

Convex Optimization
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Lecture No. # 30

In the last lecture, we had spoken about how to compute the newton steps, that is the delta x, delta y, and delta s for solving the system, rather for solving the newton system or the system **the system** or equations associated with the relaxed KKT condition, this is what we had already spoken of.

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Note

$(AXS^{-1}A^T)$ is positive definite → Homework

$\Delta y \rightarrow \Delta s = -r_d - A^T \Delta y$

$(XS^{-1}) = (XS)^{1/2} (XS^{-1})^{1/2}$ $\left\{ \begin{array}{l} B \text{ p.s.d.} \\ \exists A \text{ which psd} \\ B = A^2 \\ A = B^{1/2} \end{array} \right.$

Central Framework of primal-dual IP methods

$\langle w, A(XS^{-1})^{1/2} (XS^{-1})^{1/2} A^T w \rangle$ $= \langle (XS^{-1})^{1/2} A^T w, (XS^{-1})^{1/2} A^T w \rangle$ $= \ (XS^{-1})^{1/2} A^T w \ ^2 \geq 0$	$(XS^{-1})^{1/2} A^T w$ <hr style="width: 50%; margin: 0;"/> has full row rank
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Now, what is important for us is that to know the **the** important step for us to know that this is positive definite so, it has an inverse, because the inverse of this was used. Now, I had told you to figure it out as an complete the rest of the computations, whether how to prove that this is positive definite.

So, one thing is that you have to first show it is positive definite look, this is I **I** can write XS inverse in this form, because given any positive definite matrix positive PSD any PSD matrix. So, Positive Semi Definite matrix there always exist a matrix A, which is also positive semi definite, such that B is equal to square of A or A is written as square root of B. So, there is nothing like B to the power half, but just it is the symbolism. So, here I can write this into these two parts, and I have in this way, and I put it here in this

place. And then I take the transpose this is the symmetric matrix, so transpose is the same thing then $A^T A$ $A B$ transpose is B transpose, A transpose, and this is how the things happen.

So, now this is nothing but the norm square and you have this greater than equal to zero, what you can show is that this matrix this is anyway a full rank matrix into A transpose this has full column rank, **has a full** sorry has a full row rank **sorry** not column rank, row rank is same as column rank, but full row rank. So, once you can show that these are the full row rank. So, this equal to if this is equal to this is if and only if this W becomes equal to 0 if this has full row rank and it has if it is simple to show that it has a full row rank and that is exactly what you have to show to show that this matrix is positive Semi Definite. Now, once we look into the main primary dual framework

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$F_{\mu}(x, y, s) = 0 \rightarrow$ relaxed KKT system.

$$\left. \begin{aligned} A^T y + s - c &= 0 \\ Ax - b &= 0 \\ x_i s_i &= \mu \\ x \geq 0, s \geq 0 \end{aligned} \right\}$$
 For any $(x, y, s) \in \mathcal{F} = \mathcal{F}_P \times \mathcal{F}_D$ we will define the duality measure τ as follows

$$\tau = \frac{1}{n} \sum_{i=1}^n x_i s_i = \frac{1}{n} \langle x, s \rangle$$
 Central to developing the algorithm
 Our aim is to drive the duality measure to zero ($\tau \downarrow 0$)

Let us, go to the story once again you know we have to solve this equation. We have to solve this equation that is the relaxed KKT system. So, you know that so, the relaxed KKT system if you have forgotten let me write down once again. So, this is the system that I have we are intending to solve of **of** course, we are intending to have this, but this thing automatically means that I will have this strictly bigger than z 0 this. So, as I told you that it is very difficult to really satisfy this equation.

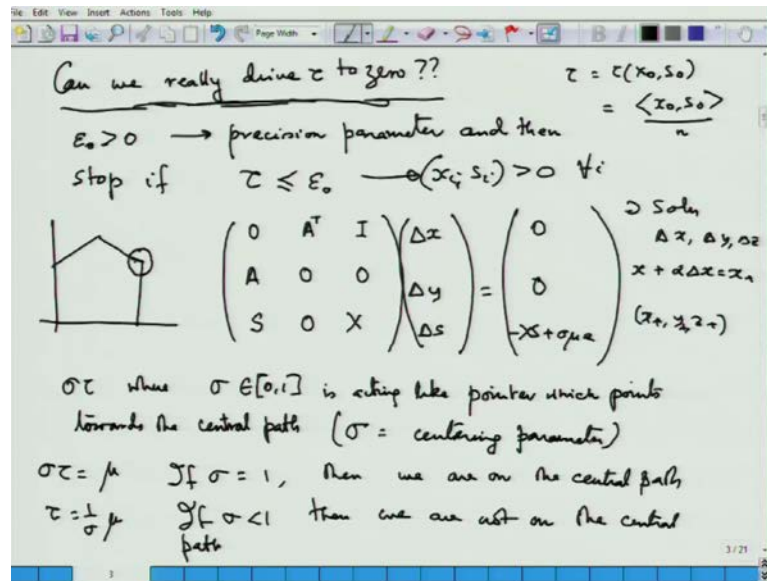
So, you want to find some solution which will approximately satisfy this, this may be that $x_i s_i$ for every i need not be equal to μ , but some number very near μ that would

be enough for a purpose. So, for any (x, y, s) which is in F naught which is nothing but F naught p cross F naught $D e$ for any **any** such thing we will define the duality measure, see what the **the** final approximate solution that I will get will not give me $x_i s_i$ is equal to μ , but they can then I will try to see on the average what is the value taken up by the product.

So, we will define the duality measure τ as follows, τ is equal to $\frac{1}{n} \sum_{i=1}^n x_i s_i$ or inner product so, this same as a inner product. Now, this τ is central to developing the algorithms, because then solutions of the approximate solutions of these equations will not give me $x_i s_i$ equal to μ . So, they would not be exactly on the central path. So, what I get is instead if this was my central path what I will get is something here nearby. So, I want to look into take those x and s and try to see. So, I am looking for let me look at the whole thing in the $x-s$ space which is much more simpler $x_1 s_1, x_2 s_2$.

Now, any point on the central path would be projected back on this path in a x in the $x-s$ space x into s space. So, unless the point x_1 and s_1 or a $x_2 s_2 x_3 s_3$ whatever that x and s they lie on the central path $x_i s_i$ be equal to μ . So, the $x-s$ point would not be on the straight line. So, it is somewhere may be here, may be here and may be here. So, then what is the corresponding average value that point is satisfying that is what we call the duality measure, our aim is to drive the duality measure to 0. So, our aim is to drive τ down to 0, that is do this now, the whole all the algorithms what we will do we will plan to drive τ to 0.

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But can we really drive tau to 0? That is the question that we want to answer. So, what we do at every step, we solve this approximate system approximately get the x_i, s_i and try to develop the algorithm in such a way that every step at every each and every step, the mu values **sorry** the tau values would continuously decrease. Now, can we really get finally, reach up to 0 the answer basically is not really true, because it may not reach you might not reach 0.

So, what we essentially want is that we fix up a small epsilon naught greater than 0 which is called the precision parameter and then **then** stop the algorithms, whatever algorithms you have stop, if your tau so, that x_i, s_i of course, they are strictly bigger than 0 you **you** will stop the algorithm there. Now, what you would get is an x_i, s_i which is whose product x_i, s_i where both of them are strictly greater than 0. So, will you **will you** really get a point on the boundary may be not you have not got a point on the boundary.

So, what you have done here is that if this is my s_0 . So, you have stopped someone very near a boundary point and then there are certain approaches which will not discuss in detail here, you can move on to the boundary you, can basically if this is not the B F S you can move on to the next B F S, you can know that if I excise this is my where I had stopped. Let me go to on to the next B F s by taking of $m - n$ points I put 0, then what **what** is the solution what **what** is the value of x_i . So, you are you can find so, you

what you do you find the near there is a technique of finding the nearest vertex to that point and that is that is the required solution.

So, but all of these works in polynomial time means, all these work within a reasonable amount of time. So, what I am going to do here is to solve an equation of this form. So, is we are trying to solve an equation the in exact heraldic condition, but we know that it is not possible to find $\mu \epsilon$ in μ every time, for every x_i s_i cannot be equal to μ every time, for every i so, what we do is say I do not care I take the duality measure, I **I** take some τ which is a there is a initial starting τ . The starting point that you have take **take** is duality measure and then so, if you have x, x_{naught} s_{naught} , you **you** take τ equal to now basically τ depending on say x_{naught} s_{naught} . So, this will be your starting τ **tau**.

So, then you use that τ in the equation and so, for τ you do not you cannot have exactly τ exactly for every x_i s_i need not be τ . So, what you do you put in a centering parameter basically instead of putting $\mu \epsilon$ in the equations what you will have is, you will have x $s \epsilon$ minus **sorry** $\sigma \tau$. So, you have not bothered this $\sigma \tau$ is acting like **like** your μ , the $\sigma \tau$ is acting exactly like your μ . So, this is acting like your μ here, the $\sigma \tau$ **the sigma tau** where σ is between 0 and 1 is acting like your μ .

So, I cannot find everything exactly equal to μ , but so I am computing the system that everything is not exactly equal to μ , but some **some** fraction of the average, the fraction of the duality measure. So, instead of μ using μ I am using $\sigma \tau$. So, when σ is equal to 1, then τ is exactly my μ and then σ is 0 of course, then I am **I am** the exact solution. So, σ is lying in between and that is not exactly μ , so it not giving me a point exactly on the central path, but somewhere as we showed that nearby. So, this is the basic framework, the σ this term this is acting like a so called so, σ is called an affine scaling direction or is acting like a pointer which points towards the central path.

So, there put $\sigma \tau$ is equal to μ . So, my σ is 1 by times μ is not exactly μ , but τ is 1 by σ times. So, μ is some fraction of this τ . So, I am exactly not on the central path, but somewhere else that is exactly what we are trying to say. So, this $\sigma \tau$, this σ is 1 then at τ is μ then I am on the central path if σ is not

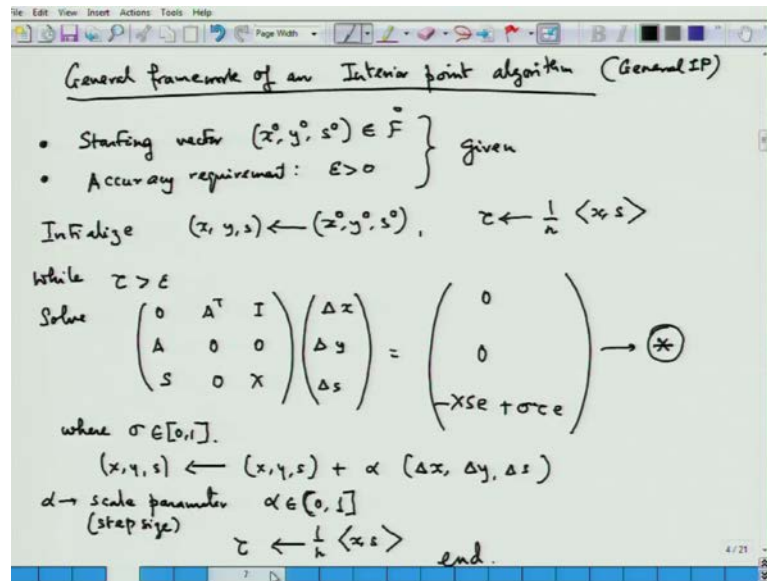
equal to 1, if σ is equal to 1 then we are on path, we are on the central path, if σ is strictly less than 1 then we are not on the central path. So, this called an affine scaling direction.

So, whatever solution we have here of this system, suppose we call this solution we can write this as $x + \sigma \tau$. So, whatever solution we have that is basically, there is a mistake here I should have written, just have to rewrite this a bit I think there is a small I have forgotten the Newton step, this is equal to of course, this is 0 0, because we have taken our points are all coming from my starting point also be an interior point x^k , s^k , f^k is belonging to f^k , the interiority conditions holds.

So, any solution Δx , Δy and Δz from there you can create a new solution that is adding Δx to x^k , Δy to y^k , Δs to s^k by putting in certain controls over here, that is you for example, you take x of x plus $\alpha \Delta x$ is my Δx plus the new one new **new** thing. So, whatever you get this x plus y plus z plus which has solutions to the final solutions and after you get the Δx this is the new point, that I have these points are pointing in the direction of the Newton solution, pointing in the direction of the central path **right**. So, this is called σ is also sometimes called σ is also called the centering parameter.

So, it is trying to force the points to go towards the central path and keep them near the central path. So, let me write down the general framework of an IP algorithm. So, that will give you a fair idea of what we had just discussed.

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So, the general framework of an IP algorithm of an interior point algorithm so, starting vector so you start with some we assume the starting vector, is element of \bar{F} naught that is given to me, accuracy requirement I need, there is a precision, these are given initiation of the algorithm. So, we will start with initialization step that is you first initialize x, y, s with the value x naught, y naught, s naught starting values.

And compute the initial tau which is 1 by n, x, s in a product. While so, we will have a while do loop, while tau is bigger than ϵ epsilon, solve and you know how to solve it if **if** I put sigma tau equal to mu we have already showed you in the last class how to solve this system or equation how to get $\Delta x, \Delta y, \Delta s$. So, you can just write a computer program simply behind which **which** will solve it out somehow you can try it at home by writing a computer program, but of course, you have to take matrices of smaller sizes, because you know unless you get just you guys are working on a PC there may be lot of overflows.

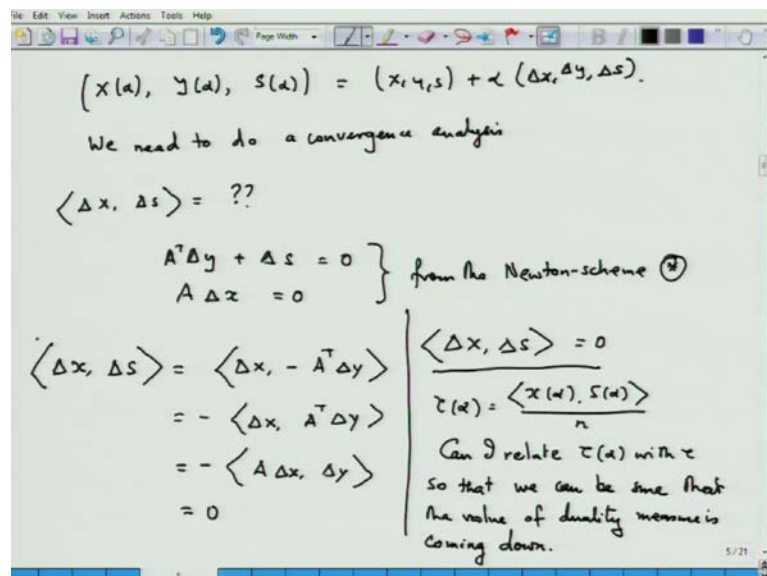
Because when you try to take the inverse inverting is the very difficult operation is a very costly operation a machine. So, I am telling you from my own experiences of trying if you trying to take slightly larger matrices try to take, very small medium size matrices here 2 by $3, 3$ by 3 and try to check it out. So, this is what you need to solve where sigma is the centering parameter or the pointer is between 0 and 1 . Now, at every step the new

x, y, s would be nothing but x, y, s into this into x, y, s is assigned the old x, y, s plus α times $\Delta x, \Delta y, \Delta s$.

So, the α is called the scaling direction, scale **scale** parameter or the scaling scale. So, this scale parameter α has to be chosen between 0 of course, it cannot be 0 that is not fair, zero means there is you are going talking about exact solution that is not possible. So, α is between 0 and 1 which is interval excluding zero and this denotes my suitable scale parameter or step size. So, it is also called step size. So, it is a while do loop, while do this solve this and once you get the new value x, y, s again assign to τ . I think you should have assign to τ the new one. So, end y end.

So, what you do is again you check if τ is so, my new x, y, s is this you my new τ is check whether τ is this and again go back and solve this and continue. So, when τ is less than equal to ϵ , stop the whole thing. So, what would be a suitable step size? So, that depends suppose this sometimes α in the short step path following method, which will start studying tomorrow you will have α is equal to 1 and that that will be giving you a lot of so, sometimes for when I am not writing an algorithm **algorithm** you can write this assignment parameters and so, it looks like program.

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But in general, I would what people would do people would write x alpha or x plus does not matter, y alpha it depend on the α , s alpha is nothing but equal to x, y, s plus α times $\Delta x, \Delta y, \Delta s$. Now, in order to study the algorithms it is very important that

we make certain estimates, this estimates will tell us whether what we were doing is true is correct. So, if I design an algorithm I have to show that if I run my algorithm I will finally, go and get what I desire, I will get tau strictly less than epsilon in certain step that has to be that is what is called the convergence analysis.

So, every algorithm we need to do **we need to do** a convergence analysis, in the sense that whatever algorithm I am writing it has it is making sense, that it is working has to be proved mathematically. So, let us look it and estimate that will require quiet often is this, what is this now how do I go about solving this, look if I look at the equation then what do I have if I look at the equation this one. So, I would have $A^T \Delta x + \Delta y = 0$ and I will have $A^T \Delta x + \Delta s = 0$ I will have $A^T \Delta x = 0$ I am **sorry** I will have a transpose delta y plus delta s equal to 0 I will have $A^T \Delta x = 0$.

So, from the Newton's equation from the Newton system so, I will have $A^T \Delta y + \Delta s = 0$, also I am having $A^T \Delta x = 0$. Now the from the newton scheme from the so, I will now write this as this newton scheme as the star scheme that is the main scheme, from the Newton scheme star. So, what I what would I have now, this means delta s I can write from here which is nothing but minus $A^T \Delta y$. So, this $A^T \Delta y$. So, I instead of delta s, I have written this taking the minus sign out so now, I can write this as $A^T \Delta x$ and what is $A^T \Delta x$ it is 0. So, I get 0.

So, we have this conclusion that if you take the newton steps of x and s first and third variable you get 0. Now an interesting question is, can I compute **can I compute** the value of tau alpha? Tau alpha of course, means so can I relate see tau alpha has to be such that at every it has to be smaller than tau, because my tau has to go down that is exactly what I want, because I want to drive my tau towards 0 and that is the whole ball game, can I relate tau and alpha with tau? So that we can be sure, that the value of the duality measure is coming down. So, let us see how can we do this?

Look at the last row of the equation this row s of Δx plus capital X of Δx is this.

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I want to compute $\tau(\alpha)$??

from \otimes $S \Delta x + x \Delta s = -x s + \sigma \tau \epsilon$

$$\begin{bmatrix} s_1 & & \\ & \ddots & \\ & & s_n \end{bmatrix} \begin{bmatrix} \Delta x_1 \\ \vdots \\ \Delta x_n \end{bmatrix} + \begin{bmatrix} x_1 & & \\ & \ddots & \\ & & x_n \end{bmatrix} \begin{bmatrix} \Delta s_1 \\ \vdots \\ \Delta s_n \end{bmatrix} = \begin{bmatrix} -x_1 s_1 \\ \vdots \\ -x_n s_n \end{bmatrix} + \begin{bmatrix} \sigma \tau \\ \vdots \\ \sigma \tau \end{bmatrix}$$

$$\begin{aligned} s_1 \Delta x_1 + x_1 \Delta s_1 &= -x_1 s_1 + \sigma \tau \\ &\vdots \\ s_n \Delta x_n + x_n \Delta s_n &= -x_n s_n + \sigma \tau \end{aligned}$$

Sum up all these equations: we have

$$\langle S, \Delta x \rangle + \langle x, \Delta s \rangle = -\langle x, s \rangle + \sigma \langle x, s \rangle$$

$$n \tau(\alpha) = \langle x(\alpha), S(\alpha) \rangle = \langle x + \alpha \Delta x, S + \alpha \Delta S \rangle$$

So, so I want to compute **I want to compute** tau alpha, let me look at the last equation. So, it will give me s of delta x plus x of this from the star equation from star. Now, I look at it component wise so, this is a vector $x_1 s_1, x_2 s_2$ these are vector sigma mu **sigma mu sigma mu** now I also want to look at this component wise this will become this s_1, s_2, \dots **dot dot** and it is $s_1 \Delta x_1, s_2 \Delta x_1, \Delta x_2, \Delta x_3$. So, let me look at it component wise what will happen **right**.

So, s is a diagonal matrix consisting of s_1, s_2, s_n in the components. So, if I look at that let us see what actually happens, if I write this in a very broader way I would have. So, here if I write it down more clearly. So, first equation here would be $s_1 \Delta x_1 + x_1 \Delta s_1 = -x_1 s_1 + \sigma \tau$. So, here there is a mistake this sigma tau epsilon. So, it should be sigma tau if you look at the equation its sigma tau not sigma mu, sigma tau here so, sigma tau and **sigma tau and** and so on. So, I can write $s_n, x_n \Delta s_n, \sigma \tau$ **sigma tau**.

Now, let the definition of sigma tau and then you **you** immediately see this will give me **sum up** sum up all **sum up all all** the all these equations, see if I sum up all these equations we have **we have** a following that is, s of delta x, x is a vector s_1, s_2, s_n plus x of delta s is minus x s plus now you add so, it will be sigma tau, tau is again sigma x s by n. So, we will get sigma x s, that is what it is now I will do n into tau alpha is equal to x alpha, s alpha that is the definition. I will write down what is x alpha, x alpha

actually for me means x plus α into Δx , s plus α into Δs . So, I will now do there detail computation

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Let us compute $n\tau(\alpha)$

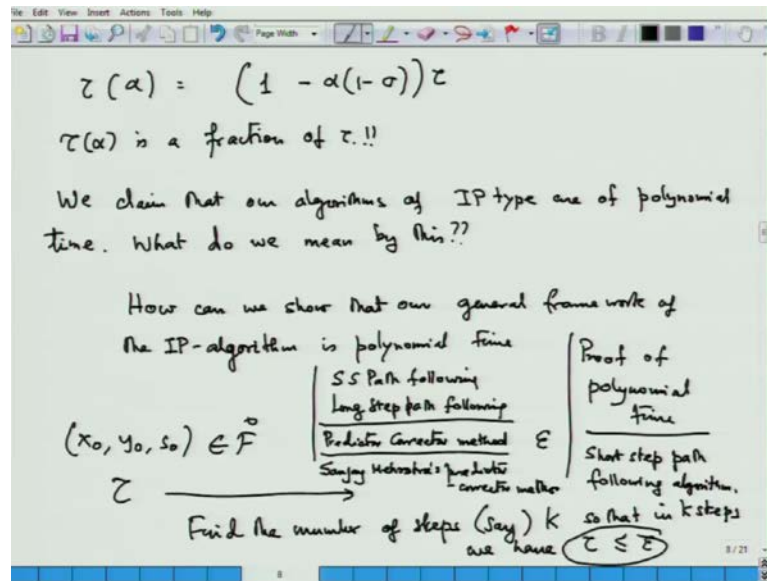
$$\begin{aligned}
 n\tau(\alpha) &= \langle x + \alpha\Delta x, s + \alpha\Delta s \rangle \\
 &= \langle x + \alpha\Delta x, s \rangle + \langle x + \alpha\Delta x, \alpha\Delta s \rangle \\
 &= \langle x, s \rangle + \alpha \langle \Delta x, s \rangle \\
 &\quad + \alpha \langle x, \Delta s \rangle + \alpha^2 \langle \Delta x, \Delta s \rangle \\
 &= \langle x, s \rangle + \alpha (\langle s, \Delta x \rangle + \langle x, \Delta s \rangle) \\
 &= \langle x, s \rangle + \alpha (-\langle x, s \rangle + \sigma \langle x, s \rangle) \\
 &= \langle x, s \rangle - \alpha \langle x, s \rangle + \alpha\sigma \langle x, s \rangle \\
 &= (1 - \alpha(1 - \sigma)) \langle x, s \rangle \\
 &= n(1 - \alpha(1 - \sigma)) \tau
 \end{aligned}$$

Let us let us let us compute out let us compute tau n n tau α . So, what I have is n tau α is equal to I am just repeating what I wrote in the last thing, s plus you will see the estimate Δx into Δs will be useful here. So, now what I will have is x plus $\alpha \Delta x$ into s plus x plus $\alpha \Delta x$ into $\alpha \Delta s$. So, I have x of s plus α times Δx into s , I just using the properties of inner products plus α into $x \Delta s$ plus α^2 times $\Delta x, \Delta s$.

Actually it is this it was important to estimate this, because we needed to find out tau α , that that was the reason to actually estimate this. In real research this thing came much later first wanted to compute this and then the other this thing was computed. So, that we know that we actually have to drive this part to 0. So, anyway we now know that this is 0. So, we have $x s$ plus α times, $s \Delta x$ plus $x \Delta s$ and this is something we have just computed, we have just computed this to be $x s$ plus α times this is nothing but minus $x s$ plus $\sigma x s$. So, it is becoming $x s$ minus $\alpha x s$ plus $\alpha \sigma x s$.

So, what I can write here is $x s$, I can take out that $x s$ as a common thing. So, I will have $1 - \alpha$ into $1 - \sigma$ times $x s$, but what is $x s$ it is n into τ . So, it is n into $1 - \alpha$ times $1 - \sigma$ times τ . So, n into tau α is this.

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So, what I would now have is tau alpha is 1 minus, again go back alpha into 1 minus sigma alpha into 1 minus sigma times tau. Now, alpha is a quantity between 0 and 1, sigma is also a quantity between 0 and 1. So, this is less than one, this is less than one, this product is less than one. So, one minus this something is bigger than 0.

So, into tau, so tau alpha is a fraction of tau. So, what we have concluded that tau alpha is a fraction of tau and that is what we require the value should come down. Now, how does the algorithm behave, if we are claiming we claim that **that** our algorithms **our algorithms** of the interior point type or the IP type are of polynomial time what do we mean by this **this** is something we really have to concentrate on now. So, what we have shown that in our general framework of IP algorithms we can reduce the tau alpha the duality measure which is of fundamental importance.

So, we have already on we have already built up something. Now what we want to show is that we can develop some framework, in this current framework we can put in some sort of little conditions which will immediately lead us to a polynomial time game, because in the sense that **sorry** it will show us that I can give you the number of steps in which your algorithm will terminate and that number of steps is not arbitrary, that number of steps is bounded on that above by a polynomial. So, if you know your number of variables in the division variables you can tell me in what number of steps you will lead to the solution.

Now, this is what we are going to discuss tomorrow, how can we show that our general framework of the IP algorithm which we have done which is actually this one **this one** is called the general IP algorithm. So, algorithm is polynomial time basically the idea is this you have a fixed x_{naught} , y_{naught} , s_{naught} that you have ϵ and now you start the algorithm, you start with τ_{naught} and you are now going pushing the τ_{naught} towards 0. Now, this is your ϵ is a precision parameter, now find the number of steps **steps** say k . So, that in k steps we have τ is less than **sorry** this is just τ .

So, I start with this and I have to show under what situations I can have or I can compute the number of step size k and we can show, that that number of steps that k that is required till we required come do this is actually bounded by a polynomial which can **which can** which tells us that this is the maximum number of steps, you would require to reach this. You can you would not need anything much more such a thing cannot be guaranteed for the simplex algorithm though it is amazingly effective in practice. So, tomorrow our first job would be to start with proof of the polynomial proof of polynomial time **proof of polynomial time.**

And then once, we have the proof of polynomial time we will start with something called short step path following algorithm. We will do its convergence so, the number or methods that we learn here are following: a short step path following, a long step path following of course, and there is something called the predictor corrector method and then once we know about the predictor corrector method, we will also give a brief outline of Sanjay Mehrotra's predictor corrector method which is the most useful predictor corrector method that is used in algorithms.

We will try to if time permits to briefly touch on what is called the potential reduction algorithms, which is also a type of IP algorithms. So, with this we end the talk here, and tomorrow we will start with proving the polynomial time, and then get in to these algorithms. So, there we would need around three, four more lectures to have a brief idea about these things, and we will give references from which you can do your further studies.