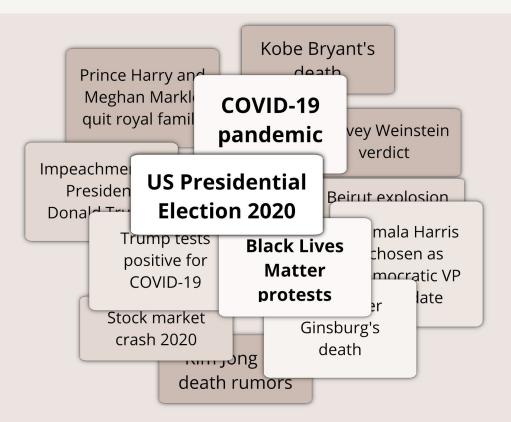
# Disinformation/Fake News Detection:

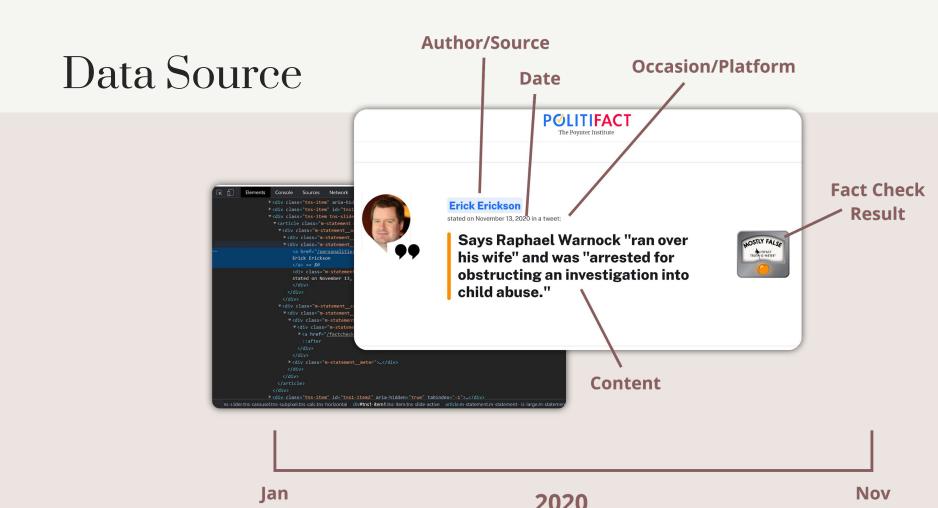
Detecting Fake News During The Year of COVID-19 and US Presidential Election

INFSCI2160

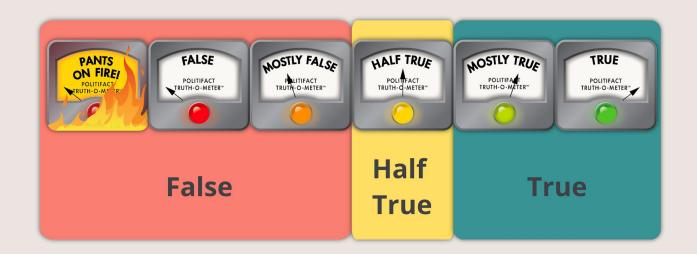
Shangbin Tang, Chengchen Wang, Taylor Herb

# Background & Aims

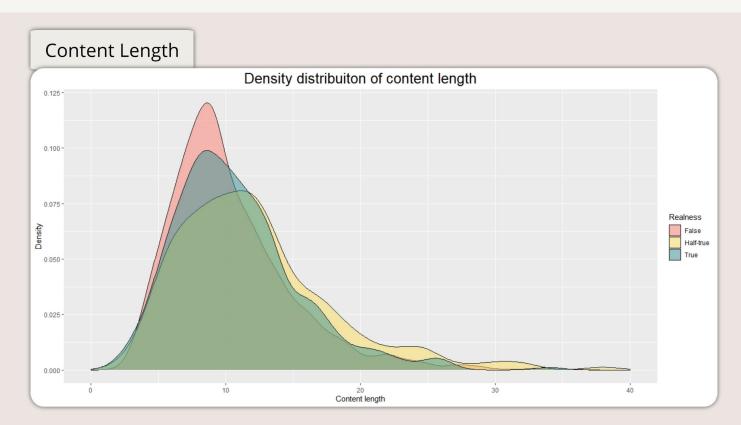




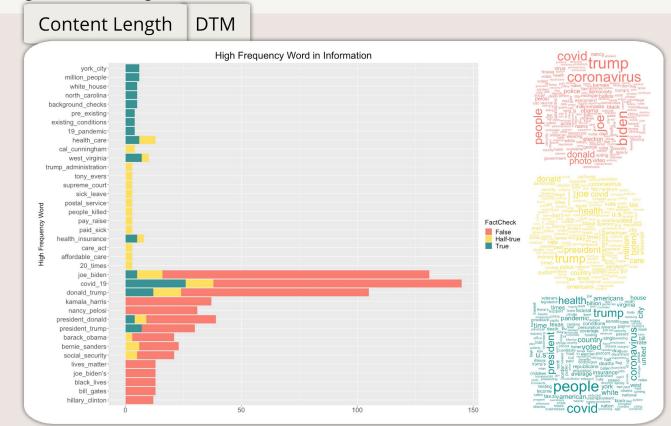
# Authenticity Level



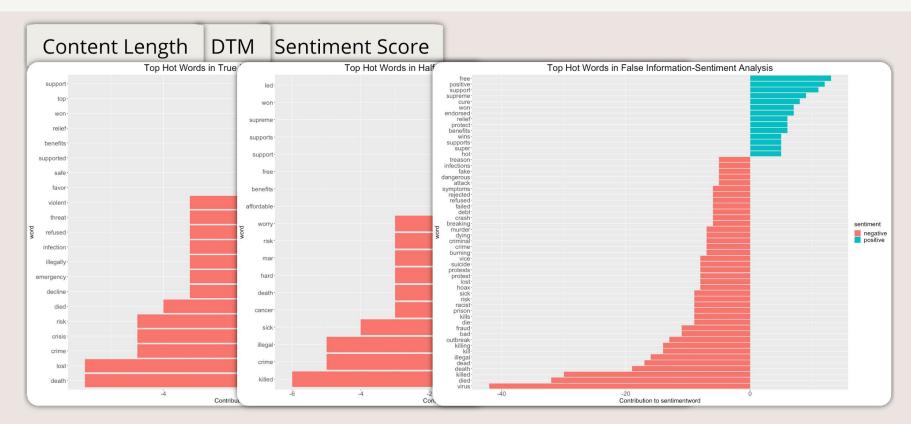
# Exploratory Analysis - Content Length



# Exploratory Analysis - Hot Words



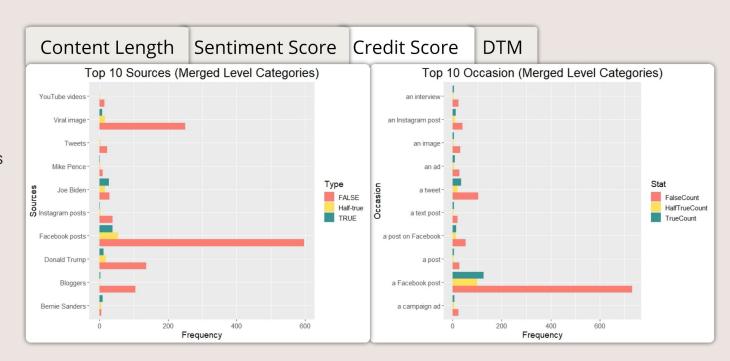
# Exploratory Analysis - Sentiment



# Exploratory Analysis - Credit Scores

INNOVATION

Historical Posts



# Data Cleaning

- Check the dimensions and summary of the dataset
- Remove missing values
- Convert the class of variables

#### Document-term Matrix

- Convert all texts to lowercase
- Remove stop words
- Remove numbers
- Remove punctuation
- Remove special characters, like @, ...
- Stem words into roots format

Filter out low frequency words in the document-term matrix

Calculate the content length:

Content length = rowSums(content\_dtm\_matrix)

ANOVA result of the variable content\_length:

```
> summary(data1AOV)
                   Df Sum Sq Mean Sq F value Pr(>F)
                  2 669 334.4 14.89 3.79e-07 ***
data1$FactCheck
Residuals 2120 47617 22.5
                 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Signif. codes:
                              > TukeyHSD(data1AOV)
                                Tukey multiple comparisons of means
                                  95% family-wise confidence level
                              Fit: aov(formula = data1$content_length ~ data1$FactCheck)
                               $`data1$FactCheck`
                                                 diff
                                                            lwr
                                                                     upr
                                                                            p adj
                              Half-true-FALSE 1.7795262 1.0072595 2.5517928 0.0000002
                                             0.4518946 -0.2226296 1.1264187 0.2583586
                              TRUE-FALSE
                              TRUE-Half-true -1.3276316 -2.2723393 -0.3829239 0.0028642
```

#### Calculate the sentiment score:

- Get sentiment dictionary by get\_sentiments("afinn")
- Join the term and scientiment list
- Multiply the frequency of terms by its sentiment score
- Use rowSums() to get the sentiment score of every document

# Classification

• First, the data was split into training and testing groups then resampled using 10-fold Cross Validation

- Three classification models were trained on the training set:
  - Random Forest
  - K-Nearest Neighbor
  - Support Vector Machine
    - Caret package was used to train the models

# Evaluation

Predictions were made using each model on the testing data set

- Each model was evaluated using a confusion matrix
  - Used to assess accuracy, specificity & sensitivity

This process remained identical for all datasets (1-4)

# Evaluation Results (Dataset I) 3 - level with credit score

## Random Forest

## KNN

## SVM

#### Sensitivity:

False - 0.9894 Half-true- 0.27273 True - 0.52874

## Specificity:

False - 0.4837 Half-true- 1.00000 True - 0.96840

#### Accuracy:

False - 0.7365 Half-true- 0.63636 True - 0.74857

#### Sensitivity:

False - 0.9257 Half-true-0.15152 True - 0.4368

## Specificity:

False - 0.4967 Half-true- 0.96552 True -0.9097

#### Accuracy:

False - 0.7ll2 Half-true- 0.55852 True -0.6732

#### Sensitivity:

False - 0.8621 Half-true- 0.18182 True - 0.36782

## Specificity:

False - 0.4706 Half-true- 0.93750 True - 0.88488

#### Accuracy:

False - 0.6663 Half-true- 0.55966 True - 0.62635

Overall accuracy: 0.8245

Overall accuracy: 0.7491

# Evaluation Results (Dataset 3) 3 - level without credit score

## Random Forest

## KNN

## SVM

#### Sensitivity:

False - 1.0000 Half-true-0.0000 True -0.0000

## Specificity:

False - 0.0000 Half-true-1.0000 True -1.0000

#### Accuracy:

False - 0.5000 Half-true-0.5000 True -0.5000

#### Sensitivity:

False - 0.93899 Half-true-0.0000 True - 0.05747l

## Specificity:

False - 0.05882 Half-true-0.991379 True -0.948081

#### **Accuracy:**

False - 0.49891 Half-true-0.495690 True -0.502776

**Sensitivity:** False - 0.8488 Half-true- 0.13636 True -0.32184

### Specificity:

False - 0.3987 Half-true-0.94181 True -0.87810

#### **Accuracy:**

False - 0.6237 Half-true-0.53909 True -0.59997

Overall accuracy: 0.7113

Overall accuracy: 0.6774

# Evaluation Results (Dataset 2) 6 - level with credit score

## Random Forest

## KNN

## SVM

Sensitivity:

False - 0.9636 Mostly-True - 0.41667 Half-true - 0.3939 Pants-Fire - 0.34146 Mostly-False - 0.33333 True - 0.58974

Specificity:

False 0.6258- Mostly-True-0.97925 Half-true-0.97629 Pants-Fire-0.93973 Mostly-False-0.96703 True-0.96538

Accuracy:

False - 0.7947 Mostly-True-0.69796 Half-true-0.68512 Pants-Fire-0.64060 Mostly-False-0.65018 True-0.77756 Sensitivity:

False - 0.8682 Mostly-True-0.14583 Half-true-0.21212 Pants-Fire-0.32927 Mostly-False-0.14667 True- 0.30769

Specificity:

False - 0.6323 Mostly-True-0.96473 Half-true-0.92888 Pants-Fire-0.90625 Mostly-False-0.92747 True-0.94094

Accuracy:

False -0.7502 Mostly-True-0.55528 Half-true-0.57050 Pants-Fire-0.61776 Mostly-False-0.53707 True-0.62431 Sensitivity:

False - 0.6409 Mostly-True-0.20833 Half-true-0.16667 Pants-Fire-0.21951 Mostly-False-0.14667 True:0.23077

Specificity:

False - 0.4516 Mostly-True-0.93154 Half-true-0.91810 Pants-Fire-0.89732 Mostly-False-0.94286 True-0.96538

Accuracy:

False - 0.5463 Mostly-True-0.56993 Half-true-0.54239 Pants-Fire-0.55842 Mostly-False-0.54476 True-0.59807

Overall accuracy: 0.6302

Overall accuracy: 0.4943

# Evaluation Results (Dataset 4) 6 - level without credit score

## Random Forest

## KNN

## SVM

#### Sensitivity:

False -1.0000 Mostly-True-0.0000 Half-true-0.0000 Pants-Fire-0.0000 Mostly-False-0.0000 True- 0.0000

Specificity:

False - 0.0000 Mostly-True-1.0000 Half-true-1.0000 Pants-Fire-1.0000 Mostly-False-1.0000 True-1.0000

Accuracy:

False - 0.5000 Mostly-True- 0.5000 Half-true- 0.5000 Pants-Fire- 0.5000 Mostly-False- 0.5000 True- 0.5000 Sensitivity:

False - 0.5682 Mostly-True-0.04166 Half-true-0.03030 Pants-Fire-0.41463 Mostly-False-0.08000 True-0.025641

Specificity:

False - 0.4806 Mostly-True - 0.94398 Half-true - 0.976293 Pants-Fire - 0.72098 Mostly-False - 0.94066 True - 0.981670

Accuracy:

False - 0.5244 Mostly-True-0.49282 Half-true-0.503298 Pants-Fire-0.56781 Mostly-False-0.51033 True- 0.503656 Sensitivity:

False - 0.6409 Mostly-True-0.20833 Half-true-0.16667 Pants-Fire- 0.21951 Mostly-False-0.14667 True-0.23077

Specificity:

False - 0.4516 Mostly-True-0.93154 Half-true-0.91810 Pants-Fire-0.89732 Mostly-False-0.94286 True-0.96538

Accuracy:

False - 0.5463 Mostly-True-0.56993 Half-true-0.54239 Pants-Fire-0.55842 Mostly-False-0.54476 True-0.59807

Overall accuracy: 0.4151

Overall accuracy: 0.3208

# Results Summary

- Best model was random forest using dataset 1 (3 level with credit score)
  - Best performance across all models in datasets that included credit score (both 3-level and 6-level)

- Worst performance was KNN using dataset 4 (6 level without credit score)
  - Models using datasets that included 6-levels performed worse than datasets that included 3-levels
  - Random forest likely had issues in datasets without credit score (scores of 0 and 1 in sensitivity and specificity is unlikely)