1 Introduction

In this notebook, we will be looking at data gathered from the esrb.org site. The data details all the descriptors and ratings given to games released for PlayStation4, Xbox One, and Nintendo Switch.

The goal is to train an effective machine learning model to predict a game's rating based on its descriptors. We will be approaching this as a classification problem, although due to the nature of game ratings (E-M), it might also be effective to approach the problem from a regression standpoint.

2 Obtain

Here we're making our necessary imports and pulling data from 'esrb_ratings.pkl', which we created in the notebook 'data_gathering.ipynb'. View that notebook to see the web-scraping process.

In [14]:

```python
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.model_selection import StratifiedKFold

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from xgboost import XGBClassifier

from sklearn.metrics import classification_report, plot_confusion_matrix
```

executed in 11ms, finished 13:54:44 2021-02-26

In [15]:

```python
# load data

df = pd.read_pickle('esrb_ratings.pkl')
df.head()
```

executed in 29ms, finished 13:54:44 2021-02-26

Out[15]:

	title	consoles	descriptors	rating
0	Blizzard Arcade Collection	[PlayStation 4, Nintendo Switch, Xbox One]	[Blood, Fantasy Violence, Language, Use of Tob...	T
1	Rez Infinite	[PlayStation 4]	[Fantasy Violence]	E10plus
2	Hotshot Racing	[PlayStation 4, Nintendo Switch]	[Alcohol Reference, Language, Mild Violence]	E10plus
3	Sea of Solitude : The Director's Cut	[Nintendo Switch]	[Fantasy Violence, Language]	T
4	Ape Out	[Nintendo Switch]	[Blood and Gore, Violence]	T

3 Scrub

Using the lists in the 'descriptors' column to one-hot encode the data.

In [16]:

```
# one-hot encode for consoles and descriptors

descriptors_ohe = pd.get_dummies(df.descriptors.apply(pd.Series).stack()).sum(level=0)

# combine into a single dataframe

df_ohe = pd.concat([df.drop(columns=['descriptors']), descriptors_ohe], axis=1)

df_ohe.head()
```

executed in 1.05s, finished 13:54:45 2021-02-26

Out[16]:

	title	consoles	rating	Alcohol Reference	Alcohol and Tobacco Reference	Animated Blood	Animated Blood and Gore	Animated Violence	Blood	Blood and Gore	...	Strong Sexual Content	Suggestive Themes
0	Blizzard Arcade Collection	[PlayStation 4, Nintendo Switch, Xbox One]	T	0	0	0	0	0	1	0	...	0	0
1	Rez Infinite	[PlayStation 4]	E10plus	0	0	0	0	0	0	0	...	0	0
2	Hotshot Racing	[PlayStation 4, Nintendo Switch]	E10plus	1	0	0	0	0	0	0	...	0	0
3	Sea of Solitude : The Director's Cut	[Nintendo Switch]	T	0	0	0	0	0	0	0	...	0	0
4	Ape Out	[Nintendo Switch]	T	0	0	0	0	0	0	1	...	0	0

5 rows × 47 columns

In [17]:

```
# rearrange columns

cols = list(df_ohe)
rating_col = cols.pop(2)
cols.append(rating_col)
df_ohe = df_ohe.reindex(columns=cols)

df_ohe.head()
```

executed in 29ms, finished 13:54:45 2021-02-26

Out[17]:

	title	consoles	Alcohol Reference	Alcohol and Tobacco Reference	Animated Blood	Animated Blood and Gore	Animated Violence	Blood	Blood and Gore	Cartoon Violence	...	Suggestive Themes	Tobacc Referenc
0	Blizzard Arcade Collection	[PlayStation 4, Nintendo Switch, Xbox One]	0	0	0	0	0	1	0	0	...	0	
1	Rez Infinite	[PlayStation 4]	0	0	0	0	0	0	0	0	...	0	
2	Hotshot Racing	[PlayStation 4, Nintendo Switch]	1	0	0	0	0	0	0	0	...	0	
3	Sea of Solitude : The Director's Cut	[Nintendo Switch]	0	0	0	0	0	0	0	0	...	0	
4	Ape Out	[Nintendo Switch]	0	0	0	0	0	0	1	0	...	0	

5 rows × 47 columns

4 Explore

First we'll split the data into training and test sets.

In [18]:

```
cat_dtype = pd.api.types.CategoricalDtype(
    categories=['E', 'E10plus', 'T', 'M'], ordered=True)

X = df_ohe.drop(columns=['title', 'consoles', 'rating'])
y = df.rating.astype(cat_dtype)

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42, stratify=y)

training_data = pd.concat([X_train, y_train], axis=1)
```

executed in 15ms, finished 13:54:45 2021-02-26

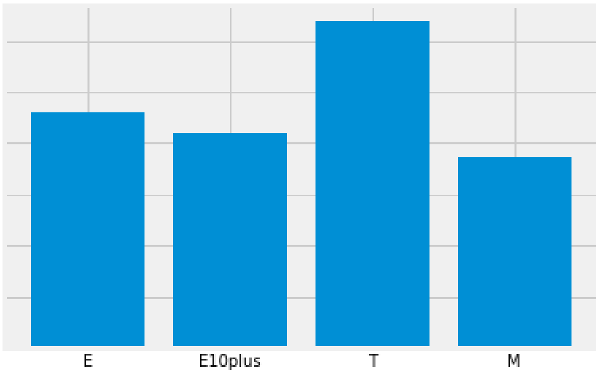
How is the balance of our data?

In [19]:

```
plt.bar(y_train.cat.categories, y_train.value_counts(sort=False))
```

executed in 123ms, finished 13:54:45 2021-02-26

Out[19]: <BarContainer object of 4 artists>



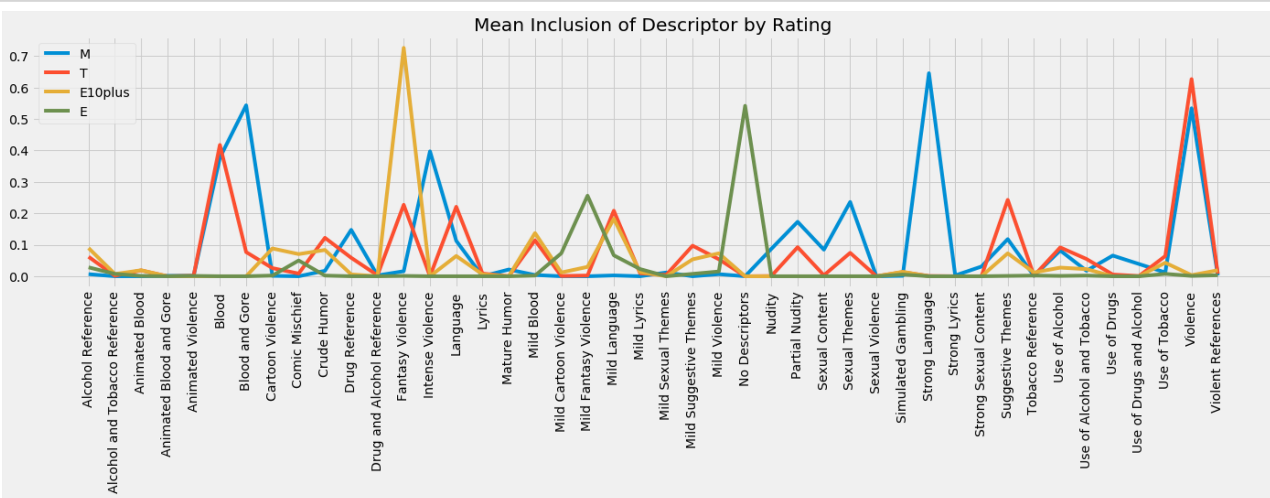
It isn't totally balanced, but it isn't terribly skewed, either.

