L90: Overview of Natural Language Processing

Lecture 3: Part-of-Speech Tagging and Log-Linear Models

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Some yinkish dripners blorked quastofically into the nindin with the pidibs

words have classes

Some/DET yinkish/ADJ dripners/NOUN blorked/VERB quastofically/ADV into/PREP the/DET nindin/NOUN with/PREP the/DET pidibs/NOUN

Lecture 3: Part-of-Speech Tagging and Log-Linear Models

1. Labeling words
2. The statistical perspective
3. Corpora
4. Log-linear models
5. Evaluation

some slides are from Ann Copestake

Labeling Words

Fish fish fish.

Fish fish fish.

fish

noun

US /fɪʃ/ **UK** /fɪʃ/

plural **fish** or **fishes**

Lew Robertson/Photolibrary /GettyImages

A1 [C or U]

an animal that lives in water, is covered with scales, and breathes by taking water in through its mouth, or the flesh of these animals eaten as food:

- *Several large fish live in the pond.*
- *Sanjay **caught** the biggest fish I've ever seen.*
- *I don't like fish (= don't like to eat fish).*

dictionary.cambridge.org/us/dictionary/english/fish

Fish fish fish.

fish ***verb*** **(ANIMAL)**

B1 [I or T]

to catch fish from a river, sea, lake, etc., or to try to do this:

- *They're fishing **for** tuna.*
- *The sea here has been fished intensely over the last ten years.*

dictionary.cambridge.org/us/dictionary/english/fish

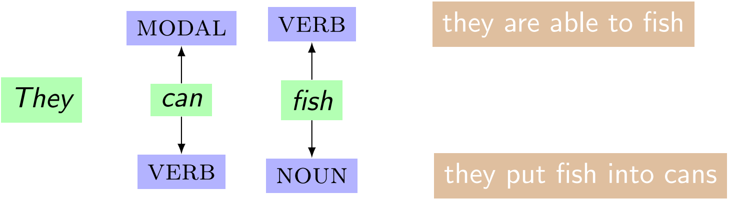
Part-of-speech tagging is useful

Fish/NOUN fish/VERB fish/NOUN

from FINDING NEMO MOVIE (2013)

photo: www.avforums.com/reviews/finding-nemo-movie-review.6237

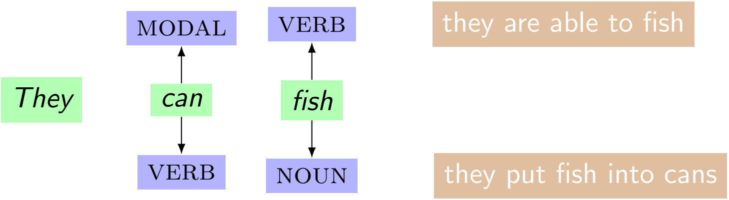
Ambiguity



Ambiguity

- *can*: modal verb, verb, singular noun
- *fish*: verb, singular noun, plural noun

Ambiguity



Ambiguity

- *can*: modal verb, verb, singular noun
- *fish*: verb, singular noun, plural noun

application-independent tags;
linguistic knowledge involved

Why POS tag?

Coarse-grained syntax / word sense disambiguation: fast, so applicable to very large corpora.

- Some linguistic research and lexicography: e.g., how often is *tango* used as a verb? *dog*?
- Named entity recognition and similar tasks (finite state patterns over POS tagged data).
- Features for machine learning e.g., sentiment classification. (e.g., *stink*/VERB vs *stink*/NOUN).
- Fast preliminary processing for full parsing: provide guesses at unknown words, cut down search space.

Information extraction (1)

Book a flight

- Leave London on 1st Dec 2020
- Arrive at London on 1st Dec 2020

FROM TO TIME		

Information extraction (1)

Book a flight

- Leave/O London/B-FROM on/O 1st/B-TIME Dec/I-TIME 2020/E-TIME
- Arrive/O at/O London/B-TO on/O 1st/B-TIME Dec/I-TIME 2020/E-TIME

FROM	London	
TO		London
TIME	1st Dec 2020	1st Dec 2020

Chunking

B	begin of X
I	inside X
E	end of X
O	outside X

Information extraction (1)

Book a flight

- Leave/O London/B-FROM on/O 1^{st}/B-TIME Dec/I-TIME 2020/E-TIME
- Arrive/O at/O London/B-TO on/O 1^{st}/B-TIME Dec/I-TIME 2020/E-TIME

FROM	London	
TO		London
TIME	1^{st} Dec 2020	1^{st} Dec 2020

Chunking

B	begin of X
I	inside X
E	end of X
O	outside X

application-dependent tags; contextual information matters

Information extraction (2)

Entity linking

from BBC news

Time is running out for Brussels and London to reach a post-Brexit trade deal.

