Textual Data: Bag-of-Words and N-Grams

Dennis Sun (modified by Jonathan Taylor)
Stanford University

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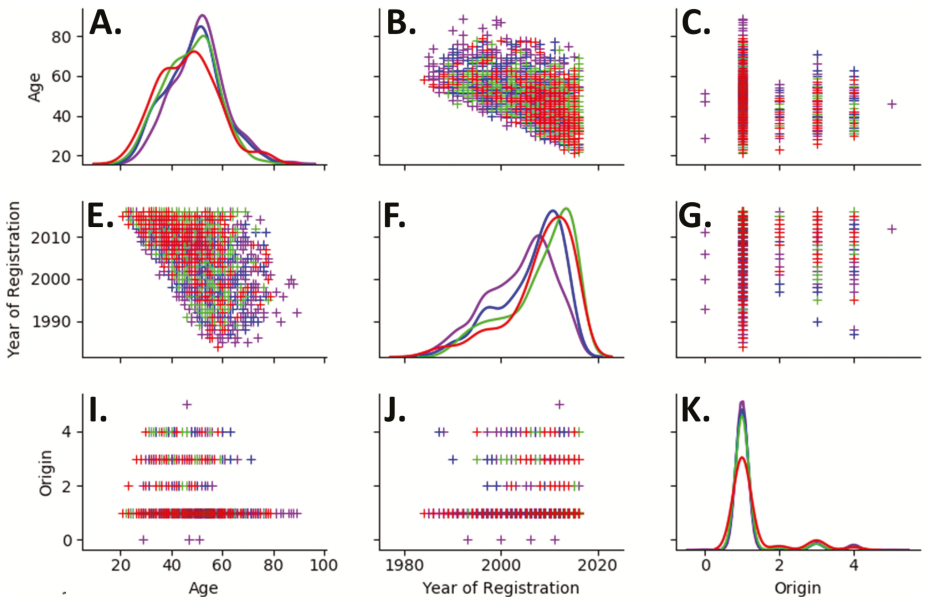

Configuration and correlations of sociodemographic variables across clusters. The diagonal (A, F, K) shows smoothed histograms, the rest of the panels shows correlations between these variables. Age: in years in 2018. Origin labels: 0 (other), 1 (white), 2 (black), 3 (Hispano-American), 4 (Asian), 5 (unknown).

Roadmap for Today

Many data science techniques assume that all the variables are quantitative.

- *Canonical example:* measuring similarity / calculating distances between observations

Last time, we learned how to convert categorical variables to quantitative variables.

Today, we will learn how to convert a completely new type of data to quantitative variables.
These are examples of *featurization*. Once data is featurized, many tasks are simpler.

1. Textual Data
2. Bag-of-Words Model
3. N-Grams

1 Textual Data

2 Bag-of-Words Model

3 N-Grams

Textual Data

A textual data set consists of multiple texts. Each text is called a **document**. The collection of texts is called a **corpus**.

Example Corpus:

0. `"I am Sam\n\nI am Sam\nSam I..."`
1. `"The sun did not shine.\nIt was..."`
2. `"Fox\nSocks\nBox\nKnox\n\nKnox..."`
3. `"Every Who\nDown in Whoville\n..."`
4. `"UP PUP Pup is up.\nCUP PUP..."`
5. `"On the fifteenth of May, in the..."`
6. `"Congratulations!\nToday is your..."`
7. `"One fish, two fish, red fish..."`

Reading in Textual Data

Documents are usually stored in different files.

```
seuss_dir = "http://dlsun.github.io/pods/data/drseuss/"
seuss_files = [
    "green_eggs_and_ham.txt", "cat_in_the_hat.txt",
    "fox_in_socks.txt", "how_the_grinch_stole_christmas.txt",
    "hop_on_pop.txt", "horton_hears_a_who.txt",
    "oh_the_places_youll_go.txt", "one_fish_two_fish.txt"]
```

We have to read them in one by one.

```
import requests

docs = {}
for filename in seuss_files:
    response = requests.get(seuss_dir + filename, "r")
    docs[filename] = response.text
```

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$\longrightarrow$

	?	?	?	
0	1	0	2	...
1	0	1	0	...
2	3	0	0	...
3	0	2	1	...
4	0	0	1	...
5	2	0	5	...
6	0	0	0	...
7	0	2	0	...

Goal: Turn this corpus into a matrix of numbers.

But what would each column represent?!

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Bag-of-Words Model

In the **bag-of-words model**, each column represents a word, and the values in the column are the word counts.

First, we need to count the words in each document

```
from collections import Counter
Counter(docs["hop_on_pop.txt"].split())
```

```
Counter({'UP': 1, 'PUP': 3, 'Pup': 4, 'is': 10, 'up.': 2, ...})
```

We stack these counts into a `DataFrame`

```
import pandas as pd
pd.DataFrame(
    [Counter(doc.split()) for doc in docs.values()],
    index=docs.keys())
```

	I	am	Sam	That	Sam-I-am	Sam-I-am!	do	not	like	that	...
green_eggs_and_ham.txt	71.0	3.0	3.0	2.0	4.0	2.0	34.0	46.0	44.0	1.0	...
cat_in_the_hat.txt	48.0	NaN	NaN	4.0	NaN	NaN	13.0	27.0	13.0	16.0	...
fox_in_socks.txt	9.0	NaN	NaN	NaN	NaN	NaN	6.0	1.0	1.0	1.0	...
hop_on_pop.txt	2.0	1.0	NaN	2.0	NaN	NaN	NaN	2.0	5.0	2.0	...
horton_hears_a_who.txt	18.0	1.0	NaN	7.0	NaN	NaN	NaN	3.0	NaN	24.0	...
how_the_grinch_stole_christmas.txt	6.0	NaN	NaN	2.0	NaN	NaN	2.0	1.0	2.0	11.0	...
oh_the_places_youll_go.txt	2.0	NaN	NaN	NaN	NaN	NaN	2.0	6.0	1.0	11.0	...
one_fish_two_fish.txt	48.0	3.0	NaN	NaN	NaN	NaN	11.0	9.0	21.0	1.0	...

8 rows × 2562 columns

To get rid of the NaNs, add `.fillna(0)`.

This is called the **term-frequency matrix**.

Bag-of-Words in Scikit-Learn

Alternatively, we can use `CountVectorizer` in scikit-learn to produce a term-frequency matrix

```
from sklearn.feature_extraction.text import CountVectorizer
vec = CountVectorizer()
vec.fit(docs.values())
vec.transform(docs.values())
```

```
<8x1344 sparse matrix of type '<class 'numpy.int64'>'
        with 2308 stored elements in Compressed Sparse Row format>
```

Wait! Why are there only 1344 words?

The set of words across a corpus is called the **vocabulary**. We can view the vocabulary in a fitted `CountVectorizer` as follows:

```
vec.vocabulary_
```

```
{'am': 23, 'sam': 935, 'that': 1138, 'do': 287, 'not': 767, ...}
```

The number here represents the column index in the matrix! (So column 23 contains the counts for "am", etc.)

Text Normalization

What's wrong with the way we counted words originally?

```
Counter({'UP': 1, 'PUP': 3, 'Pup': 4, 'is': 10, 'up.': 2, ...})
```

It's usually good to **normalize** for punctuation and capitalization.

Normalization options are specified when you initialize the `CountVectorizer`. By default, Scikit-Learn strips punctuation and converts all characters to lowercase.

But if you don't want Scikit-Learn to normalize for punctuation and capitalization, you can do the following:

```
vec = CountVectorizer(lowercase=False, token_pattern=r"[\S]+")
vec.fit(docs.values())
vec.transform(docs.values())
<8x2562 sparse matrix of type '<class 'numpy.int64'>'
        with 3679 stored elements in Compressed Sparse Row format>
```

Now we're back to 2562 words in the vocabulary!

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The Shortcomings of Bag-of-Words

Bag-of-words is easy to understand and easy to implement.

What are its disadvantages?

Consider the following documents:

1. "The dog bit her owner."
2. "Her dog bit the owner."

Both documents have the same exact bag-of-words representation:

	the	her	dog	owner	bit
1	1	1	1	1	1
2	1	1	1	1	1

But they mean something quite different!

N-grams

An **n-gram** is a sequence of n words.

Google Books Ngram Viewer

N-grams allow us to capture more of the meaning.

For example, if we count **bigrams** (2-grams) instead of words, we can distinguish the two documents from before:

1. "The dog bit her owner."
2. "Her dog bit the owner."

	the,dog	her,dog	dog,bit	bit,the	bit,her	the,owner	her,owner
1	1	0	1	0	1	0	1
2	0	1	1	1	0	1	0

N-grams in Scikit-Learn

Scikit-Learn can create n-grams.

Just pass in `ngram_range=` to the `CountVectorizer`. To get bigrams, we set the range to `(2, 2)`:

```
vec = CountVectorizer(ngram_range=(2, 2))
vec.fit(docs.values())
vec.transform(docs.values())
<8x5846 sparse matrix of type '<class 'numpy.int64'>'
        with 6459 stored elements in Compressed Sparse Row format>
```

We can also get individual words (unigrams) alongside the bigrams:

```
vec = CountVectorizer(ngram_range=(1, 2))
vec.fit(docs.values())
vec.transform(docs.values())
<8x7190 sparse matrix of type '<class 'numpy.int64'>'
        with 8767 stored elements in Compressed Sparse Row format>
```