Data Pre-Processing with Python

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About the Speakers

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Fun Project: Movie Similarity using Scripts, Predicting Movie Success

About the Speakers

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Fun Project: Predicting Employee Turnover

Overview

I. **Why Pre Processing?**
   A. Garbage in Garbage out!
II. **Working with Numerical Data**
   A. Data Cleaning
   B. Data Discretization
   C. Data Transformation
III. **Working with Categorical Data**
   A. LabelEncoding with Pandas and Sklearn
   B. OneHotEncoding with Pandas and Sklearn
IV. **Working with Text Data**
   A. Intro to Natural Language Processing
   B. CountVectorizer
V. **Dimensionality Reduction**

Warning:

The following content aims to cover many of the steps involved in data-preprocessing, but by no means is comprehensive of all available methods. Please enjoy :)

Perfect Datasets Only Exist in Classrooms

Classical Problem: Predicting housing prices

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import mpl_toolkits
%matplotlib inline
```

In [2]:
```
data = pd.read_csv("kc_house_data.csv")
```

In [3]:
```
data.head()
```

Out[3]:

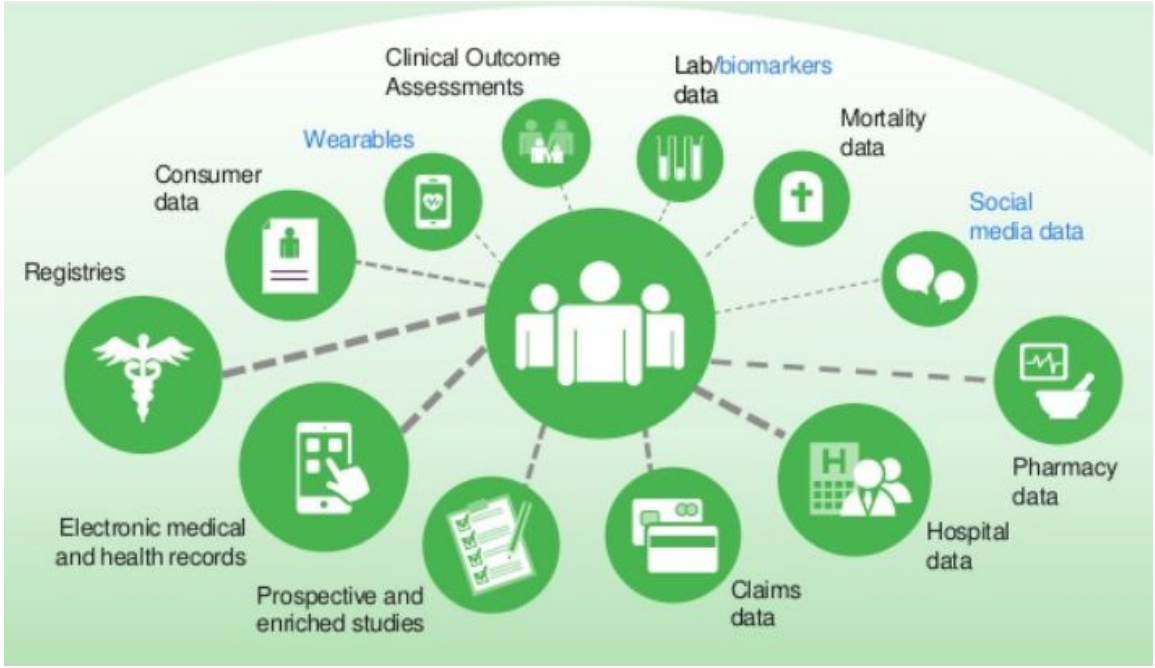
	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	...	grade	sqft_above	sqft_basement	yr_built
0	7129300520	20141013T000000	221900.0	3	1.00	1180	5650	1.0	0	0	...	7	1180	0	1955
1	6414100192	20141209T000000	538000.0	3	2.25	2570	7242	2.0	0	0	...	7	2170	400	1951
2	5631500400	20150225T000000	180000.0	2	1.00	770	10000	1.0	0	0	...	6	770	0	1933
3	2487200875	20141209T000000	604000.0	4	3.00	1960	5000	1.0	0	0	...	7	1050	910	1965
4	1954400510	20150218T000000	510000.0	3	2.00	1680	8080	1.0	0	0	...	8	1680	0	1987

5 rows × 21 columns

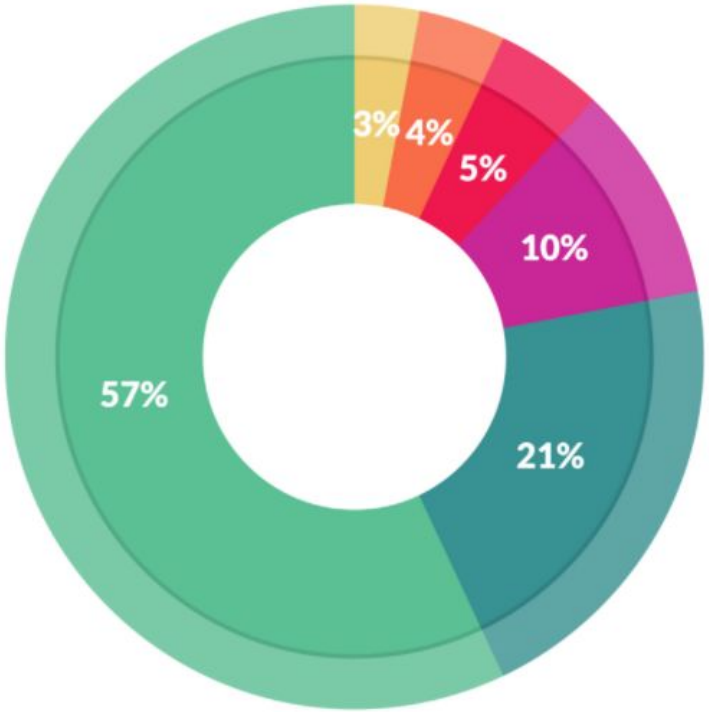
But....Real World Data is Messy

Real data is...

- Incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
- Noisy: containing errors (data entry/collection) or outliers
- Inconsistent: containing discrepancies in codes or names



What is the least enjoyable part of data science?

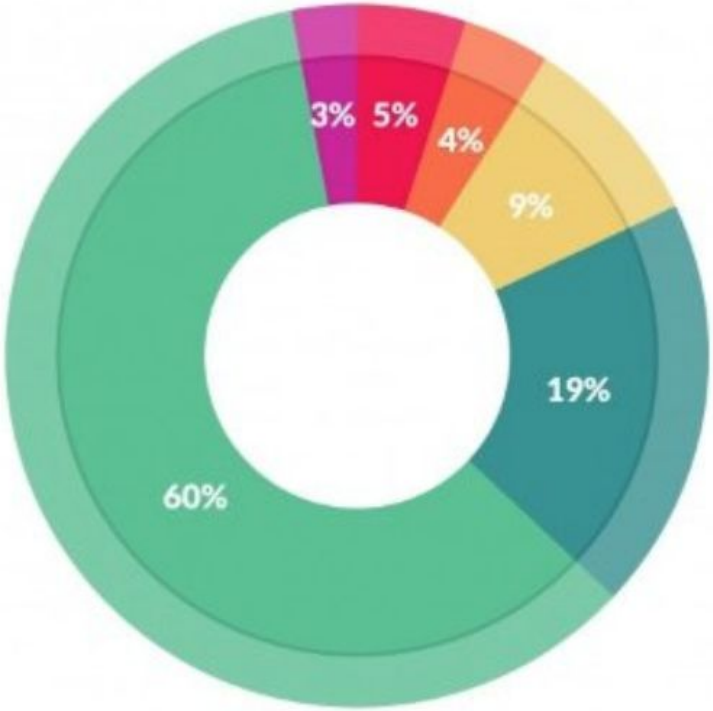


- *Building training sets: 10%*
- *Cleaning and organizing data: 57%*
- *Collecting data sets: 21%*
- *Mining data for patterns: 3%*
- *Refining algorithms: 4%*
- *Other: 5%*

"The Data is not going to clean itself..."

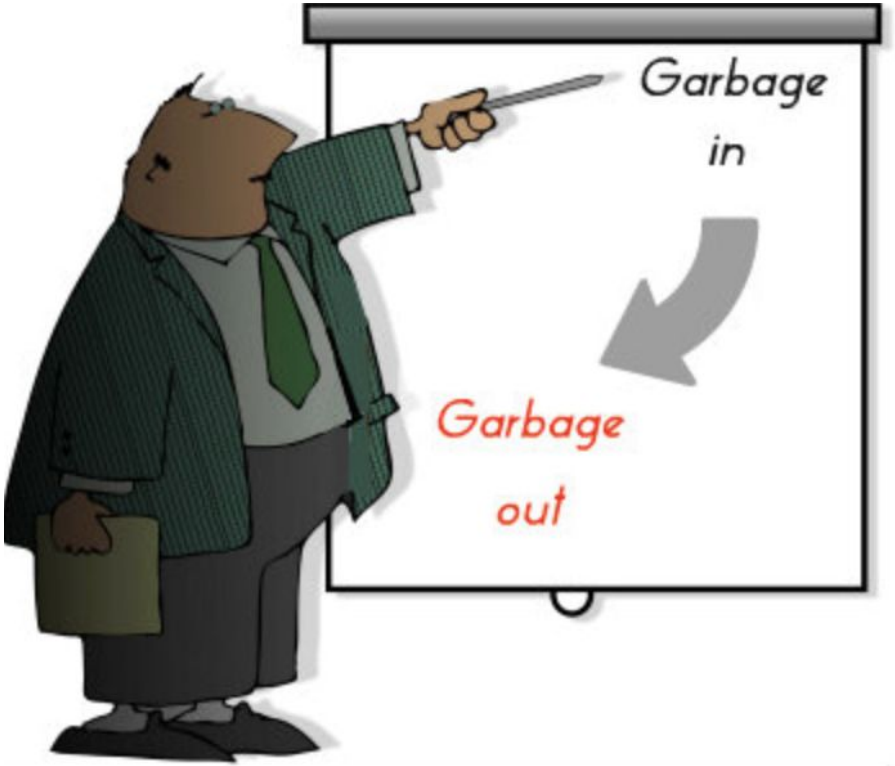
What is the least enjoyable part of data science?

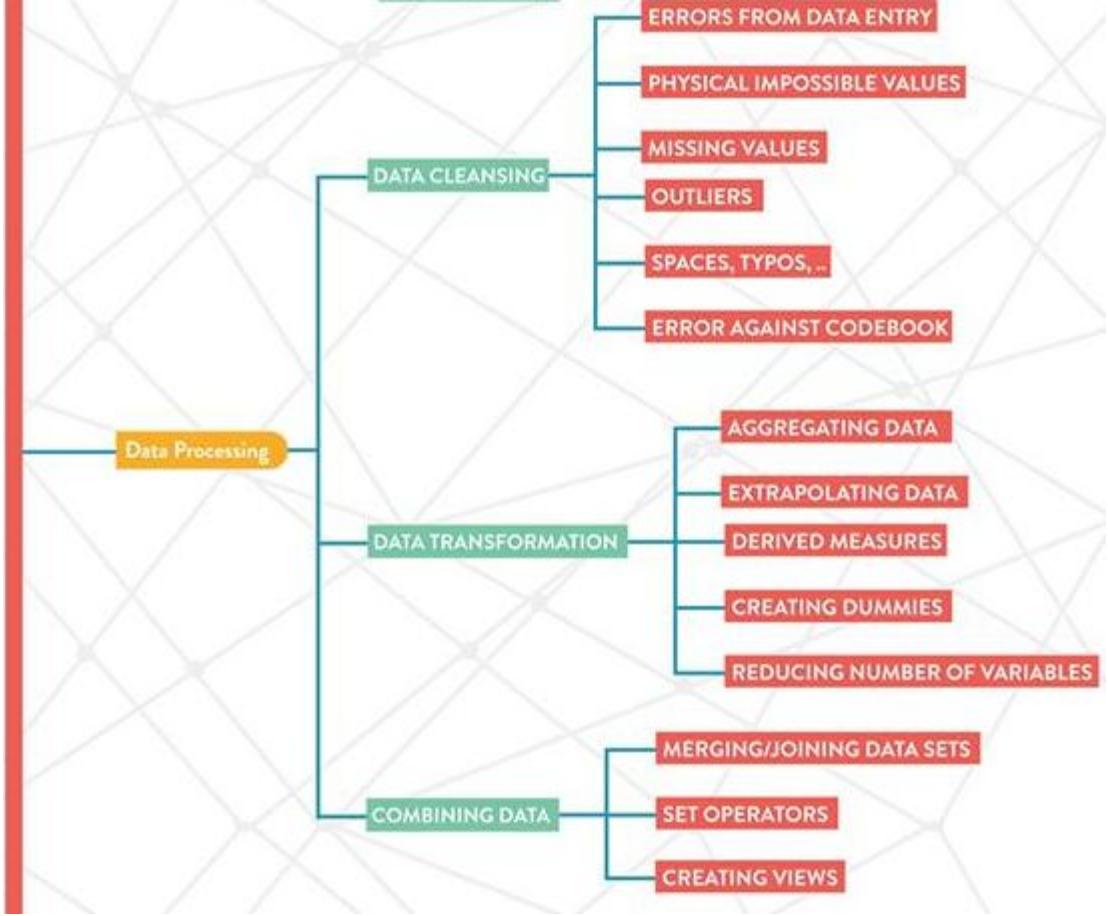
What data scientist spend the most time doing..



- Building training sets: 3%
- Cleaning and organizing data: 60%
- Collecting data sets; 19%
- Mining data for patterns: 9%
- Refining algorithms: 4%
- Other: 5%

We all know the saying...





Data Preprocessing Workflow

Types of data

Numerical data or quantitative data

=numerical values

Discrete data

If you can count it, then it is discrete:

Continuous data

If you can measure it, then it is continuous:

* length
* weight
* temperature

etc

Categorical data or qualitative data

=categories

Nominal data

If you can brand it, then it is nominal:

Gender	Colour
⊘ Female	○ Blue
○ Male	⊘ Red
	○ Green
	○ Orange

Ordinal data

If you can order or rank it, then it is ordinal:

- ○ Always
- ○ Usually
- ⊘ Sometimes
- ○ Rarely
- ○ Nev

https://www.youtube.com/watch?v=GlgA8OMgLxE

Working with Numerical Data

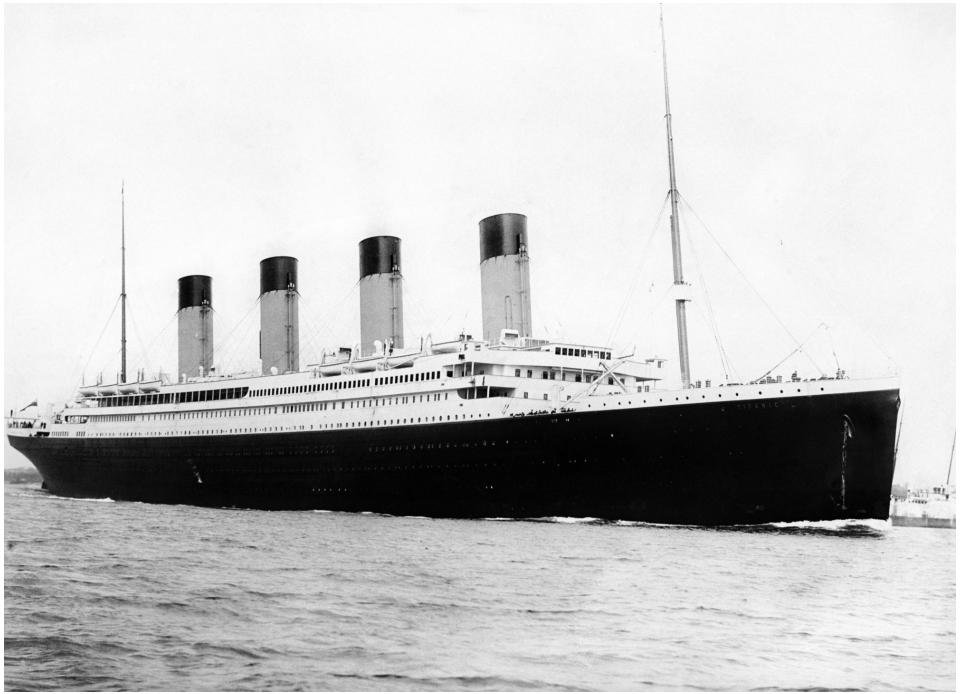
Example Dataset - Titanic

In this challenge, we ask you to complete the analysis of what sorts of people were likely to survive. In particular, we ask you to apply the tools of machine learning to **predict which passengers survived the tragedy**.

https://www.kaggle.com/c/titanic

Data Dictionary

Variable	Definition	Key
survival	Survival	0 = No, 1 = Yes
pclass	Ticket class	1 = 1st, 2 = 2nd, 3 = 3rd
sex	Sex	
Age	Age in years	
sibsp	# of siblings / spouses aboard the Titanic	
parch	# of parents / children aboard the Titanic	
ticket	Ticket number	
fare	Passenger fare	
cabin	Cabin number	
embarked	Port of Embarkation	C = Cherbourg, Q = Queenstown, S = Southampton

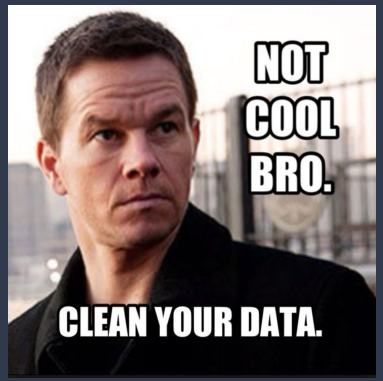


Data Cleaning

Data cleansing plays an important role in modeling.

It's important because you will:

1. Understand your data
2. Know why those values exist
3. Know why those values are missing
4. Find relationships between features



"Clean up on Row 3" - Data Janitor

First Steps..Load and look at your data

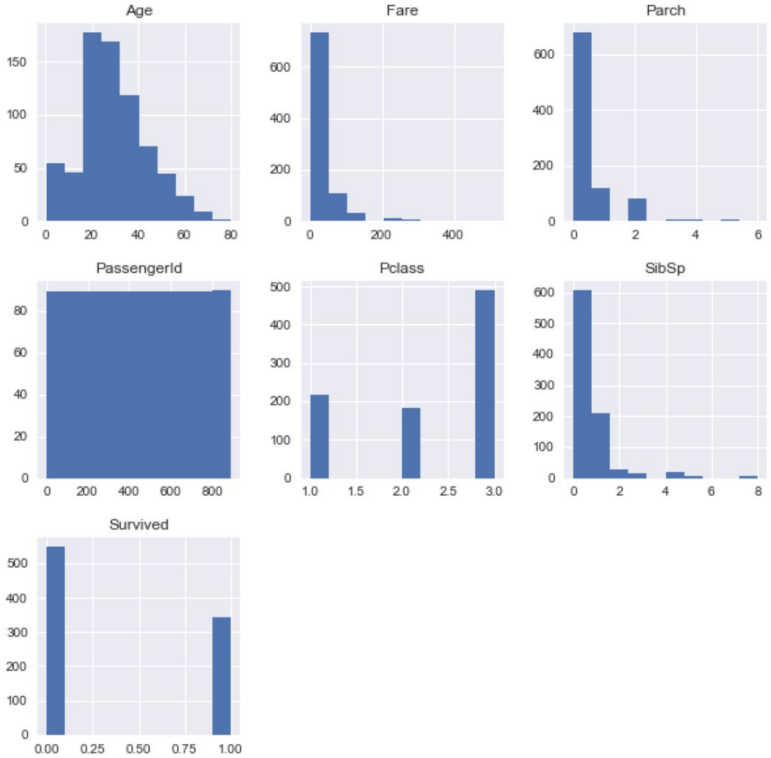
```
# manipulating dataframes
import pandas as pd

# visualizing libraries
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
```

```
titanic_train = pd.read_csv('train.csv')
```

```
titanic_train.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

First Steps..Explore and Visualize your data




```
training.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

While we are here, we can do a visual check that there are no errors or outliers.

First Steps..Get a sense for Data Types

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

```
titanic_train.dtypes
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

- **Numerical discrete**: PassengerId, Survived, Pclass, Age, Parch
- **Numerical continuous**: Fare
- **Categorical nominal**: Name, Sex, Ticket, Embarked
- **Categorical ordinal**: Cabin
- **Text**: None

Check for Missing Data

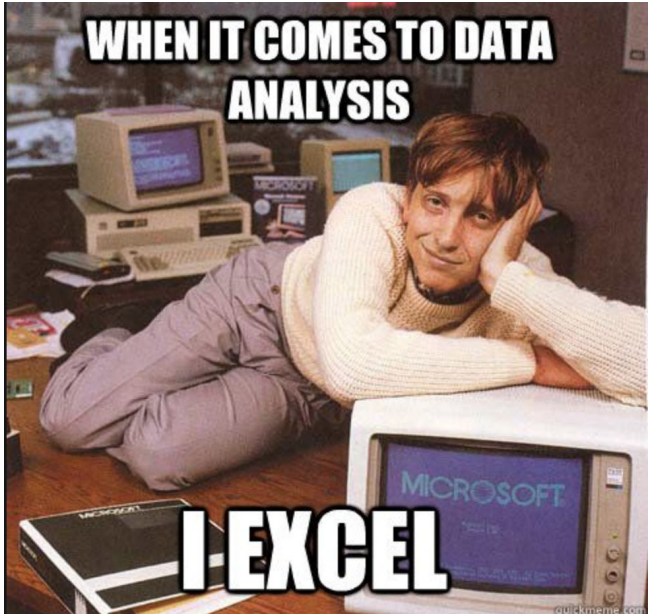
Models can not handle missing data

Simplest solution:

- Remove observations/features that have missing data

But, this might not be the ideal solution...

- If the data is "randomly" missing then you could potentially lose a lot of information from your data
- Even worse, if the data is "non-randomly" missing then you could potentially include biases
- Another approach
- Replace missing values with another value
- Tips: Impute it with either the mean, median, or frequency



Ask yourself: Why is the data missing? How much is missing?

Check for Missing Data

```
titanic_train.count()
```

```
PassengerId    891
Survived       891
Pclass         891
Name           891
Sex            891
Age            714
SibSp          891
Parch          891
Ticket         891
Fare           891
Cabin          204
Embarked       889
dtype: int64
```

Missing data:

- Age
- Cabin
- Embarked

Options:

1. Drop observations with missing values
2. Fill in with mean, median, or mode
3. Fill with random values

Handling Missing Data - Drop

```
titanic_drop_all_missing = titanic_train.dropna(how='any') # drop row if missing in any column
titanic_drop_all_missing.head()
```

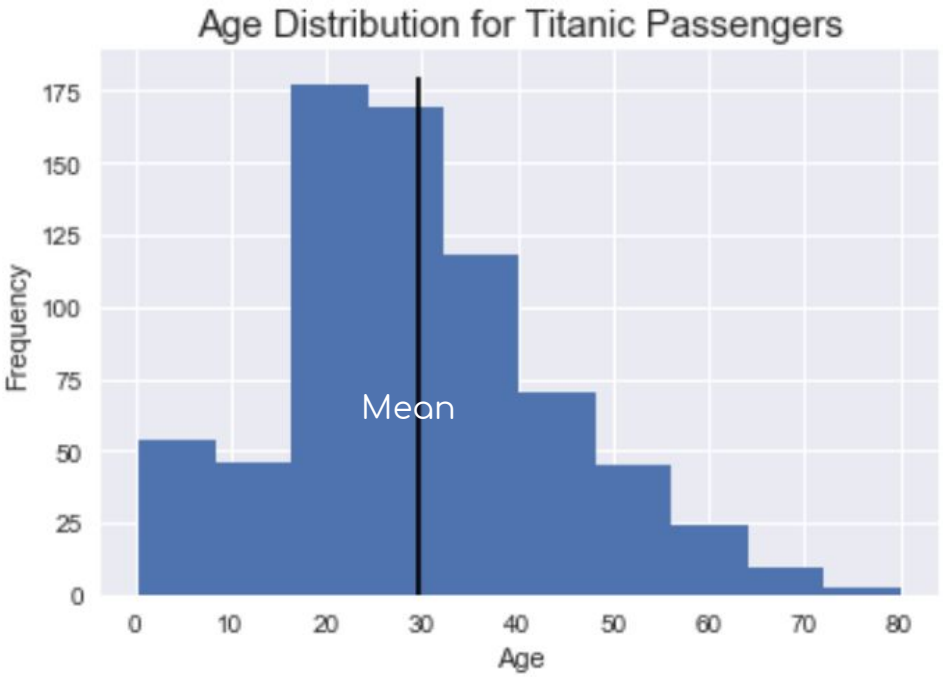
```
titanic_drop_age_missing = titanic_train.dropna(subset = ['Age'], how='all') # drop row if missing in age column
titanic_drop_age_missing.head()
```

```
print('dropping only rows with a missing age value results in', len(titanic_drop_age_missing), 'total observations')
print('dropping only rows with a missing cabin value results in', len(titanic_drop_cabin_missing), 'total observations'
print('dropping any row with a missing value results in', len(titanic_drop_all_missing), 'total observations')
```

```
dropping only rows with a missing age value results in 714 total observations
dropping only rows with a missing cabin value results in 204 total observations
dropping any row with a missing value results in 183 total observations
```

80% of our data was LOST!!!

Handling Missing Data - Impute Age




```
titanic_train.groupby(['Pclass', 'Sex'])['Age'].mean()
```

```
Pclass  Sex
1       female    34.611765
        male      41.281386
2       female    28.722973
        male      30.740707
3       female    21.750000
        male      26.507589
Name: Age, dtype: float64
```

```
titanic_train.groupby(['Pclass', 'Sex', 'Title'])['Age'].mean()
```

```
Pclass  Sex     Title
1       female  Miss      30.000000
                Mrs       40.882353
        male    Master     5.306667
                Mr        41.580460
2       female  Miss      22.390625
                Mrs       33.682927
        male    Master     2.258889
                Mr        32.768293
3       female  Miss      16.123188
                Mrs       33.515152
        male    Master     5.350833
                Mr        28.724891
Name: Age, dtype: float64
```

Detour - Feature Engineering

```
def title(x):
    if 'Mr.' in x:
        return 'Mr'
    elif 'Mrs.' in x:
        return 'Mrs'
    elif 'Master' in x:
        return 'Master'
    elif 'Miss.' in x:
        return 'Miss'
```

```
titanic_train['Title'] = titanic_train.Name.apply(title)
titanic_train.Title.value_counts()
```

```
Mr        517
Miss      182
Mrs       125
Master     40
Name: Title, dtype: int64
```

For this dataset, we are able to engineer at least three new features, namely: title, family size and single rider.

```
titanic_train['FamilySize'] = titanic_train['SibSp'] + titanic_train['Parch'] + 1
titanic_train.FamilySize.value_counts()
```

```
1     537
2     161
3     102
4      29
6      22
5      15
7      12
11      7
8       6
Name: FamilySize, dtype: int64
```

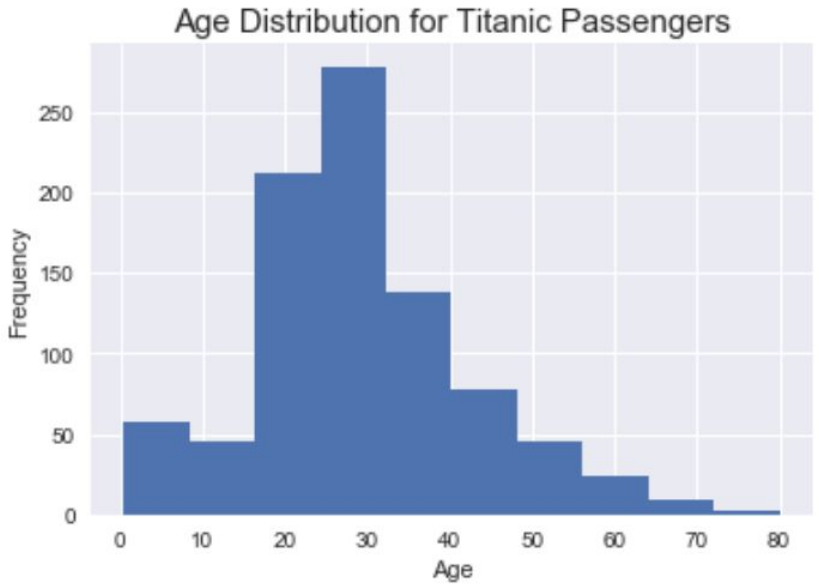
```
titanic_train['IsAlone'] = 0
titanic_train.loc[titanic_train['FamilySize'] == 1, 'IsAlone'] = 1
titanic_train.IsAlone.value_counts()
```

```
1    537
0    354
Name: IsAlone, dtype: int64
```

Handling Missing Data - Impute Age

```
def impute_age(dataset):
    for pclass in [1,2,3]:
        for sex in ['male','female']:
            for title in ['Miss', 'Mr', 'Master', 'Mrs']:
                ds = dataset[dataset['Pclass'] == pclass]
                ds = ds[ds['Sex'] == sex]
                ds = ds[ds['Title'] == title]
                median = ds['Age'].median()
                dataset.loc[
                    (dataset['Age'].isnull()) &
                    (dataset['Pclass'] == pclass) &
                    (dataset['Title'] == title) &
                    (dataset['Sex'] == sex),
                    'Age'] = median
```

```
impute_age(titanic_train)
```



Detour 2 - Data Discretization (Binning)

After we have imputed all the age values, we can use a technique called 'binning' that can help users place values into groups so as to allow for more vigorous customization of datasets.

```
age_bins = [0,18,120]
age_labels = ['minor', 'adult']

for dataset in full_dataset:
    dataset['Child'] = pd.cut(dataset['Age'], age_bins, labels=age_labels)
titanic_train.Child.value_counts()
```

```
adult    715
minor    176
Name: Child, dtype: int64
```

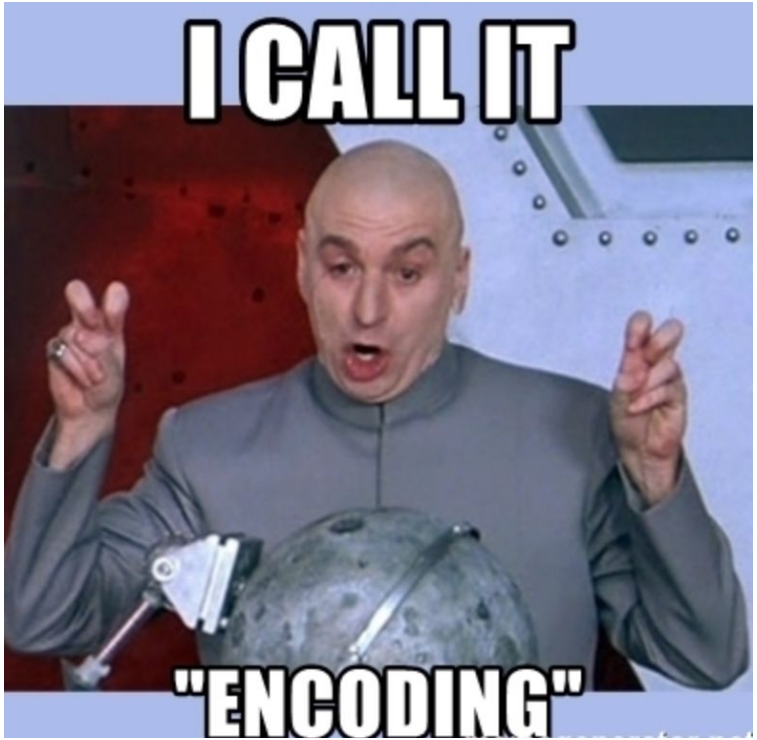
Encoding Categorical Variables

Why Encoding?

Models can only handle numeric features!

Must convert categorical and ordinal features into numeric features:

- Create dummy features
- Transform a categorical feature into a set of dummy features, each representing a unique category
- In the set of dummy features, 1 indicates the observation belongs to that category and 0 otherwise.



Approach 1 - Find and Replace

```
titanic_train.Sex.value_counts()
```

```
male      577
female    314
Name: Sex, dtype: int64
```

```
# using map function
for dataset in full_dataset:
    dataset['Sex'] = dataset['Sex'].map({'female': 0, 'male': 1}).astype(int)
```

```
titanic_train.Sex.value_counts()
```

```
1    577
0    314
Name: Sex, dtype: int64
```

```
cleanup_nums = {'Child': {'Adult': 0, 'Minor': 1},
                'Mother': {'Mother':0, 'Not Mother':1}}
```

```
# using replace
for dataset in full_dataset:
    dataset.replace(cleanup_nums, inplace=True)
```

If you review the `replace` documentation, you can see that it is a powerful command that has many options. For our uses, we are going to create a mapping dictionary that contains each column to process as well as a dictionary of the values to translate.

http://pbpython.com/categorical-encoding.html

Approach 2 - Label Encoding using Pandas

```
titanic_train.Embarked.value_counts()
```

```
S    646
C    168
Q     77
Name: Embarked, dtype: int64
```

```
for dataset in full_dataset:
    dataset["Embarked"] = dataset["Embarked"].astype('category')
titanic_train.dtypes
```

```
PassengerId       int64
Survived          int64
Pclass            int64
Name             object
Sex               int64
Age             float64
SibSp             int64
Parch             int64
Ticket           object
Fare            float64
Cabin            object
Embarked       category
Title             int64
Mother            int64
FamilySize        int64
IsAlone           int64
Child             int64
dtype: object
```

```
for dataset in full_dataset:
    dataset["Embarked"] = dataset["Embarked"].cat.codes
titanic_train.Embarked.value_counts()
```

```
2    646
0    168
1     77
Name: Embarked, dtype: int64
```

Label encoding is simply converting each value in a column to a number. This results in the same output as the find and replace method (Approach 1).

Approach 2 - LabelEncoder with Sklearn

```
from sklearn.preprocessing import LabelEncoder
```

```
titanic_train.Title.value_counts()
```

```
Mr        517
Miss      182
Mrs       125
Master     40
Other      27
Name: Title, dtype: int64
```

```
title_enc = LabelEncoder()
titanic_train['Title'] = title_enc.fit_transform(titanic_train['Title'].astype(str))
titanic_test['Title'] = title_enc.transform(titanic_test['Title'].astype(str))
```

```
titanic_train.Title.value_counts()
```

```
2    517
1    182
3    125
0     40
4     27
Name: Title, dtype: int64
```

Sklearn Workflow:

1. Import
2. Instantiate
3. Fit
4. Transform

Advantages and Disadvantages

LabelEncoder:

The approaches mentioned have the **advantage** of being straightforward and easy to implement.

However, the numeric values can be "misinterpreted" by algorithms. For example, the value of 0 is obviously less than the value of 3 but does that really mean that being a "Mrs" must have 3X more weight in our calculation than being a "Master". I don't think so..

Approach 3 - OneHotEncoder with Pandas

The basic strategy is to convert each category value into a new column and assigns a 1 or 0 (True/False) value to the column.

This has the benefit of not weighing a value improperly but does have the downside of adding more columns to the data set

This encoding is needed for feeding categorical data to many scikit-learn estimators, notably linear models and SVMs with the standard kernels.

.

```
pd.get_dummies(titanic_train, columns=["Embarked"])
```

Embarked
2
0
2
2
2

Embarked_0	Embarked_1	Embarked_2
0	0	1
1	0	0
0	0	1
0	0	1
0	0	1

Approach 3 - OneHotEncoder with Sklearn

```
titanic_train['Embarked'].value_counts()
```

```
2    646
0    168
1     77
Name: Embarked, dtype: int64
```

```
missing_cols = set( titanic_train.columns ) - set( titanic_test.columns )
for c in missing_cols:
    titanic_test[c] = 0
titanic_test = titanic_test[titanic_test.columns]
```

```
from sklearn.preprocessing import OneHotEncoder
embarked_enc = OneHotEncoder()
labels = embarked_enc.fit_transform(titanic_train['Embarked'].reshape(-1,1))
embarked_enc.transform(titanic_test['Embarked'].reshape(-1,1))
```

```
/Users/snooravi/anaconda/lib/python3.6/site-packages/ipykernel/__main__.p
y:3: FutureWarning: reshape is deprecated and will raise in a subsequent
release. Please use .values.reshape(...) instead
  app.launch_new_instance()
/Users/snooravi/anaconda/lib/python3.6/site-packages/ipykernel/__main__.p
y:4: FutureWarning: reshape is deprecated and will raise in a subsequent
release. Please use .values.reshape(...) instead
```

```
<418x3 sparse matrix of type '<class 'numpy.float64'>'
        with 418 stored elements in Compressed Sparse Row format>
```

```
titanic_train.Embarked.head(3)
```

```
0    2
1    0
2    2
Name: Embarked, dtype: int8
```

```
labels
```

```
array([[ 0.,  0.,  1.],
       [ 1.,  0.,  0.],
       [ 0.,  0.,  1.],
       ...,
       [ 0.,  0.,  1.],
       [ 1.,  0.,  0.],
       [ 0.,  1.,  0.]])
```

Data Transformation

Why Feature Scaling?

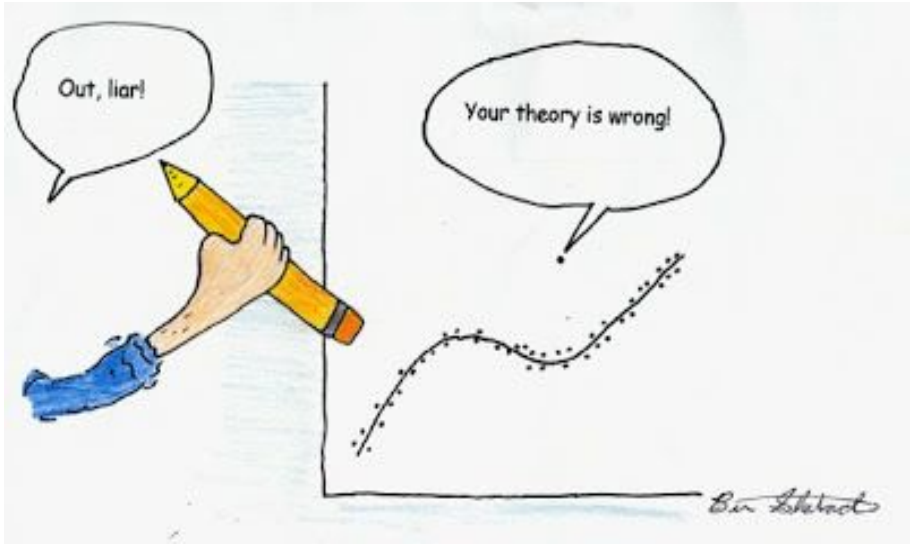
Models don't perform well when the numerical features have different scales.

Two common approaches:

1. Min-Max Scaling (Normalization)
   a. Features are scaled from 0-1
2. StandardScaler (Standardization)
   a. Features are scaled with a mean of 0 and has unit variance

Tips:

- When faced with OUTLIERS, it's better to use StandardScaler



Normalization

Sklearn Definition: Normalization is the process of scaling individual samples to have unit norm.

In other words: Normalization refers to rescaling real valued numeric attributes into the range 0 and 1.

Methods:

- L1 Normalization

$$L_1 \text{ norm: } \|\mathbf{e}\|_1 = \left[\sum_i |e_i|^1\right]$$

- L2 Normalization

$$\|\boldsymbol{X}\|_2 := \sqrt{x_1^2 + \cdots + x_n^2}.$$

- MinMaxScaling

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

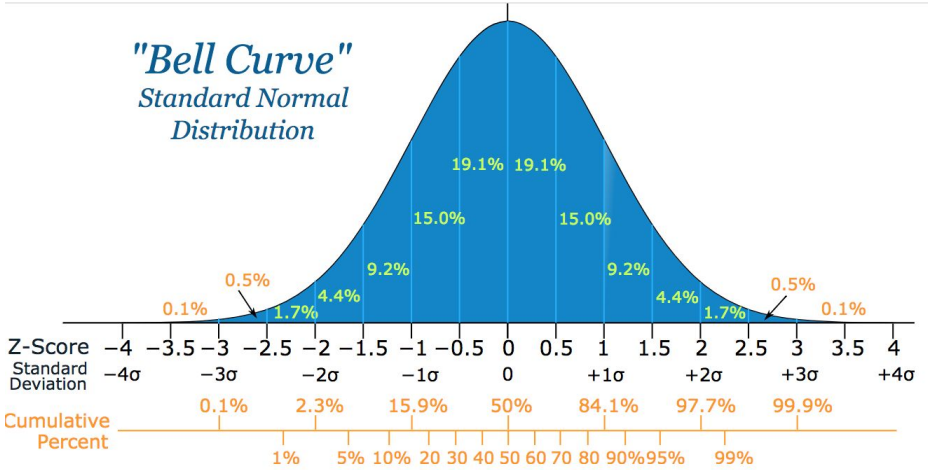
```
>>> X = [[ 1., -1.,  2.],
...      [ 2.,  0.,  0.],
...      [ 0.,  1., -1.]]
>>> X_normalized = preprocessing.normalize(X, norm='l2')

>>> X_normalized
array([[ 0.40..., -0.40...,  0.81...],
       [ 1.  ...,  0.  ...,  0.  ...],
       [ 0.  ...,  0.70..., -0.70...]])
```

```
# Create scaler
minmax_scale = preprocessing.MinMaxScaler(feature_range=(0, 1))

# Scale feature
x_scale = minmax_scale.fit_transform(x)

# Show feature
x_scale
```

Standardization

Sklearn Definition: **Standardization** of datasets is a **common requirement for many machine learning estimators** implemented in scikit-learn; they might behave badly if the individual features do not more or less look like standard normally distributed data: Gaussian with **zero mean and unit variance**

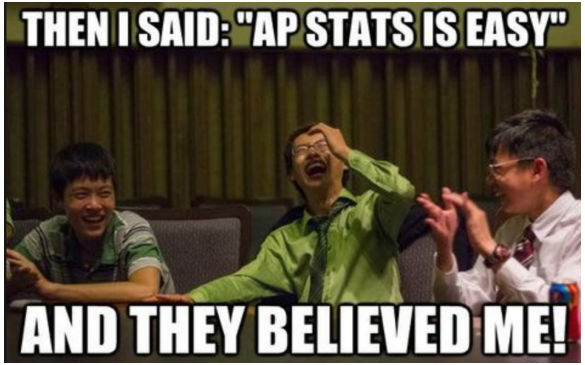
```
>>> from sklearn import preprocessing
>>> import numpy as np
>>> X_train = np.array([[ 1., -1.,  2.],
...                     [ 2.,  0.,  0.],
...                     [ 0.,  1., -1.]])
>>> X_scaled = preprocessing.scale(X_train)

>>> X_scaled
array([[ 0.  ..., -1.22...,  1.33...],
       [ 1.22...,  0.  ..., -0.26...],
       [-1.22...,  1.22..., -1.06...]])
```



Other Transformations

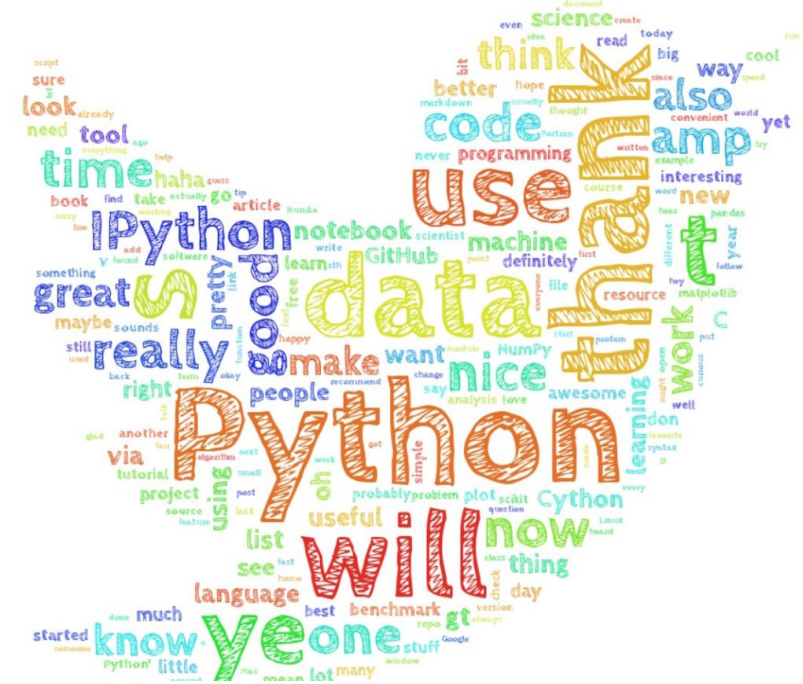
Depending on the data you have, you might want to perform one of the following common transformations.

Remember to back-transform to the original units when reporting final results! To perform a back-transform you apply the *inverse* mathematical function.



Common Transformations

Method	Math Operation	Good for:	Bad for:
Log	$\ln(x)$ $\log_{10}(x)$	Right skewed data $\log_{10}(x)$ is especially good at handling higher order powers of 10 (e.g. 1000, 100000)	Zero values Negative values
Square root	$\sqrt{x}$	Right skewed data	Negative values
Square	x^2	Left skewed data	Negative values
Cube root	$x^{1/3}$	Right skewed data Negative values	Not as effective at normalizing as log transform
Reciprocal	$1/x$	Making small values bigger and big values smaller	Zero values Negative values



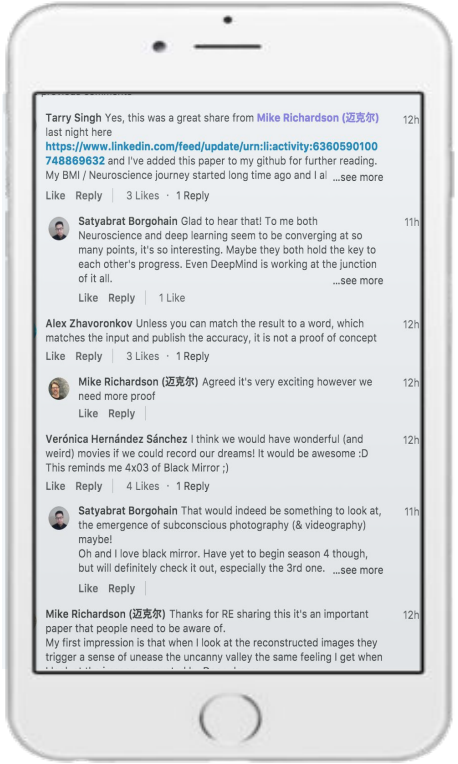
Working with Text Data

Why Text Data is so Important?

- With the advent of social media, text is EVERYWHERE.
- We see it in Reddit comments, web pages, Twitter feeds, status updates, etc...
- Many companies hold text data in the forms of medical records, complaint logs, and repair records...

Use Case of Text Data:

- In business, understanding customer feedback requires the understanding of text.
- Which can be seen through product reviews, email messages, and comments.



Handling Text Data

Text data is notorious for being called **"dirty"** or **"unstructured"** data

It must undergo some steps of **pre-processing** in order to derive meaning from it

GOAL:
Want to convert our **set of documents** into a **feature matrix** our model can understand

Terminologies

- **Text-Preprocessing**: transforming text into readable and meaningful data
- **Document**: one piece of text (could be a single sentence, a paragraph, a blog post, or youtube comment..)
- **Token**: a word
- **Corpus**: a collection of documents

Example Dataset - Mercari's challenge

Mercari's challenging you to **build an algorithm that automatically suggests the right product prices.**

You'll be provided user-inputted text descriptions of their products, including details like product category name, brand name, and item condition.

https://www.kaggle.com/c/mercari-price-suggestion-challenge

First Steps..Load and look at your data

Dataset Features

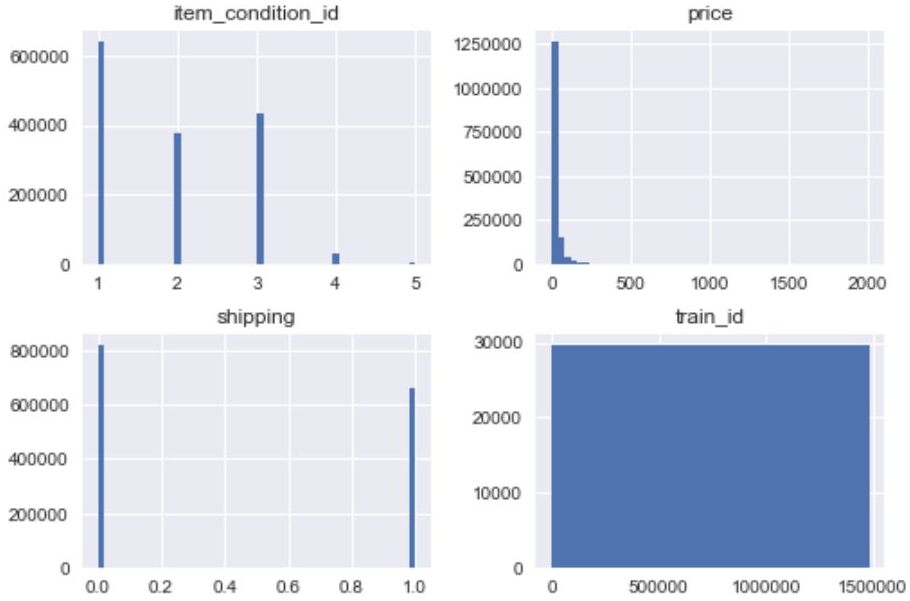
- **ID**: the id of the listing
- **Name:** the title of the listing
- **Item Condition:** the condition of the items provided by the seller
- **Category Name:** category of the listing
- **Brand Name:** brand of the listing
- **Shipping:** whether or not shipping cost was provided
- **Item Description:** the full description of the item
- **Price:** the price that the item was sold for. This is the target variable that you will predict. The unit is USD.

```
import pandas as pd
```

```
training = pd.read_csv('train.tsv', delimiter='\t')
training.head()
```

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	NaN	10.0	1	No description yet
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	0	This keyboard is in great condition and works ...
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	Target	10.0	1	Adorable top with a hint of lace and a key hol...
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	NaN	35.0	1	New with tags. Leather horses. Retail for [rm]...
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	NaN	44.0	0	Complete with certificate of authenticity

First Steps..Explore and Visualize your data




```
training.describe()
```

	train_id	item_condition_id	price	shipping
count	1.482535e+06	1.482535e+06	1.482535e+06	1.482535e+06
mean	7.412670e+05	1.907380e+00	2.673752e+01	4.472744e-01
std	4.279711e+05	9.031586e-01	3.858607e+01	4.972124e-01
min	0.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00
25%	3.706335e+05	1.000000e+00	1.000000e+01	0.000000e+00
50%	7.412670e+05	2.000000e+00	1.700000e+01	0.000000e+00
75%	1.111900e+06	3.000000e+00	2.900000e+01	1.000000e+00
max	1.482534e+06	5.000000e+00	2.009000e+03	1.000000e+00

First Steps..Get a sense for Data Types

	train_id	name	item_condition_id	category_name	brand_name	price	shipping	item_description
0	0	MLB Cincinnati Reds T Shirt Size XL	3	Men/Tops/T-shirts	NaN	10.0	1	No description yet
1	1	Razer BlackWidow Chroma Keyboard	3	Electronics/Computers & Tablets/Components & P...	Razer	52.0	0	This keyboard is in great condition and works ...
2	2	AVA-VIV Blouse	1	Women/Tops & Blouses/Blouse	Target	10.0	1	Adorable top with a hint of lace and a key hol...
3	3	Leather Horse Statues	1	Home/Home Décor/Home Décor Accents	NaN	35.0	1	New with tags. Leather horses. Retail for [rm]...
4	4	24K GOLD plated rose	1	Women/Jewelry/Necklaces	NaN	44.0	0	Complete with certificate of authenticity

```
training.dtypes
```

```
train_id              int64
name                 object
item_condition_id      int64
category_name        object
brand_name           object
price               float64
shipping              int64
item_description     object
dtype: object
```

- **Numerical discrete**: train_id, item_condition_id, shipping
- **Numerical continuous**: price
- **Categorical nominal**: category_name, brand_name
- **Categorical ordinal**: None
- **Text**: item_description

Handling Missing Data

```
training.count()
```

```
train_id             1482535
name                 1482535
item_condition_id    1482535
category_name        1476208
brand_name            849853
price                1482535
shipping             1482535
item_description     1482531
dtype: int64
```

```
mercari['item_description'] = mercari.item_description.fillna('')
```

Missing data:

- Category name
- Brand name
- Item descriptions

Options:

1. Drop observations with missing values
2. Fill in with mean, median, or mode
3. Fill in with empty string

Let's look at a few samples of item_description

```
mercari.item_description[0]
```

```
'No description yet'
```

```
mercari.item_description[1]
```

```
'This keyboard is in great condition and works like it came o
ut of the box. All of the ports are tested and work perfectl
y. The lights are customizable via the Razer Synapse app on y
our PC.'
```

```
mercari.item_description[0]
```

```
"KEEP YOUR DRINKS AS COLD AS SCIENCE ALLOWS WITH THE YETI RAMBLER 30 OZ TUMBLER If you want t
o have cold things stay cold for hours throughout the day, and HOT things HOT for hours throu
ghout the day...THEN THIS YETI IS WHAT YOU NEED! ‼DON'T MISS OUR BLOWOUT SALE, while supplie
s last‼ Good for Sweet Tea, Bloody Marys, Root Beer Floats, Large Coffee, Cold Water, Wine C
OLORS: •Hot Pink •Black •Matte Black •Tiffany Blue •Mint Green •Carolina Blue This Yeti is ma
de with: ✓Strong durable 18/8 Stainless Steel ✓Double-Wall Vacuum Insulation ✓Sweat Free De
sign ✓BPA FREE STORE'S GUARANTEES: ✅BEST CUSTOMER SERVICE ✅LESS THAN 24 HOUR SHIPMENT TO US
PS ✅LOW PRICES ✅HIGH QUALITY PRODUCTS ✅EMPATHETIC COMMUNICATION & ✅FAST COMMUNICATION TO C
USTOMERS If you would like more special presents then look at my store for Authentic Apple 1
Meter 3 Feet Chargers, Authentic Apple 2 Meter 6 Feet Chargers, Authentic Apple Headphones/Ea
rphones/Earpods, Lumee, iPhone 6/6s Cases. FriendlyTronics Coupons"
```

Especially when working with text data, you want to print out a few examples of what you will be working with as the preprocessing steps will fully depend on the data.

Consider: how you handle tweets that are short with hashtags and slang will be very different than the way we would handle text from books.

Brainstorm on Pre-processing Steps

Things to look for:

- Removing punctuation
- Removing numbers
- Removing stop words
- Part of speech tagging
- Lemmatization/Stemming
- Handling short text
- N-grams (red, wine, or red wine)

Especially crucial for social media and emails:

- Chat word removal
- Word standardization (happpy → happy)
- Website urls removal

Libraries to help with this:

- **from** string **import** punctuation
- **import** sklearn.preprocessing
- **from** nltk.corpus **import** stopwords
- **from** nltk.stem **import** WordNetLemmatizer
- **from** nltk.stem.porter **import** PorterStemmer

Apply Pre-processing Steps

after looking at a few descriptions maybe the following will suffice:

1. punctuation removal
2. lowercase
3. stop word removal
4. remove digits

Examples:

```
def remove_puncuation(x):
    for each in punctuation_symbols:
        x = x.replace(*each)
    return x
```

```
def remove_digits(x):
    x = ''.join([i for i in x if not i.isdigit()])
    return x
```

```
mercari.item_description[1482524]
```

```
'■nwot ■perfect condition ■barely worn ■no flaws ■not nike stadium athletics ■no pockets great leisure wear'
```

still not perfect...

CountVectorizer - Definition

Sklearn: Converts a collection of text documents into a **matrix** of **token counts**.

In other words:
CountVectorizer will count the **word frequencies** of words in a corpus. The importance of a word should increase with the number of times it occurs

```
In [7]: test_record=['This is amazing.Check it out.']

In [8]: test_dtm=vectorizer.transform(test_record)

In [9]: pd.DataFrame(test_dtm.toarray(),columns=vectorizer.get_feature_names())
```

Out[9]:

	amazing	and	delivered	ever	fast	higher	is	much	price	product	safe	than
0	1	0	0	0	0	0	1	0	0	0	0	0

CountVectorizer - Parameters

Parameters to consider:

ngram_range : tuple (min_n, max_n)

The lower and upper boundary of the range of n-values for different n-grams to be extracted. All values of n such that min_n <= n <= max_n will be used.

max_df : float in range [0.0, 1.0] or int, default=1.0

When building the vocabulary ignore terms that have a document frequency strictly higher than the given threshold (corpus-specific stop words). If float, the parameter represents a proportion of documents, integer absolute counts. This parameter is ignored if vocabulary is not None.

min_df : float in range [0.0, 1.0] or int, default=1

When building the vocabulary ignore terms that have a document frequency strictly lower than the given threshold. This value is also called cut-off in the literature. If float, the parameter represents a proportion of documents, integer absolute counts. This parameter is ignored if vocabulary is not None.

The most frequent words are not the most descriptive.

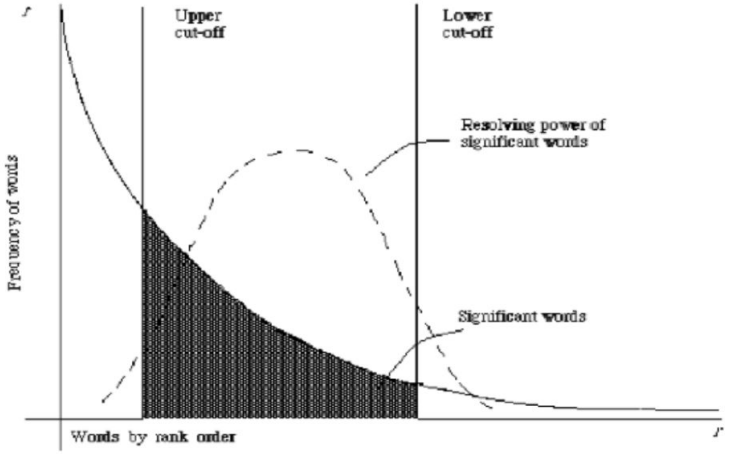


Figure 2.1. A plot of the hyperbolic curve relating f, the frequency of occurrence and r, the rank order. (Adapted from Schultz[44] page 120)

(from van Rijsbergen 79)

Apply CountVectorizer

This is great!

```
from sklearn.feature_extraction.text import CountVectorizer
```

```
min_df = 0.01
max_df = 0.90
ngram_range = 2 # accounting for bi-grams
```

```
print('feature space will include words if they appear in a minimum of ', int(min_df*len(mercari)))
print('feature space will include words if they appear in a maxiumum of ', int(max_df*len(mercari)))
```

```
feature space will include words if they appear in a minimum of  1482
feature space will include words if they appear in a maxiumum of  133428
```

```
# instantiate
countvec = CountVectorizer(stop_words='english', min_df=min_df, max_df=max_df, ngram_range=(0,2))
```

```
# fit and transform the item description
countvec_matrix = countvec.fit_transform(mercari.item_description)
```

```
'excellent condition',
'extra',
'fast',
'feel',
'feel free',
'firm',
'fit',
'fits',
'flaws',
'free',
'free home',
'free shipping',
'gently',
'gift',
'gold',
'good',
'good condition',
'gray',
'great',
'great condition',
```

Feature Space

Your new feature space resembles a "Bag of Words" model

	adjustable	ask	authentic	available	baby	bag	beautiful	best	big	black	...	white	womens	wore	work	works	worn	worn times	xl	xs	zip
0	0	0	3	0	0	0	0	1	0	2	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	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	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 231 columns

Dimensionality Reduction

Why Dimensionality Reduction?

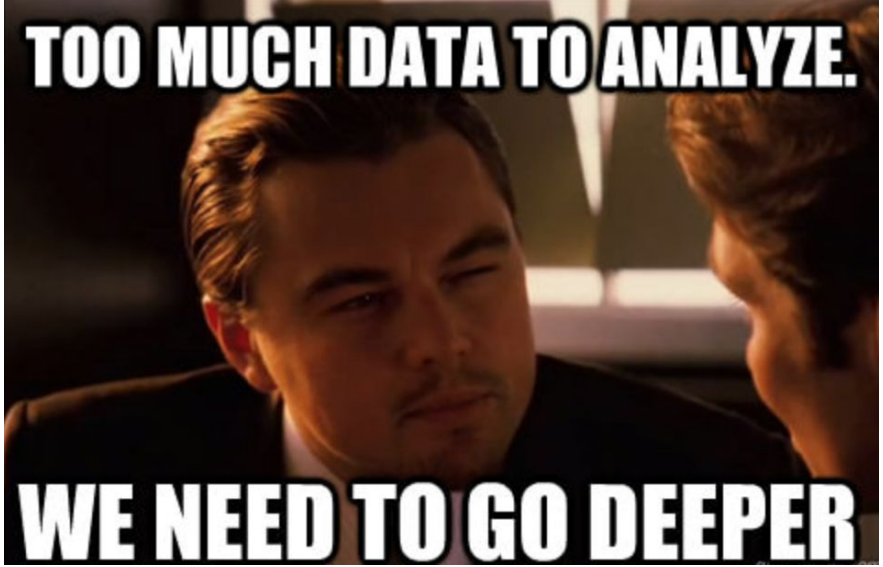
Want to reduce complexity, while not losing too much information

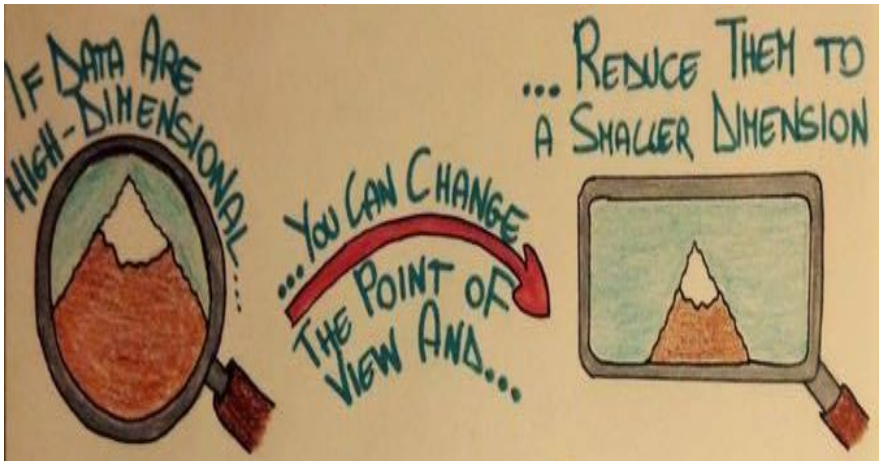
How does Dimensionality Reduction help us?

- Speeds up model training
- Good for data visualization
- Sometimes increases model performance

Disadvantages:

- Lose some data in the process





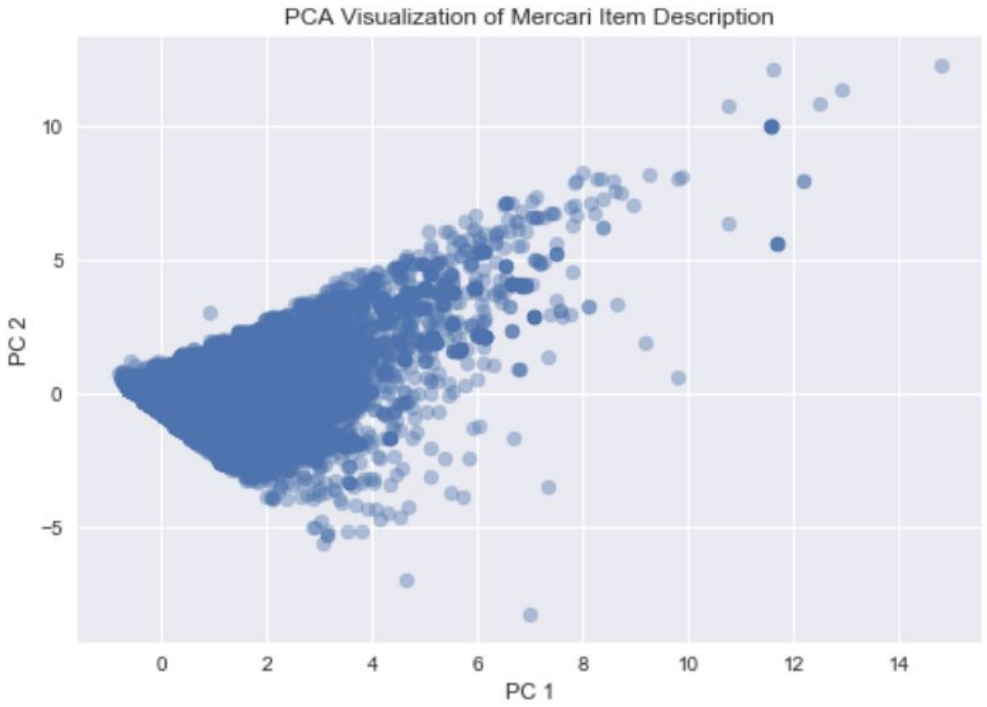
Dimensionality Reduction

Direct Method:

- **Feature Selection**: select a minimum set of attributes that is sufficient for the task

Indirect Methods:

- Principal Component Analysis: PCA
- Singular Value Decomposition: SVD



Summary

Working with Numerical Data:

- Data Cleaning
  - Handling Missing Data
  - Imputation
- Data Transformation
  - Normalization, Standardization and other common Transformation
- Data Discretization (binning)
- Feature Engineering

Working with Categorical Data:

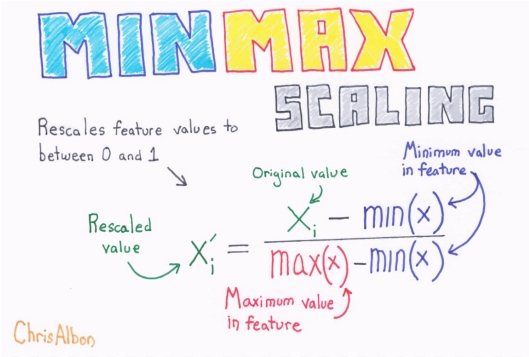
- Encoding using LabelEncoder and OneHotEncoding (Pandas and Sklearn)

Working with Text Data:

- Stopword removal, lemmatization, stemming, n-grams, min_df, max_df
- CountVectorizer
- Dimensionality Reduction

Additional Resources

- Advantages and Disadvantages for Different Dimensionality Reduction Methods: here
- Principal Component Analysis: here
- MinMaxScaling: here
- Categorical Encoding: here
- Data Pre-Processing: here
- Quick and Dirty Analysis with Pandas: here
- Data Transformation: here
- Data Transformations: here



Code and Slides

For access to all the code used to produce this presentation and the slides, see: here