not_certain

November 7, 2024

0.1 Highest Correlated Features by Model and Scaling type

[ ]:
```
# Standard Scaling
dt_importance_std = dt_model.feature_importances_
rf_importance_std = rf_model.feature_importances_
xgb_importance_std = xgb_model.feature_importances_
```

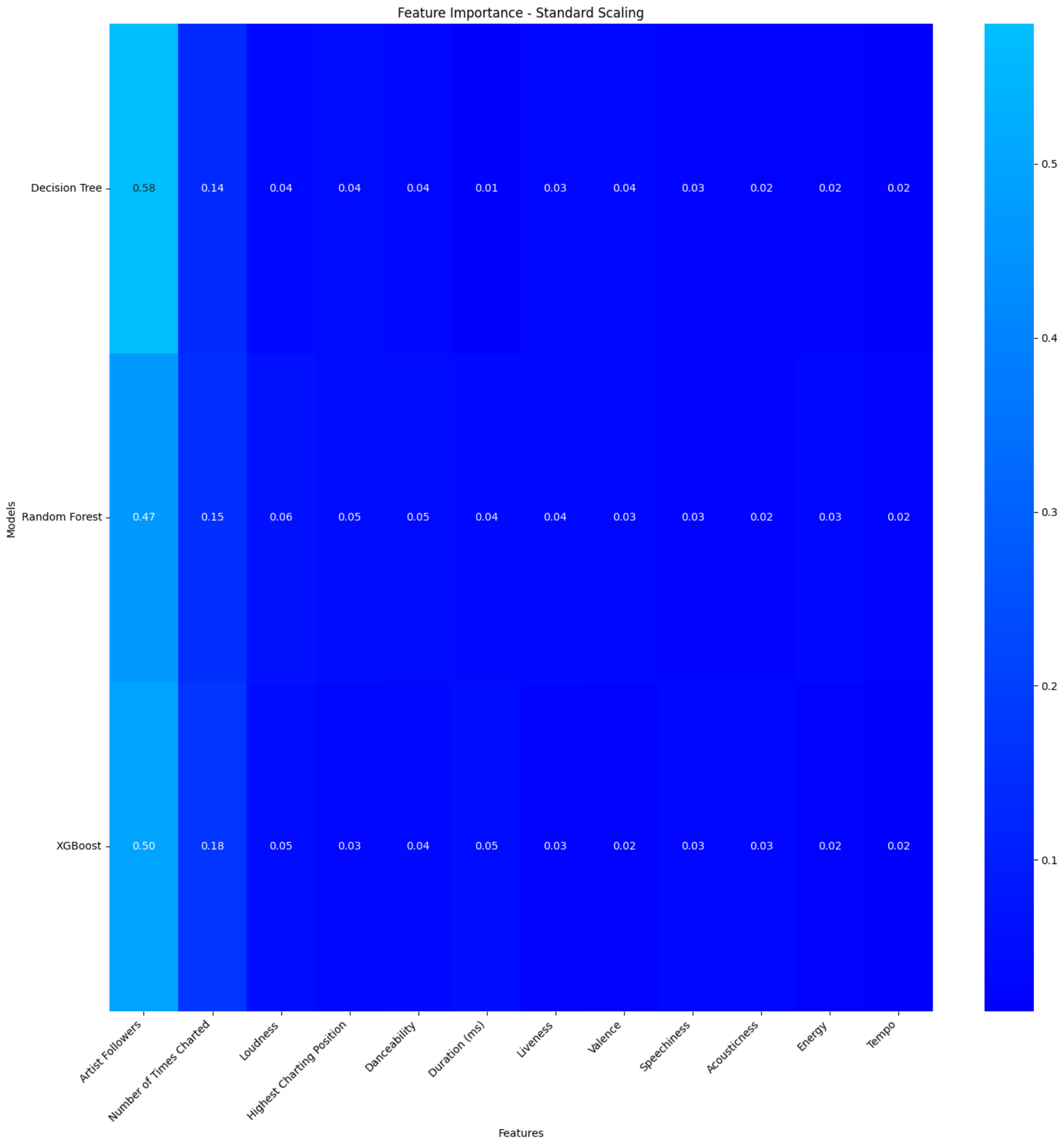
[ ]:
```
# Min-Max Scaling
dt_importance_mm = dt_model.feature_importances_### STD Model Comparison Table
results = {
    'Model': ['Linear Regression', 'Decision Tree', 'Random Forest', 'XGBoost'],
    'RMSE': [np.sqrt(mean_squared_error(y_test_1, y_pred_lr)),
             np.sqrt(mean_squared_error(y_test_1, y_pred_dt)),
             np.sqrt(mean_squared_error(y_test_1, y_pred_rf)),
             np.sqrt(mean_squared_error(y_test_1, y_pred_xgb))],
    'R2 Score': [r2_score(y_test_1, y_pred_lr),
                 r2_score(y_test_1, y_pred_dt),
                 r2_score(y_test_1, y_pred_rf),
                 r2_score(y_test_1, y_pred_xgb)]
}

results_df = pd.DataFrame(results)
print(results_df)

rf_importance_mm = rf_model.feature_importances_
xgb_importance_mm = xgb_model.feature_importances_
```

```
               Model       RMSE  R2 Score
0  Linear Regression  16.423524 -0.052112
1      Decision Tree  23.314402 -1.120204
2      Random Forest  20.237325 -0.597480
3            XGBoost  21.281860 -0.766641
```

