ML for SS: Individual traits from text

Session 7

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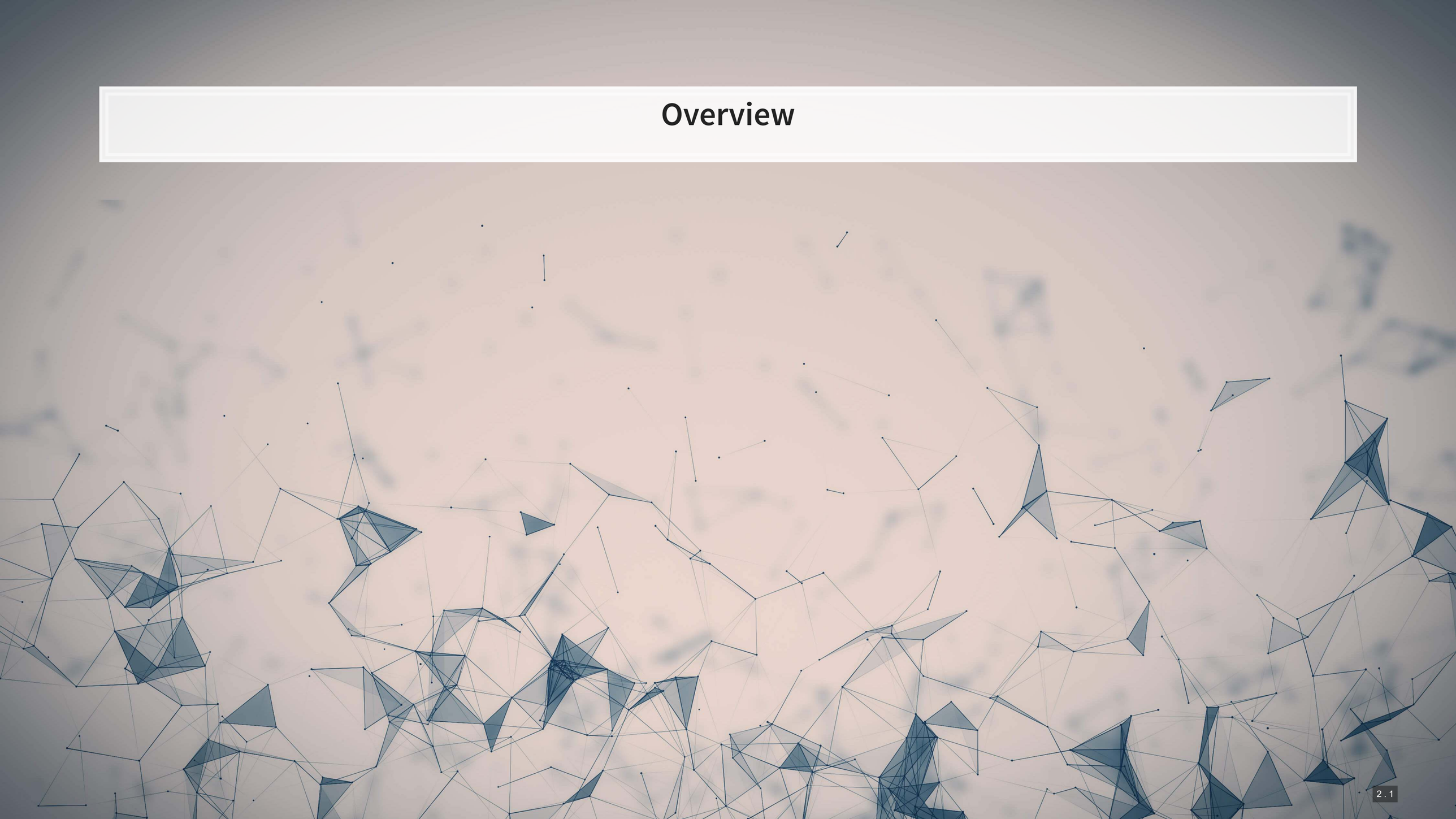
Overview



Papers

De Choudhury, Gamon, Counts, and Horvitz. “Predicting depression via social media.” (AAAI) 2013.

- Depression prediction using social media.

Eichstaedt et al. “Psychological language on Twitter predicts county-level heart disease mortality.” (2015) PS.

- Psychology + Social Media = Healthcare predictions.

Majumder, Poria, Gelbukh, and Cambria. “Deep learning-based document modeling for personality detection from text.” (2017) IEEE IS.

- Personality prediction using essay writing and a neural network

Technical Discussion

1. A bit on the methods from the papers
2. A bit on some methods that are open source (from the optional readings)

Python

- Twitter Emotion Recognition
  - A neural network approach to labeling emotion latent to tweets

Java + WEKA

- Personality Recognizer
  - A noisy but validated way to detect personality based on writing

> Tools in this space are usually one-off open source algorithms *or* methods you trained yourself

Twitter Emotion Recognition

Emotion: Ekman's 6 emotions

1. Anger
2. Surprise
3. Disgust
4. Enjoyment
5. Fear
6. Sadness

Why is this useful?

- Can be a useful IV for a regression
  - E.g., understanding emotional response to government policies

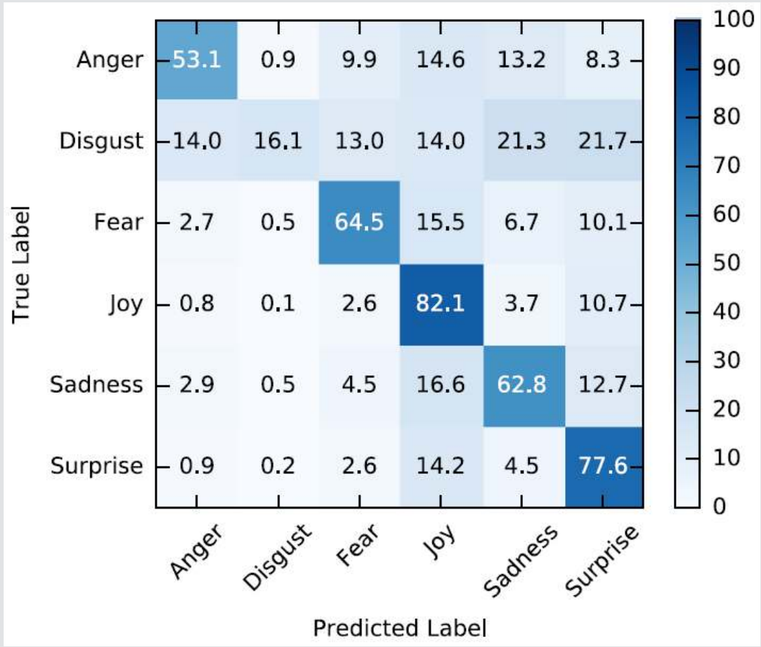
How do they do it?

1. Grabbed a collection of 73 *billion* tweets
2. Looked for tweets with hashtags directly matching the emotions, e.g., `#anger`
   - To further enforce this as a label, the hashtag must be in the last 10% of the tweet (by token)
   - Removed duplicates and retweets as well
3. Use the pre-labeled tweets as a “weak supervision” to train an RNN
   - Also tried a CNN, but it doesn’t work as well
   - The open source version is applied character-by-character; superior to the tokenized version

> Other variations

1. Single class prediction vs multiclass
2. Other emotion classification schemes: Plutchik’s 8 emotions and Profile of Mood States (POMS)

How well does it work?



Works well for Joy and surprise, and works alright for fear and sadness. Poor performance for disgust.

Doesn’t control for sarcasm. No neutral class.

Example of running the algorithm Setup

```
import os;
os.environ['KERAS_BACKEND'] = 'theano'

import pandas as pd

from emotion_predictor import EmotionPredictor

# Import the model
model = EmotionPredictor(classification='ekman', setting='mc', use_unison_model=True)

# Somewhat randomly pulled from Twitter
tweets = [
    "What saddens me most is that we seem to be fast becoming an “us vs them” society.",
    "I don't understand why the government hasn't factored in waiting for vaccinations being available to under 12's first. I'
    "Switched to Windows 11! Looking and feeling rlly great so far Star-struck",
    "I got a pint of Windows 11! IT’S SO GOOD",
    "I’m not even a top 100 earning Twitch streamer, what the fuck is my community even doing out there??"
]
```

Example of running the algorithm: Output

- Most likely label

```
predictions = model.predict_classes(tweets)
predictions['Emotion']
```

```
##                                                 Tweet   Emotion
## 0  What saddens me most is that we seem to be fas...   Sadness
## 1  I don't understand why the government hasn't f...      Fear
## 2  Switched to Windows 11! Looking and feeling rl...       Joy
## 3           I got a pint of Windows 11! IT'S SO GOOD  Surprise
## 4  I'm not even a top 100 earning Twitch streamer...     Anger
```

- Percentages

```
probabilities = model.predict_probabilities(tweets)
probabilities
```

```
##                                                 Tweet     Anger   Disgust      Fear       Joy   Sadness  Surprise
## 0  What saddens me most is that we seem to be fas...  0.010681  0.005633  0.076239  0.006292  0.898160  0.002987
## 1  I don't understand why the government hasn't f...  0.000313  0.002712  0.995694  0.000672  0.000421  0.000187
## 2  Switched to Windows 11! Looking and feeling rl...  0.010332  0.002005  0.061332  0.360945  0.320342  0.245043
## 3           I got a pint of Windows 11! IT'S SO GOOD  0.023655  0.004097  0.082532  0.173595  0.094921  0.621201
## 4  I'm not even a top 100 earning Twitch streamer...  0.430638  0.060563  0.085490  0.022956  0.318132  0.082221
```

Example of running the algorithm: Output

- If using in a neural network, the embedding level is also made available

```
embeddings = model.embed(tweets)
embeddings.shape
```

```
## (6, 801)
```

Try it out!

- The authors of the paper put out a public Binder for the algorithm
  - Binder is a cloud hosted Jupyter notebook

