COMS 4995 - Applied Machine Learning - Homework 3

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0.1 Common Imports

[2]:
```
import math
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Define a global value for scikit-learn's 'n_jobs' parameter that can be customized for different hardware:

[1]:
```
n_jobs = -1
```

---

1 Task 1 - Identify Features

- **Assemble a dataset consisting of features and target:**

[3]:
```
# Read in all vehicle data
vehicle_data = pd.read_csv('./vehicles.csv')
```

[4]:
```
# Print basic info
data_shape = vehicle_data.shape
print(f'Data has {data_shape[0]:,} rows and {data_shape[1]} columns')
```

```
Data has 509,577 rows and 25 columns
```

[5]:
```
# Separate data into raw features and target
target_col = 'price'
raw_features = vehicle_data.drop(columns=target_col)
raw_target = vehicle_data.price
```

- **What features are relevant for the prediction task?**

Certainly features that are entirely **empty** cannot be informative:

[6]:
```
empty_features = raw_features.columns[raw_features.isna().all()].to_list()
print('Entirely empty features:', empty_features)
```

```
Entirely empty features: ['county']
```

Based purely on the **column descriptions**, in their current form some features will likely be irrelevant to predict price:

- 'url', 'vin', and 'image_url' are strings that should be unique per vehicle / listing
- One-hot encoding these strings would roughly generate a unique feature per row, which would not be useful for predition.

Note: we may end up extracting new features from some of these dropped columns in Task 3.

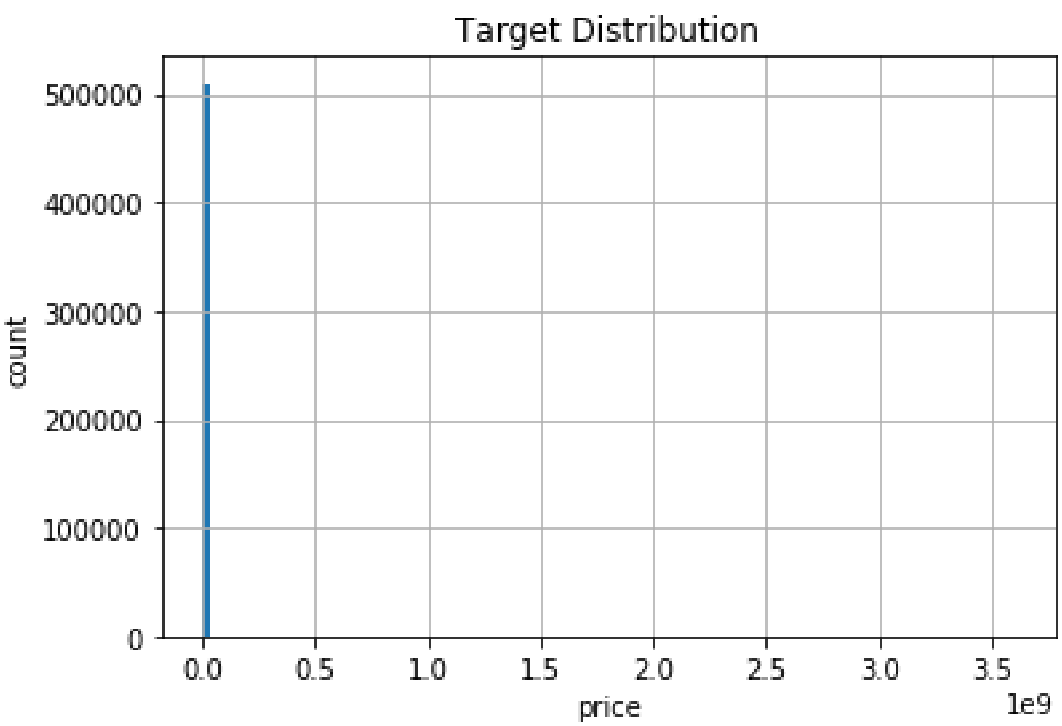
[7]:
```
irrelevant_features = ['url', 'vin', 'image_url']
```

To get a sense of how relevant the remaining features may be to predict price, we can **visualize their relationship to the target value**:

[8]:
```
relevant_features = raw_features.columns.
 ↪difference(empty_features+irrelevant_features, sort=False)
relevant_types = raw_features.dtypes[relevant_features]
```

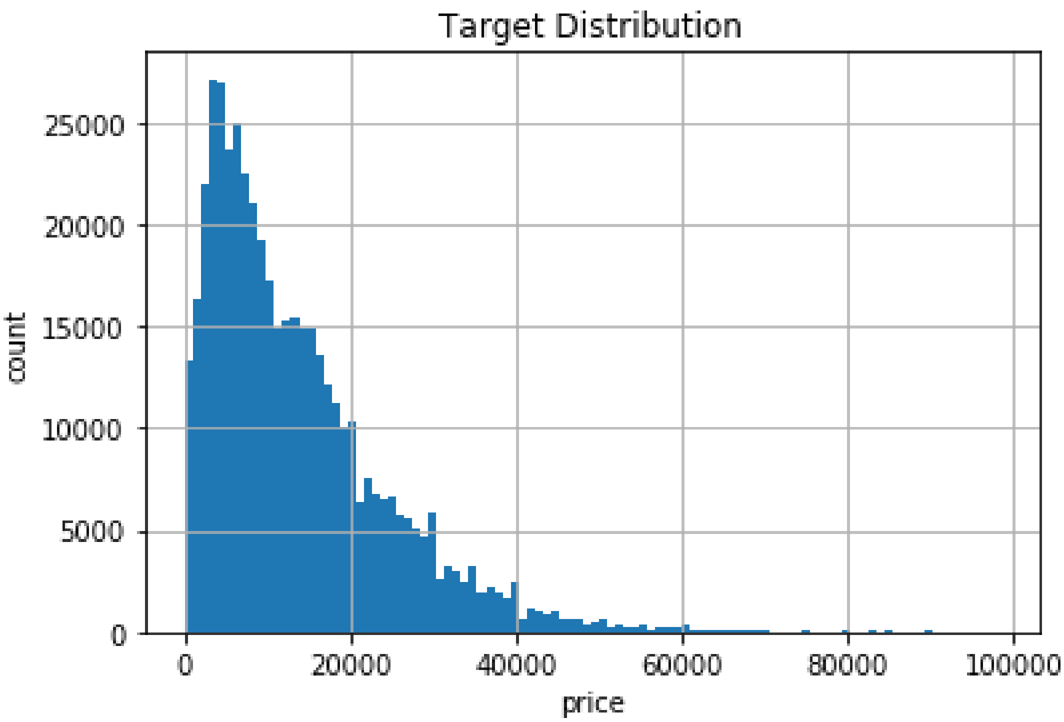
Our visualizations won't be very effective if outlier prices ruin the scaling. Let's look at the **distribution of prices** in the data:

[9]:
```
raw_target.hist(bins=100)
plt.title('Target Distribution')
plt.xlabel('price')
plt.ylabel('count');
```



Looking at the scale of the x-axis, there are clearly some **outlier prices** that will disrupt the scaling of our visualizations. To prevent this, we'll limit our visualizations to prices greater than 0 and within the 99.9th percentile of the distribution:

[10]:
```
valid_price_rows = (raw_target > 0) & (raw_target < raw_target.quantile(.999))

# Replot the histogram
raw_target[valid_price_rows].hist(bins=100)
plt.title('Target Distribution')
plt.xlabel('price')
plt.ylabel('count');
```



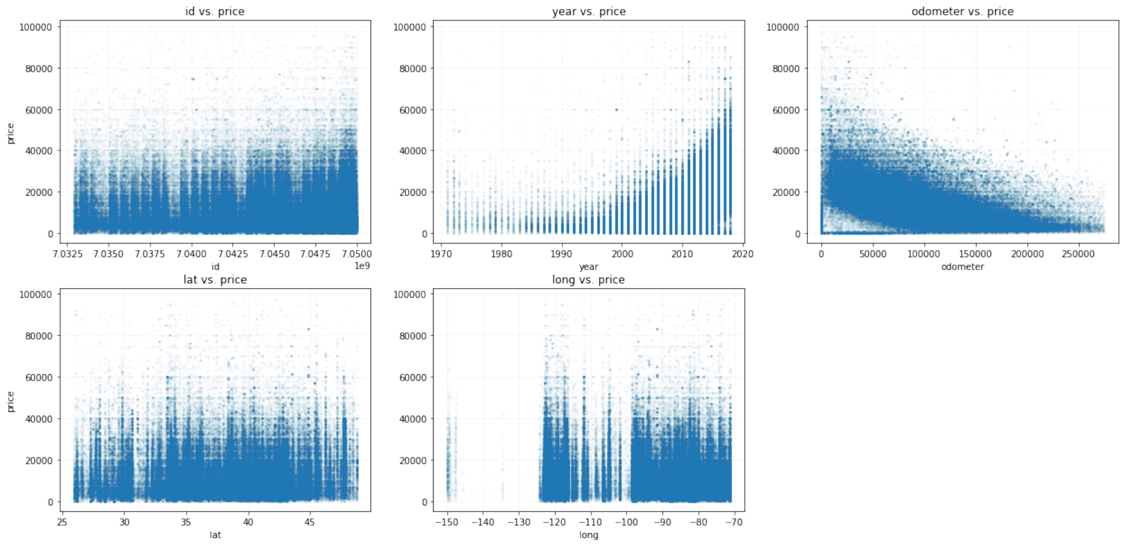
That looks like a much smoother distribution of used vehicle prices. Now we can visualize the features' relationship to the target:

1.1 Continuous Features vs. Target

[11]:
```
continuous_features = relevant_features[relevant_types != 'object']
```

[12]:
```
# Figure out an appropriate number of rows and columns
num_plots = len(continuous_features)
```

```
plot_cols = 3
plot_rows = math.ceil(num_plots / plot_cols)

# For each continuous feature...
fig, axs = plt.subplots(plot_rows, plot_cols, figsize=(7*plot_cols,␣
↪5*plot_rows), squeeze=False)
for i, feature in enumerate(continuous_features):
    # Get the axes for this feature
    row=i//plot_cols
    col=i%plot_cols
    ax=axs[row,col]

    # Decide which rows to plot for this feature
    # To avoid outliers distorting the scale of the x-axis, we'll ignore data␣
↪below the 1st percentile
    # or above the 99th percentile.
    feature_col = raw_features[feature]
    feature_rows = (feature_col > feature_col.quantile(.01)) & (feature_col <␣
↪feature_col.quantile(.99))
    rows_to_plot = valid_price_rows & feature_rows

    # Create a scatter plot for this feature vs. target
    ax.scatter(feature_col[rows_to_plot], raw_target[rows_to_plot], s=3,␣
↪alpha=0.02)
    ax.grid(alpha=0.1)
    ax.set_axisbelow(True)

    # Label the plot
    ax.set_title(feature+' vs. price')
    ax.set_xlabel(feature)
    if col==0:
        ax.set_ylabel('price')

# Hide any axis we didn't use
num_axes_to_hide = plot_rows*plot_cols - num_plots
for i in range(num_axes_to_hide):
    axs.flatten()[-(i+1)].set_axis_off()
```



From these plots, we conclude the following:

- both 'year' and 'odometer' have strong correlations with 'price' (although in opposite directions)
- 'id' may have a weak positive correlation with 'price' (although we may drop it for other reasons - see below)
- 'lat' and 'long' by themselves do not appear to have a specific relationship to 'price'.
  - These may require more advanced feature engineering to extract predictive information.
  - However, we believe the 'region' or 'region_url' columns will be equally informative with much less feature engineering (see below).

[13]:
```python
uninformative_features = ['lat', 'long']
```

1.2 Ordinal Features vs. Target

The remaining features are **discrete** (non-continuous):

[14]:
```python
relevant_features.difference(continuous_features, sort=False)
```

[14]:
```
Index(['region', 'region_url', 'manufacturer', 'model', 'condition',
       'cylinders', 'fuel', 'title_status', 'transmission', 'drive', 'size',
       'type', 'paint_color', 'description', 'state'],
      dtype='object')
```

The provided descriptions of these features suggest several of them (condition, cylinders, and size) are **ordinal** in nature (discrete and ordered):

[15]:
```python
ordinal_features = pd.Index(['condition', 'cylinders', 'size'])
```

Determine the distinct values of these features and provide an appropriate **ordering** for them using domain knowledge:

[16]:
```
raw_features['condition'].dropna().unique().tolist()
```

[16]:
```
['excellent', 'good', 'like new', 'fair', 'new', 'salvage']
```

[17]:
```
conditions = ['salvage', 'fair', 'good', 'excellent', 'like new', 'new']
```

[18]:
```
raw_features['cylinders'].dropna().unique().tolist()
```

[18]:
```
['4 cylinders',
 '8 cylinders',
 '6 cylinders',
 '10 cylinders',
 '5 cylinders',
 '3 cylinders',
 '12 cylinders',
 'other']
```

[19]:
```
cylinders = ['3 cylinders', '4 cylinders', '5 cylinders', '6 cylinders', '8␣
↪cylinders', '10 cylinders', '12 cylinders', 'other']
```

[20]:
```
raw_features['size'].dropna().unique().tolist()
```

[20]:
```
['compact', 'mid-size', 'full-size', 'sub-compact']
```

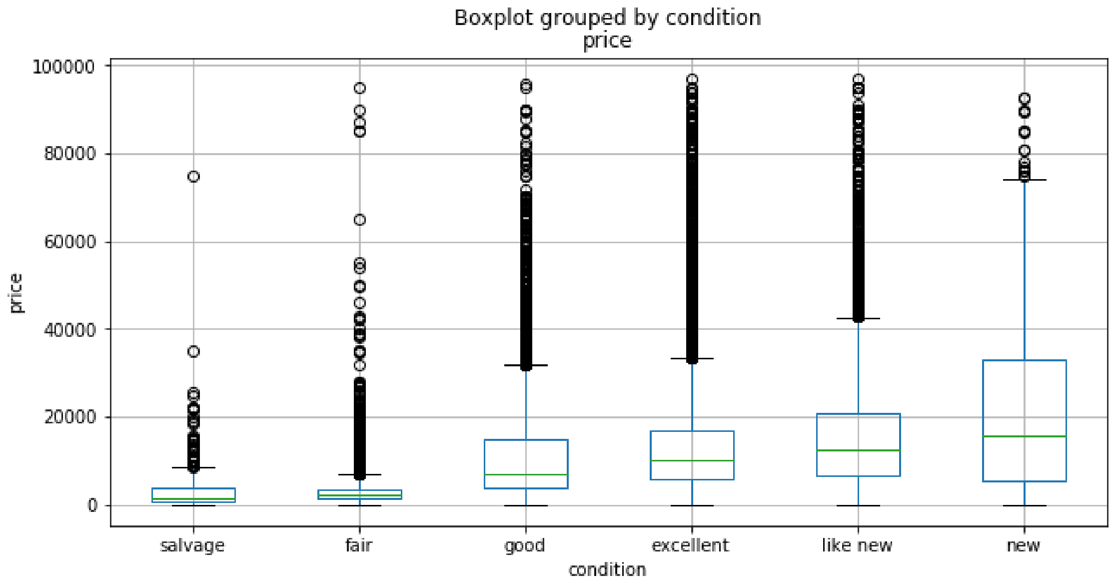
[21]:
```
sizes = ['sub-compact', 'compact', 'mid-size', 'full-size']
```

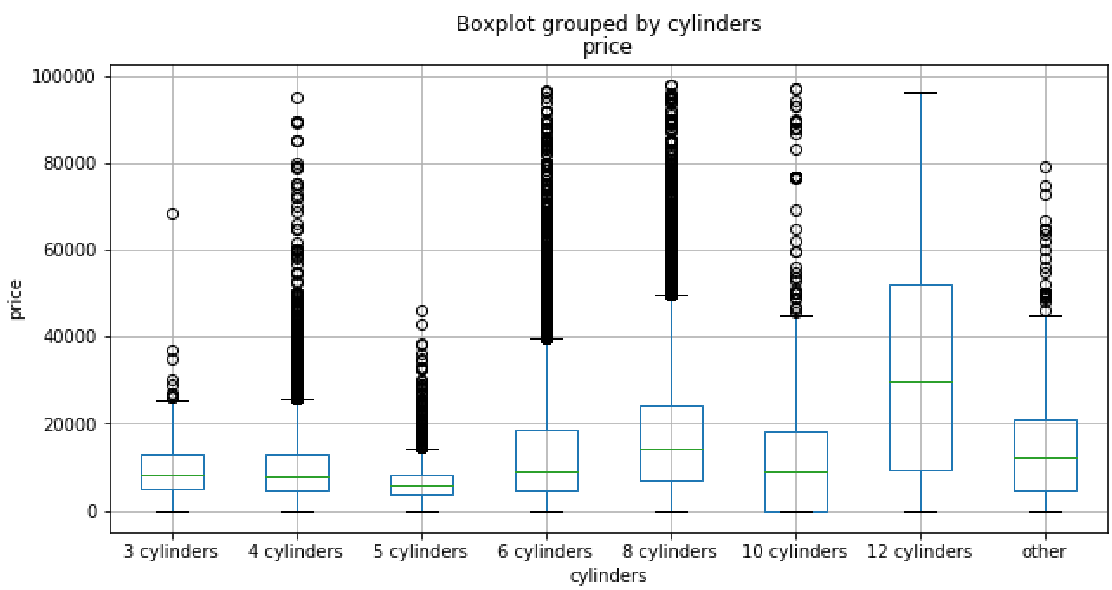
We can now convert these ordinal features into **ordered Pandas categories**:

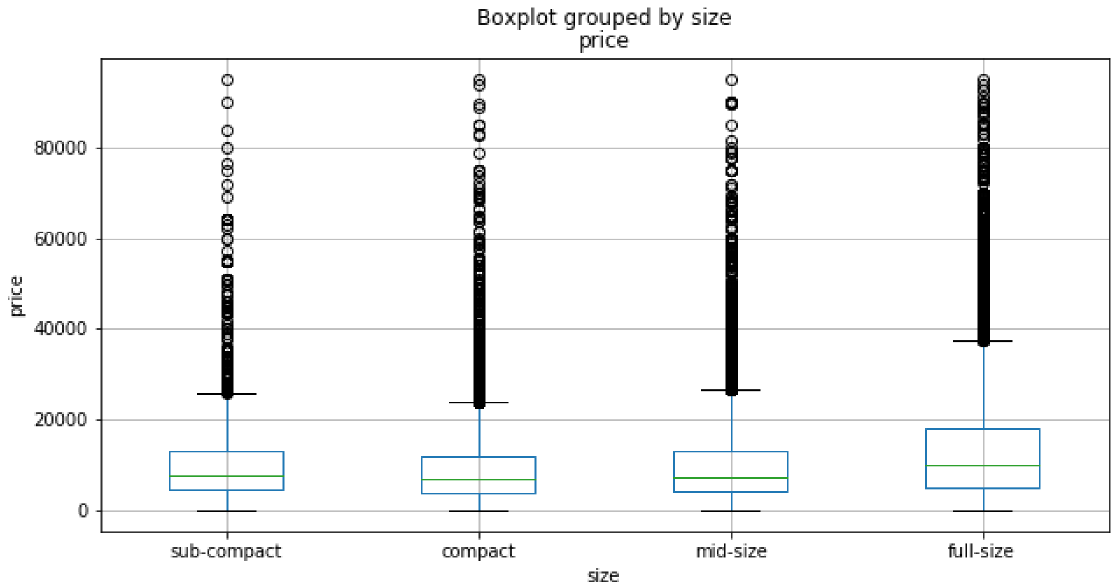
[22]:
```
from pandas.api.types import CategoricalDtype

ordinals_dict = {'condition':conditions, 'cylinders':cylinders, 'size':sizes}

for feature, ordered_values in ordinals_dict.items():
    cat_type = CategoricalDtype(categories=ordered_values, ordered=True)
    vehicle_data[feature] = vehicle_data[feature].astype(cat_type)
```

Let's **visualize the target response** to these ordinal features to see if there is the expected monotonic relationship:

[23]:
```
# For each ordinal feature...
for feature in ordinal_features:
    # Create a box plot for this feature vs. target
    ax = vehicle_data.loc[valid_price_rows, :].boxplot(column='price',␣
↪by=feature, figsize=(10, 5))
    ax.set_ylabel('price')
```


Boxplot grouped by condition
price
100000
80000
60000
40000
20000
0
price
salvage
fair
good
excellent
like new
new
condition


Boxplot grouped by cylinders
price
100000
80000
60000
40000
20000
0
price
3 cylinders
4 cylinders
5 cylinders
6 cylinders
8 cylinders
10 cylinders
12 cylinders
other
cylinders



For these plots, we conclude the following:

- Condition is a strong indicator for price. We can clearly see the increasing trend when the condition of the car is better.
- Neither 'cylinders' nor 'size' show the expected monotonic relation for an ordinal feature.
  - For example, the average price for 5-cylinder vehicles is less than that of 4-cylinder vehicles, and similarly for 10 vs. 8 cylinders.
  - There is not a significant change in the distribution of prices for sub-compact, compact, or mid-size vehicles.

Therefore, we'll only consider '**condition**' as an ordinal feature:

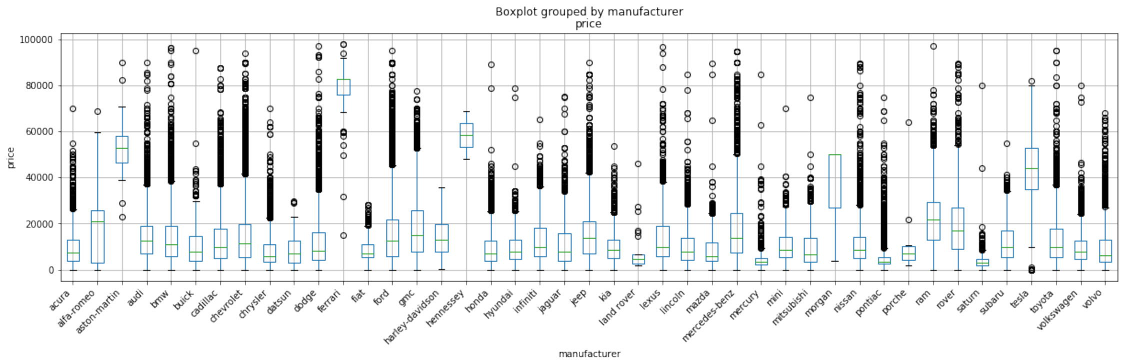
[24]:
```
ordinal_features = pd.Index(['condition'])
```

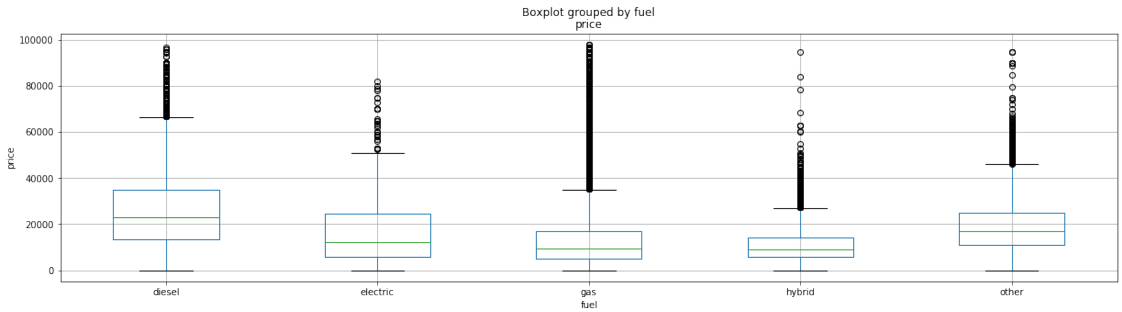
1.3 Categorical Features vs. Target

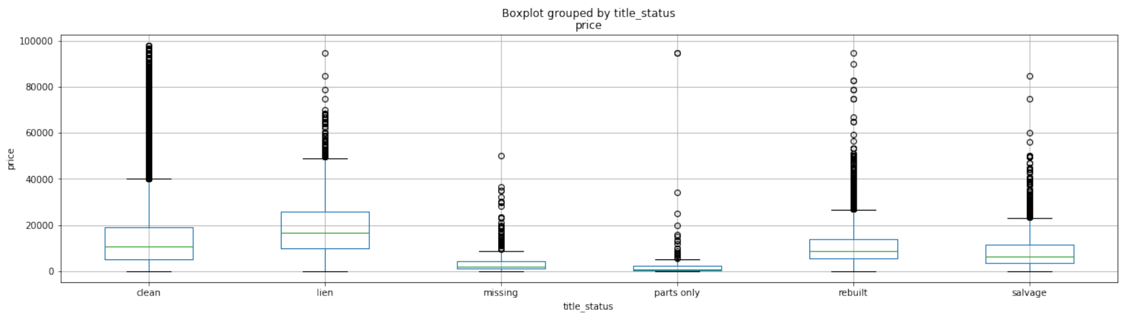
[25]:
```
categorical_features = relevant_features.difference(continuous_features.
 ↪union(ordinal_features), sort=False)
```

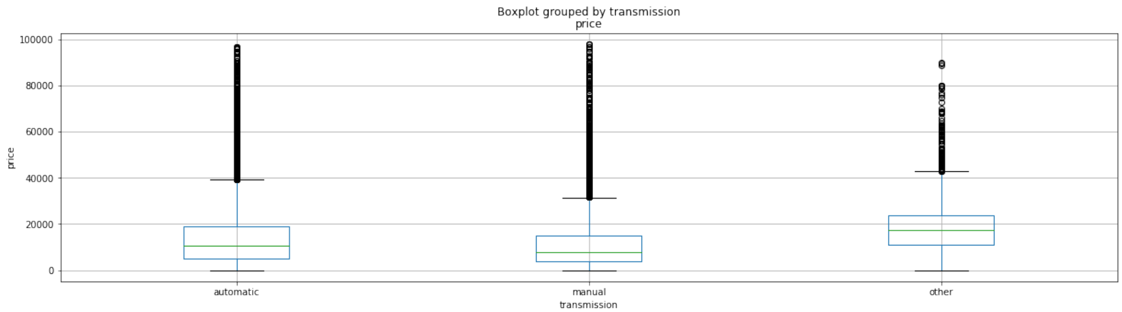
[26]:
```
# We'll only plot features with a relatively low cardinality
low_card_features = [feat for feat in categorical_features if␣
 ↪vehicle_data[feat].nunique() < 52]

for feature in low_card_features:
    # We've already shown boxplots for 'cylinders' and 'size' above, so we␣
 ↪don't need to see them again
    if feature in ['cylinders', 'size']: continue
```

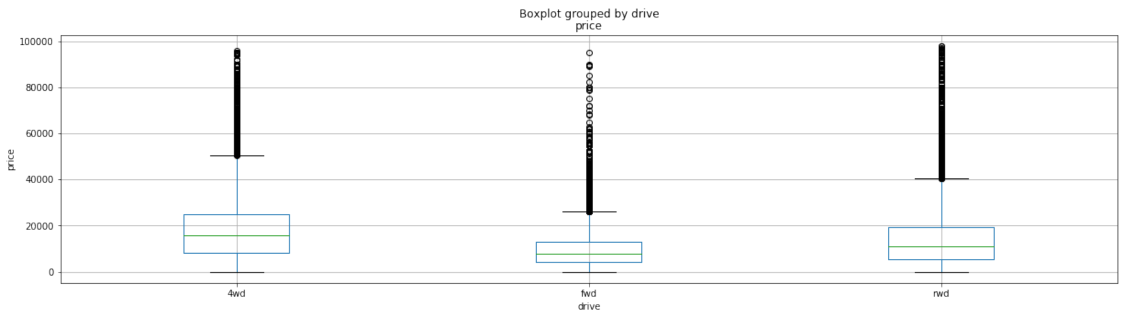
```
ax = vehicle_data.loc[valid_price_rows, :].boxplot(column='price',␣
↪by=feature, figsize=(20, 5))
if len(ax.get_xticklabels()) > 40:
    ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
ax.set_ylabel('price')
```

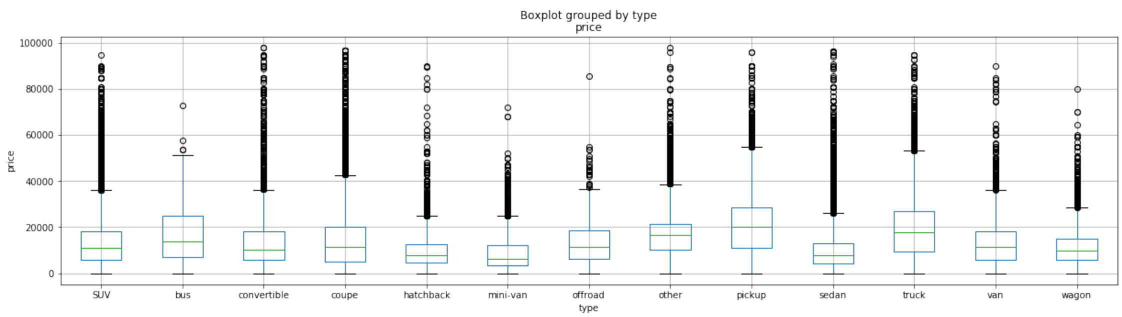


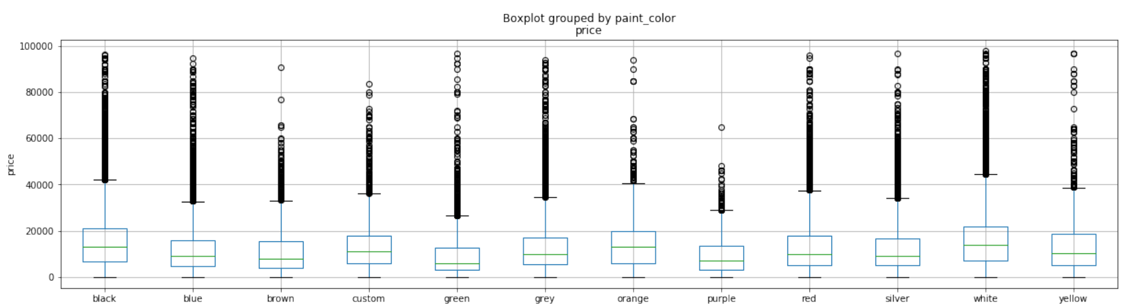


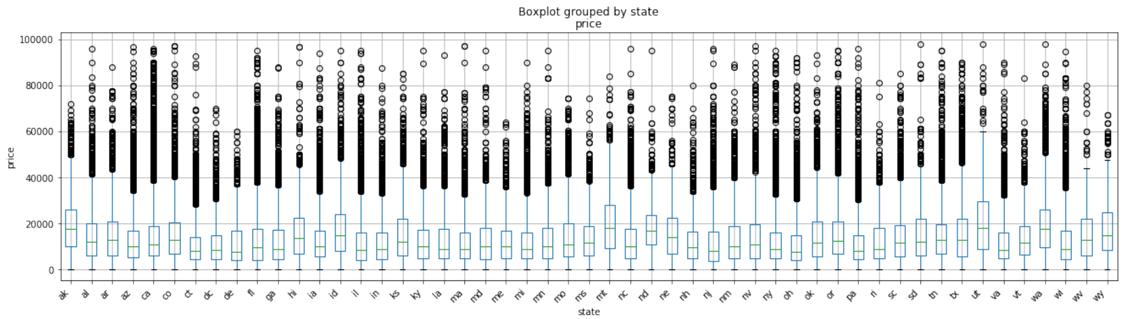



Boxplot grouped by transmission
price
price
transmission
automatic
manual
other


Boxplot grouped by drive
price
price
drive
4wd
fwd
rwd


Boxplot grouped by type
price
price
type
SUV
bus
convertible
coupe
hatchback
mini-van
offroad
other
pickup
sedan
truck
van
wagon


Boxplot grouped by paint_color
price
price
paint_color
black
blue
brown
custom
green
grey
orange
purple
red
silver
white
yellow



For these plots, we conclude the following:

- We can see logical trends in the manufacturer feature: cars like Ferrari, Tesla or Aston Martin are more expensive than the rest. We see some strange things as well, like the low price of Land Rovers, but overall the trend could be useful.
- As expected, diesel car are more expensive than the rest on average. The car market runs that way as well.
- Title status "missing" and "parts only" are much lower on average than the rest, as expected. We can see a good trend in this feature with respect to the price.
- As expected, automatic transmission cars are more expensive than manual cars. The "other" category here is not clear, but it's just 4% of the data.
- Following the trend of the market, 4wd cars are more expensive than the others. This feature proves to be useful for classification.
- In vehicle type, we cannot see a very clear trend, but we can find many differences, that can make us go one way or the other with confidence when classifying. This feature will be useful for modelling the data.
- On the real car market, paint color is a variable over the price of a car (e.g. red Ferraris are more expensive than other colors). This data is not as clear as we would like, but the most popular colors (black and white) are higher on average, showing useful trends.
- States don't show an expected pricing pattern, but we think that it will give us useful insight when combined with other variables, so we will keep it.

Regarding the remaining categorical features, it is unhelpful to plot them due to the sheer **number of categories**. For example, 'model' is a really dirty feature which needs heavy and complex cleaning before being a useful source of information. Other high-cardinality categorical variables, like 'region', are possible candidates for Target Encoding.

[27]:
```
dirty_features = ['model']
```

- **Are there any features that should be excluded because they leak the target information?**

The '**id**' feature is unique in this dataset, and therefore could be used to create a perfect mapping of id to price. Obviously this wouldn't generalize to new data. If id's are assigned sequentially, then 'id' *could* be proxy for the age of the listing. However, if we assume the overall task is to predict prices for *new* listings, then 'id' would no longer be a distinguishing feature. To avoid leaking any target information to the model, we'll drop 'id'.

We noticed that the '**description**' column could possibly leak some target information if processed correctly, as it occassionally contains pricing information.
For example, the following are excerpts from entries in the 'description' column, along with the actual target value:

- "…I am asking $39,500 for this awesome truck…" (price=39,500)
- "…asking $1000 or best offer…" (price=1,000)
- "…asking $23400 or best offer…" (price=23,400)

[28]:
```
leaky_features = ['id', 'description']
```

1.4 Region analysis

In inspecting the data, we noticed that the '**region**' column might not be specific enough to identify the actual region of the vehicle due to the same city name existing in multiple states. We see evidence of this when comparing the 'region' column to the '**region_url**' column, which appears to make more distinctions. The following are a few examples of where 'region' is duplicated:

region	region_url
albany	https://albany.craigslist.org
albany	https://albanyga.craigslist.org
athens	https://athensga.craigslist.org
athens	https://athensohio.craigslist.org
charleston	https://charleston.craigslist.org
charleston	https://charlestonwv.craigslist.org
columbus	https://columbus.craigslist.org
columbus	https://columbusga.craigslist.org

As '**region_url**' is a more specific version of the '**region**' feature and more accurately defines the true location of the vehicle, we're going to drop the 'region' feature and use only 'region_url'.

[29]:
```
unspecific_features = ['region']
```

1.5 Conclusions

From the above analyses, we're going to **drop** the following features for our baseline model:

- 'county' (entirely empty)
- 'url' (irrelevant as is, but we may extract features from it in subsequent steps)
- 'image_url' and 'vin' (irrelevant)
- 'lat' and 'long' (requires feature engineering to be informative)
- 'id' (could leak target information)
- 'description' (could leak target information, but we may extract features from it in subsequent steps)
- 'region' ('region_url' is more accurate)
- 'model' (requires extensive cleanup before it will be useful)

[30]:
```
features_to_drop = (empty_features
                    + irrelevant_features
                    + uninformative_features
                    + leaky_features
                    + unspecific_features
                    + dirty_features)
print('Features to drop for Baseline model:', features_to_drop)
```

```
Features to drop for Baseline model: ['county', 'url', 'vin', 'image_url',
'lat', 'long', 'id', 'description', 'region', 'model']
```

---

2 Task 2 - Preprocessing and Baseline Model

- **Create a simple minimum viable model by doing an initial selection of features, doing appropriate preprocessing and cross-validating a linear model.**

[31]:
```
baseline_features = raw_features.columns.difference(features_to_drop,␣
 ↪sort=False)
baseline_features
```

[31]:
```
Index(['region_url', 'year', 'manufacturer', 'condition', 'cylinders', 'fuel',
       'odometer', 'title_status', 'transmission', 'drive', 'size', 'type',
       'paint_color', 'state'],
      dtype='object')
```

2.1 Prepare Baseline Preprocessing

[32]:
```
from sklearn.pipeline import make_pipeline
from sklearn.compose import make_column_transformer

from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, OrdinalEncoder
import category_encoders as ce

# Prepare transformation pipelines for different column types
target_encode_pl = make_pipeline(ce.TargetEncoder(), StandardScaler())
median_scale_pl = make_pipeline(SimpleImputer(strategy='median'),␣
 ↪StandardScaler())
new_cat_ohe_pl = make_pipeline(SimpleImputer(strategy='constant'),␣
 ↪OneHotEncoder(handle_unknown='ignore'))
impute_good_ord_enc_scale_pl = make_pipeline(SimpleImputer(strategy='constant',␣
 ↪fill_value='good'), OrdinalEncoder(categories=[conditions]),␣
 ↪StandardScaler())
most_freq_ohe_pl = make_pipeline(SimpleImputer(strategy='most_frequent'),␣
 ↪OneHotEncoder(handle_unknown='ignore'))
```

```python
# Contruct our baseline preprocessing transformation
baseline_preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))
```

- **You don't need to validate the model on the whole dataset.**

[33]:
```python
from sklearn.model_selection import train_test_split

# We'll train and test only on the rows with a valid price
X = raw_features.loc[valid_price_rows,:]
y = raw_target[valid_price_rows]

# Set aside a test set for final evaluation
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=25)
print('X_train rows:', X_train.shape[0])
print('X_test rows:', X_test.shape[0])
```

```
X_train rows: 349115
X_test rows: 116372
```

2.2 Baseline model evaluation

In the following block, we'll generate a baseline score for a couple of different linear regressions: **OLS and Ridge**.

[34]:
```python
from sklearn.linear_model import LinearRegression, RidgeCV
from sklearn.model_selection import ShuffleSplit, cross_val_score
```

[35]:
```python
# Use a ShuffleSplit object to sub-sample the training data for faster cross␣
 ↪validataion
shuffle = ShuffleSplit(n_splits=10, train_size=50000, test_size=10000,␣
 ↪random_state=25)
```

[36]:
```python
# Gather baseline cross validation scores for some linear models
baseline_ols_pipeline = make_pipeline(baseline_preprocessor, LinearRegression())
baseline_ols_score = cross_val_score(baseline_ols_pipeline, X_train, y_train,␣
 ↪cv=shuffle).mean()
print(f"Baseline model using OLS regression score: {baseline_ols_score:.6f}")

baseline_ridge_pipeline = make_pipeline(baseline_preprocessor, RidgeCV())
baseline_ridge_score = cross_val_score(baseline_ridge_pipeline, X_train,␣
 ↪y_train, cv=shuffle).mean()
```

```
print(f"Baseline model using Ridge regression score: {baseline_ridge_score:.
↪6f}")
```

```
Baseline model using OLS regression score: 0.417436
Baseline model using Ridge regression score: 0.417438
```

These results are very similar. Going forward, we'll use the **Ridge** score as our 'baseline' score to compare against.

---

3 Task 3 - Feature Engineering

- **Create derived features and perform more in-depth preprocessing and data cleaning. Does this improve the model?**

To test out various different approaches to preprocessing, we'll define a method to consistently compare to our baseline results:

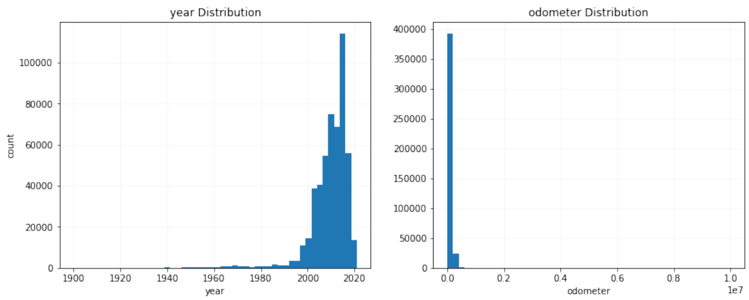
[37]:
```
def compare_to_baseline(preprocessing, description=''):
    # Compare the Ridge results to the baseline Ridge score
    ridge_pipeline = make_pipeline(preprocessing, RidgeCV())
    ridge_score = cross_val_score(ridge_pipeline, X_train, y_train, cv=shuffle).
↪mean()
    print(f"{description+' ' if description else ''}Ridge regression score:␣
↪{ridge_score:.6f}")
    print(f"(Baseline Ridge regression score: {baseline_ridge_score:.6f})")
```

3.1 Explore different Pre-Processing for Continuous features

Taking a look at histograms for the continuous features, there appear to be significant **outliers** present:

[38]:
```
# Figure out an appropriate number of rows and columns
cont_baseline_feats = continuous_features.intersection(baseline_features)
num_plots = len(cont_baseline_feats)
plot_cols = 3
plot_rows = math.ceil(num_plots / plot_cols)
fig, axs = plt.subplots(plot_rows, plot_cols, figsize=(7*plot_cols,␣
↪5*plot_rows), squeeze=False)

# For each continuous feature...
for i, feature in enumerate(cont_baseline_feats):
    # Get the axes for this feature
    row=i//plot_cols
    col=i%plot_cols
    ax=axs[row,col]
```

```
    # Create a histogram for this feature
    ax.hist(raw_features[feature].dropna(), bins=50)
    ax.grid(alpha=0.1)
    ax.set_axisbelow(True)

    # Label the plot
    ax.set_title(feature+' Distribution')
    ax.set_xlabel(feature)
    if col==0:
        ax.set_ylabel('count')

# Hide any axis we didn't use
num_axes_to_hide = plot_rows*plot_cols - num_plots
for i in range(num_axes_to_hide):
    axs.flatten()[-(i+1)].set_axis_off()
```



It looks like some of the data for 'odometer' may be invalid, since the upper range is unreasonably high.

Idea: The first thing we'll try is to simply use a **RobustScaler()** instead of the StandardScaler(), which is more robust to outlier values:

[39]:
```
# Form a pipline using RobustScaler
from sklearn.preprocessing import RobustScaler
median_robust_scale_pl = make_pipeline(SimpleImputer(strategy='median'),
 ↪RobustScaler())

# Try preprocessing with RobustScaler
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_robust_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))
```

```python
# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'RobustScaler')
```

```
RobustScaler Ridge regression score: 0.417438
(Baseline Ridge regression score: 0.417438)
```

Result: Using RobustScaler didn't appear to have any impact

Idea: A different approach would be to just **cap extreme values** to a certain percentile prior to scaling. For example, treat any value greater than the 99th percentile equivalent to the 99th percentile value.

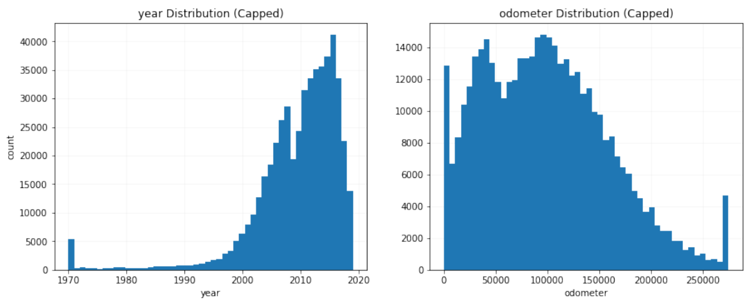
Below is a function that caps the values in a Pandas Series or DataFrame to be between the 1st and 99th percentile of the input data:

[40]:
```python
def cap_extreme_values(X):
    upper_cap = X.quantile(.99)
    lower_cap = X.quantile(.01)
    ax = 1 if isinstance(X, pd.DataFrame) else None
    X = X.mask(X>upper_cap, upper_cap, axis=ax)
    X = X.mask(X<lower_cap, lower_cap, axis=ax)
    return X
```

We can visualize the effect of using such a preprocessing technique by **re-plotting the capped histograms**:

[41]:
```python
# For each continuous feature...
fig, axs = plt.subplots(plot_rows, plot_cols, figsize=(7*plot_cols,␣
 ↪5*plot_rows), squeeze=False)
for i, feature in enumerate(cont_baseline_feats):
    # Get the axes for this feature
    row=i//plot_cols
    col=i%plot_cols
    ax=axs[row,col]

    # Create a histogram for this feature
    ax.hist(cap_extreme_values(raw_features[feature].dropna()), bins=50)
    ax.grid(alpha=0.1)
    ax.set_axisbelow(True)

    # Label the plot
    ax.set_title(feature+' Distribution (Capped)')
    ax.set_xlabel(feature)
    if col==0:
        ax.set_ylabel('count')

# Hide any axis we didn't use
```

```
num_axes_to_hide = plot_rows*plot_cols - num_plots
for i in range(num_axes_to_hide):
    axs.flatten()[-(i+1)].set_axis_off()
```



These distributions look far smoother. For example, the incredibly high odometer readings have all been capped to around 275,000 miles. Any values above that will be treated equivalently to this maximum.

Let's see if this capping has any effect on the accuracy of the model:

[42]:
```
from sklearn.preprocessing import FunctionTransformer

# Make a Transformer that uses cap_extreme_values()
capper = FunctionTransformer(cap_extreme_values)

# Make new pipelines for incorporating the capping of these continuous values
cap_median_scale_pl = make_pipeline(capper, SimpleImputer(strategy='median'),␣
↪StandardScaler())

# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (cap_median_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Capping values')
```

```
Capping values Ridge regression score: 0.524436
(Baseline Ridge regression score: 0.417438)
```

Result: Capping the extreme values made a **significant improvement** over the baseline Ridge score.

Idea: An extension of the above idea would be to fully **bin or discretize** the continuous variables, esentially transforming them into categorical variables.

To do this, we'll experiment with the **KBinsDiscretizer** transformer:

[43]:
```
from sklearn.preprocessing import KBinsDiscretizer
from sklearn.model_selection import GridSearchCV

# Make a new pipeline for incorporating the binning of these continuous values
median_bin_pl = make_pipeline(
    SimpleImputer(strategy='median'), KBinsDiscretizer(encode='onehot-dense'))

# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_bin_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare the Ridge results to the baseline
# We ran the GridSearch with a higher amount of possibilities, but it ran into␣
 ↪many warnings.
# We left only the valid results.
pipeline = make_pipeline(preprocessor, RidgeCV())
param_grid = {'columntransformer__pipeline-2__kbinsdiscretizer__n_bins':␣
 ↪range(6, 12, 2)}
grid = GridSearchCV(pipeline, param_grid=param_grid, cv=shuffle, refit=False)
grid.fit(X_train, y_train)
score = grid.best_score_
best_n_bins_pl = grid.
 ↪best_params_['columntransformer__pipeline-2__kbinsdiscretizer__n_bins']

print(("Ridge regression score: %f") % score)
print(("Best number of bins (pipeline): %d") % best_n_bins_pl)
```

```
Ridge regression score: 0.613522
Best number of bins (pipeline): 10
```

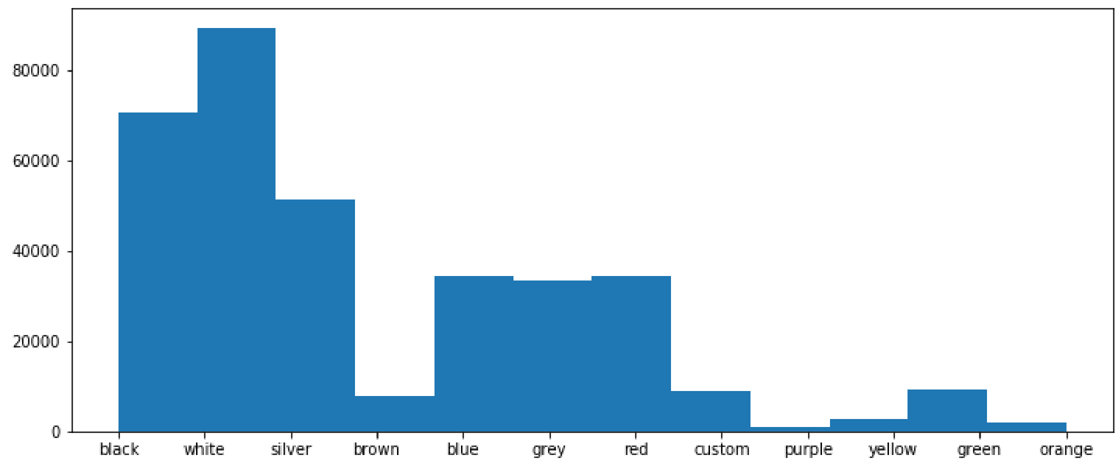
Result: Discretizing the continuous features made an **even greater improvement** over the baseline Ridge score.

3.2 Explore different Pre-Processing for Categorical features

Idea: **Sub-bin** the categorical variables like 'paint_color' to use fewer distinct values.

[44]:

```
# Show original distribution of paint_color
plt.figure(figsize=(12,5))
plt.hist(raw_features['paint_color'].dropna(), bins=12);
```

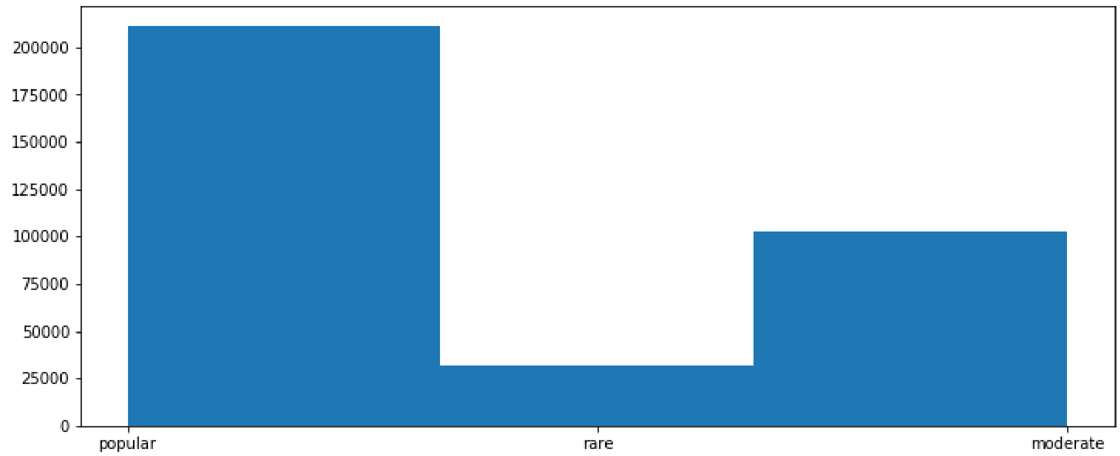


[45]:

```
def bin_colors_series(X):
    X = X.mask(X.notna() & X.str.contains('white|black|silver'), 'popular')
    X = X.mask(X.notna() & X.str.contains('blue|red|grey'), 'moderate')
    X = X.mask(X.notna() & X.str.
 ↪contains('green|custom|brown|yellow|orange|purple'), 'rare')
    return X

def bin_colors(X):
    if isinstance(X, pd.DataFrame):
        return X.apply(bin_colors_series)
    else:
        return bin_colors_series(X)
```

[46]:

```
# Show the binned distribution of paint_color
plt.figure(figsize=(12,5))
plt.hist(bin_colors(raw_features['paint_color']).dropna(), bins=3);
```



Let's see if this sub-binning of paint colors has any impact on our prediction accuracy:

[47]:
```
# Make a Transformer that uses bin_colors()
color_binner = FunctionTransformer(bin_colors)

# Make a new pipeline for incorporating the binning of paint_color
bin_color_new_cat_ohe_pl = make_pipeline(color_binner,␣
↪SimpleImputer(strategy='constant'), OneHotEncoder(handle_unknown='ignore'))

# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
↪'state']),
    (bin_color_new_cat_ohe_pl, ['paint_color']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Sub-binning Paint Colors')
```

```
Sub-binning Paint Colors Ridge regression score: 0.415314
(Baseline Ridge regression score: 0.417438)
```

Result: Sub-binning the paint_color **performed worse** than the baseline Ridge score

---

Idea: Try treating the **ordinal features as categorical** to see if that improves the model's performance

From the feature visualizations, we determined that only 'condition' appeared to have a monotonic relationship to the target, and so we treated it as an 'ordinal' feature in our baseline model. But 'condition' has low-cardinality, and could also be treated as a categorical value. How does treating it as categorical affect the model's performance?

[48]:
```
# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['condition', 'manufacturer', 'cylinders', 'drive',␣
 ↪'size', 'type', 'paint_color', 'state']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Ordinal -> Categorical features')
```

```
Ordinal -> Categorical features Ridge regression score: 0.428374
(Baseline Ridge regression score: 0.417438)
```

Result: Treating 'condition' as a categorical feature **improved the model's performance** compared to the baseline Ridge score

---

3.3 Explore using a Target Transformation

We also tried to use the logarithm of the target, but for the baseline was worse than without it

[49]:
```
# from sklearn.compose import TransformedTargetRegressor
# Try converting prices to log
# print("Testing same regressors but with logarithm of price:")
# ridge_log_regressor = TransformedTargetRegressor(RidgeCV(), func=np.log,␣
 ↪inverse_func=np.exp)
# baseline_ridge_pipeline = make_pipeline(baseline_preprocessor,␣
 ↪ridge_log_regressor)
# baseline_ridge_scores = cross_val_score(baseline_ridge_pipeline, X_train,␣
 ↪y_train)
# print(("Baseline model using Ridge regression score: %f") %␣
 ↪baseline_ridge_scores.mean())

# ols_log_regressor = TransformedTargetRegressor(LinearRegression(), func=np.
 ↪log, inverse_func=np.exp)
# baseline_ols_pipeline = make_pipeline(baseline_preprocessor,␣
 ↪ols_log_regressor)
# baseline_ols_scores = cross_val_score(baseline_ols_pipeline, X_train, y_train)
# print(("Baseline model using OLS regression score: %f") % baseline_ols_scores.
 ↪mean())
```

3.4 Explore parsing features from the URL

Idea: Use the base of the URL instead of the `'region_url'` feature

We found that the base of the `'url'` feature was different than the `'region_url'` occassionally, although they are identical in the vast majority of rows. We decided to determine which one of these two improves the performance of the model. We tried serveral combinations, leaving only the best one in the notebook: parsing `'url'`, taking its base and target enconding it.

[50]:
```
def get_base_url(X):
    return X['url'].str.extract('//(.+)[.]craigslist[.]org')
```

[51]:
```
# Updated pipeline for url parsing
base_url_target_encode_pl = make_pipeline(FunctionTransformer(get_base_url), ce.
 ↪TargetEncoder(), StandardScaler())

# Using url instead of region_url and Target Enconding it
preprocessor = make_column_transformer(
    (base_url_target_encode_pl, ['url']),
    (median_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Base URL parsing')
```

```
Base URL parsing Ridge regression score: 0.417483
(Baseline Ridge regression score: 0.417438)
```

Result: After trying several combinations, the best improvement is by parsing the url, and using target encoding. This yields a **very small improvement** over the baseline Ridge score.

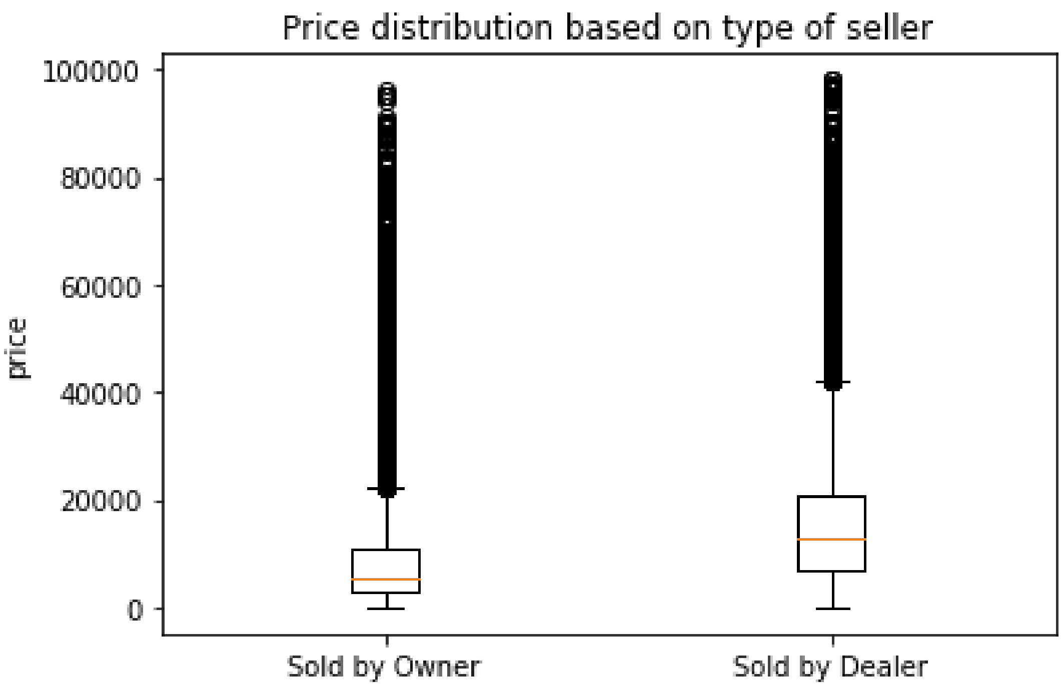
Idea: Adding `'is_ctd'` feature, parsed from the URL

We noticed the presence of '/cto/' and '/ctd/' in the craigslist URLs, which after some research, indicates whether this is an 'owner' listing (cto) or a dealer listing (ctd). We suspect that dealer listings may have a higher price on average, and thus may be useful to the model.

First, we will parse out this new feature and use a box plot to see if there's a trend:

[52]:
```
ctd_values = raw_features['url'].str.contains('/ctd/')

is_ctd_targets = y_train[ctd_values]
is_not_ctd_targets = y_train[~ctd_values]

fig, ax = plt.subplots()
ax.set_title('Price distribution based on type of seller')
```

```
ax.boxplot([is_not_ctd_targets, is_ctd_targets])
ax.set_xticklabels(['Sold by Owner', 'Sold by Dealer'])
plt.ylabel('price');
```



Looking at these distributions, we can see that there's a clear trend. The cars sold by dealers are more expensive than the ones sold by owners.

Next we will test our model by including this binary variable to the dataset:

[53]:
```
def get_ctd_feature(X):
    return X['url'].str.contains('/ctd/').to_frame()
```

[54]:
```
ctd_parser = FunctionTransformer(get_ctd_feature)

# Parsing CTO/CTD out of URL
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (ctd_parser, ['url']),
    (median_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
```

```
compare_to_baseline(preprocessor, 'CTD/CTO parsing')
```

```
CTD/CTO parsing Ridge regression score: 0.424344
(Baseline Ridge regression score: 0.417438)
```

Result: Adding this boolean feature to the model shows an **improvement** over the baseline Ridge score.

3.5 Explore Cleaning up Manufacturer / Model features

We noticed several issues regarding the ‘manufacturer’ and ‘model’ features present in the dataset:

- A significant number of rows had missing ‘manufacturer’ features, however the correct manufacturer appears in the ‘model’ column
  - This appears to occur **consistently** for the same manufacturers (e.g. isuzu, suzuki, saab, scion, etc.)
  - When this occurs, the manufacturer does not appear in the ‘manufacturer’ feature **at all**
- Occassionally, a manufacturer name appears **misspelled** in the ‘model’ feature, and in these cases the ‘manufacturer’ feature is missing
  - Similarly, many rows contain **truncated** manufacturer names in the ‘mode’l feature (e.g. ’olet’ instead of ‘chevrolet’)
- For rows in which the ‘manufacturer’ is present, the manufacturer name does **not** appear in the ‘model’ feature

From these observations, we conclude that some pre-processing of the data has likely taken place in which known manufacturers were somehow parsed out from the ‘model’ feature. This would explain both the failure to parse misspelled manufacturers, and the same set of manufacturers consistently failing to appear in the ‘manufacturer’ feature if the list of known manufacturers was incomplete.

To address this situation, we’ve **augmented the list of *known* manufacturers**, and will impute missing ‘manufacturer’ features from the ‘model’ feature when possible. In addition, we’ve included a mapping of frequently misspelled manufacturer names to their correct spelling to improve this imputation process.

The dictionary *manufacturer_map*, constructed below, will map known manufacturers to a list of strings that we’ll infer as referring to the manufacturer (e.g. misspellings of their name).

[55]:
```
# Gather the list of existing manufacturers from the entire dataset
existing_manufacturers = raw_features['manufacturer'].dropna().unique().tolist()

# Fix existing manufacturer labels for correctness and consistency
existing_manufacturers[existing_manufacturers.index('porche')] = 'porsche'
existing_manufacturers[existing_manufacturers.index('land rover')] =␣
 ↪'land-rover'

"""
Missing manufacturers
This is a list of manufacturers that appear frequently in the 'model' feature,
```

```python
    but NEVER appear in the 'manufacturer' feature
We're assuming these were not included in the list of known manufacturers when this data was originally processed
"""
missing_manufacturers = [
    'am-general', 'amc', 'austin-healey', 'bentley', 'bluebird', 'cummins', 'freightliner', 'genesis', 'geo', 'hino',
    'international', 'isuzu', 'kawasaki', 'kenworth', 'lamborghini', 'lotus', 'mack', 'maserati', 'mg', 'oldsmobile',
    'packard', 'peterbilt', 'plymouth', 'polaris', 'rolls-royce', 'saab', 'scion', 'smart', 'sterling', 'studebaker',
    'suzuki', 'triumph', 'willys', 'yamaha']

# Combine these lists
all_manufacturers = existing_manufacturers + missing_manufacturers
all_manufacturers.sort()

# Create a dictionary of manufacturer -> strings that refer to them
manufacturer_map = {m:[m] for m in all_manufacturers}   # Every manufacturer will contain at least their correct name

# For manufactuer names with a hyphen, add entry with space instead
for man, strings in manufacturer_map.items():
    if '-' in man:
        strings.append(man.replace('-', ' '))

# Add common misspellings, truncated names, and other aliases
manufacturer_map['bluebird'].append('blue bird')
manufacturer_map['cadillac'].append('caddilac')
manufacturer_map['chevrolet'].extend(['chevorlet', 'cheverolet', 'chevolet', 'chevy', 'olet'])
manufacturer_map['chrysler'].append('chysler')
manufacturer_map['mercedes-benz'].extend(['benz', 'mercedes', 'mercedez'])
manufacturer_map['nissan'].append('n')    # Frequently truncated to 'n'
manufacturer_map['oldsmobile'].append('olds')
manufacturer_map['peterbilt'].append('peterbuilt')
manufacturer_map['hyundai'].extend(['hyndai', 'huyndai', 'hyundia', 'ai'])
manufacturer_map['porsche'].append('porche')
manufacturer_map['subaru'].append('suburu')
manufacturer_map['toyota'].extend(['toyta', 'a'])     # Frequently truncated to 'a'
manufacturer_map['volkswagen'].extend(['volkswagon', 'volkwagen'])
```

As mentioned earlier, there is a LOT of variation in the 'model' feature, so much so that we couldn't include it in our baseline model without heavy cleanup.
The first part of cleaning up the 'model' feature will be simple string normalization:

```
[56]: def normalize_model_strings(X):
    # Assume input is a Pandas Series of model strings
    # Return a Series of normalized strings

    # Convert everything to lowercase
    X = X.str.lower()

    # Replace any character that is not a letter, number, dash or space with a␣
↪space
    X = X.str.replace('[^-a-z0-9 ]', ' ')

    # Collapse runs of multiple spaces into a single space
    X = X.str.replace(' +', ' ')

    # Strip any whitespace from the ends of the strings
    X = X.str.strip()

    # Return the normalized strings
    return X
```

The following method cleans up both the 'manufacturer' and 'model' features for this dataset. It does this by:

- Correcting errors and inconsistencies in the original parsing of manufacturer names
- Imputing missing 'manufacturer' values from the 'model' values, using the expanded list of known manufacturers and their frequent misspellings
- Restricting the 'model' values to only their **first word** (after normalization and manufacturer parsing), to construct a reasonable set of distinct values
  - We also append the parsed out manufacturer name (if available) to distinguish between common models / garbage data

```
[57]: def clean_manufacturer_model(X):
    """
    Assume X is a Pandas DataFrame with at least 'manufacturer' and 'model'␣
↪columns
    Return a DataFrame with cleaned up and imputed values in these same columns
    """

    # We'll operate on a copy of the input
    X = X.copy()

    # Fix existing manufacturer parsing
    X['manufacturer'].replace(['porche', 'land rover'], ['porsche',␣
↪'land-rover'], inplace=True)

    # Normalize model strings
    X['model'] = normalize_model_strings(X['model'])
```

```
# Impute missing manufacturers from the values in the 'model' column:
# Get a selection of rows with missing manufacturers
missing_manu = X.loc[X['manufacturer'].isna(), :].copy()

# For each string in our manufacturer -> strings mapping...
for manufacturer, strings in manufacturer_map.items():
    for string in strings:
        """
        Try to find the string at the beginning of the 'model' values,␣
↪skipping over any non-alpha characters
        The manufacturer string must be separated from the rest of the␣
↪model by some non-alpha character
        If found, extract the portion of the 'model' string after the␣
↪manufacturer name
        """
        manu_substring = missing_manu['model'].str.
↪extract('^[^a-z]*'+string+'([^a-z].*)', expand=False)

        # For all rows in which the find was successful, fill in the␣
↪current value in the 'manufacturer' column
        missing_manu.loc[manu_substring.notna(), 'manufacturer'] =␣
↪manufacturer

        # Also strip the manufacturer name (and any leading characters)␣
↪from the 'model' values,
        #     since it has been successfully parsed out
        missing_manu['model'].mask(manu_substring.notna(), manu_substring,␣
↪inplace=True)

"""
Repeat the process, getting a little more agressive in our search
Now, we won't require a non-alpha character to separate the manufacturer␣
↪from the model.
This should allow us to correctly parse out the manufacturer from model␣
↪strings like 'FordF150'
We'll only impute manufacturers that are still missing from the previous␣
↪step,
    and we won't do this for really short strings
"""
for manufacturer, strings in manufacturer_map.items():
    for string in strings:
        # Don't perform the agressive search if the string is too short␣
↪(not precise enough)
        if len(string) > 2:
            # Same as above, but not requiring a non-alpha character␣
↪between manufacturer and model
```

```
                manu_substring = missing_manu['model'].str.
↪extract('^[^a-z]*'+string+'(.*)', expand=False)
                # Only update manufacturers that are still empty (i.e. don't␣
↪overwrite the previous step's values)
                missing_manu.loc[
                    missing_manu['manufacturer'].isna() & manu_substring.
↪notna(), 'manufacturer'] = manufacturer
                # Updating the model value is the same
                missing_manu['model'].mask(manu_substring.notna(),␣
↪manu_substring, inplace=True)

    # Have our input (copy) take the updated values we just found
    X.update(missing_manu)

    # Discretize model strings by only considering the first word
    # Remove any whitespace potentially left over from manufacturer parsing
    X['model'] = X['model'].str.strip()
    # Remove any hyphens to improve consistency of model designations (e.g.␣
↪Honda CR-V vs CRV)
    X['model'] = X['model'].str.replace('-', '', regex=False)
    # Extract just the first word of the model string
    X['model'] = X['model'].str.extract('^([^ ]+)', expand=False)

    # Append the manufacturer name to model string, if available
    manu_space = X['manufacturer']+' '
    X['model'] = manu_space.mask(manu_space.isna(), '').str.cat(X['model'])

    # Return the cleaned up dataframe
    return X
```

Now we can try a model using cleaned up versions of the ‘manufacturer’ and ‘model’ features:

[58]:
```
# Construct a transformer that calls the clean_manufacturer_model() method
# Note that this must be called with BOTH the manufacturer and model columns
man_model_cleaner = FunctionTransformer(clean_manufacturer_model)

"""
We need BOTH the 'manufacturer' and 'model' features to properly clean up /␣
↪impute either of them.
However, after their clean up, we'll want to continue to process the columns␣
↪differently.

We'll use two separate pipelines to accomplish this, both of which extract only
    the column they need for further pre-processing.
"""
manufacturer_pl = make_pipeline(
    man_model_cleaner, FunctionTransformer(
```

```
        lambda X: X[['manufacturer']]), SimpleImputer(strategy='constant'),␣
↪OneHotEncoder(handle_unknown='ignore'))

model_pl = make_pipeline(
    man_model_cleaner, FunctionTransformer(lambda X: X[['model']]), ce.
↪TargetEncoder(), StandardScaler())

# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_scale_pl, ['year', 'odometer']),
    (manufacturer_pl, ['manufacturer', 'model']),   # Must pass BOTH columns,␣
↪but only encodes 'manufacturer'
    (model_pl, ['manufacturer', 'model']),          # Must pass BOTH columns,␣
↪but only encodes 'model'
    (new_cat_ohe_pl, ['cylinders', 'drive', 'size', 'type', 'paint_color',␣
↪'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Cleaned Manufacturer/Model')
```

```
Cleaned Manufacturer/Model Ridge regression score: 0.500348
(Baseline Ridge regression score: 0.417438)
```

Result: Cleaning up and imputing the manufacturer and model features made a **significant improvement** over the baseline Ridge score

---

3.6 Explore adding Feature Interactions

We're going to explore adding feature interactions between the 'year' and 'odometer' features. Intuitively this sounds promising, since there is a tradeoff between the age and mileage of a vehicle which regard to its value.

Idea: Add the **polynomial interactions** between 'year' and 'odometer' as new features.

[59]:
```
from sklearn.preprocessing import PolynomialFeatures

# Make a new pipeline for including the interactions between two continuous␣
↪features
median_poly_scale_pl = make_pipeline(SimpleImputer(strategy='median'),␣
↪PolynomialFeatures(), StandardScaler())

# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
```

```
    (median_poly_scale_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Year/Odometer Interactions')
```

```
Year/Odometer Interactions Ridge regression score: 0.509643
(Baseline Ridge regression score: 0.417438)
```

Result: This resulted in a **significant improvement** over the baseline Ridge score

---

Idea: Previously, we found that binning the 'year' and 'odometer' features improved our results. Now we'll try adding the **interactions between the binned results**, combining two ideas that both improved the score individually.

[60]:
```
from sklearn.feature_selection import VarianceThreshold

# Make a new pipeline for including the interactions between two binned features
# We'll use the best n_bins obtained from previous GridSearchCV
# Include a VarianceThreshold object to remove the constant (0) features created
# via interactions of one-hot encoded columns.
median_bin_poly_pl = make_pipeline(SimpleImputer(strategy='median'),␣
 ↪KBinsDiscretizer(
        n_bins=best_n_bins_pl, encode='onehot-dense'), PolynomialFeatures(),␣
 ↪VarianceThreshold())

# Try this updated preprocessing
preprocessor = make_column_transformer(
    (target_encode_pl, ['region_url']),
    (median_bin_poly_pl, ['year', 'odometer']),
    (new_cat_ohe_pl, ['manufacturer', 'cylinders', 'drive', 'size', 'type',␣
 ↪'paint_color', 'state']),
    (impute_good_ord_enc_scale_pl, ['condition']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing the baseline
compare_to_baseline(preprocessor, 'Year/Odometer Binned Interactions')
```

```
Year/Odometer Binned Interactions Ridge regression score: 0.618909
(Baseline Ridge regression score: 0.417438)
```

Result: Using both binning and feature interactions between the 'year' and 'odometer' features performs better than either of them individually, and yields a **big improvement** over the baseline Ridge score.

3.7 Task 3 Conclusions

We'll combine all of our ideas that performed better than the baseline score into a single preprocessing pipeline:

[61]:
```
# Try the full preprocessings combined
BEST_PREPROCESSOR = make_column_transformer(
    (base_url_target_encode_pl, ['url']),
    (ctd_parser, ['url']),
    (median_bin_poly_pl, ['year', 'odometer']),
    (manufacturer_pl, ['manufacturer', 'model']),
    (model_pl, ['manufacturer', 'model']),
    (new_cat_ohe_pl, ['condition', 'cylinders', 'drive', 'size', 'type',␣
↪'paint_color', 'state']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))

# Compare this preprocessing to the baseline
compare_to_baseline(BEST_PREPROCESSOR, 'All beneficial improvements at once')
```

```
All beneficial improvements at once Ridge regression score: 0.666816
(Baseline Ridge regression score: 0.417438)
```

Conclusion: By combining all the ideas that improved the score, we get an **almost 60% improvement** over the baseline R^2 score.

---

4 Task 4 - Any Model

- **Use any regression model we discussed to improve your result**.

For this task, we will try out 3 different models: **k-Nearest Neighbors, Random Forest, and Gradient Boosting**

4.1 K-Nearest Neighbors

[62]:
```
from sklearn.neighbors import KNeighborsRegressor

# Since KNN requires scaled data and can't handle missing values,
# we'll use the same preprocessing as we did for the linear models.

# Get a baseline score for k-Nearest Neighbors
knn_pipe = make_pipeline(BEST_PREPROCESSOR, KNeighborsRegressor(n_jobs=n_jobs))
knn_baseline_score = cross_val_score(knn_pipe, X_train, y_train, cv=shuffle).
↪mean()
print(f"Baseline score for kNN: {knn_baseline_score:.6f}")
```

```
Baseline score for kNN: 0.707095
```

Now we'll tune the number of neighbors using a grid search:
Note: After running a grid search over the number of neighbors at several ranges, we reduced the search to a smaller range to make the Notebook run a bit faster.

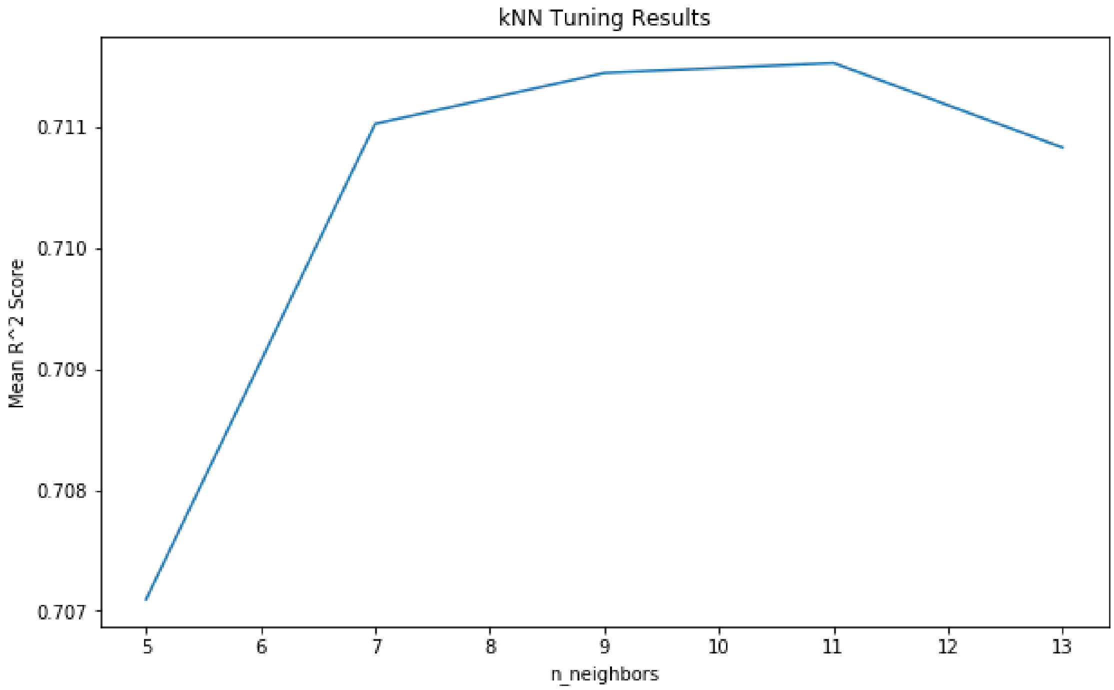
[63]:
```
param_grid = {'kneighborsregressor__n_neighbors': range(5, 15, 2)}
knn_grid = GridSearchCV(knn_pipe, param_grid=param_grid, cv=shuffle,␣
 ↪refit=False)
knn_grid.fit(X_train, y_train)

print(f"Optimized score for kNN: {knn_grid.best_score_:.6f}")
knn_tuned_n_neighbors = knn_grid.
 ↪best_params_['kneighborsregressor__n_neighbors']
print(f"Best n_neighbors: {knn_tuned_n_neighbors}")
```

```
Optimized score for kNN: 0.711528
Best n_neighbors: 11
```

The score of this model, including the hyperparameter tuning, is a **moderate improvement** over our linear regressor.

Let's plot the mean cross validation score vs. the n_neighbors parameter to see the results of the tuning:

[64]:
```
cv_results = pd.DataFrame(knn_grid.cv_results_)
plt.figure(figsize=(10, 6))
plt.plot(cv_results['param_kneighborsregressor__n_neighbors'],␣
 ↪cv_results['mean_test_score'])
plt.title('kNN Tuning Results')
plt.xlabel('n_neighbors')
plt.ylabel('Mean R^2 Score');
```



4.2 Random Forest Regressor

[65]:
```
# Since Random Forests (and trees in general) are not affected by scaling of␣
↪the data,
# we can remove the scaling steps from the best preprocessing we found in Task 3
base_url_target_encode_no_scale_pl =␣
↪make_pipeline(FunctionTransformer(get_base_url), ce.TargetEncoder())
model_no_scale_pl = make_pipeline(man_model_cleaner, FunctionTransformer(lambda␣
↪X: X[['model']]), ce.TargetEncoder())

BEST_PREPROCESSOR_NO_SCALING = make_column_transformer(
    (base_url_target_encode_no_scale_pl, ['url']),
    (ctd_parser, ['url']),
    (median_bin_poly_pl, ['year', 'odometer']),
    (manufacturer_pl, ['manufacturer', 'model']),
    (model_no_scale_pl, ['manufacturer', 'model']),
    (new_cat_ohe_pl, ['condition', 'cylinders', 'drive', 'size', 'type',␣
↪'paint_color', 'state']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))
```

[66]:
```
from sklearn.ensemble import RandomForestRegressor

# Get a baseline score for a Random Forest Regressor
rf = RandomForestRegressor(random_state=25, n_jobs=n_jobs)
```

```
rf_pipe = make_pipeline(BEST_PREPROCESSOR_NO_SCALING, rf)
rf_baseline_score = cross_val_score(rf_pipe, X_train, y_train, cv=shuffle).
 ↪mean()
print(f"Baseline score for Random Forest: {rf_baseline_score:.6f}")
```

```
Baseline score for Random Forest: 0.771385
```

Now we'll try tuning the **max__features** parameter:

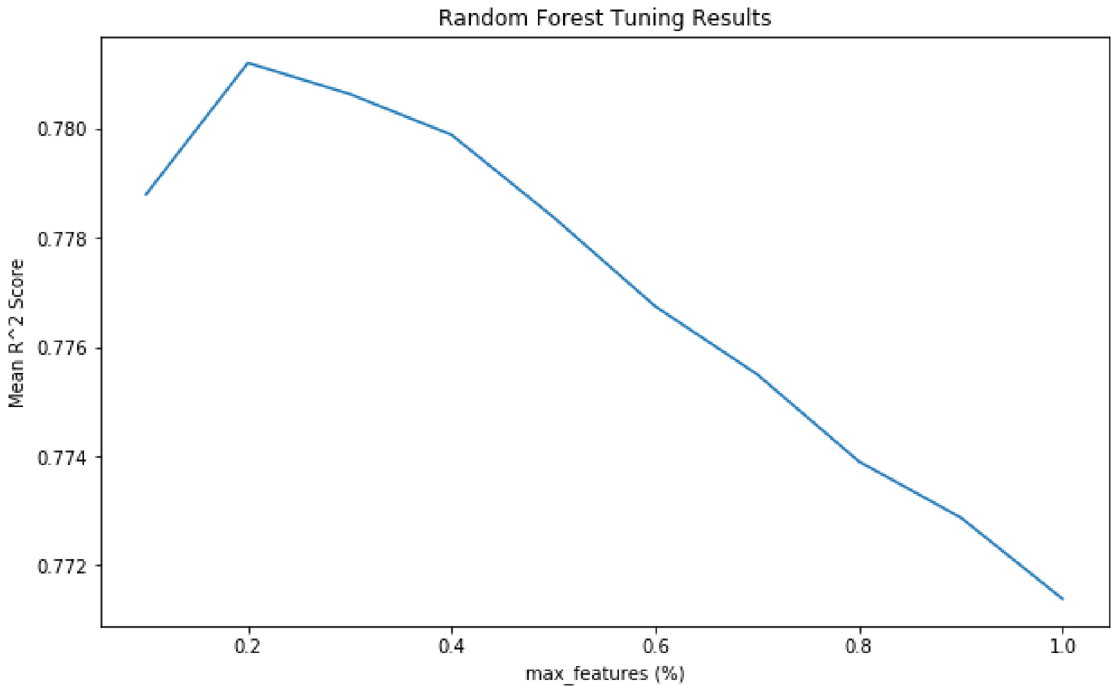
[67]:
```
param_grid = {'randomforestregressor__max_features': np.linspace(0.1, 1.0, 10)}
rf_grid = GridSearchCV(rf_pipe, param_grid, cv=shuffle, refit=False)
rf_grid.fit(X_train, y_train)

print(f"Optimized score for Random Forest: {rf_grid.best_score_:.6f}")
rf_tuned_max_features = rf_grid.
 ↪best_params_['randomforestregressor__max_features']
print(f"Best max_features: {rf_tuned_max_features}")
```

```
Optimized score for Random Forest: 0.781206
Best max_features: 0.2
```

This best score is **much better** than the results we achieved using the linear models in Tasks 2 and 3 using the same cross validation.

Let's plot the mean cross validation score vs. the max_features parameter to see the results of the tuning:

[68]:
```
cv_results = pd.DataFrame(rf_grid.cv_results_)
plt.figure(figsize=(10, 6))
plt.plot(cv_results['param_randomforestregressor__max_features'],␣
 ↪cv_results['mean_test_score'])
plt.title('Random Forest Tuning Results')
plt.xlabel('max_features (%)')
plt.ylabel('Mean R^2 Score');
```



Using the best 'max_features' parameter we found in our grid search, we can get an estimate on how well the RandomForestRegressor model will perform when trained on the entire training set by looking at the '**Out-of-Bag**' score:

[69]:
```
best_max_features = rf_grid.best_params_['randomforestregressor__max_features']
rf = RandomForestRegressor(
    n_estimators=100, max_features=best_max_features, oob_score=True,␣
 ↪n_jobs=n_jobs, random_state=25, warm_start=True)
rf_pipe = make_pipeline(BEST_PREPROCESSOR_NO_SCALING, rf)
rf_pipe.fit(X_train, y_train)
print(f"Tuned Random Forest OOB score: {rf_pipe.
 ↪named_steps['randomforestregressor'].oob_score_:.6f}")
```

```
Tuned Random Forest OOB score: 0.868018
```

While we can't compare the R^2 score of 0.868 to the sampled cross validation scores (since it is trained on much more data), this should give us a rough estimate of how well the Random Forest will perform on the test data (when using all of the training data).

Finally, we want to make sure the **number of trees** we're using is sufficient (knowing that more trees is always better).
We'll try **doubling the number of trees** to 200 and see what sort of improvement that has on the OOB score.
Since we used '**warm_start**', this should only have to add 100 trees to the existing model:

[70]:
```
rf_pipe.set_params(randomforestregressor__n_estimators=200)
rf_pipe.fit(X_train, y_train)
print(f"Tuned Random Forest OOB score (w/200 trees): {rf_pipe.
↪named_steps['randomforestregressor'].oob_score_:.6f}")
```

```
Tuned Random Forest OOB score (w/200 trees): 0.869988
```

Doubling the number of trees only had a **minor impact on the OOB score**, from which we can conclude that around 100-200 trees are sufficient to get the best results from Random Forest on this data set.

4.3 Histogram Gradient Boosting

Note: when trying to make this regressor work, we found that hyperparameter tuning is **very** slow using GridSearch. We tried many different combinations, but we ended up with a tradeoff between speed and performance in order to be able to keep working and not waiting hours to this to be optimized.

The HistGradientBoostingRegressor class **handles missing values** natively. Therefore, we'll **remove imputation** (when possible) from our preprocessing pipeline. (Some preprocessing like binning and one-hot encoding still require imputation.)

And since the model is tree-based, we also don't need to perform **scaling** in our preprocessing either.

[71]:
```
base_url_target_encode_leave_missing_no_scale_pl = make_pipeline(
    FunctionTransformer(get_base_url), ce.
↪TargetEncoder(handle_missing='return_nan'))

model_leave_missing_no_scale_pl = make_pipeline(
    man_model_cleaner, FunctionTransformer(lambda X: X[['model']]), ce.
↪TargetEncoder(handle_missing='return_nan'))

BEST_PREPROCESSOR_LEAVE_MISSING_NO_SCALING = make_column_transformer(
    (base_url_target_encode_leave_missing_no_scale_pl, ['url']),
    (ctd_parser, ['url']),
    (median_bin_poly_pl, ['year', 'odometer']),
    (manufacturer_pl, ['manufacturer', 'model']),
    (model_leave_missing_no_scale_pl, ['manufacturer', 'model']),
    (new_cat_ohe_pl, ['condition', 'cylinders', 'drive', 'size', 'type',␣
↪'paint_color', 'state']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission']))
```

[72]:
```
from sklearn.experimental import enable_hist_gradient_boosting
from sklearn.ensemble import HistGradientBoostingRegressor

# Get a baseline score for a Histogram Gradient Boosting Regressor
hgb_pipe = make_pipeline(
```

```
    BEST_PREPROCESSOR_LEAVE_MISSING_NO_SCALING,␣
↪HistGradientBoostingRegressor(random_state=25))
hgb_baseline_score = cross_val_score(hgb_pipe, X_train, y_train, cv=shuffle).
↪mean()
print(f"Baseline score for HistGradientBoosting: {hgb_baseline_score:.6f}")
```

```
Baseline score for HistGradientBoosting: 0.750230
```

Now we'll try tuning the **learning_rate** parameter:

[73]:
```
# Params optimization
# param_grid = {'histgradientboostingregressor__learning_rate': np.logspace(-1,␣
↪0, 5)}  # Initial coarse grid search
param_grid = {'histgradientboostingregressor__learning_rate': np.linspace(0.1,0.
↪3,10)}  # Fine-tuning grid search
hgb_pipe = make_pipeline(
    BEST_PREPROCESSOR_LEAVE_MISSING_NO_SCALING,
    HistGradientBoostingRegressor(max_leaf_nodes=50, max_iter=500,␣
↪random_state=25))
hgb_grid = GridSearchCV(hgb_pipe, param_grid, cv=shuffle, refit=False)
hgb_grid.fit(X_train, y_train)

print(f"Optimized score for HistGradientBoosting: {hgb_grid.best_score_:.6f}")
hgb_tuned_learning_rate = hgb_grid.
↪best_params_['histgradientboostingregressor__learning_rate']
print(f"Best learning rate: {hgb_tuned_learning_rate}")
```

```
Optimized score for HistGradientBoosting: 0.788518
Best learning rate: 0.16666666666666666
```

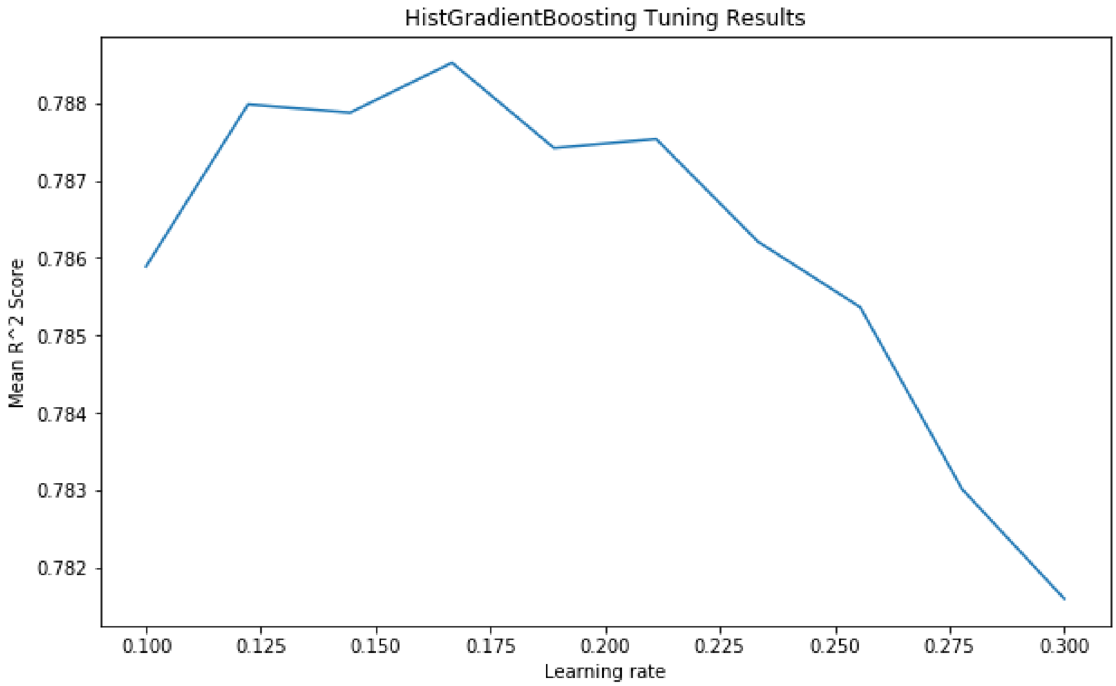
This best score is **much better** than the results we achieved using the linear models in Tasks 2 and 3 using the same cross validation, and quite close to the best score achieved by Random Forest above.

One of the parameters we tried to optimize was `max_leaf_nodes` and it continued to improve when we increased it. We moved it up to 200 and it kept improving (about 0.788), but the computation time was too large. Also we tried increasing `max_iter` up to 300. Grid searching using `max_leaf_nodes = 100` and `max_iter = 300` our score went up to 0.78, but the running time was over an hour only for the grid search itself.

Let's plot the mean cross validation score vs. the max_features parameter to see the results of the tuning:

[74]:
```
cv_results = pd.DataFrame(hgb_grid.cv_results_)
plt.figure(figsize=(10, 6))
plt.plot(cv_results['param_histgradientboostingregressor__learning_rate'],␣
↪cv_results['mean_test_score'])
plt.title('HistGradientBoosting Tuning Results')
plt.xlabel('Learning rate')
```

```
plt.ylabel('Mean R^2 Score');
```



4.4 Conclusions

- All of these models performed better than the linear models initially used, even before tuning their hyperparameters.
- Among the three, both **Random Forest** and **Histogram Gradient Boosting** performed significantly better than k-Nearest Neighbors.
- Random Forest performed very well prior to any tuning, and the increase in performance from tuning was modest.
- Histogram Gradient Boosting performed slightly worse than Random Forest during the baseline test, but achieved a slightly higher CV score after careful tuning.

The cross validation splits used to compare these models heavily sub-sample the training data in order to decrease the training times. To decide which of these two models is the best, it would help to compare their cross validation scores on a **larger sample of training data** via a traditional k-Fold CV:

[75]:
```
tuned_rf_pipe = make_pipeline(
    BEST_PREPROCESSOR_NO_SCALING,
    RandomForestRegressor(max_features=rf_tuned_max_features, random_state=25,␣
 ↪n_jobs=n_jobs))
tuned_rf_score = cross_val_score(tuned_rf_pipe, X_train, y_train, cv=5).mean()
print(f"Tuned Random Forest Score: {tuned_rf_score:.6f}")
```

```
Tuned Random Forest Score: 0.858657
```

[76]:
```
tuned_hgb_pipe = make_pipeline(
    BEST_PREPROCESSOR_LEAVE_MISSING_NO_SCALING,
    HistGradientBoostingRegressor(
        learning_rate=hgb_tuned_learning_rate, max_leaf_nodes=50, max_iter=500,␣
 ↪random_state=25))
tuned_hgb_score = cross_val_score(tuned_hgb_pipe, X_train, y_train, cv=5).mean()
print(f"Tuned HGB Score: {tuned_hgb_score:.6f}")
```

```
Tuned HGB Score: 0.836067
```

As expected, both of these scores are **significantly higher** than those achieved when the models were trained on less data.

Based on these final results, we're going to predict that **Random Forest** will generalize the best on new data.

Finally, we can evaluate our best model on the **test data**, after re-training it using the entire training dataset:

[77]:
```
BEST_MODEL = tuned_rf_pipe
BEST_MODEL.fit(X_train, y_train)
best_score = BEST_MODEL.score(X_test, y_test)
print(f"Best Model Test Score: {best_score:.6f}")
```

```
Best Model Test Score: 0.868862
```

---

5 Task 5 - Feature Selections

- **Identify features that are important for your best model.**

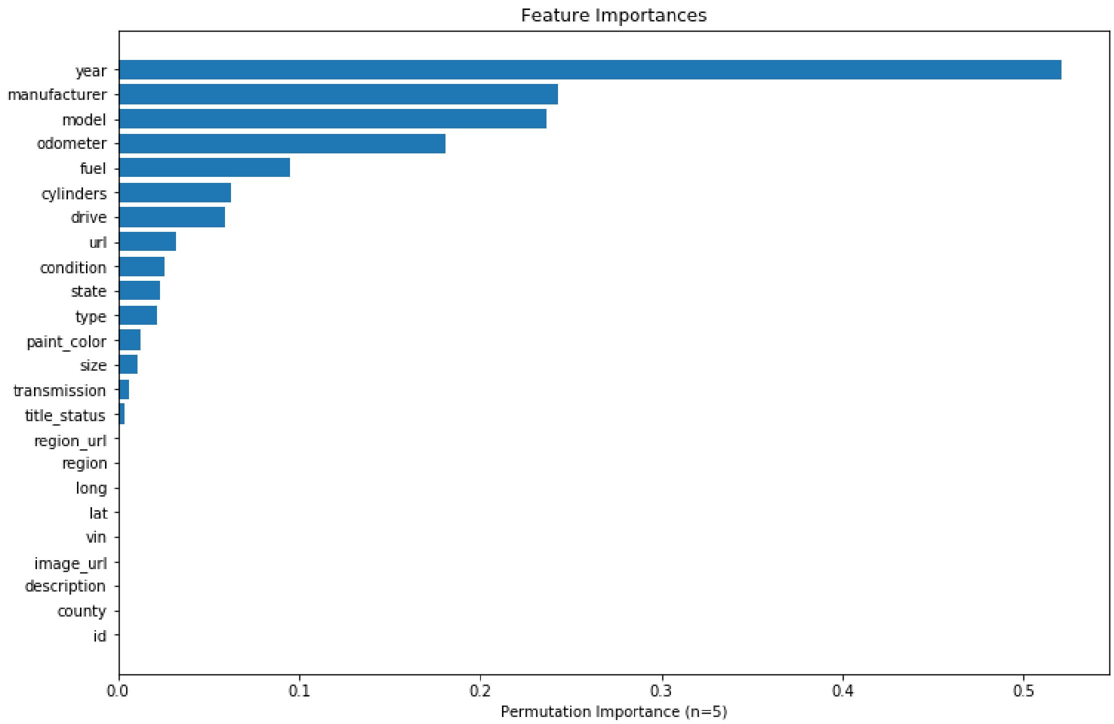
We'll use the **Permutation Importance** on the test data set to measure feature importances:

[78]:
```
from sklearn.inspection import permutation_importance

perm_results = permutation_importance(BEST_MODEL, X_test, y_test,␣
 ↪random_state=25)
```

We'll visualize these feature importances for easy reference:

[79]:
```
features = X_test.columns.tolist()
n_features = len(features)

importances = perm_results['importances_mean']
sort_idx = np.argsort(importances)
features_by_importance = np.array(features)[sort_idx]

fig,ax = plt.subplots(figsize=(12, 8))
ax.barh(range(n_features), importances[sort_idx], align='center')
```

```
ax.set_yticks(range(n_features))
ax.set_yticklabels(features_by_importance)
ax.set_xlabel('Permutation Importance (n=5)')
ax.set_title('Feature Importances');
```



- **Which features are most influential?**

These results suggest that the **year, manufacturer, model, and odometer** of a vehicle are the most important features to our pricing model, and this agrees with our intuition about how cars are typically valued.

As expected, the features not included in our preprocessing pipeline (e.g. vin, image_url, county, etc.) have a permutation importance of 0.

- **Which features could be removed without a decrease in performance?**

To answer this question, we'll **remove subsets of features in order of their permuation importance** as shown above, refit the model, and compare the results to a baseline score that includes all of the features.

[80]:
```
# Generate a baseline score against which we'll compare the models with various␣
↪features removed
tuned_rf_pipe = make_pipeline(BEST_PREPROCESSOR_NO_SCALING,
                                                  ␣
↪RandomForestRegressor(max_features=rf_tuned_max_features, random_state=25,␣
↪n_jobs=n_jobs))
```

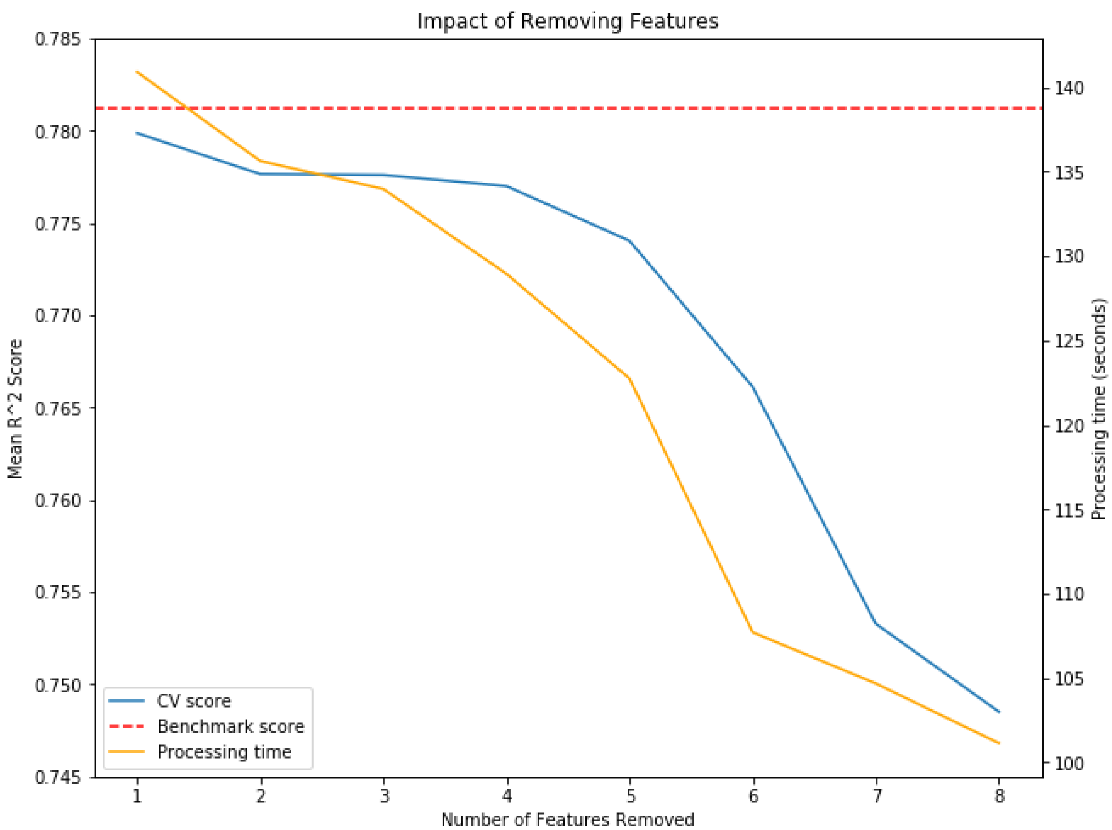
```
tuned_rf_score = cross_val_score(tuned_rf_pipe, X_train, y_train, cv=shuffle).
↪mean()
print(f"Tuned Random Forest Baseline Score: {tuned_rf_score:.6f}")
```

```
Tuned Random Forest Baseline Score: 0.781206
```

[81]:
```
from copy import deepcopy
import time

# We'll skip over the features our preprocessing drops anyway
unused_features = ['id', 'long', 'county', 'region', 'region_url',␣
↪'description', 'image_url', 'vin', 'lat']

sorted_importance = importances[sort_idx]
current_preprocessor = deepcopy(BEST_PREPROCESSOR_NO_SCALING)
mean_scores = []
last_removed_feature = []
processing_times = []

# For each feature sorted by increasing permutation importance...
for i, feature in enumerate(features_by_importance):
    if i > 16:
        # We'll only try removing so many features
        break
    if feature in unused_features:
        continue

    last_removed_feature.append(feature)

    # Remove this feature from our preprocessing
    for transformer in current_preprocessor.transformers:
        if feature in transformer[2]:
            transformer[2].remove(feature)

    # Re-score the model with the feature removed
    current_rf_pipe = make_pipeline(current_preprocessor,
                                    ␣
↪RandomForestRegressor(max_features=rf_tuned_max_features, random_state=25,␣
↪n_jobs=n_jobs))
    start_time = time.time()
    current_rf_score = cross_val_score(current_rf_pipe, X_train, y_train,␣
↪cv=shuffle).mean()
    mean_scores.append(current_rf_score)
    processing_times.append(time.time() - start_time)
```

Plot how the CV score was affected by removing various numbers of features:

[82]:
```
fig, ax = plt.subplots(figsize=(10, 8))

ax.plot(mean_scores, label='CV score')
ax.set_xticklabels(range(len(last_removed_feature) + 1))
ax.set_xlabel('Number of Features Removed')
ax.set_ylabel('Mean R^2 Score')
ax.axhline(y=tuned_rf_score, color='r', linestyle='--', label='Benchmark score')
ax.set_ylim(0.745, 0.785)

ax2 = ax.twinx()
ax2.plot(processing_times, color='orange', label='Processing time')
ax2.set_ylabel('Processing time (seconds)')

ax.set_title('Impact of Removing Features')

# ask matplotlib for the plotted objects and their labels
lines, labels = ax.get_legend_handles_labels()
lines2, labels2 = ax2.get_legend_handles_labels()
ax2.legend(lines + lines2, labels + labels2, loc=3);
```



From the plot above, we can see the following:

- Each feature removal decreases the score relative to the baseline, first with lesser impact, then with greater impact as more features are removed
- Processing times also are reduced, showing that there's a benefit in removing features
- In the end, we consider that removing **up to 3 features** could be acceptable, without a significant decrease in this scoring metric

- **Does removing irrelevant features make your model better?**

The answer to this question depends heavily on one's iterpretation of 'better'. Removing the least important features may not result in an increased score, but it does provide other tangible benefits:

- The training (and testing) time for the model decreased when using fewer features
- The size of the model (and possibly the dataset) should be smaller, requiring less memory/disk space
- The model is more interpretable with a fewer number of influential features to explain

---

6 Task 6 - Explanable Model

- **Can you create an "explainable" model that is nearly as good as your best model?**

We'll try to create both an explainable **Decision Tree** with relatively few leaf nodes, and a **linear model** with relatively few coefficients, and compare them to the results of our best model.

For a model to truly be 'explainable', one must understand **exactly which features** are being used, and how. After complex preprocessing like we've been performing, the feature matrix being passed into the model bears little resemblance to the original features from the dataset. To help us comprehend the results of the following 'explainable model' tests, we first wrote a method to extract **identifiable feature names** from a complex preprocessing pipeline.

[83]:
```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import inspect

def feature_names(obj, incoming_names=None):
    """Returns an array of feature names resulting from the supplied␣
↪transformer object (obj)
        calling .transform() on a feature matrix with the supplied original␣
↪feature names (incoming_names).
    For objects containing 'sub-transformers' (like Pipelines and␣
↪ColumnTransformers), recursively
        calls feature_names() on the sub-transformers and aggregates the␣
↪results as appropriate.
    Incoming_names can be left as None if the transformer object is a␣
↪ColumnTransformer with column names
        supplied with each tuple.

    NOTE: This is currently a FRAGILE implementation that only handles the␣
↪conditions encountered in the
```

```
        preprocessing we use in this notebook.
    """

    # Prepare to return our output names
    output_names = None

    # ColumnTransformer
    if isinstance(obj, ColumnTransformer):
        # Append the feature names resulting from each sub-transformer
        output_names = []
        for name, transformer, cols in obj.transformers_:
            # Recursively call feature_names()
            output_names.extend(feature_names(transformer, cols))

    # Pipeline
    elif isinstance(obj, Pipeline):
        # The feature names are transformed by each step of the Pipeline in␣
↪sequence
        next_names = incoming_names
        for name, transformer in obj.named_steps.items():
            # The names output from one step are the input to the next step
            next_names = feature_names(transformer, next_names)

        # Return the final transformed names
        output_names = next_names

    # FunctionTransformer
    elif isinstance(obj, FunctionTransformer):
        # Determine which function is being called
        func = obj.get_params()['func']
        func_name = func.__name__
        if func_name == (lambda: None).__name__:
            # This is a lambda function
            # Get the source of the lambda to try to guess what the output␣
↪column is going to be
            lambda_source = inspect.getsource(func)
            if 'manufacturer' in lambda_source:
                output_names = ['manufacturer']
            elif 'model' in lambda_source:
                output_names = ['model']
            else:
                output_names = [f"{func_name}({','.join(incoming_names)})"]

        elif func_name == 'clean_manufacturer_model':
            # We know what columns this function returns
            output_names = ['manufacturer', 'model']
```

```
        else:
            # Unknown output, just describe the function call
            output_names = [f"{func_name}({','.join(incoming_names)})"]

    # StandardScaler
    elif isinstance(obj, StandardScaler):
        # Feature names remain the same
        output_names = incoming_names

    # SimpleImputer
    elif isinstance(obj, SimpleImputer):
        # Feature names remain the same
        output_names = incoming_names

    # TargetEncoder
    elif isinstance(obj, ce.TargetEncoder):
        # Just append a string indicating the target encoding for each incoming␣
↪name
        output_names  = [name+' (avg price)' for name in incoming_names]

    # OrdinalEncoder
    elif isinstance(obj, OrdinalEncoder):
        # Just append a string indicating the ordinal encoding for each␣
↪incoming name
        output_names  = [name+' (ordinal)' for name in incoming_names]

    # OneHotEncoder
    elif isinstance(obj, OneHotEncoder):
        output_names = []
        # For each output feature...
        for feat_name in obj.get_feature_names():
            # Make this feature name more understandable
            feat_name = feat_name[1:]   # Strip off leading 'x'

            # Separate the feature index from the value
            under_idx = feat_name.index('_')
            feat_idx = int(feat_name[:under_idx])
            value = feat_name[under_idx+1:]

            # Generate a nicer description of this feature
            output_names.append(f'{incoming_names[feat_idx]}[{value}]')

    # KBinsDiscretizer
    elif isinstance(obj, KBinsDiscretizer):
        # The features coutput depend on the 'encode' parameter
        encoding = obj.get_params()['encode']
        if encoding == 'ordinal':
```

```
            # Append a string to indicate the bin number is used
            output_names  = [name+' (bin #)' for name in incoming_names]
        else:
            # One-Hot encoding
            # Output 'feat[bin]' each incoming feature, for each bin of that␣
↪feature
            output_names = [
                f'{feat}[bin {i}]' for feat, n_bins in zip(incoming_names, obj.
↪n_bins_) for i in range(n_bins)]

    # PolynomialFeatures
    elif isinstance(obj, PolynomialFeatures):
        output_names = []
        # For each output feature...
        for feat_name in obj.get_feature_names():
            # Make this feature name more understandable word by word
            new_feat_words = []
            for feat_word in feat_name.split():
                if feat_word.startswith('x'):
                    # Replace x# with the corresponding incoming feature name

                    # Strip off any power suffix
                    if '^' in feat_word:
                        caret_idx = feat_word.index('^')
                        suffix = feat_word[caret_idx:]
                        feat_word = feat_word[:caret_idx]
                    else:
                        suffix = ''

                    feat_idx = int(feat_word[1:])  # Ignore the leading 'x'
                    new_word = incoming_names[feat_idx] + suffix
                else:
                    # This is not a variable name (e.g. '1')
                    new_word = feat_word

                # Add this updated word to our list
                new_feat_words.append(new_word)

            # Combine words with '*' to indicate multiplication
            output_names.append(' * '.join(new_feat_words))

    # VarianceThreshold
    elif isinstance(obj, VarianceThreshold):
        # Return only the selected features
        output_names = np.array(incoming_names)[obj.get_support()]

    # Strings
```

```
    elif isinstance(obj, str):
        if obj=='drop':
            output_names = []    # Nothing output
        elif obj=='passthrough':
            output_names = incoming_names
        else:
            raise NotImplementedError('Unhandled string: ' + obj)

    else:
        raise NotImplementedError('Unhandled object type: ' + str(type(obj)))

    # Make sure we defined output_names
    assert output_names is not None, 'output_names was never defined!'

    # Return the list of resulting feature names
    return output_names
```

6.1 Decision Tree

First we'll build a single Decision Tree using the same preprocessing we used for Random Forest, but we'll **limit the number of leaf nodes** the tree can use to ensure it is 'explainable'.

We think a tree with about **10** leaf nodes is easily comprehended.

[84]:
```
from sklearn.tree import DecisionTreeRegressor

# Get a baseline score for a Decision Tree Regressor with max_leaf_nodes␣
 ↪specified
tree = DecisionTreeRegressor(max_leaf_nodes=10, random_state=25)
tree_pipe = make_pipeline(BEST_PREPROCESSOR_NO_SCALING, tree)
tree_baseline_score = cross_val_score(tree_pipe, X_train, y_train, cv=shuffle).
 ↪mean()
print(f"Baseline score for Decision Tree: {tree_baseline_score:.6f}")
```

```
Baseline score for Decision Tree: 0.473816
```

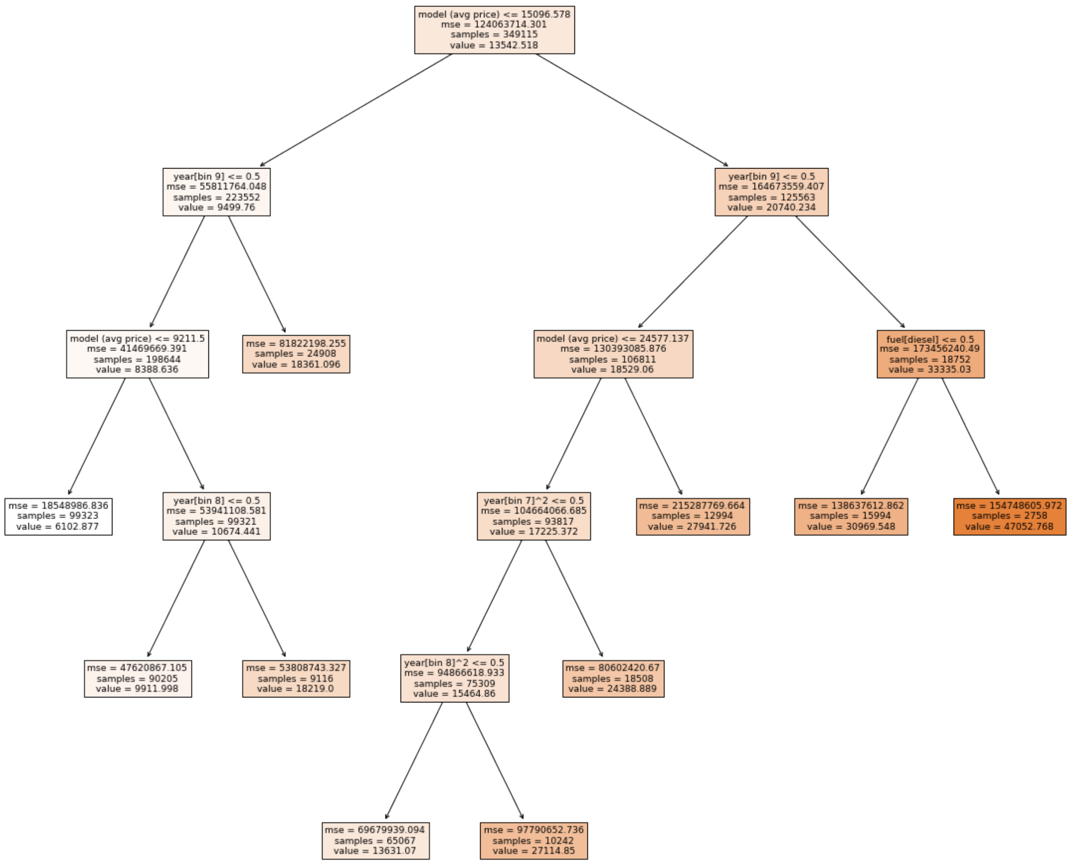
Not surprisingly, this score is **significantly worse** than what we acheived with our best models.

To understand the decisions the tree is making, let's **visualize the tree** that is constructed when trained on the entire training data:

[85]:
```
tree = DecisionTreeRegressor(max_leaf_nodes=10, random_state=25)
tree_pipe = make_pipeline(BEST_PREPROCESSOR_NO_SCALING, tree)
tree_pipe.fit(X_train, y_train);
```

[86]:
```
from sklearn.tree import plot_tree
```

```python
fix, ax = plt.subplots(figsize=(20,18))
# Use feature_names() defined above to get meaningful feature descriptions
plot_tree(tree, feature_names=feature_names(BEST_PREPROCESSOR_NO_SCALING),␣
↪filled=True, ax=ax);
```



Unfortunately, some of these **features are not easily inferred** from the dataset, or at the very least seem quite unnatural. For example, the feature 'year[bin 7]^2' is the result of binning the 'year' values, one-hot encoding the results, and squaring the 0/1 value of bin number 7. While accurate, this is not a very satisfying or intuitive explanation of how the pricing decision is being made.

Let's try a decision tree with **more natural and intuitive features**:

[87]:
```python
# Ordinal encoding the 'condition' feature is more intuitive than one-hot␣
↪encoding (since it is naturally ordered)
impute_good_ord_enc_pl = make_pipeline(
```

```
    SimpleImputer(strategy='constant', fill_value='good'),␣
↪OrdinalEncoder(categories=[conditions]))

# Binning with ordinal encoding is still quite intuitive, but we'll skip the␣
↪polynomial feature interactions.
median_bin_ordinal_enc_pl = make_pipeline(
    SimpleImputer(strategy='median'), KBinsDiscretizer(encode='ordinal',␣
↪n_bins=10))

# Target encoding the manufacturer instead of one-hot encoding avoids␣
↪inefficient, single-manufacturer splits.
manufacturer_target_no_scale_pl = make_pipeline(
    man_model_cleaner, FunctionTransformer(lambda X: X[['manufacturer']]), ce.
↪TargetEncoder())

tree_preprocessor = make_column_transformer(
    (base_url_target_encode_no_scale_pl, ['url']),
    (ctd_parser, ['url']),
    (SimpleImputer(strategy='median'), ['year']),
    (median_bin_ordinal_enc_pl, ['odometer']),
    (manufacturer_target_no_scale_pl, ['manufacturer', 'model']),
    (model_no_scale_pl, ['manufacturer', 'model']),
    (impute_good_ord_enc_pl, ['condition']),
    (new_cat_ohe_pl, ['cylinders', 'drive', 'size', 'type', 'paint_color',␣
↪'state']),
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission'])
)

exp_tree = DecisionTreeRegressor(max_leaf_nodes=10, random_state=25)
exp_tree_pipe = make_pipeline(tree_preprocessor, exp_tree)
exp_tree_score = cross_val_score(exp_tree_pipe, X_train, y_train, cv=shuffle).
↪mean()
print(f"Explainable score for Decision Tree: {exp_tree_score:.6f}")
```

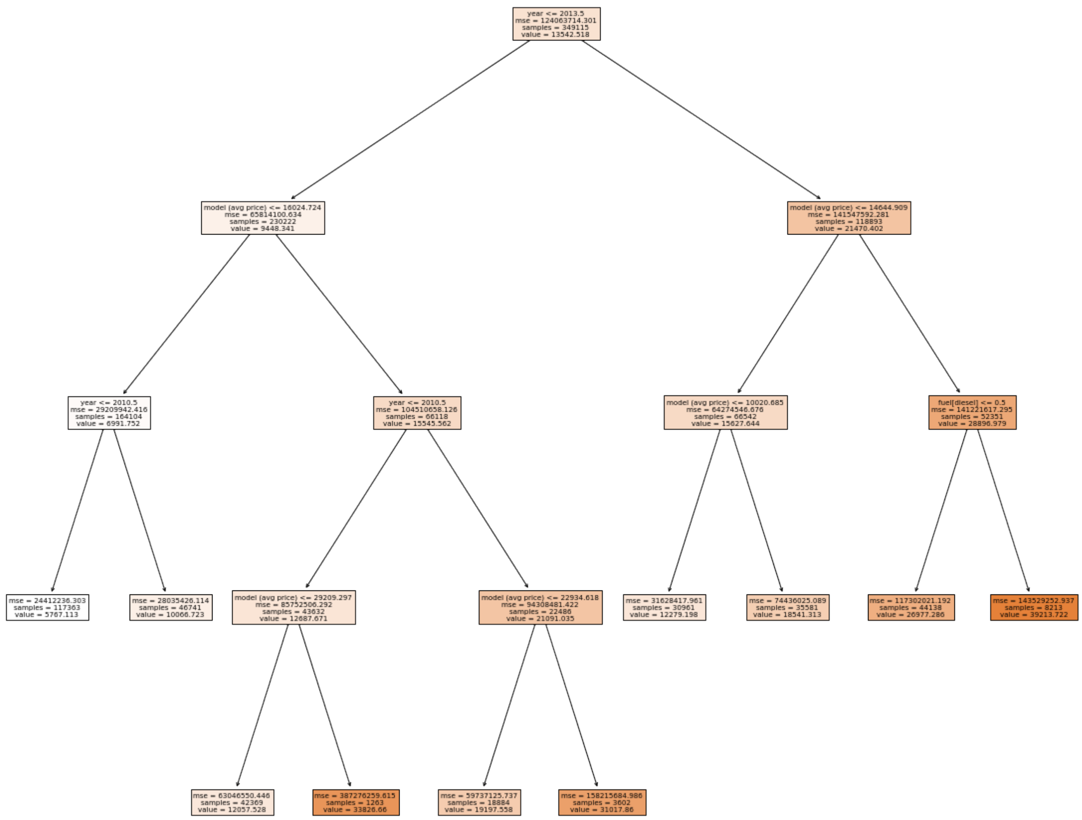
```
Explainable score for Decision Tree: 0.530580
```

The CV score for this tree with more intuitive features is actually **significantly better** than the baseline score, although still nowhere near what we acheived with our best models.

To understand the decisions the tree is making, let's **visualize the tree** that is constructed when trained on the entire training data:

[88]:
```
exp_tree = DecisionTreeRegressor(max_leaf_nodes=10, random_state=25)
exp_tree_pipe = make_pipeline(tree_preprocessor, exp_tree)
exp_tree_pipe.fit(X_train, y_train);
```

```
[89]: fix, ax = plt.subplots(figsize=(20,18))
plot_tree(exp_tree, feature_names=feature_names(tree_preprocessor),␣
 ↪filled=True, ax=ax);
```



We can see that this tree uses fairly **intuitive and natural features** to decide its splits, like the year of the vehicle, the average price of the specific model, and whether it's a diesel.

6.2 Linear Model

Next, we'll try to create an explainable linear model by **limiting the number of non-zero coefficients** it can use with **SelectFromModel()**.

We'll use **Lasso** as the feature-selecting model, and **Ridge** as the final linear model on the reduced feature set.

We think a linear model with at most **10** coefficients is easily comprehended.

First, we'll build a model with the best preprocessing we found during Task 3 (which also used Ridge):

[90]:
```
from sklearn.linear_model import LassoCV
from sklearn.feature_selection import SelectFromModel

# Get a baseline score for Ridge with Lasso-selected features
select_lassocv = SelectFromModel(LassoCV(random_state=25), max_features=10)
lasso_ridge_pipe = make_pipeline(BEST_PREPROCESSOR, select_lassocv, RidgeCV())
lasso_ridge_baseline_score = cross_val_score(lasso_ridge_pipe, X_train,␣
 ↪y_train, cv=shuffle).mean()
print(f"Baseline score for Ridge w/Lasso-selected features:␣
 ↪{lasso_ridge_baseline_score:.6f}")
```

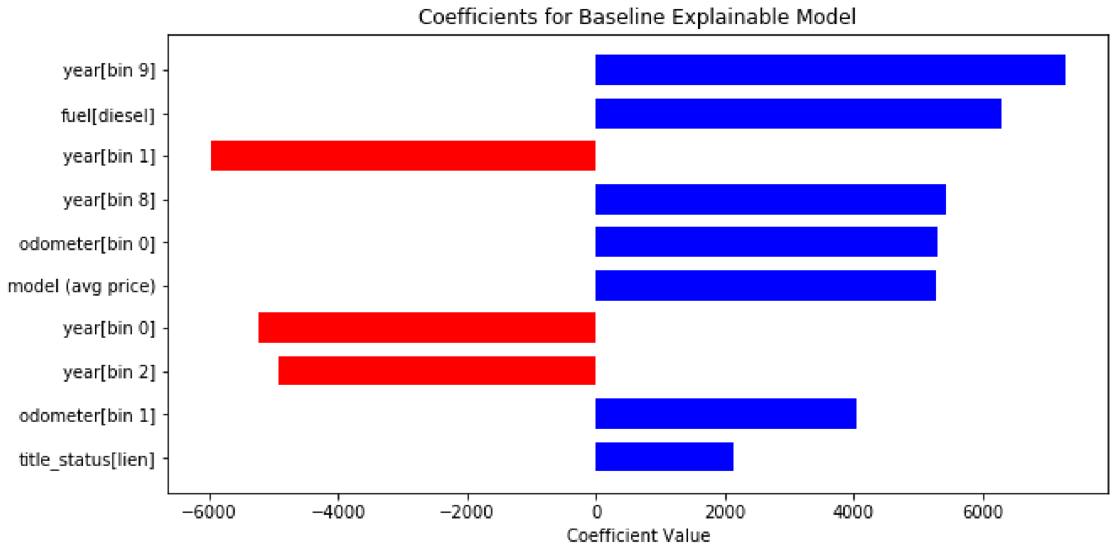
```
Baseline score for Ridge w/Lasso-selected features: 0.554246
```

This is a **moderately better** score than we achieved with an explainable Decision Tree.

Let's see **which features are selected** when we train the model using the entire training set:

[91]:
```
# Fit to all the training data
select_lassocv = SelectFromModel(LassoCV(random_state=25), max_features=10)
lasso_ridge_pipe = make_pipeline(BEST_PREPROCESSOR, select_lassocv, RidgeCV())
lasso_ridge_pipe.fit(X_train, y_train);
```

[92]:
```
# Get the features and corresponding coefficients that were selected
selected_feature_mask = lasso_ridge_pipe.named_steps['selectfrommodel'].
 ↪get_support()
selected_features = np.
 ↪array(feature_names(BEST_PREPROCESSOR))[selected_feature_mask]
selected_feat_coefs = lasso_ridge_pipe.named_steps['ridgecv'].coef_

# Sort by coefficient magnitude (absolute value)
sorted_feat_indices = np.argsort(np.abs(selected_feat_coefs))
sorted_features = selected_features[sorted_feat_indices]
sorted_coefs = selected_feat_coefs[sorted_feat_indices]

# Plot the results
fig, ax = plt.subplots(figsize=(10, 5))
ax.barh(sorted_features, sorted_coefs, height=0.7, align='center',
          color=np.where(sorted_coefs > 0,'b','r').T)
ax.set_xlabel('Coefficient Value')
ax.set_yticklabels(sorted_features)
ax.set_title('Coefficients for Baseline Explainable Model');
```



The features selected above are fairly intutitve and easily explained.

However, when restricting our model to a limited number of non-zero coefficients, high-cardinality categorical fetures that are one-hot encoded (e.g. manufacturer) generate very '**inefficient**' features that only inspect a single categorical value.

In an attempt to improve the model while maintaining the limit on non-zero coefficients, we'll try different preprocessing using features that are both **intuitive and 'dense'**:

[93]:
```
# Binning with ordinal encoding is still quite intuitive, but we'll skip the␣
↪polynomial feature interactions.
median_bin_ordinal_enc_scale_pl = make_pipeline(
    SimpleImputer(strategy='median'), KBinsDiscretizer(encode='ordinal',␣
↪n_bins=10), StandardScaler())

# Target encoding the manufacturer will make a 'dense' feature that could be␣
↪useful
manufacturer_target_scale_pl = make_pipeline(
    man_model_cleaner, FunctionTransformer(lambda X: X[['manufacturer']]), ce.
↪TargetEncoder(), StandardScaler())

exp_linear_preprocessor = make_column_transformer(
    (base_url_target_encode_pl, ['url']),
    (ctd_parser, ['url']),
    (median_scale_pl, ['year']),
    (median_bin_ordinal_enc_scale_pl, ['odometer']),
    (manufacturer_target_scale_pl, ['manufacturer', 'model']),
    (model_pl, ['manufacturer', 'model']),
    (impute_good_ord_enc_scale_pl, ['condition']),
```

```
    (new_cat_ohe_pl, ['cylinders', 'drive', 'size', 'type', 'paint_color',␣
 ↪'state']),  # OHE
    (most_freq_ohe_pl, ['fuel', 'title_status', 'transmission'])   # OHE
)

# Get a score for Ridge with explainable Lasso-selected features
select_lassocv = SelectFromModel(LassoCV(random_state=25), max_features=10)
exp_lasso_ridge_pipe = make_pipeline(exp_linear_preprocessor, select_lassocv,␣
 ↪RidgeCV())
exp_lasso_ridge_score = cross_val_score(exp_lasso_ridge_pipe, X_train, y_train,␣
 ↪cv=shuffle).mean()
print(f"Explainable score for Ridge w/Lasso-selected features:␣
 ↪{exp_lasso_ridge_score:.6f}")
```

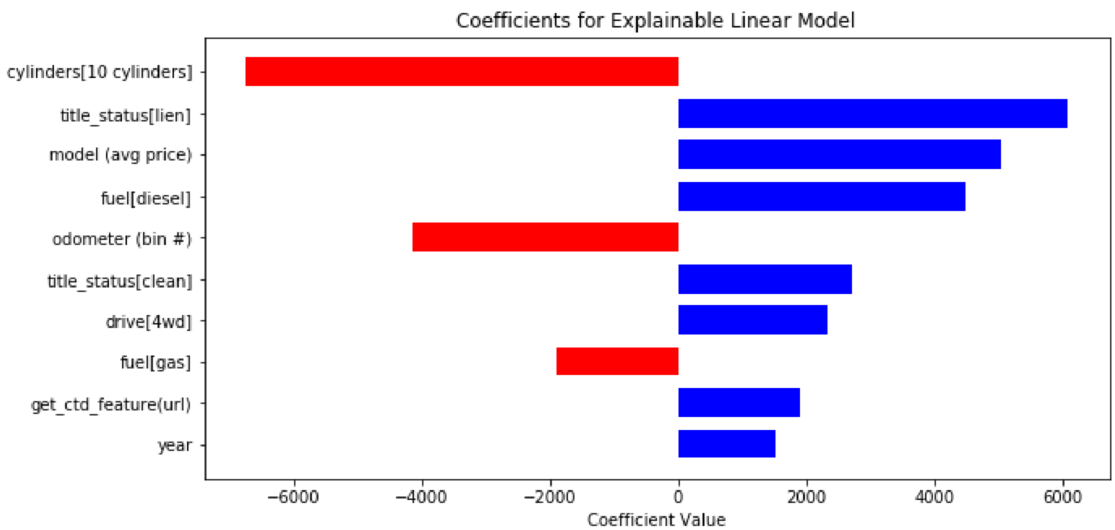
```
Explainable score for Ridge w/Lasso-selected features: 0.556647
```

This is a **very slight improvement** in the CV score over the original preprocessing.

Let's see **which features are selected** when we train the model using this preprocessing on the entire training set:

[94]:
```
# Fit to all the training data
select_lassocv = SelectFromModel(LassoCV(random_state=25), max_features=10)
exp_lasso_ridge_pipe = make_pipeline(exp_linear_preprocessor, select_lassocv,␣
 ↪RidgeCV())
exp_lasso_ridge_pipe.fit(X_train, y_train);
```

[95]:
```
# Get the features and corresponding coefficients that were selected
selected_feature_mask = exp_lasso_ridge_pipe.named_steps['selectfrommodel'].
 ↪get_support()
selected_features = np.
 ↪array(feature_names(exp_linear_preprocessor))[selected_feature_mask]
selected_feat_coefs = exp_lasso_ridge_pipe.named_steps['ridgecv'].coef_

# Sort by coefficient magnitude (absolute value)
sorted_feat_indices = np.argsort(np.abs(selected_feat_coefs))
sorted_features = selected_features[sorted_feat_indices]
sorted_coefs = selected_feat_coefs[sorted_feat_indices]

# Plot the results
fig, ax = plt.subplots(figsize=(10, 5))
ax.barh(sorted_features, sorted_coefs, height=0.7, align='center',
          color=np.where(sorted_coefs > 0,'b','r').T)
ax.set_xlabel('Coefficient Value')
ax.set_yticklabels(sorted_features)
ax.set_title('Coefficients for Explainable Linear Model');
```



6.3 Task 6 Conclusions

Since both types of explainable model (Decision Tree and Linear) have a similar R^2 score (0.55 vs 0.53), we will perform one last test to decide which one is better. We'll score both models with a full 5-fold cross-validation on the training data, rather than the strong sub-sampling we used previously for faster training. The outcome of this process will determine our best explainable model.

[96]:
```
exp_tree_cv_score = cross_val_score(exp_tree_pipe, X_train, y_train, cv=5).
 ↪mean()
print(f"Explainable score for Decision Tree on full dataset: {exp_tree_cv_score:
 ↪.6f}")
```

```
Explainable score for Decision Tree on full dataset: 0.552572
```

[97]:
```
exp_lasso_ridge_cv_score = cross_val_score(exp_lasso_ridge_pipe, X_train,␣
 ↪y_train, cv=5).mean()
print(f"Explainable score for Ridge w/Lasso-selected features on full dataset:␣
 ↪{exp_lasso_ridge_cv_score:.6f}")
```

```
Explainable score for Ridge w/Lasso-selected features on full dataset: 0.580159
```

With this result, we now choose **Ridge w/Lasso-selected features** as our best 'explainable' model. To see how this model compares with our best overall model from Task 4, we will check the score of this model on the Test Data:

[98]:
```
BEST_EXPLAINABLE_MODEL = exp_lasso_ridge_pipe
# NOTE: This model has already been .fit() on the entire Training set above
best_explainable_score = BEST_EXPLAINABLE_MODEL.score(X_test, y_test)
print(f"Best Explainable Model Test Score: {best_explainable_score:.6f}")
```

```
Best Explainable Model Test Score: 0.581967
```

- **Is the score 'nearly as good as the best model'?**

This model is **far worse than our best model** from Task 4 (R^2 score ~.87). However, we see some positive things about this model. First of all, as the task required, it is **very explainable**. We are using only 10 features, which are all very natural to evaluate in a car selling listing. It is a model that could be easily printed out and handed to someone, and it also **very small in size**. Further work could be done to improve its performance, but clearly there is a tradeoff between model performance and 'explainability'.