Appendix

In [11]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LinearRegression
import patsy
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import tree
import seaborn as sns
```

In [12]:

```
sns.set(rc = {'figure.figsize': (12, 8)})
plt.style.use('fivethirtyeight')
```

Read in the data and make necessary conversions

In [13]:

```
data = pd.read_csv("laptopData.csv", index_col=0)
data["ssd"] = data["ssd"].map({"SSD": 1, "No": 0})
data["BIN"] = data["BIN"].map({False: 0, True: 1})
data["sale"] = data["sale"].map({"SOLD": 1, "NOT SOLD": 0})
data
```

Out[13]:

	sale	price	ghz	ram	hd	ssd	BIN
1	1	404.99	2.7	8.0	NaN	1	0
2	1	355.00	2.5	8.0	128.0	1	0
3	1	449.99	2.6	4.0	128.0	0	1
4	0	499.99	2.5	4.0	320.0	0	1
5	0	199.99	NaN	NaN	NaN	0	1
...	...	...	...	...	...	...	...
216	1	480.00	NaN	6.0	128.0	1	1
217	1	452.00	2.6	8.0	240.0	1	0
218	1	358.00	2.6	4.0	128.0	0	0
219	1	450.00	NaN	4.0	128.0	1	0
220	1	299.95	2.5	4.0	320.0	0	1

220 rows × 7 columns

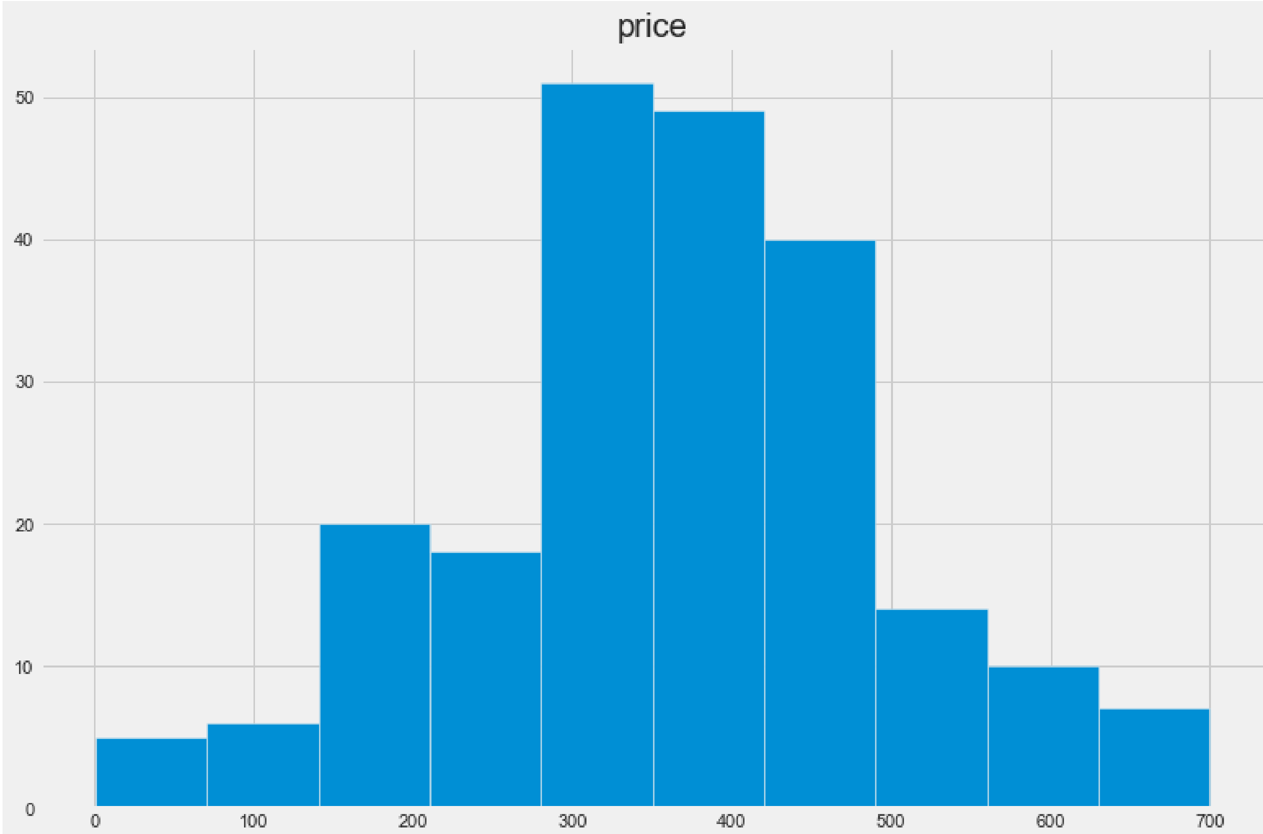
Exploratory analysis on the response variable

In [14]:

```
data.hist(column="price")
```

Out[14]:

```
array([[<AxesSubplot:title={'center':'price'}>]], dtype=object)
```



In [15]:

```
data["price"].describe()
```

Out[15]:

```
count    220.000000
mean     364.162727
std      132.301459
min        1.000000
25%      299.980000
50%      357.500000
75%      449.992500
max      699.990000
Name: price, dtype: float64
```

Drop rows where the price is anomalous

In [16]:

```
data = data.drop(data[data["price"] < 10].index)
```

In [17]:

```
data.isna().sum()
```

Out[17]:

```
sale      0
price     0
ghz      49
ram      42
hd       69
ssd       0
BIN       0
dtype: int64
```

Data Imputation for missing values

In [18]:

```
data.corr().round(2)
```

Out[18]:

	sale	price	ghz	ram	hd	ssd	BIN
sale	1.00	-0.12	0.10	-0.05	-0.05	0.16	-0.22
price	-0.12	1.00	0.28	0.25	-0.16	0.44	0.26
ghz	0.10	0.28	1.00	0.32	-0.08	0.19	-0.02
ram	-0.05	0.25	0.32	1.00	-0.02	0.29	-0.02
hd	-0.05	-0.16	-0.08	-0.02	1.00	-0.54	-0.17
ssd	0.16	0.44	0.19	0.29	-0.54	1.00	-0.01
BIN	-0.22	0.26	-0.02	-0.02	-0.17	-0.01	1.00

In [19]:

```
data[data["ssd"] == 1]["hd"].mode()
```

Out[19]:

```
0    128.0
dtype: float64
```

In [20]:

```
data[data["ssd"] == 0]["hd"].mode()
```

Out[20]:

```
0    320.0
dtype: float64
```

Fill in `hd` with most common (mode) value amongst laptops with same `ssd` value. This is because the highest correlated variable for `hd` is `ssd`

In [21]:

```
data["hd"].fillna(data["ssd"].map({1: 128, 0: 320}), inplace=True)
data.isna().sum()
```

Out[21]:

```
sale      0
price     0
ghz      49
ram      42
hd        0
ssd       0
BIN       0
dtype: int64
```

Similarly, for `ghz` and `ram`, use a stratified mode to fill in missing values

In [22]:

```
data.groupby("ghz")["ram"].agg(pd.Series.mode)
```

Out[22]:

```
ghz
2.5           4.0
2.6           4.0
2.7           8.0
2.8    [4.0, 8.0]
3.2           8.0
Name: ram, dtype: object
```

In [23]:

```
data.groupby("ram")["ghz"].agg(pd.Series.mode)
```

Out[23]:

```
ram
2.0    2.5
```

```
3.0     2.5
4.0     2.5
6.0     2.6
8.0     2.5
12.0     []
16.0     []
Name: ghz, dtype: object
```

In [24]:

```
imputed_data_ram = data["ram"].fillna(data["ghz"].map({2.5: 4, 2.6: 4, 2.7: 8, 2
imputed_data_ghz = data["ghz"].fillna(2.5) # most values are 2.5, so fill with t
data["ram"] = imputed_data_ram
data["ghz"] = imputed_data_ghz
data.isna().sum()
```

Out[24]:

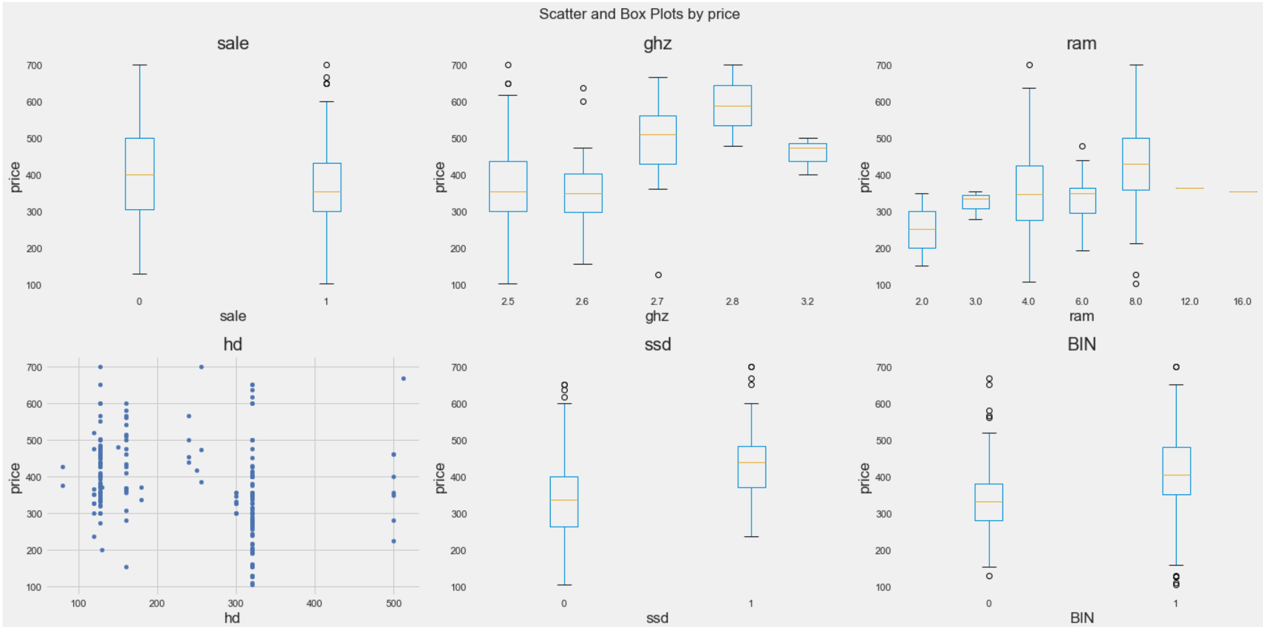
```
sale      0
price     0
ghz       0
ram       0
hd        0
ssd       0
BIN       0
dtype: int64
```

Model Selection & Variable Selection

In [25]:

```
plt.rcParams["figure.figsize"] = (20,10)
def draw_outcome_plots(df, outcome, n_rows, n_cols):
    fig=plt.figure()
    variables = df.columns.drop(outcome)
    for i, var_name in enumerate(variables):
        ax=fig.add_subplot(n_rows,n_cols,i+1)
        if len(df[var_name].unique()) > 10:
            df.plot.scatter(x= var_name, y= outcome, ax=ax)
        else:
            df.boxplot(column=outcome, by=var_name, grid = False, ax=ax)
        ax.set(ylabel=outcome)
        ax.set_title(var_name)
    fig.suptitle('Scatter and Box Plots by '+outcome)
    fig.tight_layout()
    plt.show()
draw_outcome_plots(data, 'price', 2, 3)
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be a
voided as value-mapping will have precedence in case its length matches with *x*
& *y*.  Please use the *color* keyword-argument or provide a 2-D array with a si
ngle row if you intend to specify the same RGB or RGBA value for all points.
```



Looking at boxplots, there seem to be linear trends across all variables except `sale` and `hd`. This may need further investigation.

This is indicative of a linear regression model, also because the response variable is normally distributed.

Exclude `sale` since that is being influenced by the response variable

In [26]:

```
y1, X1 = patsy.dmatrices("price ~ ghz + ram + hd + ssd + BIN", data, return_type
model1 = sm.OLS(y1, X1).fit()
print(model1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.312
Model:                            OLS   Adj. R-squared:                  0.296
Method:                 Least Squares   F-statistic:                     18.95
Date:                Thu, 08 Sep 2022   Prob (F-statistic):           1.58e-15
Time:                        15:33:47   Log-Likelihood:                -1296.4
No. Observations:                 215   AIC:                             2605.
Df Residuals:                     209   BIC:                             2625.
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   -183.0675    178.151     -1.028      0.305    -534.270     168.135
ghz          170.0113     69.891      2.433      0.016      32.230     307.793
ram            9.8137      3.703      2.650      0.009       2.514      17.113
hd            -0.0050      0.092     -0.054      0.957      -0.186       0.176
ssd           87.9694     20.529      4.285      0.000      47.498     128.441
BIN           67.1178     14.087      4.765      0.000      39.347      94.888
==============================================================================
Omnibus:                        5.752   Durbin-Watson:                   1.836
Prob(Omnibus):                  0.056   Jarque-Bera (JB):                6.366
Skew:                           0.242   Prob(JB):                       0.0415
Kurtosis:                       3.691   Cond. No.                     7.12e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
```

```
specified.
[2] The condition number is large, 7.12e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Also check with an interaction term of `hd:ssd` since that is an inference we are interested in

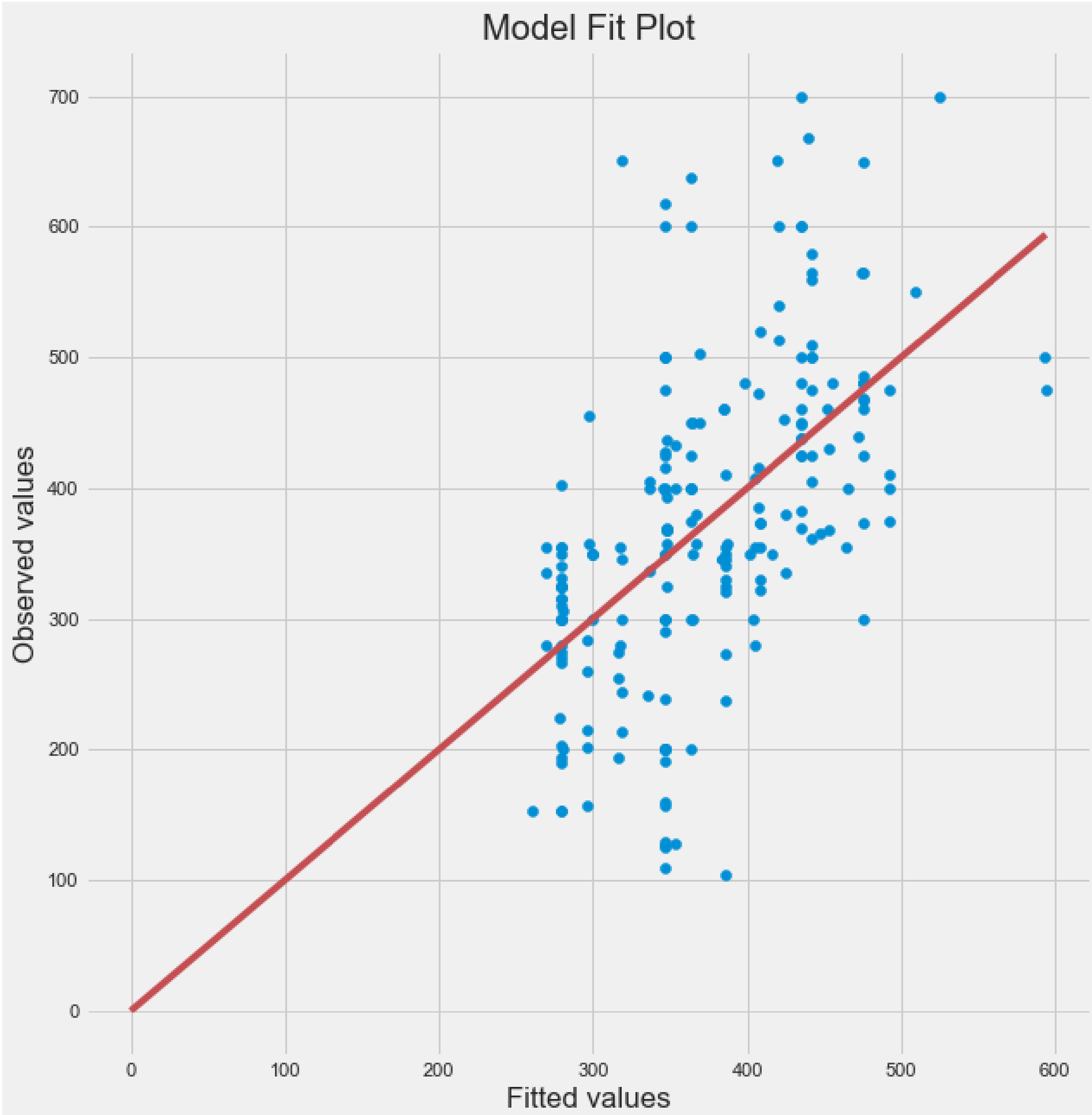
In [27]:
```python
y2, X2 = patsy.dmatrices("price ~ ghz + ram + hd*ssd + BIN", data, return_type="
model2 = sm.OLS(y2, X2).fit()
print(model2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  price   R-squared:                       0.341
Model:                            OLS   Adj. R-squared:                  0.322
Method:                 Least Squares   F-statistic:                     17.96
Date:                Thu, 08 Sep 2022   Prob (F-statistic):           9.41e-17
Time:                        15:33:47   Log-Likelihood:                -1291.7
No. Observations:                 215   AIC:                             2597.
Df Residuals:                     208   BIC:                             2621.
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -25.7613    182.228     -0.141      0.888    -385.012     333.489
ghz          124.4547     70.168      1.774      0.078     -13.877     262.786
ram            9.0168      3.641      2.476      0.014       1.838      16.195
hd            -0.1403      0.100     -1.397      0.164      -0.338       0.058
ssd          -32.5746     44.453     -0.733      0.465    -120.211      55.062
hd:ssd         0.7034      0.231      3.042      0.003       0.248       1.159
BIN           70.3974     13.859      5.080      0.000      43.076      97.719
==============================================================================
Omnibus:                        7.678   Durbin-Watson:                   1.848
Prob(Omnibus):                  0.022   Jarque-Bera (JB):                9.815
Skew:                           0.260   Prob(JB):                      0.00739
Kurtosis:                       3.908   Cond. No.                     7.50e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 7.5e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

AIC values are very similar, so prefer to keep the model without the interaction term as it is more easily interpretable, and the coefficients seem more reasonable and closer to reality

Model Diagnostics

In [44]:
```python
def diagnostic_plots(fit, response):
    fig, (ax1) = plt.subplots(1,1)
    ax1.scatter(fit.fittedvalues, response)
    abline_max = min(max(fit.fittedvalues), max(response))
    ax1.plot([0, abline_max], [0, abline_max], color='r')
    ax1.set_title('Model Fit Plot')
    ax1.set_ylabel('Observed values')
    ax1.set_xlabel('Fitted values');
    ax1.set_box_aspect(1)

diagnostic_plots(model1, data.price)
```



Recommendation

From the best model, predict prices and look at laptops that have lower prices than the predictions. These are "good" deals. Further filter based on requirements like `ssd=1` , and `BIN=0` (since this makes the price cheaper) and large HD capacity

In [36]:

```
data["savings"] =  data["price"] - model1.predict(X1)
data[(model1.predict(X1) < data["price"]) & (data["ssd"] == 1)  & (data["sale"]
```

Out[36]:

	sale	price	ghz	ram	hd	ssd	BIN	savings
6	0	699.95	2.5	4.0	128.0	1	1	264.285959
7	0	437.71	2.5	4.0	128.0	1	1	2.045959
23	0	565.00	2.5	8.0	240.0	1	1	90.639956
30	0	500.00	2.7	8.0	160.0	1	0	58.356284

	sale	price	ghz	ram	hd	ssd	BIN	savings
36	0	437.71	2.5	4.0	128.0	1	1	2.045959
39	0	499.99	2.7	8.0	128.0	1	0	58.186608
53	0	564.95	2.5	8.0	128.0	1	1	90.031090
54	0	560.00	2.7	8.0	160.0	1	0	118.356284
75	0	565.00	2.7	8.0	160.0	1	0	123.356284
100	0	579.00	2.7	8.0	160.0	1	0	137.356284

In [37]:

```
data.loc[[23, 30, 53, 100]]
```

Out[37]:

	sale	price	ghz	ram	hd	ssd	BIN	savings
23	0	565.00	2.5	8.0	240.0	1	1	90.639956
30	0	500.00	2.7	8.0	160.0	1	0	58.356284
53	0	564.95	2.5	8.0	128.0	1	1	90.031090
100	0	579.00	2.7	8.0	160.0	1	0	137.356284

In [ ]:

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