Deep Learning
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Lecture - 06
PCA: Interpretation 3 (Contd.)

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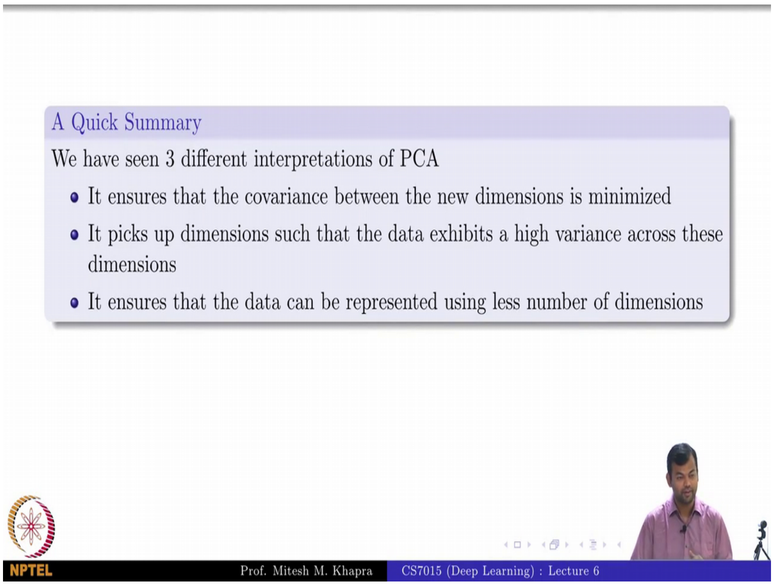

A quick summary, we have seen 3 different interpretations of PCA, and eigen vectors played a very crucial role in that; and the other thing which played a crucial role was the covariance matrix of the original data. And with these three different interpretations what we realize is that, the solution that we get or the transform data that we get projecting the original data on to the on to a basis consisting of eigen vectors, ensures that there is high variance across the new dimensions. And we can ignore of the bottom top n sorry bottom n minus k dimensions along with these variance is not high. This also ensures that the error in reconstructing the data by ignoring this dimensions is minimized right it is a lowest possible error. And it also ensures that the covariance between your retained dimensions is 0, because we are able to diagonalize the covariance matrix of the transform grid so that is what we had.

So, now if you think of it right just to connect it two things that we need later on for auto encoder right. We are trying to learn a new representation for the data right and we are trying to also compress the data, and we want this compression to be such that it is as lossless as possible right. We are going from n dimensions to k dimensions, and still we want to retain the essence of the data and do not want to lose out an much of the information in the data ok. So, that is essentially what PCA is doing. Now let us see this in practice.