BOAT PRICE PREDICTION

This project focuses on predicting boat prices using various machine learning algorithms. The dataset was sourced from Kaggle and involves multiple steps, including data extraction, transformation, loading (ETL), cleaning, exploratory data analysis (EDA), and model building. The primary objective is to develop and evaluate regression models to accurately predict boat prices based on various features.

1.0 IMPORTING THE LIBRARIES

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
import cufflinks as cf
from plotly import __version__
from plotly.offline import download_plotlyjs, init_notebook_mode,plot, iplot

%matplotlib inline
```

```
C:\ProgramData\Anaconda3\lib\site-packages\scipy\__init__.py:146: UserWarning: A NumPy version >=1.16.5 and <1.23.0 is required for
  warnings.warn(f"A NumPy version >={np_minversion} and <{np_maxversion}"
```

```
# For Notebooks connections
init_notebook_mode(connected=True)
```

```
# For offline use
#cf.go_offline()
```

2.0 DATA EXTRACTION,TRANSFORM AND LOAD (ETL) AND EXPLORATORY

2.1 LOAD, TRANSFORM THE DATASET

- Data extracted manually form Kaggle
- Transform and Load by Pandas(row and columns)
- The url (https://www.kaggle.com/datasets/mexwell/boat-price-prediction/data?select=Boats_No_Price_dataset.csv)

```
df = pd.read_csv('Boats_Cleaned_dataset.csv')
df.head()
```

	Unnamed: 0	id	type	boatClass	make	model	year	condition	length_
0	1	7252689	power	power-center	Aquasport	210 CC	1992	used	2
1	3	7228300	power	power-sportcruiser	Formula	400 Super Sport	2018	used	4
2	5	7271336	power	power-deck	Bayliner	Element 180	2020	new	1
3	6	7222952	power	power-expresscruiser	Regal	32 Express	2015	used	3
4	8	6824832	power	power-aft	Carver	440 Aft Cabin Motor Yacht	1994	used	4

5 rows × 26 columns

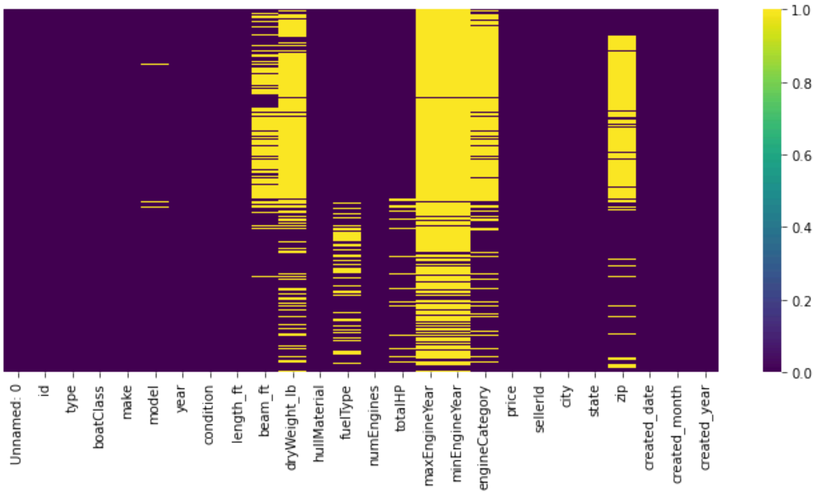
2.2 DATA EXPLORATORY

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18903 entries, 0 to 18902
Data columns (total 26 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unnamed: 0      18903 non-null  int64
 1   id              18903 non-null  int64
 2   type            18903 non-null  object
 3   boatClass       18903 non-null  object
 4   make            18903 non-null  object
 5   model           18868 non-null  object
 6   year            18903 non-null  int64
 7   condition       18903 non-null  object
 8   length_ft       18903 non-null  float64
 9   beam_ft         12399 non-null  float64
 10  dryWeight_lb    7094 non-null   float64
 11  hullMaterial    18903 non-null  object
 12  fuelType        15951 non-null  object
 13  numEngines      18903 non-null  int64
 14  totalHP         18055 non-null  float64
 15  maxEngineYear   2205 non-null   float64
 16  minEngineYear   2174 non-null   float64
 17  engineCategory  8410 non-null   object
 18  price           18903 non-null  float64
 19  sellerId        18903 non-null  int64
 20  city            18847 non-null  object
 21  state           18903 non-null  object
 22  zip             10215 non-null  object
 23  created_date    18903 non-null  object
 24  created_month   18903 non-null  int64
 25  created_year    18903 non-null  int64
dtypes: float64(7), int64(7), object(12)
memory usage: 3.7+ MB
```

```
plt.figure(figsize=(12,5))
sns.heatmap(df.isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

```
<AxesSubplot:>
```




```
# CHECK ALL COLUMN
df.keys()
```

```
Index(['Unnamed: 0', 'id', 'type', 'boatClass', 'make', 'model', 'year',
       'condition', 'length_ft', 'beam_ft', 'dryWeight_lb', 'hullMaterial',
       'fuelType', 'numEngines', 'totalHP', 'maxEngineYear', 'minEngineYear',
       'engineCategory', 'price', 'sellerId', 'city', 'state', 'zip',
       'created_date', 'created_month', 'created_year'],
      dtype='object')
```

3.0 DATA CLEANING AND PROCESSING

>> 3.1 DATA CLEANING

- DROP `'Unnamed: 0', 'id', 'created_date', 'created_month' 'sellerId', 'year'` AS IS OF NO USE

```
df.drop(['Unnamed: 0', 'id', 'created_date','created_month'], axis=1, inplace=True)
#df.drop(['Unnamed: 0', 'id', 'created_date','created_month', 'year', 'sellerId'], axis=1, inplace=True)

df.head()
```

	type	boatClass	make	model	year	condition	length_ft	beam_ft	dryWei
0	power	power-center	Aquasport	210 CC	1992	used	21.0	8.50	
1	power	power-sportcruiser	Formula	400 Super Sport	2018	used	40.0	11.00	
2	power	power-deck	Bayliner	Element 180	2020	new	18.0	7.42	
3	power	power-expresscruiser	Regal	32 Express	2015	used	32.0	10.33	
4	power	power-aft	Carver	440 Aft Cabin Motor Yacht	1994	used	44.0	15.00	

5 rows × 22 columns

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18903 entries, 0 to 18902
Data columns (total 22 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   type            18903 non-null  object 
 1   boatClass       18903 non-null  object 
 2   make            18903 non-null  object 
 3   model           18868 non-null  object 
 4   year            18903 non-null  int64  
 5   condition       18903 non-null  object 
 6   length_ft       18903 non-null  float64
 7   beam_ft         12399 non-null  float64
 8   dryWeight_lb    7094 non-null   float64
 9   hullMaterial    18903 non-null  object 
 10  fuelType        15951 non-null  object 
 11  numEngines      18903 non-null  int64  
 12  totalHP         18055 non-null  float64
 13  maxEngineYear   2205 non-null   float64
 14  minEngineYear   2174 non-null   float64
 15  engineCategory  8410 non-null   object 
 16  price           18903 non-null  float64
 17  sellerId        18903 non-null  int64  
 18  city            18847 non-null  object 
 19  state           18903 non-null  object 
 20  zip             10215 non-null  object 
 21  created_year    18903 non-null  int64  
dtypes: float64(7), int64(4), object(11)
memory usage: 3.2+ MB
```

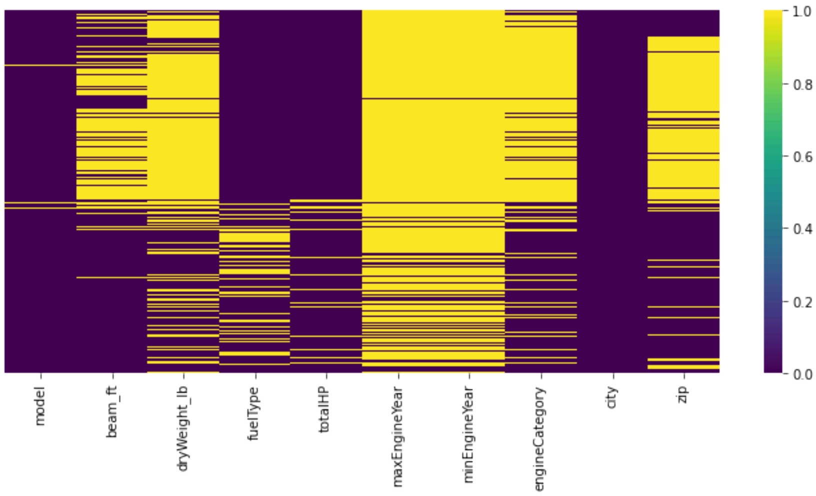
Display all Column with `null` value

```
cols_with_null = []
for col in df.keys():
    if df[col].isnull().any():
        cols_with_null.append(col)

df[cols_with_null]
```

	model	beam_ft	dryWeight_lb	fuelType	totalHP	maxEngineYear	minEngineYear
0	210 CC	8.50	3000.0	gasoline	150.0	NaN	NaN
1	400 Super Sport	11.00	16100.0	diesel	800.0	2018.0	2018.0
2	Element 180	7.42	2000.0	gasoline	75.0	2019.0	2019.0
3	32 Express	10.33	12650.0	gasoline	600.0	NaN	NaN
4	440 Aft Cabin Motor Yacht	15.00	32000.0	diesel	700.0	1994.0	1994.0
...	...	...	...	...	...	...	...
18898	250 Play	8.50	NaN	gasoline	NaN	NaN	NaN

```
plt.figure(figsize=(12,5))
sns.heatmap(df[cols_with_null].isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

<AxesSubplot:>



>> 3.2 ADVANCE DATA CLEANING

- `FOR OBJECT DATA TYPE`
    - DROP COLUMN WITH ATMOST 100 Unique Value
    - IF MISSING VALUE IS LESS THAN 3000, REMOVE THE MISSING VALUE ELSE DROP THE COLUMN
- `FOR NUMERIC DATA TYPE`
    - IF MISSING VALUE IS UP TO 1000 IN A NUMERIC TYPE COLUMN, DROP THE COLUMN
    - REMOVE ROW WITH MISSING VALUE FOR NUMERIC TYPE

>>>>3.2.1 FOR OBJECT DATA TYPE

>>>>>> 3.2.1.1 `DROP COLUMN WITH ATMOST 100 Unique Value`

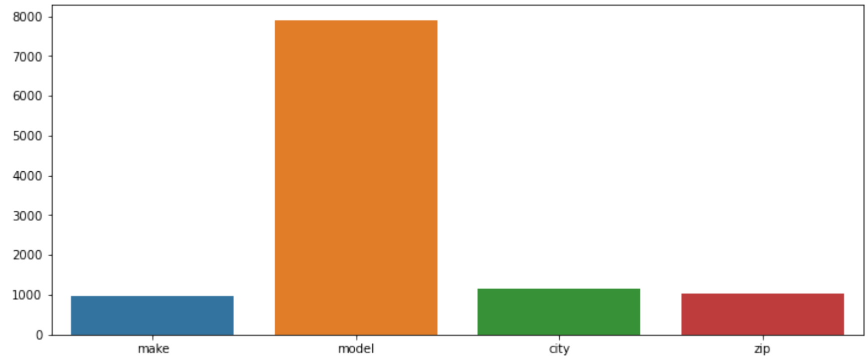
```
# CHECK FOR COLUMN OBJECT DT
df_to_drop_col_objType = []
print()
print('+ DROP COLUMN WITH 99 || > unique Value: i.e')
for col in df:
    if df[col].dtypes == 'object' and len(df[col].unique()) >99:
        df_to_drop_col_objType.append(col)

for col in df_to_drop_col_objType:
    print(col, end=' --> consists ')
    print(f'`{len(df[col].unique())}` unique value')
```

```
+ DROP COLUMN WITH 99 || > unique Value: i.e
make --> consists `960` unique value
```

```
model --> consists `7900` unique value
city --> consists `1150` unique value
zip --> consists `1047` unique value
```

```
plt.figure(figsize=(12,5))

print(df[df_to_drop_col_objType].nunique())
sns.barplot(x=df_to_drop_col_objType, y=df[df_to_drop_col_objType].nunique().values)
```

```
make      960
model    7899
city     1149
zip      1046
dtype: int64
<AxesSubplot:>
```




```
print('DROP ', df_to_drop_col_objType)
df_clean = df.drop(df_to_drop_col_objType, axis=1)
df_clean
```

```
DROP  ['make', 'model', 'city', 'zip']
```

	type	boatClass	year	condition	length_ft	beam_ft	dryWeight_lb	hullMa
0	power	power-center	1992	used	21.00	8.50	3000.0	fib
1	power	power-sportcruiser	2018	used	40.00	11.00	16100.0	fib
2	power	power-deck	2020	new	18.00	7.42	2000.0	fib
3	power	power-expresscruiser	2015	used	32.00	10.33	12650.0	fib
4	power	power-aft	1994	used	44.00	15.00	32000.0	fib
...	...	...	...	...	...	...	...	
18898	power	power-pontoon	2013	used	25.00	8.50	NaN	alu
18899	power	power-runabout	2013	used	19.33	8.00	2795.0	fib
18900	power	power-bay	2019	new	22.00	7.67	NaN	fib
18901	power	power-pontoon	2004	used	25.00	8.50	NaN	alu
18902	power	power-cruiser	2002	new	26.58	9.42	6350.0	fib

18903 rows × 18 columns

Start coding or generate with AI.

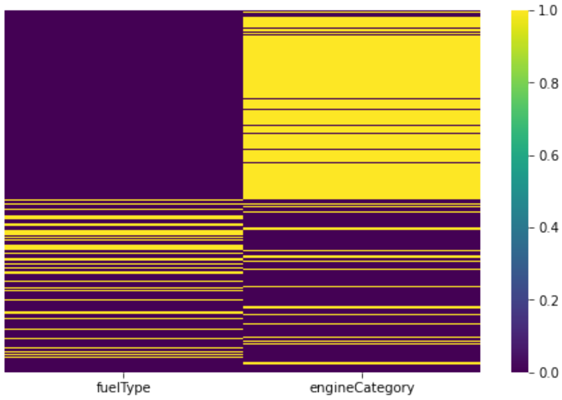
>>>>>> 3.2.1.2 IF MISSING VALUE IS LESS THAN 3000, (FILL WITH MOST FREQUENT VALUE) ELSE DROP THE COLUMN FOR OBJECT DT

```
# Check object data-type column(s) with missing value
df_nan_obj_col = []
for col in df_clean:
    if df_clean[col].dtypes == 'object' and df_clean[col].isnull().any():
        df_nan_obj_col.append(col)
        print(col.upper())
        print(df_clean[col].isnull().value_counts())
        print()
```

```
FUELTYPE
False    15951
True      2952
Name: fuelType, dtype: int64

ENGINECATEGORY
True     10493
False     8410
Name: engineCategory, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.heatmap(df_clean[df_nan_obj_col].isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

```
<AxesSubplot:>
```




```
# CHECK MISSING Value for 1st OBJECT(FuelType)

print('Missing Value in ',df_nan_obj_col[0], len(df_clean[df_clean[df_nan_obj_col[0]].isnull()]))
print(df_clean[df_nan_obj_col[0]].unique())
df_clean[df_clean[df_nan_obj_col[0]].isnull()].sample(10)
```

```
Missing Value in  fuelType 2952
['gasoline' 'diesel' nan 'other' 'electric']
```

	type	boatClass	year	condition	length_ft	beam_ft	dryWeight_lb	hullMater
12828	power	power-pontoon	2019	new	26.17	8.50	2200.0	alumir
12468	power	power-jon	2019	new	19.17	7.00	1020.0	alumir
13901	power	power-aluminum	2019	new	17.58	8.08	1525.0	alumir
17038	power	power-pontoon	2019	new	24.17	8.50	1920.0	alumir
12554	power	power-pontoon	2019	new	21.92	8.50	1700.0	alumir
13030	power	power-aluminum	2019	new	16.00	6.33	875.0	alumir
11990	power	power-jon	2019	new	14.00	6.00	562.0	alumir
18443	power	power-skiff	2019	new	19.33	7.75	1900.0	fibergl
11255	power	power-jon	2019	new	11.92	4.33	126.0	alumir
11857	power	power-jon	2019	new	14.00	6.00	562.0	alumir

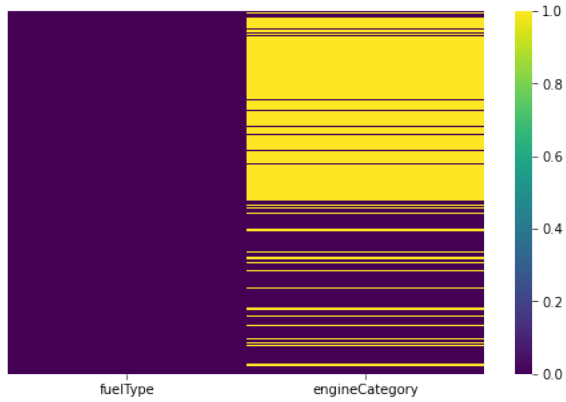
```
# Fill the missing values with the mode (most frequent value) of the column

mode_fuelType = df_clean['fuelType'].mode()[0]  # Calculate the mode of fuelType
df_clean['fuelType'].fillna(mode_fuelType, inplace=True)  # Fill missing values with the mode
df_clean
```

	type	boatClass	year	condition	length_ft	beam_ft	dryWeight_lb	hullMa
0	power	power-center	1992	used	21.00	8.50	3000.0	fib
1	power	power-sportcruiser	2018	used	40.00	11.00	16100.0	fib
2	power	power-deck	2020	new	18.00	7.42	2000.0	fib
3	power	power-expresscruiser	2015	used	32.00	10.33	12650.0	fib
4	power	power-aft	1994	used	44.00	15.00	32000.0	fib
...	...	...	...	...	...	...	...	
18898	power	power-pontoon	2013	used	25.00	8.50	NaN	alu
18899	power	power-runabout	2013	used	19.33	8.00	2795.0	fib
18900	power	power-bay	2019	new	22.00	7.67	NaN	fib
18901	power	power-pontoon	2004	used	25.00	8.50	NaN	alu
18902	power	power-cruiser	2002	new	26.58	9.42	6350.0	fib

18903 rows × 18 columns

```
plt.figure(figsize=(8,5))
sns.heatmap(df_clean[df_nan_obj_col].isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

<AxesSubplot:>




```
# CHECK NaN Value FOR 2ND OBJECT data-type COLUMN with MISSING Value

print('NaN Value in ',df_nan_obj_col[1], len(df_clean[df_clean[df_nan_obj_col[1]].isnull()]))
print(df_clean[df_nan_obj_col[1]].unique())
df_clean[df_clean[df_nan_obj_col[1]].isnull()].sample(10)
```

```
NaN Value in  engineCategory 10493
['outboard-4s' 'inboard-outboard' 'multiple' 'inboard' nan 'outboard'
 'outboard-2s' 'other' 'v-drive' 'electric']
```

	type	boatClass	year	condition	length_ft	beam_ft	dryWeight_lb	hullMater
3035	power	power-pontoon	2019	new	27.00	NaN	NaN	ot
2050	power	power-aluminum	2019	new	18.75	7.92	1720.0	alumir
8732	power	power-center	2019	used	17.00	7.00	NaN	fibergl
8728	power	power-skiwake	2007	used	22.00	NaN	NaN	fibergl
2472	power	power-pontoon	2006	used	24.00	NaN	NaN	ot
6972	power	power-pontoon	2018	new	25.00	NaN	NaN	ot
3011	power	power-pwc	2019	new	132.00	NaN	NaN	ot
18367	power	power-inflatable	2018	new	10.80	6.33	NaN	
17541	power	power-center	2003	used	19.00	7.67	NaN	fibergl
6613	power	power-cruiser	2018	used	27.00	NaN	NaN	ot

The missing Data is greater than the half of the dataset

```
+ Drop to avoid data misleading
```

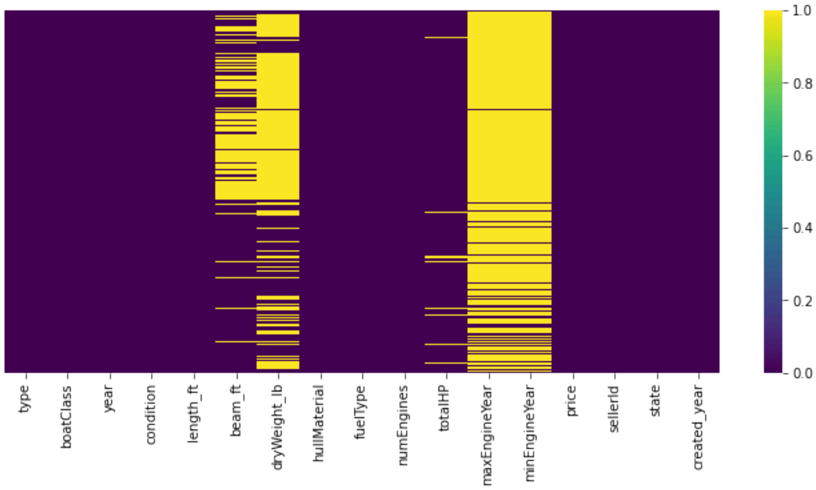
```
# DROP COLUMN
print(df_nan_obj_col[1])
df_clean = df_clean.drop([df_nan_obj_col[1]], axis=1)
df_clean
```

```
engineCategory
```

	type	boatClass	year	condition	length_ft	beam_ft	dryWeight_lb	hullMa
0	power	power-center	1992	used	21.00	8.50	3000.0	fib
1	power	power-sportcruiser	2018	used	40.00	11.00	16100.0	fib
2	power	power-deck	2020	new	18.00	7.42	2000.0	fib
3	power	power-expresscruiser	2015	used	32.00	10.33	12650.0	fib
4	power	power-aft	1994	used	44.00	15.00	32000.0	fib
...	...	...	...	...	...	...	...	
18898	power	power-pontoon	2013	used	25.00	8.50	NaN	alu
18899	power	power-runabout	2013	used	19.33	8.00	2795.0	fib
18900	power	power-bay	2019	new	22.00	7.67	NaN	fib
18901	power	power-pontoon	2004	used	25.00	8.50	NaN	alu
18902	power	power-cruiser	2002	new	26.58	9.42	6350.0	fib

```
# Preview the missing Column
plt.figure(figsize=(12,5))
sns.heatmap(df_clean.isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

```
<AxesSubplot:>
```



3.2.2 FOR NUMERIC DATA TYPE

>>>>>> 3.2.2.1 `IF MISSING VALUE IS UP TO 1000 IN A NUMERIC TYPE COLUMN, DROP THE COLUMN`

```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18903 entries, 0 to 18902
Data columns (total 17 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   type           18903 non-null  object
 1   boatClass      18903 non-null  object
 2   year           18903 non-null  int64
 3   condition      18903 non-null  object
 4   length_ft      18903 non-null  float64
 5   beam_ft        12399 non-null  float64
 6   dryWeight_lb   7094 non-null   float64
 7   hullMaterial   18903 non-null  object
 8   fuelType       18903 non-null  object
 9   numEngines     18903 non-null  int64
 10  totalHP        18055 non-null  float64
 11  maxEngineYear  2205 non-null   float64
 12  minEngineYear  2174 non-null   float64
 13  price          18903 non-null  float64
 14  sellerId       18903 non-null  int64
 15  state          18903 non-null  object
 16  created_year   18903 non-null  int64
dtypes: float64(7), int64(4), object(6)
memory usage: 2.5+ MB
```

```
# Check `int` or `Float` data-type column(s) with missing value
df_nan_num_col = []
for col in df_clean:
    if (df_clean[col].dtypes == 'float64' or df_clean[col].dtypes == 'int64') and df_clean[col].isnull().any():
        df_nan_num_col.append(col)
        print(col.upper())
        print(df_clean[col].isnull().value_counts())
        print()
```

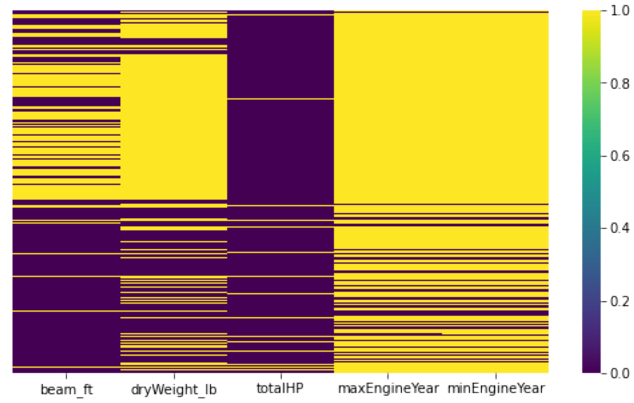
```
BEAM_FT
False    12399
True      6504
Name: beam_ft, dtype: int64

DRYWEIGHT_LB
True     11809
False     7094
Name: dryWeight_lb, dtype: int64

TOTALHP
False    18055
True       848
Name: totalHP, dtype: int64

MAXENGINEYEAR
True     16698
False     2205
Name: maxEngineYear, dtype: int64

MINENGINEYEAR
```

```
True     16729
False     2174
Name: minEngineYear, dtype: int64
```

```
Start coding or generate with AI.
```

```
# VISUAL COLUMN WITH MISSING VALUE (in NUMERKIC TYPE)
plt.figure(figsize=(9,5))
sns.heatmap(df[df_nan_num_col].isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

```
<AxesSubplot:>
```




```
# EXCLUDE COLUMN THAT DOES NOT HAVE UPTO 1,000 MISSING VALUE
df_nan_to_drop_num_col = [col for col in df_nan_num_col if col != 'totalHP']
df_nan_to_drop_num_col
```

```
['beam_ft', 'dryWeight_lb', 'maxEngineYear', 'minEngineYear']
```

```
# DROP COLUMN THAT HAVE MORE THAN 1,000 MISSING VALUE
print('DROP ', df_nan_to_drop_num_col)
df_clean = df_clean.drop(df_nan_to_drop_num_col, axis=1)
#df_clean.drop(df_nan_num_col, axis=1, inplace=True)
df_clean
```

```
DROP  ['beam_ft', 'dryWeight_lb', 'maxEngineYear', 'minEngineYear']
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	creat
0	power	power-center	1992	used	21.00	fiberglass	gasoline	1	150.0	16500.0	217053	FL	
1	power	power-sportcruiser	2018	used	40.00	fiberglass	diesel	2	800.0	539000.0	44260	MI	
2	power	power-deck	2020	new	18.00	fiberglass	gasoline	1	75.0	26995.0	220570	OH	
3	power	power-expresscruiser	2015	used	32.00	fiberglass	gasoline	2	600.0	169995.0	34834	SC	
4	power	power-aft	1994	used	44.00	fiberglass	diesel	2	700.0	109900.0	17942	MD	
...	...	...	...	...	...	...	...	...	...	...	...	...	
18898	power	power-pontoon	2013	used	25.00	aluminum	gasoline	0	NaN	31973.0	34647	GA	
18899	power	power-runabout	2013	used	19.33	fiberglass	gasoline	1	0.0	26995.0	6335	MI	
18900	power	power-bay	2019	new	22.00	fiberglass	gasoline	0	NaN	39995.0	65602	TX	

```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18903 entries, 0 to 18902
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   type          18903 non-null  object 
 1   boatClass     18903 non-null  object 
 2   year          18903 non-null  int64  
 3   condition     18903 non-null  object 
 4   length_ft     18903 non-null  float64
 5   hullMaterial  18903 non-null  object 
 6   fuelType      18903 non-null  object 
 7   numEngines    18903 non-null  int64  
 8   totalHP       18055 non-null  float64
```

```
 9   price         18903 non-null  float64
 10  sellerId      18903 non-null  int64
 11  state         18903 non-null  object
 12  created_year  18903 non-null  int64
dtypes: float64(3), int64(4), object(6)
memory usage: 1.9+ MB
```

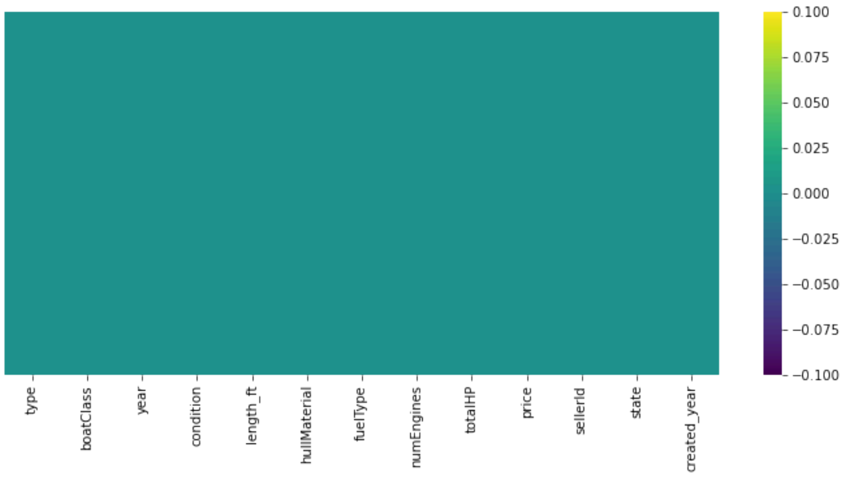
>>>>>> 3.2.2.1 `IF MISSING VALUE IS LESS THAN 1000 IN A NUMERIC TYPE COLUMN, REMOVE NaN ROW`

```
df_clean = df_clean[df_clean['totalHP'].notnull()]
df_clean
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	creat
0	power	power-center	1992	used	21.00	fiberglass	gasoline	1	150.0	16500.0	217053	FL	
1	power	power-sportcruiser	2018	used	40.00	fiberglass	diesel	2	800.0	539000.0	44260	MI	
2	power	power-deck	2020	new	18.00	fiberglass	gasoline	1	75.0	26995.0	220570	OH	
3	power	power-expresscruiser	2015	used	32.00	fiberglass	gasoline	2	600.0	169995.0	34834	SC	
4	power	power-aft	1994	used	44.00	fiberglass	diesel	2	700.0	109900.0	17942	MD	
...	...	...	...	...	...	...	...	...	...	...	...	...	
18895	power	power-house	2005	used	100.00	aluminum	gasoline	2	0.0	425000.0	34888	KY	
18896	power	power-center	1990	used	28.00	fiberglass	diesel	1	315.0	49000.0	61420	FL	
18897	power	power-pilot	1973	used	29.00	other	gasoline	1	0.0	10000.0	32168	GA	
18899	power	power-runabout	2013	used	19.33	fiberglass	gasoline	1	0.0	26995.0	6335	MI	

```
plt.figure(figsize=(12,5))
sns.heatmap(df_clean.isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

```
<AxesSubplot:>
```



4.0 EXPLORATORY DATA ANALYSIS (EDA)

>> 4.1 DATA EXPLORATORY

- Detect Outlier From numeric Column (Price, length_ft, etc)

```
# Check `int` or `Float` data-type column(s)
for col in df_clean:
    if (df_clean[col].dtypes == 'float64' or df_clean[col].dtypes == 'int64'):
        print(col)
```

```
year
length_ft
numEngines
totalHP
price
sellerId
created_year
```

```
#sns.pairplot(df_clean)
#df_clean.corr()
#df_clean.drop('sellerId', axis=1, inplace=True )
df_clean.corr()
```

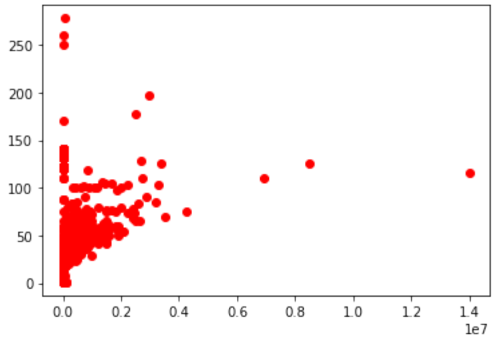
	year	length_ft	numEngines	totalHP	price	sellerId	created_year
year	1.000000	-0.222239	-0.300089	-0.194967	-0.028056	0.065940	0.275208
length_ft	-0.222239	1.000000	0.351975	0.357813	0.343944	-0.057879	-0.118081
numEngines	-0.300089	0.351975	1.000000	0.625390	0.366473	-0.084159	-0.244772
totalHP	-0.194967	0.357813	0.625390	1.000000	0.589721	-0.024495	-0.213557
price	-0.028056	0.343944	0.366473	0.589721	1.000000	-0.016534	-0.099106
sellerId	0.065940	-0.057879	-0.084159	-0.024495	-0.016534	1.000000	0.060988
created_year	0.275208	-0.118081	-0.244772	-0.213557	-0.099106	0.060988	1.000000

>>>> 4.1.1 CHECK FOR PRICE OUTLIER

```
#sns.boxplot(x='price', y='length_ft', data=df_clean)
```

```
plt.scatter(df_clean['price'], df_clean['length_ft'], color = 'red')
```

```
<matplotlib.collections.PathCollection at 0x1e32a094f10>
```

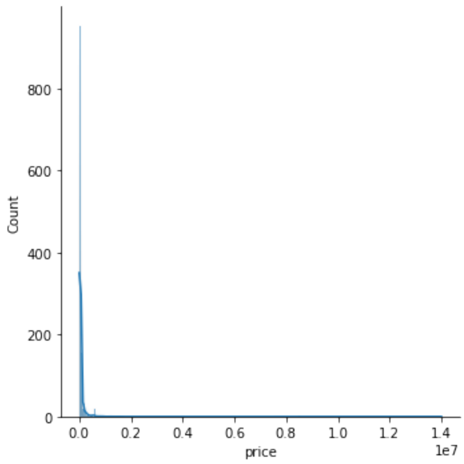



```
# Remove record with 5,000,000 up ward
print('min price', df_clean['price'].min())
print('MAX Price', df_clean['price'].max())
```

```
min price 500.0
MAX Price 14000000.0
```

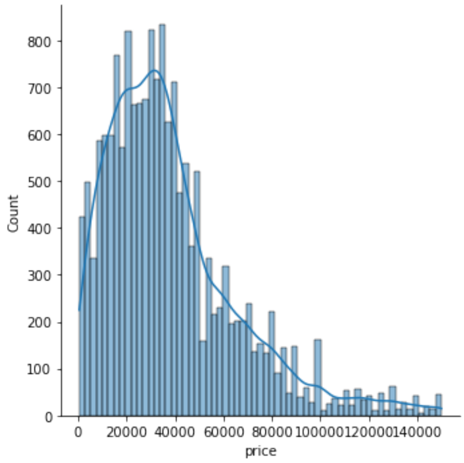
```
plt.figure(figsize=(17,9))
sns.displot(df_clean['price'], kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x1e32edecc70>
<Figure size 1224x648 with 0 Axes>
```




```
plt.figure(figsize=(17,9))
sns.displot(df_clean[(df_clean['price']<150000)]['price'], kde=True)
```

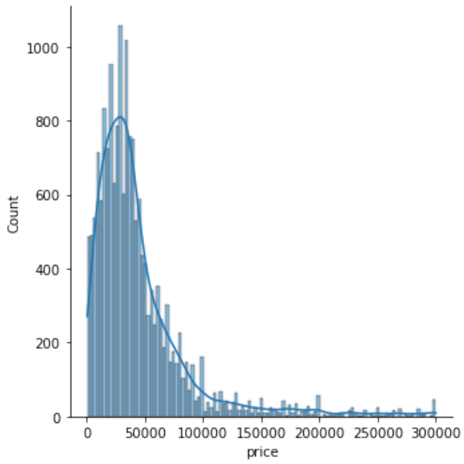
```
<seaborn.axisgrid.FacetGrid at 0x1e360314d60>
<Figure size 1224x648 with 0 Axes>
```



>>>>>> REMOVE THE OUTLIER (SET MAX PRICE TO 150,000)

```
# Remove record with 5,000,000 up ward
#df_clean_outlier =df_clean[(df_clean['price'] < 5000000)]  # 5m
#df_clean_outlier =df_clean[(df_clean['price'] < 2000000)]  #2m
#df_clean_outlier =df_clean[(df_clean['price'] < 1000000)]  #1m
#df_clean_outlier =df_clean[(df_clean['price'] < 999999)]   #1m -1
#df_clean_outlier =df_clean[(df_clean['price'] < 500000)]   #500k
#df_clean_outlier =df_clean[(df_clean['price'] < 400000)]   #400k
df_clean_outlier = df_clean[(df_clean['price']<300000)]   #300k
#df_clean_outlier = df_clean[(df_clean['price']<200000)]   #200k
#df_clean_outlier = df_clean[(df_clean['price']<150000)]   #150k


sns.displot(df_clean_outlier['price'], kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x1e32b078e80>
```




```
# Cross Check
print('min price', df_clean_outlier['price'].min())
print('MAX Price', df_clean_outlier['price'].max())
print('Lenght', df_clean_outlier.shape)
df_clean_outlier.sort_values('price',  ascending=False).head(20)
```

```
min price 500.0
MAX Price 299999.0
Lenght (17575, 13)
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	created_
3339	power	power-house	2004	used	84.00	other	other	1	0.0	299999.0	29402	MO	
16160	power	power-cruiser	2015	used	38.50	fiberglass	gasoline	1	430.0	299995.0	35188	OH	
16383	power	power-cuddy	2018	used	33.00	fiberglass	gasoline	2	600.0	299995.0	14386	FL	
16531	power	power-cruiser	2017	new	36.00	fiberglass	gasoline	2	760.0	299948.0	14353	WI	
13209	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1176	VA	
13163	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1102	FL	
13169	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1107	NC	
13174	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1110	TX	
13179	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1114	TX	
17208	power	power-center	2018	used	29.00	fiberglass	gasoline	2	600.0	299900.0	6654	MA	
13193	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1120	MD	
13197	power	power-center	2019	new	33.33	fiberglass	gasoline	2	0.0	299900.0	1166	FL	
10588	power	power-center	2017	used	34.00	fiberglass	gasoline	3	900.0	299900.0	59565	FL	

```
df_clean_outlier.info()
```

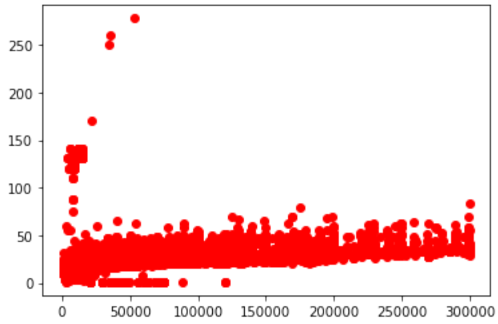
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17575 entries, 0 to 18902
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   type          17575 non-null  object 
 1   boatClass     17575 non-null  object 
 2   year          17575 non-null  int64  
 3   condition     17575 non-null  object 
 4   length_ft     17575 non-null  float64
 5   hullMaterial  17575 non-null  object 
 6   fuelType      17575 non-null  object 
 7   numEngines    17575 non-null  int64  
 8   totalHP       17575 non-null  float64
 9   price         17575 non-null  float64
 10  sellerId      17575 non-null  int64  
 11  state         17575 non-null  object 
 12  created_year  17575 non-null  int64  
dtypes: float64(3), int64(4), object(6)
memory usage: 1.9+ MB
```

```
df_clean_outlier.corr()
```

	year	length_ft	numEngines	totalHP	price	sellerId	created_year
year	1.000000	-0.209106	-0.383953	-0.243446	-0.002013	0.067254	0.277788
length_ft	-0.209106	1.000000	0.281093	0.211712	0.272732	-0.055802	-0.087105
numEngines	-0.383953	0.281093	1.000000	0.604972	0.446067	-0.079950	-0.265331
totalHP	-0.243446	0.211712	0.604972	1.000000	0.420166	-0.028428	-0.232177
price	-0.002013	0.272732	0.446067	0.420166	1.000000	-0.012126	-0.103600
sellerId	0.067254	-0.055802	-0.079950	-0.028428	-0.012126	1.000000	0.059163
created_year	0.277788	-0.087105	-0.265331	-0.232177	-0.103600	0.059163	1.000000

```
plt.scatter(df_clean_outlier['price'], df_clean_outlier['length_ft'], color = 'red')
```

```
<matplotlib.collections.PathCollection at 0x1e36060ae50>
```



>>>> 4.1.2 CHECK FOR LENGHT_FT OUTLIER

```
print(df_clean_outlier['length_ft'].min())
df_clean_outlier['length_ft'].max()
```

```
1.0
277.9
```

>>>>>> REMOVE THE OUTLIER (SET MAX LENGHT_FT TO 100)

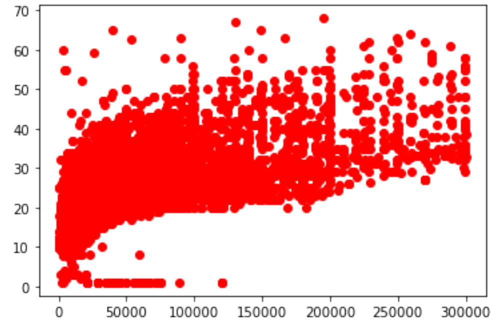
```
df_clean_outlier =df_clean_outlier[(df_clean_outlier['length_ft'] < 70)]
print('min length_ft', df_clean_outlier['length_ft'].min())
print('MAX length_ft', df_clean_outlier['length_ft'].max())
print('Lenght', len(df_clean_outlier))
df_clean_outlier.sort_values('length_ft',  ascending=False).head(20)
```

```
min length_ft 1.0
MAX length_ft 68.0
Lenght 17395
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	created_
14698	power	power-motor	1990	used	68.00	fiberglass	diesel	2	970.0	195000.0	18223	MD	
16625	power	power-house	1991	used	67.00	steel	gasoline	2	540.0	129900.0	56775	AZ	
11224	power	power-motor	1995	used	65.00	steel	diesel	2	574.0	149000.0	28309	TX	
12555	power	power-house	2014	new	65.00	aluminum	gasoline	2	440.0	39900.0	34439	AZ	
7563	power	power-motor	1991	used	64.00	fiberglass	other	1	0.0	259000.0	34373	PA	
12109	power	power-house	1978	used	63.00	aluminum	gasoline	2	330.0	89500.0	34888	KY	
15666	power	power-house	1999	used	63.00	aluminum	gasoline	1	140.0	166750.0	61430	WA	
13554	power	power-motor	1988	used	63.00	fiberglass	diesel	2	1300.0	249000.0	63935	FL	
5423	power	power-center	2019	new	62.50	fiberglass	gasoline	1	0.0	53837.0	35234	AL	
14017	power	power-flybridge	1999	used	62.00	aluminum	diesel	2	1400.0	250000.0	28311	MA	
12115	power	power-motor	1987	used	62.00	fiberglass	diesel	2	970.0	269900.0	21445	NJ	
18770	power	power-antique	1960	used	62.00	wood	diesel	1	671.0	229000.0	153142	WA	
10469	power	power-motor	1981	used	61.00	fiberglass	diesel	2	0.0	225000.0	52419	LA	

```
plt.scatter(df_clean_outlier['price'], df_clean_outlier['length_ft'], color = 'red')
```

```
<matplotlib.collections.PathCollection at 0x1e36065fa00>
```



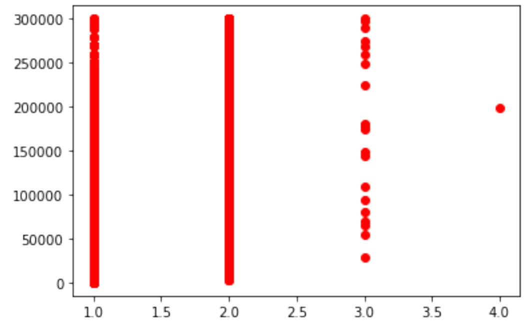

```
df_clean_outlier[(df_clean_outlier['length_ft'] <= 2)]
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	created_y
2286	power	power-pontoon	2020	new	1.0	other	other	1	0.0	45020.0	46516	MN	2
2314	power	power-pontoon	2019	new	1.0	other	other	1	0.0	29352.0	46516	MN	2
2315	power	power-pontoon	2020	new	1.0	other	other	1	0.0	45020.0	46516	MN	2
2331	power	power-pontoon	2020	new	1.0	other	other	1	0.0	67690.0	46516	MN	2
2340	power	power-pontoon	2018	new	1.0	other	other	1	0.0	37999.0	46516	MN	2
...	...	...	...	...	...	...	...	...	...	...	...	...	
10414	power	power-other	2016	used	2.0	other	gasoline	1	25.0	4899.0	57749	TX	2
11275	power	power-other	2015	used	2.0	other	other	1	250.0	15995.0	1196	SC	2

>>>> 4.1.3 CHECK FOR NUMENGINES OUTLIER

```
plt.scatter(df_clean_outlier['numEngines'], df_clean_outlier['price'], color = 'red')
```

```
<matplotlib.collections.PathCollection at 0x1e36172af40>
```



>>>>>> REMOVE THE OUTLIER (SET MAX_NO OF NUMENGINES TO 2)

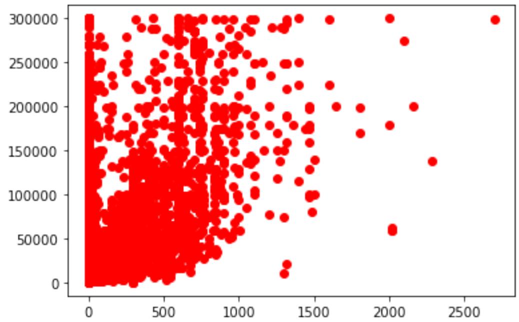
```
df_clean_outlier = df_clean_outlier[df_clean_outlier['numEngines'] < 3]
df_clean_outlier
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	creat
0	power	power-center	1992	used	21.00	fiberglass	gasoline	1	150.0	16500.0	217053	FL	
2	power	power-deck	2020	new	18.00	fiberglass	gasoline	1	75.0	26995.0	220570	OH	
3	power	power-expresscruiser	2015	used	32.00	fiberglass	gasoline	2	600.0	169995.0	34834	SC	
4	power	power-aft	1994	used	44.00	fiberglass	diesel	2	700.0	109900.0	17942	MD	
9	power	power-convertible	1971	used	42.00	fiberglass	diesel	2	840.0	59500.0	16876	CT	
...	...	...	...	...	...	...	...	...	...	...	...	...	
18894	power	power-pontoon	2017	new	22.33	aluminum	gasoline	1	90.0	37631.0	5103	MI	
18896	power	power-center	1990	used	28.00	fiberglass	diesel	1	315.0	49000.0	61420	FL	
18897	power	power-pilot	1973	used	29.00	other	gasoline	1	0.0	10000.0	32168	GA	
18899	power	power-runabout	2013	used	19.33	fiberglass	gasoline	1	0.0	26995.0	6335	MI	

>>>> 4.1.3 CHECK FOR TOTALHP OUTLIER

```
plt.scatter(df_clean_outlier['totalHP'], df_clean_outlier['price'], color = 'red')
```

```
<matplotlib.collections.PathCollection at 0x1e361793b50>
```




```
print(df_clean_outlier['totalHP'].min())
df_clean_outlier['totalHP'].max()
```

```
0.0
2700.0
```

```
df_clean_outlier[(df_clean_outlier['totalHP'] < 400) & (df_clean_outlier['totalHP'] > -1)]
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	created_
0	power	power-center	1992	used	21.00	fiberglass	gasoline	1	150.0	16500.0	217053	FL	
2	power	power-deck	2020	new	18.00	fiberglass	gasoline	1	75.0	26995.0	220570	OH	
11	sail	sail-racercruiser	1986	used	30.00	fiberglass	diesel	1	0.0	25500.0	16876	CT	
12	power	power-pontoon	2019	new	23.70	aluminum	gasoline	1	200.0	44507.0	34914	DE	
13	power	power-motor	2000	used	55.00	fiberglass	diesel	2	0.0	299000.0	6123	FL	
...	...	...	...	...	...	...	...	...	...	...	...	...	
18894	power	power-pontoon	2017	new	22.33	aluminum	gasoline	1	90.0	37631.0	5103	MI	
18896	power	power-center	1990	used	28.00	fiberglass	diesel	1	315.0	49000.0	61420	FL	

>>>>> REMOVE THE OUTLIER (SET MAX_NO OF TOTALHP TO 399 and MIN_NO TO 0)

```
df_clean_outlier =df_clean_outlier[(df_clean_outlier['totalHP'] < 400) & (df_clean_outlier['totalHP'] > -1)]
print('min totalHP', df_clean_outlier['totalHP'].min())
print('MAX totalHP', df_clean_outlier['totalHP'].max())
print('Lenght', len(df_clean_outlier))
df_clean_outlier.sort_values('totalHP',  ascending=False).head(10)
```

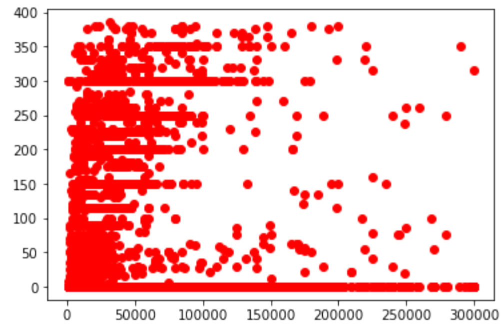
```
min totalHP 0.0
MAX totalHP 385.0
Lenght 16383
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	created_
17088	power	power-runabout	2005	used	28.67	fiberglass	gasoline	1	385.0	31900.0	5913	NJ	
11181	power	power-sportcruiser	1996	used	28.00	fiberglass	gasoline	2	380.0	23500.0	16863	NY	
18821	power	power-bowrider	2015	used	28.00	fiberglass	gasoline	1	380.0	94800.0	67460	FL	
12782	power	power-bowrider	2013	used	27.00	fiberglass	gasoline	1	380.0	84500.0	17929	NJ	
70	power	power-skiwake	2015	used	24.50	fiberglass	gasoline	1	380.0	84900.0	34745	MO	
12886	power	power-bowrider	2018	new	27.00	fiberglass	gasoline	1	380.0	179999.0	42094	MD	

```
Start coding or generate with AI.
```

```
plt.scatter(df_clean_outlier['price'], df_clean_outlier['totalHP'], color = 'red')
```

```
<matplotlib.collections.PathCollection at 0x1e361801790>
```




```
#plt.scatter(df_clean_outlier['year'], df_clean_outlier['price'], color = 'red')
```

```
df_clean_outlier.corr()
```

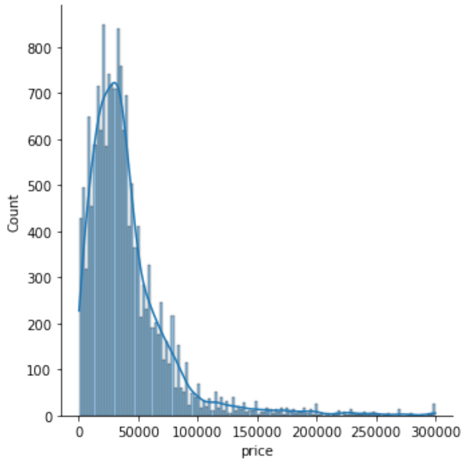
	year	length_ft	numEngines	totalHP	price	sellerId	created_year
year	1.000000	-0.375466	-0.285977	0.024782	0.102996	0.063617	0.242935
length_ft	-0.375466	1.000000	0.400038	0.075594	0.571832	-0.049062	-0.158062
numEngines	-0.285977	0.400038	1.000000	0.003977	0.251977	-0.081409	-0.197148
totalHP	0.024782	0.075594	0.003977	1.000000	0.039556	-0.002628	-0.150612
price	0.102996	0.571832	0.251977	0.039556	1.000000	-0.002543	-0.024856
sellerId	0.063617	-0.049062	-0.081409	-0.002628	-0.002543	1.000000	0.051828
created_year	0.242935	-0.158062	-0.197148	-0.150612	-0.024856	0.051828	1.000000

```
#sns.pairplot(df_clean_outlier)
```

```
#sns.pairplot(df_clean_outlier)
#plt.figure(figsize=(12,5))
#sns.heatmap(train.isnull(), yticklabels=False, cbar =True, cmap='viridis')
```

```
plt.figure(figsize=(14,7))

sns.displot(df_clean_outlier['price'], kde=True)
```

```
<seaborn.axisgrid.FacetGrid at 0x1e360618430>
<Figure size 1008x504 with 0 Axes>
```




```
df_clean_outlier
```

	type	boatClass	year	condition	length_ft	hullMaterial	fuelType	numEngines	totalHP	price	sellerId	state	created_
0	power	power-center	1992	used	21.00	fiberglass	gasoline	1	150.0	16500.0	217053	FL	
2	power	power-deck	2020	new	18.00	fiberglass	gasoline	1	75.0	26995.0	220570	OH	
11	sail	sail-racercruiser	1986	used	30.00	fiberglass	diesel	1	0.0	25500.0	16876	CT	
12	power	power-pontoon	2019	new	23.70	aluminum	gasoline	1	200.0	44507.0	34914	DE	
13	power	power-motor	2000	used	55.00	fiberglass	diesel	2	0.0	299000.0	6123	FL	
...	...	...	...	...	...	...	...	...	...	...	...	...	
18894	power	power-pontoon	2017	new	22.33	aluminum	gasoline	1	90.0	37631.0	5103	MI	
18896	power	power-center	1990	used	28.00	fiberglass	diesel	1	315.0	49000.0	61420	FL	

```
#sns.jointplot( x='fico', y='int.rate', data=df,)
```

```
#plt.figure(figsize=(11,7))
#sns.lmplot(y='int.rate',x='fico',data=df_clean_outlier, hue='credit.policy',
 #          col='not.fully.paid', palette='Set1')
```

```
0,3,5,6,
1,11
```

```
(1, 11)
```

```
Start coding or generate with AI.
```

5.0 TRANSFORMATION

```
#from sklearn.compose import ColumnTransformer
#from sklearn.preprocessing import OneHotEncoder
```

```
#ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder, [0,3,5,6])],  remainder='passthrough')
#ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [0,3,5,6])], remainder='passthrough')
#df_clean_outlier_transform = ct.fit_transform(df_clean_outlier)
#X = np.array(ct.fit_transform(X))
```

DIMENSIONAL REDUCTION

```
from sklearn.decomposition import PCA
```

```
# to select the number of n_component
for col in df_clean_outlier:
    if df[col].dtypes == 'object':
        print(col)
```

```
type
boatClass
condition
hullMaterial
fuelType
state
```

```
# Check for Object type column, get there dummies values, reduce there demensionality to 1,
df_transformed_pca = pd.DataFrame()
for col in df_clean_outlier:
    # Check for obj type
    if df[col].dtypes == 'object':
        dummy_val = pd.get_dummies(df_clean_outlier[col])
        # Reduce the demension to 1
        pca = PCA(n_components=1)
        pca_value = pca.fit_transform(dummy_val)

        pca_value = pd.DataFrame(pca_value, columns=[col+'_pca'])    # Convert the numpy data to DataFrame series
        df_transformed_pca = pd.concat([df_transformed_pca, pca_value], axis=1)  # Add to existing df
df_transformed_pca
```

	type_pca	boatClass_pca	condition_pca	hullMaterial_pca	fuelType_pca	state_pca
0	-0.017634	-0.257808	0.907935	0.750177	0.979046	0.877958
1	-0.017634	-0.234319	-0.506279	0.750177	0.979046	-0.083853
2	1.395879	-0.185880	0.907935	0.750177	0.291670	-0.080134
3	-0.017634	0.781600	-0.506279	-0.443088	0.979046	-0.074593
4	-0.017634	-0.189224	0.907935	0.750177	0.291670	0.877958
...	...	...	...	...	...	...
16378	-0.017634	0.781600	-0.506279	-0.443088	0.979046	-0.243734
16379	-0.017634	-0.257808	0.907935	0.750177	0.291670	0.877958
16380	-0.017634	-0.185179	0.907935	-0.503787	0.979046	-0.103041
16381	-0.017634	-0.203617	0.907935	0.750177	0.979046	-0.243734
16382	-0.017634	-0.254576	-0.506279	0.750177	0.979046	-0.103041

16383 rows × 6 columns

```
# Set the index of df_transformed_pca to match the index of df_clean_outlier

df_transformed_pca.index = df_clean_outlier.index
```

```
df_transformed_pca.tail(3)
```

	type_pca	boatClass_pca	condition_pca	hullMaterial_pca	fuelType_pca	state_pca
18897	-0.017634	-0.185179	0.907935	-0.503787	0.979046	-0.103041
18899	-0.017634	-0.203617	0.907935	0.750177	0.979046	-0.243734
18902	-0.017634	-0.254576	-0.506279	0.750177	0.979046	-0.103041

```
df_clean_outlier_transformed = pd.concat([df_clean_outlier, df_transformed_pca ], axis=1)
df_clean_outlier_transformed.drop(['type', 'condition', 'hullMaterial', 'fuelType', 'boatClass', 'state'], axis=1, inplace=True)
df_clean_outlier_transformed
```

	year	length_ft	numEngines	totalHP	price	sellerId	created_year	type_pca	boatClass_pca	condition_pca	hullMaterial_p
0	1992	21.00	1	150.0	16500.0	217053	2019	-0.017634	-0.257808	0.907935	0.750
2	2020	18.00	1	75.0	26995.0	220570	2019	-0.017634	-0.234319	-0.506279	0.750
11	1986	30.00	1	0.0	25500.0	16876	2011	1.395879	-0.185880	0.907935	0.750
12	2019	23.70	1	200.0	44507.0	34914	2019	-0.017634	0.781600	-0.506279	-0.443
13	2000	55.00	2	0.0	299000.0	6123	2013	-0.017634	-0.189224	0.907935	0.750
...	...	...	...	...	...	...	...	...	...	...	
18894	2017	22.33	1	90.0	37631.0	5103	2016	-0.017634	0.781600	-0.506279	-0.443
18896	1990	28.00	1	315.0	49000.0	61420	2019	-0.017634	-0.257808	0.907935	0.750
18897	1973	29.00	1	0.0	10000.0	32168	2017	-0.017634	-0.185179	0.907935	-0.503
18899	2013	19.33	1	0.0	26995.0	6335	2019	-0.017634	-0.203617	0.907935	0.750
18902	2002	26.58	1	220.0	17900.0	152266	2019	-0.017634	-0.254576	-0.506279	0.750

16383 rows × 13 columns

6.0 MODEL AND EVALUATION

- Let's start by splitting our data into a training set and test set

Splitting the dataset into the Training set and Test set

```
df_clean_outlier_transformed.shape
```

```
(16383, 13)
```

```
from sklearn.model_selection import train_test_split
```

```
X = df_clean_outlier_transformed.drop('price', axis=1)
y = df_clean_outlier_transformed['price']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Train using Linear Regression

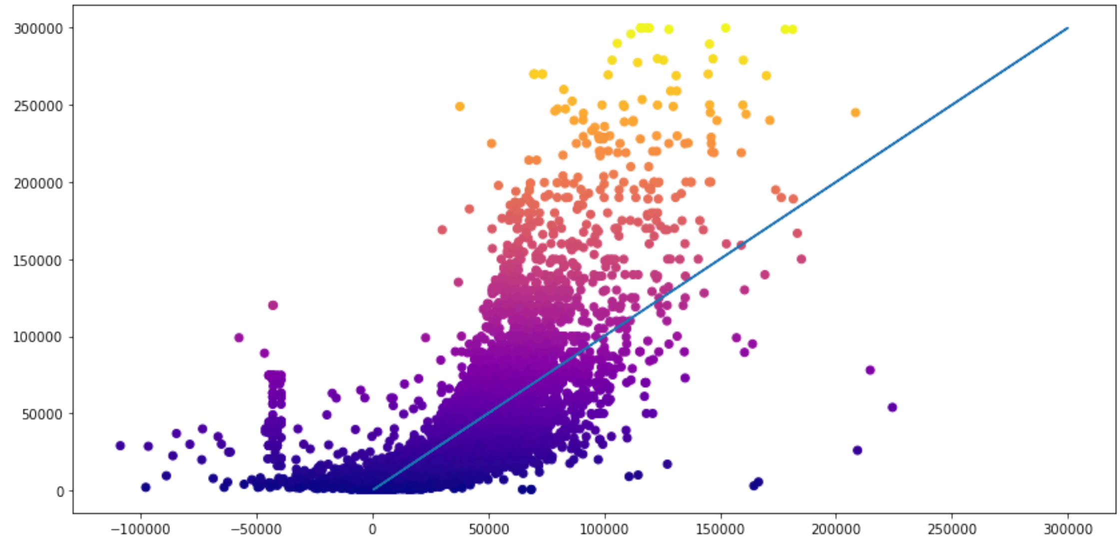
```
from sklearn.linear_model import LinearRegression

ln_regressor = LinearRegression()
ln_regressor.fit(X_train, y_train)
```

```
LinearRegression()
```

```
ln_predictions = ln_regressor.predict(X_test)
```

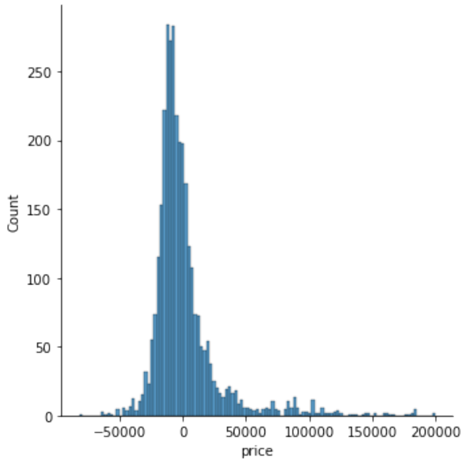
```
plt.figure(figsize=(14,7))

plt.scatter(ln_regressor.predict(X_train), y_train, c=y_train, cmap='plasma')
plt.plot(y_train, y_train, )
#plt.scatter(ln_predictions, y_test, color = 'green')
```

[<matplotlib.lines.Line2D at 0x1e363927b80>]



```
sns.displot((y_test - ln_predictions))
```

<seaborn.axisgrid.FacetGrid at 0x1e363988dc0>



```
from sklearn import metrics
```

```
metrics.mean_absolute_error(y_test, ln_predictions)
```

16750.030399701525

```
from sklearn.metrics import r2_score, adjusted_rand_score
r2_score(y_train, ln_regressor.predict(X_train)), r2_score(y_test, ln_predictions)
```

(0.4840999511126901, 0.4632075629433322)

Start coding or generate with AI.

Train using SVR model

```
#### NORMALIZATION
```

```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
sc_y = StandardScaler()
sc_X_train = sc_X.fit_transform(X_train)

sc_y_train = sc_y.fit_transform(y_train.values.reshape(len(y_train), -1))
sc_y_train
```

```
array([[-0.71927243],
       [-0.71645079],
       [-0.40903156],
       ...,
       [ 1.37617347],
```

```
       [-0.65429086],
       [ 0.31735951]])
```

```
### Import SVM library
from sklearn.svm import SVR
svr_regressor = SVR(kernel='rbf')
svr_regressor.fit(sc_X_train, sc_y_train)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel()

SVR()
```

```
svm_y_pred = sc_y.inverse_transform(svr_regressor.predict(sc_X.transform(X_test)).reshape(len(y_test), -1))
svm_y_train =sc_y.inverse_transform(svr_regressor.predict(sc_X.transform(X_train)).reshape(len(X_train), -1))
np.set_printoptions(precision=2)

#y_pred = sc_y.inverse_transform(regressor.predict(sc_X.transform(X_test)).reshape(-1,1))
#print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
svm_y_pred
```

```
array([[39230.1 ],
       [62686.64],
       [47447.55],
       ...,
       [52907.13],
       [14343.28],
       [15495.39]])
```

```
r2_score(y_train, svm_y_train), r2_score(y_test, svm_y_pred)
```

```
(0.7697508739636432, 0.7485459889347739)
```

Start coding or generate with AI.

Train using DECISION TREE

```
from sklearn.tree import DecisionTreeRegressor
decision_regressor = DecisionTreeRegressor()
```

```
decision_regressor.fit(X_train, y_train)
```

```
DecisionTreeRegressor()
```

```
decsn_tree_pred = decision_regressor.predict(X_test)
decsn_tree_pred
```

```
array([49995.  , 72969.71, 38715.  , ..., 40249.  , 20579.  , 19195.  ])
```

```
sns.displot((y_test - decsn_tree_pred))
```

```
<seaborn.axisgrid.FacetGrid at 0x1e363b9f280>
```