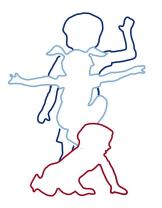


# Regularizing unpredictable variation: is learning from an unreliable speaker enough?

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## Children regularize variation

When children's input contains unpredictable variation, they regularize:

- Learning a pidgin or creole language (e.g. Sankoff 1979)
- Learning a language from late learners (Mayberry & Eichen 1991, Newport & Supalla 1980)
- Experiments with natural and artificial language show regularization (e.g. Singleton & Newport 2004, Hudson-Kam & Newport 2005)

## Children acquire variation

Children can learn and match the sociolinguistic variation in their input.

- Children have mastered constraints on -t/-d deletion early (Labov, 1989; Roberts 1997; Smith et al. 2009)
- Constraints on word final s-lenition in Spanish (Miller, 2013)

# Why do children sometimes regularize variation and other times learn it?

# Differences in the input

	Sociolinguistic (learned)	Regularization (changed)
Variation in the community	Shared Noisy	
Conditioning environment	Predictable	Not predictable
Speaker fluency	More likely	Less likely

### Speaker fluency and regularization

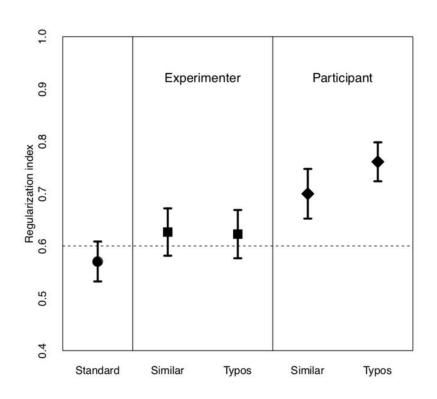
- Children are known to regularize pidgin and creole languages (Bickerton, 1984) and when learning from non-native speakers of sign language (Singleton & Newport, 2004).
- In both situations, input is produced by non-native speakers, who may provide subtle linguistic cues to indicate they are unreliable language models.
- Children may be more likely to assume variation is **noise** (e.g. mistakes by the speaker) rather than an important feature of their dialect.

# Adults regularize more when they think variation is "noisy"

- Perfors (2016) argued that adults match probabilities because they assume variation is predictable.
- When this assumption is challenged i.e. when participants are told that language input might contain mistakes Perfors (2016) finds that adults do regularize
- Argues that these results explain why children regularize unpredictable variation in natural language

#### Perfors (2016) results

- TASK: Learning Written Object Labels
- MANIPULATIONS: Reliability of the Person Providing the Labels & Type of Marker
- CONCLUSION: Adults were more likely to regularize when told the variation might be mistakes and those mistakes look like typos.



# Can adults use subtle linguistic cues to determine whether to learn or regularize a rule?

Testing rule learning

# Experiment 1 Testing rule learning

Perfors (2016) Learning labels



**DUTON** 

# Experiment 1 Testing rule learning

Perfors (2016) Learning labels



**DUTON** 

Our Experiment Plural marking rule

singular



gentif daffin

plural



gentif daffin ka

#### **Participants:**

• 134 adults on prolific

#### **Conditions:**

- Two instructions conditions: experimenter and participant
- Two plural marker conditions: distinct and typo

Instructions Exposure Test

**EXPERIMENTER** 

**PARTICIPANT** 

Instructions

Exposure

Test

#### **EXPERIMENTER**

We are studying how people learn new languages. In this experiment, you will see pictures of farm animals paired with sentences describing them in Ackvarian.

#### **PARTICIPANT**

Instructions

Exposure

Test

#### **EXPERIMENTER**

We are studying how people learn new languages. In this experiment, you will see pictures of farm animals paired with sentences describing them in Ackvarian.

#### **PARTICIPANT**

We are studying how people learn new languages when they are given sentences from other people. In this experiment, you will see pictures of farm animals paired with sentences describing them in Ackvarian. The sentences actually come from a previous participant, who hard to learn Ackvarian themselves. Some participants were given a very limited time to provide descriptions, so there might be errors.

Instructions Exposure Test

#### singular



gentif daffin

Instructions Exposure Test

#### singular



gentif daffin

#### plural



gentif daffin {marker}

Instructions

Exposure

Test

singular



gentif daffin

plural



gentif daffin {marker}

{marker}

**DISTINCT** 

**ka** po su ti je

Instructions

Exposure

Test

singular



gentif daffin

plural



gentif daffin {marker}

{marker}

#### **DISTINCT**

**ka** po su ti je

#### **TYPO**

**ka** ja kq a kka

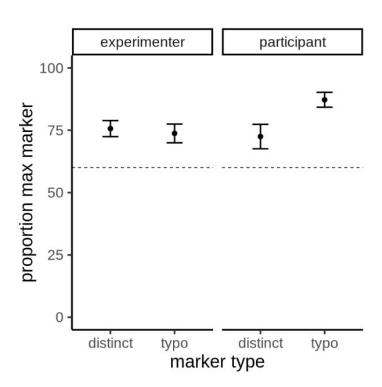
Instructions Exposure Test



Type a sentence that describes this in Ackvarian.

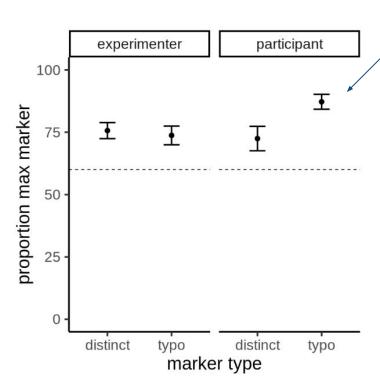
Regularization results

#### **Regularization results**



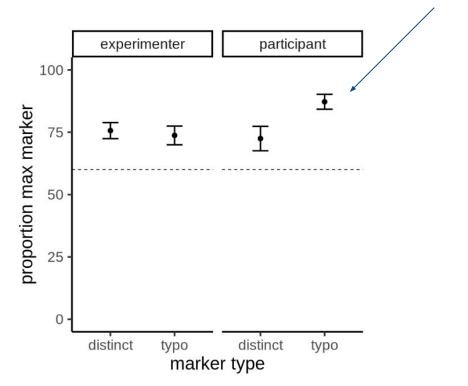
**Regularization results** 

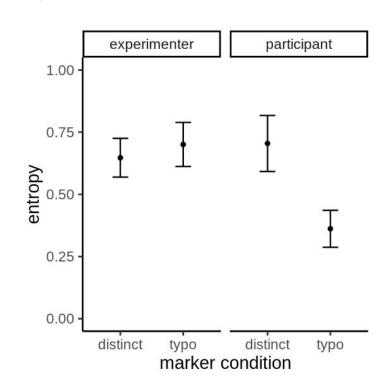
More regularization when variation can be attributed to typos



**Regularization results** 

More regularization when variation can be attributed to typos





#### Like Perfors (2016) greater regularization when

- 1. Told input might be mistakes (PARTICIPANT condition) AND
- Markers seemed like TYPOS

Unlike Perfors (2016) regularization NOT greater when told the input might be mistakes if markers were **DISTINCT** 

# Will participants regularize more if they know a speaker is nonnative?

#### **Participants:**

• 61 adults on prolific

#### **Conditions:**

- Two instructions conditions: native and nonnative
- Only the distinct plural markers

Instructions

Rate

Exposure

Test

#### **NATIVE**

The sentences actually come from a speaker of the language, Mary, who provided the descriptions.

Mary has lived in Ackvaria her whole life. She's been speaking Ackvarian since she was a baby. This means that Ackvarian is her native language and she almost never makes mistakes. Most of the time, she says things the right way in Ackvarian.

#### **NONNATIVE**

Instructions

Rate

Exposure

Test

#### **NATIVE**

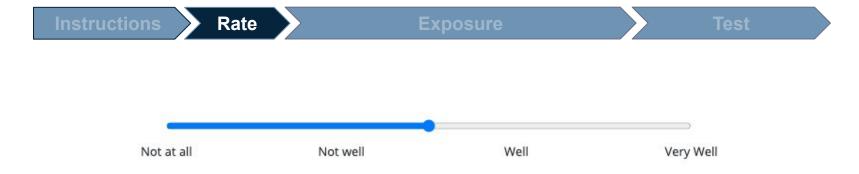
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#### **NONNATIVE**

The sentences actually come from a speaker of the language, Mary, who provided the descriptions.

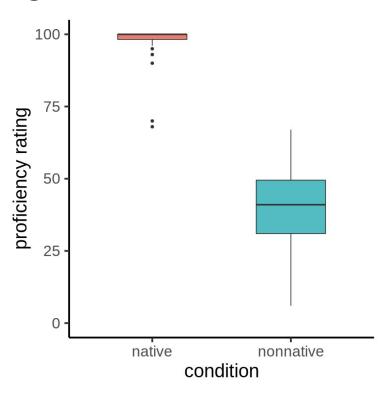
Mary **just moved to** Ackvaria. She's **only** been speaking Ackvarian **for one month**. This means that Ackvarian is **not** her native language and she **makes lots of** mistakes. **Sometimes**, she says things the **wrong** way in Ackvarian.



