

# MSc Data Mining

## Topic 05 : Classification

### Part 03 : Naive Bayes

Foundation

~~Data Handling~~

Exploratory Data  
Analysis

Data Modelling  
Fundamentals

Data Modelling  
Advanced

Rule Based

Association Rules

Recommender Systems

Unsupervised

Clustering

Anomaly Detection

Supervised

Regression

Basic Classification

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## Outline

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

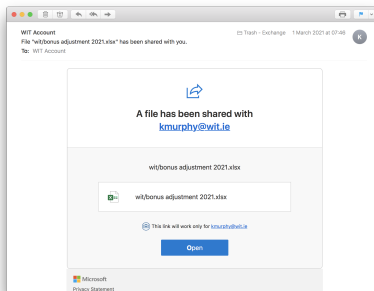
# Outline

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# 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	$\Pr(\bullet \text{spam})$	$\Pr(\bullet \text{ham})$
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	$\Pr(\bullet \text{spam})$	$\Pr(\bullet \text{ham})$
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 <u>account</u> ”	spam

Word	# in spam	# in ham	$\Pr(\bullet \text{spam})$	$\Pr(\bullet \text{ham})$
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
“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	$\Pr(\bullet \text{spam})$	$\Pr(\bullet \text{ham})$
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
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## 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	$\Pr(\bullet \text{spam})$	$\Pr(\bullet \text{ham})$
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	$\Pr(\text{ham}) = 2/6$

## What we have

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

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

## What we want

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

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



## 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	$\Pr(\bullet \text{spam})$	$\Pr(\bullet \text{ham})$
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.,

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

posterior probabilities

# Aside: Probability Laws

## Bayes Rule

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

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

## Complementary 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  $\{B_1, B_2, B_3, \dots, B_n\}$  be a set of events, exactly one of which must occur, then

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

# Classifying a Message Using a Single Word

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

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

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

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

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

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

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

- 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.

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

and

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

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and

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

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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**.

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

and

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# Classifying a Message Using Multiple Words

Now we can apply the law of total probability as before

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

And finally Bayes rule

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

and

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

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

# Classifying a Message Using Multiple Words

Now we can apply the law of total probability as before

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

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

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

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

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# 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

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Immigration	3225
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Trade	2513
Economy	2475
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Environment	1065
Biographical record	963
Taxes	857
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)
```

How many features?

$$(24323, 12718) \quad (6081, 12718)$$

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

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

0th	000	000	005	006	00pm	00pm	024	024th	028	03	036	067	085	09	0ver	10	100	100	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	148	149	1492	14th	15	150	150th	151	154	155	157	158	15th	16	160	162	164	168	169	16th	17	170	171	172	175	176		
1776	17b	18	180	1807	181	182	183	184	185	1860	187	188	1888	1890	1898s	18s	18th	19	190	1900	1900s	1906	191	1912	1913	1917	1918	192	1928	1929	1930s	19		
5	1940	195	1950	1950s	1950s0	1950s00	2000	201	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2020election	2021	2024	2025	2026	2028	2030	2032	2033	2034	204	2045			
205	206	207	208	208s	208s	20th	21	210	2100	212	215	216	218	21st	22	220	221	223	224	225	227	228	22nd	23	230	232	235	237	238	24	240	243	245	
25	250	251	252	253	256	257	259	25th	26	266	27	270	273	275	276	277	279	28	280	281	285	287	289	29	290	292	293	295	297	29th	2a	2k	2nd	2
g40	2yrs	30	300	3000	3002	304	306	307	30s	30th	31	311	312	315	31am	31st	32	320	325	326	33	330	331	337	33rd	34	340	341	342	346	348	35	350	
3000	355	356	358	35s	36	360	368	37	375	379	38	380	39	392	393n4pwt	3rd	40	400	4000	401	401k	401ks	40m	40s	41	410	412	415	42	420	424	426	4	
42an	43	435	44	440	45	450	46	462	464	468	47	470	475	48	480	49	498	495	4s	4th	50	500	5000	500th	502	504	505	506	507	51	510	517	52	520
525	527	529	53	530	533	537	539	54	546	55	550	552	556	56	565	566	57	572	575	58	59	593	5g	5l	5th	5k	60	600	6000	603	608	6minuts	60s	6
610	612	629	62	620	623	63	635	64	640	643	65	650	652	656	658	66	660	670	675	68	680	685	6h	7	700	7000	701	705	71	716	72	722	75	78
730	738	73	74	747	747s	75	750	76	77	772	774	78	780	79	790	792	7yr	80	800	807	80s	81	817	83	84	85	850	85th	86	863	87	876	88	73
880	886	89	8th	8x	90	900	9000	904	90s	91	92	922	923	93	94	940	941	945	95	959	96	97	972	975	978	98	99	991	9th	a17	a5k3u9r3d	abandon	aband	n
ab	abott	abc	abxnews	abe	abedin	abeyance	abiding	ability	abject	abize	able	abolish	abolished	abolishice	abolishing	abortion	abortions	abound	about	above	abraham	a	rams	abroad	abruptly	absence	absentee	absentia	absolute	absolutely	absurd	abu	abundant	abuse</

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

I

As before\* we import our 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.

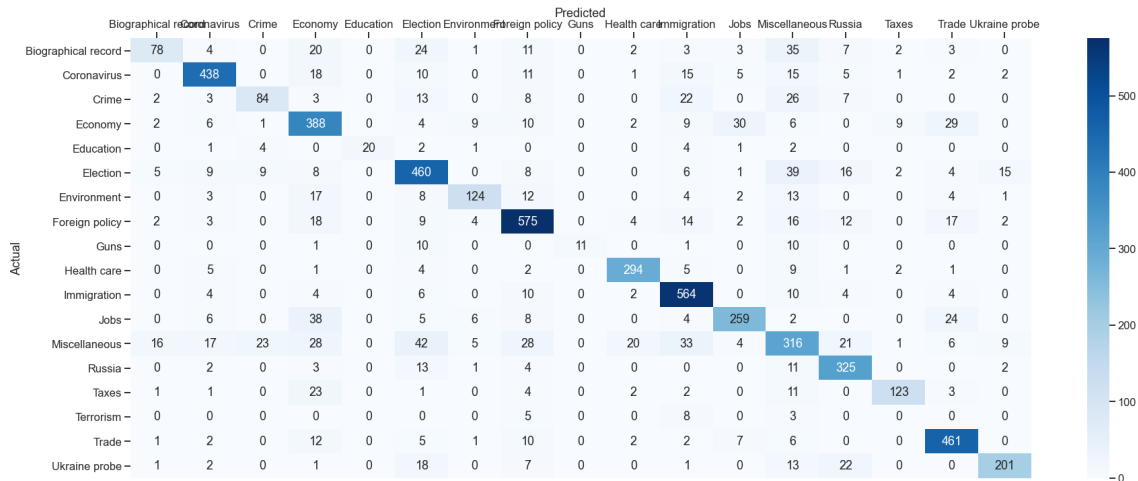
# Trump's Claims —Model Fit, Prediction and Evaluation

## 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



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

# Outline

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- |                                 |    |
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| 2. Application — Trump's Claims | 10 |
| 3. Summary                      | 18 |

# 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 (multinomial-) 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

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- 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.