# An algorithm for learning phonological classes from distributional similarity


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## 1. Introduction

**Where do features come from?**

1. Are features *innate?*
   - No learning required
2. Are features *universal?* (e.g. Chomsky & Halle, 1968)
   - Learned from general **phonetic** properties
   - Classes are phonetically coherent
3. Are features *learned* and *language-specific?* (e.g. Mielke, 2008; Archangeli & Pulleyblank, 2015)
   - Learned from **phonetics *and* data**
   - Classes need not be phonetically coherent

**Current study: can we learn features/classes *without phonetics*?**

- i.e. from *distributional information*:
  - Where sounds do and do not occur in the data

I present an algorithm that can learn complex class structures without recourse to phonetic information.

## 2. The task at hand

Our learner needs to find *distributionally salient* classes from a phonological corpus.

- We don't know how many!
- Classes may be *nested* or *overlapping*
- Learner must be robust to *distributional noise*

Most importantly, it needs to find the "right" classes…

- C vs. V would be a good start
- But how to evaluate the other classes we find?

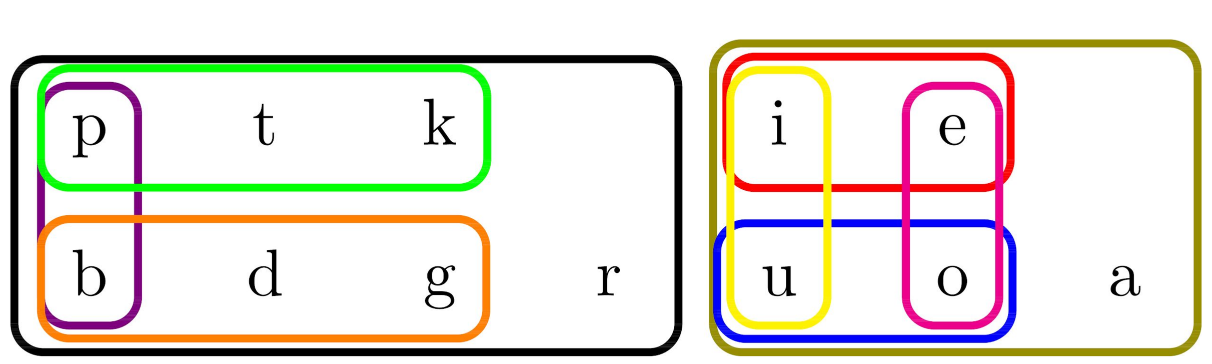
## 3. Parupa: a toy language

**Solution:** Test on a toy language with known classes!

**Parupa** is a CV language with several distributional constraints:

- Words **harmonize for backness**; /a/ is transparent
- Words **must begin** with **/p/ or /b/**
- **/p/, /t/, /k/** are followed by **high vowels** or /a/
- **/b/, /d/, /g/** are followed by **mid vowels** or /a/

*berari*
*pupabopa*
*boka*
*padoropa*
*pakubatuda*
*bopu*
*piretiba*
*pabarubo*
*barika*
*…*




Inventory and phonological classes of Parupa

## 4. The nuts and bolts of the algorithm

**<u>Step 1</u>:** Build a ***vector representation*** of each sound in the corpus

1. Count all the ***trigram contexts*** in which each sound occurs
   - These are the dimensions of the vector
2. Weight contexts using ***positive pointwise mutual information (PPMI)***
   - Emphasizes contexts where a sound occurs more frequently than chance

**Why?**

1. Representing sounds as vectors lets us find classes numerically!
   - Distributionally similar sounds should be close in space
2. Using PPMI lets us focus on sound/context pairs that are *informative*

**<u>Step 2</u>:** Perform ***Principal Component Analysis (PCA)*** on the embeddings

1. PCA projects points from a high dimensional space to a lower dimensional space while minimizing loss of variance
2. New dimensions (*principal components*) are ordered by variance captured

**Why?**

1. Highlights robust sources of variance and reduces noise
2. Different PCs reveal multiple partitions of the same set of sounds

**<u>Step 3</u>:** Perform ***clustering*** on *individual* principal components to find classes

1. Do ***1-dimensional k-means clustering*** on all PCs with "high variance"
2. Find optimal number of classes using *Bayesian Information Criterion*
3. Do clustering recursively on all discovered classes

**Why?**

1. Clustering on individual PCs allows us to find *overlapping classes*
2. Recursive clustering allows us to find *nested classes*

