Peer-graded Assignment

Project Akhir_Supervised Machine Learning: Classification

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Classification with Python

Di dalam notebook ini kami mencoba mempraktekkan semua algoritma klasifikasi yang kami pelajari di kursus ini. Kami memuat kumpulan data menggunakan perpustakaan Pandas, dan menerapkan algoritma berikut, dan menemukan yang terbaik untuk kumpulan data khusus ini dengan metode evaluasi akurasi. Mari memuat pustaka yang diperlukan terlebih dahulu.

1. Masukin Data

```
import itertools
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import NullFormatter
import pandas as pd
import numpy as np
import matplotlib.ticker as ticker
from sklearn import preprocessing
%matplotlib inline
```

2. About Dataset

Untuk Dataset ini tentang pinjaman masa lalu. Kumpulan data Loan_train.csv mencakup rincian 346 pelanggan yang pinjamannya sudah lunas atau gagal bayar. Ini mencakup bidang-bidang berikut:

Field	Description
Loan_status	Whether a loan is paid off on in collection
Principal	Basic principal loan amount at the
Terms	Origination terms which can be weekly (7 days), biweekly, and monthly payoff schedule
Effective_date	When the loan got originated and took effects
Due_date	Since it's one-time payoff schedule, each loan has one single due date
Age	Age of applicant
Education	Education of applicant
Gender	The gender of applicant

Sebelum itu download dulu datasetnya.

```
from __future__ import print_function
import os
data_path = ['loan_train']
print (data_path)
```

```
['loan_train']
```

3. Memuat Data Dari File CSV

```
df = pd.read_csv('loan_train.csv')
df.head()
```

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender
0	0	0	PAIDOFF	1000	30	9/8/2016	10/7/2016	45	High School or Below	male
1	2	2	PAIDOFF	1000	30	9/8/2016	10/7/2016	33	Bechalor	female
2	3	3	PAIDOFF	1000	15	9/8/2016	9/22/2016	27	college	male
3	4	4	PAIDOFF	1000	30	9/9/2016	10/8/2016	28	college	female
4	6	6	PAIDOFF	1000	30	9/9/2016	10/8/2016	29	college	male

```
df.shape
```

```
(346, 10)
```

4. Konversikan ke objek waktu tanggal

```
df['due_date'] = pd.to_datetime(df['due_date'])
df['effective_date'] = pd.to_datetime(df['effective_date'])
df.head()
```

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	High School or Below	male
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bechalor	female
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	college	male
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	college	female
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	college	male

5. Visualisasi data dan pra-pemrosesan

Mari kita lihat berapa banyak dari setiap kelas yang ada di kumpulan data kita.

```
df['loan_status'].value_counts()
```

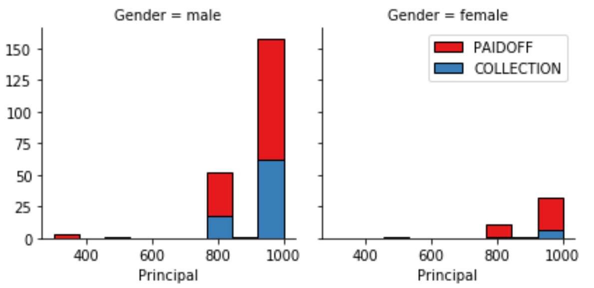
```
PAIDOFF       260
COLLECTION     86
Name: loan_status, dtype: int64
```

260 people have paid off the loan on time while 86 have gone into collection

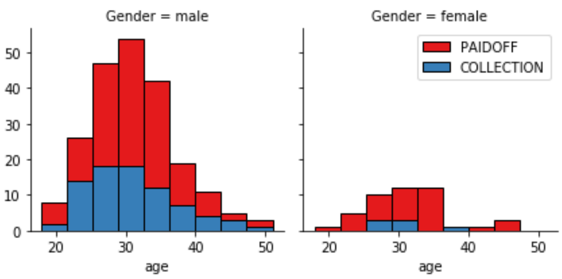
Di dalam plot terdapat beberapa kolom untuk memahami data dengan lebih baik.

