Class 18 (Week 9, T)
Induction I: constraints

To do
☐ Work on your project! (There's no more homework and no more reading.)
☐ There is no class on Thursday (Thanksgiving)
☐ Next Tuesday we meet **4-6 PM**, in **Campbell 2122** (conference room)

Overview: What if we aren't born with a constraint inventory? We'll take a tour of some proposals.

1. Discuss Hayes & Wilson (2006)

2. Naradowsky, Pater & Smith (2011): Error-driven constraint induction

- Do we really need to consider such a broad range of constraints?
- Main idea:
  - When you hear a form (say, [#n…]), compare it to a randomly sampled, hypothetical similar form (e.g., [#ŋ...])
  - If your current grammar assigns better harmony to the sampled neighbor than to the observed form, the grammar needs updating
    - Can you see a problem with this?

    - Refinement: remember the last *n* forms you heard (here, *n*=3000), and don't worry about a neigbor that's in that set

- How to construct a constraint
  - Make a lattice of all the constraints that could prefer the observed form
    - In the [#n…]/[#ŋ...] example, consider all constraints that penalize [+dorsal]
      - In the feature system used in this paper, [CORONAL] is privative
      - Which means what?

      - Let's draw some of the lattice.

  - Sample a few of these constraints (here, 3) and add them to the grammar
  - Update weights of this new constraint set
    - Use Perceptron rule to update: similar to Gradual Learning Algorithm, except it cares about the number of violations
- More precisely: see over

Algorithm 1 Learning Procedure

```
function LEARN
    model ← []
    while learning do
        o ← draw(D)
        u ← draw(neighborhood(o)
        if model.score(u) > model.score(o) then
            diff ← u.features \o.features            ▷ Constraint Induction
            cspace ← []
            for c ← allconstraints do                 ▷ Filter Space
                if c.contains(diff) then
                    cspace+ = c
                end if
                model.features+ = draw(space)         ▷ Add constraint
            end for
            for j ← 0 until model.size do             ▷ Perceptron Update
                model[j] = f.violations(u) − f.violations(o) ∗ rate
            end for
        end if
    end while
end function

function NEIGHBORHOOD(o)
    plattice ← [o.size]
    for i ← o.size do
        plattice[i] ← o[i].phones                     ▷ (Phone, Distance) pairs
    end for
    return draw(plattice.allPaths)                    ▷ Sum weight in each path
end function
```

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- Tested on English onsets, as in Hayes & Wilson (2006)
- Resulting constraints (over):
    - [__] means “any segment”, i.e. [+segmental]

Weight	Feature	Description
1.34	[_] [^-strid,+cor]	S T vs. TH S
1.28	[^+cons,+ant]	S vs ZH
1.26	[^-approx,+lab]	M vs. NG
1.26	[_] [^-cons,+cor]	G R vs. P W
1.26	[-approx,-voice] [^-ant,+cor]	G R vs. CH L
1.22	[^-son,-voice] [_]	S K vs. Z P
1.22	[^+strid][-strid,+son]	S L vs TH L
1.20	[^-son,+voice][+lab]	G R vs. P W
1.20	[^+dorsal,+cons][^+approx,-ant]	G R vs. P W
1.20	[^+dorsal][^-strid,-ant]	G R vs. CH L
1.18	[^+cont,-voice]	S vs. ZH
1.18	[+strid,+cor][^-strid]	S T vs. S S
1.18	[-son,-voice][_]	G R vs. P W
1.18	[_][^+approx,+cor]	G R vs. P Y
1.16	[-son,+ant][-ant]	S W vs. S R
1.16	[_][^+high,+approx]	S W vs. S R
1.16	[_][^+high,+son]	S W vs. S R
1.16	[^-voice][_]	T R vs. V R
1.14	[^+strid,-voice][_]	S L vs. TH L
1.14	[-son][^+ant,+lat]	S L vs. S R

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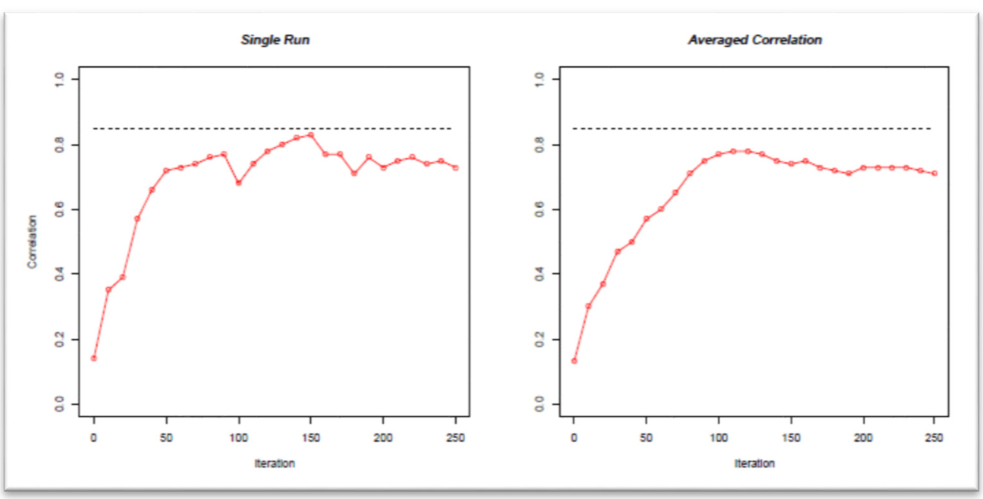
- Correlation to human judgments of English onsets: -0.829 (vs. Hayes & Wilson's -0.859)
- Interesting problem: tendency towards over-fitting as learning continues
    - As assessed by worsening correlation to human judgments



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  - See the paper for some ways to improve the model

- Discuss: Both this model and the Hayes/Wilson model are for phonotactic learning. How could we extend either of these to learning alternations?

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3. Flack (2007): inducing a constraint from perceptual experience

We got this far.

- There are languages that prohibit [p] specifically in word-initial position: *#P
  - Initial [p] has particularly short VOT, and it's more variable than initial [b]'s
  - Difference in maximum burst intensity for initial [p] and [b] is smaller than for other voiceless-voiced pairs (p. 122)

- To produce an instance of a category ([p], [b], [t], etc.) in a context, speaker samples values for various phonetic dimensions from stored distributions centered on prototype
- In perception, listener must guess the category
  - Some noise is added: perception is imperfect
  - Rather than Bayes' rule as in Kirby (2013), finds the closest prototype
- Listener gets feedback on accuracy
  - Allows listener to update prototypes
  - Listener also **stores accuracy rate** for each category, perhaps over a moving window of the past *n* tokens (here, *n*=400)
    - Specifically, **hit rate** and **false alarm rate**
    - Does anyone know these terms?

- Hit rates for each consonant as learning proceeds over time:

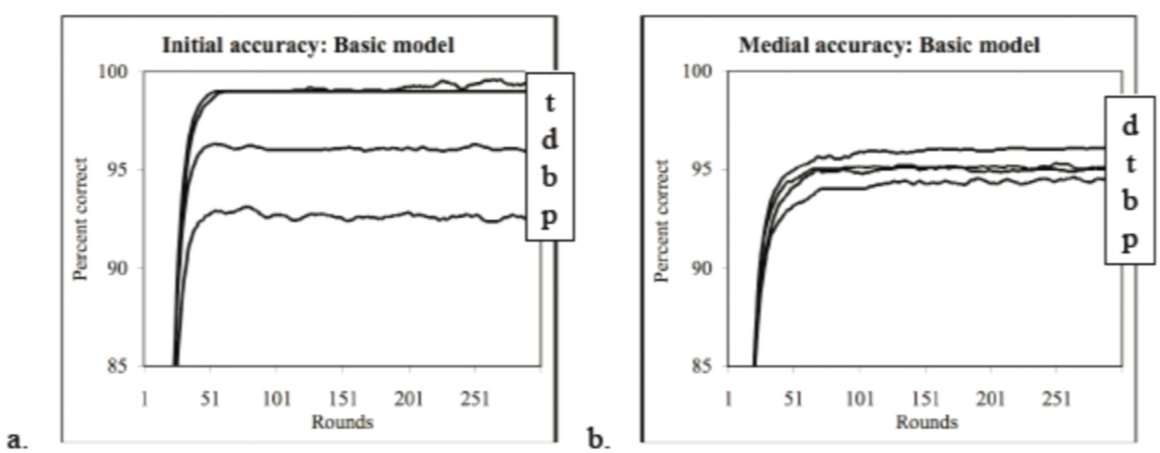

Figure 7. Model accuracy for each initial (a) and medial (b) consonant, averaged across 20,000 simulations of 300 rounds each. The lines represent moving averages across 15-round windows.

