Learning phonological features from different kinds of evidence

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1 Introduction

(1) A consequence of inducing features from phonetic and phonological data: different features can be learned at different times.
   • There are many different types of data from which to learn features.
   • Different types of data become available to the learner at different times.

(2) Reasons for wanting to induce features rather than assume innateness (Mielke, 2008a)
   • The likelihood of features emerging in the human genome has been questioned.
   • Completely different features and organization needed for signed and spoken languages.
   • Proposed feature sets fail to account for many naturally-occurring sound patterns.

(3) Phonetic categories can be learned from bimodally distributed tokens, without feedback or words with referential content (Maye and Gerken, 2000)

(4) Contrasts can be generalized to new segments (feature learning) (Maye et al., 2008)

Figure 1: Bimodal and monomodal distributions
2 Feature induction

(5) Learning features from acoustic and articulatory data (Lin, 2005; Lin and Mielke, 2007)

- An inductive approach: Attempt to induce features directly from data, instead of cross-linguistic comparisons
- Unsupervised learning: Perform phonological categorization through clustering
- Distribution-based rather than innate: Interested in the information in the data prior to paying attention to cues
- Hierarchical clustering approach to phonological categorization, resembling Dresher (2003); Clements (2001), but without a predetermined feature set.
- Each partition seen as an emergent feature.

(6) Acoustic data (Lin, 2005)

- Data: consonant segments from the TIMIT database, extracted from hand-labeled sentences
- Front-end processing: static and dynamic Mel-cepstral coefficients (MFCC)
- Clustering method: a mixture of hidden Markov models (HMM)

(7) Articulatory data (Lin and Mielke, 2007)

- Data: Ultrasound images of one native speaker of English producing consonant phonemes in CVC syllables
- Segments as arrays of cross-distances
- Mixture of probabilistic principal component analyzers (PPCA)

(8) Short summary (Lin and Mielke, 2007)

- Manner features are induced primarily from acoustic data.
- Place features are induced primarily from articulatory data.

<table>
<thead>
<tr>
<th></th>
<th>non-dorsal</th>
<th>dorsal</th>
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<tbody>
<tr>
<td></td>
<td>other</td>
<td>alveolar/palatal</td>
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<tr>
<td></td>
<td>labial+</td>
<td>alveolar</td>
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<td>dental+</td>
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<td>mellow</td>
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<td></td>
<td>grave</td>
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<tr>
<td></td>
<td>nasal/acute</td>
<td>m</td>
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</tbody>
</table>

Figure 2: Clusters based on acoustic and articulatory data
3 Timecourse for learning features

<table>
<thead>
<tr>
<th>Type of evidence</th>
<th>Expected time of availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phonotactics</td>
<td>&lt; birth</td>
</tr>
<tr>
<td>Acoustic similarity</td>
<td>&lt; birth</td>
</tr>
<tr>
<td>Visual information</td>
<td>birth (requires vision)</td>
</tr>
<tr>
<td>Articulatory similarity</td>
<td>later (requires articulation)</td>
</tr>
<tr>
<td>Alternations</td>
<td>later (can require words)</td>
</tr>
<tr>
<td>Minimal pairs</td>
<td>later (requires words)</td>
</tr>
</tbody>
</table>

Figure 3: English consonants: what could be learned from different sources of data (Acoustic and articulatory based on Lin (2005) and Lin and Mielke (2007), phonotactic and alternation information from P-base (Mielke, 2004) entries for English (Jensen, 1993; McMahon, 2002), minimal pairs based on introspection, and visual information based on speculation)
Notes on features for alternations

• Segments must be grouped into the right classes. Distinguishing segments from each other is not enough.
• Features needed for sound patterns often are not the same as features needed for lexical contrasts (Ladefoged, 2005).
• Many classes involved in rules are not phonetically natural, and need to be learned on a language-by-language basis from existing sound patterns (Mielke, 2008a).
• Classes commonly involved in sound patterns reflect common sound changes, not necessarily phonetically-salient subgroupings (Mielke, 2008b).

Different features at different times

• Lots of information from various sources potentially available to learn features
• Different for different languages (different inventory sizes, different amounts of information from sound patterns)
• Lots of predictions involving feature learning with different ambient languages

Acknowledgments

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References