

Computational modelling of infants' word acquisition

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Master Thesis intermediate presentation

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- Context overview of the work
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Twɪŋkəllɪtlstar



twinkle, twinkle, little star

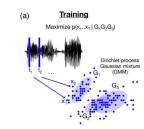


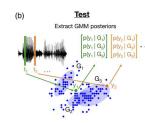


Computational models of language acquisition



- Phonetic learning
- GMM [1][2]
- (Correspondence) autoencoder [3][4]
- (Correspondence) autoencoding recurrent neural network[4][5]









twinkle, twinkle, little star







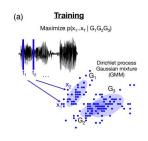
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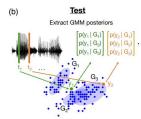
minimum description length(MDL) Bayesian model [6]





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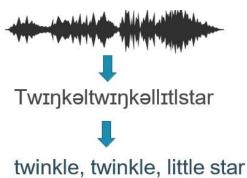












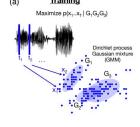
Computational models of langue acquisition

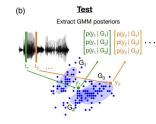
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 minimum description length(MDL) Bayesian model [6]
- · Joint learning in both phonetic category and lexical knowledge
- STELA (Statistical Learning of Early Language Acquisition)[7]

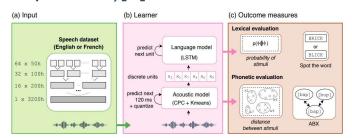
Acoustic model: Contrastive Predictive Coding

Quantizer: K-means (to simulate phonemes)

Language model: 3-layer LSTM



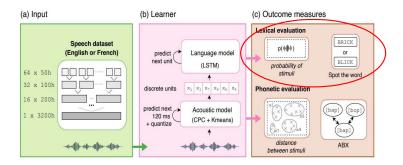








Model evaluation



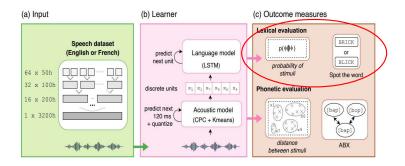
Lexical score

- Spot the word task: present the network with a minimal pair of word and non-word (e.g., 'brick' versus 'blick')
- The accuracy score was averaged across all of the pairs in the test set
- Non-words are generated by the Wuggy toolbox



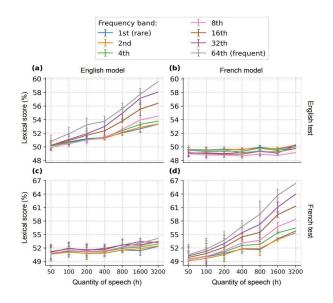


Model evaluation



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Training efficiency

-> slower increase

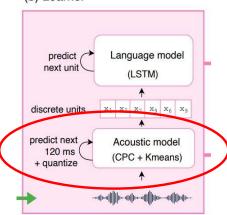
Q: How to increase the training efficiency to better simulate infants' acquisition of lexical knowledge?





Literature review and hypotheses

(b) Learner



- Hypothesis I: Speech segmentation algorithms
- 1) matching-first models [1-4]

Aim to find high quality pairs of identical segments and cluster them based on similarity

2) segmentation-first models[5-7]

Bayesian Segmental GMM and Embedded Segmental K-Means (ES-KMeans)

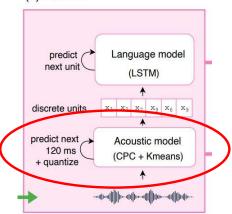
3) segmentation-only models [8-9] discover directly the likely word boundaries

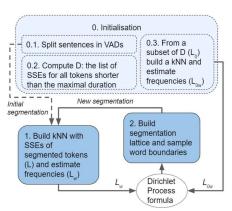




Literature review and hypotheses







- Hypothesis I: Speech segmentation algorithms
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2) segmentation-first models[5-7]

Bayesian Segmental GMM and Embedded Segmental K-Means (ES-KMeans)

- 3) segmentation-only models [8-9]
- e.g. segmental contrastive predictive coding (SCPC) framework
- 4) combination of 2) and 3)

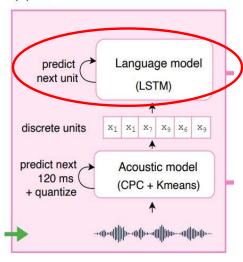
DP-Parse[10]





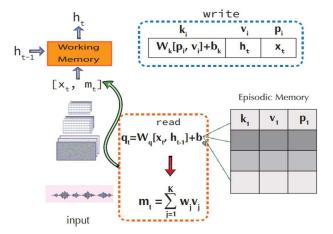
Literature review and hypotheses

(b) Learner



- Hypothesis II: External memory [1-4]
- store representations of examples or experiences
- Memory replay mechanism
- -> add previously stored instances either during training[2] or test phases [3]
- Selective mechanism[4]

Similarity-based v.s. Surprise-based

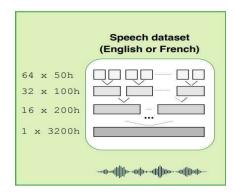






Experiment Design

- Environment of the infant
- Models trained on varying training lengths





Experiment Design

- Environment of the infant: varying training lengths
- Model Design

Unit level	Boundary type	Model	Abbreviation		
Characters	Without	Baseline LSTM	Baseline char without bound		
	vvitilout	Memory-augmented LSTM	Memory char without bound		
	Gold boundary	Baseline LSTM	Baseline char without bound		
	(word)	Memory-augmented LSTM	Memory char without bound		
	Automatic	Baseline LSTM	Baseline char with auto bound		
	boundary	Memory-augmented LSTM	Memory char with auto bound		
Phonemes	Without	Baseline LSTM	Baseline phon without bound		
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	Automatic	Baseline LSTM	Baseline phon with auto bound		
	boundary	Memory-augmented LSTM	Memory phon with auto bound		
Speech	Automatic	Baseline LSTM	Baseline speech with auto bound		
	boundary	Memory-augmented LSTM	Memory speech with auto bound		

- Input: different input modalities
- Automatic boundary: DP-Parse
- Language models

Baseline: 3-layer LSTM

Memory-augmented: local memory at test

time





Progress and future work

		Feb	Mar	Apr	May	Jun	Jul	Aug
Pre- processing	Char with/out bound							
	Phonemize (g2p)							
	DP-Parse							
LSTM construction	Baseline							
	Memory-augmented							
Evaluation	Wuggy test (p2g)							
Model type		Baseline Char with/out bound	Memory char with/out bound	Baseline/Memory char with auto bound	Baseline /Memory Phon	Baseline /Memory Phon	Baseline/Memory speech with auto bound	
Thesis writing								





Progress and future work

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Thesis writing								

- If time permits:
- Test different selective mechanisms: surprise-based v.s. similarity-based
- Morphological rules and oov words
- Other aspects of evaluation task: semantic





Thanks for your attention!