Downing Street said Johnson, 55, is in extremely good spirits at the St Thomas' Hospital ward as his father, Stanley Johnson, called on his son to rest up.

Information extraction (2)

Entity linking

from BBC news

Time is running out for Brussels/European_Council and London/Government_of_the_United_Kingdom to reach a post-Brexit trade deal.

Downing Street/Government_of_the_United_Kingdom said Johnson/Boris_Johnson, 55, is in extremely good spirits at the St Thomas' Hospital ward as his father, Stanley Johnson, called on his son to rest up.

application-dependent tags; world knowledge involved

The Statistical Perspective

The actual science of logic is conversant at present only with things either certain, impossible, or entirely doubtful, none of which (fortunately) we have to reason on. Therefore the true logic for this world is the calculus of probabilities, which takes account of the magnitude of the probability which is, or ought to be, in a reasonable man's mind.

James C Maxwell

Corpora

Data in NLP

- *Corpus*: text that has been collected for some purpose.
- *balanced corpus*: texts representing different genres
  genre is a type of text (vs domain)
- *Tagged corpus*: a corpus annotated with POS tags
- *Treebank*: a corpus annotated with parse trees
- *Specialist corpora* — e.g., collected to train or evaluate particular applications

  Movie reviews for sentiment classification
  Data collected from simulation of a dialogue system

Be careful

Data may be very *difficult to acquire*

- first language acquisition ▷ takes years to collect
- historical linguistics ▷ no longer exist
- brain activities ▷ wonderful machines, e.g. fMRI
- dolphin language ▷ ...

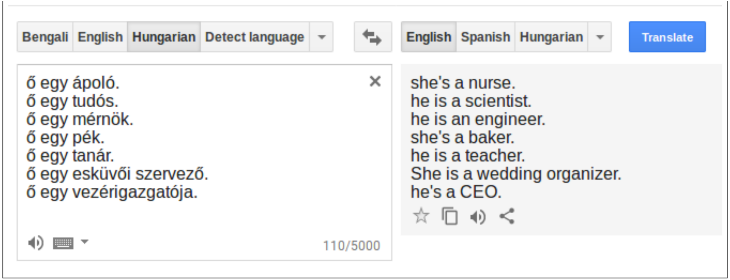
Data may be extremely *big*

- e.g. data from twitter

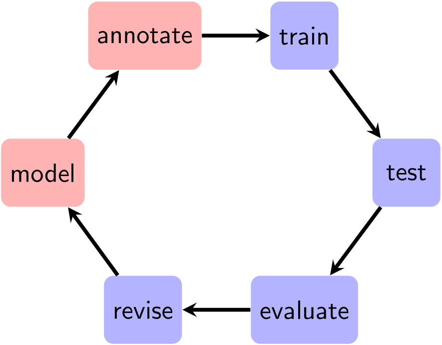
Data may be *private*

- the Cambridge Analytica/Facebook scandal

Data may be *biased* Prates et al. (2019) `https://arxiv.org/pdf/1809.02208.pdf`



Annotations in NLP



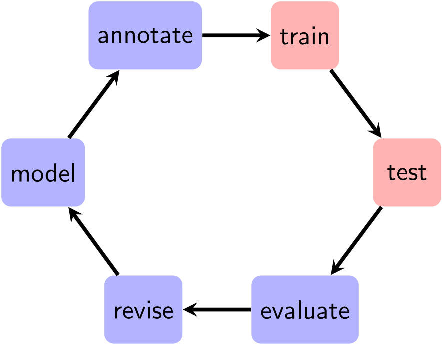
MATTER: the annotation development cycle

Model Structural descriptions provide theoretically informed attributes derived from empirical observations over the data.

Annotate An annotation scheme assumes a feature set that encodes specific structural descriptions and properties of the input data.

Pustejovsky and Stubbs (2012)

Annotations in NLP



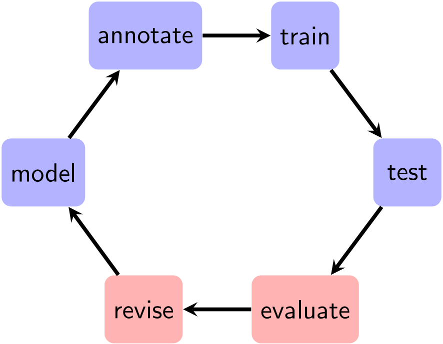
MATTER: the annotation development cycle

Train The algorithm is trained over a corpus annotated with the target feature set.

