Math Problem Set 6

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Problem 9.1. *Proof.* Let L be an unconstrained linear objective function. Suppose that L has a minimizer x^*. I'll show that L must be constant.

Suppose that L is not constant, i.e, there exists y such that $Ly \neq Lx^*$. If $Ly < Lx^*$, then x^* is not a minimizer and we have a contradiction. If $Ly > Lx^*$, then $L(x^* - y) < 0$ and we can consider the point $x^* + x^* - y$:

$$L(x^* + x^* - y) = Lx^* + L(x^* - y) < Lx^*$$

so x^* is not a minimizer and we have a contradiction □

Problem 9.2. *Proof.* Minimizing $||Ax - b||$ is equivalent to

$$\begin{aligned}(Ax - b)^T(Ax - b) &= (x^T A^T - b^T)(Ax - b)\\ &= x^T A^T Ax - x^T A^T b - b^T Ax + 2b^T b\\ &= x^T A^T Ax - 2b^T Ax + 2b^T b\end{aligned}$$

Note that $A^T A$ is positive semidefinite. Taking the FOC of this expression yields:

$$\begin{aligned}&2x^T A^T A - 2b^T A = 0\\ \iff\ & x^T A^T A = b^T A\\ \iff\ & A^T Ax = A^T b\end{aligned}$$

And because $A^T A$ is positive definite, the second order-condition

$$2A^T A > 0$$

will always be satisfied. □

Problem 9.3. Text explication - **Return here**

Problem 9.4. *Proof.* I'll need to show both directions.

- $\Leftarrow$ Suppose x_0 is chosen such that $Df(x_0)^T = Qx_0 - b$ is an eigenvector for Q, i.e, $Q(Qx_0 - b) = \lambda(Qx_0 - b)$ for some $\lambda \in \mathbb{R}$. We see that:

  $$x_1 = x_0 - \alpha Q(Qx_0 - b) = x_0 - \alpha\lambda(Qx_0 - b)$$

  I choose α to minimize $f(x_1)$. If $\alpha = \frac{1}{\lambda^2}$, then

  $$\begin{aligned} Qx_1 &= Q(x_0 - \alpha\lambda(Qx_0 - b)) \\ &= Qx_0 - \alpha\lambda^2(Qx_0 - b) \\ &= Qx_0 - Qx_0 - b \\ &= b \end{aligned}$$

  And if $Qx_1 = b$, then we know that x_1 is the minimum of the function, so I've chosen the right α, and the algorithm converges in one step.

- $\Rightarrow$ Suppose the algorithm converges in one step. Then I know that $Qx_1 = b$, and thus that

  $$Q(x_0 - \alpha Q(Qx_0 - b)) = b$$

  Now consider the kernel of $I - \alpha Q$.

  $$\begin{aligned} (I - \alpha Q)(Qx_0 - b) &= Qx_0 - b - \alpha Q(Qx_0 - b) \\ &= Q(x_0 - \alpha Q(x_0 - b)) - b \\ &= Qx_1 - b \\ &= 0 \end{aligned}$$

  So $Qx_1 - b \in \text{Ker}(I - \alpha Q)$, and therefore it is an eigenvector of Q with eigenvalue α.

$\square$

I have two different eigenvalues for the same eigenvectors - one of the directions must be wrong. Anyone see the issue?

Problem 9.5. *Proof.* I will begin by stating without proof a result of vector calculus.

Fact: The gradient of a function at a point $Df^T(x)$ is orthogonal to the level set of the function at the point x.

This fact gives some idea about where I'm going with this proof: first I'll show that I can reduce the proposition to the statement that the two gradients $Df^T(x_k)$ and $Df^T(x_{k+1})$ are orthogonal, and then I'll use the fact to show that this is indeed the case.

Consider $\langle x_{k+1} - x_k, x_{k+2} - x_{k+1}\rangle$.

$$\begin{aligned} \langle x_{k+1} - x_k, x_{k+2} - x_{k+1}\rangle &= \langle x_k - \alpha_{k+1} Df^T(x_k) - x_k, x_{k+1} - \alpha_{k+2} Df^T(x_k + 1) - x_{k+1}\rangle \\ &= \langle -\alpha_{k+1} Df^T(x_k), -\alpha_{k+2} Df^T(x_k + 1)\rangle \end{aligned}$$

And if I want to set this equal to zero, I can pull out the scalars $-\alpha_{k+1}, -\alpha_{k+2}$ and set $\langle Df^T(x_k), Df^T(x_k+1)\rangle = 0$. So we see that

$$\langle x_{k+1} - x_k, x_{k+2} - x_{k+1}\rangle = 0 \iff \langle Df^T(x_k), Df^T(x_k+1)\rangle = 0$$

I'll now show that the gradients are orthogonal.

Consider the gradient $Df^T(x_k)$. $-Df^T(x_k)$ is the direction of steepest descent, and $x_{k+1} = x_k - \alpha Df^T(x_k)$. We choose α to minimize $f(x_{k+1})$. Consider the evaluation of the gradient $Df(x_k)$ at the point x_{k+1}.

Claim: $Df(x_k)(x_{k+1}) = 0$

Proof of Claim: This will be an intuitive argument which follows from the continuity of the derivative (f is C^1). Suppose $-Df(x_k)(x_{k+1}) < 0$. Then, I can go a bit further along the descent to

$$x^* = x_k - (\alpha+\varepsilon)Df^T(x_k), \varepsilon > 0$$

such that $f(x^*) < f(x_{k+1})$. Similarly, if $-Df(x_k)(x_{k+1}) > 0$, then I can go a bit less far along the descent to

$$x^* = x_k - (\alpha-\varepsilon)Df^T(x_k), \varepsilon > 0$$

such that $f(x^*) < f(x_{k+1})$. So we see that $Df(x_k)(x_{k+1}) = 0$, which proves the claim.

Excellent. Now, $Df(x_k)(x_{k+1}) = 0$, so the gradient $Df^T(x_k)$ is tangent to the level set of f at the point x_{k+1}. We know from our fact that $Df^T(x_{k+1})$ is orthogonal to the level set of f at x_{k+1}, so it is orthogonal to $Df^T(x_k)$ as well, which concludes the proof.

See Figure 1 for some geometric intuition.

$\square$

Problem 9.6. Jupyter

Problem 9.7. Jupyter

Problem 9.8. Jupyter

Problem 9.9. Jupyter

Problem 9.10. *Proof.* We know that x^* is the unique minimizer of f iff

$$f'(x) = 0 \iff Qx^* - b = 0 \iff x^* = Q^{-1}b$$

Now let us start Newton's method from an arbitrary initial guess x_0. Calculate x_1:

$$\begin{aligned} x_1 &= x_0 - D^2f(x_0)^{-1}Df(x_0) \\ &= x_0 - Q^{-1}(Qx_0 - b) \\ &= x_0 - x_0 + Q^{-1}b = Q^{-1}b \end{aligned}$$

which is what was desired. $\square$

Problem 9.12. *Proof.* This is quick. Choose λ_i arbitrarily, and let v_i be its eigenvector. Then

$$Bv_i = (A + \mu I)v_i = Av_i + \mu I v_i = \lambda_i v_i + \mu v_i = (\lambda_i + \mu)v_i$$

□

Problem 9.15. Tedious matrix algebra - multiply the left by right, see sum is one. **RETURN HERE**

Problem 9.16.

Problem 9.17.

Problem 9.18.

Problem 9.20.