

task-1

February 22, 2024

1 Churn_Modeling

```
[1]: import pandas as pd
```

```
[2]: import numpy as np
```

```
[4]: pip install --upgrade pandas
```

Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (2.2.0)

Requirement already satisfied: numpy<2,>=1.22.4 in /usr/local/lib/python3.10/dist-packages (from pandas) (1.25.2)

Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas) (2023.4)

Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas) (2024.1)

Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2->pandas) (1.16.0)

```
[5]: pd.__version__
```

```
[5]: '2.2.0'
```

```
[12]: data = pd.read_csv("/content/churn.csv")
```

```
[13]: data
```

```
[13]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	\
0	1	15634602	Hargrave	619	France	Female	42	
1	2	15647311	Hill	608	Spain	Female	41	
2	3	15619304	Onio	502	France	Female	42	
3	4	15701354	Boni	699	France	Female	39	
4	5	15737888	Mitchell	850	Spain	Female	43	
...	
9995	9996	15606229	Obijiaku	771	France	Male	39	

9996	9997	15569892	Johnstone	516	France	Male	35
9997	9998	15584532	Liu	709	France	Female	36
9998	9999	15682355	Sabbatini	772	Germany	Male	42
9999	10000	15628319	Walker	792	France	Female	28

	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
0	2	0.00	1	1	1	
1	1	83807.86	1	0	1	
2	8	159660.80	3	1	0	
3	1	0.00	2	0	0	
4	2	125510.82	1	1	1	
...	
9995	5	0.00	2	1	0	
9996	10	57369.61	1	1	1	
9997	7	0.00	1	0	1	
9998	3	75075.31	2	1	0	
9999	4	130142.79	1	1	0	

	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0
2	113931.57	1
3	93826.63	0
4	79084.10	0
...
9995	96270.64	0
9996	101699.77	0
9997	42085.58	1
9998	92888.52	1
9999	38190.78	0

[10000 rows x 14 columns]

```
[14]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
#   Column          Non-Null Count  Dtype
---  -
0   RowNumber       10000 non-null  int64
1   CustomerId      10000 non-null  int64
2   Surname         10000 non-null  object
3   CreditScore     10000 non-null  int64
4   Geography       10000 non-null  object
5   Gender          10000 non-null  object
6   Age            10000 non-null  int64
```

```

7   Tenure          10000 non-null  int64
8   Balance          10000 non-null  float64
9   NumOfProducts    10000 non-null  int64
10  HasCrCard         10000 non-null  int64
11  IsActiveMember    10000 non-null  int64
12  EstimatedSalary   10000 non-null  float64
13  Exited            10000 non-null  int64
dtypes: float64(2), int64(9), object(3)
memory usage: 1.1+ MB

```

```
[15]: data.duplicated().sum()
```

```
[15]: 0
```

```
[16]: data.head()
```

```
[16]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	\
0	1	15634602	Hargrave	619	France	Female	42	
1	2	15647311	Hill	608	Spain	Female	41	
2	3	15619304	Onio	502	France	Female	42	
3	4	15701354	Boni	699	France	Female	39	
4	5	15737888	Mitchell	850	Spain	Female	43	

	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
0	2	0.00	1	1	1	
1	1	83807.86	1	0	1	
2	8	159660.80	3	1	0	
3	1	0.00	2	0	0	
4	2	125510.82	1	1	1	

	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0
2	113931.57	1
3	93826.63	0
4	79084.10	0

```
[17]: data.head(2)
```

```
[17]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	\
0	1	15634602	Hargrave	619	France	Female	42	
1	2	15647311	Hill	608	Spain	Female	41	

	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
0	2	0.00	1	1	1	
1	1	83807.86	1	0	1	

	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0

```
[18]: data.shape
```

```
[18]: (10000, 14)
```

```
[19]: data['Gender'].unique()
```

```
[19]: array(['Female', 'Male'], dtype=object)
```

```
[20]: data["Geography"].unique()
```

```
[20]: array(['France', 'Spain', 'Germany'], dtype=object)
```

```
[21]: data['Gender']
```

```
[21]: 0      Female
      1      Female
      2      Female
      3      Female
      4      Female
      ...
      9995    Male
      9996    Male
      9997    Female
      9998    Male
      9999    Female
      Name: Gender, Length: 10000, dtype: object
```

```
[22]: data['Gender'].value_counts()
```

```
[22]: Gender
      Male      5457
      Female  4543
      Name: count, dtype: int64
```

```
[23]: data.dtypes
```

```
[23]: RowNumber      int64
      CustomerId    int64
      Surname       object
      CreditScore    int64
      Geography     object
      Gender        object
      Age           int64
```

```

Tenure          int64
Balance         float64
NumOfProducts  int64
HasCrCard       int64
IsActiveMember int64
EstimatedSalary float64
Exited          int64
dtype: object

```

```
[24]: data.describe()
```

```

[24]:      RowNumber  CustomerId  CreditScore      Age      Tenure  \
count  10000.00000  1.000000e+04  10000.000000  10000.000000  10000.000000
mean    5000.50000  1.569094e+07   650.528800   38.921800    5.012800
std     2886.89568  7.193619e+04    96.653299   10.487806    2.892174
min         1.00000  1.556570e+07   350.000000   18.000000    0.000000
25%     2500.75000  1.562853e+07   584.000000   32.000000    3.000000
50%     5000.50000  1.569074e+07   652.000000   37.000000    5.000000
75%     7500.25000  1.575323e+07   718.000000   44.000000    7.000000
max    10000.00000  1.581569e+07   850.000000   92.000000   10.000000

      Balance  NumOfProducts  HasCrCard  IsActiveMember  \
count  10000.000000  10000.000000  10000.000000  10000.000000
mean    76485.889288    1.530200    0.70550    0.515100
std     62397.405202    0.581654    0.45584    0.499797
min         0.000000    1.000000    0.00000    0.000000
25%         0.000000    1.000000    0.00000    0.000000
50%     97198.540000    1.000000    1.00000    1.000000
75%    127644.240000    2.000000    1.00000    1.000000
max    250898.090000    4.000000    1.00000    1.000000

      EstimatedSalary  Exited
count  10000.000000  10000.000000
mean    100090.239881    0.203700
std     57510.492818    0.402769
min         11.580000    0.000000
25%     51002.110000    0.000000
50%    100193.915000    0.000000
75%    149388.247500    0.000000
max    199992.480000    1.000000

```

```
[25]: columns_to_drop = ['RowNumber', 'CustomerId', 'Surname']
```

```
[26]: data
```

```

[26]:      RowNumber  CustomerId  Surname  CreditScore  Geography  Gender  Age  \
0           1    15634602  Hargrave         619      France  Female  42

```

1	2	15647311	Hill	608	Spain	Female	41
2	3	15619304	Onio	502	France	Female	42
3	4	15701354	Boni	699	France	Female	39
4	5	15737888	Mitchell	850	Spain	Female	43
...
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9997	9998	15584532	Liu	709	France	Female	36
9998	9999	15682355	Sabbatini	772	Germany	Male	42
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...
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	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0
2	113931.57	1
3	93826.63	0
4	79084.10	0
...
9995	96270.64	0
9996	101699.77	0
9997	42085.58	1
9998	92888.52	1
9999	38190.78	0

[10000 rows x 14 columns]

2 Logistic Regression

```
[27]: from sklearn.preprocessing import LabelEncoder
```

```
[28]: labelencoder = LabelEncoder()
data['Geography'] = labelencoder.fit_transform(data['Geography'])
data['Gender'] = labelencoder.fit_transform(data['Gender'])
```

```
[29]: data
```

```
[29]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	\
0	1	15634602	Hargrave	619	0	0	42	
1	2	15647311	Hill	608	2	0	41	
2	3	15619304	Onio	502	0	0	42	
3	4	15701354	Boni	699	0	0	39	
4	5	15737888	Mitchell	850	2	0	43	
...	
9995	9996	15606229	Obijiaku	771	0	1	39	
9996	9997	15569892	Johnstone	516	0	1	35	
9997	9998	15584532	Liu	709	0	0	36	
9998	9999	15682355	Sabbatini	772	1	1	42	
9999	10000	15628319	Walker	792	0	0	28	

	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	\
0	2	0.00	1	1	1	
1	1	83807.86	1	0	1	
2	8	159660.80	3	1	0	
3	1	0.00	2	0	0	
4	2	125510.82	1	1	1	
...	
9995	5	0.00	2	1	0	
9996	10	57369.61	1	1	1	
9997	7	0.00	1	0	1	
9998	3	75075.31	2	1	0	
9999	4	130142.79	1	1	0	

	EstimatedSalary	Exited
0	101348.88	1
1	112542.58	0
2	113931.57	1
3	93826.63	0
4	79084.10	0
...
9995	96270.64	0
9996	101699.77	0
9997	42085.58	1
9998	92888.52	1
9999	38190.78	0

```
[10000 rows x 14 columns]
```

```
[30]: X=data.drop('Exited', axis=1)
      y=data['Exited']
```

```
[31]: y
```

```
[31]: 0      1
      1      0
      2      1
      3      0
      4      0
      ..
      9995    0
      9996    0
      9997    1
      9998    1
      9999    0
      Name: Exited, Length: 10000, dtype: int64
```

```
[34]: from sklearn.model_selection import train_test_split
```

```
[35]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
      ↪random_state=0)
```

```
[36]: X_train.shape
```

```
[36]: (8000, 13)
```

```
[37]: y_train.shape
```

```
[37]: (8000,)
```

```
[38]: X_test.shape
```

```
[38]: (2000, 13)
```

```
[39]: y_test.shape
```

```
[39]: (2000,)
```

```
[45]: from sklearn.linear_model import LogisticRegression
```

```
[46]: X_encoded = pd.get_dummies(X)
      X_train_encoded, X_test_encoded, y_train, y_test = train_test_split(X_encoded,
      ↪y, test_size=0.2, random_state=0)
      logreg.fit(X_train_encoded, y_train)
```

```
[46]: LogisticRegression()
```

```
[54]: X_test_aligned = X_test.reindex(columns=X_train_encoded.columns, fill_value=0)
      y_pred = logreg.predict(X_test_aligned)
```

```
[55]: y_pred
```



```
[55]: array([0, 0, 0, ..., 0, 0, 0])
```

```
[56]: X_test_aligned = X_test.reindex(columns=X_train_encoded.columns, fill_value=0)
      print("Accuracy: ", logreg.score(X_test_aligned, y_test))
```

Accuracy: 0.7975

3 Accuracy of Logistic Regression Classifier is 0.79.

```
[ ]:
```