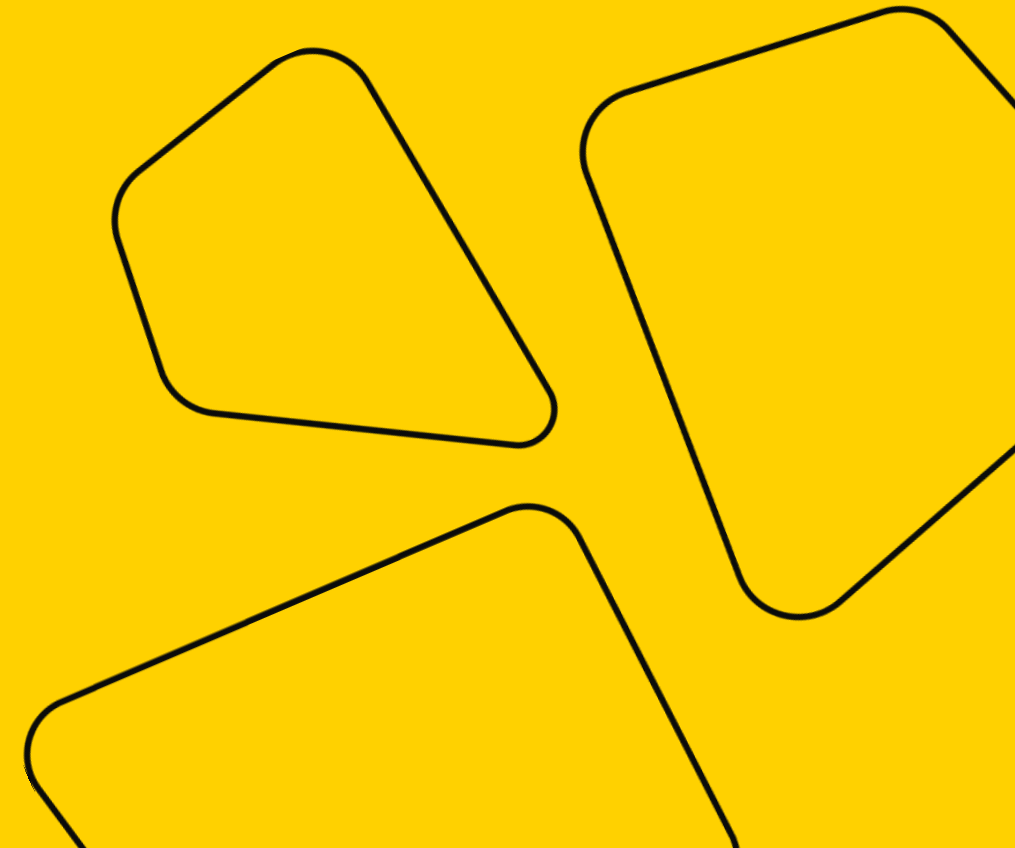




Math Refresher for DS

Practical Session 4



Plan for Today



- A short quiz
- SLE with no solutions
- Practice in Python

We (Finally) Have a Course Repo!

- <https://github.com/girafe-ai/math-basics-for-ai>
 - Slides
 - Links to colab-notebooks
 - Links to lectures / practical session recordings
 - Additional material



Short Quiz Lectures 1 - 3

<https://forms.gle/Mw28SUSTwohWWv9d7>

Solving Systems of Linear Equations

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How to find a reasonable approximate solution?

