# Lecture 5.5: Projection and least squares 

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Math 8530, Advanced Linear Algebra

## Self-adjointness

Recall that the adjoint of $A$ is the map $A^{*}: U \rightarrow X$ such that

$$
\underbrace{\left\langle x, A^{*} u\right\rangle}_{\text {product in } X}=\underbrace{\langle A x, u\rangle}_{\text {inner product in } U}
$$




## Definition

A linear map $A: X \rightarrow U$ is self-adjoint if $A^{*}=A$.

## Proposition 5.9

The linear maps $A^{*} A$ and $A A^{*}$ are self-adjoint.

## Projections and orthogonal

Recall that if $X=Y \oplus Y^{\perp}$, then the map

$$
P_{Y}: X \longrightarrow X, \quad P_{Y}: y+y^{\perp} \longmapsto y
$$

is the orthogonal projection of $X$ onto $Y$.

## Proposition 5.10

Orthogonal projections are self-adjoint.

Some books define a projection to be any linear map $P: X \rightarrow X$ such that $P^{2}=P$.
It is not hard to show that $X=R_{P} \oplus N_{P}$.

## Exercise (HW)

A projection $P: X \rightarrow X$ is an orthogonal projection if and only if it is self-adjoint.

## More on the map $A^{*} A$

## Lemma 5.11

The maps $A$ and $A^{*} A$ have the same nullspace.

Suppose $A$ is an $m \times n$ matrix $(m>n)$ with linearly independent columns. Then:

- the columns of $A$ are a basis for the range (column space) of $A$
- $A^{*} A$ is invertible.


## The map $A^{*} A$ and projection

The fact that $N_{A^{*} A}=N_{A}$, and the following, is the crux of the least squares method of finding the "best fit line."

## Corollary 5.12

Consider an underdetermined system $A x=b$, where $A: X \rightarrow U$ has trivial nullspace. The (unique) vector $x$ that minimizes $\|A x-b\|^{2}$ is the solution to $A^{*} A z=A^{*} b$.

## An example of least squares

Let's find the "best fit line" $a_{0}+a_{1} \times$ through the points $(1,1),(2,2)$, and $(3,2)$ in $\mathbb{R}^{2}$.

## The projection map $A\left(A^{*} A\right)^{-1} A^{*}$

Key idea
Let $y_{1}, \ldots, y_{k}$ be a basis for $Y$, and $A=\left[\begin{array}{llll}y_{1} & y_{2} & \cdots & y_{k}\end{array}\right]$. Then

$$
A\left(A^{*} A\right)^{-1} A^{*}
$$

is the orthogonal projection matrix onto $Y$.

