Data Science: Concepts and Practice

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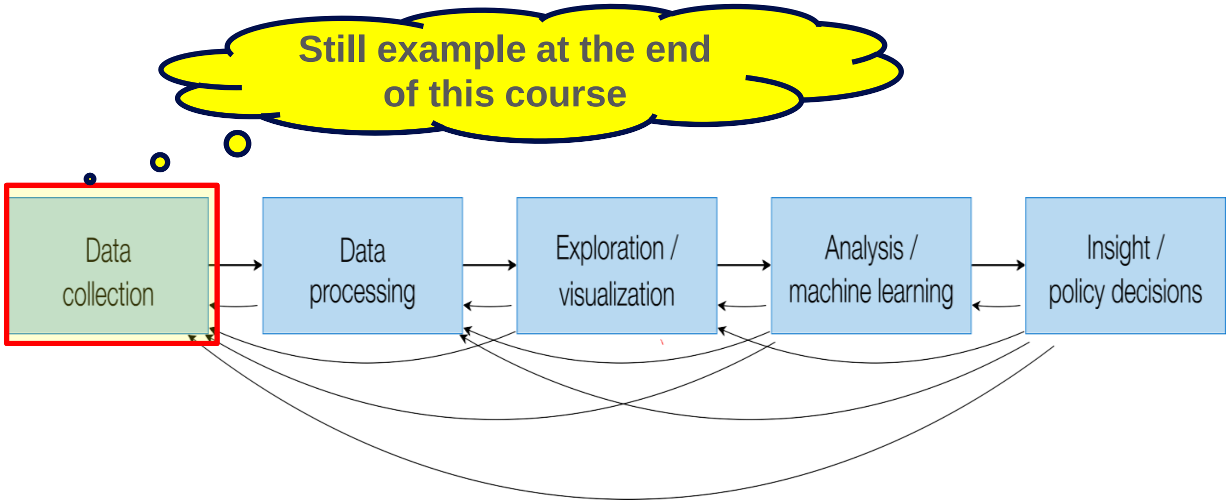
Lecture 5: Feature engineering

Data Science



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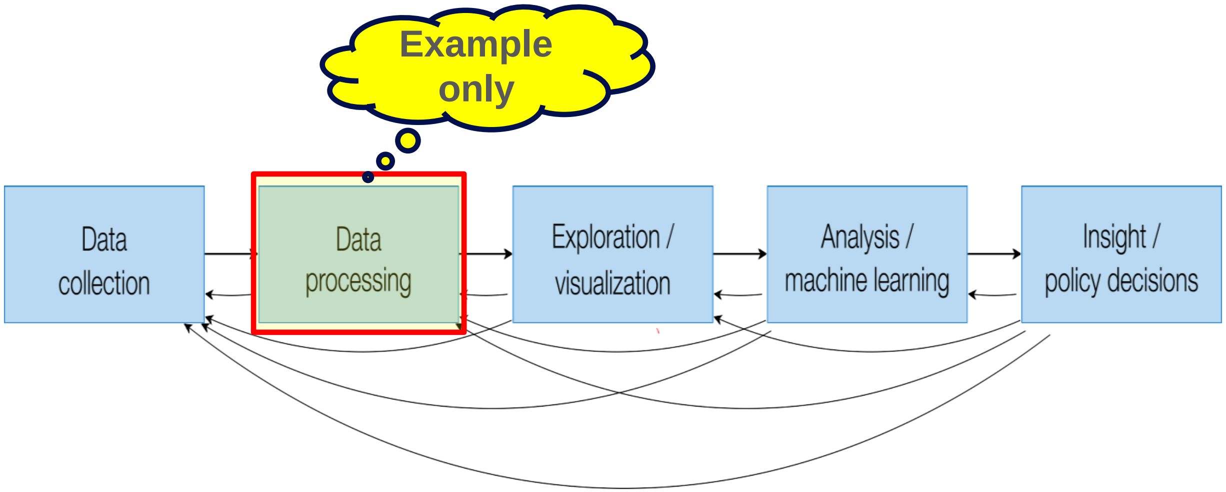
Data Science



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Data preprocessing and reading example

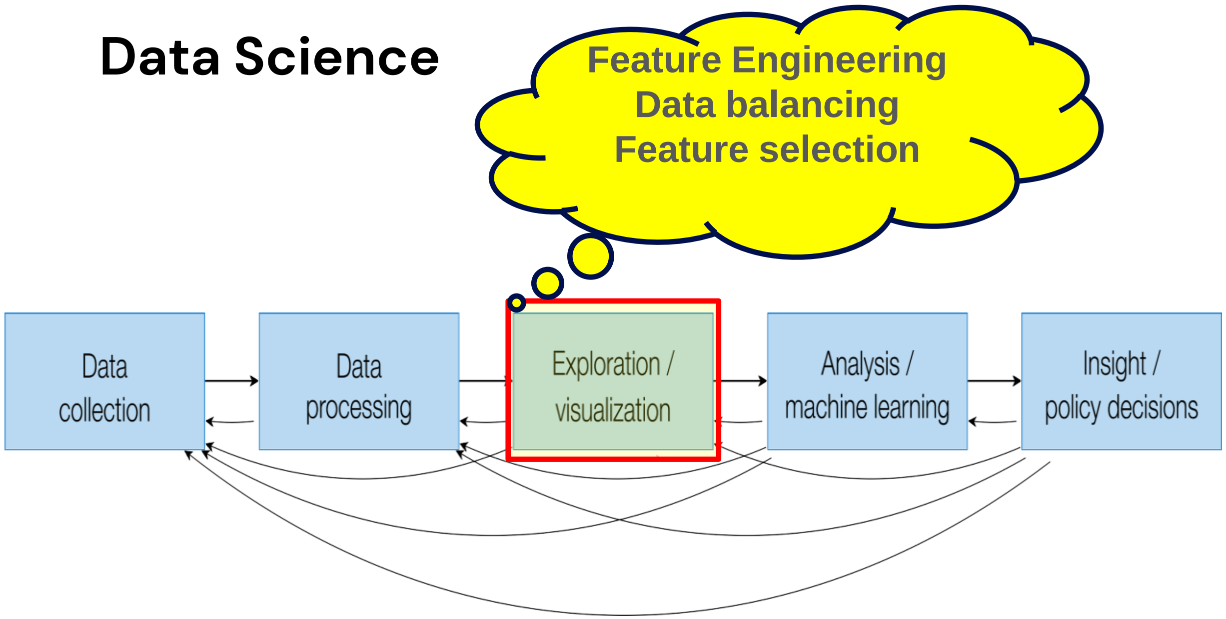
```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
# Step 1: Read CSV file
file_path = 'your_data.csv'  # Replace with your CSV file path
data = pd.read_csv(file_path)
# Display the first few rows of the dataset
print(data.head())
# Step 2: Check for missing values
print("\nMissing values in each column:")
print(data.isnull().sum())
# Step 3: Handle missing values (if any)
# You can choose to fill missing values with mean/median or drop rows/columns with missing values
data = data.fillna(data.mean())  # Filling missing values with mean
# Step 4: Remove noisy points (outliers)
# One method to detect outliers is to use the Z-score. Let's assume a Z-score threshold of 3.
from scipy.stats import zscore
z_scores = np.abs(zscore(data.select_dtypes(include=[np.number])))  # Applying Z-score on numeric columns
data_no_outliers = data[(z_scores < 3).all(axis=1)]  # Remove rows with Z-score greater than 3
```


•Commonly, data points with a Z-score greater than **3 +**or less than **3 -**are considered outliers.

Continue …

```
# Step 5: Visualize the normal distribution of the data
# Choose a numeric column to visualize its distribution
numeric_columns = data_no_outliers.select_dtypes(include=[np.number]).columns
# Visualizing the normal distribution for each numeric column
for col in numeric_columns:
    plt.figure(figsize=(8, 6))
    sns.histplot(data_no_outliers[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')
    plt.show()
# Step 6: Scaling the data (optional, if necessary for your model)
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data_no_outliers[numeric_columns])
# Optionally, you can convert the scaled data back to a DataFrame
scaled_df = pd.DataFrame(data_scaled, columns=numeric_columns)
# Show the final processed data
print("\nProcessed Data (First 5 rows):")
print(scaled_df.head())
```

Data Science



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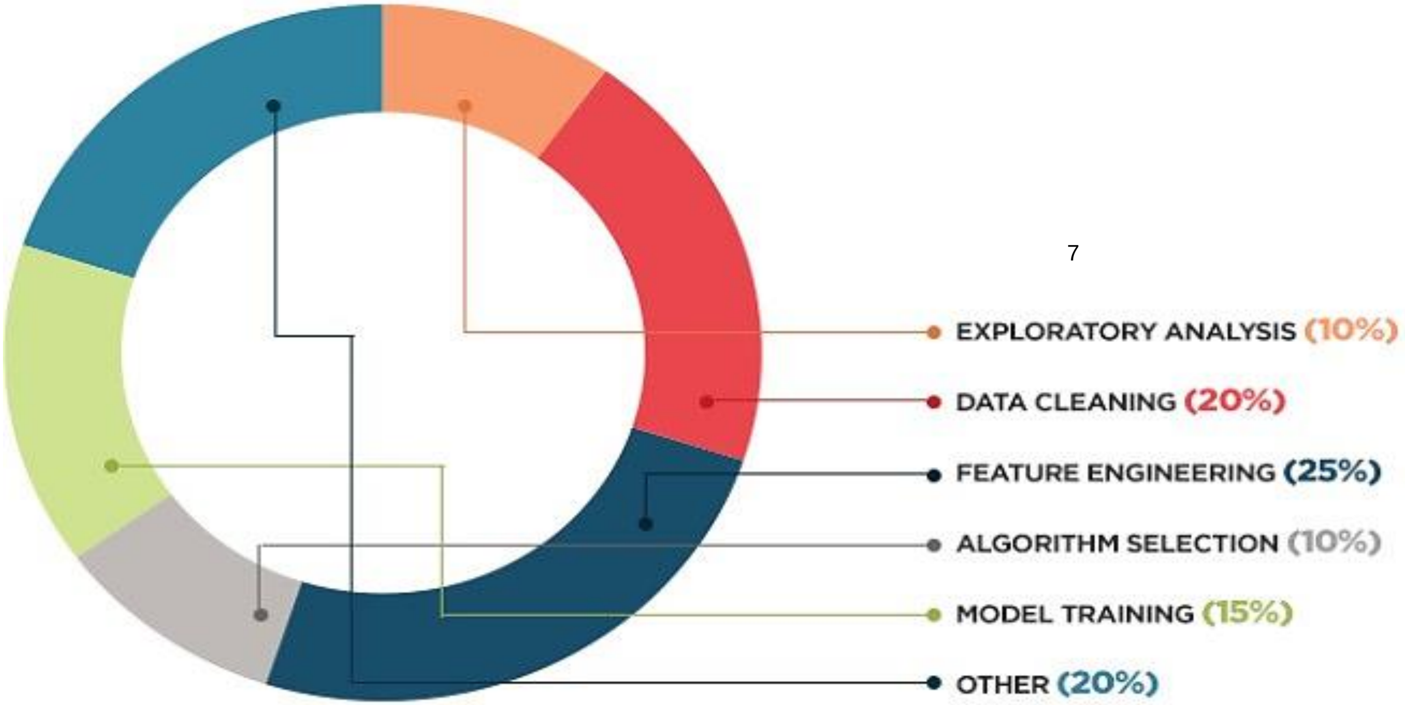
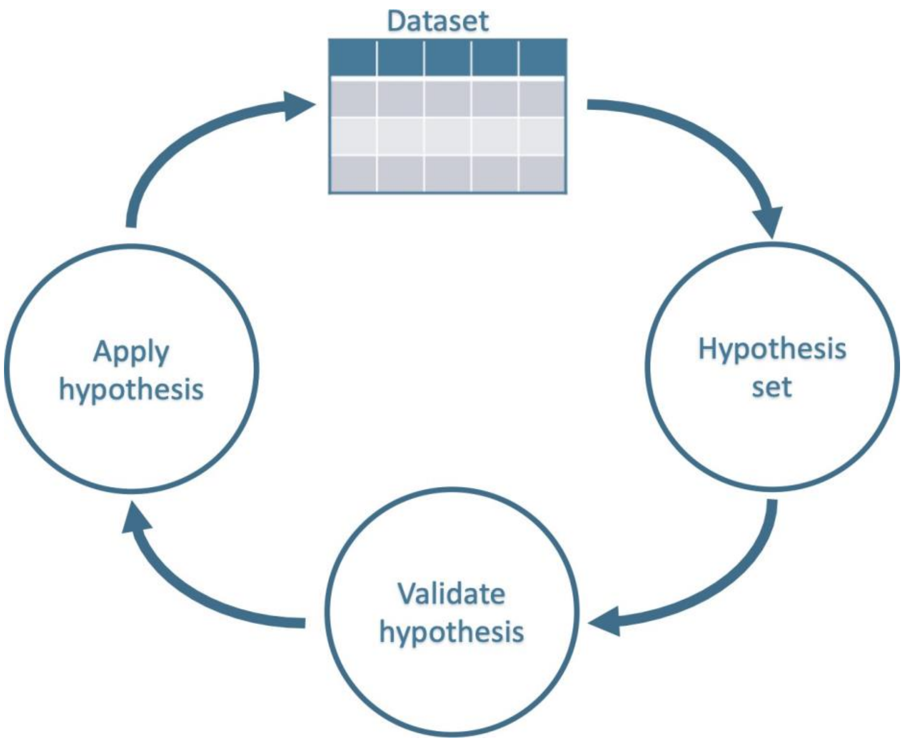
Feature Engineering

Data scientists usually spend the most time on feature engineering!



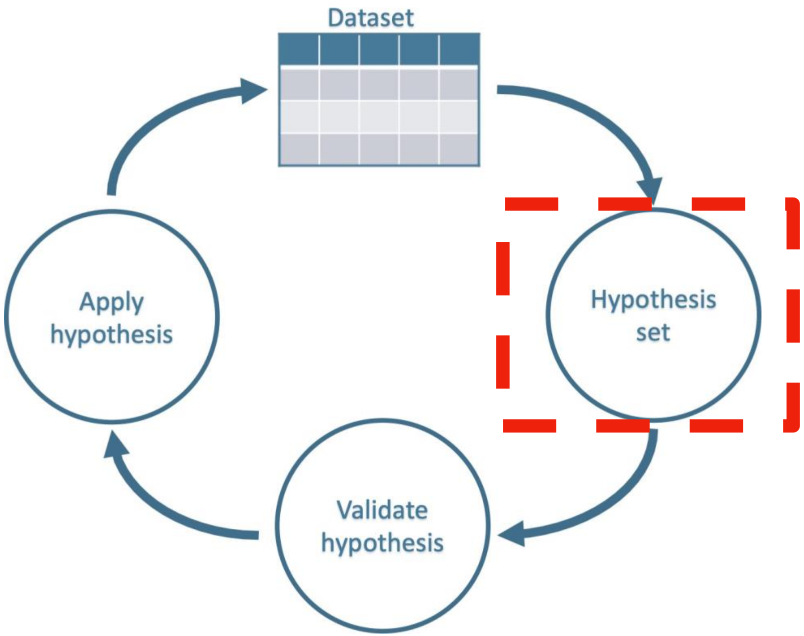
Feature engineering cycle



Not Feature Engineering

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

Feature engineering cycle



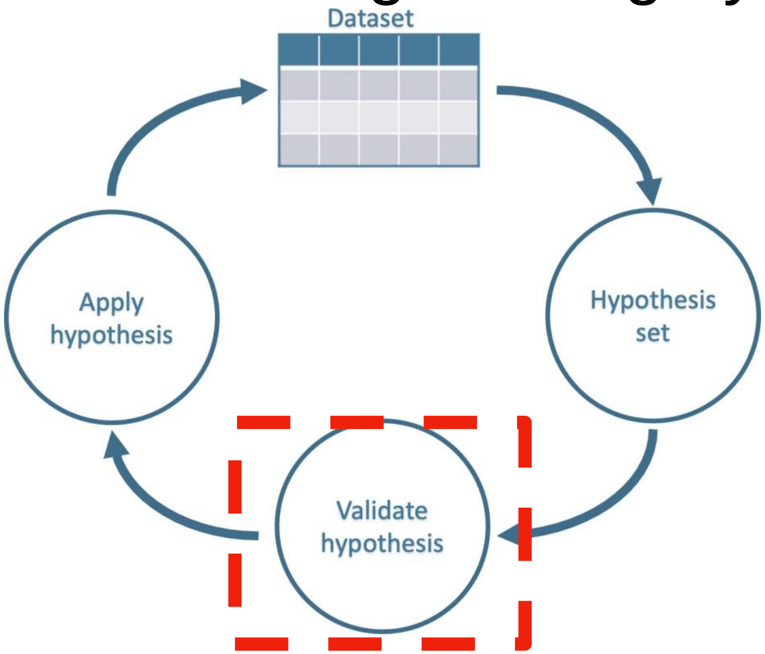
How?

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

Exploratory Data Analysis (EDA) in the context of **Feature Engineering** refers to the initial process of analyzing and visualizing the dataset to better understand its structure, relationships, and patterns

Machine learning or deep learning work for feature engineering if needs

Feature engineering cycle



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

Cross-validation is a technique used to assess the performance of a machine learning model by partitioning the dataset into multiple subsets and validating the model across these subsets

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

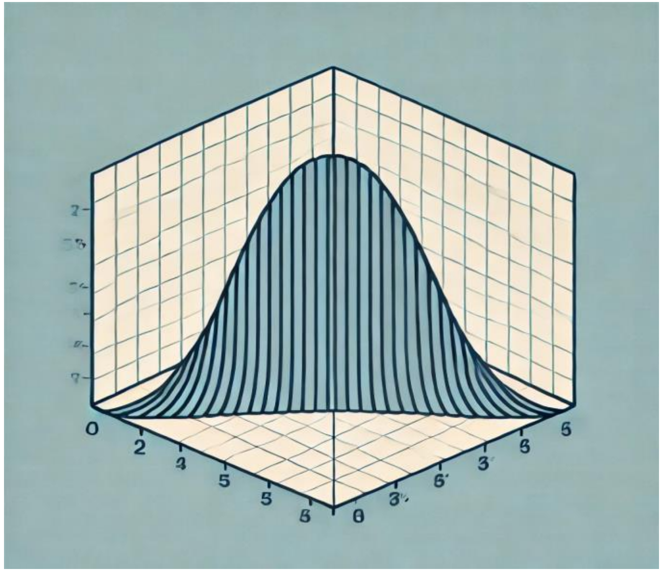
Target Transformation

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.



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?

Outliers

Outliers may introduce to the population during data collections

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

mistake ?

variance ?

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
```

Finding Outliers

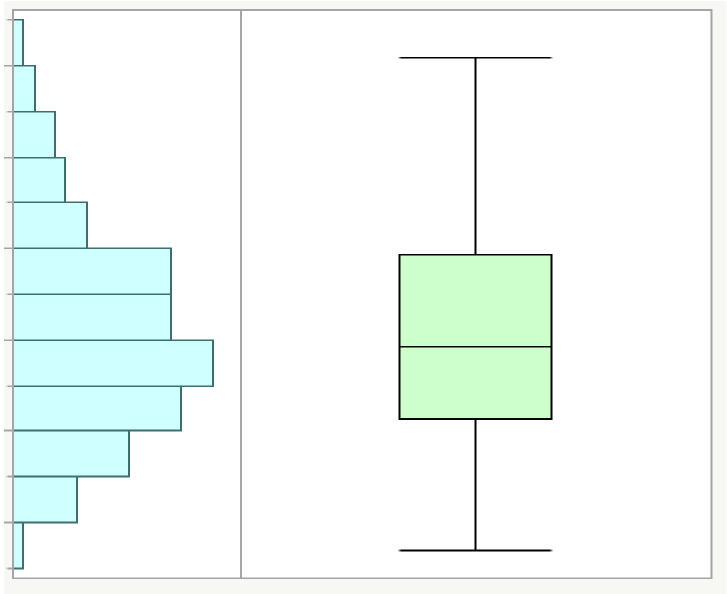
- To ease the discovery of outliers, we have plenty of methods in statistics:
- Discover outliers with visualization tools or **statistical methodologies**
    - Box plot
    - Scatter plot
    - Z-score
    - IQR score

```
# Step 4: Remove noisy points (outliers)
# One method to detect outliers is to use the Z-score. Let's assume a Z-score threshold of 3.
from scipy.stats import zscore
z_scores = np.abs(zscore(data.select_dtypes(include=[np.number])))  # Applying Z-score on numeric columns
data_no_outliers = data[(z_scores < 3).all(axis=1)]  # Remove rows with Z-score greater than 3
```

Finding Outliers

Box plot

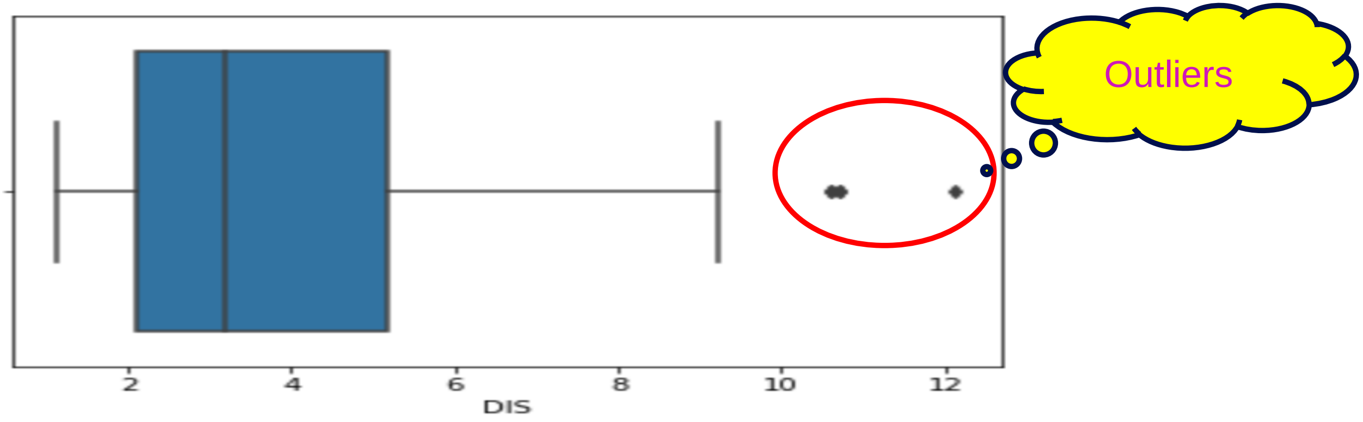
In descriptive statistics, a **box plot** is a method for graphically depicting groups of numerical data through their quartiles.



Finding Outliers

- Box plot

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



Boxplot — Distance to Employment Center

Finding Outliers

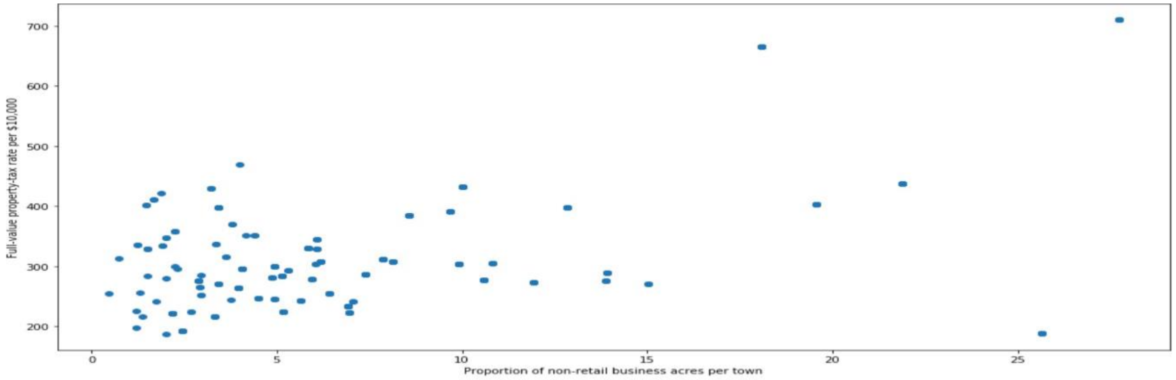
Scatter plot

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**

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()
```

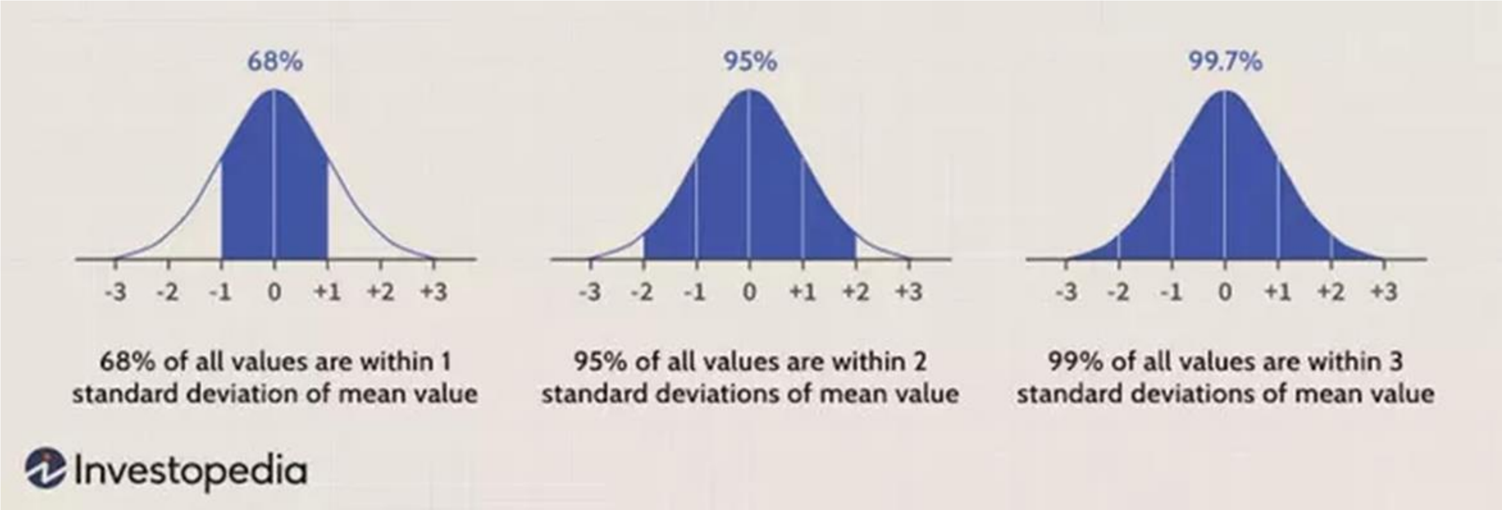


Scatter plot — Proportion of non-retail business acres per town v/s Full value property tax

Finding Outliers

Standard deviation

In statistics, the **standard deviation)SD σ** amgis rettel keerG esac rewol eht yb detneserper osla ,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.



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.

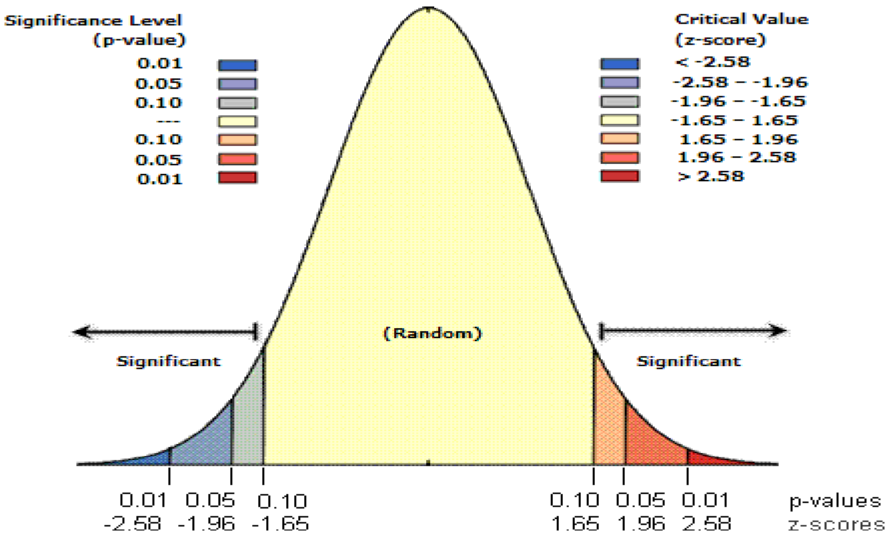
```
#Dropping the outlier rows with standard deviation
factor = 3
upper_lim = data['column'].mean () + data['column'].std () * factor
lower_lim = data['column'].mean () - data['column'].std () * factor

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.



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))
```

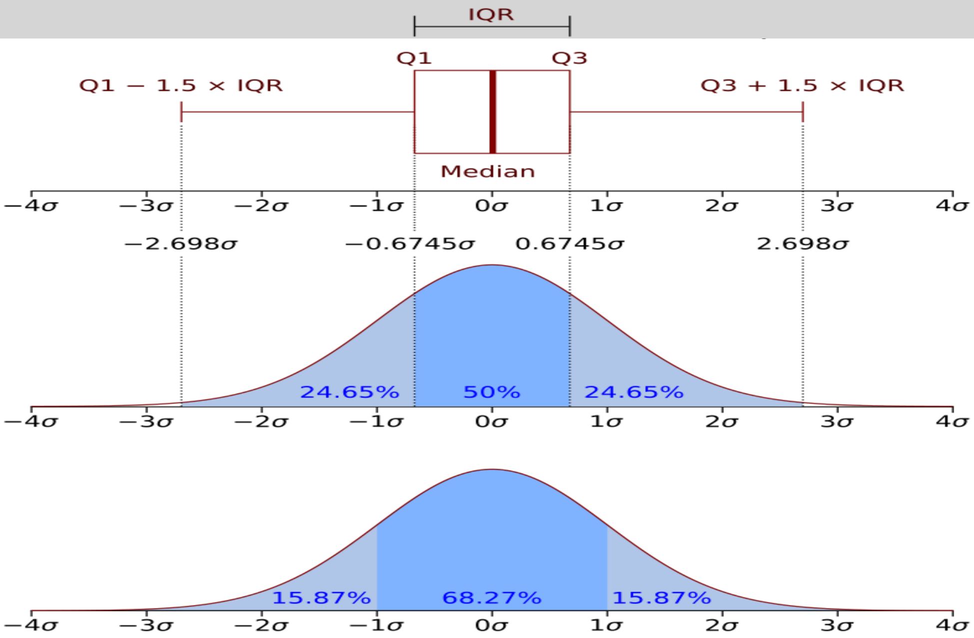
List of
Column numbers

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.**



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.

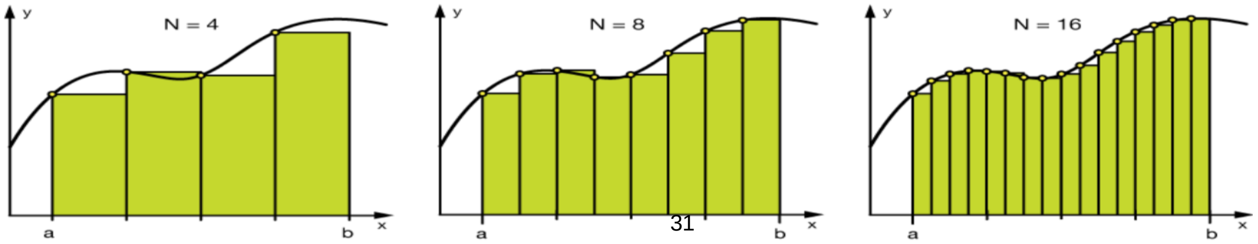
```
print(boston_df_o1 < (Q1 - 1.5 * IQR)) |(boston_df_o1 > (Q3 + 1.5 *
IQR))
```

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

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.

Log Transformation

- **Logarithm**:(mrofsnart gol ro) noitamrofsnart
  - 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

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.

  - Apply one-hot encoding

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

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

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 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**dna , **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

- Most of machine learning or deep 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

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**: 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
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

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

	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

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

	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

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

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

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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

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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
55 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
56 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	$\ln\left(\frac{(0+0.5)/_2}{(2+0.5)/_7}\right) = -0.35$	$(0 - 0.29) * -0.35 = 0.105$

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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

0.221

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
  - Clustering and using cluster IDs or/and distances to cluster centers as new features
  - Feature selection
- Feature Extraction: Textual data
  - 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
- Feature Extraction: Image data
- Feature Extraction: Relational data
- Anomaly detection (advanced):