# Spotify Hit Songs Classification

## Business Problem

There could be a number of factors that determine whether a song will be a hit or not. If we know what these factors are, we may be able to better predict how popular a song will be and therefore improve features such as user recommendations.

By looking at Spotify data, can we use certain features to predict whether or not a song will be a hit? What features are most predictive of hit songs?

## Data Understanding

To begin, I import all the neccessary tools I will need for this project as well as the dataset I will be working with. I also explore the dataset to get a better understanding of the data it contains.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import math
import seaborn as sns
sns.set(font_scale=2)
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split, cross_val_score,
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassi
from sklearn.metrics import precision_score, accuracy_score, f1_score,
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.neighbors import KNeighborsClassifier
```

In [2]:
```
data = pd.read_csv('data/dataset-of-10s.csv')
data.head()
```

Out[2]:

| | track | artist | uri | danceability | energy | key | loudness |
|---|---|---|---|---|---|---|---|
| 0 | Wild Things | Alessia Cara | spotify:track:2ZyuwVvV6Z3XJaXIFbspeE | 0.741 | 0.626 | 1 | -4.826 |
| 1 | Surfboard | Esquivel! | spotify:track:61APOtq25SCMuK0V5w2Kgp | 0.447 | 0.247 | 5 | -14.661 |
| 2 | Love Someone | Lukas Graham | spotify:track:2JqnpexlO9dmvjUMCaLCLJ | 0.550 | 0.415 | 9 | -6.557 |
| 3 | Music To My Ears (feat. Tory Lanez) | Keys N Krates | spotify:track:0cjfLhk8WJ3etPTCseKXtk | 0.502 | 0.648 | 0 | -5.698 |
| 4 | Juju On That Beat (TZ Anthem) | Zay Hilfigerrr & Zayion McCall | spotify:track:1lltf5ZXJc1by9SbPeljFd | 0.807 | 0.887 | 1 | -3.892 |

In [3]:
```
data.isna().sum()
```

Out[3]:
```
track               0
artist              0
uri                 0
danceability        0
energy              0
key                 0
loudness            0
mode                0
speechiness         0
acousticness        0
instrumentalness    0
liveness            0
valence             0
tempo               0
duration_ms         0
time_signature      0
chorus_hit          0
sections            0
target              0
dtype: int64
```

In [4]:
```
1 data.describe()
```

Out[4]:

| | danceability | energy | key | loudness | mode | speechiness | acousticness |
|---|---|---|---|---|---|---|---|
| **count** | 6398.000000 | 6398.000000 | 6398.000000 | 6398.000000 | 6398.000000 | 6398.000000 | 6398.000000 |
| **mean** | 0.568163 | 0.667756 | 5.283526 | -7.589796 | 0.645514 | 0.098018 | 0.216928 |
| **std** | 0.191103 | 0.240721 | 3.606216 | 5.234592 | 0.478395 | 0.097224 | 0.296835 |
| **min** | 0.062200 | 0.000251 | 0.000000 | -46.655000 | 0.000000 | 0.022500 | 0.000000 |
| **25%** | 0.447000 | 0.533000 | 2.000000 | -8.425000 | 0.000000 | 0.038825 | 0.008533 |
| **50%** | 0.588000 | 0.712500 | 5.000000 | -6.096500 | 1.000000 | 0.057200 | 0.067050 |
| **75%** | 0.710000 | 0.857000 | 8.000000 | -4.601250 | 1.000000 | 0.112000 | 0.311000 |
| **max** | 0.981000 | 0.999000 | 11.000000 | -0.149000 | 1.000000 | 0.956000 | 0.996000 |

In [5]:
```
1 data['target'].value_counts()
```

Out[5]:
```
1    3199
0    3199
Name: target, dtype: int64
```

To generally get a better idea of which features of the data might be related to the target, I look at the Pearson correlations.

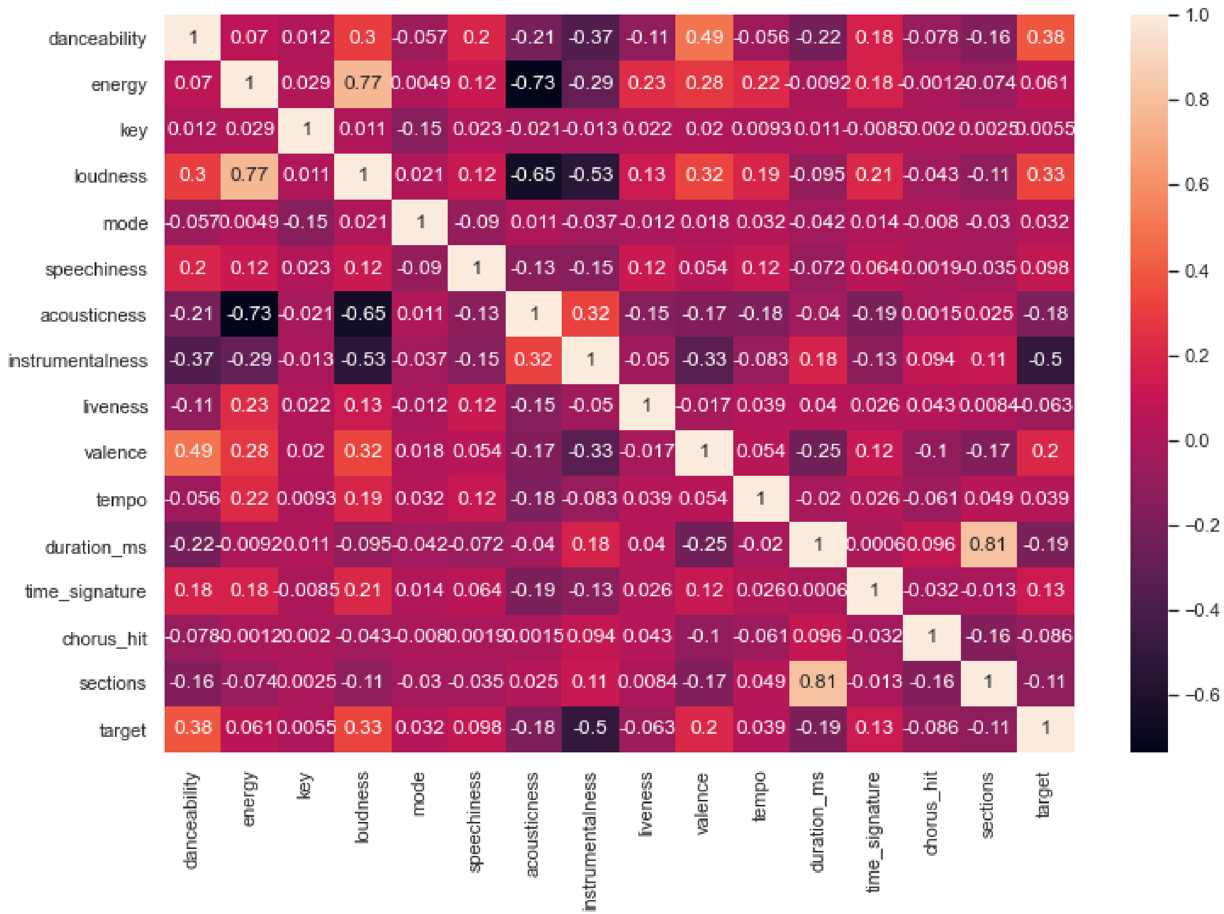
In [6]:

```
# correlation?
data.corr()
```

Out[6]:

| | danceability | energy | key | loudness | mode | speechiness | acousticness |
|---|---|---|---|---|---|---|---|
| **danceability** | 1.000000 | 0.069645 | 0.012429 | 0.300576 | -0.057280 | 0.200090 | -0.206865 |
| **energy** | 0.069645 | 1.000000 | 0.028703 | 0.774536 | 0.004929 | 0.119194 | -0.734853 |
| **key** | 0.012429 | 0.028703 | 1.000000 | 0.010824 | -0.146063 | 0.022796 | -0.021271 |
| **loudness** | 0.300576 | 0.774536 | 0.010824 | 1.000000 | 0.021064 | 0.122028 | -0.648717 |
| **mode** | -0.057280 | 0.004929 | -0.146063 | 0.021064 | 1.000000 | -0.090107 | 0.011424 |
| **speechiness** | 0.200090 | 0.119194 | 0.022796 | 0.122028 | -0.090107 | 1.000000 | -0.134226 |
| **acousticness** | -0.206865 | -0.734853 | -0.021271 | -0.648717 | 0.011424 | -0.134226 | 1.000000 |
| **instrumentalness** | -0.371334 | -0.288263 | -0.013049 | -0.533671 | -0.037132 | -0.148649 | 0.315563 |
| **liveness** | -0.107581 | 0.231393 | 0.021785 | 0.126807 | -0.011590 | 0.121075 | -0.149926 |
| **valence** | 0.494136 | 0.281031 | 0.019572 | 0.324985 | 0.018198 | 0.053836 | -0.166253 |
| **tempo** | -0.056197 | 0.216886 | 0.009259 | 0.194467 | 0.032180 | 0.117813 | -0.182050 |
| **duration_ms** | -0.224803 | -0.009228 | 0.011028 | -0.094598 | -0.042125 | -0.071826 | -0.039567 |
| **time_signature** | 0.178671 | 0.175984 | -0.008462 | 0.207436 | 0.014125 | 0.063656 | -0.191607 |
| **chorus_hit** | -0.078254 | -0.001224 | 0.001960 | -0.042665 | -0.007967 | 0.001857 | 0.001477 |
| **sections** | -0.162908 | -0.074466 | 0.002512 | -0.111469 | -0.030129 | -0.035077 | 0.024583 |
| **target** | 0.384486 | 0.060701 | 0.005548 | 0.327471 | 0.032021 | 0.097783 | -0.184479 |

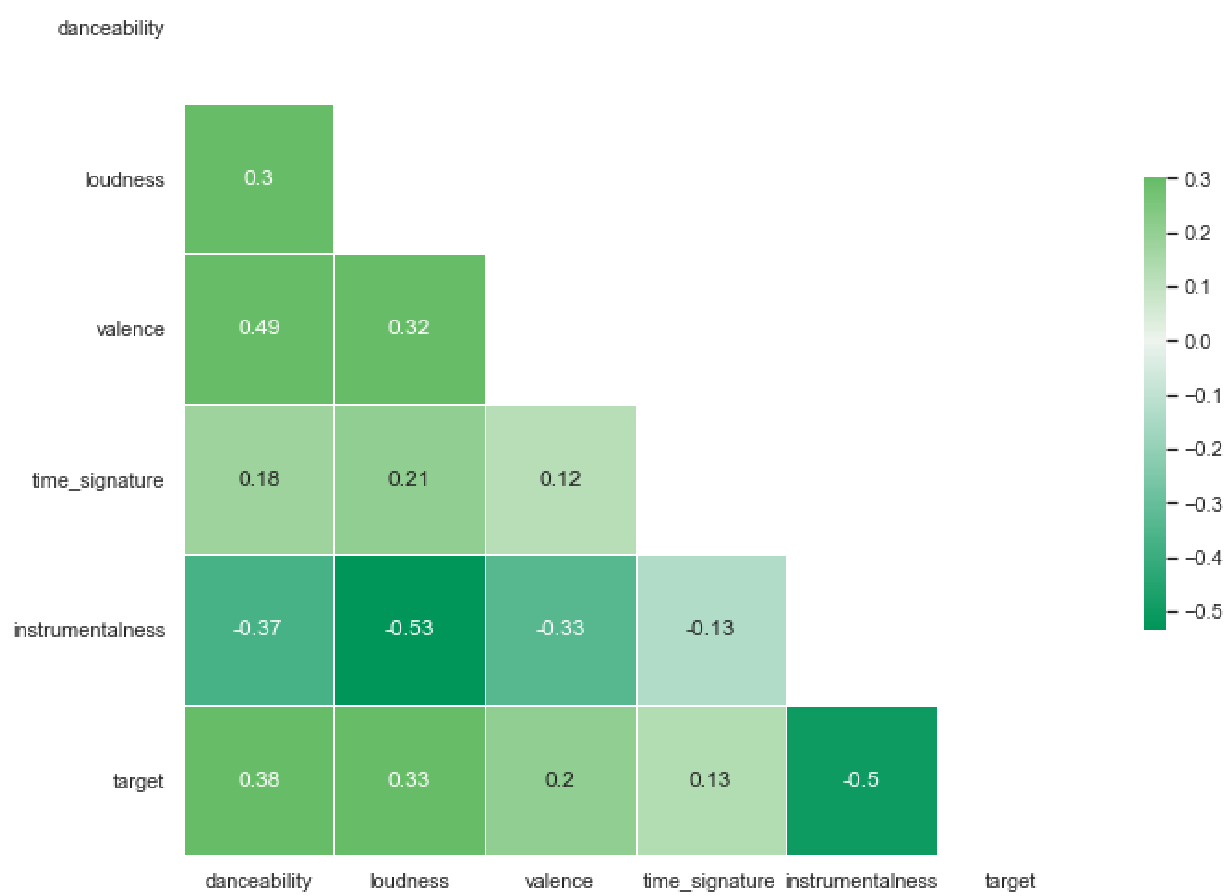
In [7]:
```python
sns.set(rc={'figure.figsize':(12,8)})
sns.heatmap(data.corr(), annot=True);
```



In [8]:

```
sns.set(style="white")
corr = data[['danceability', 'loudness', 'valence', 'time_signature', '

mask = np.triu(np.ones_like(corr, dtype=np.bool))

f, ax = plt.subplots(figsize=(11, 9))

cmap = sns.diverging_palette(160,120,215, n=3, as_cmap=True)

sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=
plt.show()
```

```
<ipython-input-8-5b51a6c4189b>:4: DeprecationWarning: `np.bool` is a depr
ecated alias for the builtin `bool`. To silence this warning, use `bool`
by itself. Doing this will not modify any behavior and is safe. If you sp
ecifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.or
g/devdocs/release/1.20.0-notes.html#deprecations (https://numpy.org/devdo
cs/release/1.20.0-notes.html#deprecations)
  mask = np.triu(np.ones_like(corr, dtype=np.bool))
```




Just by looking at this heatmap of the different features' correlations, we can see that the features that are most positively correlated with the target (whether or not the song is a hit) are danceability, loudness, valence, and time signature. Instrumentalness has a strong negative correlation with the target.

# Data Preparation

To compare later models to, first a baseline model must be created. I am using a single decision tree for the baseline model. In order to do this, I begin by assigning the target variable to y and the other features to X,performing a train-test split to evaluate the model with, and then normalizing the training data.

In [9]:
```
X = data.drop(columns=['target', 'uri', 'artist', 'track'], axis=1)
y = data['target']
X.head()
```

Out[9]:

| | danceability | energy | key | loudness | mode | speechiness | acousticness | instrumentalness | liveness |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.741 | 0.626 | 1 | -4.826 | 0 | 0.0886 | 0.02000 | 0.000 | 0.0828 |
| **1** | 0.447 | 0.247 | 5 | -14.661 | 0 | 0.0346 | 0.87100 | 0.814 | 0.0946 |
| **2** | 0.550 | 0.415 | 9 | -6.557 | 0 | 0.0520 | 0.16100 | 0.000 | 0.1080 |
| **3** | 0.502 | 0.648 | 0 | -5.698 | 0 | 0.0527 | 0.00513 | 0.000 | 0.2040 |
| **4** | 0.807 | 0.887 | 1 | -3.892 | 1 | 0.2750 | 0.00381 | 0.000 | 0.3910 |

In [10]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size= 0.
```

In [11]:
```
#normalize the data
X_train = X_train.apply(lambda x : (x - x.min()) /(x.max() - x.min()),

X_test = X_test.apply(lambda x : (x - x.min()) /(x.max() - x.min()), ax

```

# Modeling

In this section I build and evaluate my baseline decision tree model, then make changes to that model as well as try a more complex model (random forests) to see if it will perform better at correctly classifying the songs as hits or not.

For this business problem, we have a goal of recommending hit songs to Spotify users and therefore it would be better to incorrectly identify a hit song as not a hit, than to incorrectly identify a song as a hit when it isn't one. In other words, a false negative from our model is better than a false positive. We want to only recommend good-quality songs. For these reasons, the metrics used to evaluate the following models include accuracy, precision, and AUC.

In [12]:
```
# Building a "regular" tree as a baseline

baseline_tree = DecisionTreeClassifier(criterion='entropy', max_depth=5
baseline_tree.fit(X_train, y_train)

```
Out[12]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=5)
```

In [13]:
```
y_hat_train = baseline_tree.predict(X_train)
y_hat_test = baseline_tree.predict(X_test)

```

In [14]:
```
# Precision score
print("Training Precision for Decision Tree Classifier: {:.4}%".format(
print("Testing Precision for Decision Tree Classifier: {:.4}%".format(p

print("Training Accuracy for Decision Tree Classifier: {:.4}%".format(a
print("Testing Accuracy for Decision Tree Classifier: {:.4}%".format(ac

```
```
Training Precision for Decision Tree Classifier: 78.93%
Testing Precision for Decision Tree Classifier: 78.11%
Training Accuracy for Decision Tree Classifier: 82.76%
Testing Accuracy for Decision Tree Classifier: 79.81%
```

In [15]:
```
# Check the AUC of predictions
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```
Out[15]:
```
0.7983447170173967
```

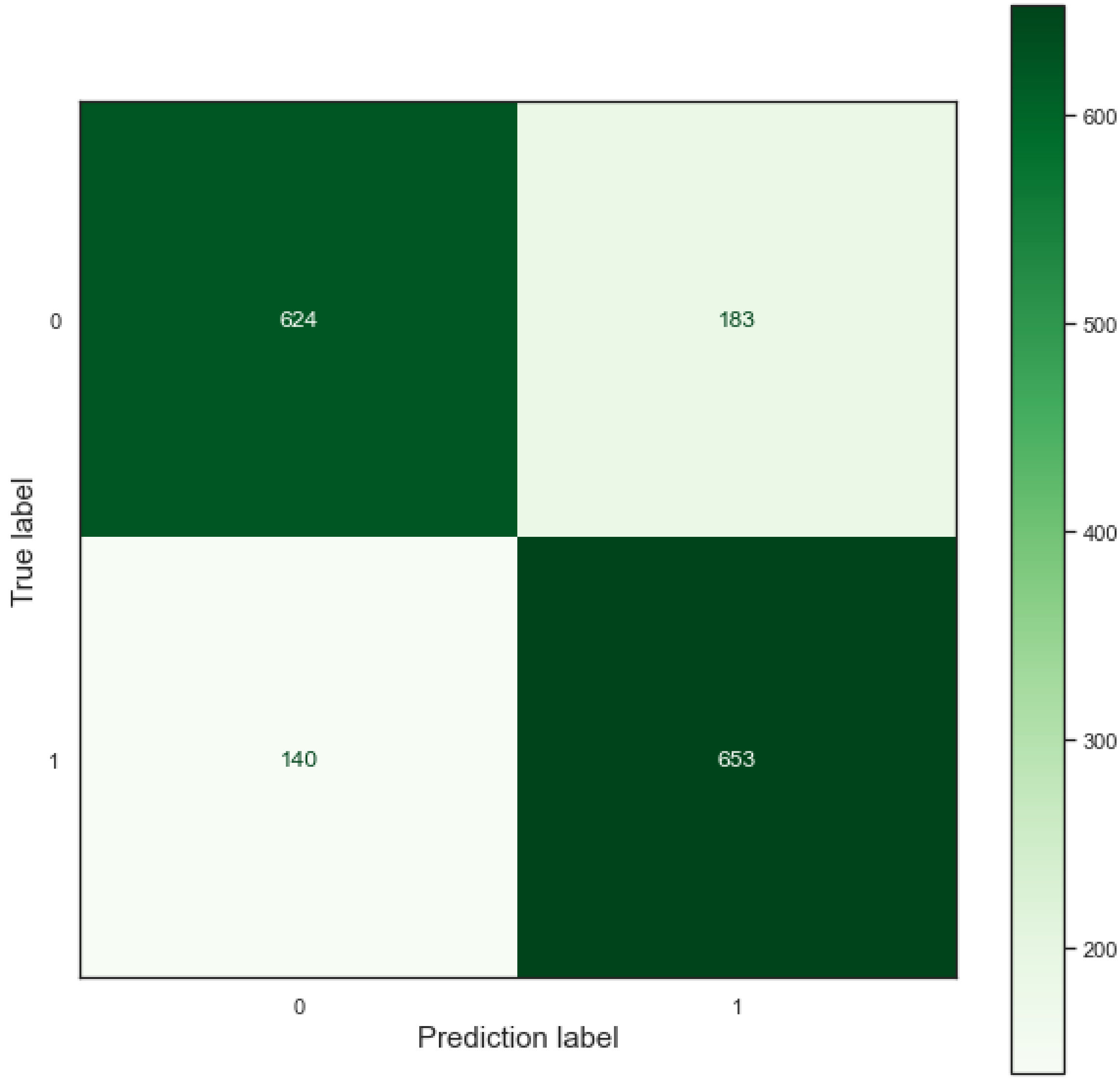
#### ***AUC interpretation:***

Because of the fact that for this business problem we would rather have a false negative (fail to identify a song as a hit when it really is one) than a false positive (incorrectly identify a song as a hit), looking at the AUC (Area Under the Curve) can provide us with more information on the rate of false negatives to false positives. We want this value to be as close to 1.0 as possible.

Our baseline model has an AUC value of about 0.80.

In [16]:
```
cnf_matrix = confusion_matrix(y_test, y_hat_test)
print('Confusion Matrix:\n', cnf_matrix)
```
```
Confusion Matrix:
 [[624 183]
 [140 653]]
```

In [17]:
```
#CM Visualization:
fig, ax = plt.subplots(figsize=(10,10))
cm_1 = ConfusionMatrixDisplay(confusion_matrix = cnf_matrix, display_la
cm_1.plot(cmap=plt.cm.Greens, ax=ax)
plt.xlabel('Prediction label',fontsize=15)
plt.ylabel('True label',fontsize=15);
```




***Confusion Matrix interpretation:***

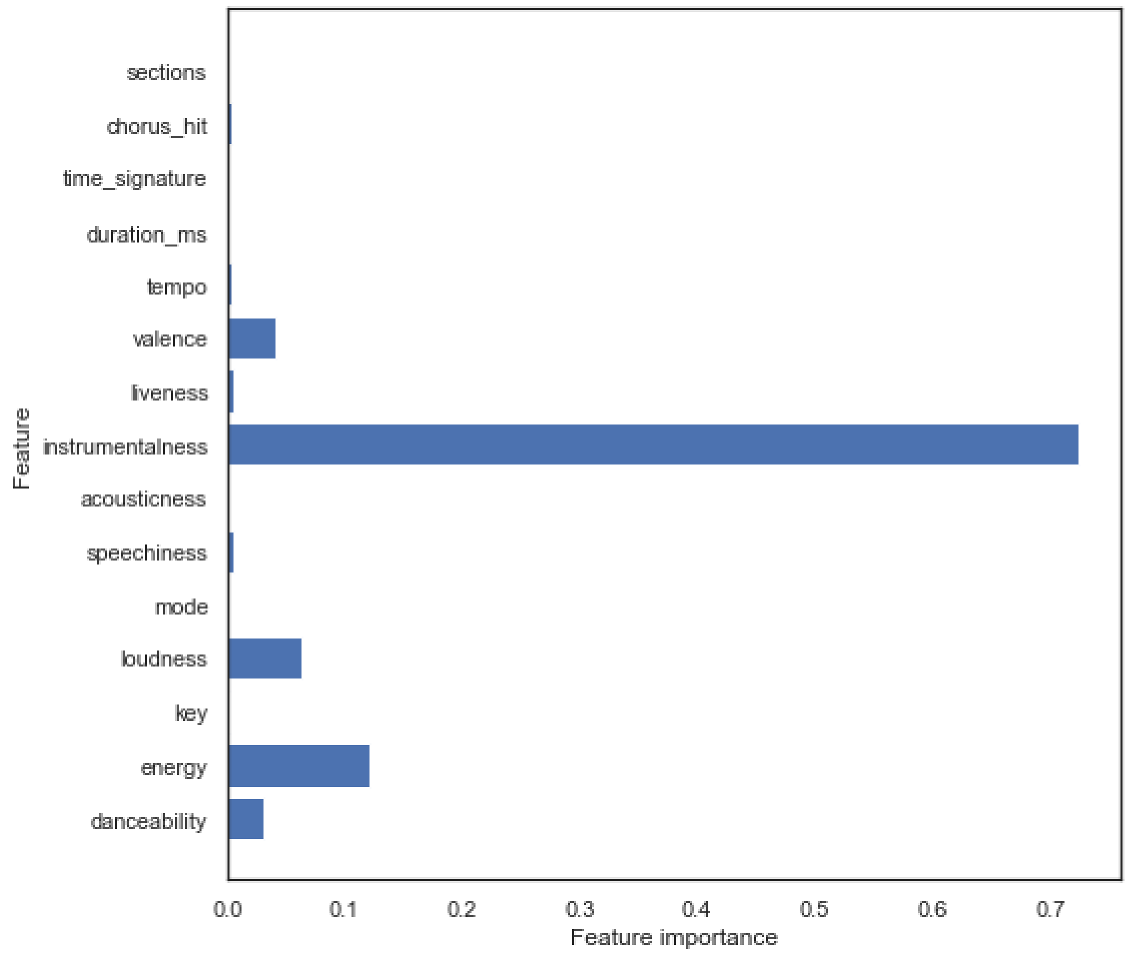
This model has 624 true positives, 140 false positives, 653 true negatives, and 183 false negatives. For this data/business problem, it is worse to have a false positive than a false negative and there are less FPs than FNs, which is a good thing.

Next, I examine how important the different features of the data are for this baseline model.

In [18]:
```
baseline_tree.feature_importances_
```

Out[18]:
```
array([0.03137781, 0.12121346, 0.00222707, 0.06339033, 0.        ,
       0.00553143, 0.        , 0.72431934, 0.00508173, 0.04098987,
       0.00312003, 0.        , 0.        , 0.00274894, 0.        ])
```

In [19]:
```
# Plotting feature importances
def plot_feature_importances(model):
    n_features = X_train.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), model.feature_importances_, align='cent
    plt.yticks(np.arange(n_features), X_train.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(baseline_tree)

```




The most important features to this baseline model are instrumentalness, energy, loudness, valence, and danceability.

Next, to try and improve this baseline model, I perform a GridSearchCV to search for the optimal combination of parameters that can make our decision tree perform the best and see if it is better than the baseline model's performance.

In [20]:
```
dt_param_grid ={
    "max_depth": [None,5,10],
    "min_samples_leaf": [2, 4, 6, 8],
    "max_features": [5, 7, 10]

}

```

In [21]:
```
# Baseline DT grid search
dt_grid_search = GridSearchCV(baseline_tree , dt_param_grid, cv=3, retu

dt_grid_search.fit(X_train, y_train)
```

Out[21]:
```
GridSearchCV(cv=3,
             estimator=DecisionTreeClassifier(criterion='entropy', max_de
pth=5),
             param_grid={'max_depth': [None, 5, 10], 'max_features': [5,
7, 10],
                         'min_samples_leaf': [2, 4, 6, 8]},
             return_train_score=True)
```

In [22]:
```
# Mean training score
dt_gs_training_score = np.mean(dt_grid_search.cv_results_["mean_train_s

# Mean test score
dt_gs_testing_score = dt_grid_search.score(X_test, y_test)

print(f"Mean Training Score: {dt_gs_training_score :.2%}")
print(f"Mean Test Score: {dt_gs_testing_score :.2%}")
print("Best Parameter Combination Found During Grid Search:")
dt_grid_search.best_params_
```

```
Mean Training Score: 87.81%
Mean Test Score: 80.25%
Best Parameter Combination Found During Grid Search:
```

Out[22]:
```
{'max_depth': 5, 'max_features': 10, 'min_samples_leaf': 6}
```

Based on this grid search, the optimal value for minimum leaf sample size is 2, and the optimal maximum tree depth is 5, and the optimal maximum number of features is 7.

In [23]:
```
# Train a classifier with optimal values identified above
dt = DecisionTreeClassifier(
                            max_depth=5,
                            min_samples_leaf=6,
                            max_features = 7,
                            random_state=42)
dt.fit(X_train, y_train)
y_pred = dt.predict(X_test)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

Out[23]:
```
0.7742975634071984
```

In [24]:
```
y_hat_train2 = dt.predict(X_train)
y_hat_test2 = dt.predict(X_test)

```

In [25]:
```
print("Training precision score for decision tree model with tuned hype
print("Testing precision score for decision tree model with tuned hyper

print("Training accuracy score for decision tree model with tuned hyper
print("Testing accuracy score for decision tree model with tuned hyperp
```

```
Training precision score for decision tree model with tuned hyperparamete
rs: 78.22%
Testing precision score for decision tree model with tuned hyperparameter
s: 77.62%
Training accuracy score for decision tree model with tuned hyperparameter
s: 82.7%
Testing accuracy score for decision tree model with tuned hyperparameter
s:77.44%
```

Changing these parameters did not improve the baseline model.

## Building a random forests model:

In [26]:
```
#Fit a random forests model
forest = RandomForestClassifier(max_features='sqrt',
                                max_samples = 0.5,
                                random_state=42)
forest.fit(X_train, y_train)
```

Out[26]:
```
RandomForestClassifier(max_features='sqrt', max_samples=0.5, random_state
=42)
```

In [27]:
```
y_hat_train3 = forest.predict(X_train)
y_hat_test3 = forest.predict(X_test)

```

In [28]:
```
print("Training precision score for random forests model: {:.4}%".forma
print("Testing precision score for random forests model: {:.4}%".format

print("Training accuracy score for random forests model: {:.4}%".format
print("Testing accuracy score for random forests model: {:.4}%".format(

```

```
Training precision score for random forests model: 95.51%
Testing precision score for random forests model: 85.84%
Training accuracy score for random forests model: 96.71%
Testing accuracy score for random forests model: 76.69%
```

***Interpretation:***

This random forests model had both a higher precision score and a higher accuracy score than our

Now, we create a parameter grid specific to our random forest classifier to try and improve its performance:

In [29]:
```

rf_param_grid = {
    "max_depth": [None, 5],
    "max_features": [5, 7, 10],
    'min_samples_leaf': [4, 6, 8, 10]
}

```

In [30]:
```
# Now perform the GridSearchCV
rf_grid_search = GridSearchCV(forest, rf_param_grid, cv=3)
rf_grid_search.fit(X_train, y_train)

print(f"Testing Accuracy: {rf_grid_search.best_score_ :.2%}")
print("")
print(f"Optimal Parameters: {rf_grid_search.best_params_}")
```

```
Testing Accuracy: 84.41%

Optimal Parameters: {'max_depth': None, 'max_features': 10, 'min_samples_
leaf': 6}
```

In [31]:
```
# Train a new random forests model with optimal values identified above
rf = RandomForestClassifier(max_depth=None,
                            max_features = 10,
                            min_samples_leaf=6,
                            random_state=42)
rf.fit(X_train, y_train)
y_train_rf = rf.predict(X_train)
y_pred_rf = rf.predict(X_test)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

Out[31]: 0.8064719017549782

In [32]:
```
ining precision score for random forests model with tuned hyperparameters: {
ting precision score for random forests model with tuned hyperparameters: {:

ining accuracy score for random forests model with tuned hyperparameters: {:
ting accuracy score for random forests model with tuned hyperparameters:{:.4
```

```
Training precision score for random forests model with tuned hyperparamet
ers: 90.48%
Testing precision score for random forests model with tuned hyperparamete
rs: 83.52%
Training accuracy score for random forests model with tuned hyperparamete
rs: 93.29%
Testing accuracy score for random forests model with tuned hyperparameter
s:80.69%
```

These metrics are better, however there is still some overfitting. If you change the maximum depth to 5, the AUC score and the precision goes down a little bit, but there is less overfitting.

In [35]:
```
rf2 = RandomForestClassifier(max_depth=5,
                             max_features = 10,
                             min_samples_leaf=6,
                             random_state=42)
rf2.fit(X_train, y_train)
y_train_rf2 = rf2.predict(X_train)
y_pred_rf2 = rf2.predict(X_test)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test,
roc_auc = auc(false_positive_rate, true_positive_rate)
roc_auc
```

Out[35]:
```
0.824217791674675
```

In [36]:
```
print("Training precision score for random forests model with tuned hyp
print("Testing precision score for random forests model with tuned hype

print("Training accuracy score for random forests model with tuned hype
print("Testing accuracy score for random forests model with tuned hyper
```

```
Training precision score for random forests model with tuned hyperparamet
ers: 79.35%
Testing precision score for random forests model with tuned hyperparamete
rs: 79.0%
Training accuracy score for random forests model with tuned hyperparamete
rs: 84.45%
Testing accuracy score for random forests model with tuned hyperparameter
s:82.38%
```

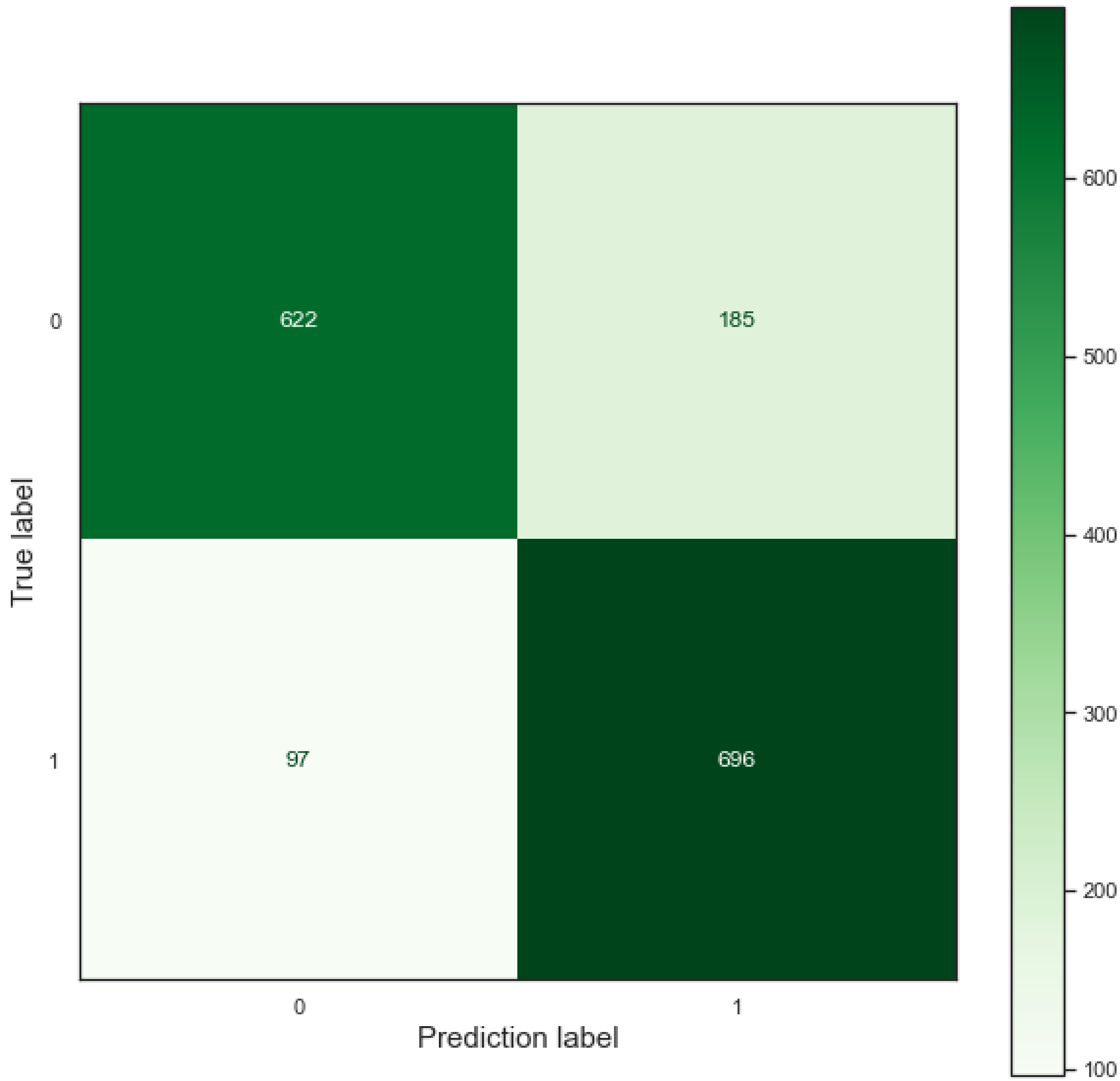
*This will be our **final model***, with:

- an AUC score of about 0.82, which is slightly better than our baseline AUC score of about 0.80
- a testing precision score of about 79.0%, which is slighly better than our baseline testing precision of about 78.1%
- a testing accuracy score of about 82.4%, which is slightly better than our baseline accuracy score of 79.8%

In [38]:
```
cnf_matrix2 = confusion_matrix(y_test, y_pred_rf2)
print('Confusion Matrix:\n', cnf_matrix2)
```

```
Confusion Matrix:
 [[622 185]
 [ 97 696]]
```

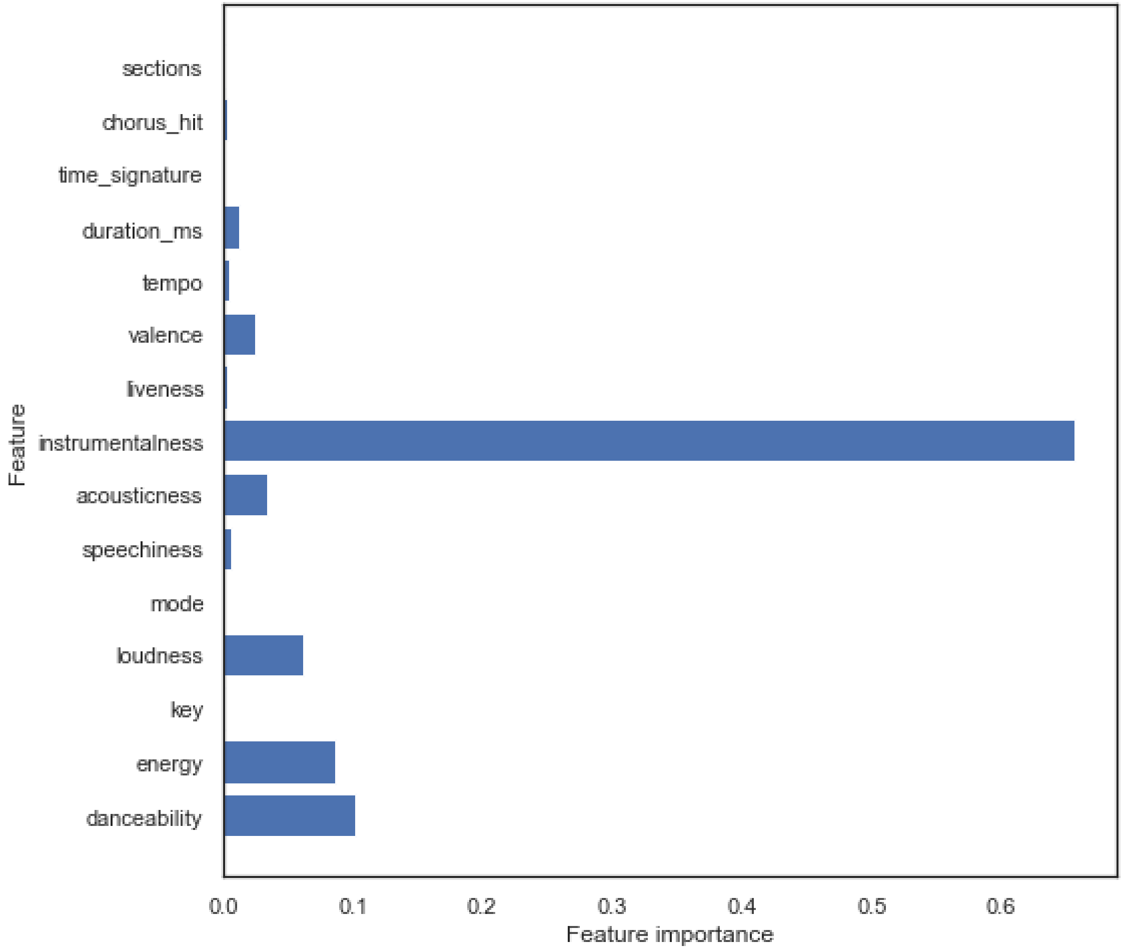
In [43]:
```
fig, ax = plt.subplots(figsize=(10,10))
cm_2 = ConfusionMatrixDisplay(confusion_matrix = cnf_matrix2, display_l
cm_2.plot(cmap=plt.cm.Greens, ax=ax)
plt.xlabel('Prediction label',fontsize=15)
plt.ylabel('True label',fontsize=15);

```




***Confusion Matrix interpretation:***

This model has 622 true positives, 97 false positives, 696 true negatives, and 185 false negatives. Once again there are less False Positives than False Negatives, which is what we want. Additionally, there are less of both FPs and FNs than there were in the baseline model.

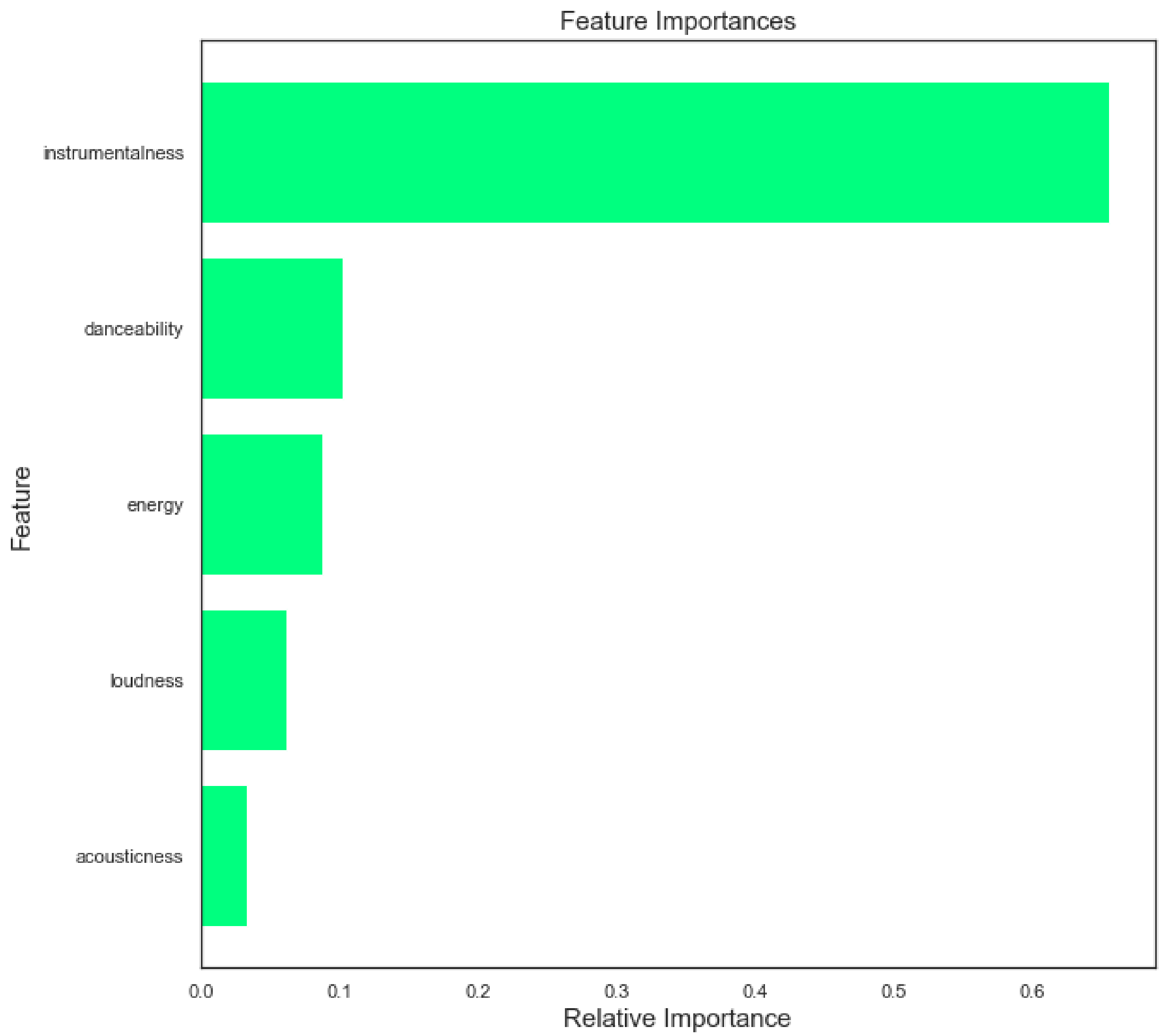
In [40]:
```
# Feature importances of final model:

plot_feature_importances(rf2)
```




The most important features for this model are instrumentalness, danceability, energy, loudness, and acousticness. These are mostly the same features that were most important to our baseline model, except acousticness is more important here.

In [41]:

```
features = X.columns
importances = rf2.feature_importances_
indices = np.argsort(importances)

num_features = 5

plt.figure(figsize=(10,10))
plt.title('Feature Importances', fontsize=15)

plt.barh(range(num_features), importances[indices[-num_features:]], col
plt.yticks(range(num_features), [features[i] for i in indices[-num_feat
plt.xlabel('Relative Importance', fontsize=15)
plt.ylabel('Feature', fontsize=15)
plt.show()
```




# Evaluation

Our final model is about 81.8% accurate and about 77.6% precise in correctly identifying songs as hits or not. The rate of false negatives to false positives (AUC) was about 0.82. This is an improvement to our baseline model which was a single decision tree before hyperparameter tuning that was about 80.3% accurate, about 76.8% precise in classifying our target and had an AUC of about 0.81

# Conclusion

**Recommendations:**

Hit songs should have the following features:

- Danceability
- Energy
- Loudness
- Acousticness

Songs should not be too high in instrumentalness, because it is highly correlated with a song *not* being a hit.