Problem statement

predicting the house price in USA. To create a model to help him estimate of what the house would sell for.

To display top 10 rows

In [3]: 1 df.head(10)

Out[3]:

	Sr. No.	Train Name	Train Number	Originating City	Originating Station	Terminal City	Terminal Station	Operator	No. of Cars	Frequency	Distance
0	1	New Delhi - Varanasi Vande Bharat Express	22435/22436	Delhi	New Delhi	Varanasi	Varanasi Junction	NR	16	Except Thursdays	759 km (472 mi)
1	2	New Delhi - Shri Mata Vaishno Devi Katra Vande	22439/22440	Delhi	New Delhi	Katra	Shri Mata Vaishno Devi Katra	NR	16	Except Tuesdays	655 km (407 mi)
2	3	Mumbai Central - Gandhinagar Capital Vande Bha	20901/20902	Mumbai	Mumbai Central	Gandhinagar	Gandhinagar Capital	WR	16	Except Wednesdays	522 km (324 mi)
3	4	New Delhi - Amb Andaura Vande Bharat Express	22447/22448	Delhi	New Delhi	Andaura	Amb Andaura	NR	16	Except Fridays	412 km (256 mi)
4	5	MGR Chennai Central - Mysuru Vande Bharat Express	20607/20608	Chennai	Chennai Central	Mysuru	Mysore Junction	SR	16	Except Wednesdays	496 km (308 mi)
5	6	Bilaspur - Nagpur Vande Bharat Express	20825/20826	Bilaspur, Chhattisgarh	Bilaspur Junction	Nagpur	Nagpur Junction	SECR	8	Except Saturdays	412 km (256 mi)
6	7	Howrah - New Jalpaiguri Vande Bharat Express	22301/22302	Kolkata	Howrah Junction	Siliguri	New Jalpaiguri Junction	ER	16	Except Wednesdays	565 km (351 mi)
7	8	Visakhapatnam - Secunderabad Vande Bharat Express	20833/20834	Visakhapatnam	Visakhapatnam Junction	Hyderabad	Secunderabad Junction	ECoR	16	Except Sundays	698 km (434 mi)
8	9	Mumbai CSMT - Solapur Vande Bharat Express	22225/22226	Mumbai	Chhatrapati Shivaji Terminus	Solapur	Solapur	CR	16	Except Wednesdays (22225), Except Thursdays (452 km (281 mi)

	Sr. No.	Train Name	Train Number	Originating City	Originating Station	Terminal City	Terminal Station	Operator	No. of Cars	Frequency	Distance	Т
9	10	Mumbai CSMT - Sainagar Shirdi Vande Bharat Exp	22223/22224	Mumbai	Chhatrapati Shivaji Terminus	Shirdi	Sainagar Shirdi	CR	16	Except Tuesdays	339 km (211 mi)	

Data Cleaning And Pre-Processing

```
In [4]: 1 df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26 entries, 0 to 25
Data columns (total 16 columns):

#	Column	Non-Null Count	Dtype
0	Sr. No.	26 non-null	int64
1	Train Name	26 non-null	object
2	Train Number	26 non-null	object
3	Originating City	26 non-null	object
4	Originating Station	26 non-null	object
5	Terminal City	26 non-null	object
6	Terminal Station	26 non-null	object
7	Operator	26 non-null	object
8	No. of Cars	26 non-null	int64
9	Frequency	26 non-null	object
10	Distance	26 non-null	object
11	Travel Time	26 non-null	object
12	Speed	26 non-null	object
13	Average Speed	26 non-null	object
14	Inauguration	26 non-null	object
15	Average occupancy	26 non-null	object

dtypes: int64(2), object(14)

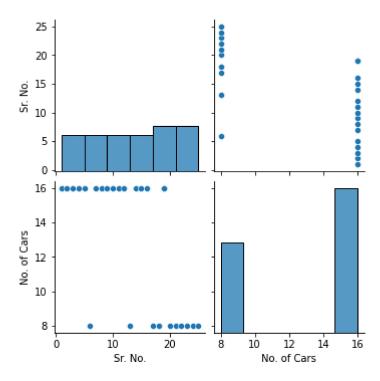
memory usage: 3.4+ KB

```
1 # Display the statistical summary
In [5]:
          2 df.describe()
Out[5]:
                  Sr. No. No. of Cars
         count 26,000000
                          26.000000
         mean 13.230769
                          12.923077
                7.306478
                           3.969112
           std
                1.000000
           min
                           8.000000
          25%
                7.250000
                           8.000000
           50% 13.500000
                          16.000000
          75% 19.000000
                          16.000000
          max 25.000000
                          16.000000
In [6]:
          1 # To display the col headings
          2 df.columns
Out[6]: Index(['Sr. No.', 'Train Name', 'Train Number', 'Originating City',
                'Originating Station', 'Terminal City', 'Terminal Station', 'Operator',
                'No. of Cars', 'Frequency', 'Distance', 'Travel Time', 'Speed',
                'Average Speed', 'Inauguration', 'Average occupancy'],
               dtype='object')
In [7]:
             cols=df.dropna(axis=1)
In [8]:
          1 cols.columns
Out[8]: Index(['Sr. No.', 'Train Name', 'Train Number', 'Originating City',
                'Originating Station', 'Terminal City', 'Terminal Station', 'Operator',
                'No. of Cars', 'Frequency', 'Distance', 'Travel Time', 'Speed',
                'Average Speed', 'Inauguration', 'Average occupancy'],
               dtype='object')
```

EDA and Visualization

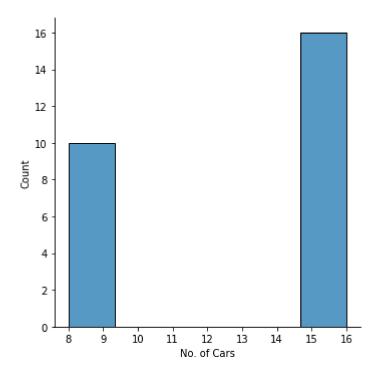
In [9]: 1 sns.pairplot(cols)

Out[9]: <seaborn.axisgrid.PairGrid at 0x1e963a001f0>



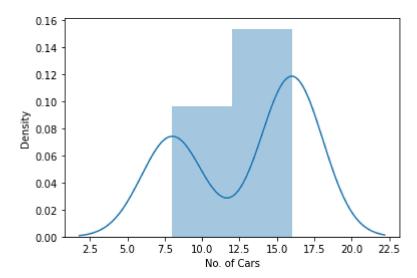
```
In [11]: | 1 | sns.displot(df['No. of Cars'])
```

Out[11]: <seaborn.axisgrid.FacetGrid at 0x1e9629f4790>



C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a dep recated 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)

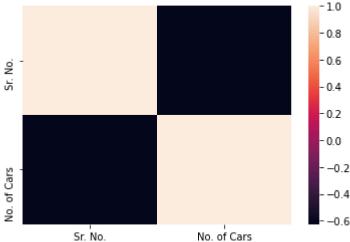
Out[12]: <AxesSubplot:xlabel='No. of Cars', ylabel='Density'>



Out[13]:

	Sr. No.	No. of Cars
0	1	16
1	2	16
2	3	16
3	4	16
4	5	16
5	6	8
6	7	16
7	8	16
8	9	16
9	10	16
10	11	16
11	12	16
12	13	8
13	14	16
14	15	16
15	16	16
16	17	8
17	18	8
18	19	16
19	19	16
20	20	8
21	21	8
22	22	8
23	23	8
24	24	8
25	25	8

```
In [14]:    1    sns.heatmap(df1.corr())
Out[14]:    <AxesSubplot:>
```



To train the model - MODEL BUILD

Going to train linear regression model; We split our data into 2 variables x and y where x is independent var(input) and y is dependent on x(output), we could ignore address col as it is not required for our model

To split the dataset into test data

```
In [18]:
           1 from sklearn.linear_model import LinearRegression
           3 lr=LinearRegression()
           4 lr.fit(x_train,y_train)
Out[18]: LinearRegression()
           1 print(lr.intercept_)
In [19]:
         [3.55271368e-15]
In [20]:
           1 print(lr.score(x_test,y_test))
         1.0
In [21]:
           1 coeff=pd.DataFrame(lr.coef_)
           2 coeff
Out[21]:
          0 -2.607996e-16 1.0
```

```
In [22]:
           1 pred = lr.predict(x_test)
           plt.scatter(y_test,pred)
Out[22]: <matplotlib.collections.PathCollection at 0x1e965f3c100>
          16
          15
          14
          13
          12
          11
          10
           9
                        10
                             11
                                  12
                                       13
                                                 15
                   9
                                            14
                                                      16
In [23]:
           1 from sklearn.linear_model import Ridge,Lasso
In [24]:
           1 rr=Ridge(alpha=10)
           2 rr.fit(x_train,y_train)
Out[24]: Ridge(alpha=10)
In [25]:
           1 rr.score(x_test,y_test)
Out[25]: 0.9995007346948294
In [26]:
           1 la=Lasso(alpha=10)
           2 la.fit(x_train,y_train)
Out[26]: Lasso(alpha=10)
           1 la.score(x_test,y_test)
In [27]:
Out[27]: 0.567380671276775
```

ELASTIC NET

```
In [28]:
           1 from sklearn.linear_model import ElasticNet
           2 en=ElasticNet()
           3 en.fit(x_train,y_train)
Out[28]: ElasticNet()
In [29]:
           1 print(en.coef_)
         [-0.00738509 0.93085556]
In [30]:
           1 print(en.intercept_)
         [0.99007318]
           1 prediction=en.predict(x_test)
In [31]:
           2 prediction
Out[31]: array([15.84683669, 15.85422179, 15.86899197, 8.28183071, 15.78037086,
                15.81729632, 8.25229034, 8.26706053])
In [32]:
           1 print(en.score(x test,y test))
         0.997017572713016
```

EVALUATION METRICS

```
In [33]: 1 from sklearn import metrics
In [34]: 1 print("Mean Absolute Error:",metrics.mean_absolute_error(y_test,prediction))
```

Mean Absolute Error: 0.20418299315749788

MODEL SAVING