In [20]:

```
# plot frequency of decriptors
plt.style.use('fivethirtyeight')
fig, ax = plt.subplots(figsize=(20,8))
for r in y_train.cat.categories[::-1]:
    plt.plot(training_data[training_data.rating==r].mean(), label=r)

plt.xticks(rotation=90)
plt.title('Mean Inclusion of Descriptor by Rating')
plt.legend()
plt.tight_layout(pad=2)
plt.savefig('./images/mean_inclusion.png', dpi=fig.dpi)
plt.show()
```

executed in 718ms, finished 13:54:46 2021-02-26



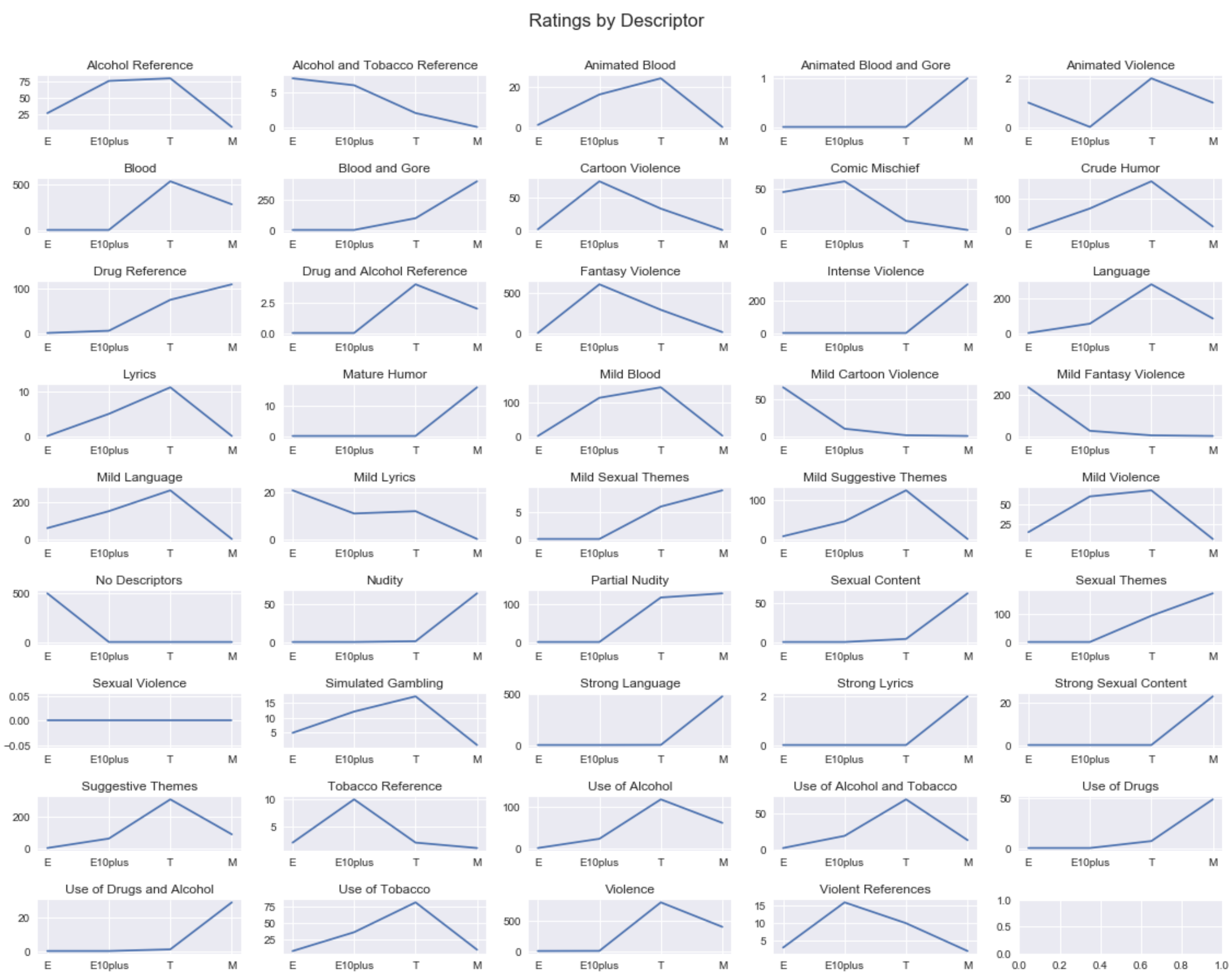
Here we can see some general indicators. Blood and Gore/Strong Language are strong indicators for M-rated games. Fantasy Violence is a very strong indicator for E10plus. No Descriptors seems to apply exclusively to E-rated games. Blood and Violence seem very close for T and M ratings.

In [21]:

```
plt.style.use('seaborn')
fig, axs = plt.subplots(9, 5, figsize=(16,13))
ind = 0
for col in X_train.columns:
    ax1 = ind//5
    ax2 = ind%5
    axs[ax1, ax2].plot(y_train.cat.categories, training_data[training_data[col]==1].rating.value_cou
    axs[ax1, ax2].set_title(col)
    ind += 1

fig.suptitle('Ratings by Descriptor')
fig.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.savefig('./images/ratings_by_descriptor.png', dpi=fig.dpi)
plt.show()
```

executed in 4.49s, finished 13:54:50 2021-02-26



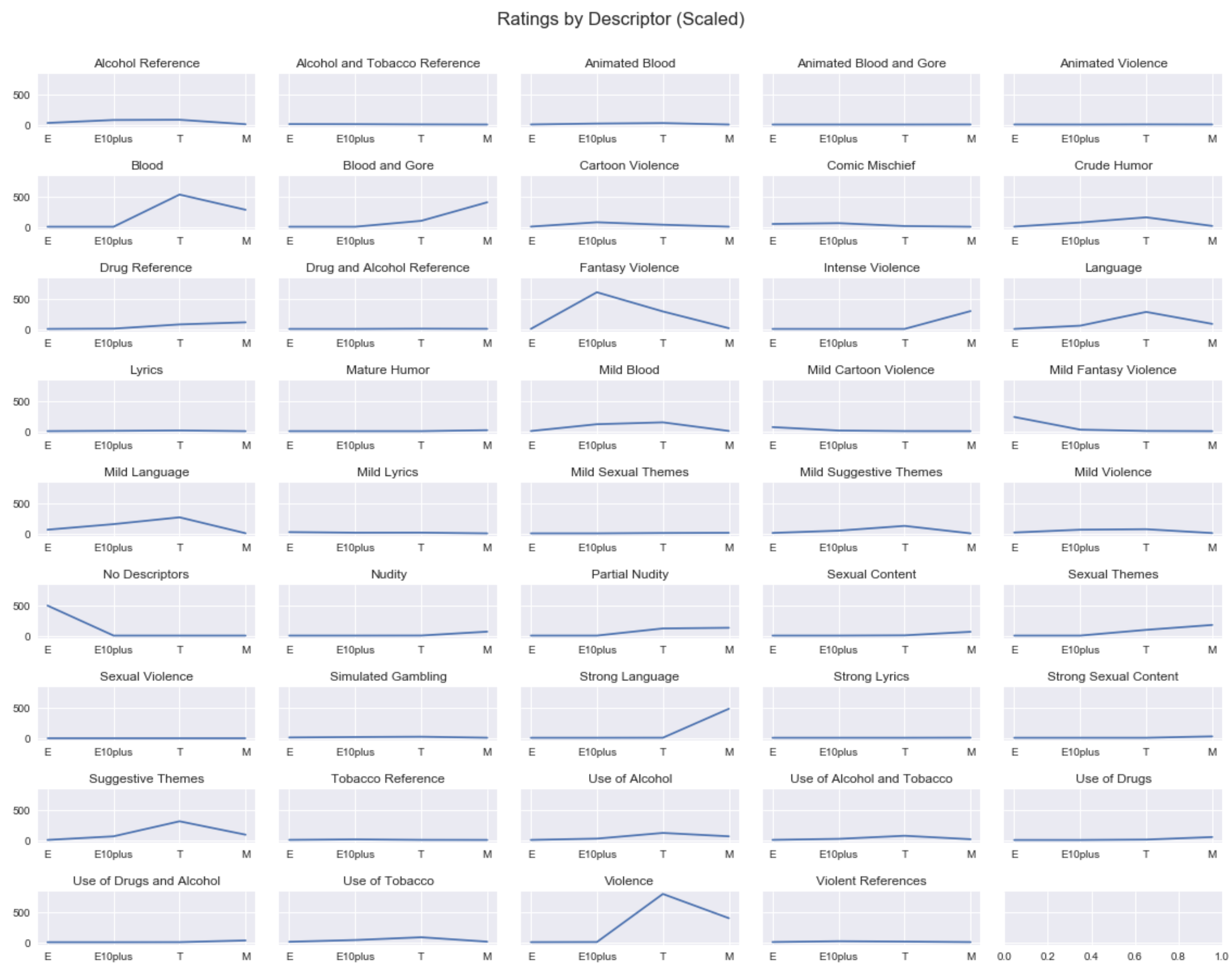
This certainly shows some trends in some descriptors. Intense Violence tends toward M, while Mild Cartoon Violence tends toward E. These subplots are individually scaled, however, and may be misleading in regard to a descriptor's actual importance. By putting all descriptors on the same scale, we can see that many of these descriptors do not appear very frequently at any rating.

In [22]:

```
fig, axs = plt.subplots(9, 5, figsize=(16,13), sharey=True)
ind = 0
for col in X_train.columns:
    ax1 = ind//5
    ax2 = ind%5
    axs[ax1, ax2].plot(y_train.cat.categories, training_data[training_data[col]==1].rating.value_cou
    axs[ax1, ax2].set_title(col)
    ind += 1

fig.suptitle('Ratings by Descriptor (Scaled)')
fig.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.savefig('./images/ratings_by_descriptor_scaled.png', dpi=fig.dpi)
plt.show()
```

executed in 4.21s, finished 13:54:55 2021-02-26



Some descriptors (such as Blood and Violence) seem to trend in an unintuitive way. If we have trouble modeling with these categorical variables, it might be worth it to combine similar descriptors and assign them a value to make them more continuous.

5 Model

Let's test a few models to get a feel for their predictive capabilities for this data.

In [23]:
```
def test_model(est, X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test):
    model = est
    model.fit(X_train, y_train)
    print(est)
    print('Training: {}, Test: {}'.format(model.score(X_train, y_train),
                                          model.score(X_test, y_test)))
    print()
```
executed in 13ms, finished 13:54:55 2021-02-26

In [24]:
```
estimators = [DecisionTreeClassifier(), RandomForestClassifier(),
          KNeighborsClassifier(), SVC()]

for estimator in estimators:
    test_model(estimator)
```
executed in 1.90s, finished 13:54:57 2021-02-26

```
DecisionTreeClassifier()
Training: 0.9305960264900662, Test: 0.8983320095313742

RandomForestClassifier()
Training: 0.9305960264900662, Test: 0.9102462271644162

KNeighborsClassifier()
Training: 0.8908609271523179, Test: 0.8721207307386815

SVC()
Training: 0.9189403973509934, Test: 0.9070691024622717
```

We can use the classification_report from sklearn to get more detailed information about each model's predictions.

In [25]:

```python
def model_stats(estimator, X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test):
    ''' Returns classification report for training and test data'''
    print(estimator)
    print('Training Data:')
    print(classification_report(y_train, estimator.predict(X_train), labels=y.cat.categories))
    print('-----'*10)
    print('Test Data:')
    print(classification_report(y_test, estimator.predict(X_test), labels=y.cat.categories))
    print('-----'*12)
    print('-----'*15)
    print('-----'*12)

for estimator in estimators:
    model_stats(estimator)
```

executed in 1.75s, finished 13:54:58 2021-02-26

```
DecisionTreeClassifier()
Training Data:
              precision    recall  f1-score   support

           E       0.98      0.98      0.98       917
     E10plus       0.87      0.95      0.90       837
           T       0.93      0.88      0.91      1276
           M       0.95      0.94      0.94       745

    accuracy                           0.93      3775
   macro avg       0.93      0.94      0.93      3775
weighted avg       0.93      0.93      0.93      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.95      0.96      0.95       306
     E10plus       0.82      0.90      0.85       279
           T       0.91      0.83      0.87       425
           M       0.92      0.93      0.93       249

    accuracy                           0.90      1259
   macro avg       0.90      0.91      0.90      1259
weighted avg       0.90      0.90      0.90      1259

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---------------------------------------------------------------------------
------------------------------------------------------------
RandomForestClassifier()
Training Data:
              precision    recall  f1-score   support

           E       0.98      0.97      0.98       917
     E10plus       0.88      0.93      0.90       837
           T       0.92      0.90      0.91      1276
           M       0.95      0.93      0.94       745

    accuracy                           0.93      3775
   macro avg       0.93      0.93      0.93      3775
weighted avg       0.93      0.93      0.93      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.95      0.96      0.96       306
     E10plus       0.85      0.89      0.87       279
           T       0.91      0.87      0.89       425
           M       0.94      0.93      0.94       249

    accuracy                           0.91      1259
   macro avg       0.91      0.91      0.91      1259
weighted avg       0.91      0.91      0.91      1259

------------------------------------------------------------
```

```
------------------------------------------------------------------------
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KNeighborsClassifier()
Training Data:
              precision    recall  f1-score   support

           E       0.90      0.98      0.94       917
     E10plus       0.83      0.85      0.84       837
           T       0.90      0.84      0.87      1276
           M       0.94      0.90      0.92       745

    accuracy                           0.89      3775
   macro avg       0.89      0.90      0.89      3775
weighted avg       0.89      0.89      0.89      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.87      0.97      0.92       306
     E10plus       0.78      0.82      0.80       279
           T       0.89      0.81      0.85       425
           M       0.95      0.91      0.93       249

    accuracy                           0.87      1259
   macro avg       0.87      0.88      0.88      1259
weighted avg       0.87      0.87      0.87      1259

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SVC()
Training Data:
              precision    recall  f1-score   support

           E       0.98      0.97      0.97       917
     E10plus       0.85      0.92      0.89       837
           T       0.91      0.88      0.89      1276
           M       0.95      0.92      0.93       745

    accuracy                           0.92      3775
   macro avg       0.92      0.92      0.92      3775
weighted avg       0.92      0.92      0.92      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.97      0.95      0.96       306
     E10plus       0.83      0.91      0.87       279
           T       0.89      0.88      0.89       425
           M       0.95      0.90      0.93       249

    accuracy                           0.91      1259
   macro avg       0.91      0.91      0.91      1259
weighted avg       0.91      0.91      0.91      1259

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```

Initial tests of vanilla models show promising results for the Random Forest model. Let's try to fine-tune the parameters a bit.

In [26]:
```python
param_grid = {
    'n_estimators': [100, 250, 500],
    'criterion': ['gini', 'entropy'],
    'max_depth': [5, 10, None],
    'min_samples_split': [2, 0.05],
    'max_features': ['auto', None]
}

kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)
gridsearch = GridSearchCV(RandomForestClassifier(), param_grid, n_jobs=-1, cv=kfold)
gridsearch.fit(X_train, y_train)

gridsearch.best_params_
```
executed in 1m 45.9s, finished 13:56:44 2021-02-26

Out[26]:
```
{'criterion': 'entropy',
 'max_depth': None,
 'max_features': 'auto',
 'min_samples_split': 2,
 'n_estimators': 100}
```

In [27]:
```python
model_stats(gridsearch.best_estimator_)
```
executed in 173ms, finished 13:56:44 2021-02-26

```
RandomForestClassifier(criterion='entropy')
Training Data:
              precision    recall  f1-score   support

           E       0.98      0.97      0.98       917
     E10plus       0.88      0.93      0.90       837
           T       0.92      0.90      0.91      1276
           M       0.95      0.93      0.94       745

    accuracy                           0.93      3775
   macro avg       0.93      0.93      0.93      3775
weighted avg       0.93      0.93      0.93      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.95      0.96      0.96       306
     E10plus       0.85      0.90      0.87       279
           T       0.92      0.87      0.89       425
           M       0.93      0.94      0.94       249

    accuracy                           0.91      1259
   macro avg       0.91      0.92      0.91      1259
weighted avg       0.91      0.91      0.91      1259

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```

91% accuracy with 93% recall on M-rated games, which is the same as our vanilla Random Forest. These are mostly the default values, with the exception of n_estimators. It seems a higher number of trees leads to better predictions.

In [28]:
```python
param_grid = {
    'n_estimators': [250, 500, 750, 1000, 1500]
}

gridsearch2 = GridSearchCV(RandomForestClassifier(), param_grid, n_jobs=-1, cv=kfold)
gridsearch2.fit(X_train, y_train)

gridsearch2.best_params_
```
executed in 23.9s, finished 13:57:08 2021-02-26

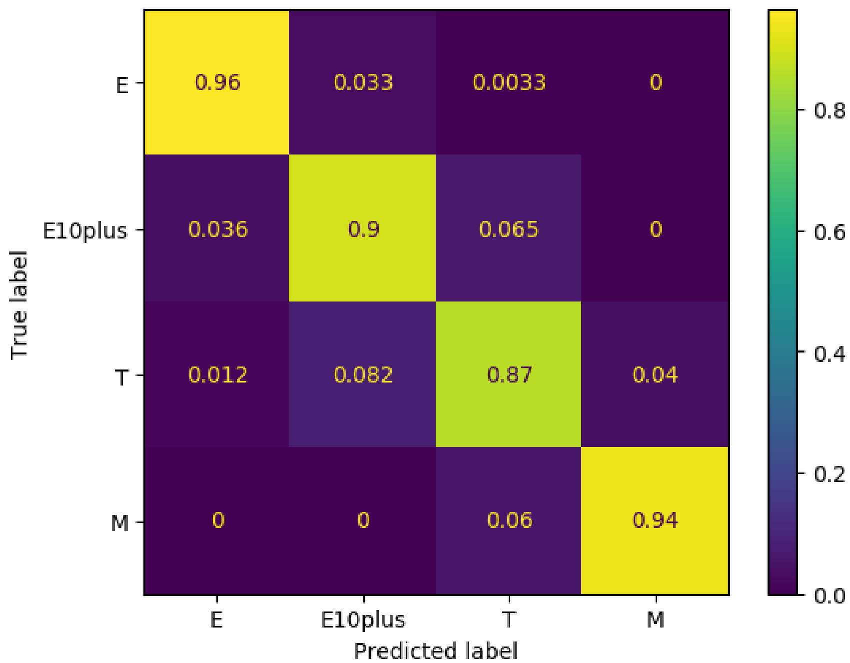
Out[28]:
```
{'n_estimators': 750}
```

Looks like 250 is the best value for n_estimators.

Let's get a better picture of the predictions.

In [29]:
```
plt.style.use('default')
plot_confusion_matrix(gridsearch.best_estimator_, X_test, y_test,
                      normalize='true', labels=y.cat.categories)
```
executed in 246ms, finished 13:57:09 2021-02-26

Out[29]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1c216430898>



This seems like a good model. My main concern is not overly misclassifying M-rated games, and this model classifies less than 7% as T and none as E or E10.

I'd like to try out XGBoost to see if it can offer any improvement.

In [30]:
```
xgb = XGBClassifier()
xgb.fit(X_train, y_train)

xgb.score(X_test, y_test)
```
executed in 1.08s, finished 13:57:10 2021-02-26

Out[30]: 0.8784749801429707

In [31]:
```
model_stats(xgb)
```
executed in 124ms, finished 13:57:10 2021-02-26

```
XGBClassifier(objective='multi:softprob')
Training Data:
              precision    recall  f1-score   support

           E       0.93      0.97      0.95       917
     E10plus       0.81      0.88      0.84       837
           T       0.89      0.83      0.86      1276
           M       0.94      0.90      0.92       745

    accuracy                           0.89      3775
   macro avg       0.89      0.89      0.89      3775
weighted avg       0.89      0.89      0.89      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.93      0.95      0.94       306
     E10plus       0.77      0.90      0.83       279
           T       0.88      0.81      0.84       425
           M       0.94      0.89      0.92       249

    accuracy                           0.88      1259
   macro avg       0.88      0.89      0.88      1259
weighted avg       0.88      0.88      0.88      1259

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```
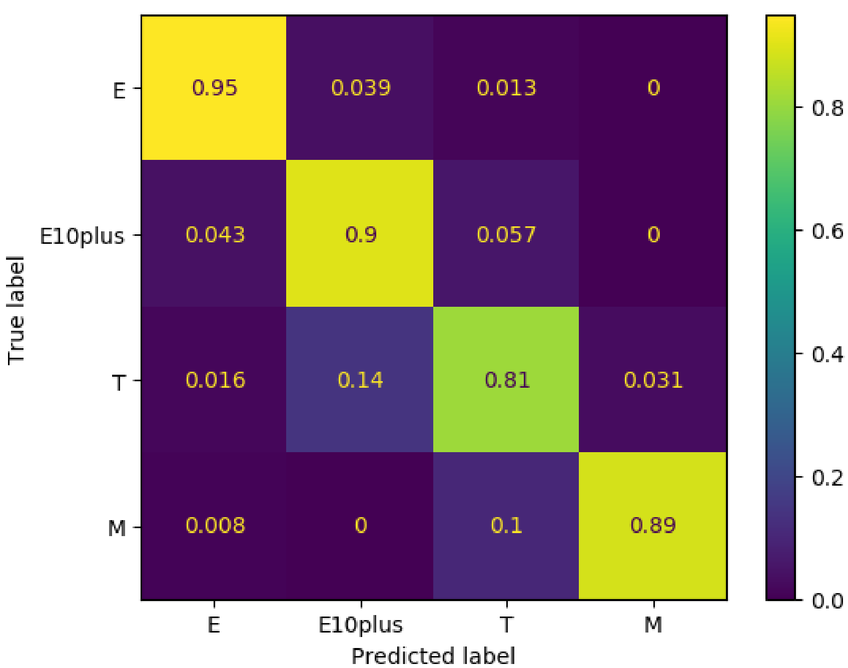

In [32]:
```
plot_confusion_matrix(xgb, X_test, y_test,
                      normalize='true', labels=y.cat.categories)
```
executed in 213ms, finished 13:57:10 2021-02-26

Out[32]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1c2167e4ba8>



This is definitely not an improvement, but let's tweak the hyperparameters and see what kind of results we can get.

In [33]:

```
param_grid = {
    'max_depth': [3, 5],
    'booster': ['gbtree', 'dart'],
    'learning_rate': [0.1, 0.2],
    'n_estimators': [100, 500],
}

grid = GridSearchCV(XGBClassifier(), param_grid, n_jobs=-1, cv=kfold)
grid.fit(X_train, y_train)

grid.best_params_
```

executed in 6m 37s, finished 14:03:47 2021-02-26

Out[33]:

```
{'booster': 'gbtree',
 'learning_rate': 0.2,
 'max_depth': 5,
 'n_estimators': 100}
```

In [34]:

```
grid.score(X_test, y_test)
```

executed in 31ms, finished 14:03:47 2021-02-26

Out[34]:

```
0.9110405083399523
```

In [35]:

```
model_stats(grid.best_estimator_)
```

executed in 138ms, finished 14:03:47 2021-02-26

```
XGBClassifier(learning_rate=0.2, max_depth=5, objective='multi:softprob')
Training Data:
              precision    recall  f1-score   support

           E       0.97      0.97      0.97       917
     E10plus       0.86      0.91      0.88       837
           T       0.90      0.88      0.89      1276
           M       0.95      0.92      0.93       745

    accuracy                           0.92      3775
   macro avg       0.92      0.92      0.92      3775
weighted avg       0.92      0.92      0.92      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.96      0.95      0.96       306
     E10plus       0.84      0.91      0.87       279
           T       0.90      0.88      0.89       425
           M       0.95      0.91      0.93       249

    accuracy                           0.91      1259
   macro avg       0.91      0.91      0.91      1259
weighted avg       0.91      0.91      0.91      1259

------------------------------------------------------------
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```
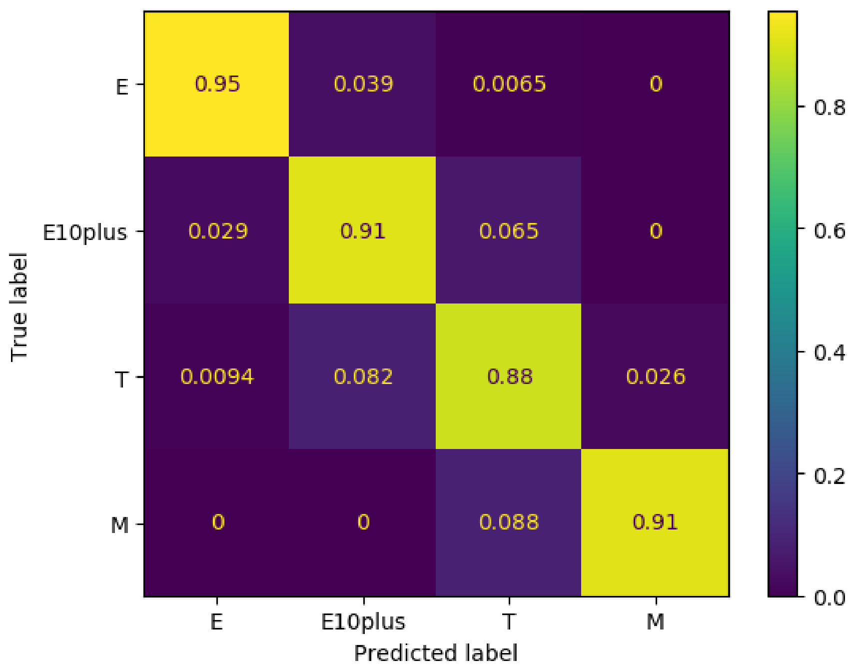

In [36]:
```
plot_confusion_matrix(grid.best_estimator_, X_test, y_test,
                      normalize='true', labels=y.cat.categories)
```
executed in 230ms, finished 14:03:48 2021-02-26

Out[36]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1c21672eeb8>



A bit of improvement. Let's tweak a little more.

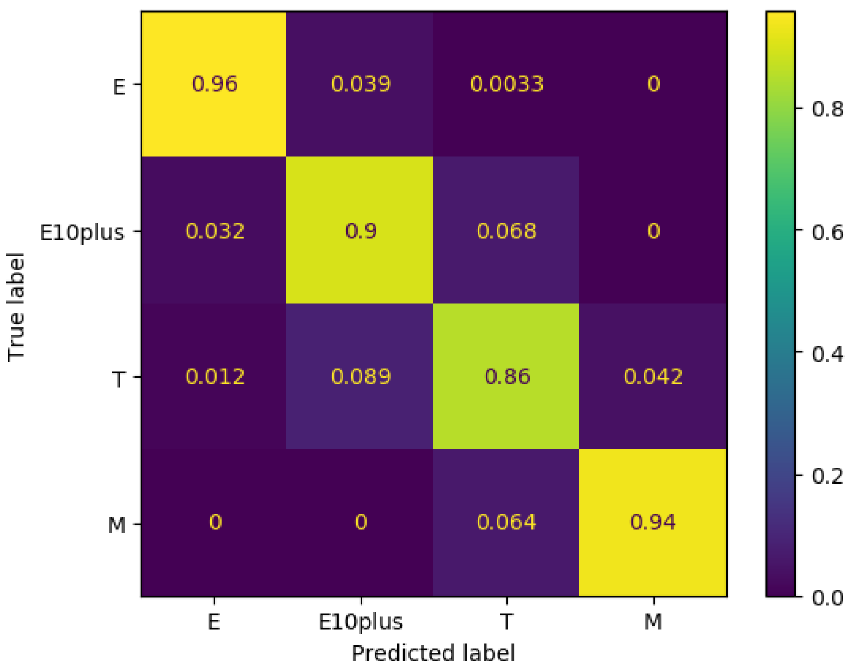
In [37]:
```
param_grid = {
    'max_depth': [5,7],
    'learning_rate': [0.2, 0.25],
    'n_estimators': [100, 500]
}

grid = GridSearchCV(XGBClassifier(), param_grid, n_jobs=-1, cv=3)
grid.fit(X_train, y_train)

grid.best_params_
```
executed in 29.1s, finished 14:04:17 2021-02-26

Out[37]: {'learning_rate': 0.25, 'max_depth': 7, 'n_estimators': 500}

In [38]:
```
plot_confusion_matrix(grid.best_estimator_, X_test, y_test,
                      normalize='true', labels=y.cat.categories)
```

executed in 296ms, finished 14:04:17 2021-02-26

Out[38]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1c2169297f0>



This shows definite improvements to recall for E and M, but at the cost of a small recall dip for E10plus and T. I think it's a good trade.

