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

Out[2]:

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	HoursLease	Sa ur
0	10.2016	1.0	United Kingdom	88253.0	London (I)	1.0	Dry	3184.764	0.0	39856
1	10.2016	1.0	United Kingdom	88253.0	London (I)	2.0	Frozen	1582.941	0.0	8272
2	10.2016	1.0	United Kingdom	88253.0	London (I)	3.0	other	47.205	0.0	43840
3	10.2016	1.0	United Kingdom	88253.0	London (I)	4.0	Fish	1623.852	0.0	30942
4	10.2016	1.0	United Kingdom	88253.0	London (I)	5.0	Fruits & Vegetables	1759.173	0.0	16551
	•••					•••		•••		
7653	06.2017	9.0	Sweden	29650.0	Gothenburg	12.0	Checkout	6322.323	0.0	388653
7654	06.2017	9.0	Sweden	29650.0	Gothenburg	16.0	Customer Services	4270.479	0.0	24
7655	06.2017	9.0	Sweden	29650.0	Gothenburg	11.0	Delivery	0	0.0	
7656	06.2017	9.0	Sweden	29650.0	Gothenburg	17.0	others	2224.929	0.0	24
7657	06.2017	9.0	Sweden	29650.0	Gothenburg	18.0	all	39652.2	0.0	388653

7658 rows × 14 columns

In [3]: df.head()

Out[3]:

	MonthYear	Time index	Country	StoreID	City	Dept_ID	Dept. Name	HoursOwn	HoursLease	Sales units	Tu
0	10.2016	1.0	United Kingdom	88253.0	London (I)	1.0	Dry	3184.764	0.0	398560.0	122
1	10.2016	1.0	United Kingdom	88253.0	London (I)	2.0	Frozen	1582.941	0.0	82725.0	38
2	10.2016	1.0	United Kingdom	88253.0	London (I)	3.0	other	47.205	0.0	438400.0	65
3	10.2016	1.0	United Kingdom	88253.0	London (I)	4.0	Fish	1623.852	0.0	309425.0	49
4	10.2016	1.0	United Kingdom	88253.0	London (I)	5.0	Fruits & Vegetables	1759.173	0.0	165515.0	32
4 6											•

In [4]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7658 entries, 0 to 7657
Data columns (total 14 columns):

#	Column	Non-Null Count	Dtype
0	MonthYear	7658 non-null	object
1	Time index	7658 non-null	float64
2	Country	7658 non-null	object
3	StoreID	7658 non-null	float64
4	City	7658 non-null	object
5	Dept_ID	7658 non-null	float64
6	Dept. Name	7658 non-null	object
7	HoursOwn	7658 non-null	object
8	HoursLease	7658 non-null	float64
9	Sales units	7658 non-null	float64
10	Turnover	7658 non-null	float64
11	Customer	7658 non-null	float64
12	Area (m2)	7658 non-null	object
13	Opening hours	7658 non-null	object
	65		

dtypes: float64(7), object(7)
memory usage: 837.7+ KB

In [5]: import seaborn as sns

In [6]: df.describe()

Out[6]:

	Time index	StoreID	Dept_ID	HoursLease	Sales units	Turnover	Customer
count	7658.000000	7658.000000	7658.000000	7658.000000	7.658000e+03	7.658000e+03	7658.0
mean	4.994777	61930.456124	9.460695	22.013058	1.075346e+06	3.717505e+06	0.0
std	2.585859	29975.929873	5.343407	133.231761	1.727560e+06	6.001448e+06	0.0
min	0.000000	0.000000	0.000000	0.000000	0.000000e+00	0.000000e+00	0.0
25%	3.000000	29650.000000	5.000000	0.000000	5.441375e+04	2.720558e+05	0.0
50%	5.000000	73949.000000	9.000000	0.000000	2.927625e+05	9.300810e+05	0.0
75%	7.000000	87703.000000	14.000000	0.000000	9.154812e+05	3.251488e+06	0.0
max	9.000000	98422.000000	18.000000	3984.000000	1.124296e+07	4.271739e+07	0.0

In []:

In [7]: sns.pairplot(df)

Out[7]: <seaborn.axisgrid.PairGrid at 0x1921cc61be0>

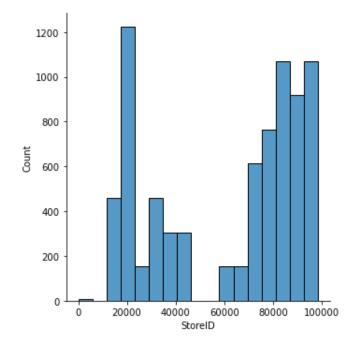


```
In [8]: df1=df.drop(['Country'],axis=1)
    df1
    df1=df1.drop(df1.index[1537:])
    df1.isna().sum()
```

```
Out[8]: MonthYear
                          0
        Time index
                          0
                          0
        StoreID
        City
                          0
                          0
        Dept_ID
        Dept. Name
                          0
        HoursOwn
                          0
        HoursLease
                          0
        Sales units
        Turnover
                          0
        Customer
                          0
        Area (m2)
                          0
        Opening hours
        dtype: int64
```

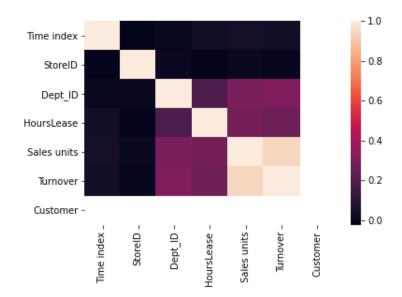
```
In [9]: sns.displot(df['StoreID'])
```

Out[9]: <seaborn.axisgrid.FacetGrid at 0x19219e54610>



```
In [10]: sns.heatmap(df1.corr())
```

Out[10]: <AxesSubplot:>



In [11]: from sklearn.model_selection import train_test_split
 from sklearn.linear_model import LinearRegression

In [12]: df1.isna().sum()

Out[12]: MonthYear 0 Time index 0 StoreID 0 City 0 Dept_ID 0 Dept. Name 0 HoursOwn 0 0 HoursLease Sales units 0 Turnover 0 Customer 0 0 Area (m2) Opening hours dtype: int64

In [13]: y=df1['Turnover']
x=df1.drop(['Turnover','MonthYear','City','Opening hours','Dept. Name','Customer','Turnover', train, x_test, y_train, y_test=train_test_split(x,y,test_size=0.3)
print(x_train)

	Time index	StoreID	Dept_ID	HoursOwn	HoursLease	Sales units
1147	2.0	85696.0	7.0	5680.335	84.0	240170.0
572	1.0	12227.0	15.0	3974.661	0.0	165.0
1515	2.0	79785.0	2.0	2278.428	0.0	92455.0
1460	2.0	34378.0	11.0	0	0.0	10.0
1217	2.0	19000.0	9.0	1595.529	0.0	41060.0
	• • •					• • •
662	1.0	98422.0	18.0	46276.635	0.0	3508675.0
783	1.0	73762.0	2.0	2426.337	0.0	182250.0
1246	2.0	20166.0	5.0	1992.051	0.0	243510.0
1242	2.0	20166.0	1.0	3449.112	0.0	557495.0
542	1.0	78325.0	17.0	2193.459	0.0	155.0

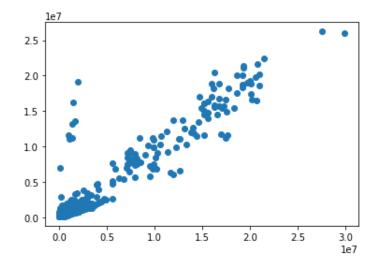
[1075 rows x 6 columns]

```
In [14]: model=LinearRegression()
    model.fit(x_train,y_train)
    model.intercept_
```

Out[14]: 71487.15112321172

```
In [15]: prediction=model.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[15]: <matplotlib.collections.PathCollection at 0x1922262a670>



```
In [16]: model.score(x_test,y_test)
```

Out[16]: 0.8844082866440194

```
In [17]: from sklearn.linear_model import Ridge,Lasso
```

```
In [18]:
         rr=Ridge(alpha=10)
         rr.fit(x_train,y_train)
Out[18]: Ridge(alpha=10)
In [19]: rr.score(x_test,y_test)
Out[19]: 0.8844074382998153
In [20]: la =Lasso(alpha=10)
         la.fit(x_train,y_train)
Out[20]: Lasso(alpha=10)
In [21]: la.score(x_test,y_test)
Out[21]: 0.884408249300056
In [22]: from sklearn.linear model import ElasticNet
         en=ElasticNet()
         en.fit(x_train,y_train)
Out[22]: ElasticNet()
In [23]:
         print(en.coef_)
         [-8.49670897e+03 -2.83657677e+00 2.80818729e+04 2.60727171e+01
           3.91533921e+01 3.07359204e+00]
In [24]:
         print(en.intercept_)
         51211.900752046145
In [25]:
         print(en.predict(x_test))
          12081313.10615316
                               318344.55719734
                                                 161808.63620064 20386487.79747214
           1104261.62469585
                             1985757.29088112
                                                1515331.45219829
                                                                   154903.21553394
           1250542.62909192
                               546798.39424928
                                                 866228.38947379
                                                                  1267149.35330232
           1049485.95428433 17454798.87082483 18277896.92037161
                                                                   526152.89263141
            322212.53734578
                               298812.19160697
                                                1101221.19750973
                                                                   245088.25842468
            341348.9338572
                             1142780.75439107
                                                 335986.78491951
                                                                   487380.15303624
           2018371.9873523
                               532543.62839248
                                                1670797.07024807
                                                                   314843.80322381
           1946713.52384728
                               526580.01513346
                                                4691939.55389973
                                                                   407220.35528643
            527200.7612785
                              7427458.75733612
                                                1590263.56950927
                                                                   736289.56119032
           1815862.82154166 18885560.24321736
                                                 383570.58251211
                                                                   529899.46255776
            415955.72426126
                               314857.84317711
                                                 360335.27297
                                                                  1483195.17038797
           2833594.396895
                             1772604.38529096
                                                 269436.8816465 15378673.112774
           8980402.98260365
                              422353.62165203
                                                 120944.20925279
                                                                   142384.21800239
            171731.73735571 7451817.89593718
                                                 466892.72012039
                                                                   336644.33983013
           6034595.82323731 11392712.30266854 16354156.15313049
                                                                  1533643.13924037
                                                                   277696.84394422
            870754.86557243 5316510.32895393
                                                8452937.38126709
           1007142.9373982
                               292356.86817356
                                                 395279.80168817
                                                                  1120197.39862718
            937535.45049221 1330982.36569508
                                                 246103.72548528
                                                                  7537691.05049852
           3879704.8851028
                               400243.89950139]
```