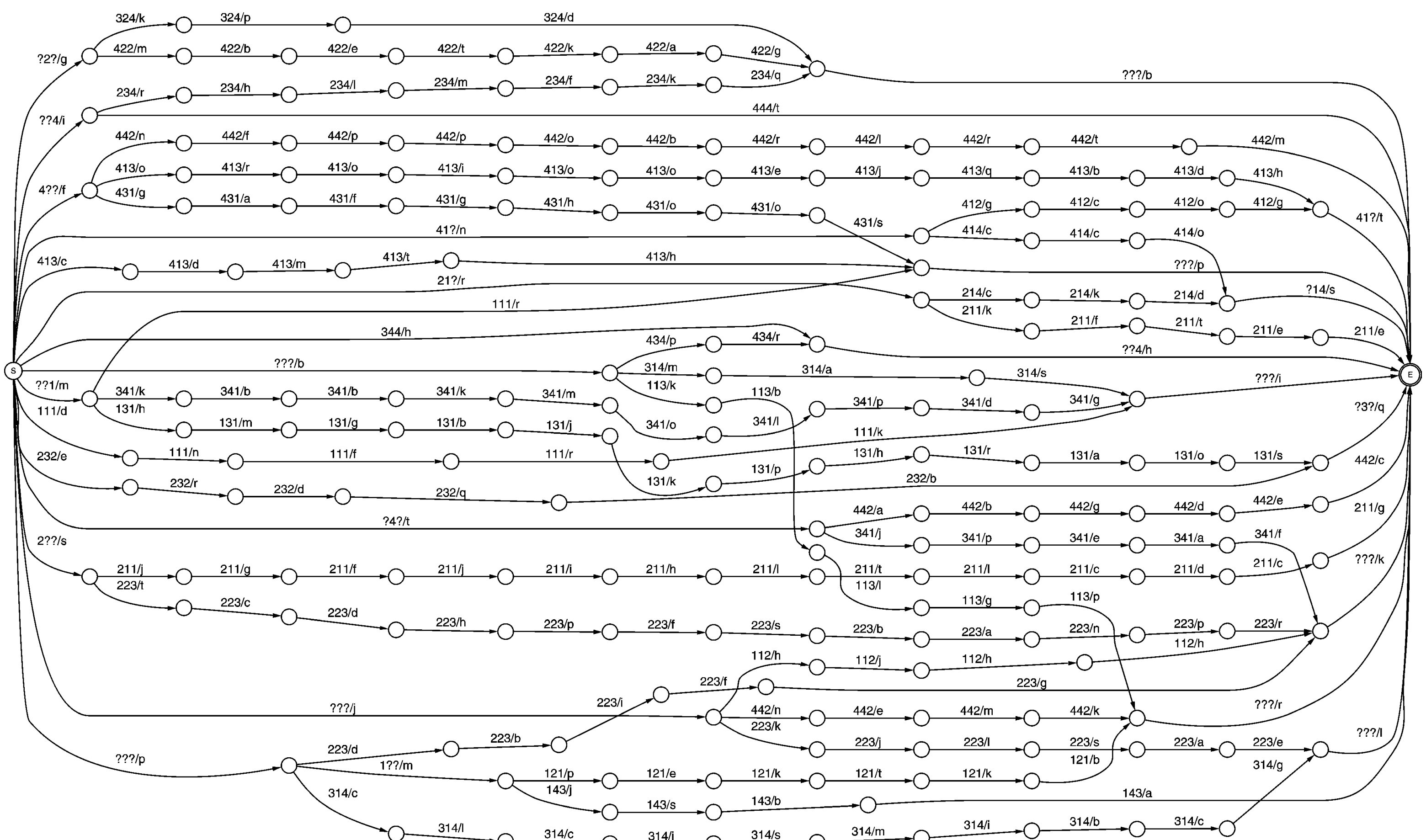
- When signals are strings, this is manifested as *compositionality*

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

Typical evolution



- Initial state: unstructured, random, inexpressive

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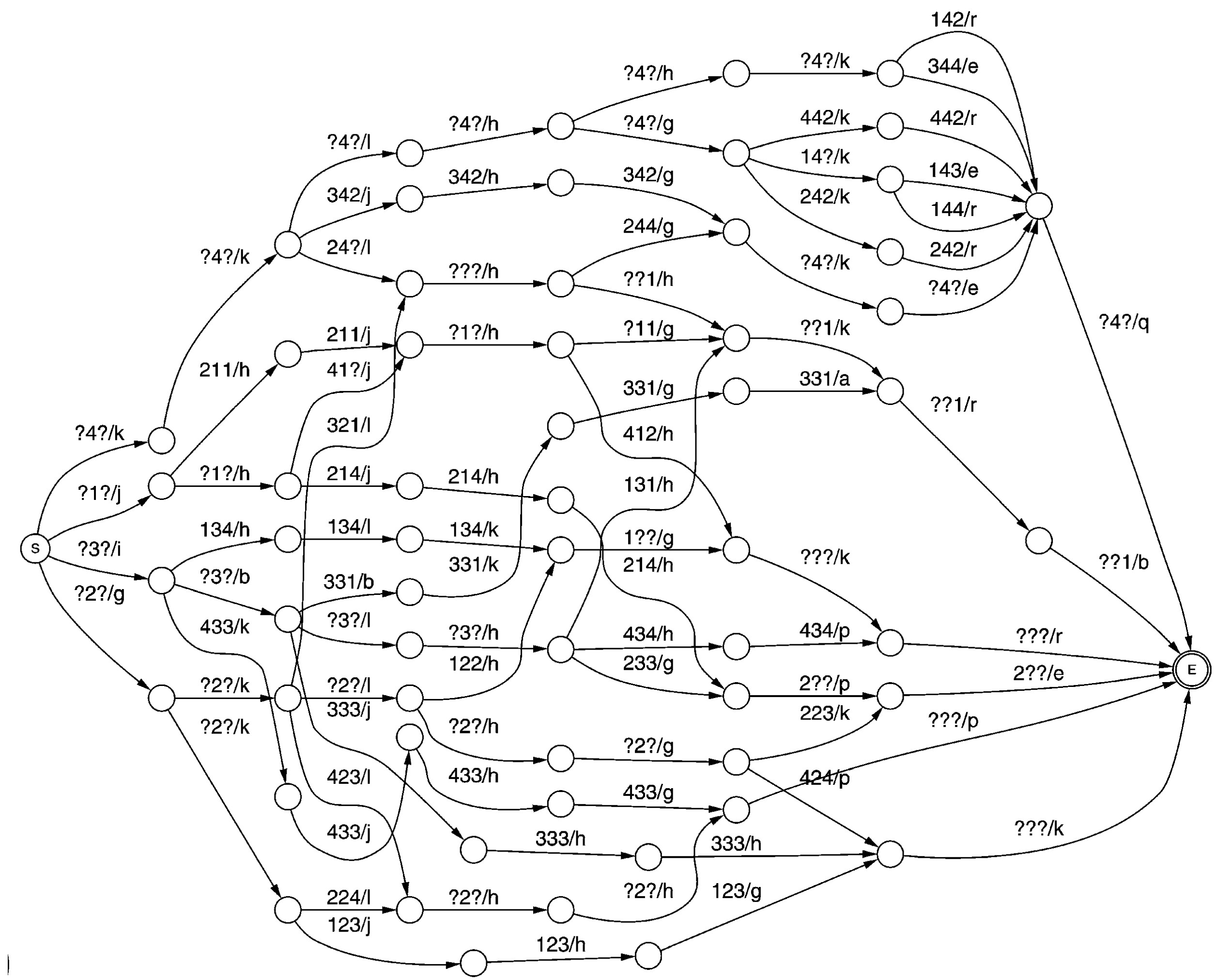

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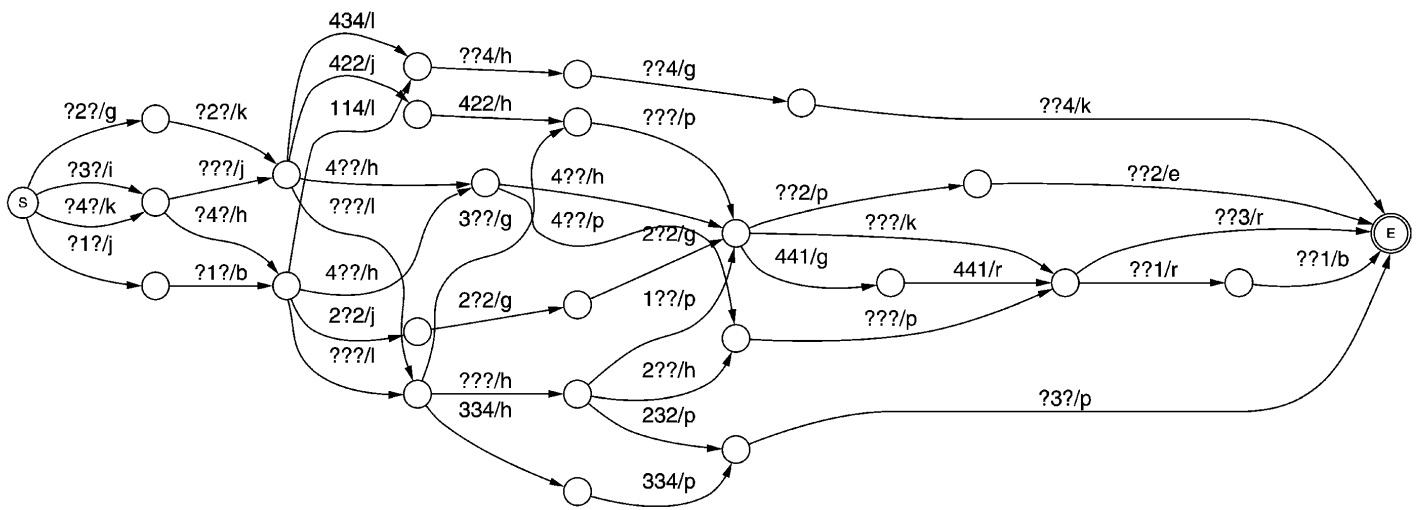

