p2

April 11, 2025

1 Part 2a

[18]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import polars as pl
import seaborn as sns
import shap

from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import VarianceThreshold
from sklearn.linear_model import LinearRegression, ElasticNetCV
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score,␣
↪accuracy_score, mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV, train_test_split,␣
↪RandomizedSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier, XGBRegressor

%matplotlib inline
```

[19]:
```
print(chr(sum(range(ord(min(str(not()))))))) # Among Us
```

[20]:
```
# Part i

# Load the dataset
file_path = "HouseholdSpend.csv"  # Change this to the updated file after␣
↪regression
df = pd.read_csv(file_path, engine='python')  # Use engine='python' for complex␣
↪CSVs

# Display the shape and column headers
print(f"Loaded dataset with shape: {df.shape}")
print("\nColumn headers:")
print(df.columns.tolist())
```

```
Loaded dataset with shape: (868970, 246)

Column headers:
['CODE', 'GEO', 'HSBASHHD', 'HSHNIAGG', 'HSAGDISPIN', 'HSAGDISCIN', 'HSTT001',
'HSTE001', 'HSTX001', 'HSTC001', 'HSSH001S', 'HSFD001S', 'HSHO001S', 'HSHC001S',
'HSHF001S', 'HSTR001S', 'HSRE001S', 'HSPC001S', 'HSCL001S', 'HSED002S',
'HSRO001S', 'HSTA001S', 'HSGC001S', 'HSME001S', 'HSEP001S', 'HSMG001S',
'HSTE001ZBS', 'HSWH002S', 'HSWH028S', 'HSWH040S', 'HSWH041S', 'HSWH042S',
'HSSH001', 'HSSH002', 'HSSH003', 'HSSH004', 'HSSH053', 'HSSH054', 'HSSH005',
'HSSH006', 'HSSH007', 'HSSH010', 'HSSH011', 'HSSH014', 'HSSH013', 'HSSH015',
'HSSH016', 'HSSH017', 'HSSH018', 'HSSH019', 'HSSH021', 'HSSH020', 'HSSH022',
'HSSH012', 'HSRM002A', 'HSRM002B', 'HSRM003A', 'HSRM003B', 'HSRM004', 'HSRM005',
'HSRM006', 'HSRM007', 'HSRM008M', 'HSRM009A', 'HSRM009B', 'HSRM010', 'HSRM011',
'HSRM012', 'HSRM013', 'HSRM015M', 'HSRM016', 'HSSH012B', 'HSOI020', 'HSOI020Z',
'HSSH030', 'HSSH031', 'HSSH031A', 'HSSH031B', 'HSSH032', 'HSSH032A', 'HSSH032B',
'HSSH033', 'HSSH033A', 'HSSH033B', 'HSSH034', 'HSSH035', 'HSSH035A', 'HSSH035B',
'HSSH036', 'HSSH036A', 'HSSH036B', 'HSSH037', 'HSSH037A', 'HSSH037B', 'HSSH040',
'HSSH041', 'HSSH042', 'HSSH043', 'HSSH044', 'HSSH045', 'HSSH046', 'HSSH046C',
'HSSH046M', 'HSSH047', 'HSSH047A', 'HSSH047C', 'HSSH047M', 'HSSH050', 'HSSH051',
'HSSH052', 'HSFD001', 'HSFD003', 'HSFD990', 'HSFD991', 'HSFD992', 'HSFD993',
'HSFD994', 'HSFD995', 'HSHO001', 'HSHO002', 'HSHO003', 'HSHO004', 'HSHO005',
'HSHO006', 'HSHO010', 'HSHO011', 'HSHO012', 'HSHO013', 'HSHO014', 'HSHO015',
'HSHO016', 'HSHO017', 'HSHO018', 'HSHO019', 'HSHO020', 'HSHO021', 'HSHO022',
'HSCC001', 'HSCC002', 'HSCC003', 'HSCC013', 'HSCC011', 'HSCC012', 'HSCC014',
'HSCS001', 'HSCS003', 'HSCS004', 'HSCS005', 'HSCS011', 'HSCS012', 'HSCS013',
'HSCS007', 'HSCS008', 'HSCS010', 'HSHC001', 'HSHC002', 'HSHC003', 'HSHC004',
'HSHC004A', 'HSHC004B', 'HSHC005', 'HSHC006', 'HSHC006A', 'HSHC006B', 'HSHC007',
'HSHC008', 'HSHC009', 'HSHC010', 'HSHC012', 'HSHC014', 'HSHC027', 'HSHC015',
'HSHC022', 'HSHC023', 'HSHC024', 'HSHC025', 'HSHF001', 'HSHF002', 'HSHF003',
'HSHF004', 'HSHF005', 'HSHF005A', 'HSHF005B', 'HSHF006', 'HSHF008', 'HSHE001',
'HSHE002', 'HSHE003', 'HSHE004', 'HSHE005', 'HSHE006', 'HSHE007', 'HSHE009',
'HSHE008', 'HSHE010', 'HSHE011', 'HSHE011A', 'HSHE011B', 'HSHE031', 'HSHE012',
'HSHE012M', 'HSHE032', 'HSHE013', 'HSHE015', 'HSHE016', 'HSHE020', 'HSHE021',
'HSHE023', 'HSTR001', 'HSTR002', 'HSTR003', 'HSTR004', 'HSTR005', 'HSTR006',
'HSTR007', 'HSTR008', 'HSTR009', 'HSTR058', 'HSTR010', 'HSTR011', 'HSTR012',
'HSTR014M', 'HSTR015', 'HSTR020', 'HSTR030', 'HSTR031', 'HSTR032', 'HSTR033',
'HSTR034', 'HSTR035', 'HSTR036', 'HSTR037', 'HSTR038', 'HSTR039', 'HSTR040',
'HSTR041', 'HSTR050', 'HSTR051', 'HSTR052', 'HSTR053', 'HSTR054', 'HSTR055',
'HSTR056', 'HSTR056A', 'HSTR056B', 'HSTR057']
```

[21]:
```python
# Part ii
# Drop rows with zero or missing income to avoid division issues
df = df[df['HSHNIAGG'] > 0].copy()
df = df.dropna(subset=['HSEP001S', 'HSHNIAGG'])

# Create the target variable
df['target'] = df['HSEP001S'] / df['HSHNIAGG']
```

```python
# Preview the result
df[['HSEP001S', 'HSHNIAGG', 'target']].head()
```

[21]:

	HSEP001S	HSHNIAGG	target
1	9.126272e+04	2.281580e+06	0.040000
2	1.114577e+06	1.865322e+07	0.059753
3	4.482669e+06	7.791174e+07	0.057535
4	8.836750e+05	1.568882e+07	0.056325
5	9.244625e+06	1.677271e+08	0.055117

[22]:

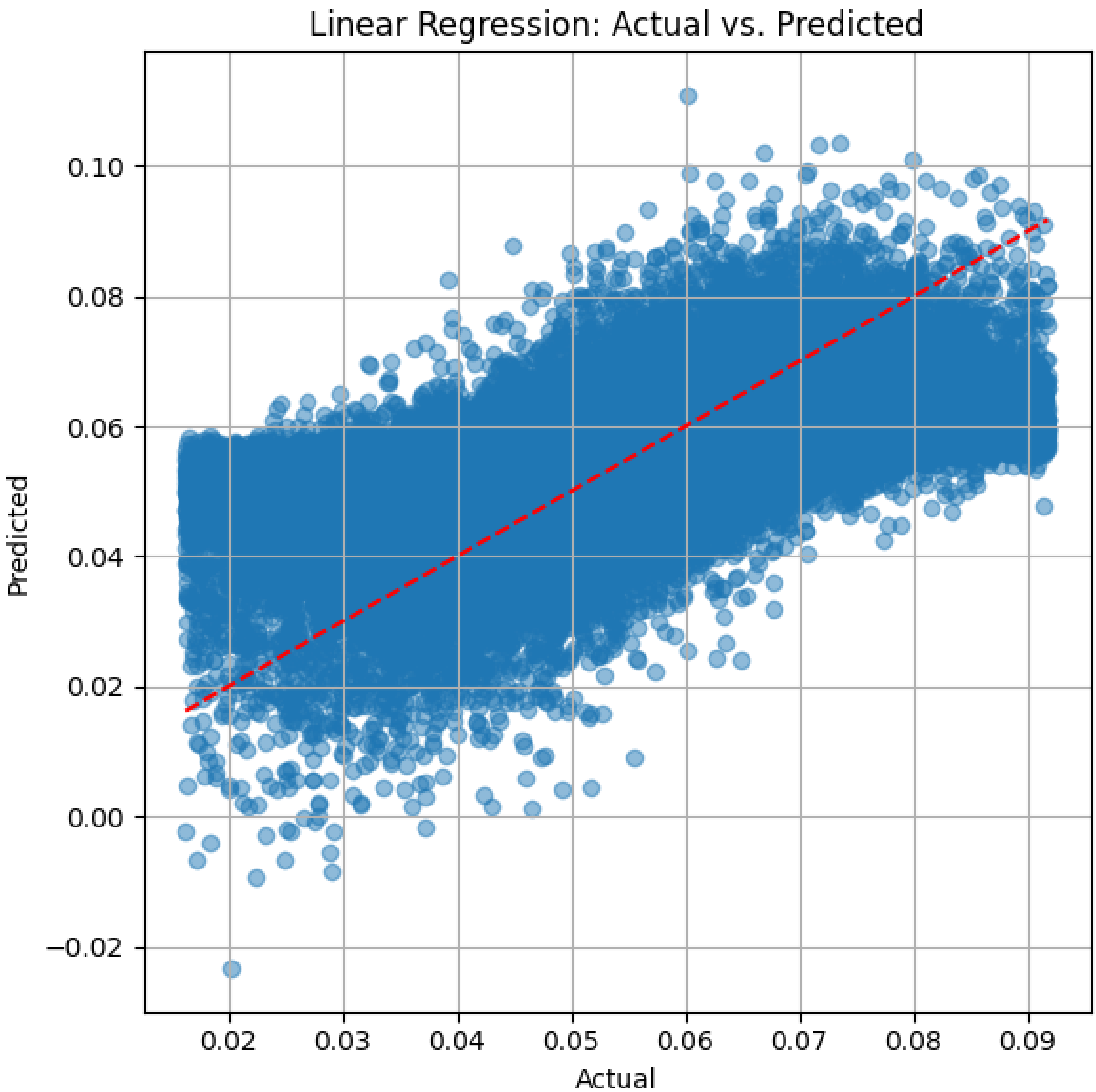
```python
# Drop unused columns
with open("droplist.txt", 'r') as file:
    droppedColumns = file.read().splitlines()
X = df.drop(columns=droppedColumns)

y = df['target']

# Drop near-constant columns
X = X.loc[:, X.nunique() > 1]

# Drop columns with too many NaNs (less than 50% missing)
X = X.loc[:, X.isnull().mean() < 0.5]

# Fill remaining NaNs with median
X = X.fillna(X.median())

# Keep the target variable aligned with cleaned X
y = y.loc[X.index]

# Remove outliers using the IQR method
def remove_outliers_iqr(df, columns, multiplier=1.5):
    """
    Remove rows from df where any of the specified numeric columns have
    values outside [Q1 - multiplier*IQR, Q3 + multiplier*IQR].
    """
    indices = df.index
    for col in columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - multiplier * IQR
        upper_bound = Q3 + multiplier * IQR
        # Only keep rows within the bounds for the current column
        indices = indices.intersection(df[(df[col] >= lower_bound) & (df[col] <= upper_bound)].index)
    return indices
```

```python
# Combine X and y for synchronized outlier removal
data = X.copy()
data['target'] = y

# Get the list of numeric columns to apply the IQR filter.
numeric_cols = data.select_dtypes(include=[np.number]).columns.tolist()

# Remove outliers across all numeric features (including target)
outlier_indices = remove_outliers_iqr(data, numeric_cols, multiplier=1.5)
data_clean = data.loc[outlier_indices]

# Separate the cleaned features and target
X = data_clean.drop(columns='target')
y = data_clean['target']

# Split first
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# Then fit scaler on training data only
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[23]:
```python
# Train a simple linear regression model
linear_model = LinearRegression()
linear_model.fit(X_train_scaled, y_train)

# Predict on test set
y_pred = linear_model.predict(X_test_scaled)

# Scatterplot: Actual vs Predicted
plt.figure(figsize=(6, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Linear Regression: Actual vs. Predicted")
plt.grid(True)
plt.tight_layout()
plt.show()

# Evaluate performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```python
print(f"\nModel Performance:")
print(f"  - Test Set MSE: {mse:.4f}")
print(f"  - Test Set R²: {r2:.4f}")

# Bootstrapped CI for R²
r2_bootstrap = []
n_boot = 1000
for _ in range(n_boot):
    idx = np.random.choice(len(y_test), len(y_test), replace=True)
    r2_bootstrap.append(r2_score(y_test.iloc[idx], y_pred[idx]))

ci_lower = np.percentile(r2_bootstrap, 2.5)
ci_upper = np.percentile(r2_bootstrap, 97.5)
print(f"  - Bootstrapped 95% CI for R²: [{ci_lower:.4f}, {ci_upper:.4f}]")

# Feature importance (coefficients)
feature_names = X.columns
coef = linear_model.coef_

coef_df = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': coef,
    'Importance': np.abs(coef)
})

top_features = coef_df.sort_values(by='Importance', ascending=False).head(5)
print("\nTop 5 Most Influential Features (Linear Regression):")
print(top_features[['Feature', 'Coefficient']])
```

```
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/sklearn/linear_model/_base.py:279: RuntimeWarning: divide by zero
encountered in matmul
  return X @ coef_ + self.intercept_
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/sklearn/linear_model/_base.py:279: RuntimeWarning: overflow encountered
in matmul
  return X @ coef_ + self.intercept_
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/sklearn/linear_model/_base.py:279: RuntimeWarning: invalid value
encountered in matmul
  return X @ coef_ + self.intercept_
```




```
Model Performance:
  - Test Set MSE: 0.0002
  - Test Set R²: 0.3350
  - Bootstrapped 95% CI for R²: [0.3306, 0.3395]

Top 5 Most Influential Features (Linear Regression):
     Feature  Coefficient
14   HSSH010    -0.113242
15   HSSH011     0.080680
16   HSSH014     0.035431
18   HSSH017     0.007405
44  HSSH032A    -0.005735
```

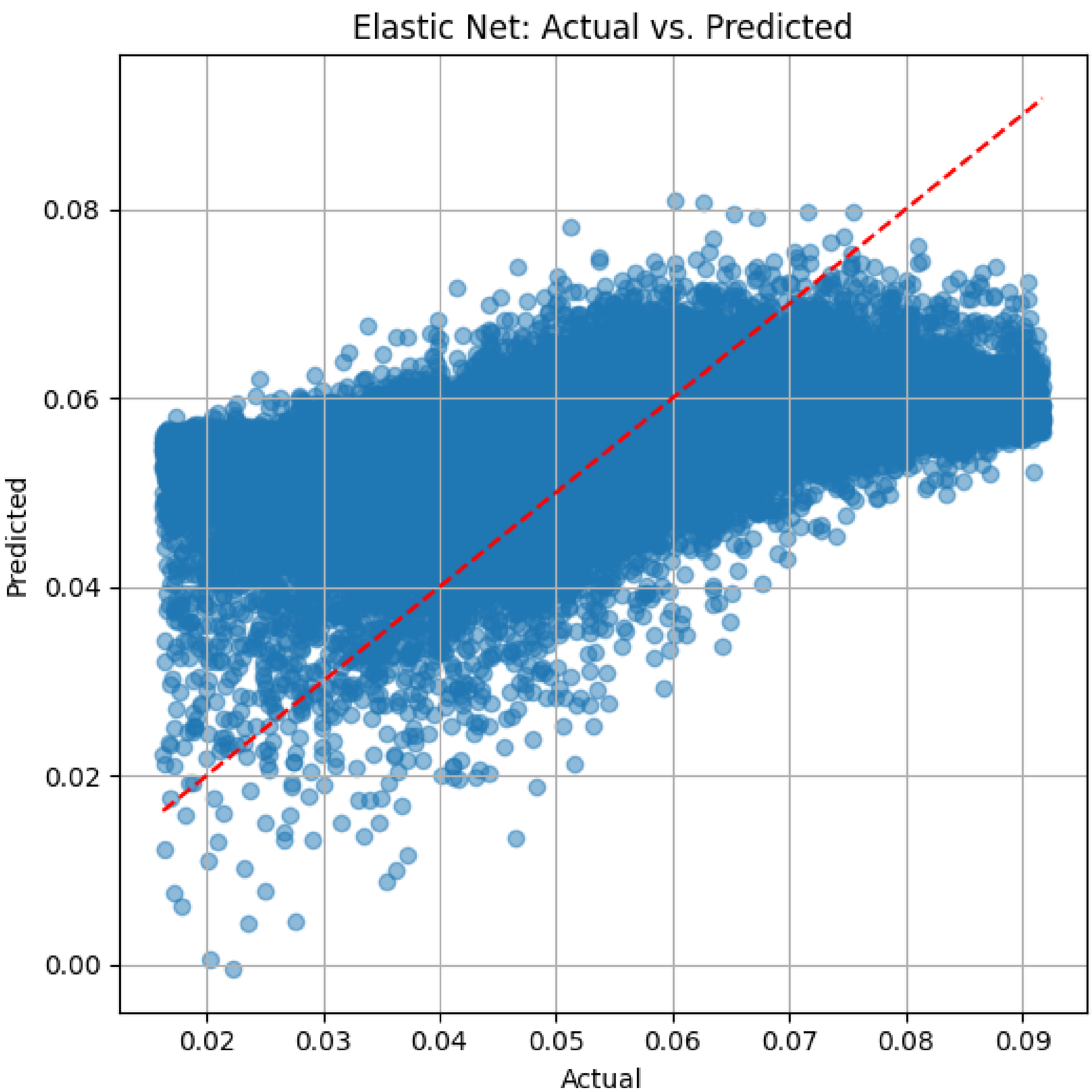
[24]:
```python
# Train ElasticNetCV with a parameter grid
elastic_cv = ElasticNetCV(
    l1_ratio=[0.1, 0.3, 0.5, 0.7],
    alphas = [0.01, 0.01, 0.3, 0.5],
    cv=5,
    random_state=42
)
elastic_cv.fit(X_train_scaled, y_train)

# Retrieve best parameters
best_alpha = elastic_cv.alpha_
best_l1_ratio = elastic_cv.l1_ratio_

# Explain parameter significance
if best_l1_ratio == 1.0:
    penalty_type = "Lasso (L1)"
elif best_l1_ratio == 0.0:
    penalty_type = "Ridge (L2)"
else:
    penalty_type = f"Elastic Net mix (L1 {best_l1_ratio:.2f} / L2 {1 -␣
 ↪best_l1_ratio:.2f})"

print(f"\nBest ElasticNet Parameters Found:")
print(f"  - Best alpha: {best_alpha}")
print(f"  - Best l1_ratio (L1 vs L2 mix): {best_l1_ratio}")

print(f"\n  Interpretation:")
print(f"The model chose alpha = {best_alpha}, indicating a moderate level of␣
 ↪regularization.")
print(f"The l1_ratio = {best_l1_ratio}, suggesting the model prefers␣
 ↪{penalty_type}.")
print("This balance helps retain important variables (L1) while stabilizing␣
 ↪predictions (L2).")

# Predict on test set
y_pred = elastic_cv.predict(X_test_scaled)

# Scatterplot: Actual vs Predicted
plt.figure(figsize=(6, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--')
plt.xlabel("Actual")
plt.ylabel("Predicted")
plt.title("Elastic Net: Actual vs. Predicted")
plt.grid(True)
plt.tight_layout()
plt.show()
```

```python
# Evaluate performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"\nModel Performance:")
print(f"  - Test Set MSE: {mse:.4f}")
print(f"  - Test Set R²: {r2:.4f}")

# Bootstrapped CI for R²
r2_bootstrap = []
n_boot = 1000
for _ in range(n_boot):
    idx = np.random.choice(len(y_test), len(y_test), replace=True)
    r2_bootstrap.append(r2_score(y_test.iloc[idx], y_pred[idx]))

ci_lower = np.percentile(r2_bootstrap, 2.5)
ci_upper = np.percentile(r2_bootstrap, 97.5)
print(f"  - Bootstrapped 95% CI for R²: [{ci_lower:.4f}, {ci_upper:.4f}]")

# Feature importance
feature_names = X.columns
coef = elastic_cv.coef_

coef_df = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': coef,
    'Importance': np.abs(coef)
})

top_features = coef_df.sort_values(by='Importance', ascending=False).head(5)
print("\nTop 5 Most Important Features (ElasticNetCV):")
print(top_features[['Feature', 'Coefficient']])
```

```
Best ElasticNet Parameters Found:
  - Best alpha: 0.01
  - Best l1_ratio (L1 vs L2 mix): 0.1

 Interpretation:
The model chose alpha = 0.01, indicating a moderate level of regularization.
The l1_ratio = 0.1, suggesting the model prefers Elastic Net mix (L1 0.10 / L2
0.90).
This balance helps retain important variables (L1) while stabilizing predictions
(L2).
```

```
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/sklearn/linear_model/_base.py:279: RuntimeWarning: divide by zero
```

```
encountered in matmul
  return X @ coef_ + self.intercept_
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/sklearn/linear_model/_base.py:279: RuntimeWarning: overflow encountered
in matmul
  return X @ coef_ + self.intercept_
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/sklearn/linear_model/_base.py:279: RuntimeWarning: invalid value
encountered in matmul
  return X @ coef_ + self.intercept_
```



```
Model Performance:
  - Test Set MSE: 0.0002
  - Test Set R²: 0.2067
  - Bootstrapped 95% CI for R²: [0.2032, 0.2098]

Top 5 Most Important Features (ElasticNetCV):
     Feature  Coefficient
5   HSMG001S    -0.003588
63   HSHO002    -0.003434
15   HSSH011     0.002166
9   HSWH041S     0.001868
19   HSSH018     0.001375
```

[25]:

```python
# Hyperparameter grid
xgb_param_grid = {
    'n_estimators': [50, 100, 150],
    'max_depth': [1, 2, 3],
    'learning_rate': [0.01, 0.1, 0.2, 0.3],
    'subsample': [0.2, 0.4, 0.6, 0.8, 1.0],
    'colsample_bytree': [0.2, 0.4, 0.6, 0.8, 1.0],
    'gamma': [0, 1, 5],
    'reg_lambda': [0, 0.01, 0.1, 1, 10, 100],
    'reg_alpha': [0, 0.01, 0.1, 1, 10, 100]
    # tree depth 1 -3
    # learning rate as big 0.1 - 0.3
    # number of trees
    # early stop
    # large amount of trees + validation
}

# Set up the model
xgb = XGBRegressor(random_state=42, verbosity=0)

# Randomized Search with 5-fold CV
random_search = RandomizedSearchCV(
    estimator=xgb,
    param_distributions=xgb_param_grid,
    n_iter=50,  # Try 50 random combinations
    cv=5,
    scoring='r2',
    n_jobs=-1,
    verbose=1,
    random_state=42
)

# Train the model
random_search.fit(X_train, y_train)
```

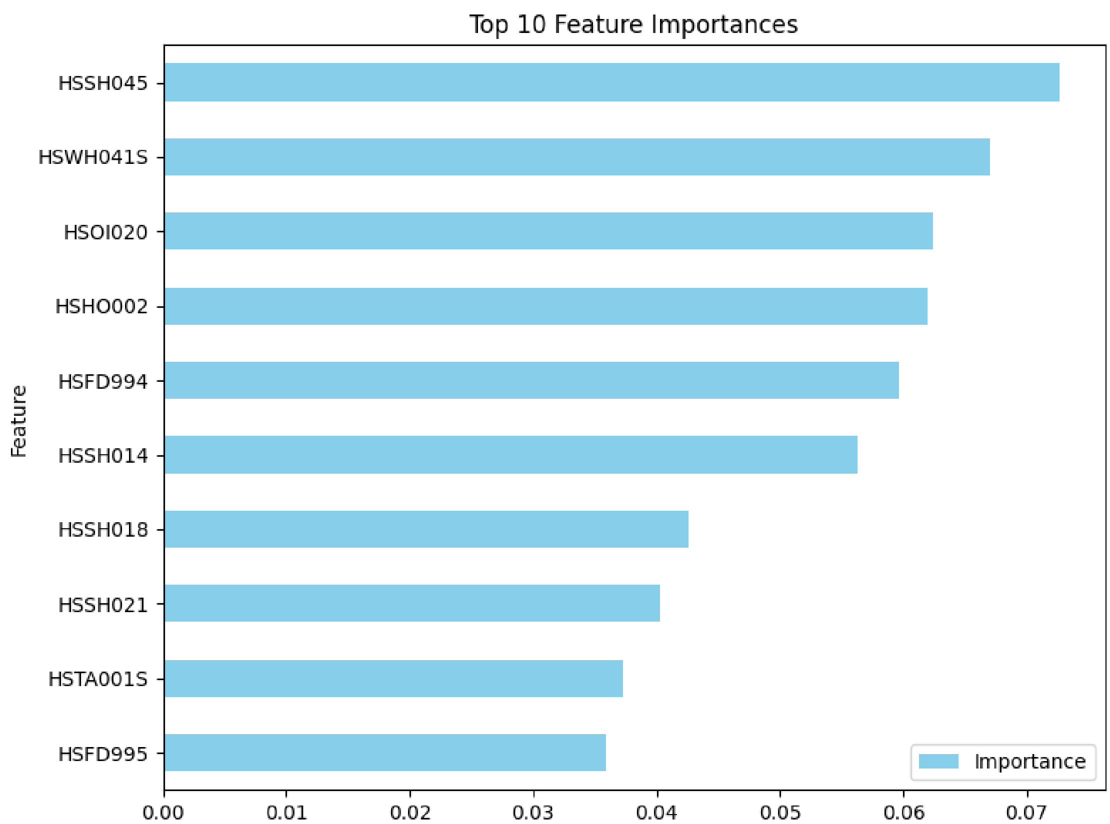
```
xgb_model = random_search.best_estimator_

# Best hyperparameters
print("\nBest Parameters Found:")
print(random_search.best_params_)

# Predict using the tuned model
y_pred = xgb_model.predict(X_test)

# Evaluation metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Bootstrapped CI for R²
n_iterations = 1000
rng = np.random.RandomState(42)
r2_scores = []

y_test_np = np.array(y_test)
y_pred_np = np.array(y_pred)

for _ in range(n_iterations):
    indices = rng.choice(len(y_test_np), len(y_test_np), replace=True)
    y_test_sample = y_test_np[indices]
    y_pred_sample = y_pred_np[indices]
    r2_scores.append(r2_score(y_test_sample, y_pred_sample))

lower_bound = np.percentile(r2_scores, 2.5)
upper_bound = np.percentile(r2_scores, 97.5)

print(f"\nTest Set MSE: {mse:.4f}")
print(f"Test Set R²: {r2:.4f}")
print(f"Bootstrapped 95% CI for R²: [{lower_bound:.4f}, {upper_bound:.4f}]")

# Feature importance from XGBoost
feature_names = X.columns
importances = xgb_model.feature_importances_

# DataFrame for feature importance
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': importances
})

top_features_xgb = importance_df.sort_values(by='Importance', ascending=False).
 ↪head(5)
print("\nTop 5 Most Important Features (XGBoost):")
```

