**Here we are given a data set diamonds.csv in which we have to predict the diamond price.**

In [727]:

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
import math
import random
import os
```

**To deal with shuffling.**

In [728]:

```
def seed():
  np.random.seed(42)
  random.seed(42)
  os.environ["PYTHONHASHSEED"] = "42"

seed()
```

In [729]:

```
ds = pd.read_csv('/content/diamonds.csv')
```

In [730]:

```
ds.loc[:20,:]
```

Out[730]:

| | Unnamed: 0 | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0.23 | Ideal | E | SI2 | 61.5 | 55.0 | 326 | 3.95 | 3.98 | 2.43 |
| **1** | 2 | 0.21 | Premium | E | SI1 | 59.8 | 61.0 | 326 | 3.89 | 3.84 | 2.31 |
| **2** | 3 | 0.23 | Good | E | VS1 | 56.9 | 65.0 | 327 | 4.05 | 4.07 | 2.31 |
| **3** | 4 | 0.29 | Premium | I | VS2 | 62.4 | 58.0 | 334 | 4.20 | 4.23 | 2.63 |
| **4** | 5 | 0.31 | Good | J | SI2 | 63.3 | 58.0 | 335 | 4.34 | 4.35 | 2.75 |
| **5** | 6 | 0.24 | Very Good | J | VVS2 | 62.8 | 57.0 | 336 | 3.94 | 3.96 | 2.48 |
| **6** | 7 | 0.24 | Very Good | I | VVS1 | 62.3 | 57.0 | 336 | 3.95 | 3.98 | 2.47 |
| **7** | 8 | 0.26 | Very Good | H | SI1 | 61.9 | 55.0 | 337 | 4.07 | 4.11 | 2.53 |
| **8** | 9 | 0.22 | Fair | E | VS2 | 65.1 | 61.0 | 337 | 3.87 | 3.78 | 2.49 |
| **9** | 10 | 0.23 | Very Good | H | VS1 | 59.4 | 61.0 | 338 | 4.00 | 4.05 | 2.39 |
| **10** | 11 | 0.30 | Good | J | SI1 | 64.0 | 55.0 | 339 | 4.25 | 4.28 | 2.73 |
| **11** | 12 | 0.23 | Ideal | J | VS1 | 62.8 | 56.0 | 340 | 3.93 | 3.90 | 2.46 |
| **12** | 13 | 0.22 | Premium | F | SI1 | 60.4 | 61.0 | 342 | 3.88 | 3.84 | 2.33 |
| **13** | 14 | 0.31 | Ideal | J | SI2 | 62.2 | 54.0 | 344 | 4.35 | 4.37 | 2.71 |
| **14** | 15 | 0.20 | Premium | E | SI2 | 60.2 | 62.0 | 345 | 3.79 | 3.75 | 2.27 |
| **15** | 16 | 0.32 | Premium | E | I1 | 60.9 | 58.0 | 345 | 4.38 | 4.42 | 2.68 |
| **16** | 17 | 0.30 | Ideal | I | SI2 | 62.0 | 54.0 | 348 | 4.31 | 4.34 | 2.68 |
| **17** | 18 | 0.30 | Good | J | SI1 | 63.4 | 54.0 | 351 | 4.23 | 4.29 | 2.70 |
| **18** | 19 | 0.30 | Good | J | SI1 | 63.8 | 56.0 | 351 | 4.23 | 4.26 | 2.71 |

| | Unnamed: 0 | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 19 | 20 | 0.30 | Very Good | J | SI1 | 62.7 | 59.0 | 351 | 4.21 | 4.27 | 2.66 |
| 20 | 21 | 0.30 | Good | I | SI2 | 63.3 | 56.0 | 351 | 4.26 | 4.30 | 2.71 |

In [731]:

```
ds.describe()
```

Out[731]:

| | Unnamed: 0 | carat | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|
| count | 53940.000000 | 53940.000000 | 53940.000000 | 53940.000000 | 53940.000000 | 53940.000000 | 53940.000000 | 53940.000000 |
| mean | 26970.500000 | 0.797940 | 61.749405 | 57.457184 | 3932.799722 | 5.731157 | 5.734526 | 3.538734 |
| std | 15571.281097 | 0.474011 | 1.432621 | 2.234491 | 3989.439738 | 1.121761 | 1.142135 | 0.705699 |
| min | 1.000000 | 0.200000 | 43.000000 | 43.000000 | 326.000000 | 0.000000 | 0.000000 | 0.000000 |
| 25% | 13485.750000 | 0.400000 | 61.000000 | 56.000000 | 950.000000 | 4.710000 | 4.720000 | 2.910000 |
| 50% | 26970.500000 | 0.700000 | 61.800000 | 57.000000 | 2401.000000 | 5.700000 | 5.710000 | 3.530000 |
| 75% | 40455.250000 | 1.040000 | 62.500000 | 59.000000 | 5324.250000 | 6.540000 | 6.540000 | 4.040000 |
| max | 53940.000000 | 5.010000 | 79.000000 | 95.000000 | 18823.000000 | 10.740000 | 58.900000 | 31.800000 |

# Null Values

**Checking for the null values**

In [732]:

```
ds.isna().sum()
```

Out[732]:

```
Unnamed: 0    0
carat         0
cut           0
color         0
clarity       0
depth         0
table         0
price         0
x             0
y             0
z             0
dtype: int64
```

# Checking unique Values

In [733]:

```
ds.nunique()
```

Out[733]:

```
Unnamed: 0    53940
carat           273
cut               5
color             7
clarity           8
depth           184
table           127
price         11602
x               554
y               552
z               375
dtype: int64
```

**We can drop the Unnamed Column as it is just indexing**

In [734]:

```
ds.drop(axis="columns", labels="Unnamed: 0", inplace=True)
ds.loc[:10,:]
```

Out[734]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.23 | Ideal | E | SI2 | 61.5 | 55.0 | 326 | 3.95 | 3.98 | 2.43 |
| **1** | 0.21 | Premium | E | SI1 | 59.8 | 61.0 | 326 | 3.89 | 3.84 | 2.31 |
| **2** | 0.23 | Good | E | VS1 | 56.9 | 65.0 | 327 | 4.05 | 4.07 | 2.31 |
| **3** | 0.29 | Premium | I | VS2 | 62.4 | 58.0 | 334 | 4.20 | 4.23 | 2.63 |
| **4** | 0.31 | Good | J | SI2 | 63.3 | 58.0 | 335 | 4.34 | 4.35 | 2.75 |
| **5** | 0.24 | Very Good | J | VVS2 | 62.8 | 57.0 | 336 | 3.94 | 3.96 | 2.48 |
| **6** | 0.24 | Very Good | I | VVS1 | 62.3 | 57.0 | 336 | 3.95 | 3.98 | 2.47 |
| **7** | 0.26 | Very Good | H | SI1 | 61.9 | 55.0 | 337 | 4.07 | 4.11 | 2.53 |
| **8** | 0.22 | Fair | E | VS2 | 65.1 | 61.0 | 337 | 3.87 | 3.78 | 2.49 |
| **9** | 0.23 | Very Good | H | VS1 | 59.4 | 61.0 | 338 | 4.00 | 4.05 | 2.39 |
| **10** | 0.30 | Good | J | SI1 | 64.0 | 55.0 | 339 | 4.25 | 4.28 | 2.73 |

**We see x(length), y(width) and z(depth) has minimum value 0 which indicates these are wrong values so we can remove those rows**

In [735]:

```
ds = ds.drop(ds[ds["x"]==0].index)
ds = ds.drop(ds[ds["y"]==0].index)
ds = ds.drop(ds[ds["z"]==0].index)
```

In [736]:

```
ds.describe()
```

Out[736]:

| | carat | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|
| **count** | 53920.000000 | 53920.000000 | 53920.000000 | 53920.000000 | 53920.000000 | 53920.000000 | 53920.000000 |
| **mean** | 0.797698 | 61.749514 | 57.456834 | 3930.993231 | 5.731627 | 5.734887 | 3.540046 |
| **std** | 0.473795 | 1.432331 | 2.234064 | 3987.280446 | 1.119423 | 1.140126 | 0.702530 |
| **min** | 0.200000 | 43.000000 | 43.000000 | 326.000000 | 3.730000 | 3.680000 | 1.070000 |
| **25%** | 0.400000 | 61.000000 | 56.000000 | 949.000000 | 4.710000 | 4.720000 | 2.910000 |
| **50%** | 0.700000 | 61.800000 | 57.000000 | 2401.000000 | 5.700000 | 5.710000 | 3.530000 |
| **75%** | 1.040000 | 62.500000 | 59.000000 | 5323.250000 | 6.540000 | 6.540000 | 4.040000 |
| **max** | 5.010000 | 79.000000 | 95.000000 | 18823.000000 | 10.740000 | 58.900000 | 31.800000 |

In [737]:

```
ds.nunique()
```

Out[737]:

```
carat          273
cut              5
color            7
clarity          8
```

```
depth        184
table        127
price      11597
x            553
y            550
z            374
dtype: int64
```

**Now we see cut, color and clarity has 5, 7 and 8 unique values. Lets check these.**

In [738]:

```
ds["cut"].unique()
```

Out[738]:

```
array(['Ideal', 'Premium', 'Good', 'Very Good', 'Fair'], dtype=object)
```

In [739]:

```
ds["color"].unique()
```

Out[739]:

```
array(['E', 'I', 'J', 'H', 'F', 'G', 'D'], dtype=object)
```

In [740]:

```
ds["clarity"].unique()
```

Out[740]:

```
array(['SI2', 'SI1', 'VS1', 'VS2', 'VVS2', 'VVS1', 'I1', 'IF'],
      dtype=object)
```

# Label Encoding

**We can do label encoding on these columns. We have to take care of some cases like:**

**Color: J= Worst(1) D= Best(7)**

**Clarity: (I1 (1), SI2, SI1, VS2, VS1, VVS2, VVS1, IF (8))**

**Cut: (Fair(1), Good, Very Good, Premium, Ideal(5))**

In [741]:

```
ds["color"] = ds["color"].map({"J": 1,"I": 2,"H": 3,"G": 4,"F": 5,"E": 6,"D": 7})
ds["clarity"] = ds["clarity"].map({"I1": 1,"SI2": 2,"SI1": 3,"VS2": 4,"VS1": 5,"VVS2": 6
,"VVS1": 7, "IF" : 8})
ds["cut"] = ds["cut"].map({"Fair": 1,"Good": 2,"Very Good": 3,"Premium": 4,"Ideal": 5})
```

In [742]:

```
ds.loc[:10,:]
```

Out[742]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.23 | 5 | 6 | 2 | 61.5 | 55.0 | 326 | 3.95 | 3.98 | 2.43 |
| **1** | 0.21 | 4 | 6 | 3 | 59.8 | 61.0 | 326 | 3.89 | 3.84 | 2.31 |
| **2** | 0.23 | 2 | 6 | 5 | 56.9 | 65.0 | 327 | 4.05 | 4.07 | 2.31 |
| **3** | 0.29 | 4 | 2 | 4 | 62.4 | 58.0 | 334 | 4.20 | 4.23 | 2.63 |
| **4** | 0.31 | 2 | 1 | 2 | 63.3 | 58.0 | 335 | 4.34 | 4.35 | 2.75 |
| **5** | 0.24 | 3 | 1 | 6 | 62.8 | 57.0 | 336 | 3.94 | 3.96 | 2.48 |
| **6** | 0.24 | 3 | 2 | 7 | 62.3 | 57.0 | 336 | 3.95 | 3.98 | 2.47 |

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 7 | 0.26 | 3 | 3 | 3 | 61.9 | 55.0 | 337 | 4.07 | 4.11 | 2.53 |
| 8 | 0.22 | 1 | 6 | 4 | 65.1 | 61.0 | 337 | 3.87 | 3.78 | 2.49 |
| 9 | 0.23 | 3 | 3 | 5 | 59.4 | 61.0 | 338 | 4.00 | 4.05 | 2.39 |
| 10 | 0.30 | 2 | 1 | 3 | 64.0 | 55.0 | 339 | 4.25 | 4.28 | 2.73 |

# Duplicate Rows

**We are removing the duplicate rows if present.**

In [743]:

```
ds.duplicated().sum()
```

Out[743]:

145

In [744]:

```
ds.drop(axis="rows", labels=ds.index[ds.duplicated()], inplace=True)
ds.duplicated().sum()
```

Out[744]:

0

# Feature Scaling

**We are now doing the feature scaling for columns x, y, z, table and depth using min-max normalization**

In [745]:

```
x = ds["x"] - np.min(ds["x"])
y = np.max(ds["x"]) - np.min(ds["x"])
ds["x"] = x/y
ds.loc[:20,:]
```

Out[745]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.23 | 5 | 6 | 2 | 61.5 | 55.0 | 326 | 0.031384 | 3.98 | 2.43 |
| 1 | 0.21 | 4 | 6 | 3 | 59.8 | 61.0 | 326 | 0.022825 | 3.84 | 2.31 |
| 2 | 0.23 | 2 | 6 | 5 | 56.9 | 65.0 | 327 | 0.045649 | 4.07 | 2.31 |
| 3 | 0.29 | 4 | 2 | 4 | 62.4 | 58.0 | 334 | 0.067047 | 4.23 | 2.63 |
| 4 | 0.31 | 2 | 1 | 2 | 63.3 | 58.0 | 335 | 0.087019 | 4.35 | 2.75 |
| 5 | 0.24 | 3 | 1 | 6 | 62.8 | 57.0 | 336 | 0.029957 | 3.96 | 2.48 |
| 6 | 0.24 | 3 | 2 | 7 | 62.3 | 57.0 | 336 | 0.031384 | 3.98 | 2.47 |
| 7 | 0.26 | 3 | 3 | 3 | 61.9 | 55.0 | 337 | 0.048502 | 4.11 | 2.53 |
| 8 | 0.22 | 1 | 6 | 4 | 65.1 | 61.0 | 337 | 0.019971 | 3.78 | 2.49 |
| 9 | 0.23 | 3 | 3 | 5 | 59.4 | 61.0 | 338 | 0.038516 | 4.05 | 2.39 |
| 10 | 0.30 | 2 | 1 | 3 | 64.0 | 55.0 | 339 | 0.074180 | 4.28 | 2.73 |
| 11 | 0.23 | 5 | 1 | 5 | 62.8 | 56.0 | 340 | 0.028531 | 3.90 | 2.46 |
| 12 | 0.22 | 4 | 5 | 3 | 60.4 | 61.0 | 342 | 0.021398 | 3.84 | 2.33 |
| 13 | 0.31 | 5 | 1 | 2 | 62.2 | 54.0 | 344 | 0.088445 | 4.37 | 2.71 |
| 14 | 0.20 | 4 | 6 | 2 | 60.2 | 62.0 | 345 | 0.008559 | 3.75 | 2.27 |
| 15 | 0.32 | 4 | 6 | 1 | 60.9 | 58.0 | 345 | 0.092725 | 4.42 | 2.68 |

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 16 | 0.30 | 5 | 2 | 2 | 62.0 | 54.0 | 348 | 0.082739 | 4.34 | 2.68 |
| 17 | 0.30 | 2 | 1 | 3 | 63.4 | 54.0 | 351 | 0.071327 | 4.29 | 2.70 |
| 18 | 0.30 | 2 | 1 | 3 | 63.8 | 56.0 | 351 | 0.071327 | 4.26 | 2.71 |
| 19 | 0.30 | 3 | 1 | 3 | 62.7 | 59.0 | 351 | 0.068474 | 4.27 | 2.66 |
| 20 | 0.30 | 2 | 2 | 2 | 63.3 | 56.0 | 351 | 0.075606 | 4.30 | 2.71 |

In [746]:

```
x = ds["price"] - np.min(ds["price"])
y = np.max(ds["price"]) - np.min(ds["price"])
ds["price"] = x/y
ds.loc[:20,:]
```

Out[746]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.23 | 5 | 6 | 2 | 61.5 | 55.0 | 0.000000 | 0.031384 | 3.98 | 2.43 |
| 1 | 0.21 | 4 | 6 | 3 | 59.8 | 61.0 | 0.000000 | 0.022825 | 3.84 | 2.31 |
| 2 | 0.23 | 2 | 6 | 5 | 56.9 | 65.0 | 0.000054 | 0.045649 | 4.07 | 2.31 |
| 3 | 0.29 | 4 | 2 | 4 | 62.4 | 58.0 | 0.000433 | 0.067047 | 4.23 | 2.63 |
| 4 | 0.31 | 2 | 1 | 2 | 63.3 | 58.0 | 0.000487 | 0.087019 | 4.35 | 2.75 |
| 5 | 0.24 | 3 | 1 | 6 | 62.8 | 57.0 | 0.000541 | 0.029957 | 3.96 | 2.48 |
| 6 | 0.24 | 3 | 2 | 7 | 62.3 | 57.0 | 0.000541 | 0.031384 | 3.98 | 2.47 |
| 7 | 0.26 | 3 | 3 | 3 | 61.9 | 55.0 | 0.000595 | 0.048502 | 4.11 | 2.53 |
| 8 | 0.22 | 1 | 6 | 4 | 65.1 | 61.0 | 0.000595 | 0.019971 | 3.78 | 2.49 |
| 9 | 0.23 | 3 | 3 | 5 | 59.4 | 61.0 | 0.000649 | 0.038516 | 4.05 | 2.39 |
| 10 | 0.30 | 2 | 1 | 3 | 64.0 | 55.0 | 0.000703 | 0.074180 | 4.28 | 2.73 |
| 11 | 0.23 | 5 | 1 | 5 | 62.8 | 56.0 | 0.000757 | 0.028531 | 3.90 | 2.46 |
| 12 | 0.22 | 4 | 5 | 3 | 60.4 | 61.0 | 0.000865 | 0.021398 | 3.84 | 2.33 |
| 13 | 0.31 | 5 | 1 | 2 | 62.2 | 54.0 | 0.000973 | 0.088445 | 4.37 | 2.71 |
| 14 | 0.20 | 4 | 6 | 2 | 60.2 | 62.0 | 0.001027 | 0.008559 | 3.75 | 2.27 |
| 15 | 0.32 | 4 | 6 | 1 | 60.9 | 58.0 | 0.001027 | 0.092725 | 4.42 | 2.68 |
| 16 | 0.30 | 5 | 2 | 2 | 62.0 | 54.0 | 0.001189 | 0.082739 | 4.34 | 2.68 |
| 17 | 0.30 | 2 | 1 | 3 | 63.4 | 54.0 | 0.001352 | 0.071327 | 4.29 | 2.70 |
| 18 | 0.30 | 2 | 1 | 3 | 63.8 | 56.0 | 0.001352 | 0.071327 | 4.26 | 2.71 |
| 19 | 0.30 | 3 | 1 | 3 | 62.7 | 59.0 | 0.001352 | 0.068474 | 4.27 | 2.66 |
| 20 | 0.30 | 2 | 2 | 2 | 63.3 | 56.0 | 0.001352 | 0.075606 | 4.30 | 2.71 |

In [747]:

```
x = ds["y"] - np.min(ds["y"])
y = np.max(ds["y"]) - np.min(ds["y"])
ds["y"] = x/y
ds.loc[:10,:]
```

Out[747]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.23 | 5 | 6 | 2 | 61.5 | 55.0 | 0.000000 | 0.031384 | 0.005433 | 2.43 |
| 1 | 0.21 | 4 | 6 | 3 | 59.8 | 61.0 | 0.000000 | 0.022825 | 0.002898 | 2.31 |
| 2 | 0.23 | 2 | 6 | 5 | 56.9 | 65.0 | 0.000054 | 0.045649 | 0.007063 | 2.31 |
| 3 | 0.29 | 4 | 2 | 4 | 62.4 | 58.0 | 0.000433 | 0.067047 | 0.009960 | 2.63 |

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 0.31 | 2 | 1 | 2 | 63.3 | 58.0 | 0.000487 | 0.087019 | 0.012133 | 2.75 |
| 5 | 0.24 | 3 | 1 | 6 | 62.8 | 57.0 | 0.000541 | 0.029957 | 0.005071 | 2.48 |
| 6 | 0.24 | 3 | 2 | 7 | 62.3 | 57.0 | 0.000541 | 0.031384 | 0.005433 | 2.47 |
| 7 | 0.26 | 3 | 3 | 3 | 61.9 | 55.0 | 0.000595 | 0.048502 | 0.007787 | 2.53 |
| 8 | 0.22 | 1 | 6 | 4 | 65.1 | 61.0 | 0.000595 | 0.019971 | 0.001811 | 2.49 |
| 9 | 0.23 | 3 | 3 | 5 | 59.4 | 61.0 | 0.000649 | 0.038516 | 0.006700 | 2.39 |
| 10 | 0.30 | 2 | 1 | 3 | 64.0 | 55.0 | 0.000703 | 0.074180 | 0.010866 | 2.73 |

In [748]:

```
x = ds["z"] - np.min(ds["z"])
y = np.max(ds["z"]) - np.min(ds["z"])
ds["z"] = x/y
ds.loc[:5,:]
```

Out[748]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.23 | 5 | 6 | 2 | 61.5 | 55.0 | 0.000000 | 0.031384 | 0.005433 | 0.044256 |
| 1 | 0.21 | 4 | 6 | 3 | 59.8 | 61.0 | 0.000000 | 0.022825 | 0.002898 | 0.040351 |
| 2 | 0.23 | 2 | 6 | 5 | 56.9 | 65.0 | 0.000054 | 0.045649 | 0.007063 | 0.040351 |
| 3 | 0.29 | 4 | 2 | 4 | 62.4 | 58.0 | 0.000433 | 0.067047 | 0.009960 | 0.050765 |
| 4 | 0.31 | 2 | 1 | 2 | 63.3 | 58.0 | 0.000487 | 0.087019 | 0.012133 | 0.054670 |
| 5 | 0.24 | 3 | 1 | 6 | 62.8 | 57.0 | 0.000541 | 0.029957 | 0.005071 | 0.045884 |

In [749]:

```
x = ds["depth"] - np.min(ds["depth"])
y = np.max(ds["depth"]) - np.min(ds["depth"])
ds["depth"] = x/y
ds.loc[:10,:]
```

Out[749]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.23 | 5 | 6 | 2 | 0.513889 | 55.0 | 0.000000 | 0.031384 | 0.005433 | 0.044256 |
| 1 | 0.21 | 4 | 6 | 3 | 0.466667 | 61.0 | 0.000000 | 0.022825 | 0.002898 | 0.040351 |
| 2 | 0.23 | 2 | 6 | 5 | 0.386111 | 65.0 | 0.000054 | 0.045649 | 0.007063 | 0.040351 |
| 3 | 0.29 | 4 | 2 | 4 | 0.538889 | 58.0 | 0.000433 | 0.067047 | 0.009960 | 0.050765 |
| 4 | 0.31 | 2 | 1 | 2 | 0.563889 | 58.0 | 0.000487 | 0.087019 | 0.012133 | 0.054670 |
| 5 | 0.24 | 3 | 1 | 6 | 0.550000 | 57.0 | 0.000541 | 0.029957 | 0.005071 | 0.045884 |
| 6 | 0.24 | 3 | 2 | 7 | 0.536111 | 57.0 | 0.000541 | 0.031384 | 0.005433 | 0.045558 |
| 7 | 0.26 | 3 | 3 | 3 | 0.525000 | 55.0 | 0.000595 | 0.048502 | 0.007787 | 0.047511 |
| 8 | 0.22 | 1 | 6 | 4 | 0.613889 | 61.0 | 0.000595 | 0.019971 | 0.001811 | 0.046209 |
| 9 | 0.23 | 3 | 3 | 5 | 0.455556 | 61.0 | 0.000649 | 0.038516 | 0.006700 | 0.042955 |
| 10 | 0.30 | 2 | 1 | 3 | 0.583333 | 55.0 | 0.000703 | 0.074180 | 0.010866 | 0.054019 |

In [750]:

```
x = ds["table"] - np.min(ds["table"])
y = np.max(ds["table"]) - np.min(ds["table"])
ds["table"] = x/y
ds.loc[:10,:]
```

Out[750]:

| | carat | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.23 | 5 | 6 | 2 | 0.513889 | 0.230769 | 0.000000 | 0.031384 | 0.005433 | 0.044256 |
| **1** | 0.21 | 4 | 6 | 3 | 0.466667 | 0.346154 | 0.000000 | 0.022825 | 0.002898 | 0.040351 |
| **2** | 0.23 | 2 | 6 | 5 | 0.386111 | 0.423077 | 0.000054 | 0.045649 | 0.007063 | 0.040351 |
| **3** | 0.29 | 4 | 2 | 4 | 0.538889 | 0.288462 | 0.000433 | 0.067047 | 0.009960 | 0.050765 |
| **4** | 0.31 | 2 | 1 | 2 | 0.563889 | 0.288462 | 0.000487 | 0.087019 | 0.012133 | 0.054670 |
| **5** | 0.24 | 3 | 1 | 6 | 0.550000 | 0.269231 | 0.000541 | 0.029957 | 0.005071 | 0.045884 |
| **6** | 0.24 | 3 | 2 | 7 | 0.536111 | 0.269231 | 0.000541 | 0.031384 | 0.005433 | 0.045558 |
| **7** | 0.26 | 3 | 3 | 3 | 0.525000 | 0.230769 | 0.000595 | 0.048502 | 0.007787 | 0.047511 |
| **8** | 0.22 | 1 | 6 | 4 | 0.613889 | 0.346154 | 0.000595 | 0.019971 | 0.001811 | 0.046209 |
| **9** | 0.23 | 3 | 3 | 5 | 0.455556 | 0.346154 | 0.000649 | 0.038516 | 0.006700 | 0.042955 |
| **10** | 0.30 | 2 | 1 | 3 | 0.583333 | 0.230769 | 0.000703 | 0.074180 | 0.010866 | 0.054019 |

In [751]:

```
ds.describe()
```

Out[751]:

| | carat | cut | color | clarity | depth | table | price | x | |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 53775.000000 | 53775.000000 | 53775.000000 | 53775.000000 | 53775.000000 | 53775.000000 | 53775.000000 | 53775.000000 | 537 |
| **mean** | 0.797536 | 3.904231 | 4.406267 | 4.052366 | 0.520784 | 0.278035 | 0.194908 | 0.285532 | |
| **std** | 0.473169 | 1.116097 | 1.701271 | 1.646733 | 0.039712 | 0.042947 | 0.215490 | 0.159574 | |
| **min** | 0.200000 | 1.000000 | 1.000000 | 1.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| **25%** | 0.400000 | 3.000000 | 3.000000 | 3.000000 | 0.500000 | 0.250000 | 0.033789 | 0.139800 | |
| **50%** | 0.700000 | 4.000000 | 4.000000 | 4.000000 | 0.522222 | 0.269231 | 0.112180 | 0.281027 | |
| **75%** | 1.040000 | 5.000000 | 6.000000 | 5.000000 | 0.541667 | 0.307692 | 0.270206 | 0.400856 | |
| **max** | 5.010000 | 5.000000 | 7.000000 | 8.000000 | 1.000000 | 1.000000 | 1.000000 | 1.000000 | |

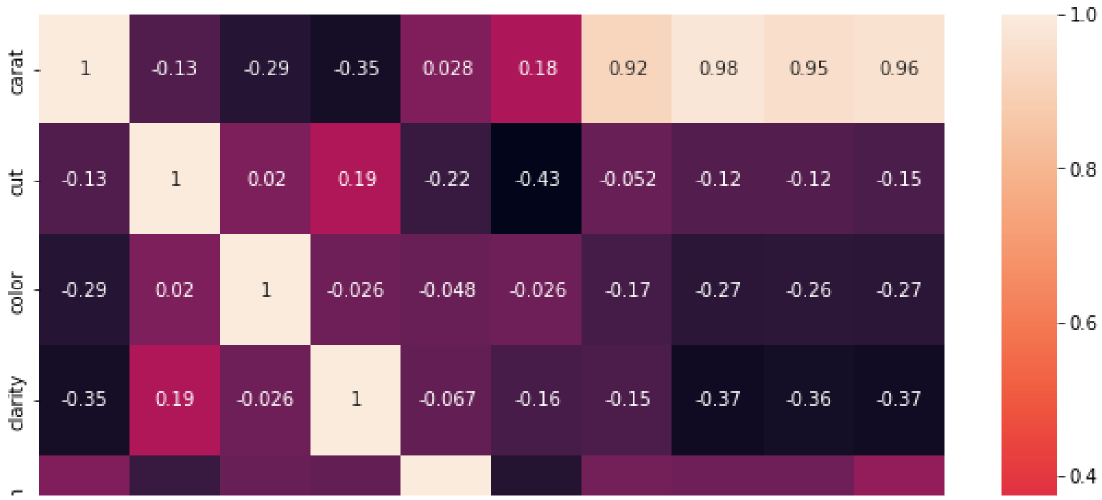
# Correlation

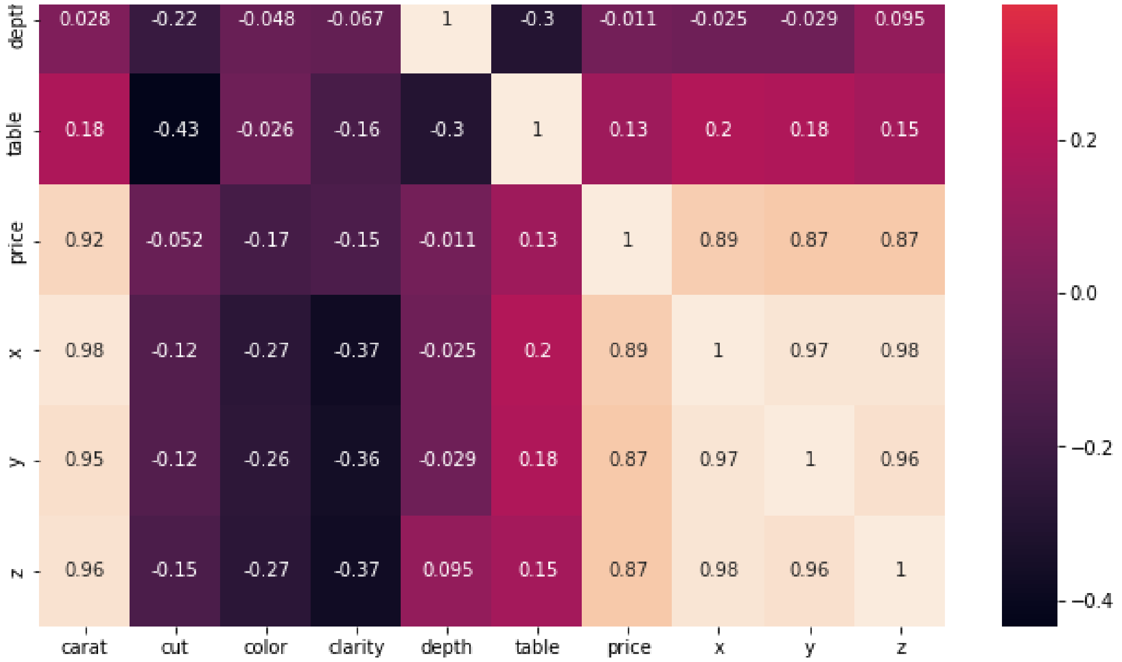
In [752]:

```
plt.figure(figsize=(11,11))
sns.heatmap(ds.corr(), annot=True)
```

Out[752]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f8950970050>





**"x", "y" and "z" show a high correlation to the "price" column. So we can drop any two columns. We also see "carat" is very much dependent on "x", "y" and "z" as it is obvious if length, width and depth increases carat will increase. So let's drop carat as it has the highest correlation.**

**"depth", "cut" and "table" show low correlation.**

In [753]:

```
ds.drop(axis="columns", labels="carat", inplace=True)
```

In [754]:

```
ds.loc[:10,:]
```

Out[754]:

| | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 5 | 6 | 2 | 0.513889 | 0.230769 | 0.000000 | 0.031384 | 0.005433 | 0.044256 |
| **1** | 4 | 6 | 3 | 0.466667 | 0.346154 | 0.000000 | 0.022825 | 0.002898 | 0.040351 |
| **2** | 2 | 6 | 5 | 0.386111 | 0.423077 | 0.000054 | 0.045649 | 0.007063 | 0.040351 |
| **3** | 4 | 2 | 4 | 0.538889 | 0.288462 | 0.000433 | 0.067047 | 0.009960 | 0.050765 |
| **4** | 2 | 1 | 2 | 0.563889 | 0.288462 | 0.000487 | 0.087019 | 0.012133 | 0.054670 |
| **5** | 3 | 1 | 6 | 0.550000 | 0.269231 | 0.000541 | 0.029957 | 0.005071 | 0.045884 |
| **6** | 3 | 2 | 7 | 0.536111 | 0.269231 | 0.000541 | 0.031384 | 0.005433 | 0.045558 |
| **7** | 3 | 3 | 3 | 0.525000 | 0.230769 | 0.000595 | 0.048502 | 0.007787 | 0.047511 |
| **8** | 1 | 6 | 4 | 0.613889 | 0.346154 | 0.000595 | 0.019971 | 0.001811 | 0.046209 |
| **9** | 3 | 3 | 5 | 0.455556 | 0.346154 | 0.000649 | 0.038516 | 0.006700 | 0.042955 |
| **10** | 2 | 1 | 3 | 0.583333 | 0.230769 | 0.000703 | 0.074180 | 0.010866 | 0.054019 |

## Test and Training Data

In [755]:

```
train = ds.sample(frac = 0.75, replace = False)
test = ds.drop(train.index)
```

In [756]:

```
train = train.to_numpy()
```

```
train = train.to_numpy()
test = test.to_numpy()
```

In [757]:

```
label_col = 5
# label_col is  price column
y_train = train[:,label_col]
x_train = np.delete(train,label_col,1)
#inserting bias b, this will work for both univariate and multivariate
x_train = np.insert(x_train, 0, np.ones(len(x_train)), axis=1)

y_test = test[:,label_col]
x_test = np.delete(test,label_col,1)
#inserting bias b
x_test = np.insert(x_test, 0, np.ones(len(y_test)), axis=1)
```

In [758]:

```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(40331, 9)
(13444, 9)
(40331,)
(13444,)
```

# Linear Regression

### Closed Form

**w = (X.T *X)^-1* X.T*Y**

In [759]:

```
def closedForm(x, y):
  return np.dot(np.dot(np.linalg.inv(np.dot(x.T, x)), x.T), y)
```

### Gradient Descent

**In X, we are adding a column of all 1's which represents our bias (b) from the equation y = w*x + b.**

**y_cap = y_pred = x *w cost = J(w) = -1/m* sigma( (y - y_cap)^2 ) for i =1 to m**

**dJ(w) / dw = -1/m *X* (y - y_cap) ; m = rows**

**a = alpha (learning rate)**

**w = w - a * dJ/dw**

In [760]:

```
def gradientDescent(x, y, w, itr, alpha):
  costs_list = [1]*itr
  for i in range(itr):
    y_cap = np.dot(x, w)
    loss = y_cap - y
    cost = np.sum(loss ** 2) / len(x)

    #each iterations cost
    costs_list[i] = cost
    if (i % 50 == 0):
      print("Cost=",cost)
    #w = w - aplha * d(loss)/dw
```

```
    grad = np.dot(x.T, loss) / len(x)
    w = w - alpha * grad
  return w, costs_list
```

### Mean Squared Error

**The Mean Squared Error measures how close a regression line is to a set of data points.**

In [761]:

```
def meanSqErr(y_pred, y_test):
  MeanSquaredError = np.mean(np.square(y_pred - y_test))
  return MeanSquaredError
```

### For Graph Plot

In [762]:

```
def plotCost(cost, method):
  plt.plot(cost)
  plt.ylabel('Cost')
  plt.xlabel('iteration')
  plt.title('Cost curve (' + method + ' solution)')
  plt.show()
```

### UniVariate

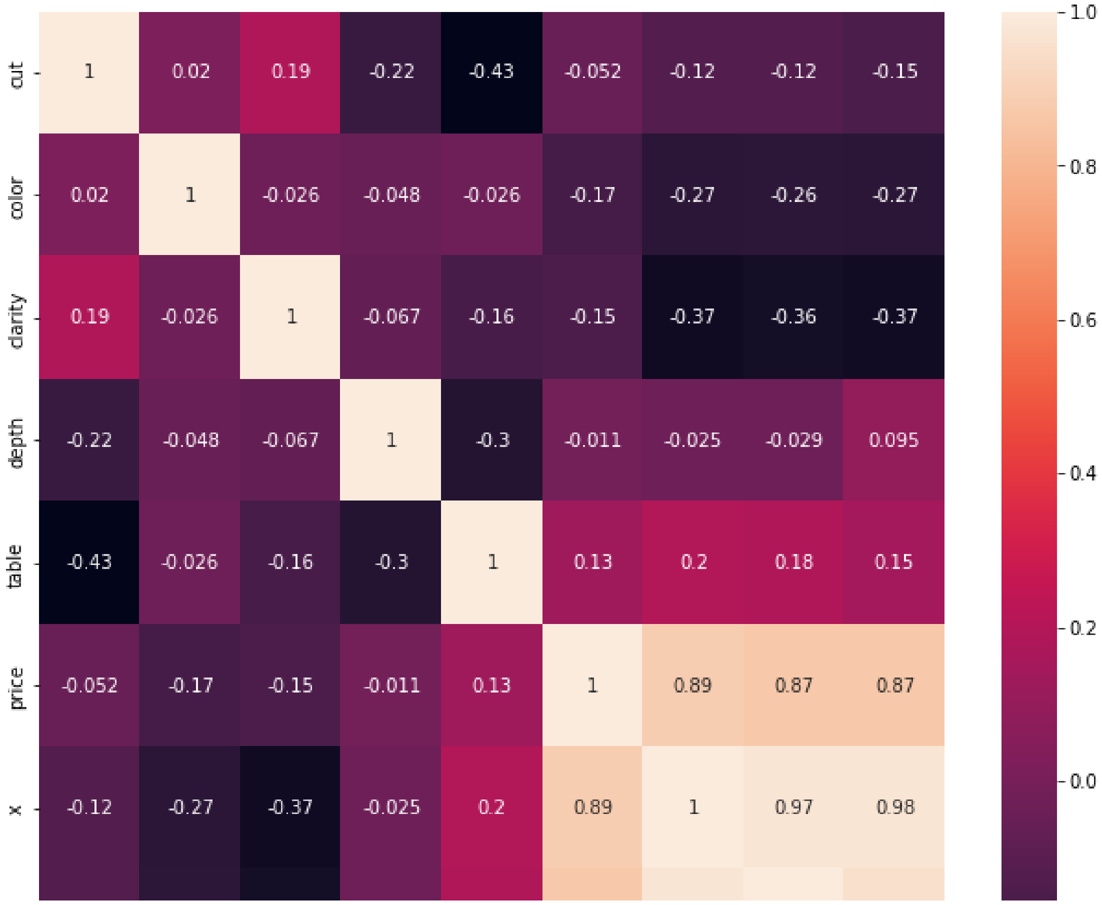
**Lets check the correlation Matrix and check which columns are most dependent on our label column**

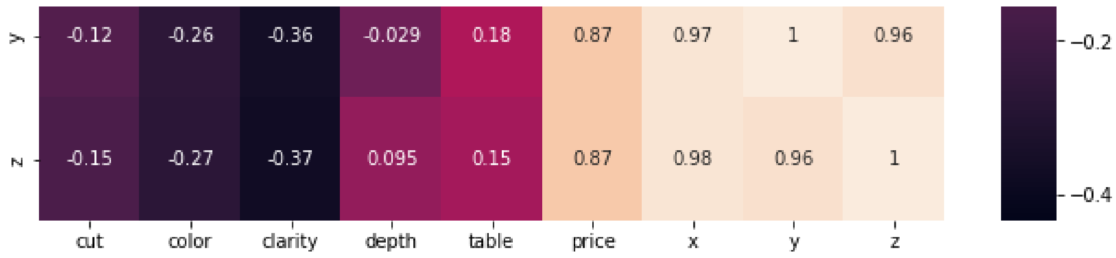
In [763]:

```
plt.figure(figsize=(11,11))
sns.heatmap(ds.corr(), annot=True)
```

Out[763]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f8950f421d0>
```






In [764]:

```
x_train
```

Out[764]:

```
array([[1.        , 5.        , 7.        , ..., 0.06419401, 0.00851141,
        0.04913765],
       [1.        , 3.        , 7.        , ..., 0.2810271 , 0.03730532,
        0.07972665],
       [1.        , 4.        , 3.        , ..., 0.53780314, 0.06700471,
        0.11096648],
       ...,
       [1.        , 5.        , 4.        , ..., 0.22253923, 0.02951829,
        0.07159128],
       [1.        , 4.        , 5.        , ..., 0.41940086, 0.05378486,
        0.10055321],
       [1.        , 2.        , 1.        , ..., 0.50071327, 0.06519377,
        0.11519688]])
```

In [765]:

```
#here we are taking two columns from our x_train and x_test
# 1st column = bias (b) and i'th column = feature on which we will apply Univariate.
def train_test_univariate(i):
  #                        bias          i'th column
  ux_train = np.array([x_train[:,0], x_train[:,i]]).T
  ux_test = np.array([x_test[:,0], x_test[:,i]]).T
  return ux_train, ux_test, y_train, y_test
```

**We can take any of the columns : x, y, z for prediction of label**

In [766]:

```
x_col = ds.columns.get_loc("x")
y_col = ds.columns.get_loc("y")
z_col = ds.columns.get_loc("z")
```

**For X Column**

In [767]:

```
ux_train, ux_test, uy_train, uy_test = train_test_univariate(x_col)
uy_train=uy_train.reshape((len(uy_train), 1))
uy_test=uy_test.reshape((len(uy_test), 1))
```

In [768]:

```
#Closed Form Solutin

weightC_UNI = closedForm(ux_train, uy_train)
y_pred_closed_UNI = np.dot(ux_test, weightC_UNI)
print("Closed form UniVariate using << X >> column Mean Squared Error = ", meanSqErr(y_pr
ed_closed_UNI, uy_test))
```

```
Closed form UniVariate using << X >> column Mean Squared Error =  0.010007017074549722
```

In [769]:

```
#Gradient Descent Solution
```

```
weightG_UNI = 0.1
itr = 600
alpha = 0.35
weightG_UNI, costsG_UNI = gradientDescent(ux_train, uy_train, weightG_UNI, itr, alpha)
```

```
Cost= 0.1230726656888536
Cost= 0.0455362687616016
Cost= 0.03102156416809773
Cost= 0.024656724709065096
Cost= 0.02187093137612901
Cost= 0.020651632045205953
Cost= 0.02011796329066754
Cost= 0.019884384601376395
Cost= 0.019782150765074398
Cost= 0.019737404571332398
Cost= 0.019717819843547355
Cost= 0.019709247906353627
```

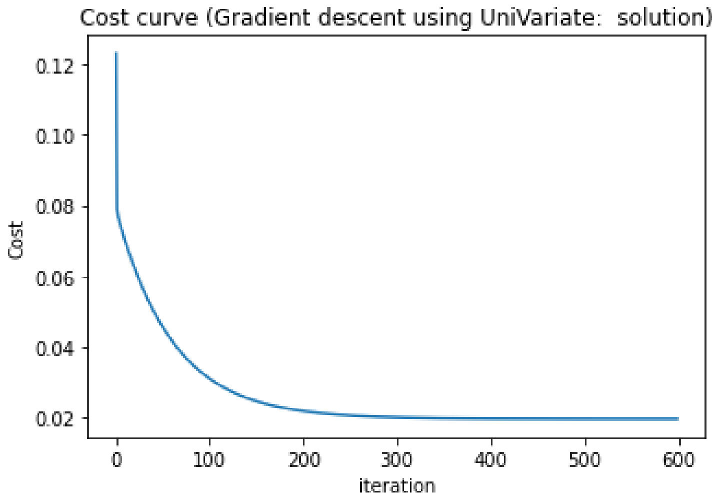
In [770]:

```
y_pred_grad_UNI = np.dot(ux_test, weightG_UNI)
print("Gradient Descent UniVariate using <X> column Mean Squared Error = ", meanSqErr(y_p
red_grad_UNI, uy_test))
```

```
Gradient Descent UniVariate using <X> column Mean Squared Error =  0.010011437186306944
```

In [771]:

```
plotCost(costsG_UNI, "Gradient descent using UniVariate: ")
```




**For Y Column**

In [772]:

```
ux_train, ux_test, uy_train, uy_test = train_test_univariate(y_col)
uy_train=uy_train.reshape((len(uy_train), 1))
uy_test=uy_test.reshape((len(uy_test), 1))
```

In [773]:

```
#Closed Form Solutin

weightC_UNI = closedForm(ux_train, uy_train)
y_pred_closed_UNI = np.dot(ux_test, weightC_UNI)
print("Closed form UniVariate using << Y >> column Mean Squared Error = ", meanSqErr(y_pr
ed_closed_UNI, uy_test))
```

```
Closed form UniVariate using << Y >> column Mean Squared Error =  0.017043747722067813
```

In [774]:

```
#Gradient Descent Solution
weightG_UNI = 0.1
```

```
itr = 1000
alpha = 0.011
weightG_UNI, costsG_UNI = gradientDescent(ux_train, uy_train, weightG_UNI, itr, alpha)
```

```
Cost= 0.13697936620553774
Cost= 0.09631344469359934
Cost= 0.09269088319243472
Cost= 0.09147294628003394
Cost= 0.09104936538727677
Cost= 0.09088820245596667
Cost= 0.09081373642459524
Cost= 0.09076791938236774
Cost= 0.0907315757084925
Cost= 0.09069837090116778
Cost= 0.09066621240927056
Cost= 0.09063440897276392
Cost= 0.090602732235794
Cost= 0.0905711067588329
Cost= 0.09053950761691729
Cost= 0.09050792657212775
Cost= 0.09047636089896492
Cost= 0.09044480969291056
Cost= 0.09041327265099361
Cost= 0.09038174966896048
```

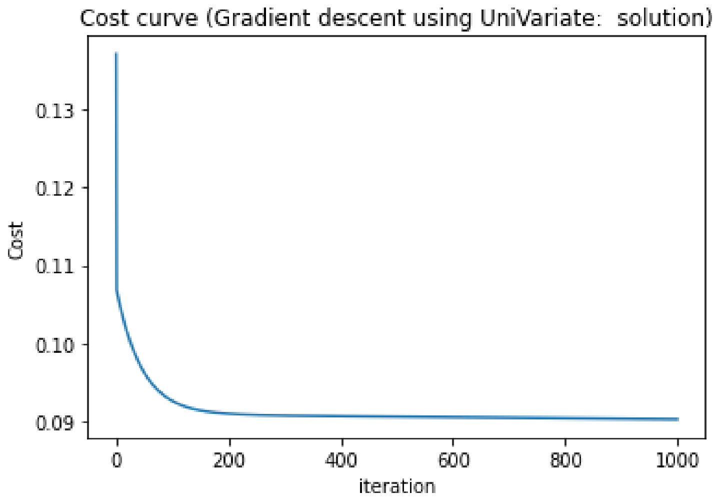
In [775]:

```
y_pred_grad_UNI = np.dot(ux_test, weightG_UNI)
print("Gradient Descent UniVariate using << Y >> column Mean Squared Error = ", meanSqErr
(y_pred_grad_UNI, uy_test))
```

```
Gradient Descent UniVariate using << Y >> column Mean Squared Error =  0.0457747901126378
3
```

