

Programming Exercise Report

Quadratic Programming with Interior Point Method

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Outline

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2 Solution with Interior Point Method

3 Comparison with quadprog

Problem Definition

Solve the following quadratic programming problem:

$$\min_{x \in \mathbb{R}^4} \frac{1}{2} x^T Q x + c^T x,$$

$$\text{s.t. } a_1^T x \leq b_1,$$

$$a_2^T x \leq b_2,$$

Where:

$$Q = \begin{pmatrix} 4 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 6 & 0 \\ 0 & 0 & 0 & 8 \end{pmatrix} \quad c = \begin{pmatrix} -8 \\ -6 \\ -4 \\ -2 \end{pmatrix}$$

$$a_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}, \quad b_1 = 3 \quad a_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}, \quad b_2 = 4$$

Step 1: Constructing the Barrier Function

The problem is transformed using a barrier function:

$$Q'(x, r) = \frac{1}{2}x^T Qx + c^T x - r \sum_{i=1}^2 \ln(b_i - a_i^T x)$$

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And the Hessian matrix \mathbf{H} is:

$$\mathbf{H} = Q + r \sum_{i=1}^2 \frac{a_i a_i^T}{(b_i - a_i^T x)^2}$$

The MATLAB Code for This Section

Define functions for $\nabla_x Q'(x, r)$ and \mathbf{H} :

```
Grad_Q_prime = @(x) (Q * x + c) - ...
    r_val * ( (-a1 / (b1 - a1' * x)) + ...
               (-a2 / (b2 - a2' * x)) );

Hessian_Q_prime = @(x) Q + r_val * ( ...
    (a1 * a1') / (b1 - a1' * x)^2 + ...
    (a2 * a2') / (b2 - a2' * x)^2 );
```

Step 2: Solving with Newton's Method

For a fixed parameter r , we find the central path by solving
 $\nabla_x Q'(x_k, r) = 0$.

① Calculate Newton step \mathbf{p}_k

$$\mathbf{H}_k \mathbf{p}_k = -\nabla_x Q'(x_k, r)$$

② Update \mathbf{x} :

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{p}_k$$

③ Stopping Condition:

$$\|\nabla_x Q'(x_k, r)\|_2 < \varepsilon$$

Step 3: The Path-Following Algorithm

The overall algorithm iteratively reduces r and solves for the new center.

```
for path_k = 1:MAX_PATH_ITER

    % Define Grad and Hessian with current r_val
    % ...

    % Solve for the central path
    x_center = newtonSolver(Grad_Q_prime, ...
                           Hessian_Q_prime, x_k);

    if r_val < R_TOLERANCE
        x_opt = x_center;
        return;
    end

    % Decrease the barrier parameter
    r_val = mu * r_val;

    x_k = x_center;
end
```

Final Solution

The solution obtained by the Interior Point Method is:

$$x_{ipm} = \begin{pmatrix} 1.333 \\ 1.667 \\ 0.667 \\ 0.25 \end{pmatrix}$$

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This can be verified using MATLAB's 'quadprog' function.

Result from 'quadprog'

The result from 'quadprog' is identical, confirming our solution.

Experiment 1: Scaling the Problem Coefficients

We scale Q and c by a factor and compare performance.

| Scale | IPM Time (s) | quadprog Time (s) | IPM Obj Val | quadprog Obj Val |
|--------|---|-------------------|--------------|------------------|
| 0.10 | 0.069796 | 0.015464 | -1.591667 | -1.591667 |
| 1.00 | 0.126931 | 0.015377 | -15.916667 | -15.916667 |
| 10.00 | 0.083019 | 0.012009 | -124.247078 | -159.166667 |
| | - Warning: For scale 10.00 , the norm of solution difference is 1.525770e+00 | | | |
| 100.00 | 0.174953 | 0.049813 | -1359.491383 | -1591.666667 |
| | - Warning: For scale 100.00 , the norm of solution difference is 1.244120e+00 | | | |

Figure: Initial Result: The method fails as scale increases.

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Figure: Initial Result: The method fails as scale increases.

Reason: The initial barrier parameter r was fixed. It should be scaled along with the problem data.

Experiment 1: Corrected Results

After scaling r with the same factor, we get correct results.

| Scale | IPM Time (s) | quadprog Time (s) | IPM Obj Val | quadprog Obj Val |
|--------|--------------|-------------------|--------------|------------------|
| 0.10 | 0.060116 | 0.020203 | -1.591667 | -1.591667 |
| 1.00 | 0.148444 | 0.017543 | -15.916667 | -15.916667 |
| 10.00 | 0.107294 | 0.011425 | -159.166667 | -159.166667 |
| 100.00 | 0.114949 | 0.054408 | -1591.666667 | -1591.666667 |

Figure: Corrected Result: The method is now stable.

Experiment 2: Scaling the Problem Size

We compare run-time by increasing the number of variables (n) and constraints (m).

- $n = [10, 40, 100]$
- $m = 0.5 \times n$
- Compare run-time of our IPM vs. 'quadprog'.

| Variables | Constraints | IPM Time (s) | quadprog Time (s) |
|-----------|-------------|--------------|-------------------|
| 10 | 5 | 0.000347 | 0.000817 |
| 40 | 20 | 0.035097 | 0.000835 |
| 100 | 50 | 0.073953 | 0.006258 |

Figure: Run-time comparison

Conclusion from Experiments

- **Correctness:** The implemented Interior Point Method is correct, but requires careful tuning of parameters like the initial barrier value r .
- **Performance:** Function 'quadprog' is faster. As the problem size increases, the performance of the interior-point method is becoming better and better, showing that the interior-point method is efficient for large-scale problems.

Thank You!