Machine Learning with Python Project

Harkirat Singh

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1 Main Project

Submitted By

`Harkirat Singh`
`Contact email: honey.harkiratsingh@gmail.com, (honey.harkirat@outlook.com)`

Submitted To

`Mr Karan Mehta`
`Course: Machine Learning with Python`
`Quantum Learnings, Knowledge Solutions India`

1.1 Project Details

These are the 4 projects that are covered in this notebook.

1. Fraud Dataset (Predicting whether the customers will be a defaulter or not)

`a. Using SVM Classification (93.04 % Accuracy Score)`
`b. Using Custom threshold for strongest filtering (86.081 % Accuracy Score)`
`c. Using K Nearest Neighbour Classification (93.41 % Accuracy Score)`

2. Diamond Price Prediction (Predicting the prices of diamonds.)

`a. Using Multiple Linear Regression (88.52 % Accuracy Score)`
`b. Using Artificial Neural Networks (94.3 % Accuracy Score)`

3. Company Attrition Data (Whether the employee would leave the company or not)

`a. Using K Nearest Neighbour Classification (96.83 % Accuracy Score)`

4. House Price Prediction (Predicting house prices)

`a. Using Random Forest Regression (100 % Accuracy Score)`

1.2 Project Structure

This project aims at studying and analysing all the datasets provided by the institute. This project considers data analysis as the most critical part, because to understand the datasets, the statistics of the data (by visualization) will help to determine which machine learning technique should be implemented. This data analysis forms the first step of my project.

1.2.1 Data Analysis

For each dataset (or subproject), the first thing that would come is data analysis. It consists of **getting information about various columns and number of rows** present in the dataset, **elimination or substitution of null values** if present, **creation of new columns from existing ones** in case the information provided is raw, and finally the **visualization of the provided data** using *Matplotlib* and *Seaborn* python libraries.

1.2.2 Splitting the dataset into test and train subsets

In order to evaluate the performance of the machine learning models, testing data is required. Before executing any algorithm, the data would be splitted into two parts: 1. The Training data (almost 67 % of the whole dataset) 2. The Testing data (almost 33 % of the whole dataset)

Only the **training dataset would be used for training the machine learning model**, and after that testing dataset would be used for evaluating the accuracy of the model.

1.2.3 Feature Scaling

In various algorithms, the units of the raw data can cause serious issues. For example, in case of KNN Algorithm which uses euclidean distance (or even manhatten), if the units of two independent features (columns) are not same then the total distance would be **highly sensitive** to that feature (or column) having big range of values.

So, in order to make sure that all the columns (or features) have same sensitivity, they are scaled to a range of (0, 1) or [-1, 1] using this technique.

How to create the scaling function?

The scaling function would be created with respect to the training data (both fitting and transforming as demonstrated in all the projects). And the test data will be *only transformed* instead of fitting.

Standardization This technique centers the values around the mean with a unit standard deviation. So it means, **the mean of the resulting standardized column would be zero**.

The formula,

$$X' = \frac{X - \mu}{\Sigma} \tag{1}$$

is used for standardizing the data.

Normalization In this technique, the values are shifted and rescaled using the minimum and maximum values present in the data, so that the range is (0, 1).

The formula,

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

is used for normalizing the data.

1.2.4 Training the model

After all the data preprocessing and analysis has been done, the final mode is trained in this step.

1.2.5 Testing and Visualization

This phase consists of evaluation of the model, and the visualization of the model to gain insights how it works.

1.3 Imports

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Other libraries (like sklearn, keras, etc) would be imported whenever they are required.

1.4 Custom Defined Functions

Below function is a helper function, that can extract maximum value from a given accuracy list.

[2]:
```
def GetMaxKV(Accu : list):
    max_index = 0
    max_value = 0.0
    for i, v in Accu:
        if max_value < v:
            max_value = v
            max_index = i
    return max_index, max_value
```

Below function is used to test a model with custom threshold value.

[3]:
```
def predict_threshold(model, X_test, threshold):
    return np.where(model.predict_proba(X_test)[:, 1] > threshold, 1, 0)
```

1.5 Project - 1 (Fraud Dataset)

The business problem would be discussed after importing the dataset.

[4]:
```
fraudDF = pd.read_csv('./Datasets/fraud_dataset.csv')
fraudDF.head()
```

[4]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	\
0	1	0	0	1	0	5849	
1	1	1	1	1	1	4583	
2	1	1	0	1	1	3000	
3	1	1	0	0	1	2583	
4	1	0	0	1	0	6000	

```
   CoapplicantIncome  LoanAmount  Loan_Term  Credit_History_Available  \
0                  0         146        360                         1
1               1508         128        360                         1
2                  0          66        360                         1
3               2358         120        360                         1
4                  0         141        360                         1

   Housing  Locality  Fraud_Risk
0        1         1           0
1        1         3           1
2        1         1           1
3        1         1           1
4        1         1           0
```

1.5.1 Business Problem Details

A dataset is given. It contains the details of customers who have taken a loan from the bank. The customer details such as gender, marital status, dependents, education status, self employed, various income data, and the details regarding amount etc are provided.

The Problem A Machine learning model has to be constructed out of the given dataset. And this model would be useful in various business situations for example, the bank can predict if there is any chance whether a customer who wants to take a loan, can become a defaulter or not. In such cases, the bank would first prefer those customers who are predicted as *safe* by the machine learning model.

1.5.2 Information of the dataset

[5]:
```python
fraudDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 827 entries, 0 to 826
Data columns (total 13 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Gender                    827 non-null    int64
 1   Married                   827 non-null    int64
 2   Dependents                827 non-null    int64
 3   Education                 827 non-null    int64
 4   Self_Employed             827 non-null    int64
 5   ApplicantIncome           827 non-null    int64
 6   CoapplicantIncome         827 non-null    int64
 7   LoanAmount                827 non-null    int64
 8   Loan_Term                 827 non-null    int64
 9   Credit_History_Available  827 non-null    int64
 10  Housing                   827 non-null    int64
 11  Locality                  827 non-null    int64
```

 12   Fraud_Risk   827 non-null   int64
dtypes: int64(13)
memory usage: 84.1 KB

1.5.3 Analysis

[6]:
```
fraudDF.isnull().sum()
```

[6]:
```
Gender                     0
Married                    0
Dependents                 0
Education                  0
Self_Employed              0
ApplicantIncome            0
CoapplicantIncome          0
LoanAmount                 0
Loan_Term                  0
Credit_History_Available   0
Housing                    0
Locality                   0
Fraud_Risk                 0
dtype: int64
```

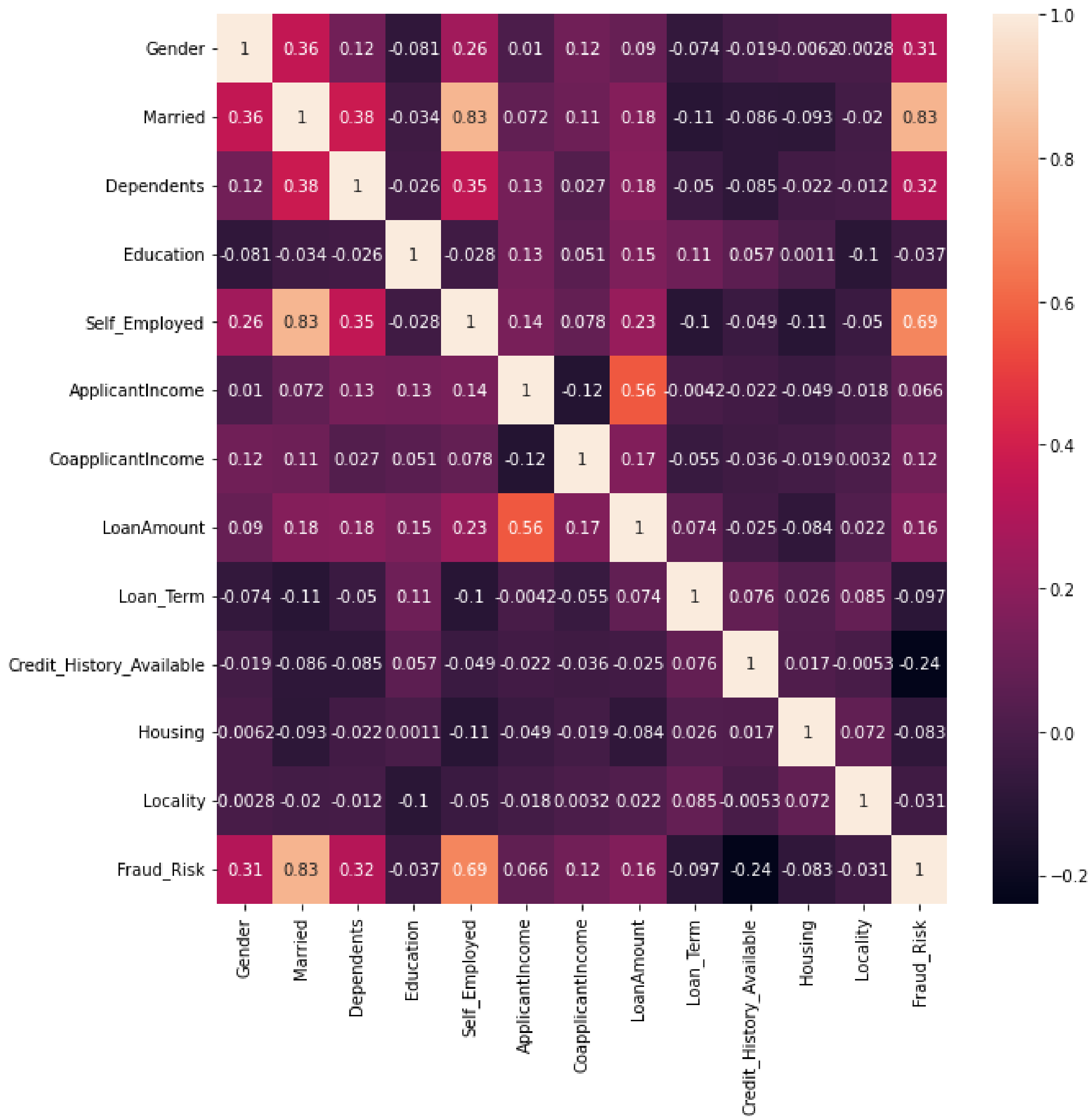
This dataset has no null value.

[7]:
```
fraudDF.describe()
```

[7]:
```
           Gender     Married  Dependents   Education  Self_Employed  \
count  827.000000  827.000000  827.000000  827.000000     827.000000
mean     0.733978    0.481258    0.652963    0.790810       0.574365
std      0.442143    0.499951    0.935835    0.406976       0.494738
min      0.000000    0.000000    0.000000    0.000000       0.000000
25%      0.000000    0.000000    0.000000    1.000000       0.000000
50%      1.000000    0.000000    0.000000    1.000000       1.000000
75%      1.000000    1.000000    1.000000    1.000000       1.000000
max      1.000000    1.000000    3.000000    1.000000       1.000000

       ApplicantIncome  CoapplicantIncome  LoanAmount   Loan_Term  \
count       827.000000         827.000000  827.000000  827.000000
mean       5212.970979        1486.050786  140.892382  338.128174
std        5593.713304        2802.847983   79.820451   75.353151
min         150.000000           0.000000    9.000000   12.000000
25%        2894.500000           0.000000  100.000000  360.000000
50%        3752.000000           0.000000  125.000000  360.000000
75%        5478.000000        2177.000000  156.500000  360.000000
max       81000.000000       41667.000000  700.000000  480.000000

       Credit_History_Available     Housing    Locality  Fraud_Risk
```

count	827.000000	827.000000	827.000000	827.000000
mean	0.885127	0.654172	1.978235	0.576784
std	0.319062	0.475925	0.771471	0.494368
min	0.000000	0.000000	1.000000	0.000000
25%	1.000000	0.000000	1.000000	0.000000
50%	1.000000	1.000000	2.000000	1.000000
75%	1.000000	1.000000	3.000000	1.000000
max	1.000000	1.000000	3.000000	1.000000

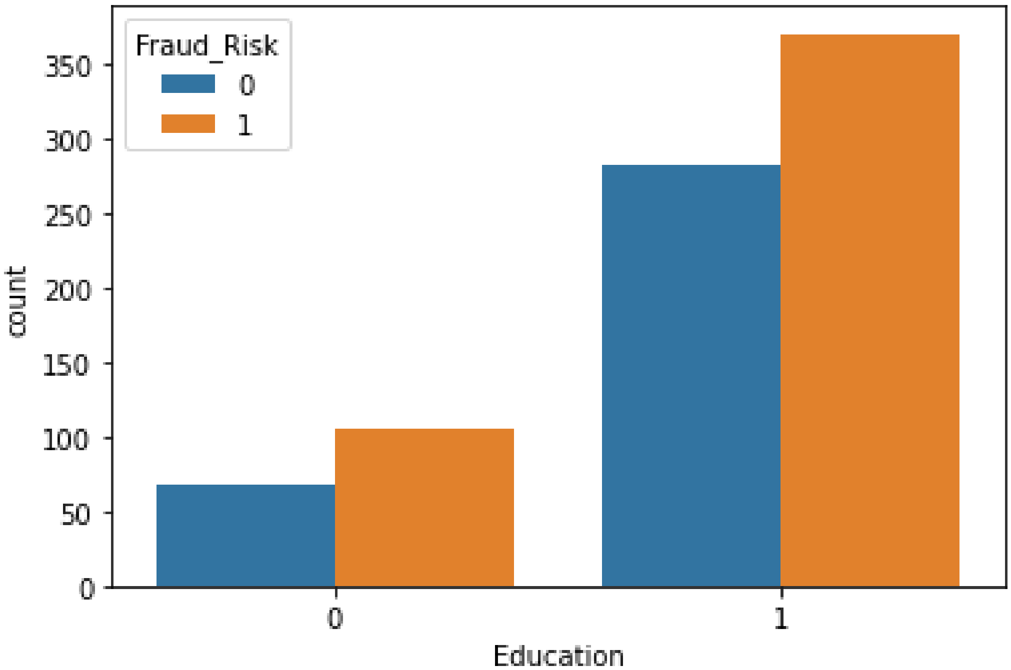
[8]:
```
plt.figure(figsize = (10, 10))

sns.heatmap(fraudDF.corr(), annot = True);
```



From the heatmap, it can be observed that the minimum variability is between **Fraud_Risk column and Education column (-0.037)** It means, it is difficult to distinguish. **The closer the number to 0, more it is difficult to distinguish (weak relationship).**

The plots look like:

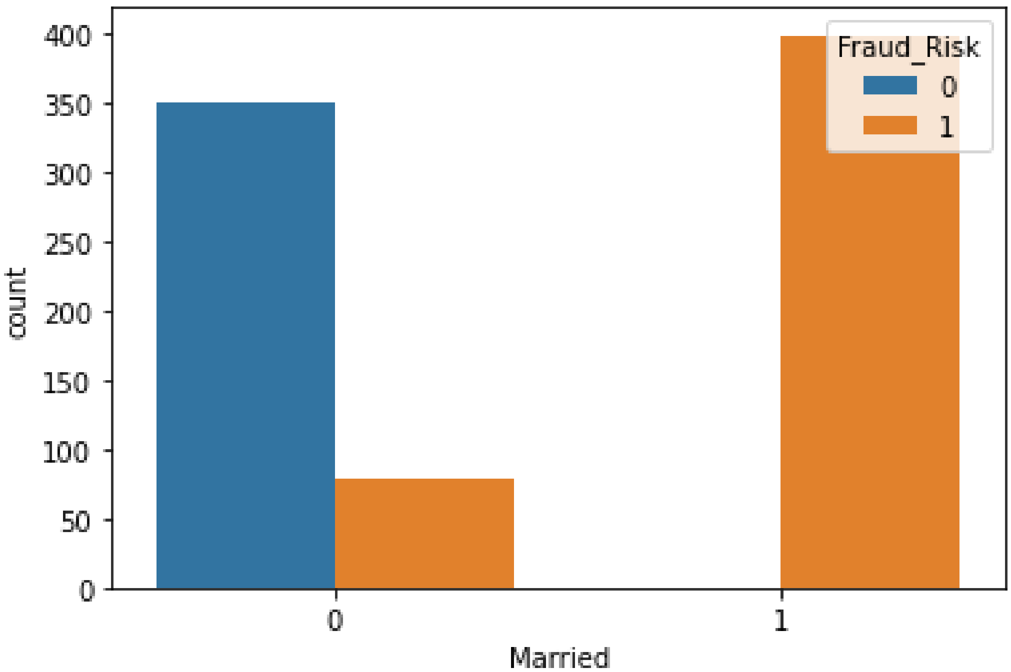
[9]:
```
sns.countplot(x = 'Education', hue = 'Fraud_Risk', data = fraudDF);
```



Although, the customers who are educated has high chance of being defaulter, but also the number of non risk customers is also high. It means another parameters are required to distinguish properly.

Between Married and Fraud_Risk columns, correlation is 0.83 (from heatmap).

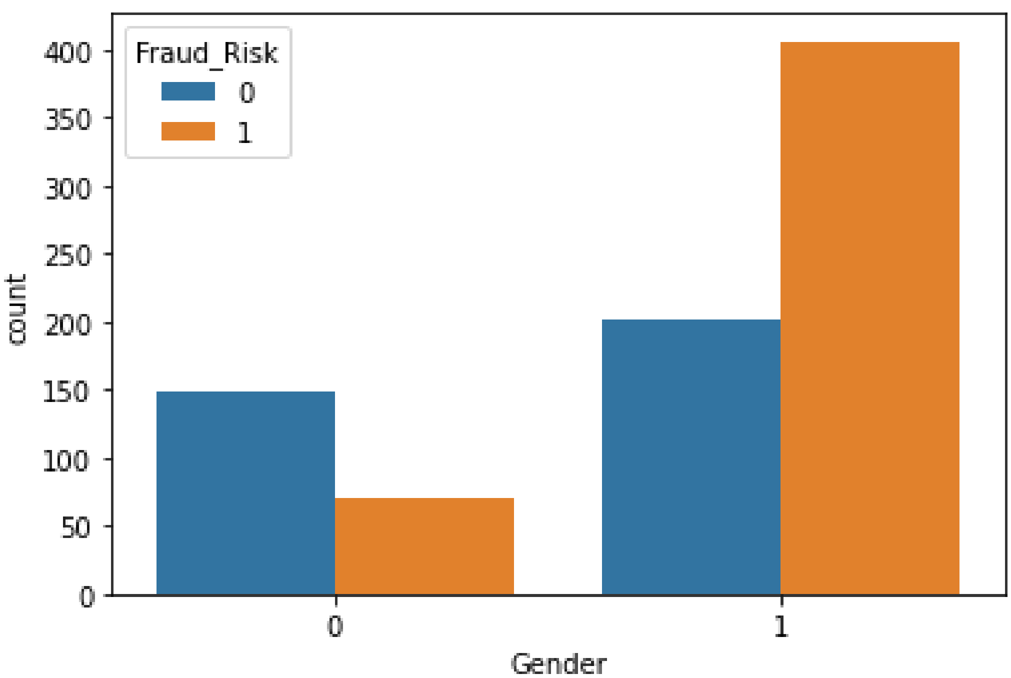
[10]:
```
sns.countplot(x = 'Married', hue = 'Fraud_Risk', data = fraudDF);
```



This shows clear distinction between fraud risk and non risk customers.

