Introduction to Natural Language Processing(600.465)

HMM Parameter Estimation: the Baum-welch algorithm

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HMM: The Tasks

- HMM(the general case):
  - five-tuple (S, S_0, Y, P_S, P_Y), where:
    - $S = \{s_1, s_2, \ldots, s_T\}$ is the set of states, S_0 is the initial state,
    - $Y = \{y_1, y_2, \ldots, y_y\}$ is the output alphabet,
    - $P_S(s_j|s_i)$ is the set of prob. distributions of transitions,
    - $P_Y(y_k|s_i, s_j)$ is the set of output (emission) probability distributions.
- Given an HMM & an output sequence $Y = \{y_1, y_2, \ldots, y_k\}$:
  - (Task 1) compute the probability of Y;
  - (Task 2) compute the most likely sequence of states which has generated Y
  - (Task 3) Estimating the parameters (transition/output distributions)

A variant of EM

- Idea($\sim$EM, for another variant see LM smoothing):
  - Start with (possibly random) estimates of P_S and P_Y.
  - Compute(fractional) "counts" of state transitions/emissions taken, from P_S and P_Y, given data Y
  - Adjust the estimates of P_S and P_Y from these "counts" (using MLE, i.e. relative frequency as the estimate).
- Remarks:
  - many m,ore parameters than the simple four-way smoothing
  - no proofs here; see Jelinek Chapter 9

Setting

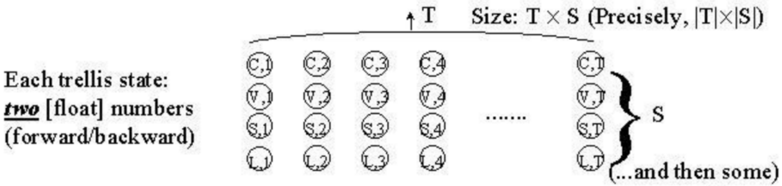
- HMM (without P_S, P_Y)(S, S_0, Y), and data $T = \{y^1 \in Y\}_{i=1\ldots|T|}$
  - will use $T \sim |T|$
- HMM structure is given: (S, S_0)
- P_S: Typically, one wants to allow "fully connected" graph
  - (i.e. no transitions forbidden $\sim$ no transitions set to hard 0)
  - why? $\rightarrow$ we better leave it on the learning phase, based on the data!
  - sometimes possible to remove some transitions ahead of time
- P_Y : should be restricted (if not, we will not get anywhere!)
  - restricted $\sim$ hard 0 probabilities of $p(y|s, s')$
  - "Dictionary": states $\leftrightarrow$ words, "m:n" mapping on $S \times Y$ (in general)

Initialization

- For computing the initial expected "counts"
- Important part
  - EM guaranteed to find a *local* maximum only (albeit a good one in most cases)
- P_Y initialization more important
  - fortunately, often easy to determine
    - together with dictionary $\leftrightarrow$ vocabulary mapping, get counts, then MLE
- P_S initialization less important
  - e.g. uniform distribution for each $p(.|s)$

Data structures

- Will need storage for:
  - The predetermined structure of the HMM (unless fully connected $\rightarrow$ need not to keep it!)
  - The parameters to be estimated (P_S, P_Y)
  - The expected counts (same size as (P_S, P_Y))
  - The training data $T = \{y^i \in Y\}_{i=1...T}$
  - The trellis (if f.c.):



The Algorithm Part I

1. Initialize P_S, P_Y
2. Compute "forward" probabilities:
   - follow the procedure for trellis (summing), compute $\alpha(s,i)$ everywhere
   - use the current values of $P_S, P_Y(p(s'|s), p(y|s,s'))$:
     $\alpha(s',i) = \sum_{s \to s'} \alpha(s,i-1) \times p(s'|s) \times p(y_i|s,s')$
   - NB: do not throw away the previous stage!
3. Compute "backward" probabilities
   - start at all nodes of the last stage, proceed backwards, $\beta(s,i)$
   - i.e., probability of the "tail" of data from stage i to the end of data
     $\beta(s',i) = \sum_{s' \leftarrow s} \beta(s,i+1) \times p(s|s') \times p(y_{i+1}|s',s)$
   - also, keep the $\beta(s,i)$ at all trellis states

