

# ASSIGNMENT-2

## REPORT

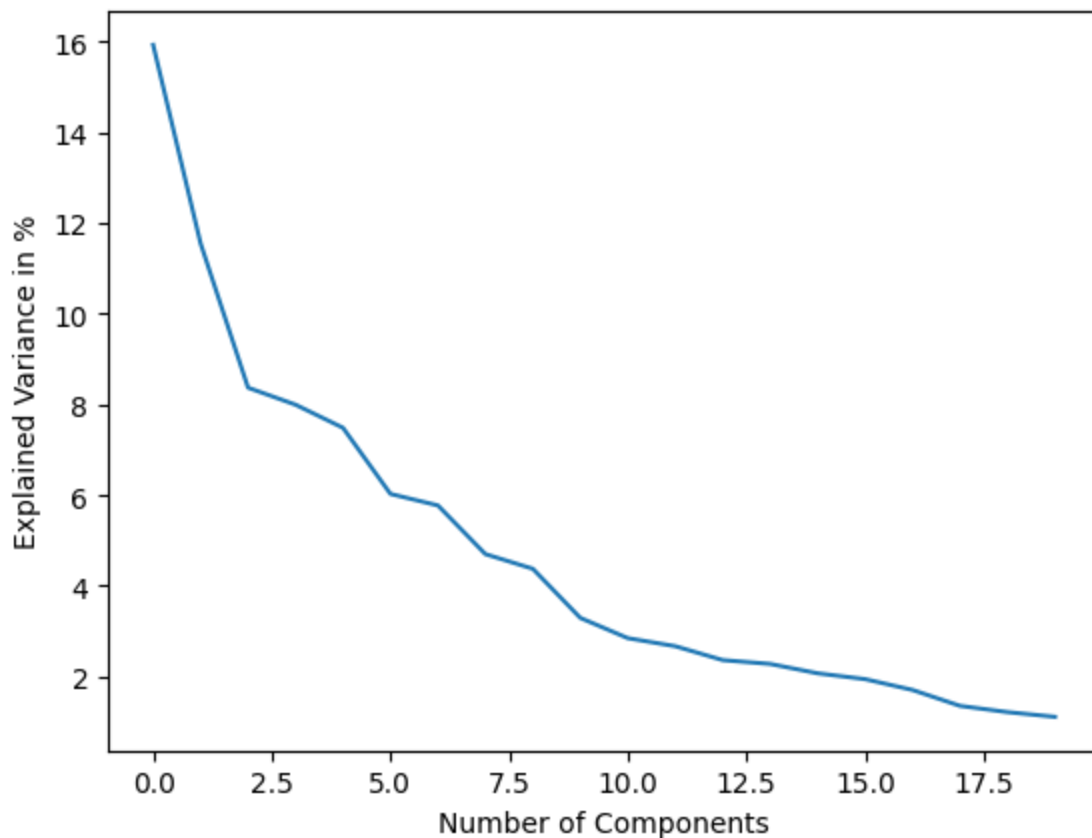
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### Q1 . A) PCA

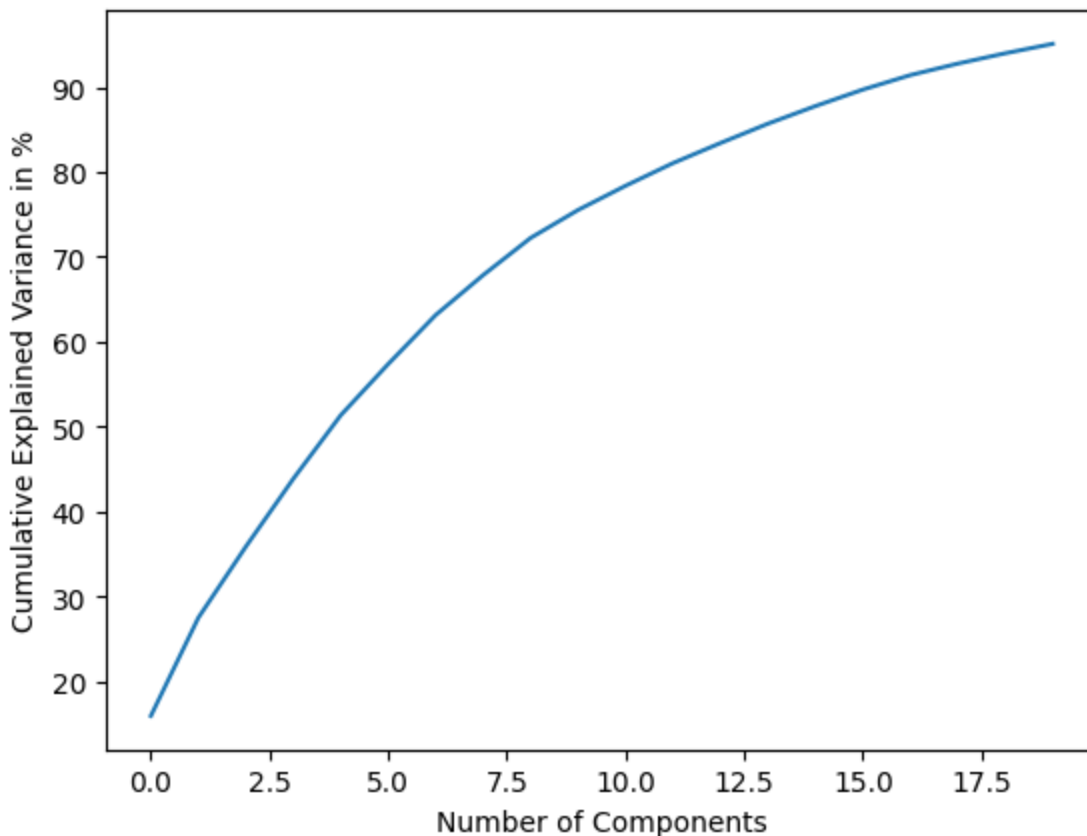
We have got the following results and observations after applying PCA, that is selecting the number of components by preserving 95% of the total variance.

a) Percentage of variance explained by each of the selected components=

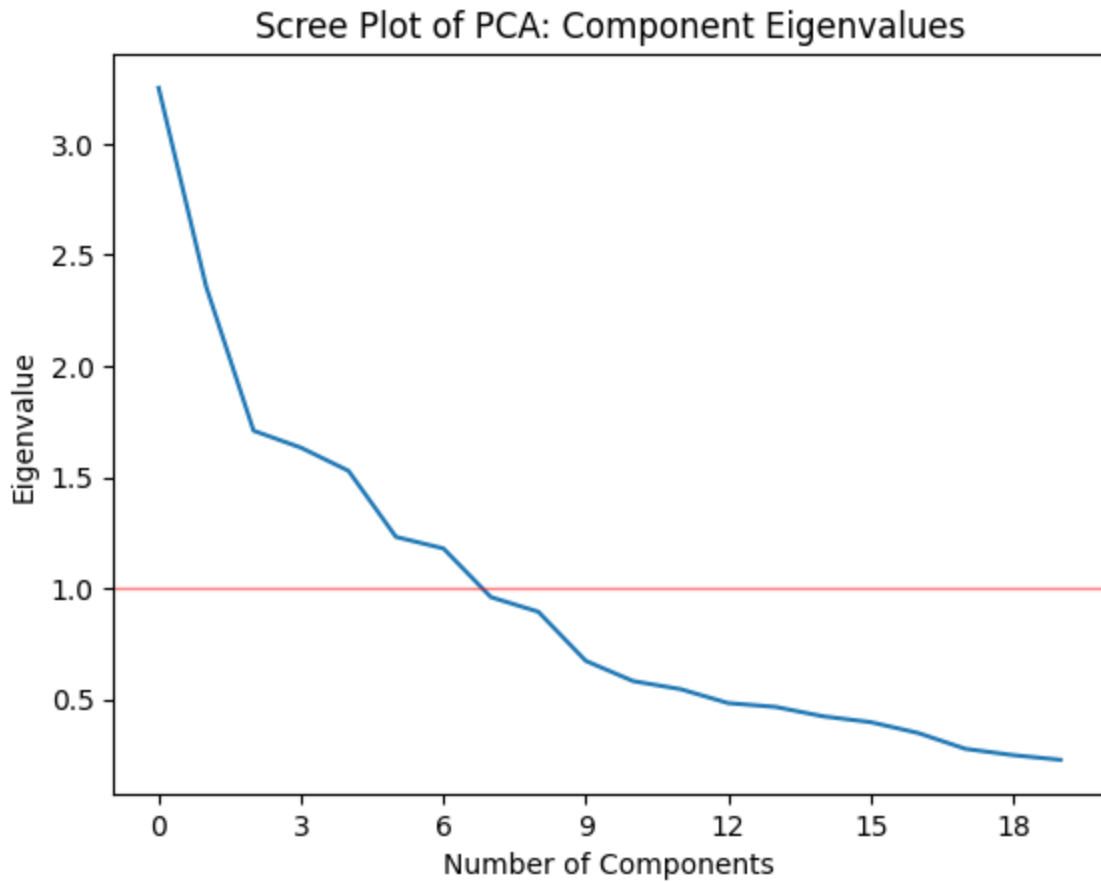
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[15.93408197 11.5545204 8.37241357 7.9973064 7.48752279 6.02951663  
5.77545494 4.70180486 4.37853618 3.29522026 2.848653 2.6709441  
2.36439057 2.27978334 2.07310441 1.94444377 1.70558373 1.35482229  
1.21711803 1.1130487 ]
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- b) Variance explained by first principal component 15.934081970326952  
Variance explained by first 2 principal components 27.488602369276926  
Variance explained by first 5 principal components 51.345845130185836  
Variance explained by first 10 principal components 75.52637800096525  
Variance explained by first 15 principal components 87.76325340996782  
Variance explained by first 19 principal components 93.98522122443343  
Variance explained by first 20 principal components 95.09826992145959
- c) Variance explained by all the principal components = 95.09826992145962
- d) The cumulative sum of the variance explained by the selected components =  
[15.93408197 27.48860237 35.86101594 43.85832234 51.34584513 57.37536176  
63.1508167 67.85262156 72.23115774 75.526378 78.375031 81.0459751  
83.41036567 85.690149 87.76325341 89.70769718 91.4132809 92.76810319  
93.98522122 95.09826992]



e) Following is the graph of Eigenvalues vs Number of Components



f) So after PCA the total number of principal components selected to preserve 95% total variance is 20.

And following is the table showing the values of selected components

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	-1.0 576 46	2.2 604 22	-1.9 857 13	-0.0 231 84	-0.7 716 33	-0.6 958 36	0.1 251 12	-0.9 054 45	0.0 477 16	0.9 171 33	-0.5 853 01	-0.9 846 61	-0.8 473 60	-0.2 105 77	0.0 063 00	-0.8 756 49	0.0 405 78	0.2 316 76	-0.1 503 53	-0.6 182 24
1	-2.0 318 24	1.2 819 74	1.5 975 89	-1.6 881 71	0.7 540 78	0.4 119 62	0.8 742 24	0.9 785 29	-0.7 351 73	0.9 223 56	-0.3 271 43	-0.6 177 48	-0.1 106 52	-0.0 199 20	-1.0 232 59	-0.1 163 89	-0.0 104 00	-0.4 733 39	-0.4 844 61	0.4 254 73
2	-1.6 010 70	-1.5 221 87	0.9 047 81	0.4 902 03	-0.2 375 50	-1.0 950 35	-1.9 154 12	0.8 107 70	-0.8 813 91	-0.4 020 55	0.1 027 92	-0.3 128 00	0.4 048 37	-1.0 885 65	-0.3 653 47	-0.1 400 85	-0.4 291 82	-0.6 248 60	0.3 328 80	0.1 431 09

3	-0.8 415 56	-1.7 380 84	0.4 843 09	2.0 970 76	1.2 554 59	-1.0 881 26	-1.5 472 77	0.4 597 30	0.1 861 26	-0.0 142 96	-0.5 928 63	0.4 051 57	-0.6 008 63	1.2 055 21	-0.5 912 62	0.8 377 80	0.4 635 42	-0.0 283 03	0.4 911 20	-0.0 729 75
4	-1.4 648 77	0.9 010 17	1.0 886 15	0.7 453 50	1.2 868 15	1.8 485 24	0.6 121 84	-0.3 598 38	0.0 149 06	0.6 014 46	-0.5 166 62	-0.7 096 63	-0.3 373 12	0.3 970 16	0.3 876 51	0.6 347 06	-0.0 271 48	-0.6 886 12	-0.5 289 90	0.6 539 30
5	-1.0 383 37	-2.7 133 45	1.0 326 84	0.8 750 25	1.5 169 34	-0.0 987 59	-0.0 382 12	0.1 556 79	-1.2 412 96	-0.1 313 95	0.4 214 81	-0.9 978 59	0.3 240 59	-0.7 207 67	0.3 940 11	0.4 267 86	0.2 173 36	0.4 363 76	-0.6 111 89	0.3 951 48
6	-1.6 809 44	-2.6 644 65	-0.1 859 08	1.0 169 89	0.3 132 60	0.5 162 09	0.0 864 83	-1.5 631 86	-1.2 273 33	0.0 566 27	-0.3 260 55	0.8 968 61	-0.3 040 80	0.0 571 71	-0.1 293 39	-0.9 386 79	-0.1 337 65	1.3 171 80	-0.0 271 16	0.2 887 57
7	-1.8 839 41	-1.0 124 22	1.4 349 32	-1.1 251 91	-1.4 858 13	1.5 461 39	2.2 902 91	0.6 757 52	1.5 659 02	-1.2 945 90	0.2 607 72	0.1 404 71	0.0 934 95	0.3 070 52	0.8 475 64	0.7 974 75	0.6 449 09	0.5 153 94	0.5 088 92	-0.1 284 48
8	-2.1 537 90	-0.5 733 95	-0.6 500 55	-1.3 521 13	-2.1 023 94	0.6 362 90	1.4 184 26	-0.3 559 34	-0.6 689 19	0.3 954 82	0.5 291 80	0.8 558 60	0.1 130 61	-0.7 184 91	-1.4 870 86	0.4 039 40	-0.6 700 49	-0.2 396 18	0.5 967 25	-0.4 118 30
9	1.3 743 54	-1.9 422 24	-0.7 994 12	-1.6 033 84	1.5 112 03	-1.0 763 86	-0.3 121 18	-0.4 597 21	2.2 389 96	0.7 351 22	-0.4 020 54	0.4 150 40	-0.8 397 71	-0.0 631 28	-0.2 119 59	-0.1 883 83	0.7 737 84	-0.3 091 47	-0.2 538 36	-0.2 774 11
10	0.5 251 13	-0.7 597 09	-0.4 690 75	1.0 555 93	-1.6 940 57	0.9 076 83	-1.0 235 97	-0.6 713 57	1.0 284 36	-0.5 030 63	1.7 200 51	-1.5 929 56	-0.4 020 16	0.8 347 67	-0.5 472 53	0.1 730 71	0.1 498 97	0.5 050 50	-0.2 650 78	0.0 988 03
11	1.6 456 46	0.3 790 62	-0.0 142 62	-0.1 317 67	-0.2 370 59	-0.3 482 77	-1.3 465 42	2.8 689 93	0.1 011 14	0.5 352 82	-0.4 377 86	0.5 236 49	0.2 708 51	-0.5 074 86	0.5 514 06	0.3 616 80	-0.0 082 02	0.9 190 15	0.2 535 37	-0.5 789 08
12	-0.2 363 52	2.8 721 40	-1.1 316 95	-0.2 854 00	-0.3 961 10	0.3 434 44	-0.8 024 12	-0.1 673 03	0.5 559 86	-0.7 889 55	-0.2 241 65	0.5 314 63	0.7 463 34	-0.6 312 42	-0.0 057 01	-0.0 387 38	0.9 046 01	0.4 347 14	-0.3 276 31	0.8 499 24
13	-1.1 670 78	2.1 581 87	0.1 600 62	0.4 661 75	1.1 586 51	0.3 929 07	0.2 630 49	0.4 896 07	0.2 698 60	0.8 912 87	-0.0 132 86	-0.1 950 51	-0.0 847 12	1.0 176 68	-0.3 226 09	-0.0 676 92	-1.0 864 49	0.5 851 44	0.0 787 03	-0.4 340 00
14	1.3 945 03	0.3 381 25	-2.2 931 93	1.0 826 98	-0.9 652 36	-0.4 229 07	0.2 845 19	-0.3 671 65	0.7 292 65	1.9 408 49	-0.3 698 43	0.1 887 79	1.1 132 67	-0.1 776 10	0.3 261 94	1.5 098 03	-0.5 934 49	0.1 921 46	-0.0 278 89	0.8 724 87
15	-0.8 585 81	-0.3 721 64	-0.9 397 46	-0.8 597 95	-0.4 898 31	0.1 279 70	-1.0 358 78	-0.6 417 26	-1.1 539 76	-0.4 858 66	0.2 487 79	0.0 534 48	0.1 982 64	-0.1 572 56	1.6 638 69	0.7 802 88	-0.3 799 88	-1.0 651 23	-0.1 621 54	-0.6 825 56

1 6	-0.0 289 80	-0.1 068 65	-0.4 266 93	-1.3 819 74	-1.6 767 38	-0.8 589 42	0.5 488 23	1.1 373 92	-1.8 282 64	-0.6 125 25	-1.5 863 55	-0.2 876 59	-0.4 593 35	0.6 646 38	-0.0 373 02	0.3 147 15	0.3 455 77	0.6 322 96	-0.7 972 51	-0.2 403 39
1 7	-0.8 553 22	-0.6 665 37	-1.4 554 18	1.5 169 35	0.4 697 96	-2.0 458 61	1.8 456 65	1.3 459 01	0.2 473 70	0.0 094 07	2.0 974 19	0.1 698 00	0.6 731 68	0.4 499 51	0.0 491 89	-0.4 892 80	-0.2 699 70	-0.2 289 49	-0.6 235 82	-0.3 733 69
1 8	-0.2 854 23	-0.5 052 51	0.2 177 17	3.1 932 57	-0.8 380 76	-0.5 481 00	1.5 408 98	-0.1 164 13	1.0 769 99	-0.9 759 04	-2.0 416 95	-0.5 624 29	0.4 744 34	-0.2 370 20	-0.0 794 63	-0.6 383 32	-0.3 502 75	-0.6 202 83	0.7 322 80	-0.0 414 40
1 9	-1.6 655 74	1.4 775 21	1.7 631 09	0.5 086 52	1.4 302 48	1.0 836 02	-0.1 466 45	1.2 369 30	0.9 723 30	0.8 455 88	0.5 169 57	0.3 911 18	-0.1 393 07	-0.9 167 56	0.5 565 75	-0.7 795 66	0.3 191 40	0.0 293 21	0.2 139 44	-0.2 510 09
2 0	-3.1 776 39	1.7 449 61	-0.1 499 58	1.1 440 88	-0.7 839 10	-0.5 156 85	-0.6 825 20	-1.2 632 42	-0.0 801 44	-0.1 735 78	0.3 412 89	1.6 458 97	-1.2 644 95	0.0 229 03	0.9 586 61	-0.0 125 63	0.1 413 76	-0.2 256 61	-0.2 320 30	0.0 496 91
2 1	-1.5 445 72	-2.6 815 20	0.1 889 78	-2.4 948 78	-0.8 076 15	-0.2 405 81	-0.9 254 86	-0.8 116 36	1.0 000 08	0.9 750 78	-0.3 429 40	-0.0 402 59	1.5 554 64	0.2 429 06	0.1 628 29	-1.0 547 18	0.3 708 68	-0.1 553 43	-0.1 257 65	0.1 498 31
2 2	3.7 877 57	0.5 586 68	3.5 431 09	0.4 059 55	-0.8 026 90	-0.7 299 08	0.4 548 10	-0.9 298 41	-0.5 375 38	0.4 788 45	0.3 832 06	1.6 936 31	0.2 532 93	0.5 709 32	-0.6 235 06	0.2 709 79	0.1 760 52	-0.2 467 73	-0.2 750 60	0.0 012 64
2 3	3.1 435 99	-0.4 682 19	-0.1 536 96	-0.7 436 89	-0.6 776 08	1.0 106 43	-0.0 504 24	0.9 480 26	-0.7 552 09	0.0 482 48	0.1 987 43	0.1 805 07	-0.2 706 91	1.2 422 15	1.1 430 23	-1.4 825 30	-0.9 074 77	-0.2 757 78	0.5 008 71	0.8 416 42
2 4	2.7 241 72	-1.4 026 89	0.7 172 69	-0.7 189 01	0.4 996 51	1.0 082 78	-0.0 787 78	-1.0 997 05	0.1 123 90	0.7 065 33	0.1 460 36	-0.7 063 14	-1.1 277 97	-1.0 296 80	0.2 509 63	0.5 219 19	-0.7 401 12	0.3 531 36	0.5 294 79	-0.4 168 35
2 5	1.7 882 70	-0.7 963 97	-2.1 082 89	-0.2 164 76	2.3 687 07	2.3 765 79	0.0 475 76	0.1 116 34	0.4 997 44	-1.6 289 20	-0.5 616 05	1.0 034 71	0.3 924 81	-0.0 427 21	-0.6 781 60	0.0 139 57	-0.7 050 64	-0.2 877 74	-0.9 062 03	-0.4 489 87
2 6	0.9 671 29	0.1 489 07	-2.0 415 89	-1.4 232 12	2.1 719 51	-1.5 119 49	1.7 851 49	0.1 886 22	-0.8 732 11	-0.5 586 90	0.5 239 53	0.0 234 53	-0.8 667 59	-0.3 418 42	-0.0 546 89	0.1 926 65	0.6 142 81	-0.1 210 86	0.9 997 59	0.8 379 52
2 7	1.7 762 36	0.8 355 27	1.6 924 11	-0.7 816 17	-1.2 253 67	-2.0 700 38	-0.1 412 12	-0.0 076 86	1.3 694 64	-1.2 718 54	0.0 091 38	-0.4 785 10	-0.8 549 33	-0.8 292 03	-0.0 965 72	-0.1 035 82	-0.9 192 76	-0.0 302 14	-0.7 584 42	0.4 100 26
2 8	1.5 676 53	2.1 473 76	1.2 631 31	-0.4 121 98	1.8 514 36	-1.1 794 53	0.7 888 09	-2.0 226 19	-0.7 546 64	-0.5 122 76	0.0 002 83	-0.7 405 58	1.5 287 52	0.2 283 02	0.5 020 50	-0.0 266 62	0.2 651 81	0.4 253 58	0.3 080 45	-0.7 280 99

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2	3.3	0.1	-0.6	2.0	-1.4	1.6	0.2	0.3	-1.1	0.4	0.2	-0.2	-0.0	-0.8	-0.3	-0.5	1.4	-0.4	-0.1	-0.3
9	751	874	983	708	477	886	795	494	005	987	995	770	889	515	439	376	799	978	376	172
	66	58	14	29	74	02	07	08	44	76	56	30	32	61	90	24	91	64	01	93
3	-0.0	0.4	-0.3	-0.9	-0.3	0.0	-1.0	0.1	-0.1	-0.0	0.0	-0.5	-0.0	1.3	-0.3	0.3	0.5	-0.7	0.4	-0.2
0	276	140	512	876	315	918	694	864	182	080	011	755	588	720	602	052	699	164	519	881
	46	74	75	09	72	07	83	81	56	52	82	80	38	62	02	61	70	39	08	48
3	-0.4	2.2	-0.2	-0.4	0.3	0.5	-2.1	-0.2	-0.0	-1.1	0.5	-0.0	0.5	-0.0	-0.8	-0.0	-0.2	0.2	0.6	0.2
1	684	200	344	392	828	352	295	006	606	960	269	395	160	692	425	545	462	583	964	918
	46	55	03	65	44	04	31	35	93	41	36	28	92	77	87	51	79	61	85	34

As the total number of selected components is 20, so it is not possible to plot and show them on a graph. (Above table is also provided in output\_1.txt file and also in form of markdown table in pca\_md.md file in the submitted directory)

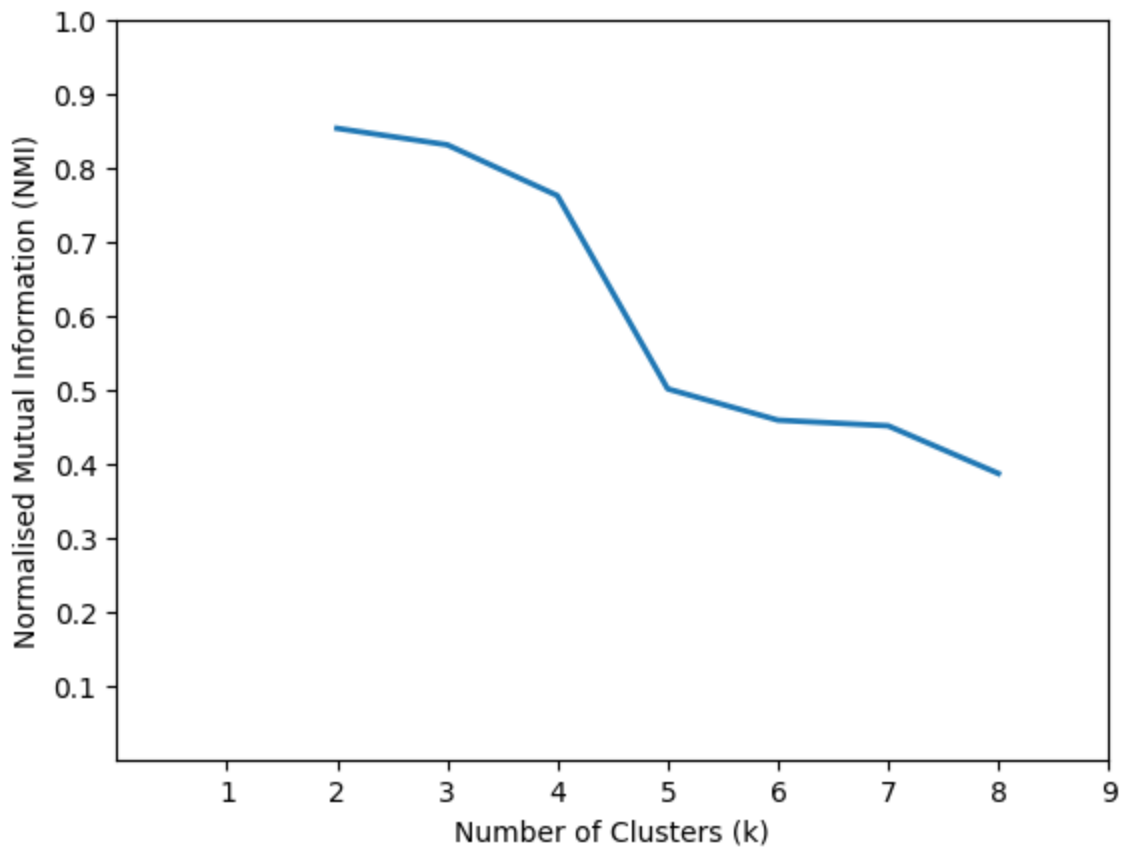
## Q1. B) K-Means Clustering

a) K vs normalised mutual information (k, nmi)

K	NMI
2	0.8537795818679155
3	0.8315056247904322
4	0.7627109912103283
5	0.50133084219317
6	0.4513535767499529
7	0.4513535767499529
8	0.38687185625050424

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b) Following is the plot of K vs NMI



c) Maximum NMI is 0.8537795818679155 and corresponding value k is = 2

d) Following shows the clusters and the data elements present in it for k= 2 and in this case the NMI is = 0.8646810327000422

Cluster 1

[[1.0, -1.06, 2.26, -1.99, -0.02, -0.77, -0.7, 0.13, -0.91, 0.05, 0.92, -0.59, -0.98, -0.85, -0.21, 0.01, -0.88, 0.04, 0.23, -0.15, -0.62], [2.0, 1.37, -1.94, -0.8, -1.6, 1.51, -1.08, -0.31, -0.46, 2.24, 0.74, -0.4, 0.42, -0.84, -0.06, -0.21, -0.19, 0.77, -0.31, -0.25, -0.28], [2.0, 0.53, -0.76, -0.47, 1.06, -1.69, 0.91, -1.02, -0.67, 1.03, -0.5, 1.72, -1.59, -0.4, 0.83, -0.55, 0.17, 0.15, 0.51, -0.27, 0.1], [2.0, 1.65, 0.38, -0.01, -0.13, -0.24, -0.35, -1.35, 2.87, 0.1, 0.54, -0.44, 0.52, 0.27, -0.51, 0.55, 0.36, -0.01, 0.92, 0.25, -0.58], [2.0, -0.24, 2.87, -1.13, -0.29, -0.4, 0.34, -0.8, -0.17, 0.56, -0.79, -0.22, 0.53, 0.75, -0.63, -0.01, -0.04, 0.9, 0.43, -0.33, 0.85], [2.0, 1.39, 0.34, -2.29, 1.08, -0.97, -0.42, 0.28, -0.37, 0.73, 1.94,

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-0.37, 0.19, 1.11, -0.18, 0.33, 1.51, -0.59, 0.19, -0.03, 0.87], [2.0, -0.03, -0.11, -0.43, -1.38, -1.68, -0.86, 0.55, 1.14, -1.83, -0.61, -1.59, -0.29, -0.46, 0.66, -0.04, 0.31, 0.35, 0.63, -0.8, -0.24], [2.0, -0.86, -0.67, -1.46, 1.52, 0.47, -2.05, 1.85, 1.35, 0.25, 0.01, 2.1, 0.17, 0.67, 0.45, 0.05, -0.49, -0.27, -0.23, -0.62, -0.37], [2.0, -0.29, -0.51, 0.22, 3.19, -0.84, -0.55, 1.54, -0.12, 1.08, -0.98, -2.04, -0.56, 0.47, -0.24, -0.08, -0.64, -0.35, -0.62, 0.73, -0.04], [3.0, 3.79, 0.56, 3.54, 0.41, -0.8, -0.73, 0.45, -0.93, -0.54, 0.48, 0.38, 1.69, 0.25, 0.57, -0.62, 0.27, 0.18, -0.25, -0.28, 0.0], [3.0, 3.14, -0.47, -0.15, -0.74, -0.68, 1.01, -0.05, 0.95, -0.76, 0.05, 0.2, 0.18, -0.27, 1.24, 1.14, -1.48, -0.91, -0.28, 0.5, 0.84], [3.0, 2.72, -1.4, 0.72, -0.72, 0.5, 1.01, -0.08, -1.1, 0.11, 0.71, 0.15, -0.71, -1.13, -1.03, 0.25, 0.52, -0.74, 0.35, 0.53, -0.42], [3.0, 1.79, -0.8, -2.11, -0.22, 2.37, 2.38, 0.05, 0.11, 0.5, -1.63, -0.56, 1.0, 0.39, -0.04, -0.68, 0.01, -0.71, -0.29, -0.91, -0.45], [3.0, 0.97, 0.15, -2.04, -1.42, 2.17, -1.51, 1.79, 0.19, -0.87, -0.56, 0.52, 0.02, -0.87, -0.34, -0.05, 0.19, 0.61, -0.12, 1.0, 0.84], [3.0, 1.78, 0.84, 1.69, -0.78, -1.23, -2.07, -0.14, -0.01, 1.37, -1.27, 0.01, -0.48, -0.85, -0.83, -0.1, -0.1, -0.92, -0.03, -0.76, 0.41], [3.0, 1.57, 2.15, 1.26, -0.41, 1.85, -1.18, 0.79, -2.02, -0.75, -0.51, 0.0, -0.74, 1.53, 0.23, 0.5, -0.03, 0.27, 0.43, 0.31, -0.73], [3.0, 3.38, 0.19, -0.7, 2.07, -1.45, 1.69, 0.28, 0.35, -1.1, 0.5, 0.3, -0.28, -0.09, -0.85, -0.34, -0.54, 1.48, -0.5, -0.14, -0.32], [3.0, -0.03, 0.41, -0.35, -0.99, -0.33, 0.09, -1.07, 0.19, -0.12, -0.01, 0.0, -0.58, -0.06, 1.37, -0.36, 0.31, 0.57, -0.72, 0.45, -0.29], [3.0, -0.47, 2.22, -0.23, -0.44, 0.38, 0.54, -2.13, -0.2, -0.06, -1.2, 0.53, -0.04, 0.52, -0.07, -0.84, -0.05, -0.25, 0.26, 0.7, 0.29]]

## Cluster 2

[[1.0, -2.03, 1.28, 1.6, -1.69, 0.75, 0.41, 0.87, 0.98, -0.74, 0.92, -0.33, -0.62, -0.11, -0.02, -1.02, -0.12, -0.01, -0.47, -0.48, 0.43], [1.0, -1.6, -1.52, 0.9, 0.49, -0.24, -1.1, -1.92, 0.81, -0.88, -0.4, 0.1, -0.31, 0.4, -1.09, -0.37, -0.14, -0.43, -0.62, 0.33, 0.14], [1.0, -0.84, -1.74, 0.48, 2.1, 1.26, -1.09, -1.55, 0.46, 0.19, -0.01, -0.59, 0.41, -0.6, 1.21, -0.59, 0.84, 0.46, -0.03, 0.49, -0.07], [1.0, -1.46, 0.9, 1.09, 0.75, 1.29, 1.85, 0.61, -0.36, 0.01, 0.6, -0.52, -0.71, -0.34, 0.4, 0.39, 0.63, -0.03, -0.69, -0.53, 0.65], [1.0, -1.04, -2.71, 1.03, 0.88, 1.52, -0.1, -0.04, 0.16, -1.24, -0.13, 0.42, -1.0, 0.32, -0.72, 0.39, 0.43, 0.22, 0.44, -0.61, 0.4], [1.0, -1.68, -2.66, -0.19, 1.02, 0.31, 0.52, 0.09, -1.56, -1.23, 0.06, -0.33, 0.9, -0.3, 0.06, -0.13, -0.94, -0.13, 1.32, -0.03, 0.29], [1.0, -1.88, -1.01, 1.43, -1.13, -1.49, 1.55, 2.29, 0.68, 1.57, -1.29, 0.26, 0.14, 0.09, 0.31, 0.85, 0.8, 0.64, 0.52, 0.51, -0.13], [1.0, -2.15, -0.57, -0.65, -1.35, -2.1, 0.64, 1.42, -0.36, -0.67, 0.4, 0.53, 0.86, 0.11, -0.72, -1.49, 0.4, -0.67, -0.24, 0.6, -0.41], [2.0, -1.17, 2.16, 0.16, 0.47, 1.16, 0.39, 0.26, 0.49, 0.27, 0.89, -0.01, -0.2, -0.08, 1.02, -0.32, -0.07, -1.09, 0.59, 0.08, -0.43], [2.0, -0.86, -0.37, -0.94, -0.86, -0.49, 0.13, -1.04, -0.64, -1.15, -0.49, 0.25, 0.05, 0.2, -0.16, 1.66, 0.78, -0.38, -1.07, -0.16, -0.68], [2.0, -1.67, 1.48, 1.76, 0.51, 1.43, 1.08, -0.15,



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1.24, 0.97, 0.85, 0.52, 0.39, -0.14, -0.92, 0.56, -0.78, 0.32, 0.03, 0.21, -0.25], [2.0, -3.18, 1.74, -0.15,  
1.14, -0.78, -0.52, -0.68, -1.26, -0.08, -0.17, 0.34, 1.65, -1.26, 0.02, 0.96, -0.01, 0.14, -0.23, -0.23,  
0.05], [2.0, -1.54, -2.68, 0.19, -2.49, -0.81, -0.24, -0.93, -0.81, 1.0, 0.98, -0.34, -0.04, 1.56, 0.24,  
0.16, -1.05, 0.37, -0.16, -0.13, 0.15]]

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## Q2. SVM and MLP classifier

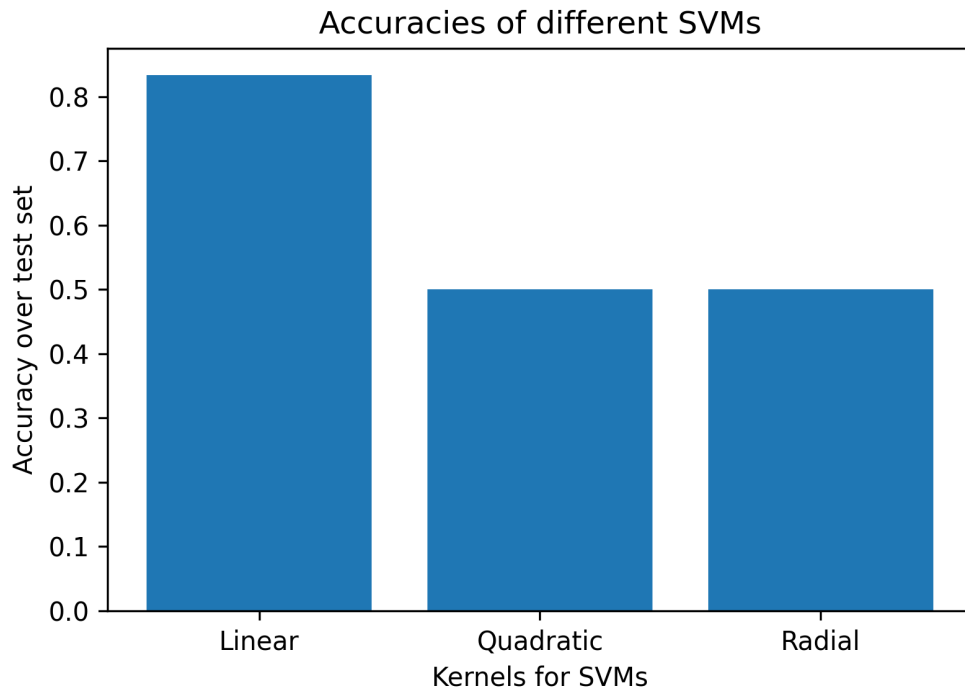
Some observations made during different phases of the task are

- 1) **Dataset analysis and normalisation:** Given dataset ([link](#)) has the following features:
  - a) Number of Instances: 32
  - b) Number of Attributes: 57 (1 class attribute[0], 56 predictive[1:56])
  - c) Attribute Information:
    - i) Attribute 1 is the class label.
    - ii) All predictive attributes have values 0-3
  - d) Missing Attribute Values: Attributes 5 and 39 (\*)
  - e) Class distribution: {1->9, 2->13, 3->10}
  - f) Normalisation is not necessary since the spread in predictive attributes takes values(0-3), and the spread is nominal. However, Standard Scalar Normalisation is applied according to assignment instructions:

$$x_i = (x_i - \text{mean}()) / \text{var}(x)$$

- g) Test-train split resulted in a (6-26) division of instances.
- 2) **Support Vector Machine Classifier:** Implemented the required SVM classifiers using the ScikitLearn Library and trained them over the train set (26 instances). The resulting accuracies are:
  - a) Linear Kernel SVM: 0.83
  - b) Quadratic Kernel SVM: 0.50
  - c) Radial Kernel SVM: 0.50

\*\*From the results, the training set seems to be linearly separable (higher accuracy for linear kernel)



3) **Multilayer Perceptron Classifier:** Implemented the required MLP classifiers using the ScikitLearn Library and trained them over the train set (26 instances). The resulting accuracies (for learning rate=0.001) are:

- a) MLP with one hidden layer [16]: 0.67
- b) MLP with two hidden layers[256, 16]: 0.83

Since the MLP with two hidden layers gives better accuracy, so it is selected for as best accuracy model for further steps

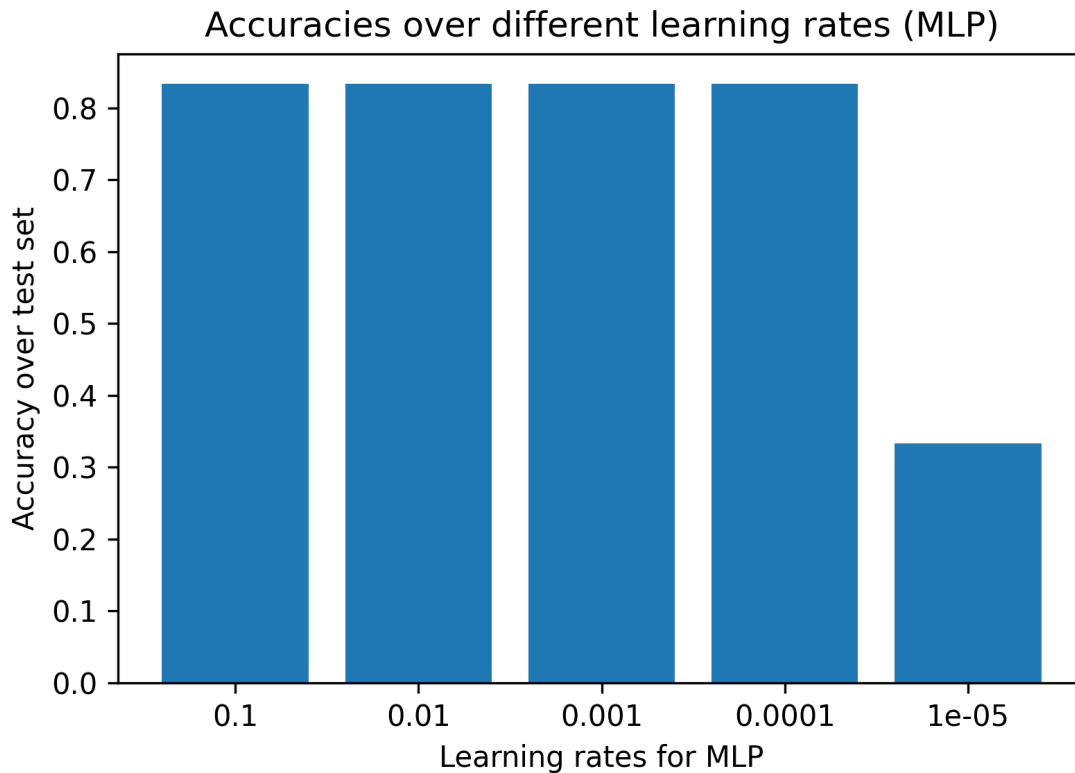
4) **Learning rate vs accuracy:** Using the best accuracy MLP classifier from previous part (dual layer [256, 16]), varied the accuracies as required and obtained following accuracies:

- a) Learning rate 0.1 : 0.83
- b) Learning rate 0.01 : 0.83
- c) Learning rate 0.001 : 0.83
- d) Learning rate 0.0001 : 0.83
- e) Learning rate 0.00001 : 0.33

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Model with the highest accuracy is again selected for the following steps (in this case learning rate of 0.1 is chosen).

\*\*Batch size of 32 is not possible since there are only 26 training samples, so take  $\min(32, \text{sizeof}(\text{train\_set}))$  as batch\_size.



5) **Forward Selection Method:** Implemented the 'SequentialForwardSelector' class to collect features which produce the maximum accuracy gain iteratively. Stop when adding any feature results in accuracy loss. On applying this to the best accuracy model, the Features are selected through the following steps:

- a) 1 best features give a score of 0.83
- b) 2 best features give a score of 0.83
- c) 3 best features give a score of 1.00
- d) 4 best features give a score of 1.00
- e) 5 best features give a score of 1.00
- f) 6 best features give a score of 1.00

- 
- g) 7 best features give a score of 1.00
  - h) 8 best features give a score of 1.00
  - i) 9 best features give a score of 1.00
  - j) 10 best features give a score of 1.00
  - k) 11 best features give a score of 1.00
  - l) 12 best features give a score of 1.00
  - m) 13 best features give a score of 1.00
  - n) 14 best features give a score of 1.00
  - o) 15 best features give a score of 1.00
  - p) 16 best features give a score of 1.00

The final features obtained are(indices of columns):

Selected features: [16, 38, 8, 1, 9, 22, 20, 2, 10, 5, 4, 7, 11, 13, 3, 14]

- 6) **Ensemble Learning (max voting technique):** Implemented 'EnsembleLearner' class initialised with models (SVM with quadratic, SVM with radial basis function and the best accuracy model from part 3). Employed maximum Voting technique(mode of predicted labels) to decide among classes output by different models. Got an accuracy of **0.50%** (lower than MLP and Linear kernel SVM).

### Observations:

The Multilayer Perceptron (having two layers) performs better than both single layer perceptron and Support Vector Machine. However, due to the nature of the dataset (almost linearly separable) Linear kernel for SVM performs better (on par with MLP classifier) than both Quadratic and Radial Basis kernels.

Due to the large size of feature space, the forward selection method gives a huge boost to accuracy by discarding less useful features.

Interestingly, the Ensemble learner gives worse accuracy than component models in this case!