What is Principal Component Analysis?

Principal Component Analysis(PCA) is one of the best-unsupervised algorithms. Also, it is the most popular dimensionality Reduction Algorithm.

PCA is used in various Operations. Such as-

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1. Noise Filtering.
2. Visualization.
3. Feature Extraction.
4. Stock Market Prediction.
5. Gene Data Analysis.
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The goal of PCA is to identify and detect the correlation between attributes. If there is a strong correlation and it is found. Then PCA reduces the dimensionality.

The main working of PCA is-

The Principal Component Analysis reduces the dimensions of a d-dimensional dataset by projecting it onto a k-dimensional subspace (where k<d).

In which problem, The principal component analysis is used?

So the problem is Overfitting. PCA is used for the Overfitting problem.

Overfitting is the problem when you supply extra data at the training phase. When we train the model, we supply data to the model. This data is known as Training Data.

But, If we supply extra data, then the overfitting problem occurs.

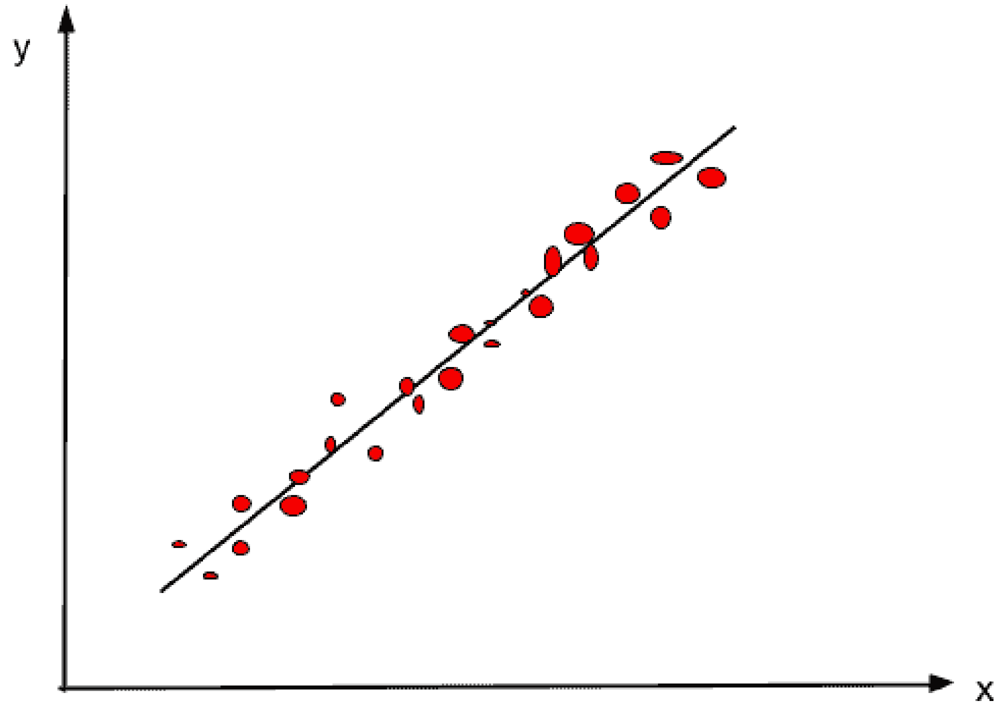
In simple words, you can consider overfitting as overeating. When you eat extra food, you face digestive problems.

Similarly, the same problem occurs in overfitting. When you supply extra data, we will face a problem.

I hope, now we better understand Overfitting. Right?

Now, let’s see how the PCA solves overfitting problems.

Suppose after the training phase, this hypothesis is generated.\



So, What this hypothesis or model is doing?

This model is trying to reach at each point. The single straight line is trying to touch each point. And that's the overfitting problem.

So we can solve this problem.

PCA tries to convert high dimensionality into the set of low dimensionality.

PCA reduces the features and attributes into a low dimension, in order to solve overfitting.

And that's the main motive or purpose of PCA.

Now, let's see how PCA works?

How Principal Component Analysis work?

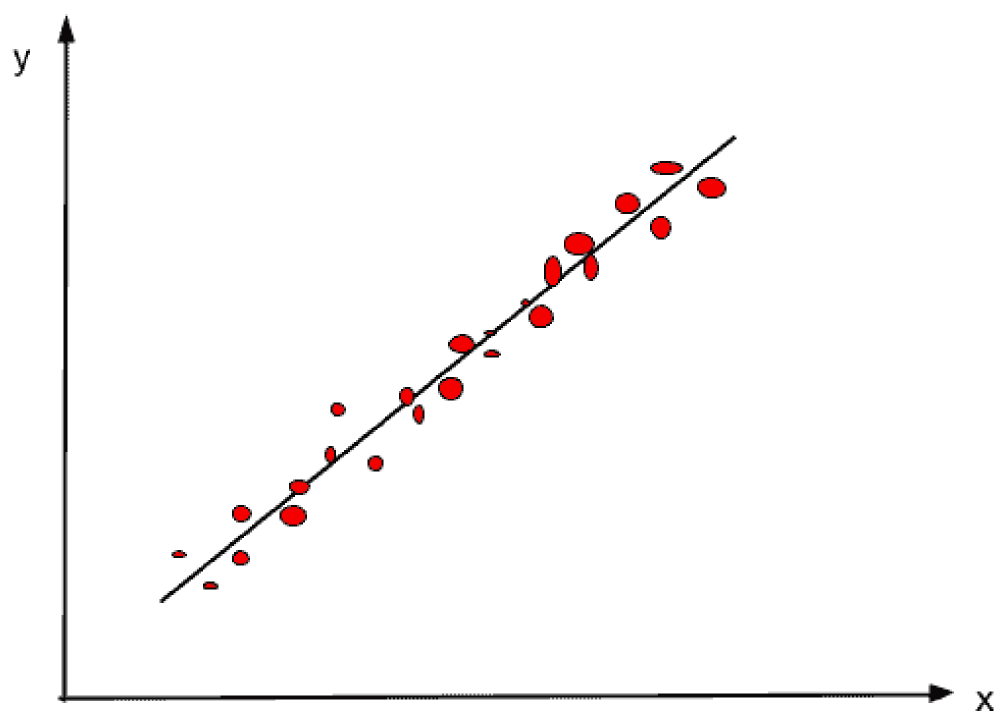
In the previous section, we can understand the whole concept of Overfitting.

Assume we have given data in such a format for the training phase. It is just for your reference. Ok

Age	Salary
40	20 LPA
25	8 LPA
35	15 LPA

The data has only two attributes the Age, and salary. We train our model on these two attributes. And after training, we get this hypothesis.

One attribute is on the x-axis, and the second one is on the y-axis.



Here, we found that our model is facing the overfitting problem. So to solve overfitting we use principal component analysis.

And for that work, we need to find a **PC (Principal Components).**

So, the next question is-

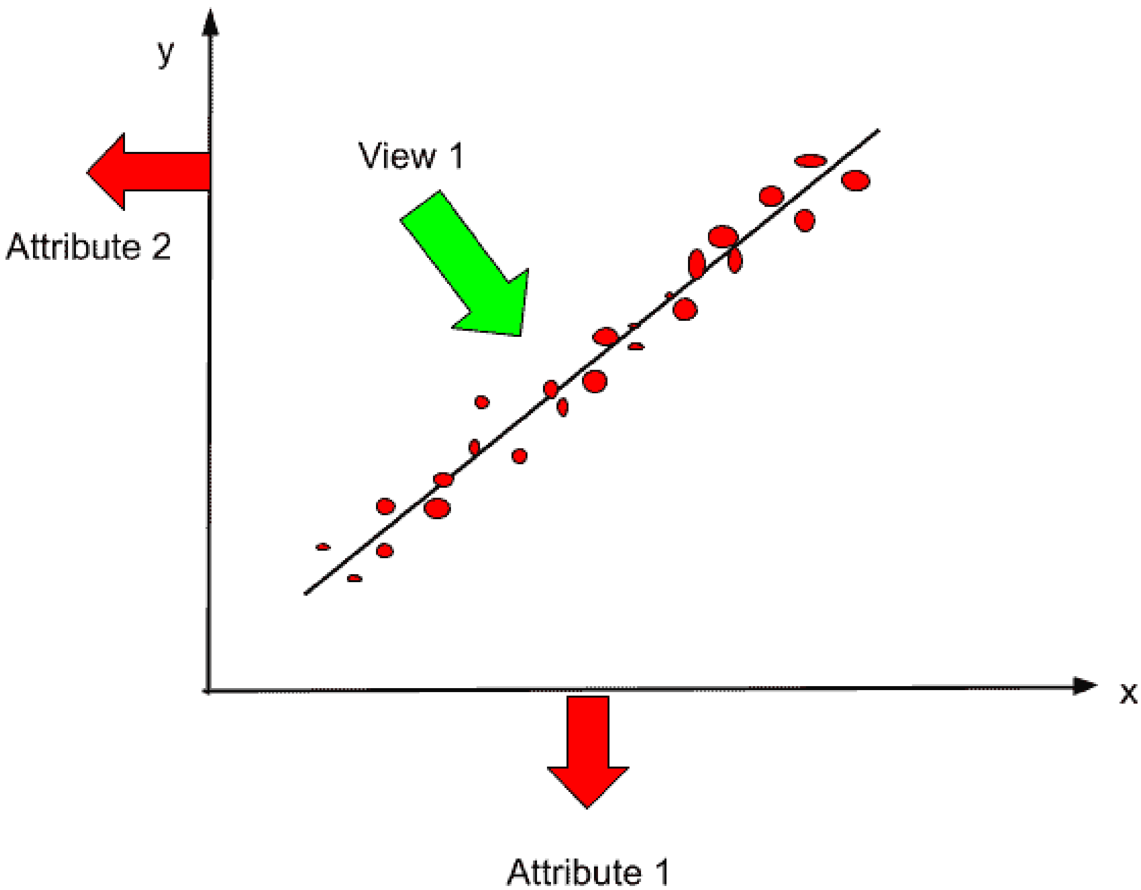
How to find PCs?

To find PCs, there is another term used, and that is Views.

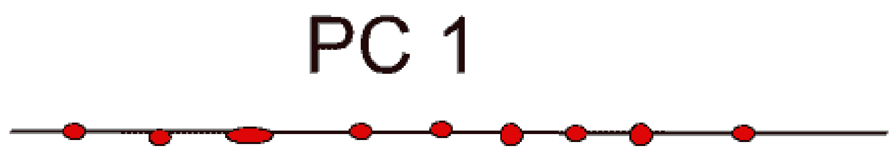
Views are nothing but different angles from where you saw your data or hypothesis.

Suppose we saw our hypothesis from the top level, so how it looks?.

Let' see in the below image.



If I see my data points from that point, so I will see one line. And on that line, there will be some points mapped on that line. Just see in the image below.



So what we have done here?.

Before we have two dimensions x and y. And now we have only one. So basically we reduce from two-dimension to one-dimension.

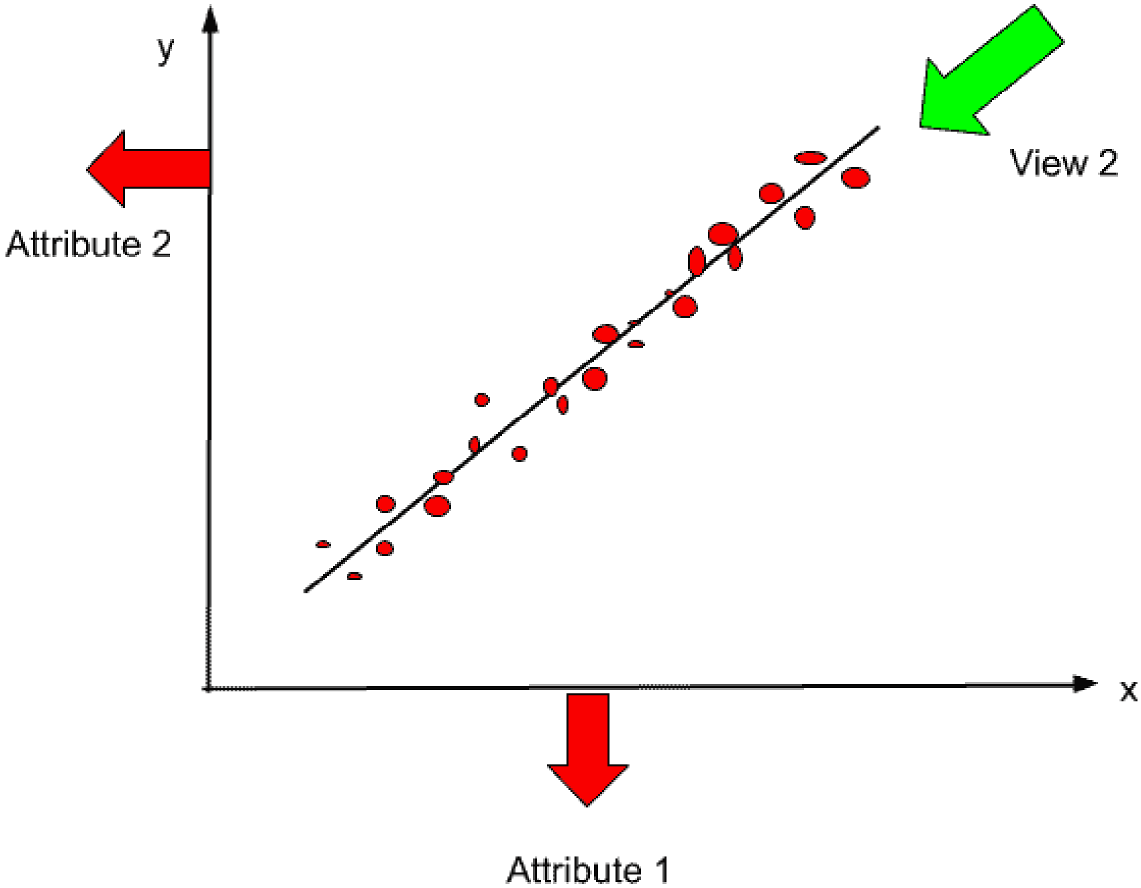
As we discussed the definition of PCA in the first section, that PCA reduces d-dimensional dataset into a k-dimensional subspace.

So, here d-dimensional dataset is the two-dimensional dataset- age, and salary. And PCA reduced it into a k-dimensional subspace that is a one-dimensional single line.

now we can call it PC1. Similarly, we can find more PCs by looking at different angles or views.

Let’s see how to generate the Second PC?

If we see the hypothesis from that view, then let’s see how it will look.



So from that view How it will look?.

Are you thinking that only one point will be seen?

If yes, then sorry we are thinking wrong. we will not see only a single dot point.

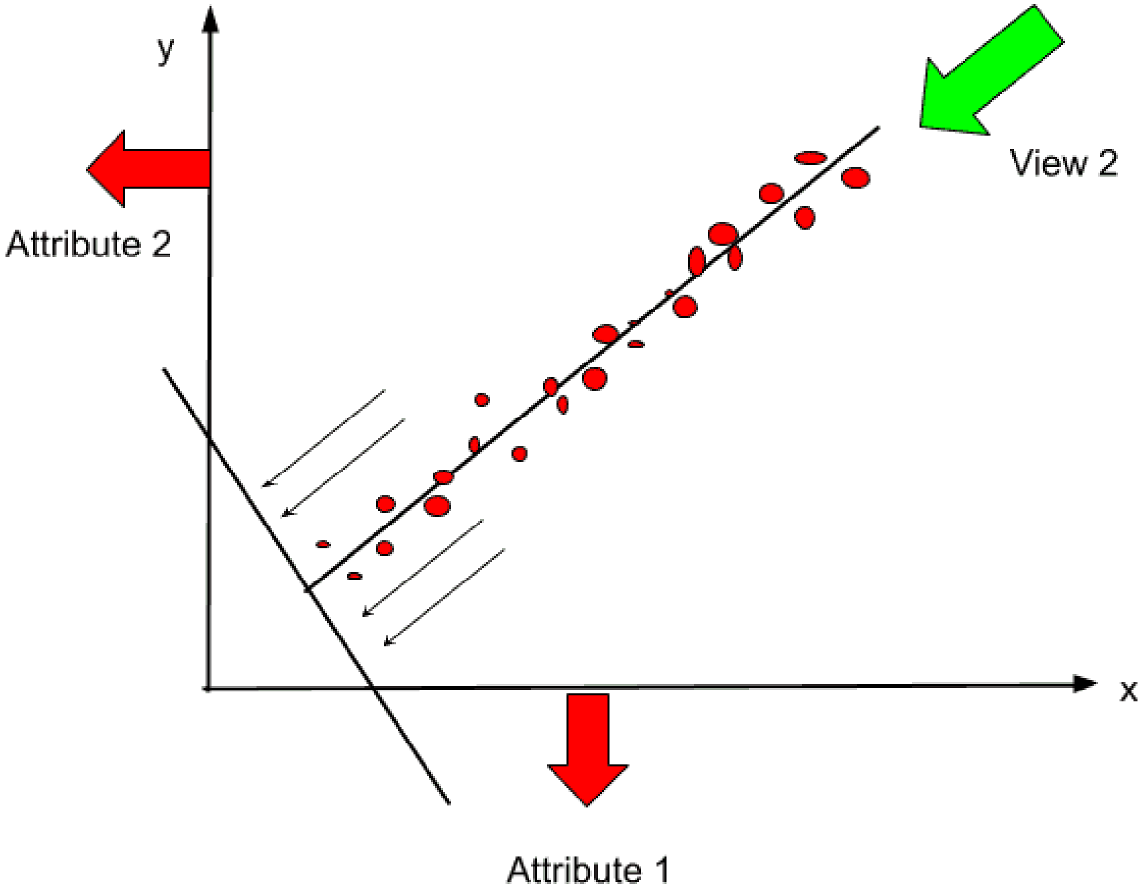
Now, we have a question Why we will not see only one point?

So to understand, we need to go in little more detail.

We can imagine one line horizontal to this straight line, and all these points will be mapped on that line.

Confused?

Don’t worry. Just look at this image, and then you will understand.

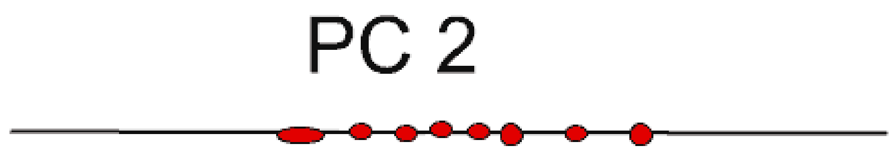


Now I hope you understand what I was saying.

Right?.

So, now when we plot this line, and all these points will be mapped on that line. So how it will look?.

Let’s see in this image.



Very much similar to PC1. So as of now, we have generated two principal components PC1, and PC2.

The very important point we should keep in our mind is that the number of principal components can be less than or equal to the number of attributes.

That means our Principal Components (like PC1, and PC2) should be equal to or less than the attributes (in that example age, and salary).

Got it?.

Now, the next question is-

What to do when we have more than two attributes?

So in that case, we can also reduce the dimension in the same way.

Suppose we have generated 5 principal components PC1, PC2, PC3, PC4, and PC5. So whom to give more preference above 5?

The answer is PC1.

Suppose in this example, we have generated two Principal Components PC1 and PC2. But we will give preference to PC1.

There is one more Property. And that is the Orthogonal Property.

So, What is Orthogonal Property?

There should be orthogonal property between PC1 and PC2. That means both PC1 and PC2 should be independent with each other. No one should be dependent on each other.

In simple words, PC1 should not dependent upon PC2 and vise versa.