Understanding Semantics and Context in Learned Word Representations

EECS 273

Akshay Bhatia

MS EECS @ UC Merced
akshaybhatia10.github.io

Table of contents

Introduction

Introduction

"After stealing money from the **bank vault**, the **bank robber** was seen fishing on the Mississippi **river bank**."

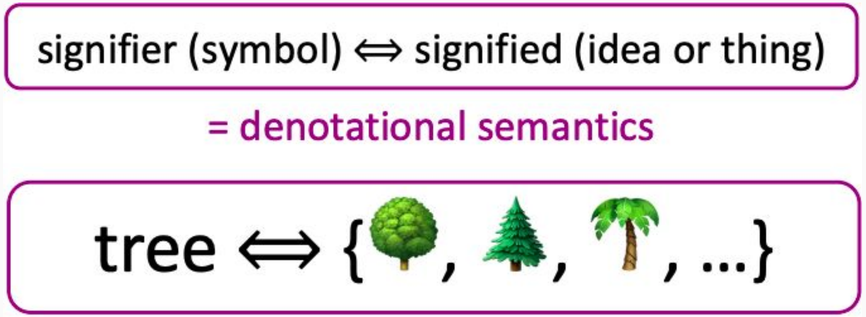
"You shall know a word by the company it keeps" (J. R. Firth 1957: 11)

Goal

What is meaning of a word? → The idea that a person wants to express

Problem: How to represent that idea?

Solution: Linguistic way of thinking about meaning



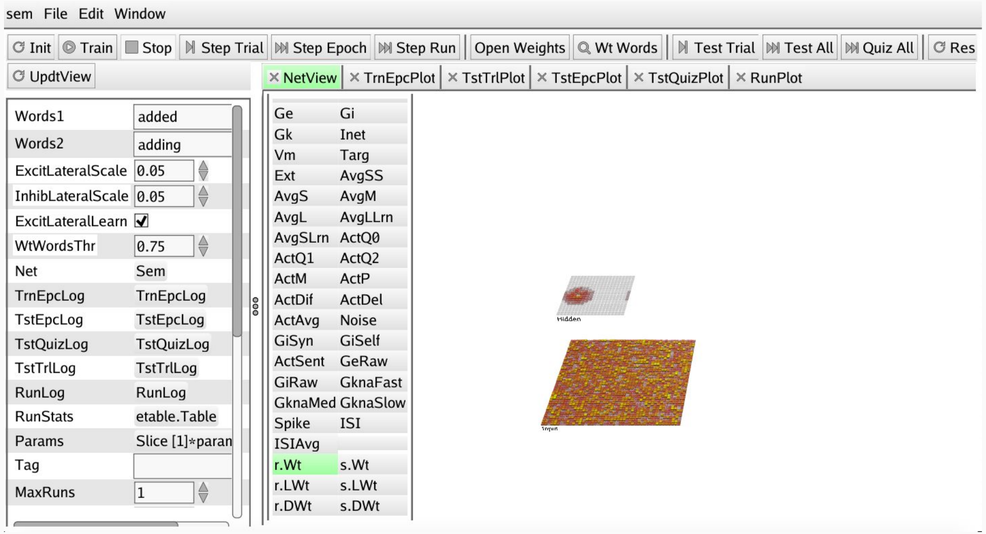
Source: CS224n Stanford

Models

- Leabra Hebbian Word Semantics Model
- Co-occurrence Matrix
- Bag of Words
- Word Embeddings - word2vec
- Transformer Language Models - BERT

Leabra Hebbian Word Semantics Model

- Understand word meaning by company it keeps - statistics of word co-occurrence
- Uses BCM-style learning mechanism
- Includes recurrent lateral excitatory and inhibitory connections
- As in the ***'sem'*** simulation Ch. 9



Co-occurrence Matrix

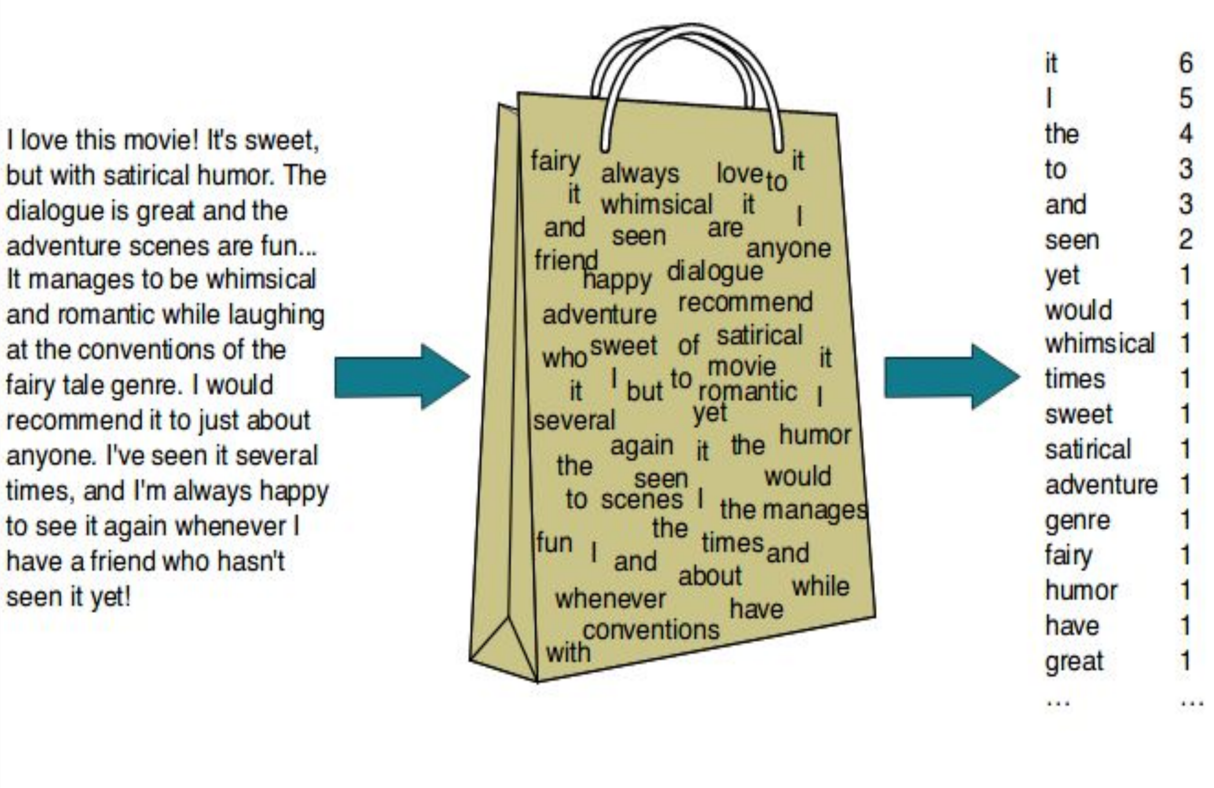
"After stealing money from the **bank vault**, the **bank robber** was seen fishing on the Mississippi **river bank**."

- Start with a *n* x *n* matrix where *n* is vocab size
- Record co-occurrence for each word in a specific window size, say 5
- No learning required

	after	bank	fishing	from	mississippi	money	on	river	robber	seen	stealing	the	vault	was
after	0	1	0	1	0	1	0	0	0	0	1	1	0	0
bank	1	1	2	2	1	1	2	1	2	1	1	5	2	2
fishing	0	2	0	0	1	0	1	1	1	1	0	2	0	1
from	1	2	0	0	0	1	0	0	0	0	1	2	1	0
mississippi	0	1	1	0	0	0	1	1	0	1	0	1	0	1
money	1	1	0	1	0	0	0	0	0	0	1	2	1	0
on	0	2	1	0	1	0	0	1	1	1	0	1	0	1
river	0	1	1	0	1	0	1	0	0	1	0	1	0	0
robber	0	2	1	0	0	0	1	0	0	1	0	3	1	1
seen	0	1	1	0	1	0	1	1	1	0	0	2	1	1
stealing	1	1	0	1	0	1	0	0	0	0	0	1	1	0
the	1	5	2	2	1	2	1	1	3	2	1	1	2	2
vault	0	2	0	1	0	1	0	0	1	1	1	2	0	1
was	0	2	1	0	1	0	1	0	1	1	0	2	1	0

Bag of Words

- Represent a sentence as bag(multiset) of its words
- Disregards grammar and word order while keeping multiplicity
- No learning required



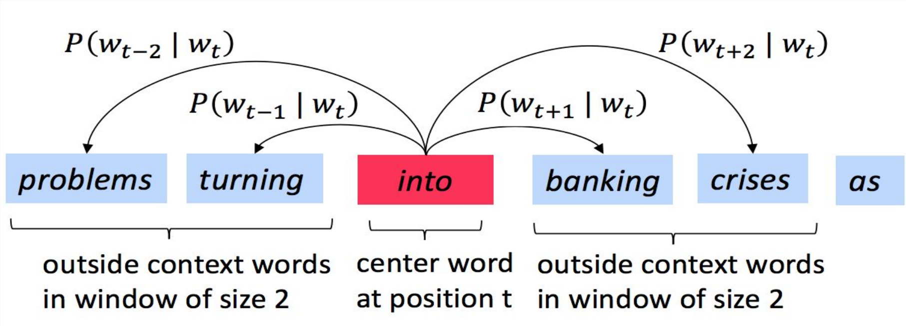
Source: https://dudeperf3ct.github.io/lstm/gru/nlp/2019/01/28/Force-of-LSTM-and-GRU/

Word Embeddings - word2vec

- Represent each word in some *n*-dimensional space
- **Idea: A word's meaning is given by the words that frequently appear close-by**
- Trained on large text corpus from co occurrence statistics

Football →

0.2	1.2	0.4	2.9	1.8	0.3

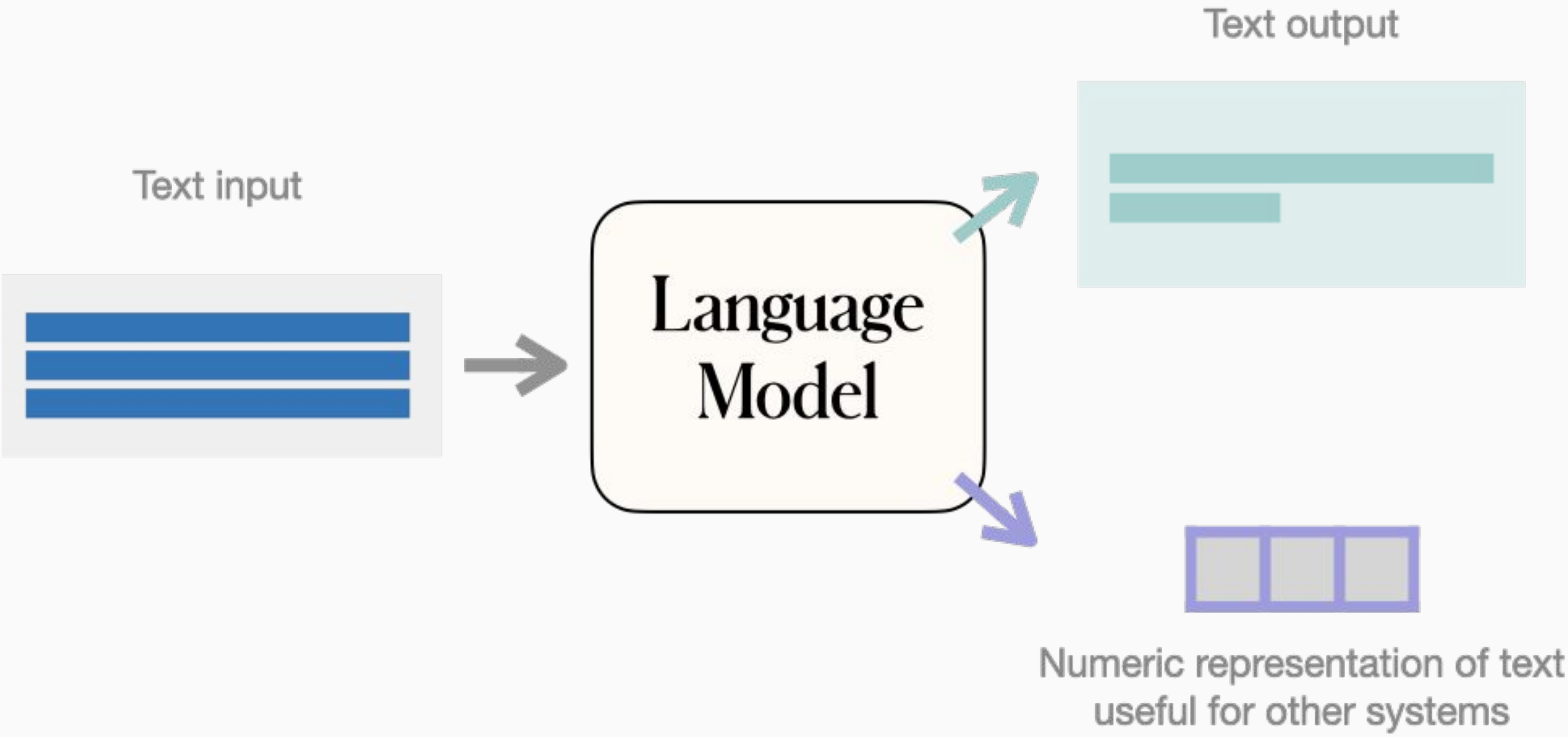


Source: CS224n Stanford

Problems solved:

- Encode general semantic relationship
- Incorporate similarity between words
- Fixed vector size for every word(50, 100, 300) instead of vocab size
- Word order remains intact

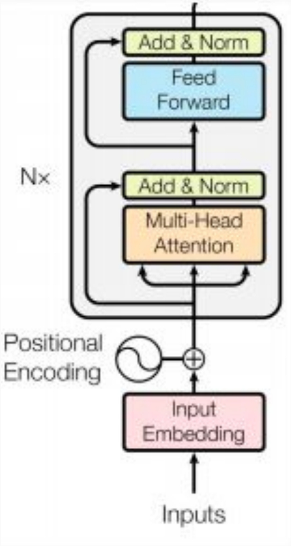
Transformer Language Models - BERT

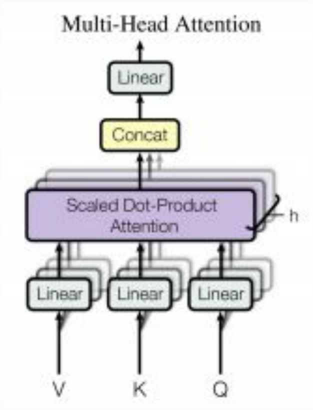


Transformer Language Models - BERT

- BERT(Bidirectional Encoder Representations from Transformers) by Devlin et. al 2018
- Large Neural Network with billions of parameters
- Trains 2 *auxiliary* tasks:
    - Masked Language Model
    - Next sentence prediction
- Outperforms all other models on many NLP benchmarks

Transformer Architecture





Masked Language Modelling Task

```
                        store                  gallon
                          ↑                      ↑
the man went to the [MASK] to buy a [MASK] of milk
```

Next Sentence Prediction Task

Sentence A = `The man went to the store.` **Sentence B** = `He bought a gallon of milk.` **Label** = `IsNextSentence`	**Sentence A** = `The man went to the store.` **Sentence B** = `Penguins are flightless.` **Label** = `NotNextSentence`

Source: BERT. Devlin et. al 2018

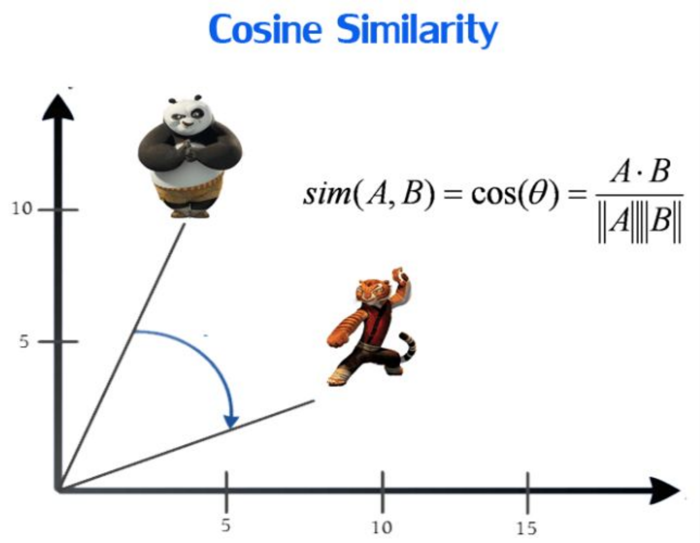
Experiments and Results

Experiments

Hebbian Learning v/s

Co-Occurrence
BoW
word2vec
BERT

Added vs Adding



Dyslexia vs reading problem

Results - Same Root(Lemma) Words

Word Pair	Leabra	Co-Occurrence	BoW	Word Emb	Word Emb(Gen)	BERT
Added vs Adding	0.0350	**0.3185**	0.0	-0.1311	0.7415	**0.9247**
Summary vs Summarize	-0.0199	**0.0435**	0.0	-0.0611	0.5143	**0.5922**
Introducing vs Introduction	**-0.0194**	0.0	0.0	-0.0607	0.6485	**0.7805**
Continuous vs Continuum	-0.0086	**0.0757**	0.0	-0.0309	0.2267	**0.6488**
Receptive vs Receptors	-0.027	0.0370	0.0	**0.0727**	0.0700	**0.5904**

Results - General Topics

Word Pair	Leabra	Co-Occurrence	BoW	Word Emb	Word Emb(Gen)	BERT
Dyslexia vs Reading problem	0.128	**0.1412**	0.0216	0.0038	0.3448	**0.5202**
Dyslexia vs Speech Problem	**0.109**	0.0954	0.0114	-0.0610	0.2674	**0.6410**
Dyslexia vs Speaking Problem	-0.040	**0.0597**	0.0122	-0.0736	0.2450	**0.3625**
Dyslexia vs Reading	**0.561**	0.2367	0.0217	0.0510	0.2974	0.3129
Dyslexia vs Speech	**0.479**	0.1301	0.0	-0.0382	0.1965	0.3852
Dyslexia vs Speaking	-0.021	**0.0279**	0.0	-0.0627	0.1710	**0.2603**

Results - Multiple-Choice Quiz

Based on your knowledge of the textbook, which of the options following each "question" provides the best match to the meaning?

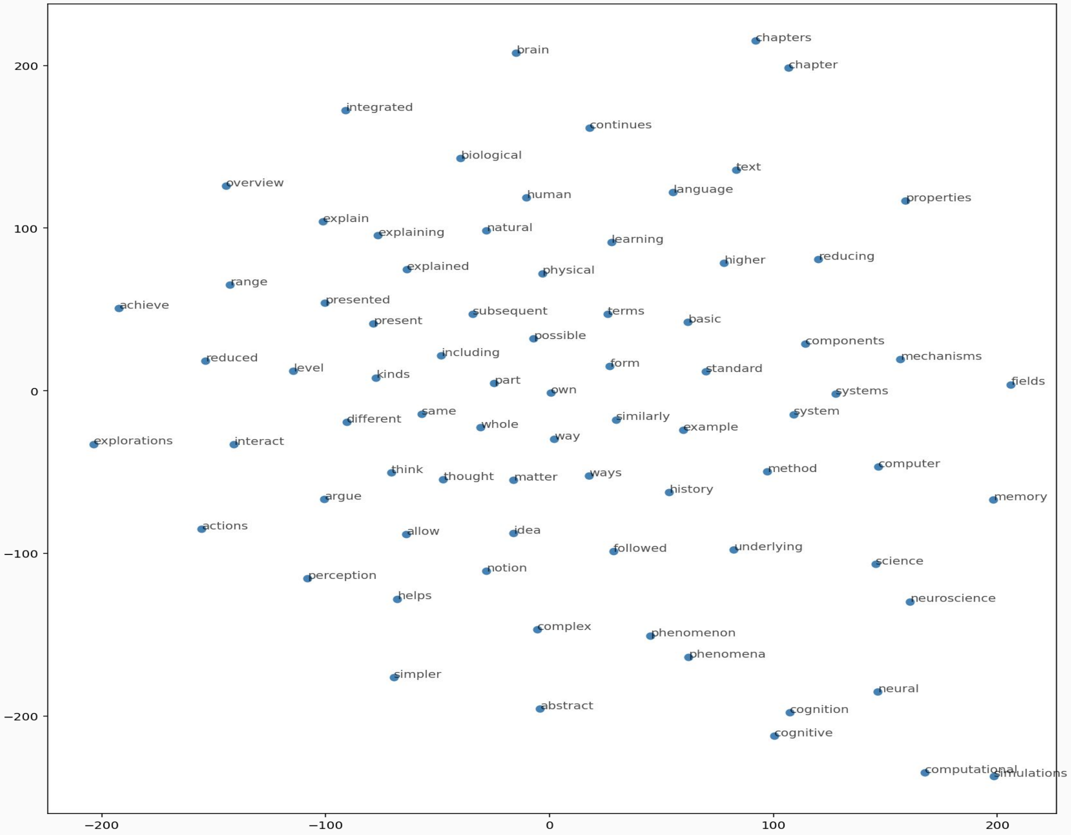
Dyslexia

A. surface deep phonological reading problem damage
B. speech output hearing language nonwords
C. competition inhibition selection binding

Model	Accuracy
Leabra	**0.8**
Co-occurrence Matrix	0.6
BoW	**0.8**
Word Embedding	0.5
Word Embedding(Gen)	0.3
BERT	0.5

Conclusion

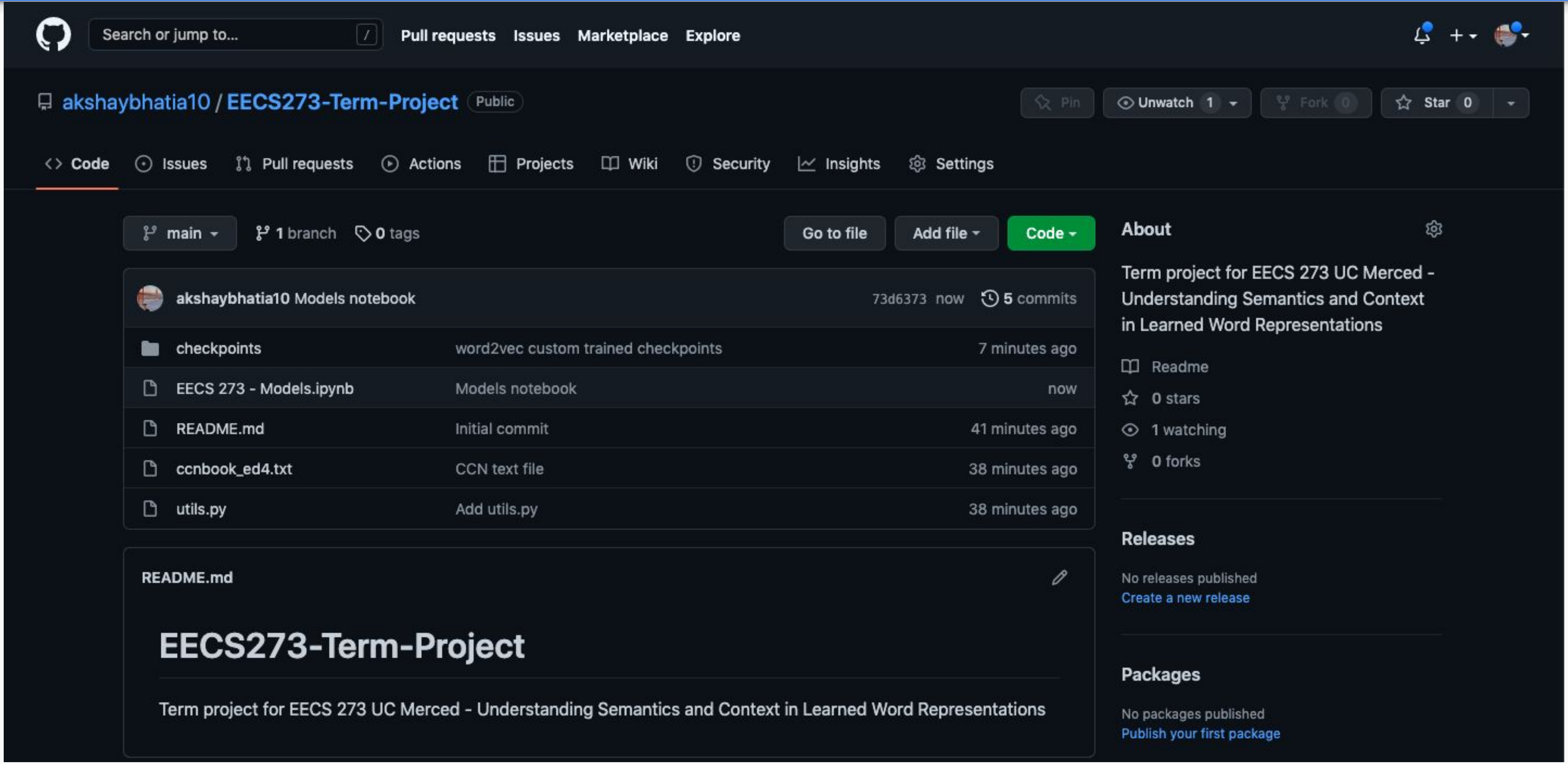
Conclusion - Model Explainability



Visualization of word embeddings in 2D space

Attention(Hidden Layer) weights of BERT for sentiment analysis

Code



https://github.com/akshaybhatia10/EECS273-Term-Project

Thank You!

Questions?

Akshay Bhatia

Email: abhatia8@ucmerced.edu
Website: akshaybhatia10.github.io