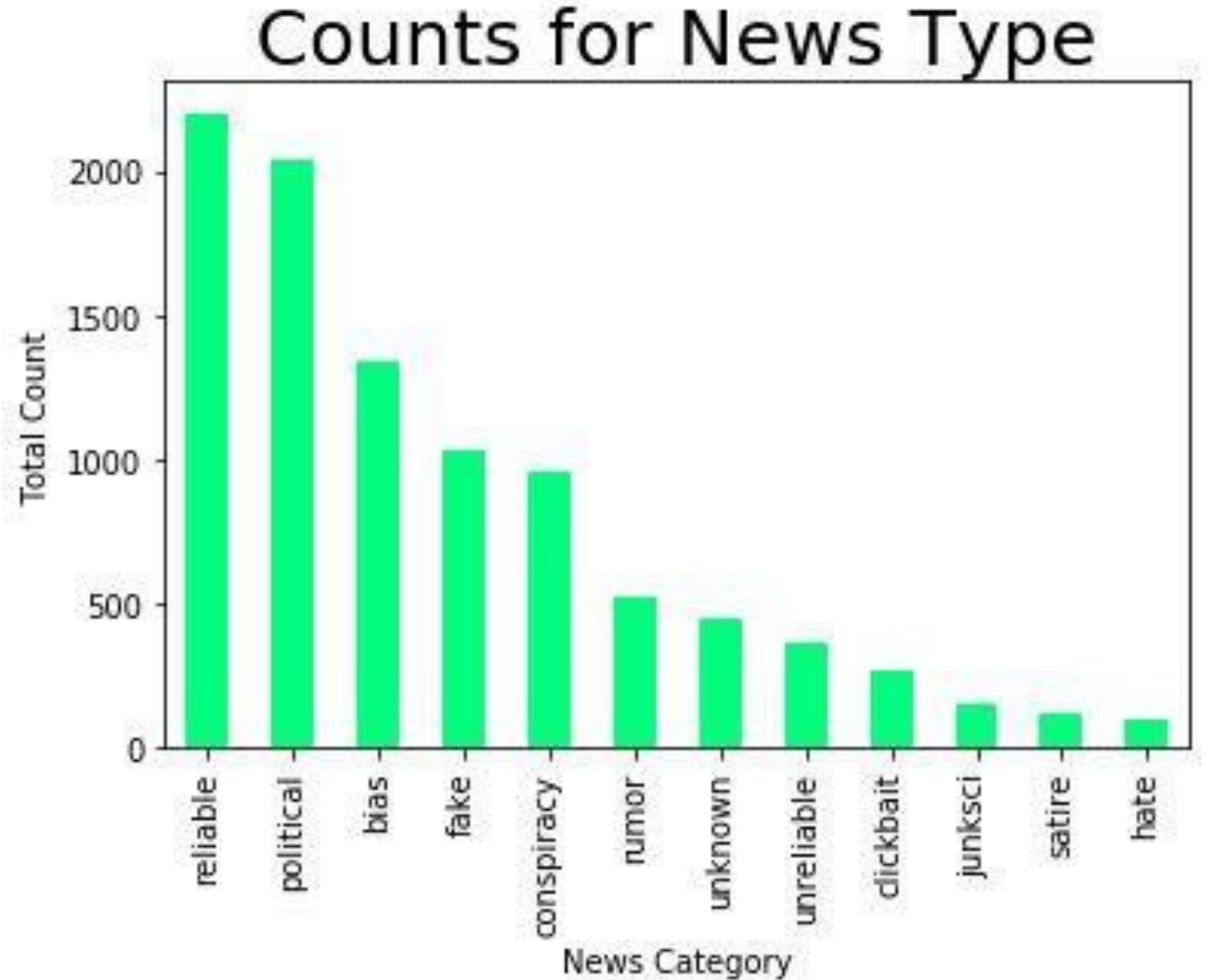


Fake News Project

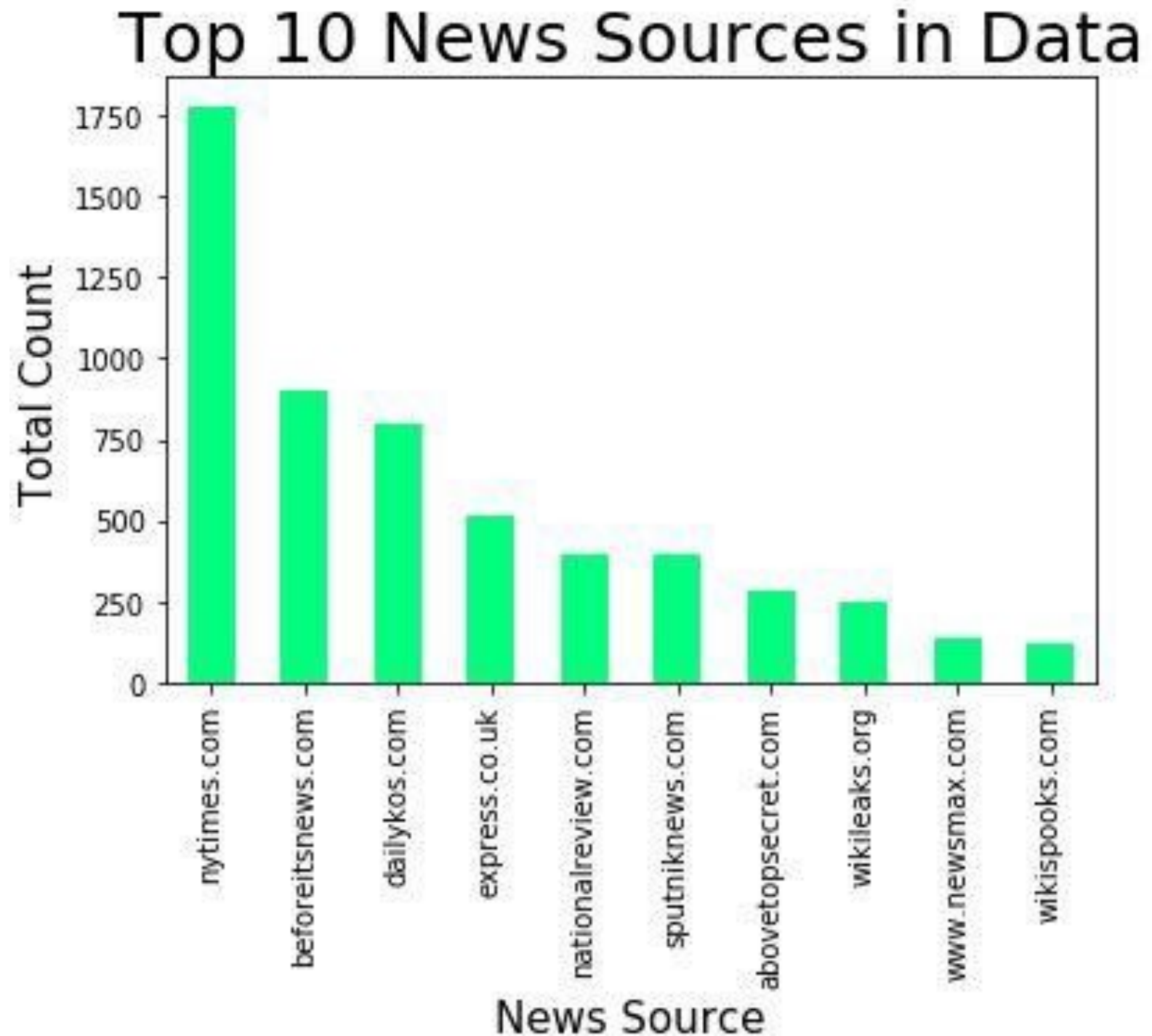
Introduction

- What can machine learning techniques tell us about fake news detection?
- How do different styles of sampling data influence results?

