First things first!

Take the quiz for today!

Quiz Lecture 2 in Module 2.

(It times out soon.)

When you are done, please download:

- **Titanic.csv**
- **ML&O Lecture 2 – Exercise Book.ipynb**

Make sure they are in the same folder!

The Business School for the World®

Machine Learning and Optimization
Lecture 2

Data and Feature Engineering

Professor Georgina Hall

Agenda for today

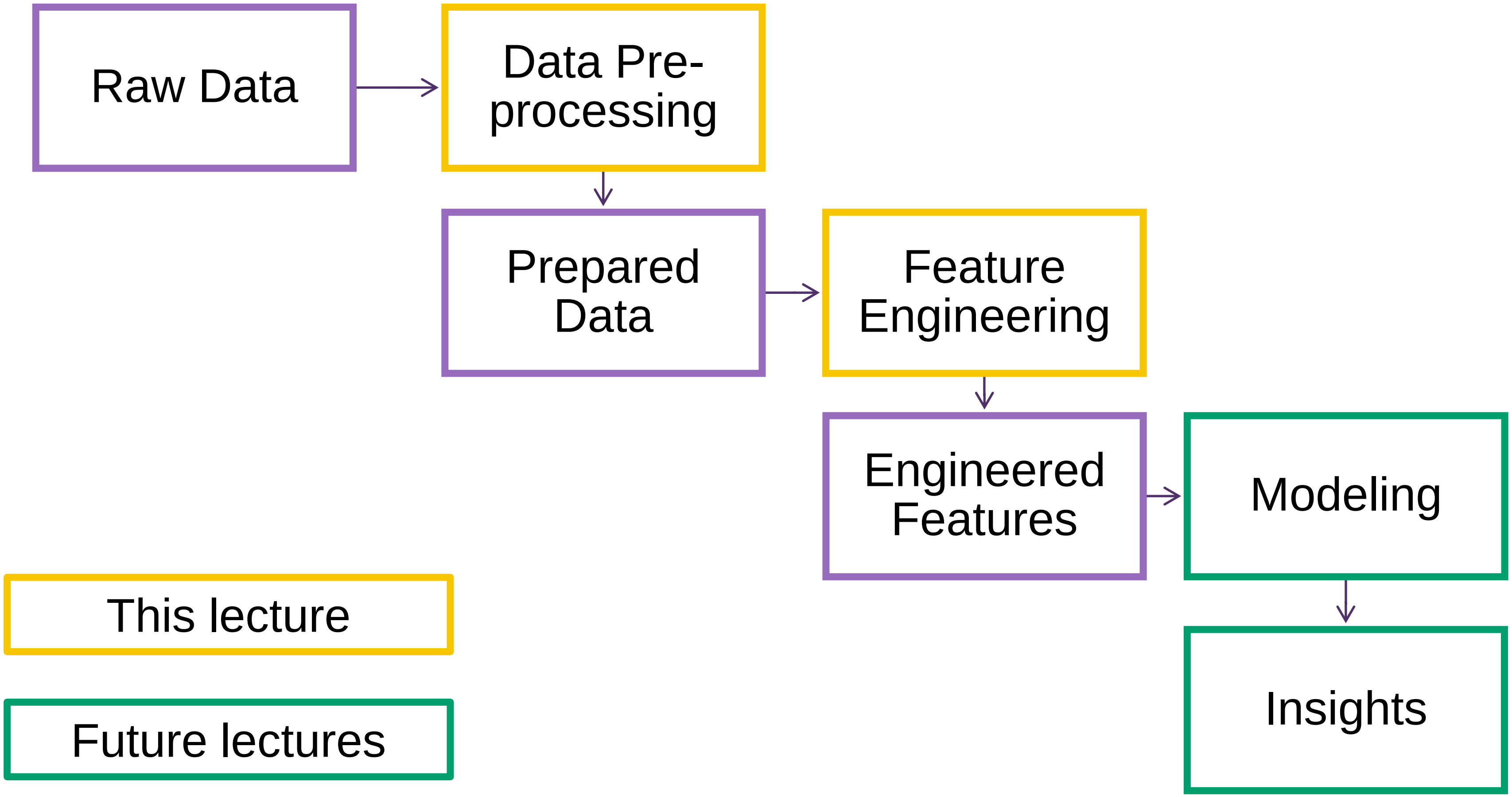
Learning objectives:

- Understand the key issues that can be faced when considering raw data
- Learn how to identify and deal with them

How will we get there?

- Appeal to your intuition: if you had to identify these issues how would you go about it? How would you deal with them?
- Use of the **Titanic Dataset**

The Machine Learning pipeline



About this lecture

A very important part of the process.

- Many, many techniques for data preprocessing and feature engineering
- Often requires business knowledge/detective work combined with good technical knowledge to identify and correct
- Focus on the main issues, give some work-arounds and how to use Python to deal with these issues

The Titanic Dataset (1/2)

- Gives **a list of passengers on the Titanic** with some of their features and whether they survived (see Lectures 5 and 6)

- Discover the dataset using **df.head(), df.info()**
  - ⇒ what are the features? do you understand them all?
  - ⇒ how many observations?

```
Titanic.head()
```

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

Observation

Feature

The Titanic Dataset (2/2)

```
Titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 893 entries, 0 to 892
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  893 non-null    int64
 1   Pclass       893 non-null    object
 2   Name         893 non-null    object
 3   Sex          893 non-null    object
 4   Age          716 non-null    float64
 5   SibSp        893 non-null    int64
 6   Parch        893 non-null    int64
 7   Ticket       893 non-null    object
 8   Fare         893 non-null    float64
 9   Cabin        205 non-null    object
 10  Embarked     891 non-null    object
dtypes: float64(2), int64(3), object(6)
memory usage: 76.9+ KB
```

- 11 features, 893 observations
- 2 are floats, 3 are integers and 6 are objects (objects are either strings or mixed strings and numbers)

Difference between categorical and numerical variables

A **numerical variable** denotes a **measurement or a count.**
Examples: fare, age, sibsp

A **categorical variable** denotes membership to a **category** (can be a number but the number is a stand in for a category).
Examples: Pclass, sex

Raw data

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What could be some issues encountered in raw data?

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Data
Pre-Processing

Data cleansing

A dataset may have any of the following **issues**:

- Values that are not in the right **format** (e.g., a number that's been written as a string)

- **Invalid values** (e.g., negative values for a variable that is only positive)

- Features that bring no additional information: they contain the same **value** for all observations or different values for all observations with no useful pattern

- **Duplicate observations**

- Observations/Features that have **missing elements**

Corrupt and invalid values (1/4)

How to detect **corrupt or invalid values** in a dataset?

For **values that are numbers**: use **df.describe()** to understand what is going on

Does anything seem off to you?

```
Titanic.describe()
```

	PassengerId	Age	SibSp	Parch	Fare
count	893.000000	716.000000	893.000000	893.000000	893.000000
mean	447.000000	29.649679	0.521837	0.380739	32.076091
std	257.931192	14.540967	1.101784	0.805355	49.725466
min	1.000000	0.420000	0.000000	0.000000	-50.000000
25%	224.000000	20.000000	0.000000	0.000000	7.895800
50%	447.000000	28.000000	0.000000	0.000000	14.454200
75%	670.000000	38.000000	1.000000	0.000000	31.000000
max	893.000000	80.000000	8.000000	6.000000	512.329200

- A fare should be positive…
- Everything seems okay except for this
- Where does the negative fare occur?

Corrupt and invalid values (2/4)

We filter the dataset based on the fare being negative:

```
Titanic[Titanic["Fare"]<0]
```

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
892	893	err	err	err	5.0	0	0	err	-50.0	err	err

Row 892 is completely corrupt! We need to remove it… How to delete it?

df.drop(index=number)

```
Titanic=Titanic.drop(index=892)
```

```
Titanic.describe()
```

	PassengerId	Age	SibSp	Parch	Fare
count	892.000000	715.000000	892.000000	892.000000	892.000000
mean	446.500000	29.684154	0.522422	0.381166	32.168105
std	257.642517	14.521835	1.102264	0.805706	49.677238
min	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.750000	20.000000	0.000000	0.000000	7.895800
50%	446.500000	28.000000	0.000000	0.000000	14.454200
75%	669.250000	38.000000	1.000000	0.000000	31.000000
max	892.000000	80.000000	8.000000	6.000000	512.329200

All good now!

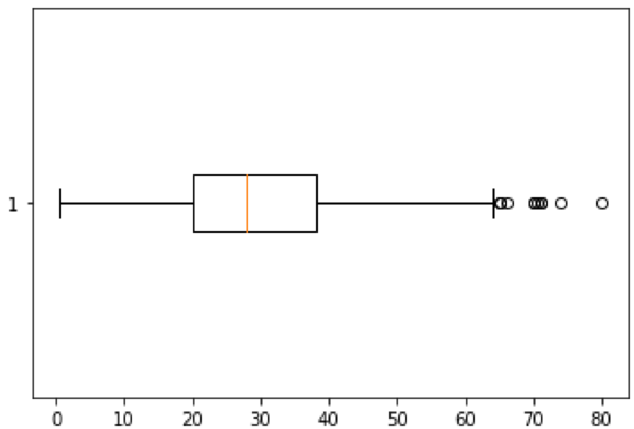
Corrupt and invalid values (3/4)

Looking for outliers:

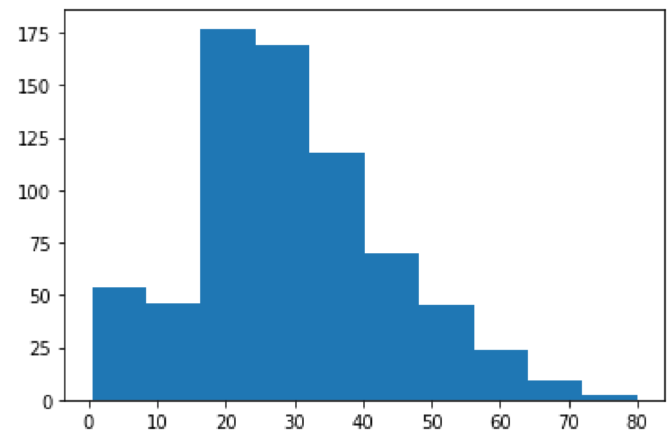
An outlier is an observation that doesn't "fit" into your dataset.

- This can be due to corrupt data, typos, or real outliers (e.g., Michael Jordan)
- Three main ways of checking for outliers: boxplots, Z-score charts (numbers above 3 or below -3), anomaly detection (unsupervised learning technique)
- Serves to flag possible outliers: area-specific knowledge to discard/keep

```
plt.boxplot(Titanic.loc[~Titanic["Age"].isna(),"Age"],vert=False)
```




```
plt.hist(Titanic["Age"])
```



Corrupt and invalid values (4/4)

How to detect **corrupt or invalid values** in a dataset?

For **values that are strings or objects**: use **df[“column”].unique()**

Does anything seem off to you?

```
Titanic["Pclass"].unique()
```

```
array(['third', 'first', 'second'], dtype=object)
```

```
Titanic["Name"].unique().shape
```

```
(891,)
```

```
Titanic["Sex"].unique()
```

```
array(['male', 'female'], dtype=object)
```

```
Titanic["Ticket"].unique().shape
```

```
(681,)
```

```
Titanic["Cabin"].unique().shape
#some are missing: there are "nan"
```

```
(148,)
```

```
Titanic["Embarked"].unique()
```

```
array(['S', 'C', 'Q', nan], dtype=object)
```

- Two passengers share the same name
- Some passengers share ticket numbers
- There are missing values in “embarked” and “cabin”
- Valid values otherwise

Features with no information

How to **delete columns/features?**

- **Delete** features which are unique to each observation and bring no additional info (e.g., allocated at random)
- **Delete** features which are the same for every observation

What could we delete here?

Use df.drop(columns=[“column1”, “column2”])

```
Titanic=Titanic.drop(columns=["PassengerId"])
```

```
Titanic
```

	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	third	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	first	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	third	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	first	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	third	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...
887	first	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	third	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	first	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C
890	third	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7500	NaN	Q
891	third	Johnson, Mr. William Cahoone Jr	male	19.0	0	0	LINE	0.0000	NaN	S

892 rows × 10 columns

Duplicates

How to detect and delete **duplicate rows?**

Your turn!

```
dups=Titanic.duplicated() #checks each row of the dataset and returns TRUE or FALSE depending on whether it is a duplicate
print(dups.any()) #returns TRUE if there is any value in dups that is equal to TRUE
Titanic[dups] #returns the problematic row
```

```
True
```

	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
891	0	third	Johnson, Mr. William Cahoone Jr	male	19.0	0	0	LINE	0.0	NaN	S

Don’t need to run this every time: can simply delete duplicates in an automated way using Python:

```
print(Titanic.shape) #gives current size of dataset
Titanic.drop_duplicates(inplace=True) # delete duplicate rows
print(Titanic.shape)
```

```
(892, 10)
(891, 10)
```

Scaling and Normalizing (1/2)

What is **scaling/normalizing** data? Only for **numerical features.**

Makes sure that your data is on scales that are comparable.

Normalizing: operation that ensures that your data is **between 0 and 1**

Scaling: operation that ensures that the **mean** of your data is **0** and the **std dev** is **1**

Your turn!

```
from sklearn import preprocessing
```

```
X = np.array([[ 1., -1.,  2.],
...                [ 2.,  0.,  0.],
...                [ 0.,  1., -1.]])
```

```
min_max_scaler=preprocessing.MinMaxScaler()
X_minmax = min_max_scaler.fit_transform(X)
X_minmax
```

```
array([[0.5       , 0.        , 1.        ],
       [1.        , 0.5       , 0.33333333],
       [0.        , 1.        , 0.        ]])
```

Normalizing

```
X_scaled = preprocessing.scale(X)
X_scaled
```

```
array([[ 0.        , -1.22474487,  1.33630621],
       [ 1.22474487,  0.        , -0.26726124],
       [-1.22474487,  1.22474487, -1.06904497]])
```

Scaling

Scaling and Normalizing (2/2)

When should I use it?

- **Useful for certain machine learning algorithms only**.
  - Useful for regressions, PCA. Not for tree algorithms.
  - If your algorithm takes features and multiplies them by numbers etc., then chances are scaling/normalizing could improve it.

- Some use cases:
  - Some columns are **orders of magnitude different** (e.g., column A has values around 1 and column B has values around 10,000,000,000)
  - Your algorithm is returning **warning message** of the type “poor condition number”
  - The **output** you get from your algorithm is **incomprehensible** (e.g., NAs)

Data Imputation (1/5)

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How to **detect empty cells in the rows or columns**?

df.isna().any() tells you which columns are empty.
df.isna().sum() tells you how many of the entries are empty.

Your turn!

```
Titanic.isna().any()
```

```
Pclass      False
Name        False
Sex         False
Age          True
SibSp       False
Parch       False
Ticket      False
Fare        False
Cabin        True
Embarked     True
dtype: bool
```

```
Titanic.isna().sum()/891
```

```
Pclass      0.000000
Name        0.000000
Sex         0.000000
Age         0.198653
SibSp       0.000000
Parch       0.000000
Ticket      0.000000
Fare        0.000000
Cabin       0.771044
Embarked    0.002245
dtype: float64
```

Three columns have missing entries:
Age, Cabin, Embarked

Activity (with your neighbor): what could be different ways of dealing with the empty **Age** cells?
How would this change if you consider a missing observation for the **Embarked** feature?

Data imputation (2/5)

Easy

Numerical variables

Delete the row(s)/column(s) where values are missing

Replace the value with the **mean/the largest value/the smallest value**

Find the observation that is **“closest”** to it in other observations and use the value there

Find a **couple of observations** that are “close” to it and **randomly pick one of them**

Run a **regression** on rows where all the data is present and infer from it the missing values

Run a regression on rows where all the data is present and infer from it the missing values then **add noise** to the missing values

Hard

Data imputation (3/5)

Categorical variables

Easy

Delete the row(s)/column(s) where values are missing

Create a new category: missing values

Replace the value with the **value that appears most/least**

Find the observation that is **“closest”** to it in other observations and use the value there

Find observations that are **close** to it in other observations and randomly pick one

Run a **prediction algorithm** on rows that outputs a categorical variable (Lecture 5)

Hard

Data imputation (4/5)

	Sales	Size	Color
1	221	NA	Blue
2	157	Large	NA
3	NA	Medium	Red
4	50	NA	Green
5	122	Large	Red

Missing completely at random
(no pattern to the missing entries)

	Age	Mammography results
1	23	NA
2	55	Negative
3	34	Positive
4	18	NA
5	62	Positive

Missing at random
(absent entries depend on another feature)

	Weight (kgs)	Age	Diabetes
1	80	77	1
2	90	40	0
3	NA	62	1
4	50	18	0
5	NA	54	1

Missing not at random
(entries are absent due to their value or a feature not accounted for)

- The methods discussed work well for **missing completely at random/missing at random**
- For **Missing not at random**: much harder, can be mitigated by adding features

Data Imputation (5/5)

Back to Titanic dataset…

```
Titanic.isna().sum()/891
```

```
Pclass      0.000000
Name        0.000000
Sex         0.000000
Age         0.198653
SibSp       0.000000
Parch       0.000000
Ticket      0.000000
Fare        0.000000
Cabin       0.771044
Embarked    0.002245
dtype: float64
```

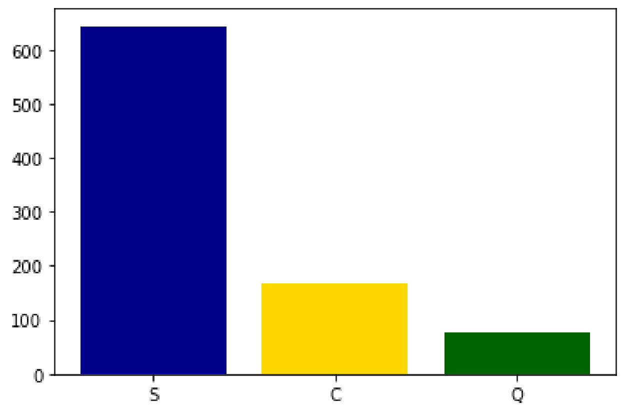
- Cabin has too many missing values

⇒ we drop this column: **df.drop(columns=[“column1”])**

- What do with Age and Embarked?

Use the package **sklearn.impute**

Embarked: most frequent value is “S”.
⇒ Replace missing with **S** (see notebook)



Age: replace, e.g., with the age of the observation that is closest on other features (see notebook)

Feature Engineering

Numerical ↔ Categorical (1/3)

- Some algorithms only accept one kind of input (generally numerical, e.g., regression).
- Useful to know how to go from one “type” of data to another

Categorical → Numerical

Activity (with neighbor): can you see a difference between these two sets of categorical entries? How would you propose to make them numbers?

Pclass
Second
First
Third

Embarked
S
C
Q

Numerical ↔ Categorical (2/3)

INSEAD

Pclass
Second
First
Third

⇒

Pclass
2
1
3

Ordinal variables
(these entries can be ranked)

Exercise left for homework

Embarked
S
C
Q

Nominal variables
(these entries cannot be ranked)

⇒

	S	C	Q
Observation 1	1	0	0
Observation 2	0	1	0
Observation 3	0	0	1

One-Hot Encoding

⇒

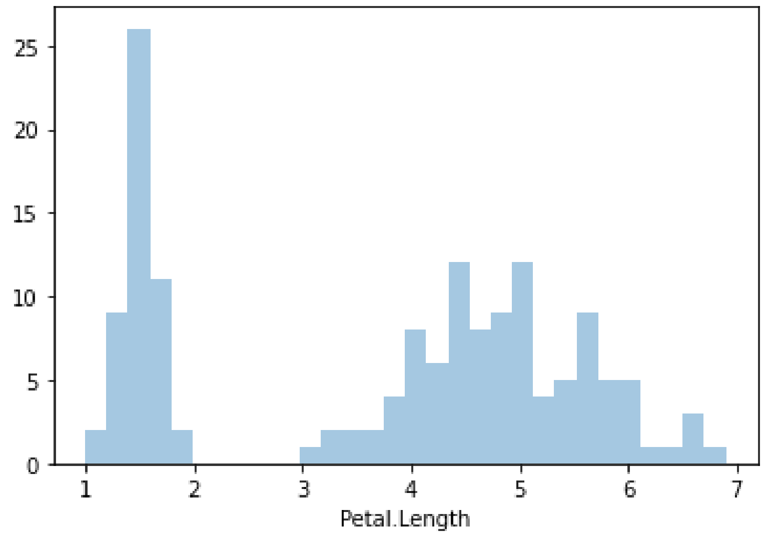
	S	C
Observation 1	1	0
Observation 2	0	1
Observation 3	0	0

Drop redundant column

```
Titanic=pd.get_dummies(Titanic,columns=["Sex","Embarked"], drop_first=True)
```

Numerical ↔ Categorical (3/3)

Numerical → Categorical



Idea: use bucketization or data binning. Take average for each bucket. Number of buckets=number of categories.

Can also serve to aggregate observations.

Feature selection/dimension reduction

- **Feature selection**

  Involves picking the **“right” features** for the model out of all possible features

- **Dimension reduction**

  - Involves “**merging**” features together to get as **few features** as possible to explain the variability in the data
  - Covered in unsupervised learning (Lecture 8)

Transforms & interactions

- Depending on the set-up it may be useful to **transform a feature**:
  - take powers of it
  - subtract/add a constant to it
  - divide/multiply by a constant
  - take an exponential of it or a log

Example in your homework on“Fare”: converting pounds from 1912 to today’s euros.

- **Feature interactions** involve adding/multiplying/dividing etc. two features together to obtain a new feature.

Example in your homework linking “ParCh” and “SibSp”

Wrap-up & Next time

Today, we:

- Discussed some challenges faced to deal with (1) corrupt data; (2) duplicates; (3) scaling issues; (4) missing data
- Understood how to go from numerical ↔ categorical
- Defined feature selection/transforms and dimension reduction

Taking a step back:

- Importance of business knowledge when doing data pre-processing
- Fundamental role of data pre-processing to get a good ML model

Next time:

- Regression recap and the basics of supervised learning
- Mini-quiz at the beginning of lecture + homework

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