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Math 56 Winter 2025 Midterm Exam

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Date: 02/23/2025

Start/end time: 5:50pm - 11:11pm

This exam contains 16 pages (including this cover page) and 8 questions. The total number of possible points is 63.

- Take the exam in one six-hour sitting, and mark your starting/ending times at the top of the exam in the space provided. The exam should not take the full six hours. You are allowed to take reasonably short breaks.
- The exam is open-book and open-note, but NOT “open-internet” or “open-neighbor”. Discussion about the exam with other students (or other people) is not allowed. This includes chat-bots such as ChatGPT. An exception to the internet rule are the YouTube videos I have prepared for the course, as well as the classroom lecture recordings on Panapto.
- Organize your work, in a reasonably neat and coherent way, in the space provided. Work scattered all over the page without a clear ordering will receive less credit. *There may be more blank space provided than is actually needed to answer each question.*
- Use of calculators/code is permitted.
- Mysterious or unsupported answers will not receive full credit. A correct answer, unsupported by calculations, explanation, or algebraic work will receive no credit; an incorrect answer supported by substantially correct calculations and explanations may still receive partial credit.
- Provide exact answers unless otherwise instructed.
- Simplify all answers as much as possible.
- Clearly identify your final answer for each problem from any scratch work.

Question	Points	Score
1	10	
2	12	
3	5	
4	5	
5	5	
6	8	
7	12	
8	6	
Total:	63	

Do not write in the table to the right. Good luck!

1. (10 points) Let $A \in \mathbb{R}^{m \times n}$. Prove that

$$A^\dagger = \lim_{\delta \rightarrow 0^+} (A^T A + \delta I)^{-1} A^T. \quad (1)$$

Hint: use the SVD, and pick a convenient matrix norm.

Consider the Frobenius norm

$$\lim_{\delta \rightarrow 0} \| (A^T A + \delta I)^{-1} A^T - A^\dagger \|_F = 0 \in \mathbb{R}, \text{ subsequently if } \epsilon = 0, \text{ the matrices are equal.}$$

Let $A \in \mathbb{R}^{m \times n}$ have the SVD decomposition, where;

$$A = U \Sigma V^T$$

• $U \in \mathbb{R}^{m \times m}$, $V \in \mathbb{R}^{n \times n}$ are orthogonal matrices

• $\Sigma \in \mathbb{R}^{m \times n}$ is a diagonal matrix with

singular values $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \dots \geq \sigma_r > 0$, where $r = \text{rank}(A)$
and zero values everywhere else.

Now observe that:

$$A^T = (V \Sigma^T U^T)$$

$$\text{which gives us } A^T A = V \Sigma^T U^T (U \Sigma V^T)$$

$$\text{as } U, U^T \text{ are orthogonal} = V \Sigma^T \Sigma V^T.$$

Now recall that $V I = V$, $V I V^T = I$, as V is orthogonal.

plugging this back gives us:

$$\begin{aligned} A^T A + \delta I &= V \Sigma^T \Sigma V^T + V \delta I V^T \\ &= V (\Sigma^T \Sigma + \delta I) V^T \end{aligned}$$

now consider:

$$\begin{aligned} (A^T A + \delta I)^{-1} &= (V (\Sigma^T \Sigma + \delta I) V^T)^{-1} \quad \text{ } V \text{ is orthogonal} \\ &= V (\Sigma^T \Sigma + \delta I)^{-1} V^T \end{aligned}$$

$$(A^T A + \delta I)^{-1} A^T = V(\Sigma^T \Sigma + \delta I)^{-1} V^T (V^T \Sigma^T U^T)$$

$$= V(\Sigma^T \Sigma + \delta I)^{-1} \Sigma^T U^T$$

Recall that $A^T = V \Sigma^T U^T$ subsequently power up on

Σ^T and $(\Sigma^T \Sigma + \delta I)^{-1} \Sigma^T$ suffices, as V, V^T do not affect singular values and the F -norm.

