Data Preprocessing

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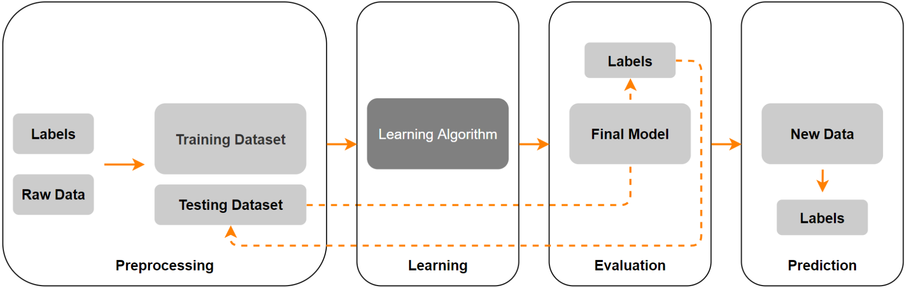
Overview

Roadmap

5 major steps:

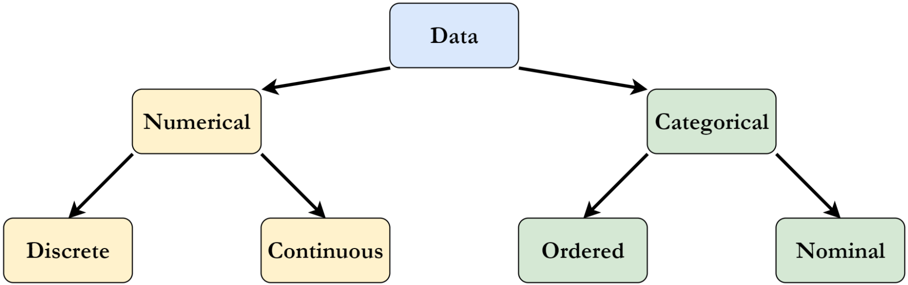
- Data Pre-processing
- Model Learning
- Model Evaluation
- Prediction
- Model Deployment



Overview

1. A roadmap for building machine learning system
2. Data Pre-processing
3. K-Nearest Neighbors
4. Model Evaluation

Types of Data



Numerical: quantitative data

- Discrete: the number of students, the age of a person, ...
- Continuous: the height of a person, the score of a student, ...

Categorical: qualitative data

- Ordered: food ratings (excellent, good, bad), feelings (happy, not bad, bad), ...
- Nominal: the name of students, ...

How to load data?

Syntax (load)

pandas.read_csv(*filepath*)

Examples

```
>> import pandas as pd
>> data = pd.read_csv('/content/drive/MyDrive/Colab/mini_data.csv')
```

Syntax (show)

pandas.DataFrame.head(n)

Examples

```
>> data.head(n = 5)
```

Data Representation

	ID	Age	Sex	Height	Grade	Good-looking
0	1	21.0	Male	171.0	Good	Yes
1	2	20.0	Male	170.0	Bad	No
2	3	19.0	Female	NaN	Bad	No
3	4	17.0	Male	165.0	Excellent	Yes
4	5	NaN	Female	166.0	Good	Yes

Independent variables should NOT contain

- Missing or NULL values
- Outliers
- Data on different scales
- Special characters
- ...

Data Cleaning

- The processes of detecting and correcting (or removing) missing values or outliers.
- Ensuring data is correct, consistent and usable.

Missing values

- In .csv files, missing values are usually represented as empty, 'NA', 'N/A', 'null', 'nan', 'NaN'.

	ID	Age	Sex	Height	Grade	Good-looking
0	1	21.0	Male	171.0	Good	Yes
1	2	20.0	Male	170.0	Bad	No
2	3	19.0	Female	$\boxed{\text{NaN}}$	Bad	No
3	4	17.0	Male	165.0	Excellent	Yes
4	5	$\boxed{\text{NaN}}$	Female	166.0	Good	Yes

Missing values (cont.)

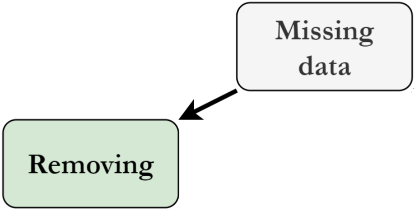
Syntax (count 'NaN')

pandas.DataFrame.isna().sum()

Examples

> countNULL = data.isna().sum()
> null_columns = countNULL[countNULL > 0]
> null_columns

How to handle?



Removing

Syntax

pandas.DataFrame.dropna(*inplace*)

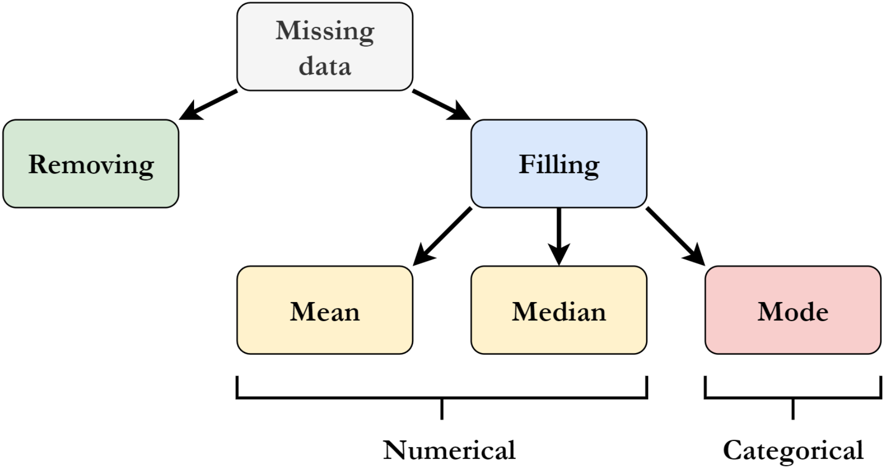
Examples

$>$ data.dropna($inplace = True$)

or

$>$ data $=$ data.dropna($inplace = False$)

How to handle? (cont.)



Filling

Examples

Find the mean, median, and mode for the following list of values:
13, 18, 13, 14, 13, 16, 14, 21, 13

Mean

- $mean = (13 + 18 + 13 + 14 + 13 + 16 + 14 + 21 + 13)/9 = 15$

Median

- Sorting the list: 13, 13, 13, 13, 14, 14, 16, 18, 21
- $median = 14$

Mode

- $mode = 13$

Filling (cont.)

Step 1: Calculating the filling values

Syntax (calculate the mean)

pandas.DataFrame.mean()

Examples

```
> mean_age = data['Age'].mean()
> mean_age
```

Syntax (calculate the median)

pandas.DataFrame.median()

Examples

```
> median_height = data['Height'].median()
> median_height
```

Filling (cont.)

Step 1: Calculating the filling values

Syntax (calculate the mode)

pandas.DataFrame.mode()[0]

Examples

> mode_grade = data['Grade'].mode()[0]
> mode_grade

Filling (cont.)

Step 2: Replacing 'NaN' by the filling values

Syntax

pandas.DataFrame.fillna(*value*, *inplace*)

Examples

$>$ data['Age'].fillna($value = mean\_age, inplace = True$)
$>$ data['Height'].fillna($value = median\_height, inplace = True$)
$>$ data['Grade'].fillna($value = mode\_grade, inplace = True$)

Outliers

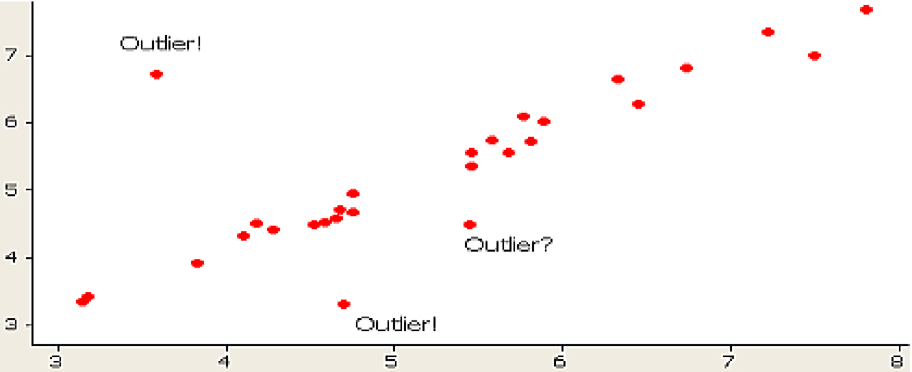


Figure: Examples of outliers

Outliers

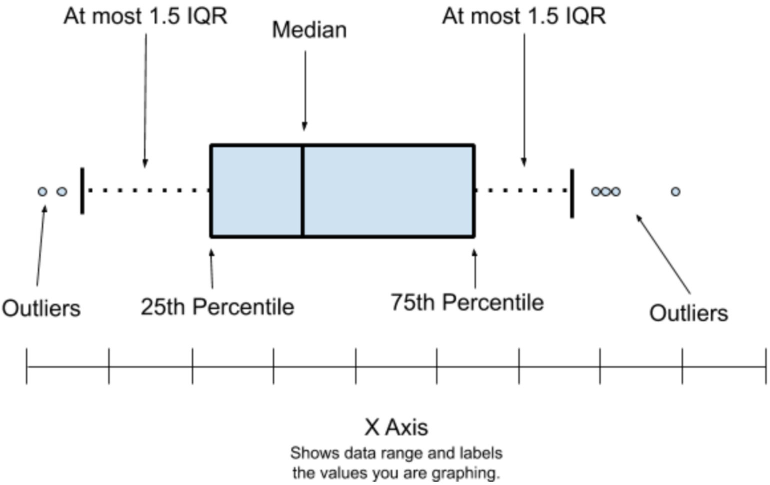
Syntax (plot the outliers)

seaborn.boxplot(*data*)

Examples

```
>> import seaborn as sbn
>> sbn.boxplot(data['Height'])
```

Outliers



At most 1.5 IQR
Median
At most 1.5 IQR
Outliers
25th Percentile
75th Percentile
Outliers
X Axis
Shows data range and labels
the values you are graphing.

Outliers

Examples

Find the outliers on 71, 70, 90, 70, 70, 60, 70, 72, 72, 320, 71, 69

Outliers

Examples

Find the outliers on 71, 70, 90, 70, 70, 60, 70, 72, 72, 320, 71, 69

Solution

- Sort the data: 60, 69, 70, 70, 70, 70, 71, 71, 72, 72, 90, 320
- Calculate the median (Q2) $\rightarrow (70 + 71)/2 = 70.5$
- Calculate the lower quartile (Q1) $\rightarrow (70 + 70)/2 = 70.0$
- Calculate the upper quartile (Q3) $\rightarrow (72 + 72)/2 = 72$
- Calculate the interquartile range (IQR) $\rightarrow$ Q3 – Q1 = 72 – 70 = 2
- Find the upper and lower fences.
  Lower fence = Q1 – 1.5 * IQR = 70 – 1.5 * 2 = 67
  Upper fence = Q3 + 1.5 * IQR = 71.5 + 1.5 * 2 = 74.5
- The data points that are lower than the lower fence and greater than the upper fence are outliers $\rightarrow$ outliers: 60; 90; 320.

Outliers (cont.)

Examples

$>>$ $\text{Q1} = \text{data['Height'].quantile(0.25)}$
$\text{Q3} = \text{data['Height'].quantile(0.75)}$
$IQR = Q3 - Q1$

$>>$ $low\_fence = Q1 - (1.5 * IQR)$
$up\_fence = Q3 + (1.5 * IQR)$

$>>$ $\text{data[((data['Height']} < \text{low\_fence)} | \text{(data['Height']} > \text{up\_fence))]}$

$>>$ $\text{data} = \text{data[}\sim\text{((data['Height']} < \text{low\_fence)} | \text{(data['Height']} > \text{up\_fence))]}$

Data Transformation

Label Encoding: replacing each value in a categorical column with numbers from 0 to $N-1$

Syntax (initialize)

sklearn.preprocessing.LabelEncoder()

Examples

```
>> from sklearn.preprocessing import LabelEncoder
>> label_encoder = LabelEncoder()
```

Label Encoding

Syntax (fit & transform)

sklearn.preprocessing.LabelEncoder().fit_transform(X)

Examples

>> data['Sex'] = label_encoder.fit_transform(data['Sex'])

Data Transformation (cont.)

One-hot Encoding: dividing a categorical column into *n* number of columns with *n* is the total number of unique labels in that column.

Syntax (initialize)

sklearn.preprocessing.OneHotEncoder(*sparse*)

Examples

```
>> from sklearn.preprocessing import OneHotEncoder
>> one_hot_encoder = OneHotEncoder(sparse = False)
```

One-hot Encoding

Syntax (fit & transform)

sklearn.preprocessing.OneHotEncoder().fit_transform(X)

Examples

```
>> column = 'Grade'
>> data_new_column = one_hot_encoder.fit_transform(data[[name_col]])
>> new_column = pd.DataFrame(data=data_new,
   columns=encoder.get_feature_names([column]))
>> data = pd.concat([data.drop(columns=[column, 'Good-looking']),
   new_column, data['Good-looking']], axis=1)
```

Data Scaling

Normalization: involves to the rescaling of the features to a range of $[0, 1]$

$$x_{norm}^{(i)} = \frac{x^{(i)} - x_{min}}{x_{max} - x_{min}}$$

where:

- x_{max}: the largest value of column x
- x_{min}: the smallest value of column x

Standardization: centers the columns at the mean 0 with the standard deviation 1

$$x_{std}^{(i)} = \frac{x^{(i)} - \mu_x}{\sigma_x}$$

where:

- μ_x: the mean of column x
- σ_x: the standard deviation of column x

Normalization

Syntax

sklearn.preprocessing.MinMaxScaler()

Examples

```
>> from sklearn.preprocessing import MinMaxScaler
>> min_max_scaler = MinMaxScaler()
>> data[['Age']] = min_max_scaler.fit_transform(data[['Age']])
```

Standardization

Syntax

sklearn.preprocessing.StandardScaler()

Examples

```
>> from sklearn.preprocessing import StandardScaler
>> std_scaler = StandardScaler()
>> data[['Height']] = std_scaler.fit_transform(data[['Height']])
```

Data Splitting

Syntax

sklearn.model_selection.train_test_split$(X, y, test\_size, random\_state)$

Examples

$>>$ **from** sklearn.model_selection **import** train_test_split

$>>$ X $=$ data.drop($columns$ $=$ ['Good-looking', 'ID'])
y $=$ data['Good-looking']

$>>$ X_train, X_test, y_train, y_test $=$ train_test_split$(X, y, test_size = 0.3)$

Exercises

DataPreprocessing_exercise.pdf

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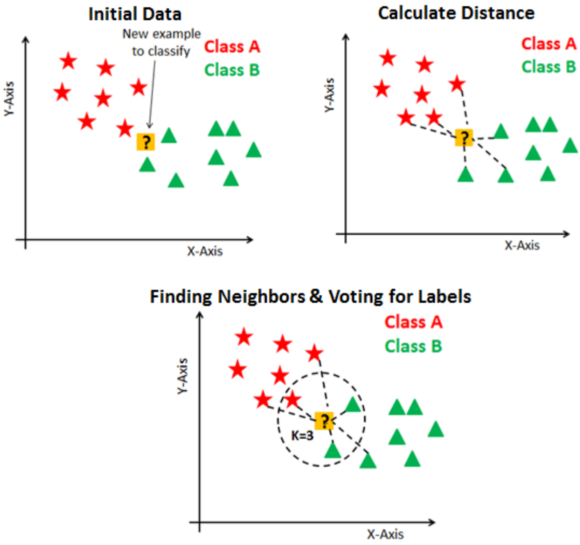
Recall



Initial Data
New example to classify
Class A
Class B
Y-Axis
X-Axis
?
Calculate Distance
Class A
Class B
Y-Axis
X-Axis
?
Finding Neighbors & Voting for Labels
Class A
Class B
Y-Axis
X-Axis
?
K=3

How to implement?

Syntax (initialize)

sklearn.neighbors.KNeighborsClassifier(*n_neighbors*, *p*)

where:

- n_neighbors: the number of neighbors (K)
- p: power parameter for the Minkowski metric.
  - $p = 1$: Manhattan distance
  - $p = 2$: Euclidean distance
  - $p > 2$: Minkowski distance

Examples

```
>> from sklearn.neighbors import KNeighborsClassifier
>> clf = KNeighborsClassifier(n_neighbors = 3, p = 2)
```

How to implement? (cont.)

Syntax (fit)

sklearn.neighbors.KNeighborsClassifier().fit(X, y)

Examples

$>>$ clf.fit(X_train, y_train)

Syntax (predict)

sklearn.neighbors.KNeighborsClassifier().predict(X)

Examples

$>>$ y_pred $=$ clf.predict(X_test)

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Performance Metrics

Classification

- Accuracy
- Confusion matrix
- Precision and Recall
- F1 score

Regression

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Root Mean Squared Error (RMSE)
- R-Squared

Syntax (import)

```
from sklearn.metrics import ...
```

Examples

```
>> from sklearn.metrics import accuracy_score
>> accuracy = accuracy_score(y_test, y_pred)
   accuracy
```

Exercise

KNN_exercise.pdf