Between Gender and Fraud_Risk columns, correlation is 0.31 (from heatmap).

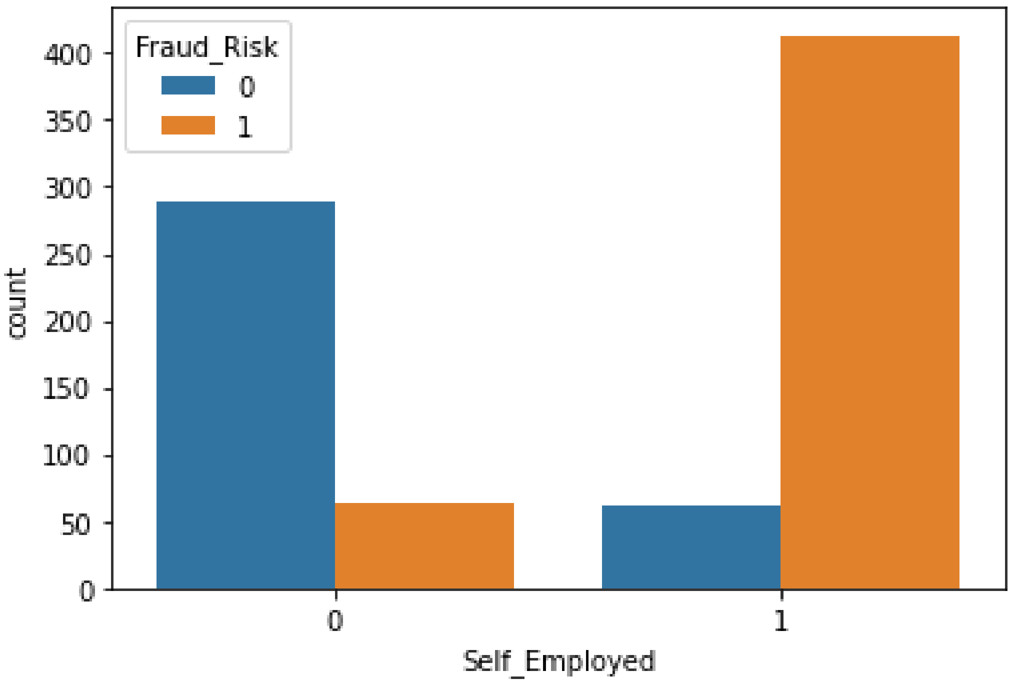
[11]:
```
sns.countplot(x = 'Gender', hue = 'Fraud_Risk', data = fraudDF);
```



Again this is weak relation.

Between Self_Employed and Fraud_Risk, correlation is 0.69.

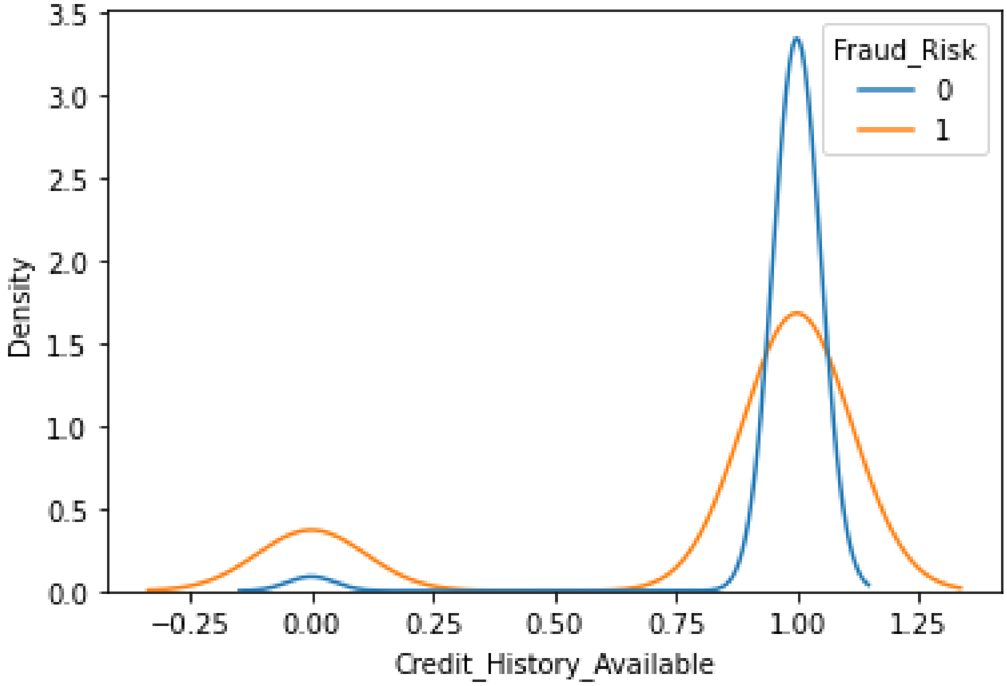
[12]:
```
sns.countplot(x = 'Self_Employed', hue = 'Fraud_Risk', data = fraudDF);
```



It has more clear distinction.

Between Credit_History_Available and Fraud_Risk the correlation is 0.24.

[13]:
```
sns.kdeplot(x = 'Credit_History_Available', hue = 'Fraud_Risk', data = fraudDF);
```

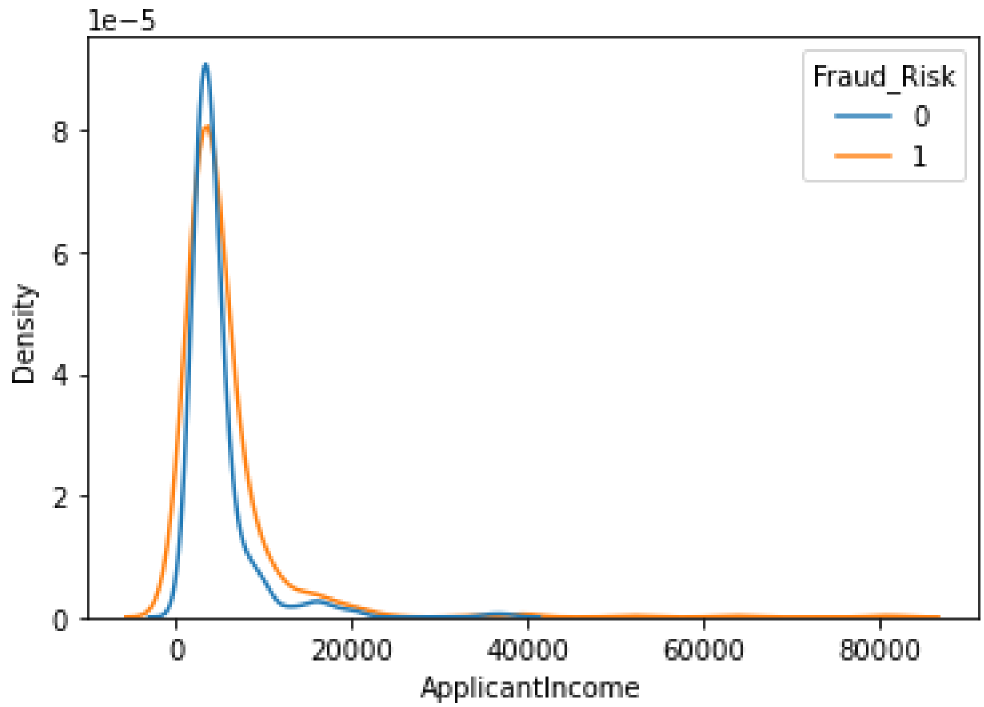


Note since Credit__History__Available has non discrete values, KDE Plot is used.

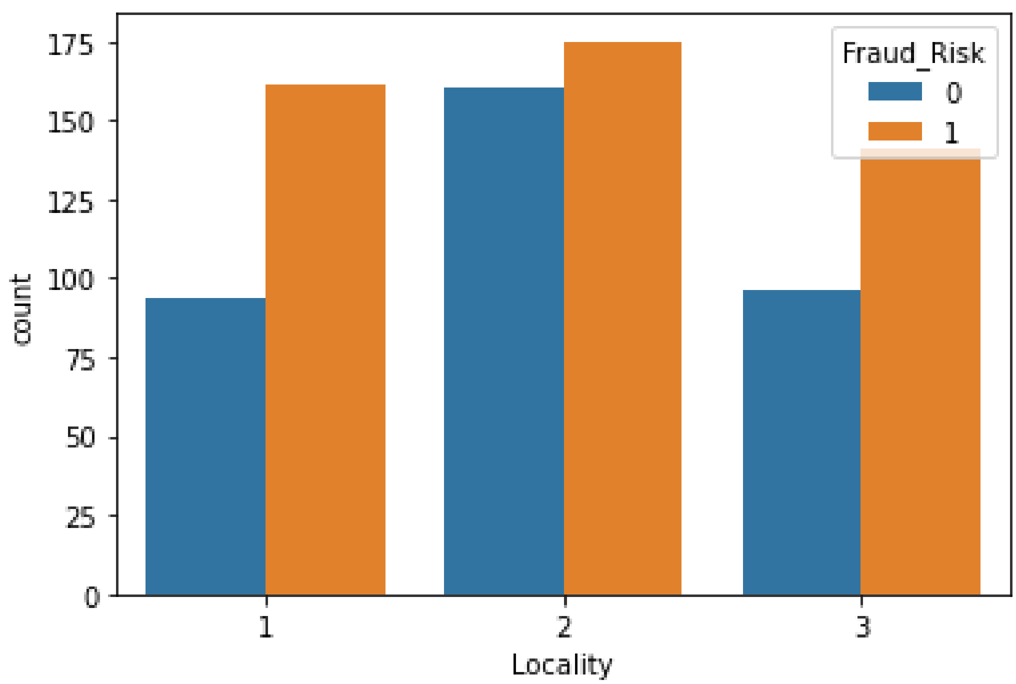
Other columns having correlation with Fraud__Risk, closer to 0.

All other plots are between Fraud_Risk and the columns having non discrete values (like value belonging to a range). And since all other columns have correlation with Fraud_Risk closer to 0, it means that they are difficult to distinguish. The lines of *Fraud Risk* and *Not Fraud Risk* are very near to each other.

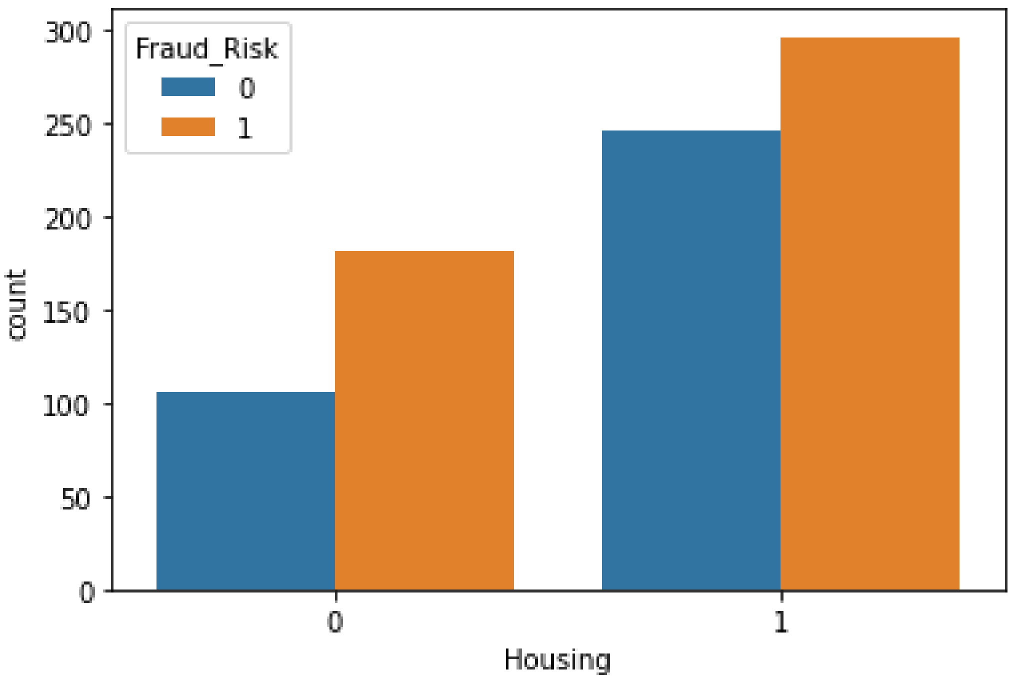
[14]:
```
sns.kdeplot(x = 'ApplicantIncome', hue = 'Fraud_Risk', data = fraudDF);
```



[15]:
```
sns.countplot(x = 'Locality', hue = 'Fraud_Risk', data = fraudDF);
```



[16]:
```
sns.countplot(x = 'Housing', hue = 'Fraud_Risk', data = fraudDF);
```



All the features need to be considered together, because each feature is independent of other features. Hence clustering algorithm cannot be used. Also each feature is independent of other features, it means there is no mathematical relation. So Logistic Regression would give very poor result. The maximum accuracy that might be achieved would be near to 80 % if only Married and Fraud_Risk columns are considered. But the project requirements states that more than 85% of accuracy is required.

Hence, KNN Alogrithm shall be used to build this machine learning model.

1.5.4 Independent and Dependent Features

[17]:
```
fraud_X = fraudDF.iloc[:, :-1]
fraud_X.head()
```

[17]:
```
   Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
0       1        0           0          1              0             5849
1       1        1           1          1              1             4583
2       1        1           0          1              1             3000
3       1        1           0          0              1             2583
4       1        0           0          1              0             6000

   CoapplicantIncome  LoanAmount  Loan_Term  Credit_History_Available  \
0                  0         146        360                         1
```

```
1              1508        128        360                          1
2                 0         66        360                          1
3              2358        120        360                          1
4                 0        141        360                          1

   Housing  Locality
0        1         1
1        1         3
2        1         1
3        1         1
4        1         1
```

[18]:
```
fraud_y = fraudDF.iloc[:, -1]
fraud_y.head()
```

[18]:
```
0    0
1    1
2    1
3    1
4    0
Name: Fraud_Risk, dtype: int64
```

1.5.5 Splitting the data

[19]:
```
from sklearn.model_selection import train_test_split

fraud_X_train, fraud_X_test, fraud_y_train, fraud_y_test =␣
 ↪train_test_split(fraud_X, fraud_y, test_size = 0.33,
                                                                                   ␣
 ↪stratify = fraudDF['Fraud_Risk'],
                                                                                   ␣
 ↪random_state = 43)
```

1.5.6 Standardizing the data

[20]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

fraud_X_train = scaler.fit_transform(fraud_X_train)
fraud_X_test = scaler.transform(fraud_X_test)
```

1.5.7 Using the SVM Classification

[21]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score

fraud_svm_classifier = SVC(probability = True)
fraud_svm_classifier.fit(fraud_X_train, fraud_y_train)
pred_svm_fraud = fraud_svm_classifier.predict(fraud_X_test)

print(f'Accuracy: {round(accuracy_score(fraud_y_test, pred_svm_fraud) * 100,␣
↪2)} %')
```

```
Accuracy: 93.04 %
```

The confusion matrix

[22]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix(fraud_y_test, pred_svm_fraud)
```

[22]:
```
array([[114,   2],
       [ 17, 140]], dtype=int64)
```

The Classification Report

[23]:
```
from sklearn.metrics import classification_report

print(classification_report(fraud_y_test, pred_svm_fraud))
```

```
              precision    recall  f1-score   support

           0       0.87      0.98      0.92       116
           1       0.99      0.89      0.94       157

    accuracy                           0.93       273
   macro avg       0.93      0.94      0.93       273
weighted avg       0.94      0.93      0.93       273
```

Creating the strongest model for eliminating risky customers

[24]:
```
strongest_filter = 17
strongest_filter_threshold = 0

for i in np.round(np.arange(0, 1, 0.005), 3):
    y_predict = predict_threshold(fraud_svm_classifier, fraud_X_test, i)
    cfm = confusion_matrix(fraud_y_test, y_predict)
    acc = accuracy_score(fraud_y_test, y_predict)
    if cfm[1][0] < strongest_filter and acc > 0.85:
```

```
        strongest_filter = cfm[1][0]
        strongest_filter_threshold = i

print('Threshold :', strongest_filter_threshold)
strongest_fraud_pred = predict_threshold(fraud_svm_classifier, fraud_X_test,␣
 ↪strongest_filter_threshold)
print(confusion_matrix(fraud_y_test, strongest_fraud_pred))
print('Accuracy Score: ', np.round(accuracy_score(fraud_y_test,␣
 ↪strongest_fraud_pred), 5) * 100, '%')
```

```
Threshold : 0.115
[[ 82  34]
 [  4 153]]
Accuracy Score:  86.081 %
```

At the above threshold, it can put a few of the actual risky customers in the risk category. However, it will also put some non risky customers in risk category.

The above threshold can be used when there is a need of strong identification of risky customers. However, it might also mistakenly identify non risk customers as risky ones.

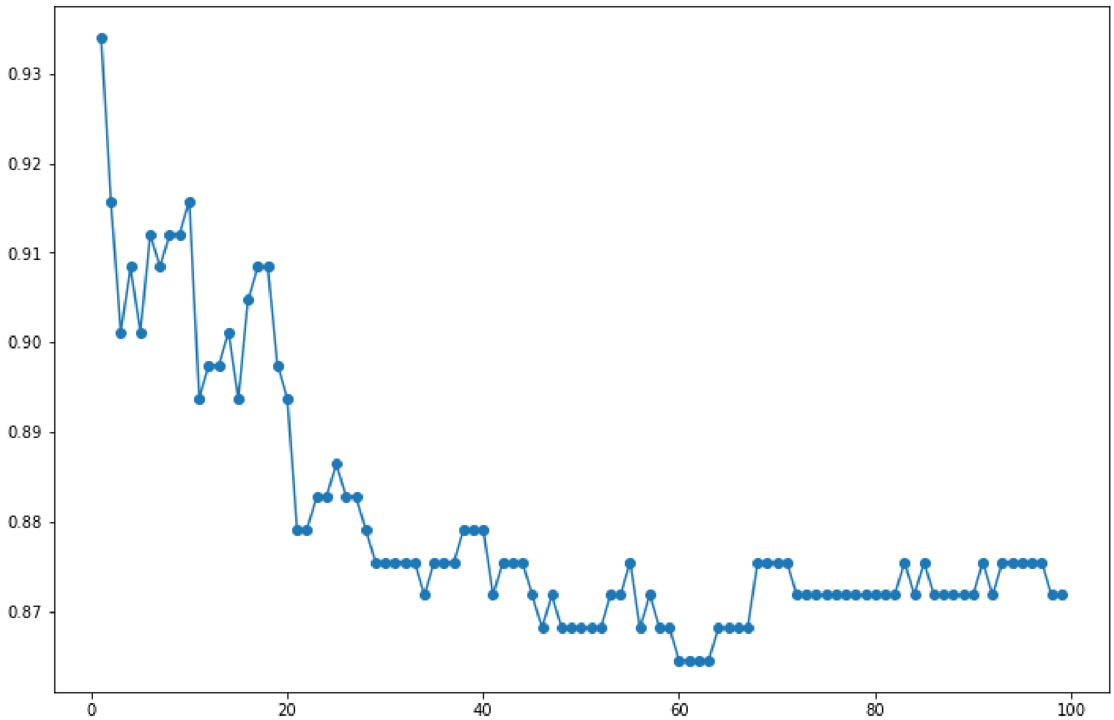
Without threshold

[25]:
```
pred_svm_fraud = fraud_svm_classifier.predict(fraud_X_test)

print(f'Accuracy Score: {round(accuracy_score(fraud_y_test, pred_svm_fraud) *␣
 ↪100, 2)} %')
```

