

Deep Learning
Prof. Mithesh M. Khapra
Department of Computer Science and Engineering
Indian Institute of Technology, Madras

Module – 6.3
Eigenvalue Decomposition

Lecture – 06

And before that we will have to see something known as Eigenvalue decomposition. So, the answer to that was actually which I was hoping all of you will give because all of you have done 2 prerequisite, which is linear algebra and machine learning, both of them teach you principal component analysis. So, I was hoping that you will give that answer.

Now, can you give that answer he already of course, gave that answer, is that make sense ok? So, we relate it to that so, but before going to principle component analysis, we look at Eigen value decomposition, how many of you have seen Eigenvalue decomposition before ok? Quite a few.

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- Let u_1, u_2, \dots, u_n be the eigenvectors of a matrix A and let $\lambda_1, \lambda_2, \dots, \lambda_n$ be the corresponding eigenvalues.
- Consider a matrix U whose columns are u_1, u_2, \dots, u_n .
- Now

$$\begin{aligned}
 AU &= A \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow \\ u_1 & u_2 & \dots & u_n \\ \downarrow & \downarrow & \dots & \downarrow \end{bmatrix} = \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow \\ Au_1 & Au_2 & \dots & Au_n \\ \downarrow & \downarrow & \dots & \downarrow \end{bmatrix} \\
 &= \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow \\ \lambda_1 u_1 & \lambda_2 u_2 & \dots & \lambda_n u_n \\ \downarrow & \downarrow & \dots & \downarrow \end{bmatrix} \\
 &= \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow \\ u_1 & u_2 & \dots & u_n \\ \downarrow & \downarrow & \dots & \downarrow \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \dots & 0 & \lambda_n \end{bmatrix} = U\Lambda
 \end{aligned}$$

This is very straightforward. So, let u_1 to u_n be the Eigenvectors of a matrix A and let λ_1 to λ_n be the corresponding Eigenvalues ok.

Now, I am going to construct a matrix U , such that the columns of U are these vectors u_1 to u_n , is that fine, what u looks like. And now I am going to do this product I am

taking a the product of the matrix A with the product of with the matrix U, where U is this right. It is the all the Eigen vectors tagged one after the other is this fine. The next step I am just pushing the matrix inside. If you know the 4 different ways of multiplying a matrix you will know that this is correct ok. Or else for now just thing that you can just push the matrix inside ok.

Now, what is this I can replace them by the lambda 1 u 1 lambda 2, because a u 1 is equal to lambda 1 u 1 by definition ok. Now can you write this again as a product of 2 matrices, one is of course, the matrix U and the other is.

Student: Diagonal.

Diagonal. So, the diagonal matrix will come first or the matrix U will come first? How many if you say U will come first? How many if you say the diagonal matrix will come first? The sum is never one ok.

So, it is going to be like this ok. And you can write this as U lambda. So, U is again the vector the matrix containing the Eigenvectors of A and lambda is a diagonal matrix where every diagonally element is a corresponding Eigen value.


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$$AU = U\Lambda$$

- If U^{-1} exists, then we can write,

$$A = U\Lambda U^{-1} \quad [\text{eigenvalue decomposition}]$$

$$U^{-1}AU = \Lambda \quad [\text{diagonalization of } A]$$
- Under what conditions would U^{-1} exist?
 - If the columns of U are linearly independent [\[See proof here\]](#)
 - i.e. if A has n linearly independent eigenvectors.
 - i.e. if A has n distinct eigenvalues sufficient condition, proof : Slide 19 Theorem 1]



Now, this is what we have so far A into U is equal to U into lambda. Now suppose U inverse exists, I will assume that U inverse exists and later on I will tell you under what

conditions it exists, then I could write it as this any of these 2 forms in one case. I am post multiplying by U inverse in the other case I am pre multiplying with universe ok.

So, this is known as the Eigenvalue decomposition of a matrix. And the other way of writing it is known as diagonalization of the matrix right. You take a matrix apply some operations to it so that, the result is a diagonal matrix is this clear to all of you is very straightforward ok. And again Eigen vectors play an important role in this. Now the important question is under what conditions would U inverse exist. U inverse would exist if the columns of the matrix U are.

Student: Linearly independent.

Linearly independent ok. Do we know the columns of the matrix are linearly independent?

Student: Yes.

Yes, because it is a.

Student: (Refer Time: 03:10).

Set of Eigenvectors and we already saw the proof that the Eigen vectors are linearly independent ok. This just follows whatever I say ok. Now do we need proof for this I slide 19 we did this ok, I did not realize it fine.

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- If A is symmetric then the situation is even more convenient.
- The eigenvectors are orthogonal [proof : Slide 19 Theorem 2]
- Further let's assume, that the eigenvectors have been normalized [$u_i^T u_i = 1$]

$$Q = U^T U = \begin{bmatrix} \leftarrow u_1 \rightarrow \\ \leftarrow u_2 \rightarrow \\ \dots \\ \leftarrow u_n \rightarrow \end{bmatrix} \begin{bmatrix} \uparrow u_1 \downarrow & \uparrow u_2 \downarrow & \dots & \uparrow u_n \downarrow \end{bmatrix}$$

- Each cell of the matrix, Q_{ij} is given by $u_i^T u_j$

$$Q_{ij} = u_i^T u_j = \begin{cases} 0 & \text{if } i \neq j \\ 1 & \text{if } i = j \end{cases}$$

$$\therefore U^T U = \mathbb{I} \text{ (the identity matrix)}$$

- U^T is the inverse of U (very convenient to calculate)



Now if A is symmetric the situation is always more convenient, why is it?

Student: (Refer Time: 03:40).

What would U be?

Student: Orthogonal matrix.

What is an orthogonal matrix actually?

Student: (Refer Time: 03:47).

So the Eigenvectors are orthogonal. So, we have this situation right. Suppose I want to do $U^T U$ ok. This is how that operation would look like ok. Now what is the ij th entry of the resultant matrix ?

Student: Dot product.

It is the dot product between the.

Student: u_i and u_j .

u_i and u_j . Everyone gets this right, the ij th entry of this product is going to be the dot product between u_i and u_j . This dot product would be dash if i is not equal to j .

Student: j .

J and there is no point in this. So, each cell of the matrix Q_{ij} is given by the dot product and it is going to be 0 if i not equal to j , and it is going to be 1 if i is equal to j ok. So, $U^T U$ is equal to the identity matrix; that means, U^T is the inverse of U .

Student: (Refer Time: 04:45).

Transpose of U and of course, inverse also ok. So, U^T is the inverse of U . And it is very convenient to calculate what is the complexity of inverse? So now, you appreciate that that is a that has high complexity and in this case if the vector if the matrix is orthogonal; that means, it is a collection of orthogonal vectors and the inverse just comes for free right ok.

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Something to think about

- Given the EVD, $A = U\Sigma U^T$, what can you say about the sequence x_0, Ax_0, A^2x_0, \dots in terms of the eigen values of A .
(Hint: You should arrive at the same conclusion we saw earlier)

$A = U\Sigma U^T$

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So now given this situation, and do not read the hint as if this is going to help, but yeah, what can you now say about the sequence? The same sequence that you saw earlier. So, I have given you that the EVD of A is equal to $U \Sigma U^T$, where U is the collection of the Eigenvectors and Σ is the Eigen values the diagonal matrix containing the Eigenvalues.

Now, what given this and ignoring the knowledge of the first section of this lecture can you tell me something about this series? What would be the n th element of the series?

Student: $U \Sigma^n$.

$U \Sigma$.

Student: Σ^n .

Σ^n .

Student: U^T .

U^T and you arrive at the same conclusion right? Where I was talking about this operation right. So, if we can say something about this matrix then we can say something about this series what can you say about this matrix, if the largest Eigenvalue is greater than 1 as you keep raising it is power that value is going to explode. And hence, the

entire product is going to explode less than 1. That product is going to vanish and everything else would be less than that right remember is the dominant Eigen value ok.

So, everything would be less than that. So, that product will vanish ok. So, the same conclusions you can arrive at right. So, that is why I want to do these sections again. So, you would have done these in linear algebra, but you would have not arrived at these conclusions from a very different interpretation, but I want to focus on the interpretations that I care about. I do not, how many of you have seen this series in the course on linear algebra? You have ok, but I do not see why anyone else would teach this is not required is only required for some things that I want to do in the course right, that is why; I wanted to do this section.

So, everyone is comfortable with Eigenvalue decomposition it is a very simple stuff right I mean there is no proof or anything involved there we just use some properties of Eigenvectors and Eigenvalues and do it ok.

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Theorem (one more important property of eigenvectors)

If A is a square symmetric $N \times N$ matrix, then the solution to the following optimization problem is given by the eigenvector corresponding to the largest eigenvalue of A .

$$\begin{aligned} \max_x & x^T A x \\ \text{s.t.} & \|x\| = 1 \end{aligned}$$

and the solution to

$$\begin{aligned} \min_x & x^T A x \\ \text{s.t.} & \|x\| = 1 \end{aligned}$$

is given by the smallest eigenvalue of A .

Proof: Next slide.

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Now, there is one more important property of Eigenvectors, which we'll use today. So, let us see what this means right. You have a matrix A which is an n cross n matrix ok. And you're interested in computing this value, $x^T A x$ where x belongs to \mathbb{R}^n x belongs to \mathbb{R}^n ok.

So, what am I trying to do here of all these vectors possible in R^n , I want that vector which maximizes this quantity. What is this quantity scalar, vector, matrix, tensor?

Student: Scalar.

Scalar ok, such that x is equal to 1. This is the problem that I have been given to solve why it is not clear as of now, but suppose this is a problem I am trying to solve, or the inverse of this which is minimize the same thing, of all the vectors in R^n find the vector which minimizes this quantity, subject to these constraints. Then the solution for this is given by the smallest or largest the solution is the smallest Eigen value of A .

And x is the Eigenvector corresponding to that. So, if you are trying to minimize and the solution is a smallest Eigenvalue, we need to clarify that if you are trying to maximize and the solution is the largest Eigenvalue is that clear and the value of x would be the corresponding Eigen value. So, largest Eigen vector is the same as something that we have defined today dominant Eigen vector right.

So, let me just repeat. So, that there is no confusion. Let us focus on this problem. The solution to this problem that is the x which will give me the maximum which will maximize this is the dominant Eigen vector of the matrix A right, is that clear? Fine ok. And if you want to minimize it is going to be the smallest Eigen vector; that means, the inverse of the dominant ok.

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- This is a constrained optimization problem that can be solved using Lagrange Multipliers:

$$L = x^T A x - \lambda(x^T x - 1)$$
$$\frac{\partial L}{\partial x} = 2Ax - \lambda(2x) = 0 \Rightarrow Ax = \lambda x$$

- Hence x must be an eigenvector of A with eigenvalue λ .
- Multiplying by x^T :

$$x^T A x = \lambda x^T x = \lambda (\text{since } x^T x = 1)$$

- Therefore, the critical points of this constrained problem are the eigenvalues of A .
- The maximum value is the largest eigenvalue, while the minimum smallest eigenvalue.



So, there is a proof for that I will not go over the proof you can take a look at it at your own leisure.

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The story so far...

- The eigenvectors corresponding to different eigenvalues are linearly independent.
- The eigenvectors of a square symmetric matrix are orthogonal.
- The eigenvectors of a square symmetric matrix can thus form a convenient basis.
- We will put all of this to use.

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So, what has been the story so far. The story has been that the Eigenvectors corresponding to different Eigen values are linearly independent ok.

If you are dealing with the square symmetric matrix, which is something that we will deal with soon. Then things are even more convenient because the Eigen vectors are actually orthogonal ok. And they form a very convenient basis, and now we are going to put this to use when we talk about principal component.