Category Counts in Initial Sampling



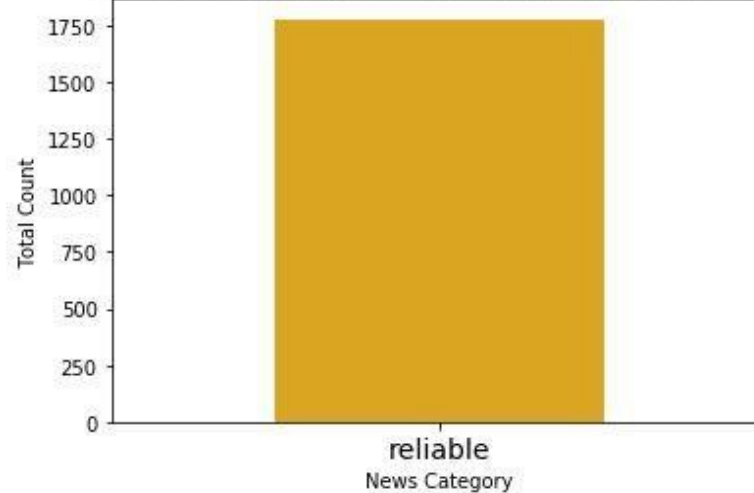
News Source
Counts in
Initial
Sampling



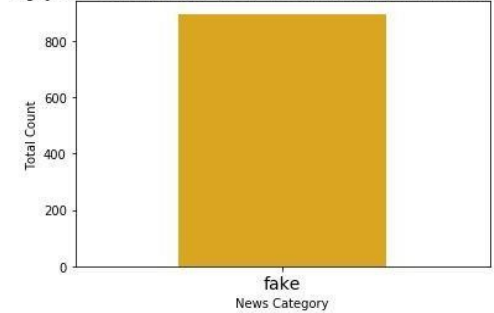
Every single
article from a
given source is in
one category in
the data

Is this problematic?

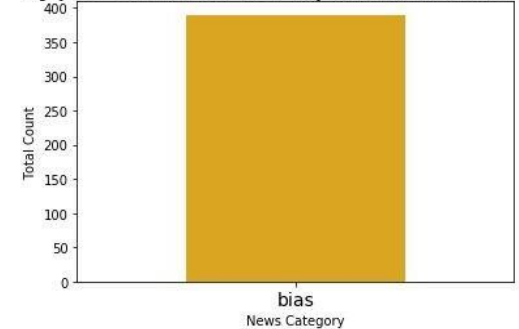
'Type' Counts for nytimes.com



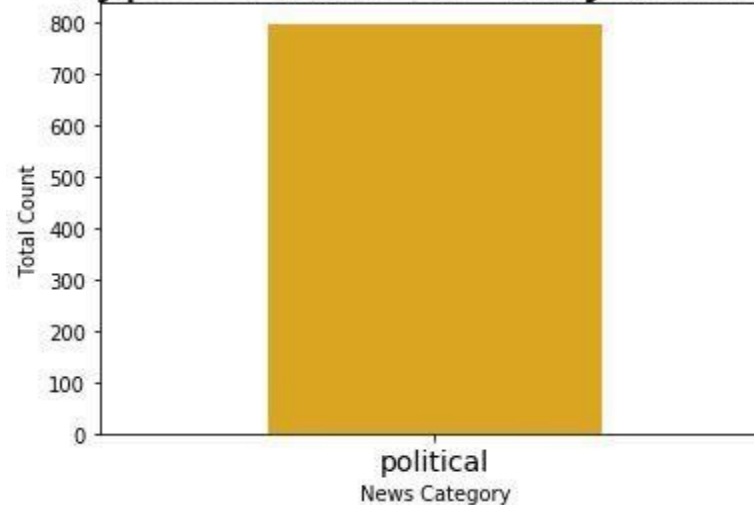
'Type' Counts for Beforeitsnews.com



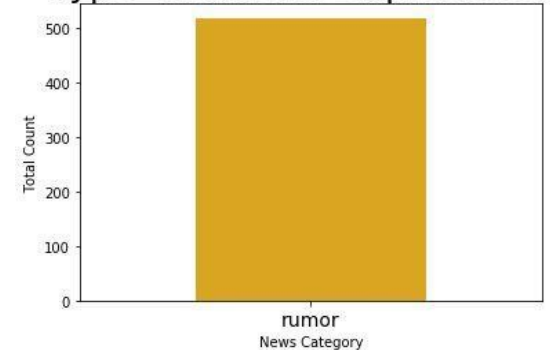
'Type' Counts for sputniknews.com



'Type' Counts for dailykos.com

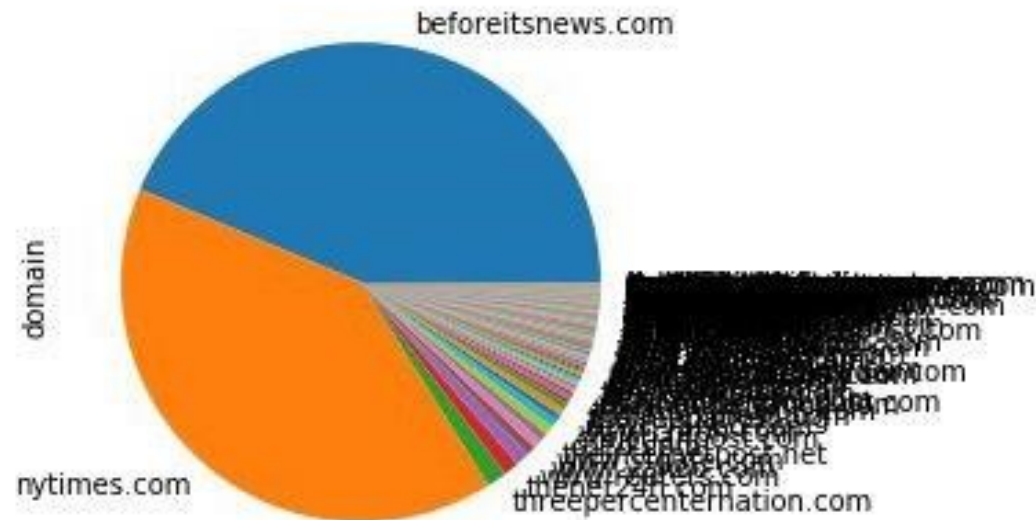


'Type' Counts for express.co.uk

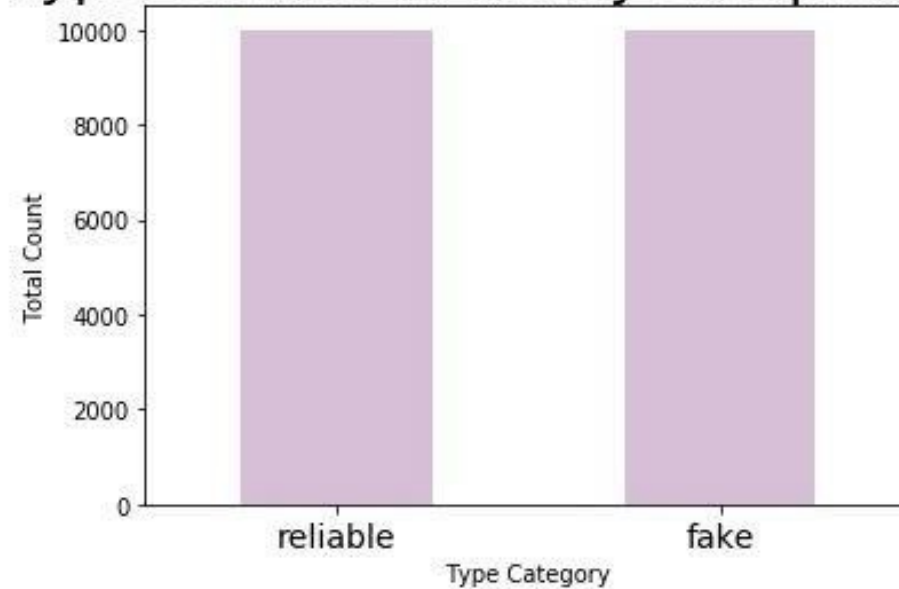


Initial Analysis – Reliable vs. Fake

News Source (domain)



'Type' Counts in Newly Sampled Data



Sentiment Analysis

	Label	SIA Polarity Score	TextBlob Polarity Score	TextBlob Subjectivity
Fake News	1	5468	983	1128
	-1	3013	67	5784
	0	5013	7944	3088
Reliable News	1	6721	1175	762
	-1	2581	73	6800
	0	698	8752	2438

Predictive Modeling – Reliable vs. Fake

Bag-of-words Vectorization

