Chapter 4 Orthogonality

- Overdetermined linear system $A\vec{x} = \vec{b}$

$A \in \mathbb{R}^{m \times n}$, $m > n$: more equations than unknowns

$$\begin{array}{ccc} m\times n & n\times 1 & m\times 1 \\ A & \vec{x} & = \vec{b} \end{array}$$

n cols $\Rightarrow$ $\dim(\mathrm{Col}(A)) \le n < m$

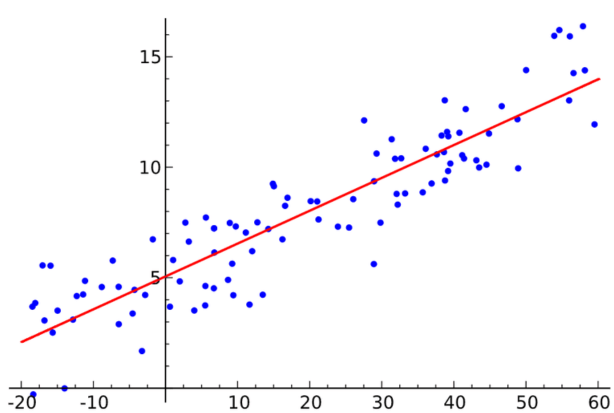
col rank

$\mathrm{Col}(A) \subseteq \mathbb{R}^m \Rightarrow \mathrm{Col}(A) \neq \mathbb{R}^m$

$\Rightarrow$ There are vectors $\vec{b} \in \mathbb{R}^m$ that are not in $\mathrm{Col}(A)$

$\vec{b} \notin \mathrm{Col}(A) \Rightarrow A\vec{x} = \vec{b}$ has no sols.

- It comes from finding Line / Curve fitting data



We are given data of coordinates (x_i, y_i) $i = 1, \dots, m$

Want a line $y = ax + c$ s.t.

$$y_1 = ax_1 + c$$
$$y_2 = ax_2 + c$$
$$\vdots$$
$$y_m = ax_m + c$$

$$\overset{A}{\begin{pmatrix} x_1 & 1 \\ \vdots & \vdots \\ x_m & 1 \end{pmatrix}} \overset{\vec{x}}{\begin{pmatrix} a \\ c \end{pmatrix}} = \overset{\vec{b}}{\begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}} \qquad \vec{x} = \begin{pmatrix} a \\ c \end{pmatrix}$$

First, we do not have the perfect line passing all the data points, i.e., $A\vec{x} = \vec{b}$ is overdetermined thus no sol.

Second, we only want the line that is the "closest" to all points, i.e., we want to find (a, c) for minimizing the "errors":

$$\text{Line Fitting Error} = \sum_{i=1}^{m} |ax_i + c - y_i|^2$$

$$\underline{A\vec{x}} = \begin{pmatrix} \boxed{\begin{matrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{matrix}} & \boxed{\begin{matrix} 1 \\ 1 \\ \vdots \\ 1 \end{matrix}} \end{pmatrix} \underline{\begin{pmatrix} a \\ c \end{pmatrix}} = \begin{pmatrix} ax_1 + c \\ ax_2 + c \\ \vdots \\ ax_m + c \end{pmatrix}$$

$$\vec{b} = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}$$

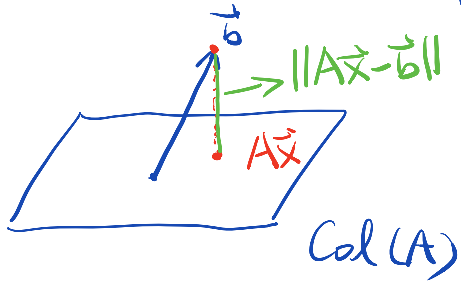
$$A\vec{x} - \vec{b} = \begin{pmatrix} ax_1 + c - y_1 \\ \vdots \\ ax_m + c - y_m \end{pmatrix}$$

$$\text{Line Fitting Error} = \|A\vec{x} - \vec{b}\|^2$$

$$A\vec{x} = a\begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} + c\begin{pmatrix} | \\ \vdots \\ | \end{pmatrix} \in \mathrm{Col}(A)$$

$\begin{cases} m=3 \\ n=2 \end{cases}$

$\vec{x} = \begin{pmatrix} a \\ c \end{pmatrix}$



$$\min_{\vec{x}\in\mathbb{R}^2} \|A\vec{x}-\vec{b}\|^2$$

① $A\vec{x}$ is a vector in Col (A)

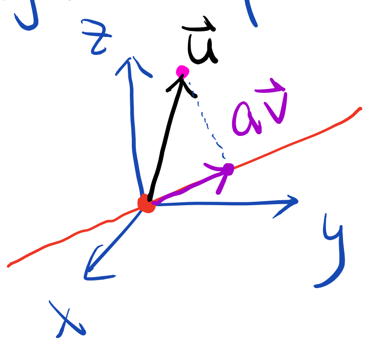
② Any vector in Col (A) can be written as

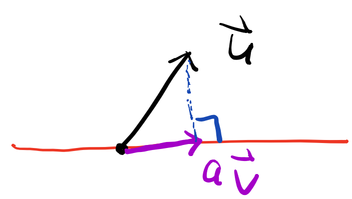
$$s\begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} + t\begin{pmatrix} | \\ \vdots \\ | \end{pmatrix} = \begin{pmatrix} x_1 & | \\ \vdots & \vdots \\ x_n & | \end{pmatrix}\begin{pmatrix} s \\ t \end{pmatrix} = A\hat{x} \quad \text{where } \hat{x} = \begin{pmatrix} s \\ t \end{pmatrix}$$

So minimizing the fitting error is the same as find the shortest distance between $\vec{b}$ and the subspace Col (A).

Review of Projection Onto a Line

Projection of a vector onto another one:





So we look for a vector $a\vec{v}$ satisfying

$$(\vec{u} - a\vec{v}) \perp \vec{v}$$

$$\Leftrightarrow \langle \vec{u} - a\vec{v}, \vec{v} \rangle = 0$$

$$\Leftrightarrow \langle \vec{u}, \vec{v} \rangle - a\langle \vec{v}, \vec{v} \rangle = 0$$

$$\Leftrightarrow a\langle \vec{v}, \vec{v} \rangle = \langle \vec{u}, \vec{v} \rangle$$

$$\Leftrightarrow a = \frac{\langle \vec{u}, \vec{v} \rangle}{\langle \vec{v}, \vec{v} \rangle} = \frac{\vec{v}^T\vec{u}}{\vec{v}^T\vec{v}} = \frac{\vec{u}\cdot\vec{v}}{\vec{v}\cdot\vec{v}}$$

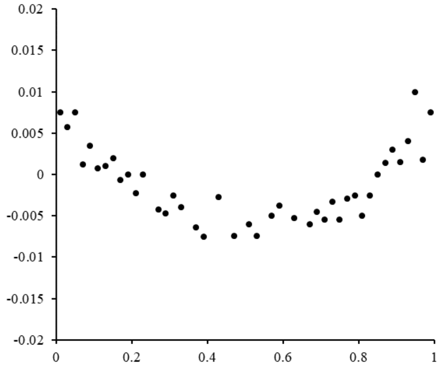
$$= \frac{\vec{u}\cdot\vec{v}}{\|\vec{v}\|^2}$$

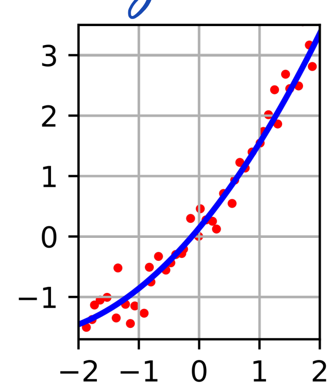
For $\vec{u}, \vec{v} \in \mathbb{R}^n$, the projection of $\vec{u}$ onto $\vec{v}$ is $P_{\vec{v}}(\vec{u}) = \frac{\vec{u}\cdot\vec{v}}{\|\vec{v}\|^2}\vec{v}$

Ex: Projection of $\vec{u} = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix}$ onto $\vec{v} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$

$$P_{\vec{v}}(\vec{u}) = \frac{\vec{u}\cdot\vec{v}}{\|\vec{v}\|^2}\vec{v} = \frac{6}{(1+1+1)}\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2 \\ 2 \\ 2 \end{bmatrix}.$$

- Curve Fitting: in general we can consider curves by using polynomials, trigonometrics, etc.





We are given data of coordinates (x_i, y_i)

$i = 1, \dots, m$

Want a quadratic fit:

$$
\begin{aligned}
y_1 &= dx_1^2 + ax_1 + c \\
y_2 &= dx_2^2 + ax_2 + c \\
&\vdots \\
y_m &= dx_m^2 + ax_m + c
\end{aligned}
$$

Want a cubic fit

$$
\begin{aligned}
y_1 &= ex_1^3 + dx_1^2 + ax_1 + c \\
y_2 &= ex_1^3 + dx_2^2 + ax_2 + c \\
&\vdots \\
y_m &= ex_m^3 + dx_m^2 + ax_m + c
\end{aligned}
$$

$$
\begin{pmatrix} x_1^2 & x_1 & 1 \\ x_2^2 & x_2 & 1 \\ \vdots & \vdots & \vdots \\ x_m^2 & x_m & 1 \end{pmatrix}
\begin{pmatrix} d \\ a \\ c \end{pmatrix}
=
\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix}
$$

$$A \vec{x} = \vec{b}$$

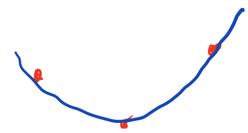
$$
\begin{pmatrix} x_1^3 & x_1^2 & x_1 & 1 \\ & \vdots & & \\ x_m^3 & x_m^2 & x_m & 1 \end{pmatrix}
\begin{pmatrix} e \\ d \\ a \\ c \end{pmatrix}
=
\begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}
$$

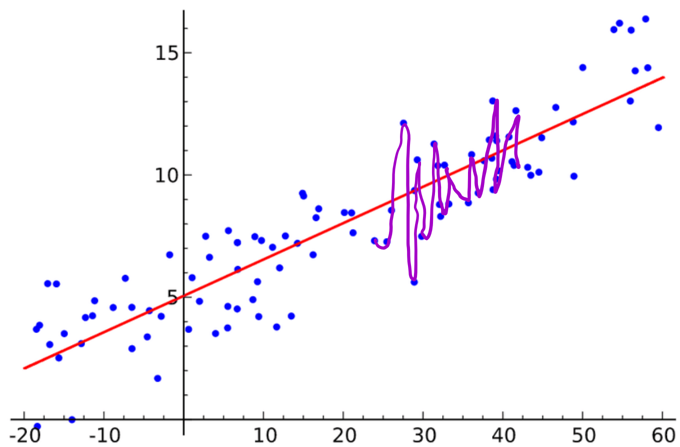
$$A \vec{x} = \vec{b}$$

$\boxed{\text{Remark}}$: For the same data, the best fitting error using quadratics is smaller than the best fitting error using lines.

For <u>m points</u>, we can get a perfect fit using <u>polynomial of degree m-1</u>, but that is overfitting, which should be avoided.

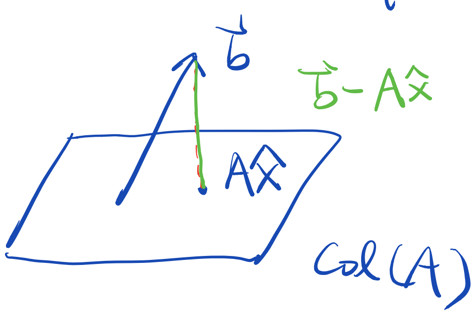
Overfitting means too many terms are used ($n > \sqrt{m}$) and the coefficients from too many terms represent the noise rather than the true model of data





$m = 100$

- Now consider how to find projection of $\vec{b} \in \mathbb{R}^m$ onto the col space of $A \in \mathbb{R}^{m \times n}$.



Want to find $\hat{x} = \begin{pmatrix} \hat{x}_1 \\ \vdots \\ \hat{x}_n \end{pmatrix}$ s.t.

$$\|A\hat{x} - \vec{b}\| = \min_{\vec{x} \in \mathbb{R}^n} \|A\vec{x} - \vec{b}\|$$

Intuition : $\vec{b} - A\hat{x}$ is 90° to the plane $Col(A)$.

Let cols of A be $\underbrace{\vec{a}_1, \dots, \vec{a}_n}_{\text{Assume they are independent.}}$

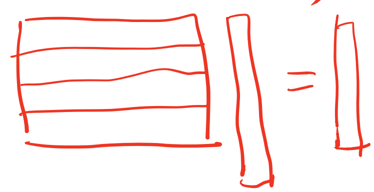
$$(\vec{b} - A\hat{x}) \perp Col(A) \iff (\vec{b} - A\hat{x}) \perp \vec{a}_i, \ \forall i$$

$$\langle \vec{b} - A\hat{x}, \vec{a}_i \rangle = 0$$

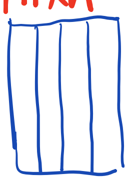
$$\iff \vec{a}_i^T(\vec{b} - A\hat{x}) = 0, \ \forall i$$

$$\iff \begin{cases} \vec{a}_1^T(\vec{b} - A\hat{x}) = 0 \\ \vdots \\ \vec{a}_n^T(\vec{b} - A\hat{x}) = 0 \end{cases}$$

$$A^T(\vec{b} - A\hat{x}) = \vec{0}$$

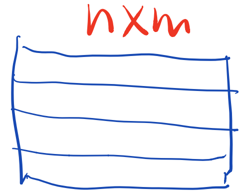


$m \times n$

$A =$ 

$\vec{a}_1 \cdots \vec{a}_n$

$n \times m$

$A^T =$ 

$\vec{a}_1^T$

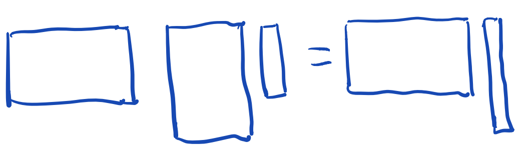
$\vdots$

$\vec{a}_n^T$

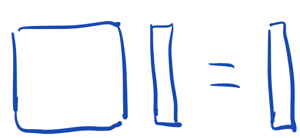
So $A^T(\vec{b} - A\hat{x}) = \vec{0}$

$$A^T\vec{b} = A^TA\hat{x}$$

$$A^TA\hat{x} = A^T\vec{b}$$



$$\underline{A^TA}\,\hat{x} = \underline{A^T\vec{b}}$$



$n\times m$ $m\times n$ $n\times m$ $m\times 1$ $n\times n$ $n\times 1$

How to find projection of $\vec{b}$ onto $Col(A)$:

① $\hat{x} = (A^TA)^{-1}A^T\vec{b}$

② The projection of $\vec{b}$ is $A\hat{x} = A(A^TA)^{-1}A^T\vec{b}$

③ Least Square Solution to $A\vec{x}=\vec{b}$ is $\hat{x}$.

If we assume cols of A are independent,

then A^TA is invertible

Proof: Want to show $\underline{(A^TA)\vec{x}=\vec{0}}$ has only zero sol

$$A^T\underbrace{A\vec{x}}_{\vec{y}}=\vec{0} \iff \vec{y}=A\vec{x} \text{ is a sol to } A^T\vec{y}=\vec{0}$$

$$\iff A\vec{x} \in Null(A^T)$$

Since $A\vec{x} \in Col(A)$, we know

$$A\vec{x} \in Col(A) \cap Null(A^T)$$

$Col(A) \perp Null(A^T) \Rightarrow$

$$A\vec{x} \perp A\vec{x}$$

$$\Rightarrow \langle A\vec{x}, A\vec{x}\rangle = 0$$

$$\Rightarrow A\vec{x} = \vec{0}$$

$\left.\begin{array}{l}\text{Independence}\\ \text{of Cols of } A\end{array}\right\} \Rightarrow \vec{x} = \vec{0}$. $\square$

Review

① Column Space of A : $\mathrm{Col}(A) \subseteq \mathbb{R}^m$

② Row Space of A : $\mathrm{Col}(A^T) \subseteq \mathbb{R}^n$

③ Null Space of A : $\mathrm{Null}(A) \subseteq \mathbb{R}^n$

④ Left Null Space of A : $\mathrm{Null}(A^T) \subseteq \mathbb{R}^m$

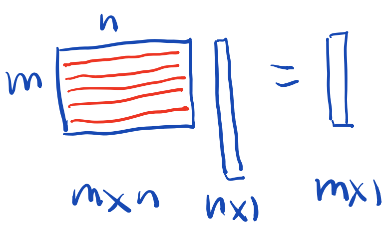
$$\mathrm{Null}(A) = \{\vec{x} \in \mathbb{R}^n : A\vec{x} = \vec{0}\}$$

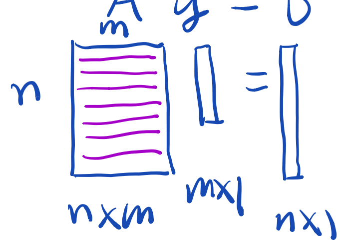
$$\mathrm{Null}(A^T) = \{\vec{y} \in \mathbb{R}^m : A^T\vec{y} = \vec{0}\}$$

$\mathrm{Col}(A^T) \perp \mathrm{Null}(A)$

$\mathrm{Col}(A) \perp \mathrm{Null}(A^T)$

$A\vec{x} = \vec{0}$ $\qquad\qquad$ $A^T\vec{y} = \vec{0}$





If $A\vec{x} = \vec{0}$, then each row of A is $\perp$ to $\vec{x}$

$\Rightarrow$ $\mathrm{Col}(A^T) \perp \mathrm{Null}(A)$

If $A^T\vec{y} = \vec{0}$, then each row of A^T is $\perp$ to $\vec{y}$

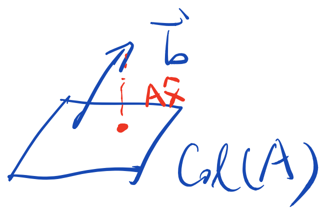
$\Rightarrow$ each col of A is $\perp$ to $\vec{y}$

$\Rightarrow$ $\mathrm{Col}(A) \perp \mathrm{Null}(A^T)$

Example: Find projection of $\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ onto

$$\mathrm{Span}\left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} \right\}$$

Sol: $\quad A = \begin{bmatrix} 1 & 2 \\ 1 & 2 \\ 0 & 1 \end{bmatrix}$, $\vec{b} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$



$$A^TA = \begin{bmatrix} 2 & 4 \\ 4 & 9 \end{bmatrix}$$

$$A^T\vec{b} = \begin{bmatrix} 1 & 1 & 0 \\ 2 & 2 & 1 \end{bmatrix}\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \begin{bmatrix} 3 \\ 6 \end{bmatrix}$$

$$A^TA\hat{x} = A^T\vec{b}$$

$$\left[\begin{array}{cc|c} 2 & 4 & 3 \\ 4 & 9 & 6 \end{array}\right]$$

$$\rightarrow \left[\begin{array}{cc|c} 1 & 2 & 3/2 \\ 1 & 9/4 & 3/2 \end{array}\right]$$

$$\rightarrow \left[\begin{array}{cc|c} 1 & 2 & 3/2 \\ 0 & 1/4 & 0 \end{array}\right]$$

$$\rightarrow \left[\begin{array}{cc|c} 1 & 0 & 3/2 \\ 0 & 1 & 0 \end{array}\right]$$

$$\Rightarrow \hat{x} = \begin{pmatrix} 3/2 \\ 0 \end{pmatrix}$$

$$A\hat{x} = \begin{bmatrix} 1 & 2 \\ 1 & 2 \\ 0 & 1 \end{bmatrix}\begin{bmatrix} 3/2 \\ 0 \end{bmatrix} = \begin{bmatrix} 3/2 \\ 3/2 \\ 0 \end{bmatrix}$$

So projection of $\begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$ onto

Span$\left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 2 \\ 2 \\ 1 \end{bmatrix} \right\}$ is $\begin{bmatrix} 3/2 \\ 3/2 \\ 0 \end{bmatrix}$.