## **APPENDIX**

## (A)

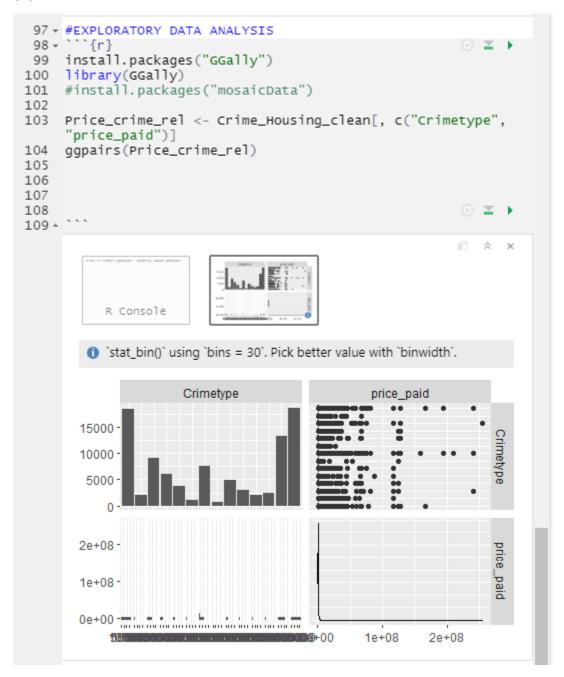
```
2 title: "Distributed Data Analysis"
3 author: "2012754"
 4 date: "21/03/21"
 5 output: html_notebook
 6 - ---
 7
 8 This is an [R Markdown] (http://rmarkdown.rstudio.com)
    Notebook. When you execute code within the notebook, the
    results appear beneath the code.
10 Try executing this chunk by clicking the *Run* button
    within the chunk or by placing your cursor inside it and
    pressing *Ctrl+Shift+Enter*.
11
12 + #HOUSING DATA
13 + ```{r}
14 library(dplyr)
15 #import dataset and inspect file
16 housing <- read.csv("C:/Users/tochi/Desktop/Housing_Data_</p>
    GreaterLondon_2018-20.csv", header = TRUE)
17 str(housing)
18 summary(housing)
19
20 #drop columns
21 housing_clean <- select(housing, -'saon', -'paon',</pre>
    -'estate_type', -'street', -'linked_data_uri', -'county',
-'transaction_category', -'street', -'locality')
22 view(housing_clean)
23 #convert into correct date format
24 housing_clean$deed_date <-</pre>
    as.Date(housing_clean$deed_date, format = "%Y-%m-%d")
25
26 #convert into categorical
27 housing_clean$property_type <-</p>
    as.factor(housing_clean$property_type)
28 housing_clean$new_build <-</pre>
    as.factor(housing_clean$new_build)
29
30 #change deed date to date prior to our join
31 names(housing_clean)[3] <- 'date'</pre>
32
33 #format to just month and year
34 housing_clean$date <- format(housing_clean$date, "%m/%Y")</pre>
35
36 - ` ` `
```

(B)

```
36 ^ ```
37 ▼ ##DATA JOINING STREET CRIME WITH HOUSING
38
39 + ```{r}
                                                      ⊕ ≚ ▶
40 library(zoo)
41 library(anytime)
42
43
44 #read in the street data and inspect it
45 street_crime <-
    read.csv('C:/Users/tochi/Desktop/metropolitan-street-fina
    1.csv')
46 str(street_crime)
47
48 #convert into categorical
49 street_crime$Crime.type <-
    as.factor(street_crime$Crime.type)
50 street_crime$postcode <- as.factor(street_crime$postcode)</pre>
51
52 street_crime$Month <- anytime(street_crime$Month)</p>
53 street_crime$Month <- as.Date(street_crime$Month, format</p>
    = "%Y-%m-%d")
54 street_crime$Month <- format(street_crime$Month, '%m/%Y')
55
56 names(street_crime)[2] <- 'date'
57
58 #inner join on postcode
59 Crime_Housing <- merge(housing_clean, street_crime, by =</p>
    c("postcode", "date"), all.x = TRUE, all.y = TRUE)
60 #create a csv file with our df
61 write.csv(Crime_Housing,
    'C:/Users/tochi/Desktop/Crime_Housing.csv', row.names =
    FALSE)
62 str(Crime_Housing)
63 plot(Crime_Housing$price_paid, ylab = "price_paid")
64 plot(Crime_Housing$Crime.type, ylab -= "Crimetype")
65
66 * ```
```

(C)

```
69 - #Removing Outliers and Duplicate Rows
70 + ```{r}
71
72 str(Crime_Housing)
73 summary(Crime_Housing)
74 boxplot(Crime_Housing$price_paid)
75 Crime_Housing_boxplot <-</p>
    boxplot(Crime_Housing$price_paid)
76
77
78 Crime_Housing_boxplot$out
79
80 min(Crime_Housing_boxplot$out)
81
82 Crime_Housing[Crime_Housing$price_paid >=
   min(Crime_Housing_boxplot$out), ]
83
84 #to remove duplicate rows
85 Crime_Housing_clean <- unique(Crime_Housing)
86 str(Crime_Housing_clean)
87
88 ##to visualise graphically
89 Crime.type.freq <- xtabs(~ Crimetype, data =
   Crime_Housing)
90 Crime.type.prop <- prop.table(Crime.type.freq)
91 Crime.type.prop
92
93 Price_paid.hist <- ggplot(data = Crime_Housing, aes(x =
    price_paid)) + geom_histogram(binwidth =10, color =
    "black", fill = "lightgrey") + xlab("Price_Paid") +
    ylab("Frequency")
94
95
96 - ` ` `
```



```
In [1]: import pandas as pd
  import datetime#, timedelta
           import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
           from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