In [39]:

```python
xgb = XGBClassifier()
param_grid = {
    'max_depth': [7, 9],
    'learning_rate': [0.25, 0.3],
    'n_estimators': [500, 1000]
}
grid_search = GridSearchCV(xgb, param_grid,
                           n_jobs=-1, cv=kfold)
grid_result=grid_search.fit(X_train, y_train)

print('Best %f using %s' % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print('%f (%f) with: %r' % (mean, stdev, param))
```

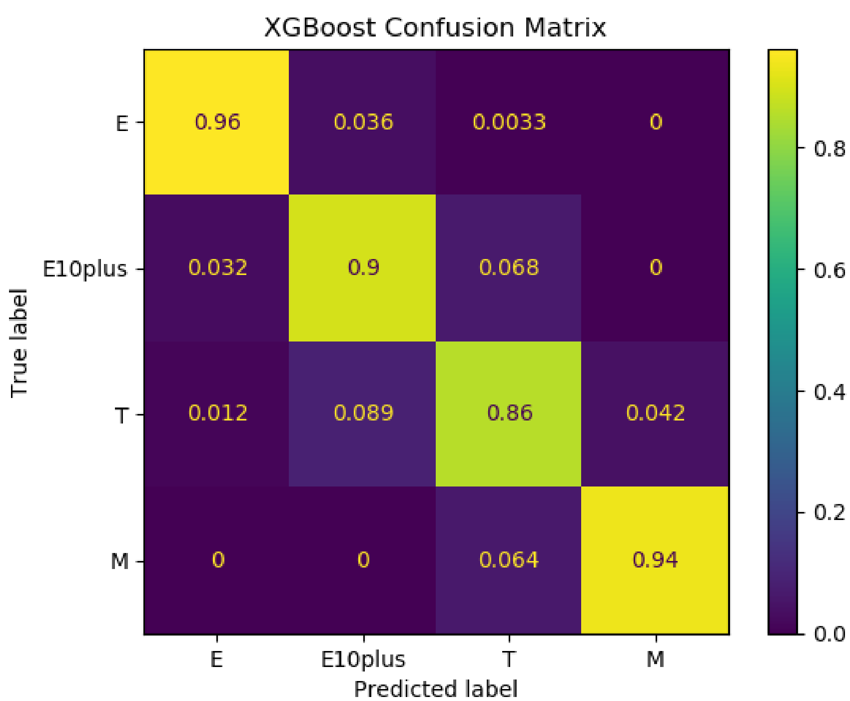
executed in 4m 15s, finished 14:08:32 2021-02-26

```
Best 0.894298 using {'learning_rate': 0.3, 'max_depth': 7, 'n_estimators': 500}
0.892973 (0.008731) with: {'learning_rate': 0.25, 'max_depth': 7, 'n_estimators': 500}
0.892710 (0.008796) with: {'learning_rate': 0.25, 'max_depth': 7, 'n_estimators': 1000}
0.892708 (0.008487) with: {'learning_rate': 0.25, 'max_depth': 9, 'n_estimators': 500}
0.892442 (0.009657) with: {'learning_rate': 0.25, 'max_depth': 9, 'n_estimators': 1000}
0.894298 (0.008335) with: {'learning_rate': 0.3, 'max_depth': 7, 'n_estimators': 500}
0.893770 (0.007603) with: {'learning_rate': 0.3, 'max_depth': 7, 'n_estimators': 1000}
0.892176 (0.010083) with: {'learning_rate': 0.3, 'max_depth': 9, 'n_estimators': 500}
0.892176 (0.011078) with: {'learning_rate': 0.3, 'max_depth': 9, 'n_estimators': 1000}
```

In [40]:

```python
plot_confusion_matrix(grid_result, X_test, y_test, normalize='true', labels=y.cat.categories)
plt.title('XGBoost Confusion Matrix')
plt.savefig('./images/best_confusion_matrix.png', dpi=fig.dpi)
```

executed in 376ms, finished 14:08:33 2021-02-26



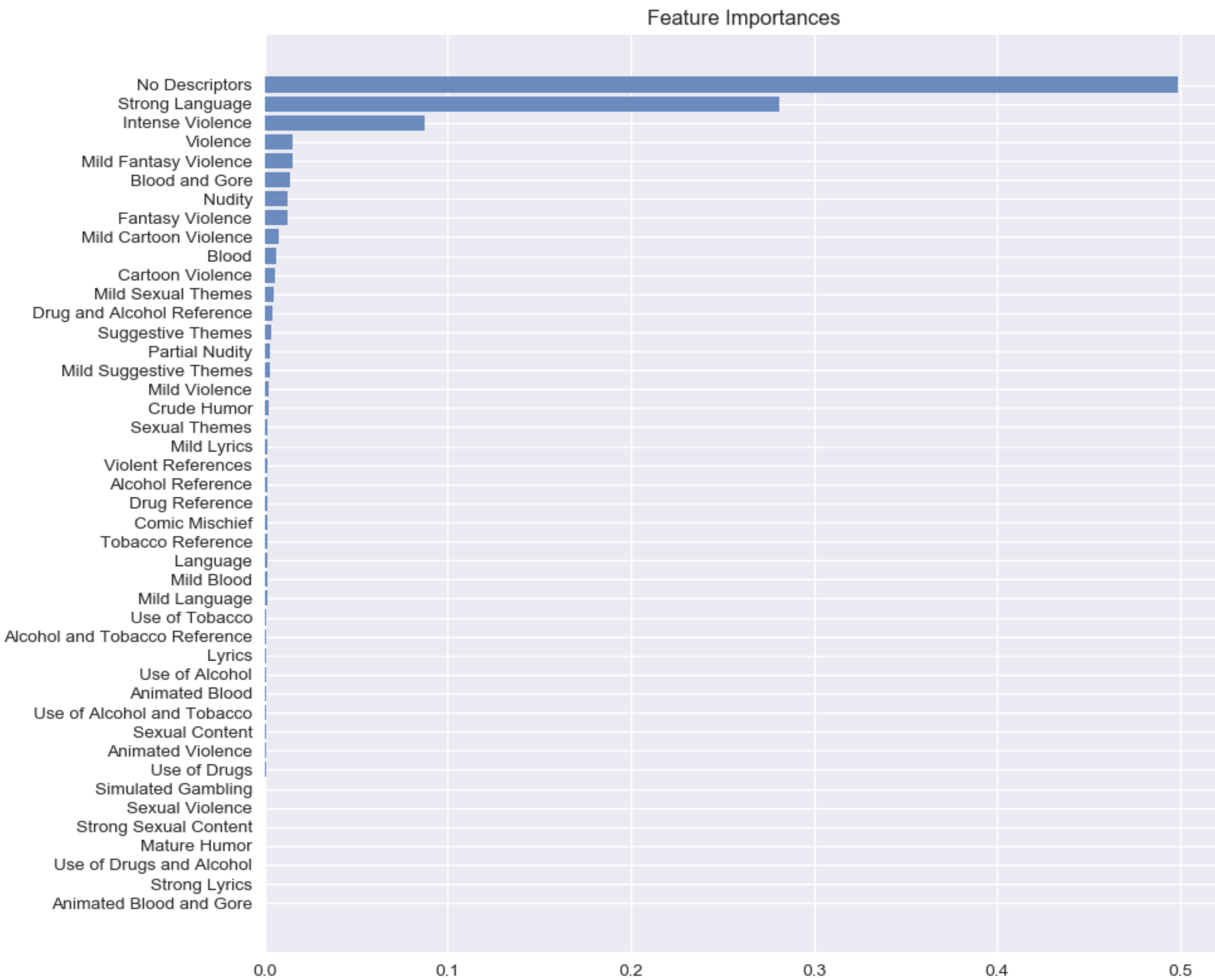
In [41]:
```
1 model_stats(grid_result.best_estimator_, X_train, X_test, y_train, y_test)
```
executed in 469ms, finished 14:08:33 2021-02-26

```
XGBClassifier(learning_rate=0.3, max_depth=7, n_estimators=500,
              objective='multi:softprob')
Training Data:
              precision    recall  f1-score   support

           E       0.98      0.97      0.98       917
     E10plus       0.88      0.93      0.90       837
           T       0.92      0.90      0.91      1276
           M       0.95      0.92      0.94       745

    accuracy                           0.93      3775
   macro avg       0.93      0.93      0.93      3775
weighted avg       0.93      0.93      0.93      3775

--------------------------------------------------
Test Data:
              precision    recall  f1-score   support

           E       0.95      0.96      0.96       306
     E10plus       0.84      0.90      0.87       279
           T       0.91      0.86      0.88       425
           M       0.93      0.94      0.93       249

    accuracy                           0.91      1259
   macro avg       0.91      0.91      0.91      1259
weighted avg       0.91      0.91      0.91      1259

------------------------------------------------------------
---------------------------------------------------------------------------
------------------------------------------------------------
```

In [42]:

```
feature_dict = {k:v for (k,v) in zip(X_train.columns, grid_result.best_estimator_.feature_importance
feature_dict = {'Feature': feature_dict.keys(), 'Importance': feature_dict.values()}
fi_df = pd.DataFrame(feature_dict)
fi_df = fi_df.iloc[fi_df.Importance.argsort()]
fi_df
plt.style.use('seaborn')
fig,ax = plt.subplots(figsize=(10,8))
plt.barh(fi_df.Feature, fi_df.Importance, alpha=0.8)
plt.title('Feature Importances')
plt.tight_layout()
plt.savefig('./images/feature_importances', dpi=fig.dpi)
plt.show()
```

executed in 816ms, finished 14:08:34 2021-02-26



'No Descriptors' is the most important feature by far, followed by 'Strong Language' and 'Intense Violence.' There are seven features with zero importance to the model, however, I hesitate to remove them from the model since some ('Strong Sexual Content', 'Sexual Violence', 'Use of Drugs and Alcohol') seem like they would, in fact, be good indicators of M-rated games should more games with those descriptors be released in the future.

6 iNterpret

6.1 Best model: XGBoost

In [43]:
```
print('Best Model: {}'.format(grid_result.best_estimator_))
print(classification_report(y_test, grid_result.best_estimator_.predict(X_test),
      labels=y.cat.categories))
```

executed in 140ms, finished 14:08:34 2021-02-26

```
Best Model: XGBClassifier(learning_rate=0.3, max_depth=7, n_estimators=500,
              objective='multi:softprob')
              precision    recall  f1-score   support

           E       0.95      0.96      0.96       306
     E10plus       0.84      0.90      0.87       279
           T       0.91      0.86      0.88       425
           M       0.93      0.94      0.93       249

    accuracy                           0.91      1259
   macro avg       0.91      0.91      0.91      1259
weighted avg       0.91      0.91      0.91      1259
```

After some tweaking, our best model is XGBoost. With this model, we get 94% recall on M-rated games, which I believe is the most important label to classify correctly. As we can see from the confusion matrix, however, there is some confusion between T and M ratings. We should look into the data to see if we can identify the problem.

6.2 Identifying the reasons for misclassification

In [44]:

```
# training data with predictions attached
training_with_preds = training_data.copy()
training_with_preds['prediction'] = grid_result.predict(X_train)

training_with_preds.head()
```

executed in 296ms, finished 14:08:34 2021-02-26

Out[44]:

	Alcohol Reference	Alcohol and Tobacco Reference	Animated Blood	Animated Blood and Gore	Animated Violence	Blood	Blood and Gore	Cartoon Violence	Comic Mischief	Crude Humor	...	Tobacco Reference	Use of Alcohol	A To
1881	0	0	0	0	0	1	0	0	0	0	...	0	0	
2346	0	0	0	0	0	0	0	0	0	0	...	0	0	
525	0	0	0	0	0	1	0	0	0	0	...	0	0	
1215	0	0	0	0	0	0	0	0	0	0	...	0	0	
603	0	0	0	0	0	0	1	0	0	0	...	0	0	

5 rows × 46 columns

In [45]:

```
# dataframe of misclassified games
wrong_df = training_with_preds[training_with_preds['rating']!=training_with_preds['prediction']]
wrong_df.shape
```

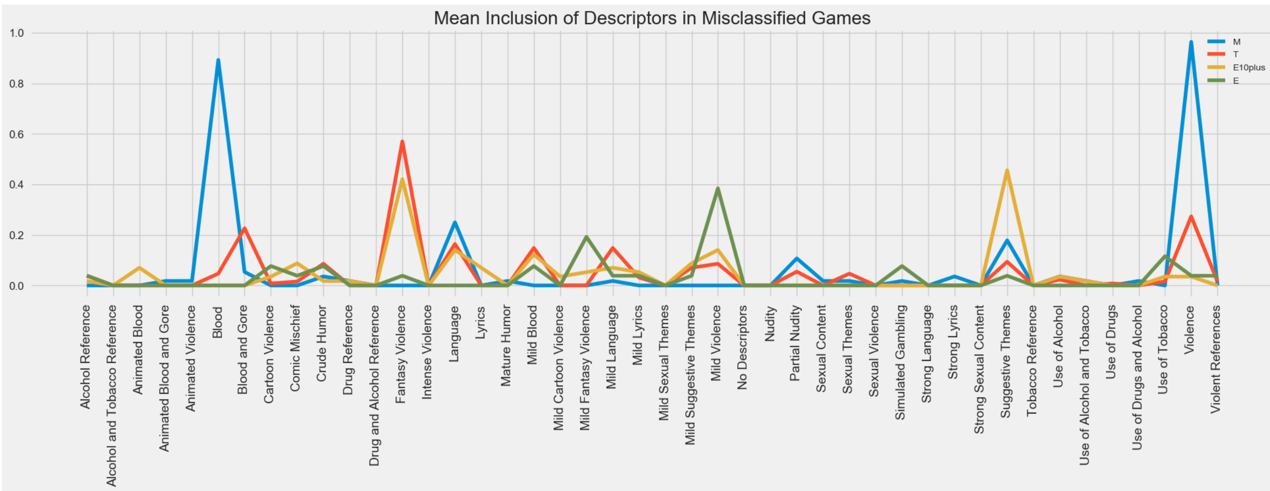
executed in 14ms, finished 14:08:34 2021-02-26

Out[45]: (267, 46)

267 games misclassified in the training set. What are the prominent descriptors in these games?

In [46]:
```
# plot of descriptor frequency
plt.style.use('fivethirtyeight')
fig, ax = plt.subplots(figsize=(20,8))
for r in y.cat.categories[::-1]:
    plt.plot(wrong_df.drop(columns=['prediction'])[wrong_df.rating==r].mean(), label=r)

plt.xticks(rotation=90)
plt.title('Mean Inclusion of Descriptors in Misclassified Games')
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.legend()
plt.tight_layout(pad=2)
plt.savefig('./images/mean_misclassified.png', dpi=fig.dpi)
plt.show()
```

executed in 833ms, finished 14:08:35 2021-02-26



> We can see here that about 90% of misclassified M-rated games contained the 'Blood' descriptor and about 95% percent had the 'Violence' descriptor. 'Fantasy Violence' was used as a descriptor for about 60% of T-rated games and 40% of E10plus games. About 40% of misclassified E-rated games had the descriptor 'Mild Violence.' There are also a decent spike for 'Suggestive Themes' in E10plus games.