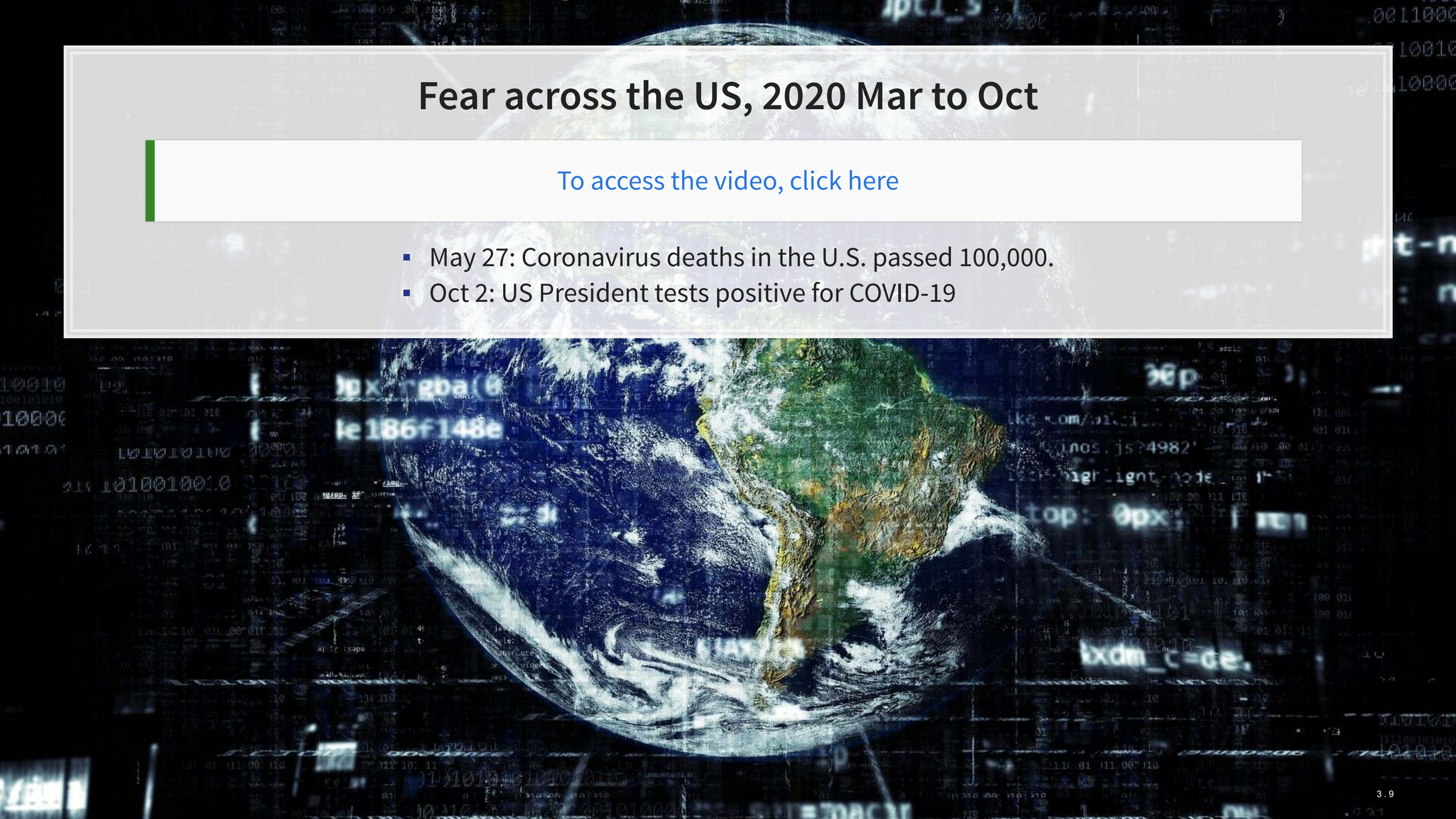
> Click here to access it

- Note:
  1. It's a bit slow to run because the neural network it's using is quite a large file
  2. You can try your own tweets by replacing the list `tweets` in cell number 4

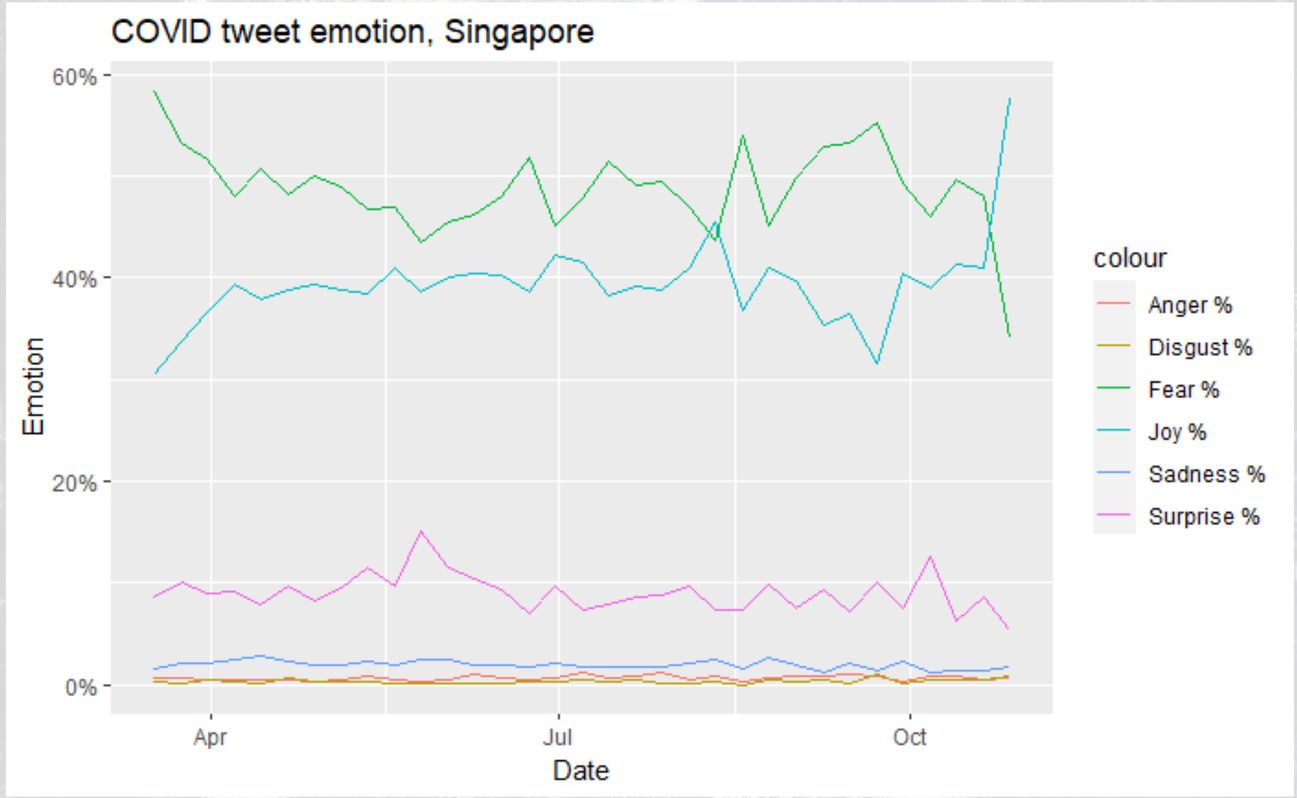
Fear across the US, 2020 Mar to Oct

To access the video, click here

- May 27: Coronavirus deaths in the U.S. passed 100,000.
- Oct 2: US President tests positive for COVID-19



Singapore emotion and COVID-19



Personality Recognizer

Personality: The Big 5

1. Extraversion
2. Emotional stability
3. Agreeableness
4. Conscientiousness
5. Openness to experience

> The idea is to use cues from text (either written or transcribed) to identify a person's personality

- There are a lot of documented differences in speech across personality types, so the hope is to learn these from text and build it all into a model

The algorithm

1. Run a psychology experiment to collect text corpora and administer personality tests
   - Already done in Pennebaker and King 1999 (written text) and Mehl et al. 2001 (transcribed conversations)
2. Process the corpora
   - Examine word counts in a number of word lists from LIWC
   - Examine word counts from te MRC Psycholinguistic database
   - Other linguistic aspects: commands, prompts, questioning. assertion
   - For speech: voice pitch statistics, intensity, time, and speed
3. Try to build a model to determine personalities
   - Only SVM can capture all Big-5 characteristics in a statistically significant manner for text
   - None accomplish this for audio; best would be to use Adaboost for extraversion and SVM for the others

Example workflow

- Following Green et al. (2019 TAR), as used in Crowley, Huang and Lu (2020)
  1. Collect all conference call Q&A text from StreetEvents per executive
     - Exact match on executive name + company to Execucomp
       - Leverage genealogy table nickname data from Old Dominion
       - Fuzzy + manual match on the rest
     - 163,099 observations, ~36/executive
  2. Apply an SVM model with linear kernel called *Personality Recognizer*
     - From Mairesse et al. (2007)
  3. Average across calls per manager
     - Keep only executives with ≥3 call Q&As

Working with the code

Note: It is likely you will run into missing files using the source code from Mairesse' website. There are repositories that contain the missing files online, e.g., on github.

```
# Make sure your preferences are properly set in PersonalityRecognizer.properties first!

# -d : process a directory
# -i : input data
# -m : model to use, 1=OLS, 2=M5 Model Tree, 3=M5 Reg Tree, 4=SVM
# -a : output to arff file (can be converted into a csv later using Python)
./PersonalityRecognizer -i ../../Proc/Sentic -d -m 4 -a ../../{your file}.arff
```

Output is in the `arff` file format – there is an arff package for python that can handle this

Speeding it up a bit

- Since the script is single threaded, it is faster to split your data up into multiple folders and process multiple times. E.g., with 12 folders and 4 threads, consider something like the following:

Saved in a script named parallel.sh:

```
./PersonalityRecognizer -i ../../Proc/SE_QAs-1 -d -m 4 -a ../../SE_QAs_Mairesse-1.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-2 -d -m 4 -a ../../SE_QAs_Mairesse-2.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-3 -d -m 4 -a ../../SE_QAs_Mairesse-3.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-4 -d -m 4 -a ../../SE_QAs_Mairesse-4.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-5 -d -m 4 -a ../../SE_QAs_Mairesse-5.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-6 -d -m 4 -a ../../SE_QAs_Mairesse-6.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-7 -d -m 4 -a ../../SE_QAs_Mairesse-7.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-8 -d -m 4 -a ../../SE_QAs_Mairesse-8.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-9 -d -m 4 -a ../../SE_QAs_Mairesse-9.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-10 -d -m 4 -a ../../SE_QAs_Mairesse-10.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-11 -d -m 4 -a ../../SE_QAs_Mairesse-11.arff
./PersonalityRecognizer -i ../../Proc/SE_QAs-12 -d -m 4 -a ../../SE_QAs_Mairesse-12.arff
```

To execute in parallel (on *nix systems)

```
parallel --delay 2 --jobs 12 --no-notice < parallel.sh
```

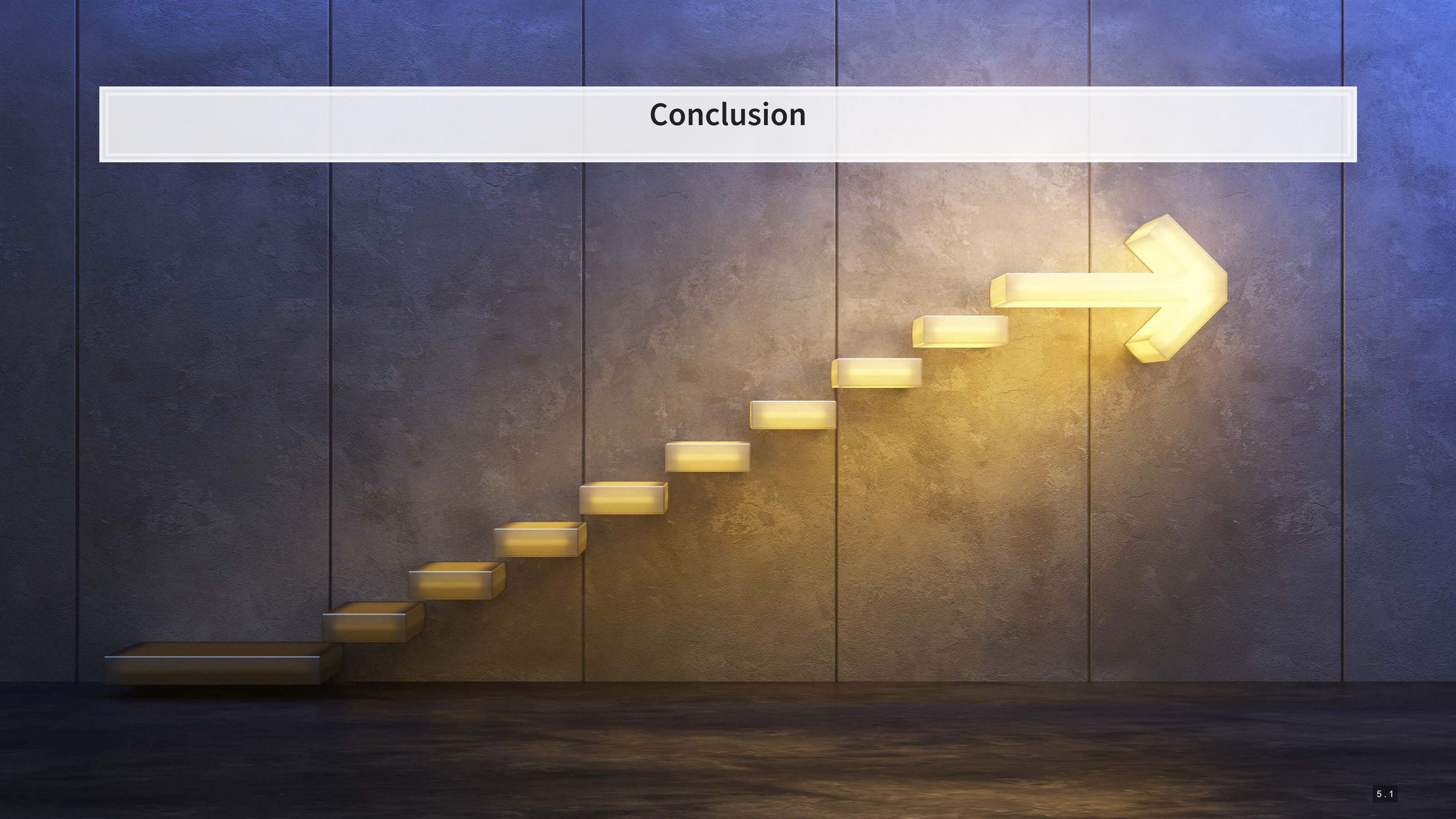
Output

```
@relation features_/media/Data/Research/T013_TwitterMgmt_py3/Libraries/PersonalityRecognizer-master/../../Proc/SE_QAs-1

@attribute filename string
@attribute AOA numeric
@attribute BROWN-FREQ numeric
@attribute CONC numeric
@attribute FAM numeric
@attribute IMAG numeric
@attribute K-F-FREQ numeric
@attribute K-F-NCATS numeric
@attribute K-F-NSAMP numeric
@attribute MEANC numeric
@attribute MEANP numeric
@attribute NLET numeric
@attribute NPHON numeric
@attribute NSYL numeric
@attribute T-L-FREQ numeric
@attribute WC numeric
@attribute WPS numeric
@attribute Qmarks numeric
```

The above is an `arff` file. It's essentially a `csv` file but where the header is a list of attributes instead of a comma separated line.

