1. Imports

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.svm import SVC
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

- **`numpy`** : Used for numerical computations, especially for creating grids in visualization.
- **`matplotlib.pyplot`** : For plotting graphs and visualizations.
- **`pandas`** : For loading and handling datasets as DataFrames.
- **`sklearn.svm.SVC`** : The Support Vector Classifier from `scikit-learn`, which helps create and train SVM models.
- **`LabelEncoder`** : Encodes categorical labels into numerical format so the model can process them.
- **`accuracy_score`, `classification_report`, `confusion_matrix`** : Metrics for evaluating the model's performance.

2. Loading the Data

In [2]:

```
# Load the datasets
data = pd.read_csv('../train.csv')
test_data = pd.read_csv('../test.csv')
gender_submission = pd.read_csv('../gender_submission.csv')  # Load gender_submission.csv for actual test results
```

- `train.csv` : Training data containing features and target (survived status).
- `test.csv` : Test data used for prediction.
- `gender_submission.csv` : A sample submission file that includes the actual survival status of passengers for comparison purposes.

3. Handling Missing Values

In [3]:

```
# Handle missing values in the training and test data
data['Age'].fillna(data['Age'].median(), inplace=True)
data['Embarked'].fillna(data['Embarked'].mode()[0], inplace=True)
data['Fare'].fillna(data['Fare'].median(), inplace=True)

test_data['Age'].fillna(test_data['Age'].median(), inplace=True)
test_data['Fare'].fillna(test_data['Fare'].median(), inplace=True)
```

- **Missing Data Imputation**:
  - For `Age` : Median value is used as a replacement, as it is less affected by outliers compared to the mean.
  - For `Embarked` : The mode (most common value) fills missing entries.
  - For `Fare` : Median is used to handle missing values.

4. Label Encoding

In [4]:

```
# Initialize LabelEncoder
label_encoder = LabelEncoder()
```

In [5]:

```
# Fit the encoder on the combined 'Sex' column to handle both train and test data
combined_sex = pd.concat([data['Sex'], test_data['Sex']], axis=0)
label_encoder.fit(combined_sex)
```

Out[5]:

```
▾ LabelEncoder ⓘ ?
LabelEncoder()
```

(https://scikit-learn.org/1.4/modules/generated/sklearn.preprocessing.LabelEncoder.html)

In [6]:

```
# Transform the 'Sex' column for both datasets
data['Sex'] = label_encoder.transform(data['Sex'])
test_data['Sex'] = label_encoder.transform(test_data['Sex'])  # Same encoder
```

- **Label Encoding for `Sex`**:
  - `LabelEncoder` converts categorical data (`'male'` , `'female'`) into numerical format (e.g., `0` and `1`).
  - `fit` on the combined data ensures consistent encoding across training and test sets.
  - `transform` applies the transformation to each DataFrame.

5. Encoding the `Embarked` Column

In [7]:

```
# Initialize LabelEncoder for 'Embarked' column with handle_unknown='ignore' for unseen labels
embarked_encoder = LabelEncoder()
embarked_encoder.fit(data['Embarked'].dropna())  # Fit on the training data only
```

Out[7]:

```
▾ LabelEncoder
LabelEncoder()
```

(https://scikit-learn.org/1.4/modules/generated/sklearn.preprocessing.LabelEncoder.html)

In [8]:

```
# Transform the 'Embarked' column for both datasets with 'ignore' for unknown labels
data['Embarked'] = embarked_encoder.transform(data['Embarked'])
test_data['Embarked'] = embarked_encoder.transform(test_data['Embarked'])
```

- The `Embarked` column, which indicates the port of embarkation, is also encoded similarly to `Sex` using `LabelEncoder`.
- Fitting is done only on non-null values from the training set to avoid issues with missing values.

6. Feature Selection

In [9]:

```
# Select features for model training and testing
features = ['Age', 'Fare']
X_train = data[features]
y_train = data['Survived']
X_test = test_data[features]
y_test = gender_submission['Survived']  # Use actual 'Survived' from gender_submission.csv
```

- **Feature Selection**:
  - Only `Age` and `Fare` are used as features (`X_train` and `X_test`).
  - `y_train` is the target variable from the training data.
  - `y_test` from `gender_submission` serves as the true labels for the test set to evaluate model performance.

7. Creating and Training the SVM Model

In [10]:

```
# Create and train the SVM model
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)
```

Out[10]:

```
▾ SVC
SVC(kernel='linear')
```

(https://scikit-learn.org/1.4/modules/generated/sklearn.svm.SVC.html)

- **SVC with `kernel='linear'`**:
  - `kernel='linear'` means the algorithm looks for a linear decision boundary to separate classes.
  - **Support Vector Machine** works by finding the hyperplane that maximizes the margin between different classes.
- **Training (`fit`)**:
  - The model learns the relationships between features (`Age` and `Fare`) and the target (`Survived`).

8. Making Predictions

In [11]:

```
# Make predictions on the test data
y_pred = svm_model.predict(X_test)
```

- Predictions (y_pred) are made on the test data using the trained model.

9. Evaluating the Model

In [12]:

```
# Evaluate the model
print("Accuracy Score:", accuracy_score(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy Score: 0.6411483253588517

Classification Report:
               precision    recall  f1-score   support

           0       0.66      0.91      0.76       266
           1       0.52      0.18      0.26       152

    accuracy                           0.64       418
   macro avg       0.59      0.54      0.51       418
weighted avg       0.61      0.64      0.58       418


Confusion Matrix:
 [[241  25]
 [125  27]]
```

- **Accuracy Score**: Measures the proportion of correctly classified instances out of total instances.
- **Classification Report**:
  - Provides metrics like precision, recall, and F1-score for each class.
- **Confusion Matrix**:
  - Shows true positives, true negatives, false positives, and false negatives in a matrix form, helping to visualize prediction performance.

10. Visualization of the Decision Boundary

In [13]:

```
# Visualization of the decision boundary
plt.figure(figsize=(10, 6))
```

Out[13]:

```
<Figure size 1000x600 with 0 Axes>
```

```
<Figure size 1000x600 with 0 Axes>
```

In [14]:

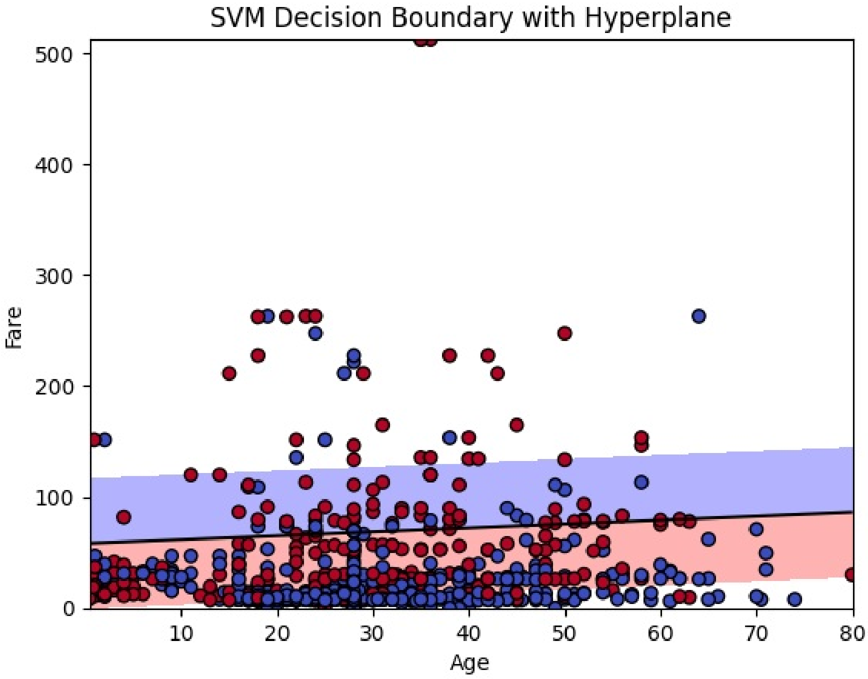
```
# Create a grid to evaluate the model
xx, yy = np.meshgrid(np.linspace(X_train['Age'].min(), X_train['Age'].max(), 100),
                     np.linspace(X_train['Fare'].min(), X_train['Fare'].max(), 100))
Z = svm_model.decision_function(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
```

```
c:\Users\Muskan Computer\AppData\Local\Programs\Python\Python312\Lib\site-packages\sklearn\base.py:4
93: UserWarning: X does not have valid feature names, but SVC was fitted with feature names
  warnings.warn(
```

In [15]:

```
# Plot the hyperplane
plt.contourf(xx, yy, Z, levels=[-1, 0, 1], alpha=0.3, colors=['red', 'blue', 'green'])
plt.contour(xx, yy, Z, colors='k', levels=[0], linestyles=['-'])
# Plot the points
plt.scatter(X_train['Age'], X_train['Fare'], c=y_train, cmap='coolwarm', edgecolors='k')

plt.xlabel('Age')
plt.ylabel('Fare')
plt.title('SVM Decision Boundary with Hyperplane')
plt.show()
```



- **Visualization**:
  - `np.meshgrid` creates a grid over the feature space.
  - `decision_function` calculates the margin distance for each point on the grid.
  - `plt.contourf` and `plt.contour` plot the decision boundary and margins.
- **Scatter Plot**:
  - Shows actual data points in the `Age` vs. `Fare` space, colored based on their class.

Understanding SVM in Depth:

- **Support Vectors**: Data points that lie closest to the decision boundary; they influence the position and orientation of the hyperplane.
- **Hyperplane**: A line (in 2D) or a plane (in higher dimensions) that separates classes.
- **Kernel Trick**: Allows SVM to find a non-linear decision boundary by transforming data into a higher-dimensional space (not needed here as `kernel='linear'`).

SVM Objective:

- To maximize the margin between the decision boundary and the nearest data points from any class, ensuring better generalization.

This code is a complete workflow for training, predicting, and visualizing an SVM model using `Age` and `Fare` as features to classify passengers based on survival probability.