In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
import matplotlib.pyplot as plt
import dtreeviz
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, accuracy_scor
```

# Data Preparation

In [ ]:
```
df = pd.read_csv("./data/nan_removed_cleaned_data.csv")
df.columns
```

Out[ ]:
```
Index(['budget', 'genres', 'id', 'imdb_id', 'original_title', 'overview',
       'popularity', 'poster_path', 'release_date', 'revenue', 'runtime',
       'spoken_languages', 'tagline', 'title', 'vote_average', 'vote_count',
       'log_popularity', 'title_length', 'num_languages', 'num_genres',
       'imdb_rating', 'imdb_budget', 'imdb_revenue', 'budget_currency',
       'revenue_currency', 'converted_budget', 'converted_revenue',
       'combined_budget', 'combined_revenue'],
      dtype='object')
```

Note: Python's sklearn decision trees functionality can only work with numeric data.

Looking at our columns above, the only non-numeric columns that *could* contribute to our decision trees are:

- genres
- spoken_languages
- release_date

It's not a huge deal if we disregard `genres` and `spoken_languages`, since we already have `num_genres` and `num_languages` respectively.

However, the `release_date` could prove very useful in our supervised learning. Let's convert this column to its unix timestamp equivalent:

In [ ]:
```
# Convert our datetime objects to Unix timestamps
df['release_unix'] = pd.to_datetime(df['release_date'])
df['release_unix'] = df.release_unix.values.astype(np.int64) // 10 ** 9

# Select specific columns
df = df[['runtime', 'vote_count', 'log_popularity', 'title_length', 'num_languages'
          'num_genres', 'imdb_rating', 'combined_budget', 'combined_revenue', 'rele

# We only want data where we have an IMDB rating
df = df[df['imdb_rating'].notna()]

df.describe()
```

Out[ ]:

| | runtime | vote_count | log_popularity | title_length | num_languages | num_genres | i |
|---|---|---|---|---|---|---|---|
| **count** | 13894.000000 | 13894.000000 | 13894.000000 | 13894.000000 | 13894.000000 | 13894.000000 | 13 |
| **mean** | 79.427235 | 411.985605 | 1.287343 | 16.518497 | 1.194185 | 1.886066 | |
| **std** | 39.160793 | 1570.239035 | 0.958684 | 9.578765 | 0.589630 | 1.022621 | |
| **min** | 0.000000 | 0.000000 | 0.470004 | 1.000000 | 1.000000 | 1.000000 | |
| **25%** | 70.000000 | 1.000000 | 0.470004 | 10.000000 | 1.000000 | 1.000000 | |
| **50%** | 90.000000 | 6.000000 | 0.875469 | 14.000000 | 1.000000 | 2.000000 | |
| **75%** | 101.000000 | 79.000000 | 1.963013 | 20.000000 | 1.000000 | 3.000000 | |
| **max** | 540.000000 | 27894.000000 | 8.270913 | 112.000000 | 8.000000 | 8.000000 | |

Now we have our numeric data.

For most machine learning techniques (including this one), we need to separate our data into a training and testing set.

In [ ]:

```
# Separate into train and test
train = df.sample(frac=0.8,random_state=1612)
test = df.drop(train.index)
```

Additionally, we need to assign labels to our data.

For this, we can use the IMDB ratings, putting them into bins.

Let's do 1-5.99 and 6-10 as bad(0) and good(1) respectively:

In [ ]:

```
def num_ranking(entry):
    if entry['imdb_rating'] >= 6:
        return 1
    else:
        return 0

class_names = ['bad', 'good']

# Apply to train and test separately
train_labels = train.apply(num_ranking, axis=1)
test_labels = test.apply(num_ranking, axis=1)

