# Predicting Titanic Survival

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A step-by-step machine learning journey using Kaggle's Titanic dataset, guided by ChatGPT, following the CRISP-DM data science framework.

## Introduction

In this project, I used Kaggle's Titanic dataset to predict passenger survival. With the help of ChatGPT and the CRISP-DM framework, I explored the data, prepared it, trained machine learning models, and compared their performance. The goal was not only to build a predictive model but also to learn how AI tools like ChatGPT can guide the entire data science process.

```
import pandas as pd

df = pd.read_csv('/content/train.csv')

df.head()
```

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S |
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 | C85 | C |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 | NaN | S |

Next steps: Generate code with df View recommended plots New interactive sheet

## Data Understanding

The dataset includes demographic, ticket, and travel details such as class, sex, age, fare, and cabin. Some columns contain missing values.

```python
df.info()

df.describe(include='all').T.head(15)
```

```
<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
```

| | count | unique | top | freq | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PassengerId | 891.0 | NaN | NaN | NaN | 446.0 | 257.353842 | 1.0 | 223.5 | 446.0 | 668.5 | 891.0 |
| Survived | 891.0 | NaN | NaN | NaN | 0.383838 | 0.486592 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| Pclass | 891.0 | NaN | NaN | NaN | 2.308642 | 0.836071 | 1.0 | 2.0 | 3.0 | 3.0 | 3.0 |
| Name | 891 | 891 | Dooley, Mr. Patrick | 1 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Sex | 891 | 2 | male | 577 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Age | 714.0 | NaN | NaN | NaN | 29.699118 | 14.526497 | 0.42 | 20.125 | 28.0 | 38.0 | 80.0 |
| SibSp | 891.0 | NaN | NaN | NaN | 0.523008 | 1.102743 | 0.0 | 0.0 | 0.0 | 1.0 | 8.0 |
| Parch | 891.0 | NaN | NaN | NaN | 0.381594 | 0.806057 | 0.0 | 0.0 | 0.0 | 0.0 | 6.0 |
| Ticket | 891 | 681 | 347082 | 7 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Fare | 891.0 | NaN | NaN | NaN | 32.204208 | 49.693429 | 0.0 | 7.9104 | 14.4542 | 31.0 | 512.3292 |
| Cabin | 204 | 147 | G6 | 4 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Embarked | 889 | 3 | S | 644 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

```
missing = df.isna().mean().sort_values(ascending=False)
missing.head(15)
```

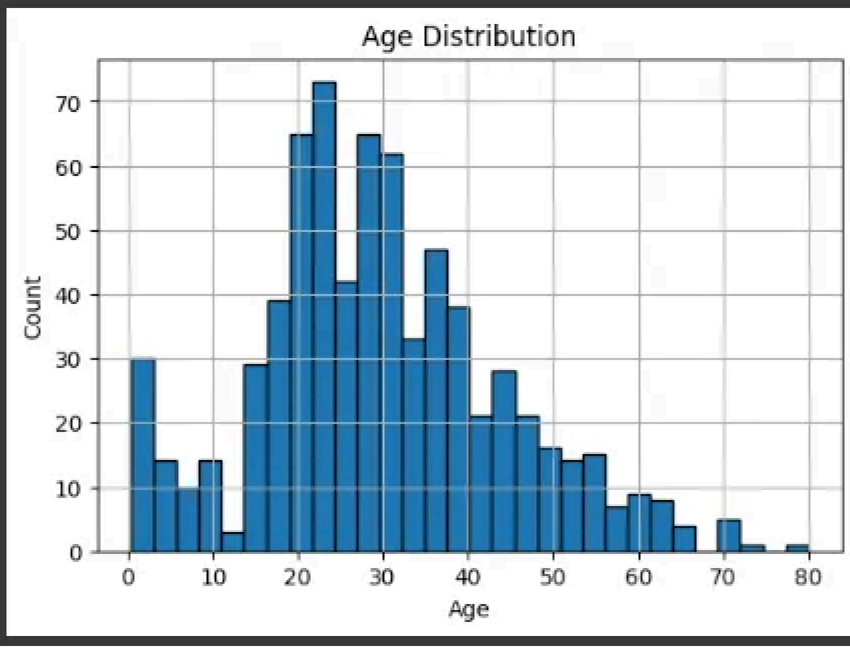
| | 0 |
|---|---|
| Cabin | 0.771044 |
| Age | 0.198653 |
| Embarked | 0.002245 |
| PassengerId | 0.000000 |
| Name | 0.000000 |
| Pclass | 0.000000 |
| Survived | 0.000000 |
| Sex | 0.000000 |
| Parch | 0.000000 |
| SibSp | 0.000000 |
| Fare | 0.000000 |
| Ticket | 0.000000 |

