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Using PCA to Reduce Number of Parameters in a Neural Network by 30x Times

While still getting even better performance! — Neural Networks and Deep Learning Course: Part 17

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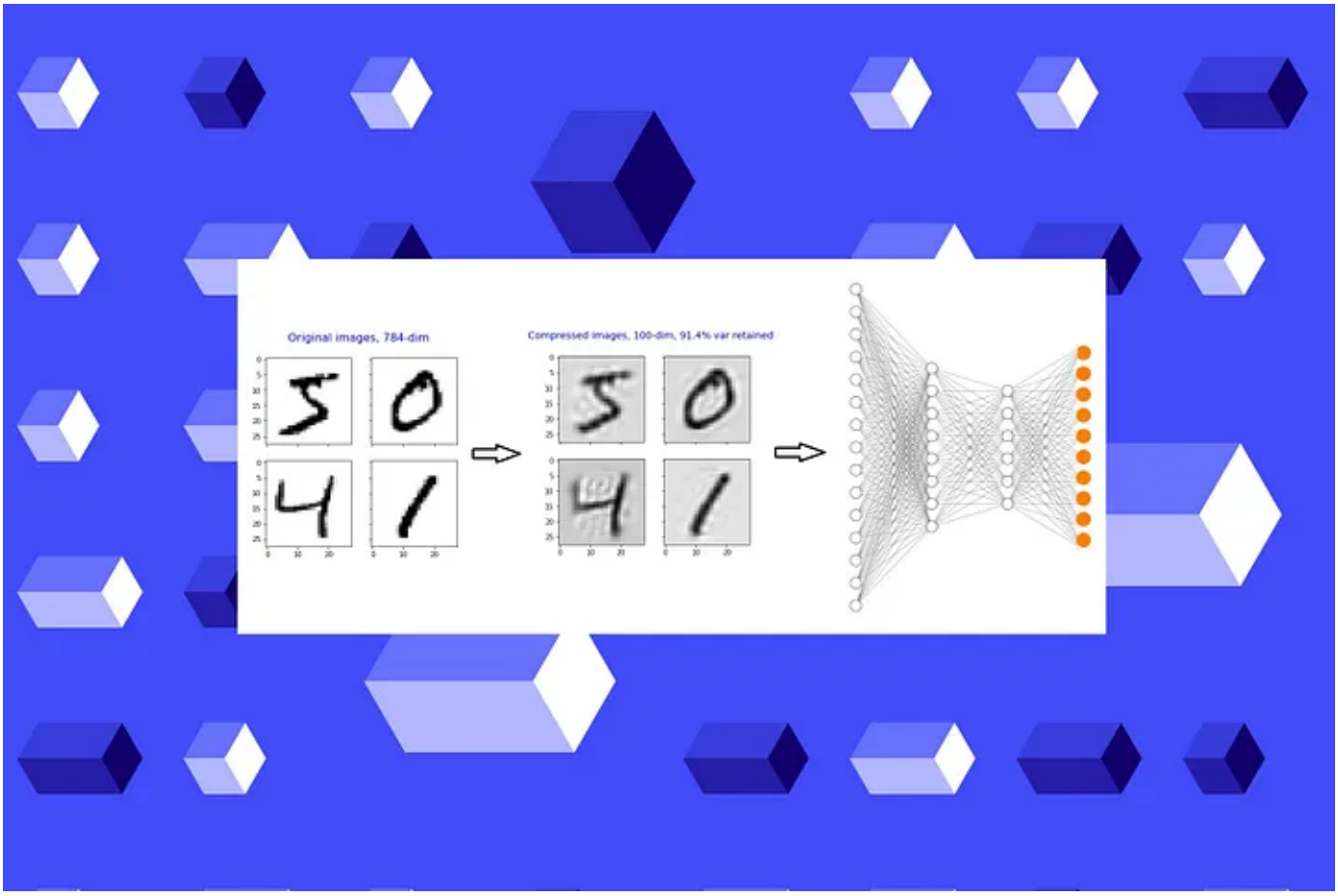
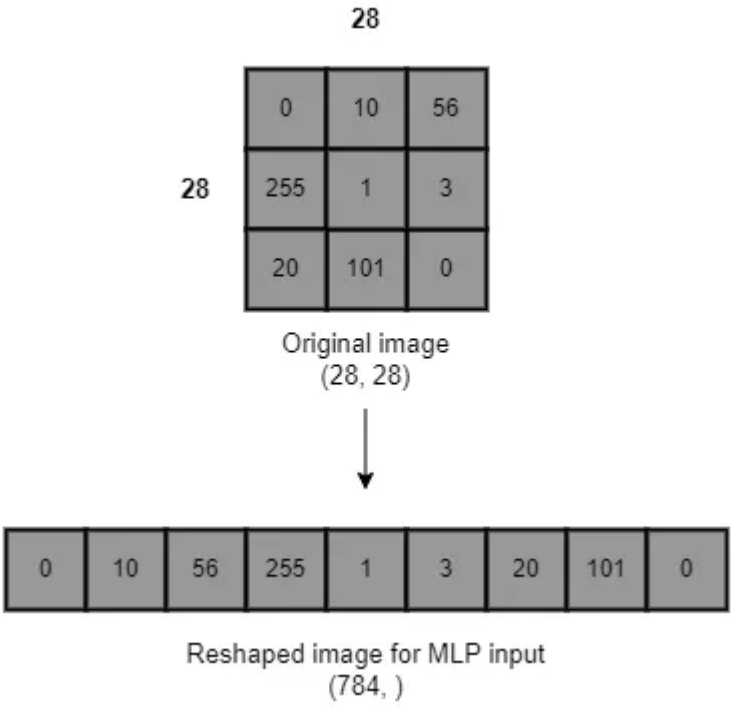