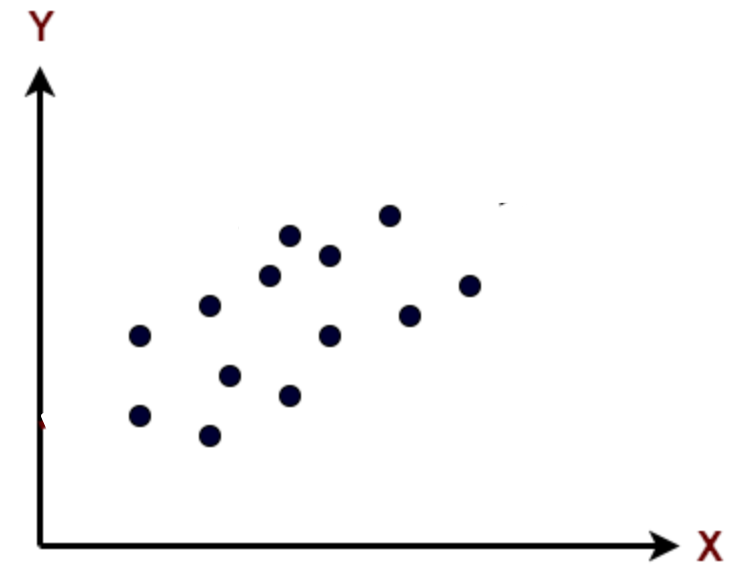
Least Squares



Motivating Example

- Imagine that you have m observations:

$(x_1, y_1), \quad (x_2, y_2), \quad \dots, \quad (x_m, y_m)$

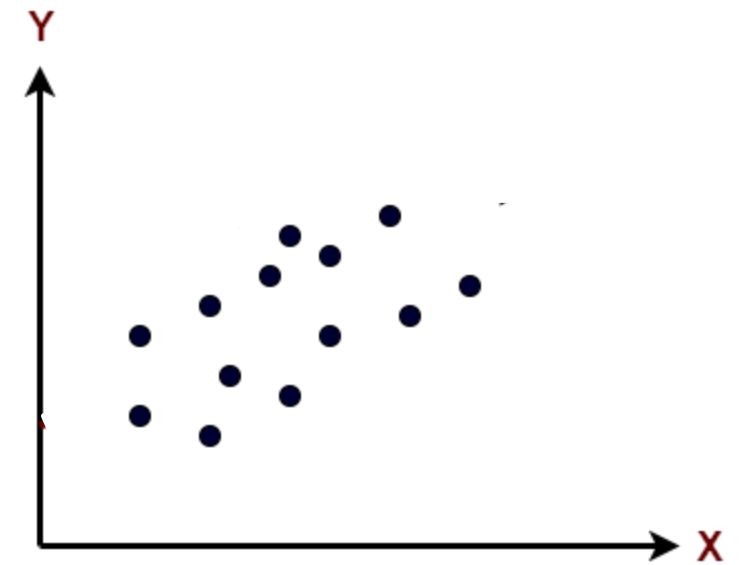


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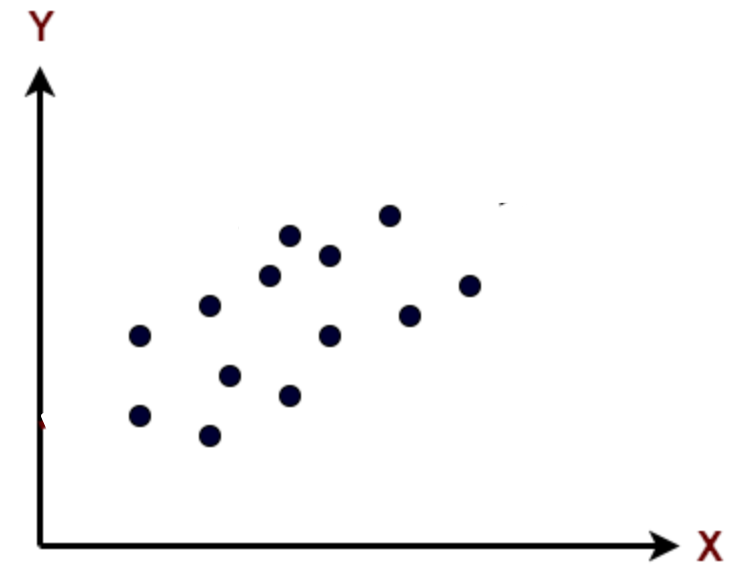
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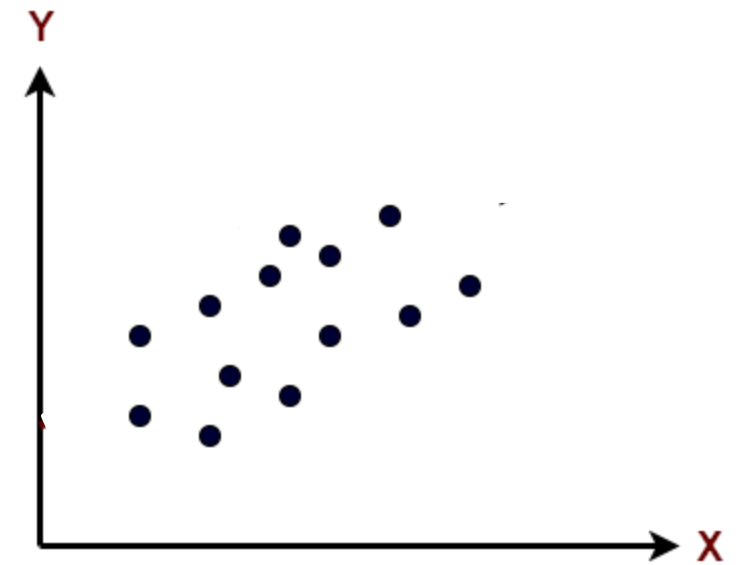


