Feature Engineering

IFT6758 - Data Science

Sources:

https://towardsdatascience.com/feature-engineering-for-machine-learning-3a5e293a5114

https://towardsdatascience.com/ways-to-detect-and-remove-the-outliers-404d16608dba

https://www.slideshare.net/0xdata/feature-engineering-83511751

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Announcements

- **Midterm**: October 31 at 16:30 – 18:30
  (those who cannot make it at 16:30, send us an email asap. We will arrange a room for them to do the same exam at 14:30 – 16:30)

- **Project evaluation**: The teams with the results same as baseline on the scoreboard for Evaluation1 got the full grade for the first project assignment, i.e., User05, User06, User08, User09, User14, User17, User22, User25, User26, User29, User30.

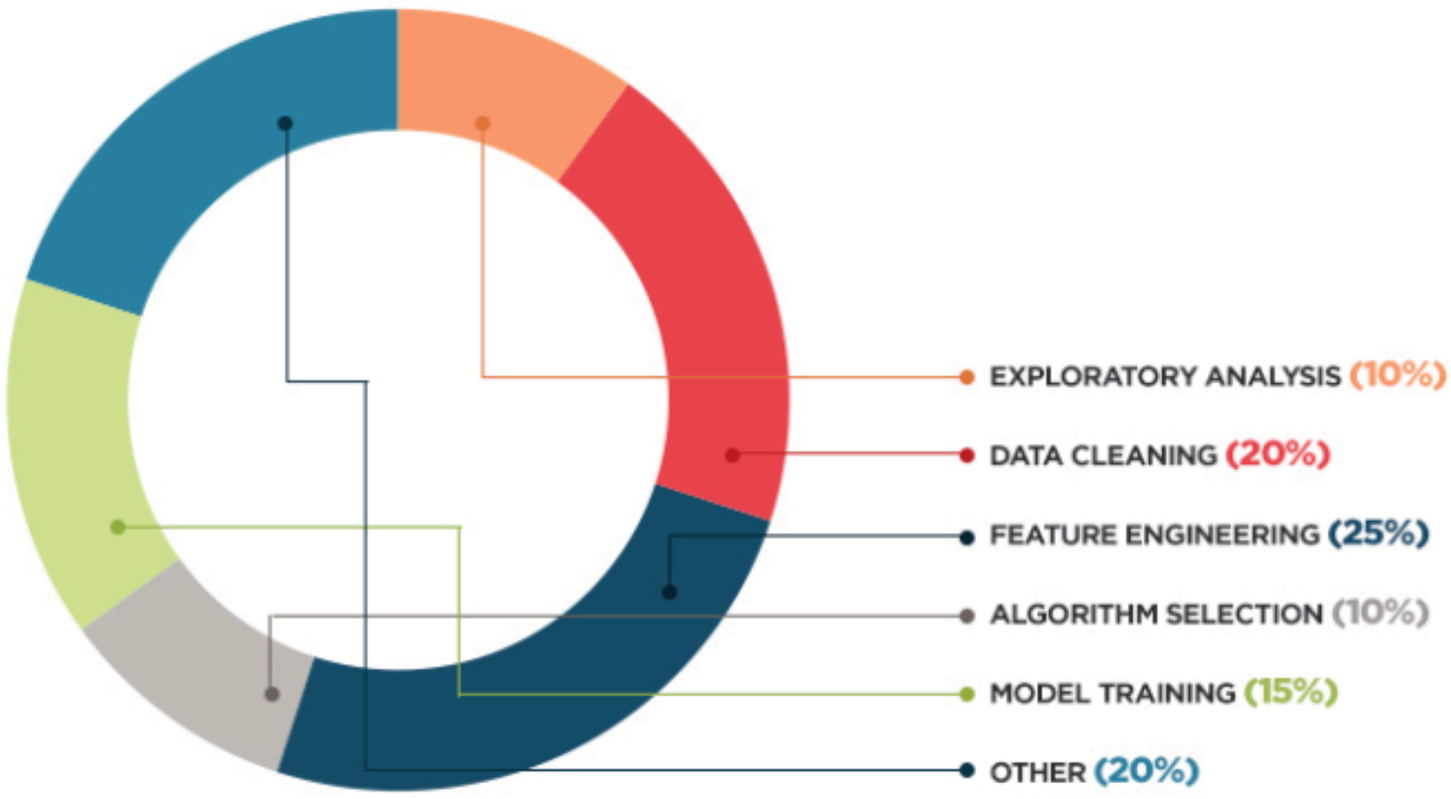
- The other teams will be graded this week based on their scores for Evaluation 2.

- We have two invited talks next week on Tuesday (Geospatial and Time series data analysis) and Thursday (Privacy and Transparency in Machine Learning).

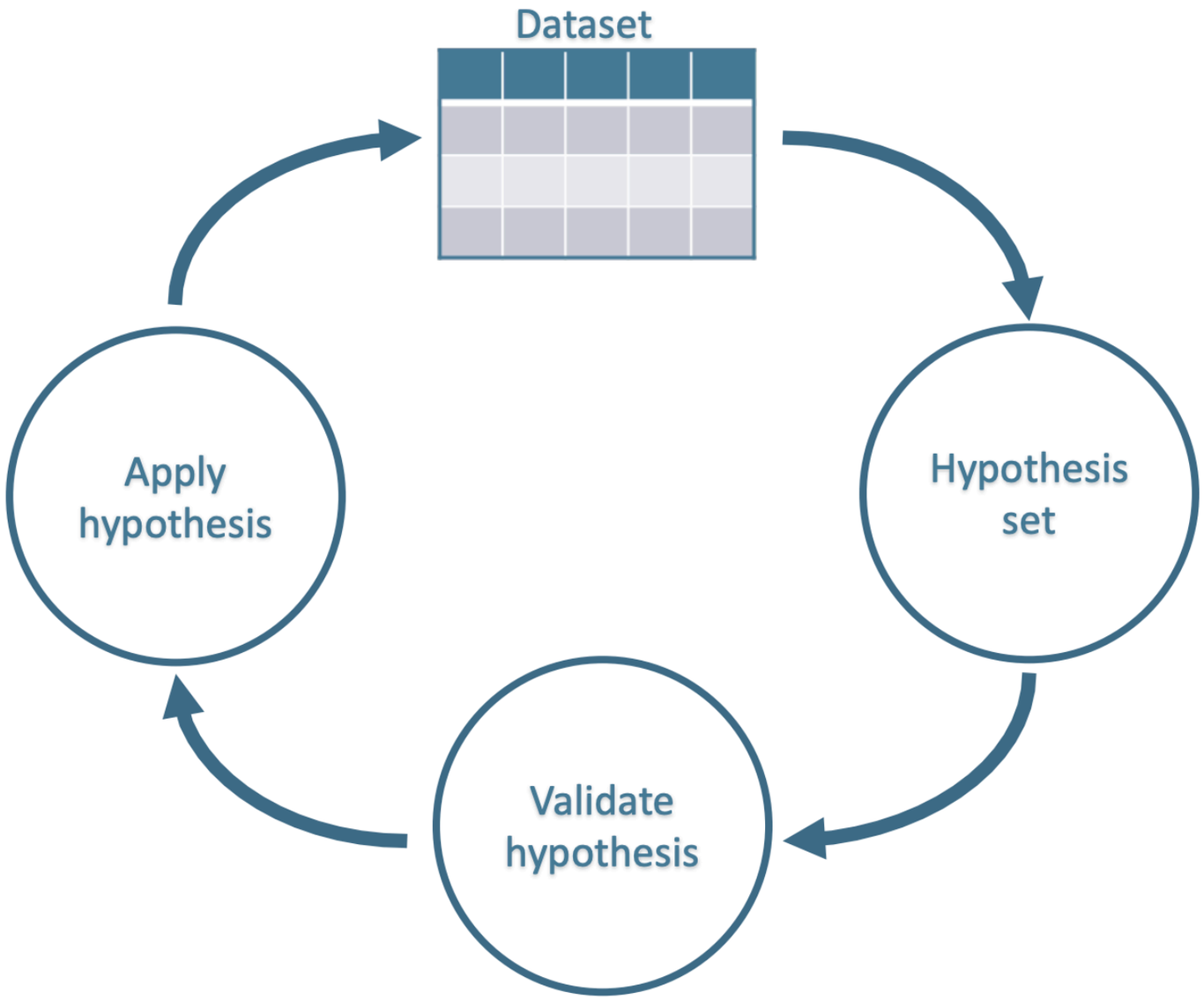
- **Project Presentation** will take place on **November 5**

Feature Engineering

Data scientists usually spend the most time on feature engineering!



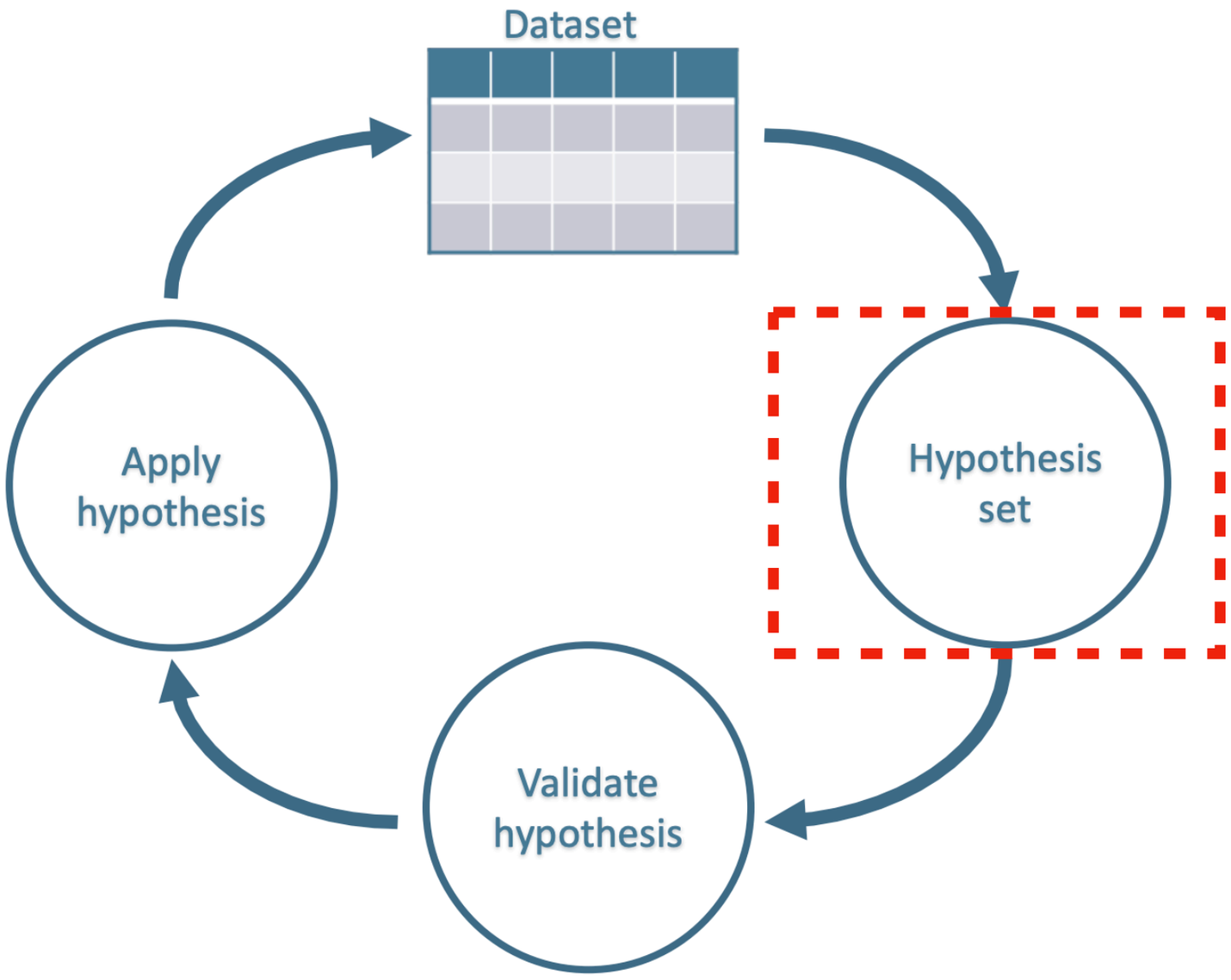
Feature engineering cycle



Not Feature Engineering

- data collection
- Creating the target variable
- Removing duplicates
- Fixing mislabeled classes.

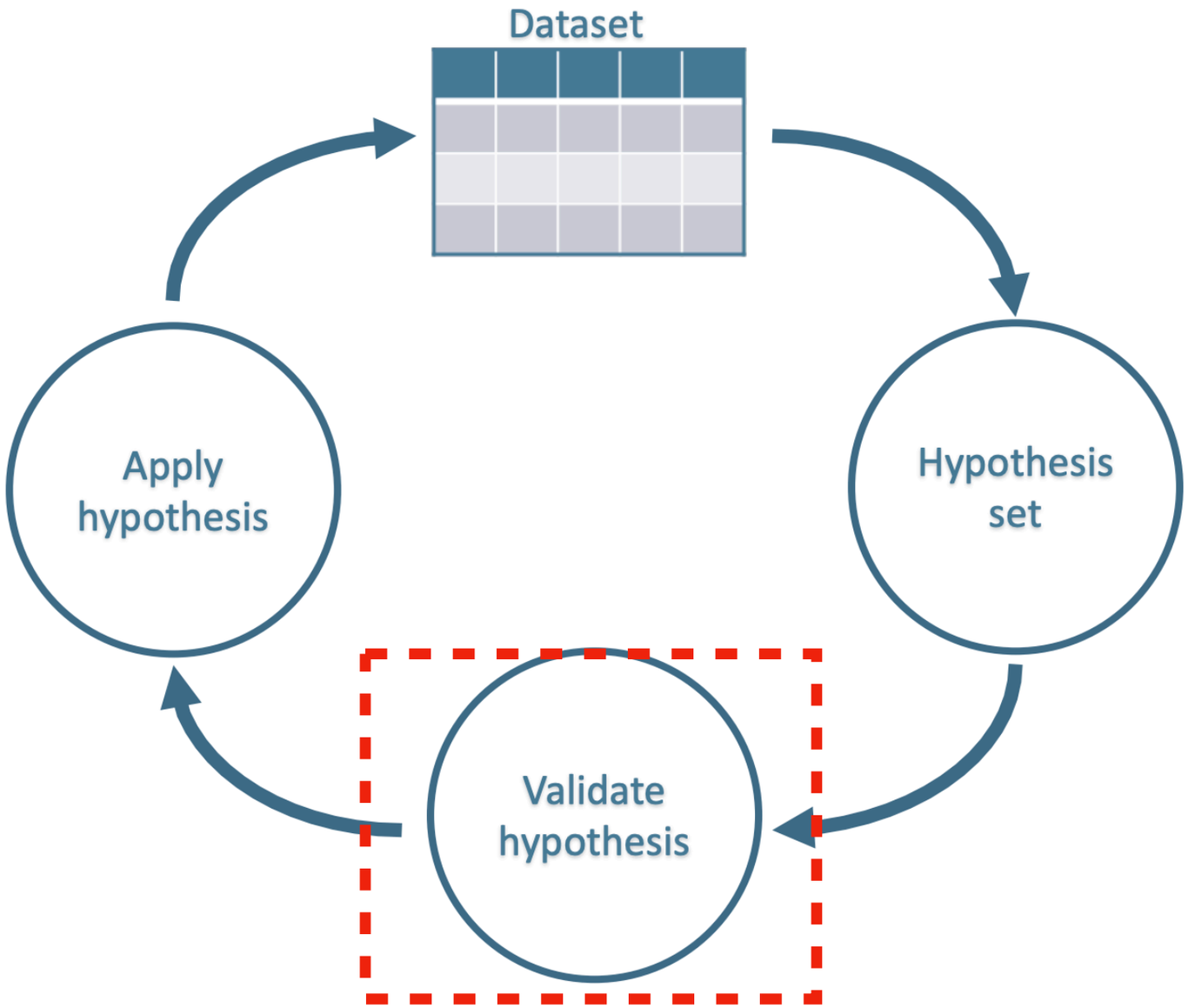
Feature engineering cycle



How?

