crossValidation_hw_FishDataset_CMPE188

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1. Perform full EDA on fish dataset (FishDataset.csv provided under ML data bank on Canvas). Assume the weight column to be the output and the rest of columns as inputs. Column zero (categorical data) should be converted to numbers using encoding (use preprocessing.LabelEncoder() from sklearn library).

[59]:
```
from numpy import set_printoptions, logspace, mean, std
import matplotlib.pyplot as plt
import pandas as pd
from pandas import set_option
from pandas import read_csv
from pandas.plotting import scatter_matrix

from sklearn.preprocessing import StandardScaler, Normalizer, LabelEncoder
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.feature_selection import RFE
from sklearn.model_selection import KFold, GridSearchCV, cross_val_score

import seaborn as sns
```

[45]:
```
filename = 'FishDataset.csv'
data = read_csv(filename)
set_printoptions(precision=3)
data.head(5)
```

[45]:

	Species	Weight	Length1	Length2	Length3	Height	Width
0	Bream	242.0	23.2	25.4	30.0	11.5	4.0
1	Bream	290.0	24.0	26.3	31.2	12.5	4.3
2	Bream	340.0	23.9	26.5	31.1	12.4	4.7
3	Bream	363.0	26.3	29.0	33.5	12.7	4.5
4	Bream	430.0	26.5	29.0	34.0	12.4	5.1

[46]:
```
print(data.isnull().sum())
```

```
Species    0
Weight     0
Length1    0
Length2    0
```

```
Length3    0
Height     0
Width      0
dtype: int64
```

[47]:
```
label_encoder = LabelEncoder()
data['Species'] = label_encoder.fit_transform(data['Species'])
print(data['Species'].value_counts())
```

```
Species
2    56
0    35
4    20
3    17
5    14
1    11
6     6
Name: count, dtype: int64
```

[48]:
```
array = data.values
Y1 = data['Weight']
X1 = data.drop('Weight', axis=1)
X1names = X1.columns
```

[49]:
```
data_norm = X1.copy()
# Normalize
norm_scaler = Normalizer().fit(data_norm)
data_norm = norm_scaler.transform(data_norm)
# add output to normalized data
data_norm = pd.DataFrame(data_norm, columns=X1names, index=X1.index)
X1_norm = data_norm.copy()
#data_norm['Weight'] = Y1

data_stand = X1.copy()
# Standardize
stand_scaler = StandardScaler().fit(data_stand)
data_stand = stand_scaler.transform(data_stand)
# add output to standardized data
data_stand = pd.DataFrame(data_stand, columns=X1names, index=X1.index)
X1_stand = data_stand.copy()
#data_stand['Weight'] = Y1
data_objects = ((data_norm, 'data_norm'), (data_stand, 'data_stand'), (data,␣
↪"data_raw"))
```

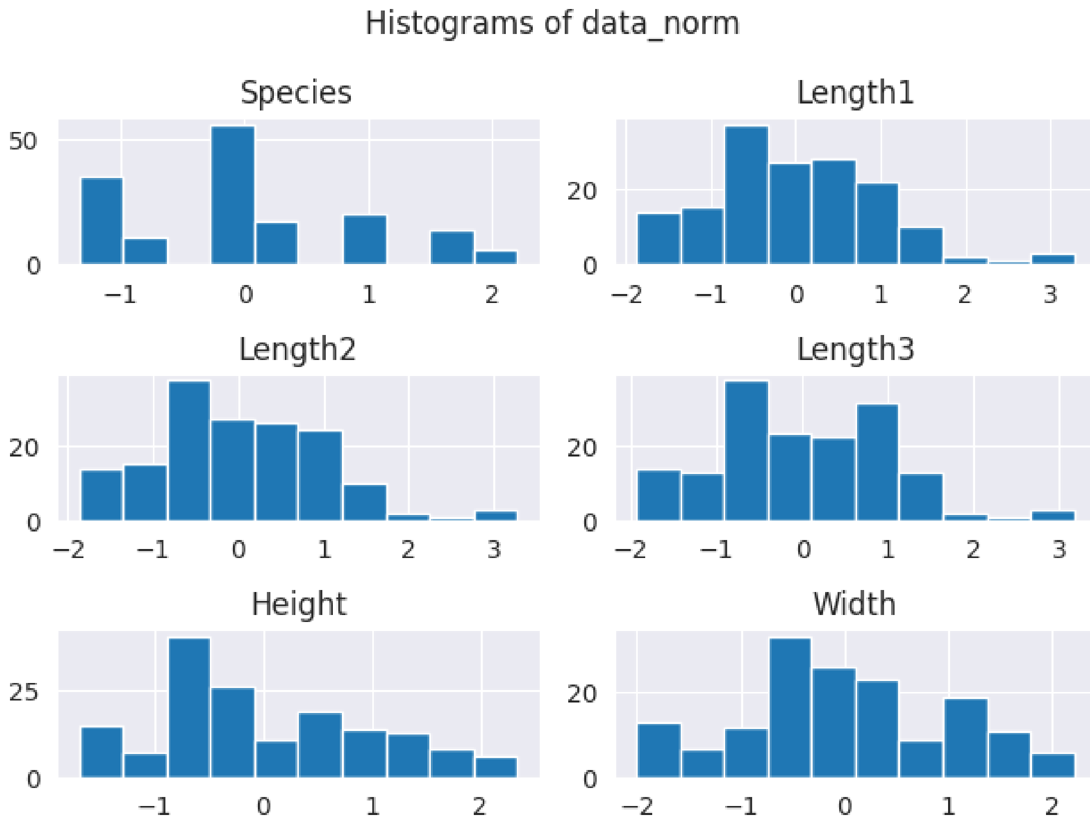
[50]:
```
# Descriptive stats
set_option('display.width', 100)
set_option('display.precision', 1)
for data, name in data_objects:
```

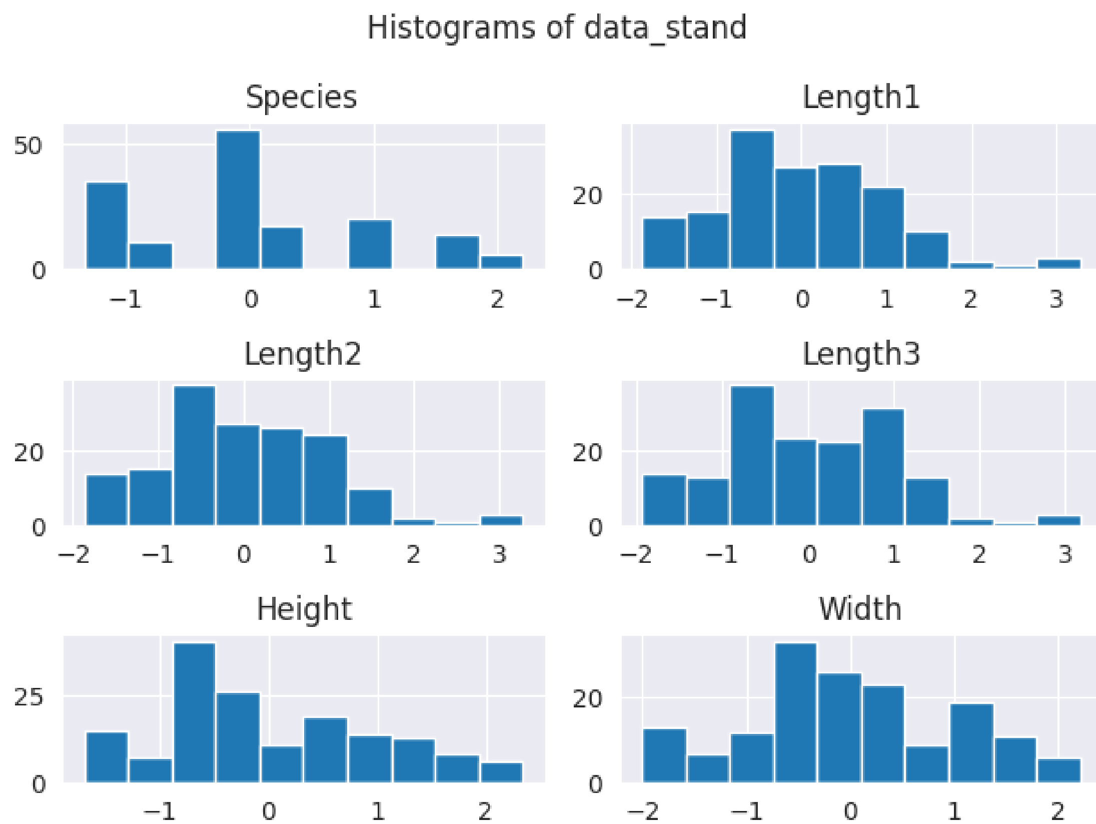
```python
    print(f"Data: {name}")
    print(data.describe())
```

```
Data: data_norm
       Species  Length1  Length2  Length3   Height    Width
count  1.6e+02  1.6e+02  1.6e+02  1.6e+02  1.6e+02  1.6e+02
mean   6.0e-02  5.1e-01  5.6e-01  6.1e-01  1.7e-01  8.6e-02
std    6.5e-02  1.4e-02  1.3e-02  1.1e-02  5.3e-02  1.4e-02
min    0.0e+00  4.9e-01  5.4e-01  5.9e-01  8.9e-02  5.2e-02
25%    2.6e-02  5.0e-01  5.5e-01  6.0e-01  1.5e-01  8.3e-02
50%    4.2e-02  5.2e-01  5.6e-01  6.1e-01  1.7e-01  8.9e-02
75%    8.2e-02  5.3e-01  5.7e-01  6.2e-01  2.3e-01  9.4e-02
max    2.8e-01  5.4e-01  5.8e-01  6.3e-01  2.8e-01  1.3e-01
Data: data_stand
       Species  Length1  Length2  Length3   Height    Width
count  1.6e+02  1.6e+02  1.6e+02  1.6e+02  1.6e+02  1.6e+02
mean   2.2e-17 -1.1e-16 -1.5e-16 -7.8e-17  4.5e-17 -2.8e-16
std    1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00  1.0e+00
min   -1.3e+00 -1.9e+00 -1.9e+00 -1.9e+00 -1.7e+00 -2.0e+00
25%   -7.4e-01 -7.2e-01 -6.9e-01 -7.0e-01 -7.1e-01 -6.1e-01
50%   -1.6e-01 -1.1e-01 -1.0e-01 -1.6e-01 -2.8e-01 -1.0e-01
75%    7.3e-01  6.5e-01  6.6e-01  7.3e-01  7.9e-01  6.9e-01
max    2.2e+00  3.3e+00  3.3e+00  3.2e+00  2.3e+00  2.2e+00
Data: data_raw
       Species  Weight  Length1  Length2  Length3  Height  Width
count    159.0   159.0    159.0    159.0    159.0   159.0  159.0
mean       2.3   398.3     26.2     28.4     31.2     9.0    4.4
std        1.7   358.0     10.0     10.7     11.6     4.3    1.7
min        0.0     0.0      7.5      8.4      8.8     1.7    1.0
25%        1.0   120.0     19.1     21.0     23.1     5.9    3.4
50%        2.0   273.0     25.2     27.3     29.4     7.8    4.2
75%        3.5   650.0     32.7     35.5     39.7    12.4    5.6
max        6.0  1650.0     59.0     63.4     68.0    19.0    8.1
```

[51]:

```python
# Histograms
for data, name in data_objects:
    data_stand.hist()
    plt.suptitle(f"Histograms of {name}")
    plt.tight_layout()
    plt.show()
```

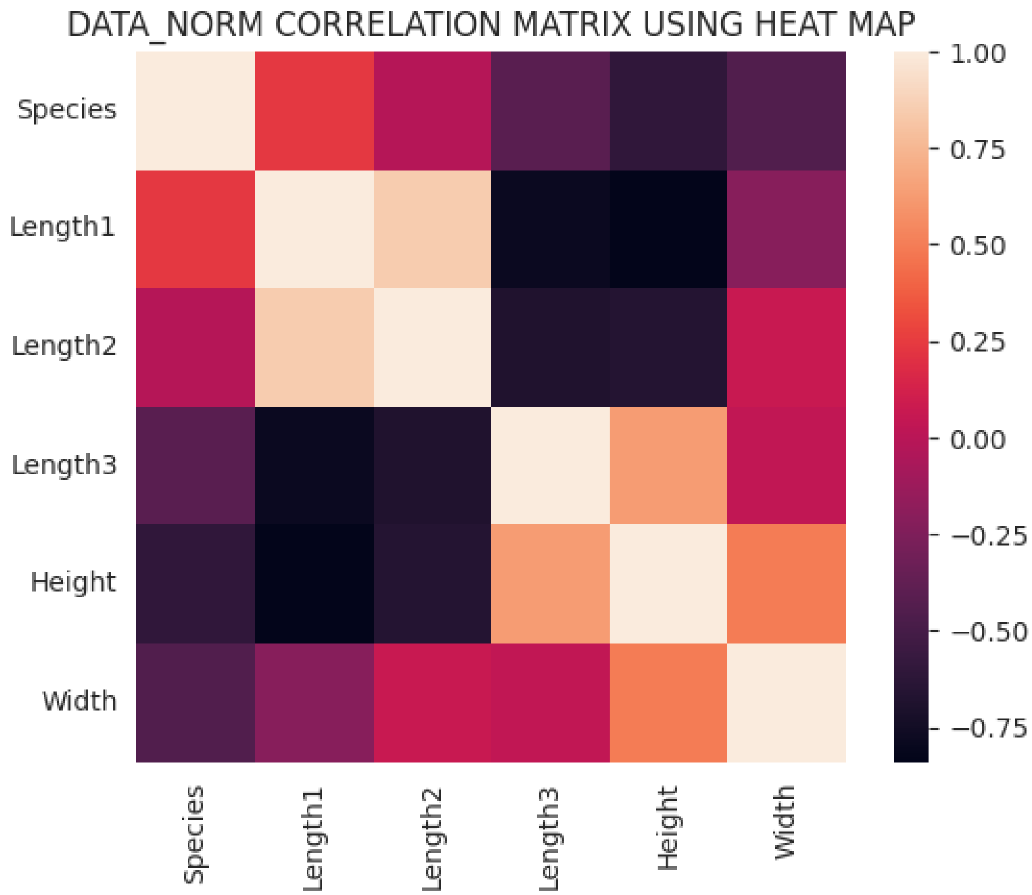

Histograms of data_norm
Species
Length1
Length2
Length3
Height
Width


Histograms of data_stand
Species
Length1
Length2
Length3
Height
Width

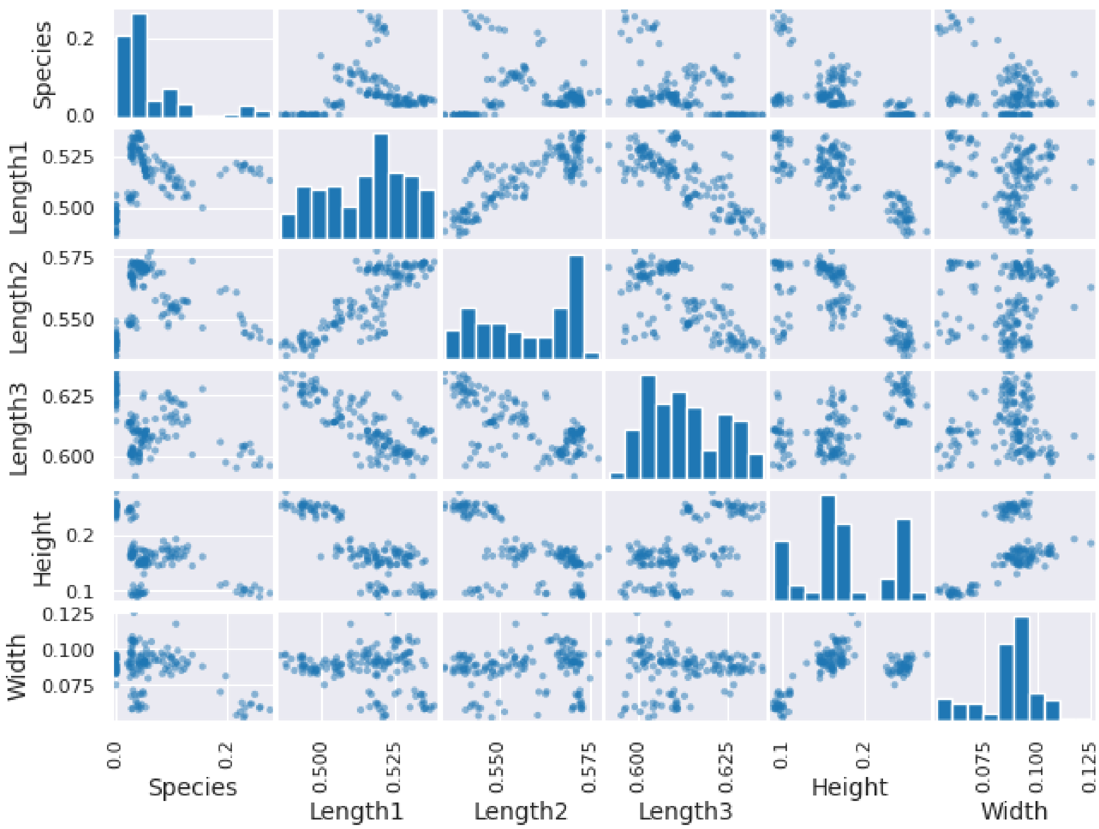
[52]:
```
for data, name in data_objects:
    plt.figure() # new plot
    #plt.tight_layout()
    corMat = data_norm.corr(method='pearson')
    print(corMat)
    ## plot correlation matrix as a heat map
    sns.heatmap(corMat, square=True)
    plt.yticks(rotation=0)
    plt.xticks(rotation=90)