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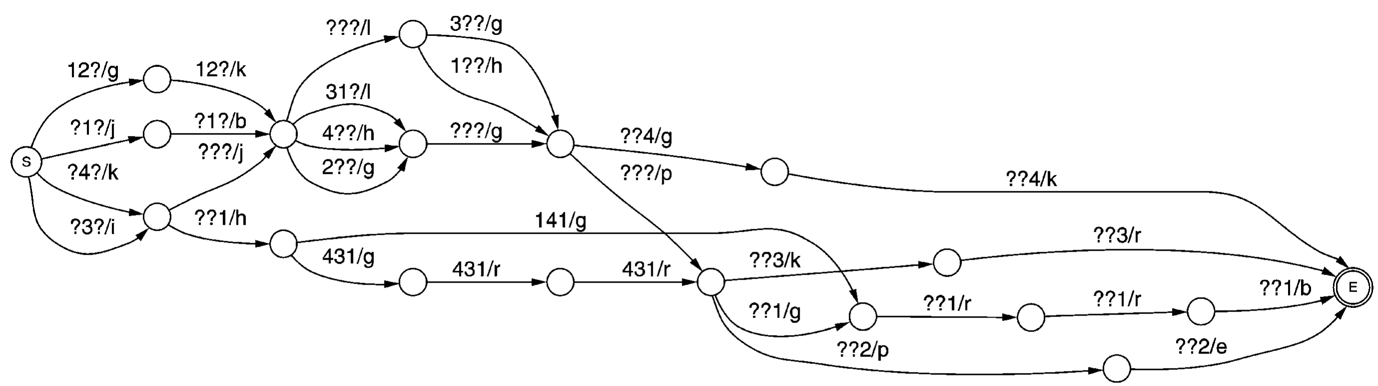

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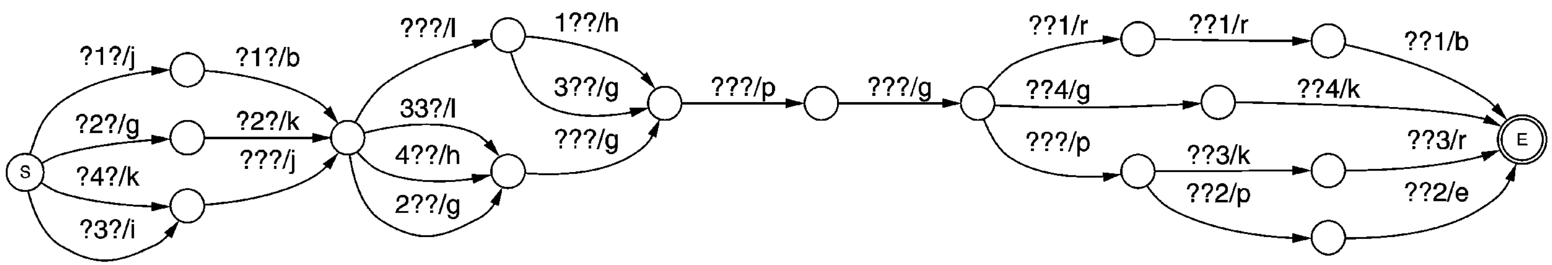

- Stable end state: compositional, expressive
- BUT: this only happens when there is a *bottleneck* on transmission

What's going on?

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- Cultural evolution leads to *compressible representational systems*

Cultural evolution and language

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- Cultural evolution has a profound effect
  - Properties of bottleneck shape language structure
  - We don't need natural selection
- So what exactly is the contribution of innate constraints?
  - Need a flexible model of innate constraints
  - and a way of telling what universals they predict.

Bayesian Iterated Learning

Kirby, Dowman & Griffiths (2007), *PNAS*

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- Learners combine *experience* with innately provided *prior bias* to calculate the probability of each language

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$$p(h|d) \propto p(d|h)p(h)$$

- Allows us to provide a model of innateness, *p(h)*, and predict what language (hypothesis), *h*, a learner will pick given a given set of data, *d*

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"score" for each language

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model of language

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$$\cdots \rightarrow d_0 \xrightarrow{p(h_{\text{is chosen}}|d)} h_1 \xrightarrow{p(d|h)} d_1 \xrightarrow{p(h_{\text{is chosen}}|d)} h_2 \cdots \rightarrow$$

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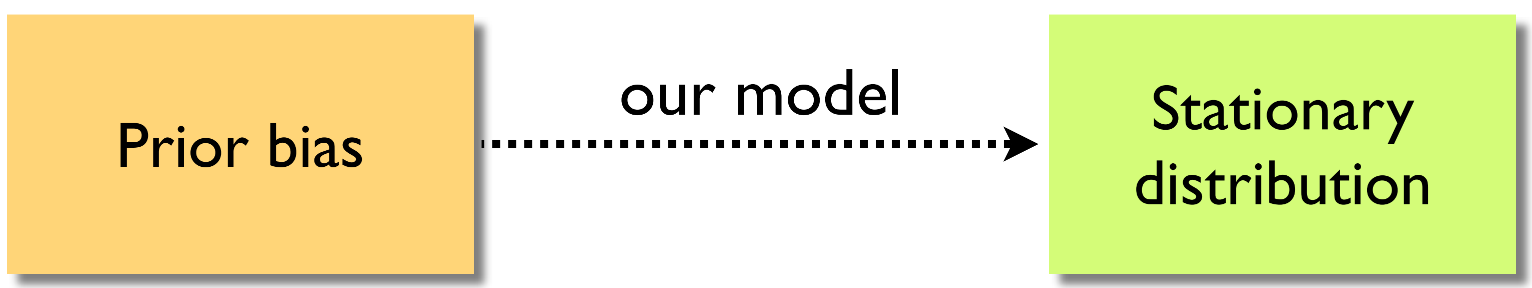
- We can use this to calculate a "Q-matrix" (e.g. Nowak, Komarova, Niyogi 2001)
- From this we can compute the expected *stationary distribution* of languages

From innateness to universals

- To recap:
  - If we think of innateness in terms of *prior bias*
  - then we can work out what languages will emerge from iterated learning



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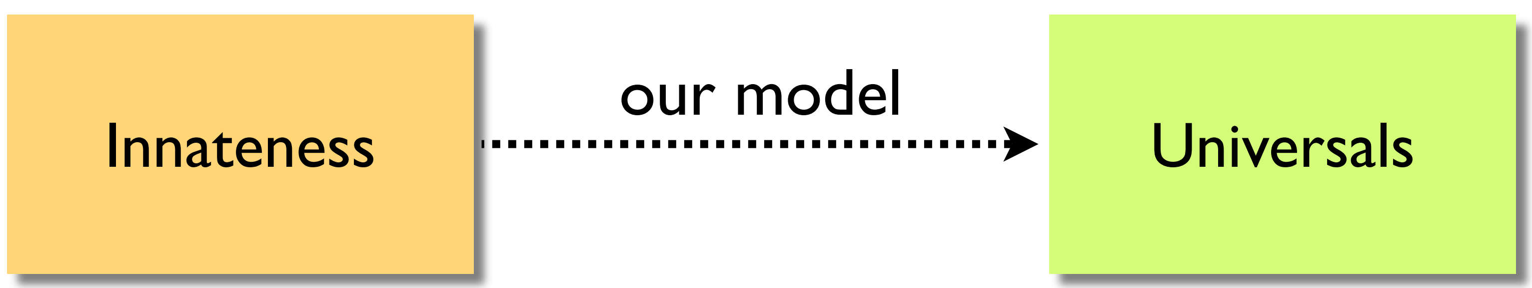

