Using Support Machine Vectors for Classification

The objective of this notebook is to explore different support machine vector algorithms and use them to classify items within our Spotify dataset.

Note: If you have any suggestions about the code in the notebook to improve effeciency, or you have questions about any of the code in the notebook please feel free to leave a comment!

In [1]:

```
#Imports
import numpy as np, pandas as pd, matplotlib.pyplot as plt, seaborn as sns
```

Exploring the Data

In [2]:

```
df = pd.read_csv('songs_normalize.csv')
df.head(5)
```

Out[2]:

	artist	song	duration_ms	explicit	year	popularity	danceability	energy	key	loudness	mode	speechine
0	Britney Spears	Oops!...I Did It Again	211160	False	2000	77	0.751	0.834	1	-5.444	0	0.043
1	blink-182	All The Small Things	167066	False	1999	79	0.434	0.897	0	-4.918	1	0.048
2	Faith Hill	Breathe	250546	False	1999	66	0.529	0.496	7	-9.007	1	0.029
3	Bon Jovi	It's My Life	224493	False	2000	78	0.551	0.913	0	-4.063	0	0.046
4	*NSYNC	Bye Bye Bye	200560	False	2000	65	0.614	0.928	8	-4.806	0	0.051

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 18 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   artist            2000 non-null   object 
 1   song              2000 non-null   object 
 2   duration_ms       2000 non-null   int64  
 3   explicit          2000 non-null   bool   
 4   year              2000 non-null   int64  
 5   popularity        2000 non-null   int64  
 6   danceability      2000 non-null   float64
 7   energy            2000 non-null   float64
 8   key               2000 non-null   int64  
 9   loudness          2000 non-null   float64
 10  mode              2000 non-null   int64  
 11  speechiness       2000 non-null   float64
 12  acousticness      2000 non-null   float64
```

```
 13  instrumentalness  2000 non-null   float64
 14  liveness          2000 non-null   float64
 15  valence           2000 non-null   float64
 16  tempo             2000 non-null   float64
 17  genre             2000 non-null   object
dtypes: bool(1), float64(9), int64(5), object(3)
memory usage: 267.7+ KB
```

Since there are so many different artists/songs, these two columns will most likely be dropped for our SVM analysis. We will most likely create dummy variables for the columns 'year' and 'key'.

In [4]:

```
df.describe()
```

Out[4]:

	duration_ms	year	popularity	danceability	energy	key	loudness	mode	sp
count	2000.000000	2000.00000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	20
mean	228748.124500	2009.49400	59.872500	0.667437	0.720366	5.378000	-5.512435	0.553500	
std	39136.569008	5.85996	21.335577	0.140416	0.152745	3.615059	1.933482	0.497254	
min	113000.000000	1998.00000	0.000000	0.129000	0.054900	0.000000	-20.514000	0.000000	
25%	203580.000000	2004.00000	56.000000	0.581000	0.622000	2.000000	-6.490250	0.000000	
50%	223279.500000	2010.00000	65.500000	0.676000	0.736000	6.000000	-5.285000	1.000000	
75%	248133.000000	2015.00000	73.000000	0.764000	0.839000	8.000000	-4.167750	1.000000	
max	484146.000000	2020.00000	89.000000	0.975000	0.999000	11.000000	-0.276000	1.000000	

Luckily for us, this dataset is very clean! Later on we will probably have to one-hot encode some of the features, but for the most part our data is ready to go.

Example Problem:

A friend of ours owns a small bar in town that has a decent sized dance floor for patrons. They would like us to provide a method of determining whether or not a song would be suitable for their clientelle (is the song adequetly "danceable"). We decide to use our Spotify dataset to build a model that will predict if a song would be appropriate for our friend's bar. For this job we will consider any song with a danceablity rating greater than 0.7 as "Suitable".

Points of Interest

In [5]:

```
#Most popular song
df[['song','artist']][df['popularity'] == df['popularity'].max()]
```

Out[5]:

	song	artist
1322	Sweater Weather	The Neighbourhood

In [6]:

```
#Number of songs with popularity rating of 0
df['song'][df['popularity'] == df['popularity'].min()].nunique()
```

Out[6]:

```
126
```

In [7]:
```
#Most 'danceable' song
df[['song','artist']][df['danceability'] == df['danceability'].max()]
```

Out[7]:

	song	artist
714	Give It To Me	Timbaland

In [8]:
```
#Least 'danceable' song
df[['song','artist']][df['danceability'] == df['danceability'].min()]
```

Out[8]:

	song	artist
573	You Raise Me Up	Westlife

Feature Engineering/ Data Prep

In [9]:
```
#Create a column for our target class: Suitable vs. Non-suitable
df['Suitable'] = [1 if num >= 0.7 else 0 for num in df['danceability']]

#Bool to binary for 'explicit'
df['explicit'] = [1 if entry == True else 0 for entry in df['explicit']]
```

In [10]:
```
#Dummy Variables
year = pd.get_dummies(df['year'])
key = pd.get_dummies(df['key'],prefix= 'Key Value')
```

In [11]:
```
df.drop(['danceability','artist','song','key','year'],axis=1,inplace=True)

#Modified DF
mod_df = pd.concat([df,year,key],axis=1)
```

In [12]:
```
#Creating columns for each genre listed in the dataset. Some songs belong to mupltiple ge

def extract_genres(df_column):
    df_column = [item.casefold() for item in df_column] #casefold all strings
    df_column = [item.split(', ') for item in df_column] #convert multiple genre strings i
    flat_list = [x for xs in df_column for x in xs] #flatten list of lists
    return list(np.unique(flat_list)) #return unique values in the flattened list

def get_genre_dummies(df,df_genre_column):
    df_genre_column = [item.casefold() for item in df_genre_column] #casefold all strings
    labels = extract_genres(df_genre_column) #unique genres
    for i, item in enumerate(labels):
        df[labels[i]] = [1 if labels[i] in genre else 0 for genre in df_genre_column] #one
```

In [13]:
```
#Add dummy variables to indicate genre for each song
get_genre_dummies(mod_df,mod_df['genre'])
```

In [14]:
```
#Check that the dummy variables were added correctly
mod_df.columns
```

Out[14]:
```
Index([      'duration_ms',          'explicit',        'popularity',
                'energy',          'loudness',              'mode',
           'speechiness',      'acousticness',  'instrumentalness',
```

```
                 'liveness',               'valence',                  'tempo',
                    'genre',             'Suitable',                    1998,
                       1999,                    2000,                    2001,
                       2002,                    2003,                    2004,
                       2005,                    2006,                    2007,
                       2008,                    2009,                    2010,
                       2011,                    2012,                    2013,
                       2014,                    2015,                    2016,
                       2017,                    2018,                    2019,
                       2020,          'Key Value_0',           'Key Value_1',
              'Key Value_2',          'Key Value_3',           'Key Value_4',
              'Key Value_5',          'Key Value_6',           'Key Value_7',
              'Key Value_8',          'Key Value_9',          'Key Value_10',
             'Key Value_11',                'blues',             'classical',
                  'country',     'dance/electronic',        'easy listening',
            'folk/acoustic',              'hip hop',                  'jazz',
                    'latin',                'metal',                   'pop',
                      'r&b',                 'rock',                 'set()',
       'world/traditional'],
      dtype='object')
```

In [15]:

```python
#Inspect distribution of genres; some samples fall into more than one genre!
mod_df[['blues','classical','country','dance/electronic','easy listening','folk/acoustic',
        'hip hop','jazz','latin','metal','pop','r&b','rock','set()','world/traditional']].
```

Out[15]:

```
blues                   4
classical               1
country                21
dance/electronic      390
easy listening          7
folk/acoustic          20
hip hop               778
jazz                    2
latin                  64
metal                  66
pop                  1633
r&b                   452
rock                  234
set()                  22
world/traditional      10
dtype: int64
```

In [16]:

```python
#Drop the genre column now that we have our dummies
mod_df.drop('genre',axis=1,inplace=True)
```

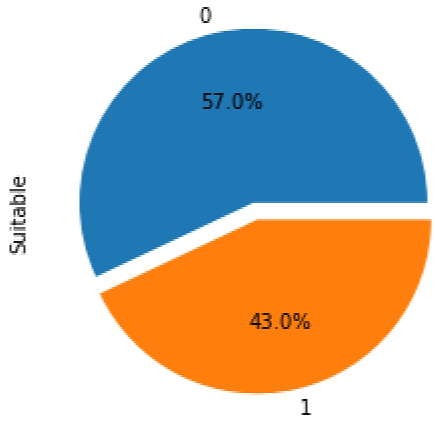
Visualizations

In [17]:

```python
#Examine proportion of Suitable vs. Non-suitable songs
mod_df['Suitable'].value_counts().plot.pie(autopct='%1.1f%%', explode=[0.05, 0.05])
```

Out[17]:

```
<AxesSubplot:ylabel='Suitable'>
```



Seems like our data isn't too biased towards one particular class which is a good thing for our analysis.

In [18]:

```
sns.pairplot(df.drop(['explicit','mode'],axis=1),hue='Suitable')
```

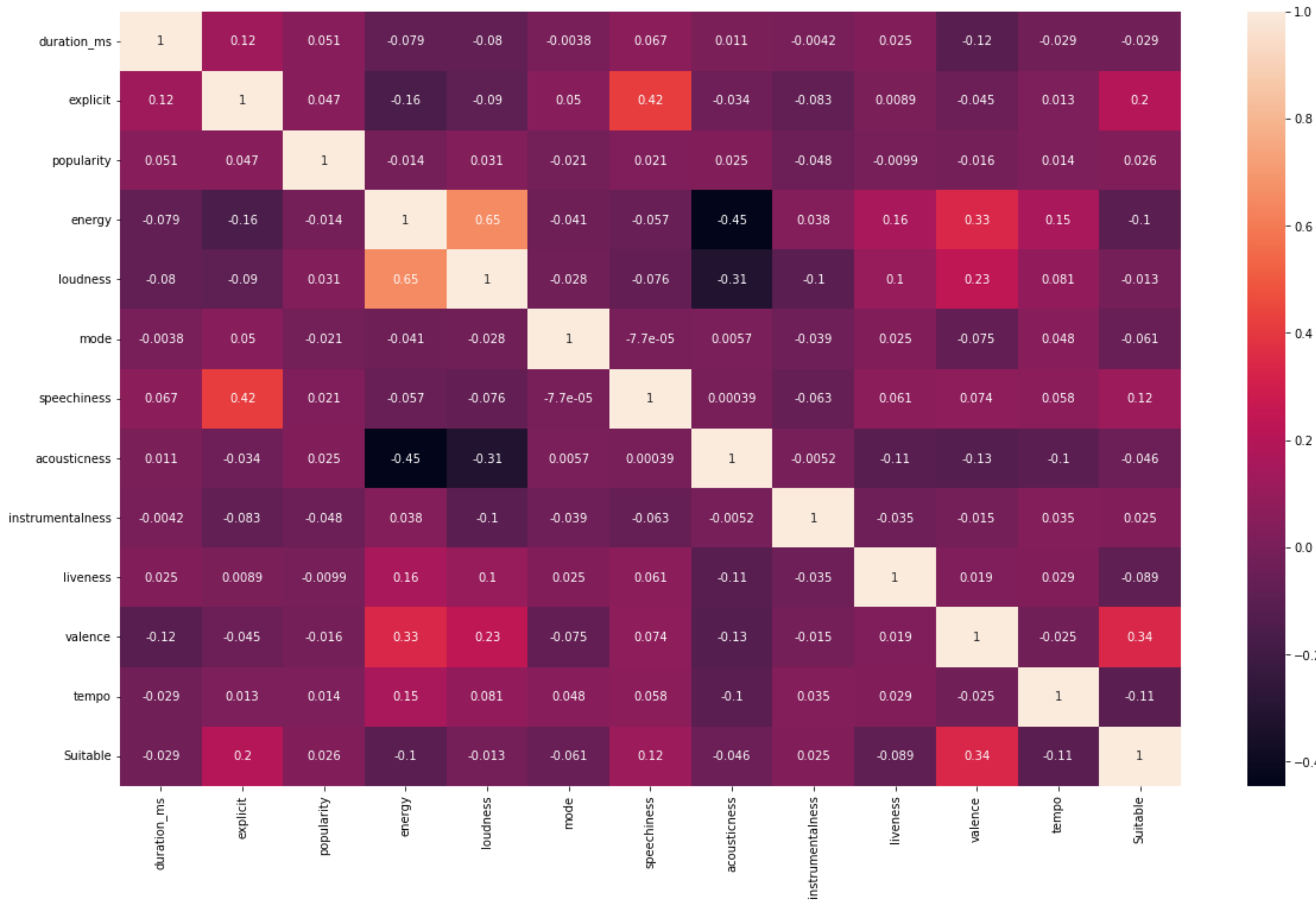
Out[18]: <seaborn.axisgrid.PairGrid at 0x1d082269940>

From the pairplots we can see that the target class is mixed and hard to separate in some variable comparisons, while in others there seems to be a trend where our SVM models could separate the classes.

Variable Interactions that seem to be separable:
(1) valence/duration_ms
(2) valence/ popularity
(3) valence/ loudness

In general it looks like the valence plots are the most separable, so valence might be one of the more important features. This will be explored more in the predictive modeling section.

In [19]:
```
sns.heatmap(data=df.corr(), annot=True)

fig=plt.gcf()
fig.set_size_inches(20,12)
plt.show()
```



The correlations based on our df (before adding in the dummies) seem to be okay. There are a couple noteworthy correlations that should be mentioned:

(1) loudness & energy = 0.65
(2) speechiness & explicit = 0.42
(3) acousticness & energy = -0.45

These correlations aren't too worrysome (maybe just loudness and energy). If we find it to be an issue in our predictive modeling section we can try to use Principal Component analysis to work around this.

Note: Valence is the variable most correlated with Suitable which seems to agree with our findings from the pairplots.

Predictive Modeling

In [20]:

```
#Imports
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, accuracy_s
from sklearn.svm import SVC
from sklearn.preprocessing import MinMaxScaler
```

In [21]:

```
#Prepping the data for analysis
X = np.array(mod_df.drop('Suitable',axis=1))
Y = np.array(mod_df['Suitable'])

#Split the data
XTRAIN, XTEST, YTRAIN, YTEST = train_test_split(X,Y)
```

In [22]:

```
#Scaling the X data
scaler = MinMaxScaler()
scaler.fit(XTRAIN)

XTRAIN = scaler.transform(XTRAIN)
XTEST = scaler.transform(XTEST)
```

Linear SVC

In [23]:

```
SVM=SVC(kernel="linear")
SVM.fit(XTRAIN,YTRAIN)
linear_preds = SVM.predict(XTEST)
print(classification_report(YTEST,linear_preds))
```

```
              precision    recall  f1-score   support

           0       0.75      0.77      0.76       283
           1       0.69      0.66      0.67       217

    accuracy                           0.72       500
   macro avg       0.72      0.71      0.72       500
weighted avg       0.72      0.72      0.72       500
```

In [24]:

```
print(confusion_matrix(YTEST,linear_preds))
```

```
[[218  65]
 [ 74 143]]
```

An accuracy of 73% is okay; we should try some of the other SVM models to see if we can get a better fit! We should also note that this linear SVC model had more false positives than false negatives. This means that if we used this model to make predictions about songs for our friend, they might end up with some non-suitable songs in their bar playlist!

Radial Basis Function SVM

In [25]:

```
RBF=SVC(kernel="rbf", gamma=100)
RBF.fit(XTRAIN,YTRAIN)
```

```
rbf_preds = RBF.predict(XTEST)
print(classification_report(YTEST,rbf_preds))
```

```
              precision    recall  f1-score   support

           0       0.57      1.00      0.73       283
           1       1.00      0.03      0.06       217

    accuracy                           0.58       500
   macro avg       0.79      0.52      0.40       500
weighted avg       0.76      0.58      0.44       500
```

The results from our first RBF model were worse than the linear. This might be because the parameters chosen were not optimal for our data so we will try a grid search to see if we can improve the performance of our RBF model.

In [26]:
```
from sklearn.model_selection import GridSearchCV
```

In [53]:
```
#Create our parameter grid
param_grid = {'C': [0.1,1,10,100,1000,10000],
              'gamma': [10,1,0.1,0.01,0.001,0.0001,0.00001],
              'shrinking': [True,False],
              'class_weight': [None,'balanced'],
              'kernel': ['rbf']}

grid = GridSearchCV(SVC(),param_grid,refit=True,verbose=0)
```

In [54]:
```
#Takes some time
grid.fit(XTRAIN,YTRAIN)
```

Out[54]:
```
GridSearchCV(estimator=SVC(),
             param_grid={'C': [0.1, 1, 10, 100, 1000, 10000],
                         'class_weight': [None, 'balanced'],
                         'gamma': [10, 1, 0.1, 0.01, 0.001, 0.0001, 1e-05],
                         'kernel': ['rbf'], 'shrinking': [True, False]})
```

In [29]:
```
#Results from the grid search
grid.best_params_
```

Out[29]:
```
{'C': 1000,
 'class_weight': None,
 'gamma': 0.001,
 'kernel': 'rbf',
 'shrinking': True}
```

In [30]:
```
gridrbf_preds = grid.predict(XTEST)
```

In [31]:
```
print(classification_report(YTEST,gridrbf_preds))
```