Since 'Blood' and 'Violence' are the most promiment for M-rated games, let's look at the games that contain those descriptors.

6.3 A deeper look into Blood and Violence

In [47]:
```python
# dataframe of misclassified games containing blood or violence
bv_df = wrong_df[(wrong_df['Blood']==1) | (wrong_df['Violence']==1)]
# filter out columns that are no longer relevant
bv_df = bv_df.loc[:, (bv_df != 0).any(axis=0)]
display(bv_df.head())
bv_df.shape
```

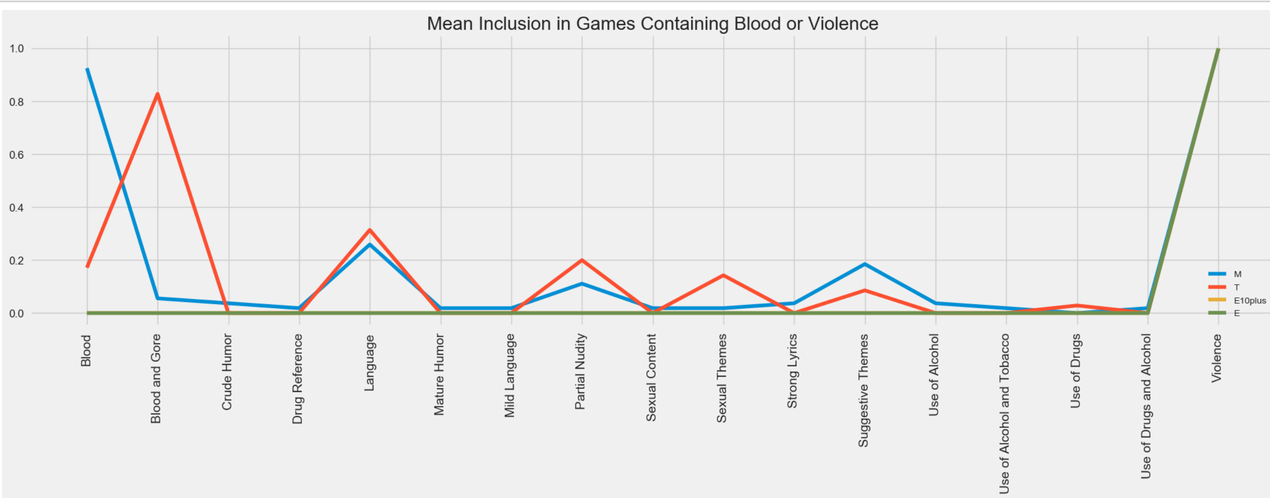
executed in 30ms, finished 14:08:35 2021-02-26

	Blood	Blood and Gore	Crude Humor	Drug Reference	Language	Mature Humor	Mild Language	Partial Nudity	Sexual Content	Sexual Themes	Strong Lyrics	Suggestive Themes	Use of Alcohol	U Al Tol
1881	1	0	0	1	1	0	0	0	0	1	0	0	0	
603	0	1	0	0	0	0	0	0	0	0	0	0	0	
3113	0	1	1	0	0	0	0	0	0	0	0	0	0	
107	1	0	0	0	0	0	0	0	0	0	0	1	0	
4720	1	0	0	0	0	0	0	0	0	0	0	1	0	

Out[47]: (92, 19)

In [48]:
```python
# plot frequency
fig, ax = plt.subplots(figsize=(20,8))
for r in y.cat.categories[::-1]:
    plt.plot(bv_df.drop(columns=['prediction'])[bv_df.rating==r].mean(), label=r)

plt.xticks(rotation=90)
plt.title('Mean Inclusion in Games Containing Blood or Violence')
plt.xticks(fontsize=14)
plt.yticks(fontsize=12)
plt.legend()
plt.tight_layout(pad=2)
plt.savefig('./images/mean_blood_or_violence.png', dpi=fig.dpi)
plt.show()
```

executed in 472ms, finished 14:08:36 2021-02-26



This graph shows mean descriptor inclusion in all misclassified games containing 'Blood' or 'Violence.' As we can see, most misclassified M-ratings contain 'Blood,' while an almost equal percentage of misclassified T-ratings contain 'Blood and Gore.'

What about games where 'Blood' and 'Violence' are the only descriptors?

In [49]:
```
# dataframe of all training data including blood and violence
bv_df2 = training_with_preds[(training_with_preds['Blood']==1) & training_with_preds['Violence']==1]
# drop any rows containing any other descriptor
bv_df2 = bv_df2.drop(index=[bv_df2.index[i] for i in range(len(bv_df2))
                            if bv_df2.loc[:, 'Alcohol Reference':'Violent References'].iloc[i].sum()
bv_df2
```

executed in 421ms, finished 14:08:36 2021-02-26

Out[49]:

	Alcohol Reference	Alcohol and Tobacco Reference	Animated Blood	Animated Blood and Gore	Animated Violence	Blood	Blood and Gore	Cartoon Violence	Comic Mischief	Crude Humor	...	Tobacco Reference	Use of Alcohol	A Tc
4397	0	0	0	0	0	1	0	0	0	0	...	0	0	
1394	0	0	0	0	0	1	0	0	0	0	...	0	0	
4601	0	0	0	0	0	1	0	0	0	0	...	0	0	
4758	0	0	0	0	0	1	0	0	0	0	...	0	0	
2863	0	0	0	0	0	1	0	0	0	0	...	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
3613	0	0	0	0	0	1	0	0	0	0	...	0	0	
2822	0	0	0	0	0	1	0	0	0	0	...	0	0	
3442	0	0	0	0	0	1	0	0	0	0	...	0	0	
1030	0	0	0	0	0	1	0	0	0	0	...	0	0	
1252	0	0	0	0	0	1	0	0	0	0	...	0	0	

177 rows × 46 columns

In [50]:
```
# rows with correct predictions
bv_df2[bv_df2.rating == bv_df2.prediction].rating.value_counts()
```

executed in 14ms, finished 14:08:36 2021-02-26

Out[50]:
```
T          152
M            0
E10plus      0
E            0
Name: rating, dtype: int64
```

177 games from our training set have 'Blood' and 'Violence' as their only descriptors. Our model correctly identified 152 of them as T-rated games, but there was no way for the model to identify the other 25 as being M-rated games.

6.4 What have we learned?

While the XGBoost model is very effective at classifying games based on the given descriptors, it is limited by inconsistent labeling by the ESRB. As we saw above, games with identical descriptors are sometimes given different ratings.

This doesn't seem ideal, as it puts the burden on the consumer to determine for themselves what those descriptors might mean in the context of the overall rating. If a game is rated T for Blood and Violence, how is that different from a game rated M for Blood and Violence? Rather that put that burden on the consumer, the ESRB should focus on a more unified and transparent rating system.

6.5 Recommendation

The ESRB seems to default to more generalized descriptors in spite of the fact that that there are more specific descriptors available. Better, more frequent use of these more descriptive content warnings would be helpful both to consumers and the predictive algorithm.

Another option would be to use more descriptors. What sets an M-rated game with Blood and Violence apart from a T-rated game? It could be Dark Themes, Horror, or Disturbing Imagery. Anything that could cement the reason that one game is rated for more mature audiences than the other would be helpful.