What drives the price of a car?

OVERVIEW

In this application, you will explore a dataset from kaggle that contains information on 3 million used cars. Your goal is to understand what factors make a car more or less expensive. As a result of your analysis, you should provide clear recommendations to your client -- a used car dealership -- as to what consumers value in a used car.

CRISP-DM Framework

To frame the task, throughout our practical applications we will refer back to a standard process in industry for data projects called CRISP-DM. This process provides a framework for working through a data problem. Your first step in this application will be to read through a brief overview of CRISP-DM here. After reading the overview, answer the questions below.

Business Understanding

From a business perspective, we are tasked with identifying key drivers for used car prices. In the CRISP-DM overview, we are asked to convert this business framing to a data problem definition. Using a few sentences, reframe the task as a data task with the appropriate technical vocabulary.

We are trying to understand the price of used cars.

Using historic used car data, we want to identify what factors are the best indicators of used car prices.

Using the best model we build using the model, we believe that any car dealership can offer competitive prices on used cars.

Consumers also benefit because they can now purchase used cars at reasonable and fair prices.

Data Understanding

After considering the business understanding, we want to get familiar with our data. Write down some steps that you would take to get to know the dataset and identify any quality issues within. Take time to get to know the dataset and explore what information it contains and how this could be used to inform your business understanding.

In [ ]:

```
pip install category_encoders
```

In [421…

```
import pandas as pd
import numpy as np
import statistics
from datetime import datetime
```

```python
from category_encoders import TargetEncoder

import seaborn as sns
import matplotlib.pyplot as plt
```

In [702…

```python
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.compose import make_column_transformer
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.preprocessing import PolynomialFeatures, StandardScaler, OneHotEncoder, La
from sklearn.inspection import permutation_importance
from sklearn.feature_selection import SequentialFeatureSelector
from sklearn.metrics import mean_squared_error, mean_absolute_error

from sklearn.impute import SimpleImputer
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer

from sklearn import set_config
set_config(display="diagram")

import warnings
warnings.filterwarnings('ignore')
```

In [160…

```python
vehicles = pd.read_csv('data/vehicles.csv')
```

In [45]:

```python
vehicles.head()
```

Out[45]:

	id	region	price	year	manufacturer	model	condition	cylinders	fuel	odometer	t
0	7222695916	prescott	6000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	7218891961	fayetteville	11900	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	7221797935	florida keys	21000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	7222270760	worcester / central MA	1500	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	7210384030	greensboro	4900	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In [46]:

```python
vehicles.tail()
```

Out[46]:

	id	region	price	year	manufacturer	model	condition	cylinders	fuel	o
426875	7301591192	wyoming	23590	2019.0	nissan	maxima s sedan 4d	good	6 cylinders	gas	
426876	7301591187	wyoming	30590	2020.0	volvo	s60 t5 momentum sedan 4d	good	NaN	gas	

	id	region	price	year	manufacturer	model	condition	cylinders	fuel	o
426877	7301591147	wyoming	34990	2020.0	cadillac	xt4 sport suv 4d	good	NaN	diesel	
426878	7301591140	wyoming	28990	2018.0	lexus	es 350 sedan 4d	good	6 cylinders	gas	
426879	7301591129	wyoming	30590	2019.0	bmw	4 series 430i gran coupe	good	NaN	gas	

In [48]:

```
vehicles.shape
```

Out[48]:

```
(426880, 18)
```

In [49]:

```
vehicles.columns
```

Out[49]:

```
Index(['id', 'region', 'price', 'year', 'manufacturer', 'model', 'condition',
       'cylinders', 'fuel', 'odometer', 'title_status', 'transmission', 'VIN',
       'drive', 'size', 'type', 'paint_color', 'state'],
      dtype='object')
```

In [50]:

```
vehicles.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 426880 entries, 0 to 426879
Data columns (total 18 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   id            426880 non-null  int64  
 1   region        426880 non-null  object 
 2   price         426880 non-null  int64  
 3   year          425675 non-null  float64
 4   manufacturer  409234 non-null  object 
 5   model         421603 non-null  object 
 6   condition     252776 non-null  object 
 7   cylinders     249202 non-null  object 
 8   fuel          423867 non-null  object 
 9   odometer      422480 non-null  float64
 10  title_status  418638 non-null  object 
 11  transmission  424324 non-null  object 
 12  VIN           265838 non-null  object 
 13  drive         296313 non-null  object 
 14  size          120519 non-null  object 
 15  type          334022 non-null  object 
 16  paint_color   296677 non-null  object 
 17  state         426880 non-null  object 
dtypes: float64(2), int64(2), object(14)
memory usage: 58.6+ MB
```

Examine null values

In [51]:

```
vehicles.isnull().any()
```

Out[51]:
```
id                False
region            False
price             False
year               True
manufacturer       True
model              True
condition          True
cylinders          True
fuel               True
odometer           True
title_status       True
transmission       True
VIN                True
drive              True
size               True
type               True
paint_color        True
state             False
dtype: bool
```

In [60]:
```
#Count null values
vehicles.isnull().sum()
```

Out[60]:
```
id                   0
region               0
price                0
year              1205
manufacturer     17646
model             5277
condition       174104
cylinders       177678
fuel              3013
odometer          4400
title_status      8242
transmission      2556
VIN             161042
drive           130567
size            306361
type             92858
paint_color     130203
state                0
dtype: int64
```

Data Preparation

After our initial exploration and fine tuning of the business understanding, it is time to construct our final dataset prior to modeling. Here, we want to make sure to handle any integrity issues and cleaning, the engineering of new features, any transformations that we believe should happen (scaling, logarithms, normalization, etc.), and general preparation for modeling with `sklearn`.

Drop VIN and id as they are unique to each vehicle and don't add to the analysis

In [55]:
```
vehicles2 = vehicles.drop(columns=['VIN', 'id'], axis =1)
```

In [90]:
```
vehicles2.shape
```

Out[90]:

```
(426880, 16)
```

Convert data types

In [56]:

```python
vehicles2  = vehicles2.convert_dtypes()
```

In [57]:

```python
vehicles2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 426880 entries, 0 to 426879
Data columns (total 16 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   region        426880 non-null  string
 1   price         426880 non-null  Int64 
 2   year          425675 non-null  Int64 
 3   manufacturer  409234 non-null  string
 4   model         421603 non-null  string
 5   condition     252776 non-null  string
 6   cylinders     249202 non-null  string
 7   fuel          423867 non-null  string
 8   odometer      422480 non-null  Int64 
 9   title_status  418638 non-null  string
 10  transmission  424324 non-null  string
 11  drive         296313 non-null  string
 12  size          120519 non-null  string
 13  type          334022 non-null  string
 14  paint_color   296677 non-null  string
 15  state         426880 non-null  string
dtypes: Int64(3), string(13)
memory usage: 53.3 MB
```

Create 'age' variable from the year

In [422...

```python
vehicles2['age'] = datetime.now().year - vehicles2['year']
print(datetime.now().year)
```

```
2022
```

Examine numeric fields stats and correlation

In [423...

```python
vehicles2.describe()
```

Out[423...

	price	year	odometer	age
count	4.268800e+05	425675.000000	4.224800e+05	425675.000000
mean	7.519903e+04	2011.235191	9.804333e+04	10.764809
std	1.218228e+07	9.452120	2.138815e+05	9.452120
min	0.000000e+00	1900.000000	0.000000e+00	0.000000
25%	5.900000e+03	2008.000000	3.770400e+04	5.000000
50%	1.395000e+04	2013.000000	8.554800e+04	9.000000

	price	year	odometer	age
75%	2.648575e+04	2017.000000	1.335425e+05	14.000000
max	3.736929e+09	2022.000000	1.000000e+07	122.000000

In [427…

```
vehicles2.drop('year', axis=1, inplace=True)
```

In [428…

```
vehicles2.corr()
```

Out[428…

	price	odometer	age
price	1.000000	0.010032	0.004925
odometer	0.010032	1.000000	0.157215
age	0.004925	0.157215	1.000000

Examine price and odometer for zeroes further

In [429…

```
vehicles2.eq(0).sum()
```

Out[429…

```
region              0
price           32895
manufacturer        0
model               0
condition           0
cylinders           0
fuel                0
odometer         1965
title_status        0
transmission        0
drive               0
size                0
type                0
paint_color         0
state               0
age               133
dtype: int64
```

In [430…

```
#Mode of price
statistics.mode(vehicles2.price)
```

Out[430…

```
0
```

Drop observations with price 0 or less(none in this dataset) as it doesn't make sense for modeling

In [450…

```
vehicles3a = vehicles2.query("price > 0", engine ='python')
```

In [451…

```
vehicles3a.shape
```

Out[451…

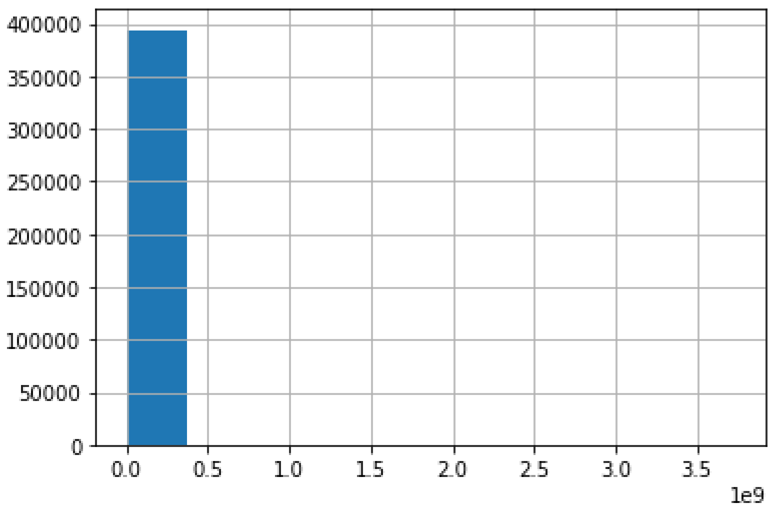
```
(393985, 16)
```

In [452…

```
#Histogram of price
vehicles3a.price.hist()
```

Out[452…

```
<AxesSubplot:>
```



Drop observations with age 0 or less(none in this dataset) as a threshold for used cars

In [453…

```
vehicles3 = vehicles3a.query("age > 0", engine ='python')
```

In [454…

```
vehicles3.shape
```

Out[454…

```
(392706, 16)
```

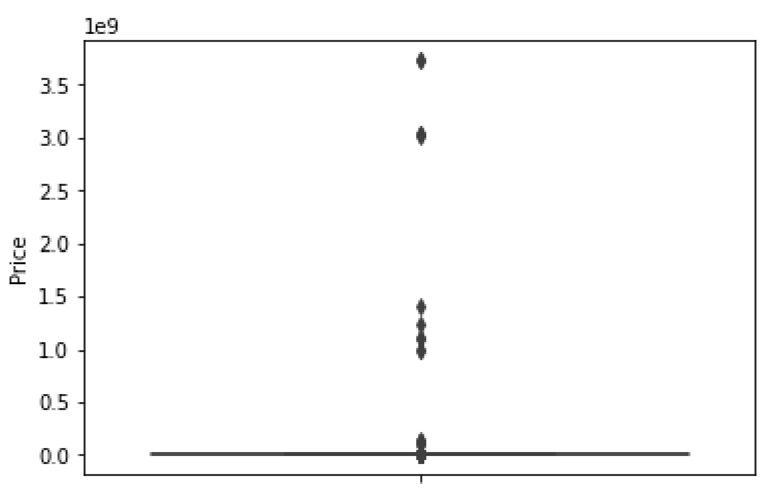
Check for outliers in terms of price and odometer

In [119…

```
#Box Plot price
sns.boxplot(y='price',data=vehicles3)
plt.xticks(rotation=90)
plt.ylabel('Price')
```

Out[119…

```
Text(0, 0.5, 'Price')
```

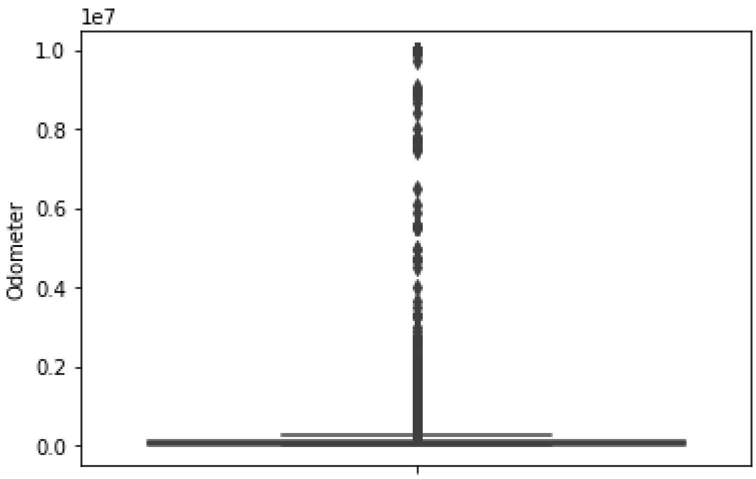


In [120…

```
#Box Plot odometer
sns.boxplot(y='odometer',data=vehicles3)
plt.xticks(rotation=90)
plt.ylabel('Odometer')
```

Out[120…

```
Text(0, 0.5, 'Odometer')
```



Use IQR function to remove outliers

In [455…

```
# Outliers Function
cols = ['price', 'odometer'] # one or more columns

Q1 = vehicles3[cols].quantile(0.25)
Q3 = vehicles3[cols].quantile(0.75)
IQR = Q3 - Q1

vehicles4 = vehicles3[~((vehicles3[cols] < (Q1 - 1.5 * IQR)) |(vehicles3[cols] > (Q3 +
```

In [456…

```
#Number of rows remaining
vehicles4.shape
```

Out[456…

```
(381376, 16)
```

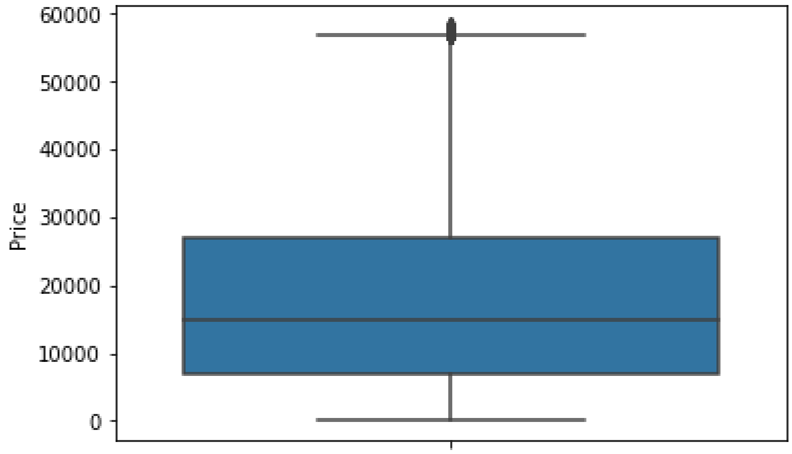
Check box plots after removing outliers

In [885…

```
#Box Plot price
sns.boxplot(y='price',data=vehicles4)
plt.xticks(rotation=90)
plt.ylabel('Price')
```

Out[885…

```
Text(0, 0.5, 'Price')
```

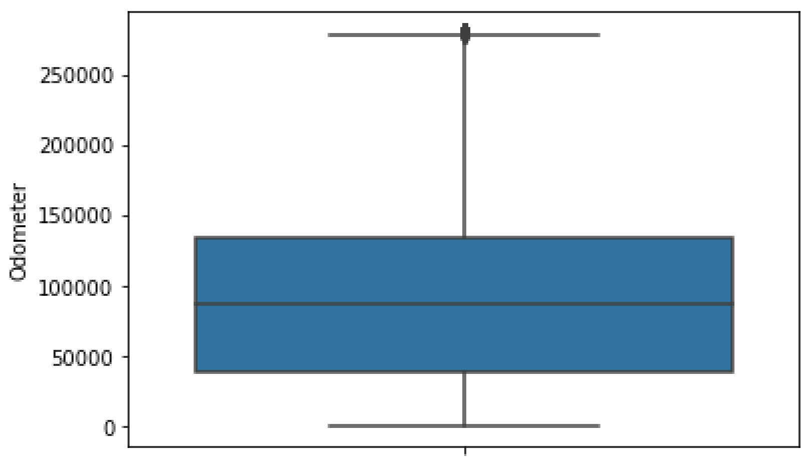


In [886…

```
#Box Plot odometer
sns.boxplot(y='odometer',data=vehicles4)
plt.xticks(rotation=90)
plt.ylabel('Odometer')
```

Out[886…

```
Text(0, 0.5, 'Odometer')
```



Alternative method, using DBSCAN to remove outliers in price. -------------> NOT USED

In [98]:

```
from sklearn.cluster import DBSCAN
```

In [99]:

```
def remove_outliers_DBSCAN(df,eps,min_samples):
    outlier_detection = DBSCAN(eps = eps, min_samples = min_samples)
    clusters = outlier_detection.fit_predict(df.values.reshape(-1,1))
    data = pd.DataFrame()
    data['cluster'] = clusters
    return data['cluster']
```

In [101…

```
clusters=remove_outliers_DBSCAN((vehicles3[['price']]),0.5,5)
clusters.value_counts().sort_values(ascending=False)
```

Out[101…

```
-1      18750
 85      3169
 768     3129
 364     2867
```

```
223         2837
          ...
3514           5
3519           5
2536           5
3523           5
4726           5
Name: cluster, Length: 4728, dtype: int64
```

In [102…

```python
df_cluster=pd.DataFrame(clusters)
ind_outlier=df_cluster.index[df_cluster['cluster']==-1]
ind_outlier
```

Out[102…

```
Int64Index([   192,    193,    194,    235,    266,    285,    331,    360,
               420,    421,
            ...
            393545, 393547, 393548, 393550, 393581, 393585, 393685, 393732,
            393751, 393798],
           dtype='int64', length=18750)
```

In [104…

```python
len(ind_outlier)
```

Out[104…

```
18750
```

In [105…

```python
vehicles4_alt = vehicles3[~(vehicles3.index.isin(ind_outlier))]
```

In [107…

```python
vehicles4_alt.shape
```

Out[107…

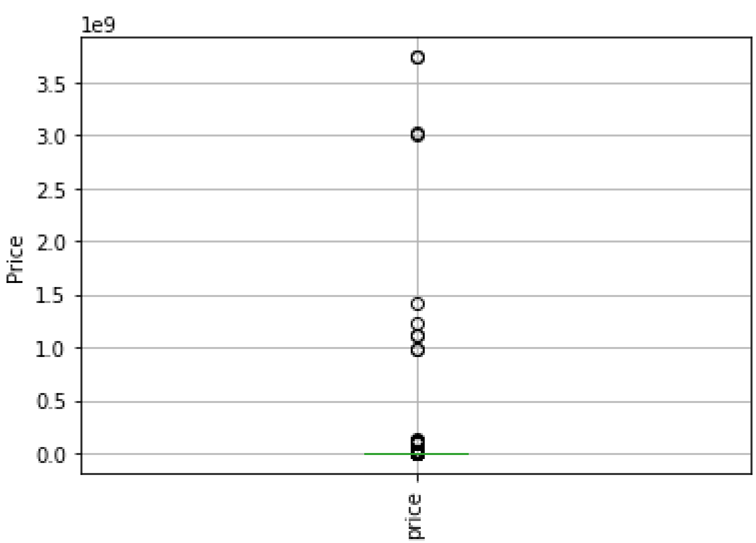
```
(376579, 16)
```

In [113…

```python
vehicles4_alt.boxplot('price')
plt.xticks(rotation=90)
plt.ylabel('Price')
```

Out[113…

```
Text(0, 0.5, 'Price')
```



End of DBSCAN process -------------> NOT USED

Examine NA values

In [126…

```
vehicles4.isnull().sum()
```

Out[126…

```
region               0
price                0
year               988
manufacturer     14536
model             4203
condition       145107
cylinders       155210
fuel              2544
odometer          2212
title_status      7521
transmission      1746
drive           116909
size            274217
type             82661
paint_color     113376
state                0
dtype: int64
```

In [127…

```
vehicles4.isna().mean()
```

Out[127…

```
region          0.000000
price           0.000000
year            0.002583
manufacturer    0.038007
model           0.010989
condition       0.379406
cylinders       0.405822
fuel            0.006652
odometer        0.005784
title_status    0.019665
transmission    0.004565
drive           0.305678
size            0.716986
type            0.216131
paint_color     0.296440
state           0.000000
dtype: float64
```

Examine the 'size' field for NA as about 70% of data has missing value for the field

In [134…

```
vehicles4.value_counts('size', dropna = False)
```

Out[134…

```
size
NaN            274217
full-size       56558
mid-size        31518
compact         17326
sub-compact      2839
dtype: int64
```

In [133…

```
vehicles4['size'].unique()
```

```
<StringArray>
```

Out[133…
```
[<NA>, 'full-size', 'mid-size', 'compact', 'sub-compact']
Length: 5, dtype: string
```

We will remove any field that has less than 50% of data available before imputing.

There is some useful information in this column (size) but it's scarely populated. Could consider keeping if there is no memory/prerformance issue

In [457…
```
vehicles5 = vehicles4.drop(vehicles4.columns[vehicles4.isna().mean()> 0.5], axis = 1)
```

In [458…
```
vehicles5.columns #Size column gets dropped
```

Out[458…
```
Index(['region', 'price', 'manufacturer', 'model', 'condition', 'cylinders',
       'fuel', 'odometer', 'title_status', 'transmission', 'drive', 'type',
       'paint_color', 'state', 'age'],
      dtype='object')
```

Impute Missing Data and Encode

Reset Index and drop some additional fields: Use higher aggregation level manufacturer(not model) and state(not region) for performance

In [ ]:
```
vehicles6 = vehicles5.reset_index().convert_dtypes().replace({pd.NA: np.nan})
vehicles6.drop(columns=['index','model','region'], axis =1,inplace= True)
vehicles6
```

In [ ]:
```
vehicles6.dtypes
```

Split data into training and test sets

In [ ]:
```
X, y = vehicles6.drop(columns='price'), vehicles6['price']
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42, test_size
```

In [726…
```
X_train.value_counts('drive', dropna=False) #Drive has few unique values: use OneHotEnc
```

Out[726…
```
drive
NaN    81455
4wd    80449
fwd    67565
rwd    37494
dtype: int64
```

In [680…
```
numeric_features = ['odometer','age']
```

In [681…
```
oneHot_features = ['drive']
```

In [682…
```
categorical_features = ['condition', 'cylinders', 'fuel', 'title_status','transmission'
                        'type', 'paint_color']
```

In [683…
```
numeric_transformer = Pipeline(steps=[
    ('imputer',  IterativeImputer(random_state=42))
    #('imputer', SimpleImputer(strategy='median'))
    #,('scaler', StandardScaler())
    ])
```

In [684…
```
oneHot_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent', fill_value='missing'))
    ,('onehot', OneHotEncoder(drop = 'if_binary', sparse=False))
    ])

    #('imputer',  IterativeImputer(random_state=42)),
    #('onehot', OneHotEncoder(handle_unknown='ignore',drop = 'if_binary'))])
```

In [697…
```
categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent', fill_value='missing'))
    ,('target', TargetEncoder())])

#Same thing using OrdinalEncoder instead
#categorical_transformer = Pipeline(steps=[
#    ('imputer', SimpleImputer(strategy='constant', fill_value='missing'))
#    ,('ordinal', OrdinalEncoder())])
```

In [698…
```
#preprocessor = ColumnTransformer(
preprocessor = make_column_transformer((numeric_transformer, numeric_features),
                                       (categorical_transformer, categorical_features),
                                       (oneHot_transformer, oneHot_features),
                                       remainder = "drop")
```

Modeling

With your (almost?) final dataset in hand, it is now time to build some models. Here, you should build a number of different regression models with the price as the target. In building your models, you should explore different parameters and be sure to cross-validate your findings.

Basic Models for benchmark

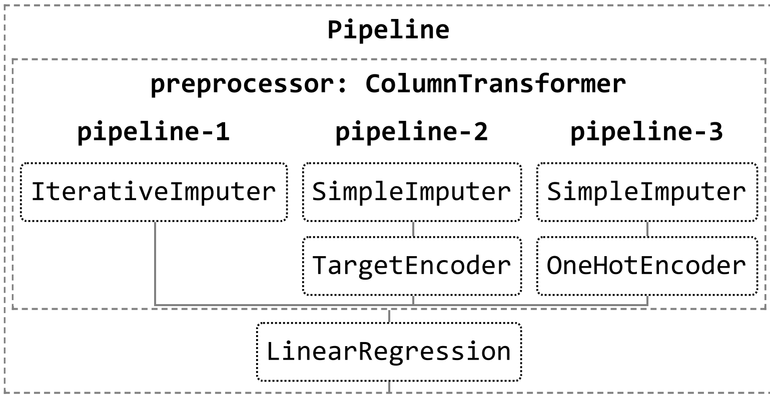
Linear Regression

In [718…
```
pipe = Pipeline([('preprocessor', preprocessor),
                 ('regression', LinearRegression())
                ])
pipe.fit(X_train, y_train)
mse_train2 = mean_squared_error(y_train, pipe.predict(X_train))
mse_test2 = mean_squared_error(y_test, pipe.predict(X_test))
print('Linear Reg MSE train:', mse_train2)
print('Linear Reg MSE test :', mse_test2)
print('The R2 score is:', pipe.score(X_test,y_test))
pipe
```

```
Linear Reg MSE train: 74317408.04531045
Linear Reg MSE test : 74916482.32898577
```

```
The R2 score is: 0.5427530679376411
```

Out[718…



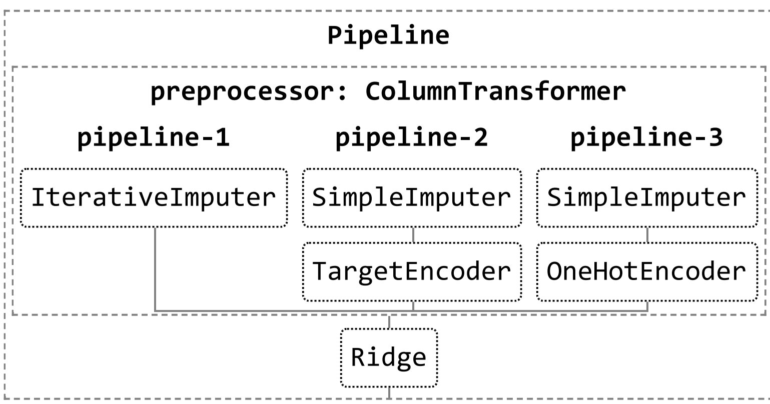
Ridge

In [719…

```python
pipe0 = Pipeline([('preprocessor', preprocessor),
                  ('regressor', Ridge())])
pipe0.fit(X_train, y_train)
mse_train2 = mean_squared_error(y_train, pipe0.predict(X_train))
mse_test2 = mean_squared_error(y_test, pipe0.predict(X_test))
print('Ridge MSE train:', mse_train2)
print('Ridge MSE test :', mse_test2)
print('The R2 score is:', pipe0.score(X_test,y_test))
pipe0
```

```
Ridge MSE train: 74317408.04588023
Ridge MSE test : 74916484.52984537
The R2 score is: 0.5427530545048656
```

Out[719…



Lasso for feature Selection and apply to Linear Regression

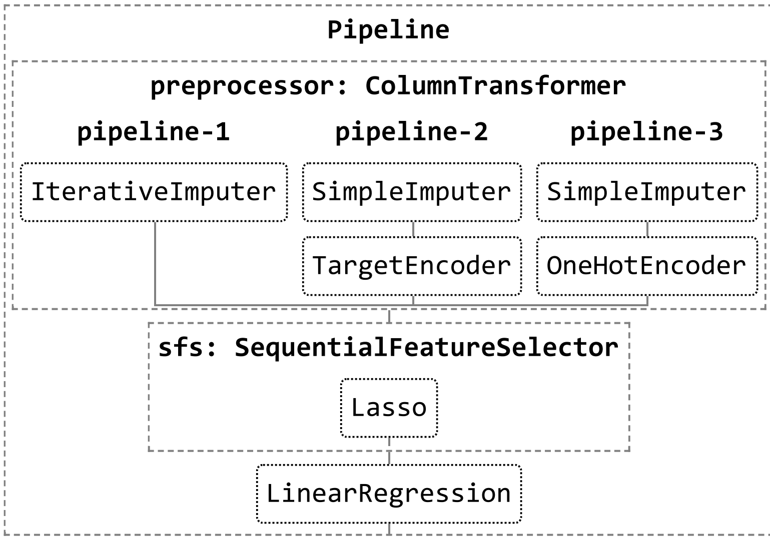
In [720…

```python
pipe1 = Pipeline([('preprocessor', preprocessor),
    ('sfs', SequentialFeatureSelector(n_features_to_select = 4, estimator=Lasso())),
    ('regression', LinearRegression())
])
pipe1.fit(X_train, y_train)
mse_train2 = mean_squared_error(y_train, pipe1.predict(X_train))
mse_test2 = mean_squared_error(y_test, pipe1.predict(X_test))
print('SFS with LASSO MSE train:', mse_train2)
print('SFS with LASSO MSE test :', mse_test2)
print('The R2 score is:', pipe1.score(X_test,y_test))
pipe1
```

```
SFS with LASSO MSE train: 86509276.415559
```

```
SFS with LASSO MSE test : 87480537.46430765
The R2 score is: 0.4660693331133017
```

Out[720…



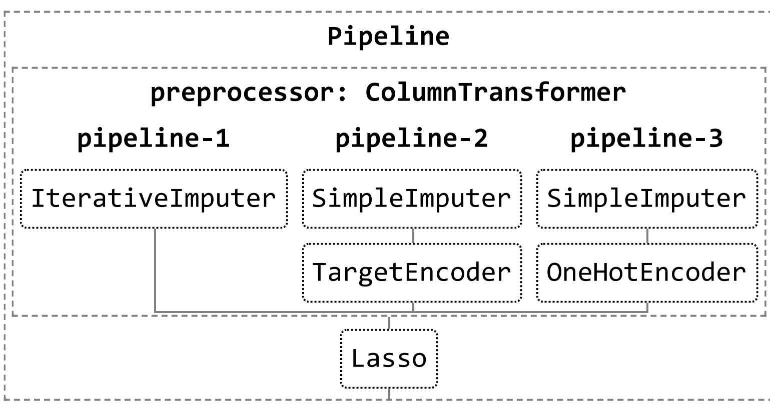
Lasso

In [760…

```python
# Lasso by itself
pipe_lasso = Pipeline([('preprocessor', preprocessor),
                       ('regressor', Lasso())]) # default alpha = 1
pipe_lasso.fit(X_train, y_train)
print(list(zip(X_train.columns, pipe_lasso['regressor'].coef_)))
print('The R2 score is:', pipe_lasso.score(X_test,y_test))
pipe_lasso
```

```
[('manufacturer', -0.08565954935532444), ('condition', -299.0395439552127), ('cylinder
s', 0.18053630956340347), ('fuel', 0.42001410882243356), ('odometer', 0.56065351395607
5), ('title_status', 0.5468612051756497), ('transmission', 0.002997722385016729), ('driv
e', 0.4334041799648083), ('type', 0.5619418627103584), ('paint_color', 0.499851189496386
85), ('state', 0.14106840331805068), ('age', -0.0)]
The R2 score is: 0.5427507626877753
```

Out[760…



Linear Regression, Ridge and Lasso perform roughly the same. When selecting features using LASSO and applying it to Linear Regression it performs a bit worse.

Models

Model 1

In [722…

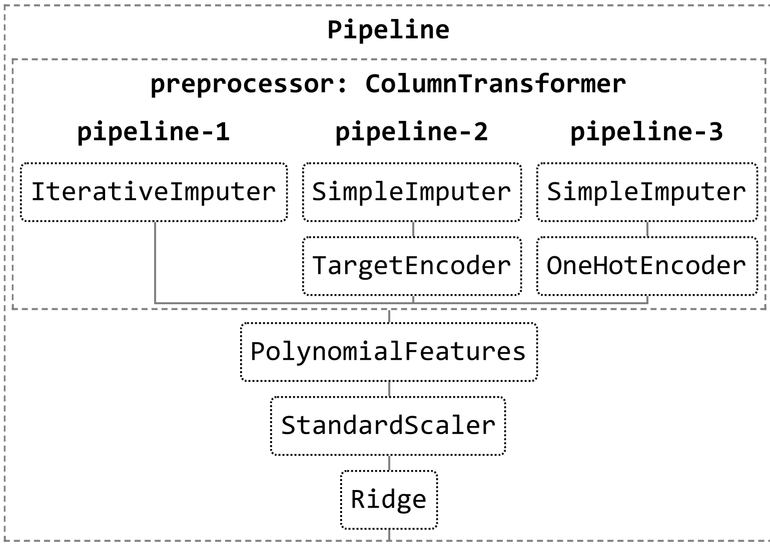
```python
pipe2 = Pipeline([('preprocessor', preprocessor),
```

```
                    ('poly_features',(PolynomialFeatures(degree=2, include_bias=False))),
                    ('scaler', StandardScaler()),
                    ('regressor', Ridge())])
```

In [723…

```
pipe2.fit(X_train, y_train)
```

Out[723…



In [894…

```
mse_train2 = mean_squared_error(y_train, pipe2.predict(X_train))
mse_test2 = mean_squared_error(y_test, pipe2.predict(X_test))
print('SFS with LASSO MSE train:', mse_train2)
print('SFS with LASSO MSE test :', mse_test2)
print('The R2 score is:', pipe2.score(X_test,y_test))
```

```
SFS with LASSO MSE train: 58223095.4375152
SFS with LASSO MSE test : 58765939.23884018
The R2 score is: 0.6413266534762773
```

Grid Search CV - To find best model

Get indices for GridSearchCV

In [727…

```
training_indices = (pd.DataFrame(X_train).index)
training_indices
```

Out[727…

```
Int64Index([257221, 333264, 326473, 293211, 182656, 197089,   9030, 319935,
             67506, 310387,
            ...
            137337,  54886, 207892, 110268, 119879, 259178, 365838, 131932,
            146867, 121958],
           dtype='int64', length=266963)
```

In [728…

```
test_indices = (pd.DataFrame(X_test).index)
test_indices
```

Out[728…

```
Int64Index([ 21683, 310950, 260878, 167058, 351007, 163164, 301310, 233631,
            254153, 106125,
            ...
            327003, 344096, 187760, 252400, 364525, 110185, 247730,  83083,
```

```
            3286, 128697],
         dtype='int64', length=114413)
```

In [729...

```python
params_to_try = {'regressor__alpha': [0.01,0.1,1,10,100,1000]}
```

In [731...

```python
pipe3 = Pipeline([('preprocessor', preprocessor),
                  ('poly_features',(PolynomialFeatures(degree=2, include_bias=False))),
                  ('scaler', StandardScaler()),
                  ('regressor', Ridge())])
```

In [742...

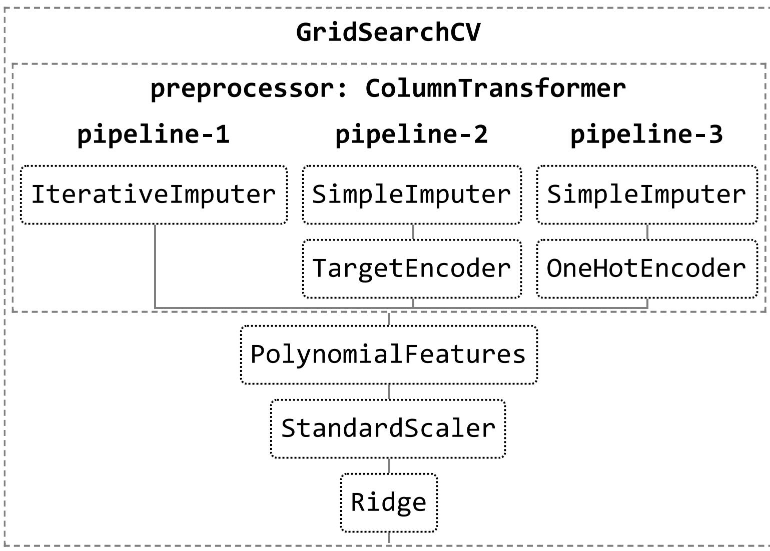
```python
model_finder = GridSearchCV(estimator = pipe3,
                           param_grid = params_to_try,
                           scoring = ["neg_mean_squared_error", 'r2'], refit='r2',
                           cv = [[training_indices, test_indices]])
```

Grid Search CV - Using Log Transformation on the target 'price'

In [743...

```python
model_finder.fit(X,np.log1p(y)) # We transform target using natural log before fitting
```

Out[743...



In [745...

```python
best_model = model_finder.best_estimator_
model_finder.cv_results_
```

Out[745...

```
{'mean_fit_time': array([5.40378404, 5.08030844, 5.11777759, 5.06895638, 5.128901  ,
        5.17256808]),
 'std_fit_time': array([0., 0., 0., 0., 0., 0.]),
 'mean_score_time': array([0.78436637, 0.72143674, 0.7088027 , 0.75270438, 0.7834053 ,
        0.72157836]),
 'std_score_time': array([0., 0., 0., 0., 0., 0.]),
 'param_regressor__alpha': masked_array(data=[0.01, 0.1, 1, 10, 100, 1000],
              mask=[False, False, False, False, False, False],
        fill_value='?',
             dtype=object),
 'params': [{'regressor__alpha': 0.01},
  {'regressor__alpha': 0.1},
  {'regressor__alpha': 1},
  {'regressor__alpha': 10},
```

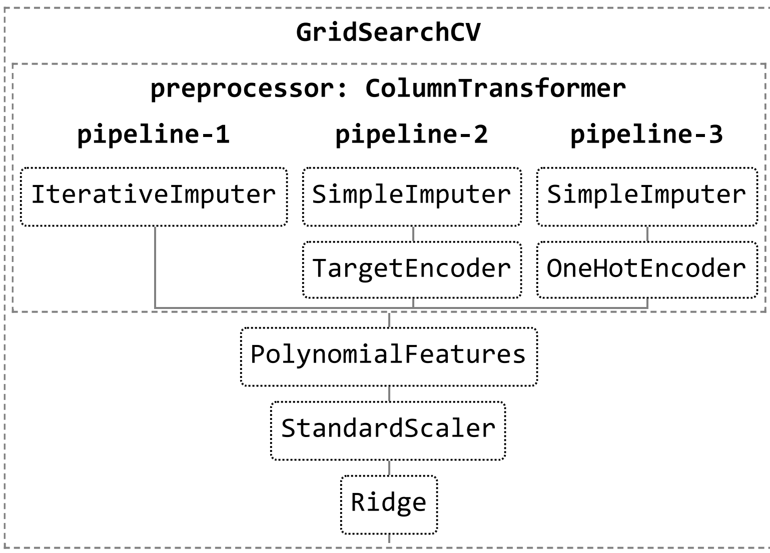
```
 {'regressor__alpha': 100},
 {'regressor__alpha': 1000}],
'split0_test_neg_mean_squared_error': array([-0.98364946, -0.9837718 , -0.98440542, -0.
98697951, -1.00060168,
        -1.01936672]),
'mean_test_neg_mean_squared_error': array([-0.98364946, -0.9837718 , -0.98440542, -0.98
697951, -1.00060168,
        -1.01936672]),
'std_test_neg_mean_squared_error': array([0., 0., 0., 0., 0., 0.]),
'rank_test_neg_mean_squared_error': array([1, 2, 3, 4, 5, 6]),
'split0_test_r2': array([0.33027319, 0.3301899 , 0.32975849, 0.3280059 , 0.31873112,
        0.30595477]),
'mean_test_r2': array([0.33027319, 0.3301899 , 0.32975849, 0.3280059 , 0.31873112,
        0.30595477]),
'std_test_r2': array([0., 0., 0., 0., 0., 0.]),
'rank_test_r2': array([1, 2, 3, 4, 5, 6])}
```

Grid Search CV - Without log transformation of target

In [746…

```
model_finder.fit(X,y) # Fit without log transform
```

Out[746…



In [747…

```
best_model1 = model_finder.best_estimator_
model_finder.cv_results_
```

Out[747…

```
{'mean_fit_time': array([5.16315246, 5.02787781, 5.07544756, 5.07495332, 5.12175298,
        5.15994167]),
 'std_fit_time': array([0., 0., 0., 0., 0., 0.]),
 'mean_score_time': array([0.73703694, 0.70619249, 0.71425009, 0.78434777, 0.80001926,
        0.72131252]),
 'std_score_time': array([0., 0., 0., 0., 0., 0.]),
 'param_regressor__alpha': masked_array(data=[0.01, 0.1, 1, 10, 100, 1000],
              mask=[False, False, False, False, False, False],
        fill_value='?',
             dtype=object),
 'params': [{'regressor__alpha': 0.01},
  {'regressor__alpha': 0.1},
  {'regressor__alpha': 1},
  {'regressor__alpha': 10},
  {'regressor__alpha': 100},
  {'regressor__alpha': 1000}],
```

```
 'split0_test_neg_mean_squared_error': array([-58765948.40583091, -58765935.24614283, -5
8765939.23884018,
        -58776504.96347149, -59046772.92071968, -59838164.65544808]),
 'mean_test_neg_mean_squared_error': array([-58765948.40583091, -58765935.24614283, -587
65939.23884018,
        -58776504.96347149, -59046772.92071968, -59838164.65544808]),
 'std_test_neg_mean_squared_error': array([0., 0., 0., 0., 0., 0.]),
 'rank_test_neg_mean_squared_error': array([3, 1, 2, 4, 5, 6]),
 'split0_test_r2': array([0.6413266 , 0.64132668, 0.64132665, 0.64126217, 0.63961261,
        0.63478241]),
 'mean_test_r2': array([0.6413266 , 0.64132668, 0.64132665, 0.64126217, 0.63961261,
        0.63478241]),
 'std_test_r2': array([0., 0., 0., 0., 0., 0.]),
 'rank_test_r2': array([3, 1, 2, 4, 5, 6])}
```

In [748…

```python
model_finder.best_score_
```

Out[748…

```
0.6413266778453954
```

Since we found model without log transformation of target with alpha=0.1 to be the best. We compute permutation importance for Ridge model with alpha = 0.1 after applying all transformations

In [750…

```python
features = [c for c in ['manufacturer','condition','cylinders','fuel','odometer','title
pipe = Pipeline([('preprocessor', preprocessor),
                 ('poly_features',(PolynomialFeatures(degree=2, include_bias=False))),
                 ('scaler', StandardScaler()),
                 ('regressor', Ridge(alpha = 0.1))])

model = pipe.fit(X_train, y_train)
# score with test set
print('model r^2 :', model.score(X_test, y_test))
# permutation importance
r = permutation_importance(model, X_test, y_test, n_repeats = 50, random_state = 93)
print('importance:', r.importances_mean)
pd.DataFrame({"Column":X.columns, "Importance":r.importances_mean}).sort_values(
        by = "Importance", ascending = False)
```

```
model r^2 : 0.6413266778453954
importance: [0.04381244 0.02862781 0.05894518 0.08394188 0.19742747 0.00888315
 0.02170606 0.04201124 0.0564302  0.00143146 0.01361455 0.31154223]
```

Out[750…

	Column	Importance
11	age	0.311542
4	odometer	0.197427
3	fuel	0.083942
2	cylinders	0.058945
8	type	0.056430
0	manufacturer	0.043812
7	drive	0.042011
1	condition	0.028628

	Column	Importance
6	transmission	0.021706
10	state	0.013615
5	title_status	0.008883
9	paint_color	0.001431

Evaluation

With some modeling accomplished, we aim to reflect on what we identify as a high quality model and what we are able to learn from this. We should review our business objective and explore how well we can provide meaningful insight on drivers of used car prices. Your goal now is to distill your findings and determine whether the earlier phases need revisitation and adjustment or if you have information of value to bring back to your client.

Adjusted model

We see that paint_color and title_status are not as important (<10% importance). We will exclude those 2 columns in our future modeling.

