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1 Dataset Overview and Project Description

1.0.1 This problem involves the Carseats data set data set containing sales of child car seats at 400 different stores. A number of characteristics are recorded:

- Sales: Unit sales (in thousands) at each location
- CompPrice: Price charged by competitor at each location
- Income: Community income level (in thousands of dollars)
- Advertising: Local advertising budget for company at each location (in thousands of dollars)
- Population: Population size in region (in thousands)
- Price: Price company charges for car seats at each site
- ShelveLoc: A factor with levels Bad, Good and Medium indicating the quality of the shelving location for the car seats at each site
- Age: Average age of the local population
- Education: Education level at each location
- Urban: A factor with levels No and Yes to indicate whether the store is in an urban or rural location
- US: A factor with levels No and Yes to indicate whether the store is in the US or not

1.0.2 Please build a model to understand the determination of sales using the first 300 observations.

2 Libraries, Ignore Some Warnings, and Data

[11]:
```
import numpy as np
import pandas as pd
from ISLP import load_data

import warnings
warnings.filterwarnings("ignore")

Carseats = load_data('Carseats')
data = Carseats.head(300)

data.info() # data.shape[0] for number of rows, data.shape[1] for number of␣
↪columns
```

```
numeric_data = data.select_dtypes(include=['int64','float64'])
categorical_data = data.select_dtypes(include='category')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300 entries, 0 to 299
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Sales        300 non-null    float64
 1   CompPrice    300 non-null    int64
 2   Income       300 non-null    int64
 3   Advertising  300 non-null    int64
 4   Population   300 non-null    int64
 5   Price        300 non-null    int64
 6   ShelveLoc    300 non-null    category
 7   Age          300 non-null    int64
 8   Education    300 non-null    int64
 9   Urban        300 non-null    category
 10  US           300 non-null    category
dtypes: category(3), float64(1), int64(7)
memory usage: 20.1 KB
```

[2]:
```
print("Duplicates in numeric data:", numeric_data.duplicated().sum())
print("\nNumber of nulls for each column:\n",data.isnull().sum())
print("\nNumber of infinite values for each column:\n\n",np.isinf(numeric_data).
  ↪sum())
```

```
Duplicates in numeric data: 0

Number of nulls for each column:
 Sales          0
CompPrice      0
Income         0
Advertising    0
Population     0
Price          0
ShelveLoc      0
Age            0
Education      0
Urban          0
US             0
dtype: int64

Number of infinite values for each column:

 Sales          0
CompPrice      0
Income         0
```

```
Advertising    0
Population     0
Price          0
Age            0
Education      0
dtype: int64
```

From the 300 observations we are using as our dataset, we see that we have no missing values, infinite values or duplicated rows in our dataset. There are 7 numerical variables and 3 category variables being ShelveLoc, Urban, and US.

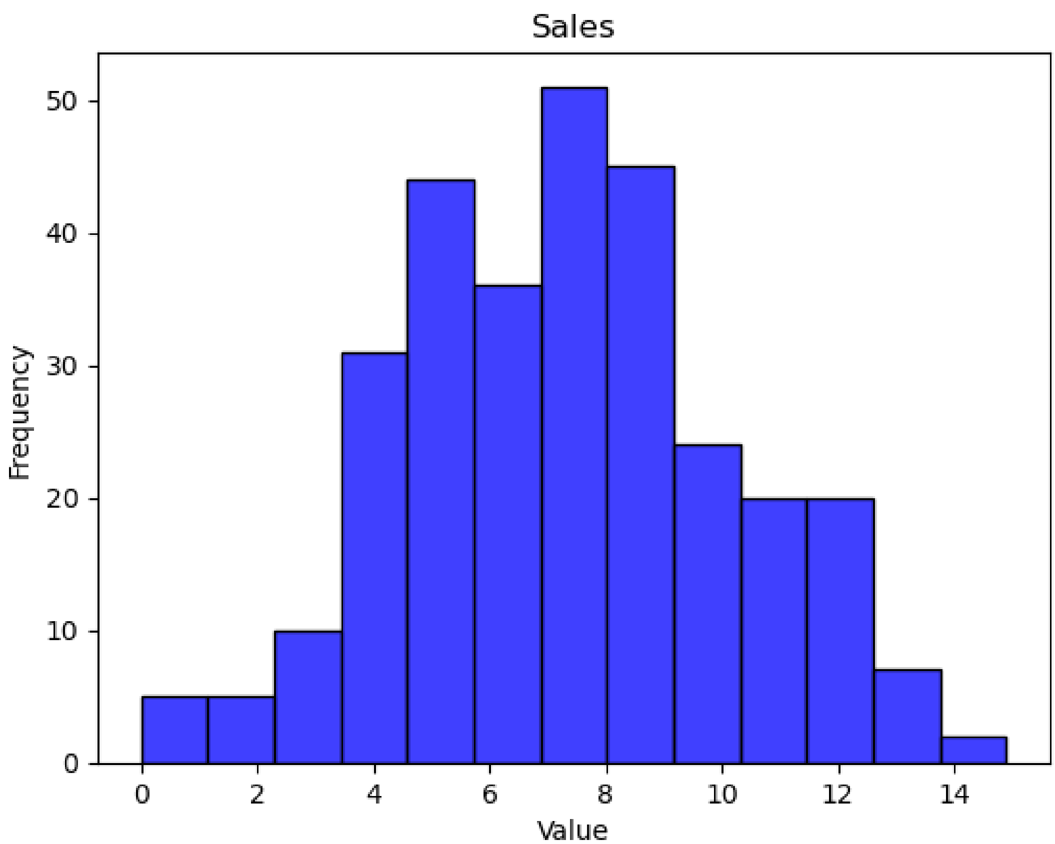
[3]:
```
data.describe().transpose()
```

[3]:
```
             count        mean         std   min      25%      50%     75%  \
Sales        300.0    7.362967    2.835229   0.0    5.255    7.445    9.11
CompPrice    300.0  124.536667   15.343840  77.0  115.000  123.500  135.00
Income       300.0   69.843333   27.716291  21.0   44.750   70.500   91.25
Advertising  300.0    6.036667    6.262538   0.0    0.000    5.000   11.00
Population   300.0  260.716667  147.445959  10.0  136.250  265.500  391.50
Price        300.0  115.490000   23.655199  24.0   99.750  117.000  131.00
Age          300.0   53.743333   16.298761  25.0   39.750   55.500   66.00
Education    300.0   14.020000    2.702581  10.0   12.000   14.000   16.25

               max
Sales         14.9
CompPrice    162.0
Income       120.0
Advertising   25.0
Population   509.0
Price        191.0
Age           80.0
Education     18.0
```

3 Visualizing Target Variable (Sales)

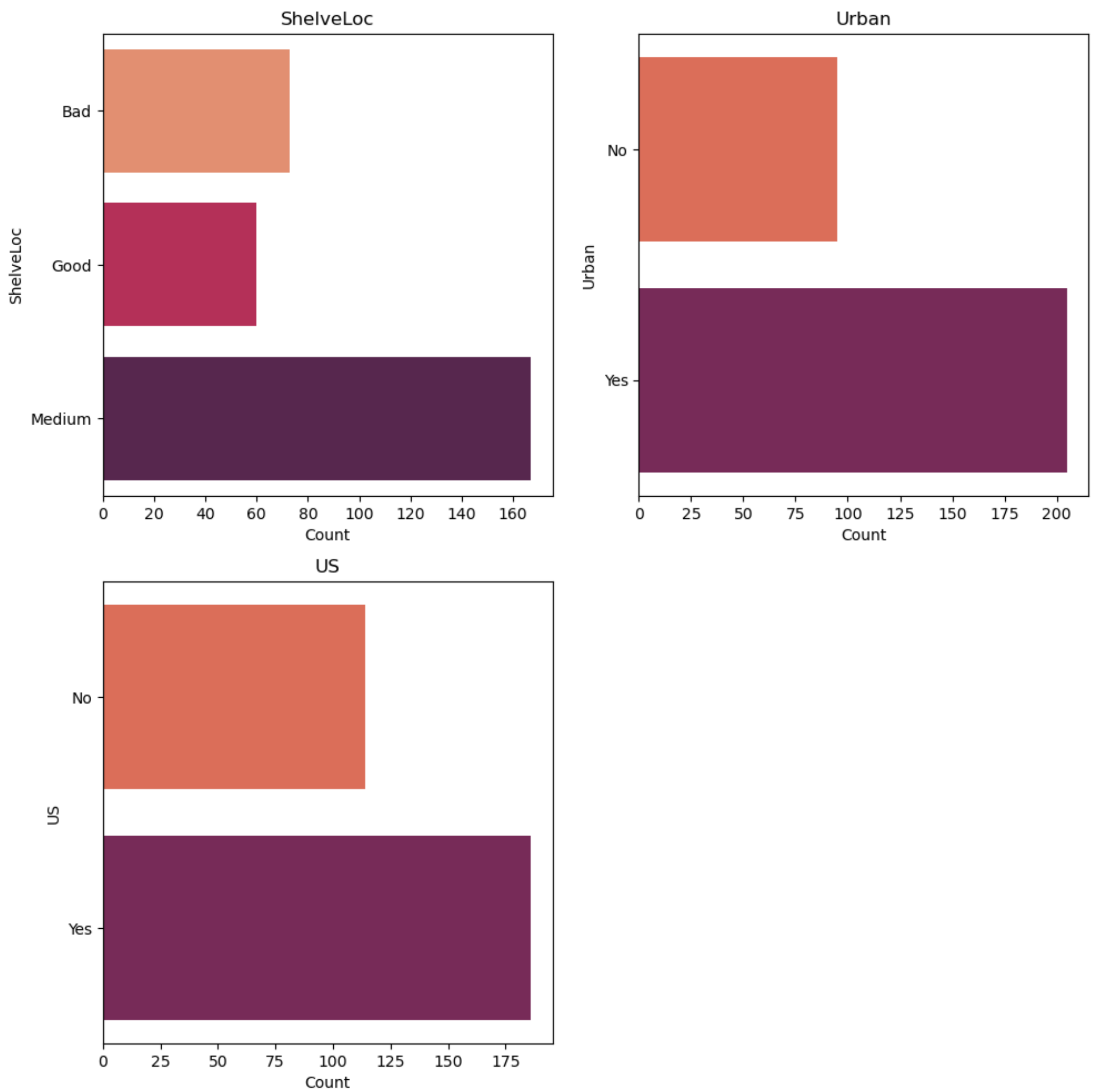
[4]:
```
from matplotlib import pyplot as plt
import seaborn as sns

sns.histplot(data['Sales'],color='blue')
plt.title(f"{'Sales'}")
plt.xlabel("Value")
plt.ylabel("Frequency")
```

[4]:
```
Text(0, 0.5, 'Frequency')
```



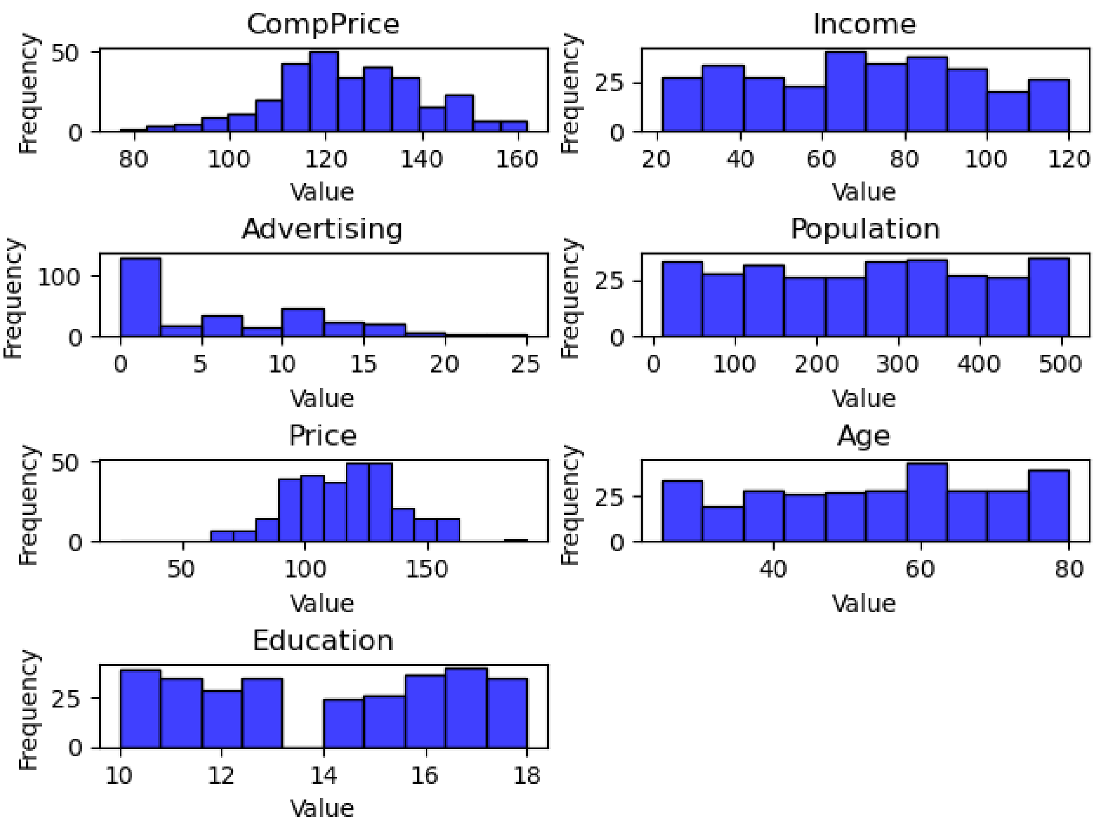
4 Visualizing Categorical Variables

[5]:
```
plt.figure(figsize=(10,10))
for i, feature in enumerate(categorical_data.columns):
    counts = data[feature].value_counts().head(10)
    plt.subplot(2, 2, i+1)
    sns.barplot(x=counts.values, y=counts.index, palette='rocket_r')
    plt.title(f"{feature}")
    plt.xlabel("Count")
plt.tight_layout(pad=1.0)
#plt.savefig("categorical_features_plots.png"); plt.clf();
```



5 Visualizing Numeric Features/Inputs

[6]:
```
for i, feature in enumerate(numeric_data.columns[1:]): # Sales is first column, so it is excluded since it is target variable
    plt.subplot(4,2,i+1) # rows (first param) * cols (second param) = 8
    sns.histplot(data[feature],color='blue')
    plt.title(f"{feature}")
    plt.xlabel("Value")
    plt.ylabel("Frequency")
plt.tight_layout(pad=0.5)
#plt.savefig("continuous_features_plots.png"); plt.clf()
```



From some summary statistics and exploratory data analysis,the average Sales from each location is 7.326 (in thousands). From the bell-shaped curve of our target variable we see that the sistribution of sales is approximately normal. The majority of Store Locations (observations) from our dataset show that the shevling location was medium, in a urban location and stores were located in the US. From visualizing the numerical features distributions apart of the dataset, CompPrice and Price can be assumed to be approximatley normal. Advertisting is skewed right, with education, income, population, and age all being uniformly distributed.

6 Data Pre-Processing

1. Scale numeric features with RobustScaler (robust to outliers by scaling with 25th-75th percentiles of dataset)
2. Encode categorical variables with OneHotEncoder

- 1 and 2 are combined in ColumnTransformer (alternative could be using Pipeline object storing all preprocessing)

3. Split into training and testing

[7]:
```
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import OneHotEncoder, RobustScaler
from sklearn.pipeline import Pipeline

X = data.drop('Sales',axis=1)
y = data['Sales']

numeric_features = ['CompPrice', 'Income', 'Advertising', 'Population','Price',␣
 ↪'Age', 'Education']
categorical_features = ['ShelveLoc', 'Urban', 'US']

preprocessor = ColumnTransformer(transformers = [('num', RobustScaler(),␣
 ↪numeric_features),
        ('cat', OneHotEncoder(sparse_output=False), categorical_features) ])

X = preprocessor.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
```

7 Models (Uses K-Fold Cross-Validation With K = 5)

7.0.1 1. Train model with GridSearchCV

7.0.2 2. Predict testing data with best model from step 1

7.0.3 3. Metrics: R-squared for all, Correlation Matrix in Regression, Feature Importance in Ensembles

7.0.4 Linear Regression

[8]:
```
import sklearn.model_selection as skm
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.linear_model import LinearRegression, Ridge, Lasso

kfold = skm.KFold(5, random_state=42, shuffle=True)

linear_grid = skm.GridSearchCV(
        LinearRegression(),
        {}, # no hyperparameter tuning
        refit=True,
        cv=kfold,
        scoring='accuracy')

linear_grid.fit(X_train,y_train)
best_linear = linear_grid.best_estimator_

y_pred_train = best_linear.predict(X_train)
```

```
y_pred_test = best_linear.predict(X_test)

coefficients_rounded = [f'{num:.4f}' for num in best_linear.coef_]

print(f"Intercept: {best_linear.intercept_:.4f}\nCoefficients:␣
 ↪{coefficients_rounded}")
print(f"Training R-Squared: {r2_score(y_train,y_pred_train):.4f}")

print(f'Testing R-Squared: {r2_score(y_test, y_pred_test):.4f}')
```

```
Intercept: 7.1272
Coefficients: ['1.9296', '0.7849', '1.6044', '0.0029', '-2.9583', '-1.1465',
'-0.1119', '-2.1860', '2.5370', '-0.3509', '-0.0544', '0.0544', '0.2406',
'-0.2406']
Training R-Squared: 0.8786
Testing R-Squared: 0.8887
```

From our linear regression model in predicting the sales of carseats, we see after cross validation our training set model has a R-squared value of 0.8786. In testing our model accuary we see that are model preformed very well.When tested against the best training model, we see that the testing R-squared value is 0.8887. We can conclude that 88.87% of the variation in Carseat sales can be exlained by our independent variables.

7.0.5 Ridge Regression With Parameter Tuning

For Ridge and LASSO, alpha would not work in param_grid in GridSearchCV, so for loop was implemented

[9]:
```
columns = ['Model','Intercept','Training R-Squared','Testing␣
 ↪R-Squared','Coefficients']
ridge_models = pd.DataFrame(index=[0,1,2],columns=columns)
ridge_models.loc[0,'Model'] = Ridge(alpha=5)
ridge_models.loc[1,'Model'] = Ridge(alpha=1)
ridge_models.loc[2,'Model'] = Ridge(alpha=0.1)

for i in ridge_models.index:
    ridge_grid = skm.GridSearchCV(
        ridge_models.loc[i,'Model'],
        {}, # no hyperparameter tuning in grid search cv
        refit=True,
        cv=kfold,
        scoring='accuracy')

    ridge_grid.fit(X_train,y_train)
    best_ridge = ridge_grid.best_estimator_

    y_pred_train = best_ridge.predict(X_train)
    y_pred_test = best_ridge.predict(X_test)
```

```
    ridge_models.loc[i,'Intercept'] = f'{best_ridge.intercept_:.4f}'
    ridge_models.loc[i,'Coefficients'] = [f'{num:.4f}' for num in best_ridge.
 ↪coef_]
    ridge_models.loc[i,'Training R-Squared'] =␣
 ↪f'{r2_score(y_train,y_pred_train):.4f}'
    ridge_models.loc[i,'Testing R-Squared'] = f'{r2_score(y_test, y_pred_test):.
 ↪4f}'

ridge_models
```

[9]:

```
              Model Intercept Training R-Squared Testing R-Squared  \
0    Ridge(alpha=5)    7.1281             0.8725            0.8805
1    Ridge(alpha=1)    7.1272             0.8783            0.8881
2  Ridge(alpha=0.1)    7.1272             0.8786            0.8887

                                        Coefficients
0  [1.7514, 0.7374, 1.3991, -0.0079, -2.7286, -1…
1  [1.8911, 0.7748, 1.5573, 0.0008, -2.9091, -1.1…
2  [1.9257, 0.7839, 1.5995, 0.0027, -2.9533, -1.1…
```

Using Ridge Regression, we see that the model using an alpha set at 0.1 preformed the best with a training and testing R-squared of 0.8786 and 0.8887 respectively.

7.0.6 LASSO Regression With Parameter Tuning

[10]:

```
columns = ['Model','Intercept','Training R-Squared','Testing␣
 ↪R-Squared','Coefficients']
lasso_models = pd.DataFrame(index=[0,1,2],columns=columns)
lasso_models.loc[0,'Model'] = Lasso(alpha=0.1)
lasso_models.loc[1,'Model'] = Lasso(alpha=0.01)
lasso_models.loc[2,'Model'] = Lasso(alpha=0.0001)

for i in lasso_models.index:
    lasso_grid = skm.GridSearchCV(
        lasso_models.loc[i,'Model'],
        {}, # no hyperparameter tuning in grid search cv
        refit=True,
        cv=kfold,
        scoring='accuracy')

    lasso_grid.fit(X_train,y_train)
    best_lasso = lasso_grid.best_estimator_

    y_pred_train = best_lasso.predict(X_train)
    y_pred_test = best_lasso.predict(X_test)

    lasso_models.loc[i,'Intercept'] = f'{best_lasso.intercept_:.4f}'
```

```
    lasso_models.loc[i,'Coefficients'] = [f'{num:.4f}' for num in best_lasso.
 ↪coef_]
    lasso_models.loc[i,'Training R-Squared'] =␣
 ↪f'{r2_score(y_train,y_pred_train):.4f}'
    lasso_models.loc[i,'Testing R-Squared'] = f'{r2_score(y_test, y_pred_test):.
 ↪4f}'

lasso_models
```

[10]:

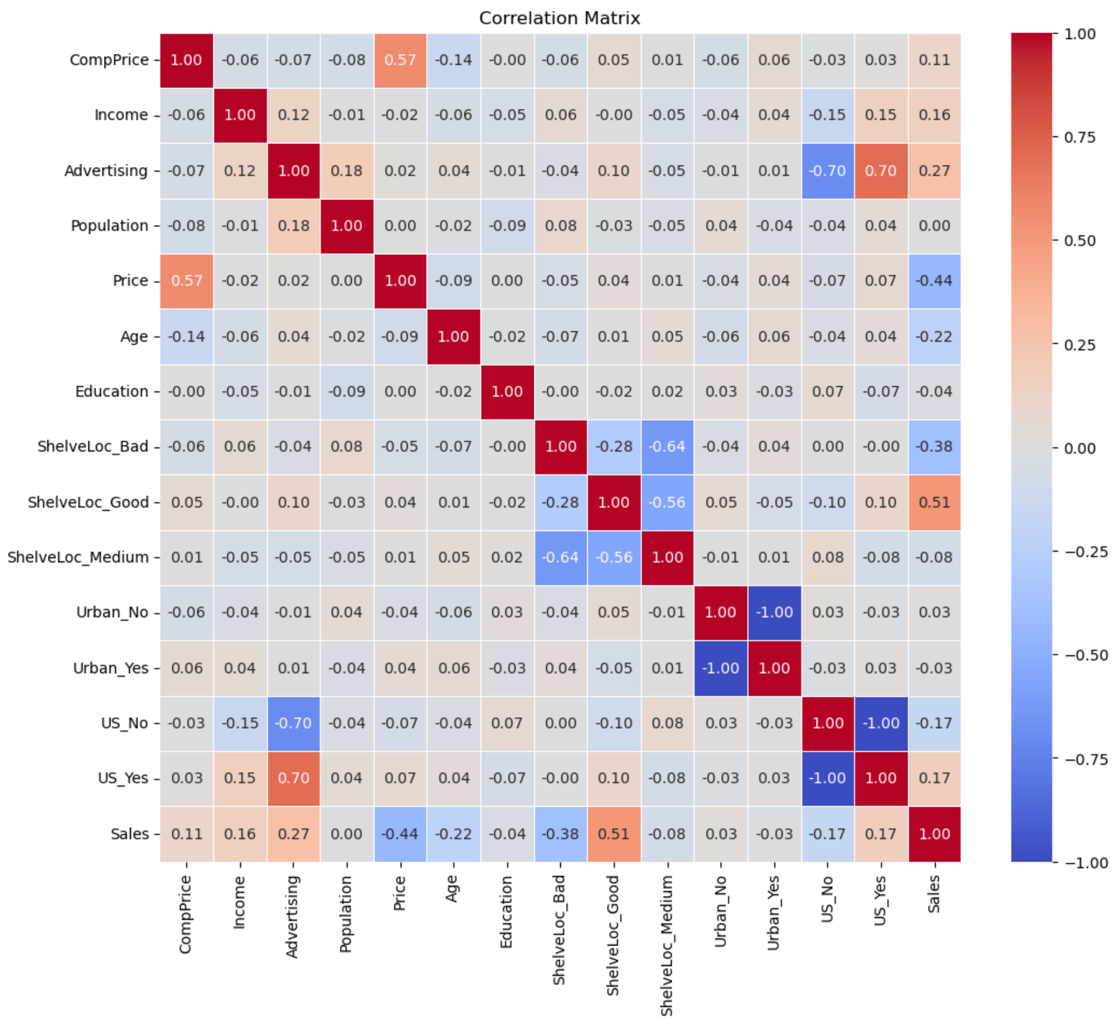
```
                   Model Intercept Training R-Squared Testing R-Squared  \
0     Lasso(alpha=0.1)    6.8200             0.8411            0.8582
1    Lasso(alpha=0.01)    6.6507             0.8779            0.8898
2  Lasso(alpha=0.0001)    6.6916             0.8786            0.8887

                                        Coefficients
0  [1.5302, 0.5154, 0.9997, 0.0000, -2.4998, -0.8…
1  [1.8878, 0.7572, 1.4796, 0.0000, -2.9160, -1.1…
2  [1.9292, 0.7846, 1.6031, 0.0027, -2.9579, -1.1…
```

Using Lasso Regression, we see that the model using an alpha set at 0.0001 preformed the best with a training and testing R-squared of 0.8786 and 0.8887 respectively.

