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

In [4]:
    dataFrame = pd.read_excel("mercedes.xlsx")

In [5]:
    dataFrame
```

Out[5]: transmission tax mpg engineSize year price mileage **0** 2005 5200 63000 325 1.8 Automatic 32.1 **1** 2017 34948 Automatic 27000 20 61.4 2.1 **2** 2016 49948 6200 555 28.0 5.5 Automatic **3** 2016 61948 Automatic 16000 325 30.4 4.0 **4** 2016 73948 Automatic 4000 325 30.1 4.0 **13114** 2020 35999 Automatic 500 145 55.4 2.0 **13115** 2020 24699 145 Automatic 2500 55.4 2.0 **13116** 2019 30999 Automatic 11612 145 41.5 2.1 **13117** 2019 37990 Automatic 2426 145 45.6 2.0 **13118** 2019 54999 2.9 Automatic 2075 145 52.3

13119 rows  $\times$  7 columns

```
In [6]: dataFrame.describe()
```

30.03.2021

Out[6]:		year	price	mileage	tax	mpg	engineSize
	count	13119.000000	13119.000000	13119.000000	13119.000000	13119.000000	13119.000000
	mean	2017.296288	24698.596920	21949.559037	129.972178	55.155843	2.071530
	std	2.224709	11842.675542	21176.512267	65.260286	15.220082	0.572426
	min	1970.000000	650.000000	1.000000	0.000000	1.100000	0.000000
	25%	2016.000000	17450.000000	6097.500000	125.000000	45.600000	1.800000
	50%	2018.000000	22480.000000	15189.000000	145.000000	56.500000	2.000000
	75%	2019.000000	28980.000000	31779.500000	145.000000	64.200000	2.100000
	max	2020.000000	159999.000000	259000.000000	580.000000	217.300000	6.200000

```
In [7]: #null değerleri temizleme
   dataFrame = dataFrame.dropna(axis=0) #null içeren satırları sil
   dataFrame
```

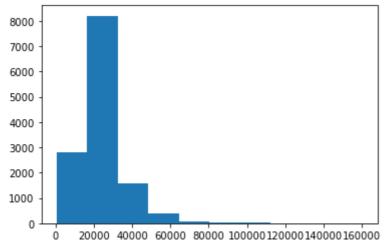
Out[7]:

	year	price	transmission	mileage	tax	mpg	engineSize
0	2005	5200	Automatic	63000	325	32.1	1.8
1	2017	34948	Automatic	27000	20	61.4	2.1
2	2016	49948	Automatic	6200	555	28.0	5.5
3	2016	61948	Automatic	16000	325	30.4	4.0
4	2016	73948	Automatic	4000	325	30.1	4.0
•••							
13114	2020	35999	Automatic	500	145	55.4	2.0
13115	2020	24699	Automatic	2500	145	55.4	2.0
13116	2019	30999	Automatic	11612	145	41.5	2.1
13117	2019	37990	Automatic	2426	145	45.6	2.0
13118	2019	54999	Automatic	2075	145	52.3	2.9

13119 rows × 7 columns

```
In [8]:
# veri dağılımını kontrol etme (histogram)
plt.hist(dataFrame["price"])
```

```
Out[8]: (array([2.792e+03, 8.199e+03, 1.594e+03, 3.930e+02, 9.100e+01, 1.800e+01, 1.300e+01, 7.000e+00, 9.000e+00, 3.000e+00]), array([ 650., 16584.9, 32519.8, 48454.7, 64389.6, 80324.5, 96259.4, 112194.3, 128129.2, 144064.1, 159999.]), <BarContainer object of 10 artists>)
```



```
In [9]:
    # veri dağılımını kontrol etme (distribution)
    sbn.distplot(dataFrame["price"])

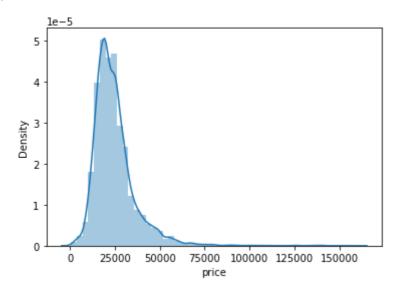
# çok pahalı arabalar azınlıkta, modelimizi olumsuz etkileyebilir
    # fiyatı 75 bin'den pahalıları silsek iyi olur
    # zira onlar için ayrı bir model oluşturulabilir
```

C:\Users\Mehmet KAHRAMAN\.conda\envs\tensorflow\lib\site-packages\seaborn\distributi ons.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

