Movies Performance Prediction

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Introduction and Motivation

The movie industry is a complex and dynamic field, with many factors influencing the success of a movie. Independent movie producers often have limited resources at their disposal, and face significant challenges in producing and marketing their movies.
The motivation of this project is to provide them with the data tools they need to effectively optimize their budgets and compete with larger production houses. Using data analytics, financiers and producers can

In this project, we used different classification and regression techniques to predict various movie characteristic such as ratings, and to identify patterns and trends in the data. In this report, we will describe the data used in the analysis, the methods and models employed, and the results obtained. We will also discuss the implications of these findings and suggest potential areas for future research.

Data Preprocessing

The data for this analysis was obtained from the Rotten Tomatoes API. Before using the data for modelling, several preprocessing and cleaning steps were performed. The first step was to drop any rows with null values, to ensure that the dataset was complete and consistent. This required careful examination of the data to identify and remove any incomplete records.

Next, the names of the columns were changed to lower-case to improve consistency and readability. Punctuation and digits were also removed from the data. This required the use of regular expressions and string manipulation techniques to clean the text.
The data was then tokenized, which involved splitting the text into individual words or phrases. Stopwords, which are common words that do not add significant meaning to the text, were also removed. Stemming was performed to reduce words to their base form, which can improve the performance of some algorithms. After preprocessing and cleaning, the data was detokenized and a document-term matrix was formed. This matrix provides a numerical representation of the data, which can be used as input to machine learning algorithms.

Overall, the data fetching and cleaning process required careful attention to detail and the use of various techniques and tools. The resulting dataset was in a format suitable for analysis, and ready to be used in the next stage of the project.

Data Modeling

The project has two different kinds of analysis. First, we analyze critics' reviews to predict a movies performance using text analysis. The kind of reviews a movie received based on lot of parameters such as runtime, genre etc. was used to train a decision tree model using algorithms such Decision Tree Regression with cross validation, RandomForest and XGBoost.
These algorithms are powerful tools for predicting continuous values such as audience ratings.
This involved dividing the dataset into multiple subsets and training the models on some of the subsets while evaluating them on the remaining subsets. This allowed us to estimate the models' performance on unseen data, and to identify any overfitting or underfitting.

The second analysis is about classifying a movie based on parameters such as actors tomatometer_status runtime content_rating genres production_company directors. Here we transformed actor attributed to vectorised form so that we can analyse the effect of each actor on a films performance.
Here we also used classification models to classify the movie data into different categories. These models included linear discriminant analysis (LDA), CART (classification and regression trees), and random forest classification. These algorithms were used to classify the data into "rotten", "certified fresh", and "fresh" categories based on audience ratings and other characteristics.

The use of regression and classification models, together with cross-validation, allowed us to accurately predict audience ratings, revenue, and other movie characteristics from the data. This provided valuable insights into the factors that influence audience response and the success of a movie by just having parameters of the movie beforehand. This model can help the producers to decide the best combination of genre, actors, directors and runtime to accurate predict if the movie will perform well. This will ensure maximum returns of the investment made in producing a movie. Overall, the use of these models demonstrated their effectiveness and versatility as tools for predictive modelling.

Results

The models shown above give extremely satisfactory results as summarized below
The regression models used in this analysis produced the following results:

- Decision Tree Regression: ccp_alpha=0.003393 CV R2 = 0.73233, OSR2 = 0.73475
- Random Forest Regression: CV R2=0.74529, OSR2 = 0.75124
- Boosting (using XGBoost): CV R2: 0.7427 OSR2: 0.75172
- The confidence interval contains Zero, we can say with 95% confidence that our model will generate very similar result on future datasets (please refer to Jupyter Notebook attached in the end).

The classification models used in this analysis produced the following results:

- LDA: Model Precision (OSR2) = 0.45067
- CART Model: Model Precision (R2) = 0.4171, Model Precision (OSR2) = 0.418
- Random Forest Classification Model: Model Precision (R2) = 0.58671, Model Precision (OSR2) = 0.56733

The results can be seen in detail in the Jupyter Notebook attached at the end of this report.

Conclusion and Future Work

The use of regression and classification models allowed us to gain valuable insights into the factors that influence audience response and the success of a movie. These insights can be used by movie studios, producers, and other stakeholders to make informed decisions about movie production and marketing, which is still often driven by heuristics.

There are several potential avenues for future study based on the results of this analysis. One possibility would be to expand the dataset by including additional variables, such as the budget and marketing spend for each movie. This could provide additional insights into the factors that influence audience response and the success of a movie.

The code and the results can be viewed in the notebook attached in the appendix.

In [73]:
```
import os
import pandas as pd
import numpy as np
from string import punctuation
import nltk
import seaborn as sns
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.tokenize.treebank import TreebankWordDetokenizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import precision_score, recall_score, multilabel_confusion_matrix, ConfusionMatrixDisplay, confusi
```

In [2]:
```
f_name = 'rotten_tomatoes_movies.csv'
raw_data = pd.read_csv(f_name)
raw_data.head(2)
```

Out[2]:

	rotten_tomatoes_link	movie_title	movie_info	critics_consensus	content_rating	genres	directors	authors	actors	original_release_date	...	producti
0	m/0814255	Percy Jackson & the Olympians: The Lightning T...	Always trouble-prone, the life of teenager Per...	Though it may seem like just another Harry Pot...	PG	Action & Adventure, Comedy, Drama, Science Fic...	Chris Columbus	Craig Titley, Chris Columbus, Rick Riordan	Logan Lerman, Brandon T. Jackson, Alexandra Da...	2010-02-12	...	20t
1	m/0878835	Please Give	Kate (Catherine Keener) and her husband Alex (...	Nicole Holofcener's newest might seem slight i...	R	Comedy	Nicole Holofcener	Nicole Holofcener	Catherine Keener, Amanda Peet, Oliver Platt, R...	2010-04-30	...	

2 rows × 22 columns

Column Description

movie_title: title of the movie as displayed on the Rotten Tomatoes website.
critics_consensus: comment from Rotten Tomatoes
content_rating: category based on the movie suitability for audience
genres: movie genres separated by commes, if multiple
runtime: movie runtume (in minutes)
tomatometer_status: tomatometer value of "Rotten" (less than 60% positive reviews), "Fresh" (at least 60% of positive reviews), and "Certified Fresh" (at least 75% of positive reviews, at least 80 reviews of which at least 5 from top critics)
tomatometer_rating: percentage of positive critic ratings
audience_status: audience value of "Spilled" (less than 60% of users gave a rating of at least 3.5) or "Upright" (at least 60% of users gave a rating of at least 3.5)
audience_rating: percentage of positive user ratings

In [3]:
```
#selecting needed columns
columns = ['movie_title', 'audience_rating', 'runtime', 'content_rating', 'audience_status',
           'audience_status', 'genres', 'critics_consensus']
movies_info =raw_data[columns]
movies_info.head(2)
```

Out[3]:

	movie_title	audience_rating	runtime	content_rating	audience_status	audience_status	genres	critics_consensus
0	Percy Jackson & the Olympians: The Lightning T...	53.0	119.0	PG	Spilled	Spilled	Action & Adventure, Comedy, Drama, Science Fic...	Though it may seem like just another Harry Pot...
1	Please Give	64.0	90.0	R	Upright	Upright	Comedy	Nicole Holofcener's newest might seem slight i...

In [4]:
```
#depending on what analysis we will like to do, we can drop rows with NULL values
movies_info.info()
movies_info.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17712 entries, 0 to 17711
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   movie_title       17712 non-null  object 
 1   audience_rating   17416 non-null  float64
 2   runtime           17398 non-null  float64
 3   content_rating    17712 non-null  object 
 4   audience_status   17264 non-null  object 
 5   audience_status   17264 non-null  object 
 6   genres            17693 non-null  object 
 7   critics_consensus  9134 non-null   object 
dtypes: float64(2), object(6)
memory usage: 1.1+ MB
```

Out[4]:

	audience_rating	runtime
count	17416.000000	17398.000000
mean	60.554260	102.214048
std	20.543369	18.702511
min	0.000000	5.000000
25%	45.000000	90.000000
50%	63.000000	99.000000
75%	78.000000	111.000000
max	100.000000	266.000000

colums_for_predicting_genre = ['movie_title', 'runtime', 'genres', 'actors', 'directors', 'production_company'] genre_info = raw_data[colums_for_predicting_genre]

genre_info.head(2)

Workinging on movie info

In [5]:
```
#Dropping nan values first since we have alot of missing value in the critice_consensus column
movie_nona = movies_info.dropna()
movie_nona.reset_index(drop=True).head(2)
```

Out[5]:

	movie_title	audience_rating	runtime	content_rating	audience_status	audience_status	genres	critics_consensus
0	Percy Jackson & the Olympians: The Lightning T...	53.0	119.0	PG	Spilled	Spilled	Action & Adventure, Comedy, Drama, Science Fic...	Though it may seem like just another Harry Pot...
1	Please Give	64.0	90.0	R	Upright	Upright	Comedy	Nicole Holofcener's newest might seem slight i...

1.1 Data Prep for Analysis

Text Analysis (critics_concensus)

In [6]:
```
text = movie_nona['critics_consensus'].astype(str)
text.head(2)
```

Out[6]:
```
0    Though it may seem like just another Harry Pot...
1    Nicole Holofcener's newest might seem slight i...
Name: critics_consensus, dtype: object
```

In [7]:
```
#change to lower_case
text_lowercase = text.str.lower()
text_lowercase.astype(str).head(2)
```

Out[7]:
```
0    though it may seem like just another harry pot...
1    nicole holofcener's newest might seem slight i...
Name: critics_consensus, dtype: object
```

In [8]:
```
#Removing Punctuation and digits
def remove_punct_dig(document):
    no_punct = ''.join([character for character in document if character not in punctuation])
    no_punct_dij = ''.join([character for character in no_punct if not character.isdigit()])
    return no_punct_dij
```

In [9]:
```
text_no_p_d = text_lowercase.apply(remove_punct_dig)
text_no_p_d.head(2)
```

Out[9]:
```
0    though it may seem like just another harry pot...
1    nicole holofceners newest might seem slight in...
Name: critics_consensus, dtype: object
```

In [10]:
```
#Tokenization
text_tokenized = text_no_p_d.apply(word_tokenize)
text_tokenized.head(2)
```

Out[10]:
```
0    [though, it, may, seem, like, just, another, h...
1    [nicole, holofceners, newest, might, seem, sli...
Name: critics_consensus, dtype: object
```

In [11]:
```
#Removing Stopwords
stop_words = set(stopwords.words('english'))

def remove_stopwords(document):
    words = [word for word in document if not word in stop_words]
    return words
```

In [12]:
```
text_no_stop = text_tokenized.apply(remove_stopwords)
text_no_stop.head(2)
```

Out[12]:
```
0    [though, may, seem, like, another, harry, pott...
1    [nicole, holofceners, newest, might, seem, sli...
Name: critics_consensus, dtype: object
```

In [13]:
```
#Stemming
porter = PorterStemmer()

def stemmer(document):
    stemmed_document = [porter.stem(word) for word in document]
    return stemmed_document
```

In [14]:
```
text_stemmed = text_no_stop.apply(stemmer)
text_stemmed.head(2)
```

Out[14]:
```
0    [though, may, seem, like, anoth, harri, potter...
1    [nicol, holofcen, newest, might, seem, slight,...
Name: critics_consensus, dtype: object
```

In [15]:
```
#Detokenization
text_detokenized = text_stemmed.apply(TreebankWordDetokenizer().detokenize)
text_detokenized.head(2)
```

Out[15]:
```
0    though may seem like anoth harri potter knocko...
1    nicol holofcen newest might seem slight place ...
Name: critics_consensus, dtype: object
```

In [16]:
```
# Document-term Matrix
countvec = CountVectorizer(min_df=0.03)

sparse_dtm = countvec.fit_transform(text_detokenized)
sparse_dtm
```

Out[16]:
```
<8898x46 sparse matrix of type '<class 'numpy.int64'>'
        with 19277 stored elements in Compressed Sparse Row format>
```

In [17]:
```
dtm_pre = pd.DataFrame(sparse_dtm.toarray(), columns=countvec.get_feature_names_out(), index=text.index)
dtm = dtm_pre.add_suffix('_critic')
```

In [18]:
```
frequencies = dtm_pre.sum().sort_values(ascending=False)
print(frequencies[frequencies > 30])
```

```
perform      1360
stori         857
film          712
cast          704
movi          626
make          592
offer         588
comedi        539
charact       505
enough        500
may           456
drama         449
thriller      435
director      431
plot          430
visual        427
entertain     411
work          390
effect        379
action        376
talent        373
look          369
power         367
charm         359
one           353
viewer        345
though        342
star          340
lack          339
funni         335
fan           332
direct        323
thrill        318
featur        316
humor         312
script        309
genr          307
life          305
strong        304
take          295
even          284
classic       276
horror        274
time          274
lead          273
origin        271
dtype: int64
```

In [19]:
```
#combining into one
movies_info_pre_processed = movie_nona[['audience_rating', 'runtime', 'content_rating',
                                       'audience_status', 'genres']].join(dtm)

movies_info_pre_processed.head(2)
```

Out[19]:

	audience_rating	runtime	content_rating	audience_status	audience_status	genres	action_critic	cast_critic	charact_critic	charm_critic	...	strong_critic
0	53.0	119.0	PG	Spilled	Spilled	Action & Adventure, Comedy, Drama, Science Fic...	0	1	0	0	...	1
1	64.0	90.0	R	Upright	Upright	Comedy	0	0	1	0	...	0

2 rows × 52 columns

In [20]:
```
# FOrmular to convert audience_rating to range between 0-10

def get_range(value):
    if pd.isna(value):
        return 0
    else:
        digit = value / 10
        return int(digit)
```

In [21]:
```
new_rating = movies_info_pre_processed['audience_rating'].apply(get_range)
new_rating
```

Out[21]:
```
0        5
1        6
2        5
3        9
4        7
        ..
17704    8
17705    2
17706    3
17708    9
17710    9
Name: audience_rating, Length: 8898, dtype: int64
```

In [22]:
```
movies_info_pre_processed['audience_rating'] = new_rating
movies_info_pre_processed.head(2)
```

Out[22]:

	audience_rating	runtime	content_rating	audience_status	audience_status	genres	action_critic	cast_critic	charact_critic	charm_critic	...	strong_critic
0	5	119.0	PG	Spilled	Spilled	Action & Adventure, Comedy, Drama, Science Fic...	0	1	0	0	...	1
1	6	90.0	R	Upright	Upright	Comedy	0	0	1	0	...	0

2 rows × 52 columns

In [23]:
```
# Changing categorical varieables in columns to numerical data
movies_info_processed = pd.get_dummies(movies_info_pre_processed, columns=['content_rating', 'audience_status', 'genres
movies_info_processed.head(2)
```