The Algorithm Part II

1. Collect counts:
   - for each output/transition pair compute

$$c(y,s,s') = \Sigma_{i=0..k-1,\, y=y_{i+1}} \alpha(s,i)\; \underbrace{p(s'|s)\; p(y_{i+1}|s,s')}_{\text{this transition prob} \times \text{output prob}}\; \beta(s',i+1)$$

one pass through data, only stop at (output) y

prefix prob.

tail prob

   $c(s,s') = \sum_{y \in Y} c(y,s,s')$ (assuming all observed y_i in Y)
   $c(s) = \sum_{s' \in S} c(s,s')$

2. Reestimate: $p'(s'|s) = c(s,s')/c(s)$
   $p'(y|s,s') = c(y,s,s')/c(s,s')$
3. Repeat 2-5 until desired convergence limit is reached

Baum-Welch: Tips & Tricks

- Normalization badly needed
  - long training data $\rightarrow$ extremely small probabilities
- Normalize α, β using the same norm.factor:

  $N(i) = \sum_{s \in S} \alpha(s, i)$

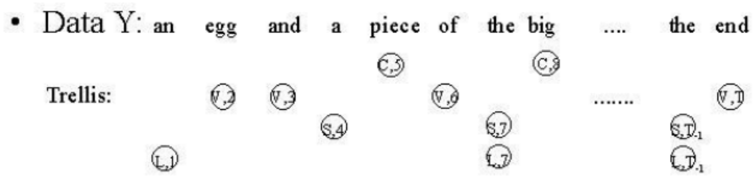
  as follows:
  - compute $\alpha(s, i)$ as usual (Step 2 of the algorithm), computing the sum $N(i)$ at the given stage i as you go.
  - at the end of each stage, recompute all *alphas*(for each state s):

    $\alpha * (s, i) = \alpha(s, i)/N(i)$
  - use the same $N(i)$ for βs at the end of each backward (Step 3) stage:

    $\beta * (s, i) = \beta(s, i)/N(i)$

Example

- Task: pronunciation of "the"
- Solution: build HMM, fully connected, 4 states:
  - S - short article, L - long article, C,V - word starting w/consonant, vowel
  - thus, only "the" is ambiguous (a, an, the - not members of C,V)
- Output form states only ($p(w|s,s') = p(w|s')$)

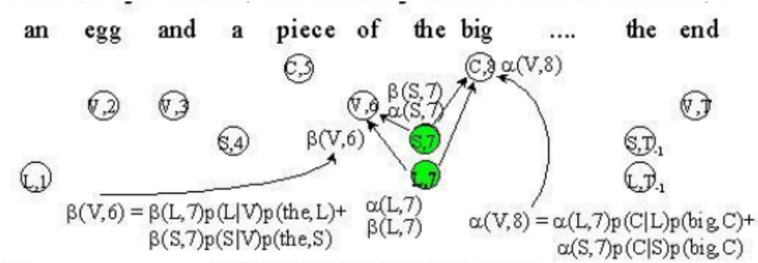


Example: Initialization

- Output probabilities:
  - $p_{init}(w|c) = c(c,w)/c(c)$; where
    $c(S, the) = c(L, the) = c(the)/2$
    (other than that, everything is deterministic)
- Transition probabilities:
  - $p_{init}(c'|c) = 1/4(uniform)$
- Don't forget:
  - about the space needed
  - initialize $\alpha(X, 0) = 1$ (X : the never-occuring front buffer st.)
  - initialize $\beta(s, T) = 1$ for all s (except for $s = X$)

Fill in alpha, beta

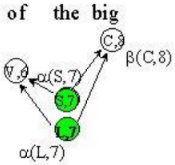
- Left to right, alpha:
  $\alpha(s', i) = \sum_{s \rightarrow s'} \alpha(s, i-1) \times p(s'|s) \times p(w_i|s')$, where s' is the output from states
- Remember normalization (N(i)).
- Similary, beta (on the way back from the end).



