Car Trim and Price Prediction Project

By Roger Qiu

Objective

Given a training dataset of vehicles sold at different dealerships, accurately predict a vehicles trim and price given numerous features in a test set using machine learning models.

EDA and Feature Transformation

Based on initial EDA, fields with only 1 unique value were removed. Listing ID was dropped from features, these fields do not provide useful info. Dataset is then split into features set and the 2 labels fields.

The dataset included a variety of feature types, each needed different preprocessing methods to convert the fields into numerical values for the models:

1. **Numerical Features**: scaled and imputed using normalization to ensure no nulls and that they contributed equally to the model.
2. **Categorical Features**: One-hot encoding was applied to convert categorical features into a numerical format.
3. **Boolean Features**: transformed into binary 0 and 1 values.
4. **List Features (VehFeats)**: converted into multi-hot encoded features where the presence of each feature was encoded as a separate binary feature.
5. **Text Features (VehSellerNotes)**: Used TF-IDF vectorization to convert text into tokens, remove unnecessary stop words and then into numerical features as a matrix.

Dimensionality Reduction with PCA and splitting

After the preprocessing steps above, the feature set had high dimensionality, with 4909 features. To fix this issue and increase efficiency, Principal Component Analysis was used to reduce the number of features to those that explained 95% of the variance, resulting in 788 new fields. This transformation ensured that the essential information was retained while greatly reducing the number of fields. Records are then split into 70/30 for training and validation of model's performance.

Model Selection and Tuning

Two separate sets models were trained and validated: classification models for predicting trim and regression models for price. Best models (highest accuracy and F1, lowest RMSE and highest R^2) for each were then optimized with GridsearchCV hyperparameter tuning to find optimal parameters.

1. **Predicting Vehicle Trim**:
   - **Best Model**: Logistic Regression
   - **Best Hyperparameters**: C = 10, max_iter = 1000, solver = 'liblinear'

- **Performance**: Achieved an accuracy and F1 score of 86%.

2. **Predicting Dealer Listing Price**:
    - **Model**: Linear (Ridge) Regression
    - **Best Hyperparameters**: alpha = 1, solver = 'saga'
    - **Performance**: Achieved an RMSE of 2917 and an R^2 score of 86%.

Test data pre-processing, predictions and write-out

Using the same pre-processing techniques as earlier, we apply them to the test set. After PCA, the test set should have the same number of fields: 788. The test set is then fed into optimized logistic regression model and the linear (ridge) regression. The predictions are created, for the trim, the prediction results are numerical so they must be then un-encoded to product the original text trim values. These results are appended back to the original dataset, only the 3 required fields are kept, and the results are written out. Finally, spot checks on the output and visualizations were performed to ensure the predictions seemed reasonable

Appendix

Car Trim and Price Prediction

By Roger Qiu

Objective: Given a training dataset of vehicles sold at different dealerships, accurately predict a vehicles trim and price given numerous features in a test set.

import libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, cross_val_score,
cross_val_predict
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder,
LabelEncoder, StandardScaler, Normalizer
from sklearn.metrics import *
from sklearn.linear_model import *
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
import random
from sklearn.impute import SimpleImputer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.ensemble import *
from sklearn.naive_bayes import *
from sklearn.decomposition import *
from sklearn.tree import *
from sklearn.svm import *
from sklearn.neighbors import *

# show all columns
pd.set_option('display.max_columns', None)

# ignore all warnings
import warnings
warnings.filterwarnings('ignore')

# download stopwords from NLTK
from wordcloud import WordCloud
import matplotlib.pyplot as plt
from nltk.corpus import stopwords
import nltk

# set random to 42 to repeat results
random.seed(42)
np.random.seed(42)
```

EDA

```
train_data = pd.read_csv('Training_DataSet.csv')
train_data.head()
```

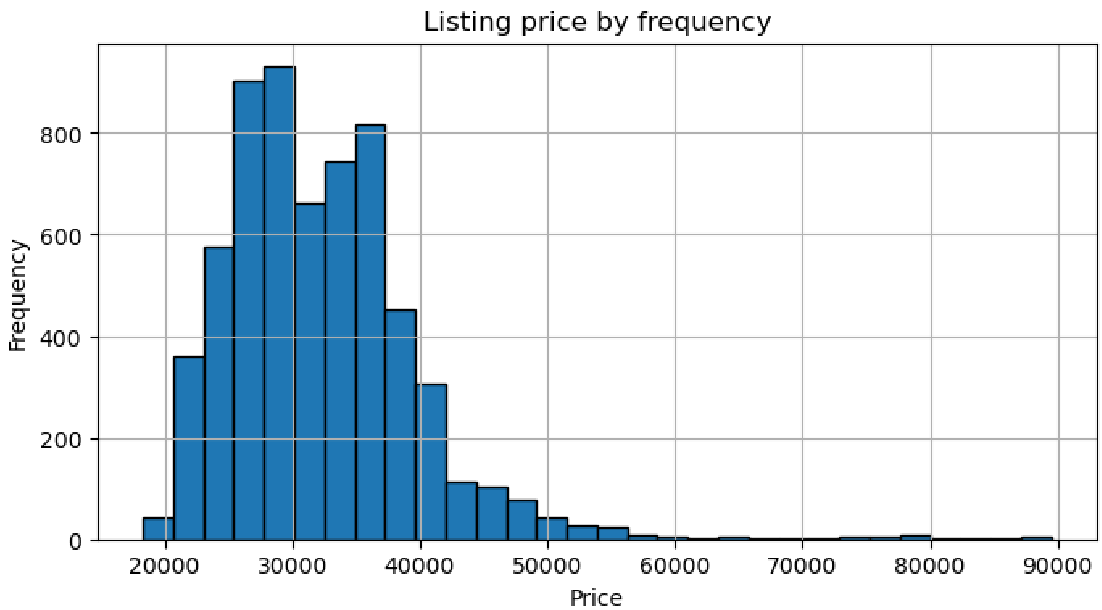
```
   ListingID   SellerCity  SellerIsPriv              SellerListSrc  \
0       3287       Warren         False    Inventory Command Center
1       3920        Fargo         False  Cadillac Certified Program
2       4777     Waukesha         False      Jeep Certified Program
3       6242   Wentzville         False    Inventory Command Center
4       7108  Fayetteville        False          HomeNet Automotive

                               SellerName  SellerRating  SellerRevCnt  \
0                            Prime Motorz           5.0            32
1                Gateway Chevrolet Cadillac          4.8          1456
2  Wilde Chrysler Jeep Dodge Ram &amp; Subaru          4.8          1405
3           Century Dodge Chrysler Jeep RAM          4.4            21
4         Superior Buick GMC of Fayetteville         3.7            74

  SellerState  SellerZip VehBodystyle  VehCertified  \
0          MI    48091.0          SUV         False
1          ND    58103.0          SUV          True
2          WI    53186.0          SUV          True
3          MO    63385.0          SUV         False
4          AR    72703.0          SUV         False

                       VehColorExt VehColorInt VehDriveTrain  \
0                            White       Black           4X4
1                            Black         NaN           NaN
2  Brilliant Black Crystal Pearlcoat      Black       4x4/4WD
3    Diamond Black Crystal Pearlcoat      Black           4WD
4            Radiant Silver Metallic     Cirrus           FWD

                    VehEngine  \
0                    3.6L V6
1                        NaN
2  Regular Unleaded V-6 3.6 L/220
3                    3.6L V6
4             Gas V6 3.6L/222.6

                                            VehFeats   VehFuel  \
0  ['Adaptive Cruise Control', 'Antilock Brakes',...  Gasoline
1                                                NaN  Gasoline
2  ['18 WHEEL &amp; 8.4 RADIO GROUP-inc: Nav-Capa...  Gasoline
3  ['Android Auto', 'Antilock Brakes', 'Apple Car...  Gasoline
4  ['4-Wheel Disc Brakes', 'ABS', 'Adjustable Ste...  Gasoline

                                          VehHistory  VehListdays   VehMake
\
0  1 Owner, Non-Personal Use Reported, Buyback Pr...     8.600069      Jeep
```