In [776]:

```
plotCost(costsG_UNI, "Gradient descent using UniVariate: ")
```




### Z Column

In [777]:

```
#Gradient Descent Solution
weightG_UNI = 0.1
itr = 1000
alpha = 0.011
weightG_UNI, costsG_UNI = gradientDescent(ux_train, uy_train, weightG_UNI, itr, alpha)
```

```
Cost= 0.13697936620553774
Cost= 0.09631344469359934
Cost= 0.09269088319243472
Cost= 0.09147294628003394
Cost= 0.09104936538727677
Cost= 0.09088820245596667
```

```
Cost= 0.09081373642459524
Cost= 0.09076791938236774
Cost= 0.0907315757084925
Cost= 0.09069837090116778
Cost= 0.09066621240927056
Cost= 0.09063440897276392
Cost= 0.090602732235794
Cost= 0.0905711067588329
Cost= 0.09053950761691729
Cost= 0.09050792657212775
Cost= 0.09047636089896492
Cost= 0.09044480969291056
Cost= 0.09041327265099361
Cost= 0.09038174966896048
```

In [778]:

```
ux_train, ux_test, uy_train, uy_test = train_test_univariate(z_col)
uy_train=uy_train.reshape((len(uy_train), 1))
uy_test=uy_test.reshape((len(uy_test), 1))
```

In [779]:

```
#Closed Form Solutin

weightC_UNI = closedForm(ux_train, uy_train)
y_pred_closed_UNI = np.dot(ux_test, weightC_UNI)
print("Closed form UniVariate using << Z >> column Mean Squared Error = ", meanSqErr(y_pr
ed_closed_UNI, uy_test))
```

```
Closed form UniVariate using << Z >> column Mean Squared Error =  0.014940489937509394
```

In [780]:

```
#Gradient Descent Solution
weightG_UNI = 0.1
itr = 1000
alpha = 0.012
weightG_UNI, costsG_UNI = gradientDescent(ux_train, uy_train, weightG_UNI, itr, alpha)
```

```
Cost= 0.1352712007544064
Cost= 0.09508750523039379
Cost= 0.09196686550196595
Cost= 0.09101135470391955
Cost= 0.09069821895911043
Cost= 0.09057568290888587
Cost= 0.09050971242647102
Cost= 0.09046054184024391
Cost= 0.09041637333653367
Cost= 0.09037370669260293
Cost= 0.09033150344076013
Cost= 0.09028945547445004
Cost= 0.09024747137293321
Cost= 0.09020552400249734
Cost= 0.09016360530231136
Cost= 0.09012171287015225
Cost= 0.0900798459826169
Cost= 0.09003800441438607
Cost= 0.0899961880879201
Cost= 0.0899543969695295
```

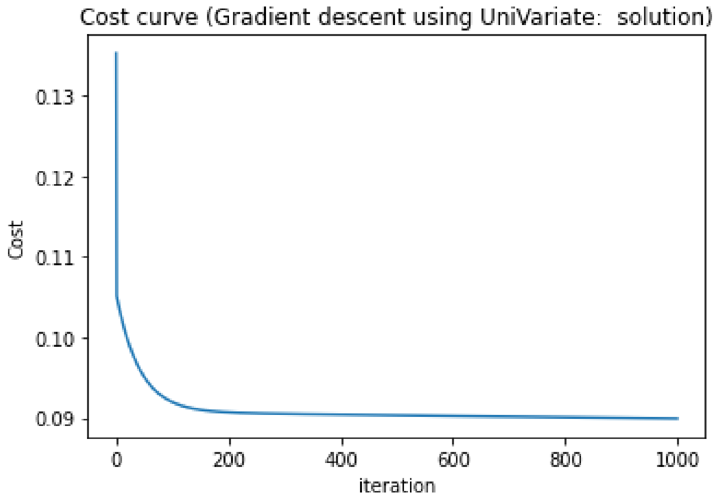
In [781]:

```
y_pred_grad_UNI = np.dot(ux_test, weightG_UNI)
print("Gradient Descent UniVariate using << Z >> column Mean Squared Error = ", meanSqErr
(y_pred_grad_UNI, uy_test))
```

```
Gradient Descent UniVariate using << Z >> column Mean Squared Error =  0.0455579780196802
2
```

In [782]:

```
plotCost(costsG_UNI, "Gradient descent using UniVariate: ")
```




## MultiVariate

In [783]:

```
#Closed Form Solution

weightC = closedForm(x_train, y_train)

#Gradient Descent Solution

weightG = [0.1] * len(x_train[0])
itr = 220
alpha = 0.001
weightG, costsG = gradientDescent(x_train, y_train,weightG, itr, alpha)
```

```
Cost= 1.7276138171175495
Cost= 0.04461621990072215
Cost= 0.038621204751832144
Cost= 0.038480786396332324
Cost= 0.03836601866517273
```

In [784]:

```
#closed form prediction
y_pred_closed = np.dot(x_test, weightC)

#gradient descent prediction
y_pred_grad = np.dot(x_test, weightG)
```

In [785]:

```
print("Closed form Mean Squared Error = ", meanSqErr(y_pred_closed, y_test))
```

```
Closed form Mean Squared Error =  0.011663738954442171
```

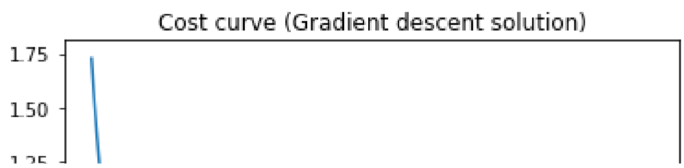
In [786]:

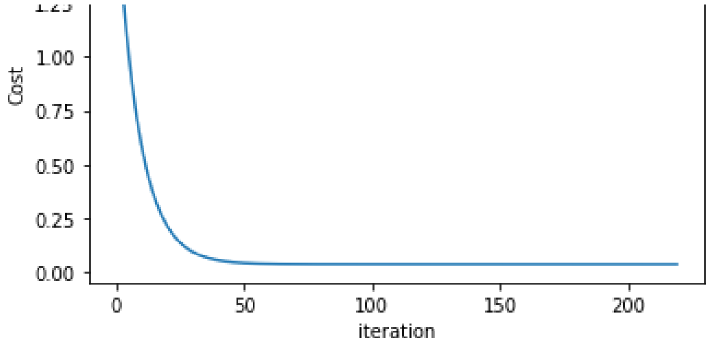
```
print("Gradient descent Mean Squared Error = ", meanSqErr(y_pred_grad, y_test))
```

```
Gradient descent Mean Squared Error =  0.03892606575592581
```

