NLP 101

Maury Courtland (www.maury.science)

June 11, 2019

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- Image credits in accompanying Markdown file as image alttext

Linguistics/Theoretical Background

Information

- Shannon information/entropy/surprisal

$$H = -\sum_i p_i \log_2 (p_i)$$

Figure 1: Shannon Entropy

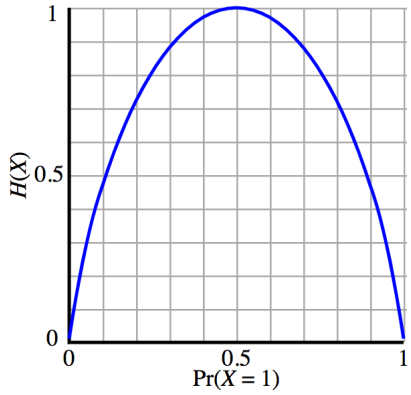

Figure 2: Binomial Entropy Function

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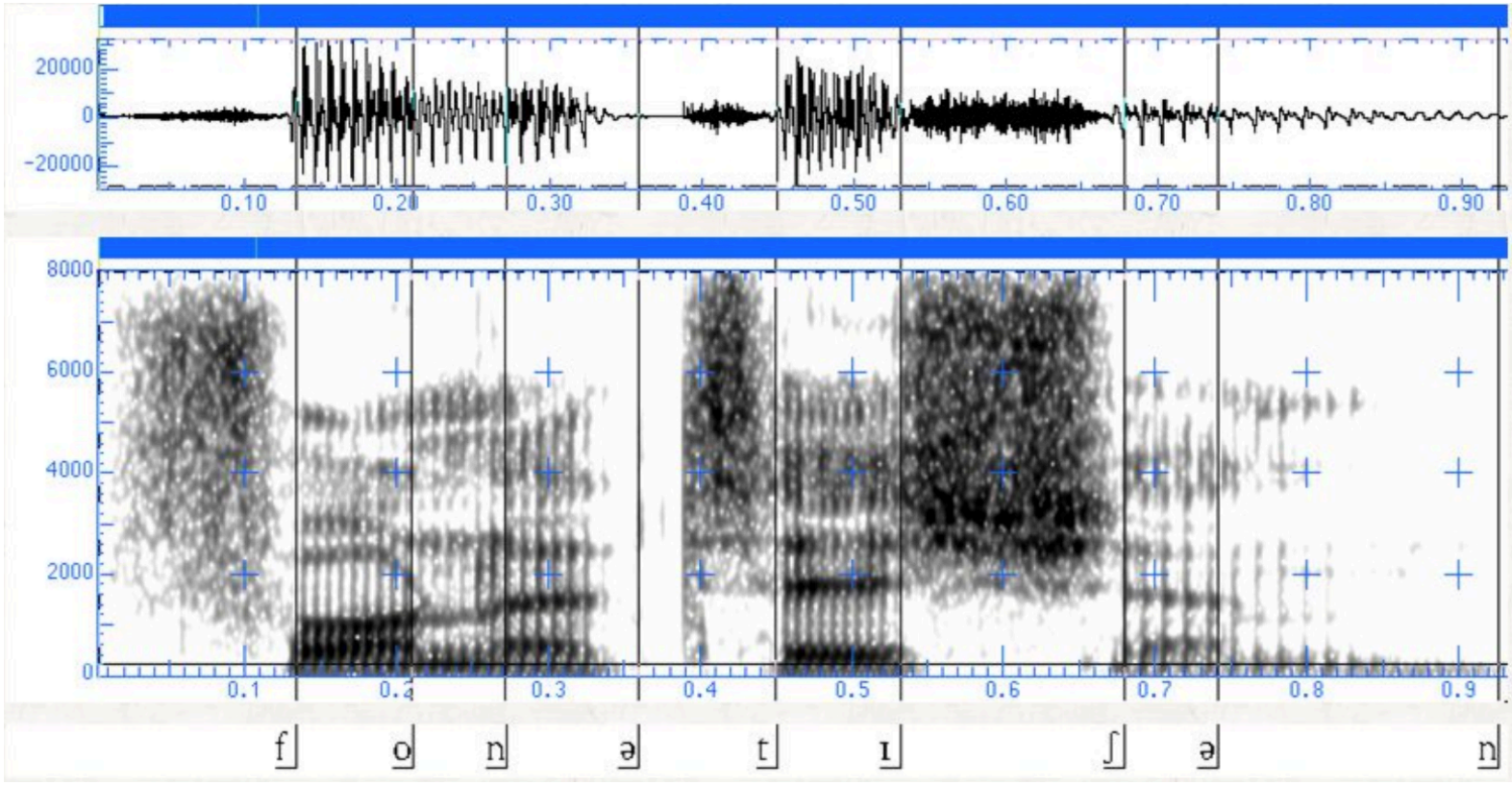
  - BUT if you don't yet have cancer, we don't say you're in "premission"
  - Time is always marching forward so you have to be careful about the implications of modeling choices of uni-directional vs. bi-directional

Speech (TEMPORAL) vs. Language (ATEMPORAL)

- Sublexical sound units



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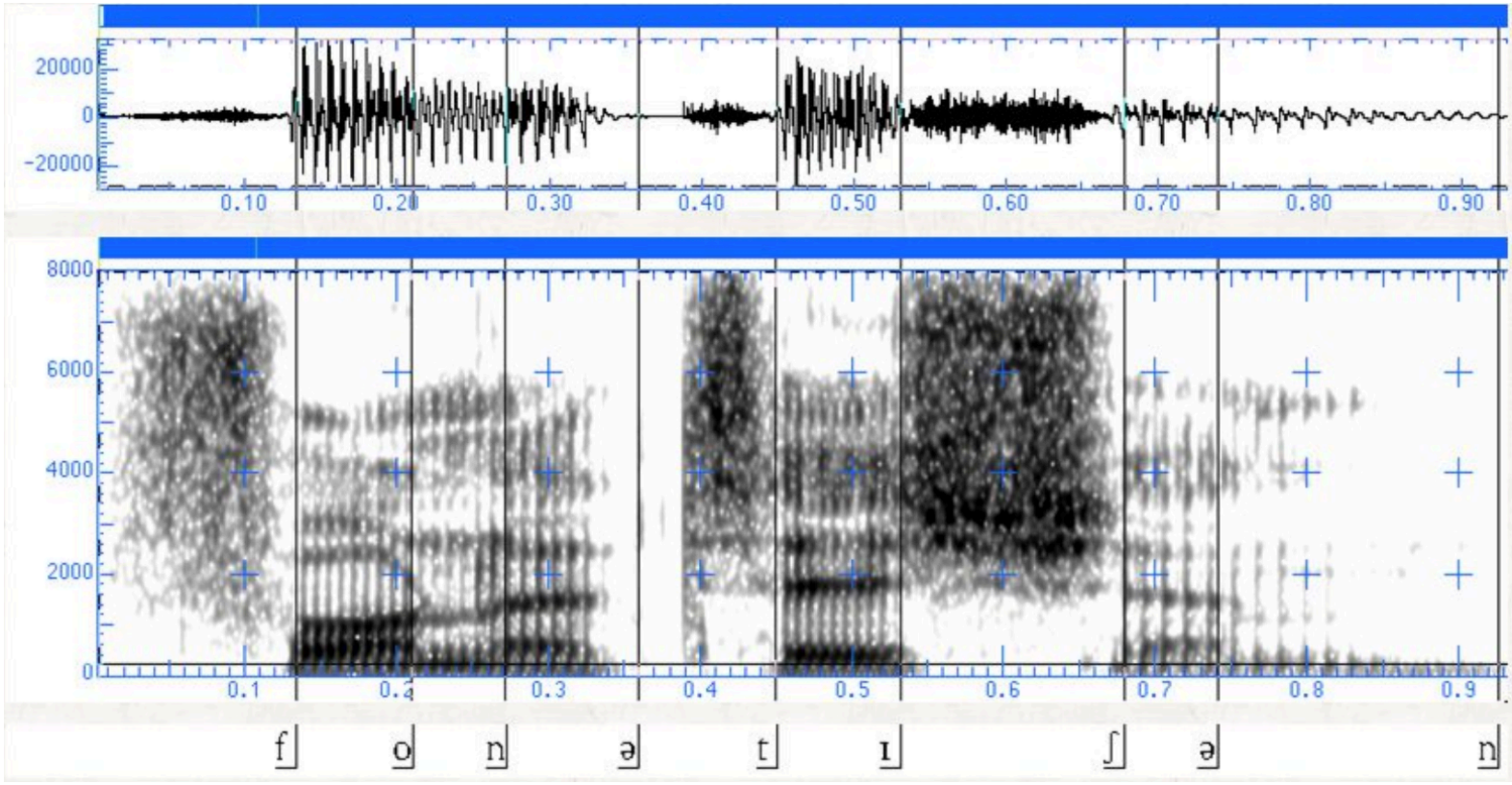


