Deep Learning

April 18, 2019

Data Science CSCI 1951A

Brown University

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HTAs: Wennie Zhang, Maulik Dang, Gurnaaz Kaur

Announcements

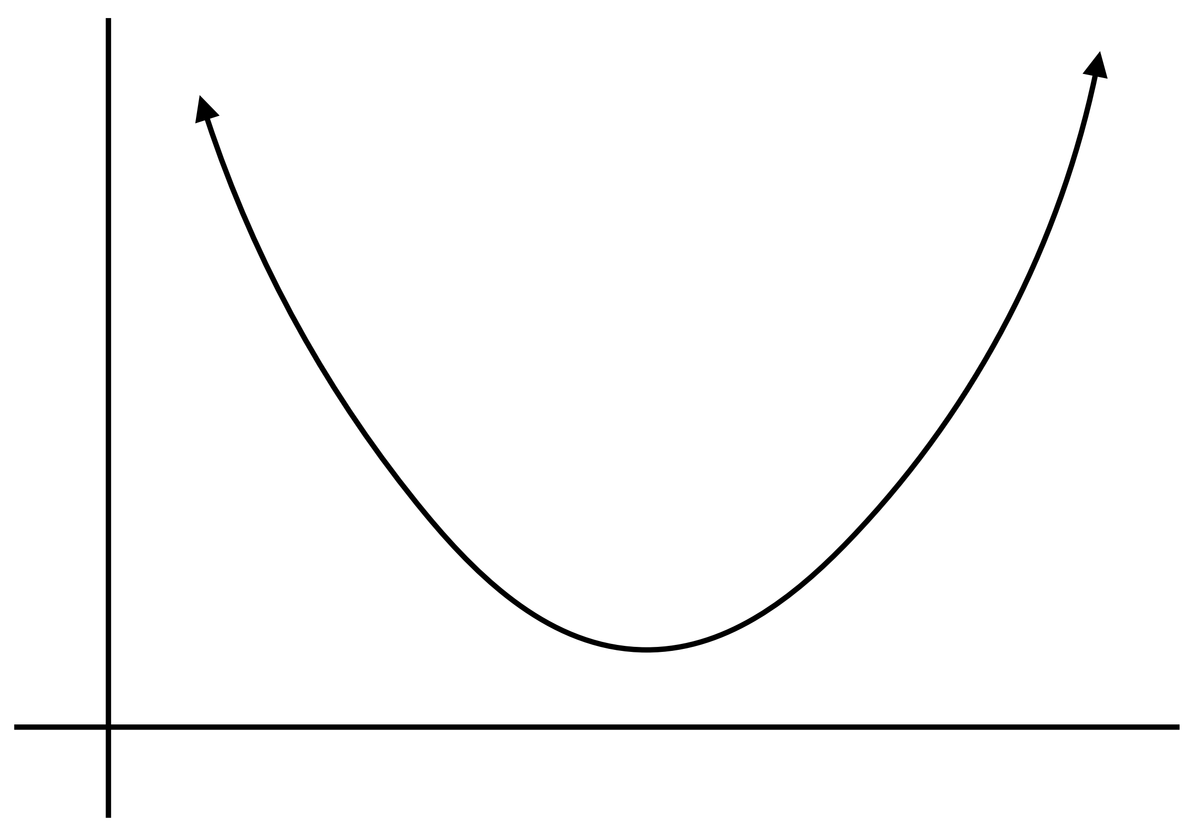
- Extra Office Hours next week—talk to me about your project woes (getting close to your last chance)

Today

- Deep Learning — roughly what is it?
- Why is it such a big deal (now)?
- Should I use deep learning for my thing?

Gradient Descent

minimize $$\sum_{i=1}^{n}(Y_i - \hat{Y})^2$$



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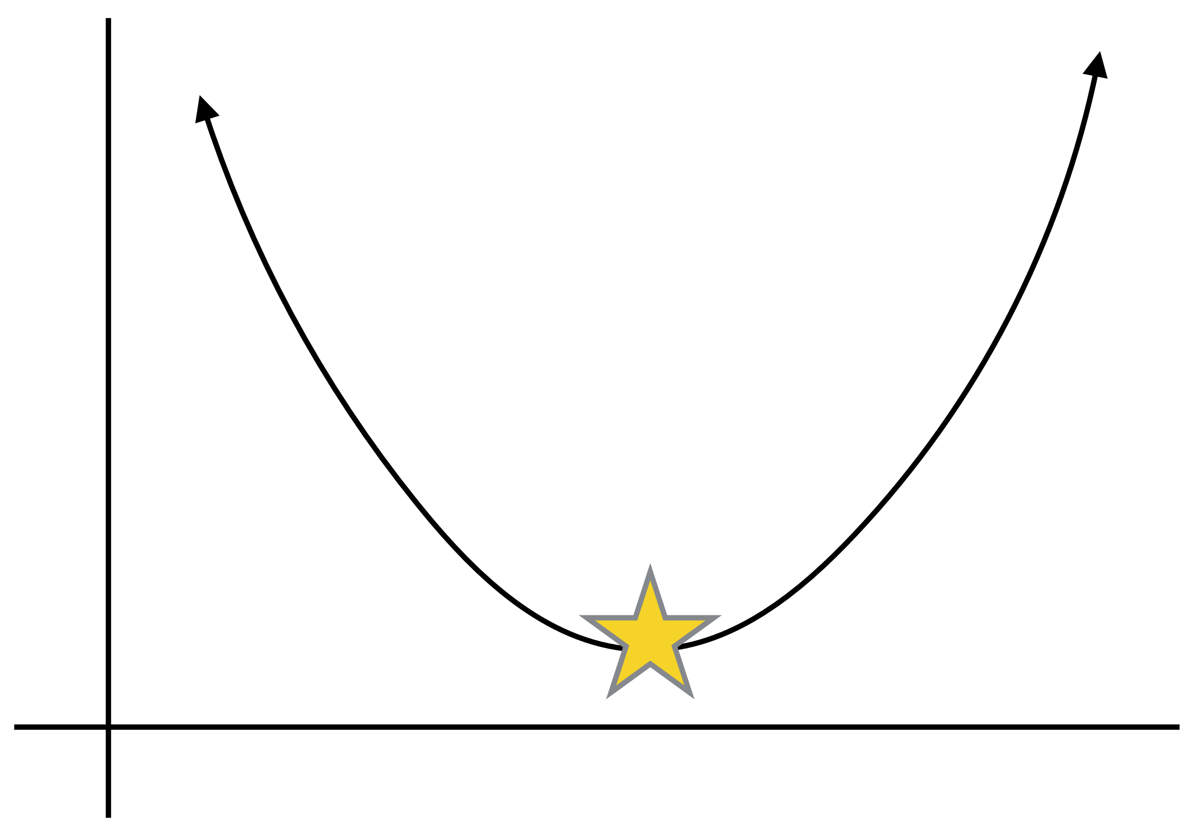

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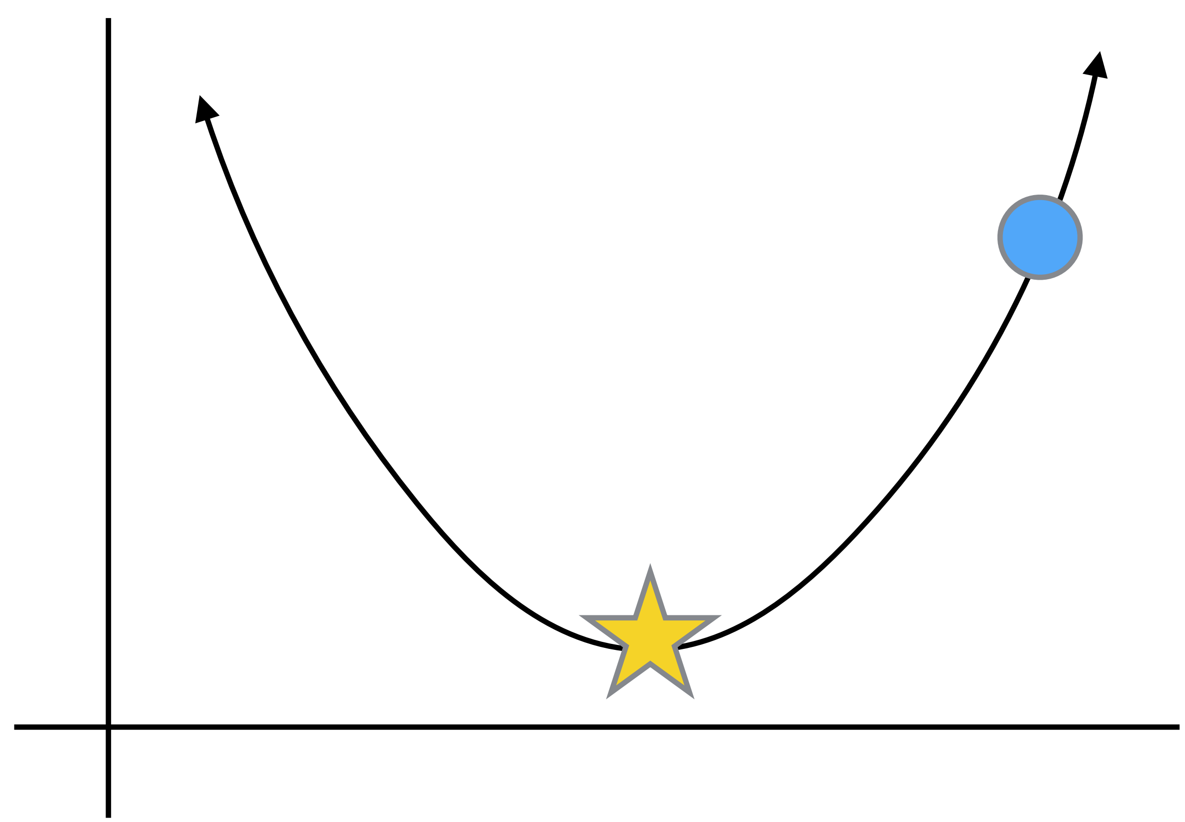

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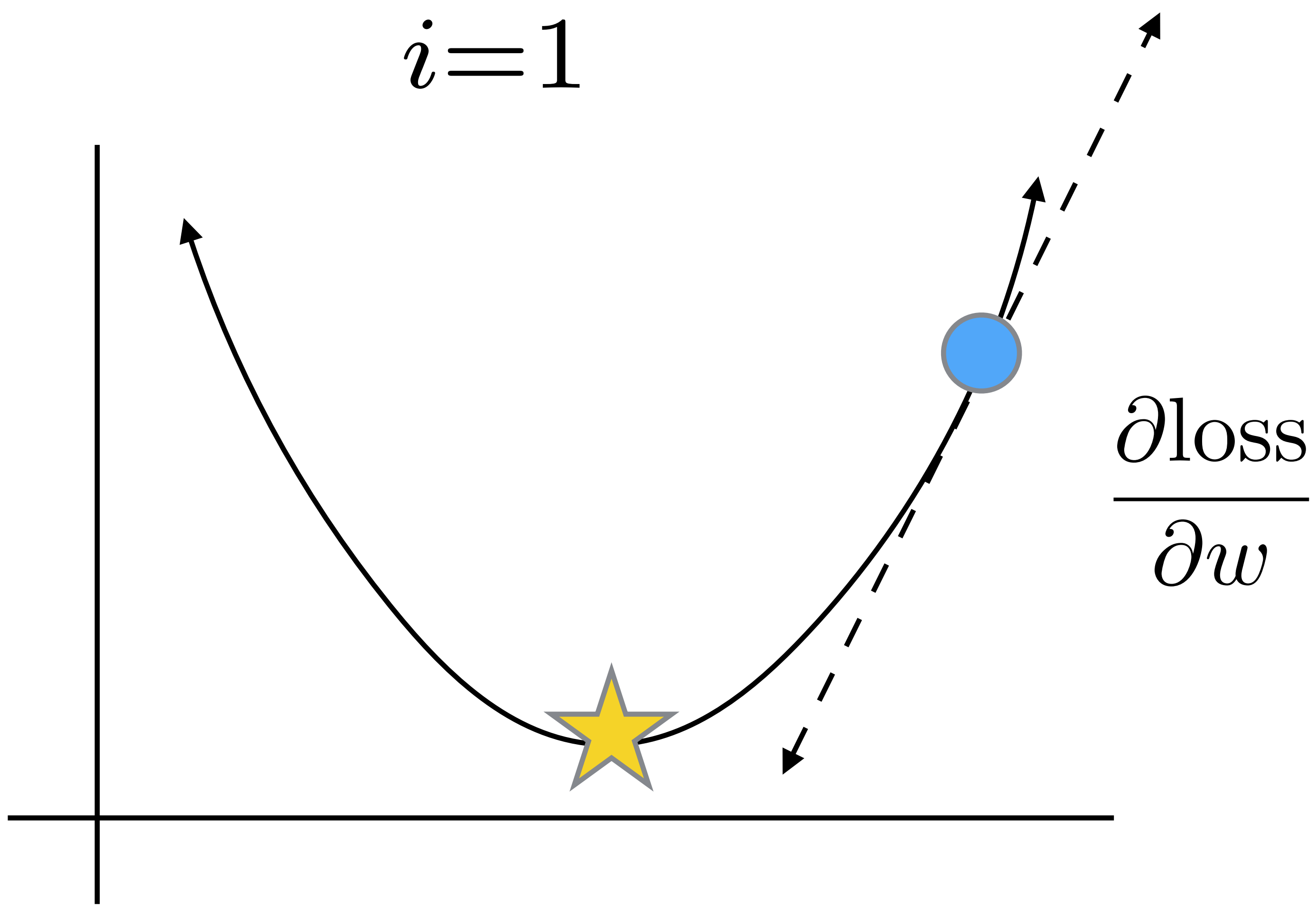

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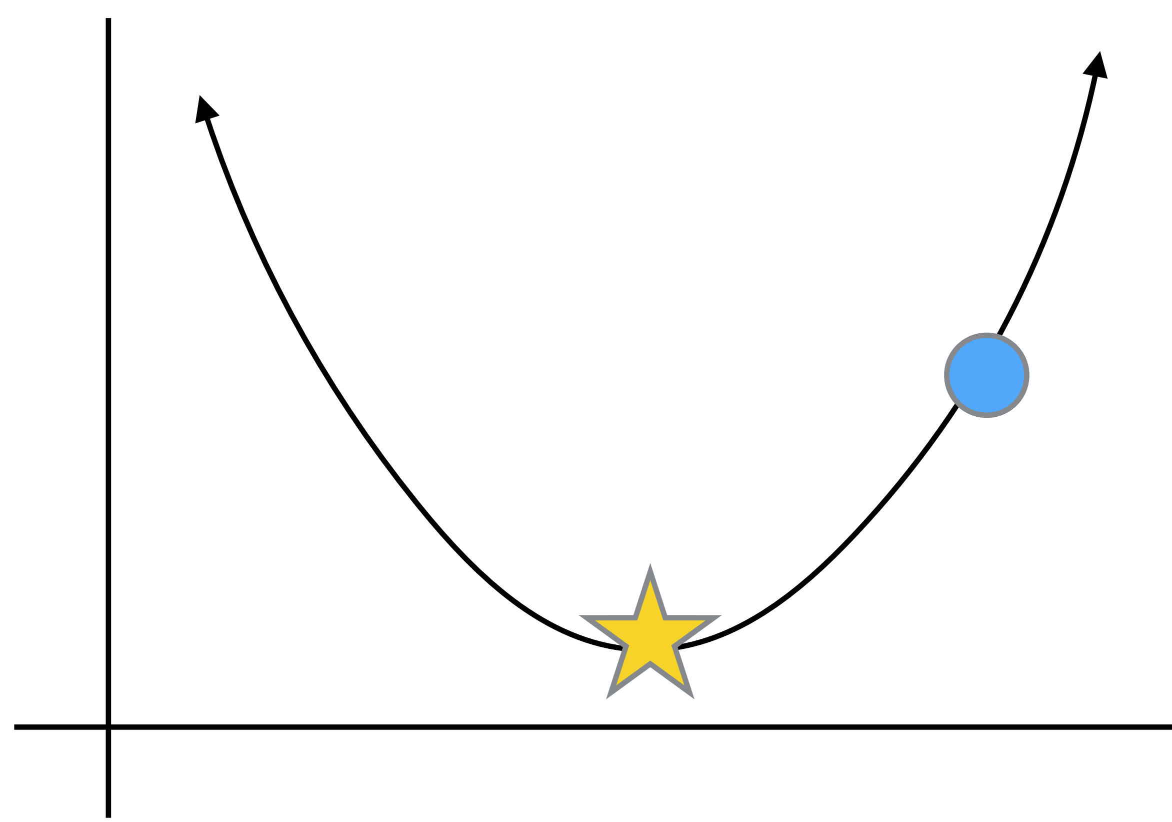
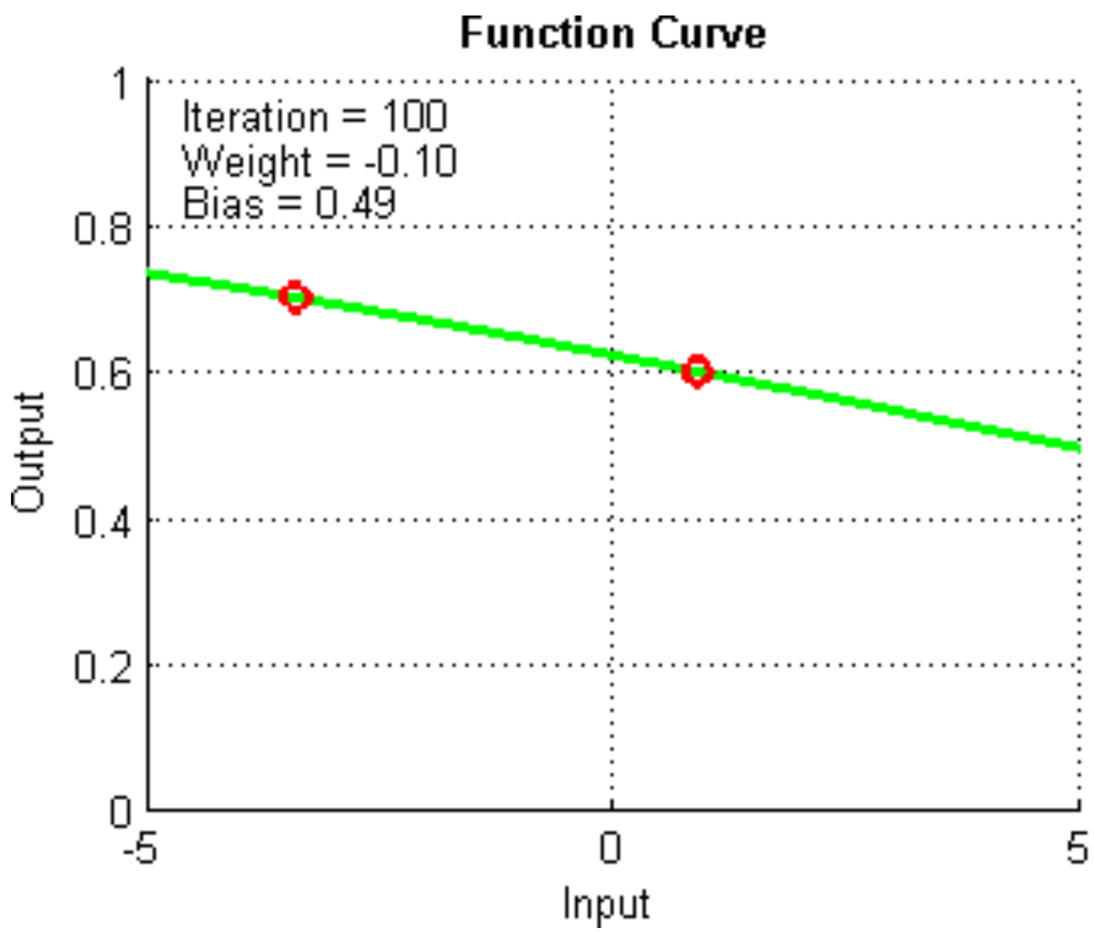
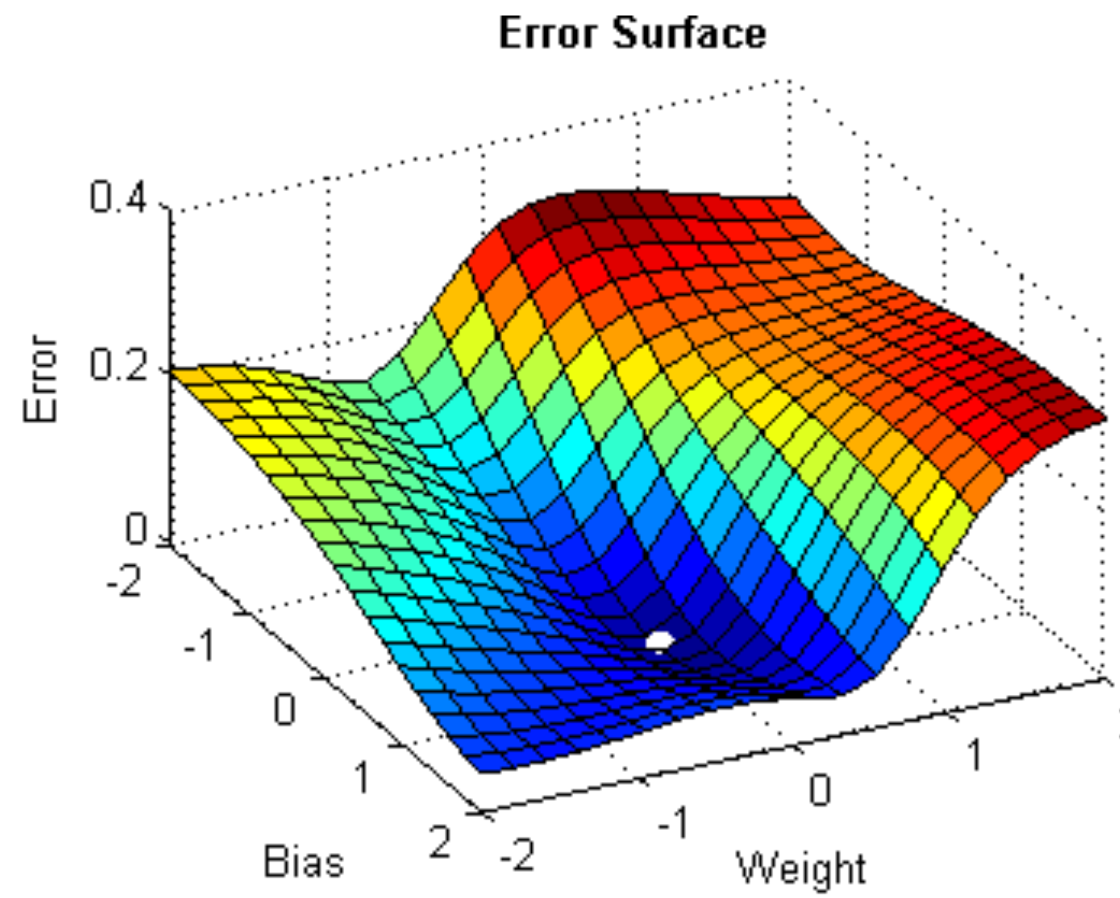