**dtype:** float64

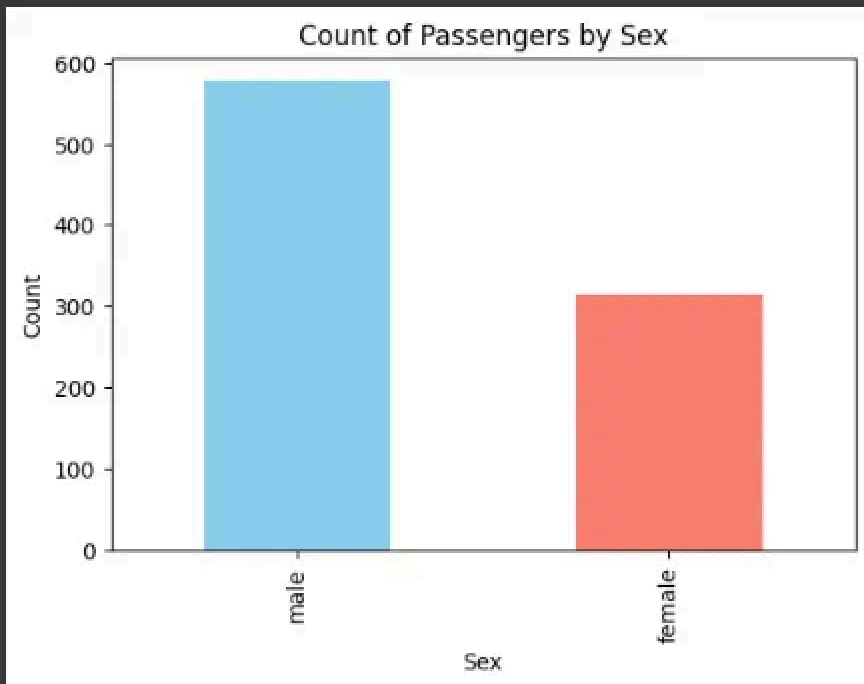
## Exploratory Data Analysis (EDA)

To better understand patterns, I plotted distributions:

```
import matplotlib.pyplot as plt

plt.figure(figsize=(6,4))
df['Age'].hist(bins=30, edgecolor='black')
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



```
plt.figure(figsize=(6,4))
df['Sex'].value_counts().plot(kind='bar', color=['skyblue','salmon'])
plt.title('Count of Passengers by Sex')
plt.xlabel('Sex')
plt.ylabel('Count')
plt.show()
```




Majority of passengers were male. Age distribution is right-skewed, with many young adults.

### Data Preparation

I dropped text-heavy columns (Name, Ticket, Cabin) and split the data into training and test sets (80/20).

```
from sklearn.model_selection import train_test_split


drop_cols = ['PassengerId', 'Name', 'Ticket', 'Cabin']
df_model = df.drop(columns=drop_cols, errors='ignore')

X = df_model.drop(columns=['Survived'])
y = df_model['Survived']

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

len(X_train), len(X_test)
```

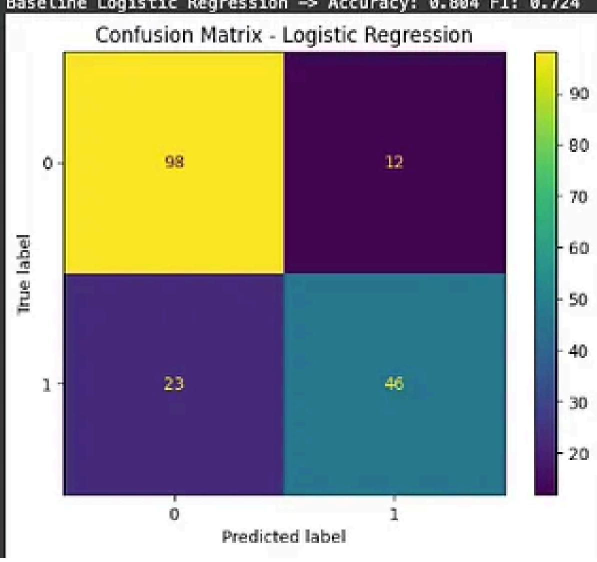
```
(712, 179)
```

## Baseline Model — Logistic Regression

I built a pipeline with imputation, scaling, and one-hot encoding, then trained a Logistic Regression model.