Given her experience, how well do you think Mary speaks Ackvarian?

Continue

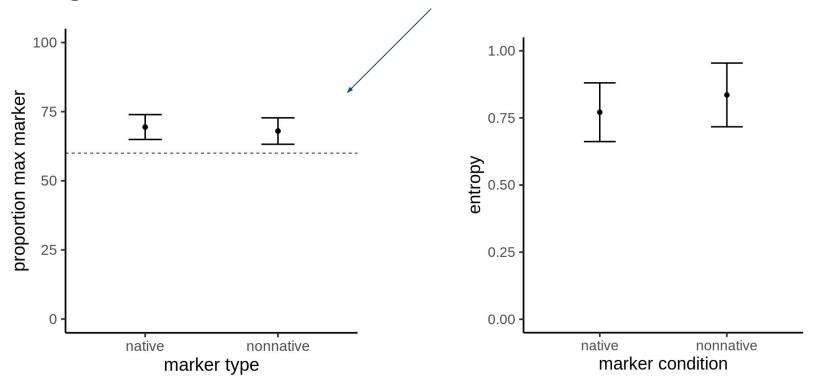
**Proficiency rating results** 



Regularization results

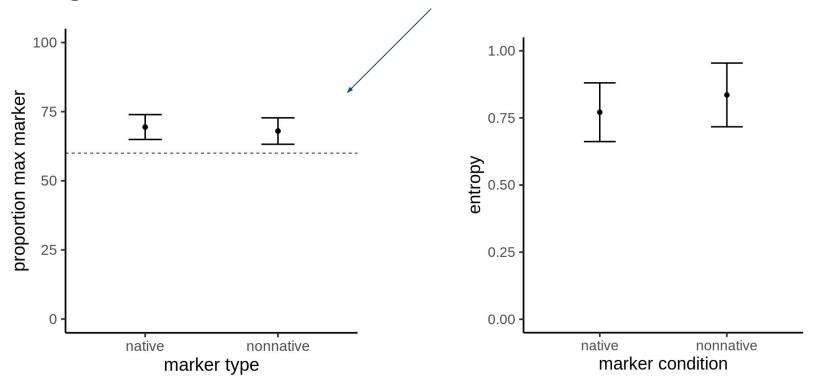
**Regularization results** 

Do not regularize significantly more

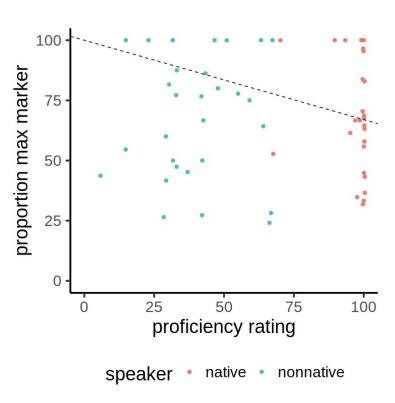


**Regularization results** 

Do not regularize significantly more



Regularization by proficiency rating



#### Conclusion

- In experiment 1, adults regularized more when they were told the input might contain mistakes, but only if the markers resembled typos.
- In experiment 2, adults did not regularize more when learning from an unreliable language model (nonnative speaker).
- In both experiments, knowing the input contained mistakes was not enough to alter rule learning behavior.

#### **Future directions**

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 Rule anchors - do learners need an entrypoint to the underlying rule in order to find the rule among the noise?

#### **Future directions**

- Rule anchors do learners need an entrypoint to the underlying rule in order to find the rule among the noise?
- Red flags do learners need a signal during learning that a mistake has likely occurred?
  - Disfluencies (..uh..., ...um...)
  - Facial expressions

# Thank You

Thanks to the Language and Cognition Lab and the Language Evolution Lab at Penn for helpful comments and suggestions.

# Questions

# Aux slides

# Perfors (2016) design

#### **Cover Story**

#### **EXPERIMENTER**

We are studying how people learn language. You'll see pictures of common objects with labels from an artificial language.

#### **PARTICIPANT**

The labels actually come from a previous participant, who had to learn the fake language themselves. Some were given a very limited time to provide the labels so there might be errors.

#### **Exposure**



#### **DUTON**

200 image-label pairs 10 nouns, 20x each

One main affix (60%) Four noise affixes (10% each)

**TYPO:** noise affixes like typos **SIMILAR:** not like typos

#### <u>Test</u>



Enter a label 40 trials, 4 per noun