

### [Special Topics] Homework 3

Cs 4301.001

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1-1

We can rewrite  $x^T A x$  as  $x^T t x$  where  $t$  is an eigen of  $A$ . Then the problem becomes:

min  $-t$

such that  $t$  is an eigen of  $A$

$$\begin{aligned} \mathcal{L} &= x^T A x - \lambda(x^T x - 1) = x^T A x + \lambda x^T x - \lambda \\ \frac{\partial \mathcal{L}}{\partial x} &= 2Ax + 2\lambda x = 0 \quad (A + \lambda I)x = 0 \\ \text{But since } x \neq 0, & \quad A + \lambda I = 0 \\ x^T (A + \lambda I)x - \lambda &= 0 \\ g(\lambda) &= -\lambda \end{aligned}$$

The dual is maximizing  $g(\lambda)$  over  $\lambda$ , such that  $-\lambda$  is an eigenvalue of  $A$ , which we get from rearranging  $2Ax + 2\lambda x$ .

1-2

We can't use Slater's because it requires the problem to be convex. The solution to the primal problem is the largest eigenvalue. We know that such an largest eigenvalue exists, because  $x^T A x$  is psd and symmetric, meaning there must exist  $n$  distinct eigenvalues.

1-3

We rewrite to get

$$\min g(\lambda) = \lambda \text{ s.t. } Ax + \lambda x = 0$$

$$\begin{aligned} \mathcal{L}(\lambda, \mu) &= -\lambda + \mu (Ax + \lambda x) = \lambda + \mu Ax + \mu \lambda x \\ \frac{\partial \mathcal{L}}{\partial \lambda} &= 1 + \mu x = 0 \\ \text{subst.} &\Rightarrow \mu Ax + \lambda(0) = \mu Ax \\ \min_{\mu} \mu Ax &\text{ such that } \mu x = -1 \end{aligned}$$

2-1

You can divide this subproblem into two parts- the original objective and the new  $g_k$  sum term.

>> The added  $g_k$  term is a nonnegative weighted sum of convex functions. The log function is concave, so its negative is convex.

>> The original objective is convex because the norm squared preserves convexity because it just element squares every term (like a parabola, which we know to be convex). The inside of the norm is affine in  $\lambda$ .

>> When we add these two parts together, it is another nonnegative weighted sum, so the whole thing is convex.

2-2

[https://colab.research.google.com/drive/1SmeaVGSKZXIMN\\_02Q5jsEJDp\\_qBN05osD?usp=sharing](https://colab.research.google.com/drive/1SmeaVGSKZXIMN_02Q5jsEJDp_qBN05osD?usp=sharing)

2-3

If the norm between subsequent iterations is sufficiently small, we can converge. However, this criteria won't work for flatter functions and will terminate early.

3-1

<https://colab.research.google.com/drive/1YstOaknKEBWIJcxELkGWEvA6rqnjGyKQ?usp=sharing>

3-2

You should pick it close to a guess of what the vector could be. For example, for the matrix  $\begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix}$ , I would start my guess at  $[1, 1]$ . But if you pick a vector orthogonal of the eigenvector with dominant eigenvalue, the method will compute  $0/0$  for its update and fail.

3-3

I think as stated in the slides, you should pick the eigenvector orthogonal to dominant eigenvector. Similarly for the third largest eigen you should pick a vector perpendicular to the other two.

3-4

Yes, it is possible if the iterating vector and all the possible eigenvectors of the matrix become close to orthogonal.