```
warnings.warn(msg, FutureWarning)
```

<AxesSubplot:xlabel='price', ylabel='Density'>

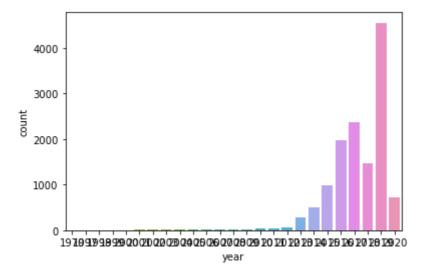
Out[9]:



```
In [10]: sbn.countplot(dataFrame["year"])
```

C:\Users\Mehmet KAHRAMAN\.conda\envs\tensorflow\lib\site-packages\seaborn\\_decorator
s.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From versio
n 0.12, the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
 warnings.warn(

Out[10]: <AxesSubplot:xlabel='year', ylabel='count'>



```
In [11]:
# Korelasyon analizi
# veri özellikleri arasında doğrusal bir ilişki olup olmadığını,
# varsa bu ilişkinin katsayısını veren matematiksel yöntemdir.
# örneğin araba yılı ile araba fiyatı arasında pozitif korelasyon vardır
# az da olsa hata oranı barındırır

dataFrame.corr()["price"].sort_values() #fiyatı etkileyen korelasyonlar
```

```
Out[11]: mileage -0.537214
mpg -0.438445
tax 0.268717
engineSize 0.516126
year 0.520712
price 1.000000
Name: price, dtype: float64
```

```
In [12]: # String Sütununu silme (Transmission sütunu)
```

dataFrame = dataFrame.drop("transmission", axis=1)
dataFrame

## Out[12]:

	year	price	mileage	tax	mpg	engineSize
0	2005	5200	63000	325	32.1	1.8
1	2017	34948	27000	20	61.4	2.1
2	2016	49948	6200	555	28.0	5.5
3	2016	61948	16000	325	30.4	4.0
4	2016	73948	4000	325	30.1	4.0
•••						
13114	2020	35999	500	145	55.4	2.0
13115	2020	24699	2500	145	55.4	2.0
13116	2019	30999	11612	145	41.5	2.1
13117	2019	37990	2426	145	45.6	2.0
13118	2019	54999	2075	145	52.3	2.9

13119 rows × 6 columns

In [13]:

```
# en pahali arabalari listele
dataFrame.sort_values("price",ascending=False).head(50)
```

Out[13]:

	year	price	mileage	tax	mpg	engineSize
6199	2020	159999	1350	145	21.4	4.0
10044	2020	154998	3000	150	21.4	4.0
5	2011	149948	3000	570	21.4	6.2
8737	2019	140319	785	150	22.1	4.0
6386	2018	139995	13046	145	21.4	4.0
8	2019	139948	12000	145	21.4	4.0
9133	2019	139559	1000	145	22.1	4.0
8821	2020	138439	1000	145	22.1	4.0
5902	2018	135771	19000	145	21.4	4.0
7864	2018	135124	18234	150	21.4	4.0
8673	2019	134219	1000	145	24.8	4.0
6210	2019	129990	1000	145	24.8	4.0
4759	2019	126000	250	145	24.6	4.0
2647	2019	125796	637	145	24.8	4.0
6223	2019	124999	1500	145	31.7	4.0
4094	2019	124366	880	145	24.8	4.0
2629	2019	123846	2951	145	22.1	4.0
7134	2019	115359	1000	145	30.1	4.0

	year	price	mileage	tax	mpg	engineSize
9159	2019	114199	891	145	22.6	4.0
1980	2019	109995	4688	150	31.7	4.0
8745	2018	109989	2122	145	24.8	4.0
13060	2017	109495	1755	145	24.8	4.0
7828	2019	109445	195	145	22.6	4.0
5311	2019	105000	6807	150	22.6	4.0
1011	2019	104999	5822	150	22.6	4.0
4087	2019	104590	3671	145	31.7	4.0
4209	2018	104400	3796	145	31.7	4.0
3978	2019	102502	8691	150	11.0	3.0
9241	2017	100124	439	145	24.8	4.0
686	2019	99950	2013	145	22.6	4.0
5662	2015	99850	10000	570	20.5	5.5
10281	2019	97900	163	145	30.1	4.0
7128	2019	95099	1022	145	34.0	4.0
4779	2018	94522	1736	145	24.8	4.0
8672	2019	93499	1000	145	34.0	4.0
10807	2018	90900	9141	145	24.8	4.0
7312	2019	90759	1000	145	34.0	4.0
965	2019	89999	1400	145	34.0	4.0
3597	2018	89995	2928	145	31.7	4.0
11940	2018	89990	6800	145	24.8	4.0
4053	2019	89880	50	145	28.0	5.5
9275	2019	88995	200	145	28.0	4.0
8671	2019	87478	1257	145	34.0	4.0
8670	2019	87459	1493	145	23.7	5.5
7135	2019	86699	1314	145	34.0	4.0
8750	2019	86399	1912	145	34.0	4.0
11700	2018	84500	3695	145	24.8	4.0
8682	2018	82099	1952	145	34.0	4.0
10566	2019	81900	21442	145	32.1	4.0
3858	2019	80650	221	145	28.0	5.5

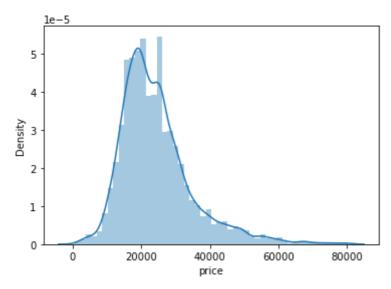
```
In [14]:
# fiyatr yüksek olanlara göre sıralanmış dataframe üzerinde,
# ilk 50 tanesini bırak 50.sıradan sonuna kadar dataFrame'i güncelle

