modelling-data

November 17, 2023

[27]:
```
import warnings; warnings.simplefilter('ignore')
import pandas as pd, matplotlib.pyplot as plt
import time, numpy as np, seaborn as sns
from sklearn import  tree
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.metrics import precision_score, recall_score, f1_score
from sklearn.model_selection import cross_val_score
from sklearn.impute import SimpleImputer
import matplotlib.pyplot as plt
from sklearn.pipeline import make_pipeline
sns.set(style="ticks", color_codes=True)
"Done"
```

[27]:
```
'Done'
```

[8]:
```
import pandas as pd
df = pd.read_csv('/content/drive/MyDrive/Asesmen Data Science/Data_PreProcessed.
 ↪csv')
df.head(10)

N, P = df.shape # Ukuran Data
print('baris = ', N, ', Kolom (jumlah variabel) = ', P)
print("Tipe Variabe df = ", type(df))
df
```

```
baris =  668 , Kolom (jumlah variabel) =  15
Tipe Variabe df =  <class 'pandas.core.frame.DataFrame'>
```

[8]:
```
     umur  jml_pinjaman   jkw  jml_angsuran_per_bulan  saldo_nominatif  \
0    40.0      345000.0   1.0                345000.0         345000.0
1    31.0      350000.0   7.0                 55716.0         390000.0
2    34.0     3055499.0   8.0                     NaN        3055499.0
3    27.0     4435001.0   8.0                671098.0        4435001.0
4    49.0     1443750.0  15.0                107800.0        1617000.0
..    …            …     …                      …               …
```

