SI231b: Matrix Computations

Lecture 7: Least Squares and Orthogonal Projection

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Brief Overview

Overdetermined System: Ax = b, $A \in \mathbb{R}^{m \times n}$ (m > n), the equation

often has no solution, since

$$b \in \mathbb{R}^m$$
, while $\mathcal{R}(A) \subset \mathbb{R}^n$

has unique solution when

$$b \in \mathcal{R}(A)$$
 and $rank(A) = n$

has infinite solutions when

$$b \in \mathcal{R}(A)$$
 and $rank(A) < n$

In practice, we need to find the full rank least square (LS) solution x_{LS} ,

$$x_{LS} = \arg\min \|b - Ax\|_2^2,$$

where $\|\cdot\|_2$ represents the vector 2-norm and A is full rank.

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Outline

- ► Motivation Applications
- ► Geometric Interpretation of Least Square
- ► Projection onto Subspaces
- Orthogonal Projection

Linear Representation

In many applications, we can use the following representation

$$y = Ax$$

or

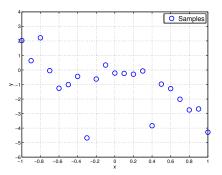
$$y = Ax + v$$

where

- ▶ y is known (given data);
- ► A is given or stipulated;
- x is to be determined;
- v models the noise or error.

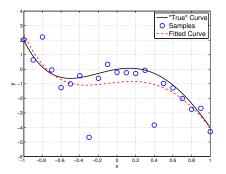
Data Fitting

Given a set of input-output data pairs $(x_i, y_i) \in \mathbb{R}^2$, i = 1, ..., m, find a function f(x) that fits the data well.



Data Fitting Using Polynomials

Applying a polynomial model $f(x) = \sum_{i=0}^{p} a_i x_i$ and use LS



"True" curve: the true f(x), p = 5.

Fitted curve: estimated f(x), a obtained by LS with p = 5.

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Autoregessive (AR) Model for Time Series

model current output y_t as being related to its past values in a linear manner

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \ldots + a_q y_{t-q} + v_t, \quad t = 0, 1, \ldots$$

for some coefficient $\mathsf{a} \in \mathbb{R}^q$ and some positive integer q (correlation length).

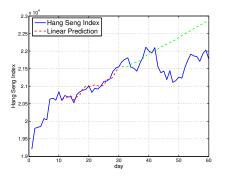
using AR model predictions can also be made

$$\hat{y}_{t+d} = a_1 \hat{y}_{t+d-1} + a_2 \hat{y}_{t+d-2} + \ldots + a_q \hat{y}_{t+d-q}, \quad d = 1, 2, \ldots$$

where we denote $\hat{y}_{t-i} = y_{t-i}$ for i = 1, ..., q.

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AR Model for Stock Market



- blue: Hang Seng Index during a certain time period.
- **red**: training phase, $\hat{y}_t = \sum_{i=1}^q a_i y_{t-i}$, a is obtained by LS, and q = 10.
- **Proof** green: prediction phase, $\hat{y}_{t+d} = \sum_{i=1}^{q} a_i \hat{y}_{t+d-i}$.

Polynomial Model for Time Series

$$y_t = a_0 + a_1t + a_2t^2 + \ldots + a_pt^p + v_t, \quad t = 0, 1, \ldots,$$

- once a computed, predictions of time series can be made
- ▶ to compute a, we make use of

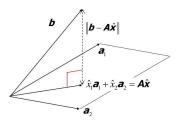
$$\begin{bmatrix}
y_0 \\
\vdots \\
y_t \\
\vdots \\
y_{T-1}
\end{bmatrix} = \begin{bmatrix}
1 & 0 & \cdots & 0 \\
\vdots & & & \vdots \\
1 & t & \cdots & t^p \\
\vdots & & & \vdots \\
1 & T-1 & \cdots & (T-1)^p
\end{bmatrix} \begin{bmatrix}
a_0 \\
a_1 \\
\vdots \\
a_p
\end{bmatrix} + \begin{bmatrix}
v_0 \\
\vdots \\
v_t \\
\vdots \\
v_{T-1}
\end{bmatrix}$$

- ► A is Vandermonde with distinct roots
- ▶ thus A has full rank (recall the determinant of a Vandermonde matrix)

Geometric Interpretation of Least Square

$$\mathsf{x}_{LS} = \arg\min_{\mathsf{x} \in \mathbb{R}^n} \|\mathsf{b} - \mathsf{A}\mathsf{x}\|_2^2$$

- 1. find $\tilde{b} \in \mathcal{R}(A)$ such that $\|b \tilde{b}\|_2$ is minimized
 - recall the distance between two vectors using vector norms
- 2. solve $Ax_{LS} = \tilde{b}$ to obtain x_{LS}



Question: how to obtain $\tilde{b} \in \mathcal{R}(A)$?

Projection

Projectors

A projector is a square matrix that satisfies

$$P^2 = P$$
.

- such a matrix is call idempotent
- ▶ geometric interpretation?

Note: this definition of projectors include both

- orthogonal projectors (key in our course)
- oblique projectors (will not be addressed)

Question: onto which subspace does P project?

Answer: $\mathcal{R}(P)$

Projection Direction

How to distinguish orthogonal and oblique projection?

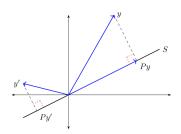


Figure 1: orthogonal projection

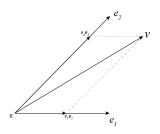


Figure 2: oblique projection

Answer: the projection direction Pv - v

Note: P(Pv - v) = 0, which means $(Pv - v) \in \mathcal{N}(P)$.

Complementary Projector

If P is a projector, then I - P is also a projector (why?)

$$(I - P)^2 = I - 2P + P^2 = (I - P)$$

The projector I - P is called the complementary projector of P.

Question: onto which subspace does I - P project?

Answer: $\mathcal{N}(P)$

First, $\mathcal{N}(P) \subset \mathcal{R}(I - P)$ (give your explanation here)

Second, $\mathcal{R}(I-P) \subset \mathcal{N}(P)$ (you are supposed to work it out indepently)

Then,

$$\mathcal{R}(I-P) = \mathcal{N}(P)$$
 and $\mathcal{R}(P) = \mathcal{N}(I-P)$
$$\mathcal{R}(P) \cap \mathcal{N}(P) = \{0\}$$

Projection onto Subspaces

Direct Sum

Let \mathcal{U} , \mathcal{W} be subspaces of \mathcal{V} . Then \mathcal{V} is said to be the direct sum of \mathcal{U} and \mathcal{W} , and we write $\mathcal{V} = \mathcal{U} \oplus \mathcal{W}$, if $\mathcal{V} = \mathcal{U} + \mathcal{W}$ and $\mathcal{U} \cap \mathcal{W} = \{0\}$.

Projection onto subspaces

Suppose $\mathcal{V} = \mathcal{U} \oplus \mathcal{W}$, then there is a projector P such that $\mathcal{R}(P) = \mathcal{U}$ and $\mathcal{N}(\mathsf{P}) = \mathcal{W}$, we say that P is a projector onto \mathcal{U} along \mathcal{W} .

Orthogonal projector

An orthogonal projector P is the one that projects onto a subspace $\mathcal U$ along a subspace \mathcal{W} when \mathcal{U} and \mathcal{W} are orthogonal.

Warning: orthogonal projectors are not orthogonal matrices.

Orthogonal Projection

Previous analysis show that $\mathsf{P} \in \mathbb{R}^{m \times m}$ seperates \mathbb{R}^m into two subspaces

- ▶ R(P)
- ▶ *N*(P)

and P projects onto $\mathcal{R}(P)$ along $\mathcal{N}(P)$.

Theorem

A projector P is orthogonal if and only if $P = P^T$.