- Domain knowledge
- Prior experience
- EDA
- ML model feedback

Feature engineering cycle



How?

- Cross-validation
- Measurement of desired metrics
- Avoid leakage

Feature engineering is hard

- Powerful feature transformations (like target encoding) can introduce leakage when applied wrong
- Usually requires domain knowledge about how features interact with each other
- Time-consuming, need to run thousand of experiments
- Why Feature Engineering matters
    - Extract more new gold features, remove irrelevant or noisy features
    - Simpler models with better results

Key Elements of Feature Engineering

Target Transformation

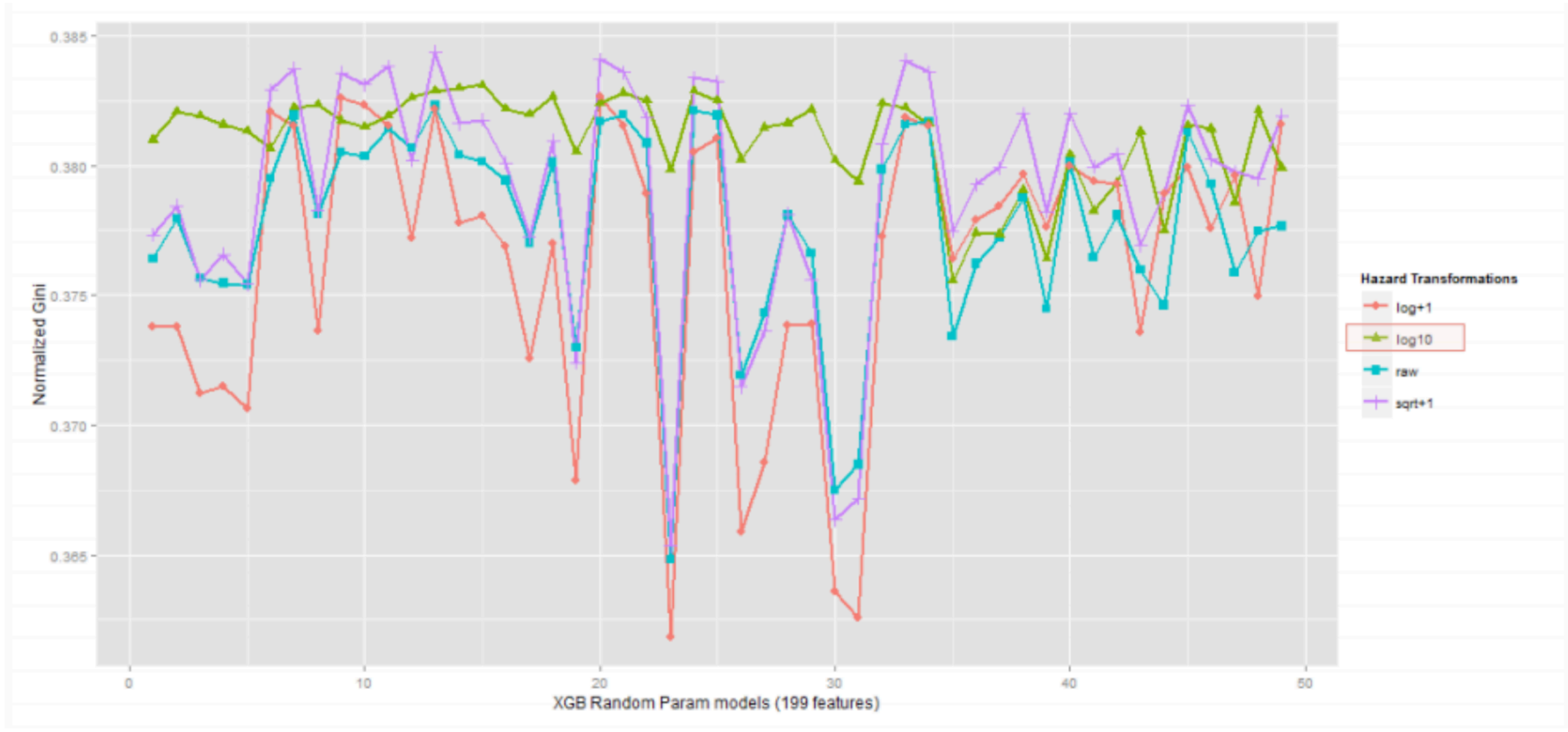
Feature Extraction

Feature Encoding

Target Transformation

- Predictor/Response Variable Transformation
- Use it when variable shows a skewed distribution make the residuals more close to “normal distribution” (bell curve)
- Can improve model fit
  e.g., log(x), log(x+1), sqrt(x), sqrt(x+1), etc.

Target Transformation



Different transformations might lead to different results

Key Elements of Feature Engineering

Target Transformation

Feature Extraction

Feature Encoding

Imputation

- Common problem in preparing the data: **Missing Values**
- Why we have missing values?
  - Human errors
  - Interruptions in the data flow
  - Privacy concerns
- What to do?

Imputation

- Common problem in preparing the data: **Missing Values**
- Why we have missing values?
  - Human errors
  - Interruptions in the data flow
  - Privacy concerns
- What to do?
  - Simple solution: drop the row/column
  - Preferable option: **Imputation**

Imputation

- **Numerical Imputation**
    - Assing zero
    - Assing NA
    - Default value or medians of the columns (Note that averages are sensitive to outlier values)
- **Categorical Imputation**
    - maximum occurred value
    - There is not a dominant value, imputing a category like “Other”

Outliers

Outliers may introduce to the population during data collections

Players	Scores
Player1	500
Player2	350
Player3	10
Player4	300
Player5	450

mistake ?

variance ?

Outlier detection

- **Outlier**: A data object that deviates significantly from the normal objects as if it were generated by a different mechanism
  Ex.: Unusual credit card purchase, sports: Michael Jordon, Wayne Gretzky, …

- **Outliers are different from the noise data**
  Noise is random error or variance in a measured variable
  Noise should be removed before outlier detection

- Outliers are interesting: It violates the mechanism that generates the normal data
  Outlier detection vs. novelty detection: early stage, outlier; but later merged into the model

- Applications:
  Credit card fraud detection
  Telecom fraud detection
  Customer segmentation
  Medical analysis

Types of Outliers

- Three kinds: *global, contextual* and *collective* outliers
- **Global outlier** (or point anomaly)
  - Object is O_g if it significantly deviates from the rest of the data set
  - Ex. Intrusion detection in computer networks
  - Issue: Find an appropriate measurement of deviation
- **Contextual outlier** (or *conditional outlier*)
  - Object is O_c if it deviates significantly based on a selected context
  - Ex. 80^o F in Urbana: outlier? (depending on summer or winter?)
  - Attributes of data objects should be divided into two groups
    - Contextual attributes: defines the context, e.g., time & location
    - Behavioral attributes: characteristics of the object, used in outlier evaluation, e.g., temperature
  - Can be viewed as a generalization of *local outliers*—whose density significantly deviates from its local area
  - Issue: How to define or formulate meaningful context?

Types of Outliers

- **Collective Outliers**
  - A subset of data objects *collectively* deviate significantly from the whole data set, even if the individual data objects may not be outliers
  - Applications: E.g., *intrusion detection*:
    - When a number of computers keep sending denial-of-service packages to each other
  - Detection of collective outliers
    - Consider not only behavior of individual objects, but also that of groups of objects
    - Need to have the background knowledge on the relationship among data objects, such as a distance or similarity measure on objects.
- A data set may have multiple types of outlier
- One object may belong to more than one type of outlier

Finding Outliers

- To ease the discovery of outliers, we have plenty of methods in statistics:
- Discover outliers with visualization tools or **statistical methodologies**
    - Box plot
    - Scatter plot
    - Z-score
    - IQR score

We will cover more advanced techniques for anomaly detection (after the mid-term)

Finding Outliers

Box plot

In descriptive statistics, a **box plot** is a method for graphically depicting groups of numerical data through their quartiles**.** Box plots may also have **lines extending vertically** from the boxes (whiskers) **indicating variability** outside the upper and lower quartiles, hence the terms box-and-whisker plot and box-and-whisker diagram. **Outliers** may be **plotted** as **individual** points**.**

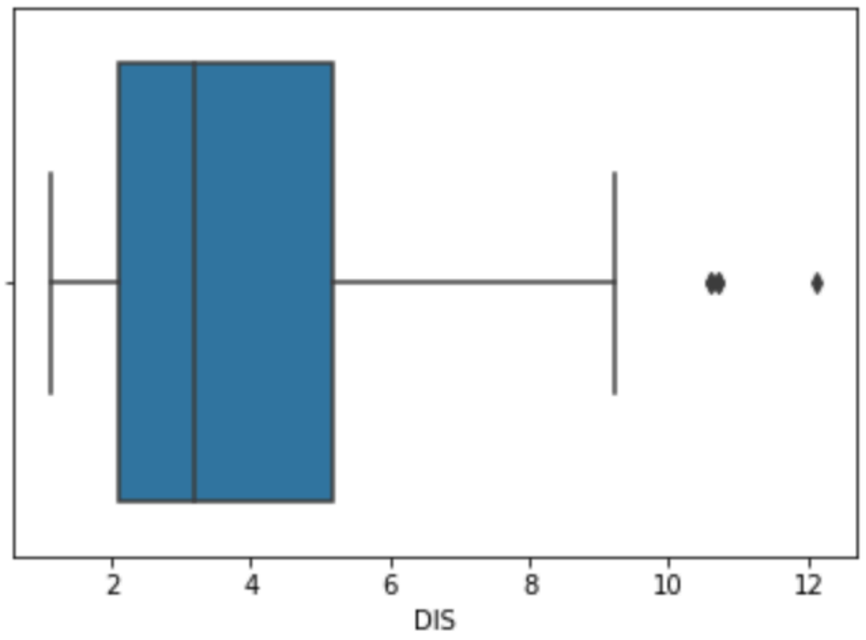
Wikipedia Definition

- This definition suggests, that if there is an outlier it will plotted as point in boxplot but other population will be grouped together and display as boxes.

Finding Outliers

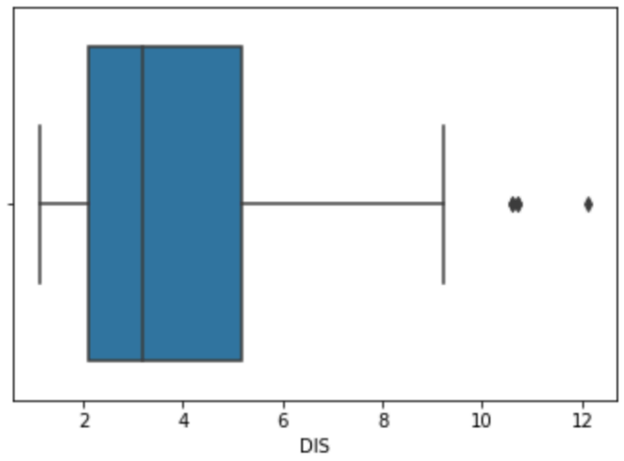
- Box plot

```
import seaborn as sns
sns.boxplot(x=boston_df['DIS'])
```



Boxplot — Distance to Employment Center

Finding Outliers



Boxplot — Distance to Employment Center

- Above plot shows three points between 10 to 12, these are outliers as there are not included in the box of other observation i.e no where near the quartiles.

- Here we analysed Uni-variate outlier i.e. we used DIS column only to check the outlier.

- We can do multivariate outlier analysis too. Can we do the multivariate analysis with Box plot? Well it depends, if you have a categorical values then you can use that with any continuous variable and do multivariate outlier analysis.

Finding Outliers

Scatter plot

A **scatter plot** , is a type of plot or mathematical diagram using Cartesian coordinates to display values for typically two variables for a set of data. The data are displayed as a **collection of points**, each having the value of **one variable** determining the position on the **horizontal** axis and the value of the **other variable** determining the position on the **vertical** axis.

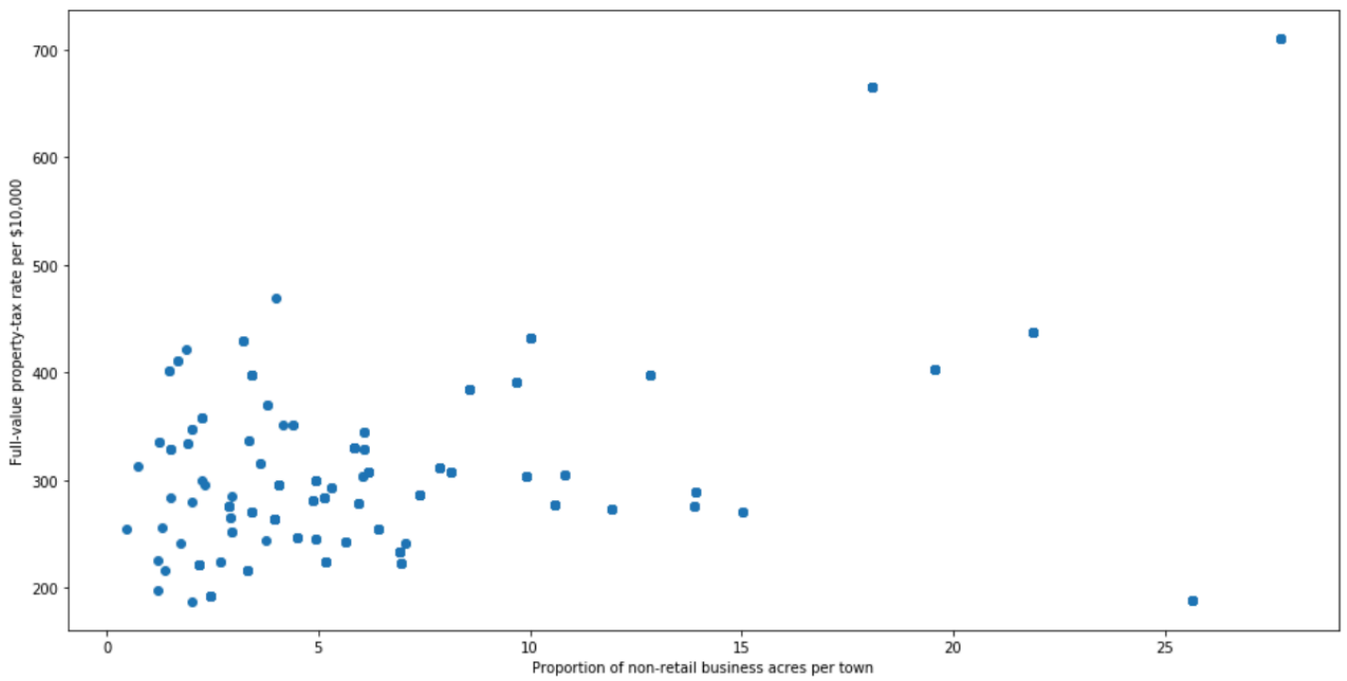
Wikipedia Definition

- This definition suggests, the scatter plot is the collection of points that shows values for two variables.

