```
import pandas as pd

from sklearn.metrics import mean_squared_error, r2_score

from sklearn.model_selection import train_test_split, RepeatedStratifiedKFold, c

from sklearn.linear_model import LinearRegression

import numpy as np

import re

import matplotlib.pyplot as plt

from sklearn.linear_model import Lasso

from sklearn.linear_model import Ridge

from sklearn.ensemble import RandomForestRegressor

import seaborn as sns
```

```
# read into pandas dataframe
df = pd.read_csv("used_car_sales.csv")
```

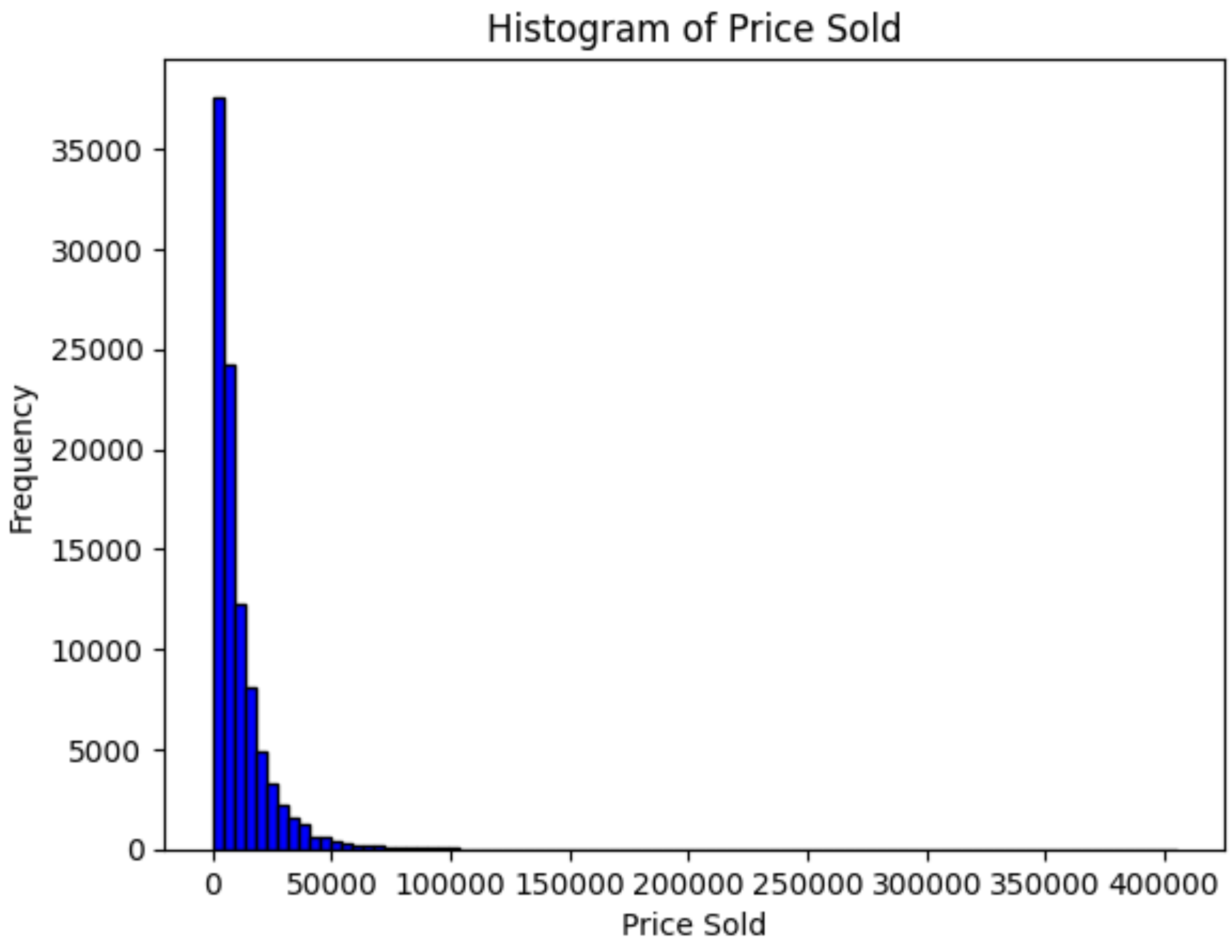
```
df
```

	ID	pricesold	yearsold	zipcode	Mileage	Make	Model	Year
0	137178	7500	2020	786**	84430	Ford	Mustang	1988
1	96705	15000	2019	81006	0	Replica/Kit Makes	Jaguar Beck Lister	1958
2	119660	8750	2020	33449	55000	Jaguar	XJS	1995
3	80773	11600	2019	07852	97200	Ford	Mustang	1968
4	64287	44000	2019	07728	40703	Porsche	911	2002
...	...	...	...	...	...	...	...	...
122139	14948	4200	2019	80233	102700	Ford	Mustang	1977
122140	58814	6500	2019	53132	128000	Ford	E-Series Van	2012
122141	2156	2000	2019	77536	50000	Ford	Bronco	1978
122142	29096	2280	2019	92131	164337	BMW	3-Series	2000
122143	52391	5000	2019	18951	163111	Nissan	300ZX	1990

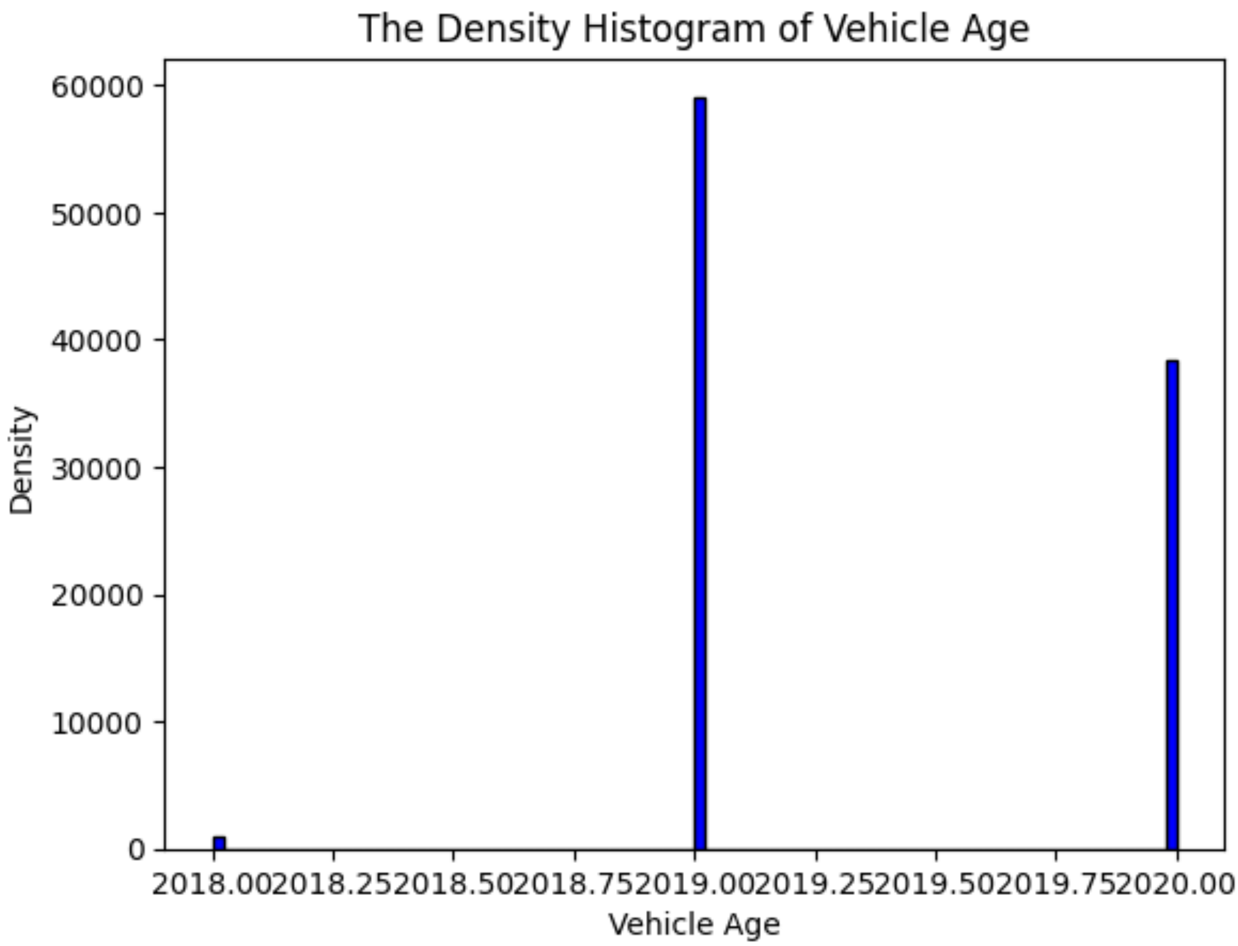
```
df.describe()
```

	ID	pricesold	yearsold	Mileage	Year	Num
count	122144.000000	122144.000000	122144.000000	1.221440e+05	1.221440e+05	1.2
mean	85094.212397	10808.560715	2019.375467	1.404291e+06	3.959362e+03	1.7
std	47786.970812	13987.295760	0.503671	3.335593e+07	1.984514e+05	6.1
min	1.000000	0.000000	2018.000000	0.000000e+00	0.000000e+00	0.0
25%	44547.250000	2950.000000	2019.000000	4.479225e+04	1.977000e+03	4.0
50%	85555.500000	6500.000000	2019.000000	9.000000e+04	2.000000e+03	6.0
75%	127078.500000	13800.000000	2020.000000	1.402000e+05	2.008000e+03	8.0
max	165801.000000	404990.000000	2020.000000	1.235669e+09	2.014000e+07	2.1

```
# Plotting the histogram with more bins
plt.hist(df['pricesold'], bins=90, color='blue', edgecolor='black')

# Adding labels and title
plt.xlabel('Price Sold')
plt.ylabel('Frequency')
plt.title('Histogram of Price Sold')

# Displaying the plot
plt.show()
```



```
# Plotting the histogram with more bins
plt.hist(df['yearsold'], bins=90, color='blue', edgecolor='black')

# Adding labels and title
plt.xlabel('Vehicle Age')
plt.ylabel('Density')
plt.title('The Density Histogram of Vehicle Age')

# Displaying the plot
plt.show()
```




```
# read into pandas dataframe
df = pd.read_csv("used_car_sales.csv")

# dropping
to_drop = ['ID', 'zipcode', 'Trim']


df.drop(to_drop, inplace=True, axis=1)
```

```
# types left
print(df.dtypes)
# pricesold, yearsold, mileage, make, model, year

# drop missing values
#df.dropna()

count_initial = len(df.index)
print(count_initial)

# max and min price
max_price = 50000
min_price = 1000
df = df[max_price > df.pricesold]
df = df[min_price < df.pricesold]
count_price = len(df.index)
print("price removed:  " + str(count_initial - count_price) + "  outliers"

# max and min mileage
max_mileage = 200000
min_mileage = 1000
df = df[max_mileage > df.Mileage]
df = df[min_mileage < df.Mileage]
count_mileage = len(df.index)
print(count_price)
print("price removed:  " + str(count_price - count_mileage) + "  outliers"

# make year numeric, and remove outliers
maximum_age = 50
minimum_age = 0
df['Year'] = df['yearsold'] - df['Year']
df = df[maximum_age > df.Year]
df = df[minimum_age < df.Year]
count_age = len(df.index)
print(count_mileage)
print("price removed:  " + str(count_mileage - count_age) + "  outliers")


def try_to_find_from_engine(number, engine_value: str) -> str:
    if number != 0:
        return str(number).strip()
    found = re.search('v[0-9]+', engine_value, re.IGNORECASE)
    if found:
        return found.group()[1:].strip()
    else:
        return np.NaN

df['NumCylinders'] = df.apply(
```

```
    lambda row: try_to_find_from_engine(int(row['NumCylinders']), str(row[
)

engine_patterns = [
    (df['Engine'].str.contains('gas', case=False, regex=False, na=False),
    (df['Engine'].str.contains('diesel', case=False, regex=False, na=False
]

criteria, values = zip(*engine_patterns)
df['FuelType'] = np.select(criteria, values, "unknown")



body_type_patterns = [
    (df['BodyType'].str.contains('hatchback', case=False, regex=False, na=
    (df['BodyType'].str.contains('coupe', case=False, regex=False, na=Fals
    (df['BodyType'].str.contains('suv', case=False, regex=False, na=False)
    (df['BodyType'].str.contains('sedan', case=False, regex=False, na=Fals
    (df['BodyType'].str.contains('pickup', case=False, regex=False, na=Fal
    (df['BodyType'].str.contains('truck', case=False, regex=False, na=Fals
    (df['BodyType'].str.contains('convertible', case=False, regex=False, n
    (df['BodyType'].str.contains('van', case=False, regex=False, na=False)
    (df['BodyType'].str.contains('wagon', case=False, regex=False, na=Fals
]
criteria, values = zip(*body_type_patterns)
df['BodyType'] = np.select(criteria, values, "unknown")

drive_type_patterns = [
    (df['DriveType'].str.contains('RWD', case=False, regex=False, na=False
    (df['DriveType'].str.contains('FWD', case=False, regex=False, na=False
    (df['DriveType'].str.contains('4WD', case=False, regex=False, na=False
    (df['DriveType'].str.contains('AWD', case=False, regex=False, na=False
]

criteria, values = zip(*drive_type_patterns)
df['DriveType'] = np.select(criteria, values, "unknown")

def convert_engine_to_liters(engine_value: str):
    found = re.search('[0-9]\.[0-9]', engine_value, re.IGNORECASE)
    if found:
        return float(found.group())
    else:
        return np.NaN

df['Engine'] = df.apply(
    lambda row: convert_engine_to_liters(str(row['Engine'])), axis=1
)

df.dropna(subset=['NumCylinders', 'Engine'], inplace=True, axis=0)
```

```
count_engine_numCylinders = len(df.index)
print(count_age)
print("price removed:  " + str(count_age - count_engine_numCylinders) + "


# get rid of rare models

# def delete_occurrences_fewer_than(data, model, threshold: int = 300) ->
#     if len(data[data['Model'] == model]) < threshold:
#         return 'Rare'
#     return model
#
#
# df['Model'] = df['Model'].apply(
#     lambda x: delete_occurrences_fewer_than(data=df, model=x)
# )
#df = df.groupby('Model').map((lambda x: x.value_counts() < 200), 'Other')

df = df.groupby('Make').filter(lambda x: len(x) > 100)
df['Model'] = df['Model'].mask(df['Model'].map(df['Model'].value_counts())
df.drop('Make', inplace=True, axis=1)
df = df.groupby('NumCylinders').filter(lambda x: len(x) > 100)

df.dropna(subset=['Model'], inplace=True, axis=0)
#df.corr()


df = pd.get_dummies(data=df)
# for col in df.columns:
#     print(col)
print(df.shape)


# df_log2['pricesold'] = np.log2(df['pricesold'])

# splitting
# df_2019 = df[df["yearsold"] == 2019]
# df_2020 = df[df["yearsold"] == 2019]
# to_drop = ['yearsold']
# df_2019.drop(to_drop, inplace=True, axis=1)
# df_2020.drop(to_drop, inplace=True, axis=1)

year_sold_patterns = [
    (df['yearsold'] == 2018, 1),
    (df['yearsold'] == 2019, 2),
    (df['yearsold'] == 2020, 3),
]
```

```
criteria, values = zip(*year_sold_patterns)
df['yearsold'] = np.select(criteria, values, np.NAN)
df.dropna()


# df_2019_target = df_2019.pop('pricesold')
# df_2020_target = df_2020.pop('pricesold')

percentiles_price = np.percentile(df.pricesold, [25, 50, 75])

df_target = df.pop('pricesold')

# price is log2, shown by graph
df_target_log2 = np.log2(df_target) * 100
sns.displot(data=df_target_log2, kde=True)
plt.show()


# test data

x_train, x_test, y_train, y_test = train_test_split(df, df_target, test_si

# combine with price for test
x_test["pricesold"] = y_test

# make array from percentiles, to try
percentiles_array = [x_test[x_test["pricesold"].between(0, percentiles_pri
                     x_test[x_test["pricesold"].between(percentiles_price[
                     x_test[x_test["pricesold"].between(percentiles_price[
                     x_test[x_test["pricesold"].between(percentiles_price[

x_test.pop('pricesold')

# create separate array with price
percentiles_targets = []
for p in percentiles_array:
    print(len(p))
    percentiles_targets.append(p.pop('pricesold'))

y_train_log2 = np.log2(y_train) * 100

#train, val = train_test_split(train, test_size=0.2)
print(len(x_train), 'train examples')
#print(len(val), 'validation examples')
print(len(x_test), 'test examples')
```

```
# sklearn regression

    # Defining MAPE function
    def MAPE(Y_actual, Y_Predicted):
        mape = np.mean(np.abs((Y_actual - Y_Predicted) / Y_actual)) * 100
        return mape

    # Defining prediction plot
    def PLOT_ACTUAL_VS_PREDICTED(Y_actual, Y_predicted, line_of_best_fit=True)

        # add points to plot
        plt.scatter(Y_actual, Y_predicted)
        plt.xlabel('actual price')
        plt.ylabel('predicted price')
        plt.title('Best fit line with actual and predicted price')
        plt.legend()
        plt.tight_layout()

        if(line_of_best_fit):
            # find line of best fit
            a, b = np.polyfit(Y_actual.flatten(), Y_predicted.flatten(), 1)

            # add line of best fit to plot
            plt.plot(Y_actual, a * Y_actual + b, color='green', linewidth=6)
            plt.plot(Y_actual, Y_actual, color='orange', linewidth=6)
        plt.show()



    # linear
    lr = LinearRegression()
    lr.fit(x_train, y_train_log2)
    print("Linear Regression:")

    # # predictions
    # for d in percentiles_array:
    #     pred_train_lr = lr.predict(x_train)
    #     pred_train_lr = np.exp2(pred_train_lr * 0.01)
    #     print(MAPE(y_train, pred_train_lr))

    # predictions
    pred_train_lr = lr.predict(x_train)
    pred_train_lr = np.exp2(pred_train_lr * 0.01)
    print("linear MAPE: "+str(MAPE(y_train, pred_train_lr)))
    print("linear RSME: "+str(np.sqrt(mean_squared_error(y_train, pred_train_l
    print("linear R2: "+str(r2_score(y_train, pred_train_lr)))

    PLOT_ACTUAL_VS_PREDICTED(y_train.values, pred_train_lr)
```

```
pred_test_lr = lr.predict(x_test)
pred_test_lr = np.exp2(pred_test_lr * 0.01)
print("linear MAPE: "+str(MAPE(y_test, pred_test_lr)))
print("linear RSME: "+str(np.sqrt(mean_squared_error(y_test, pred_test_lr)
print("linear R2: "+str(r2_score(y_test, pred_test_lr)))

PLOT_ACTUAL_VS_PREDICTED(y_test.values, pred_test_lr)

# ridge
rr = Ridge(alpha=0.01)
rr.fit(x_train, y_train_log2)
print("Ridge Regression:")

# predictions
pred_train_rr = rr.predict(x_train)
pred_train_rr = np.exp2(pred_train_rr * 0.01)
print("ridge MAPE: "+str(MAPE(y_train, pred_train_rr)))
print("ridge RSME: "+str(np.sqrt(mean_squared_error(y_train, pred_train_rr
print("ridge R2: "+str(r2_score(y_train, pred_train_rr)))

PLOT_ACTUAL_VS_PREDICTED(y_train.values, pred_train_rr)

pred_test_rr = rr.predict(x_test)
pred_test_rr = np.exp2(pred_test_rr * 0.01)
print("ridge MAPE: "+str(MAPE(y_test, pred_test_rr)))
print("ridge RSME: "+str(np.sqrt(mean_squared_error(y_test, pred_test_rr))
print("ridge R2: "+str(r2_score(y_test, pred_test_rr)))

PLOT_ACTUAL_VS_PREDICTED(y_test.values, pred_test_rr)



# Lasso Regression
model_lasso = Lasso(alpha=0.01)
model_lasso.fit(x_train, y_train_log2)

# predictions
pred_train_lasso = model_lasso.predict(x_train)
pred_train_lasso = np.exp2(pred_train_lasso * 0.01)
print("lasso MAPE: "+str(MAPE(y_train, pred_train_lasso)))
print("lasso RSME: "+str(np.sqrt(mean_squared_error(y_train, pred_train_la
print("lasso R2: "+str(r2_score(y_train, pred_train_lasso)))

PLOT_ACTUAL_VS_PREDICTED(y_train.values, pred_train_lasso)

pred_test_lasso = model_lasso.predict(x_test)
pred_test_lasso = np.exp2(pred_test_lasso * 0.01)
print("lasso MAPE: "+str(MAPE(y_test, pred_test_lasso)))
```

```
    print("lasso RSME: "+str(np.sqrt(mean_squared_error(y_test, pred_test_lass
    print("lasso R2: "+str(r2_score(y_test, pred_test_lasso)))

    PLOT_ACTUAL_VS_PREDICTED(y_test.values, pred_test_lasso)



    # Random Forest Regression
    # important to test many times because it is stochastic
    # get a list of models to evaluate
    # def get_models():
    #     models = dict()
    #     # exp2lore number of features from 1 to 7
    #     for i in range(4, 6):
    #         models[str(i)] = RandomForestClassifier(max_features=i)
    #     return models
    #
    # # evaluate a given model using cross-validation
    # def evaluate_model(model, X, y):
    #     # define the evaluation procedure
    #     cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=
    #     # evaluate the model and collect the results
    #     scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_j
    #     return scores

    # Random Forest
    rf = RandomForestRegressor(random_state=0)
    rf.fit(x_train, y_train_log2)
    print("RF Regression:")

    # predictions
    pred_train_rf = rf.predict(x_train)
    pred_train_rf = np.exp2(pred_train_rf * 0.01)
    print("RF MAPE: "+str(MAPE(y_train, pred_train_rf)))
    print("RF RSME: "+str(np.sqrt(mean_squared_error(y_train, pred_train_rf)))
    print("RF R2: "+str(r2_score(y_train, pred_train_rf)))

    PLOT_ACTUAL_VS_PREDICTED(y_train.values, pred_train_rf)

    pred_test_rf = rf.predict(x_test)
    pred_test_rf = np.exp2(pred_test_rf * 0.01)
    print("RF MAPE: "+str(MAPE(y_test, pred_test_rf)))
    print("RF RSME: "+str(np.sqrt(mean_squared_error(y_test, pred_test_rf))))
    print("RF R2: "+str(r2_score(y_test, pred_test_rf)))

    PLOT_ACTUAL_VS_PREDICTED(y_test.values, pred_test_rf)


# Get MAPE boxplot
```

```
def graph_MAPE_by_price(array_to_predict):

    # create plot
    fig, ax = plt.subplots()
    index = np.arange(4)
    bar_width = 0.15
    opacity = 1
    colors = ['r', 'b', 'g', 'y']

    for i in range(4):

        results = []

        # lr
        pred_test = lr.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        # rr
        pred_test = rr.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        # lasso_r
        pred_test = model_lasso.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        # rf
        pred_test = rf.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        rects = plt.bar(index + bar_width * i, results, bar_width,
                        alpha=opacity,
                        color=colors[i],
                        label=str(i * 25) + 'th to '+str((i+1) * 25) + 'th

    plt.xlabel('Algorithm')
    plt.ylabel('MAPE')
    plt.title('MAPE by Algorithm for price percentile')
    plt.xticks(index + bar_width, ('Linear', 'Ridge', 'Lasso', 'RandomFore
    plt.legend(bbox_to_anchor=(1.1, 1.05))
    plt.tight_layout()
    plt.show()
```

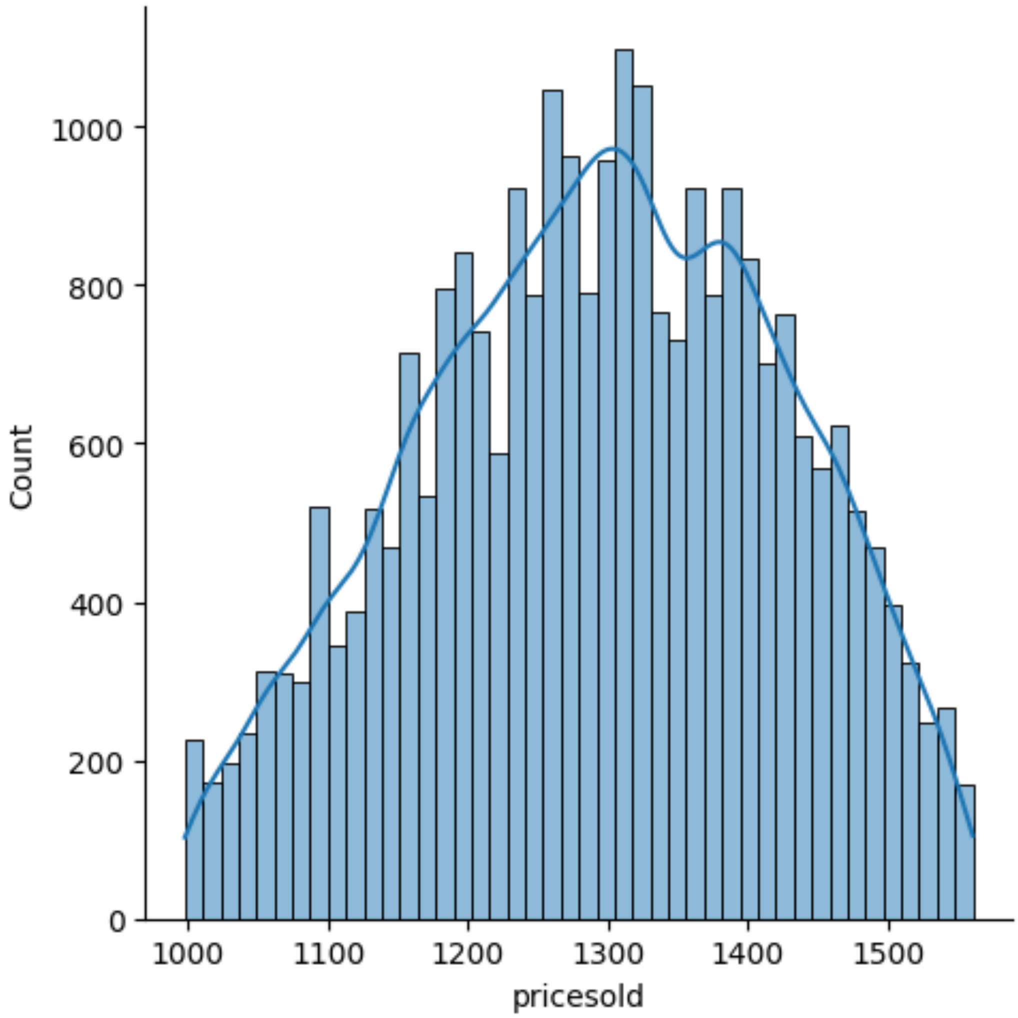
```
    graph_MAPE_by_price(percentiles_array)


    # numeric features
    # numeric_feature_names = ['mileage', 'hp', 'year']
    # numeric_features = df[numeric_feature_names]
    # numeric_features.sort_values(['hp'], axis=0, ascending=True, inplace=Tru
    # print(numeric_features)
    # print(numeric_features.dtypes)
    # print(numeric_features.shape)


# plot the density histograms

    def increment_year(dataframe):
        dataframe["Year"] += 1
        dataframe["yearsold"] += 1
        dataframe["Mileage"] += 14263

    # return average prediction list from dataframe array
    # feed for one year
    # return list for 2019, 2018
    def get_average_prediction(df_arr):

        def percentage_difference(result_old, result_new):
            result_old = np.average(np.exp2(result_old * 0.01))
            result_new = np.average(np.exp2(result_new * 0.01))
            decrease = result_old - result_new
            return (decrease / result_old) * 100

        linreg = percentage_difference(lr.predict(df_arr[0]), lr.predict(df_ar
        ridgereg = percentage_difference(rr.predict(df_arr[0]), rr.predict(df_
        lassoreg = percentage_difference(model_lasso.predict(df_arr[0]), model_
        randomreg = percentage_difference(rf.predict(df_arr[0]), rf.predict(df_

        # return tuple with all data for one year
        # actual data too?
        return linreg, ridgereg, lassoreg, randomreg



    # 2019 dataset
    df_2019 = df[df["yearsold"] == 2]

    # split into 2-4
    df_2019_newer = df_2019[df_2019["Year"].between(2, 4)]
```

```
df_2020_newer = df_2019_newer.copy()
increment_year(df_2020_newer)

newer_depreciation = get_average_prediction([df_2019_newer, df_2020_newer]

# split into 13-15
df_2019_older = df_2019[df_2019["Year"].between(13, 15)]

df_2020_older = df_2019_older.copy()
increment_year(df_2020_older)

older_depreciation = get_average_prediction([df_2019_older, df_2020_older]

# create plot
fig, ax = plt.subplots()
index = np.arange(4)
bar_width = 0.35
opacity = 0.8

rects1 = plt.bar(index, newer_depreciation, bar_width,
                 alpha=opacity,
                 color='b',
                 label='2-4 year old cars')

rects2 = plt.bar(index + bar_width, older_depreciation, bar_width,
                 alpha=opacity,
                 color='g',
                 label='13-15 year old cars')

plt.xlabel('Algorithm')
plt.ylabel('Depreciation')
plt.title('Depreciation by Algorithm')
plt.xticks(index + bar_width, ('Linear', 'Ridge', 'Lasso', 'RandomForest')
plt.legend()
plt.tight_layout()
plt.show()

# find the most common occurrences all columns in dataframe
# most common mileage: 100,000
sns.distplot(df['Mileage'], hist=True, kde=True, kde_kws={'linewidth': 3},

# most common Year: 5-15
sns.distplot(df['Year'], hist=True, kde=True, kde_kws={'linewidth': 3}, la
plt.show()

# most common Engine: 3.8 - 4.8
sns.distplot(df['Engine'], hist=True, kde=True, kde_kws={'linewidth': 3},
```

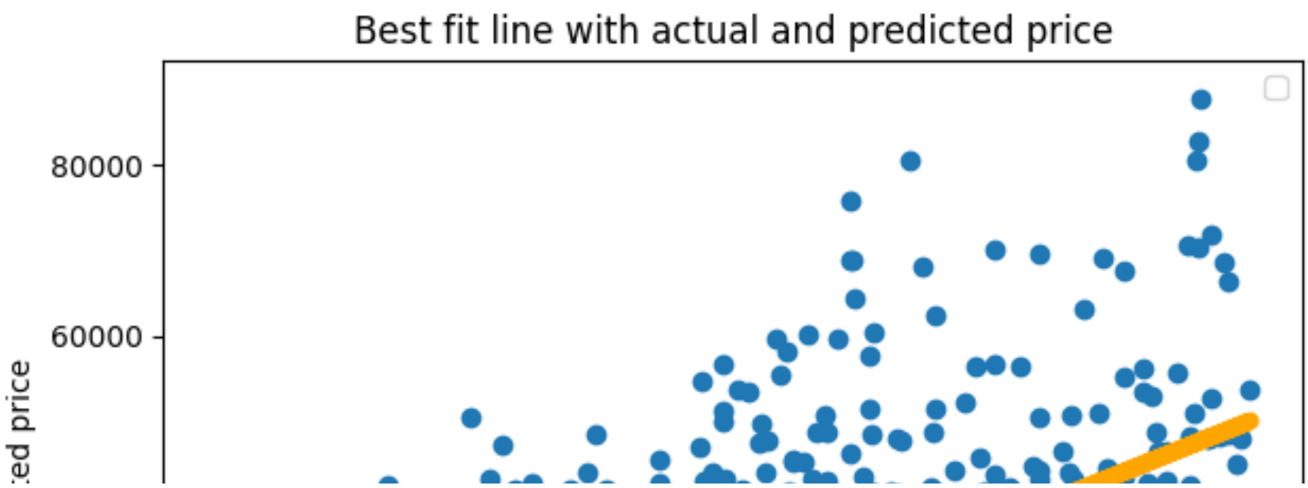
```
print(list(df))


model_results = [(pred_test_rr, 'RidgeRegression'), (pred_test_lasso, 'Las

for i in range(4):
    # Draw the density plot
    result = model_results[i]
    sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}

sns.distplot(y_test.values, hist=False, kde=True, kde_kws={'linewidth': 1}

# Plot formatting
plt.legend(title='Price')
plt.title('Density Plot with Multiple Model Prediction Prices')
plt.xlabel('Price (USD)')
plt.ylabel('Density')
plt.show()
```

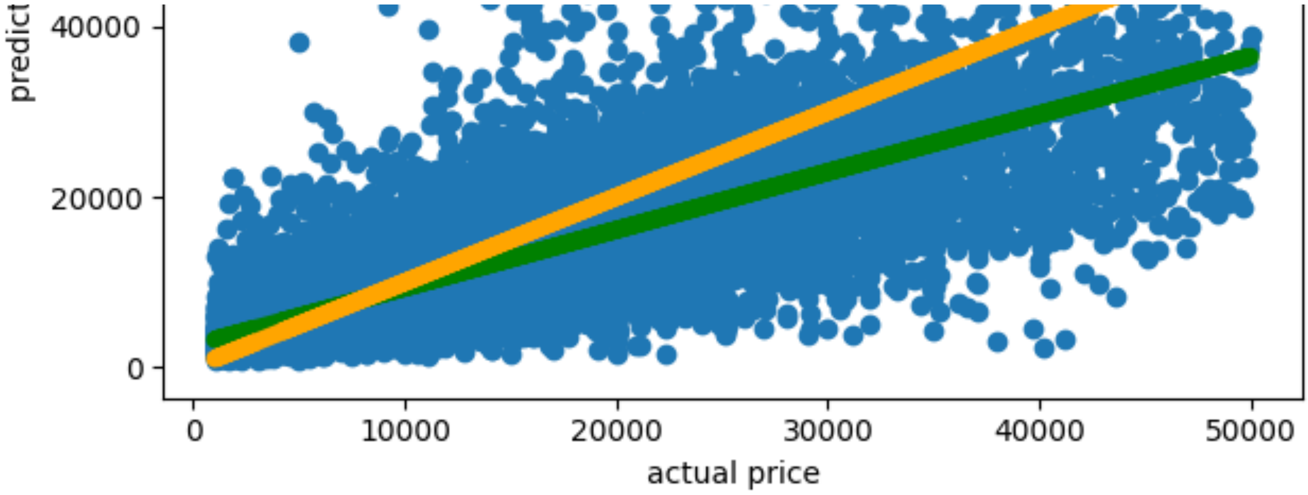
```
pricesold         int64
yearsold          int64
Mileage           int64
Make             object
Model            object
Year              int64
Engine           object
BodyType         object
NumCylinders      int64
DriveType        object
dtype: object
122144
price removed:  11743  outliers
110401
price removed:  13950  outliers
96451
price removed:  15902  outliers
80549
price removed:  38562  outliers
```

```
(26422, 129)
```



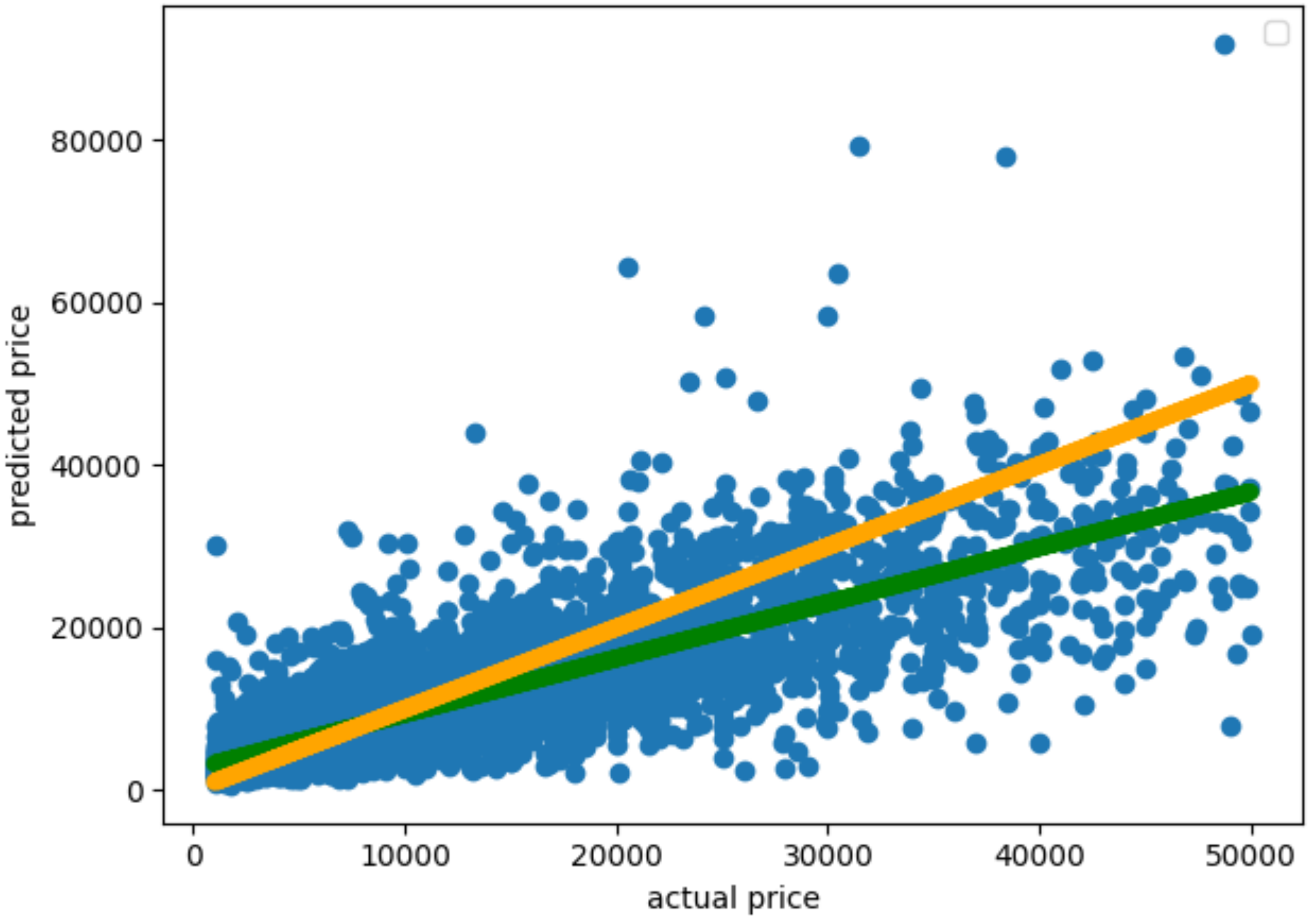

```
1360
1320
1277
1377
21137 train examples
5285 test examples
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
Linear Regression:
linear MAPE: 44.890548775416754
linear RSME: 5820.681978626334
linear R2: 0.6457558729716408
```





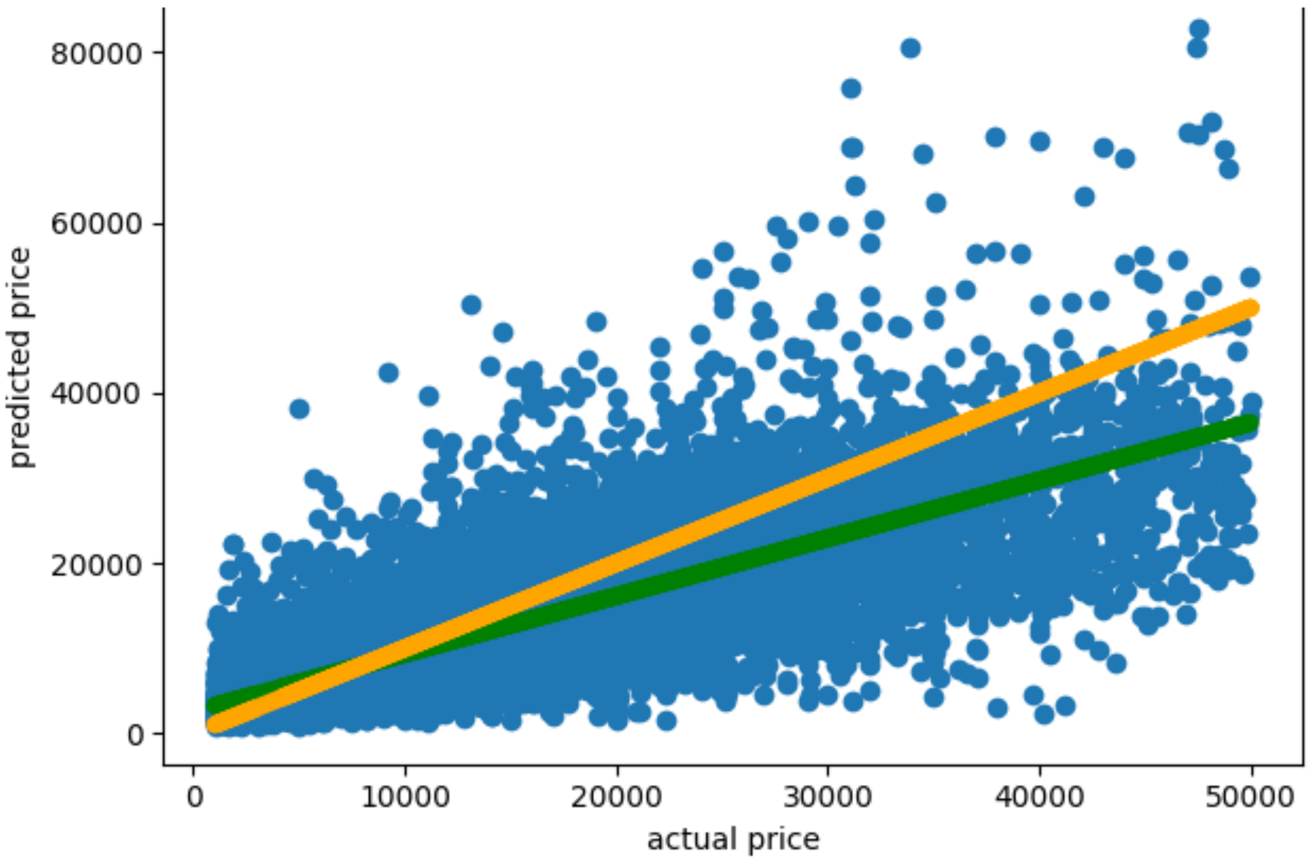

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
linear MAPE: 46.325834113513146
linear RSME: 5969.136375597109
linear R2: 0.6499672700215979
```

Best fit line with actual and predicted price

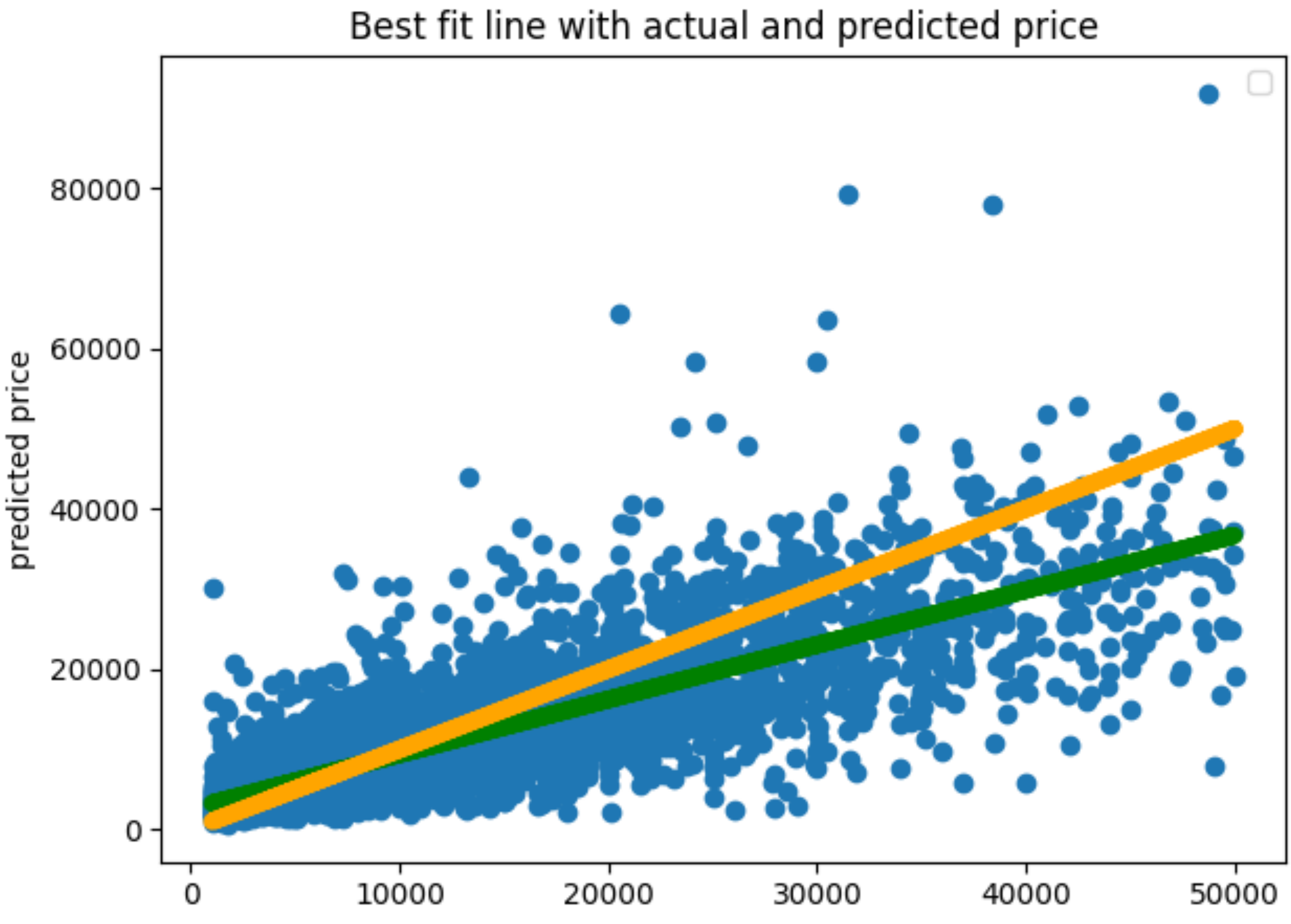



```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
Ridge Regression:
ridge MAPE: 44.89056805904398
ridge RSME: 5820.616925861155
ridge R2: 0.6457637910923425
```

Best fit line with actual and predicted price

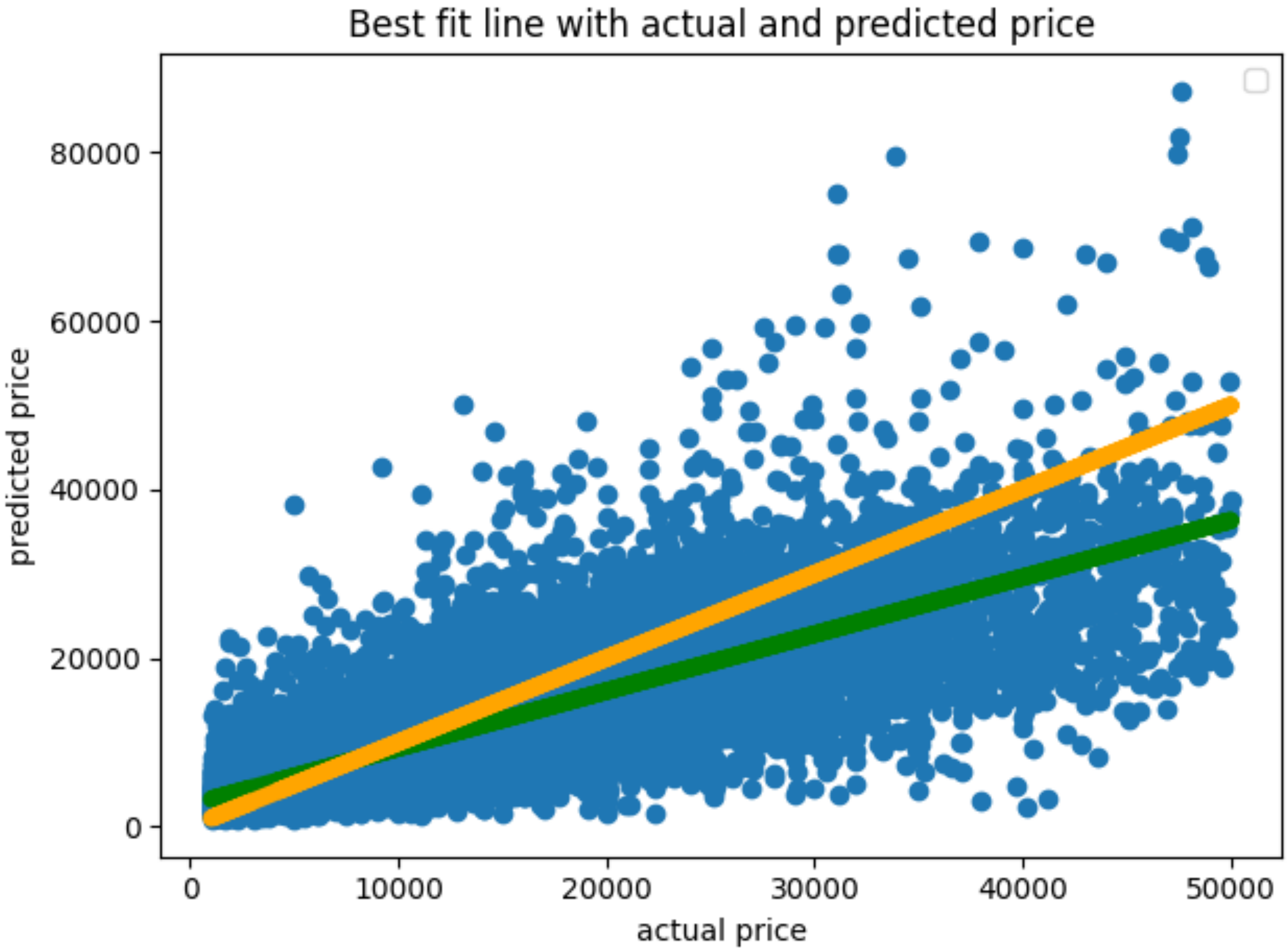



```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
ridge MAPE: 46.325875278531505
ridge RSME: 5969.059965121119
ridge R2: 0.6499762314507358
```

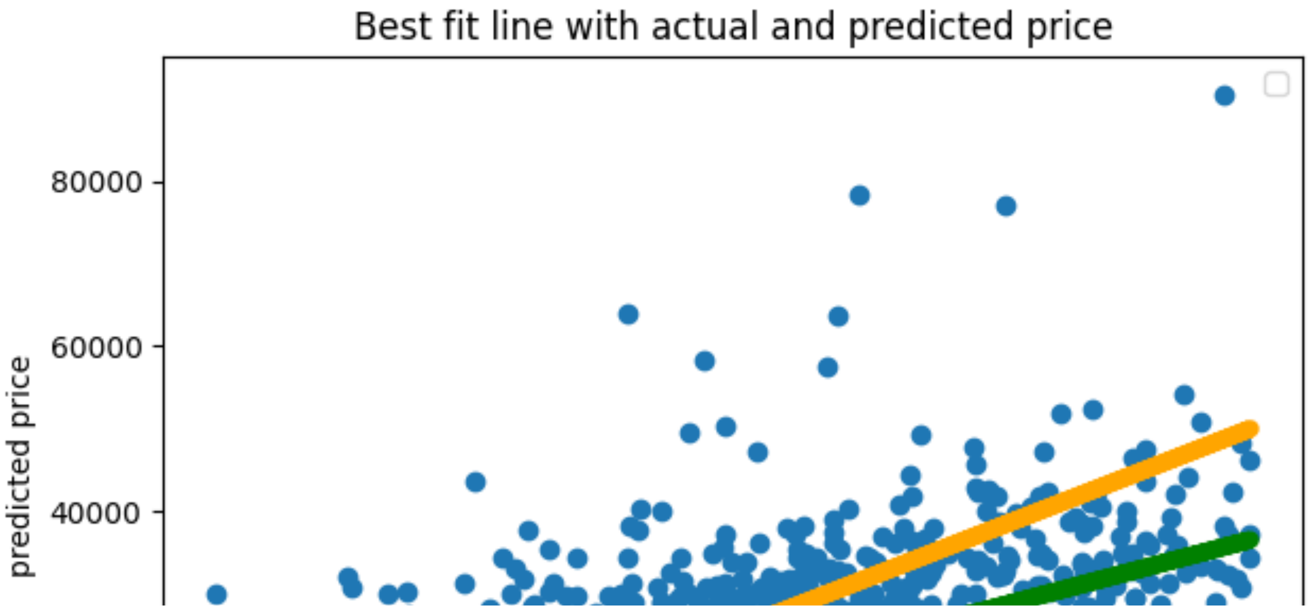


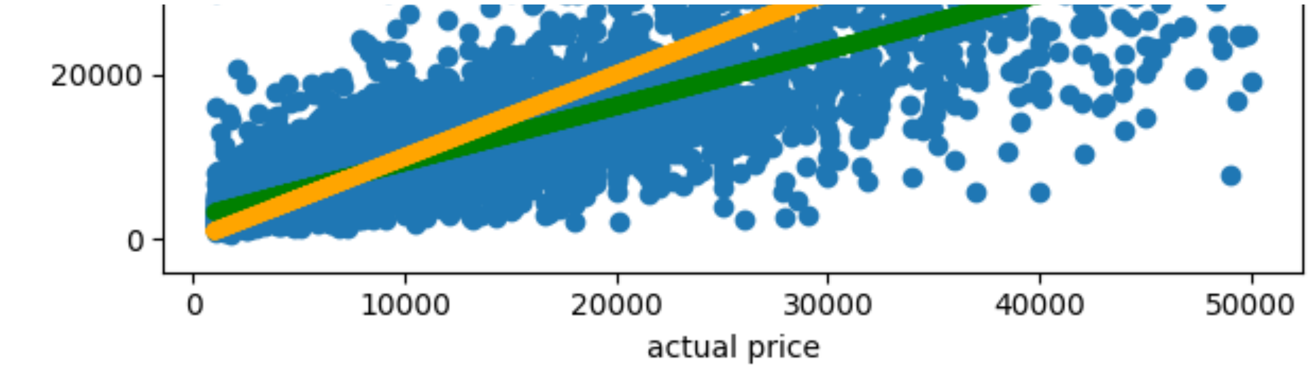
actual price

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
lasso MAPE: 44.91314130816676
lasso RSME: 5816.5046086727
lasso R2: 0.6462641562846697
```

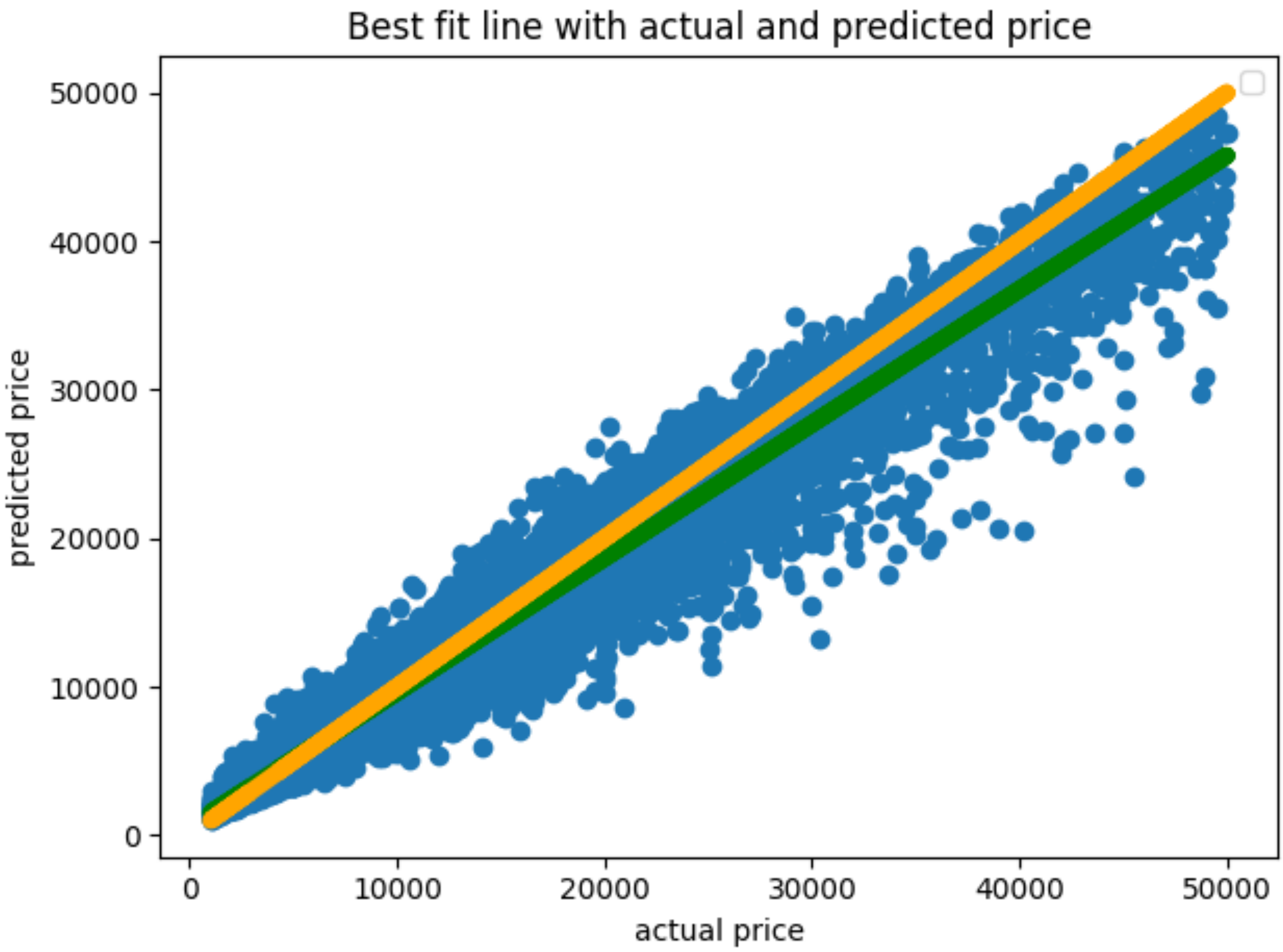



```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  N
lasso MAPE: 46.36972694931304
lasso RSME: 5966.075482583576
lasso R2: 0.6503261621518037
```

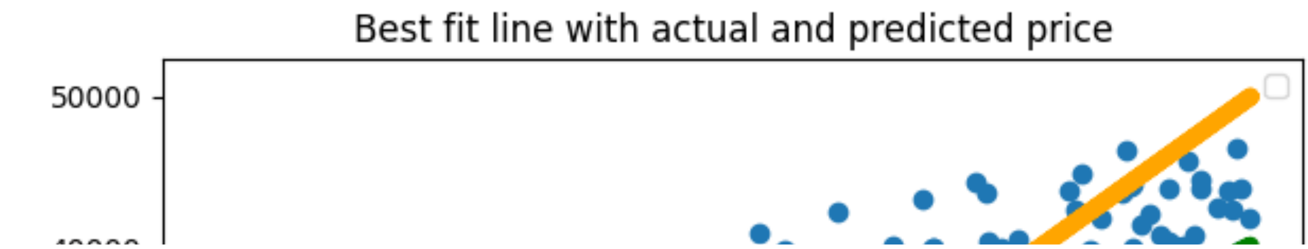


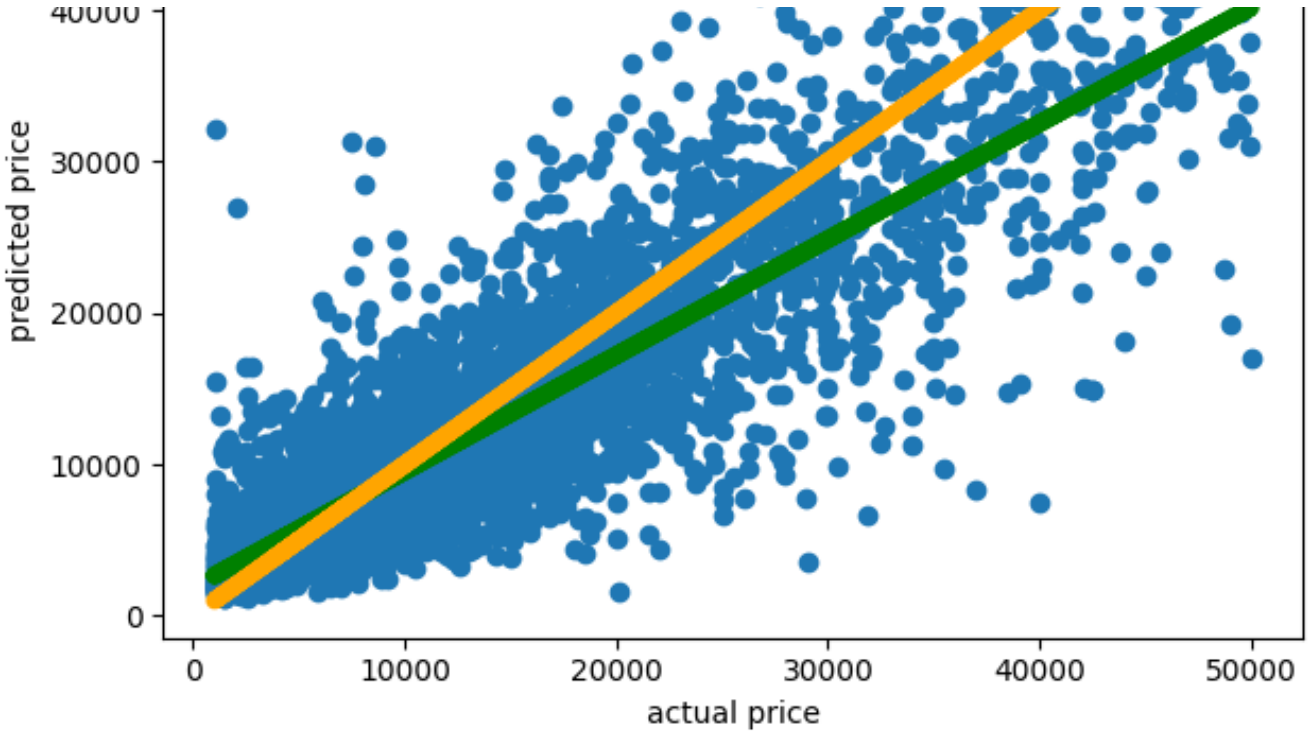



```
RF Regression:
WARNING:matplotlib.legend:No artists with labels found to put in legend.
RF MAPE: 12.869616615915424
RF RSME: 1982.8458212550986
RF R2: 0.9588913884761017
```

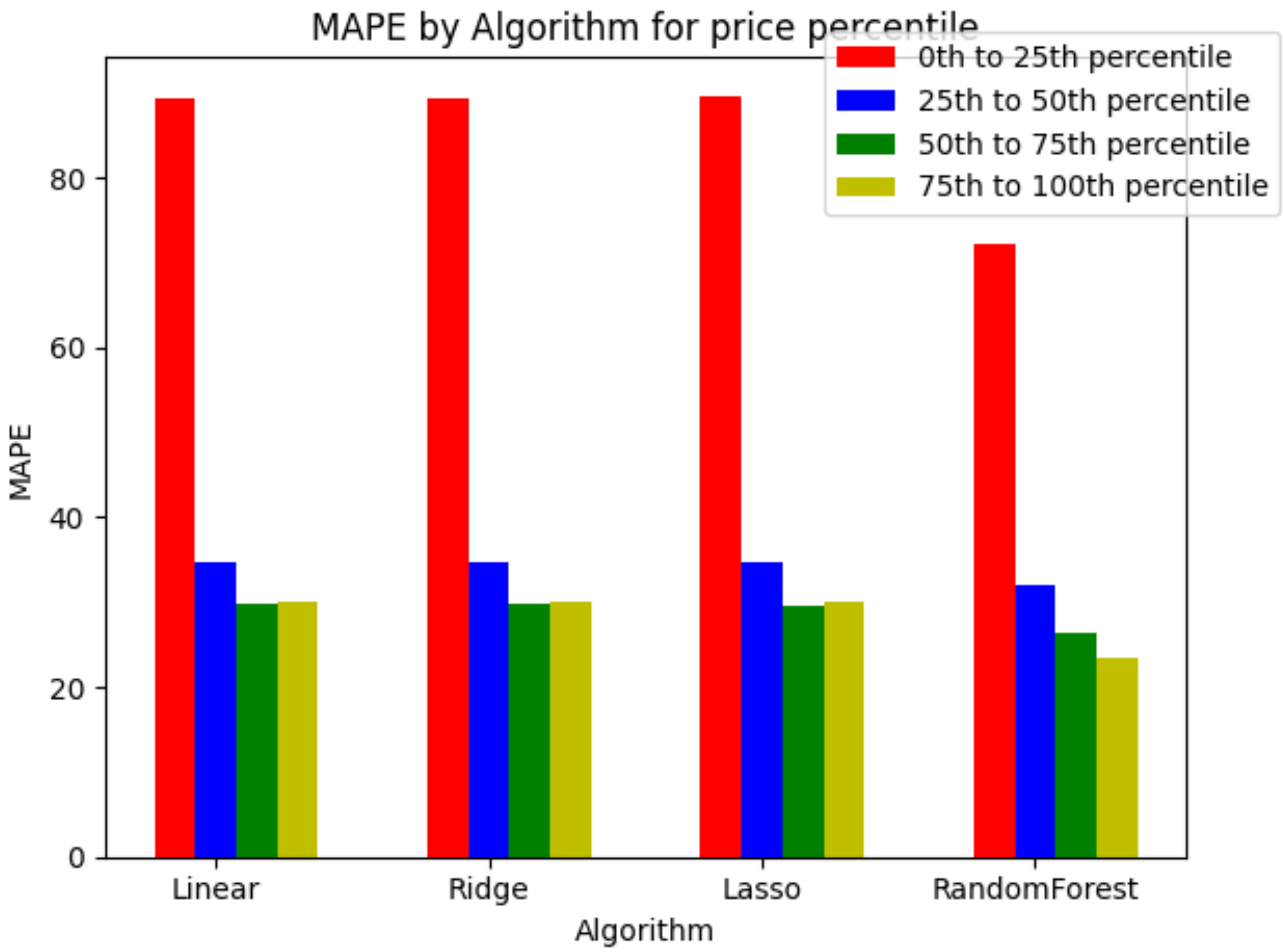



```
WARNING:matplotlib.legend:No artists with labels found to put in legend.
RF MAPE: 38.81974326298702
RF RSME: 4760.2520313657415
RF R2: 0.7773895504128551
```

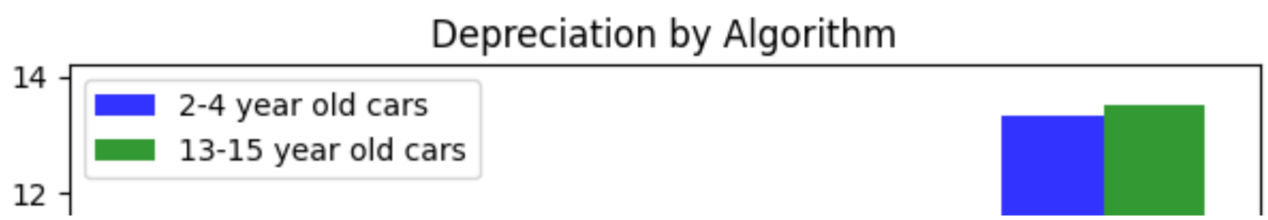




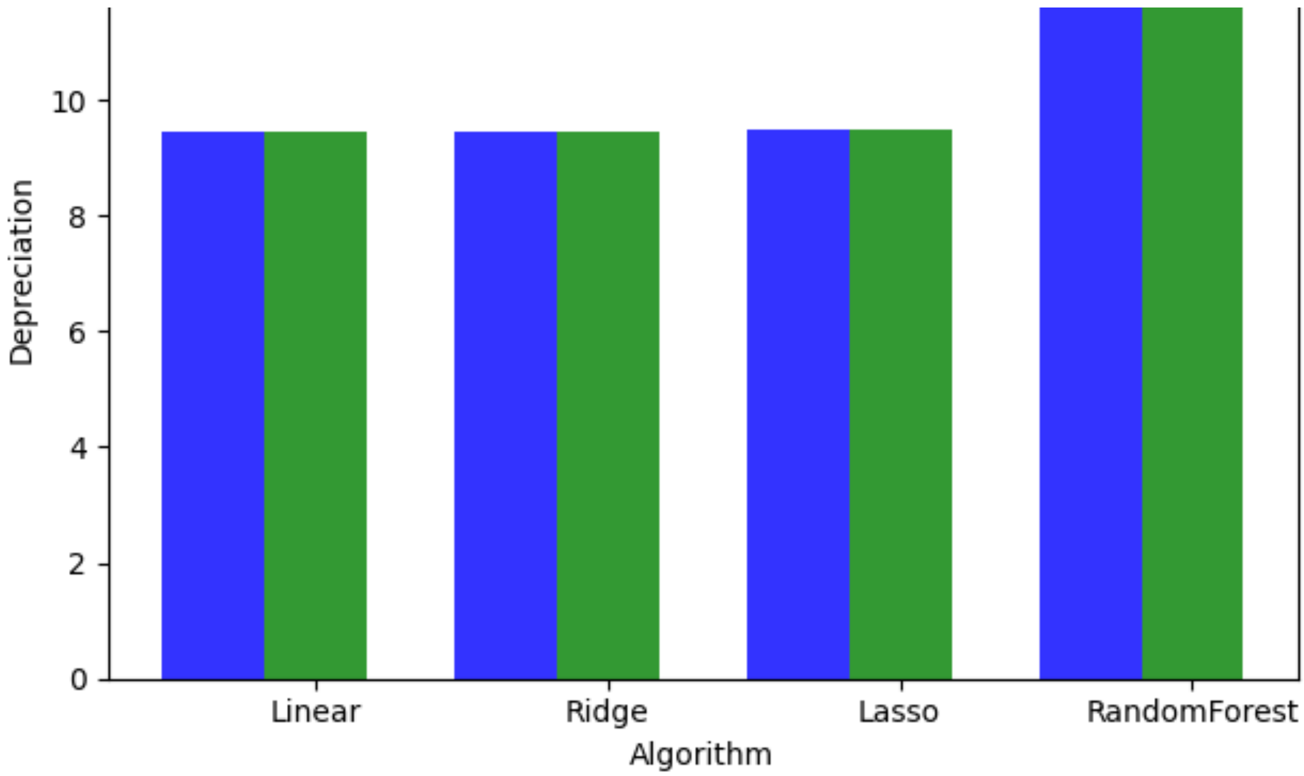
predicted price
actual price
0
10000
20000
30000
40000
50000



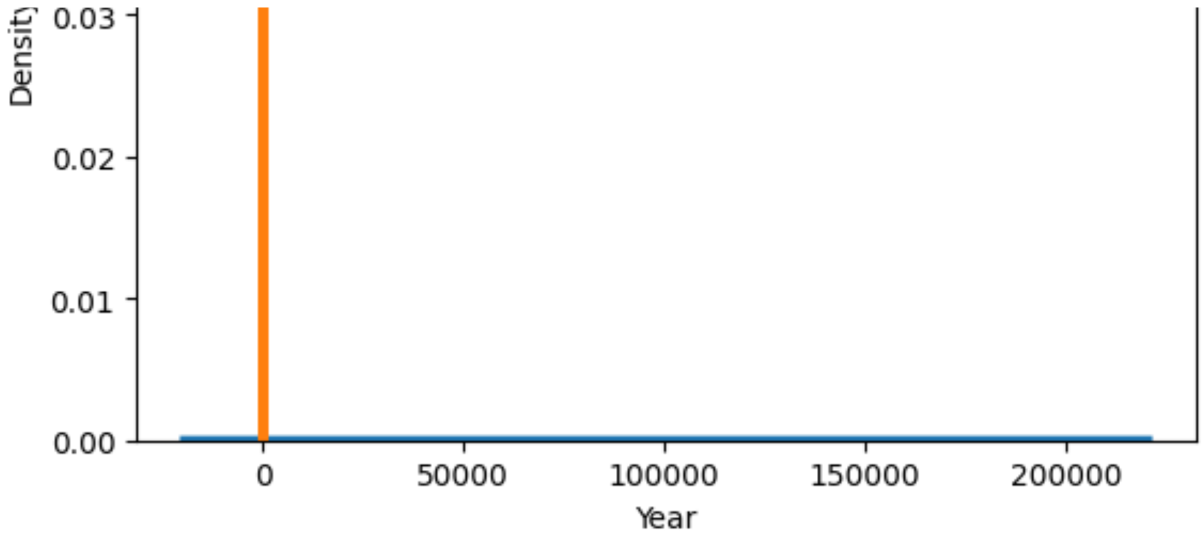
MAPE by Algorithm for price percentile
0th to 25th percentile
25th to 50th percentile
50th to 75th percentile
75th to 100th percentile
MAPE
0
20
40
60
80
Linear
Ridge
Lasso
RandomForest
Algorithm



Depreciation by Algorithm
2-4 year old cars
13-15 year old cars
12
14




```
<ipython-input-37-3e5cefc59bde>:480: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Mileage'], hist=True, kde=True, kde_kws={'linewidth': 3}
<ipython-input-37-3e5cefc59bde>:483: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Year'], hist=True, kde=True, kde_kws={'linewidth': 3}, l
```




```
<ipython-input-37-3e5cefc59bde>:487: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
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For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Engine'], hist=True, kde=True, kde_kws={'linewidth': 3},
['yearsold', 'Mileage', 'Year', 'Engine', 'Model_1500', 'Model_3-Series', '
<ipython-input-37-3e5cefc59bde>:497: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-37-3e5cefc59bde>:497: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
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https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-37-3e5cefc59bde>:497: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
```

```
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

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https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-37-3e5cefc59bde>:497: UserWarning:

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  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-37-3e5cefc59bde>:499: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(y_test.values, hist=False, kde=True, kde_kws={'linewidth': 1
```
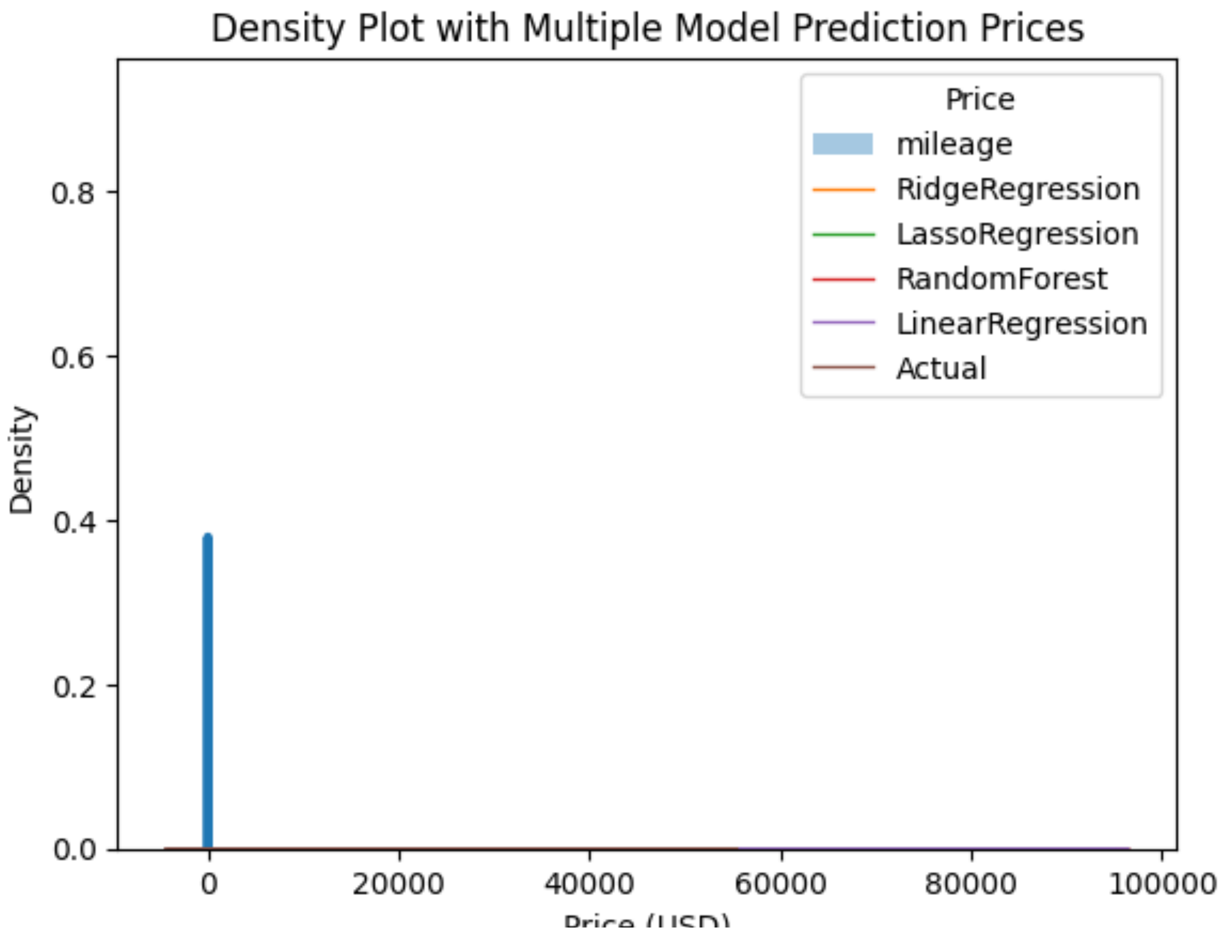
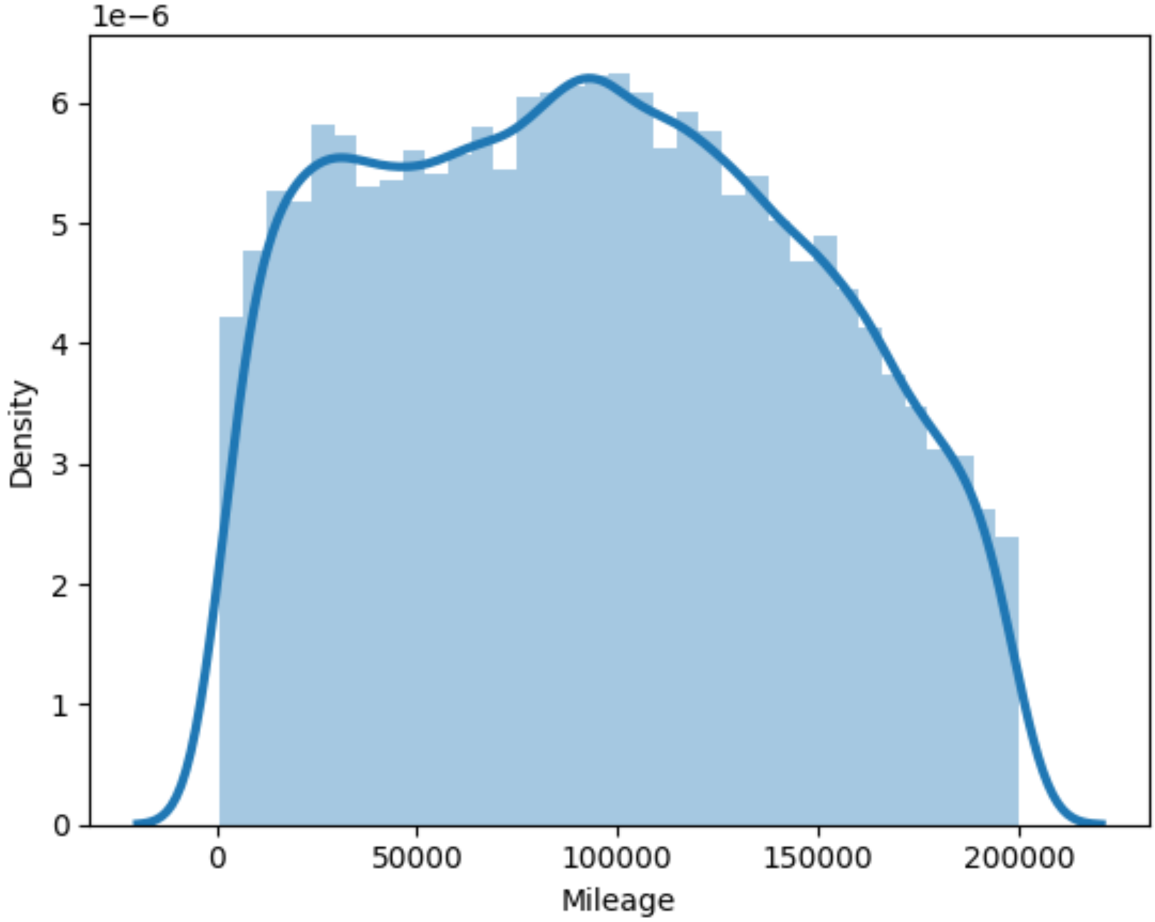



Price (USD)

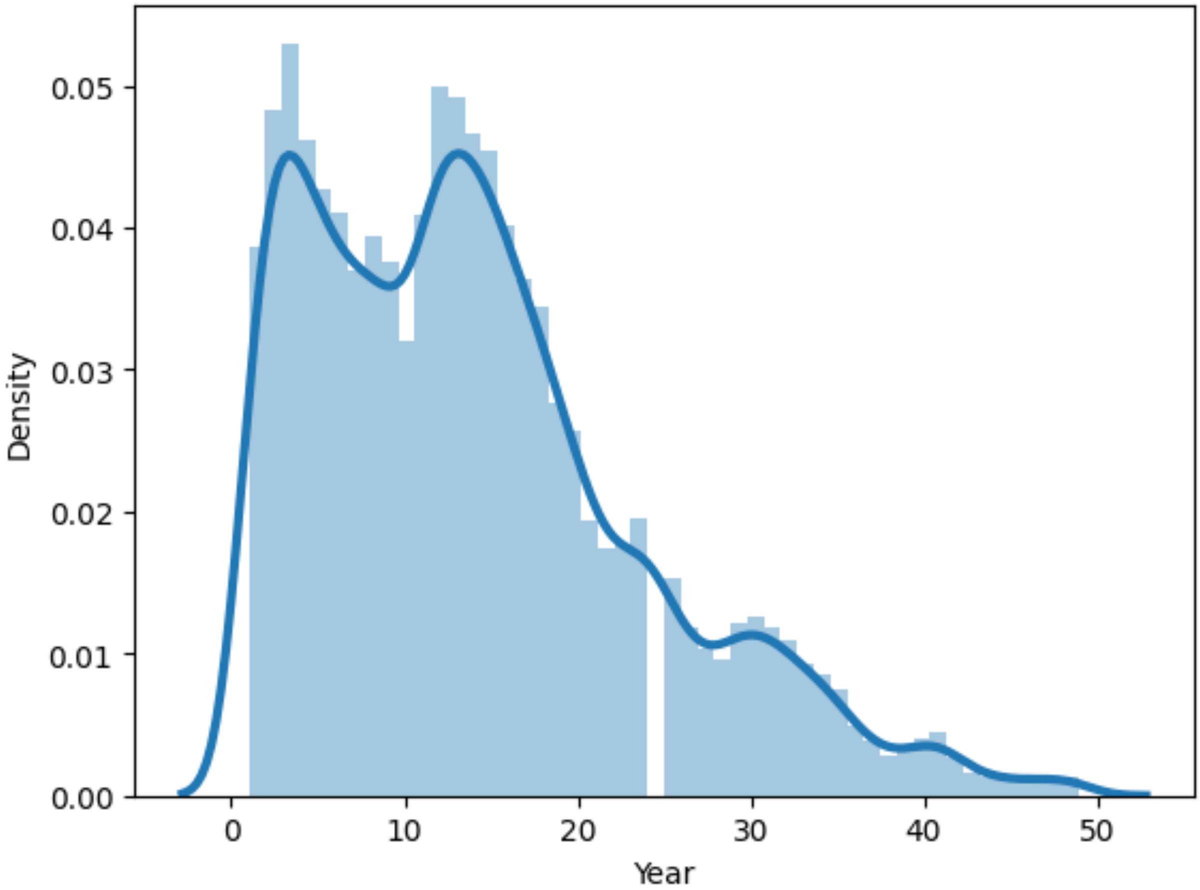
```
sns.distplot(df['Mileage'], hist=True, kde=True, kde_kws={'linewidth': 3}, lab
plt.show()
```

```
<ipython-input-16-b416db703a07>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Mileage'], hist=True, kde=True, kde_kws={'linewidth': 3}
```



```
sns.distplot(df['Year'], hist=True, kde=True, kde_kws={'linewidth': 3}, label=
plt.show()
```

```
&lt;ipython-input-17-f10485ea5b97&gt;:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Year'], hist=True, kde=True, kde_kws={'linewidth': 3}, l
```



```
sns.distplot(df['Engine'], hist=True, kde=True, kde_kws={'linewidth': 3}, labe
plt.show()
```

```
<ipython-input-18-0da71dec8133>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `histplot` (an axes-level function for histograms).

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https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(df['Engine'], hist=True, kde=True, kde_kws={'linewidth': 3},
```
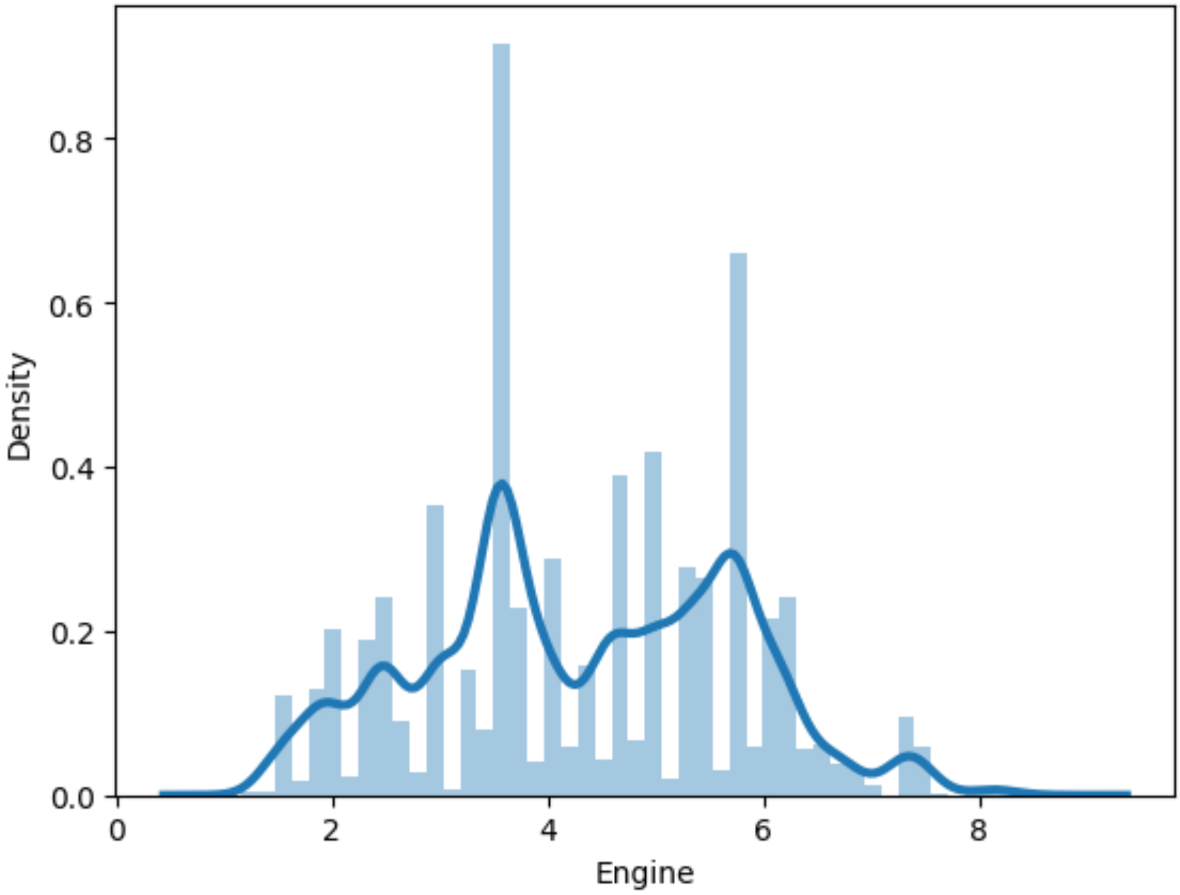
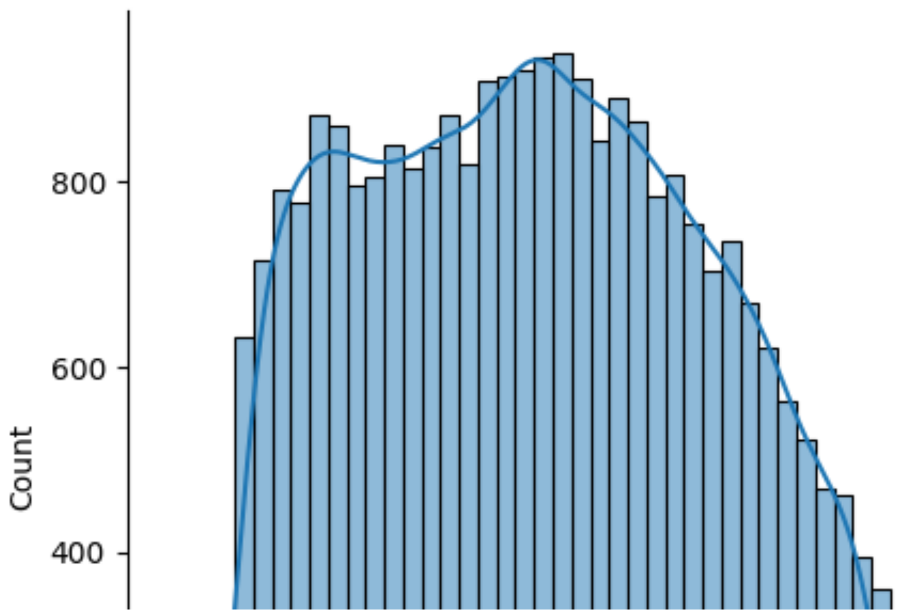
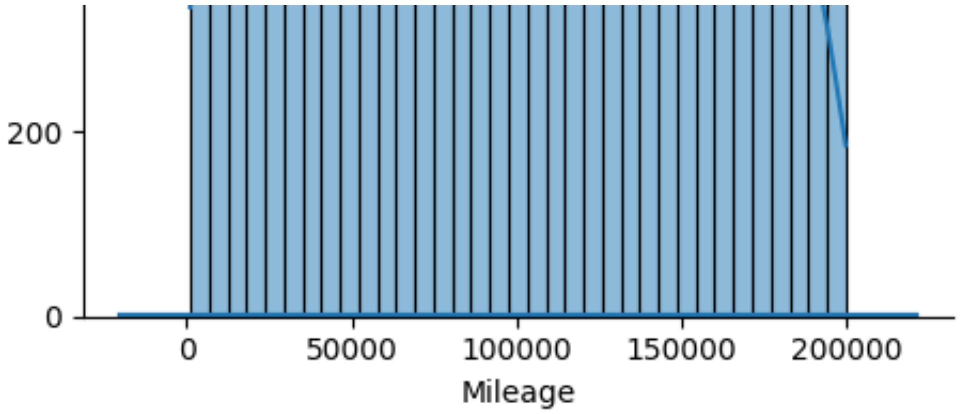
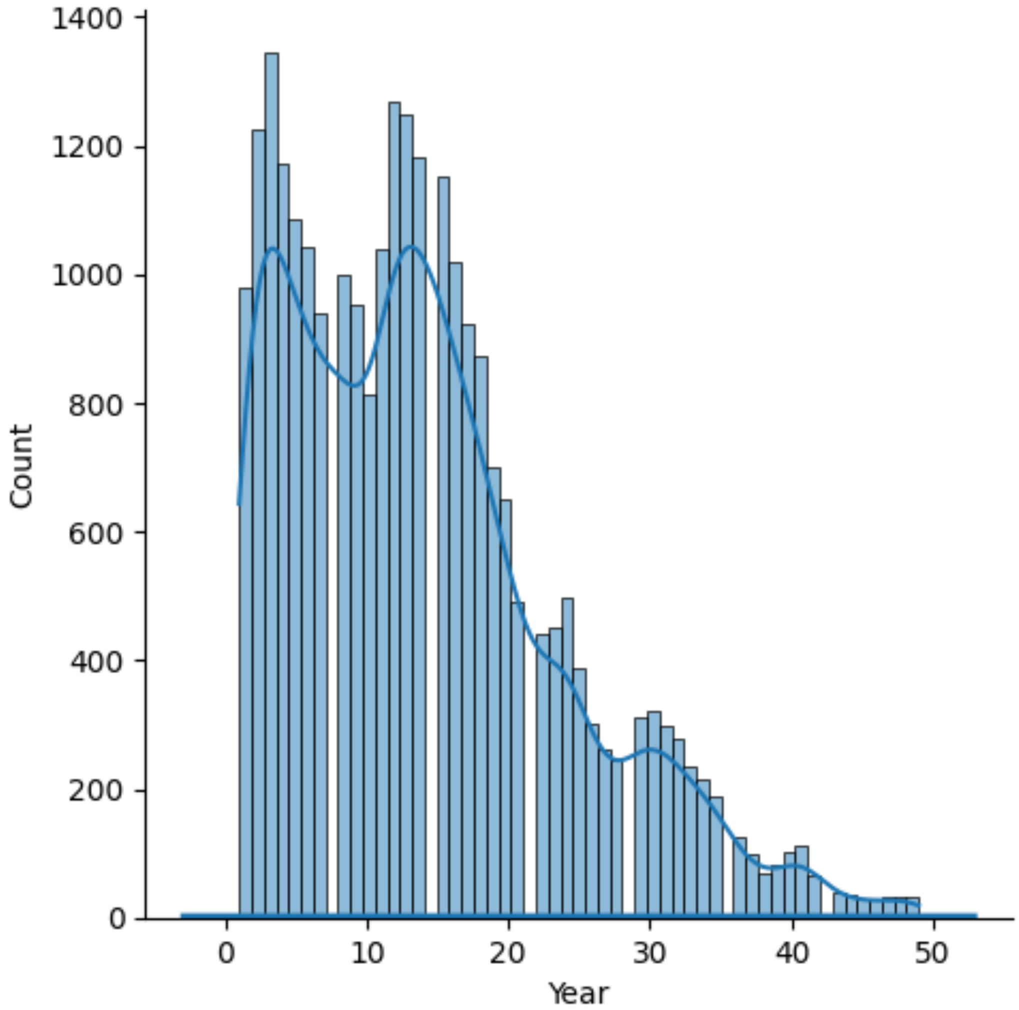



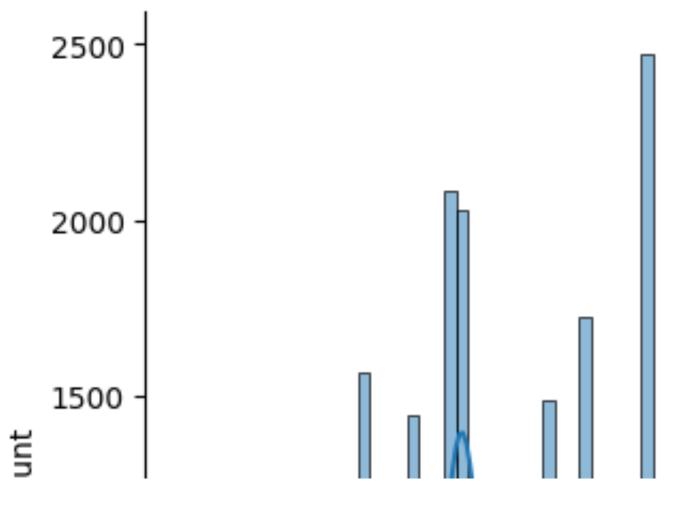

```
import seaborn as sns
import matplotlib.pyplot as plt

# Most common mileage: 100,000
sns.displot(df['Mileage'], kde=True, label="Mileage")
sns.kdeplot(df['Mileage'], linewidth=3)  # Specify the linewidth directly for
```

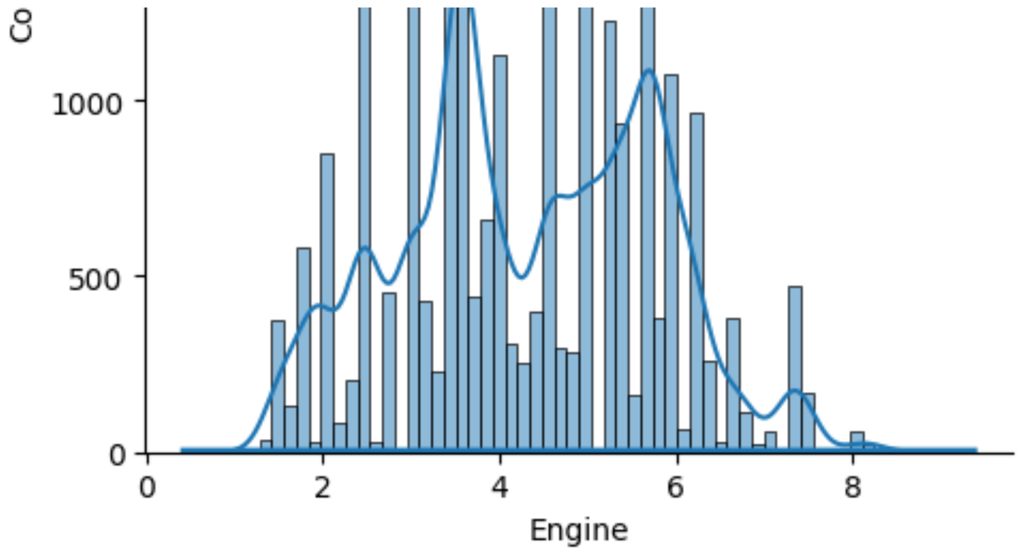
```
plt.show()

# Most common Year: 5-15
sns.displot(df['Year'], kde=True, label="Year")
sns.kdeplot(df['Year'], linewidth=3)
plt.show()

# Most common Engine: 3.8 - 4.8
sns.displot(df['Engine'], kde=True, label="Engine")
sns.kdeplot(df['Engine'], linewidth=3)
plt.show()

print(list(df))

model_results = [
    (pred_test_rr, 'RidgeRegression'),
    (pred_test_lasso, 'LassoRegression'),
    (pred_test_rf, 'RandomForest'),
    (pred_test_lr, 'LinearRegression')
]

for i in range(4):
    # Draw the density plot
    result = model_results[i]
    sns.displot(result[0], kde=True, label=result[1])
    sns.kdeplot(result[0], linewidth=1)
    plt.show()

sns.displot(y_test.values, kde=True, label='Actual')
sns.kdeplot(y_test.values, linewidth=1)
plt.show()
```



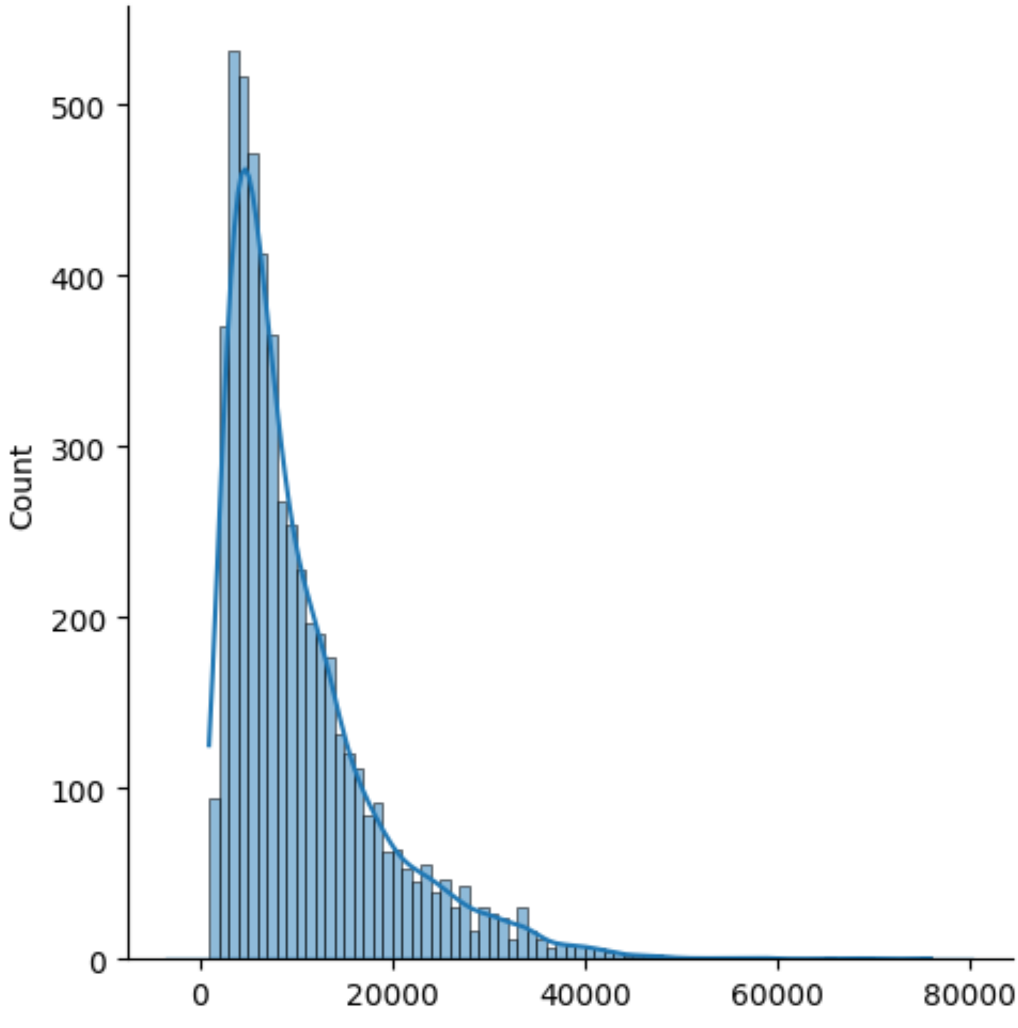

200
0
0
50000
100000
150000
200000
Mileage

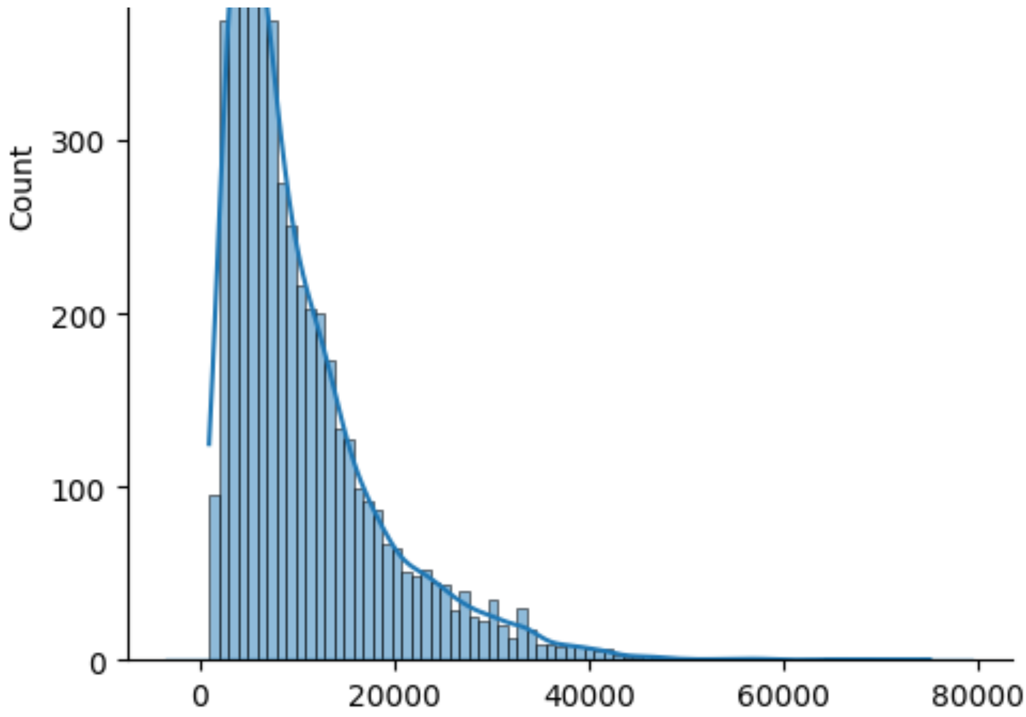

1400
1200
1000
800
600
400
200
0
Count
0
10
20
30
40
50
Year

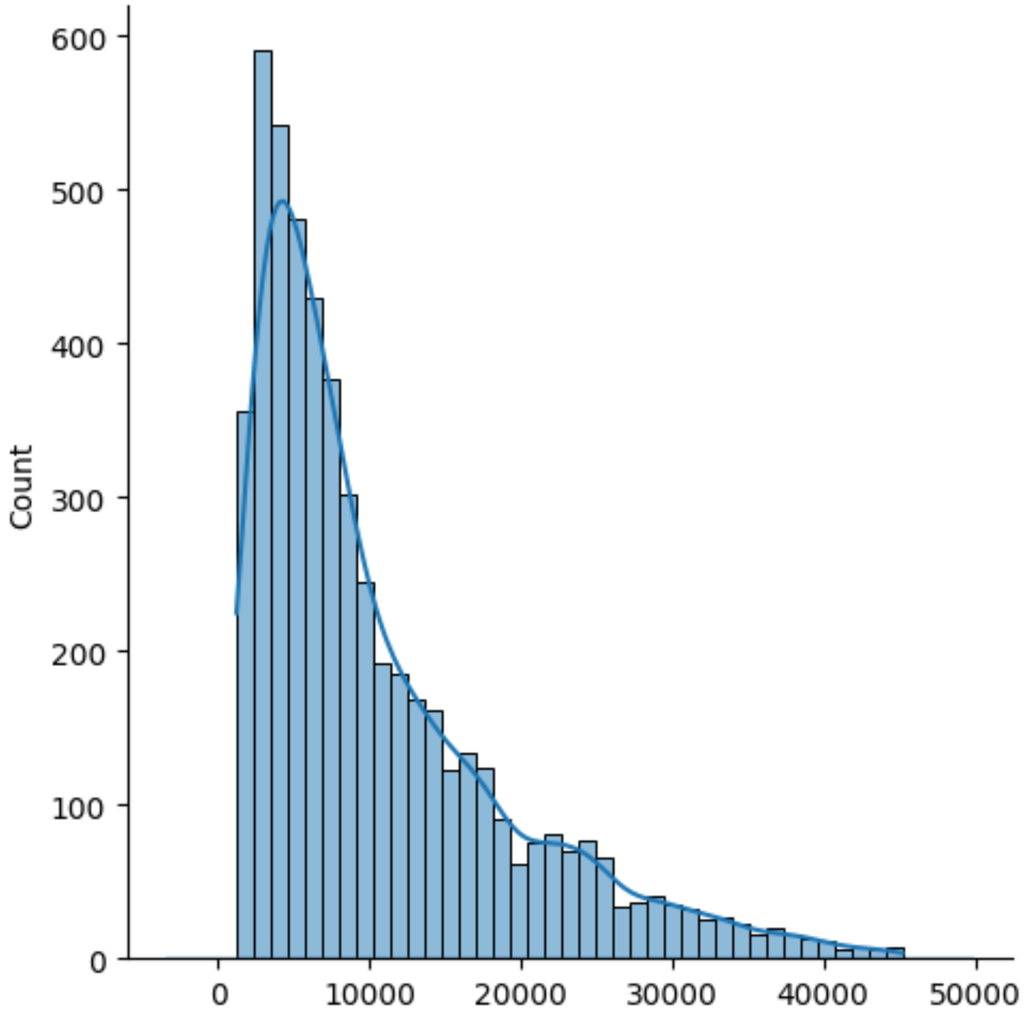

2500
2000
1500
unt



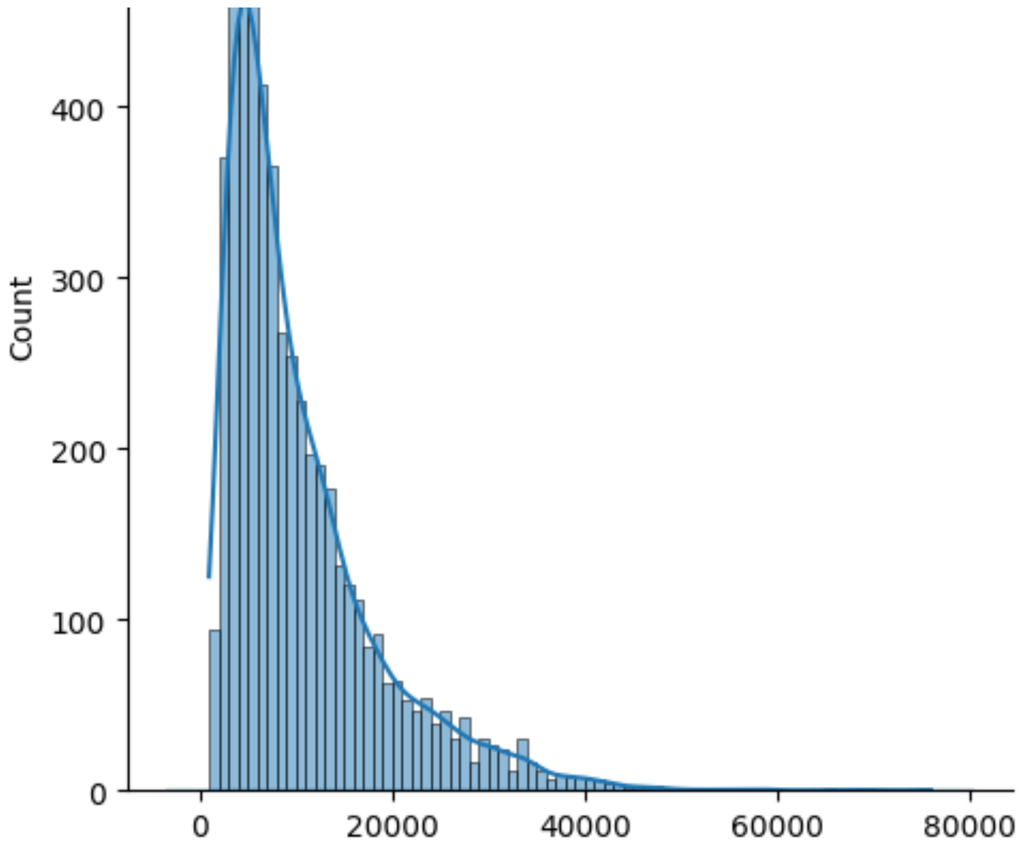
['yearsold', 'Mileage', 'Year', 'Engine', 'Model_1500', 'Model_3-Series', '

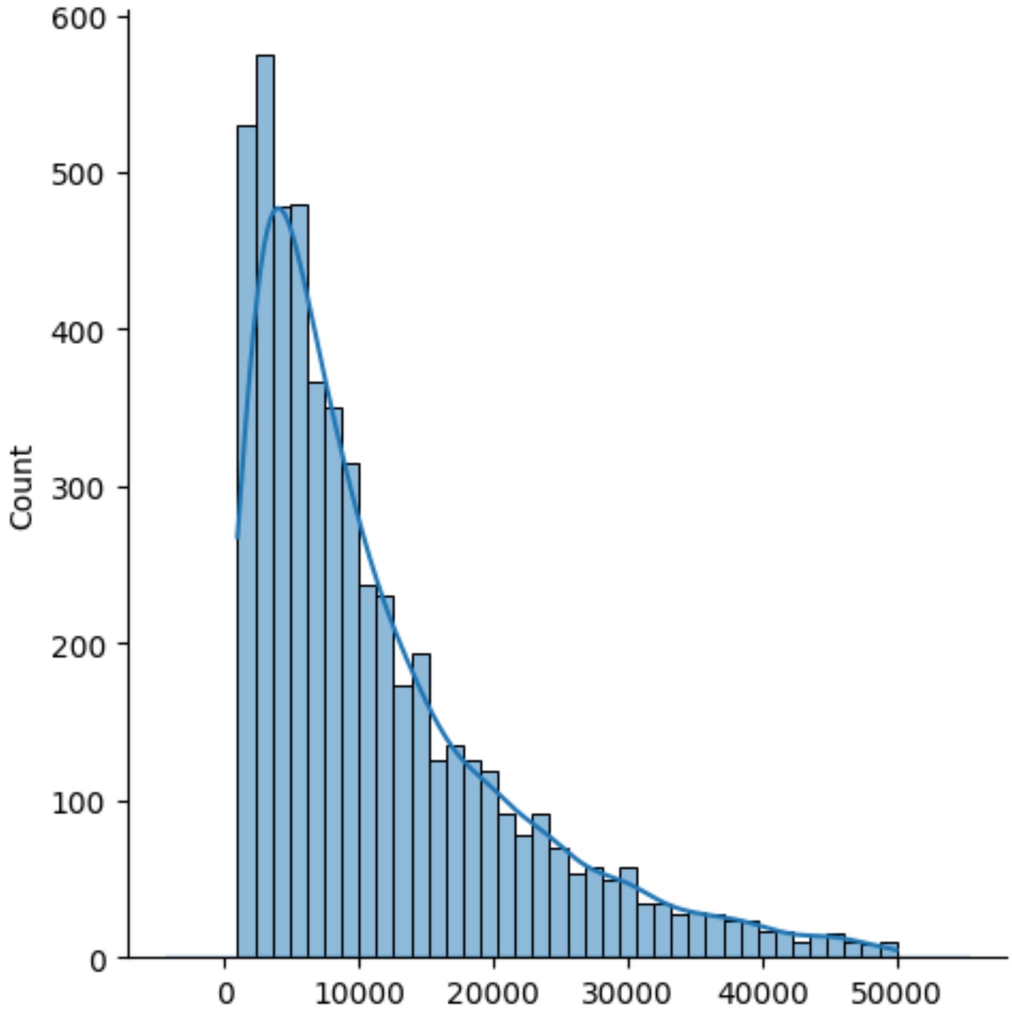



Count
0
100
200
300
0
20000
40000
60000
80000


Count
0
100
200
300
400
500
600
0
10000
20000
30000
40000
50000


500


Count
0
100
200
300
400
0
20000
40000
60000
80000


Count
0
100
200
300
400
500
600
0
10000
20000
30000
40000
50000

```
for i in range(4):
    result = model_results[i]
    sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, la
sns.distplot(y_test.values, hist=False, kde=True, kde_kws={'linewidth': 1}, la
plt.legend(title='Price')
plt.title('Multiple Model Prediction Prices')
plt.xlabel('Price (USD)')
plt.ylabel('Density')
plt.show()
```

```
<ipython-input-30-09c6eb27e06f>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-30-09c6eb27e06f>:3: UserWarning:

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  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-30-09c6eb27e06f>:3: UserWarning:

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https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-30-09c6eb27e06f>:3: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit
```
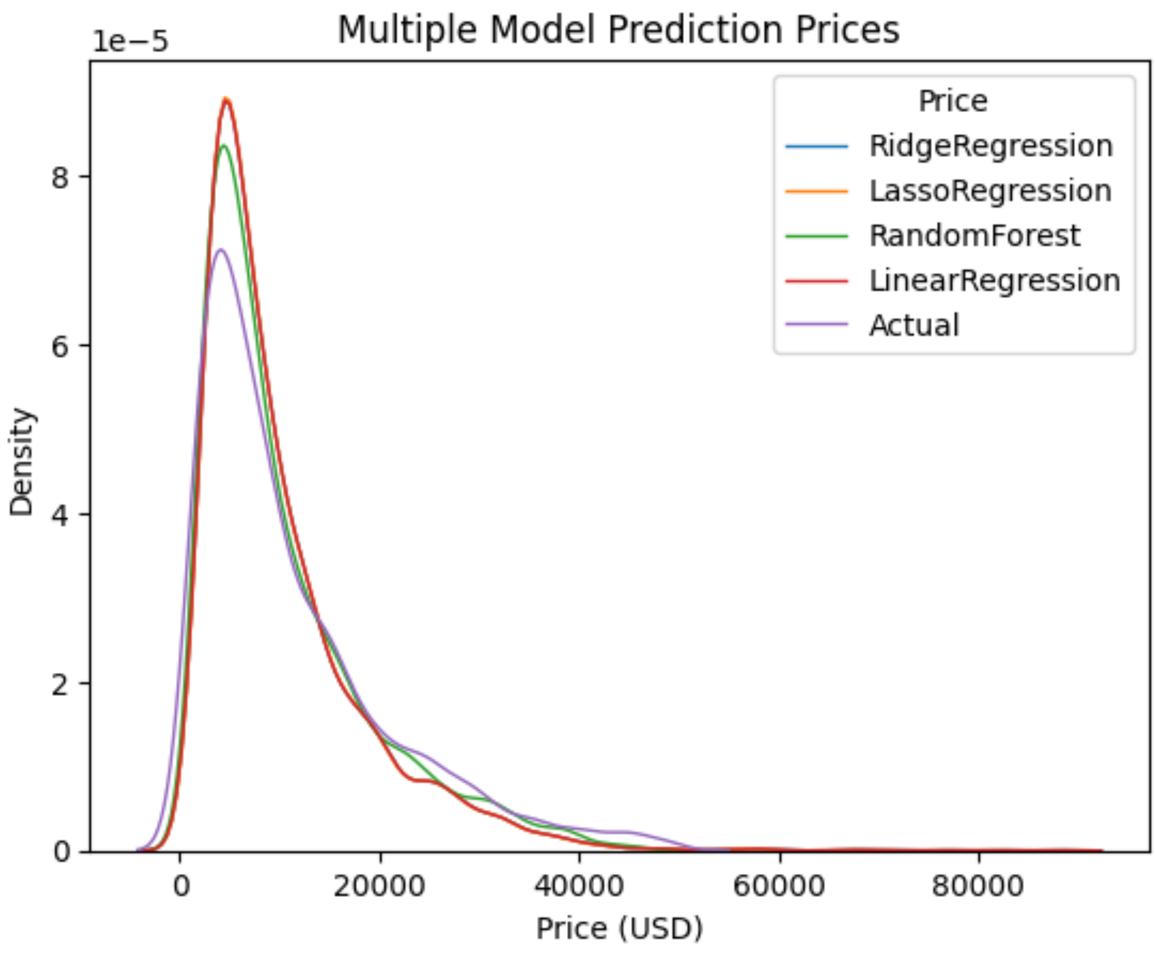
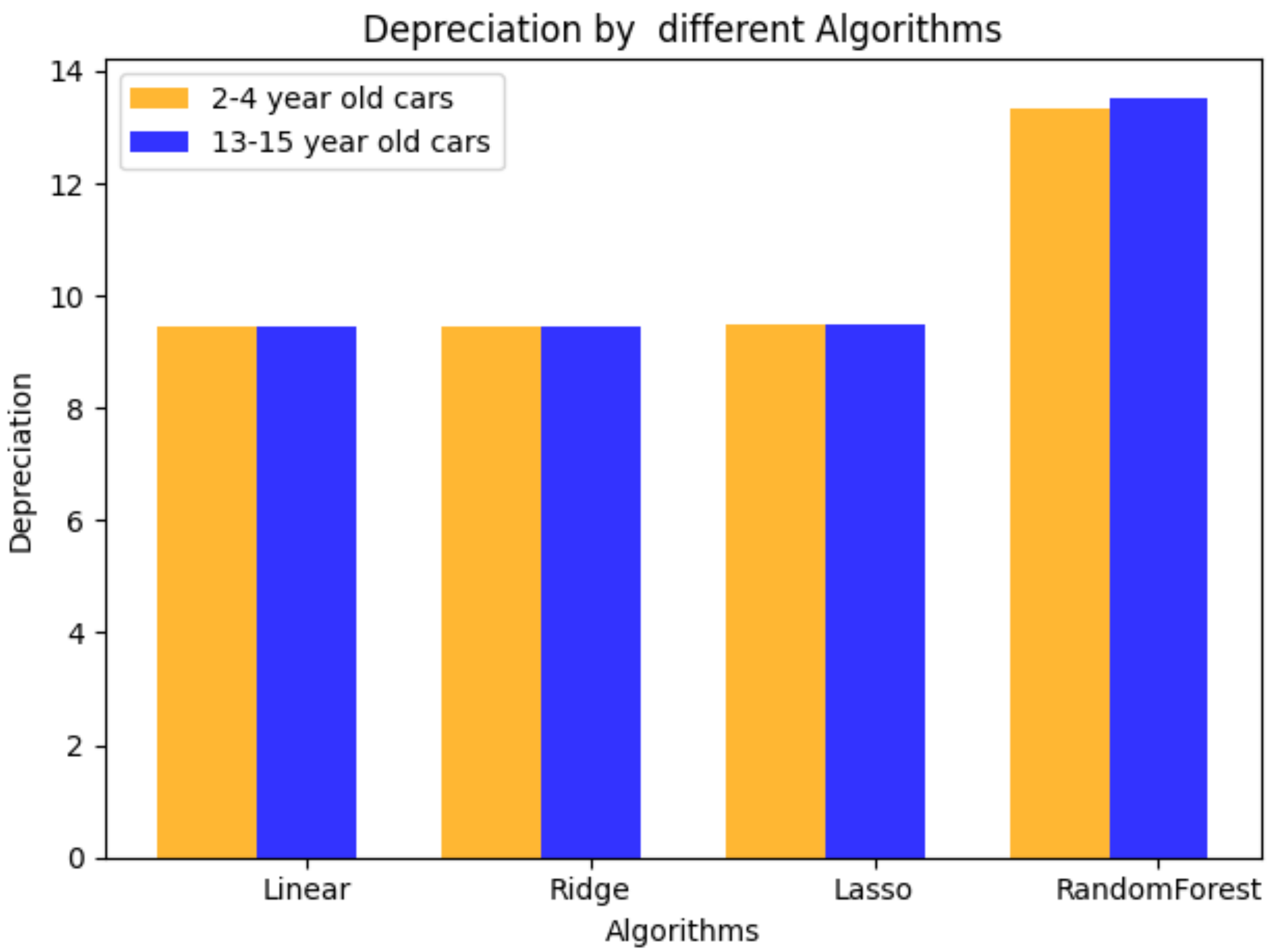

```
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1}, l
<ipython-input-30-09c6eb27e06f>:4: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(y_test.values, hist=False, kde=True, kde_kws={'linewidth': 1
```



Customizing Charts

```
# Plot
rects1 = plt.bar(index, newer_depreciation, bar_width, alpha=opacity, color='o
rects2 = plt.bar(index + bar_width, older_depreciation, bar_width, alpha=opaci

# Customizing plot
plt.xlabel('Algorithms')
plt.ylabel('Depreciation')
plt.title('Depreciation by  different Algorithms')
plt.xticks(index + bar_width, ('Linear', 'Ridge', 'Lasso', 'RandomForest'))
plt.legend()
plt.tight_layout()

# Show plot
plt.show()
```




```
# Define colors
colors = ['orange', 'red', 'green', 'black', 'purple']

# Plot KDE plots for each model result
for i in range(4):
    result = model_results[i]
```

```
    sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1, 'co

# Plot KDE plot for actual values
sns.distplot(y_test.values, hist=False, kde=True, kde_kws={'linewidth': 1, 'co

# Customizing plot
plt.legend(title='Price')
plt.title('Multiple Model Prediction Prices')
plt.xlabel('Price')
plt.ylabel('Density')
plt.show()
```

```
<ipython-input-43-e71a4df6781a>:7: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

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  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1, 'c
<ipython-input-43-e71a4df6781a>:7: UserWarning:

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  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1, 'c
<ipython-input-43-e71a4df6781a>:7: UserWarning:

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Please adapt your code to use either `displot` (a figure-level function wit
similar flexibility) or `kdeplot` (an axes-level function for kernel densit

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1, 'c
<ipython-input-43-e71a4df6781a>:7: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
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```

```
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  sns.distplot(result[0], hist=False, kde=True, kde_kws={'linewidth': 1, 'c
<ipython-input-43-e71a4df6781a>:10: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function wit
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For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(y_test.values, hist=False, kde=True, kde_kws={'linewidth': 1
```
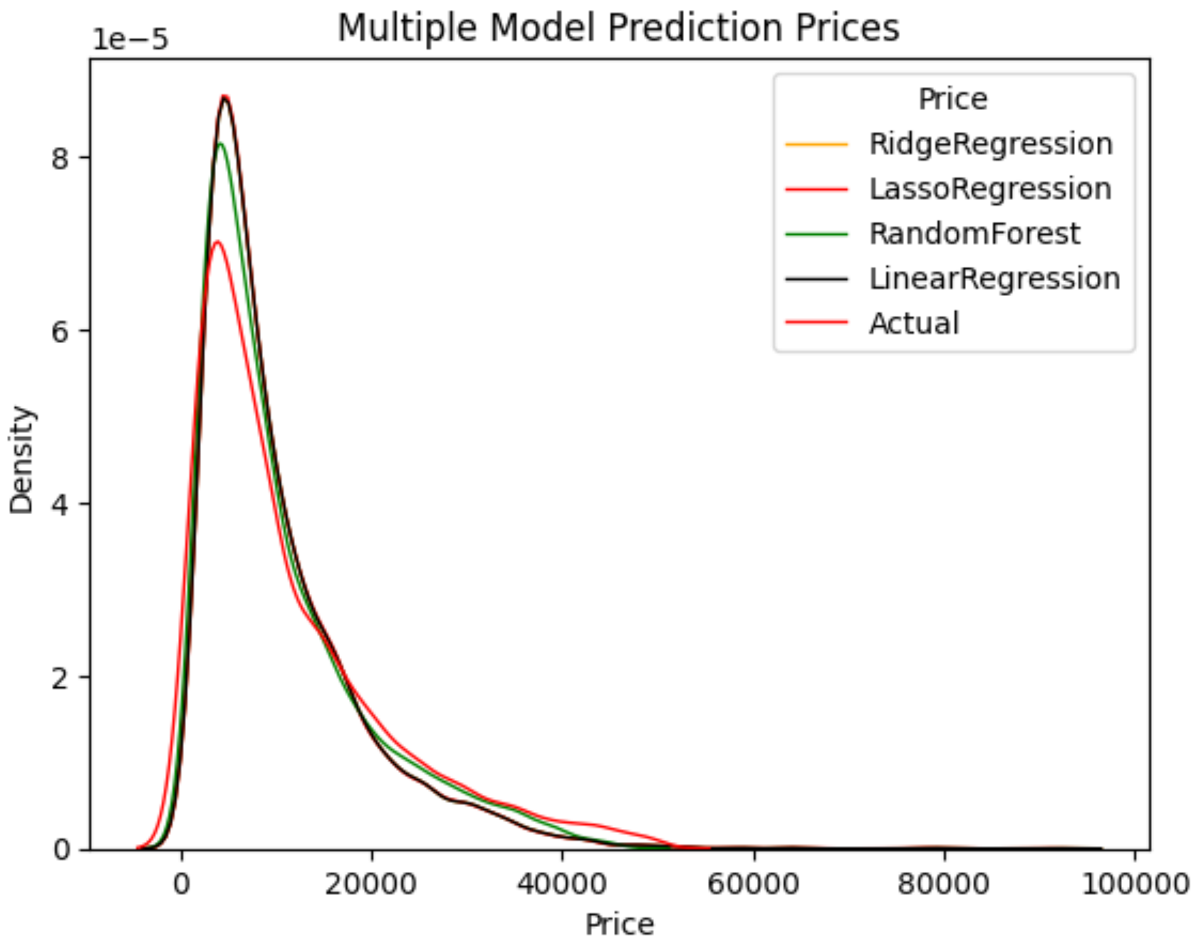
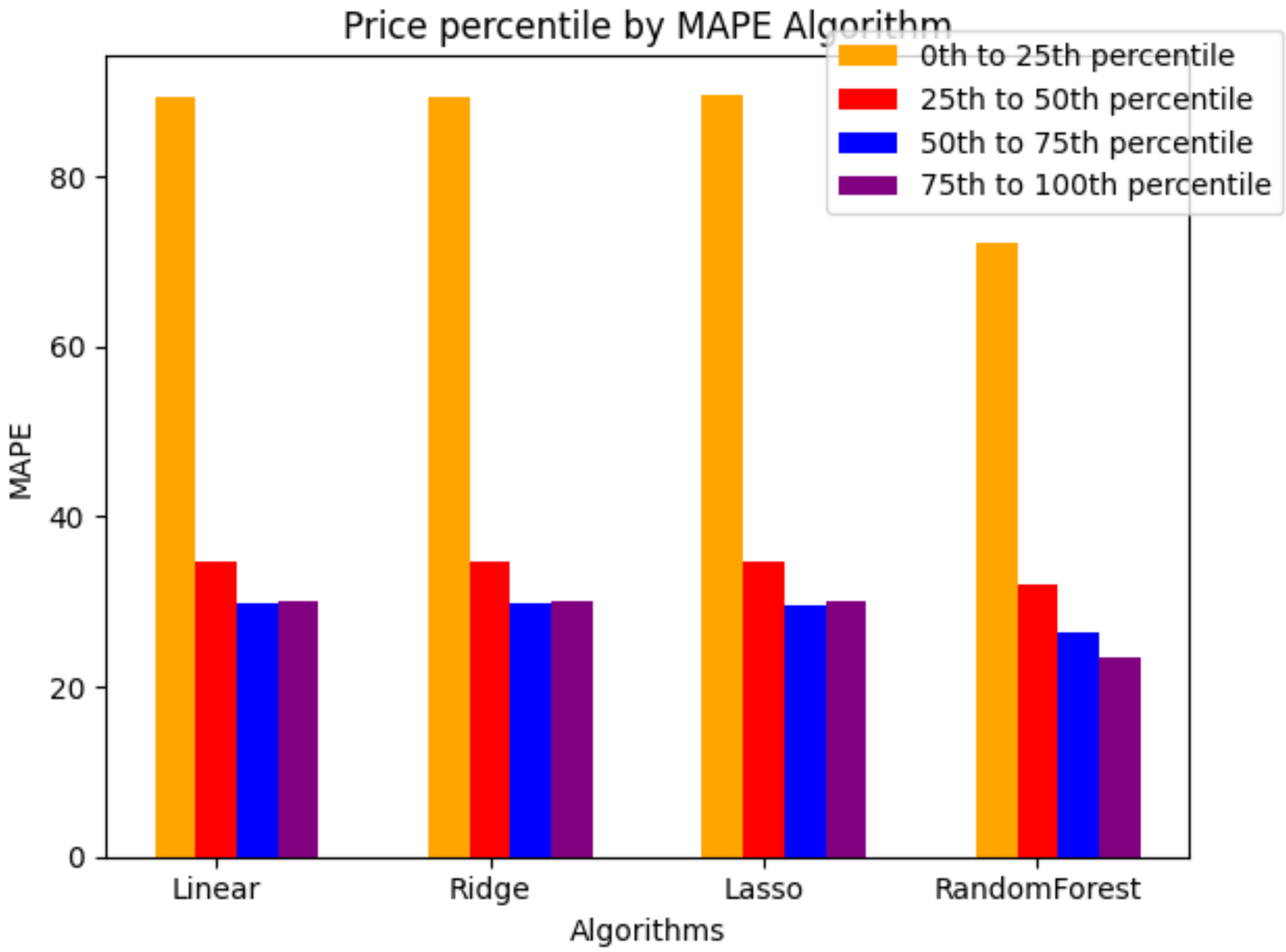



```
import matplotlib.pyplot as plt
import numpy as np

def graph_MAPE_by_price(array_to_predict):

    # Create plot
    fig, ax = plt.subplots()
    index = np.arange(4)
    bar_width = 0.15
    opacity = 1
    colors = ['orange', 'red', 'blue', 'purple']  # Modify colors here

    for i in range(4):
        results = []

        # lr
        pred_test = lr.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        # rr
        pred_test = rr.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        # lasso_r
        pred_test = model_lasso.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        # rf
        pred_test = rf.predict(array_to_predict[i])
        pred_test = np.exp2(pred_test * 0.01)
        results.append(MAPE(percentiles_targets[i], pred_test))

        rects = plt.bar(index + bar_width * i, results, bar_width,
                        alpha=opacity,
                        color=colors[i],
                        label=str(i * 25) + 'th to '+str((i+1) * 25) + 'th per

    plt.xlabel('Algorithms')
    plt.ylabel('MAPE')
    plt.title('Price percentile by MAPE Algorithm')
```

```
    plt.xticks(index + bar_width, ('Linear', 'Ridge', 'Lasso', 'RandomForest'))
    plt.legend(bbox_to_anchor=(1.1, 1.05))
    plt.tight_layout()
    plt.show()

graph_MAPE_by_price(percentiles_array)
```



```
# Defining prediction plot
def PLOT_ACTUAL_VS_PREDICTED(Y_actual, Y_predicted, line_of_best_fit=True):

    # Add points to plot with orange color
    plt.scatter(Y_actual, Y_predicted, color='orange', label='Predicted vs Act

    plt.xlabel('actual price')
    plt.ylabel('predicted price')
    plt.title('Best fit line with actual and predicted price')
    plt.legend()
    plt.tight_layout()

    if(line_of_best_fit):
        # find line of best fit
        a, b = np.polyfit(Y_actual.flatten(), Y_predicted.flatten(), 1)

        # add line of best fit to plot
        plt.plot(Y_actual, a * Y_actual + b, color='green', linewidth=6)
        plt.plot(Y_actual, Y_actual, color='red', linewidth=6)
    plt.show()
```

```
# Fit your regression models (lr, rr, model_lasso) before running this code

# Extract feature names
feature_names = df.columns

# Create a table header
print("MODEL\tFEATURE COEFFICIENTS")

# Loop through each model
for model_name, model in [("LINEAR REGRESSION", lr),
                          ("RIDGE REGRESSION", rr),
                          ("LASSO REGRESSION", model_lasso)]:
    # Get coefficients from the model
    coefficients = model.coef_

    # Print model name
    print(model_name)

    # Print feature coefficients
    for feature_name, coef in zip(feature_names, coefficients):
        print(f"{feature_name}\t{coef:.4f}")

    print("\n")  # Add a newline between models
```

```
MODEL   FEATURE COEFFICIENTS
LINEAR REGRESSION
yearsold        9.3502
Mileage -0.0012
Year    -5.5789
Engine  29.6578
Model_1500      8993526.0152
Model_3-Series  8993571.6430
Model_300 Series        8993526.8578
Model_300-Series        8993633.2913
Model_4Runner   8993605.4687
Model_5-Series  8993567.2221
Model_6-Series  8993619.4876
Model_7-Series  8993566.7584
Model_911       8993793.5632
Model_A4        8993510.1030
Model_A6        8993553.1100
Model_Acadia    8993552.9886
Model_Accord    8993533.1636
Model_Altima    8993484.0556
Model_Blazer    8993538.4395
Model_Boxster   8993611.3963
Model_Bronco    8993626.1665
Model_C-10      8993663.4768
Model_C-Class   8993540.2520
Model_C/K Pickup 1500   8993561.8117
Model_CR-V      8993538.2315
Model_CTS       8993543.5640
Model_Camaro    8993554.1613
Model_Camry     8993538.0222
Model_Cayenne   8993608.3271
Model_Challenger        8993553.1737
Model_Charger   8993526.2959
Model_Cherokee  8993548.6398
Model_Civic     8993519.1144
Model_Corolla   8993516.9811
Model_Corvette  8993578.0350
Model_Crown Victoria    8993426.5565
Model_DeVille   8993469.6129
Model_Durango   8993500.4397
Model_E-Class   8993570.1419
Model_E-Series Van      8993501.5954
Model_Edge      8993546.3422
Model_Eldorado  8993530.9130
Model_Enclave   8993560.1990
Model_Equinox   8993501.3459
Model_Escalade  8993580.1012
Model_Escape    8993491.2169
Model_Excursion 8993595.4337
Model_Expedition        8993522.7769
Model_Explorer  8993522.1694
Model_Express   8993507.0000
Model_F-150     8993552.4776
Model_F-250     8993523.6694
```

```
Model_F-350      8993539.3002
Model_Firebird   8993576.3094
Model_Focus      8993451.6029
Model_Forester   8993495.6941
Model_Fusion     8993504.6685
```

```
# Define the headers for the table
print("PERCENTILE\tSTART PRICE\tEND PRICE")

# Define the percentile labels and corresponding start and end prices
percentile_labels = ["0TH-25TH", "25TH-50TH", "50TH-75TH", "75TH-100TH"]
start_prices = [min_price, percentiles_price[0], percentiles_price[1], percentil
end_prices = [percentiles_price[0], percentiles_price[1], percentiles_price[2],

# Iterate through the percentiles and print the corresponding start and end pric
for label, start_price, end_price in zip(percentile_labels, start_prices, end_pr
    print(f"{label}\t\t${start_price:.2f}\t\t${end_price:.2f}")
```

```
PERCENTILE      START PRICE     END PRICE
0TH-25TH                $1000.00                $4050.00
25TH-50TH               $4050.00                $8050.00
50TH-75TH               $8050.00                $15500.00
75TH-100TH              $15500.00               $50000.00
```

```
df.describe()
```

	yearsold	Mileage	Year	Engine	Model_1500	Mo
count	26422.000000	26422.000000	26422.000000	26422.000000	26422.000000	26422.
mean	2.372228	93189.599198	14.163311	4.319590	0.004352	0
std	0.503428	52704.345670	9.778808	1.434038	0.065830	0.
min	1.000000	1011.000000	1.000000	1.000000	0.000000	0.
25%	2.000000	48851.000000	6.000000	3.400000	0.000000	0.
50%	2.000000	92000.000000	13.000000	4.300000	0.000000	0.
75%	3.000000	134898.250000	19.000000	5.500000	0.000000	0.
max	3.000000	199999.000000	49.000000	8.800000	1.000000	1.

8 rows × 128 columns