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- 1) In Affine Scaling Approach move direction is calculated as  $\Delta \mathbf{x} = \mp \mathbf{P} \mathbf{c}$ . Why does the projection matrix  $\mathbf{P} = \mathbf{I} - \mathbf{A}^T (\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A}$  generate a feasible direction?

In the affine scaling method, feasibility is defined with respect to the equality constraints

$$\mathbf{A} \mathbf{x} = \mathbf{b}$$

When we take a step, the new point must also satisfy:

$$\mathbf{A}(\mathbf{x} + \Delta \mathbf{x}) = \mathbf{b}$$

This holds only if:

$$\mathbf{A} \Delta \mathbf{x} = \mathbf{0}$$

$$\mathbf{P} = \mathbf{I} - \mathbf{A}^T (\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A}$$

$$\mathbf{A} \mathbf{P} = \mathbf{A} (\mathbf{I} - \mathbf{A}^T (\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A}) = \mathbf{A} - \mathbf{A} \mathbf{A}^T (\mathbf{A} \mathbf{A}^T)^{-1} \mathbf{A} = \mathbf{A} - \mathbf{A} = \mathbf{0}$$

$$\mathbf{A} \Delta \mathbf{x} = \mathbf{A} (\mp \mathbf{P} \mathbf{c}) = \mathbf{0}$$

Because of  $\mathbf{A} \mathbf{P} = \mathbf{0}$ , any direction calculated using  $\mathbf{P}$  (such as  $\Delta \mathbf{x} = \mp \mathbf{P} \mathbf{c}$ ) ensures that  $\mathbf{A} \Delta \mathbf{x} = \mathbf{0}$ . Therefore, the equality constraint remain satisfied, making the direction feasible.

- 2) In the Affine Scaling Approach, the following equation is used in the final step of an iteration:

$$\tilde{\mathbf{x}}_{\text{new}} = \tilde{\mathbf{x}} + \frac{\alpha}{\nu} \mathbf{c}_P$$

What do  $\alpha$  and  $\nu$  represent in this equation? Explain the rationale for using each of these parameters.

**$\nu$ :** Negative components of  $\mathbf{c}_P$  indicate directions in which some variables decrease. If the step is too large, a variable may become zero or negative, violating feasibility ( $\tilde{x}_i > 0$ ). Dividing by  $\nu$  normalizes the step so that the largest decrease is scaled to a safe unit level.

This ensures the algorithm moves in the descent direction without leaving the feasible region.

**$\alpha$ :** controls how much of the maximum feasible step is actually taken.

A larger  $\alpha$  gives faster progress toward optimality, while a smaller  $\alpha$  improves numerical stability.

$\alpha$  is chosen:

- small enough that we don't approach the bound of the feasible region too much,
- large enough to make progress.

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**Question:**

Consider the following non-linear program.

$$\text{Minimize} \quad f(x_1, x_2, x_3) = x_1 \cdot x_2 + e^{x_2} + (x_3 - 5x_1)^2 - 4x_1$$

Subject to

$$x_1^2 + x_2^2 + x_3 \leq 25$$

$$x_1 + 3x_3 \geq 12$$

$$x_2 \geq 0$$

Write down the Karush-Kuhn-Tucker (KKT) conditions necessary for optimality. (Do not solve the system, just list the equations explicitly).

**Solution:**

$$g_1(x) = x_1^2 + x_2^2 + x_3 \quad b_1 = 25$$

$$g_2(x) = x_1 + 3x_3 \quad b_2 = 12$$

$$g_3(x) = x_2 \quad b_3 = 0$$

- complementary slackness conditions

$$\lambda_1(25 - x_1^2 - x_2^2 - x_3) = 0$$

$$\lambda_2(12 - x_1 - 3x_3) = 0$$

$$\lambda_3(-x_2) = 0$$

- sign restrictions

$$\lambda_1 \leq 0$$

$$\lambda_2 \geq 0$$

$$\lambda_3 \geq 0$$

- gradient equation

$$\nabla f(x) = \sum_{i=1}^3 \lambda_i \nabla g_i(x)$$

$$\nabla f(x) = \begin{pmatrix} x_2 + 2(x_3 - 5x_1)(-5) - 4 \\ x_1 + e^{x_2} \\ 2(x_3 - 5x_1) \end{pmatrix} = \begin{pmatrix} x_2 - 10(x_3 - 5x_1) - 4 \\ x_1 + e^{x_2} \\ 2(x_3 - 5x_1) \end{pmatrix}$$

$$\nabla g_1(x) = \begin{pmatrix} 2x_1 \\ 2x_2 \\ 1 \end{pmatrix}$$

$$\nabla g_2(x) = \begin{pmatrix} -1 \\ 0 \\ -3 \end{pmatrix}$$

$$\nabla g_3(x) = \begin{pmatrix} 0 \\ -1 \\ 0 \end{pmatrix}$$

$$x_2 - 10(x_3 - 5x_1) - 4 + 2\lambda_1 x_1 - \lambda_2 = 0$$

$$x_1 + e^{x_2} + 2\lambda_1 x_2 - \lambda_3 = 0$$

$$2(x_3 - 5x_1) + \lambda_1 - 3\lambda_2 = 0$$

• **primal constraints of the original NLP model**

$$x_1^2 + x_2^2 + x_3 \leq 25$$

$$x_1 + 3x_3 \geq 12$$

$$x_2 \geq 0$$