# L101: Machine Learning for Language Processing

Lecture 2

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# Today’s Lecture

- Recap
- Part-of-speech tagging
- Hidden Markov Model (HMM)

# Recap – Models

$$f : x \mapsto y$$

- Non-probabilistic: $f$
- Discriminative: $P(y|x)$
- Generative: $P(x, y)$

# Recap – Naive Bayes

- Fixed vocabulary
- Feature vectors $x_i$
  - Binary (Bernoulli NB)
  - Bag of words (Multinomial NB)
- Parameters $P(x_i|y)$, $P(y)$
- Train using observed counts

# Vocabulary Size

**Zipf's Law** : word frequency follows a power law distribution; many words only appear once (long tail)

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⇒ Some words unseen at test time

# Part-of-Speech Tagging

| They | can | fish | . |
|---|---|---|---|
| PNP | VM0 | VVI | PUN |

CLAWS-5 tagset includes:

| | | | |
|---|---|---|---|
| NN1 | singular noun | VVB | verb, base form |
| NN2 | plural noun | VVI | verb, infinitive |
| PNP | personal pronoun | VM0 | verb, modal |
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| PNP | VVB | NN2 | PUN | |
| PNP | VM0 | NN2 | PUN | no full parse! |

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# Part-of-Speech Lexicon Fragment

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|---|---|
| they | PNP |
| can | VM0, NN1, VVB, VVI |
| fish | NN2, NN1, VVB, VVI |

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- Could be hand-written
- ML: aim to learn from data

# Why Do Part-of-Speech Tagging?

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- For applications:
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  - Input features for other tasks
- For linguistics:
  - Lexicography
  - Corpus linguistics

# Defining The Task

- Which language? (dialect?)
- Tagset? Syntactic analysis?
- Genre? Domain?

# Defining The Task

- Errors in the input?
  They walked into into the room
- Errors in the annotations?
- Rare words / rare usages of words?

# Defining The Task

- Sequence labelling
  - Input: sequence
  - Output: sequence of same length
- Usually supervised

# Data

- Limited training data
  - Requires trained annotators
  - Annotation guidelines are lengthy
- High inter-annotator agreement

# Hidden Markov Model

$$\underset{t_1 \cdots t_n}{\operatorname{argmax}} P(t_1 \cdots t_n | w_1 \cdots w_n)$$

# Hidden Markov Model

$$
\begin{aligned}
& \operatorname*{argmax}_{t_1 \cdots t_n} P(t_1 \cdots t_n | w_1 \cdots w_n) \\
= \; & \operatorname*{argmax}_{t_1 \cdots t_n} P(t_1 \cdots t_n) P(w_1 \cdots w_n | t_1 \cdots t_n)
\end{aligned}
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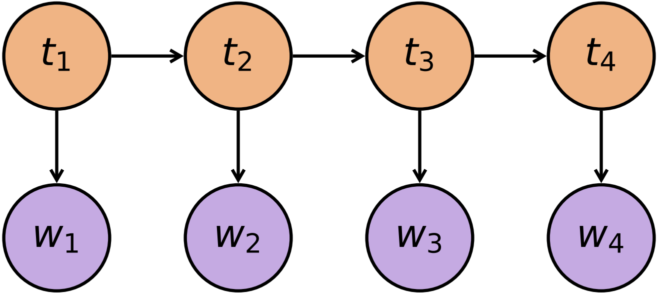
= & \underset{t_1 \cdots t_n}{\operatorname{argmax}}\ P(t_1 \cdots t_n) P(w_1 \cdots w_n | t_1 \cdots t_n) \\
\approx & \underset{t_1 \cdots t_n}{\operatorname{argmax}} \prod_{i=1}^{n} P(t_i | t_{i-1}) P(w_i | t_i)
\end{aligned}
$$

# Hidden Markov Model



# Hidden Markov Model

- Parameters:
  - $P(t_i|t_{i-1})$ – transition probabilities
  - $P(w_i|t_i)$ – emission probabilities

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- Parameters:
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- Train using observed counts
- Smoothing hyperparameters

# Backoff

For higher *n*-grams, can use backoff:

$$\hat{P}(t_i|t_{i-1},t_{i-2}) = \lambda P_{\text{trigram}}(t_i|t_{i-1},t_{i-2}) + (1-\lambda)P_{\text{bigram}}(t_i|t_{i-1})$$

$P_{\text{trigram}}$, $P_{\text{bigram}}$ calculated using counts

# Inference

- An HMM learns $P(t_1 \cdots t_n, w_1 \cdots w_n)$
- Dynamic programming:
  - Most likely sequence
    $\rightarrow$ Viterbi Algorithm
  - Most likely tag for each word
    $\rightarrow$ Forward-Backward Algorithm

# Unknown Words

- Frequency of open-class tags
- Morphology (e.g. “-ing”)
- Capitalisation (e.g. “Bill” vs. “bill”)

# Discriminative POS-Tagging

- Conditional Random Fields
- Recurrent Neural Networks (details in future lecture)

# State of the Art

- Plank et al. (2016), in course readings
- Performance close to ceiling
- Return to question: what is the task?