

# Research seminar week 5

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# This week: learning algorithms

- Online learning: error driven learning
  - TLA for P&P
  - EDCCD and GLA for OT (and HG)
- Offline learning:
  - RCD for OT (and HG)
- Iterated learning

# Error driven learning

## GENERAL ERROR DRIVEN LEARNING ALGORITHM

Input:  $H_0$  starting hypothesis; learning data set

$H \leftarrow H_0$

Repeat read  $w$  from data set

    If  $w$  not in language generated by  $H$

        then change  $H$  to some (good/better) hypothesis

Until no more change is needed

Return  $H$

# Triggering Learning Algorithm (TLA) for P&P

- “Hill climbing 2”-type of learning. Memoryless.
- If  $w$  not in  $H$ : select one parameter at random, and flip it. If  $w$  in new grammar, then change  $H$  to it.

# Triggering Learning Algorithm (TLA) for P&P

- Local optima.
- Alternatives: change more than one parameter; always move (no greediness).  
Niyogi 4.2: improves TLA.

# Learning in OT (and HG)

- Observed form (winner) vs. form generated by current hypothesis hierarchy (loser).
- Demote constraints violated by winner and not by loser below at least one constraint violated by loser and not by winner.

# Learning in OT (and HG)

- Online: Error Driven Constraint Demotion (EDCD; by Tesar)
- Online + stochastic OT: Gradual Learning Algorithm (GLA; by Boersma)
- Offline: Recursive Constraint Demotion (RCD; by Tesar)
- (and many other, more recent variants...)

# Basic idea of learning in OT

Winner form  $w$  observed, loser form  $l$  produced by current ranking:

	...	$C_1$	$C_2$	...	$C_k$	...
$w$		2	3		1	...
$l$		1	0		3	...

- Ignore constraints  $C_i$  s. t.  $C_i(w) = C_i(l)$ .



# Basic idea of learning in OT

- $l$  wins for this hierarchy because  $l$  has less violations than  $w$  at the highest constraint  $C_i$  such that  $C_i(w) \neq C_i(l)$ .
- In order to get a hierarchy in which  $w$  wins to  $l$ , **all** constraints for which  $C_i(w) > C_i(l)$  must be lower ranked than at least **one** constraint for which  $C_i(w) < C_i(l)$ .

# EDCD: Error Driven Constraint Demotion (by B. Tesar)

- In each step, if actual hypothesis hierarchy produces form  $l$  different from observed data  $w$ , then
  - find highest ranked constraint  $C_k$  such that  $C_k(w) < C_k(l)$ ;

- find all constraints  $C_i$  such that  $C_i(w) > C_i(l)$  and  $C_i$  is currently ranked higher than  $C_k$ ;
- demote all the latter ones below  $C_k$ .
- Algorithm gets stuck if errors in data.
- For details (which should not necessarily be followed), such as the idea of strata, refer to *Tesar and Smolensky 2000*.

# GLA: Gradual Learning Algorithm

(by P. Boersma)

- Each constraint  $C_i$  is assigned a *rank*, that is, a real number  $r_i$ . A higher rank means a higher position in the hierarchy.
- In each step, if actual hypothesis hierarchy produces form  $l$  different from observed data  $w$ , then
  - find all constraints  $C_k$  s. t.  $C_k(w) < C_k(l)$ ;

increase their rank  $r_i$  by a small number  $p$  (“plasticity”);

- find all constraints  $C_i$  such that  $C_i(w) > C_i(l)$ ; and decrease their rank  $r_i$  by a small number  $p$  (“plasticity”).

- Algorithm is robust to small percentage of errors.
- For details, such as how plasticity can be used and the use of this learning algorithm for *Stochastic OT*, refer to Boersma and Hayes 2001.

# RCD: Recursive Constraint Demotion (by B. Tesar)

- Collect all winner forms. Compare them to all their losing competitors.
- Create a table: for each (winner  $w$ , loser  $l$ ) pair: winner marks (constraints such that  $C(w) > C(l)$ ) vs. loser marks (constraints such that  $C(w) < C(l)$ ).

- Build hierarchy from the top:
  1. Add constraint  $C$  to hierarchy if  $C$  never appears in the table as winner mark.
  2. Remove rows from table where  $C$  appears as loser mark.
  3. Go back to step 1 if table is not empty.
- Algorithm detects errors and stops (table not empty, and yet all constraints appear somewhere as winner mark).

# A note on HG

- You can employ same algorithms as in OT: work with hierarchies.
- Exponential weights: assign weight  $-1$  to lowest ranked constraint,  $-q$  to second lowest ranked constraint,  $-q^2$  to third lowest ranked constraint, etc. ( $q > 1$ ; test different  $q$  values, such as 2, 10, etc.)



# By next week:

- Your presentations