Billboard Hot 100 Analysis &

Machine Learning Project

Name:

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Details

Use some supervised learning techniques to determine the top hits of the Billboard Hot 100 (1958 to 2020)

- For this final portion we will use the hot100df_distinct
- working with a shape of (13058,21)
- Data Prep and Preprocessing
- One Hot Encoding
- Scaling
- Model building
- Model Evaluation ## Supervised Learning Part 3

I will use various models to predict the number 1 spot for the Billboard Hot 100

In [1]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib as mpl
from matplotlib import cm
import numpy as np
import pandas as pd
import os
import pickle
%matplotlib inline
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# Where to save the figures
PROJECT_ROOT_DIR = "."
FOLDER = "figures"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, FOLDER)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)

# Set columns view to max
pd.set_option('display.max_columns', None)
```

Import pickled hot100df_distinct

In [2]:
```
ml_df = pd.read_pickle('hot100df_distinct.pkl')
ml_df
```

Out[2]:

	performer	song_performer	song	track_duration_s	danceability	energy	key	loudness	mode	speech
0	Andy Williams	......And Roses And Roses | Andy Williams	......And Roses And Roses	166.106	0.154	0.185	F	-14.063	major	0
1	Britney Spears	...Baby One More Time | Britney Spears	...Baby One More Time	211.066	0.759	0.699	C	-5.745	minor	0
2	Paul Davis	'65 Love Affair | Paul Davis	'65 Love Affair	219.813	0.647	0.686	D	-4.247	minor	0
3	Tammy Wynette	'til I Can Make It On My Own | Tammy Wynette	'til I Can Make It On My Own	182.080	0.450	0.294	G	-12.022	major	0
4	Luther Vandross	'Til My Baby Comes Home | Luther Vandross	'Til My Baby Comes Home	332.226	0.804	0.714	B	-6.714	minor	0
...	...	...	...	...	...	...	...	...	...	
13053	The Trammps	Zing Went The Strings Of My Heart | The Trammps	Zing Went The Strings Of My Heart	202.693	0.667	0.851	E	-5.257	major	0
13054	The Five Americans	Zip Code | The Five Americans	Zip Code	175.040	0.393	0.594	A	-5.986	major	0
13055	Bad Wolves	Zombie | Bad Wolves	Zombie	254.805	0.448	0.826	D	-3.244	minor	0
13056	Herb Alpert & The Tijuana Brass	Zorba The Greek | Herb Alpert & The Tijuana Brass	Zorba The Greek	264.853	0.531	0.642	F	-12.702	major	0
13057	K7	Zunga Zeng | K7	Zunga Zeng	273.000	0.846	0.657	C#	-9.642	major	0

13058 rows × 23 columns

In [3]:
```
# Check dtypes
print(ml_df.dtypes)
```

```
performer                  object
song_performer             object
song                       object
track_duration_s          float64
danceability              float64
energy                    float64
key                        object
loudness                  float64
```

```
mode                          object
speechiness                  float64
acousticness                 float64
instrumentalness             float64
liveness                     float64
valence                      float64
tempo                        float64
time_signature               float64
date                  datetime64[ns]
rank                           int64
last_week                    float64
peak_rank                      int64
weeks_on_board                 int64
key_signature                 object
year                           int64
dtype: object
```

Data Preparation Processing

- First we need to OnHotEncode the peak_rank column for predictions
- create a new column top_hit in the ml_df
- set to 1 if value of peak_rank column is less than or equal to 1, and otherwise 0.
- use sklearn to OnHotEncode

In [4]:
```
# First Import sklearn
from sklearn.preprocessing import OneHotEncoder
```

In [5]:
```
ml_df['top_hit'] = np.where(ml_df['peak_rank'] <= 1, 1, 0)

# One-hot encode the top_hit column
encoder = OneHotEncoder(sparse_output=False)
top_hit_encoded = encoder.fit_transform(ml_df[['top_hit']])
top_hit_encoded_df = pd.DataFrame(top_hit_encoded, columns=encoder.get_feature_names_out

# Concatenate the one-hot encoded top_hit column with the original DataFrame
ml_df = pd.concat([ml_df, top_hit_encoded_df], axis=1)

# Drop the original top_hit column and the first and sixteenth columns
ml_df = ml_df.drop(['top_hit'], axis=1)
```

In [6]:
```
# Rename top_hit_1 to top_hit_pos and drop top_hit_0 negative class
ml_df = ml_df.drop(['top_hit_0'], axis=1)
ml_df = ml_df.rename(columns={'top_hit_1': 'top_hit_pos'})
ml_df
```

Out[6]:

	performer	song_performer	song	track_duration_s	danceability	energy	key	loudness	mode	speech
0	Andy Williams	......And Roses And Roses | Andy Williams	......And Roses And Roses	166.106	0.154	0.185	F	-14.063	major	0
1	Britney Spears	...Baby One More Time | Britney Spears	...Baby One More Time	211.066	0.759	0.699	C	-5.745	minor	0
2	Paul Davis	'65 Love Affair | Paul Davis	'65 Love Affair	219.813	0.647	0.686	D	-4.247	minor	0
3	Tammy Wynette	'til I Can Make It On My Own |	'til I Can	182.080	0.450	0.294	G	-12.022	major	0

		Tammy Wynette	Make It On My Own							
4	Luther Vandross	'Til My Baby Comes Home | Luther Vandross	'Til My Baby Comes Home	332.226	0.804	0.714	B	-6.714	minor	0
...	...	...	...	...	...	...	...	...	...	
13053	The Trammps	Zing Went The Strings Of My Heart | The Trammps	Zing Went The Strings Of My Heart	202.693	0.667	0.851	E	-5.257	major	0
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13055	Bad Wolves	Zombie | Bad Wolves	Zombie	254.805	0.448	0.826	D	-3.244	minor	0
13056	Herb Alpert & The Tijuana Brass	Zorba The Greek | Herb Alpert & The Tijuana Brass	Zorba The Greek	264.853	0.531	0.642	F	-12.702	major	0
13057	K7	Zunga Zeng | K7	Zunga Zeng	273.000	0.846	0.657	C#	-9.642	major	0

13058 rows × 24 columns

In [7]:

```python
# Let's drop the date column, this is unnecessary
ml_df = ml_df.drop(['date'], axis=1)
ml_df
```

Out[7]:

	performer	song_performer	song	track_duration_s	danceability	energy	key	loudness	mode	speech
0	Andy Williams	......And Roses And Roses | Andy Williams	......And Roses And Roses	166.106	0.154	0.185	F	-14.063	major	0
1	Britney Spears	...Baby One More Time | Britney Spears	...Baby One More Time	211.066	0.759	0.699	C	-5.745	minor	0
2	Paul Davis	'65 Love Affair | Paul Davis	'65 Love Affair	219.813	0.647	0.686	D	-4.247	minor	0
3	Tammy Wynette	'til I Can Make It On My Own | Tammy Wynette	'til I Can Make It On My Own	182.080	0.450	0.294	G	-12.022	major	0
4	Luther Vandross	'Til My Baby Comes Home | Luther Vandross	'Til My Baby Comes Home	332.226	0.804	0.714	B	-6.714	minor	0
...	...	...	...	...	...	...	...	...	...	

13053	The Trammps	Zing Went The Strings Of My Heart | The Trammps	Zing Went The Strings Of My Heart	202.693	0.667	0.851	E	-5.257	major	0
13054	The Five Americans	Zip Code | The Five Americans	Zip Code	175.040	0.393	0.594	A	-5.986	major	0
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13056	Herb Alpert & The Tijuana Brass	Zorba The Greek | Herb Alpert & The Tijuana Brass	Zorba The Greek	264.853	0.531	0.642	F	-12.702	major	0
13057	K7	Zunga Zeng | K7	Zunga Zeng	273.000	0.846	0.657	C#	-9.642	major	0

13058 rows × 23 columns

In [8]:
```
print(ml_df.dtypes)
```