 # notice: installing seaborn might takes a few minutes
#!conda install -c anaconda seaborn -y

```
import seaborn as sns

bins = np.linspace(df.Principal.min(), df.Principal.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'Principal', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



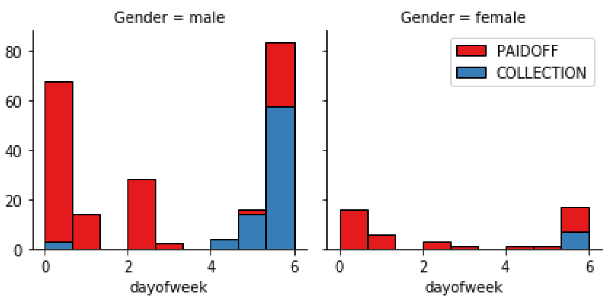

```
bins = np.linspace(df.age.min(), df.age.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'age', bins=bins, ec="k")

g.axes[-1].legend()
plt.show()
```



6. Pra-pemrosesan: Pemilihan fitur

   Mari kita lihat hari dalam seminggu orang mendapatkan pinjaman.

```
df['dayofweek'] = df['effective_date'].dt.dayofweek
bins = np.linspace(df.dayofweek.min(), df.dayofweek.max(), 10)
g = sns.FacetGrid(df, col="Gender", hue="loan_status", palette="Set1", col_wrap=2)
g.map(plt.hist, 'dayofweek', bins=bins, ec="k")
g.axes[-1].legend()
plt.show()
```



Kami melihat bahwa orang yang mendapatkan pinjaman pada akhir minggu tidak melunasinya, jadi menggunakan Binerisasi Fitur untuk menetapkan nilai ambang kurang dari hari ke-4.

```
df['weekend'] = df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)
df.head()
```

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender	dayofweek	weekend
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	High School or Below	male	3	0
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bechalor	female	3	0
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	college	male	3	0
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	college	female	4	1
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	college	male	4	1

7. Mengonversi fitur Kategorikal menjadi nilai numerik

   Mari kita lihat jenis kelamin:

```
df.groupby(['Gender'])['loan_status'].value_counts(normalize=True)
```

```
Gender  loan_status
female  PAIDOFF        0.865385
        COLLECTION     0.134615
male    PAIDOFF        0.731293
        COLLECTION     0.268707
Name: loan_status, dtype: float64
```

86 % of female pay there loans while only 73 % of males pay there loan

Mari kita ubah laki-laki menjadi 0 dan perempuan menjadi 1:

```
df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)
df.head()
```

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender	dayofweek	weekend
0	0	0	PAIDOFF	1000	30	2016-09-08	2016-10-07	45	High School or Below	0	3	0
1	2	2	PAIDOFF	1000	30	2016-09-08	2016-10-07	33	Bechalor	1	3	0
2	3	3	PAIDOFF	1000	15	2016-09-08	2016-09-22	27	college	0	3	0
3	4	4	PAIDOFF	1000	30	2016-09-09	2016-10-08	28	college	1	4	1
4	6	6	PAIDOFF	1000	30	2016-09-09	2016-10-08	29	college	0	4	1

8. One Hot Encoding

   - Bagaimana dengan pendidikan?

```
df.groupby(['education'])['loan_status'].value_counts(normalize=True)
```

```
education             loan_status
Bechalor              PAIDOFF        0.750000
                      COLLECTION     0.250000
High School or Below  PAIDOFF        0.741722
                      COLLECTION     0.258278
Master or Above       COLLECTION     0.500000
                      PAIDOFF        0.500000
college               PAIDOFF        0.765101
                      COLLECTION     0.234899
Name: loan_status, dtype: float64
```

   - Fitur sebelum One Hot Encoding

```
df[['Principal','terms','age','Gender','education']].head()
```

	Principal	terms	age	Gender	education
0	1000	30	45	0	High School or Below
1	1000	30	33	1	Bechalor
2	1000	15	27	0	college
3	1000	30	28	1	college
4	1000	30	29	0	college

9. Gunakan satu teknik enkode panas untuk mengonversi variabel kategori menjadi variabel biner dan menambahkannya ke fitur Data Frame.

```
Feature = df[['Principal','terms','age','Gender','weekend']]
Feature = pd.concat([Feature,pd.get_dummies(df['education'])], axis=1)
Feature.drop(['Master or Above'], axis = 1,inplace=True)
Feature.head()
```

	Principal	terms	age	Gender	weekend	Bechalor	High School or Below	college
0	1000	30	45	0	0	0	1	0
1	1000	30	33	1	0	1	0	0
2	1000	15	27	0	0	0	0	1
3	1000	30	28	1	1	0	0	1
4	1000	30	29	0	1	0	0	1

Pemilihan fitur Mari tentukan set fitur, X:

```
X = Feature
X[0:5]
```

	Principal	terms	age	Gender	weekend	Bechalor	High School or Below	college
0	1000	30	45	0	0	0	1	0
1	1000	30	33	1	0	1	0	0
2	1000	15	27	0	0	0	0	1
3	1000	30	28	1	1	0	0	1
4	1000	30	29	0	1	0	0	1

10. Normalize Data

Standardisasi Data memberikan rata-rata nol data dan varian unit (secara teknis harus dilakukan setelah pemisahan uji kereta).

```
X= preprocessing.StandardScaler().fit(X).transform(X)
X[0:5]
```

```
array([[ 0.51578458,  0.92071769,  2.33152555, -0.42056004, -1.20577805,
        -0.38170062,  1.13639374, -0.86968108],
       [ 0.51578458,  0.92071769,  0.34170148,  2.37778177, -1.20577805,
         2.61985426, -0.87997669, -0.86968108],
       [ 0.51578458, -0.95911111, -0.65321055, -0.42056004, -1.20577805,
        -0.38170062, -0.87997669,  1.14984679],
       [ 0.51578458,  0.92071769, -0.48739188,  2.37778177,  0.82934003,
        -0.38170062, -0.87997669,  1.14984679],
       [ 0.51578458,  0.92071769, -0.3215732 , -0.42056004,  0.82934003,
        -0.38170062, -0.87997669,  1.14984679]])
```

11. Classification

Sekarang giliran Anda, gunakan set pelatihan untuk membuat model yang akurat. Kemudian gunakan set pengujian untuk melaporkan keakuratan model. Anda harus menggunakan algoritma berikut:

- K Nearest Neighbor(KNN)
- Decision Tree
- Support Vector Machine
- Logistic Regression

Notice

- Anda dapat pergi ke atas dan mengubah pra-pemrosesan, pemilihan fitur, ekstraksi fitur, dan seterusnya, untuk membuat model yang lebih baik.

- Anda harus menggunakan pustaka scikit-learn, Scipy, atau Numpy untuk mengembangkan algoritma klasifikasi.
- Anda harus menyertakan kode algoritma di sel berikut.

K Nearest Neighbor(KNN)

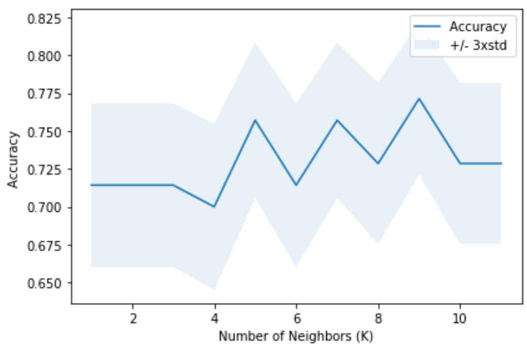
Perhatian: Anda harus menemukan k terbaik untuk membangun model dengan akurasi terbaik. peringatan: Anda tidak boleh menggunakan loan_test.csv untuk menemukan k terbaik, namun, Anda dapat membagi train_loan.csv menjadi train dan test untuk menemukan k terbaik.

```
#Train-Test Split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
#Training
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics

Ks = 12
mean_acc = np.zeros((Ks-1))
std_acc = np.zeros((Ks-1))
ConfustionMtx=[];
for n in range(1,Ks):
    neigh = KNeighborsClassifier(n_neighbors=n).fit(X_train, y_train)
    yhat = neigh.predict(X_test)
    mean_acc[n-1] = metrics.accuracy_score(y_test, yhat)
    std_acc[n-1] = np.std(yhat==y_test)/np.sqrt(yhat.shape[0])
mean_acc
```

```
array([0.71428571, 0.71428571, 0.71428571, 0.7       , 0.75714286,
       0.71428571, 0.75714286, 0.72857143, 0.77142857, 0.72857143,
       0.72857143])
```

```
plt.plot(range(1,Ks),mean_acc)
plt.fill_between(range(1,Ks),mean_acc - 1 * std_acc,mean_acc + 1 * std_acc, alpha=0.10)
plt.legend(('Accuracy ', '+/- 3xstd'))
plt.ylabel('Accuracy ')
plt.xlabel('Number of Neighbors (K)')
plt.tight_layout()
plt.show()

print( "The best accuracy was with", mean_acc.max(), "with k=", mean_acc.argmax()+1)

neigh = KNeighborsClassifier(n_neighbors=mean_acc.argmax()+1).fit(X_train, y_train)
```



The best accuracy was with 0.7714285714285715 with k= 9

```
print( "The best accuracy was with", mean_acc.max(), "with k=", mean_acc.argmax()+1)
```

The best accuracy was with 0.7857142857142857 with k= 1

```
# Set value of k as 7
k = 7
# Train Model and Predict
loanknn = KNeighborsClassifier(n_neighbors = k).fit(X_train,y_train)
loanknn
```

KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
metric_params=None, n_jobs=None, n_neighbors=7, p=2, weights='uniform')

```python
print("Train set Accuracy: ", metrics.accuracy_score(y_train, loanknn.predict(X_train)))
print("Test set Accuracy: ", metrics.accuracy_score(y_test, yhat))
```

Train set Accuracy: 0.8188405797101449
Test set Accuracy: 0.7222222222222222

```python
from sklearn.metrics import classification_report

print (classification_report(y_test, yhat))
```

	precision	recall	f1-score	support
COLLECTION	0.44	0.29	0.35	14
PAIDOFF	0.78	0.88	0.82	40
accuracy			0.72	54
macro avg	0.61	0.58	0.59	54
weighted avg	0.69	0.72	0.70	54

```python
from sklearn.metrics import f1_score
f1_score(y_test, yhat, average='weighted')
```

0.7001989201477693

```python
from sklearn.metrics import jaccard_similarity_score
jaccard_similarity_score(y_test, yhat)
```

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

0.7222222222222222

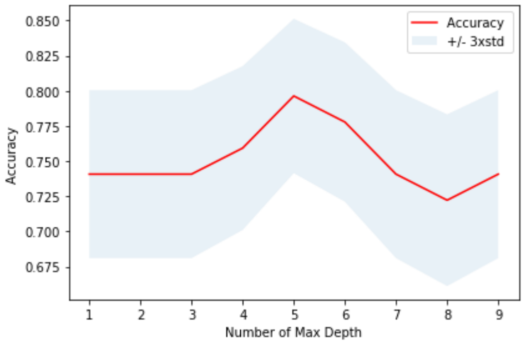
Decision Tree

```python
# Import the decision tree model

from sklearn.tree import DecisionTreeClassifier
```

```python
md = 10
mean_acc = np.zeros((md-1))
std_acc = np.zeros((md-1))
ConfustionMx = [];
for n in range(1,md):

    #Train Model and Predict
    loant = DecisionTreeClassifier(criterion="entropy", max_depth = n).fit(X_train,y_train)
    yhat=loant.predict(X_test)
    mean_acc[n-1] = metrics.accuracy_score(y_test, yhat)


    std_acc[n-1]=np.std(yhat==y_test)/np.sqrt(yhat.shape[0])

mean_acc
```

array([0.74074074, 0.74074074, 0.74074074, 0.75925926, 0.7962963 ,
       0.77777778, 0.74074074, 0.72222222, 0.74074074])

```
plt.plot(range(1,md),mean_acc,'r')
plt.fill_between(range(1,md),mean_acc - 1 * std_acc,mean_acc + 1 * std_acc, alpha=0.10)
plt.legend(('Accuracy ', '+/- 3xstd'))
plt.ylabel('Accuracy ')
plt.xlabel('Number of Max Depth')
plt.tight_layout()
plt.show()
```




```
#Building the decision tree with max depth of 6
loandt = DecisionTreeClassifier(criterion="entropy", max_depth = 6)

# Check the default parameters
loandt

# Train the Decision tree model
loandt.fit(X_train,y_train)

# Predict using the model
yhat= loandt.predict(X_test)
```

```
#Calculating the train and test accuracy
print("Train set Accuracy: ", metrics.accuracy_score(y_train, loandt.predict(X_train)))
print("Test set Accuracy: ", metrics.accuracy_score(y_test, yhat))
#Building the confusion matrix
print (classification_report(y_test, yhat))
```

```
Train set Accuracy:  0.7934782608695652
Test set Accuracy:  0.7777777777777778
              precision    recall  f1-score   support

  COLLECTION       0.57      0.57      0.57        14
     PAIDOFF       0.85      0.85      0.85        40

    accuracy                           0.78        54
   macro avg       0.71      0.71      0.71        54
weighted avg       0.78      0.78      0.78        54
```

```
# Calculate the F1 score
f1_score(y_test, yhat, average='weighted')
```

0.7777777777777778

```
# Calculate the jaccard index
jaccard_similarity_score(y_test, yhat)
```

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

0.7777777777777778

```
'''dot_data = StringIO()
filename = "loantree.png"
featureNames = Feature.columns
targetNames = df['loan_status'].unique().tolist()
out=tree.export_graphviz(loandt,feature_names=featureNames, out_file=dot_data, class_names= np.unique(y_train), filled=True,  special_characters=True,
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png(filename)
img = mpimg.imread(filename)
plt.figure(figsize=(100, 200))
plt.imshow(img,interpolation='nearest')'''
```

'dot_data = StringIO()\nfilename = "loantree.png"\nfeatureNames = Feature.columns\ntargetNames = df[\'loan_status\'].unique().tolist()\nout=tree.export_graphviz(loandt,feature_names=featureNames, out_file=dot_data, class_names= np.unique(y_train), filled=True, special_characters=True,rotate=False)\ngraph = pydotplus.graph_from_dot_data(dot_data.getvalue()) \ngraph.write_png(filename)\nimg = mpimg.imread(filename)\nplt.figure(figsize=(100, 200))\nplt.imshow(img,interpolation=\'nearest\')'

Support Vector Machine

```
# Import the library for SVM Classifier
from sklearn import svm

# Build a SVM Classifier with a Radial base Function Kernel
loansvm1 = svm.SVC(kernel='rbf').fit(X_train, y_train)
yhat1 = loansvm1.predict(X_test)
svm_r = metrics.accuracy_score(y_test, yhat1)

# Build a SVM Classifier with a Linear Kernel
loansvm2 = svm.SVC(kernel='linear').fit(X_train, y_train)
yhat2 = loansvm2.predict(X_test)
svm_l = metrics.accuracy_score(y_test, yhat2)

# Build a SVM Classifier with a Polynomial Kernel
loansvm3 = svm.SVC(kernel='poly').fit(X_train, y_train)
yhat3 = loansvm3.predict(X_test)
svm_p = metrics.accuracy_score(y_test, yhat3)

# Build a SVM Classifier with a Sigmoid Kernel
loansvm4 = svm.SVC(kernel='sigmoid').fit(X_train, y_train)
yhat4 = loansvm4.predict(X_test)
svm_s = metrics.accuracy_score(y_test, yhat4)

print(svm_r,svm_l,svm_p,svm_s)
```

0.7777777777777778 0.7407407407407407 0.7407407407407407 0.7037037037037037

```
# Find if labels are missing in the SVM models
print("The label missing in the first model with rbf kernel",set(y_test) - set(yhat1))
print("The label missing in the second model with linear",set(y_test) - set(yhat2))
print("The label missing in the third model with polynomial kernel",set(y_test) - set(yhat3))
print("The label missing in the fourth model with sigmoid kernel",set(y_test) - set(yhat4))
```

```
The label missing in the first model with rbf kernel set()
The label missing in the second model with linear {'COLLECTION'}
The label missing in the third model with polynomial kernel set()
The label missing in the fourth model with sigmoid kernel set()
```

```
#Predicting the test values using the SVM model
yhat = loansvm.predict(X_test)
yhat [0:5]
```

```
array(['PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'PAIDOFF', 'COLLECTION'],
      dtype=object)
```

```
print("Train set Accuracy: ", metrics.accuracy_score(y_train, loansvm.predict(X_train)))
print("Test set Accuracy: ", metrics.accuracy_score(y_test, yhat))

print (classification_report(y_test, yhat))
```

```
Train set Accuracy:  0.7681159420289855
Test set Accuracy:  0.7777777777777778
              precision    recall  f1-score   support

  COLLECTION       0.67      0.29      0.40        14
     PAIDOFF       0.79      0.95      0.86        40

    accuracy                           0.78        54
   macro avg       0.73      0.62      0.63        54
weighted avg       0.76      0.78      0.74        54
```

```
# Calculate the f1 score
f1_score(y_test, yhat, average='weighted')
```

0.7434343434343433

```
#Calculate the Jaccard index
jaccard_similarity_score(y_test, yhat)
```

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

0.7777777777777778

Logistic Regression

```
# Import the library for Logistice regression
from sklearn.linear_model import LogisticRegression

# Build and train the logestic regression model
loanlr1 = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
yhat1 = loanlr1.predict(X_test)
loanlr_a1 = metrics.accuracy_score(y_test, yhat1)

# Build and train the logestic regression model
loanlr2 = LogisticRegression(C=0.01, solver='sag').fit(X_train,y_train)
yhat2 = loanlr2.predict(X_test)
loanlr_a2 = metrics.accuracy_score(y_test, yhat2)

# Build and train the logestic regression model
loanlr3 = LogisticRegression(C=0.01, solver='saga').fit(X_train,y_train)
yhat3 = loanlr3.predict(X_test)
loanlr_a3 = metrics.accuracy_score(y_test, yhat3)

# Build and train the logestic regression model
loanlr4 = LogisticRegression(C=0.01, solver='newton-cg').fit(X_train,y_train)
yhat4 = loanlr4.predict(X_test)
loanlr_a4 = metrics.accuracy_score(y_test, yhat4)

# Build and train the logestic regression model
loanlr5 = LogisticRegression(C=0.01, solver='lbfgs').fit(X_train,y_train)
yhat5 = loanlr5.predict(X_test)
loanlr_a5 = metrics.accuracy_score(y_test, yhat5)


print('LR model with liblinear solver',loanlr_a1)
print('LR model with sag solver',loanlr_a2)
print('LR model with saga solver',loanlr_a3)
print('LR model with newton-cg solver',loanlr_a4)
print('LR model with lbfgs solver',loanlr_a5)
```

LR model with liblinear solver 0.7592592592592593
LR model with sag solver 0.7407407407407407
LR model with saga solver 0.7407407407407407
LR model with newton-cg solver 0.7407407407407407
LR model with lbfgs solver 0.7407407407407407

```
# Find if labels are missing in the models
print("The label missing in the LR model with liblinear solver",set(y_test) - set(yhat1))
print("The label missing in the LR model with sag solver",set(y_test) - set(yhat2))
print("The label missing in the LR model with saga solver",set(y_test) - set(yhat3))
print("The label missing in the LR model with newton-cg solver",set(y_test) - set(yhat4))
print("The label missing in the LR model with lbfgs solver",set(y_test) - set(yhat5))
```

The label missing in the LR model with liblinear solver set()
The label missing in the LR model with sag solver {'COLLECTION'}
The label missing in the LR model with saga solver {'COLLECTION'}
The label missing in the LR model with newton-cg solver {'COLLECTION'}
The label missing in the LR model with lbfgs solver {'COLLECTION'}

```
print("Train set Accuracy: ", metrics.accuracy_score(y_train, loanlr.predict(X_train)))
print("Test set Accuracy: ", metrics.accuracy_score(y_test, yhat))
print (classification_report(y_test, yhat))
```

```
Train set Accuracy:  0.7536231884057971
Test set Accuracy:  0.7592592592592593
              precision    recall  f1-score   support

  COLLECTION       1.00      0.07      0.13        14
     PAIDOFF       0.75      1.00      0.86        40

    accuracy                           0.76        54
   macro avg       0.88      0.54      0.50        54
weighted avg       0.82      0.76      0.67        54
```

```
# Calculate the f1 score
f1_score(y_test, yhat, average='weighted')
```

0.6717642373556352

```
#Calculate the Jaccard index
jaccard_similarity_score(y_test, yhat)
```

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

0.7592592592592593

12. Model Evaluation Using Test Set

```
from sklearn.metrics import jaccard_similarity_score
from sklearn.metrics import f1_score
from sklearn.metrics import log_loss
```

Pertama, unduh dan muat set pengujian:

- Load Test Set for Evaluation

```
test_df = pd.read_csv('loan_test.csv')
test_df.head()
```

	Unnamed: 0	Unnamed: 0.1	loan_status	Principal	terms	effective_date	due_date	age	education	Gender
0	1	1	PAIDOFF	1000	30	9/8/2016	10/7/2016	50	Bechalor	female
1	5	5	PAIDOFF	300	7	9/9/2016	9/15/2016	35	Master or Above	male
2	21	21	PAIDOFF	1000	30	9/10/2016	10/9/2016	43	High School or Below	female
3	24	24	PAIDOFF	1000	30	9/10/2016	10/9/2016	26	college	male
4	35	35	PAIDOFF	800	15	9/11/2016	9/25/2016	29	Bechalor	male

```
# shape of the test data set
test_df.shape
```

(54, 10)

```
# Count of the loan status
test_df['loan_status'].value_counts()
```

PAIDOFF 40
COLLECTION 14
Name: loan_status, dtype: int64

```python
df = test_df

df['due_date'] = pd.to_datetime(df['due_date'])
df['effective_date'] = pd.to_datetime(df['effective_date'])
df['dayofweek'] = df['effective_date'].dt.dayofweek
df['weekend'] = df['dayofweek'].apply(lambda x: 1 if (x>3)  else 0)

df.groupby(['Gender'])['loan_status'].value_counts(normalize=True)
df['Gender'].replace(to_replace=['male','female'], value=[0,1],inplace=True)

df.groupby(['education'])['loan_status'].value_counts(normalize=True)

Feature = df[['Principal','terms','age','Gender','weekend']]
Feature = pd.concat([Feature,pd.get_dummies(df['education'])], axis=1)
Feature.drop(['Master or Above'], axis = 1,inplace=True)

X_test = Feature

y_test = df['loan_status'].values

X_test = preprocessing.StandardScaler().fit(X_test).transform(X_test)
```

```python
# KNN model testing
yhat_knn = loanknn.predict(X_test)

# Calculate the f1 score
f1_knn = f1_score(y_test, yhat_knn, average='weighted')

#Calculate the Jaccard index# Predict using the model
jsc_knn = jaccard_similarity_score(y_test, yhat_knn)

print('f1 score: ',f1_knn)
print('Jaccard index: ',jsc_knn)
```

f1 score: 0.7001989201477693
Jaccard index: 0.7222222222222222

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

```python
# Predict using the model
yhat_dt= loandt.predict(X_test)

# Calculate the f1 score
f1_dt = f1_score(y_test, yhat_dt, average='weighted')

#Calculate the Jaccard index# Predict using the model
jsc_dt = jaccard_similarity_score(y_test, yhat_dt)

print('f1 score: ',f1_dt)
print('Jaccard index: ',jsc_dt)
```

f1 score: 0.7777777777777778
Jaccard index: 0.7777777777777778

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

```
# Predict using the model
yhat_lr = loanlr.predict(X_test)

# Calculate the f1 score
f1_lr = f1_score(y_test, yhat_lr, average='weighted')

#Calculate the Jaccard index# Predict using the model
jsc_lr = jaccard_similarity_score(y_test, yhat_lr)

# Calculate Log loss
yhat_lr_prob = loanlr.predict_proba(X_test)
ll_lr = log_loss(y_test, yhat_lr_prob)


print('f1 score: ',f1_lr)
print('Jaccard index: ',jsc_lr)
print('Log Loss: ',ll_lr)
```

f1 score: 0.6717642373556352
Jaccard index: 0.7592592592592593
Log Loss: 0.5693569109817576

```
A:\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:664: FutureWarning: jaccard_similarity_score has been deprecated and replaced with j
accard_score. It will be removed in version 0.23. This implementation has surprising behavior for binary and multiclass classification tasks.
  FutureWarning)
```

```
Jaccard = [jsc_knn,jsc_dt,jsc_svm,jsc_lr]
F1_score = [f1_knn,f1_dt,f1_svm,f1_lr]
LogLoss = ['NA','NA','NA',ll_lr]


df = {'Algorithm': ['KNN', 'Decistion Tree', 'SVM', 'LogisticRegression'], \
     'Jaccard': Jaccard, 'F1-score': F1_score, 'LogLoss': LogLoss}

Report = pd.DataFrame(data=df, columns=['Algorithm', 'Jaccard', 'F1-score', 'LogLoss'], index=None)
Report
```

	Algorithm	Jaccard	F1-score	LogLoss
0	KNN	0.722222	0.700199	NA
1	Decistion Tree	0.777778	0.777778	NA
2	SVM	0.777778	0.743434	NA
3	LogisticRegression	0.759259	0.671764	0.569357

Laporan

Anda harus dapat melaporkan keakuratan model yang dibangun menggunakan matrik evaluasi yang berbeda:

Algorithm	Jaccard	F1-score	LogLoss
KNN	?	?	NA
Decision Tree	?	?	NA
SVM	?	?	NA
LogisticRegression	?	?	?

Referensi :

1.coursera-Machine-Learning-with-Python/Week-6-Peer-Graded-Assignment.ipynb at master

2. https://www.youtube.com/watch?v=TjjdJJ-k1nQ

1. https://www.kaggle.com/code/rubengijon/ibm-machine-learning-with-python-final-project
2.