

# Detecting Depression from Text

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# Hello!

## I'm Varun!

I am a data scientist.



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Depression is a common mood disorder, and in severe cases can be debilitating.

# What Characterizes Depression?

- Excessive Sadness
- Anhedonia
- Insomnia
- Anxiety
- Appetite Loss
- Loss of self-worth
- Difficulty thinking/concentrating
- Thoughts of suicide

# Mental Health is Worsening in 2020

## **Depression Rates are Increasing**

62% increase in voluntary screenings for depression over 2019, with 8 out of 10 screened scoring moderate-severe

## **Mental Health Among Young People is at its Worst**

Screening for depression and anxiety has increased, as have rates of severe depression.

## **Suicidal Ideation is Increasing**

Over 460,000 from last year on the same dataset

## **Depression Effects are Non-Uniform**

Disproportionately high rates among LGBTQ+ youth and youth who identify as mixed race

The background features two wavy, horizontal lines composed of small, light blue dots. These lines flow from the left side towards the right, creating a sense of movement and depth against the solid blue background.

Many cases may be  
undiagnosed.

# 1. How We Can Help

What can we do to address this issue?

# We may be able to detect these from text

- Excessive Sadness
- Anhedonia
- Insomnia
- Anxiety
- Appetite Loss
- Loss of self-worth
- Difficulty thinking/concentrating
- Thoughts of suicide



# We want to

Better understand what depression **sounds like**  
from the **patient-perspective**

Find insights into the **causes** of depression

Use **machine learning** to **detect** depression  
from **text**

# This is happening right now

- **“The Distress Analysis Interview Corpus of human and computer interviews,”** USC Institute for Creative Technologies
- **“Text-based depression detection on sparse data,”** Heinrich Dinkel, Mengyue Wu, Kai Yu
- **“82% of people believe robots can support their mental health better than humans can,”** a [survey](#) by Oracle and Workplace Intelligence

## 2. Data

We need real text corpi to investigate depression

# Datasets

- **Reddit training corpus:** 30,000 posts scraped from Reddit's Depression community, and another 30,000 neutral text from r/happy and r/CasualConversation.
- **DAIC-WOZ:** An interview-based text corpus created during a study conducted by USC to support diagnostic methods for psychological distress
- **Time to Change:** A UK-based blog sharing real posts and stories from people struggling with depression

# 3. Building a Model

Let's teach a machine to understand depression!

# Capturing Semantic Meaning

bERT word  
embeddings

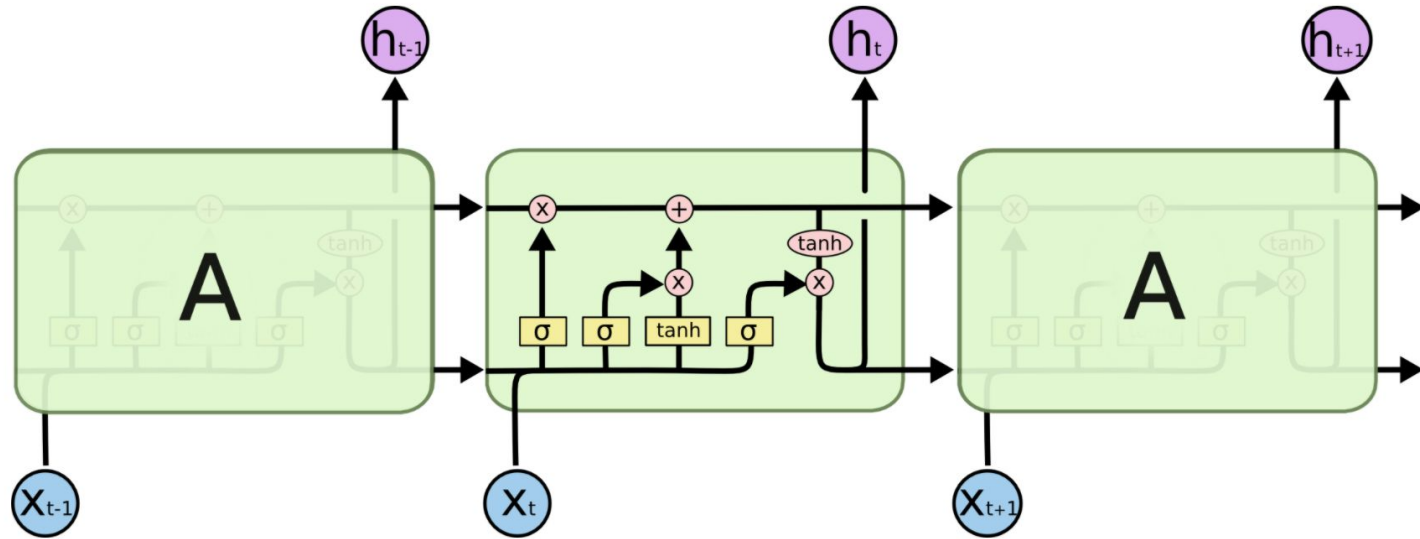


Bidirectional  
Long-Short-Term  
Memory Network

# bERT: Bidirectional Encoder Representations

- Representations of text that go beyond word count → semantic meaning
  - “Apple pie is delicious”
  - “Apple stocks are up”

# Long-Short-Term-Memory Network



The repeating module in an LSTM contains four interacting layers.



# Bi-LSTM

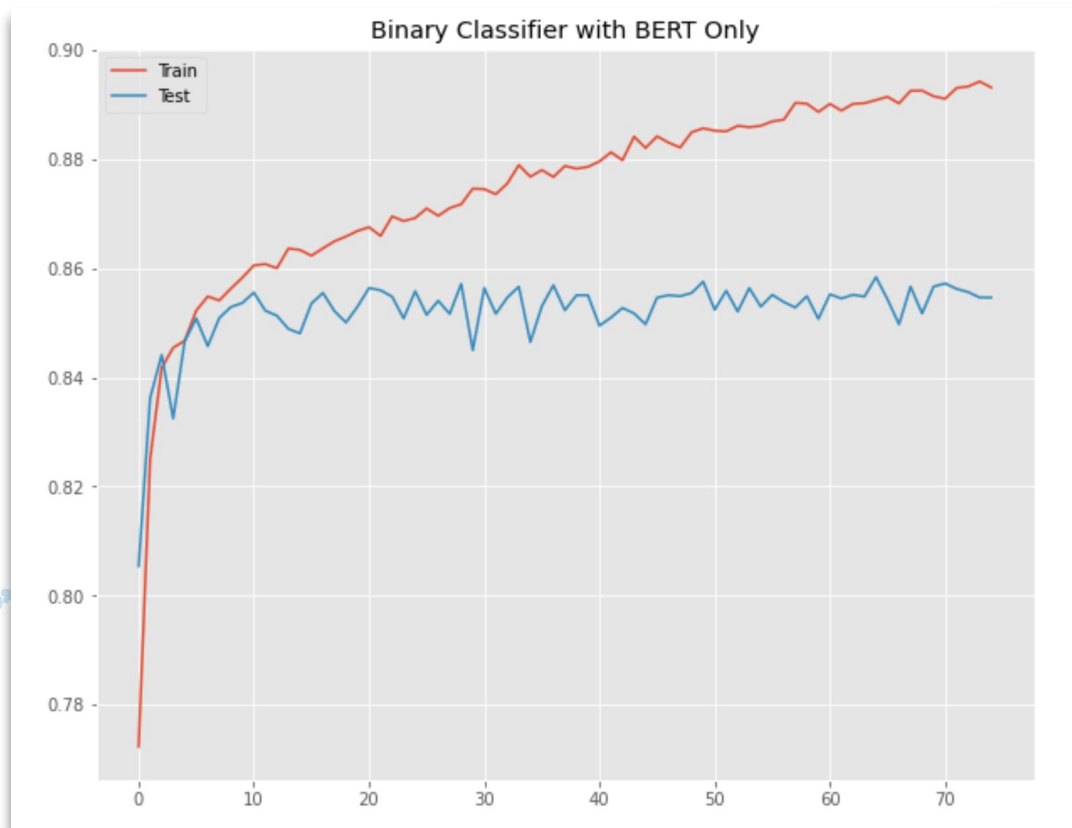


“I grew up in France... I speak fluent French.”

The diagram shows two horizontal arrows: a top arrow pointing left and a bottom arrow pointing right, representing the bidirectional processing of the text. Below the text, there is a decorative wavy line composed of many small blue dots that spans the width of the slide.

Bi-LSTM processes in both directions, and accounts for long-term dependencies.

# Model Performance: Accuracy



# Integrating a Second Model

- **vaderSentiment** scores were correctly accounting for basic linguistic negation
- A classifier was built on sentiment scores; this had a slightly clearer/**more observable disparity** between classes.
- This made it better for **basic/shorter** sentences, but also led to more **misclassification** for more complex sentences

# Weighted Average

$$\text{preds} = (0.7 * \text{preds}_l) + (0.3 * \text{preds}_s)$$

\*plus a rule to default to sentiment when the other model gets confused

Model	Accuracy	Recall
bERT-BiLSTM	0.85	0.86
vaderSentiment	0.78	0.78
Combined	0.86	0.87

The background is a solid blue color. Overlaid on this are several wavy, horizontal lines composed of small, light blue dots. These lines create a sense of motion and depth, flowing across the frame from left to right. The word "Demo!" is centered in the middle of the image, in a large, white, sans-serif font.

# Demo!

# Key Takeaways: Analyzing Depression

## **More Verbose = More Signal**

In particular with the more complex Bi-LSTM model, more verbose text gives the semantic analysis/LTD more to work with

## **Simpler Text, Simpler Model**

A simple sentiment-based model performs better with less text, when less information needs to be extracted from the text.

# How Can We Use This?

## **Part of Therapy Schedule**

Patients can use the application to track mood/likelihood of depression over periods of time; sent directly to psychiatrist

## **Holistic Analysis Over Many Users**

If deployed to an open platform, then with consent and permission, we could anonymously analyze factors that correlate with higher rates of depression

# The Good News

- Depression is **treatable**
- Most successful treatments include therapy **combined** with some form of antidepressant
- **Early detection** can potentially help prevent cases from getting worse and refine treatment techniques





The background features several wavy, horizontal lines composed of small dots. These lines are arranged in a series of overlapping, undulating bands that sweep across the frame from left to right. The dots are a slightly darker shade of blue than the background, creating a subtle, textured effect.

# Thank You!

Questions?

# Appendix

The background of the slide is a solid blue color. Overlaid on this background are several wavy, horizontal lines composed of small, dark blue dots. These lines create a sense of motion and depth, with some lines appearing more prominent than others. The dots are arranged in a way that suggests a three-dimensional effect, with some lines curving upwards and others downwards, creating a rhythmic pattern across the slide.

# bERT + BiLSTM Model Architecture

```
model_1 = Sequential()

model_1.add(Conv1D(32, 7, activation = 'relu'))
model_1.add(MaxPooling1D())
model_1.add(Bidirectional(LSTM(24)))
model_1.add(Dense(64,activation='relu',kernel_regularizer=l2(0.001)))
model_1.add(Dropout(0.5))
model_1.add(Dense(64,activation='relu',kernel_regularizer=l2(0.001)))
model_1.add(Dropout(0.5))
model_1.add(Dense(32,activation='relu',kernel_regularizer=l2(0.001)))

model_1.add(Dense(1,activation='sigmoid'))
```

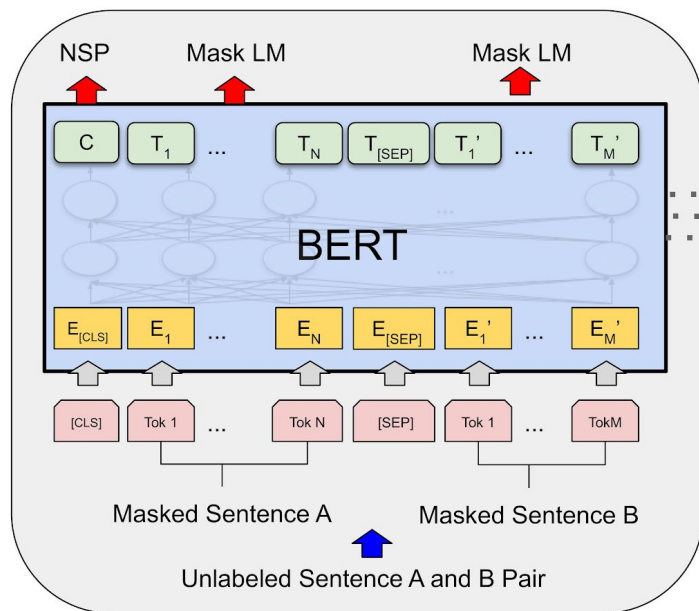
# Sentiment Model Architecture

```
model_s = Sequential()

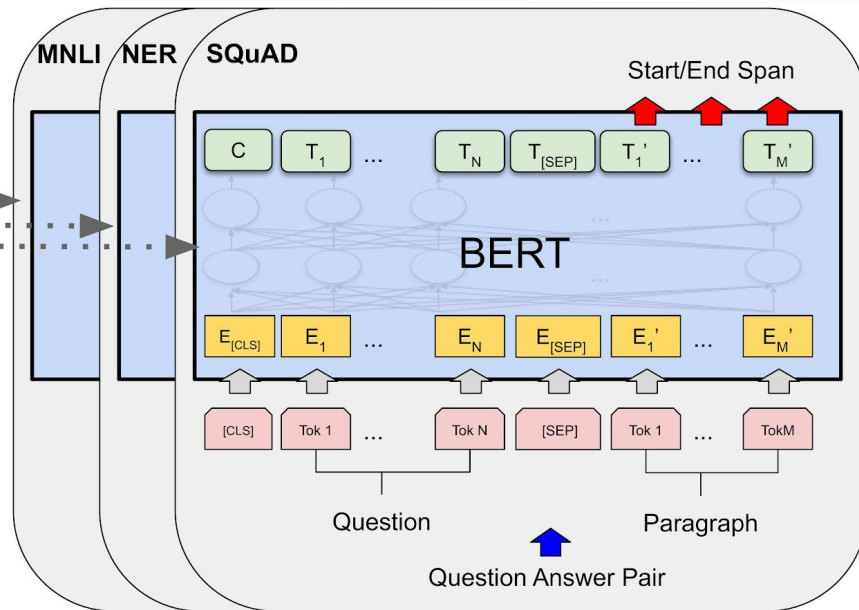
model_s.add(Input(shape=(X_train.shape[1],)))
model_s.add(Dense(64,activation='relu'))
model_s.add(Dropout(0.5))
model_s.add(Dense(64,activation='relu'))
model_s.add(Dropout(0.5))
model_s.add(Dense(32,activation='relu'))

model_s.add(Dense(1,activation='sigmoid'))
```

# bERT



Pre-training



Fine-Tuning

# Frequently Occurring Words in Depression Corpus

job

friends

work

life

parents

year

school

family

# Confusion Matrix: Combined Model

