Name : ANJISHNU ROY

Registration No. : 21401007

Department : MBA DA

Subject : Business Intelligence

Assignment : Implemeting Supervised/Unsupervised Machine Learning Algorithms along with NLP/Neural Networks

Importing Libraries

In [59]:
```
import base64
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import r2_score
from sklearn.cluster import KMeans
import scipy.cluster.hierarchy as shc
from sklearn.cluster import AgglomerativeClustering
from mlxtend.frequent_patterns import apriori, association_rules
from collections import Counter
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.decomposition import NMF, LatentDirichletAllocation
import plotly.offline as py
import plotly.graph_objs as go
py.init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.tools as tls
import nltk
from nltk.stem import WordNetLemmatizer
import keras
from keras.models import Sequential
from keras.layers import Conv2D, Lambda, MaxPooling2D # convolution layers
from keras.layers import Dense, Dropout, Flatten # core layers
from keras.preprocessing.image import ImageDataGenerator
from keras.utils.np_utils import to_categorical
import tensorflow as tf
from keras.utils import np_utils
```

Supervised Learning : We try to implement some regression models on the popular SAS cars dataset

Cleaning up the data

In [2]:
```
df = pd.read_csv('./cars.csv')
df.head()
```

Out[2]:

	Make	Model	Type	Origin	DriveTrain	MSRP	Invoice	EngineSize	Cylinders	Horsepower	M
0	Acura	MDX	SUV	Asia	All	36945.0	33337.0	3.5	6.0	265.0	

	Make	Model	Type	Origin	DriveTrain	MSRP	Invoice	EngineSize	Cylinders	Horsepower	M
1	Acura	RSX Type S 2dr	Sedan	Asia	Front	23820.0	21761.0	2.0	4.0	200.0	
2	Acura	TSX 4dr	Sedan	Asia	Front	26990.0	24647.0	2.4	4.0	200.0	
3	Acura	TL 4dr	Sedan	Asia	Front	33195.0	30299.0	3.2	6.0	270.0	
4	Acura	3.5 RL 4dr	Sedan	Asia	Front	43755.0	39014.0	3.5	6.0	225.0	

In [3]:
```
df.shape
```

Out[3]:
```
(428, 15)
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Make           0
Model          0
Type           0
Origin         0
DriveTrain     0
MSRP           0
Invoice        0
EngineSize     0
Cylinders      2
Horsepower     0
MPG_City       0
MPG_Highway    0
Weight         0
Wheelbase      0
Length         0
dtype: int64
```

In [5]:
```
df = df.dropna()
```

In [6]:
```
df.shape
```

Out[6]:
```
(426, 15)
```

Let's make a correlation matrix w/ the numerical variables

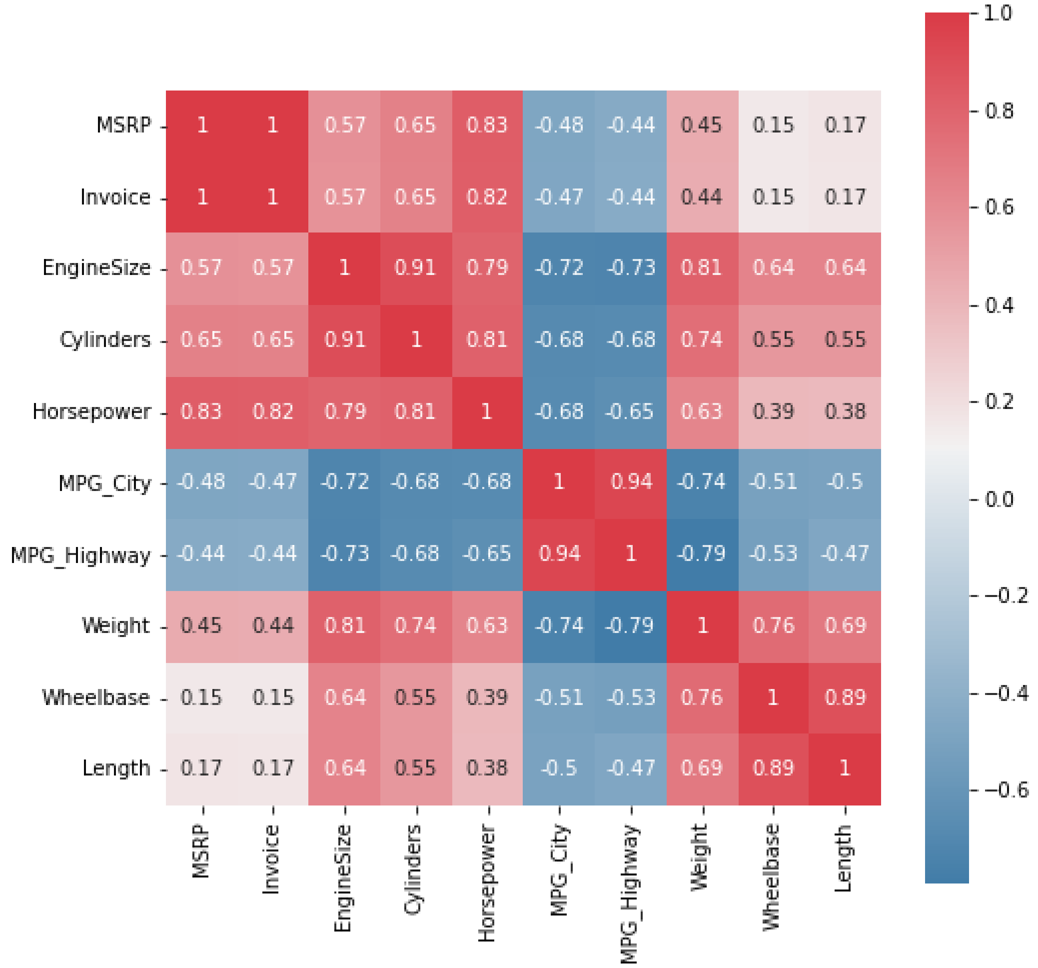
In [7]:
```
#List of the numerical variables
df.select_dtypes(include=np.number).columns.tolist()
```

Out[7]:
```
['MSRP',
 'Invoice',
 'EngineSize',
 'Cylinders',
 'Horsepower',
 'MPG_City',
 'MPG_Highway',
 'Weight',
 'Wheelbase',
 'Length']
```

In [8]:
```python
df_corr = df.select_dtypes(include=np.number)
```

In [9]:
```python
plt.figure(figsize = (8,8))
corr = df_corr.corr()
sns.heatmap(corr, annot= True, cmap=sns.diverging_palette(240,10,as_cmap=True),squar
```

Out[9]: <AxesSubplot:>



Let us imagine that our dependent variable is EngineSize
We can see that the variables : Weight, Horsepower, Cylinders have high positive correlation w/ EngineSize

It makes sense to normalize the data for multiple regression models

In [10]:
```python
def normalize(df_,features):
    result = df_.copy()
    for feature_name in features:
        max_value = df_[feature_name].max()
        min_value = df_[feature_name].min()
        result[feature_name] = (df_[feature_name] - min_value) / (max_value - min_va
    return result
```

In [11]:
```python
df_mod = normalize(df_corr,['EngineSize','Weight','Horsepower','Cylinders'])
```

In [12]:
```
y = df_mod[['EngineSize']]
x = df_mod[['Weight','Horsepower','Cylinders']]
```

In [13]:
```
x.head()
```

Out[13]:

	Weight	Horsepower	Cylinders
0	0.487079	0.449649	0.333333
1	0.173783	0.297424	0.111111
2	0.258427	0.297424	0.111111
3	0.323034	0.461358	0.333333
4	0.380150	0.355972	0.333333

In [14]:
```
y.head()
```

Out[14]:

	EngineSize
0	0.304348
1	0.086957
2	0.144928
3	0.260870
4	0.304348

In [15]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

In [16]:
```
lin_reg = LinearRegression()
lin_reg.fit(x_train,y_train)
```

Out[16]:
```
▾ LinearRegression
LinearRegression()
```

In [17]:
```
y_pred=lin_reg.predict(x_test)
```

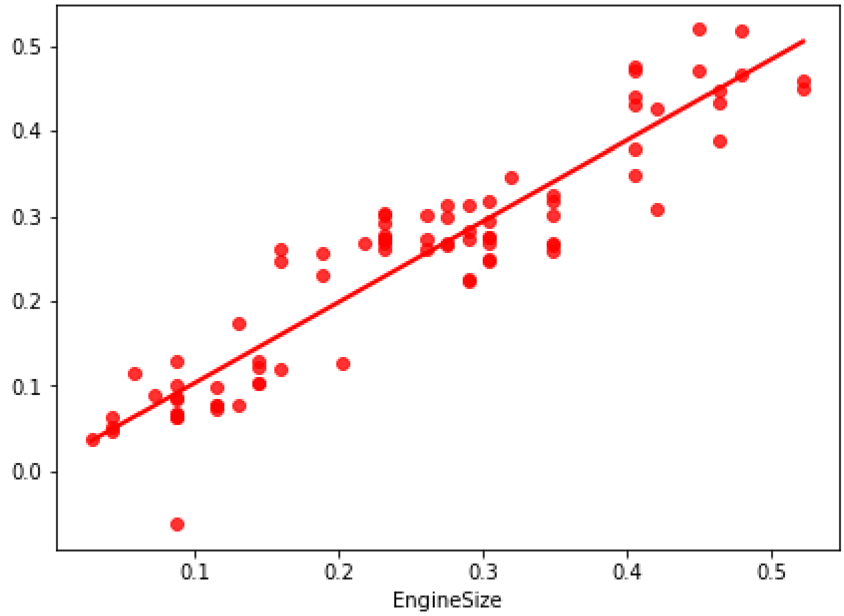
Evaluating Accuracy : We use the r^2 value; which has a range of [0,1]

In [18]:
```
Accuracy=r2_score(y_test,y_pred)*100
print(" Accuracy of the model is %.2f %%" %Accuracy)
```

```
 Accuracy of the model is 86.11 %
```

In [19]:
```
plt.figure(figsize=(7,5))
sns.regplot(x=y_test,y=y_pred,ci=None,color ='red')
```

Out[19]:
```
<AxesSubplot:xlabel='EngineSize'>
```



Logistic regression

Titanic dataset is used for this

In [25]:
```
titanic = pd.read_csv("./titanic/train.csv")
```

In [26]:
```
titanic.head()
```

Out[26]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN

In [27]:
```
ports = pd.get_dummies(titanic.Embarked , prefix='Embarked')
ports.head()
```

Out[27]:

	Embarked_C	Embarked_Q	Embarked_S
0	0	0	1
1	1	0	0
2	0	0	1
3	0	0	1
4	0	0	1

In [28]:

```
titanic = titanic.join(ports)
titanic.drop(['Embarked'], axis=1, inplace=True)
```

In [29]:

```
titanic.Sex = titanic.Sex.map({'male':0, 'female':1})
```

In [31]:

```
y = titanic.Survived.copy() # copy “y” column values out
```

In [32]:

```
X = titanic.drop(['Survived'], axis=1) # then, drop y column
```

In [33]:

```
X.drop(['Cabin'], axis=1, inplace=True)
```

In [34]:

```
X.drop(['Ticket'], axis=1, inplace=True)
```

In [35]:

```
X.drop(['Name'], axis=1, inplace=True)
X.drop(['PassengerId'], axis=1, inplace=True)
```

In [36]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 9 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   Pclass      891 non-null    int64  
 1   Sex         891 non-null    int64  
 2   Age         714 non-null    float64
 3   SibSp       891 non-null    int64  
 4   Parch       891 non-null    int64  
 5   Fare        891 non-null    float64
 6   Embarked_C  891 non-null    uint8  
 7   Embarked_Q  891 non-null    uint8  
 8   Embarked_S  891 non-null    uint8  
dtypes: float64(2), int64(4), uint8(3)
memory usage: 44.5 KB
```

In [37]:

```
X.isnull().values.any()
```

Out[37]: True

In [38]:

```
X.Age.fillna(X.Age.mean(), inplace=True)  # replace NaN with average age
```

In [39]:

```
X.isnull().values.any()
```

Out[39]:

```
False
```

In [40]:

```
from sklearn.model_selection import train_test_split
  # 80 % go into the training test, 20% in the validation test
X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_st
```

In [43]:

```
model = LogisticRegression()
```

In [44]:

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

```
d:\SoftWare\Python\lib\site-packages\sklearn\linear_model\_logistic.py:444: Converge
nceWarning:

lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
```

Out[44]:

```
▾ LogisticRegression
LogisticRegression()
```

In [45]:

```
model.score(X_train, y_train)
```

Out[45]:

```
0.8089887640449438
```

In [46]:

```
model.score(X_valid, y_valid)
```

Out[46]:

```
0.7541899441340782
```

Implementing binary classification with Decision Tree Classifier

Entropy is the measure of randomness at every stage of the decision tree
Reduction of Entropy is the goal

In [48]:

```
model = DecisionTreeClassifier()
```

In [49]:

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

Out[49]:

```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [50]:

```
model.score(X_train, y_train)
```

Out[50]: 0.9831460674157303

In [51]:
```
model.score(X_valid, y_valid)
```

Out[51]: 0.7318435754189944

Now implemeting the Naive Bayes algorithm

We observe that train score and validation score are much closer here This may be the best classifier overall

In [54]:
```
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Out[54]:
```
▾ GaussianNB
GaussianNB()
```

In [55]:
```
classifier.score(X_train, y_train)
```

Out[55]: 0.797752808988764

In [56]:
```
classifier.score(X_valid, y_valid)
```

Out[56]: 0.770949720670391

Unsupervised Learning

We will attempt to implemet a k-means clustering algorithm

Steps to be implemeted :

1. Determine value of K
2. Selecting random K points
3. Assigning data points to closest centroid
4. Calculating variance and determining new centroids
5. Step 3 repeated - If reassignment occurs : goto Step 4 ; Else : goto Step 6
6. END

We will continue with the cars dataset

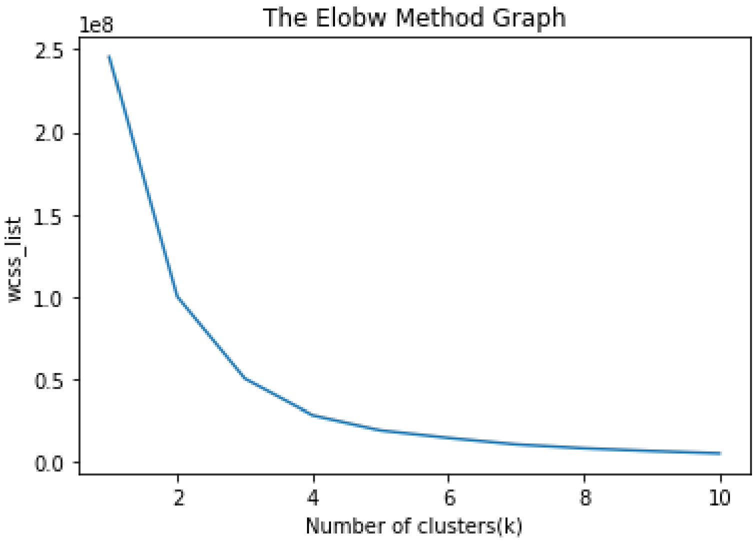
In [ ]:
```
df = pd.read_csv('./cars.csv')
```

In [20]:
```
x = df[['Weight','Wheelbase']].values
```

In [21]:
```
wcss_list= []
```

In [22]:
```
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state= 42)
    kmeans.fit(x)
    wcss_list.append(kmeans.inertia_)
```

```
plt.plot(range(1, 11), wcss_list)
plt.title('The Elobw Method Graph')
plt.xlabel('Number of clusters(k)')
plt.ylabel('wcss_list')
plt.show()
```



From the plot generated above - it looks like the optimal value for k is 3 (elbow point)

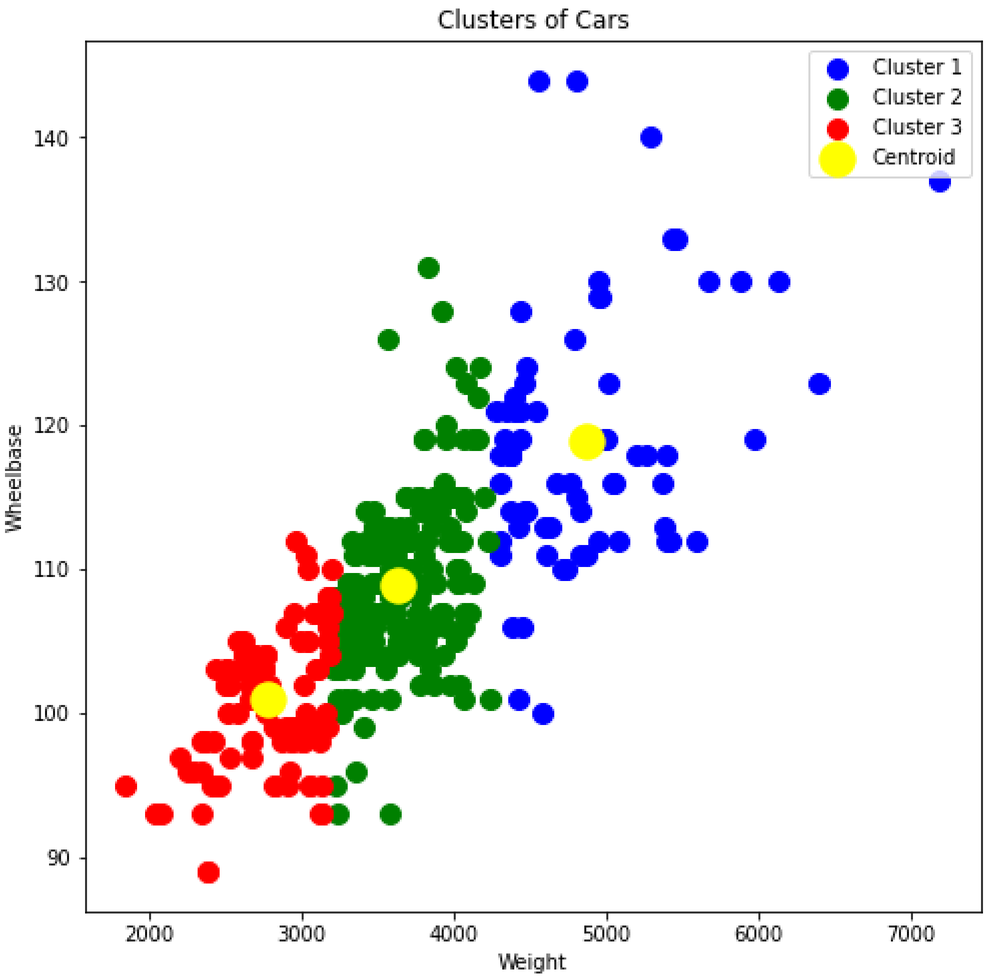
In [23]:

```
kmeans = KMeans(n_clusters=3, init='k-means++', random_state= 42)
y_predict= kmeans.fit_predict(x)
```

Plotting the optimal clusters

In [24]:

```
plt.figure(figsize=(8,8))
plt.scatter(x[y_predict == 0, 0], x[y_predict == 0, 1], s = 100, c = 'blue', label =
plt.scatter(x[y_predict == 1, 0], x[y_predict == 1, 1], s = 100, c = 'green', label
plt.scatter(x[y_predict== 2, 0], x[y_predict == 2, 1], s = 100, c = 'red', label = '
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c
plt.title('Clusters of Cars')
plt.xlabel('Weight')
plt.ylabel('Wheelbase')
plt.legend()
plt.show()
```



Hierarchical clustering:

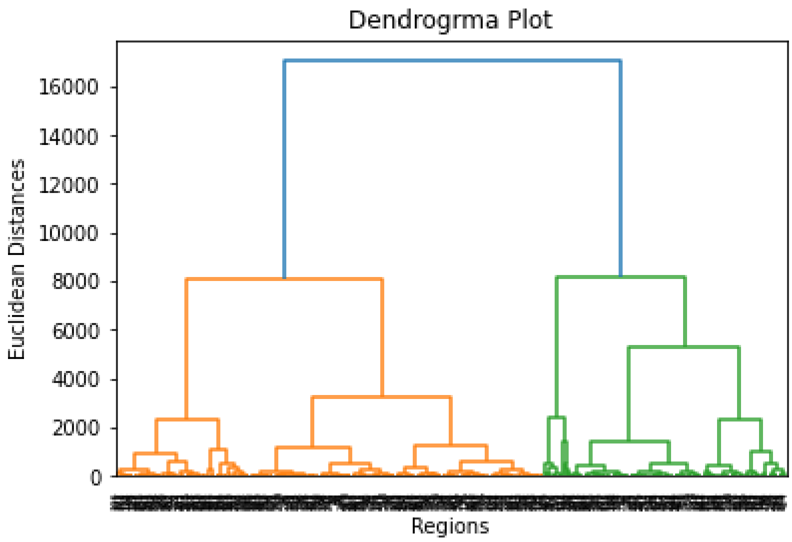
1. Data Pre-processing
2. Finding the optimal number of clusters using the Dendrogram
3. Training the hierarchical clustering model
4. Visualizing the clusters

In [25]:

```
x = df[['Weight','Wheelbase']].values
```

In [28]:

```
dendro = shc.dendrogram(shc.linkage(x, method="ward"))
plt.title("Dendrogrma Plot")
plt.ylabel("Euclidean Distances")
plt.xlabel("Regions")
plt.show()
```



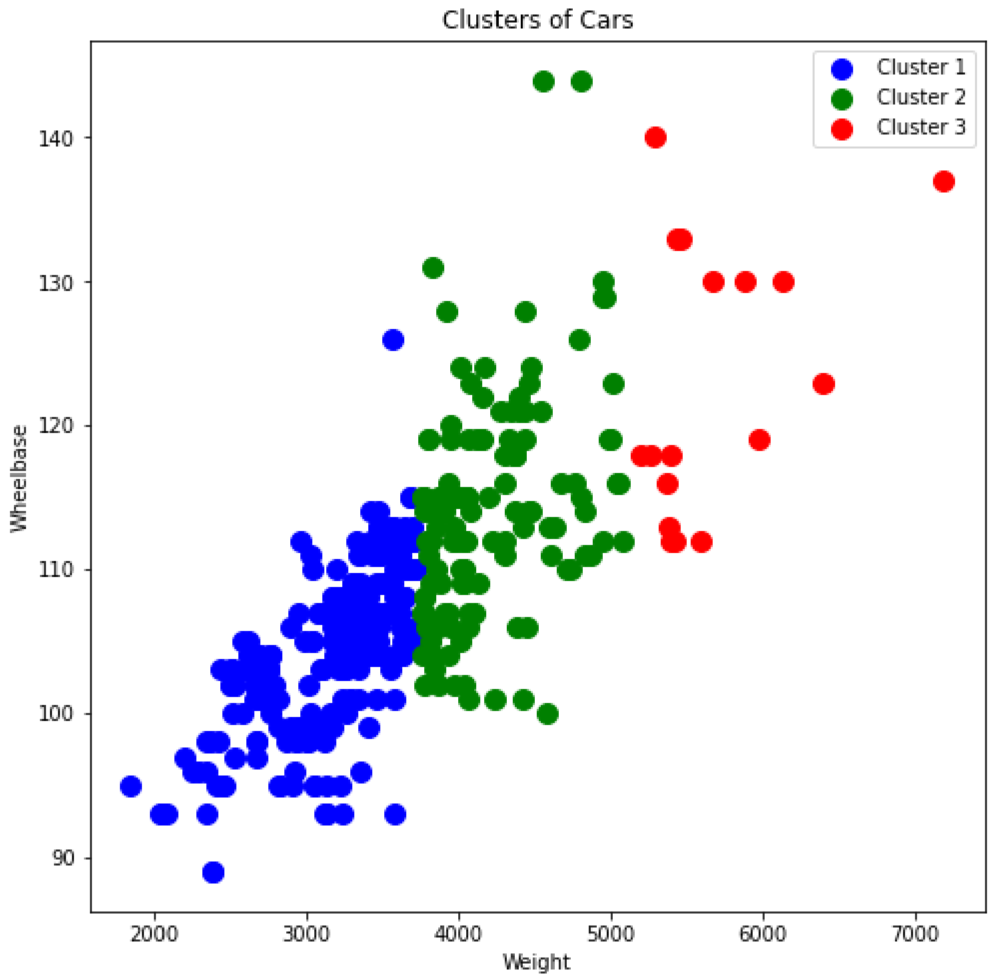
Using this Dendrogram, we will now determine the optimal number of clusters for our model. For this, we will find the maximum vertical distance that does not cut any horizontal bar. Consider the below diagram:

In [30]:

```
hc= AgglomerativeClustering(n_clusters=3, affinity='euclidean', linkage='ward')
y_pred= hc.fit_predict(x)
```

In [32]:

```
plt.figure(figsize=(8,8))
plt.scatter(x[y_pred == 0, 0], x[y_pred == 0, 1], s = 100, c = 'blue', label = 'Clus
plt.scatter(x[y_pred == 1, 0], x[y_pred == 1, 1], s = 100, c = 'green', label = 'Clu
plt.scatter(x[y_pred == 2, 0], x[y_pred == 2, 1], s = 100, c = 'red', label = 'Clust
plt.title('Clusters of Cars')
plt.xlabel('Weight')
plt.ylabel('Wheelbase')
plt.legend()
plt.show()
```



Association rules (Apriori) :

Used to implement reccomender systems based on products already in consumers purchases

In [4]:

```
data1 = pd.read_excel('.\Online_Retail.xlsx')
data1.head()
```

```
<>:1: DeprecationWarning: invalid escape sequence \O
<>:1: DeprecationWarning: invalid escape sequence \O
C:\Users\Anjishnu Roy\AppData\Local\Temp\ipykernel_16756\407837724.py:1: Deprecation
Warning: invalid escape sequence \O
  data1 = pd.read_excel('.\Online_Retail.xlsx')
```

Out[4]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
			HOT WATER BOTTLE					
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom

We will strip the extra spaces in the description

In [6]:

```
data1['Description'] = data1['Description'].str.strip()
```

Drop the rows which does not have any invoice number

In [7]:

```
data1.dropna(axis = 0, subset = ['InvoiceNo'], inplace = True)
data1['InvoiceNo'] = data1['InvoiceNo'].astype('str')
```

We will drop all transactions which were done on credit

In [8]:

```
data1 = data1[~data1['InvoiceNo'].str.contains('C')]
```

Split data by region

In [9]:

```
basket1_France = (data1[data1['Country'] == "France"]
        .groupby(['InvoiceNo', 'Description'])['Quantity']
        .sum().unstack().reset_index().fillna(0)
        .set_index('InvoiceNo'))

basket1_UK = (data1[data1['Country'] == "United Kingdom"]
        .groupby(['InvoiceNo', 'Description'])['Quantity']
        .sum().unstack().reset_index().fillna(0)
        .set_index('InvoiceNo'))

basket1_Por = (data1[data1['Country'] == "Portugal"]
        .groupby(['InvoiceNo', 'Description'])['Quantity']
        .sum().unstack().reset_index().fillna(0)
        .set_index('InvoiceNo'))

basket1_Sweden = (data1[data1['Country'] == "Sweden"]
        .groupby(['InvoiceNo', 'Description'])['Quantity']
        .sum().unstack().reset_index().fillna(0)
        .set_index('InvoiceNo'))
```

Implemeting one hot encoding (limiting values to 0 or 1)

In [10]:

```
def hot_encode1(P):
    if(P<= 0):
        return 0
    if(P>= 1):
        return 1
```

In [11]:

```
basket1_encoded = basket1_France.applymap(hot_encode1)
basket1_France = basket1_encoded

basket1_encoded = basket1_UK.applymap(hot_encode1)
```

```
basket1_UK = basket1_encoded

basket1_encoded = basket1_Por.applymap(hot_encode1)
basket1_Por = basket1_encoded

basket1_encoded = basket1_Sweden.applymap(hot_encode1)
basket1_Sweden = basket1_encoded
```

Implemeting a model for France

In [12]:

```
frq_items1 = apriori(basket1_France, min_support = 0.05, use_colnames = True)
```

```
d:\SoftWare\Python\lib\site-packages\mlxtend\frequent_patterns\fpcommon.py:110: Depr
ecationWarning: DataFrames with non-bool types result in worse computationalperforma
nce and their support might be discontinued in the future.Please use a DataFrame wit
h bool type
  warnings.warn(
```

In [14]:

```
rules1 = association_rules(frq_items1, metric = "lift", min_threshold = 1)
rules1 = rules1.sort_values(['confidence', 'lift'], ascending = [False, False])
rules1.head()
```

Out[14]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage
44	(JUMBO BAG WOODLAND ANIMALS)	(POSTAGE)	0.076531	0.765306	0.076531	1.000	1.306667	0.017961
259	(PLASTERS IN TIN CIRCUS PARADE, RED TOADSTOOL ...	(POSTAGE)	0.051020	0.765306	0.051020	1.000	1.306667	0.011974
271	(PLASTERS IN TIN WOODLAND ANIMALS, RED TOADSTO...	(POSTAGE)	0.053571	0.765306	0.053571	1.000	1.306667	0.012573
301	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	(SET/6 RED SPOTTY PAPER PLATES)	0.102041	0.127551	0.099490	0.975	7.644000	0.086474
300	(SET/20 RED RETROSPOT PAPER NAPKINS, SET/6 RED...	(SET/6 RED SPOTTY PAPER CUPS)	0.102041	0.137755	0.099490	0.975	7.077778	0.085433

Text Mining

In [2]:

```
train = pd.read_csv("./spooky-author-identification/train/train.csv")
```

Authors and their text

In [3]:

```
train.head()
```

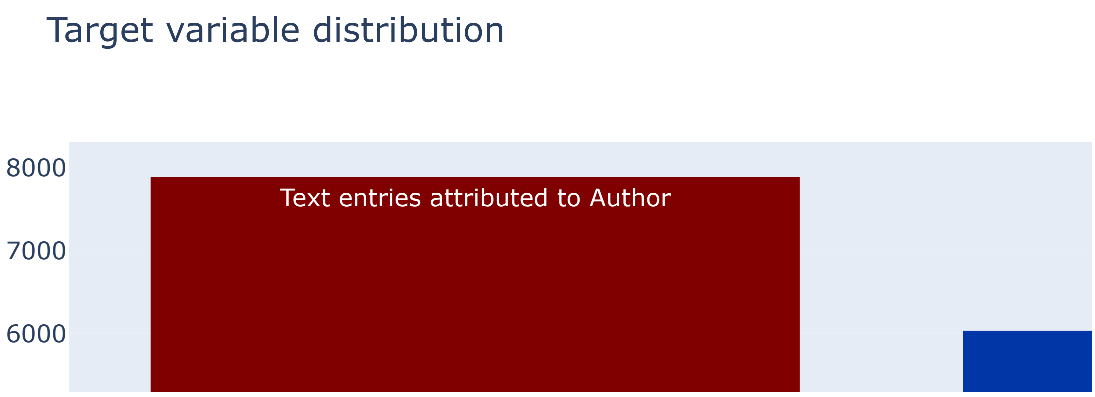
Out[3]:

	id	text	author
0	id26305	This process, however, afforded me no means of...	EAP
1	id17569	It never once occurred to me that the fumbling...	HPL
2	id11008	In his left hand was a gold snuff box, from wh...	EAP
3	id27763	How lovely is spring As we looked from Windsor...	MWS
4	id12958	Finding nothing else, not even gold, the Super...	HPL

EDA

In [4]:

```
z = {'EAP': 'Edgar Allen Poe', 'MWS': 'Mary Shelley', 'HPL': 'HP Lovecraft'}
data = [go.Bar(
            x = train.author.map(z).unique(),
            y = train.author.value_counts().values,
            marker= dict(colorscale='Jet',
                         color = train.author.value_counts().values
                        ),
            text='Text entries attributed to Author'
    )]

layout = go.Layout(
    title='Target variable distribution'
)

fig = go.Figure(data=data, layout=layout)

py.iplot(fig, filename='basic-bar')
```



NLP :

1. **Tokenization** - Segregation of the text into its individual constitutent words.
2. **Stopwords** - Throw away any words that occur too frequently as its frequency of occurrence will not be useful in helping detecting relevant texts. (as an aside also consider throwing away words that occur very infrequently).
3. **Stemming** - combine variants of words into a single parent word that still conveys the same meaning
4. **Vectorization** - Converting text into vector format. One of the simplest is the famous bag-of-words approach, where you create a matrix (for each document or text in the corpus). In the simplest form, this matrix stores word frequencies (word counts) and is oft referred to as vectorization of the raw text.

In [7]:

```
first_text = train.text.values[0]
print(first_text)
print("="*90)
print(first_text.split(" "))
```

```
This process, however, afforded me no means of ascertaining the dimensions of my dun
geon; as I might make its circuit, and return to the point whence I set out, without
being aware of the fact; so perfectly uniform seemed the wall.
=========================================================================================
======
['This', 'process,', 'however,', 'afforded', 'me', 'no', 'means', 'of', 'ascertainin
g', 'the', 'dimensions', 'of', 'my', 'dungeon;', 'as', 'I', 'might', 'make', 'its',
'circuit,', 'and', 'return', 'to', 'the', 'point', 'whence', 'I', 'set', 'out,', 'wi
thout', 'being', 'aware', 'of', 'the', 'fact;', 'so', 'perfectly', 'uniform', 'seeme
d', 'the', 'wall.']
```

In [8]:

```
first_text_list = nltk.word_tokenize(first_text)
print(first_text_list)
```

```
['This', 'process', ',', 'however', ',', 'afforded', 'me', 'no', 'means', 'of', 'asc
ertaining', 'the', 'dimensions', 'of', 'my', 'dungeon', ';', 'as', 'I', 'might', 'ma
ke', 'its', 'circuit', ',', 'and', 'return', 'to', 'the', 'point', 'whence', 'I', 's
et', 'out', ',', 'without', 'being', 'aware', 'of', 'the', 'fact', ';', 'so', 'perfe
ctly', 'uniform', 'seemed', 'the', 'wall', '.']
```

In [9]:

```
stopwords = nltk.corpus.stopwords.words('english')
len(stopwords)
```

Out[9]: 179

In [10]:

```
first_text_list_cleaned = [word for word in first_text_list if word.lower() not in s
print(first_text_list_cleaned)
print("="*90)
print("Length of original list: {0} words\n"
      "Length of list after stopwords removal: {1} words"
      .format(len(first_text_list), len(first_text_list_cleaned)))
```

```
['process', ',', 'however', ',', 'afforded', 'means', 'ascertaining', 'dimensions',
'dungeon', ';', 'might', 'make', 'circuit', ',', 'return', 'point', 'whence', 'set',
',', 'without', 'aware', 'fact', ';', 'perfectly', 'uniform', 'seemed', 'wall', '.']
```

```
=============================================================================
======
Length of original list: 48 words
Length of list after stopwords removal: 28 words
```

Stemming and Lemmatization

In [11]:

```
stemmer = nltk.stem.PorterStemmer()
```

In [12]:

```
print("The stemmed form of running is: {}".format(stemmer.stem("running")))
print("The stemmed form of runs is: {}".format(stemmer.stem("runs")))
print("The stemmed form of run is: {}".format(stemmer.stem("run")))
```

```
The stemmed form of running is: run
The stemmed form of runs is: run
The stemmed form of run is: run
```

In [13]:

```
print("The stemmed form of leaves is: {}".format(stemmer.stem("leaves")))
```

```
The stemmed form of leaves is: leav
```

In [16]:

```
nltk.download('omw-1.4')
```

```
[nltk_data] Downloading package omw-1.4 to C:\Users\Anjishnu
[nltk_data]     Roy\AppData\Roaming\nltk_data...
```

Out[16]:

```
True
```

In [17]:

```
lemm = WordNetLemmatizer()
print("The lemmatized form of leaves is: {}".format(lemm.lemmatize("leaves")))
```

```
The lemmatized form of leaves is: leaf
```

Vectorizing the text

Bag of Words

In [18]:

```
sentence = ["I love to eat Burgers",
            "I love to eat Fries"]
vectorizer = CountVectorizer(min_df=0)
sentence_transform = vectorizer.fit_transform(sentence)
```

In [19]:

```
print("The features are:\n {}".format(vectorizer.get_feature_names()))
print("\nThe vectorized array looks like:\n {}".format(sentence_transform.toarray())
```

```
The features are:
 ['burgers', 'eat', 'fries', 'love', 'to']

The vectorized array looks like:
 [[1 1 0 1 1]
 [0 1 1 1 1]]
d:\SoftWare\Python\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning:

Function get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and
will be removed in 1.2. Please use get_feature_names_out instead.
```

In [20]:

```
sentence_transform
```

Out[20]:
```
<2x5 sparse matrix of type '<class 'numpy.int64'>'
	with 8 stored elements in Compressed Sparse Row format>
```

Modelling

In [21]:
```
# Define helper function to print top words
def print_top_words(model, feature_names, n_top_words):
    for index, topic in enumerate(model.components_):
        message = "\nTopic #{}:".format(index)
        message += " ".join([feature_names[i] for i in topic.argsort()[:-n_top_words
        print(message)
        print("="*70)
```

In [22]:
```
lemm = WordNetLemmatizer()
class LemmaCountVectorizer(CountVectorizer):
    def build_analyzer(self):
        analyzer = super(LemmaCountVectorizer, self).build_analyzer()
        return lambda doc: (lemm.lemmatize(w) for w in analyzer(doc))
```

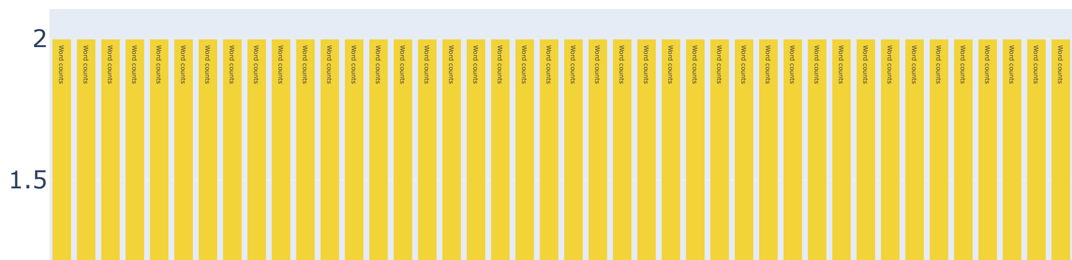
In [23]:
```
# Storing the entire training text in a list
text = list(train.text.values)
# Calling our overwritten Count vectorizer
tf_vectorizer = LemmaCountVectorizer(max_df=0.95,
                                     min_df=2,
                                     stop_words='english',
                                     decode_error='ignore')
tf = tf_vectorizer.fit_transform(text)
```

In [24]:
```
feature_names = tf_vectorizer.get_feature_names()
count_vec = np.asarray(tf.sum(axis=0)).ravel()
zipped = list(zip(feature_names, count_vec))
x, y = (list(x) for x in zip(*sorted(zipped, key=lambda x: x[1], reverse=True)))
# Now I want to extract out on the top 15 and bottom 15 words
Y = np.concatenate([y[0:15], y[-16:-1]])
X = np.concatenate([x[0:15], x[-16:-1]])

# Plotting the Plot.ly plot for the Top 50 word frequencies
data = [go.Bar(
            x = x[0:50],
            y = y[0:50],
            marker= dict(colorscale='Jet',
                         color = y[0:50]
                        ),
            text='Word counts'
    )]

layout = go.Layout(
    title='Top 50 Word frequencies after Preprocessing'
)

fig = go.Figure(data=data, layout=layout)

py.iplot(fig, filename='basic-bar')

# Plotting the Plot.ly plot for the Top 50 word frequencies
data = [go.Bar(
            x = x[-100:],
            y = y[-100:],
            marker= dict(colorscale='Portland',
```

```
                         color = y[-100:]
                        ),
            text='Word counts'
    )]

layout = go.Layout(
    title='Bottom 100 Word frequencies after Preprocessing'
)

fig = go.Figure(data=data, layout=layout)

py.iplot(fig, filename='basic-bar')
```

Top 50 Word frequencies after Preprocessing

Bottom 100 Word frequencies after Preprocessing



Neural Network

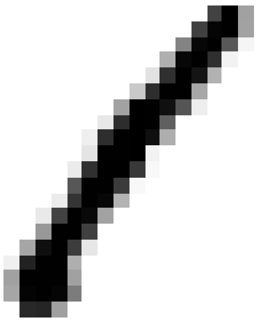
In [41]:
```
train = pd.read_csv('./digit-recognizer/train.csv')
test = pd.read_csv('./digit-recognizer/test.csv')
```

In [42]:
```
X, y = train.drop(["label"], axis = 1), train["label"]
```

In [43]:
```
first_image = X.iloc[0]
```

In [44]:
```
plt.imshow(first_image.to_numpy().reshape(28,28), cmap='binary')
plt.axis("off")
plt.show
```

Out[44]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



Normalization

In [45]:
```
X = X / 255
```

Reshape

In [46]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_stat
```

In [47]:
```
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)
```

CNN

Define the model

Model Definition

In [48]:

```
model = Sequential()
model.add(Dense(128, activation = "relu", input_shape =(784,)))
model.add(Dense(64, activation = "relu"))
model.add(Dense(10, activation ="softmax"))
```

In [49]:

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_6 (Dense)             (None, 128)               100480

 dense_7 (Dense)             (None, 64)                8256

 dense_8 (Dense)             (None, 10)                650

=================================================================
Total params: 109,386
Trainable params: 109,386
Non-trainable params: 0
_________________________________________________________________
```

In [50]:

```
model.compile(loss="categorical_crossentropy",
              optimizer="Adam",
              metrics = ['accuracy'])
```

In [51]:

```
tf.config.run_functions_eagerly(True)
import warnings
warnings.filterwarnings("ignore")
```

In [52]:

```
model.fit(X_train, y_train, batch_size = 100, epochs = 10, validation_data = (X_test
```

```
Epoch 1/10
378/378 [==============================] - 8s 22ms/step - loss: 0.3855 - accuracy:
0.8894 - val_loss: 0.2119 - val_accuracy: 0.9400
Epoch 2/10
378/378 [==============================] - 9s 23ms/step - loss: 0.1527 - accuracy:
0.9550 - val_loss: 0.1617 - val_accuracy: 0.9545
Epoch 3/10
378/378 [==============================] - 9s 23ms/step - loss: 0.1035 - accuracy:
0.9694 - val_loss: 0.1311 - val_accuracy: 0.9624
Epoch 4/10
378/378 [==============================] - 9s 24ms/step - loss: 0.0768 - accuracy:
0.9758 - val_loss: 0.1190 - val_accuracy: 0.9667
Epoch 5/10
378/378 [==============================] - 8s 21ms/step - loss: 0.0591 - accuracy:
0.9822 - val_loss: 0.1110 - val_accuracy: 0.9702
Epoch 6/10
378/378 [==============================] - 9s 23ms/step - loss: 0.0464 - accuracy:
0.9860 - val_loss: 0.1243 - val_accuracy: 0.9662
Epoch 7/10
378/378 [==============================] - 8s 22ms/step - loss: 0.0373 - accuracy:
0.9879 - val_loss: 0.1237 - val_accuracy: 0.9679
```

```
Epoch 8/10
378/378 [==============================] - 9s 23ms/step - loss: 0.0301 - accuracy:
0.9913 - val_loss: 0.1160 - val_accuracy: 0.9683
Epoch 9/10
378/378 [==============================] - 9s 23ms/step - loss: 0.0236 - accuracy:
0.9932 - val_loss: 0.1282 - val_accuracy: 0.9679
Epoch 10/10
378/378 [==============================] - 9s 24ms/step - loss: 0.0225 - accuracy:
0.9933 - val_loss: 0.1254 - val_accuracy: 0.9679
```

Out[52]: <keras.callbacks.History at 0x2642e6515e0>

In [53]:

```python
test_loss, test_acc = model.evaluate(X_test, y_test)
```

```
132/132 [==============================] - 1s 8ms/step - loss: 0.1254 - accuracy: 0.
9679
```

In [54]:

```python
print(test_acc)
```

```
0.9678571224212646
```

In [55]:

```python
y_pred = model.predict(X_test)
y_pred_classes = np.argmax(y_pred, axis = 1)
```

```
132/132 [==============================] - 0s 2ms/step
```

In [56]:

```python
print(np.round(y_pred[0]))
```

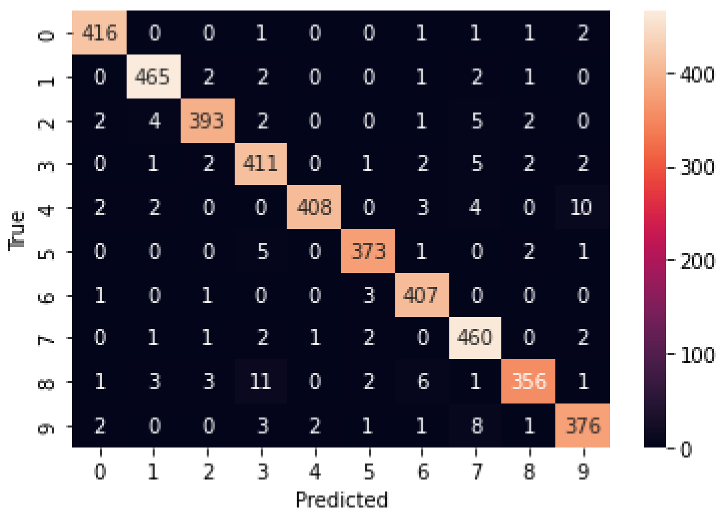
```
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
```

In [57]:

```python
y_true = np.argmax(y_test, axis = 1)
```

In [60]:

```python
confusion = confusion_matrix(y_true, y_pred_classes)
sns.heatmap(confusion, annot=True, fmt='d')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



In [61]:

```python
print(classification_report(y_true, y_pred_classes))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       422
```

1	0.98	0.98	0.98	473
2	0.98	0.96	0.97	409
3	0.94	0.96	0.95	426
4	0.99	0.95	0.97	429
5	0.98	0.98	0.98	382
6	0.96	0.99	0.97	412
7	0.95	0.98	0.96	469
8	0.98	0.93	0.95	384
9	0.95	0.95	0.95	394
accuracy			0.97	4200
macro avg	0.97	0.97	0.97	4200
weighted avg	0.97	0.97	0.97	4200