In [1]:

```
import pandas
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.manifold import MDS
from scipy.cluster import hierarchy
```

In [2]:

```
dfmovies = pandas.read_csv('datasets/movies/movies_description.txt',sep='|',header=N
one)
dfusers = pandas.read_csv('datasets/movies/users_description.txt',sep='|',header=Non
e)
dfscores = pandas.read_csv('datasets/movies/movies_users.txt',sep='\t',header=None)
```

In [3]:

```
nusers = len(dfusers.values)
nmovies = len(dfmovies.values)
print('nusers',nusers)
print('nmovies',nmovies)
```

```
nusers 943
nmovies 1682
```

In [4]:

```
evaluations = np.zeros((nmovies,nusers))
evaluations[ dfscores.values[:,1]-1, dfscores.values[:,0]-1 ] = dfscores.values[:,2]

dfevaluations = pandas.DataFrame(evaluations,index=dfmovies.values[:,1],columns=np.a
range(nusers)+1)
dfevaluations
```

Out[4]:

	1	2	3	4	5	6	7	8	9	10	...	934	935	936	937	938	939
Toy Story (1995)	5.0	4.0	0.0	0.0	4.0	4.0	0.0	0.0	0.0	4.0	...	2.0	3.0	4.0	0.0	4.0	0.0
GoldenEye (1995)	3.0	0.0	0.0	0.0	3.0	0.0	0.0	0.0	0.0	0.0	...	4.0	0.0	0.0	0.0	0.0	0.0
Four Rooms (1995)	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	4.0	0.0	0.0	0.0
Get Shorty (1995)	3.0	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	4.0	...	5.0	0.0	0.0	0.0	0.0	0.0
Copycat (1995)	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
Mat' i syn (1997)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
B. Monkey (1998)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
Sliding Doors (1998)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
You So Crazy (1994)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0
Scream of Stone (Schrei aus Stein) (1991)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0

1682 rows × 943 columns

Filtering

In [5]:

```
tmovies = np.array(list(dfevaluations.index))
idusers = dfevaluations.columns
for i in range(nmovies):
    tmovies[i] = tmovies[i][:10]
print(tmovies[:5])
```

```
['Toy Story ' 'GoldenEye ' 'Four Rooms' 'Get Shorty' 'Copycat (1']
```

In [6]:

```
bevaluations = evaluations!=0
```

In [7]:

```
# Filtering movies
neval = np.sum( bevaluations, axis=1 )
idx = np.argsort(neval)[::-1]
idx = idx[:50]

evaluations = evaluations[idx,:]
tmovies = tmovies[idx]
```

In [8]:

```
# Filtering users
neval = np.sum( bevaluations, axis=0 )
idx = np.argsort(neval)[::-1]
idx = idx[:100]

evaluations = evaluations[:,idx]
idusers = idusers[idx]
```

In [9]:

```
dfevaluations = pandas.DataFrame(evaluations,index=tmovies,columns=idusers)
dfevaluations
```

Out[9]:

	405	655	13	450	276	416	537	303	234	393	...	184	788	314	894	666
Star Wars	5.0	4.0	5.0	5.0	5.0	5.0	4.0	5.0	4.0	5.0	...	4.0	0.0	0.0	4.0	3.0
Contact (1	0.0	2.0	4.0	4.0	5.0	5.0	4.0	4.0	2.0	4.0	...	3.0	4.0	0.0	4.0	4.0
Fargo (199	0.0	3.0	5.0	4.0	5.0	5.0	4.0	5.0	4.0	1.0	...	5.0	5.0	0.0	4.0	4.0
Return of	5.0	3.0	5.0	4.0	5.0	5.0	2.0	5.0	3.0	4.0	...	4.0	0.0	0.0	0.0	2.0
Liar Liar	0.0	3.0	2.0	4.0	4.0	4.0	1.0	4.0	3.0	4.0	...	0.0	3.0	5.0	0.0	3.0
English Pa	0.0	3.0	3.0	4.0	0.0	5.0	3.0	5.0	3.0	0.0	...	4.0	5.0	0.0	5.0	5.0
Scream (19	5.0	3.0	1.0	3.0	4.0	5.0	2.0	4.0	3.0	3.0	...	0.0	0.0	5.0	3.0	3.0
Toy Story	0.0	2.0	3.0	4.0	5.0	5.0	2.0	5.0	3.0	3.0	...	4.0	3.0	5.0	4.0	0.0
Air Force	0.0	3.0	1.0	4.0	4.0	4.0	1.0	1.0	3.0	0.0	...	0.0	5.0	0.0	4.0	3.0
Independen	0.0	3.0	5.0	3.0	4.0	5.0	1.0	3.0	0.0	4.0	...	2.0	4.0	4.0	3.0	3.0
Raiders of	5.0	3.0	4.0	5.0	5.0	5.0	3.0	5.0	3.0	0.0	...	3.0	2.0	0.0	0.0	3.0
Godfather,	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	4.0	0.0	...	5.0	0.0	0.0	0.0	5.0
Pulp Ficti	4.0	3.0	5.0	4.0	5.0	5.0	5.0	5.0	3.0	2.0	...	3.0	3.0	1.0	0.0	4.0
Twelve Mon	0.0	3.0	2.0	4.0	5.0	4.0	4.0	4.0	2.0	4.0	...	3.0	4.0	4.0	4.0	4.0
Silence of	4.0	4.0	4.0	4.0	5.0	5.0	3.0	5.0	4.0	0.0	...	4.0	5.0	0.0	0.0	4.0
Jerry Magu	0.0	3.0	5.0	5.0	5.0	3.0	3.0	5.0	3.0	4.0	...	4.0	4.0	5.0	4.0	3.0
Rock, The	0.0	2.0	3.0	4.0	4.0	5.0	2.0	3.0	2.0	4.0	...	2.0	4.0	4.0	3.0	0.0