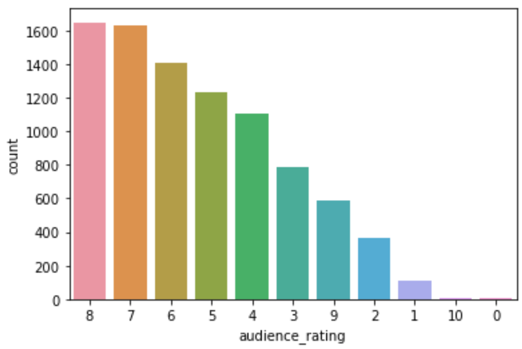
Out[23]:

	audience_rating	runtime	action_critic	cast_critic	charact_critic	charm_critic	classic_critic	comedi_critic	direct_critic	director_critic	...	genres_Mystery & Suspense, Special Interest	g
0	5	119.0	0	1	0	0	0	0	0	0	...	0	
1	6	90.0	0	0	1	0	0	0	0	0	...	0	

2 rows × 743 columns

In [24]:
```
#Checking if our classed are evenly distributed
sns.countplot(movies_info_processed['audience_rating'], order=movies_info_processed['audience_rating'].value_counts().i
print(movies_info_processed['audience_rating'].value_counts())
```

```
/Users/adedeji/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following
variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

8     1648
7     1632
6     1409
5     1234
4     1108
3      784
9      592
2      367
1      112
10       8
0        4
Name: audience_rating, dtype: int64
```



1.2 Decision Tree Regression

In [25]:
```
y = movies_info_processed['audience_rating']
x = movies_info_processed.drop(['audience_rating'], axis=1)
```

In [26]:
```
y.isna().sum()
```

Out[26]:
```
0
```

In [27]:
```
x.isna().sum()
```

Out[27]:
```
runtime                                          0
action_critic                                    0
cast_critic                                      0
charact_critic                                   0
charm_critic                                     0
                                                ..
genres_Science Fiction & Fantasy, Romance        0
genres_Science Fiction & Fantasy, Special Interest    0
genres_Science Fiction & Fantasy, Western        0
genres_Television                                0
genres_Western                                   0
Length: 742, dtype: int64
```

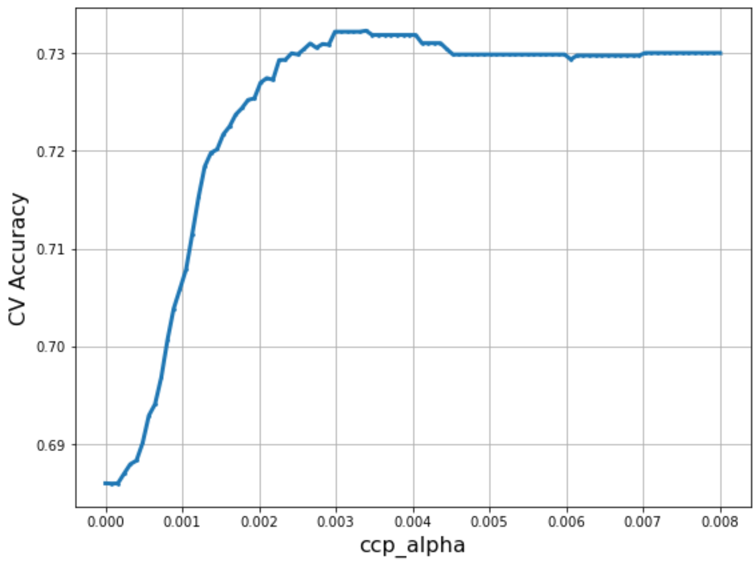
In [28]:
```
from sklearn.model_selection import train_test_split

y = y.astype('int32')

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3, stratify=y, random_state=88)
x_train.shape, x_test.shape
```

Out[28]:
```
((6228, 742), (2670, 742))
```

In [29]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeRegressor

grid_values = {'ccp_alpha': np.linspace(0, 0.008, 100),
              'min_samples_leaf': [5],
               'min_samples_split': [20],
               'max_depth': [30],
               'random_state': [88]}

dtc = DecisionTreeRegressor(random_state=88)
dtc_cv = GridSearchCV(dtc, param_grid=grid_values,  cv=2).fit(x_train, y_train)
```

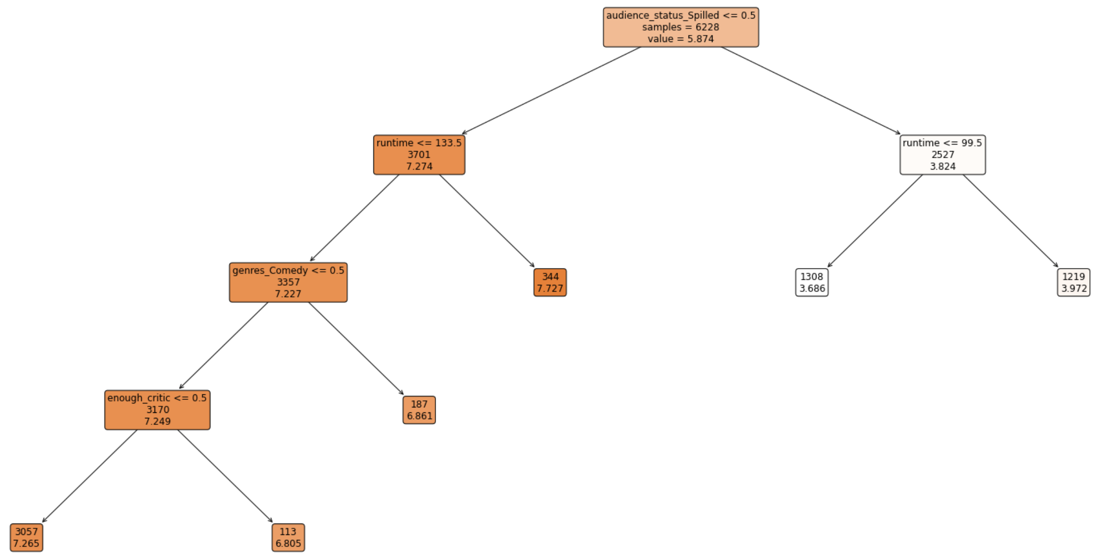
In [ ]:

In [30]:
```
import matplotlib.pyplot as plt

ccp_alpha = dtc_cv.cv_results_['param_ccp_alpha'].data
ACC_scores = dtc_cv.cv_results_['mean_test_score']

plt.figure(figsize=(8, 6))
plt.xlabel('ccp_alpha', fontsize=16)
plt.ylabel('CV Accuracy', fontsize=16)
plt.scatter(ccp_alpha, ACC_scores, s=3)
plt.plot(ccp_alpha, ACC_scores, linewidth=3)
plt.grid(True, which='both')

plt.tight_layout()
plt.show()

print('Best ccp_alpha', dtc_cv.best_params_)
```




```
Best ccp_alpha {'ccp_alpha': 0.0033939393939393939394, 'max_depth': 30, 'min_samples_leaf': 5, 'min_samples_split': 20,
'random_state': 88}
```

In [31]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(30,15))
plot_tree(dtc_cv.best_estimator_,
          feature_names=x_train.columns,
          class_names=['0','1'],
          filled=True,
          impurity=False,
          rounded=True,
          fontsize=12,
          max_depth = 5,
          label='root')
plt.show()
```



In [32]:
```
from sklearn.metrics import r2_score

print('CV R2:', round(dtc_cv.best_score_, 5))
print('OSR2:', round(r2_score(y_test, dtc_cv.predict(x_test)), 5))
```

```
CV R2: 0.73233
OSR2: 0.73475
```

In [ ]:

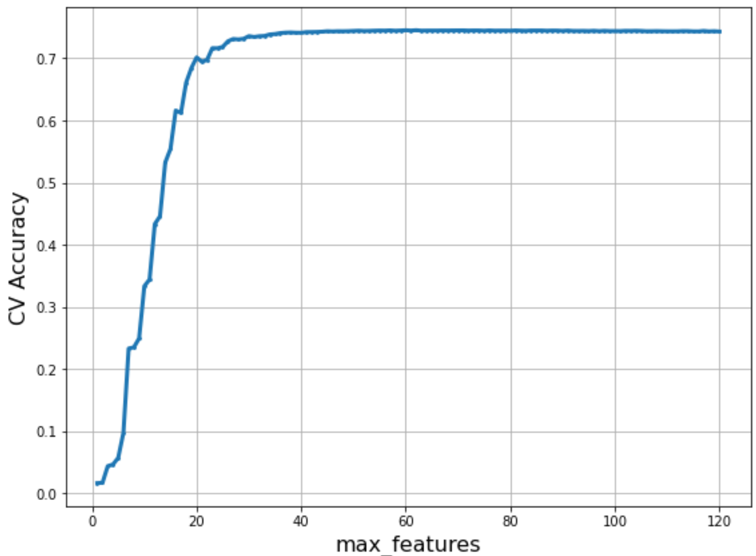
1.3 Random Forest

In [33]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [35]:
```
### Random Forest Regressor with CV
import time

grid_values = {'max_features': np.linspace(1,120,120, dtype='int32'),
               'min_samples_leaf': [5],
               'n_estimators': [100],
               'random_state': [88]}

tic = time.time()

rf = RandomForestRegressor()
rf_cv = GridSearchCV(rf, param_grid=grid_values, cv=5)
rf_cv.fit(x_train, y_train)

toc = time.time()

print('time:', round(toc-tic, 2),'s')
```

```
time: 760.41 s
```

In [36]:
```
max_features = rf_cv.cv_results_['param_max_features'].data
ACC_scores = rf_cv.cv_results_['mean_test_score']

plt.figure(figsize=(8, 6))
plt.xlabel('max_features', fontsize=16)
plt.ylabel('CV Accuracy', fontsize=16)
plt.scatter(max_features, ACC_scores, s=3)
plt.plot(max_features, ACC_scores, linewidth=3)
plt.grid(True, which='both')

plt.tight_layout()
plt.show()

print('Best parameters', rf_cv.best_params_)
```




```
Best parameters {'max_features': 62, 'min_samples_leaf': 5, 'n_estimators': 100, 'random_state': 88}
```

In [37]:
```
x_test['runtime'].size
```

Out[37]: 2670

In [38]:
```
pd.DataFrame({'Feature' :x_train.columns,
              'Importance score': 100*rf_cv.best_estimator_.feature_importances_}).round(1)
```

Out[38]:

	Feature	Importance score
0	runtime	2.4
1	action_critic	0.0
2	cast_critic	0.1
3	charact_critic	0.0
4	charm_critic	0.1
...	...	...
737	genres_Science Fiction & Fantasy, Romance	0.0
738	genres_Science Fiction & Fantasy, Special Inte...	0.0
739	genres_Science Fiction & Fantasy, Western	0.0
740	genres_Television	0.0
741	genres_Western	0.0

742 rows × 2 columns

In [39]:
```
from sklearn.metrics import r2_score

print('CV R2:', round(rf_cv.best_score_, 5))
print('OSR2:', round(r2_score(y_test, rf_cv.predict(x_test)), 5))
```

```
CV R2: 0.74529
OSR2: 0.75124
```

In [ ]:

1.4 XGBost for Regression

In [40]:
```
import xgboost as xg
from sklearn.metrics import mean_squared_error as MSE
```

In [41]:
```
#This is to deal with the error assocoated with uniquness of our features(duplicate columns)
X_train = x_train.loc[:,~x_train.columns.duplicated()].copy()
X_test = x_test.loc[:,~x_test.columns.duplicated()].copy()
```

In [42]:
```
# Various hyper-parameters to tune
xgb1 = xg.XGBRegressor()
parameters = {'nthread':[4], #when use hyperthread, xgboost may become slower
              'objective':['reg:squarederror'],
              'learning_rate': [.03, 0.05, .07], #so called `eta` value
              'max_depth': [5, 6, 7],
              'min_child_weight': [4],
              'silent': [1],
              'subsample': [0.7],
              'colsample_bytree': [0.7],
              'n_estimators': [500]}

xgb_grid = GridSearchCV(xgb1,
                        parameters,
                        cv = 2,
                        n_jobs = 5,
                        verbose=False)

xgb_grid.fit(X_train,
         y_train)
```

```
[23:26:48] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.
```

Out[42]:
```
GridSearchCV(cv=2,
             estimator=XGBRegressor(base_score=None, booster=None,
                                    callbacks=None, colsample_bylevel=None,
                                    colsample_bynode=None,
                                    colsample_bytree=None,
                                    early_stopping_rounds=None,
                                    enable_categorical=False, eval_metric=None,
                                    feature_types=None, gamma=None, gpu_id=None,
                                    grow_policy=None, importance_type=None,
                                    interaction_constraints=None,
                                    learning_rate=None, m...
                                    monotone_constraints=None, n_estimators=100,
                                    n_jobs=None, num_parallel_tree=None,
                                    predictor=None, random_state=None, ...),
             n_jobs=5,
             param_grid={'colsample_bytree': [0.7],
                         'learning_rate': [0.03, 0.05, 0.07],
                         'max_depth': [5, 6, 7], 'min_child_weight': [4],
                         'n_estimators': [500], 'nthread': [4],
                         'objective': ['reg:squarederror'], 'silent': [1],
                         'subsample': [0.7]},
             verbose=False)
```

In [43]:
```
print('CV R2:', xgb_grid.best_score_, 5)
XG_OSR2 = r2_score(y_test, xgb_grid.predict(X_test))
print('OSR2:', round(XG_OSR2, 5))
print('Best parameters', xgb_grid.best_params_)
```

```
CV R2: 0.7427905573929963 5
OSR2: 0.75172
Best parameters {'colsample_bytree': 0.7, 'learning_rate': 0.03, 'max_depth': 5, 'min_child_weight': 4, 'n_estimator
s': 500, 'nthread': 4, 'objective': 'reg:squarederror', 'silent': 1, 'subsample': 0.7}
```

1.5 Bootstrap Validation with Confidence Interval Plot

Since oure best model is XGBoost with OSR2 of 0.75172, we will like to know with certainty how it will perform on future data

In [44]:
```
# manual implementation of bootstrap for model valiation.
def bootstrap_validation(test_data, test_label, train_label, model, metrics_list, sample=500, random_state=66):
    n_sample = sample
    n_metrics = len(metrics_list)
    output_array=np.zeros([n_sample, n_metrics])
    output_array[:]=np.nan
    print(output_array.shape)
    for bs_iter in range(n_sample):
        bs_index = np.random.choice(test_data.index, len(test_data.index), replace=True)
        bs_data = test_data.loc[bs_index]
        bs_label = test_label.loc[bs_index]
        bs_predicted = model.predict(bs_data)
        for metrics_iter in range(n_metrics):
            metrics = metrics_list[metrics_iter]
            output_array[bs_iter, metrics_iter]=metrics(bs_label, bs_predicted)
    output_df = pd.DataFrame(output_array)
    return output_df
```

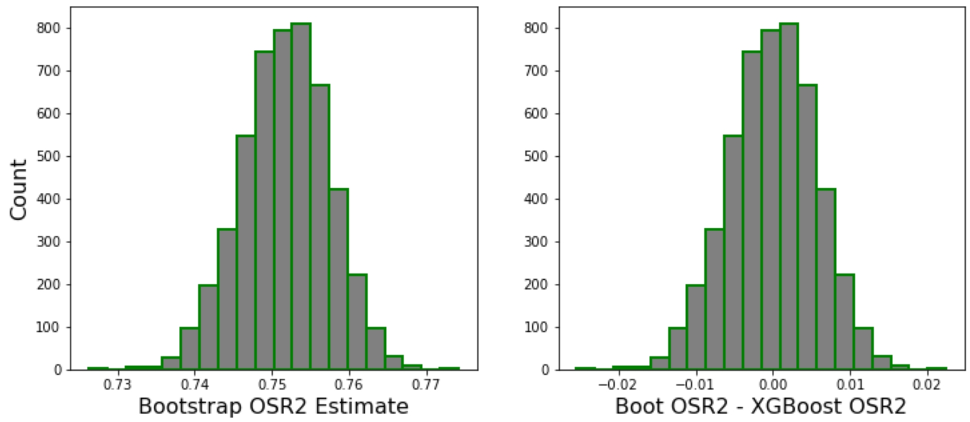
In [45]:
```
bs_output = bootstrap_validation(X_test,y_test,y_train,xgb_grid,
                                 metrics_list=[r2_score],
                                 sample = 5000)
```

```
(5000, 1)
[23:18:16] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:20:37] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:22:34] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:18:16] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:21:00] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:23:20] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:18:16] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:20:37] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:22:57] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:24:54] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:18:16] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:20:15] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:22:57] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:24:55] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:18:16] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:20:15] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:22:12] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.

[23:24:56] WARNING: /Users/runner/work/xgboost/xgboost/python-package/build/temp.macosx-10.9-x86_64-cpython-38/xgboos
t/src/learner.cc:767:
Parameters: { "silent" } are not used.
```

2.3.1 Basic plot and centered plot

In [46]:
```
fig, axs = plt.subplots(ncols=2, figsize=(12,5))
axs[0].set_xlabel('Bootstrap OSR2 Estimate', fontsize=16)
axs[1].set_xlabel('Boot OSR2 - XGBoost OSR2', fontsize=16)
axs[0].set_ylabel('Count', fontsize=16)
axs[0].hist(bs_output.iloc[:,0], bins=20,edgecolor='green', linewidth=2,color = "grey")
axs[1].hist(bs_output.iloc[:,0]-XG_OSR2, bins=20,edgecolor='green', linewidth=2,color = "grey")
```

Out[46]:
```
(array([  1.,    0.,    5.,    7.,   26.,   96., 195., 328., 548., 743., 793.,
        810., 666., 423., 223.,   95.,   30.,   10.,    0.,    1.]),
 array([-0.02541116, -0.02301906, -0.02062697, -0.01823487, -0.01584277,
        -0.01345068, -0.01105858, -0.00866648, -0.00627439, -0.00388229,
        -0.0014902 ,  0.0009019 ,  0.003294  ,  0.00568609,  0.00807819,
         0.01047029,  0.01286238,  0.01525448,  0.01764658,  0.02003867,
         0.02243077]),
 <BarContainer object of 20 artists>)
```



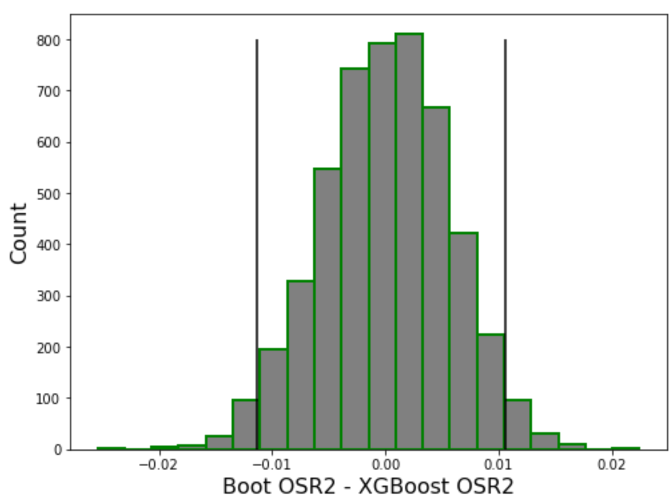
manual CI + plot

In [47]:
```
# The 95% confidence interval
CI= np.quantile(bs_output.iloc[:,0]-XG_OSR2,np.array([0.025,0.975]))
print("The 95-percent confidence interval of OSR2 is %s" % CI)
```

```
The 95-percent confidence interval of OSR2 is [-0.01138854  0.01064887]
```

In [48]:
```
fig, axs = plt.subplots(ncols=1, figsize=(8,6))
axs.set_xlabel('Boot OSR2 - XGBoost OSR2', fontsize=16)
axs.set_ylabel('Count', fontsize=16)
axs.hist(bs_output.iloc[:,0]-XG_OSR2, bins=20,edgecolor='green', linewidth=2,color = "grey")
#axs.set_xlim([-0.15,0.15])
axs.vlines(x=CI[0], ymin = 0, ymax =800, color = "black")
axs.vlines(x=CI[1], ymin = 0, ymax =800, color = "black")
```

Out[48]:
```
<matplotlib.collections.LineCollection at 0x7fbeb0a4fa00>
```



In conclusion, since our confident interval contains Zero, we can say with 95% cofidence that our model will generate very similar result on future datasets

In [ ]:

Second Analysis

2.1 Data Prep for Analysis

Text analysis for Actor column

In [49]:
```
pre_text = raw_data[['actors', 'tomatometer_status', 'runtime', 'content_rating',
                     'genres','production_company','directors']]
pre_text_no_na = pre_text.dropna()
pre_text_no_na.reset_index(drop=True).head(2)
```

Out[49]:

	actors	tomatometer_status	runtime	content_rating	genres	production_company	directors
0	Logan Lerman, Brandon T. Jackson, Alexandra Da...	Rotten	119.0	PG	Action & Adventure, Comedy, Drama, Science Fic...	20th Century Fox	Chris Columbus
1	Catherine Keener, Amanda Peet, Oliver Platt, R...	Certified-Fresh	90.0	R	Comedy	Sony Pictures Classics	Nicole Holofcener

In [50]:
```
text = pre_text_no_na['actors'].astype(str)
text.head(2)
```

Out[50]:
```
0    Logan Lerman, Brandon T. Jackson, Alexandra Da...
1    Catherine Keener, Amanda Peet, Oliver Platt, R...
Name: actors, dtype: object
```

In [51]:
```
#change to lower_case
text_lowercase = text.str.lower()
text_lowercase.astype(str).head(2)
```

Out[51]:
```
0    logan lerman, brandon t. jackson, alexandra da...
1    catherine keener, amanda peet, oliver platt, r...
Name: actors, dtype: object
```

In [52]:
```
text_no_p_d = text_lowercase.apply(remove_punct_dig)
text_no_p_d.head(2)
```

Out[52]:
```
0    logan lerman brandon t jackson alexandra dadda...
1    catherine keener amanda peet oliver platt rebe...
Name: actors, dtype: object
```

In [53]:
```
text_tokenized = text_no_p_d.apply(word_tokenize)
text_tokenized.head(2)
```

Out[53]:
```
0    [logan, lerman, brandon, t, jackson, alexandra...
1    [catherine, keener, amanda, peet, oliver, plat...
Name: actors, dtype: object
```

In [54]:
```
text_no_stop = text_tokenized.apply(remove_stopwords)
text_no_stop.head(2)
```

Out[54]:
```
0    [logan, lerman, brandon, jackson, alexandra, d...
1    [catherine, keener, amanda, peet, oliver, plat...
Name: actors, dtype: object
```

In [55]:
```
text_stemmed = text_no_stop.apply(stemmer)
text_stemmed.head(2)
```

Out[55]:
```
0    [logan, lerman, brandon, jackson, alexandra, d...
1    [catherin, keener, amanda, peet, oliv, platt, ...
Name: actors, dtype: object
```

In [56]:
```
#Detokenization
text_detokenized = text_stemmed.apply(TreebankWordDetokenizer().detokenize)
text_detokenized.head(2)
```

Out[56]:
```
0    logan lerman brandon jackson alexandra daddari...
1    catherin keener amanda peet oliv platt rebecca...
Name: actors, dtype: object
```