In [787]:

```
plotCost(costsG, "Gradient descent")
```





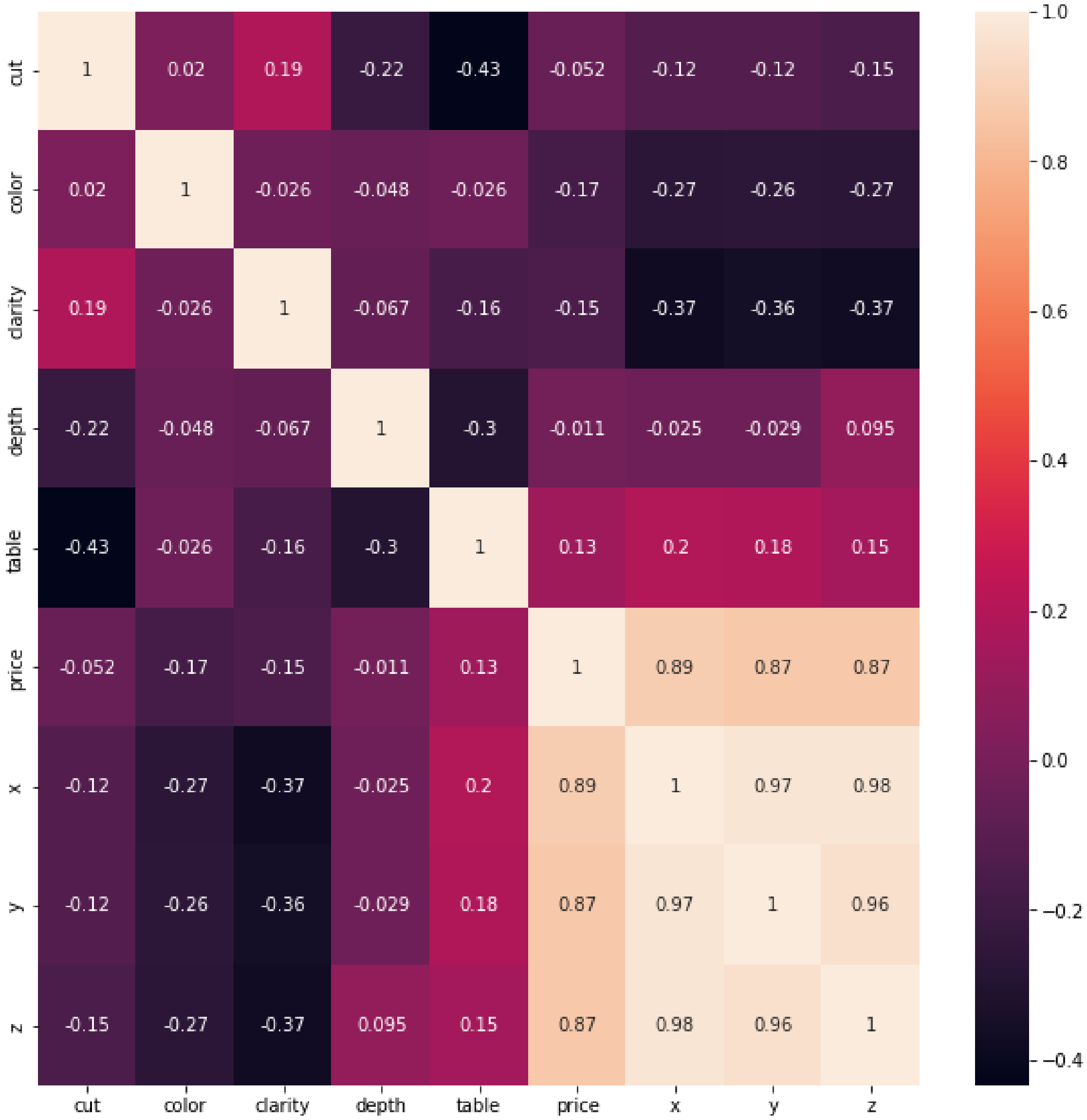

### Further checking for correlated columns and checking for results

In [788]:

```
plt.figure(figsize=(11,11))
sns.heatmap(ds.corr(), annot=True)
```

Out[788]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f895031fe50>
```




| | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|
| cut | 1 | 0.02 | 0.19 | -0.22 | -0.43 | -0.052 | -0.12 | -0.12 | -0.15 |
| color | 0.02 | 1 | -0.026 | -0.048 | -0.026 | -0.17 | -0.27 | -0.26 | -0.27 |
| clarity | 0.19 | -0.026 | 1 | -0.067 | -0.16 | -0.15 | -0.37 | -0.36 | -0.37 |
| depth | -0.22 | -0.048 | -0.067 | 1 | -0.3 | -0.011 | -0.025 | -0.029 | 0.095 |
| table | -0.43 | -0.026 | -0.16 | -0.3 | 1 | 0.13 | 0.2 | 0.18 | 0.15 |
| price | -0.052 | -0.17 | -0.15 | -0.011 | 0.13 | 1 | 0.89 | 0.87 | 0.87 |
| x | -0.12 | -0.27 | -0.37 | -0.025 | 0.2 | 0.89 | 1 | 0.97 | 0.98 |
| y | -0.12 | -0.26 | -0.36 | -0.029 | 0.18 | 0.87 | 0.97 | 1 | 0.96 |
| z | -0.15 | -0.27 | -0.37 | 0.095 | 0.15 | 0.87 | 0.98 | 0.96 | 1 |

**Let's also try with dropping x, y and z values as they are highly correlated to our target column**

In [789]:

```
x_col = ds.columns.get_loc("x")
y_col = ds.columns.get_loc("y")
z_col = ds.columns.get_loc("z")
```

In [790]:

```
ds.head()
```

Out[790]:

| | cut | color | clarity | depth | table | price | x | y | z |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 5 | 6 | 2 | 0.513889 | 0.230769 | 0.000000 | 0.031384 | 0.005433 | 0.044256 |
| **1** | 4 | 6 | 3 | 0.466667 | 0.346154 | 0.000000 | 0.022825 | 0.002898 | 0.040351 |
| **2** | 2 | 6 | 5 | 0.386111 | 0.423077 | 0.000054 | 0.045649 | 0.007063 | 0.040351 |
| **3** | 4 | 2 | 4 | 0.538889 | 0.288462 | 0.000433 | 0.067047 | 0.009960 | 0.050765 |
| **4** | 2 | 1 | 2 | 0.563889 | 0.288462 | 0.000487 | 0.087019 | 0.012133 | 0.054670 |

In [791]:

```
ds.drop(axis="columns", labels="y", inplace=True)
ds.drop(axis="columns", labels="x", inplace=True)
ds.drop(axis="columns", labels="z", inplace=True)
```

### Again calculating x_train, x_test, y_train and y_test after dropping columns and checking for multivariate values

In [792]:

```
ds.head()
```

Out[792]:

| | cut | color | clarity | depth | table | price |
|---|---|---|---|---|---|---|
| **0** | 5 | 6 | 2 | 0.513889 | 0.230769 | 0.000000 |
| **1** | 4 | 6 | 3 | 0.466667 | 0.346154 | 0.000000 |
| **2** | 2 | 6 | 5 | 0.386111 | 0.423077 | 0.000054 |
| **3** | 4 | 2 | 4 | 0.538889 | 0.288462 | 0.000433 |
| **4** | 2 | 1 | 2 | 0.563889 | 0.288462 | 0.000487 |

### Removing from test and train sets

In [793]:

```
label_col = 5
# label_col is  price column
y_train = train[:,label_col]

#removing label_column and x, y, z columns
x_train = np.delete(train,[label_col, x_col, y_col, z_col],1)

#inserting bias b, this will work for both univariate and multivariate
x_train = np.insert(x_train, 0, np.ones(len(x_train)), axis=1)

y_test = test[:,label_col]

#removing label_column and x, y, z columns
x_test = np.delete(test,[label_col, x_col, y_col, z_col],1)

#inserting bias b
x_test = np.insert(x_test, 0, np.ones(len(y_test)), axis=1)
```

### Final Solution after removing all the correlated columns

In [794]:

```
#Closed Form Solution
```

```
weightC = closedForm(x_train, y_train)

#Gradient Descent Solution
weightG = [0.1] * len(x_train[0])
itr = 220
alpha = 0.001
weightG, costsG = gradientDescent(x_train, y_train,weightG, itr, alpha)
```

```
Cost= 1.6398328097028203
Cost= 0.05199669078742636
Cost= 0.046331486882540414
Cost= 0.046238802235241565
Cost= 0.04617420689155505
```

In [795]:

```
#closed form prediction
y_pred_closed = np.dot(x_test, weightC)

#gradient descent prediction
y_pred_grad = np.dot(x_test, weightG)
```

In [796]:

```
print("Closed form Mean Squared Error = ", meanSqErr(y_pred_closed, y_test))
```

```
Closed form Mean Squared Error =  0.044246800117223595
```

In [797]:

```
print("Gradient descent Mean Squared Error = ", meanSqErr(y_pred_grad, y_test))
```

```
Gradient descent Mean Squared Error =  0.04680266014458536
```

In [798]:

```
plotCost(costsG, "Gradient descent")
```