```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, ConfusionMatrixDisplay
import matplotlib.pyplot as plt


num_cols = X.select_dtypes(include='number').columns.tolist()
cat_cols = [c for c in X.columns if c not in num_cols]

numeric = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler())
])

categorical = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])

preprocessor = ColumnTransformer([
    ('num', numeric, num_cols),
    ('cat', categorical, cat_cols)
])

clf_lr = Pipeline([
    ('preprocessor', preprocessor),
    ('model', LogisticRegression(max_iter=1000))
])

clf_lr.fit(X_train, y_train)


y_pred = clf_lr.predict(X_test)


acc = accuracy_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

ConfusionMatrixDisplay.from_estimator(clf_lr, X_test, y_test)
plt.title("Confusion Matrix - Logistic Regression")
plt.show()
```

```
Baseline Logistic Regression -> Accuracy: 0.804 F1: 0.724
```




## Tuned Model — Random Forest

I trained a Random Forest with GridSearchCV to tune parameters.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

rf_pipe = Pipeline([
    ('preprocessor', preprocessor),
    ('model', RandomForestClassifier(random_state=42))
])

param_grid = {
    'model__n_estimators': [100, 200],
    'model__max_depth': [None, 5, 10],
    'model__min_samples_split': [2, 5]
}

grid = GridSearchCV(rf_pipe, param_grid, cv=3, n_jobs=-1, scoring='accuracy')
grid.fit(X_train, y_train)

best_rf = grid.best_estimator_
y_pred_rf = best_rf.predict(X_test)

acc_rf = accuracy_score(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)
print("Best Params:", grid.best_params_)
print("RandomForest -> Accuracy:", round(acc_rf,3), "F1:", round(f1_rf,3))
```

```
Best Params: {'model__max_depth': 10, 'model__min_samples_split': 5, 'model__n_estimators': 100}
RandomForest -> Accuracy: 0.81 F1: 0.726
```

## Feature Importance

Random Forest highlighted the most influential predictors of survival.

```
import numpy as np

best = best_rf

ohe = best.named_steps['preprocessor'].named_transformers_['cat'].named_steps['encoder']
num_names = X.select_dtypes(include='number').columns.tolist()
cat_names = list(ohe.get_feature_names_out([c for c in X.columns if c not in num_names]))
feature_names = num_names + cat_names

importances = best.named_steps['model'].feature_importances_
top_idx = np.argsort(importances)[::-1][:10]

print("Top 10 features:")
for i in top_idx:
    print(f"{feature_names[i]:25s} {importances[i]:.4f}")
```

```
Top 10 features:
Fare                      0.2127
Sex_male                  0.1980
Age                       0.1786
Sex_female                0.1738
Pclass                    0.1104
SibSp                     0.0454
Parch                     0.0415
Embarked_S                0.0182
Embarked_C                0.0128
Embarked_Q                0.0084
```

## Model Comparison

```
def summarize_models():
    print("Summary:")
    print(f"- LogisticRegression: acc={acc:.3f}, f1={f1:.3f}")
    print(f"- RandomForest (tuned): acc={acc_rf:.3f}, f1={f1_rf:.3f}")
    winner = "RandomForest" if acc_rf > acc else "LogisticRegression"
    print(f"Winner: {winner}")

summarize_models()
```

```
Summary:
- LogisticRegression: acc=0.804, f1=0.724
- RandomForest (tuned): acc=0.810, f1=0.726
Winner: RandomForest
```

### Key Takeaways

Being female, younger, and in 1st class improved survival chances.
Fare was a strong predictor.
A tuned Random Forest outperformed Logistic Regression.

### Limitations & Next Steps

Could add feature engineering (e.g., titles from names, family size)
Try advanced models like XGBoost or deep learning
Perform fairness analysis across subgroups.

### Conclusion

This project showed how the CRISP-DM framework and ChatGPT can guide the entire data science process. From understanding the dataset to preparing the data, building baseline and tuned models, and extracting insights, ChatGPT helped me stay organized and efficient. Random Forest emerged as the best model, and the approach can be extended to more complex datasets.

## Written by Siddharth Rao Kartik

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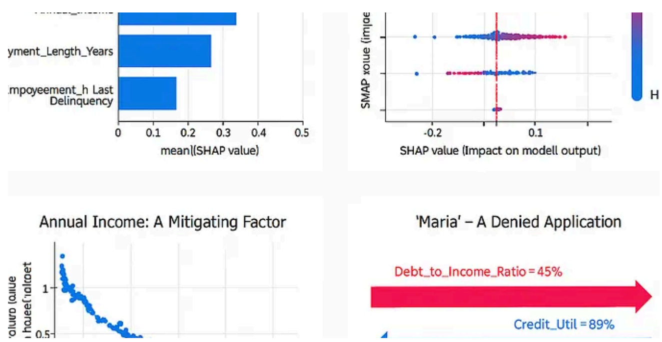


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