Weakly Supervised Part-of-Speech Tagging for Morphologically-Rich, Resource-Scarce Languages

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Unsupervised POS Tagging

- Goal: POS-tag an unlabeled corpus given a POS lexicon, subject to the constraints imposed by the lexicon

Common Approach

- Train an HMM (i.e., learn its parameters, θ, which consists of the tag-transition distributions and the output distributions) to maximize the likelihood of the unlabeled corpus using EM
- Problem: Tagging accuracy is sensitive to many factors (e.g., parameter initializations)

Alternative: Goldwater and Griffiths's (2007) Nonparametric Fully-Bayesian Approach

- Adopts an HMM as the underlying model as before, but:
  1. integrates over all possible parameter values, rather than committing to a particular θ
  $$P(\mathbf{t}|\mathbf{w}) = \int P(\mathbf{t}|\mathbf{w},\theta)P(\theta|\mathbf{w})d\theta$$
  2. favours the learning of **skewed** tag-transition and output distributions via the use of a prior, $P(\theta|\mathbf{w})$
- Performs inference using Gibbs sampling
- Still makes the usual (unrealistic) assumption that a perfect POS lexicon is available

Our Goals

1. Relax this unrealistic assumption by learning the lexicon **automatically** from a small set of tagged sentences
2. Propose two extensions to G&G's approach for tagging for morphologically-rich, resource-scarce languages
   - Use **Bengali** as our representative language

Extension 1: Induced Suffix Emission (IS)

Motivation: Suffixes are useful indicators of POS tags

A (somewhat naive) way of exploiting suffixes:

1. Generate a list of induced suffixes from an unlabeled corpus (using Keshava and Pitler's (2006) algorithm)
2. Create a **suffix-based POS lexicon** by replacing each word in the original (i.e., word-based) POS lexicon, W, with its suffix induced in Step 1
3. Have the HMM emit suffixes rather than words, subject to the constraints in the suffix-based POS lexicon

Potential problem: Over-generalization

Our solution: Adopt a hybrid approach:
Emit a word if it is in W, otherwise emit its suffix

Extension 2: Discriminative Prediction (DP)

Motivation: We can learn from the POS-tagged sentences, L, how to exploit **contextual** information to tag a word. How?

- Learn three types of probabilities from L:
  1. $P(t_i|w_{i-2}, w_{i-1})$: probability of tag t_i following a word bigram
  2. $P(t_i|w_{i-1})$: probability of tag t_i following a word
  3. $P(t_i|w_i)$: probability of a word having tag t_i
- Apply the Discriminative Prediction Algorithm:
  - **If** w_i is in L, assign t_i to w_i with $P(t_i|w_i)$
  - **Else if** (w_{i-2}, w_{i-1}) is in L, assign t_i to w_i with $P(t_i|w_{i-2}, w_{i-1})$
  - **Else if** w_{i-1} is in L, assign t_i to w_i with $P(t_i|w_{i-1})$
  - **Else** obtain the tag using the Gibbs sampler

Evaluation

Goal: Evaluate our two extensions to G&G's tagging model using POS lexicons constructed by three methods

Corpus: Bengali dataset from IJCNLP-08 workshop, which comprises a 50K-token training set & a 30K-token test set
Training set: for constructing POS lexicons
Test set: for evaluating model accuracy
Tagset: IIIT Hyderabad's POS tagset reduced to 15 tags
Inference: running 5K iterations of the Gibbs sampler; hyperparameters learned by Metropolis-Hastings

Lexicon Construction Methods

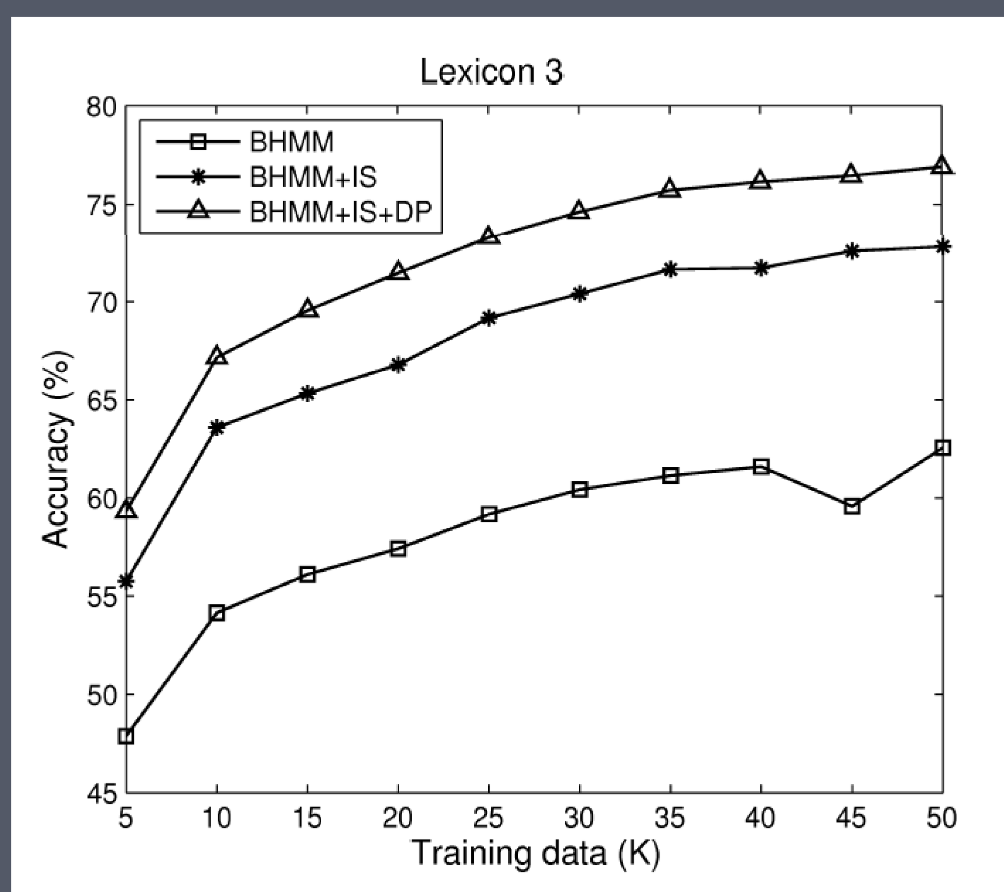
Lexicon 1: Includes only the words that appear at least d times in the test data
Lexicon 2: Includes only the words that appear at least d times in the training data
Lexicon 3: Includes only the words and their tags that appear in the training data (L)

Results using Lexicon 3

POS tagging models:

- **BHMM (Baseline)**: G&G's fully-Bayesian tagging model
- **BHMM+IS**: BHMM with the induced suffix extension
- **BHMM+IS+DP**: BHMM with both extensions

Learning curves of the POS tagging models:



Discussions

- Results show that both extensions are useful – BHMM+IS and BHMM+IS+DP outperform BHMM by 8–13% and 12–17%, respectively
- **Major sources of errors:** NN vs. NNP (8.4%), NN vs. JJ (6.9%), VM vs. VAUX (5.9%), VM vs. NN (5.1%)
- **Ambiguous token rate** ranges from 57.7% with 5.1 tags/token (50K) to 61.5% with 8.1 tags/token (5K)
- **Unseen word rate** ranges from 25% (50K) to 50% (5K)
- BHMM+IS also outperforms BHMM using Lexicon 1 and Lexicon 2 by 4–9% and 5–10%, respectively