Finding Outliers

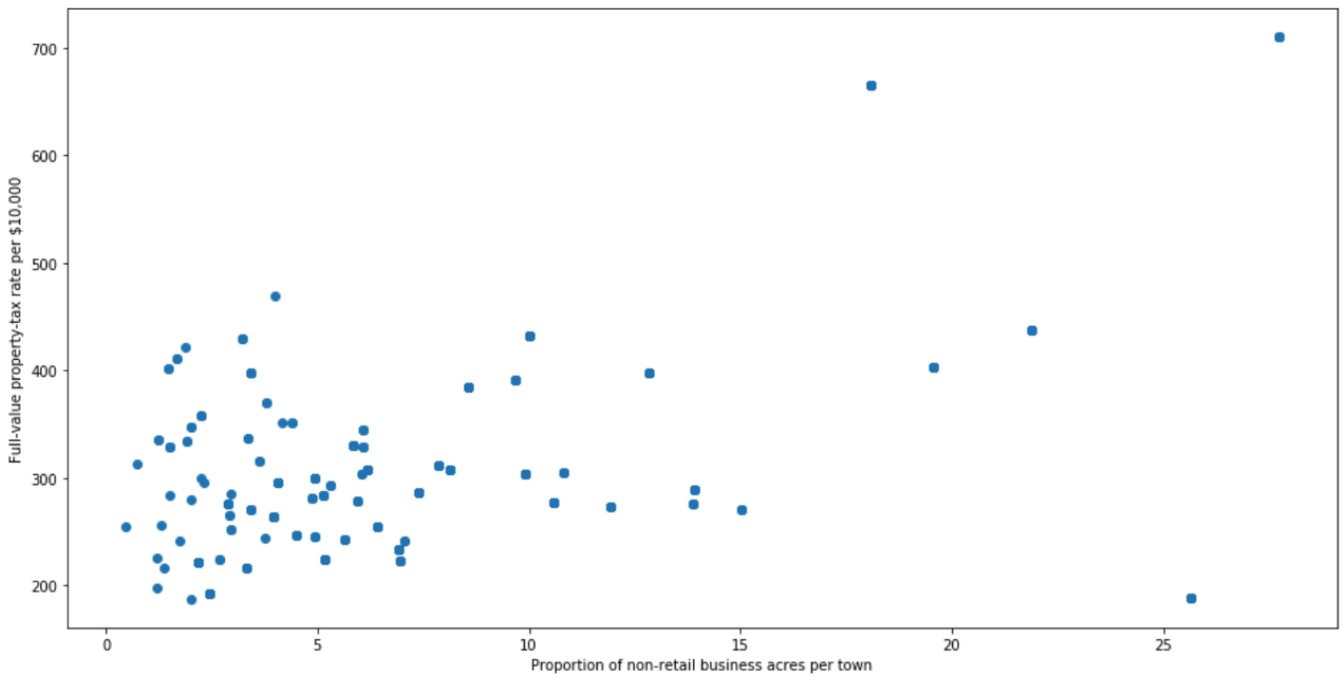
- We can try and draw scatter plot for two variables from our housing dataset.

```
fig, ax = plt.subplots(figsize=(16,8))
ax.scatter(boston_df['INDUS'], boston_df['TAX'])
ax.set_xlabel('Proportion of non-retail business acres per town')
ax.set_ylabel('Full-value property-tax rate per $10,000')
plt.show()
```



Scatter plot — Proportion of non-retail business acres per town v/s Full value property tax

Finding Outliers



Scatter plot — Proportion of non-retail business acres per town v/s Full value property tax

- Looking at the plot above, we can most of data points are lying bottom left side but there are points which are far from the population like top right corner.

Finding Outliers

Standard deviation

In statistics, the **standard deviation** (**SD**, also represented by the lower case Greek letter sigma **σ** for the population standard deviation or the Latin letter s for the sample standard deviation) is a measure of the amount of variation or dispersion of a set of values.

Wikipedia Definition

Finding Outliers

- If a value has a distance to the average higher than ***x * standard deviation*****,**it can be assumed as an outlier**.** Then what **x** should be?

- Usually, a value between 2 and 4 seems practical**.**

```
#Dropping the outlier rows with standard deviation
factor = 3
upper_lim = data['column'].mean () + data['column'].std () * factor
lower_lim = data['column'].mean () - data['column'].std () * factor

data = data[(data['column'] < upper_lim) & (data['column'] >
lower_lim)]
```

Finding Outliers

Z-score

The **Z-score** is the signed number of standard deviations by which the value of an observation or data point is above the mean value of what is being observed or measured.

Wikipedia Definition

- The intuition behind Z-score is to describe any data point by finding their relationship with the Standard Deviation and Mean of the group of data points. Z-score is finding the distribution of data where mean is 0 and standard deviation is 1 i.e. normal distribution.

Finding Outliers

- Z-score: While calculating the Z-score we re-scale and center the data and look for data points which are too far from zero. These data points which are way too far from zero will be treated as the outliers. In most of the cases a threshold of 3 or -3 is used i.e if the Z-score value is greater than or less than 3 or -3 respectively, that data point will be identified as outliers.
- We will use Z-score function defined in scipy library to detect the outliers.

```
from scipy import stats
import numpy as np


z = np.abs(stats.zscore(boston_df))
print(z)
```

```
[[0.41771335 0.28482986 1.2879095  ... 1.45900038 0.44105193 1.0755623 ]
 [0.41526932 0.48772236 0.59338101 ... 0.30309415 0.44105193 0.49243937]
 [0.41527165 0.48772236 0.59338101 ... 0.30309415 0.39642699 1.2087274 ]
 ...
 [0.41137448 0.48772236 0.11573841 ... 1.17646583 0.44105193 0.98304761]
 [0.40568883 0.48772236 0.11573841 ... 1.17646583 0.4032249  0.86530163]
 [0.41292893 0.48772236 0.11573841 ... 1.17646583 0.44105193 0.66905833]]
```

Z-score of Boston Housing Data

Finding Outliers

- Looking the code and the output above, it is difficult to say which data point is an outlier. Let's try and define a threshold to identify an outlier.

```
threshold = 3
print(np.where(z > 3))
```

List of arrow numbers

```
(array([ 55,  56,  57, 102, 141, 142, 152, 154, 155, 160, 162, 163, 199,
        200, 201, 202, 203, 204, 208, 209, 210, 211, 212, 216, 218, 219,
        220, 221, 222, 225, 234, 236, 256, 257, 262, 269, 273, 274, 276,
        277, 282, 283, 283, 284, 347, 351, 352, 353, 353, 354, 355, 356,
        357, 358, 363, 364, 364, 365, 367, 369, 370, 372, 373, 374, 374,
        380, 398, 404, 405, 406, 410, 410, 411, 412, 412, 414, 414, 415,
        416, 418, 418, 419, 423, 424, 425, 426, 427, 427, 429, 431, 436,
        437, 438, 445, 450, 454, 455, 456, 457, 466], dtype=int64), array([ 1,  1,  1, 11, 12,  3,  3,
3,  3,  3,  3,  3,  1,  1,  1,  1,  1,
        1,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  5,  3,  3,  1,  5,
        5,  3,  3,  3,  3,  3,  3,  1,  3,  1,  1,  7,  7,  1,  7,  7,  7,
        3,  3,  3,  3,  3,  5,  5,  5,  3,  3,  3, 12,  5, 12,  0,  0,  0,
        0,  5,  0, 11, 11, 11, 12,  0, 12, 11, 11,  0, 11, 11, 11, 11, 11,
       11,  0, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11],
      dtype=int64))
```

List of Column numbers

Data points where Z-scores is greater than 3

Finding Outliers

IQR score

The **interquartile range** (**IQR**), also called the **midspread** or **middle 50%**, or technically **H-spread**, is a measure of statistical dispersion, being equal to the difference between 75th and 25th percentiles, or between upper and lower quartiles, IQR = Q3 – Q1.

Wikipedia Definition

- It is a measure of the dispersion similar to standard deviation or variance, but is much more robust against outliers.

Finding Outliers

- Let’s find out we can box plot uses IQR and how we can use it to find the list of outliers as we did using Z-score calculation. First we will calculate IQR

```
Q1 = boston_df_o1.quantile(0.25)
Q3 = boston_df_o1.quantile(0.75)
IQR = Q3 - Q1
print(IQR)
```

```
CRIM         3.565378
ZN          12.500000
INDUS       12.910000
CHAS         0.000000
NOX          0.175000
RM           0.738000
AGE         49.050000
DIS          3.088250
RAD         20.000000
TAX        387.000000
PTRATIO      2.800000
B           20.847500
LSTAT       10.005000
dtype: float64
```

IQR for each column

Finding Outliers

- The data point where we have False that means these values are valid whereas True indicates presence of an outlier.

```
print(boston_df_o1 < (Q1 - 1.5 * IQR)) |(boston_df_o1 > (Q3 + 1.5 *
IQR))
```

4	False	False	False	False	False	False	False	False	False	False	False	False	False
5	False	False	False	False	False	False	False	False	False	False	False	False	False
6	False	False	False	False	False	False	False	False	False	False	False	False	False
7	False	False	False	False	False	False	False	False	False	False	False	False	False
8	False	False	False	False	False	False	False	False	False	False	False	False	False
9	False	False	False	False	False	False	False	False	False	False	False	False	False
10	False	False	False	False	False	False	False	False	False	False	False	False	False
11	False	False	False	False	False	False	False	False	False	False	False	False	False
12	False	False	False	False	False	False	False	False	False	False	False	False	False
13	False	False	False	False	False	False	False	False	False	False	False	False	False
14	False	False	False	False	False	False	False	False	False	False	False	False	False
15	False	False	False	False	False	False	False	False	False	False	False	False	False
16	False	False	False	False	False	False	False	False	False	False	False	False	False
17	False	False	False	False	False	False	False	False	False	False	False	False	False
18	False	False	False	False	False	False	False	False	False	False	False	True	False
19	False	False	False	False	False	False	False	False	False	False	False	False	False
20	False	False	False	False	False	False	False	False	False	False	False	False	False
21	False	False	False	False	False	False	False	False	False	False	False	False	False

Detecting outlier with IQR

Finding Outliers

Percentiles

- Another mathematical method to detect outliers is to use percentiles.

- You can assume a certain percent of the value from the top or the bottom as an outlier.

- A common mistake is using the percentiles according to the range of the data, e.g., if your data ranges from **0** to **100**, your top **5%** is not the values between **96** and **100**. Top **5%** means the values that are out of the **95th** percentile of data.

Handling Outliers

An Outlier Dilemma: Drop or Cap

- Correcting

```
#Capping the outlier rows with Percentiles
upper_lim = data['column'].quantile(.95)
lower_lim = data['column'].quantile(.05)

data.loc[(df[column] > upper_lim),column] = upper_lim
data.loc[(df[column] < lower_lim),column] = lower_lim
```

- Removing
  - Z-score:

```
boston_df_o = boston_df_o[(z < 3).all(axis=1)]
```

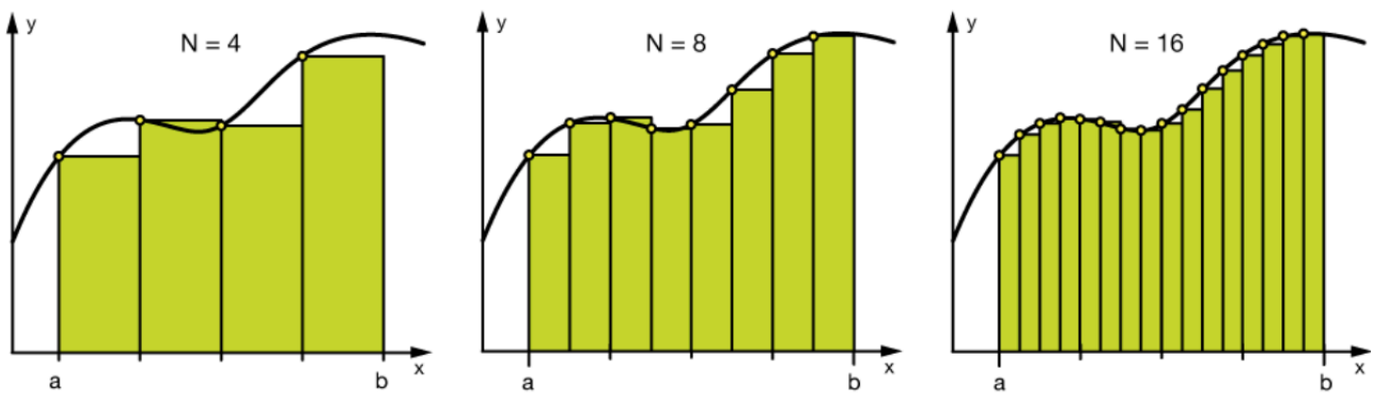
  - IQR score:

```
boston_df_out = boston_df_o1[~((boston_df_o1 < (Q1 - 1.5 * IQR)) |
(boston_df_o1 > (Q3 + 1.5 * IQR))).any(axis=1)]


boston_df_out.shape
```

Binning

- Binning can be applied on both categorical and numerical data:



Binning illustration of numerical data

- Example

```
#Numerical Binning Example

Value      Bin
0-30   ->  Low
31-70  ->  Mid
71-100 ->  High

#Categorical Binning Example

Value      Bin
Spain  ->  Europe
Italy  ->  Europe
Chile  ->  South America
Brazil ->  South America
```

Binning

- The main motivation of binning is to make the model more **robust** and prevent **overfitting**, however, it has a cost to the performance**.**

- The trade-off between **performance** and **overfitting** is the key point of the binning process**.**

- Numerical binning: binning might be redundant due to its effect on model performance.

- Categorical binning: the labels with low frequencies probably affect the robustness of statistical models negatively. Thus, assigning a general category to these less frequent values helps to keep the robustness of the model.

Log Transformation

- Logarithm transformation (or log transform):
    - It helps to handle skewed data and after transformation, the distribution becomes more approximate to normal.
    - In most of the cases the magnitude order of the data changes within the range of the data.
    - It also decreases the effect of the outliers, due to the normalization of magnitude differences and the model become more robust.

Log Transformation

- The data you apply log transform must have only positive values, otherwise you receive an error. Also, you can add **1** to your data before transform it. Thus, you ensure the output of the transformation to be positive.

```
#Log Transform Example
data = pd.DataFrame({'value':[2,45, -23, 85, 28, 2, 35, -12]})

data['log+1'] = (data['value']+1).transform(np.log)


#Negative Values Handling
#Note that the values are different
data['log'] = (data['value']-data['value'].min()+1)
.transform(np.log)
```

	value	log(x+1)	log(x-min(x)+1)
0	2	1.09861	3.25810
1	45	3.82864	4.23411
2	-23	nan	0.00000
3	85	4.45435	4.69135
4	28	3.36730	3.95124
5	2	1.09861	3.25810
6	35	3.58352	4.07754
7	-12	nan	2.48491

Grouping

- Tidy data where each row represents an instance and each column represent a feature.

> *Tidy datasets are easy to manipulate, model and visualise, and have a specific structure: each variable is a column, each observation is a row, and each type of observational unit is a table.*
>
> *— Hadley Wickham*

- Datasets such as transactions rarely fit the definition of tidy data -> we use grouping.

- The key point of group by operations is to decide the aggregation functions of the features.

Grouping

- Aggregating **categorical columns**:
    - Highest frequency: the **max** operation for categorical columns

```
data.groupby('id').agg(lambda x: x.value_counts().index[0])
```

    - Make a Pivot table: This would be a good option if you aim to go beyond binary flag columns and merge multiple features into aggregated features, which are more informative.

User	City	Visit Days
1	Roma	1
2	Madrid	2
1	Madrid	1
3	Istanbul	1
2	Istanbul	4
1	Istanbul	3
1	Roma	3

→

User	Istanbul	Madrid	Roma
1	3	1	4
2	4	2	0
3	1	0	0

Pivot table example: Sum of Visit Days grouped by Users

- Apply one-hot encoding

Grouping

- Numerical columns are mostly grouped using:
    - Sum
    - Mean

```
#sum_cols: List of columns to sum
#mean_cols: List of columns to average


grouped = data.groupby('column_to_group')

sums = grouped[sum_cols].sum().add_suffix('_sum')
avgs = grouped[mean_cols].mean().add_suffix('_avg')

new_df = pd.concat([sums, avgs], axis=1)
```

Splitting

- Most of the time the dataset contains string columns that violates tidy data principles.

- **Split** function is a good option, however, there is no one way of splitting features

```
data.name
0  Luther N. Gonzalez
1    Charles M. Young
2        Terry Lawson
3       Kristen White
4      Thomas Logsdon


#Extracting first names
data.name.str.split(" ").map(lambda x: x[0])
0     Luther
1    Charles
2      Terry
3    Kristen
4     Thomas


#Extracting last names
data.name.str.split(" ").map(lambda x: x[-1])
0    Gonzalez
1       Young
2      Lawson
3       White
4     Logsdon
```

Scaling

- In most cases, the numerical features of the dataset do not have a certain **range** and they differ from each other.

- In real life, it is nonsense to expect **age** and **income** columns to have the same range. But from the machine learning point of view, how these two columns can be compared?

- It is important for algorithms that work based on distance: such as **k-NN** or **k-Means**

- Basically, there are two common ways of scaling: **Normalization**, and **Standardization**

Normalization

- Normalization (or **min-max normalization**) scale all values in a fixed range between **0** and **1.**

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

- This transformation does **not change the distribution of the feature.**

- But due to the decreased standard deviations, the effects of the **outliers** increases. So before normalization, it is recommended to handle the outliers.

Normalization

- Example:

```
data = pd.DataFrame({'value':[2,45, -23, 85, 28, 2, 35, -12]})

data['normalized'] = (data['value'] - data['value'].min()) /
(data['value'].max() - data['value'].min())
```

	value	normalized
0	2	0.23
1	45	0.63
2	-23	0.00
3	85	1.00
4	28	0.47
5	2	0.23
6	35	0.54
7	-12	0.10

Standardization

- Standardization (or **z-score normalization**) scales the values while taking into account standard deviation.

- In the following formula of standardization, the **mean** is shown as μ and the **standard deviation** is shown as σ.

$$z = \frac{x - \mu}{\sigma}$$

- If the **standard deviation** of features is different, their range also would differ from each other. This **reduces** the effect of the **outliers** in the features.

Standardization

- Example:

```
data = pd.DataFrame({'value':[2,45, -23, 85, 28, 2, 35, -12]})

data['standardized'] = (data['value'] - data['value'].mean()) /
data['value'].std()
```

	value	standardized
0	2	-0.52
1	45	0.70
2	-23	-1.23
3	85	1.84
4	28	0.22
5	2	-0.52
6	35	0.42
7	-12	-0.92

Key Elements of Feature Engineering

Target Transformation

Feature Extraction

Feature Encoding

Feature Encoding

- Turn categorical features into numeric features to provide more fine-grained information

- Help explicitly capture non-linear relationships and interactions between the values of features

- Most of machine learning tools only accept numbers as their input
  e.g., xgboost, gbm, glmnet, libsvm, liblinear, etc.

Feature Encoding

- **Labeled Encoding**
  Interpret the categories as ordered integers (mostly wrong)
  Python scikit-learn: LabelEncoder • Ok for tree-based methods

A	0
B	1
C	2

Feature 1	Encoded Feature 1
A	0
A	0
A	0
A	0
B	1
B	1
B	1
C	2
C	2

- **One Hot Encoding**
  Transform categories into individual binary (0 or 1) features
  Python scikit-learn: DictVectorizer, OneHotEncoder • Ok for K-means, Linear, NNs, etc.

One Hot Encoding

- **One-hot-encoding**: is one of the most common encoding methods in machine learning.

- This method spreads the values in a column to multiple flag columns and assigns **0** or **1** to them. These binary values express the relationship between grouped and encoded column.

User	City
1	Roma
2	Madrid
1	Madrid
3	Istanbul
2	Istanbul
1	Istanbul
1	Roma

User	Istanbul	Madrid
1	0	0
2	0	1
1	0	1
3	1	0
2	1	0
1	1	0
1	0	0

One hot encoding example on City column

```
encoded_columns = pd.get_dummies(data['column'])
data = data.join(encoded_columns).drop('column', axis=1)
```

Frequency encoding

- Encoding of categorical levels of feature to values between 0 and 1 based on their relative frequency

A	0.44 (4 out of 9)
B	0.33 (3 out of 9)
C	0.22 (2 out of 9)

Feature	Encoded Feature
A	0.44
A	0.44
A	0.44
B	0.33
B	0.33
B	0.33
C	0.22
C	0.22

Target mean encoding

- Instead of dummy encoding of categorical variables and increasing the number of features we can encode each level as the mean of the response.

A	0.75 (3 out of 4)
B	0.66 (2 out of 3)
C	1.00 (2 out of 2)

Feature	Outcome	MeanEncode
A	1	0.75
A	0	0.75
A	1	0.75
A	1	0.75
B	1	0.66
B	1	0.66
B	0	0.66
C	1	1.00
C	1	1.00

Target mean encoding

- It is better to calculate weighted average of the overall mean of the training set and the mean of the level:

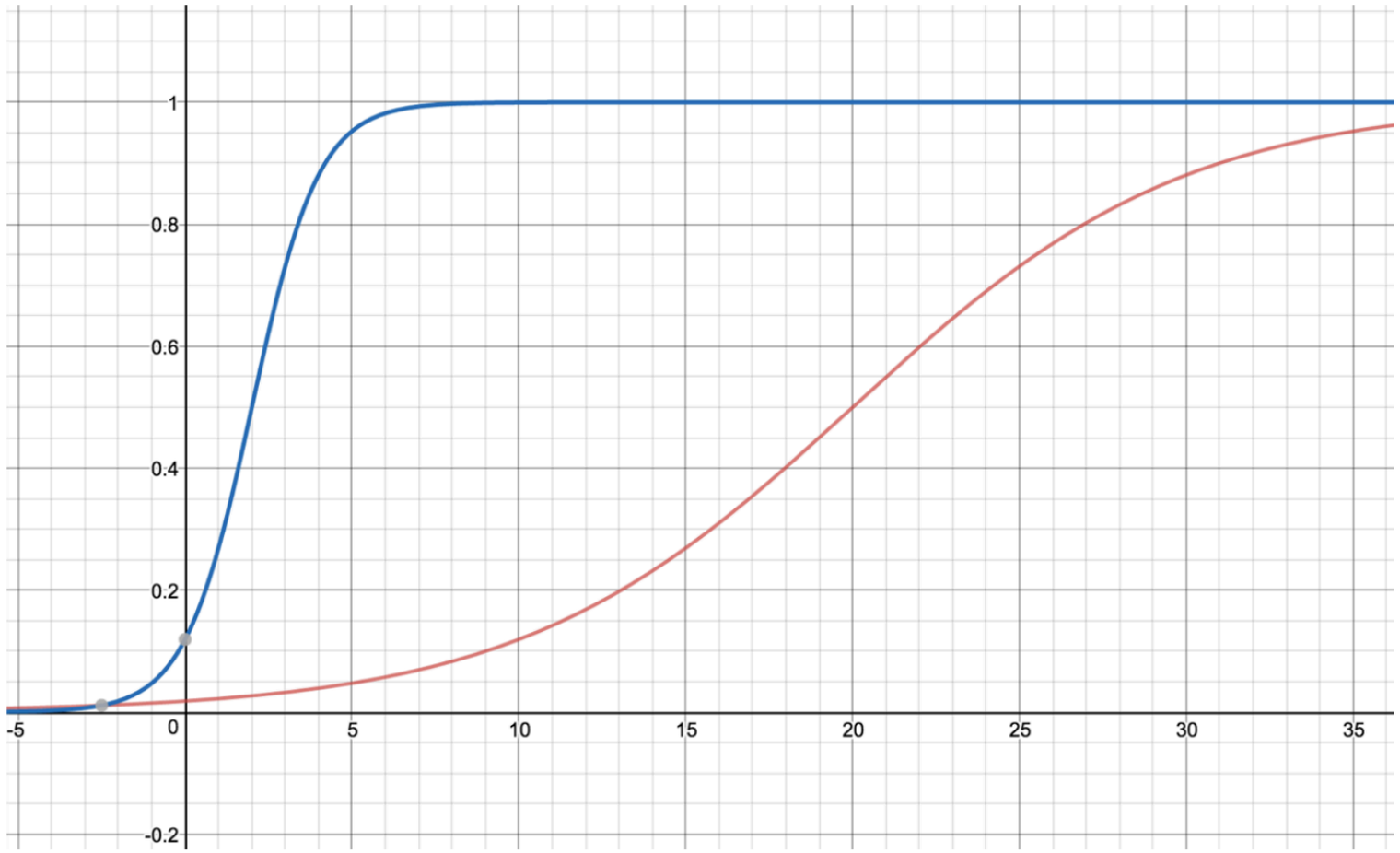
$$\lambda(n) * mean(level) + \big(1 - \lambda(n)\big) * mean(dataset)$$

- The weights are based on the frequency of the levels i.e. if a category only appears a few times in the dataset then its encoded value will be close to the overall mean instead of the mean of that level.

Target mean encoding
Smoothing

$$\frac{1}{1 + exp(\frac{-(x-k)}{f})}$$

x = frequency
k = inflection point
f = steepness



Target mean encoding
Smoothing

$$\lambda = \frac{1}{1 + \exp(-\frac{(x-2)}{0.25})}$$

	x	level	dataset	λ	
A	4	0.75	0.77	0.99	0.99*0.75 + 0.01*0.77 = 0.7502
B	3	0.66	0.77	0.98	0.98*0.66 + 0.02*0.77 = 0.6622
C	2	1.00	0.77	0.5	0.5*1.0 + 0.5*0.77 = 0.885

Feature	Outcome
A	1
A	0
A	1
A	1
B	1
B	1
B	0
C	1
C	1

$$\lambda = \frac{1}{1 + \exp(-\frac{(x-3)}{0.25})}$$

	x	level	dataset	λ	
A	4	0.75	0.77	0.98	0.98*0.75 + 0.01*0.77 = 0.7427
B	3	0.66	0.77	0.5	0.5*0.66 + 0.5*0.77 = 0.715
C	2	1.00	0.77	0.017	0.017*1.0 + 0.983*0.77 = 0.773

Target mean encoding leave-one-out schema

- To avoid overfitting we could use leave-one-out schema

Feature	Outcome
A	1
A	**0**
A	**1**
A	**1**
B	1
B	1
B	0
C	1
C	1

LOOencode
0.66

Target mean encoding leave-one-out schema

- To avoid overfitting we could use leave-one-out schema

Feature	Outcome
A	**1**
A	0
A	**1**
A	**1**
B	1
B	1
B	0
C	1
C	1

LOOencode
0.66
1.00

Target mean encoding leave-one-out schema

- To avoid overfitting we could use leave-one-out schema

Feature	Outcome
A	**1**
A	**0**
A	1
A	**1**
B	1
B	1
B	0
C	1
C	1

LOOencode
0.66
1.00
0.66

Target mean encoding leave-one-out schema

- To avoid overfitting we could use leave-one-out schema

Feature	Outcome
A	**1**
A	**0**
A	**1**
A	1
B	1
B	1
B	0
C	1
C	1

LOOencode
0.66
1.00
0.66
0.66

Target mean encoding leave-one-out schema

- To avoid overfitting we could use leave-one-out schema

Feature	Outcome
A	1
A	0
A	1
A	1
B	1
B	1
B	0
C	**1**
C	1

LOOencode
0.66
1.00
0.66
0.66
0.50
0.50
1.00
1.00
1.00

Weight of Evidence and Information Value

- Weight of evidence:

$$WoE = \ln(\frac{\%\ non - events}{\%\ events})$$

- To avoid division by zero:

$$WoE_{adj} = \ln(\frac{\text{Number of non-events in a group} + 0.5 \,/\, \text{Number of non-events}}{\text{Number of events in a group} + 0.5 \,/\, \text{Number of events}})$$

- Information Value:

$$IV = \sum(\%\ non - events\ - \%\ events) * WoE$$

Weight of Evidence and Information Value

	Non-events	Events	% of non-events	% of events	WoE	IV
A	1	3	50	42	$\ln\left(\frac{(1+0.5)/2}{(3+0.5)/7}\right) = 0.4$	$(0.5 - 0.42) * 0.4 = 0.032$
B	1	2	50	29	$\ln\left(\frac{(1+0.5)/2}{(2+0.5)/7}\right) = 0.74$	$(0.5 - 0.29) * 0.4 = 0.084$
C	0	2	0	29	$\ln\left(\frac{(0+0.5)/2}{(2+0.5)/7}\right) = -0.35$	$(0 - 0.29) * -0.35 = 0.105$

0.221

Feature	Outcome	WoE
A	1	0.4
A	0	0.4
A	1	0.4
A	1	0.4
B	1	0.74
B	1	0.74
B	0	0.74
C	1	-0.35
C	1	-0.35

Weight of Evidence and Information Value

Information Value	Variable Predictiveness
Less than 0.02	Not useful for prediction
0.02 to 0.1	Weak predictive Power
0.1 to 0.3	Medium predictive Power
0.3 to 0.5	Strong predictive Power
>0.5	Suspicious Predictive Power

More of Feature Engineerings …

- Feature Extraction: Numerical data
  - Dimensionality reduction techniques – SVD and PCA **(Week 3)**
  - Clustering and using cluster IDs or/and distances to cluster centers as new features **(Week 3)**
  - Feature selection **(Week 6)**

- Feature Extraction: Textual data **(Week 10)**
  - e.g., Bag-of-Words: extract tokens from text and use their occurrences (or TF/IDF weights) as features

- Feature Extraction: Time series and GEO location **(Week 7)**

- Feature Extraction: Image data **(Week 11)**

- Feature Extraction: Relational data **(Week 12)**

- Anomaly detection (advanced): **(Week 13)**