

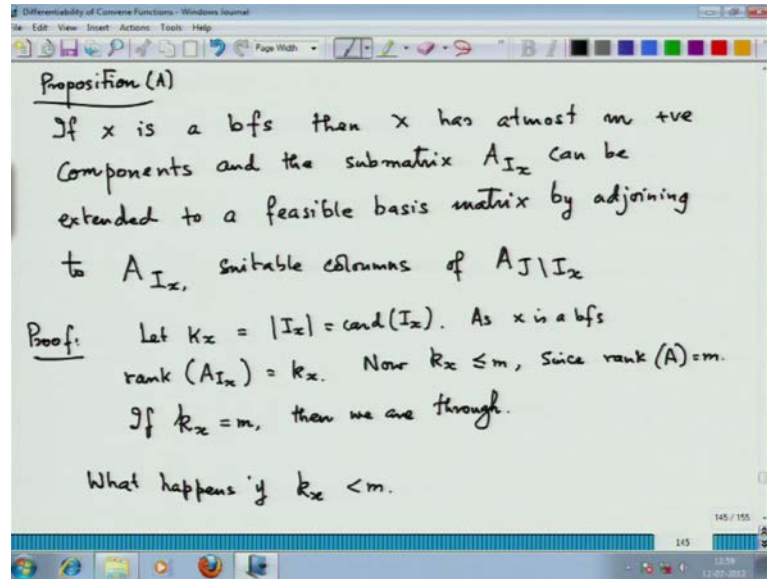
Convex Optimization
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Lecture No. # 24

Welcome once again to this little journey we are taking on linear programming as a part of **the** our course on convex optimization. Now, what I am going to do today, these are the two fundamental theorems of linear programming. A proposition first which will help us to prove the fundamental theorem of linear programming which has two **two** components. At every feasible set, if it is really non-empty, it will have a bfs and every optimal solution; if there is an optimal solution, **there is a** there is an optimal solution which is also in bfs.

Now, since most of you would be seeing this course through the YouTube, **I would** and you have the facility of going back and forth which is not possible in real time. So, it is very important that you look over these proofs which are now carry out of this fundamental theorem, because **the** in the proof of the fundamental theorem, the whole idea of pivoting, **of** the whole idea of the technique of doing simplex method is inherent. So, I would request to you that just do not look at this lecture once, but look at it two-three times. So, you get a hang of how the proof is done. It is those simple linear algebra, but it has slight it means slight tricks. So, just have a look at them.

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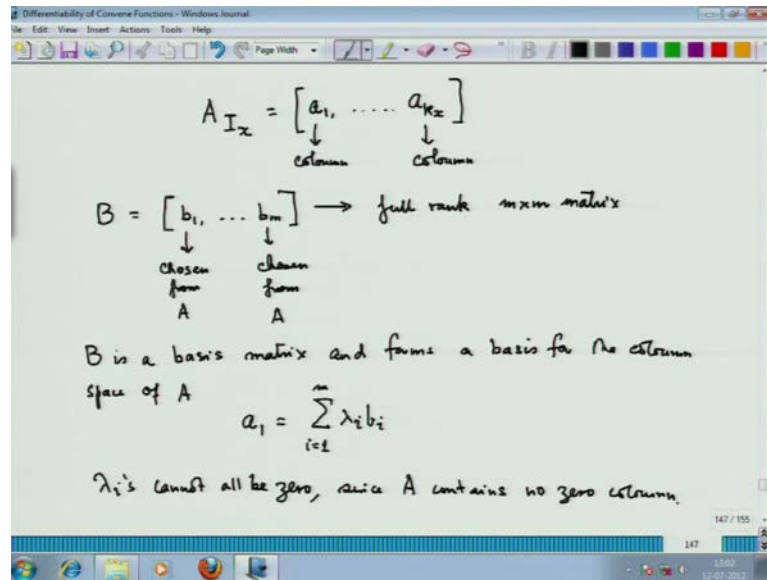
So, I start with this very important proposition which is needed to prove the fundamental theorem of linear programming which says that if x is a bfs that is I give you a bfs, then x has at most m positive components, because the blank of the matrix is m , we can at most have a m cross n sub matrix which is invertible, which is a full rank.

So, there cannot be more than m positive components **in the basis** in the basic feasible solution, because rest the non-basic part is considering as zero. Though some basic solution can become zero which is the case of degenerate basic feasible solution, but it cannot be more than m . And the sub matrix A_{I_x} which we have done, which we have defined earlier in the last class or in the last lecture that can be actually formed in to a feasible basis matrix by adjoining some columns from the matrix $A \setminus I_x$. So, let us get into the proof of this. So, write it down step by step.

So, **let k_x** as before let k_x is the cardinality of the set I_x , which can also be symbolize like this, this absolute value signs. Now, as x is a bfs, rank of A_{I_x} is nothing but k_x . Now, k_x is less than equal to m , since the maximum number of linear independent columns or rows you can have in the **...** This matrix is m , it has m rows and some columns and the say k_x columns. So, the number of linearly independent **rows that you** column that you will have cannot exceed k_x . So, if x is the bfs it is k_x , so and that k_x cannot exceed m . So, x **x** is the bfs, this is by definition of bfs, this is true and now that k_x cannot be more than m , because m is the maximum number of linearly independent

columns allowed, because the matrix rank is m . This is true since rank of all matrix is m . Now, observe that if $k \times$ is equal to m , then we are through. The most important question is what happens when $k \times$; what happens if $k \times$ is strictly less than m and that is what we are going to look into.

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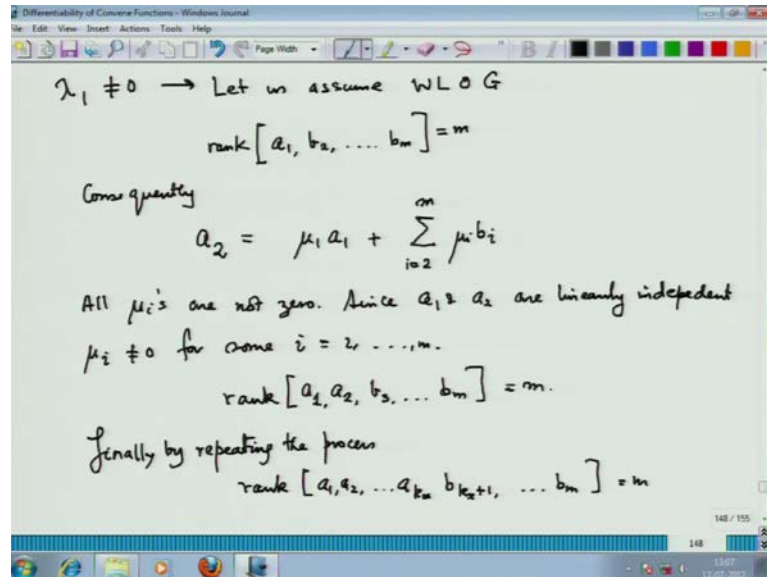


Now, what is this matrix A_{I_x} ? It is a matrix formed of columns $a_1, \dots, a_{k \times}$. I am just because we have assumed without loss of generality that the first $k \times$ columns belong to the matrix A_{I_x} . So, this is the matrix A_{I_x} and all of these are columns of the matrix. Now, from the matrix A construct the matrix B with m columns. So, this is B is a full rank $m \times m$ matrix. Now, this b_1, b_2, b_m these are also chosen from m . These are all chosen from the set A sorry not the set A , I want to correct myself, chosen from the set from the matrix A . So, these are the columns chosen from among the columns of A , and you form a linearly independent set of columns and then what you have is a full rank matrix.

Now, so B is a basis matrix and forms a basis for the column space away. We will you should know what is a column space away, if not just go and brush up your linear algebra bit, because we need a bit of linear algebra; quite a bit you see. Now, what does this show? It simply shows that the column a_1 can be written as summation $\lambda_i b_i$, i is equal to 1 sorry m vectors, I guess I am quite adopted making mistakes specially in this sort of things, anyway just a bit of fun on the way. And you see here λ is

cannot all be 0, because if all are 0 then a 1 is 0, but I have said that the matrix A contains no 0 column. So, λ_i (s) cannot all be 0, since A contains no 0 column.

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So, let me assume for simplicity that λ_1 , let us assume this without loss of generality; let us assume without loss of generality WLOG. So, we assume λ_1 is not equal to 0. So, what would happen? I can express now b_1 in terms of b_2, b_3, \dots, b_m and a_1 . So, I can basically replace b_1 in the expression in terms of a_1 . Hence if I now make the new matrix, I will make a new matrix where I keep the a_1 column, I will now will change the matrix b of it and then I keep b_2 . Then basically what happens I have just change one of the vectors, this is called replacement theorem in linear algebra that we will change one vector, but you still get a basis. So, the rank of this a_1, b_2, \dots, b_m , this would still remain m , because this would now become linearly independent. Because you just write b_1 in terms of a_1 and that is enough; b_1 in terms of a_1 and the others.

Consequently this now becomes a basis for the column space. I can write a_2 as $\mu_1 a_1 + \mu_2 b_2 + \dots + \mu_m b_m$. μ_2 is equal to 2 not 1, because the b_1 is not replaced by a_1 . Now, can μ_2 be equal to 0, μ_2 not equal to 0 see. So, all μ_i (s) are not 0 of course, because a_2 is not 0. Now, a_1 and a_2, a_3, \dots, a_k they form a linearly independent set of vectors. So, a_2 and a_1 is linearly independent. So, you can not have all the μ_i (s) to be 0, so μ_i from 2 to m . So, if all these are 0, then you have the μ_1

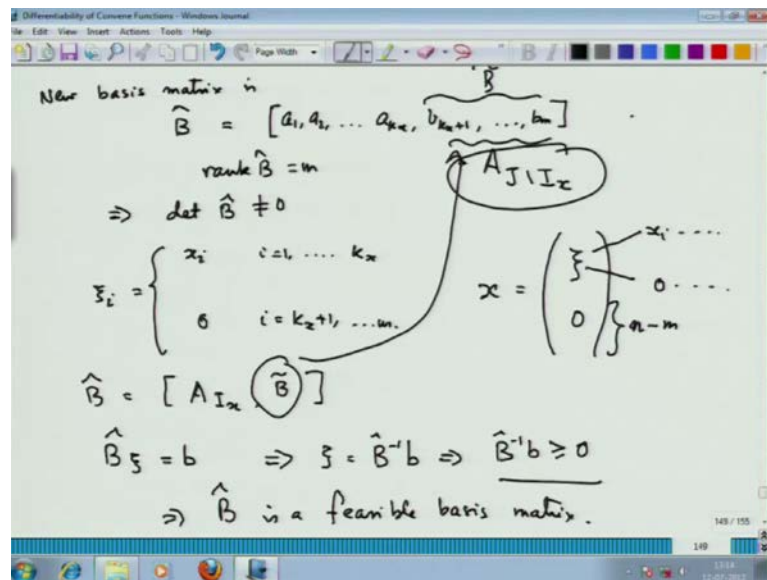
cannot be 0, so a 2 equal to mu 1 into a 1. So, a 2 would be linearly dependent on a 1 which is not true, because a 2 and a 1 are linearly independent. Since think over it a bit, a 1 and a 2 are linearly independent, because they are from the matrix $A I x$; mu i is not equal to 0 for some i is equal to 1 to **sorry** i equal to 2 to m, some i between 2 to m, this is not equal to 0; that is one step.

So, what I am able to do now, I can replace a b 2, because mu 1 would be of course, has to be zero. So, assume that mu 2 is not 0, so and the rest is 0. So, what you can do? If mu 2 is not 0, **you can replace b 2 in terms of** you can replace b 2 and express it in terms of a 2 a 1, b 2, **b** b 3, b 4, dot, dot dot b m. So, min(s) now I can make a new matrix by altering the columns of b that is a 1, a 2, b 3, b m and the rank of this matrix would become m. So, you can repeat the procedure. So, we had have in our hand in our disposal k x columns of a k x. So, what we can finally have? Finally by repeating the process...

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b k x plus 1, this indexing and b m, this is a m.

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Now, let us now our new basis matrix, a new basis matrix is b hat which be give us follows.

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Is a 1, a 2...

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Now of course, you have this, is not **sorry** I should draw this. So, you have this B and rank of B that we have just shown is m . So, B is a square matrix, m cross m full rank matrix. So, this implies the determinant of B is not equal to 0, fine. Now, x was a bfs, now ψ_i , let me set this ψ_i equal to x_i , for i equal to 1 to k and ψ_i is equal to basically I should be more nicer writing like instead of writing like this, I can write like this which is standard in books; ψ_i is equal to x_i if it is this and if 0, if i is equal to... Now, if I look at this matrix, if I look at this then what is B in terms of... So, B is $A I x$ and some other part. So, only the elements with $A I x$, the $A I k x$ this **this** matrix. So, B hat actually has been broken into $A I x$ and some matrix which I am writing for example N for the time **(())** or may be better way to it write it as say B tilde.

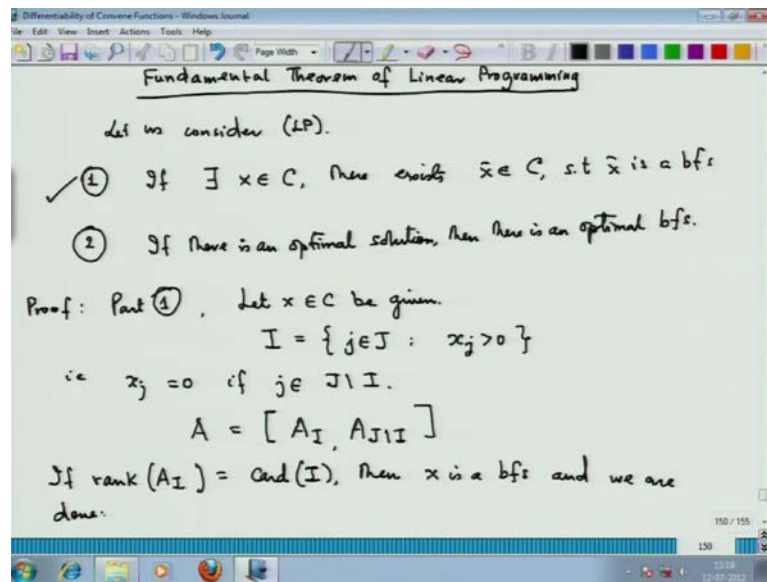
Now, $A I x$, because it is a basis matrix and I have assumed that... I have at most $k x$, I know that there are at least means there is at least $k x$, for sure $k x$ non-zero quantities **right**, because the rank is $k x$ of $A I x$. **So...** And the remaining I am assuming zero. So, if I put this then if I multiply this x_i comes from my original x the bfs. So, what would happen? Because in the original bfs from $k x$ plus 1 to m everything is 0; that is surely, because **because** of the rank i **rank i** is equal to $k x$, $k x$ is the number of non-zero quantities.

So, what I have now what a basis matrix and using the given bfs; I have constructed new variable which is like this, which is exactly basically the B original bfs. So, now I can show that B hat of ψ whose components are $\psi_1, \psi_2, \dots, \psi_n$, B hat of ψ . So, up to beyond m it is all 0. So, up to m what is the situation? So, basically my original x is not divided like this ψ and 0, this ψ is what I am now writing like this, **x_i and x** x_i and 0; x_i for some components, 0 for some components. So, this... So, part of the first m is non-zero and part is 0, and the remaining n minus m the non-basic part has to be 0. So, **B of ψ** , B hat of ψ is anyway equal to b **right**, because B of x is equal to b , so B hat of x is obviously equal to b , but it is B hat of x is what, B hat of ψ plus $A I x$ of ψ plus 0, $A I x$ of ψ is actually giving me nothing but b **right**. So, you can easily prove this fact.

Now... So, this would imply because B hat is having determinant not equal to 0 which means that B hat is an invertible matrix, so ψ can be written as B inverse of b . And of

course, ψ is greater than equal to 0 which implies that B inverse of b . So that is exactly what we wanted to prove some not **sorry** b B hat inverse. So, what we have done by adjoining matrix may certain... So, this $b \times$ plus $b \times$ plus 1 dot, dot, dot $b \times m$, this part must come from the matrix A which is quite natural. So, adjoining these things, adjoining these things to the matrix $A \ I \times$ that is B hat; this is your B hat. So, adjoining this thing this columns from the matrix $A \ J$ minus $I \times$ from this matrix, I have been able to get a basis matrix which is also feasible. So, implies that B hat is a feasible basis matrix and that is exactly what I wanted.

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Now, we come and prove the fundamental theorem of linear programming. So, hold your breath.

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Let us that is the theorem; let us consider LP - a standard linear programming problem. If there exists x element of C , there exists \bar{x} element of C which is a bfs. See we know is a set $A \ x$ equal to b and x greater than equal to 0 - the feasible set; \bar{x} is a bfs. If there is an optimal solution, then there is an optimal basic feasible solution. This two are the fundamental things. Once you know this, this is exactly the simplest method; this is simplest method will expert this idea.

So, we start again the proof those who are intimidated by the fact that so much proof is done has to realize that what we are doing is a piece of beautiful mathematics, and **you** in mathematics you need to demonstrate the statements you make. So, proof is if you do not want to **(())** proved, do not **(())** proved, the French could **(())**. So, you are demonstrating what you have said **right**. Like giving a proof in the quote of law, so it is to the mathematicians you are basically doing the same thing. You are giving a proof in giving a demonstration on what you are telling that he has, what I have said is correct in the frame work in which we are working. Part 1 - I am proving this part now.

So, let x element of C be given. So, I will given you this. Now, x would have some 0 part may be have all 0 part, **may be have** it may be all the components has 0, all the component has strictly greater than 0, some greater than 0, some non-zero. So, we assume the most general case and we did. Instead of writing $I x$ now, I will write I because if I continue to write $I x$ the things will get to much complicated **right**. So, I am just writing I , because you know that **this is** this I will correspond to this particular x that is all J in capital J which consists of 1 to n which we have already noted earlier. So, it is an index of those components of x which has positive value **right**. That is if this is true and if this does not cover the whole of j , if i is not equal to j , then x_j is equal to 0 if J is element of **...**. So, it might be that either this is empty or this is **this is** empty or that is immaterial.

So, now I can partition A the matrix again into two parts, again I am assuming the first part first columns, I columns corresponding to the indexes in the set I or in the first part of the matrix that is just assumption we can make without loss of generality. So, I have broken it up into. Of course, you have to say **it into** it is more correct to put an x here, but just I am not doing, because the symbols would get quite complicated. So, just to avoid the complications in the symbol, but if you want to write $I x$ there is no harm if you write $I x$. If rank of $A I$ or $A I x$ is nothing but cardinality of $I x$ or I , then x is a bfs and we are done.

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Let $\text{rank}(A_I) < \text{card}(I)$
 There exist $\lambda_j, j \in I$, such that

$$\sum_{j \in I} \lambda_j a_j = 0$$
 Where all λ_j 's are not zero. w.l.o.g., let us assume that
 $\lambda_j > 0$ for some index j and define

$$\frac{x_r}{\lambda_r} = \min \left\{ \frac{x_j}{\lambda_j} : \lambda_j > 0, j \in I \right\} \quad (\lambda_j > 0)$$
 Define

$$y_j = x_j - \frac{x_r}{\lambda_r} \lambda_j \quad \text{for } j \in I$$

$$y_j = 0, \quad \text{for } j \in J \setminus I$$

$$\left. \begin{array}{l} \frac{x_r}{\lambda_r} \leq \frac{x_j}{\lambda_j} \\ x_j - \frac{x_r}{\lambda_r} \lambda_j \geq 0 \end{array} \right| y_j \geq 0, j=1, \dots, n$$

Interesting parts starts when $\text{rank}(A_I) < \text{card}(I)$; now, let $\text{rank}(A_I)$ is strictly less than the cardinality of I . This is the fun part, because **this will** this is the part where you know you are not having what you want, you know **you know** that x is no longer a bfs, but somehow I have to generate a bfs **so let** so let us see. I have to construct a point from the given data that will give me a bfs. So, what happens?

Now, $\text{rank}(A_I)$ is strictly less than I which means that there exists λ_j, j is element of I that is corresponding to the those components those columns; such that $\text{rank}(A_I)$ is not cardinality of I . So, $\text{rank}(A_I)$ is a maximum number of linearly independent columns. **Now, if I take so**, but here there are I columns. So, **the number of** maximum number of linearly independent columns here is strictly less than the number of indexes in I . So, if I take all the columns in this, they form not a linearly independent set, but a linearly dependent set. As a result of which I can have this where all λ_j (s) are not 0. So, again without loss of generality, because this is 0 on both side you can just change sides.

Let us assume that λ_j is strictly greater than 0 for some index j and define this process. This is called the **pivot** what I am going to write down now is called the pivoting process and this is but is used in the simplest method or in the Gaussian elimination **in for** in that case. I should write r may be uniformly, so I will write x_r divided by λ_r , this. So, of all j, x_j is j element of i, x_j is greater than 0, but λ_j could be greater

than 0 could be not. But you have set that there is only some index for which this is greater than 0. So, there may be more than one also. So, you collect all those ratios and take the minimum of that. So, because there only finite number of such elements; the minimum would be one among them.

Now define, so now I am constructing my bfs y as x_j minus x_r by λ_r λ_j for j in i , and y_j you set as 0 for j element of \dots . You can keep on putting i x that is no problem, but just I avoid complicity, so up to this it is clear. Now, let us see, what is a nature of $y(s)$? If you observe here x_r by λ_r whenever λ_j is strictly bigger than 0, this is less than equal to x_j by λ_j , this is the case when λ_j is strictly bigger than 0. So, you can immediately write again put the λ_j here and take it on the other side. So, I will have x_j minus x_r by λ_r λ_j to be greater than equal to 0. Now, if λ_j is equal to 0 less than equal to 0 **right**; λ_j is equal to 0, this is x_j . So, x_j is anyway greater than equal to 0, because x_j is a feasible point. And if λ_j is strictly less than 0 then this would be negative. This would be negative, so negative into negative positive. So, the whole thing would be non-zero. So, what I conclude from here is that y_j **is equal to** is greater than equal to 0 for j is equal to 1 to n . So, the first step of $y(s)$ feasibility is proved, an important step.

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The image shows a whiteboard with the following handwritten mathematical derivation:

$$\begin{aligned}
 Ay &= \sum_{j \in I} \left(x_j - \frac{x_r}{\lambda_r} \lambda_j \right) a_j \\
 &= \sum_{j \in I} x_j a_j - \frac{x_r}{\lambda_r} \sum_{j \in I} \lambda_j a_j \\
 &= Ax - 0 = b \\
 Ay = b, \quad y \geq 0 &\} \Rightarrow y \text{ is feasible.} \\
 y_r &= x_r - \frac{x_r}{\lambda_r} \lambda_r = 0 \\
 \text{non-zero components of } y \text{ at most is } |I| - 1 \\
 \Rightarrow |I_y| &\leq |I| - 1 < |I| \\
 I_y &= \{ j \in J : y_j > 0 \} \text{ if } \text{rank}(A_{I_y}) = \text{Card}(I_y) \\
 &\text{Then } y \text{ is bfs; if not repeat the process.}
 \end{aligned}$$

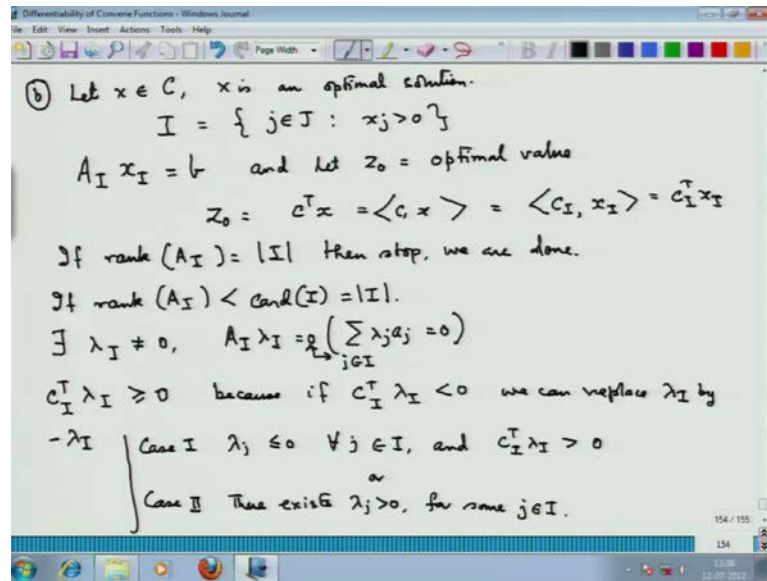
So, now what I am going to check is I will going to write Ay . Now, Ay is what? So, I can be divided into two parts; j belonging to i and j belonging to capital J , but not to I . But

for that $y_j(s)$ are zeros. So, Ay is nothing but $\sum_j y_j$ belonging to I now and that y_j is nothing but x_j minus λ_j . So, we have just writing down matrix multiplication. I would not go on explicitly how do you write things in matrix multiplication, because I am assuming you know this basics stuff. So, this is what you would have and then you would have $x_r - \lambda_r$ can be taken out, because it is fixed some minimum value. But you see this, this part λ_j , this part is equal to 0, but $x_j - \lambda_j$ this part, because it is feasible **right** and λ_j is only a non-zero part, so which means this is nothing but Ax . So, Ax is equal to $Ax - 0$, but Ax is equal to b . So, Ay is equal to b and y is obviously greater than equal to 0 what we have proved earlier implying that y is feasible.

Now, observed what is the value of y_r ? y_r is $x_r - \lambda_r$. So, how many positive components y has? It has definitely the positive components of y , so non-zero components of y at most is x_r . There could be others which have the same value as x_r , **so** **x**. So, this would be at most is now it cannot be more than this. So, this implies that if I denote the new set I_y the **set of y is for** set of the components of y is which are strictly greater than 0, then this is strictly less than I_y is strictly less than this, because this is maximum this is equal to **this is equal to** less than equal to this and strictly less than this.

But I_y if you are not feeling what I am writing, I_y is nothing but j element of J such that y_j is strictly bigger than 0. So, if now if $\text{rank } A_{I_y}$ is equal to cardinality of I_y , then y is a bfs if not repeat the process. Then y is bfs if not repeat the process; stop here and think what it is. It is just like an computer program an algorithm, you take certain steps, you compute certain thing; if this happens you stop the problem, stop the program, if not repeat the problem. So, it is basically a repeat until loop or a do while sort of loops. So, do this **sorry** not do while, is repeat until do, repeat this process until this happens. So, basically if you observe this, this whole theorem gives you and **a very algorithmic** is of a very algorithmic flavor. **So...** So now, we are going into the second thing. So, by repeating this argument finite number of times we will finally get a bfs of course, because we have only finite number of components. Now, how we will get the equality? You have to think of it, I will leave it to you as homework.

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Now, we will go to the major part that part b. Let x be element of C and x is an optimal solution; that is good. Now, again I break up for x , I know that this is a solution. Now, then $A_I x_I$, so x_I is the part of x whose all components are zero. So, I am formed a small new vector with all non-zero components of x strictly bigger than 0 components of x , and that is of course equal to b . And let z_0 is the optimal value; of course, it is a finite optimal value, we are not now that is obvious.

So, z_0 is equal to $c^T x$ equal to $c_I^T x_I$, but in other words it can be written as $c_I^T x_I$ that is only those components of the vector c corresponding to this components in x_I or you can write if you want, I am giving many, many ways to write the same thing. So, A_I is of course partition that is I those columns corresponding to the indexes I and those columns which are not. Again you see there is an algorithmic flavor. So, this is the first step, if $\text{rank}(A_I) = |I|$ stop, if not do. So, repeat until this is coming. Basically, the new matrix that you are getting it is assigned to the spot of the whole matrix. So, the whole thing has an algorithmic flavor, and this is exactly the simplest method. The beauty is that the mathematics itself is generating the algorithm.

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Then stop we are done; that x is itself is a bfs, if not then continue; strictly less than the cardinality of I which is also written as this. Now, again, so there exist, because now if I take all the columns of A_I they are linearly dependent. So, λ_I is a vector whose

components **corresponded** corresponds those indexes in J which are in I . So, basically I am writing... So, this thing is nothing but writing this. So, this is more a matrix way **(())** compact way of representing this, same as this; this is same as this. See I can always consider $c^T \lambda_I$ to be greater than equal to 0, because if $C^T \lambda_I$ is strictly less than 0, we can replace λ_I by minus λ_I ; because the same λ minus λ **we will** we will also work for this. So, now we will divide the whole thing into two cases. So, let me just write down; case one, case two; case one is this. You might be **(())** I am writing this for all j element of I , and this or the case two. So, **this is a** this is the all 0 and also this is occurring and...

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$$\text{If } c_I^T \lambda_I = 0 \text{ we are in case (2)}$$

$$y \rightarrow \text{as constructed in (a)}$$

$$\langle c, y \rangle = \langle c_I, y_I \rangle$$

$$= \sum_{j \in I} c_j x_j - \frac{x_r}{\lambda_r} \sum_{j \in I} c_j \lambda_j$$

$$= c_I^T x_I - \frac{x_r}{\lambda_r} c_I^T \lambda_I$$

$$= z_0 - \frac{x_r}{\lambda_r} c_I^T \lambda_I$$

$$\text{If } c_I^T \lambda_I = 0 \Rightarrow \langle c, y \rangle = z_0$$

$$\hookrightarrow y \text{ can be w.l.o.g. considered a bfs}$$

$$c_I^T \lambda_I > 0 \Rightarrow \langle c, y \rangle < z_0$$

$$\Rightarrow z_0 \text{ is not the minimum value:}$$

$$\text{which is a contradiction}$$

Note if $c^T \lambda_I = 0$ then we are case two, because sign of λ_I is immaterial. Suppose I have this, it does not matter, if all of them are negative also I can take the whole thing on the other side and make all of them positive or if I want to make some positive I can make some positive. So, we can always get, so if this is 0, we are in case two, because the sign does not matter; how did I write it case 100 **(())**, so case one, so we are in case two **right**.

Now, we will consider the expression, we will consider a y as constructed in a; y as constructed in case a. So, then we will compute the c of y that is $c^T y$, because on the other part is 0 you know, it will be same as $\sum c_j x_j$ and j element of y minus $\frac{x_r}{\lambda_r} \sum c_j \lambda_j$. So, basically you have $c^T x_I$ minus $\frac{x_r}{\lambda_r} \sum c_j \lambda_j$ or you

can write it more compactly, this is nothing but $c^T y$. Now, this if I this I know to be 0, now this is nothing but the objective value z_0 .

Now, if θ is equal to 0, then it implies that $c^T y$ is equal to z_0 . Now, this y can be assumed without loss of generality by looking at the case a, y can be assumed to be the bfs. Because y has been constructed, if it is not a bfs we will again apply the same thing that we applied on x on y and get a bfs. So, finally we will get some y . So, let us take this y to be the bfs. So, y can be without loss of generality considered a bfs. So, $c^T y$ is equal to z_0 . Now, what would happen? If $c^T y$ would be strictly bigger than z_0 , then this would be a strictly bigger than 0 quantity which means this would imply $c^T y$ would be strictly less than z_0 , but y is feasible that we have already proved are in the part a. This would imply that z_0 is not the optimal value which is a contradiction.

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Now we show that case I is not possible.

$$y_j = x_j - \theta \lambda_j \quad \text{for } j \in I$$

$$y_j = 0 \quad \text{for } j \in J \setminus I$$

$$y(\theta) = \begin{pmatrix} x_1 - \theta \lambda_1 \\ \vdots \\ x_n - \theta \lambda_n \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$\theta \geq 0$

$$A y(\theta) = \sum_{j \in I} y_j a_j + \sum_{j \in J \setminus I} y_j a_j = 0$$

$$= \sum_{j \in I} x_j a_j - \theta \sum_{j \in I} \lambda_j a_j$$

$$= b - 0 = b$$

\exists case $\lambda_j \leq 0 \quad \forall j$

$$y \geq 0 \quad \& \quad A y = b$$

y is feasible

$$z(\theta) = c^T y(\theta) = \sum_{j \in I} c_j x_j - \theta \sum_{j \in I} c_j \lambda_j$$

$$= z_0 - \theta c^T \lambda_I$$

$\exists \theta \rightarrow +\infty \quad z(\theta) \rightarrow -\infty$

(LP) is unbounded \Rightarrow hence case I cannot hold.

Now, we show that case one is not possible, because if case one is possible will show that the problem is unbounded. So, let us construct some y , but this is not the y that we constructed in a, we are now constructed in it like on our own.

(No audio from 41:01 to 41:13)

So, this is the standard construction, this θ is just a non-negative quantity, I have nothing to do with the original one there. Now, A of y can be written as summation in the same way $y_j a_j$ plus $y_j a_j$ whereas partition in the indexes over i and j not in i . So,

this will I am applying for j here. So, this part goes to 0 and so what I will have is summation $x_j a_{ij}$ element of i minus theta summation $\lambda_j a_{ij}$ element of j minus not j minus i is gone, so it is j minus i . Now, basically this part goes to 0. So, I am just now analyzing this part and this part takes into this two. Now, this is nothing but b and this is 0 which you know. So, this is b . So, now if theta is positive and λ_j , because in this particular case λ_j is so in the case one, so λ_j is chosen to be negative in case one λ_j is less than equal to 0 for all j . So, means this is becoming positive; negative-negative positive. So, this is anyway positive right and y_j is any the this part is 0. So, y vector in this particular case, which of course y , y should write this y to be depending on theta. So, this y is greater than equal to 0 and Ay is equal to b , so y is feasible.

So, let me try to compute the optimal value with this. So, let me compute the $Z = c^T y$ transpose y which will be summation j element of $I c_j x_j$ minus theta times summation $c_j \lambda_j$. Now, in case one, $c_j \lambda_j$ had been consider to be strictly bigger than 0; so this is strictly bigger than 0, this is greater than equal to 0. Now, this is my $z = 0$ minus theta times $c^T \lambda$. Now, this is strictly less than 0. Now, this thing depends on theta, so z naturally is depending on theta, you can put as $z = z(\theta)$ does not matter, if you put y in this case, this whole all this components adjoin of into a vector for $y(\theta)$.

So, if theta goes to plus infinity, because this is now for the case one, this is now positive, the whole thing is negative. So, if theta goes to plus infinity which I can obviously take this whole thing goes to minus infinity. So, if theta goes to plus infinity, so moving along this direction $z(\theta)$ goes to minus infinity. So, if the case one holds I can show that I can create feasible elements $y(\theta)$. So, I can take $y(\theta)$ to be a vector consisting of this of the form $x_1 - \theta \lambda_1$. Suppose I has $k \times n$ number of elements cardinality of $I = A \times n - \theta \lambda_k \times n$ and then 0, 0, 0; this is my $y(\theta)$, and this is this $y(\theta)$ I am operating on here right. This you can write this also as $y(\theta)$ if you; does not matter. So, what I am telling there? I can again create a sequence again show that if I increase theta then I can get a sequence of points $y(\theta)$ which at which on which the objective values keep on decreasing and decreasing and decreasing and decreasing without bound.

So, this would imply LP is unbounded. So, case one cannot hold, because I have assume there is an optimal solution. This would imply LP is unbounded and hence case one cannot hold. So, this means only case two holds and we are done that there is optimal bfs, and with this I end my talk today and I would request you that when you see this on the You Tube repeat the run once again and carefully go through the arguments. Thank you very much.