Interior Point Methods (I)

Lecture 14, Convex Optimization

National Taiwan University

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Inequality constrained minimization problems (1/2)

- In this chapter, we discuss **interior-point methods** for solving convex optimization problems that include inequality constraints,

$$\begin{aligned} \text{minimize} \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 0, \quad i = 1, ..., m \\ & Ax = b, \end{aligned}$$

  where $f_0, ..., f_m : \mathbf{R}^n \to \mathbf{R}$ are convex and twice continuously differentiable, and $A \in \mathbf{R}^{p \times n}$ with rank $A = p < n$.
- We assume that an optimal x^* exists and denote the optimal value $f_0(x^*)$ as p^*.

Inequality constrained minimization problems (2/2)

- We also assume that the problem is strictly feasible, i.e., there exists $x \in \textbf{relint}\ \mathcal{D}$ that satisfies $Ax = b$ and $f_i(x) < 0$ for $i = 1, \ldots, m$. (i.e., Slater's constraint qualification holds), so there exist dual optimal $\lambda^* \in \mathbf{R}^m$ and $\nu^* \in \mathbf{R}^p$, which together with x^* satisfy the KKT conditions

$$
\begin{aligned}
Ax^* &= b, \\
f_i(x^*) &\leq 0, \quad i = 1, \ldots, m \\
\lambda^* &\succeq 0 \\
\nabla f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* \nabla f_i(x^*) + A^T \nu^* &= 0 \\
\lambda_i^* f_i(x^*) &= 0, \quad i = 1, \ldots, m.
\end{aligned}
$$

Interior-Point Methods and the Barrier Method (1/2)

- Interior-point methods solve the optimization problem (or the corresponding KKT conditions) by applying Newton's method to a sequence of equality constrained problems, or to a sequence of modified versions of the KKT conditions.
- We will concentrate on a particular interior-point algorithm, the **barrier method**.
- We can view interior-point methods as another level in the hierarchy of convex optimization algorithms.
  - Linear equality constrained quadratic problems $\rightarrow$ Newton's method $\rightarrow$ Interior-point methods

Interior-Point Methods and the Barrier Method (2/2)

- Linear equality constrained quadratic problems are the simplest. For these problems the KKT conditions are a set of linear equations, which can be solved analytically.
- Newton's method is the next level in the hierarchy. We can think of Newton's method as a technique for solving a linear equality constrained optimization problem, with twice differentiable objective, by reducing it to a sequence of linear equality constrained quadratic problems.
- Interior-point methods form the next level in the hierarchy: they solve an optimization problem with linear equality and inequality constraints by reducing it to a sequence of linear equality constrained problems.

Examples (1/2)

- Many problems are already in the form of a convex optimization problem, and satisfy the assumption that the objective and constraint functions are twice differentiable.
- Obvious examples are LPs, QPs, QCQPs, and GPs in convex form; another example is linear inequality constrained entropy maximization,

$$\begin{array}{ll} \text{minimize} & \sum_{i=1}^{n} x_i \log x_i \\ \text{subject to} & Fx \preceq g \\ & Ax = b, \end{array}$$

with domain $\mathcal{D} = \mathbf{R}^n_{++}$.

Examples (2/2)

- Many other problems do not have the required form with twice differentiable objective and constraint functions, but can be reformulated in the required form.
- We have already seen many examples of this, such as the transformation of an unconstrained convex piecewise-linear minimization problem

$$\text{minimize} \quad \max_{i=1,\ldots,m} (a_i^T x + b_i)$$

(with nondifferentiable objective), to the LP

$$\begin{array}{ll} \text{minimize} & t \\ \text{subject to} & a_i^T x + b_i \leq t, i = 1, \ldots, m \end{array}$$

(having twice differentiable objective and constraint functions).

Eliminating Inequality Constraints (1/2)

- Goal: approximately formulate the inequality constrained problem as an equality constrained problem to which Newton's method can be applied.
- Our first step is to rewrite the problem

$$\begin{array}{ll} \text{minimize} & f_0(x) \\ \text{subject to} & f_i(x) \leq 0, \quad i = 1, ..., m \\ & Ax = b, \end{array}$$

making the inequality constraints implicit in the objective.

Eliminating Inequality Constraints (2/2)

- As a result, we obtain the following equivalent problem:

$$\begin{array}{ll} \text{minimize} & f_0(x) + \sum_{i=1}^{m} I_-(f_i(x)) \\ \text{subject to} & Ax = b, \end{array}$$

where $I_- : \mathbf{R} \to \mathbf{R}$ is the indicator function for the nonpositive reals, i.e., $\mathbf{dom}\ I_- = -\mathbf{R}_+$, and $I_-(u) = 0 \ \ \forall u \in -\mathbf{R}_+$, or its extended-value extension $\tilde{I}_-$ has the form

$$\tilde{I}_-(u) = \begin{cases} 0 & u \leq 0 \\ \infty & u > 0. \end{cases}$$

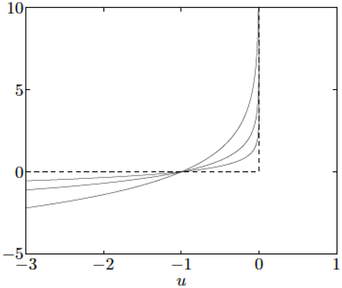
- The reformulated problem has no inequality constraints, but its objective function is not (in general) differentiable, so Newton's method cannot be applied.

Logarithmic barrier (1/4)

- We approximate the indicator function I_- by the function

$$\hat{I}_-(u) = -(1/t)\log(-u), \quad \textbf{dom}\ \hat{I}_- = -\mathbf{R}_{++},$$

where $t > 0$ is a parameter for the approximation accuracy.



- Like I_-, the function $\hat{I}_-$ is convex and nondecreasing, and takes on the value ∞ for $u > 0$. However, unlike I_-, $\hat{I}_-$ is differentiable and closed: it increases to ∞ as u increases to 0.

Logarithmic barrier (2/4)

- As t increases, the approximation becomes more accurate.
- Substituting $\hat{I}_{-}$ for I_{-} gives the approximation

$$\begin{array}{ll} \text{minimize} & f_0(x) + \sum_{i=1}^{m} -(1/t)\log(-f_i(x)) \\ \text{subject to} & Ax = b. \end{array}$$

- The objective here is convex, since $-(1/t)\log(-u)$ is convex and increasing in u, and differentiable. So, Newton's method can be used to solve it, assuming an appropriate closedness condition holds.

Logarithmic barrier (3/4)

- The function $\phi(x) = -\sum_{i=1}^{m} \log(-f_i(x))$, with **dom** $\phi = \{x \in \mathbf{R}^n \mid f_i(x) < 0, i = 1, ..., m\}$, is called the **logarithmic barrier** (or log barrier) for the original problem.
- Its domain is the set of points that strictly satisfy the inequality constraints of the original problem. The logarithmic barrier, $\phi(x)$, grows without bound if $f_i(x) \to 0$, for any i.
- Note that the problem

$$\begin{array}{ll} \text{minimize} & f_0(x) + \displaystyle\sum_{i=1}^{m} -(1/t)\log(-f_i(x)) \\ \text{subject to} & Ax = b. \end{array}$$

  is just an approximation of the original problem. But it can be shown that the quality of the approximation improves as the parameter t grows.

Logarithmic barrier (4/4)

- On the other hand, when the parameter t is large, the function $f_0 + (1/t)\phi$ is difficult to minimize by Newton's method, since its Hessian varies rapidly near the boundary of the feasible set.
- We will see that this problem can be circumvented by solving a sequence of approximated problems, increasing the parameter t at each step, and starting each Newton minimization at the solution of the problem for the previous value of t.

Gradient and Hessian of the logarithmic barrier function

- For future reference, we note that the gradient and Hessian of the logarithmic barrier function ϕ are given by

$$\nabla \phi(x) = \sum_{i=1}^{m} \frac{1}{-f_i(x)} \nabla f_i(x)$$

and

$$\nabla^2 \phi(x) = \sum_{i=1}^{m} \frac{1}{f_i(x)^2} \nabla f_i(x) \nabla f_i(x)^T + \sum_{i=1}^{m} \frac{1}{-f_i(x)} \nabla^2 f_i(x).$$

- To see this, we can apply the following chain rules

$$\begin{aligned} \nabla h(x) &= g'(f(x)) \nabla f(x) \\ \nabla^2 h(x) &= g''(f(x)) \nabla f(x) \nabla f(x)^T + g'(f(x)) \nabla^2 f(x) \end{aligned}$$

for $f : \mathbf{R}^n \to \mathbf{R}$, $g : \mathbf{R} \to \mathbf{R}$, and $h : \mathbf{R}^n \to \mathbf{R}$, $h(x) = g(f(x))$.

Central path (1/3)

- We now consider in more detail the minimization problem

$$\begin{array}{ll} \text{minimize} & f_0(x) + \sum_{i=1}^{m} -(1/t)\log(-f_i(x)) \\ \text{subject to} & Ax = b. \end{array}$$

- To simplify notation, we multiply the objective by t, and consider the equivalent problem

$$\begin{array}{ll} \text{minimize} & tf_0(x) + \phi(x) \\ \text{subject to} & Ax = b, \end{array}$$

which has the same minimizers.

Central path (2/3)

- We assume that the problem

$$\begin{array}{ll} \text{minimize} & tf_0(x) + \phi(x) \\ \text{subject to} & Ax = b, \end{array}$$

can be solved via Newton's method, and that it has a unique solution for each $t > 0$.
- For $t > 0$ we define $x^*(t)$ as the solution of the above problem.
- The **central path** associated with the original problem is defined as the set of points $x^*(t), t > 0$, which we call the **central points**.

Central path (3/3)

- Points on the central path are characterized by the following necessary and sufficient conditions: $x^*(t)$ is strictly feasible, i.e., satisfies

$$Ax^*(t) = b, \quad f_i(x^*(t)) < 0, \quad i = 1, \ldots, m,$$

and there exists a $\hat{\nu} \in \mathbf{R}^p$ such that

$$\begin{aligned} 0 &= t\nabla f_0(x^*(t)) + \nabla \phi(x^*(t)) + A^T \hat{\nu} \\ &= t\nabla f_0(x^*(t)) + \sum_{i=1}^{m} \frac{1}{-f_i(x^*(t))} \nabla f_i(x^*(t)) + A^T \hat{\nu} \end{aligned}$$

holds, which is referred to the **centrality condition**.

  - Recall that the central point $x^*(t)$ satisfies the KKT conditions of the problem

$$\begin{array}{ll} \text{minimize} & tf_0(x) + \phi(x) \\ \text{subject to} & Ax = b. \end{array}$$

Example – Inequality form linear programming (1/4)

- The logarithmic barrier function for an LP in inequality form,

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax \preceq b, \end{array}$$

is given by

$$\phi(x) = -\sum_{i=1}^{m} \log(b_i - a_i^T x), \textbf{dom } \phi = \{x \mid Ax \prec b\},$$

where $a_1^T, \ldots, a_m^T$ are the rows of A.

Example – Inequality form linear programming (2/4)

- The gradient and Hessian of the barrier function are

$$\nabla \phi(x) = \sum_{i=1}^{m} \frac{1}{b_i - a_i^T x} a_i, \quad \nabla^2 \phi(x) = \sum_{i=1}^{m} \frac{1}{(b_i - a_i^T x)^2} a_i a_i^T.$$

- By defining $d_i = 1/(b_i - a_i^T x)$, we reach a more compact form

$$\nabla \phi(x) = A^T d, \quad \nabla^2 \phi(x) = A^T \mathbf{diag}\ (d)^2 A,$$

where $d \in \mathbf{R}^m$.

- Since x is strictly feasible, we have $d \succ 0$, so the Hessian of ϕ is nonsingular if and only if A has rank n.

Example – Inequality form linear programming (3/4)

- The centrality condition

$$\begin{aligned} 0 &= t\nabla f_0(x^*(t)) + \nabla\phi(x^*(t)) \\ &= t\nabla f_0(x^*(t)) + \sum_{i=1}^{m} \frac{1}{-f_i(x^*(t))}\nabla f_i(x^*(t)) \end{aligned}$$

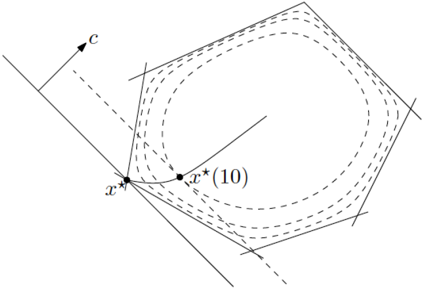
implies

$$tc + \sum_{i=1}^{m} \frac{1}{b_i - a_i^T x} a_i = tc + A^T d = 0.$$

- We can give a simple geometric interpretation of the centrality condition as in the next slide.

Example – Inequality form linear programming (4/4)

- The centrality condition implies
$$tc + \sum_{i=1}^{m} \frac{1}{b_i - a_i^T x} a_i = tc + A^T d = 0.$$
- At a point $x^*(t)$ on the central path the gradient $\nabla\phi(x^*(t))$, which is normal to the level set of ϕ through $x^*(t)$, must be parallel to $-c$.
- In other words, the hyperplane $c^T x = c^T x^*(t)$ is tangent to the level set of ϕ through $x^*(t)$.



Dual points from central path (1/3)

- Recall that the central point $x^*(t)$ satisfies the KKT conditions of the problem

$$\begin{array}{ll} \text{minimize} & tf_0(x) + \phi(x) \\ \text{subject to} & Ax = b, \end{array}$$

and there exists $\hat{\nu} \in \mathbf{R}^p$ such that

$$0 = t\nabla f_0(x^*(t)) + \sum_{i=1}^{m} \frac{1}{-f_i(x^*(t))} \nabla f_i(x^*(t)) + A^T\hat{\nu}$$

- Now, we can derive an important property of the central path: Every central point yields a dual feasible point, and hence a lower bound on the optimal value p^*.
- Specifically, we define

$$\lambda_i^*(t) = -\frac{1}{tf_i(x^*(t))}, \quad i = 1, \dots, m, \quad \nu^*(t) = \hat{\nu}/t.$$

Dual points from central path (2/3)

- With the definitions

$$\lambda_i^*(t) = -\frac{1}{tf_i(x^*(t))}, \quad i = 1, \dots, m, \quad \nu^*(t) = \hat{\nu}/t,$$

  we claim that the pair $(\lambda^*(t), \nu^*(t))$ is dual feasible
  (i.e., $g(\lambda^*(t), \nu^*(t)) > -\infty$ and $\lambda^*(t) \succeq 0$).
- First, it is clear that $\lambda^*(t) \succ 0$ because $f_i(x^*(t)) < 0, \quad i = 1, \dots, m$.
- Next, note that the centrality condition can be expressed as

$$\nabla f_0(x^*(t)) + \sum_{i=1}^{m} \lambda_i^*(t) \nabla f_i(x^*(t)) + A^T \nu^*(t) = 0.$$

- We see that $x^*(t)$ minimizes the Lagrangian

$$L(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \nu^T (Ax - b),$$

  for $\lambda = \lambda^*(t)$ and $\nu = \nu^*(t)$, which means that $(\lambda^*(t), \nu^*(t))$ is a dual feasible pair.

Dual points from central path (3/3)

- Therefore, the dual function $g(\lambda^*(t), \nu^*(t))$ is finite, and

$$\begin{aligned} g(\lambda^*(t), \nu^*(t)) &= f_0(x^*(t)) + \sum_{i=1}^{m} \lambda_i^*(t) f_i(x^*(t)) + \nu^*(t)^T (Ax^*(t) - b) \\ &= f_0(x^*(t)) - m/t. \end{aligned}$$

- In particular, the duality gap associated with $x^*(t)$ and the dual feasible pair $(\lambda^*(t), \nu^*(t))$ is simply m/t. As an important consequence, we have

$$f_0(x^*(t)) - p^* \leq m/t,$$

i.e., $x^*(t)$ is no more than m/t-suboptimal.

- This confirms the intuitive idea that $x^*(t)$ converges to an optimal point as $t \to \infty$.

Example – Inequality form linear programming (1/2)

- Let us revisit the inequality form LP

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax \preceq b. \end{array}$$

- The dual problem of the inequality form LP is

$$\begin{array}{ll} \text{maximize} & -b^T \lambda \\ \text{subject to} & A^T \lambda + c = 0 \\ & \lambda \succeq 0. \end{array}$$

Example – Inequality form linear programming (2/2)

- From the optimality conditions

$$tc + \sum_{i=1}^{m} \frac{1}{b_i - a_i^T x} a_i = tc + A^T d = 0,$$

it is clear that

$$\lambda_i^*(t) = \frac{1}{t(b_i - a_i^T x^*(t))}, \quad i = 1, \dots, m,$$

is dual feasible, with dual objective value

$$-b^T \lambda^*(t) = c^T x^*(t) + (Ax^*(t) - b)^T \lambda^*(t) = c^T x^*(t) - m/t.$$

Interpretation via KKT conditions (1/2)

- We can interpret the centrality conditions

$$\begin{aligned} 0 &= t\nabla f_0(x^*(t)) + \nabla\phi(x^*(t)) + A^T\hat{\nu} \\ &= t\nabla f_0(x^*(t)) + \sum_{i=1}^m \frac{1}{-f_i(x^*(t))}\nabla f_i(x^*(t)) + A^T\hat{\nu} \end{aligned}$$

as a continuous deformation of the KKT optimality conditions.

- A point x equals $x^*(t)$ if and only if there exist λ and ν such that

$$\begin{aligned} Ax &= b \\ f_i(x) &\leq 0, \quad i = 1, \dots, m \\ \lambda &\succeq 0 \\ \nabla f_0(x) + \sum_{i=1}^m \lambda_i \nabla f_i(x) + A^T\nu &= 0 \\ -\lambda_i f_i(x) &= 1/t, \quad i = 1, \dots, m. \end{aligned}$$

Interpretation via KKT conditions (2/2)

- The only difference between the KKT conditions and the centrality conditions is that the complementarity condition $-\lambda_i f_i(x) = 0$ is replaced by the condition $-\lambda_i f_i(x) = 1/t$.
- In particular, for large t, $x^*(t)$ and the associated dual point $\lambda^*(t), \nu^*(t)$ 'almost' satisfy the KKT optimality conditions.

Force field interpretation (1/3)

- We can give a simple mechanics interpretation of the central path in terms of potential forces acting on a particle in the strictly feasible set C.
- For simplicity we assume that there are no equality constraints.
- We associate with each constraint the force

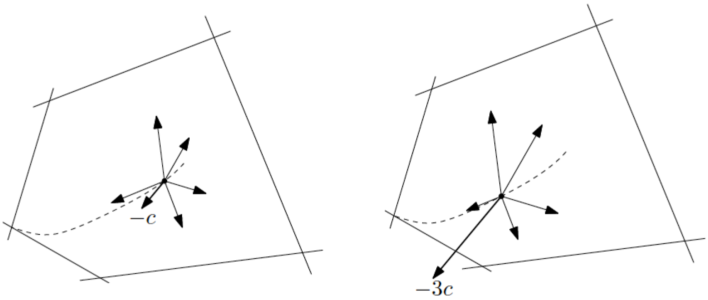
$$F_i(x) = -\nabla(-\log(-f_i(x))) = \frac{1}{f_i(x)}\nabla f_i(x)$$

acting on the particle when it is at position x.
- Now we imagine another force acting on the particle, given by

$$F_0(x) = -t\nabla f_0(x),$$

when the particle is at position x.

Force field interpretation (2/3)



- This objective force field acts to pull the particle in the negative gradient direction (i.e., toward smaller f_0).
- The central point $x^*(t)$ is the point where the constraint forces exactly balance the objective force felt by the particle.

Force field interpretation (3/3)

- As the parameter t increases, the particle is more strongly pulled toward the optimal point, but it is always trapped in C by the barrier potential, which becomes infinite as the particle approaches the boundary.

The barrier method (1/5)

- We have seen that the point $x^*(t)$ is m/t-suboptimal, and that a certificate of this accuracy is provided by the dual feasible pair $\lambda^*(t), \nu^*(t)$.
- This suggests a very straightforward method for solving the original problem with a guaranteed specified accuracy ϵ: We simply take $t = m/\epsilon$ and solve the equality constrained problem

$$\begin{array}{ll} \text{minimize} & (m/\epsilon) f_0(x) + \phi(x) \\ \text{subject to} & Ax = b \end{array}$$

using Newton's method.

The barrier method (2/5)

- This method could be called the unconstrained minimization method, since it allows us to solve the inequality constrained problem to a guaranteed accuracy by solving an unconstrained (or linearly constrained) problem.
- It works well for small problems, good starting points, and moderate accuracy (i.e., ϵ not too small). However, it does not work well in other cases, and is rarely used.

The barrier method (3/5)

- A simple extension of the unconstrained minimization method does work well, based on solving a sequence of unconstrained (or linearly constrained) minimization problems, using the last point found as the starting point for the next unconstrained minimization problem.
- In other words, we compute $x^*(t)$ for a sequence of increasing values of t, until $t \geq m/\epsilon$, which guarantees that we have an ϵ-suboptimal solution of the original problem.

The barrier method (4/5)

- A simple version of the method is as follows.

  Algorithm 11.1 Barrier method.

  given strictly feasible $x, t := t^{(0)} > 0, \mu > 1$, tolerance $\epsilon > 0$.

  repeat

  1. *Centering step.* Compute $x^*(t)$ by minimizing $tf_0 + \phi$, subject to $Ax = b$, starting at x.
  2. *Update.* $x := x^*(t)$.
  3. *Stopping criterion.* **quit** if $m/t < \epsilon$.
  4. *Increase t.* $t := \mu t$.

- At each iteration (except the first one) we compute the central point $x^*(t)$ starting from the previously computed central point, and then increase t by a factor $\mu > 1$.

The barrier method (5/5)

- The algorithm can also return $\lambda = \lambda^*(t)$, and $\nu = \nu^*(t)$, a dual ϵ-suboptimal point, or certificate for x.
- We refer to each execution of step 1 as a **centering step** (since a central point is being computed) or an outer iteration.
- Although any method for linearly constrained minimization can be used in step 1, we will assume that Newton's method is used.
- We refer to the Newton iterations or steps executed during the centering step as inner iterations.
- At each inner step, we have a primal feasible point; we have a dual feasible point, however, only at the end of each outer (centering) step.

Accuracy of centering (1/2)

- We should make some comments on the accuracy to which we solve the centering problems.
- Computing $x^*(t)$ exactly is not necessary since the central path has no significance beyond the fact that it leads to a solution of the original problem as $t \to \infty$; inexact centering will still yield a sequence of points $x^{(k)}$ that converges to an optimal point.
- Inexact centering, however, means that the points $\lambda^*(t), \nu^*(t)$, computed from

$$\lambda_i^*(t) = -\frac{1}{tf_i(x^*(t))}, \quad i = 1, \dots, m, \quad \nu^*(t) = \hat{\nu}/t,$$

are not exactly dual feasible.

Accuracy of centering (2/2)

- The cost of computing an extremely accurate minimizer of $tf_0 + \phi$, as compared to the cost of computing a good minimizer of $tf_0 + \phi$, is only marginally more, i.e., a few Newton steps at most.
- So it is usually reasonable to assume exact centering.

Choice of μ (1/3)

- The choice of the parameter μ involves a trade-off in the number of inner and outer iterations required.
- If μ is small (i.e., near 1) then at each outer iteration t increases by a small factor. As a result, the initial point for the Newton process, i.e., the previous iterate x, is a very good starting point, and the number of Newton steps needed to compute the next iterate is small.
- Thus for small μ we expect a small number of Newton steps per outer iteration, but a large number of outer iterations.
- In this case the iterates (and indeed, the iterates of the inner iterations as well) closely follow the central path.
- This explains the alternate name path-following method.

Choice of μ (2/3)

- On the other hand, if μ is large we have the opposite situation.
- After each outer iteration t increases a large amount, so the current iterate is probably not a very good approximation of the next iterate.
- Thus we expect many more inner iterations.
- This 'aggressive' updating of t results in fewer outer iterations, since the duality gap is reduced by the large factor μ at each outer iteration, but more inner iterations.
- With a large μ, the iterates are widely separated on the central path; the inner iterates veer way off the central path.

Choice of μ (3/3)

- In practice, small values of μ (i.e., near one) result in many outer iterations, with just a few Newton steps for each outer iteration.
- For μ in a fairly large range, from around 3 to 100 or so, the two effects nearly cancel, so the total number of Newton steps remains approximately constant.
- This means that the choice of μ is not particularly critical; values from around 10 to 20 or so seem to work well.

Linear programming in inequality form (1/6)

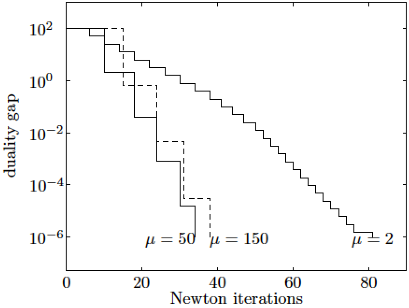
- Consider an example of a small LP in inequality form,

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax \preceq b \end{array}$$

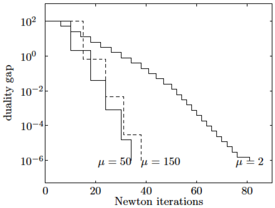
  with $A \in \mathbf{R}^{100 \times 50}$.
- The data were generated randomly, so that the problem is strictly primal and dual feasible, with optimal value $p^* = 1$.
- The initial point $x^{(0)}$ is on the central path, with a duality gap of 100.
- The barrier method is terminated when the duality gap is less than 10^{-6}.
- The centering problems are solved by Newton's method with backtracking, using parameters $\alpha = 0.01, \beta = 0.5$.

Linear programming in inequality form (2/6)

- The stopping criterion for Newton's method is $\lambda(x)^2/2 \leq 10^{-5}$, where $\lambda(x)$ is the Newton decrement of the function $tc^T x + \phi(x)$.
- The progress of the barrier method, for three values of the parameter μ, is shown below.



Linear programming in inequality form (3/6)



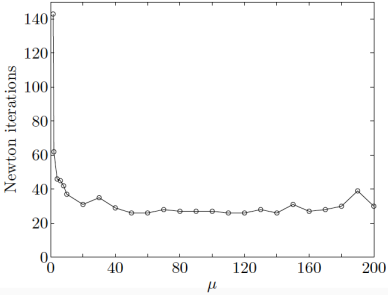
- Each of the plots has a staircase shape, with each stair associated with one outer iteration.
- The width of each stair tread (i.e., horizontal portion) is the number of Newton steps required for that outer iteration.
- The height of each stair riser (i.e., the vertical portion) is exactly equal to (a factor of) μ, since the duality gap is reduced by the factor μ at the end of each outer iteration.

Linear programming in inequality form (4/6)

- The following comments are noted.
- First of all, the method works very well, with approximately linear convergence of the duality gap.
- The plots clearly show the trade-off in the choice of μ. For $\mu = 2$, the treads are short; the number of Newton steps required to re-center is around 2 or 3. But the risers are also short, since the duality gap reduction per outer iteration is only a factor of 2.
- At the other extreme, when $\mu = 150$, the treads are longer, typically around 7 Newton steps, but the risers are also much larger, since the duality gap is reduced by the factor 150 in each outer iteration.

Linear programming in inequality form (5/6)

- The trade-off in choice of μ is further examined in the following figure.



- Here, we use the barrier method to solve the LP, for 25 values of μ between 1.2 and 200.
- The vertical axis shows the total number of Newton steps required to reduce the duality gap from 100 to 10^{-3}, as a fucntion of the parameter μ.

Linear programming in inequality form (6/6)

- This plot shows that the barrier method performs very well for a wide range of values of μ, from around 3 to 200.
- One interesting observation is that the total number of Newton steps does not vary much for values of μ larger than around 3. Thus, as μ increases over this range, the decrease in the number of outer iterations is offset by an increase in the number of Newton steps per outer iteration.
- For even larger values of μ, the performance of the barrier method becomes less predictable (i.e., more dependent on the particular problem instance). Since the performance does not improve with larger values of μ, a good choice is in the range $10 - 100$.

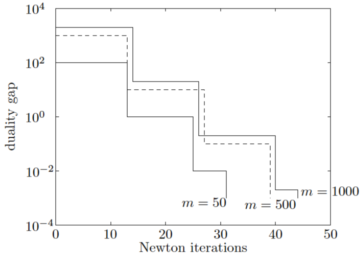
Barrier Method Performance v.s. Problem Dimensions (1/2)

- We consider LPs in standard form,

$$\begin{array}{ll} \text{minimize} & c^T x \\ \text{subject to} & Ax = b, \\ & x \succeq 0 \end{array}$$

  with $A \in \mathbf{R}^{m \times n}$, and explore the total number of Newton steps required as a function of the number of variables n and number of equality constraints m, for a family of randomly generated problem instances.
- We take $n = 2m$, i.e., twice as many variables as constraints, and compare performance plots with various values of m.

Barrier Method Performance v.s. Problem Dimensions (2/2)



Left The duality gap v.s. iteration number for three problem instances, with dimensions $m = 50$, $m = 500$, and $m = 1000$.

Right The mean and standard deviation of the number of Newton steps, for each value of m.