$$\frac{\partial \text{loss}}{\partial w}$$

Gradient Descent

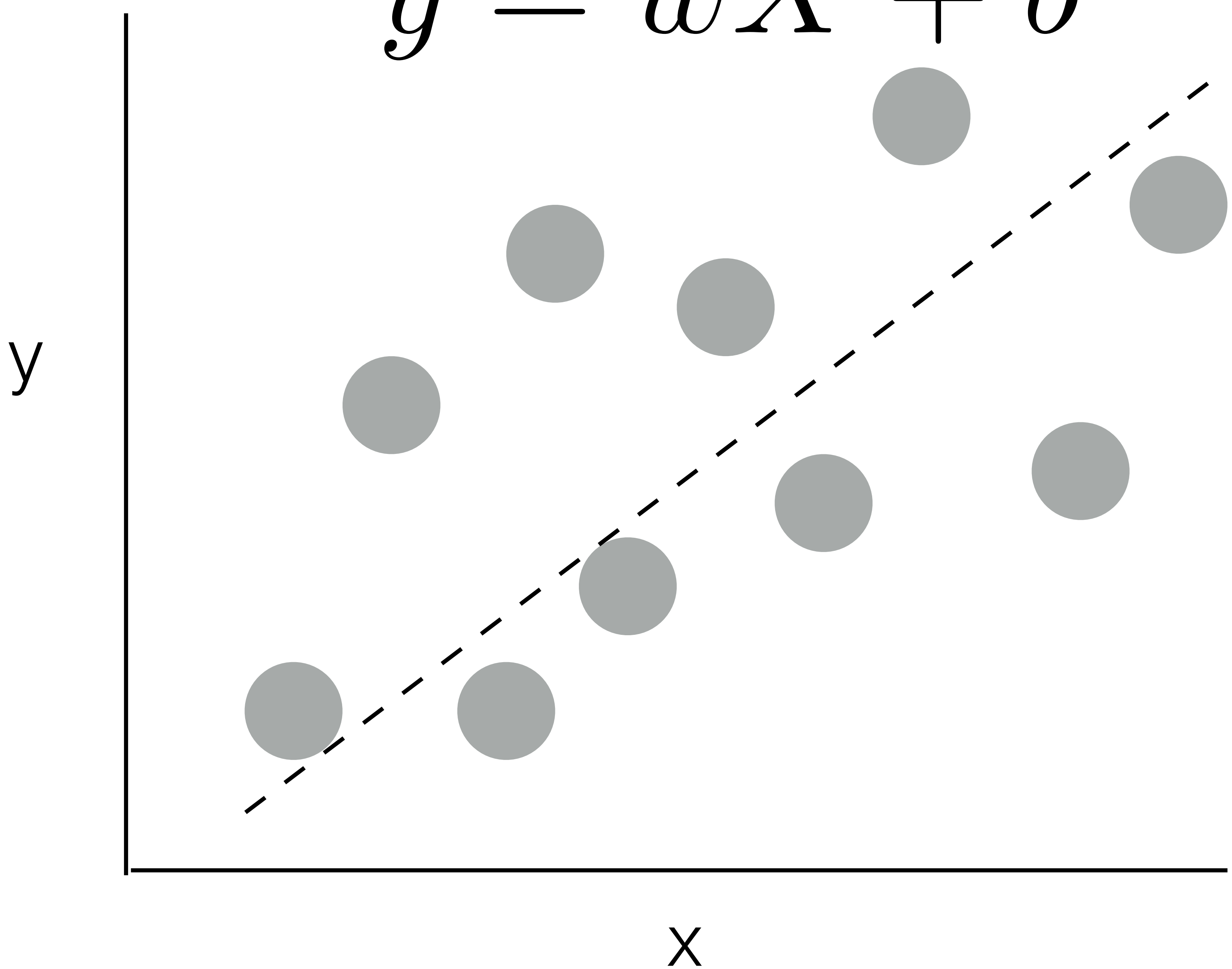




https://independentseminarblog.com/2018/01/12/moving-below-the-surface-3-gradient-descent-william/

Linear Regression

$$y = wX + b$$



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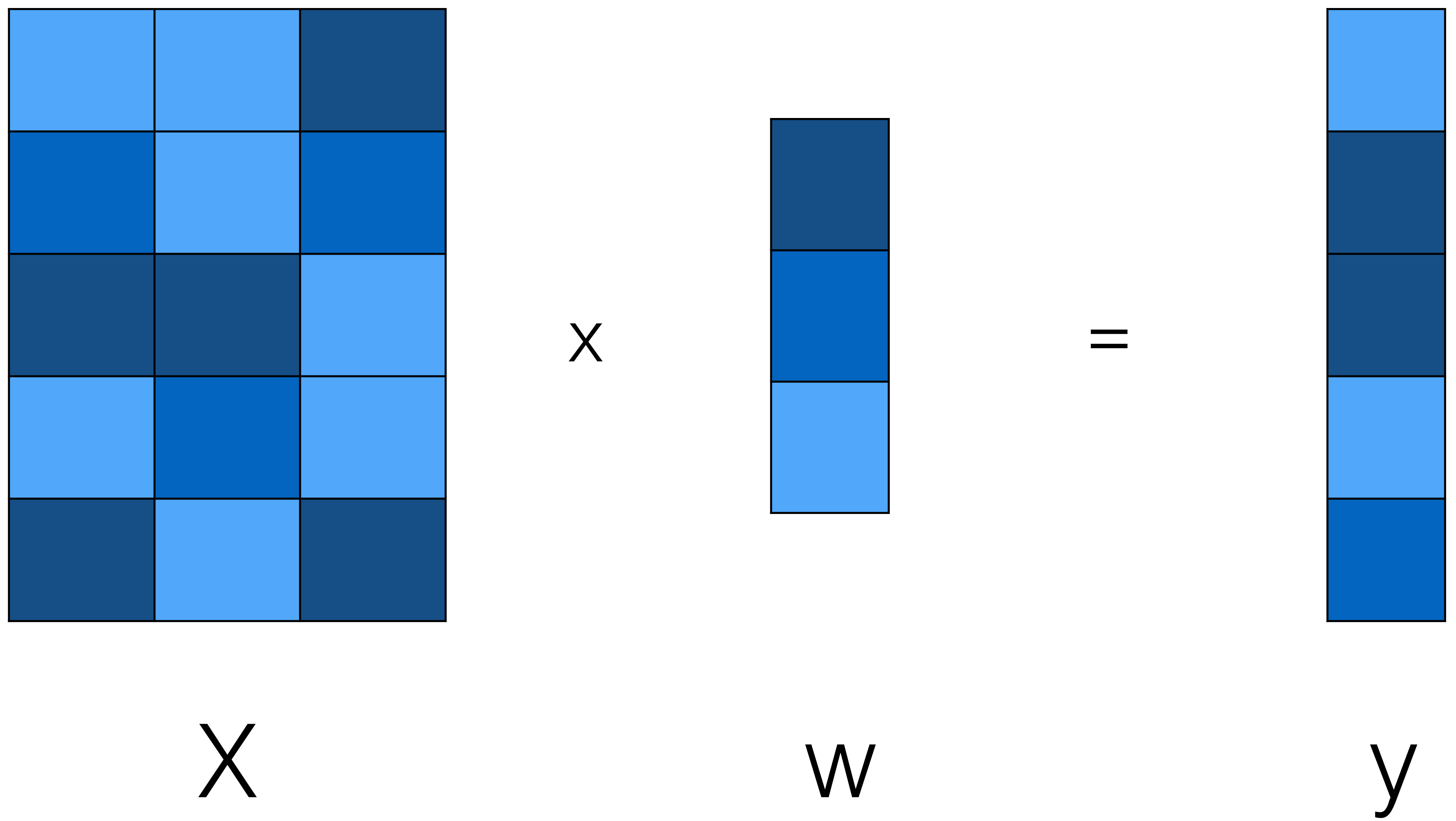
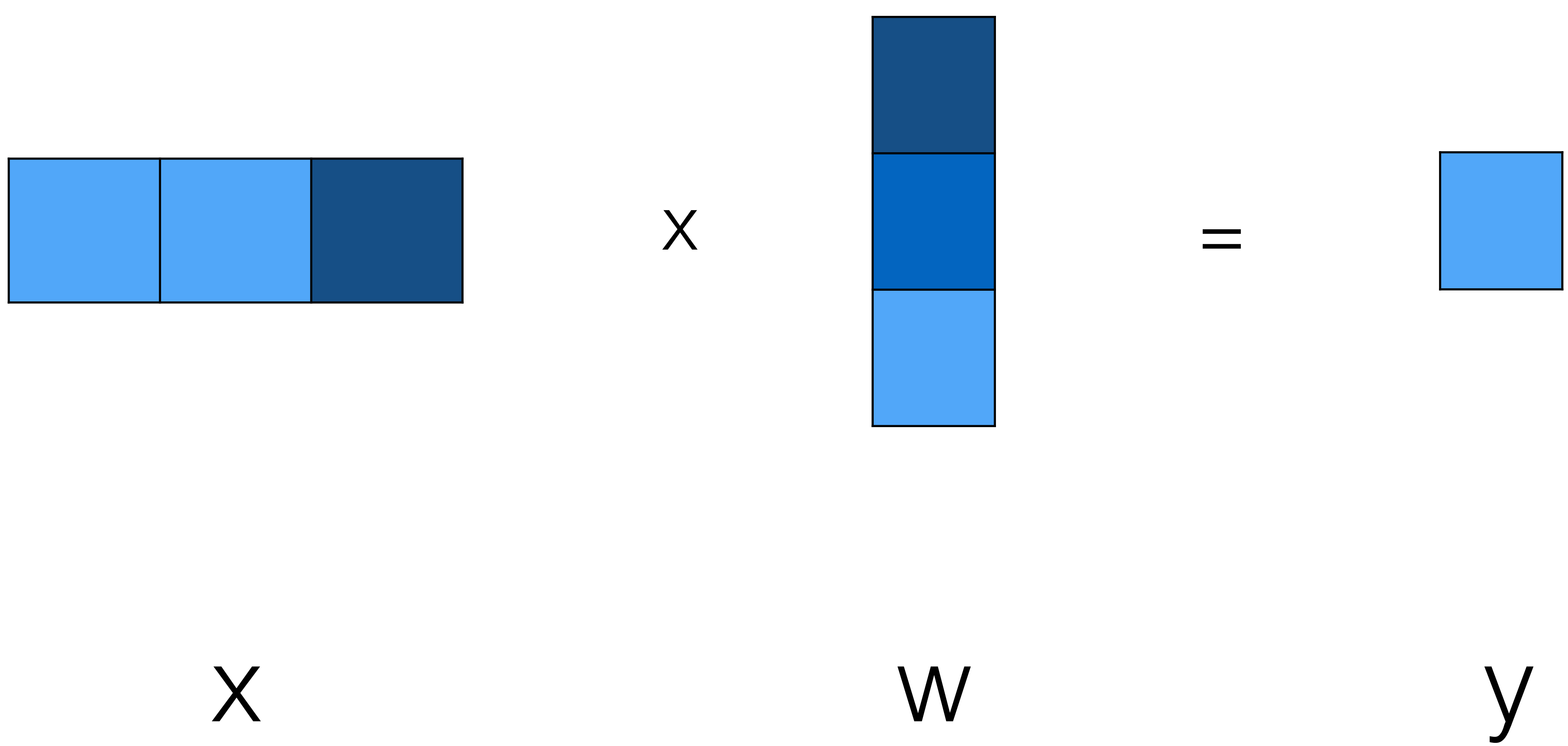


The most basic “network”

$$y = \vec{w} \cdot \vec{x}$$



The most basic “network”

“Perceptron”
(on-line linear
regression)

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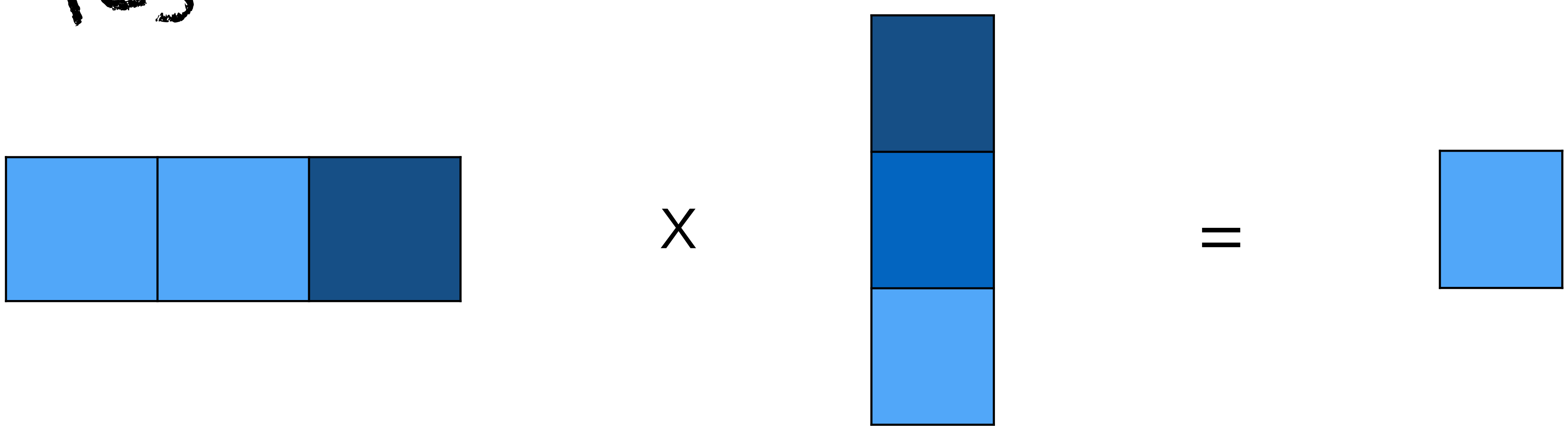

x w y

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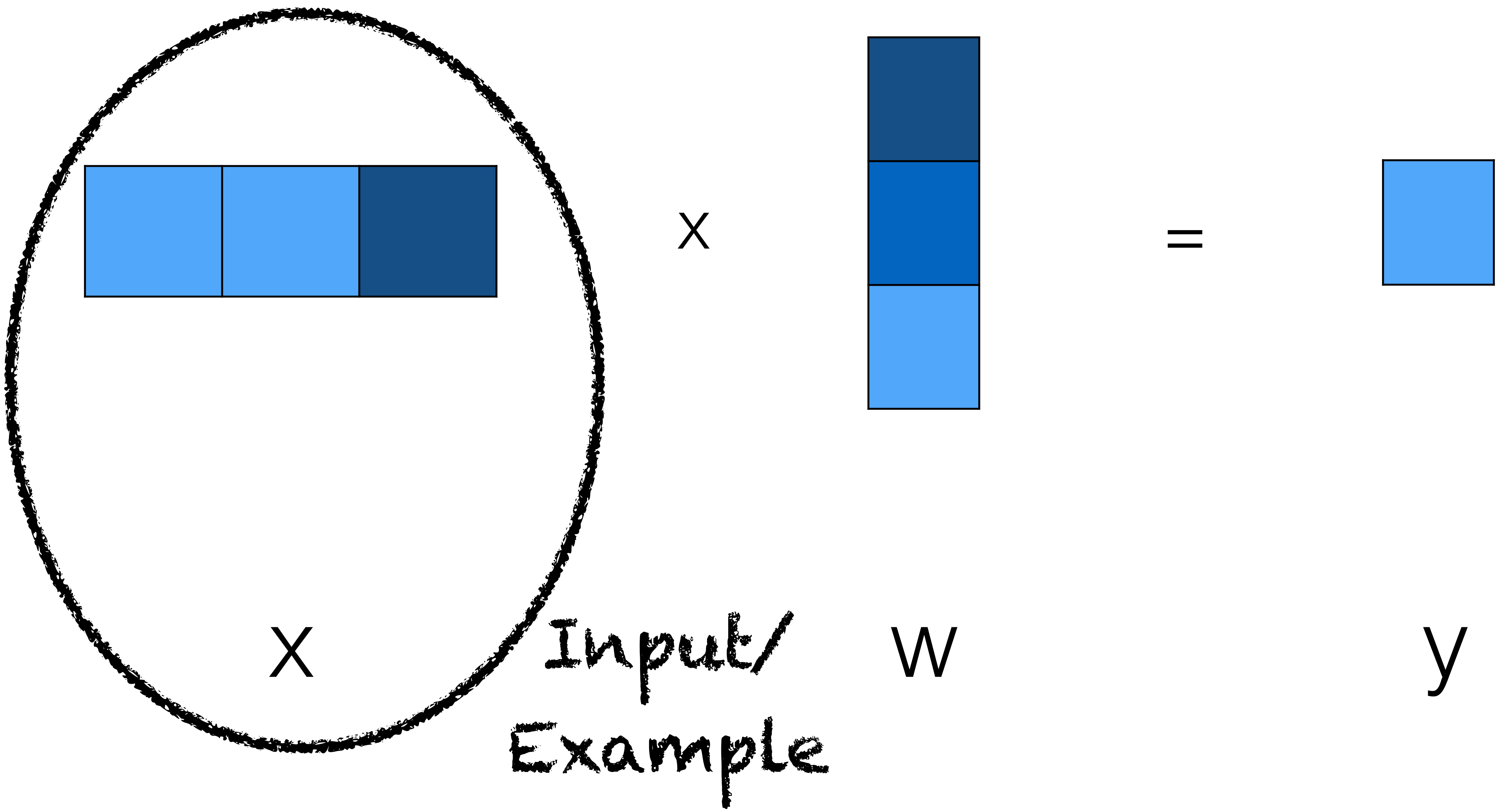

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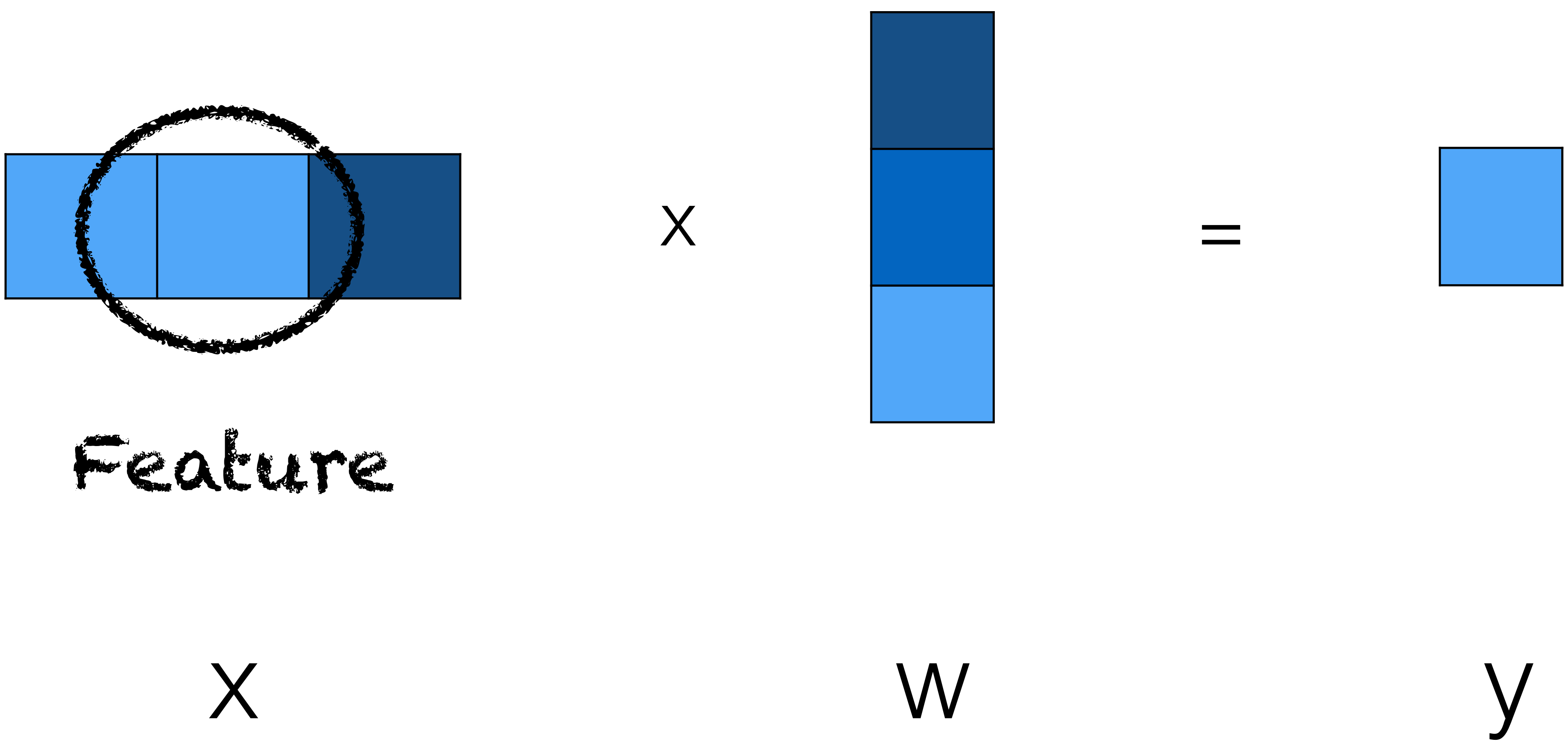

