eda

December 10, 2025

1 Ursprung der Daten

Titanic Datensatz von kaggle heruntergeladen am 21.11.2025 um 19:22 Uhr.

2 Imports

[32]:
```
%matplotlib inline

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import joblib
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve,␣
↪roc_auc_score
```

3 Daten laden und erste Eindrücke sammeln

[33]:
```
df = pd.read_csv("./data/Titanic-Dataset.csv")
```

3.1 Head

[34]:
```
df.head()
```

[34]:
```
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
```

```
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

3.2 Info

[35]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

3.3 Describe

[36]:
```python
df.describe()
```

[36]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
```

```
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

3.4 Unique Values

[37]:
```
df.nunique().sort_values()
```

[37]:
```
Survived         2
Sex              2
Pclass           3
Embarked         3
SibSp            7
Parch            7
Age             88
Cabin          147
Fare           248
Ticket         681
PassengerId    891
Name           891
dtype: int64
```

3.5 Erkenntnisse aus den ersten Eindrücken

- bei Cabin fehlen zu viele Daten.
- bei Ticket, PassengerId und Name gibt es zu viele unterschiedliche Daten
- bei Age gibt es 177 Null-Werte
- Sex und Embarked müss encoded werden

4 Datenbereinigung

4.1 Cabin, Ticket, PassengerId und Name entfernen

[38]:
```
df.drop(columns=["PassengerId", "Name", "Cabin", "Ticket"], axis=1,␣
 ↪inplace=True)
```

4.2 Null-Werte bei Age mit dem Durchschnitt auffüllen

4.2.1 Verteilung des Alters

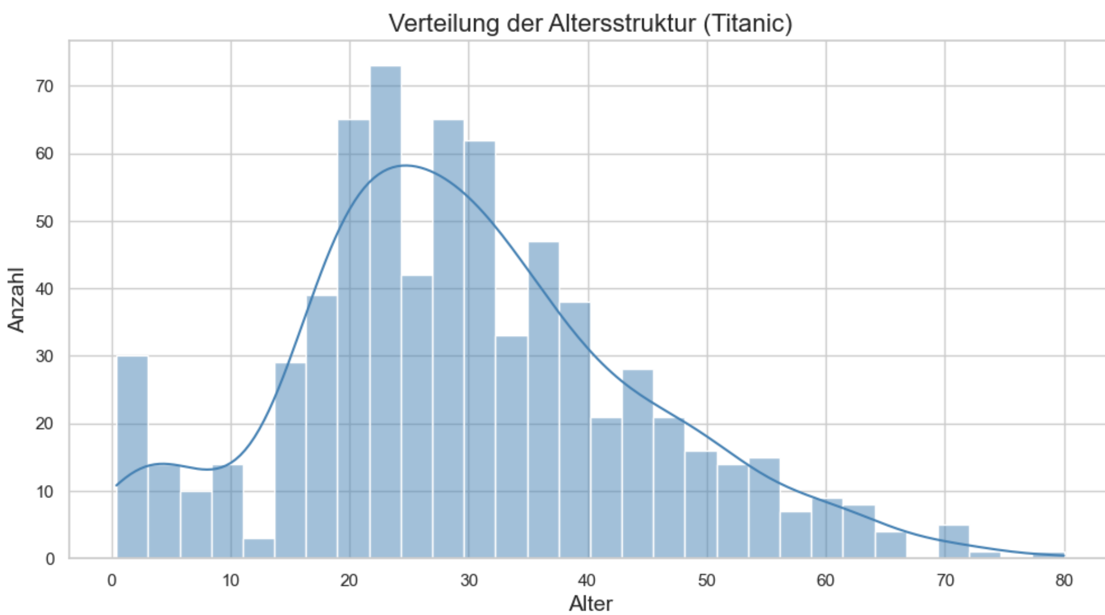
[39]:
```
sns.set(style="whitegrid")

plt.figure(figsize=(12, 6))

sns.histplot(df["Age"], bins=30, kde=True, color="steelblue")

plt.title("Verteilung der Altersstruktur (Titanic)", fontsize=16)
plt.xlabel("Alter", fontsize=14)
plt.ylabel("Anzahl", fontsize=14)

plt.show()
print(f"Durchschnittsalter {df['Age'].mean()}")
print(f"Median-Alter {df['Age'].median()}")
```




```
Durchschnittsalter 29.69911764705882
Median-Alter 28.0
```

Durchschnittsalter und Median sind ähnlich hoch, der Median wird nun aber bevorzugt verwendet, da dieser die Ausreißer kompensieren soll.

[40]:
```
df['Age'] = df['Age'].fillna(df['Age'].median())
```

4.3 Encoding vom Sex

[41]:
```
df['Sex'] = df['Sex'].map({'male': 0, 'female': 1})
```

4.4 Auffüllen und Encoding von Embarked (Abfahrtsort)

4.4.1 Null-Werte werden mit den am häufigsten vorkommendem Wert aufgefüllt

[42]:
```
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
```

4.4.2 One-Hot-Encoding

Aus der Spalte 'Embarked' werden die binären Spalten 'Embarked_S' und 'Embarked_Q'. Der Abfahrtsort C wird abgeleitet und trifft dann zu, wenn 'Embarked_S' und 'Embarked_Q' beide 0 sind.

[43]:
```
df = pd.get_dummies(df, columns=['Embarked'], drop_first=True)
```

5 Daten nach der Bereinigung

5.1 Head

[44]:
```
df.head()
```

[44]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked_Q	Embarked_S
0	0	3	0	22.0	1	0	7.2500	False	True
1	1	1	1	38.0	1	0	71.2833	False	False
2	1	3	1	26.0	0	0	7.9250	False	True
3	1	1	1	35.0	1	0	53.1000	False	True
4	0	3	0	35.0	0	0	8.0500	False	True

5.2 Info

[45]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Survived    891 non-null    int64
 1   Pclass      891 non-null    int64
 2   Sex         891 non-null    int64
 3   Age         891 non-null    float64
 4   SibSp       891 non-null    int64
 5   Parch       891 non-null    int64
 6   Fare        891 non-null    float64
 7   Embarked_Q  891 non-null    bool
 8   Embarked_S  891 non-null    bool
```

```
dtypes: bool(2), float64(2), int64(5)
memory usage: 50.6 KB
```

6 Train-Test-Split

[46]:
```
X = df.drop(columns=["Survived"])
y = df['Survived']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

7 Modell-Auswahl und Training

Bei dem Datensatz soll eine Klassifikation vorgenommen werden, daher eignet sich beispielsweise Logistische Regression

[47]:
```
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
```

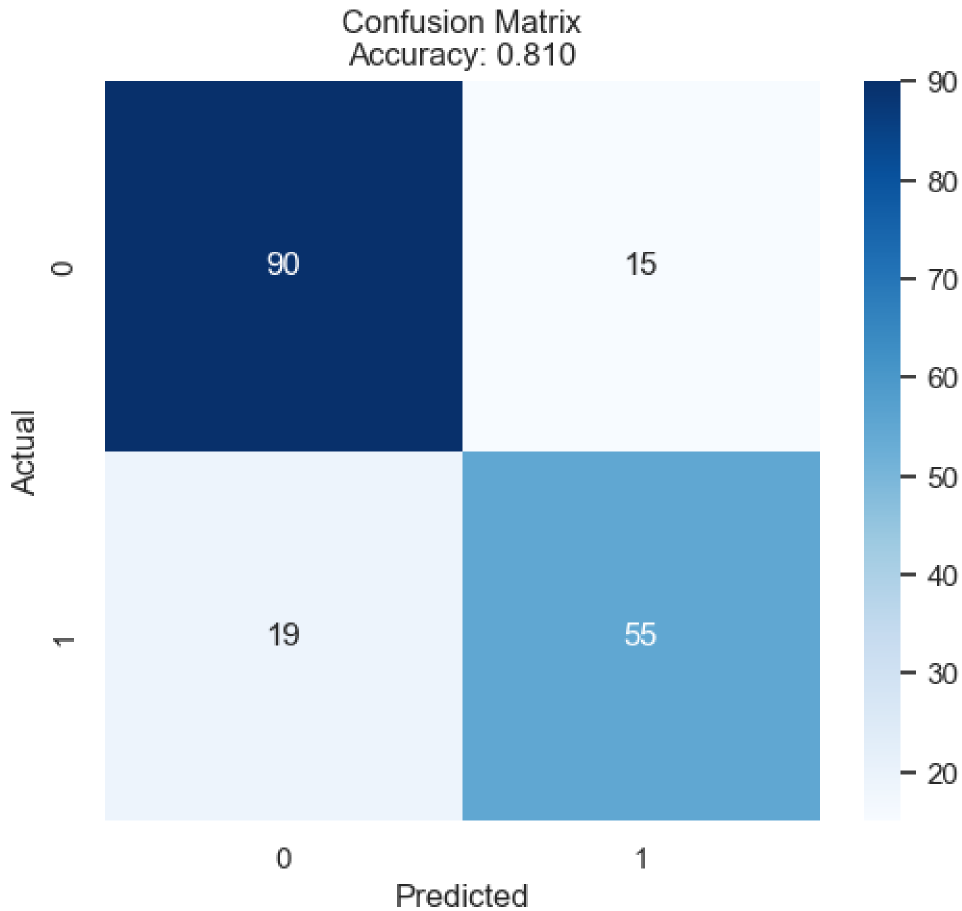
[47]:
```
LogisticRegression(max_iter=1000)
```

8 Metriken

[48]:
```
y_pred = model.predict(X_test)
acc = accuracy_score(y_test, y_pred)
```

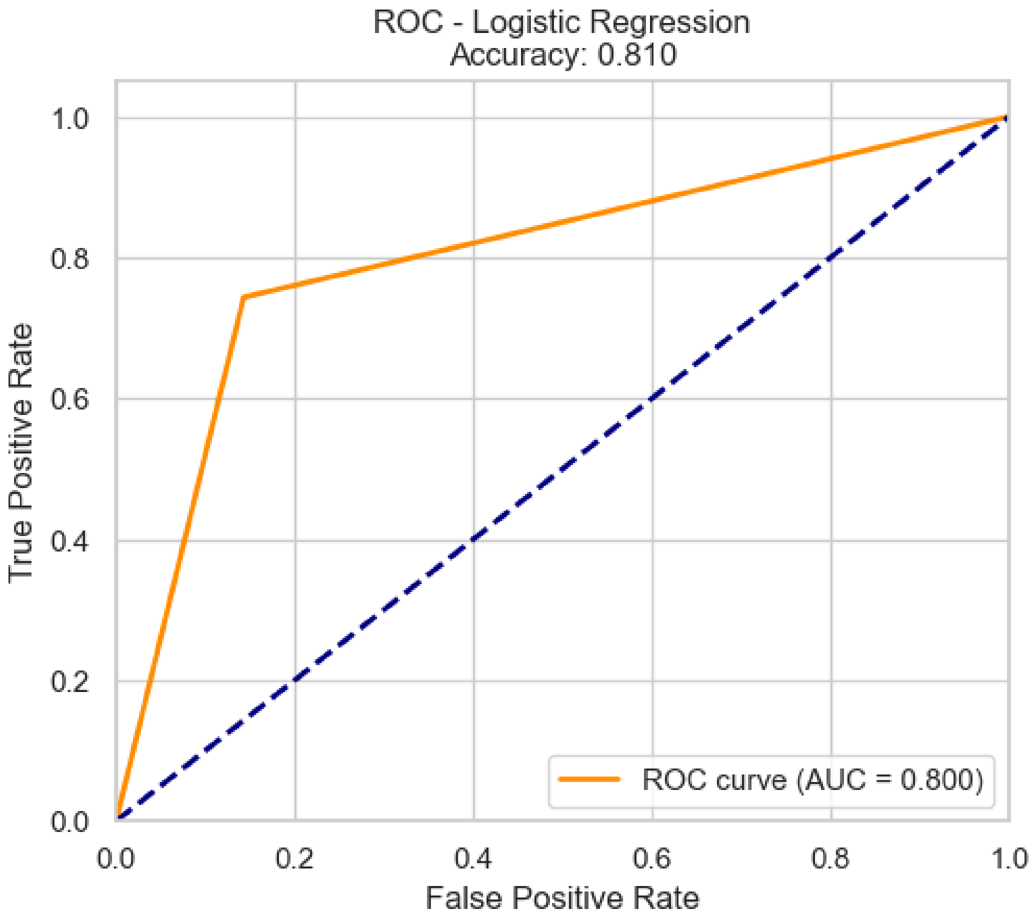
8.1 Confusion Matrix

[49]:
```
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title(f'Confusion Matrix\nAccuracy: {acc:.3f}')
plt.savefig('./data/confusion_matrix.png', bbox_inches='tight')
plt.show()
```



9 ROC

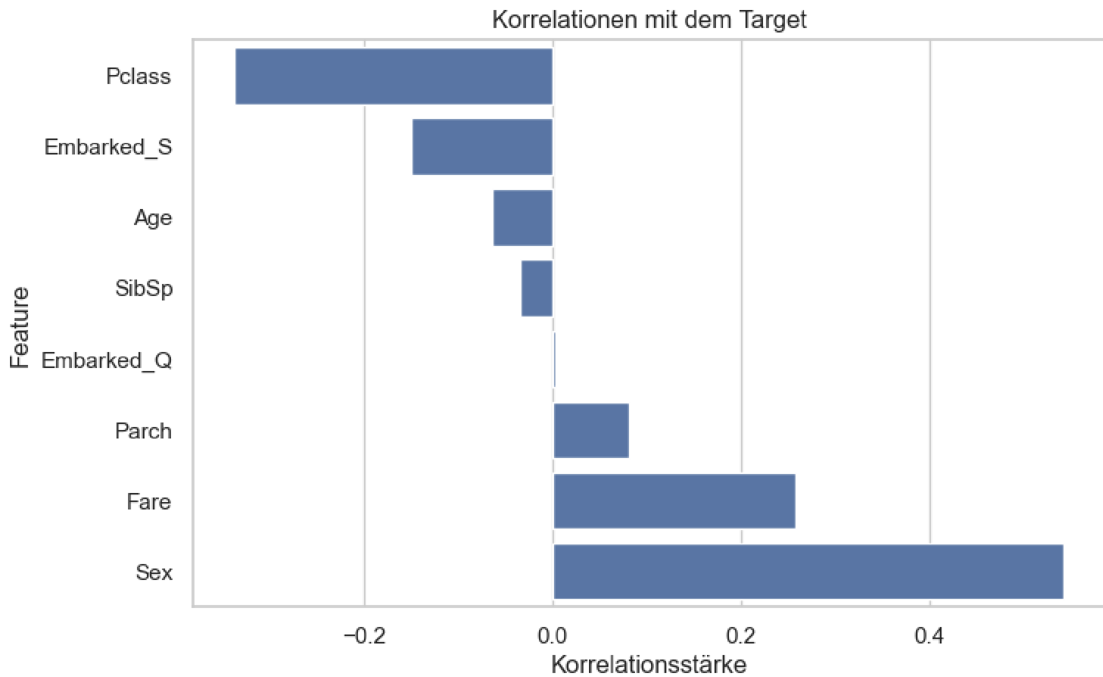
[50]:
```
roc_auc = roc_auc_score(y_test, y_pred)
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
 ↪3f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(f'ROC - Logistic Regression\nAccuracy: {acc:.3f}')
plt.legend(loc="lower right")
plt.savefig('./data/roc_curve.png', bbox_inches='tight')
plt.show()
```



9.1 Korrelationen

[51]:
```
corr = df.corr()["Survived"].drop("Survived").sort_values()

plt.figure(figsize=(8, 5))
sns.barplot(x=corr.values, y=corr.index)
plt.title("Korrelationen mit dem Target")
plt.xlabel("Korrelationsstärke")
plt.ylabel("Feature")
plt.savefig('./data/correlations.png', bbox_inches='tight')
plt.show()
```



10 Modell speichern

[52]:
```
joblib.dump(model, "./data/model.pkl")
joblib.dump(X.columns, "./data/feature_names.pkl")
```

[52]: ['./data/feature_names.pkl']