SIT330-770: Natural Language Processing

Week 7 - Neural Networks and Neural LMs

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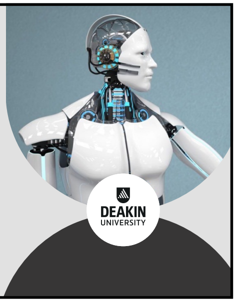

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Andrew Ng

Neural Networks and Deep Learning

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SIT330-770: Natural Language Processing

Week 7.11 - Applying feedforward networks to NLP tasks

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Use cases for feedforward networks

- Let's consider 2 (simplified) sample tasks:

1. Text classification
2. Language modeling

- State-of-the-art systems use more powerful neural architectures, but simple models are useful to consider!

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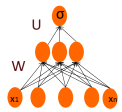
Classification: Sentiment Analysis

- We could do exactly what we did with logistic regression
- Input layer are binary features as before
- Output layer is 0 or 1



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Sentiment Features

Var	Definition
x_1	count(positive lexicon) $\in$ doc)
x_2	count(negative lexicon) $\in$ doc)
x_3	$\begin{cases} 1 & \text{if "no"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_4	count(1st and 2nd pronouns $\in$ doc)
x_5	$\begin{cases} 1 & \text{if "!"} \in \text{doc} \\ 0 & \text{otherwise} \end{cases}$
x_6	log(word count of doc)

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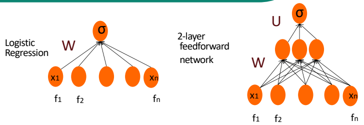
Feedforward nets for simple classification



- Just adding a hidden layer to logistic regression
  - allows the network to use non-linear interactions between features
  - which may (or may not) improve performance.

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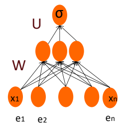
Even better: representation learning

- The real power of deep learning comes from the ability to **learn** features from the data
- Instead of using hand-built human-engineered features for classification
- Use learned representations like embeddings!



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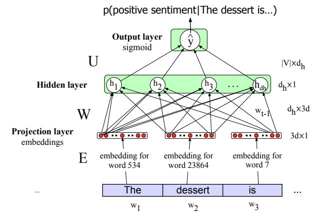
Neural Net Classification with embeddings as input features!



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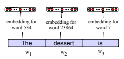
Issue: texts come in different sizes



- This assumes a fixed size length (3)!
- Kind of unrealistic.
- Some simple solutions (more sophisticated solutions later)

1. Make the input the length of the longest review
   - If shorter then pad with zero embeddings
   - Truncate if you get longer reviews at test time
2. Create a single "sentence embedding" (the same dimensionality as a word) to represent all the words
   - Take the mean of all the word embeddings
   - Take the element-wise max of all the word embeddings
     - For each dimension, pick the max value from all words

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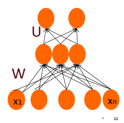
Reminder: Multiclass Outputs

- What if you have more than two output classes?
  - Add more output units (one for each class)
  - And use a "softmax layer"

$$\text{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad 1 \le i \le D$$



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Neural Language Models (LMs)

- **Language Modeling**: Calculating the probability of the next word in a sequence given some history.
  - We've seen N-gram based LMs
  - But neural network LMs far outperform n-gram language models
- State-of-the-art neural LMs are based on more powerful neural network technology like Transformers
- But **simple feedforward LMs** can do almost as well!

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Simple feedforward Neural Language Models

Task: predict next word w_t

given prior words $w_{t-1}, w_{t-2}, w_{t-3}, \ldots$

Problem: Now we're dealing with sequences of arbitrary length.

Solution: Sliding windows (of fixed length)

$$P(w_t|w_1^{t-1}) \approx P(w_t|w_{t-N+1}^{t-1})$$

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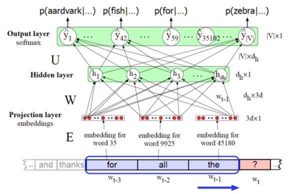
Neural Language Model



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Why Neural LMs work better than N-gram LMs

- **Training data:**
  - We've seen: I have to make sure that the cat gets fed.
  - Never seen: dog gets fed
- **Test data:**
  - I forgot to make sure that the dog gets ___
- N-gram LM can't predict "fed"!
- Neural LM can use similarity of "cat" and "dog" embeddings to generalize and predict "fed" after dog

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