7.0.7 Correlation Matrix

[11]:

```
encoded_categories = preprocessor.named_transformers_['cat'].
 ↪get_feature_names_out(categorical_features)
column_names = numeric_features + list(encoded_categories)
transformed_df = pd.DataFrame(X, columns=column_names)
transformed_df['Sales'] = y.reset_index(drop=True)

plt.figure(figsize=(12, 10))
sns.heatmap(transformed_df.corr(), annot=True, fmt=".2f", linewidths=0.5,␣
 ↪cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()
```



7.0.8 Random Forest With Parameter Tuning

[12]:
```
from sklearn.ensemble import RandomForestRegressor

rf_grid = skm.GridSearchCV(
        RandomForestRegressor(random_state=42),
        param_grid={
            'ccp_alpha': [0.01,0.1,10],
            'max_features': [3,5,None],
            'min_samples_split': [5,10,50]
        },
        refit=True,
        cv=kfold,
        scoring='accuracy')
```

```
rf_grid.fit(X_train,y_train)
best_rf = rf_grid.best_estimator_

y_pred_train = best_rf.predict(X_train)
y_pred_test = best_rf.predict(X_test)

print(f"Best parameters after tuning/cv: {rf_grid.best_params_}")
print(f"Training R-Squared: {r2_score(y_train,y_pred_train):.4f}")

print(f'Testing R-Squared: {r2_score(y_test, y_pred_test):.4f}')

feature_importances = best_rf.feature_importances_
features = transformed_df.drop('Sales',axis=1).columns

pd.DataFrame({
    'Feature': features,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)
```

```
Best parameters after tuning/cv: {'ccp_alpha': 0.01, 'max_features': 3,
'min_samples_split': 5}
Training R-Squared: 0.8751
Testing R-Squared: 0.6346
```

[12]:

	Feature	Importance
4	Price	0.205083
8	ShelveLoc_Good	0.173927
5	Age	0.095422
1	Income	0.092040
0	CompPrice	0.089748
2	Advertising	0.084315
7	ShelveLoc_Bad	0.075530
3	Population	0.069298
6	Education	0.041614
9	ShelveLoc_Medium	0.033297
12	US_No	0.011867
11	Urban_Yes	0.010020
10	Urban_No	0.009192
13	US_Yes	0.008646

From our random forest model setting alpha as 0.01 we see that our training R-squared value is high at 0.8751 but our testing R-squared value was 0.6346 which shows that 63.46% of our variability in Sales can be explained by our independent variables. Also from our random forest model we see that our top three features in our model were Price, Good Shelving Location, and Age.

7.0.9 XGBoost With Parameter Tuning

[13]:
```python
import xgboost as xgb

xgb_grid = skm.GridSearchCV(
    xgb.XGBRegressor(),
    param_grid={
        'max_features': [3,5,None],
        'min_samples_split': [5,10,50]
    },
    refit=True,
    cv=kfold,
    scoring='accuracy')

xgb_grid.fit(X_train,y_train)
best_xgb = xgb_grid.best_estimator_

y_pred_train = best_xgb.predict(X_train)
y_pred_test = best_xgb.predict(X_test)

print(f"Best parameters after tuning/cv: {xgb_grid.best_params_}")
print(f"Training R-Squared: {r2_score(y_train,y_pred_train):.4f}")

print(f'Testing R-Squared: {r2_score(y_test, y_pred_test):.4f}')

feature_importances = best_xgb.feature_importances_
features = transformed_df.drop('Sales',axis=1).columns

pd.DataFrame({
    'Feature': features,
    'Importance': feature_importances
}).sort_values(by='Importance', ascending=False)
```

```
Best parameters after tuning/cv: {'max_features': 3, 'min_samples_split': 5}
Training R-Squared: 1.0000
Testing R-Squared: 0.7026
```

[13]:

	Feature	Importance
8	ShelveLoc_Good	0.743838
7	ShelveLoc_Bad	0.114637
4	Price	0.056540
2	Advertising	0.021581
5	Age	0.021372
0	CompPrice	0.015734
1	Income	0.010088
6	Education	0.005808
10	Urban_No	0.004618
3	Population	0.003483

9	ShelveLoc_Medium	0.001313
12	US_No	0.000987
11	Urban_Yes	0.000000
13	US_Yes	0.000000

From our gradient boosted tree our testing R-squared value was 0.7026. We also see that the shelving location was the most important feature in our model.