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Course name: AIML 2022 Project Report

Title: Image compression using SVD, PCA, K-mean algorithm

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Date of Submission: 29/11/2022

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#### 1.1 Data compression in machine learning application

For training a machine learning model when there is large amount of unlabelled data, several unsupervised learning algorithms can helps in the understanding of the data.

- Unsupervised learning also can help in dimensionality reduction.
- Dimensionality reduction again can help in data visualization
- When the data is reduced, the complexity of the model can be reduced, so as the training time.

### 1.2 The Techniques, data and scope

Three unsupervised algorithms namely Singular value decomposition (SDV), Principal component analysis (PCA) and K-mean are experimented as a part of this work.

The algorithms are applied as a part of pre-processing of task, with goal for experimental study on data reduction or compression for high resolution image.

The data file is with dimension 570X 985 x 3, image of Cosmic object, Captured by James Webb Space Telescope (publicly available in NASA website)



Figure 1 Sample data file of image dimension 570X 985 x 3

#### 1.2 A Brief overview of the methods

| Method<br>Singular Value  | Inventor   | Purpose                                       | General overview   |
|---|--|---|--|
| Singular Value Decomposition(SVD) - https://en.wikipedia.org/wiki /Singular_value_decompositi on          | Independently Eugenio<br>Beltrami, Camille Jordon<br>over 100 yrs back       | To predict a set of optimal factors.          | Original U 5 V* mus material must present para material pa |
| Principal comonent Analysis(PCA) - https://en.wikipedia.org/wiki /Principal_component_analy sis reduction | Karl Pearson in 1901,<br>later in 1930,<br>developped by Harold<br>Hotelling | Dimnetionalit<br>y reduction                  | x1 x0  |
| K-Means clustering -<br>https://en.wikipedia.org/wiki<br>/K-means_clustering                              | First used by James<br>MacQueen in 1967 ,used<br>by Steinhaus in 1956        | In pulse code<br>modulation(b<br>y Steinhaus) |  |

### The Advantages:

- 1. **SVD**: SDV simplifies data, can remove noise also it can be used for coloured image to segregation components for computational efficiency
- 2. **PCA**: Dimensionality reduction is the biggest advantage preserving most significant data. PCA can also be used in data exploratory analysis and visualization
- 3. **K-Mean**: Simplicity and guarantees convergence. It provides good representation of reduced features/ data.

### 1.3 The implementation and results

The algorithms are implemented in python. The Python libraries scikitlearn, matplotlib libraries are used for visualizations. The details about the project is stored in the readme.md file in Github repository <a href="https://github.coom/Gitpabora/Data reduction compression">https://github.coom/Gitpabora/Data reduction compression</a>. The source code and results are shared in google colab bnotepads links in table 2.

Table 1 Detailed implemenatation

| PCA        | https://drive.google.com/file/d/1_pBJL6v9sRRetdD0tLqvmihOVvtvivf8/view?usp=share_link    |
|------------|--|
| SVD        | https://colab.research.google.com/drive/1eG843MHVTwohPAqRmsQa8JToxPNJZR1M?usp=share_link |
| K-<br>Mean | https://drive.google.com/file/d/1VFxHAb34riaiYDiqaN0uYt8Jw4hqJbUk/view?usp=sharing       |

Table 2 The Algorithms flow

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| PCA                                    | SVD                                     | K-Mean                                 |
|--|---|--|
| <b>Step1</b> . Calculate the           | <b>Step1</b> . getting three            | Step 1. An optimal number of           |
| covariance matrix of the data          | component matrices with Red ,           | clusters (K) is chosen.                |
|  | Blue and green constituents             |  |
| <b>step2.</b> Extract the eigenvectors |   | <b>Step 2</b> . k number of points     |
| and the eigenvalues of that            | <b>Step2</b> . Applying SVD on each of  | "centroids" are initialized            |
| matrix                                 | the three components to                 | randomly within the data area.         |
|  | generate three vectors for              |  |
| <b>Step3</b> . Select the number of    | each of the matrices                    | <b>Step 3</b> . Each data or           |
| desired dimensions and filter          |   | observation is attributed to           |
| the eigenvectors to match it,          | <b>Step3</b> . Preserving only K i.e.   | own closest centroid.                  |
| sorting them by their                  | Selecting k columns from U              |  |
| associated eigenvalue                  | matrix and k rows from VT               | <b>Step 4.</b> Updating is done for    |
|  | matrix, and resetting rest to           | the centroids to hold the value        |
| <b>Step4</b> . Multiply the original   | zero                                    | corresponding to the centre of         |
| space by the feature vector            | <b>Step4</b> . Reconstructing the       | its all attributed observations.       |
| generated in the previous step.        | coloured components from U              |  |
|  | and V                                   | <b>Step 5</b> . Steps 3-4 are repeated |
|  | <b>Step5</b> . Final image is formed by | a number of times / until all of       |
|  | oncatenating the three                  | the centroids are prominent.           |
|  | components                              |  |
|  |   |  |

## The measurement for compression or data reduction:

- The compression ratio is calculated using the below formula:

  Compression ratio = ((original\_number\_of\_image\_element -new\_number\_of\_values after applying the algorithm)/original\_number\_of\_image element)\*100.
- The same is experimented for varying parameters like number of principal components in case of PCA, number of component selected in case of SVD and number of clusters in case of K-mean respectively.

Table 4 The results & Observations (Note:all numeric results are rounded to 2decimal places)

| #components(Principal   | Compression ratio (%) | Compression ratio (%) | Compression ratio (%) |
|-------------------------|-----------------------|-----------------------|-----------------------|
| component) /component   | PCA                   | SVD                   | K-Mean                |
| SVD/ cluster for K-mean |                       |                       |                       |
| 10                      | 99.08                 | 97.23                 | 98.25                 |
| 20                      | 98.15                 | 94.46                 | 96.49                 |
| 30                      | 97.23                 | 91.69                 | 94.74                 |
| 40                      | 96.30                 | 88.91                 | 92.98                 |
| 50                      | 95.38                 | 86.14                 | 91.23                 |
| 60                      | 94.46                 | 83.37                 | 89.47                 |
| 70                      | 93.53                 | 80.60                 | 87.72                 |
| 80                      | 92.61                 | 77.83                 | 85.96                 |
| 90                      | 91.69                 | 75.06                 | 84.21                 |
| 100                     | 90.76                 | 72.29                 | 82.46                 |

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Table 5 Reconstructed Images for PCA & SVD , Kmean clustering

| #components( Principal component) /component SVD/ cluster for K-mean | PCA reconstructed image                               | Reconstructed Image after SVD  | K-mean Scatter plot  |
|--|---|--|--|
| 10   | Percentage Reduction in Image Size for components =10 | 100 - 200 - 400 - 600 - 600 - 600  | sctterplot for n_cluster is =10  175  130  125  100  75  23  23 50 75 100 125 150 175 200  |
| 20   | Percentage Reduction in Image Size for components =20 | 200 200 400 600 860  | sctterplot for n_cluster is =20  175 150 125 100 - 75 25 26 75 100 125 150 175 200   |
| 30   | Percentage Reduction in Image Size for components =30 |  | sctterplot for n_cluster is =30  173 - 130 - 1312 - 130 - 1312 - 130 - 1312 - 130 - 1312 - 130 - 1312 - 131 |
| 40   | Percentage Reduction in Image Size for components =40 | 9<br>200<br>200<br>800<br>800<br>800<br>800<br>800<br>800<br>800<br>800  | sctterplot for n_cluster is =40  175  180  188  100  75  50  29  29  25  50  75  180  125  180  175  260   |
| 50   | Percentage Reduction in Image Size for components =50 |  | sctterplot for n_cluster is =50  175 130 1315 100 75 25 25 25 26 27 160 125 150 175 260  |
| 60   | Percentage Reduction in Image Size for components =60 |  | sctterplot for n_cluster is =60  175- 180 - 123 - 100 75- 50- 25 50 75 160 125 150 175 200   |
| 70   | Percentage Reduction in Image Size for components =70 | 0<br>200 -<br>300 -<br>400 -<br>500 -<br>400 -<br>500 | sctterplot for n_cluster is =70  175  130  120  175  29  20  75  100  125  150  175  260   |

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### **Observations:**

- 1. Note: The image for K mean clustering is placed only showing the cluster formation, not comparable in terms of reconstruction.
- 2. In both the algorithms for PCA and SVD as the Number of principal component or K the compression ratio decreases.
- 2. Reconstruction for PCA is better at a lower value of number of principal components
- 3. The compression ratio higher in PCA for the same value of component in PCA and K value in SVD

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## 2.1 Future scope:

- 1. Exploring other data reduction techniques for Machine learning.
- 2. Most importantly
- (a) Experimenting with large dataset and setting up github CI
- (b) test for the measures of these algorithms in terms of the impact on the model performance (c) when which algorithm is suitable.

The applicability which algorithm is most appropriate can only be experimented after evaluating accuracy of the model for the pre-treated data by these algorithms

Other References: 1) <a href="https://arxiv.org/pdf/1608.05148.pdf">https://bair.berkeley.edu/blog/2019/09/19/bit-swap/</a>

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