Original photo by MagicPattern on Unsplash, edited by author

In the previous article, we created a Multilayer Perceptron (MLP) classifier model to identify handwritten digits.

We used two hidden layers with 256 neurons for the network architecture. Even with such a small network, we got 269,322 total parameters (weights and bias terms). The main reason for getting such a big number of parameters for the network is the large size of the input layer.

Because the input layer of an MLP takes 1D tensors, we need to reshape 2-dimensional MNIST image data into 1-dimensional data. This process is technically called ***flattening*** the image.



(Image by author, made with draw.io)

Each pixel in the image represents an input. If there are 784 pixels in the image, we need 784 neurons in the input layer of the MLP. When the size of the input layer increases, we get a large number of total parameters in the network. That's why MLPs are not parameter efficient. The size of the input layer significantly increases when we use high-pixel value image data, for example, 500 x 500 px images.

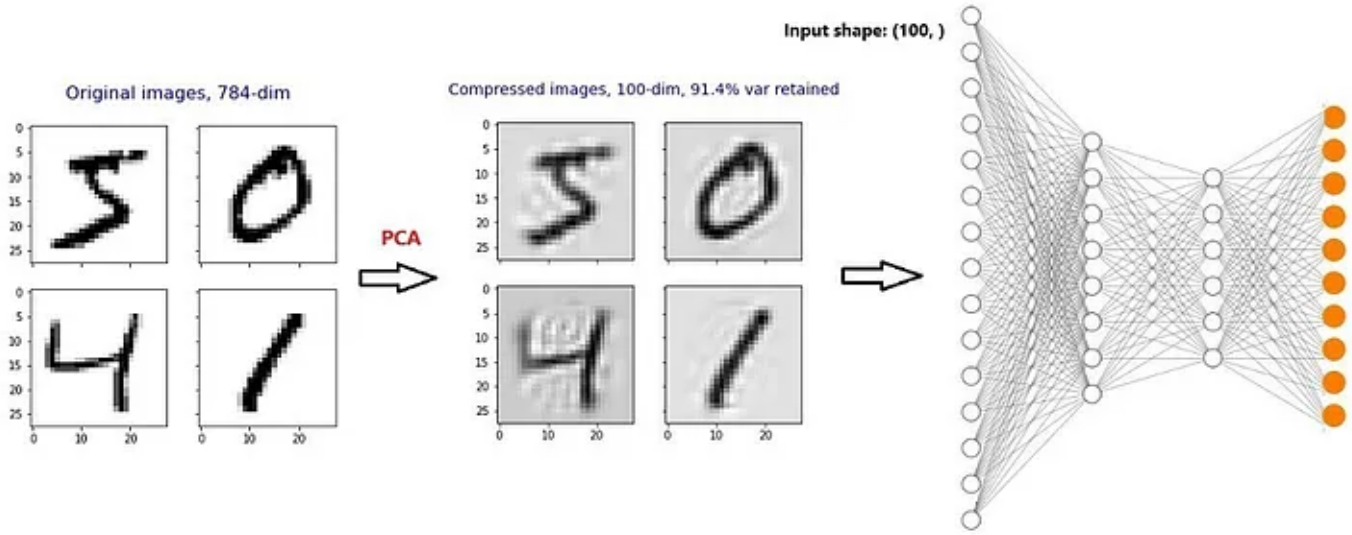
The problem with getting a large number of total parameters in the network is that we need a lot of computational resources to train the neural network and it is also time-consuming.

MLPs are not suitable for image data. There is an even better neural network architecture called **Convolutional Neural Network (CNN or ConvNets)** designed to work with image data. Its input layer can take high-dimensional data so we do not need to flatten the images.

We can still use MLPs with image data efficiently if there is a way to reduce the number of pixels in the image without losing much of the image quality. If we can do it, the size of the input layer will be significantly small and the MLP model will be parameter efficient.

We can apply **Principal Component Analysis (PCA)** to the flattened images to significantly reduce the number of pixels while still getting almost the same image quality but with fewer pixels now!

The general workflow is:



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First, we apply PCA to the MNIST digits data and reduce dimensionality (number of pixels) by 7.48x times while keeping 91.4% image quality! Then, we build the same MLP model that we built in Part 16. Now, the input shape is (100,), not (784,). This will reduce the number of total parameters in the network significantly. Moreover, we have the opportunity to decrease the number of neurons in the hidden layers because the input size is small now. That will also help to reduce the number of total parameters in the network significantly.

Apply PCA to the MNIST data

If you acquire the MNSIT data through the Keras API, you will get 60,000 grayscale images of handwritten digits for the training set and 10,000 grayscale images of handwritten digits for the testing set. Each grayscale image is 2-dimensional with 28 px width and 28 px height.

```
Train images shape: (60000, 28, 28)

Test images shape:  (10000, 28, 28)
```

(Image by author)

We need to flatten these images before applying PCA. After flattening, we get:

```
Train images shape: (60000, 784)
Test images shape:  (10000, 784)
```

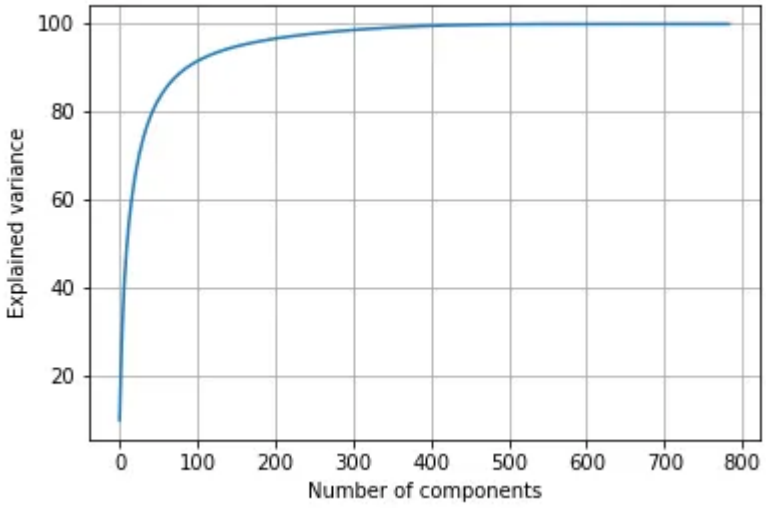
(Image by author)

We can think of this new array of training set images as a simple dataset with 60,000 rows (number of images) and 784 columns (number of pixels in an image). Now, we can apply PCA as usual. Note that we apply PCA to both train and test sets separately.

When considering a single flattened image, the number of pixels represents its dimensionality. When we reduce the dimensionality, we reduce the number of pixels in the image.

Apply PCA to the MNSIT data to select the best number of principal components (Code by author)

After running the above code, we get the following output.



Select the best number of principal components (Image by author)

We can see that the first 100 components capture about 90% of the variability in the original image data. That is enough to retain the quality of the original images. So, we select the first 100 components and apply PCA again with that number of selected components.

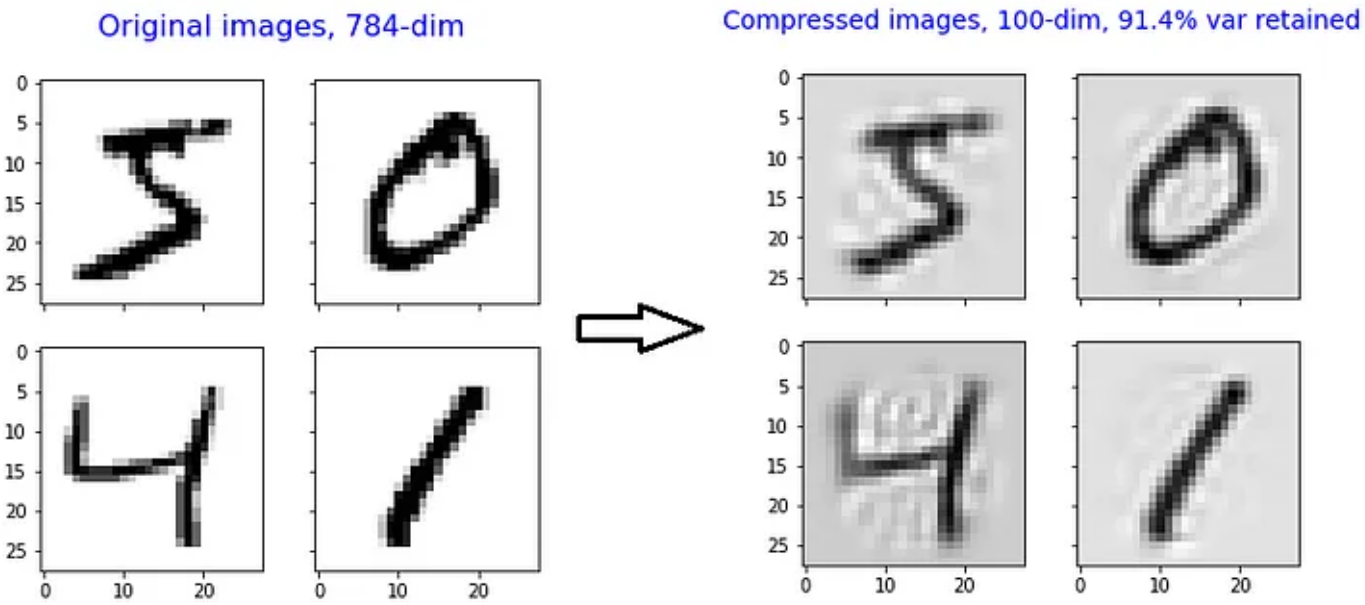
Apply PCA again with the selected components (Code by author)

```
Train images shape: (60000, 100)
Test images shape:  (10000, 100)

Var retained (%): 91.431076
```

(Image by author)

We have reduced the dimensionality of the original image data by 7.84x times (784/100) while keeping 91.43% variability in the original data.



A sample of images: Before and after applying PCA (Image by author)

The compressed images are still identifiable!

Note: I'm not going to explain more about the PCA process here. Kindly refer to the following article series (written by me) to learn everything about PCA and dimensionality reduction.

Click on this image to access my PCA and Dimensionality Reduction Special Collection (Screenshot by author)

Build the MLP classifier with compressed (reduced) image data

Now, we build the same MLP classifier model as we built in Part 16, but with compressed image data (fewer dimensions and fewer pixels)!

(Code by author)

```
Test loss: 0.10373429208993912
Test accuracy: 0.9745000004768372
```

(Image by author)

This time we get an accuracy score of 0.9745. Previously (i.e. before applying PCA), we got an accuracy score of 0.9804. We only lose a very small amount of accuracy score. That is 0.0059.

If we check the number of total parameters now, we get:

```
MLP.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                6464

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 10)                330

=================================================================
Total params: 8,874
Trainable params: 8,874
Non-trainable params: 0
```

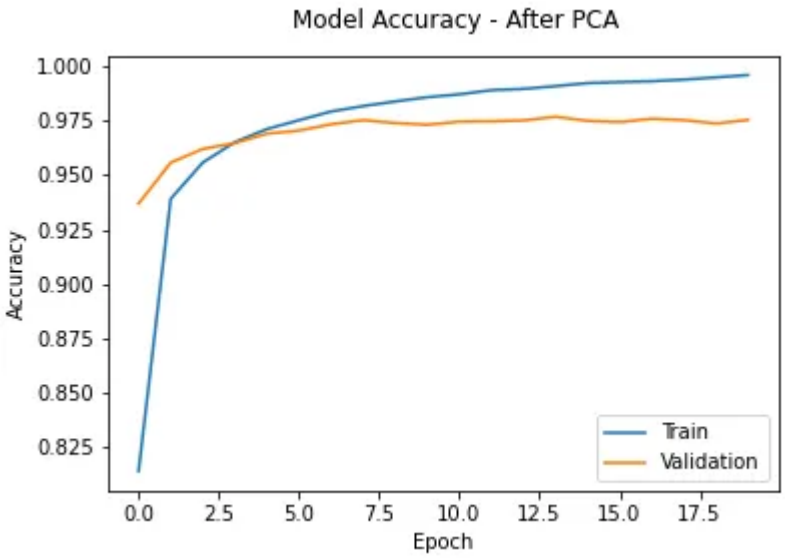
Number of trainable parameters after applying PCA (Image by author)

Previously (i.e. before applying PCA), we got 269,322 total parameters. This time we only got 8,874 total parameters. So, we've reduced the number of total parameters by 30x times (269,322 / 8,874) after applying PCA! We only lost 0.0059 model accuracy.

We can get even better results by applying PCA. This time I'm talking about the problem of overfitting.

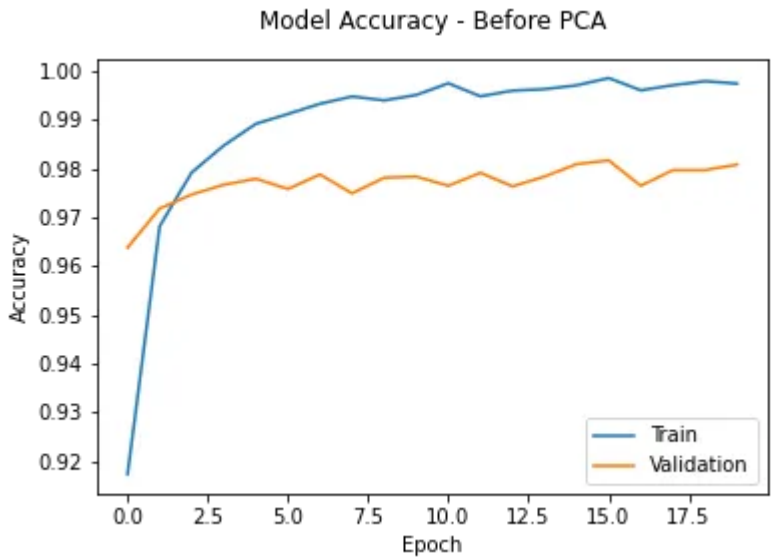
I measured the performance of the model during the training.

(Code by author)



(Image by author)

This can be compared with the corresponding previous case: before applying PCA.



(Image by author)

It is very clear that the ***model is less overfitting after applying PCA***. The model generalizes well on the new unseen data (test data). The reason is that:

> *PCA removes the noise in the data and keeps only the most important features in the dataset. That will mitigate the overfitting of the data and increase the model's performance on unseen data. In addition to that, a model can become more complex when there are many features in the data. Complex models tend to overfit the data. PCA takes care of model complexity by reducing the number of features (dimensionality) in the data — Source:* ***How to Mitigate Overfitting with Dimensionality Reduction*** *(my own article)*

Summary

- We applied PCA to the MNIST data and successfully reduced the dimensionality of the original image data by 7.84x times. So, we could significantly reduce the size of the MLP input layer. We kept 91.43% variability in the original data. So, images are still identifiable.

- We only lost a very small amount of accuracy after applying PCA.

- We could reduce the number of total parameters in our MLP model by 30x times! This is because we significantly reduced the size of the MLP input layer and the number of neurons in the hidden layers. Because the input size is small now, we have the opportunity to decrease the number of neurons in the hidden layers. You will not get much performance improvement by increasing the number of neurons

in the hidden layers. However, it is better to do some experiments by setting different values and then measuring the performance.

- After applying PCA, the model is less overfitting. I explained the reason for that. Also, note that the model is still overfitting because we haven't applied any regularization technique to the model yet.
- It is easy to apply PCA for MNIST image data because the images are grayscale which are represented as two-dimensional (2D) tensors. The PCA process is complicated with RGB images which are represented as three-dimensional (3D). Read this article to learn how to apply PCA to an RGB image. To learn the difference between RGB and grayscale images, read this article.

This is the end of today's post.

Please let me know if you've any questions or feedback.

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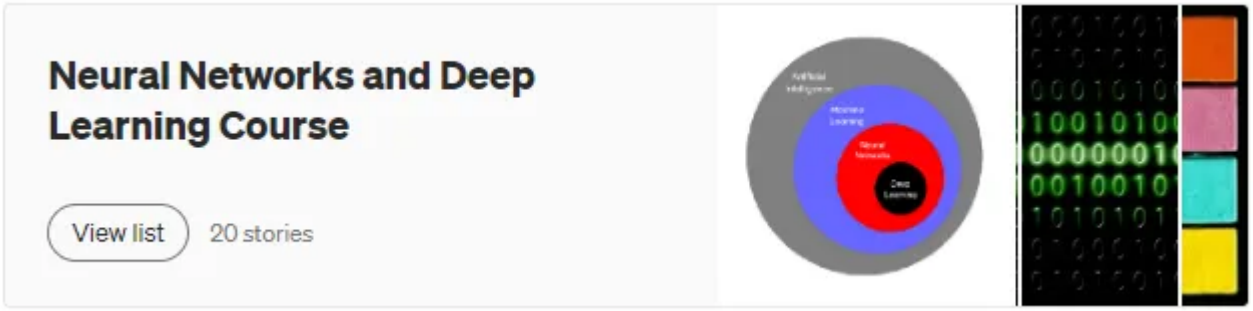

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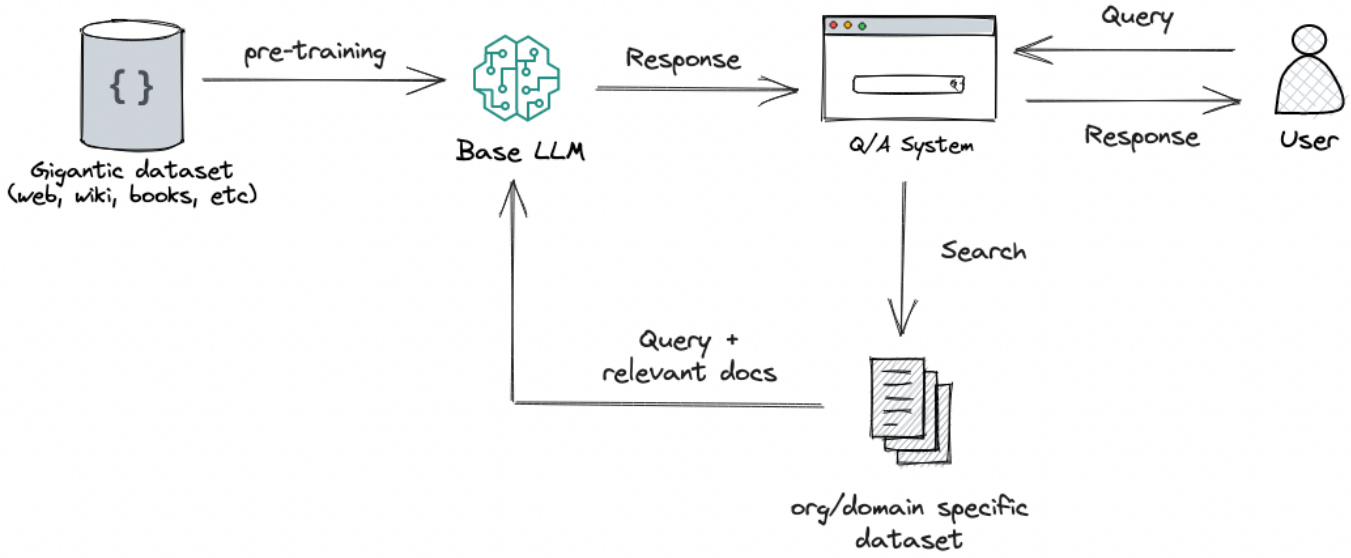

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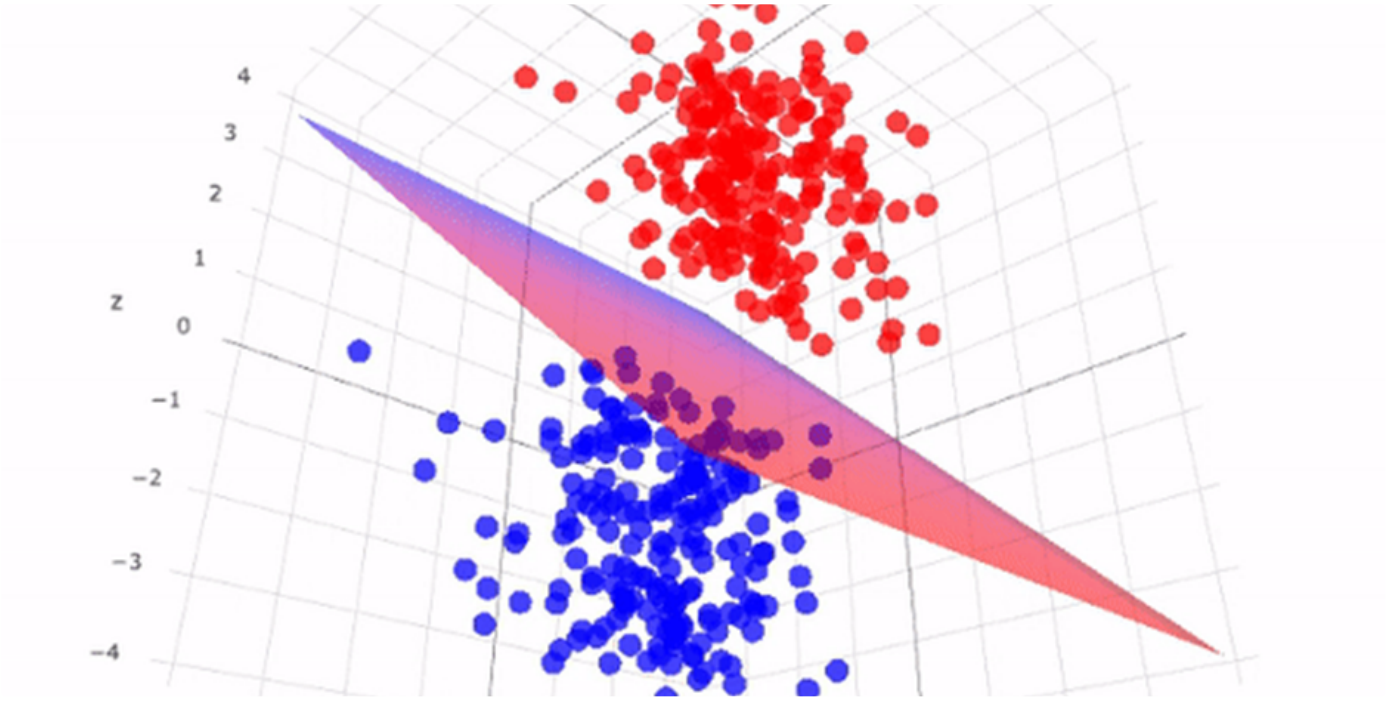

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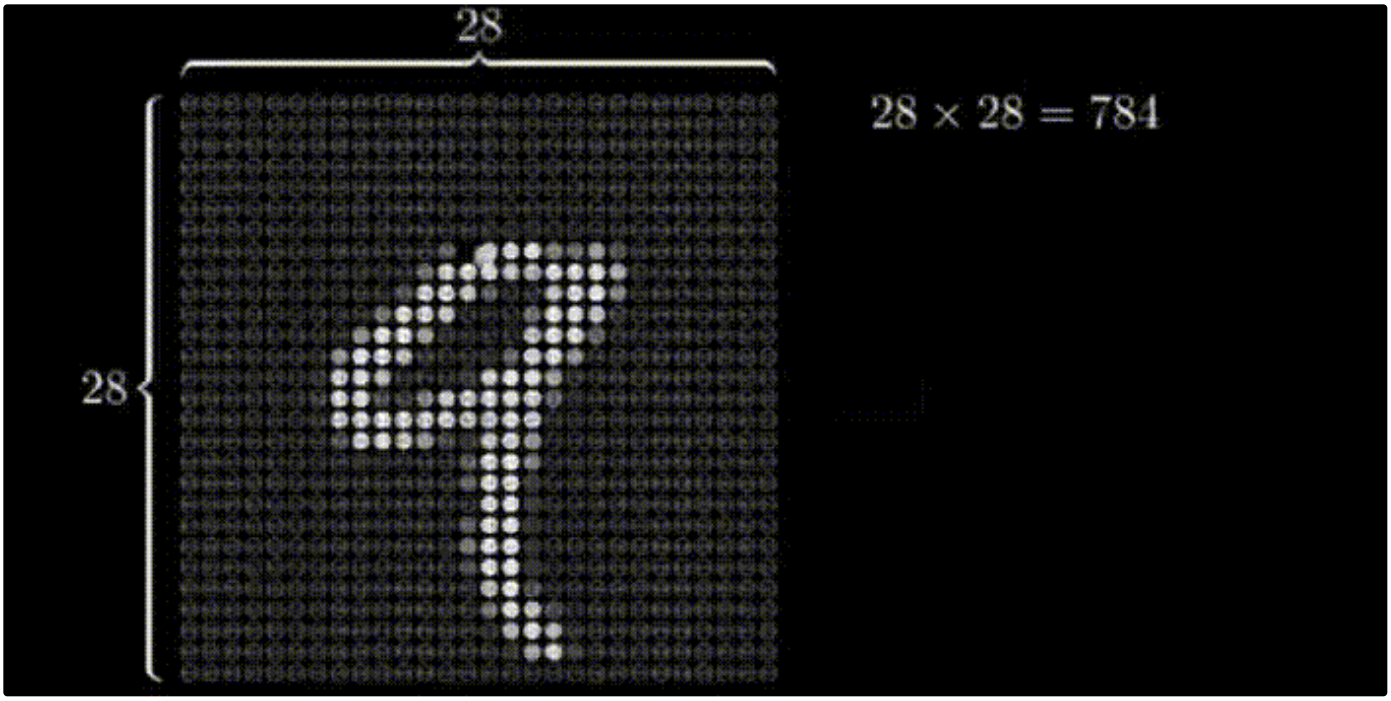

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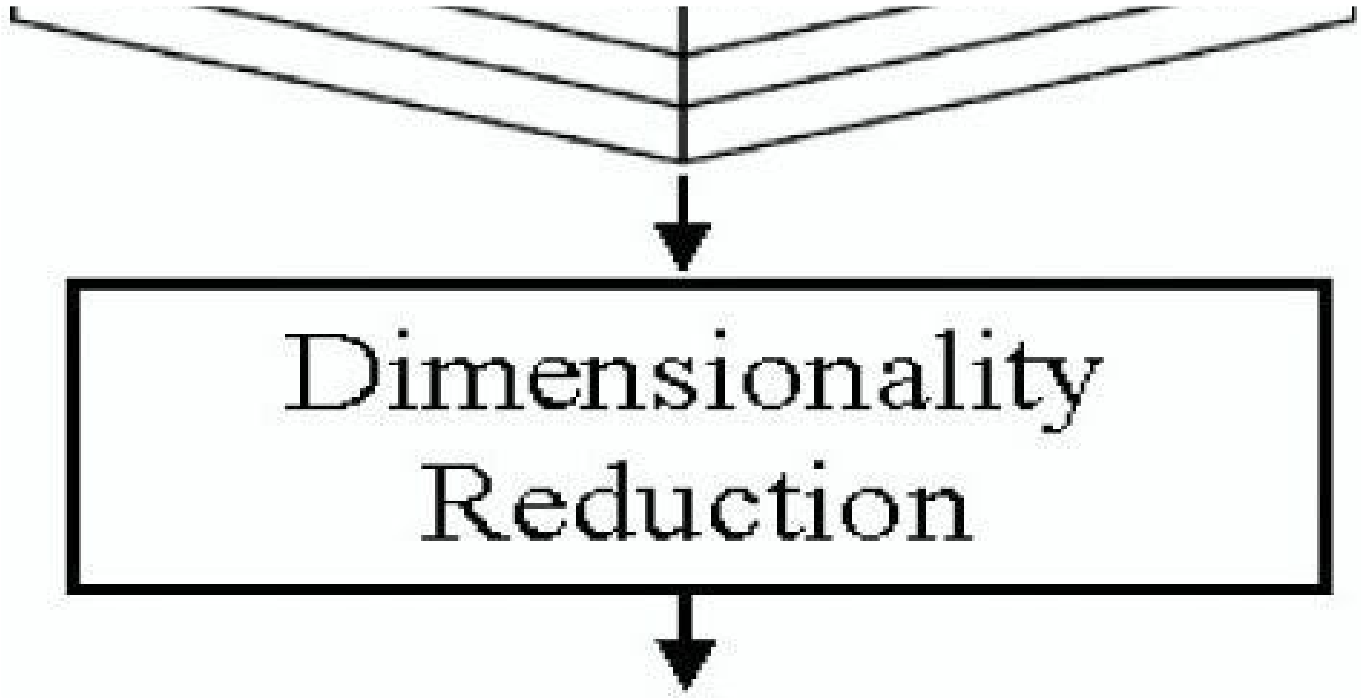

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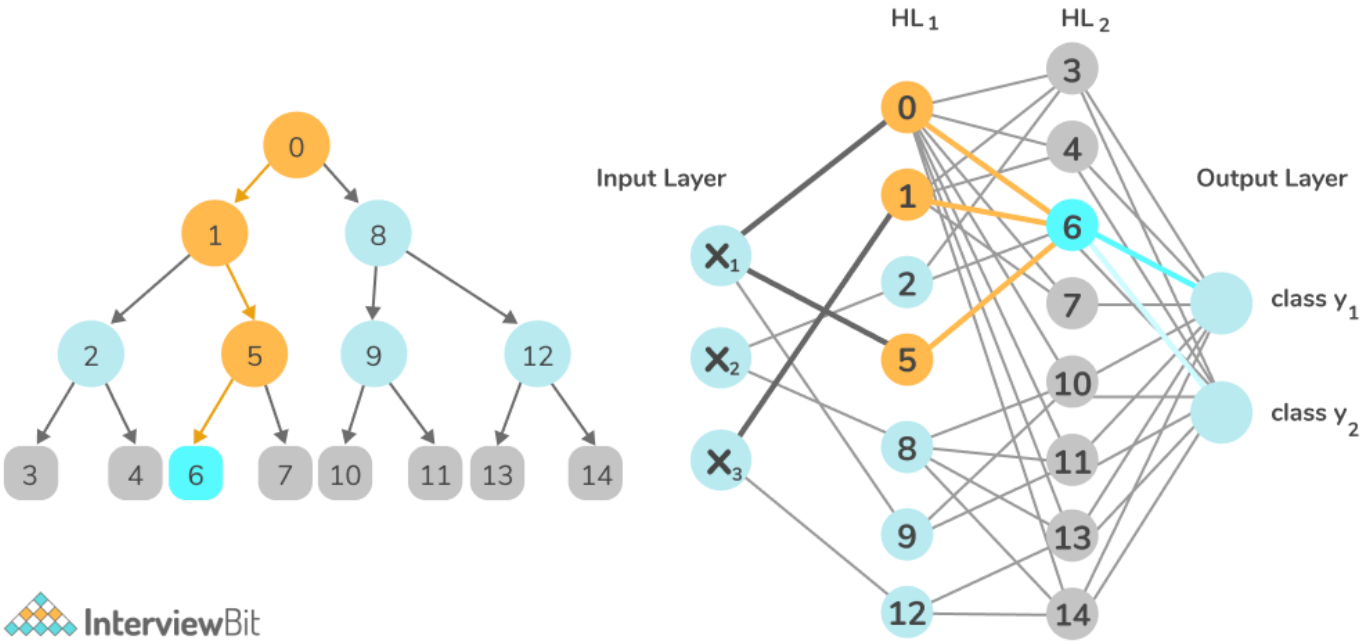

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