```
1              1 Owner, Buyback Protection Eligible     2.920127  Cadillac
2              1 Owner, Buyback Protection Eligible    28.107014      Jeep
3  1 Owner, Non-Personal Use Reported, Buyback Pr...    59.816875      Jeep
4  1 Owner, Non-Personal Use Reported, Buyback Pr...    98.665301  Cadillac

   VehMileage        VehModel VehPriceLabel  \
0     39319.0  Grand Cherokee    Fair Price
1     30352.0             XT5     Good Deal
2     38957.0  Grand Cherokee     Good Deal
3     20404.0  Grand Cherokee     Good Deal
4     19788.0             XT5     Good Deal

                                      VehSellerNotes VehType  \
0                                                NaN    Used
1  Come take a look at our great pre-owned invent...    Used
2  Backed by a rigorous 125-point inspection by f...    Used
3  Drop by to see us and you will quickly see how...    Used
4  Luxury, Exterior Parking Camera Rear, Front Du...    Used

           VehTransmission  VehYear   Vehicle_Trim  Dealer_Listing_Price
0       Automatic 8-Speed     2015  High Altitude               30990.0
1                     NaN     2017            NaN               34860.0
2  8-Speed Automatic w/OD     2015         Laredo               23249.0
3               Automatic     2018        Limited               31977.0
4       8-Speed Automatic     2018         Luxury               33495.0
```

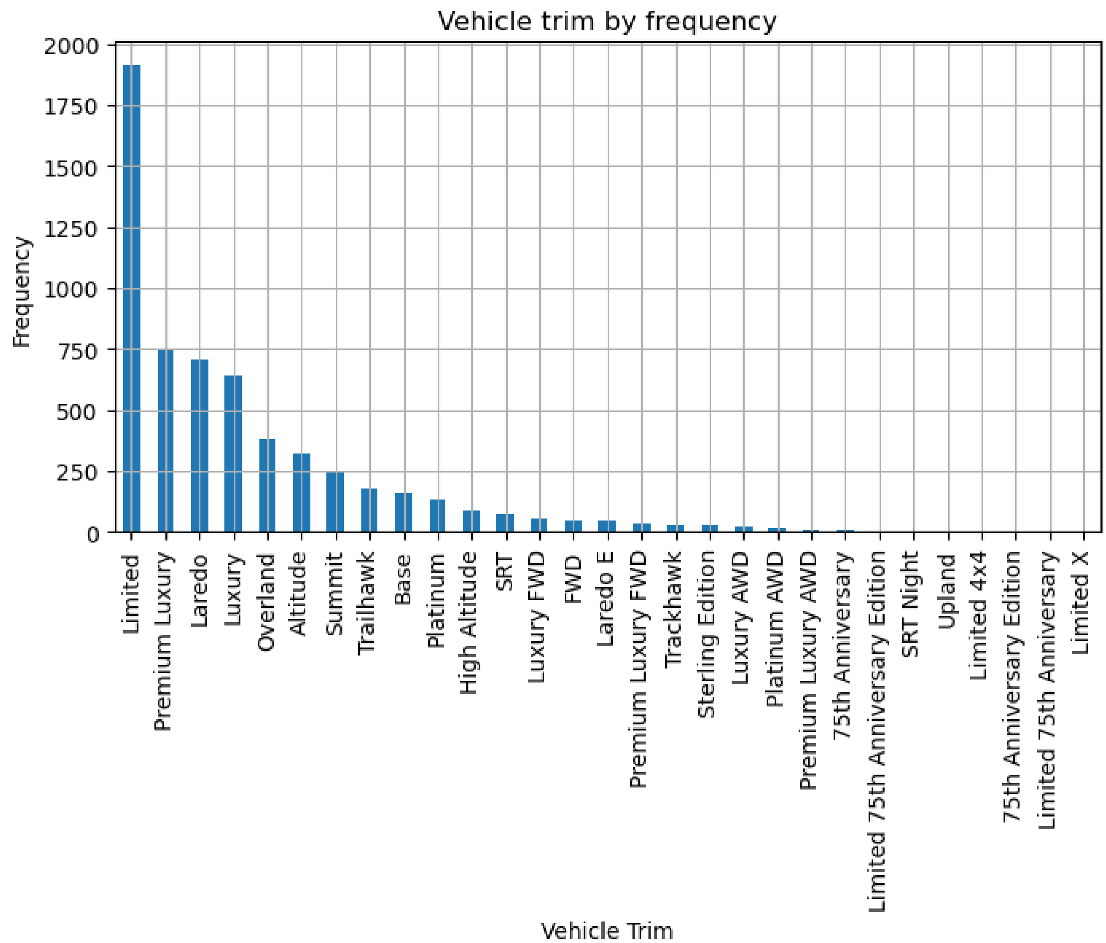
```python
# 29 fields, 6298 records
print(train_data.shape)
```

```
(6298, 29)
```

```python
# histogram of Dealer_Listing_Price
plt.figure(figsize=(8, 4))
plt.hist(train_data['Dealer_Listing_Price'], bins=30, edgecolor='black')
plt.title('Listing price by frequency')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```




```
# bar chart of Vehicle_Trim
plt.figure(figsize=(8, 4))
train_data['Vehicle_Trim'].value_counts().plot(kind='bar')
plt.title('Vehicle trim by frequency')
plt.xlabel('Vehicle Trim')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```




```python
# check nulls

# count the null values in each field, print where more than 0 nulls
null_counts = train_data.isnull().sum()
print(null_counts[null_counts > 0])
```

```
SellerListSrc          2
SellerZip              2
VehColorExt           73
VehColorInt          728
VehDriveTrain        401
VehEngine            361
VehFeats             275
VehFuel                2
VehHistory           201
VehListdays            2
VehMileage             2
VehPriceLabel        285
VehSellerNotes       243
VehTransmission      197
Vehicle_Trim         405
```

```
Dealer_Listing_Price     52
dtype: int64
```

pre-processing

```
# field columns with only one unique value
columns_to_remove = [col for col in train_data.columns if
train_data[col].nunique() == 1]
columns_to_remove
```

```
['VehBodystyle', 'VehType']
```

```
# remove these 2 field from the dataset, they provide no additional info
train_data = train_data.drop(columns=columns_to_remove)
train_data.shape
```

```
(6298, 27)
```

```
# drop records with null Vehicle_Trim or Dealer_Listing_Price, these are our
labels which we need values in
train_data = train_data.dropna(subset=['Vehicle_Trim',
'Dealer_Listing_Price'])

# count the null values in each field, print where more than 0 nulls
null_counts = train_data.isnull().sum()
print(null_counts[null_counts > 0])
```

```
SellerListSrc        2
SellerZip            2
VehColorExt         42
VehColorInt        426
VehDriveTrain       68
VehEngine           28
VehFeats            23
VehFuel              2
VehHistory         197
VehListdays          2
VehPriceLabel      233
VehSellerNotes      74
VehTransmission     32
dtype: int64
```

```
# instead of 6298 records, now its 5841
print(train_data.shape)
```

```
(5841, 27)
```

```
# create features by dropping id field and labels
X_train = train_data.drop(columns=['Vehicle_Trim', 'Dealer_Listing_Price',
'ListingID'])
print(X_train.shape)
```

```
(5841, 24)
```

```
# create the 2 labels fields
y_trim_train = train_data['Vehicle_Trim']
y_price_train = train_data['Dealer_Listing_Price']

print(y_trim_train.head())
print(y_price_train.head())
```

```
0    High Altitude
2           Laredo
3          Limited
4           Luxury
5          Limited
Name: Vehicle_Trim, dtype: object
0    30990.0
2    23249.0
3    31977.0
4    33495.0
5    27900.0
Name: Dealer_Listing_Price, dtype: float64
```