Observe that:

$$\Sigma^T \Sigma + \delta I = \begin{bmatrix} \sigma_1^2 + \delta & & & \\ & \sigma_2^2 + \delta & & \\ & & \ddots & \\ & & & \sigma_r^2 + \delta \\ & & & & \delta & & \\ & & & & & \ddots & \\ & & & & & & \delta \end{bmatrix}$$

subsequently its inverse must be:

$$(\Sigma^T \Sigma + \delta I)^{-1} = \begin{bmatrix} \frac{1}{\sigma_1^2 + \delta} & & & \\ & \ddots & & \\ & & \ddots & \\ & & & \frac{1}{\sigma_r^2 + \delta} \\ & & & & \frac{1}{\delta} & & \\ & & & & & \ddots & \\ & & & & & & \frac{1}{\delta} \end{bmatrix}$$

$$\text{and } (\Sigma^T \Sigma + \delta I)^{-1} \Sigma^T = \begin{bmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \frac{\sigma_r}{\sigma_r^2 + \delta} & \\ & & & 0 \\ & & & & 0 \end{bmatrix}$$

$$\text{now recall that } \Sigma^T = \begin{bmatrix} \frac{1}{\sigma_1} & & & \\ & \ddots & & \\ & & \frac{1}{\sigma_r} & \\ & & & 0 \\ & & & & 0 \end{bmatrix}$$

now for every non-zero diagonal entry σ_i , we have

$$\lim_{\delta \rightarrow 0} \frac{\sigma_i}{\sigma_i^2 + \delta} - \frac{1}{\sigma_i} \rightarrow \frac{\sigma_i}{\sigma_i^2} - \frac{1}{\sigma_i} = 0$$

$$\text{as all eigenvalues are } 0, \sum_{i=1}^r \left(\frac{\sigma_i}{\sigma_i^2 + \delta} - \frac{1}{\sigma_i} \right) = 0 = e$$

which proves our statement.

2. (12 points) *Part (a)*: Find an elementary lower triangular matrix \mathbf{M} such that

$$\mathbf{M} \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}. \quad (2)$$

Part (b): Find the Householder reflector $\mathbf{H} = \mathbf{I} - 2\mathbf{u}\mathbf{u}^T \in \mathbb{R}^{3 \times 3}$ (with \mathbf{u} a unit vector) such that

$$\mathbf{H} \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} \star \\ 0 \\ 0 \end{bmatrix}, \quad (3)$$

where “ \star ” denotes a generic nonzero entry. You can simply state the vector \mathbf{u} and do not need to explicitly compute the entries of \mathbf{H} .

Part (c): Find (you do not need to give the entries explicitly) an orthogonal matrix $\mathbf{Q} \in \mathbb{R}^{5 \times 5}$ such that

$$\mathbf{Q} \begin{bmatrix} 5 \\ 4 \\ 2 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} \star \\ \star \\ \star \\ 0 \\ 0 \end{bmatrix} \quad (4)$$

a) Recall that an elementary lower triangular matrix is defined as:

$$\mathbf{M} = \begin{bmatrix} 1 & 0 & 0 \\ -l_{21} & 1 & 0 \\ -l_{23} & 0 & 1 \end{bmatrix}$$

now observe that:

$$\begin{bmatrix} 1 & 0 & 0 \\ -l_{21} & 1 & 0 \\ -l_{23} & 0 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ -2l_{21} + 2 \\ -2l_{23} + 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 0 \\ 0 \end{bmatrix}$$

This gives us:

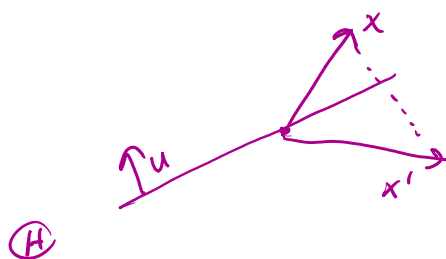
$$-2l_{21} = -2 \rightarrow -l_{21} = -1$$

$$-2l_{23} = -1 \rightarrow l_{23} = \frac{1}{2}$$

Subsequently our matrix is:

$$\begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ -\frac{1}{2} & 0 & 1 \end{bmatrix}$$

- b) Recall that a Householder reflector $H = I - 2uu^T$ reflects any vector x through the plane defined by u (perpendicular to u)



For ease of computation, let $\|x'\| = \|x\|$, which gives us $\|x'\| = \sqrt{2^2 + 2^2 + 1} = 3$, thus $x' = \langle 3, 0, 0 \rangle$.

Now notice that the difference of these vectors x, x' gives us a vector parallel to u .

Subsequently we get:

$$u = \frac{x - x'}{\|x - x'\|} = \frac{\langle 2, 2, 1 \rangle - \langle 3, 0, 0 \rangle}{\sqrt{(-1)^2 + 2^2 + 1^2}} = \frac{1}{\sqrt{6}} \langle -1, 2, 1 \rangle$$

c) using the same reasoning as part b), now observe

$$\text{we can choose } x^2 + y^2 + z^2 = 5^2 + 4^2 + 3^2 + 2^2 + 1^2$$

$$x^2 = \textcircled{5}^2 \quad y^2 = \textcircled{4}^2 \quad z^2 = \textcircled{3}^2$$

This gives us $v' = \langle 5, 4, 3, 0, 0 \rangle$

Deriving u , we get:

$$u = \frac{v - v'}{\|v - v'\|} = \frac{\langle 5, 4, 2, 2, 1 \rangle - \langle 5, 4, 3, 0, 0 \rangle}{\sqrt{(-1)^2 + 2^2 + 1^2}}$$

$$= \frac{1}{\sqrt{6}} \langle 0, 0, -1, 2, 1 \rangle$$

$$H = I - 2uu^T,$$

3. (5 points) Let $\mathbf{A} = \hat{\mathbf{Q}}\hat{\mathbf{R}}$ be the economic QR decomposition where $\mathbf{A} \in \mathbb{R}^{n \times n}$ is a symmetric positive definite matrix. Explain how the Cholesky factorization $\mathbf{A} = \mathbf{L}\mathbf{L}^T$ can be obtained directly from the QR decomposition with no additional cost.

Recall that $\hat{\mathbf{R}}$ is an upper triangular matrix and $\hat{\mathbf{Q}}$ is an orthogonal matrix, (eg. $\hat{\mathbf{Q}}^T \hat{\mathbf{Q}} = \mathbf{I}$)

Now since \mathbf{A} is symmetric pos. definite, we know:

$$\mathbf{A} = \hat{\mathbf{Q}}\hat{\mathbf{R}} = \hat{\mathbf{R}}^T \hat{\mathbf{Q}}^T = \mathbf{A}^T$$

Now observe that

$$\hat{\mathbf{R}} = \hat{\mathbf{Q}}^T \mathbf{A}, \quad \hat{\mathbf{R}}^T = \mathbf{A}^T \hat{\mathbf{Q}}$$

multiplying these gives us:

$$\mathbf{A}^T \hat{\mathbf{Q}} \hat{\mathbf{Q}}^T \mathbf{A} = \hat{\mathbf{R}}^T \hat{\mathbf{R}}$$

$$\mathbf{A}^T \mathbf{A} = \hat{\mathbf{R}}^T \hat{\mathbf{R}}, \quad \text{which is the Cholesky}$$

$$\text{factorization of } \mathbf{A}^T \mathbf{A} = \mathbf{A} \mathbf{A}$$

$$\begin{aligned} \mathbf{R}^T &= (\hat{\mathbf{Q}}^T \mathbf{A})^T \\ &= \mathbf{A}^T (\hat{\mathbf{Q}}^T)^T \\ &= \mathbf{A} \cdot \hat{\mathbf{Q}} \end{aligned}$$

4. (5 points) Explain how the decomposition $\mathbf{PAQ} = \mathbf{LU}$ arising in Gaussian elimination with complete pivoting (GECP) can be used to solve a linear system $\mathbf{Ax} = \mathbf{b}$, where $\mathbf{A} \in \mathbb{R}^{n \times n}$ is invertible.

observe that $\mathbf{PAQ} = \mathbf{LU} \Rightarrow \mathbf{A} = \mathbf{P}^{-1} \mathbf{L} \mathbf{U} \mathbf{Q}^{-1}$

which gives us $\mathbf{P}^{-1} \mathbf{L} \mathbf{U} \mathbf{Q}^{-1} \mathbf{x} = \mathbf{b}$.

now let $\mathbf{y}' = \mathbf{L} \mathbf{U} \mathbf{Q}^{-1} \mathbf{x}$, $\mathbf{y}'' = \mathbf{U} \mathbf{Q}^{-1} \mathbf{x}$ and $\mathbf{y}''' = \mathbf{Q} \mathbf{x}$

we proceed as follows:

- $\mathbf{P}^{-1} \mathbf{y}' = \mathbf{b} \rightarrow \mathbf{y}' = \mathbf{P} \mathbf{b}$ which is solved by multiplication
- $\mathbf{L} \mathbf{y}'' = \mathbf{y}'$ which is solved by forward substitution
- $\mathbf{U} \mathbf{y}''' = \mathbf{y}''$ " " " " backward "
- $\mathbf{Q}^{-1} \mathbf{x} = \mathbf{y}''' \rightarrow \mathbf{x} = \mathbf{Q} \mathbf{y}'''$, which is solved by multiplication

This gives us the solution \mathbf{x} to the expression $\mathbf{Ax} = \mathbf{b}$;
 [we know such a solution exists as \mathbf{A} is invertible.]

5. (5 points) Let $\mathbf{Ax} = \mathbf{b}$ where $\mathbf{A} \in \mathbb{R}^{n \times n}$ where is invertible. Suppose that $\|\mathbf{Ay} - \mathbf{b}\|_2$ is "small". Does this imply that $\|\mathbf{y} - \mathbf{x}\|_2$ is "small" as well? Why or why not? Explain.

Observe that:

$$\mathbf{A}(\mathbf{y} - \mathbf{x}) = \mathbf{Ay} - \mathbf{Ax} = \mathbf{Ay} - \mathbf{b} \quad \text{thus,} \quad \mathbf{A}^{-1}\mathbf{A}(\mathbf{y} - \mathbf{x}) = \mathbf{A}^{-1}(\mathbf{Ay} - \mathbf{b}) = \mathbf{y} - \mathbf{x}$$

recall the norm inequality $\|\mathbf{AB}\|_2 \leq \|\mathbf{A}\|_2 \|\mathbf{B}\|_2$; applying this gives us:

$$\|\mathbf{y} - \mathbf{x}\|_2 \leq \|\mathbf{A}^{-1}\|_2 \|\mathbf{Ay} - \mathbf{b}\|_2$$

subsequently $\|\mathbf{y} - \mathbf{x}\|_2$ is only "small" if $\|\mathbf{A}^{-1}\|_2$ is small as well.

6. (8 points) Suppose that we have computed the economic QR decomposition $\mathbf{A}_n = \hat{\mathbf{Q}}_n \hat{\mathbf{R}}_n$ where $\mathbf{A}_n = [\mathbf{a}_1, \dots, \mathbf{a}_n] \in \mathbb{R}^{m \times n}$ ($m > n$) has full column rank. Assuming that $\mathbf{a}_{n+1} \notin \text{col}(\mathbf{A}_n)$, explain how the economic QR decomposition $\mathbf{A}_{n+1} = [\mathbf{A}_n, \mathbf{a}_{n+1}] = \tilde{\mathbf{Q}}_{n+1} \tilde{\mathbf{R}}_{n+1}$ can be computed cheaply by making use of the previously computed factors $\hat{\mathbf{Q}}_n$ and $\hat{\mathbf{R}}_n$. Bonus: how can this procedure be modified to still apply even when $\mathbf{a}_{n+1} \in \text{col}(\mathbf{A}_n)$?

case 1: if $\mathbf{a}_{n+1} \notin \text{col}(\mathbf{A}_n)$:

Recall that $\hat{\mathbf{Q}}_{n+1}$ is an orthogonal matrix, namely all its columns are orthogonal with each other. As \mathbf{a}_{n+1} is NOT in the column space, it can be decomposed as:

$$\mathbf{a}_{n+1} = \tilde{\mathbf{Q}}_n \mathbf{b} + \mathbf{v} \rightarrow \tilde{\mathbf{Q}}_n^T \mathbf{a}_{n+1} = \mathbf{b} + \underbrace{\tilde{\mathbf{Q}}_n^T \mathbf{v}}_{\mathbf{0} \text{ as it is orthogonal}}$$

where \mathbf{v} is the orthogonal component and $\tilde{\mathbf{Q}}_n \mathbf{b}$ is the component that lies on $\tilde{\mathbf{Q}}_n$.

Subsequently we get:

$$\tilde{\mathbf{Q}}_{n+1} = [\tilde{\mathbf{Q}}_n, \mathbf{u}], \text{ where } \mathbf{u} \text{ is the unit vector in the direction of } \mathbf{v}.$$

we know that $\tilde{\mathbf{R}}_{n+1} = \begin{bmatrix} \mathbf{r}_n & r_{n+1} \\ 0 & r_{n+1} \end{bmatrix}$, as it is an upper triangular matrix,

r_n, r_{n+1} are the relevant coefficients.

Note that we need:

$$\begin{aligned} \tilde{\mathbf{A}}_{n+1} &= [\tilde{\mathbf{Q}}_{n+1}] \begin{bmatrix} \tilde{\mathbf{R}}_{n+1} \\ \mathbf{r}_{n+1} \end{bmatrix} \\ &= \begin{bmatrix} \tilde{\mathbf{A}}_n & \underbrace{\tilde{\mathbf{Q}}_n \mathbf{r}_n + \mathbf{u} r_{n+1}}_{\mathbf{a}_{n+1}} \end{bmatrix} \end{aligned}$$

observe that $\mathbf{r}_n = \mathbf{b}$, found by $\tilde{\mathbf{Q}}_n^T \mathbf{a}_{n+1}$,

$$\text{and } \mathbf{u} r_{n+1} = \mathbf{v} = \underbrace{\mathbf{a}_{n+1} - \tilde{\mathbf{Q}}_n \mathbf{b}}_{\text{subtraction, multiplication.}}$$

$$\text{subsequently } \mathbf{u} = \frac{\mathbf{v}}{\|\mathbf{v}\|}$$

$$\text{and } r_{n+1} = \|\mathbf{v}\|$$

(BONUS)

CASE 2: When $a_{n+1} \in \text{col}(A_n)$ there is no independent vector u that could be added. Subsequently $a_{n+1} = Q_n b$.

As Q does not change, R_{n+1} simply becomes $[R_n \ b]$ to account for the new column.

Observe that

$$\begin{aligned} [Q_n] [R_n \ b] &= [A_n \ Q_n b] \\ &= [A_n \ a_{n+1}] = A_{n+1} \end{aligned}$$

7. (12 points) Part (a): Let $C \in \mathbb{R}^{n \times n}$ be of the form $C = I + uu^T$ for some $u \in \mathbb{R}^n$. Show that C is symmetric positive definite, and find an expression for C^{-1} . *Hint: C^{-1} has the form $C^{-1} = I + auu^T$ for some $a \in \mathbb{R}$.*

Part (b): Let $A \in \mathbb{R}^{n \times n}$ be of the form $A = B + uu^T$ where B is symmetric positive definite and $u \in \mathbb{R}^n$. Show that A can be factorized as

$$A = L(I + vv^T)L^T \quad (5)$$

where L is invertible lower-triangular and $v \in \mathbb{R}^n$ is some vector (to be found).

Part (c): Assume that the Cholesky factorization of B has already been computed. Outline an efficient procedure to solve $Ax = b$ without computing the Cholesky factorization of A , where A is of the form in Part (b). How many flops does your procedure require? "Big-O" notation is fine.

PART a) Observe that for any nonzero vector $x \in \mathbb{R}^n$:

$$\begin{aligned} x^T C x &= x^T (I + uu^T) x \\ &= \underbrace{x^T I x}_{x^T x} + x^T u u^T x \end{aligned}$$

now observe that $x^T u = u^T x = c \in \mathbb{R}$, and

$$x^T x = \|x\|^2. \text{ Plugging these in, we get:}$$

$$= \|x\|^2 + c^2 > 0$$

- now observe that

$$\begin{aligned} C^T &= (I + uu^T)^T = I^T + (uu^T)^T \\ &= I + uu^T, \text{ as } uu^T \text{ is symmetric.} \\ &= C \end{aligned}$$

as $x^T C x > 0$ for any nonzero vector

$$x \in \mathbb{R}^n, \text{ and } C^T = C$$

by definition, it is symmetric positive definite.

Let $C^{-1} = (I + \alpha uu^T)$ for some $\alpha \in \mathbb{R}$

- Now consider:

$$I = (I + \alpha uu^T)(I + uu^T)$$

$$I = I^2 + uu^T + \alpha uu^T + \alpha uu^T uu^T$$

- we know that $u^T u = c$ for some $c \in \mathbb{R}$. Plugging this in:

$$= I + (\alpha+1)uu^T + \alpha u(c)u^T$$

re-organizing, we get:

$$= I + (\alpha+1)uu^T + \alpha c uu^T$$

$$= I + (\alpha+1+ac)uu^T$$

- we need $\alpha+1+ac = 0$. The α that satisfies this is given by:

$$\alpha(1+c) = -1$$

$$\alpha = \frac{-1}{(1+c)}$$

PART b

observe that $B = LL^T$ for some $n \times n$ lower triangular matrix L . Now observe that:

$$A = LIL^T + uu^T$$

Now consider, as L is invertible,

$$Lv = u \Rightarrow v = L^{-1}u, \quad v^T = (L^T u)^T$$

$$\text{This gives us: } uu^T = (Lv)(Lv)^T = Lv \cdot v^T L^T$$

Plugging it back:

$$\begin{aligned} A &= LIL^T + Lv v^T L^T \\ &= L(I + vv^T)L^T \end{aligned}$$

This proves our statement.

PART c

Recall from part b) if we know the Cholesky factorization of $B = LL^T$, we also have

$$A = L(I + vv^T)L^T \quad \text{where} \quad v = L^{-1}u.$$

Now consider $Ax = b$, let $(I + vv^T)L^T x = y'$

$$\text{and} \quad L^T x = y''.$$

- $Ax = Ly' = b$ can be solved via forward subs. $\left. \begin{array}{l} \text{requiring } O(n^2) \text{ flops.} \end{array} \right\} O(n^2)$
- $(I + vv^T)y'' = y'$ requires computation of $Lv = u$ through forward subs. $\rightarrow O(n^2)$, addition $\rightarrow O(n)$, matrix vector multiplication $\rightarrow O(n^2)$, transposing $u \rightarrow O(1)$ $\left. \begin{array}{l} \end{array} \right\} O(n^2)$
- $L^T x = y''$ can be solved with back substitution, $\left. \begin{array}{l} \text{requiring } \rightarrow O(n^2) \text{ flops.} \end{array} \right\} O(n^2)$

Adding all the steps gives us $O(n^2) + O(n^2) + O(n^2) = O(n^2)$ flops for solving $Ax = b$.

8. (6 points) You have been hired as a computational scientist at Pseudoinverse Inc., and your first task is to design a specialized method for computing matrix-vector products of the form $L^\dagger x$ given an input vector $x \in \mathbb{R}^n$, where L is given by

$$L = \begin{bmatrix} 1 & -1 & & \\ & \ddots & \ddots & \\ & & 1 & -1 \end{bmatrix} \in \mathbb{R}^{(n-1) \times n}. \quad (6)$$

→ similar to what we had in the first lab...

Describe every numerical method that you know (number them individually, clearly) which could be used to compute these matrix-vector products. Then, choose the method you believe is the best for the job and write a short pitch (2-3 sentences) for your boss to read detailing why this is the best. *Hint: amongst other methods, you might consider the approximation $L^\dagger \approx (L^T L + \delta I)^{-1} L^T$. Also, depending on the argument you make, there may not be a single best method.*

① Use $L^\dagger \approx (L^T L + \delta I)^{-1} L^T$

② Compute the QR decomposition, $L = QR \rightarrow L^\dagger = R^{-1} Q^T$
↳ costly

③ SVD: $L^\dagger = V \Sigma^+ U^T \rightarrow$ costly

④ An iterative method like gradient descent

PITCH:

The method I propose is ①! As L is a sparse matrix, the computations $L^T L$, $(L^T L + \delta I)^{-1} L^T$ are not very expensive. This matters especially while we're dealing with large matrices. Furthermore as we know for $\lim_{\delta \rightarrow 0} (L^T L + \delta I)^{-1} L^T = I$, we avoid unexpected large errors!

