Clustering

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1 Introduction

When you have unlabeled data and no prior information, clustering is used to group them together based on their feature similarity. The number of groups is K (K-means clustering). The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided. The objects in a single cluster are similar to each other that the objects in another cluster. The K means clustering algorithm repeats two steps iteratively:

- 1. Data Assignment Step: In this stem the object is assigned to the cluster that it has the least euclidean distance to.
- 2. Center updating step: After every time a data object is assigned to a cluster, the center of the cluster is recalculated. This is done by taking the mean of all data points assigned to that centroid's cluster.

These two steps are repeated until a certain criteria is met.

2 Data Set

We work with "20 Newsgroups" dataset. It is a collection of approximately 20,000 documents, partitioned (nearly) evenly across 20 different newsgroups, each corresponding to a different topic. Each topic can be viewed as a "class". The following eight categories are loaded, each belonging to two distinct classes. The documents belonging to these classes are used to test the clustering algorithm and measure performance parameters.

- comp.graphics
- comp.os.ms-windows.misc
- comp.sys.ibm.pc.hardware
- comp.sys.mac.hardware
- rec.autos

- rec.motorcycles
- rec.sport.baseball
- rec.sport.hockey

3 Question 1

Proper document representation and the non inclusion of irrelevant words in the document is important for computation accuracy of the algorithm. Hence, common words, stopping words, punctuation and the like are being excluded from the documents. The goal of the question is to tokenize the document, remove stopping words, punctuations and represent the occurrence of words in the document and the data set.

Words that occur in a less that three documents are removed by setting mindf = 3.

By performing vectorization, we are representing the document in terms of numerical values and occurrence of words in the document irrespective of their position in the document. The data can be represented as a matrix wherein each row represents a document and each column represents a token (word). TF-IDF transformation is done on the data set in order to obtain a vector representation of the document based on the frequency of occurrence of words in the documents.

Dimension of TF-IDF Matrix: (7882, 18469)

4 Question 2

In this section we run the K-means algorithm on the TF-IDF Matrix that we got from the last question with k=2 and evaluate the performances. This will cluster the documents into two different categories based on their euclidean distance from the center of the cluster.

Once the clustering is done, the performance of the clustering algorithm can be compared to the ground truth. There are various purity measures to do so.

Homogeneity: Homogeneity is a metric that is satisfied if all the data points in a cluster belong to only one class.

Completeness: Completeness is satisfied if all cluster have data points belonging only to a single class.

V Measure: V Measure is the harmonic mean of Completeness and Homogeneity.

Rand Index: Rand Index is an accuracy measure that gives us the similarity between the clustering labels and the ground truth.

Mutual Index: Mutual Information gives the MI between cluster labels and ground truth.

The following results were observed:

Homogeneity	0.426939956854
Completeness	0.463834468349
V-Measure	0.444623155541
Adjusted Rand Index	0.43718683605
Adjusted Mutual Index	0.42688749143

Table 1: Stats for K-means clustering with k=2

2606	1297
38	3941

38	3941
2606	1297

Table 2: Contingency Matrix

We do not get good results for the algorithm due to the high dimensionality of the TF-IDF Matrix. In the next parts, we aim to reduce the dimensionality and hence better the performance of the clustering algorithm.

5 Question 3

The TF-IDF vector representation of the document may have very high dimensions, and the algorithms may not perform well on them. This is because the K means algorithm assumes that the clusters are in a shape of a circle, which is why reducing the Euclidean distance seems like the best option.

5.1 Part a

In this part, the aim is to reduce the dimensions of the vector by Latent Semantic Indexing (LSI) and Non-negative Matrix Factorization (NMF) . LSI reduces dimension by reducing the SVD of the term document matrix to its best rank k approximation. The aim is to inspect the top singular values of TF-IDF matrix and find out which ones are relevant in reconstructing the matrix with SVD. We can do this by calculating the ratio of variance of original data that is retained after SVD reduction.

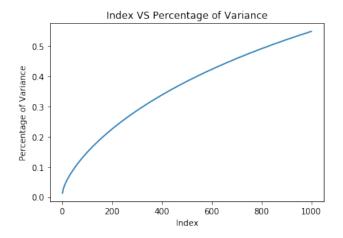


Figure 1: Percentage of Variance VS r

5.2 Part b

In this part, we analyze the performance of the algorithm for various values of r (principle components). We measure the performance metrics for r=1,2,3,5,10,20,50,100,300.

Index	Homogeneity	Completeness	V Measure	ARI	AMI
1	0.0606	0.0616	0.0611	0.0815	0.0605
2	0.4161	0.4499	0.4324	0.4348	0.4160
3	0.4168	0.4506	0.4331	0.4358	0.4168
5	0.4009	0.4464	0.4224	0.3924	0.4008
10	0.4169	0.4554	0.4353	0.4238	0.4168
20	0.4193	0.4579	0.4378	0.4258	0.4193
50	0.4180	0.4574	0.4368	0.4228	0.4180
100	0.1840	0.2821	0.2227	0.1045	0.1839
300	0.1812	0.2800	0.2200	0.1017	0.1811

Table 3: Stats for SVD against various index values

2210	1693
1122	2857

Table 4: Contingency Matrix for r=1(SVD)

1283	2620
3920	59

Table 5: Contingency Matrix for r=2(SVD)

2623	1280
59	3920

Table 6: Contingency Matrix for r=3(SVD)

2454	1449
23	3956

Table 7: Contingency Matrix for r=5(SVD)

2566	1337
38	3941

Table 8: Contingency Matrix for r=10(SVD)

1333	2570
3943	36

Table 9: Contingency Matrix for r=20(SVD)

1344	2559
3945	34

Table 10: Contingency Matrix for r=50(SVD)

3899	4
2662	1317

Table 11: Contingency Matrix for r=100(SVD)

3899	4
2679	1300

Table 12: Contingency Matrix for r=200 (SVD)

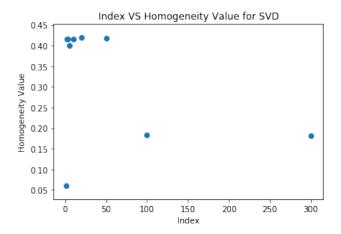


Figure 2: Homogeneity VS r (SVD)

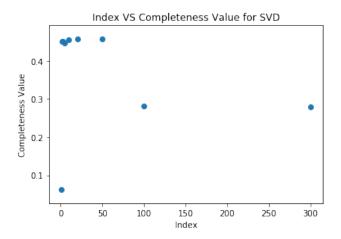


Figure 3: Completeness VS r (SVD)

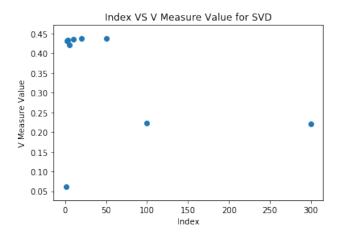


Figure 4: V Measure VS r (SVD)

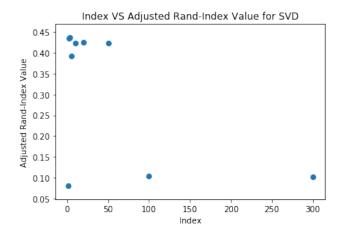


Figure 5: ARI VS r (SVD)

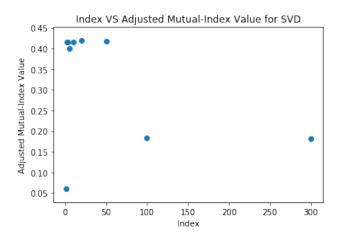


Figure 6: AMI VS r (SVD)

Index	Homogeneity	Completeness	V Measure	ARI	AMI
1	0.0600	0.0610	0.0605	0.0809	0.0599
2	0.3778	0.3930	0.3852	0.4314	03777
3	0.4633	0.4819	0.4724	0.5203	0.4632
5	0.1349	0.2471	0.1746	0.0668	0.1348
10	0.1179	0.2271	0.1552	0.0481	0.1178
20	0.1130	0.2290	0.1513	0.0420	0.1129
50	0.0552	0.1559	0.0815	0.0132	0.0551
100	0.0022	0.0966	0.0044	-6.7533	0.0021
300	0.0194	0.1437	0.0342	0.0021	0.0193

Table 13: Stats for NMF against various index values

1684	2219
2844	1135

Table 14: Contingency Matrix for r=1 (NMF)

3701	202
1150	2829

Table 15: Contingency Matrix for r=2 (NMF)

984	2919	
3865	114	

Table 16: Contingency Matrix for r=3 (NMF)

2916	987
3974	5

Table 17: Contingency Matrix for r=5 (NMF)

3896	7
3068	911

Table 18: Contingency Matrix for r=10 (NMF)

3901	2
3130	849

Table 19: Contingency Matrix for r=20 (NMF)

3886	17
3469	510

Table 20: Contingency Matrix for r=50 (NMF)

0	3903
18	3961

Table 21: Contingency Matrix for r=100 (NMF)

3754	149
3979	0

Table 22: Contingency Matrix for r=200 (NMF)

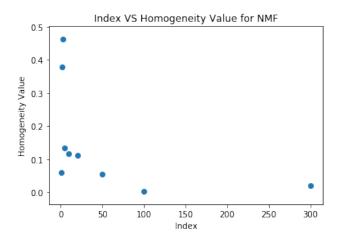


Figure 7: Homogeneity VS r (NMF)

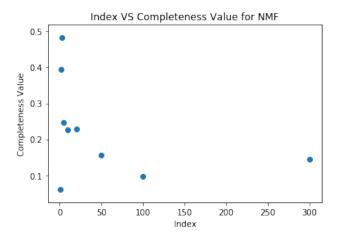


Figure 8: Completeness VS r (NMF)

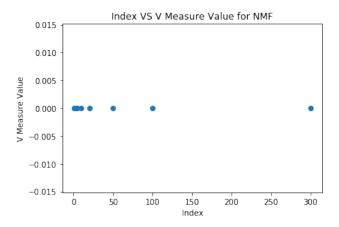


Figure 9: V Measure VS r (NMF)

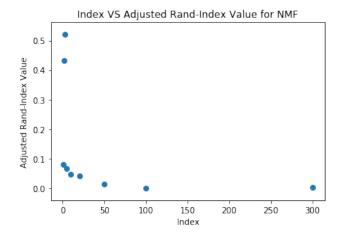


Figure 10: ARI VS r (NMF)

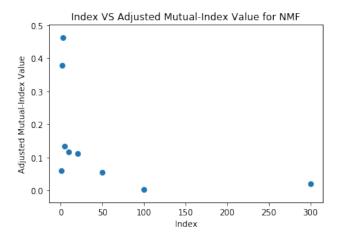


Figure 11: AMI VS r (NMF)

We conclude that the algorithm performs best for r=2 in SVD and r=3 in NMF. We also notice that the performance decays as we increase the value of r from its optimal point.

6 Question 4

6.1 Part a

In this section we represent the clustering in color coded form. The clustering was done from the best r that was obtained from the previous part.

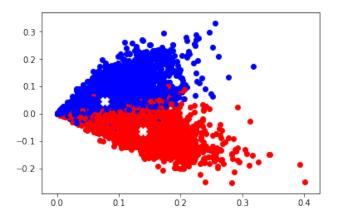


Figure 12: Color coded clustering result for SVD for r=2

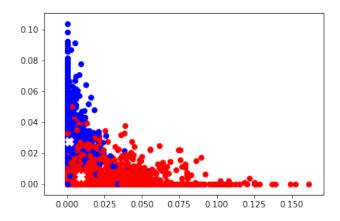


Figure 13: Color coded clustering result for NMF for r=3

6.2 Part b

K-means clustering is isotropic in all directions of space and therefore tends to produce more or less round (rather than elongated) clusters. Due to this, leaving variance that is unequal will invariably put more weight on variables with smaller values. Though normalization does not always improve result, it mostly does not degrade it either.

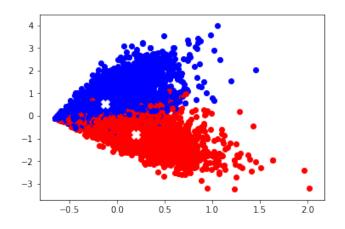


Figure 14: Clustering of Normalized Data (SVD)

• Homogeneity: 0.475905197552

 \bullet Completeness: 0.494126141691

• V-measure: 0.484844539684

• Adjusted Rand-Index: 0.533608766189

• Adjusted Mutual-Index: 0.475857215875

• Contingency Matrix: [[956 2947] [3873 106]]

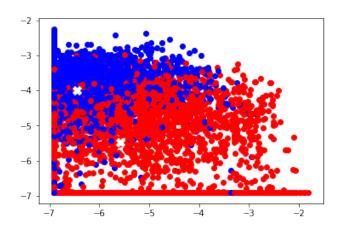


Figure 15: Clustering after logarithmic transformation (NMF)

• Homogeneity: 0.505891837486

 \bullet Completeness: 0.506595279058

 \bullet V-measure: 0.506243313908

• Adjusted Rand-Index: 0.61311822321

 \bullet Adjusted Mutual-Index: 0.505846601723

• Contingency Matrix: [[497 3406] [3621 358]]

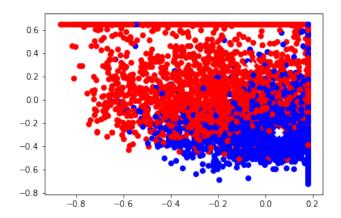


Figure 16: Clustering after performing logarithmic transformation then normalizing (NMF)

• Homogeneity: 0.466101019428

 \bullet Completeness: 0.466366307243

• V-measure: 0.466233625598

• Adjusted Rand-Index: 0.572481255597

• Adjusted Mutual-Index: 0.466052140817

• Contingency Matrix: [[3384 519] [440 3539]]

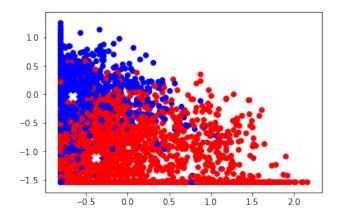


Figure 17: Clustering after normalizing then performing logarithmic transformation then normalizing (NMF)

• Homogeneity: 0.46486810155

• Completeness: 0.465035993491

• V-measure: 0.464952032365

• Adjusted Rand-Index: 0.571329701944

• Adjusted Mutual-Index: 0.464819110069

• Contingency Matrix: [[3393 510] [452 3527]]

We notice that normalizing the data does not have a huge effect on the data in SVD. However, there is a noticeable difference after performing a logarithmic transformation. When the distribution of the continuous data is non-normal, transformations of data are applied to make the data as normal as possible and, thus, increase the validity of the associated statistical analyses. The log transformation is, the most popular among the different types of transformations used to transform skewed data to approximately conform to normality. Here, the log transformation is to spread out the data and that in turn gives better clustering performance. Since the log transformation can only be used for positive outcomes, it is common to add a small positive constant, M, to all observations before applying this transformation. We have added a value of "0.718657278385" to all observations.

7 Question 5

In this part, we work with 20 sub classes instead of the eight as we did with the previous parts.

Dimensions of TF-IDF Matrix: 18846, 35684

Index	Homogeneity	Completeness	V Measure	ARI	AMI
1	0.0148	0.0161	0.0154	0.0029	0.0116
2	0.1730	0.1847	0.1786	0.0506	0.1703
3	0.2116	0.2308	0.2208	0.0679	0.2091
5	0.2666	0.2989	0.2818	0.0881	0.2642
10	0.2753	0.3089	0.2911	0.0887	0.2730
20	0.2713	0.3382	0.3011	0.0681	0.2689
50	0.2687	0.3422	0.3010	0.0625	0.2663
100	0.2610	0.3541	0.3005	0.0591	0.2586
300	0.2489	0.3732	0.2986	0.0603	0.2464

Table 23: Stats for SVD against various index values

Figure 18: Contingency matrix for r=1

Figure 19: Contingency matrix for r=2

```
Contingency Matrix: [[ 18     5     0    82    32    169     0    94    17    113     0    3    13    14    72     0    53    3    3    108]
[0 221 198     1     0 14    83     0 31    54    56    23    76     0    74     0     0    139
[2 1]
[0 152 249     2     0    8    92     0 14    30 212     7    44     0    88     0     0 82
[1 1 4]
[0 179 202     1     0 4 187     0 15    24    65     13    68     0 45     0 0 178
[1 1 0]
[1 221 100     2     0 3 123     0 31    49    10    26    102     0 83     0 0 208
[3 3 1]
[0 321 227     3     0 5    56     0 12 33    43     5    68     0 74     0 0 138
[1 0 321 227     3     0 5    56     0 12 33    43     5    68     0 74     0 0 138
[1 0 177 73     1     0 9 77     0 30 108     19    14 252     0 80     3 0 112
[1 7 37     1 18     0 66     1 1 188 212     0 39 161     0 126 14     0 29
[86 4]
[2 34     2 30     0 125     0 2 148 272     0 28 121     0 116     9 0 15
[8 5 7]
[15 24     7 29     0 75     0 1 69 222     0 11 31     0 107 140     1 7
[252 3]
[13 8 2 20 0 38 1 0 108 6 2 187 112 8 114 112     0 81 23     0 43
[2 9 3]
[14 52 6 11 81 0 108 6 2 187 112 8 114 112     0 81 23     0 43
[2 9 3]
[1 0 133 3]
[8 48 4 73 1 197 3 5 105 233 1 20 0 111 1 103 3 2 16
[8 49 7]
[1 3 3 9 8 48 0 125 5 0 151 251 0 36 137 0 98 4 0 28
[4 9 7]
[3 13 39 8 48 0 125 5 5 0 151 251 0 36 137 0 98 4 0 28
[4 9 7]
[3 13 39 8 48 0 125 5 5 0 151 251 0 36 137 0 98 4 0 28
[4 9 7]
[3 14 9 4 0 253 1 305 1 14 18 167 0 1 10 0 2 67 4 2 0
[2 11]
[4 9 4 0 253 1 305 1 14 18 167 0 1 10 0 2 67 4 2 0
[2 2 2]
[1 1 2 5 1 69 2 100 1 5 9 12 95 0 1 5 5 0 1 5 1 5 30 71 0 49 0
```

Figure 20: Contingency matrix for r=3

```
Contingency Matrix: [[110 37 52 2 0 2 189 48 194 65 0 1 12 19 2 0 0 1
Contingency Matrix: [110 37 52 2 0 0 2 189 48 194 65 0 65 0] [91 0 26 246 0 2 0 6 72 1 1 27 263 0 111 68 0 58] [109 0 13 268 4 0 2 2 2 24 6 15 33 153 0 61 211 1 83] [66 0 17 53 89 1 1 1 1 1 3 0 4 162 193 93 0 65 15 0 190] [117 0 21 28 28 1 1 3 349 3 114 266 100 0 92 4 0 136] [90 0 11 315 0 0 0 1 2 7 3 0 9 375 0 79 67 70 0 10]
         0 265 8 0 16 6 13 290 19 4 86 47 0 31 0 1
      0]
0 95 9 0 327 5 6 150 3 0 3 30 0 8 1 165
      0 10 1 0 14 4 0 424 4 6 89 1 0 3 15 0 1 1 274 0 16 15 0 1 3 46 126 251 0 12 36 0 64 9 0 2:
 [113
       0 10 15 0
0]
0 68 30 1 4 3 0 250 17 17 125 126 0 160 1
 1153
 [188
        ]
154 10 0 1 14 27 400 54 0 2 89 1 44
 [189
        ]
144 20 0 4 11 37 354 76 0 18 63 0 70
0 64 4 0 3 30 113 233 210 0 2 5 0 6 0 0 0
1 0]

[113 33 23 2 0 2 137 35 130 52 0 0 6 32 4 0

59 0]]
```

Figure 21: Contingency matrix for r=5

Figure 22: Contingency matrix for r=10

Figure 23: Contingency matrix for r=20

```
Contingency Matrix: [[ 22  1 41  1 294  2  2  0  0  0  8  0  3  0  0 104  0  6  313  2]
[55  0 44  0 281  2 256  0  0 54 142  3  0 29 86  0  0  0  0  21  0]
[32  0 30  0 227  1 147  0  0  77 64  1  0 304 65  1 16  0
         27 0 183 3 27 0 0 160 81
                                         1 0 39 228
       2]
1 34 0 221
                   1 16
      27]
0 112  1 431  1  3  0  0  0  30  2  0  0  14  0  3
39 0 350 343 21 0 0 1 18 1 0 5 31 0
         74 0 504 7 21 0 0
                                  8 75 1 0 3 180
     2 /4 0 504 . 2-

16]

0 64 1 578 0 3 0 71 0 50 0 0 1 6
      0 /3 ...
1]
0 21 1 286 0 0 0
                              0 0 21 0 2 1 0 335
      0 21 1 286 0 0 0 0 0 0 21 0 2 1 0 335 0 4 01 1 37 1 385 1 1 1 0 0 0 1 6 3 2 0 0 0 3 0 206 4 1 0 32 0 288 0 0 162 0 0 6 0 1 0 0 0 1 0 6 0 1 1 6 2 2 2 7 0 258 0 1 0 2 0 5 0 3 0 0 99 0 48 2]
```

Figure 24: Contingency matrix for r=50

```
Contingency Matrix: [[ 0 0 342 8 95 209 0 23 0 0 7 24 82 0 1 4 2 0
2 0]
[59 29 366 168 0 20 0 0 0 1 54 49 0 0 0 11 189 24
[ 59  29  366  168  0  20  0  0  0  1  54  49  0  0  0  11  189  24  3  0] [ 71  296  270  71  0  14  0  0  0  3  1  37  39  1  16  0  8  128  29  1  0] [ 183  44  222  123  0  3  0  0  73  1  150  31  0  127  3  1  12  5  4  0] [ 111  4  295  122  0  6  0  0  0  32  1  254  33  0  89  1  5  8  1
     0]
18 252 61 0 8 0 0 11 51 335 93 0 66 21 1 2 1
01
       ]
386 41 0 43 0 0 0 2 484 24 0 3 0 0
      0]
0 489 31 0 46 0 0 0 0 378 27 2 17
0]
0 486 41 0 38 0 0 0 1 12 34 1 0 3
                                 1 12 34 1 0 378
      0]
5 384 17 0 165 0 0 0 1 29 26 0 1 0 3 13
     0]
0 355 5 6 496
                                 3 10 21 3 0 2
      0]
0 326         4         6 412 161         0         0
                                 1 0 25 5 0 0
      0]
0 295 6 133 130 0 0 0 0 5 5 51 0 0
1]]
```

Figure 25: Contingency matrix for r=100

Figure 26: Contingency matrix for r=300

We observe the best results for r=10

Index	Homogeneity	Completeness	V Measure	ARI	AMI
1	0.0152	0.0164	0.0158	0.0031	0.0120
2	0.1637	0.1768	0.1700	0.0485	0.1610
3	0.1748	0.1910	0.1825	0.0503	0.1721
5	0.2413	0.2759	0.2574	0.0724	0.2388
10	0.2703	0.3212	0.2936	0.0757	0.2680
20	0.2256	0.2775	0.2489	0.0484	0.2230

Table 24: Stats for NMF against various index values

Figure 27: Contingency matrix for r=1

```
Contingency Matrix: [[182  0  1  61  97  35  2  0 172  39  8  1  12  0 143  37  2  5
2 0]
[ 6 126 81 47 0 49 158 17 1 0 90 143 14 9 19 22 21 69
  27 74]
6 164 64 72 1 16 101 93 2 0 67 122 2 8 14 12 13 46
26 156]
1 163 82 37 0 11 123 62 1 0 66 186 2 4 6 8 13 53
       82 37 0 11 123 62 1 0 66 186 2 4 6 8 13 53
       ]
95 60 0 41 162 13 0 0 97 147 5 2 10 11 25 71
    103 95 60 0 41 102 1 5 5 5 5 9 1 93 77 39 1 21 204 15 1 0 137 206 2 8 7 10 17 77 47 1 76 63 68 0 64 195 19 0 0 154 122 5 1 15 17 12 98 50 1 4 20 132 11 173 30 0 39 1 54 4 29 0 126 138 46 96
        9 125 10 152 16 0 53 0 60 3 26 0 192 125 29 54
[139
      3 3 143 45 75 16 0 130 3 24 6 19 0 224 71 6 19
1203
     1]
0 3 118 52 72 8 0 165 3 26 4 14 0 234 31 3 12
[253
    10 113 21 124 22 1 88 2 38 9 25 1 195 108 22 67
       20 111 16 167 25 1 47 5 46 12 40 0 153 133 28 74
[ 94
[174
        5 57 202 26 2 1 241 92 5 5 19 0 98 46 5 17
     [174
     [271
     [202
     0 0 68 82 28 2 0 127 41 7 1 7 0 111 31 3 2
0
[117
```

Figure 28: Contingency matrix for r=2

Figure 29: Contingency matrix for r=3

```
0 30 0 3 0 27 96
                 0
                  1 75
                      4 16 36 10 146 117
0 0]
[ 1 52 40 8 0 5 137 0 22 2 236 11 3 25 6 286 159 0
13 0]
0 348
0
    0 13 1 20 0 0 57 3 0 104 2 184 8 15 232
 0 3]
[ 5 292
0 0'
     0 1 2 80 0 0 5 11 0 20 0 326 0 11 144 0
 0 2]
3 273
    0 3 0 87 0 0 3 4 1 23 1 243 1 15 117 0
 0 11 0 150 0 2 30 26 0 0 8 108 3 10 0 89 1 4 140 0 0 5711
```

Figure 30: Contingency matrix for r=5

Figure 31: Contingency matrix for r=10

Figure 32: Contingency matrix for r=20

We observe the best results for r=10

Non Linear Logarithmic Transformation:

• Homogeneity: 0.308791294432

• Completeness: 0.312854824595

• V-measure: 0.310809778422

• Adjusted Rand-Index: 0.148654837272

• Adjusted Mutual-Index: 0.306560380024

Normalized SVD Data:

• Homogeneity: 0.279789283219

 \bullet Completeness: 0.326832036631

• V-measure: 0.301486605465

 \bullet Adjusted Rand-Index: 0.083093485568

• Adjusted Mutual-Index: 0.277448098245

Performing Logarithmic transformation first and then normalizing data:

• Homogeneity: 0.301911394335

 \bullet Completeness: 0.30585182322

• V-measure: 0.303868834905

 \bullet Adjusted Rand-Index: 0.146377258257

• Adjusted Mutual-Index: 0.299658294371

Normalizing the data first then performing logarithmic transformation:

• Homogeneity: 0.057676261021

• Completeness: 0.25036945454

• V-measure: 0.0937547466643

• Adjusted Rand-Index: 0.0309288799046

 \bullet Adjusted Mutual-Index: 0.057517290138