Data Intensive Linguistics — Lecture 5
Tagging (I): Part-of-speech tagging with HMM

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Parts of Speech

- **Open class words** (or content words)
  - nouns, verbs, adjectives, adverbs
  - mostly content-bearing: they refer to objects, actions, and features in the world
  - *open* class, since there is no limit to what these words are, new ones are added all the time (*email, website*).
- **Close class words**
  - pronouns, determiners, prepositions, connectives, ...
  - there is a limited number of these
  - mostly functional: to tie the concepts of a sentence together

Parts of Speech (2)

- There are about 30-100 parts of speech
  - distinguish between names and abstract nouns?
  - distinguish between plural noun and singular noun?
  - distinguish between past tense verb and present tense word?
- Identifying the parts of speech is a first step towards syntactic analysis

Ambiguous words

- For instance: *like*
  - verb: *I like the class.*
  - preposition: *He is like me.*
- Another famous example: *Time flies like an arrow*
- Most of the time, the local context disambiguated the part of speech

Part-of-speech tagging

- Task: Given a text of English, identify the parts of speech of each word
- Example
  - Input: Word sequence
    Time flies like an arrow
  - Output: Tag sequence
    Time/NN *flies*/VB *like*/P *an*/DET *arrow*/NN
- What will help us to tag words with their parts-of-speech?

Relevant knowledge for POS tagging

- The word itself
  - Some words may only be nouns, e.g. *arrow*
  - Some words are ambiguous, e.g. *like, flies*
  - Probabilities may help, if one tag is more likely than another
- Local context
  - two determiners rarely follow each other
  - two base form verbs rarely follow each other
  - determiner is almost always followed by adjective or noun

Bayes rule

- We want to find the best part-of-speech tag sequence T for a sentence S:

$$\text{argmax}_T\ p(T|S)$$

- Bayes rule gives us:

$$p(T|S) = \frac{p(S|T)\ p(T)}{p(S)}$$

- We can drop $p(S)$ if we are only interested in argmax_T:

$$\text{argmax}_T\ p(T|S) = \text{argmax}_T\ p(S|T)\ p(T)$$

Decomposing the model

- The mapping $p(S|T)$ can be decomposed into

$$p(S|T) = \prod_i p(w_i|t_i)$$

- $p(T)$ could be called a *part-of-speech language model*, for which we can use an n-gram model:

$$p(T) = p(t_1)\ p(t_2|t_1)\ p(t_3|t_1,t_2) ... p(t_n|t_{n-2},t_{n-1})$$

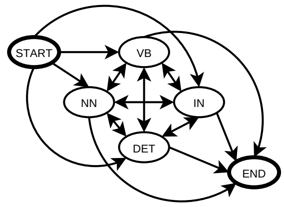
- We can estimate $p(S|T)$ and $p(T)$ with maximum likelihood estimation (and maybe some smoothing)

Hidden Markov Model (HMM)

- The model we just developed is a **Hidden Markov Model**
- Elements of an HMM model:
  - a set of states (here: the tags)
  - an output alphabet (here: words)
  - intitial state (here: beginning of sentence)
  - state transition probabilities (here: $p(t_n|t_{n-2}, t_{n-1})$)
  - symbol emission probabilities (here: $p(w_i|t_i)$)

Graphical representation

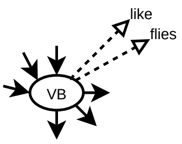
- When tagging a sentence, we are walking through the state graph:



- State transition probabilities: $p(t_n|t_{n-1})$

Graphical representation (2)

- At each state we emit a word:



- Symbol emission probabilities: $p(w_i|t_i)$

Search for the best tag sequence

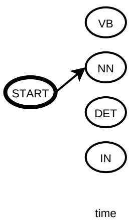
- We have defined a model, but how do we use it?
  - given: word sequence
  - wanted: tag sequence
- If we consider a specific tag sequence, it is straight-forward to compute its probability

$$p(S|T)\,p(T) = \prod_i p(w_i|t_i)\,p(t_i|t_{i-2}, t_{i-1})$$

- Problem: if we have on average c choices for each of the n words, there are c^n possible tag sequences, maybe too many to efficiently evaluate

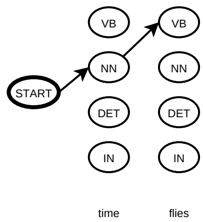
Walking through the states

- First, we go to state *NN* to emit *time*:



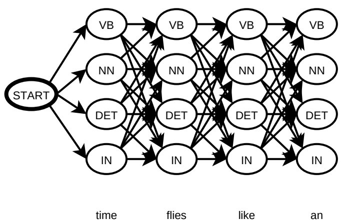
Walking through the states (2)

- Then, we go to state *VB* to emit *flies*:



Walking through the states (3)

- Of course, there are many possible paths:



Viterbi algorithm

- Intuition: Since state transition out of a state only depend on the current state (and not previous states), we can record for each state the optimal path
- We record:
  - cheapest cost to state j at step s in $\delta_j(s)$
  - backtrace from that state to best predecessor $\psi_j(s)$
- Stepping through all states at each time steps allows us to compute
  - $\delta_j(s+1) \;=\; \max_{1\leq i\leq N}\, \delta_i(s)\, p(t_i|t_j)\, p(w_s|t_j)$
  - $\psi_j(s+1) = \text{argmax}_{1\leq i\leq N}\, \delta_i(s)\, p(t_i|t_j)\, p(w_s|t_j)$
- Best final state is $\text{argmax}_{1\leq i\leq N}\, \delta_i(S+1)$, we can backtrack from there

Other tagging tasks

- A number of problems can be framed as tagging problems:
- **BaseNP chunking:** for text processing purposes it is useful to detect base noun phrases that correspond to concepts, e.g. *department of defense*
- **Named entity recognition:** it may also be useful to find names of persons, organizations, etc. in the text, e.g. *Tony Blair*
- **Accent restoration:** When keyboards lack the proper keys, it is common to not write the accents in Spanish or French. We may want to restore them.
- **Case restoration:** If we just get lowercased text, we may want to restore proper casing, e.g. *the river Thames*

BaseNP chunking

- Task: find basic noun phrases (facilitates parsing, information extraction)
- Example: *[the student] said [the exam question] is hard*
- Three tags
  - B = beginning of baseNP
  - I = continuing baseNP (internal)
  - O = other word
- Example: *the*/B *student*/I *said*/O *the*/B *exam*/I *question*/I *is*/O *hard*/O
- Tagging task: assign tags (B, I, O) to each word