In [57]:
```
# Document-term Matrix
countvec22 = CountVectorizer(min_df=0.01)

sparse_dtm1 = countvec22.fit_transform(text_detokenized)
sparse_dtm1
```

Out[57]:
```
<16512x707 sparse matrix of type '<class 'numpy.int64'>'
	with 356288 stored elements in Compressed Sparse Row format>
```

In [58]:
```
dtm_pre = pd.DataFrame(sparse_dtm1.toarray(), columns=countvec22.get_feature_names_out(), index=text.index)
dtm = dtm_pre.add_suffix('_actor')
```

In [59]:
```
ining both data sets
_raw_data = pre_text_no_na[['tomatometer_status', 'runtime', 'content_rating',
                          'genres','production_company','directors']].join(dtm)
_raw_data = pd.get_dummies(new_raw_data, columns=['content_rating', 'genres','production_company','directors'], drop_fi
```

In [60]:
```
new_raw_data=new_raw_data[0:10000]
```

In [61]:
```
## converting string category of tomatometer_status into int

def get_status_score(value):
    if value =='Rotten':
        return 0
    elif value == 'Fresh':
        return 1
    elif value == 'Certified-Fresh':
        return 2
    else:
        return 0
```

In [62]:
```
new_score = new_raw_data['tomatometer_status'].apply(get_status_score)
new_raw_data['tomatometer_status_score'] = new_score.astype(int)

new_raw_data.head(3)
```

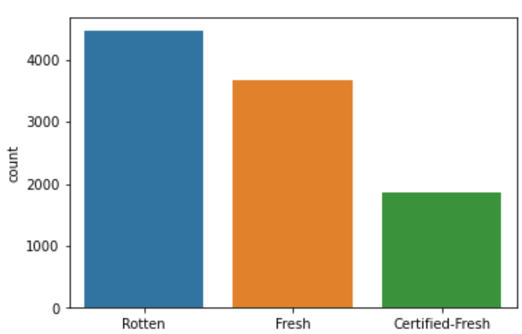
Out[62]:

	tomatometer_status	runtime	aaron_actor	abraham_actor	adam_actor	adrian_actor	al_actor	alan_actor	albert_actor	alec_actor	...	directors_Zoe Lister-Jones	director
0	Rotten	119.0	0	0	0	0	0	0	0	0	...	0	
1	Certified-Fresh	90.0	0	0	0	0	0	0	0	0	...	0	
2	Fresh	122.0	0	0	0	1	0	0	0	0	...	0	

3 rows × 12967 columns

In [63]:
```
#Checking if our classed are evenly distributed
sns.countplot(new_raw_data['tomatometer_status'], order=new_raw_data['tomatometer_status'].value_counts().index);
print(new_raw_data['tomatometer_status'].value_counts())
```

```
Rotten             4463
Fresh              3676
Certified-Fresh    1861
Name: tomatometer_status, dtype: int64

/Users/adedeji/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following
variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [64]:
```
#Separating dataset into dependent(Y) and independent(X) sets
y = new_raw_data['tomatometer_status_score']
x = new_raw_data.drop(['tomatometer_status_score', 'tomatometer_status'], axis=1)
new_raw_data.describe()
```

Out[64]:

	runtime	aaron_actor	abraham_actor	adam_actor	adrian_actor	al_actor	alan_actor	albert_actor	alec_actor	alex_actor	...	direc Lis
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	...	1(
mean	102.873400	0.042000	0.010600	0.099600	0.024800	0.040500	0.081300	0.029400	0.014000	0.067400	...	
std	18.864394	0.210334	0.103386	0.342186	0.161826	0.215092	0.301163	0.178714	0.119186	0.271044	...	
min	8.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
25%	91.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
50%	100.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
75%	111.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	
max	254.000000	3.000000	2.000000	4.000000	2.000000	3.000000	3.000000	2.000000	2.000000	4.000000	...	

8 rows × 12966 columns

In [65]:
```
from sklearn.model_selection import train_test_split

train_x, test_x, train_y, test_y  = train_test_split(x, y, test_size=0.3, random_state=88)
train_x.shape, test_x.shape
```

Out[65]: ((7000, 12965), (3000, 12965))

2.2 LDA

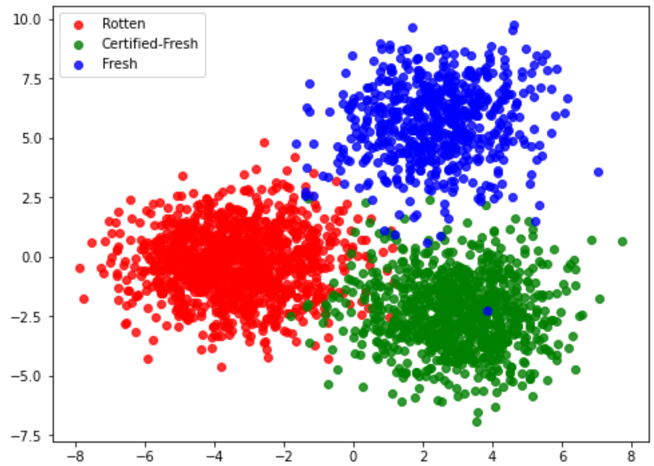
In [66]:
```
data_train_y=train_y.to_numpy()
data_train_x=train_x.to_numpy()

data_test_y=test_y.to_numpy()
data_test_x=test_x.to_numpy()
```

In [68]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.metrics import accuracy_score
lda = LinearDiscriminantAnalysis(
)
lda.fit(data_train_x,data_train_y)
```

Out[68]: LinearDiscriminantAnalysis()

In [69]:
```
data_plot = lda.transform(data_train_x)
```

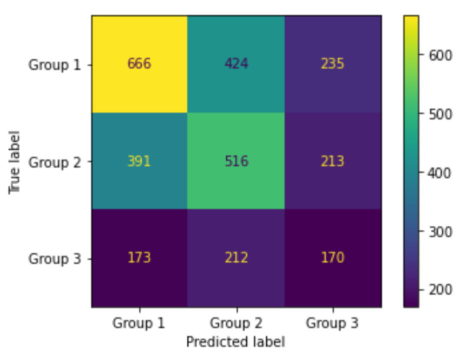
In [70]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
plt.figure(figsize=(8, 6))

## set up the label and color of different classes for plotting.

tomatometer_status = new_raw_data.tomatometer_status
colors = ['red', 'green', 'blue']
lw = 2

for color, i, target_name in zip(colors, [0, 1, 2], tomatometer_status):
    plt.scatter(data_plot[data_train_y == i, 0], data_plot[data_train_y == i, 1], alpha=.8, color=color,
                label=target_name)

plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()
```



In [71]:
```
#predicting test set

y_prob_lda = lda.predict(data_test_x)
OSR2_lda = lda.score(data_test_x, data_test_y)
print('Model Precision (OSR2): ',round(OSR2_lda, 5))
```

```
Model Precision (OSR2):  0.45067
```

In [74]:
```
#Generating Confustion matrix fort the LDA Model.
cm_lda1 = confusion_matrix(data_test_y, y_prob_lda)
class_names = ['Group 1', 'Group 2', 'Group 3']
cm_display = ConfusionMatrixDisplay(confusion_matrix = cm_lda1, display_labels = class_names)

cm_display.plot()
plt.show()
```



In [75]:
```
def TPR_FPR_ACC(cnf_matrix):
    FP = cnf_matrix.sum(axis=0) - np.diag(cnf_matrix)
    FN = cnf_matrix.sum(axis=1) - np.diag(cnf_matrix)
    TP = np.diag(cnf_matrix)
    TN = cnf_matrix.sum() - (FP + FN + TP)

    FP = FP.astype(float)
    FN = FN.astype(float)
    TP = TP.astype(float)
    TN = TN.astype(float)

    # Sensitivity, hit rate, recall, or true positive rate
    TPR = TP/(TP+FN)

    # Fall out or false positive rate
    FPR = FP/(FP+TN)

    # Overall accuracy for each class
    ACC = (TP+TN)/(TP+FP+FN+TN)
    return TPR, FPR, ACC
```

In [77]:
```
LDA_TPR, LDA_FPR, LDA_ACC = TPR_FPR_ACC(cm_lda1)
print('LDA_TPR : ',LDA_TPR)
print('LDA_FPR : ',LDA_FPR)
print('LDA_ACC : ',LDA_ACC)
```

```
LDA_TPR :  [0.50264151 0.46071429 0.30630631]
LDA_FPR :  [0.33671642 0.33829787 0.18323108]
LDA_ACC :  [0.59233333 0.58666667 0.72233333]
```

2.3 CART Model

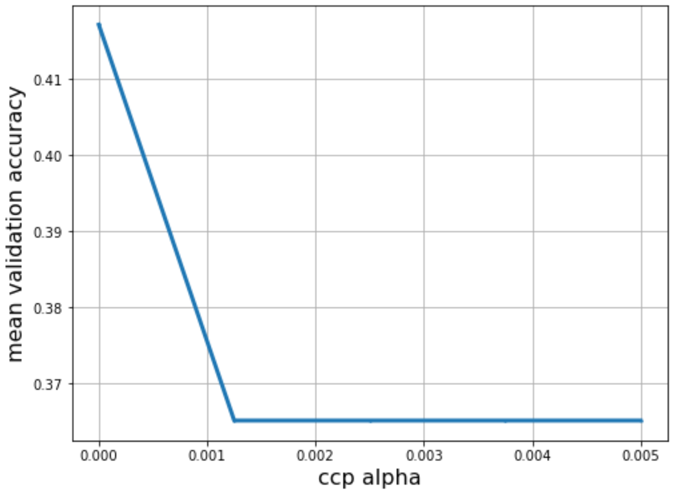
In [78]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
# this package can apply to find best combination of parameters....

#Exhaustive search over specified parameter values for an estimator.

grid_values = {'ccp_alpha': np.linspace(0.0, 0.005, 5),
               'min_samples_leaf': [5],
               'min_samples_split': [20],
               'max_depth': [30],
               'class_weight' : [{0: 1, 1: 20}],
               'random_state': [88]}

dtc = DecisionTreeClassifier(class_weight = 'balanced')

#best combo of  paramters to find best accuracy
dtc_cv_acc = GridSearchCV(dtc, param_grid = grid_values, scoring = 'accuracy', cv=10, verbose=0)

# default scoring metric to optimize is accuracy, used as default if none given.
training = dtc_cv_acc.fit(train_x, train_y)
```

In [79]:
```
acc = dtc_cv_acc.cv_results_['mean_test_score']
# what sklearn calls mean_test_score is the holdout set, i.e. the validation set.
ccp = dtc_cv_acc.cv_results_['param_ccp_alpha'].data

pd.DataFrame({'ccp alpha' : ccp, 'Validation Accuracy': acc}).head(20)

#to find ccp value we test across different values.....
#verbose is the report meassgae about what you are modeling..
```

Out[79]:

	ccp alpha	Validation Accuracy
0	0.0	0.417143
1	0.00125	0.365143
2	0.0025	0.365143
3	0.00375	0.365143
4	0.005	0.365143

In [80]:
```
plt.figure(figsize=(8, 6))
plt.xlabel('ccp alpha', fontsize=16)
plt.ylabel('mean validation accuracy', fontsize=16)
plt.scatter(ccp, acc, s=2)
plt.plot(ccp, acc, linewidth=3)
plt.grid(True, which='both')
plt.show()

#visaulization is a good way to show why you are choosing thay parameter!!!
```



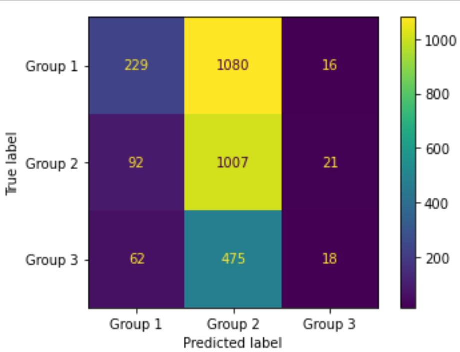
In [81]:
```
print('Grid best parameter (max. Accuracy): ', dtc_cv_acc.best_params_)
print('Node count =', dtc_cv_acc.best_estimator_.tree_.node_count)
```

```
Grid best parameter (max. Accuracy):  {'ccp_alpha': 0.0, 'class_weight': {0: 1, 1: 20}, 'max_depth': 30, 'min_samples
_leaf': 5, 'min_samples_split': 20, 'random_state': 88}
Node count = 427
```

In [84]:
```

y_pred_cart = dtc_cv_acc.predict(test_x)
cm_cart = confusion_matrix(test_y, y_pred_cart)

print('Model Precision (R2): ', dtc_cv_acc.best_score_)
CART_OSR2 = precision_score(test_y, y_pred_cart, average='micro')
print('Model Precision (OSR2):', round(CART_OSR2, 5))
```

```
Model Precision (R2):  0.4171428571428571
Model Precision (OSR2): 0.418
```

In [85]:
```
#plotting Confussion Matrix
#fig, axs = plt.subplots(ncols=3, figsize=(12,5))
cm_display1 = ConfusionMatrixDisplay(confusion_matrix = cm_cart, display_labels = class_names)


cm_display1.plot()

plt.show()
```



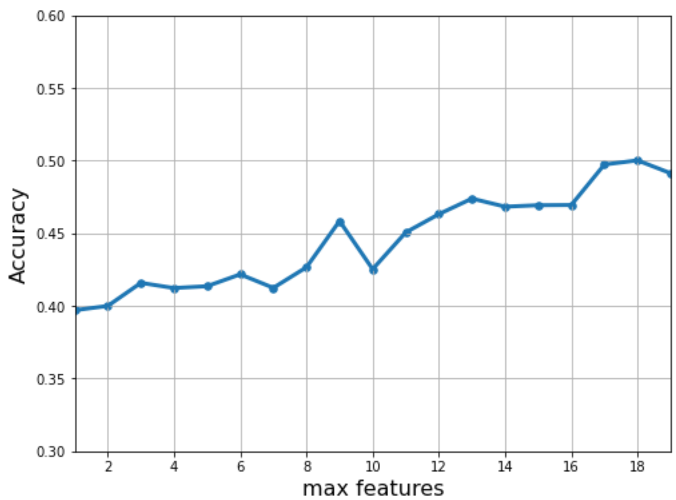
2.4 Random Forest Classification Model

In [86]:
```
from sklearn.ensemble import RandomForestClassifier
import time

grid_values = {'max_features': np.linspace(1,100,100, dtype='int32'),
              'min_samples_leaf': [5],
              'n_estimators': [100],
              'random_state': [88]}

tic = time.time()

rf = RandomForestClassifier(class_weight = 'balanced')
rf_cv = GridSearchCV(rf, param_grid=grid_values, scoring='accuracy', cv=10)
rf_cv.fit(train_x, train_y)

toc = time.time()
print('time:', round(toc-tic, 2),'s')
```

```
time: 5948.82 s
```

In [87]:
```
max_features = rf_cv.cv_results_['param_max_features'].data
R2_scores = rf_cv.cv_results_['mean_test_score']

plt.figure(figsize=(8, 6))
plt.xlabel('max features', fontsize=16)
plt.ylabel('Accuracy', fontsize=16)
plt.scatter(max_features, R2_scores, s=30)
plt.plot(max_features, R2_scores, linewidth=3)
plt.grid(True, which='both')
plt.xlim([1, 19])
plt.ylim([0.3, 0.6])
```