    plt.title(f"{name.upper()} CORRELATION MATRIX USING HEAT MAP")
    plt.show()

    ## scatter plot of all data
    plt.figure()
    # # The output overlaps itself, resize it to display better (w padding)
    scatter_matrix(data_norm)
    plt.tight_layout(pad=0.1)
    plt.show()
```

```
         Species  Length1  Length2  Length3  Height    Width
Species  1.0e+00      0.2 -1.3e-02 -4.1e-01    -0.6 -4.4e-01
```

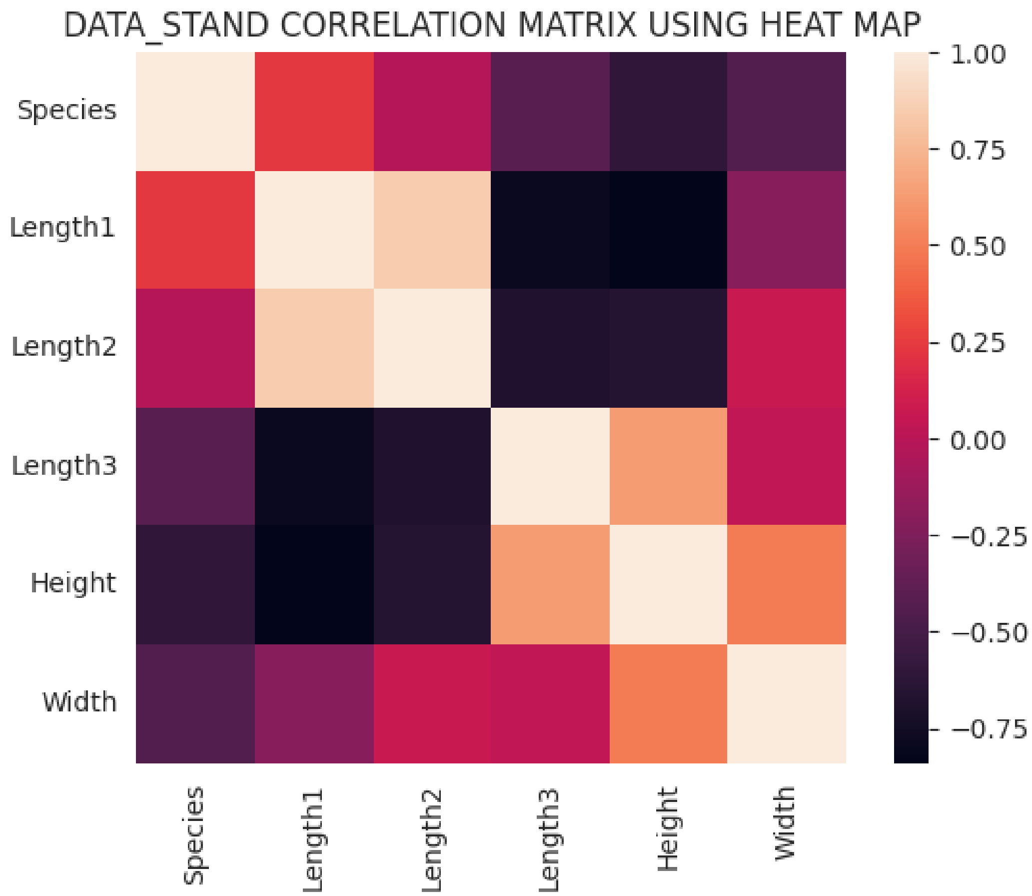
Length1	2.4e-01	1.0	8.5e-01	-7.8e-01	-0.8	-2.1e-01
Length2	-1.3e-02	0.8	1.0e+00	-6.9e-01	-0.7	6.9e-02
Length3	-4.1e-01	-0.8	-6.9e-01	1.0e+00	0.6	3.2e-02
Height	-6.1e-01	-0.8	-6.6e-01	6.3e-01	1.0	5.0e-01
Width	-4.4e-01	-0.2	6.9e-02	3.2e-02	0.5	1.0e+00



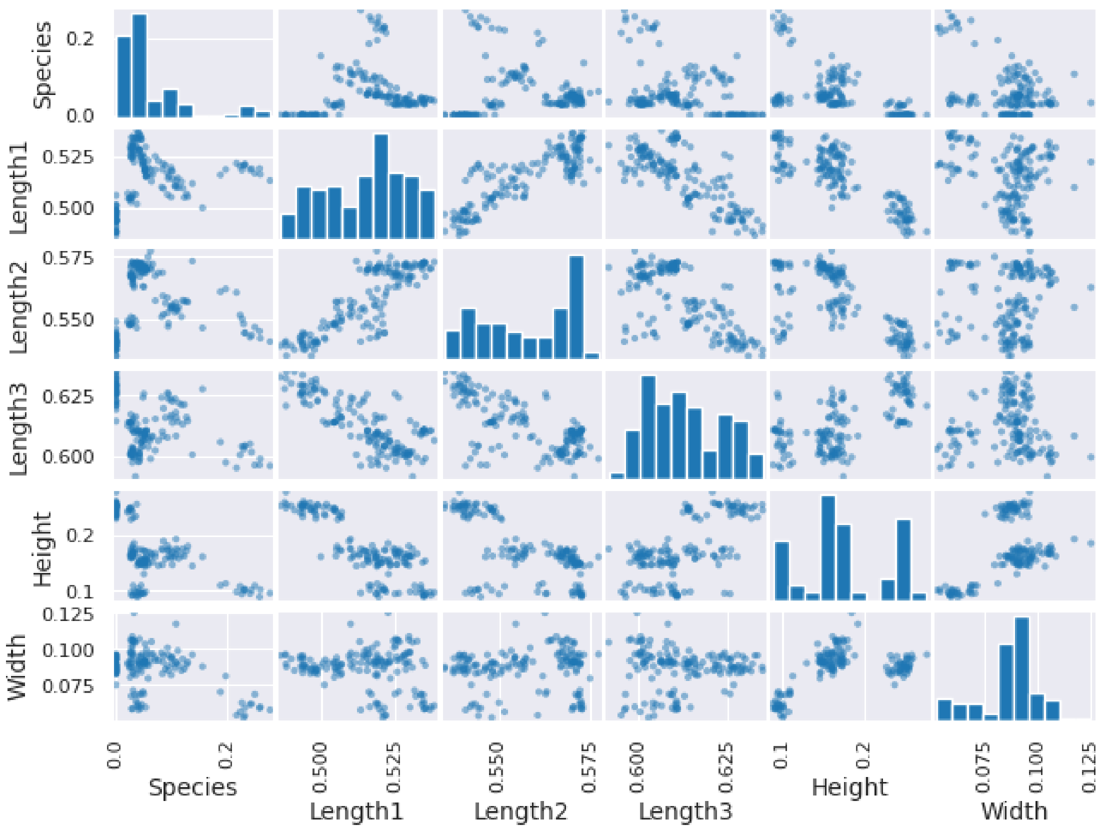
<Figure size 640x480 with 0 Axes>



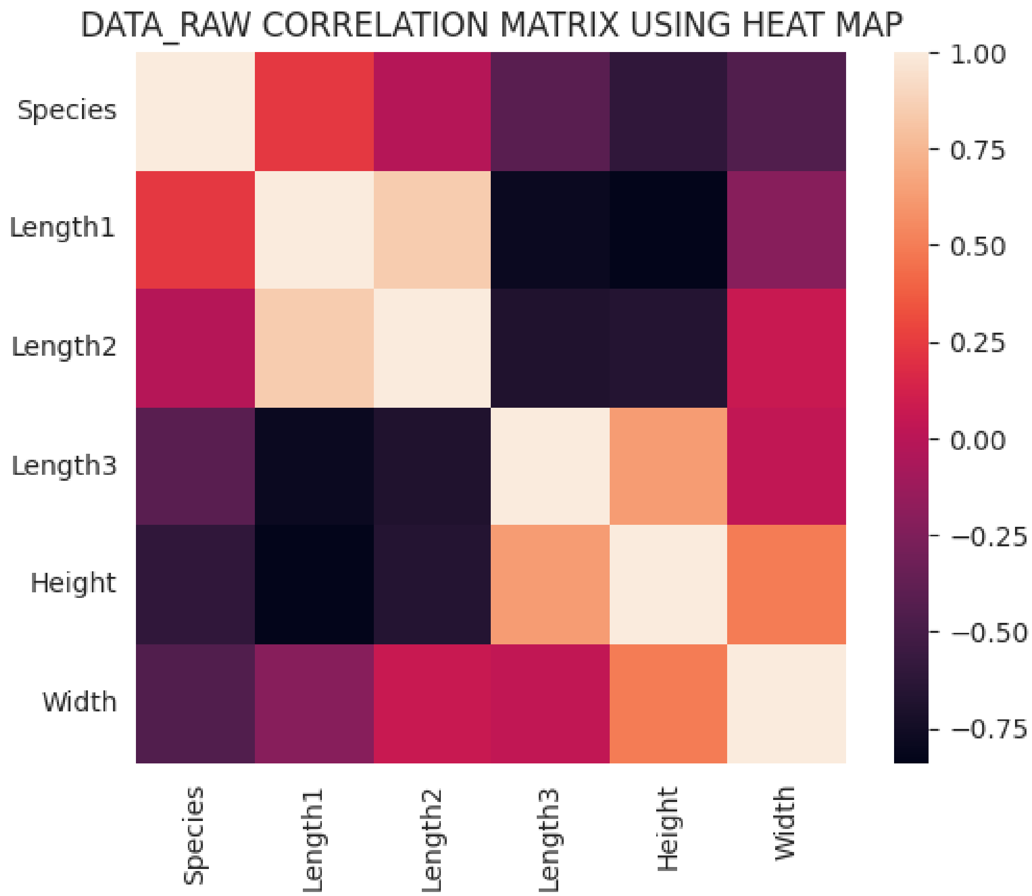
	Species	Length1	Length2	Length3	Height	Width
Species	1.0e+00	0.2	-1.3e-02	-4.1e-01	-0.6	-4.4e-01
Length1	2.4e-01	1.0	8.5e-01	-7.8e-01	-0.8	-2.1e-01
Length2	-1.3e-02	0.8	1.0e+00	-6.9e-01	-0.7	6.9e-02
Length3	-4.1e-01	-0.8	-6.9e-01	1.0e+00	0.6	3.2e-02
Height	-6.1e-01	-0.8	-6.6e-01	6.3e-01	1.0	5.0e-01
Width	-4.4e-01	-0.2	6.9e-02	3.2e-02	0.5	1.0e+00



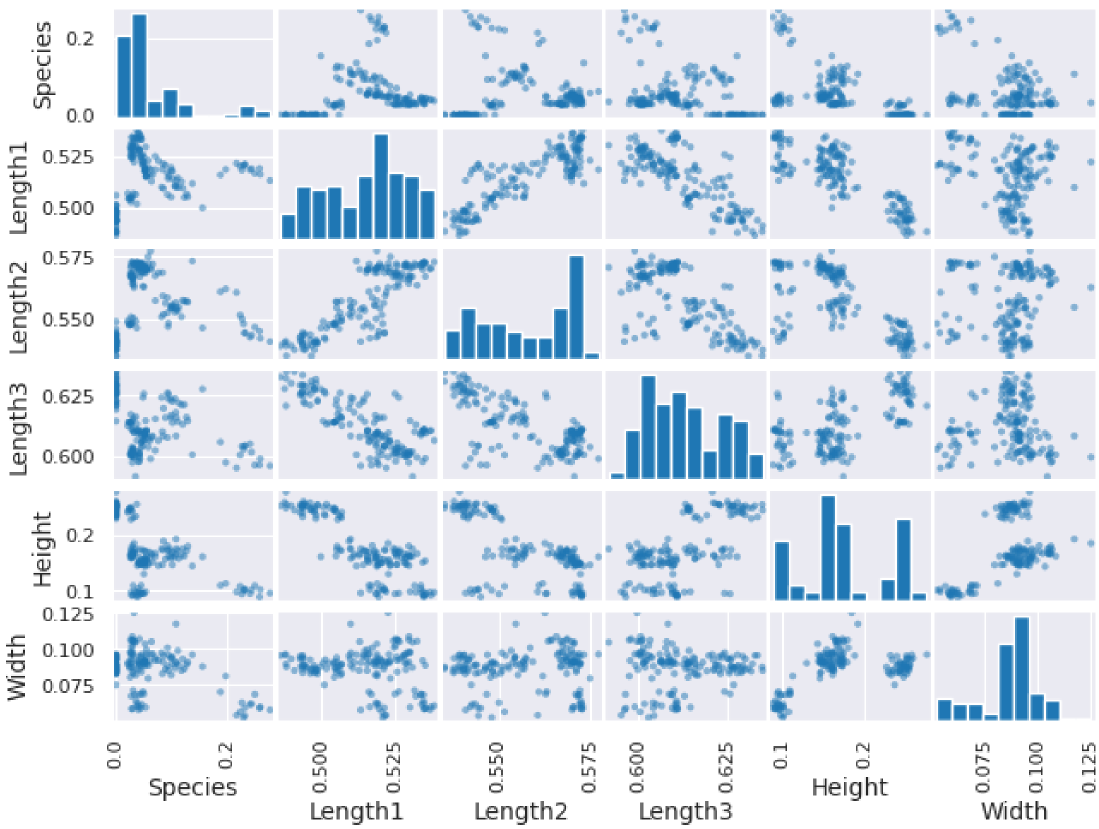
<Figure size 640x480 with 0 Axes>



	Species	Length1	Length2	Length3	Height	Width
Species	1.0e+00	0.2	-1.3e-02	-4.1e-01	-0.6	-4.4e-01
Length1	2.4e-01	1.0	8.5e-01	-7.8e-01	-0.8	-2.1e-01
Length2	-1.3e-02	0.8	1.0e+00	-6.9e-01	-0.7	6.9e-02
Length3	-4.1e-01	-0.8	-6.9e-01	1.0e+00	0.6	3.2e-02
Height	-6.1e-01	-0.8	-6.6e-01	6.3e-01	1.0	5.0e-01
Width	-4.4e-01	-0.2	6.9e-02	3.2e-02	0.5	1.0e+00




```
<Figure size 640x480 with 0 Axes>
```



[53]:
```python
model = LinearRegression()

rfe_6 = RFE(model, n_features_to_select=6)
rfe_6.fit(data_stand, Y1)
features_6 = X1names[rfe_6.support_]

rfe_5 = RFE(model, n_features_to_select=5)
rfe_5.fit(data_stand, Y1)
features_5 = X1names[rfe_5.support_]

rfe_4 = RFE(model, n_features_to_select=4)
rfe_4.fit(data_stand, Y1)
features_4 = X1names[rfe_4.support_]


print("Features selected for 6-feature model:", features_6.tolist())
print("Features selected for 5-feature model:", features_5.tolist())
print("Features selected for 4-feature model:", features_4.tolist())
```

```
Features selected for 6-feature model: ['Species', 'Length1', 'Length2',
'Length3', 'Height', 'Width']
```

```
Features selected for 5-feature model: ['Species', 'Length1', 'Length2',
'Length3', 'Height']
Features selected for 4-feature model: ['Length1', 'Length2', 'Length3',
'Height']
```

[54]:
```
# Prepare models for cross-validation
models = []

# Add basic linear models with different feature counts
X_6 = data_stand[features_6]
X_5 = data_stand[features_5]
X_4 = data_stand[features_4]

models.append(('X_6', model, X_6))
models.append(('X_5', model, X_5))
models.append(('X_4', model, X_4))
```

[55]:
```
def find_best_alpha(X_data, y_data, model_type: str) -> float:
    alphas = logspace(-4, 4, 20)  # 20 values from 0.0001 to 10000
    param_grid = {'alpha': alphas}

    if model_type == 'ridge':
        model = Ridge(max_iter=10000, tol=0.001)
    else:  # lasso
        model = Lasso(max_iter=50000, tol=0.001, warm_start=True)

    grid_search = GridSearchCV(model, param_grid, cv=5, scoring='r2')
    grid_search.fit(X_data, y_data)

    best_alpha = grid_search.best_params_['alpha']
    best_score = grid_search.best_score_

    print(f"{model_type.capitalize()} model with {X_data.shape[1]} features:␣
↪Best alpha = {best_alpha}, Score = {best_score:.4f}")

    results = pd.DataFrame(grid_search.cv_results_)
    top_indices = results['rank_test_score'].sort_values().head(3).index
    for idx in top_indices:
        alpha = results.loc[idx, 'param_alpha']
        score = results.loc[idx, 'mean_test_score']
        print(f"  Alpha: {alpha:.6f}, Score: {score:.4f}")

    return best_alpha
```

[56]:
```
# Find best alphas for each feature set and model type
ridge_alpha_6 = find_best_alpha(X_6, Y1, 'ridge')
ridge_alpha_5 = find_best_alpha(X_5, Y1, 'ridge')
```

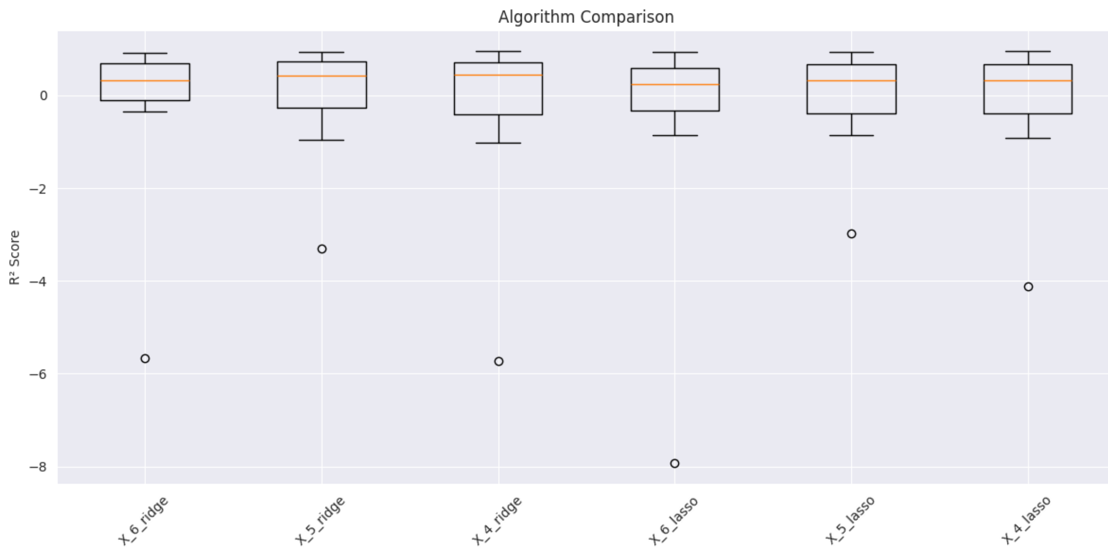
```python
ridge_alpha_4 = find_best_alpha(X_4, Y1, 'ridge')

lasso_alpha_6 = find_best_alpha(X_6, Y1, 'lasso')
lasso_alpha_5 = find_best_alpha(X_5, Y1, 'lasso')
lasso_alpha_4 = find_best_alpha(X_4, Y1, 'lasso')

# Print best alpha values
print(f"Best Ridge alpha for 6 features: {ridge_alpha_6}")
print(f"Best Ridge alpha for 5 features: {ridge_alpha_5}")
print(f"Best Ridge alpha for 4 features: {ridge_alpha_4}")
print(f"Best Lasso alpha for 6 features: {lasso_alpha_6}")
print(f"Best Lasso alpha for 5 features: {lasso_alpha_5}")
print(f"Best Lasso alpha for 4 features: {lasso_alpha_4}")
```

```
Ridge model with 6 features: Best alpha = 29.763514416313132, Score = 0.5798
  Alpha: 29.763514, Score: 0.5798
  Alpha: 11.288379, Score: 0.5179
  Alpha: 78.475997, Score: 0.4881
Ridge model with 5 features: Best alpha = 29.763514416313132, Score = 0.5813
  Alpha: 29.763514, Score: 0.5813
  Alpha: 11.288379, Score: 0.4925
  Alpha: 78.475997, Score: 0.4449
Ridge model with 4 features: Best alpha = 29.763514416313132, Score = 0.5562
  Alpha: 29.763514, Score: 0.5562
  Alpha: 11.288379, Score: 0.5539
  Alpha: 4.281332, Score: 0.5410
Lasso model with 6 features: Best alpha = 11.288378916846883, Score = 0.5090
  Alpha: 11.288379, Score: 0.5090
  Alpha: 4.281332, Score: 0.4218
  Alpha: 29.763514, Score: 0.3570
Lasso model with 5 features: Best alpha = 11.288378916846883, Score = 0.5454
  Alpha: 11.288379, Score: 0.5454
  Alpha: 29.763514, Score: 0.5192
  Alpha: 4.281332, Score: 0.3659
Lasso model with 4 features: Best alpha = 11.288378916846883, Score = 0.5658
  Alpha: 11.288379, Score: 0.5658
  Alpha: 4.281332, Score: 0.5541
  Alpha: 1.623777, Score: 0.5461
Best Ridge alpha for 6 features: 29.763514416313132
Best Ridge alpha for 5 features: 29.763514416313132
Best Ridge alpha for 4 features: 29.763514416313132
Best Lasso alpha for 6 features: 11.288378916846883
Best Lasso alpha for 5 features: 11.288378916846883
Best Lasso alpha for 4 features: 11.288378916846883
```

[63]:
```python
models.clear()
```

```
models.append(('X_6_ridge', Ridge(alpha=ridge_alpha_6, max_iter=10000, tol=0.
  ↪001), X_6))
models.append(('X_5_ridge', Ridge(alpha=ridge_alpha_5, max_iter=10000, tol=0.
  ↪001), X_5))
models.append(('X_4_ridge', Ridge(alpha=ridge_alpha_4, max_iter=10000, tol=0.
  ↪001), X_4))
models.append(('X_6_lasso', Lasso(alpha=lasso_alpha_6, max_iter=50000, tol=0.
  ↪001, warm_start=True), X_6))
models.append(('X_5_lasso', Lasso(alpha=lasso_alpha_5, max_iter=50000, tol=0.
  ↪001, warm_start=True), X_5))
models.append(('X_4_lasso', Lasso(alpha=lasso_alpha_4, max_iter=50000, tol=0.
  ↪001, warm_start=True), X_4))
results = []
names = []

scoring = 'r2'
kfold = KFold(n_splits=10)

for name, model, X_data in models:
    cv_results = cross_val_score(model, X_data, Y1, cv=kfold, scoring=scoring)
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)

# Create boxplot for model comparison
plt.figure(figsize=(12, 6))
plt.title('Algorithm Comparison')
plt.boxplot(results)
plt.xticks(range(1, len(names) + 1), names, rotation=45)
plt.ylabel('R² Score')
plt.tight_layout()
plt.show()

means = [mean(result) for result in results]

best_model_index = means.index(max(means))
best_model_name, best_model, best_X = models[best_model_index]

print(f"\nBest model: {best_model_name} with mean R² score of {max(means):.4f}")
best_model.fit(best_X, Y1)

coefs = pd.DataFrame({'Feature': best_X.columns, 'Coefficient': best_model.
  ↪coef_})
print("\nCoefficients for best model:")
print(coefs.sort_values('Coefficient', ascending=False))
```

```
X_6_ridge: -0.241371 (1.854025)
X_5_ridge: -0.074963 (1.221238)
X_4_ridge: -0.323107 (1.898637)
X_6_lasso: -0.591483 (2.504922)
X_5_lasso: -0.082241 (1.125021)
X_4_lasso: -0.189527 (1.431666)
```




```
Best model: X_5_ridge with mean R² score of -0.0750

Coefficients for best model:
   Feature  Coefficient
1  Length1         91.2
2  Length2         90.9
4   Height         85.3
3  Length3         80.5
0  Species         21.1
```

- All models show negative R^2 scores, indicating poor generalization.
- All models have high standard deviation, indicating high variance and overfitting.
- Fight lengths are present in all models and identified in RFE as important features.
- Lasso performs worse than Ridge on this dataset, indicating too high of an L1 penalty.
- Species is the least impactful feature in the best models as seen in a drastically smaller coefficient compared to other features.