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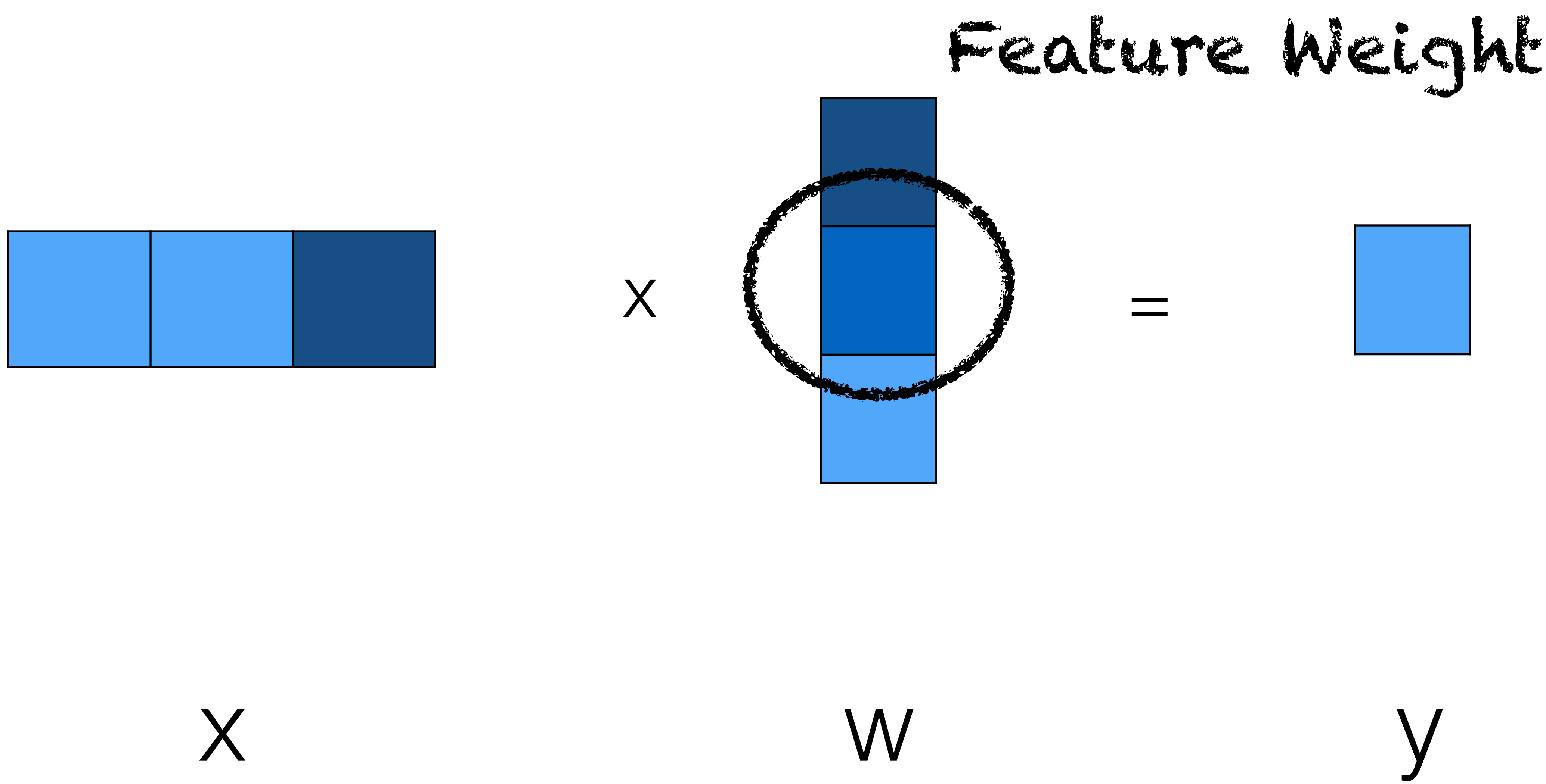

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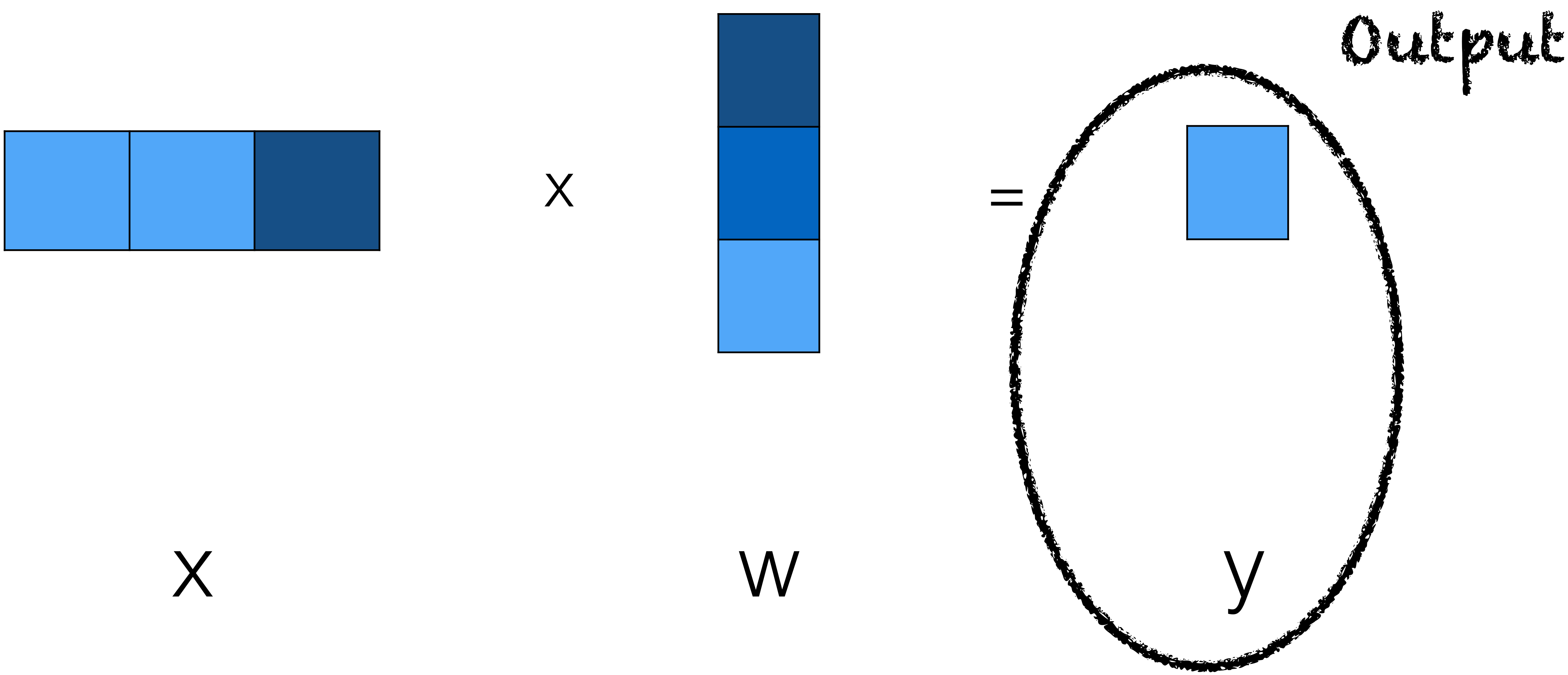
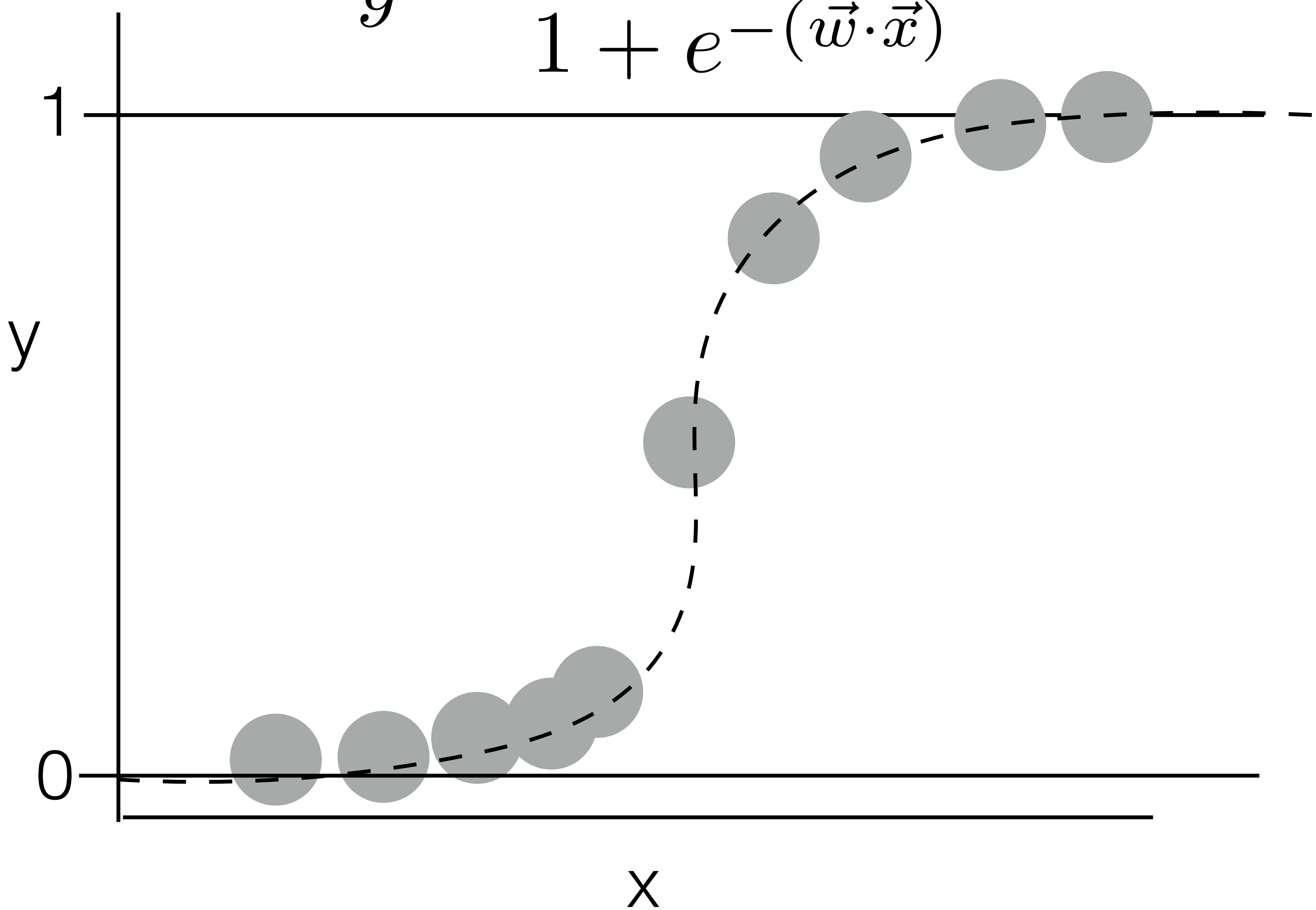


Logistic Regression

$$y = \frac{1}{1 + e^{-(\vec{w} \cdot \vec{x})}}$$



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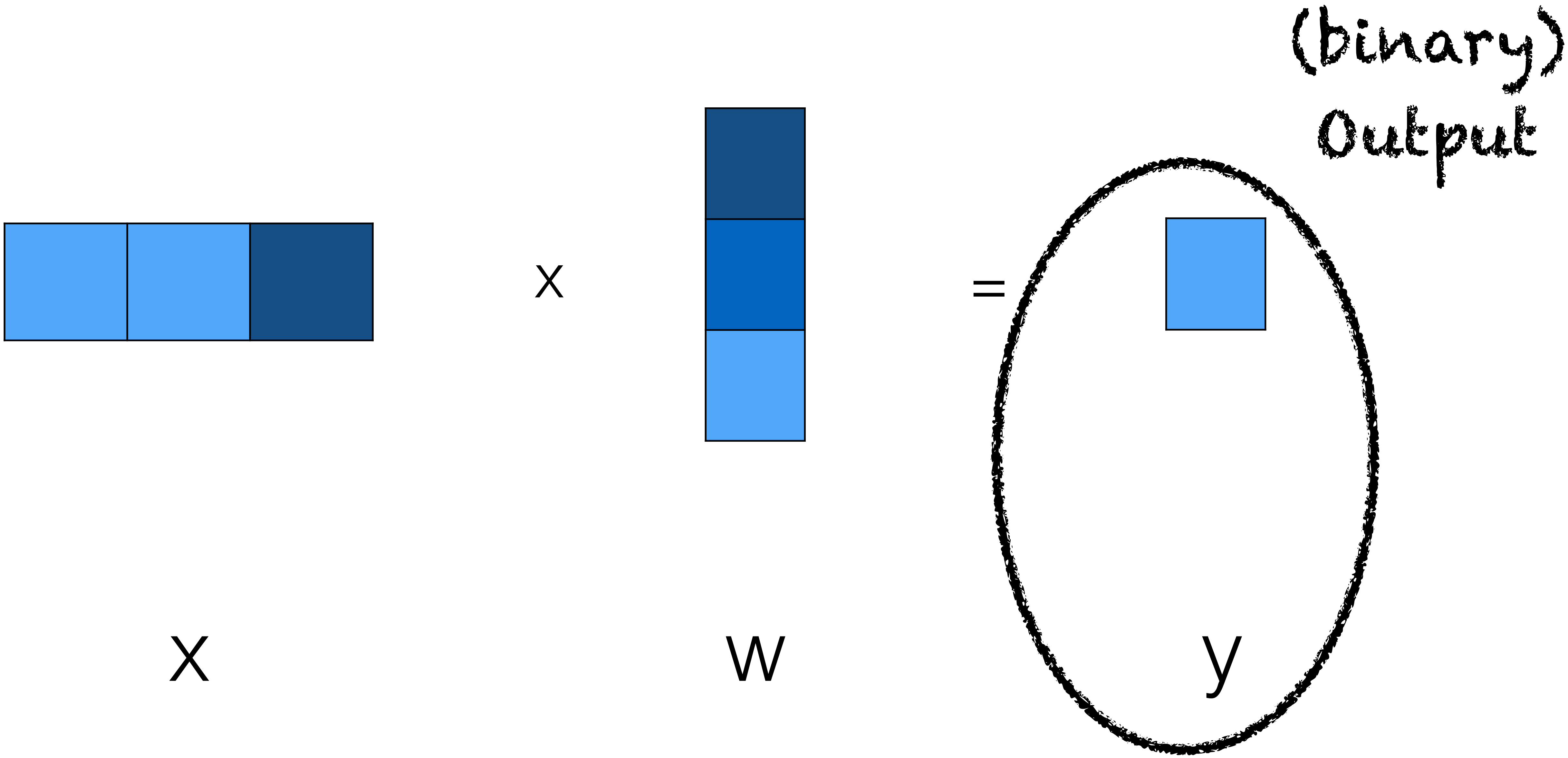
$$y = 1 \text{ if } \vec{w} \cdot \vec{x} > \tau \text{ else } 0$$



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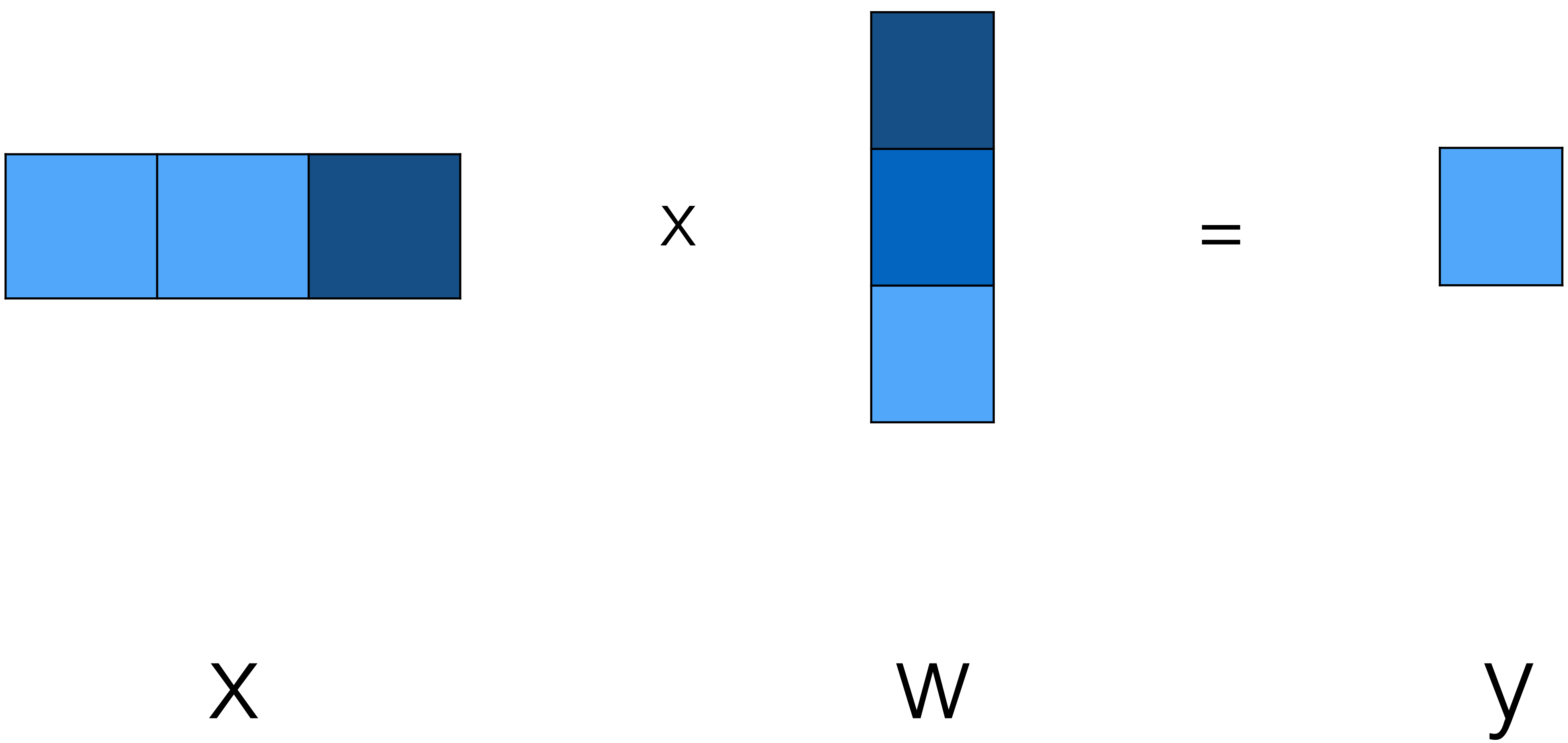
"activation function"



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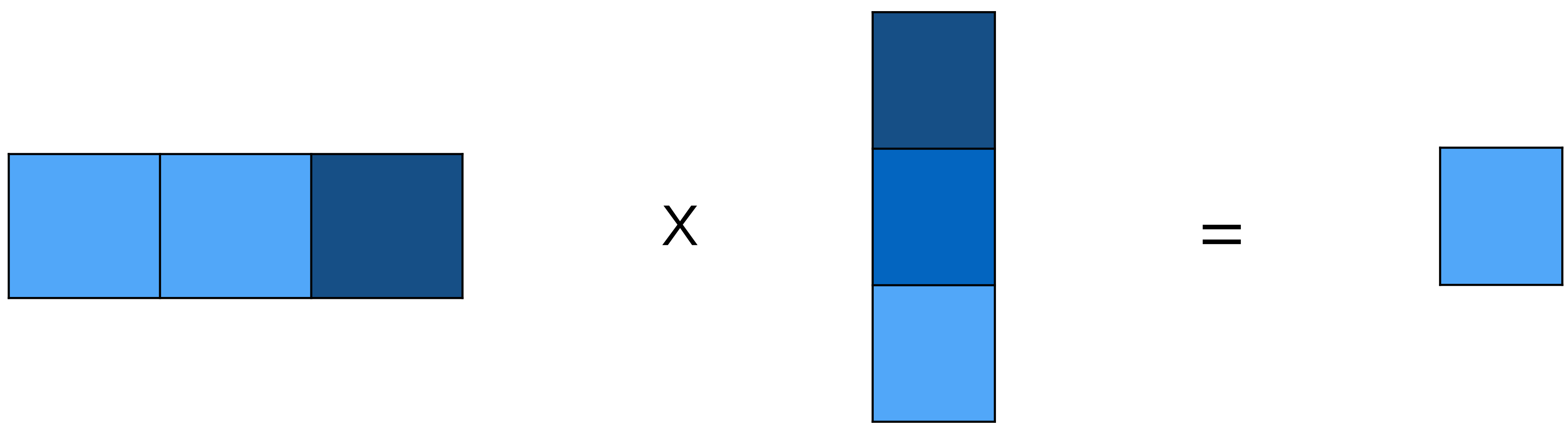
= non-linearity



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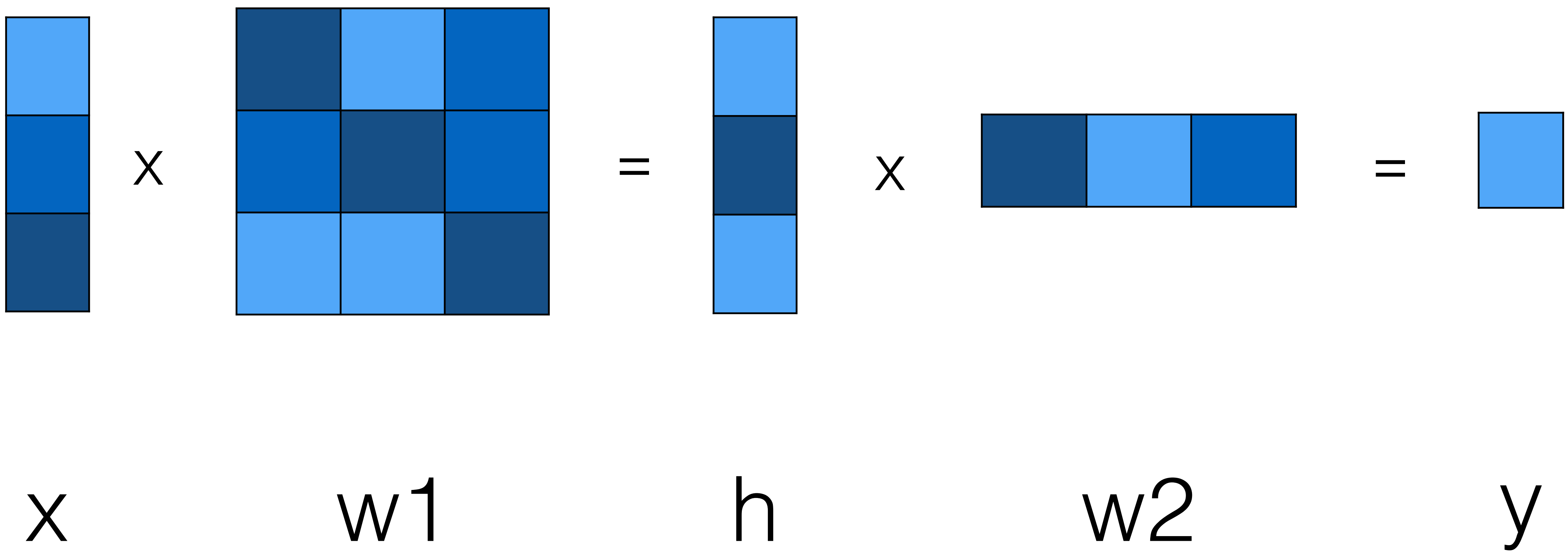

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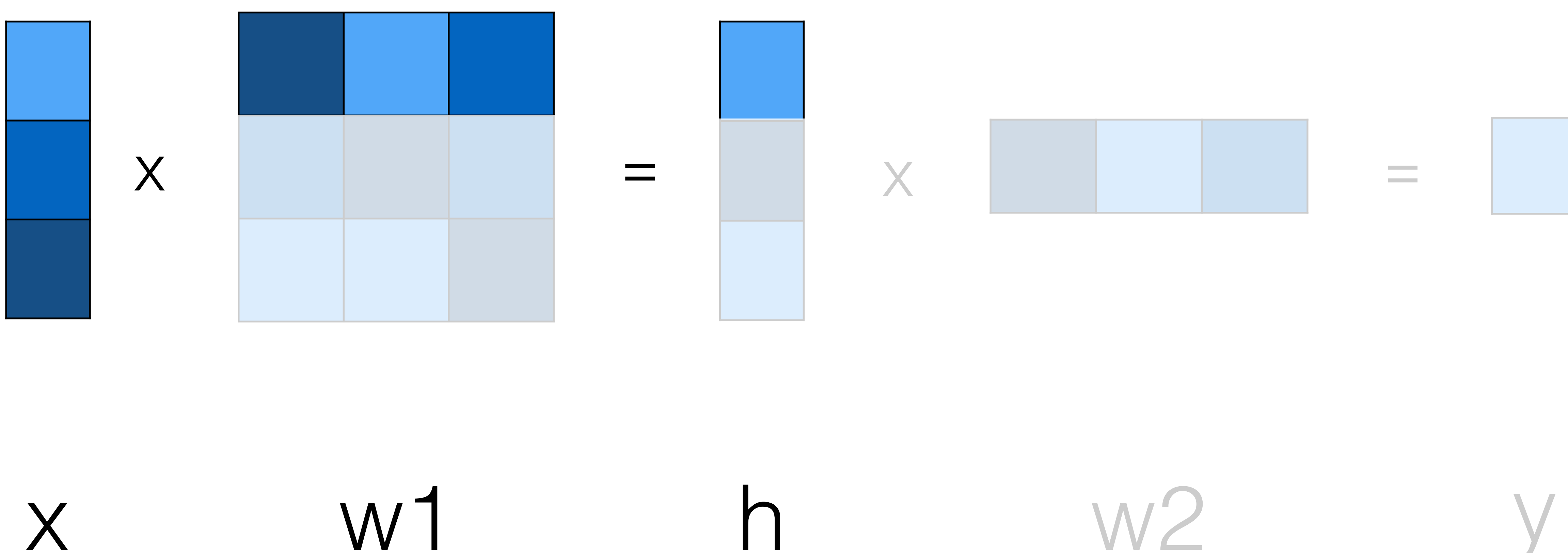
just a logistic regression



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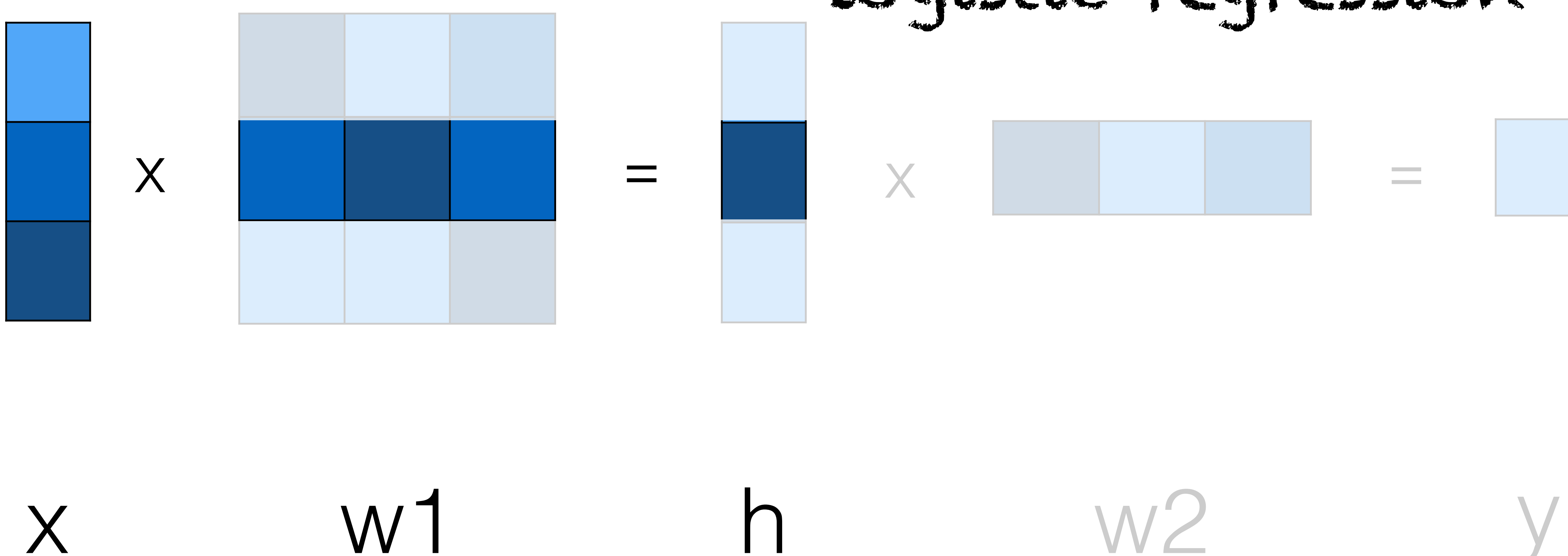
$$y = 1 \text{ if } \vec{w} \cdot \vec{x} > \tau \text{ else } 0$$

and another
logistic regression



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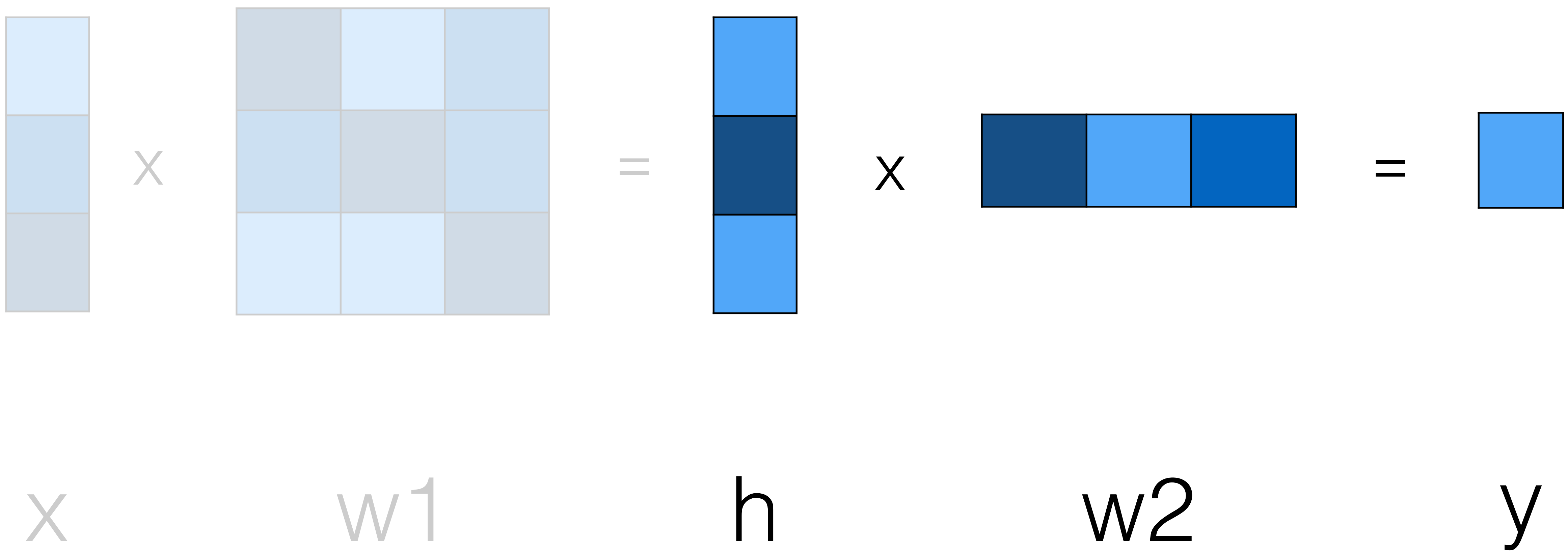
so many logistic regressions



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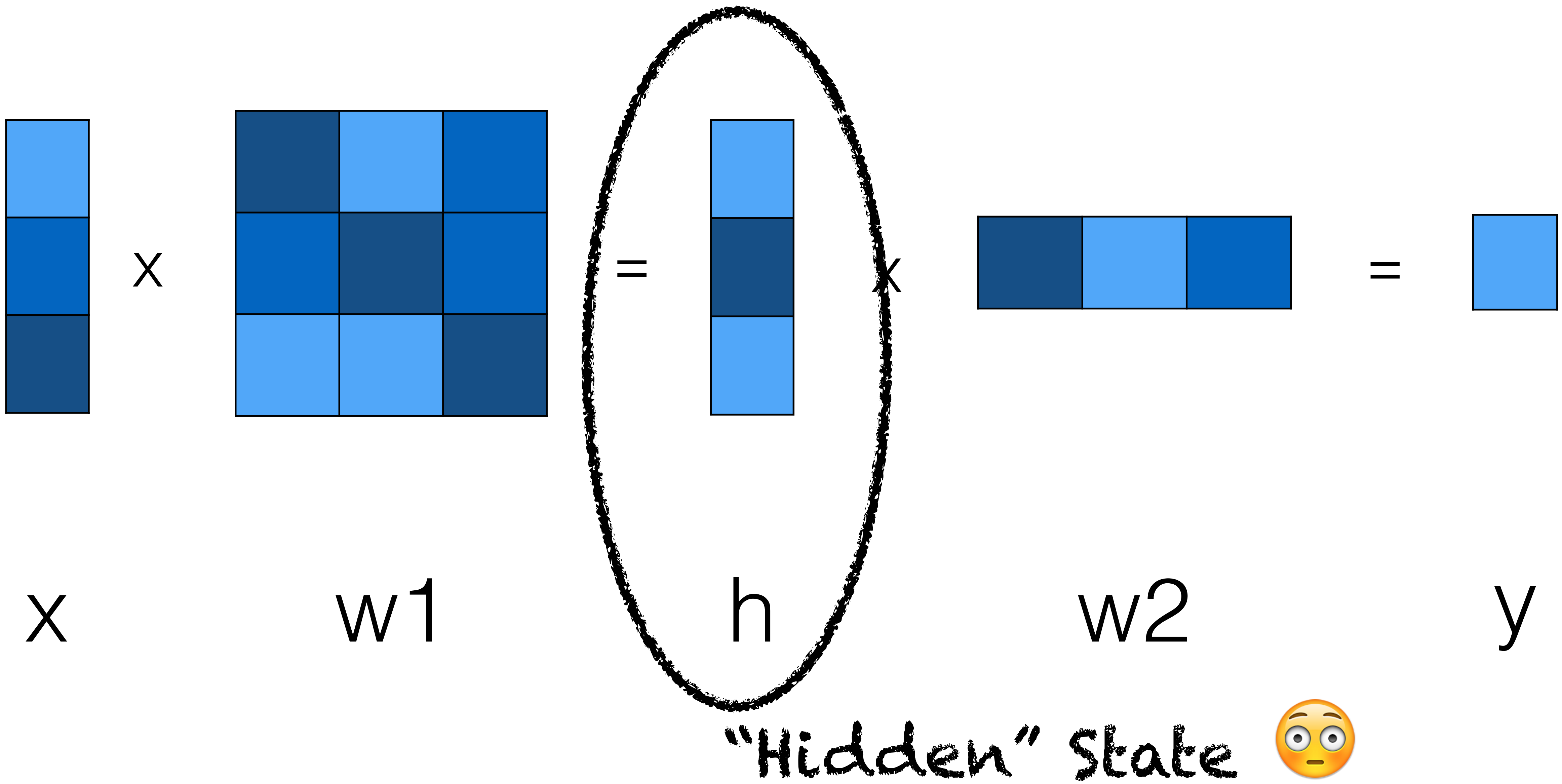

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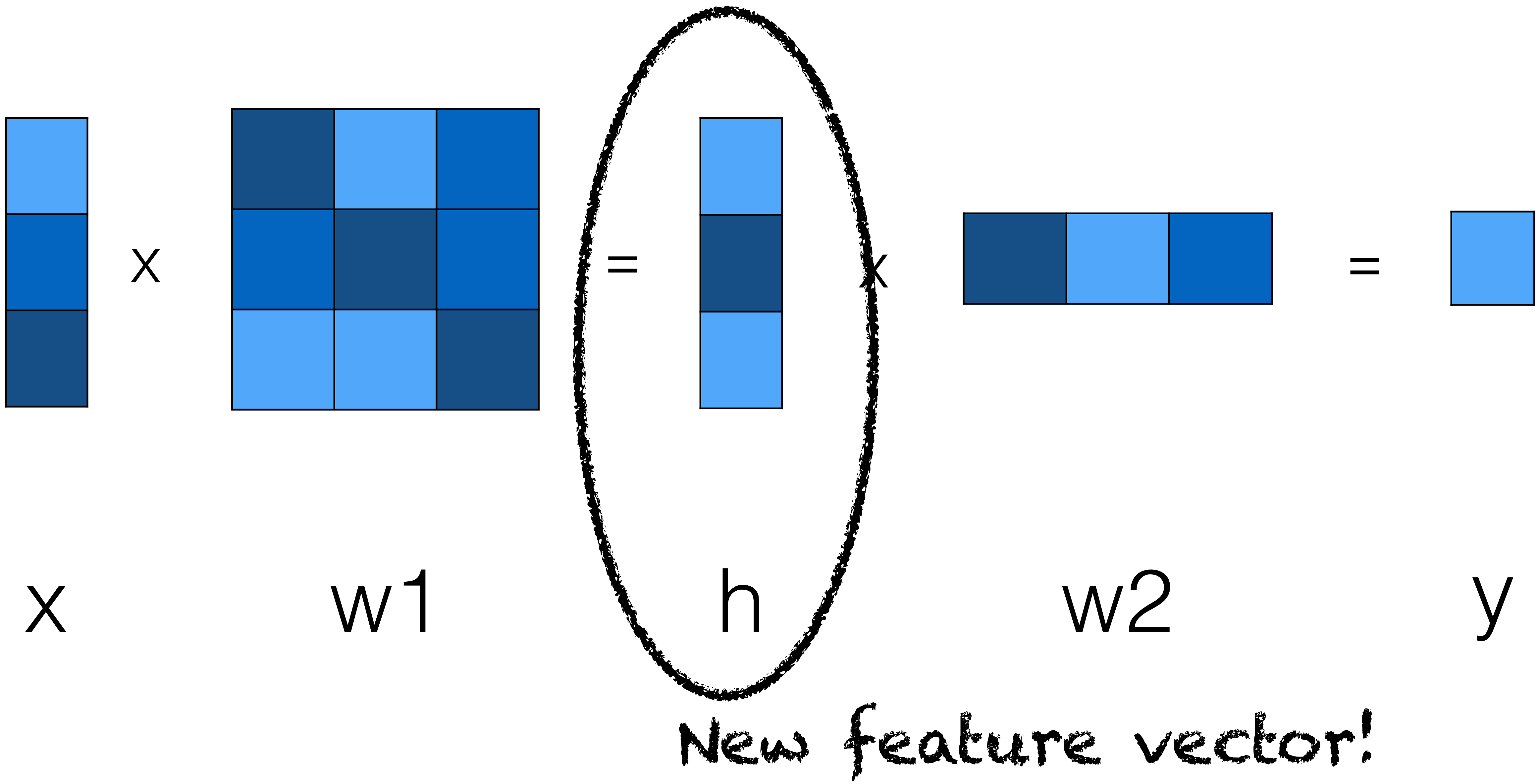

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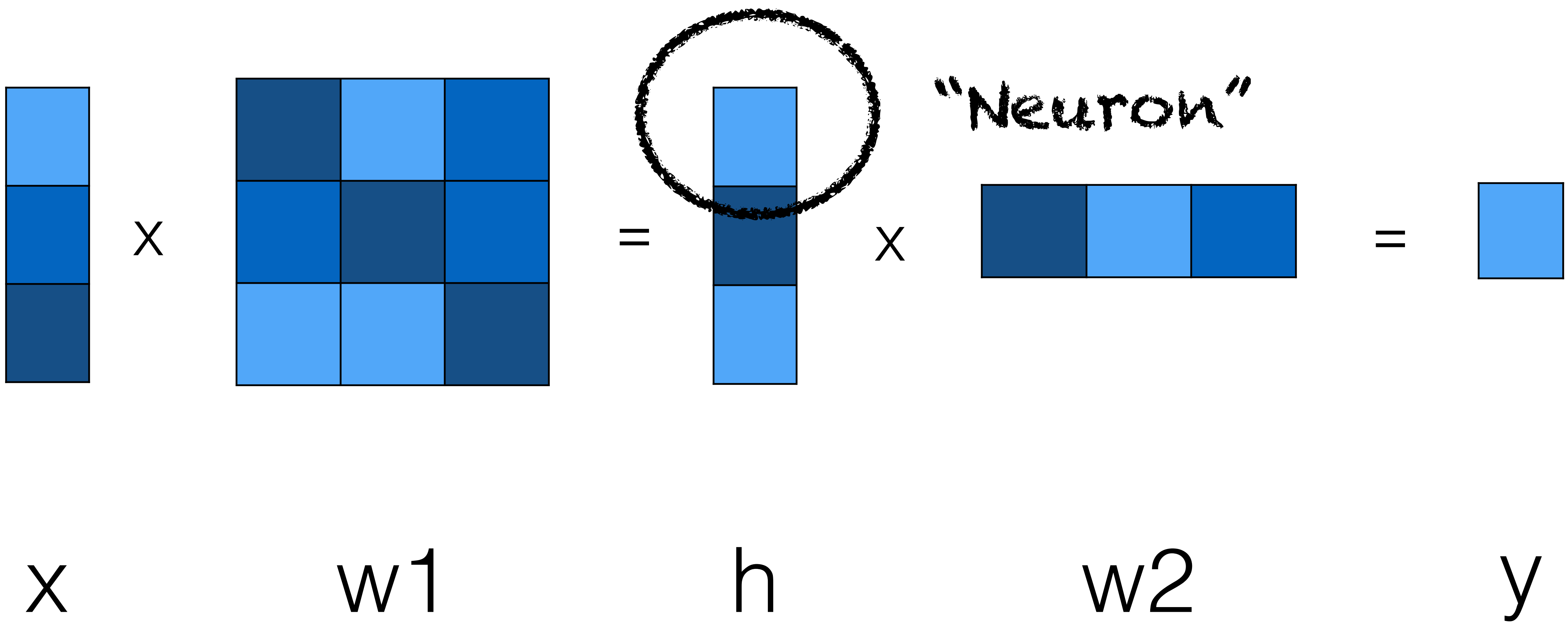

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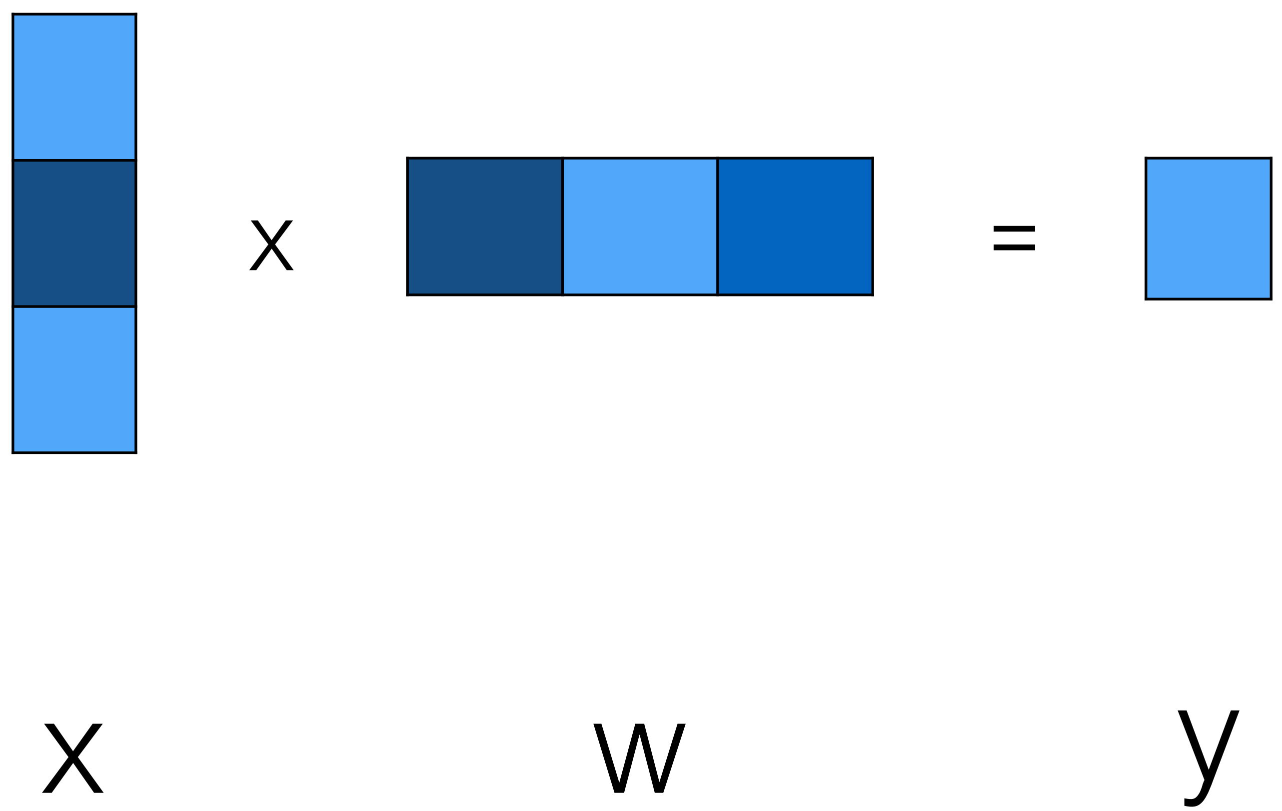

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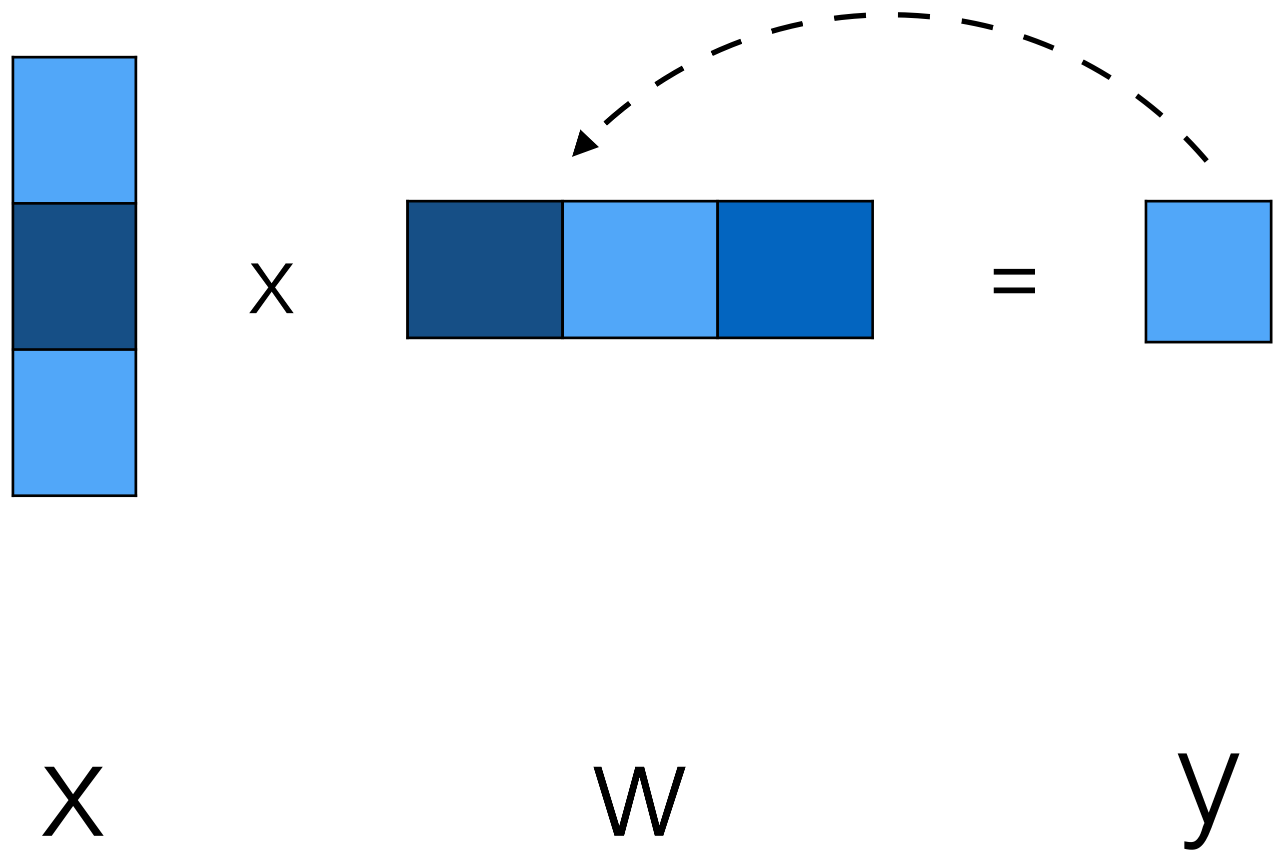
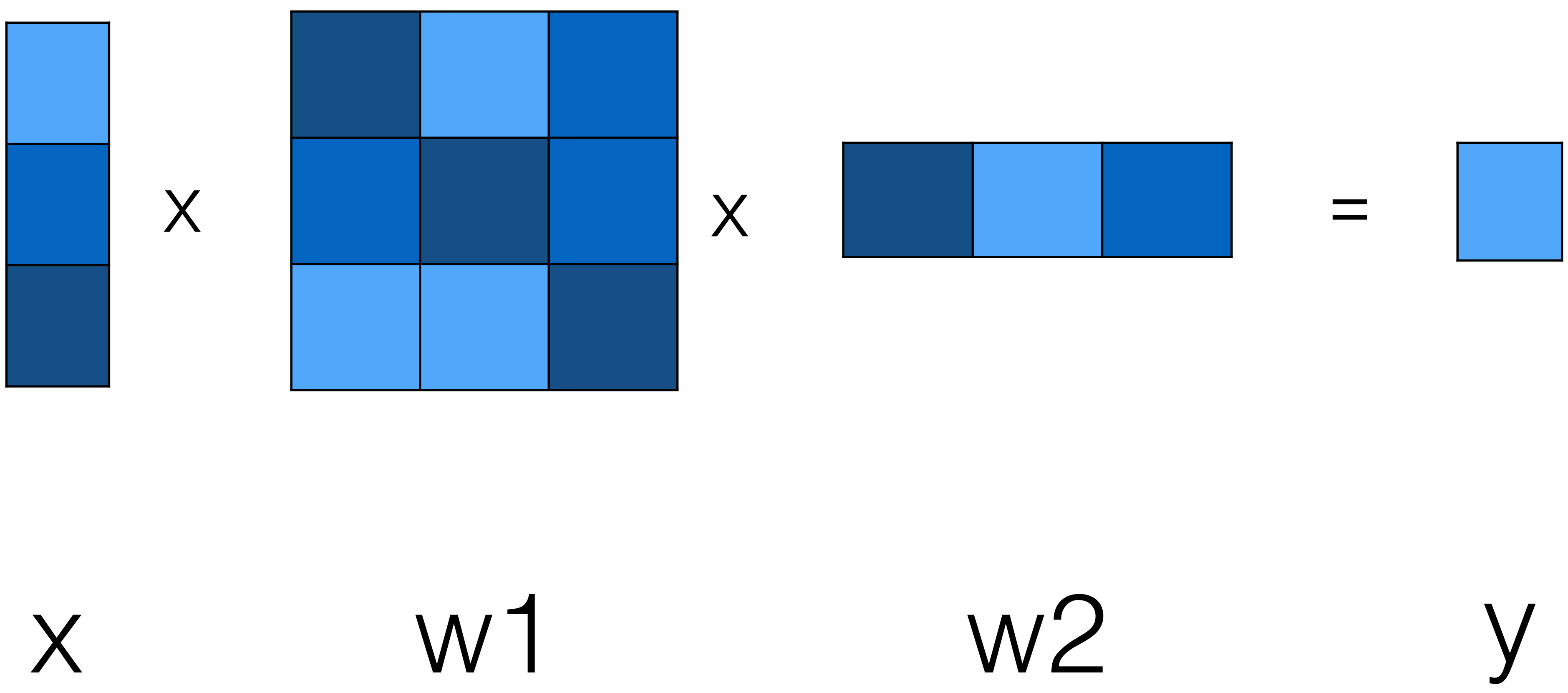
$$\frac{\partial \text{loss}}{\partial w}$$



The most basic network

$$y = W_2 \cdot (W_1 \cdot \vec{x})$$



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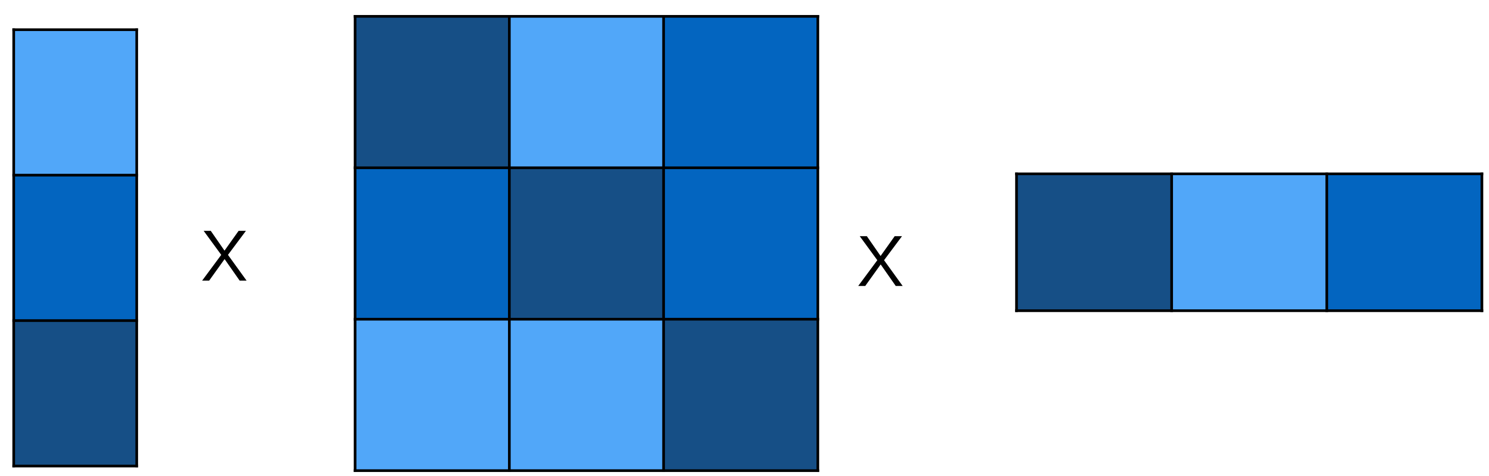


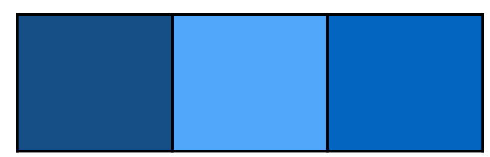
x w1 w2 y

The most basic network

$$y = W_2 \cdot (W_1 \cdot \vec{x})$$

$$f = \mathcal{L}(W_2 \cdot g(\vec{x}))$$

$$g = W_1 \cdot \vec{x}$$



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$$g = W_1 \cdot \vec{x}$$

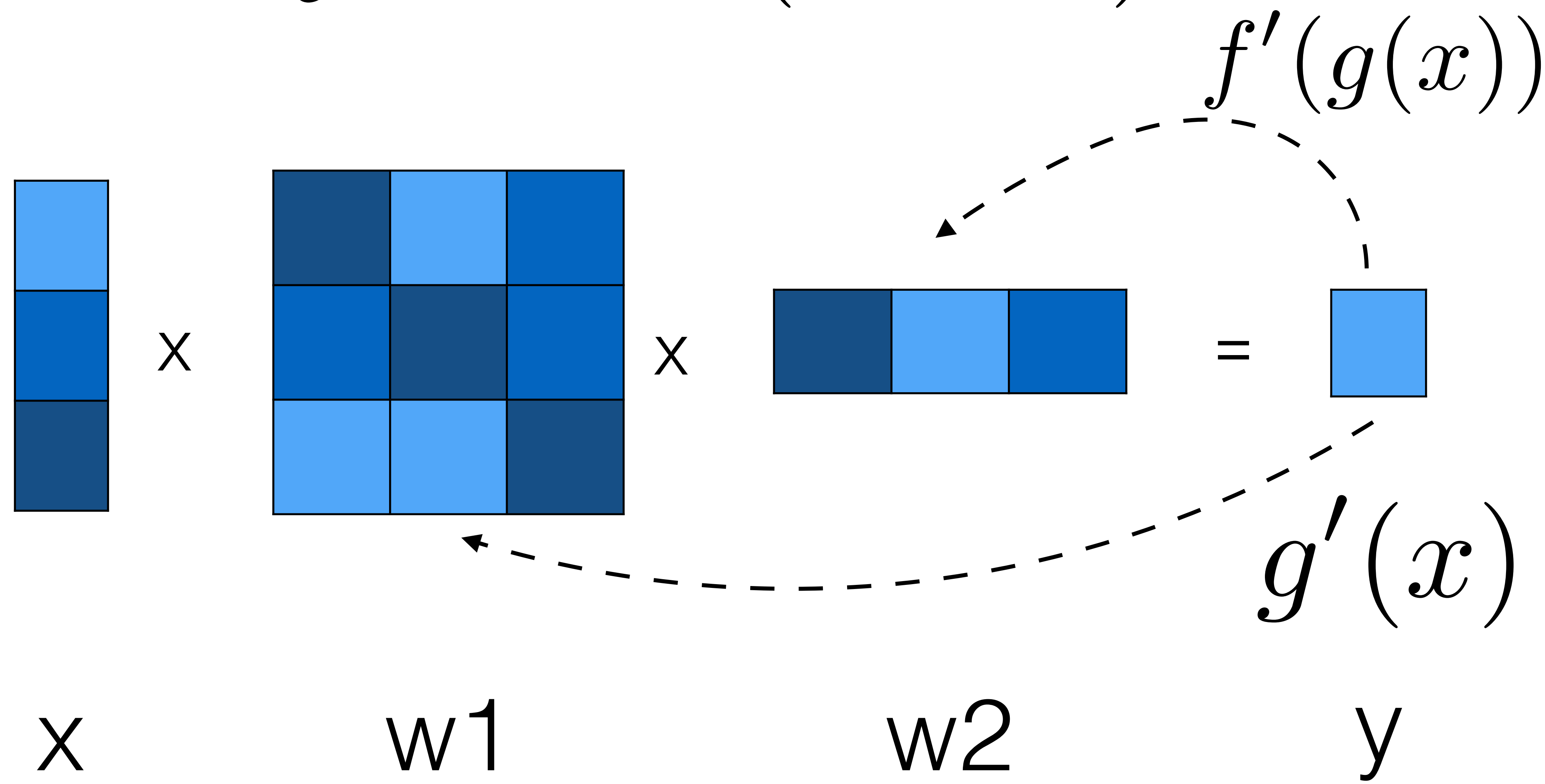
$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g}\frac{\partial g}{\partial x}$$

x w1

Chain Rule!

The most basic network

$$y = W_2 \cdot (W_1 \cdot \vec{x})$$



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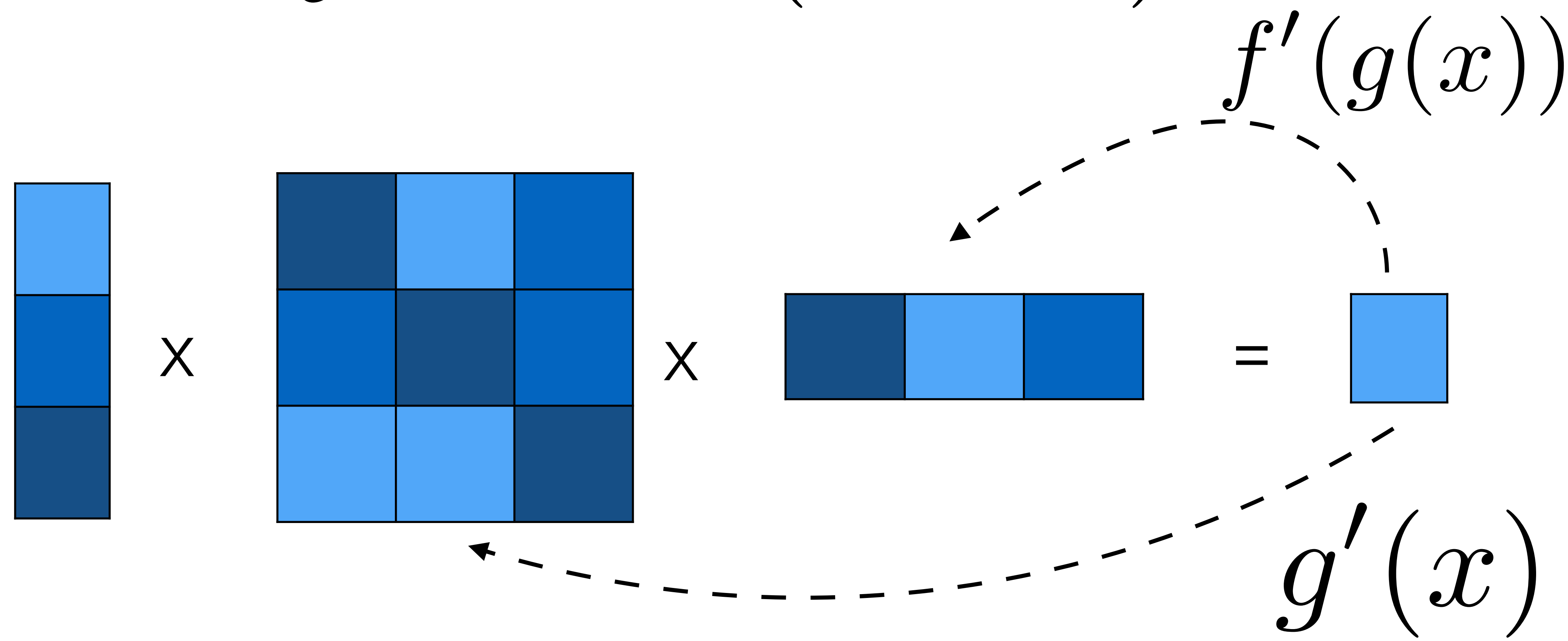

X

Backpropagation
("backprop")

y

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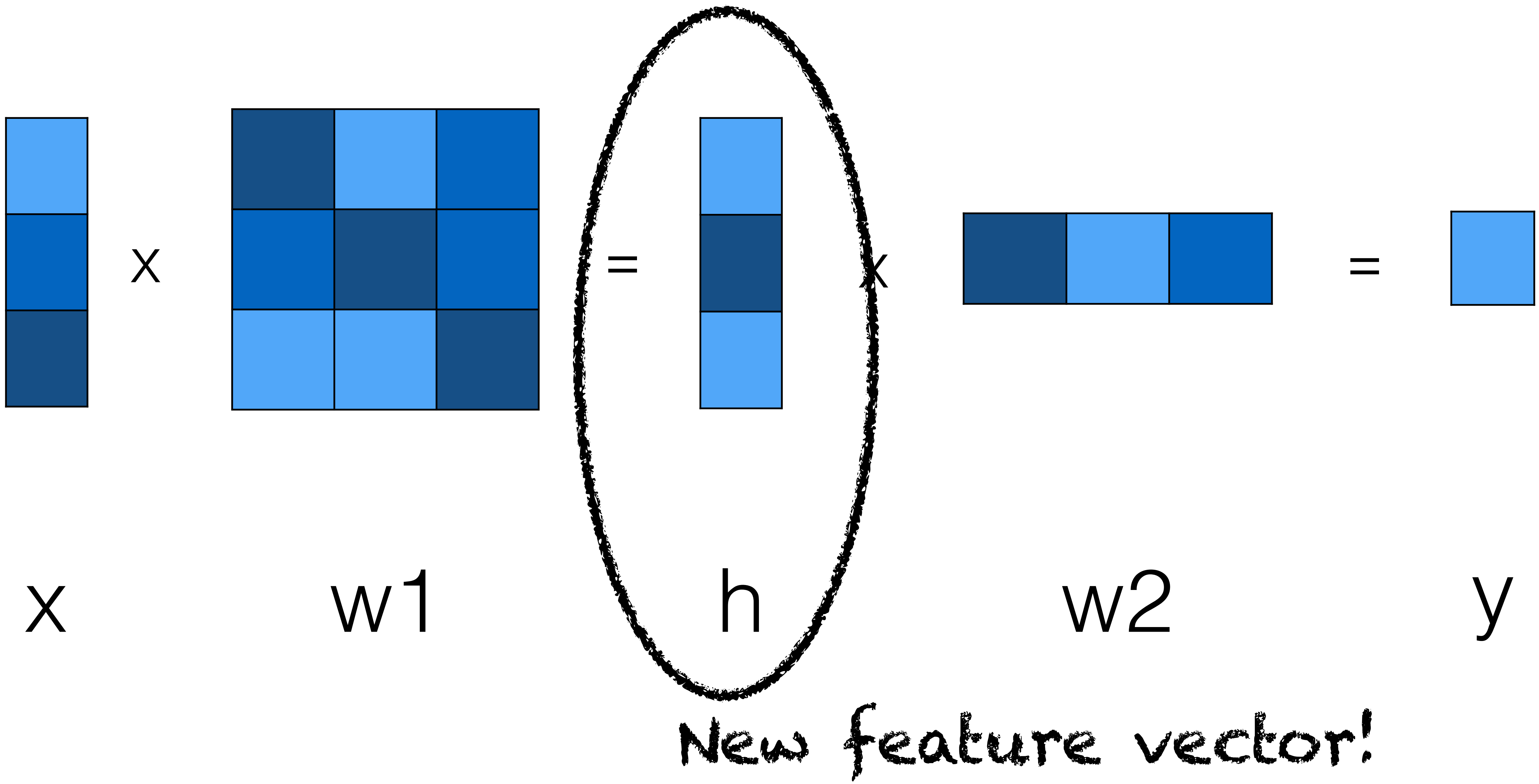

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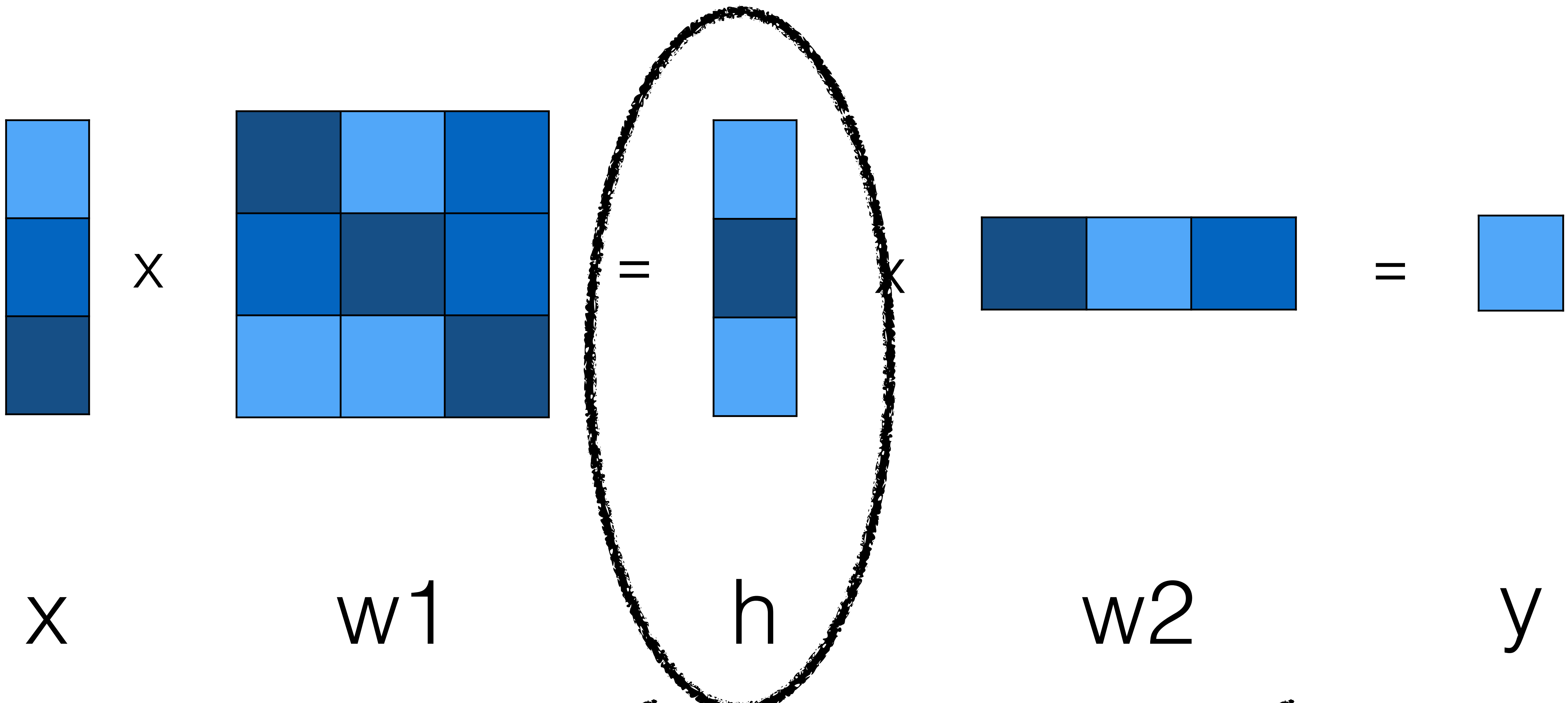
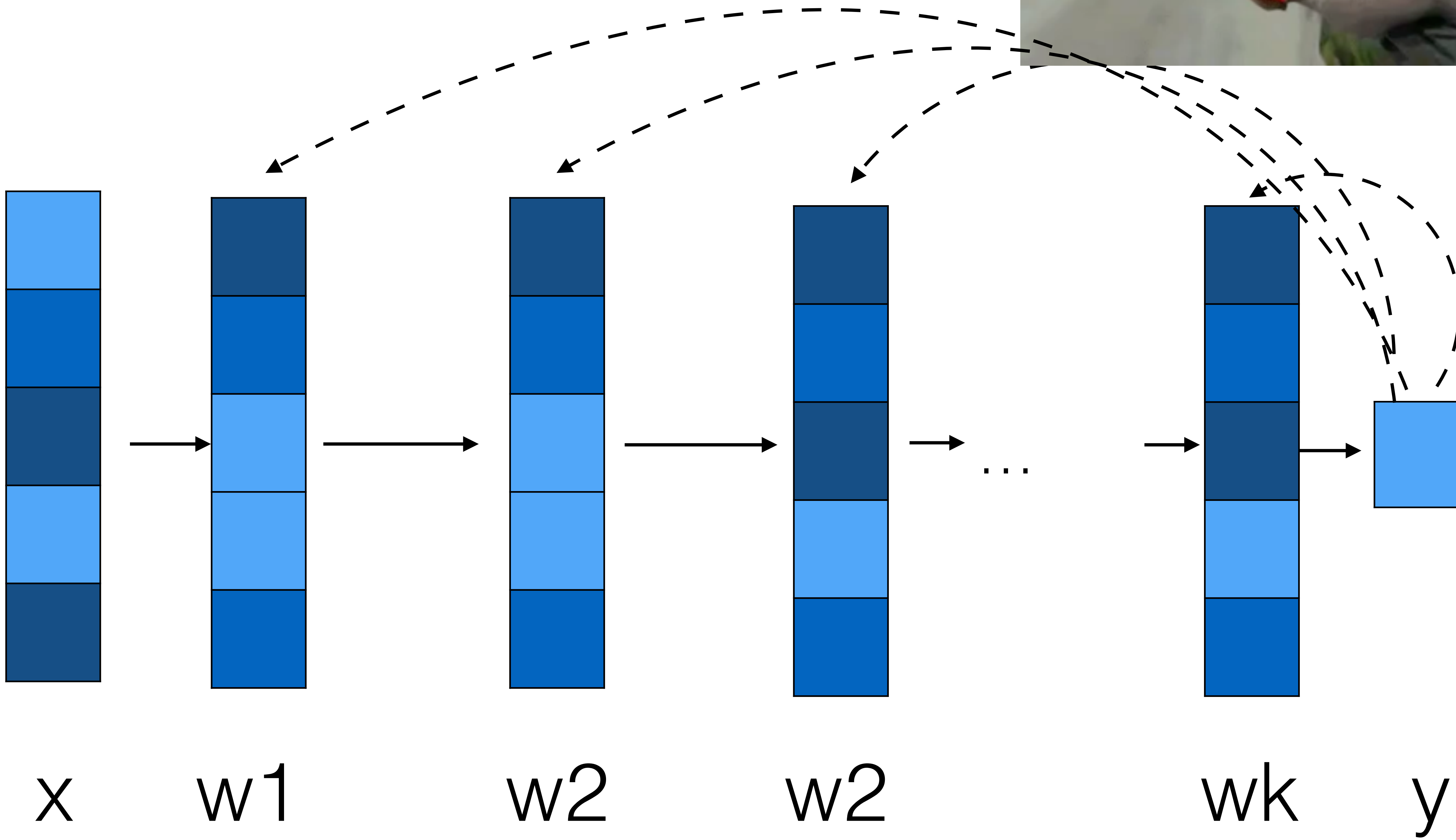


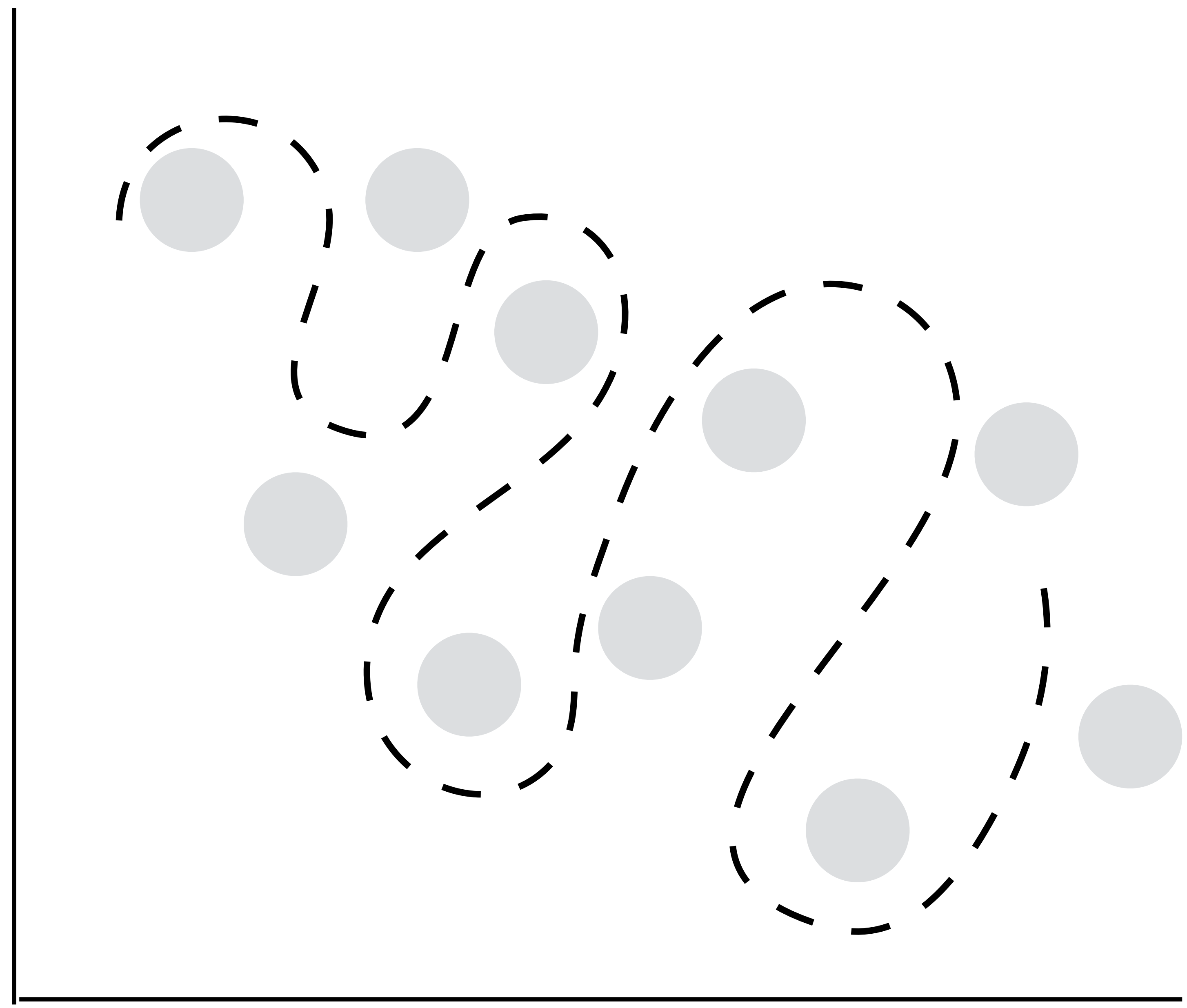
Specifically, whatever features help you solve the task best!

Weeeeeeee!!!!



* vector dimensions not to scale :)

tons of nonlinear parameters
= tons of flexibility



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- A vanilla MLP can theoretically approximate any function (“universal approximator”)
- (Note: “can” != “do”)

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- Backprop (/autodiff): now we can build deep networks and actually train them
- GPUs: and we can train them fast
- Data: and we can train on enough data that they actually converge to something useful

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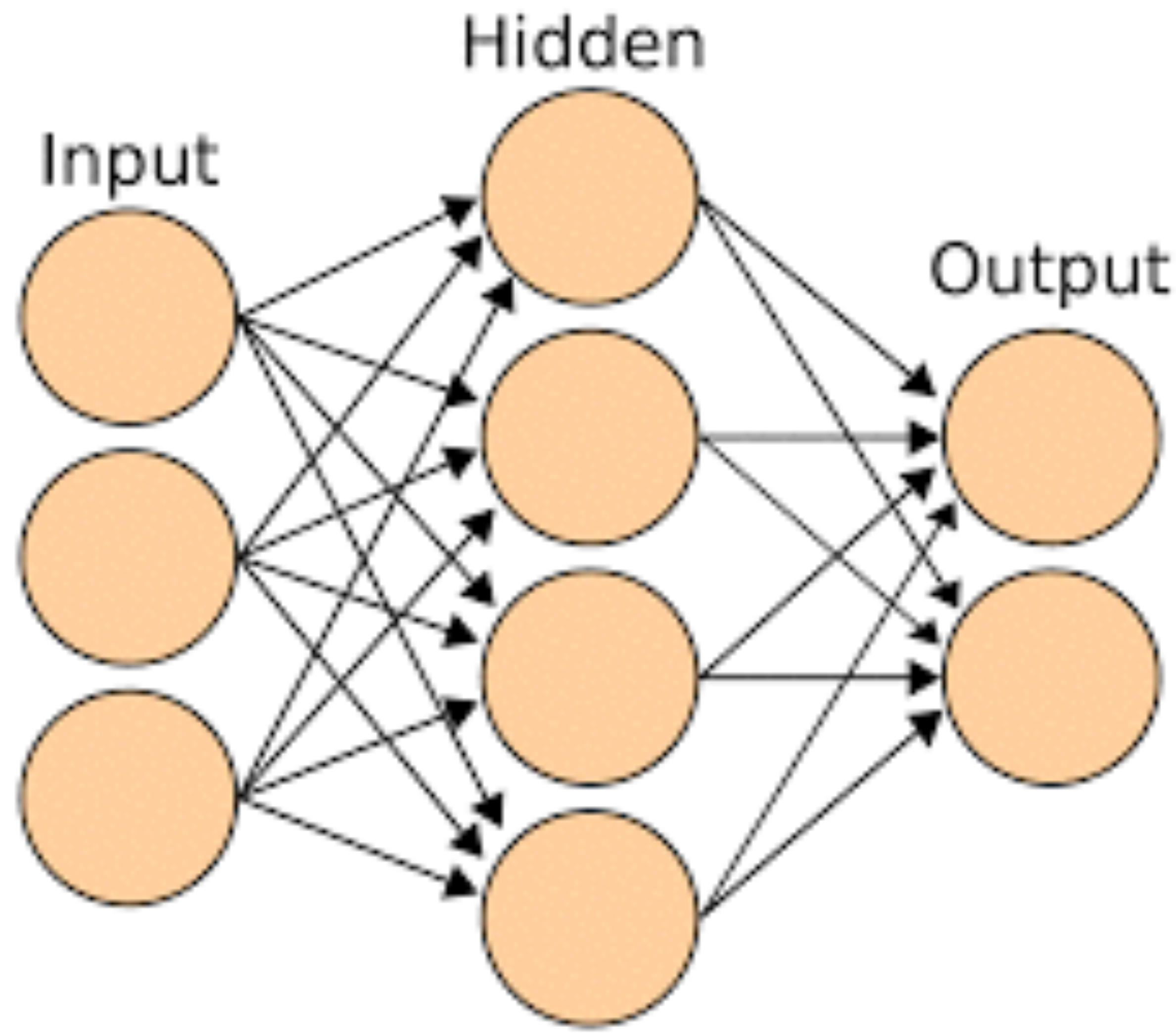
Why are they so much better, though?

- “Its how the brain works.” —> NO!
- End-to-end training—optimize directly for the thing you care about
- Dense/denoised representations—similar inputs get similar predictions (like MF, more in a bit)
- Uniform representations across sub-disciplines of AI (i.e. vision, language, sensor inputs)—“its all just vectors anyway”

NNs as classifiers

- You already have linear regression, naive bayes, logistic regression, svm…
- Now you have neural nets too!

Multilayer Perceptron



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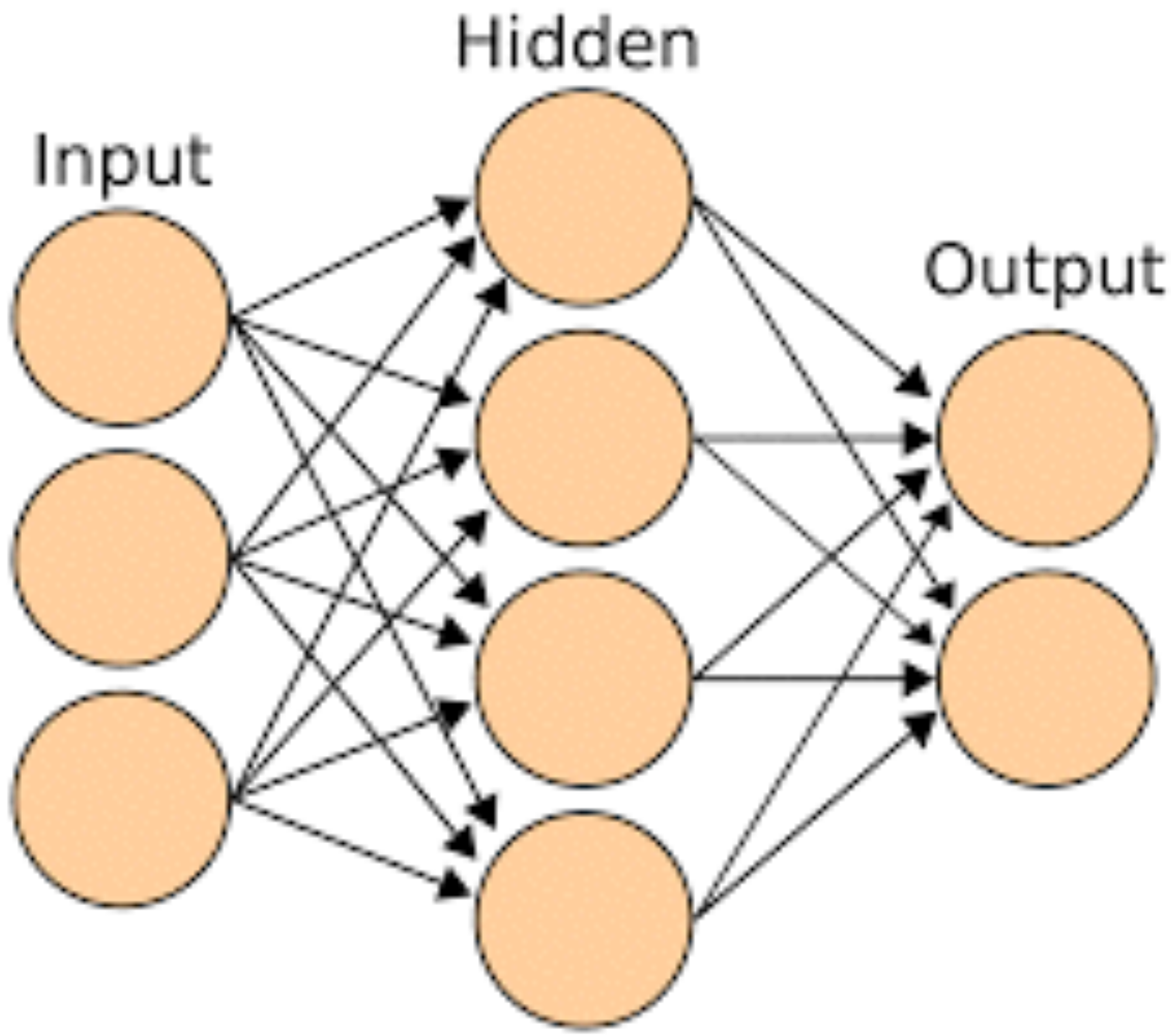
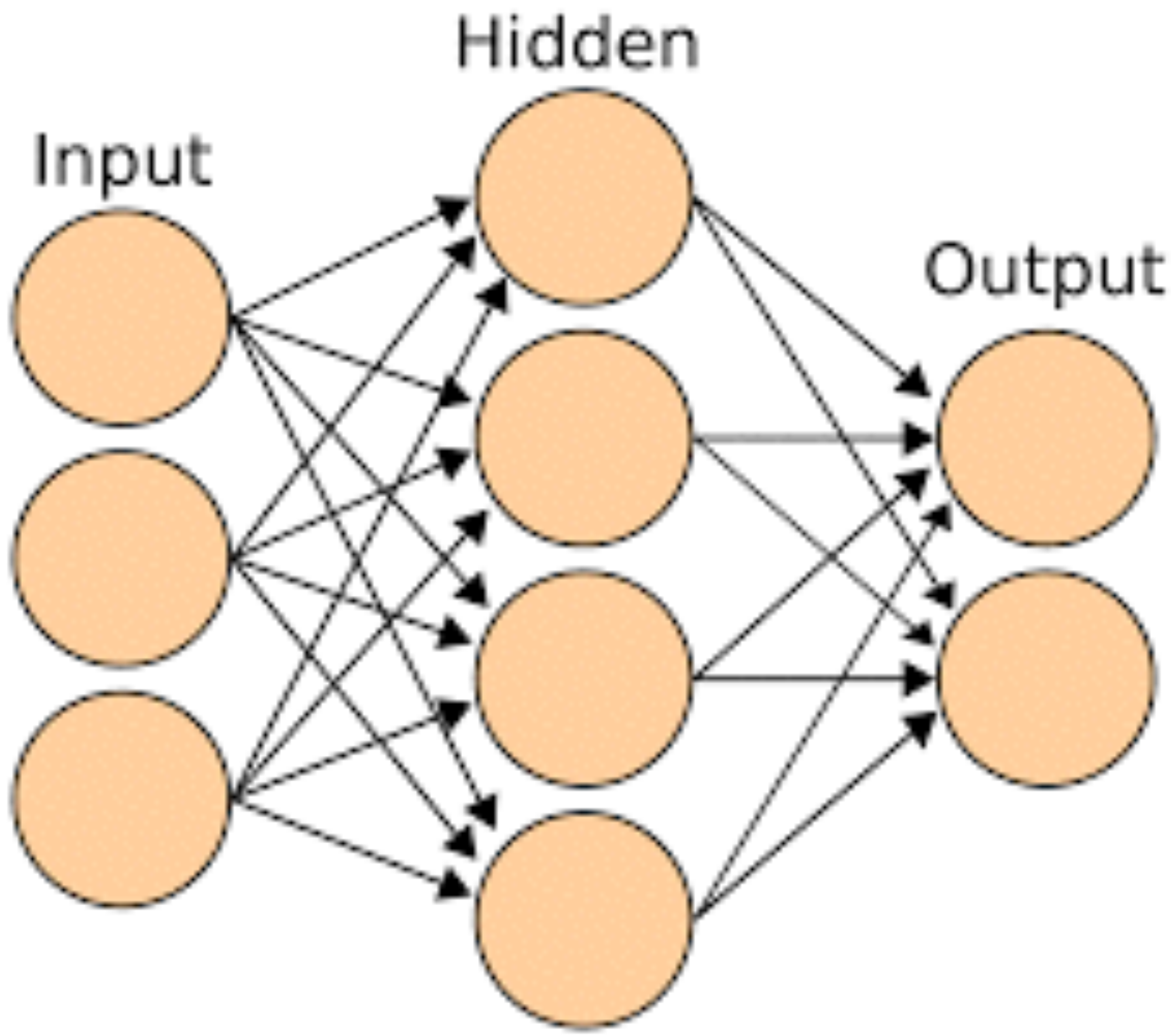


“Feed Forward Net”

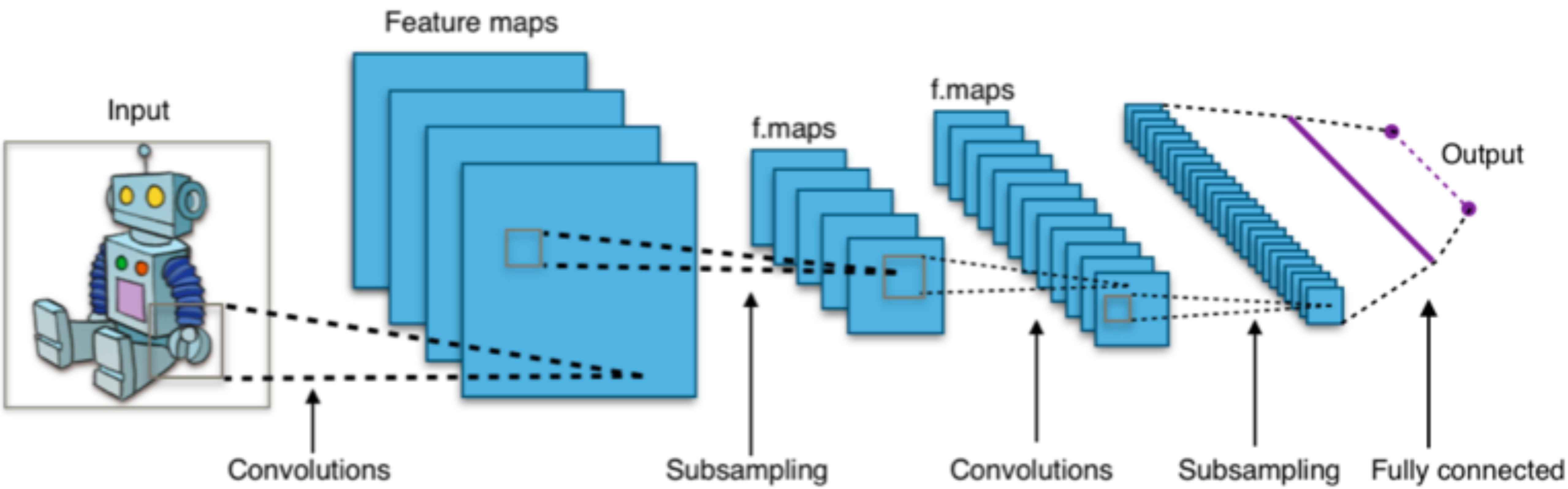
“Fully Connected Layer”

Multilayer Perceptron



Arbitrary, non-linear combinations of input features.
No prior on the structure of those features.

Convolutional Neural Net (CNN)



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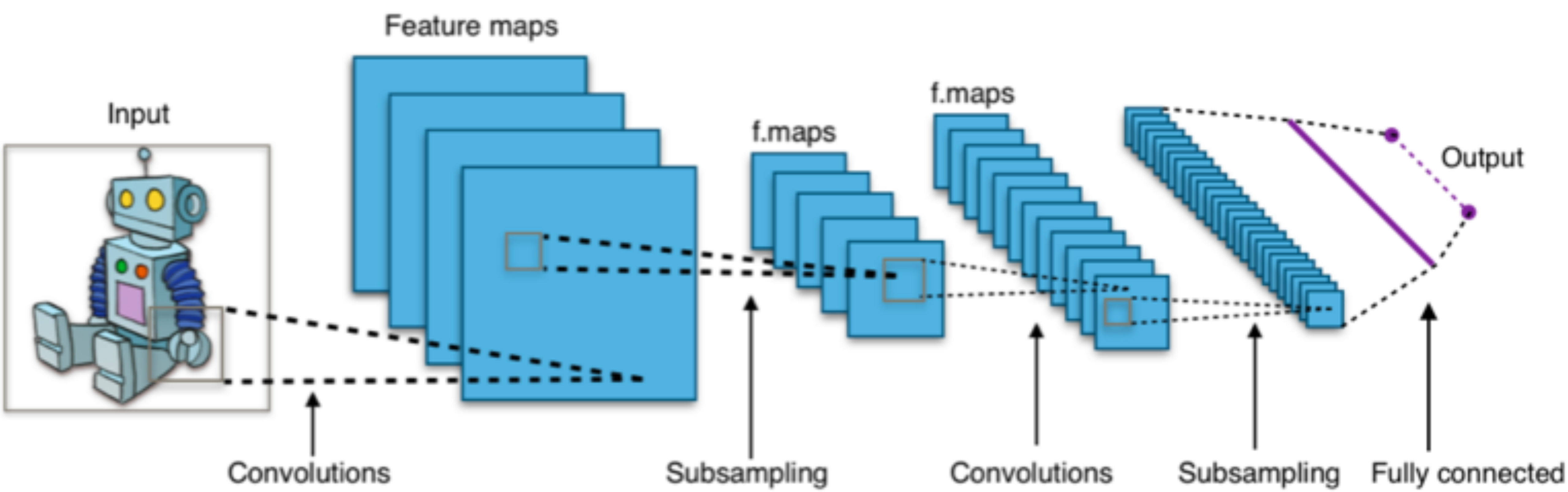
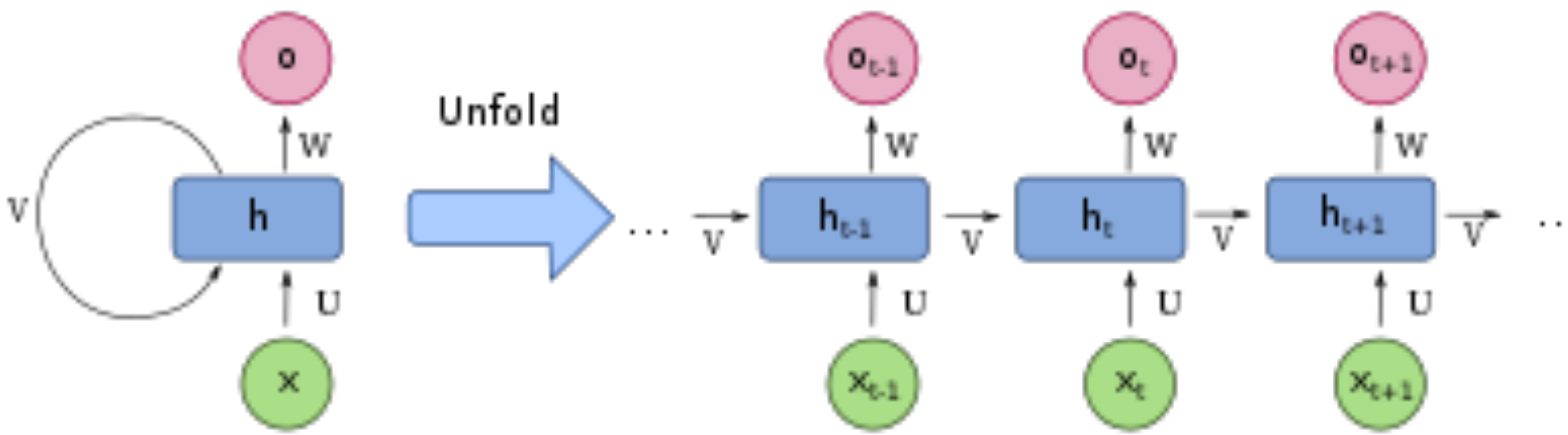


Used for vision. Assumes spatial structure to the data.

Recurrent Neural Net (RNN)



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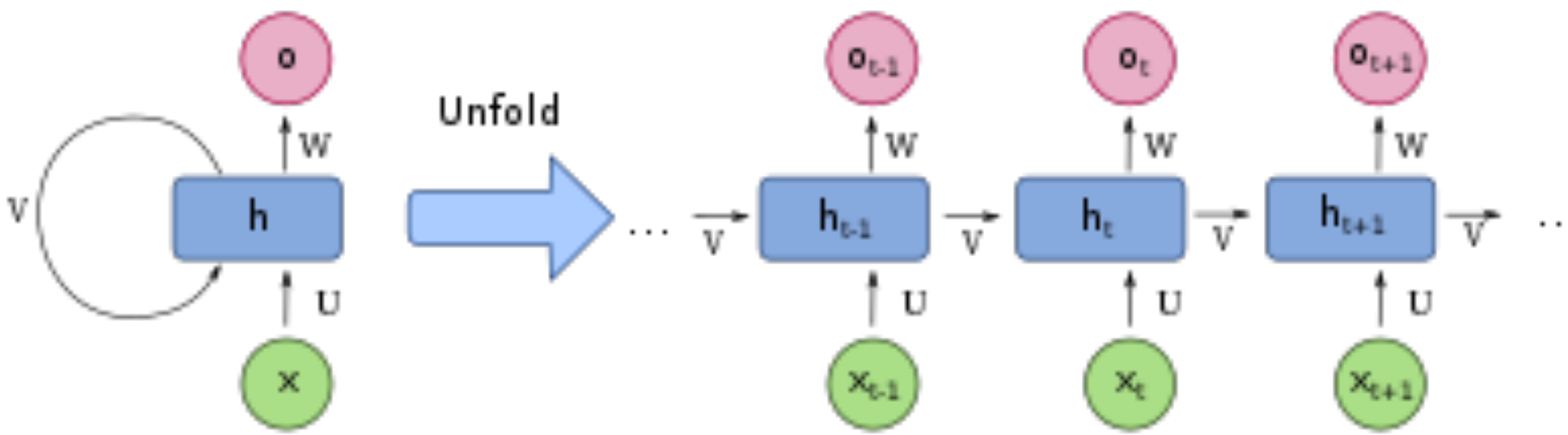

Used for language (and other things).
Assumes linear/temporal structure to the data.

Transfer Learning

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"Pretraining"

- Train a model to do some task T1 (for which you have a lot of data)
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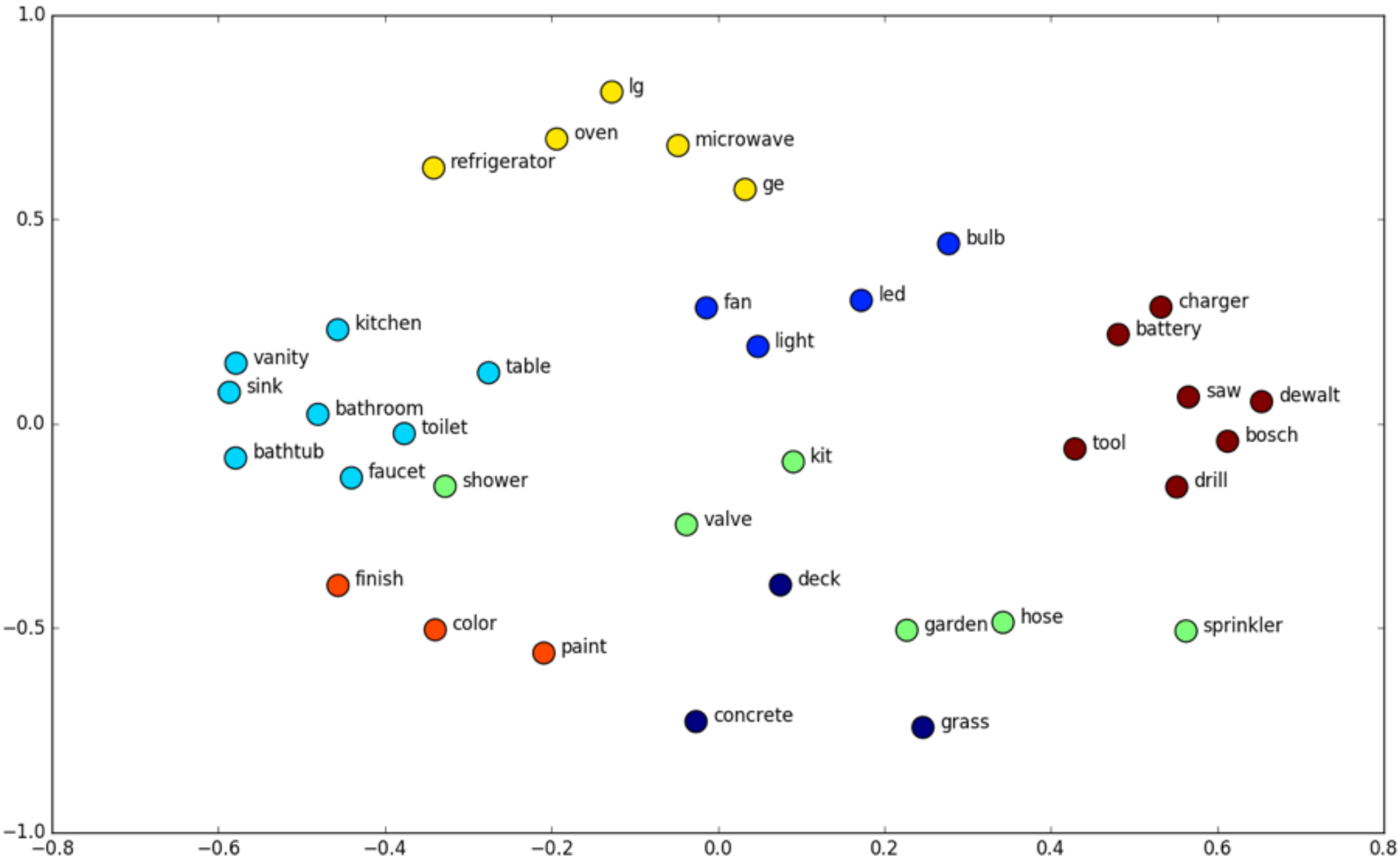
Word Embeddings



Word Embeddings

Factorization of the term-context matrix

	the	congress	parliament	US	UK
the	1	1	1	1	1
congress	1	1	0	1	0
parlaiment	1	0	1	1	1
US	1	1	1	1	0
UK	1	0	1	0	1

Word Embeddings

	the	con-gress	parlia-ment	US	UK
the	1	1	1	1	1
congress	1	1	0	1	0
parlaiment	1	0	1	1	1
US	1	1	1	1	0
UK	1	0	1	0	1

Embeddings!

=

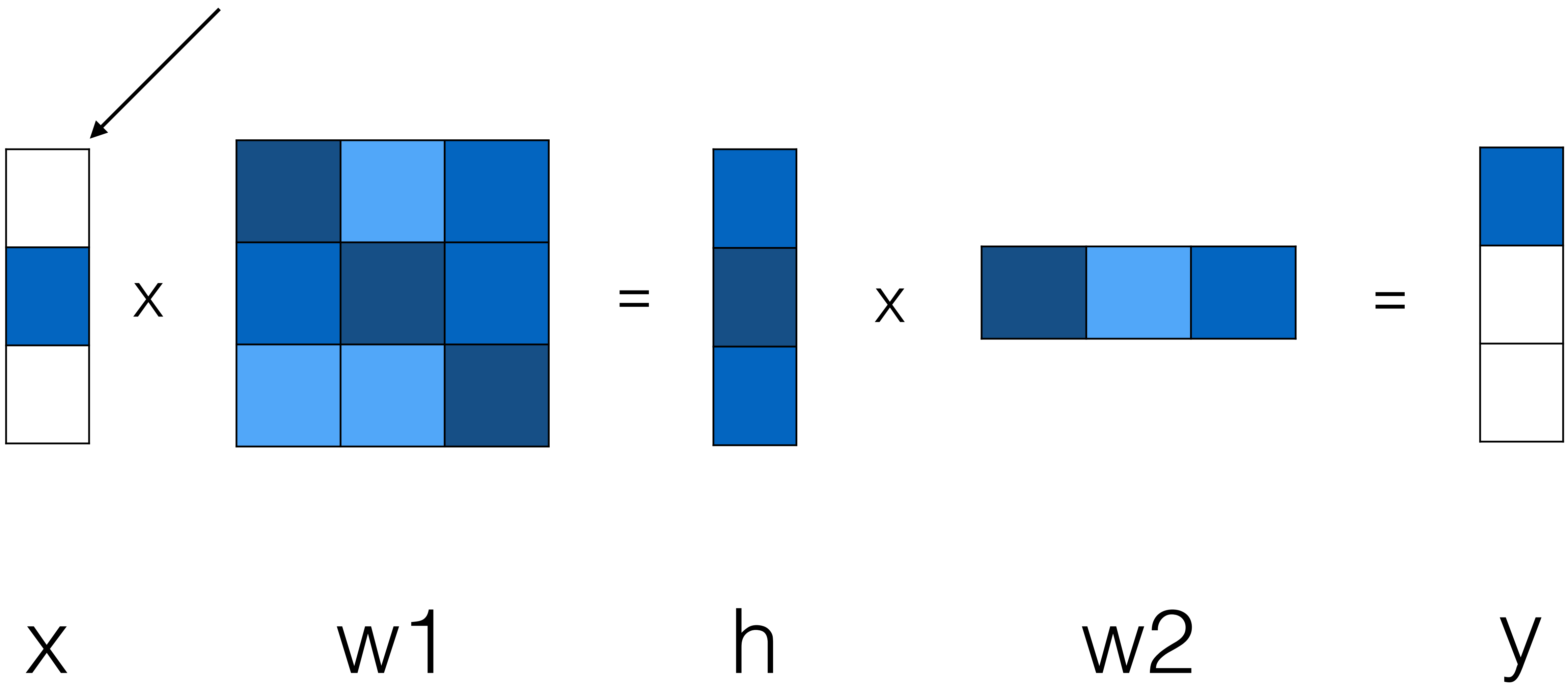
the	-0.60	-0.39	0.70	0.00
congress	-0.48	0.50	-0.12	-0.71
parliament	-0.43	-0.58	-0.69	0.00
US	-0.48	0.50	-0.12	0.71
UK	0.02	0.79	0.02	-0.44

×

-0.65	-0.34	-0.51	-0.34	-0.31
0.02	-0.54	0.34	-0.54	0.56
-0.42	0.02	0.79	0.02	-0.44
-0.63	0.27	0.00	0.37	0.63
-0.04	0.73	0.00	-0.68	0.04

Word Embeddings

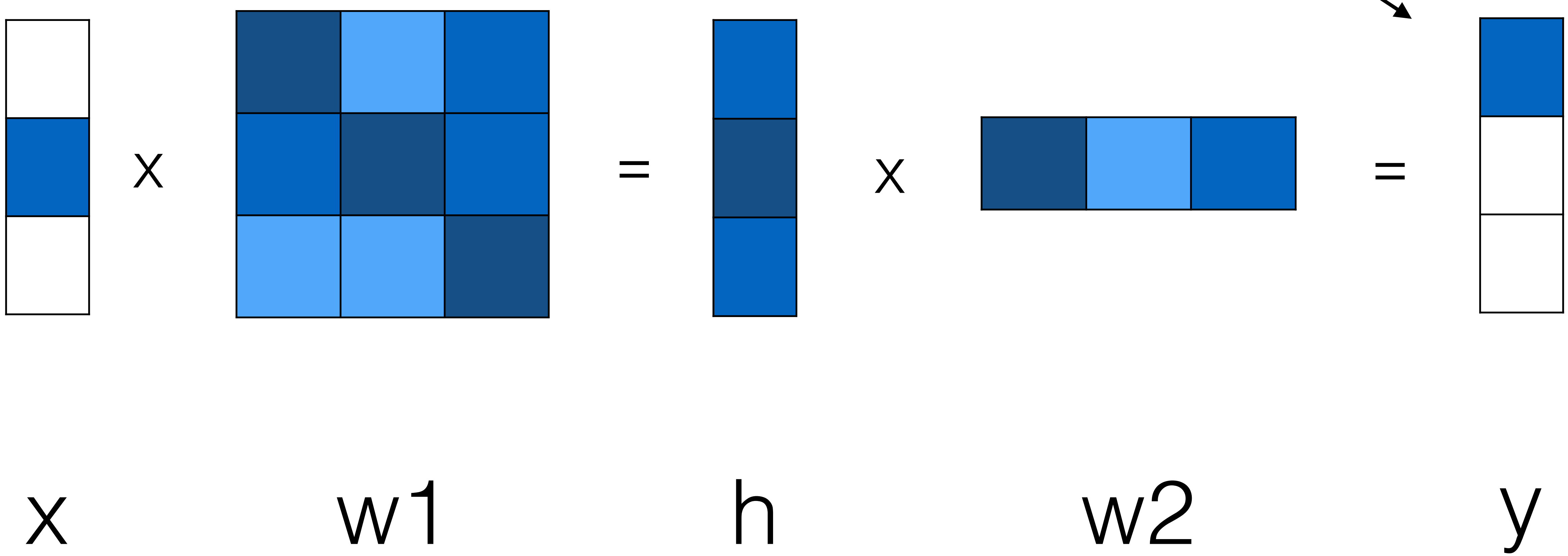
one hot encoding, i.e.: the word "congress"