```
              precision    recall  f1-score   support

           0       0.74      0.78      0.76       283
           1       0.69      0.65      0.67       217

    accuracy                           0.72       500
   macro avg       0.72      0.71      0.71       500
weighted avg       0.72      0.72      0.72       500
```

In [32]:
```
print(confusion_matrix(YTEST,gridrbf_preds))
```

```
[[221  62]
 [ 77 140]]
```

Although the accuracy for our RBF model is similar to the Linear SVC model, we can see that the balance between false negatives and false positives is a little better in the RBF model which might be a reason to use it over the linear. Let's try a few more models!

Polynomial SVC

In [33]:
```
#These parameters were obtained from the grid search below
POLY=SVC(kernel="poly",C=1,degree=3,gamma=0.1,coef0=1,class_weight='balanced')
POLY.fit(XTRAIN,YTRAIN)
poly_preds = POLY.predict(XTEST)
print(classification_report(YTEST,poly_preds))
```

```
              precision    recall  f1-score   support

           0       0.77      0.72      0.75       283
           1       0.67      0.71      0.69       217

    accuracy                           0.72       500
   macro avg       0.72      0.72      0.72       500
weighted avg       0.72      0.72      0.72       500
```

In [34]:
```
print(confusion_matrix(YTEST,poly_preds))
```

```
[[205  78]
 [ 62 155]]
```

In [35]:
```
#THIS CODE TAKES A LONG TIME TO RUN ~1 hour
# param_grid2 = {'C': [0.1,1,10,100,1000,10000],
#                'degree': [2,3,4,5,6],
#                'gamma': [1,0.1,0.01,0.001,0.0001],
#                'coef0':[0.1,0,1,2],
#                'shrinking': [True,False],
#                'class_weight': [None,'balanced'],
#                'kernel': ['poly']}

# grid2 = GridSearchCV(SVC(),param_grid2,refit=True,verbose=2)

#grid2.fit(XTRAIN,YTRAIN)

#Results from the grid search
#grid2.best_params_
```

After the grid search we were able to obtain an accuracy and confusion matrix similar to our RBF model. This may lead us to believe that the best we can do with SVM methods is around 72%. Let's try one more model!

Sigmoid SVC

In [36]:
```
#These parameters were obtained from the grid search below
SIG=SVC(C=10000,kernel="sigmoid",gamma=0.0001,coef0=1,class_weight=None)
SIG.fit(XTRAIN,YTRAIN)
sig_preds = SIG.predict(XTEST)
print(classification_report(YTEST,sig_preds))
```

```
              precision    recall  f1-score   support

           0       0.75      0.77      0.76       283
           1       0.69      0.66      0.67       217

    accuracy                           0.72       500
   macro avg       0.72      0.72      0.72       500
weighted avg       0.72      0.72      0.72       500
```

In [37]:

```
print(confusion_matrix(YTEST,sig_preds))
```

```
[[219  64]
 [ 74 143]]
```

After our grid search for the sigmoid SVC, we were able to tune the model to achieve 73% accuracy. One downside to this model is that is has a higher rate of false positives vs. false negatives like the linear SVC we built earlier. For this reason we will probably not choose to use the sigmoid SVC.

In [38]:

```
#THIS CODE TAKES ~ 9 MINUTES
# param_grid3 = {'C': [0.1,1,10,100,1000,10000],
#                'gamma': [10,1,0.1,0.01,0.001,0.0001],
#                'coef0':[0,1,2,3],
#                'shrinking': [True,False],
#                'class_weight': [None,'balanced'],
#                'kernel': ['sigmoid']}

# grid3 = GridSearchCV(SVC(),param_grid3,refit=True,verbose=2)

# grid3.fit(XTRAIN,YTRAIN)
```

In [39]:

```
#Results from the grid search
#grid3.best_params_
```

Final Model Selection and Testing

Based on the 4 different SVC models we tried, the two best ones were the Radial Basis Function (RBF) and Polynomial SVC (POLY). We will now compare the average performance of these two models based on different train/test splits in order to choose our final model.

In [40]:

```
#Function for generalizing performance across multiple train/test splits
#Will take some time to run depending on the number of splits

def Avg_Model_Accuracy(X,Y,model,model_name,nsplits,test_size=0.3,kde=False):
    model_acc =[]
    for split in range(nsplits):
        XTRAIN, XTEST, YTRAIN, YTEST=train_test_split(X,Y,test_size=test_size) #Split the

        scaler = MinMaxScaler() #Scale the data for SVC
        scaler.fit(XTRAIN)
        XTRAIN = scaler.transform(XTRAIN)
        XTEST = scaler.transform(XTEST)

        model.fit(XTRAIN,YTRAIN) #Fit the model
        YPRED = model.predict(XTEST)
        model_acc.append(accuracy_score(YTEST,YPRED))

    model_mean = round(np.mean(model_acc),3)
    model_2sd=round(2*np.std(model_acc),3)
```

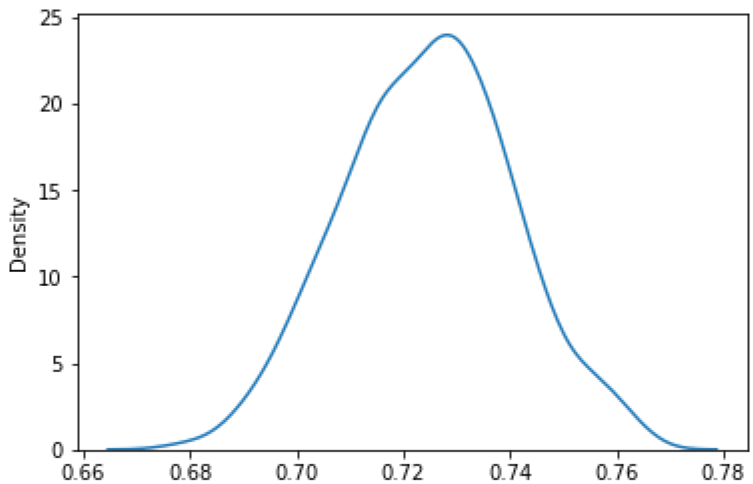
```
    print(f'{model_name} Mean Accuracy: {model_mean} +/- {model_2sd}')

    if kde == True:
        sns.kdeplot(model_acc) #Optional plot
```

RBF Model

In [41]:
```
RBF_final=SVC(C=10000,kernel="rbf",gamma=0.001,class_weight='balanced')
```

In [42]:
```
Avg_Model_Accuracy(X,Y,RBF_final,"RBF",nsplits=500,kde=True)
```

```
RBF Mean Accuracy: 0.725 +/- 0.032
```

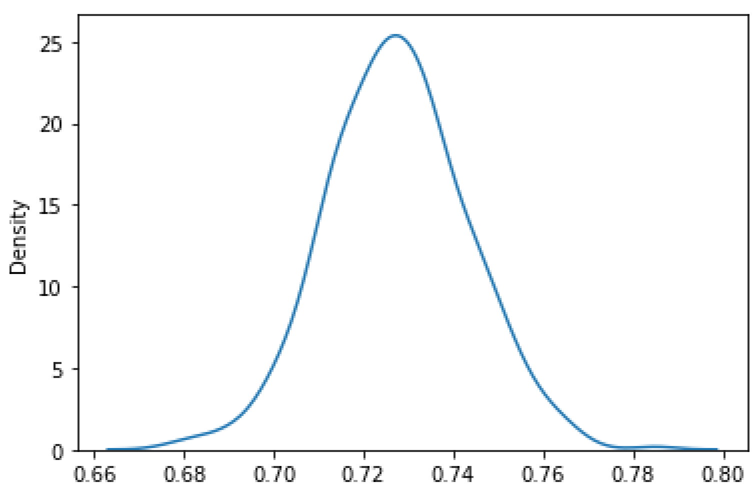


POLY Model

In [43]:
```
POLY_final =SVC(kernel="poly",C=1,degree=3,gamma=0.1,coef0=1,class_weight='balanced')
```

In [44]:
```
Avg_Model_Accuracy(X,Y,POLY_final,"POLY",nsplits=500,kde=True)
```

```
POLY Mean Accuracy: 0.727 +/- 0.031
```



Conclusions

After gauging the generalized performance of both models, they both seem to be performing around the same level. Since the POLY model performed slightly better we will choose this to be our final model. Let's go ahead and explore the model a bit more before we get back to our bar-owning friend and let them know how we can help them choose suitable songs for their patrons!

Which features were most important for our model?

In [45]:

```
#Indivual classifications for each feature to compare affect on accuracy.

#For Xdata we pass in a feature dataframe

def feature_accuracy(Xdata,Y,model,test_size=0.3,top_features=5):
    feat_accs = {}

    for i in range(len(Xdata.columns)):
        X = np.array(Xdata[Xdata.columns[i]]).reshape(-1,1)
        XTRAIN, XTEST, YTRAIN, YTEST=train_test_split(X,Y,test_size=test_size,random_state

        scaler = MinMaxScaler() #Scale the data for SVC
        scaler.fit(XTRAIN)
        XTRAIN = scaler.transform(XTRAIN)
        XTEST = scaler.transform(XTEST)

        model.fit(XTRAIN,YTRAIN) #Fit the model
        YPRED = model.predict(XTEST)

        accuracy = np.round(accuracy_score(YTEST,YPRED),3)
        feature_name=Xdata.columns[i]

        feat_accs[str(feature_name)] = accuracy
    #Returns a dictionary of features and their accuracies

    acc_df = pd.DataFrame(columns=['Feature','Accuracy']) #Create empty dataframe for top
    for j in range(top_features):
        max_value = max(feat_accs.values()) #Highest accuracy in dictionary
        max_key= max(feat_accs, key=feat_accs.get) #Feature name with highest accuracy

        acc_df.loc[len(acc_df)] = [max_key,max_value] #Insert new row into our dataframe

        feat_accs.pop(max_key) #Remove the feature we just added so it does not get select

    return acc_df #Dataframe of top features
```

In [46]:

```
#Display the top 10 features for our model
#POLY
feature_accuracy(mod_df.drop('Suitable',axis=1),Y,POLY_final,top_features=10)
```

Out[46]:

	Feature	Accuracy
0	valence	0.643
1	explicit	0.632
2	hip hop	0.625
3	r&b	0.600
4	speechiness	0.598
5	2018	0.595
6	Key Value_1	0.595
7	2004	0.580

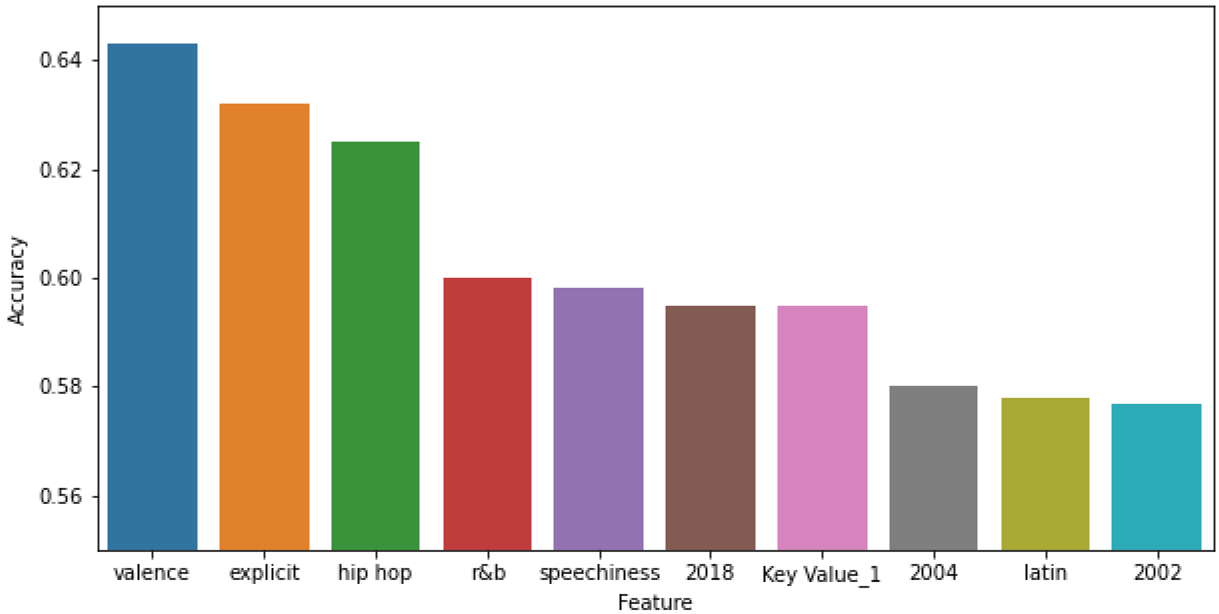
	Feature	Accuracy
8	latin	0.578
9	2002	0.577

In [47]:

```
#Visualizing individual feature performance
top_feats = feature_accuracy(mod_df.drop('Suitable',axis=1),Y,POLY_final,top_features=10)

plt.figure(figsize = (10,5))
plt.ylim(0.55,0.65)
sns.barplot(x='Feature',y='Accuracy',data=top_feats)
```

Out[47]:

```
<AxesSubplot:xlabel='Feature', ylabel='Accuracy'>
```



As we anticipated from our initial exploratory analysis, valence was the top contributor to accurate predictions. It is interesting that the second best feature was if the song was considered 'explicit' or not! We can also see that some of our dummy variables are outperforming some of the base features. Noteable genres were hip hop, r&b, and latin which makes sense in the context of a "danceable" song. Interestly we also had some years pop up as top features (2018,2004,2002).

How much did our engineered features help the analysis?

Before we offer our final conclusion to our bar-owning friend, let's take a look at how our model would perform on the base dataset without some of the engineered features. This will give us an idea of how useful it was to breakup the years, key, and genre columns.

In [48]:

```
#Prep base dataset
base_df = pd.read_csv('songs_normalize.csv')

#Create a column for our target class: Suitable vs. Non-suitable
base_df['Suitable'] = [1 if num >= 0.7 else 0 for num in base_df['danceability']]

#Bool to binary for 'explicit'
base_df['explicit'] = [1 if entry == True else 0 for entry in base_df['explicit']]

base_df.drop(['danceability','artist','song','key','year','genre'],axis=1,inplace=True)
```

In [49]:

```
base_df.head(3)
```

Out[49]:

	duration_ms	explicit	popularity	energy	loudness	mode	speechiness	acousticness	instrumentalness	liveness
0	211160	0	77	0.834	-5.444	0	0.0437	0.3000	0.000018	0.355
1	167066	0	79	0.897	-4.918	1	0.0488	0.0103	0.000000	0.612
2	250546	0	66	0.496	-9.007	1	0.0290	0.1730	0.000000	0.251

In [50]:

```
x = np.array(base_df.drop('Suitable',axis=1))
y = np.array(base_df['Suitable'])
```

In [51]:

```
# Just a reminder of our final model
# POLY_final =SVC(kernel="poly",C=1,degree=3,gamma=0.1,coef0=1,class_weight='balanced')
```

In [52]:

```
Avg_Model_Accuracy(x,y,POLY_final,"base_df",nsplits=500)
Avg_Model_Accuracy(X,Y,POLY_final,"feature_engineered_df",nsplits=500)
```

```
base_df Mean Accuracy: 0.703 +/- 0.032
feature_engineered_df Mean Accuracy: 0.728 +/- 0.03
```

Based on the results of our Avg_Model_Accuracy function, we can see that including the engineered features improved the accuracy by about 2%. This isn't the greatest of improvements but not much work goes into extracting those features if we continue to get song data in the form of this dataset, so we should suggest using the engineered features when making predicitons about new data points.

Final Words

Now that we've gone through our dataset and tried some different models, we can recommend the use of our Polynomial Support Vector Classifier for their business. The following must be performed on any new data:

(1) Extract features/create dummy variables
(2) Scale the data
(3) Make predictions with the model

With this model, we can expect around 72% of the songs to be considered 'Suitable' for our bar-owning friend's clientelle. Since our model's accuracy was still relatively low, we would also suggest that the bar-owner collect data from their patrons about new songs that were chosen as 'Suitable', and see if it was preferred or disliked. Since taste in music is subjective, it will be up to the owner to make decisions about what genres to include in their playlists and pay close attention to the response from their guests. Hopefully this model helps bring great music to their bar!

If you enjoyed the notebook or have any questions regarding the methods of the analysis, please feel free to leave a comment! Thank you!!

In [ ]: