Contents

- Import packages and classes
- Load dataset
- Select variables & Drop NaN values
- Train-test split
- Sklean Linear Regression
- Prediction
- Evaluation


```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
import statsmodels.api as sm
```

```
data_raw = pd.read_csv('../datasets/Greece - Agriculture and Rural
Development/agriculture-and-rural-development_grc.csv')
pd.set_option('display.max_columns', 4)
data_raw.head()
```

	Agricultural land (% of land area)	Agricultural land (sq. km)	...	Rural population growth (annual %)	Surface area (sq. km)
0	NaN	NaN	...	NaN	NaN
1	69.123351	89100.0	...	-0.387316	131960.0
2	69.061288	89020.0	...	-1.462143	131960.0
3	69.984484	90210.0	...	-1.718278	131960.0
4	69.751746	89910.0	...	-1.758920	131960.0

5 rows × 23 columns

```
variable_x = "Crop production index (2014-2016 = 100)"
variable_y = "Cereal production (metric tons)"
data = data_raw[[variable_x, variable_y]].dropna().reset_index(drop=True)
data.head()
```

	Crop production index (2014-2016 = 100)	Cereal production (metric tons)
0	62.570000	2243876.0
1	50.700001	2426843.0
2	57.430000	2122537.0
3	57.150002	2874641.0
4	61.770000	2940922.0

```
data.shape
```

```
(58, 2)
```

```
X_train, X_test, y_train, y_test = train_test_split(data[variable_x].to_numpy(),
data[variable_y].to_numpy(), test_size=0.2, random_state=42)
```

```
model = LinearRegression().fit(X_train.reshape(-1, 1), y_train)
```

```
print(f"Intercept: {model.intercept_}")
print(f"Slope: {model.coef_}")
```

```
Intercept: -338797.3306638906
Slope: [51647.36492435]
```

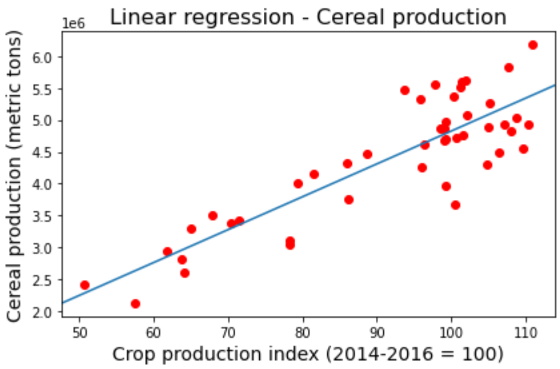
```
y_pred = np.around(model.predict(X_test.reshape(-1, 1)), 1)
y_pred
```

```
array([2892778.3, 2960952.8, 5072813.5, 3795574.4, 5177141.4, 4196357.7,
       4998957.8, 4700952.6, 4551691.8, 3424746.3, 4813543.9, 2612849.7])
```

```
fig, ax = plt.subplots()
plt.scatter(X_train, y_train, color='red')
ax.axline((X_test[1], y_pred[1]), slope=model.coef_[0])

plt.title('Linear regression - Cereal production', fontsize=16)
plt.xlabel(variable_x, fontsize=14)
plt.ylabel(variable_y, fontsize=14)

plt.tight_layout()
plt.show()
```




```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,
y_pred)))
```

```
Mean Absolute Error: 300467.2
Mean Squared Error: 142457458025.50165
Root Mean Squared Error: 377435.36933560116
```

```
print("R-Square value:", metrics.r2_score(y_test, y_pred))
```

```
R-Square value: 0.8563623217388497
```

```
X_stat = sm.add_constant(X_train)
regsummary = sm.OLS(y_train, X_stat).fit()
regsummary.summary()
```

Dep. Variable:	y	**R-squared:**	0.744
Model:	OLS	**Adj. R-squared:**	0.738
Method:	Least Squares	**F-statistic:**	127.6
Date:	Fri, 16 Dec 2022	**Prob (F-statistic):**	1.36e-14
Time:	14:35:49	**Log-Likelihood:**	-668.16
No. Observations:	46	**AIC:**	1340.
Df Residuals:	44	**BIC:**	1344.
Df Model:	1		
Covariance Type:	nonrobust		

OLS Regression Results

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-3.388e+05	4.26e+05	-0.796	0.430	-1.2e+06	5.19e+05
x1	5.165e+04	4571.889	11.297	0.000	4.24e+04	6.09e+04

Omnibus:	0.370	**Durbin-Watson:**	1.986
Prob(Omnibus):	0.831	**Jarque-Bera (JB):**	0.538
Skew:	-0.082	**Prob(JB):**	0.764
Kurtosis:	2.496	**Cond. No.**	534.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

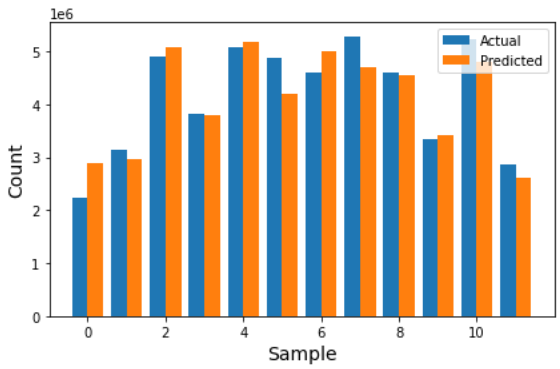
```
fig, ax = plt.subplots()
x_axis = np.arange(12)

plt.bar(x_axis-0.2, y_test, width=0.4, label = "Actual")
plt.bar(x_axis+0.2, y_pred, width=0.4, label = "Predicted")

plt.xlabel("Sample", fontsize=14)
plt.ylabel("Count", fontsize=14)

plt.legend()

plt.tight_layout()
plt.show()
```



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