



Fake News Detection
via
Natural Language Processing

The Problem of Fake News

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Lawmakers have also begun discussing regulation of our platforms both in the U.S. and Europe.

The Problem of Fake News

As part of an internal panel on developing a response stratagem, the Data Science department has launched multiple parallel projects to explore feasible action plans.

Our Team's Project :

Explore the possibility of
detecting fake news articles
on posts shared by our users

What is Fake News?

- Objectively false facts?
- Technically true but maliciously misleading?
- Things believed to be true but later demonstrated false?
- Satire and parody content?

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Methodology

1. Scrape posts from two subreddits: *r/news* and *r/TheOnion*.
 - a. Only use post titles to mimic news headlines.
 - b. Investigate 2 separate situations of balanced and imbalanced classes.
2. Use *Count encoding*, *TF-IDF*, *SIA*, and *Word2Vec* to encode text as numeric data.
3. Train a discriminator to identify which posts came from where.
 - a. Naive Bayes, Logistic Regression, SVM, and Neural Network.
 - b. Bagged Trees, Random Forest, AdaBoost and Gradient Boosting

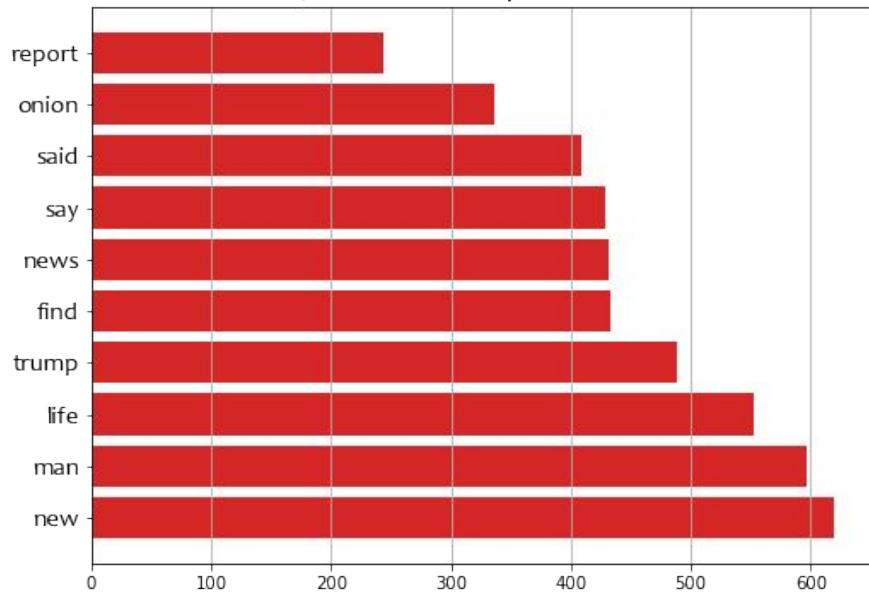
Some
Data
Insights

Data Size

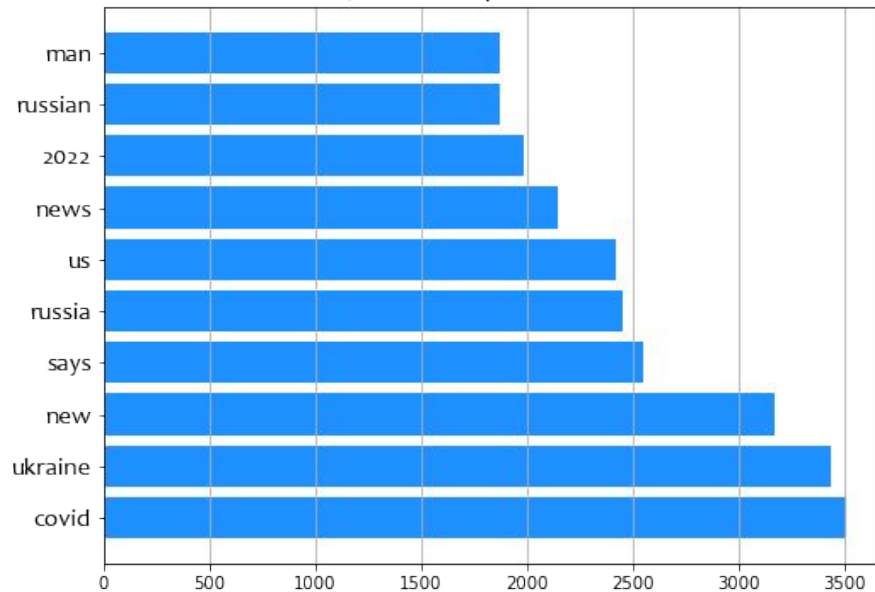
- Scraped 100,000 *r/news* posts vs 17,000 *r/TheOnion* posts.
- Purged duplicates and non-ASCII titles; 80,000 training examples remained.
- Scenario 1: treat this as an imbalanced class problem with *r/news* vs *r/TheOnion* ratio at 7:1.
- Scenario 2: reduce down to 20,000 training examples but with 50:50 split (basically equivalent to Random Under Sampling).

Top 10 Words

r/TheOnion Top 10 Words

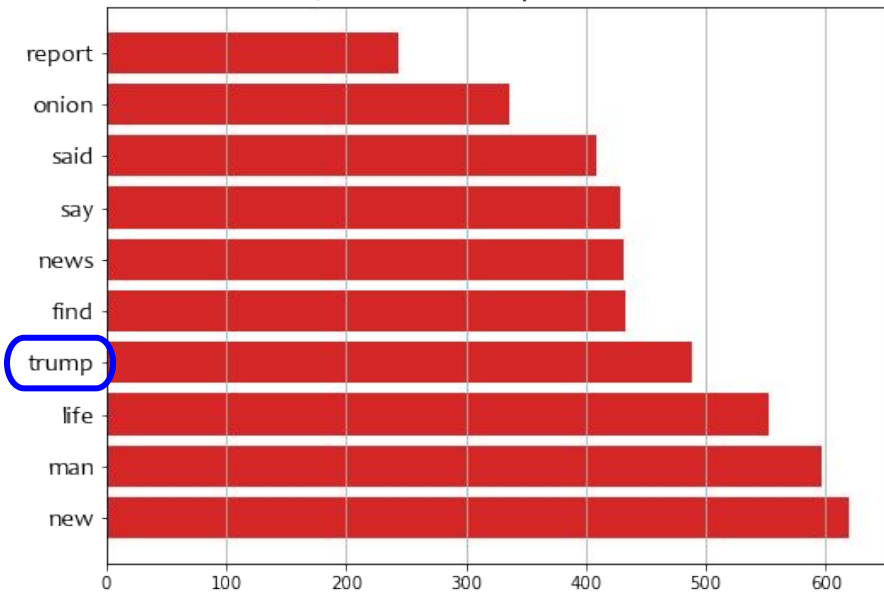


r/news Top 10 Words

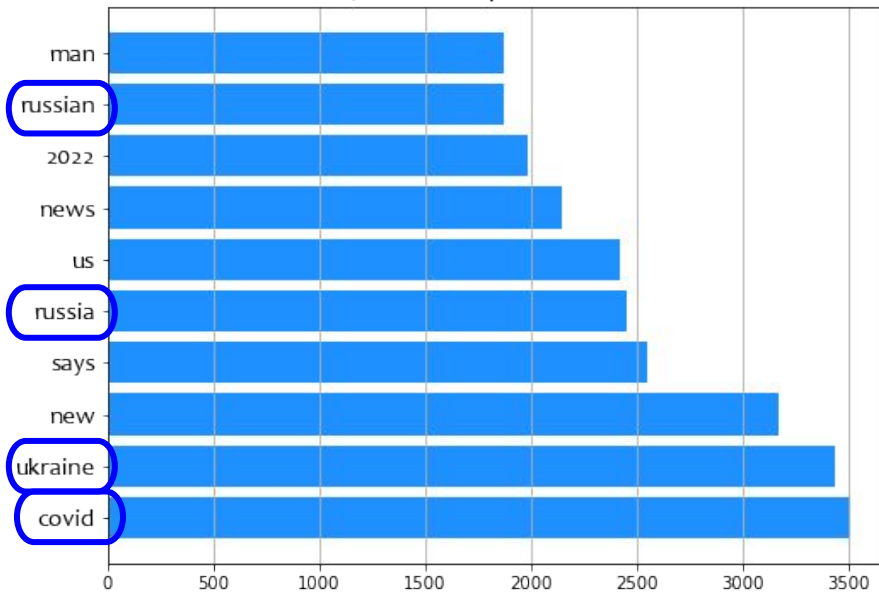


Top 10 Words

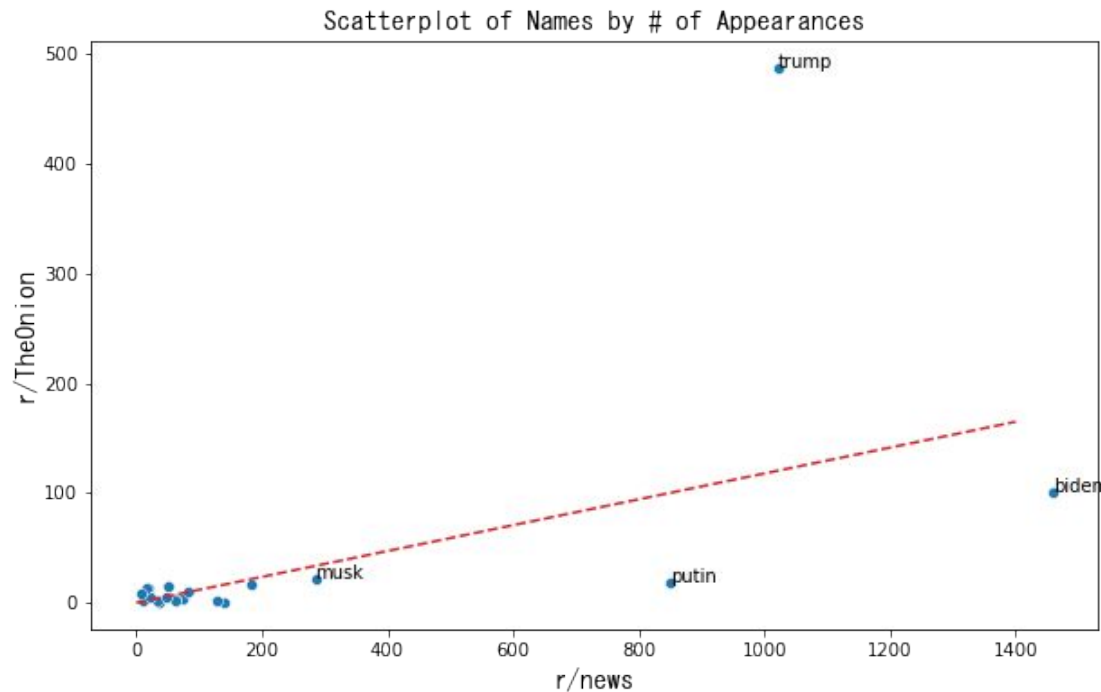
r/TheOnion Top 10 Words



r/news Top 10 Words

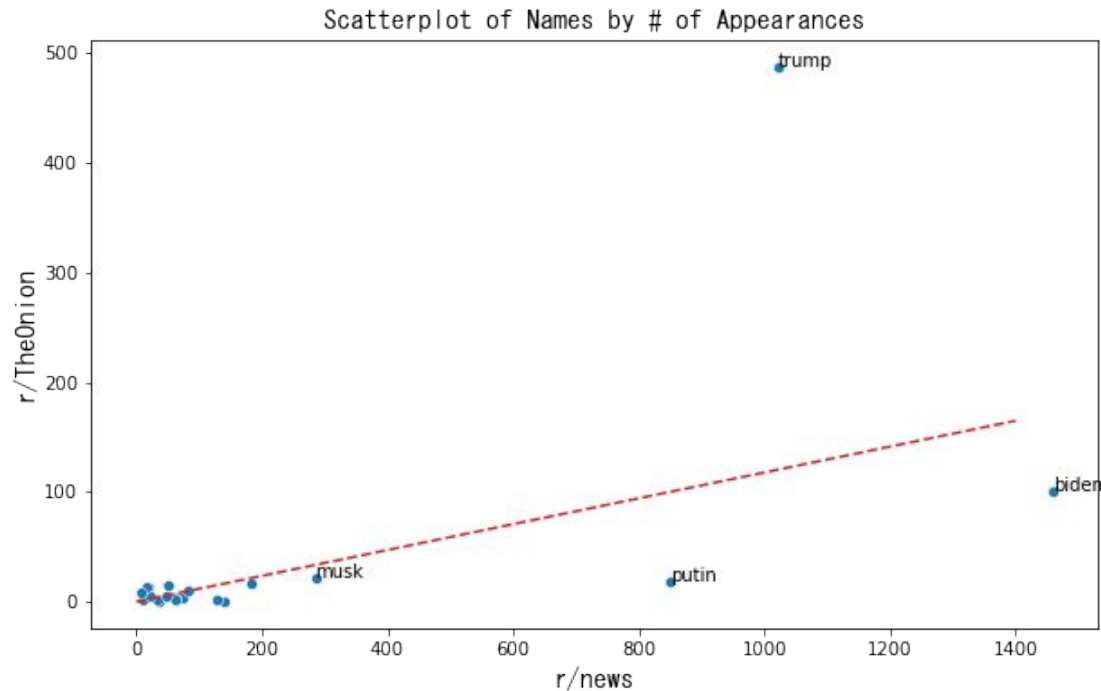


Name Mentions



Name	r/TheOnion	r/news
"trump"	488	1021
"biden"	101	1458
"putin"	19	849
"macron"	1	37
"trudeau"	3	73
"kardashian"	2	61
"kanye"	10	81
"bezos"	15	50
"gates"	15	52
"musk"	22	285

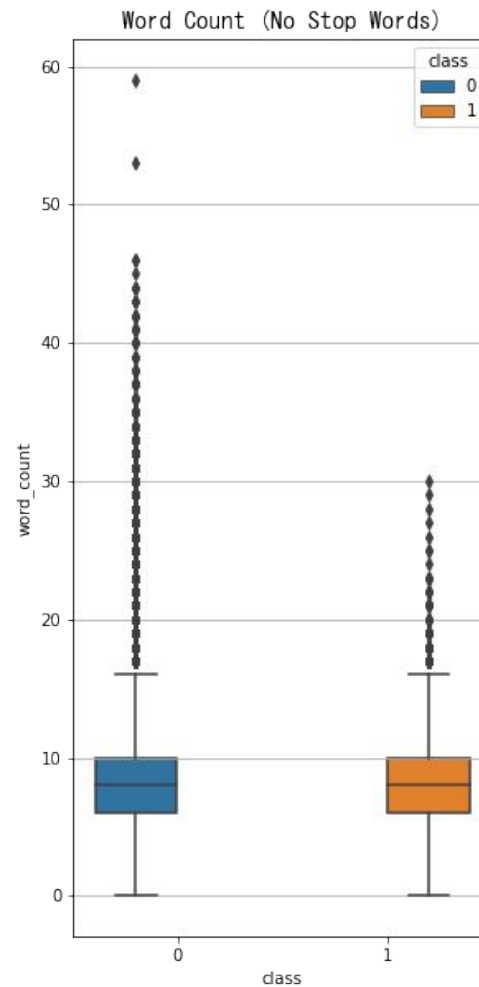
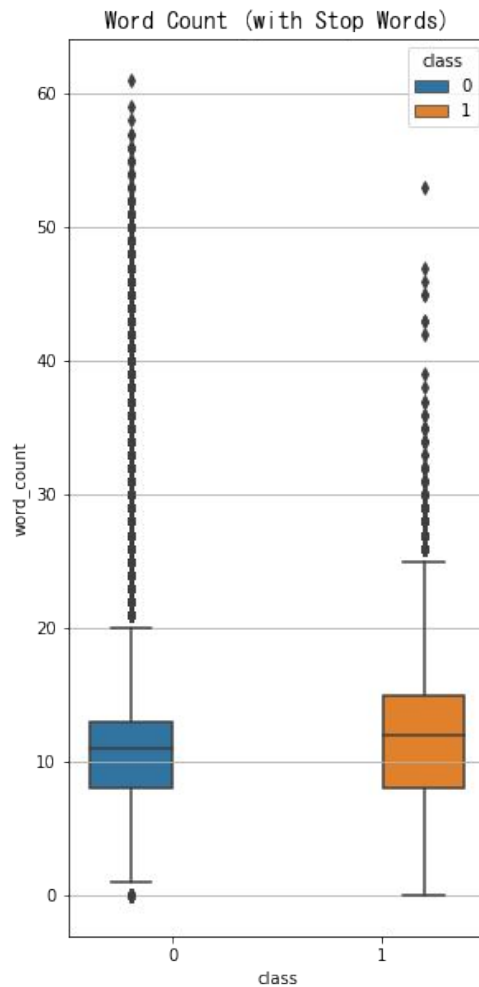
Name Mentions



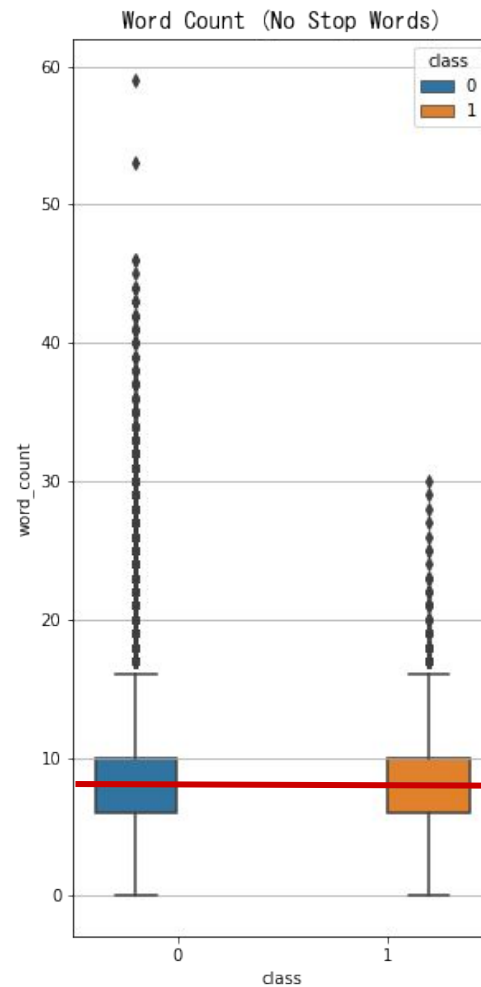
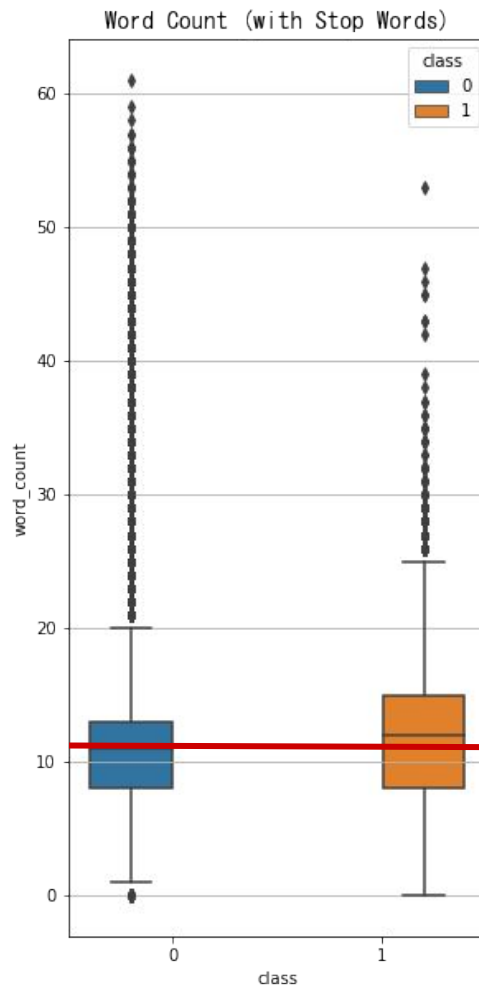
Red line = 7:1 ratio of *r/news* to *r/TheOnion*.

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Title Lengths



Title Lengths



Scenario 1: Imbalanced Classes

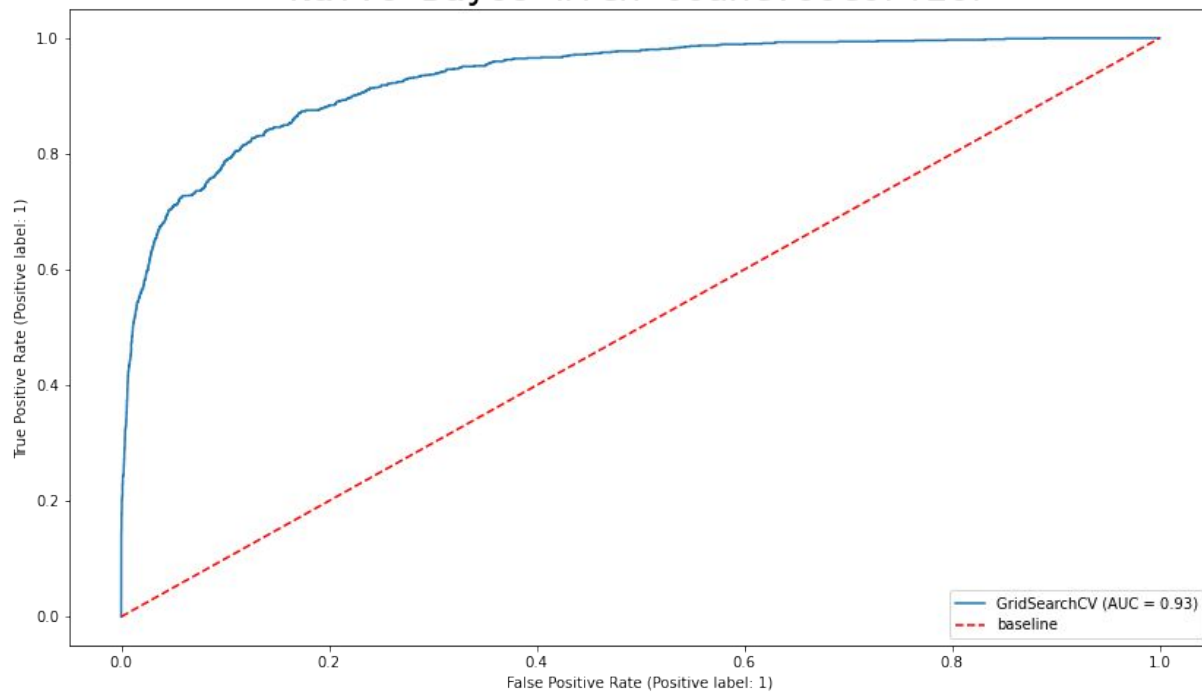
Naive Bayes

Encoding	Accuracy	Recall	Precision	F1	AUC
Baseline	87%	-	-	-	0.5
CountVectorizer	93%	59%	78%	67%	0.93
TF-IDF	88%	5%	100%	10%	0.86
SIA	87%	8%	13%	1%	0.55

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Naive Bayes with CountVectorizer



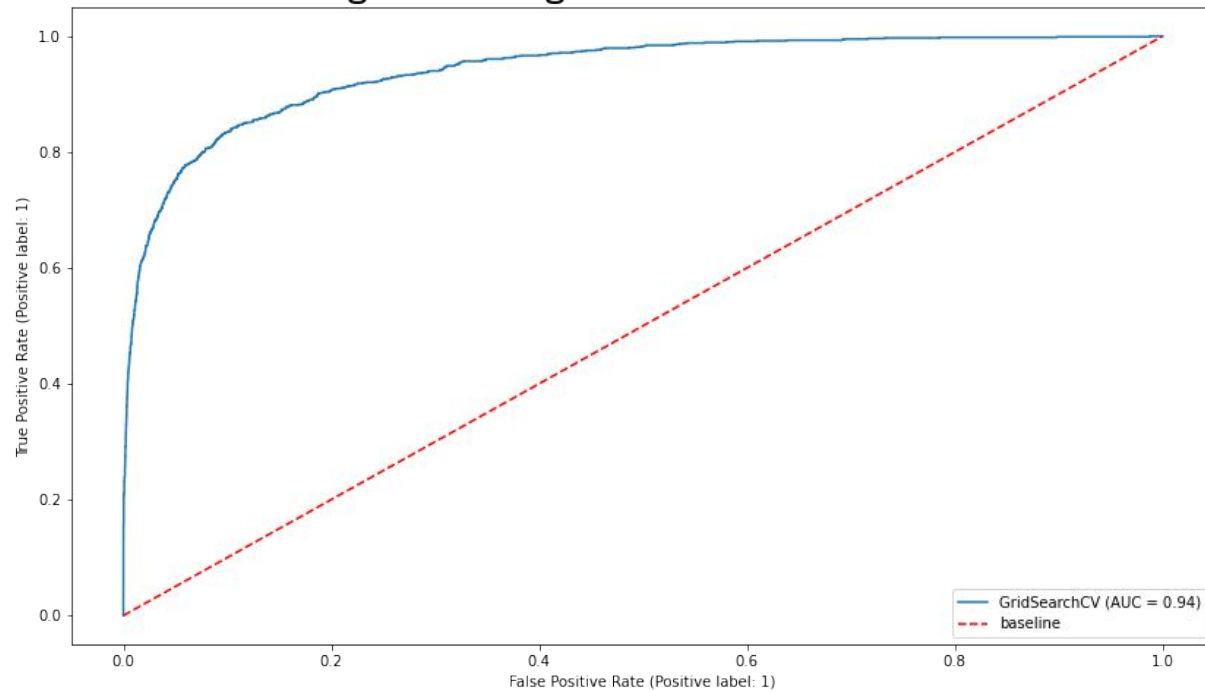
Logistic Regression

Encoding	Accuracy	Recall	Precision	F1	AUC
Baseline	87%	-	-	-	0.5
CountVectorizer	93.2%	55%	80%	67%	0.94
TF-IDF	93.3%	57%	85%	69%	0.94
SIA	87%	0%	0	0	0.56

Logistic Regression

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Baseline	87%	-	-	-	0.5
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Logistic Regression with TF-IDF



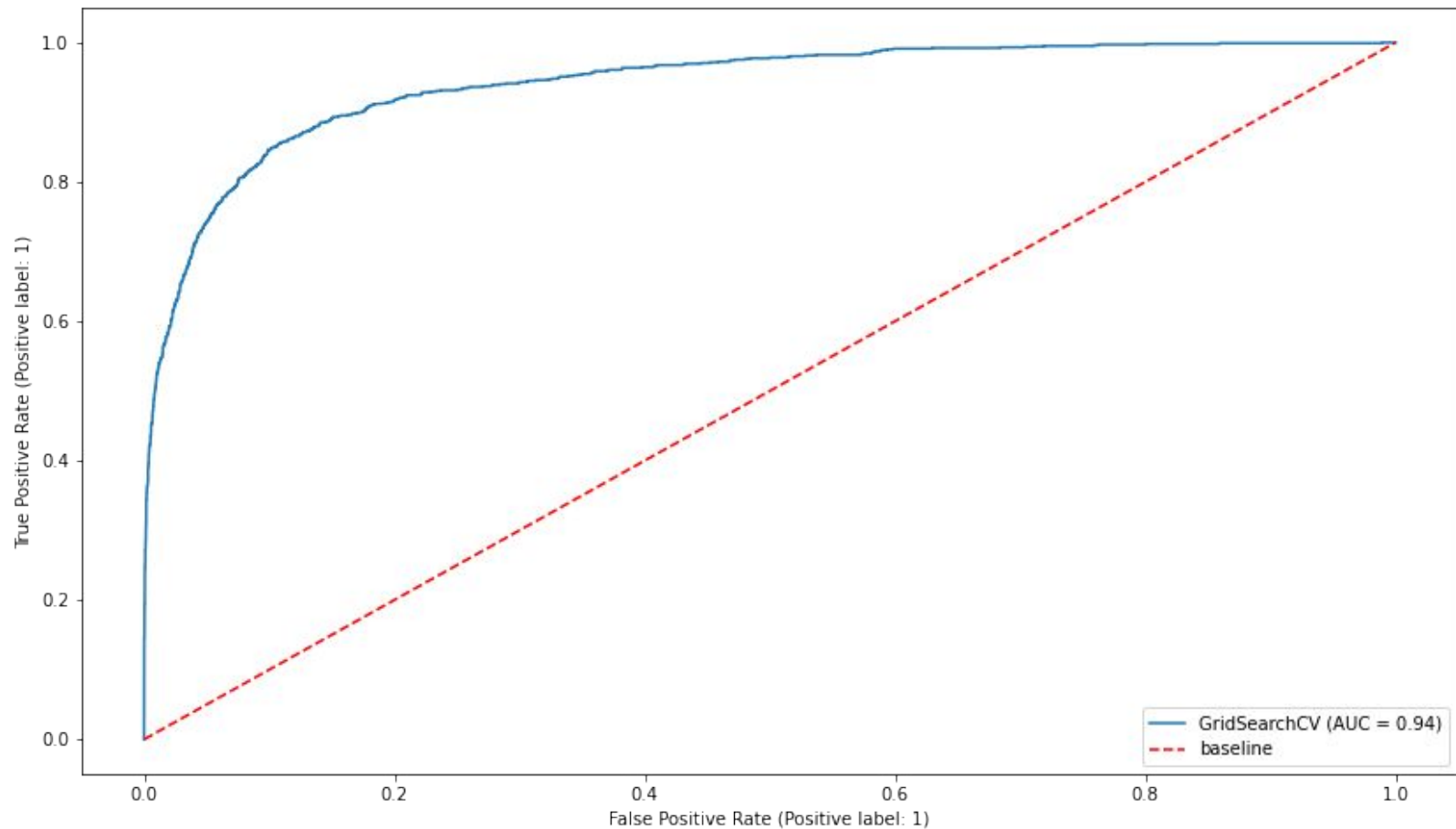
Support Vector Machine

Encoding	Accuracy	Recall	Precision	F1	AUC
Baseline	87%	-	-	-	0.5
CountVectorizer	93.3%	54%	88%	67%	0.94
TF-IDF	93.4%	56%	87%	67%	0.94

Support Vector Machine

Encoding	Accuracy	Recall	Precision	F1	AUC
Baseline	87%	-	-	-	0.5
CountVectorizer	93.3%	54%	88%	67%	0.94
TF-IDF	93.4%	56%	87%	67%	0.94

SVM with TF-IDF



Word2Vec (via Gensim)

- Word2Vec: ML model takes words and assigns them to vectors.
- The “closer” two words are in meaning, the closer the assigned vectors are too (closeness is measured by the cosine of their angle).
- Because vectors can be added/subtracted, we can now do arithmetic on words!

“King” - “Man” + “Woman” = “Queen”

“OnionNet” (W.I.P.)

1. Use GloVe (Stanford’s pre-trained Word2Vec model) to map each document to an array of vectors.
2. Flatten array into a single long vector. Now each document is a vector, the meaning of the words are encoded, and ordering of words is preserved!
3. Use these long vectors as inputs to a Neural Network (1 hidden layer, 2000 hidden units).

“OnionNet” (W.I.P.)

Results:

- Trained for 10 epochs; **Accuracy 90.7%** (worse than Naive Bayes and Logistic Regression!). Only Marginally better than baseline :(
- Currently unable to handle people names (ignoring A LOT of info!)
- Might perform better with a larger vocabulary (currently using GloVe with 6 billion tokens, maybe try 840 billion tokens model).
- Might perform better if it had millions of training examples.

Scenario 2: Balanced Classes

Balanced Classes

- Alternatively, we can balance the classes by Under Sampling.
- This has the added benefit of reducing the data down to a more manageable amount (20,000 examples instead of 80,000)
- Faster training time and more feasible to prototype models with.

SVM + Ensemble Methods



SVM + Ensemble Methods (with TF-IDF)

Model	Accuracy	Recall	Precision	F1	AUC
Baseline	50%	-	-	-	0.5
SVM (rbf kernel)	76%	93%	70%	80%	0.88
Bagged Trees	72%	63%	77%	69%	0.80
Random Forest	79%	73%	83%	78%	0.89
AdaBoost	72%	72%	72%	72%	0.78
Gradient Boosting	78%	75%	80%	77%	0.87
OnionNet	79%	78%	80%	79%	-

SVM + Ensemble Methods (with TF-IDF)

Model	Accuracy	Recall	Precision	F1	AUC
Baseline	50%	-	-	-	0.5
SVM (rbf kernel)	76%	93%	70%	80%	0.88
Bagged Trees	72%	63%	77%	69%	0.80
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AdaBoost	72%	72%	72%	72%	0.78
Gradient Boosting	78%	75%	80%	77%	0.87
OnionNet	79%	78%	80%	79%	-

Final Results:

Situation	Best Model	Training Set	Validation Set	Final Test Set
Imbalanced	Linear SVM	99.29%	93.4%	93.85%
Balanced	Random Forest	91%	79%	85%

Conclusions and Recommendations

- Logistic Regression and Linear SVM with TF-IDF did ok.
 - Probably biased towards buzzwords and current news.
 - Evidence that a good model can be built with enough research.
- Sentiment Analysis NOT effective in classifying satire/humor/non-serious headlines.
- Invest in cloud computing / big data frameworks to train ensemble methods.
- Can work if we find a good way to encode document structure (word2vec just the start).