# Now, drop the imdb_rating column from each
train = train.drop('imdb_rating', axis=1)
test = test.drop('imdb_rating', axis=1)

display(train_labels.value_counts())
test_labels.value_counts()
```

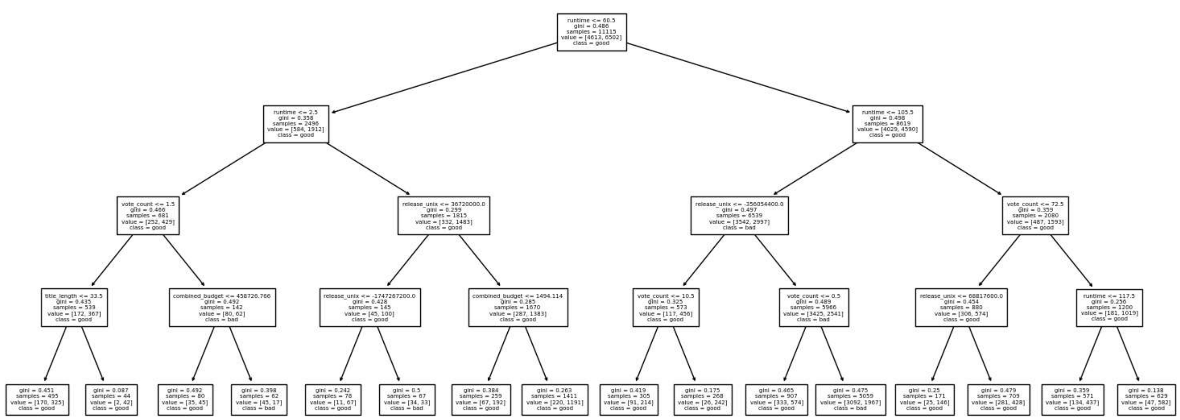
```
1    6502
0    4613
dtype: int64
```

Out[ ]:
```
1    1651
0    1128
dtype: int64
```

Perfect! Now we can apply a decision tree to this data.

# Decision Tree

In [ ]:
```
# Prepare the decision tree
film_DT = DecisionTreeClassifier(criterion='gini',
                                 splitter='best',
                                 max_depth=4,
                                 min_samples_split=2,
                                 random_state=None,
                                 max_leaf_nodes=None,
                                 min_impurity_decrease=0.0)

# Fit to our training data
film_DT.fit(train, train_labels)
# Plot our tree
fig = plt.figure(figsize=(15, 6))
tree.plot_tree(film_DT,
               max_depth=None,
               feature_names=train.columns,
               class_names=class_names,
               fontsize=5)
fig.tight_layout()
plt.savefig('./imgs/dt_ims/tree_plot.png')
```



We can also visualize this tree based on distributions of values within each node:

In [ ]:
```
viz = dtreeviz.model(film_DT, train, train_labels,
                     target_name="target",
                     feature_names=list(train.columns),
                     class_names=class_names)

viszualization = viz.view().show()
```

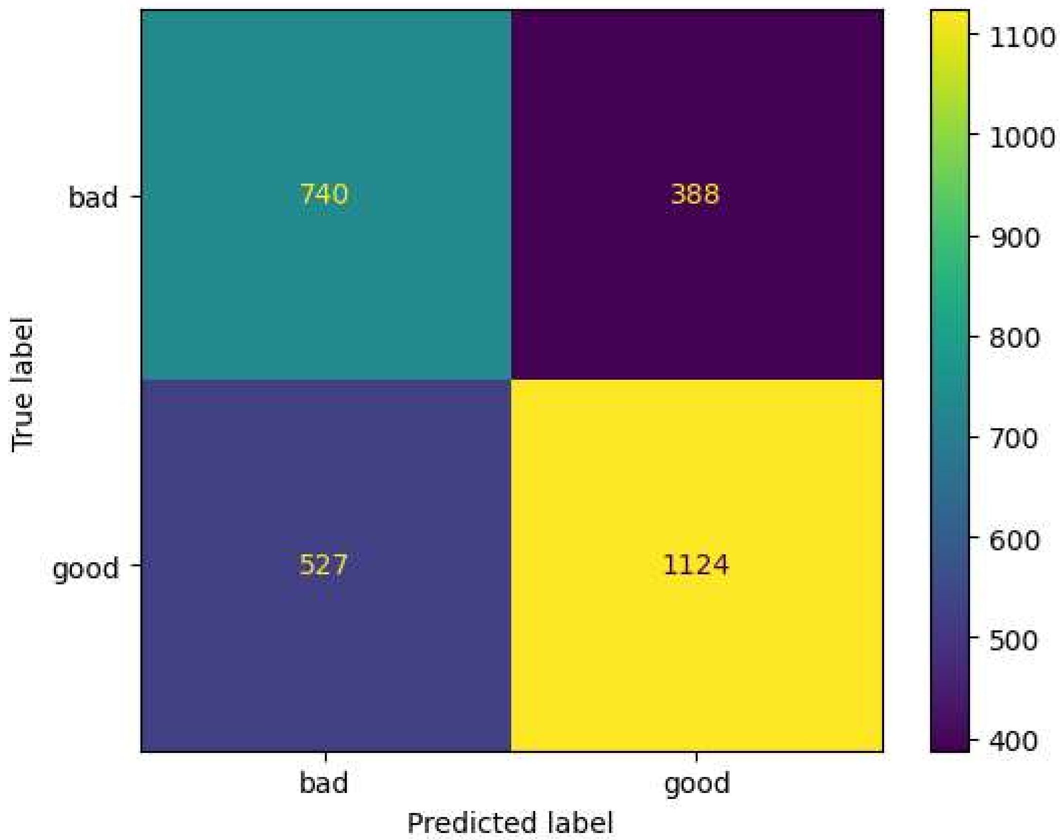
```
C:\Users\Peter\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2k
fra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\base.py:450: User
Warning: X does not have valid feature names, but DecisionTreeClassifier was fitte
d with feature names
```

And we can calculate metrics for our Decision Tree performance on the test set

In [ ]:

```python
feature_names = train.columns
# Show the predictions from the DT on the test set
DT_pred = film_DT.predict(test)

# Show the confusion matrix
bn_matrix = confusion_matrix(test_labels, DT_pred)
print("\nThe confusion matrix is:")
disp = ConfusionMatrixDisplay(bn_matrix, display_labels=class_names)
disp.plot()
plt.savefig('./imgs/dt_ims/confusion_matrix.png')
plt.show()

# Print out metrics
print("Metrics for Test Data")
print("---------------------")
print(f"Accuracy: {accuracy_score(test_labels, DT_pred)}")

test_prec, test_recall, test_f1, test_support = precision_recall_fscore_support(tes
print("Precision:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_prec[idx]}")

print("Recall:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_recall[idx]}")

print("F1 Score:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_f1[idx]}")

print("Support:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_support[idx]}")


FeatureImp = film_DT.feature_importances_
indices = np.argsort(FeatureImp)[::-1]
# Print out the important features:
print("\nImportant Features:")
for f in range(train.shape[1]):
    if FeatureImp[indices[f]] > 0:
        print(f"{f+1}. Feature {feature_names[indices[f]]} ({FeatureImp[indices[f]]
```

```
The confusion matrix is:
```

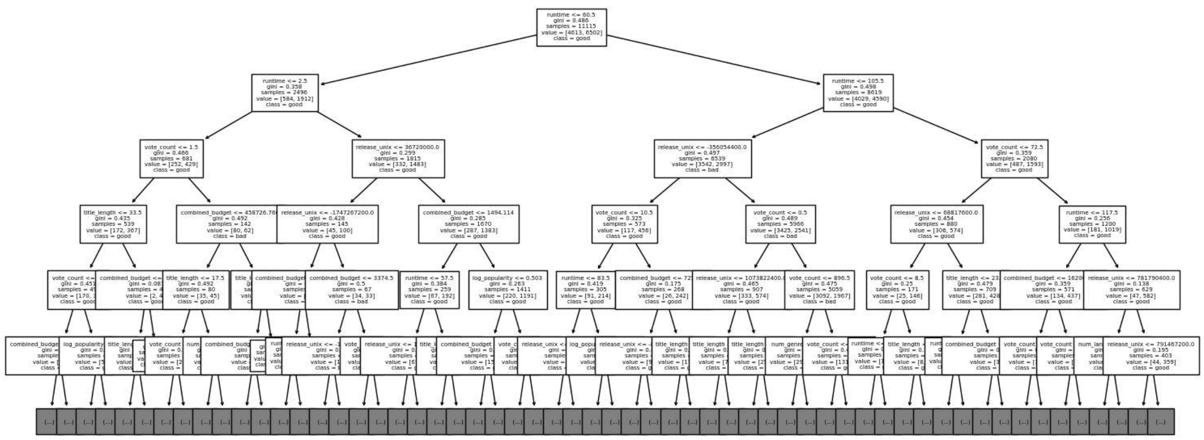



```
Metrics for Test Data
---------------------
Accuracy: 0.6707448722562073
Precision:
    ->bad: 0.5840568271507498
    ->good: 0.7433862433862434
Recall:
    ->bad: 0.6560283687943262
    ->good: 0.6807995154451847
F1 Score:
    ->bad: 0.6179540709812109
    ->good: 0.7107176730951629
Support:
    ->bad: 1128
    ->good: 1651

Important Features:
1. Feature runtime (0.6160903553221975)
2. Feature release_unix (0.1928014704755356)
3. Feature vote_count (0.171723134749567)
4. Feature combined_budget (0.011483644968251055)
5. Feature title_length (0.007901394484448878)
```

We also want to show what happens when we don't limit the depth of our tree:

In [ ]:
```
#Prepare the decision tree
film_DT_large = DecisionTreeClassifier(criterion='gini',
                            splitter='best',
                            min_samples_split=2,
                            random_state=None,
```

```
                              max_leaf_nodes=None,
                              min_impurity_decrease=0.0)

# Fit to our training data
film_DT_large.fit(train, train_labels)
# Plot our tree
fig = plt.figure(figsize=(15, 6))
tree.plot_tree(film_DT_large,
               max_depth=5,
               feature_names=train.columns,
               class_names=class_names,
               fontsize=5)
fig.tight_layout()
plt.savefig('./imgs/dt_ims/tree_plot_large.png')
```



```
In [ ]: print(f'The large, un-restricted decision tree has depth {film_DT_large.get_depth()
```

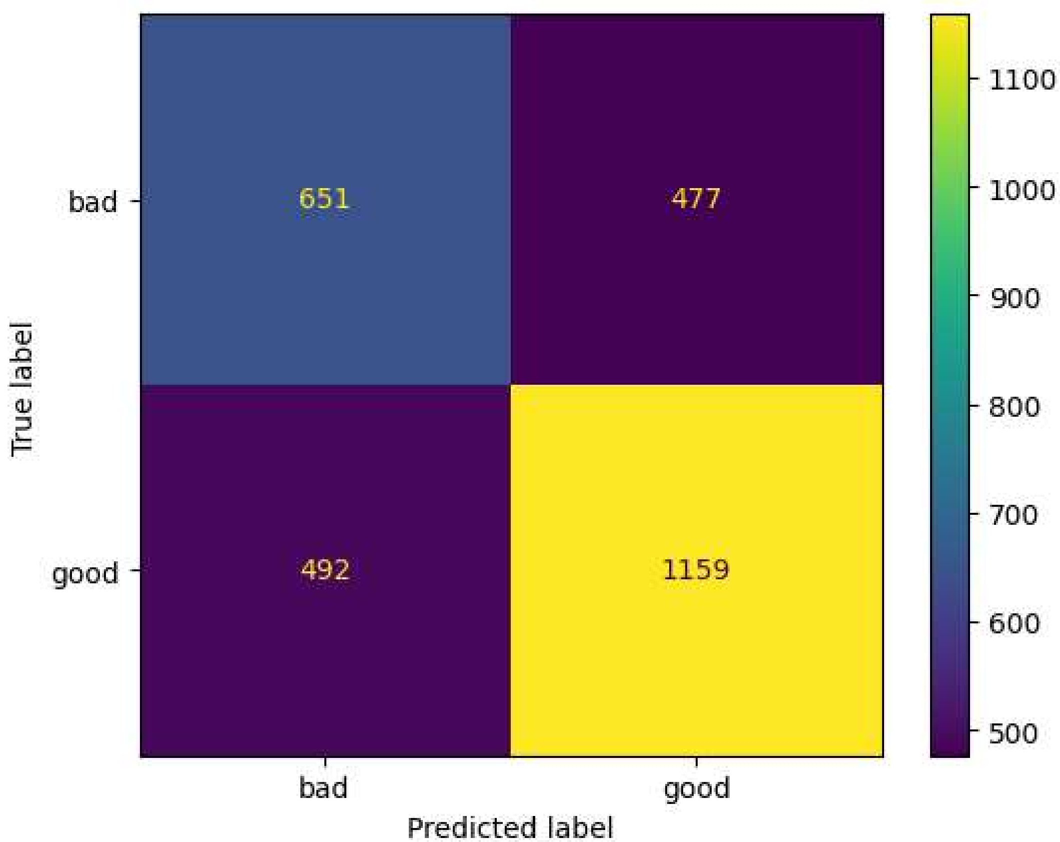
```
The large, un-restricted decision tree has depth 31
```

And show the metrics:

```
In [ ]: feature_names = train.columns
# Show the predictions from the DT on the test set
DT_pred = film_DT_large.predict(test)

# Show the confusion matrix
bn_matrix = confusion_matrix(test_labels, DT_pred)
print("\nThe confusion matrix is:")
disp = ConfusionMatrixDisplay(bn_matrix, display_labels=class_names)
disp.plot()
plt.savefig('./imgs/dt_ims/confusion_matrix_large.png')
plt.show()

# Print out metrics
print("Metrics for Test Data (Large model)")
print("---------------------")
print(f"Accuracy: {accuracy_score(test_labels, DT_pred)}")

test_prec, test_recall, test_f1, test_support = precision_recall_fscore_support(tes
print("Precision:")
for idx, i in enumerate(class_names):
```

```
    print(f"    ->{i}: {test_prec[idx]}")

print("Recall:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_recall[idx]}")

print("F1 Score:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_f1[idx]}")

print("Support:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_support[idx]}")


FeatureImp = film_DT.feature_importances_
indices = np.argsort(FeatureImp)[::-1]
# Print out the important features:
print("\nImportant Features:")
for f in range(train.shape[1]):
    if FeatureImp[indices[f]] > 0:
        print(f"{f+1}. Feature {feature_names[indices[f]]} ({FeatureImp[indices[f]]
```

```
The confusion matrix is:
```



```
Metrics for Test Data (Large model)
---------------------
Accuracy: 0.6513134220942786
Precision:
    ->bad: 0.5695538057742782
    ->good: 0.7084352078239609
Recall:
    ->bad: 0.5771276595744681
    ->good: 0.7019987886129618
F1 Score:
    ->bad: 0.5733157199471598
    ->good: 0.7052023121387284
Support:
    ->bad: 1128
    ->good: 1651

Important Features:
1. Feature runtime (0.6160903553221975)
2. Feature release_unix (0.1928014704755356)
3. Feature vote_count (0.171723134749567)
4. Feature combined_budget (0.011483644968251055)
5. Feature title_length (0.007901394484448878)
```

Interestingly, this shows that making our tree better doesn't necessarily help our performance.

Next, let's construct a decision tree on our data, splitting the data into 3 categories instead of 2.

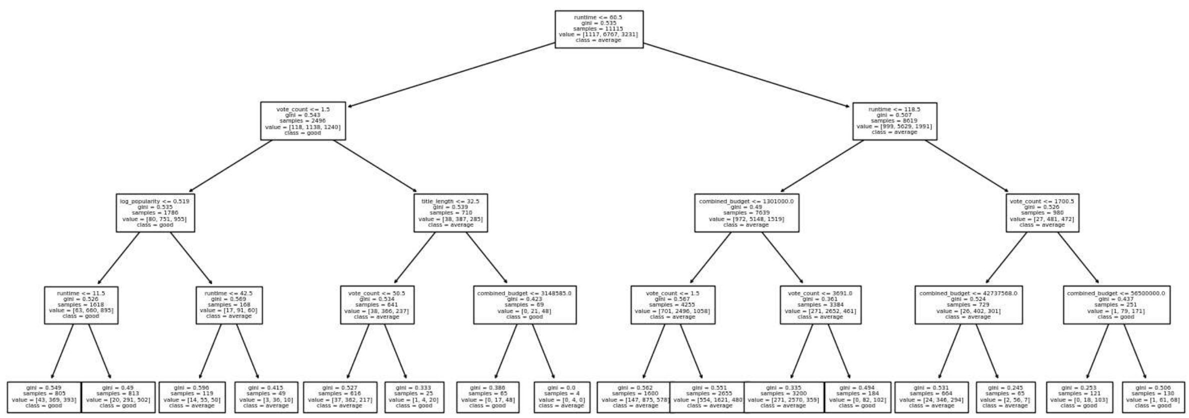
Let's do 1-3.99, 4-6.99, 7-10, as bad(0), average(1), good(2):

In [ ]:
```
# We need to re-separate into train and test
train = df.sample(frac=0.8,random_state=1612)
test = df.drop(train.index)

def num_ranking(entry):
    if entry['imdb_rating'] >= 7:
        return 2
    elif entry['imdb_rating'] >= 4:
        return 1
    else:
        return 0

class_names = ['bad', 'average', 'good']

# Apply to train and test separately
train_labels = train.apply(num_ranking, axis=1)
test_labels = test.apply(num_ranking, axis=1)

# Now, drop the imdb_rating column from each
train = train.drop('imdb_rating', axis=1)
test = test.drop('imdb_rating', axis=1)
```

Now, construct the tree for this 3-class data:

In [ ]:

```python
#Prepare the decision tree
film_DT_three = DecisionTreeClassifier(criterion='gini',
                            splitter='best',
                            min_samples_split=2,
                            max_depth=4,
                            random_state=None,
                            max_leaf_nodes=None,
                            min_impurity_decrease=0.0)

# Fit to our training data
film_DT_three.fit(train, train_labels)
# Plot our tree
fig = plt.figure(figsize=(15, 6))
tree.plot_tree(film_DT_three,
               max_depth=None,
               feature_names=train.columns,
               class_names=class_names,
               fontsize=5)
fig.tight_layout()
plt.savefig('./imgs/dt_ims/tree_plot_three.png')
```

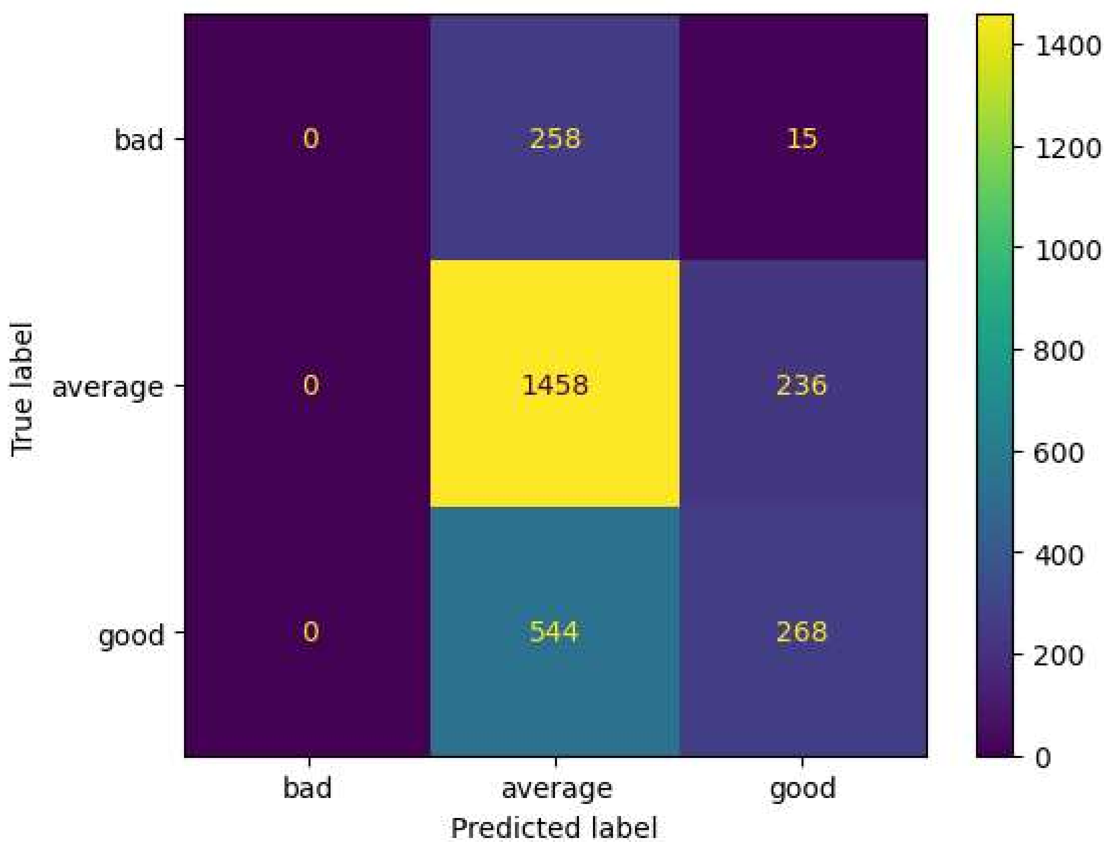


In [ ]:

```python
feature_names = train.columns
# Show the predictions from the DT on the test set
DT_pred = film_DT_three.predict(test)

# Show the confusion matrix
bn_matrix = confusion_matrix(test_labels, DT_pred)
print("\nThe confusion matrix is:")
disp = ConfusionMatrixDisplay(bn_matrix, display_labels=class_names)
disp.plot()
plt.savefig('./imgs/dt_ims/confusion_matrix_three.png')
plt.show()

# Print out metrics
print("Metrics for Test Data (Three class)")
print("---------------------")
print(f"Accuracy: {accuracy_score(test_labels, DT_pred)}")

test_prec, test_recall, test_f1, test_support = precision_recall_fscore_support(tes
print("Precision:")
for idx, i in enumerate(class_names):
```

```
    print(f"    ->{i}: {test_prec[idx]}")

print("Recall:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_recall[idx]}")

print("F1 Score:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_f1[idx]}")

print("Support:")
for idx, i in enumerate(class_names):
    print(f"    ->{i}: {test_support[idx]}")


FeatureImp = film_DT.feature_importances_
indices = np.argsort(FeatureImp)[::-1]
# Print out the important features:
print("\nImportant Features:")
for f in range(train.shape[1]):
    if FeatureImp[indices[f]] > 0:
        print(f"{f+1}. Feature {feature_names[indices[f]]} ({FeatureImp[indices[f]]
```

The confusion matrix is:



```
Metrics for Test Data (Three class)
---------------------
Accuracy: 0.6210867218423893
Precision:
    ->bad: 0.0
    ->average: 0.6451327433628319
    ->good: 0.5163776493256262
Recall:
    ->bad: 0.0
    ->average: 0.8606847697756789
    ->good: 0.33004926108374383
F1 Score:
    ->bad: 0.0
    ->average: 0.7374810318664644
    ->good: 0.4027047332832457
Support:
    ->bad: 273
    ->average: 1694
    ->good: 812

Important Features:
1. Feature runtime (0.6160903553221975)
2. Feature release_unix (0.1928014704755356)
3. Feature vote_count (0.171723134749567)
4. Feature combined_budget (0.011483644968251055)
5. Feature title_length (0.007901394484448878)
```

```
C:\Users\Peter\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.10_qbz5n2k
fra8p0\LocalCache\local-packages\Python310\site-packages\sklearn\metrics\_classifi
cation.py:1334: UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` paramete
r to control this behavior.
```

As we can see, we do a poor job predicting on the "bad" category when we extend this to 3 classes.