

Advanced Linear Algebra Week 9 Day 1

2018/11/12 – Jonathan Hayase, updated by Prof. Weiqing GU

1 A Big Picture of Linear ALgebra

Suppose you have $A\mathbf{x} = \mathbf{b}$. Then let $\overline{A} = [A \mid \mathbf{b}]$. Then there is a solution if and only if $\text{rank } A = \text{rank } \overline{A}$.

On the other hand, if $\det A = 0$ then there is a nontrivial solution to $A\mathbf{x} = \mathbf{0}$. But if $\det A \neq 0$ then we have the trivial solution only to $A\mathbf{x} = \mathbf{0}$.

Things like rank, det, tr are the invariants of A .

Suppose we have a torus and a sphere. We can always slide a rubber band off a sphere, but that is not so for a torus, so they are not equivalent topologically.

Similarly, if we care about geometry, then an ellipsoid and sphere are not the same.

1.1 Differential Geometry

Given a differentiable manifold, we can always find a tangent plane, which lets us push the problem into linear algebra.

Inverse function on manifold: If $[d\phi]$ is invertible, then ϕ is locally invertible.

1.2 Multivariate Taylor

$$f(\mathbf{x}) = \underbrace{f(\mathbf{x}_0) + \nabla f(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)}_{\text{tangent plane}} + \frac{1}{2!}(\mathbf{x} - \mathbf{x}_0)^T \nabla^2 f(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)$$

If \mathbf{x}_0 is a critical point, then $\nabla f(\mathbf{x}_0) = \mathbf{0}$.

$$\begin{aligned} f(\mathbf{x}) - f(\mathbf{x}_0) &= \frac{1}{2!}(\mathbf{x} - \mathbf{x}_0)^T \nabla^2 f(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0) \\ &= \frac{1}{2!} \langle \mathbf{x} - \mathbf{x}_0, \mathbf{x} - \mathbf{x}_0 \rangle_{\nabla^2 f(\mathbf{x}_0)} \end{aligned}$$

Where $\langle \mathbf{x}, \mathbf{y} \rangle_M = \mathbf{x}^T M \mathbf{y}$ as long as M is positive definite.

1.3 Current Research Area in Linear Algebra

Research on approximation algorithms for matrices which cannot fit in memory and/or are sparsely represented.

Topological data analysis can only tell us how many “holes” a piece of data has, which is why it “hasn’t gone very far”.

Example: Suppose given $A \in M^{n \times k}$ and $B \in M^{k \times n}$ which cannot fit into (your) memory. But we would still like to find AB . Suppose we went for some subset C of A and D of B such that the result of multiplying the two is still $n \times m$.

Then suppose our goal was to stochastically achieve $\|AB - CD\| < \epsilon$ with probability 99%.

Prof Gu says: 左行右列

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} a & 0 \\ c & 0 \end{bmatrix}$$

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} b & d \\ a & c \end{bmatrix}$$

This means we can do things like

$$\overbrace{\begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_2 & \mathbf{v}_3 & \mathbf{v}_4 & \mathbf{v}_5 \end{bmatrix}}^A \begin{bmatrix} 1 & 0 & 0 & \dots \\ 0 & 0 & 0 & \dots \\ \vdots & \vdots & 1 & \dots \\ \vdots & \vdots & \vdots & \dots \\ 0 & 0 & 0 & \dots \end{bmatrix} = \begin{bmatrix} \mathbf{v}_1 & \mathbf{v}_3 \end{bmatrix}$$

Also want to solve $A_{n \times k} x_{k \times 1} = b$. Then we might calculate $S Ax = Sb$, where S means we will select “important rows” of A , such that $\{\tilde{x}^* \mid S Ax = Sb\}$ and $\{x^* \mid Ax = b\}$ where \tilde{x}^* and x^* are close to each other with probability 0.99 (or more generally $1 - \delta$).

Another problem: If A is large, then we can't fit into (your) computer's memory. But we want to find the eigenvalues and vectors of A .

1.4 Applications

Suppose you have a UAV flying along a curve, we can attach a frame to every point along the curve representing the local coordinate system of the UAV.

Consider the Lie group (Lie groups are both manifolds and groups)

$$SO(3) = \left\{ A \mid A^T A = I, \det A = 1 \right\}.$$

That is all.

Now, suppose you have a compact manifold. It's really $\mathbb{R}P^3$, the real projective plane, whose double cover is S^3 . However, once we go into the tangent plane, then this becomes linear algebra. Tangent plane at I is called the Lie algebra of the Lie group.

Suppose we have a curve $A(t)$ on the manifold starting at I , then $A^T(t)A(t) = I$ and $A(0) = I$. Suppose we want

$$\begin{aligned} \left[A^T(t) \right]' A(t) + A^T(t) A'(t) &= 0 \\ \left[A^T(0) \right]' A(0) + A^T(0) A'(0) &= 0 & \text{plugging in } t = 0 \left[A^T(0) \right]' + A'(0) &= 0 \\ \left[A'(0) \right]^T + A'(0) &= 0 \end{aligned}$$

So $A'(0)$ is a skew-symmetric 3×3 matrix. In fact the Lie algebra is the set of skew symmetric matrices.

A Lie algebra is a vector space equipped with the commutator bracket:

$$[A, B] = AB - BA$$

Satisfying the Jacobi identity:

$$[[a, B], C] + [[B, C], A] + [[C, A], B] = 0.$$

2 Convex optimization

Suppose f is twice differentiable. Then f is convex if and only if $Hf \succ 0$.