

# Titanic Survival Prediction Model Deployment with Flask

Name: Deployment on Flask (Titanic Survival Prediction Model Deployment with Flask)

Report date: 2025.02.26

Internship Batch: LISUM42

Version: 1.0

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## Titanic Tabular data details:

|                                     |        |
|-------------------------------------|--------|
| <b>Total number of observations</b> | 891    |
| <b>Total number of files</b>        | 1      |
| <b>Total number of features</b>     | 12     |
| <b>Base format of the file</b>      | .csv   |
| <b>Size of the data</b>             | 83.7KB |

## Dataset Selection

The dataset chosen for this task is the Titanic dataset, which contains passenger details and survival status. The goal is to build a model that predicts whether a passenger survived or not based on their Pclass, Gender, Age, and Fare.

# Import Libraries

```
: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
import numpy as np
from flask import Flask, request, jsonify
import pickle

import warnings
warnings.filterwarnings("ignore")
```

## Understanding Data

```
url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv"
df = pd.read_csv(url)
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        |

```
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
```

```
df.describe()
```

|       | PassengerId | Survived   | Pclass     | Age        | SibSp      | Parch      | Fare       |
|-------|-------------|------------|------------|------------|------------|------------|------------|
| count | 891.000000  | 891.000000 | 891.000000 | 714.000000 | 891.000000 | 891.000000 | 891.000000 |
| mean  | 446.000000  | 0.383838   | 2.308642   | 29.699118  | 0.523008   | 0.381594   | 32.204208  |
| std   | 257.353842  | 0.486592   | 0.836071   | 14.526497  | 1.102743   | 0.806057   | 49.693429  |
| min   | 1.000000    | 0.000000   | 1.000000   | 0.420000   | 0.000000   | 0.000000   | 0.000000   |
| 25%   | 223.500000  | 0.000000   | 2.000000   | 20.125000  | 0.000000   | 0.000000   | 7.910400   |
| 50%   | 446.000000  | 0.000000   | 3.000000   | 28.000000  | 0.000000   | 0.000000   | 14.454200  |
| 75%   | 668.500000  | 1.000000   | 3.000000   | 38.000000  | 1.000000   | 0.000000   | 31.000000  |
| max   | 891.000000  | 1.000000   | 3.000000   | 80.000000  | 8.000000   | 6.000000   | 512.329200 |

Let's preprocess data by handling missing values and encoding categorical variables.

```
df = df[['Pclass', 'Sex', 'Age', 'Fare', 'Survived']].dropna()
df['Sex'] = df['Sex'].map({'male': 0, 'female': 1})
```

```
df.head()
```

|   | Pclass | Sex | Age  | Fare    | Survived |
|---|--------|-----|------|---------|----------|
| 0 | 3      | 0   | 22.0 | 7.2500  | 0        |
| 1 | 1      | 1   | 38.0 | 71.2833 | 1        |
| 2 | 3      | 1   | 26.0 | 7.9250  | 1        |
| 3 | 1      | 1   | 35.0 | 53.1000 | 1        |
| 4 | 3      | 0   | 35.0 | 8.0500  | 0        |

# Model Training

Let's select features and target

```
X = df[['Pclass', 'Sex', 'Age', 'Fare']]  
y = df['Survived']
```

```
# Split data into test and train  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

To train our model, we will use Random Forest Classifier

```
# Train model  
model = RandomForestClassifier()  
model.fit(X_train, y_train)
```

```
▼ RandomForestClassifier ⓘ ⓘ  
RandomForestClassifier()
```

```
# Save model  
with open("titanic_model.pkl", "wb") as f:  
    pickle.dump(model, f)
```

## Deploying Model with Flask

First, we load the trained model

```
: # Load the Titanic model  
with open("titanic_model.pkl", "rb") as f:  
    model = pickle.load(f)
```

```

app = Flask(__name__)

@app.route('/')
def home():
    return "Titanic Survival Prediction API is running!"

@app.route('/predict', methods=['POST'])
def predict():
    data = request.get_json() # Get JSON data from request

    # Extract features from the incoming JSON data
    pclass = data.get("Pclass")
    sex = data.get("Sex")
    age = data.get("Age")
    fare = data.get("Fare")

    # Convert categorical variable (Sex) to numerical
    sex_numeric = 1 if sex.lower() == 'male' else 0

    # Prepare the features array
    features = np.array([[pclass, sex_numeric, age, fare]])

    # Make prediction
    prediction = model.predict(features)

    # Return prediction result as JSON
    return jsonify({"survived": int(prediction[0])})

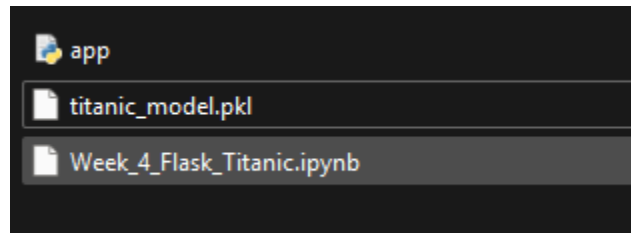
```

```

if __name__ == '__main__':
    app.run(use_reloader=False, port=5000) # Run on port 5000

* Serving Flask app '__main__'
* Debug mode: off

```



```
C:\Users\treme\Data_glacier_w4\new>curl -X POST http://127.0.0.1:5000/predict -H "Content-Type: application/json" -d "{\"Pclass\": 1, \"Sex\": \"male\", \"Age\": 22, \"Fare\": 7.25}" {"survived":1}

C:\Users\treme\Data_glacier_w4\new>curl -X POST http://127.0.0.1:5000/predict -H "Content-Type: application/json" -d "{\"Pclass\": 3, \"Sex\": \"male\", \"Age\": 40, \"Fare\": 7}" {"survived":0}
```

The Flask API that predicts whether a passenger survived based on Pclass, Sex, Age, and Fare has been successfully created and working well.

- For a male passenger in **1st class** who is **22 years old** and paid **\$7.25**, the prediction returned {"survived": 1} (indicating survival).
- For a male passenger in **3rd class** who is **40 years old** and paid **\$7**, the prediction returned {"survived": 0} (indicating no survival).