dataFrame = dataFrame.sort_values("price",ascending=False).iloc[50:]
sbn.distplot(dataFrame["price"])
```

C:\Users\Mehmet KAHRAMAN\.conda\envs\tensorflow\lib\site-packages\seaborn\distributi ons.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

warnings.warn(msg, FutureWarning)

Out[14]: <AxesSubplot:xlabel='price', ylabel='Density'>



```
In [15]: # araba yılına göre ortalama fiyatlar
    dataFrame.groupby("year").mean()["price"]
# 1970 model arabaların ort fiyatı uyumsuz
```

```
24999.000000
         1970
         1997
                   9995.000000
         1998
                   8605.000000
         1999
                   5995.000000
          2000
                   5743.333333
                   4957.900000
          2001
                   5820.444444
          2002
                   4878.000000
          2003
          2004
                  4727.615385
          2005
                   4426.111111
          2006
                  4036.875000
          2007
                   5136.045455
          2008
                   6967,437500
          2009
                   6166.764706
          2010
                   8308,473684
          2011
                   8913,459459
          2012
                  10845,140351
          2013
                  11939,842466
          2014
                  14042.936864
          2015
                  16647,822222
          2016
                  19307.892948
          2017
                  21444.282472
          2018
                  25119.638736
          2019
                  30752.414952
                  34948.455307
         2020
         Name: price, dtype: float64
In [16]:
          # bozuk veriyi sorqulayarak silme
          dataFrame = dataFrame.query("year != 1970")
          dataFrame.groupby("year").mean()["price"]
```

Out[15]: year

```
1997
                 9995.000000
                  8605.000000
         1998
         1999
                 5995.000000
                 5743.333333
         2000
         2001
                 4957.900000
         2002
                5820.444444
         2003
                 4878.000000
         2004
                 4727.615385
                4426.111111
         2005
         2006
                 4036.875000
         2007
                5136.045455
                6967.437500
         2008
         2009
                6166.764706
                8308.473684
         2010
         2011
                8913.459459
         2012 10845.140351
         2013 11939.842466
         2014 14042.936864
         2015
               16647.822222
         2016
                19307.892948
         2017
                21444.282472
         2018
                25119.638736
         2019
                30752.414952
         2020
                 34948.455307
         Name: price, dtype: float64
In [17]:
         # x (özellikler) ve y (label hedefi) değerlerini oluşturma
          y = dataFrame["price"].values
          x = dataFrame.drop("price",axis=1).values
In [18]:
          # veri setinin test-train oranına ayrılması
          from sklearn.model selection import train test split
          x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.3)
In [19]:
          # veri ölçeklendirme
          from sklearn.preprocessing import MinMaxScaler
          scaler = MinMaxScaler()
          x_train = scaler.fit_transform(x_train)
          x_test = scaler.transform(x_test)
In [20]:
          # modeli oluşturma
          import tensorflow as tf
          from tensorflow.keras import models
          from tensorflow.keras import layers
          model = models.Sequential()
          # 5 araba özelliği olduğundan bir katmanda en az 5 nöron olmalı
          model.add(layers.Dense(12, activation="relu"))
          model.add(layers.Dense(12, activation="relu"))
          model.add(layers.Dense(12, activation="relu"))
          model.add(layers.Dense(12, activation="relu"))
          model.add(layers.Dense(1))
          model.compile(optimizer="adam",loss="mse")
```

```
In [21]: # modeli eğitme

#validation --> ek olarak test verilerine göre de loss oranını çıkar
model.fit(x_train,y_train, validation_data=(x_test,y_test), batch_size=500, epochs=4
```

```
Epoch 1/400
oss: 689768064.0000
Epoch 2/400
ss: 689735552.0000
Epoch 3/400
ss: 689674048.0000
Epoch 4/400
ss: 689553152.0000
Epoch 5/400
ss: 689312256.0000
Epoch 6/400
ss: 688829632.0000
Epoch 7/400
ss: 687935104.0000
Epoch 8/400
ss: 686328320.0000
Epoch 9/400
ss: 683609024.0000
Epoch 10/400
ss: 679264512.0000
Epoch 11/400
ss: 672653568.0000
Epoch 12/400
ss: 662955840.0000
Epoch 13/400
ss: 649249344.0000
Epoch 14/400
ss: 630543872.0000
Epoch 15/400
ss: 605852608.0000
Epoch 16/400
ss: 574076416.0000
Epoch 17/400
ss: 534337440.0000
Epoch 18/400
ss: 486737152.0000
Epoch 19/400
ss: 431883264.0000
Epoch 20/400
ss: 371522560.0000
Epoch 21/400
ss: 308631712.0000
Epoch 22/400
```

```
ss: 248069760.0000
Epoch 23/400
ss: 194182576.0000
Epoch 24/400
ss: 151519088.0000
Epoch 25/400
ss: 122170080.0000
Epoch 26/400
ss: 105267128.0000
Epoch 27/400
ss: 97153784.0000
Epoch 28/400
ss: 94142008.0000
Epoch 29/400
ss: 93056952.0000
Epoch 30/400
ss: 92569176.0000
Epoch 31/400
ss: 92191552.0000
Epoch 32/400
ss: 91833752.0000
Epoch 33/400
s: 91475304.0000
Epoch 34/400
s: 91113872.0000
Epoch 35/400
s: 90761992.0000
Epoch 36/400
s: 90430240.0000
Epoch 37/400
s: 90085072.0000
Epoch 38/400
s: 89770888.0000
Epoch 39/400
s: 89439680.0000
Epoch 40/400
s: 89106016.0000
Epoch 41/400
s: 88811792.0000
Epoch 42/400
s: 88495016.0000
Epoch 43/400
s: 88184704.0000
Epoch 44/400
s: 87863120.0000
Epoch 45/400
```

```
s: 87568224.0000
Epoch 46/400
s: 87280696.0000
Epoch 47/400
s: 86964896.0000
Epoch 48/400
s: 86680672.0000
Epoch 49/400
s: 86371432.0000
Epoch 50/400
s: 86083032.0000
Epoch 51/400
s: 85791240.0000
Epoch 52/400
s: 85471328.0000
Epoch 53/400
s: 85196872.0000
Epoch 54/400
s: 84914232.0000
Epoch 55/400
s: 84650520.0000
Epoch 56/400
s: 84297400.0000
Epoch 57/400
s: 84013056.0000
Epoch 58/400
s: 83730408.0000
Epoch 59/400
s: 83416592.0000
Epoch 60/400
s: 83142152.0000
Epoch 61/400
s: 82861488.0000
Epoch 62/400
s: 82562632.0000
Epoch 63/400
s: 82273232.0000
Epoch 64/400
s: 81943112.0000
Epoch 65/400
s: 81672304.0000
Epoch 66/400
s: 81390616.0000
Epoch 67/400
s: 81104280.0000
Epoch 68/400
```

```
s: 80796728.0000
Epoch 69/400
s: 80531712.0000
Epoch 70/400
s: 80210640.0000
Epoch 71/400
s: 79922472.0000
Epoch 72/400
s: 79619840.0000
Epoch 73/400
s: 79292640.0000
Epoch 74/400
s: 79020632.0000
Epoch 75/400
s: 78734776.0000
Epoch 76/400
s: 78418160.0000
Epoch 77/400
s: 78103232.0000
Epoch 78/400
s: 77809632.0000
Epoch 79/400
s: 77518848.0000
Epoch 80/400
s: 77208144.0000
Epoch 81/400
s: 76898264.0000
Epoch 82/400
s: 76621432.0000
Epoch 83/400
s: 76302192.0000
Epoch 84/400
s: 75986656.0000
Epoch 85/400
s: 75691672.0000
Epoch 86/400
s: 75379328.0000
Epoch 87/400
s: 75053216.0000
Epoch 88/400
s: 74750368.0000
Epoch 89/400
s: 74412448.0000
Epoch 90/400
s: 74087576.0000
Epoch 91/400
```