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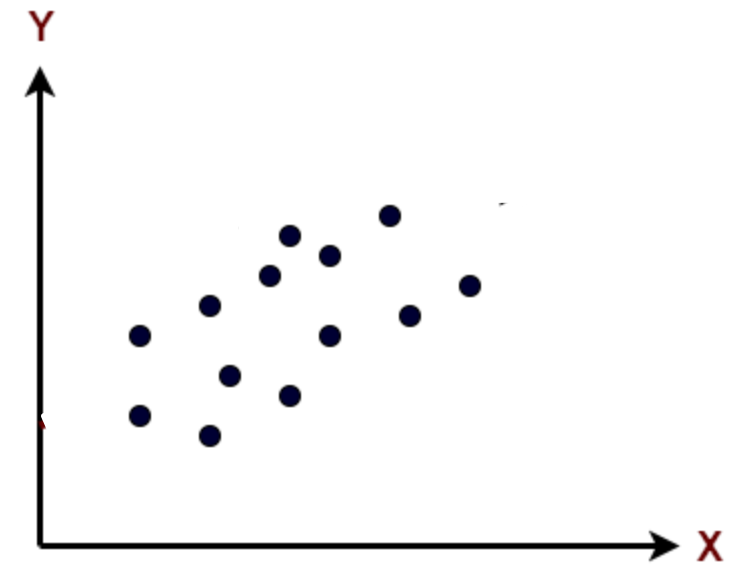
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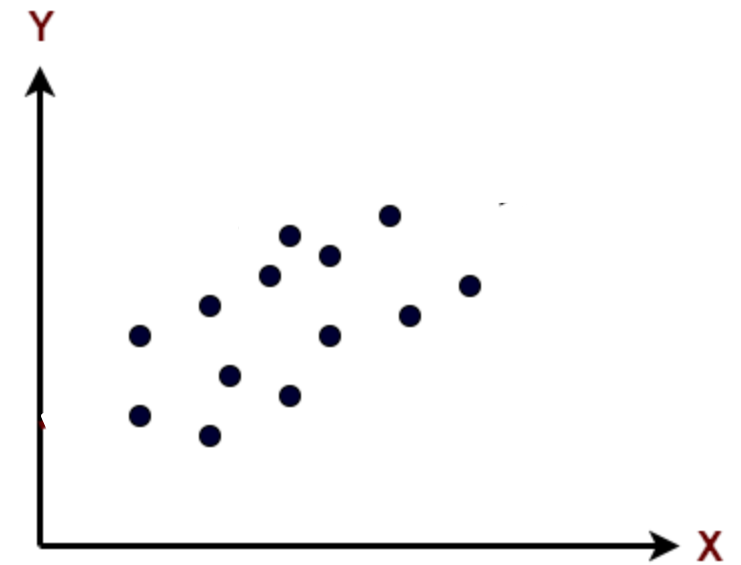
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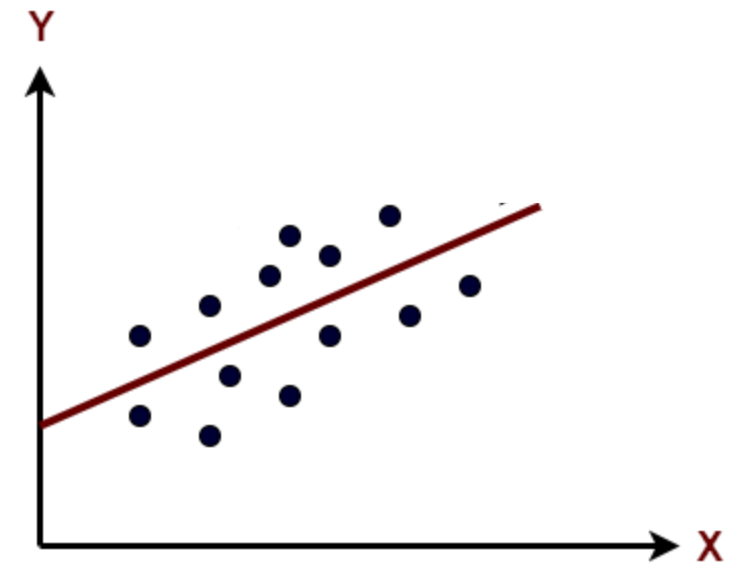
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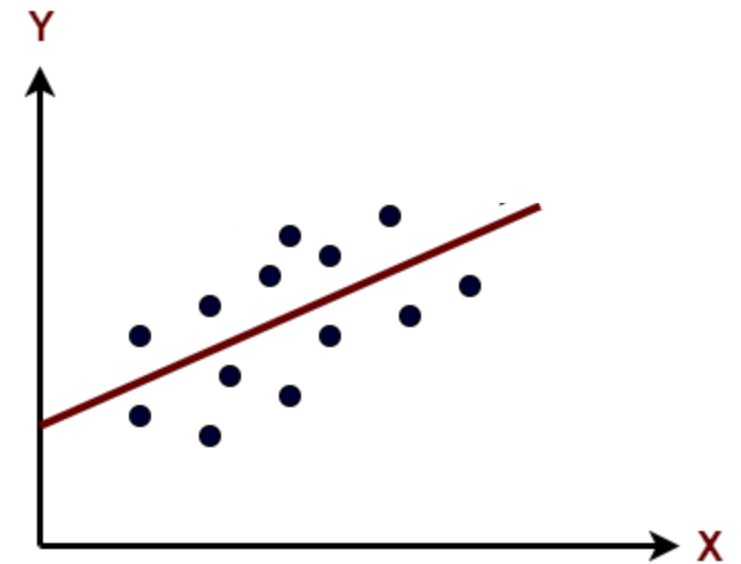
