Numerical Optimization

Finding the best feasible solution

Edward P. Gatzke

Department of Chemical Engineering University of South Carolina

Ed Gatzke (USC CHE)

Numerical Optimization

ECHE 589, Spring 2011 1 / 32

Review: Unconstrained Optimization

- "Objective Function" or "Cost Function"
 - May be function of many variables
- Ex: $\min x^2 + y^2$
 - 2D problem defines manifold (surface) in 3D space

•
$$z = x^2 + y^2$$

• Must find point where gradient of function = 0

$$\nabla f(x,y) = \left[\begin{array}{c} \frac{\delta f}{\delta x}\\ \frac{\delta f}{\delta y} \end{array}\right]$$

$$f(x,y) = x^3 y^2$$

• Question: What is equivalent to the gradient of the above function evaluated at the point x = 1, y = 1

• [A]
$$\begin{bmatrix} 3x \\ 2y \end{bmatrix}$$
 [B] $\begin{bmatrix} 3 \\ 2 \end{bmatrix}$ [C] $\begin{bmatrix} 3x^2y^2 \\ 2x^3y \end{bmatrix}$

- [D] All of the above.
- [E] I have no clue.
- Answer:

• ???



$$f(x,y) = 3x - 2y$$

• Question: What is the gradient of the above function at x = 1, y = 1

• [A]
$$\begin{bmatrix} 0\\0 \end{bmatrix}$$
 [B] $\begin{bmatrix} 3\\2 \end{bmatrix}$ [C] $\begin{bmatrix} 3\\-2 \end{bmatrix}$

- [D] All of the above.
- [E] I have no clue.
- Answer:
 - ???



Review: Unconstrained Optimization

- For minimization, $-\nabla f$ points "downhill" in steepest direction
- Trick for maximization problems:

$$\max_{\underline{x}} f(\underline{x}) = \min_{\underline{x}} - f(\underline{x})$$

- Steepest Descent Method:
 - Start at initial guess, <u>x</u>₀
 - Evaluate $-\nabla f$ at current point
 - Perform line search in improving direction
 - Update current best point and repeat until $-\nabla f$ is "small"



Review: Constrained Optimization

• Standard form with N constraints:

 $\min_{\underline{x}} f(\underline{x})$ subject to $g_1(\underline{x}) \le 0$ $g_2(\underline{x}) \le 0$ \vdots $g_N(\underline{x}) \le 0$

Bounds on variables in standard form:

$$1 \le x \le 10$$

 $\begin{array}{l} 1-x\leq 0\\ x-10\leq 0\end{array}$



Review: Constrained Optimization

• Standard form with *N* constraints:

$$\min_{\underline{x}} f(\underline{x})$$
subject to $g_1(\underline{x}) \le 0$
 $g_2(\underline{x}) \le 0$
 \vdots
 $g_N(\underline{x}) \le 0$

• Equality constraints in standard form:

$$x = y^{2}$$
$$0 \le x - y^{2} \le 0$$
$$x - y^{2} \le 0$$
$$-x + y^{2} \le 0$$

Ed Gatzke (USC CHE)

Review: Linear vs. Nonlinear

• Linear examples and general form for sets of linear equality and inequality constraints:

Numerical Optimization

$$2x + 3y = 4$$
$$x - y \le 2$$
$$\underline{\underline{A}} \underline{x} = \underline{b}$$
$$\underline{A} x \le b$$

• Nonlinear examples and general form for nonlinear constraints:

$$2x^2 + y^2 = 4$$
$$y = e^x$$

$$g(\underline{x}) \le 0$$
$$h(\underline{x}) = 0$$



ECHE 589, Spring 2011

Review: Convex vs. Nonconvex

- Eigenvalues of Hessian must be ≥ 0 to be convex function
- Graphically: In a convex set you may pick any two points and the line between the two points contains only points inside the set.
- Get problem in standard form, check Hessian eigenvalues:

$$y \ge x^{2}$$

$$x^{2} - y \le 0$$

$$\nabla f(\underline{x}) = \begin{bmatrix} 2x \\ -1 \end{bmatrix} H = \begin{bmatrix} \frac{\partial^{2}f}{\partial x^{2}} & \frac{\partial^{2}f}{\partial y\partial x} \\ \frac{\partial^{2}f}{\partial x\partial y} & \frac{\partial^{2}f}{\partial y^{2}} \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$$

Eigenvalues are 2, 0 so $y \ge x^2$ is a convex constraint.