```
s: 73763688.0000
Epoch 92/400
s: 73454520.0000
Epoch 93/400
s: 73147496.0000
Epoch 94/400
s: 72785208.0000
Epoch 95/400
s: 72496472.0000
Epoch 96/400
s: 72163768.0000
Epoch 97/400
s: 71828688.0000
Epoch 98/400
s: 71459160.0000
Epoch 99/400
s: 71133120.0000
Epoch 100/400
s: 70782016.0000
Epoch 101/400
s: 70450584.0000
Epoch 102/400
s: 70078016.0000
Epoch 103/400
s: 69745368.0000
Epoch 104/400
s: 69406472.0000
Epoch 105/400
s: 69049448.0000
Epoch 106/400
s: 68699600.0000
Epoch 107/400
s: 68331928.0000
Epoch 108/400
s: 67936960.0000
Epoch 109/400
s: 67554152.0000
Epoch 110/400
s: 67265168.0000
Epoch 111/400
s: 66841400.0000
Epoch 112/400
s: 66454800.0000
Epoch 113/400
s: 66070152.0000
Epoch 114/400
```

```
s: 65667164.0000
Epoch 115/400
s: 65292684.0000
Epoch 116/400
s: 64881680.0000
Epoch 117/400
s: 64487468.0000
Epoch 118/400
s: 64116228.0000
Epoch 119/400
s: 63683864.0000
Epoch 120/400
s: 63296244.0000
Epoch 121/400
s: 62832108.0000
Epoch 122/400
s: 62436296.0000
Epoch 123/400
s: 61966028.0000
Epoch 124/400
19/19 [======================== ] - 0s 4ms/step - loss: 66746684.0000 - val_los
s: 61564632.0000
Epoch 125/400
s: 61164104.0000
Epoch 126/400
19/19 [========================] - 0s 5ms/step - loss: 65767896.0000 - val_los
s: 60683316.0000
Epoch 127/400
s: 60210948.0000
Epoch 128/400
s: 59748892.0000
Epoch 129/400
s: 59287016.0000
Epoch 130/400
s: 58818076.0000
Epoch 131/400
s: 58343520.0000
Epoch 132/400
s: 57844976.0000
Epoch 133/400
s: 57398904.0000
Epoch 134/400
s: 56856768.0000
Epoch 135/400
s: 56420224.0000
Epoch 136/400
s: 55835944.0000
Epoch 137/400
```

```
s: 55384476.0000
Epoch 138/400
s: 54852124.0000
Epoch 139/400
s: 54272580.0000
Epoch 140/400
s: 53767196.0000
Epoch 141/400
s: 53254540.0000
Epoch 142/400
s: 52627904.0000
Epoch 143/400
s: 52114484.0000
Epoch 144/400
s: 51506916.0000
Epoch 145/400
s: 50994308.0000
Epoch 146/400
s: 50433036.0000
Epoch 147/400
19/19 [========================] - 0s 5ms/step - loss: 53697012.0000 - val_los
s: 49803232.0000
Epoch 148/400
s: 49269028.0000
Epoch 149/400
s: 48649252.0000
Epoch 150/400
s: 48076232.0000
Epoch 151/400
s: 47466652.0000
Epoch 152/400
s: 46884732.0000
Epoch 153/400
s: 46279272.0000
Epoch 154/400
s: 45688464.0000
Epoch 155/400
s: 45133132.0000
Epoch 156/400
s: 44528364.0000
Epoch 157/400
s: 43928444.0000
Epoch 158/400
s: 43353128.0000
Epoch 159/400
s: 42777200.0000
Epoch 160/400
```

```
s: 42212156.0000
Epoch 161/400
s: 41669808.0000
Epoch 162/400
s: 41101612.0000
Epoch 163/400
s: 40585396.0000
Epoch 164/400
s: 40057384.0000
Epoch 165/400
s: 39497032.0000
Epoch 166/400
s: 39000920.0000
Epoch 167/400
s: 38507456.0000
Epoch 168/400
s: 38078044.0000
Epoch 169/400
s: 37570764.0000
Epoch 170/400
s: 37114596.0000
Epoch 171/400
s: 36706824.0000
Epoch 172/400
s: 36268020.0000
Epoch 173/400
s: 35876680.0000
Epoch 174/400
s: 35473736.0000
Epoch 175/400
s: 35086868.0000
Epoch 176/400
s: 34720084.0000
Epoch 177/400
s: 34378760.0000
Epoch 178/400
s: 34021672.0000
Epoch 179/400
s: 33682480.0000
Epoch 180/400
s: 33373276.0000
Epoch 181/400
s: 33039512.0000
Epoch 182/400
s: 32717992.0000
Epoch 183/400
```

```
s: 32405742.0000
Epoch 184/400
s: 32103590.0000
Epoch 185/400
s: 31805816.0000
Epoch 186/400
s: 31537150.0000
Epoch 187/400
s: 31256974.0000
Epoch 188/400
s: 31002942.0000
Epoch 189/400
s: 30780078.0000
Epoch 190/400
s: 30555026.0000
Epoch 191/400
s: 30363384.0000
Epoch 192/400
s: 30194994.0000
Epoch 193/400
s: 29974000.0000
Epoch 194/400
s: 29845434.0000
Epoch 195/400
s: 29643014.0000
Epoch 196/400
s: 29492774.0000
Epoch 197/400
s: 29320302.0000
Epoch 198/400
s: 29123866.0000
Epoch 199/400
s: 28945522.0000
Epoch 200/400
s: 28750252.0000
Epoch 201/400
s: 28519992.0000
Epoch 202/400
s: 28327936.0000
Epoch 203/400
s: 28092254.0000
Epoch 204/400
s: 27875982.0000
Epoch 205/400
s: 27656126.0000
Epoch 206/400
```

```
s: 27460786.0000
Epoch 207/400
s: 27273124.0000
Epoch 208/400
s: 27075898.0000
Epoch 209/400
s: 26943164.0000
Epoch 210/400
s: 26779368.0000
Epoch 211/400
s: 26680052.0000
Epoch 212/400
s: 26576720.0000
Epoch 213/400
s: 26451416.0000
Epoch 214/400
s: 26398282.0000
Epoch 215/400
s: 26286396.0000
Epoch 216/400
s: 26222506.0000
Epoch 217/400
s: 26154602.0000
Epoch 218/400
s: 26071912.0000
Epoch 219/400
s: 25971998.0000
Epoch 220/400
s: 25934498.0000
Epoch 221/400
s: 25862704.0000
Epoch 222/400
s: 25746908.0000
Epoch 223/400
s: 25678226.0000
Epoch 224/400
s: 25581384.0000
Epoch 225/400
s: 25512208.0000
Epoch 226/400
s: 25394866.0000
Epoch 227/400
s: 25283528.0000
Epoch 228/400
s: 25151326.0000
Epoch 229/400
```

```
s: 25035928.0000
Epoch 230/400
s: 24873640.0000
Epoch 231/400
s: 24742474.0000
Epoch 232/400
s: 24598374.0000
Epoch 233/400
s: 24433192.0000
Epoch 234/400
s: 24282426.0000
Epoch 235/400
s: 24164914.0000
Epoch 236/400
s: 24009708.0000
Epoch 237/400
s: 23870982.0000
Epoch 238/400
s: 23766318.0000
Epoch 239/400
s: 23648582.0000
Epoch 240/400
s: 23559410.0000
Epoch 241/400
s: 23489414.0000
Epoch 242/400
s: 23417486.0000
Epoch 243/400
s: 23371306.0000
Epoch 244/400
s: 23285160.0000
Epoch 245/400
s: 23228910.0000
Epoch 246/400
s: 23161776.0000
Epoch 247/400
s: 23107118.0000
Epoch 248/400
s: 23079056.0000
Epoch 249/400
s: 22996402.0000
Epoch 250/400
s: 22950212.0000
Epoch 251/400
s: 22894598.0000
Epoch 252/400
```

```
s: 22839268.0000
Epoch 253/400
s: 22780850.0000
Epoch 254/400
s: 22757458.0000
Epoch 255/400
s: 22673478.0000
Epoch 256/400
s: 22627148.0000
Epoch 257/400
s: 22583302.0000
Epoch 258/400
s: 22524072.0000
Epoch 259/400
s: 22506252.0000
Epoch 260/400
s: 22433468.0000
Epoch 261/400
s: 22409592.0000
Epoch 262/400
s: 22383046.0000
Epoch 263/400
s: 22310760.0000
Epoch 264/400
s: 22284574.0000
Epoch 265/400
s: 22236190.0000
Epoch 266/400
s: 22205382.0000
Epoch 267/400
s: 22191640.0000
Epoch 268/400
s: 22132906.0000
Epoch 269/400
s: 22096568.0000
Epoch 270/400
s: 22059444.0000
Epoch 271/400
s: 22032202.0000
Epoch 272/400
s: 22021722.0000
Epoch 273/400
s: 21959436.0000
Epoch 274/400
s: 21988040.0000
Epoch 275/400
```

```
s: 21894696.0000
Epoch 276/400
s: 21870532.0000
Epoch 277/400
s: 21842086.0000
Epoch 278/400
s: 21833332.0000
Epoch 279/400
s: 21796320.0000
Epoch 280/400
s: 21777220.0000
Epoch 281/400
s: 21733482.0000
Epoch 282/400
s: 21720682.0000
Epoch 283/400
s: 21682700.0000
Epoch 284/400
s: 21653042.0000
Epoch 285/400
s: 21638220.0000
Epoch 286/400
s: 21604638.0000
Epoch 287/400
s: 21582144.0000
Epoch 288/400
s: 21572888.0000
Epoch 289/400
s: 21537596.0000
Epoch 290/400
s: 21514622.0000
Epoch 291/400
s: 21492294.0000
Epoch 292/400
s: 21495308.0000
Epoch 293/400
s: 21454266.0000
Epoch 294/400
s: 21487388.0000
Epoch 295/400
s: 21422674.0000
Epoch 296/400
s: 21426532.0000
Epoch 297/400
s: 21385172.0000
Epoch 298/400
```

