

Lecture 14

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1 Conjugate function

Example: Consider (trivial) problem of minimizing $f(x)$ under constraint $x = 0$. Lagrange function is

$$L(x, \lambda) = f(x) + \langle x, \lambda \rangle$$

and

$$h(\lambda) = \inf_x (f(x) + \langle x, \lambda \rangle) = - \sup(\langle x, -\lambda \rangle - f(x)).$$

The function

$$f^*(\lambda) = \sup_x (\langle x, \lambda \rangle - f(x))$$

is called Legendre transform or conjugate of f . With this notation we have

$$h(\lambda) = -f^*(-\lambda)$$

To get more explicit example, consider single variable $f(x) = x \log(x)$. To maximize $\langle x, \lambda \rangle - f(x)$ compute derivative

$$\partial_x (\langle x, \lambda \rangle - f(x)) = \lambda - \log(x) - 1.$$

Hence, for optimal x we have

$$\log(x) = \lambda - 1$$

that is

$$x = \exp(\lambda - 1).$$

Now

$$\begin{aligned} \langle x, \lambda \rangle - f(x) &= \exp(\lambda - 1)\lambda - \exp(\lambda - 1) \log(\exp(\lambda - 1)) \\ &= \exp(\lambda - 1)\lambda - \exp(\lambda - 1)(\lambda - 1) = \exp(\lambda - 1) \end{aligned}$$

so

$$f^*(\lambda) = \exp(\lambda - 1)$$

Similar, calculation shows that for $p > 1$ and $f(x) = \frac{1}{p}x^p$ we have

$$f^*(\lambda) = \frac{1}{q}\lambda^q$$

where q solves $\frac{1}{p} + \frac{1}{q} = 1$, that is $q = \frac{p}{p-1}$.

For $f(x) = |x|$, when $|\lambda| > 1$ the expression

$$\langle x, \lambda \rangle - f(x) = x\lambda - |x|$$

is unbounded, so λ is not in domain of f^* . When $\lambda \in [-1, 1]$, then expression above is non-positive and maximum is attained for $x = 0$, so $f^*(\lambda) = 0$.

For $f(x) = 0$ with domain $[-1, 1]$, we get

$$f^*(\lambda) = \sup_{x \in [-1, 1]} x\lambda.$$

When $\lambda \geq 0$ maximum is at $x = 1$, so $f^*(\lambda) = \lambda$. When $\lambda \leq 0$ maximum is at $x = -1$ so $f^*(\lambda) = -\lambda$. In other words

$$f^*(\lambda) = |\lambda|.$$

Recalling previous example, we get

$$(f^*)^* = f.$$

This in fact is general equality for convex f .

Let $B = \{x : \|x\| \leq 1\}$ be unit ball in \mathbb{R}^n and let $f(x) = 0$ with domain B . We have

$$f^*(\lambda) = \sup_{x \in B} \langle x, \lambda \rangle$$

Clearly,

$$\langle x, \lambda \rangle \leq \|x\| \|\lambda\| \leq \|\lambda\|.$$

For nonzero λ taking $x = \frac{\lambda}{\|\lambda\|}$ we have

$$\langle x, \lambda \rangle = \left\langle \frac{\lambda}{\|\lambda\|}, \lambda \right\rangle = \frac{\|\lambda\|^2}{\|\lambda\|} = \|\lambda\|$$

so

$$f^*(\lambda) = \|\lambda\|$$

(it is easy to check that this equality is also true for $\lambda = 0$).

2 Proximal methods

Assume that $f(x) = g(x) + h(x)$ where g is smooth and h is convex.

Example:

$$g(x) + \|x\|_1$$

(l^1 norm promotes sparsity). In particular LASSO problem is of this form.

Example: For matrices instead of l^1 norm it is natural to use nuclear norm. For positive definite matrices nuclear norm is just sum of eigenvalues. In general one can compute nuclear norm using singular value decomposition. We use

$$g(X) + \|X\|_*$$

where X goes over matrices and $\|X\|_*$ is nuclear norm to promote low rank matrices as solutions.

For differentiable f steepest descent is

$$x_{i+1} = x_i - \alpha_i \nabla f(x_i).$$

We can think that steepest descent minimizes quadratic approximation to f :

$$x_{i+1} = \operatorname{argmin}_x f(x_i) + \langle \nabla f(x_i), x \rangle + \frac{1}{2\alpha_i} \|x - x_i\|^2.$$

When h is nonsmooth natural idea is to take quadratic approximation to g and leave h as is. That is

$$\begin{aligned} x_{i+1} &= \operatorname{argmin}_x g(x_i) + \langle \nabla g(x_i), x \rangle + \frac{1}{2\alpha_i} \|x - x_i\|^2 + h(x) \\ &= \operatorname{argmin}_x \frac{\alpha_i}{2} \|\nabla g(x_i)\|^2 + \langle \nabla g(x_i), x - x_i \rangle + \frac{1}{2\alpha_i} \|x - x_i\|^2 + h(x) \\ &= \operatorname{argmin}_x \frac{1}{2} \|x - x_i\|^2 + \langle \alpha_i \nabla g(x_i), x - x_i \rangle + \frac{1}{2} \|\alpha_i \nabla g(x_i)\|^2 + \alpha_i h(x) \\ &= \operatorname{argmin}_x \frac{1}{2} \|x - x_i + \alpha_i \nabla g(x_i)\|^2 + \alpha_i h(x). \end{aligned}$$

where we obtained second equality by changing constant term and third equality multiplying by α_i .

The last expression is called proximal operator. More formally for arbitrary convex function $h : \mathbb{R}^n \mapsto \mathbb{R} \cup \infty$ we define

$$\operatorname{prox}_h(x) = \operatorname{argmin}_y \left(\frac{1}{2} \|y - x\|^2 + h(y) \right).$$

With such notation we have

$$x_{i+1} = \operatorname{prox}_{\alpha_i h(x)}(x_i - \alpha_i \nabla g(x_i)).$$

Resulting algorithm is called proximal gradient algorithm.

Why this is good?

- (con) above each step requires minimization of auxiliary function which in principle can be expensive.
- there are examples where proximal operator can be computed in closed form and is quite cheap to evaluate.

- proximal operator has nice theoretical properties, in particular satisfies remarkable equalities.
- some other algorithms can be viewed as proximal gradient algorithm with appropriate h .

Example: $h(x) = \|x\|_1 = \sum_{j=1}^n |x_j|$. Then

$$\begin{aligned} \text{prox}_{\lambda h}(x) &= \operatorname{argmin}_y \left(\frac{1}{2} \|y - x\|^2 + \lambda \|y\|_1 \right) \\ &= \operatorname{argmin}_y \left(\sum_{j=1}^n \left(\frac{1}{2} (y_j - x_j)^2 + \lambda |y_j| \right) \right). \end{aligned}$$

This is sum of functions of separate variables, so it is enough to minimize each term separately, that is compute

$$\operatorname{argmin}_z \frac{1}{2} (z - x_j)^2 + \lambda |z|.$$

Now, $\phi_{t,\lambda}(z) = \frac{1}{2}(z - t)^2 + \lambda|z|$ is differentiable when $z \neq 0$, so optimum is attained either at $z = 0$ or at point where derivative is 0.

Differentiating we get

$$\phi'_{t,\lambda}(z) = z - t + \lambda$$

for $z > 0$ and

$$\phi'_{t,\lambda}(z) = z - t - \lambda$$

for $z < 0$.

The first gives condition

$$z - t + \lambda = 0$$

that is $z = t - \lambda$. Similarly the second expression gives $z = t + \lambda$. Since $\phi_{t,\lambda}$ is convex when one of conditions above hold, than this gives minimum. Otherwise, minimum is a 0. So

$$\operatorname{argmin}_z \phi_{t,\lambda} = \begin{cases} t - \lambda & \text{when } t > \lambda \\ 0 & \text{when } t \in [-\lambda, \lambda] \\ t + \lambda & \text{when } t < -\lambda \end{cases}$$

For original problem we get

$$\text{prox}_{\lambda h}(x) = S_\lambda(x)$$

where

$$S_\lambda(x)_j = \begin{cases} x_j - \lambda & \text{when } x_j > \lambda \\ 0 & \text{when } x_j \in [-\lambda, \lambda] \\ x_j + \lambda & \text{when } x_j < -\lambda \end{cases}$$

is called soft thresholding.

For LASSO problem, that is minimizing $f(x) + \lambda\|x\|_1$ where

$$f(x) = \frac{1}{2}\|Ax - y\|^2$$

proximal gradient algorithm now is:

$$x_{i+1} = S_{\alpha_i\lambda}(x_i - \alpha_i A^T(Ax - y)).$$

This is called ISTA (iterative soft thresholding).

Example: When C is closed convex set and $h(x) = 0$ for $x \in C$ and $h(x) = \infty$ otherwise, we get

$$\text{prox}_h(x) = \operatorname{argmin}_{y \in C} \frac{1}{2}\|y - x\|^2 = \text{Proj}_C(x).$$

So corresponding proximal gradient algorithm is just projected gradient algorithm.

Proximal operator is nonexpansive:

Lemma 2.1

$$\begin{aligned} \|\text{prox}_h(x_2) - \text{prox}_h(x_1)\|^2 &\leq \langle \text{prox}_h(x_2) - \text{prox}_h(x_1), x_2 - x_1 \rangle, \\ \|\text{prox}_h(x_2) - \text{prox}_h(x_1)\| &\leq \|x_2 - x_1\|. \end{aligned}$$

Remark: In particular projection operator is nonexpansive.

Proof: Second inequality follows from the first using Schwartz inequality, so it is enough to prove the first.

By definition

$$\text{prox}_h(x) = \operatorname{argmin}_z \frac{1}{2}\|z - x\|^2 + h(z)$$

so when $z_0 = \text{prox}_h(x)$ than for any z we have

$$\frac{1}{2}\|z - x\|^2 + h(z) \geq \frac{1}{2}\|z_0 - x\|^2 + h(z_0).$$

We have

$$\|z - x\| = \|z - z_0\|^2 + 2\langle z - z_0, z_0 - x \rangle + \|z_0 - x\|^2$$

so

$$\frac{1}{2}\|z - z_0\|^2 + \langle z - z_0, z_0 - x \rangle + h(z) \geq h(z_0).$$

Since h is convex we can drop $\|z - z_0\|^2$ from the left hand side.

Namely

$$\langle z - z_0, z_0 - x \rangle + h(z) \geq h(z_0) - \frac{1}{2}\|z - z_0\|^2.$$

Graph of convex function has supporting hyperplane at $z = z_0$, but due to inequality above the only possible supporting plane is $t = h(z_0)$. So, we have

$$\langle z - z_0, z_0 - x \rangle + h(z) \geq h(z_0).$$

Now, applying this to $x = x_1$, $z_0 = z_1 = \text{prox}_h(x_1)$ and z_2 we get

$$\langle z_2 - z_1, z_1 - x_1 \rangle + h(z_2) \geq h(z_1).$$

By symmetry, when $z_2 = \text{prox}_h(x_2)$ we get

$$\langle z_1 - z_2, z_2 - x_2 \rangle + h(z_1) \geq h(z_2).$$

Adding both together we get

$$\langle z_2 - z_1, (z_1 - x_1) - (z_2 - x_2) \rangle + h(z_2) + h(z_1) \geq h(z_1) + h(z_2)$$

so

$$\langle z_2 - z_1, (z_1 - z_2) + (x_2 - x_1) \rangle \geq 0$$

so

$$\langle z_2 - z_1, x_2 - x_1 \rangle - \|z_2 - z_1\| \geq 0$$

and indeed

$$\langle z_2 - z_1, x_2 - x_1 \rangle \geq \|z_2 - z_1\|^2$$

□

Lemma 2.2 *Let $h^*(x) = \sup_z \langle x, z \rangle - h(z)$ is Legendre transform of h . Then*

$$x = \text{prox}_h(x) + \text{prox}_{h^*}(x)$$

Proof: When $u = \text{prox}_h(x)$, then as in previous lemma we have

$$\langle z - u, u - x \rangle + h(z) \geq h(x)$$

that is

$$\langle x - u, u \rangle - h(x) \geq \langle x - u, z \rangle - h(z)$$

so supremum in definition of $h^*(x - u)$ is attained at $z = u$.

Moreover

$$h^*(z) \geq \langle z, u \rangle - h(u) = \langle z - (x - u), u \rangle + h^*(x - u).$$

We have $z - x = (z - (x - u)) - u$ so

$$\frac{1}{2}\|z - x\|^2 = \frac{1}{2}\|z - (x - u)\|^2 - \langle z - (x - u), u \rangle + \frac{1}{2}\|u\|^2.$$

Adding inequality for $h^*(z)$ we get

$$\begin{aligned} \frac{1}{2}\|z - x\|^2 + h^*(z) &\geq \frac{1}{2}\|z - (x - u)\|^2 + \frac{1}{2}\|u\|^2 + h^*(x - u). \\ &\geq \frac{1}{2}\|u\|^2 + h^*(x - u). \end{aligned}$$

We have equality when $z = x - u$, so

$$\text{prox}_{h^*}(x) = x - u$$

and

$$\text{prox}_h(x) + \text{prox}_{h^*}(x) = u + x - u = x.$$

□

Example: When C is a convex cone, then $I_C^* = I_{-C^*}$ where C^* is dual cone: $C^* = \{z : \langle z, x \rangle \geq 0 \text{ for all } x \in C\}$. So we get

$$x = \text{Proj}_C(x) + \text{Proj}_{-C^*}(x).$$

Example: When C is closed and convex we define support function S_C as

$$S_C(x) = \sup_{z \in C} \langle x, z \rangle.$$

Then

$$\text{prox}_{S_C}(x) = x - \text{Proj}_C(x)$$

Namely, $S_C = I_C^*$ so

$$x = \text{prox}_{S_C}(x) + \text{prox}_{I_C}(x) = \text{prox}_{S_C}(x) + \text{Proj}_C(x).$$

Example: $\text{prox}_{\|\cdot\|_1}(x) = x - \text{Proj}_{B_\infty}(x)$ where B_∞ is unit ball in l^∞ norm. This is easy to compute explicitly and gives another derivation of soft thresholding operator.

Example: $\text{prox}_{\|\cdot\|_\infty}(x) = x - \text{Proj}_{B_1}(x)$ where B_1 is unit ball in l^1 norm. Projection onto B_1 can be computed efficiently.

Note: in general when B is unit ball in some norm, then S_B is the norm.

Example: Let $h(x) = \max\{x_1, \dots, x_n\}$. Then

$$\text{prox}_h(x) = x - \text{Proj}_\Delta(x)$$

where

$$\Delta = \{t : t \geq 0, \sum_{j=1}^n t_j = 1\}$$

is probability simplex.

Indeed, again $h = S_\Delta$.

Example: Let

$$\Delta = \{t : t \geq 0, \sum_{j=1}^n t_j = 1\}$$

be probability simplex. Recall that

$$\text{Proj}_\Delta(x) = \operatorname{argmin}_{z \in \Delta} \frac{1}{2} \|z - x\|^2.$$

We claim that optimality condition in minimization above is

$$z = (x - \lambda \mathbf{1})_+$$

where $\mathbf{1}$ is vector with all coordinates equal to 1 and $(x - \lambda \mathbf{1})_+$ means that we replace negative coordinates of $x - \lambda \mathbf{1}$ by 0. λ can be determined from condition

$$\|(x - \lambda \mathbf{1})_+\|_1 = 1.$$

Namely, let $I = \{i : z_i = 0\}$. Write

$$\begin{aligned} f(z) &= \frac{1}{2} \|z - x\|^2, \\ g_0(z) &= -1 + \sum_{i=1}^n z_i = \langle z, \mathbf{1} \rangle - 1, \\ g_i(z) &= -z_i. \end{aligned}$$

Clearly, finding $\text{Proj}_\Delta(x)$ is equivalent to finding z which minimizes $f(z)$ under constraints $g_0(z) = 0$, $g_i(z) \leq 0$ for $i = 1, \dots, n$. I is set of active inequality constraints. Since $\sum_{i=1}^n z_i = 1$ at least one inequality constraint is inactive. Hence, $\nabla g_i(z)$ with $i \in \{0\} \cup I$ are linearly independent. By KKT conditions we have

$$\nabla f(z) - c_0 \nabla g_0(z) + \sum_{i \in I} c_i \nabla g_i(z) = 0$$

Since $\nabla f(z) = z - x$, in coordinates we have:

$$z_i - x_i - c_0 = 0$$

for $i \notin I$ and

$$z_i - x_i - c_0 - c_i = 0$$

for $i \in I$. Since $c_i \geq 0$ and $z_i = 0$ for $i \in I$ this implies

$$-x_i \geq c_0$$

so

$$x_i \leq -c_0.$$

Put $\lambda = -c_0$. By inequality above for $i \in I$ we have

$$(x_i - \lambda)_+ = 0 = z_i$$

For $i \notin I$ we have

$$z_i - x_i - c_0 = z_i - x_i + \lambda.$$

Hence, for $i \notin I$

$$z_i = x_i - \lambda$$

For $i \notin I$ we have $z_i > 0$ so

$$z_i = (x_i - \lambda)_+.$$

So, we proved that

$$z = (x - \lambda \mathbf{1})_+.$$

Note that

$$\sum_{i=1}^n (x_i - \lambda)_+$$

decreases when λ is increased, so λ is uniquely determined by condition

$$\sum_{i=1}^n (x_i - \lambda)_+ = 1$$

It remains to give efficient method to find λ . Note that

$$\sum_{i=1}^n (x_i - \lambda)_+ = \sum_{i \notin I} (x_i - \lambda) = -\lambda(n - |I|) + \sum_{i \notin I} x_i$$

where $|I|$ denotes number of elements of I . So once I is known we can easily compute λ . To find I we use bisection. More precisely, we take trial value of λ . For correct λ we have $I = \{i : z_i \leq \lambda\}$. If trial λ gives too large sum, then we need to increase λ , when sum is too small we need to decrease λ . We take one of x_i as trial value, starting from median. Median and sums can be computed in linear time and after single trial problem size is reduced by half so whole computation can be done in linear time (one needs to reuse previously computed sums).

Example: Let $C = \{t : t_j \geq 0, \sum_{j=1}^n t_j \leq 1\}$. This can be reduced to previous one. Procedure is as follows:

1. Let y be x with negative coordinates replaced by 0
2. If y is in C then return it, otherwise return $\text{Proj}_\Delta(y)$

To justify this, first note that when for some i coordinate x_i is negative, then $(\text{Proj}_C(x))_i = 0$. Namely, if $(\text{Proj}_C(x))_i$ were positive, then replacing $(\text{Proj}_C(x))_i$ by 0 we would get point in C which is closer to x . So $\text{Proj}_C(x) = \text{Proj}_C(y)$. Of course, when $y \in C$, then $\text{Proj}_C(y) = y$. Otherwise line joining y and $\text{Proj}_C(y)$ must have common point with hyperplane given by equation $\sum_{j=1}^n y_j = 1$. Since distance of this point to y is not bigger than distance between $\text{Proj}_C(y)$ and y , the common point is $\text{Proj}_C(y)$, that is $\text{Proj}_C(y) \in \Delta$, so $\text{Proj}_C(y) = \text{Proj}_\Delta(y)$.

Example: Projection onto l^1 unit ball. Let $s_i = 1$ when $x_i \geq 0$ and $s_i = -1$ when $x_i < 0$. Let operator S be defined by equality $S(z)_i = s_i z_i$. We have $S(x) \geq 0$. But we also have $S(B_1) = B_1$ where B_1 is unit ball in l^1 norm. Since $\|S(x) - S(y)\|_2 = \|x - y\|_2$ we have

$$\text{Proj}_{B_1}(S(z)) = S(\text{Proj}_{B_1}(z))$$

Put $y = S(x)$. We have $x = S(y)$ so

$$\text{Proj}_{B_1}(x) = S(\text{Proj}_{B_1}(y)).$$

To compute $\text{Proj}_{B_1}(y)$ note that $\text{Proj}_{B_1}(y) = \text{Proj}_C(y)$ (this is similar to what happened for C).

Lemma 2.3 When gradient g is Lipschitz continuous with constant M , with constant step $\alpha_i = \frac{1}{M}$ we have

$$f(x_{i+1}) \leq f(x_i).$$

Assuming optimal point x_∞ exist we have

$$\begin{aligned} \|x_{i+1} - x_\infty\| &\leq \|x_i - x_\infty\| \\ f(x_i) - f(x_\infty) &\leq \frac{M\|x_0 - x_\infty\|^2}{2i}. \end{aligned}$$

In other words both objective function and distance to optimum is non-increasing and we have convergence.

Lemma 2.4 If $mI \leq \nabla^2 g(x) \leq MI$, with constant step $\alpha_i = \frac{1}{M}$ we have

$$\|x_i - x_\infty\|^2 \leq \left(1 - \frac{m}{M}\right)^i \|x_0 - x_\infty\|^2$$

Remark: This estimate is essentially the same as for steepest descent.

Convergence analysis of proximal gradient algorithm is based on following lemma:

Lemma 2.5 If gradient of g is Lipschitz continuous with constant M , $z = \text{prox}_{\frac{1}{M}h}(y - \frac{1}{M}\nabla g(y))$, then for all x

$$f(z) - f(x) \leq \frac{M}{2}\|x - y\|^2 - \frac{M}{2}\|x - z\|^2 - r(x, y)$$

where $r(x, y) = g(x) - g(y) - \langle \nabla g(y), x - y \rangle \geq 0$.

Proof: $r(x, y) \geq 0$ by convexity. Put

$$\begin{aligned} \phi(t) &= g(y) + \langle \nabla g(y), t - y \rangle + \frac{M}{2}\|t - y\|^2 + h(t) \\ &= g(y) - \frac{M}{2}\left\|\frac{1}{M}\nabla g(y)\right\|^2 + \frac{M}{2}\left\|t - \left(y - \frac{1}{M}\nabla g(y)\right)\right\|^2 + h(t) \end{aligned}$$

so $z = \text{argmin}_t \phi(t)$. We can rewrite ϕ as

$$\phi(x) = \psi(x) + \frac{M}{2}\|x - z\|^2$$

with convex ψ . Note that ψ must have minimum at z . Namely, in opposite case there would be v such that

$$\psi(z + v) < \psi(z).$$

By convexity for $0 < t < 1$ we have

$$\psi(z + tv) \leq t\psi(z + v) + (1 - t)\psi(z)$$

$$= t(\psi(z+v) - \psi(z)) + \psi(z).$$

If $\psi(z+v) - \psi(z) < 0$, then for small positive t term $t(\psi(z+v) - \psi(z))$ has bigger absolute value than $\|z+tv - z\|^2 = t^2\|v\|^2$, so also $\phi(z+tv)$ would be smaller than $\phi(z)$.

Hence, we have

$$\phi(x) \geq \phi(z) + \frac{M}{2}\|x-z\|^2.$$

On the other hand

$$g(z) \leq g(y) + \langle \nabla g(y), t-y \rangle + \frac{M}{2}\|t-y\|^2$$

so

$$f(z) \leq \phi(z).$$

Together we get

$$\phi(x) \geq f(z) + \frac{M}{2}\|x-z\|^2.$$

Now, by definition of ϕ :

$$g(y) + (\langle \nabla g(y), x-y \rangle + \frac{M}{2}\|x-y\|^2 + h(x)) \geq f(z) + \frac{M}{2}\|x-z\|^2.$$

But

$$\begin{aligned} & g(y) + \langle \nabla g(y), x-y \rangle + h(x) \\ &= g(x) + h(x) + (g(y) - g(x) + \langle \nabla g(y), x-y \rangle) = f(x) - r(x, y) \end{aligned}$$

so

$$f(x) - r(x, y) + \frac{M}{2}\|x-y\|^2 \geq f(z) + \frac{M}{2}\|x-z\|^2$$

and finally

$$f(z) - f(x) \leq \frac{M}{2}\|x-y\|^2 - \frac{M}{2}\|x-z\|^2 - r(x, y)$$

Taking $x = y = x_i$ in the lemma we get $z = x_{i+1}$ and

$$f(x_{i+1}) - f(x_i) \leq -\frac{M}{2}\|x_i - x_{i+1}\|^2 - r(x, y) \leq 0$$

so

$$f(x_{i+1}) \leq f(x_i)$$

Taking $x = x_\infty$, $y = x_i$ we get $z = x_{i+1}$ and

$$f(x_{i+1}) - f(x_\infty) \leq \frac{M}{2}\|x_i - x_\infty\|^2 - \frac{M}{2}\|x_{i+1} - x_\infty\|^2 - r(x, y)$$

so

$$0 \leq \frac{M}{2}\|x_i - x_\infty\|^2 - \frac{M}{2}\|x_{i+1} - x_\infty\|^2$$

so

$$\|x_{i+1} - x_\infty\| \leq \|x_i - x_\infty\|.$$

Using estimate above in better way we get

$$f(x_{i+1}) - f(x_\infty) \leq \frac{M}{2} \|x_i - x_\infty\|^2 - \frac{M}{2} \|x_{i+1} - x_\infty\|^2$$

Adding up inequalities for $j = 0, \dots, i - 1$ we get

$$\sum_{j=0}^{i-1} (f(x_{j+1}) - f(x_\infty)) \leq \frac{M}{2} \|x_0 - x_\infty\|^2 - \frac{M}{2} \|x_i - x_\infty\|^2.$$

But we know $f(x_i) \leq f(x_{j+1})$ so

$$f(x_i) - f(x_\infty) \leq \frac{M}{2i} \|x_0 - x_\infty\|^2$$

Using assumption $mI \leq \nabla^2 g(x)$ we see that

$$r(x, y) \geq \frac{m}{2} \|x - y\|^2$$

so main lemma gives

$$f(x_{i+1}) - f(x_\infty) \leq \frac{M}{2} \|x_i - x_\infty\|^2 - \frac{M}{2} \|x_{i+1} - x_\infty\|^2 - \frac{m}{2} \|x_i - x_\infty\|^2$$

so

$$0 \leq \frac{M - m}{2} \|x_i - x_\infty\|^2 - \frac{M}{2} \|x_{i+1} - x_\infty\|^2$$

that is

$$\|x_{i+1} - x_\infty\|^2 \leq \frac{M - m}{M} \|x_i - x_\infty\|^2 = \left(1 - \frac{m}{M}\right) \|x_i - x_\infty\|^2$$

which proves rate of convergence in strictly convex case.

There are similar results for proximal gradient algorithm with line search. In line search we start with reasonably large α , check if

$$g(x_i - \alpha d_i) \leq g(x_i) - \alpha \langle \nabla g(x_i), d_i \rangle + \frac{\alpha}{2} \|d_i\|^2$$

where d_i is direction and otherwise we shrink α . The condition above allows proofs of convergence rate (with slightly worse constant) to go on.

2.1 References

This material is relatively new and most is *not* present in the books we use. More examples of support functions, Legendre transform and projection is in:

Stephen Boyd, Lieven Vandenberghe, Convex Optimization, chapter 2, 3, 5 and 8.

Research level survey:

Neal Parikh, Stephen Boyd, Proximal Algorithms, Foundations and Trends in Optimization Vol. 1, No. 3 (2013) 123–231.