Classification Models Comparison

```
# get data
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

comparisons = pd.read_csv('https://raw.githubusercontent.com/sudarshan-koirala/K-Nearest-N
print(comparisons.shape)
print(comparisons.head())
print(comparisons.info())
```

```
(400, 5)
    User ID  Gender   Age  EstimatedSalary  Purchased
0  15624510    Male  19.0          19000.0          0
1  15810944    Male  35.0          20000.0          0
2  15668575  Female  26.0          43000.0          0
3  15603246  Female  27.0          57000.0          0
4  15804002    Male  19.0          76000.0          0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   User ID          400 non-null    int64  
 1   Gender           400 non-null    object 
 2   Age              400 non-null    float64
 3   EstimatedSalary  400 non-null    float64
 4   Purchased        400 non-null    int64  
dtypes: float64(2), int64(2), object(1)
memory usage: 15.8+ KB
None
```

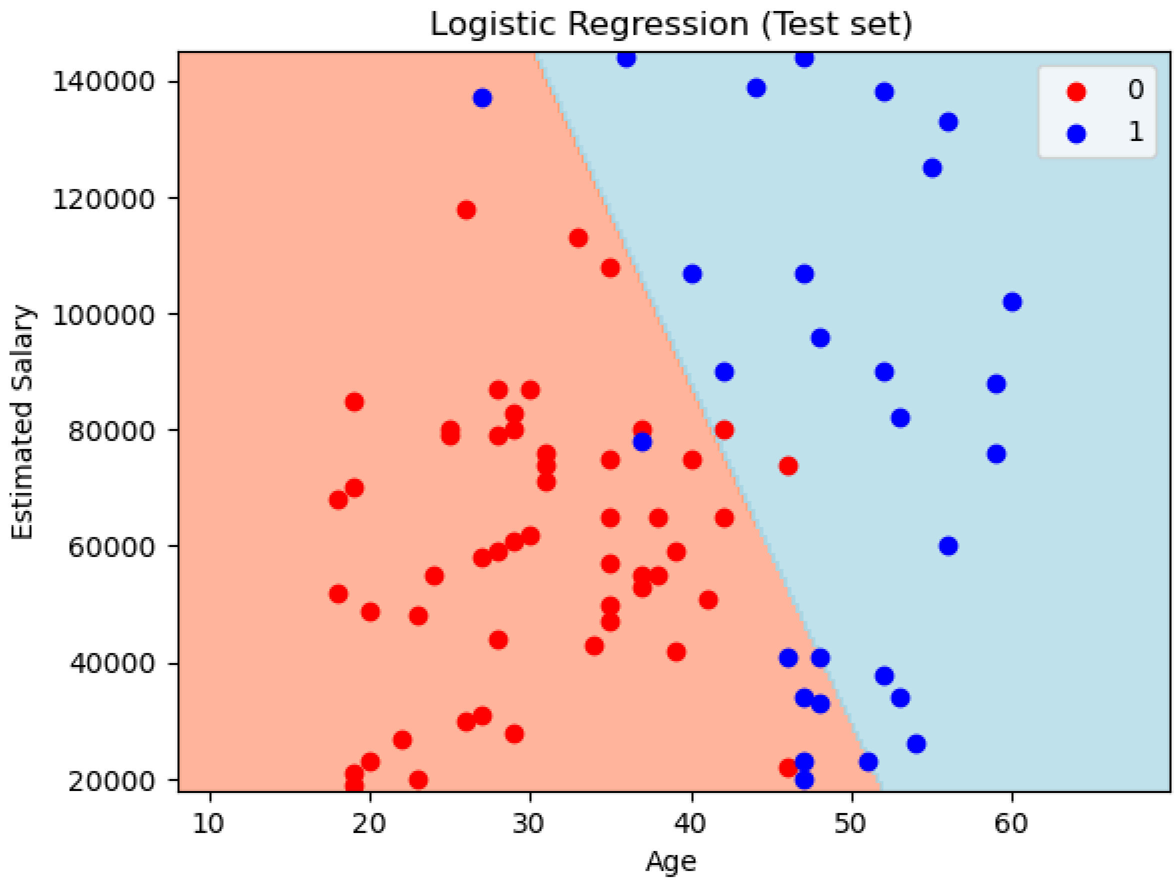
```
# get X and y and train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(comparisons.drop(['User ID', 'Gender
                                                    comparisons.Purchased,
                                                    test_size=0.2, random_state=42)
```

```
# scale data
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train = sc.fit_transform(X_train.values)
X_test = sc.transform(X_test.values)
```

Logistic Regression

```
# model, predict, evaluate, and plot
from matplotlib.colors import ListedColormap
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score

model = LogisticRegression(random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)

print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))

X_set, y_set = sc.inverse_transform(X_test), y_test
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 10, stop = X_set[:, 0].max() -
                     np.arange(start = X_set[:, 1].min() - 1000, stop = X_set[:, 1].max(

plt.contourf(X1, X2, model.predict(sc.transform(np.array([X1.ravel(), X2.ravel()]).T)).re
             alpha = 0.75, cmap = ListedColormap(('lightsalmon', 'lightblue')))

plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
    plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], color = ListedColormap(('red

plt.title('Logistic Regression (Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

```
[[50  2]
 [ 9 19]]
0.8625
```



Multinomial Logistic Regression

See Week 10 - Multinomial Logistic Regression

K Nearest Neighbor

- https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm#/media/File:KnnClassification.svg
- Choose the number of K neighbors
- Within the perimeter, count the number of each class
- New data point is assigned the class with the highest count

```
from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=5, metric='minkowski', p=2)
model.fit(X_train, y_train)
predictions = model.predict(X_test)

print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))
```

```
[[48  4]
 [ 3 25]]
0.9125
```

Support Vector Classifier

https://en.wikipedia.org/wiki/Support-vector_machine#/media/File:SVM_margin.png

The Support Vector Classifier (SVC) is a powerful, non-probabilistic linear model used for classification. Its fundamental goal is to find the optimal boundary—the **hyperplane**—that maximally separates two classes of data.

The Geometric Goal

For two-class classification, the SVC process focuses on geometric optimization:

1. **Identify the Hyperplane:** The **hyperplane** is the decision boundary used to separate the two classes (e.g., Class A and Class B). In a two-dimensional space, this is a line; in a three-dimensional space, it's a plane. It's mathematically analogous to a "line of best fit," but its purpose is separation, not prediction along a continuous scale.
2. **Maximize the Margin:** The algorithm's primary objective is to maximize the **margin**, which is the distance between the two closest data points belonging to different classes. This produces the most robust, generalizable boundary.
3. **Identify Boundary Hyperplanes:** The SVC identifies a **negative hyperplane** and a **positive hyperplane**, which run parallel to the main decision hyperplane and pass through the closest points of each class.

Support Vectors: The Key Data Points

The name "Support Vector" comes from the crucial data points that define the margin:

- **Support Vectors:** These are the data points (the "apples that look like oranges and vice versa") that lie **on the boundary hyperplanes**. They are the hardest-to-classify examples and are the only observations that matter in defining the final decision boundary.
- **Significance:** Only the support vectors are used to compute the maximum margin and the position of the final separating hyperplane. If all other non-support vector data points were removed, the resulting hyperplane would not change.

Handling Linearly Separable Data

The concepts described above—finding a straight hyperplane and maximizing the margin—apply directly when the data is **linearly separable**, meaning a single straight line or flat plane can completely divide the two classes. For non-linearly separable data, SVM uses the **Kernel Trick** to transform the data into a higher dimension where it *can* be separated by a plane.

```
from sklearn.svm import SVC

model = SVC(kernel='linear', random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)

print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))
```

```
[[50  2]
 [ 9 19]]
0.8625
```

SVC with Kernel

```
from sklearn.svm import SVC

model = SVC(kernel='rbf', random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)

print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))
```

```
[[47  5]
 [ 1 27]]
0.925
```

More on Support Vectors

See Week 10 - Support Vectors

Naive Bayes

```
from sklearn.naive_bayes import GaussianNB

model = GaussianNB()
model.fit(X_train, y_train)
predictions = model.predict(X_test)

print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))
```

```
[[50  2]
 [ 3 25]]
0.9375
```

More on Naive Bayes

See Week 10 - Naive Bayes

Decision Tree Classifier

- https://www.kdnuggets.com/2020/01/decision-tree-algorithm-explained.html

Terms

- Root node
- Splitting
- Decision node
- Leaf / terminal node
- Pruning
- Branch
- Parent and child nodes

Attribute Selection Measures

- Gini index
- Entropy
- Information gain
- Gain ratio
- Reduction in variance
- Chi-square

More next week

```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(criterion='entropy', random_state=42)
model.fit(X_train, y_train)
predictions = model.predict(X_test)

print(confusion_matrix(y_test, predictions))
print(accuracy_score(y_test, predictions))
```

```
[[46  6]
 [ 7 21]]
0.8375
```

Random Forest Classifier

- Random sample of X_train when building trees

- Random subsets of features
- Bagging

More next week

```
from sklearn.ensemble import RandomForestClassifier
```