## **Problem statement**

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

```
In [1]: 1 import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
4 import seaborn as sns
In [2]: 1 df=pd.read_csv("Horse Racing Results")
```

# To display top 10 rows

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

Out[3]:

	Dato	Track	Race Number	Distance	Surface	Prize money	Starting position	Jockey	Jockey weight	Country	 TrainerName	Race time	Path	Final place	F
0	03.09.2017	Sha Tin	10	1400	Gress	1310000	6	K C Leung	52	Sverige	 CH Yip	83,38	2	9	_
1	16.09.2017	Sha Tin	10	1400	Gress	1310000	14	C Y Ho	52	Sverige	 CH Yip	81,56	3	4	
2	14.10.2017	Sha Tin	10	1400	Gress	1310000	8	C Y Ho	52	Sverige	 CH Yip	82,36	1	6	
3	11.11.2017	Sha Tin	9	1600	Gress	1310000	13	Brett Prebb <b>l</b> e	54	Sverige	 CH Yip	96,53	0	8	
4	26.11.2017	Sha Tin	9	1600	Gress	1310000	9	C Y Ho	52	Sverige	 CH Yip	94,17	0	3	
5	10.12.2017	Sha Tin	1	1800	Gress	1310000	4	C Y Ho	52	Sverige	 CH Yip	107,92	2	3	
6	01.01.2018	Sha Tin	9	1800	Gress	1310000	9	C Schofield	54	Sverige	 CH Yip	108,63	5	1	
7	04.02.2018	Sha Tin	5	1800	Gress	1310000	6	Joao Moreira	57	Sverige	 CH Yip	108,19	0	4	
8	03.03.2018	Sha Tin	8	1800	Gress	1310000	3	C Y Ho	56	Sverige	 CH Yip	107,65	1	3	
9	11.03.2018	Sha Tin	10	1600	Gress	1310000	8	C Y Ho	57	Sverige	 CH Yip	94,46	1	6	
10	10 rows × 21 columns														

# **Data Cleaning And Pre-Processing**

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

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27008 entries, 0 to 27007
Data columns (total 21 columns):

	COTAMID (COCAT ET	201411115/	
#	Column	Non-Null Count	Dtype
0	Dato	27008 non-null	object
1	Track	27008 non-null	object
2	Race Number	27008 non-null	int64
3	Distance	27008 non-null	int64
4	Surface	27008 non-null	object
5	Prize money	27008 non-null	int64
6	Starting position	27008 non-null	int64
7	Jockey	27008 non-null	object
8	Jockey weight	27008 non-null	int64
9	Country	27008 non-null	object
10	Horse age	27008 non-null	int64
11	TrainerName	27008 non-null	object
12	Race time	27008 non-null	object
13	Path	27008 non-null	int64
14	Final place	27008 non-null	int64
15	FGrating	27008 non-null	int64
16	Odds	27008 non-null	object
17	RaceType	27008 non-null	object
18	HorseId	27008 non-null	int64
19	JockeyId	27008 non-null	int64
20	TrainerID	27008 non-null	int64
dtyne	$as \cdot int64(12)$ ohie	ct(9)	

dtypes: int64(12), object(9)

memory usage: 4.3+ MB

```
In [5]:
           1 # Display the statistical summary
           2 df.describe()
Out[5]:
                        Race
                                                            Starting
                                                                          Jockey
                                  Distance
                                            Prize money
                                                                                     Horse age
                                                                                                      Path
                                                                                                              Final place
                                                                                                                             FGrating
                     Number
                                                            position
                                                                          weight
          count 27008.000000
                              27008.000000 2.700800e+04 27008.000000 27008.000000 27008.000000 27008.000000 27008.000000
                                                                                                                        27008.000000
                    5.268624
                               1401.666173 1.479445e+06
                                                            6.741447
                                                                        55.867373
                                                                                      5.246408
                                                                                                   1.678021
                                                                                                                6.685834
                                                                                                                           113.428318
          mean
                    2.780088
                               276.065045 2.162109e+06
                                                            3.691071
                                                                         2.737006
                                                                                      1.519880
                                                                                                   1.631784
                                                                                                                3.664551
                                                                                                                            13.314949
            std
                    1.000000
                               1000.000000 6.600000e+05
                                                                                                                1.000000
                                                            1.000000
                                                                        47.000000
                                                                                      2.000000
                                                                                                   0.000000
                                                                                                                            -5.000000
            min
           25%
                    3.000000
                               1200.000000 9.200000e+05
                                                                        54.000000
                                                            4.000000
                                                                                      4.000000
                                                                                                   0.000000
                                                                                                                4.000000
                                                                                                                           106.000000
            50%
                    5.000000
                               1400.000000 9.670000e+05
                                                           7.000000
                                                                        56.000000
                                                                                      5.000000
                                                                                                   1.000000
                                                                                                                7.000000
                                                                                                                           114.000000
           75%
                    8.000000
                               1650.000000 1.450000e+06
                                                           10.000000
                                                                        58.000000
                                                                                                   3.000000
                                                                                                               10.000000
                                                                                                                           122.000000
                                                                                      6.000000
                    11.000000
                              2400.000000 2.800000e+07
                                                           14.000000
                                                                        63.000000
                                                                                     12.000000
                                                                                                  11.000000
                                                                                                               14.000000
                                                                                                                           157.000000
           max
In [6]:
           1 # To display the col headings
           2 df.columns
Out[6]: Index(['Dato', 'Track', 'Race Number', 'Distance', 'Surface', 'Prize money',
                 'Starting position', 'Jockey', 'Jockey weight', 'Country', 'Horse age',
                 'TrainerName', 'Race time', 'Path', 'Final place', 'FGrating', 'Odds',
                 'RaceType', 'HorseId', 'JockeyId', 'TrainerID'],
                dtype='object')
In [7]:
              cols=df.dropna(axis=1)
In [8]:
              cols.columns
Out[8]: Index(['Dato', 'Track', 'Race Number', 'Distance', 'Surface', 'Prize money',
                  'Starting position', 'Jockey', 'Jockey weight', 'Country', 'Horse age',
```

'TrainerName', 'Race time', 'Path', 'Final place', 'FGrating', 'Odds',

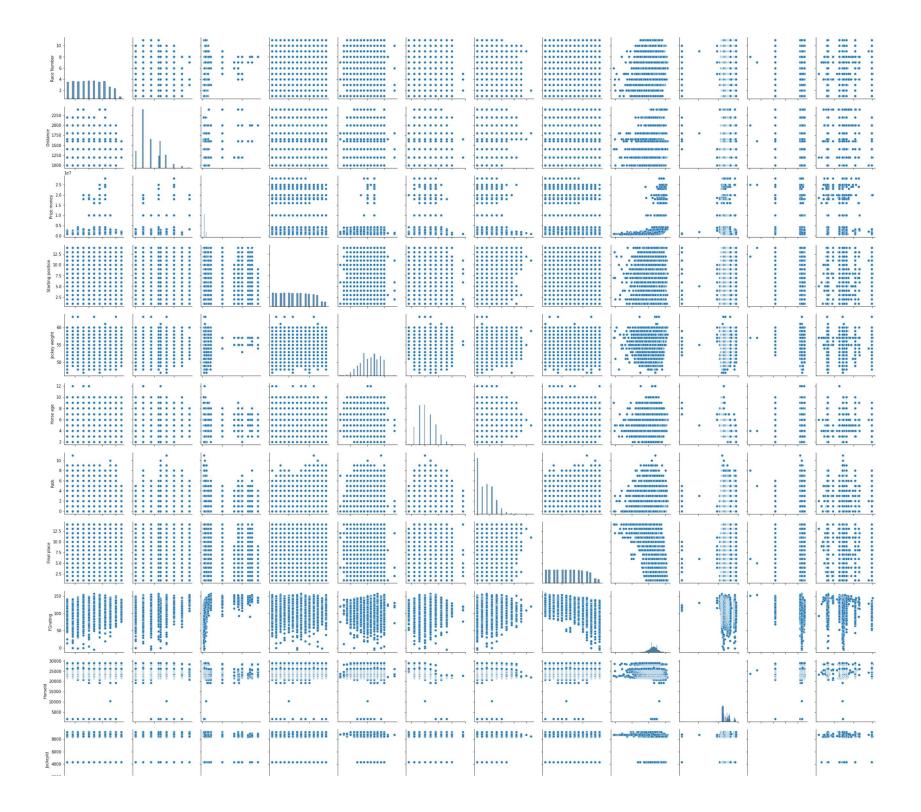
'RaceType', 'HorseId', 'JockeyId', 'TrainerID'],

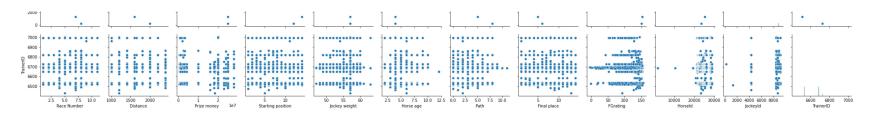
dtype='object')

# **EDA** and Visualization

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

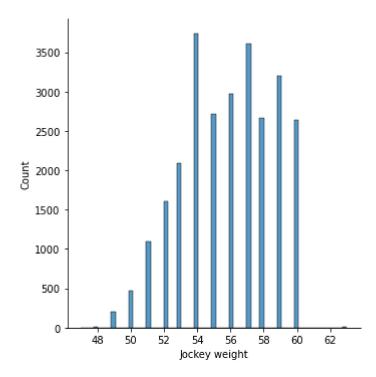
Out[9]: <seaborn.axisgrid.PairGrid at 0x1b6182f23d0>





In [10]: 1 sns.displot(df['Jockey weight'])

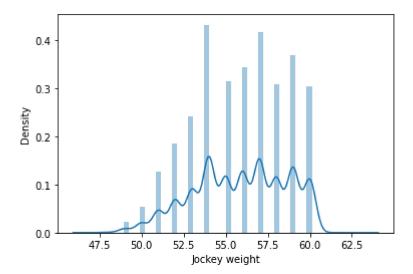
Out[10]: <seaborn.axisgrid.FacetGrid at 0x1b62e14eee0>



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[11]: <AxesSubplot:xlabel='Jockey weight', ylabel='Density'>



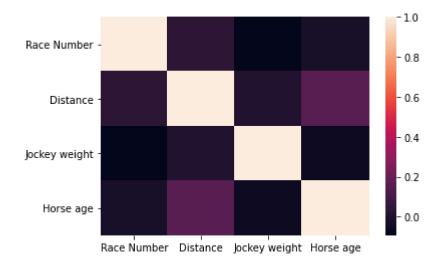
### Out[12]:

	Race Number	Distance	Jockey weight	Horse age
0	10	1400	52	7
1	10	1400	52	7
2	10	1400	52	7
3	9	1600	54	7
4	9	1600	52	7
27003	11	1200	59	3
27004	2	1200	57	3
27005	4	1200	57	3
27006	5	1200	57	3
27007	11	1200	55	4

27008 rows × 4 columns

```
In [13]: 1 sns.heatmap(df1.corr())
```

#### Out[13]: <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 [16]:
           1 x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.3)
In [17]:
           1 from sklearn.linear_model import LinearRegression
           3 lr=LinearRegression()
           4 lr.fit(x_train,y_train)
Out[17]: LinearRegression()
In [18]:
           1 print(lr.intercept_)
         [-6.82121026e-13]
In [19]:
           1 print(lr.score(x_test,y_test))
         1.0
In [20]:
           1 coeff=pd.DataFrame(lr.coef_)
           2 coeff
Out[20]:
                                    2
                      0
                                               3
```

**0** -1.293701e-15 1.0 8.004529e-17 7.520177e-16

```
In [21]:
           1 pred = lr.predict(x_test)
           plt.scatter(y_test,pred)
Out[21]: <matplotlib.collections.PathCollection at 0x1b62ffecd90>
           2400
           2200
           2000
          1800
          1600
          1400
          1200
          1000
                                      1800
                                            2000
               1000
                     1200
                          1400
                                1600
                                                  2200
                                                        2400
           1 from sklearn.linear_model import Ridge,Lasso
In [22]:
In [23]:
             rr=Ridge(alpha=10)
             rr.fit(x_train,y_train)
Out[23]: Ridge(alpha=10)
In [24]:
           1 rr.score(x_test,y_test)
Out[24]: 1.0
In [25]:
           1 la=Lasso(alpha=10)
             la.fit(x_train,y_train)
Out[25]: Lasso(alpha=10)
           1 la.score(x_test,y_test)
In [26]:
Out[26]: 0.999999831678777
```

### Elastic net

```
In [27]:
           1 from sklearn.linear_model import ElasticNet
           2 en=ElasticNet()
           3 en.fit(x_train,y_train)
Out[27]: ElasticNet()
In [28]:
           1 print(en.coef_)
         [0.
                     0.99998703 0.
                                           0.
In [29]:
           1 print(en.intercept_)
         [0.01818225]
           1 prediction=en.predict(x_test)
In [30]:
           2 prediction
Out[30]: array([1200.00261376, 1649.99677557, 1200.00261376, ..., 1649.99677557,
                1400.00001901, 1200.00261376])
In [31]:
           1 print(en.score(x test,y test))
         0.99999999831681
```

## **EVALUATION METRICS**

Mean Absolute Error: 0.002922189737464215

Root Mean Squared Error: 0.0035335623102073703