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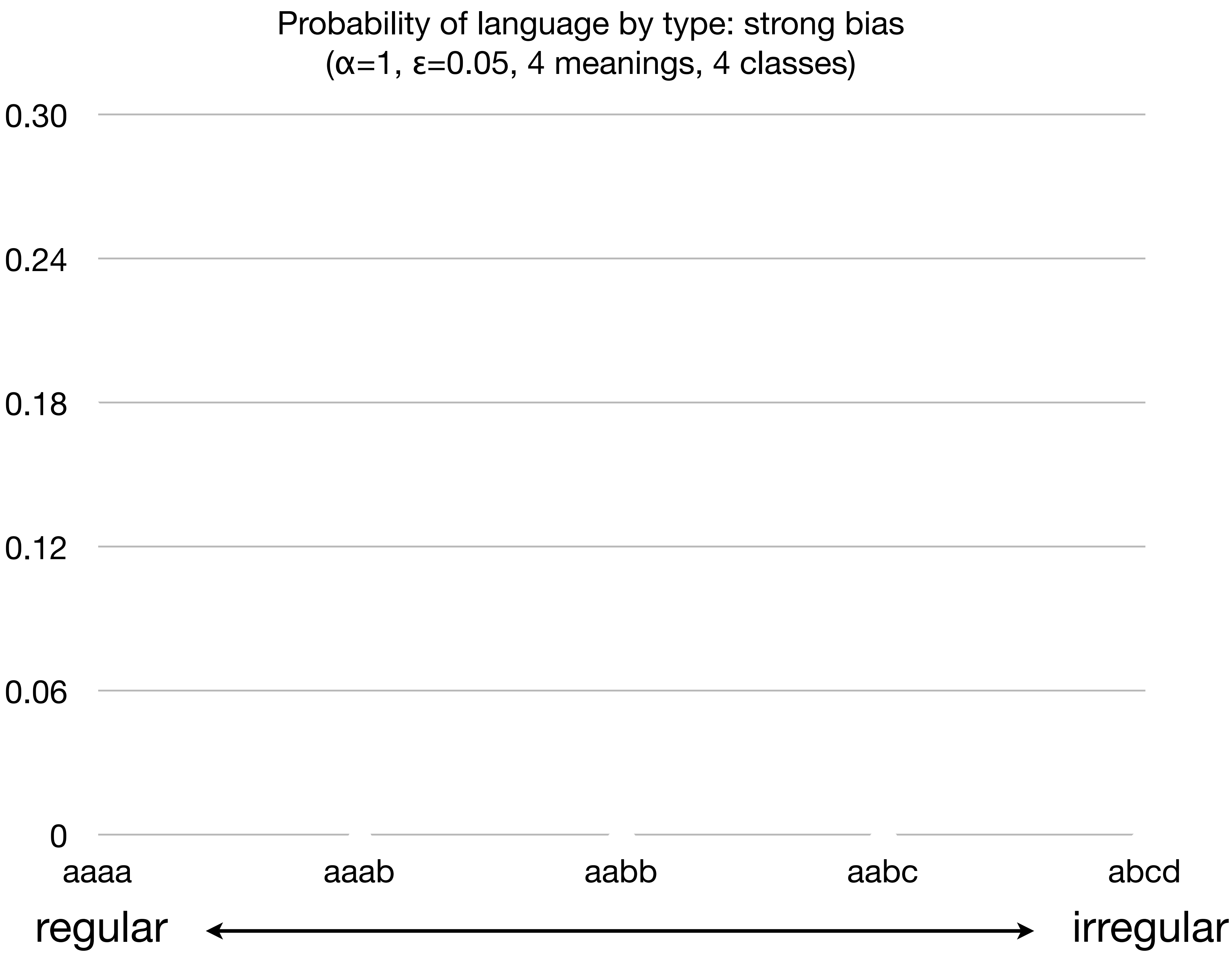
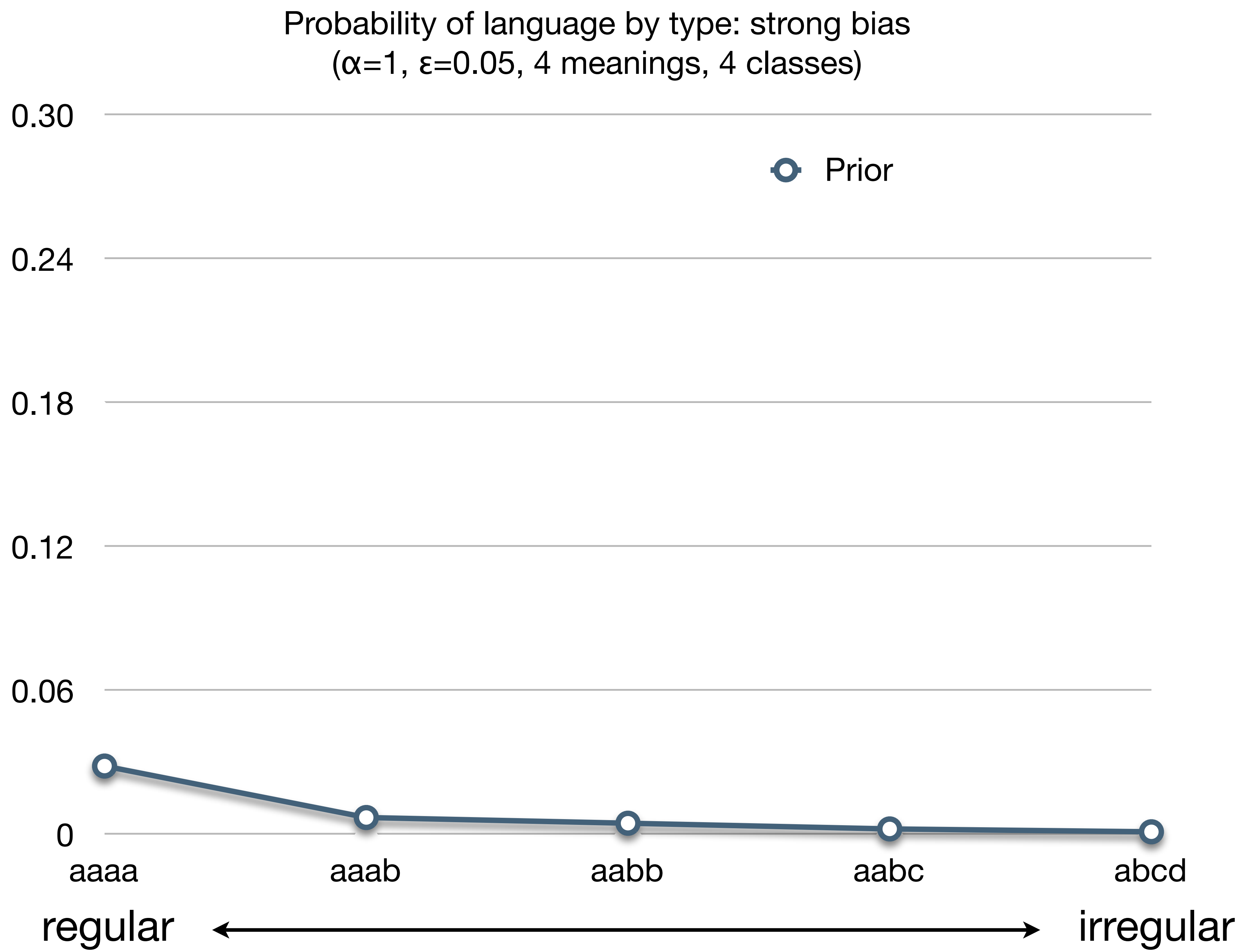
- Assume learners pick the best hypothesis
- What happens?


Probability of language by type: strong bias
(α=1, ε=0.05, 4 meanings, 4 classes)
0.30
0.24
0.18
0.12
0.06
0
aaaa
aaab
aabb
aabc
abcd
regular
irregular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0.30
0.24
0.18
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0.06
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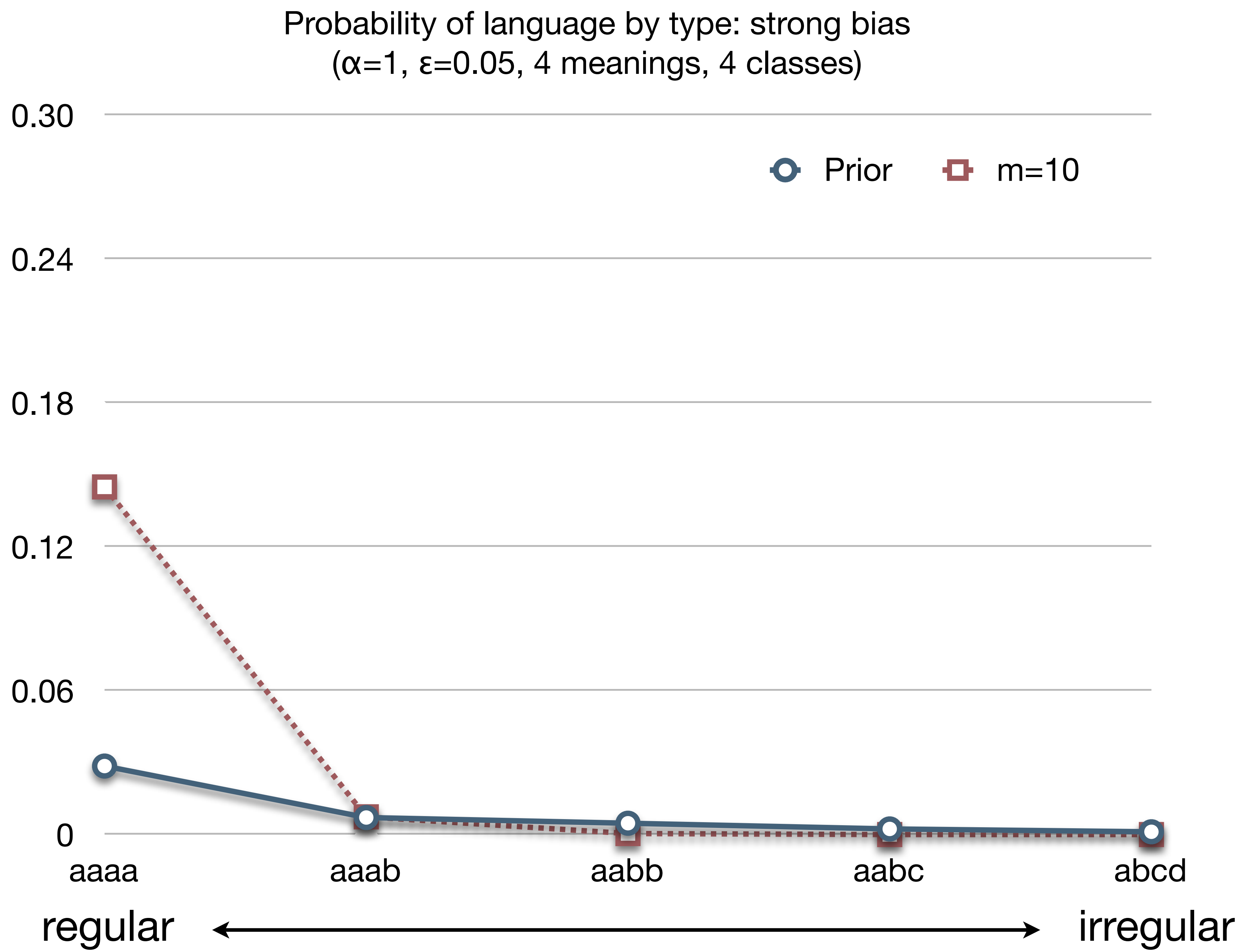
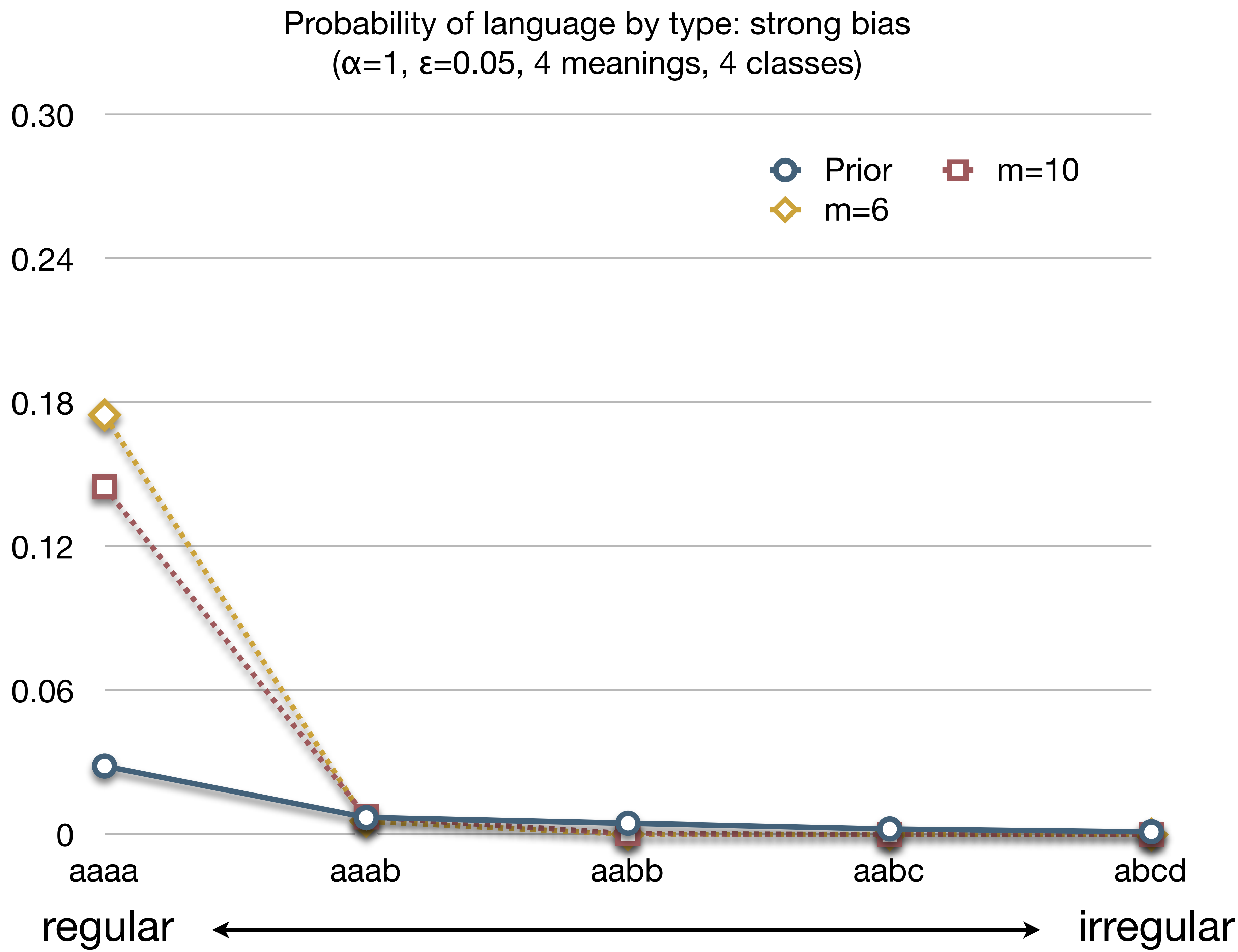
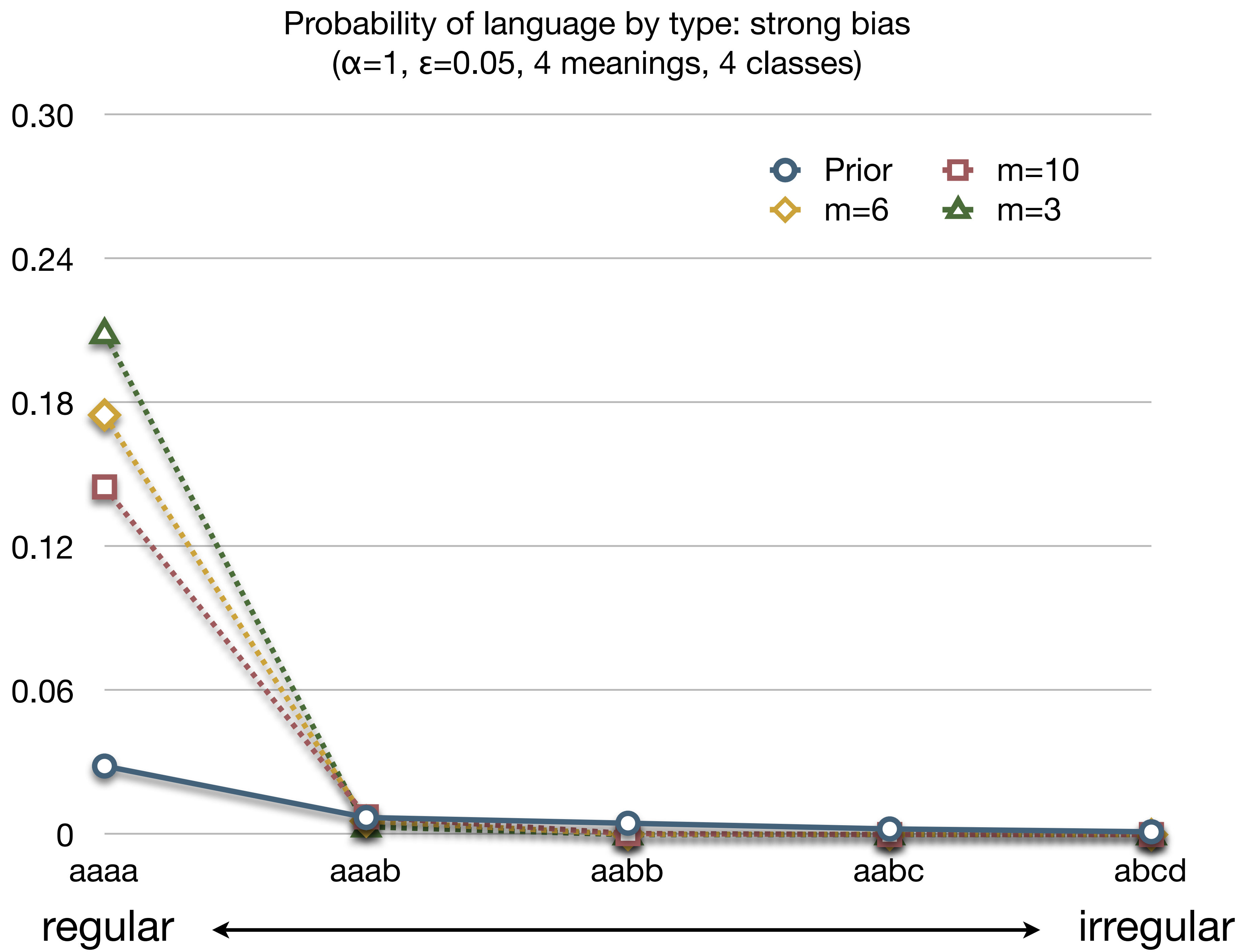
Prior
aaaa
aaab
aabb
aabc
abcd
regular
irregular


Probability of language by type: strong bias
(α=1, ε=0.05, 4 meanings, 4 classes)
0.30
0.24
0.18
0.12
0.06
0
Prior
m=10
aaaa
aaab
aabb
aabc
abcd
regular
irregular


Probability of language by type: strong bias
(α=1, ε=0.05, 4 meanings, 4 classes)
0.30
0.24
0.18
0.12
0.06
0
Prior
m=10
m=6
aaaa
aaab
aabb
aabc
abcd
regular
irregular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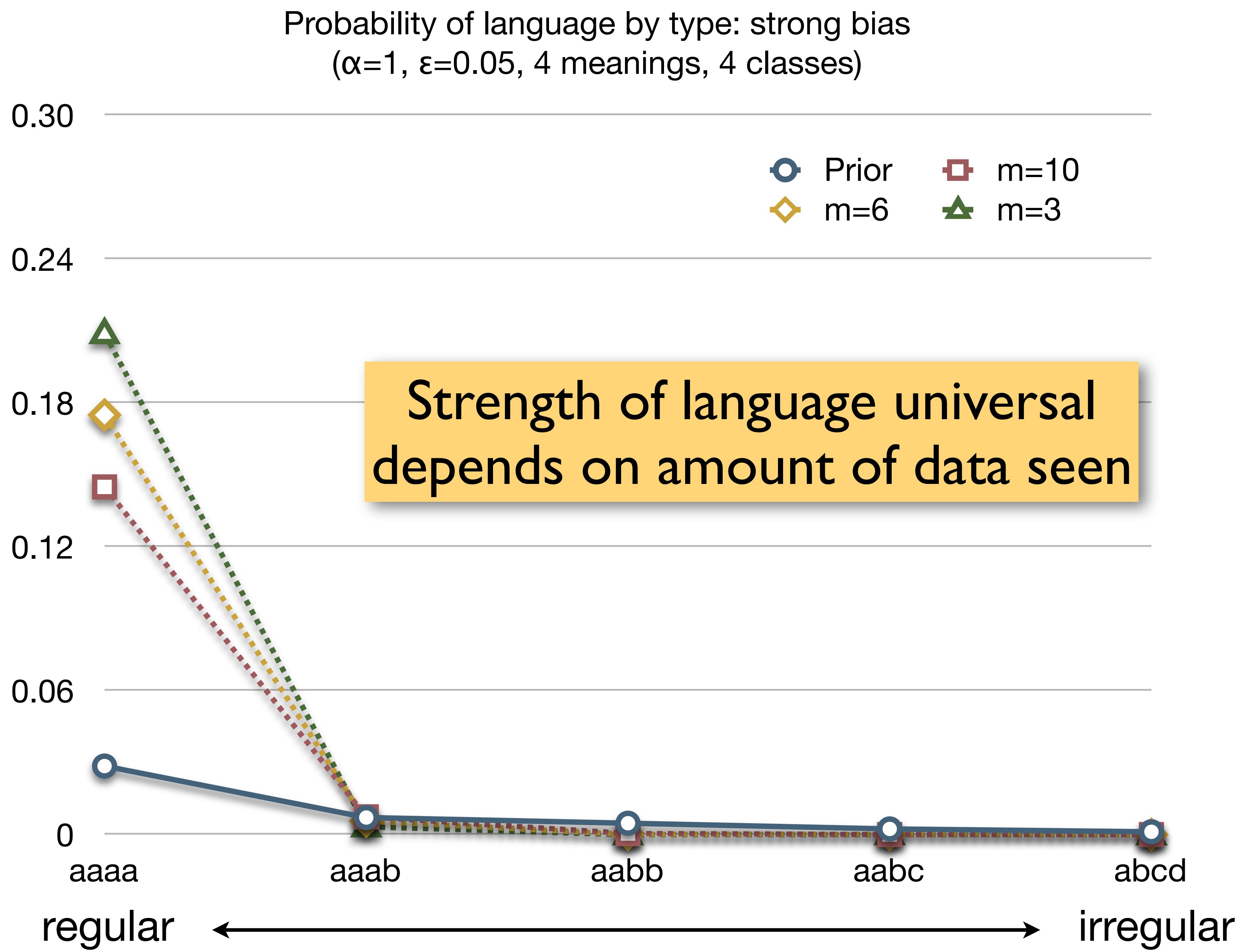
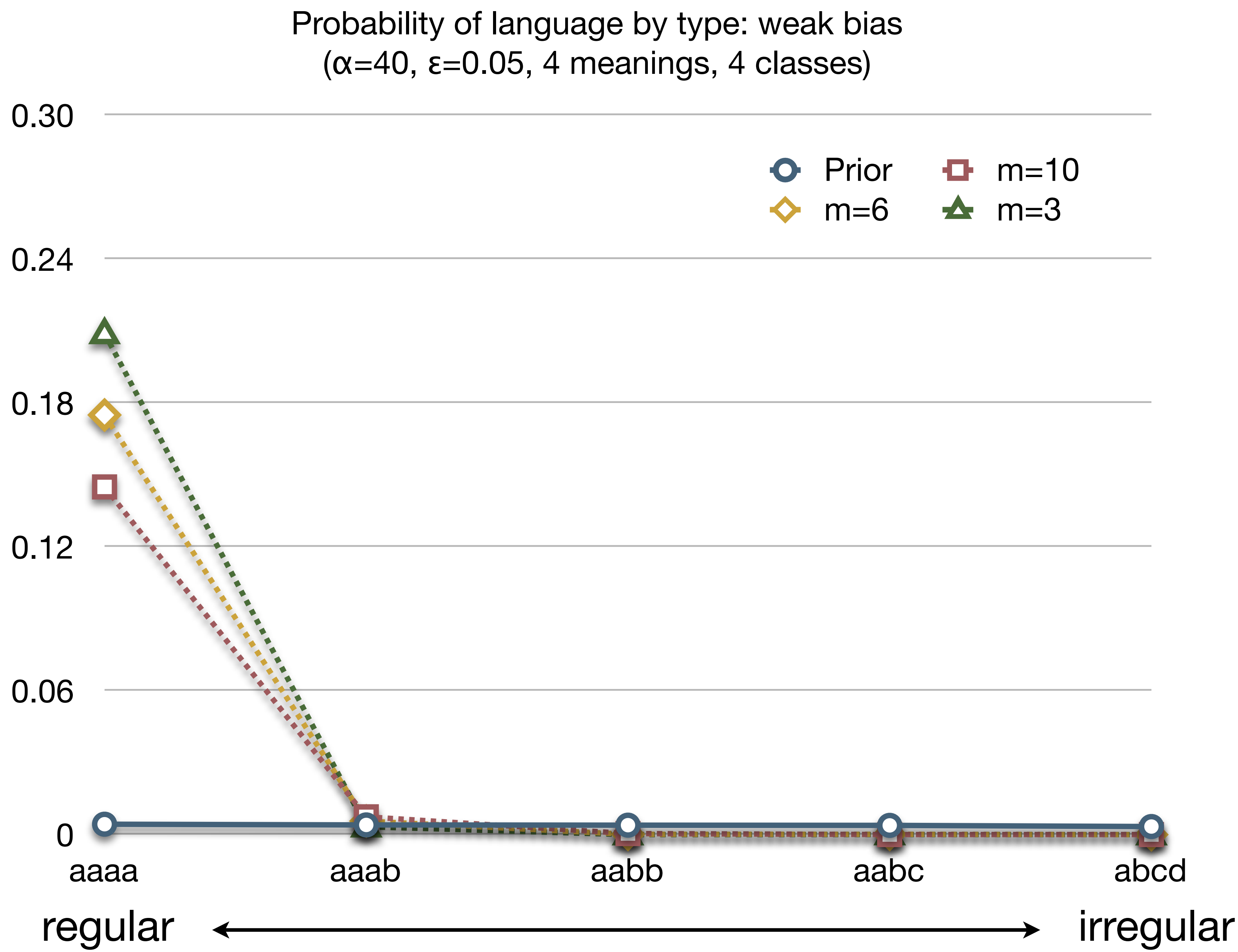
0.30
0.24
0.18
0.12
0.06
0
Prior
m=10
m=6
m=3
aaaa
aaab
aabb
aabc
abcd
regular
irregular


Probability of language by type: strong bias
(α=1, ε=0.05, 4 meanings, 4 classes)
0.30
0.24
0.18
0.12
0.06
0
Prior
m=10
m=6
m=3
Strength of language universal depends on amount of data seen
aaaa
aaab
aabb
aabc
abcd
regular
irregular


Probability of language by type: weak bias
(α=40, ε=0.05, 4 meanings, 4 classes)
0.30
0.24
0.18
0.12
0.06
0
Prior
m=6
m=10
m=3
aaaa
aaab
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abcd
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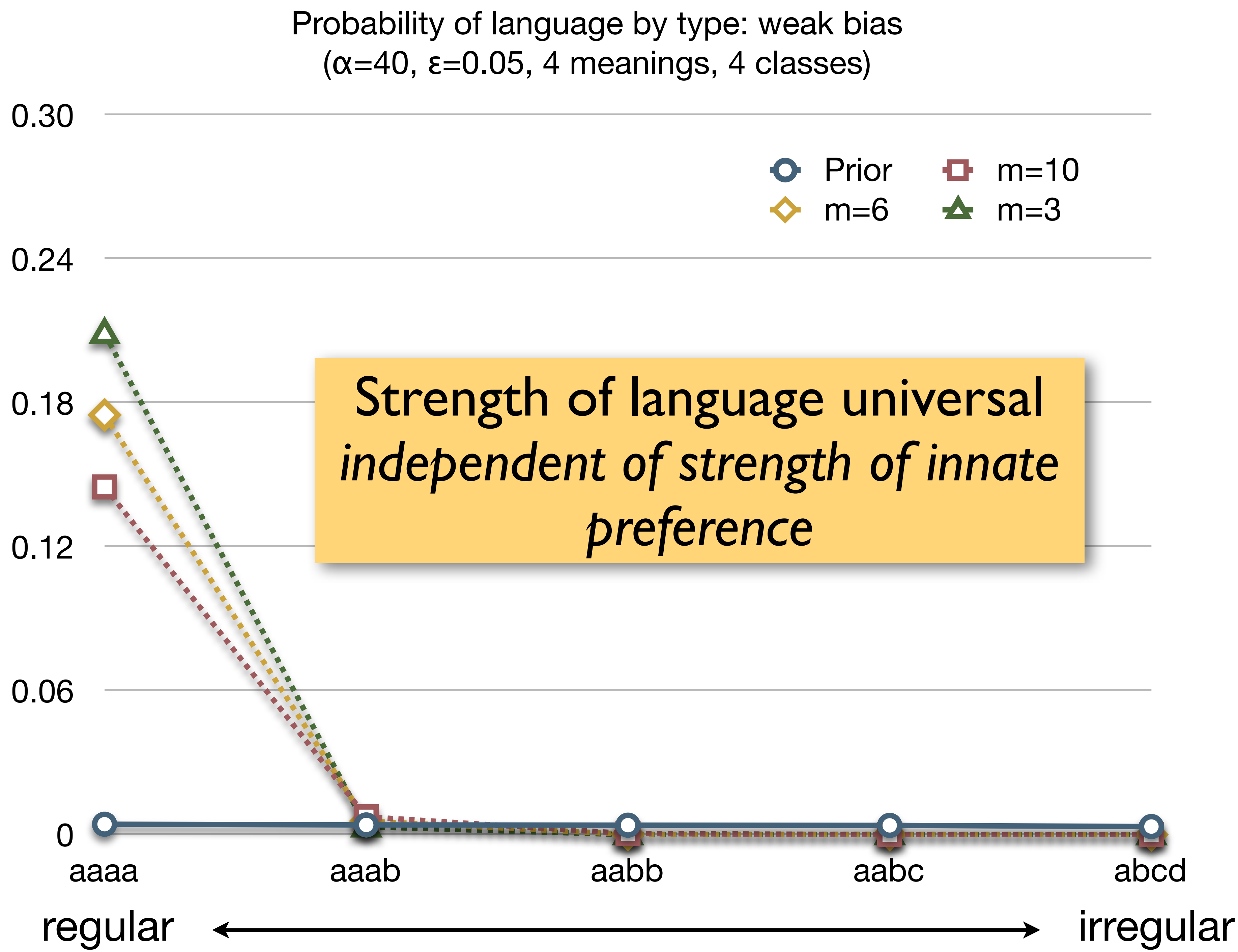
irregular



Probability of language by type: weak bias
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0.30
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0.12
0.06
0
Prior
m=10
m=6
m=3
Strength of language universal
independent of strength of innate preference
aaaa
aaab
aabb
aabc
abcd
regular
irregular

What does this mean?

- What's innate matters, but you can't predict language universals from innateness
- Equally, you can't infer innateness from universals.
- Strong universals do not imply strong innate constraints
- (Neatly predicts Dediu & Ladd's (2007) genes/tone correlation)

Linguistic adaptation

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- Language is *adapting* culturally
- The languages we see are the ones optimised for transmission
  - No need for natural selection

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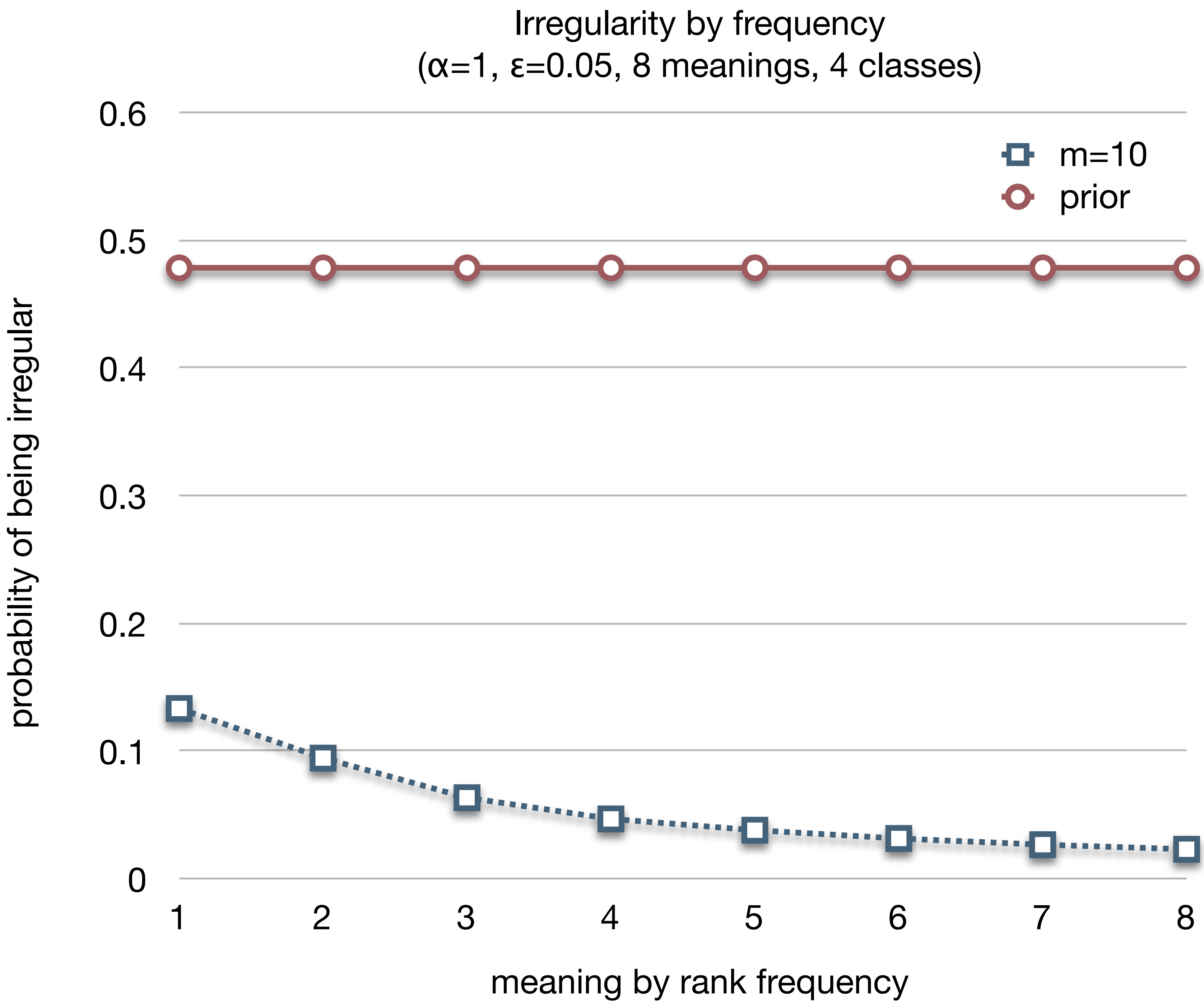
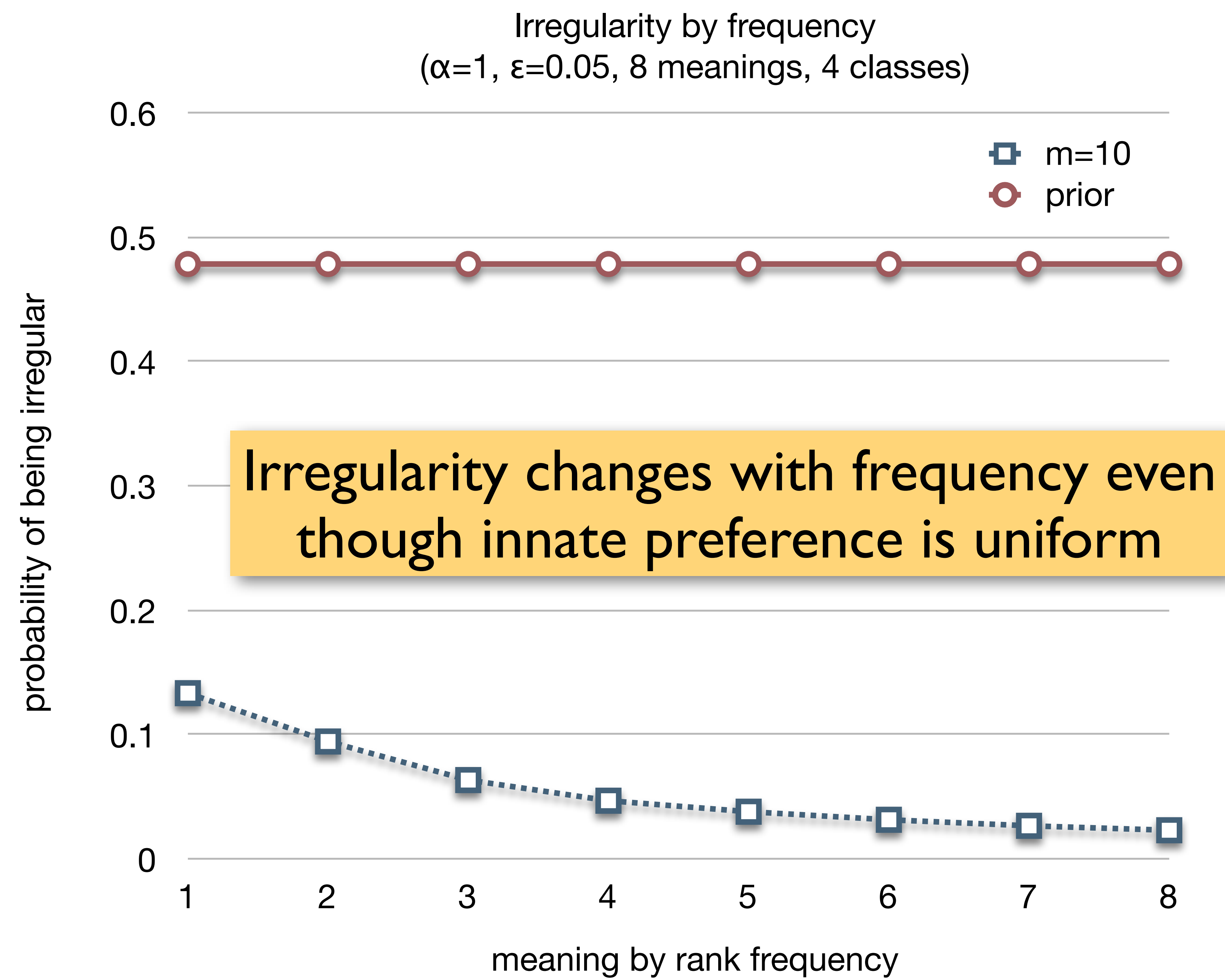
- Language is *adapting* culturally
- The languages we see are the ones optimised for transmission
  - No need for natural selection
- The tougher the transmission “bottleneck”, the more pressure there is to adapt
  - Turns the poverty of the stimulus problem on its head
  - Explains the frequency/irregularity correlation in morphology


Irregularity by frequency
(α=1, ε=0.05, 8 meanings, 4 classes)
0.6
0.5
0.4
0.3
0.2
0.1
0
m=10
prior
probability of being irregular
1
2
3
4
5
6
7
8
meaning by rank frequency



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meaning by rank frequency
Irregularity changes with frequency even though innate preference is uniform

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- Can we be sure this would work in real human agents?

Modelling only takes you so far... what about real people?

- Models suggest that a culturally transmitted system will spontaneously adapt to aid its own survival
- Can we be sure this would work in real human agents?
- Can we show adaptation of a language through cultural transmission *without intentional design on the part of the learners of the language?*

An experimental paradigm

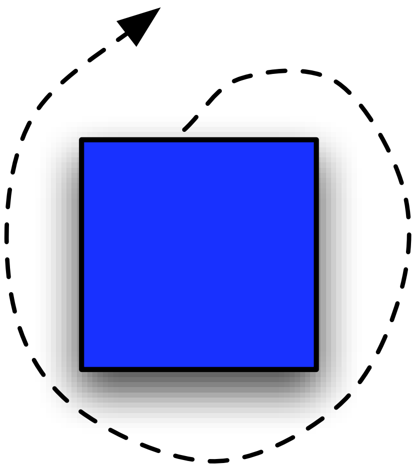
Cornish, K. Smith, Tamariz, A. Smith, Flaherty, Beqa

An experimental paradigm

Cornish, K. Smith, Tamariz, A. Smith, Flaherty, Beqa

- Participants exposed to artificial language made up of picture/string pairs (typically initially random)

kunige



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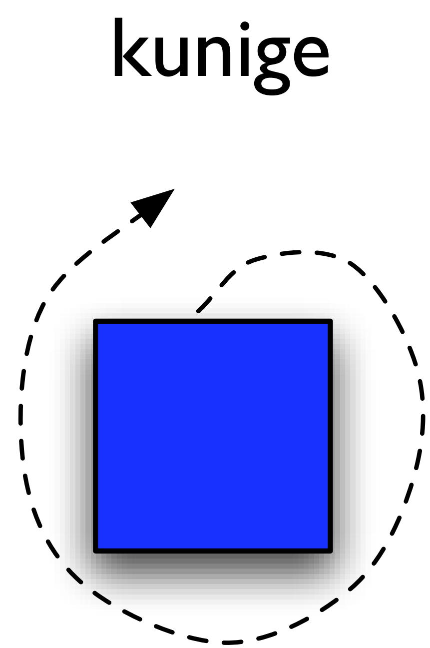

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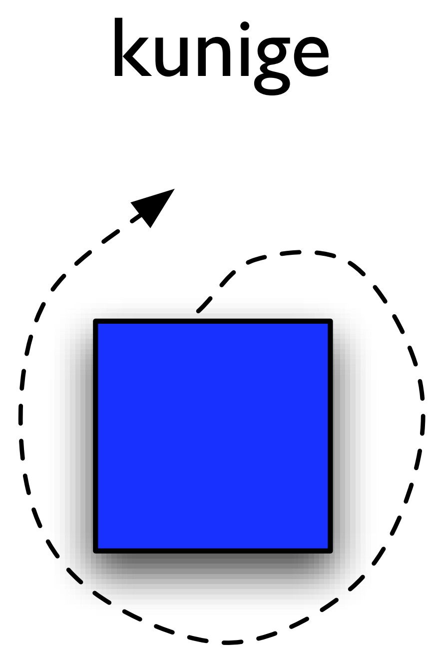

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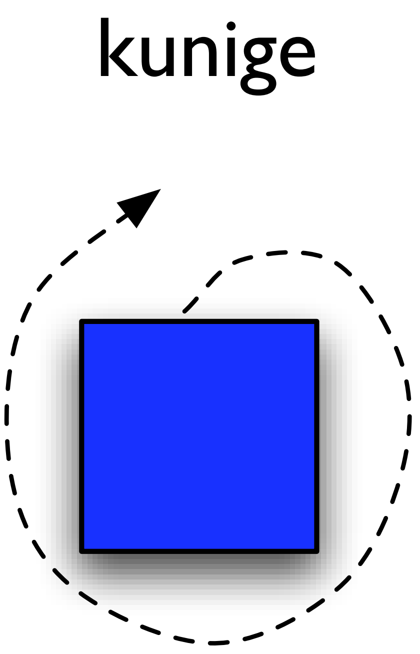
- Try and learn this
- Tested on full set of “meanings”
- Output on test used as input language for next participant



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  - How much of the language the subjects are exposed to
  - Frequency of meanings
  - Structure of meaning space
- What are the results?

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  - Language adapts

Study 1:
Emergence of structure

Kirby, Cornish & Smith (forthcoming), *PNAS*

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  - 3 x 3 x 3 meaning space
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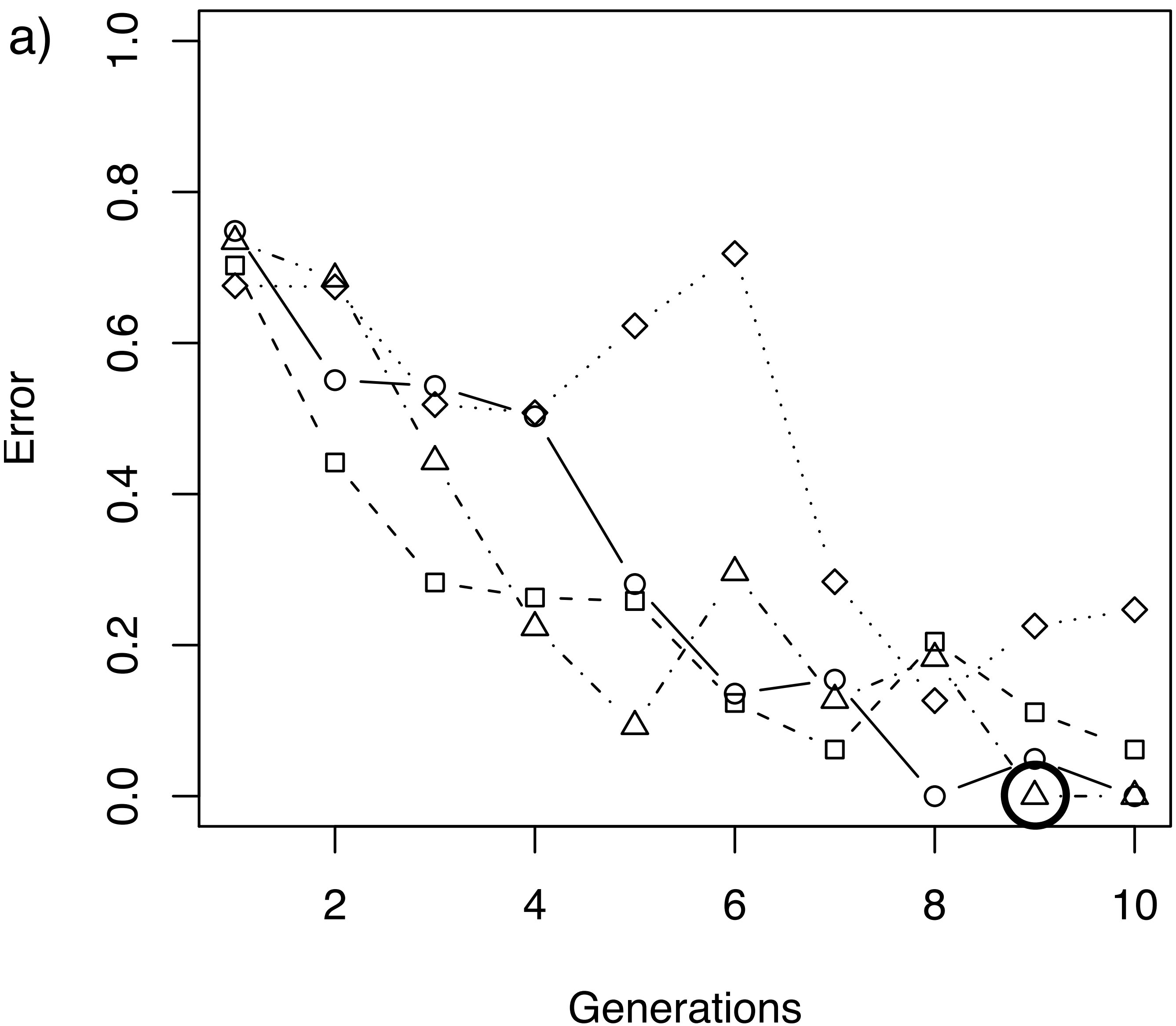
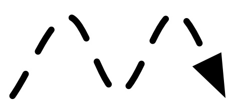
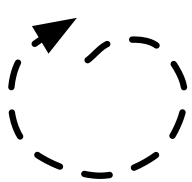
Language becomes easier to learn



Example initial language

	wimaku	miniki	gepinini	□
	nihepi	wigemi	mahekuki	○
	wikima	nipikuge	hema	△
	miwiniku	pinipi	kihemiwi	□
	kinimapi	wikuki	kikumi	○
	miwimi	nipi	wige	△
	gepihemi	kunige	miki	□
	pikuhemi	kimaki	pimikihe	○
	mihe	winige	kinimage	△

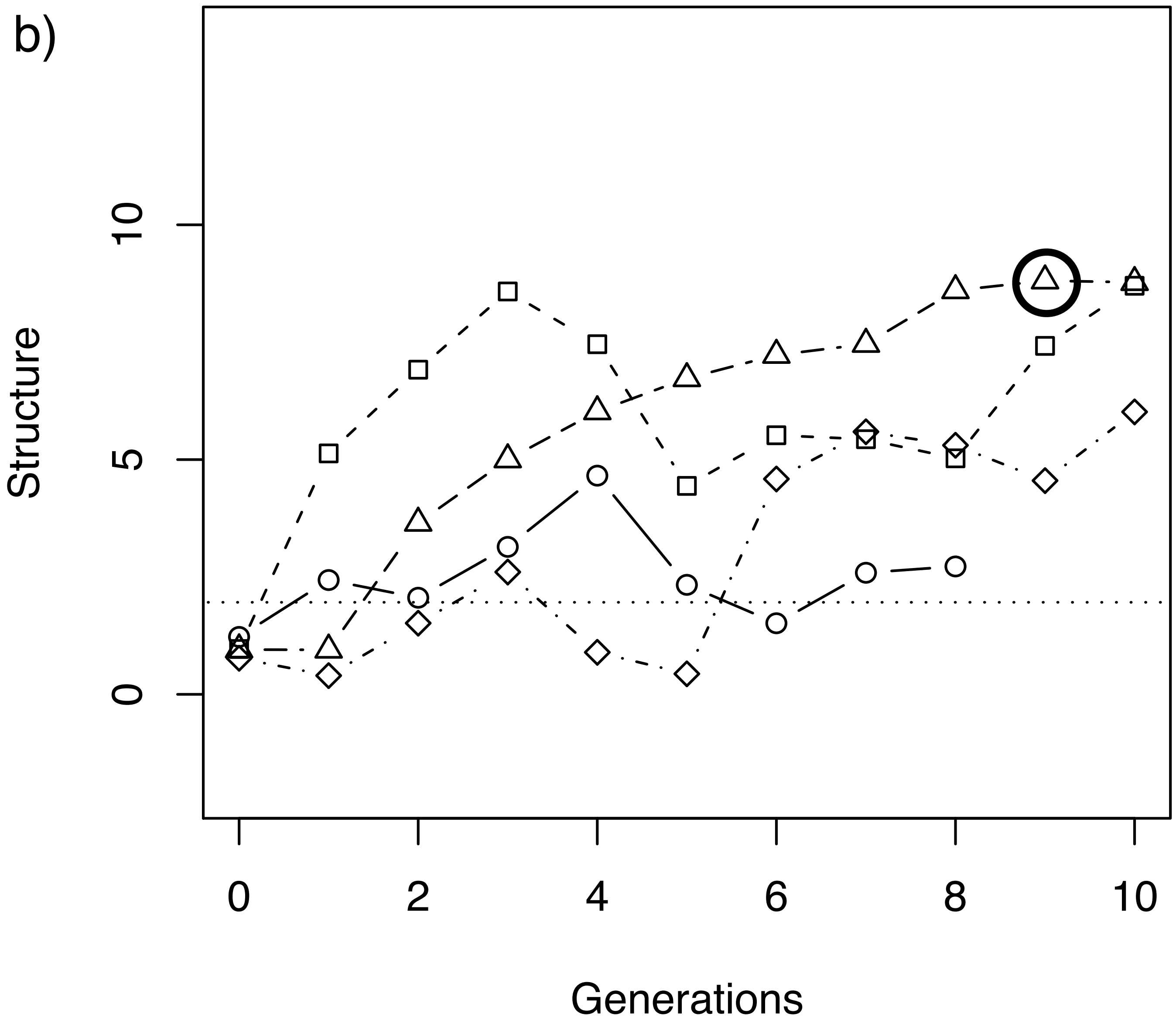
Example final language

(10 “generations” later)

Need a general measure of structure

- To what extent is the mapping between meanings and signals *systematic*?
  - If the mapping is systematic, similar signals should map to similar meanings
- Measure the distance between all pairs of meanings, and all pairs of signals
- Calculate correlation between all pairs
  - Normalise resulting coefficient by comparing with thousands of randomised mappings

Language becomes systematic



More interesting structure?

- This *systematic underspecification* is structured, but...
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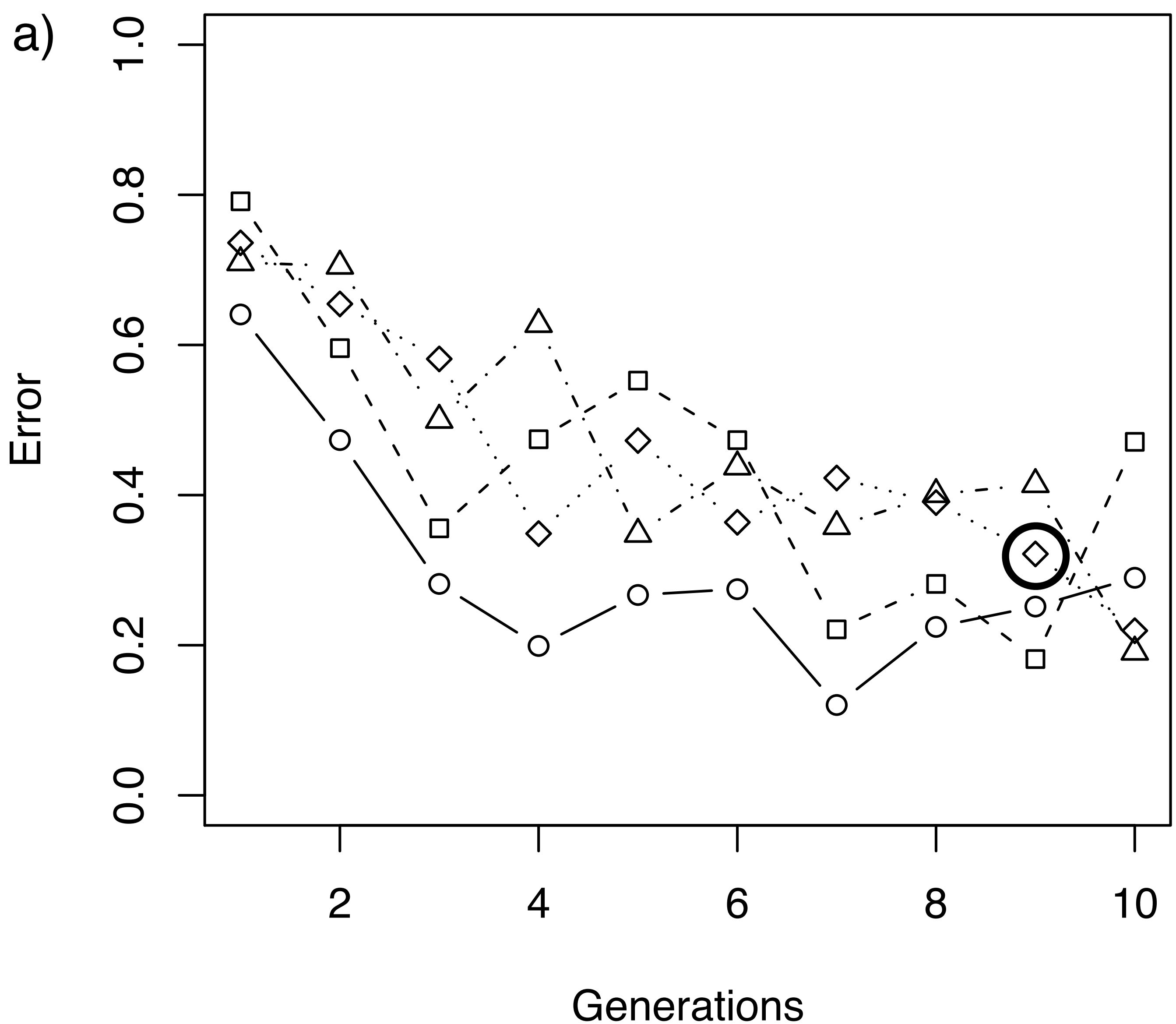
- Simple modification: filter out all ambiguous items from SEEN set before subjects see them

Language becomes easier to learn



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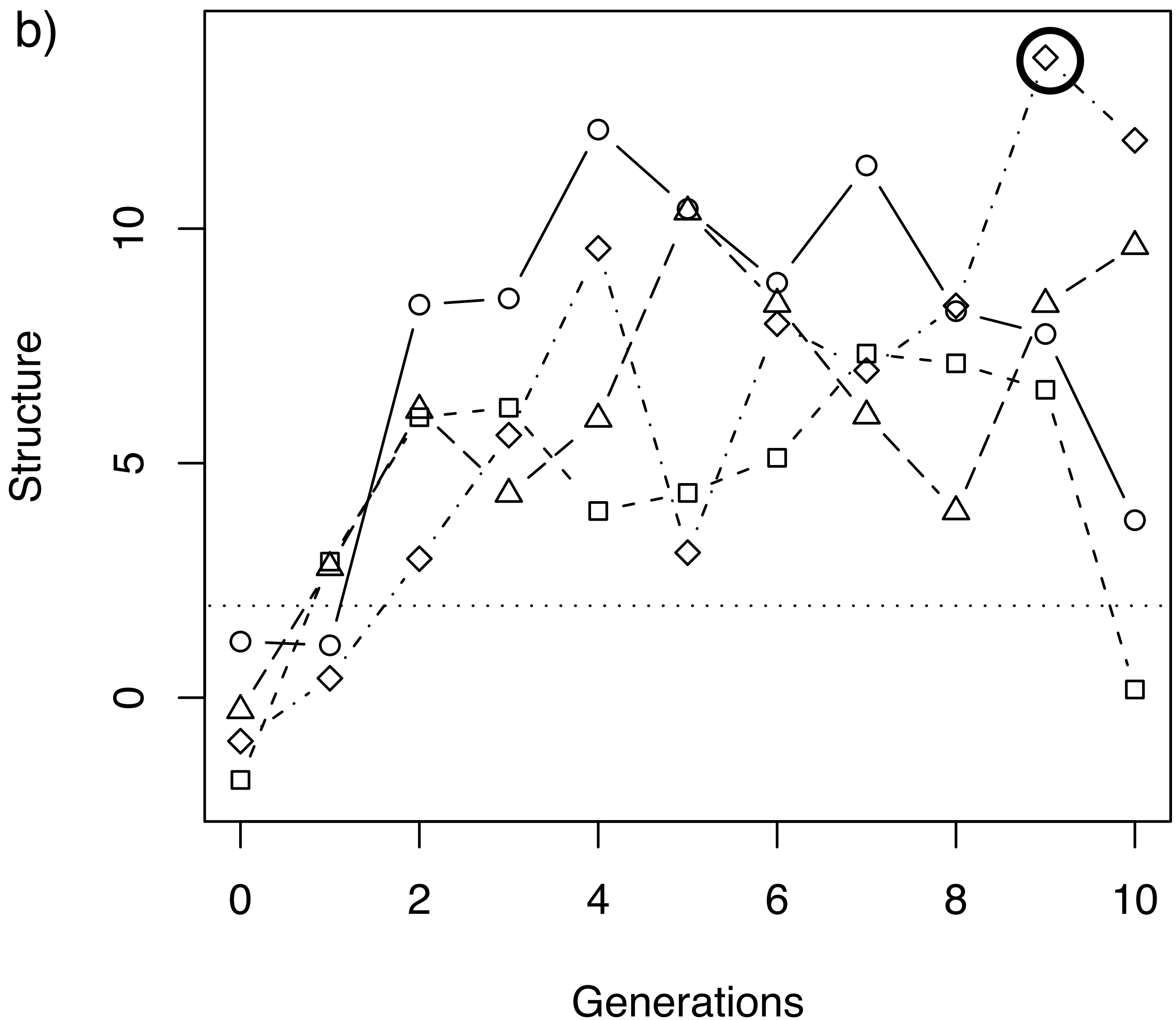
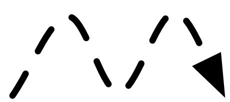
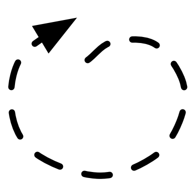


Example initial language

	lumonamo	kinahune	lahupine	□
	nelu	kanehu	namopihu	○
	kapihu	humo	lahupiki	△
	moki	luneki	lanepi	□
	kalu	mola	pihukimo	○
	nane	kalakihu	mokihuna	△
	kilamo	kahuki	neluka	□
	pilu	neki	pinemohu	○
	luki	namola	lumoka	△

Example final language
(10 “generations” later)

n-ere-ki	l-ere-ki	renana	□
n-ehe-ki	l-aho-ki	r-ene-ki	○
n-eke-ki	l-ake-ki	r-ahe-ki	△
n-ere-plo	l-ane-plo	r-e-plo	□
n-eho-plo	l-aho-plo	r-eho-plo	○
n-eki-plo	l-aki-plo	r-aho-plo	△
n-e-pilu	l-ane-pilu	r-e-pilu	□
n-eho-pilu	l-aho-pilu	r-eho-pilu	○
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- Morphological/syntactic structure is a solution to this problem
- Note: subjects cannot be aware of the filtering, but language structure is very different
  - Demonstrates that adaptation is *non-intentional*
  - Culture gives us *design without a designer*

Study 2: Frequency/irregularity

Beqa (2007); Beqa, Kirby & Hurford (forthcoming)

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- Over generations:
  - language becomes easier to learn
  - *infrequent* irregulars regularise

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Frequency/irregularity

Frequent	vipirir / vipirar	→	rivipir / rivipar
	tada / sinefu	→	*tada / senoufe*
Infrequent	ridetir / ridetar	→	ravipir / ravipar
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- Cultural evolution is just as important (if not more so) than biological evolution in understanding human language
  - This means we need to abandon some of the idealisations of the orthodox, individual-based approach
- Can we study cultural evolution in the lab?
  - Yes! Novel experimental techniques inspired by computational models give us a way.
  - In a very real sense we can observe the evolution of language in miniature in laboratory conditions.
  - Suggests a way of thinking about culture itself as a computational system

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- Models build a lot in:
  - Learning complex signals
  - Inferring meanings
- The real evolutionary story?
  - Not: natural selection of innate constraints that determine language structure
  - Instead: pre-adaptations that enable iterated learning

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- Transmitted by iterated learning, but do not carry semantics
- Evolves for other reasons
  - Complex learned song is fitness indicator
    (e.g. Ritchie, Kirby & Hawkey; Okanoya)

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- Possible cline of abilities in other primates
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- Intentional inference plausibly evolves for reasons other than communication

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- Still much work to be done, but multiple modelling strategies represent the best approach.