

# Linear regression in Sklearn

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# Linear regression - Sklearn

```
import numpy as np

from sklearn.linear_model import LinearRegression

X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
y = np.dot(X, np.array([1, 2])) + 3

reg = LinearRegression().fit(X, y)

reg.score(X, y) #return the coefficient of determination of the prediction.

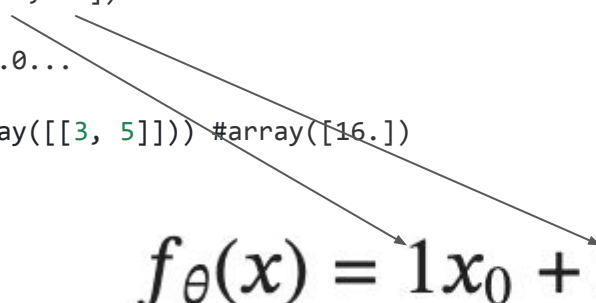
reg.coef_ #array([1., 2.])
reg.intercept_ # 3.0...
reg.predict(np.array([[3, 5]])) #array([16.])
```

model:

$$f_{\theta}(x) = \theta^T x$$

error:

$$\square(x, y, \theta) = (f_{\theta}(x) - y)^2$$



The diagram shows two arrows originating from the output of the sklearn model. One arrow points from the value 1.0 in the `reg.coef_` array to the coefficient 1 in the equation  $f_{\theta}(x) = 1x_0 + 2x_1 + 3$ . The other arrow points from the value 2.0 in the `reg.coef_` array to the coefficient 2 in the same equation.

$$f_{\theta}(x) = 1x_0 + 2x_1 + 3$$

# Coefficient of determination

```
from sklearn.metrics import r2_score
```

```
r2 = r2_score(y_test, y_pred)
```

$$R^2 := \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \geq 0,$$

Diagram illustrating the components of the R-squared formula:

- $y_{\text{pred}}$  points to  $\hat{y}_i$  in the numerator.
- $y_{\text{test}}$  points to  $y_i$  in the denominator.
- mean of  $y_{\text{test}}$  points to  $\bar{y}$  in the denominator.

## Model: prediction Life expectancy

	Country	GDP per capita	Life expectancy	Population	Continent
0	Lesotho	2598	47.1	2174645	Africa
1	Central African Republic	599	49.6	4546100	Africa
2	Swaziland	6095	51.8	1319011	Africa
3	Afghanistan	1925	53.8	33736494	Asia
4	Somalia	624	54.2	13908129	Africa

$$y_{life-expectancy} = \theta_2 * X_{GPD-per-capita} + \theta_1 * X_{Population} + \theta_0$$

# Normalization and test / train split

## Approach:

```
import pandas as pd

data = data = pd.read_csv('income.csv', sep=';')

X = data[['Life expectancy']].to_numpy()
y = data[['GDP per capita']].to_numpy()

train_size = int(0.8 * len(X)) #80%
X_train, y_train = X[:train_size], y[:train_size]
X_test, y_test = X[train_size:], y[train_size:]

X_train = (X_train - X_train.mean()) / X_train.std()
```

## New approach:

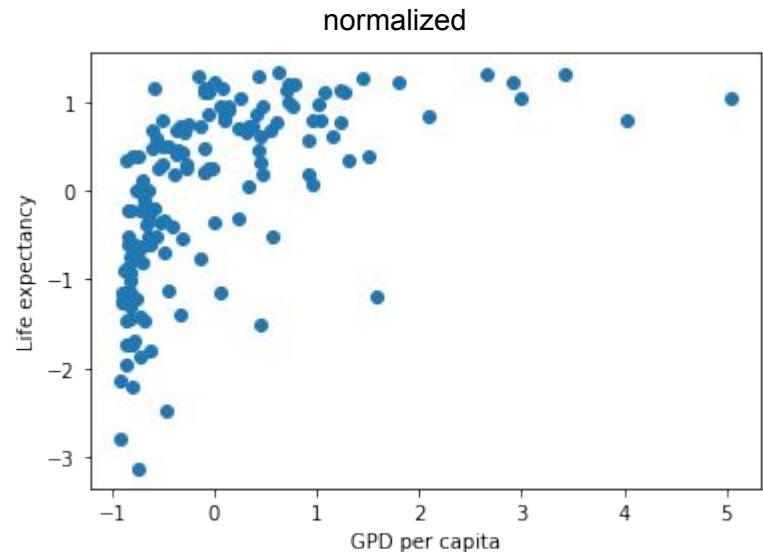
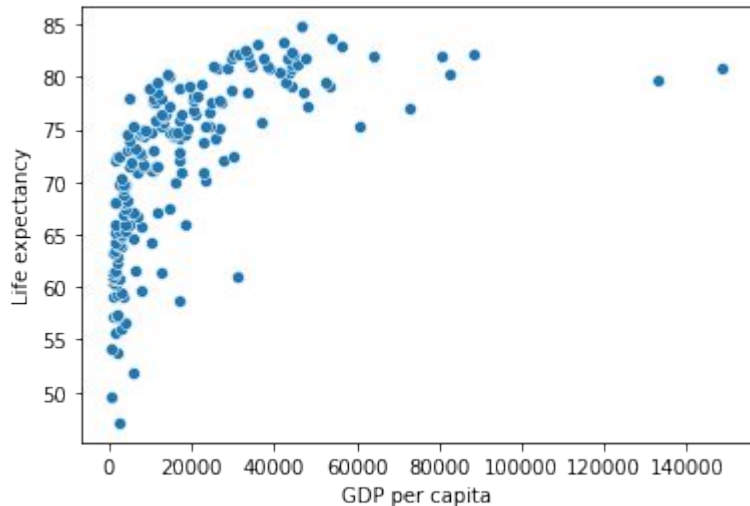
```
from sklearn.model_selection import train_test_split
import pandas as pd
data = pd.read_csv('income.csv', sep=';')

train_data, test_data = train_test_split(data, test_size= 0.2,
random_state=42)

X_test = test_data[['Life expectancy', 'Population']]
y_test = test_data[['GDP per capita']]
X_train = train_data[['Life expectancy', 'Population']]
y_train = train_data[['GDP per capita']]

scaler = StandardScaler()
scaler.fit(X_train)
X_train = scaler.transform(X_train)
scaler.fit(X_test)
X_test = scaler.transform(X_test)
```

# Normalization and test / train split

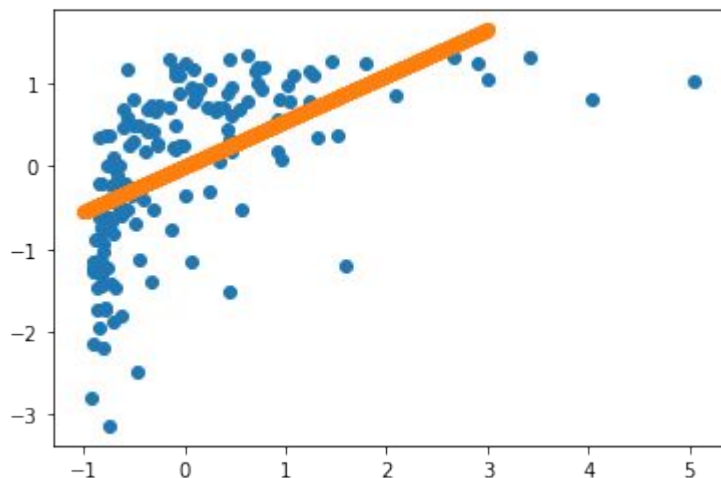


```
X = df_income[['Life expectancy']].to_numpy()
y = df_income[['GDP per capita']].to_numpy()

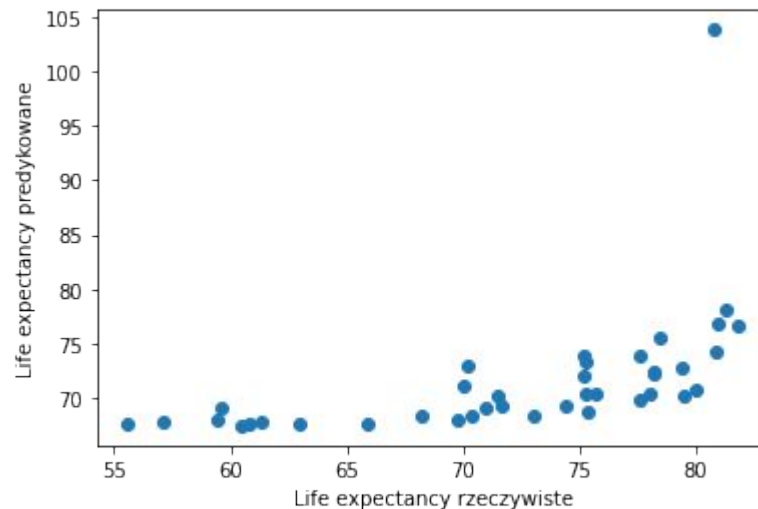
train_size = int(0.8 * len(X)) #80%
X_train, y_train = X[:train_size], y[:train_size]
X_test, y_test = X[train_size:], y[train_size:]
```

```
X_train = (X_train - X_train.mean()) / X_train.std()
y_train = (y_train - y_train.mean()) / y_train.std()
```

# Score:



```
xs = np.linspace(-1, 3, 1000)
theta = reg.coef_
plt.scatter(y_train, X_train)
plt.scatter(xs, xs * theta[0])
```



```
plt.scatter(y_test, y_pred)
plt.xlabel("Life expectancy rzeczywiste")
plt.ylabel("Life expectancy predykowane")
```

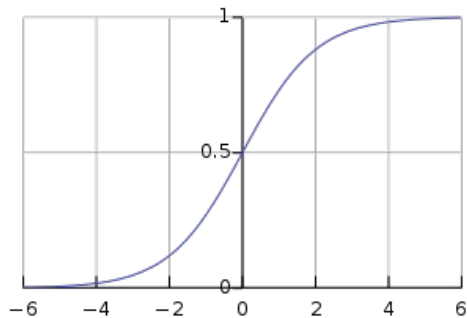
# Logistic regression

```
import numpy as np
from sklearn.linear_model import LogisticRegression
X = np.array([[1, 1], [1, 2], [2, 2], [2, 3]])
y = np.array([1, 0, 0, 1])

reg = LogisticRegression().fit(X, y)
reg.score(X, y) #accuracy
reg.coef_ #array([1., 2.])
reg.intercept_ # 3.0...
reg.predict(np.array([[3, 5]])) #array([16.] )
```

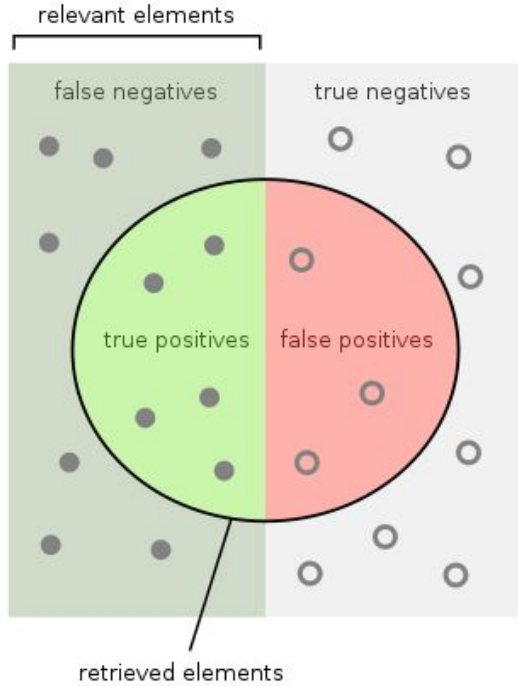
$$f_{\theta}(x) = \frac{1}{1 + e^{-\theta^T x}}$$

binary classification





# Precision and recall



How many retrieved items are relevant?

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

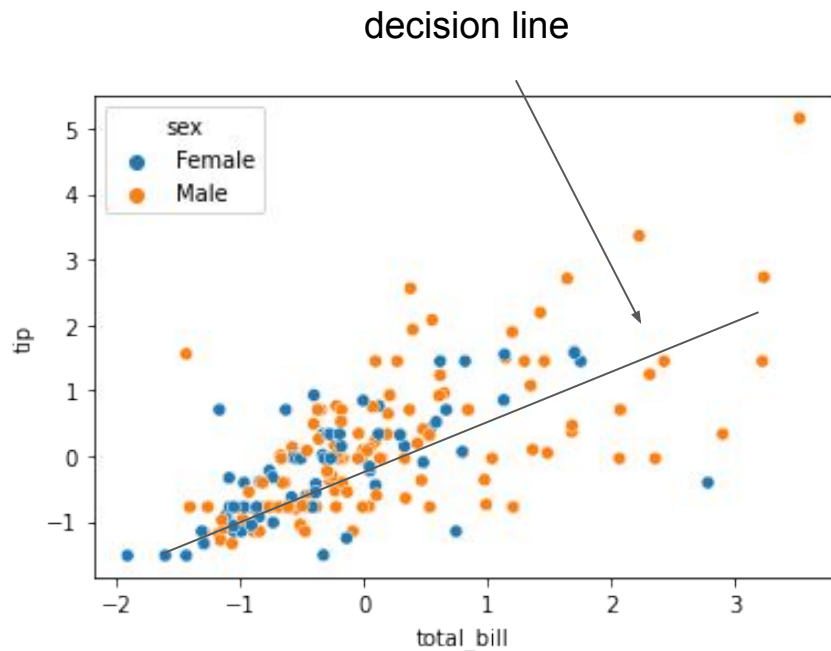
How many relevant items are retrieved?

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

	Predicted Value	
	Positive	Negative
Actual Value Positive	True Positive	False Negative
Actual Value Negative	False Positive	True Negative

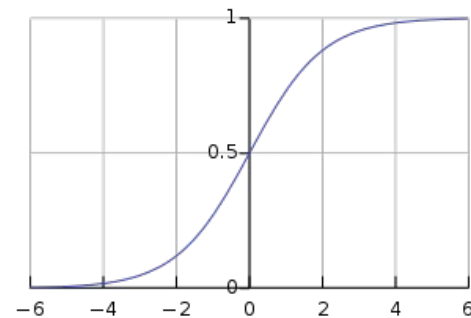
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

# Sex prediction - bad model



```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(random_state=0, max_iter=1000).fit(X_train, y_train)
clf.score(X_test, y_test) #mean accuracy
```

**#accuracy 0.6122448979591837**



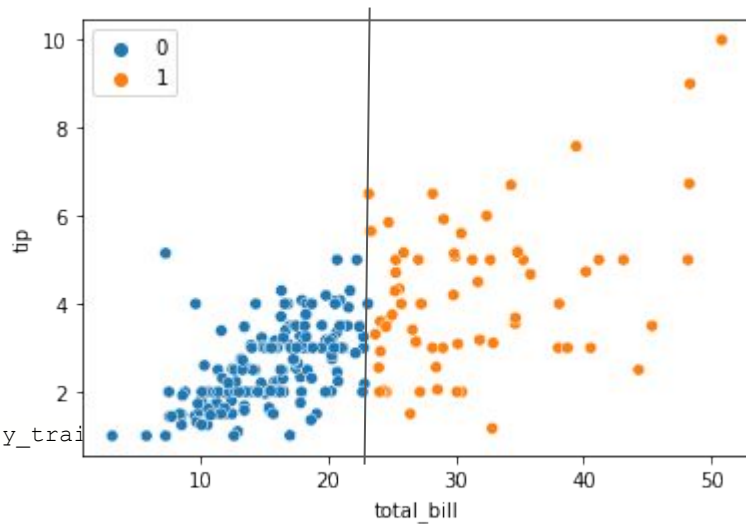
Where is the decision line?

# Toy example

```
from sklearn.cluster import KMeans
from sklearn.linear_model import LogisticRegression
```

```
kmeans = KMeans(n_clusters=2, random_state=0).fit(X)
y = kmeans.labels_
#...split data
clf = LogisticRegression(random_state=0, max_iter=100).fit(X_train, y_train)
clf.score(X_test, y_test) #1.0
y_pred = clf.predict(X_test)
```

```
# ocena jakości modelu
precision = precision_score(y_test, y_pred, average='macro')
recall = recall_score(y_test, y_pred, average='macro')
f1 = f1_score(y_test, y_pred, average='macro')
print("Precyzja:", precision)
print("Czułość:", recall)
print("F1-score:", f1)
```

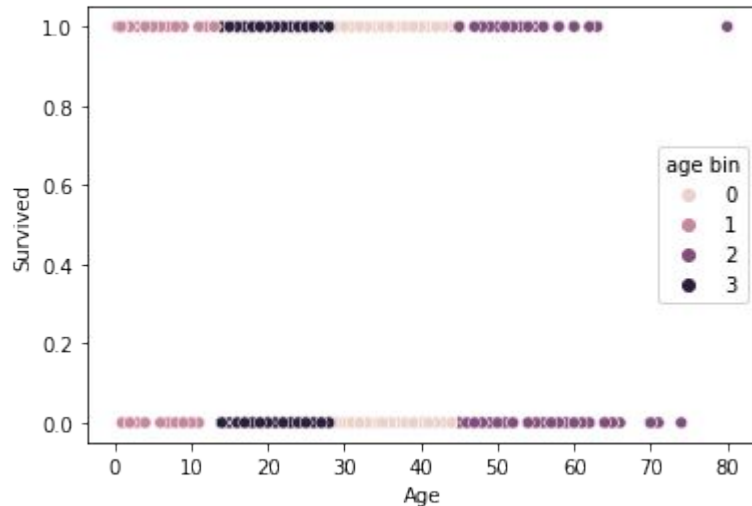


# Model: prediction continent

	Country	GDP per capita	Life expectancy	Population	Continent
0	Lesotho	2598	47.1	2174645	Africa
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# Feature extraction

```
df = pd.read_csv('titanic.csv')
age_data = df[['Age', 'Survived']].dropna()
kmeans = KMeans(n_clusters=4, random_state=0).fit(age_data)
age_group = kmeans.labels_
age_data['age bin'] = age_group
```



	Age	Survived	age bin
0	22.0	0	3
1	38.0	1	0
2	26.0	1	3
3	35.0	1	0
4	35.0	0	0