Ed Gatzke (USC CHE)

Numerical Optimization

SOUTH CAROLINA

ECHE 589, Spring 2011

Review: Convex vs. Nonconvex

• Unconstrained example

$$\min_{x,y} x^2 + y^2$$

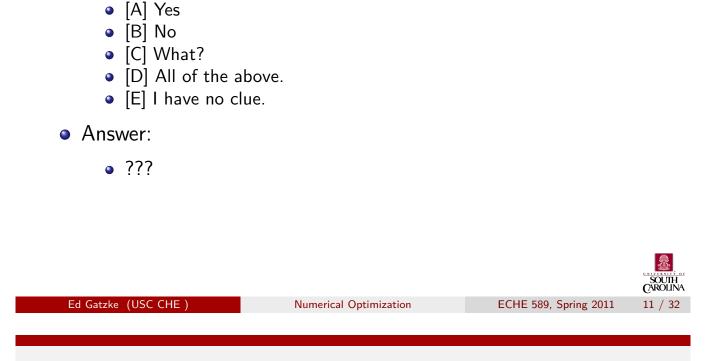
$$\nabla f(\underline{x}) = \begin{bmatrix} 2x\\2y \end{bmatrix} H = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2} & \frac{\partial^2 f}{\partial y \partial x} \\ \\ \frac{\partial^2 f}{\partial x \partial y} & \frac{\partial^2 f}{\partial y^2} \end{bmatrix} = \begin{bmatrix} 2 & 0\\ 0 & 2 \end{bmatrix}$$

Eigenvalues are 2, 0 so $x^2 + y^2$ is a convex constraint.





 $x^2 + y^2 \ge 9$



Review: Convex vs. Nonconvex

Question: Is the constraint convex?

• General form for constrained optimization:

 $\min_{\underline{x}} f(\underline{x})$ subject to $g_1(\underline{x}) \le 0$ $g_2(\underline{x}) \le 0$ $h_1(\underline{x}) = 0$ $h_2(\underline{x}) = 0$

• Rules. Nonconvex problem if any of following are true:

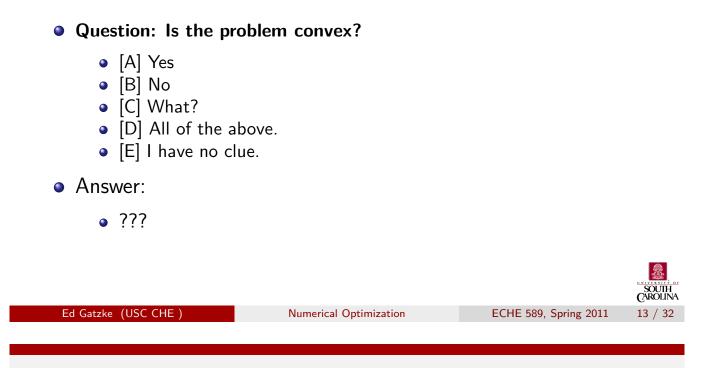
- $f(\underline{x})$ is a nonconvex function in the domain of \underline{x}
- Any $g_i(\underline{x})$ inequality constraint is a nonconvex function in the domain of \underline{x}
- Any $h_i(\underline{x})$ equality constraint is nonlinear

• Convex problems have a single solution



ECHE 589, Spring 2011

$$\min_{x,y} -2x + y$$
$$x^2 + y^2 \le 9$$



Review: KKT Conditions

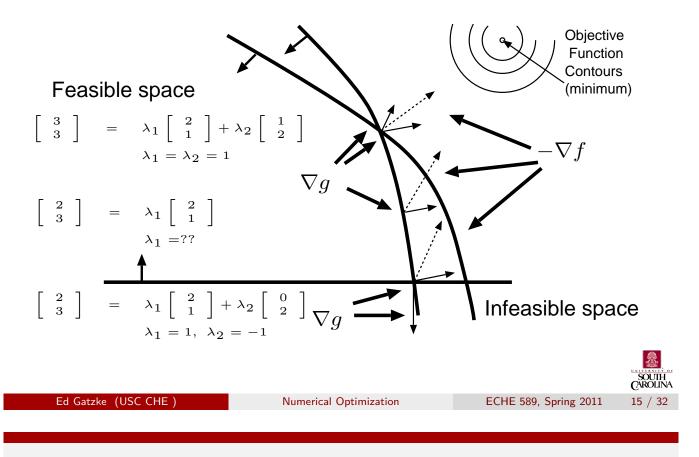
- Check to see if a point \underline{x}^* is optimal in constrained optimization
 - Put problem in standard form with only inequality constraints
 - Find any active constraints, $g_i(\underline{x}^*) = 0$
 - Solve for Lagrange multipliers

$$-\nabla f(\underline{x}^*) = \sum \lambda_i g_i(\underline{x}^*)$$
$$\lambda_i \ge 0$$

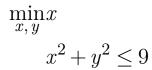
- Lagrange multipliers represent how "hard" the problem "pushes" against the constraints
- Lagrange multipliers must all be positive for the point to be a KKT point



Review: KKT Conditions



Question 5



• Question: Is the point x = -3, y = 0 a KKT point?

- [A] Yes
- [B] No
- [C] What?
- [D] All of the above.
- [E] I have no clue.
- Answer:
 - ???



• Question: Why do we care about optimization?

- [A] Gatzke told me to
- [B] Model Predictive Control (MPC)
- [C] Parameter estimation
- [D] It is a useful tool for many problems
- [E] All of the above

Answer:

• ???



Motivation: Process Design

- Objective function: Maximize profits, minimize cost
- Decision variables:
 - Number and size of components
 - Flow rates, temperatures, pressures
- Constraints
 - Mass and energy balances / design equations
 - Environmental limits, product limits



Motivation: Process Modeling

- Objective function: minimize the error between data and model
- Decision variables:
 - Model parameters (kinetic parameters)
- Constraints:
 - Model equations
 - Assumed limits on parameters
 - Physical limits on variables (concentrations positive)



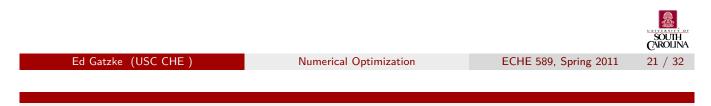
Motivation: Process Scheduling

- Objective function: minimize the cost for your process
- Decision variables:
 - When to make products
 - What equipment to use
- Constraints:
 - Limits on batch sizes
 - Limits on storage
 - Order fulfillment requirements



Motivation: Process Control

- Objective function: minimize future deviation from setpoint
- Decision variables:
 - Future process input values
- Constraints:
 - Dynamic model equations for prediction
 - Limits on the inputs
 - Process variable limits



Problems: Linear Programming (LP)

Space for Notes Below



Problems: Quadratic Programming (QP)

Space for Notes Below



Problems: Nonlinear Programming (NLP)

Space for Notes Below



Problems: Mixed-Integer Linear Programming (MILP)

Space for Notes Below

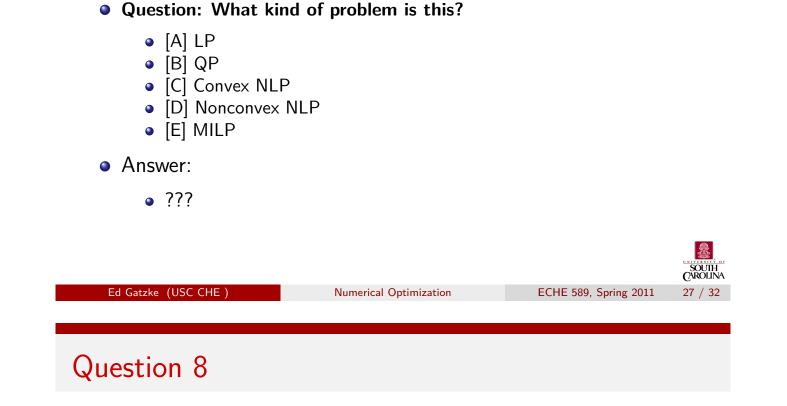


Problems: Mixed-Integer Nonlinear Programming (MINLP)

Space for Notes Below



$$\min_{\substack{x,y \\ x^2 + y^2 \le 9}} - x$$

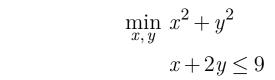


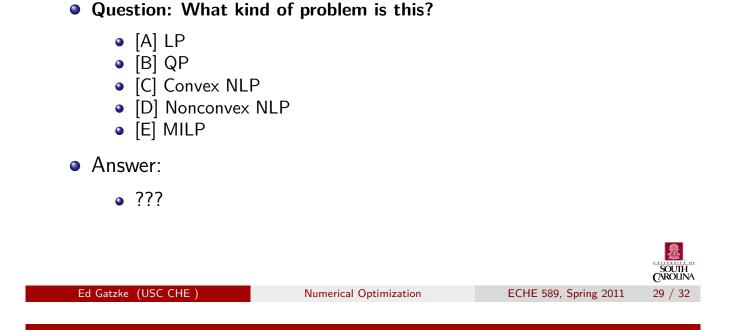
$$\min_{x,y} - x$$
$$x + y \le 9$$
$$y - x = 7$$

• Question: What kind of problem is this?

- [A] LP
- [B] QP
- [C] Convex NLP
- [D] Nonconvex NLP
- [E] MILP
- Answer:
 - ???







LP / NLP / QP Solution Strategies

- Active set (simplex)
 - Pick set of active constraints
 - Solve problem in form Ax = b
 - Check to see if KKT holds

Interior point

- Put constraints into objective function
- Find improving direction
- Polynomial time algorithm



NLP / MILP / MINLP Stochastic Solution Strategies

- Genetic Algorithms
 - Make a "population" of random points, evaluate [0 1 1 0 0 1]
 - "Breed" based on resulting objective function values
 - "Mutate" some points randomly
- Simulated Annealing
 - Start at some initial guess
 - Search randomly nearby
 - As system "cools" limit search area
- Particle Swarm
 - Start with a random group of points
 - Get group information to move in better direction

			CAROLINA
Ed Gatzke (USC CHE)	Numerical Optimization	ECHE 589, Spring 2011	31 / 32

Question 10

- What is the most confusing optimization topic?
 - [A] Convexity of functions / constraints
 - [B] KKT conditions
 - [C] Problem classification
 - [D] Solution strategies
 - [E] Other
- Answer:
 - ???