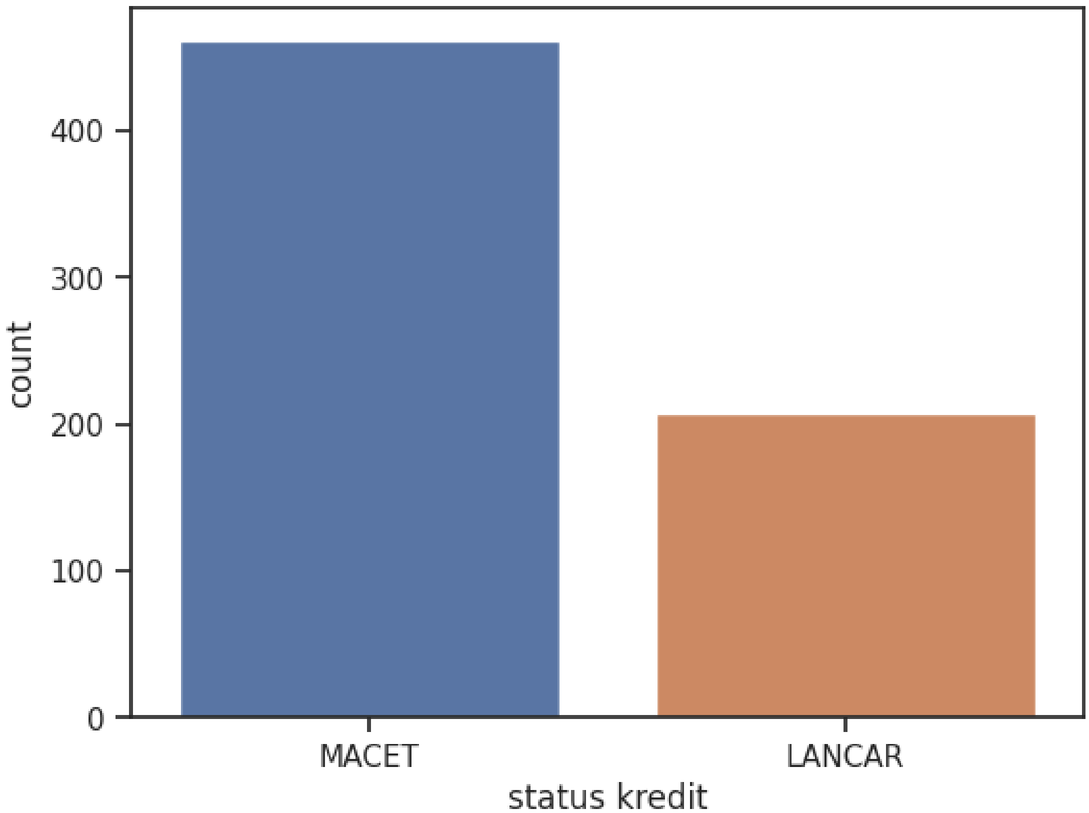
```
663  24.0     1500000.0  16.0                  105000.0         700000.0
664  38.0     1000000.0  16.0                   70000.0         812500.0
665  36.0     1000000.0  12.0                       NaN         429000.0
666  31.0     1312500.0   7.0                  198750.0        1312500.0
667  36.0     2000000.0   4.0                  550000.0        1000000.0

     tunggakan_pokok  tunggakan_bunga status kredit  bi_gol_penjamin__0  \
0           345000.0              0.0         MACET                   0
1           111428.0              0.0         MACET                   0
2                NaN              0.0         MACET                   0
3                0.0              0.0        LANCAR                   0
4          1078000.0              0.0         MACET                   0
..               …                …           …                   …
663         700000.0          90000.0         MACET                   1
664         812500.0          97500.0         MACET                   1
665         429000.0          45000.0         MACET                   1
666        1312500.0          78750.0         MACET                   1
667        1000000.0         100000.0         MACET                   1

     bi_gol_penjamin__800  bi_gol_penjamin__835  bi_gol_penjamin__874  \
0                       0                     0                     0
1                       0                     0                     0
2                       0                     0                     0
3                       0                     0                     0
4                       0                     0                     0
..                    …                     …                     …
663                     0                     0                     0
664                     0                     0                     0
665                     0                     0                     0
666                     0                     0                     0
667                     0                     0                     0

     bi_gol_penjamin__875  _L  _P
0                       1   0   1
1                       1   1   0
2                       1   0   1
3                       1   1   0
4                       1   1   0
..                    …  ..  ..
663                     0   0   1
664                     0   1   0
665                     0   0   1
666                     0   0   1
667                     0   0   1

[668 rows x 15 columns]
```

Lakukan Splitting Data

[9]:
```
predictor = df.loc[:, ~df.columns.isin(['status kredit'])]
target = df['status kredit']

# Splitting into train-test split
xTrain, xTest, yTrain, yTest = train_test_split(predictor, target, test_size=0.
↪3, random_state=33)
print(xTrain.shape, yTrain.shape)
print(xTest.shape, yTest.shape)
```

```
(467, 14) (467,)
(201, 14) (201,)
```

[10]:
```
# Visual Python: Visualization > Seaborn
from collections import Counter

sns.countplot(data=df, x='status kredit')
plt.show()

D = Counter(df['status kredit'])
print(D)
print("MACET = ", D['MACET']*100/(len(df['status kredit'])), '% LANCAR =␣
↪',D['LANCAR']*100/(len(df['status kredit'])) ,'%')
```




```
Counter({'MACET': 461, 'LANCAR': 207})
MACET =  69.0119760479042 % LANCAR =  30.98802395209581 %
```

Logistic Regression

[14]:
```
# Membuat pipeline dengan SimpleImputer dan Logistic Regression
pipeline = make_pipeline(SimpleImputer(strategy='mean'), LogisticRegression())

# Melatih model menggunakan pipeline
pipeline.fit(xTrain, yTrain)

# Melakukan prediksi
prediksi_regLog = pipeline.predict(xTest)

# Evaluasi model
print(confusion_matrix(yTest, prediksi_regLog))
print(classification_report(yTest, prediksi_regLog))
```

```
[[ 54  13]
 [  8 126]]
              precision    recall  f1-score   support
```

```
      LANCAR       0.87      0.81      0.84        67
       MACET       0.91      0.94      0.92       134

    accuracy                           0.90       201
   macro avg       0.89      0.87      0.88       201
weighted avg       0.89      0.90      0.89       201
```

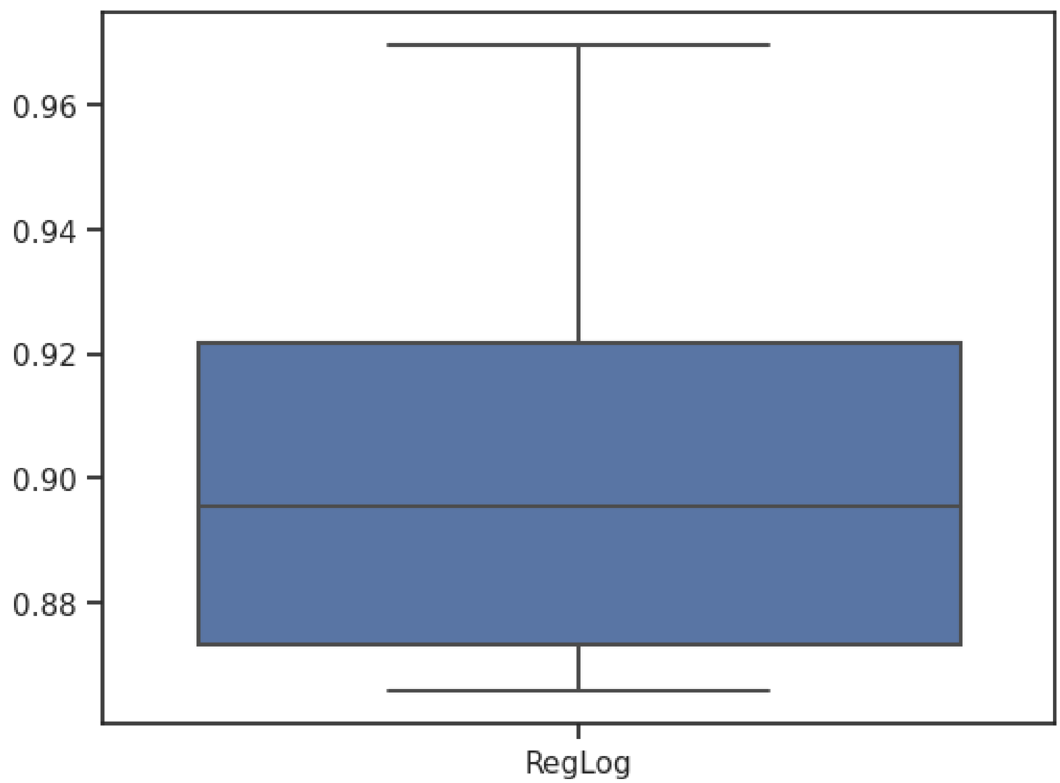
Cross Validation

[16]:
```python
# Mengukur waktu eksekusi
mulai = time.time()

# Menghitung skor cross-validation
scores_regLog = cross_val_score(pipeline, predictor, target, cv=10)

# Mengukur waktu eksekusi
waktu = time.time() - mulai

# Menampilkan hasil
print("Accuracy Regresi Logistik: %0.2f (+/- %0.2f), Waktu = %0.3f detik" %
 ↪(scores_regLog.mean(), scores_regLog.std() * 2, waktu))
```

```
Accuracy Regresi Logistik: 0.90 (+/- 0.07), Waktu = 0.108 detik
```

[17]:
```python
# Visualisasi untuk mengevaluasi & membandingkan model dengan lebih baik lagi
df_ = pd.DataFrame({'RegLog': scores_regLog})
p = sns.boxplot(data = df_)
df_.min()
```

[17]:
```
RegLog    0.865672
dtype: float64
```




```
[21]: # Melatih model menggunakan pipeline
pipeline.fit(predictor, target)

# Mendapatkan koefisien dari model
koefisien_reglog = pipeline.named_steps['logisticregression'].coef_[0]

# Menampilkan koefisien
print("Koefisien Regresi Logistik:", koefisien_reglog)
```

```
Koefisien Regresi Logistik: [ 5.04484881e-09 -7.15361276e-07  2.72062282e-08
-6.21188527e-06
  2.40649782e-07  1.13897425e-05  4.29157191e-06 -1.08412202e-09
  1.52664662e-11  7.35802842e-12  3.67715783e-11  1.08312788e-09
 -2.37741784e-10  2.96143715e-10]
```

Decision Tree

```
[29]: # Decision Tree Algorithm
# Decision Tree: http://scikit-learn.org/stable/modules/tree.html
# Membagi data menjadi data latih dan data uji
xTrain, xTest, yTrain, yTest = train_test_split(predictor, target, test_size=0.
↪2, random_state=42)
```

```
# Menggunakan SimpleImputer untuk mengisi nilai-nilai yang hilang
imputer = SimpleImputer(strategy='mean')
xTrain_imputed = imputer.fit_transform(xTrain)
xTest_imputed = imputer.transform(xTest)

# Membuat dan melatih model DecisionTreeClassifier
DT = DecisionTreeClassifier(random_state=0)
DT.fit(xTrain_imputed, yTrain)

# Melakukan prediksi
prediksi_DT = DT.predict(xTest_imputed)

# Evaluasi model
print(confusion_matrix(yTest, prediksi_DT))
print(classification_report(yTest, prediksi_DT))
```

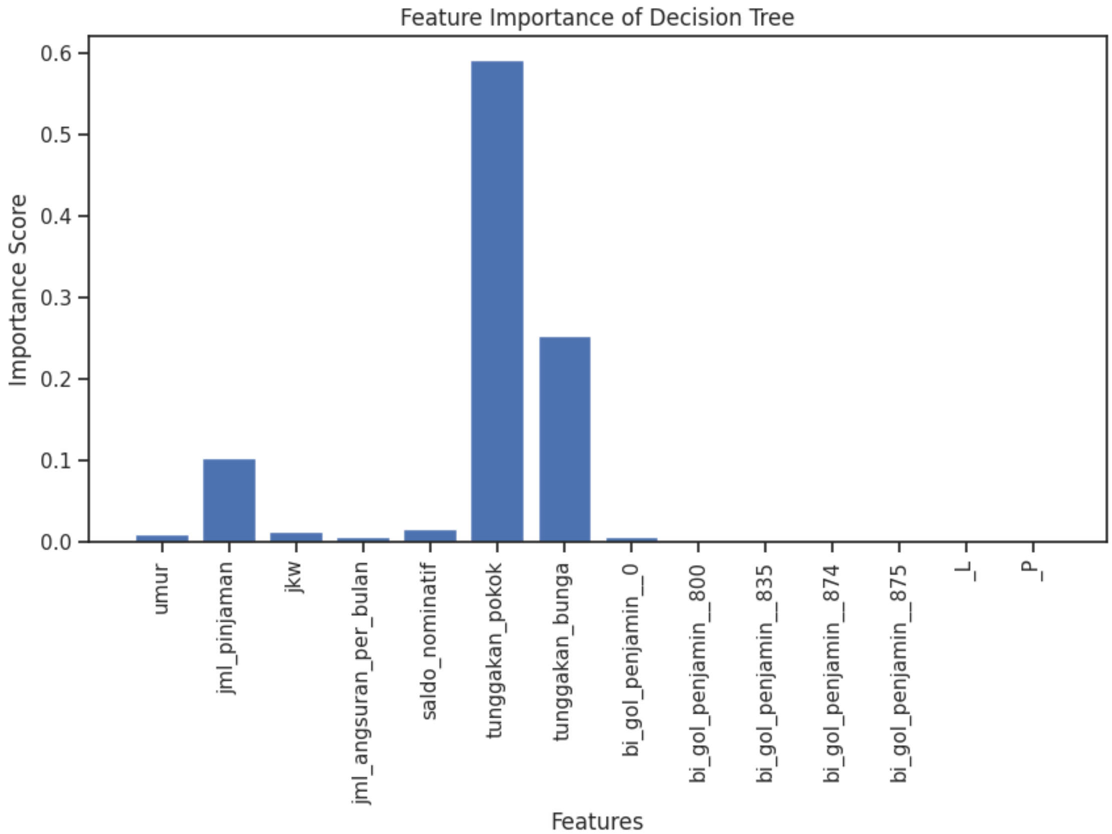
```
[[33  4]
 [ 3 94]]
              precision    recall  f1-score   support

      LANCAR       0.92      0.89      0.90        37
       MACET       0.96      0.97      0.96        97

    accuracy                           0.95       134
   macro avg       0.94      0.93      0.93       134
weighted avg       0.95      0.95      0.95       134
```

[30]:
```
# Varible importance - Salah satu kelebihan Decision Tree
DT.feature_importances_
```

[30]:
```
array([0.00985725, 0.10363044, 0.01368315, 0.00621651, 0.01635083,
       0.5914697 , 0.25303905, 0.00575307, 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        ])
```

[31]:
```
# Assuming your model is fitted, you can access feature importances
feature_importances = DT.feature_importances_

# Assuming you have feature names (replace feature_names with your actual␣
↪feature names)
feature_names = df.drop('status kredit', axis=1).columns

# Visualize the feature importances
plt.figure(figsize=(10, 5))
plt.bar(feature_names, feature_importances)
plt.xlabel('Features')
plt.ylabel('Importance Score')
```

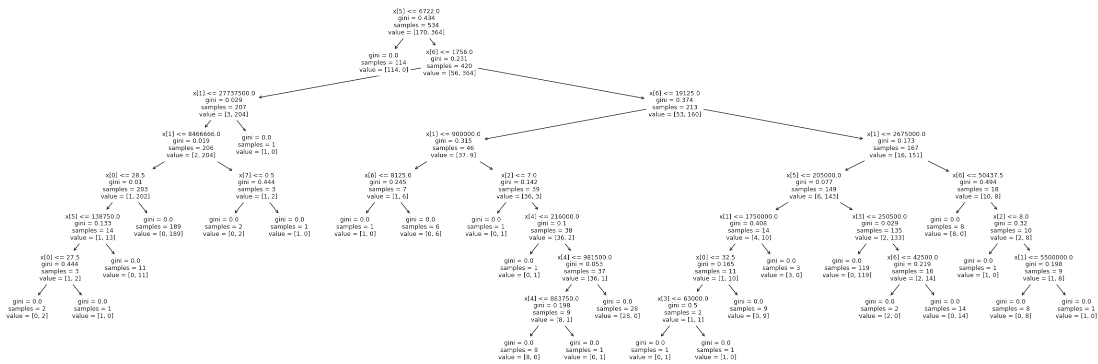
```
plt.title('Feature Importance of Decision Tree')
plt.xticks(rotation=90)
plt.show()
```



[33]:
```
# Membuat pipeline dengan SimpleImputer dan DecisionTreeClassifier
pipeline = make_pipeline(SimpleImputer(strategy='mean'),␣
 ↪DecisionTreeClassifier(random_state=0))

# Menghitung skor cross-validation
mulai = time.time()
scores_dt = cross_val_score(pipeline, predictor, target, cv=10)
waktu = time.time() - mulai

# Menampilkan hasil
print("Accuracy Decision Tree: %0.2f (+/- %0.2f), Waktu = %0.3f detik" %␣
 ↪(scores_dt.mean(), scores_dt.std() * 2, waktu))
```