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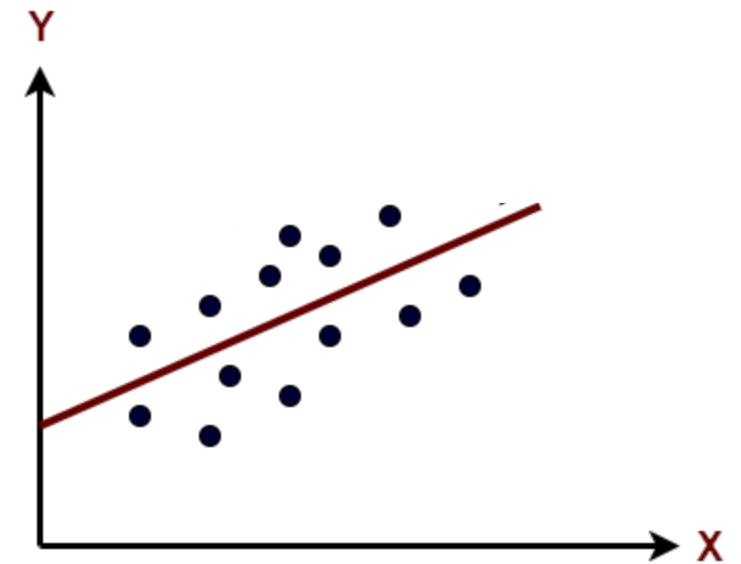
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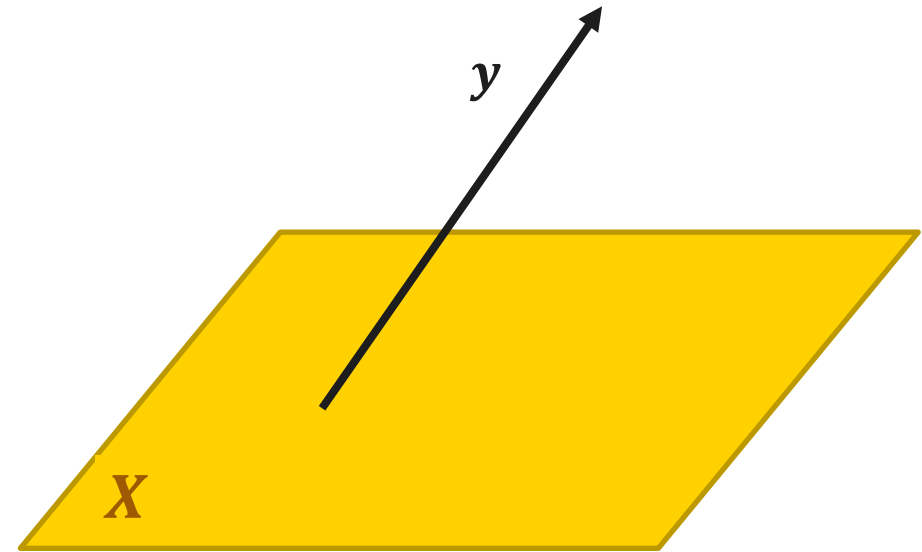
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- Let's look at it from the Linear Algebra perspective.

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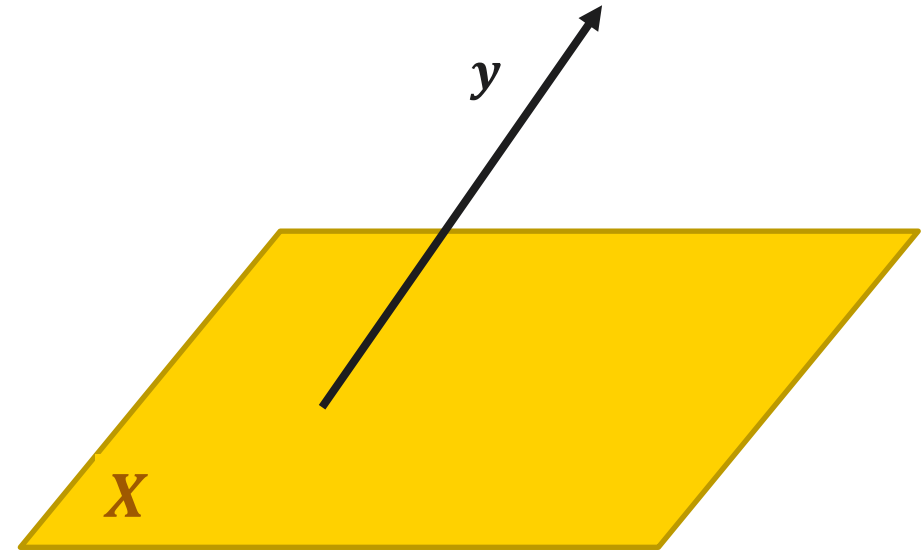
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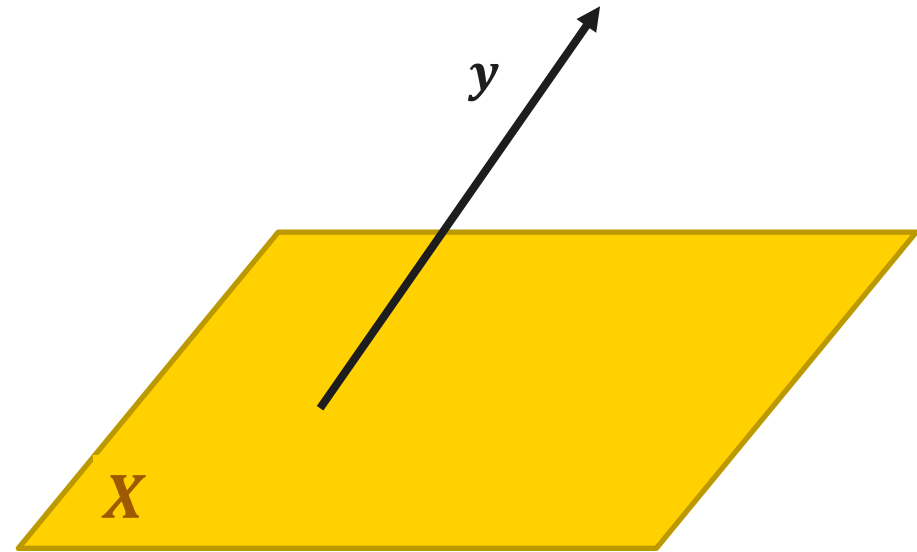


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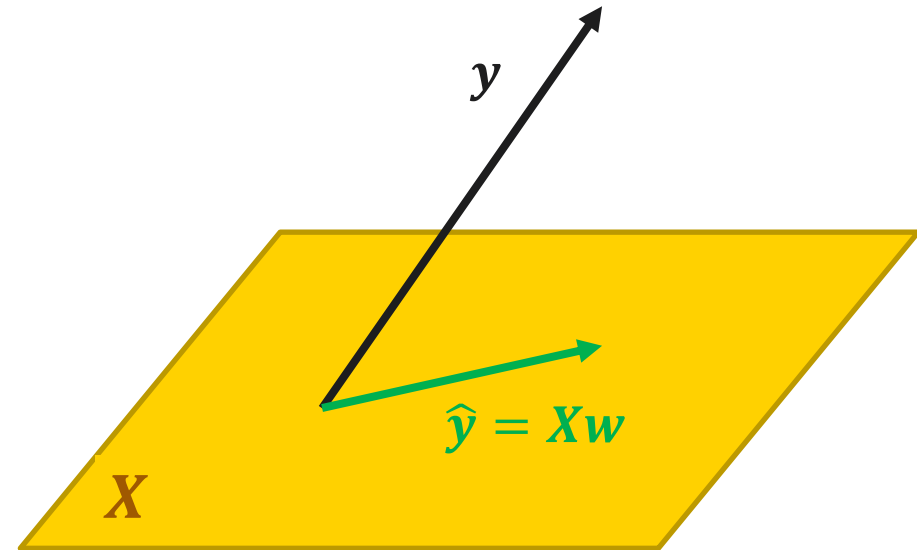
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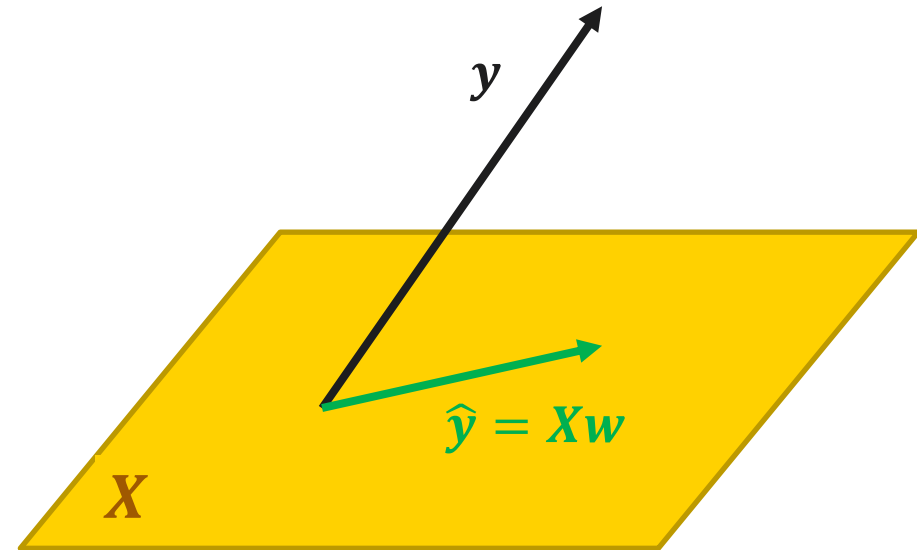
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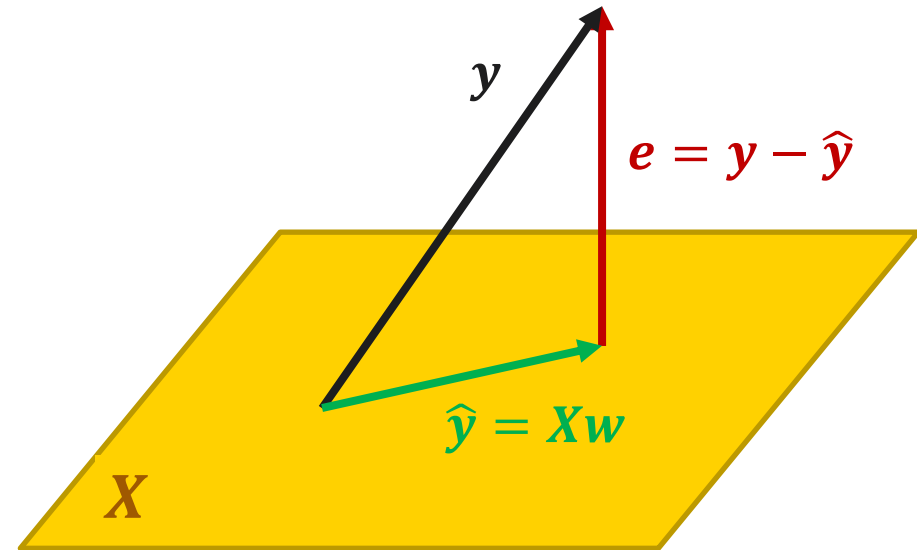
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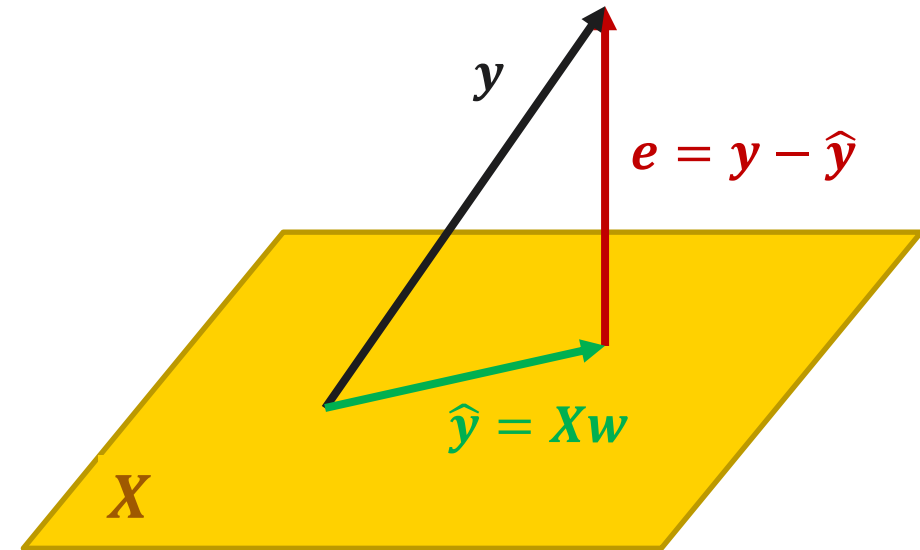
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- What do \hat{y} and e look like?



Orthogonal Projections



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- Example:

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$$W = \text{span} \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \right\}, \quad W_{\perp} = \text{span} \left\{ \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$$

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- x_W is the closest vector to x in W .