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- Important point about phonologization
  - Once *#P has been promoted high enough, the learner gets no experience of initial [p]!
  - But they do still have one important piece of information listed above—can you guess what?

- The learner's rule for inducing a constraint:

(117) Some segment *x* is perceptually difficult in some context $Context_Z$ if either:

a. Accuracy($x/Context_Z$) < *threshold*

and

Accuracy($x/Context_Z$) < Accuracy($y/Context_Z$) ➔ Constraint *$x/Context_Z$

This difference must be significant ($\alpha = 0.01$).

b. Accuracy($x/Context_Z$) < FalseAlarm($x/Context_Z$) ➔ Constraint *$x/Context_Z$

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  - ▪ Where "accuracy" means hit rate
  - ▪ If there is no hit rate, because the sound never actually occurs in that context, treat it as 0.
  - ○ So how would this work for a language with no initial [p]? Let's draw a possible confusion matrix.

- Results: both a learner of simplified French (has initial [p], but it is perceptually difficult) and a learner of simplified Cajonos Zapotec (no initial [p]) learn *#P in nearly all runs

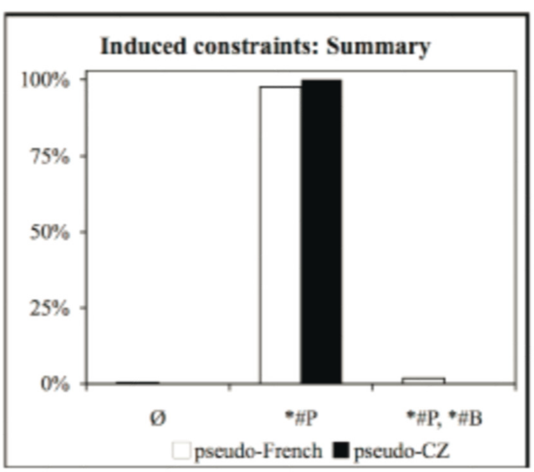

Figure 23. Constraints induced in each of 250 simulations of 40,000 rounds each.

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4. A selection of other approaches that we won't have time to cover in depth

- Hayes (1999): as we saw last time, generate lots of features according to a set of templates, and then select the ones that match the phonetic map well, with a bias favoring simpler constraints

- Boersma & Pater (2007): in Harmonic Grammar, construct *positive* constraints for every property that the observed form has (as well as some other constraints, including negative ones)
  - e.g., on observing Canadian English [ʔʌɪs] 'ice', construct these, among many others:

(17) *Observed structure* *Constructed constraint*

a. D
[-low] RAISED DIPHTHONG: A diphthong must be [-low]
(Assign a reward of 1 to each diphthong that is [-low])

b. D C
[-low][-vce] RAISED/VOICELESS: A diphthong preceding a voiceless consonant must be raised
(Assign a reward of 1 to each diphthong that is [-low] that precedes a voiceless consonant)

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  - Pater (2014) proposes something similar for the same case, but now without positive constraints

- Moreton (2010): explore infinite space of possible constraints with evolutionary algorithm
  - Every subpart of every possible representation is a constraint
  - Start with a random set of constraints
  - Error-driven: if current grammar selects a candidate that doesn't match the observed true winner…
    - constraints that favor observed forms (correct winners) are allowed to breed.
    - breeding = combine two constraints to produce a new, offspring constraint with aspects of each parent. Offspring can also mutate.

- Pizzo (2013): Inducing constraints to handle alternations (Turkish vowel harmony and devoicing)
  - On making an error, create a constraint at random
  - According to certain templates
  - Can be faithfulness or markedness
  - Must penalize some way in which the spurious winner differs from the observed winner
  - The researcher can set parameters for how much stem-faithfulness and tier-markedness constraints show be allowed/favored

- Alderete, Tupper & Frisch (2013): Connectionst model of OCP-Place in Arabic roots

5. Coming up next Tuesday (there is no class this Thursday)

- Inducing feature and natural classes

References

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