```
performer             object
song_performer        object
song                  object
track_duration_s     float64
danceability         float64
energy               float64
key                   object
loudness             float64
mode                  object
speechiness          float64
acousticness         float64
instrumentalness     float64
liveness             float64
valence              float64
tempo                float64
time_signature       float64
rank                   int64
last_week            float64
peak_rank              int64
weeks_on_board         int64
key_signature         object
year                   int64
top_hit_pos          float64
dtype: object
```

Now let's finish up Preprocessing

In [9]:
```
# Import libraries
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
```

In [10]:
```
# Split into inputs and outputs
X = ml_df.drop(columns='top_hit_pos')
y = ml_df['top_hit_pos']
```

In [11]:
```
# determine categorical and numerical features
numerical_ix = X.select_dtypes(include=['int64', 'float64']).columns
categorical_ix = X.select_dtypes(include=['object', 'bool']).columns
```

In [12]:
```
# define the data preparation for the columns
t = [('cat', OneHotEncoder(), categorical_ix), ('num', MinMaxScaler(), numerical_ix)]
col_transform = ColumnTransformer(transformers=t)
```

In [13]:
```
# Apply the transformations to the data
X_transformed = col_transform.fit_transform(X)
```

Split for train test and import rft classifier

In [14]:
```
# Import Libs
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
```

In [15]:
```
# Split data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_transformed, y, test_size=0.2, ran
```

Create Random Forest Classifier model

In [16]:
```
# Create and fit the Random Forest model
rfcl = RandomForestClassifier()
rfcl.fit(X_train, y_train)
```

Out[16]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

Make Prediction with test set and evaluate model performance

In [17]:
```
# Make predictions on the test set
y_pred = rfcl.predict(X_test)
```

In [18]:
```
# Evaluate the model preformance
accuracy = rfcl.score(X_test, y_test)
print(f'Accuracy: {accuracy:.2f}')
```

```
Accuracy: 1.00
```

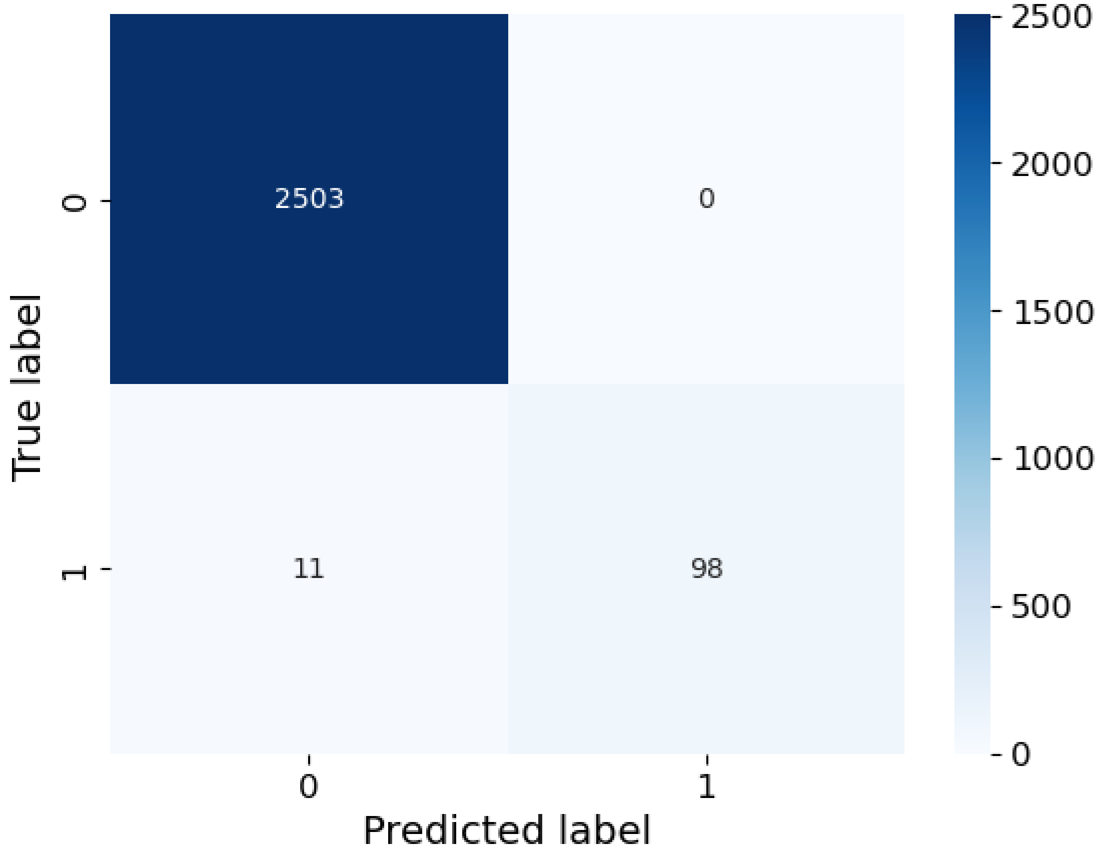
Visualize with a confusion matrix

- from sklearn.metrcis import cm

In [19]:
```
from sklearn.metrics import confusion_matrix
```

In [20]:
```
# create confusion matrix object
rfcl_cm = confusion_matrix(y_test, y_pred)

# Create a heatmap plot of the confusion matrix
sns.heatmap(rfcl_cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted label')
plt.ylabel('True label')
plt.show()
```



Evaluate model scores

In [21]:
```
# import libs for metrics
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

In [22]:
```
# Calculate the accuracy, precision, and recall scores for the RandomForestClassifier
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

# Print the accuracy, precision, and recall scores for the RandomForestClassifier
print(f'Accuracy: {accuracy:.2f}')
print(f'Precision: {precision:.2f}')
print(f'Recall: {recall:.2f}')
print(f'F1-score: {f1:.2f}')
```

```
Accuracy: 1.00
Precision: 1.00
Recall: 0.90
F1-score: 0.95
```

Let's try a KNN Classifier

In [23]:
```
# Import libs
from sklearn.neighbors import KNeighborsClassifier
```

In [24]:
```
# Create and fit KNN model
knn = KNeighborsClassifier()
knn.fit(X_train, y_train)
```

Out[24]:

```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

Make Prediction with test set and evaluate model performance

In [25]:
```
# Make predictions on the test set
knn_y_pred = knn.predict(X_test)
```

In [26]:
```
# Evaluate the model preformance
knn_accuracy = knn.score(X_test, y_test)
print(f'KNN Accuracy: {knn_accuracy:.2f}')
```

```
KNN Accuracy: 0.96
```

In [27]:
```
# Calculate the accuracy, precision, and recall scores for the KNN
knn_accuracy = accuracy_score(y_test, knn_y_pred)
knn_precision = precision_score(y_test, knn_y_pred)
knn_recall = recall_score(y_test, knn_y_pred)
knn_f1 = f1_score(y_test, knn_y_pred)

# Print the accuracy, precision, and recall scores for the KNN
print(f'KNN Accuracy: {knn_accuracy:.2f}')
print(f'KNN Precision: {knn_precision:.2f}')
print(f'KNN Recall: {knn_recall:.2f}')
print(f'KNN F1-score: {knn_f1:.2f}')
```

```
KNN Accuracy: 0.96
KNN Precision: 0.38
KNN Recall: 0.03
KNN F1-score: 0.05
```

BOOM

We can see the RandomForestClassifier is most suited for predictions

- with a Precision score of 1
- and a Recall score of .75

Thirdly, Let's try a SVM

In [28]:
```
# Import lib
from sklearn.svm import SVC
```

In [29]:
```
# Create a SVM classifier with a linear kernel
svc_model = SVC(kernel='linear')
# Train the classifier on the training data
svc_model.fit(X_train, y_train)
```

Out[29]:
```
▾ SVC
SVC(kernel='linear')
```

In [31]:
```
# Make predictions on the test data
svc_y_pred = svc_model.predict(X_test)
```

In [32]:
```
# Calculate the accuracy, precision, and recall scores for SVC
```

```python
svc_accuracy = accuracy_score(y_test, svc_y_pred)
svc_precision = precision_score(y_test, svc_y_pred)
svc_recall = recall_score(y_test, svc_y_pred)
svc_f1 = f1_score(y_test, svc_y_pred)

# Print the accuracy, precision, and recall scores for SVC
print(f'SVC Accuracy: {svc_accuracy:.2f}')
print(f'SVC Precision: {svc_precision:.2f}')
print(f'SVC Recall: {svc_recall:.2f}')
print(f'SVC F1-score: {svc_f1:.2f}')
```

```
SVC Accuracy: 0.96
SVC Precision: 0.77
SVC Recall: 0.18
SVC F1-score: 0.30
```

Pickle ml_df

In [ ]:

```python
ml_df.to_pickle('ml_df.pkl')
```