```
Accuracy Score: 93.04 %
```

1.5.8 Using the K - Nearest Neighbours Classification

[26]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

Accu = list()
for i in range(1, 100):
    knn = KNeighborsClassifier(n_neighbors = i)
    knn.fit(fraud_X_train, fraud_y_train)
    pred_i = knn.predict(fraud_X_test)
    Accu.append((i, accuracy_score(fraud_y_test, pred_i)))

Accu = np.array(Accu)

plt.figure(figsize = (12, 8))
plt.scatter(np.reshape(Accu[:, 0], (-1, 1)), np.reshape(Accu[:, 1], (-1, 1)))
plt.plot(np.reshape(Accu[:, 0], (-1, 1)), np.reshape(Accu[:, 1], (-1, 1)));
```



Accuracy

[27]:
```
max_index, max_value = GetMaxKV(Accu)
print(f'The maximum accuracy is {round(max_value * 100, 2)} % for k =␣
↪{max_index} neighbours.')
```

```
The maximum accuracy is 93.41 % for k = 1.0 neighbours.
```

[28]:
```
fraud_classifier = KNeighborsClassifier(n_neighbors = int(max_index))
fraud_classifier.fit(fraud_X_train, fraud_y_train)
```

[28]:
```
KNeighborsClassifier(n_neighbors=1)
```

[29]:
```
fraud_y_pred = fraud_classifier.predict(fraud_X_test)

acc = accuracy_score(fraud_y_test, fraud_y_pred)
print(f'This model has an accuracy of {round(acc * 100, 2)} %.')
```

```
This model has an accuracy of 93.41 %.
```

The Confusion Matrix

[30]:
```
from sklearn.metrics import confusion_matrix, classification_report

confusion_matrix(fraud_y_test, fraud_y_pred)
```

[30]:
```
array([[110,   6],
       [ 12, 145]], dtype=int64)
```

From the above matrix, it can be observed that 12 people who were actually in fraud risk category were identified to be safe from any risk.

Since this model is based on calculating the nearest neighbours and then deciding what maximum neighbours belong to which category, the threshold will not have any effect on this model.

[31]:
```python
print(classification_report(fraud_y_test, fraud_y_pred))
```

```
              precision    recall  f1-score   support

           0       0.90      0.95      0.92       116
           1       0.96      0.92      0.94       157

    accuracy                           0.93       273
   macro avg       0.93      0.94      0.93       273
weighted avg       0.94      0.93      0.93       273
```

1.5.9 Final Conclusion

If there is a need of avoiding people having slightest chance of any risk, then the SVM Model with 0.115 threshold as discussed above (in detail) can be used.

However, if the accuracy is the main concern, then the K - Nearest Neighbour Classifier can be used.

1.6 Project - 2 (Diamond Price Prediction)

The Business problem will be discussed after importing the dataset.

[32]:
```python
diamondDF = pd.read_csv('./Datasets/Diamond Price Prediction.csv')
diamondDF.head()
```

[32]:
```
   Unnamed: 0  carat      cut color clarity  depth  table  price     x     y  \
0           1   0.23    Ideal     E     SI2   61.5   55.0    326  3.95  3.98
1           2   0.21  Premium     E     SI1   59.8   61.0    326  3.89  3.84
2           3   0.23     Good     E     VS1   56.9   65.0    327  4.05  4.07
3           4   0.29  Premium     I     VS2   62.4   58.0    334  4.20  4.23
4           5   0.31     Good     J     SI2   63.3   58.0    335  4.34  4.35

      z
0  2.43
1  2.31
2  2.31
3  2.63
4  2.75
```

1.6.1 Information of dataset

[33]:
```
diamondDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53940 entries, 0 to 53939
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Unnamed: 0  53940 non-null  int64
 1   carat       53940 non-null  float64
 2   cut         53940 non-null  object
 3   color       53940 non-null  object
 4   clarity     53940 non-null  object
 5   depth       53940 non-null  float64
 6   table       53940 non-null  float64
 7   price       53940 non-null  int64
 8   x           53940 non-null  float64
 9   y           53940 non-null  float64
 10  z           53940 non-null  float64
dtypes: float64(6), int64(2), object(3)
memory usage: 4.5+ MB
```

1.6.2 Business Problem

The dataset of diamonds is provided. It contains various details like carat, cut, color, clarity, depth, table, price, x, y and z etc. The problem is to make a machine learning model, which can learn from the provided data and then predict the price of diamonds from the details provided to it. This model should be able to make enough accurate predictions that the predicted prices are at least 85 % accurate.

1.6.3 Analysis

[34]:
```
diamondDF.describe()
```

[34]:
```
         Unnamed: 0         carat         depth         table         price  \
count  53940.000000  53940.000000  53940.000000  53940.000000  53940.000000
mean   26970.500000      0.797940     61.749405     57.457184   3932.799722
std    15571.281097      0.474011      1.432621      2.234491   3989.439738
min        1.000000      0.200000     43.000000     43.000000    326.000000
25%    13485.750000      0.400000     61.000000     56.000000    950.000000
50%    26970.500000      0.700000     61.800000     57.000000   2401.000000
75%    40455.250000      1.040000     62.500000     59.000000   5324.250000
max    53940.000000      5.010000     79.000000     95.000000  18823.000000

                  x             y             z
count  53940.000000  53940.000000  53940.000000
mean       5.731157      5.734526      3.538734
```

```
std         1.121761     1.142135     0.705699
min         0.000000     0.000000     0.000000
25%         4.710000     4.720000     2.910000
50%         5.700000     5.710000     3.530000
75%         6.540000     6.540000     4.040000
max        10.740000    58.900000    31.800000
```

Removing the Unnamed: 0 column This is an indexing column, it is not required.

[35]:
```python
diamondDF.drop(columns = ['Unnamed: 0'], inplace = True)
diamondDF.describe()
```

[35]:
```
              carat         depth         table         price             x  \
count  53940.000000  53940.000000  53940.000000  53940.000000  53940.000000
mean       0.797940     61.749405     57.457184   3932.799722      5.731157
std        0.474011      1.432621      2.234491   3989.439738      1.121761
min        0.200000     43.000000     43.000000    326.000000      0.000000
25%        0.400000     61.000000     56.000000    950.000000      4.710000
50%        0.700000     61.800000     57.000000   2401.000000      5.700000
75%        1.040000     62.500000     59.000000   5324.250000      6.540000
max        5.010000     79.000000     95.000000  18823.000000     10.740000

                  y             z
count  53940.000000  53940.000000
mean       5.734526      3.538734
std        1.142135      0.705699
min        0.000000      0.000000
25%        4.720000      2.910000
50%        5.710000      3.530000
75%        6.540000      4.040000
max       58.900000     31.800000
```

[36]:
```python
diamondDF.shape
```

[36]:
```
(53940, 10)
```

This is a large dataset.

1.6.4 Checking if this dataset has null values

[37]:
```python
diamondDF.isnull().sum()
```

[37]:
```
carat      0
cut        0
color      0
clarity    0
depth      0
```

```
table      0
price      0
x          0
y          0
z          0
dtype: int64
```

1.6.5 Using Label Encoder to encode the cut, color and clarity column

[38]:
```
print(diamondDF['cut'].value_counts())
print(diamondDF['color'].value_counts())
print(diamondDF['clarity'].value_counts())
```

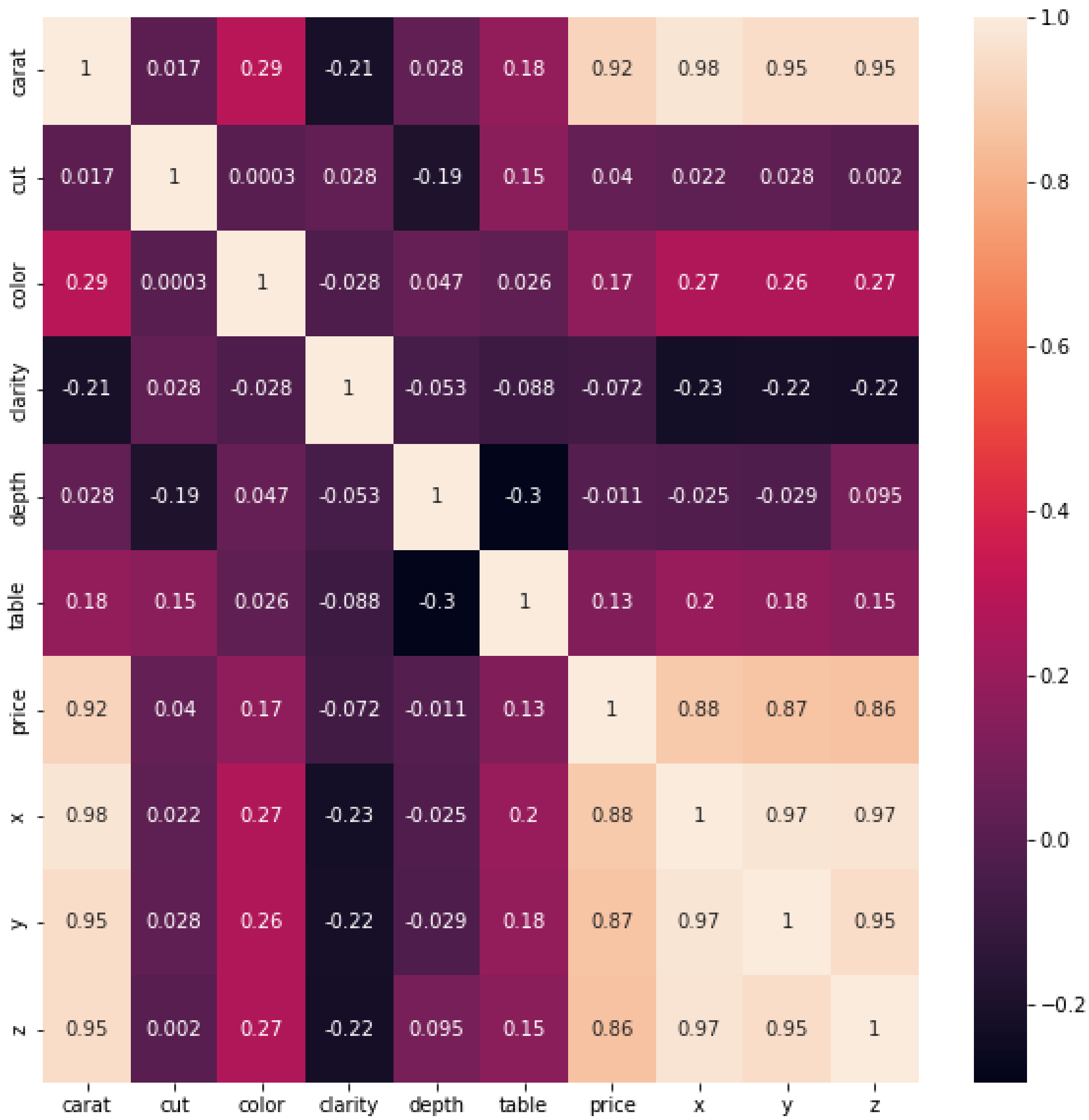
```
Ideal        21551
Premium      13791
Very Good    12082
Good          4906
Fair          1610
Name: cut, dtype: int64
G    11292
E     9797
F     9542
H     8304
D     6775
I     5422
J     2808
Name: color, dtype: int64
SI1     13065
VS2     12258
SI2      9194
VS1      8171
VVS2     5066
VVS1     3655
IF       1790
I1        741
Name: clarity, dtype: int64
```

[39]:
```
from sklearn.preprocessing import LabelEncoder

diamond_cut_le = LabelEncoder()
diamond_color_le = LabelEncoder()
diamond_clarity_le = LabelEncoder()

diamondDF['cut'] = diamond_cut_le.fit_transform(diamondDF['cut'])
diamondDF['color'] = diamond_color_le.fit_transform(diamondDF['color'])
diamondDF['clarity'] = diamond_clarity_le.fit_transform(diamondDF['clarity'])
```

[40]:
```
print(diamondDF['cut'].value_counts())
print(diamondDF['color'].value_counts())
print(diamondDF['clarity'].value_counts())
```

```
2    21551
3    13791
4    12082
1     4906
0     1610
Name: cut, dtype: int64
3    11292
1     9797
2     9542
4     8304
0     6775
5     5422
6     2808
Name: color, dtype: int64
2    13065
5    12258
3     9194
4     8171
7     5066
6     3655
1     1790
0      741
Name: clarity, dtype: int64
```

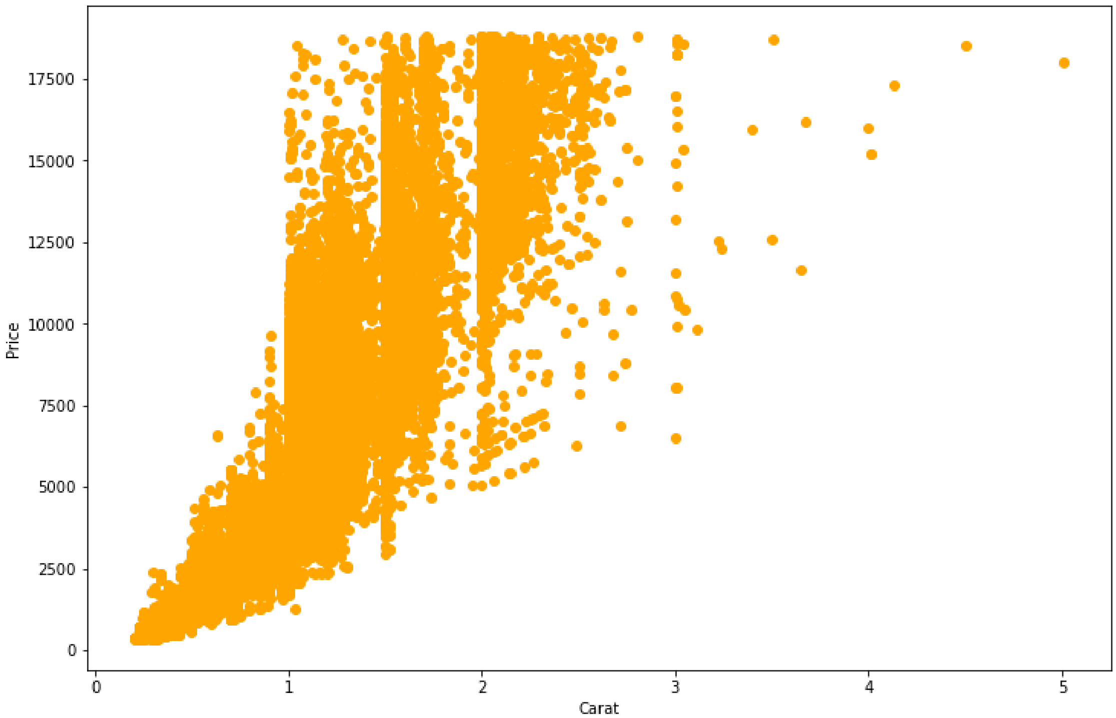
[41]:
```
plt.figure(figsize = (10, 10))

sns.heatmap(diamondDF.corr(), annot = True);
```



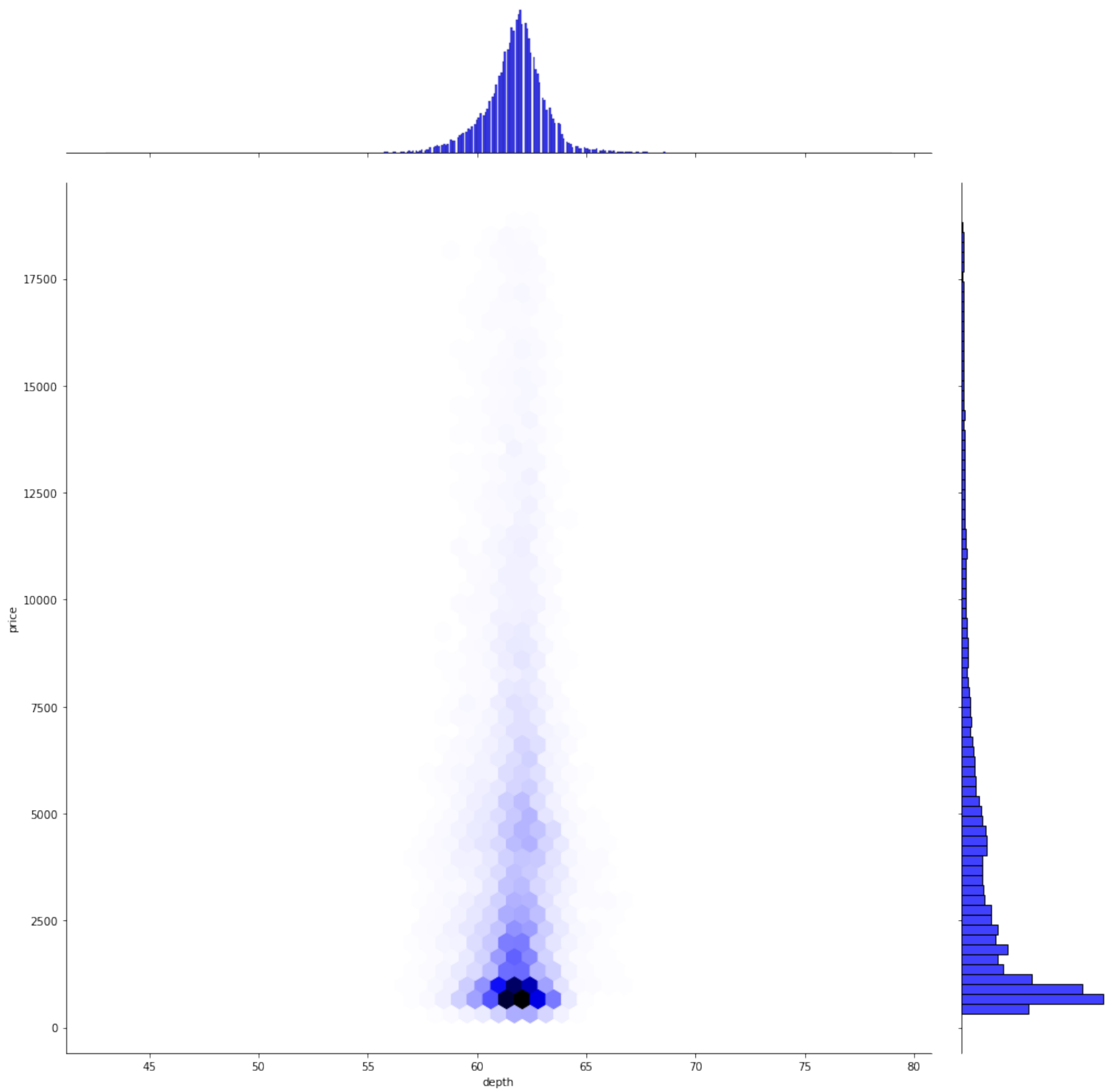
This dataset is very large, that it would talk a long time to calculate and plot pair plots.