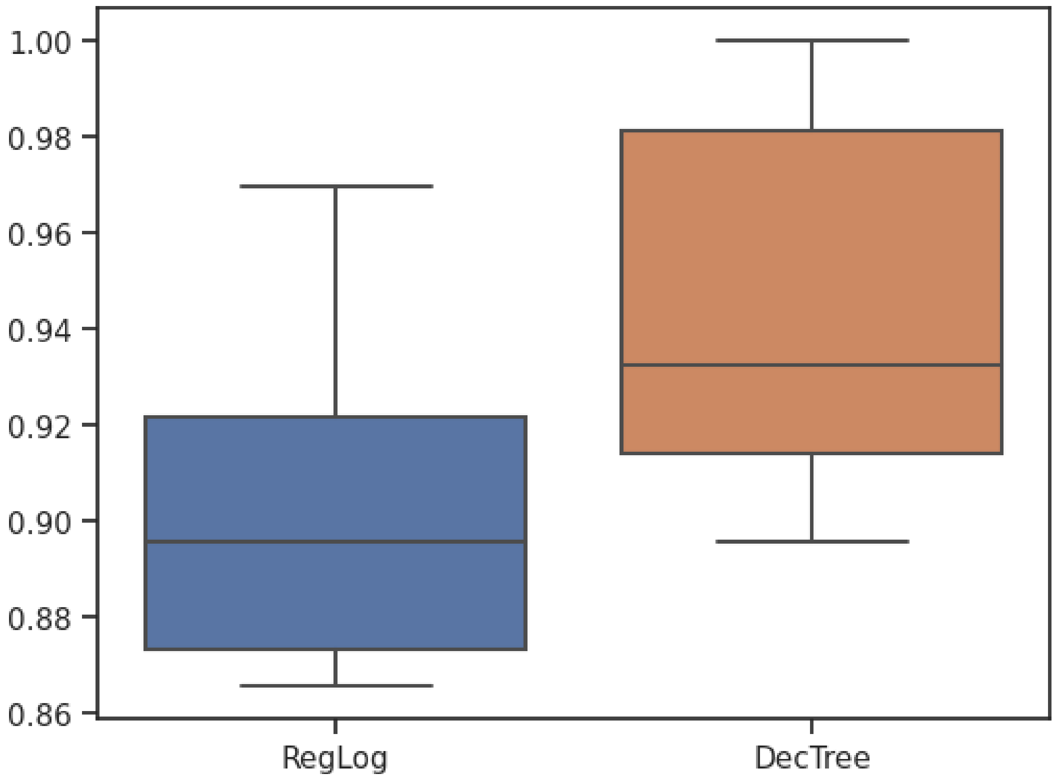
```
Accuracy Decision Tree: 0.94 (+/- 0.08), Waktu = 0.322 detik
```

[35]:
```python
plt.figure(figsize=(30,10))
p = tree.plot_tree(DT)
```



[39]:
```python
# Visualisasi untuk mengevaluasi & membandingkan model dengan lebih baik lagi
df_ = pd.DataFrame({'RegLog': scores_regLog, "DecTree":scores_dt})
p = sns.boxplot(data = df_)

# Menampilkan nilai minimum dari kedua model
print("Minimum Score RegLog:", df_scores['RegLog'].min())
print("Minimum Score DecTree:", df_scores['DecTree'].min())
print("Maximum Score RegLog:", df_scores['RegLog'].max())
print("Maximum Score DecTree:", df_scores['DecTree'].max())
```

```
Minimum Score RegLog: 0.8656716417910447
Minimum Score DecTree: 0.8955223880597015
Maximum Score RegLog: 0.9696969696969697
Maximum Score DecTree: 1.0
```


1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
RegLog
DecTree

```
[ ]:
```