BDP_Assignment4

March 6, 2023

0.1 1) Data Exploration

a.

[3]:
```python
from pyspark.sql import SparkSession
spark = SparkSession.builder.appName("Python Spark regression example").
 ↪config("config.option", "value").getOrCreate()


df = spark.read.csv('mpst_full_data.csv',␣
 ↪escape='"',sep=",",encoding='UTF-8',comment=None,␣
 ↪header=True,multiLine=True,inferSchema=True)
# colNumber
print("countNumber: ",df.count())

# show50col
df.show(50)

result = df.select('tags').rdd.flatMap(lambda x: x).flatMap(lambda x: x.
 ↪split(", ")).countByValue()


sortTags = sorted(result.items(), key=lambda item:item[1],reverse=True)
list = []
for num in range(0,10):
    list.append(sortTags[num])
```

```
countNumber:  14828
+---------+--------------------+--------------------+--------------------+-----
+---------------+
|  imdb_id|               title|       plot_synopsis|
tags|split|synopsis_source|
+---------+--------------------+--------------------+--------------------+-----
+---------------+
|tt0057603|I tre volti della…|Note: this synops…|cult, horror, got…|train|
imdb|
|tt1733125|Dungeons & Dragon…|Two thousand year…|            violence|train|
imdb|
|tt0033045|The Shop Around t…|Matuschek's, a gi…|            romantic| test|
```

```
imdb|
|tt0113862|  Mr. Holland's Opus|Glenn Holland, no…|inspiring, romant…|train|
imdb|
|tt0086250|            Scarface|In May 1980, a Cu…|cruelty, murder, …|  val|
imdb|
|tt1315981|        A Single Man|George Falconer (…|romantic, queer, …|  val|
imdb|
|tt0249380|           Baise-moi|Baise-moi tells t…|gothic, cruelty, …|train|
wikipedia|
|tt0408790|          Flightplan|Kyle Pratt (Jodie…|mystery, suspense…|train|
imdb|
|tt0021079|       Little Caesar|Small-time Italia…|            violence|train|
imdb|
|tt1615065|             Savages|The movie begins …|revenge, neo noir…|train|
imdb|
|tt0089606|   Mitt liv som hund|The action takes …|         cult, prank|train|
wikipedia|
|tt0078908|           The Brood|At the Somafree I…|cult, psychedelic…|train|
imdb|
|tt0795493|   Cassandra's Dream|Brothers Terry (C…|tragedy, dramatic…|train|
wikipedia|
|tt0093389|    The Last Emperor|Arrival.\nA train…|              murder|train|
imdb|
|tt0120899|      My Life So Far|The film tells th…|flashback, autobi…|train|
wikipedia|
|tt1937113|Call of Duty: Mod…|Hours after the e…|    good versus evil| test|
imdb|
|tt1232776|           Fish Tank|We open with Mia …|suspenseful, depr…|train|
imdb|
|tt0402399|       The New World|Over a shot of tr…|boring, murder, c…|train|
imdb|
|tt1619029|              Jackie|The film begins w…|           flashback|  val|
imdb|
|tt0102007|          The Haunted|This creepy and s…|paranormal, horro…| test|
imdb|
|tt0398712|Assault on Precin…|On New Years Eve,…|suspenseful, neo …|  val|
imdb|
|tt0036868|The Best Years of…|After World War I…|romantic, histori…|train|
wikipedia|
|tt0116571|        House Arrest|The film is told …|romantic, home movie|train|
wikipedia|
|tt0104779|          Bitter Moon|Nigel Dobson (Hug…|comedy, cruelty, …|train|
imdb|
|tt2005374|   The Frozen Ground|The film opens in…|    dramatic, murder| test|
wikipedia|
|tt0865556|The Forbidden Kin…|South Boston teen…|fantasy, murder, …|train|
wikipedia|
|tt1454029|            The Help|In civil-rights e…|historical, feel-…|  val|
```

```
imdb|
|tt1411238| No Strings Attached|15 years agoWe se…|boring, adult com…| test|
imdb|
|tt0118689|                Bean|Mr. Bean (Rowan A…|cult, comedy, ent…|train|
imdb|
|tt1716772|The Inbetweeners …|Four teenage misf…|bleak, comedy, hu…|train|
imdb|
|tt0055505|       Taste of Fear|** CONTAINS SPOIL…|              murder|train|
imdb|
|tt0053559|           13 Ghosts|The movie opens w…|     revenge, murder| test|
imdb|
|tt0370032|         Ultraviolet|In the mid-21st c…|cult, stupid, atm…|  val|
imdb|
|tt0087472|      The Initiation|Kelly Fairchild i…|cult, murder, vio…|train|
imdb|
|tt5700672|          Busanhaeng|A truck approache…|            violence|train|
imdb|
|tt0350774|    Dead & Breakfast|Six friends, Chri…|cult, murder, fla…| test|
wikipedia|
|tt0365485|         The Matador|Julian Noble (Pie…|psychedelic, come…|train|
imdb|
|tt0120102|Seven Years in Tibet|The introduction …|violence, historical| test|
imdb|
|tt0219653|        Dracula 2000|1897 England: The…|comedy, suspensef…|train|
imdb|
|tt0298228|         Whale Rider|The film's plot f…|    dramatic, boring|train|
wikipedia|
|tt4731136| A Cure for Wellness|In the opening sc…|paranormal, suspe…|  val|
imdb|
|tt0093603|             Nayakan|An anti-governmen…|revenge, cruelty,…| test|
wikipedia|
|tt0373283| Saints and Soldiers|In 1944, Allied t…|   murder, flashback| test|
wikipedia|
|tt0948470|The Amazing Spide…|Scientist Richard…|murder, violence,…|train|
imdb|
|tt1109624|          Paddington|An explorer named…|              comedy|train|
imdb|
|tt4226388|            Victoria|Berlin, 04:00. Af…|             tragedy|train|
imdb|
|tt0046521|         I vitelloni|As summer draws t…|            romantic|train|
wikipedia|
|tt3832914|            War Room|Ms. Clara (Karen …|      christian film|train|
imdb|
|tt0070222|Invasion of the B…|In a cheap motel …|tragedy, pornogra…|  val|
imdb|
|tt0233298|Batman Beyond: Re…|Late one night in…|comedy, gothic, m…| test|
imdb|
+---------+--------------------+--------------------+--------------------+-----
```

```
+----------------+
only showing top 50 rows
```

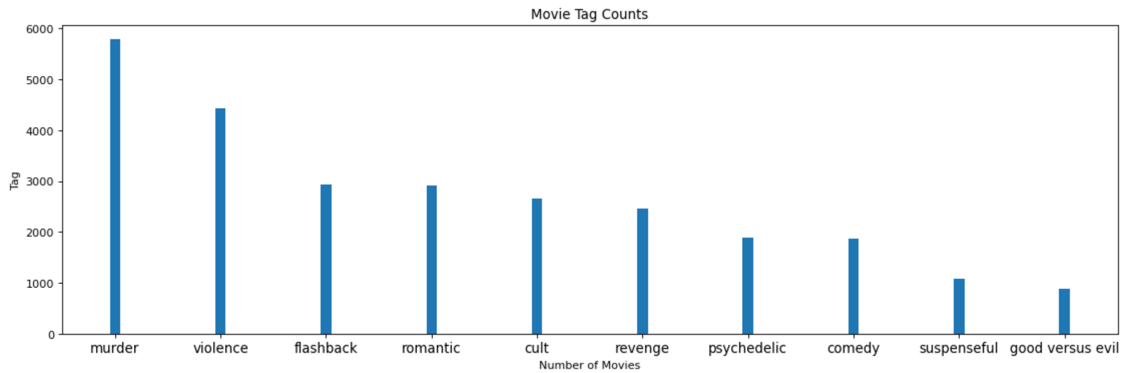
b.

[7]:
```
df.describe().show()
```

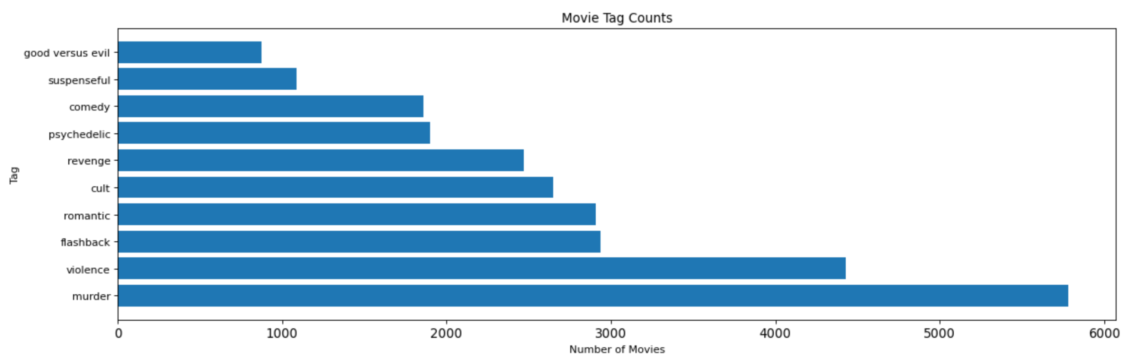
```
+-------+---------+------------------+------------------------+-----------------
---+-----+---------------+
|summary|  imdb_id|             title|           plot_synopsis|
tags|split|synopsis_source|
+-------+---------+------------------+------------------------+-----------------
---+-----+---------------+
|  count|    14828|             14828|                   14828|
14828|14828|          14828|
|   mean|     null|615.7078947368421|                    null|
null| null|           null|
| stddev|     null|820.9172438097585|                    null|
null| null|           null|
|    min|tt0000091|                 $|     ".hack//Roots" fo…|
absurd| test|           imdb|
|    max|tt6583664|         Üç Maymun|   Dragon Tiger…|whimsical, violen…|
val|      wikipedia|
+-------+---------+------------------+------------------------+-----------------
---+-----+---------------+
```

c and d.

[4]:
```
import numpy as np
import matplotlib.pyplot as plt
x1=np.arange(10)
y1=np.
 ↪array([list[0][1],list[1][1],list[2][1],list[3][1],list[4][1],list[5][1],list[6][1],list[7]
bar_width=0.1
plt.figure(figsize=(17, 5), dpi=80)
plt.
 ↪bar(x1,y1,tick_label=[list[0][0],list[1][0],list[2][0],list[3][0],list[4][0],list[5][0],lis
plt.xticks(fontsize=12)
plt.title("Movie Tag Counts")
plt.xlabel("Number of Movies")
plt.ylabel("Tag")
plt.show()
```




```
[10]: plt.figure(figsize=(17, 5), dpi=80)
plt.
 ↪barh(x1,y1,tick_label=[list[0][0],list[1][0],list[2][0],list[3][0],list[4][0],list[5][0],li
plt.xticks(fontsize=12)
plt.title("Movie Tag Counts")
plt.xlabel("Number of Movies")
plt.ylabel("Tag")
plt.show()
```



0.2 2). Build Models

a).

```
[26]: from pyspark.ml import Pipeline
from pyspark.ml.classification import LogisticRegression
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.feature import HashingTF, IDF, RegexTokenizer, StopWordsRemover
from pyspark.sql.functions import when

top_tags =␣
 ↪[list[0][0],list[1][0],list[2][0],list[3][0],list[4][0],list[5][0],list[6][0],list[7][0],li
```

[27]:
```
from pyspark.sql.functions import split, explode
# Filter the DataFrame to only include movies with one of the top 10 tags
df_c= df.withColumn('tag',explode(split('tags',',')))
df_filtered = df_c.filter(df_c.tag.isNotNull()).filter(df_c.tag.isin(top_tags))
# Create a column for the target variable by converting the tag column to a␣
↪binary variable
df_filtered = df_filtered.withColumn("target", when(df_filtered.tag.
↪isin(top_tags), 1).otherwise(0))
# Split the data into training and testing sets
(trainingData, testData) = df_filtered.randomSplit([0.8, 0.2], seed=1234)
```

[36]:
```
df_filtered.show(5)
```

```
+---------+--------------------+--------------------+--------------------+-----
+---------------+--------+------+
|  imdb_id|               title|       plot_synopsis|
tags|split|synopsis_source|     tag|target|
+---------+--------------------+--------------------+--------------------+-----
+---------------+--------+------+
|tt0057603|I tre volti della…|Note: this synops…|cult, horror, got…|train|
imdb|    cult|     1|
|tt1733125|Dungeons & Dragon…|Two thousand year…|            violence|train|
imdb|violence|     1|
|tt0033045|The Shop Around t…|Matuschek's, a gi…|            romantic| test|
imdb|romantic|     1|
|tt1315981|         A Single Man|George Falconer (…|romantic, queer, …|  val|
imdb|romantic|     1|
|tt0021079|        Little Caesar|Small-time Italia…|            violence|train|
imdb|violence|     1|
+---------+--------------------+--------------------+--------------------+-----
+---------------+--------+------+
only showing top 5 rows
```

b) and c)

[29]:
```
# Define the tokenizer and stopwords remover
tokenizer = RegexTokenizer(inputCol="plot_synopsis", outputCol="tokens",␣
↪pattern="\\W")
stopwords_remover = StopWordsRemover(inputCol=tokenizer.getOutputCol(),␣
↪outputCol="filtered_tokens")

# Define the vectorizers
hashingTF = HashingTF(inputCol=stopwords_remover.getOutputCol(),␣
↪outputCol="raw_features")
idf = IDF(inputCol=hashingTF.getOutputCol(), outputCol="features")
```

```python
# Define the logistic regression model
lr = LogisticRegression(labelCol="target", maxIter=10)
```

[34]:
```python
# Define the pipeline
pipeline = Pipeline(stages=[tokenizer, stopwords_remover, hashingTF, idf, lr])

# Train the model
model = pipeline.fit(trainingData)

# Make predictions on the test data
predictions = model.transform(testData)
```

[35]:
```python
predictions.show(5)
```

```
+---------+--------------------+--------------------+--------------------+-----
+---------------+-----------+------+--------------------+--------------------+--
------------------+--------------------+--------------------+-----------+-------
---+
|  imdb_id|               title|       plot_synopsis|
tags|split|synopsis_source|        tag|target|              tokens|
filtered_tokens|        raw_features|            features|
rawPrediction|probability|prediction|
+---------+--------------------+--------------------+--------------------+-----
+---------------+-----------+------+--------------------+--------------------+--
------------------+--------------------+--------------------+-----------+-------
---+
|tt0000966|A Midsummer Night…|The play consists…|   romantic, fantasy|train|
wikipedia|   romantic|     1|[the, play, consi…|[play, consists,
…|(262144,[1923,399…|(262144,[1923,399…|[-Infinity,Infinity]|  [0.0,1.0]|
1.0|
|tt0002130|           L'Inferno|The exhumation of…|psychedelic, viol…|train|
wikipedia|psychedelic|     1|[the, exhumation,…|[exhumation,
lizz…|(262144,[2409,248…|(262144,[2409,248…|[-Infinity,Infinity]|
[0.0,1.0]|       1.0|
|tt0011904|   The Ace of Hearts|The film is divid…|suspenseful, murd…|train|
wikipedia|suspenseful|     1|[the, film, is, d…|[film, divided,
t…|(262144,[1623,473…|(262144,[1623,473…|[-Infinity,Infinity]|  [0.0,1.0]|
1.0|
|tt0013030|The Cowboy and th…|Mary Smith (Merle…|            romantic|train|
wikipedia|   romantic|     1|[mary, smith, mer…|[mary, smith,
mer…|(262144,[329,1232…|(262144,[329,1232…|[-Infinity,Infinity]|
[0.0,1.0]|       1.0|
|tt0013140|       Foolish Wives|The silent drama …|   comedy, melodrama| test|
wikipedia|     comedy|     1|[the, silent, dra…|[silent, drama,
t…|(262144,[6512,841…|(262144,[6512,841…|[-Infinity,Infinity]|  [0.0,1.0]|
1.0|
+---------+--------------------+--------------------+--------------------+-----
```

```
+---------------+-----------+------+--------------------+--------------------+--
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---+
only showing top 5 rows
```

d)

[55]:
```python
pipeline = Pipeline(stages=[tokenizer, stopwords_remover, hashingTF, idf])
# Train the model
model = pipeline.fit(df_filtered)

# Make predictions on the test data
predictions = model.transform(df_filtered)
```

[56]:
```python
predictions.show(5)
```

```
+---------+--------------------+--------------------+--------------------+-----
+---------------+--------+------+--------------------+--------------------+-----
---------------+--------------------+
|  imdb_id|               title|       plot_synopsis|
tags|split|synopsis_source|     tag|target|              tokens|
filtered_tokens|        raw_features|            features|
+---------+--------------------+--------------------+--------------------+-----
+---------------+--------+------+--------------------+--------------------+-----
---------------+--------------------+
|tt0057603|I tre volti della…|Note: this synops…|cult, horror, got…|train|
imdb|    cult|     1|[note, this, syno…|[note, synopsis,
…|(262144,[329,917,…|(262144,[329,917,…|
|tt1733125|Dungeons & Dragon…|Two thousand year…|            violence|train|
imdb|violence|     1|[two, thousand, y…|[two, thousand,
y…|(262144,[10077,12…|(262144,[10077,12…|
|tt0033045|The Shop Around t…|Matuschek's, a gi…|            romantic| test|
imdb|romantic|     1|[matuschek, s, a,…|[matuschek,
gift,…|(262144,[102,329,…|(262144,[102,329,…|
|tt1315981|       A Single Man|George Falconer (…|romantic, queer, …|  val|
imdb|romantic|     1|[george, falconer…|[george,
falconer…|(262144,[619,1818…|(262144,[619,1818…|
|tt0021079|        Little Caesar|Small-time Italia…|            violence|train|
imdb|violence|     1|[small, time, ita…|[small, time,
ita…|(262144,[1546,459…|(262144,[1546,459…|
+---------+--------------------+--------------------+--------------------+-----
+---------------+--------+------+--------------------+--------------------+-----
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only showing top 5 rows
```

[57]:
```python
from pyspark.sql.functions import col
```

[46]:
```python
import pyspark.sql.functions as F
categ = predictions.select('tag').distinct().rdd.flatMap(lambda x:x).collect()
exprs = [F.when(F.col('tag') == cat,1).otherwise(0)\
            .alias(str(cat)) for cat in categ]
pred1 = predictions.select(exprs+predictions.columns)
```

[47]:
```python
pred1.show(5)
```

```
+--------+---------+---------------+------+--------+-------+----+-----------+--
---------+------+---------+--------------------+--------------------+-----------
---------+-----+---------------+--------+------+--------------------+-----------
---------+--------------------+--------------------+
|romantic|flashback|good versus
evil|murder|violence|revenge|cult|suspenseful|psychedelic|comedy|  imdb_id|
title|       plot_synopsis|                tags|split|synopsis_source|
tag|target|              tokens|     filtered_tokens|        raw_features|
features|
+--------+---------+---------------+------+--------+-------+----+-----------+--
---------+------+---------+--------------------+--------------------+-----------
---------+-----+---------------+--------+------+--------------------+-----------
---------+--------------------+--------------------+
|       0|        0|              0|     0|       0|      0|   1|          0|
0|     0|tt0057603|I tre volti della…|Note: this synops…|cult, horror,
got…|train|           imdb|    cult|     1|[note, this, syno…|[note,
synopsis, …|(262144,[329,917,…|(262144,[329,917,…|
|       0|        0|              0|     0|       1|      0|   0|          0|
0|     0|tt1733125|Dungeons & Dragon…|Two thousand year…|
violence|train|           imdb|violence|     1|[two, thousand, y…|[two,
thousand, y…|(262144,[10077,12…|(262144,[10077,12…|
|       1|        0|              0|     0|       0|      0|   0|          0|
0|     0|tt0033045|The Shop Around t…|Matuschek's, a gi…|
romantic| test|           imdb|romantic|     1|[matuschek, s, a,…|[matuschek,
gift,…|(262144,[102,329,…|(262144,[102,329,…|
|       1|        0|              0|     0|       0|      0|   0|          0|
0|     0|tt1315981|        A Single Man|George Falconer (…|romantic, queer,
…|  val|           imdb|romantic|     1|[george, falconer…|[george,
falconer…|(262144,[619,1818…|(262144,[619,1818…|
|       0|        0|              0|     0|       1|      0|   0|          0|
0|     0|tt0021079|       Little Caesar|Small-time Italia…|
violence|train|           imdb|violence|     1|[small, time, ita…|[small,
time, ita…|(262144,[1546,459…|(262144,[1546,459…|
+--------+---------+---------------+------+--------+-------+----+-----------+--
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```

[48]:
```
pred1 = pred1.select('plot_synopsis', 'features', 'romantic', 'flashback',␣
↪'good versus evil', 'murder', 'violence', 'revenge', 'cult', 'suspenseful',␣
↪'psychedelic', 'comedy', 'split')
```

[49]:
```
pred1.show(5)
```

```
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+
|       plot_synopsis|            features|romantic|flashback|good versus
evil|murder|violence|revenge|cult|suspenseful|psychedelic|comedy|split|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+
|Note: this synops…|(262144,[329,917,…|       0|        0|               0|
0|       0|      0|   1|          0|          0|     0|train|
|Two thousand year…|(262144,[10077,12…|       0|        0|               0|
0|       1|      0|   0|          0|          0|     0|train|
|Matuschek's, a gi…|(262144,[102,329,…|       1|        0|               0|
0|       0|      0|   0|          0|          0|     0| test|
|George Falconer (…|(262144,[619,1818…|       1|        0|               0|
0|       0|      0|   0|          0|          0|     0|  val|
|Small-time Italia…|(262144,[1546,459…|       0|        0|               0|
0|       1|      0|   0|          0|          0|     0|train|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+
only showing top 5 rows
```

e)

[51]:
```
trainingData = pred1.filter(pred1.split == 'train')
testingData = pred1.filter(pred1.split == 'test')
valData = pred1.filter(pred1.split == 'val')
```

[63]:
```
trainingData.show(5)
```

```
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+
|       plot_synopsis|            features|romantic|flashback|good versus
evil|murder|violence|revenge|cult|suspenseful|psychedelic|comedy|split|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+
|Note: this synops…|(262144,[329,917,…|       0|        0|               0|
0|       0|      0|   1|          0|          0|     0|train|
|Two thousand year…|(262144,[10077,12…|       0|        0|               0|
0|       1|      0|   0|          0|          0|     0|train|
|Small-time Italia…|(262144,[1546,459…|       0|        0|               0|
0|       1|      0|   0|          0|          0|     0|train|
|The movie begins …|(262144,[476,535,…|       0|        0|               0|
```

```
0|       0|      1|   0|          0|          0|     0|train|
|The action takes …|(262144,[7853,836…|       0|        0|                0|
0|       0|      0|   1|          0|          0|     0|train|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+-----+-----+
only showing top 5 rows
```

[64]:
```python
testingData.show(5)
```

```
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+-----+-----+
|       plot_synopsis|            features|romantic|flashback|good versus
evil|murder|violence|revenge|cult|suspenseful|psychedelic|comedy|split|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+-----+-----+
|Matuschek's, a gi…|(262144,[102,329,…|       1|        0|                0|
0|       0|      0|   0|          0|          0|     0| test|
|Hours after the e…|(262144,[134,365,…|       0|        0|                1|
0|       0|      0|   0|          0|          0|     0| test|
|The movie opens w…|(262144,[1277,154…|       0|        0|                0|
0|       0|      1|   0|          0|          0|     0| test|
|Six friends, Chri…|(262144,[956,3280…|       0|        0|                0|
0|       0|      0|   1|          0|          0|     0| test|
|The introduction …|(262144,[303,329,…|       0|        0|                0|
0|       1|      0|   0|          0|          0|     0| test|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+-----+-----+
only showing top 5 rows
```

[65]:
```python
valData.show(5)
```

```
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+-----+-----+
|       plot_synopsis|            features|romantic|flashback|good versus
evil|murder|violence|revenge|cult|suspenseful|psychedelic|comedy|split|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+-----+-----+
|George Falconer (…|(262144,[619,1818…|       1|        0|                0|
0|       0|      0|   0|          0|          0|     0|  val|
|The film begins w…|(262144,[212,432,…|       0|        1|                0|
0|       0|      0|   0|          0|          0|     0|  val|
|On New Years Eve,…|(262144,[329,781,…|       0|        0|                0|
0|       0|      0|   0|          1|          0|     0|  val|
|In the mid-21st c…|(262144,[2325,392…|       0|        0|                0|
0|       0|      0|   1|          0|          0|     0|  val|
|A couple is seen …|(262144,[134,1133…|       0|        0|                0|
```

```
0|        1|       0|    0|            0|            0|      0|   val|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+------+
only showing top 5 rows
```

f)

```
[67]: # Define
from pyspark.ml.classification import OneVsRest, LogisticRegression
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.feature import HashingTF, IDF, RegexTokenizer, StopWordsRemover
from pyspark.sql.functions import col
```

romantic

```
[87]: # Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_romantic = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
 ↪'features', labelCol='romantic')

# Fit the model to the data.
lgModel_romantic = lg_romantic.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_romantic = lgModel_romantic.transform(testingData)
```

```
[88]: lg_pred_romantic.show(5)
```

```
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+---------------
-----+--------------------+----------+
|       plot_synopsis|            features|romantic|flashback|good versus
evil|murder|violence|revenge|cult|suspenseful|psychedelic|comedy|split|
rawPrediction|         probability|prediction|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+-----------+------+-----+---------------
-----+--------------------+----------+
|Matuschek's, a gi…|(262144,[102,329,…|       1|        0|                0|
0|        0|       0|    0|            0|            0|      0|
test|[-0.9334870266008…|[0.28221780821405…|       1.0|
|Hours after the e…|(262144,[134,365,…|       0|        0|                1|
0|        0|       0|    0|            0|            0|      0|
test|[13.3895760501503…|[0.99999846898184…|       0.0|
|The movie opens w…|(262144,[1277,154…|       0|        0|                0|
0|        0|       1|    0|            0|            0|      0|
test|[36.0422097529107…|[0.99999999999999…|       0.0|
|Six friends, Chri…|(262144,[956,3280…|       0|        0|                0|
0|        0|       0|    1|            0|            0|      0|
```

```
test|[3.69286463559780…|[0.97570440540253…|       0.0|
|The introduction …|(262144,[303,329,…|       0|        0|                0|
0|        1|       0|    0|           0|           0|      0|
test|[-7.1916366269239…|[7.52289601601269…|       1.0|
+--------------------+--------------------+--------+---------+----------------+-
-----+--------+-------+----+-----------+----------+------+-----+---------------
-----+--------------------+----------+
only showing top 5 rows
```

[89]:
```
eval_accuracy = MulticlassClassificationEvaluator(labelCol="romantic",␣
  ↪predictionCol="prediction", metricName="accuracy")
accuracy_romantic = eval_accuracy.evaluate(lg_pred_romantic)
accuracy_romantic
```

[89]: 0.7982767359351242

[90]:
```
eval_f1 = MulticlassClassificationEvaluator(labelCol="romantic",␣
  ↪predictionCol="prediction", metricName="f1")
f1score_romantic = eval_f1.evaluate(lg_pred_romantic)
f1score_romantic
```

[90]: 0.8143428005463075

flashback

[75]:
```
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_flashback = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
  ↪'features', labelCol='flashback')

# Fit the model to the data.
lgModel_flashback = lg_flashback.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_flashback = lgModel_flashback.transform(testingData)
```

[76]:
```
eval_accuracy = MulticlassClassificationEvaluator(labelCol="flashback",␣
  ↪predictionCol="prediction", metricName="accuracy")
accuracy_flashback = eval_accuracy.evaluate(lg_pred_flashback)

eval_f1 = MulticlassClassificationEvaluator(labelCol="flashback",␣
  ↪predictionCol="prediction", metricName="f1")
f1score_flashback = eval_f1.evaluate(lg_pred_flashback)
```

good versus evil

[77]:
```python
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_good_versus_evil = LogisticRegression(maxIter=10,regParam=0.01, featuresCol␣
↪= 'features', labelCol='good versus evil')

# Fit the model to the data.
lgModel_good_versus_evil = lg_good_versus_evil.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_good_versus_evil = lgModel_good_versus_evil.transform(testingData)
```

[78]:
```python
eval_accuracy = MulticlassClassificationEvaluator(labelCol="good versus evil",␣
↪predictionCol="prediction", metricName="accuracy")
accuracy_good_versus_evil = eval_accuracy.evaluate(lg_pred_good_versus_evil)

eval_f1 = MulticlassClassificationEvaluator(labelCol="good versus evil",␣
↪predictionCol="prediction", metricName="f1")
f1score_good_versus_evil = eval_f1.evaluate(lg_pred_good_versus_evil)
```

murder

[79]:
```python
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_murder = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
↪'features', labelCol='murder')

# Fit the model to the data.
lgModel_murder = lg_murder.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_murder = lgModel_murder.transform(testingData)

eval_accuracy = MulticlassClassificationEvaluator(labelCol="murder",␣
↪predictionCol="prediction", metricName="accuracy")
accuracy_murder = eval_accuracy.evaluate(lg_pred_murder)

eval_f1 = MulticlassClassificationEvaluator(labelCol="murder",␣
↪predictionCol="prediction", metricName="f1")
f1score_murder = eval_f1.evaluate(lg_pred_murder)
```

violence

[80]:
```python
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_violence = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
↪'features', labelCol='violence')
```

```
# Fit the model to the data.
lgModel_violence = lg_violence.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_violence = lgModel_violence.transform(testingData)

eval_accuracy = MulticlassClassificationEvaluator(labelCol="violence",␣
 ↪predictionCol="prediction", metricName="accuracy")
accuracy_violence = eval_accuracy.evaluate(lg_pred_violence)

eval_f1 = MulticlassClassificationEvaluator(labelCol="violence",␣
 ↪predictionCol="prediction", metricName="f1")
f1score_violence = eval_f1.evaluate(lg_pred_violence)
```

revenge

[81]:
```
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_revenge = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
 ↪'features', labelCol='revenge')

# Fit the model to the data.
lgModel_revenge = lg_revenge.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_revenge = lgModel_revenge.transform(testingData)

eval_accuracy = MulticlassClassificationEvaluator(labelCol="revenge",␣
 ↪predictionCol="prediction", metricName="accuracy")
accuracy_revenge = eval_accuracy.evaluate(lg_pred_revenge)

eval_f1 = MulticlassClassificationEvaluator(labelCol="revenge",␣
 ↪predictionCol="prediction", metricName="f1")
f1score_revenge = eval_f1.evaluate(lg_pred_revenge)
```

cult

[82]:
```
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_cult = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
 ↪'features', labelCol='cult')

# Fit the model to the data.
lgModel_cult = lg_cult.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_cult = lgModel_cult.transform(testingData)
```

```
eval_accuracy = MulticlassClassificationEvaluator(labelCol="cult",␣
↪predictionCol="prediction", metricName="accuracy")
accuracy_cult = eval_accuracy.evaluate(lg_pred_cult)

eval_f1 = MulticlassClassificationEvaluator(labelCol="cult",␣
↪predictionCol="prediction", metricName="f1")
f1score_cult = eval_f1.evaluate(lg_pred_cult)
```

suspenseful

[83]:
```
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_suspenseful = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
↪'features', labelCol='suspenseful')

# Fit the model to the data.
lgModel_suspenseful = lg_suspenseful.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_suspenseful = lgModel_suspenseful.transform(testingData)

eval_accuracy = MulticlassClassificationEvaluator(labelCol="suspenseful",␣
↪predictionCol="prediction", metricName="accuracy")
accuracy_suspenseful = eval_accuracy.evaluate(lg_pred_suspenseful)

eval_f1 = MulticlassClassificationEvaluator(labelCol="suspenseful",␣
↪predictionCol="prediction", metricName="f1")
f1score_suspenseful = eval_f1.evaluate(lg_pred_suspenseful)
```

psychedelic

[84]:
```
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_psychedelic = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
↪'features', labelCol='psychedelic')

# Fit the model to the data.
lgModel_psychedelic = lg_psychedelic.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_psychedelic = lgModel_psychedelic.transform(testingData)

eval_accuracy = MulticlassClassificationEvaluator(labelCol="psychedelic",␣
↪predictionCol="prediction", metricName="accuracy")
accuracy_psychedelic = eval_accuracy.evaluate(lg_pred_psychedelic)
```

```
eval_f1 = MulticlassClassificationEvaluator(labelCol="psychedelic",␣
 ↪predictionCol="prediction", metricName="f1")
f1score_psychedelic = eval_f1.evaluate(lg_pred_psychedelic)
```

comedy

[85]:
```
# Define the logistic regression model
# Set parameters for Logistic Regression maxIter=10, regParam=0.01
lg_comedy = LogisticRegression(maxIter=10,regParam=0.01, featuresCol =␣
 ↪'features', labelCol='comedy')

# Fit the model to the data.
lgModel_comedy = lg_comedy.fit(trainingData)

# Given a dataset, predict each point's label, and show the results.
lg_pred_comedy = lgModel_comedy.transform(testingData)

eval_accuracy = MulticlassClassificationEvaluator(labelCol="comedy",␣
 ↪predictionCol="prediction", metricName="accuracy")
accuracy_comedy = eval_accuracy.evaluate(lg_pred_comedy)

eval_f1 = MulticlassClassificationEvaluator(labelCol="comedy",␣
 ↪predictionCol="prediction", metricName="f1")
f1score_comedy = eval_f1.evaluate(lg_pred_comedy)
```

[93]:
```
from pyspark.sql.types import StructType,StructField, StringType, FloatType
model_performance = [("romantic", accuracy_romantic, f1score_romantic),
    ("flashback", accuracy_flashback, f1score_flashback),
    ("good versus evil", accuracy_good_versus_evil, f1score_good_versus_evil),
    ("murder", accuracy_murder, f1score_murder),
    ("violence", accuracy_violence, f1score_violence),
    ("revenge", accuracy_revenge, f1score_revenge),
    ("cult", accuracy_cult, f1score_cult),
    ("suspenseful", accuracy_suspenseful, f1score_suspenseful),
    ("psychedelic", accuracy_psychedelic, f1score_psychedelic),
    ("comedy",accuracy_comedy, f1score_comedy)
  ]

schema = StructType([ \
    StructField("Model",StringType(),True), \
    StructField("Accuracy Score",FloatType(),True), \
    StructField("F1 Score ",FloatType(),True)
  ])

df_model_performance = spark.
 ↪createDataFrame(data=model_performance,schema=schema)
df_model_performance.printSchema()
```

```
df_model_performance.show()
```

```
root
 |-- Model: string (nullable = true)
 |-- Accuracy Score: float (nullable = true)
 |-- F1 Score : float (nullable = true)

+----------------+--------------+---------+
|           Model|Accuracy Score|F1 Score |
+----------------+--------------+---------+
|        romantic|     0.7982767|0.8143428|
|       flashback|    0.93005574|0.9283128|
|good versus evil|    0.91028893|0.9179823|
|          murder|    0.75722253| 0.766153|
|        violence|    0.74961984|0.7549499|
|         revenge|    0.80334514|0.8029887|
|            cult|      0.797263|0.8135181|
|     suspenseful|     0.9239736|0.9262491|
|     psychedelic|    0.88596046|0.8890193|
|          comedy|     0.7987836|0.8061023|
+----------------+--------------+---------+
```

0.3 3). Inference

The data comes from the link: https://www.kaggle.com/datasets/jrobischon/wikipedia-movie-plots

[99]:
```
moive_wiki = spark.read.csv('wiki_movie_plots_deduped.csv',␣
  ↪escape='"',sep=",",encoding='UTF-8',comment=None,␣
  ↪header=True,multiLine=True,inferSchema=True)
# colNumber
print("countNumber: ",moive_wiki.count())

# show50col
moive_wiki_plot = moive_wiki.select('Plot')
```

```
countNumber:  34886
```

[105]:
```
moive_wiki_plot_sample = moive_wiki_plot.limit(10)
moive_wiki_plot_sample = moive_wiki_plot_sample.withColumnRenamed('Plot',␣
  ↪'plot_synopsis')
```

[106]:
```
pipeline = Pipeline(stages=[tokenizer, stopwords_remover, hashingTF, idf])
# Train the model
model_wiki = pipeline.fit(moive_wiki_plot_sample)

# Make predictions on the test data
```

```
predictions_wiki = model.transform(moive_wiki_plot_sample)
```

[107]:
```
predictions_wiki.show(5)
```

```
+--------------------+--------------------+--------------------+----------------
----+--------------------+
|       plot_synopsis|              tokens|     filtered_tokens|
raw_features|            features|
+--------------------+--------------------+--------------------+----------------
----+--------------------+
|A bartender is wo…|[a, bartender, is…|[bartender,
worki…|(262144,[181,5592…|(262144,[181,5592…|
|The moon, painted…|[the, moon, paint…|[moon, painted,
s…|(262144,[303,4213…|(262144,[303,4213…|
|The film, just ov…|[the, film, just,…|[film, minute,
lo…|(262144,[1066,542…|(262144,[1066,542…|
|Lasting just 61 s…|[lasting, just, 6…|[lasting, 61,
sec…|(262144,[1232,219…|(262144,[1232,219…|
|The earliest know…|[the, earliest, k…|[earliest,
known,…|(262144,[7286,748…|(262144,[7286,748…|
+--------------------+--------------------+--------------------+----------------
----+--------------------+
only showing top 5 rows
```

[108]:
```
training_wiki = predictions_wiki.select('features')
```

[114]:
```
# Define
from pyspark.ml.classification import OneVsRest, LogisticRegression
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.ml.feature import HashingTF, IDF, RegexTokenizer, StopWordsRemover
from pyspark.sql.functions import col

wiki_pred_romantic = lgModel_romantic.transform(training_wiki)
wiki_pred_flashback = lgModel_flashback.transform(training_wiki)
wiki_pred_good_versus_evil = lgModel_good_versus_evil.transform(training_wiki)
wiki_pred_murder = lgModel_murder.transform(training_wiki)
wiki_pred_violence = lgModel_violence.transform(training_wiki)
wiki_pred_revenge = lgModel_revenge.transform(training_wiki)
wiki_pred_cult = lgModel_cult.transform(training_wiki)
wiki_pred_suspenseful = lgModel_suspenseful.transform(training_wiki)
wiki_pred_psychedelic = lgModel_psychedelic.transform(training_wiki)
wiki_pred_comedy = lgModel_comedy.transform(training_wiki)
```

[115]:
```
wiki_pred_romantic.show()
```

```
+--------------------+--------------------+--------------------+----------+
```

```
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[2.07135010381483...|[0.88808721630644...|       0.0|
|(262144,[303,4213...|[2.41387110652224...|[0.91787894740529...|       0.0|
|(262144,[1066,542...|[2.27591722165508...|[0.90686277683432...|       0.0|
|(262144,[1232,219...|[1.71034360502258...|[0.84688084607307...|       0.0|
|(262144,[7286,748...|[1.89366175980711...|[0.86917247859793...|       0.0|
|(262144,[3329,728...|[2.23173144313786...|[0.90306303568782...|       0.0|
|(262144,[7123,142...|[3.18847688853240...|[0.96039833198283...|       0.0|
|(262144,[16004,17...|[2.32400122548836...|[0.91084539899789...|       0.0|
|(262144,[535,2437...|[1.70504454752687...|[0.84619243400640...|       0.0|
|(262144,[1272,270...|[2.15597093818353...|[0.89622542174317...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[117]:

```
wiki_pred_flashback.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[3.95693490303349...|[0.98123714227814...|       0.0|
|(262144,[303,4213...|[3.78990653122303...|[0.97790165807609...|       0.0|
|(262144,[1066,542...|[3.64375105909204...|[0.97451254592611...|       0.0|
|(262144,[1232,219...|[3.62634839760577...|[0.97407671332826...|       0.0|
|(262144,[7286,748...|[3.78124528710908...|[0.97771371176895...|       0.0|
|(262144,[3329,728...|[4.28628808663425...|[0.98643076558894...|       0.0|
|(262144,[7123,142...|[3.68725168947373...|[0.97557099285090...|       0.0|
|(262144,[16004,17...|[3.62832726073838...|[0.97412663528555...|       0.0|
|(262144,[535,2437...|[4.86997426936395...|[0.99238487242812...|       0.0|
|(262144,[1272,270...|[3.02942236665353...|[0.95388577085693...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[118]:

```
wiki_pred_good_versus_evil.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[3.48790023807144...|[0.97034152673400...|       0.0|
|(262144,[303,4213...|[4.03519932273671...|[0.98262507088866...|       0.0|
|(262144,[1066,542...|[4.05792921508301...|[0.98300891200259...|       0.0|
|(262144,[1232,219...|[4.14865233030748...|[0.98445963906970...|       0.0|
|(262144,[7286,748...|[3.97483569154402...|[0.98156388687170...|       0.0|
|(262144,[3329,728...|[3.35616867963486...|[0.96630625738744...|       0.0|
|(262144,[7123,142...|[4.31545577570531...|[0.98681568970776...|       0.0|
|(262144,[16004,17...|[4.12722142786632...|[0.98412834377110...|       0.0|
|(262144,[535,2437...|[4.82831561091284...|[0.99206350681538...|       0.0|
|(262144,[1272,270...|[4.01234080136624...|[0.98223047032800...|       0.0|
```

```
+--------------------+--------------------+--------------------+----------+
```

[119]:
```python
wiki_pred_murder.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[3.20820572714314...|[0.96114190820444...|       0.0|
|(262144,[303,4213...|[1.70295178379977...|[0.84591986175713...|       0.0|
|(262144,[1066,542...|[3.21205358521103...|[0.96128536382229...|       0.0|
|(262144,[1232,219...|[3.41316790525303...|[0.96811353999202...|       0.0|
|(262144,[7286,748...|[3.39304997508385...|[0.96748662241125...|       0.0|
|(262144,[3329,728...|[3.00228900052112...|[0.95267742915972...|       0.0|
|(262144,[7123,142...|[3.09931143613804...|[0.95686433353759...|       0.0|
|(262144,[16004,17...|[3.23141788297708...|[0.96199961952470...|       0.0|
|(262144,[535,2437...|[3.61734083901943...|[0.97384828713753...|       0.0|
|(262144,[1272,270...|[3.17790280987863...|[0.95999420041109...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[120]:
```python
wiki_pred_violence.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[3.51472969498456...|[0.97110398045793...|       0.0|
|(262144,[303,4213...|[3.28037472985846...|[0.96374937765590...|       0.0|
|(262144,[1066,542...|[2.70346002051378...|[0.93723050337513...|       0.0|
|(262144,[1232,219...|[1.95229611291855...|[0.87569679379208...|       0.0|
|(262144,[7286,748...|[3.33808748450592...|[0.96571257184943...|       0.0|
|(262144,[3329,728...|[2.66570120365400...|[0.93497215611493...|       0.0|
|(262144,[7123,142...|[3.361363771806,-...|[0.96647499252146...|       0.0|
|(262144,[16004,17...|[2.95052546974276...|[0.95028831773288...|       0.0|
|(262144,[535,2437...|[2.88613778727555...|[0.94715690862494...|       0.0|
|(262144,[1272,270...|[2.97627878857275...|[0.95149090345884...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[121]:
```python
wiki_pred_revenge.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[2.84943962172208...|[0.94528970888917...|       0.0|
|(262144,[303,4213...|[3.15622808853997...|[0.95915342564862...|       0.0|
|(262144,[1066,542...|[3.22270232121130...|[0.96167972432411...|       0.0|
|(262144,[1232,219...|[3.86683521308330...|[0.97950437415438...|       0.0|
```

```
|(262144,[7286,748...|[3.00939097181442...|[0.95299658097893...|       0.0|
|(262144,[3329,728...|[3.53886588195029...|[0.97177362020616...|       0.0|
|(262144,[7123,142...|[1.96316546138345...|[0.87687511984340...|       0.0|
|(262144,[16004,17...|[3.31278988746492...|[0.96486498226762...|       0.0|
|(262144,[535,2437...|[0.39010736385245...|[0.59630854469133...|       0.0|
|(262144,[1272,270...|[2.81207497271404...|[0.94332485570867...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[122]:
```
wiki_pred_cult.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[2.70151208529733...|[0.93711580969783...|       0.0|
|(262144,[303,4213...|[3.44104195301703...|[0.96896286667425...|       0.0|
|(262144,[1066,542...|[3.42560708029973...|[0.96849530583942...|       0.0|
|(262144,[1232,219...|[2.34762693781628...|[0.91274541901547...|       0.0|
|(262144,[7286,748...|[3.84672633643086...|[0.97909676069824...|       0.0|
|(262144,[3329,728...|[3.19201133073144...|[0.96053254022136...|       0.0|
|(262144,[7123,142...|[2.37299393913563...|[0.91474463866372...|       0.0|
|(262144,[16004,17...|[3.21906495327168...|[0.96154545532157...|       0.0|
|(262144,[535,2437...|[3.30926749147186...|[0.96474537538702...|       0.0|
|(262144,[1272,270...|[3.36233175464216...|[0.96650634205407...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[123]:
```
wiki_pred_suspenseful.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[3.54717801654356...|[0.97200072726380...|       0.0|
|(262144,[303,4213...|[3.81164218002364...|[0.97836651851946...|       0.0|
|(262144,[1066,542...|[3.61234216079153...|[0.97372067980934...|       0.0|
|(262144,[1232,219...|[3.48997253158643...|[0.97040110686134...|       0.0|
|(262144,[7286,748...|[3.67075304440542...|[0.97517469284433...|       0.0|
|(262144,[3329,728...|[4.09547155128620...|[0.98362471983416...|       0.0|
|(262144,[7123,142...|[2.15311886595804...|[0.89595986366427...|       0.0|
|(262144,[16004,17...|[3.74405663612789...|[0.97688882611903...|       0.0|
|(262144,[535,2437...|[4.13857655040866...|[0.98430473632504...|       0.0|
|(262144,[1272,270...|[3.65281504211333...|[0.97473671006149...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[124]:
```
wiki_pred_psychedelic.show()
```

```
+--------------------+--------------------+--------------------+----------+
```

```
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[2.91917782266424...|[0.94878636356625...|       0.0|
|(262144,[303,4213...|[2.35053199063295...|[0.91297650371929...|       0.0|
|(262144,[1066,542...|[2.28065446012291...|[0.90726212623976...|       0.0|
|(262144,[1232,219...|[2.00960584847894...|[0.88180194703428...|       0.0|
|(262144,[7286,748...|[2.17793934214530...|[0.89825089024607...|       0.0|
|(262144,[3329,728...|[1.17533674967441...|[0.76410830324837...|       0.0|
|(262144,[7123,142...|[3.09973268106238...|[0.95688171706799...|       0.0|
|(262144,[16004,17...|[1.94076993776204...|[0.87443670483400...|       0.0|
|(262144,[535,2437...|[3.28173672940937...|[0.96379693112988...|       0.0|
|(262144,[1272,270...|[2.50635706522031...|[0.92458627400009...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

[125]:
```
wiki_pred_comedy.show()
```

```
+--------------------+--------------------+--------------------+----------+
|            features|       rawPrediction|         probability|prediction|
+--------------------+--------------------+--------------------+----------+
|(262144,[181,5592...|[3.86259456187510...|[0.97941906739125...|       0.0|
|(262144,[303,4213...|[4.45579956512564...|[0.98852223630044...|       0.0|
|(262144,[1066,542...|[3.96737190963153...|[0.98142833402416...|       0.0|
|(262144,[1232,219...|[4.49619602259118...|[0.98897164549281...|       0.0|
|(262144,[7286,748...|[3.38987192232869...|[0.96738650410305...|       0.0|
|(262144,[3329,728...|[3.76833172054003...|[0.97743058753958...|       0.0|
|(262144,[7123,142...|[4.33412943350293...|[0.98705644740338...|       0.0|
|(262144,[16004,17...|[4.19634352766091...|[0.98517265103716...|       0.0|
|(262144,[535,2437...|[-1.1565720794988...|[0.23929071405344...|       1.0|
|(262144,[1272,270...|[3.98355363639040...|[0.98172098819929...|       0.0|
+--------------------+--------------------+--------------------+----------+
```

From the prediction, we can see that only one movie is predicted to be comedy from our model. This means that the rest of nine belongs to the genre that do not appear in these top tags.

[ ]: