Machine Learning Practice 1

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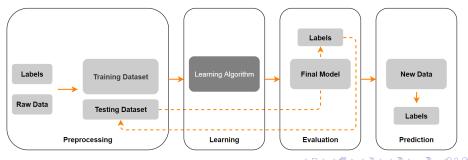
Overview

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

Roadmap

5 major steps:

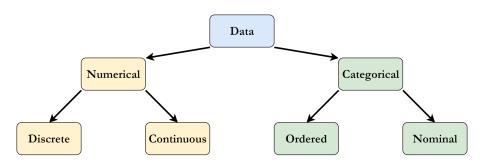
- Data Pre-processing
- Model Learning
- Model Evaluation
- Prediction
- Model Deployment



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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

>> df = pd.read_csv('/content/drive/MyDrive/Colab/iris.csv')

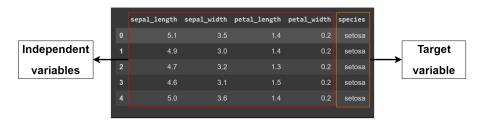
Syntax (show)

pandas. Data Frame. head(n)

Examples

>> df.head(n = 7)

Data Representation



Indepedent variables should NOT contain

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

Data Cleaning

- Including processes of detecting and correcting (or removing) missing values or <u>outliers</u>.
- 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,Name,Age,Grade 1,Nguyen Van A,21,Good 2,Nguyen Van B,,Excellent 3,Nguyen Van C,20,Good 4,Nguyen Van D,25,

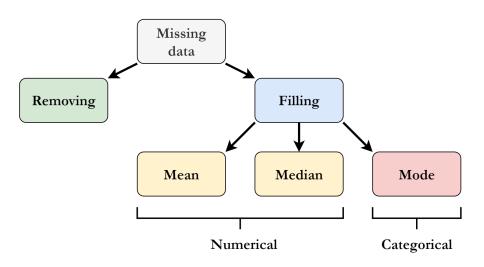
	ID	Name	Age	Grade
0	1	Nguyen Van A	21.0	Good
1	2	Nguyen Van B	NaN	Excellent
2	3	Nguyen Van C	20.0	Good
3	4	Nguyen Van D	25.0	NaN
		b.		

Syntax (count 'NaN')

pandas.DataFrame.isna().sum()

- $> \mathsf{countNULL} = \mathsf{df.isna().sum()}$
- > null_columns = countNULL[countNULL > 0]
- > null_columns

How to handle?



Removing

Syntax

pandas.DataFrame.dropna(inplace)

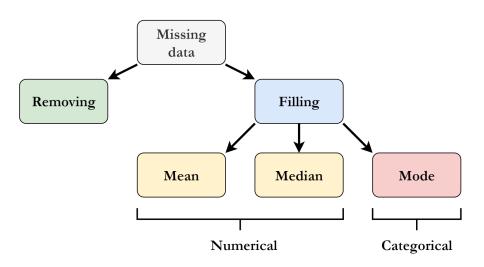
Examples

> df.dropna(inplace = True)

or

> df = df.dropna(inplace = False)

How to handle?



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, 14, 14, 16, 18, 21
- *median* = 14

Mode

• *mode* = 13

Step 1: Calculating the filling values

Syntax (calculate the mean)

pandas. Data Frame.mean()

Examples

- > mean_age = df['Age'].mean()
- > mean_age

Syntax (calculate the median)

pandas.DataFrame.median()

- > median_height = df['Height'].median()
- > median_height

Step 1: Calculating the filling values

Syntax (calculate the mode)

 ${\bf pandas. Data Frame. mode}()[0]$

- $> mode_grade = df['Grade'].mode()[0]$
- $> {\sf mode_grade}$

Step 2: Replacing 'NaN' by the filling values

Syntax

pandas.DataFrame.fillna(value, inplace)

- > df['Age'].fillna(value = mean_age, inplace = True)
- > df['Height'].fillna(value = median_height, inplace = True)
- > df['Grade'].fillna(value = mode_grade, inplace = True)

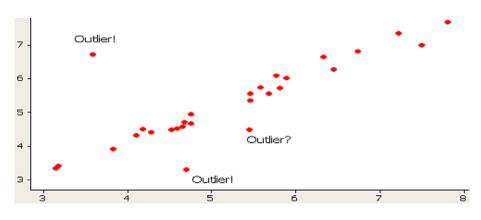


Figure: Examples of outliers

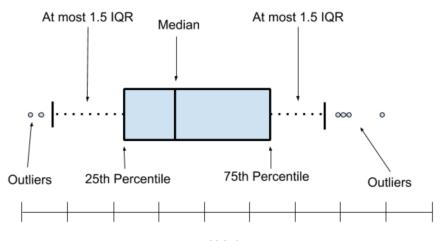
Syntax (plot the outliers)

seaborn.boxplot(data)

Examples

>> import seaborn as sbn

>> sbn.boxplot(df['Height'])



X Axis

Shows data range and labels the values you are graphing.

Examples

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

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 $(Q2) \to (70 + 71)/2 = 70.5$
- Calculate the lower quartile $(Q1) \rightarrow (70 + 70)/2 = 70.0$
- Calculate the upper quartile (Q3) \rightarrow (72 + 72)/2 = 72
- \bullet 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 = 67Upper fence = Q3 + 1.5 * IQR = 71.5 + 1.5 * 2 = 74.5
- Any data points lower than the lower fence and greater than the upper fence are outliers → outliers: 60; 90; 320.

```
>> Q1 = df['Height'].quantile(0.25)

Q3 = df['Height'].quantile(0.75)

IQR = Q3 - Q1

>> low\_fence = Q1 - (1.5 * IQR)

up\_fence = Q3 + (1.5 * IQR)

>> df[((df['Height'] < low\_fence)|(df['Height'] > up\_fence))]

>> df = df[\sim((df['Height'] < low\_fence)|(df['Heigh'] > 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()

- >> from sklearn.preprocessing import LabelEncoder
- >> encoder = LabelEncoder()

Label Encoding

Syntax (fit & transform)

 ${\bf sklearn.preprocessing.LabelEncoder}(). {\bf fit_transform}(X)$

Examples

>> df['Sex'] = encoder.fit_transform(df['Sex'])

Data Transformation

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)

- >> **from** sklearn.preprocessing **import** OneHotEncoder
- >> encoder = OneHotEncoder(sparse = False)

One-hot Encoding

Syntax (fit & transform)

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

- >> name_col = 'Grade'
- >> data_new = encoder.fit_transform(df[[name_col]])
- >> grade_column = pd.DataFrame(data=data_new, columns=encoder.get_feature_names([name_col]))
- >> df = pd.concat([df.drop(columns=[name_col, 'Good-looking']), grade_column, df['Good-looking']], axis=1)

Data Splitting

Syntax

 $sklearn.model_selection.train_test_split(X, y, test_size, random_state)$

- >> from sklearn.model_selection import train_test_split
- >> X = df.drop(columns = ['Good-looking', 'ID']) y = df['Good-looking']
- $>> X_{train}, X_{test}, y_{train}, y_{test} = train_{test_split}(X, y, test_size = 0.3)$

Data Scaling

Normalization: refers 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

Note:

Be careful when scaling the data

Normalization

Syntax

sklearn.preprocessing.MinMaxScaler()

- >> from sklearn.preprocessing import MinMaxScaler
- >> scaler = MinMaxScaler()

Standardization

Syntax

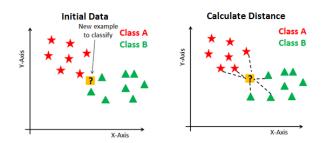
sklearn.preprocessing.StandardScaler()

- >> from sklearn.preprocessing import StandardScaler
- >> scaler = StandardScaler()
- $>> X_{train}[['Age']] = scaler.fit_transform(X_{train}[['Age']])$ $X_{test}[['Age']] = scaler.fit_transform(X_{test}[['Age']])$

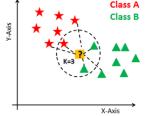
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Recall







How to implement it?

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
 - ightharpoonup p > 2: Minkowski distance

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

How to implement it?

Syntax (fit)

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

Examples

>> clf.fit(X_train, y_train)

Syntax (predict)

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

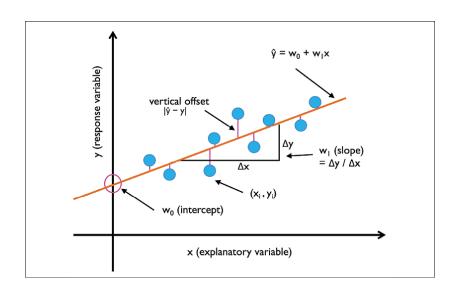
Examples

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

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Recall



How to implement it?

Solution 1

Syntax (initialize)

sklearn.linear_model.SGDRegression(fit_intercept, random_state)

Examples

>> from sklearn.linear_model import SGDRegression

>> reg = SGDRegression(fit_intercept = True, random_state = 1)

How to implement it?

Syntax (fit)

sklearn.linear_model.SGDRegression().fit(X, y)

Examples

>> reg.fit(X_train, y_train)

Syntax (predict)

 $sklearn.linear_model.SGDRegression().predict(X)$

Examples

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

Using scikit-learn library

Solution 2

Syntax (initialize)

sklearn.linear_model.LinearRegression(*fit_intercept*, *random_state*)

- >> from sklearn.linear_model import LinearRegression
- >> reg = LinearRegression(fit_intercept = True, random_state = 1)

How to implement it?

Syntax (fit)

 $sklearn.linear_model.LinearRegression().fit(X, y)$

Examples

>> reg.fit(X_train, y_train)

Syntax (predict)

 $sklearn.linear_model.LinearRegression().predict(X)$

Examples

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

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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 ...

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