Counts & Reestimation

- One pass through data
- At each position i, go through all pairs (s_i, s_{i+1})
- Increment appropriate counters by frac. counts (Step 4):
  - $\text{inc}(y_{i+1}, s_i, s_{i+1}) = a(s_i, i)p(s_{i+1}|s_i)p(y_{i+1}|s_{i+1})b(s_{i+1,i+1})$
  - $c(y, s_i, s_{i+1}) += \text{inc}$ (for y at pos i+1)
  - $c(s_i, s_{i+1}) += \text{inc}$ (always)
  - $c(s_i) += \text{inc}$ (always)

    inc(big,L,C)=$\alpha(L,7)p(C|L)p(\text{big}, C)\beta(V,8)$
    inc(big,S,C)=$\alpha(S,7)p(C|S)p(\text{big}, C)\beta(V,8)$
- Reestimate $p(s'|s), p(y|s)$
  - and hope for increase in $p(C|S)$ and $p(V|L)$ . . . !!



HMM: Final Remarks

- Parameter "tying"
  - keep certain parameters same ($\sim$ just one "counter" for all of them)
  - any combination in principle possible
  - ex.: smoothing (just one set of lambdas)
- Real Numbers Output
  - Y of infinite size (R, R^n)
    - parametric (typically: few) distribution needed (e.g., "Gaussian")
- "Empty" transitions: do not generate output
  - $\sim$ vertical areas in trellis; do not use in "counting"

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HMM Tagging

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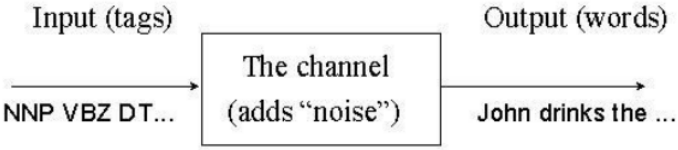
Review

- Recall:
  - tagging $\sim$ morphological disambiguation
  - tagset $V_T \subset (C_1, C_2, \ldots C_n)$
    - C_i - morphological categories, such as POS, NUMBER, CASE, PERSON, TENSE, GENDER,...
  - mapping $w \to \{t \in V_T\}$ exists
    - restriction of Morphological Analysis: $A^+ \to 2^{(L,C2,C2,\ldots,Cn)}$ where A is the language alphabet, L is the set of lemmas
  - extension of punctuation, sentence boundaries (treated as words)

The Setting

- Noisy Channel setting:



- Goal (as usual): discover "input" to the channel (T, the tag seq.) given the "output" (W, the word sequence)
  - $p(T|W) = p(W|T)p(T)/p(W)$
  - $p(W)$ fixed (W given)...
    $argmax_T p(T|W) = argmax_T p(W|T)p(T)$

The Model

- Two models ($d = |W| = |T|$ word sequence length):
  - $p(W|T) = \Pi_{i=1...d} p(w_i|w_1, \ldots, w_{i-1}, t_1, \ldots, t_d)$
  - $p(T) = \Pi_{i=1...d} p(t_i|t_1, \ldots, t_{i-1})$
- Too much parameters (as always)
- Approximation using the following assumptions:
  - words do not depend on the context
  - tag depends on limited history:
    $p(t_i|t_1, \ldots, t_{i-1}) \cong p(t_i|t_{i-n+1}, \ldots, t_{i-1})$
    - n-gram tag "language" model
  - word depends on tag only:
    $p(w_i|w_1, \ldots, w_{i-1}, t_1, \ldots, t_d) \cong p(w_i|t_i)$

The HMM Model Definition

- (Almost) general HMM:
  - output (words) emitted by states (not arcs)
  - states: (n-1)-tuples of tags if n-gram tag model used
  - five-tuple (S, s_0, Y, P_S, P_Y) where:
    - $S = \{s_0, s_1, \ldots, s_T\}$ is the set of states, s_0 is the initial state,
    - $Y = \{y_1, y_2, \ldots, y_y\}$ is the output alphabet (the words),
    - $P_S(s_j|s_i)$ is the set of prob. distributions of transitions
      -$P_S(s_j|s_i) = p(t_i|t_{i-n+1}, \ldots, t_{i-1}); s_j = (t_{i-n+2}, \ldots, t_i), s_i = (t_{i-n+1}, \ldots, t_{i-1})$
    - $P_Y(y_k|s_i)$ is the set of output (emission) probability distributions
      -another simplification: $P_Y(y_k|s_j)$ if s_i and s_j contain the same tag as the rightmost element: $P_Y(y_k|s_i) = p(w_i|t_i)$

Supervised Learning (Manually Annotated Data Available)

- Use MLE
  - $p(w_i|t_i) = c_{wt}(t_i, w_i)/c_t(t_i)$
  - $p(t_i|t_{i-n+1},) =$
    $c_{tn}(t_{i-n+1}, \ldots, t_{i-1}, t_i)/c_{t(n-1)}(t_{i-n+1}, \ldots, t_{i-1})$
- Smooth(both!)
  - $p(w_i|t_i)$: "Add 1" for all possible tag, word pairs using a predefined dictionary (thus some 0 kept!)
  - $p(t_i|t_{i-n+1}, \ldots, t_{i-1})$: linear interpolation:
    - e.g. for trigram model:
      $p'_\lambda(t_i|t_{i-2}, t_{i-1}) =$
      $\lambda_3 p(t_i|t_{i-2}, t_{i-1}) + \lambda_2 p(t_i|t_{i-1}) + \lambda_1 p(t_i) + \lambda_0/|V_T|$

Unsupervised Learning

- Completely unsupervised learning impossible
  - at least if we have the tagset given- how would we associate words with tags?
- Assumed (minimal) setting:
  - tagset known
  - dictionary/morph. analysis available (providing possible tags for any word)
- Use: Baum-Welch algorithm (see class 15,10/13)
  - "tying": output (state-emitting only, same dist. from two states with same "final" tag)

Comments on Unsupervised Learning

- Initialization of Baum-Welch
  - is some annotated data available, use them
  - keep 0 for impossible output probabilities
- Beware of:
  - degradation of accuracy (Baum-Welch criterion: entropy, not accuracy!)
  - use heldout data for cross-checking
- Supervised almost always better

Unknown Words

- "OOV" words (out-of-vocabulary)
  - we do not have list of possible tags for them
  - and we certainly have no output probabilities
- Solutions:
  - try all tags (uniform distribution)
  - try open-class tags (uniform, unigram distribution)
  - try to "guess" possible tags (based on suffix/ending) - use different output distribution based on the ending (and/or other factors, such as capitalization)

Running the Tagger

- Use Viterbi
  - remember to handle unknown words
  - single-best, n-best possible
- Another option
  - assign always the best tag at each word, but consider all possibilities for previous tags (no back pointers nor a path-backpass)
  - introduces random errors, implausible sequences, but might get higher accuracy (less secondary errors)

(Tagger) Evaluation

- **A must.** Test data (S), previously unseen (in training)
  - change test data often if at all possible! ("feedback cheating")
  - Error-rate based
- Formally:
  - Out(w) = set of output "items" for an input "item" w
  - True(w) = single correct output (annotation) for w
  - Errors(S) = $\sum_{i=1..|S|} \delta\ (\mathrm{Out}(w_i) \neq \mathrm{True}(w_i))$
  - Correct(S) = $\sum_{i=1..|S|} \delta\ (\mathrm{True}(w_i) \in \mathrm{Out}(w_i))$
  - Generated(S) = $\sum_{i=1..|S|} \delta|\mathrm{Out}(w_i)|$

Evaluation Metrics

- Accuracy: Single output (tagging: each word gets a single tag)
  - Error rate: $\text{Err}(S) = \text{Errors}(S)/|S|$
  - Accuracy: $\text{Acc}(S) = 1-(\text{Errors}(S)/|S|) = 1-\ \text{Err}(S)$
- What if multiple (or no) output?
  - Recall: $\text{R(S)} = \text{Correct(S)}/|S|$
  - Precision: $\text{P(S)} = \text{Correct(S)}/\text{Generated(S)}$
  - Combination: F measure: $F = 1/(\alpha/P + (1-\alpha)/R)$
    - α is a weight given to precision vs. recall; for $\alpha = 5, F = 2PR/(R+P)$

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Transformation-Based Tagging

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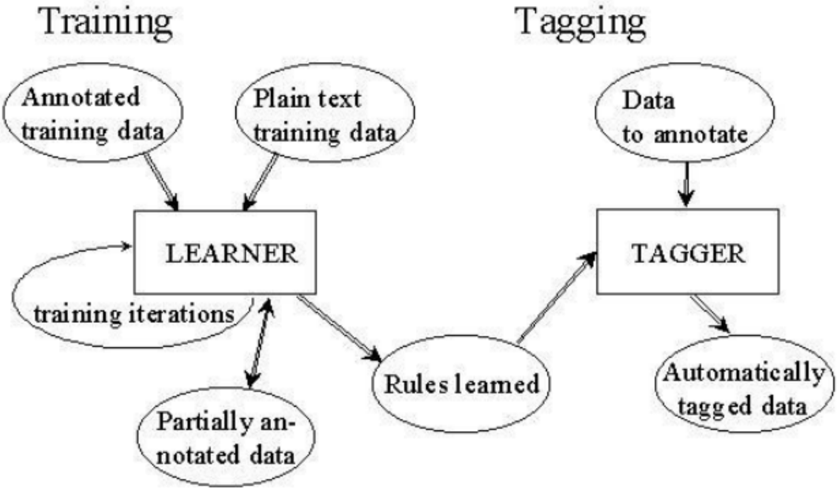
The Task, Again

- Recall:
  - tagging $\sim$ morphological disambiguation
  - tagset $V_T \in (C_1, C_2, \ldots, C_n)$
    - C_i - moprhological categories, such as POS, NUMBER, CASE, PERSON, TENSE, GENDER,....
  - mapping $w \rightarrow \{t \in V_T\}$ exists
    - restriction of Morphological Analysis: $A^+ \rightarrow 2^{(L, C1, C2, \ldots, Cn)}$, where A is the language alphabet, L is the set of lemmas
  - extension to punctuation, sentence boundaries (treated as word)

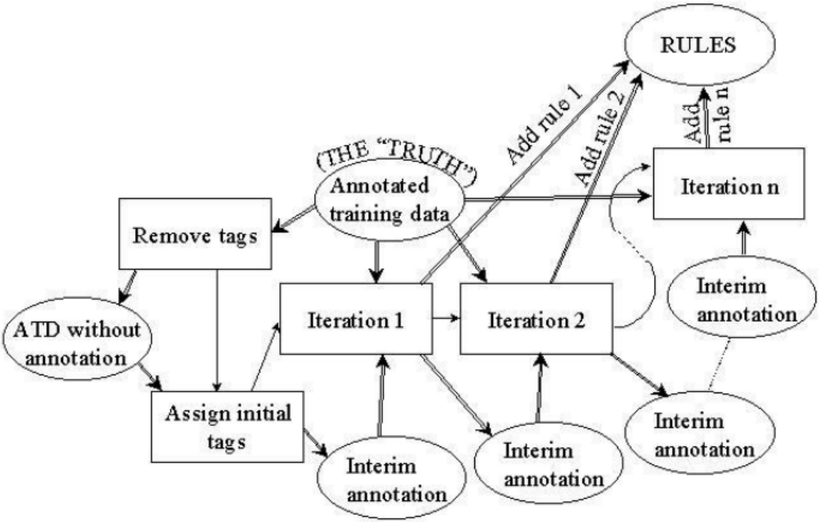
Setting

- **Not** a source channel view
- **Not** even a probabilistic model (no "numbers" used when tagging a text after a model is developed)
- Statistical, yes:
  - uses training data (combination of supervised [manually annotated data available] and unsupervised [plain text, large volume] training)
  - learning [rules]
  - criterion: accuracy (that's what we are interested in in the end after all!)

The General Scheme



The Learner


RULES
Add rule 1
Add rule 2
Add rule n
(THE "TRUTH")
Annotated training data
Iteration n
Remove tags
Interim annotation
ATD without annotation
Iteration 1
Iteration 2
Assign initial tags
Interim annotation
Interim annotation
Interim annotation

The I/O of an Iteration

- In (iteration i):
  - Intermediate data (initial or the result of previous iteration)
  - The TRUTH (the annotated training data)
  - $$poolofpossiblerules$$
- Out:
  - One rule $r_{selected(i)}$ to enhance the set of rules learned so far
  - Intermediate data (input data transformed by the rule learned in this iteration, $r_{selected(i)}$)

The Initial Assignment of Tags

- One possibilty:
  - NN
- Another:
  - the most frequent tag for a given word form
- Even:
  - use an HMM tagger for the initial assignment
- Not particulary sensitive

The Criterion

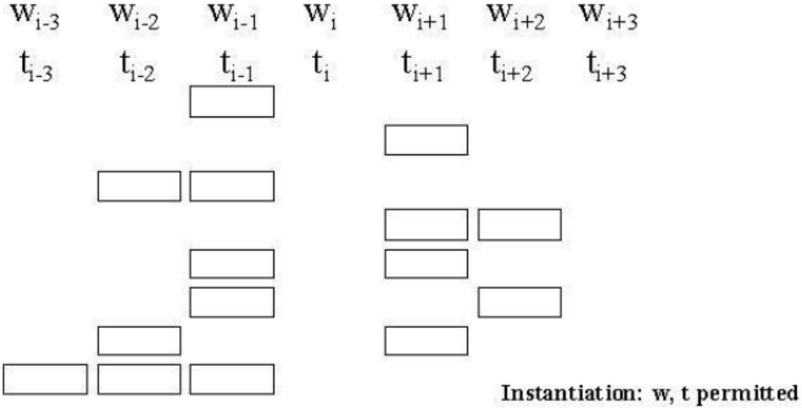
- Error rate (or Accuracy):
  - beginning of an iteration: some error rate E_{in}
  - each possible rule r, when applied at every data position:
    - makes an improvement somewhere in the data ($c_{improved}(r)$)
    - makes it worse at sme places ($c_{worsened}(r)$)
    - and, of course, does not touch the remaining data
- Rule contribution to the improvement of the error rate:
  - contrib(r) $= c_{improved(r)} - c_{worsened}(r)$
- Rule selection at iteration i:
  - $r_{selected(i)} = argmax_r contrib(r)$
- New error rate: $E_{out} = E_{in} - contrib(r_{selected(i)})$

The Stopping Criterion

- Obvious:
  - no improvement can be made
    - contrib(r) ≤ 0
  - or improvement too small
    - contrib(r) $\leq$ Threshold
- NB: prone to overtraining!
  - therefore, setting a reasonable threshold advisable
- Heldout?
  - maybe: remove rules which degrade performance on H

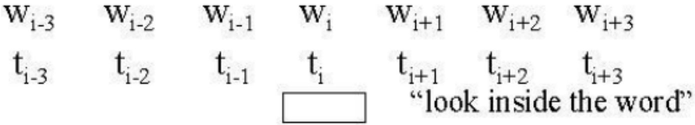
The Pool of Rules(Templates)

- Format: *change tag at position i from a to b / condition*
- Context rules (condition definition - "template"):



Lexical Rules

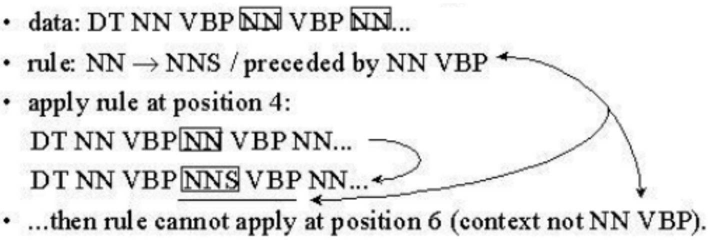
- Other type: lexical rules



- Example:
  - w_i has suffix -ied
  - w_i has prefix ge-

Rule Application

- Two possibilities:
  - immediate consequences (left-to-right):



  - delayed ("fixed input"):
    - use original input for context
    - the above rule then applies twice

In Other Words...

1. Strip the tags off the truth, keep the original truth
2. Initialize the stripped data by some simple method
3. Start with an empty set of selected rules S.
4. Repeat until the stopping criterion applies:
   - compute the contribution of the rule r, for each r: $contrib(r) = c_{improved}(r) - c_{worsened}(r)$
   - select r which has the biggest contribution contrib(r), add it to the final set of selected rules S.
5. Output the set S

The Tagger

- Input:
  - untagged data
  - rules (S) learned by the learner
- Tagging:
  - use the same initialization as the learner did
  - for $i = 1..n$ (n - the number of rules learnt)
    - apply the rule i to the whole intermediate data, changing (some) tags
  - the last intermediate data is the output

N-best & Unsupervised Modifications

- N-best modification
  - allow adding tags by rules
  - criterion: optimal combination of accuracy and the number of tags per word (we want: close to $\downarrow 1$)
- Unsupervised modification
  - use only unambiguous words for evaluation criterion
  - work extremely well for English
  - does not work for languages with few unambiguous words