APS360 Fundamentals of AI

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Lecture 9; Feb 7, 2019

Agenda

- Project
- Unsupervised Learning
- Autoencoders (continued)
- Word Embeddings

Group Project

Guidelines

https://www.cs.toronto.edu/~lczhang/360/project.html

Teams

- Teams of 3 only
- Teams of 2 or 4 only if there are extremuous circumstances, or if there is an odd number of people
 - Let me knows ASAP

Examples

- http://www.eecg.utoronto.ca/~jayar/mie324/sortinghat.pdf
- http://www.eecg.utoronto.ca/~jayar/mie324/hawkeye.pdf
- http://www.eecg.utoronto.ca/~jayar/mie324/musicgenre.pdf
- http://www.eecg.utoronto.ca/~jayar/mie324/sparselang.pdf
- http://www.eecg.utoronto.ca/~jayar/mie324/enhance.pdf
- http://www.eecg.utoronto.ca/~jayar/mie324/highhoeps.pdf

Project Uniqueness

Each project must be unique

- The goal must be unique
- The dataset used must be unique
- Send an email to Lisa with 1-2 sentence description of topic
 - "you have uniqueness approval"
 - "please try again, that topic is taken"

You must obtain uniqueness approval by Feb 15th 9pm.

Where to get datasets?

- Collect your own
- Kaggle https://www.kaggle.com/
- UCI ML Repo https://archive.ics.uci.edu/ml/index.php
- https://medium.com/datadriveninvestor/the-50-best-publicdatasets-for-machine-learning-d80e9f030279

There must be a data cleaning component to your project.

Project Timeline

- Proposal (Feb 24)
- Progress Meeting (Mar 4-11)
- Progress Report (Mar 17)
- Presentation Slides (Mar 29)
- Project Report (Apr 5)

Project Repository

- Open source repository on GitHub
- Speak to be regarding alternatives if you don't want your code to be open source

Project Proposal

- Maximum of 1200 words
- Sections:
 - Introduction
 - Source of Data
 - Overall Structure of your software
 - Plan
 - Risks
 - Things to Learn
 - Ethical Issues
 - References

Project Proposal Word Limit

- ▶ There is a 1% penalty for every word in excess of the 1200 limit
- Please count the words in your document, compute the penalty, and put it on the front page.
- If you can present your ideas in much less than 1200 words, please do so.

Office Hours

More to be posted...

Unsupervised Learning

Supervised vs Unsupervised Learning

Supervised Learning:

- Predict an output/target feature given the input features
- Use labelled data

Unsupervised Learning:

- Unlabelled data, no clear target
- The goal is to find "structure" in the data
 - find clusters
 - generate new data

Classification vs Regression

Classification:

- A type of supervised learning problem where the target feature is categorical
 - Cancer vs no cancer
 - Cats vs dogs
 - Digits 0-9

Regression:

- A type of supervised learning problem where the target feature is continuous
 - Predict real-estate value
 - Predict stock price

Building an "Autoencoder" like last week is an example of unsupervised learning

- No target labels
- Find a low-dimensional representation of digits
- Denoising (e.g. removing noise in an image)
- Inpainting (e.g. filling in an image)
- Imputing missing features

Why low-dimensional embedding?

What happens if we used a high-dimensional representation?

Representation Learning

- Finding a low-dimensional embedding of some data is a common unsupervised learning task
- It can be a pre-cursor to other tasks (e.g. clustering)

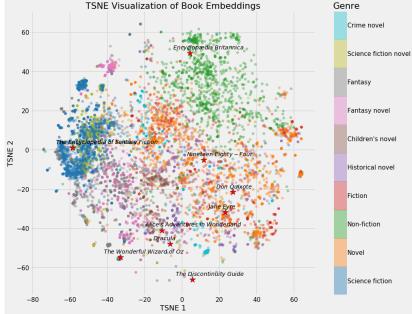
Denoising Autoencoder Example

https://cs.stanford.edu/people/karpathy/convnetjs/demo/auto

Snapshot of 2D Representation

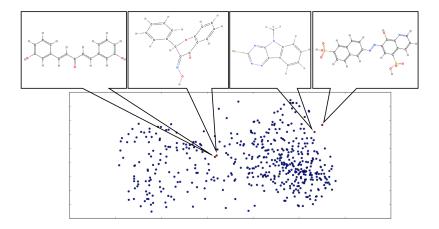


Embedding of Books



https://towardsdatascience.com/neural-network-embeddings-evplained-4d028e6f0526

Embedding of Molecules



https://openreview.net/pdf?id=BkSqjHqxg

How to train embeddings

- Encoder: data -> embedding
- Decoder: embedding -> data

How to train embeddings (alternative)

- Encoder: data -> embedding
- Decoder: embedding -> data some feature of the data

How to train embeddings (denoising)

- Encoder: noisy data -> embedding
- Decoder: embedding -> denoised data

Word Embeddings

History

- ▶ The term "Word embedding" coined in 2003 (Bengio et al.)
- word2vec model proposed in 2013 (Mikolov et al.)
- GloVe vectors released in 2014 (Pennington et al.)

Training Word Embedding

- Encoder: word(??) -> embedding
- Decoder: embedding -> ???

How do we encode the word?

What is our target?

One-hot embedding

- Used for categorical features
- Each word has its own "index"

One-hot embedding as input to the encoder

- Encoder: one-hot embedding -> low-dim embedding
- Decoder: low-dim embedding -> ???

Taking a step back

- What data do we have?
 - ► Large corpus of text (e.g. wikipedia, news article, tweets, etc)
- What determines the "meaning" of a word?
- What properties do we want our embedding space to have?

- Hard to find the meaning of a word on its own
- Figure out meaning of words based on its context nearby words

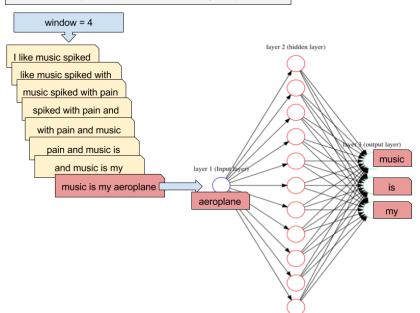
There is evidence that children learns words this way!

Key idea

- Encoder: one-hot embedding -> low-dim embedding
- Decoder: low-dim embedding -> nearby words

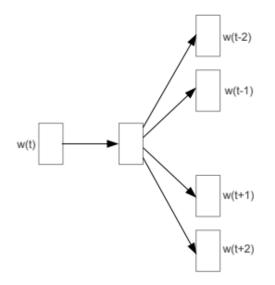
Architecture

I like music spiked with pain and music is my aeroplane ...



Skip-Gram Model

INPUT PROJECTION OUTPUT



Structure

https://nlp.stanford.edu/projects/glove/ https://github.com/stanfordnlp/GloVe

Language Modelling Tasks

- Text generation, correction, completion, summarization
- Image captioning
- Machine Translation
- Sentiment Analysis
- Named entity detection