In [775…

```
categorical_features1 = ['condition', 'cylinders', 'fuel', 'transmission', 'manufacture
```

In [776…

```
preprocessor1 = make_column_transformer((numeric_transformer, numeric_features),
                                        (categorical_transformer, categorical_features1)
                                        (oneHot_transformer, oneHot_features),
                                        remainder = "drop")
```

In [777…

```
pipe4 = Pipeline([('preprocessor1', preprocessor1),
                  ('poly_features',(PolynomialFeatures(degree=2, include_bias=False))),
                  ('scaler', StandardScaler()),
                  ('regressor', Ridge())])
```

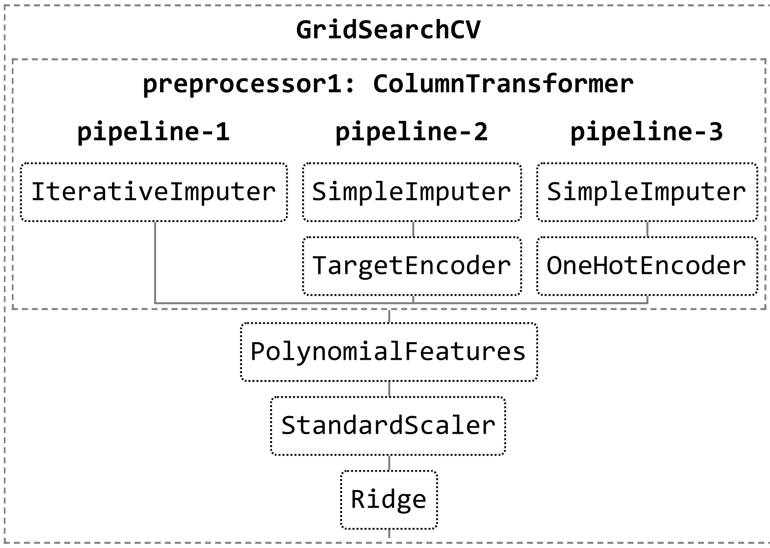
In [778…

```
model_finder = GridSearchCV(estimator = pipe4,
                            param_grid = params_to_try,
                            scoring = ["neg_mean_squared_error", 'r2'], refit='r2',
                            cv = [[training_indices, test_indices]])
```

In [779…

```
#Remove features with low importance and fit model
X1 = X.drop(['paint_color','title_status'], axis=1)
model_finder.fit(X1,y)
```

Out[779…



In [896…

```
best_model = model_finder.best_estimator_
model_finder.cv_results_
```

Out[896…

```
{'mean_fit_time': array([4.31562614, 4.02383661, 4.002002  , 3.93019915, 4.1906271 ,
        4.07324719]),
 'std_fit_time': array([0., 0., 0., 0., 0., 0.]),
 'mean_score_time': array([0.66118073, 0.58324552, 0.56508088, 0.6277585 , 0.5961597 ,
        0.613096  ]),
 'std_score_time': array([0., 0., 0., 0., 0., 0.]),
 'param_regressor__alpha': masked_array(data=[0.01, 0.1, 1, 10, 100, 1000],
              mask=[False, False, False, False, False, False],
        fill_value='?',
             dtype=object),
 'params': [{'regressor__alpha': 0.01},
  {'regressor__alpha': 0.1},
  {'regressor__alpha': 1},
  {'regressor__alpha': 10},
  {'regressor__alpha': 100},
  {'regressor__alpha': 1000}],
 'split0_test_neg_mean_squared_error': array([-59394175.54750731, -59394188.15516831, -5
9394428.12654306,
        -59405765.25080516, -59662696.05564089, -60400217.49066035]),
 'mean_test_neg_mean_squared_error': array([-59394175.54750731, -59394188.15516831, -593
94428.12654306,
        -59405765.25080516, -59662696.05564089, -60400217.49066035]),
 'std_test_neg_mean_squared_error': array([0., 0., 0., 0., 0., 0.]),
 'rank_test_neg_mean_squared_error': array([1, 2, 3, 4, 5, 6]),
 'split0_test_r2': array([0.63749226, 0.63749219, 0.63749072, 0.63742153, 0.63585337,
        0.63135196]),
 'mean_test_r2': array([0.63749226, 0.63749219, 0.63749072, 0.63742153, 0.63585337,
        0.63135196]),
 'std_test_r2': array([0., 0., 0., 0., 0., 0.]),
 'rank_test_r2': array([1, 2, 3, 4, 5, 6])}
```

Even after excluding these two columns, we get a R2 of about .63 meaning 63% of the variation is explained by our model. The best R2 is obtained with alpha = 0.01.

In [891…

```
r = permutation_importance(best_model, X1, y, n_repeats = 50, random_state = 93)
print('importance:', r.importances_mean)
```

```
pd.DataFrame({"Column":X1.columns, "Importance":r.importances_mean}).sort_values(
        by = "Importance", ascending = False)
```

```
importance: [0.04522502 0.03025452 0.06006291 0.08451121 0.19334099 0.02174225
 0.04314349 0.05796849 0.01365548 0.32120401]
```

Out[891…

	Column	Importance
9	age	0.321204
4	odometer	0.193341
3	fuel	0.084511
2	cylinders	0.060063
7	type	0.057968
0	manufacturer	0.045225
6	drive	0.043143
1	condition	0.030255
5	transmission	0.021742
8	state	0.013655

Cross Validation

In [893…

```
#Cross Validation
result = cross_val_score(best_model, X1, y,  cv=3)
print(result)
```

```
[0.60109648 0.64947036 0.62237556]
```

Prediction on test data

In [901…

```
y_predicted = model_finder.predict(X_test.drop(['paint_color','title_status'], axis=1))
```

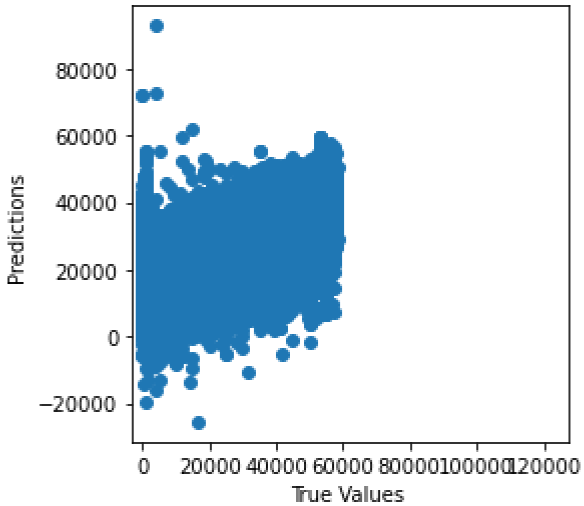
Plot true vs predicted prices

In [919…

```
g=plt.scatter(y_test, y_predicted)
#g.axes.set_yscale('log')
#g.axes.set_xscale('log')
g.axes.set_xlabel('True Values ')
g.axes.set_ylabel('Predictions ')
g.axes.axis('equal')
g.axes.axis('square')
#p1 = max(max(predicted_value), max(true_value))
#p2 = min(min(predicted_value), min(true_value))
#plt.plot([p1, p2], [p1, p2], 'b-')
```

Out[919…

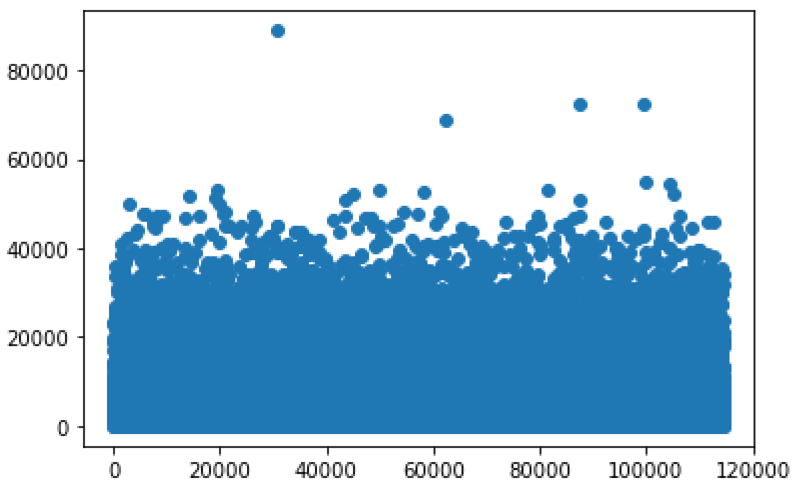
```
(-2921.15, 127410.96666187714, -31480.491578392943, 98851.62508348419)
```



Plot difference in true vs predicted prices (absolute values)

In [925…

```
#PLot absolute value of differences
y_diff=np.array(y_test - y_predicted)
g = plt.plot(abs(y_diff),marker='o',linestyle='')
```



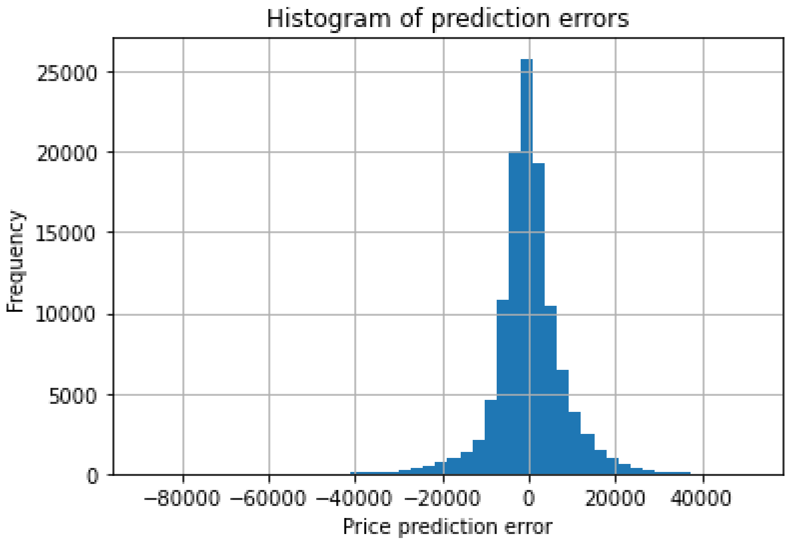
Plot Histogram of prediction errors

In [924…

```
diff = y_test - y_predicted
diff.hist(bins = 50)
plt.title('Histogram of prediction errors')
plt.xlabel('Price prediction error')
plt.ylabel('Frequency')
```

Out[924…

```
Text(0, 0.5, 'Frequency')
```

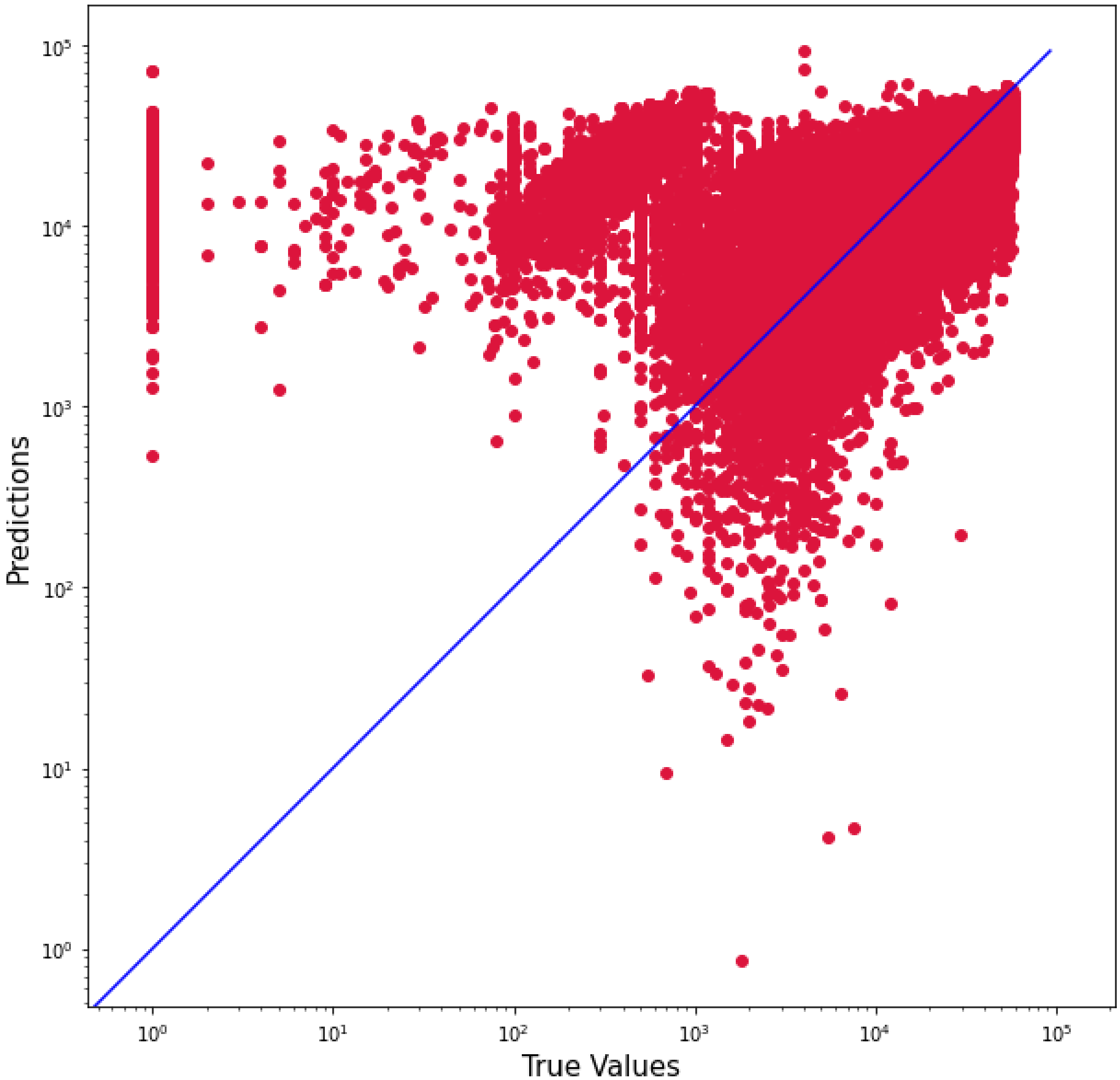


Plot true vs predicted prices using log scale

In [910…

```
plt.figure(figsize=(10,10))
plt.scatter(y_test, y_predicted, c='crimson')
plt.yscale('log')
plt.xscale('log')

p1 = max(max(y_predicted), max(y_test))
p2 = min(min(y_predicted), min(y_test))
plt.plot([p1, p2], [p1, p2], 'b-')
plt.xlabel('True Values', fontsize=15)
plt.ylabel('Predictions', fontsize=15)
plt.axis('equal')
plt.show()
```



We have our final adjusted model and done cross validation on it after dropping the low importance features. We have the top 10 features that have an impact on price of used cars with age(current year - manufacture year) and odometer(miles driven) being the top two features. The model overall explains more than 60% of the variation in used car prices.

Deployment

Now that we've settled on our models and findings, it is time to deliver the information to the client. You should organize your work as a basic report that details your primary findings. Keep in mind that your audience is a group of used car dealers interested in fine tuning their inventory.

Based on our dataset and current models, we have a model that will predict about 62% variation in used car prices.

Age of car(Current year - Manufacture year) and odometer(miles driven) are the top two important features that determine used car prices. Newer and less driven cars have higher prices.

You can use this model to predict the price of used cars. I recommend in the future selecting cars whose actual values are less than the values predicted by this model so that you can maximize the profit. YOu can buy cars for lower price than it is worth to keep in inventory.

In the future, we can apply more advanced modeling techniques like Logistic Regression, XGBoost, RandomForest and such to improve the performance of our model.