assignment_01

October 15, 2023

1 Assignment #1

[1]:
```
# -*- coding: utf-8 -*-
# ================load library================
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# for spliting data into train and test
from sklearn.model_selection import train_test_split

# load accuracy method
from sklearn.metrics import accuracy_score

# load model method
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis,␣
↪QuadraticDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
# ============================================
```

1.1 1. Titanic

[2]:
```
# ================load dataset================
titanic = pd.read_csv("data/titanic/train.csv")

# select columns to use
titanic = titanic[["Pclass", "Sex", "Age", "SibSp", "Survived"]]
# ============================================
titanic.head()
```

[2]:

	Pclass	Sex	Age	SibSp	Survived
0	3	male	22.0	1	0
1	1	female	38.0	1	1
2	3	female	26.0	0	1
3	1	female	35.0	1	1

```
4       3    male  35.0      0         0
```

[3]:
```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    891 non-null    int64  
 1   Sex       891 non-null    object 
 2   Age       714 non-null    float64
 3   SibSp     891 non-null    int64  
 4   Survived  891 non-null    int64  
dtypes: float64(1), int64(3), object(1)
memory usage: 34.9+ KB
```

[4]:
```
# ===========preprocessing data==============
# convert data type in "Sex" columns from object to int
titanic["Sex"] = titanic["Sex"].map({"male":1, "female":2})

# fill Nan values in "Age" columns
titanic["Age"] = titanic["Age"].fillna(titanic["Age"].mean())

# convert data type in "Age" from float to int
titanic["Age"] = titanic["Age"].astype("int")
# ============================================
titanic.head()
```

[4]:

	Pclass	Sex	Age	SibSp	Survived
0	3	1	22	1	0
1	1	2	38	1	1
2	3	2	26	0	1
3	1	2	35	1	1
4	3	1	35	0	0

[5]:
```
titanic.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Pclass    891 non-null    int64
 1   Sex       891 non-null    int64
 2   Age       891 non-null    int64
 3   SibSp     891 non-null    int64
 4   Survived  891 non-null    int64
```

```
dtypes: int64(5)
memory usage: 34.9 KB
```

[6]:
```
# split dataset into 7:3
X_titanic = titanic.drop(["Survived"], axis=1)
y_titanic = titanic["Survived"]
X_train, X_test, y_train, y_test = train_test_split(X_titanic, y_titanic,␣
 ↪test_size=0.3, random_state=42)
# ============================================
print(f"============ train set ============\nX_train: {X_train.shape}, y_train:␣
 ↪{y_train.shape}")
print(f"============ test  set ============\nX_test:  {X_test.shape}, y_test: ␣
 ↪{y_test.shape}\n===================================")
```

```
============ train set ============
X_train: (623, 4), y_train: (623,)
============ test  set ============
X_test:  (268, 4), y_test:  (268,)
===================================
```

1.1.1 1.1. Logistic Regression

[7]:
```
# ================train model================
# train
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)

# predict
lr_y_train = lr_model.predict(X_train)
lr_y_test = lr_model.predict(X_test)
# ============================================

# =================Accuracy=================
lr_train_acc = round(accuracy_score(y_train, lr_y_train)*100, 2)
lr_acc = round(accuracy_score(y_test, lr_y_test)*100, 2)
# ============================================
print(f"Accuracy of LR train : {lr_train_acc}")
print(f"Accuracy of LR test  : {lr_acc}")
```

```
Accuracy of LR train : 79.29
Accuracy of LR test  : 81.72
```

Interprete Logistic Regression Model

[8]:
```
coef = pd.DataFrame({'Feature': X_train.columns, 'Coefficient': lr_model.
 ↪coef_[0]})
print(f"Logistic Regression Coefficients for Titanic Data:\n{coef}")
```