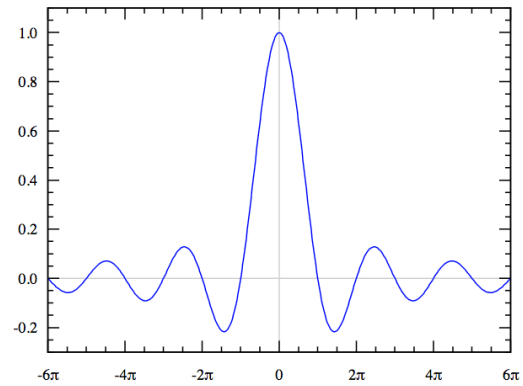
- Sublexical orthographic units = letters

Speech vs. Language: Differences

- Variance in acoustics/articulation and invariance in orthography (except handwriting)

$$\operatorname{sinc}(x) = \frac{\sin(\pi x)}{\pi x} \,.$$

Figure 3: Sinc Equation



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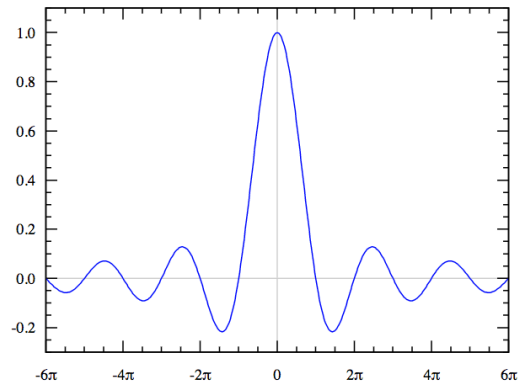

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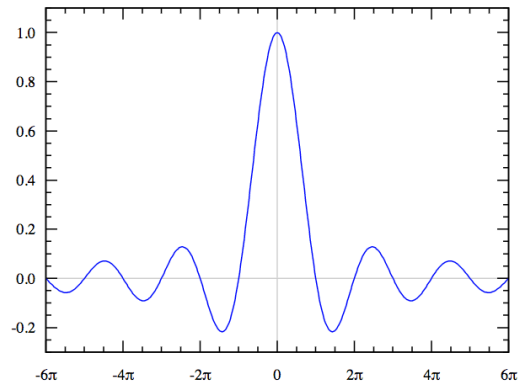

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  - Speech sampling, the sinc function, perfect reconstruction (with max fs/2)

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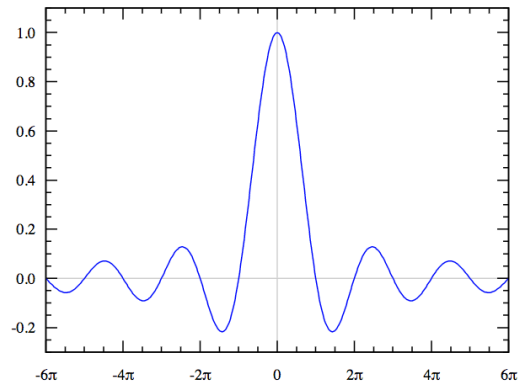

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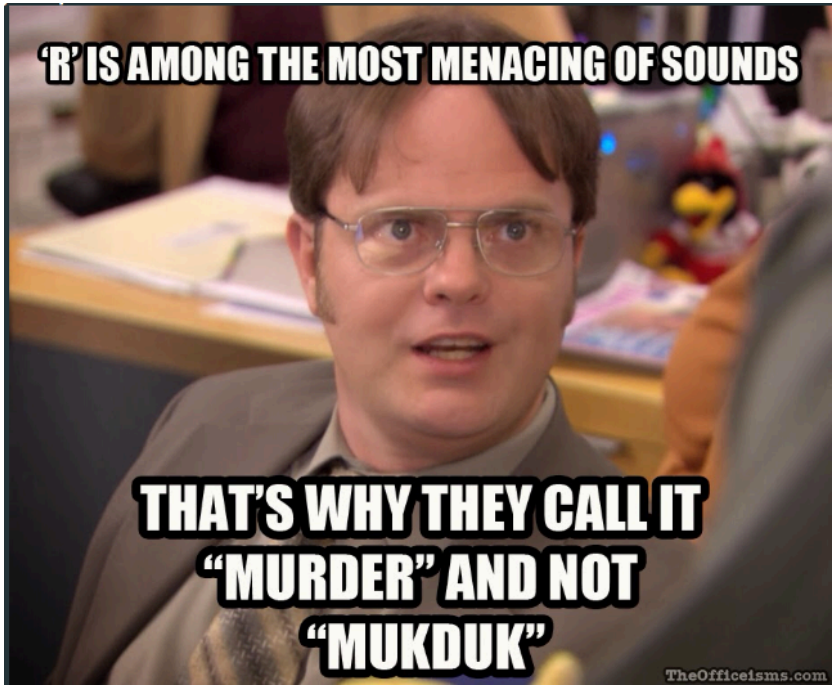
Speech vs. Language: Similarities

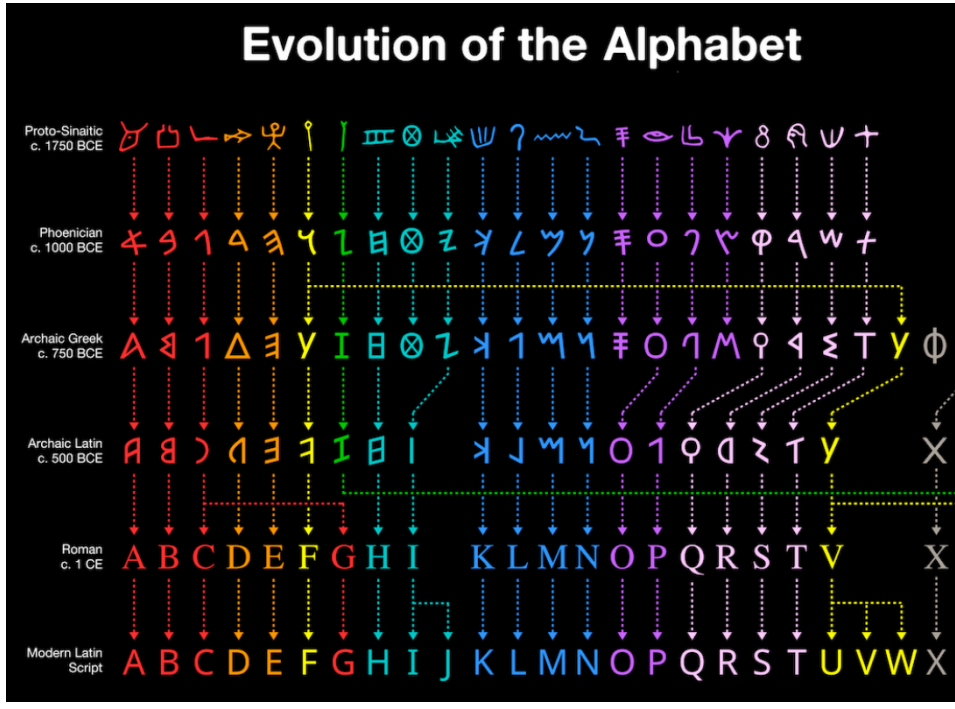
- Both are arbitrary:

Sounds:



(minus onomatopoeias)

Letters:



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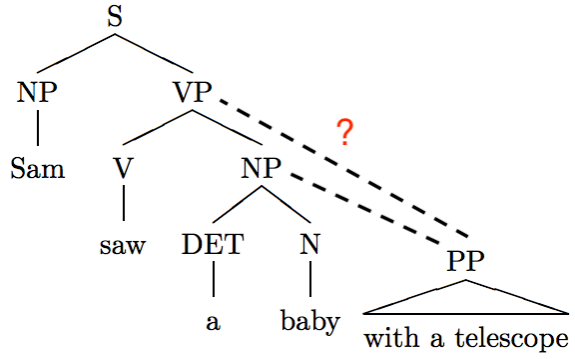

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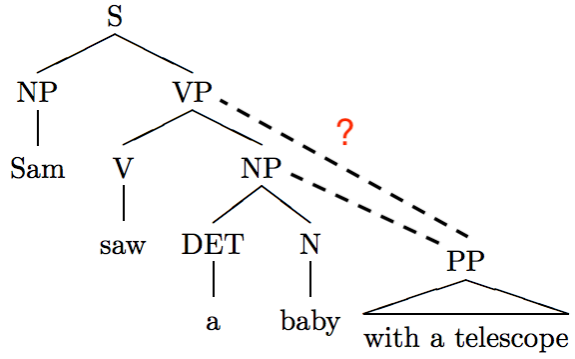

- Meaning is not really constrained by time, this makes things like Bidirectional LSTMs kosher

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- How does dialog (alternatively, narrative) evolve over time?

Design questions

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- Documents: definitely infinite possibilities, but we still need to be able to cluster them based on sentiment, topic, etc. to be useful to extend to out of training instances (which will be almost all documents)

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- Document?: TF-IDF, LDA, etc.

(Some) common problems and why we care

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  - Suicide prevention on online forums/ from online presences

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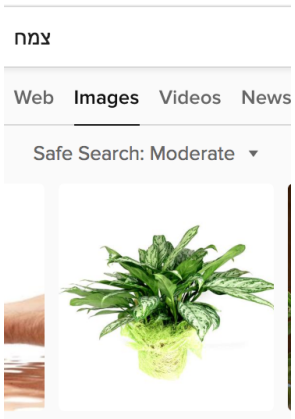

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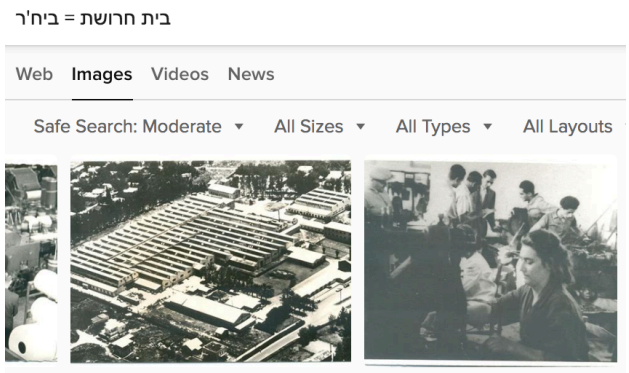

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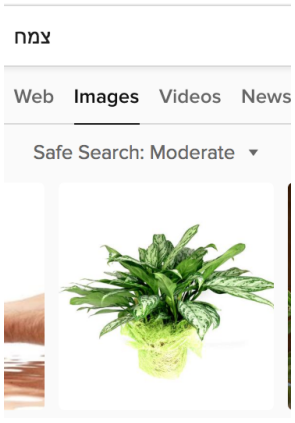

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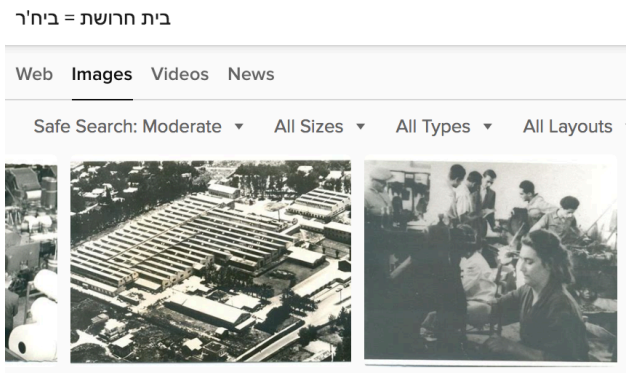

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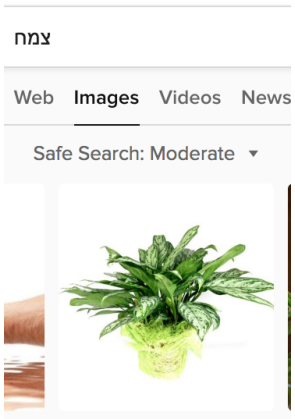

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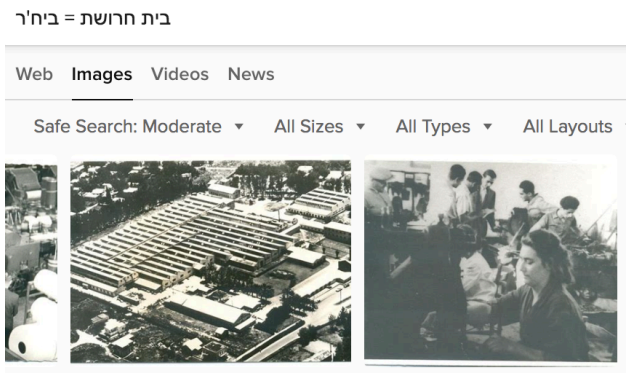

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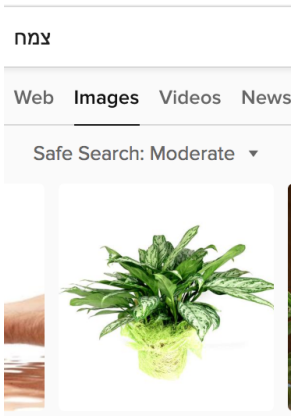

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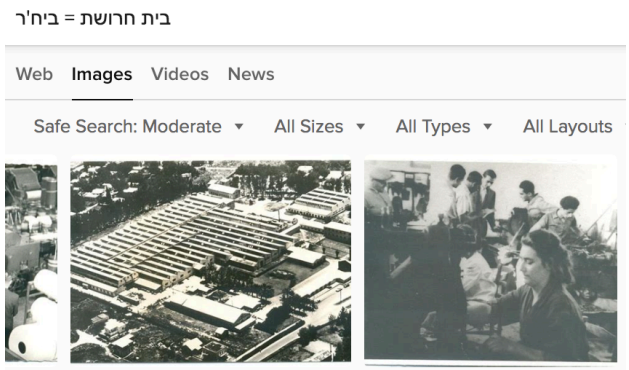

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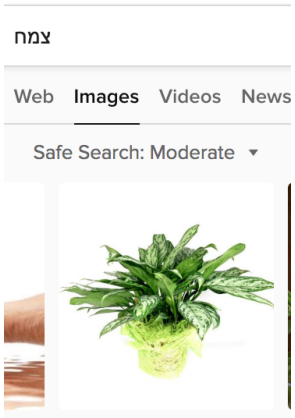

