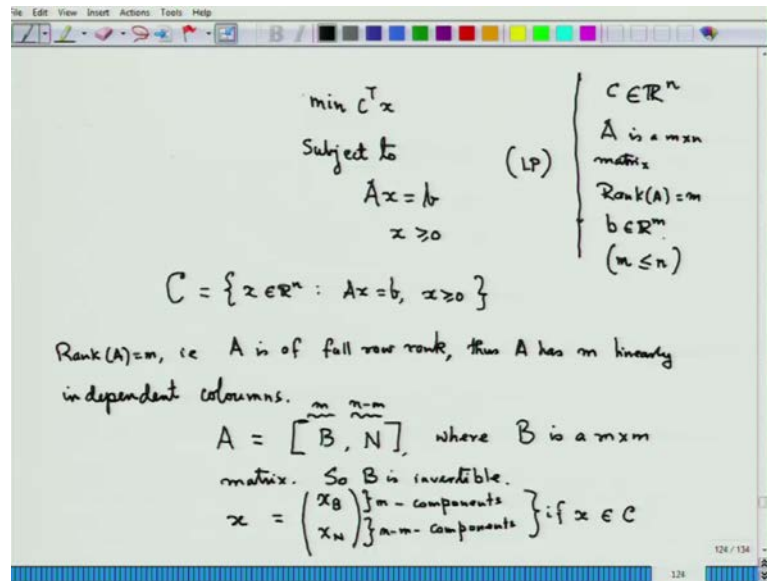


Convex Optimization
Prof. Joydeep Dutta
Department of Mathematics and Statistics
Indian Institute of Technology, Kanpur.

Module No. # 01
Lecture No. # 21

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So, let us again indulge ourselves in the pleasures of linear programming. So, here is the problem that we are going to study, minimize C transpose x subject to $A x$ equal to b greater than equal to 0. I will just list down everything, where C is in \mathbb{R}^n could be anything it could be 2,3,4,5 it does not matter. A is m cross n matrix and, the rank of A is m , b is of course element of \mathbb{R}^m . x the decision vector naturally is in \mathbb{R}^n which I do not have to specify, because you take an inner product.

Now, if I want to solve this problem, it is very important to know what is the feasible set, there is do I or can I find points of the following set, now how do I go about doing this what is the easiest way of finding point? Now, this thing can be done through a little trick. The trick is as follows that, because you know that rank of A is m that is A is of full row rank, what we can do is the following, we know that thus A has m , linearly independent columns of course, m is less than equal to n . This is quite a standard thing,

because the maximum number of linearly independent vectors that you can have in n space \mathbb{R}^n , is n . So, thus m has m linearly independent columns.

Now, suppose by a stroke of luck or by what we call multiplication with permutation matrices, I find that the first m columns that I have of the matrix A is actually linearly independent. So, it may not be so easy to determine which vectors are linearly independent if the matrix is very large then there is certain trick by which **we do something** we can do something, but let us just assume for the time being that I can partition the matrix into B and N , where B is m cross m matrix

So, B is a matrix whose rows as well as columns. So, this first m rows and these are N minus m rows m columns. So, the first m columns of away a linearly independent, and taking those columns and the rows themselves I form a matrix B . So, B is an m cross m matrix, and you know this I have partitioned the columns. So, this is m cross m matrix B is invertible, because it has m linearly independent rows, and m linearly independent columns. So, B is invertible. Now, because I portioned the matrix into B , and N any feasible vector can be portioned into two parts x_B and x_N .

So, take any vector x , let us write it down as x_B and x_N . So, x_B corresponds to the indices the vector, corresponding to indices or the indices of the first m rows, the next one corresponding to the indices of the first, last n minus m rows. So, here I have m components, and here I have n minus m components, and let us assume that x is in C , if x is in C , then I must have A of x is equal to b .

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The image shows a whiteboard with the following handwritten content:

$$Ax = b$$
$$[B, N] \begin{bmatrix} x_B \\ x_N \end{bmatrix} = b$$
$$Bx_B + Nx_N = b$$
$$Bx_B = b - Nx_N$$
$$\Rightarrow x_B = B^{-1}b - B^{-1}Nx_N$$

So to compute a feasible x , we have x_N free and putting any values to the components of x_N I get the vector x_B . Now if I choose $x_N = 0$ we have

$$x_B = B^{-1}b \} \text{ then } x = \begin{pmatrix} B^{-1}b \\ 0 \end{pmatrix}$$

If I have **A** x of equal A of x equal to b , I can write down this as B, N . So, this is a partition matrix, but you know you can think of this itself as a matrix with two components, and then you can go on doing whatever you want in the same policy, in the same way you do matrix multiplication.

So, now what you have is B times x_B , matrix B multiplied with the vector x_B , and N times x_N is b . So, x of B is B minus Nx_N . So, this would imply **sorry** B of x_B is b minus N of x_N . So, x of B using the invertibility of B is $B^{-1}b$, minus $B^{-1}Nx_N$. So, what do I get from here. So, x_N is free, see if I can choose whatever x_N , **I want** I can put any value to x_N , then I can get x and hence I get the vector x .

So, to compute a feasible x , we have x_N free and putting in any values to the components of x_N , as I did desire whatever I want, the components of x_N I get **I get** the vector x_B , this is clear to everyone. Now, if I choose x_N is equal to 0, Now you might ask me, why you have written as x_B and x_N we will very soon come to the point, just for the time being just take on this symbols, and I will come to the point very soon why x_B and x_N , if we choose x_N equal to 0, we have x of B is equal to $B^{-1}b$ and then x , this vector is called **B is** $B^{-1}b, 0$.

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If $B^{-1}b \geq 0$, $\Rightarrow x \in C$

If $x \in C$ & $x = \begin{pmatrix} B^{-1}b \\ 0 \end{pmatrix}$, then x is called a Basic feasible solution

$x = \begin{pmatrix} x_B \\ x_N \end{pmatrix}$ } $\left. \begin{array}{l} \text{basic part} \\ \text{non-basic} \end{array} \right\}$ Can you find a convex set which does not have an extreme point.

Theorem: Let $C = \{x \in \mathbb{R}^n : Ax = b, x \geq 0\}$. If x is an extreme point of C , then x is a bfs and vice versa. In other words, x is an extreme point if and only if A can be decomposed into $[B, N]$ such that

Now, if $B^{-1}b$ is greater than or equal to 0, it implies that x is a member of the feasible set C , because it satisfies $Ax = b$, and $x \geq 0$. So, any feasible solution so, if x is element of C , and x is written as $B^{-1}b, 0$, then x is called a basic feasible solution, and that is why this x_B, x_N equal to x , this is called the basic part and this is called the non basic part. So, a non basic components are all 0 feasible solution that we get is called the basic feasible solution. So, this is a basic feasible solution.

The most fundamental result in linear programming is that a basic feasible solution corresponds to an extreme point of the convex feasible polyhedron. So, if you take the polyhedron set which is the feasible set C , then every extreme point of C is a basic feasible solution to the linear programming problem, and every basic feasible solution is an extreme point, and in fact, it can be shown that any optimum solution is a basic feasible solution, and hence is attained at an extreme point itself as an extreme point.

So, what we are doing in linear programming is computing the functional values over the extreme points and then trying to find which is minimum, but there could be huge number of extreme points if you have problem data is large that is there is lot of decision variables could be millions, and trillions of extreme points. I think which you cannot view nobody can view it so, difficult to think about it.

Now, if that is the scenario then you cannot geometrically view it, neither can you do enumeration of a huge number of points, the function value it will simply slow down the whole process. So, the whole question is that if I know that, I have a I am at an extreme point which is a bfs, but it is not a solution to the original problem, we will show under what conditions you can check that it is not a solution to the original problem.

Then what we can do is by a clever way, which is called the simplest method is we can move from one vertex to another vertex. So, that the functional value the value of C transpose x actually goes down as I go to a new extreme point. So, I have to find clever way to keep on moving from one extreme point to the other, but at the same time keep on decreasing the function value as I keep on moving over the extreme points.

So, I do not cover all extreme points only cover some few of them, but I will I reach the solution. So, it saves an enormous amount of computing time, and enormous amount of effort enormous amount of mental stress and so thing, so much that. This process which is achieved by the simplest method in quite a simple way is as a result very **very** popular, and is one of the most elegant algorithms in optimization theory.

So, what is the idea? So, let us write down the theorem, we have not written a theorems for long time. So, you write down the theorem need not give it a number, but mathematicians likes to state very **very** state of that important result, I would say not set of the very important fundamental results are usually given as theorems. So, now, you might ask me, how do I know, that there will be an extreme point of this convex set, could there be a convex set, which does not have an extreme point, could there be a convex set which does not have an extreme point, I am asking with this question think of an example.

Can you find convex set which does not have an extreme point. Now consider this feasible set, if x is an extreme point of C , actually there is a major result in convex geometry we say that every convex polyhedral set has an extreme point. If x is an extreme point, then x is a basic feasible solution whose short hand throughout the world in any optimization book is always bfs, and bfs an x is a bfs and vice versa.

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$$x = \begin{bmatrix} x_B \\ x_N \end{bmatrix} = \begin{pmatrix} B^{-1}b \\ 0 \end{pmatrix}$$

where B is an invertible $m \times m$ matrix satisfying $B^{-1}b \geq 0$.

Proof: Suppose A can be decomposed into $[B, N]$ with $x = \begin{pmatrix} B^{-1}b \\ 0 \end{pmatrix}$, $B^{-1}b \geq 0$. To show that x is an extreme point of C .

Step 1: Let us first show that $x \in C$

$$Ax = [B, N] \begin{bmatrix} x_B \\ x_N \end{bmatrix} = [B, N] \begin{pmatrix} B^{-1}b \\ 0 \end{pmatrix} = BB^{-1}b + N0 = b$$

In other words x is an extreme point if and only if the matrix A can be decomposed into the partition B and N , such that x_B equal to $B^{-1}b$, x_N equal to 0 . Where, B is an invertible matrix. So, if x is an extreme point it can be represented like this, and if x can be represented like this then x is an extreme point. Where B is an invertible m cross m matrix satisfying $B^{-1}b \geq 0$. So, this is what? It is called the bfs.

So, anything or any made thing will give some slightly more general versions of this very different way of defining things. So, what we have is this following result, which is very very fundamental found in any linear programming book. Now given any point x in the set C , you know x can be represented as any vector which has some point 0 some point non 0 , you can always represent them, may be the number of non 0 variables, non 0 components are not there all are positive it could be like that, because there could be something internal x must be strictly greater than equal to 0 , but in general I can always write a point with some 0 , some non 0 .

So, let me just tell you, how to go about proving this very very important result. Now let me do the proof. Suppose A can be decomposed, I want to show that, if I have a bfs it is actually an extreme point. A can be decomposed into B, N with x equal to this whatever I have assumed in the result.

Now, to show that x is an extreme point of C . Now, x is of course if I have this x is of course, feasible. So, step one that show that x is feasible. So, let us show first where I know just this decomposition, I know that x is greater than equal to 0, all the components are greater than equal to 0, but let you not know whether it satisfies $Ax = b$, which is the major thing that we have to check.

Let us first show that that x is in C , to show that let, me compute Ax which is Ax , because by the hypothesis A is decomposed into two parts B and N . where, B is an invertible matrix m cross m , and $x = B^{-1}b + N_0$, which is $B^{-1}b + N_0$, which is $B^{-1}b + N_0$ and $B^{-1}b + N_0$ which would give me $B^{-1}b + N_0$. So, that will be nothing, but this would be identity, because this is invertible matrix being to be inverse b is identity so, its b . So, what I get is $Ax = b$, showing that x is belonging to C . So, to first show the extreme x is an extreme point my first step is to show that x is in C , and then show that x is an extreme point of C .

Now, the next step we will do or prove by the method of contradiction or reduction **(())** as known to mix, but many mathematicians would not really like proves by contradiction, they would rather like straight forward proofs straight forward or may be constructive proof, but in certain cases it is much more easier to prove by contradiction, that is whatever we want to prove we take an hypothesis completely opposite to that the negation of that, and then we reach a contradiction that is some actually given hypothesis is contradicted, because we have assumed that our original claim is wrong.

So, it means if our original claim is not correct then there is a contradiction in or actual hypothesis, which means if our actual hypothesis is true it implies that our original claim is also true. So, it is $P \implies Q$ negation of $Q \implies$ the negation of P . So, this logical you know structure is used in the proof by contradiction.

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So we will prove by contradiction:

Let x be not an extreme point. $\exists x_1 \neq x_2, x_1, x_2 \in C$
 and $\lambda \in (0, 1)$ such that

$$x = \lambda x_1 + (1-\lambda)x_2$$

$$\begin{pmatrix} B^{-1}b \\ 0 \end{pmatrix} = \lambda \begin{pmatrix} x_{11} \\ x_{12} \end{pmatrix} + (1-\lambda) \begin{pmatrix} x_{21} \\ x_{22} \end{pmatrix}$$

$\Rightarrow x_{12} = x_{22} = 0$ (Check up as homework)

$Ax_1 = b \Rightarrow Bx_{11} + Nx_{12} = b \Rightarrow x_{11} = B^{-1}b$
 $Ax_2 = b \Rightarrow Bx_{21} + Nx_{22} = b \Rightarrow x_{21} = B^{-1}b$

$\Rightarrow x = x_1 = x_2$, It contradicts that $x_1 \neq x_2$.
 $\Rightarrow x$ is an extreme point.

So, let us do the same thing. So, we will prove by contradiction. So, let x be not an extreme point. Not a good English, any does not matter, if you understand what I am trying to say it is fine. **Now, what** Now, which means that there must be two distinct points in a C . So, when I take a convex combination of them with λ between 0 and one, then x is one of those points. So, there exist x_1 not equal to x_2 , x_1, x_2 in C , and λ in $(0, 1)$ such that so, x is represented as $B^{-1}b, 0$. So, $B^{-1}b$ consists of few vectors, few rows and columns.

So, I am writing corresponding to the x B part, I am dividing x_1 into x_{11} , and x_{12} , and I am breaking up x_2 into x_{21} , x_{22} . You could as well as write x_{1b} , x_{1m} , x_{2b} , x_{2m} does not matter, what I would have is that this has the same number of components as x B , this has the same number of components as x N , this has the same number of component x B , and this has the same number of components as x N .

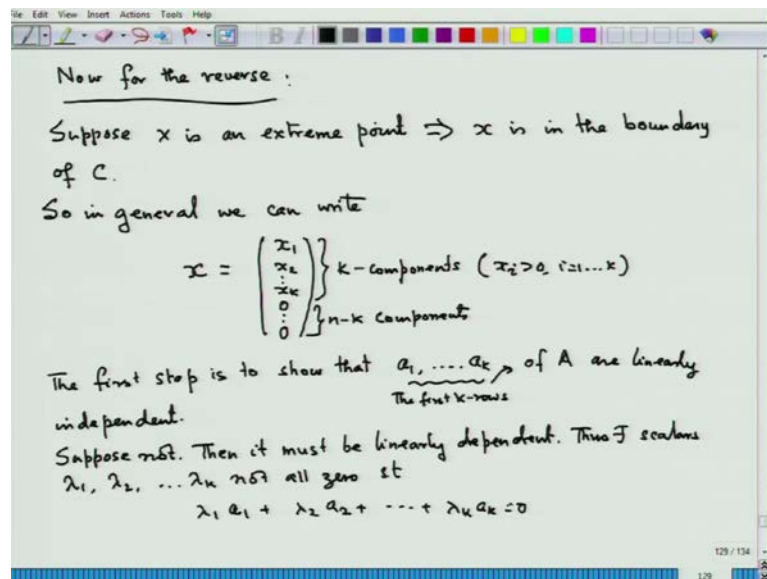
Now, what would immediately happen is that I equate with these vectors components, here I equate the components of these two vectors. Now, because this part in the non basic part everything is 0. So, here just by convex combination, because x_{12} is greater than equal to 0, x_{22} is also greater than equal to 0, it would imply which I will leave as the homework further the details.

Now, let us see what it means? It means the following so, some part is 0. Now, I have A of, because x_1 is feasible, I have A of x_1 is equal to b , which would imply again by the

partition $Bx_1 + Nx_2 = b$, but $x_2 = 0$ from here, from the above line and this would imply $x_1 = B^{-1}b$. The same goes for x_2 , because that been an element of C , and because it is already greater than equal to 0, it also has to satisfy it is greater than equal to 0, and also has to satisfy $x_2 = b$.

So, this would imply $Bx_1 + Nx_2 = b$, where again from the previous line we have $x_2 = 0$ implying that $x_1 = B^{-1}b$. So, that would simply imply that $x_1 = x_2$. So, it contradicts that x_1 , **contradicts that** and hence it is an extreme point. So, this implies that x is an extreme point.

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Other part the reverse is slightly tricky. Now, for the reverse: suppose x is an extreme point. So, x is not an interior point. So, this implies that x is in the boundary of C . So, in general so, without loss of generality basically in general we can write x is equal to. So, the first k -components are non 0. Where, x is an element of C , it is an extreme point, in minus k -components. So, it could be that in minus k is 0, that is n is equal to k , but in general you can always write extreme point in this way.

Now, corresponding to this k rows there are k columns in the matrix A . So, we are going to show that, the first k rows suppose these are 0, k -components x_i strictly greater than 0 are equal to 1 to k . So, these are non 0 components, and these are 0 components. So, the first step is to show that, the first k rows a_1, a_k . The first k rows of A are linearly independent. Again we will go by the method of contradiction suppose not.

Then it must be linearly dependent. So, this set of vectors must be linearly dependent. Thus there exist scalars as a real number, as we are in real field $\lambda_1, \lambda_2, \dots, \lambda_k$ not all 0, such that $\lambda_1 a_1 + \lambda_2 a_2 + \dots + \lambda_k a_k$ is actually 0.

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Construct $\lambda \in \mathbb{R}^m$ s.t.

$$\lambda = \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_k \\ 0 \\ \vdots \\ 0 \end{pmatrix} \left. \begin{array}{l} \text{ } \\ \text{ } \\ \text{ } \\ \text{ } \\ \text{ } \end{array} \right\} \begin{array}{l} k \\ m-k \end{array}$$

$$\left. \begin{array}{l} x_1 = x + \alpha \lambda \\ x_2 = x - \alpha \lambda \end{array} \right\} \alpha > 0$$

Show that we can choose $\alpha > 0$, in such a way that $x_1 \geq 0, x_2 \geq 0$ (Spend some time with this).

$$\begin{aligned} Ax_1 &= Ax + \alpha A\lambda \\ &= Ax + \alpha \sum_{j=1}^m \lambda_j a_j = b \end{aligned}$$

$$Ax_2 = b \text{ (prove yourself)}$$

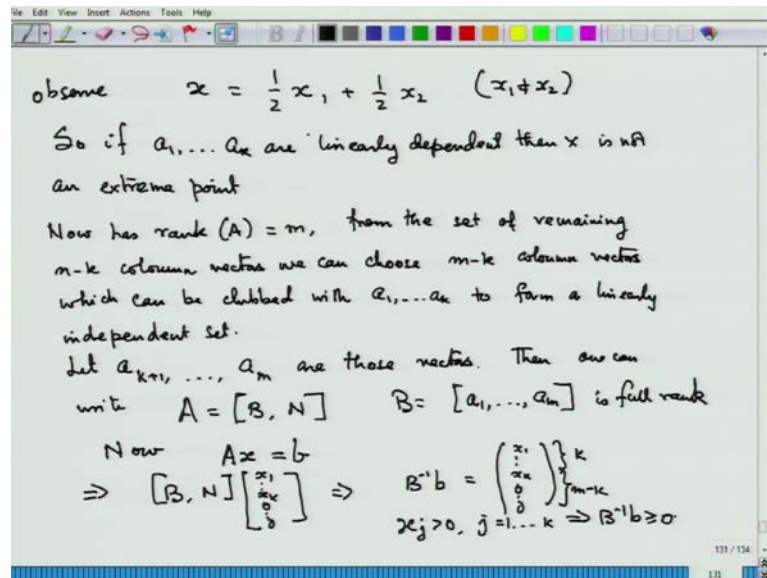
Now, construct the vector, construct a λ in \mathbb{R}^n , such that λ is $\lambda_1, \lambda_2, \dots, \lambda_k$ and 0. k -components in $m-k$ -components. Now I will construct from the given vector x , two more vector x_1, x_2 . So, I will take an α , now the homework you prove show that, we can choose α greater than 0, in such a way that x_1 is greater than equal to 0, x_2 is greater than equal to 0, spend some time with this is a good exercise

Now, let us see what is Ax_1, x_1 I have got it to be greater than equal to 0, is Ax plus $\alpha A\lambda$. Now this is giving me Ax plus α times summation $\lambda_j a_j$. Where, j is equal to 1 to m , because beyond m **sorry** this is not k , this m in \mathbb{R}^n , because this corresponds to m components, m columns which are so maximum number of linearly independent columns is m .

So, if k is bigger than m we have to do something, if k is smaller than m then fine we already have it. So, if k is bigger than m , I can always reduce that number, I can always bring down and show that if once k is bigger than m **you cannot have** they cannot be linearly independent, and that is the whole idea of doing so.

Now, this is 0, because first k component is non 0, which gives you the linear independent thing the other part is 0. So, this is nothing, but other lambda is 0. So, this is b similarly $A \times 2$ is b.

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So, which you prove yourself. Now, once I know this fact observe that I can write x observe, write x as half x_1 plus half x_2 , where x_1 is not equal to x_2 .

So, if a_1, a_2, a_k are so, if a_1, a_2, a_k are linearly independent linearly dependent, that is what Then x is not an extreme point. So, what I want to show is that if a_1, a_2, a_k are now, linearly independent. I should know that, because I have full a has full rank m , I still have and if k is and of course, k has to be strictly less than m , k is not equal to m if k is strictly less than m . Then I can choose m minus k vectors from the remaining m minus k vectors, and just join them up with this a_1, a_2, a_k and form a linearly independent set of columns.

Now, as rank of A from I can write rank as full or big letter or small letter is m from the set of remaining m minus k column vectors, we can choose m minus k column vectors which can be clubbed up clubbed with a_1, a_2, a_k to form a linearly independent set. Because there are there are m in linearly independent columns.

Let a_1, a_2, a_k plus 1 to an m are these vectors. For simplicity, they are or really just to make a multiplication with the permutation matrix. So, a_1, a_2, a_k plus dot, a_m are those

vectors then one can write $Ax = b$. With B formed of the first m columns m columns is full rank, full row and column rank, full rank. And now, because x is in C we have $Ax = b$ implying $Bx = b$. So, our x is x_1, x_2, \dots, x_k . So, $B^{-1}b$ is x_1, x_2, \dots, x_k assuming that k is strictly less than or equal to m . So, here I have k rows, and here I have $m - k$ rows.

So, since $x_j \geq 0$, and j is equal to 1 to k this implies that $B^{-1}b$ is greater than equal to 0. And that is exactly what we wanted? If x is an extreme point then I can represent $Ax = b$. Where, B has all its rows and all its columns linearly independent, and x can be represented as $B^{-1}b$. So, anyway N the remaining part $N - k$ is anyway 0. So, and the $B^{-1}b$ has to be greater than equal to 0 and that is our result.

Now, that a polyhedral set as an extreme point is something we are not going to prove, because that it will take us of what we want to do, but it is not a very difficult one, and we can possibly do that and the whole idea of bfs might come into play there again. But the whole idea of this proof will come there again, but that is not a very big issue, the proof idea of this extreme point business whether that the polyhedral set as an extreme point when comes from the idea proof or the theory or theorem. So, we will not get into this business, but I will just ask you to think that for a polyhedral set extreme points are always finite just think about it why.

Today we end the or talk with this one, this proof which has taken quite a good amount of time, and we want to say that in the next class, tomorrow we are going to prove a very fundamental result, this is something you have to remember, this is one of the most important results in optimization theory in convex optimization.

That if I know that a linear function has a lower bound, that which means that the dual problem is feasible. Once you know that the dual problem is feasible, you know that the linear program has a lower bound, and once it has a lower bound there exist a minimize for this problem. So, there is an extreme point where the solution will be attained where the minimum will be attained. So, this is exactly what are going to prove in the next class.

Thank you, very much, and I hope you have followed this proof, and you have enjoyed this fascinating fact that every extreme point corresponds to some special type of feasible

point of C. And actually the optimal point, if the optima exist, it is in the in one of these basic feasible solution that is exactly what is we are going to show tomorrow.

And we will prove this very **very** important fact and since, you have already learnt about duality, and you know from weak duality that is very is if I just construct the dual problem and check it is feasibility, and we will tell you how to check feasibility of a system or linear equations very soon. And that can be done by one of the type of simplest methods, and we will tell you that once you know that there is a lower bound it is immediately cleared that there is a minimize, this is a very **very** important fact from the point of view of computation.

Because now a days there many standard algorithms which once you give in the input of the primal they know the inputs of the dual, because the dual inputs dual data is generated out of the primary data, there is no extra data anywhere. So, in optimization be where if you are studying duality, if you see any dual problem, which has some data which does not simply appear in the primal and suddenly come into, the dual then b where of such duals.

Any dual problem has to be created out of the data of the primal, because that is the only data you have, any other problem that you want to say is come running side by side with the same problem has to be generated with the data of the original problem, and that is something you have to keep in mind.

So, **thank you**, good night, and good bye.