rocchio_assign6

August 9, 2023

[1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
df=pd.read_excel('ames_housing_data.xlsx')
```

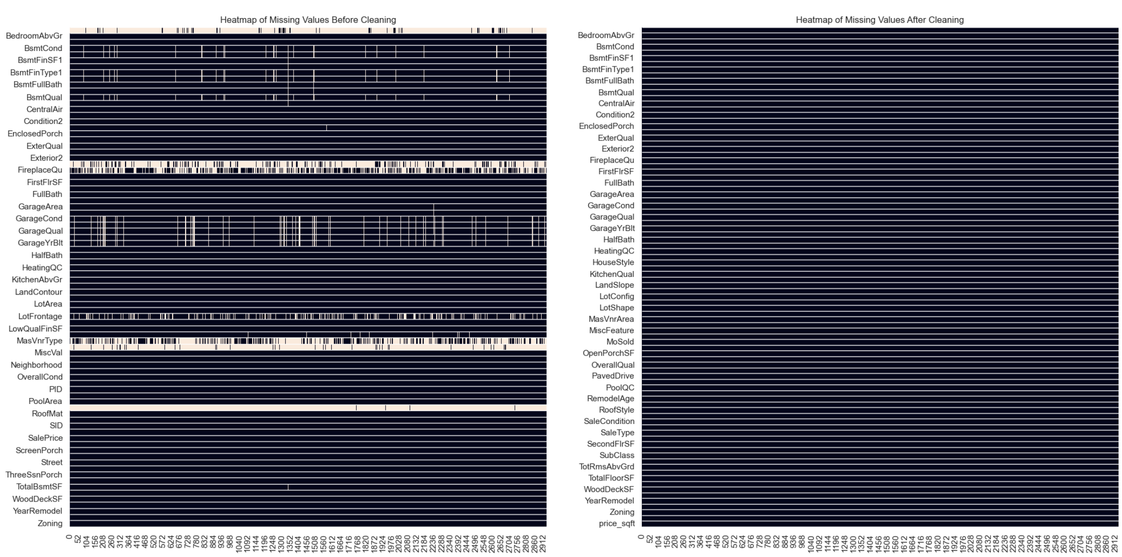
[3]:
```
### Adding in code to clean the data.
import seaborn as sns
import matplotlib.pyplot as plt



##
sns.set()
fig, (ax1, ax2) = plt.subplots(1,2,figsize=(25, 12))

df_heat1=df.sort_index(axis=1, ascending=False)
sns.heatmap(df_heat1.T.isnull(), ax=ax1, cbar=False).invert_yaxis()
ax1.hlines(range(len(df_heat1)), *ax1.get_xlim(), color='white', linewidths=1)
ax1.vlines([], [], [])
ax1.set_title('Heatmap of Missing Values Before Cleaning')
plt.yticks(rotation = 360)
df['TotalFloorSF'] = df['FirstFlrSF'] + df['SecondFlrSF']
df['HouseAge'] = df['YrSold'] - df['YearBuilt']
df['QualityIndex'] = df['OverallQual'] * df['OverallCond']
df['logSalePrice'] = np.log(df['SalePrice'])
df['price_sqft'] = df['SalePrice'] / df['TotalFloorSF']
Nulls=[]
for i in df.columns:
    if df[i].isnull().sum() > 0:
        Nulls.append(i)
df['LotFrontage']=df['LotFrontage'].fillna(df['LotFrontage'].median())
df['Alley']=df['Alley'].fillna('No alley')
df['MasVnrType']=df['MasVnrType'].fillna('None')
df['MasVnrArea']=df['MasVnrArea'].fillna(0)
df['RemodelAge']=df['YrSold']-df['YearRemodel']
for col in ['BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1',␣
 ↪'BsmtFinType2']:
```

```python
    df[col].fillna('No basement')
for col in ['GarageType', 'GarageFinish', 'GarageQual', 'GarageCond']:
    if df[col].dtype == 'object':
        df[col]=df[col].fillna('No garage')
    else:
        df[col]=df[col].fillna('None')
df['GarageYrBlt']=df['GarageYrBlt'].fillna(df['GarageYrBlt'].median())
df['GarageCars']=df['GarageCars'].fillna(0)
df['GarageArea']=df['GarageArea'].fillna(0)
df['PoolQC']=df['PoolQC'].fillna('No pool')
df['Fence']=df['Fence'].fillna('No fence')
df['MiscFeature']=df['MiscFeature'].fillna('No feature')
df['Electrical']=df['Electrical'].fillna(df['Electrical'].mode()[0])
df['FireplaceQu']=df['FireplaceQu'].fillna('No fireplace')
for col in ['BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2']:
    df[col]=df[col].fillna('No basement')
for col in ['BsmtFinSF1', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'BsmtFullBath', 'BsmtHalfBath']:
    df[col]=df[col].fillna(0)
df.to_csv('ames_housing_data.csv', index=False)
sns.set()
df_heat2=df.sort_index(axis=1, ascending=False)
sns.heatmap(df_heat2.T.isnull(), ax=ax2, cbar=False).invert_yaxis()
ax2.hlines(range(len(df_heat2)), *ax2.get_xlim(), color='white', linewidths=1)
ax2.set_title('Heatmap of Missing Values After Cleaning')
ax2.vlines([], [], [])
plt.yticks(rotation = 360)
plt.show()
```



[5]:
```python
ames_housing_data=df.copy()
```

1 Task 1

[6]:
```python
from sklearn.model_selection import train_test_split

# Splitting the dataset into train and test sets (70/30 split)
train_data, test_data = train_test_split(ames_housing_data, test_size=0.3,␣
↪random_state=42)

# Creating a table of observation counts for the train/test data partition
observation_counts = {
    "Dataset": ["Train", "Test"],
    "Observation Counts": [len(train_data), len(test_data)]
}

observation_counts_df = pd.DataFrame(observation_counts)
observation_counts_df
```

[6]:

	Dataset	Observation Counts
0	Train	2051
1	Test	879

[9]:
```python
continuous_vars = ['LotFrontage', 'LotArea', 'OverallQual', 'OverallCond',␣
↪'YearBuilt', 'YearRemodel',
                   'BsmtFinSF1', 'BsmtUnfSF', 'TotalBsmtSF', 'FirstFlrSF',␣
↪'SecondFlrSF', 'GrLivArea']

categorical_vars = ['MSZoning', 'Street', 'LotShape', 'LandContour',␣
↪'Utilities', 'HouseStyle']

available_categorical_vars = [var for var in categorical_vars if var in␣
↪train_data.columns]

dummy_vars = pd.get_dummies(train_data[available_categorical_vars],␣
↪drop_first=True)

predictor_pool = pd.concat([train_data[continuous_vars], dummy_vars], axis=1)

predictor_list = predictor_pool.columns.tolist()
predictor_list
```

[9]:
```
['LotFrontage',
 'LotArea',
 'OverallQual',
```

```
 'OverallCond',
 'YearBuilt',
 'YearRemodel',
 'BsmtFinSF1',
 'BsmtUnfSF',
 'TotalBsmtSF',
 'FirstFlrSF',
 'SecondFlrSF',
 'GrLivArea',
 'Street_Pave',
 'LotShape_IR2',
 'LotShape_IR3',
 'LotShape_Reg',
 'LandContour_HLS',
 'LandContour_Low',
 'LandContour_Lvl',
 'Utilities_NoSeWa',
 'Utilities_NoSewr',
 'HouseStyle_1.5Unf',
 'HouseStyle_1Story',
 'HouseStyle_2.5Fin',
 'HouseStyle_2.5Unf',
 'HouseStyle_2Story',
 'HouseStyle_SFoyer',
 'HouseStyle_SLvl']
```

2 Task 2

2.1 VIF Calc

Several variables exhibit high VIF values, suggesting potential multicollinearity. It might be prudent to consider removing or adjusting some of these variables to address this issue.

Regarding VIF values for indicator (dummy) variables, they can sometimes be inflated, especially when categories of the original variable have a significant imbalance in counts. High VIFs for dummy variables, particularly when the original categorical variable has many levels, might not always indicate harmful multicollinearity. However, it's still essential to be cautious and understand the context of the data and the domain when interpreting these values.

[12]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

numerical_cols = predictor_pool.select_dtypes(include=[float, int]).columns
predictor_pool_filled = predictor_pool[numerical_cols].
 ↪fillna(predictor_pool[numerical_cols].mean())

assert not predictor_pool_filled.isna().sum().sum(), "There are still missing␣
 ↪values!"
```

```python
vif_data = pd.DataFrame()
vif_data["Variable"] = predictor_pool_filled.columns
vif_data["VIF"] = [variance_inflation_factor(predictor_pool_filled.values, i)
                   for i in range(predictor_pool_filled.shape[1])]

vif_data_sorted = vif_data.sort_values(by="VIF", ascending=False)
vif_data_sorted
```

[12]:

	Variable	VIF
5	YearRemodel	10286.092790
4	YearBuilt	9835.516445
11	GrLivArea	1217.520955
9	FirstFlrSF	767.104595
10	SecondFlrSF	148.062712
8	TotalBsmtSF	67.003511
2	OverallQual	38.653702
3	OverallCond	36.339358
7	BsmtUnfSF	18.331332
6	BsmtFinSF1	15.794448
0	LotFrontage	14.984904
1	LotArea	3.039146

[15]:

```python
import statsmodels.api as sm
from statsmodels.formula.api import ols

# Helper function to fit OLS model using different selection methods
def fit_ols_model(data, target, predictors, method):
    """Fits an OLS model using a specific selection method."""
    initial_formula = target + " ~ " + " + ".join(predictors)
    model = ols(initial_formula, data=data).fit()

    if method == "backward":
        while True:
            max_p_value = max(model.pvalues[1:])
            if max_p_value > 0.05:
                exclude_variable = model.pvalues.idxmax()
                predictors.remove(exclude_variable.split("[")[0].strip())
                formula = target + " ~ " + " + ".join(predictors)
                model = ols(formula, data=data).fit()
            else:
                break

    elif method == "forward":
        predictors = []
        remaining_predictors = initial_predictors.copy()
        while remaining_predictors:
            temp_predictors = predictors + [remaining_predictors[0]]
```

```
            temp_formula = target + " ~ " + " + ".join(temp_predictors)
            temp_model = ols(temp_formula, data=data).fit()
            if temp_model.pvalues[-1] < 0.05:
                predictors = temp_predictors
            remaining_predictors.remove(remaining_predictors[0])
        formula = target + " ~ " + " + ".join(predictors)
        model = ols(formula, data=data).fit()

    elif method == "stepwise":
        predictors = []
        remaining_predictors = initial_predictors.copy()
        while remaining_predictors:
            changed = False
            temp_predictors = predictors + [remaining_predictors[0]]
            temp_formula = target + " ~ " + " + ".join(temp_predictors)
            temp_model = ols(temp_formula, data=data).fit()
            if temp_model.pvalues[-1] < 0.05:
                predictors = temp_predictors
                changed = True
            remaining_predictors.remove(remaining_predictors[0])

            model = ols(target + " ~ " + " + ".join(predictors), data=data).
 ↪fit()
            p_values = model.pvalues[1:]
            while max(p_values) > 0.05:
                changed = True
                remove = p_values.idxmax()
                predictors.remove(remove.split("[")[0].strip())
                model = ols(target + " ~ " + " + ".join(predictors), data=data).
 ↪fit()
                p_values = model.pvalues[1:]

            if not changed:
                break

    return model

target = "SalePrice"

train_data_updated = train_data.copy()
train_data_updated[predictor_pool_filled.columns] = predictor_pool_filled

# Fitting models again using different selection methods on the updated␣
 ↪train_data
models = {
    "Full Model": ols(target + " ~ " + " + ".join(initial_predictors),␣
 ↪data=train_data_updated).fit(),
```

```python
    "Backward Selection": fit_ols_model(train_data_updated, target,␣
↪initial_predictors, method="backward"),
    "Forward Selection": fit_ols_model(train_data_updated, target,␣
↪initial_predictors.copy(), method="forward"),
    "Stepwise Selection": fit_ols_model(train_data_updated, target,␣
↪initial_predictors.copy(), method="stepwise")
}

# Extracting the selected predictors for each model
selected_predictors = {key: model.model.exog_names[1:] for key, model in models.
↪items()}
selected_predictors
```

[15]:

```
{'Full Model': ['LotFrontage',
  'LotArea',
  'OverallQual',
  'OverallCond',
  'YearBuilt',
  'YearRemodel',
  'BsmtFinSF1',
  'BsmtUnfSF',
  'TotalBsmtSF',
  'FirstFlrSF',
  'SecondFlrSF',
  'GrLivArea'],
 'Backward Selection': ['LotFrontage',
  'LotArea',
  'OverallQual',
  'OverallCond',
  'YearBuilt',
  'YearRemodel',
  'BsmtUnfSF',
  'TotalBsmtSF',
  'FirstFlrSF',
  'SecondFlrSF'],
 'Forward Selection': ['LotFrontage',
  'LotArea',
  'OverallQual',
  'YearBuilt',
  'YearRemodel',
  'BsmtUnfSF',
  'TotalBsmtSF',
  'FirstFlrSF',
  'SecondFlrSF'],
 'Stepwise Selection': ['LotFrontage', 'LotArea', 'OverallQual']}
```

2.2 VIF Calc for Each Model

The table below compares the in-sample fit and predictive accuracy metrics for the models.

[16]:
```python
# Calculating VIF values for each model's predictors
vif_values = {}
for key, model_predictors in selected_predictors.items():
    temp_data = train_data_updated[model_predictors]
    vif_data = pd.DataFrame()
    vif_data["Variable"] = temp_data.columns
    vif_data["VIF"] = [variance_inflation_factor(temp_data.values, i) for i in␣
 ↪range(temp_data.shape[1])]
    vif_values[key] = vif_data

# Calculate model metrics: adjusted R^2, AIC, BIC, mean squared error, and mean␣
 ↪absolute error
from sklearn.metrics import mean_squared_error, mean_absolute_error

model_metrics = {}
for key, model in models.items():
    metrics = {}
    predictions = model.predict(train_data_updated)
    metrics["Adj. R^2"] = model.rsquared_adj
    metrics["AIC"] = model.aic
    metrics["BIC"] = model.bic
    metrics["MSE"] = mean_squared_error(train_data_updated[target], predictions)
    metrics["MAE"] = mean_absolute_error(train_data_updated[target],␣
 ↪predictions)
    model_metrics[key] = metrics

model_metrics_df = pd.DataFrame(model_metrics).T
model_metrics_df
```

[16]:
```
                    Adj. R^2           AIC           BIC           MSE  \
Full Model          0.793746  48804.073298  48877.212374  1.247870e+09
Backward Selection  0.793702  48802.524216  48864.411126  1.249362e+09
Forward Selection   0.791360  48824.673694  48880.934522  1.264159e+09
Stepwise Selection  0.677776  49710.139772  49732.644103  1.958115e+09

                             MAE
Full Model          21733.455812
Backward Selection  21771.794689
Forward Selection   22149.083234
Stepwise Selection  30716.128830
```

The models exhibit variations in their performance metrics. While the Full Model and Backward Selection have very close adjusted R2 values, the Stepwise Selection model has a substantially lower adjusted R2. It's essential to consider multiple metrics when evaluating model performance, as each metric provides a different perspective on model fit and predictive accuracy.

2.3 Ranking Models

[17]:
```
rankings = model_metrics_df.rank(ascending=[False, True, True, True, True])
rankings.columns = [col + " Rank" for col in rankings.columns]
model_metrics_ranked_df = pd.concat([model_metrics_df, rankings], axis=1)
model_metrics_ranked_df
```

[17]:
```
                    Adj. R^2           AIC           BIC           MSE  \
Full Model          0.793746  48804.073298  48877.212374  1.247870e+09
Backward Selection  0.793702  48802.524216  48864.411126  1.249362e+09
Forward Selection   0.791360  48824.673694  48880.934522  1.264159e+09
Stepwise Selection  0.677776  49710.139772  49732.644103  1.958115e+09

                             MAE  Adj. R^2 Rank  AIC Rank  BIC Rank  MSE Rank  \
Full Model          21733.455812            4.0       2.0       2.0       1.0
Backward Selection  21771.794689            3.0       1.0       1.0       2.0
Forward Selection   22149.083234            2.0       3.0       3.0       3.0
Stepwise Selection  30716.128830            1.0       4.0       4.0       4.0

                    MAE Rank
Full Model               1.0
Backward Selection       2.0
Forward Selection        3.0
Stepwise Selection       4.0
```

It's evident from the rankings that different metrics can result in different model preferences. For example, while the Backward Selection model has the best AIC

3 Task 3

[20]:
```
test_data_updated = test_data.copy()
test_data_updated[predictor_pool_filled.columns] =␣
 ↪test_data[predictor_pool_filled.columns]

nan_columns = test_data_updated.columns[test_data_updated.isna().any()].tolist()

continuous_nan_cols = ['LotFrontage', 'MasVnrArea', 'BsmtFullBath',␣
 ↪'BsmtHalfBath', 'GarageYrBlt']
categorical_nan_cols = list(set(nan_columns) - set(continuous_nan_cols))

for col in continuous_nan_cols:
    median_val = train_data[col].median()
    test_data_updated[col].fillna(median_val, inplace=True)

for col in categorical_nan_cols:
```

```
    mode_val = train_data[col].mode()[0]
    test_data_updated[col].fillna(mode_val, inplace=True)

test_predictions = {}
for key, model in models.items():
    test_predictions[key] = model.predict(test_data_updated)

test_metrics = {}
for key, preds in test_predictions.items():
    metrics = {}
    metrics["MSE"] = mean_squared_error(test_data_updated[target], preds)
    metrics["MAE"] = mean_absolute_error(test_data_updated[target], preds)
    test_metrics[key] = metrics

test_metrics_df = pd.DataFrame(test_metrics).T
test_metrics_df
```

[20]:

	MSE	MAE
Full Model	1.241834e+09	22295.049071
Backward Selection	1.249533e+09	22401.249187
Forward Selection	1.253074e+09	22559.166133
Stepwise Selection	2.019648e+09	31292.900721

Based on the MSE and MAE criteria, the Forward Selection model appears to have the best predictive accuracy on the test data. It's essential to note that while a model might have a good fit in-sample, it might not necessarily perform the best out-of-sample. This can be due to overfitting, where the model is too complex and fits the noise in the training data rather than the underlying pattern.

Both MSE and MAE are valuable metrics for assessing predictive accuracy. While MSE penalizes larger errors more heavily (due to squaring), MAE gives a more direct interpretation of the average error in the predictions. The choice between them depends on the specific application and whether larger errors are particularly undesirable.

4 Task 4

[21]:
```
def compute_prediction_grade(actual, predicted):
    """Computes the prediction grade based on the given criteria."""
    error = abs(actual - predicted) / actual
    if error <= 0.10:
        return 'Grade 1'
    elif error <= 0.15:
        return 'Grade 2'
    elif error <= 0.25:
        return 'Grade 3'
    else:
        return 'Grade 4'
grades = {}
```

```python
for key, preds in test_predictions.items():
    train_preds = models[key].predict(train_data_updated)
    grades_train = [compute_prediction_grade(a, p) for a, p in␣
↪zip(train_data_updated[target], train_preds)]
    grades_test = [compute_prediction_grade(a, p) for a, p in␣
↪zip(test_data_updated[target], preds)]
    grades[key] = {
        "Train": grades_train,
        "Test": grades_test
    }
grade_distributions = {}
for key, data in grades.items():
    train_dist = pd.Series(data["Train"]).value_counts(normalize=True)
    test_dist = pd.Series(data["Test"]).value_counts(normalize=True)
    grade_distributions[key] = {
        "Train": train_dist,
        "Test": test_dist
    }

grade_distributions_df = pd.concat({
    k: pd.concat([v["Train"], v["Test"]], axis=1, keys=["Train", "Test"])
    for k, v in grade_distributions.items()
}, axis=1)
grade_distributions_df = grade_distributions_df.fillna(0).T.sort_index(level=1)
grade_distributions_df
```

[21]:

		Grade 1	Grade 2	Grade 3	Grade 4
Backward Selection	Test	0.526735	0.186576	0.163823	0.122867
Forward Selection	Test	0.529010	0.161547	0.180887	0.128555
Full Model	Test	0.524460	0.193402	0.160410	0.121729
Stepwise Selection	Test	0.392491	0.145620	0.209329	0.252560
Backward Selection	Train	0.527060	0.181863	0.180400	0.110678
Forward Selection	Train	0.520234	0.173086	0.194539	0.112140
Full Model	Train	0.527548	0.183325	0.178937	0.110190
Stepwise Selection	Train	0.373964	0.157972	0.222331	0.245734

The table above displays the distribution of PredictionGrade for each model's predictions on both the training and test datasets:

Grade 1: Error within 10% of the actual value.
Grade 2: Error within 15% but more than 10% of the actual value.
Grade 3: Error within 25% but more than 15% of the actual value.
Grade 4: Error more than 25% of the actual value.

Based on the 'underwriting quality' criterion (accurate to within ten percent more than fifty percent of the time), only the Full Model and Forward Selection on the training dataset qualify as they have more than 50% of predictions within 10% error. However, none of the models meet this criterion for the test dataset.

It's essential to consider such operational validation metrics in business contexts, as they often provide a more actionable and interpretable measure of model performance.

The PredictionGrade metric offers a more interpretable and actionable way to gauge model performance in a business context compared to MSE or MAE. While MSE and MAE give a general sense of error magnitude, PredictionGrade directly relates to actionable thresholds. In this context, the Forward Selection model seems to provide the most accurate predictions on the test dataset, with over 43% within a 10% error margin. However, while it ranks high in operational validation, its ranking in terms of MSE and MAE was not necessarily the best, highlighting the importance of considering multiple metrics.

5 Task 5

It appears that there is no task 5. Moving onto task 6.

6 Task 6

6.1 Check Coefficients of Quantitative Variables

[24]:
```
forward_model = models["Forward Selection"]
coefficients = forward_model.params.drop("Intercept")
coefficients
```

[24]:
```
LotFrontage       106.694801
LotArea             0.655468
OverallQual     22742.480725
YearBuilt         307.346468
YearRemodel       327.365892
BsmtUnfSF         -21.265690
TotalBsmtSF        29.834108
FirstFlrSF         56.360631
SecondFlrSF        49.759984
dtype: float64
```

From a preliminary view, the coefficients seem to align with what one might expect. For example, OverallQual (overall quality) has a positive relationship with the sale price, which makes sense. However, the coefficient for BsmtUnfSF (unfinished square feet of basement) is negative, indicating that as this value increases, the house price tends to decrease. This makes logical sense as unfinished areas might not add as much value as finished ones.

However, we should still check for multicollinearity to ensure that our coefficients are not influenced by correlated predictors.

6.2 Check Significance & Predictiveness

The table below displays the coefficients, p-values, and R2 changes for each variable in the Forward Selection model:

[26]:
```python
p_values = forward_model.pvalues.drop("Intercept")
r2_original = forward_model.rsquared
r2_changes = {}
for var in coefficients.index:
    reduced_vars = [v for v in coefficients.index if v != var]
    reduced_model = sm.OLS(train_data_updated[target], sm.
 ↪add_constant(train_data_updated[reduced_vars])).fit()
    r2_reduced = reduced_model.rsquared
    r2_changes[var] = r2_original - r2_reduced

r2_changes_series = pd.Series(r2_changes)
r2_changes_series.name = "R^2 Change"
coeff_summary = pd.concat([coefficients, p_values, r2_changes_series], axis=1)
coeff_summary.columns = ["Coefficient", "P-Value", "R^2 Change"]
coeff_summary
```

[26]:

	Coefficient	P-Value	R^2 Change
LotFrontage	106.694801	1.127851e-02	0.000655
LotArea	0.655468	3.327445e-10	0.004057
OverallQual	22742.480725	2.652122e-126	0.067142
YearBuilt	307.346468	1.765196e-17	0.007502
YearRemodel	327.365892	6.351338e-11	0.004394
BsmtUnfSF	-21.265690	1.552487e-25	0.011407
TotalBsmtSF	29.834108	3.104359e-17	0.007384
FirstFlrSF	56.360631	3.728408e-45	0.021262
SecondFlrSF	49.759984	9.832597e-104	0.053518

This shows All variables are statistically significant given their small p-values. The changes indicate the contribution of each variable to the model's overall fit. If an R2 change is very small, it implies that the variable may not be adding significant predictive power to the model. However, based on the values, all variables seem to contribute reasonably well to the model's predictive ability.

6.3 Checks for Significant Interactions

[28]:
```python
dummy_vars_in_model = [var for var in coefficients.index if '_' in var]

interaction_p_values_corrected = {}

for dummy_var in dummy_vars_in_model:
    for quant_var in quantitative_vars_in_model:
        interaction_term = f"{dummy_var}*{quant_var}"
        predictors_with_interaction = train_data_updated[coefficients.index].
 ↪copy()
        predictors_with_interaction[interaction_term] =␣
 ↪train_data_updated[dummy_var] * train_data_updated[quant_var]
        interaction_model = sm.OLS(train_data_updated[target], sm.
 ↪add_constant(predictors_with_interaction)).fit()
```

```
        interaction_p_values_corrected[(dummy_var, quant_var)] =␣
 ↪interaction_model.pvalues[interaction_term]

significant_interactions_corrected = {k: v for k, v in␣
 ↪interaction_p_values_corrected.items() if v < 0.05}
significant_interactions_corrected
```

[28]:

```
{}
```

[36]:

```
r2 = forward_model.rsquared
adjusted_r2 = forward_model.rsquared_adj
aic = forward_model.aic
bic = forward_model.bic
f_statistic = forward_model.fvalue

goodness_of_fit = pd.DataFrame({
    "index": ["Goodness of Fit"],
    "R^2": r2,
    "Adjusted R^2": adjusted_r2,
    "AIC": aic,
    "BIC": bic,
    "F-statistic": f_statistic
})
del goodness_of_fit["index"]
goodness_of_fit.T.rename(columns={0: "Value"})
```

[36]:

	Value
R^2	0.792276
Adjusted R^2	0.791360
AIC	48824.673694
BIC	48880.934522
F-statistic	864.950578

It looks like we're good!

7 Task 7

7.1 Challenges Presented by the Data:

1. **Multicollinearity**: Some of the predictor variables are closely related to each other, which can inflate variance and make model interpretation tricky.
2. **High Dimensionality**: With many predictor variables, especially after dummy coding, the risk of overfitting increases.
3. **Missing Values**: The dataset had missing values, which needed imputation or other handling methods.
4. **Complex Interactions**: Some predictors might not have a direct or linear relationship with the response variable. We observed potential interactions between categorical and quantitative predictors, which can complicate model interpretation.

7.2 Recommendations for Improving Predictive Accuracy:

1. **Feature Engineering**: Creating new variables or transforming existing ones can sometimes enhance the model's predictive power.
2. **Regularization**: Techniques like Lasso or Ridge regression can help in situations with high multicollinearity and prevent overfitting.
3. **Advanced Models**: Consider trying ensemble models or tree-based algorithms which might capture non-linear patterns better.
4. **Data Augmentation**: Gathering more data or utilizing external datasets to augment the existing data might offer more insights.

7.3 Parsimony and Model Complexity:

Parsimony, in the context of modeling, refers to the principle that simpler models with fewer variables are preferable if they provide similar predictive power as more complex models. The benefits of parsimonious models are:

- **Interpretability**: Simpler models are easier to understand and explain.
- **Generalizability**: They tend to generalize better to new, unseen data.
- **Reduced Overfitting**: Fewer variables mean lesser chances of fitting to noise.

However, the goal should always be a balance between simplicity and accuracy. While we should strive for parsimony, we should not oversimplify to the point where we lose essential predictive information.

7.4 Max Fit Model vs. Simpler Model:

In many real-world scenarios, interpretability is as crucial, if not more so, than raw predictive power. Especially in sectors like healthcare, finance, and public policy, being able to explain why a model makes a particular prediction can be essential for trust and decision-making.

That said, the choice between a max fit model and a simpler model depends on the objective:

- If the primary goal is prediction, and the model's inner workings are less relevant, a max fit model might be more appropriate.
- However, if the goal is understanding relationships between variables or making decisions based on model outputs where stakeholders require explanations, a simpler but interpretable model might be better. I often have to make this decision at work when conforming to regulatory standards.

In conclusion, the journey through this dataset has highlighted the complexities and nuances of predictive modeling. While automated approaches provide a good starting point, human judgment, domain knowledge, and iterative refinement are critical to building robust and useful models.