Predictions were 86.7% accurate with Multinomial Naïve Bayes.

87% accurate with LinearSVC().

87.5% accurate with XGBoost().

Predictive Modeling – Reliable vs. Fake

Tf-idf Vectorization

Predictions were 87.2% accurate with Multinomial Naïve Bayes.

90.8% accurate with LinearSVC().

89.0% accurate with XGBoost().

Predictive Modeling – Reliable vs. Fake

Tf-idf Vectorization with Bigrams

Predictions were 90.4% accurate with Multinomial NB.

91.7% accurate with LinearSVC().

83.3% accurate with XGBClassifier().

Most Predictive features for Initial Reliable vs. Fake Analysis

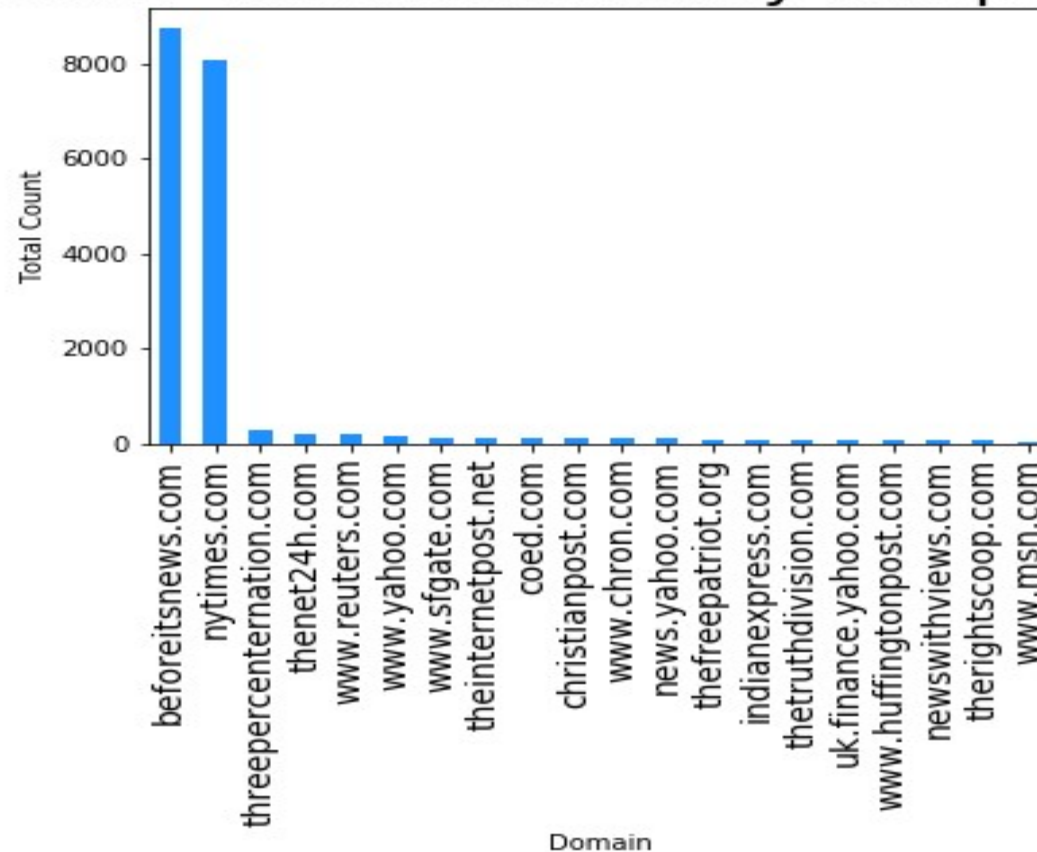
6.2862	main stori
6.2685	read main
5.9580	advertis continu
5.6588	continu read
4.7699	new york
4.2447	to re
2.3737	an articl
1.9920	next in
1.7252	said would

- These results indicate that the fact that a given article is from the New York Times is more predictive than anything else in the data. Because of this, the data was resampled (see following slide)

Resampling

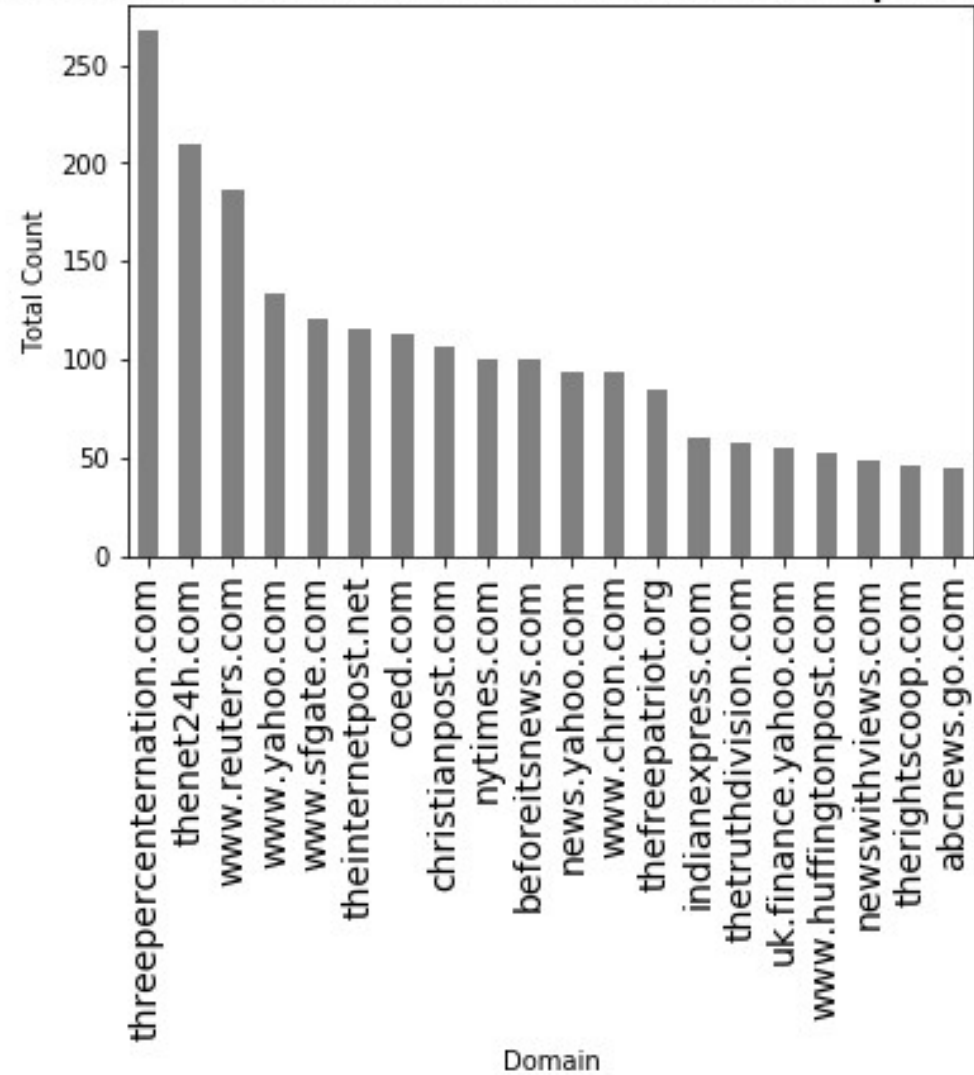
The New York Times and beforeitsnews.com were vastly overrepresented in the initial sample:

'Domain' Counts in Initially Sampled Data



Resampling –
data was
resampled for
better balance
across domain

'Domain' Counts in Undersampled Data



Predictive Accuracy

BAG-OF-WORDS	Tf-idf	Tf-idf with two bigrams
Predictions were 78.4% accurate with Multinomial NB.	Predictions were 63.9% accurate with Multinomial NB.	Predictions were 66.0% accurate with Multinomial NB.
80.7% accurate with LinearSVC().	85.6% accurate with LinearSVC().	82.1% accurate with LinearSVC().
79.8% accurate with XGBClassifier().	84.6% accurate with XGBClassifier().	78.7% accurate with XGBClassifier().

Predictive Features

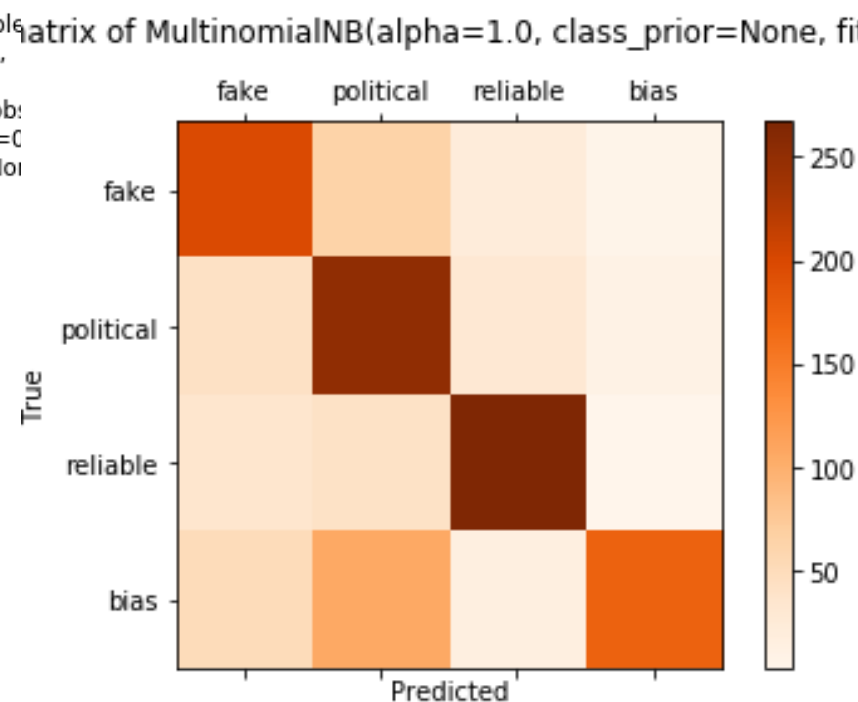
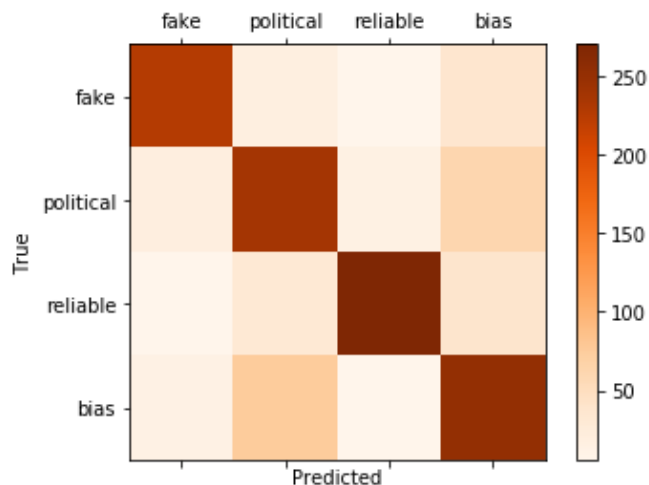
Unigrams

2.8374	2016
2.3298	ap
2.2535	nov
2.1699	november
1.9041	said
1.5876	reuters
1.4786	photo
1.4026	film
1.3945	also
1.2465	percent
1.2073	says

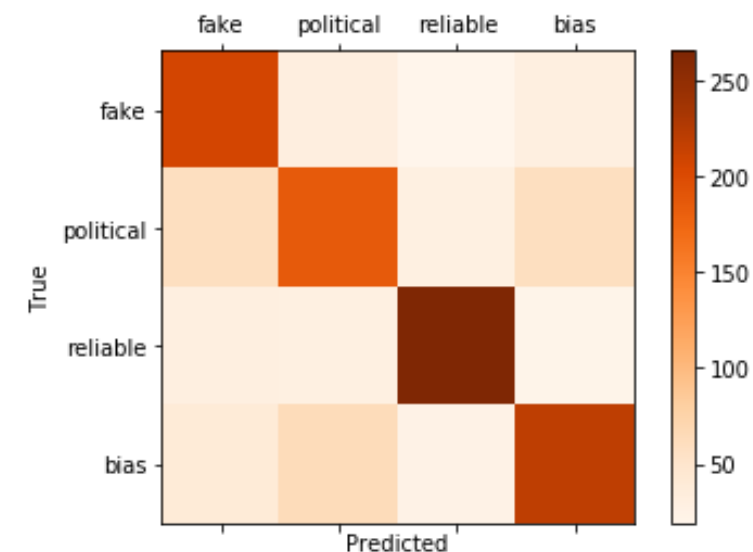
Bigrams

-4.2017	budget rep
-4.5269	aliens tend
-4.6422	aiding abetting
-4.6732	asking doctor
-4.7910	becoming nurse
-5.0097	books hillbilly
-5.2696	500 name
-5.3058	black sea
-5.3252	bar great
-5.3520	apartment metrocare
-5.3822	cabinet bloomberg
-5.3951	babies kinkade

Confusion matrix of XGBClassifier(base_score=0.5, booster='gbtree', colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=3, min_child_weight=1, missing=None, n_estimators=100, n_jobs=1, nthread=None, objective='multi:softprob', random_state=None, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None, silent=None, subsample=1, verbosity=1)



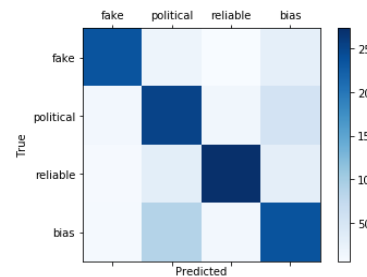
Confusion matrix of LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True, intercept_scaling=1, loss='squared_hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None, tol=0.0001, verbose=0)



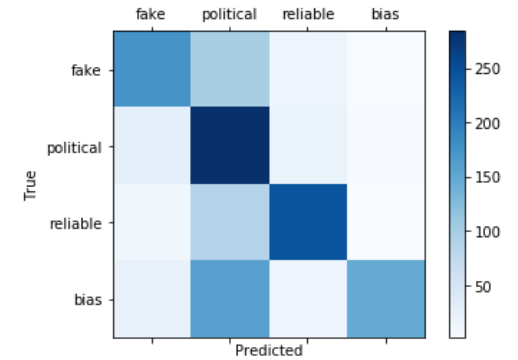
Multiclass Classification with count vectorization

Multiclass Classification with tf-idf vectorization

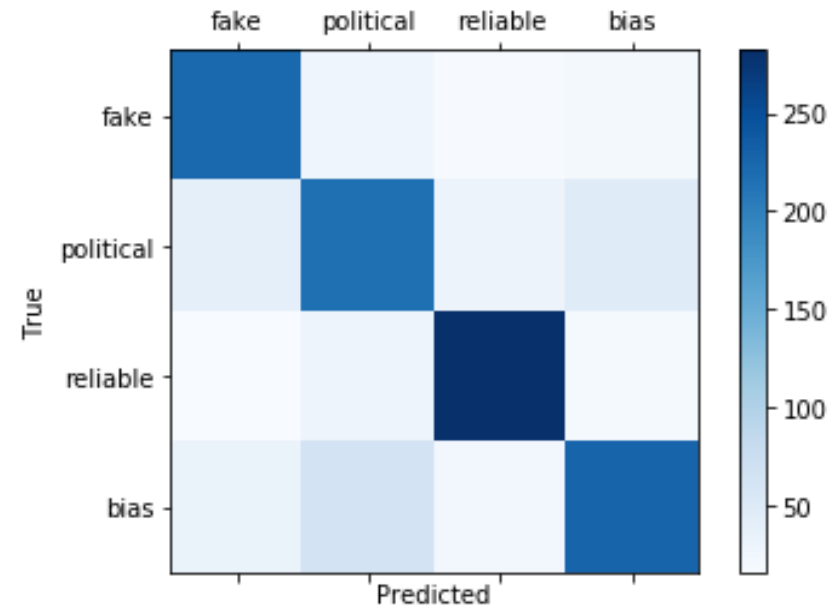
Confusion matrix of XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1, max_delta_step=0, max_depth=3, min_child_weight=1, missing=None, n_estimators=100, n_jobs=1, nthread=None, objective='multi:softprob', random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None, silent=None, subsample=1, verbosity=1)



Confusion matrix of MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)

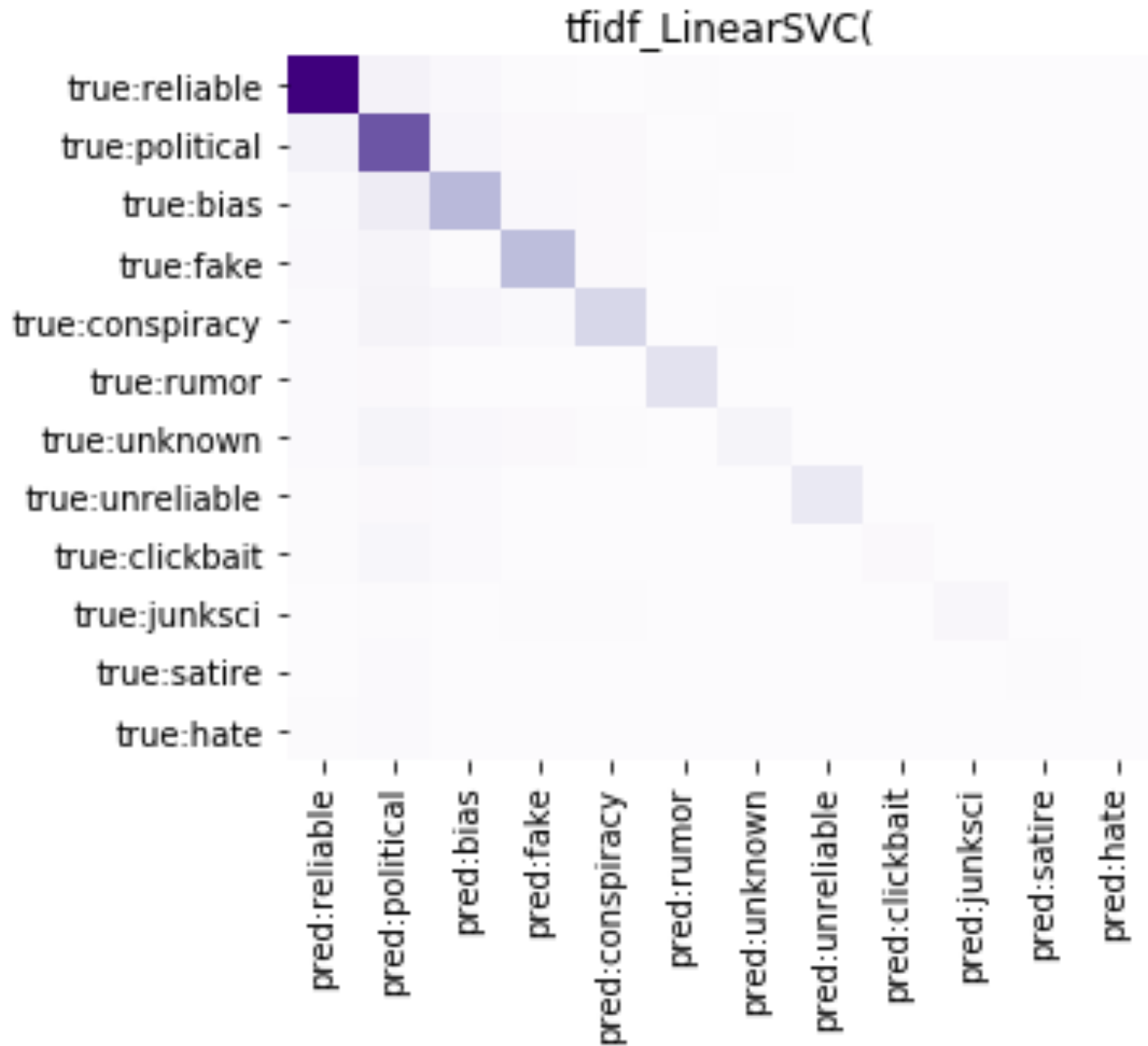


Confusion matrix of LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True, intercept_scaling=1, loss='squared_hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None, tol=0.0001, verbose=0)



More Classes

- The same six pairs of vectorization and classification method were applied to the data, but for all of the classes (instead of just the four largest ones). There were too few observations of the the smaller classes for such an analysis to be very useful. Results were similar to the analysis with just the four largest classes.



Takeaway Points

- Machine learning classification can, with a significant degree of accuracy, predict fake news.
- Prediction seems to be inherently tied to source, as some of the most informative features were direct references to the site or online newspaper that articles came from.
 - This highlights the problem of designating all articles from a given source with the same reliability category.
- This analysis was conducted with a smaller subset of data from the very large dataset. Conducting the analysis with a larger amount of data may yield more interesting results.