MSc Data Mining

Topic 05 : Classification

Part 03 : Naive Bayes

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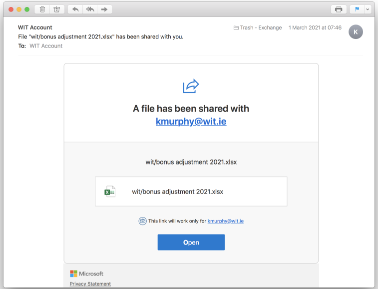
Outline

- Motivation behind naive Bayes
- Sample application
- Summary of properties

Outline

Spam Filtering

Reality



Simplified Problem

Assume that we have the following set of messages previously classified as spam or ham.

Message	Class
"send us your password"	spam
"send us your review"	ham
"password review"	ham
"review us"	spam
"send your password"	spam
"send us your account"	spam

We are interested in classifying the following new message as spam or ham:

Message	Class
"review us now"	?

Count occurrences … compute probabilities

Message	Class
“send us your password”	spam
“send us your review”	ham
“password review”	ham
“review us”	spam
“send your password”	spam
“send us your account”	spam

Word	# in spam	# in ham	Pr(•|spam)	Pr(•|ham)
account				
password				
review				
send				
us				
your				

Class	Count	Probability
spam		
ham		

Count occurrences … compute probabilities

Message	Class
“send us your password”	spam
“send us your review”	ham
“password review”	ham
“review us”	spam
“send your password”	spam
“send us your account”	spam

Word	# in spam	# in ham	$\Pr(\bullet \mid \text{spam})$	$\Pr(\bullet \mid \text{ham})$
account				
password				
review				
send				
us				
your				

Class	Count	Probability
spam	4	$\Pr(\text{spam}) = 4/6$
ham	2	$\Pr(\text{ham}) = 2/6$

Count occurrences . . . compute probabilities

Message	Class
“send us your password”	spam
“send us your review”	ham
“password review”	ham
“review us”	spam
“send your password”	spam
“send us your account”	spam

Word	# in spam	# in ham	$\Pr(\bullet \mid \text{spam})$	$\Pr(\bullet \mid \text{ham})$
account	1	0	1/4	0/2
password				
review				
send				
us				
your				

Class	Count	Probability
spam	4	$\Pr(\text{spam}) = 4/6$
ham	2	$\Pr(\text{ham}) = 2/6$

Count occurrences . . . compute probabilities

Message	Class
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"send us your review"	ham
"password review"	ham
"review us"	spam
"send your password"	spam
"send us your account"	spam

Word	# in spam	# in ham	$\Pr(\bullet \mid \text{spam})$	$\Pr(\bullet \mid \text{ham})$
account	1	0	1/4	0/2
password	2	1	2/4	1/2
review	1	2	1/4	2/2
send	3	1	3/4	1/2
us	3	1	3/4	1/2
your	3	1	3/4	1/2

Class	Count	Probability
spam	4	$\Pr(\text{spam}) = 4/6$
ham	2	$\Pr(\text{ham}) = 2/6$

Count occurrences . . . compute probabilities

Message	Class
"send us your password"	spam
"send us your review"	ham
"password review"	ham
"review us"	spam
"send your password"	spam
"send us your account"	spam

Word	# in spam	# in ham	$\Pr(\bullet \mid \text{spam})$	$\Pr(\bullet \mid \text{ham})$
account	1	0	1/4	0/2
password	2	1	2/4	1/2
review	1	2	1/4	2/2
send	3	1	3/4	1/2
us	3	1	3/4	1/2
your	3	1	3/4	1/2

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spam	4	$\Pr(\text{spam}) = 4/6$
ham	2	$\Pr(\text{ham}) = 2/6$

What we have

The probability that a message contains, say the word review, among our message classed as spam, i.e.,

$$\Pr(\text{review} \mid \text{spam}) = 1/4$$

What we want

The probability that a message is spam given that it contains, say the word review, i.e.,

$$\Pr(\text{spam} \mid \text{review}) = ?$$

Count occurrences … compute probabilities

Message	Class
"send us your password"	spam
"send us your review"	ham
"password review"	ham
"review us"	spam
"send your password"	spam
"send us your account"	spam

Word	# in spam	# in ham	$\Pr(\bullet \mid \text{spam})$	$\Pr(\bullet \mid \text{ham})$
account	1	0	1/4	0/2
password	2	1	2/4	1/2
review	1	2	1/4	2/2
send	3	1	3/4	1/2
us	3	1	3/4	1/2
your	3	1	3/4	1/2

Class	Count	Probability
spam	4	$\Pr(\text{spam}) = 4/6$
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prior probabilities

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What we want

The probability that a message is spam given that it contains, say the word review, i.e.,

$$\Pr(\text{spam} \mid \text{review}) = ?$$

posterior probabilities

Aside: Probability Laws

Bayes Rule

$$\overbrace{\Pr(A|B)\Pr(B)}^{\text{conditional}\times\text{marginal}} = \overbrace{\Pr(A \text{ AND } B)}^{\text{joint}} = \underbrace{\Pr(B|A)\Pr(A)}^{\text{conditional}\times\text{marginal}}$$

$$\Pr(A|B)\Pr(B) = \Pr(B|A)\Pr(A) \longrightarrow \Pr(B|A) = \frac{\Pr(A|B)\Pr(B)}{\Pr(A)}$$

Complementry Rule

$$\Pr(\text{NOT } A) = 1 - \Pr(A)$$

Independent Events

If events A and B are independent, then $\Pr(A \text{ AND } B) = \Pr(A)\Pr(B)$

Law of total of probability

Let A be any event. Let $\{B_1, B_2, B_3, \ldots, B_n\}$ be a set of events, exactly one of which must occur, then

$$\Pr(A) = \Pr(A|B_1)\Pr(B_1) + \Pr(A|B_2)\Pr(B_2) + \cdots + \Pr(A|B_n)\Pr(B_n)$$

Classifying a Message Using a Single Word

Applying the law of total probability, with $A = \textsf{review}$, and $B_1 = \text{spam}$ and $B_2 = \text{ham}$, then we have

$$\Pr(\textsf{review}) = \Pr(\textsf{review}|\text{spam})\Pr(\text{spam}) + \Pr(\textsf{review}|\text{ham})\Pr(\text{ham}) = \frac{1}{4}\cdot\frac{4}{6} + \frac{2}{2}\cdot\frac{2}{6} = \frac{3}{6}$$

Now we can apply Bayes rule, with $A = \textsf{review}$ and $B = \text{spam}$ we have

$$\Pr(\text{spam}|\textsf{review}) = \frac{\Pr(\textsf{review}|\text{spam})\Pr(\text{spam})}{\Pr(\textsf{review})} = \frac{\frac{1}{4}\cdot\frac{4}{6}}{\frac{3}{6}} = \frac{1}{3} = 33.3\%$$

And we can apply Bayes rule, with $A = \textsf{review}$ and $B = \text{ham}$ to get

$$\Pr(\text{ham}|\textsf{review}) = \frac{\Pr(\textsf{review}|\text{ham})\Pr(\text{ham})}{\Pr(\textsf{review})} = \frac{\frac{2}{2}\cdot\frac{2}{6}}{\frac{3}{6}} = \frac{2}{3} = 66.7\%$$

So on receiving a message containing the word review we can classify it a spam with probability 33.3% and ham with probability 66.7%.

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Classifying a Message Using Multiple Words I

- We can now (hopefully) do this for each word in our test message ("review us now"), but what about classifying using multiple words? . . . here comes the naïve bit . . .

  Naïve Bayes assumes that presence of each word are independent events

  Recall: independent events means can multiply to get joint probabilities.

- We are interested in classifying the message

  review us now

- We don't have data on the word now so only looking at messages containing review and us and not containing account, password. send, or your.

$$\Pr(\{\text{review}, \text{us}\}|\text{spam}) = \underbrace{\left(1 - \frac{1}{4}\right)}_{\cancel{\text{account}}} \underbrace{\left(1 - \frac{2}{4}\right)}_{\cancel{\text{password}}} \underbrace{\left(\frac{1}{4}\right)}_{\text{review}} \underbrace{\left(1 - \frac{3}{4}\right)}_{\cancel{\text{send}}} \underbrace{\left(\frac{3}{4}\right)}_{\text{us}} \underbrace{\left(1 - \frac{3}{4}\right)}_{\cancel{\text{your}}} = 0.0044$$

and

$$\Pr(\{\text{review}, \text{us}\}|\text{ham}) = \underbrace{\left(1 - \frac{0}{2}\right)}_{\cancel{\text{account}}} \underbrace{\left(1 - \frac{1}{2}\right)}_{\cancel{\text{password}}} \underbrace{\left(\frac{2}{2}\right)}_{\text{review}} \underbrace{\left(1 - \frac{1}{2}\right)}_{\cancel{\text{send}}} \underbrace{\left(\frac{1}{2}\right)}_{\text{us}} \underbrace{\left(1 - \frac{1}{2}\right)}_{\cancel{\text{your}}} = 0.0625$$

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and

$$\Pr(\{\mathsf{review}, \mathsf{us}\}|\text{ham}) = \underbrace{\left(1-\frac{0}{2}\right)}_{\cancel{\text{account}}}\underbrace{\left(1-\frac{1}{2}\right)}_{\cancel{\text{password}}}\underbrace{\left(\frac{2}{2}\right)}_{\text{review}}\underbrace{\left(1-\frac{1}{2}\right)}_{\cancel{\text{send}}}\underbrace{\left(\frac{1}{2}\right)}_{\text{us}}\underbrace{\left(1-\frac{1}{2}\right)}_{\cancel{\text{your}}} = 0.0625$$

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Classifying a Message Using Multiple Words II

Now we can apply the law of total probability as before

$$\Pr(\{\text{review}, \text{us}\}) = \Pr(\{\text{review}, \text{us}\}|\text{spam}) \Pr(\text{spam}) + \Pr(\{\text{review}, \text{us}\}|\text{ham}) \Pr(\text{ham})$$
$$= 0.0044 \left(\frac{4}{6}\right) + 0.0625 \left(\frac{2}{6}\right) = 0.0237$$

And finally Bayes rule

$$\Pr(\text{spam}|\{\text{review}, \text{us}\}) = \frac{\Pr(\{\text{review}, \text{us}\}|\text{spam}) \Pr(\text{spam})}{\Pr(\{\text{review}, \text{us}\})} = \frac{0.0044 \left(\frac{4}{6}\right)}{0.0237} = 0.123$$

and

$$\Pr(\text{ham}|\{\text{review}, \text{us}\}) = \frac{\Pr(\{\text{review}, \text{us}\}|\text{ham}) \Pr(\text{ham})}{\Pr(\{\text{review}, \text{us}\})} = \frac{0.0625 \left(\frac{2}{6}\right)}{0.0237} = 0.877$$

Hence, the probability that the message is spam is 12.3%, and ham is 87.7%.

Classifying a Message Using Multiple Words II

Now we can apply the law of total probability as before

$$\begin{aligned}\Pr(\{\text{review}, \text{us}\}) =& \Pr(\{\text{review}, \text{us}\}|\text{spam}) \Pr(\text{spam}) + \Pr(\{\text{review}, \text{us}\}|\text{ham}) \Pr(\text{ham}) \\ =& 0.0044 \left(\frac{4}{6}\right) + 0.0625 \left(\frac{2}{6}\right) = 0.0237\end{aligned}$$

And finally Bayes rule

$$\Pr(\text{spam}|\{\text{review}, \text{us}\}) = \frac{\Pr(\{\text{review}, \text{us}\}|\text{spam}) \Pr(\text{spam})}{\Pr(\{\text{review}, \text{us}\})} = \frac{0.0044 \left(\frac{4}{6}\right)}{0.0237} = 0.123$$

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$$\Pr(\text{ham}|\{\text{review}, \text{us}\}) = \frac{\Pr(\{\text{review}, \text{us}\}|\text{ham}) \Pr(\text{ham})}{\Pr(\{\text{review}, \text{us}\})} = \frac{0.0625 \left(\frac{2}{6}\right)}{0.0237} = 0.877$$

Hence, the probability that the message is spam is 12.3%, and ham is 87.7%.

Classifying a Message Using Multiple Words III

A final comment:

- The classifier picks the class with the largest probability, so in this case

$$\Pr(\text{spam}|\{\text{review}, \text{us}\}) = \frac{\Pr(\{\text{review}, \text{us}\}|\text{spam}) \Pr(\text{spam})}{\Pr(\{\text{review}, \text{us}\})} = \frac{0.0044 \left(\frac{4}{6}\right)}{0.0237} = 0.123$$

  and

$$\Pr(\text{ham}|\{\text{review}, \text{us}\}) = \frac{\Pr(\{\text{review}, \text{us}\}|\text{ham}) \Pr(\text{ham})}{\Pr(\{\text{review}, \text{us}\})} = \frac{0.0625 \left(\frac{2}{6}\right)}{0.0237} = 0.877$$

- We can skip the computation of $\Pr(\{\text{review}, \text{us}\})$ involving the law of total probability step since that is a common denominator in above formula, And instead look are relative likelihood

$$\frac{\Pr(\text{spam}|\{\text{review}, \text{us}\})}{\Pr(\text{ham}|\{\text{review}, \text{us}\})} = \frac{\Pr(\{\text{review}, \text{us}\}|\text{spam}) \Pr(\text{spam})}{\Pr(\{\text{review}, \text{us}\}|\text{ham}) \Pr(\text{ham})} \implies \begin{cases} > 1 & \text{pick spam} \\ < 1 & \text{pick ham} \end{cases}$$

Outline

Trump’s Claims — Dataset

The Washington Post has released a curated list of Donald Trump’s false claims while in office. The claim’s have been categorised and cross linked. We will see how well a naïve Bayes classifier will do on this dataset.

```
df = pd.read_csv("wapo_trumpclaims_export-012021.csv.gz")
print(df.shape)
df.head(5)
```

```
(30573, 9)
```

	id	location	claim	analysis	pinocchios	category	repeated_ids	repeated_count	date
0	31608.0	Remarks	“We also got tax cuts, the largest tax cut and...	This is Trump’s second favorite falsehood, and...	4.0	Taxes	31608, 31581, 31305, 31183, 31530, 30920, 3085...	296	01/20/2021
1	31609.0	Remarks	“We just got seventy five million votes. And t...	When the counting was finished, Trump had rece...	NaN	Election	31609, 31292, 31155, 31016, 31082, 30992, 3156...	19	01/20/2021
2	31610.0	Remarks	“One of the things we're very, very proud of i...	Contrary to his boasts, Trump did not achieve ...	NaN	Miscellaneous	31610, 31598, 31187, 30918, 30374, 29845, 2922...	84	01/20/2021
3	31611.0	Remarks	“Our first lady has been a woman of great grac...	In reality, Melania Trump leaves the White Hou...	NaN	Miscellaneous	NaN	0	01/20/2021
4	31612.0	Remarks	“That's why [regulation cuts] we have such goo...	Leaving aside Trump's claim about the impact o...	NaN	Jobs	NaN	0	01/20/2021

Trump's Claims — Dataset

2

```
df.category.value_counts(dropna=False)
```

```
Immigration            3225
Foreign policy         3165
Election               3037
Miscellaneous          2767
Coronavirus            2521
Trade                  2513
Economy                2475
Russia                 1838
Jobs                   1732
Health care            1629
Ukraine probe          1377
Environment            1065
Biographical record     963
Taxes                   857
Crime                   852
NaN                     169
Guns                    165
Education               151
Terrorism                72
Name: category, dtype: int64
```

Trump's Claims — Dataset

3
```
df.category.value_counts(dropna=False)
```

```
Immigration            3225
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Crime                   852
NaN                     169
Guns                    165
Education               151
Terrorism                72
Name: category, dtype: int64
```

General observations ...

- Some classes are relatively rare.
- Some classifications would appear to overlap `Russia` ↔ `Election`.
- There are 169 unclassified observations, missing values ... **these need** to be removed/encoded before model building.
- Total of 30,573 false claims! He was busy between golf sessions ... sorry, I could not resist.

Trump's Claims — Data Preprocessing II

We perform our standard train-test split

4
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    df.claim, df.category, test_size=0.2, random_state=42)
```

Next we need to reproduce the word extraction and counts that we did for the simple example earlier:

5
```
from sklearn.feature_extraction.text import CountVectorizer
count_vectorizer = CountVectorizer()

X_train_counts = count_vectorizer.fit_transform(X_train)
X_test_counts = count_vectorizer.transform(X_test)
```

Use the train dataset to determine parameters for the operation (`fit`). Then, apply (`transform`) to both train and test

Notice the function calls `fit_transform` on `X_train` and `transform` on `X_test`. The function `fit_transform` is two separate steps: `fit` and `transform` and could be written as

6
```
count_vectorizer.fit(X_train)
X_train_counts = count_vectorizer.transform(X_train)
```

or

7
```
X_train_counts = count_vectorizer.fit(X_train).transform(X_train)
```

Trump's Claims — Data Preprocessing II

How many features?

8

```python
X_train_counts.shape
```

```
(24323, 12718)
```

9

```python
X_test_counts.shape
```

```
(6081, 12718)
```

A look at the first 1,000 features . . .

10

```python
print(count_vectorizer.get_feature_names()[:1000])
```

```
['00', '000', '005', '006', '00pm', '00pme', '024', '024th', '028', '03', '036', '067', '085', '09', '0ver', '10', '100', '1000', '100th', '101', '102', '1024', '1024th', '103', '104', '1040', '105', '106', '107', '108', '109', '10s', '
0th', '11', '110', '112', '113', '115', '116', '117', '118', '119', '11th', '12', '120', '121', '122', '123', '125', '126', '127', '128', '129', '12th', '13', '130', '132', '133', '134', '135', '135th', '138', '139', '13th', '14', '140'
'141', '142', '143', '144', '144th', '145', '147', '149', '1492', '14th', '15', '150', '150th', '151', '154', '155', '157', '158', '15th', '16', '160', '161', '162', '164', '168', '169', '16th', '17', '170', '171', '172', '175', '176',
1776', '17b', '18', '180', '1807', '181', '182', '1824', '183', '184', '185', '1860', '187', '188', '1888', '1890', '1890s', '18s', '18th', '19', '190', '1900s', '191', '1912', '1913', '1917', '1918', '192', '1928', '1929', '1930s', '19
5', '1940s', '195', '1950', '1950s', '1951', '1952', '196', '1960', '1960s', '1962', '197', '1972', '1974', '1976', '1977', '198', '1980', '1980s', '1982', '1986', '1990', '1992', '1994', '1996', '1997', '19th', '1k', '1liskyevng', '1st
, '20', '200', '2000', '2001', '2006', '2008', '2009', '201', '2010', '2011', '2012', '2013', '2014', '2015', '2016', '2017', '2018', '2019', '2020', '2020election', '2021', '2024', '2025', '2026', '2028', '2030', '2032', '2035', '204',
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'3500', '355', '356', '358', '35s', '36', '360', '368', '37', '375', '379', '38', '380', '39', '392', '3crnij4pwt', '3rd', '40', '400', '4000', '401', '401k', '401ks', '40m', '40s', '41', '410', '412', '415', '42', '420', '424', '426',
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rlines', 'airplane', 'airplanes', 'airport', 'airports', 'airtime', 'airwaves', 'ajitpaifcc', 'ak', 'al', 'alabama', 'alan', 'alandersh', 'alarmed', 'alaska', 'albaghdadi', 'alcindor', 'alcohol', 'alec', 'alert', 'alerted', 'alerting',
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icipation', 'antifa', 'antiquated', 'antitrust', 'antiviral', 'antonio', 'anwr', 'any', 'anybody', 'anymore', 'anyone', 'anyplace', 'anything', 'anytime', 'anyway', 'anyways', 'anywhere', 'aoc', 'ap', 'apache', 'apart', 'apartment', 'ap
rtments', 'apiece', 'apologies', 'apologize', 'apologized', 'apologizes', 'apology', 'apostrophe', 'appalling', 'apparatus', 'apparent', 'appeal', 'appealed', 'appeals', 'appear', 'appeared', 'appearing', 'appears', 'appease', 'appeased
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```

Trump's Claims —Model Fit, Prediction and Evaluation I

As before* we import or model and create an instance of it

11
```
from sklearn.naive_bayes import MultinomialNB
model = MultinomialNB()
```

Fit our model using the train dataset

12
```
model.fit(X_train_counts, y_train)
```

Generate predictions using the test dataset

13
```
y_pred = model.predict(X_test_counts)
```

How well did it do? ... using accuracy score we have

14
```
from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_pred)
```

```
0.7763525735898701
```

This is not bad . . . there are lots of class levels and some overlap between classes.

*This is the beauty of sklearn — consistent interface to all models, pre-/post- processing steps.

Trump's Claims —Model Fit, Prediction and Evaluation II

Predicted	Biographical record	Coronavirus	Crime	Economy	Education	Election	Environment	Foreign policy	Guns	Health care	Immigration	Jobs	Miscellaneous	Russia	Tax
Actual															
Biographical record	78	4	0	20	0	24	1	11	0	2	3	3	35	7	2
Coronavirus	0	438	0	18	0	10	0	11	0	1	15	5	15	5	1
Crime	2	3	84	3	0	13	0	8	0	0	22	0	26	7	0
Economy	2	6	1	388	0	4	9	10	0	2	9	30	6	0	9
Education	0	1	4	0	20	2	1	0	0	0	4	1	2	0	0
Election	5	9	9	8	0	460	0	8	0	0	6	1	39	16	2
Environment	0	3	0	17	0	8	124	12	0	0	4	2	13	0	0
Foreign policy	2	3	0	18	0	9	4	575	0	4	14	2	16	12	0
Guns	0	0	0	1	0	10	0	0	11	0	1	0	10	0	0
Health care	0	5	0	1	0	4	0	2	0	294	5	0	9	1	2
Immigration	0	4	0	4	0	6	0	10	0	2	564	0	10	4	0
Jobs	0	6	0	38	0	5	6	8	0	0	4	259	2	0	0
Miscellaneous	16	17	23	28	0	42	5	28	0	20	33	4	316	21	1
Russia	0	2	0	3	0	13	1	4	0	0	0	0	11	325	0
Taxes	1	1	0	23	0	1	0	4	0	2	2	0	11	0	123
Terrorism	0	0	0	0	0	0	0	5	0	0	8	0	3	0	0
Trade	1	2	0	12	0	5	1	10	0	2	2	7	6	0	0
Ukraine probe	1	2	0	1	0	18	0	7	0	0	1	0	13	22	0

Trump's Claims —Model Fit, Prediction and Evaluation III

Predicted

Actual	Biographical record	Coronavirus	Crime	Economy	Education	Election	Environment	Foreign policy	Guns	Health care	Immigration	Jobs	Miscellaneous	Russia	Taxes	Trade	Ukraine probe
Biographical record	78	4	0	20	0	24	1	11	0	2	3	3	35	7	2	3	0
Coronavirus	0	438	0	18	0	10	0	11	0	1	15	5	15	5	1	2	2
Crime	2	3	84	3	0	13	0	8	0	0	22	0	26	7	0	0	0
Economy	2	6	1	388	0	4	9	10	0	2	9	30	6	0	9	29	0
Education	0	1	4	0	20	2	1	0	0	0	4	1	2	0	0	0	0
Election	5	9	9	8	0	460	0	8	0	0	6	1	39	16	2	4	15
Environment	0	3	0	17	0	8	124	12	0	0	4	2	13	0	0	4	1
Foreign policy	2	3	0	18	0	9	4	575	0	4	14	2	16	12	0	17	2
Guns	0	0	0	1	0	10	0	0	11	0	1	0	10	0	0	0	0
Health care	0	5	0	1	0	4	0	2	0	294	5	0	9	1	2	1	0
Immigration	0	4	0	4	0	6	0	10	0	2	564	0	10	4	0	4	0
Jobs	0	6	0	38	0	5	6	8	0	0	4	259	2	0	0	24	0
Miscellaneous	16	17	23	28	0	42	5	28	0	20	33	4	316	21	1	6	9
Russia	0	2	0	3	0	13	1	4	0	0	0	0	11	325	0	0	2
Taxes	1	1	0	23	0	1	0	4	0	2	2	0	11	0	123	3	0
Terrorism	0	0	0	0	0	0	0	5	0	0	8	0	3	0	0	0	0
Trade	1	2	0	12	0	5	1	10	0	2	2	7	6	0	0	461	0
Ukraine probe	1	2	0	1	0	18	0	7	0	0	1	0	13	22	0	0	201

- Look at the largest, off main-diagonal entries.

Outline

Naïve Bayes Classifier — Review

When to Consider

- Assumption of independence holds
- Categorical features.
- Spam filtering, Sentiment Analysis, and Recommendation Systems (with collaborative filtering).
- Variants exist for numeric (Gaussian-), binary (Bernoulli-) and multi-class (mulinomial-) featured Naïve Bayes.

Advantages

- It is easy and fast to predict class. It also perform well in multi-class prediction.
- When assumption of independence holds, performs better compare to other models like logistic regression and needs less training data.

Disadvantages

- Ignores feature relationships
- If categorical variable has a category (in test data set), which was not observed in training data set, then model will assign a 0 (zero) probability and will be unable to make a prediction. This is often known as “Zero Frequency”. To solve this, we can use the smoothing technique. One of the simplest smoothing techniques is Laplace estimation.
- If continuous features, then assumes normality conditions — often too restrictive.

Resources

- A Gentle Introduction to Bayes Theorem for Machine Learning
  https://machinelearningmastery.com/bayes-theorem-for-machine-learning/
  This is well worth a read over a cup of coffee. The author, Jason Brownlee, is worth following.