18.06

Projection Matrices: Motivation

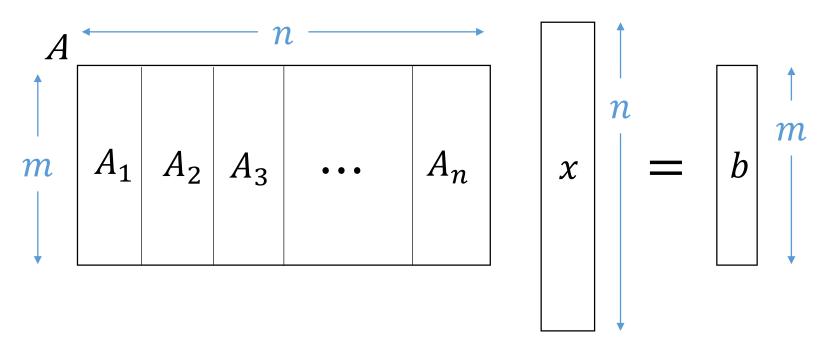
Consider equation Ax = bGiven an $m \times n$ matrix AAnd vector $b \in \mathbb{R}^m$

Does any $x \in \mathbb{R}^n$ satisfy equation?

How many $x \in \mathbb{R}^n$ satisfy equation?

Can we describe set of all $x \in \mathbb{R}^n$ that satisfy equation?

Equation Ax = b



Column space col(
$$A$$
) = {all linear combinations of columns }
= $\{c_1A_1 + c_2A_2 + \dots + c_nA_n | c_i \in \mathbb{R}\}$
= $\{Ax|x \in \mathbb{R}^n\}$
= {all $y \in \mathbb{R}^m$, such that $y = Ax$, for some x }

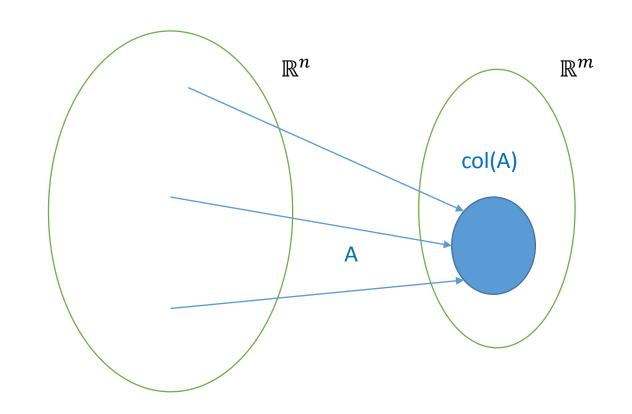
Equation Ax = b has at least one solution exactly when $b \in col(A)$

Equation Ax = b

For an $m \times n$ matrix A A is a function $\text{input: } x \in \mathbb{R}^n$

output: $y \in \mathbb{R}^m$

y = Ax



Equation Ax = b has at least one solution exactly when $b \in col(A)$

Goal: Determine if $b \in col(A)$

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Using col(A) = \{c_1A_1 + c_2A_2 + \dots + c_nA_n | c_i \in \mathbb{R}\}
       Seems hard to determine if b \in col(A)
Instead:
       col(A) is a vector space, which lives inside \mathbb{R}^m
       Find \tilde{b} \in col(A) that is closest to b
               If \tilde{b} = b, b \in col(A)
               If \tilde{b} \neq b, b \notin col(A)
       "Project" b onto col(A) (find \tilde{b} \in col(A))
In general, for vector space V with vector space W inside it
        "Project" b \in V onto W (find \tilde{b} \in W)
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Projection Onto x-axis in \mathbb{R}^2

Given
$$b = \begin{bmatrix} x \\ y \end{bmatrix} \in \mathbb{R}^2$$

Goal: find \tilde{b}

b points along x-axis

 \tilde{b} as close to b as possible

$$e = \tilde{b} - b$$

 $\|e\| = \|\tilde{b} - b\|$ as small as possible

Say \tilde{b} is projection of b onto x-axis

Projection Onto x-axis in \mathbb{R}^2

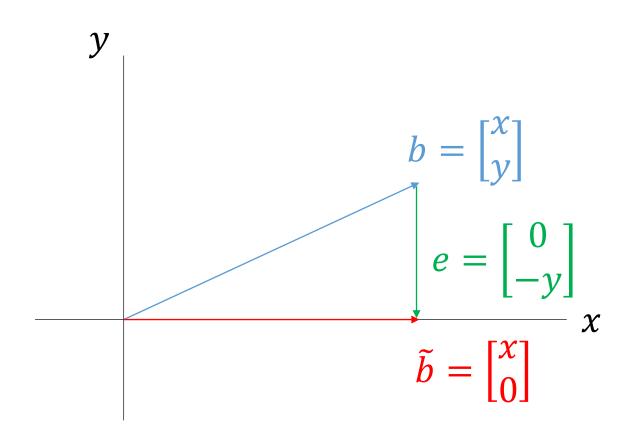
Next: Want Projection matrix P

$$\tilde{b} = Pb$$

$$\begin{bmatrix} x \\ 0 \end{bmatrix} = P \begin{bmatrix} x \\ y \end{bmatrix}$$

$$\begin{bmatrix} x \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

$$P = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$



Projection Onto Line Through Origin in \mathbb{R}^2

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Given b \in \mathbb{R}^2 and \hat{u} \in \mathbb{R}^2, ||\hat{u}|| = 1
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Goal: find \tilde{b}

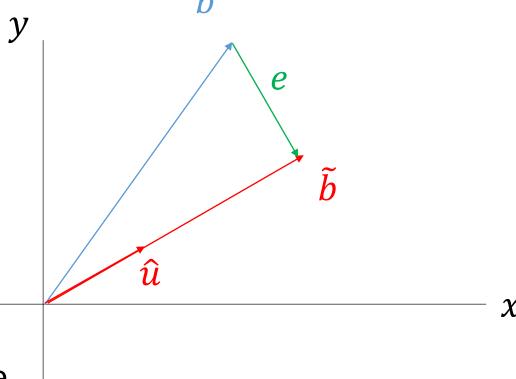
 \tilde{b} points along \hat{u}

 \tilde{b} as close to b as possible

$$e = \tilde{b} - b$$

 $\|e\| = \|\tilde{b} - b\|$ as small as possible

Say \tilde{b} is projection of b onto line through \hat{u}



Projection Onto Line Through Origin in \mathbb{R}^2

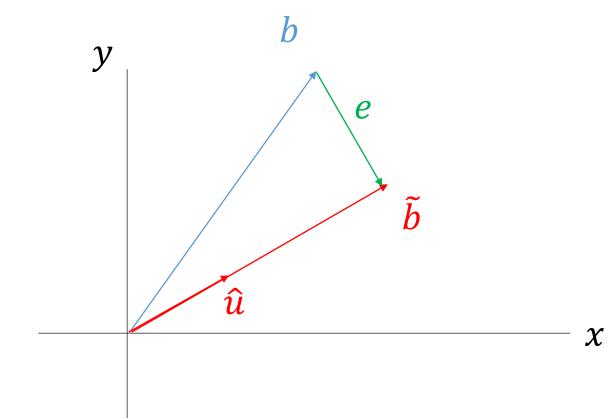
Next: Write expression for \tilde{b}

$$\tilde{b} = \alpha \hat{u}, \alpha \in \mathbb{R}$$

$$\hat{\mathbf{u}} \cdot \mathbf{e} = 0
\hat{\mathbf{u}} \cdot (\tilde{\mathbf{b}} - \mathbf{b}) = 0
\hat{\mathbf{u}} \cdot (\alpha \hat{\mathbf{u}} - \mathbf{b}) = 0
\alpha \hat{\mathbf{u}} \cdot \hat{\mathbf{u}} - \hat{\mathbf{u}} \cdot \mathbf{b} = 0
\alpha - \hat{\mathbf{u}} \cdot \mathbf{b} = 0$$

$$\alpha = \hat{u} \cdot b$$

$$\tilde{b} = (\hat{u} \cdot b)\hat{u}$$



Projection Onto Line Through Origin in \mathbb{R}^2

Next: Want Projection matrix P

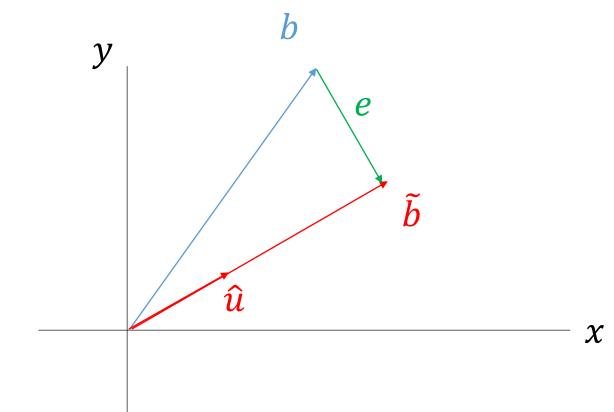
$$\tilde{b} = Pb$$

$$\tilde{b} = (\hat{u} \cdot b) \hat{u}
= \hat{u} (\hat{u} \cdot b)
= \hat{u} (\hat{u}^{\mathsf{T}} b)
= (\hat{u} \hat{u}^{\mathsf{T}}) b$$

$$P_{\widehat{u}} = \widehat{u}\widehat{u}^{\mathsf{T}}$$

Check: Projection onto x-axis

$$\hat{u} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, P_{\begin{bmatrix} 1 \\ 0 \end{bmatrix}} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$$



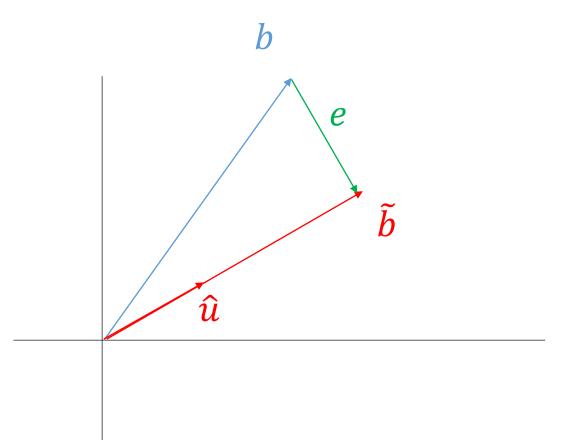
Projection Onto Line Through Origin in \mathbb{R}^n

Next: Want Projection matrix P

$$\tilde{b} = Pb$$

$$\tilde{b} = (\hat{u} \cdot b) \hat{u}
= \hat{u} (\hat{u} \cdot b)
= \hat{u} (\hat{u}^{\mathsf{T}} b)
= (\hat{u} \hat{u}^{\mathsf{T}}) b$$

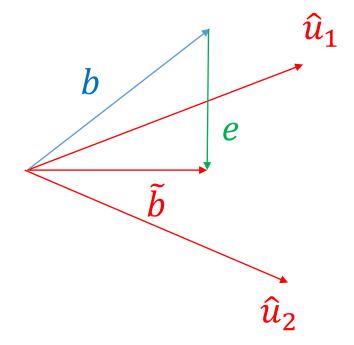
$$P_{\widehat{u}} = \widehat{u}\widehat{u}^{\mathsf{T}}$$



Projection Onto Plane Through Origin in \mathbb{R}^3

Given $b \in \mathbb{R}^3$ and $\hat{u}_1, \hat{u}_2 \in \mathbb{R}^3$ such that \hat{u}_1, \hat{u}_2 are orthonormal

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Goal: find \tilde{b}
\tilde{b} \in \operatorname{span}(\hat{u}_1, \hat{u}_2)
(all linear combinations of \hat{u}_1, \hat{u}_2)
\tilde{b} \text{ as close to } b \text{ as possible}
e = \tilde{b} - b
\|e\| = \|\tilde{b} - b\| \text{ as small as possible}
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Projection Onto Plane Through Origin in \mathbb{R}^3

Next: Write expression for \tilde{b}

$$\tilde{b} = \alpha_1 \hat{u}_1 + \alpha_2 \hat{u}_2, \ \alpha_1, \alpha_2 \in \mathbb{R}$$

 $\hat{u}_1 \cdot e = 0 \text{ and } \hat{u}_2 \cdot e = 0$

$$\hat{u}_1 \cdot e = 0$$

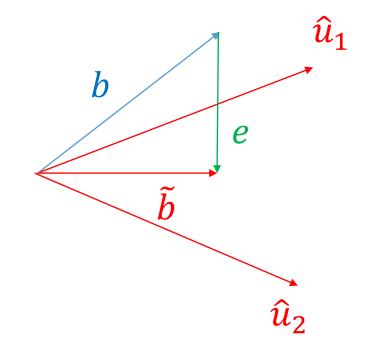
$$\hat{u}_1 \cdot (\tilde{b} - b) = 0$$

$$\hat{u}_1 \cdot (\alpha_1 \hat{u}_1 + \alpha_2 \hat{u}_2 - b) = 0$$

$$\alpha_1 \hat{u}_1 \cdot \hat{u}_1 + \alpha_2 \hat{u}_1 \cdot \hat{u}_2 - \hat{u}_1 \cdot b = 0$$

$$\alpha_1 - \hat{u}_1 \cdot b = 0$$

$$\alpha_1 = \hat{u}_1 \cdot b$$
looks familiar...



$$\tilde{b} = (\hat{u}_1 \cdot b)\hat{u}_1 + (\hat{u}_2 \cdot b)\hat{u}_2$$

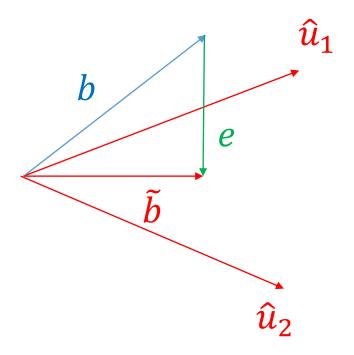
Projection Onto Plane Through Origin in \mathbb{R}^3

$$\tilde{b} = (\hat{u}_1 \cdot b)\hat{u}_1 + (\hat{u}_2 \cdot b)\hat{u}_2$$

 $(\hat{u}_1 \cdot b)\hat{u}_1$ is projection of b onto line through \hat{u}_1 $(\hat{u}_2 \cdot b)\hat{u}_2$ is projection of b onto line through \hat{u}_2

 \tilde{b} (projection of b onto plane spanned by \hat{u}_1, \hat{u}_2)
= sum of these two projections

$$P_{\widehat{u}_1,\widehat{u}_2} = \widehat{u}_1 \widehat{u}_1^{\mathsf{T}} + \widehat{u}_2 \widehat{u}_2^{\mathsf{T}}$$



Projection Onto col(U)

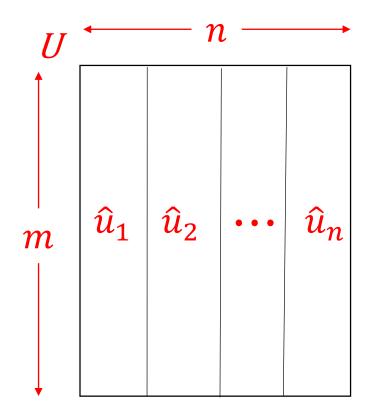
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Given: vector b \in \mathbb{R}^m
U an m \times n orthogonal matrix (either square or "tall-skinny")

Goal: find \tilde{b}
\tilde{b} \in \operatorname{col}(U)
\tilde{b} as close to b as possible
e = \tilde{b} - b
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 $\|e\| = \|\tilde{b} - b\|$ as small as possible

Projection Onto col(U)

By definition, U orthogonal means columns of U orthonormal



$$\hat{u}_1, \hat{u}_2, \dots, \hat{u}_n$$
 are orthonormal $col(U) = span(\hat{u}_1, \hat{u}_2, \dots, \hat{u}_n)$

Projection onto
$$col(U)$$
 given by
$$P_{U} = u_{1}u_{1}^{\mathsf{T}} + u_{2}u_{2}^{\mathsf{T}} + \dots + u_{n}u_{n}^{\mathsf{T}}$$

$$= UU^{\mathsf{T}}$$

Equation Ax = b

Recall:

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Ax = b has at least one solution exactly when b \in \operatorname{col}(A) If A has (compact) SVD A = U_1 \Sigma_r V_1^{\mathsf{T}} \operatorname{col}(A) = \operatorname{col}(U_1) If \tilde{b} = U_1 U_1^{\mathsf{T}} b, then \tilde{b} is closest element in \operatorname{col}(U_1) to b b \in \operatorname{col}(U_1) exactly when b = \tilde{b} = U_1 U_1^{\mathsf{T}} b
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Ax = b has at least one solution exactly when $b = U_1 U_1^{\top} b$

Why Use the SVD?

Ax = b has at least one solution exactly when $b \in col(A)$

Why not immediately project b onto col(A)?

Not clear how

Previous argument gets much messier

Important Vector Space Definitions

Given vector space V over \mathbb{R} (e.g., \mathbb{R}^3 , col(A)) And vectors $v_1, v_2, \dots, v_k \in V$

Say v_1, v_2, \dots, v_k span V if, for each vector $x \in V$ Can write x as lin. combo. of v_1, v_2, \dots, v_k $x = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_k v_k$, for $\alpha_1, \alpha_2, \dots, \alpha_k \in \mathbb{R}$

Say $v_1, v_2, ..., v_k$ are linearly independent if No non-trivial lin. combo. of $v_1, v_2, ..., v_k$ is zero (zero vector) $\alpha_1 v_1 + \alpha_2 v_2 + \cdots + \alpha_k v_k = 0 \text{ only when } \alpha_1 = \alpha_2 = \cdots = \alpha_k = 0$

Say v_1, v_2, \dots, v_k are a basis of V if they span V and are linearly independent

Why Use the SVD?

If A has (compact) SVD $A = U_1 \Sigma_r V_1^{\mathsf{T}}$, then $\operatorname{col}(A) = \operatorname{col}(U_1)$

Columns of U_1 span col(A)

Columns of A span col(A)

Columns of U_1 are linearly independent Columns of A may or may not be linearly independent

Columns of U_1 form a basis of col(A)Columns of A may or may not form a basis of col(A)