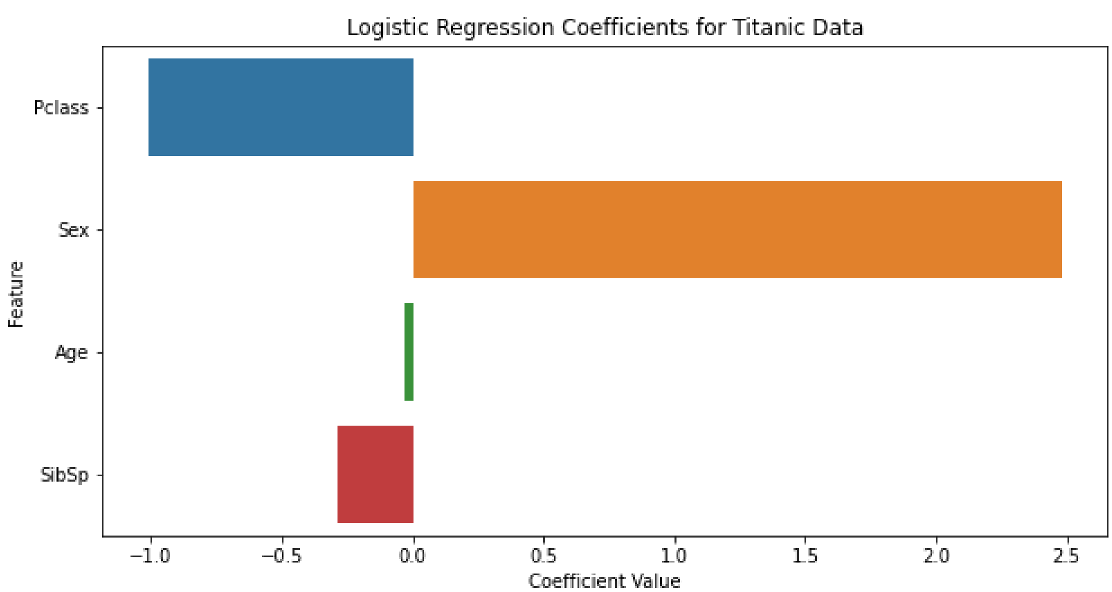
```
Logistic Regression Coefficients for Titanic Data:
  Feature  Coefficient
0  Pclass    -1.012470
1     Sex     2.481025
2     Age    -0.034253
3   SibSp    -0.289395
```

[9]:

```python
plt.figure(figsize=(10, 5))
sns.barplot(x='Coefficient', y='Feature', data=coef, orient='h')
plt.title('Logistic Regression Coefficients for Titanic Data')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()

# In Korean
# print(f"\n- Pclass:           (        )        ")
# print(f"- Sex\t:          (    (1    < 2  ))        ")
# print(f"- Age\t:                  ")
# print(f"- SibSp\t:  ,  ,                  ")

print(f"\n- Pclass: The lower number for class (the higher class), the higher chance of survival")
print(f"- Sex\t: The higher number of your sex (the more likely to be female (1 male < 2 female), the higher chance of survival")
print(f"- Age\t: The younger age, the higher chance of survival")
print(f"- SibSp\t: The lower number of brothers, sisters, and spouses, the higher chance of survival")
```



```
- Pclass: The lower number for class (the higher class), the higher chance of
survival
- Sex   : The higher number of your sex (the more likely to be female (1 male <
2 female), the higher chance of survival
- Age   : The younger age, the higher chance of survival
- SibSp : The lower number of brothers, sisters, and spouses, the higher chance
of survival
```

1.1.2 1.2. LDA

[10]:
```python
# =================train model================
# train
lda_model = LinearDiscriminantAnalysis()
lda_model.fit(X_train, y_train)

# predict
lda_y_train = lda_model.predict(X_train)
lda_y_test = lda_model.predict(X_test)
# ============================================

# ==================Accuracy==================
lda_train_acc = round(accuracy_score(y_train, lda_y_train)*100, 2)
lda_acc = round(accuracy_score(y_test, lda_y_test)*100, 2)
# ============================================
print(f"Accuracy of LDA train : {lda_train_acc}")
print(f"Accuracy of LDA test  : {lda_acc}")
```

```
Accuracy of LDA train : 79.78
Accuracy of LDA test  : 80.6
```

1.1.3 1. 3. QDA

[11]:
```python
# =================train model================
# train
qda_model = QuadraticDiscriminantAnalysis()
qda_model.fit(X_train, y_train)

# predict
qda_y_train = qda_model.predict(X_train)
qda_y_test = qda_model.predict(X_test)
# ============================================

# ==================Accuracy==================
qda_train_acc = round(accuracy_score(y_train, qda_y_train)*100, 2)
qda_acc = round(accuracy_score(y_test, qda_y_test)*100, 2)
# ============================================
print(f"Accuracy of QDA train : {qda_train_acc}")
```

```
print(f"Accuracy of QDA test  : {qda_acc}")
```

```
Accuracy of QDA train : 81.38
Accuracy of QDA test  : 81.72
```

1.1.4 1. 4. Naïve Bayes

[12]:
```
# ================train model================
# train
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

# predict
nb_y_train = nb_model.predict(X_train)
nb_y_test = nb_model.predict(X_test)
# ============================================

# =================Accuracy==================
nb_train_acc = round(accuracy_score(y_train, nb_y_train)*100, 2)
nb_acc = round(accuracy_score(y_test, nb_y_test)*100, 2)
# ============================================
print(f"Accuracy of NB train : {nb_train_acc}")
print(f"Accuracy of NB test  : {nb_acc}")
```

```
Accuracy of NB train : 77.21
Accuracy of NB test  : 77.61
```

1.1.5 Result

[13]:
```
print("================Accuracy==============")
print("Model\t\t\t|Train\t|Test")
print("------------------------|-------|-----")
print(f"Logistic Regression\t|{lr_train_acc}\t|{lr_acc}")
print(f"LDA\t\t\t|{lda_train_acc}\t|{lda_acc}")
print(f"QDA\t\t\t|{qda_train_acc}\t|{qda_acc}")
print(f"Naïve Bayes\t\t|{nb_train_acc}\t|{nb_acc}")
print("======================================")
```

```
================Accuracy==============
Model                   |Train  |Test
------------------------|-------|-----
Logistic Regression     |79.29  |81.72
LDA                     |79.78  |80.6
QDA                     |81.38  |81.72
Naïve Bayes             |77.21  |77.61
======================================
```

1.2 2. Bank Note

[14]:
```
# ================load dataset================
banknote = pd.read_csv("data/banknote.txt", sep=",", header=None)

# rename columns
banknote.columns = ["var.image", "skew.image", "curtosis.imgae", "entropy.
↪image", "class"]

# select columns to use
banknote = banknote[["var.image", "skew.image", "entropy.image", "class"]]
# # ============================================
banknote.head()
```

[14]:

	var.image	skew.image	entropy.image	class
0	3.62160	8.6661	-0.44699	0
1	4.54590	8.1674	-1.46210	0
2	3.86600	-2.6383	0.10645	0
3	3.45660	9.5228	-3.59440	0
4	0.32924	-4.4552	-0.98880	0

[15]:
```
banknote.info() # no need to preprocess
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1372 entries, 0 to 1371
Data columns (total 4 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   var.image      1372 non-null   float64
 1   skew.image     1372 non-null   float64
 2   entropy.image  1372 non-null   float64
 3   class          1372 non-null   int64
dtypes: float64(3), int64(1)
memory usage: 43.0 KB
```

[16]:
```
# split dataset into 7:3
X_banknote = banknote.drop(["class"], axis=1)
y_banknote = banknote["class"]
X_train, X_test, y_train, y_test = train_test_split(X_banknote, y_banknote,␣
↪test_size=0.3, random_state=42)
# ============================================
print(f"============ train set ============\nX_train: {X_train.shape}, y_train:␣
↪{y_train.shape}")
print(f"============ test  set ============\nX_test:  {X_test.shape}, y_test: ␣
↪{y_test.shape}\n===================================")
```

```
============ train set ============
X_train: (960, 3), y_train: (960,)
```

```
============ test  set ============
X_test:  (412, 3), y_test:  (412,)
===================================
```

1.2.1 2.1. Logistic Regression

[17]:
```python
# =================train model=================
# train
lr_model = LogisticRegression()
lr_model.fit(X_train, y_train)

# predict
lr_y_train = lr_model.predict(X_train)
lr_y_test = lr_model.predict(X_test)
# ============================================

# ==================Accuracy==================
lr_train_acc = round(accuracy_score(y_train, lr_y_train)*100, 2)
lr_acc = round(accuracy_score(y_test, lr_y_test)*100, 2)
# ============================================
print(f"Accuracy of LR train : {lr_train_acc}")
print(f"Accuracy of LR test  : {lr_acc}")
```

```
Accuracy of LR train : 87.92
Accuracy of LR test  : 87.62
```

Interprete Logistic Regression

[18]:
```python
coef = pd.DataFrame({'Feature': X_train.columns, 'Coefficient': lr_model.
 ↪coef_[0]})
print(f"Logistic Regression Coefficients for Titanic Data:\n{coef}")
```

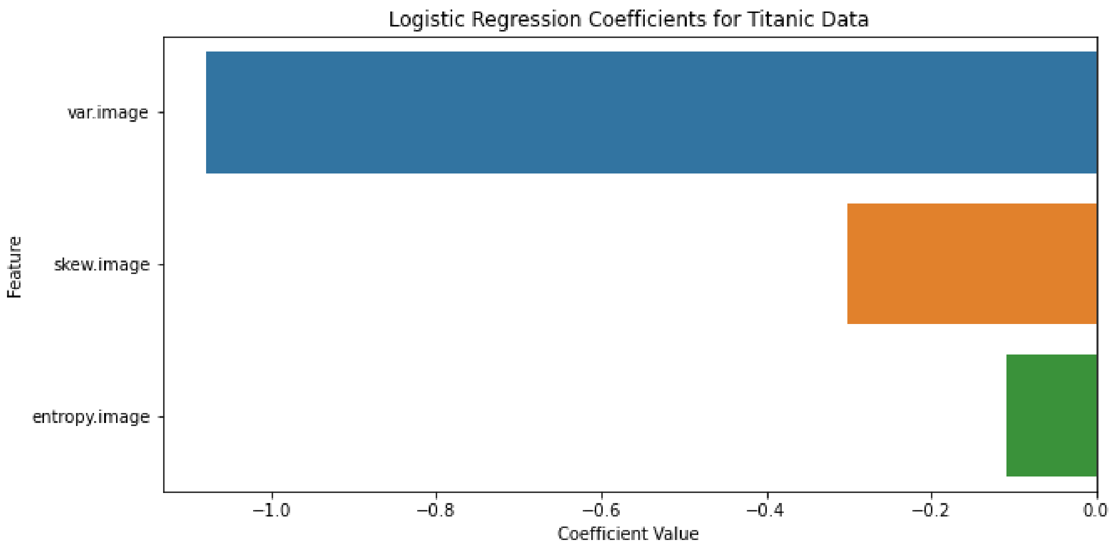
```
Logistic Regression Coefficients for Titanic Data:
         Feature  Coefficient
0      var.image    -1.078808
1     skew.image    -0.301609
2  entropy.image    -0.109653
```

[19]:
```python
plt.figure(figsize=(10, 5))
sns.barplot(x='Coefficient', y='Feature', data=coef, orient='h')
plt.title('Logistic Regression Coefficients for Titanic Data')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()

# In Korean
# print(f"\n- var.image :                    (         )")
# print(f"- skew.image:                    (         )")
```

```
# print(f"- skew.image:                 (         )")

print(f"\n- var.image: the lower variance of the image, the more likely it is␣
↪genuine banknote (less likely it is forged banknote)")
print(f"- skew.image: the lower skew of the image, the more likely it is␣
↪genuine banknote (less likely it is forged banknote)")
print(f"- entropy.image: the lower entropy of the image, the more likely it is␣
↪genuine banknote (less likely it is forged banknote)")
```




```
- var.image: the lower variance of the image, the more likely it is genuine
banknote (less likely it is forged banknote)
- skew.image: the lower skew of the image, the more likely it is genuine
banknote (less likely it is forged banknote)
- entropy.image: the lower entropy of the image, the more likely it is genuine
banknote (less likely it is forged banknote)
```

1.2.2 2.2. LDA

[20]:
```
# ================train model================
# train
lda_model = LinearDiscriminantAnalysis()
lda_model.fit(X_train, y_train)

# predict
lda_y_train = lda_model.predict(X_train)
lda_y_test = lda_model.predict(X_test)
# ==========================================
```

```
# =================Accuracy=================
lda_train_acc = round(accuracy_score(y_train, lda_y_train)*100, 2)
lda_acc = round(accuracy_score(y_test, lda_y_test)*100, 2)
# ============================================
print(f"Accuracy of LDA train : {lda_train_acc}")
print(f"Accuracy of LDA test  : {lda_acc}")
```

```
Accuracy of LDA train : 87.92
Accuracy of LDA test  : 88.35
```

1.2.3 2.3. QDA

[21]:
```
# ================train model================
# train
qda_model = QuadraticDiscriminantAnalysis()
qda_model.fit(X_train, y_train)

# predict
qda_y_train = qda_model.predict(X_train)
qda_y_test = qda_model.predict(X_test)
# ============================================

# =================Accuracy=================
qda_train_acc = round(accuracy_score(y_train, qda_y_train)*100, 2)
qda_acc = round(accuracy_score(y_test, qda_y_test)*100, 2)
# ============================================
print(f"Accuracy of QDA train : {qda_train_acc}")
print(f"Accuracy of QDA test  : {qda_acc}")
```

```
Accuracy of QDA train : 89.17
Accuracy of QDA test  : 89.08
```

1.2.4 2.4. Naïve Bayes

[22]:
```
# ================train model================
# train
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

# predict
nb_y_train = nb_model.predict(X_train)
nb_y_test = nb_model.predict(X_test)
# ============================================

# =================Accuracy=================
nb_train_acc = round(accuracy_score(y_train, nb_y_train)*100, 2)
nb_acc = round(accuracy_score(y_test, nb_y_test)*100, 2)
```

```
# ============================================
print(f"Accuracy of NB train : {nb_train_acc}")
print(f"Accuracy of NB test  : {nb_acc}")
```

```
Accuracy of NB train : 87.71
Accuracy of NB test  : 85.44
```

1.2.5 Result

[23]:
```
print("================Accuracy==============")
print("Model\t\t\t|Train\t|Test")
print("------------------------|-------|-----")
print(f"Logistic Regression\t|{lr_train_acc}\t|{lr_acc}")
print(f"LDA\t\t\t|{lda_train_acc}\t|{lda_acc}")
print(f"QDA\t\t\t|{qda_train_acc}\t|{qda_acc}")
print(f"Naïve Bayes\t\t|{nb_train_acc}\t|{nb_acc}")
print("======================================")
```

```
================Accuracy==============
Model                   |Train  |Test
------------------------|-------|-----
Logistic Regression     |87.92  |87.62
LDA                     |87.92  |88.35
QDA                     |89.17  |89.08
Naïve Bayes             |87.71  |85.44
======================================
```