Part-of-speech tagging. Part 2.[1]

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[1] With materials used from "Speech and Language Processing", D. Jurafsky and J. H. Martin.

Usage of part of speech

- Estimation of HMM
  - both outputs and states are known in the training set.
  - $\prod_{k=1}^{K} p(X_k, Y_k|A, B, \pi) \to \max_{A,B,\pi}$ where
    - K is the number of sentences,
    - X_k is k-th sentence
    - Y_k is corresponding tags sequence.
  - Emission and transition probabilities will be estimated with empirical frequencies.
- Application of HMM:
  - For given sentence X, recover sequence of tags Y using

$$\widehat{Y} = \arg\max_{Y} p(Y|X) = \arg\max_{Y} \frac{p(Y)p(X|Y)}{p(X)}$$
$$= \arg\max_{Y} p(Y)p(X|Y)$$

Details of HMM application

- Generated word depends only on part-of-speech:

$$p(X|Y) = \prod_{n=1}^{N} p(x_n|y_n)$$

- Next tag depends only on previous tag:

$$p(Y) = p(y_1) \prod_{n=2}^{N} p(y_n|y_{n-1})$$

- Final estimation

$$\widehat{Y} = \arg\max_{Y} \overbrace{p(y_1) \prod_{n=2}^{N} p(y_n|y_{n-1})}^{\text{transition}} \overbrace{\prod_{n=1}^{N} p(x_n|y_n)}^{\text{emission}}$$

  - argmax is found with Viterbi algorithm.

Advanced use of HMM[2][3]

- Emission probability conditioned on 2 previous states:

$$p(Y) = p(y_1, y_2) \prod_{n=3}^{N} p(y_n | y_{n-1}, y_{n-2})$$

  - state - position in 2 states, instead of 1.

- Transition probability is replaced with

$$p(Y) = \prod_{n=1}^{N+1} p(y_n | y_{n-1}, y_{n-2})$$

  where y_0, y_{-1} are special «before sentence tags» and y_{N+1} is «after sentence tag».

- To estimate $p(y_t | y_{t-1}, y_{t-2})$ with insufficient data use smoothing:

$$p(y_t | y_{t-1}, y_{t-2}) = \lambda_3 \widehat{p}(y_t | y_{t-1}, y_{t-2}) + \lambda_2 \widehat{p}(y_t | y_{t-1}) + \lambda_1 \widehat{p}(y_t)$$

- Parameters $\lambda_1, \lambda_2, \lambda_3$ can be set with cross validation or using heuristic «deleted interpolation» method.

[2] Scott T., Harper M. 1999. A Second-Order Hidden Markov Model for

Suffix

- for unknown words we can deduce POS using suffix
- suffix - informative for POS tagging:
  - ...able: likely adjective, ...ed: likely past tense of verb, etc.
- so we estimate $p(y|word[-k:])$
  - try to estimate this with maximal $k = 10$
  - if for big k we have no statistics, we fallback to probability for smaller k (*backoff* method)
- in HMM we need to generate observable suffixes, so we use:

$$p(word[-k:]|y) = \frac{p(word[-k:])p(y|word[-k:])}{p(y)}$$

  - these probabilities are estimated separately for capitalizxed and uncapitalized words.
- replace (y_i) with pair $(y_i, \mathbb{I}[\text{word i is capitalized}])$ to treat capitalized words differently.
  - doubles number of states

MEMM

- Consider sentence $x_1 ... x_N$ with POS tags $y_1 ... y_N$.
- HMM prediction

$$\widehat{Y} = \arg\max_{Y} p(y_1) \prod_{n=2}^{N} p(y_n | y_{n-1}) \prod_{n=1}^{N} p(x_n | y_n)$$

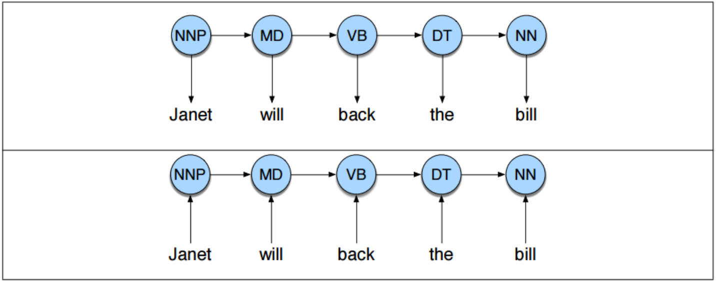
- MEMM (maximum entropy Markov model[4]) prediction

$$\widehat{Y} = \arg\max_{Y} p(Y|X) = \arg\max_{Y} \prod_{n=1}^{N} p(y_n | x_n, y_{n-1})$$

[4] Maximum entropy name comes from the fact that most commonly logistic regression is used as classifier, which posesses the «maximum entropy» prediction properties.

MEMM vs HMM

- Graphical structuire of HMM (top) and MEMM (bottom):



- HMM - generative model and MEMM - discriminative.
    - it is easier to add new features to MEMM
    - in HMM need to add new features to $p(x_n|y_n)$
        - harder to model

Typical features in MEMM for predicting y_n

- neigbourhood words $\langle w_{n+k} \rangle$, $k = -2, -1, ...2.$
- neigbourhood word pairs $\langle w_{n+k-1}, w_{n+k} \rangle$, $k = 0, 1.$
- previous tags: $\langle y_{n-1} \rangle, \langle y_{n-1} \rangle, \langle y_{n-2} \rangle, \langle y_{n-1}, y_{n-2} \rangle$
- tag&word combination $\langle x_n, y_{n-1} \rangle$
- current word x_n:

contains a particular prefix (from all prefixes of length ≤ 4)
contains a particular suffix (from all suffixes of length ≤ 4)
contains a number
contains an upper-case letter
contains a hyphen
is all upper case
s word shape
s short word shape
is upper case and has a digit and a dash (like *CFC-12*)
is upper case and followed within 3 words by Co., Inc., etc.

word-shape encoding of x_n as feature

- rules:
    - letter->x
        - uppercase letter->X
        - digit->d
        - puctuation->puctuation (no change)
    - example:
        - U.S.A->X.X.X
        - FD-rsa18->XX-xxxdd
        - well-dressed->xxxx-xxxxxxx
- reduced word-shape: takes *word-shape encoding* symbols but without repetitions
    - examples:
        - FD-rsa18->X-xd
        - well-dressed->x-x
- rarely occuring (<5 times) shapes are not included to feature set.

Application of MEMM

- For simplicity consider conditioning y_n only on X and y_{n-1}.
- Greedy MEMM decoding:

for $n = 1, 2, ...N$: $\quad y_n = \arg\max_y p(y \vert y_{n-1}, X)$

  - fast
  - makes greedy, local decisions
  - cannot correct earlier decisions from later inconsistencies
- Viterbi algorithm gives a consistent sequence of predictions for whole sentence!

Viterbi algorithm: forward pass

Assume $p(y_t|history) = p(y_t|x_t, y_{t-1})$. Definitions:

$$\varepsilon_t(i, X) := \max_{y_{1,\dots}y_{t-1},} p\left(y_1 \dots y_{t-1} y_t = i | x \dots x_t\right)$$

$$v_t(i, X) := \arg\max_j p(y_1 \dots y_{t-2}, y_{t-1} = j, y_t = i | x_1 \dots x_t)$$

Init:

$$\varepsilon_1(i, X) = p(y_1 = i | x_1) = \text{output of classifier}$$

For $t = 1, \dots T - 1$:

$$\begin{aligned}
\varepsilon_{t+1}(i, X) &= \max_{y_1 \dots y_{t-1}, j} p(y_1 \dots y_{t-1} y_t = j, y_{t+1} = i | x_1 \dots x_t x_{t+1}) \\
&= \max_j \max_{y_1 \dots y_{t-1}} p(y_1 \dots y_{t-1} y_t = j | x_1 \dots x_{t+1}) p(y_{t+1} = i | y_1 \dots y_{t-1} y_t = j, x_1 \dots x_{t+1}) \\
&= \max_j \max_{y_1 \dots y_{t-1}} p(y_1 \dots y_{t-1} y_t = j | x_1 \dots x_t) p(y_{t+1} = i | y_t = j, x_{t+1}) \\
&= \max_j \varepsilon_t(j, X) p(y_{t+1} = i | y_t = j, x_{t+1}) \\
v_{t+1}(i, X) &= \arg\max_j \varepsilon_t(j, X) p(y_{t+1} = i | y_t = j, x_{t+1})
\end{aligned}$$

Viterbi algorithm: backward pass

Definitions

$$y_1^*, ...y_T^* := \arg\max_{y_1,...y_T} p(y_1, ...y_T | x_1, ...x_T)$$

$$\varepsilon_t(i, X) := \max_{y_1,...y_{t-1},} p\left(y_1...y_{t-1} y_t = i | x_1...x_t\right)$$

$$v_t(i, X) := \arg\max_j p(y_1...y_{t-2}, y_{t-1} = j | y_t = i, x_1...x_t)$$

Init:

$$p^*(X) = \max_j \varepsilon_T(j, X)$$

$$y_T^*(X) = \arg\max_j \varepsilon_T(j, X)$$

For $t = T-1, T-2, ...1$:

$$y_t^*(X) = v_{t+1}(y_{t+1}^*(X))$$

Comments

- We could define $\varepsilon_t(i, X) := \max_{y_{1,\dots y_{t-1}},} p\left(y_1 \dots y_{t-1} y_t = i | x \dots x_{t+k}\right)$ for some lookahead horizon $k > 0$.
- we could condition y_t on several states before $y_{t-1}, y_{t-2}, \dots$
- We use left-to-right classification. Similarly we could use right-to-left classification and combine their outputs with meta-model.
- Also we could make several passes:
    - first pass: obtain most likely $y_1, \dots y_N$
    - second pass: make classification both on past *and future*.

Brill tagger[5]

- Generates a data-driven set of rules.
- Top rules for known words (in the dictionary):

	Change Tag		
#	From	To	Condition
1	NN	VB	Previous tag is *TO*
2	VBP	VB	One of the previous three tags is *MD*
3	NN	VB	One of the previous two tags is *MD*
4	VB	NN	One of the previous two tags is *DT*
5	VBD	VBN	One of the previous three tags is *VBZ*

- Top rules for unknown woprds:

	Change Tag		
#	From	To	Condition
1	NN	NNS	Has suffix **-s**
2	NN	CD	Has character **.**
3	NN	JJ	Has character **-**
4	NN	VBN	Has suffix **-ed**
5	NN	VBG	Has suffix **-ing**
6	??	RB	Has suffix **-ly**
7	??	JJ	Adding suffix **-ly** results in a word.
8	NN	CD	The word **$** can appear to the left.
9	NN	JJ	Has suffix **-al**
10	NN	VB	The word **would** can appear to the left.

Algorithm

- Brill tagger algorithm:

INIT: set most probable tag to each word

REPEAT until quality changes significantly:
   for each rule pattern $R(\cdot)$
      for each rule pattern instantiation $\gamma \in \Gamma$
         evaluate rule $R(\gamma)$
   select most successful rule $R^*(\gamma^*)$
   apply most successful rule $R^*(\gamma^*)$ to training dataset
   add $R^*(\gamma^*)$ to the end of selected rules list

OUTPUT: selected rules list

Rule patterns

Example of rule patterns for known and unknown words:

Change tag **a** *to tag* **b** *when:*

The preceding (following) word is tagged z.

The word two before (after) is tagged z.

One of the two preceding (following) words is tagged z.

One of the three preceding (following) words is tagged z.

The preceding word is tagged z and the following word is tagged w.

The preceding (following) word is tagged z and the word two before (after) is tagged w.

where a, b, z and w are variables over the set of parts of speech.

Change the tag of an unknown word (from X) to Y if:

Deleting the prefix (suffix) x, $|x| \leq 4$, results in a word (x is any string of length 1 to 4).

The first (last) (1,2,3,4) characters of the word are x.

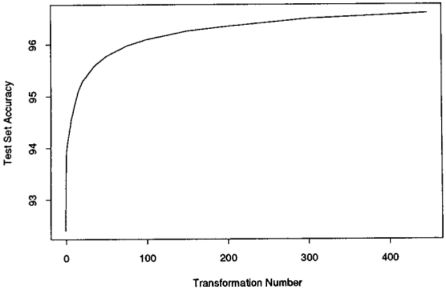
Adding the character string x as a prefix (suffix) results in a word ($|x| \leq 4$).

Word w ever appears immediately to the left (right) of the word.

Character z appears in the word.

Comments

- Brill tagger gives comparative performance with HMM, but less than MEMM.
- Gives interpretable list of rules
- Accuracy on Wall Street Journal corpus 96.6%
- First rules give the most impact:



Comments

- Brill tagger works very slow - needs to look through all rule patterns and all instantiations
- Possible improvements:
    - look only through those rule instantiations that improve at least 1 word tagging
    - use inverted index on rule conditions

General sequence labelling

Sequence labelling: assign $x_1...x_N$ labels $y_1, ...y_N$ where neighbouring labels are dependent.
Applications of sequence labelling:

- Part-of-speech tagging
- Speech recognition
- Handwriting recognition
- Video analysis (e.g. activity tagging)