

# **TTIC 31230, Fundamentals of Deep Learning**

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## **Pretraining for NLP**

# Pretraining for NLP

In NLP unsupervised pretraining is now required for strong benchmark performance.

## Pretrained Word Embeddings

Advances in Pre-Training Distributed Word Representations,  
Mikolov et al., 2017

We want a mapping from a word  $w$  to a vector  $e(w)$  — a word embedding.

**fastText** from Facebook is currently popular.

It provides both contextual bag of words (cbow) and byte pair encoding (BPE) word vectors.

## **cbow word vectors**

We construct a population distribution on pairs  $(c, w)$  here  $c$  is a bag of word context and  $w$  is a word.

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{c,w} - \ln P(w|c)$$

$\Phi$  consists of a matrix  $e[w, i]$  where  $e[w, I]$  is the word embedding of  $w$ , and a matrix  $e'[w, i]$  giving the embedding of the word  $w$  when it appears in a context.

A score  $s(w|c)$  is defined by

$$s(w|c) = \frac{1}{|c|} \sum_{w' \in c} e(w)^\top e'(w')$$

## Negative Sampling in cbow

Rather than define  $P_{\Phi}(w|c)$  by a softmax over  $w$ , one uses restricted negative sampling.

We construct a training set of triples  $(w, c, N_C)$

$$\Phi^* = \operatorname{argmin}_{\Phi} E_{w,c,N_C} \ln \left( 1 + e^{-s(w,c)} \right) + \sum_{n \in N_C} \ln \left( 1 + e^{s(n,c)} \right)$$

## Byte Pair Encoding (BPE)

BPE constructs a set of character n-grams by starting with the unigrams and then greedily merging most common bigrams of n-grams.

Given a set of character n-grams each word is treated as a bag of character n-grams.

$$e[w] = \frac{1}{N} \sum_{n \in w} e(n)$$

Current systems use byte pairs but train the byte pair embeddings as part of transformer training.

## **BERT: Blank Language Modeling**

We replace a random subset of the words with a blank token.

We run a transformer on a block of text containing some blanks.

For a blank occurring at position  $t$  we predict the word at position  $t$ :

$$P(w) = \operatorname{softmax}_w h[t, J]e[w, J]$$

Blank language modeling outperforms language modeling when used for pretraining in classification tasks such as the GLUE tasks.

# GLUE

## GLUE: General Language Understanding Evaluation













ArXiv 1804.07461

Corpus	Train	Test	Task	Metrics	Domain
Single-Sentence Tasks					
CoLA	8.5k	<b>1k</b>	acceptability	Matthews corr.	misc.
SST-2	67k	1.8k	sentiment	acc.	movie reviews
Similarity and Paraphrase Tasks					
MRPC	3.7k	1.7k	paraphrase	acc./F1	news
STS-B	7k	1.4k	sentence similarity	Pearson/Spearman corr.	misc.
QQP	364k	<b>391k</b>	paraphrase	acc./F1	social QA questions
Inference Tasks					
MNLI	393k	<b>20k</b>	NLI	matched acc./mismatched acc.	misc.
QNLI	105k	5.4k	QA/NLI	acc.	Wikipedia
RTE	2.5k	3k	NLI	acc.	news, Wikipedia
WNLI	634	<b>146</b>	coreference/NLI	acc.	fiction books


Table 1: Task descriptions and statistics. All tasks are single sentence or sentence pair classification, except STS-B, which is a regression task. MNLI has three classes; all other classification tasks have two. Test sets shown in bold use labels that have never been made public in any form.



## GLUE Leader Board as of February 27, 2020

Rank	Name	Model	URL	Score
1	T5 Team - Google	T5		90.3
2	ERNIE Team - Baidu	ERNIE		90.1
3	Microsoft D365 AI & MSR AI & GATECH MT-DNN-SMART			89.9
	4 王玮	ALICE v2 large ensemble (Alibaba DAMO NLP)		89.7
	5 Microsoft D365 AI & UMD	FreeLB-RoBERTa (ensemble)		88.4
6	Junjie Yang	HIRE-RoBERTa		88.3
7	Facebook AI	RoBERTa		88.1
	8 Microsoft D365 AI & MSR AI	MT-DNN-ensemble		87.6
9	GLUE Human Baselines	GLUE Human Baselines		87.1

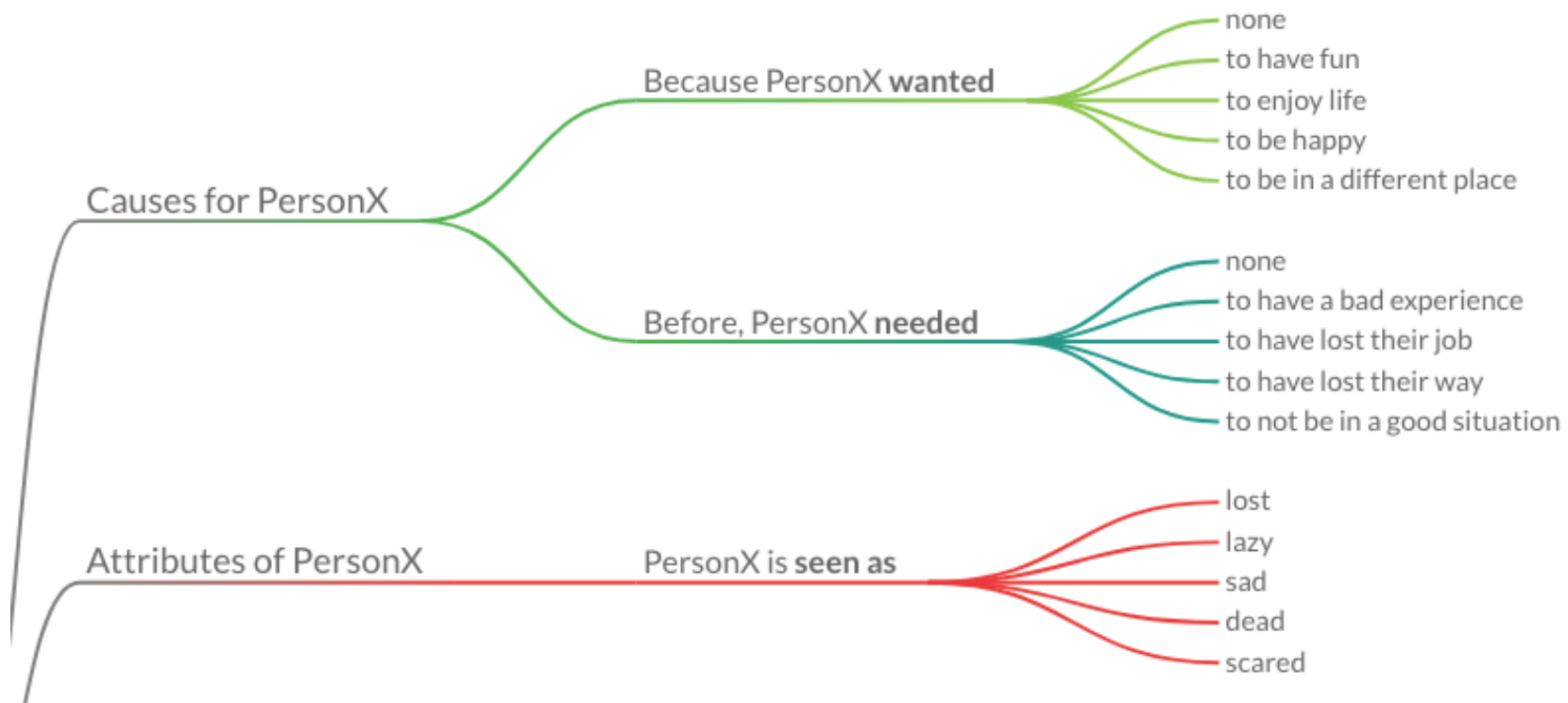
## SuperGLUE Leader Board as of February 27, 2020

Rank	Name	Model	URL	Score
1	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8
+	2	T5 Team - Google	T5	89.3
	3	Zhuiyi Technology	RoBERTa-mtl-adv	85.7
	4	Facebook AI	RoBERTa	84.6
	5	IBM Research AI	BERT-mtl	73.5

# Fine Tuning on Question Answering

COMET: Busselut et al, June 2019.

Charlie is drifting though life:



# The Chatbot Meena

**User:** *How are things?*

**Meena:** They're good. How about you?

**User:** *I'm trying to decide what to watch*

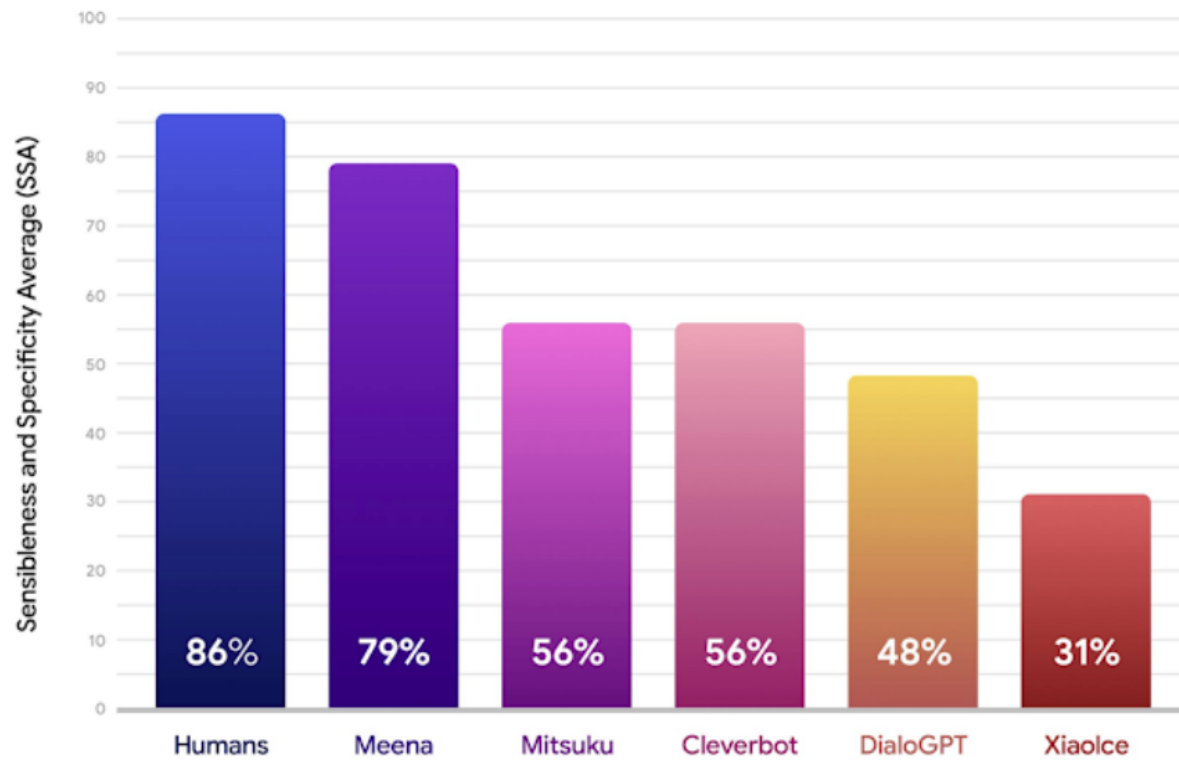
**Meena:** What are some of your favorite shows?

**User:** *I like the Good Place*

**Meena:** I haven't watched that. My favorite shows are Supernatural, and Star Trek: TNG.

**User:** *What is TNG?*

# The Chatbot Meena



**END**