```
s: 21359130.0000
Epoch 299/400
s: 21339794.0000
Epoch 300/400
s: 21396072.0000
Epoch 301/400
s: 21325986.0000
Epoch 302/400
s: 21355522.0000
Epoch 303/400
s: 21322682.0000
Epoch 304/400
s: 21305434.0000
Epoch 305/400
s: 21236952.0000
Epoch 306/400
s: 21278836.0000
Epoch 307/400
s: 21256350.0000
Epoch 308/400
19/19 [========================] - 0s 4ms/step - loss: 21938194.0000 - val_los
s: 21214274.0000
Epoch 309/400
s: 21183250.0000
Epoch 310/400
19/19 [========================] - 0s 5ms/step - loss: 21871726.0000 - val_los
s: 21157584.0000
Epoch 311/400
s: 21139926.0000
Epoch 312/400
s: 21120048.0000
Epoch 313/400
s: 21100934.0000
Epoch 314/400
s: 21088162.0000
Epoch 315/400
s: 21085980.0000
Epoch 316/400
s: 21053954.0000
Epoch 317/400
s: 21063328.0000
Epoch 318/400
s: 21023210.0000
Epoch 319/400
s: 21030894.0000
Epoch 320/400
s: 20987920.0000
Epoch 321/400
```

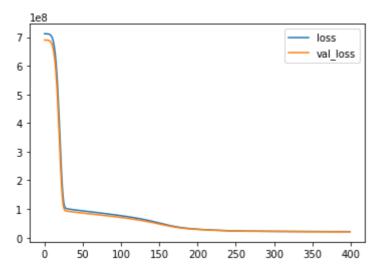
```
s: 20971926.0000
Epoch 322/400
s: 20957720.0000
Epoch 323/400
s: 20940466.0000
Epoch 324/400
s: 20924762.0000
Epoch 325/400
s: 20913682.0000
Epoch 326/400
s: 20901322.0000
Epoch 327/400
s: 20880818.0000
Epoch 328/400
s: 20891378.0000
Epoch 329/400
s: 20849050.0000
Epoch 330/400
s: 20834944.0000
Epoch 331/400
19/19 [========================] - 0s 4ms/step - loss: 21558092.0000 - val_los
s: 20859732.0000
Epoch 332/400
s: 20814264.0000
Epoch 333/400
19/19 [========================] - 0s 4ms/step - loss: 21540624.0000 - val_los
s: 20795186.0000
Epoch 334/400
s: 20771216.0000
Epoch 335/400
s: 20755938.0000
Epoch 336/400
s: 20746766.0000
Epoch 337/400
s: 20731376.0000
Epoch 338/400
s: 20717908.0000
Epoch 339/400
s: 20719834.0000
Epoch 340/400
s: 20694892.0000
Epoch 341/400
s: 20684720.0000
Epoch 342/400
s: 20670730.0000
Epoch 343/400
s: 20663662.0000
Epoch 344/400
```

```
s: 20643782.0000
Epoch 345/400
s: 20627154.0000
Epoch 346/400
s: 20636800.0000
Epoch 347/400
s: 20601062.0000
Epoch 348/400
s: 20594216.0000
Epoch 349/400
s: 20578138.0000
Epoch 350/400
s: 20568810.0000
Epoch 351/400
s: 20556080.0000
Epoch 352/400
s: 20553762.0000
Epoch 353/400
s: 20531988.0000
Epoch 354/400
19/19 [========================] - 0s 3ms/step - loss: 21278594.0000 - val_los
s: 20523964.0000
Epoch 355/400
s: 20510956.0000
Epoch 356/400
19/19 [========================] - 0s 3ms/step - loss: 21250412.0000 - val_los
s: 20497302.0000
Epoch 357/400
s: 20530732.0000
Epoch 358/400
s: 20496666.0000
Epoch 359/400
s: 20502304.0000
Epoch 360/400
s: 20459296.0000
Epoch 361/400
s: 20453264.0000
Epoch 362/400
s: 20439102.0000
Epoch 363/400
s: 20430568.0000
Epoch 364/400
s: 20486404.0000
Epoch 365/400
s: 20441200.0000
Epoch 366/400
s: 20459556.0000
Epoch 367/400
```

```
s: 20401734.0000
Epoch 368/400
s: 20386502.0000
Epoch 369/400
s: 20383160.0000
Epoch 370/400
s: 20384210.0000
Epoch 371/400
s: 20364870.0000
Epoch 372/400
s: 20361444.0000
Epoch 373/400
s: 20349998.0000
Epoch 374/400
s: 20342672.0000
Epoch 375/400
s: 20328526.0000
Epoch 376/400
s: 20321668.0000
Epoch 377/400
19/19 [========================] - 0s 3ms/step - loss: 21080436.0000 - val_los
s: 20332422.0000
Epoch 378/400
s: 20315202.0000
Epoch 379/400
19/19 [========================] - 0s 4ms/step - loss: 21046398.0000 - val_los
s: 20296608.0000
Epoch 380/400
s: 20287758.0000
Epoch 381/400
19/19 [=================== ] - 0s 4ms/step - loss: 21021114.0000 - val_los
s: 20283468.0000
Epoch 382/400
s: 20274836.0000
Epoch 383/400
s: 20272242.0000
Epoch 384/400
s: 20268626.0000
Epoch 385/400
s: 20250728.0000
Epoch 386/400
s: 20239332.0000
Epoch 387/400
19/19 [================== ] - 0s 3ms/step - loss: 20980614.0000 - val los
s: 20235608.0000
Epoch 388/400
s: 20243696.0000
Epoch 389/400
s: 20240398.0000
Epoch 390/400
```

```
s: 20227216.0000
    Epoch 391/400
    s: 20214380.0000
    Epoch 392/400
    s: 20217562.0000
    Epoch 393/400
    s: 20211964.0000
    Epoch 394/400
    s: 20194316.0000
    Epoch 395/400
    s: 20183826.0000
    Epoch 396/400
    s: 20175052.0000
    Epoch 397/400
    s: 20183070.0000
    Epoch 398/400
    s: 20168256.0000
    Epoch 399/400
    s: 20164704.0000
    Epoch 400/400
    s: 20152546.0000
Out[21]: <tensorflow.python.keras.callbacks.History at 0x17956e4edc0>
In [22]:
    # Loss değerlerinin minimize olma eğrisi
    loss_df = model.history.history
    loss_train = loss_df["loss"]
                   # type --> liste
    loss_train = np.array(loss_train) # train verisine göre loss
    loss_test = loss_df["val_loss"] # test verisine göre validasyon loss
    loss_test = np.array(loss_test)
    axis = range(0,400) # epoch --> 400
    plt.plot(axis,loss train, label="loss")
    plt.plot(axis,loss_test, label="val_loss")
    plt.legend()
```

Out[22]: <matplotlib.legend.Legend at 0x1795855e190>



```
In [23]: # Tahminler

tahminler = model.predict(x_test)
say1 = tahminler.shape[0]
tahminler = pd.Series(tahminler.reshape(say1,))

resultFrame = pd.DataFrame(y_test,columns=["Gerçek Fiyat"])
resultFrame["Tahmin"] = tahminler
resultFrame
```

Out[23]:		Gerçek Fiyat	Tahmin
	0	23780	20585.091797
	1	14991	14599.619141
	2	21498	22662.232422
	3	13000	14559.989258
	4	17000	19074.125000
	•••		
	3916	14990	17351.855469
	3917	17299	20213.093750
	3918	24810	22377.546875
	3919	20640	21893.986328
	3920	26995	19470.316406

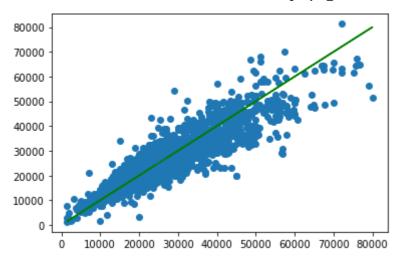
3921 rows × 2 columns

```
In [24]:
    plt.scatter(y_test,tahminler)
    plt.plot(y_test,y_test,color="green")
```

Out[24]: [<matplotlib.lines.Line2D at 0x17958663bb0>]

Out[26]: array([[64345.66]], dtype=float32)

In [ ]:



```
In [25]: # Hata orani değerlendirilmesi
    from sklearn.metrics import mean_absolute_error
    sapma = round(mean_absolute_error(resultFrame["Gerçek Fiyat"],resultFrame["Tahmin"])
    ort_fiyat = round(dataFrame["price"].mean())
    # yüzde hesabi
    # 24078 pound fiyatta 3170 pound sapiyorsa % yüzde kaç sapar?
    yuzde_sapma = (100 * sapma) / ort_fiyat
    dogruluk_orani = round(100 - yuzde_sapma)
    dogruluk_orani # --> %87

Out[25]: 87

In [26]: deneme = pd.Series([2019,1000,145,22.1,4.0]) # gerçek fiyat --> 75729
    deneme = scaler.transform(deneme.values.reshape(-1,5)) # 5 özelliği matrise çevir model.predict(deneme)
```