

Optimization in Chemical Engineering
Prof. Debasis Sarkar
Department of Chemical Engineering
Indian Institute of Technology, Kharagpur

Lecture – 47
Constrained Nonlinear Programming (Contd.)

Welcome to lecture 47, this is week 10 and we were talking about Constraint Non-linear Programming in this week. In our previous lecture we have talked about successive linear programming for solution of non-linear programming problems. In today's lecture we will talk about a similar method and this is successive quadratic programming approximation of a general non-linear programming problem and a solution method based on that.

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Karush - Kuhn - Tucker (KKT) Conditions: Review

Minimize $f(\mathbf{x})$ $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$ **The Lagrangian:**

Subject to $g_j(\mathbf{x}) \leq 0$ for $j=1, 2, \dots, p$ $L(\mathbf{x}, \mathbf{u}, \mathbf{v}) = f(\mathbf{x}) + \sum_{i=1}^m v_i h_i(\mathbf{x}) + \sum_{j=1}^p u_j g_j(\mathbf{x})$

$h_k(\mathbf{x}) = 0$ for $k=1, 2, \dots, m$

$\Rightarrow L(\mathbf{x}, \mathbf{u}, \mathbf{v}) = f(\mathbf{x}) + \mathbf{v}^T \mathbf{h}(\mathbf{x}) + \mathbf{u}^T \mathbf{g}(\mathbf{x})$

1. Gradient conditions:

$$\frac{\partial L(\mathbf{x}^*, \mathbf{u}^*, \mathbf{v}^*)}{\partial x_i} = \frac{\partial f(\mathbf{x}^*)}{\partial x_i} + \sum_{j=1}^m v_j^* \frac{\partial h_j(\mathbf{x}^*)}{\partial x_i} + \sum_{j=1}^p u_j^* \frac{\partial g_j(\mathbf{x}^*)}{\partial x_i} = 0, \quad i=1, 2, \dots, n$$

2. Feasibility check:

$g_j(\mathbf{x}^*) \leq 0, \quad j=1, 2, \dots, p$

$h_i(\mathbf{x}^*) = 0, \quad i=1, 2, \dots, m$

3. Switching conditions: $u_j^* g_j = 0, \quad j=1, 2, \dots, p$

4. Non-negativity of Lagrange multipliers for inequalities: $u_j^* \geq 0, \quad j=1, 2, \dots, p$

5. Regularity check: Gradients of active constraints must be linearly independent.

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So, again we start with a brief review of KKT conditions we will make use of KKT conditions in today's lecture. So, we have a general non-linear programming problem minimization of objective function $f(\mathbf{x})$, which is the function of n variables subject to p inequality constraints all are less or equal to type and m number of equality constraints.

So, we first formulate the Lagrangian, define Lagrange multiplier and KKT multiplier for each of the constraints and then formulate the Lagrangian. The Gradient conditions which is $\frac{\partial L}{\partial x_i} = 0$. So, this will lead to n equations corresponding to n decision variables. Feasibility check, which says that the inequality constrained and the

equality constraints must be satisfied. Switching conditions, which says the product of Lagrange multiplier or the KKT multiplier with the inequality constrained will be equal to 0. Non- negativity of Lagrange multipliers for inequality constraints and finally, regularity check which says the gradients of active constraints must be linearly independent.

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Quadratic Programming Problems

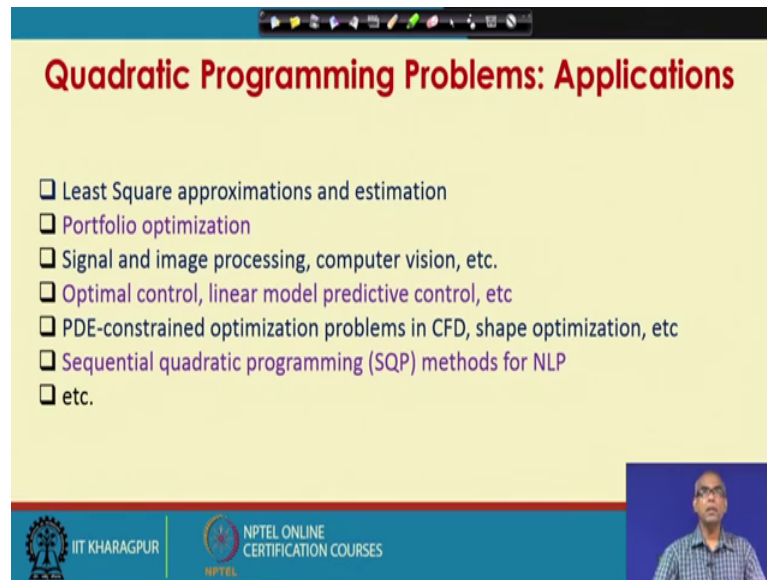
<p>A general NLP:</p> $\text{Minimize } f(\mathbf{x}) \quad \mathbf{x} = [x_1, x_2, \dots, x_n]^T$ $\text{Subject to } g_j(\mathbf{x}) \leq 0 \quad \text{for } j = 1, 2, \dots, p$ $h_k(\mathbf{x}) = 0 \quad \text{for } k = 1, 2, \dots, m$ <p>Here, $f(x)$, $g(x)$, $h(x)$ all are, in general, nonlinear functions.</p>	<p>The quadratic programming problem:</p> $\text{Minimize } f(\mathbf{x}) \quad \mathbf{x} = [x_1, x_2, \dots, x_n]^T$ $\text{Subject to } g_j(\mathbf{x}) \leq 0 \quad \text{for } j = 1, 2, \dots, p$ $h_k(\mathbf{x}) = 0 \quad \text{for } k = 1, 2, \dots, m$ <p>Here, the objective function $f(x)$ is quadratic function. The constraints $g(x)$, $h(x)$ are linear functions.</p>
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Now, let us first talk about quadratic programming problems. We are familiar with the structure of a general non-linear programming problem. In general in a non-linear programming problem you will have an objective function which is non-linear and inequality constraints and the equality constraints are all non-linear functions of decision variables. We have seen in case of linear programming, problem the objective function and all the constraints are linear functions of decision variable. In case of quadratic programming problem the objective function is a quadratic function, but the constraints are all linear functions.

So, quadratic programming problem the objective function is a quadratic function, but all the constraints are linear. So, quadratic programming problem has a special form where the objective function is non-linear, but to the extent that it is a quadratic function and similar to linear programming problem all the constraints are linear functions. So, perhaps we can intuitively think at this stage that it may be possible to solve a quadratic programming problem by use of a linear programming problem. The way we have solve

linear programming problem maybe it is possible by some modifications we will also be able to solve the quadratic programming problem following the method of solution of linear programming problem.

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The slide is titled "Quadratic Programming Problems: Applications" in red text. It features a list of applications, each preceded by a small square icon. The applications listed are: Least Square approximations and estimation, Portfolio optimization, Signal and image processing, computer vision, etc., Optimal control, linear model predictive control, etc., PDE-constrained optimization problems in CFD, shape optimization, etc., Sequential quadratic programming (SQP) methods for NLP, and etc. The slide also includes logos for IIT KHARAGPUR and NPTEL ONLINE CERTIFICATION COURSES at the bottom, and a small video inset of a speaker in the bottom right corner.

- ❑ Least Square approximations and estimation
- ❑ Portfolio optimization
- ❑ Signal and image processing, computer vision, etc.
- ❑ Optimal control, linear model predictive control, etc
- ❑ PDE-constrained optimization problems in CFD, shape optimization, etc
- ❑ Sequential quadratic programming (SQP) methods for NLP
- ❑ etc.

There are various applications of linear programming problems, sorry there are various applications for quadratic programming problems some of them are listed here least square approximation and estimation. The least square approximations and estimation lead to a quadratic programming problem, portfolio optimization, signal and image processing, computer vision etcetera, optimal control, linear model predictive control, Partial Differential Equation- constrained optimization problems in Computational Fluid Dynamics, shape optimization, sequential quadratic programming methods for solution of Non-Linear Programming problems etcetera.

So, there are various interesting applications of quadratic programming problems some of those are listed here.

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Quadratic Programming Problems

Let us define a general quadratic programming (QP) problem as follows:

$$\text{Minimize } q(\mathbf{x}) = \mathbf{c}^T \mathbf{x} + \frac{1}{2} \mathbf{x}^T H \mathbf{x}$$

Subject to $A^T \mathbf{x} \leq \mathbf{b}$

$$B^T \mathbf{x} = \mathbf{e}$$
$$\mathbf{x} \geq 0$$

$\mathbf{x} = [x_1, x_2, \dots, x_n]^T$, $\mathbf{c} = [c_1, c_2, \dots, c_n]^T$

$\mathbf{b} = [b_1, b_2, \dots, b_m]^T$, $\mathbf{e} = [e_1, e_2, \dots, e_p]^T$

$H = n \times n$ Hessian matrix, $A = n \times m$ Constant matrix, $B = n \times p$ Constant matrix

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So, let us now define a general quadratic programming problem, as you have mentioned that for a quadratic programming problem the objective function is the quadratic function. So, we can note that the objective function here is $\mathbf{c}^T \mathbf{x}$ plus half $\mathbf{x}^T H \mathbf{x}$ which you know that is a standard expression of a quadratic function.

Here \mathbf{c} is an n vector, \mathbf{x} is also n vector, each component is decision variables so, there n decision variables and \mathbf{c} are the corresponding coefficients. So, it is like $c_1 x_1 + c_2 x_2$ like that. So, $\mathbf{c}^T \mathbf{x}$ will lead to an equation like that, H is n cross n Hessian matrix. So, this is about the objective function which is a quadratic in \mathbf{x} , subject to set of inequality and equality constraints and they are all linear.

So, the inequality constrained is written as $A^T \mathbf{x} \leq \mathbf{b}$, where \mathbf{b} is m vector. So, basically you will have A matrix, you will have \mathbf{x} vector and then you will have \mathbf{b} vector. So, A is n cross m constrained matrix and this is n vector, next you have a set of equality constrained. Similarly equality constraints are written as $B^T \mathbf{x} = \mathbf{e}$, where B is the constrained matrix n cross p and \mathbf{e} is a p vector which represents the right hand side.

So, $A^T \mathbf{x} \leq \mathbf{b}$, \mathbf{b} represents the right hand side vector, $B^T \mathbf{x} = \mathbf{e}$, \mathbf{e} represents the right hand side vector and non negativity constrained on the decision variables. So, this is a general formulation of a quadratic programming problem where you have the objective function is a quadratic function $\mathbf{c}^T \mathbf{x}$ plus half $\mathbf{x}^T H \mathbf{x}$

transpose Hx subject to A transpose x less or equal to b as in equality constrained B transpose x equal to e as equality constraints and the non negativity constraints on decision variable x which is written as x greater equal to 0.

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Quadratic Programming Problems

$\text{Min } f(x) = -6x_1 + 2x_1^2 - 2x_1x_2 + 2x_2^2$ $\text{Min } f(x) = [-6 \ 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + [x_1 \ x_2] \begin{bmatrix} 4 & -2 \\ -2 & 4 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$
 $\text{s.t. } x_1 + x_2 = 2$
 $x_1, x_2 \geq 0$ $\text{s.t. } [1 \ 1] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = 2$

Compare with:

Minimize $q(x) = c^T x + \frac{1}{2} x^T H x$ $c = [-6 \ 0]$
 Subject to $A^T x \leq b$ $H = \begin{bmatrix} 4 & -2 \\ -2 & 4 \end{bmatrix}$
 $B^T x = e$ $B = [1 \ 1]$
 $x \geq 0$ $e = [2]$

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So, let us take an example, objective function is given as minus 6x 1 plus 2x 1 square minus 2x 1 x 2 plus 2x 2 square subject to x 1 plus x 2 equal to 2 and x 1 x 2 both are nonnegative. The objective function is a quadratic function compare now, with the general form. So, can you rewrite this equations into this form we can do that you need to identify that this expressions can be written as this note this part is c transpose x and this part is x transpose Hx, x is the n vector. So, x transposes is rho vector. So, x transpose Hx and c transpose x with help of that you can re write this original quadratic equation.

Similarly, x 1 plus x 2 equal to 2 can also be written as B transpose x equal to 2 note that c H B e are identified as shown. So, I will suggest you take similar such expressions and try to rewrite them in the standard form; that means, right in the form c transpose x plus half x transpose a Hx for the objective function. So, identify c and H and depending on whether you have equality constraints, inequality constraints or both you try to identify A and B and also write the constraints in the matrix notation.

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Quadratic Programming Problems: KKT Conditions

Minimize $q(x) = c^T x + \frac{1}{2} x^T H x$ Introduce slack variables S to transform inequalities to equalities.

Subject to $A^T x \leq b$

$B^T x = e$ $A^T x + S = b, S \geq 0$

$x \geq 0$

Define Lagrangian:

$L = c^T x + \frac{1}{2} x^T H x + u^T (A^T x + S - b) + v^T (B^T x - e) - w^T x$ Note that the non-negativity constraint $x \geq 0$ has been written as $-x \leq 0$.

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So, now let us write down the KKT conditions for the quadratic programming problems. So, the first thing is to introduce the slack variable to transform the inequality constraints to equality constraints, $A^T x \leq b$ or my inequality constraints. So, let us introduce slack variables S to each of these inequality constraints and in vector matrix notation we can write $A^T x + S = b$ and S is non 0 sorry S is non negative. We know that the slack variables will be non negative. So, note that S is a vector. So, we have now converted then equality constraints to equality constraints. So, I now have a objective function which is quadratic and all the constraints which are of equality type.

So, let us now define the Lagrangian. So, the Lagrangian is define following the usual practice this is my equality constraints which are transformed from the inequality constraints. So, in the Lagrangian formulation I have u as multipliers. So, $u^T (A^T x + S - b)$, this term I get for this equality constraints. Similarly for the original equality constraints in the original problem $v^T (B^T x - e)$ gets reflected in the Lagrangian as $v^T (B^T x - e)$.

And then finally, $x \geq 0$ is written as $-x \leq 0$ and I define the multiplied w . So, this becomes $-w^T x$ and we add all these thing terms to the objective function $c^T x + \frac{1}{2} x^T H x$. So, this is how the Lagrangian is formulated, the objective function these are the inequality constraints

which I converted to equality constrained by addition of slack variables. This is for the equality constraints which are already present in the original quadratic programming problem and this is due to non negativity restrictions on the decision variables. So, once I have this Lagrangian I can now apply the first order optimality conditions or we can write down the KKT conditions.

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Quadratic Programming Problems: KKT Conditions

Minimize $q(x) = c^T x + \frac{1}{2} x^T H x$ $L = c^T x + \frac{1}{2} x^T H x + u^T (A^T x + S - b) + v^T (B^T x - e) - w^T x$

Subject to $A^T x \leq b$ $\frac{\partial L}{\partial x} = c + Hx + Au + Bv - w = 0$

$B^T x = e$ $A^T x + S - b = 0$

$x \geq 0$ $B^T x - e = 0$

Complimentary slackness: $\begin{cases} u_i S_i = 0, i = 1, \dots, m; & S_i, u_i \geq 0, i = 1, \dots, m \\ w_i x_i = 0, i = 1, \dots, n; & w_i \geq 0, i = 1, \dots, n \end{cases}$

Solve these conditions for $x, u, v, S,$ and $w.$

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So, the KKT conditions we write down now, first is the gradient of the Lagrangian with respect to the decision variables equal to 0. So, this gives me this expression. So, this is Lagrangian take the derivative of L with respect to each decision variable.

So, if you do that I get c from this term, I get Hx from this term, I get Au from this term, I get Bv from this term and I get minus w from this term, note that this is a linear expression. And then you have the feasibility check so, this was gradient condition, this is the feasibility check the feasibility check says that these constraints must be satisfied. So, A transpose x plus S minus b equal to 0, B transpose x minus e equal to 0. And then the complementary slackness which says $u_i S_i$ equal to 0 for i equal to 1 to m and $w_i x_i$ equal to 0 for i equal to 1 to n . Note that there are n number of constraints in equality constraints note that there are n number of inequality constraints. So, for each of them you need slack variables.

So, these leads to $u_i S_i$ equal to 0 and this n decision variables needs $w_i x_i$ equal to 0 for i equal to 1 to n , note that S_i, u_i and w_i are all constrained to be greater or equal to 0,

the slack variables and the Lagrangian multipliers for the inequality constraints are nonnegative. So, that is why this greater or equal to 0 terms here. So, now, we can solve this conditions for x, u, v, s and w that will give me the KKT point and that maybe a candidate for optimal point.

So, now we have seen that these are basically linear equations, this is linear and these were already linear. So, now, these equations can be written in a compact form using matrix notations. So, let us see how we will do that.

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Transformation of KKT Conditions

Lagrangian multiplier for equality constraint is free in sign. Write it as: $v = y - z$ with $y, z \geq 0$

We can define the following matrix and vectors:

$$N = \begin{bmatrix} H & A & -I_{(n)} & 0_{(m \times m)} & B & -B \\ A^T & 0_{(m \times m)} & 0_{(m \times n)} & I_{(n)} & 0_{(m \times n)} & 0_{(m \times n)} \\ B^T & 0_{(p \times m)} & 0_{(p \times n)} & 0_{(p \times m)} & 0_{(p \times p)} & 0_{(p \times p)} \end{bmatrix}_{(n+m+p) \times (2n+2m+2p)}$$

$$X = \begin{bmatrix} x \\ u \\ w \\ s \\ y \\ z \end{bmatrix}_{(2n+2m+2p)}$$

$$D = \begin{bmatrix} -c \\ b \\ e \end{bmatrix}_{(n+m+p)}$$

Now, the KKT conditions can be written as:

$$NX = D$$

Complementary slackness conditions reduces to:

$$X_i X_{n+m+i} = 0, i = 1, \dots, (n+m) \quad \text{and} \quad X_i \geq 0, i = 1, \dots, (2n+2m+2p)$$

Note only complimentary slackness condition is nonlinear in variable X_i

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So, before doing that let us identify that the Lagrange multipliers for the equality constraint; that means, these v are free in sign, in other words they can take both positive and negative values.

So, we can express them as the difference of 2 non negative terms. So, this is what we do. So, replace v as y minus z with y greater equal to 0, z greater equal to 0, but u at the Lagrange multipliers for inequality constraints and they are already greater equal to 0. So, now, this I define X as a vector which contains all these variables decision variables, the Lagrangian multipliers, for the in equality constraints, the w for the x greater equal to 0, the slack variables and y and z that replaces v. So, I can define a vector of size 2 n plus 2 m plus 2 p.

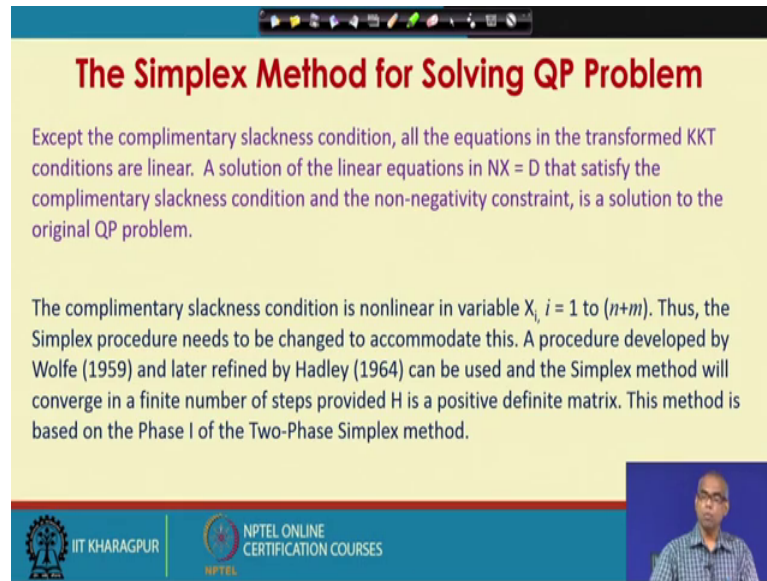
Similarly I define a D vector which is minus c b and e as components. So, it is n plus m plus p vector. Now if we define an N matrix using H as a Hessian matrix A and B and identity matrix and null matrix I basically represents the linear systems of equations that we obtained when you applied the KKT conditions; that means, these set of equations.

So, these set of linear systems can be represented in matrix notations using this definition of N, this definition of X and this definition of D, by $NX = D$. So, those KKT conditions the linear systems corresponding to KKT conditions can be written as $NX = D$, where N is this matrix, X and D are this vector and this vector respectively. The complementary slackness which are $u_i S_i = 0$ and $w_i x_i = 0$ can be written as $X_i X_{n+m+i} = 0$, for $i = 1$ to $n+m$ and $X_i \geq 0$ for $i = 1$ to $2n+2m+2p$, note that this is capital X.

So, this capital X is a vector with the decision variable vector X u w s y and z. So, now, if you look at these set of equations $NX = D$ and this new complementary slackness condition we see that except this complementary slackness conditions I have a linear set of linear systems I have a set of linear systems only the complementary slackness condition is non-linear in variable X i.

So, the solution to $NX = D$ if that solution satisfies the complementary slackness condition then it becomes a solution to the KKT point or solution to the original Quadratic Programming problem. So, I repeat the KKT conditions of the Quadratic Programming problem can be written as $NX = D$ which is a set of linear systems, which is a set of linear equations, the complementary slackness condition is non-linear. So, the solutions of $NX = D$, if the solution of $NX = D$ satisfies the complementary slackness condition, then the solution become a KKT point and this becomes a solution to the original Quadratic Programming problem.

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The Simplex Method for Solving QP Problem

Except the complimentary slackness condition, all the equations in the transformed KKT conditions are linear. A solution of the linear equations in $NX = D$ that satisfy the complimentary slackness condition and the non-negativity constraint, is a solution to the original QP problem.

The complimentary slackness condition is nonlinear in variable $X_i, i = 1$ to $(n+m)$. Thus, the Simplex procedure needs to be changed to accommodate this. A procedure developed by Wolfe (1959) and later refined by Hadley (1964) can be used and the Simplex method will converge in a finite number of steps provided H is a positive definite matrix. This method is based on the Phase I of the Two-Phase Simplex method.

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So, except the complementary slackness condition, all the equations in the transformed KKT conditions are linear. A solution of the linear equations in NX equal to D that satisfy the complementary slackness condition and the non negativity constraint, is a solution to the original quadratic programming problem.

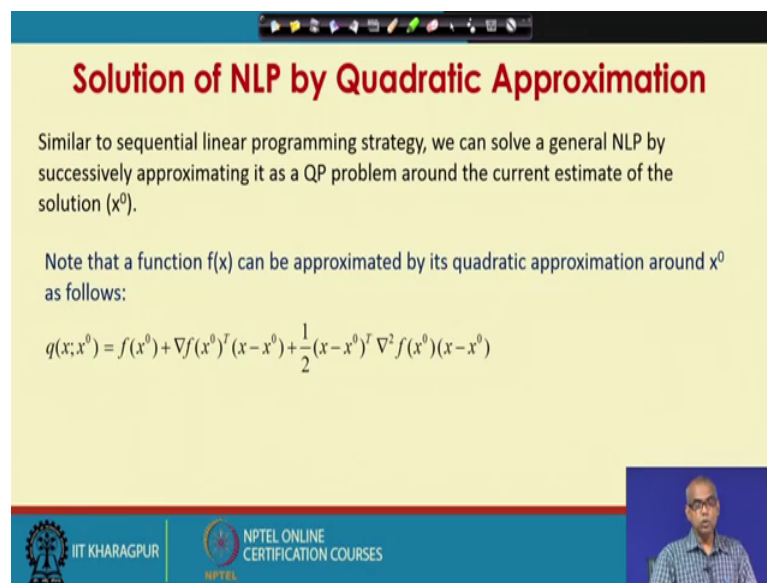
The complementary slackness condition is non-linear in variable X_i, i equal to 1 to n plus same. Thus, the simplest procedure needs to be changed to accommodate this. A procedure developed by Wolfe and later refined by Hadley can be used and the Simplex method will converge in a finite number of steps provided the Hessian matrix H is a positive definite matrix. This method is based on the phase one of the two- Phase Simplex Method that you have discussed earlier.

So, what we get it is that. The solution to the set of equation NX equal to D we need to find out and if that solution satisfies the complementary slackness condition I have a solution to the original programming problem. Now since the complementary slackness condition is non-linear the regular simplex method needs to be modified, that modification has been proposed by Wolfe and Hadley and the modified method can be used and the Simplex method then converges in a finite number of steps provided the Hessian matrixes of a positive definite matrix. So, we can conclude that the quadratic programming problem can be solved using a Simplex method where the Simplex method

needs to be modified to accommodate the non-linear complementary slackness conditions.

So, let us assume that we are able to solve a quadratic programming problem with non-linear complementary slackness condition by modified simplex method. So, then we know how to solve a quadratic programming problem.

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Solution of NLP by Quadratic Approximation

Similar to sequential linear programming strategy, we can solve a general NLP by successively approximating it as a QP problem around the current estimate of the solution (x^0).

Note that a function $f(x)$ can be approximated by its quadratic approximation around x^0 as follows:

$$q(x; x^0) = f(x^0) + \nabla f(x^0)^T (x - x^0) + \frac{1}{2} (x - x^0)^T \nabla^2 f(x^0) (x - x^0)$$

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So, similar to sequential linear programming strategy we can now solve a general non-linear programming problem by successively approximating it as a quadratic programming problem around the current estimate of the solution. Similar to sequential linear programming strategy we can solve a general non-linear programming problem by successively approximating it as a quadratic programming problem around the current estimate of the solution x^0 , note that a function $f(x)$ can be approximated by quadratic approximation around x^0 as shown.

So, this is $f(x^0)$ plus gradient of f at x^0 into $x - x^0$ plus half $(x - x^0)^T$ Hessian evaluated at x^0 into $x - x^0$. So, any function $f(x)$ can be approximated by its quadratic approximation which is this.

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Solution of NLP by Successive Quadratic Approximation: Algorithm

Step - 1: Formulate the QP problem

Minimize $\nabla f(x^{(t)})^T d + \frac{1}{2} d^T \nabla^2 f(x^{(t)}) d$

Subject to: $g_j(x^{(t)}) + \nabla g_j(x^{(t)}) d \geq 0, \quad j = 1, \dots, J$

$h_k(x^{(t)}) + \nabla h_k(x^{(t)}) d = 0, \quad k = 1, \dots, K$

$x_i \geq 0, \quad i = 1, \dots, N$

Step - 2: Solve the QP problem and set: $x^{(t+1)} = x^{(t)} + d$

Step - 3: Check for convergence. If converged, *Stop*. Else go to *Step - 1*

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So, we now give the algorithm for successive quadratic approximation. So, formulate the quadratic programming problem as shown; that means, the objective function is the quadratic function and note that the constraints has been converted to linear functions by performing Taylor series expansion this we have learnt during successive linear programming.

So, the inequality constraints and the equality constraints all are linearized by Taylor series expansion. So, this is the quadratic formulation. So, the quadratic objective function linearized inequality constrained by Taylor series expansion and retaining only first order term and also the equality constraints linearized equality constrained by Taylor series expansion retaining the first order term and the non negativity restrictions.

So, we solve now the quadratic programming problem and set the next estimate of the solution as $x^{t+1} = x^t + d$. So, this d is like $x - x_0$ that you have seen in the previous slide.

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Solution of NLP by Quadratic Approximation

Similar to sequential linear programming strategy, we can solve a general NLP by successively approximating it as a QP problem around the current estimate of the solution (x^0).

Note that a function $f(x)$ can be approximated by its quadratic approximation around x^0 as follows:

$$q(x; x^0) = f(x^0) + \nabla f(x^0)^T (x - x^0) + \frac{1}{2} (x - x^0)^T \nabla^2 f(x^0) (x - x^0)$$

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So, now, we check for the convergence in the step 3 if conversely stop otherwise you go to step 1; that means, with the current estimate again we reinitialize the quadratic programming problem and solve again and continue until we converge.

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**Solution of NLP by Successive Quadratic Programming:
Example**

Solve by successive QP strategy.

Minimize $f(x) = 6\frac{x_1}{x_2} + \frac{x_2}{x_1^2}$

Subject to: $g(x) = x_1 + x_2 - 1 \geq 0$
 $h(x) = x_1 x_2 - 2 = 0$

Initial feasible estimate: $x^0 = (2, 0)$

$f(x^0) = 12.25, h(x^0) = 0, g(x^0) = 2 > 0$

$$\nabla f(x) = \begin{bmatrix} 6x_2^{-1} - 2x_2 x_1^{-3} \\ -6x_1 x_2^{-2} + x_1^{-2} \end{bmatrix}$$

$$\nabla^2 f(x) = \begin{bmatrix} 6x_2 x_1^{-4} & -6x_2^{-2} - 2x_1^{-3} \\ -6x_1^{-2} - 2x_1^{-3} & 12x_1 x_2^{-3} \end{bmatrix}$$

$$\nabla h(x) = \begin{bmatrix} x_2 \\ x_1 \end{bmatrix}$$

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So, now let us take an example. So, you want to solve the problem $6x_1/x_2 + x_2/x_1^2$ by x_1 square and g equal to $x_1 + x_2 - 1$ greater equal to 0, h equal to $x_1 x_2 - 2$ equal to 0. So, you have equality constraints as non-linear objective function as

non-linear. So, we start with an initial feasible estimate of x^0 equal to 2, 0 that mean x_1 equal to 2, x_2 equal to 0.

So, find out the function value add x_1 equal to 2 x_2 equal to 0 find out the value of the objective function and find out the value of the constraints h at x equal to x^0 equal to 0 g at x^0 equal to 2. So, h is greater than 0 the point is feasible. So, evaluate the gradient write down the expression for the gradient hessian and the gradient of the equality constrained, note that in equality constrained is already linear.

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Solution of NLP by Successive Quadratic Programming: Example

The first QP sub-problem will be:

$$\text{Minimize } \begin{pmatrix} 23 \\ 4 \end{pmatrix} + \begin{pmatrix} -47 \\ 4 \end{pmatrix} d + \frac{1}{2} d^T \begin{bmatrix} 3 & -25 \\ 8 & 4 \\ -25 & 24 \end{bmatrix} d$$

Subject to: (1, 1) $d_1 + 2 \geq 0$
 (1, 2) $d_2 = 0$

The second constraints can be use to write: $d_1 = -2d_2$

Now the solution of single variable problem can be obtained as:
 $d^0 = (-0.9207, 0.4604)$

The new point becomes:
 $x^{(1)} = x^0 + d^0 = (1.0793, 1.4604)$
 $f(x^{(1)}) = 5.687$
 $h(x^{(1)}) = -0.424$
 $g(x^{(1)}) > 0$

The objective function has improved. However, equality constraint is violated. We can continue the procedure and find the optimum with high accuracy. True optimum is: $x^* = (1, 2), f(x^*) = 5$. We are already not very far in just one iteration.

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So, you can write down the first quadratic programming sub problem as this, note this is coming from this. The gradient of f the gradient of the objective function evaluated the current estimate in to d plus half transpose Hessian evaluated at current estimate in to d . So, you make use of these to write this.

So, this is the gradient of the objective function evaluate at the current estimate 2 0, this is Hessian evaluated at point 2 0 and inequality constrained linearized equality constraints. Now, the second constrained this you can use to write d_1 equal to minus 2 d_2 . So, you can express any of this d_1 or d_2 in terms of the other one, note that d is a vector with components d_1 and d_2 .

So, d_1 can be written as minus 2 d_2 . So, then the solution of the single variable problem can be obtained analytically. So, note that this is you have compare it with c transpose x

plus half $x^T H x$, here x is d , d has components d_1 and d_2 . Now once I express d_1 as $-2d_2$, I have a single variable problem this can be solved analytically I get the solution as d_0 equal to $-0.9207, 0.4604$. So, once I have the solution d_0 , I can get the new point x_1 as x_0 plus d_0 which is $1.0793, 1.4604$ as x_1 and x_2 . So, this is x_1 , this is x_2 .

So, this has components like this. So, evaluate the function 5.687 , equality constraint is -0.424 , inequality constraint is greater than 0 . So, the equality constraint is violated, objective function is improved. So, you have to continue the procedure and then you can find the optimum with high accuracy; the true optimum is x_1 equal to 1 , x_2 equal to 2 , objective function equal to 5 .

So, we are already the objective function value at 5.687 . So, if you do the next iteration you will see that you have obtained the solution with high accuracy very close to 5 . So, how will you do that? We have now the value x_1 as $1.0793, 1.4604$ so, with this estimate again you have to reinitialize the problem; that means, you have to put the values of x_1 and x_2 in these.

And, then you will write the problem in this form; that means, you will obtain the second quadratic programming sub problem and then you will solve for d you will solve for d_1 , then you will solve for x_2 which will be x_1 and d_1 . So, that solution we will see that is very close to true solution $1, 2$ and the objective function value will also be very close to 5 . So, this is how you will be able to solve a general non-linear programming problem using successive quadratic programming. With this we stop lecture 47 here.