```
# check feature field types
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5841 entries, 0 to 6297
Data columns (total 24 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   SellerCity      5841 non-null   object
 1   SellerIsPriv    5841 non-null   bool
 2   SellerListSrc   5839 non-null   object
 3   SellerName      5841 non-null   object
 4   SellerRating    5841 non-null   float64
 5   SellerRevCnt    5841 non-null   int64
 6   SellerState     5841 non-null   object
 7   SellerZip       5839 non-null   float64
 8   VehCertified    5841 non-null   bool
 9   VehColorExt     5799 non-null   object
 10  VehColorInt     5415 non-null   object
 11  VehDriveTrain   5773 non-null   object
 12  VehEngine       5813 non-null   object
 13  VehFeats        5818 non-null   object
 14  VehFuel         5839 non-null   object
 15  VehHistory      5644 non-null   object
 16  VehListdays     5839 non-null   float64
 17  VehMake         5841 non-null   object
 18  VehMileage      5841 non-null   float64
 19  VehModel        5841 non-null   object
 20  VehPriceLabel   5608 non-null   object
 21  VehSellerNotes  5767 non-null   object
```

```
 22  VehTransmission  5809 non-null   object
 23  VehYear          5841 non-null   int64
dtypes: bool(2), float64(4), int64(2), object(16)
memory usage: 1.0+ MB
```

```
# select all the groups of fields by type: numerical, categorical, boolean,
text and list features
num_cols = X_train.select_dtypes(include=['int64', 'float64']).columns
cat_cols =
X_train.select_dtypes(include=['object']).columns.difference(['VehSellerNotes
','VehFeats'])
bool_cols = X_train.select_dtypes(include=['bool']).columns
text_col = 'VehSellerNotes'
list_col = 'VehFeats'

print(num_cols)
print(cat_cols)
print(bool_cols)
print(text_col)
print(list_col)

# still 24 fields
print(len(num_cols) + len(cat_cols) + len(bool_cols) + 1 + 1)
```

```
Index(['SellerRating', 'SellerRevCnt', 'SellerZip', 'VehListdays',
       'VehMileage', 'VehYear'],
      dtype='object')
Index(['SellerCity', 'SellerListSrc', 'SellerName', 'SellerState',
       'VehColorExt', 'VehColorInt', 'VehDriveTrain', 'VehEngine', 'VehFuel',
       'VehHistory', 'VehMake', 'VehModel', 'VehPriceLabel',
       'VehTransmission'],
      dtype='object')
Index(['SellerIsPriv', 'VehCertified'], dtype='object')
VehSellerNotes
VehFeats
24
```

pre-process numerical features

```
# for numerical features, impute missing values and scale them
num_imputer = SimpleImputer(strategy='median')
scaler = StandardScaler()

# fit on numerical fields for training data
X_train_num = num_imputer.fit_transform(X_train[num_cols])
X_train_num = scaler.fit_transform(X_train_num)

print(X_train_num[:5])
print(X_train_num.shape)
```

```
[[ 0.73661031 -0.32105247  0.14769339 -0.6983788   0.97497474 -1.45127235]
 [ 0.56213936  0.72258538  0.40213716 -0.41007283  0.94719888 -1.45127235]
 [ 0.21319747 -0.32941374  0.91147418  0.05858808 -0.47635222  1.01844168]
 [-0.39745085 -0.28912764  1.37681414  0.63275454 -0.52361722  1.01844168]
 [-1.00809917 -0.30661029 -1.51685333 -0.36779582  0.61665082  1.01844168]]
(5841, 6)
```

pre-process categorical features

```
# impute missing values with 'missing' and one hot encode categorical
features
cat_imputer = SimpleImputer(strategy='constant', fill_value='missing')
encoder = OneHotEncoder(handle_unknown='ignore', sparse=False)

# fit on categorical training data
X_train_cat = cat_imputer.fit_transform(X_train[cat_cols])
X_train_cat = encoder.fit_transform(X_train_cat)

print(X_train_cat[:5])
print(X_train_cat.shape)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
(5841, 4004)
```

pre-process boolean features

```
# preprocess boolean features, convert true or false 1 or 0
X_train_bool = X_train[bool_cols].astype(int).values

print(X_train_bool[:5])
print(X_train_bool.shape)
```

```
[[0 0]
 [0 1]
 [0 0]
 [0 0]
 [0 0]]
(5841, 2)
```

pre-process seller notes text

```
# check values
X_train[text_col].head()
```

```
0                                                  NaN
2    Backed by a rigorous 125-point inspection by f...
3    Drop by to see us and you will quickly see how...
4    Luxury, Exterior Parking Camera Rear, Front Du...
```

```
5    Priced below KBB Fair Purchase Price! Clean CA...
Name: VehSellerNotes, dtype: object
```

```
nltk.download('stopwords')

# remove stopwords and concatenate all text
stop_words = set(stopwords.words('english'))
print(list(stop_words)[:5])
```

```
["needn't", 'between', 'in', 'can', 'when']

[nltk_data] Downloading package stopwords to
[nltk_data]     /Users/roger.qiu/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

```
# full nulls with empty strings
X_train[text_col] = X_train[text_col].fillna('')
X_train[text_col].head()
```

```
0
2    Backed by a rigorous 125-point inspection by f...
3    Drop by to see us and you will quickly see how...
4    Luxury, Exterior Parking Camera Rear, Front Du...
5    Priced below KBB Fair Purchase Price! Clean CA...
Name: VehSellerNotes, dtype: object
```

```
# combine all text data in a single string
text_data = ' '.join(X_train[text_col])
text_data[:50]
```

```
' Backed by a rigorous 125-point inspection by fact'
```

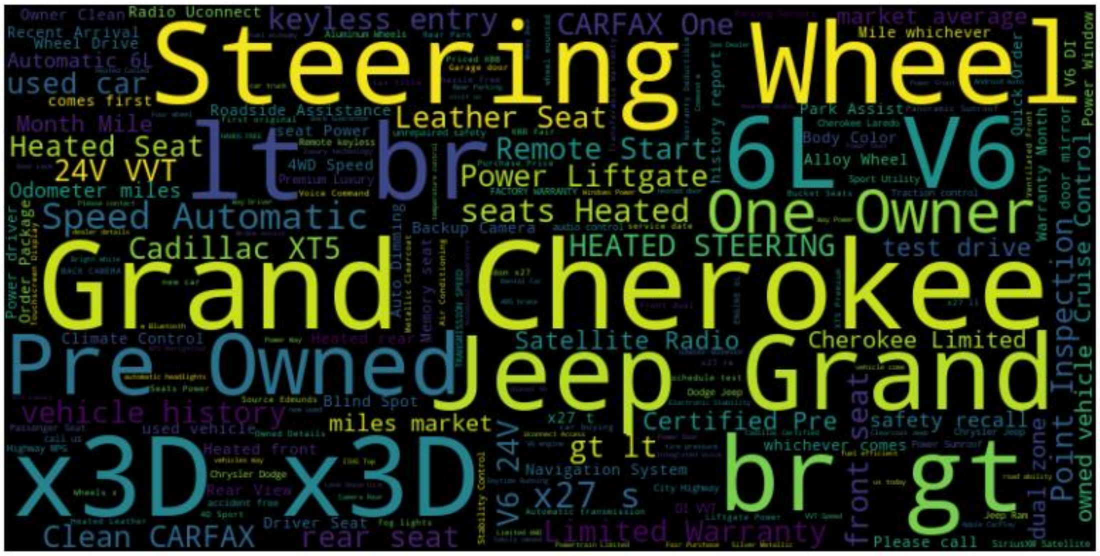
```
# remove stopwords
filtered_words = [word for word in text_data.split() if word.lower() not in
stop_words]
filtered_words[:5]
```

```
['Backed', 'rigorous', '125-point', 'inspection', 'factory-trained']
```

```
# combine again into a single string
filtered_text = ' '.join(filtered_words)
filtered_text[:50]
```

```
'Backed rigorous 125-point inspection factory-train'
```

```
# create and display the word cloud
wordcloud = WordCloud(width=800, height=400,
background_color='black').generate(filtered_text)
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```




```
# create tfidf to convert text values into vectors
# remove stopwords that dont provide info and use 100 of the top ranked terms
across the corpus
vectorizer = TfidfVectorizer(stop_words='english', max_features=100)

# fit the vectorizer to the text column
X_train_text =
vectorizer.fit_transform(X_train[text_col].fillna('')).toarray()

print(X_train_text[2])
print(X_train_text.shape)
```

```
[0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.74619032 0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.         0.         0.         0.         0.
 0.         0.66573269 0.         0.        ]
(5841, 100)
```

pre-process vehicle features list

```
# check values
X_train[list_col].head()
```

```
0    ['Adaptive Cruise Control', 'Antilock Brakes',...
2    ['18 WHEEL &amp; 8.4 RADIO GROUP-inc: Nav-Capa...
3    ['Android Auto', 'Antilock Brakes', 'Apple Car...
4    ['4-Wheel Disc Brakes', 'ABS', 'Adjustable Ste...
5    ['1st and 2nd row curtain head airbags', '4-wh...
Name: VehFeats, dtype: object
```

```
# fill nulls, convert list to text
X_train[list_col] = X_train[list_col].fillna('[]').apply(eval).apply(lambda
x: ','.join(x))
X_train[list_col].head()
```

```
0    Adaptive Cruise Control,Antilock Brakes,Audio ...
2    18 WHEEL &amp; 8.4 RADIO GROUP-inc: Nav-Capabl...
3    Android Auto,Antilock Brakes,Apple CarPlay,Aud...
4    4-Wheel Disc Brakes,ABS,Adjustable Steering Wh...
5    1st and 2nd row curtain head airbags,4-wheel A...
Name: VehFeats, dtype: object
```

```
# use one hot encoder to convert comma seperated strings into a matrix with 1
or 0 for if the feature is present
feats_encoder = OneHotEncoder(handle_unknown='ignore', sparse=False)
X_train_feats =
feats_encoder.fit_transform(X_train[list_col].values.reshape(-1, 1))

print(X_train_feats[:5])
print(X_train_feats.shape)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
(5841, 797)
```

combine features then use PCA to reduce dimentionality

```
# combine all preprocessed features together using hstack to horizontally
concat the arrays
X_train_preprocessed = np.hstack((X_train_num, X_train_cat, X_train_bool,
X_train_text, X_train_feats))

print(X_train_preprocessed[:1])
print(X_train_preprocessed.shape)
```

```
[[ 0.73661031 -0.32105247  0.14769339 ...  0.          0.
   0.        ]]
(5841, 4909)
```

```
# almost 5000 fields, so use principal component analysis to retain 95% of variance
pca = PCA(n_components=0.95, random_state=42)
X_train_pca = pca.fit_transform(X_train_preprocessed)

# only 788 fields now
print(X_train_preprocessed.shape[1])
print(X_train_pca.shape[1])

4909
788

# check how the records look now
print(X_train_preprocessed[0][:5])
print(X_train_pca[0][:5])

[ 0.73661031 -0.32105247  0.14769339 -0.6983788   0.97497474]
[-1.37042827  0.24928243 -0.69933417  0.31303048 -0.11801419]
```

preprocess trim label

```
print(y_trim_train.head())
print(y_price_train.head())

0    High Altitude
2           Laredo
3          Limited
4           Luxury
5          Limited
Name: Vehicle_Trim, dtype: object
0    30990.0
2    23249.0
3    31977.0
4    33495.0
5    27900.0
Name: Dealer_Listing_Price, dtype: float64

# encode categorical target variable y_trim_train
label_encoder = LabelEncoder()
y_trim_train_encoded = label_encoder.fit_transform(y_trim_train)

print(y_trim_train_encoded[:5])
print(y_trim_train_encoded.shape)

[ 5  6  8 13  8]
(5841,)

# create a mapping from the original labels to the encoded numbers
trim_mapping = dict(zip(label_encoder.classes_,
label_encoder.transform(label_encoder.classes_)))
```

```python
for trim, number in trim_mapping.items():
    print(f"{trim}: {number}")
```

```
75th Anniversary: 0
75th Anniversary Edition: 1
Altitude: 2
Base: 3
FWD: 4
High Altitude: 5
Laredo: 6
Laredo E: 7
Limited: 8
Limited 4x4: 9
Limited 75th Anniversary: 10
Limited 75th Anniversary Edition: 11
Limited X: 12
Luxury: 13
Luxury AWD: 14
Luxury FWD: 15
Overland: 16
Platinum: 17
Platinum AWD: 18
Premium Luxury: 19
Premium Luxury AWD: 20
Premium Luxury FWD: 21
SRT: 22
SRT Night: 23
Sterling Edition: 24
Summit: 25
Trackhawk: 26
Trailhawk: 27
Upland: 28
```

split training data for validation set

```python
# split features, trim label and price label into 70/30 for train and validation sets
X_train_final, X_val, y_trim_train_final, y_trim_val, y_price_train_final, y_price_val = train_test_split(
    X_train_pca, y_trim_train_encoded, y_price_train, test_size=0.3, random_state=42)

print(X_train_final.shape)
print(X_val.shape)

print(y_trim_train_final.shape)
print(y_trim_val.shape)

print(y_price_train_final.shape)
print(y_price_val.shape)
```

```
(4088, 788)
(1753, 788)
(4088,)
(1753,)
(4088,)
(1753,)
```

```
X_val[0][:5]
```

```
array([ 1.8161653 , -0.17188878, -1.66012565, -0.48802285,  0.29540282])
```

```
y_trim_val[0]
```

```
13
```

```
y_price_val[:1]
```

```
6147    35500.0
Name: Dealer_Listing_Price, dtype: float64
```

evaluate classification models on trim labels

```
# train and logistic regression model
logistic_reg = LogisticRegression(max_iter=1000)
logistic_reg.fit(X_train_final, y_trim_train_final)

# create trim predictions given validation set
y_trim_val_pred = logistic_reg.predict(X_val)

# check predictions vs actuals
print(y_trim_val_pred[:5])
print(y_trim_val[:5])
```

```
[13  2  8 25  8]
[13  2  2 25  8]
```

```
# check accuracy and f1 of the predictions compared to actuals
print(accuracy_score(y_trim_val, y_trim_val_pred))
print(f1_score(y_trim_val, y_trim_val_pred, average='weighted'))
```

```
0.8539646320593268
0.8459025699506811
```

```
# now train and test on random forest
random_forest = RandomForestClassifier(random_state=42)
random_forest.fit(X_train_final, y_trim_train_final)

y_trim_val_pred = random_forest.predict(X_val)

print(accuracy_score(y_trim_val, y_trim_val_pred))
print(f1_score(y_trim_val, y_trim_val_pred, average='weighted'))
```

```
0.6948088990302339
0.6440930059841969
```

```
# now train and test on k nearest neighbor
knn_clf = KNeighborsClassifier()
knn_clf.fit(X_train_final, y_trim_train_final)

y_trim_val_pred = knn_clf.predict(X_val)

print(accuracy_score(y_trim_val, y_trim_val_pred))
print(f1_score(y_trim_val, y_trim_val_pred, average='weighted'))
```

```
0.6936679977181974
0.6737595332560347
```

```
# now train and test on naive bayes
naive_bayes = GaussianNB()
naive_bayes.fit(X_train_final, y_trim_train_final)

y_trim_val_pred = naive_bayes.predict(X_val)

print(accuracy_score(y_trim_val, y_trim_val_pred))
print(f1_score(y_trim_val, y_trim_val_pred, average='weighted'))
```

```
0.4015972618368511
0.4207431829020433
```

hyperparameter tuning to get best model with best parameters

```
# define the parameter grid for log reg
# C changes regularization amount while solver chooses different optimization
type
param_grid_lr = {
    'C': [0.01, 0.1, 1, 10],
    'solver': ['liblinear', 'lbfgs']
}

# create the log reg model again
logistic_reg = LogisticRegression(max_iter=1000)

# perform grid search with cross-validation
grid_search_lr = GridSearchCV(logistic_reg, param_grid_lr, cv=5,
scoring='accuracy')
grid_search_lr.fit(X_train_final, y_trim_train_final)

# get the best parameters and the best model
best_params_lr = grid_search_lr.best_params_
best_model_lr = grid_search_lr.best_estimator_

print(best_params_lr)
print(best_model_lr)
```

```
{'C': 10, 'solver': 'liblinear'}
LogisticRegression(C=10, max_iter=1000, solver='liblinear')
```

```
# create predictions from validation features
y_trim_val_pred_lr = best_model_lr.predict(X_val)
print(y_trim_val_pred_lr[:5])
```

```
[13  2  2 25  8]
```

```
print(accuracy_score(y_trim_val, y_trim_val_pred_lr))
print(f1_score(y_trim_val, y_trim_val_pred_lr, average='weighted'))
```

```
0.8585282373074729
0.8544483011681455
```

```
# Define the parameter grid for Random Forest
param_grid_rf = {
    'n_estimators': [50, 100, 200],
    'max_depth': [5, 10, 20]
}

# Initialize the Random Forest model
random_forest = RandomForestClassifier(random_state=42)

# Perform Grid Search with cross-validation
grid_search_rf = GridSearchCV(random_forest, param_grid_rf, cv=5,
scoring='accuracy')
grid_search_rf.fit(X_train_final, y_trim_train_final)

# Get the best parameters and the best model
best_params_rf = grid_search_rf.best_params_
best_model_rf = grid_search_rf.best_estimator_

print(best_params_rf)
print(best_model_rf)
```

```
{'max_depth': 20, 'n_estimators': 100}
RandomForestClassifier(max_depth=20, random_state=42)
```

```
# Predict on the validation set
y_trim_val_pred_rf = best_model_rf.predict(X_val)

# Calculate metrics
print(accuracy_score(y_trim_val, y_trim_val_pred_rf))
print(f1_score(y_trim_val, y_trim_val_pred_rf, average='weighted'))
```

```
0.679406731317741
0.6259801300356478
```

```
# best classification model is LogisticRegression(C=10, max_iter=1000,
solver='liblinear')
# with accuracy and f1 of 86%
```

evaluate regression models on price labels

```
# train Linear Regression
linear_reg = LinearRegression()
linear_reg.fit(X_train_final, y_price_train_final)

# predict prices
y_price_val_pred = linear_reg.predict(X_val)

print(y_price_val_pred[:5])
print(y_price_val[:5])
```

```
[32079.35250155 33094.18363729 30619.49401673 37255.49237462
 29743.81160114]
6147    35500.0
184     28637.0
174     28695.0
6021    38880.0
2533    29790.0
Name: Dealer_Listing_Price, dtype: float64
```

```
print(mean_squared_error(y_price_val, y_price_val_pred, squared=False))
print(r2_score(y_price_val, y_price_val_pred))
```

```
3007.7656746136336
0.8548957604797974
```

```
# Train Decision Tree Regressor
decision_tree_reg = DecisionTreeRegressor(random_state=42)
decision_tree_reg.fit(X_train_final, y_price_train_final)

# Predict and evaluate
y_price_val_pred = decision_tree_reg.predict(X_val)

print(mean_squared_error(y_price_val, y_price_val_pred, squared=False))
print(r2_score(y_price_val, y_price_val_pred))
```

```
6096.547938474299
0.40384376542526457
```

```
# Train Random Forest Regressor
random_forest_reg = RandomForestRegressor(random_state=42)
random_forest_reg.fit(X_train_final, y_price_train_final)

# Predict and evaluate
y_price_val_pred = random_forest_reg.predict(X_val)
```

```python
print(mean_squared_error(y_price_val, y_price_val_pred, squared=False))
print(r2_score(y_price_val, y_price_val_pred))
```

```
4423.212391470294
0.6861893408328988
```

```python
# Train Support Vector Regressor
svr = SVR()
svr.fit(X_train_final, y_price_train_final)

# Predict and evaluate
y_price_val_pred = svr.predict(X_val)

print(mean_squared_error(y_price_val, y_price_val_pred, squared=False))
print(r2_score(y_price_val, y_price_val_pred))
```

```
7926.585226717974
-0.007776834190083237
```

```python
# Train K-Nearest Neighbors Regressor
knn_reg = KNeighborsRegressor()
knn_reg.fit(X_train_final, y_price_train_final)

# Predict and evaluate
y_price_val_pred = knn_reg.predict(X_val)

print(mean_squared_error(y_price_val, y_price_val_pred, squared=False))
print(r2_score(y_price_val, y_price_val_pred))
```

```
4478.120847999408
0.6783498762953561
```

hyperparameter tuning on the best linear regression model

```python
# parameter grid for best ridge regression
# alpha controls regularization, solver is the optimizer
param_grid_ridge = {
    'alpha': [0.01, 0.1, 1, 10, 50],
    'solver': ['auto', 'svd', 'cholesky', 'lsqr', 'sag', 'saga']
}

# initialize model
ridge_reg = Ridge()

# perform grid search, scoring rmse
grid_search_ridge = GridSearchCV(ridge_reg, param_grid_ridge, cv=5,
scoring='neg_mean_squared_error')
grid_search_ridge.fit(X_train_final, y_price_train_final)

# get best parameter and model
best_params_ridge = grid_search_ridge.best_params_
```

```
best_model_ridge = grid_search_ridge.best_estimator_

# predict on validation set
y_price_val_pred_ridge = best_model_ridge.predict(X_val)

y_price_val_pred_ridge[:5]
```

```
array([32433.81369174, 32258.65822153, 30668.6735075 , 37517.93789474,
       29725.2143707 ])
```

```
best_model_ridge
```

```
Ridge(alpha=1, solver='saga')
```

```
print(mean_squared_error(y_price_val, y_price_val_pred_ridge, squared=False))
print(r2_score(y_price_val, y_price_val_pred_ridge))
```

```
2917.171100317708
0.8635052621153299
```

```
# parameter grid for lasso regression
# alpha controls regularization, max iter is iterations
param_grid_lasso = {
    'alpha': [0.01, 0.1, 1, 10, 50],
    'max_iter': [1000, 2000, 3000]
}

# initialize model
lasso_reg = Lasso()

# perform grid search
grid_search_lasso = GridSearchCV(lasso_reg, param_grid_lasso, cv=5,
scoring='neg_mean_squared_error')
grid_search_lasso.fit(X_train_final, y_price_train_final)

# get best param and model
best_params_lasso = grid_search_lasso.best_params_
best_model_lasso = grid_search_lasso.best_estimator_

# predict on validation set
y_price_val_pred_lasso = best_model_lasso.predict(X_val)

print(y_price_val_pred_lasso[:5])
print(y_price_val[:5])
```

```
[32944.60322573 32262.39268183 30667.2036255  37623.06597038
 29721.26259184]
6147    35500.0
184     28637.0
174     28695.0
6021    38880.0
```

```
2533    29790.0
Name: Dealer_Listing_Price, dtype: float64
```

```
# get rmse and r2
print(mean_squared_error(y_price_val, y_price_val_pred_lasso, squared=False))
print(r2_score(y_price_val, y_price_val_pred_lasso))
```

```
2955.8838259114113
0.8598584791657555
```

```
# best regression model for price
best_model_ridge
```

```
Ridge(alpha=1, solver='saga')
```

```
# best classification model for trim
best_model_lr
```

```
LogisticRegression(C=10, max_iter=1000, solver='liblinear')
```

- Best model to predict trim: LogisticRegression(C=10, max_iter=1000, solver='liblinear') with accuracy and f1 of 86%
- Best model to predict price: Ridge(alpha=1, solver='saga') with RMSE of 2917 and R2 of 86%

use best models to predict price and trim on test set

```
test_data = pd.read_csv('Test_DataSet.csv')
test_data.head()
```

```
   ListingID  SellerCity  SellerIsPriv             SellerListSrc  \
0    8622015      Seneca         False         HomeNet Automotive
1    8625693     Bedford         False  Inventory Command Center
2    8625750     Webster         False    Jeep Certified Program
3    8626885  Louisville         False  Digital Motorworks (DMi)
4    8627430     Palmyra         False  Digital Motorworks (DMi)

                                  SellerName  SellerRating  SellerRevCnt  \
0        Lake Keowee Chrysler Dodge Jeep Ram           2.5            59
1                      North Coast Auto Mall           4.7          2116
2  Marina Chrysler Dodge Jeep Mitsubishi RAM           3.9            46
3                        Oxmoor Ford Lincoln           4.5          1075
4                      F.C. Kerbeck &amp; Sons           4.6           162

  SellerState  SellerZip VehBodystyle  VehCertified  \
0          SC      29678          SUV         False
1          OH      44146          SUV         False
2          NY      14580          SUV          True
3          KY      40222          SUV         False
4          NJ       8065          SUV         False

                         VehColorExt VehColorInt     VehDriveTrain  \
```

```
0            Stellar Black Metallic      Cirrus                FWD
1               True Blue Pearlcoat       Black  Four Wheel Drive
2  Brilliant Black Crystal Pearlcoat       Black               4WD
3  Brilliant Black Crystal Pearlcoat       Black               4WD
4              Harbor Blue Metallic   Jet Black               AWD

                            VehEngine  \
0                   Gas V6 3.6L/222.6
1                    3.6L V6 CYLINDER
2  3.6L V6 24V MPFI DOHC Flexible Fuel
3               3.6L V6 24V MPFI DOHC
4                3.6L V6 24V GDI DOHC

                                            VehFeats        VehFuel  \
0  ['4-Wheel Disc Brakes', 'ABS', 'Active Suspens...       Gasoline
1  ['12v Power Outlet', 'ABS Brakes', 'Air Condit...       Gasoline
2  ['1st and 2nd row curtain head airbags', '4-wh...  E85 Flex Fuel
3  ['1st and 2nd row curtain head airbags', '4-wh...       Gasoline
4  ['1st and 2nd row curtain head airbags', '4-wh...       Gasoline

                                          VehHistory  VehListdays   VehMake
\
0  1 Owner, Non-Personal Use Reported, Buyback Pr...   143.991262  Cadillac
1  1 Owner, Accident(s) Reported, Non-Personal Us...   138.770486      Jeep
2              1 Owner, Buyback Protection Eligible    31.951088      Jeep
3              1 Owner, Buyback Protection Eligible     5.950127      Jeep
4  1 Owner, Non-Personal Use Reported, Buyback Pr...    24.672986  Cadillac

   VehMileage        VehModel VehPriceLabel  \
0     13625.0             XT5     Good Deal
1     42553.0  Grand Cherokee     Good Deal
2     48951.0  Grand Cherokee     Good Deal
3     44179.0  Grand Cherokee     Good Deal
4     22269.0             XT5     Good Deal

                                      VehSellerNotes VehType  \
0  Thank you for visiting another one of Lake Keo...    Used
1  This 2017 Jeep Grand Cherokee 4dr Limited 4x4 ...    Used
2  Certified. Brilliant Black Crystal Pearlcoat 2...    Used
3  2015 Jeep Grand Cherokee ***THIS VEHICLE IS AT...    Used
4  AWD, CarFax One Owner! Navigation, Back-up Cam...    Used

     VehTransmission  VehYear
0  8-Speed Automatic     2018
1  8-Speed Automatic     2017
2  8-Speed Automatic     2015
3  8-Speed Automatic     2015
4  8-Speed Automatic     2018
```

```python
# field columns with only one unique value
columns_to_remove = [col for col in test_data.columns if
test_data[col].nunique() == 1]
columns_to_remove
```

```
['VehBodystyle', 'VehType']
```

```python
# remove these 2 field from the dataset, they provide no additional info
test_data = test_data.drop(columns=columns_to_remove)
test_data.shape
```

```
(1000, 25)
```

```python
# create features by dropping id field
X_test = test_data.drop(columns=['ListingID'])
print(X_test.shape)
```

```
(1000, 24)
```

```python
# check feature field types
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 24 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   SellerCity       1000 non-null   object
 1   SellerIsPriv     1000 non-null   bool
 2   SellerListSrc    1000 non-null   object
 3   SellerName       1000 non-null   object
 4   SellerRating     1000 non-null   float64
 5   SellerRevCnt     1000 non-null   int64
 6   SellerState      1000 non-null   object
 7   SellerZip        1000 non-null   int64
 8   VehCertified     1000 non-null   bool
 9   VehColorExt      993 non-null    object
 10  VehColorInt      892 non-null    object
 11  VehDriveTrain    936 non-null    object
 12  VehEngine        942 non-null    object
 13  VehFeats         963 non-null    object
 14  VehFuel          1000 non-null   object
 15  VehHistory       973 non-null    object
 16  VehListdays      1000 non-null   float64
 17  VehMake          1000 non-null   object
 18  VehMileage       999 non-null    float64
 19  VehModel         1000 non-null   object
 20  VehPriceLabel    962 non-null    object
 21  VehSellerNotes   959 non-null    object
 22  VehTransmission  973 non-null    object
 23  VehYear          1000 non-null   int64
```

```
dtypes: bool(2), float64(3), int64(3), object(16)
memory usage: 174.0+ KB
```

```
# select all the groups of fields by type: numerical, categorical, boolean,
text and list features
num_cols = X_test.select_dtypes(include=['int64', 'float64']).columns
cat_cols =
X_test.select_dtypes(include=['object']).columns.difference(['VehSellerNotes'
,'VehFeats'])
bool_cols = X_test.select_dtypes(include=['bool']).columns
text_col = 'VehSellerNotes'
list_col = 'VehFeats'

print(num_cols)
print(cat_cols)
print(bool_cols)
print(text_col)
print(list_col)

# still 24 fields
print(len(num_cols) + len(cat_cols) + len(bool_cols) + 1 + 1)
```

```
Index(['SellerRating', 'SellerRevCnt', 'SellerZip', 'VehListdays',
       'VehMileage', 'VehYear'],
      dtype='object')
Index(['SellerCity', 'SellerListSrc', 'SellerName', 'SellerState',
       'VehColorExt', 'VehColorInt', 'VehDriveTrain', 'VehEngine', 'VehFuel',
       'VehHistory', 'VehMake', 'VehModel', 'VehPriceLabel',
       'VehTransmission'],
      dtype='object')
Index(['SellerIsPriv', 'VehCertified'], dtype='object')
VehSellerNotes
VehFeats
24
```

pre-process numerical features

```
# for numerical features, impute missing values and scale them
# fit on numerical fields for training data
X_test_num = num_imputer.transform(X_test[num_cols])
X_test_num = scaler.transform(X_test_num)

print(X_test_num[:5])
print(X_test_num.shape)
```

```
[[-1.44427654 -0.30052937 -0.77184994  1.30265674 -0.99649737  1.01844168]
 [ 0.47490389  1.26302713 -0.04931951  1.22549546  1.22311597  0.19520367]
 [-0.22297991 -0.31041086 -1.52584252 -0.35325873  1.71402742 -1.45127235]
 [ 0.30043294  0.47174744 -0.24528367 -0.73754404  1.34787715 -1.45127235]
 [ 0.38766841 -0.22223752 -1.85120095 -0.46082658 -0.33325284  1.01844168]]
(1000, 6)
```

pre-process categorical features

```
# impute missing values with 'missing' and one hot encode categorical
features
# fit on categorical training data
X_test_cat = cat_imputer.transform(X_test[cat_cols])
X_test_cat = encoder.transform(X_test_cat)

print(X_test_cat[:5])
print(X_test_cat.shape)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
(1000, 4004)
```

pre-process boolean features

```
# preprocess boolean features, convert true or false 1 or 0
X_test_bool = X_test[bool_cols].astype(int).values

print(X_test_bool[:5])
print(X_test_bool.shape)
```

```
[[0 0]
 [0 0]
 [0 1]
 [0 0]
 [0 0]]
(1000, 2)
```

pre-process seller notes text

```
# check values
X_test[text_col].head()
```

```
0    Thank you for visiting another one of Lake Keo...
1    This 2017 Jeep Grand Cherokee 4dr Limited 4x4 ...
2    Certified. Brilliant Black Crystal Pearlcoat 2...
3    2015 Jeep Grand Cherokee ***THIS VEHICLE IS AT...
4    AWD, CarFax One Owner! Navigation, Back-up Cam...
Name: VehSellerNotes, dtype: object
```

```
# create tfidf to convert text values into vectors
# remove stopwords that dont provide info and use 100 of the top ranked terms
across the corpus
# fit the vectorizer to the text column
X_test_text = vectorizer.transform(X_test[text_col].fillna('')).toarray()

print(X_test_text[2])
print(X_test_text.shape)
```

```
[0.2438432  0.2444744  0.09450755 0.         0.08205055 0.06905422
 0.06154613 0.15340564 0.         0.08194329 0.         0.05672536
 0.         0.07859434 0.         0.         0.         0.
 0.17426451 0.         0.         0.25816392 0.0621827  0.09179497
 0.         0.         0.         0.17352975 0.06491281 0.08563113
 0.         0.07734391 0.         0.         0.         0.
 0.07625276 0.07695312 0.         0.08781169 0.0649596  0.06216842
 0.         0.         0.1483974  0.08275679 0.16667804 0.07795112
 0.08146509 0.05885015 0.07757607 0.         0.         0.13559938
 0.         0.07432454 0.         0.23672637 0.         0.
 0.         0.06709033 0.06474184 0.05772639 0.         0.
 0.08096808 0.10976387 0.0687887  0.         0.06629873 0.08232031
 0.07517658 0.         0.28666402 0.         0.06861293 0.
 0.         0.         0.         0.06749372 0.         0.06299329
 0.         0.12970106 0.         0.         0.08497588 0.
 0.11662966 0.35989446 0.         0.07111084 0.38761589 0.05971019
 0.         0.         0.         0.        ]
(1000, 100)
```

pre-process vehicle features list

```
# check values
X_test[list_col].head()
```

```
0    ['4-Wheel Disc Brakes', 'ABS', 'Active Suspens...
1    ['12v Power Outlet', 'ABS Brakes', 'Air Condit...
2    ['1st and 2nd row curtain head airbags', '4-wh...
3    ['1st and 2nd row curtain head airbags', '4-wh...
4    ['1st and 2nd row curtain head airbags', '4-wh...
Name: VehFeats, dtype: object
```

```
# fill nulls, convert list to text
X_test[list_col] = X_test[list_col].fillna('[]').apply(eval).apply(lambda x:
','.join(x))
X_test[list_col].head()
```

```
0    4-Wheel Disc Brakes,ABS,Active Suspension,Adju...
1    12v Power Outlet,ABS Brakes,Air Conditioning,A...
2    1st and 2nd row curtain head airbags,4-wheel A...
3    1st and 2nd row curtain head airbags,4-wheel A...
4    1st and 2nd row curtain head airbags,4-wheel A...
Name: VehFeats, dtype: object
```

```
# use one hot encoder to convert comma seperated strings into a matrix with 1
or 0 for if the feature is present
X_test_feats = feats_encoder.transform(X_test[list_col].values.reshape(-1,
1))

print(X_test_feats[:5])
print(X_test_feats.shape)
```

```
[[0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
(1000, 797)
```

combine features then use PCA to reduce dimentionality

```
# combine all preprocessed features together using hstack to horizontally concat the arrays
X_test_preprocessed = np.hstack((X_test_num, X_test_cat, X_test_bool, X_test_text, X_test_feats))

print(X_test_preprocessed[:1])
print(X_test_preprocessed.shape)
```

```
[[-1.44427654 -0.30052937 -0.77184994 ...  0.          0.
   0.        ]]
(1000, 4909)
```

```
# use principal component analysis from earlier to retain 95% of variance
X_test_pca = pca.transform(X_test_preprocessed)

# only 788 fields now
print(X_test_preprocessed.shape[1])
print(X_test_pca.shape[1])
```

```
4909
788
```

```
# check how the records look now
print(X_test_preprocessed[0][:5])
print(X_test_pca[0][:5])
```

```
[-1.44427654 -0.30052937 -0.77184994  1.30265674 -0.99649737]
[ 2.02366936 -1.58549429  0.60574677  0.11481991  1.33805313]
```

```
# predict prices on test set
y_price_pred_ridge = best_model_ridge.predict(X_test_pca)
y_price_pred_ridge[:5]
```

```
array([44726.30988604, 23094.37984588, 21849.13222156, 24999.6774848 ,
       41616.42091966])
```

```
# predict trim on test set
y_trim_pred_lr = best_model_lr.predict(X_test_pca)
y_trim_pred_lr[:5]
```

```
array([19,  8,  6,  8, 19])
```

```
# conver trim from numerical back into categorical text
y_trim_pred_text = label_encoder.inverse_transform(y_trim_pred_lr)
y_trim_pred_text[:5]
```

```
array(['Premium Luxury', 'Limited', 'Laredo', 'Limited', 'Premium Luxury'],
      dtype=object)
```

```
test_data = pd.read_csv('Test_DataSet.csv')

# add the predictions back to the test_data
test_data['Vehicle_Trim'] = y_trim_pred_text
test_data['Dealer_Listing_Price'] = y_price_pred_ridge

test_data.head()
```

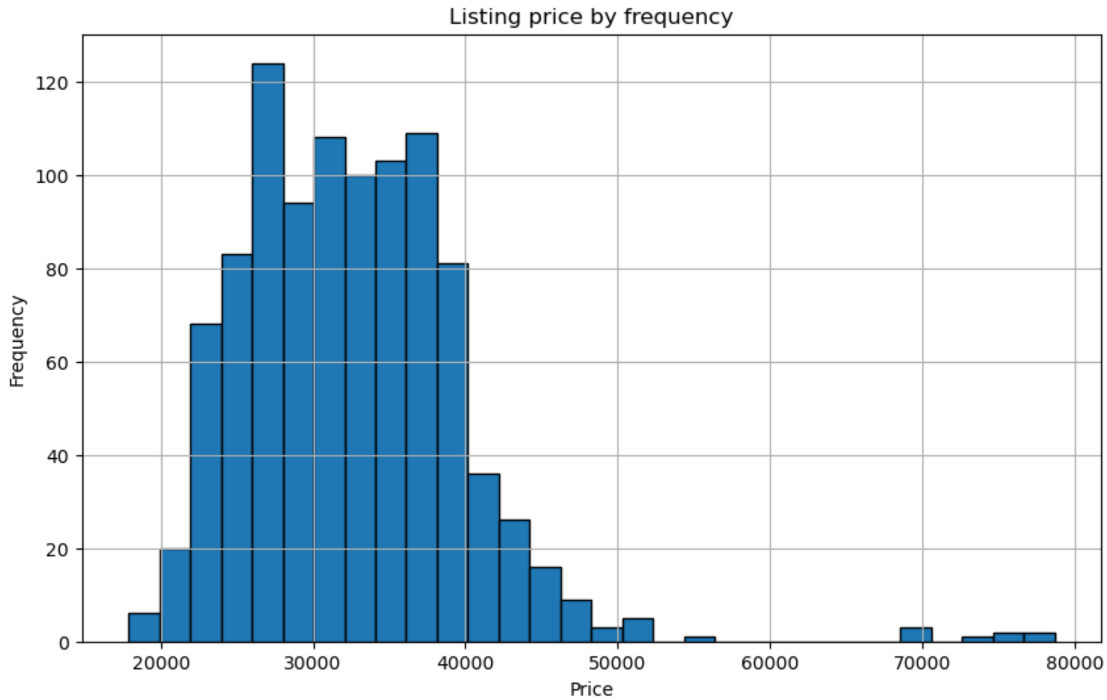
```
   ListingID  SellerCity  SellerIsPriv             SellerListSrc  \
0    8622015      Seneca         False         HomeNet Automotive
1    8625693     Bedford         False  Inventory Command Center
2    8625750     Webster         False    Jeep Certified Program
3    8626885  Louisville         False  Digital Motorworks (DMi)
4    8627430     Palmyra         False  Digital Motorworks (DMi)

                              SellerName  SellerRating  SellerRevCnt  \
0        Lake Keowee Chrysler Dodge Jeep Ram           2.5            59
1                     North Coast Auto Mall           4.7          2116
2  Marina Chrysler Dodge Jeep Mitsubishi RAM           3.9            46
3                     Oxmoor Ford Lincoln           4.5          1075
4                    F.C. Kerbeck &amp; Sons           4.6           162

  SellerState  SellerZip VehBodystyle  VehCertified  \
0          SC      29678          SUV         False
1          OH      44146          SUV         False
2          NY      14580          SUV          True
3          KY      40222          SUV         False
4          NJ       8065          SUV         False

                     VehColorExt VehColorInt     VehDriveTrain  \
0            Stellar Black Metallic      Cirrus               FWD
1               True Blue Pearlcoat       Black  Four Wheel Drive
2  Brilliant Black Crystal Pearlcoat       Black               4WD
3  Brilliant Black Crystal Pearlcoat       Black               4WD
4              Harbor Blue Metallic   Jet Black               AWD

                              VehEngine  \
0                     Gas V6 3.6L/222.6
1                      3.6L V6 CYLINDER
2  3.6L V6 24V MPFI DOHC Flexible Fuel
3                 3.6L V6 24V MPFI DOHC
4                  3.6L V6 24V GDI DOHC
```

```
                                            VehFeats        VehFuel  \
0  ['4-Wheel Disc Brakes', 'ABS', 'Active Suspens...       Gasoline
1  ['12v Power Outlet', 'ABS Brakes', 'Air Condit...       Gasoline
2  ['1st and 2nd row curtain head airbags', '4-wh...  E85 Flex Fuel
3  ['1st and 2nd row curtain head airbags', '4-wh...       Gasoline
4  ['1st and 2nd row curtain head airbags', '4-wh...       Gasoline

                                          VehHistory  VehListdays   VehMake
\
0  1 Owner, Non-Personal Use Reported, Buyback Pr...   143.991262  Cadillac
1  1 Owner, Accident(s) Reported, Non-Personal Us...   138.770486      Jeep
2              1 Owner, Buyback Protection Eligible    31.951088      Jeep
3              1 Owner, Buyback Protection Eligible     5.950127      Jeep
4  1 Owner, Non-Personal Use Reported, Buyback Pr...    24.672986  Cadillac

   VehMileage        VehModel VehPriceLabel  \
0     13625.0             XT5    Good Deal
1     42553.0  Grand Cherokee    Good Deal
2     48951.0  Grand Cherokee    Good Deal
3     44179.0  Grand Cherokee    Good Deal
4     22269.0             XT5    Good Deal

                                      VehSellerNotes VehType  \
0  Thank you for visiting another one of Lake Keo...    Used
1  This 2017 Jeep Grand Cherokee 4dr Limited 4x4 ...    Used
2  Certified. Brilliant Black Crystal Pearlcoat 2...    Used
3  2015 Jeep Grand Cherokee ***THIS VEHICLE IS AT...    Used
4  AWD, CarFax One Owner! Navigation, Back-up Cam...    Used

     VehTransmission  VehYear    Vehicle_Trim  Dealer_Listing_Price
0  8-Speed Automatic     2018  Premium Luxury          44726.309886
1  8-Speed Automatic     2017         Limited          23094.379846
2  8-Speed Automatic     2015          Laredo          21849.132222
3  8-Speed Automatic     2015         Limited          24999.677485
4  8-Speed Automatic     2018  Premium Luxury          41616.420920
```

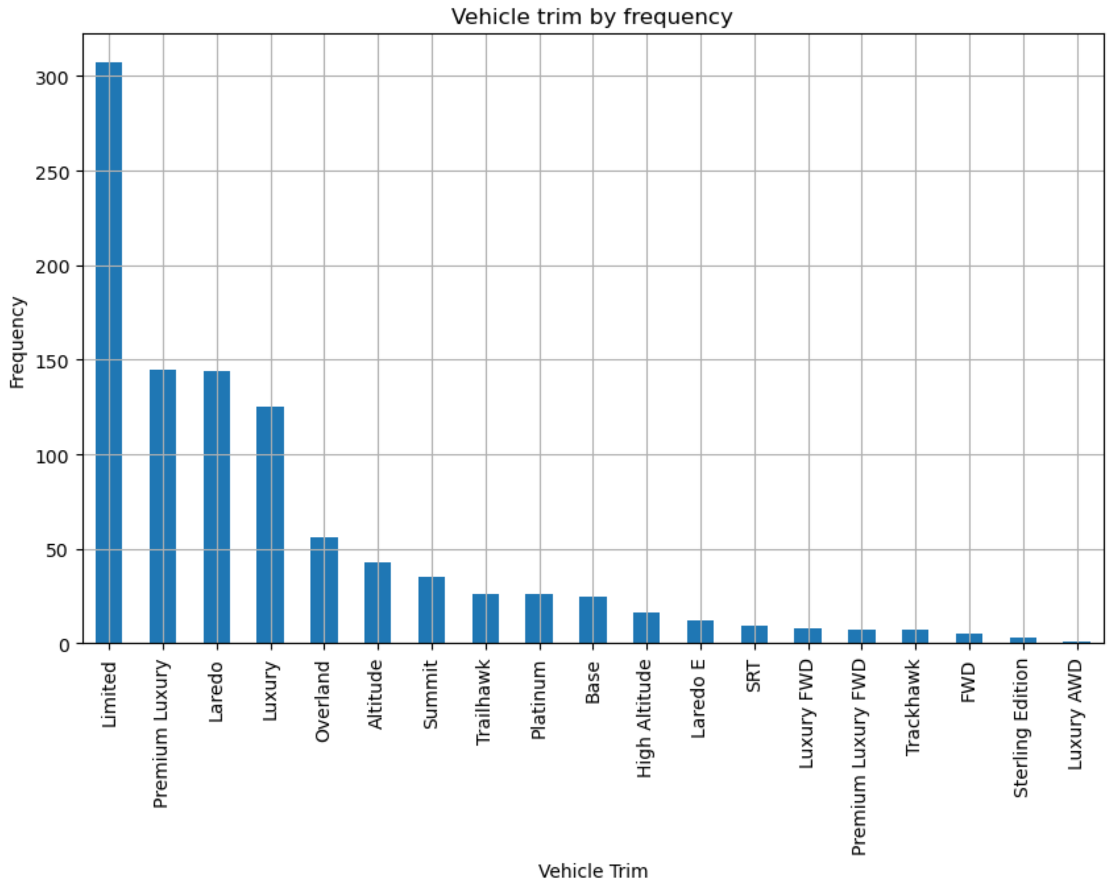
```
# select 3 required fields and write out
output_data = test_data[['ListingID', 'Vehicle_Trim',
'Dealer_Listing_Price']]
output_data.to_csv('test_data_with_predictions.csv', index=False)
```

prediction visualizations

```
# gistogram of Dealer_Listing_Price
plt.figure(figsize=(10, 6))
plt.hist(output_data['Dealer_Listing_Price'], bins=30, edgecolor='black')
plt.title('Listing price by frequency')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```




```
# bar Chart of Vehicle_Trim
plt.figure(figsize=(10, 6))
output_data['Vehicle_Trim'].value_counts().plot(kind='bar')
plt.title('Vehicle trim by frequency')
plt.xlabel('Vehicle Trim')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



Conclusion:

Based on our 2 models, we were able to correctly predict trims on validation data by an accuracy and F1 of 85%. The accuracy means that of 100 predictions for vehicle trims, 85 were correct.The F1 means the balance between correctly predicted trims and identifying all relevant trims is good.

On the price predictions, we were able to predict prices with an RMSE of 2917 and an R^2 score of 86%. The RMSE tells us that on average, the price predictions are off by $2917 and the R^2 tells us the model explains 86% of the variation in vehicle prices.