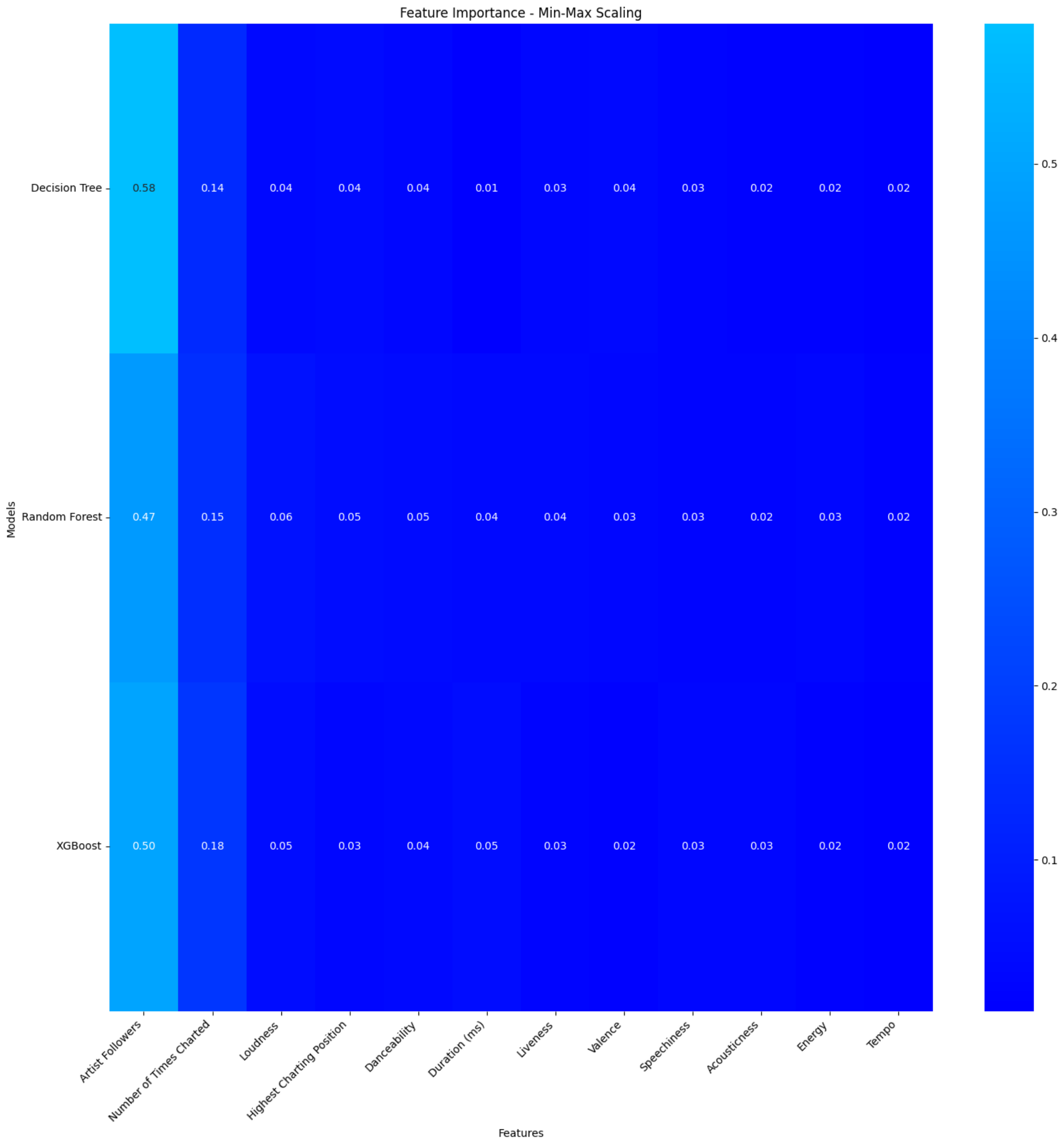
[ ]:
```
feature_names = X_train_1.columns
```

[ ]:
```
def plot_feature_importance(importances, feature_names, model_names, title):
    plt.figure(figsize=(15, 15))
    # Create a DataFrame with feature importances
    df = pd.DataFrame(importances, index=model_names, columns=feature_names)

    # Sort features by average importance across all models
    avg_importance = df.mean()
    sorted_features = avg_importance.sort_values(ascending=False).index

    # Create a custom color map from blue to cerulean
    colors = ["#0000FF", "#00BFFF"]  # Blue to Cerulean
    n_bins = 100
    cmap = mcolors.LinearSegmentedColormap.from_list("custom", colors, N=n_bins)

    # Create heatmap
    sns.heatmap(df[sorted_features], annot=True, cmap=cmap, fmt='.2f')

    plt.title(title)
    plt.xlabel('Features')
    plt.ylabel('Models')
    plt.xticks(rotation=45, ha='right')
    plt.yticks(rotation=0)
    plt.tight_layout()
    plt.show()
```

[ ]:
```
# Standard Scaling
importances_std = [dt_importance_std, rf_importance_std, xgb_importance_std]
model_names = ['Decision Tree', 'Random Forest', 'XGBoost']
plot_feature_importance(importances_std, feature_names, model_names, 'Feature␣
 ↪Importance - Standard Scaling')

# Min-Max Scaling
importances_mm = [dt_importance_mm, rf_importance_mm, xgb_importance_mm]
plot_feature_importance(importances_mm, feature_names, model_names, 'Feature␣
 ↪Importance - Min-Max Scaling')
```



	Artist Followers	Number of Times Charted	Loudness	Highest Charting Position	Danceability	Duration (ms)	Liveness	Valence	Speechiness	Acousticness	Energy	Tempo
Decision Tree	0.58	0.14	0.04	0.04	0.04	0.01	0.03	0.04	0.03	0.02	0.02	0.02
Random Forest	0.47	0.15	0.06	0.05	0.05	0.04	0.04	0.03	0.03	0.02	0.03	0.02
XGBoost	0.50	0.18	0.05	0.03	0.04	0.05	0.03	0.02	0.03	0.03	0.02	0.02


Feature Importance - Min-Max Scaling
Models
Decision Tree
Random Forest
XGBoost
0.58
0.14
0.04
0.04
0.04
0.01
0.03
0.04
0.03
0.02
0.02
0.02
0.47
0.15
0.06
0.05
0.05
0.04
0.04
0.03
0.03
0.02
0.03
0.02
0.50
0.18
0.05
0.03
0.04
0.05
0.03
0.02
0.03
0.03
0.02
0.02
Artist Followers
Number of Times Charted
Loudness
Highest Charting Position
Danceability
Duration (ms)
Liveness
Valence
Speechiness
Acousticness
Energy
Tempo
Features
0.5
0.4
0.3
0.2
0.1