



**Predicting product sales through ads  
delivered on Social Networking Sites using  
K.N.N**

**Computer Structure (INS 611)**

**Final Presentation**

**MASTER OF INTERNET SYSTEMS**

**SUBMITTED TO**

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## I. Problem Scenario

**TASK:** Given the dataset of social network users and their decisions for purchasing a car that was shown to them as an advertisement, develop a model that should predict the behavior of future users on after seeing the same advertisement.

Marking: the models which be assigned marks based on their prediction scores and how the quality of the presentation such as motivating the choice of certain parameters.

## II. Data Set to be used.



Social\_Network\_Ads.  
csv

### How to choose machine learning model for the problem?

several factors have impact on our decision to select best algorithm. Some problems are unique that specific algorithms are defines for these problems like recommendation system. Or in other cases these points can be helpful to decide best algorithm.

- i. Study the data.
- ii. Understand the business problem.
- iii. Always keep in mind the constraints by the data or business.
- iv. Accuracy or speed, which really matters for the case.

### Solution

Predicting product sales through ads delivered on Social Networking Sites using k-N.N. in Python

### K.Nearest Neighbors(k-N.N.)

#### A Gentle Introduction

The k-NN algorithm is among the simplest of all machine learning algorithms. The input consists of the k closest training examples in the feature space while the output depends on whether k-NN is used for classification or regression:

In **k-NN classification**, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor.

In **k-NN regression**, the output is the property value for the object. This value is the average of the values of its k nearest neighbors.

Well in this particular case we are dealing with a classification problem as we need to classify

users as those who would but the car or not.

### HOW DOES THE ALGORITHM WORK?

1. Choose the number K of neighbors
2. Take the K nearest neighbors of the new data point, according to Euclidean Distance
3. Among these K neighbors, count the number of data points in each category
4. Assign the new data point to the category where you counted the most neighbors.

## Part 1 — Data Preprocessing

### # Importing the libraries

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

Importing the dataset

***The Dataset contains information about users on a Social Networking site and using that info as Features for our ML model, we try to predict that whether a particular user after clicking on an ad on the Social networking site goes on to buy a particular product or not.***

***Well this particular Social Network has a Business client which as mentioned earlier is a car company which advertises itself by putting adds on the social networking site. Now the work of the social network here is to gather information as to whether the user bought the product or not. The dependent variable in this case is Purchased which is 1 if user purchases the car and 0 otherwise.***

***So the goal here is to create a classifier which would put each user into the correct category by predicting as to whether he's buying the product or not.***

```
dataset = pd.read_csv('Social_Network_Ads.csv')
```

# printing the first few entries of the Dataset

```
print(dataset.head())
```

# Attention:

The following features will be considered as the independent variables...

**...1)Age**

**...2)Estimated Salary**

Now some of you might be wondering that the dataset also contains 3 more columns and why are we leaving them?

Well the answer to that is quite simple...and we will soon see the reason as to why each of

them is being dropped.

...1) **UserId**- The **UserId** has no effect on whether the user would purchase the Car or not

...2) **Gender**- Some might say that **Gender** would play a role but that is really subjective to discuss.

Moreover, since **gender** is a **Categorical variable** we would have to use Variable Encoder for it.

```
X = dataset.iloc[:, [2, 3]].values
```

Storing the dependent variable in y i.e. Purchased which is 1 if user purchases the car and 0 otherwise.

```
y = dataset.iloc[:, 4].values
```

This is what the Dataset actually looks lik...

User ID	Gender	Age	Estimated Purchased	Purchased
15834510	Male	19	19000	0
15810944	Male	35	20000	0
15668575	Female	26	43000	0
15603246	Female	27	57000	0
15804002	Male	19	76000	0
15728773	Male	27	58000	0
15598044	Female	27	84000	0
15694829	Female	32	150000	1
15600575	Male	25	33000	0
15727311	Female	35	65000	0
15570769	Female	26	80000	0
15606274	Female	26	52000	0
15746139	Male	20	46000	0
15704987	Male	32	18000	0
15628972	Male	18	82000	0
15697686	Male	29	80000	0
15733883	Male	47	25000	1
15617462	Male	45	26000	1
15704583	Male	46	28000	1
15621083	Female	48	29000	1
15649487	Male	45	22000	1

## Splitting the dataset into the Training set and Test set

Importing the Cross Validation library which is now known as ModelSelection in newer versions of Python

```
from sklearn.model_selection import train_test_split
```

We divide the data into 75% data for training and 25% for testing our data

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)
```

Now are we going to apply Feature Scaling?

Yes, definitely we will be applying feature scaling because we want accurate prediction i.e. we want to predict which users are going to buy the car or not.

Feature Scaling

Importing Libraries

```
from sklearn.preprocessing import StandardScaler
```

Creating the standard Scalar Object of the Preprocessing Class

```
sc = StandardScaler()
```

Scaling X\_train by fitting the Standard Scalar object to our Matrix of Features X\_train

```
X_train = sc.fit_transform(X_train)
```

Scaling X\_test in the same basis

```
X_test = sc.transform(X_test)
```

To actually see the difference and confirm that they are almost upto the same scale, if you want you can...

```
print(X_train)
```

```
print(X_test)
```

## **Part 2 — Fitting our k-N.N. Model**

Fitting K-NN to the Training set

So we need to import the scikit.neighbours library and from it we would import the KNN Classifier

```
from sklearn.neighbors import KNeighborsClassifier
```

Creating an object of the class...

Inspect the classifier by pressing Ctrl+Q to show the Documentation and seeing all the parameters with their def accordingly

→ No of nearest neighbors=5(Default)

→ Specify metric as 'minkowski' and power as '2' for using the Euclidean Distance for k-N.N.==> set p=2

```
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
```

Now we fit the classifier object to our training set

```
classifier.fit(X_train, y_train)
```

## **Part 3 — Predicting the Test set results**

Since the classifier has been fit to the Dataset we can predict the Outcomes of the test set.

```
y_pred = classifier.predict(X_test)
```

Displaying out the predicted values

```
print(y_pred)
```

Now to calculate the accuracy of our model...

```
c=0
```

```
for i in range(0,len(y_pred)):
```

```
    if(y_pred[i]==y_test[i]):
```

```
        c=c+1
```

```
accuracy=c/len(y_pred)
print("Accuracy is")
print(accuracy)
```

So when you run this you get an accuracy of about 93% which is a great achievement for our classifier.

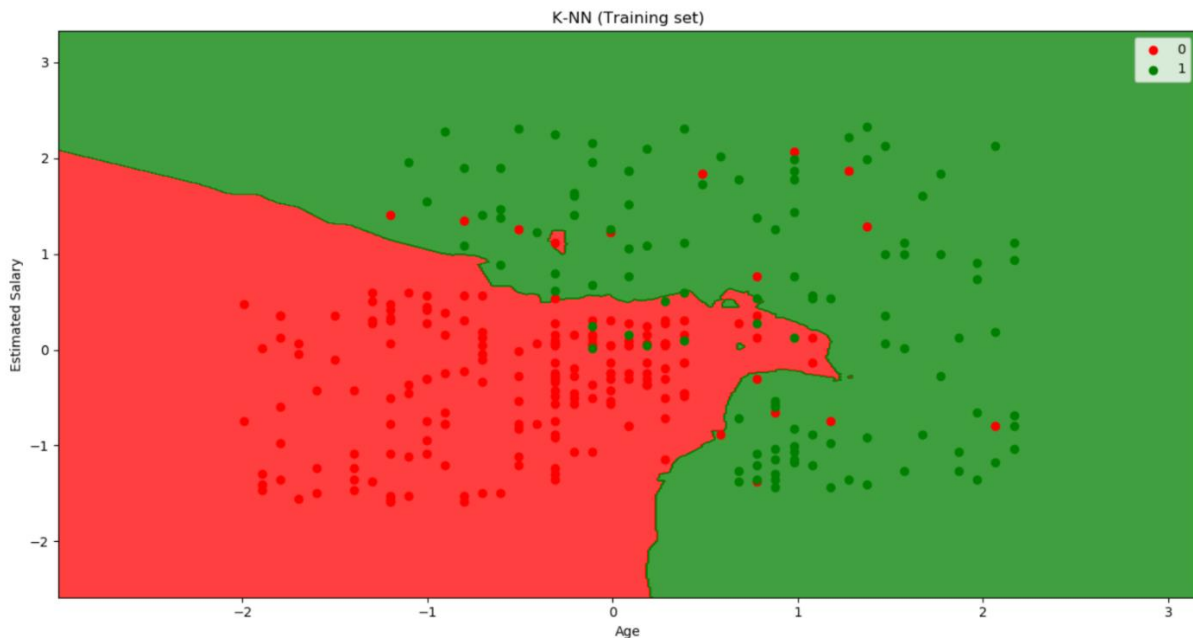
With this we end our predictions. Now the next section is of data visualization, which helps us visualize the accuracy and the errors of our model.

#### **Part-4 — Data Visualization and Confusion matrix**

Visualising the Training set results

```
from matplotlib.colors import ListedColormap
X_set, y_set = X_train, y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1, step =
0.01),
                    np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
             alpha = 0.75, cmap = ListedColormap(('red', 'green')))
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],
               c = ListedColormap(('red', 'green'))(i), label = j)
plt.title('K-NN (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

So now something like this would show after running the above code...

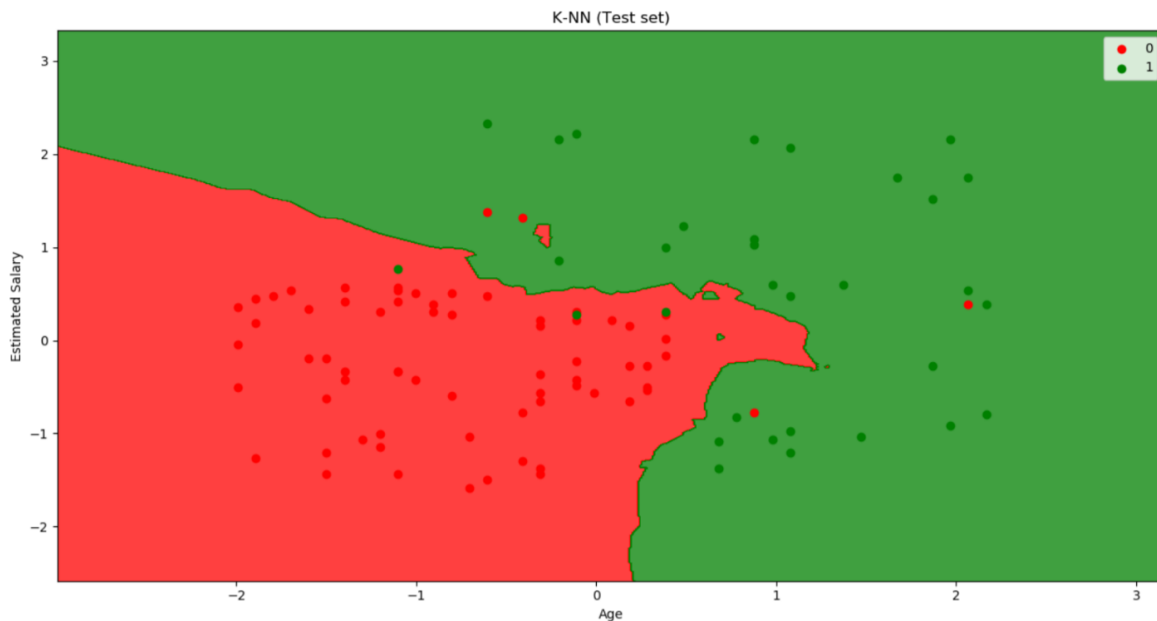


As it might be visible in the newly opened graph of the Training Set that we have a Non-Linear Classifier which fits the Data pretty well.

Well apart from the very few misclassified points...Red points in Green region or vice versa our Model does a pretty decent job in classifying these points.

### Visualizing the Test set results

```
from matplotlib.colors import ListedColormap
X_set, y_set = X_train, y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop =
X_set[:, 0].max() + 1, step = 0.01),
np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1,
step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),
X2.ravel()])).T.reshape(X1.shape),
alpha = 0.75, cmap = ListedColormap(('red', 'green')))
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],
c = ListedColormap(('red', 'green'))(i), label = j)
plt.title('K-NN (Training set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```



## Conclusion

Just as we had performed an Analysis on the Graph of the Training set before we now perform one on the Test set results...

Yet Again we see that most of the points are correctly classified just with a few exceptions which is fine by the way to have, because we are trying to prevent our model from Over-fitting which we know can be a serious threat.

So now that we have even visualized the training and the test set graphs, we have officially completed building our model along with Data visualization.

Yayy!! So I just built a k-N.N. Model for predicting the sales of a product being advertised on a Social Media. The Car company which had hired someone as a Data Scientist would now be able to make a wise decision of targeting the correct crowd in order to advertise its brand new car and It would be the reason for its tremendous sales. Well I hope you are feeling proud already!!



## Variable Explorers menu on Spyder

The screenshot shows the Spyder Python IDE interface. The left pane displays a Python script named `diabetedetection.py` with code for splitting a dataset, applying feature scaling using `StandardScaler`, and fitting a K-NN classifier. The right pane shows the **Variable Explorer** menu, which lists variables in the current workspace. The variables and their types are:

Name	Type	Size	Value
accuracy	float	1	0.93
c	int	1	93
classifier	neighbors_classification.KNeighborsClassifier	1	KNeighborsClassifier object of skl...
cm	Array of int64	(2, 2)	[[64 4] [ 3 29]]
dataset	DataFrame	(400, 5)	Column names: User ID, Gender, Age, EstimatedSalary, Purchased
i	int	1	1
j	int64	1	1
sc	preprocessing_data.StandardScaler	1	StandardScaler object of sklearn.preprocessing_data module
X	Array of int64	(400, 2)	[[ 19 19000] [ 35 20000]]
X1	Array of float64	(592, 616)	[[ -2.99318916 -2.98318916 -2.97318...
X2	Array of float64	(592, 616)	[[ -2.58254245 -2.58254245 -2.58254...
X_set	Array of float64	(100, 2)	[[ -0.80480212 0.50496393] [ -0.81254409 -0.5677824 ]
X_test	Array of float64	(100, 2)	[[ -0.80480212 0.50496393] [ -0.81254409 -0.5677824 ]

The **Variable Explorer** menu is highlighted, and the **Console** pane shows the output of the script, including the accuracy value of 0.93.

## Plots:

The screenshot shows the Spyder Python IDE interface with a scatter plot titled **K-NN (Test set)**. The plot displays the relationship between **Age** (x-axis) and **Estimated Salary** (y-axis). The data points are colored based on the predicted class (0 or 1). The plot shows a clear separation between the two classes, with class 0 (red) clustered on the left and class 1 (green) clustered on the right. The plot is titled **K-NN (Test set)** and includes a legend for the classes.

The **Console** pane shows the output of the script, including the accuracy value of 0.93. The **Plots** menu is highlighted, and the **Console** pane shows the output of the script, including the accuracy value of 0.93.

## References:

1. <https://www.kaggle.com/learn/intro-to-machine-learning>
2. <https://towardsdatascience.com/machine-learning-basics-with-the-k-nearest-neighbors-algorithm-6a6e71d01761>
3. <https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html>
4. [https://www.tutorialspoint.com/scikit\\_learn/scikit\\_learn\\_kneighbors\\_classifier.htm](https://www.tutorialspoint.com/scikit_learn/scikit_learn_kneighbors_classifier.htm)
5. <https://machinelearningmastery.com/machine-learning-in-python-step-by-step/>
6. <https://rjunaidraza.medium.com/comparison-of-classification-algorithms-lr-dt-rf-svm-knn-6631493e300f>