EE 628
Deep Learning
Fall 2019

Lecture 9

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Overview

- Last lecture we covered
  - Modern Convolutional Neural Networks

- Today, we will cover
  - Text Processing
  - Recurrent Neural Networks

Recurrent Neural Networks

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- For instance, the words written here are in sequence, and would be hard to understand if you permute randomly.
- Likewise, image frames in a video, the audio signal in a conversation, or the browsing behavior on a website, all follow sequential order.
- Thus we need specialized models for such data.

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- While CNNs process spatial information, RNNs are designed to better handle sequential information.
- These networks introduce state variables to store past information and, together with the current input, determine the current output.
- Many of the examples for using RNNs are based on text data. Hence, we will emphasize language models in this lecture.

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- Let's denote the prices by $x_t \geq 0$.
- For traders to do well in the stock market on day t, they want to predict x_t via

$$x_t \sim p(x_t | x_{t-1}, \ldots x_1).$$

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  2. Keep some summary h_t of the past observations around and update that in addition to the actual prediction. This leads to models that estimate $p(x_t, x_{t-1}, h_{t-1})$ and moreover updates of the form $h_t = g(h_{t-1}, x_{t-1})$. These models are called latent autoregressive models. LSTMs and GRUs are examples of this.

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- A common assumption is that while the specific values of x_t might change, at least the dynamics of the time series itself won’t.
- Statisticians call dynamics that don’t change stationary.
- Regardless of what we do, we will thus get an estimate of the entire time series via

$$p(x_1, \ldots x_T) = \prod_{t=1}^{T} p(x_t | x_{t-1}, \ldots x_1).$$

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- Such models are particularly nice since dynamic programming can be used to compute values along the chain exactly.

$$p(x_{t+1} | x_{t-1}) = \sum_{x_t} p(x_{t+1} | x_t) p(x_t | x_{t-1}).$$

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- In many cases, however, there exists a natural direction for the data, namely going forward in time.
- It is clear that future events cannot influence the past.

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  3. Builds a vocabulary for these tokens to map them into numerical indices
  4. Maps all tokens in the data into indices to facilitate to feed into models

Open notebook IN_CLASS Text_Data_Example.ipynb

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- Language models are incredibly useful. For instance, an ideal language model would be able to generate a natural text just on its own by drawing one word at a time

$$w_t \sim p(w_t | w_{t-1}, \ldots w_1).$$

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- For example, the probability of a text sequence containing four tokens consisting of words and punctuation would be given as:

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- In order to compute the language model, we need to calculate the probability of a word given the previous few words.

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- Moving on, we could attempt to estimate $\hat{p}(\text{is}|\text{Statistics}) = \dfrac{n(\text{Statistics is})}{n(\text{Statistics})}$.
- Estimating the probability of a word pair is somewhat difficult, since the occurrences of 'Statistics is' are a lot less frequent. Things get worse for 3 word combinations.

Estimating a language model

- Laplace Smoothing: add a small constant to all counts.
- Unfortunately, models like this get unwieldy rather quickly:
    - we need to store all counts
    - This entirely ignores the meaning of the words

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- Higher orders correspond to longer dependencies.
- This leads to a number of approximations that we could apply to a model sequence:

$$p(w_1, w_2, w_3, w_4) = p(w_1)p(w_2)p(w_3)p(w_4) \longrightarrow \text{unigram}$$

$$p(w_1, w_2, w_3, w_4) = p(w_1)p(w_2|w_1)p(w_3|w_2)p(w_4|w_3) \longrightarrow \text{bigram}$$

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