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Prediction of Category in News Text
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The Purpose

Natural language processing is ubiquitous for the internet and the IOT universe. Classification provides an important tool for identifying subject matter of content. Results of classification models may provide information for composition that is easily classified and potentially insights on text that is not easily classified.

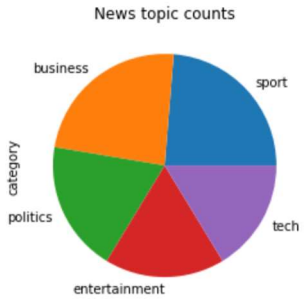
Summary of Findings

This analysis compares five standard Scikit Learn classification models and two extractors on the full text of more than 2000 news articles. The focus is on the discrete words for five news categories: business; entertainment; politics; sport; and tech. The models classify by the words, with no information on parts of speech, sequences or contexts in which they are used. The Logistic Regression, Naïve Bayes and Gradient Boosting classifiers, with default parameters, perform with an accuracy greater than nine out of ten on the two extraction types. The twenty most frequent words are found for the five respective categories.

The Data

The BBC news data set composed of 2225 full-text articles and appears in the Kaggle competition data sets. Downloaded as a comma separated file, the set has two variables: news category ('category') and full text of the articles ('text'). The text was already converted to lower case with punctuation removed. Data cleaning included removing duplicates.

	category	percentages
sport	504	24.0
business	503	24.0
politics	403	19.0
entertainment	369	17.0
tech	347	16.0



There remained 2126 articles and five categories.

The article text was prepared for tokenization by removing special characters. The list of "stopwords," articles, and other often used, meaningless words when taken out of context, was provided in the Natural Language Toolkit package. The stopwords were removed in separate

steps so the length of the articles, in this case, number of tokens, could be compared with and without stopwords. Stopwords could be generated according to frequency for this corpus (or hand compiled) as a parameter tuning for the Bag of Words and Term Frequency-Inverse Document Frequency (TF-IDF) extractors in SciKit-Learn.

20 Most Common Words for Each Category

Business

	term	count
0	said	1655
1	us	787
2	year	623
3	mr	596
4	would	459
5	also	432
6	market	417
7	company	412
8	new	401
9	growth	362
10	firm	358
11	last	356
12	economy	342
13	government	335
14	bank	331
15	sales	316
16	2004	304
17	could	302
18	economic	302
19	oil	291

Entertainment

	term	count
0	said	803
1	film	711
2	best	563
3	music	423
4	also	382
5	one	350
6	us	350
7	year	346
8	show	318
9	new	315
10	awards	268
11	first	238
12	last	231
13	award	230
14	years	220
15	uk	216
16	two	206
17	tv	205
18	people	203
19	band	203

Politics

	term	count
0	said	2174
1	mr	1614
2	would	1005
3	labour	728
4	government	712
5	people	607
6	party	544
7	election	536
8	blair	535
9	also	438
10	new	419
11	minister	413
12	could	372
13	brown	356
14	told	340
15	uk	335
16	howard	309
17	public	304
18	plans	302
19	one	302

Sport

	term	count
0	said	927
1	game	468
2	england	455
3	first	432
4	win	408
5	would	396
6	world	374
7	last	367
8	one	354
9	two	349
10	time	325
11	also	323
12	back	316
13	players	304
14	play	291
15	cup	290
16	new	285
17	side	267
18	year	265
19	team	263

Tech

	term	count
0	said	1368
1	people	828
2	also	460
3	mr	451
4	technology	450
5	new	449
6	one	437
7	could	426
8	mobile	420
9	would	415
10	games	382
11	users	343
12	use	337
13	us	325
14	game	311
15	many	310
16	music	310
17	net	306
18	digital	298
19	software	298

Text Data Preparation for Classification Models

In preparation for the classification models, the tokens were extracted and vectorized, converted to numeric coding, for machine learning models. The two extraction outputs were: a "Bag of Words," word counts in the entire body of texts, the "corpus;" and Term Frequency-Inverse Document Frequency ("TF-IDF"), words weighted for importance.

Bag of Words

CountVectorizer was used to extract a Bag of Words, words pooled with no use or sequence information, for the corpus. This extractor creates a feature for each token. In its default setting, "ngram_range; tuple (min_n, max_n), default=(1, 1)" *from Scikit-Learn documentation*, a token is one word. Token, word and term will be used interchangeably, as will document and article because one refers to the other in this analysis.

The Bag of Words, in its transformed output, is a document-term matrix, composed of word features in the columns – a vocabulary of 29,241 and rows corresponding to the 2,126 articles. The cells in the matrix are filled with the count of how many times the word (feature column) occurred in the article designated by the row.

Glimpse of the Document-Term Matrix

	00	000	0001	000bn	000m	000s	000th	001	001and	001st	...	zooms	zooropa	zornotza	zorro	zubair	zuluaga	zurich
0	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
1	0	1	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0

3 rows × 29421 columns

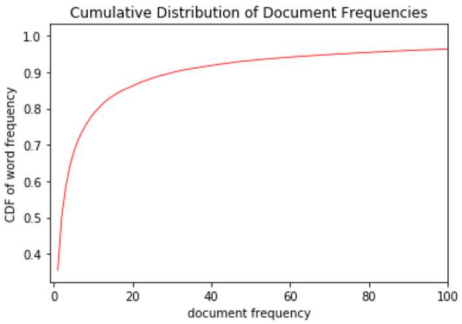
The above graphic shows a glimpse of the document-term matrix. The table shows the numeric code for the word and the sum of the frequency the words occurred for all the articles. The second column corresponds to the sum of every column in the matrix above, word code "000" occurs 756 times.

Word-Document Frequency Table

	Word	Article_Frequency
0	00	6
1	000	756
2	0001	1
3	000bn	1
4	000m	41

One intuitive parameter to tune in CountVectorizer is directing the extractor with respect to the minimum occurrence of that term. Called the minimum document frequency, "min_df," or the cut-off, the default is one time (min_df = 1). Cumulative distribution of document frequencies

By inspecting the cumulative distribution of word frequencies by number of documents, the minimum probably is greater than one. The fitted and transformed text with CountVectorizer with the minimum document frequency of 2 (min_df= 2).



This reduces the total number of features, the vocabulary, to 17240.

For optimal tuning, the model is considered. A combination of trial parameters for the extractor and the respective preferred model(s) may be needed for optimization.

Classification Models

The performance of the supervised machine learning classification models on the Bag of Words was generally good, with at least 94% accuracy in three models. The data was randomly split for training on 70 percent and testing on 30 percent. This proportion was used throughout the analysis.

The classification models included K-Nearest Neighbors (KNN), Logistic Regression, Random Forest, Gradient Boosting, and Naïve Bayes, the multinomial classifier (Naïve Bayes). They were all run with their default parameter in Scikit-Learn.

The table below shows the performance metrics that were calculated and displayed in a classification report for each model. Confusion matrices show detailed summaries of how particular models classified on the news categories correctly (true positives and negatives) or incorrectly (false positives and negatives). The best performing model, Naïve Bayes, made a 97 percent accurate classification of the categories on the test data, the 30 percent held out when the model was fitted. The models are arranged in descending performance in the table below.

Sequence left to right and top to bottom is: business; entertainment; politics; sport; tech.

Naïve Bayes

```
[[144   1   2   0   3]
 [  1 105   2   0   2]
 [  2   1 116   0   0]
 [  0   0   0 155   0]
 [  3   1   1   0  99]]
```

	precision	recall	f1-score	support
business	0.96	0.96	0.96	150
entertainment	0.98	0.96	0.97	110
politics	0.95	0.97	0.96	119
sport	1.00	1.00	1.00	155
tech	0.95	0.94	0.95	104
accuracy			**0.97**	638

Logistic Regression

```
[[144   0   4   0   2]
 [  2 105   1   0   2]
 [  2   2 114   1   0]
 [  0   0   0 155   0]
 [  7   2   1   0  94]]
```

	precision	recall	f1-score	support
business	0.93	0.96	0.94	150
entertainment	0.95	0.95	0.95	110
politics	0.95	0.95	0.95	119
sport	0.99	0.99	0.99	155
tech	0.94	0.89	0.92	104
accuracy			**0.95**	638

Gradient Boost

```
[[140   3   5   0   2]
 [  3 105   0   0   2]
 [  8   0 108   2   1]
 [  0   0   0 155   0]
 [  9   1   1   0  93]]
```

	precision	recall	f1-score	support
business	0.89	0.93	0.91	150
entertainment	0.93	0.95	0.94	110
politics	0.95	0.90	0.92	119
sport	0.99	1.00	0.99	155
tech	0.95	0.89	0.92	104
accuracy			**0.94**	638

Random Forest

```
[[143   1   3   1   2]
 [  4 100   2   3   1]
 [ 12   4 100   2   1]
 [  5   3   4 143   0]
 [ 16   6   3   6  73]]
```

	precision	recall	f1-score	support
business	0.78	0.97	0.87	150
entertainment	0.88	0.77	0.82	110
politics	0.93	0.84	0.88	119
sport	0.89	0.97	0.93	155
tech	0.95	0.73	0.83	104
accuracy			**0.87**	638

KNN

```
[[129   0   2  17   2]
 [ 19  59   2  28   2]
 [ 25   4  81   8   1]
 [  5   3   2 143   2]
 [ 38   7   7   4  48]]
```

	precision	recall	f1-score	support
business	0.59	0.88	0.71	150
entertainment	0.76	0.52	0.62	110
politics	0.86	0.68	0.76	119
sport	0.75	0.92	0.83	155
tech	0.88	0.47	0.61	104
accuracy			**0.72**	638

The best performing model with an accuracy of .97 is unlikely to get better. Logistic Regression, second best, was sensitive to whether the special characters had been removed or not (not shown here), performed with f1-scores of .95 and .96 respectively. This model potentially could perform better on the Bag of Words with the tuning of the regularization parameter, "C." The default value is 1.

The parameter “C” was tuned by running a GridSearchCV, on 5 folds of the data, with alternative values of the parameter and the default. Cross validation partitioned the training data into fifths, withholding a partition for testing, and running every combination of the remaining 4 partitions. *Smaller values of “C” specify stronger regularization – Scikit-Learn documentation*. The default parameter, with alternatives 0.5 and 5.0, was the best with a score of .967.

Also, the small difference between the scoring on the Bag of Words with and without special characters could be an artefact of Scikit-Learn. The documentation notes that “the underlying C implementation uses a random number generator to select features when fitting the model. It is thus not uncommon, to have slightly different results for the same input data.”

Classification models on TF-IDF ("term importance") text –
Three best performing models: Naive Bayes; Logistic Regression; Gradient Boosting

The final step is using a less general extractor with the top performing models. The TF-IDF extraction calculates the term frequency in the documents weighted by the frequency of the term in the corpus for a relative importance measure. The Count Vectorizer and TF-IDF Vectorizer required the same processing and split of the data.

The Logistic Regression model classifies the news categories best on the TF-IDF extracted text. The table below shows the three classification models run the two extractions of the article text.

Confusion matrix, sequence left to right and top to bottom is: business; entertainment; politics; sport; tech.

Bag of Words		Importance weighted	
NaiveBayes [[144 1 2 0 3] [1 105 2 0 2] [2 1 116 0 0] [0 0 0 155 0] [3 1 1 0 99]]	f1 = .97 sport accuracy = 1	NaiveBayes on TF-IDF [[148 0 1 0 1] [5 87 7 11 0] [2 0 115 2 0] [0 0 0 155 0] [6 0 5 7 86]]	f1 = .93 accuracy decreases from Bag of Words decrease in accuracy in predicting politics and tech
LogisticRegression [[144 0 4 0 2] [2 105 1 0 2] [2 2 114 1 0] [0 0 0 155 0] [7 2 1 0 94]]	f1 = .95 f1 = .96 (w/o removing special characters) sport accuracy = 1	LogisticRegression on TF-IDF [[147 0 1 0 2] [3 104 0 0 3] [3 1 114 1 0] [0 0 0 155 0] [6 0 1 1 96]]	f1 = .97 accuracy increases from Bag of Words
GradientBoost	f1 = .94	GradientBoosting on TF-IDF	f1 = .94

[[140 3 5 0 2] [3 105 0 0 2] [8 0 108 2 1] [0 0 0 155 0] [9 1 1 0 93]]	sport accuracy = 1	[[142 2 4 0 2] [6 101 0 1 2] [6 1 110 2 0] [0 0 1 154 0] [5 3 1 0 95]]	sport accuracy = .99

The Logistic Regression classifier had an average accuracy of .96 across the two extractions of the text. Naïve Bayes averaged .95 and Gradient Boosting remained the same at .94. These classification models, with default parameters, classified the words associated with the five categories better than nine out of ten times and showed very little sensitivity to the method of extraction.

More research

Performance of unsupervised models, cluster analysis and principal component analysis, would be interesting for comparison.