Test The algorithm is tested against held-out data.

Pustejovsky and Stubbs (2012)

Annotations in NLP



MATTER: the annotation development cycle

Evaluate A standardized evaluation of results is conducted.

Revise The model and the annotation specification are revisited in order to make the annotation more robust and reliable with use in the algorithm.

Pustejovsky and Stubbs (2012)

Tagset (CLAWS 5)

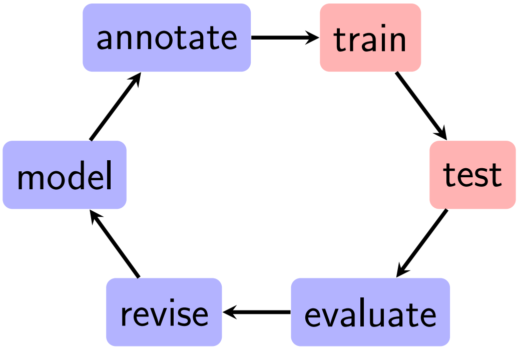
tagset: standardized codes for fine-grained parts of speech.

CLAWS 5: over 60 tags, including:

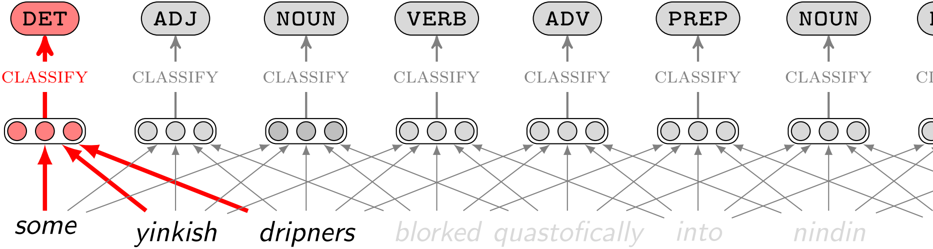
NN1	singular noun	NN2	plural noun
PNP	personal pronoun	VM0	modal auxiliary verb
VVB	base form of verb	VVI	infinitive form of verb

- They/PNP can/VM0 fish/VVI ./PUN
- They/PNP can/VVB fish/NN2 ./PUN
- They/PNP can/VM0 fish/NN2 ./PUN no full parse
- etc

Log-Linear Models



POS tagging and prediction



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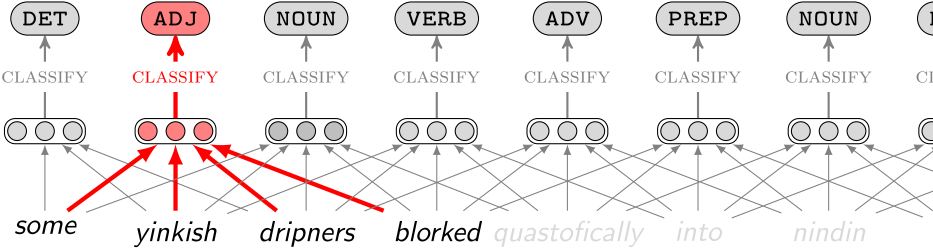

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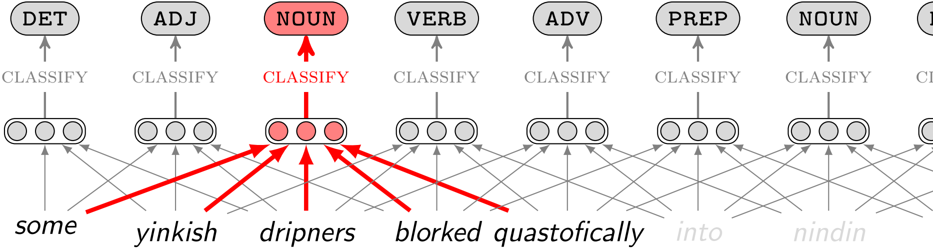

Aspects of POS tagging

Some yinkish dripners blorked quastofically into the nindin with . . .

Aspects of POS tagging

word=*dripners*

Some yinkish dripners blorked quastofically into the nindin with . . .

the word itself

Aspects of POS tagging

word=*dripners*

Some yinkish dripners blorked quastofically into the nindin with . . .

$\text{suf}_{-3,-2}$=*er*
suf_{-1}=*s*

morphological features

Aspects of POS tagging

word$_{i-2}$=*some*
word$_{i-1}$=*yinkish*

word=*dripners*

Some yinkish dripners blorked quastofically into the nindin with . . .

suf$_{-3,-2}$=*er*
suf$_{-1}$=*s*

POS can be defined distributionally

Aspects of POS tagging

word$_{i-2}$=*some*
word$_{i-1}$=*yinkish*

word$_{i+2}$=*quastofically*
word$_{i+1}$=*blorked*

word=*dripners*

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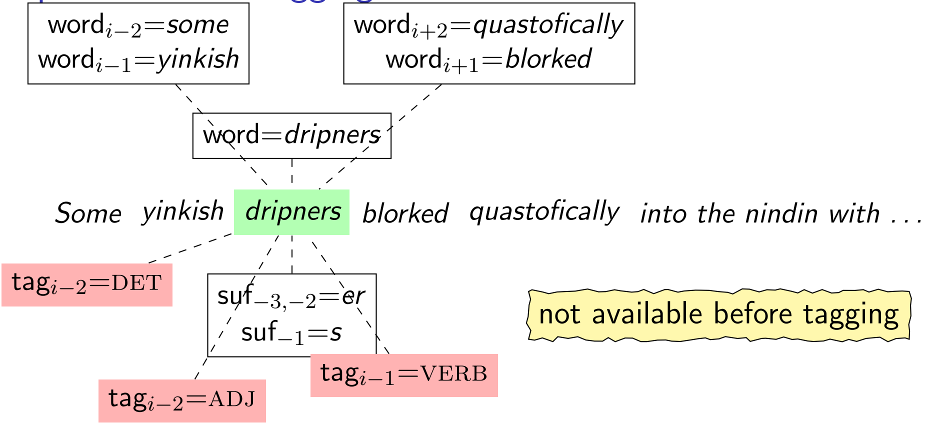

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Some yinkish dripners blorked quastofically into the nindin with . . .

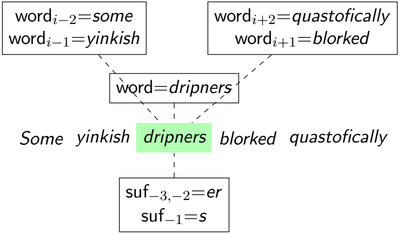
suf$_{-3,-2}$=*er*
suf$_{-1}$=*s*

The task: model the distribution

$$p(t_i|w_1, \ldots, w_n)$$

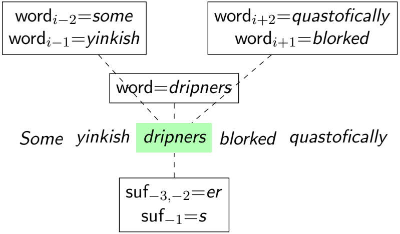
Many *features* may be relevant. Usually we only consider *local* features.

Feature vector representations



···																	···
	0	0	1	0	1	0	0	1	0	1	0	0	0	0	0	0	

Feature vector representations

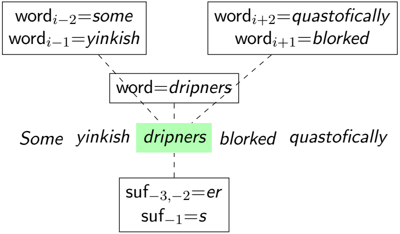


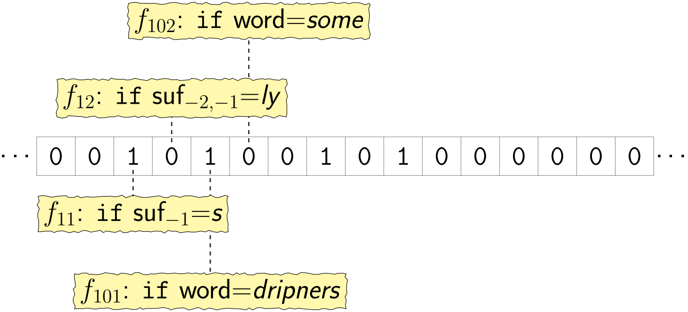
f_{102}: `if` word=*some*

$\cdots$	0	0	1	0	1	0	0	1	0	1	0	0	0	0	0	0	$\cdots$

f_{101}: `if` word=*dripners*

Feature vector representations





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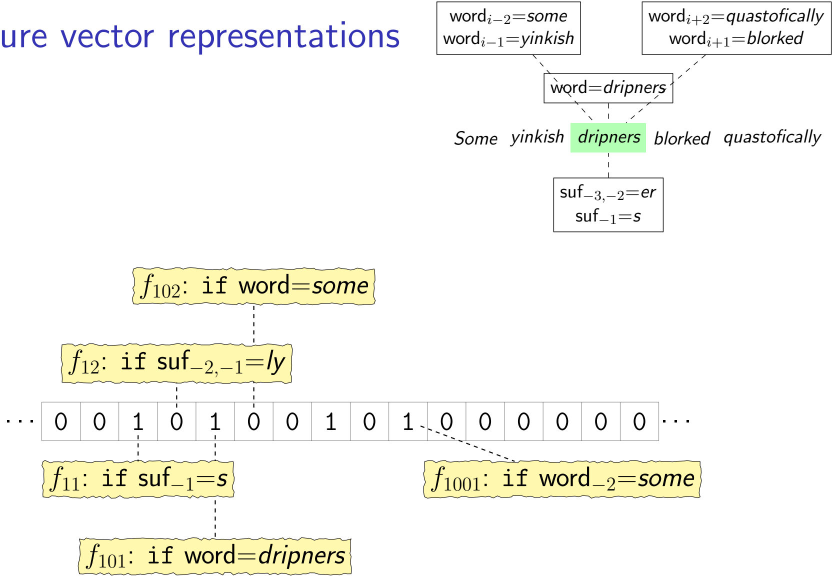

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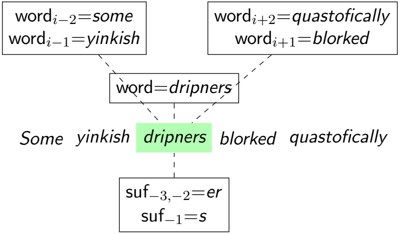

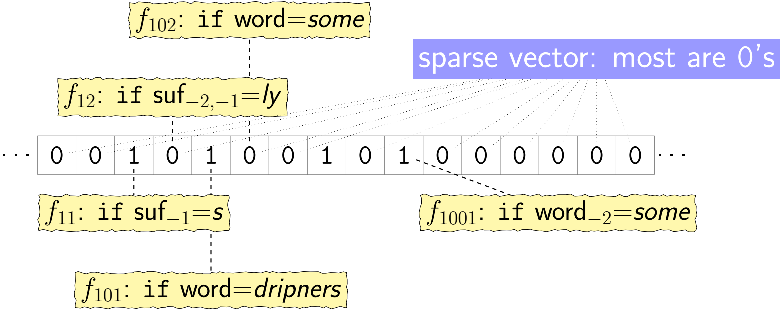

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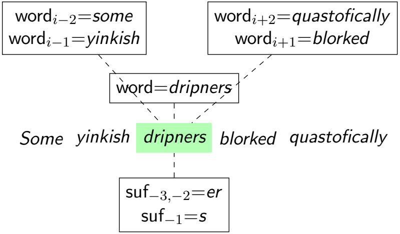

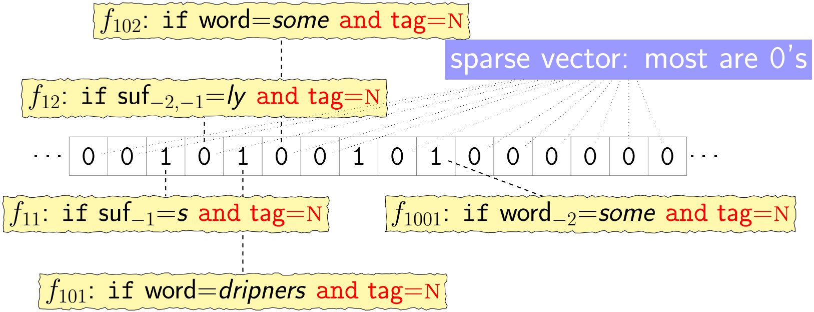

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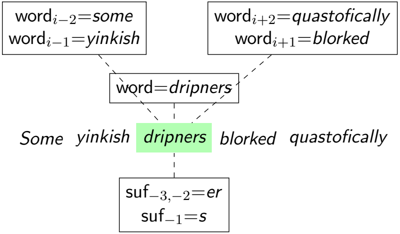

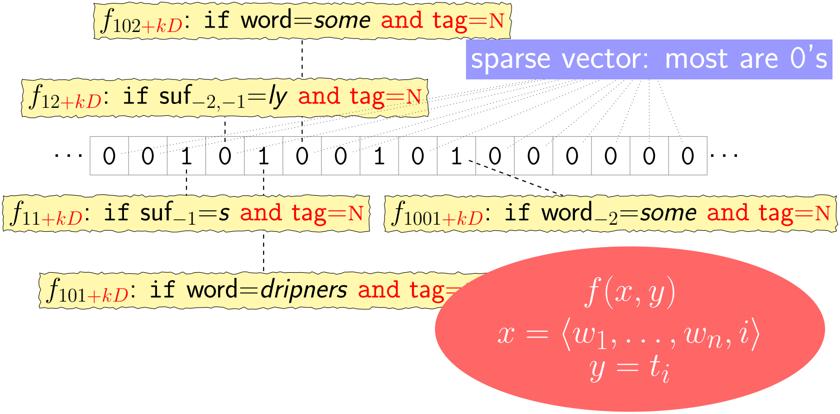

Log-linear models (multinomial logistic regression)

Assume we have a *parameter vector* $\theta \in \mathbb{R}^m$.

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We define

$$p(y|x;\theta) = \frac{\exp(\theta^\top f(x,y))}{\sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x,y'))}$$

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Why the name

$$\log p(y|x;\theta) = \underbrace{\theta^\top f(x,y)}_{\textit{linear term}} \underbrace{- \log \sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x,y'))}_{\textit{normalization term}}$$

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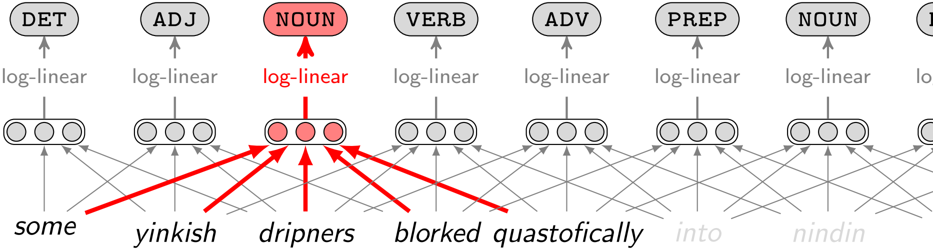
Prediction/ranking/scoring

$$\arg\max_{y' \in \mathcal{Y}} p(y|x;\theta) = \arg\max_{y' \in \mathcal{Y}} \log p(y|x;\theta) = \arg\max_{y' \in \mathcal{Y}} \underbrace{\theta^\top f(x,y')}_{\textit{linear function}}$$

POS tagging and prediction



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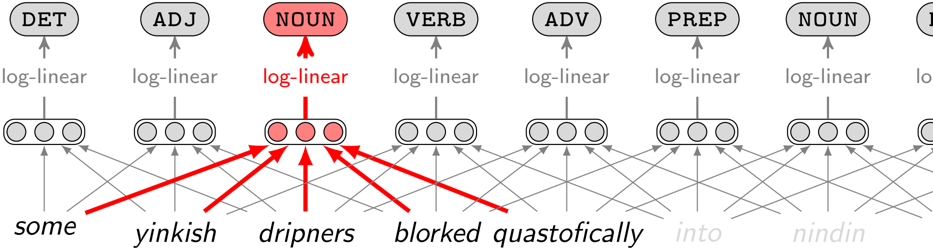
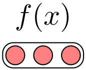


$f(x) \longrightarrow f(x, y)$



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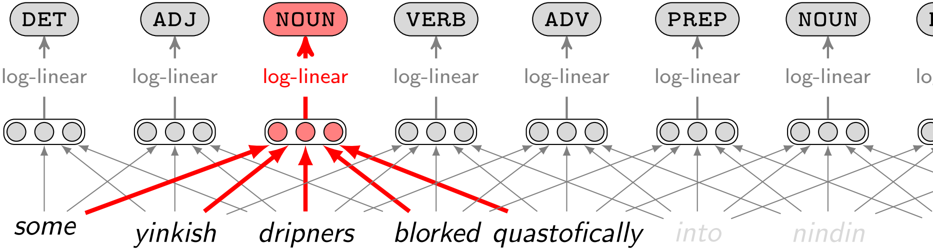

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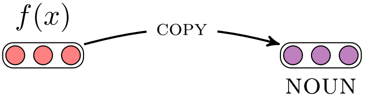

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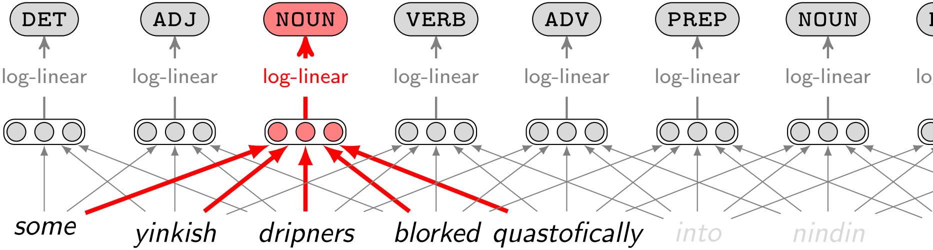

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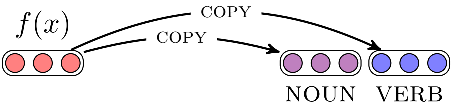

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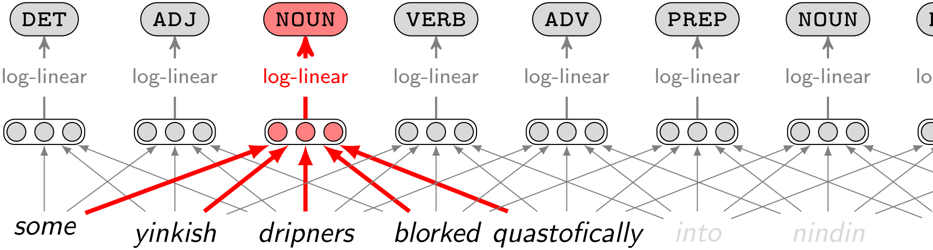

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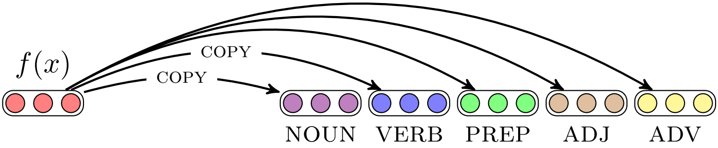

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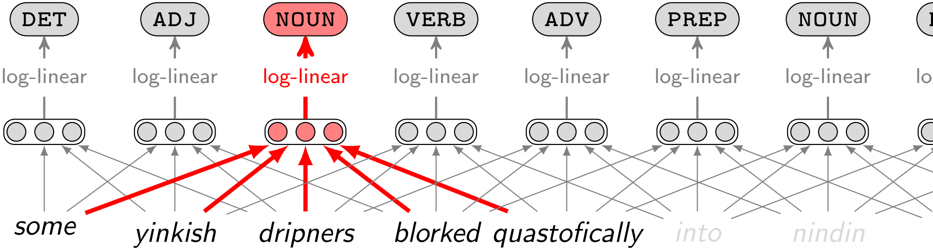

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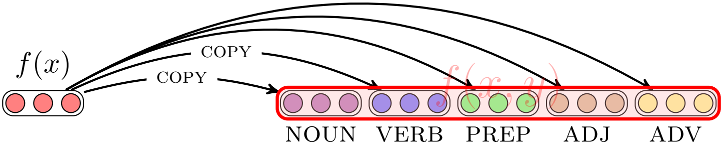


About weights

$$p(y|x;\theta) = \frac{\exp(\theta^\top f(x,y))}{\sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x,y'))}$$

f_{102}: if word=*some* and tag=N

f_{12}: if suf$_{-2,-1}$=*ly* and tag=N

$\cdots$ | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | $\cdots$

f_{11}: if suf$_{-1}$=*s* and tag=N

f_{1001}: if word$_{-2}$=*some* and tag=N

f_{101}: if word=*dripners* and tag=N

About weights

$$p(y|x;\theta) = \frac{\exp(\theta^\top f(x,y))}{\sum_{y' \in \mathcal{Y}} \exp(\theta^\top f(x,y'))}$$

⋯	0	0	1	0	1	0	0	1	0	1	0	0	0	0	0	0	⋯

f_{1001}: if word$_{-2}$=*some* and tag=N

is θ_{1001} positive large?
vote for yes

About $\exp()$

$$
\begin{aligned}
p(y|x;\theta) &= \frac{\exp(\theta^\top f(x,y))}{\sum_{y'\in\mathcal{Y}} \exp(\theta^\top f(x,y'))} \\
&= \frac{1}{1 + \frac{\sum_{y'\in\mathcal{Y}\wedge y'\neq y} \exp(\theta^\top f(x,y'))}{\exp(\theta^\top f(x,y))}}
\end{aligned}
$$

$$
\frac{\sum_{y'\in\mathcal{Y}\wedge y'\neq y} \exp(\theta^\top f(x,y'))}{\exp(\theta^\top f(x,y))} \quad \textbf{vs} \quad \frac{\sum_{y'\in\mathcal{Y}\wedge y'\neq y} \theta^\top f(x,y')}{\theta^\top f(x,y)}
$$

Parameter estimation

How can we get a good parameter vector?

- Supervised learning: Assume there is a good *annotated* corpus

$$\left\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(l)}, y^{(l)})\right\}$$

- Unsupervised learning: only *raw* texts are available.

$$\left\{x^{(1)}, x^{(2)}, \ldots, x^{(u)}\right\}$$

  unknown tagset: word clustering, word sense induction, etc.

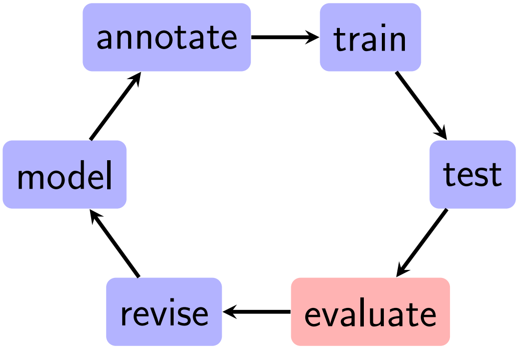
- Semi-supervised learning: a *mixture* of data.

$$\left\{(x_l^{(1)}, y_l^{(1)}), (x_l^{(2)}, y_l^{(2)}), \ldots, (x_l^{(n)}, y_l^{(n)})\right\} \cup \left\{x_u^{(1)}, x_u^{(2)}, \ldots, x_u^{(m)}\right\}$$

  n is smaller: semi-unsupervised learning

To be continued in Lecture 6

Evaluation



Experimental Science

- Experiments are run to test hypotheses
- Hypotheses are tentative theoretical explanations

  morphological segmentation facilitates syntactic parsing

  system A outperforms system B on data set C

- Validating hypotheses requires repeated testing

slide from J Nivre's ACL Presidential Address 2017 — *Challenges for ACL*

Intrinsic evaluation

- Creating a test set that contains a sample of test sentences for input, along with the ground truth.
- Quantifying the system's agreement with the ground truth.

- *Training data and test data* Test data must be kept unseen, often 90% training and 10% test data.
- *Baseline*
- *Ceiling Human performance* on the task, where the ceiling is the percentage agreement found between two annotators (inter annotator agreement)
- *Error analysis* Error rates are nearly always unevenly distributed.
- *Replicability* and *reproducibility*

Inter-annotator agreement

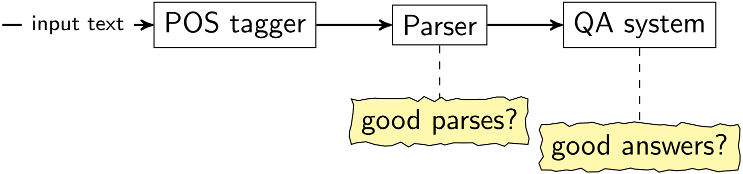
- It is common practice to compare the performance of multiple human annotators.
- If human beings cannot reach substantial agreement about what annotations are correct, it is likely either that the task is too difficult or that it is poorly defined.
- It is generally agreed that human inter-annotator agreement defines the upper limit on our ability to measure automated performance.

Gale et al. (1992) observed that

> *our ability to measure performance is largely limited by our ability [to] obtain reliable judgments fromhuman informants*

Extrinsic evaluation

- Measuring the quality of the system by looking at its impact on the effectiveness of downstream applications.
- Can be applied to compare *heterogeneous* resources.



Evaluation of POS tagging

- Tested against held-out data: percentage of correct tags

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- Different tagsets give slightly different results: utility of tag to end users vs predictive power

Benchmarking and “fair” comparisons – fast science

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- Balanced corpora may be better, but still don't cover all text types
- Communication aids: extreme difficulty in obtaining data, text corpora don't give good prediction for real data

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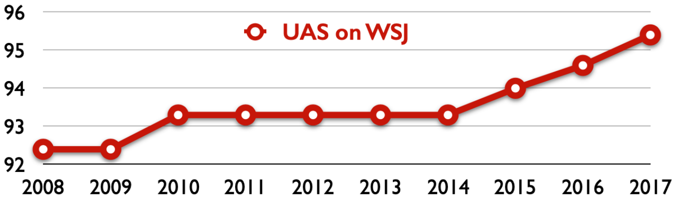
Good Science



"Measurement as a virtue in itself"

"Lots of numbers with very small differences"

"What are the research questions?"

slide from J Nivre's ACL Presidential Address 2017 — *Challenges for ACL*

Readings

Required

- Ann's lecture notes.
  `www.cl.cam.ac.uk/teaching/1920/NLP/materials.html`
- M Collins' note
  `www.cs.columbia.edu/~mcollins/loglinear.pdf`

Optional

- D Jurafsky and J Martin. Speech and Language Processing. chapter 5.
  `https://web.stanford.edu/~jurafsky/slp3/5.pdf`