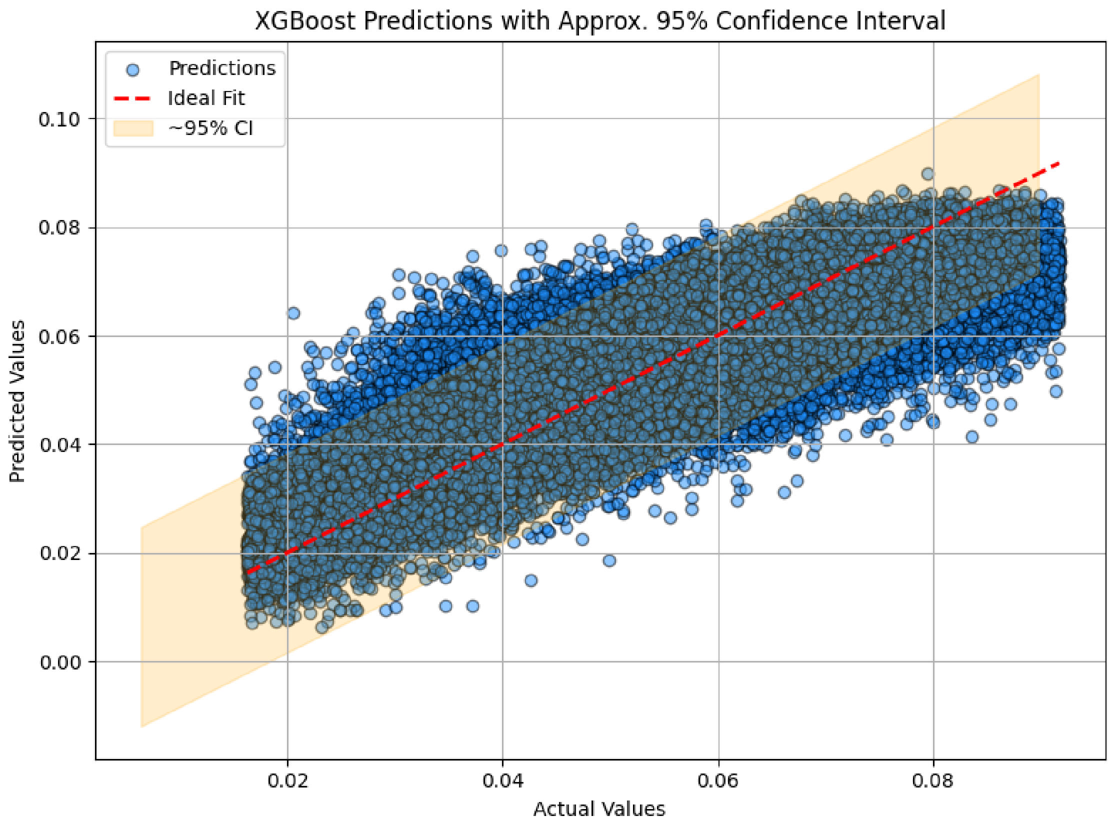
```
print(top_features_xgb[['Feature', 'Importance']])

# Bar plot of top 10 feature importances
importance_df.sort_values(by='Importance', ascending=False).head(10).plot(
    x='Feature', y='Importance', kind='barh', figsize=(8, 6), color='skyblue')
plt.title('Top 10 Feature Importances')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

# Residuals + 95% CI plot
residuals = y_test_np - y_pred_np
residual_std = np.std(residuals)
ci_upper = y_pred_np + 1.96 * residual_std
ci_lower = y_pred_np - 1.96 * residual_std

sorted_idx = np.argsort(y_pred_np)

plt.figure(figsize=(8, 6))
plt.scatter(y_test_np, y_pred_np, alpha=0.5, color='dodgerblue',␣
 ↪edgecolors='k', label='Predictions')
plt.plot([y_test_np.min(), y_test_np.max()], [y_test_np.min(), y_test_np.
 ↪max()], 'r--', lw=2, label='Ideal Fit')
plt.fill_between(
    y_pred_np[sorted_idx],
    ci_lower[sorted_idx],
    ci_upper[sorted_idx],
    color='orange',
    alpha=0.2,
    label='~95% CI'
)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('XGBoost Predictions with Approx. 95% Confidence Interval')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
```

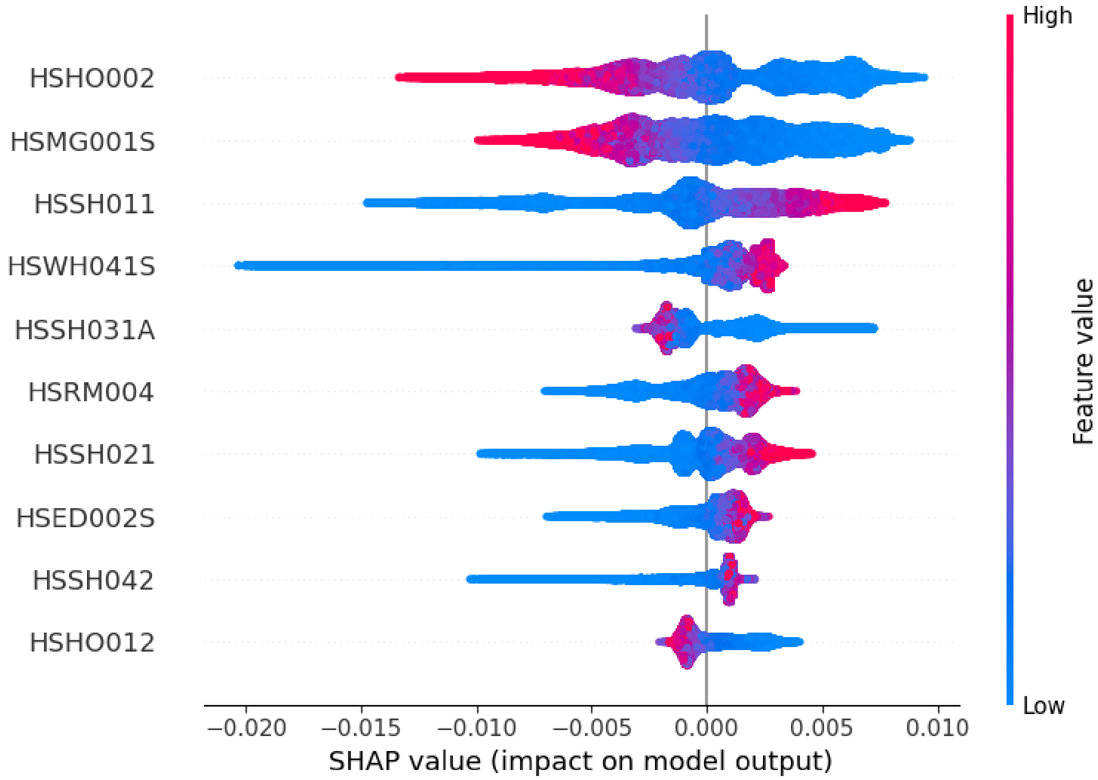
```
/Users/emilyberlinghoff/Desktop/School/Year
3/DS3000Project/.venv/lib/python3.13/site-
packages/joblib/externals/loky/process_executor.py:752: UserWarning: A worker
stopped while some jobs were given to the executor. This can be caused by a too
short worker timeout or by a memory leak.
  warnings.warn(
```

```
Best Parameters Found:
{'subsample': 0.8, 'reg_lambda': 0.01, 'reg_alpha': 1, 'n_estimators': 100,
'max_depth': 3, 'learning_rate': 0.3, 'gamma': 0, 'colsample_bytree': 0.4}

Test Set MSE: 0.0001
Test Set R²: 0.6651
Bootstrapped 95% CI for R²: [0.6609, 0.6695]

Top 5 Most Important Features (XGBoost):
     Feature  Importance
50   HSSH045    0.072732
9   HSWH041S    0.067052
40   HSOI020    0.062430
63   HSHO002    0.061915
61   HSFD994    0.059614
```





[26]:
```
# Initialize SHAP Explainer with the model
explainer = shap.Explainer(xgb_model)

# Calculate SHAP values for the training data
shap_values = explainer(X_train)

# Assuming X_train is the scaled version and X was the original dataset
original_columns = X.columns.tolist()

# Use the original column names in SHAP summary plot
shap.summary_plot(shap_values, X_train, max_display=10,␣
 ↪feature_names=original_columns)
```


HSHO002
HSMG001S
HSSH011
HSWH041S
HSSH031A
HSRM004
HSSH021
HSED002S
HSSH042
HSHO012
−0.020
−0.015
−0.010
−0.005
0.000
0.005
0.010
SHAP value (impact on model output)
High
Low
Feature value