Conclusion



Wrap-up

Many ways to approach these types of problems

- Much more approachable when there is an open source implementation

Emotion recognition can work, but it can be noisy

- Better for some emotions than others.

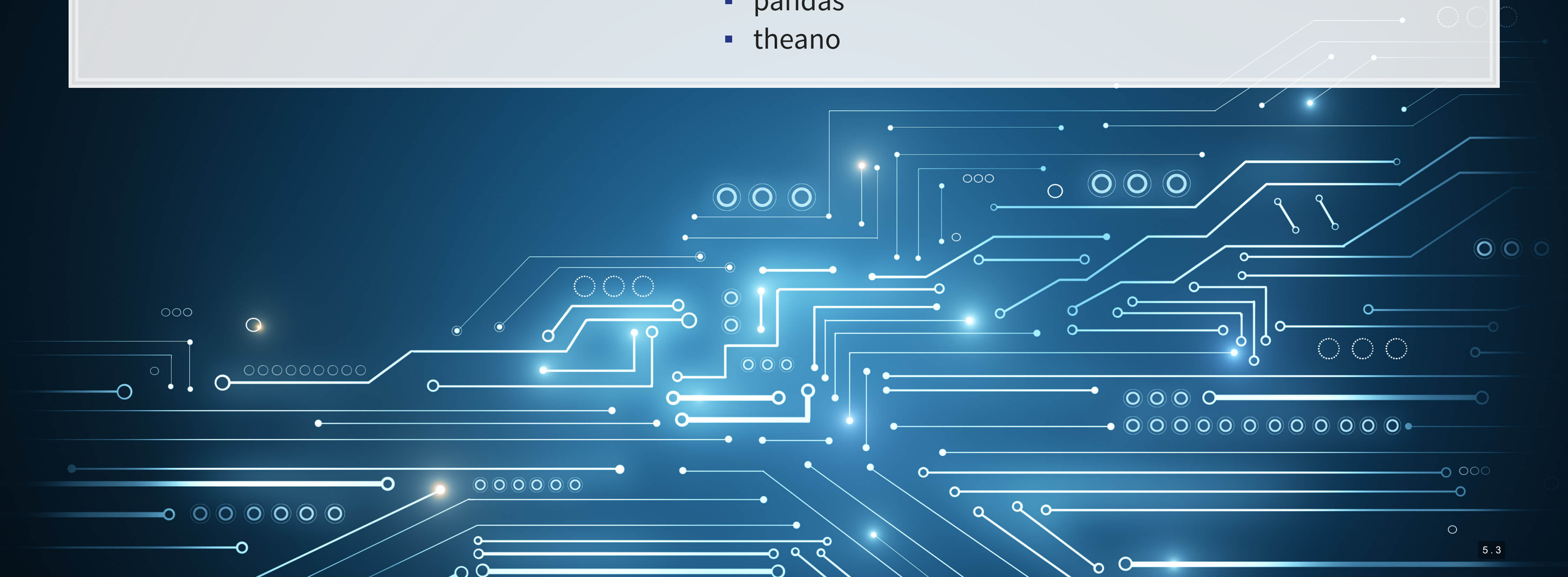
Personality recognition can work, but it is noisy when automated

- Need enough data that the noise isn’t a concern

Packages used for these slides

Python

- arff
- numpy
- pandas
- theano



References

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- Eichstaedt, Johannes C., Hansen Andrew Schwartz, Margaret L. Kern, Gregory Park, Darwin R. Labarthe, Raina M. Merchant, Sneha Jha et al. “Psychological language on Twitter predicts county-level heart disease mortality.” Psychological science 26, no. 2 (2015): 159-169.
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