Empire Str	5.0	4.0	5.0	4.0	5.0	5.0	3.0	5.0	3.0	5.0	...	4.0	3.0	0.0	0.0	3.0
Star Trek:	0.0	2.0	3.0	3.0	4.0	0.0	2.0	3.0	3.0	4.0	...	0.0	3.0	0.0	0.0	3.0
Titanic (1	4.0	4.0	4.0	5.0	5.0	5.0	4.0	0.0	4.0	4.0	...	4.0	0.0	0.0	4.0	0.0
Back to th	5.0	3.0	5.0	4.0	5.0	5.0	3.0	4.0	2.0	4.0	...	0.0	3.0	5.0	0.0	3.0
Mission: I	0.0	2.0	2.0	4.0	3.0	5.0	2.0	4.0	0.0	4.0	...	2.0	4.0	4.0	3.0	2.0
Fugitive,	5.0	5.0	3.0	4.0	4.0	5.0	3.0	5.0	3.0	4.0	...	3.0	4.0	0.0	0.0	3.0
Indiana Jo	5.0	3.0	3.0	3.0	4.0	5.0	3.0	4.0	3.0	4.0	...	4.0	0.0	0.0	0.0	2.0
Willy Wonk	0.0	0.0	0.0	5.0	5.0	3.0	2.0	5.0	3.0	0.0	...	0.0	1.0	4.0	0.0	2.0
Princess B	5.0	0.0	2.0	5.0	5.0	5.0	4.0	5.0	3.0	5.0	...	0.0	0.0	1.0	0.0	4.0
Forrest Gu	4.0	3.0	4.0	4.0	4.0	4.0	2.0	5.0	4.0	4.0	...	3.0	4.0	5.0	0.0	3.0
Monty Pyth	1.0	0.0	4.0	5.0	5.0	5.0	4.0	5.0	3.0	4.0	...	0.0	0.0	0.0	0.0	4.0
Saint, The	0.0	0.0	4.0	4.0	3.0	4.0	0.0	2.0	0.0	3.0	...	0.0	3.0	0.0	3.0	0.0
Full Monty	0.0	3.0	2.0	5.0	4.0	4.0	3.0	5.0	0.0	0.0	...	0.0	0.0	0.0	3.0	5.0
Men in Bla	0.0	3.0	0.0	0.0	4.0	3.0	0.0	4.0	0.0	4.0	...	0.0	0.0	5.0	3.0	3.0
Terminator	5.0	3.0	3.0	4.0	5.0	5.0	3.0	4.0	2.0	3.0	...	0.0	3.0	0.0	0.0	3.0
E.T. the E	5.0	3.0	5.0	5.0	5.0	4.0	2.0	4.0	4.0	3.0	...	4.0	5.0	4.0	0.0	3.0
Dead Man W	0.0	3.0	3.0	0.0	5.0	5.0	0.0	5.0	3.0	4.0	...	5.0	4.0	4.0	4.0	0.0
Schindler'	5.0	4.0	3.0	5.0	5.0	5.0	4.0	5.0	4.0	3.0	...	5.0	5.0	5.0	5.0	5.0

	405	655	13	450	276	416	537	303	234	393	...	184	788	314	894	666
Leaving La	0.0	4.0	5.0	0.0	4.0	3.0	4.0	4.0	3.0	0.0	...	4.0	0.0	1.0	5.0	0.0
L.A. Confi	4.0	4.0	5.0	5.0	5.0	5.0	4.0	4.0	0.0	4.0	...	0.0	4.0	0.0	4.0	5.0
Braveheart	5.0	2.0	4.0	5.0	5.0	5.0	2.0	5.0	4.0	4.0	...	3.0	5.0	4.0	0.0	0.0
Terminator	3.0	3.0	4.0	4.0	5.0	4.0	3.0	5.0	2.0	4.0	...	0.0	3.0	0.0	0.0	3.0
Conspiracy	0.0	2.0	3.0	4.0	4.0	5.0	2.0	3.0	2.0	5.0	...	0.0	4.0	4.0	4.0	0.0
Birdcage,	0.0	3.0	1.0	3.0	4.0	4.0	2.0	4.0	3.0	2.0	...	4.0	0.0	3.0	2.0	3.0
Mr. Hollan	0.0	3.0	0.0	3.0	0.0	4.0	3.0	3.0	3.0	3.0	...	3.0	0.0	5.0	3.0	0.0
Twister (1	0.0	2.0	4.0	3.0	3.0	2.0	0.0	2.0	0.0	4.0	...	2.0	3.0	0.0	0.0	3.0
Alien (197	1.0	4.0	4.0	4.0	5.0	5.0	3.0	5.0	4.0	0.0	...	4.0	5.0	0.0	0.0	5.0
When Harry	2.0	4.0	3.0	5.0	0.0	5.0	3.0	5.0	3.0	0.0	...	4.0	0.0	3.0	0.0	3.0
Aliens (19	1.0	2.0	3.0	4.0	5.0	4.0	2.0	5.0	3.0	0.0	...	4.0	5.0	0.0	0.0	4.0
Shawshank	5.0	4.0	5.0	4.0	5.0	5.0	3.0	5.0	4.0	4.0	...	4.0	5.0	5.0	0.0	4.0
Jaws (1975	5.0	3.0	5.0	3.0	5.0	5.0	3.0	5.0	4.0	0.0	...	0.0	3.0	0.0	0.0	3.0
Groundhog	4.0	2.0	5.0	4.0	4.0	4.0	3.0	5.0	3.0	3.0	...	3.0	0.0	5.0	0.0	5.0
Apollo 13	4.0	3.0	5.0	4.0	4.0	5.0	3.0	3.0	4.0	4.0	...	0.0	5.0	5.0	0.0	3.0

50 rows × 100 columns

Principal Component Analysis

In [10]:

```
X = evaluations
n = len(X)
```

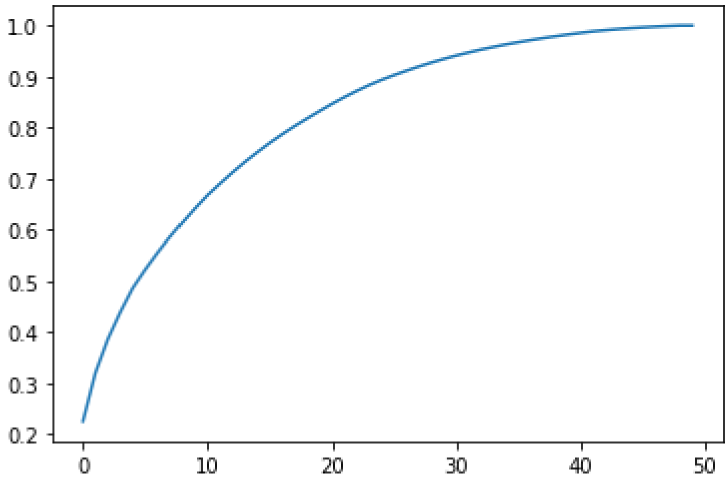
In [11]:

```
model = PCA()
model.fit(X)
X2 = model.transform(X)
X2 = X2[:,:2]
```

In [12]:

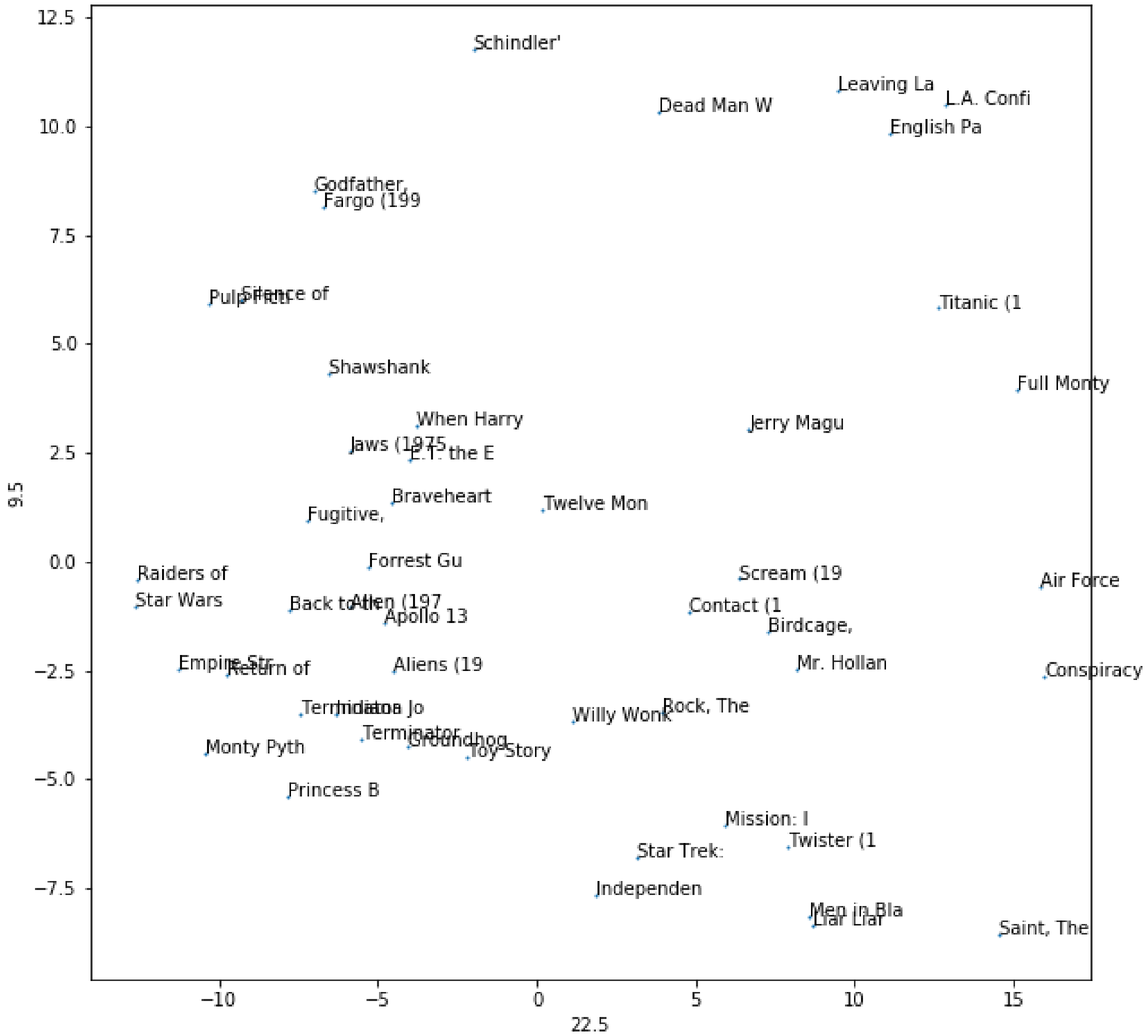
```
exp_var = model.explained_variance_ratio_
print(np.round(exp_var,3))
exp_var_acum = np.cumsum(exp_var)
plt.figure()
plt.plot(exp_var_acum)
plt.show()
```

```
[0.225 0.095 0.066 0.053 0.047 0.036 0.033 0.031 0.029 0.027 0.026 0.023
 0.022 0.021 0.019 0.018 0.017 0.016 0.015 0.014 0.014 0.013 0.012 0.011
 0.01  0.009 0.009 0.008 0.008 0.007 0.007 0.006 0.006 0.005 0.005 0.004
 0.004 0.004 0.004 0.003 0.003 0.003 0.002 0.002 0.002 0.002 0.001 0.001
 0.001 0.   ]
```



In [13]:

```
plt.figure(figsize=(10,10))
plt.scatter(X2[:,0],X2[:,1],s=1)
for i in range(n):
    plt.text(X2[i,0],X2[i,1], tmovies[i])
plt.xlabel(np.round(exp_var[0],3)*100)
plt.ylabel(np.round(exp_var[1],3)*100)
plt.show()
```


Schindler'
Leaving La
L.A. Confi
Dead Man W
English Pa
Godfather,
Fargo (199
Pulp Ficti
Silence of
Titanic (1
Shawshank
Full Monty
When Harry
Jerry Magu
Jaws (1975
E.T. the E
Braveheart
Twelve Mon
Fugitive,
Forrest Gu
Raiders of
Scream (19
Air Force
Star Wars
Back to th
Alien (197
Apollo 13
Contact (1
Birdcage,
Empire Str
Return of
Aliens (19
Mr. Hollan
Conspiracy
Terminato
Indiana Jo
Willy Wonk
Rock, The
Terminator
Groundhog
Toy Story
Monty Pyth
Princess B
Mission: I
Twister (1
Star Trek:
Independen
Men in Bla
Liar Liar
Saint, The
9.5
22.5

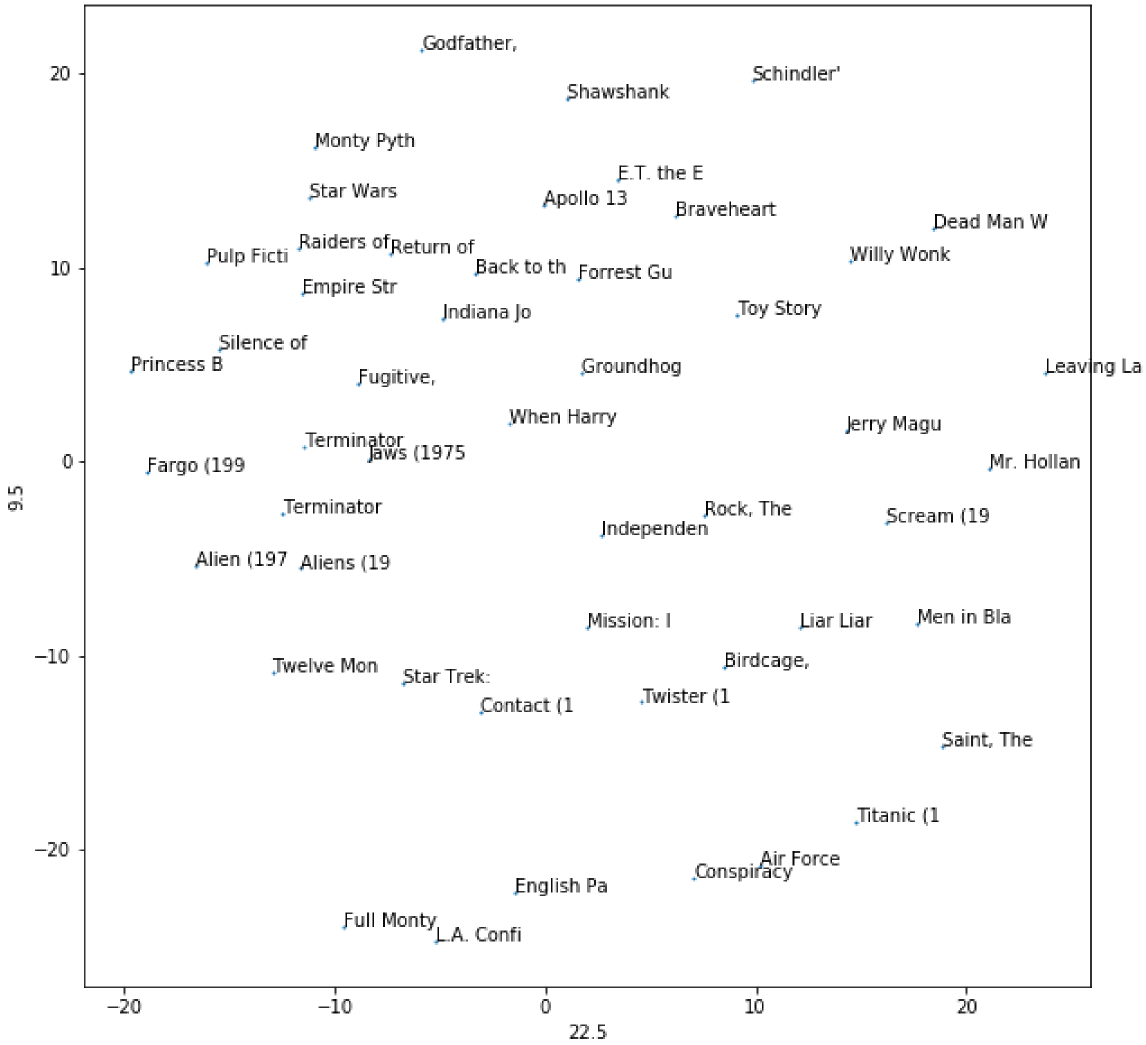
MDS

In [14]:

```
model = MDS(n_components=2)
X2 = model.fit_transform(X)
```

In [15]:

```
plt.figure(figsize=(10,10))
plt.scatter(X2[:,0],X2[:,1],s=1)
for i in range(n):
    plt.text(X2[i,0],X2[i,1], tmovies[i])
plt.xlabel(np.round(exp_var[0],3)*100)
plt.ylabel(np.round(exp_var[1],3)*100)
plt.show()
```

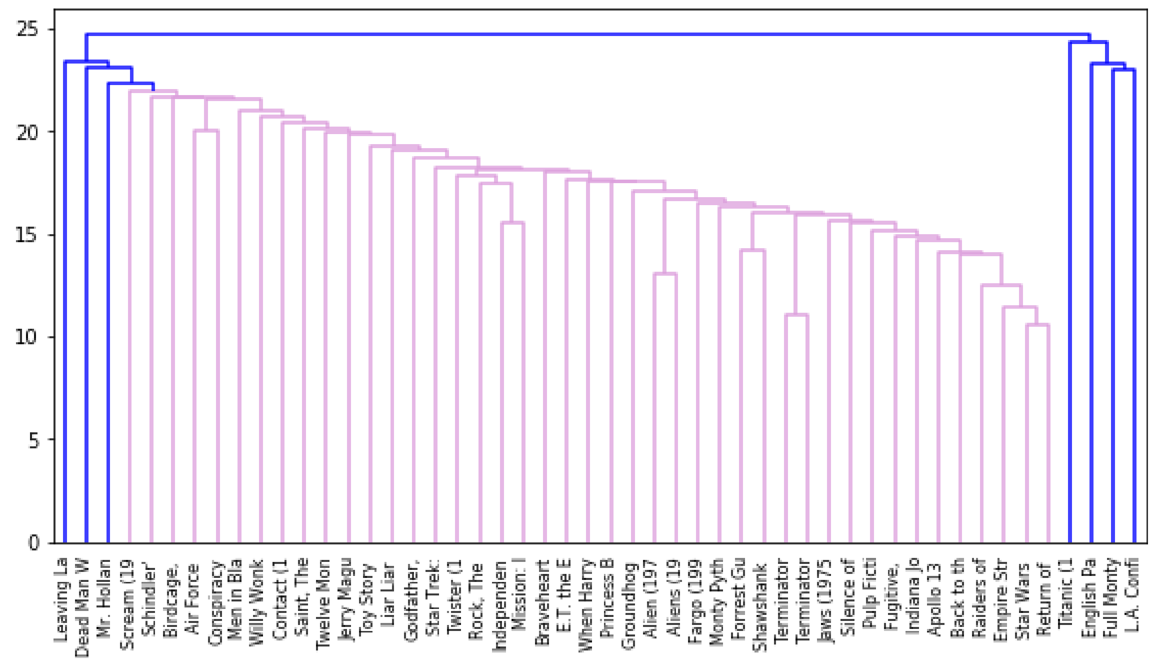


Hierarchical clustering

In [16]:

```
hierarchy.set_link_color_palette(['plum','lightseagreen', 'silver'])

plt.figure(figsize=(10,5))
Z = hierarchy.linkage(X)
dn = hierarchy.dendrogram(Z, labels=tmovies, color_threshold=22)
plt.show()
```



In [17]:

```
g = hierarchy.fcluster(Z,criterion='distance',t=22.0)
print(g)
```

```
[1 1 1 1 1 7 1 1 1 1 1 1 1 1 1 1 1 1 1 8 1 1 1 1 1 1 1 1 1 5 1 1 1 3 1 4
6
 1 1 1 1 2 1 1 1 1 1 1 1 1]
```

In [20]:

```
groups = np.unique(g)
for group in groups:
    print(tmovies[g==group])
```

```
['Star Wars ' 'Contact (1' 'Fargo (199' 'Return of ' 'Liar Liar '
 'Scream (19' 'Toy Story ' 'Air Force ' 'Independen' 'Raiders of'
 'Godfather,' 'Pulp Ficti' 'Twelve Mon' 'Silence of' 'Jerry Magu'
 'Rock, The ' 'Empire Str' 'Star Trek:' 'Back to th' 'Mission: I'
 'Fugitive, ' 'Indiana Jo' 'Willy Wonk' 'Princess B' 'Forrest Gu'
 'Monty Pyth' 'Saint, The' 'Men in Bla' 'Terminator' 'E.T. the E'
 "Schindler'" 'Braveheart' 'Terminator' 'Conspiracy' 'Birdcage, '
 'Twister (1' 'Alien (197' 'When Harry' 'Aliens (19' 'Shawshank '
 'Jaws (1975' 'Groundhog ' 'Apollo 13 ']
['Mr. Hollan']
['Dead Man W']
['Leaving La']
['Full Monty']
['L.A. Confi']
['English Pa']
['Titanic (1']
```