Artificial language learning workshop: Lecture 2

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Artificial grammar learning

Part I: Artificial grammar learning

Artificial grammar learning

A question...

How do adults (or infants) make sense of speech?

https://www.youtube.com/watch?v=nDaTTVR2JXY

Saffran, Aslin & Newport (1996)

Artificial grammar learning

A prediction...

Speech has statistical information that can help the listener segment the complex stream

Saffran, Aslin & Newport (1996)

Artificial grammar learning

An example...

Ling_ _ _

Krom_ _ _

Sch_ _ _

Ing_ _ _

Artificial grammar learning

An example...

Linguistics
Kroměříž
School
Inglorious

Artificial grammar learning

A theory...

Transitional probabilities occur in natural language making word boundaries easier to identify

Artificial grammar learning

A problem...

Natural language is noisy and contains much more information than just transitional probabilities

Artificial grammar learning

A solution...

Create an artificial language that incorporates only transitional probabilities, controlling for other variables, and test learning

Artificial grammar learning

An experiment...

Frost & Monaghan (2017)

Artificial grammar learning

Which one is part of the language?

1

2

Frost & Monaghan (2017)

Artificial grammar learning

A design...

- Artificial language with 18 syllables

- Tri-syllabic ‘words’ with AXB structure
- e.g. /maʊ fəʊ li/ – highly likely

- Tri-syllabic ‘part-words’ with BAX structure
  e.g. /tæ gæ sɔ/ - highly unlikely

Frost & Monaghan (2017)

Artificial grammar learning

A result...

- Test if participants can learn the structure of the language, by discriminating between two choices (2 alternative forced choice 2AFC)

- Can even be used to test generalisation to new stimuli e.g. $A_x X B_y$ vs $B_y A_x X$... before and after sleep

Frost & Monaghan (2017)

Artificial word learning

Part II:
Artificial word learning

Artificial word learning

A question...

How do we learn new words?

Smith and Yu (2008)

Artificial word learning

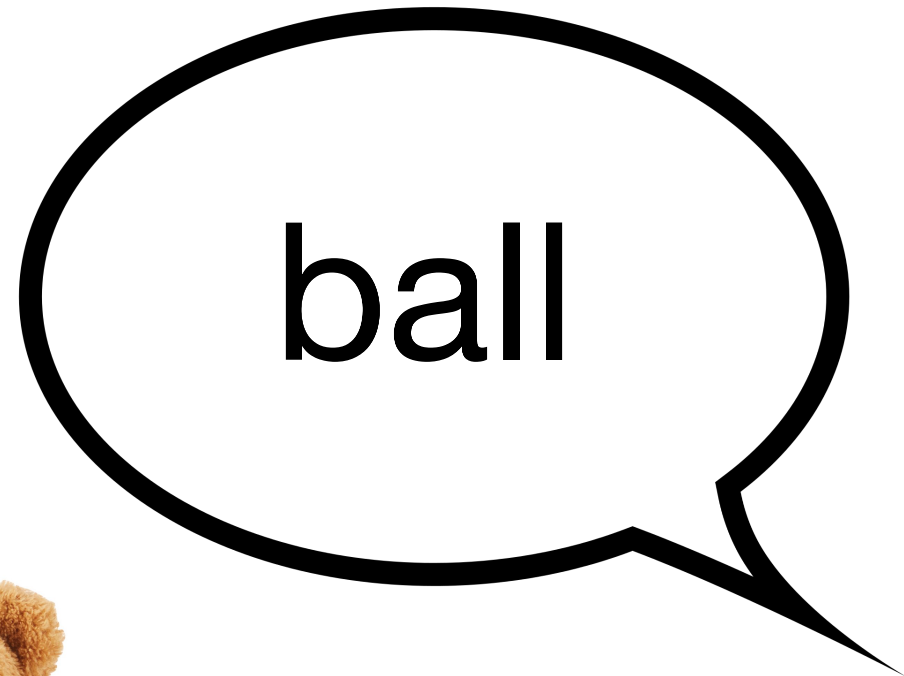
A prediction...

We use cues in the environment that are statistically reliable to help us learn

Smith and Yu (2008)

Artificial word learning

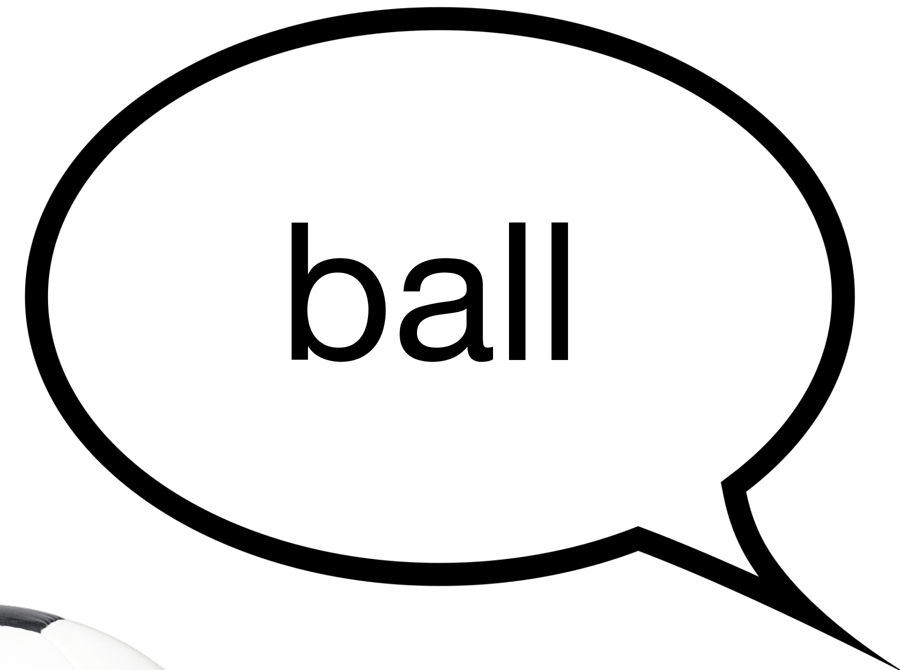
An example...



Smith and Yu (2008)

Artificial word learning

An example...



Smith and Yu (2008)

Artificial word learning

An example...

Smith and Yu (2008)

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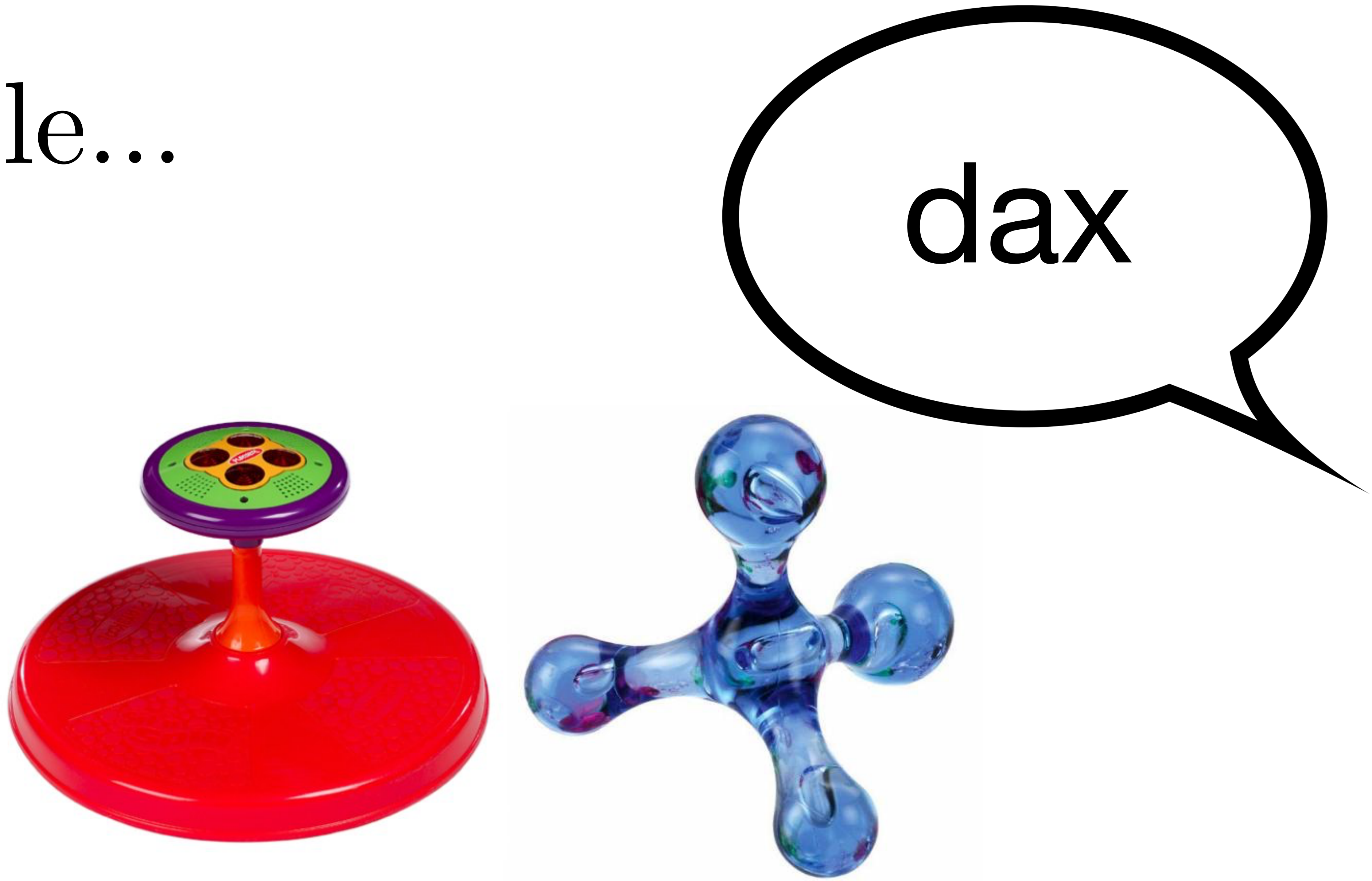


Smith and Yu (2008)

Artificial word learning

A theory...

Learners exploit multiple cues in the environment to assist their learning over time (cross-situational learning)

Monaghan et al. (2017)

Artificial word learning

A problem...

Learning environments are noisy and it is hard to test the theory with natural language

Monaghan et al. (2017)

Artificial word learning

A solution...

Use artificial language learning to assess learning from multiple cues

Monaghan et al. (2017)

Artificial word learning

An experiment...

Monaghan et al. (2017)

Artificial word learning

An experiment...

Monaghan et al. (2017)

Artificial word learning

A design...

- 16 novel word-meaning mappings
  e.g. 'thislin' always occurs with the circle meaning
- Manipulate frequency of prosodic and gestural cues, e.g. 25%, 50%, 75%, 100% conditions
- 2AFC each trial

Monaghan et al. (2017)

Artificial word learning

A result...

- Assess learning over the course of the experiment
- Test learning after training by removing all cues
- Compare between conditions i.e. 25%, 50%, 75%, 100% cue present

Monaghan et al. (2017)

Artificial word learning

Another theory...

Learning of individual words is easier when there is sound-symbolism... but only in a small vocabulary set

Brand, Monaghan & Walker (2017)

Artificial word learning

Another problem...

Corpora do not allow for specific control over the variables of interest

Brand, Monaghan & Walker (2017)

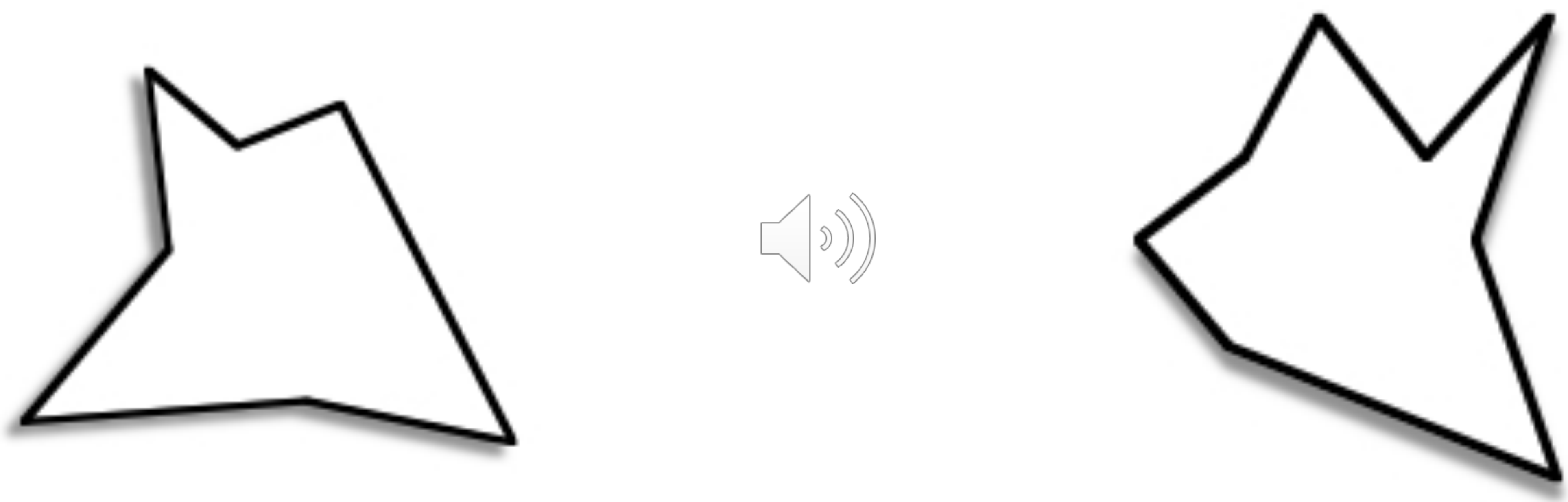
Artificial word learning

Another experiment...

Brand, Monaghan & Walker (2017)

Artificial word learning

Another experiment...



Brand, Monaghan & Walker (2017)

Artificial word learning

Another design...

- Present congruent and incongruent mappings
- Vary the number of mappings during training
  e.g. small = 8, medium = 12, large = 16
- Vary the trial type
  categorical learning (semantically distinct)
  individual learning (semantically similar)

Brand, Monaghan & Walker (2017)

Artificial word learning

Another result...

- Sound-symbolism boosts learning of categories
- Sound-symbolism boots learning of individual words (semantically similar) but only in small vocabulary size

Brand, Monaghan & Walker (2017)

Artificial orthography learning

Part III:
Artificial orthography learning

Artificial orthography learning

A question...

How do we learn to read?

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

A prediction...

We use semantics and phonology to aid learning of reading

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

An example...

How do you pronounce:

g h o t i

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

An example...

/f/ /ɪ/ /ʃ/

cou**gh** w**o**men mo**ti**on

g h o t i

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

A theory...

Phonology and semantics are important components of any model of reading

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

A problem...

Psycholinguistic properties can only be used as a proxy for an individual's experience

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

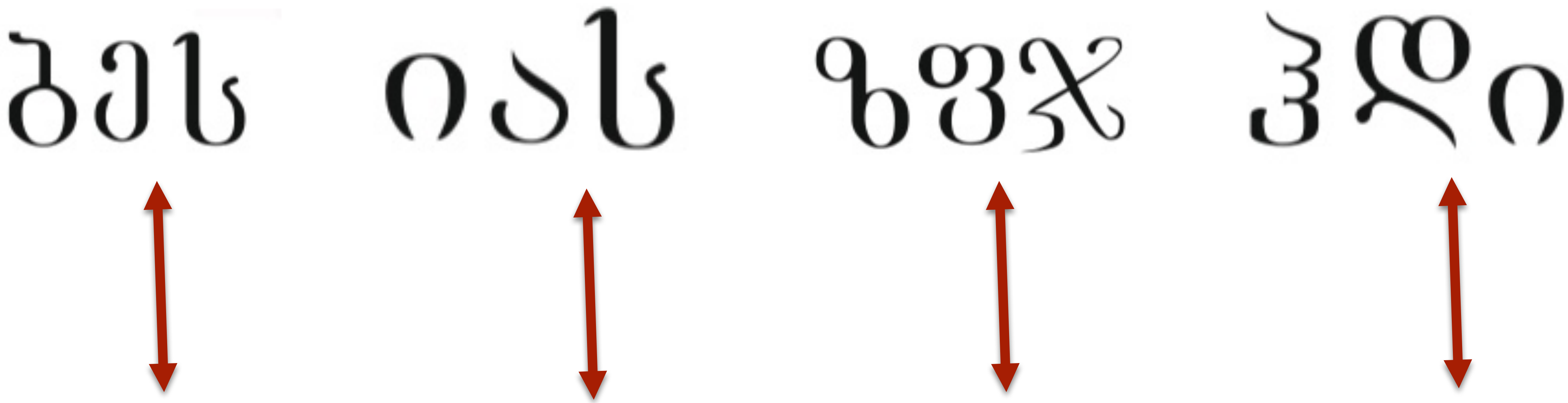
A solution...

Design an artificial orthography where you can train participants and control psycholinguistic properties

Taylor, Plunkett & Nation (2011)

Artificial orthography learning

An experiment...

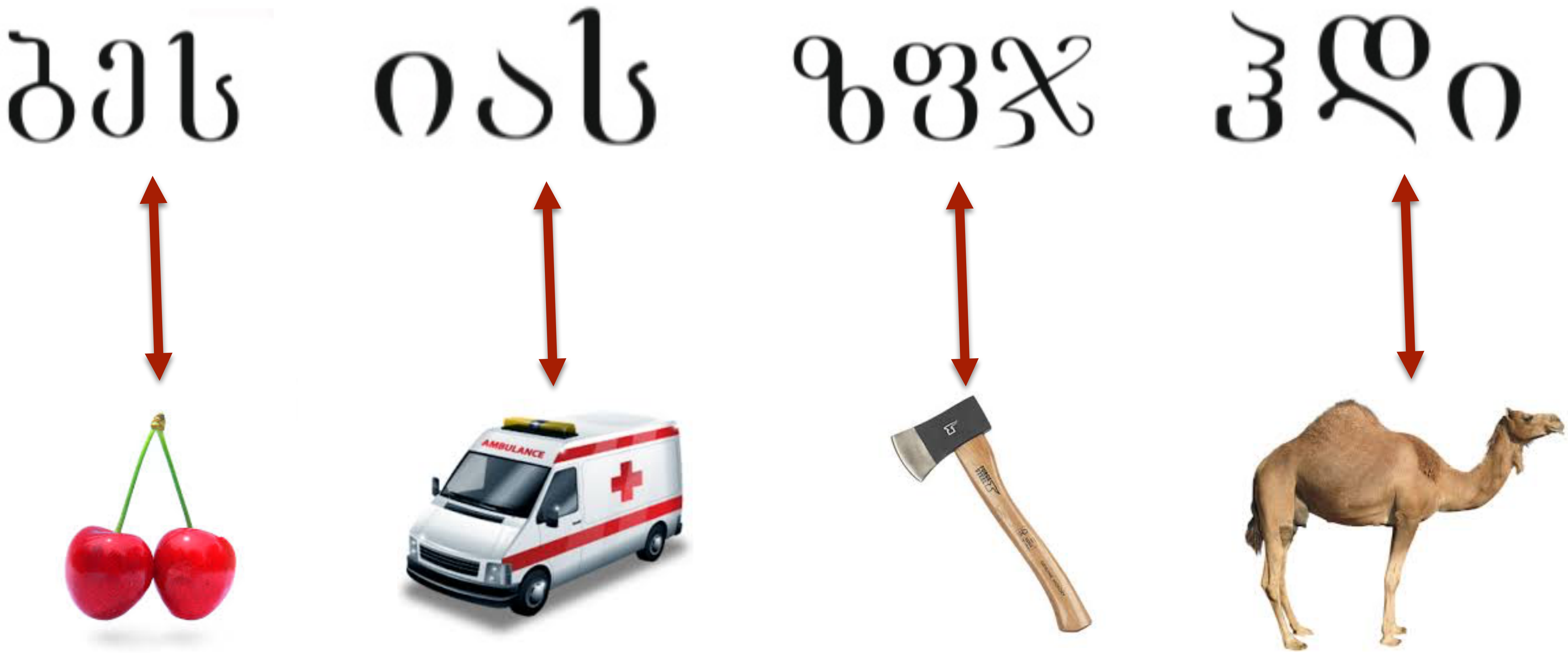


/bəʊs/ /kes/ /faɪm/ /gʌk/

Taylor, Davis & Rastle (2017)

Artificial orthography learning

An experiment...



Taylor, Davis & Rastle (2017)

Artificial orthography learning

A design...

- Train participants on orthography – phonology
- Train participants on orthography – semantics
- Control over psycholinguistic properties e.g. frequency, length, age of acquisition
- Train over the course of several days

Taylor, Davis & Rastle (2017)

Artificial orthography learning

A result...

- Assess learning through reading aloud
- Assess learning through picture naming
- Assess learning through word recognition

Taylor, Davis & Rastle (2017)

Iterated learning

Part IV:
Iterated learning

Iterated learning

A question...

How does language evolve?

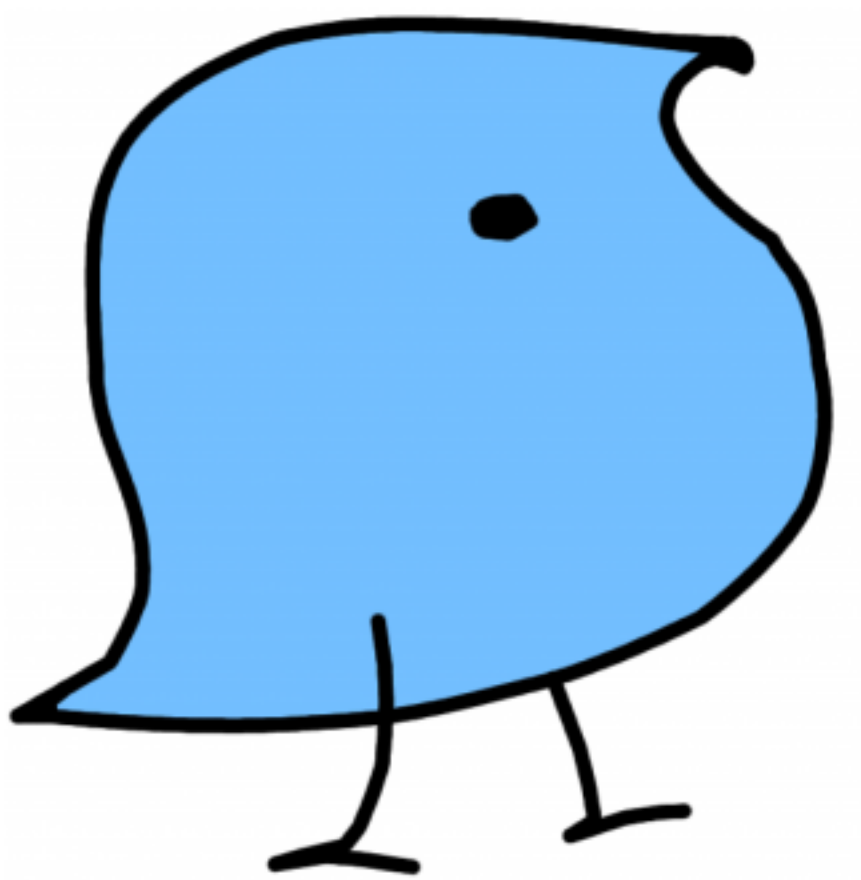
Iterated learning

A prediction...

Features of language emerge as a result of cognitive biases

Iterated learning

An example...

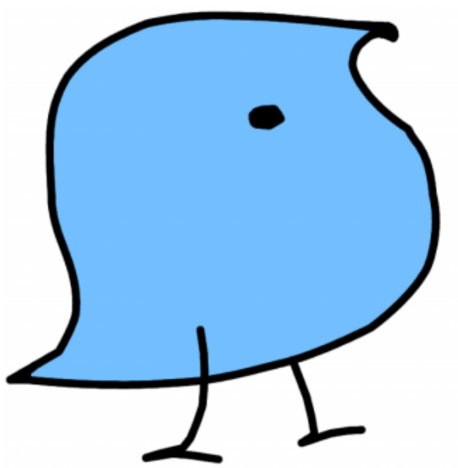


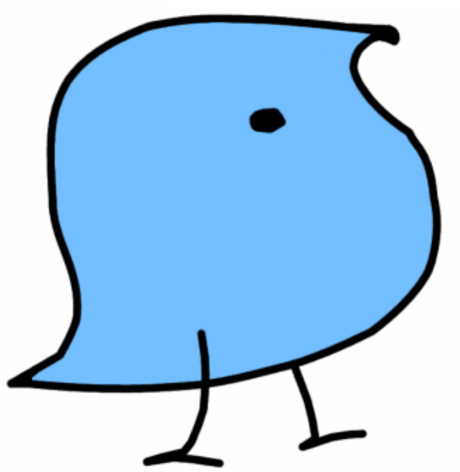
This is a wug

Berko (1958)

Iterated learning

An example...





Now there is another one

There are two of them

There are two ___

Berko (1958)

Iterated learning

A theory...

Human languages tend to avoid unpredictable variation because regularity is easier to learn

Iterated learning

A problem...

We have no definitive historical evidence of how regularity emerged in human language

Iterated learning

A solution...

Use artificial language learning and iterated learning to explore how unpredictable variation is eliminated over time

Iterated learning

An experiment...

glim cow
(singular NOUN moves)

Smith & Wonnacott (2010)

Iterated learning

75% - glim cow fip

(plural$_x$ NOUN moves)

Smith & Wonnacott (2010)

Iterated learning

25% - glim cow tay
(plural$_y$ NOUN moves)

Smith & Wonnacott (2010)

Iterated learning

A design...

- Manipulate the frequency of plural markers shown during training
- Observe plural marker use in single generation
- Pass the testing output to the next generation
- Observe plural marker use across several generations

Smith & Wonnacott (2010)

Iterated learning

A result...

- Individual learners do not show a change in plural marking
- Over the course of iterated learning, the bias towards regularity emerges
- Unpredictable variation is eliminated through cultural transmission

Smith & Wonnacott (2010)