# Web Science cs532-s16

## Assignment 9 Report

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### Problem 1

Choose a blog or a newsfeed (or something similar with an Atom or RSS feed). Every student should do a unique feed, so please "claim" the feed on the class email list (first come, first served). It should be on a topic or topics of which you are qualified to provide classification training data. Find something with at least 100 entries (or items if RSS).

Create between four and eight different categories for the entries in the feed:

examples:

work, class, family, news, deals

liberal, conservative, moderate, libertarian

sports, local, financial, national, international, entertainment

metal, electronic, ambient, folk, hip-hop, pop

Download and process the pages of the feed as per the week 12 class slides.

#### Answer

I took me a long time to find a web page with over 100 RSS feeds. I eventually used PlayStation's RSS feeds for movies, which has over 10 thousand feeds. I downloaded the feeds with the curl -o command and saved it as psMovies.xml. Next, I picked out the categories for classifying the entries, which are:

action - a film genre in which the characters are thrust into a series of challenges that involve physical feats, extended fight scenes, violence, and frantic chases.

comedy - a genre of film in which the main emphasis is on humour. These films are designed to make the audience laugh through amusement and most often work by exaggerating characteristics for humorous effect. Films in this style traditionally have a happy ending (black comedy being an exception).

scifi - a film genre that uses science fiction: speculative, fictional science-based depictions of phenomena that are not fully accepted by mainstream science, such as extraterrestrial life forms, alien worlds, extrasensory perception and time travel, along with futuristic el-

ements such as spacecraft, robots, cyborgs, interstellar space travel or other technologies. Science fiction films have often been used to focus on political or social issues, and to explore philosophical issues like the human condition.

horror - unsettling films designed to frighten and panic, cause dread and alarm, and to invoke our hidden worst fears, often in a terrifying, shocking finale, while captivating and entertaining us at the same time in a cathartic experience.

romance - romantic love stories recorded in visual media for broadcast in theaters and on television that focus on passion, emotion, and the affectionate romantic involvement of the main characters and the journey that their genuinely strong, true and pure romantic love takes them through dating, courtship or marrige. Romance films make the romantic love story or the search for strong and pure love and romance the main plot focus.

other - other movie genres that are not included above. (The movie genre definitions are from WIKIPEKIA)

## Problem 2

Manually classify the first 50 entries, and then classify (using the fisher classifier) the remaining 50 entries.

Create a table with the title, predicted category, actual category, and cprob() and fisherprob() for the actual category.

#### Answer

I copy and modified the files docclass.py and feedfilter.py to solve this problem. The program feedfilter.py reads and parse the entries from psMovies.xml. And for each of the top 50 entries, I enter an actual classification which is use to call the classifier.train() function in docclass.py. This is used to train the classifier and enables it to make predictions of the category of the movies based on my input. I also get the fisher's conditional probability by calling the classifier.cprob() and classifier.fisherprob() functions, the actual category is to those functions to calculate the probabilities .

Manually classify first					
Title	Prediction	Actual	cprob	fisherprob	
Holy Ghost People	None	other	1.0	0.75	
Bad Ass 2: Bad Asses	other	action	0.0	0.8861	
Dom Hemingway - Theatrical Tralier	other	comedy	0.0	0.75	
Nymphomaniac: Volume 2	other	other	1.0	0.75	
In The Blood	action	action	1.0	0.75	
10 Rules for Sleeping Around	action	romance	1.0	0.75	
The Unknown Known	action	other	1.0	0.75	
Afflicted	action	horror	1.0	0.75	
Alien Abduction	horror	horror	0.0	0.8861	
Alan Partridge	action	comedy	1.0	0.75	
The Occupants	action	horror	1.0	0.75	
The Little Rascals Save the Day	action	comedy	1.0	0.75	
Seal Team Eight: Behind Enemy Lines	horror	action	1.0	0.75	
The Pirate Fairy	horror	other	1.0	0.75	
The Pirate Fairy (3D)	other	other	1.0	0.8333	
Ages and Stages: The Story of the Meligrove Band	other	other	1.0	0.875	
Blumenthal	action	comedy	1.0	0.75	
Let Timmy Smoke	other	other	0.0	0.8861	
I Am Divine	action	other	1.0	0.75	
				0.75	
Four Seasons About A Zombie	horror	romance		0.7428	
	action	horror	0.0		
The Living Matrix	other	other	1.0	0.8333	
Herbert Nitsch: Back from the Abyss	comedy	other	1.0	0.75	
HazMat	horror	horror	1.0	0.75	
Battle of the Empires	action	action	1.0	0.75	
Volcom: True to This	horror	other	0.0	0.8861	
E.T.X.R.	horror	scifi	0.0	0.8738	
Hide Your Smiling Faces	horror	other	1.0	0.75	
Locker 13	other	other	1.0	0.75	
Airplane vs Volcano	horror	scifi	1.0	0.75	
Mistaken For Strangers	other	comedy	1.0	0.75	
Red Bull X Fighters 2013	horror	other	0.2632	0.3421	
The Appearing	horror	horror	0.0	0.8861	
SSI: Sex Squad Investigation	other	comedy	1.0	0.75	
Black Roots	horror	other	0.0	0.8861	
Happy Camp	horror	horror	1.0	0.75	
Odd Thomas	horror	comedy	0.0	0.8861	
Countdown	horror	horror	1.0	0.75	
Awake Zion	horror	other	1.0	0.75	
Beast of the Bering Sea	other	scifi	1.0	0.75	
Wendy Liebman: Taller on TV	horror	comedy	0.0	0.9188	
How to Follow Strangers	comedy	romance	1.0	0.75	
In Heaven There is No Beer	horror	other	0.4848	0.4886	
Come Back, Africa	horror	other	0.3077	0.3718	
Home	horror	other	1.0	0.75	
Scooby-Doo! Wrestlemania Mystery	comedy	comedy	0.0	0.8861	
Avengers Confidential: Black Widow & Punisher	comedy	scifi	1.0	0.75	
Bad Words - Theatrical Tralier	comedy	comedy	0.0	0.6207	
Cheap Thrills	horror	horror	1.0	0.75	
The French Minister	comedy	comedy	0.0	0.8861	
ING FIGHOR MINISTEL	comedy	comedy	0.0	0.0001	

Title	Prediction		cprob	fisherprob
Mardock Scramble: Third Exhaust	other	action	0.0	0.5
Blood Ties (2014)	horror	other	0.0	0.25
Maladies	comedy	other	0.0	0.5
Divergent - Theatrical Trailer	comedy	scifi	0.0	0.5
McCanick	horror	action	0.0	0.5
Nymphomaniac: Volume 1	other	other	0.0	0.7428
Battle of the Undead	horror	horror	0.0	0.5
American Virgins	horror	comedy	0.0	0.0714
Almost Sharkproof	horror	comedy		0.5
Sparks	horror	action	0.0	0.5
The Wrath of Vajra	action	action		0.5399
The Laughing Matter	horror	comedy	1.0	0.8333
Tom Hollands Twisted Tales	horror	horror	0.0	0.5
Jeff Dunhams Achmed Saves America: The Animated Movie	horror	comedy		0.4752
Waking	horror	romance		0.5
Romeo, Romeo	horror	romance		0.5
CyberGeddon	horror	other	0.0	0.5
Signature Sounds: Music of WWE	horror	other	0.0	0.25
Maidentrip	romance	other	0.0	0.5
Foxfire				0.1
	romance	other	0.0	
Danny MacAskills Imaginate Documentary	comedy	other	0.0	0.5
Buck Wild	comedy	comedy	0.0	0.5
5th Street	horror	action		0.5
How to Be a Man	other	comedy	0.0	0.3997
UFC Event Replays   UFC 171: Hendricks vs. Lawler	horror	other	0.0	0.5
Patrick: Evil Awakens	horror	horror	0.0	0.5
Better Living Through Chemistry	horror	comedy		0.2358
The Den	horror	horror	0.0	0.5
The Art of the Steal	horror	comedy	0.0	0.5
uwantme2killhim?	horror	horror	0.0	0.5
The Right Kind of Wrong	other	romance	0.0	0.5
Need for Speed - Theatrical Trailer	comedy	action	0.0	0.5
Veronica Mars	horror	comedy	0.0	0.5
The Last Days	scifi	scifi	0.0	0.5
WWE WCWs Greatest PPV Matches Vol. 1	other	other	0.0	0.5966
Bubble Guppies: Animals Everywhere!	other	other	0.0	0.3964
End of the World	comedy	scifi	0.0	0.5
A Cross to Bear	horror	other	0.0	0.5966
Shadowboxing	horror	comedy	0.0	0.5
Dark House	horror	horror	0.0	0.5
The Hungover Games	other	comedy	0.0	0.5
The Hungover Games (Unrated)	other	comedy	0.0	0.5
A Dance for Bethany	horror	romance	0.0	0.5
WWE WCWs Greatest PPV Matches Vol. 3	other	other	0.0	0.5966
WWE WCWs Greatest PPV Matches Vol. 2	other	other	0.0	0.5966
Soap Life	other	other	0.0	0.5966
Hated	other	other		0.6077
In the Name of the King 3: The Last Mission	other	action	0.0	0.5
	other	other	0.3426	
Celebrating the Music of "Inside Llewyn Davis"				

```
import feedparser
import re
import math
import docclass

savefile = open("data.txt", "a")

# Takes a filename or URL of a blog feed and classifies the entries
def read(feed, classifier):
```

```
splitRegexp = re.compile(r"<[^>>]+>")
12
             num=0
              # Get feed entries and loop over them
14
              f=feedparser.parse(feed)
16
               string1 = '-
                                                                                                                                                                     - Manually classify first 50
17
                   entries -
               dividline = "_" * 100 + " \n"
18
               print string1
19
               savefile.write(string1)
20
               string2 = {(36)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}
21
                   Actual", 'cprob', 'fisherprob', "\n")
               print string2
22
               savefile.write(string2)
23
               savefile.write(dividline)
24
25
               for entry in f['entries'][0:50]:
26
                     num=num +1
27
                     # Print the contents of the entry
28
                      title=entry['title'].encode('utf-8').replace("'","")
29
                      print 'Title:
                                                                                    '+ title
30
31
                     summary = splitRegexp.sub( "", entry[ "summary" ] )
32
                      print summary #entry['summary'].encode('utf-8')
34
35
                     # Combine all the text to create one item for the classifier
                     #fulltext='%s\n%s\n%s' % (entry['title'], entry['publisher'], entry['summary
37
                      fulltext='%s\n%s' % (entry['title'], entry['summary'])
38
                     # Remove apostrophes
                      fulltext=fulltext.replace("',","")
40
                     # Print the best guess at the current category
41
                      predicted=str(classifier.classify(fulltext))
42
                      print 'Predicted category: ', predicted
43
44
                     # Ask the user to specify the correct category and train on that
45
                      actual=raw_input('Actual category: ')
46
                       classifier.train(fulltext, actual)
47
48
                      feature=raw_input('Enter string classifier: ')
49
50
                     #classifier.train(entry, cl)
                     # probability the item should be in this category
                      cp=round(classifier.cprob(feature, predicted),4)
53
                      fcp=round(classifier.fisherprob(feature, predicted),4)
                      print 'cprob: ', str(cp)
                      print 'fisherprob: ', str(fcp)
                      string3 = {(30)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}{(31)}
57
                    actual, str(cp), str(fcp), "\n")
                      savefile.write(string3)
58
```

```
# Save the manual classifications
              # num, entry, feature, predicted, actual, cprob=None
 61
               classifier.manualClassdb(num, title, feature, predicted, actual, cp, fcp)
          savefile.write(dividline)
 63
 64 #def autoClassify (feed, classifier):
 65
          num=50
          string4 = '\n-
                                                                                                 - Other 50 automaticly classified
 66
             entries -
          print string4
 67
          savefile.write(string4)
          savefile.write(string2)
          savefile.write(dividline)
 70
          # Get feed entries and loop over them
 71
          #f=feedparser.parse(feed)
 72
          for entry in f['entries'][50:100]:
 73
              num=num+1
 74
             # Print the contents of the entry
 75
              title=entry['title'].encode('utf-8').replace("'","")
 76
              print 'Title:
                                                   '+ title
 77
              summary = splitRegexp.sub( "", entry[ "summary" ] )
 78
 79
              print summary #entry ['summary'].encode('utf-8')
 80
 81
              # Combine all the text to create one item for the classifier
 82
              #fulltext='%s\n%s\n%s' % (entry['title'], entry['publisher'], entry['summary
              fulltext='%s\n%s' % (entry['title'], entry['summary'])
 84
              fulltext=fulltext.replace(",",")
 85
              # Print the best guess at the current category
              predicted=str(classifier.classify(fulltext))
 87
              print 'Predicted: ', predicted
 89
              # Ask the user to specify the correct category
              actual=raw_input('Actual category: ')
 91
              feature=raw_input('Enter string classifier: ')
 92
 93
 94
              # probability the item should be in this category
 95
              cp=round(classifier.cprob(feature, predicted),4)
 96
              fcp=round (classifier.fisherprob(feature, predicted),4)
 97
              print 'cprob: ', str(cp)
 98
              print 'fisherprob: ', str(fcp)
 99
100
              string6 = "{:<60}{:<12}{:<10}{:<10}{:<10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10}{:>10
             actual, str(cp), str(fcp), "\n")
              savefile.write(string6)
              # Save the trained classifications
103
              # num, entry, feature, predicted, cprob(feature, predicted)
104
               classifier.autoClassdb(num, title, feature, predicted, actual, cp, fcp)
          #return classifier
106
          savefile.write(dividline)
107
def entryfeatures (entry):
      splitter=re.compile('\\W*')
```

```
f = \{\}
111
112
     # Extract the title words and annotate
113
     titlewords=[s.lower() for s in splitter.split(entry['title'])
114
              if len(s) > 2 and len(s) < 20
     for w in titlewords: f['Title:'+w]=1
117
     # Extract the summary words
118
     summarywords=[s.lower() for s in splitter.split(entry['summary'])
119
              if len(s)>2 and len(s)<20
     # Count uppercase words
123
     for i in range(len(summarywords)):
124
       w=summarywords [ i ]
       f[w]=1
126
       if w.isupper(): uc+=1
127
128
       # Get word pairs in summary as features
       if i < len (summarywords) - 1:
130
         twowords=' '.join (summarywords[i:i+1])
         f [twowords]=1
132
133
    # Removed: Keep creator and publisher whole
134
    #f['Publisher:'+entry['publisher']]=1
135
136
     # UPPERCASE is a virtual word flagging too much shouting
     if float (uc)/len (summarywords) > 0.3: f ['UPPERCASE']=1
138
139
     return f
140
141
142
   cl=docclass.fisherclassifier(docclass.getwords)
cl.setdb('psMovies.db')
read ('psMovies.xml', cl)
 1 #from pysqlite2 import dbapi2 as sqlite
 2 from sqlite3 import dbapi2 as sqlite
 з import re
  import math
 4
   def getwords(doc):
 6
     splitter=re.compile('\\W*')
     #print doc
    ## Remove all the HTML tags
 9
     doc=re.compile(r'<[^>]+>').sub('',doc)
     # Split the words by non-alpha characters
     words=[s.lower() for s in splitter.split(doc)
              if len(s) > 2 and len(s) < 20
13
14
    # Return the unique set of words only
     return dict ([(w,1) \text{ for } w \text{ in } words])
17
18 class classifier:
```

```
def __init__ (self, getfeatures, filename=None):
                   # Counts of feature/category combinations
20
                    self.fc={}
21
                   # Counts of documents in each category
                    self.cc=\{\}
23
                   ## extract features for classification
24
                    self.getfeatures=getfeatures
26
             def setdb (self, dbfile):
27
                    self.con=sqlite.connect(dbfile)
28
                    self.con.execute('create table if not exists rss(num, entry, feature,
29
                  predicted, actual, cprob)')
                    self.con.execute('create table if not exists fc(feature, category, count)')
30
                     self.con.execute('create table if not exists cc(category, count)')
                   # remove old data from previous sessions
                    self.con.execute('delete from rss')
33
                    self.con.execute('delete from fc')
34
                    self.con.execute('delete from cc')
35
36
             def manualClassdb (self, num, entry, feature, predicted, actual, cp, fcp):
37
                    self.con.execute("insert into rss values ('%s', '%s', 
38
                 s ')"
                                                                          % (num, entry, feature, predicted, actual, fcp))
39
                    self.con.commit()
40
41
             def autoClassdb (self, num, entry, feature, predicted, actual, cp, fcp):
42
                    self.con.execute("insert into rss values ('%s', '%s', 
43
                 s ')"
                                                                          % (num, entry, feature, predicted, actual, fcp))
44
                    self.con.commit()
45
             ## Increase the count of a feature/category pair
46
             def incf(self,f,cat):
47
                    count=self.fcount(f,cat)
                    if count==0:
49
                           self.con.execute("insert into fc values ('%s','%s',1)"
50
                                                                                 % (f, cat.lower())
                    else:
                           self.con.execute(
53
                                 "update fc set count=%d where feature='%s' and category='%s'"
54
                                \% (count+1,f, cat.lower())
56
             ## The number of times a feature has appeared in a category
57
             def fcount (self, f, cat):
58
                    res=self.con.execute(
59
                            'select count from fc where feature="%s" and category="%s";
60
                          %(f, cat)).fetchone()
61
                    if res=None: return 0
                    else: return float (res[0])
64
             ## Increase the count of a category
65
             def incc (self, cat):
66
                    count=self.catcount(cat)
67
                    if count==0:
68
                           self.con.execute("insert into cc values ('%s',1)" % (cat.lower()))
```

```
else:
         self.con.execute("update cc set count=%d where category='%s'"
71
                           \% (count+1,cat))
72
73
     ## The number of items in a category
74
     def catcount (self, cat):
75
       res=self.con.execute('select count from cc where category="%s"'
76
                             %(cat)).fetchone()
77
       if res=None: return 0
78
       else: return float (res[0])
79
80
     ## The list of all categories
81
     def categories (self):
82
       cur=self.con.execute('select category from cc');
       return [d[0] for d in cur]
84
85
    ## The total number of items
86
     def totalcount (self):
87
       res=self.con.execute('select sum(count) from cc').fetchone();
88
       if res=None: return 0
89
       return res[0]
90
91
92
    ## The train method takes an item (document) and a classification.
93
    ## It uses the getfeatures function to the break the item into its
94
    ## separate features. It then calls incf to increase the counts for
95
    ## this classification for every feature. Finally, it increases
96
    ## the total count for this classification.
97
     def train (self, item, cat):
       features=self.getfeatures(item)
99
       # Increment the count for every feature with this category
100
       for f in features:
101
         self.incf(f,cat)
103
       # Increment the count for this category
104
       self.incc(cat)
105
       self.con.commit()
106
    ## Probability is a number between 0 and 1, indicating
108
    ## the likelihood of an event. You calculate the probability of
109
    ## a word in a particular category by dividing the number of
    ## times the word appears in a document in that category
111
    ## by the total number of documents in the category.
     def fprob(self, f, cat):
113
       if self.catcount(cat)==0: return 0
114
       # The total number of times this feature appeared in this
116
       # category divided by the total number of items in this category
117
       return self.fcount(f, cat)/self.catcount(cat)
118
119
     def weightedprob (self, f, cat, prf, weight=1.0, ap=0.5):
120
       # Calculate current probability
       basicprob=prf(f,cat)
123
```

```
# Count the number of times this feature has appeared in
       # all categories
       totals=sum([self.fcount(f,c) for c in self.categories()])
126
       # Calculate the weighted average
128
       bp=((weight*ap)+(totals*basicprob))/(weight+totals)
129
       return bp
130
134
   class naivebayes(classifier):
136
     def __init__(self, getfeatures):
137
       classifier.__init__(self, getfeatures)
       self.thresholds={}
139
140
     def docprob (self, item, cat):
141
       features=self.getfeatures(item)
142
143
       # Multiply the probabilities of all the features together
144
145
       for f in features: p*=self.weightedprob(f, cat, self.fprob)
146
       return p
147
148
     def prob(self, item, cat):
149
       catprob=self.catcount(cat)/self.totalcount()
150
       docprob=self.docprob(item, cat)
       return docprob*catprob
     def setthreshold (self, cat, t):
154
       self.thresholds[cat]=t
156
     def getthreshold (self, cat):
157
       if cat not in self.thresholds: return 1.0
158
       return self.thresholds[cat]
159
160
     def classify (self, item, default=None):
161
       probs={}
162
       # Find the category with the highest probability
163
       \max = 0.0
164
       for cat in self.categories():
165
         probs[cat] = self.prob(item, cat)
         if probs [cat]>max:
           max=probs [cat]
168
            best=cat
169
170
       # Make sure the probability exceeds threshold*next best
       for cat in probs:
         if cat=best: continue
173
         if probs[cat]*self.getthreshold(best)>probs[best]: return default
174
       return best
176
177 ## This function will return the probability that an item with the
```

```
## specified feature belongs in the specified category, assuming there
   ## will be an equal number of items in each category.
   class fisherclassifier (classifier):
180
     def cprob(self, f, cat):
181
       # The frequency of this feature in this category
182
       clf=self.fprob(f,cat)
183
       if clf == 0: return 0
185
       # The frequency of this feature in all the categories
       freqsum = sum([self.fprob(f,c) for c in self.categories()])
188
       # The probability is the frequency in this category divided by
189
       # the overall frequency
190
       p=clf/(freqsum)
193
       return p
194
195
     def fisherprob(self,item,cat):
196
       # Multiply all the probabilities together
197
       p=1
198
       features=self.getfeatures(item)
199
       for f in features:
200
         p*=(self.weightedprob(f,cat,self.cprob))
201
202
       # Take the natural log and multiply by -2
203
       fscore = -2*math.log(p)
204
205
       # Use the inverse chi2 function to get a probability
       return self.invchi2 (fscore, len (features) *2)
207
208
     ## Inverse chi-squared function
209
     def invchi2 (self, chi, df):
       m = chi / 2.0
211
       sum = term = math.exp(-m)
212
       for i in range (1, df//2):
213
            term *= m / i
214
           sum += term
       return min(sum, 1.0)
216
217
     def __init__(self, getfeatures):
218
       classifier.__init__(self, getfeatures)
219
       self.minimums={}
220
     def setminimum (self, cat, min):
222
       self.minimums[cat]=min
223
224
     def getminimum(self, cat):
225
       if cat not in self.minimums: return 0
226
       return self.minimums[cat]
227
228
     def classify (self, item, default=None):
       # Loop through looking for the best result
230
231
       best=default
```

```
max=0.0
for c in self.categories():
    p=self.fisherprob(item,c)
    # Make sure it exceeds its minimum
    if p>self.getminimum(c) and p>max:
        best=c
    max=p
    return best
```

## Problem 3

Assess the performance of your classifier in each of your categories by computing precision, recall, and F-measure.

#### Answer

In order to calculate the precision, recall, and F-measures. I first have to get the false positive, false negative, and true positive of the predictions. Where the prediction matched my actual input for each category is the true positive for each category. The false positive and false negative is obtained by subtracting the TP from predicted and actual counts of each category. Then use the formulas from lecture slides to calculated the precision, recall, and F-measures.

```
Precision = TP / (TP+FP)
Recall = TP / (TP+FN)
F-Measure = 2 * P*R / (P+R)
```

Categories	FP	FN	TP	Precision	Recall	F-measure
Action	10	7	3	0.23	0.3	0.26
Comedy	8	19	4	0.33	0.17	0.22
Horror	35	3	12	0.26	0.8	0.39
Other	10	24	14	0.58	0.37	0.45
Romance	2	7	0	0	0	0
Scifi	0	6	1	1	0.14	0.25

Based on the result, the classifier did not perform well at all, but it was expected, since I only trained it with 50 entries.