INSTRUCTIONS ON RUNNING THIS NOTEBOOK

- It requires nltk and tries to download it using !pip install command
- It by default it is using a large training set so the model tuning and feature importance calcluations can be accurate
- It is by default set to NOT , REPEAT NOT, RUN TIME CONSUMING CALCULATIONS.
- As you work throught the notebook, some cells will ask you to manually set OK_TO_RUN_TUNING or OK_TO_RUN_FEAT_IMPORT to True.
- Doing so will trigger the lengthy calcuations - up to an hour
- I have included images of the key charts in the README.MD file and in this notebook if you want to see the results without running the full notebook
- With the default OK_TO_RUN_TUNING or OK_TO_RUN_FEAT_IMPORT set to False, the notebook runs in about 20 seconds

In [1]:
```
# KEY CONFIGURATION VALUES
# Change this to fun for specific states (less run time)
# Example: STATE_FILTER = ['tx']
STATE_FILTER = []

BEST_ALPHA = 1 # DEFAULT ALPHA FOR RIDGE() but value can be changed if tuning is ru

# Set this False to skip tuning, especially if you don't have a state filter. It ma
OK_TO_RUN_TUNING = True

# Set this to Flase to skip basic feature importance calcuation, especially if you
OK_TO_RUN_FEAT_IMPORT = True

# Set this to False to skip more advanced intensive feature importance calcuations,
OK_TO_RUN_FEAT_IMPORT_ADDITIONAL = False
```

What drives the price of a car?

OVERVIEW

In this application, you will explore a dataset from kaggle. The original dataset contained information on 3 million used cars. The provided dataset contains information on 426K cars to ensure speed of processing. 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

No description has been provided for this image

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.

Background: Used car sales dealerships want to fine tune their inventory to improve profits. Their strategy is to identify what factors make a car more or less expensive. Implicit in this strategy is understanding profit margin and return on investment, not just selling more and higher priced vehicles. However, the focus of this study is on understanding what features in a car customers value. We make the assumption that customers express this 'value' by paying a higher price for cars with more valuable features versus those with less valuable features.

Data Problem Definition:

Business Objective:

- Identify the car features in the data that have the strongest positive correlation with selling price.
- The ability to identify these corelations should be part of a bigger discussion with stakeholders about the wider business project goals. Assuming ROI of investment in inventory is the ultimate goal, clarify that developing a causal-based model and subsequently factoring in profit margins of car features would be important 2nd and 3rd stages of the project.
- This correlation study, along with future causal and profit-margin analysis projects can enable dealers to optimize the ROI of their businesses by more systematically choosing their inventory of cars to sell.

Data Analytics Objective: Develop a model and process to ingest used car data, analyze it and rank the most significant features of a car and the least significant features of a car. These rankings will be made based on how they impact the price at which the car sells. Use the most significant features to predict the price that customers would pay for a given set of features.

Data Sources: Kaggle data set of information about 426K used cars

Key Performance Indicators (KPIs): % of rows of data with valid data in most feature columns: If too much data is missing or invalid, then steps to address this issue must be taken prior to successfully completing the project

Feature Importance: Relative feature importance using the coefficients of a linear regression model tuned and regularized for this context

Change in Error by Feature: Differences in mean squared error for several linear regression models using different subsets of features

Error for Optimized Model: Mean squared error of the best performing linear regression model

Overfitting Check: Difference in training error vs validation error across multiple hyper parameters

Success Criteria:

- The ranking process identifies the top 5 MOST signifcant features correlated to sale price of a car based on above KPIs
- The optimized model has a test data MSE less than 5% of the average price of the cars in inventory

Our result at this stage will be a correlation study. An additional success criteria for this stage is that the analysis guides the efficient design of a randomized control experiments to determine causal impact of features on sale price.

In [ ]:

```

```

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.

Steps to take to gain understanding:

- Evaluate total number of rows and also number of rows per various categorical groupings.
- Is there a massive amount of data to be managed such that simple queries, regressions and etc will be time-consuming and expensive?
- Examine the schema (structure and type) of the data. Identify the sales price numerical field(s).
- Are any fields compound or nested data that needs to be further processed (de-normalized, flattended) to be understood?

- Is the data spread out across many data sources such as a relational datamodel with foreign keys?
- Does the data need to be concatenated over multiple similar data sources?
- Visually review the data distribution and range of values of the data. Look for obvious patterns using histograms and box plots.
- Compare subsets of the data by feature columns grouping to look for relationships like correlation.
- Note if there are major imbalances in the category groupings of the data.
- Look for nulls, suspicious duplicates, outliers, and invalid values.
- Look for data mistakes/inconsistencies in which two domain values are different on different rows, but likely meant to be the same value. Example: 'Blue' and 'blue'.
- Look at mode, frequency and averages of the total and a variety of subgroups of the data, especially in regards to the fields holding the sale price.
- Identify if the data has a time-series aspects like date of sale. Examine the range and distribution of sales price along these time-series axes.

Code and observations regarding data structure and size

In [2]:
```
# All imports needed to run this notebook code
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.calibration import LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.model_selection import StratifiedKFold, cross_val_score, train_test_sp
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SequentialFeatureSelector, SelectFromModel
from sklearn.model_selection import GridSearchCV
import math
import re
import string
import itertools
import time
import random
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import make_column_transformer
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error
#!pip install statsmodels
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.decomposition import PCA
from sklearn.feature_selection import VarianceThreshold, SelectKBest, f_classif
import pickle
#!pip install nltk
import nltk
```

```
from sklearn.preprocessing import FunctionTransformer
from sklearn.inspection import permutation_importance
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn import set_config
import winsound # Remove this if not on windows machine. Using to signal when a lon
```

In [3]:
```
def beep():
  winsound.Beep(frequency=1000, duration=7000)
```

In [4]:
```
car_df = pd.read_csv('data/vehicles.csv')
```

In [5]:
```
print(f"Car df number of rows: {car_df.shape[0]} and column count: {car_df.shape[1]
```

```
Car df number of rows: 426880 and column count: 18
```

In [6]:
```
car_df.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
```

In [7]:
```
print("@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@")
print("@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@")
print("@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@")
#print(f"EXPERIMENT FILTERING TO A SINGLE TYPE")
if len(STATE_FILTER) > 0:
    state_filter = STATE_FILTER
    print(f"Running by State of {state_filter}")
    car_state_df = car_df[car_df['state'].isin(state_filter)]
    car_df = car_state_df
else:
    print("running as normal")
```

```
print("@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@")
print("@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@")
print("@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@@")
```

```
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running as normal
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```

Comments on the structure:

- The 'id' fields looks to be a unique value per row
- 'price' seems to be the target value and the rest besides ID are features
- The structure of the data source is simple - one file. No need for joins, concatenation or integrations
- There are a reasonable number of rows and columns. Not too many to work with using standard tools.

Code block to help with visual analysis of distribution

In [8]:

```
# eval_col_counts() gives a sense of the distribution of different distinct values
# For columns with less distinct values less than max_detail(default=15), a bar cha
# with that value of that column is show for each distinct value.
# For columns with more than max_detail distinct values, it shows the top max_detai
# It also creates a column 'Rest of values' and shows the count of the remaining va
# This approach lets us get a sense of the distribution visually even for categorie
# You can sort the bar chart by the highest count or by the column value (e.g., sho
# To do the latter, set sort_by_col parameter to True

import pandas as pd

def get_value_counts(data, column_name, sort_by_col=False):
  # Use value_counts() to get the counts and reset the index to create a DataFrame
  if sort_by_col:
      return data[column_name].value_counts().reset_index(name='count').sort_values
  else:
      return data[column_name].value_counts().reset_index(name='count')

def get_all_value_counts(data, col_list):
    # Assuming your data is loaded into a pandas DataFrame named 'df'
    for column_to_count in col_list:
        value_counts_df = get_value_counts(car_df, column_to_count)
        print(value_counts_df)


def eval_col_counts(data, col_list, max_detail = 15, sort_by_col = False):
    for column_to_count in col_list:
        value_counts_df = get_value_counts(data, column_to_count, sort_by_col)
        unq_count = value_counts_df.shape[0]
        print(f"{column_to_count} has {unq_count} distinct values")
```

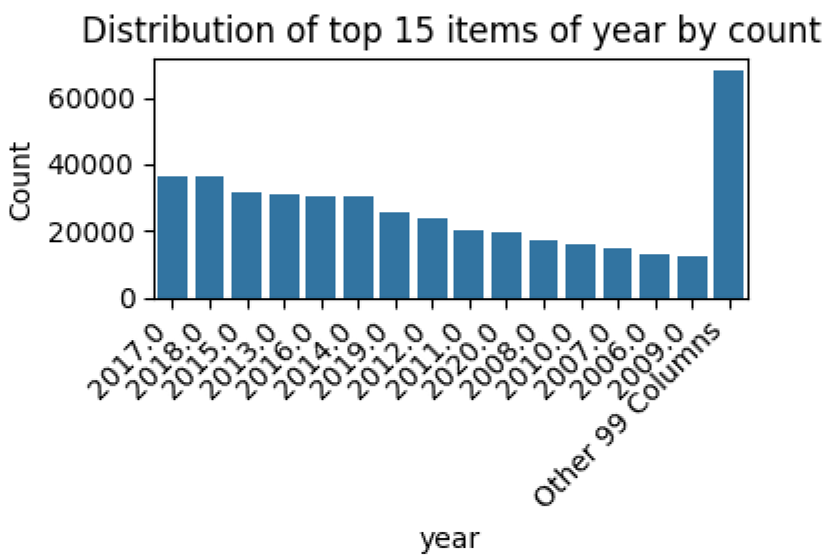
```
        disp_count = min(max_detail,unq_count)
        print(f"See {disp_count} of them")
        print(value_counts_df.head(disp_count))
        if unq_count < 10:
            plt_title = f'Distribution of {column_to_count}'
            plt_data = value_counts_df.copy()
        else:
            plt_title = f'Distribution of top {max_detail} items of {column_to_coun
            plt_data_slice = value_counts_df.head(max_detail)
            plt_data = plt_data_slice.copy()
            plt_data_sum = sum(plt_data['count'])
            all_data_sum = sum(value_counts_df['count'])
            rest_data_sum = all_data_sum - plt_data_sum
            print(f'Count of the rest of the values not shown: {rest_data_sum}')
            # Create a dictionary for the new row
            #new_row = pd.Series({column_to_count: 'Other Columns', 'count': rest_d
            plt_data.loc[len(plt_data)] = [f'Other {unq_count-max_detail} Columns',

        plt.figure(figsize=(4, 3))  # Adjust figure size as needed
        sns.barplot(x=column_to_count, y="count", data=plt_data)
        plt.xlabel(column_to_count)
        plt.ylabel('Count')
        plt.title(plt_title)
        plt.xticks(rotation=45, ha='right')  # Rotate category labels for readabili
        plt.tight_layout()  # Adjust spacing between elements
        plt.show()

        print("----")
```

Distribution of data charts

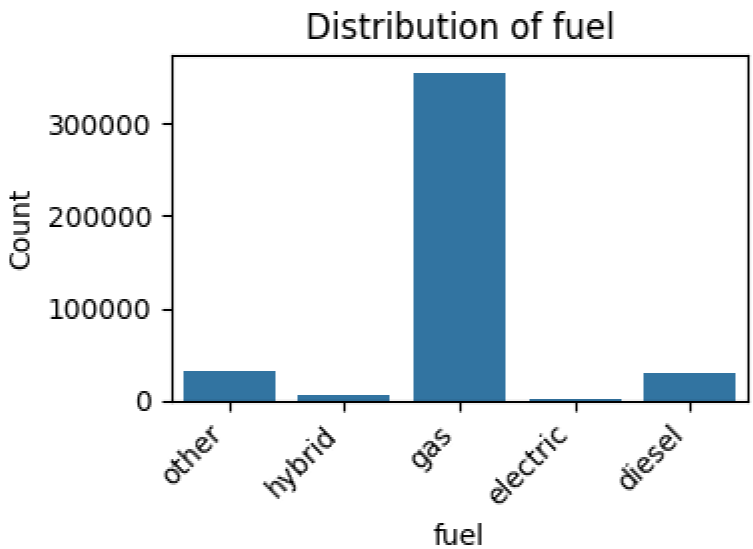
In [9]:

```
# Grader: I have run with all columns but for submission only listing interesting c
#col_list = ['region', 'year', 'manufacturer', 'model', 'condition', 'cylinders','f
#            'odometer','title_status', 'transmission','drive','size','type','paint
freq_sort_col_list = [ 'manufacturer', 'model', 'condition', 'cylinders','fuel',
            'odometer','title_status', 'transmission','drive','size','type','paint_
max_detail = 15
freq_sort_col_list = ['year']
eval_col_counts(car_df, freq_sort_col_list, max_detail = max_detail, sort_by_col =

col_sort_col_list = ['fuel','type','manufacturer', 'state', 'size']
eval_col_counts(car_df, col_sort_col_list, max_detail = max_detail,  sort_by_col =
```

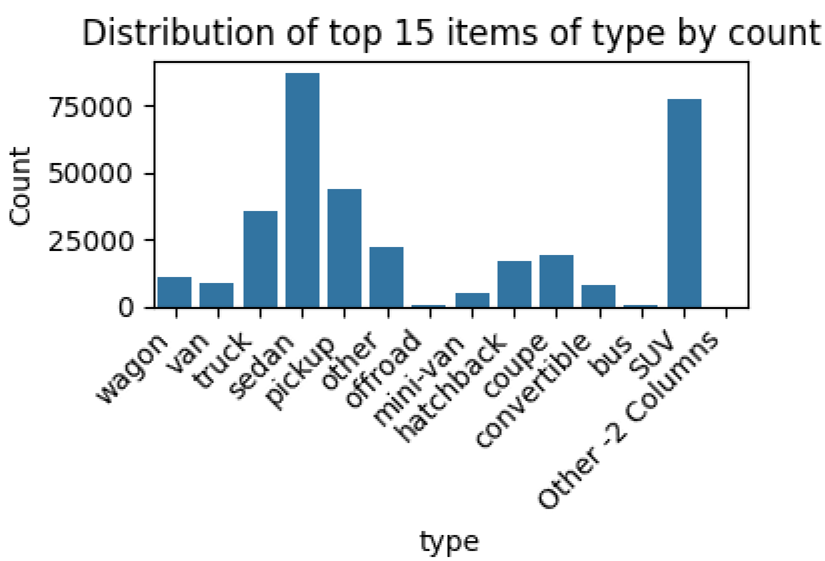
```
year has 114 distinct values
See 15 of them
      year  count
0   2017.0  36420
1   2018.0  36369
2   2015.0  31538
3   2013.0  30794
4   2016.0  30434
5   2014.0  30283
6   2019.0  25375
7   2012.0  23898
8   2011.0  20341
9   2020.0  19298
10  2008.0  17150
11  2010.0  15829
12  2007.0  14873
13  2006.0  12763
14  2009.0  12185
Count of the rest of the values not shown: 68125
```



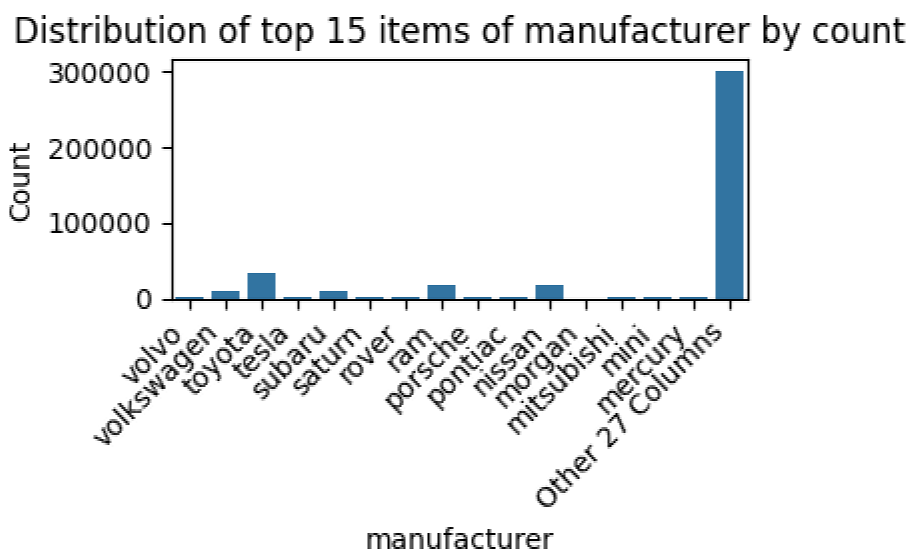

```
----
fuel has 5 distinct values
See 5 of them
       fuel   count
1     other   30728
3    hybrid    5170
0       gas  356209
4  electric    1698
2    diesel   30062
```



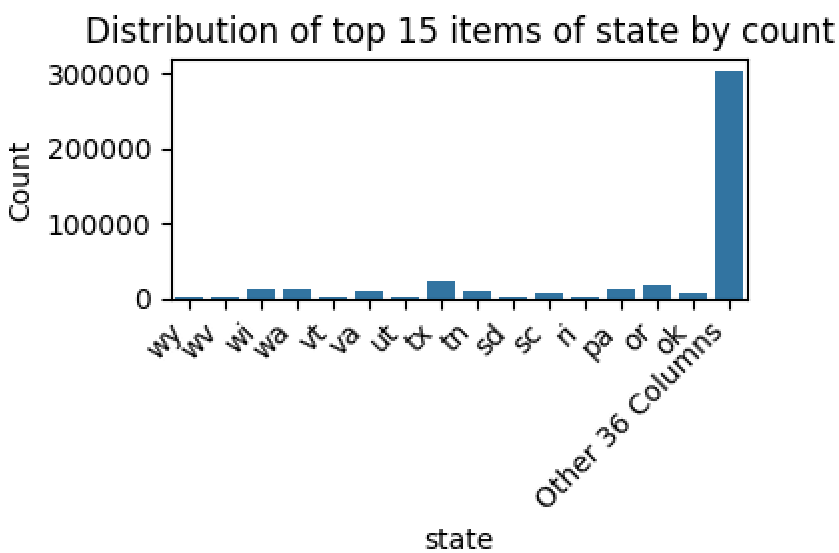

```
----
type has 13 distinct values
See 13 of them
           type  count
7         wagon  10751
8           van   8548
3         truck  35279
0         sedan  87056
2        pickup  43510
4         other  22110
11      offroad    609
10     mini-van   4825
6     hatchback  16598
5         coupe  19204
9   convertible   7731
12          bus    517
1           SUV  77284
Count of the rest of the values not shown: 0
```



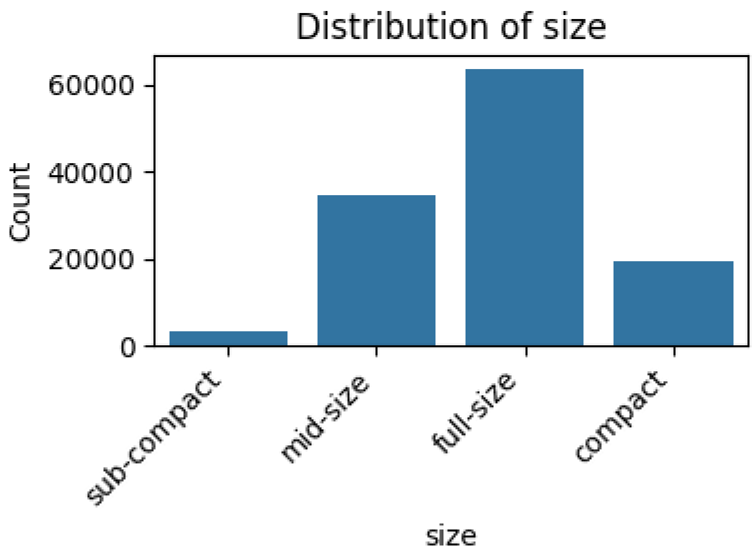
```
----
manufacturer has 42 distinct values
See 15 of them
   manufacturer  count
24        volvo   3374
13   volkswagen   9345
2        toyota  34202
34        tesla    868
12       subaru   9495
32       saturn   1090
28        rover   2113
6           ram  18342
30      porsche   1384
27      pontiac   2288
4        nissan  19067
41       morgan      3
25   mitsubishi   3292
26         mini   2376
31      mercury   1184
Count of the rest of the values not shown: 300811
```



```
----
state has 51 distinct values
See 15 of them
   state  count
49    wy    610
45    wv   1052
10    wi  11398
8     wa  13861
41    vt   2513
13    va  10732
44    ut   1150
2     tx  22945
12    tn  11066
43    sd   1302
23    sc   6327
42    ri   2320
9     pa  13753
5     or  17104
22    ok   6792
Count of the rest of the values not shown: 303955
```




```
----
size has 4 distinct values
See 4 of them
         size  count
3  sub-compact   3194
1     mid-size  34476
0    full-size  63465
2      compact  19384
```



Code block to show relationship of price to each feature column

In [10]:
```
# support functions for eval_col_avg_price()

def get_average_car_price(data, col):
    average_price_per_category = data.groupby(col)['price'].mean().reset_index()
    return average_price_per_category.sort_values(by=['price','count'], ascending=F


def get_average_and_count_car_price(data, col):
    average_price_per_category = data.groupby(col).agg(price=('price', 'mean'), cou
    return average_price_per_category.sort_values(by='price', ascending=False)


def filter_by_price_quantile(data, lower_price_q, upper_price_q):
    price_quantiles = data['price'].quantile([lower_price_q, upper_price_q])
    price_lower_bound = price_quantiles[lower_price_q]
    price_upper_bound = price_quantiles[upper_price_q]

    # Filter DataFrame
    filtered_df = data[(data['price'] >= price_lower_bound) & (data['price'] <= pri

    return filtered_df


def filter_by_price_and_count_quantile(data, lower_price_q, upper_price_q, lower_co
    price_quantiles = data['price'].quantile([lower_price_q, upper_price_q])
    price_lower_bound = price_quantiles[lower_price_q]
    price_upper_bound = price_quantiles[upper_price_q]

    # Calculate quantiles for count
    count_quantiles = data['count'].quantile([lower_count_q, upper_count_q])
    count_lower_bound = count_quantiles[lower_count_q]
    count_upper_bound = count_quantiles[upper_count_q]
```

```
    # Filter DataFrame
    filtered_df = data[(data['price'] >= price_lower_bound) & (data['price'] <= pri
                     (data['count'] >= count_lower_bound) & (data['count'] <= count_upp

    return filtered_df

def drop_outlier(data, target_col, IQR_mult):
    # Calculate Interquartile Range (IQR) for price
    Q1 = data[target_col].quantile(0.25)
    Q3 = data[target_col].quantile(0.75)
    IQR = Q3 - Q1

    # Define outlier threshold (1.5 times IQR)
    threshold = IQR_mult * IQR

    # Identify outliers (outside lower and upper bounds)
    lower_bound = Q1 - threshold
    upper_bound = Q3 + threshold
    outliers = data[(data[target_col] < lower_bound) | (data[target_col] > upper_bo
    print(f"drop_outlier(): lower bound = {lower_bound}")
    print(f"drop_outlier(): upper bound = {upper_bound}")
    # Drop outliers (consider alternative approaches if needed)
    return data.drop(outliers.index)

def handle_extreme_min_max(data_slice, column_to_get_avg, categories, subtitle, siz
        sample_avg = data_slice['price'].mean()

        # min
        min_value_index = data_slice["price"].idxmin()
        category_w_min_value = data_slice.loc[min_value_index][column_to_get_avg]
        min_value = data_slice.loc[min_value_index]["price"]
        # max
        max_value_index = data_slice["price"].idxmax()
        category_w_max_value = data_slice.loc[max_value_index][column_to_get_avg]
        max_value = data_slice.loc[max_value_index]["price"]

        show_min = min_value > size_mult*sample_avg
        show_max =  max_value < size_mult*sample_avg

        if not show_min:
            if len(subtitle)>0:
                subtitle = subtitle + '\n'
            if prefix is None:
                subtitle = f"{subtitle} MIN is not shown: {category_w_min_value} =
            else:
               subtitle = f"{subtitle} {prefix} not shown: {category_w_min_value} =

        if not show_max:
            if len(subtitle)>0:
                subtitle = subtitle + '\n'
            if prefix is None:
                subtitle = f"{subtitle} MAX is not shown: {category_w_max_value} =
            else:
                subtitle = f"{subtitle} {prefix} is not shown: {category_w_min_valu
```

```
        plt_categories = []
        for category in categories:
            ok_to_add = True
            if category == category_w_min_value:
                ok_to_add =  show_min
            if category == category_w_max_value:
                ok_to_add = show_max
            if ok_to_add:
                plt_categories.append(category)

        return plt_categories, subtitle

def show_min_max_calc(full_avg_data, sample_data_slice, column_to_get_avg, categori

        # min
        min_value_index = full_avg_data["price"].idxmin()
        category_w_min_value = full_avg_data.loc[min_value_index][column_to_get_avg
        min_value = full_avg_data.loc[min_value_index]["price"]
        min_row = full_avg_data.loc[min_value_index]
        # max
        max_value_index = full_avg_data["price"].idxmax()
        category_w_max_value = full_avg_data.loc[max_value_index][column_to_get_avg
        max_value = full_avg_data.loc[max_value_index]["price"]
        max_row = full_avg_data.loc[max_value_index]


        sample_plus_min_max = sample_data_slice.copy()
        sample_plus_min_max.loc[len(sample_plus_min_max)] = min_row
        sample_plus_min_max.loc[len(sample_plus_min_max)] = max_row

        sample_avg = sample_plus_min_max['price'].mean()


        show_min = min_value > size_mult*sample_avg
        show_max =  max_value < size_mult*sample_avg

        plt_categories = []
        if not show_min:
            if len(subtitle)>0:
                subtitle = subtitle + '\n'
            subtitle = f"{subtitle} MIN is not shown: {category_w_min_value} = {min
        else:
            plt_categories.append(category_w_min_value)

        if not show_max:
            if len(subtitle)>0:
                subtitle = subtitle + '\n'
            subtitle = f"{subtitle} MAX is not shown: {category_w_max_value} = {max
        else:
            plt_categories.append(category_w_max_value)

        for category in categories:
            ok_to_add = True
            if category == category_w_min_value:
                ok_to_add =  show_min
            if category == category_w_max_value:
```

```
                ok_to_add = show_max
            if ok_to_add:
                plt_categories.append(category)

        return plt_categories, subtitle

def handle_many_distinct_averages(data, column_to_get_avg, value_avg_df, subtitle):

        plt_title = f'Average price and spread of min avg, max avg and sample of {m

        # too many categoires to show on a chart so get a sample of max_detail of t
        # sample 2 more than I need so I can drop ones that might put out of scale
        sample_data_slice = value_avg_df.sample(max_detail).sort_values(by='price')
        initial_len = sample_data_slice.shape[0]
        sample_data_slice = sample_data_slice[1:initial_len-1]
        sample_categories = sample_data_slice[column_to_get_avg]

        # add overall min and max but handlife if it so vastly different than sampl
        plt_categories, subtitle = show_min_max_calc(value_avg_df, sample_data_slic

        plt_data = data[data[column_to_get_avg].isin(plt_categories)]

        return plt_data, plt_title, subtitle
```

In [11]:

```
# eval_col_avg_price() routine helps get a sense of the rawnge of values for each c
# For columns with less than max_detail(default=15) distinct values, it shows each
# For columns with more, it shows the min, max and a sample of 13 values.
# Specifically, it finds the average for each distinct column into a separate dataf
# then it samples (max_detail - 2) columnns from that set of averages
# finally it shows the box plot for the min, the samples, and the max average.
# By default it does not include outliers in the chart but passing a parameter can
# Note 1: outliers can scale the chart such that it hard to read for other boxplots
# Note 2: For the column values corresponding to the min/max average are less/more
# the boxplot for it is not shown but the average is shown in a subtitle of the plo
# This solution reduces the chance of big mis matches in scale for boxplots shown.
# If the sampling of averages hits a particularly high or low value, the chart will

def draw_box_plot(plt_data_orig, column_to_get_avg, showfliers_flag,  subtitle, plt

    plt_data = plt_data_orig.copy()
    plt_data[column_to_get_avg] = plt_data[column_to_get_avg].astype(str).str[:30].
    plt.figure(figsize=(8, 5))  # Adjust figure size as needed
    sns.boxplot(
        x = column_to_get_avg,
        y = "price",
        showmeans=True,  # Add means (optional)
        showfliers = showfliers_flag,
        data=plt_data)

    plt.xlabel(column_to_get_avg)
    plt.ylabel('Average Price')
    plt.title(subtitle)
    plt.suptitle(plt_title)
    plt.xticks(rotation=45, ha='right')  # Rotate category labels for readability
    plt.tight_layout()  # Adjust spacing between elements
```

```
    plt.show()

    plt.cla()
    plt.clf()

def draw_price_and_count_plot(plt_data_orig, column_to_get_avg, title, subtitle, ma

    # next check if need to downsample
    print("Processing Avg Price and Count Chart - May take up to 30 seconds for som
    skip_data_msg = ""
    orig_row_count = plt_data_orig.shape[0]
    if orig_row_count > 2000:
        skip_amount = plt_data_orig.shape[0] // 2000
        plt_data = plt_data_orig.iloc[::skip_amount]
        row_count_w_skip = plt_data.shape[0]
        skip_data_msg = f"\nLarge # of values({orig_row_count:,.0f}), charting ever
    else:
        plt_data = plt_data_orig
    duplicates = plt_data[column_to_get_avg].duplicated()
    has_duplicates = plt_data[column_to_get_avg].duplicated().any()
    if has_duplicates:
        print("has duplicates")
    else:
        print("no duplicates")

    # Create the plot
    fig, ax1 = plt.subplots(figsize=(5, 3))

    #Line plot for value1 (left y-axis)
    if plt_data.shape[0] <max_detail:
            ax1.plot(
                plt_data[column_to_get_avg].astype(str).str[:30].replace('$', ' ',
                plt_data["price"], label='Average Price', marker= 'o')
    else:
        if len(skip_data_msg)>0:
             ax1.plot(
                plt_data[column_to_get_avg],
                #plt_data[column_to_get_avg],
                plt_data["price"], label='Average Price')
        else:
                ax1.plot(
                plt_data[column_to_get_avg].astype(str).str[:30].replace('$', ' ',
                #plt_data[column_to_get_avg],
                plt_data["price"], label='Average Price')

    ax1.set_ylabel('Average Price', color='b')
    ax1.tick_params(axis='y', labelcolor='b')


    if plt_data.shape[0] <= max_detail:
        ax1.tick_params(axis='x', rotation=45)  # Rotate x-axis labels
    else:
        plt.xticks([])

    # Bar chart for value2 (right y-axis)
    ax2 = ax1.twinx()  # Create a twin axes for value2
```

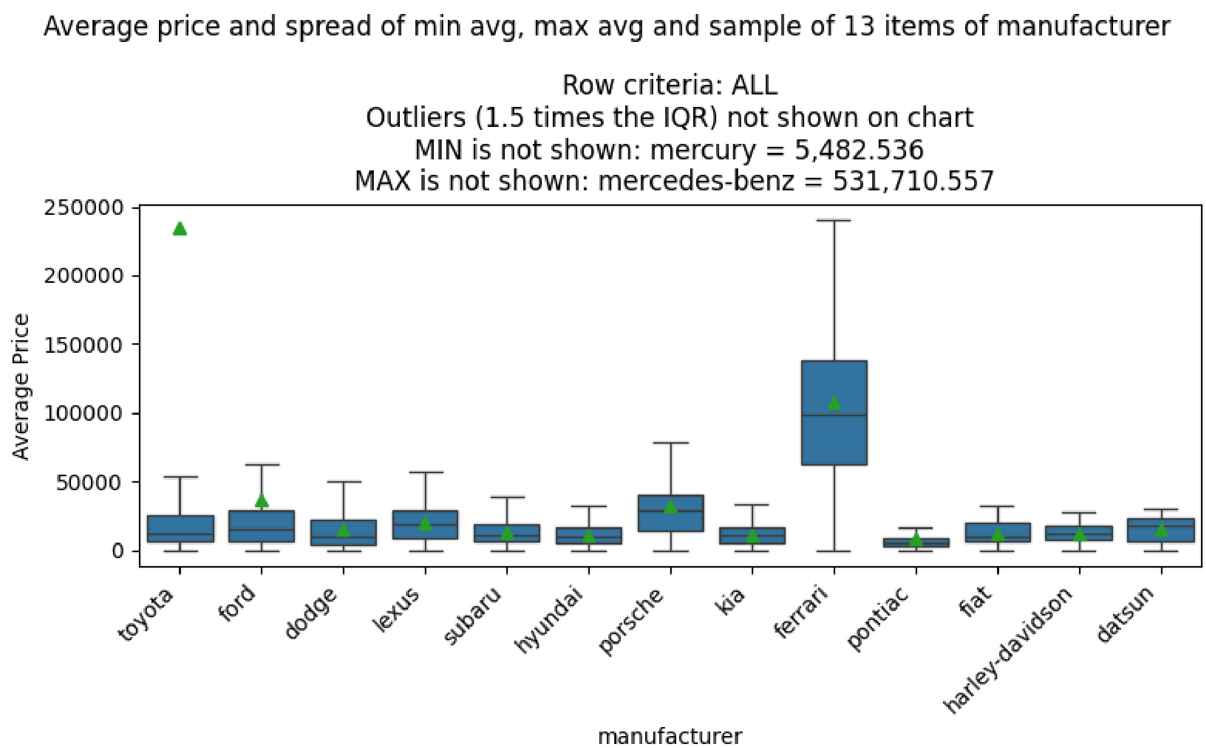
```
    ax2.bar(plt_data[column_to_get_avg].astype(str).str[:30].replace('$', ' ', rege
    ax2.set_ylabel('Count', color='g')
    ax2.tick_params(axis='y', labelcolor='g')

    # Customize the plot
    plt.title(f"{subtitle}" + skip_data_msg )
    plt.suptitle(title)
    plt.xlabel(column_to_get_avg)


    if plt_data.shape[0] <= max_detail:
        ax2.tick_params(axis='x', rotation=45)  # Rotate x-axis labels
    else:
        plt.xticks([])

    lines1, labels1 = ax1.get_legend_handles_labels()
    lines2, labels2 = ax2.get_legend_handles_labels()
    plt.legend(lines1 + lines2, labels1 + labels2, loc='upper center')
    plt.tight_layout()

    # show
    plt.show()

    # release shared mem related to plotting
    plt.cla()
    plt.clf()

def set_base_box_subtitle(showfliers_flag,
                        lower_price_q, upper_price_q, lower_count_q, upper_count_q)

    if lower_price_q == 0 and upper_price_q ==1 and lower_count_q == 0 and upper_co
        box_subtitle = "Row criteria: ALL"
    else:
        box_subtitle = f"Price criteria: start % = {lower_price_q:.2%}, end % = {up
        box_subtitle = box_subtitle + f"\nCount criteria: start % = {lower_count_q:
    if showfliers_flag:
        box_subtitle = box_subtitle + "\nOutliers (1.5 times the IQR) shown"
    else:
        box_subtitle = box_subtitle + "\nOutliers (1.5 times the IQR) not shown on
    return box_subtitle

def get_quantile(data, column_name, value, data_max, data_quantiles):

  if value < data_quantiles[0.25]:
    return 'Zero to 25th quantile'
  elif value < data_quantiles[0.5]:
    return 'Above 25th to 50th quantile'
  elif value < data_quantiles[0.75]:
    return 'Above 50th to 75th quantile'
  else:
    return 'Above 75th to 100th quantile'

def eval_col_avg_price(data, col_list, max_detail = 15, showfliers_flag = False,
                        lower_price_q = 0, upper_price_q = 1, lower_count_q = 0, up
    for column_to_get_avg in col_list:
        base_box_subtitle = set_base_box_subtitle(showfliers_flag,
```

```
                    lower_price_q, upper_price_q, lower_count_q, upper_count_q)
        # aggregate primary data to get avg price and count

        value_avg_df_orig = get_average_and_count_car_price(data, column_to_get_avg

        # apply percentile criteria to value averages.
        # goal is to filter by quantiles so to reduce the number of categories incl
        # goal is NOT to limit/filter the core price data set by quantile for the c
        value_avg_df = filter_by_price_and_count_quantile(value_avg_df_orig,
                    lower_price_q, upper_price_q, lower_count_q, upper_count_q)
        # Saving to database to manually reivew for bad data set in excel
        #value_avg_df.to_csv(f'saved_output/{column_to_get_avg}_avg_prices.csv')

        # share some basic info about the column
        unq_count = value_avg_df.shape[0]
        print(f"{column_to_get_avg} has {unq_count} distinct values")
        disp_count = min(max_detail,unq_count)
        print(f"See {disp_count} of them")
        top_of_value_avg_df = value_avg_df.head(disp_count)
        top_of_value_avg_df = top_of_value_avg_df.copy()
        top_of_value_avg_df['price'] = top_of_value_avg_df['price'].apply(lambda x:
        print(top_of_value_avg_df)

        # prepare to plot the box plot
        if disp_count != 0:
            if unq_count < max_detail:
                box_plt_title = f'Average price and spread of {column_to_get_avg}'
                categories = value_avg_df[column_to_get_avg]
                plt_categories, box_subtitle = handle_extreme_min_max(value_avg_df,
                print("Will display all categories:")
                print(plt_categories)
                plt_data = data[data[column_to_get_avg].isin(plt_categories)]
            else:
                plt_data, box_plt_title, box_subtitle = handle_many_distinct_averag


            # draw boxplot of price for category
            draw_box_plot(plt_data, column_to_get_avg, showfliers_flag,  box_subtit

            # prepare to plot both average price and count per category value on sa
            # first get a version without outlier averages
            IQR_mult = 1.5
            data_no_outlier = drop_outlier(value_avg_df, "price", IQR_mult)
            print(f"Potential outliers for {column_to_get_avg} = {value_avg_df.shap

            # set title
            multi_title = f"Plot of Avg Price and Count for {column_to_get_avg}"
            multi_subtitle = base_box_subtitle
            draw_price_and_count_plot(data_no_outlier, column_to_get_avg, multi_tit
        else:
            print(f"****No values of {column_to_get_avg} are in the given critera s

        print("----")
```

Charts relating price to feature columns

In [12]:
```
col_list = ['manufacturer','condition','fuel',
            'state','year']

eval_col_avg_price(car_df, col_list,
                    lower_price_q = 0.0, upper_price_q = 1, lower_count_q = 0.0, up
```

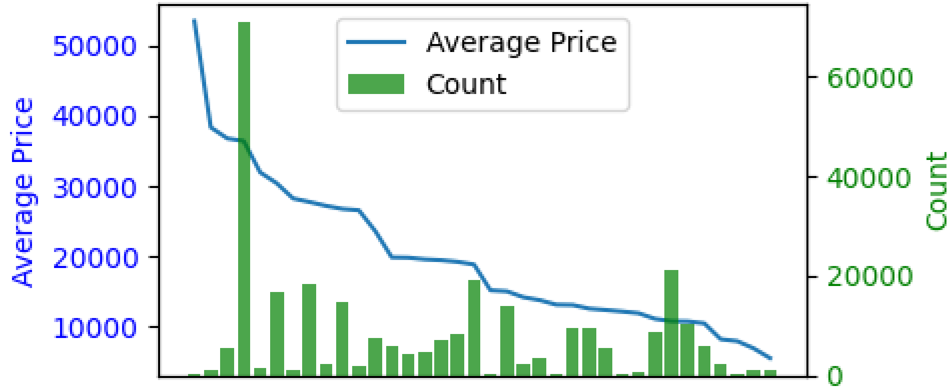
```
manufacturer has 42 distinct values
See 15 of them
     manufacturer     price  count
26  mercedes-benz  $531,711  11817
41          volvo  $383,755   3374
39         toyota  $234,295  34202
20           jeep  $150,718  19014
7       chevrolet  $115,676  55064
11        ferrari  $107,439     95
2    aston-martin   $53,495     24
38          tesla   $38,354    868
5           buick   $36,785   5501
13           ford   $36,412  70985
33        porsche   $31,946   1384
14            gmc   $30,406  16785
1      alfa-romeo   $28,237    897
34            ram   $27,728  18342
35          rover   $27,183   2113
```




```
drop_outlier(): lower bound = -16357.821852737696
drop_outlier(): upper bound = 60312.317671952274
Potential outliers for manufacturer = 6
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```

Plot of Avg Price and Count for manufacturer

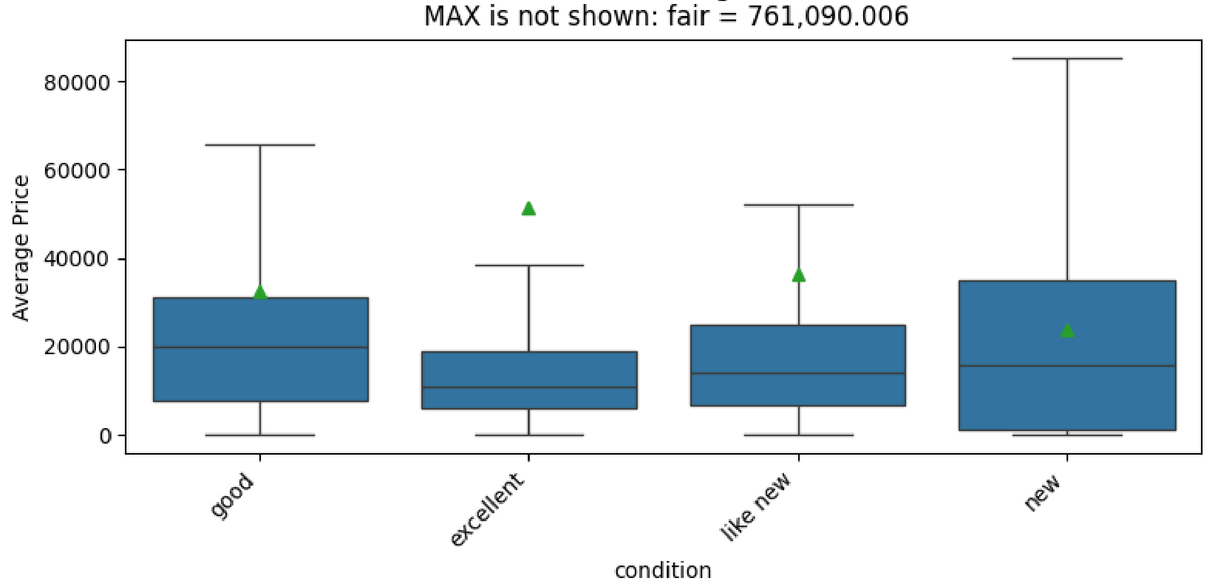
Row criteria: ALL
Outliers (1.5 times the IQR) not shown on chart



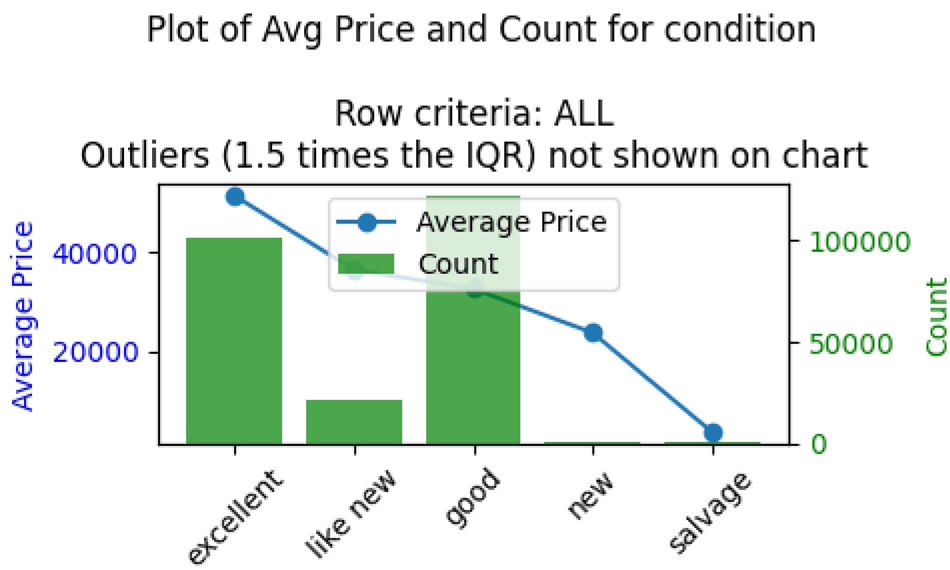

```
----
condition has 6 distinct values
See 6 of them
   condition     price   count
1       fair  $761,090    6769
0  excellent   $51,347  101467
3   like new   $36,402   21178
2       good   $32,545  121456
4        new   $23,657    1305
5    salvage    $3,606     601
Will display all categories:
['excellent', 'like new', 'good', 'new']
<Figure size 640x480 with 0 Axes>
```

Average price and spread of condition

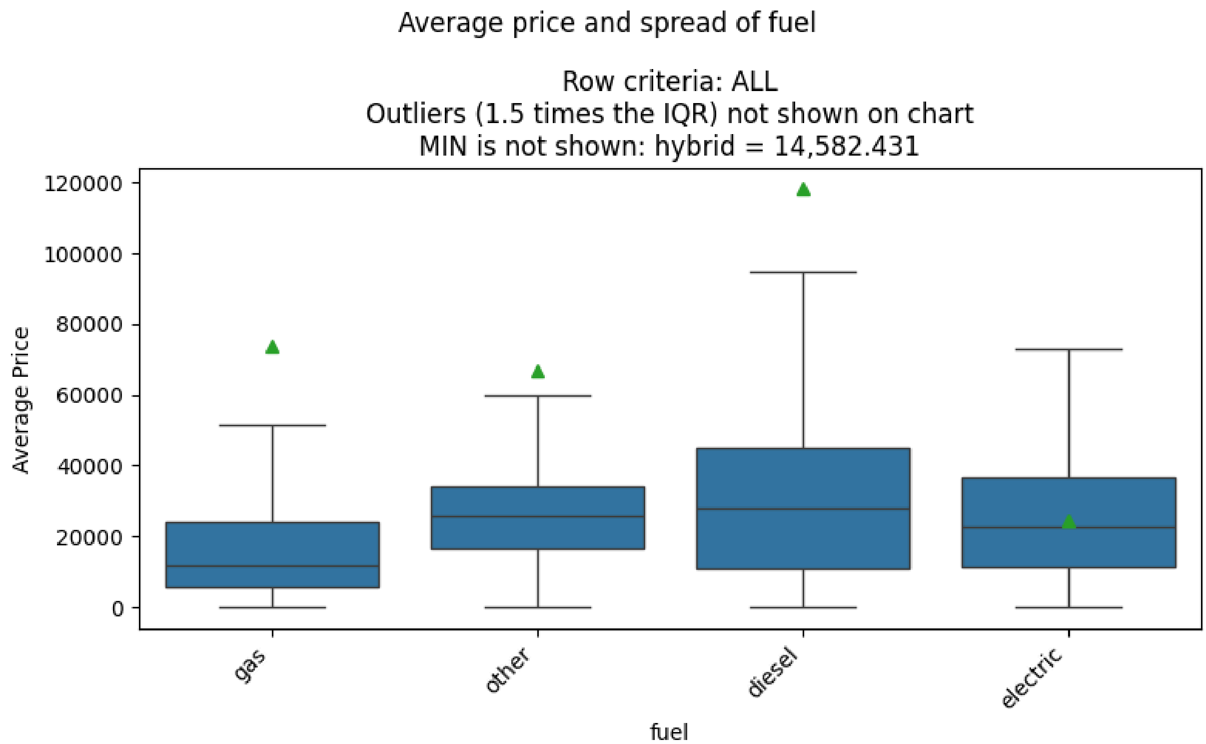
Row criteria: ALL
Outliers (1.5 times the IQR) not shown on chart
MIN is not shown: salvage = 3,605.534
MAX is not shown: fair = 761,090.006



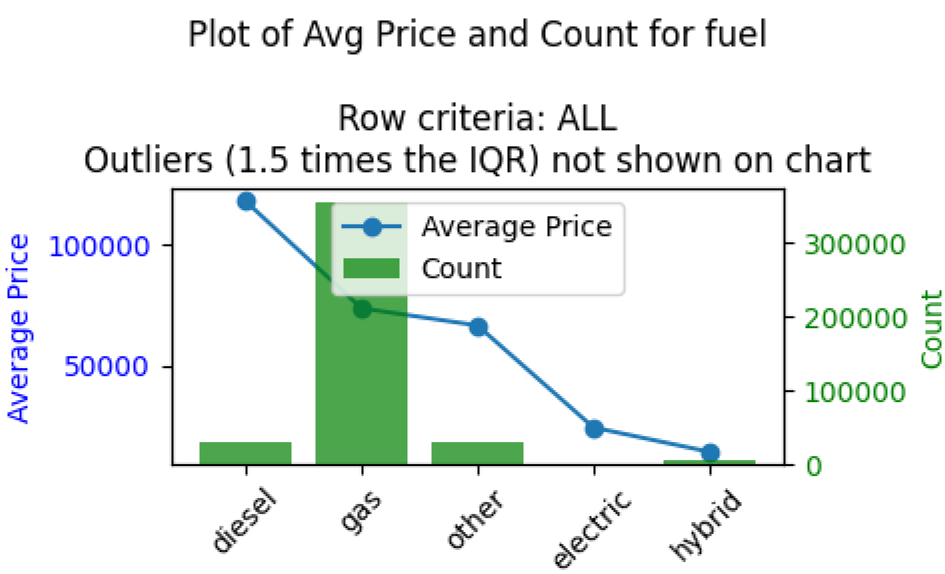
```
drop_outlier(): lower bound = -6717.818000021456
drop_outlier(): upper bound = 80207.69873494114
Potential outliers for condition = 1
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```



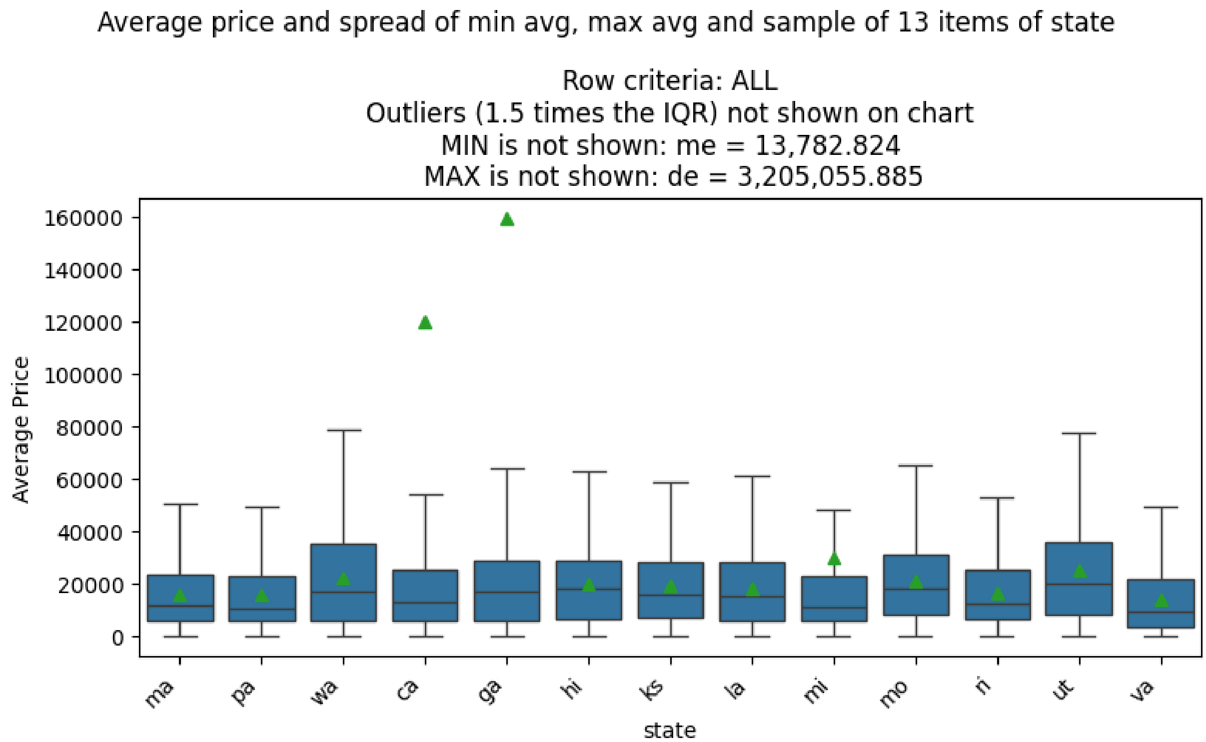

```
----
fuel has 5 distinct values
See 5 of them
       fuel     price   count
0    diesel  $118,178   30062
2       gas   $73,902  356209
4     other   $66,811   30728
1  electric   $24,648    1698
3    hybrid   $14,582    5170
Will display all categories:
['diesel', 'gas', 'other', 'electric']
<Figure size 640x480 with 0 Axes>
```




```
drop_outlier(): lower bound = -49232.48401200412
drop_outlier(): upper bound = 147783.10586217412
Potential outliers for fuel = 0
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```



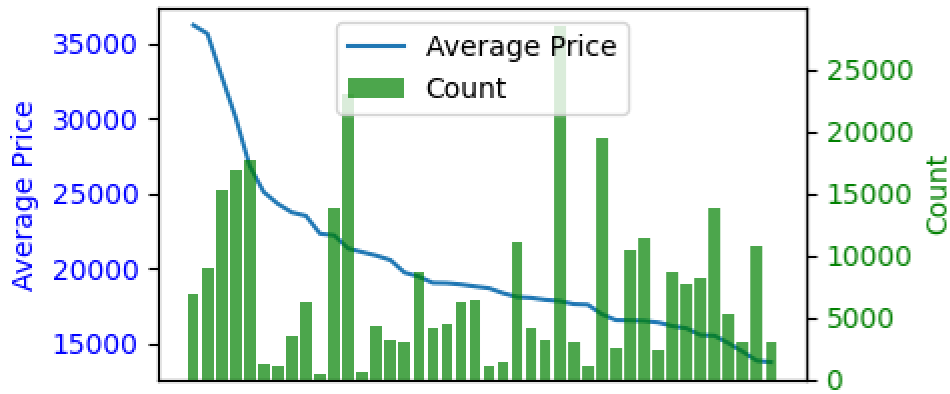
```
----
state has 51 distinct values
See 15 of them
   state        price  count
8     de  $3,205,056    949
42    tn    $369,348  11066
31    nj    $325,457   9742
20    md    $312,340   4778
1     al    $239,643   4955
15    in    $235,833   5704
37    or    $234,169  17104
10    ga    $159,261   7003
4     ca    $120,121  50614
36    ok     $36,207   6792
13    id     $35,638   8961
27    nc     $32,829  15277
22    mi     $30,073  16900
35    oh     $26,834  17696
44    ut     $25,100   1150
<Figure size 640x480 with 0 Axes>
```




```
drop_outlier(): lower bound = 553.1469334329231
drop_outlier(): upper bound = 45193.09295804804
Potential outliers for state = 9
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```

Plot of Avg Price and Count for state

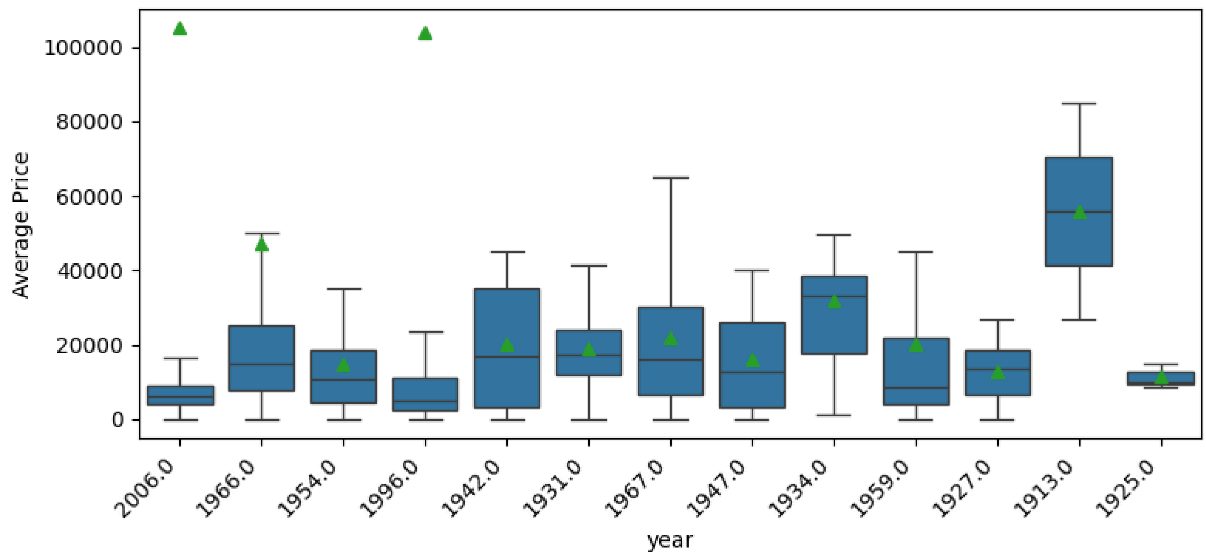
Row criteria: ALL
Outliers (1.5 times the IQR) not shown on chart




```
----
year has 114 distinct values
See 15 of them
       year        price  count
51   1960.0  $16,480,579    120
80   1989.0   $2,478,353    571
91   2000.0   $1,700,951   3572
2    1902.0   $1,666,666      1
90   1999.0   $1,615,212   3094
112  2021.0   $1,338,055   2396
71   1980.0     $428,606    272
56   1965.0     $359,413    365
98   2007.0     $261,163  14873
84   1993.0     $149,827    712
97   2006.0     $105,033  12763
87   1996.0     $103,956   1302
111  2020.0      $91,898  19298
46   1955.0      $86,121    226
7    1913.0      $56,000      2
<Figure size 640x480 with 0 Axes>
```

Average price and spread of min avg, max avg and sample of 13 items of year

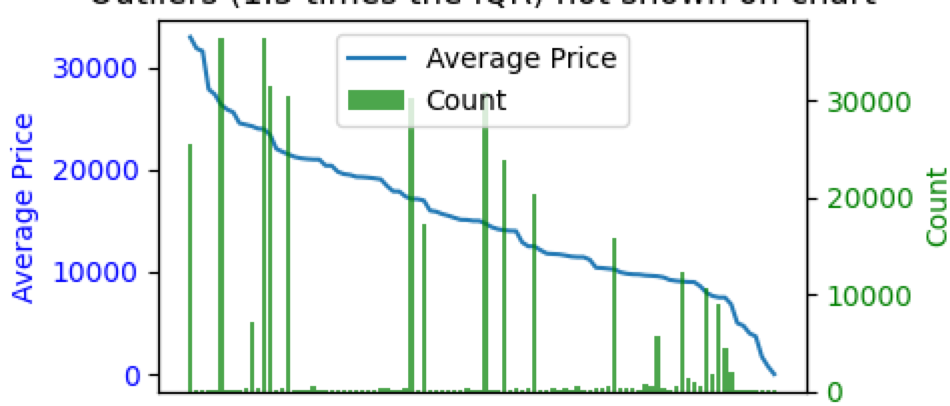
Row criteria: ALL
Outliers (1.5 times the IQR) not shown on chart
MIN is not shown: 1903.0 = 0.000
MAX is not shown: 1960.0 = 16,480,579.075




```
drop_outlier(): lower bound = -10329.854234136907
drop_outlier(): upper bound = 44930.20825086217
Potential outliers for year = 18
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```

Plot of Avg Price and Count for year

Row criteria: ALL
Outliers (1.5 times the IQR) not shown on chart




```
----
<Figure size 640x480 with 0 Axes>
```

Observations from chart analysis

Task: Visually review the data distribution and range of values of the data. Look for obvious patterns using histograms and box plots.

The following features look to have interesting combination of high volume of sales and at a high price:

- feature: cylinders, value = 6
- feature: title_status, value = lien
- feature: drive, value = 4wd
- feature: type, value = SUV
- feature: paint_color, values: (Black, White)
- feature: manufacturer, value: will drill down but one manufacturer has a relatively high avg price and very high volume

NOTE: There are other more obvious relationship of high volume and price combinations not mentioned (like condition:excellent)

- There are many price-volume variations for features state, manufacturer, model and year. However, there are so many distinct values of each of these features that it is hard to visualize pattern.
- So I have built into the visualizations a way to slice the data by quantiles of price and sales volume(count) and look at those charts. Will do so after clean-up.

Task: Note if there are major imbalances in the category groupings of the data.

The most non-obvious category data imbalances are:

- condition: fair has very low volume compared to good and excellent. I expected 'fair' to be lower but it is several times lower volume
- paint_color: Both black and white are significantly more popular than other colors.

NOTE: Will redo these charts after the outlier and null data clean-up

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`.

Remove VIN feature

- VIN is a unique number per vehicle (per row)
- We will drop this row from our modeling analysis because it will not have general predictive power

Data with nulls

```
In [13]: print(f"Before Clean-up: Total cells in dataframe with NULLs = { car_df.isnull().su
```

```
Before Clean-up: Total cells in dataframe with NULLs = 1215152
```

```
In [14]: print(f"Before Clean-up: Total rows with one or more NULLs  = {car_df.isnull().any(
```

```
Before Clean-up: Total rows with one or more NULLs  = 392012
```

Code to identify trade off of null data and number of features

```
In [15]: def nan_count_in_a_col(data, col):
             return data[col].isnull().sum()

         def nan_count_by_col(data):
             nans_df = pd.DataFrame(columns=['src_col', 'nan_count'])
             for col in data.columns:
                 nan_count = nan_count_in_a_col(data, col)
                 new_row = {'src_col': col, 'nan_count':nan_count}
                 nans_df.loc[len(nans_df)] = new_row
             nans_df = nans_df.sort_values(by='nan_count', ascending = False)

             return nans_df
```

```
In [ ]:
```

```
In [16]: def find_feat_to_max_non_null_rows(car_df, start_count, end_count,
                                           col_list = ['region', 'manufactur
                                           'title_status', 'transmission','d
                                           use_previous_run = True):
             # Uses itertools.combinations() to search for the best combinations of features
             # It finds combinations of length start_count to end_count
             # Returns two lists: max_non_null_count, max_non_null_combo
             # NOTE: The run time for this function is over an hour when used with start_cou
             # Therefore, I have a hard-coded list for that size and a flag to use that cach
             if use_previous_run == True:
                 final_list_counts_from_previous_run = [426880, 426880, 425675, 423187, 4210
                 final_list_features_from_previous_run = [['region'], ['region', 'state'], [
                                                         ['region', 'fuel', 'transmission',
                                                         ['region', 'model', 'fuel', 'trans

                                                         ['region', 'manufacturer', 'model'
                                                         ['region', 'manufacturer', 'model'
                                                         ['region', 'manufacturer', 'model'
                                                         ['region', 'manufacturer', 'model'
                                                         ['region', 'manufacturer', 'model'
                                                          'paint_color', 'state', 'odometer

                                                         ['region', 'manufacturer', 'model'
                                                          'type', 'paint_color', 'state', '
                 return final_list_counts_from_previous_run,final_list_features_from_previou
             else:
                 # Longer run-time branch so use print() statements to keep user informed
                 cur_non_null_row_count = []
```

```
        max_non_null_count = []
        max_non_null_combo  = []
        col_list = ['region', 'manufacturer', 'model', 'condition', 'cylinders','fu
                   'title_status', 'transmission','drive','size','type','paint_col
        total_rows = car_df.shape[0]
        start_count = 0
        end_count = 15
        cur_non_null_row_count = [None]*(end_count)
        max_non_null_count = [None]*(end_count)
        max_non_null_combo = [None]*(end_count)
        for col_len in range(start_count,end_count):
                print("new outer loop")
                print(col_len)
                #cur_non_null_row_count.append(None)
                #max_non_null_count.append(None)
                #max_non_null_combo.append(None)
                combinations = list(itertools.combinations(col_list, col_len+1))
                print(f"Combos to process: {len(combinations)}")
                start_time = time.time()
                for combo in combinations:
                    combo_list = list(combo)
                    #print(f"new combo: {combo_list}")
                    cur_count_of_rows_wth_nulls = car_df[car_df[combo_list].isnull(
                    cur_non_null_row_count[col_len] = total_rows - cur_count_of_row
                    if max_non_null_count[col_len] is None or cur_non_null_row_coun
                        max_non_null_count[col_len] = cur_non_null_row_count[col_le
                        max_non_null_combo[col_len] = combo_list
                end_time = time.time()
                elapsed_time = end_time - start_time
                print("Elapsed time:", elapsed_time, "seconds")
                print("---")

        print(max_non_null_count)
        print(max_non_null_combo)
        return max_non_null_count, max_non_null_combo

#rows_with_nulls = car_df[combo][car_df[combo].isnull().any(axis=1)].reset_index()
#rows_with_nulls.rename(columns={'index': 'src_index'}, inplace=True)
```

In [17]:
```
max_non_null_count, max_non_null_combo = find_feat_to_max_non_null_rows(car_df,0,15
```

In [18]:
```
def chart_features_vs_non_null_rows(max_non_null_count, max_non_null_combo):
    final_list = zip(max_non_null_count, max_non_null_combo)
    feature_choices = pd.DataFrame(final_list, columns = ['non_null_row_count', 'fe
    f_c = feature_choices[feature_choices['features'].notnull()]
    f_c = f_c.copy()
    f_c['p_features'] = f_c['features'].shift(periods=1,fill_value = ['no features'
    f_c['feature_change'] = f_c.apply(lambda row: list(set(row['features']) - set(r
    f_c['feature_change_desc'] = f_c.apply(lambda row: "Add " +  " , ".join(row['fe
    f_c
    sns.barplot(x='feature_change_desc', y='non_null_row_count', data=f_c)
    plt.xlabel('Feature added to previous feature list')
    plt.ylabel('Rows without Nulls for this feature set')
    plt.suptitle('Impact of feature inclusion on non-null row count')
    plt.title('Read left to right. \nEach bar ads a feature to the data set')
```

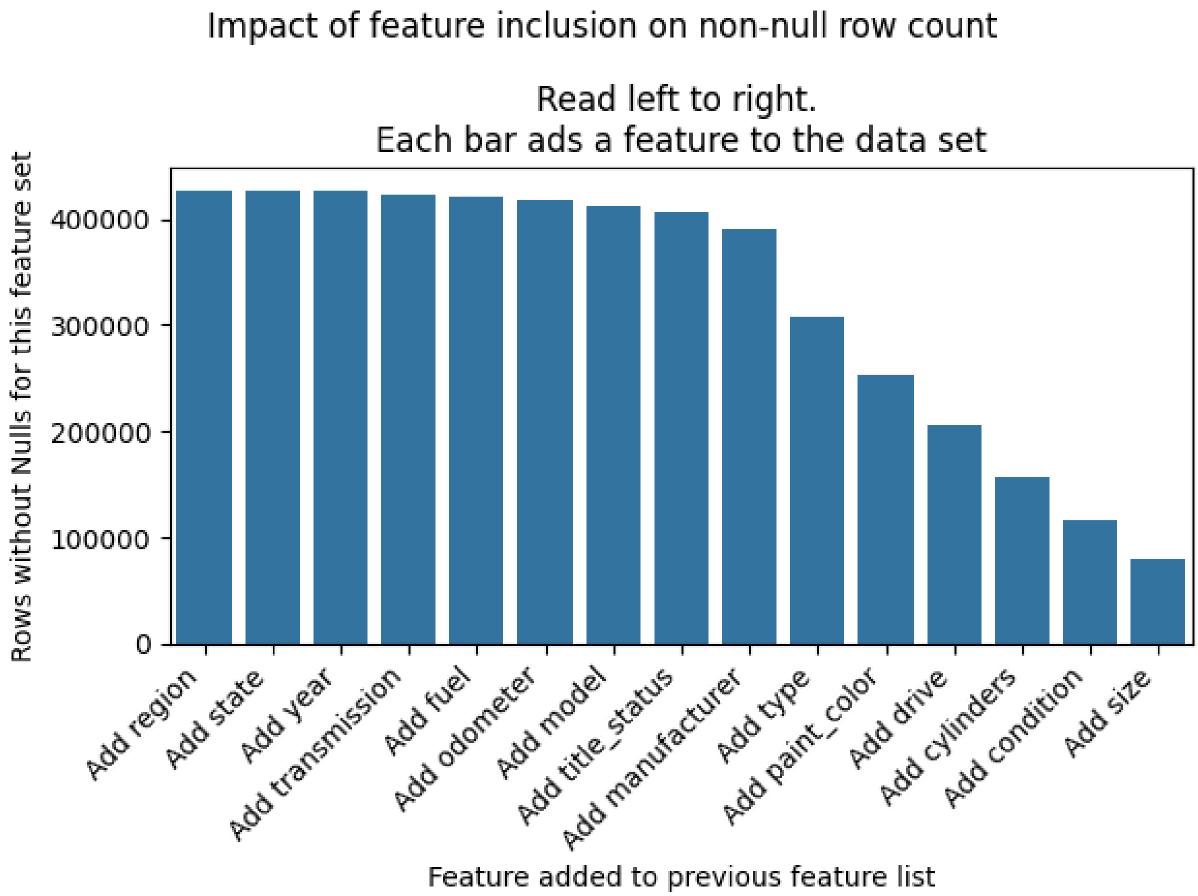
```
    plt.xticks(rotation=45, ha='right')  # Rotate category labels for readability
    plt.tight_layout()  # Adjust spacing between elements
    plt.show()
    plt.cla()
    plt.clf()
```

Charts to identify trade off of null data and number of features

In [19]:
```
print(nan_count_by_col(car_df))
```

```
         src_col  nan_count
14          size     306361
7      cylinders     177678
6      condition     174104
12           VIN     161042
13         drive     130567
16    paint_color    130203
15          type      92858
4   manufacturer      17646
10  title_status       8242
5          model       5277
9       odometer       4400
8           fuel       3013
11  transmission       2556
3           year       1205
0             id          0
1         region          0
2          price          0
17         state          0
```

In [20]:
```
chart_features_vs_non_null_rows(max_non_null_count, max_non_null_combo)
```




```
<Figure size 640x480 with 0 Axes>
```

Strategy to handle null data

The above chart (Imapct of feature inclusion...) is a useful tool I created to make practical decisions about outliers. If there is value in including all the above features, then our total data set shrinks from over 400K rows to under 100K rows. While 100K rows is significant, losing 300K+ rows of information could easily degrade predictive capabilities. This chart helps evaluate the combinations that manage this trade-off.

We won't know until we run actual modeling how valuable a given feature is. However, looking at the price-volume charts in the previous section we can estimate the potential of **size, condition, cylinders, drive, paint color and type**. Each of these columns significantly reduce the number of non-null rows.

- size has good price and volumne variation but the most null values
- drive, fuel, cylinders, and condition do not have strong variation in BOTH price and volume and they significantly reduce rows available for training and testing.
- type and paint color are attractive to keep because they do have strong price and volume variation while reducing the number of available rows less significantly than others.

Thus, our best initial estimates of features to explore further are including up to paint_color in our main data set. Making for a feature list as follows:

- region, state, year, transmission, fuel, odometer, model, title_status, manufacturer, type, paint_color
- This will give us rows of data 252,977 - a loss of 40% of the rows available
- Note this won't be a good choice if there is significant collinearity of paint_color and type with region, state, year, transmission, fuel, odometer, model, title_status, or manufacturer. This will show up when we do linear regression. Therefore, we will start with this column list and revisit as needed

NOTE: Time permitting and as needed, we will also repeat the modeling assuming we have all features (79,195 rows) and also assuming we have only up to manufacturer (drop type and paint color for total of 389,604 rows)

Code to remove outliers

In [21]:

```
balanced_col = ['region', 'manufacturer', 'model', 'fuel', 'title_status', 'transmi
print(f"original dataframe row count = {car_df.shape[0]}")
balanced_col_keep = balanced_col.copy()
balanced_col_keep.append('id')
balanced_col_keep.append('price')
car_df_no_nulls_balanced = car_df[balanced_col_keep][car_df[balanced_col].notnull()
print(f"balanced dataframe row count = {car_df_no_nulls_balanced.shape[0]}")
print(car_df_no_nulls_balanced.columns)

# for later try more rows and less features
more_rows_col = ['region', 'manufacturer', 'model', 'fuel', 'title_status', 'transm
more_rows_col_keep = more_rows_col.copy()
more_rows_col_keep.append('id')
more_rows_col_keep.append('price')

car_df_no_nulls_more_rows = car_df[more_rows_col_keep][car_df[more_rows_col].notnul
print(f"'more rows' dataframe row count = {car_df_no_nulls_more_rows.shape[0]}")

# Try these if time or if above doesn't perform well
# don't use 'size' in any case. probably overlap with type and cylinder and cuts to
more_feat_col =   ['region', 'manufacturer', 'model', 'condition', 'cylinders', 'fu
                                                    'type', 'paint_color', 'state', '
more_feat_col_keep = more_feat_col.copy()
more_feat_col_keep.append('id')
more_feat_col_keep.append('price')

car_df_no_nulls_more_feat = car_df[more_feat_col_keep][car_df[more_feat_col].notnul
print(f"'more features' dataframe row count = {car_df_no_nulls_more_feat.shape[0]}"
```

```
original dataframe row count = 426880
balanced dataframe row count = 252977
Index(['region', 'manufacturer', 'model', 'fuel', 'title_status',
       'transmission', 'type', 'paint_color', 'state', 'odometer', 'year',
       'id', 'price'],
      dtype='object')
'more rows' dataframe row count = 389604
'more features' dataframe row count = 115988
```

In [22]:

```
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("Choice of null data strategy")
print("I choose 'balanced'")
cars_no_nulls = car_df_no_nulls_balanced
#print("I choose 'more_feat'")
#cars_no_nulls = car_df_no_nulls_more_feat
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print("^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^")
print(cars_no_nulls.info())

print("cars_no_nulls row count:")
print(cars_no_nulls.shape[0])
```

```
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
Choice of null data strategy
I choose 'balanced'
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
<class 'pandas.core.frame.DataFrame'>
Index: 252977 entries, 27 to 426878
Data columns (total 13 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   region        252977 non-null  object
 1   manufacturer  252977 non-null  object
 2   model         252977 non-null  object
 3   fuel          252977 non-null  object
 4   title_status  252977 non-null  object
 5   transmission  252977 non-null  object
 6   type          252977 non-null  object
 7   paint_color   252977 non-null  object
 8   state         252977 non-null  object
 9   odometer      252977 non-null  float64
 10  year          252977 non-null  float64
 11  id            252977 non-null  int64
 12  price         252977 non-null  int64
dtypes: float64(2), int64(2), object(9)
memory usage: 27.0+ MB
None
cars_no_nulls row count:
252977
```

Outliers

Typical approach is to look at 1.5 times the IQR

- For this project we will model twice: once using 1.5 X IQR and again using 3.0 X IQR
- Important to understand if there are traunches or clusters of outliers. This could be legitimate data when data gets segregated by a particular feature combination
- For example, Ferraris cost far more than Mercuries. The Ferrari price might seem like an outlier but compared to other luxury manufacturers it will be legitimate data

For category fields with a manageable range of distinct values we will try to manually review all outliers and decide based on judgment

Lastly, an outlier may be a bad data point or it may be a datapoint with a typo or other recognizable mistake that if corrected would no longer be an outlier.

- We will try to identify these situations

Code to analyze outlier removal process

In [23]:
```
def plot_outliers_vs_orig(orig, no_nulls, outlier_level1_removed, outlier_level2_re
  plt.figure(figsize=(5, 3))

  # assumption we would never plot 10 million points
  cur_min = 1000000
  if samp_size == 'All' and ids_to_use is None:
      if 1 in plots:
          cur_min = min(orig.shape[0], cur_min)
      if 2 in plots:
          cur_min = min(no_nulls.shape[0], cur_min)
      if 3 in plots:
          cur_min = min(outlier_level1_removed.shape[0], cur_min)
      if 4 in plots:
          cur_min = min(outlier_level2_removed.shape[0], cur_min)
      plt_samp_size = cur_min
  else:
      if ids_to_use is None:
          plt_samp_size = samp_size
      else:
          plt_samp_size = ids_to_use.shape[0]

  if ids_to_use is None:
      plt_id = orig.sample(plt_samp_size)
  else:
      plt_id = ids_to_use

  plt_orig = pd.merge(plt_id["id"], orig, on='id', how='left')
  plt_no_nulls = pd.merge(plt_id["id"], no_nulls, on='id', how='left')
  plt_outlier_level1_removed = pd.merge(plt_id["id"], outlier_level1_removed, on='i
  plt_outlier_level2_removed = pd.merge(plt_id["id"], outlier_level2_removed, on='i

  plt_orig = plt_orig.sort_values(by="id")
  plt_no_nulls = plt_no_nulls.sort_values(by="id")
  plt_outlier_level1_removed = plt_outlier_level1_removed.sort_values(by="id")
  plt_outlier_level2_removed = plt_outlier_level2_removed.sort_values(by="id")

  # adjust values so less overlap
  adj_range = 0
  plt_orig_a = plt_orig.copy()
  plt_orig_a['price'] = plt_orig_a['price'] + random.randint(-adj_range, adj_range)
  plt_no_nulls_a = plt_no_nulls.copy()
  plt_no_nulls_a['price'] = plt_no_nulls_a['price'] + random.randint(-adj_range, ad
  plt_outlier_level1_removed_a = plt_outlier_level1_removed.copy()
  plt_outlier_level1_removed_a['price'] = plt_outlier_level1_removed_a['price'] + r
  plt_outlier_level2_removed_a = plt_outlier_level2_removed.copy()
  plt_outlier_level2_removed_a['price'] = plt_outlier_level2_removed_a['price'] + r

  # Plot each DataFrame with a different color
  if 1 in plots:
      plt.plot(plt_orig_a['id'], plt_orig_a['price'], label='orig', color='black')
  if 2 in plots:
      plt.plot(plt_no_nulls_a['id'], plt_no_nulls_a['price'], label='Before outlier
  if 3 in plots:
      plt.plot(plt_outlier_level1_removed_a['id'], plt_outlier_level1_removed_a['pr
  if 4 in plots:
```

```
    plt.plot(plt_outlier_level2_removed_a['id'], plt_outlier_level2_removed_a['pr


# Add labels and title
plt.xlabel('ID')
plt.ylabel('Price')
plt.title(f'Comparison of Prices \n(Sample Size = {plt_samp_size})')


# Add legend
plt.legend()

plt.show()
return ids_to_use
```

Data and charts about outlier removal

In [24]:

```
# drop price outliers 1.5 and 2.0 IQR
# base assumption of outliers
IQR_mult1=1.5
car_df_no_outliers_1_IQR = drop_outlier(cars_no_nulls, 'price', IQR_mult1)
rows_removed1 = cars_no_nulls.shape[0]  - car_df_no_outliers_1_IQR.shape[0]
rows_removed_pct1 = rows_removed1/cars_no_nulls.shape[0]
# 2nd assumption: keep more outliers in the analysis
IQR_mult2=3

# chart with sample size equal to all the rows after dropping nulls
car_df_no_outliers_2_IQR = drop_outlier(cars_no_nulls, 'price', IQR_mult2)
rows_removed2 = cars_no_nulls.shape[0]  - car_df_no_outliers_2_IQR.shape[0]
rows_removed_pct2 = rows_removed2/cars_no_nulls.shape[0]
print(f"Rows before outlier removal = {cars_no_nulls.shape[0]}")
print(f"With IQR*{IQR_mult1} assumption, {rows_removed1} rows are removed ({rows_re
print(f"With IQR*{IQR_mult2} assumption, {rows_removed2} rows are removed ({rows_re

ids_to_use1 = cars_no_nulls.sample(cars_no_nulls.shape[0])
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out

# now show smaller sample size to get a better feel
ids_to_use2 = car_df_no_nulls_balanced.sample(min(1000,car_df_no_nulls_balanced.sha
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,car_df_no_out
#ids_used = plot_outliers_vs_orig(car_df, cars_no_nulls,car_df_no_outliers_1_IQR,ca
```

```
drop_outlier(): lower bound = -23897.5
drop_outlier(): upper bound = 58482.5
drop_outlier(): lower bound = -54790.0
drop_outlier(): upper bound = 89375.0
Rows before outlier removal = 252977
With IQR*1.5 assumption, 4134 rows are removed (1.63%) leaving 248843 rows in data s
et
With IQR*3 assumption, 364 rows are removed (0.14%) leaving 252613 rows in data set
```

Make choice on outlier strategy

- choice IQR 1(mult is 1.5) or IQR 2(mult is 3)
- CHOOSING IQR 1

In [25]:
```python
car_df_no_outliers = car_df_no_outliers_1_IQR
```

Unrealistically low prices

The above outlier approach used InterQuartileRange approach to identifying outliers. We should also look at unrealistic prices from a business perspective. Prices for a car less then $100 are most likely invalid transactions/bad data

In [26]:
```python
# find prices less than $100
car_w_price_lt_100 = car_df_no_outliers[car_df_no_outliers['price'] < 100]
car_w_price_lt_100.sample(10)
count_car_w_price_lt_100 = car_w_price_lt_100.shape[0]
print(f'count of cars with price less than $100 = {count_car_w_price_lt_100:,.0f}')
```

```
count of cars with price less than $100 = 17,845
```

In [27]:
```python
# let's analyze these very cheap cars
# use the commented col_list to see all columns
#col_list =  car_w_price_lt_100.columns
# I ran this and most look very 'normal' in terms of count distribution
# See manufacturer
col_list = ['manufacturer']
max_detail = 15
#eval_col_counts(car_w_price_lt_100, col_list, max_detail = max_detail, sort_by_col

col_list = ['year']
max_detail = 15
#eval_col_counts(car_w_price_lt_100, col_list, max_detail = max_detail, sort_by_col
```

In [28]:
```python
def plot_cars_data(data, samp_size = 'All', title = 'Price chart', ids_to_use=None)
  plt.figure(figsize=(10, 6))

  if samp_size == 'All' and ids_to_use is None:
      plt_samp_size = data.shape[0]
  else:
      if ids_to_use is None:
          plt_samp_size = samp_size
      else:
          plt_samp_size = ids_to_use.shape[0]
```

```
    if ids_to_use is None:
        plt_id = data.sample(plt_samp_size)
    else:
        plt_id = ids_to_use

    plt_data = pd.merge(plt_id["id"], data, on='id', how='left')

    plt_data = plt_data.sort_values(by="id")

    # Plot each DataFrame with a different color
    plt.plot(plt_data['id'], plt_data['price'], label='Price', color='black')

    # Add labels and title
    plt.xlabel('ID')
    plt.ylabel('Price')
    plt.title(f'{title} \n(Sample Size = {plt_samp_size})')

    # Add legend
    plt.legend()

    plt.show()
    return ids_to_use
```

In [29]:
```
cars_clean_df = car_df_no_outliers_1_IQR[car_df_no_outliers_1_IQR['price'] >= 100]
print(f'By dropping rows that have price less than $100, we now have {cars_clean_df
print(cars_clean_df.columns)
#plot_cars_data(cars_clean_df)
#plot_cars_data(cars_clean_df, samp_size = 1000)

print(cars_clean_df.isnull().any().sum())
print(cars_clean_df['year'])
```

```
By dropping rows that have price less than $100, we now have 230,998 rows in the pri
mary data set
Index(['region', 'manufacturer', 'model', 'fuel', 'title_status',
       'transmission', 'type', 'paint_color', 'state', 'odometer', 'year',
       'id', 'price'],
      dtype='object')
0
27        2014.0
28        2010.0
29        2020.0
30        2017.0
31        2013.0
           ...
426873    2018.0
426874    2018.0
426876    2020.0
426877    2020.0
426878    2018.0
Name: year, Length: 230998, dtype: float64
```

Decision about cars less than $100

- I will drop these cars from the analysis for now.

- I do not see a clear pattern or justification for the price being so low for a vehicle in the USA
- Keeping these would skew the data analysis (and may have already skewed the IQR outlier analysis)
- For now we will not redo the IQR outlier analysis
- The cleanest data set so far is now called 'cars_clean_df'

Recap of price outlier removal

I will use IQR times 1.5 on the price column to remove outliers

- They are mostly large unrealistic numbers. Even if they are real, they are rare situations and not helpful to the core project goals of managing overall inventory optimally

I will drop prices less than $100, reducing available rows

The cleanest data set so far is now called 'cars_clean_df'

Unusual characters analysis

In [30]:
```
def detect_unusual_chars(df, allowed_chars=None):
  if allowed_chars is None:
    allowed_chars = string.ascii_letters + string.digits + string.punctuation + ' '

  def has_unusual_chars(text):
    return bool(re.search(f'[^{allowed_chars}]', text))

  string_cols = df.select_dtypes(include=['object'])
  mask = string_cols.apply(lambda col: col.map(has_unusual_chars))
  mask = mask.any(axis=1)

  return df[mask]
```

In [31]:
```
# find unusual characters in string columns
fld = 'model'
u_df = detect_unusual_chars(car_df[[fld]].astype(str))
unique = u_df[fld].unique()
print(f"{len(unique)} rows have unusual charaters in the column {fld}:")
print(unique)
print()
# find characters with $ embedded in string columns
dollar_rows = car_df[car_df[fld].astype(str).str.contains('\$')]
print(f"Number of rows with $ in field {fld} is {dollar_rows.shape[0]}")
```

```
50 rows have unusual charaters in the column model:
['🔥GMC Sierra 1500 SLE🔥 4X4 🔥' 'altima ￼' 'corolla￼￼' '50’s'
 'c-class c 43 amg®' '12’ flatbed atruck' '1937 Willy’s'
 'flex sel sport – 3rd row' 'Plymouth Volaré' '300 touring édition'
 'corolla “s”' '𝓜𝓮𝓻𝓬𝓮𝓭𝓮𝓼 𝓫𝓮𝓷𝔃 𝓶𝓵 350' 'VMI-CHRYSLER-♿' '♿ vmi'
 '\u200b\u200bsorento lx' '/ vmi / ♿' '* vmi * ♿' 'elantra\u200b gls'
 '/ vmi ♿' 'CHRYSLER-VMI ♿' 'vmi ♿' '// vmi ♿' 'f150 xlt 4×4'
 '// vmi // ♿' 'CHRYSLER-VMI-♿' 'VMI-CHRYSLER ♿' '♿' 'sonata limited￼'
 '1500 4×4' 'protégé 5' 'lesabre limited￼' '♦ALL TADES WELCOME!♦'
 'coupe devilleº' 'liberty sport 4×4' 'corvette coupe lt1🌟'
 'escalade esv￼' 'X5M' 'monterey￼' 'f-100 ×2' '350 4×4 dauly'
 '89’ geo tracker' 'c-class c 63 amg®' '1970 Plymouth’Cuda'
 'hd3500 diésel' '2500 diésel 4x4' 'charger 🚙🚙' 'Expedición'
 '1968 Rolls Royce￼' 'eldorado￼' 'willy’s']

Number of rows with $ in field model is 226
```

Decision about unusual characters

- We will keep the unusual characters discovered in the 'model' feature. This feature has almost 30,000 unique values and in its current form cannot be very helpful in our analysis (see section 'Interpreting the Model Feature' further down in this notebook)
- We will keep the '$' in the model feature but will need to account for it while doing string parsing code routines.
- The other features in the data set do not have unusual characters

Quality of the domain of feature values

All feature field domains (range of distinct values) have been manually reviewed

The 'region' field has some potential duplicates or at minimum unclear values:

- 'bloomington' and 'bloomington-normal'
- 'kansas city' and 'kansas city/MO'
- 'florence' and 'florence / muscle shoals'

The 'drive' field has approximately 50,000 rows with value 'rwd':

- This may be a typo as I assume it means 'rear wheel drive' which every car has

We will keep these values in the data set until we see the impact of them on the regression. They are not neccessarily wrong but unclear.

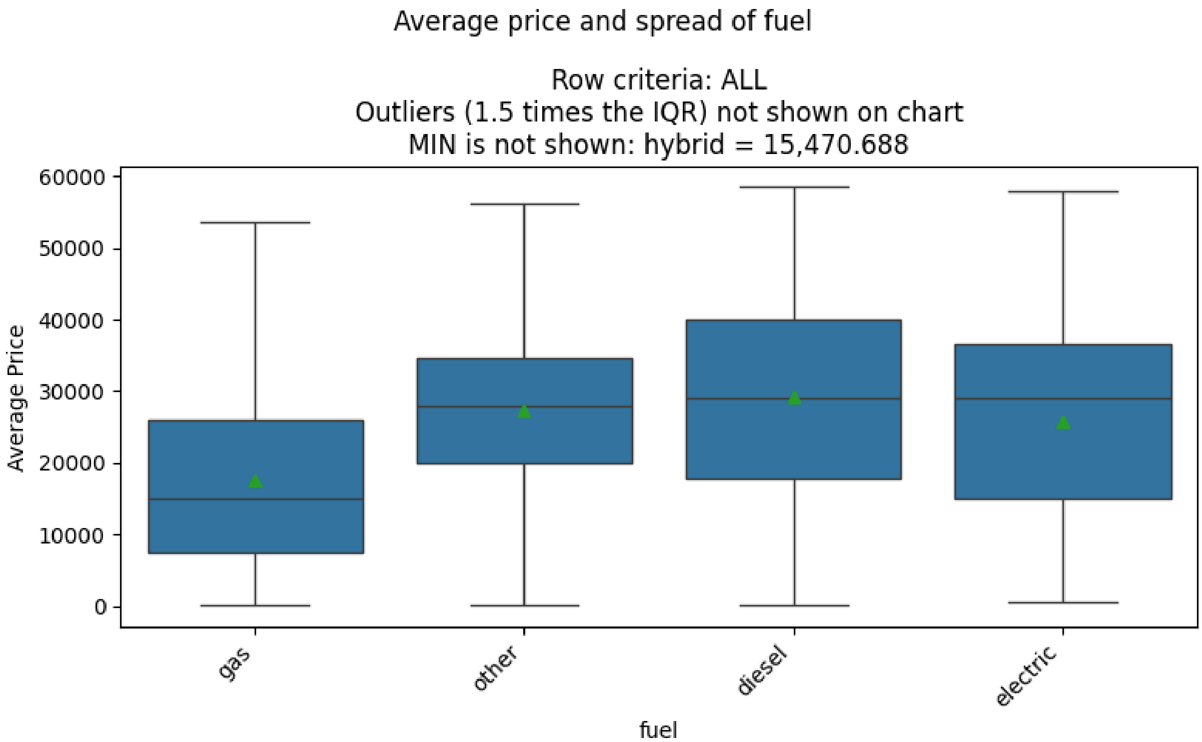
The other fields besides 'model' and 'drive' have reasonable values upon visual inspection of each .csv file generated

Revisit price and count charts after clean-up

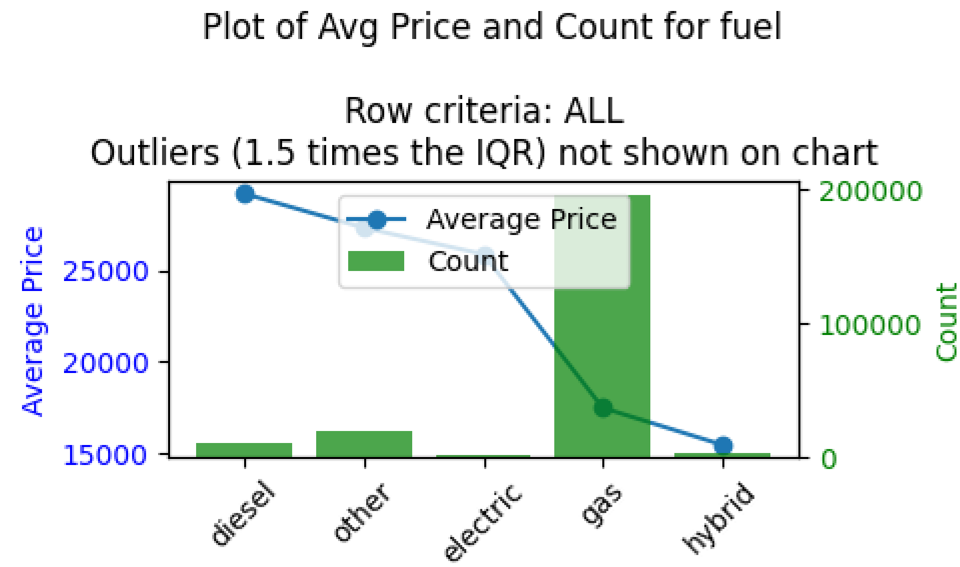
In [32]:
```python
col_list = ['fuel','year']
```

```
eval_col_avg_price(cars_clean_df, col_list,
                    lower_price_q = 0.0, upper_price_q = 1, lower_count_q = 0.0, up
```

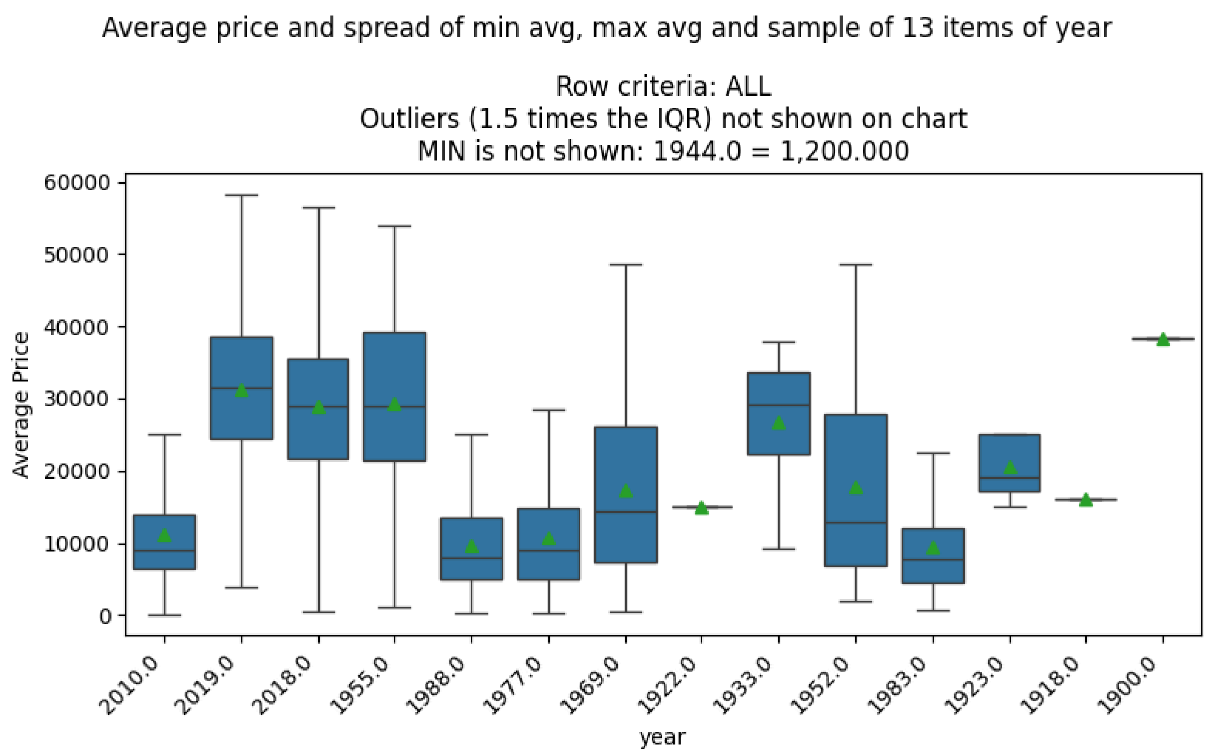
```
fuel has 5 distinct values
See 5 of them
       fuel    price   count
0    diesel  $29,165   10755
4     other  $27,306   19550
1  electric  $25,873    1021
2       gas  $17,486  196481
3    hybrid  $15,471    3191
Will display all categories:
['diesel', 'other', 'electric', 'gas']
```



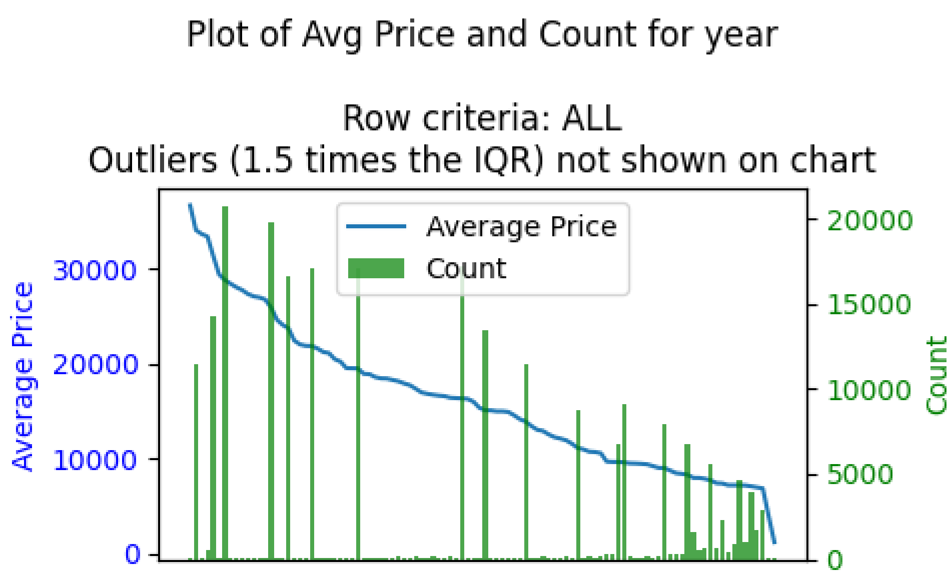

```
drop_outlier(): lower bound = 2755.0265078632747
drop_outlier(): upper bound = 42036.929547967455
Potential outliers for fuel = 0
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```




```
----
year has 103 distinct values
See 15 of them
        year    price  count
0     1900.0  $38,250      1
16    1934.0  $36,702     16
100   2020.0  $34,103  11455
14    1932.0  $33,688     21
101   2021.0  $33,429    563
99    2019.0  $31,364  14315
35    1955.0  $29,441     63
98    2018.0  $28,842  20739
19    1937.0  $28,441     14
10    1928.0  $28,075     17
17    1935.0  $27,780      5
22    1940.0  $27,364     21
12    1930.0  $27,112     24
2     1913.0  $27,000      1
15    1933.0  $26,775      6
<Figure size 640x480 with 0 Axes>
```




```
drop_outlier(): lower bound = -7315.322124352817
drop_outlier(): upper bound = 37693.76470318312
Potential outliers for year = 1
Processing Avg Price and Count Chart - May take up to 30 seconds for some charts
no duplicates
<Figure size 640x480 with 0 Axes>
```




```
----
<Figure size 640x480 with 0 Axes>
```

Let's drill down on data where avg price is high and count is also high

- Simplistically, these would seem to be valuable cars to the dealer
- This rule might help us understand data and get some intuition about features that drive revenue

In [33]:
```
print('interactive tool to use')
print('Uncomment to run if want to explore different quantiles')
col_list = ['region', 'manufacturer', 'model', 'fuel',
            'title_status', 'transmission','type','paint_color','state','year']
# Choose lower_price_q (quantile lower bound for average price)
# Choose lower_count_q (quantile lower bound for quantity sold)
#eval_col_avg_price(cars_clean_df, col_list,
#                    lower_price_q = 0.7, upper_price_q = 1, lower_count_q = 0.4, u
```

```
interactive tool to use
Uncomment to run if want to explore different quantiles
```

Recap of charts drilling down to top 30% in price and top 60% in volume

- Diesel fel and type pick-ups and trucks seem to sell in this high price-high volume range
- White and black color seem popular
- GMC, audi, and cadilac are more common manufacturers in this range
- States from middle and southern part of the USA have highest volume in this range

In [34]:
```
cars_clean_df['paint_color']
```

Out[34]:
```
27         white
28          blue
29           red
30           red
31         black
           ...
426873     white
426874     white
426876       red
426877     white
426878    silver
Name: paint_color, Length: 230998, dtype: object
```

Recap of outlier section

Prices outliers have been removed bsaed on IQR and how close price is to $0 (<$100 removed)

The cleanest data set is called 'cars_clean_df' with 230,998 rows and 10 feature columns

Data Split

- I need a hold our or test data set to test our final model
- I will use a k-fold cross-validation technique for hyperparamter tuning (cv=5)
- However, to also vary the feature set, we have an explicit valiation set of 10% also
- We will use 70% of data for training, 10% for feature validation, and cross-validatoin and 20% for final testing

```
In [35]: def train_val_test_split(X, y, test_size=0.2, val_size=0.1, random_state=42):
           # Split into train and test sets
           X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, ra

           # Split the training set into train and validation sets
           X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=val

           return X_train, X_val, X_test, y_train, y_val, y_test
```

```
In [36]: X_df = cars_clean_df.drop(columns=['id','price'])
         print(f"Feature columns are: {X_df.columns}")
         y = cars_clean_df['price']

         X_train, X_val, X_test, y_train, y_val, y_test = train_val_test_split(X_df, y, test
```

```
Feature columns are: Index(['region', 'manufacturer', 'model', 'fuel', 'title_statu
s',
       'transmission', 'type', 'paint_color', 'state', 'odometer', 'year'],
      dtype='object')
```

Feature engineering and hyperparamter tuning

To improve our ability to predict car prices form the input data we will:

- Create useful columns from categorical columns (OneHotEncoding)
- Create standard scaled polynomial features for numerical columns

There are many, many other options but will focus on tools discussed to this point (Module 11) in the course

```
In [37]: # Create one hot columns from the words in the model column.
         # Use nltk to parse into lower case punctuation-free words without stop words.
         # Also make sure the resulting list does not repeat values in the 'type' and 'manuf
         # Use this list and resulting histogram count to create a large number of one_hot_c
         # if a given wword has a count more than 50 in the given data frame (X_train usuall
         #
         # Keep a separate list one_hot_cols of these columns to instruct the system's prepr
         # Eventually could
```

```
In [38]: nltk.download('stopwords')
         from nltk.corpus import stopwords

         the_stop_words = stopwords.words('english')
         def identify_model_keywords( X_df,  sample_size=1000000, src_col_name = 'model', st
             #todo: 7000 min for testing - move to 50
             # custom feature for model column for now
             if stop_words is None:
                 print("stop words invalid")
             col_to_clean = src_col_name
             act_sample_size = min(sample_size,X_df.shape[0])
             df = X_df[col_to_clean].reset_index().sample(act_sample_size).copy()
             #print(df.head())
```

```
    # Define stopwords list (includes 'the')
    stop_words = stop_words
    #print(f"the available df columns are: {X_df.columns}")
    type_words_set = set(X_df['type'])
    type_words = list(type_words_set)
    manufacturer_words_set = set(X_df['manufacturer'])
    manufacturer_words = list(manufacturer_words_set)

    # as we find one_hots that have low importance can add here to officially drop
    learned_low_value_words = []

    # Function to clean text and remove stopwords
    # Assumes inner function can see variables in outer scope
    def clean_text(text):
      # Lowercase text
      text = text.lower()
      # Remove punctuation
      text = re.sub(r'[^\w\s]', '', text)
      # Tokenize words
      words = text.split()
      # Remove stopwords
      filtered_words1 = [word for word in words if word not in stop_words]

      filtered_words2 = [word for word in filtered_words1 if word not in type_words

      filtered_words3 = [word for word in filtered_words2 if word not in manufactur

      filtered_words4 = [word for word in filtered_words3 if word not in learned_lo

      return filtered_words4


    # Apply cleaning function to 'text' column
    df['cleaned_text'] = df[col_to_clean].apply(clean_text)

    # Combine all cleaned text into a single list
    all_words = []
    for words in df['cleaned_text']:
      all_words.extend(words)

    # Create a dictionary to store word frequencies
    word_counts = {}
    for word in all_words:
      if word not in word_counts:
        word_counts[word] = 0
      word_counts[word] += 1

    # Filter out low-frequency words (optional)
    min_count = min_occurrence  # Adjust minimum count as needed

    filtered_counts = {word: count for word, count in word_counts.items() if count
    if verbose:
        print(f"word count is {len(filtered_counts)} using minimum occurrence level

    return filtered_counts
```

```python
#todo: get rid of this one after we get things working
def plot_model_keyword(filtered_counts_df):
    # Create a histogram
    plt.bar(filtered_counts_df.index, filtered_counts_df['word_count'])
    plt.xlabel("Word From Model feature")
    plt.ylabel("Frequency")
    plt.title("Histogram of Words (excluding stopwords, types, and manufacturers)")
    if filtered_counts_df.shape[0] > 30:
        plt.xticks([])
    else:
        plt.xticks(rotation=90)  # Rotate x-axis labels for better readability

    plt.show()
    plt.cla()
    plt.clf()

def get_expected_one_hot_cols(filtered_counts):
    return ['my_one_hot_' + word for word in filtered_counts.keys()]
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\bbfor\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [39]:

```python
class ModelofCarTransformer(TransformerMixin,BaseEstimator):
    def __init__(self, column_names, stop_words, min_occurrence = 4000, max_one_hot
        self.column_names = column_names # it better be called 'model'!
        self.transformed_feature_names = []
        self.min_occurrence = min_occurrence
        self.max_one_hots = max_one_hots
        self.valid_words = valid_words # normally and recommended created by fit()
        # requires nltk only lightly for stopwords. could pickle?
        self.stop_words = stop_words
        self.my_one_hot_prefix = 'my_one_hot_col_'
        self.already_fit = False

    def identify_model_keywords( self, X_df, min_occurrence = 7000, sample_size=100
        #print("in ModelofCarTransformer, calling identify_model_keywords()")
        return identify_model_keywords( X_df, sample_size, src_col_name, stop_words

    # Create one_hot features from the model field
    def gen_model_one_hots( self, data, filtered_counts, valid_words):

        # Function for replacement
        def remove_special_chars(text):
            return re.sub(r'[^\w\s]', '', text)

        # Function to check if word exists (vectorized for efficiency)
        def check_for_word(text, word):
          # added lower case conversion
          return  text.str.lower().str.contains(word, case=False)

        df = data.copy()
        new_col_and_data = []
        new_col_list = []
        new_data_list = []
```

```
        count = 1
        df['model_w_o_special'] = 0
        sorted_filtered_words_list = sorted(filtered_counts.keys(), key=lambda x: x
        for word_to_find in sorted_filtered_words_list:
            if count > self.max_one_hots:
                break
            if word_to_find in valid_words:
                #print(f'preparing {word_to_find} to be a one_hot_col')
                #new_col_array_bool = empty_array = np.empty(min(self.max_one_hots,
                #new_col_array_int = empty_array = np.empty(min(self.max_one_hots,
                new_col_array_bool = np.empty(df.shape[0])
                new_col_array_int = np.empty(df.shape[0])

                # Apply the function with vectorized operations

                df['model_w_o_special'] = df['model'].apply(remove_special_chars)
                new_col_array_bool = check_for_word(df['model_w_o_special'], word_t

                # Convert the boolean column to 0 or 1 (optional)
                new_col_array_int = new_col_array_bool.astype(int)

                # make sure you found some non-zero values
                condition = new_col_array_int == 1
                non_zeros = np.where(condition)
                if len(non_zeros[0]) > 0:
                    # create a dictionary of the column name and the associated ar
                    # todo: check for characters of word_to_find that can't be used
                    new_col_name = self.my_one_hot_prefix+ word_to_find
                    new_col_dict = {'new_col_name': new_col_name, 'new_col_one_hot'
                    new_col_and_data.append(new_col_dict)
                    new_col_list.append(new_col_name)
                    new_data_list.append(new_col_array_int)

                else:
                    #todo: raise exception here
                    print(f"************************************all zeros for : {wo
                    # for debug reasons
                    print(f"non_zeros : {non_zeros}")
                    print(f"new_col_array_int : {new_col_array_int}")
                    print(f"new_col_array_bool : {new_col_array_bool}")
            else:
                print(f"skipping {word_to_find}")


        #print("in fit,gen_model, df rows = ", df.shape[0])
        if len(new_data_list)>0:
            #print("length of new_data_list", len(new_data_list))
            #print("df",np.shape(df))
            #print("df columns:", df.columns)
            # Stack arrays horizontally
            data_array = np.column_stack(new_data_list)
            #print("data_array",np.shape(data_array))

            df_merge_cols = [col for col in df.columns]
            for col in new_col_list:
                df_merge_cols.append(col)
```

```
            df_merged = pd.DataFrame(np.column_stack([df.to_numpy(), data_array]),
            #print("df_final",np.shape(df_merged))

            df_final = df_merged.copy()
            #print("df_final",np.shape(df_final))
            #print("df_final cols", list(df_final.columns))
        else:
            df_final = df

        return df_final

    def fit(self, X, y=None):
        if 'model' in X.columns:
            X_df = pd.DataFrame(X)
            if self.already_fit:
                print("Already fit but refitting")
            #print("in ModelofCarTransformer.fit(), calling identify_model_keywords
            filtered_counts =self.identify_model_keywords(X_df)
            self.valid_words = filtered_counts.keys()
        else:
            self.valid_words = None

        return self


    def rationalize_cols(self, X_w_some_one_hots):
        #print("In rationalize_cols()")
        new_zero_col_list = []
        for col in self.cols_after_fit:
            if not col in X_w_some_one_hots:
                if self.my_one_hot_prefix in col:
                    #print(f"adding {col} to rationalize shape to the original fit"
                    new_zero_col_list.append(col)

        if len(new_zero_col_list)>0:
            #print(f"shape to create zeros col array {X_w_some_one_hots.shape[0]} ,
            new_zero_col_array = np.zeros((X_w_some_one_hots.shape[0],len(new_zero_
            X_w_some_one_hot_rationalized = X_w_some_one_hots.copy()
            #print("length of new_data_list", len(new_zero_col_list))
            #print("X_w_some_one_hot_rationalized",np.shape(X_w_some_one_hot_ration
            #print("X_w_some_one_hot_rationalized columns:", X_w_some_one_hot_ratio
            #print("new_zero_col_array",np.shape(new_zero_col_array))

            df_merge_cols = [col for col in X_w_some_one_hot_rationalized.columns]
            for col in new_zero_col_list:
                df_merge_cols.append(col)

            df_merged = pd.DataFrame(np.column_stack([X_w_some_one_hot_rationalized

            #print("df_final",np.shape(df_merged))

            df_final = df_merged.copy()
            #print("df_final cols", list(df_final.columns))
        else:
            df_final = X_w_some_one_hots
        return df_final
```

```
    def transform(self, X):
        X_transformed = X.copy()  # Copy the input DataFrame to avoid modifying the
        if 'model' in X.columns:
            #print("in ModelofCarTransformer,transform()")
            X_transformed = X.copy()  # Copy the input DataFrame to avoid modifying
            #print("in ModelofCarTransformer.transform(), calling identify_model_ke
            filtered_counts =self.identify_model_keywords(X_transformed)
            #todo: should raise or warn if valid_words is empty
            X_w_one_hots = self.gen_model_one_hots(X_transformed, filtered_counts,
            X_w_one_hots = X_w_one_hots.drop(['model_w_o_special'], axis=1)

            for col in self.column_names:
                X_w_one_hots = X_w_one_hots.drop([col], axis=1)

        else:
            print("^^^^^^^^^^^^^^^^^^  NO MODEL COL ^^^^^^^^^^^^^^^^^^^^")
            X_transformed['model_inactive'] = 1
            X_w_one_hots = X_transformed[X_transformed['model_inactive']]

        self.transformed_feature_names = X_w_one_hots.columns
        if not self.already_fit:
            self.cols_after_fit = X_w_one_hots.columns
            self.already_fit = True
        else:
            # rationalize_columns creates any one_hot columns that were missing fro
            # column set of my_one_hots matches what was there at fit
            # Set them to zeros (because we know we didn't see any of these values
            X_w_one_hots = self.rationalize_cols(X_w_one_hots)

        #X_w_one_hots.to_csv("saved_output/last_transform.csv")
        #print(f"I was transformed: {self.transformed_feature_names} columns now")
        print("in modelofcartransform, X_w_one_hots shape",np.shape(X_w_one_hots))

        return X_w_one_hots

    def get_feature_names_out(self, input_features):
        return self.transformed_feature_names
```

In [40]:

```
def set_up_one_hot_preprocessors(custom_model_cols, categorical_cols, numerical_col

    my_model_of_car_transformer = ModelofCarTransformer(column_names=['model','manu
    #todo: target_col
    my_one_hot_preprocessor = make_column_transformer(
        (my_model_of_car_transformer, custom_model_cols),
        (Pipeline([
            ('scaler', StandardScaler()),
            ('poly', PolynomialFeatures(degree=degrees))
        ]), numerical_cols),
        (OneHotEncoder(sparse_output=False,drop='first', handle_unknown='ignore'),
        remainder="drop"
    )

    return my_one_hot_preprocessor

def set_up_pipeline(preprocessor, alpha=None):
```

```
    if alpha is None:
        pipeline1 = Pipeline([
        ('preprocessor', preprocessor),
        ('selector', SelectFromModel(Lasso(max_iter = 3000, alpha = 100))),
        ('regressor', Ridge(max_iter=1000))
        ])
    else:
        pipeline1 = Pipeline([
        ('preprocessor', preprocessor),
        ('selector', SelectFromModel(Lasso(max_iter = 3000, alpha = 100))),
        ('regressor', Ridge(alpha=alpha, max_iter = 1000))
        ])
    return pipeline1
```

In [41]:
```
# Default global. Set by gridsearch to discovered value

def run_gridsearchcv(pipeline1, X_train,y_train, param_grid = {'regressor__alpha':
    grid_search = GridSearchCV(pipeline1, param_grid, scoring='neg_mean_squared_err
    grid_search.fit(X_train, y_train)
    best_alpha = grid_search.best_params_['regressor__alpha']
    print("best alpha",best_alpha)

    return grid_search, best_alpha
```

In [42]:
```
def prep_to_save_grid_search_details(grid_search, categorical_cols, numerical_cols,
    # Get the best model and its coefficients
    best_model = grid_search.best_estimator_
    best_lasso = best_model.named_steps['regressor']
    best_coef = best_lasso.coef_
    #print(best_coef)

    # Get feature names
    feature_names_in = categorical_cols + numerical_cols
    feat_names_preprocessor = grid_search.best_estimator_.named_steps['preprocessor
    feat_names_selector = grid_search.best_estimator_.named_steps['selector'].get_f

    # Get the best score
    best_score = grid_search.best_score_
    print("Best score:", best_score)

    # get mse
    best_model = grid_search.best_estimator_
    y_pred = best_model.predict(X_val)
    mse = mean_squared_error(y_val, y_pred)
    print("mse:",mse)

    # Calculate RMSE
    rmse_train = np.sqrt(mse_train)
    print("RMSE train:", rmse_train)

    rmse_val = np.sqrt(mse_val)
    print("RMSE val:", rmse_val)

    alpha = grid_search.best_params_['regressor__alpha']
    print("alpha:", alpha)
```

```python
    # Set global BEST_ALPHA
    BEST_ALPHA = alpha

    details = {'alpha':alpha, 'best_score': best_score,'best_model': best_model, \
               'feature_names_in': feature_names_in, \
               'feat_names_preprocessor': feat_names_preprocessor, 'feat_names_sele
               'mse_train': mse_train, 'mse_val': mse_val, \
               'rmse_train': rmse_train, 'rmse_val': rmse_val}
    return details
```

In [43]:
```python
def run_pipe_and_predict(pipeline2, X_train, y_train, X_val, y_val, verbose=True):
    if verbose:
        print("Running fit")
    pipeline2.fit(X_train, y_train)
    if verbose:
        print("running predict for X_train")
    train_pred = pipeline2.predict(X_train)
    if verbose:
        print("running predict for X_val")
    val_pred = pipeline2.predict(X_val)
    mse_train = mean_squared_error(y_train, train_pred)
    mse_val = mean_squared_error(y_val, val_pred)
    if verbose:
        print(f"model predict rmse_train: {np.sqrt(mse_train):,f}")
        print(f"model predict rmse_val: {np.sqrt(mse_val):,f}")
        print(f"model predict rmse gap :{abs(np.sqrt(mse_train)-np.sqrt(mse_val)):,


    return mse_train, mse_val
```

In [44]:
```python
def run_grid_search_experiment(categorical_cols, numerical_cols, target_col, X_trai
    try:
        details = None
        best_alpha = None
        set_config(transform_output="default")
        start_time = time.time()
        time_struct = time.localtime(start_time)
        formatted_time = time.strftime("%I:%M:%S", time_struct)
        print(f'Starting experiment {exp_id} at {formatted_time}')
        details_list = []

        model_cols = ['manufacturer', 'type', 'model']

        preprocessor = set_up_one_hot_preprocessors(model_cols, categorical_cols, n

        pipeline1 = set_up_pipeline(preprocessor)

        param_grid = {'regressor__alpha': [ 1e4, 1, 1e2, 1e-2, 1e-1]}
        grid_search, best_alpha = run_gridsearchcv(pipeline1, X_train,y_train, para

        if best_alpha is None:
            best_alpha = 1
        end_time = time.time()
        elapsed_time = end_time - start_time
```

```
        print(f"Grid Search done. Elapsed_time: {elapsed_time}")
        pipeline2 = set_up_pipeline(preprocessor, best_alpha)

        mse_train, mse_val = run_pipe_and_predict(pipeline2, X_train, y_train, X_va
        end_time = time.time()
        elapsed_time = end_time - start_time
        print(f"Pipe and Predict done. Elapsed_time: {elapsed_time}")
        print("train ",mse_train, " val", mse_val)
        details = prep_to_save_grid_search_details(grid_search, categorical_cols, n

        details_list.append(details)

        if dump_to_pickle:
            with open(f"saved_output/{exp_id}_details.pickle", "wb") as f:
              # Pickle the list and write it to the file
              pickle.dump(details, f)
        end_time = time.time()
        elapsed_time = end_time - start_time
        print(f"finished experiment elapsed_time: {elapsed_time}")
    finally:
        set_config(transform_output="default")

    return details
```

In [45]:
```
print(cars_clean_df.columns)
print(X_train.shape)
print(X_test.shape)
```

```
Index(['region', 'manufacturer', 'model', 'fuel', 'title_status',
       'transmission', 'type', 'paint_color', 'state', 'odometer', 'year',
       'id', 'price'],
      dtype='object')
(161698, 11)
(46200, 11)
```

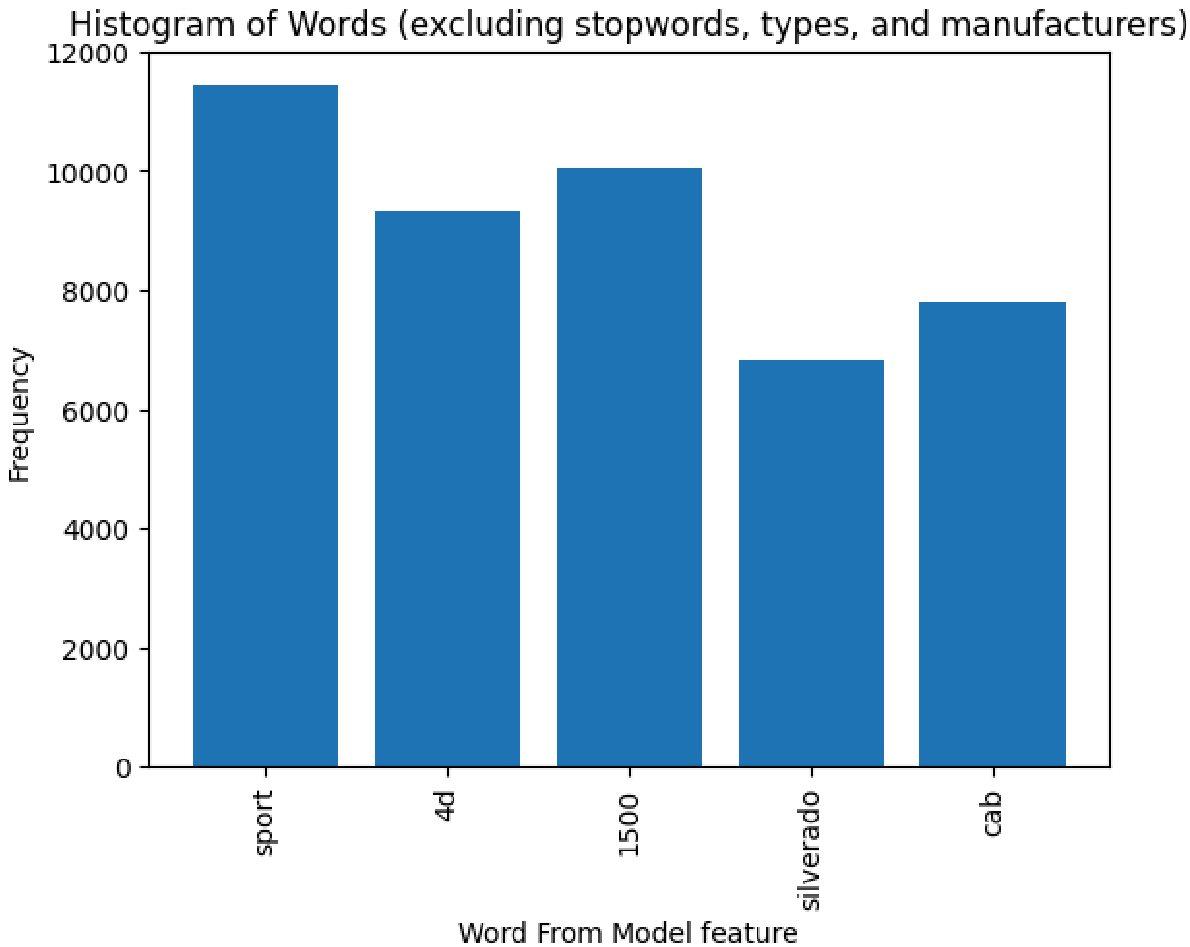
We created a dynamic one-hot encoding based on phrase in the model field

- The above process uses them but if you want to see examples of popular words used to encode, use this cell below

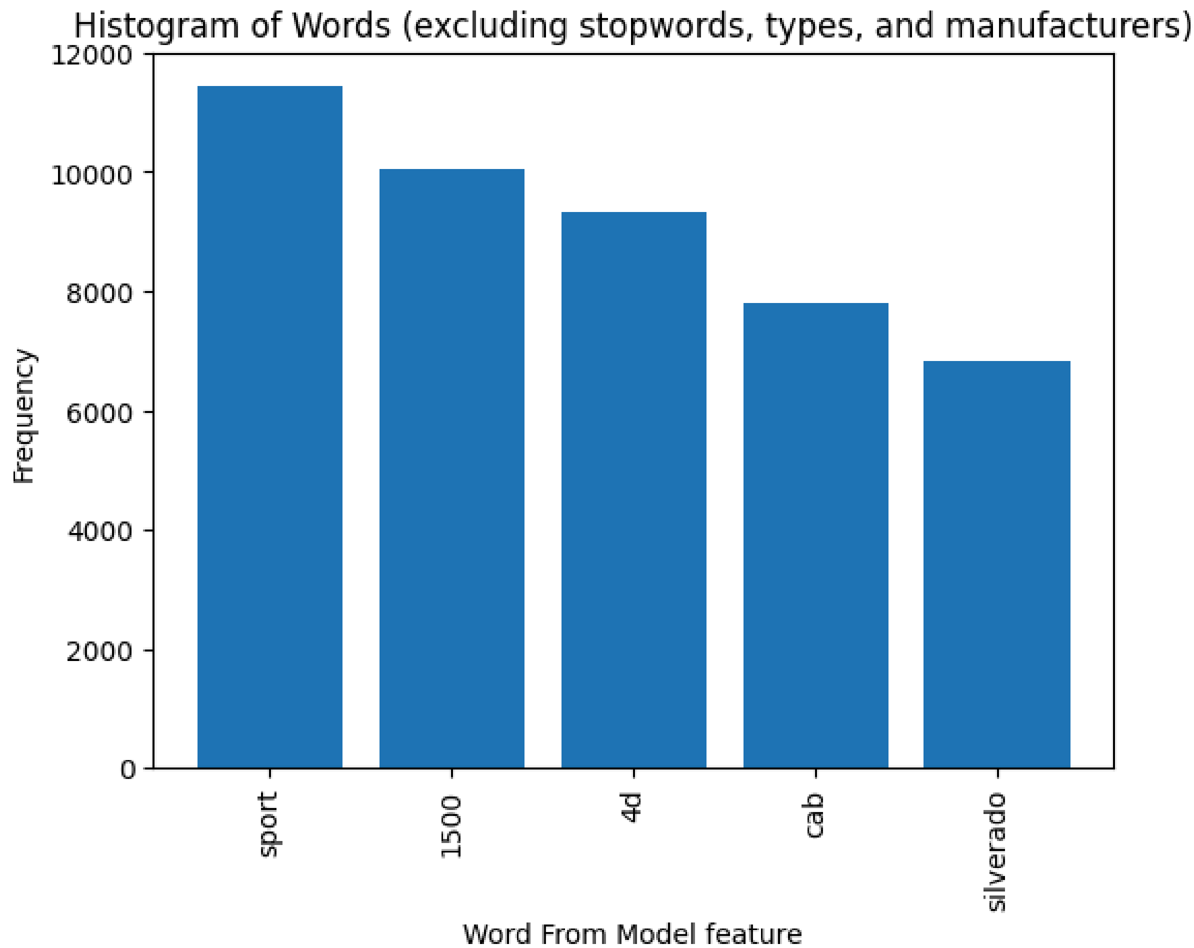
In [ ]:
```

```

In [46]:
```
# Set min_occurrence to different values to see the distribution of popular words i
# % of rows in X_train
pct_tuning_min_occurrence = 4
tuning_min_occurrence = round(pct_tuning_min_occurrence/100*X_train.shape[0]) #
filtered_counts =identify_model_keywords(X_train, min_occurrence = tuning_min_occur
filtered_counts_df = pd.DataFrame.from_dict(filtered_counts, orient='index', column
plot_model_keyword(filtered_counts_df)
print("number of one hots to be created for model", filtered_counts_df.shape[0])
```

```
df_sorted = filtered_counts_df.sort_values(by='word_count', ascending=False)
top_values_df = df_sorted.iloc[:15]
plot_model_keyword(top_values_df)
```




```
number of one hots to be created for model 5
```




```
<Figure size 640x480 with 0 Axes>
```

THIS CODE WILL TAKE MANY MINUTES TO RUN.

SET OK_TO_RUN_TUNING = True, if you want to run it

In [47]:

```
if OK_TO_RUN_TUNING:
    #categorical_cols = ['region', 'manufacturer', 'model', 'fuel', 'title_status',

    #categorical_cols =  ['region', 'manufacturer', 'model', 'condition', 'cylinder
    #                                                  'type', 'paint_color', 'stat

    #categorical_cols =  [ 'manufacturer', 'model', 'fuel', 'title_status', 'transm
    #                                                  'type', 'paint_color', 'stat

    #categorical_cols = ['state', 'type', 'manufacturer','paint_color','fuel', 'tit
    #categorical_cols = [ 'type']
    #categorical_cols = ['state', 'type', 'manufacturer','paint_color','fuel', 'tit
    #categorical_cols = ['state', 'type', 'manufacturer','paint_color','fuel', 'tit
    #categorical_cols = ['type', 'state', 'manufacturer', 'fuel','title_status', 't
    categorical_cols = ['type', 'state', 'manufacturer', 'fuel','title_status', 'tr


    numerical_cols = ['year']
    #numerical_cols = ['year']
    #numerical_cols = []
```

```
    target_col = 'price'
    details = run_grid_search_experiment(categorical_cols, numerical_cols, target_c
    #beep()
```

```
Starting experiment 1 at 12:13:19
Fitting 2 folds for each of 5 candidates, totalling 10 fits
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
C:\Users\bbfor\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\pre
processing\_encoders.py:242: UserWarning: Found unknown categories in columns [2, 7]
during transform. These unknown categories will be encoded as all zeros
  warnings.warn(
[CV] END ...........................regressor__alpha=10000.0; total time= 2.7min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
[CV] END ...........................regressor__alpha=10000.0; total time= 3.4min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
C:\Users\bbfor\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\pre
processing\_encoders.py:242: UserWarning: Found unknown categories in columns [2, 7]
during transform. These unknown categories will be encoded as all zeros
  warnings.warn(
[CV] END .................................regressor__alpha=1; total time= 3.1min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
[CV] END .................................regressor__alpha=1; total time= 3.1min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
C:\Users\bbfor\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\pre
processing\_encoders.py:242: UserWarning: Found unknown categories in columns [2, 7]
during transform. These unknown categories will be encoded as all zeros
  warnings.warn(
[CV] END .............................regressor__alpha=100.0; total time= 3.1min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
[CV] END .............................regressor__alpha=100.0; total time= 3.3min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
C:\Users\bbfor\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\pre
processing\_encoders.py:242: UserWarning: Found unknown categories in columns [2, 7]
during transform. These unknown categories will be encoded as all zeros
  warnings.warn(
[CV] END ..............................regressor__alpha=0.01; total time= 3.0min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
[CV] END ..............................regressor__alpha=0.01; total time= 3.3min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
C:\Users\bbfor\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\pre
processing\_encoders.py:242: UserWarning: Found unknown categories in columns [2, 7]
during transform. These unknown categories will be encoded as all zeros
  warnings.warn(
```

```
[CV] END ...............................regressor__alpha=0.1; total time= 3.1min
in modelofcartransform, X_w_one_hots shape (80849, 0)
in modelofcartransform, X_w_one_hots shape (80849, 0)
[CV] END ...............................regressor__alpha=0.1; total time= 3.3min
in modelofcartransform, X_w_one_hots shape (161698, 5)
best alpha 1
Grid Search done. Elapsed_time: 2151.41307926178
Running fit
in modelofcartransform, X_w_one_hots shape (161698, 5)
running predict for X_train
in modelofcartransform, X_w_one_hots shape (161698, 5)
running predict for X_val
in modelofcartransform, X_w_one_hots shape (23100, 5)
model predict rmse_train: 7,308.044497
model predict rmse_val: 7,371.475785
model predict rmse gap :63.431287
Pipe and Predict done. Elapsed_time: 2417.599880218506
train  53407514.37474363  val 54338655.24387697
Best score: -53458274.96133304
in modelofcartransform, X_w_one_hots shape (23100, 5)
mse: 54338655.24387697
RMSE train: 7308.044497315519
RMSE val: 7371.47578466327
alpha: 1
finished experiment elapsed_time: 2418.06142783165
```

In [48]:
```
#details
```

In [ ]:
```
```

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.

Feature Selection

I will let the lasso regularization decide the feature selection through linear regression coefficients

- I will use the GridSearchCV to find the optimal lasso regression hyperparameter

To improve our ability to predict car prices form the input data we will generate 3 types of features: polynomial, interaction (x1*x2) and exponential.

There are many, many other options but will focus on tools discussed to this point (Module 11) in the course

•

In [ ]:

In [ ]:

In [53]:
```
# feat import after encoding
def get_importance_by_partial_match(feat_map, search_string):
    print(feat_map)
    matching_keys = [key for key in feat_map.keys() if search_string in key]
    feat_impt = 0
    for a_match in matching_keys:
        feat_impt = feat_impt + feat_map[a_match]

    return feat_impt

def run_feat_importance_perm(X_train, y_train, X_val, y_val, feat_cols, preprocesso


    X_train_cols = X_train[feat_cols]
    X_val_cols = X_val[feat_cols]

    if verbose:
        print('X_train passed in cols',X_train.columns)
        print('X_train feature cols',X_train_cols.columns)
    pipeline = set_up_pipeline(preprocessor, alpha = alpha)

    #pipeline.fit(X_train_cols, y_train)
    pipeline.fit(X_train, y_train)




    if verbose:
        print("original feature names")
        print(feat_cols)
        print("---")
        print(f"Number original features is {len(X_train.columns)}")

    preprocessor_feature_names = pipeline.named_steps['preprocessor'].get_feature_n
    selector_feature_names = pipeline.named_steps['selector'].get_feature_names_out

    if verbose:
        print(f"Number features in preprocessor step (feature engineering) is {len(
        print("Number of features sent to model after feature selection is ", len(s
        print("---")

        print("Run with all features to get MSE and RMSE")
    mse_train, mse_val = run_pipe_and_predict(pipeline, X_train_cols, y_train, X_va
    if verbose:
        print(f"MSE train: {mse_train:,.0f}")
        print(f"MSE val: {mse_val:,.0f}")

    print("----")
```

```
    print("Calculating permutations to find feature importance per feature")
    # Calculate permutation importance using the pipeline
    feat_import_results = permutation_importance(estimator=pipeline, X=X_val_cols,


    return feat_import_results, pipeline, mse_train, mse_val
```

In [54]:
```
def prep_to_save_feat_import_details(feat_import_results, pipeline, feat_cols, targ



    print("Feature columns with mean - 2*std GREATER THAN  0")
    for i in feat_import_results.importances_mean.argsort()[::-1]:
        if feat_import_results.importances_mean[i] - 2 * feat_import_results.import
            print(f"{feat_cols[i]:<40}"
                  f"{feat_import_results.importances_mean[i]:,.0f}"
                  f" +/- {feat_import_results.importances_std[i]:,.0f}")
    print("----")
    if verbose:
        print("Feature columns with mean - 2*std LESS THAN OR EQUAL TO 0")
        for i in feat_import_results.importances_mean.argsort()[::-1]:
            if feat_import_results.importances_mean[i] - 2 * feat_import_results.im
                print(f"{feat_cols[i]:<40}"
                      f"{feat_import_results.importances_mean[i]:,.0f}"
                      f" +/- {feat_import_results.importances_std[i]:,.0f}")

    # capture the change in rmse of the model field
    for i in feat_import_results.importances_mean.argsort()[::-1]:
        if feat_cols[i] == 'model':
            if math.isnan(feat_import_results.importances_mean[i]):
                mean = 0
            else:
                mean = feat_import_results.importances_mean[i]

            if math.isnan(feat_import_results.importances_std[i]):
                std = 0
            else:
                std = feat_import_results.importances_std[i]

            mean_change_rmse_for_model_field = np.sqrt(abs(mean))
            std_change_rmse_for_model_field = np.sqrt(abs(std))


    importance_map = dict(zip(feat_cols, feat_import_results.importances_mean))
    if verbose:
        print("Full list of feature columns")
        for orig_feat in feat_cols:
            orig_impt = importance_map[orig_feat]
            print(f"Original Feature: {orig_feat}, Average Importance (MSE change):

        # Get feature names

    preprocessor_feature_names = pipeline.named_steps['preprocessor'].get_feature_n
    selector_feature_names = pipeline.named_steps['selector'].get_feature_names_out
```

```
    # Calculate RMSE
    rmse_train = np.sqrt(mse_train)
    print("RMSE train:", rmse_train)

    rmse_val = np.sqrt(mse_val)
    print("RMSE val:", rmse_val)


    details = {'alpha':alpha, 'min_occurrence': min_occurrence,
            'feature_names_in': feat_cols,
            'preprocessor_feature_names': preprocessor_feature_names, 'selector_fea
            'mse_train': mse_train, 'mse_val': mse_val,
            'rmse_train': rmse_train, 'rmse_val': rmse_val,
            'orig_feat_importance_map': importance_map,
            'raw_feat_importance_mean' : feat_import_results.importances_mean,
            'raw_feat_importance_std' : feat_import_results.importances_std,
            'mean_change_rmse_for_model_field' : mean_change_rmse_for_model_field,
            'std_change_rmse_for_model_field' : std_change_rmse_for_model_field
            }
    return details
```

In [55]:
```
def run_feat_import_experiment(categorical_cols, numerical_cols, target_col, X_trai
                               y_train, X_val, y_val, alpha, min_occurrence = None,
    start_time = time.time()
    time_struct = time.localtime(start_time)
    formatted_time = time.strftime("%I:%M:%S", time_struct)
    print(f'Starting experiment {xp_id} at {formatted_time}')
    if verbose:
        print("rows in training data",X_train.shape[0])
        print("rows in validation data",X_val.shape[0])

    model_cols = ['manufacturer','model', 'type']
    if verbose:
        print(min_occurrence)
    if min_occurrence is not None:
        preprocessor = set_up_one_hot_preprocessors(model_cols, categorical_cols, n
    else:
        preprocessor = set_up_one_hot_preprocessors(model_cols, categorical_cols, n

    feat_cols = categorical_cols + numerical_cols
    for col in model_cols:
        if col not in feat_cols:
            feat_cols.append(col)

    feat_import_results, pipeline, mse_train, mse_val = run_feat_importance_perm(X_

    details = prep_to_save_feat_import_details(feat_import_results, pipeline, feat_

    if dump_to_pickle:
        with open(f"saved_output/{xp_id}_feat_import_details.pickle", "wb") as f:
          # Pickle the list and write it to the file
          pickle.dump(details, f)
    end_time = time.time()
    elapsed_time = end_time - start_time
```

```
    print(f"finished experiment {xp_id} in elapsed_time: {elapsed_time}")
    return details
```

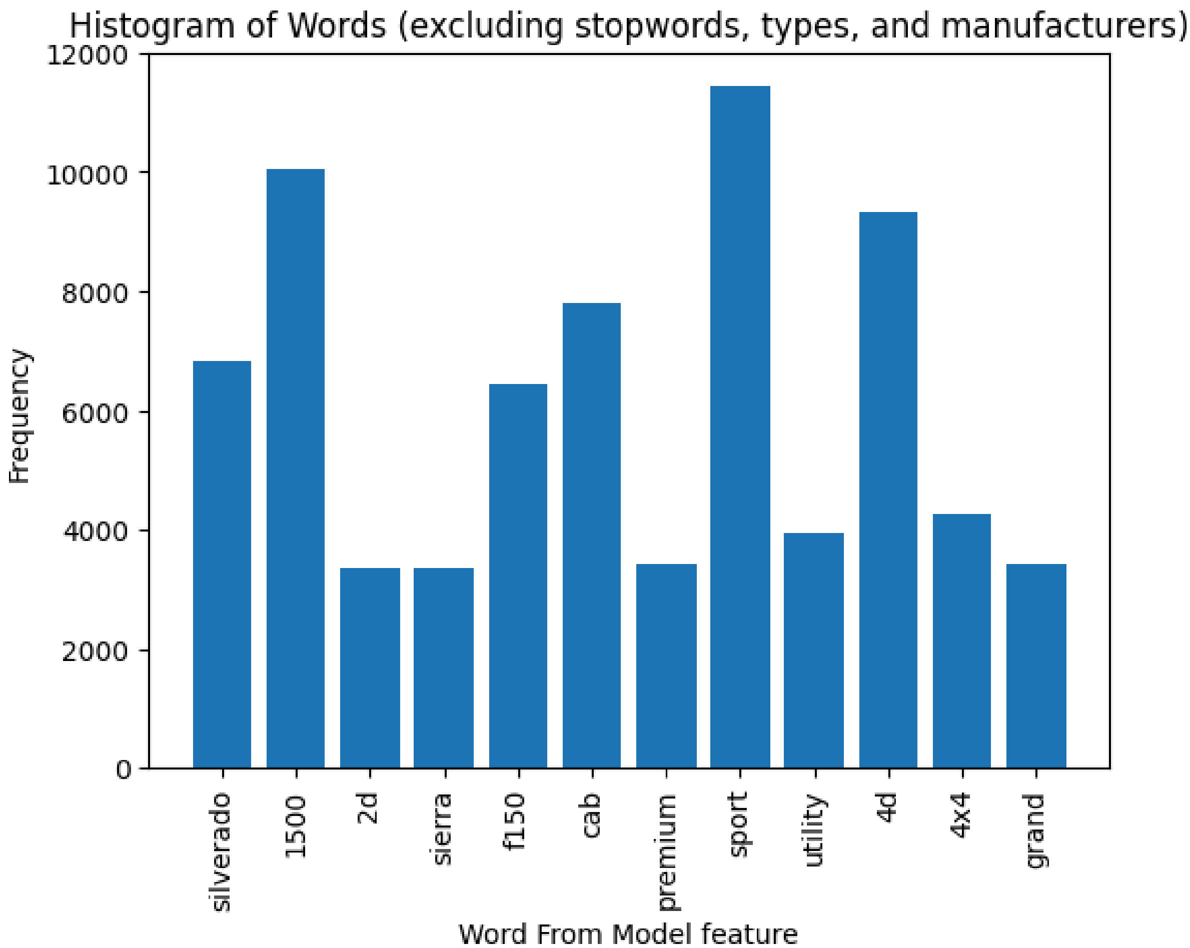
Evaluation

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.

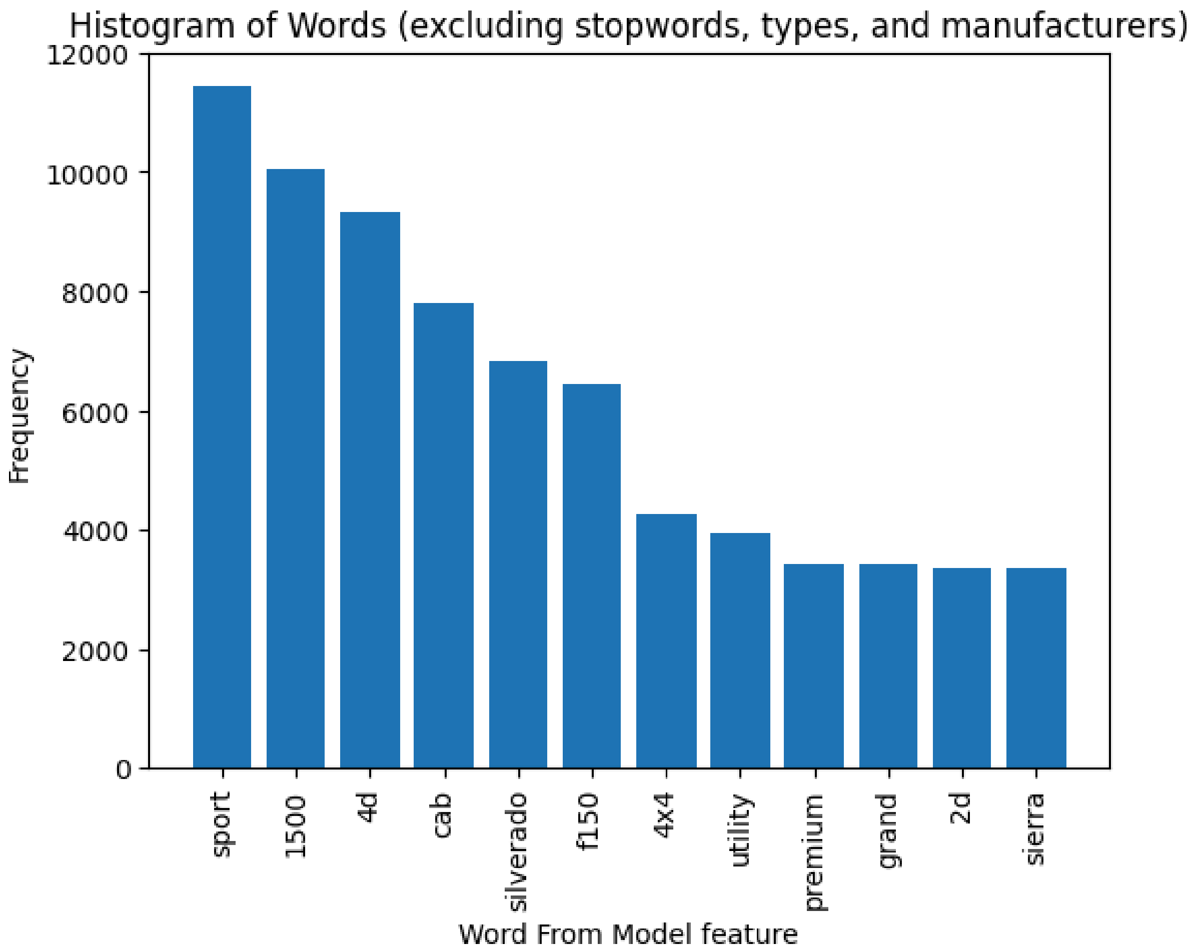
This code may run for many tens of minutes or more depending on data size.

- Set OK_TO_RUN_FEAT_IMPORT = True, if you want to run it

In [57]:
```
# Set min_occurrence to different values to see the distribution of popular words i
# % of rows in X_train
pct_feat_import_min_occurrence = 2
feat_import_min_occurrence = round(pct_feat_import_min_occurrence/100*X_train.shape
filtered_counts =identify_model_keywords(X_train, min_occurrence = feat_import_min_
filtered_counts_df = pd.DataFrame.from_dict(filtered_counts, orient='index', column
plot_model_keyword(filtered_counts_df)
print("number of one hots to be created for model", filtered_counts_df.shape[0])
df_sorted = filtered_counts_df.sort_values(by='word_count', ascending=False)
top_values_df = df_sorted.iloc[:15]
plot_model_keyword(top_values_df)
```




```
number of one hots to be created for model 12
```




```
<Figure size 640x480 with 0 Axes>
```

In [58]:
```
if OK_TO_RUN_FEAT_IMPORT:
    categorical_cols = ['type', 'state', 'manufacturer', 'fuel','title_status', 'tr
    #one_hot_cols  = [col for col in df2.columns if col.startswith('my_one')]
    numerical_cols = ['year']
    target_col  = 'price'
    alpha = BEST_ALPHA
    feat_import_details = run_feat_import_experiment(categorical_cols, numerical_co
                                                     X_train, y_train, X_test, y_te
```

```
Starting experiment default at 02:50:38
in modelofcartransform, X_w_one_hots shape (161698, 12)
Running fit
in modelofcartransform, X_w_one_hots shape (161698, 12)
running predict for X_train
in modelofcartransform, X_w_one_hots shape (161698, 12)
running predict for X_val
in modelofcartransform, X_w_one_hots shape (46200, 12)
model predict rmse_train: 7,308.044497
model predict rmse_val: 7,321.352984
model predict rmse gap :13.308487
----
Calculating permutations to find feature importance per feature
in modelofcartransform, X_w_one_hots shape (46200, 12)
Feature columns with mean - 2*std GREATER THAN  0
year                                    126,074,178 +/- 765,389
type                                    37,320,989 +/- 251,973
manufacturer                            8,502,581 +/- 161,971
fuel                                    5,782,596 +/- 143,481
transmission                            3,629,142 +/- 96,402
state                                   1,091,588 +/- 41,338
paint_color                             99,058 +/- 10,778
----
RMSE train: 7308.044497315519
RMSE val: 7321.352984300726
finished experiment default in elapsed_time: 659.7278189659119
```

This code may run for more than an hour depending on data size.

- Set OK_TO_RUN_FEAT_IMPORT_ADDITIONAL = True, if you want to run it

In [59]:
```python
if OK_TO_RUN_FEAT_IMPORT_ADDITIONAL:
    # run for several alpha values and chart rmse
    alphas = [1e-2,1e-1,1,BEST_ALPHA, 1e1,1e2,1e3]
    alphas = list(set(alphas))
    alphas.sort()
    exp_alphas = []
    for alpha in alphas:
        xp_id = "exp_alpha_"+f"{alpha}"
        print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
        print(f"Running experiment {xp_id} for alpha: {alpha:,.4f}")
        feat_import_details = run_feat_import_experiment(categorical_cols, numerica
                                                         X_train, y_train, X_test, y_te
        rmse_train = feat_import_details['rmse_train']
        rmse_val = feat_import_details['rmse_val']
        exp_dict = {'alpha':alpha, 'rmse_train':rmse_train, 'rmse_val':rmse_val}
        exp_alphas.append(exp_dict)
        print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
        print('')
```

In [ ]:
```python
details
```

In [ ]:
```python
def overfit_plot_check(df, x, y_train,y_test, xlabel, ylabel, xlog=False):

    # Create the lineplot
```

```
    sns.lineplot(df,x=x,y=y_train, label='Train Error', marker='o')
    sns.lineplot(df, x=x, y=y_test, label='Test Error', marker='o')

    # Customize plot (optional)
    plt.legend()  # Add a legend
    if xlog:
        xlabel = xlabel + '(log scale)'
        plt.xscale('log')

    # Add labels and title
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.title('Check for overfitting. RMSE vs Alpha hyperparameter values')
    # Show the plot
    plt.show()
    plt.cla()
    plt.clf()
```

In [ ]:
```
if OK_TO_RUN_FEAT_IMPORT_ADDITIONAL:
    df = pd.DataFrame(exp_alphas)
    overfit_plot_check(df, 'alpha', 'rmse_train', 'rmse_val', 'Alpha', 'RMSE', xlog
```

In [ ]:
```
if OK_TO_RUN_FEAT_IMPORT_ADDITIONAL:
    # minimumn occurrence settings as a function of the percent size of the X_train
    min_occurrences = [max(2, round((i/100)*X_train.shape[0]))for i in [0.05,0.5,1,
    min_occurrences = list(set(min_occurrences))

    print(min_occurrences)
```

In [ ]:
```
# run for several min_occurence values and chart rmse
min_occurrences = [max(2, round((i/100)*X_train.shape[0]))for i in [0.25,0.5,1,2,3,
min_occurrences = list(set(min_occurrences))
print(f"Running experiments for this range of minimum occurrences: {min_occurrences
exp_min_o = []
if OK_TO_RUN_FEAT_IMPORT_ADDITIONAL:
    for min_occurrence in min_occurrences:
        xp_id = "exp_min_occurrence_"+f"{min_occurrence}"
        print("++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
        print(f"Running experiment {xp_id} for min_occurrence: {min_occurrence:,.4f
        feat_import_details = run_feat_import_experiment(categorical_cols, numerica
                                                          X_train, y_train, X_test, y_te
        rmse_train = feat_import_details['rmse_train']
        rmse_val = feat_import_details['rmse_val']
        mean_change_rmse_for_model_field = feat_import_details['mean_change_rmse_fo
        std_change_rmse_for_model_field = feat_import_details['std_change_rmse_for_

        exp_dict = {'min_occurrence':min_occurrence, 'rmse_train':rmse_train, 'rmse
                    'mean_change_rmse_for_model_field':mean_change_rmse_for_model_f
                    'std_change_rmse_for_model_field':std_change_rmse_for_model_fie
                    }
        exp_min_o.append(exp_dict)
```

```
        print("+++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++")
        print('')
```

In [ ]:
```
if OK_TO_RUN_FEAT_IMPORT_ADDITIONAL:
    df = pd.DataFrame(exp_min_o)
    overfit_plot_check(df, 'min_occurrence', 'rmse_train', 'rmse_val', 'Minimum Occ
```

In [ ]:
```
def feat_import_check_plot_w_std(x, y_mean, y_err, xlabel, ylabel, xlog=False):

    # Create the error bar plot
    plt.errorbar(x, y_mean, yerr=y_err, fmt='o-', capsize=5)

    # Add labels and title
    plt.title(f'Mean Plot with Standard Deviation for {xlabel}')

    # Customize plot (optional)
    if xlog:
        xlabel = xlabel + '(log scale)'
        plt.xscale('log')

    # Add labels and title
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)

    plt.axhline(y=0, color='red', linestyle='--', linewidth=2)  # Adjust styles as

    # Show the plot
    plt.show()
    plt.cla()
    plt.clf()
```

In [ ]:
```
if OK_TO_RUN_FEAT_IMPORT_ADDITIONAL:
    df.fillna(0, inplace=True)
    df = df.sort_values(by='min_occurrence', ascending=True)
    feat_import_check_plot_w_std(df['min_occurrence'], df['mean_change_rmse_for_mod
    df_non_zero = df[df['mean_change_rmse_for_model_field'] != 0]
    feat_import_check_plot_w_std(df_non_zero['min_occurrence'], df_non_zero['mean_c
```

In [ ]:
```
beep()
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: