Language Models: Evaluation & Neural Models

CMSC 470

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Slides credit: Jurasky & Martin

Language Models
What you should know

- What is a language model
  - A probability model that assigns probabilities to sequences of words
  - Can be used to score or generate sequences
- N-gram language models
  - How they are defined, and what approximations are made in this definition (the Markov Assumption)
  - How they are estimated from data: count and normalize
  - But we need specific techniques to deal with zeros
    - word sequences unseen in training: add 1 smoothing, backoff
    - word types unseen in training: open vocabulary models with UNK token

Pros and cons of n-gram models

- Really easy to build, can train on billions and billions of words
- Smoothing helps generalize to new data
- Only work well for word prediction if the test corpus looks like the training corpus
- Only capture short distance context

Evaluating Language Models

Evaluation:
How good is our model?

- Does our language model prefer good sentences to bad ones?
  - Assign higher probability to “real” or “frequently observed” sentences
    - Than “ungrammatical” or “rarely observed” sentences?

- Extrinsic vs intrinsic evaluation

An intrinsic evaluation metric for language models: Perplexity

The best language model is one that best predicts an unseen test set

- Gives the highest P(sentence)

Perplexity is the inverse probability of the test set, normalized by the number of words:

$$PP(W) = P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}}$$

$$= \sqrt[N]{\frac{1}{P(w_1 w_2 \ldots w_N)}}$$

Chain rule:

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1 \ldots w_{i-1})}}$$

For bigrams:

$$\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$$

Minimizing perplexity is the same as maximizing probability

Interpreting perplexity as a branching factor

- Let's suppose a sentence consisting of random digits
- What is the perplexity of this sentence according to a model that assign P=1/10 to each digit?

$$
\begin{aligned}
\mathrm{PP}(W) &= P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}} \\
&= \left(\frac{1}{10}^{N}\right)^{-\frac{1}{N}} \\
&= \frac{1}{10}^{-1} \\
&= 10
\end{aligned}
$$

The Branching factor of a language is the number of possible next words that can follow any word.
We can think of **perplexity as the weighted average branching factor** of a language.

Lower perplexity = better model

- Comparing models on data from the Wall Street Journal
- Training: 38 million words, test: 1.5 million words

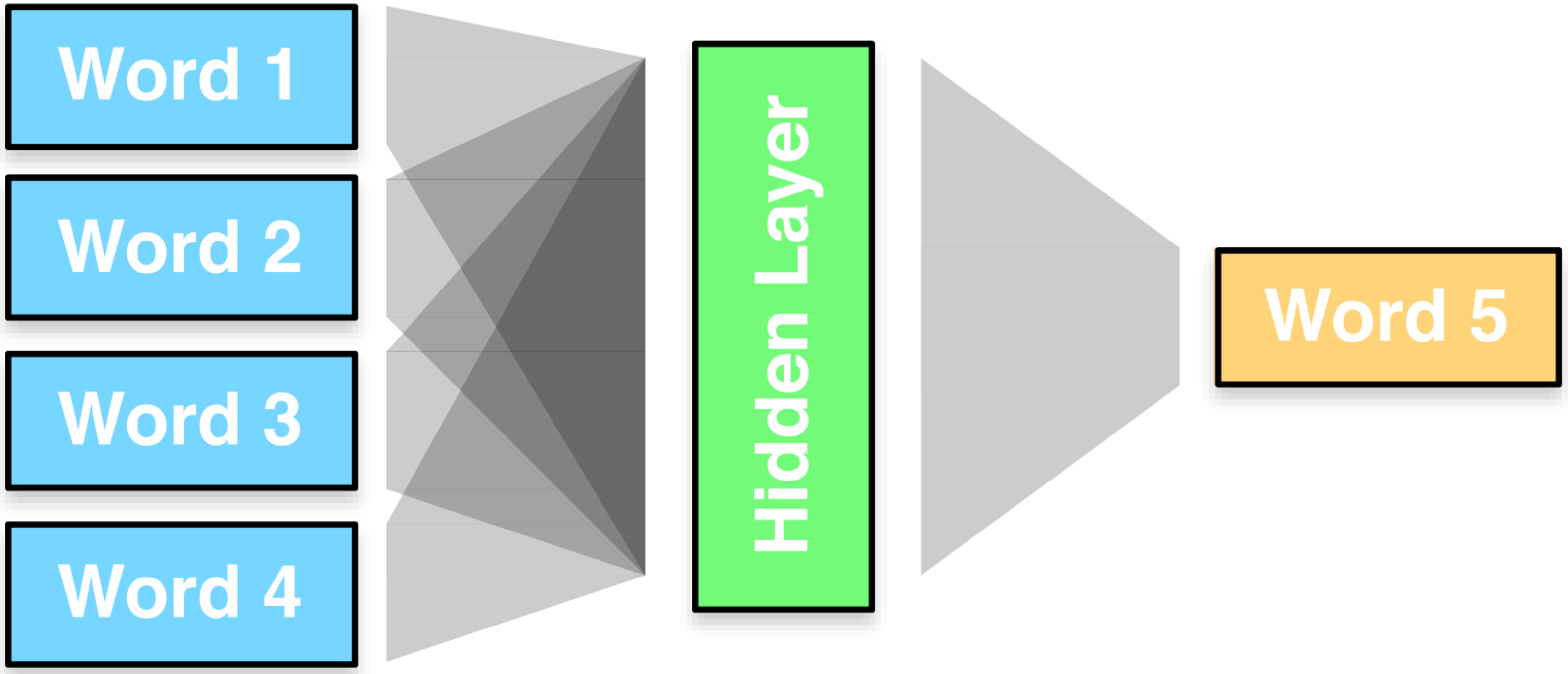
N-gram Order	Unigram	Bigram	Trigram
Perplexity	962	170	109

The perils of overfitting

- N-grams only work well for word prediction if the test corpus looks like the training corpus
- In real life, it often doesn't!
- We need to train robust models that generalize
    - Smoothing is important
    - Choose n carefully

A Neural Network-based Language Model

Toward a Neural Language Model



Figures by Philipp Koehn (JHU)

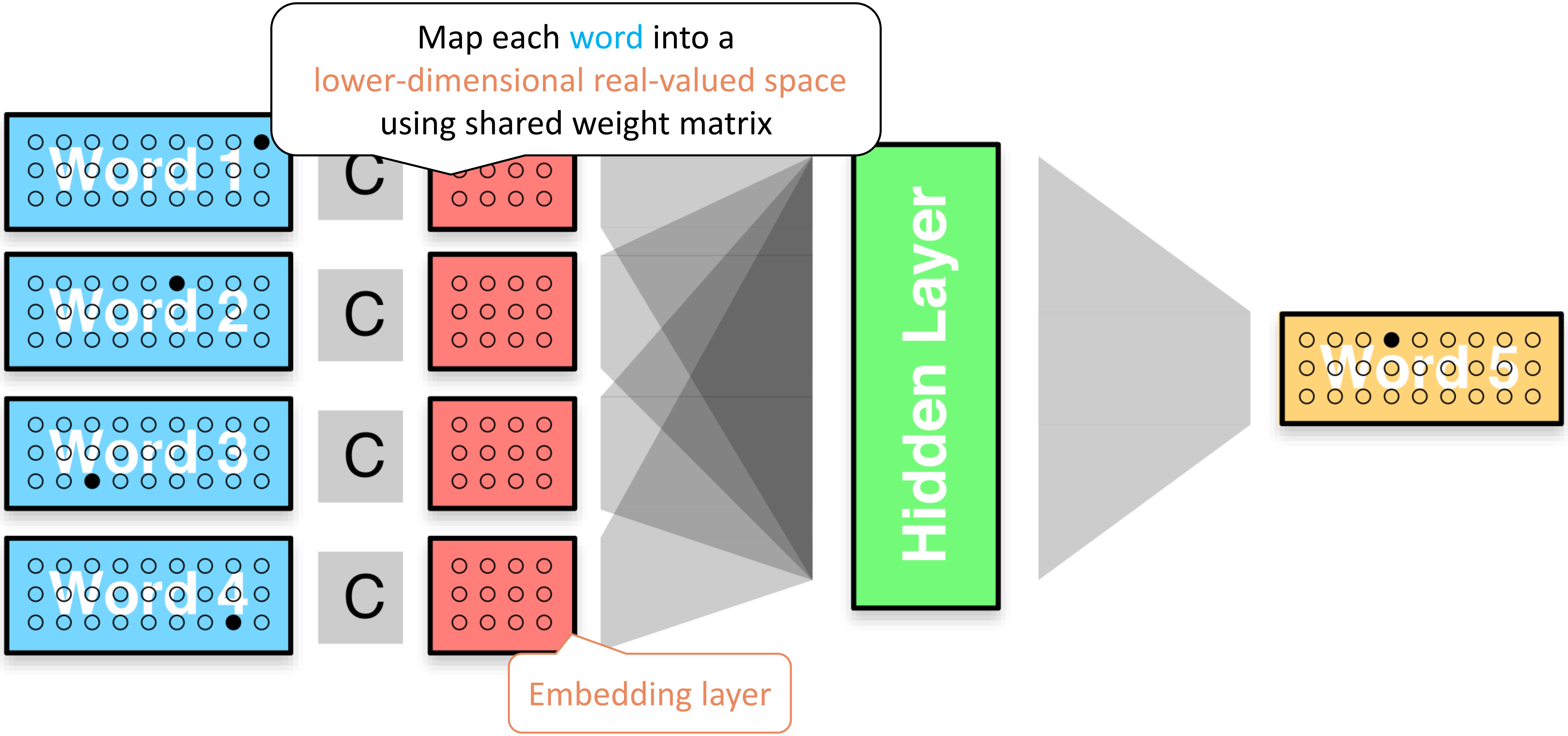
Representing Words

- “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 …]
```

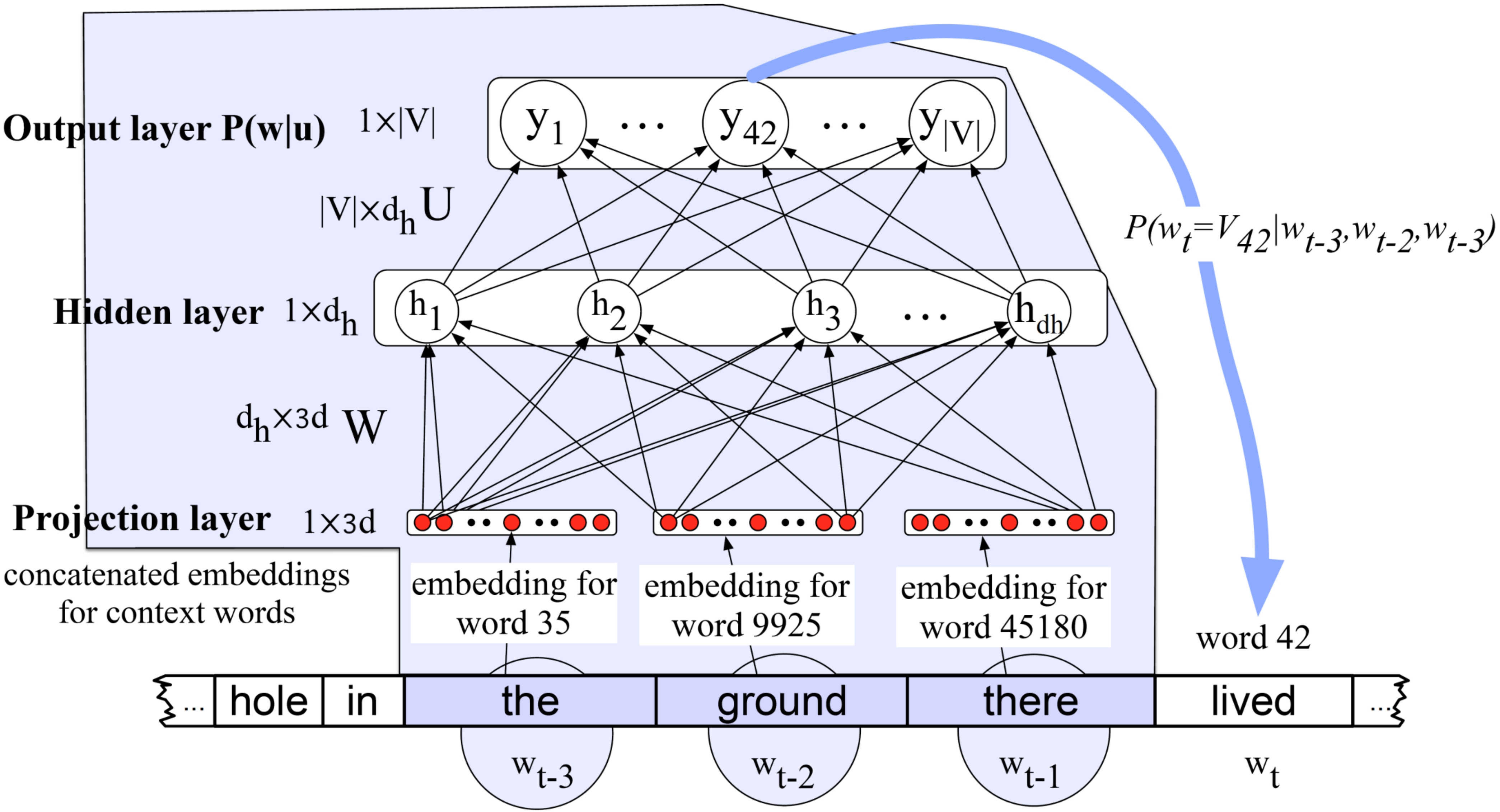
- That’s a large vector! practical solutions:
    - limit to most frequent words (e.g., top 20000)
    - cluster words into classes
    - break up rare words into subword units

Language Modeling with Feedforward Neural Networks

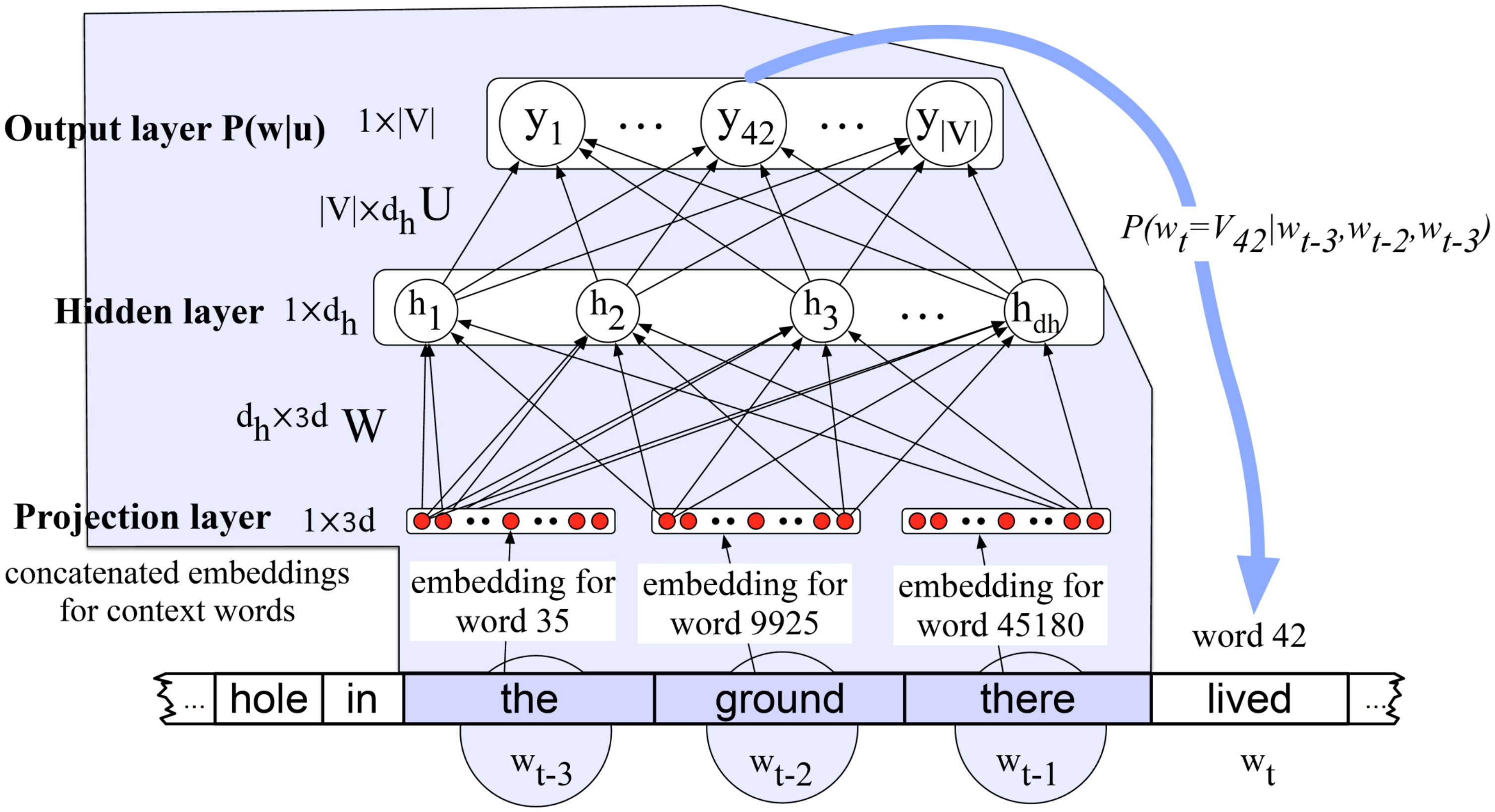


Bengio et al. 2003

Example: Prediction with a Feedforward LM



Example: Prediction with a Feedforward LM



$$
\begin{aligned}
e &= (Ex_1, Ex_2, \ldots, Ex) \\
h &= \sigma(We + b) \\
z &= Uh \\
y &= \text{softmax}(z)
\end{aligned}
$$

Note: bias omitted in figure

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

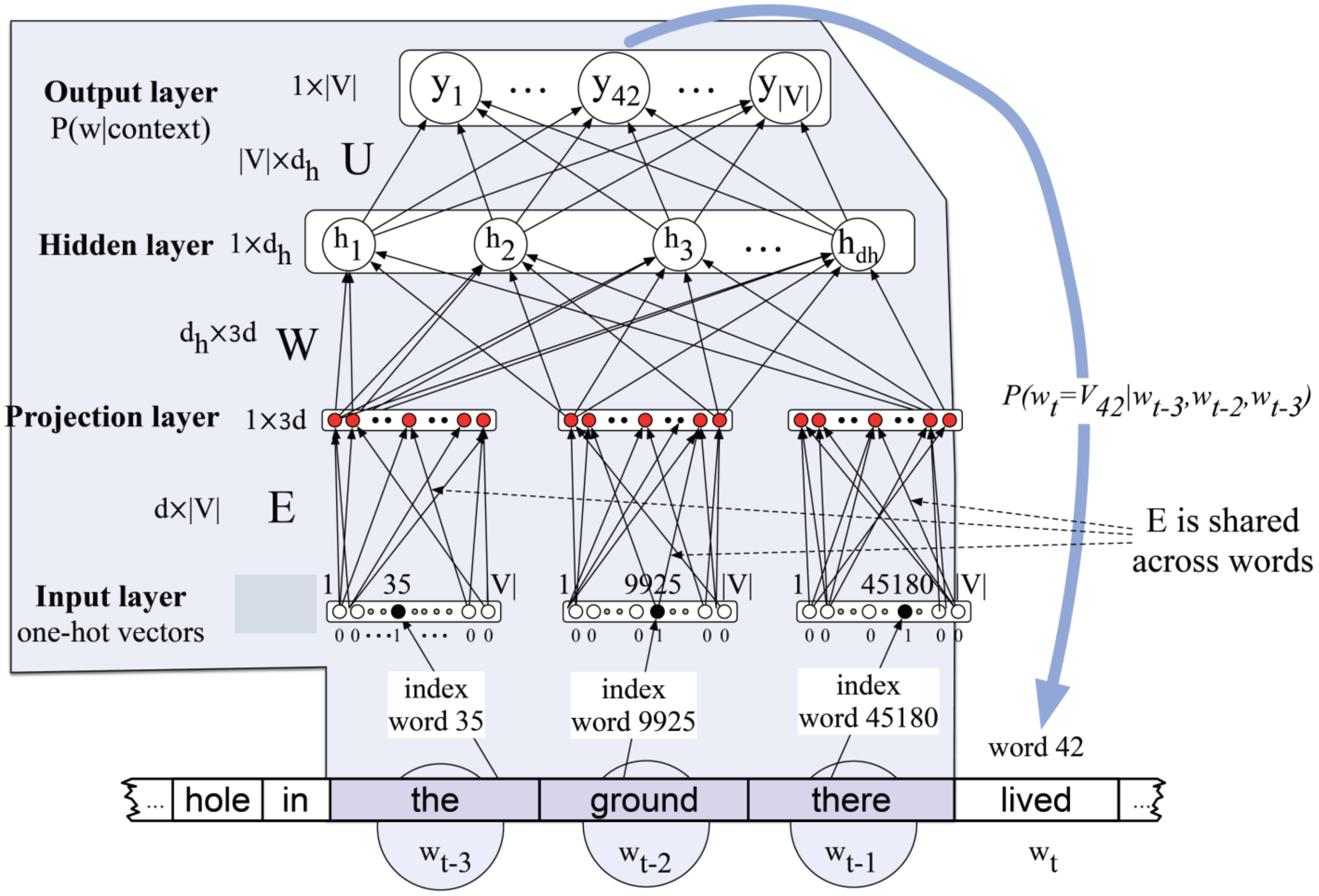
This is the same loss as the one we saw earlier for Multiclass Logistic Regression

- Loss function for a single example

$$L_{CE}(\hat{y}, y) = -\sum_{k=1}^{K} 1\{y = k\} \log p(y = k|x)$$

1{ } is an indicator function that evaluates to 1 if the condition in the brackets is true, and to 0 otherwise

Example: Parameter Estimation



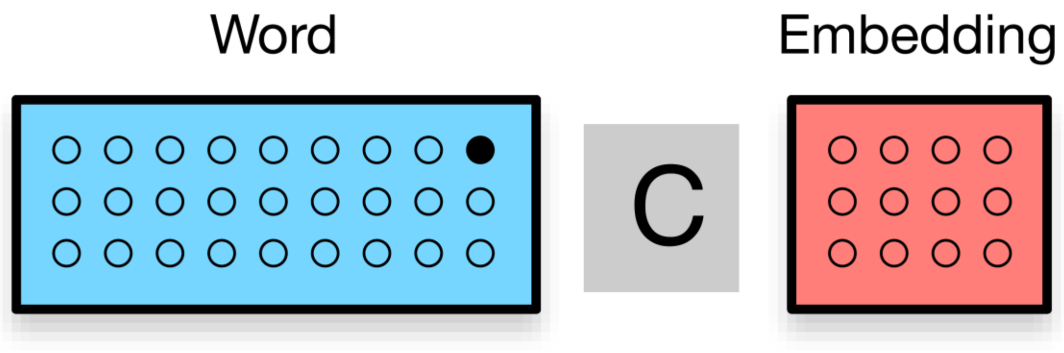
Loss function at each position t

$$L = -\log p(w_t | w_{t-1}, \ldots, w_{t-n+1})$$

Parameter update rule

$$\theta_{t+1} = \theta_t - \eta \frac{\partial - \log p(w_t | w_{t-1}, \ldots, w_{t-n+1})}{\partial \theta}$$

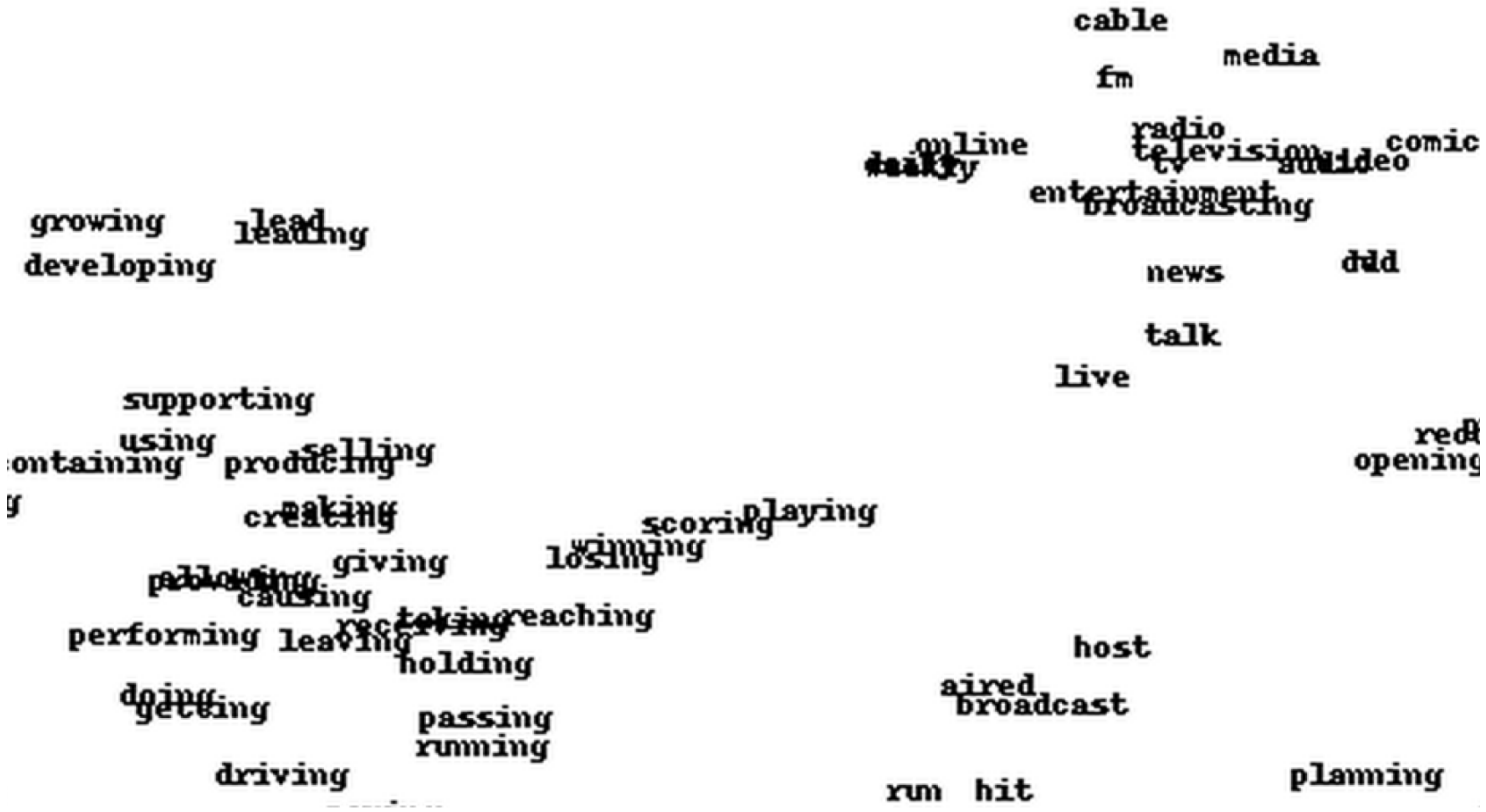
Word Embeddings: a useful by-product of neural LMs



- 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

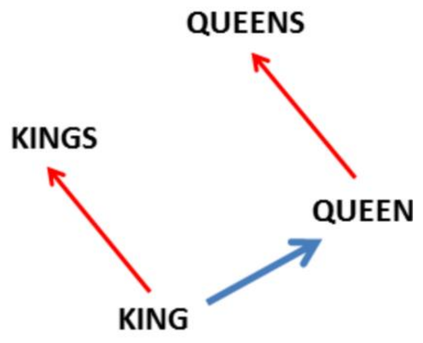


Word Embeddings Capture Useful Regularities

Morpho-Syntactic

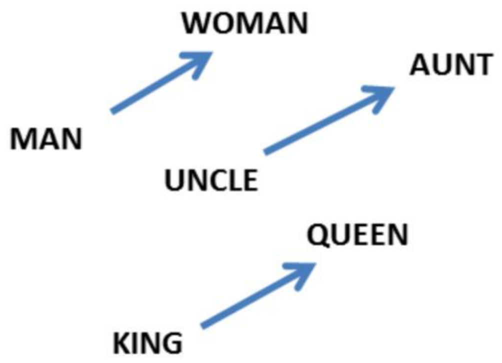
- Adjectives: base form vs. comparative
- Nouns: singular vs. plural
- Verbs: present tense vs. past tense

[Mikolov et al. 2013]

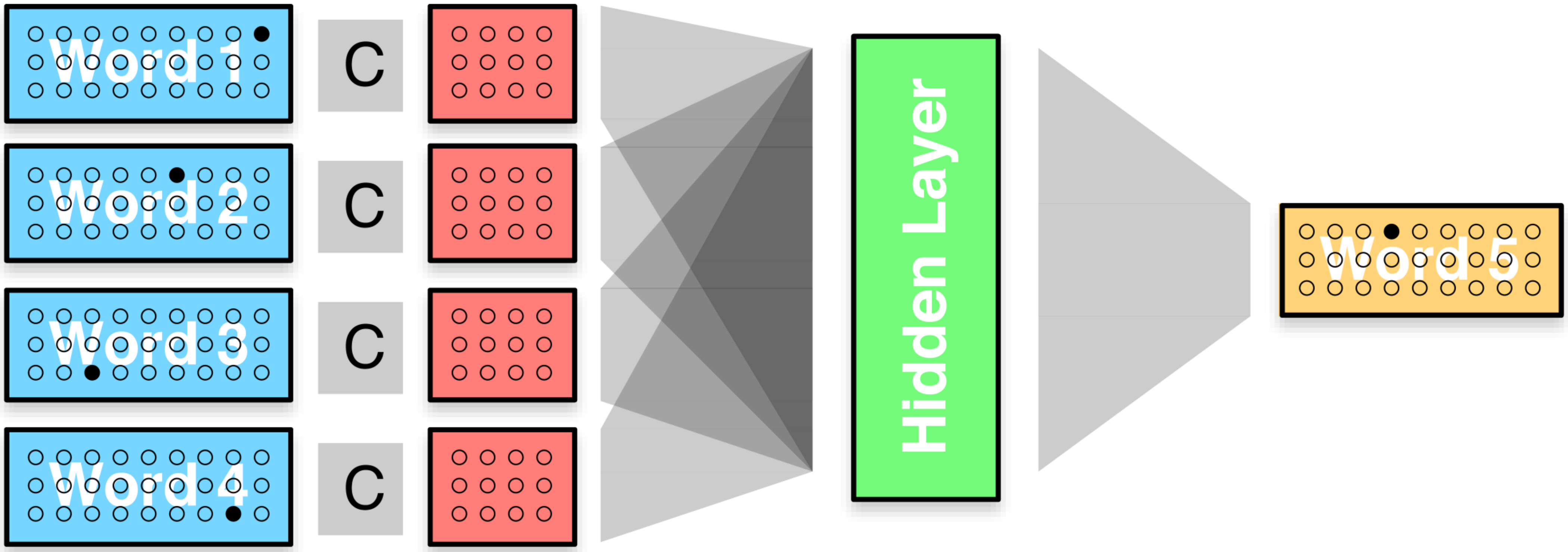


Semantic

- 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

Count-based n-gram models vs. feedforward neural networks

- Pros of feedforward neural LM
  - Word embeddings capture generalizations across word typesq

- Cons of feedforward neural LM
  - Closed vocabulary
  - Training/testing is more computationally expensive

- Weaknesses of both types of model
  - Only work well for word prediction if the test corpus looks like the training corpus
  - Only capture short distance context

Language Models
What you should know

- What is a language model
- N-gram language models
- Evaluating language models with perplexity
- Feedforward neural language models
  - Use a neural network as a probabilistic classifier to compute probability of the next word given the previous n words
  - Trained like any neural network by backpropagation
  - Learn word embeddings in the process of language modeling
- Strengths and weaknesses of n-gram and neural language models