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Regression module

In our notebook,the module tried to identify the patterns and relationships among the features to bring out the desired outcomes in term of the popularity score of a song. We have also figured out that over the decades the factors affecting the popularity of a song have been changing, which also indicates that the music industry is also evolving as per the tastes of the audience.

Reprocessing

We retain all numeric data for analysis and apply one-hot encoding to transform it into a format suitable for modeling to address categorical data. Furthermore, we modified the dataset based on our understanding of real-life circumstances to add more useful figures to our dataset, including combining music with year and artist, filling in missing values, etc. However, these modifications introduced significant bias, adversely affecting the predictive accuracy of the final prediction on the test dataset. Consequently, we reverted to using the original dataset without these alterations to ensure the integrity of our results.

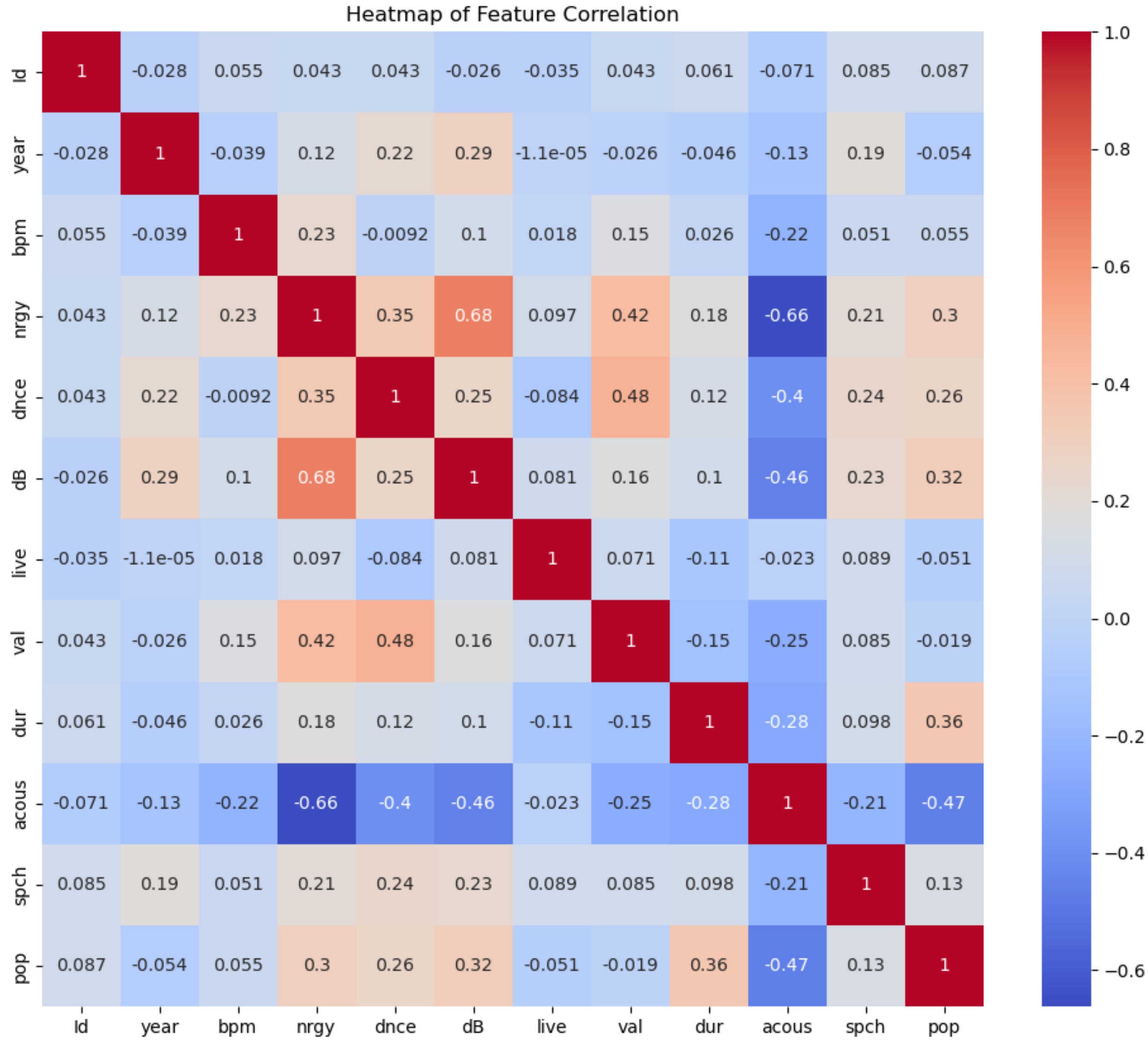
In [1]:
```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV, train_test_split, cross_val_score,Ra
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor, VotingR
from sklearn.svm import SVR
from sklearn.preprocessing import OneHotEncoder,StandardScaler
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# Read the CSV files of training into DataFrames df
df = pd.read_csv('CS98XRegressionTrain.csv',encoding = "ISO-8859-1")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 453 entries, 0 to 452
Data columns (total 15 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   Id         453 non-null    int64 
 1   title      453 non-null    object
 2   artist     453 non-null    object
 3   top genre  438 non-null    object
 4   year       453 non-null    int64 
 5   bpm        453 non-null    int64 
 6   nrgy       453 non-null    int64 
 7   dnce       453 non-null    int64 
 8   dB         453 non-null    int64 
 9   live       453 non-null    int64 
 10  val        453 non-null    int64 
 11  dur        453 non-null    int64 
 12  acous      453 non-null    int64 
 13  spch       453 non-null    int64 
 14  pop        453 non-null    int64 
dtypes: int64(12), object(3)
memory usage: 53.2+ KB
```

In [3]:

```python
# Plot the heatmap, showing the correlation of training feature with predicting
plt.figure(figsize=(12, 10))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title('Heatmap of Feature Correlation')
plt.show()
```



In [4]:
```
#transform categorical values in the 'artist' column of a DataFrame into a one-hot enc
onehot_encoder = OneHotEncoder(sparse=False)

artist_onehot_encoded = onehot_encoder.fit_transform(df[['artist']])
artist_onehot_encoded_df = pd.DataFrame(artist_onehot_encoded, columns=onehot_encoder.

df = df.join(artist_onehot_encoded_df, lsuffix='_original', rsuffix='_onehot')
```

In [5]:
```
#drops specified columns ('title', 'artist', 'Id') from the DataFrame (df) to create a
columns_to_drop = ['title','artist','Id']
df_train_figures = df.drop(columns=[col for col in columns_to_drop if col in df.column


#standardizes the numeric features in the DataFrame df_train_figures using StandardSca
numeric_features = ['year', 'bpm', 'nrgy', 'dnce', 'dB', 'live', 'val', 'dur', 'acous'

scaler = StandardScaler()

df_train_figures[numeric_features] = scaler.fit_transform(df_train_figures[numeric_fea

df_train_figures = pd.get_dummies(df_train_figures, columns=['top genre'], drop_first=
```

In [6]:
```
df_train_figures
```

Out[6]:

	year	bpm	nrgy	dnce	dB	live	val	dur	acous
0	0.271894	-0.452169	-1.310624	-0.941668	0.234142	-0.344348	-1.283649	-1.197460	1.424453
1	1.167012	-0.174511	-0.724531	-0.424450	0.234142	-0.344348	-0.508542	-1.370145	0.543019
2	-0.742572	-0.531500	-1.085204	0.222073	-0.045716	-0.344348	0.307359	0.293907	-0.745230
3	-0.682898	2.046756	-1.445876	-0.812364	-2.004725	-0.344348	-1.079673	0.089825	-0.270612
4	-1.100619	0.103148	-0.589278	-0.230493	0.234142	-0.199578	-0.794108	-0.522420	0.407414
...	...	...	...	...	...	...	...	...	...
448	-1.936062	-1.523137	-1.716381	-2.687280	-2.284583	-0.561503	-1.773190	-0.192750	2.000775
449	1.107337	1.174116	0.943582	-0.424450	-1.165150	0.379502	1.490416	-1.244556	0.576921
450	0.629941	1.967425	-0.228605	0.868596	0.234142	0.162347	0.062588	0.984645	-0.338414
451	0.510592	1.848429	1.214086	0.286725	1.073717	-0.851043	1.164055	-0.553817	-0.948637
452	0.629941	-0.531500	0.582909	0.545334	0.234142	-0.271963	1.408826	0.859056	-0.745230

453 rows × 441 columns

In [7]:

```
#the dataset into training and testing sets, with 80% of the data used for training an
X = df_train_figures.drop(['pop'], axis=1)
y = df_train_figures['pop']

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

Model Selection and Tuning

In this process, we began by testing various basic models and using Root Mean Square Error (RMSE) on the training data to determine their effectiveness. The differences in performance of basic models are minor, therefore we chose the best-performing ones by using the voting strategy. Besides, we applied hyperparameter tuning with grid search to enhance their performance to find the optimal settings, then we used cross-validation for a more accurate evaluation. To further improve our model accuracy, the bagging strategy was implemented to create many various subsets of the original dataset, which resulted in a more accurate and robust predictive model.

In [8]:

```
#Optimizes a Random Forest Regressor using RandomizedSearchCV, evaluates its performan
param_distributions = {
    'n_estimators': [100, 200, 500],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['auto', 'sqrt', 'log2']
}
```

```python
# Configure RandomizedSearchCV to optimize the Random Forest Regressor.
random_search = RandomizedSearchCV(
    estimator=RandomForestRegressor(random_state=42),
    param_distributions=param_distributions,
    n_iter=50,
    cv=5,
    verbose=2,
    random_state=42,
    n_jobs=-1
)


random_search.fit(X_train, y_train)
# Extract the best parameters.
print("Best parameters:", random_search.best_params_)


best_model = random_search.best_estimator_
y_pred_optimized = best_model.predict(X_test)


rmse_optimized = np.sqrt(mean_squared_error(y_test, y_pred_optimized))
print(f'Optimized Random Forest Regressor RMSE: {rmse_optimized:.4f}')
rmse_optimized


# Define parameter grids for different regressors to be used in grid search.
param_grid_rf = {'n_estimators': [100, 200], 'max_depth': [None, 10, 20]}
param_grid_gbr = {'n_estimators': [100, 200], 'learning_rate': [0.1, 0.01]}
param_grid_svr = {'C': [0.1, 1, 10], 'kernel': ['rbf', 'linear']}


# Initialize regressor instances with a fixed random state for reproducibility.
rf = RandomForestRegressor(random_state=42)
gbr = GradientBoostingRegressor(random_state=42)
svr = SVR()

# Configure GridSearchCV with specified parameter grids.
grid_search_rf = GridSearchCV(rf, param_grid_rf, cv=5, scoring='neg_mean_squared_error
grid_search_gbr = GridSearchCV(gbr, param_grid_gbr, cv=5, scoring='neg_mean_squared_er
grid_search_svr = GridSearchCV(svr, param_grid_svr, cv=5, scoring='neg_mean_squared_er

# Find the best model parameters for each regressor.
grid_search_rf.fit(X_train, y_train)
grid_search_gbr.fit(X_train, y_train)
grid_search_svr.fit(X_train, y_train)

# Extract the best estimator for each regressor.
best_rf = grid_search_rf.best_estimator_
best_gbr = grid_search_gbr.best_estimator_
best_svr = grid_search_svr.best_estimator_

# Construct a Voting Regressor ensemble with the optimized models.
voting_reg = VotingRegressor(estimators=[('rf', best_rf), ('gbr', best_gbr), ('svr', b

voting_reg.fit(X_train, y_train)


y_pred = voting_reg.predict(X_test)
```

```
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print(f"VOTING RMSE: {rmse}")
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
Best parameters: {'n_estimators': 200, 'min_samples_split': 2, 'min_samples_leaf': 1,
'max_features': 'log2', 'max_depth': None}
Optimized Random Forest Regressor RMSE: 11.2283
VOTING RMSE: 10.71552365257033
```

In [9]:
```
voting_reg
```

Out[9]:
```
VotingRegressor
rf                       gbr                          svr
RandomForestRegressor    GradientBoostingRegressor    SVR
```

In [10]:
```
bagging_model = BaggingRegressor(estimator=voting_reg, n_estimators=10, random_state=4

bagging_model.fit(X_train, y_train)


y_pred_bagging = bagging_model.predict(X_test)

rmse = np.sqrt(mean_squared_error(y_test, y_pred_bagging))
print(f"BEGGING RMSE: {rmse}")
```

```
BEGGING RMSE: 10.84095881905858
```

In [11]:
```
bagging_model
```

Out[11]:
```
BaggingRegressor
estimator: VotingRegressor
rf                       gbr                          svr
RandomForestRegressor    GradientBoostingRegressor    SVR
```

Preporcess and Predict the Target Dataset

In the final process, we applied the same preprocessing steps as used with the training data to the imported target dataset. Due to the differences in the 'top genre' categories between the test and training datasets, we merged the one-hot encoded columns to align the shape of the datasets. Consequently, we re-fit the Begging model with modified training data and make the prediction of the target data.

In [12]:
```
# Now read the CSV files of test dataset into DataFrames df_test
df_test = pd.read_csv('CS98XRegressionTest.csv')
#save a copy of test dataset for the final prediction output file
df_test_copy=df_test
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114 entries, 0 to 113
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   Id         114 non-null    int64 
 1   title      114 non-null    object
 2   artist     114 non-null    object
 3   top genre  113 non-null    object
 4   year       114 non-null    int64 
 5   bpm        114 non-null    int64 
 6   nrgy       114 non-null    int64 
 7   dnce       114 non-null    int64 
 8   dB         114 non-null    int64 
 9   live       114 non-null    int64 
 10  val        114 non-null    int64 
 11  dur        114 non-null    int64 
 12  acous      114 non-null    int64 
 13  spch       114 non-null    int64 
dtypes: int64(11), object(3)
memory usage: 12.6+ KB
```

In [13]:
```
# preporocess the dataset as same as the training dataset

artist_onehot_encoded = onehot_encoder.fit_transform(df_test[['artist']])


artist_onehot_encoded_df_test = pd.DataFrame(artist_onehot_encoded, columns=onehot_enc
df_test = df_test.join(artist_onehot_encoded_df, lsuffix='_original', rsuffix='_onehot

df_test['top genre'] = df_test['top genre'].fillna('Unknown')
columns_to_drop = ['title','artist','Id']
df_prediction = df_test.drop(columns=[col for col in columns_to_drop if col in df.colu
```

In [14]:
```
#Standardizes the numeric features in the prediction DataFrame using StandardScaler ar
numeric_features = ['year', 'bpm', 'nrgy', 'dnce', 'dB', 'live', 'val', 'dur', 'acous'

scaler = StandardScaler()

df_prediction[numeric_features] = scaler.fit_transform(df_prediction[numeric_features]

df_prediction = pd.get_dummies(df_prediction, columns=['top genre'], drop_first=True)
```

In [15]:
```
#alignment between the features of the training and prediction datasets before using t
for column in X_train.columns:
    if column not in df_prediction.columns:
        df_prediction[column] = 0

for column in df_prediction.columns:
    if column not in X_train.columns:
        df_prediction.drop(column, axis=1, inplace=True)
df_prediction = df_prediction[X_train.columns]
```

In [16]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 453 entries, 0 to 452
Columns: 440 entries, year to top genre_yodeling
dtypes: float64(355), uint8(85)
memory usage: 1.3 MB
```

In [17]:
```
df_prediction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114 entries, 0 to 113
Columns: 440 entries, year to top genre_yodeling
dtypes: float64(355), int64(58), uint8(27)
memory usage: 371.0 KB
```

In [18]:
```
#fit the model with all the data from the training dataset and predict the test datase
bagging_model.fit(X, y)
result_pred = bagging_model.predict(df_prediction)
```

In [19]:
```
# generate the prediction output file
df_test_copy['pop']=result_pred
predictions_df = df_test_copy[['Id','pop']]
predictions_df.to_csv('predictions.csv', index=False)
```

Summary:

Our final prediction score was 7.60786 up to the time we uploaded, which placed us in the top third of the leaderboard in the Kaggle competition. While our predictive model shows potential for further optimization, we encountered challenges related to computational resources, as optimizing for better parameters required exponentially more computing power. Additionally, as the model runs the "black box", it was difficult to interpret some results that contradicted our expectations. We also observed that adding more features to the original data introduced more bias, leading to suboptimal predictions. Despite these issues, our model still provided relatively good predictions, representing a challenging yet rewarding endeavor in machine learning.