Midterm Review

Topics to Go Over

- TF-IDF
- Logistic Regression
- Feature Engineering
- Word2Vec
- Recurrent Neural Network

TF-IDF

- Helps us with ranked retrieval
 - User's query + document corpus and compute score for every document compared to query, and how relevant they are
- General idea
 - Vectors that encode both the query and the document
 - Take similarity of vectors as a proxy for relevance!

TF-IDF

- If a word appears a lot in the document, it's probably relevant to that document (i.e if I have a document discussing pasta, and I see the word pasta 50 times, it's definitely relevant!)
- Not all words are equally useful (the, of, a)
- TF: Term Frequency
 - How often does an individual word appear in the document?
- IDF: Inverse Document Frequency
 - How many documents does a word appear in?
- If a word appears a lot in a given document, it's probably important.
 - BUT if a word appears in many documents, probably not as important

TF-IDF

$$w_{i,j} = f_{i,j} \log (D / d_i)$$

- Weight of word i in document j
- f_{i, j} = frequency of word i in document j
 - Divide number of times word appears in a document by the total number of words in the document
- D = total number of documents in collection
- d_i = number of times word appears in any document in corpus
- Vector representation of both search queries and documents

TF-IDF Example

Doc 1	I love cats. Cats are cute.
Doc 2	I love animals, animals are loyal.
Doc 3	I love birds and cats.

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$$f(cat, doc1) = 2$$

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Doc 1	I love cats. Cats are cute.
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Term Frequency (Cats) in document 1:

$$f(cat, doc1) = 2$$

Inverse Document Frequency:

$$N = 3$$

 $df(cats) = 2$

$$IDF = log(3/2)$$

TF-IDF Examples (2)

Doc 1: He loves to watch basketball and baseball but prefers basketball

Doc 2: Janet likes to play basketball

Doc 3: Julia loves to play baseball, and wishes she could play more often

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- 1. Tf-idf of "basketball" in Doc 1 = ?
- 2. Tf-idf of "play" in Doc 2 = ?
- 3. Tf-idf of "she" in Doc 3 = ?
- 4. Tf-idf of "baseball" in Doc 3 = ?

TF-IDF Examples (2)

Doc 1: He loves to watch basketball and baseball but prefers basketball

Doc 2: Janet likes to play basketball

Doc 3: Julia loves to play baseball, and wishes she could play more often

- 1. Tf-idf of "basketball" in Doc $1 = (2/10) * \log (3/2)$
- 2. Tf-idf of "play" in Doc $2 = (\frac{1}{5}) * \log (3 / 2)$
- 3. Tf-idf of "she" in Doc $3 = (1/12) * \log (3 / 1)$
- 4. Tf-idf of "baseball" in Doc 3 = 0 (if you didn't use nltk.word_tokenize() and just did a.split()!)

- Algorithm
- Simple workout examples
- Softmax function
- Back propagation and Gradient Descent

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- Examples: χ_i
- Bias term: β_0
- $\exp(x) \rightarrow e^x$
- Logistic function $\sigma(z) = \frac{1}{1+e^{-z}}$ squashes numbers into [0,1]

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Softmax
$$P(Y=0|X) = \frac{1}{1 + \exp\left[\beta_0 + \sum_i \beta_i X_i\right]}$$
$$P(Y=1|X) = \frac{\exp\left[\beta_0 + \sum_i \beta_i X_i\right]}{1 + \exp\left[\beta_0 + \sum_i \beta_i X_i\right]}$$

Logistic Regression in Vector Form

- Logistic Regression is an example of classification (instead of predicting a real number, i.e house price, age of child, etc), we'll predict probabilities of a set of outcomes
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- Examples: X_i
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Imagine we have feature vector $x_i = [1, 2, 2]$ and corresponding actual label $y_i = 1$ for the ith example in our training set.

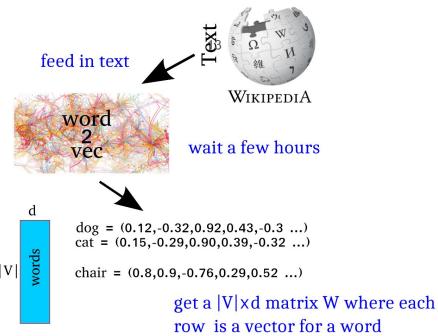
Suppose we have our current parameter vector be $\beta = [-1, 2, -1]$.

Q1. Which class will the logistic regression classifier predict at this stage?

Class Example: https://users.umiacs.umd.edu/~ying/teaching/CMSC_470/lr_ex.pdf

Word2Vec

 Represent words with their meaning (semantics)



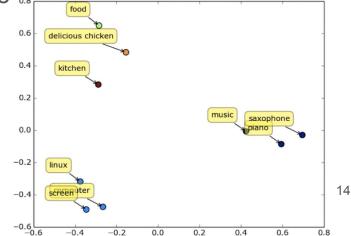
Word2Vec

 Distributional hypothesis: Learn something about a meaning of a word based on the other words it appears with

Encode words with similar context to be 0.8
close in some vector space

How to measure similarity?

cosine similarity!

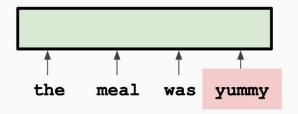


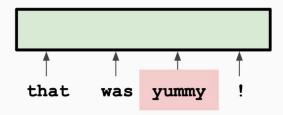
https://users.umiacs.umd.edu/~jbg/teaching/CMSC_470/06b_word2vec.pdf

RNN

Network Architecture

- Why RNNs? Why not feedforward neural networks (or FFNNs)?
 - Variable length input sequences are naturally varying in length
 - With FFNNs, each position in the input embedding has some fixed semantics





- Ideally, we can process these tokens in a uniform manner
- Exploit context!

Adapted from Greg

RNN Computation

For each time step computation, the hidden unit computation is:

$$egin{aligned} h_t &= f(W_{xh}x_t + W_{hh}h_{t-1}) \ & \ y_t &= W_{hy}h_t \end{aligned}$$

f is activation function. (tanh)

RNN Computation (Example)

For each time step computation, the hidden unit computation is:

$$h_t = f(W_{xh}x_t + W_{hh}h_{t-1})$$
 $y_t = \operatorname{softmax}(W_{hy}h_t)$ $x_1 = \begin{bmatrix} 1 \ 0 \end{bmatrix}, \quad x_2 = \begin{bmatrix} 0 \ 1 \end{bmatrix}, \quad x_3 = \begin{bmatrix} 1 \ 1 \end{bmatrix}$

$$W_{xh} = egin{bmatrix} 0.5 & 0.2 \ 0.1 & 0.3 \end{bmatrix}, \quad W_{hh} = egin{bmatrix} 0.4 & 0.1 \ 0.2 & 0.5 \end{bmatrix}, \quad h_0 = egin{bmatrix} 0 \ 0 \end{bmatrix} \quad W_{hy} = egin{bmatrix} 1 & -1 \ -1 & 1 \ 0.5 & 0.5 \end{bmatrix} ext{ donut fish burger}$$

What is next word?

Concepts Need to know

TF-IDF / Information Retrieval

- What is TF? IDF?
- How are TF-IDF terms computed?
- How does a TF-IDF system work in practice?
- What does TF-IDF frequency and Rank plot look like?
- What are some of the drawbacks of TF-IDF systems?

Distributional Semantics

- What is distributional semantics?
- What is word2vec, how does it work?
- What are context vectors and Weight vectors? How are they computed?

Regression

- What is linear regression?
- Logistic regression?
 - What is the logistic function?
- How to interpret logistic regression weights?
- Evaluation: how to interpret confusion matrix for binary classification

Recurrent Neural Networks

- What is Embedding from Language Models? How is it used in RNN?
- How do you initialize weights for a neural network?

More Concepts Need to know

Byte Pair Encoding (BPE)

- How does it work?
- How does BPE differ from traditional word-level tokenization?
- How to handle new (unseen) tokens?
- Go through homework BPE implementation.

Hidden Markov Models

- What is HMM used for?
- Describe how it works.

Dependency Parsing and Part-of-Speech

- What is the meaning of parsing objective?
- What is POS?
- What models are usually used to train POS?
- Evaluation: how to evaluate POS? What are some metrics?

Adam

Basic computation of Adam