Scatter plot

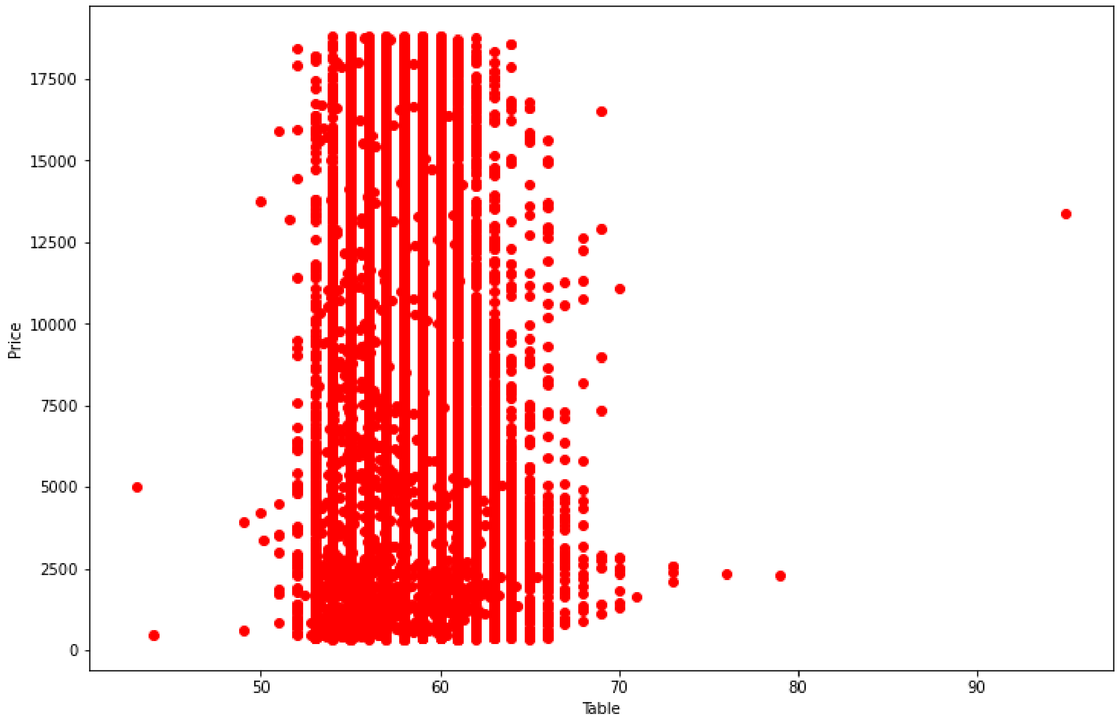
[42]:
```
plt.figure(figsize = (12, 8))

plt.scatter(diamondDF['carat'], diamondDF['price'], c = 'orange')

plt.xlabel('Carat')
plt.ylabel('Price');
```



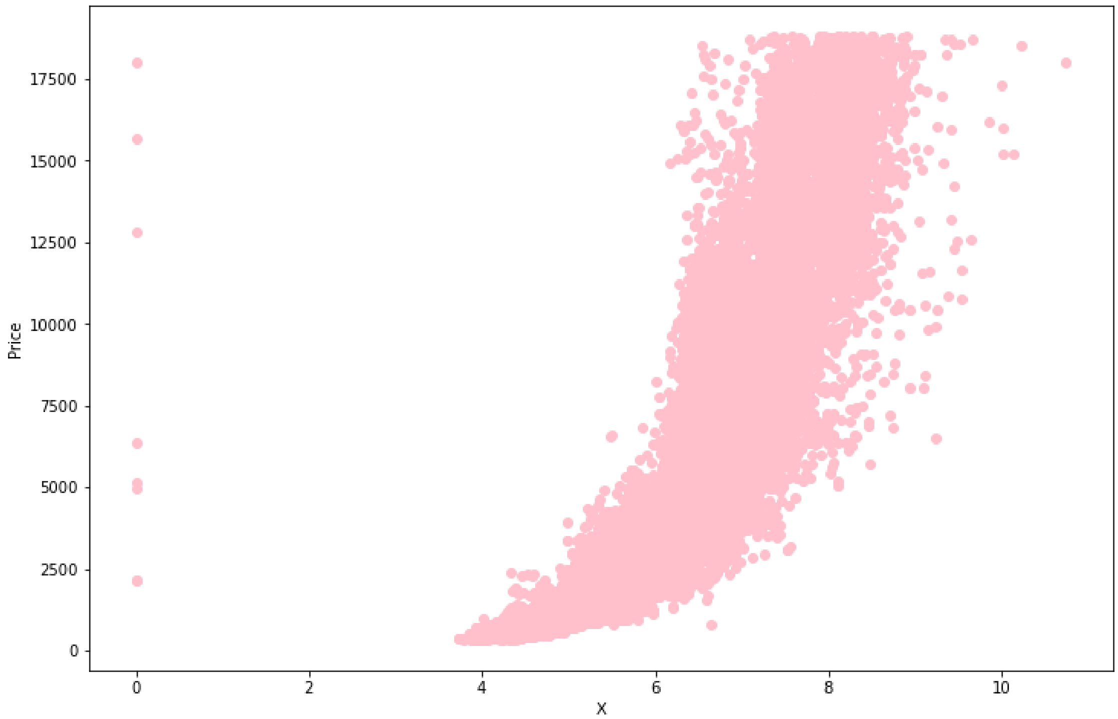
[43]:
```
sns.jointplot(x = diamondDF['depth'], y = diamondDF['price'], kind = 'hex',␣
↪color = 'blue', height = 14);
```



[44]:
```
plt.figure(figsize = (12, 8))

plt.scatter(diamondDF['table'], diamondDF['price'], c = 'red')

plt.xlabel('Table')
plt.ylabel('Price');
```

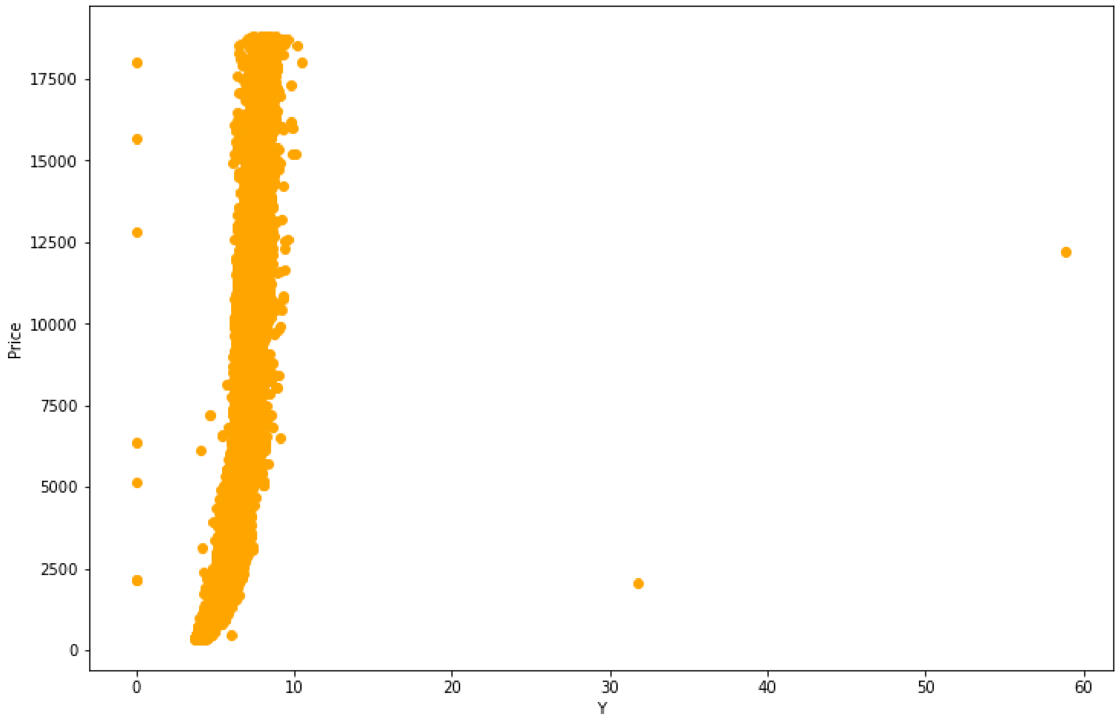


[45]:
```
plt.figure(figsize = (12, 8))

plt.scatter(diamondDF['x'], diamondDF['price'], c = 'pink')

plt.xlabel('X')
plt.ylabel('Price');
```

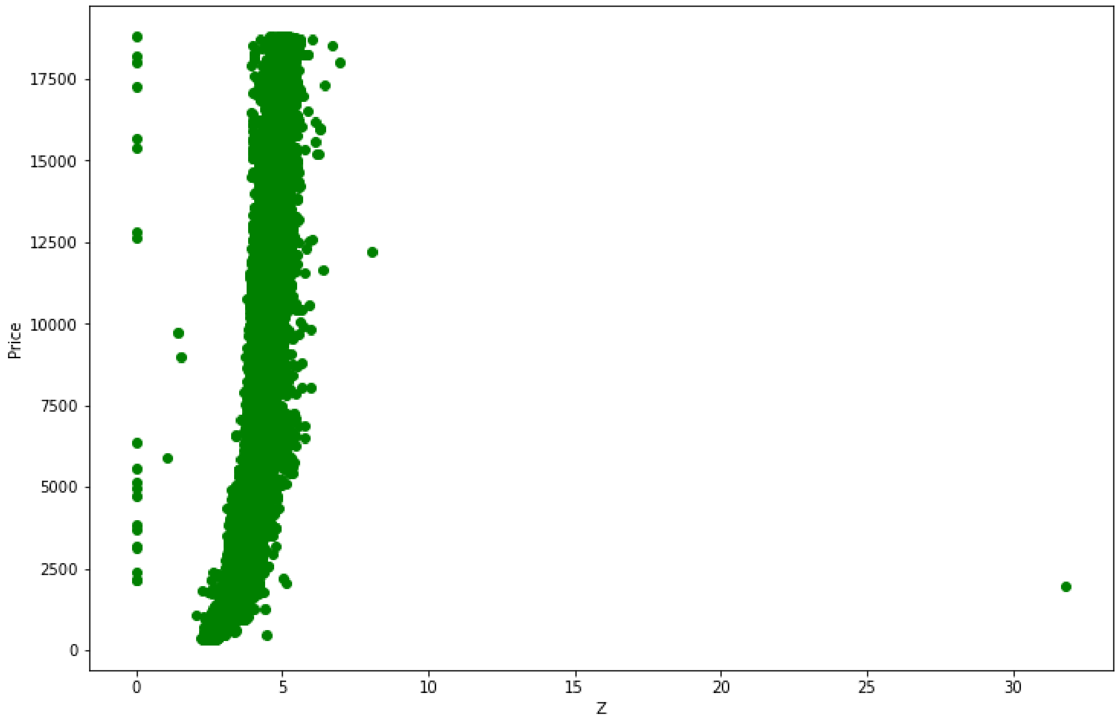


[46]:

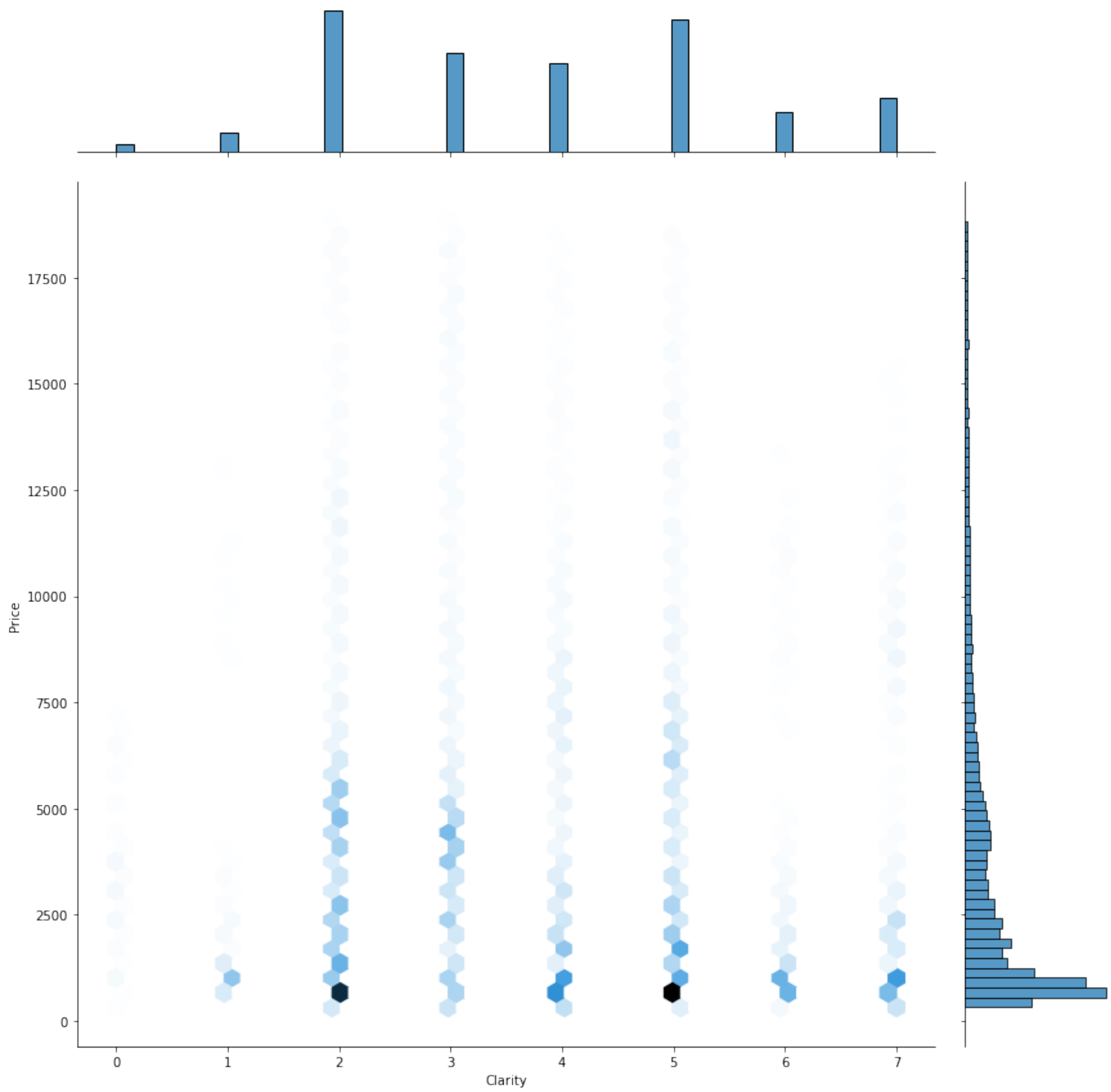
```
plt.figure(figsize = (12, 8))

plt.scatter(diamondDF['y'], diamondDF['price'], c = 'orange')

plt.xlabel('Y')
plt.ylabel('Price');
```



[47]:
```
plt.figure(figsize = (12, 8))

plt.scatter(diamondDF['z'], diamondDF['price'], c = 'green')

plt.xlabel('Z')
plt.ylabel('Price');
```




```
[48]: sns.jointplot(x = diamondDF['clarity'], y = diamondDF['price'], kind = 'hex',
       ↪height = 12)

      plt.xlabel('Clarity')
      plt.ylabel('Price');
```



This problem would be solved with the following techniques:

1. Using Multiple Linear Regression
2. Using Artificial Nerual Networks

1.6.6 Independent and Dependent Features

All columns

[49]:
```
diamondDF.columns
```

[49]:
```
Index(['carat', 'cut', 'color', 'clarity', 'depth', 'table', 'price', 'x', 'y',
       'z'],
      dtype='object')
```

[50]:
```python
diamond_X = diamondDF.drop(columns = ['price'])
diamond_X.head()
```

[50]:

	carat	cut	color	clarity	depth	table	x	y	z
0	0.23	2	1	3	61.5	55.0	3.95	3.98	2.43
1	0.21	3	1	2	59.8	61.0	3.89	3.84	2.31
2	0.23	1	1	4	56.9	65.0	4.05	4.07	2.31
3	0.29	3	5	5	62.4	58.0	4.20	4.23	2.63
4	0.31	1	6	3	63.3	58.0	4.34	4.35	2.75

[51]:
```python
diamond_y = diamondDF.iloc[:, 6]
diamond_y.head()
```

[51]:
```
0    326
1    326
2    327
3    334
4    335
Name: price, dtype: int64
```

Splitting the dataset

[52]:
```python
from sklearn.model_selection import train_test_split

diamond_X_train, diamond_X_test, diamond_y_train, diamond_y_test = ␣
↪train_test_split(diamond_X, diamond_y, test_size = 0.33,                                ␣
↪    random_state = 43)
```

Standardizing the datasets

[53]:
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

diamond_X_train = scaler.fit_transform(diamond_X_train)
diamond_X_test = scaler.transform(diamond_X_test)
```

1.6.7 Using Multiple Linear Regression

Creating the model

[54]:
```python
from sklearn.linear_model import LinearRegression

multiple_reg = LinearRegression()
```

[55]:
```python
multiple_reg.fit(diamond_X_train, diamond_y_train)
```

[55]: LinearRegression()

Testing the model

[56]:
```
from sklearn.metrics import r2_score

diamond_y_pred = multiple_reg.predict(diamond_X_test)
```

[57]:
```
print(f'The accuracy of the above trained model is approximately␣
↪{round(r2_score(diamond_y_test, diamond_y_pred) * 100, 2)} %.')
```

```
The accuracy of the above trained model is approximately 88.52 %.
```

SVM took about 5 minutes to train. And same amount of time even for testing. And the R2 score was around 83% for linear type of kernel and standardized data. And for other kernel types it was even less. Since the project requirements state that the score must be more than 85%, therefore SVM model is discarded.

1.6.8 Using the Artificial Neural Networks

[58]:
```
import keras
from keras.layers import Dense
from keras.models import Sequential
```

[59]:
```
model=Sequential()

#First Layer
model.add(Dense(9, activation = "relu", input_dim = 9))

for i in range(3):
    model.add(Dense(units = 27, activation = "relu"))

#Output Layer
model.add(Dense(units = 1))

#Compiling the ANN
model.compile(optimizer = "adam", loss = "mean_squared_error", metrics =␣
↪['mae', 'mse', 'mape'])

#Fitting the ANN to the training Dataset
model.fit(diamond_X_train, diamond_y_train, batch_size = 30, epochs = 100)
```

```
Epoch 1/100
1205/1205 [==============================] - 4s 2ms/step - loss: 6953664.5000 -
mae: 1372.3706 - mse: 6953664.5000 - mape: 41.4379
Epoch 2/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1602700.3750 -
mae: 717.5458 - mse: 1602700.3750 - mape: 23.8950
```

```
Epoch 3/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1488335.5000 -
mae: 698.2144 - mse: 1488335.5000 - mape: 24.3226
Epoch 4/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1407846.2500 -
mae: 680.8730 - mse: 1407846.2500 - mape: 23.9194
Epoch 5/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1339964.0000 -
mae: 662.6890 - mse: 1339964.0000 - mape: 23.2231
Epoch 6/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1291291.0000 -
mae: 647.3705 - mse: 1291291.0000 - mape: 22.6555
Epoch 7/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1239687.3750 -
mae: 631.8548 - mse: 1239687.3750 - mape: 21.7940
Epoch 8/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1200761.8750 -
mae: 618.4058 - mse: 1200761.8750 - mape: 21.1459
Epoch 9/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1169176.2500 -
mae: 606.2889 - mse: 1169176.2500 - mape: 20.3157
Epoch 10/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1141613.7500 -
mae: 597.7314 - mse: 1141613.7500 - mape: 19.6399
Epoch 11/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1123256.2500 -
mae: 589.2486 - mse: 1123256.2500 - mape: 18.9222
Epoch 12/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1107468.6250 -
mae: 581.5971 - mse: 1107468.6250 - mape: 18.3450
Epoch 13/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1101249.2500 -
mae: 576.7926 - mse: 1101249.2500 - mape: 17.8830
Epoch 14/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1089973.6250 -
mae: 573.0398 - mse: 1089973.6250 - mape: 17.4972
Epoch 15/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1083123.2500 -
mae: 566.9428 - mse: 1083123.2500 - mape: 17.0306
Epoch 16/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1080634.8750 -
mae: 565.8483 - mse: 1080634.8750 - mape: 16.8343
Epoch 17/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1070883.5000 -
mae: 561.0584 - mse: 1070883.5000 - mape: 16.5139
Epoch 18/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1069822.8750 -
mae: 559.2219 - mse: 1069822.8750 - mape: 16.2379
```

```
Epoch 19/100
1205/1205 [==============================] - 3s 3ms/step - loss: 1060557.2500 -
mae: 554.1410 - mse: 1060557.2500 - mape: 15.8989
Epoch 20/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1056483.1250 -
mae: 551.7396 - mse: 1056483.1250 - mape: 15.7011
Epoch 21/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1052214.8750 -
mae: 549.8562 - mse: 1052214.8750 - mape: 15.5811
Epoch 22/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1049925.3750 -
mae: 548.5662 - mse: 1049925.3750 - mape: 15.4215
Epoch 23/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1046000.5625 -
mae: 547.6224 - mse: 1046000.5625 - mape: 15.3824
Epoch 24/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1042651.2500 -
mae: 545.1421 - mse: 1042651.1250 - mape: 15.2629
Epoch 25/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1039264.0000 -
mae: 543.8834 - mse: 1039264.0000 - mape: 15.1893
Epoch 26/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1037815.8125 -
mae: 542.7623 - mse: 1037815.8125 - mape: 15.1693
Epoch 27/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1035909.4375 -
mae: 543.5322 - mse: 1035909.4375 - mape: 15.1458
Epoch 28/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1029524.0000 -
mae: 540.7136 - mse: 1029524.0000 - mape: 15.0553
Epoch 29/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1027118.6875 -
mae: 540.5454 - mse: 1027118.6875 - mape: 15.0173
Epoch 30/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1023425.6875 -
mae: 538.1948 - mse: 1023425.6875 - mape: 15.0007
Epoch 31/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1019210.5000 -
mae: 536.0350 - mse: 1019210.5000 - mape: 14.8447
Epoch 32/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1014336.6250 -
mae: 536.4562 - mse: 1014336.6250 - mape: 14.8805
Epoch 33/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1013537.5625 -
mae: 536.5089 - mse: 1013537.5625 - mape: 14.9246
Epoch 34/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1010864.5625 -
mae: 536.4017 - mse: 1010864.5625 - mape: 14.9272
```

```
Epoch 35/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1008887.0000 -
mae: 535.5551 - mse: 1008887.0000 - mape: 14.9021
Epoch 36/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1002166.6250 -
mae: 532.8461 - mse: 1002166.6250 - mape: 14.7897
Epoch 37/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1001661.4375 -
mae: 533.4882 - mse: 1001661.4375 - mape: 14.8649
Epoch 38/100
1205/1205 [==============================] - 3s 2ms/step - loss: 1001592.6250 -
mae: 533.7238 - mse: 1001592.6250 - mape: 14.8932
Epoch 39/100
1205/1205 [==============================] - 3s 2ms/step - loss: 997056.1875 -
mae: 533.1597 - mse: 997056.1875 - mape: 14.9085
Epoch 40/100
1205/1205 [==============================] - 3s 2ms/step - loss: 993770.6875 -
mae: 531.0468 - mse: 993770.6875 - mape: 14.8295
Epoch 41/100
1205/1205 [==============================] - 3s 2ms/step - loss: 989566.5625 -
mae: 531.9600 - mse: 989566.5625 - mape: 15.0371
Epoch 42/100
1205/1205 [==============================] - 3s 2ms/step - loss: 988566.0000 -
mae: 531.6643 - mse: 988566.0000 - mape: 14.9753
Epoch 43/100
1205/1205 [==============================] - 3s 2ms/step - loss: 988270.6250 -
mae: 531.0163 - mse: 988270.6250 - mape: 14.9564
Epoch 44/100
1205/1205 [==============================] - 3s 3ms/step - loss: 983140.3125 -
mae: 530.7774 - mse: 983140.3125 - mape: 14.9819
Epoch 45/100
1205/1205 [==============================] - 3s 2ms/step - loss: 977867.6250 -
mae: 530.1738 - mse: 977867.6250 - mape: 14.9704
Epoch 46/100
1205/1205 [==============================] - 3s 2ms/step - loss: 979066.7500 -
mae: 529.5806 - mse: 979066.7500 - mape: 14.9843
Epoch 47/100
1205/1205 [==============================] - 3s 2ms/step - loss: 972746.2500 -
mae: 527.7315 - mse: 972746.2500 - mape: 14.9973
Epoch 48/100
1205/1205 [==============================] - 3s 2ms/step - loss: 967913.8750 -
mae: 527.8165 - mse: 967913.8750 - mape: 15.0238
Epoch 49/100
1205/1205 [==============================] - 3s 2ms/step - loss: 968305.8750 -
mae: 527.0990 - mse: 968305.8750 - mape: 15.0404
Epoch 50/100
1205/1205 [==============================] - 3s 2ms/step - loss: 964466.5000 -
mae: 524.8968 - mse: 964466.5000 - mape: 14.9251
```

```
Epoch 51/100
1205/1205 [==============================] - 3s 2ms/step - loss: 962043.7500 -
mae: 526.4765 - mse: 962043.7500 - mape: 15.1183
Epoch 52/100
1205/1205 [==============================] - 3s 2ms/step - loss: 960844.5000 -
mae: 524.5032 - mse: 960844.5000 - mape: 15.0098
Epoch 53/100
1205/1205 [==============================] - 3s 2ms/step - loss: 957336.2500 -
mae: 524.1253 - mse: 957336.2500 - mape: 14.9571
Epoch 54/100
1205/1205 [==============================] - 3s 3ms/step - loss: 957402.9375 -
mae: 525.2717 - mse: 957402.9375 - mape: 15.0756
Epoch 55/100
1205/1205 [==============================] - 3s 2ms/step - loss: 948511.0000 -
mae: 522.1719 - mse: 948511.0000 - mape: 14.9290
Epoch 56/100
1205/1205 [==============================] - 3s 2ms/step - loss: 951298.1875 -
mae: 522.5687 - mse: 951298.1875 - mape: 14.9431
Epoch 57/100
1205/1205 [==============================] - 3s 2ms/step - loss: 944476.0625 -
mae: 519.5585 - mse: 944476.0625 - mape: 14.7036
Epoch 58/100
1205/1205 [==============================] - 3s 2ms/step - loss: 943075.5625 -
mae: 519.4711 - mse: 943075.5625 - mape: 14.8239
Epoch 59/100
1205/1205 [==============================] - 3s 2ms/step - loss: 938579.5000 -
mae: 518.1314 - mse: 938579.5000 - mape: 14.7198
Epoch 60/100
1205/1205 [==============================] - 3s 2ms/step - loss: 937323.0625 -
mae: 517.9427 - mse: 937323.0625 - mape: 14.6881
Epoch 61/100
1205/1205 [==============================] - 3s 2ms/step - loss: 935701.5000 -
mae: 517.7393 - mse: 935701.5000 - mape: 14.7239
Epoch 62/100
1205/1205 [==============================] - 3s 2ms/step - loss: 935647.5000 -
mae: 516.6925 - mse: 935647.5000 - mape: 14.6676
Epoch 63/100
1205/1205 [==============================] - 3s 2ms/step - loss: 934359.3125 -
mae: 516.8128 - mse: 934359.3125 - mape: 14.6577
Epoch 64/100
1205/1205 [==============================] - 3s 2ms/step - loss: 929782.6875 -
mae: 515.3497 - mse: 929782.6875 - mape: 14.5838
Epoch 65/100
1205/1205 [==============================] - 3s 2ms/step - loss: 926872.6250 -
mae: 514.0991 - mse: 926872.5625 - mape: 14.5764
Epoch 66/100
1205/1205 [==============================] - 3s 2ms/step - loss: 927764.1875 -
mae: 512.2206 - mse: 927764.1875 - mape: 14.5553
```

```
Epoch 67/100
1205/1205 [==============================] - 3s 2ms/step - loss: 926618.0000 -
mae: 513.8453 - mse: 926618.0000 - mape: 14.5941
Epoch 68/100
1205/1205 [==============================] - 3s 2ms/step - loss: 922038.2500 -
mae: 512.5817 - mse: 922038.2500 - mape: 14.4755
Epoch 69/100
1205/1205 [==============================] - 3s 2ms/step - loss: 919864.1250 -
mae: 511.3427 - mse: 919864.1250 - mape: 14.5156
Epoch 70/100
1205/1205 [==============================] - 3s 2ms/step - loss: 917968.3750 -
mae: 511.7860 - mse: 917968.3750 - mape: 14.5643
Epoch 71/100
1205/1205 [==============================] - 3s 2ms/step - loss: 918166.0000 -
mae: 510.6875 - mse: 918166.0000 - mape: 14.4546
Epoch 72/100
1205/1205 [==============================] - 3s 2ms/step - loss: 916009.9375 -
mae: 510.3484 - mse: 916009.9375 - mape: 14.4226
Epoch 73/100
1205/1205 [==============================] - 3s 2ms/step - loss: 915186.6250 -
mae: 509.9912 - mse: 915186.6250 - mape: 14.4740
Epoch 74/100
1205/1205 [==============================] - 4s 3ms/step - loss: 915752.8125 -
mae: 509.9557 - mse: 915752.8125 - mape: 14.5107
Epoch 75/100
1205/1205 [==============================] - 3s 2ms/step - loss: 915059.3750 -
mae: 508.3425 - mse: 915059.3750 - mape: 14.4015
Epoch 76/100
1205/1205 [==============================] - 3s 2ms/step - loss: 910702.0000 -
mae: 507.7232 - mse: 910702.0000 - mape: 14.3806
Epoch 77/100
1205/1205 [==============================] - 3s 2ms/step - loss: 906234.9375 -
mae: 506.7026 - mse: 906234.9375 - mape: 14.3513
Epoch 78/100
1205/1205 [==============================] - 3s 2ms/step - loss: 911417.0625 -
mae: 505.9401 - mse: 911417.0625 - mape: 14.2706
Epoch 79/100
1205/1205 [==============================] - 3s 2ms/step - loss: 907274.4375 -
mae: 504.9110 - mse: 907274.4375 - mape: 14.2510
Epoch 80/100
1205/1205 [==============================] - 3s 2ms/step - loss: 907790.4375 -
mae: 506.0738 - mse: 907790.4375 - mape: 14.3320
Epoch 81/100
1205/1205 [==============================] - 3s 2ms/step - loss: 906208.4375 -
mae: 506.4141 - mse: 906208.4375 - mape: 14.3743
Epoch 82/100
1205/1205 [==============================] - 3s 2ms/step - loss: 905953.6875 -
mae: 504.5332 - mse: 905953.6875 - mape: 14.2286
```

```
Epoch 83/100
1205/1205 [==============================] - 3s 2ms/step - loss: 906469.5000 -
mae: 503.9951 - mse: 906469.5000 - mape: 14.1380
Epoch 84/100
1205/1205 [==============================] - 3s 2ms/step - loss: 901555.1250 -
mae: 502.3738 - mse: 901555.1250 - mape: 14.1545
Epoch 85/100
1205/1205 [==============================] - 3s 2ms/step - loss: 901507.8125 -
mae: 503.2253 - mse: 901507.8125 - mape: 14.1909
Epoch 86/100
1205/1205 [==============================] - 3s 2ms/step - loss: 901033.1250 -
mae: 501.6938 - mse: 901033.1250 - mape: 14.0784
Epoch 87/100
1205/1205 [==============================] - 3s 2ms/step - loss: 901230.6250 -
mae: 501.4472 - mse: 901230.6250 - mape: 14.0761
Epoch 88/100
1205/1205 [==============================] - 3s 2ms/step - loss: 899713.9375 -
mae: 500.2846 - mse: 899713.9375 - mape: 14.0152
Epoch 89/100
1205/1205 [==============================] - 3s 2ms/step - loss: 901548.9375 -
mae: 502.5410 - mse: 901548.9375 - mape: 14.1271
Epoch 90/100
1205/1205 [==============================] - 3s 2ms/step - loss: 897855.6250 -
mae: 500.7972 - mse: 897855.6250 - mape: 14.0288
Epoch 91/100
1205/1205 [==============================] - 3s 2ms/step - loss: 896552.3125 -
mae: 499.2139 - mse: 896552.3125 - mape: 13.9561
Epoch 92/100
1205/1205 [==============================] - 3s 3ms/step - loss: 897613.1250 -
mae: 499.7262 - mse: 897613.1875 - mape: 14.0366
Epoch 93/100
1205/1205 [==============================] - 3s 2ms/step - loss: 896843.2500 -
mae: 498.9048 - mse: 896843.2500 - mape: 13.9088
Epoch 94/100
1205/1205 [==============================] - 3s 3ms/step - loss: 896402.0625 -
mae: 498.7642 - mse: 896402.0625 - mape: 13.9792
Epoch 95/100
1205/1205 [==============================] - 3s 2ms/step - loss: 890566.9375 -
mae: 496.9295 - mse: 890566.9375 - mape: 13.9762
Epoch 96/100
1205/1205 [==============================] - 3s 2ms/step - loss: 890159.0000 -
mae: 497.1740 - mse: 890159.0000 - mape: 13.9282
Epoch 97/100
1205/1205 [==============================] - 3s 3ms/step - loss: 891909.0000 -
mae: 497.6976 - mse: 891909.0000 - mape: 13.9256
Epoch 98/100
1205/1205 [==============================] - 3s 2ms/step - loss: 888078.5625 -
mae: 495.9995 - mse: 888078.5625 - mape: 13.9183
```

```
Epoch 99/100
1205/1205 [==============================] - 3s 2ms/step - loss: 890563.1875 -
mae: 497.3430 - mse: 890563.1875 - mape: 13.9917
Epoch 100/100
1205/1205 [==============================] - 3s 3ms/step - loss: 891732.6250 -
mae: 496.8784 - mse: 891732.6250 - mape: 13.8886
```

[59]:
```
<keras.callbacks.History at 0x15f4bf18190>
```

[60]:
```
model.evaluate(diamond_X_test, diamond_y_test)
```

```
557/557 [==============================] - 1s 2ms/step - loss: 916414.3125 -
mae: 503.5201 - mse: 916414.3125 - mape: 14.1053
```

[60]:
```
[916414.3125, 503.5201416015625, 916414.3125, 14.105281829833984]
```

[61]:
```
diamond_y_pred = model.predict(diamond_X_test)
```

```
557/557 [==============================] - 1s 2ms/step
```

[62]:
```
print(f'The accuracy of the above trained model is approximately␣
↪{round(r2_score(diamond_y_test, diamond_y_pred) * 100, 2)} %.')
```

```
The accuracy of the above trained model is approximately 94.3 %.
```

1.6.9 Final Conclusion

Both of the models have accuracy more than 85%. Thus, they can be used to make reliable predictions regarding diamond prices.

1.7 Project - 3 (Company Attrition Data)

Business problem will be discussed after importing the company attrition dataset.

[63]:
```
compAttDF = pd.read_csv('Datasets/Company Attrition Data.csv')
compAttDF.head()
```

[63]:
```
   satisfaction_level  last_evaluation  number_project  average_montly_hours  \
0                0.38             0.53               2                   157
1                0.80             0.86               5                   262
2                0.11             0.88               7                   272
3                0.72             0.87               5                   223
4                0.37             0.52               2                   159

   time_spend_company  Work_accident  left  promotion_last_5years  \
0                   3              0     1                      0
1                   6              0     1                      0
2                   4              0     1                      0
3                   5              0     1                      0
```

```
4                    3              0     1                      0

   Sales_Occured  salary
0          sales     low
1          sales  medium
2          sales  medium
3          sales     low
4          sales     low
```

1.7.1 Information of dataset

[64]:
```
compAttDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64
 3   average_montly_hours   14999 non-null  int64
 4   time_spend_company     14999 non-null  int64
 5   Work_accident          14999 non-null  int64
 6   left                   14999 non-null  int64
 7   promotion_last_5years  14999 non-null  int64
 8   Sales_Occured          14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

1.7.2 Business Problem

A dataset of a company having employee details is provided. And the problem is to predict what chances are there whether an employee would leave or not. This can help a company to estimate how many employees may leave in future, and they can take advance steps like hiring new employees or improving the work environment by listening to employee's complaints.

1.7.3 Null values

[65]:
```
compAttDF.isnull().sum()
```

[65]:
```
satisfaction_level       0
last_evaluation          0
number_project           0
average_montly_hours     0
time_spend_company       0
Work_accident            0
```

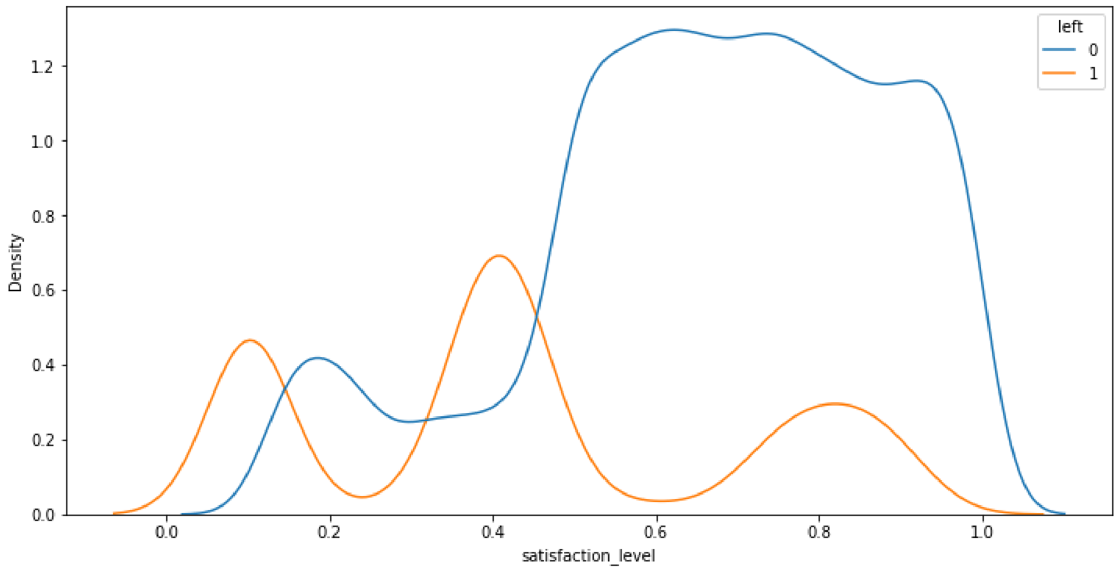
```
left                    0
promotion_last_5years   0
Sales_Occured           0
salary                  0
dtype: int64
```

1.7.4 Analysis

[66]:
```python
compAttDF.describe()
```

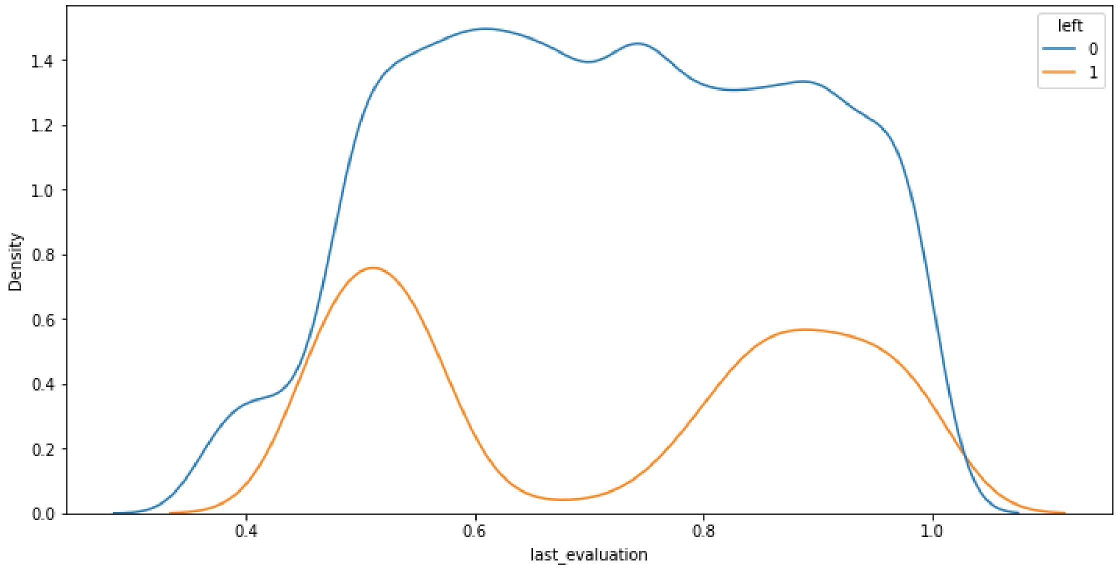
[66]:
```
       satisfaction_level  last_evaluation  number_project  \
count        14999.000000     14999.000000    14999.000000
mean             0.612834         0.716102        3.803054
std              0.248631         0.171169        1.232592
min              0.090000         0.360000        2.000000
25%              0.440000         0.560000        3.000000
50%              0.640000         0.720000        4.000000
75%              0.820000         0.870000        5.000000
max              1.000000         1.000000        7.000000

       average_montly_hours  time_spend_company  Work_accident          left  \
count          14999.000000        14999.000000   14999.000000  14999.000000
mean             201.050337            3.498233       0.144610      0.238083
std               49.943099            1.460136       0.351719      0.425924
min               96.000000            2.000000       0.000000      0.000000
25%              156.000000            3.000000       0.000000      0.000000
50%              200.000000            3.000000       0.000000      0.000000
75%              245.000000            4.000000       0.000000      0.000000
max              310.000000           10.000000       1.000000      1.000000

       promotion_last_5years
count           14999.000000
mean                0.021268
std                 0.144281
min                 0.000000
25%                 0.000000
50%                 0.000000
75%                 0.000000
max                 1.000000
```

[67]:
```python
plt.figure(figsize = (12, 6))

sns.kdeplot(x = 'satisfaction_level',
            hue = 'left',
            data = compAttDF);
```



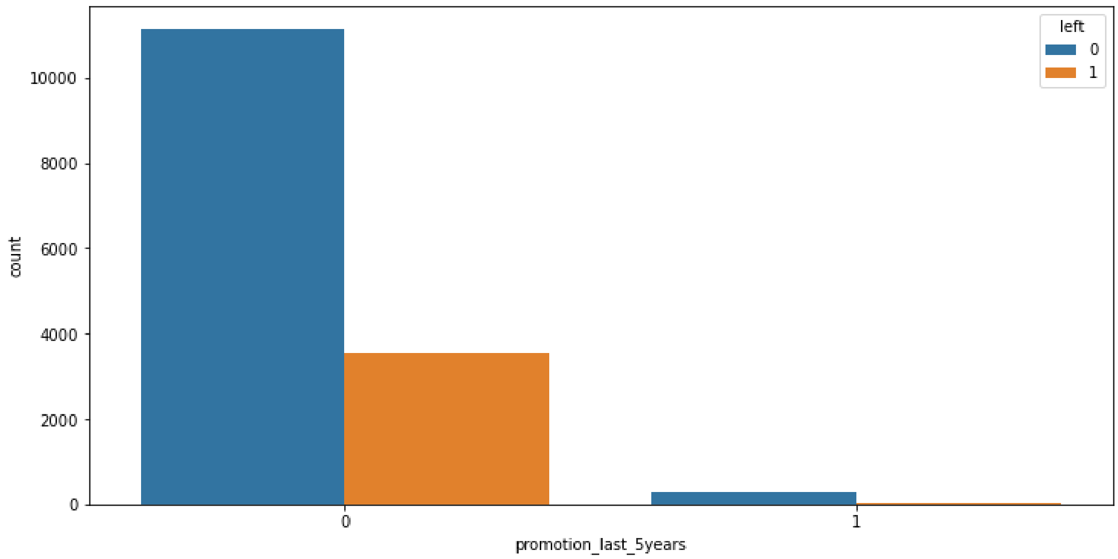
From the above graph it can be inferred that employees having good satisfaction level stayed in the company.

[68]:
```
plt.figure(figsize = (12, 6))

sns.kdeplot(x = 'last_evaluation',
            hue = 'left',
            data = compAttDF);
```



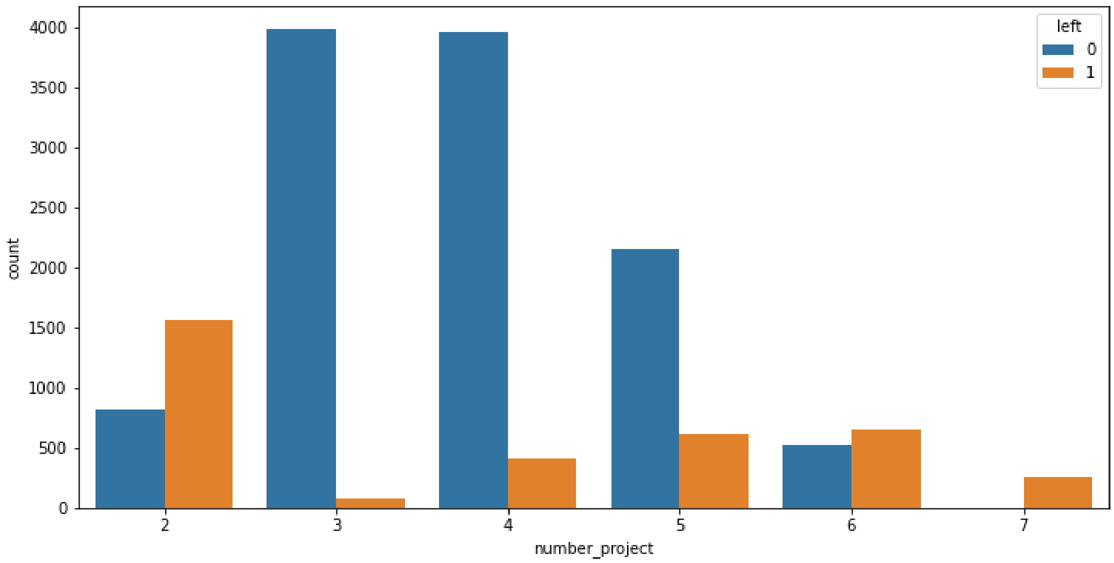
Looks like there is no strong connection between Last Evaluation and the chance of an employee leaving the company.

[69]:
```
plt.figure(figsize = (12, 6))

sns.countplot(x = 'promotion_last_5years',
              hue = 'left', data = compAttDF);
```



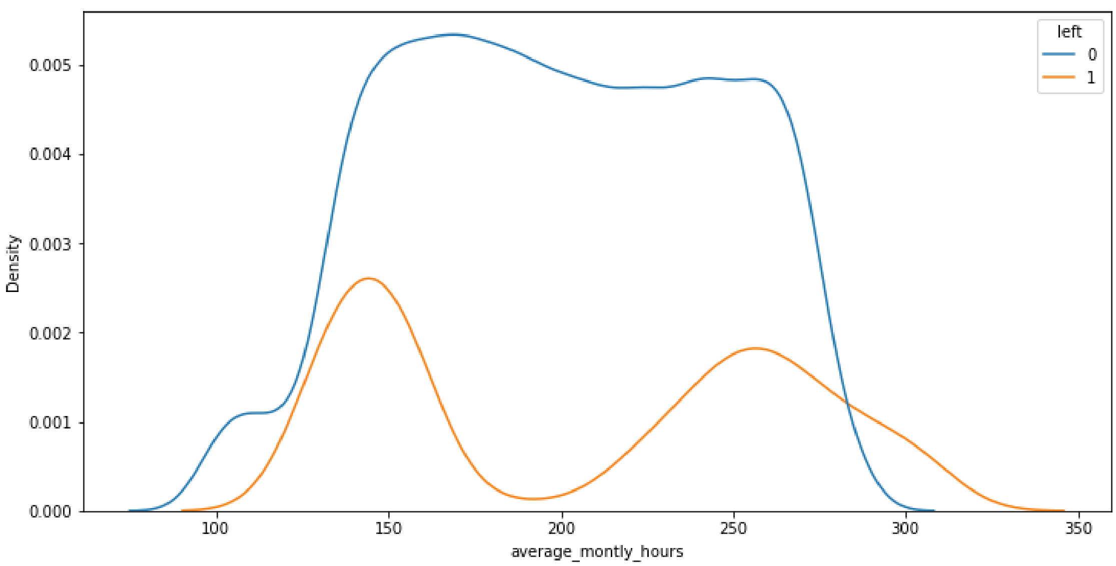
Still a weak connection. It means not getting promoted is not a major reason for the employees to leave the company.

[70]:
```
plt.figure(figsize = (12, 6))

sns.countplot(x = 'number_project',
              hue = 'left',
              data = compAttDF);
```



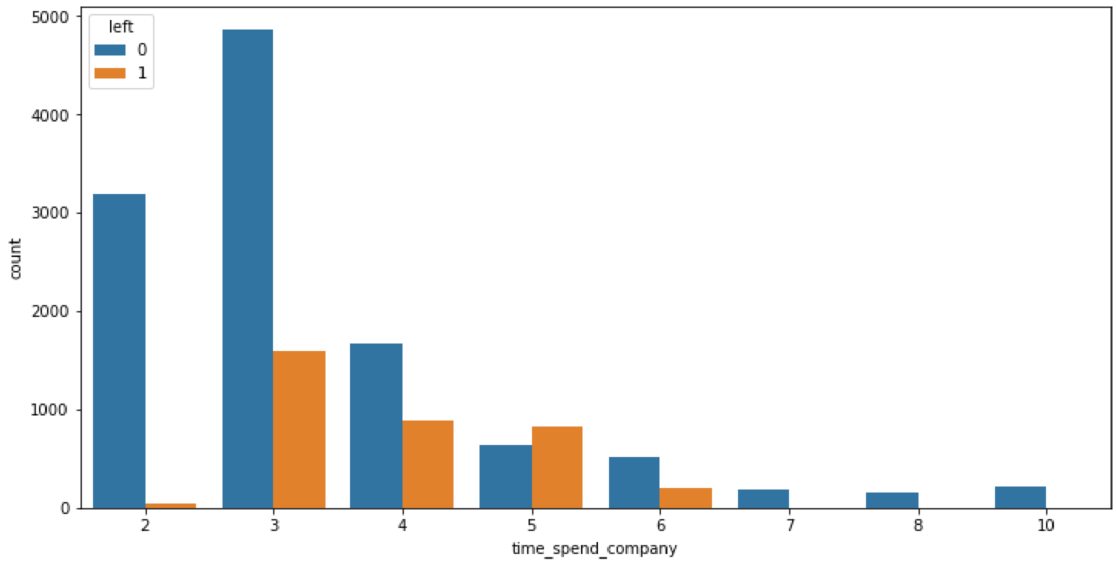
The employees who have completed 3, 4 or 5 number of projects had a high chance of staying.

[71]:
```
plt.figure(figsize = (12, 6))

sns.kdeplot(x = 'average_montly_hours',
            hue = 'left', data = compAttDF);
```



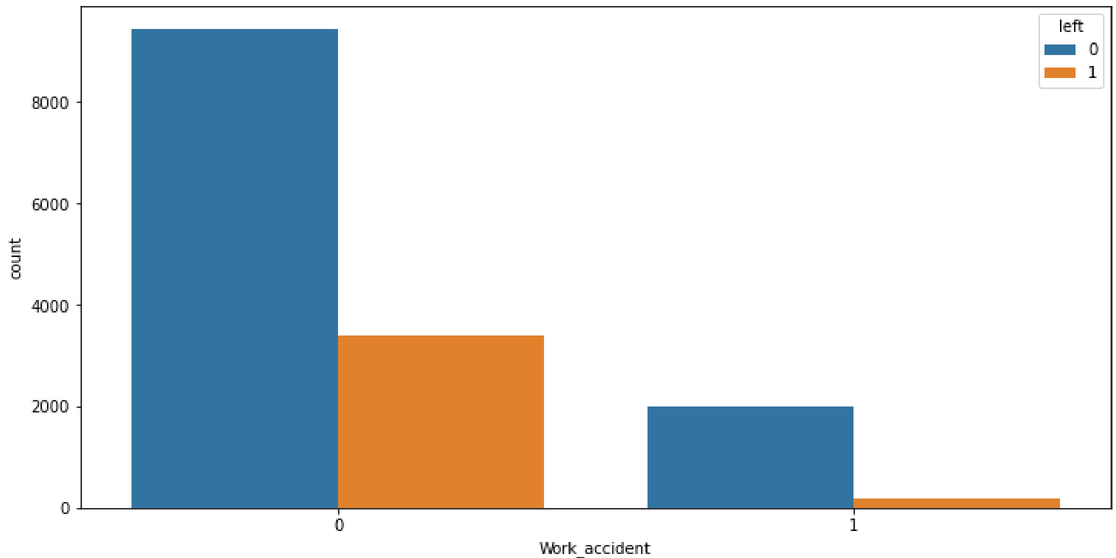
Some people left the company who had more that 300 monthly hours.

[72]:
```
plt.figure(figsize = (12, 6))

sns.countplot(x = 'time_spend_company',
              hue = 'left',
              data = compAttDF);
```



It looks like employees who worked 2 or 3 years, stayed in the company. And also those employees who worked for more than 6 years stayed in the company. Others had appreciable number of chances for leaving the company.

[73]:
```
plt.figure(figsize = (12, 6))

sns.countplot(x = 'Work_accident',
              hue = 'left',
              data = compAttDF);
```

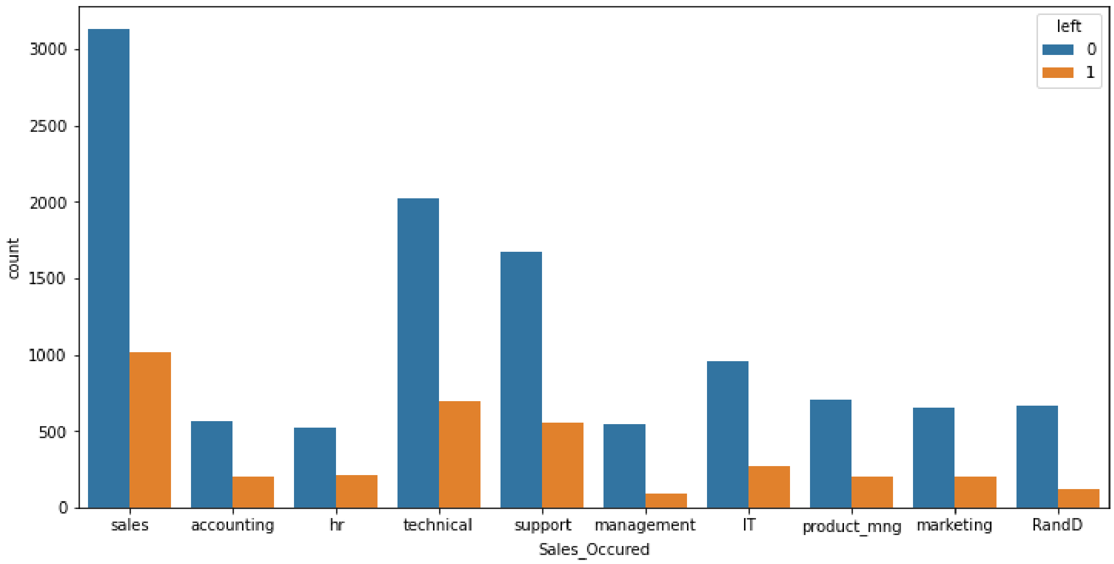


Work accidents may not be one of the major reasons an employee might leave a company.

[74]:
```
compAttDF['Sales_Occured'].value_counts()
```

[74]:
```
sales           4140
technical       2720
support         2229
IT              1227
product_mng      902
marketing        858
RandD            787
accounting       767
hr               739
management       630
Name: Sales_Occured, dtype: int64
```

[75]:
```
plt.figure(figsize = (12, 6))

sns.countplot(x = 'Sales_Occured',
              hue = 'left',
              data = compAttDF);
```

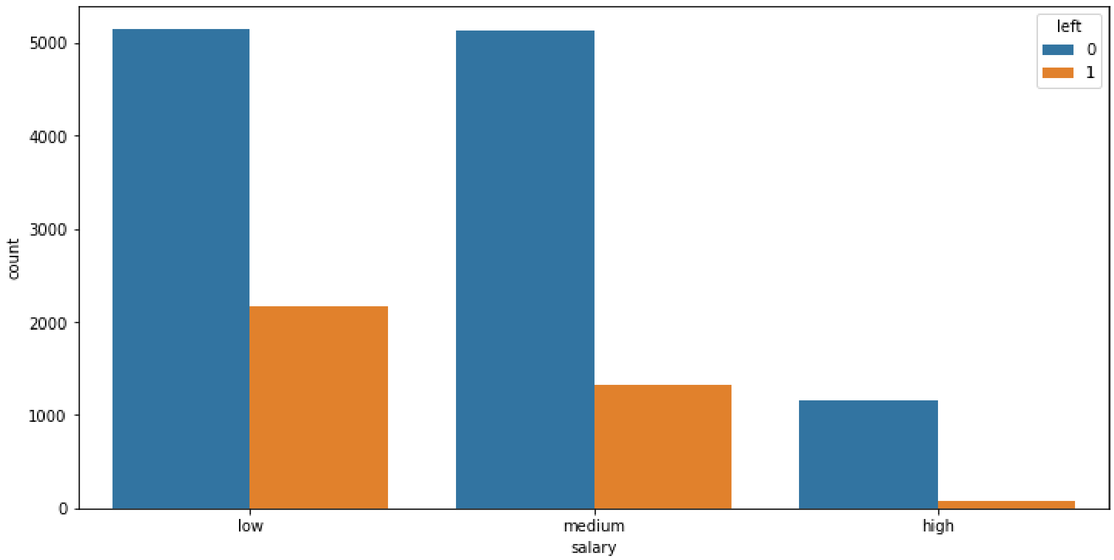


Most of the people who left the company belonged to sales, technical and support departments. (The red coloured label).

[76]:
```
compAttDF['salary'].value_counts()
```

[76]:
```
low       7316
medium    6446
high      1237
Name: salary, dtype: int64
```

[77]:
```
plt.figure(figsize = (12, 6))

sns.countplot(x = 'salary',
              hue = 'left',
              data = compAttDF);
```



Employees having low and medium salary had a chance of leaving the company.

1.7.5 Using Label Encoder to encode the salary and Sales_Occured departments

[78]:
```
from sklearn.preprocessing import LabelEncoder

sales_le = LabelEncoder()
salary_le = LabelEncoder()
```

[79]:
```
compAttDF['Sales_Occured'] = sales_le.fit_transform(compAttDF['Sales_Occured'])
compAttDF['salary'] = salary_le.fit_transform(compAttDF['salary'])
```

1.7.6 Independent and Dependent Features

[80]:
```
X_compAttDF = compAttDF.drop(columns = ['left'])
X_compAttDF.head()
```

[80]:
```
   satisfaction_level  last_evaluation  number_project  average_montly_hours  \
0                0.38             0.53               2                   157
1                0.80             0.86               5                   262
2                0.11             0.88               7                   272
3                0.72             0.87               5                   223
4                0.37             0.52               2                   159

   time_spend_company  Work_accident  promotion_last_5years  Sales_Occured  \
0                   3              0                      0              7
1                   6              0                      0              7
2                   4              0                      0              7
```

```
3                    5               0                       0              7
4                    3               0                       0              7

   salary
0       1
1       2
2       2
3       1
4       1
```

[81]:
```python
y_compAttDF = compAttDF['left']
y_compAttDF.head()
```

[81]:
```
0    1
1    1
2    1
3    1
4    1
Name: left, dtype: int64
```

1.7.7 Stratified Splitting into Test and Training Data

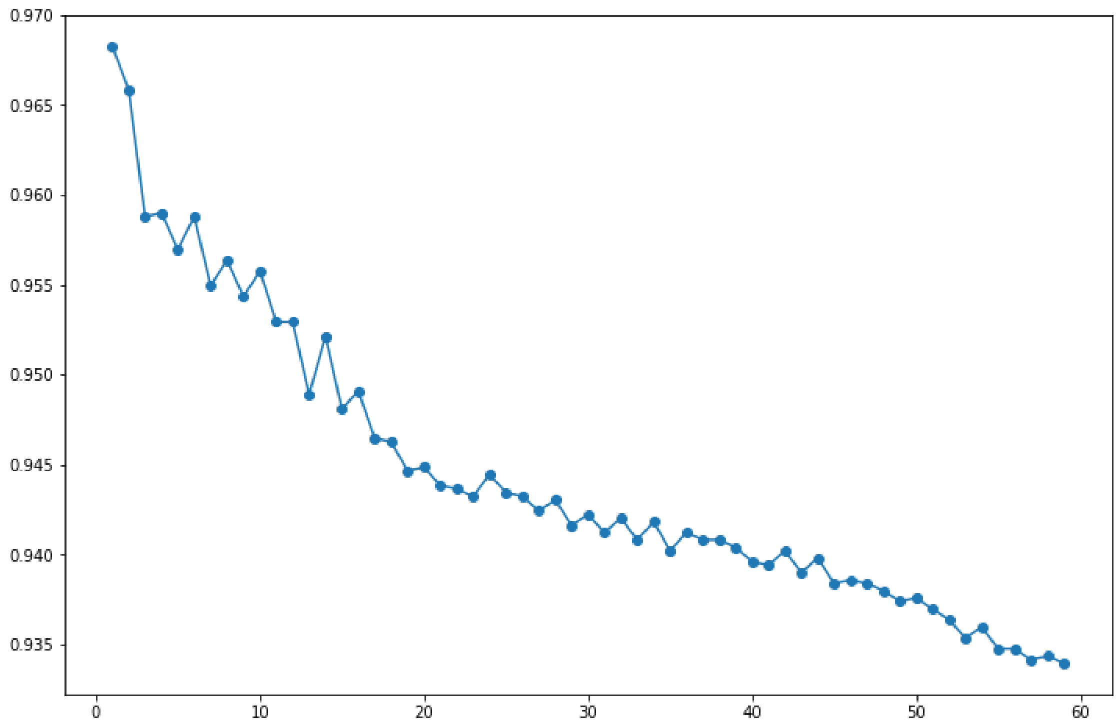
[82]:
```python
from sklearn.model_selection import train_test_split

X_compAttDF_train, X_compAttDF_test, y_compAttDF_train, y_compAttDF_test = train_test_split(X_compAttDF, y_compAttDF,
              test_size = 0.33,
              stratify = compAttDF['left'],
              random_state = 43)
```

1.7.8 Standardizing the Datasets

[83]:
```python
from sklearn.preprocessing import StandardScaler

compAtt_scaler = StandardScaler()

X_compAttDF_train = compAtt_scaler.fit_transform(X_compAttDF_train)
X_compAttDF_test = compAtt_scaler.transform(X_compAttDF_test)
```

1.7.9 Choosing the best K value

[84]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

Accu = list()
for i in range(1, 60):
    knn = KNeighborsClassifier(n_neighbors = i)
    knn.fit(X_compAttDF_train, y_compAttDF_train)
    pred_i = knn.predict(X_compAttDF_test)
    Accu.append((i, accuracy_score(y_compAttDF_test, pred_i)))

Accu = np.array(Accu)

plt.figure(figsize = (12, 8))
plt.scatter(np.reshape(Accu[:, 0], (-1, 1)), np.reshape(Accu[:, 1], (-1, 1)))
plt.plot(np.reshape(Accu[:, 0], (-1, 1)), np.reshape(Accu[:, 1], (-1, 1)));
```



[85]:
```
max_index, max_value = GetMaxKV(Accu)
print(f'The maximum accuracy is {round(max_value * 100, 2)} % for k =␣
↪{max_index} neighbours.')
```

```
The maximum accuracy is 96.83 % for k = 1.0 neighbours.
```

1.7.10 Final Model

[86]:
```
classifier = KNeighborsClassifier(n_neighbors = int(max_index))
classifier.fit(X_compAttDF_train, y_compAttDF_train)
```

[86]:
```
KNeighborsClassifier(n_neighbors=1)
```

1.7.11 Accuracy Tests

[87]:
```
y_compAttDF_pred = classifier.predict(X_compAttDF_test)

acc = accuracy_score(y_compAttDF_test, y_compAttDF_pred)
print(f'This model has an accuracy of {round(acc * 100, 2)} %.')
```

```
This model has an accuracy of 96.83 %.
```

1.7.12 Confusion Matrix

[88]:
```
from sklearn.metrics import confusion_matrix, classification_report

confusion_matrix(y_compAttDF_test, y_compAttDF_pred)
```

[88]:
```
array([[3659,  112],
       [  45, 1134]], dtype=int64)
```

[89]:
```
print(classification_report(y_compAttDF_test, y_compAttDF_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.97      0.98      3771
           1       0.91      0.96      0.94      1179

    accuracy                           0.97      4950
   macro avg       0.95      0.97      0.96      4950
weighted avg       0.97      0.97      0.97      4950
```

1.7.13 Final Conclusion

The above trained model can help to identify whether an employee would leave or not. The KNN classifier is very helpful. Theoretically, employees having interactions and those who discuss same things regarding the company structure, having the probability that they might take decisions together.

Another criteria is such that most of the employees leave the company because of similar reasons, there is very less chance, that they have to leave suddenly. Most of the time, it is the environment, treatment by the company which forces the employees to leave. The KNN algorithm calculates whether the given employee details matches with an employee who left or not based on the parameters that a company know.

If the company monitors the employee data closely, then more accurate machine learning models can be constructed.

1.8 Project - 4 (House Price Prediction)

Business Problem shall be discussed after importing the dataset.

[90]:
```
houseDF = pd.read_csv('./Datasets/house_price.csv')
houseDF.head()
```

[90]:

	Location	BHK	Furnishing	Sq.ft	Old(years)	Floor	Price
0	Bommanahalli	3	1	3000	1	3	28000
1	Bommanahalli	3	1	1650	10	0	18000
2	Whitefield	2	0	1000	5	3	16400
3	Whitefield	3	0	1600	1	9	27000
4	Whitefield	2	1	1200	5	1	20000

1.8.1 Business Problem

This dataset consists of data about the kinds of houses (in Bommanahalli and Whitefield) and their prices. The objective is to make a machine learning price regression model that can accurately predict the house prices based on the user's requirements.

1.8.2 Description of the dataset

[91]:
```
houseDF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Location    1000 non-null   object
 1   BHK         1000 non-null   int64
 2   Furnishing  1000 non-null   int64
 3   Sq.ft       1000 non-null   int64
 4   Old(years)  1000 non-null   int64
 5   Floor       1000 non-null   int64
 6   Price       1000 non-null   int64
dtypes: int64(6), object(1)
memory usage: 54.8+ KB
```

Presence of null values

[92]:
```
houseDF.isnull().sum()
```

[92]:
```
Location      0
BHK           0
Furnishing    0
```

```
Sq.ft         0
Old(years)    0
Floor         0
Price         0
dtype: int64
```

1.8.3 Analysis

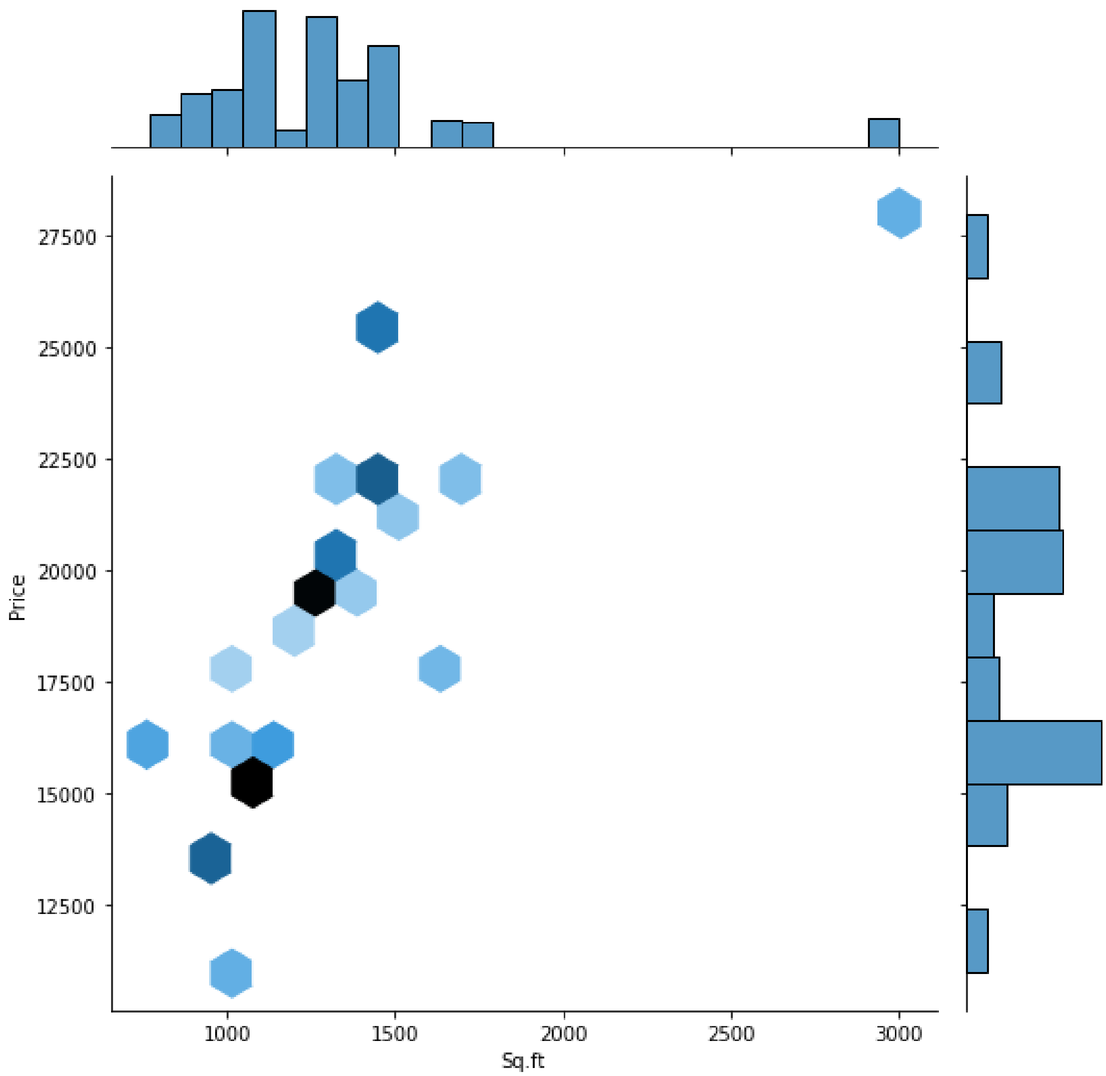
[93]:
```python
houseDF['Location'].value_counts()
```

[93]:
```
Bommanahalli    504
Whitefield      496
Name: Location, dtype: int64
```

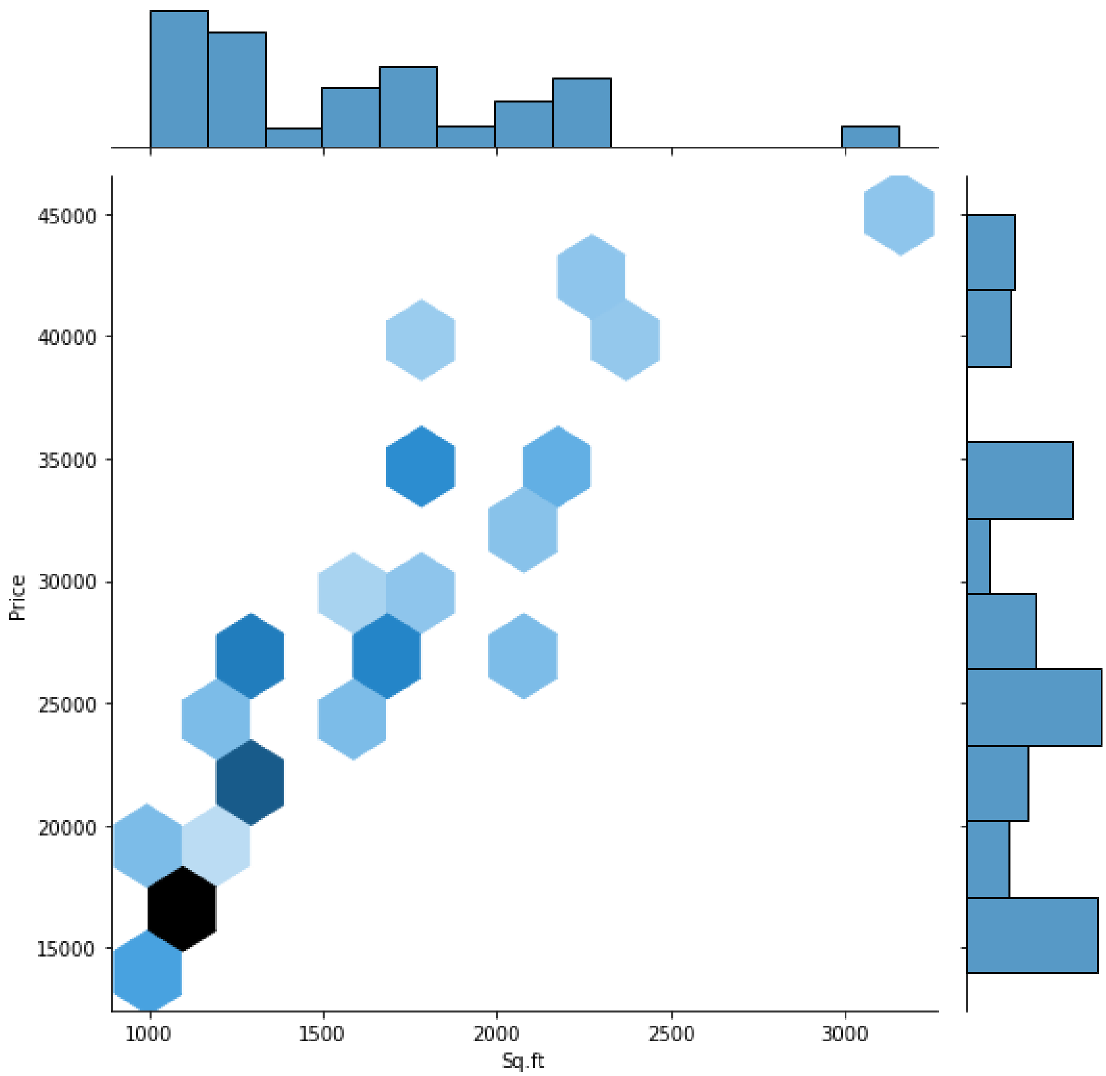
[94]:
```python
houseDF['Furnishing'].value_counts()
```

[94]:
```
0    652
1    348
Name: Furnishing, dtype: int64
```

[95]:
```python
sns.jointplot(x = 'Sq.ft', y = 'Price',
              data = houseDF[
                  houseDF['Location'] == 'Bommanahalli'
              ],
              kind = 'hex', height = 8);
```

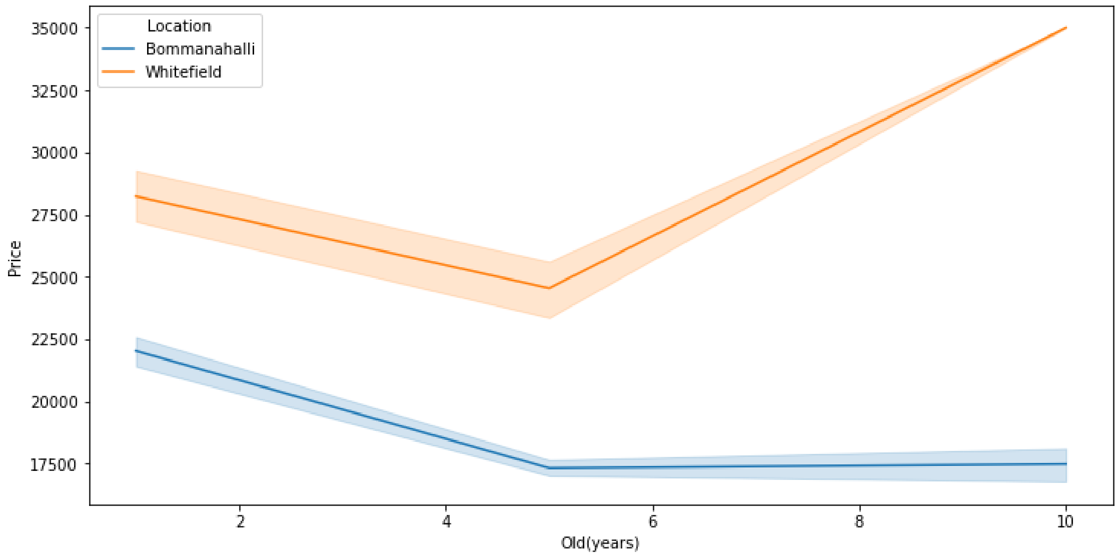


[96]:
```
sns.jointplot(x = 'Sq.ft', y = 'Price',
              data = houseDF[
                  houseDF['Location'] == 'Whitefield'
              ], kind = 'hex', height = 8);
```

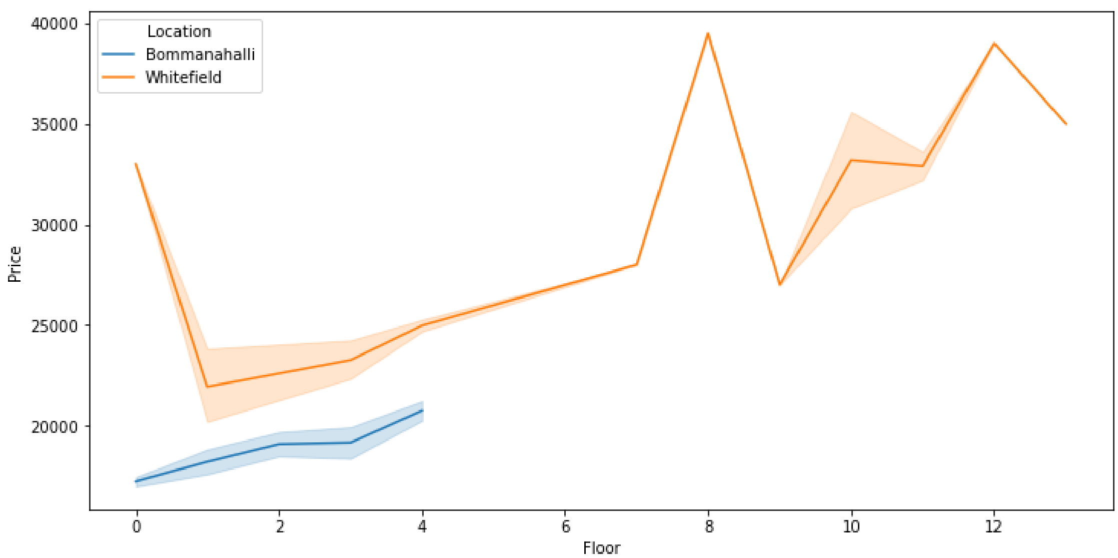


Variability of house prices with respect to area and location.

[97]:
```
plt.figure(figsize = (12, 6))

sns.lineplot(x = 'Old(years)', y = 'Price', hue = 'Location', data = houseDF);
```



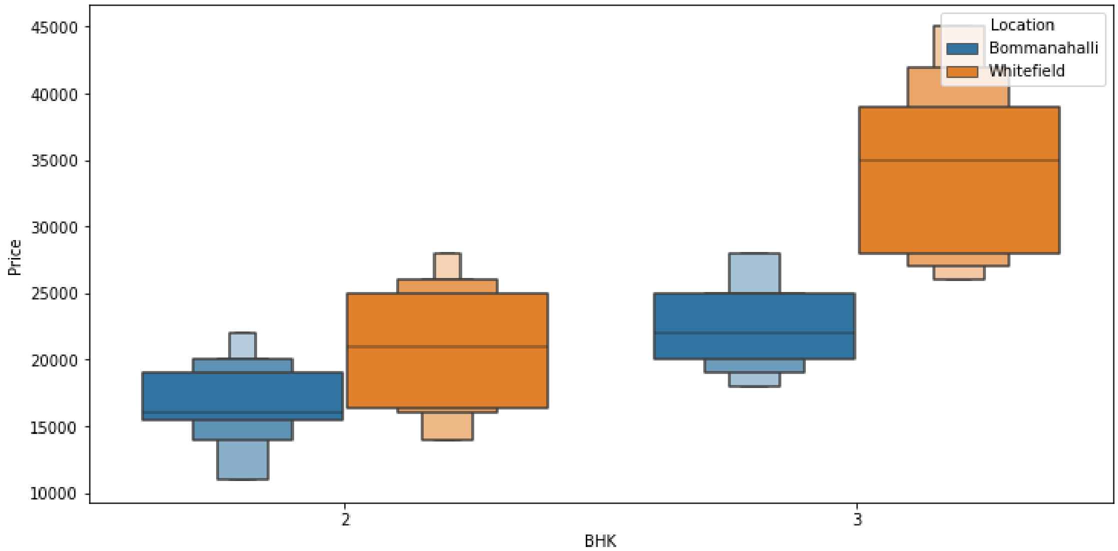
[98]:
```
plt.figure(figsize = (12, 6))

sns.lineplot(x = 'Floor', y = 'Price', hue = 'Location', data = houseDF);
```



[99]:
```
houseDF['BHK'].value_counts()
```

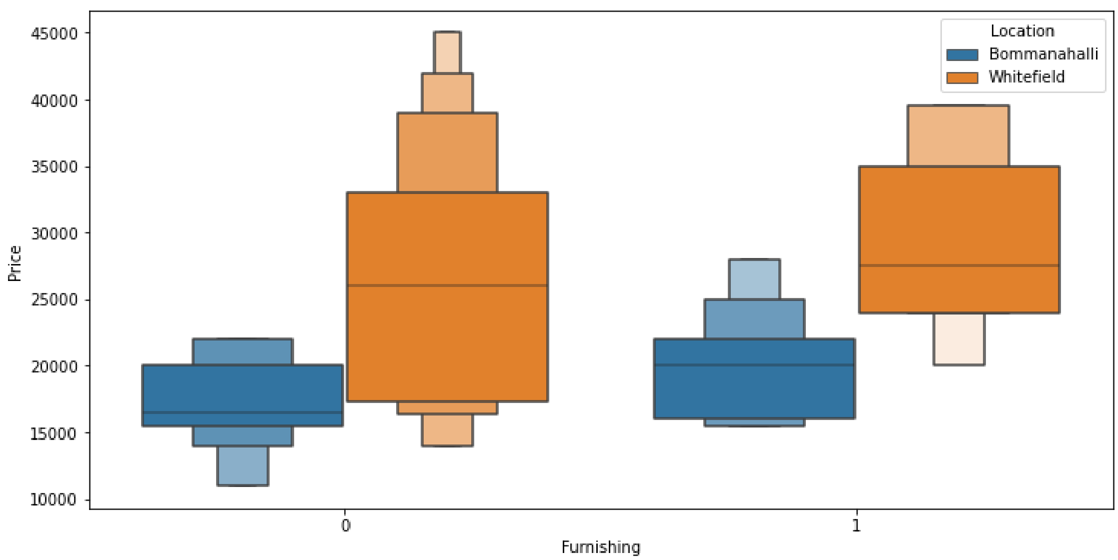
[99]:
```
2    564
3    436
Name: BHK, dtype: int64
```

[100]:
```
plt.figure(figsize = (12, 6))

sns.boxenplot(x = 'BHK', y = 'Price', hue = 'Location', data = houseDF);
```



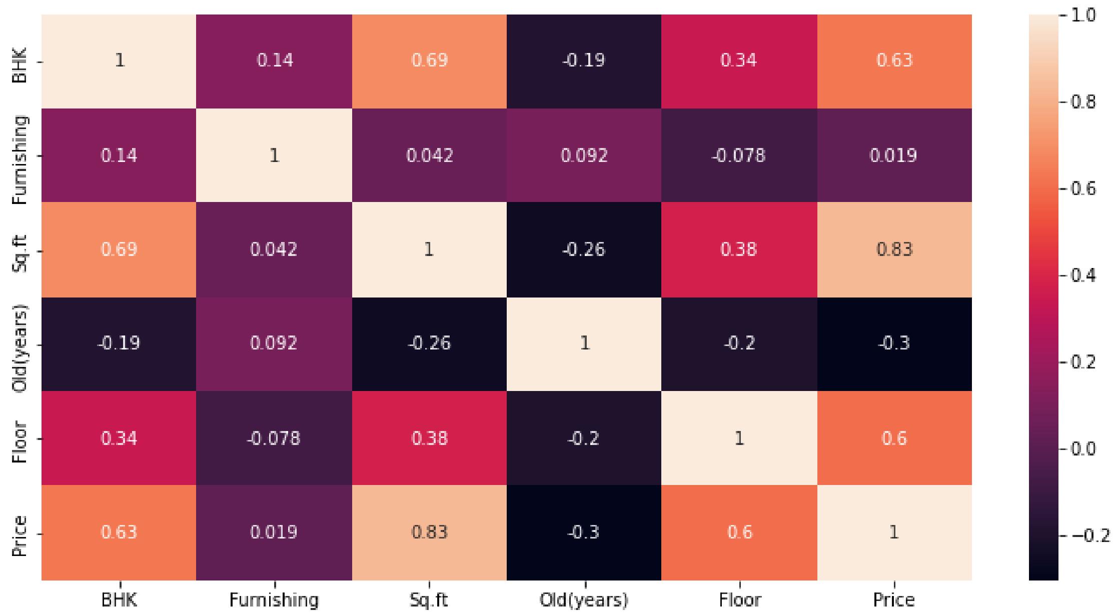
Houses in Bommanahalli has lower prices than those in Whitefield. Also the houses having *Bedroom-Hall-Kitchen* value 3 has more price.

[101]:
```
plt.figure(figsize = (12, 6))

sns.boxenplot(x = 'Furnishing', y = 'Price', hue = 'Location', data = houseDF);
```



This is a weak parameter for guessing the house price.

[102]:
```
plt.figure(figsize = (12, 6))

corrM = houseDF.corr()

sns.heatmap(corrM, annot = True);
```



Most important features are BHK, Area (Sq.ft) and the floor.

1.8.4 Label encoding the Location

[103]:
```
houseDF['Location'].value_counts()
```

[103]:
```
Bommanahalli    504
Whitefield      496
Name: Location, dtype: int64
```

[104]:
```
from sklearn.preprocessing import LabelEncoder

location_le = LabelEncoder()

houseDF['Location'] = location_le.fit_transform(houseDF['Location'])
houseDF['Location'].value_counts()
```

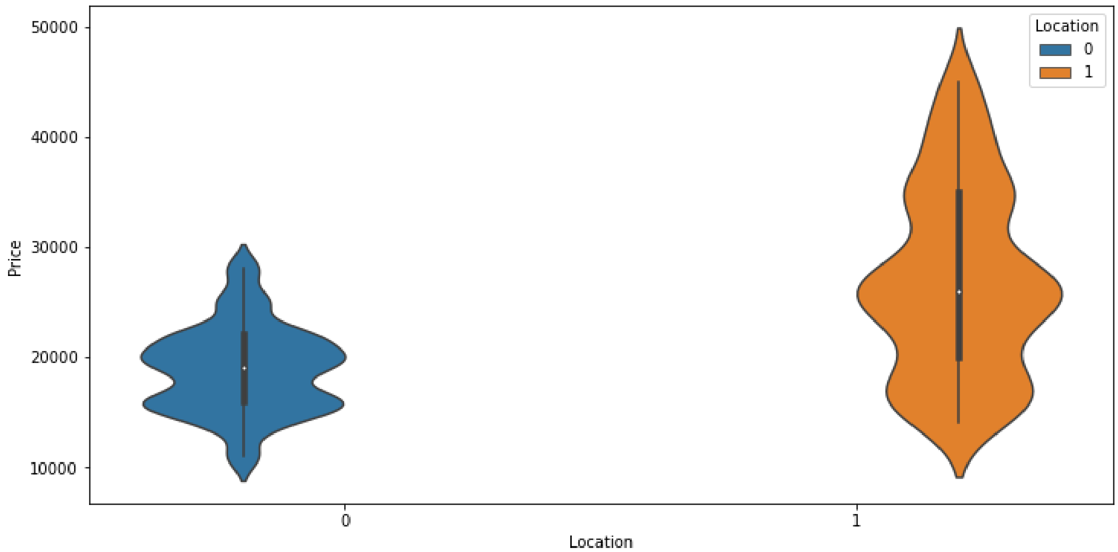
[104]:
```
0    504
1    496
```

```
Name: Location, dtype: int64
```

Bommanahalli is 0

Whitefield is 1

[105]:
```
plt.figure(figsize = (12, 6))

sns.violinplot(x = 'Location', y = 'Price', hue = 'Location', data = houseDF);
```



Whitefield despite having lower number of houses has a wide range of prices.

1.8.5 Independent and dependent features

[106]:
```
house_X = houseDF.drop(columns = ['Price'])
house_X.head()
```

[106]:

	Location	BHK	Furnishing	Sq.ft	Old(years)	Floor
0	0	3	1	3000	1	3
1	0	3	1	1650	10	0
2	1	2	0	1000	5	3
3	1	3	0	1600	1	9
4	1	2	1	1200	5	1

[107]:
```
house_y = houseDF.iloc[:, -1]
house_y.head()
```

[107]:
```
0    28000
1    18000
```

```
2    16400
3    27000
4    20000
Name: Price, dtype: int64
```

1.8.6 Stratified splitting based on location

[108]:
```
from sklearn.model_selection import train_test_split

house_X_train, house_X_test, house_y_train, house_y_test =␣
 ↪train_test_split(house_X, house_y, test_size = 0.33,
                                                                                              ␣
 ↪stratify = house_X[['Location', 'BHK']],
                                                                                              ␣
 ↪random_state = 1)
```

1.8.7 Feature Scaling

[109]:
```
from sklearn.preprocessing import MinMaxScaler

house_scaler = MinMaxScaler()

house_X_train = house_scaler.fit_transform(house_X_train)
house_X_test = house_scaler.transform(house_X_test)
```

1.8.8 The Model

[110]:
```
from sklearn.ensemble import RandomForestRegressor

house_reg = RandomForestRegressor()
house_reg.fit(house_X_train, house_y_train)
house_pred = house_reg.predict(house_X_test)

from sklearn.metrics import r2_score

acc = r2_score(house_y_test, house_pred) # R2 Accuracy
print(f'This model has an accuracy of {round(acc * 100, 2)} %.')
```

```
This model has an accuracy of 100.0 %.
```

The model made using random forest regressor is the most accurate model.

1.8.9 Final Conclusion

The above model can make accurate predictions of house prices most of the time.

Predicting from the user input

[111]:

```python
def predict_house_price_from_user():
    # Inputing location
    print('Enter the location option NUMBER:\n1. Bommanahalli\n2. Whitefield: ')
    inp = int(input())
    location = 'Bommanahalli' if inp == 1 else 'Whitefield' if inp == 2 else␣
↪'Invalid'
    if location == 'Invalid':
        print('Exiting')
        return
    location = location_le.transform([location])
    # Inputing BHK (Bedroom Hall Kitchen)
    print('Enter the BHK (Bedroom Hall Kitchen) units (2 or 3): ', end = '')
    bhk = int(input())
    if bhk not in [2, 3]:
        print('Exiting. Only 2 or 3 BHK are available.')
        return
    # Furnishing
    print('Furnishing (0 if not required else 1): ', end = '')
    furnishing = int(input())
    if furnishing not in [0, 1]:
        print('Invalid input. Exiting.')
        return
    # Area
    print('Enter area in square feet: ', end = '')
    sqft = int(input())
    # Years old
    print('How many years old? ', end = '')
    old = int(input())
    # Floors
    print('How many floors?: ', end = '')
    floor = int(input())
    datapoint = house_scaler.transform(pd.DataFrame({'Location': location,␣
↪'BHK': bhk, 'Furnishing': furnishing, 'Sq.ft': sqft,
                                        'Old(years)': old, 'Floor': floor}))
    price = house_reg.predict(datapoint)
    return price


price = predict_house_price_from_user()[0]
print('The price would be: $' + str(price))
```

```
Enter the location option NUMBER:
1. Bommanahalli
2. Whitefield:
2
Enter the BHK (Bedroom Hall Kitchen) units (2 or 3): 3
Furnishing (0 if not required else 1): 1
```

```
Enter area in square feet: 2400
How many years old? 3
How many floors?: 2
The price would be: $39160.0
```

1.9 References

1. Stratified Cross Validation in Machine Learning (https://towardsdatascience.com/what-is-stratified-cross-validation-in-machine-learning-8844f3e7ae8e)
2. Correlation (https://en.wikipedia.org/wiki/Correlation)
3. Feature Scaling in correct way (https://stats.stackexchange.com/questions/174823/how-to-apply-standardization-normalization-to-train-and-testset-if-prediction-i)
4. Random Forest Regression (https://www.geeksforgeeks.org/random-forest-regression-in-python/)
5. Seaborn multiple lineplots (https://www.marsja.se/seaborn-line-plots-multiple/)