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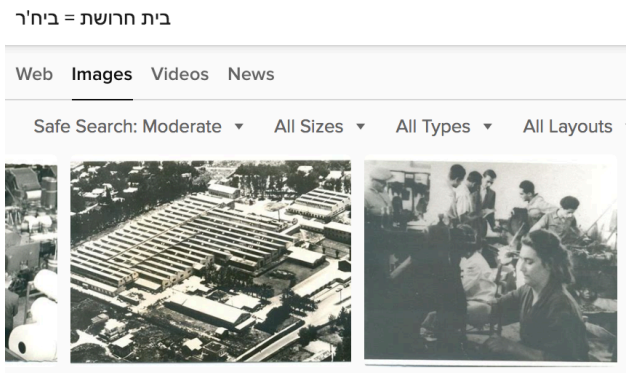

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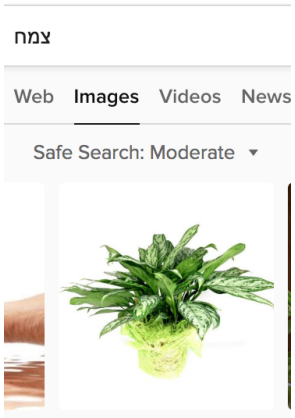

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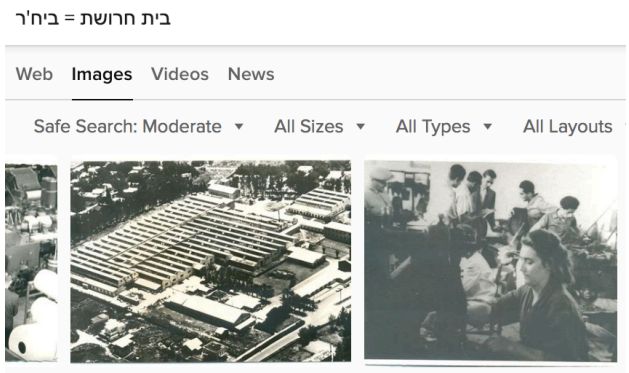

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- Whether you believe ML is "just statistics" or not, it certainly stems from stats, leverages its history, and borrows heavily from the discipline so while the ML approach is novel, it is not necessarily categorically different from old approaches

Machine translation

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- Abandoned in the 60s due to overhype (sound like an AI story you've heard of?)
- Then statistical methods took the scene and with the ever growing amount of data (particularly parallel corpora, e.g. EUROPARL (EU), Hansard (CA)) took off

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  - Then lots of n-gram tricks (e.g. backoff and skipgrams) were invented to be more robust to sparsity and provide better estimates for the true probability of the sentence

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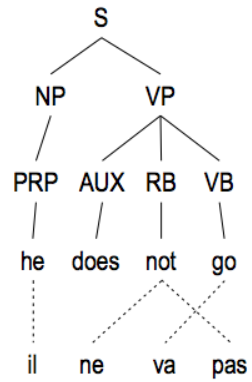

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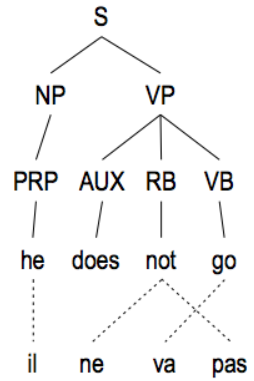

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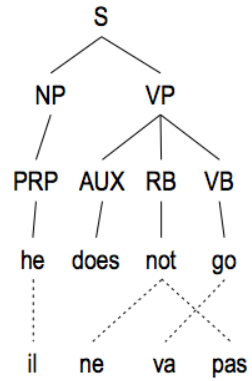

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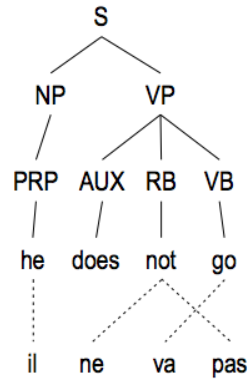

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$$\log \mathrm{BLEU} = \min(1 - \frac{r}{c}, 0) + \sum_{n=1}^{N} w_n \log p_n.$$

In our baseline, we use $N = 4$ and uniform weights $w_n = 1/N$.

- Then sums over ngrams

Text Classification

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- Because of the model simplicity, it needs way less training data
- Easy to train, you just need to count words and count labeled documents, maybe use stop words (close-class words etc.)

Naive Bayes Math

- Start with base equation

$$p(C_k \mid \mathbf{x}) = \frac{p(C_k)\, p(\mathbf{x} \mid C_k)}{p(\mathbf{x})}$$

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$$\begin{aligned} p(C_k \mid x_1, \ldots, x_n) &\propto p(C_k, x_1, \ldots, x_n) \\ &= p(C_k)\, p(x_1 \mid C_k)\, p(x_2 \mid C_k)\, p(x_3 \mid C_k) \cdots \\ &= p(C_k) \prod_{i=1}^{n} p(x_i \mid C_k)\,, \end{aligned}$$

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- Choose the class that maximizes your likelihood

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- In the multinomial case, this is a linear classifier

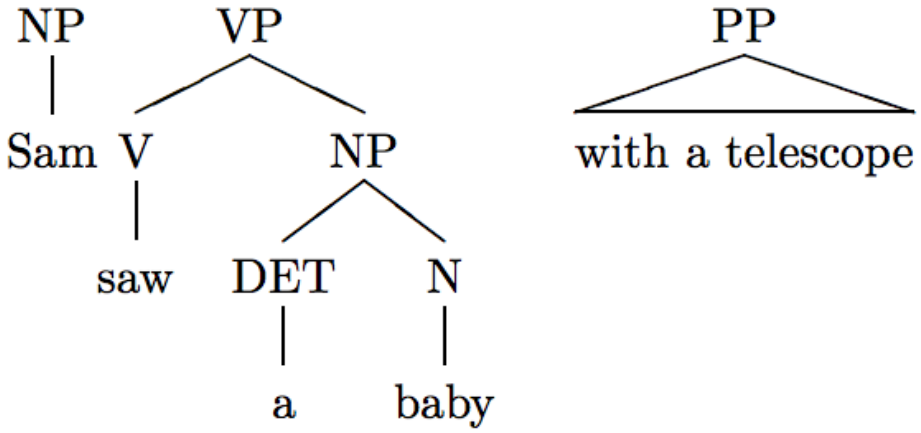
$$\begin{aligned} \log p(C_k \mid \mathbf{x}) &\propto \log \left(p(C_k) \prod_{i=1}^{n} {p_{ki}}^{x_i} \right) \\ &= \log p(C_k) + \sum_{i=1}^{n} x_i \cdot \log p_{ki} \\ &= b + \mathbf{w}_k^\top \mathbf{x} \end{aligned}$$

where $b = \log p(C_k)$ and $w_{ki} = \log p_{ki}$.

Grammar Parsing, etc.

Chart Parsing

- Attempts to overcome the fact that parse trees are mutually exclusive and often cannot share information between them (they have completely different structures)



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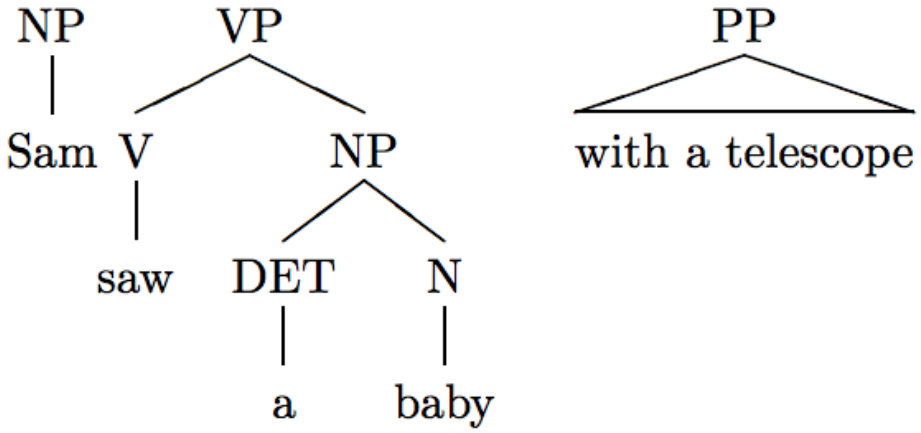

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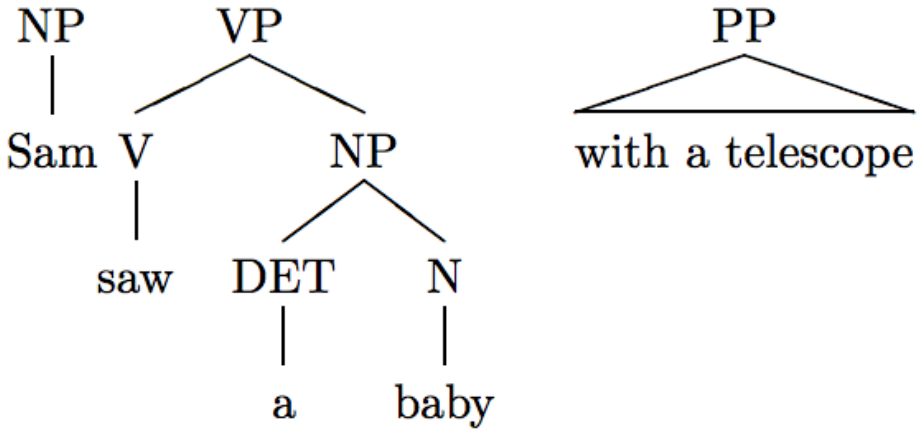


- Additionally, before they achieve closure, they're not really possible or meaningful to store as individual constituents
- Uses dynamic programming to build solutions that both can store different intermediary steps (taking care of pre-closure representations) and represent different paths to solutions (taking care of separate storage of ambiguity)

Quick Dynamic Programming Review

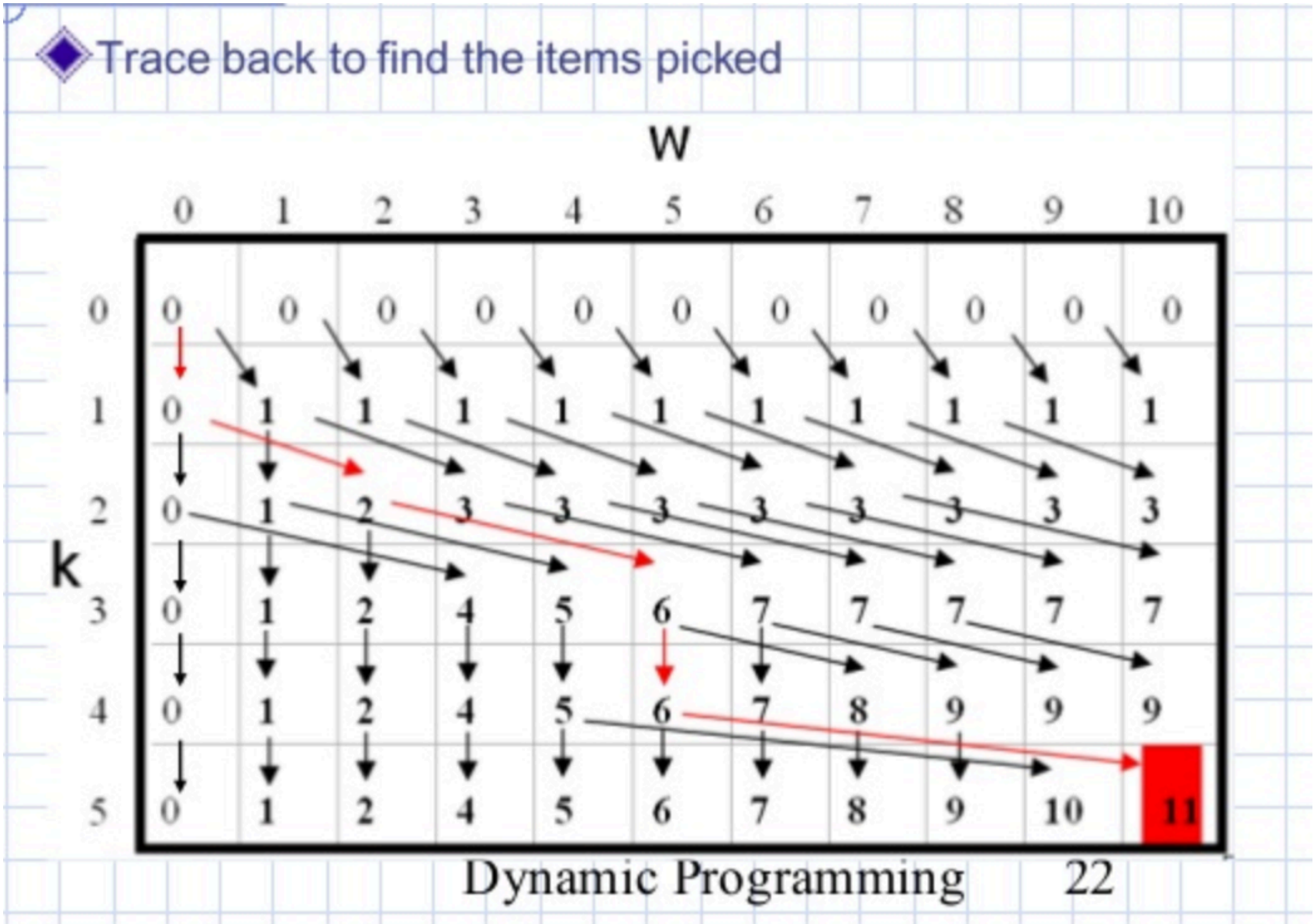
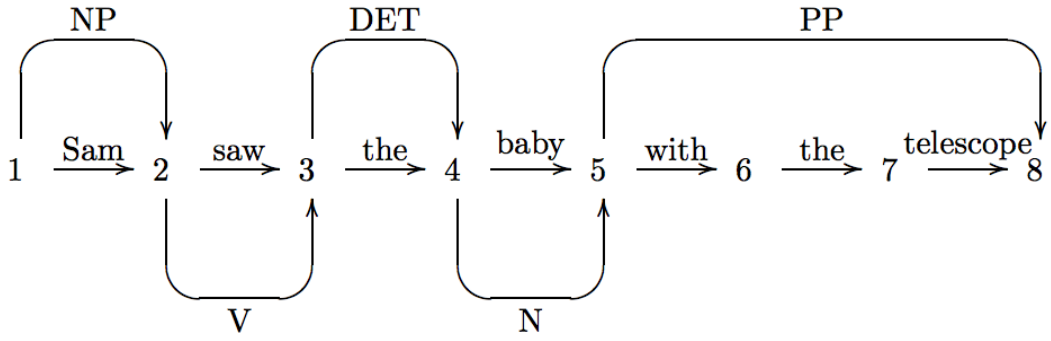


Figure 5: Dynamic Programming

Chart Parsing Cont.

- Represents sentences as a DAG with word and POS arcs



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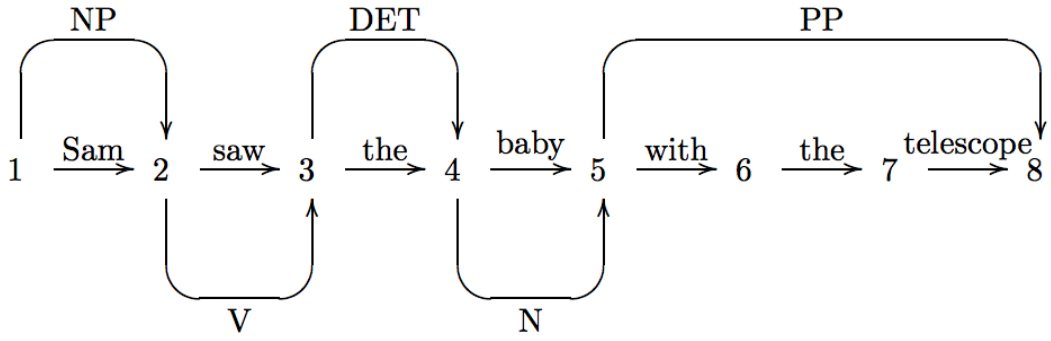

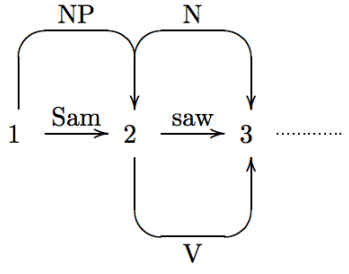

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Chart Parsing Cont.

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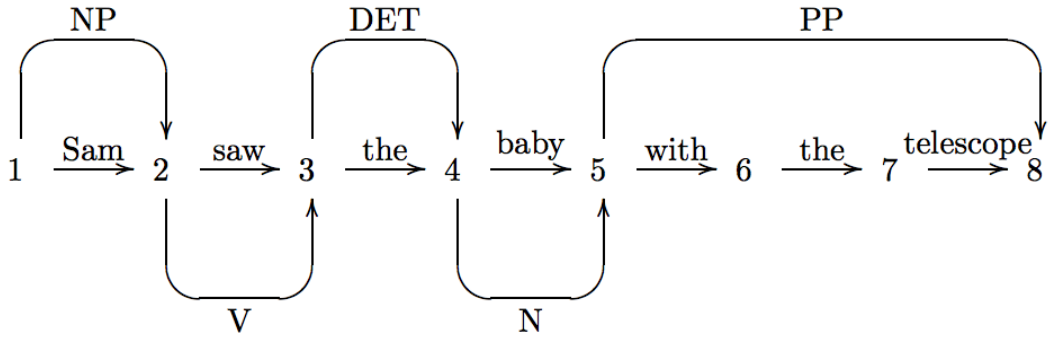
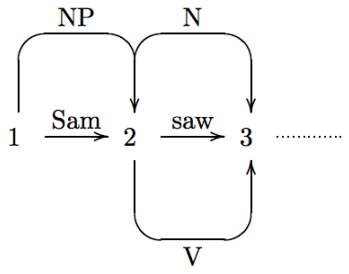
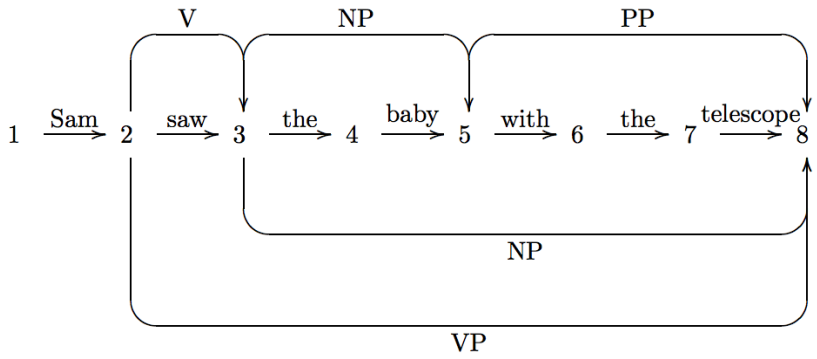




- Allows incomplete parses in the chart
- Allows multiple correct parses to be stored in the graph



Word Sense Disambiguation

WordNet

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- Also contains for nouns hypernyms and hyponyms (superclass/subclass), meronyms and holonyms (is part of/contains); for verbs hypernym, troponym (specific way of doing something), entailment (necessary precondition)

WordNet UI

Word to search for: plant Search WordNet

Display Options: (Select option to change) Change

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **plant**, works, industrial plant (buildings for carrying on industrial labor) *"they built a large plant to manufacture automobiles"*
- S: (n) **plant**, flora, plant life ((botany) a living organism lacking the power of locomotion)
- S: (n) **plant** (an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience)
- S: (n) **plant** (something planted secretly for discovery by another) *"the police used a plant to trick the thieves"; "he claimed that the evidence against him was a plant"*

Verb

- S: (v) **plant**, set (put or set (seeds, seedlings, or plants) into the ground) *"Let's plant flowers in the garden"*
- S: (v) implant, engraft, embed, imbed, **plant** (fix or set securely or deeply) *"He planted a knee in the back of his opponent"; "The dentist implanted a tooth in the gum"*
- S: (v) establish, found, **plant**, constitute, institute (set up or lay the groundwork for) *"establish a new department"*
- S: (v) **plant** (place into a river) *"plant fish"*
- S: (v) **plant** (place something or someone in a certain position in order to secretly observe or deceive) *"Plant a spy in Moscow"; "plant bugs in the dissident's apartment"*

WordNet Cont.

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- Given this database, you can do the numerous analyses that are possible on graphs to learn relations in the network
- A simple approach might be to substitute in all the possible synonyms of each sense and see how many of those are attested in the corpus

Neural Approaches:

The problem

- Seeks to solve the vanishing/exploding gradient problem (don't they all...): i.e. given N layers to a network, the gradient is raised to the N by the time it gets back to the first layer

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- In 1997 Hochreiter and Schmidhuber come up with a solution

LSTM V1

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- Form "memory cell" units that have internal topologies but all receive the same input from the input gate and whose combined outputs are fed to the output gate

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- Backward Pass
  - Output gate decides how much error to keep in the CEC to prevent vanishing/exploding error
  - Input gate decided how much error to throw away before passing it on to the previous time step/memory cell

LSTM Gates Syntax

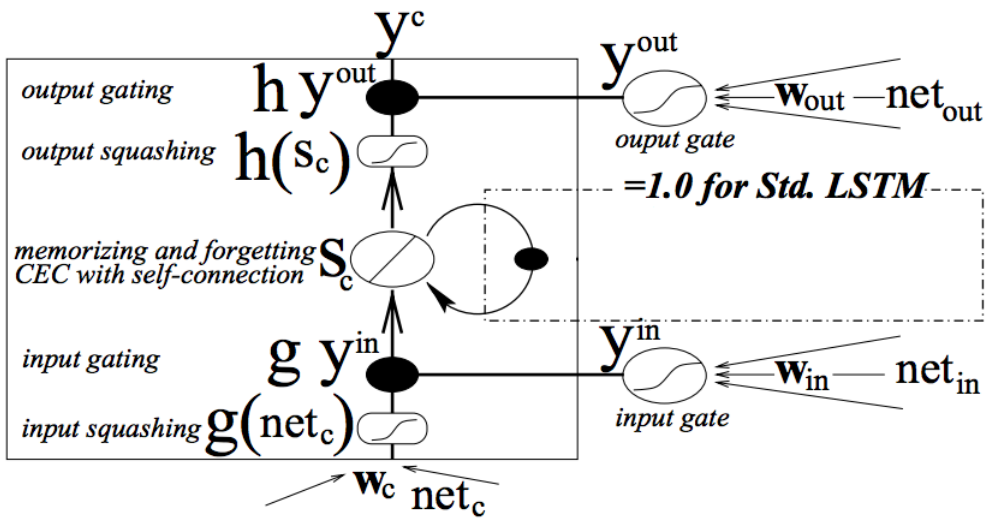

Figure 1: The standard LSTM cell has a linear unit with a recurrent self-connection with weight 1.0 (CEC). Input and output gates regulate read and write access to the cell whose state is denoted s_c. The function g squashes the cell's input; h squashes the cell's output. See the text for details.

$$
\begin{aligned}
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
c_t &= \quad c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \\
h_t &= o_t \circ \sigma_h(c_t)
\end{aligned}
$$

LSTM V2: Forgetting

- Rather than letting the error backpropogate unobstructed through the network, let the network decide what to let through the CEC

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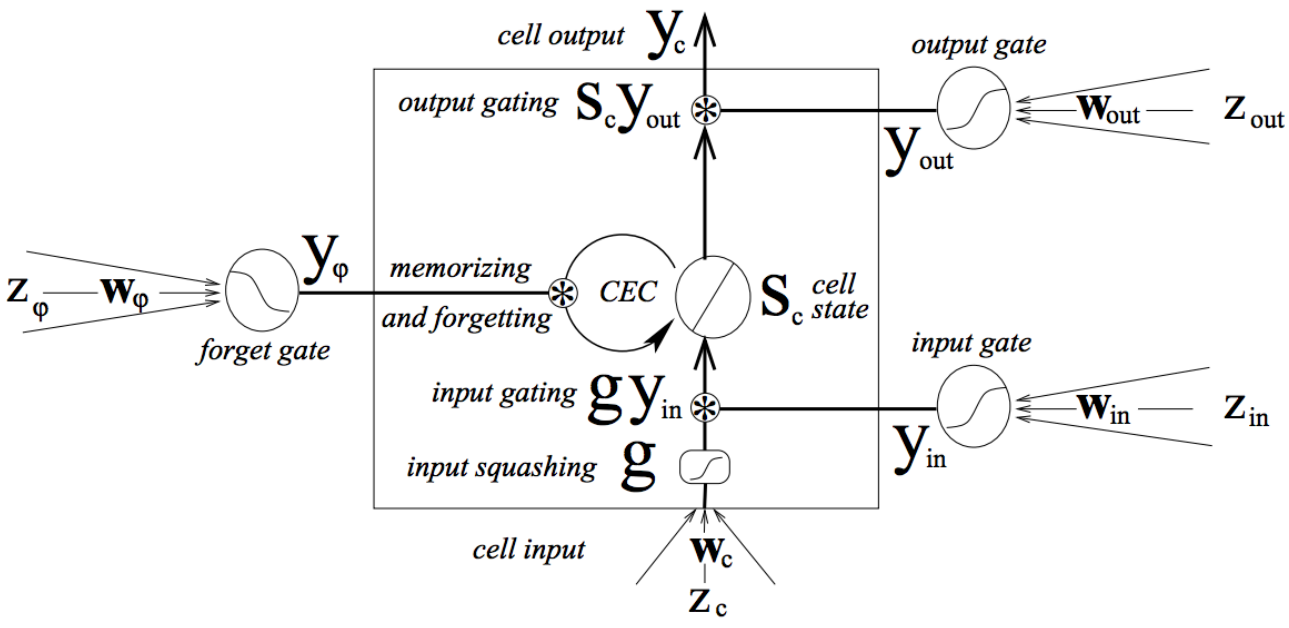
- Rather than letting the error backpropogate unobstructed through the network, let the network decide what to let through the CEC
  - Add in forget gate that controls what is let through from the previous cell memory/hidden state

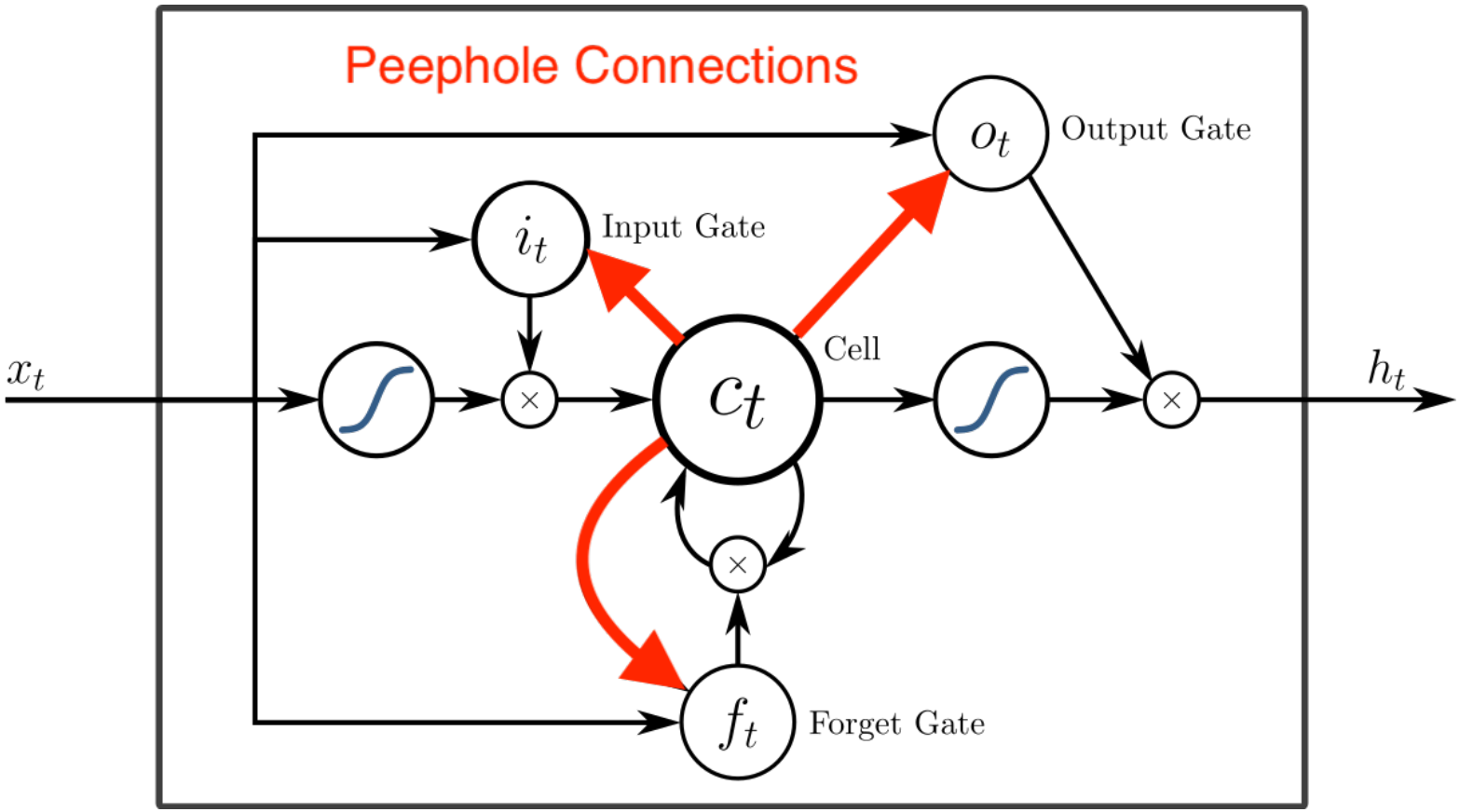
Forgetting LSTM



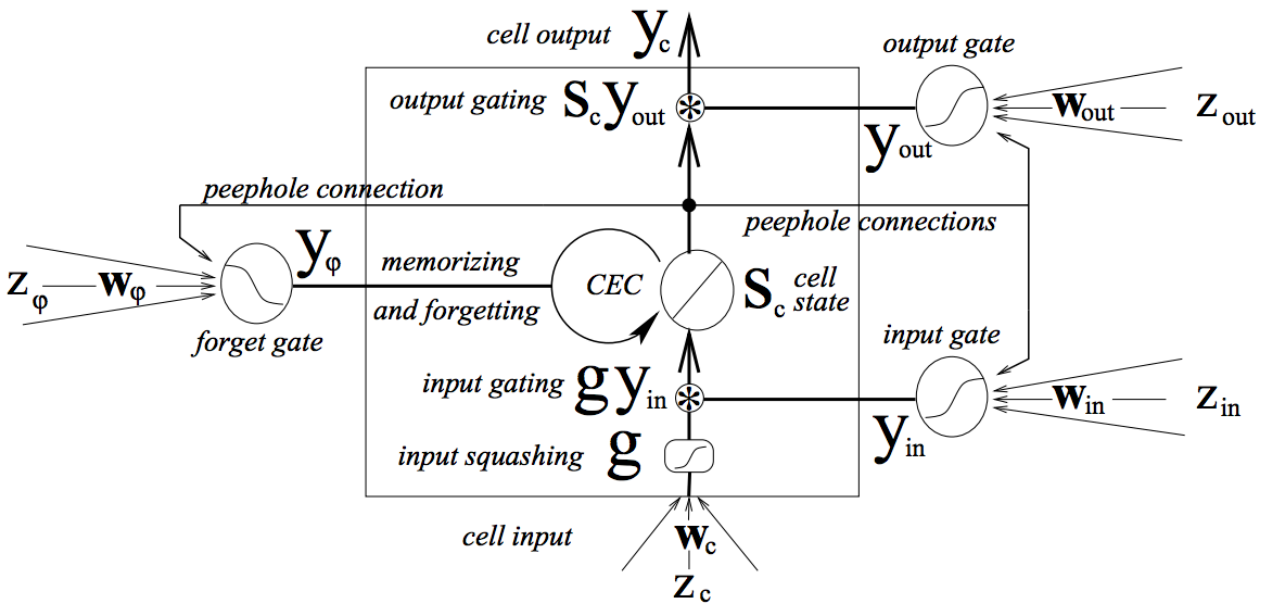
$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c)$$
$$h_t = o_t \circ \sigma_h(c_t)$$

LSTM V3: Peephole

- Let the previous state of the memory cell directly influence what will be forgotten, let in, and let out



LSTM V3: Peephole Cont.



$$f_t = \sigma_g(W_f x_t + U_f c_{t-1} + b_f)$$
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$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + b_c)$$
$$h_t = \sigma_h(o_t \circ c_t)$$

LSTM: Marrying semantics and syntax

$$f_{t(m\times1)} = \sigma(W_{xf(m\times n)}x_{t(n\times1)} + W_{hf(m\times m)}h_{t-1(m\times1)} + b_{f(m\times1)})$$

$$c_{t(m\times1)} = i_{t(m\times1)} \circ .* u_{t(m\times1)} + f_{t(m\times1)} .* c_{t-1(m\times1)}$$

.* = pointwise multiplication

$$o_{t(m\times1)} = \sigma(W_{xo(m\times n)}x_{t(n\times1)} + W_{ho(m\times m)}h_{t-1(m\times1)} + b_{o(m\times1)})$$

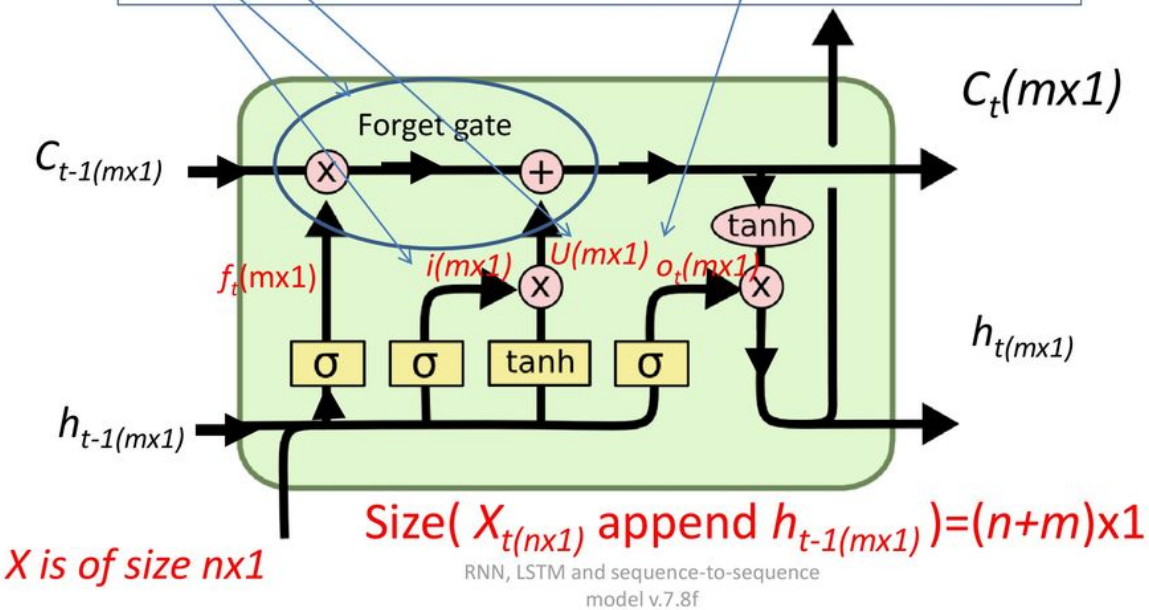
- $$u_{t(m\times1)} = \tanh(W_{xu(m\times n)}x_{t(n\times1)} + W_{hu(m\times m)}h_{t-1(m\times1)} + b_{u(m\times1)})$$

$$i_{t(m\times1)} = \sigma(W_{xi(m\times n)}x_{t(n\times1)} + W_{hi(m\times m)}h_{t-1(m\times1)} + b_{i(m\times1)})$$

X is of size nx1

h is of size mx1

http://kvitajakub.github.io/2016/04/14/rnn-diagrams/



LSTM V4: Coupled forget and input gates

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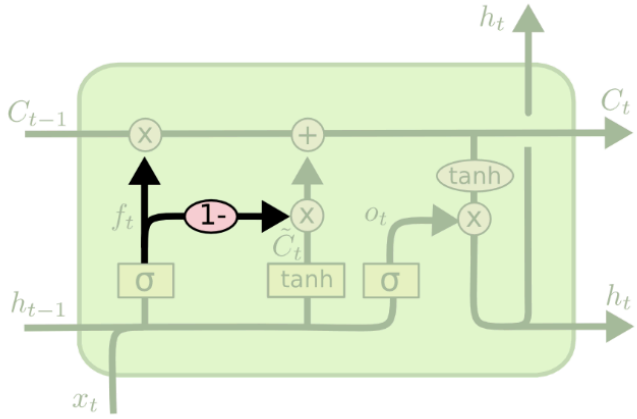
  - Get rid of input gate parameters and determine wholly from forget gate
  - Gives a tug-of-war relationship to information preservation vs. onboarding



$$C_t = f_t * C_{t-1} + (1 - \boldsymbol{f_t}) * \tilde{C}_t$$

Simplified LSTM: GRU

- Simplify, simplify, simplify (at the cost of power)

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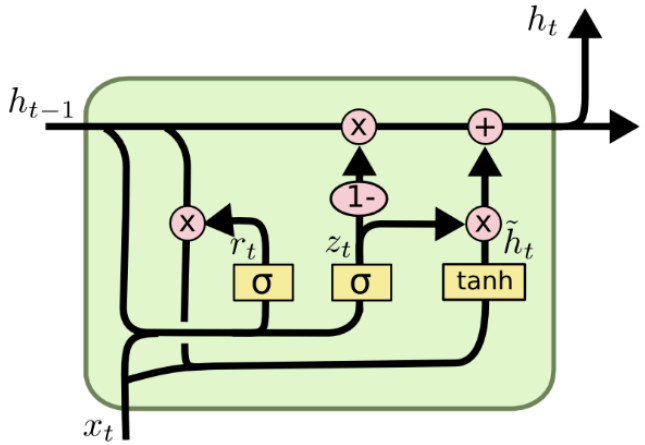
Simplified LSTM: GRU

- Simplify, simplify, simplify (at the cost of power)
  - Combine forget and input gates (why stop at coupling them?) into "update gate" z_t
  - Do away with separate hidden state and cell memory and have just hidden state
  - Introduce a reset vector to allow "forgetting"



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$