In [2]: housing_Crime_Data = pd.read_csv(r"C:\Users\tochi\Desktop\Crime_Housing.csv")
housing_Crime_Data.describe()
                        price_paid
            count 1.344350e+05
             mean 9.119420e+05
             std 5.360636e+06
              min 1.000000e+02
             25% 3.170000e+05
              50% 4.350000e+05
            75% 6.450000e+05
              max 2.550000e+08
In [3]: housing_Crime_Data.dtypes
Out[3]: Month
           Crime.type
postcode
price_paid
                                   object
object
int64
           property_type object
new_build object
town object
district object
                                   object
            dtype: object
In [4]: housing_Crime_Data.columns
```

```
In [4]: housing_Crime_Data.columns
   In [5]:
housing_Crime_Data['Crime.type'] = pd.Categorical(housing_Crime_Data['Crime.type'])
housing_Crime_Data['postcode'] = pd.Categorical(housing_Crime_Data['postcode'])
housing_Crime_Data['Month'] = pd.Categorical(housing_Crime_Data['Month'])
housing_Crime_Data['property_type'] = pd.Categorical(housing_Crime_Data['property_type'])
housing_Crime_Data['new_build'] = pd.Categorical(housing_Crime_Data['new_build'])
housing_Crime_Data['district'] = pd.Categorical(housing_Crime_Data['district'])
housing_Crime_Data['town'] = pd.Categorical(housing_Crime_Data.loc[:,'town'])
    In [6]: housing_Crime_Data.dtypes
   Out[6]: Month
                                      Crime.type
                                                                                                         category
category
                                       postcode
                                       price_paid
                                                                                                               int64
                                       property_type
new_build
                                                                                                         category
                                                                                                          category
                                       town
                                                                                                          category
                                       district
                                                                                                          category
                                       dtype: object
   In [8]: Housing_CrimeData_Clean_Cat = housing_Crime_Data.select_dtypes(include=['category'])
Housing_CrimeData_Clean_num = housing_Crime_Data.select_dtypes(exclude=['category'])
                                      X_encoded = pd.get_dummies(Housing_CrimeData_Clean_Cat)
   In [9]: frames = [X_encoded, Housing_CrimeData_Clean_num]
combo_enc = pd.concat(frames, axis = 1)
In [10]: Housing_CrimeData_Clean_Cat_freq = Housing_CrimeData_Clean_Cat.copy()
    for c in Housing_CrimeData_Clean_Cat_freq.columns.to_list():
        Housing_CrimeData_Clean_Cat_freq[c] = Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housi
In [11]: frames_freq = [Housing_CrimeData_Clean_Cat_freq, Housing_CrimeData_Clean_num]
combo_enc_freq = pd.concat(frames_freq, axis = 1)
```

```
In [9]: frames = [X_encoded, Housing_CrimeData_Clean_num]
combo_enc = pd.concat(frames, axis = 1)
In [10]: Housing_CrimeData_Clean_Cat_freq = Housing_CrimeData_Clean_Cat.copy()
for c in Housing_CrimeData_Clean_Cat_freq.columns.to_list():
                                    Housing_CrimeData_Clean_Cat_freq[c] = Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Clean_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_CrimeData_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housing_Cat_freq.groupby(c).transform('count')/len(Housi