## 5. Results on Parupa

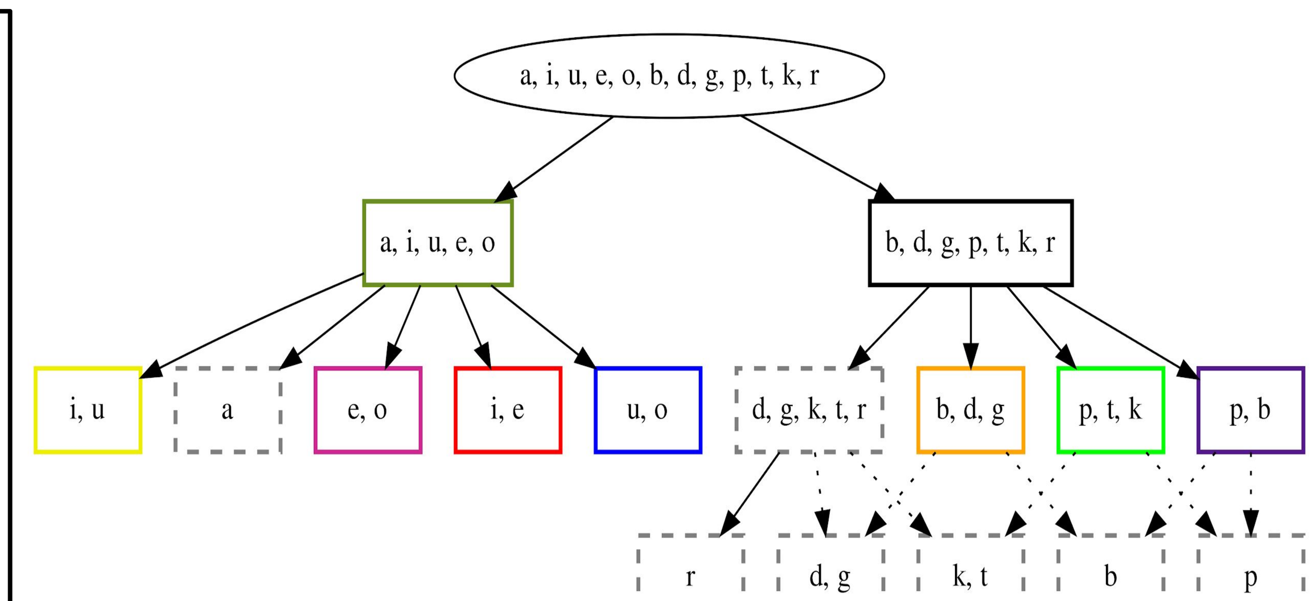
Run on corpus of ~18k word types

Finds **all expected classes**!

- Other classes found are *derivable* from expected classes (complements, intersections)

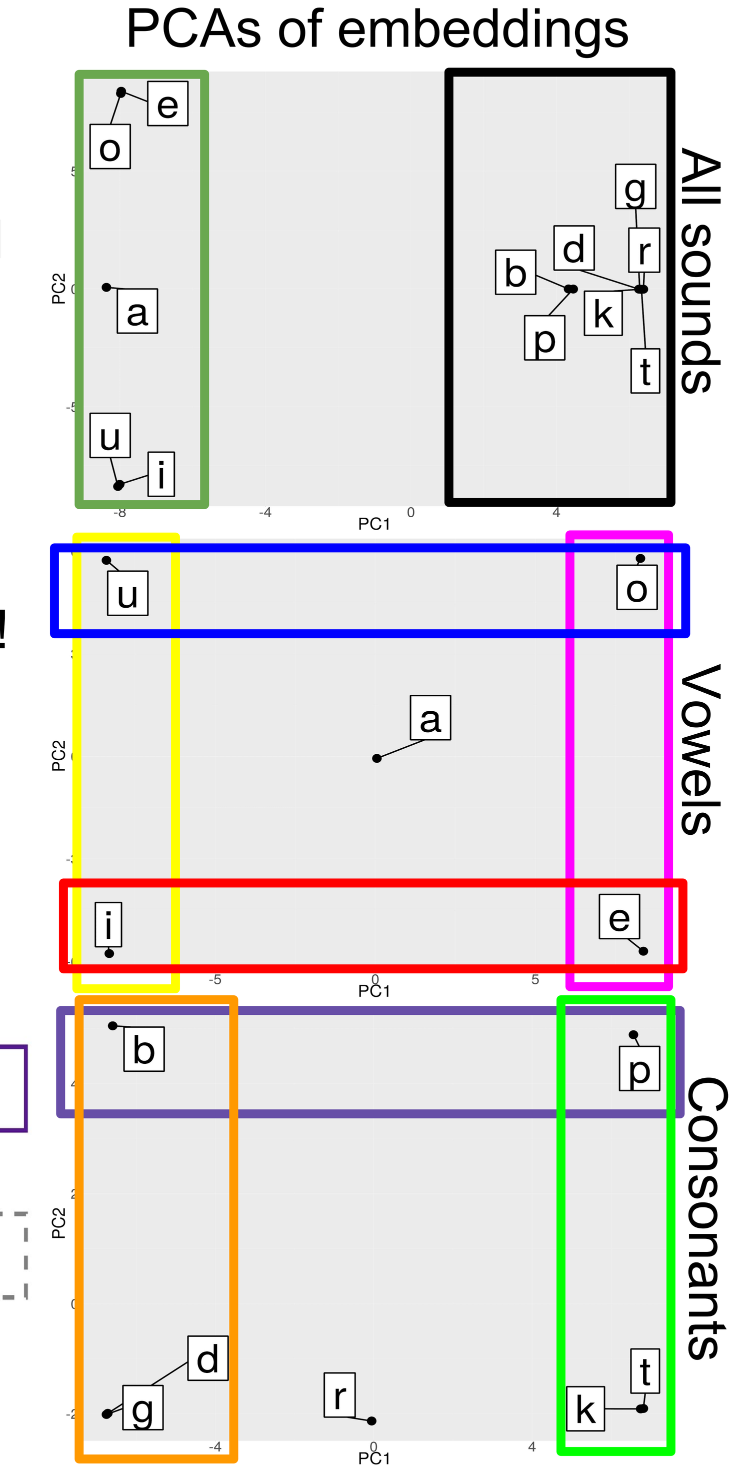
Performs well **even as noise is added**

- Allow some percentage of words to violate phonotactic constraints (except CV)
- Most expected classes found in up to 90% noise!




Discovered classes displayed hierarchically. Colors match those in the inventory diagram in section 3. Dashed boxes indicate "unexpected" classes.

PCAs of embeddings




## 6. Results on natural languages

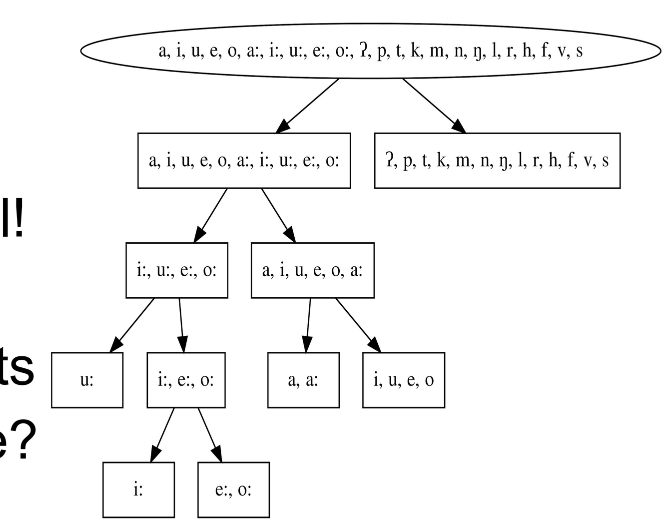
Successfully distinguishes C vs. V in four languages, and finds classes suggesting...

- **English**
  - tense vs. lax vowels
  - coronals & nasals vs. other consonants
- **French**
  - liquids vs. glides vs. other consonants
  - nasal & marked rounding vs. other vowels
- **Samoan**
  - long vs. short vowels
- **Finnish**
  - front vs. back vs. neutral vowels

## 7. A short example: Samoan vowels

Vowel are split into long vs. short, except for /a:/

- VV sequences are common
- V:V, VV:, V:V: are not
  - In 76% of these, V: is /a:/
- /a:/ patterns like a short vowel!




No structure found in consonants

- Due to strict (C)(V)V structure?
- Trigram window too small?

## 8. Discussion/Future Directions

This algorithm learns nested/overlapping classes from a phonological corpus with no phonetic information

**Why is this interesting?**

- Provides insight into which classes are distributionally salient in a language
- Improves on performance of past attempts (e.g. Goldsmith & Xanthos, 2009)
- May be combined with other sources (e.g. phonetics) for more realistic learnability models
- Can be used as input for testing productivity of distributionally salient classes using artificial grammar learning tasks

Next step: Moving beyond trigram counts…

**See paper on my website for *much* more detail!**

## Selected References


Archangeli, D., & Pulleyblank, D. (2015). Phonology without universal grammar. *Frontiers in Psychology, 6*, 1229.

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