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COLLEGE OF ENGINEERING

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SPACESHIP TITANIC

Melek Derman

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What is Spaceship Titanic dataset?

- Spaceship Titanic is a Kaggle competition to help learners understand the basics of Machine Learning.
- It is a classification problem.
- It has more than 8000 data in train set.

Problem Description


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- It is the year 2912. A transmission from 4 lightyears away has been received.
- An interstellar passenger liner, the Spaceship Titanic, was carrying passengers from our solar system to three newly habitable exoplanets orbiting nearby stars.
- Devastatingly, the ship collided with a spacetime anomaly hidden within a dust cloud, resulting in half of the passengers being transported to an alternate dimension!
- Our goal is to retrieve the lost passengers by predicting which passengers were transported using the records. Help save them and change history!

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Dataset and Features

- There are 8,693 passenger records
- 6 numerical and 6 categorical features
- Numerical Features:
  - Age, RoomService, FoodCourt, ShoppingMall, Spa, VRDeck
- Categorical Features:
  - HomePlanet, CryoSleep, Cabin, Destination, VIP, Name
- The features are mostly unbalanced.
- There are missing values in all categories.

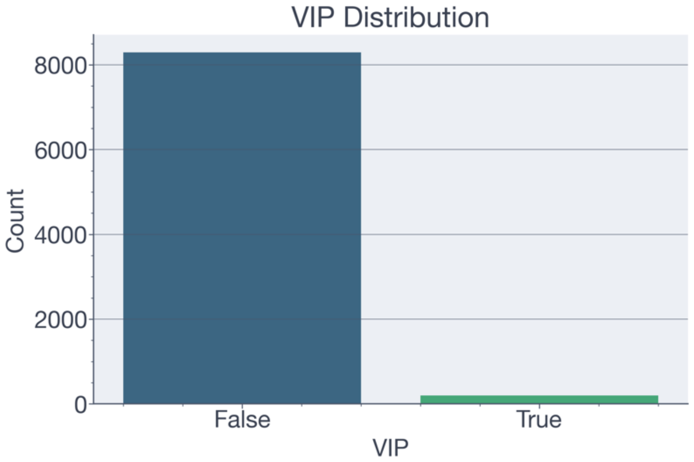
```
Train data info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8693 entries, 0 to 8692
Data columns (total 14 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   PassengerId   8693 non-null   object
 1   HomePlanet    8492 non-null   object
 2   CryoSleep     8476 non-null   object
 3   Cabin         8494 non-null   object
 4   Destination   8511 non-null   object
 5   Age           8514 non-null   float64
 6   VIP           8490 non-null   object
 7   RoomService   8512 non-null   float64
 8   FoodCourt     8510 non-null   float64
 9   ShoppingMall  8485 non-null   float64
 10  Spa           8510 non-null   float64
 11  VRDeck        8505 non-null   float64
 12  Name          8493 non-null   object
```

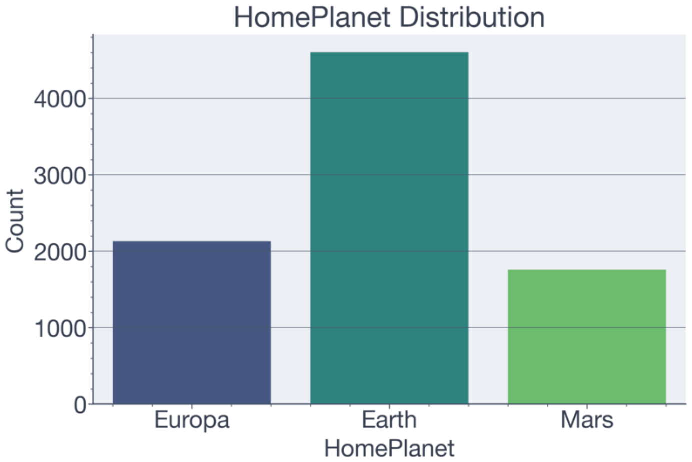
```
Number of unique values in each column:
PassengerId     8693
HomePlanet         3
CryoSleep          2
Cabin           6560
Destination        3
Age               80
VIP                2
RoomService     1273
FoodCourt       1507
ShoppingMall    1115
Spa             1327
VRDeck          1306
Name            8473
Transported        2
```

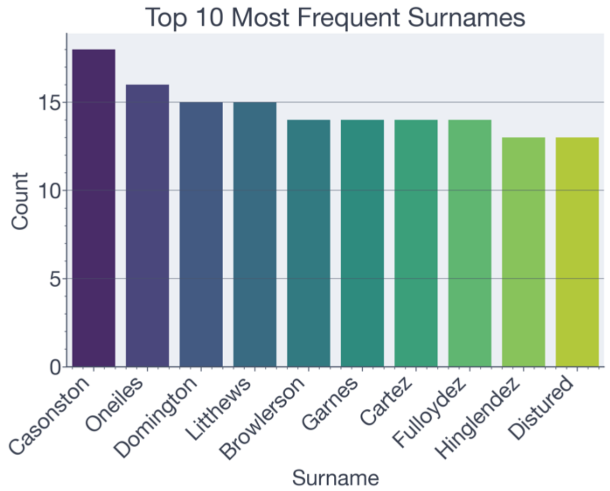
Missing Values:

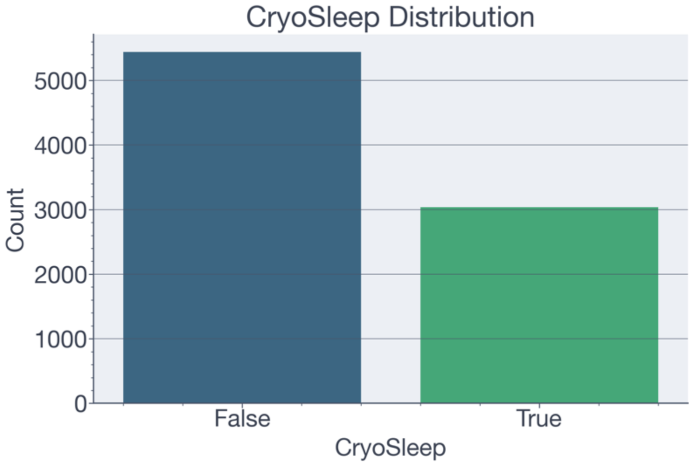
```
HomePlanet      201
CryoSleep       217
Cabin           199
Destination     182
Age             179
VIP             203
RoomService     181
FoodCourt       183
ShoppingMall    208
Spa             183
VRDeck          188
Name            200
```

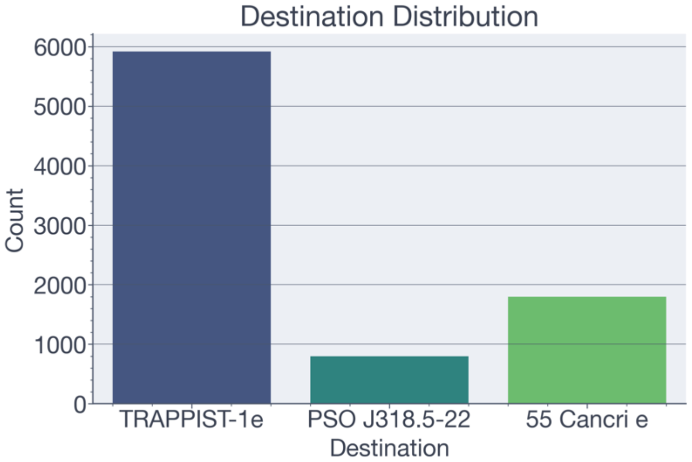
- Categorical Features

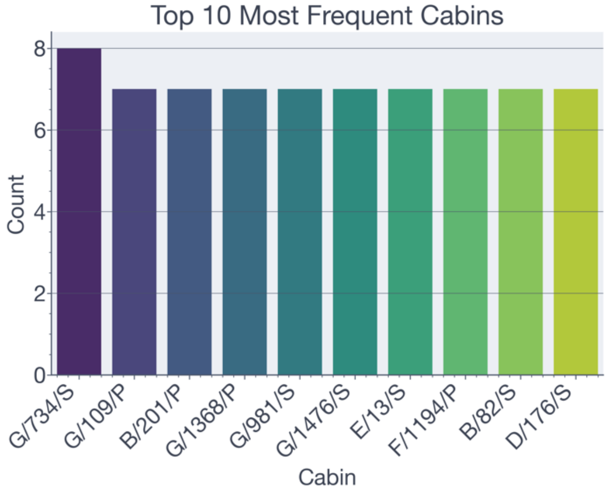






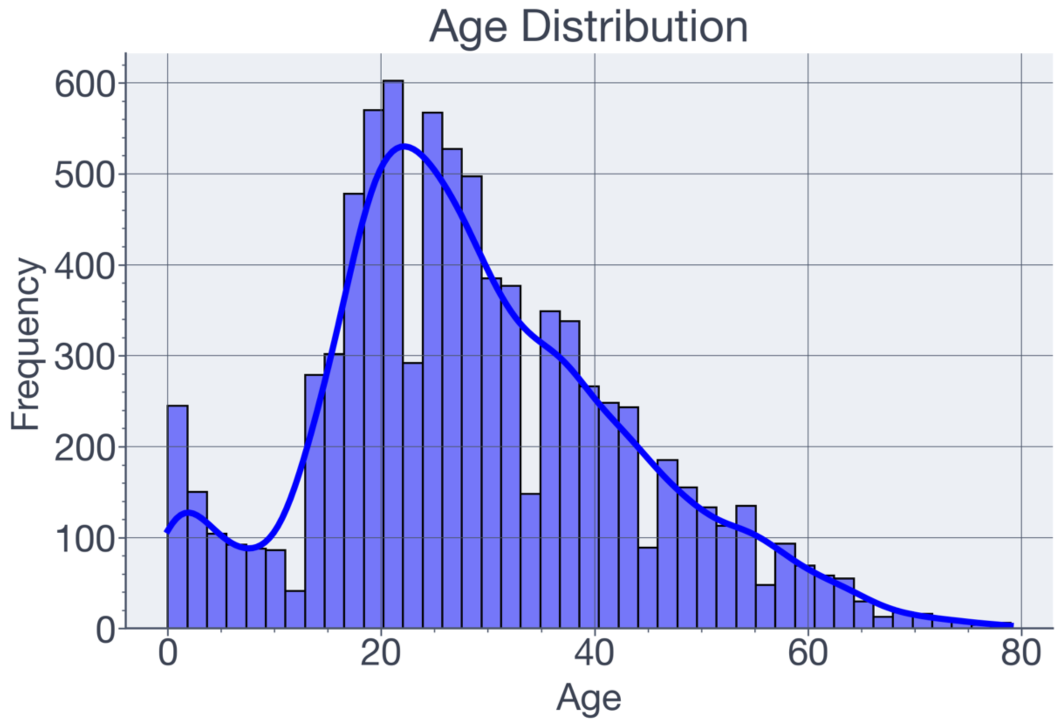




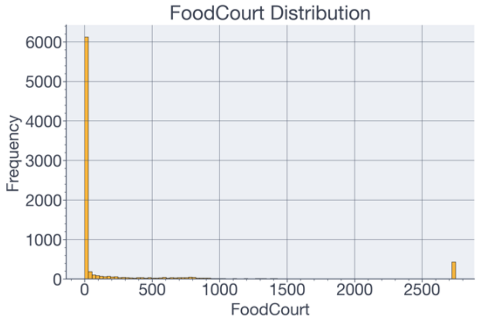


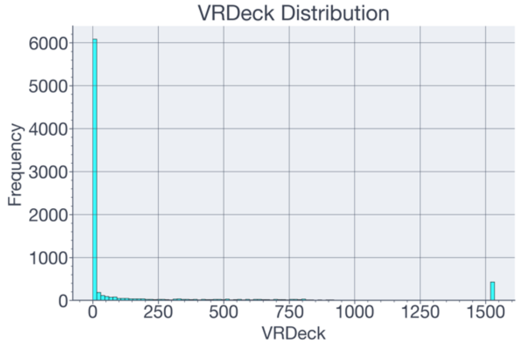
* CryoSleep indicates whether the passenger elected to be put into suspended animation for the duration of the voyage.

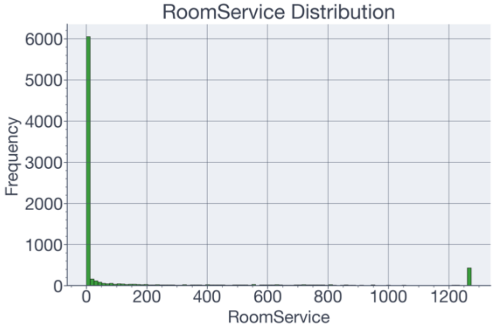
- Numerical Features

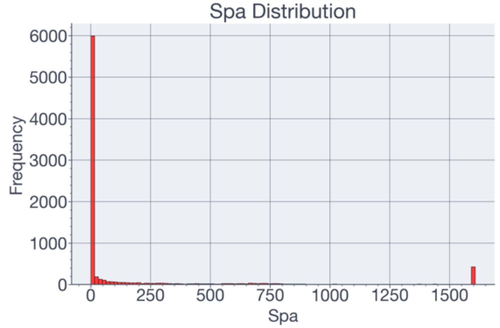


* RoomService, FoodCourt, ShoppingMall, Spa, VRDeck - Amount the passenger has billed at each of the *Spaceship Titanic*'s many luxury amenities.









Methodology for Features

- The “Name” column was split into individual words, enabling the analysis of family members.
- For missing values, the ‘mean’ strategy was used for numerical columns, and the ‘most_frequent’ strategy was applied for categorical features (Simple Imputer)
- Numerical Features → Standard Scaler
- Categorical Features → OneHotEncoder

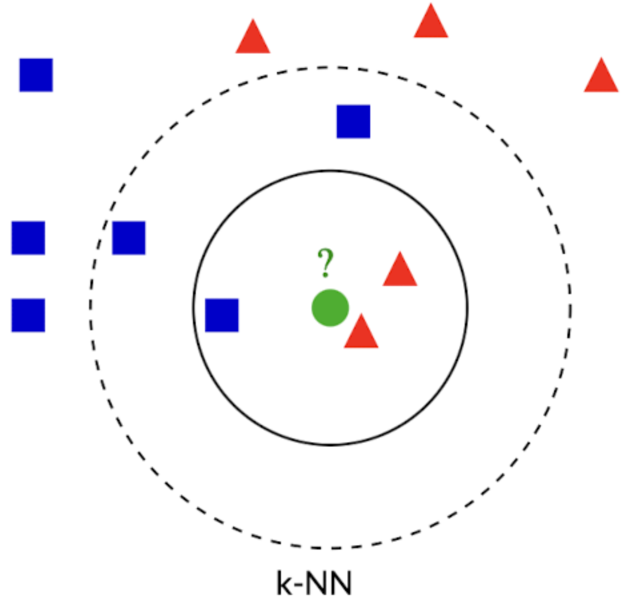
```
numerical_features = X_train.select_dtypes(include=['float64']).columns.tolist()
categorical_features = X_train.select_dtypes(include=['object']).columns.tolist()

numerical_features = [col for col in num_cols if col in X.columns]
categorical_features = [col for col in X.columns if col not in numerical_features]

numerical_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('onehot', OneHotEncoder(handle_unknown='ignore', sparse_output=False))
])

preprocessor = ColumnTransformer(transformers=[
    ('num', numerical_transformer, numerical_features),
    ('cat', categorical_transformer, categorical_features)
])
```

Methodology – k Nearest Neighbor Classifier

- The nearest neighbor classifier is a simple machine learning algorithm that is often used for classification tasks.
- It works by finding the "nearest" training example to a new, unlabeled example in the feature space, and assigning the label of that nearest example to the new example. Predictions are based on the similarity of a new data point to the data points in the training set.
- The algorithm is called "lazy" because it does not actually learn a model from the training data; instead, it simply memorizes the training examples and uses them to make predictions at test time.

Methodology _ Nearest Neighbor Classifier

- For a given data point (test point), KNN calculates its distance to all other points in the dataset.
- It selects the k nearest neighbors (based on the smallest distances).
- KNN assumes that similar data points are close to each other in the feature space. Therefore, the prediction for a new data point is based on its proximity to other known data points.



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Methodology K-NN Hyperparameters

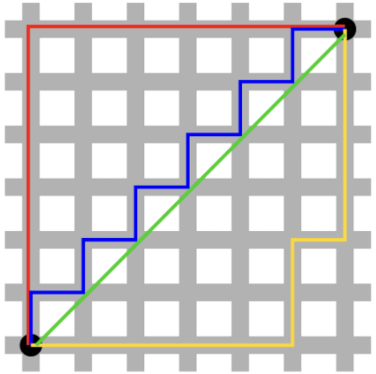
- **Number of Neighbors (k):** Determines how many closest neighbors are considered when making a prediction.
  - Small k: The model is sensitive to noise and may overfit.
  - Large k: The model becomes too generalized and may underfit.
- **Distance Metric:** The choice of distance metric determines how the algorithm measures similarity between points.
  - **Euclidean Distance:** Works well when the features have similar scales.
  - **Manhattan Distance:** More robust when dealing with grid-like data or features with varying scales

Now the Euclidean distance is simply the ℓ_2-norm:

$$\ell_2(x, y) = \sqrt{|x_1 - y_1|^2 + \ldots + |x_d - y_d|^2}$$

and the Manhattan distance is simply the ℓ_1-norm:

$$\ell_1(x, y) = |x_1 - y_1| + \ldots + |x_d - y_d|$$



Manhattan vs. Euclidean Distances

- **Weighting of Neighbors:** Neighbors can be weighted based on their distance to the test point:
  - Uniform Weighting: All neighbors have equal importance.
  - Distance Weighting: Closer neighbors have more influence.

Methodology - Tuning

To optimize the performance of the KNN algorithm, we need to tune the hyperparameters:

Split the Data:

- Use the training data to tune the hyperparameters using cross-validation and evaluate the performance on a separate test set.

Hyperparameter Tuning:

- k: Test odd values such as [1, 3, 5, 7, 9, 11, ...] to avoid tie-breaking votes.
- Distance metric: Try Euclidean, Manhattan.
- Weighting: Test both uniform and distance-based weighting.
- Use cross-validation to test each combination of hyperparameters and select the combination that gives the best performance.

Optimal Hyperparameters:

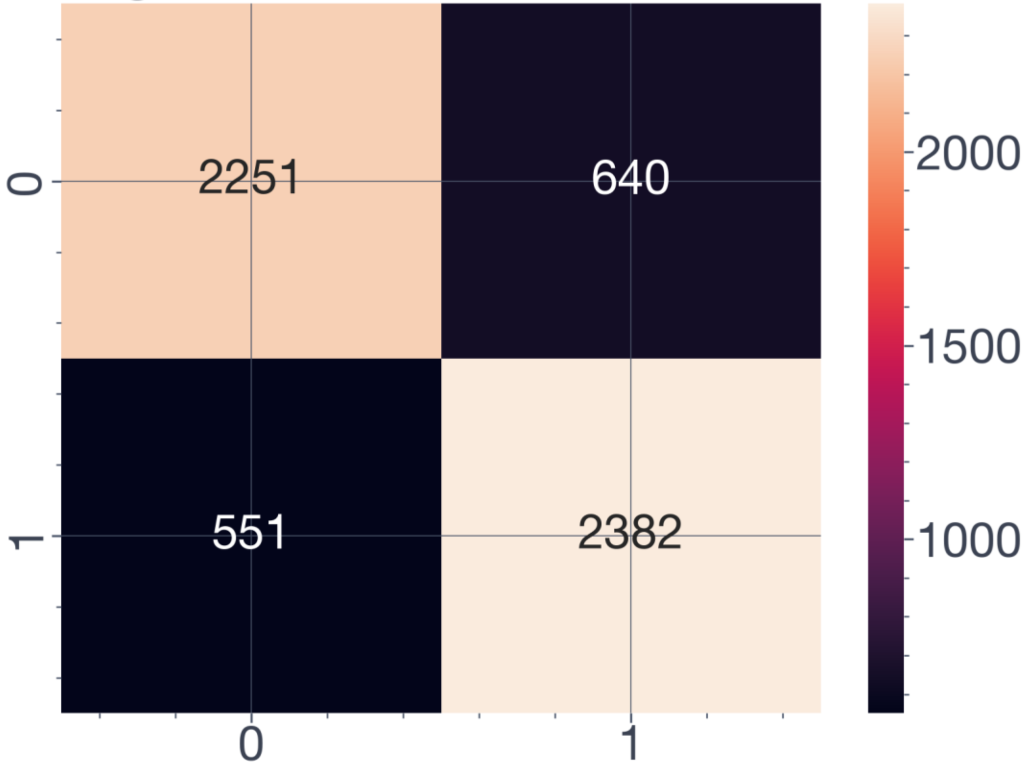
- After testing various combinations, select the hyperparameters that maximize a performance metric (e.g., accuracy, precision, recall).

Final Evaluation:

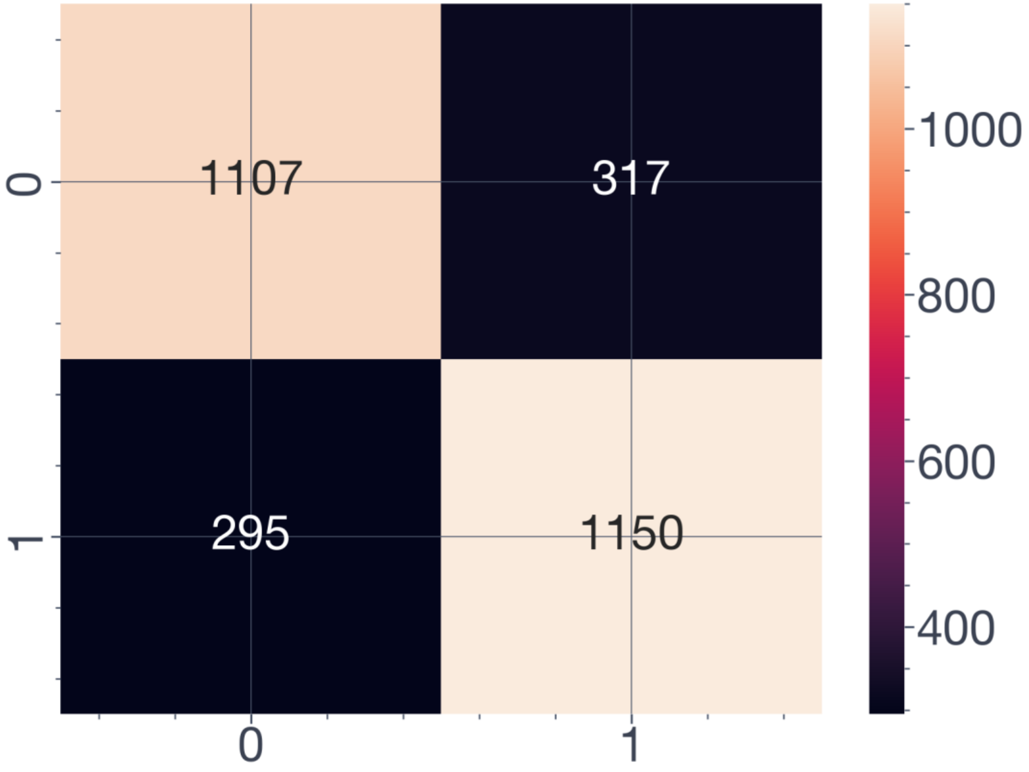
- Train the KNN model on the entire training set using the optimal hyperparameters.
- Evaluate the performance on the test set and submit the test predictions to Kaggle.

Results

Training Set Confusion Matrix for k-nn



Test Set Confusion Matrix for k-nn



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Results

```
Best hyperparameters: n_neighbors=41, metric=manhattan, weight=uniform with a balanced accuracy of 0.7828
Balanced Accuracy for k-NN on train set: 0.7953805283288025
Accuracy for k-NN on train set: 0.7955013736263736
Precision for k-NN on train set: 0.7957872343239749
Recall for k-NN on train set: 0.7953805283288025
Balanced Accuracy for k-NN on test set: 0.786617695657245
Accuracy for k-NN on test set: 0.7866852561868247
Precision for k-NN on test set: 0.7867495261905526
Recall for k-NN on test set: 0.786617695657245
```

```
Cross-validation balanced accuracy scores for each combination:
n_neighbors=1, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7109
n_neighbors=3, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7476
n_neighbors=5, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7622
n_neighbors=7, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7694
n_neighbors=9, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7689
n_neighbors=11, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7699
n_neighbors=13, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7706
n_neighbors=15, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7785
n_neighbors=17, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7784
n_neighbors=19, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7771
n_neighbors=21, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7772
n_neighbors=23, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7778
n_neighbors=25, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7783
n_neighbors=27, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7788
n_neighbors=29, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7797
n_neighbors=31, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7800
n_neighbors=33, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7805
n_neighbors=35, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7788
n_neighbors=37, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7819
n_neighbors=39, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7805
n_neighbors=41, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7793
n_neighbors=43, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7792
n_neighbors=45, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7821
n_neighbors=47, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7823
n_neighbors=49, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7816
n_neighbors=51, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7809
n_neighbors=53, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7795
n_neighbors=55, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7799
n_neighbors=57, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7811
n_neighbors=59, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7809
n_neighbors=61, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7808
n_neighbors=63, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7797
n_neighbors=65, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7806
n_neighbors=67, metric=euclidean, weight=uniform: Mean Balanced Accuracy = 0.7816
```

```
n_neighbors=41, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7813
n_neighbors=43, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7820
n_neighbors=45, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7808
n_neighbors=47, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7792
n_neighbors=49, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7796
n_neighbors=51, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7798
n_neighbors=53, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7812
n_neighbors=55, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7806
n_neighbors=57, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7807
n_neighbors=59, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7808
n_neighbors=61, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7803
n_neighbors=63, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7796
n_neighbors=65, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7807
n_neighbors=67, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7807
n_neighbors=69, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7812
n_neighbors=71, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7817
n_neighbors=73, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7814
n_neighbors=75, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7800
n_neighbors=77, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7806
n_neighbors=79, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7801
n_neighbors=81, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7808
n_neighbors=83, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7799
n_neighbors=85, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7803
n_neighbors=87, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7808
n_neighbors=89, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7796
n_neighbors=91, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7800
n_neighbors=93, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7803
n_neighbors=95, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7801
n_neighbors=97, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7803
n_neighbors=99, metric=manhattan, weight=distance: Mean Balanced Accuracy = 0.7802
```

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Thank you!

Questions?

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Kaggle Test Results

final_submission_svm.csv Complete · 7h ago	0.79331
final_submission.csv Complete · 8h ago · knn	0.75941
sample_submission.csv Complete · 5d ago	0.49310