Neural Language Models

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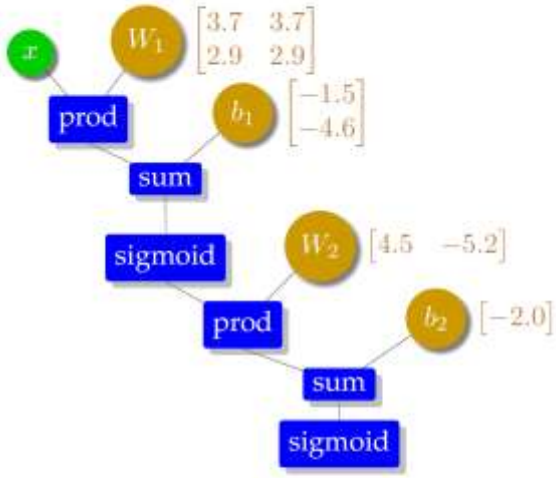
Based on slides by Philipp Koehn (JHU)

Recap: Computation Graph



- To build a system, we only need to:
  - Define network structure
  - Define error/loss function
  - Provide data
  - (and set a few more hyperparameters to control training)

- Given network structure
  - Prediction is done by forward pass through graph (forward propagation)
  - Training is done by backward pass through graph (back propagation)
  - Based on simple matrix vector operations

- Forms the basis of neural network libraries
  - Tensorflow, Pytorch, mxnet, etc.

Language Modeling

- Goal: compute the probability of a sentence or sequence of words

  $P(E) = P(e_1,e_2,e_3,e_4,e_5 \ldots e_n)$

- Related task: probability of an upcoming word

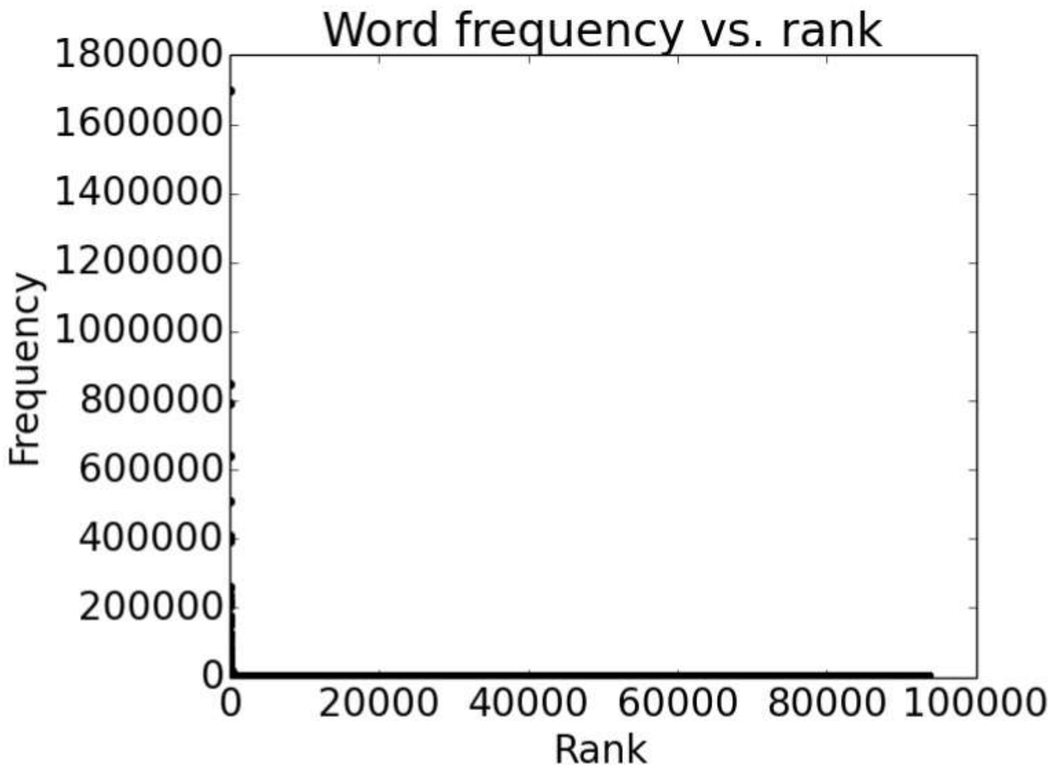
  $P(e_5 | e_1,e_2,e_3,e_4)$

- A model that computes either of these:

  $P(E)$ or $P(e_n | e_1,e_2 \ldots e_{n-1})$

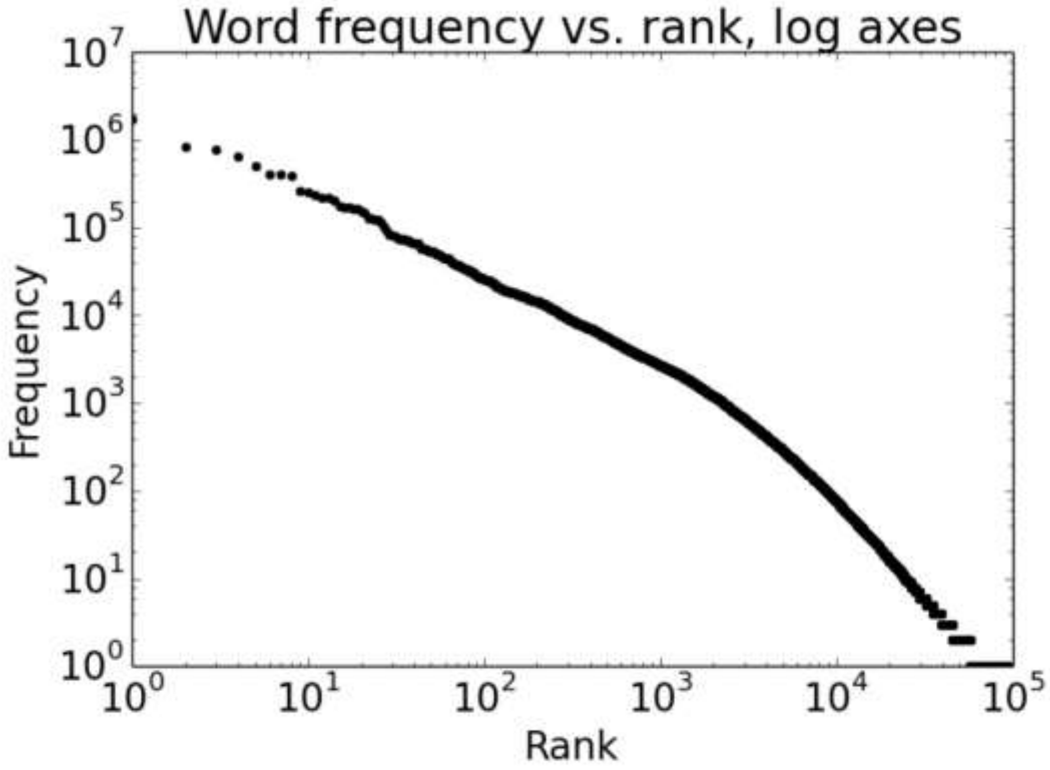
  is called a **language model**.

Zipf’s Law



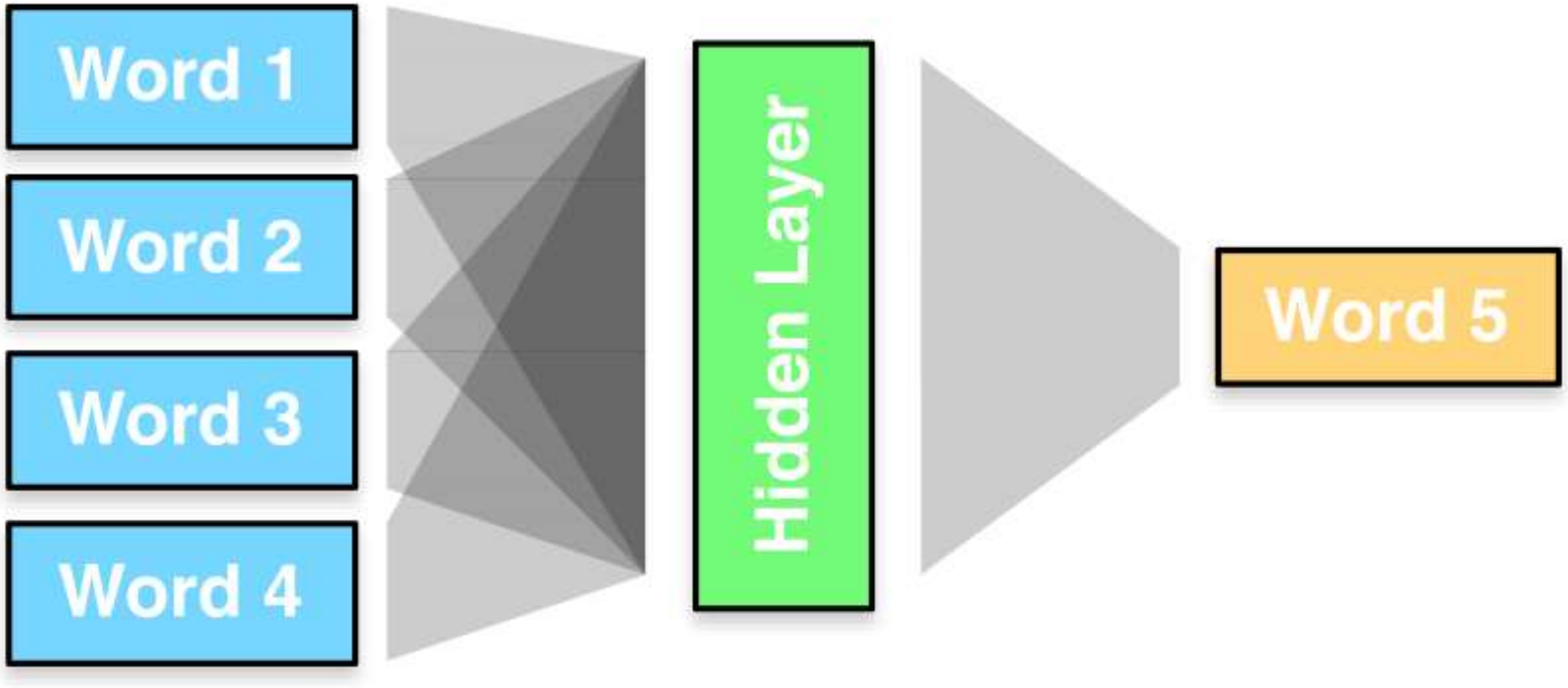
Word frequency vs. rank
1800000
1600000
1400000
1200000
1000000
800000
600000
400000
200000
0
Frequency
0
20000
40000
60000
80000
100000
Rank

Zipf's Law



- Even in a very large corpus, there will be a lot of infrequent words
- The same holds for many other levels of linguistic structure
- NLP/MT challenge: we need to be able to make predictions for things we have rarely or never seen

Toward a Neural Language Model



Figures by Philipp Koehn (JHU)

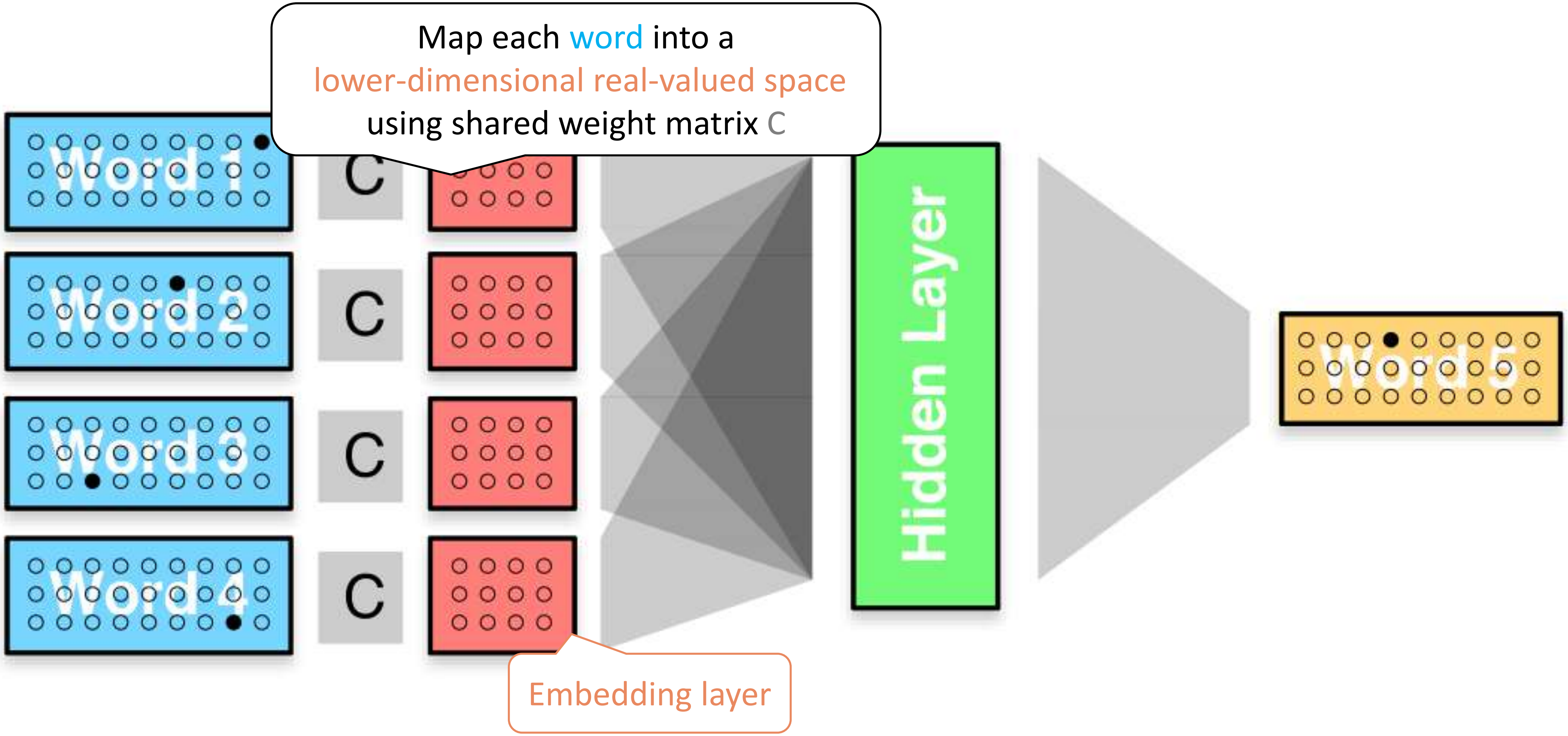
Representing Words

- "one hot vector"

```
dog = [ 0, 0, 0, 0, 1, 0, 0, 0 …]
cat = [ 0, 0, 0, 0, 0, 0, 1, 0 …]
eat = [ 0, 1, 0, 0, 0, 0, 0, 0 …]
```

- That's a large vector! practical solutions:
  - limit to most frequent words (e.g., top 20000)
  - cluster words into classes
  - break up rare words into subword units

Language Modeling with Feedforward Neural Networks



Bengio et al. 2003

An Output Layer to Predict Words

- Network will output a probability for each word in the vocabulary V
- Step 1: compute a score for each word in V $\quad s = Wx + b$

$s \in \mathbb{R}^{|V|}$ $\quad$ $W \in \mathbb{R}^{|V| \times N}$ $\quad$ $b \in \mathbb{R}^{|V|}$

- Step 2: turn scores into probabilities using softmax function

$$p = \mathrm{softmax}(s)$$

Where the probability of the j-th word in V is $p_j = \dfrac{e^{s_j}}{\sum_{\tilde{j}} e^{s_{\tilde{j}}}}$

Estimating Model Parameters

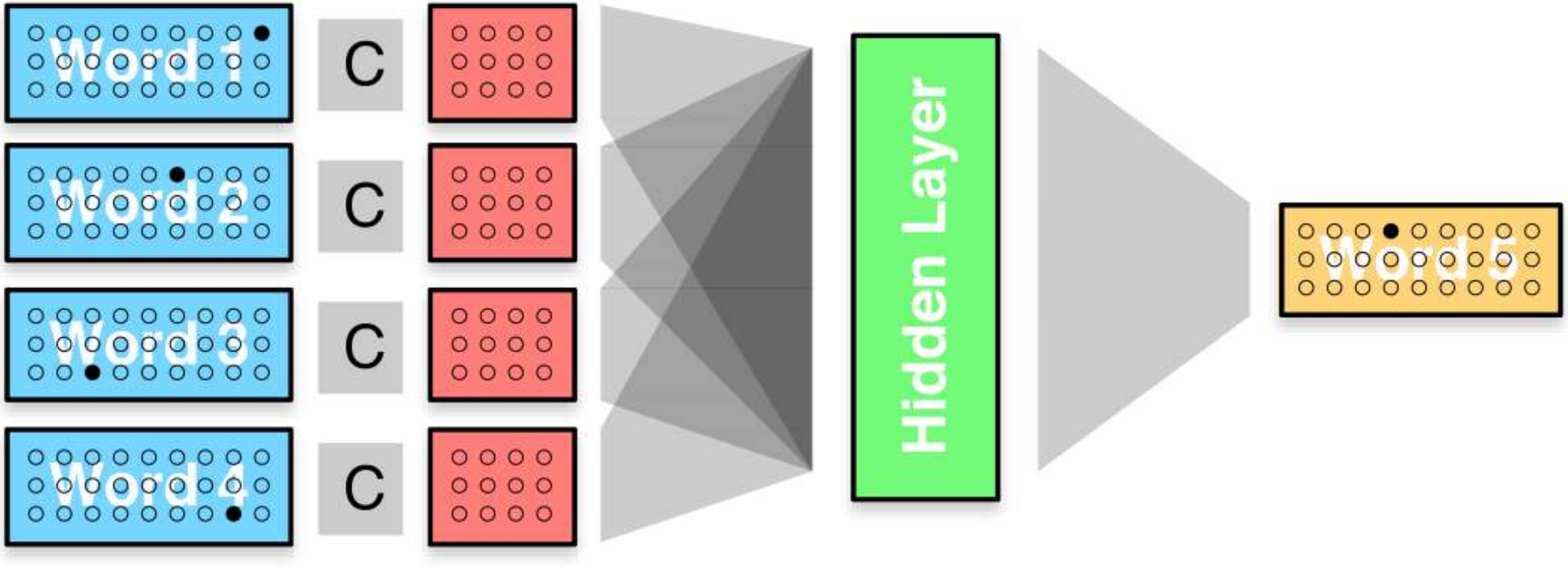
- Intuition: a model is good if it gives high probability to existing word sequences

- Training examples:
    - sequences of words in the language of interest

- Error/loss: negative log likelihood
    - At the corpus level $\text{error}(\lambda) = -\sum_{E \text{ in corpus}} \log P_\lambda(E)$

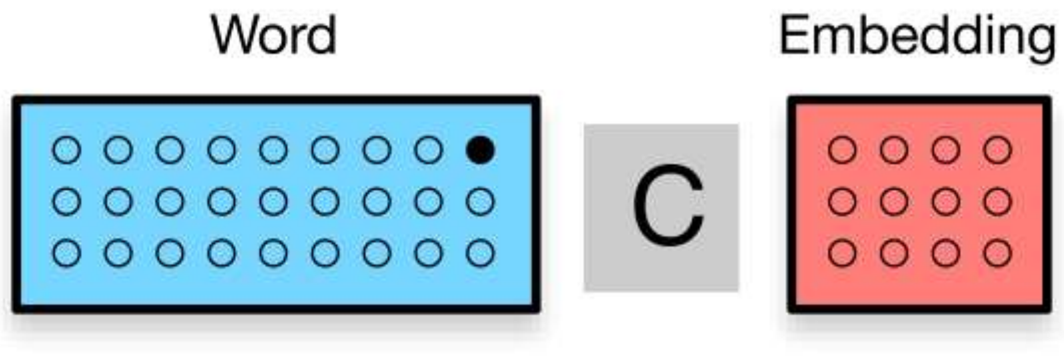
    - At the word level $\text{error}(\lambda) = -\log P_\lambda(e_t | e_1 \dots e_{t-1})$

Language Modeling with Feedforward Neural Networks



Bengio et al. 2003

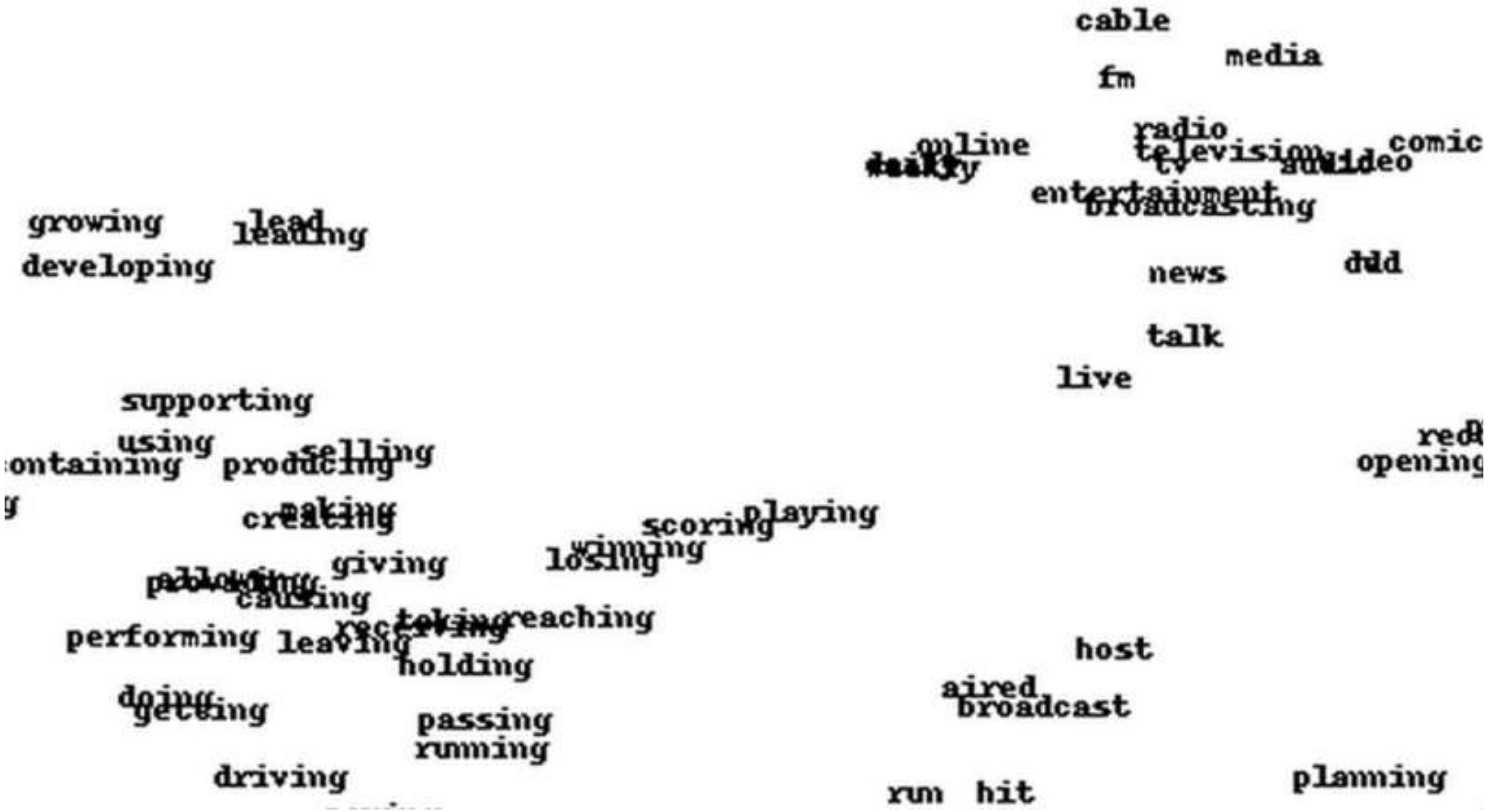
Word Embeddings: a useful by-product of neural LMs



- Words that occurs in similar contexts tend to have similar embeddings
- Embeddings capture many usage regularities
- Useful features for many NLP tasks

Word Embeddings

Word Embeddings



Word Embeddings Capture Useful Regularities

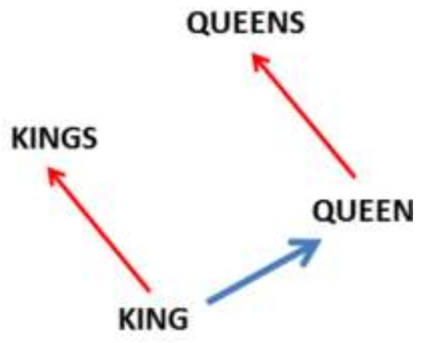
Morpho-Syntactic

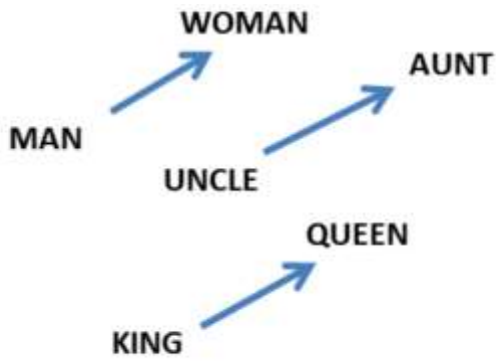
- Adjectives: base form vs. comparative
- Nouns: singular vs. plural
- Verbs: present tense vs. past tense

[Mikolov et al. 2013]

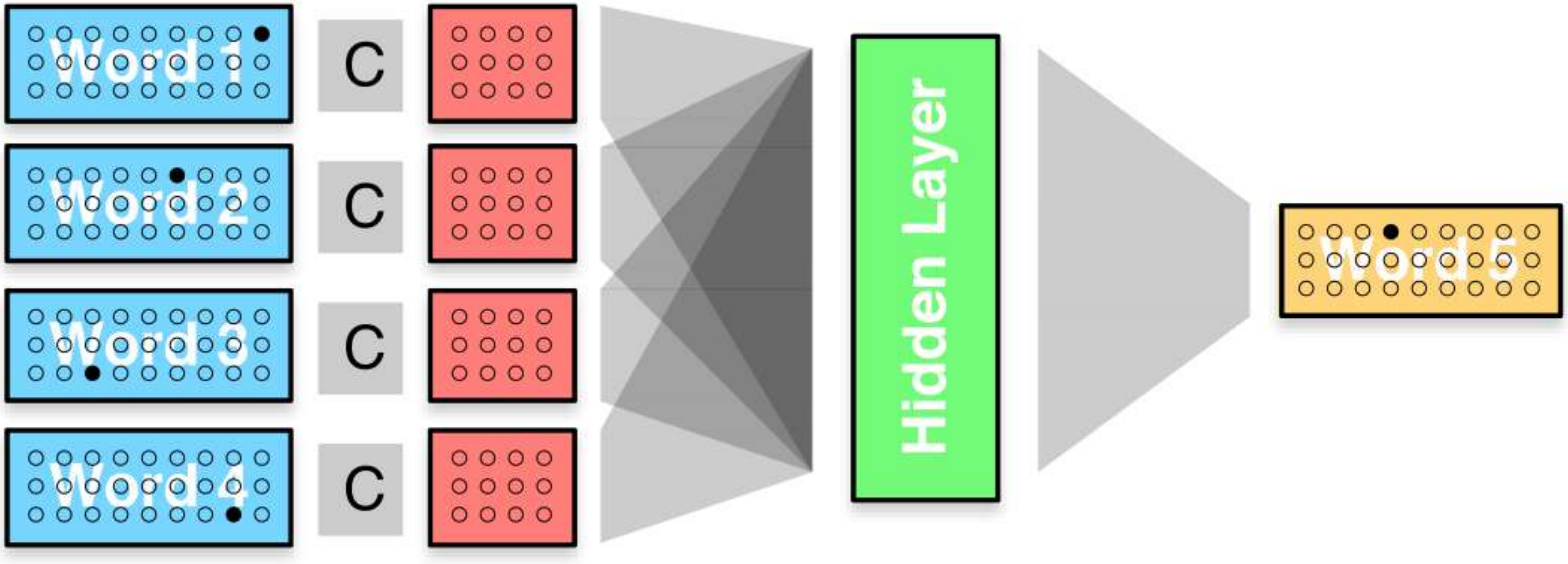
Semantic

- Word similarity/relatedness
- Semantic relations
- But tends to fail at distinguishing
  - Synonyms vs. antonyms
  - Multiple senses of a word





Language Modeling with Feedforward Neural Networks



Bengio et al. 2003

Language Modeling with Recurrent Neural Networks

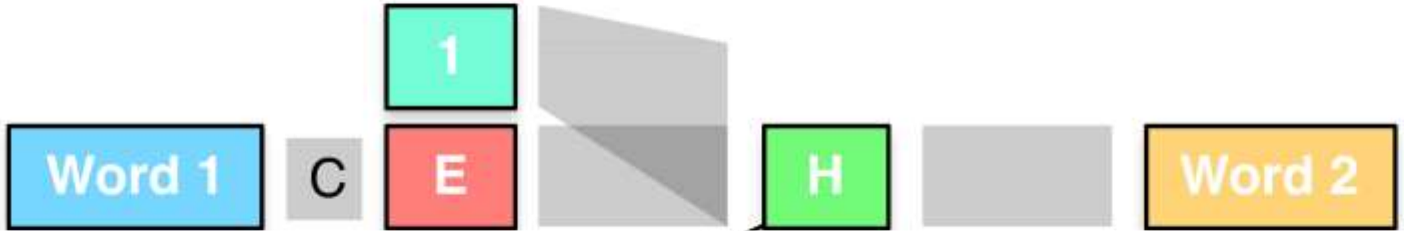
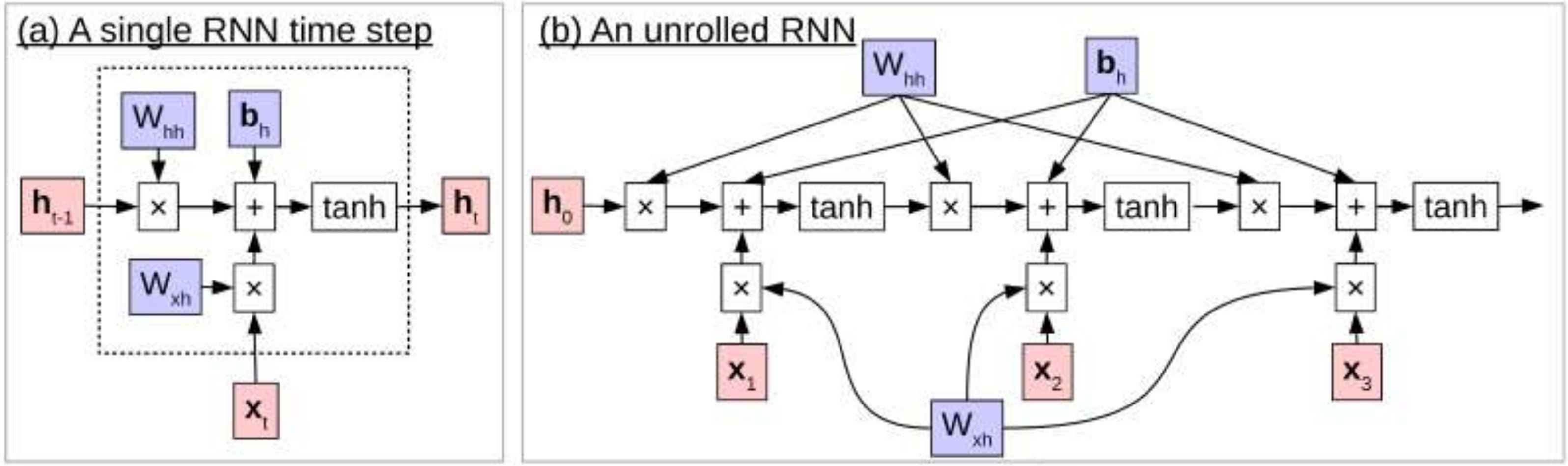


Figure by Philipp Koehn

Formalizing our Recurrent Language Model



$$\boldsymbol{m}_t = M_{\cdot, e_{t-1}}$$

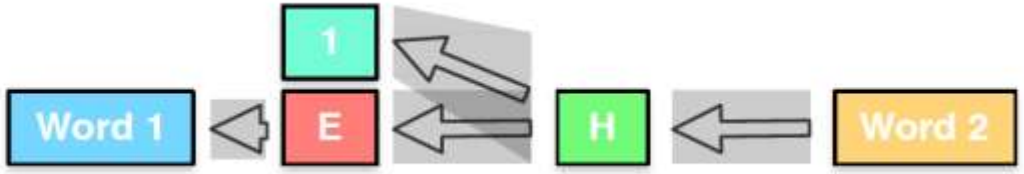
$$\boldsymbol{h}_t = \begin{cases} \tanh(W_{mh}\boldsymbol{m}_t + W_{hh}\boldsymbol{h}_{t-1} + \boldsymbol{b}_h) & t \geq 1, \\ \boldsymbol{0} & \text{otherwise.} \end{cases}$$

$$\boldsymbol{p}_t = \text{softmax}(W_{hs}\boldsymbol{h}_t + b_s).$$

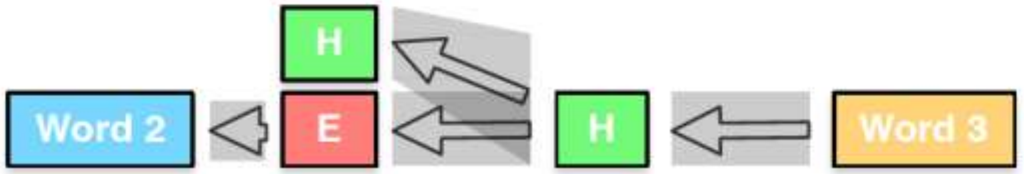
Figure by Graham Neubig

Training

- Process 1st example
- Update weights with backprop



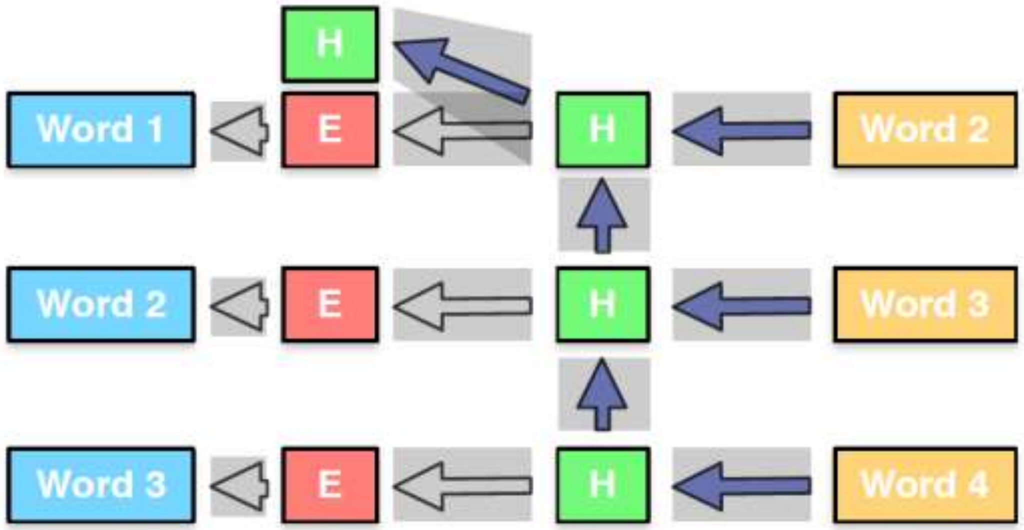
- Process 2nd example
- Update weights with backprop



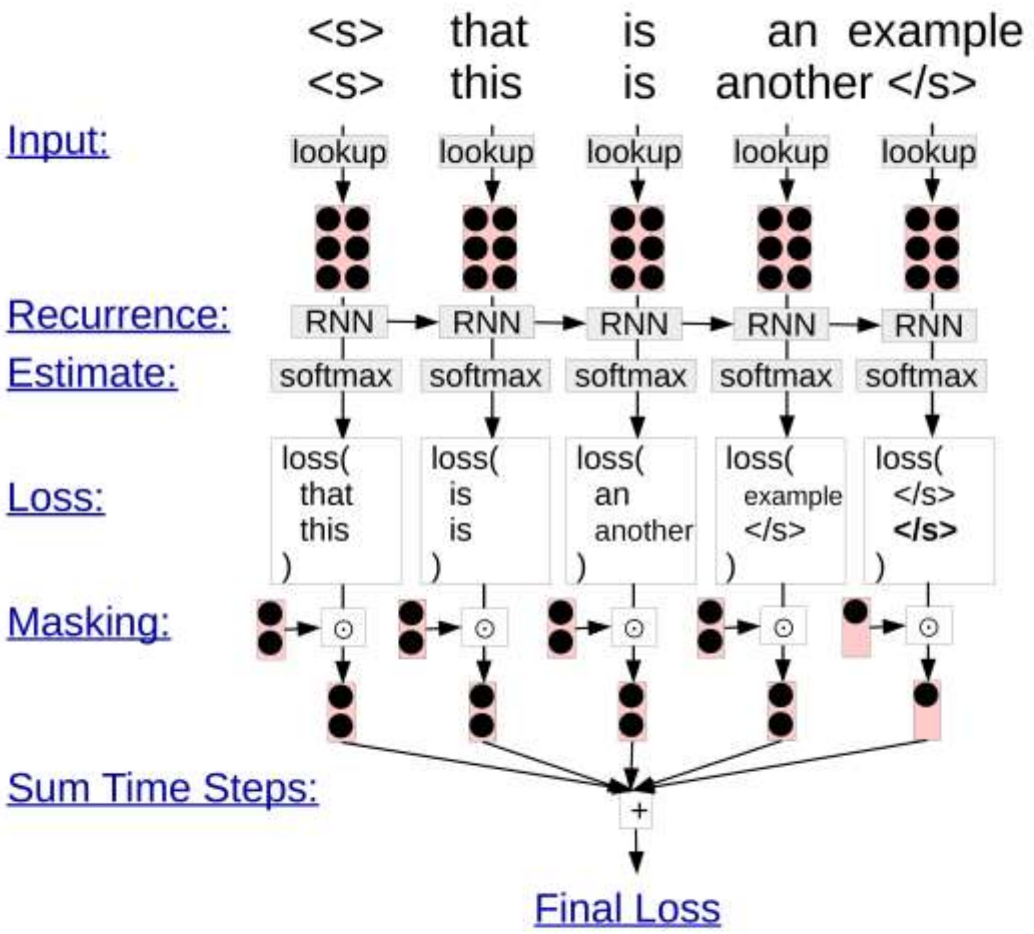
- No feedback to previous history!

Training: Backpropagation Through Time

- Process a few examples
- Backpropagate through unfolded neural network



Practical Training Issues



- Compute parameter updates based on a "minibatch" of examples
  - instead of using one example at a time
- More efficient
  - matrix-matrix operations as opposed to multiple matrix-vector operations
- Can lead to better model parameters
  - middle ground between online and batch training

Figure by Graham Neubig

Practical Training Issues: vanishing/exploding gradients

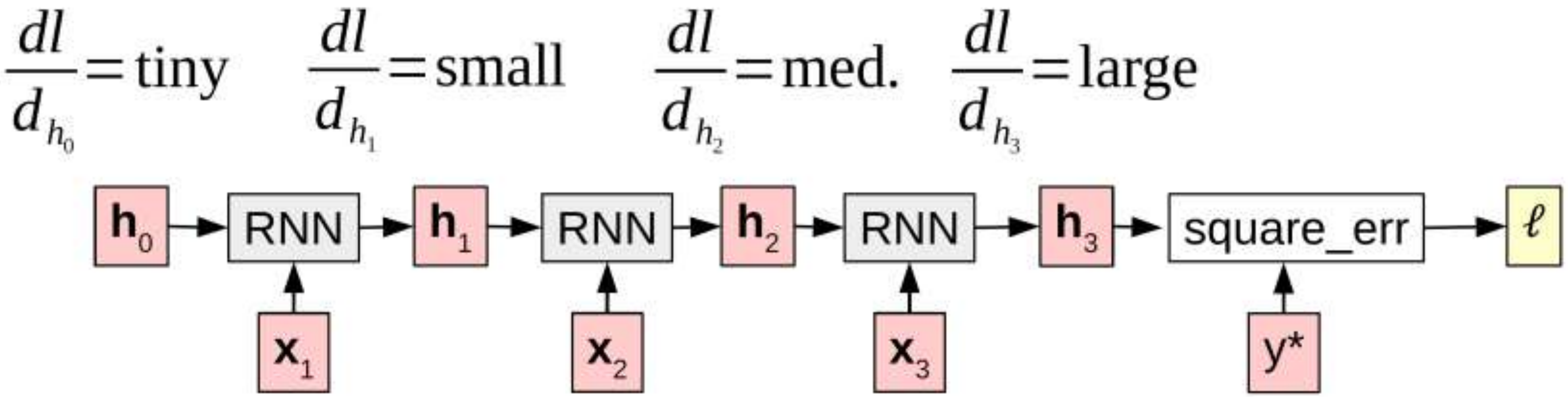


Figure 16: An example of the vanishing gradient problem.

Figure by Graham Neubig

Multiple ways to work around this problem:

- ReLU activations help

- Dedicated RNN architecture (Long Short Term Memory Networks)

Aside: Long Short Term Memory Networks

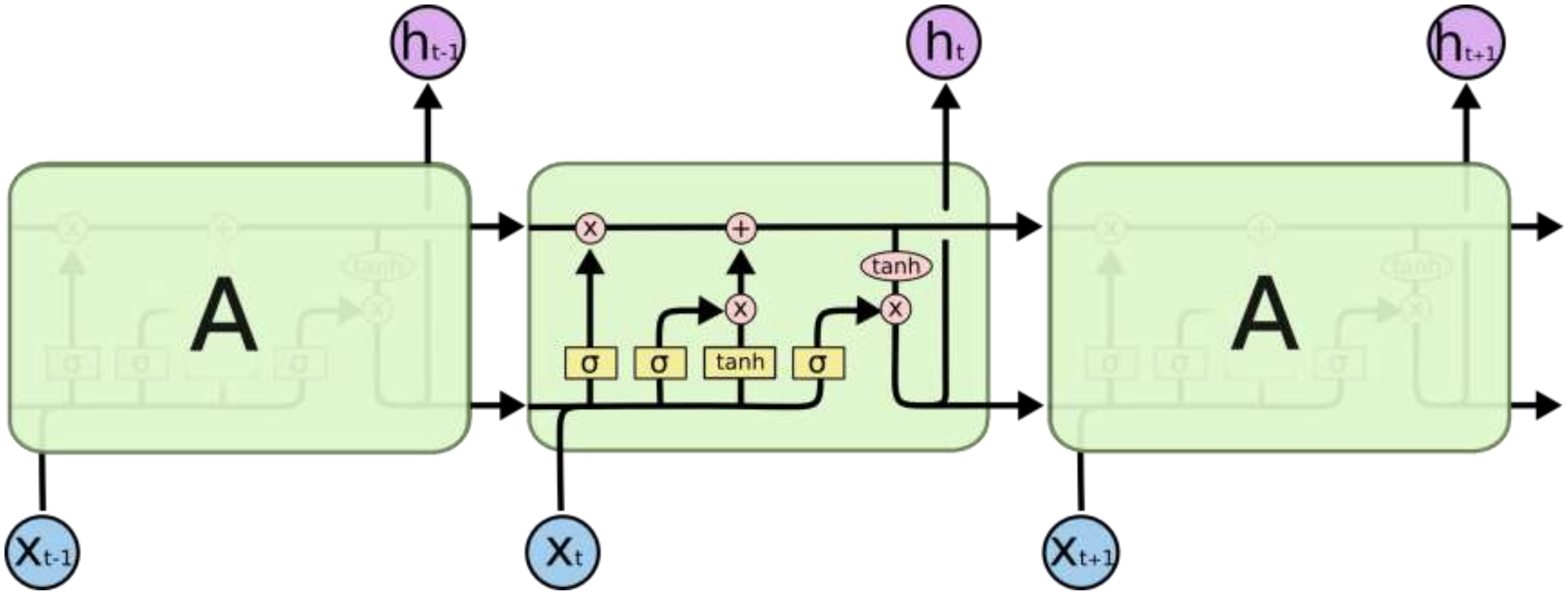


Figure by Christopher Olah

What do Recurrent Language Models Learn?

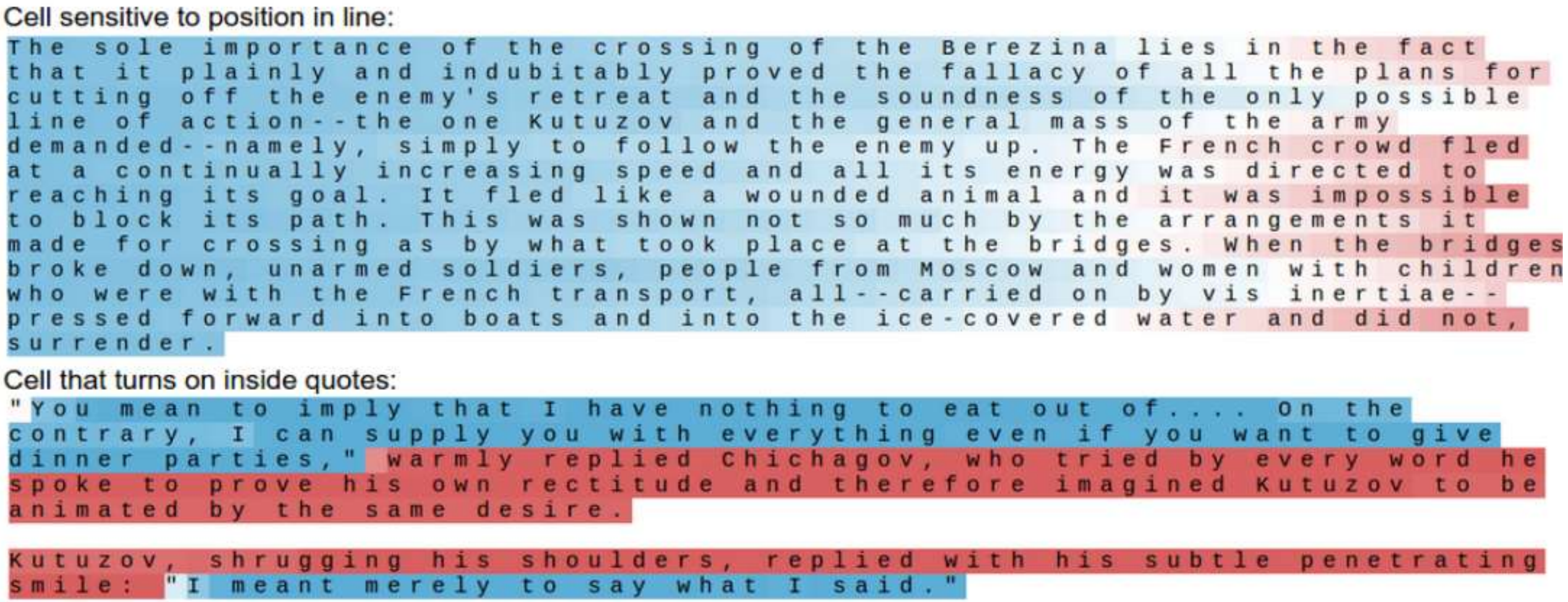


Figure from Karpathy 2015

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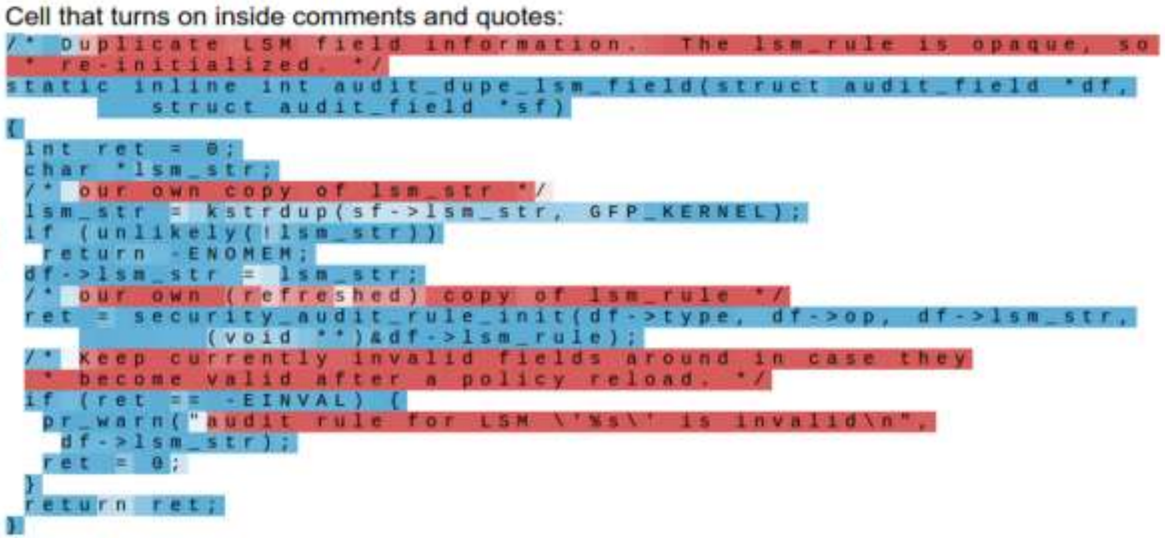


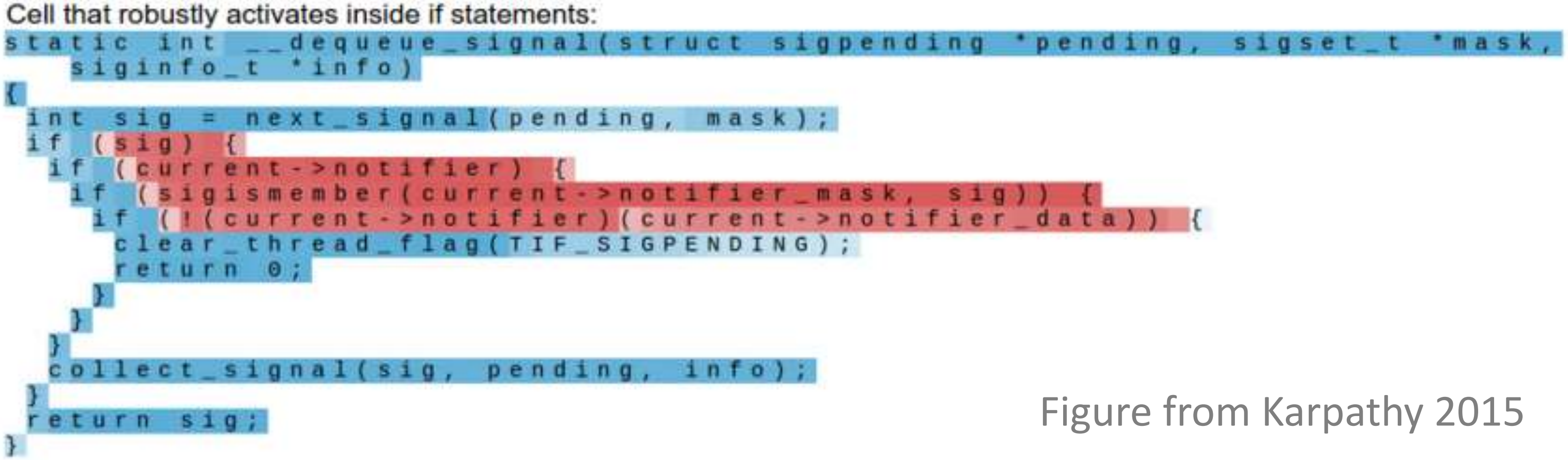


Figure from Karpathy 2015

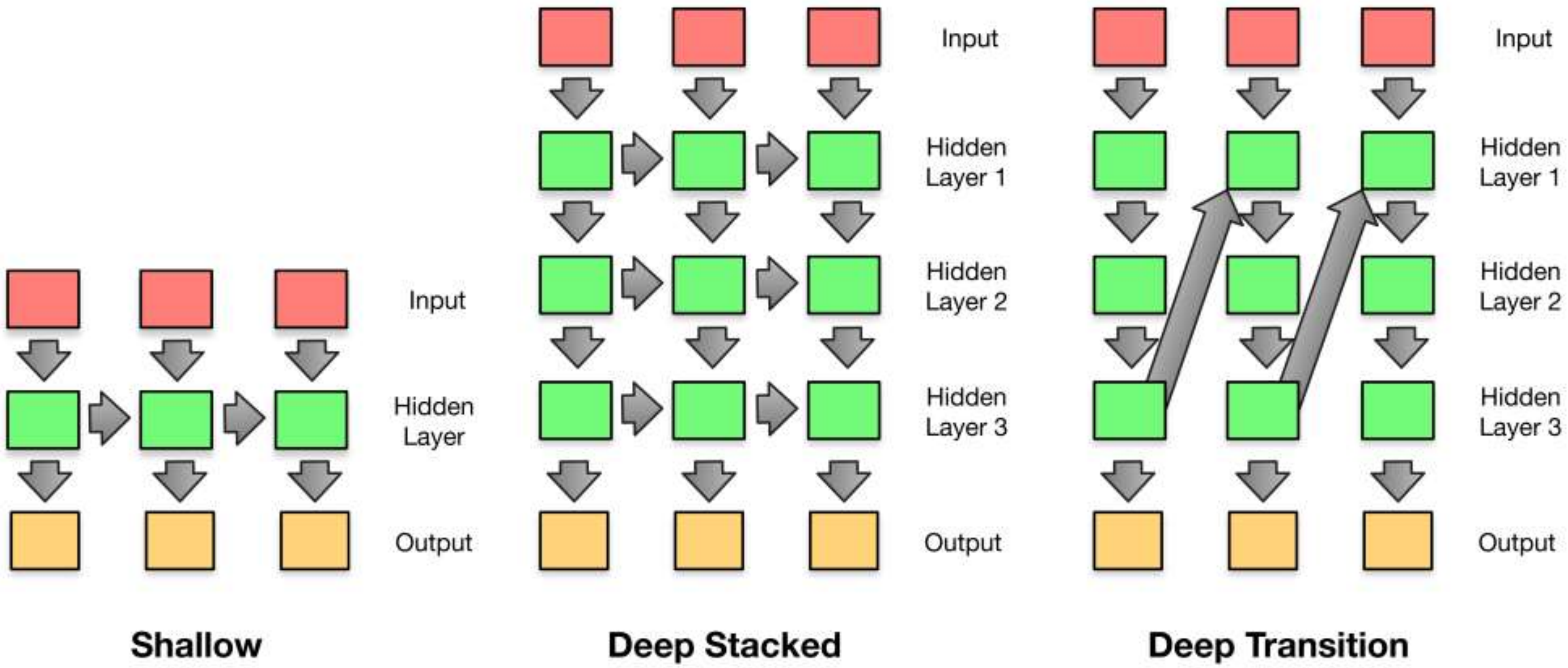
What do Recurrent Language Models Learn?

- Can capture (some) long-distance dependencies

```
After much economic progress over the years, the country has…

The country, which has made much economic progress over the years, still has…
```

Deeper Models



Neural Language Models Summary

- A powerful tool for modeling language
  - Captures generalizations over words via embeddings
  - Captures some long-distance dependencies

- Build on computation graphs
  - some tricks required to train and predict efficiently

- Not just a building block of Neural MT systems
  - Have proved useful in statistical machine translation (Devlin et al. 2014)