Out[87]:
```
(0.3, 0.6)
```



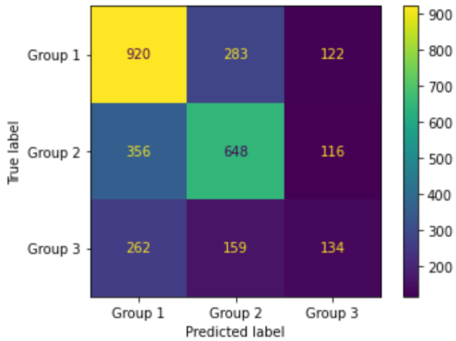
In [88]:
```
print(rf_cv.best_params_)
```

```
{'max_features': 98, 'min_samples_leaf': 5, 'n_estimators': 100, 'random_state': 88}
```

In [89]:
```
y_pred = rf_cv.predict(test_x)

cm_rf = confusion_matrix(test_y, y_pred)

print('Model Precision (R2):', round(rf_cv.best_score_, 5))
RF_OSR2 = precision_score(test_y, y_pred, average='micro')
print('Model Precision (OSR2):', round(RF_OSR2, 5))
```

```
Model Precision (R2): 0.58671
Model Precision (OSR2): 0.56733
```

In [90]:
```
#plotting Confussion Matrix

cm_display2 = ConfusionMatrixDisplay(confusion_matrix = cm_rf, display_labels = class_names)


cm_display2.plot()

plt.show()
```



2.5 Bootstrap Validation with Confidence Interval Plot

Since our best model is Random Forest model with OSR2 of 0.56733, we will like to know with certainty how it will perform on future data

In [91]:
```
# manual implementation of bootstrap for model valiation.
def bootstrap_validation2(test_data, test_label, train_label, model, metrics_list, sample=500, random_state=66):
    n_sample = sample
    n_metrics = len(metrics_list)
    output_array=np.zeros([n_sample, n_metrics])
    output_array[:]=np.nan
    print(output_array.shape)
    for bs_iter in range(n_sample):
        bs_index = np.random.choice(test_data.index, len(test_data.index), replace=True)
        bs_data = test_data.loc[bs_index]
        bs_label = test_label.loc[bs_index]
        bs_predicted = model.predict(bs_data)
        for metrics_iter in range(n_metrics):
            metrics = metrics_list[metrics_iter]
            output_array[bs_iter, metrics_iter]=metrics(bs_label, bs_predicted, average='micro')
    output_df = pd.DataFrame(output_array)
    return output_df
```

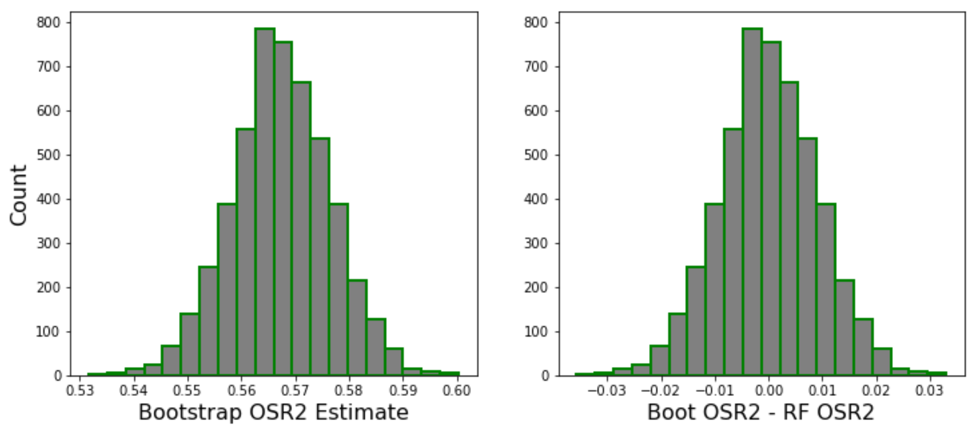
In [97]:
```
#Carrying out Bootstrap for CART Model
bs_output_rf = bootstrap_validation2(test_x,test_y,train_y,rf_cv,
                                 metrics_list=[precision_score],
                                 sample = 5000)
```

```
(5000, 1)
```

In [ ]:

In [98]:
```
fig, axs = plt.subplots(ncols=2, figsize=(12,5))
axs[0].set_xlabel('Bootstrap OSR2 Estimate', fontsize=16)
axs[1].set_xlabel('Boot OSR2 - RF OSR2', fontsize=16)
axs[0].set_ylabel('Count', fontsize=16)
axs[0].hist(bs_output_rf.iloc[:,0], bins=20,edgecolor='green', linewidth=2,color = "grey")
axs[1].hist(bs_output_rf.iloc[:,0]-RF_OSR2, bins=20,edgecolor='green', linewidth=2,color = "grey")
```

Out[98]:
```
(array([  1.,    4.,   14.,   24.,   67., 138., 245., 388., 557., 785., 756.,
        665., 537., 389., 214., 128.,   59.,   15.,    9.,    5.]),
 array([-0.03566667, -0.03223333, -0.0288    , -0.02536667, -0.02193333,
        -0.0185    , -0.01506667, -0.01163333, -0.0082    , -0.00476667,
        -0.00133333,  0.0021    ,  0.00553333,  0.00896667,  0.0124    ,
         0.01583333,  0.01926667,  0.0227    ,  0.02613333,  0.02956667,
         0.033     ]),
 <BarContainer object of 20 artists>)
```

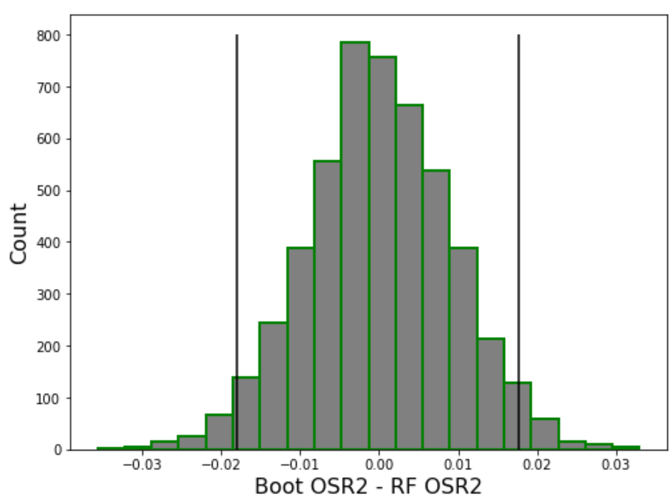


In [99]:
```
# The 95% confidence interval
CI_RF = np.quantile(bs_output_rf.iloc[:,0]-RF_OSR2,np.array([0.025,0.975]))
print("The 95-percent confidence interval of OSR2 is %s" % CI_RF)
```

```
The 95-percent confidence interval of OSR2 is [-0.018       0.01766667]
```

In [101]:
```
fig, axs = plt.subplots(ncols=1, figsize=(8,6))
axs.set_xlabel('Boot OSR2 - RF OSR2', fontsize=16)
axs.set_ylabel('Count', fontsize=16)
axs.hist(bs_output_rf.iloc[:,0]-RF_OSR2, bins=20,edgecolor='green', linewidth=2,color = "grey")
axs.vlines(x=CI_RF[0], ymin = 0, ymax =800, color = "black")
axs.vlines(x=CI_RF[1], ymin = 0, ymax =800, color = "black")
```

Out[101]:
```
<matplotlib.collections.LineCollection at 0x7fbe6d461a00>
```



In conclusion, since our confident interval contains Zero, we can say with 95% cofidence that our model will generate very similar result on future datasets

In [ ]:

In [ ]: