CSC2515 Fall 2008
Introduction to Machine Learning

Applications of machine learning to language modeling

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Statistical language modelling

- Goal: Model the joint distribution of words in a sentence.

- Such a model can be used to
  - predict the next word given several preceding ones
  - arrange bags of words into sentences
  - assign probabilities to documents

- Applications: speech recognition, machine translation, information retrieval.

- Most statistical language models are based on the Markov assumption:
  - The distribution of the next word depends on only n words that immediately precede it.
  - This assumption is clearly wrong but useful – it makes the task much more tractable.

n-gram models

- n-gram models are simply conditional probability tables for $P(w_n|w_{1:n-1})$.
  - estimated by counting n-tuples of words and normalizing
  - smoothing the estimates is essential for good performance
  - many different smoothing methods exist
- n-gram models are the most widely used statistical language models due to their simplicity and excellent performance.
- Curse of dimensionality: number of model parameters is exponential in n.

Training n-gram models

- Let $\#s$ be the number of times a sequence of words s occurs in the training set.
- Then we can estimate a trigram model as follows:

$$P(w_3|w_1, w_2) = \frac{\#w_1 w_2 w_3}{\#w_1 w_2}$$

- Problem: if $w_3 w_2 w_1$ does occur in the training set, it is assigned zero probability.
- That's bad – the model does not generalize to new word triples!
- One solution: smooth the trigram estimates by interpolating them with the bigram estimates

$$P(w_3|w_1, w_2) = \lambda \times \frac{\#w_1 w_2 w_3}{\#w_1 w_2} + (1 - \lambda) \times \frac{\#w_2 w_3}{\#w_2}$$

- Can also smooth with the unigram estimates and the uniform distribution.

Why n-gram models are hopeless for large n

- n-gram models don't take advantage of the fact that some words are used in similar ways.
- Suppose you know that words *snow* and *rain* are used in similar ways, as are *Monday* and *Tuesday*.
- If you are told that the following sentence is probable:
  - *It's going to rain on Monday.*
- Then you can infer that the following sentence is also probable:
  - *It's going to snow on Tuesday.*
- n-gram models cannot generalize this way because all words are treated as arbitrary symbols, with each word being equally (dis)similar to all others.
- Using distributed representations for words allows similarity between words to be captured.

Distributed representations

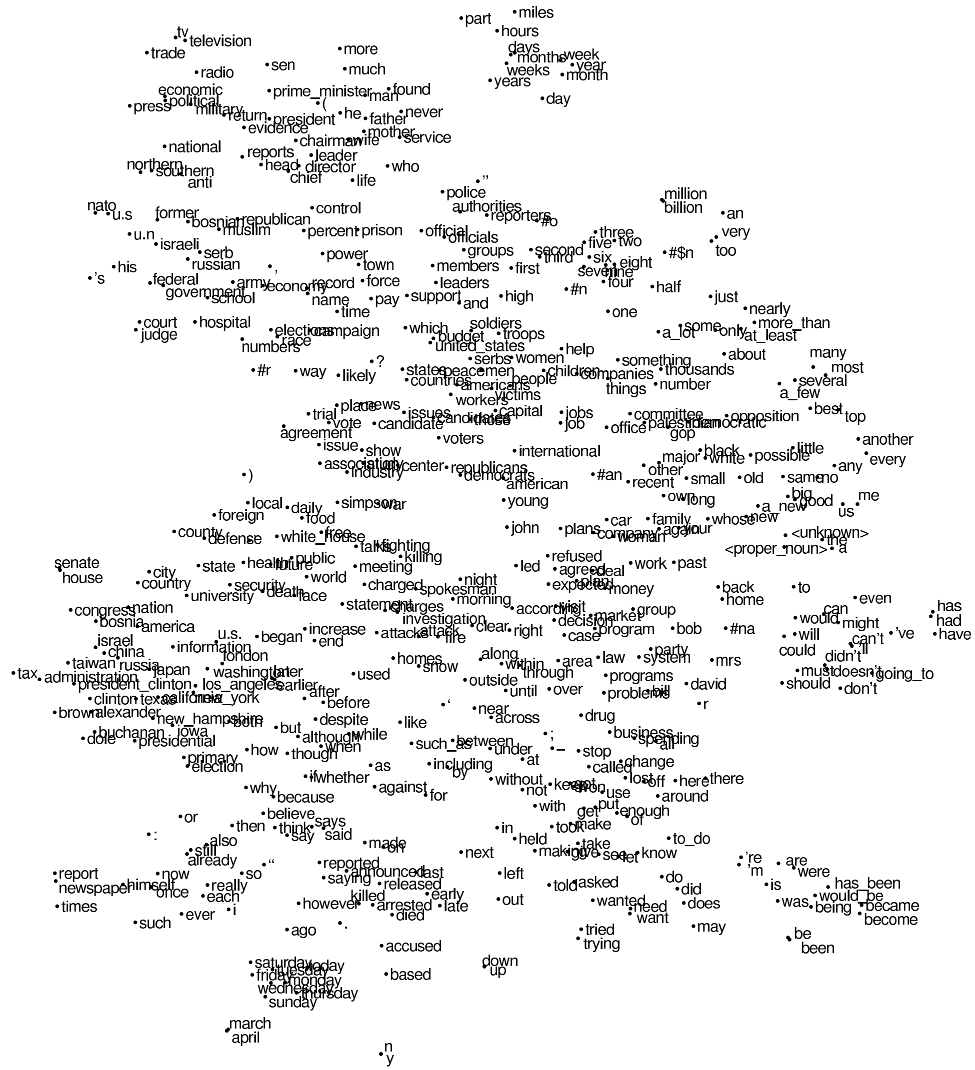
- Estimation of high-dimensional discrete distributions from data is hard.
  - the number of parameters is exponential
  - no a priori smoothness constraint on parameters / probabilities

- Estimation of distributions over continuous spaces is easier due to automatic smoothing.

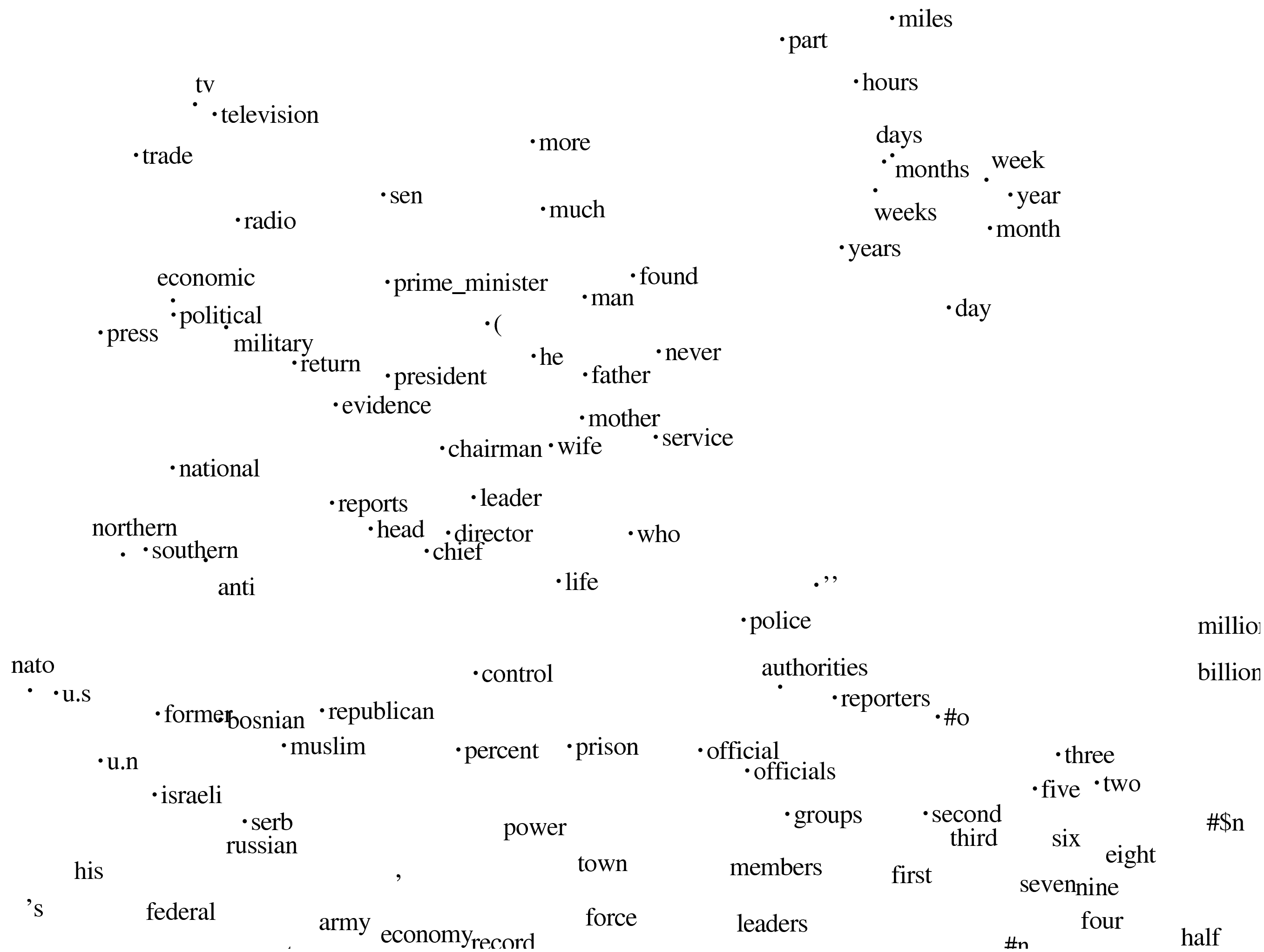
- Idea: map discrete inputs to continuous vectors and learn a smooth function that maps them to probability distributions.

- Used for language modelling with neural nets and Bayes nets.

Word representations embedded in 2D (I)



Word representations embedded in 2D (II)



Distributed / neural language models

- A number of neural probabilistic language models based on distributed representations have been proposed.
- Common approach:
  - Represent each word with a real-valued feature vector
  - Represent the context by the sequence of the context word feature vectors
  - Train a neural network to output the distribution for the next word from the context representation.
  - Learn word feature vectors jointly with other neural net parameters

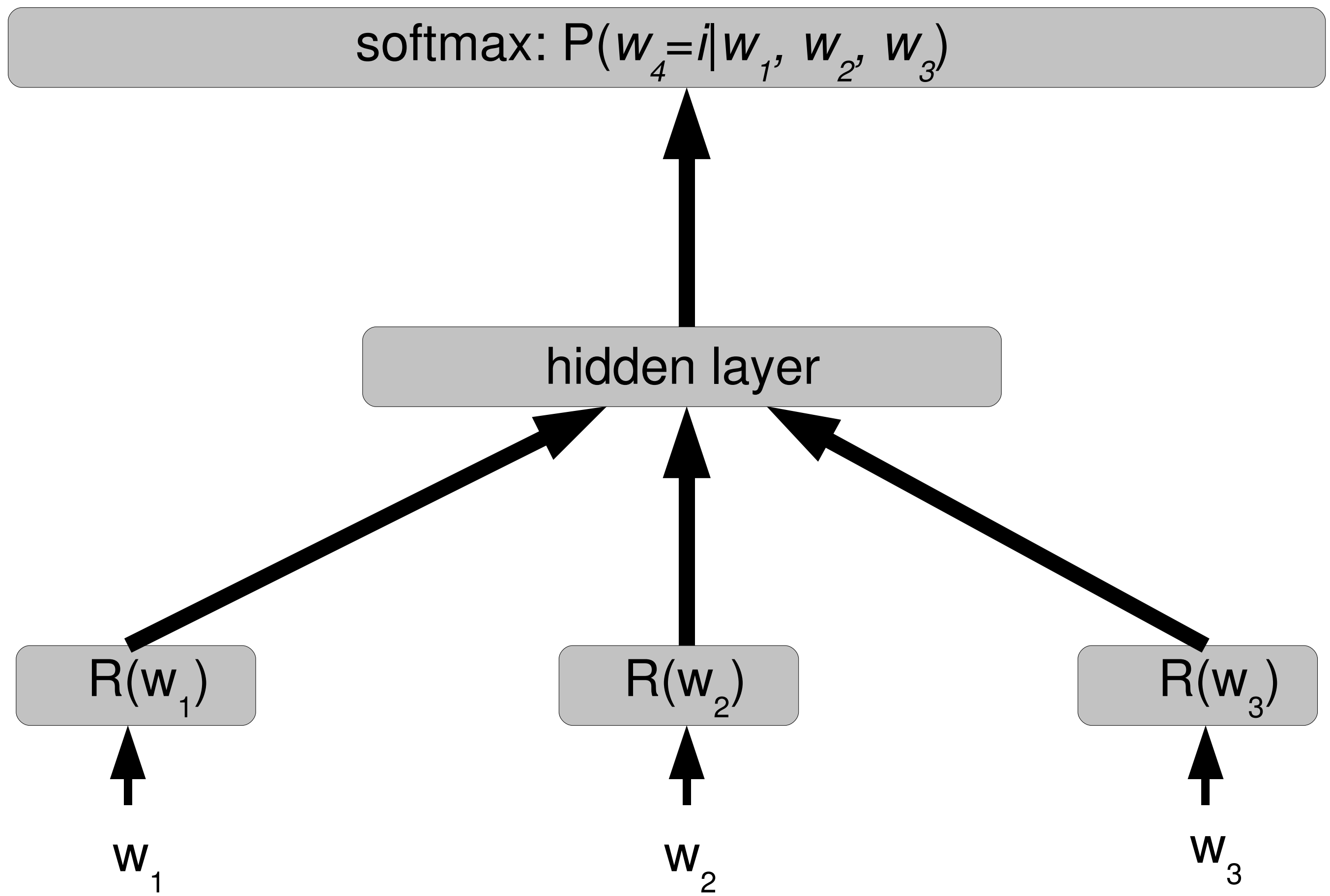
- Neural language models can outperform n-gram language models, especially when little training data is available.

- Main drawback: very long training and testing times.

Neural Probabilistic Language Model (Bengio et al., 2000)

- The original and still the most popular neural language model.
- A lookup table is used to map context words to feature vectors.
- Architecture: 1-hidden layer neural net
  - Input: sequence of the context word feature vectors.
  - Output: distribution over the next word (softmax over words).
- Outperforms n-gram models on small ($\sim$ 1M words) datasets.
- For better results, predictions of a NPLM are interpolated with those of an n-gram model.

Neural Probabilistic Language Model



Log-bilinear model (Mnih & Hinton, 2007)

- The LBL model is similar to the NPLM, but is simpler and slightly faster.
  - Does not have non-linearities.
- Given the context $w_{1:n-1}$, the LBL model predicts the representation for the next word w_n by linearly combining the representations for the context words:

$$\hat{r} = \sum_{i=1}^{n-1} C_i r_{w_i}$$

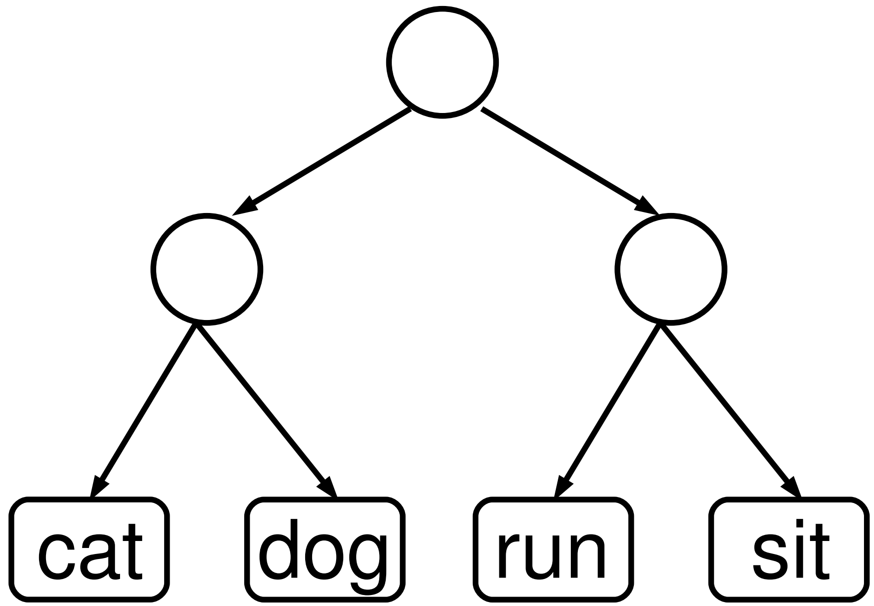
- Then the distribution for the next word is computed based on the similarity between the predicted representation and the representations of all words in the vocabulary:

$$P(w_n = w | w_{1:n-1}) = \frac{\exp(\hat{r}^T r_w)}{\sum_j \exp(\hat{r}^T r_j)}.$$

Structuring the vocabulary

- Computing the probability of the given word being the next word requires considering all N words in the vocabulary.
  - Need to normalize over all words because the space of words is unstructured.
- Idea (due to Bengio): Organize words in the vocabulary into a (somewhat balanced) binary tree and exploit its structure to speed up normalization.
  - Construct a binary tree over words
    - words are associated with leaf nodes
    - one word per leaf
  - Predicting the next word: replace one N-way decision by a sequence of $O(\log N)$ two-way decision.
    - Can achieve exponential speedup!

Tree-based factorization



- To define a distribution over leaf nodes:
  - Specify the probability of taking the left branch at each non-leaf node.
  - Then the probability of a leaf node is simply the probability of the sequence of left/right decisions that lead from the root node to the leaf node.

Approaches to tree construction

- The approach of Morin and Bengio:
  - Start with the WordNet IS-A hierarchy (which is a DAG)
  - Manually select one parent node per word
  - Use clustering to make the resulting tree binary
  - Use the NPLM model for making the left/right decisions

- Drawbacks: tree construction uses expert knowledge; the resulting model does not work as well as its non-hierarchical counterpart.
- An alternative (Mnih & Hinton, 2008):
  - Construct the word tree from data alone (no experts needed)
  - Allow each word to occur more than once in the tree
  - Use the simplified log-bilinear language model for making the left/right decisions

Hierarchical log-bilinear model (Mnih & Hinton, 2008)

- Let d be the binary string / code that encodes the sequence of left-right decisions in the tree that lead to word w.
- Each non-leaf node in the tree is given a feature vector that captures the difference between the words in its left and right subtrees.
- The probability of taking the left branch at a particular node is given by

$$P(d_i = 1 | q_i, w_{1:n-1}) = \sigma(\hat{r}^T q_i),$$

  where $\hat{r}$ is computed as in the LBL model and q_i is the feature vector for the node.
- Then the probability of word w being the next word is simply the probability of d under the binary decision model:

$$P(w_n = w | w_{1:n-1}) = \prod_i P(d_i | q_i, w_{1:n-1}).$$

Data-driven tree construction

- We would like to cluster words based on the distribution of contexts in which they occur.
- This distribution is hard to estimate and work with due to the high dimensionality of the space of contexts (the same sparsity problem n-gram models suffer from).

- To avoid this problem, we represent contexts using distributed representations and cluster words based on their *expected* context representation.
- To construct a word tree:
  1. Train a model using a random (balanced) tree over words.
  2. Compute the expected predicted representation over all occurrences of the given word.
  3. Perform hierarchical clustering on these expected representations.

Hierarchical clustering

- We "cluster" the feature vectors using top-down hierarchical clustering.
- At each step, we fit a mixture of two Gaussians with spherical covariances using EM to the current group of word representations.
- Once the mixture has been fit, we assign the words to the two components based on the mixture component responsibilities.
- We considered several splitting rules:
  - BALANCED: Sort the responsibilities and make the split to ensure a balanced tree.
  - ADAPTIVE: Assign the word to the component with the greater responsibility.
  - ADAPTIVE(ϵ): Assign the word to a component if its responsibility for the word is at least 0.5-ϵ.

Dataset and evaluation

- We compared the models on the APNews dataset:
  - A collection of Associated Press news stories (16 million words)
  - Training/validation/test split: 14M/1M/1M words
- Preprocessing (Bengio):
  - convert all words to lower case
  - map all rare words and proper nouns to special symbols
  - Result: just under 18000 unique words.
- Models were compared based on the perplexity they assigned to the test set.
- Perplexity is the geometric average of $\frac{1}{P(w_n|w_{1:n-1})}$.

Random vs. non-random trees

The effect of the feature dimensionality and the tree-building algorithm on the test set perplexity of the model.

Feature dimensionality	Perplexity using a RANDOM tree	Perplexity using a BALANCED tree	Reduction in perplexity
25	191.6	162.4	29.2
50	166.4	141.7	24.7
75	156.4	134.8	21.6
100	151.2	131.3	19.9

Model evaluation

Perplexity on the test set:

Model type	Tree generating algorithm	Perplexity	Minutes per epoch
HLBL	RANDOM	151.2	4
HLBL	BALANCED	131.3	4
HLBL	ADAPTIVE	127.0	4
HLBL	ADAPTIVE(0.25)	124.4	6
HLBL	ADAPTIVE(0.4)	123.3	7
HLBL	ADAPTIVE(0.4) $\times$ 2	115.7	16
HLBL	ADAPTIVE(0.4) $\times$ 4	112.1	32
LBL	–	117.0	6420
KN3	–	129.8	–
KN5	–	123.2	–

- LBL and HLBL used 100D feature vectors and a context size of 5.
- KNn is a Kneser-Ney n-gram model.

Observations

- Hierarchical distributed language models can outperform non-hierarchical models when they use sufficiently well-constructed trees over words.
  - Expert knowledge is not needed for building good trees.
  - Allowing words to occur more than once in a tree is essential for good performance.

- Even when very large trees are used, the hierarchical LBL model is more than two orders of magnitude faster than the LBL model.

THE END