

**Selected Topics in Decision Modeling**  
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**Lecture - 27**  
**Constrained NLP: KKT Conditions**

So, good morning in our course Selected Topics in Decision Modeling today we are in our 27th lecture that is Constrained Non-linear Programming: KKT Conditions that is Karush-Kuhn-Tucker conditions.

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**NLPs with Inequality Constraints**

**Basic Features:**

1. Objective function can be linear or non-linear.
2. Constraints can also be linear or non-linear.
3. Constraints can be of any type i.e. inequality or equality.

**A General Form:**

$$\begin{array}{ll} \text{Maximize } f(x) & x = [x_1, x_2, \dots, x_n] \\ \text{subject to } h_i(x) \leq b_i & i = [1, 2, \dots, m] \end{array}$$

3

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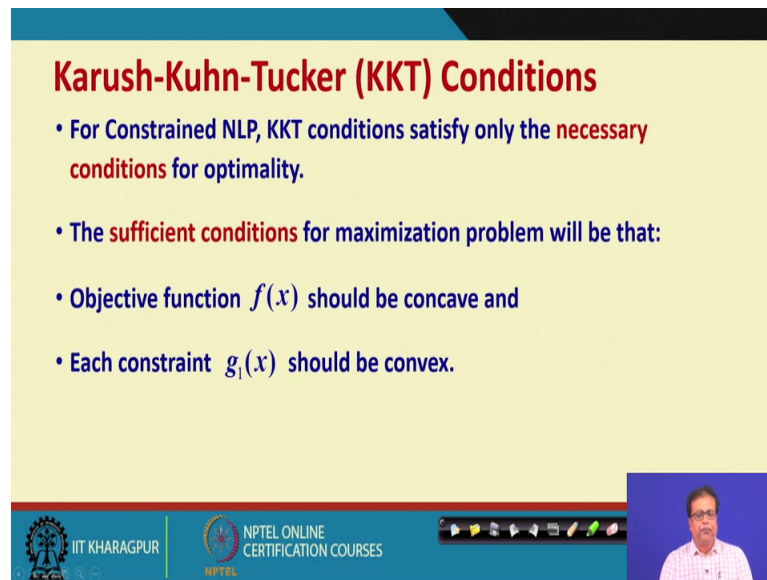
So, we have seen that, how to solve non-linear programming problem with equality constraints in our last class. There we had use Lagrange's multipliers and differentiated the function, to find out conditions for optimality. Whereas, for inequality constraints Lagrange's multiplier cannot be utilized, we need to go for a little more involved calculations with the help of KKT conditions.

So, some of the basic features the objective function can be linear or non-linear, constraints can also be linear or non-linear and constraints can be of any type that is inequality or equality. If you recall I have told in our last class that the Lagrange's multiplier is a special case of KKT conditions.

So, at some other time I will also show you that how it is really happening. So, you see any linear programming problem can be put in maximization general form. If it is not happening then we must ensure how to do it is alright. So, the first of all let me just tell its right in the beginning that all the conditions and all the discussions that we are going to have, we shall you know assume the programming problem the non-linear programming problem is available in the general form, that is maximized  $f$  which is a function of  $x$  really speaking  $x$  is having several variables  $x_1, x_2$  to  $x_n$ .

And subject to conditions  $h_i(x) \leq b_i$ , you know where  $i$  is  $1, 2, \dots, m$  is it alright. So, that is the general form that we are going to use for all the KKT conditions.

(Refer Slide Time: 03:04)



**Karush-Kuhn-Tucker (KKT) Conditions**

- For Constrained NLP, KKT conditions satisfy only the **necessary conditions** for optimality.
- The **sufficient conditions** for maximization problem will be that:
- Objective function  $f(x)$  should be concave and
- Each constraint  $g_i(x)$  should be convex.

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Now, Karush-Kuhn-Tucker conditions or in short KKT conditions, where you know obtained by Kuhn-Tucker, but then Karush independently obtain them actually earlier right in his thesis work. So, that is the reason why these conditions and known as Karush-Kuhn-Tucker conditions. But just remember this that these conditions they are not the only conditions required for optimality, infant there only the necessary conditions right.

So, KKT conditions are the necessary conditions for the NLP problem, the sufficiency condition is still you know the for the maximization problem the  $f(x)$  should be concave and each constrain should be convex is it alright. So, you just recall our discussions that for maximization, but you require the objective function should be concave and the constraints should be convex.

Now, sometimes we have linear constraints, the linear constraints are both convex and concave at the same time. So, if I have linear objective function, then automatically we can assume the objective function to be concave or if we have constraints some of the constraints a linear, than those linear constraints can be also assume to be convex. Because linear constraints or objective functions at are both concave and convex at the same time.

But if it is non-linear, then the concavity has to be seen, either by the nature of the plot or by obtaining the second differential that is you know in when multiple variables are

involved, then obtaining the Hessian matrix. So, we will see that in due course of time right.

(Refer Slide Time: 05:23)

**Karush-Kuhn-Tucker (KKT) Conditions**

KKT conditions provide a general approach in solving constrained nonlinear problems.

**Theorem:** Assume that  $f(x)$ ,  $g_1(x)$ ,  $g_2(x)$ , ...,  $g_m(x)$  are differentiable functions satisfying certain regularity condition.

Then  $x^* = (x_1^*, x_2^*, \dots, x_n^*)$  can be an optimal solution for the NLP problem only if, there exist  $m$  numbers  $u_1, u_2, \dots, u_m$  such that all the following KKT conditions are satisfied.

5

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So, let us look at the KKT conditions. So, first of all when we are solving in a general approach to constrained non-linear problems, let us assume that we have certain functions that is  $f(x)$ ,  $g_1(x)$ ,  $g_2(x)$  to  $g_m(x)$  they are all differentiable functions and having certain regularity conditions as well. Then the  $x^*$  which is a combination of  $n$  unknown variables or decision variables, can be an optimal solution for the NLP problem, only if they are exist  $m$  number of multipliers  $u_1$  to  $u_m$  such that a number of KKT conditions are satisfied.


So, what are the things that we said? Just imagine you know just remember that the our original problem was maximizing  $f(x)$  subject to number of conditions those  $g_i(x)$  less than equal to  $b_i$ . So, they all should be differentiable that is first requirement and you know they are exist certain multipliers that is  $u_1$  to  $u_m$ , you know along with them we will have those KKT conditions which must be satisfied for  $x^*$  to become optimal right. So, these are the certain preconditions now let us look at the KKT conditions.


(Refer Slide Time: 07:02)

## Karush-Kuhn-Tucker (KKT) Conditions


KKT conditions are as follows:

1.  $\frac{\partial f}{\partial x_j} - \sum_{i=1}^m u_i \frac{\partial g_i}{\partial x_j} \leq 0$  at  $x = x^*$ , for  $j = 1, 2, \dots, n$ .  
w.s
2.  $x_j^* \left( \frac{\partial f}{\partial x_j} - \sum_{i=1}^m u_i \frac{\partial g_i}{\partial x_j} \right) = 0$  at  $x = x^*$ , for  $j = 1, 2, \dots, n$ .  
At  $x_1 = x_1^*$
3.  $g_i(x^*) - b_i \leq 0$  for  $i = 1, 2, \dots, m$ .  
 $g_i(x_1) \leq b_i$   
 $\Rightarrow g_i(x_1) - b_i \leq 0$





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6

So, the first condition as you can see is  $\frac{\partial f}{\partial x_j} - \sum u_i \frac{\partial g_i}{\partial x_j} \leq 0$  at  $x = x^*$ , for  $j = 1, 2, \dots, n$ . This means each of these sums is taken over each of the constraints  $u_i \frac{\partial g_i}{\partial x_j}$  less than or equal to 0. That is, the first condition is valid at the optimal point and for each of the  $x$  variables.

So, this is more like the differential condition, but the condition you see we have you know the objective function and we also have a series of constraints. So, if I multiply those constraints by our multiplier, that is the  $u_i$ s. So, each safest constraint multiplied by  $u_1$ , second multiplied by  $u_2$ , third by  $u_3$  etcetera etcetera and then we differentiate you know by taking appropriately that is very important the negative sign.

These negative sign of combination usually is used for maximization problem sometimes plus is used for minimization, but we can generalize with negative also we will have some discussion later. The second condition is just the first part whatever the first condition left hand side you see the same portions. So, if you see the first part, see this is the LHS of the first condition.

So, this is the LHS of the first condition. So, that multiplied by  $x_j^*$  is it alright. So, the LHS whatever the differential part you get for the first condition, if you multiplied by  $x_j^*$  that should be 0 that is the second condition. That means, either these first constraint is equality or  $x_j$  equal to 0,  $x_j^*$  equal to 0. So, what that second condition says is that, either the first condition is an equality or the corresponding  $x$  variable that is  $x_j^*$  should be equal to 0 is it alright that is the second condition says. The third

condition is again very straight forward because we see that you know  $g_i(x)$  is less than equal to  $b_i$  that is our specific constraint. So, it is the same constraint written in a another form. So, really the third constraint is nothing new, because the original constraint we have is  $g_i(x) \leq b_i$ .

So, the same constraint, we have written in this form. So, this is the constraint itself and at  $x_1$  equal to  $x_1^*$  at  $x_1$  equal to  $x_1^*$  these should be star. So, see this was our original constraint. So, the same original constraint has been rewritten in these form. So, that is our third constraint. So, you can understand that although they look you know rather big, but really speaking now the constraints are very simple in fact, the first one is nothing, but the differentiation, the differentiation should be less than equal to 0.

The second condition is either the LHS of the first condition that becomes 0 that means,  $\frac{\partial f}{\partial x_j}$  should be equal to these term or the corresponding  $x$  variables should be 0 and the third one is nothing, but the constraints the corresponding constraints themselves right.

(Refer Slide Time: 11:30)

**Karush-Kuhn-Tucker (KKT) Conditions**

KKT conditions are as follows (continued):

4.  $u_i [g_i(x^*) - b_i] = 0$  for  $i = 1, 2, \dots, m$ .
5.  $x_j^* \geq 0$  for  $j = 1, 2, \dots, n$ .
6.  $u_i \geq 0$  for  $i = 1, 2, \dots, m$ .

Handwritten notes on the right side of the slide:

$$g_i(x^*) - b_i \leq 0$$

$$u_i (g_i(x^*) - b_i) = 0$$

7

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So, we have seen those first 3 conditions let us see the last few conditions. So, see like we said in the case of the constraints, the differentiation. So, our original constraints has been rewritten as  $g_i(x^*) - b_i \leq 0$  so,  $b_i$ . So, that is that is has been written. So, again so, multiply by the corresponding multiplier multiply by the corresponding multiplier should be equal to 0. So, that is the fourth condition.

So, once again and fifth and sixth condition should be the all the multiplier should be greater than equal to 0, and all the decision variable at the optimal point should be also greater than equal to 0. So, these are our six KKT conditions. So, just look at them once again you know the if you if you if you really see, then the yeah.

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**Karush-Kuhn-Tucker (KKT) Conditions**

Solve the following NLP:

Maximize  $f(x_1, x_2)$

Subject to

$g_1(x_1, x_2) \leq b_1$

$g_2(x_1, x_2) \leq b_2$

$f(x_1, x_2), g_1(x_1, x_2), g_2(x_1, x_2)$  are differentiable.

$x^* = (x_1^*, x_2^*)$  can be an optimal solution for the NLP problem if and only if there exist  $u_1, u_2$  such that all the KKT conditions are satisfied.

Handwritten notes in red:

- Max  $f(x)$
- s.t.  $g_1(x) \leq b_1$
- $g_2(x) \leq b_2$

KKT Conditions:

$$\frac{\partial f}{\partial x_1} - u_1 \frac{\partial g_1}{\partial x_1} - u_2 \frac{\partial g_2}{\partial x_1} \leq 0 \quad \dots 1(a)$$

$$\frac{\partial f}{\partial x_2} - u_1 \frac{\partial g_1}{\partial x_2} - u_2 \frac{\partial g_2}{\partial x_2} \leq 0 \quad \dots 1(b)$$

$$x_1^* \left( \frac{\partial f}{\partial x_1} - u_1 \frac{\partial g_1}{\partial x_1} - u_2 \frac{\partial g_2}{\partial x_1} \right) = 0 \quad \dots 2(a)$$

$$x_2^* \left( \frac{\partial f}{\partial x_2} - u_1 \frac{\partial g_1}{\partial x_2} - u_2 \frac{\partial g_2}{\partial x_2} \right) = 0 \quad \dots 2(b)$$

Handwritten notes for equations 2(a) and 2(b):

- For 2(a):  $g_1(x_1^*) = b_1$
- For 2(b):  $g_2(x_2^*) = b_2$

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So, this is these are the KKT conditions, the first condition is the differential partial differentiation with respect to each variable. So, we had n unknown variable each variable should be taken one at a time. The first part is the objective function part, the second part is the individual constraints multiplied by the multiplier and then taking the negative of the you know the partial differentiation. The second constraint is the LHS of the first part should be either 0 or the corresponding decision variables should be 0.

The third constraint is the original you know the constraint itself written in another form, the fourth constraint is either the you know it becomes equality. The constraint become equality or the corresponding Lagrange the multiplier become equality and the fifth and sixth conditions are basically you know non-negativity constraints both for the decision variables and for the multipliers is it alright.

So, this is how we begin with the KKT conditions, these are the six KKT conditions. So, for improving our understanding let us look at a particular problem very simple one, simplified version of the KKT conditions once again. So, let us say we have a 2 variable problem maximize  $f(x_1, x_2)$  to. So, a function which is having  $f(x_1, x_2)$  and subject to 2



constraints only that is  $g_1(x_1, x_2)$ , in short we can also write these thing as this that maximize  $f(x)$  subject to  $g_1(x) \leq b_1$  and  $g_2(x) \leq b_2$ . So, that is all is our problem very simple problem we take.

Now, the condition that is required is all the 3 functions that is  $f(x)$ ,  $g_1(x)$  and  $g_2(x)$  should be differentiable that is the requirement. Now  $x^* = (x_1^*, x_2^*)$  can be an optimal solution for the NLP problem, if and only if there exist  $u_1, u_2$  multipliers such that they are actual equivalent to Lagrange's multipliers. So, such that all the KKT conditions are satisfied is it alright. So, this is the requirement.

So, let us see once again what exactly is you know this conditions are essentially. So, first condition you see suppose I write a function a let us say total you know the function the combination function.

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**Karush-Kuhn-Tucker (KKT) Conditions**

**Solve the following NLP:**  
 Maximize  $f(x_1, x_2)$   
 Subject to  
 $g_1(x_1, x_2) \leq b_1$   
 $g_2(x_1, x_2) \leq b_2$   
 $f(x_1, x_2), g_1(x_1, x_2), g_2(x_1, x_2)$  are differentiable.  
 $x^* = (x_1^*, x_2^*)$  can be an **optimal solution** for the NLP problem if and only if there exist  $u_1, u_2$  such that all the **KKT conditions** are satisfied.

*Handwritten notes:*  
 Combined for  $f(x) - u_1 g_1(x) - u_2 g_2(x)$   
 $\frac{\partial}{\partial x_1} [f(x) - u_1 g_1(x) - u_2 g_2(x)] \leq 0$

**KKT Conditions:**

$$\frac{\partial f}{\partial x_1} - u_1 \frac{\partial g_1}{\partial x_1} - u_2 \frac{\partial g_2}{\partial x_1} \leq 0 \quad \dots 1(a)$$

$$\frac{\partial f}{\partial x_2} - u_1 \frac{\partial g_1}{\partial x_2} - u_2 \frac{\partial g_2}{\partial x_2} \leq 0 \quad \dots 1(b)$$

$$x_1^* \left( \frac{\partial f}{\partial x_1} - u_1 \frac{\partial g_1}{\partial x_1} - u_2 \frac{\partial g_2}{\partial x_1} \right) = 0 \quad \dots 2(a)$$

$$x_2^* \left( \frac{\partial f}{\partial x_2} - u_1 \frac{\partial g_1}{\partial x_2} - u_2 \frac{\partial g_2}{\partial x_2} \right) = 0 \quad \dots 2(b)$$

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So, let us call it combined function. The combined is  $f(x) - u_1 g_1(x) - u_2 g_2(x)$ .

So, what is this combine function? This combined function is obtained by combining the function  $f(x)$  along with the 2 constraints  $g_1(x) \leq b_1$  and  $g_2(x) \leq b_2$ . So, if I combined them then what you get is,  $f(x) - u_1 g_1(x) - u_2 g_2(x)$ . So, now you see the first constraint is nothing, but the differentiation of this function with respect to  $x_1$  and with respect to  $x_2$ . So, please differentiate these with respect to  $x_1$  what do you get?  $\frac{\partial f}{\partial x_1} - u_1 \frac{\partial g_1}{\partial x_1} - u_2 \frac{\partial g_2}{\partial x_1}$ .



So, precisely that is what is written here  $g_1$  is nothing, but  $g_1 \times g_2$  is nothing, but  $g_2 \times$ . So, that should be less than equal to 0 that is the first condition. So, similarly the second condition is again the differentiation of the combined function, that is  $\frac{\partial f}{\partial x_2} - u_1 \frac{\partial g_1}{\partial x_2} - u_2 \frac{\partial g_2}{\partial x_2} \leq 0$ .

So, that is the second condition of the first condition second part the second condition again will be the either you know these partial differentiation of the combined function should be equal to 0 or the corresponding optimal variable that the at the optimal point. So, either the equation becomes equality or the variable corresponding variable is 0, right.

So, either these equal to 0 right this term is 0 or the corresponding decision variable equal to 0 same thing holds for  $x_2$  also. So, I hope the first two conditions which are the most important KKT conditions you have understood clearly is it alright. So, if you have understood these two conditions clearly, let us see the remaining conditions the remaining conditions are again.

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**Karush-Kuhn-Tucker (KKT) Conditions**

**Solve the following NLP:**  
 Maximize  $f(x_1, x_2)$   
 Subject to  
 $g_1(x_1, x_2) \leq b_1$   
 $g_2(x_1, x_2) \leq b_2$   
 $f(x_1, x_2), g_1(x_1, x_2), g_2(x_1, x_2)$  are differentiable.  
 $x^* = (x_1^*, x_2^*)$  can be an optimal solution for the NLP problem if and only if there exist  $u_1, u_2$  such that all the KKT conditions are satisfied.

*Handwritten notes:*  
 $g_1(x_1^*, x_2^*) - b_1 \leq 0$   
 $g_2(x_1^*, x_2^*) - b_2 \leq 0$

**KKT Conditions:**  
 $g_1(x_1^*, x_2^*) - b_1 \leq 0 \quad \dots 3(a)$   
 $g_2(x_1^*, x_2^*) - b_2 \leq 0 \quad \dots 3(b)$   
 $u_1 [g_1(x_1^*, x_2^*) - b_1] = 0 \quad \dots 4(a)$   
 $u_2 [g_2(x_1^*, x_2^*) - b_2] = 0 \quad \dots 4(b)$   
 $x_1^* \geq 0 \quad \dots 5(a)$   
 $x_2^* \geq 0 \quad \dots 5(b)$   
 $u_1, u_2 \geq 0 \quad \dots 6(a), 6(b)$

9

For the same problem you know how the third condition is nothing, but the constraint itself. The constraint itself that is  $g_1 \times 1 \times 2$  or we can write  $g_1 \times$  less than equal to 0 and  $g_2 \times 1 \times 2$  minus  $b_2$  less than equal to 0 at the optimal point.

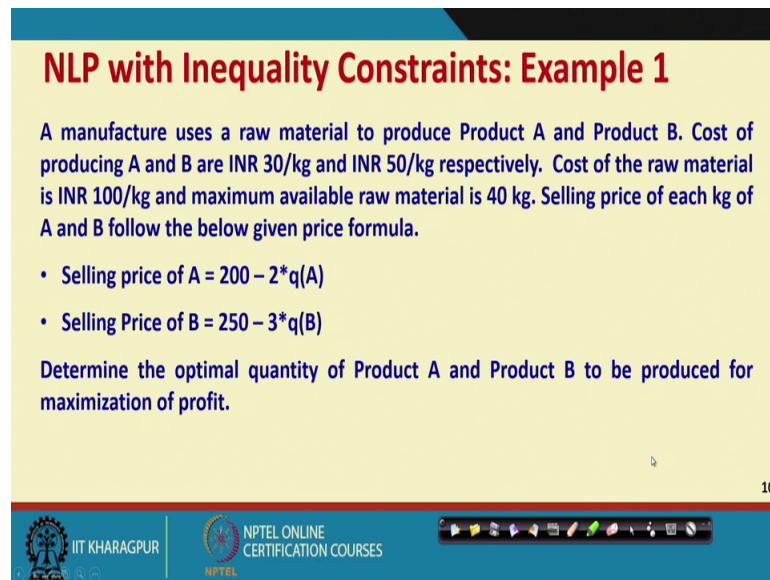
So, the star we can write star sometimes, but to you know make simply see for simplification, we may not write star in between calculations, but we should know that we are calculating the variable at the optimal point because all these KKT conditions are true not always, but at the point of optimality is it alright. So, that is the third condition and the fourth condition is either these constraints become equality or the corresponding multiplier becomes 0 is it alright. So, that is what is essentially they say they the these are the fourth conditions.

The fifth conditions are the at the optimal point the variables should be greater than equal to 0 the sixth condition has not come properly. So, that should means  $u_1$  should be greater than equal to 0 and  $u_2$  should be greater than equal to 0 right.

So, these are the sixth conditions. So, this is how you can see that how the at the optimal point, the necessary conditions are that the KKT conditions must hold right. So, you understood so, once again that we are having non-linear programming problem with you know inequality constraints, which also includes the equality constraints also. In fact, equality constraints are a special case in case of equality constraints really see what happens.

These automatically it becomes 0. So, if these becomes 0 so, it is not really necessary that  $u_1$  and  $u_2$  to become 0 also and the first constraints then become trivial is it alright. So, we will discuss it some other time now let us look at a particular problem and see how optimal solution can be obtained for a particular problem by making use of the KKT conditions right.

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**NLP with Inequality Constraints: Example 1**

A manufacture uses a raw material to produce Product A and Product B. Cost of producing A and B are INR 30/kg and INR 50/kg respectively. Cost of the raw material is INR 100/kg and maximum available raw material is 40 kg. Selling price of each kg of A and B follow the below given price formula.

- Selling price of A =  $200 - 2 \cdot q(A)$
- Selling Price of B =  $250 - 3 \cdot q(B)$

Determine the optimal quantity of Product A and Product B to be produced for maximization of profit.

10

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So, let us take these problem; manufacturer uses a raw material produced product A and product B right. Now for producing this product A and product B first of all there is a cost, the cost is 30 rupees per kg for A and 50 rupees per kg for B. Now the cost of raw material is rupees 100 per kg and maximum available raw material is 40 kg right.

The selling price of each kg of A and B follow the given price formula what is the price formula. The selling price of A is 200 minus 2 into quantity of A and selling price of B is 250 minus 3 into quantity of B. So, determine the optimal quantity of product A and product B to be produced for maximization of profit right.

So, these looks like a simple optimization problem, but there is a catch the selling price is not linear. I mean its linear now, but when you convert it to objective function then it will become non-linear right. So, let us see how to formulate the problem first.

(Refer Slide Time: 23:30)

**NLPs with Inequality Constraints: Example 1**

**Decision Variables**

- $x_1$  : Amount of Product A in kg
- $x_2$  : Amount of Product B in kg
- $x_3$  : Amount of Raw Material used

**Cost of producing A: INR 30/kg**  
**Cost of producing B: INR 50/kg**  
**Cost of Raw Material: INR 100/kg**  
**Maximum available raw material: 40 kg.**

**Selling price of A =  $200 - 2 \cdot q(A)$**   
**Selling Price of B =  $250 - 3 \cdot q(B)$**   
**Determine optimal quantity of Product A and Product B for maximization of profit.**

**Profit = Quantity x Selling Price – Cost**  
$$= x_1(200 - 2x_1) + x_2(250 - 3x_2) - 30x_1 - 50x_2 - 100x_3$$
$$= 170x_1 - 2x_1^2 + 200x_2 - 3x_2^2 - 100x_3$$

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So, these are the decision variable, suppose  $x_1$  is the amount of product A to be produced in kg,  $x_2$  is the amount of product B to be produced in kg and  $x_3$  is the amount of raw material used is alright. So, what is the profit equation? Profit will be quantity into selling price minus cost is alright. So, what is the quantity? Quantity is  $x_1$  and  $x_2$  what is the selling price?  $200 - 2x_1$  into quantity, that is  $200 - 2x_1$  and here  $250 - 3x_2$  right.

So, that will be the quantity into selling price and what is the cost? Cost is 30 50 and 100. So,  $30x_1$ ,  $50x_2$ ,  $100x_3$  is it alright. So, that is the thing that the therefore, you can simplify. So, you see this is  $200x_1 - 2x_1^2 - 30x_1$ . So,  $170x_1$ ,  $250x_2 - 3x_2^2 - 50x_2$  so  $200x_2$  and minus  $2x_1^2 - 3x_2^2 - 100x_3$ . So, this is our objective function right. So, first part is done. So, we have obtained the profit, but there are some constraints also right

So, what is the constraint? Constraint is very clear that the 2 product  $x_1$  and  $x_2$  should not be the sum of these should not be more than the raw material available because that is a constraint, you cannot produce without the raw material. So, let us see what is that constraints here. So, let us see that.

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**NLPs with Inequality Constraints: Example 1**

**Objective Function**

Maximize  $f(x_1, x_2, x_3)$   
 $= 170x_1 - 2x_1^2 + 200x_2 - 3x_2^2 - 100x_3$

**Constraints**

$x_1 + x_2 \leq x_3$  i.e.  $x_1 + x_2 - x_3 \leq 0$   
 $x_3 \leq 40$   
 $x_1 \geq 0, x_2 \geq 0, x_3 \geq 0$

**Parameters:**  
Cost of producing A: INR 30/kg  
Cost of producing B: INR 50/kg  
Cost of Raw Material: INR 100/kg  
Maximum available raw material: 40 kg.  
Selling price of A =  $200 - 2 \cdot q(A)$   
Selling Price of B =  $250 - 3 \cdot q(B)$   
Determine optimal quantity of Product A and Product B for maximization of profit.

**Decision Variables:**  
 $x_1$ : Amount of Product A in kg  
 $x_2$ : Amount of Product B in kg  
 $y_1$ : Amount of Raw Material in kg

See the constraint therefore, will be  $x_1 + x_2 \leq x_3$  why because this is the first product this is the second product. So, if you add them that should be less than the raw material that is the quantity  $x_3$ . So, these kind be reformulated as  $x_1 + x_2$  minus  $x_3$  less than equal to 0.

So, see this side is the variables and this side because  $x_3$  is not b.i. So, b.i. has to be a constraint right cannot be a variable. So, since here we have a variable called  $x_3$  so; obviously, should be put as  $x_1 + x_2$  minus  $x_3$  less than equal to 0. So, these 0 is like b.i. So, this is our b.i., these are the variables right.

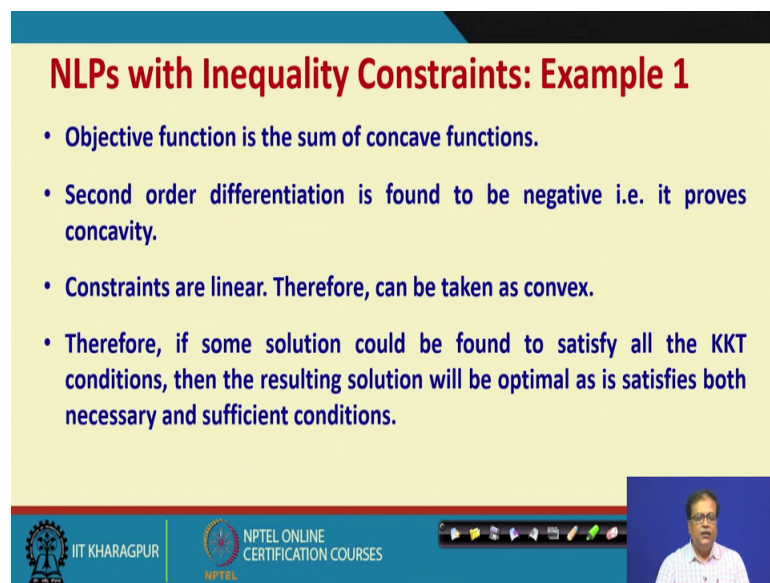
So, that is what we have that the first constraint. Now, the second constraint is also there that is  $x_3$  should be less than 40, because that is the total amount if you look at the problem that is the total amount that is available and obviously, since it is a real problem  $x_1, x_2, x_3$  all should be greater than equal to 0.

So, that is our starting point we have an objective function that is  $f(x_1, x_2, x_3)$  and maximize  $170x_1 - 2x_1^2 + 200x_2 - 3x_2^2 - 100x_3$  and these are our constraints right. So, the first question is how do we go ahead solving the problem. But before even that we should see that if we take the KKT conditions now, the KKT conditions will really provide the necessary conditions. The sufficient condition should be we have to ensure that the function is concave.

Now, incidentally we these function is concave, but then can we take the hessian matrix and find out whether the matrix is really concave I mean this objective function is really concave no problem about constraints because constraints are all linear.

So, all of them are linear constraints. So, with linear constraints automatically they are convex so, no issue there.

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**NLPs with Inequality Constraints: Example 1**

- Objective function is the sum of concave functions.
- Second order differentiation is found to be negative i.e. it proves concavity.
- Constraints are linear. Therefore, can be taken as convex.
- Therefore, if some solution could be found to satisfy all the KKT conditions, then the resulting solution will be optimal as it satisfies both necessary and sufficient conditions.


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So, let us see how we can see that these are concave. So, objective function is the sum of concave functions. So, if they are automatically the second order differentiation would be negative, that is it proves concavity. Constraints are linear so, therefore, they can be taken as convex.


Therefore, if some solution could be found to satisfy all the KKT conditions in the resulting solution will be optimal, as it satisfies both necessary and sufficient conditions.

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**Example 1: Checking Concavity of Obj. Fn.**

$$\text{Max } f(x_1, x_2, x_3) = x_1(200 - 2x_1) + x_2(250 - 3x_2) - 30x_1 - 50x_2 - 100x_3$$
$$\text{i.e. Max } f(x_1, x_2, x_3) = 170x_1 - 2x_1^2 + 200x_2 - 3x_2^2 - 100x_3$$
$$\nabla f(x_1, x_2, x_3) = \left( \frac{\partial f}{\partial x_1} \quad \frac{\partial f}{\partial x_2} \quad \frac{\partial f}{\partial x_3} \right) = ((170 - 4x_1) \quad (200 - 6x_2) \quad (-100))$$
$$\text{Hessian Matrix } H = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} & \frac{\partial^2 f}{\partial x_1 \partial x_3} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} & \frac{\partial^2 f}{\partial x_2 \partial x_3} \\ \frac{\partial^2 f}{\partial x_3 \partial x_1} & \frac{\partial^2 f}{\partial x_3 \partial x_2} & \frac{\partial^2 f}{\partial x_3^2} \end{bmatrix} = \begin{bmatrix} -4 & 0 & 0 \\ 0 & -6 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$


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So, let us look at the Hessian matrix. So, you see this is our function right that is the total function this is the simplified the function,  $170x_1$  minus  $2x_1^2$  plus  $200x_2$  minus  $3x_2^2$  minus  $100x_3$ . So, the gradient will be  $\frac{\partial f}{\partial x_1}$   $\frac{\partial f}{\partial x_2}$   $\frac{\partial f}{\partial x_3}$ . So, what should be? With respect to  $x_1$  if you differentiate you get  $170$  minus  $4x_1$ . With respect to  $x_2$   $200$  minus  $6x_2$ , and with respect to  $x_3$  minus  $100$ . So, this is our gradient. So, we got the gradient.

Next will be the hessian matrix. Now, you see since they are pure terms of  $x_1$   $x_2$ . So, all these terms you know they will be  $0$ . So, all of them are  $0$ . So, with respect to these  $\frac{\partial^2 f}{\partial x_1^2}$ , that becomes minus  $4$ .  $\frac{\partial^2 f}{\partial x_2^2}$  that becomes minus  $6$  and since there is no term this will become  $0$ . So, this is our Hessian matrix right.



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**Example 1: Checking Concavity of Obj. Fn.**

$$\begin{vmatrix} -4 & 0 & 0 \\ 0 & -6 & 0 \\ 0 & 0 & 0 \end{vmatrix} - \begin{vmatrix} \lambda & 0 & 0 \\ 0 & \lambda & 0 \\ 0 & 0 & \lambda \end{vmatrix} = 0$$

$(4 + \lambda) * (6 + \lambda) * \lambda = 0$

So we will have 3 different values for lambda.  
The values will be the following:


$$\lambda_1 = -4; \lambda_2 = -6; \lambda_3 = 0$$

As all the **eigenvalues** are found to be  $\leq 0$ ,  
the Hessian matrix is then '**Negative Semidefinite**'.


Solving this using the following equation,

$$(-4 - \lambda)[(-6 - \lambda) * (0 - \lambda)] = 0$$



Hence, The function will return Maximum value.



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So, we obtain the Hessian matrix now, we take the eigenvalue by making use of characteristic equation and this is eigenvalue equation and very simple this one, it comes to you know these kind of equations that is 4 plus lambda plus star 6 plus lambda star lambda equal to 0.

So, 3 different values of lambda could be minus 4 minus 6 and 0. So, all the eigenvalues are less than equal to 0. So, what is our conclusion? The conclusion is the Hessian matrix is negative semidefinite because one of the term is 0. So, automatically since the eigenvalues are negative only one is 0. So, we can say the function is concave and we can have maximum value out of these is alright.

So, I will stop here in our next lecture we continue the discussion on KKT conditions specifically, the problem that we are doing we shall complete the one.