In [11]: frames_freq = [Housing_CrimeData_Clean_Cat_freq, Housing_CrimeData_Clean_num]
                         combo_enc_freq = pd.concat(frames_freq, axis = 1)
combo_enc_freq.shape
Out[11]: (134435, 8)
In [12]: combo_enc_freq.tail()
combo_enc_freq.info()
                          <class 'pandas.core.frame.DataFrame'>
                         RangeIndex: 134435 entries, 0 to 134434
Data columns (total 8 columns):
                          # Column
                                                                           Non-Null Count
                                                                                 -----
                           0 Month
                                                                                 134435 non-null float64
                             1 Crime.type
                                                                                 134435 non-null float64
                                                                                134435 non-null float64
                             2 postcode
                            postcour 134435 non-null float64
new_build 134435 non-null float64
town 134435 non-null float64
                             6 district
                                                                                 134435 non-null
                         7 price_paid 134435 no
dtypes: float64(7), int64(1)
                                                                            134435 non-null int64
                          memory usage: 8.2 MB
```

```
In [14]: from sklearn.neural_network import MLPRegressor
In [15]: from sklearn.datasets import make_regression
In [43]: regr = MLPRegressor(random_state=1, max_iter=15000).fit(Xtrain, ytrain)
           C:\Users\tochi\anaconda3\lib\site-packages\sklearn\neural_network\_multilayer_perceptron.py:582: ConvergenceWarning: Stochastic Optimizer: Maximum iterations (15000) reached and the optimization hasn't converged yet.
            warnings.warn(
In [44]: regr.predict(Xtest)
Out[44]: array([ 672271.06936196, 3195774.85376639, 489987.51534799, ..., 3268704.75471761, 279349.94606583, 555175.15235468])
In [45]: regr.score(Xtest, ytest)
Out[45]: 0.027650184831768065
In [51]: #R_Square and Adjusted R Square
           import statsmodels.api as sm
          X_addC = sm.add_constant(Xtest)
result = sm.OLS(ytest, X_addC).fit()
print(result.rsquared, result.rsquared_adj)
           0.019493542853790125 0.019289276754566154
In [69]: from sklearn.metrics import mean_squared_error
           import math
           pred_y = regr.predict(Xtest)
           print(mean_squared_error(ytest, pred_y))
           print(math.sqrt(mean_squared_error(ytest, pred_y)))
           30351495581054.434
           5509219.14440281
In [67]: from sklearn.metrics import mean_absolute_error
          print(mean_absolute_error(ytest, pred_y))
           807765.0093318874
```

```
In [1]: !pip install spark
                       Collecting spark
                      Downloading spark-0.2.1.tar.gz (41 kB)

| The state of th
                      Created wheel for spark: filename=spark-0.2.1-py3-none-any.whl size=58738 sha256=d2ef5ba9f0c493d0136c93f2823ea36a0b39720c8858 7af5f94bfa2849ac1357
                            Stored\ in\ directory:\ /Users/sne2909/Library/Caches/pip/wheels/c5/19/ff/9b16f354528bc9698ec3286be7947ebbf1f8391325553961d4
                      Successfully built spark
Installing collected packages: spark
                       Successfully installed spark-0.2.1
In [2]: !pip install imblearn
                       Collecting imblearn
                            Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
                       Collecting imbalanced-learn
                      Downloading imbalanced learn-0.8.0-py3-none-any.whl (206 kB)
| Downloading imbalanced learn-0.8.0-py3-none-any.whl (206 kB)
| Requirement already satisfied: joblib>=0.11 in /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages (from imbalanced-learn->imblearn) (0.15.1)
Requirement already satisfied: scipy>=0.19.1 in /Users/sne2909/Library/Python/3.8/lib/python/site-packages (from imbalanced-learn-)
                       rn->imblearn) (1.4.1)
                       Requirement already satisfied: numpy>=1.13.3 in /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages (from imbalanced-learn->imblearn) (1.19.5)
                       Collecting scikit-learn>=0.24
                      Installing collected packages: scikit-learn, imbalanced-learn, imblearn
                            Attempting uninstall: scikit-learn Found existing installation: scikit-learn 0.23.1
                                  Uninstalling scikit-learn-0.23.1:
                                       Successfully uninstalled scikit-learn-0.23.1
                       Successfully installed imbalanced-learn-0.8.0 imblearn-0.0 scikit-learn-0.24.1
In [3]: !pip install pyspark
                      Collecting pyspark
```

```
Uninstalling scikit-learn-0.23.1:
                     Successfully uninstalled scikit-learn-0.23.1
Successfully installed imbalanced-learn-0.8.0 imblearn-0.0 scikit-learn-0.24.1
 In [3]: !pip install pyspark
                     Collecting pyspark
                          Downloading pyspark-3.1.1.tar.gz (212.3 MB)
                      Collecting py4j==0.10.9
                    f4d79199faeb7529e3ec45b21f5325fa
                          Stored in directory: /Users/sne2909/Library/Caches/pip/wheels/b3/0e/81/264aeed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e43b9f6ba9ec81c8c540d2d7dccc52c6b51cbf22aed961e45b9f6ba9ec81c8c540d2d7dccc52c6b51e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961e46b961
                      Successfully built pyspark
                      Installing collected packages: py4j, pyspark
                     Successfully installed py4j-0.10.9 pyspark-3.1.1 Note: you may need to restart the kernel to use updated packages.
In [4]: from pyspark.sql import SQLContext
    from pyspark.sql import DataFrameNaFunctions
                      from pyspark.ml import Pipeline
                      from pyspark.ml.classification import DecisionTreeClassifier
                      from pyspark.ml.classification import LogisticRegression
                      from pyspark.ml.feature import Binarizer
                     from pyspark.ml.feature import OneHotEncoder, VectorAssembler, StringIndexer, VectorIndexer from pyspark.ml.classification import RandomForestClassifier
                      from pyspark.sql.functions import avg
                      import pandas as pd
                    import numpy as np
import matplotlib.pyplot as plt
                      %matplotlib inline
                     From pyspark.ml.evaluation import MulticlassClassificationEvaluator from imblearn.over_sampling import SMOTE
                     from imblearn.combine import SMOTEENN
from pyspark.mllib.evaluation import MulticlassMetrics
                      from pyspark.ml.evaluation import BinaryClassificationEvaluator
                      from sklearn.model_selection import train_test_split
                     from collections import Counter
 In [5]: from pyspark.context import SparkContext
```

```
Installing collected packages: py4j, pyspark
Successfully installed py4j-0.10.9 pyspark-3.1.1
Note: you may need to restart the kernel to use updated packages.
 In [4]: from pyspark.sql import SQLContext
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              from pyspark.ml.feature import OneHotEncoder, VectorAssembler, StringIndexer, VectorIndexer from pyspark.ml.classification import RandomForestClassifier
              from pyspark.sql.functions import avg
              import pandas as pd
import numpy as np
              import matplotlib.pyplot as plt
              %matplotlib inline
              from pyspark.ml.evaluation import MulticlassClassificationEvaluator
              from imblearn.over_sampling import SMOTE
from imblearn.combine import SMOTEENN
from pyspark.mllib.evaluation import MulticlassMetrics
              from pyspark.ml.evaluation import BinaryClassificationEvaluator from sklearn.model_selection import train_test_split from collections import Counter
 In [5]: from pyspark.context import SparkContext
              from pyspark.sql.session import SparkSession
sc = SparkContext()
              spark = SparkSession(sc)
 In [8]: crime_housing = sqlContext.read.csv("./Crime_Housing.csv", header=True, inferSchema= True)
crime_housing.columns
 Out[8]: ['Month',
                 'Crimetype',
'postcode',
                 'price_paid',
                 'property_type',
'new_build',
                'town',
'district']
In [10]: crime_housing.printSchema()
```

```
'district']
In [10]: crime_housing.printSchema()
                    root
|-- Month: string (nullable = true)
|-- Crimetype: string (nullable = true)
|-- postcode: string (nullable = true)
|-- price_paid: integer (nullable = true)
|-- property_type: string (nullable = true)
|-- new_build: string (nullable = true)
|-- town: string (nullable = true)
|-- district: string (nullable = true)
In [25]:
import seaborn as sns
#t0 VISUALISE 1D view of my dataset
from scipy.stats import norm
sns.distplot(dataframe_2[['price_paid']], fit=norm, kde=False)
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe2015eeeb0>
                    2.00
                    1.75
                    1.50
                    1.25
                    1.00
                    0.75
                    0.50
                    0.25
                    0.00
In [28]: dataframe_1.groupby('Crimetype').count().sort_values('Month', ascending=False)
Out[28]:
                                                               Month postcode property_type new_build town district
                                              Crimetype
```

```
In [28]: dataframe_1.groupby('Crimetype').count().sort_values('Month', ascending=False)
Out[28]:
                                   Month postcode property_type new_build town district
                         Crimetype
              Anti-social behaviour 28256 28256 28256 28256 28256 28256
           Violence and sexual offences 23130
                                            23130
                                                        23130
                                                                  23130 23130 23130
                      Vehicle crime 12724
                                           12724 12724 12724 12724 12724
                          Burglary 8759
                                            8759
                                                         8759
                                                                   8759 8759
                        Other theft 8561
                                          8561 8561
                                                                8561 8561
            Criminal damage and arson 5754
                                                         5754
                            Drugs 3706
                         Shoplifting 2980
                                          2980 2980 2980 2980
                          Robbery 2977
                                             2977
                                                         2977
                                                                   2977 2977
                Theft from the person 2735
                                          2735
                                                      2735
                                                                2735 2735 2735
                       Bicycle theft 1826
                                                         1826
                                             1826
                                                                   1826 1826
                                                                                1826
                       Other crime 860 860
                                                       860
                                                                860 860 860
               Possession of weapons 561
                                          561
                                                         561
                                                                    561 561
                                                                                 561
In [43]: # replace predictor variable with categorical labels instead... using pandas quantile cut we can do that crime_housing_clean = crime_housing.toPandas().copy()
         pd.qcut(crime_housing_clean['price_paid'], q=[0, .1, 0.25, .5, .75, .9, 1]).unique()
Out[43]: [(220000.0, 317000.0], (99.999, 220000.0], (317000.0, 435000.0], (435000.0, 645000.0], (645000.0, 1100000.0], (1100000.0, 25500
          0000.0]]
         Gategories (6, interval[float64]): [(99.999, 220000.0] < (220000.0, 317000.0] < (317000.0, 435000.0] < (435000.0, 645000.0] < (645000.0, 1100000.0) < (1100000.0, 255000000.0]]
In [52]: crime_housing_clean['price_paid_categories'] = pd.qcut(crime_housing_clean['price_paid'], q=[0, .1, 0.25, .5, .75, .9, 1], labels
         # extract month from Month (date) column
crime_housing_clean['month_int'] = crime_housing_clean['Month'].apply(lambda x: pd.to_datetime(x).month)
         4
```

## (L-1)

```
In [53]: crime_housing_clean.head()
Out[53]:
                                        Crimetype postcode price_paid property_type new_build
                                                                                                                             district price_paid_categories month_int
                                                                                                                       BARKING AND
DAGENHAM
             0 01/11/2019
                               Anti-social behaviour RM6 5PJ
                                                                250000
                                                                                               N ROMFORD
                                                                                                                                               220k-317k
                                                                                                                       BARKING AND
             1 01/11/2019
                               Anti-social behaviour RM6 5JJ
                                                                215000
                                                                                               N ROMFORD
                                                                                                                                                   < $220k
                                                                                                                       BARKING AND
DAGENHAM
             2 01/11/2019
                                          Burglary RM6 5JP
                                                                290000
                                                                                               N ROMFORD
                                                                                                                                               220k-317k
                                                                                                                       BARKING AND
DAGENHAM
                               Criminal damage and arson
             3 01/11/2019
                                                                                               N ROMFORD
                                                                                                                                               220k-317k
                                                   RM6 5PJ
                                                                250000
                                                                                                                       BARKING AND
                               Criminal damage and arson
             4 01/11/2019
                                                   RM6 5PJ
                                                                250000
                                                                                               N ROMFORD
                                                                                                                                               220k-317k
                                                                                                                         DAGENHAM
In [107]: crime_housing_clean.town.nunique()
Out[107]: 72
In [77]: crime_housing_clean.columns = crime_housing_clean.columns.str.lower()
            cols = crime_housing_clean.columns
In [108]: sdf_crime_housing = spark.createDataFrame(crime_housing_clean)
            # Encode categorical variables before test/train split
categoricalCols = ['crimetype','property_type','town','new_build','district']
            stages = []
            featureIndexers = [StringIndexer(inputCol=catCol, outputCol=catCol+'Index') for catCol in categoricalCols]
            stages += featureIndexers
            labelIndexer = [StringIndexer(inputCol=labelCol, outputCol='label') for labelCol in ['price_paid_categories']] stages += labelIndexer
            numericCols = ['month_int']
            assemblerInputs = [col + 'Index' for col in categoricalCols] + numericCols
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
            stages += [assembler]
            pipeline = Pipeline(stages=stages)
sdf = pipeline.fit(sdf_crime_housing).transform(sdf_crime_housing)
            selectedCols = ['label', 'features'] + cols.tolist()
```

```
pipeline = Pipeline(stages=stages)
           sdf = pipeline.fit(sdf_crime_housing).transform(sdf_crime_housing)
           selectedCols = ['label', 'features'] + cols.tolist()
           sdf = sdf.select(selectedCols)
           sdf.printSchema()
             |-- label: double (nullable = false)
            |-- features: vector (nullable = true)
|-- month: string (nullable = true)
             -- crimetype: string (nullable = true)
            |-- postcode: string (nullable = true)
|-- price_paid: long (nullable = true)
             |-- property_type: string (nullable = true)
|-- new_build: string (nullable = true)
|-- town: string (nullable = true)
              -- district: string (nullable = true)
            |-- price_paid_categories: string (nullable = true)
|-- month_int: long (nullable = true)
In [109]: sdf.show(5)
           llahell
                              features| month|
                                                               crimetype|postcode|price_paid|property_type|new_build| town|
           ----4------
           | 3.0|[0.0,1.0,1.0,0.0,...|01/11/2019|Anti-social behav...| RM6 5PJ| 250000|

ENHAM| $220k - $317k| 1|

| 4.0|[0.0,0.0,1.0,0.0,...|01/11/2019|Anti-social behav...| RM6 5JJ| 215000|

ENHAM| < $220k| 1|
                                                                                                              TI
                                                                                                                         N|ROMFORD|BARKING AND DAG
                                                                                                              F
                                                                                                                         N|ROMFORD|BARKING AND DAG
              3.0|[3.0,1.0,1.0,0.0,...|01/11/2019|
                                                                 Burglary| RM6 5JP|
                                                                                          290000
                                                                                                              T
                                                                                                                         N|ROMFORD|BARKING AND DAG
           ENHAM| $220k - $317k| 1|
| 3.0|[5.0,1.0,1.0,0.0,...|01/11/2019|Criminal damage a...| RM6 5PJ|
ENHAM| $220k - $317k| 1|
                                                                                          2500001
                                                                                                              ΤI
                                                                                                                         N|ROMFORD|BARKING AND DAG
           ENHAM| $220K - $317K| 1| | 3.0|[5.0,1.0,1.0,0.0,...|01/11/2019|Criminal damage a...| RM6 5PJ| ENHAM| $220K - $317K| 1| +----+
                                                                                          250000
                                                                                                              T
                                                                                                                         N|ROMFORD|BARKING AND DAG
           only showing top 5 rows
```

```
|-- new_build: string (nullable = true)
|-- town: string (nullable = true)
|-- district: string (nullable = true)
            |-- price_paid_categories: string (nullable = true)
|-- month_int: long (nullable = true)
In [109]: sdf.show(5)
                             features
           llabel|
                                           month
                                                             crimetype|postcode|price_paid|property_type|new_build| town|
                                                                                                                                            dis
           trict|price_paid_categories|month_int|
           | 3.0|[0.0,1.0,1.0,0.0,...|01/11/2019|Anti-social behav...| RM6 5PJ|
                                                                                                           T
                                                                                                                     N|ROMFORD|BARKING AND DAG
            NHAM| $220k - $317k| 1| 4.0|[0.0,0.0,1.0,0.0,...|01/11/2019|Anti-social behav...| RM6 5JJ|
          ENHAM
                                                                                      215000
                                                                                                          F
                                                                                                                     N|ROMFORD|BARKING AND DAG
           ENHAM| < $220k| 1|
| 3.0|[3.0,1.0,1.0,0.0,...|01/11/2019|
ENHAM| $220k - $317k| 1|
                                                                                                           T
                                                               Burglary| RM6 5JP|
                                                                                       290000
                                                                                                                     N|ROMFORD|BARKING AND DAG
          250000
                                                                                                          T
                                                                                                                     N|ROMFORD|BARKING AND DAG
                                                                                                                     N|ROMFORD|BARKING AND DAG
          only showing top 5 rows
In [164]: # split data in train & test
          train, test = sdf.randomSplit([0.8, 0.2], seed=25)
print("Training Dataset Count: " + str(train.count()))
print("Test Dataset Count: " + str(test.count()))
          Training Dataset Count: 107432
          Test Dataset Count: 27003
```

```
In [165]: dt = DecisionTreeClassifier(featuresCol = 'features', labelCol = 'label', maxDepth = 3, maxBins=100)
           dtModel = dt.fit(train)
predictions = dtModel.transform(test)
           predictions.select('crimetype', 'postcode', 'property_type', 'new_build', 'town', 'district', 'month_int', 'label', 'prediction').show(1
                      crimetype|postcode|property_type|new_build| town|district|month_int|label|prediction|
            |Violence and sexu...|SW16 2SN|
                                                                      N | LONDON | LAMBETH |
           | Violence and sexu...| SW9 9UQ|
| Vehicle crime| SW8 2EU|
                                                                      N LONDON LAMBETH
                                                                                                  1 0.0
                                                                                                                   0.0
                                                           Εİ
                                                                      N LONDON LAMBETH
                                                                                                      0.0
            |Criminal damage a...|SW16 6JD|
| Robbery|SW16 5LJ|
                                                           Εİ
                                                                      NILONDONI LAMBETHI
                                                                                                  1
                                                                                                      0.0
                                                                                                                   0.0
                                                           Εİ
                                                                      N LONDON LAMBETH
                                                                                                  11
                                                                                                      0.0
                                                                                                                   0.0
                    Bicycle theft|SE24 0NS|
                                                           F
                                                                      N LONDON LAMBETH
                                                                                                       0.0
                                                                                                                   0.0
            |Anti-social behav...| SW9 8QH|
|Anti-social behav...| SW9 8QH|
                                                                      NILONDONI LAMBETHI
                                                                                                  1
                                                                                                      0.0
                                                                                                                   1.0
                                                                      N LONDON LAMBETH
                                                           T
                                                                                                  1 0.0
                                                                                                                   1.0
            |Anti-social behav...| SW9 8QH
                                                                      N LONDON LAMBETH
            |Anti-social behav...|SW16 3LJ|
                                                                      Y LONDON | LAMBETH
                                                                                                  1
                                                                                                      0.0
                                                                                                                   0.0
           only showing top 10 rows
In [166]: # evaluate decision tree
           evaluator = MulticlassClassificationEvaluator(predictionCol='prediction', labelCol='label', metricName='accuracy')
           accuracy = evaluator.evaluate(predictions)
           print("Test Error = %g " % (1.0 - accuracy))
print("Accuracy = %g " % accuracy)
           Test Error = 0.65415
           Accuracy = 0.34585
```

(O)

```
In [167]: from pyspark.ml.classification import RandomForestClassifier
          rf = RandomForestClassifier(featuresCol = 'features', labelCol = 'label', maxBins=100)
          rfModel = rf.fit(train)
          predictions = rfModel.transform(test)
          predictions.select('crimetype', 'postcode', 'property_type', 'new_build', 'town', 'district', 'month_int', 'label', 'prediction').show(1
                    crimetype|postcode|property_type|new_build| town|district|month_int|label|prediction|
           |Violence and sexu...|SW16 2SN|
                                                               N|LONDON| LAMBETH|
                                                                                          1 0.0
           |Violence and sexu...| SW9 9UQ|
                                                               NILONDONI LAMBETHI
                                                                                          11
                                                                                             0.0
                                                                                                         1.0
                  Vehicle crime | SW8 2EU
                                                               N LONDON LAMBETH
                                                                                         1 0.0
                                                                                                         1.0
           Criminal damage a...|SW16 6JD|
                                                               N LONDON LAMBETH
                                                                                             0.0
                                                                                                         1.0
                       Robbery SW16 5LJ
                                                               N LONDON LAMBETH
                                                                                          1
                                                                                              0.0
                                                                                                         1.0
                  Bicvcle theft|SE24 0NS|
                                                      FΙ
                                                               N | LONDON | LAMBETH |
                                                                                          11
                                                                                             0.0
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           Anti-social behav... SW9 8QH
                                                      т
                                                               N LONDON LAMBETH
                                                                                              0.0
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           Anti-social behav... | SW9 8QH
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           |Anti-social behav...| SW9 8QH|
                                                      ΤI
                                                               N|LONDON| LAMBETH|
                                                                                          11
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           |Anti-social behav...|SW16 3LJ|
                                                               Y LONDON LAMBETH
                                                                                          1 0.0
                                                                                                         1.0
          only showing top 10 rows
In [168]: evaluator = MulticlassClassificationEvaluator(predictionCol='prediction', labelCol='label', metricName='accuracy')
          accuracy = evaluator.evaluate(predictions)
          print("Test Error = %g " % (1.0 - accuracy))
print("Accuracy = %g " % accuracy)
          Test Error = 0.598193
          Accuracy = 0.401807
```

```
In [169]: lr = LogisticRegression(featuresCol = 'features', labelCol = 'label', maxIter=10)
            lrModel = lr.fit(train)
In [170]: predictions = lrModel.transform(test)
             predictions.select('crimetype', 'postcode', 'property_type', 'new_build', 'town', 'district', 'month_int', 'label', 'prediction').show(1
            4
                        crimetype|postcode|property_type|new_build| town|district|month_int|label|prediction|
             |Violence and sexu...|SW16 2SN|
|Violence and sexu...|SW9 9UQ|
                                                                             N|LONDON| LAMBETH|
N|LONDON| LAMBETH|
                                                                                                             1 0.0
                                                                                                                                0.01
                                                                                                             1 0.0
                                                                                                                                0.0
                      Vehicle crime | SW8 2EU
                                                                              N LONDON LAMBETH
                                                                                                             1 0.0
                                                                                                                                0.0
             | Criminal damage a...|SW16 6JD|
| Robbery|SW16 5LJ|
                                                                                                             1 0.0
1 0.0
                                                                             NÍLONDONÍ LAMBETHÍ
                                                                                                                                0.01
                                                                              N LONDON LAMBETH
                                                                                                                                0.0
             | RODDERY|SWIG 5LJ|
| Bicycle theft|SE24 0MS|
|Anti-social behav...| SW9 8QH|
|Anti-social behav...| SW9 8QH|
|Anti-social behav...| SW9 8QH|
|Anti-social behav...| SW16 3LJ|
                                                                              NILONDONI LAMBETHI
                                                                                                             1
                                                                                                                  0.0
                                                                                                                                0.0
                                                                              N LONDON LAMBETH
                                                                                                                  0.0
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                                                                             N LONDON LAMBETH
                                                                                                                  0.0
                                                                                                                                1.0
                                                                                                             11
                                                                                                                  0.0
                                                                                                                                1.0
                                                                              Y LONDON LAMBETH
                                                                                                                  0.0
             only showing top 10 rows
In [171]: evaluator = MulticlassClassificationEvaluator(predictionCol='prediction', labelCol='label', metricName='accuracy')
             accuracy = evaluator.evaluate(predictions)
            print("Test Error = %g " % (1.0 - accuracy))
print("Accuracy = %g " % accuracy)
            Test Error = 0.714254
Accuracy = 0.285746
  In [ ]:
```