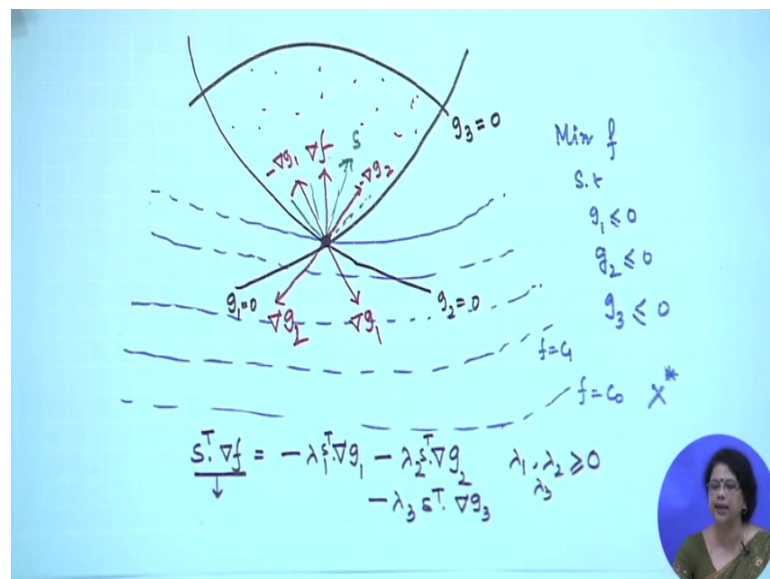


Constrained and Unconstrained Optimization
Prof. Debjani Chakraborty
Department of Mathematics
Indian Institute of Technology, Kharagpur

Lecture - 48
Constrained Optimization

Now, today the non-linear programming with inequality constraint. Now before going to the detail of KKT conditions and just to talk more on the feasible direction and other things that is why let me just recapitulate the concept I told you in the last class that is there are 3 constraints g_1, g_2, g_3 ; is my g_1 , this is g_2 and this is g_3 .

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Now, the objective function is moving in this direction our problem is to find out minimization of f subject to g_1 less than is equal to 0, g_2 less than equal to 0, and g_3 less than equal to 0. If this is the level curve of the objective function f that means, objective functional value is increasing in this direction and at this stage once objective function is coming here we are getting the optimal solution x^* ok. Now, if this is the optimal solution you see from here we can draw that this is the grad direction $\text{grad } f$ direction because objective functional value is increasing in this direction.

If we consider g_1 equal to 0 this one then this must be grad g_1 direction and this is

minus $\text{grad } g_1$ similarly, if we consider g_2 direction this one then this is $-\text{grad } g_2$ and the opposite direction is the $\text{grad } g_1$. Now, we are talking g_2 now we are talking about the feasible direction now this is the feasible space that is why from here if I just move this way then this is the direction of the feasible direction, and if I move within the space anywhere then this is the feasible direction that is why this is the feasible direction this is the feasible these are all the feasible directions, there is no doubt about it these are all the feasible direction; these are all the feasible directions with the green. Now, if I consider that this is one of the direction say S , now in the last class I showed you that if we consider the feasible direction S then $\text{grad } f$ is equal to $-\lambda_1 \text{grad } g_1 - \lambda_2 \text{grad } g_2$.

Now what else we said that this is this must be positive, why this is positive because the feasible direction and the gradient of f mix the acute angle and we are considering the inner product of 2 vectors one is S that is the feasible direction and another one is the gradient of the objective function gradient vector. Now, on the other hand the feasible direction and the $\text{grad } g_1$ that is the gradient of the first constraint this is making the obtuse angle that is why this is negative and similarly $\text{grad } g_2$ also if a just this is must be $S \cdot T$, $S \cdot T \cdot S$ and g_2 this is also obtuse angle this is also negative that is why to adjust the sign we have said that $\lambda_1 \lambda_2$ must be greater than 0 in this case equal to will be there if we are having the inactive constraint in the group. Since g_3 is the inactive the corresponding λ will be 0 that is why $\lambda_1 \lambda_2 \lambda_3$ is greater than 0 where λ_1 and λ_2 these are all strictly positive, but λ_3 is 0 here.

Now, with this idea I am going to the formal definition of the feasible direction decent direction etcetera.

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Feasible Direction

Consider a feasible point x_k . That is, $x_k \in \Omega$, where Ω denotes the feasible region defined by the collection of all points that satisfy all the constraints.

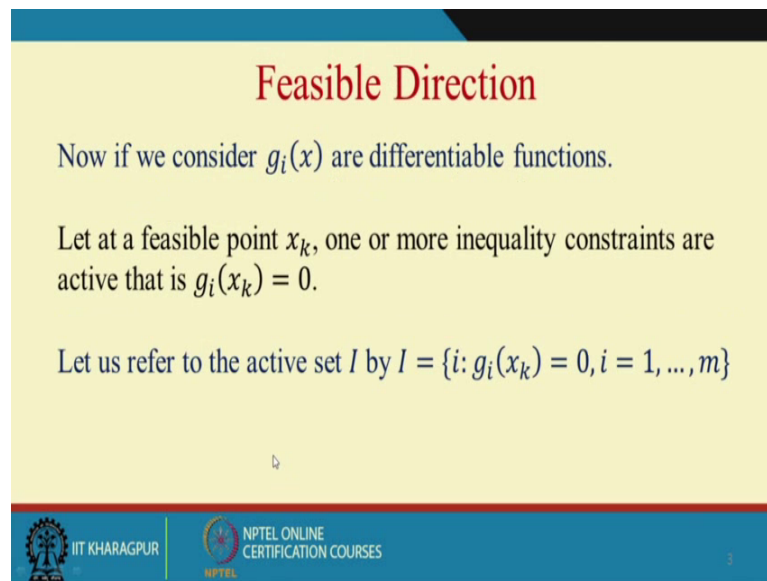
We say that d is a feasible direction at x_k if there is a $\alpha^- > 0$ such that $(x_k + \alpha d) \in \Omega$ for all $\alpha, 0 \leq \alpha \leq \alpha^-$.

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Now, we can say that if x_k is a point which is the point within the feasible space here I showed you the feasible space that if we consider the feasible region as row then, collection of all points satisfying the constraints can be named as the feasible space. Now we can say that if I move from x_k to any direction d in such a way that $x_k + \alpha d$ will remain within the feasible space then d can be said as the feasible direction that means, from the figure if I just want to tell you same this is my x_k .

Now I am moving in this direction this is the directions say d and how far I will move I will move with the step length α that is why I am moving from x_k to $x_k + \alpha d$, where α will remain from 0 to α^- then this direction is the feasible direction. From x_k if I just go in this up to this point such that α is beyond this α^- value just put me beyond the feasible space then direction is the feasible direction, but we are not reaching to the feasible point that is the definition of the feasible direction.

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Feasible Direction

Now if we consider $g_i(x)$ are differentiable functions.

Let at a feasible point x_k , one or more inequality constraints are active that is $g_i(x_k) = 0$.

Let us refer to the active set I by $I = \{i: g_i(x_k) = 0, i = 1, \dots, m\}$

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Now, if I just say that $g_i(x)$ is the constraint where that is the differentiable function then at the feasible point one or more inequality constraints at the if x_k is the optimal solution, then one or more inequalities will be with the equality side because these are all the active constraints. That is why if I consider a group of active constraints as I showed you the example here the active constraints are g_1 and g_2 g_3 is not the active constraint that is why if I consider g_1 and g_2 then the we can say at the point optimal point g_1 equal to 0 and g_2 is equal to 0 then only these are all the active constraints.

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A feasible point x_k is said to be a regular point if the gradient vectors $\nabla g_i(x_k), i \in I$, are linearly independent. Then we can say that a vector d is a feasible direction if $\nabla g_i^T d < 0$ for $i \in I$

Which will ensure that for sufficiently small $\alpha > 0, (x_k + \alpha d)$ will be feasible or $g_i(x_k + \alpha d) < 0, i = 1, \dots, m$.

In fact $\nabla g_i^T d < 0$ for $i \in I$ defines a half-space, and the intersection of all these half-spaces forms a "**feasible cone**" within which d should lie.

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Now then we can say that if d is the feasible direction then $\text{grad of } g_i^T \cdot d$ must be less than 0 where I is in the group of active constraints I showed you that is why it can be said that if we just take a sufficiently small increment α in the direction d that is the feasible direction then g_i of x_k plus αd must be lesser than 0.

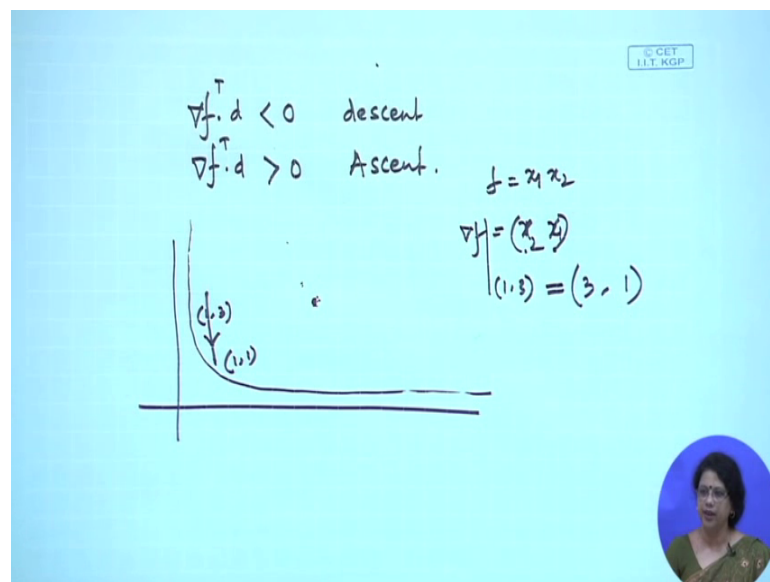
Because, as I said that that is the grad of grad of g_i of this thing with the feasible direction must be lesser than 0 that is why we can say that grad of $g_i \cdot d$ is less than 0, if we consider all active constraints together then we can show that every constraint grad $g_i \cdot d$ grad $g_i \cdot d$ that is a inner product makes less than 0 makes half space.

If we consider the half spaces of with all active constraints then it will form a feasible cone. Here we can say that in this one we can say that here there is one plane that is the half space over g_1 there is 1 plane over g_2 half space and whatever, if we consider the combination of half planes in the feasible space that will form the feasible cone. Now we will show you more about it. Now another part is that now we know that in this direction the objective functional value is increasing that is why we can say that in this direction grad $f \cdot d$ instead of S here we are calling about the feasible direction as d , then the grad f of d must be greater than 0. But if I consider the other way that is the just opposite to grad f direction; that means, if I just consider this direction this is minus grad f that is why we can say that this minus grad f makes an obtuse angle with the d thus the descent

direction can be defined as $\text{grad } f \cdot d$ must be less than 0.

Now, why we are talking all about this feasible direction, descent direction, ascent direction, all these directions because in the next phase of my lecture you will see we will deal with the methodology to solve the constraint non-linear programming problem. There we can see that this feasible direction descent direction all this mathematics will help us a lot.

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That is why we need to understand that the $\text{grad } f \cdot d$ is less than 0 this is the descent direction similarly $\text{grad } f \cdot d$ greater than 0 is the ascent direction we need to remember this 2 things together. Now, therefore, in that direction if I just move.

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Descent Direction

The vector d is a descent direction at a point x_k if

$$\nabla f^T d < 0$$

for sufficiently small $\alpha > 0$, the inequality

$$f(x_k + \alpha d) < f(x_k)$$

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Further we will see that in the descent direction if you move further we will see the functional value will decrease further and further.

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Example

$f = x_1 x_2, x^0 = [1, 3]^T, d = [1, 1]^T$
Is d a descent direction?

Ans: $\nabla f(x^0) = [3, 1]^T$.
The dot product $\nabla f(x^0) d = 4 > 0$
Thus d is **not** a descent direction

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Now I can show you one example now see this is the function given to us $X_1 X_2$ is the function for us now there is a point 1 3 within the space, now the direction is given as 1,1

direction have you has been given 1 because from 1 3 if you move in the direction 1,1 for a just if I consider the a 2 dimensional space, $x_1 \times x_2$ is the function; that means, the function would be like this $x_1 \times x_2$ this is one of the level curve of the function.

Now, there is a point that is 1 3 say this is 1 3 this is the point 1 3 now there is a direction 1,1 this is the direction it has been said that we have to check if I move from 1, 3 to 1,1 whether this is a descent direction for the function $x_1 \times x_2$ or not. Now the function has been given as $x_1 \times x_2$ then in the descent direction just now we have learnt $\text{grad of } f \cdot d$ must be less than 0 in the descent direction.

That is why let us find out what is the $\text{grad } f$ for it if f is $x_1 \times x_2$ then $\text{grad } f$ must be is equal to 1 1 that is why if I consider the $\text{grad } f$ at the point 1 3 then it must be yeah 1 1 actually this is x_2 this is x_1 because with respect to x_1 we are differentiating and this is with respect to x_2 we are differentiating that is why at the point 1 3 this point at 1 3 will become 3 1 alright. That is why if we consider the $\text{grad } f \cdot d$ then we can see 3 1 and 1 1 if we just multiply we can get the value of that would be equal to 4 that is why we can say d is not the descent direction certainly this is the ascent direction of $x_1 \times x_2$.

Now let us deal with another example there one optimization problem has been said, problem has been given as f is equal to minus x_1 plus x_2 alright and t 3 constraints are given one constraint is g_1 is equal to given x_1 square plus $4 x_2$ square minus 1 less than equal to 0, g_2 has been given as minus x_1 less than is equal to 0 rather x_1 is greater than 0 to make it in the same direction all the inequalities we can consider this way.

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$d_3 = (0, -1)$
 $f = -(x_1 + x_2)$
 $\nabla f = (-1, -1)$
 $\nabla f^T \cdot d_1 = (-1, -1) \begin{pmatrix} 1 \\ 0 \end{pmatrix} = -1 < 0 \Rightarrow d_1 \text{ is descent direction}$
 $\nabla f^T \cdot d_2 = (-1, -1) \begin{pmatrix} 1 \\ -0.5 \end{pmatrix} = -1 + 0.5 = -0.5 < 0 \Rightarrow d_2 \text{ is descent}$
 $\nabla f^T \cdot d_3 = (-1, -1) \begin{pmatrix} 0 \\ -1 \end{pmatrix} = 1 > 0 \Rightarrow d_3 \text{ is ascent dir.}$
 $\frac{1}{5} + \frac{4}{5} - 1 = 0 \Rightarrow g_1 \text{ is active constraint}$
 $\nabla g_1 \cdot d_1 > 0 \rightarrow d_1 \text{ is feasible direction}$

This basically, the non negativity constraints for the decision variables, now there is a point has been given 1 by root 5 and 1 by root 5. Now there are 3 directions are given we need to find out the that all the directions are the feasible and or descent direction not the direction can be feasible the direction can be infeasible the direction can be descent the direction can be ascent with that idea we are just going one by one. If we consider the grad f value certainly the grad f will come as here if I just differentiate with respect to x 1 partially, then this is minus 1 and differentiate with respect to x 2 this is minus 1. Now, if I consider grad f t dot d 1 now my d 1 direction is 1 0 that is why it is becoming minus 1 minus 1 0 that is why this value is coming as minus 1. Now we can say that if we now one thing is that the point has been given here as x not has been given 1 by root 5 by 1 by root 5, but there is no effect on it because the gradient of f is not a function of x 1 x 2 that is why always the grad f would be minus 1 minus 1.

Now, if I just move in this direction then this will become less than 0 then what is the conclusion from here we can conclude that this direction is the descent direction because this is negative alright. Let me do the same calculations for d 2 d 3 as well - grad f d 2 minus 1 minus 1 d 2 direction is my 1 minus 0.5 then this is becoming minus 1 plus 0.5 that is why again this is coming as minus 0.5 less than 0 that is why again we can conclude that d 2 is the descent direction alright.

Now if I do further calculations for d_3 $\text{grad } f$ d_3 minus 1 minus 1 and 0,1 if we just consider this is becoming 0,1 0 minus 1 rather because d_3 let please consider d_3 as 0 minus 1 not 0,1 alright 0 minus 1 if we consider this is becoming 1. That is why we can consider we can say that d_3 is ascent direction not descent direction alright. Now this is all about the descent or ascent direction, but we did not say about the feasible direction yet now we need to check the feasible direction. One thing is that you see if this is the point is there now let us see which is the active constraints because feasible direction can only be defined with respect to the constraint set descent direction or ascent direction can be defined with respect to the function objective function, but feasible direction can only be defined with respect to the constraint set.

If I just show you this one you could see that feasible direction can only be defined because this is collection of feasible points that is the collection of points which satisfy all the constraints together that is why feasible direction with respect to the constraint set. Now, if we see the constraint set what we could see that this point first of all g_2 is not active constraint, g_3 is not an active constraint, is that known because minus 1 minus 1 by root 5 is not being we cannot say this is equal to 0 that is why this is not active this is not active, but let us see whether this point is being satisfied with this or not.

If I just substitute the values here then we can say that $1 \text{ by } 5 \text{ plus } 4 \text{ by } 5$ that is $x^2 + x - 1$ square plus $4x - 2$ square minus 1 this is equal to 0 that is why we can conclude from here that g_2 is the active constraint, g_1 is the active constraint. If g_1 is the active constraints if we can prove that $\text{grad } g_1 \cdot d$; that means, $\text{grad } g_1$ is making the obtuse angle obtuse angle with the direction of d then we can say that just you see this is my $\text{grad } g_1$. Now $\text{grad } g_1$ with this direction its making the obtuse angle that is why if we can show that $\text{grad } g_1$ is making the obtuse angle that is greater than 0 then we can say that d is the feasible direction if this is true then we can say that d is feasible direction alright let us see.

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$\nabla g_1^T \Big|_{x_0} \cdot d_1 = \left(\frac{2}{\sqrt{5}}, \frac{8}{\sqrt{5}} \right) \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \frac{2}{\sqrt{5}} > 0$
 $\Rightarrow d_1$ is feasible direction descent
 $\nabla g_1 = (2x_1, 8x_2)$ at $\left(\frac{1}{\sqrt{5}}, \frac{1}{\sqrt{5}} \right)$
 $\nabla g_1^T \Big|_{x_0} \cdot d_2 = \left(\frac{2}{\sqrt{5}}, \frac{8}{\sqrt{5}} \right) \begin{pmatrix} 1 \\ -5 \end{pmatrix} = \frac{2}{\sqrt{5}} - \frac{40}{\sqrt{5}} = -\frac{38}{\sqrt{5}} < 0$
 $\Rightarrow d_2$ is not a feasible direction descent
 $\nabla g_1^T \Big|_{x_0} \cdot d_3 = \left(\frac{2}{\sqrt{5}}, \frac{8}{\sqrt{5}} \right) \begin{pmatrix} 0 \\ -1 \end{pmatrix} = -\frac{8}{\sqrt{5}} < 0$
 $\Rightarrow d_3$ is feasible direction ascent.

Grad of g 1 dot d 1 now grad of g 1 just now we have we did not find it out grad of g 1 is equal to $2 \times \frac{1}{\sqrt{5}}, 8 \times \frac{1}{\sqrt{5}}$ now at $\frac{1}{\sqrt{5}}$ by root 5, $\frac{1}{\sqrt{5}}$ by root 5 grad g 1 value is coming as $\frac{2}{\sqrt{5}}$ and $\frac{8}{\sqrt{5}}$ ok.

That is why grad g 1 at point x not d 1 this is at point x not in the d direction if we consider then this would be is equal to $\frac{2}{\sqrt{5}}, \frac{8}{\sqrt{5}}$ and my d one direction is one 0 that is why we can say his is equal to $\frac{2}{\sqrt{5}}$ this is greater than 0 that is why what we can conclude that d 1 is feasible direction ok. Now let me calculate the same for other d 2 and d 3, $\frac{2}{\sqrt{5}}, \frac{8}{\sqrt{5}}$ and $1 - 0.5$ that is why it is coming $\frac{2}{\sqrt{5}}$, minus $\frac{40}{\sqrt{5}}$ it is coming minus $\frac{38}{\sqrt{5}}$ that is why this is negative. What is the conclusion from here? The conclusion is that d 2 is not a feasible direction let me do the same for d 3, d 3 the d 3 direction is $0 - 1$, if we just do it we can say this is my coming minus $\frac{8}{\sqrt{5}}$ this is less than 0 that is why again we can say that the d 3 is the is feasible direction. If we keep all together in the previous case we could see that d 1 is descent direction, d 2 is descent direction and d 3 is ascent direction.

That is why we can conclude that only d 1 is feasible and descent direction or other directions are not the feasible and the descent direction that is why for the minimization problem we should move through d 1 we can conclude that.

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Optimization problem with inequality constraint

Let us take a minimization problem with inequality constraint

$$\begin{aligned} & \text{Minimize } f(X) \\ & \text{Subject to } g_j(X) \leq b_j \end{aligned}$$

Where, $X = (x_1, x_2, \dots, x_n)$ and $j = 1, 2, \dots, m$

After introducing non-negative slack variables the problem becomes

$$\begin{aligned} & \text{Minimize } f(X) \\ & \text{Subject to } g_j(X) + s_j^2 = b_j, j = 1, 2, \dots, m \end{aligned}$$

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Now, if we just move to again to the KKT condition if we consider the minimization problem minimization of $f(x)$ subject to $g_j(x) \leq b_j$ as I said we can say the KKT conditions are can be defined.

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Inequality constrained problems

- Consider problem with only inequality constraints:
$$\begin{aligned} \min_x & f(x) & x \in \mathbb{R}^n \\ \text{s. t.} & g_i(x) \leq 0 & i = 1 \dots m \end{aligned}$$
- At optimum, only *active* constraints matter:
$$\begin{aligned} \min_x & f(x) & x \in \mathbb{R}^n \\ \text{s. t.} & \bar{g}_j(x) = 0 & j = 1 \dots k \leq m \end{aligned}$$
- Optimality conditions similar to equality constrained problem

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Now here we are again considering there is a set of active constraints and there is a set of

in active constraints if we consider that there are few number of constraints k number of constraints which are active constraints if we just make the group of those then we can say that similarly for the inactive constraints also if we just do it we can say this is the first order optimality condition.


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Inequality constraints

- First order optimality:

$$L(\mathbf{x}) = f(\mathbf{x}) + \boldsymbol{\mu}^T \bar{\mathbf{g}}(\mathbf{x}) \Rightarrow \begin{cases} \bar{\mathbf{g}} = \mathbf{0} \\ \boldsymbol{\mu}^T = -\frac{\partial f}{\partial \mathbf{x}} \left(\frac{\partial \bar{\mathbf{g}}}{\partial \mathbf{x}} \right)^{-1} \\ \frac{\partial f}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \bar{\mathbf{g}}}{\partial \mathbf{x}} = \mathbf{0}^T \end{cases}$$
- Consider feasible local variation around optimum:

$$\frac{\partial f}{\partial \mathbf{x}} + \boldsymbol{\mu}^T \frac{\partial \bar{\mathbf{g}}}{\partial \mathbf{x}} = \mathbf{0}^T \Rightarrow \frac{\partial f}{\partial \mathbf{x}} \partial \mathbf{x} + \boldsymbol{\mu}^T \frac{\partial \bar{\mathbf{g}}}{\partial \mathbf{x}} \partial \mathbf{x} = 0$$



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Because we have done the first order derivative of the Lagrange function with respect to decision variable we are getting the first order optimality condition and if we consider these are few calculations I will speak more on this in the next, but one thing wanted to tell you that $\frac{\partial f}{\partial \mathbf{x}}$ is greater than 0, but this is less than 0 in the feasible direction that is why we can say this is positive alright.

And this is the graph of it, if this is my g_1 and this is my g_2 then this is the feasible direction because not only the feasible direction this is ascent direction because functional value is moving further with this direction with the positive value. And this is a grad g_1 and this is my grad of g_2 , these are the normal direction at this point and from here we can say that this is the minus grad f direction. And with these today I am concluding my lecture because I will speak more on this in the next class and I will show you the examples how to handle with KKT condition in the next class.

Thank you very much for today.