CA4012

Statistical Machine Translation

Week 10: Neural Language Models

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Language models

A language model assigns a probability to a sequence of words, such that $\sum_{w \in \Sigma^*} p(w) = 1$:

Given the observed training text, how probable is this new utterance?

Thus we can compare different orderings of words (e.g. Translation):

$$p(\text{he likes apples}) > p(\text{apples likes he})$$

or choice of words (e.g. Speech Recognition):

$$p(\text{he likes apples}) > p(\text{he licks apples})$$

Language models

Much of Natural Language Processing can be structured as (conditional) language modelling:

Translation

$$p_{\text{LM}}(\text{Les chiens aiment les os} \;|||\; \text{Dogs love bones})$$

Question Answering

$$p_{\text{LM}}(\text{What do dogs love?} \;|||\; \text{bones .} \mid \beta)$$

Dialogue

$$p_{\text{LM}}(\text{How are you?} \;|||\; \text{Fine thanks. And you?} \mid \beta)$$

Language models

Most language models employ the chain rule to decompose the joint probability into a sequence of conditional probabilities:

$$p(w_1, w_2, w_3, \ldots, w_N) =$$
$$p(w_1)\ p(w_2|w_1)\ p(w_3|w_1, w_2) \times \ldots \times p(w_N|w_1, w_2, \ldots w_{N-1})$$

Note that this decomposition is exact and allows us to model complex joint distributions by learning conditional distributions over the next word (w_n) given the history of words observed ($w_1, \ldots, w_{n-1}$).

Language models

The simple objective of modelling the next word given the observed history contains much of the complexity of natural language understanding.

Consider predicting the extension of the utterance:

$$p(\cdot|\text{ There she built a})$$

With more context we are able to use our knowledge of both language and the world to heavily constrain the distribution over the next word:

$$p(\cdot|\text{ Alice went to the beach. There she built a})$$

There is evidence that human language acquisition partly relies on future prediction.

Evaluating a Language Model

A good model assigns real utterances w_1^N from a language a high probability. This can be measured with cross entropy:

$$H(w_1^N) = -\frac{1}{N}\log_2 p(w_1^N)$$

Intuition 1: Cross entropy is a measure of how many bits are needed to encode text with our model.

Alternatively we can use **perplexity**:

$$\text{perplexity}(w_1^N) = 2^{H(w_1^N)}$$

Intuition 2: Perplexity is a measure of how surprised our model is on seeing each word.

N-Gram Models: The Markov Chain Assumption

Markov assumption:

- only previous history matters
- limited memory: only last $k-1$ words are included in history (older words less relevant)
- ***k*th order Markov model**

For instance 2-gram language model:

$$
\begin{aligned}
p(w_1, w_2, w_3, \quad \ldots \quad , w_n) \\
&= p(w_1)\, p(w_2|w_1)\, p(w_3|w_1, w_2) \times \ldots \\
&\quad \times p(w_n|w_1, w_2, \ldots w_{n-1}) \\
&\approx p(w_1)\, p(w_2|w_1)\, p(w_3|w_2) \times \ldots \times p(w_n|w_{n-1})
\end{aligned}
$$

N-Gram Models: Estimating Probabilities

Maximum likelihood estimation for 3-grams:

$$p(w_3|w_1, w_2) = \frac{\text{count}(w_1, w_2, w_3)}{\text{count}(w_1, w_2)}$$

Collect counts over a large text corpus. Billions to trillions of words are easily available by scraping the web.

Provisional Summary

Good

- Count based n-gram models are exceptionally scalable and are able to be trained on trillions of words of data,
- fast constant time evaluation of probabilities at test time,
- sophisticated smoothing techniques match the empirical distribution of language.[5]

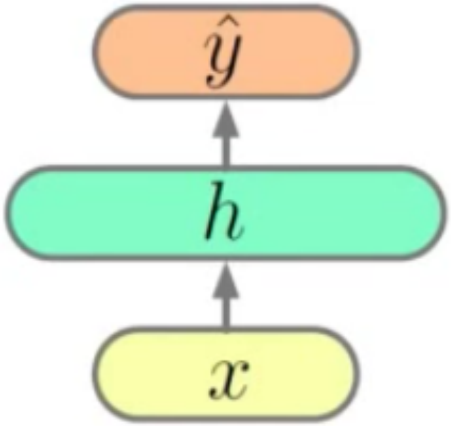
Bad

- Large ngrams are sparse, so hard to capture long dependencies,
- symbolic nature does not capture correlations between semantically similary word distributions, e.g. cat $\leftrightarrow$ dog,
- similarly morphological regularities, running $\leftrightarrow$ jumping, or gender.

Neural Language Models

Feed forward network

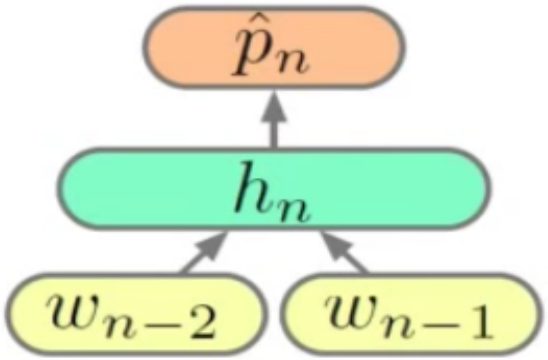
$$
\begin{aligned}
h &= g(Vx + c) \\
\hat{y} &= Wh + b
\end{aligned}
$$



Neural Language Models

Trigram NN language model

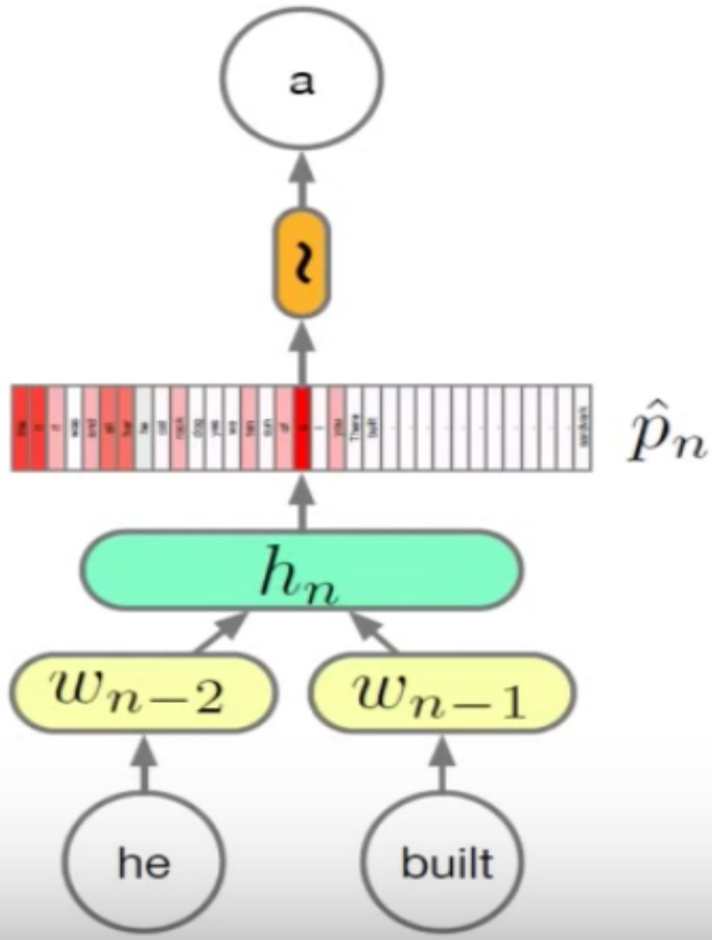
$$
\begin{aligned}
h_n &= g(V[w_{n-1}; w_{n-2}] + c) \\
\hat{p}_n &= \mathrm{softmax}(Wh_n + b) \\
\mathrm{softmax}(u)_i &= \frac{\exp u_i}{\sum_j \exp u_j}
\end{aligned}
$$



- w_i are one hot vetors and $\hat{p}_i$ are distributions,
- $|w_i| = |\hat{p}_i| = V$ (words in the vocabulary),
- V is usually very large $> 1e5$.

Neural Language Models: Sampling

$$w_n | w_{n-1}, w_{n-2} \quad \sim \quad \hat{p}_n$$



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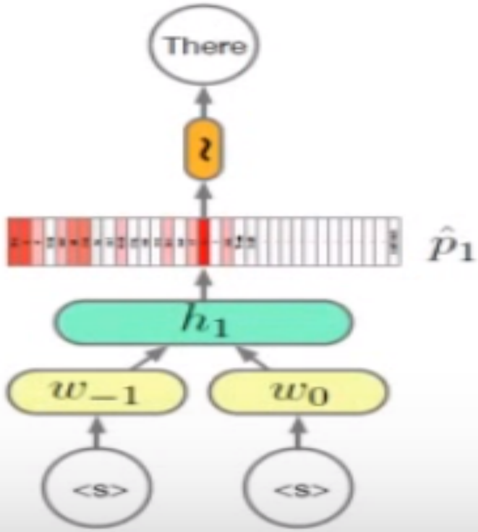

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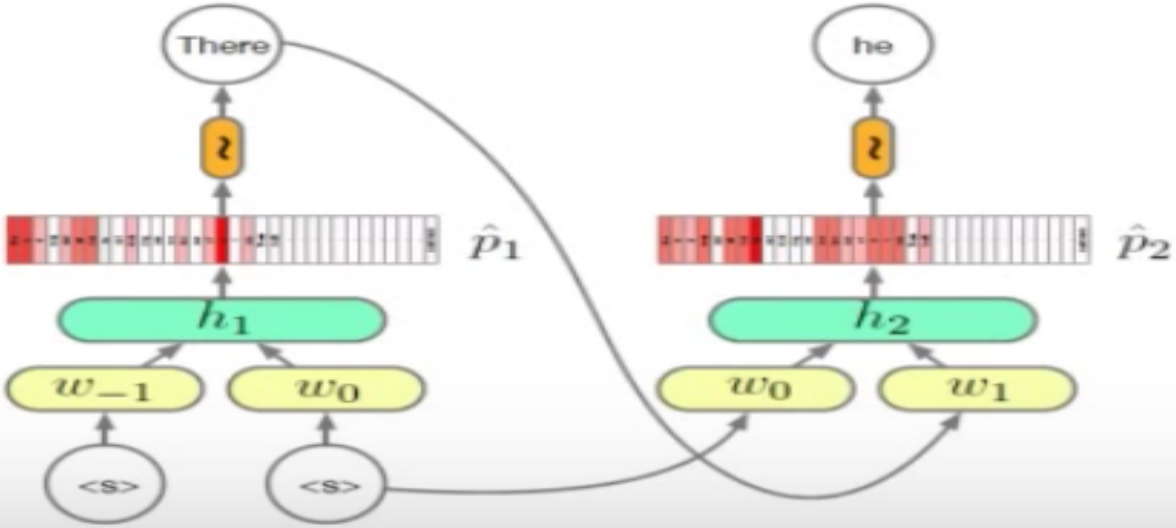

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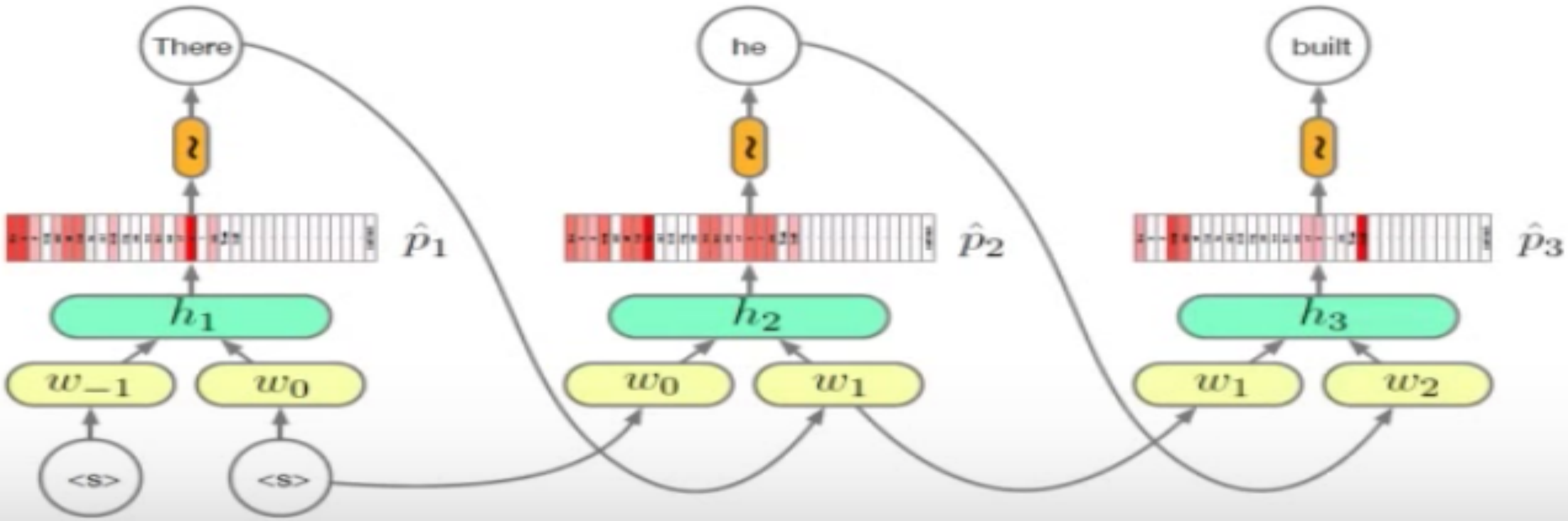

Neural Language Models: Sampling

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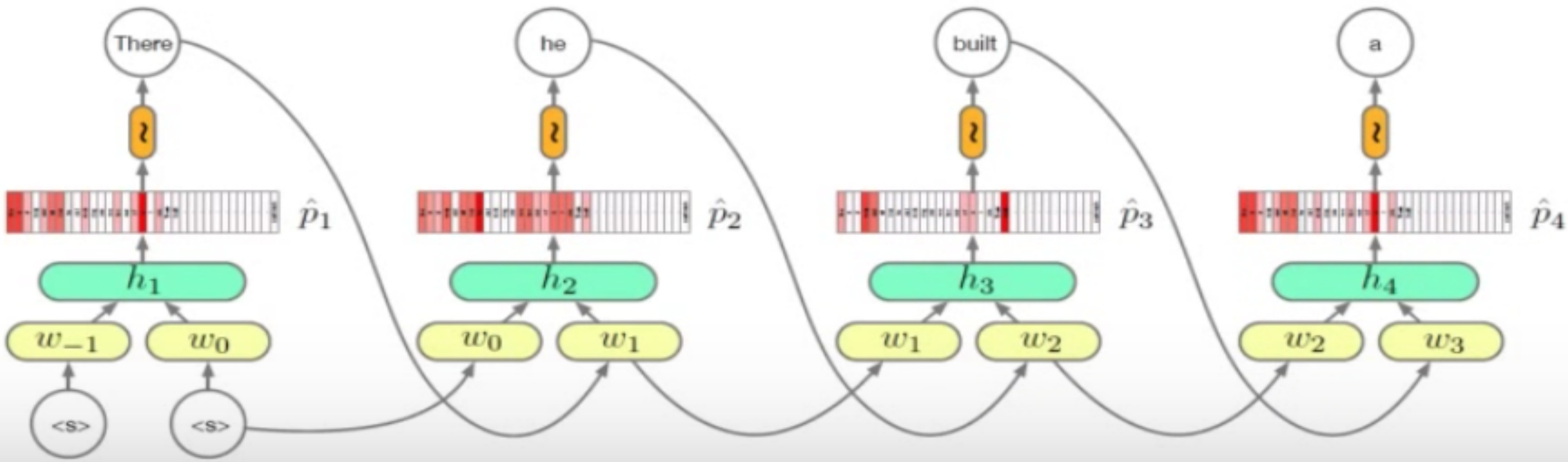


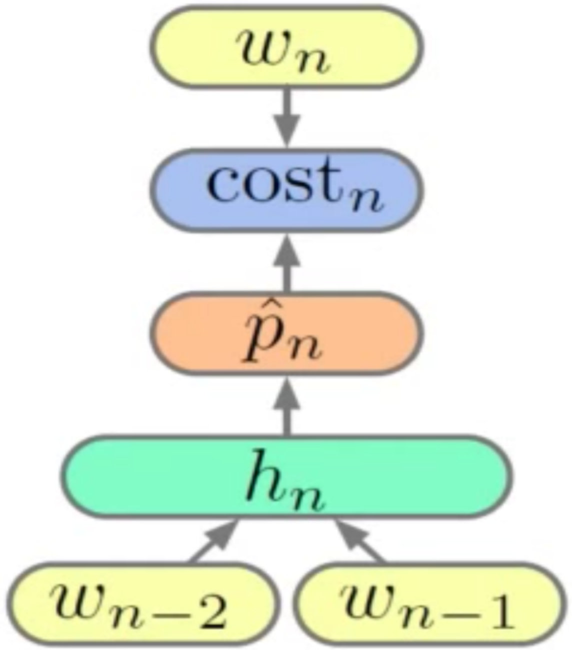
The usual training objective is the cross entropy of the data given the model (MLE):

$$\mathcal{F} = -\frac{1}{N}\sum_{n} \mathrm{cost}_n(w_n, \hat{p}_n)$$

The cost function is simply the model's estimated log-probability of w_n:

$$\mathrm{cost}(a, b) = a^T \log b$$

(assuming w_i is a one hot encoding of the word)

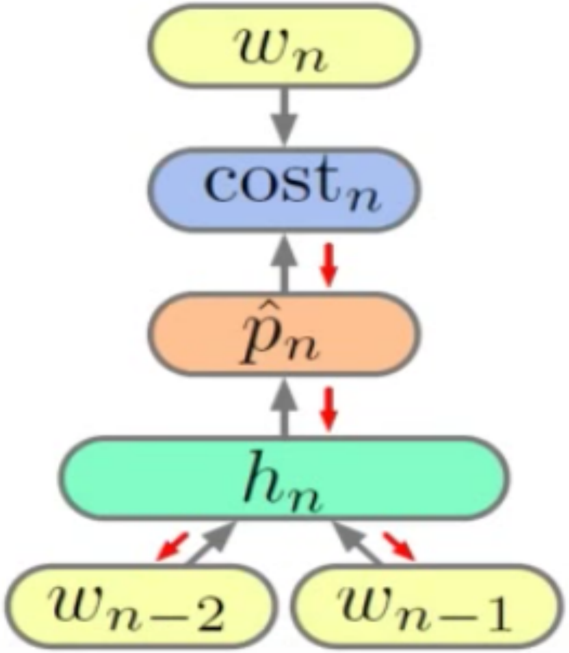


Neural Language Models: Training

Calculating the gradients is straightforward with back propagation:

$$\frac{\partial \mathcal{F}}{\partial W} = -\frac{1}{N}\sum_n \frac{\partial \text{cost}_n}{\partial \hat{p}_n}\frac{\partial \hat{p}_n}{\partial W}$$

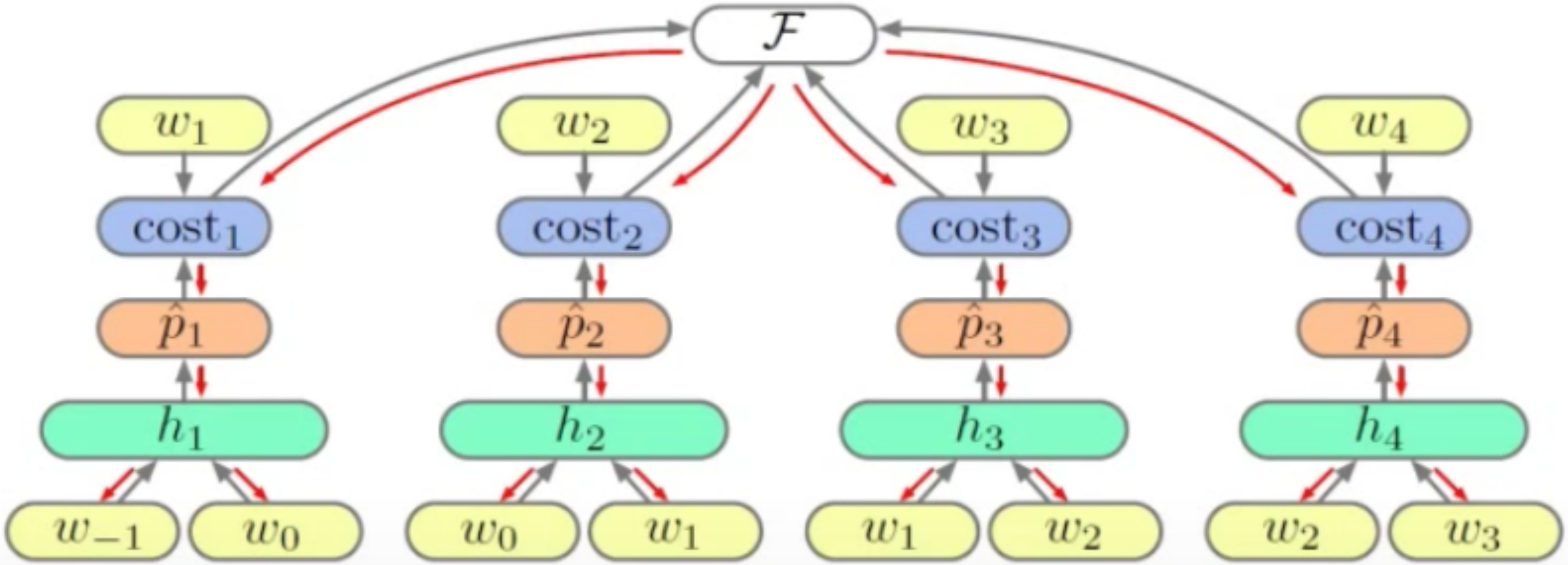
$$\frac{\partial \mathcal{F}}{\partial V} = -\frac{1}{N}\sum_n \frac{\partial \text{cost}_n}{\partial \hat{p}_n}\frac{\partial \hat{p}_n}{\partial h_n}\frac{\partial h_n}{\partial V}$$



Neural Language Models: Training

Calculating the gradients is straightforward with back propagation:

$$\frac{\partial \mathcal{F}}{\partial W} = -\frac{1}{4}\sum_{n=1}^{4} \frac{\partial \text{cost}_n}{\partial \hat{p}_n}\frac{\partial \hat{p}_n}{\partial W} \quad , \quad \frac{\partial \mathcal{F}}{\partial V} = -\frac{1}{4}\sum_{n=1}^{4} \frac{\partial \text{cost}_n}{\partial \hat{p}_n}\frac{\partial \hat{p}_n}{\partial h_n}\frac{\partial h_n}{\partial V}$$



Comparison with Count Based N-Gram LMs

Good

- Better generalisation on unseen n-grams, poorer on seen n-grams. Solution: direct (linear) ngram features.
- Simple NLMs are often an order magnitude smaller in memory footprint than their vanilla n-gram cousins (though not if you use the linear features suggested above!).

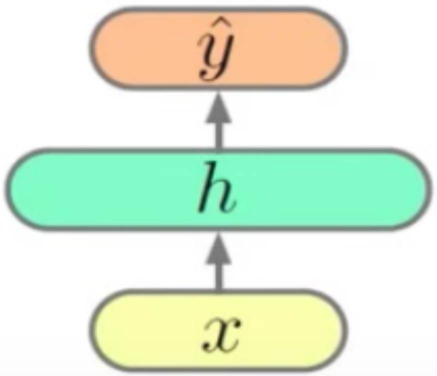
Bad

- The number of parameters in the model scales with the n-gram size and thus the length of the history captured.
- The n-gram history is finite and thus there is a limit on the longest dependencies that an be captured.

Recurrent Neural Network Language Models

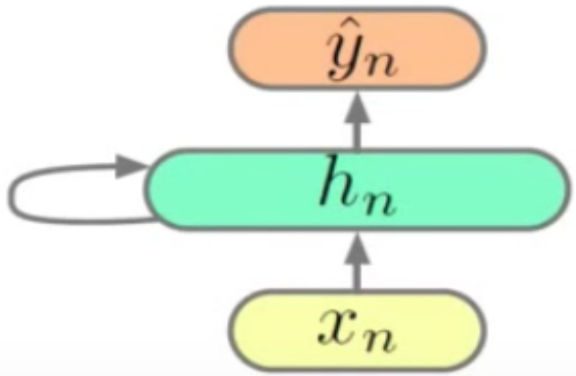
Feed Forward

$$
\begin{aligned}
h &= g(Vx + c) \\
\hat{y} &= Wh + b
\end{aligned}
$$



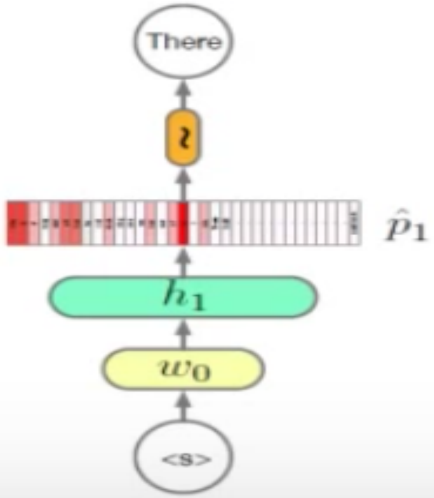
Recurrent Network

$$
\begin{aligned}
h_n &= g(V[x_n; h_{n-1}] + c) \\
\hat{y}_n &= Wh_n + b
\end{aligned}
$$



Recurrent Neural Network Language Models

$$h_n = g(V[x_n; h_{n-1}] + c)$$



Recurrent Neural Network Language Models

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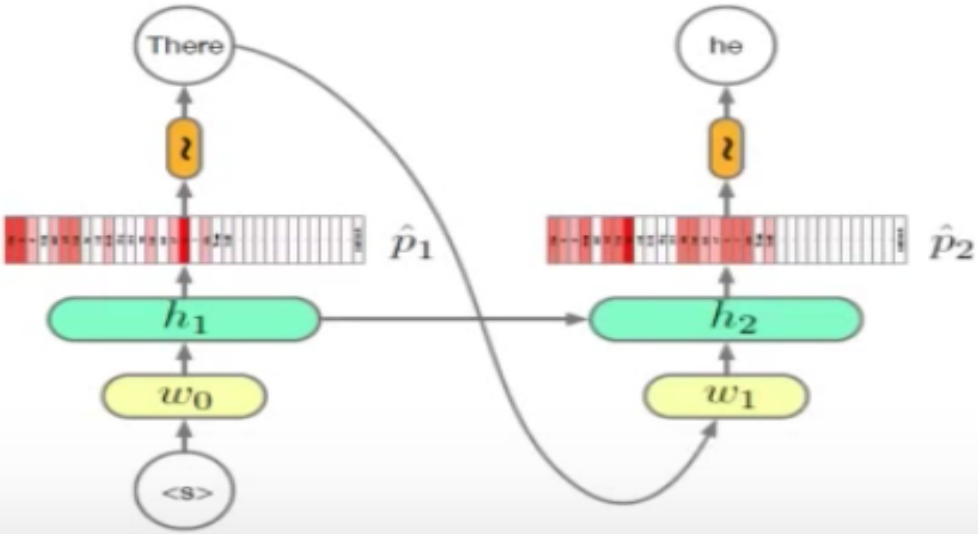

Recurrent Neural Network Language Models

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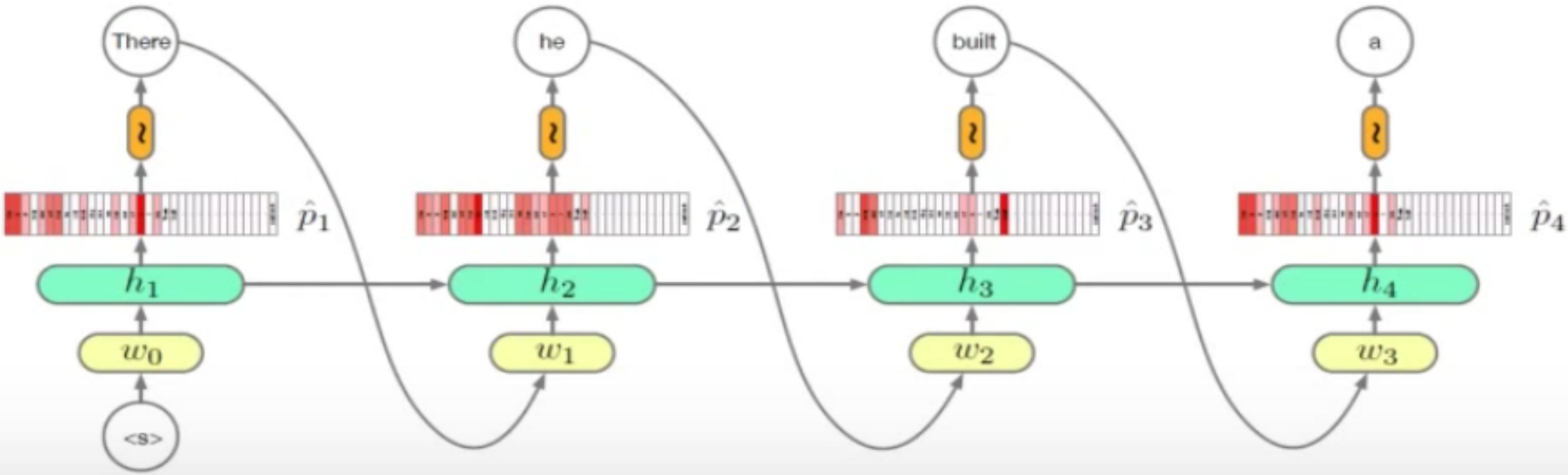

Recurrent Neural Network Language Models

Feed Forward

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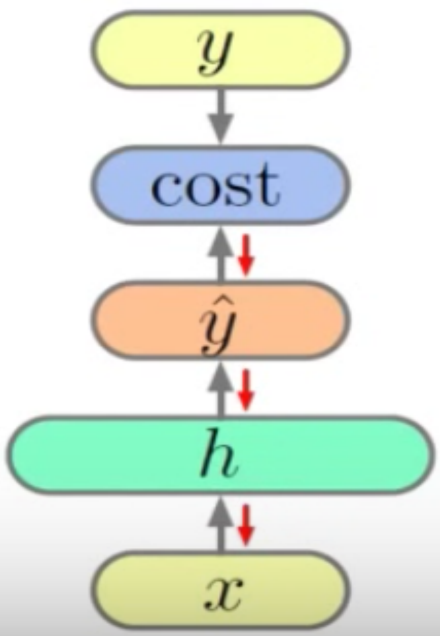

Recurrent Network

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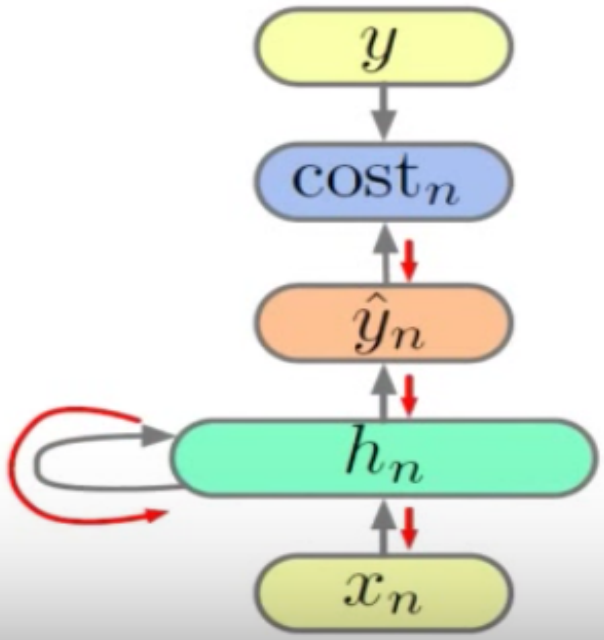
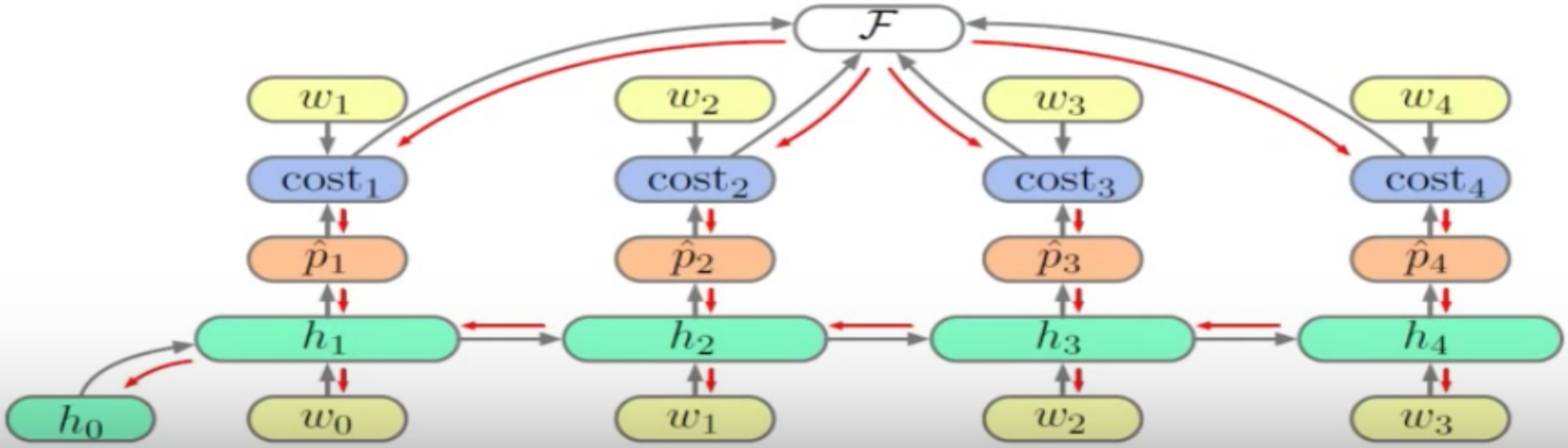


Recurrent Neural Network Language Models

The unrolled recurrent network is a directed acyclic computation graph. We can run backpropagation as usual:

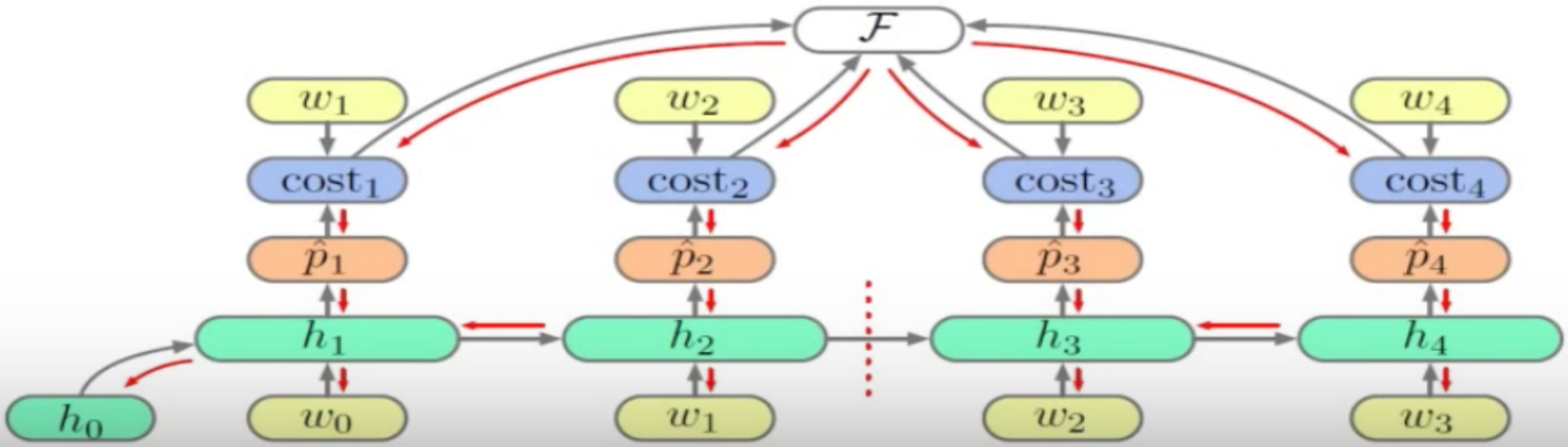
$$\mathcal{F} = -\frac{1}{4}\sum_{n=1}^{4} \text{cost}_n(w_n, \hat{p}_n)$$



Recurrent Neural Network Language Models

If we break these depdencies after a fixed number of timesteps we get Truncated Back Propagation Through Time (TBPTT):

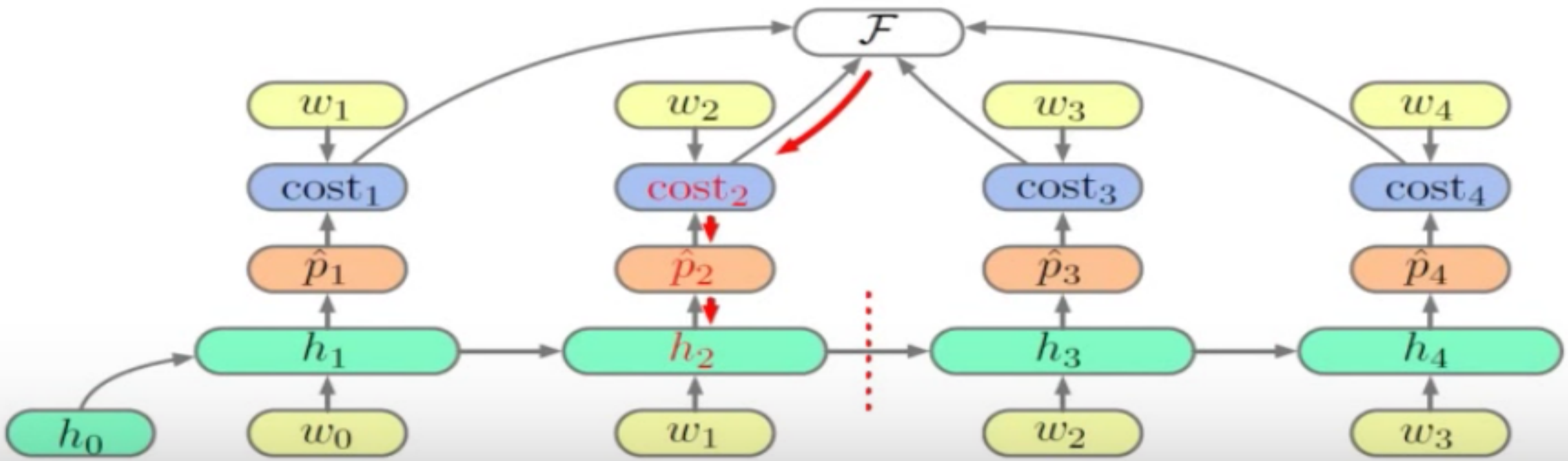
$$\mathcal{F} = -\frac{1}{4}\sum_{n=1}^{4} \text{cost}_n(w_n, \hat{p}_n)$$



Recurrent Neural Network Language Models

If we break these depdencies after a fixed number of timesteps we get Truncated Back Propagation Through Time (TBPTT):

$$\frac{\partial \mathcal{F}}{\partial h_2} \approx \frac{\partial \mathcal{F}}{\partial \text{cost}_2} \frac{\partial \text{cost}_2}{\partial \hat{p}_2} \frac{\partial \hat{p}_2}{\partial h_2}$$



Comparison with N-Gram LMs

Good

- RNNs can represent unbounded dependencies, unlike models with a fixed n-gram order.
- RNNs compress histories of words into a fixed size hidden vector.
- The number of parameters does not grow with the length of dependencies captured, but they do grow with the amount of information stored in the hidden layer.

Bad

- RNNs are hard to learn and often will not discover long range dependencies present in the data
- Increasing the size of the hidden layer, and thus memory, increases the computation and memory quadratically.

References

Textbook

Deep Learning, Chapter 10.
`www.deeplearningbook.org/contents/rnn.html`

Blog Posts

Andrej Karpathy: The Unreasonable Effectiveness of Recurrent Neural Networks
`karpathy.github.io/2015/05/21/rnn-effectiveness/`

Yoav Goldberg: The unreasonable effectiveness of Character-level Language Models
`nbviewer.jupyter.org/gist/yoavg/d76121dfde2618422139`

Stephen Merity: Explaining and illustrating orthogonal initialization for recurrent neural networks.
`smerity.com/articles/2016/orthogonal_init.html`