# Apertium part-of-speech tagger internals

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https://www.github.com/frankier/tagger-internals-slides/

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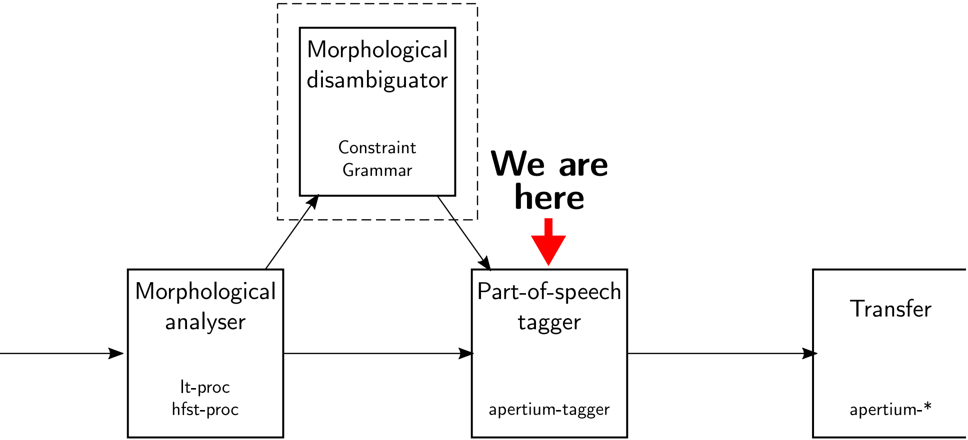
# Orientation



# An idealised part-of-speech tagger


- Hard-working linguist picks the correct morphological analysis of every sentence that ever has been or will be.
- Tagger looks up all the analyses of our input sentence. Outputs the most frequent analysis of each word.
- $\arg\max_{t_i \in T} P(t_i | w_0, w_1, \ldots, w_n)$
- "Pick the most likely tag for the word in the context of the sentence"

# Not so ideal

- This is impossible. Instead our linguist works for a while and comes back with a tagged corpus of 10 000 sentences.
- If the sentence to tag isn't in our corpus, the previous algorithm can't do anything. Our tagger must deal with data sparsity.
- If the sentence is in our corpus once, it could be tagged with a rare interpretation. Our tagger shouldn't overfit.
- How? Reduce the number of parameters and smooth over incomplete data.

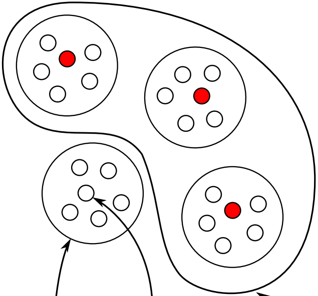
# A zero-parameter, zero-gram model

- Assume that all tags are uniformly distributed independently from context.
- Since they are evenly distributed, we can just pick the first one.
- Usually implemented with Apertium as `cg-proc -1`.
- This is our baseline.

# Unigram tagger

- In general, discard all context apart from the word itself.
- $\arg\max_{t_i \in T} P(t_i|w_i)$
- In Apertium, result of a Google Code-In project by m5w based on `http://coltekin.net/cagri/papers/trmorph-tools.pdf` — Supervised (needs a tagged corpus).
- Model one: Just pick the most frequent whole analysis. So if our corpus is just $work\langle n\rangle\langle sg\rangle$ once and $work\langle vblex\rangle\langle imp\rangle$ zero times our tagger always picks $work\langle n\rangle\langle sg\rangle$. If a word isn't in our corpus at all this acts like the zero-gram case due to smoothing ("cross fading" between different models).
- Model two: decompose using Bayes' theorem: $P(t) = P(root, analysis) = P(root|analysis)P(analysis)$. So count each analysis string and count for each analysis how many of each roots it has to estimate. From previous example, our model can now tag an unseen word as $\langle n\rangle\langle sg\rangle$.

# From analyses to coarse tags and ambiguity classes




- Cluster morphological analyses into coarse tags — reduces number of parameters.
- *coarsen*: *Analysis* → *Coarse Tag*; *coarsen*(di⟨vblex⟩⟨imp⟩⟨p2⟩⟨sg⟩) = *VLEXIMP*
- *coarsen-many*: *Analyses* → *AmbiguitySet*; *coarsen-many*( {*work*⟨*n*⟩⟨*sg*⟩, *work*⟨*vblex*⟩⟨*imp*⟩}) = *NOUNSG*, *VBLEXIMP*
- *discriminate*: *Analyses*, *CoarseTag* → *Analysis*; *discriminate*({*work*⟨*n*⟩⟨*sg*⟩, ⟨*vblex*⟩⟨*imp*⟩}, *NOUNSG*) = *work*⟨*n*⟩⟨*sg*⟩
- *coarsen-many* and *discriminate* can be implemented in terms of *coarsen*.

# The reduced morphological disambiguation problem

- First run, *coarsen-many* for each incoming token to get a stream of ambiguity classes.
- Then, run our coarse tagging tagger on the ambiguity classes to get a coarse tag for each token.
- Then, run *discriminate* on each tag in the resulting coarse tag stream to get stream of disambiguated morphological analyses.
- Coarse tags are defined by globbing (pattern matching) fine tags and sometimes additionally by listing lemmas.
- This scheme deals with multiwords (tokens made of a series of (lemma, fine tags) pairs, eg compound words) by assigning a tag for the whole token, usually made by combining other coarse tags eg maan-kamera is made up of a NOUNGEN followed by a NOUNSG so we make a new tag, NOUNGEN_NOUNSG.

# Picking coarse tags

- Currently you need to define coarse tags for your language in a tsx file.
- `https://github.com/jimregan/tag-clusterer` is a wrapper around `mkcls`[1] which picks coarse tags for you based on a corpus.
- *mkcls* maximises $P(x_i | coarsen(x_i))$: the probability we can guess the correct analysis given a coarse tag. Usually it should be possible to get this value near 1 ($\Rightarrow$ the *discriminate* step is reliable).
- This program also tries to maximises $P(coarsen(x_i) | coarsen(x_{i-1}))$, that is the probability we can predict a coarse tag from a previous coarse tag. Very common lemmas to sometimes end up with their own coarse tag.

[1] More info at `http://statmt.blogspot.fi/2014/07/understanding-mkcls.html`

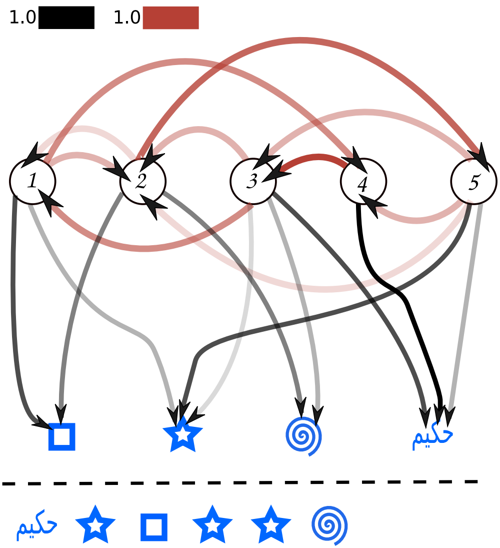
# Coarse tags unigram tagger (not in Apertium)

- Not in Apertium — explained here to help motivate what follows.
- Estimate $P(tag|ambiguity\text{-}class)$.
- Model consists of triples: $(ambiguity\text{-}class, tag, occurrence\text{-}count)$.
- Supervised training: Inspect each tagged token and increment *occurrence-count* in the corresponding triple.
- Tagging: For each input ambiguity class, pick the *tag* with the highest *occurrence-count*.

# Hidden Markov Model bigram tagger

- Now we use the tag the previous word has received as context. We now try to estimate P(current-tag|previous-tag) the transition probabilites.
- The actual tags are the hidden part of the model.
- We can observe the ambiguity class — HMM jargon: they are "emitted" by the model.
- $P(ambiguity\text{-}class|tag)$ (conditional inverted from previous slide) is the emission probabilities.

# Diagram + intuition of tagging process



# Viterbi tagging algorithm

- Keep track of the path probabilities through the Markov model.
- At an unambigious token, backtrack and output the tags we've remembered.
- First step, set the probability of a sentinel tag to 1: $V_{1,START} = 1$
- At step $n$ for each possible *tag* we calcuate $V_{n,tag}$
- We consider each prev-tag (from all possible previous tags S),

$$V_{n,tag} = \max_{prev\text{-}tag \in S} (P(ambg\text{-}class|tag) \cdot P(tag|prev\text{-}tag) \cdot V_{n-1,prev\text{-}tag})$$

- At each step $n$ for each *tag* we save the value of the *prev-tag* for use during backtracking.

# Training

- Supervised training: just estimate the probabilies with their frequency in the corpus.
- Unsupervised training using Baum-Welch. Idea: iteratively improve our model to maximise the probability of the observations in our untagged corpus. We “fit our model to our data”.

# Lightweight Sliding Window Part of Speech Tagger (LSWPoST)

- Based on work in 2005 by Sanchez-Villamil, M. L. Forcada, and R. C. Carrasco.
- In Apertium, considers a context of the previous and next tag.
- It estimates the best tag by summing all possible $P(\mathit{prev\text{-}tag}, \mathit{tag}, \mathit{next\text{-}tag} | \mathit{prev\text{-}ambg\text{-}class}, \mathit{tag}, \mathit{next\text{-}ambg\text{-}class})$ (no search/decoding process)
- Unsupervised learning of these probabilies by an interative process.
- Paper at `http://arxiv.org/pdf/1509.05517v1.pdf`.

# Comparison

- For Catalan:

| Model | Per token accuracy (%) |
|---|---|
| 0-gram | 86.50 |
| Bigram unsupervised | 91.51±1.16 |
| LSWPoST | 92.99±0.84 |
| Unigram model 1 | 93.86±1.13 |
| Unigram model 2 | 93.90±1.09, |
| Bigram supervised | 96.00±0.87. |

- Take with a pinch of salt. Per token means includes full stops. If we have sentences 20 tokens long: 86.5% token accuracy means 5.4% sentence rate, 96% accuracy means 44.2% sentence rate.
- A lot more info available at `http://wiki.apertium.org/wiki/Comparison_of_part-of-speech_tagging_systems`

# Comparison cont.

| Model | untagged crp | tagged crp | tsx |
|---|---|---|---|
| 0-gram | ✗ | ✗ | ✗ |
| Unigram | ✗ | ✓ | ✗ |
| Bigram unsup | ✓ | ✗ | ✓ |
| LSWPoST | ✓ | ✗ | ✓ |
| Bigram sup | ✗ | ✓ | ✓ |

# My work on the tagger

- In process GSOC project trying to improve apertium-tagger in two directions.
- Experimenting with different ways to integrate lt-proc output and CG disambiguated output into the current tagger training and tagging processes.
- A new tagger based on the generalised perceptron aiming to:
    - Improve accuracy rates over the bigram tagger for supervised tagging.
    - Provide a usable tagger for languages where writing a complete tsx ranges from very annoying to infeasible, e.g. Turkic languages
    - Possibly in the process provide a more usable tagger for other languages too.
    - Allow user configuration over which features within the sentence are used for disambiguating tokens, and which parts of a candidate token to consider important for disambiguation.

# Further reading

- See the links throughout the presentation (these slides are available at `https://www.github.com/frankier/tagger-internals-slides/`)
- At `https://www.github.com/frankier/apertium-hmm2dot` there are some tools I made to explore some of the tagger internals. This includes a tool to visualise bigram HMM tagger models, tools to show what's inside a tagger model file, and tools to show the input streams to the taggers.
- Read the source code