Word Embeddings

predict one hot encoding of next word, i.e.:

the word "stagnated"



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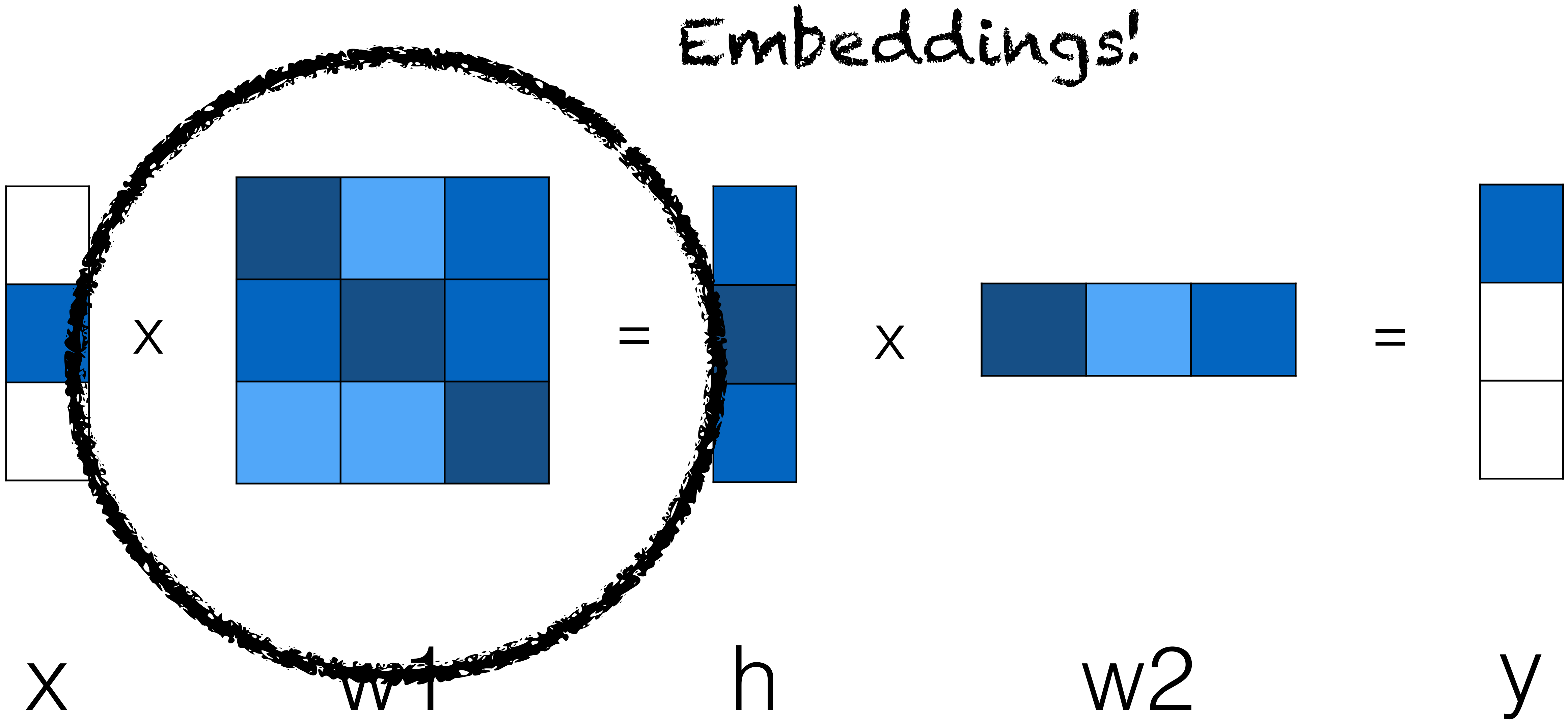
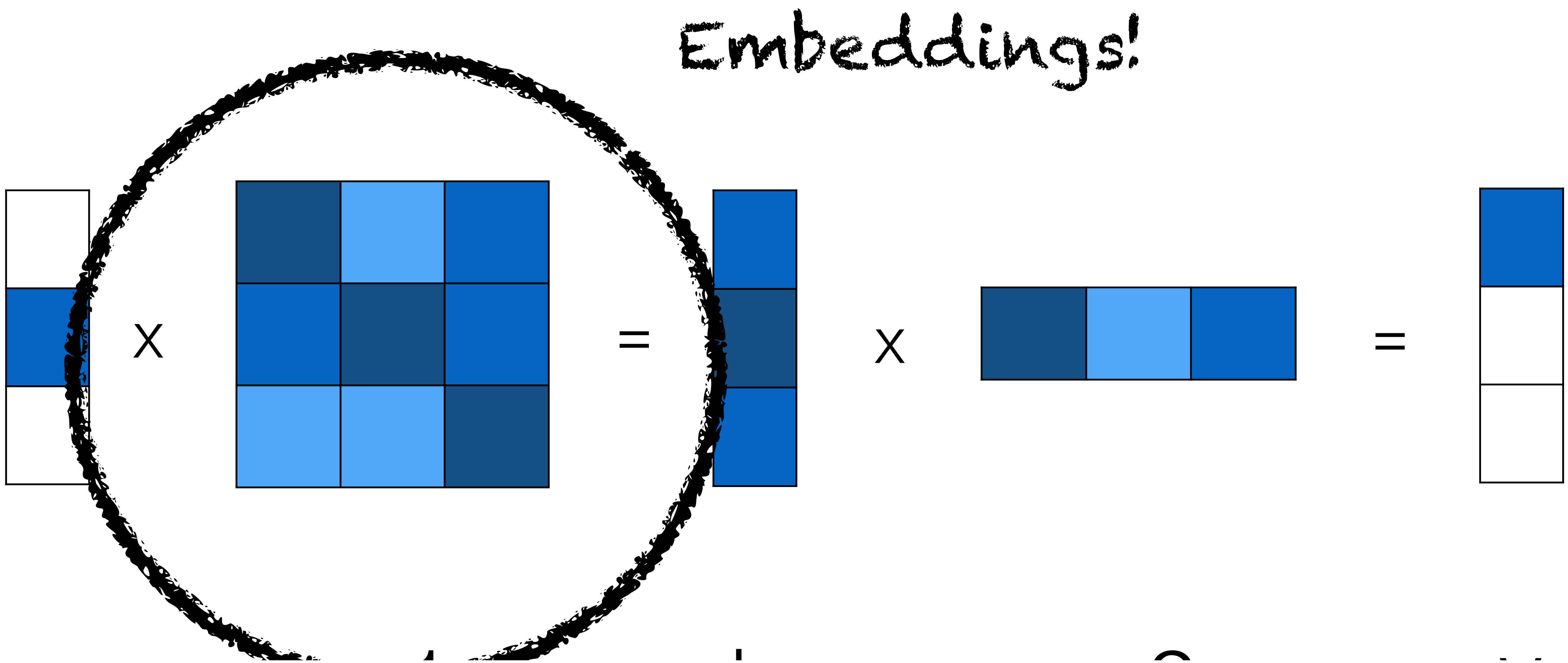
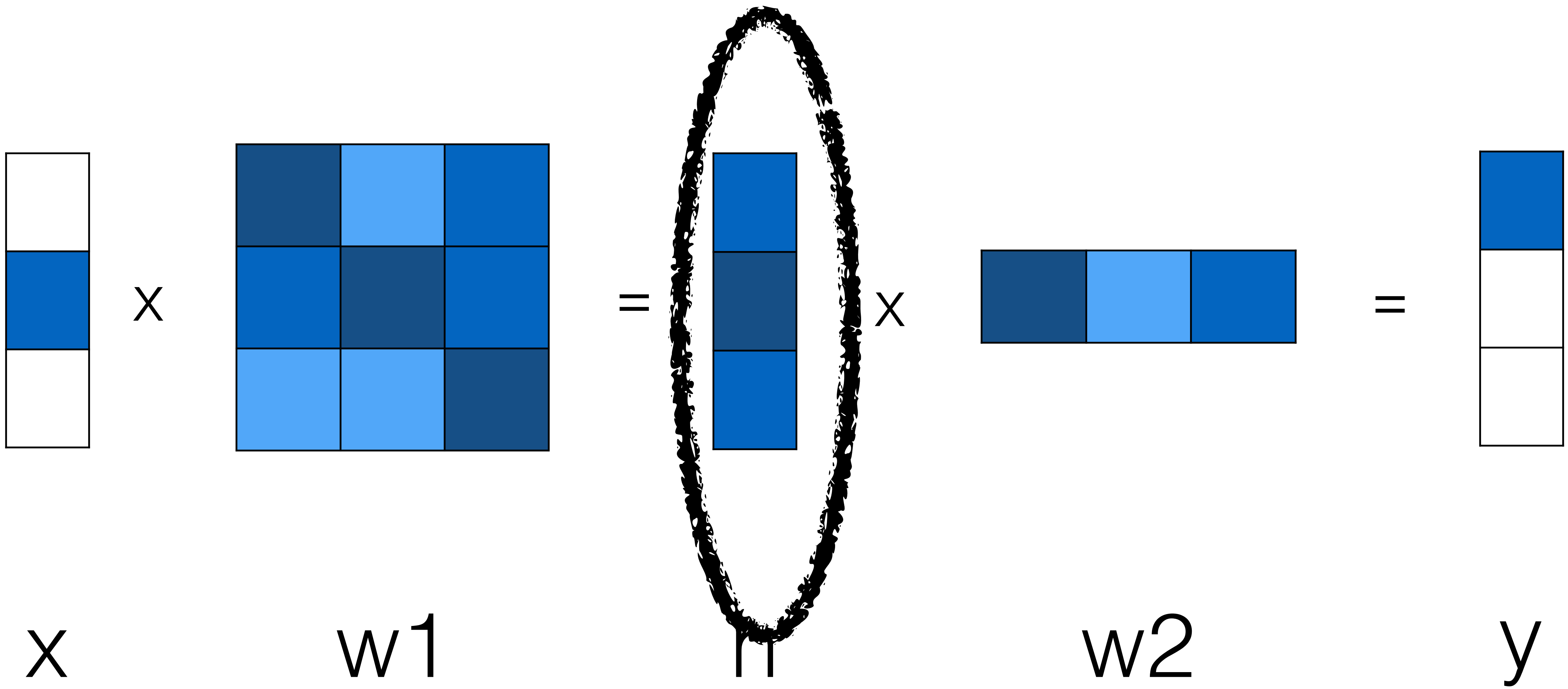


Word Embeddings



Actually the same as the MF embeddings
(assuming a linear network...)
Levy and Goldberg (2014)

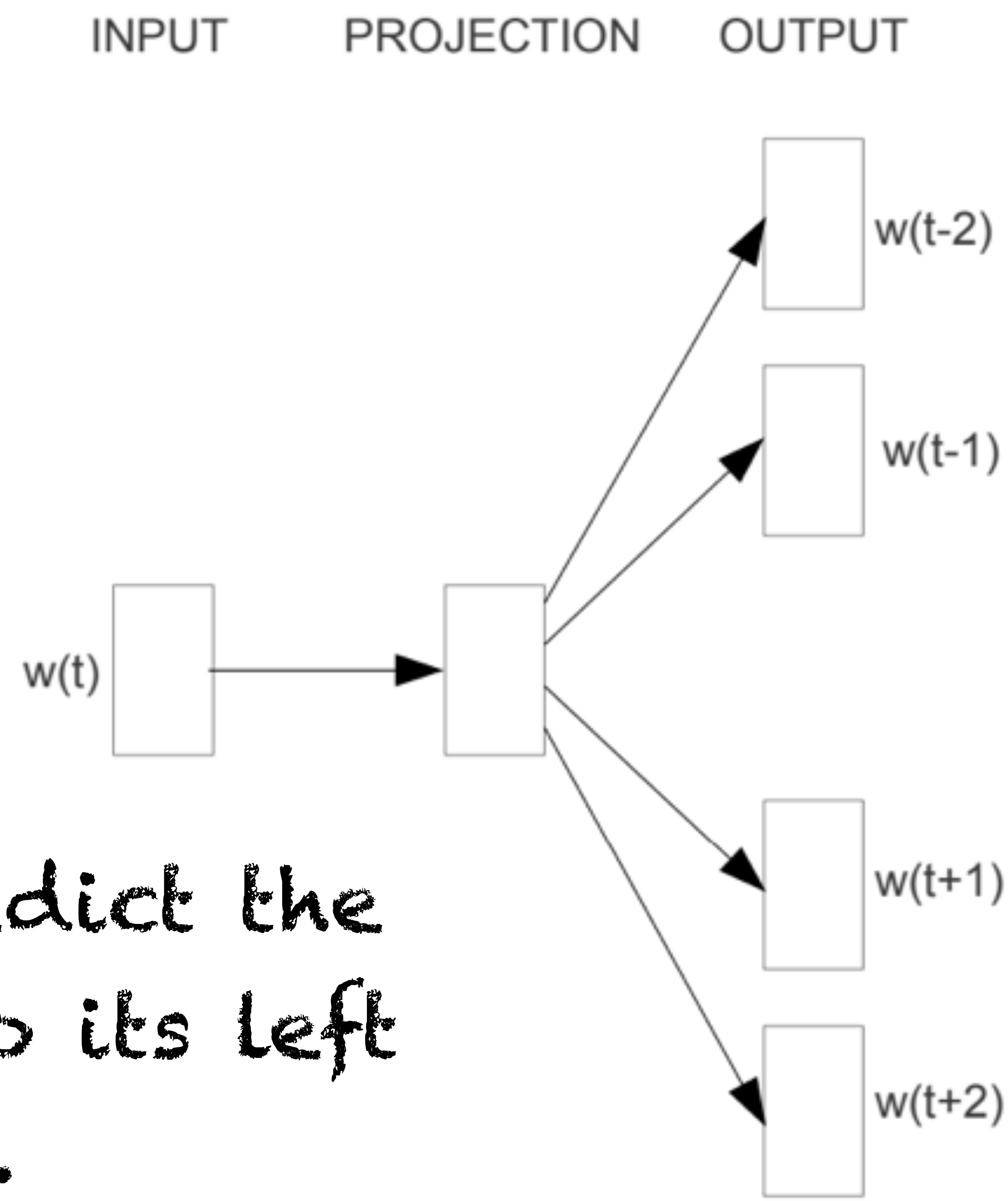
Word Embeddings



Allows parameter sharing over similar words.

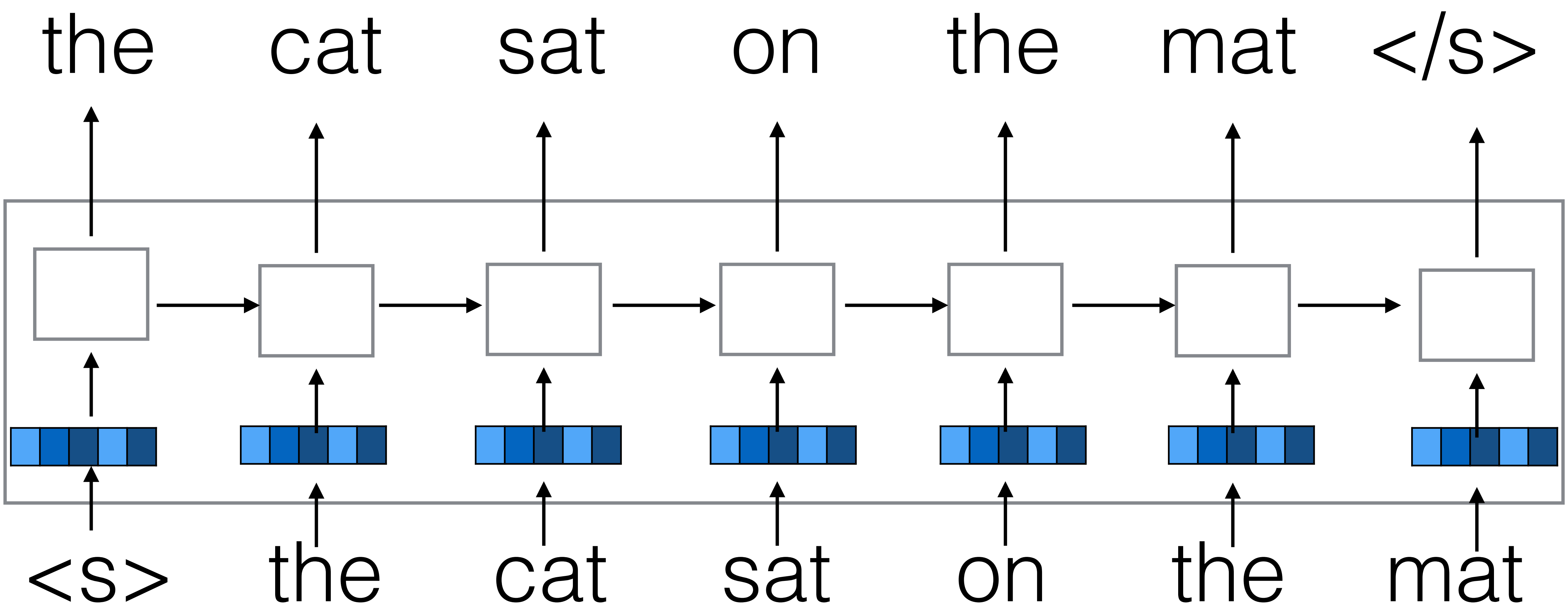
Word Embeddings

For your homework: Skipgram



Given a word, predict the words that come to its left and right...

Word Embeddings



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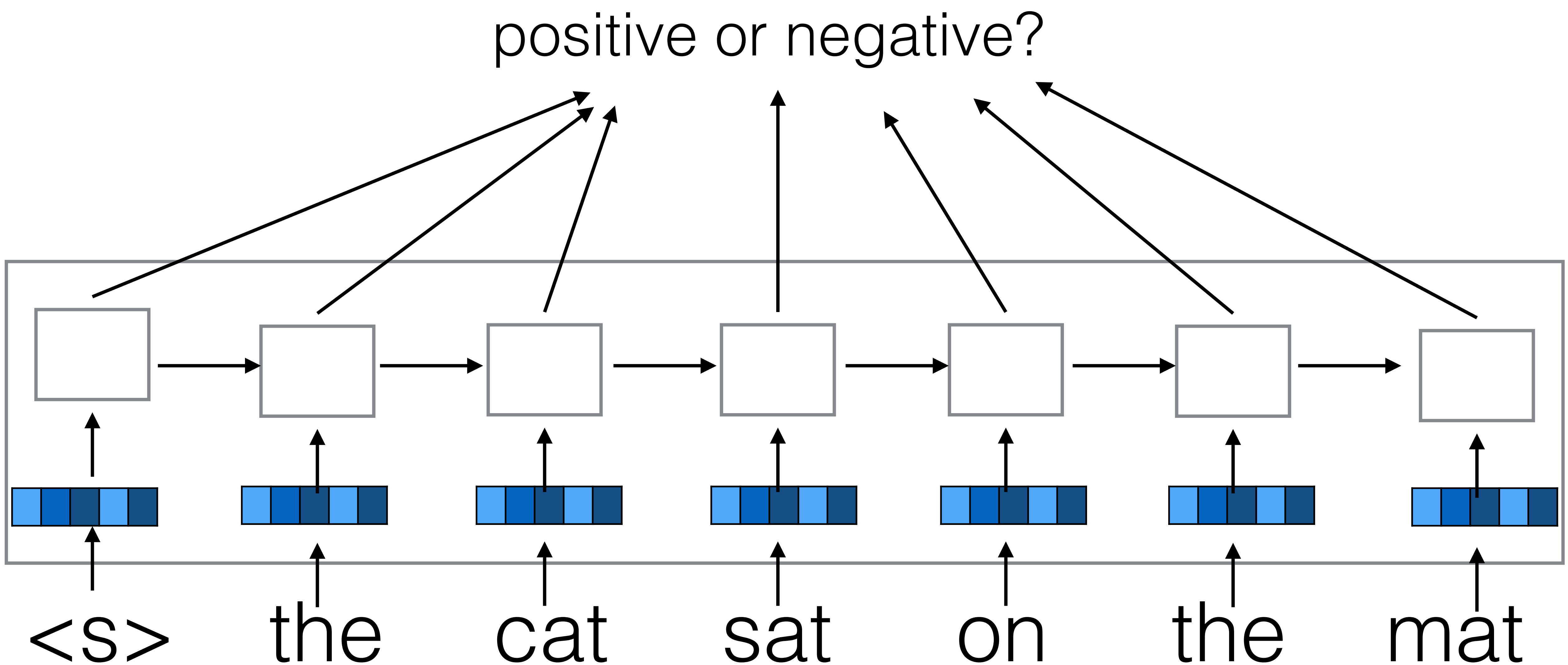

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- Feature engineering has been replaced with architecture engineering/hyperparameter hacking. Metalearning?
- End-to-end-training hurts generalizability. Inductive biases on the hypothesis space?
- The ***big*** reason: its really really hard to formulate most problems as ML problems

I have a thing. Should I deep learn it?

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$\boxed{\text{Do you have a ton of data?}}$

I have a thing. Should I deep learn it?

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No

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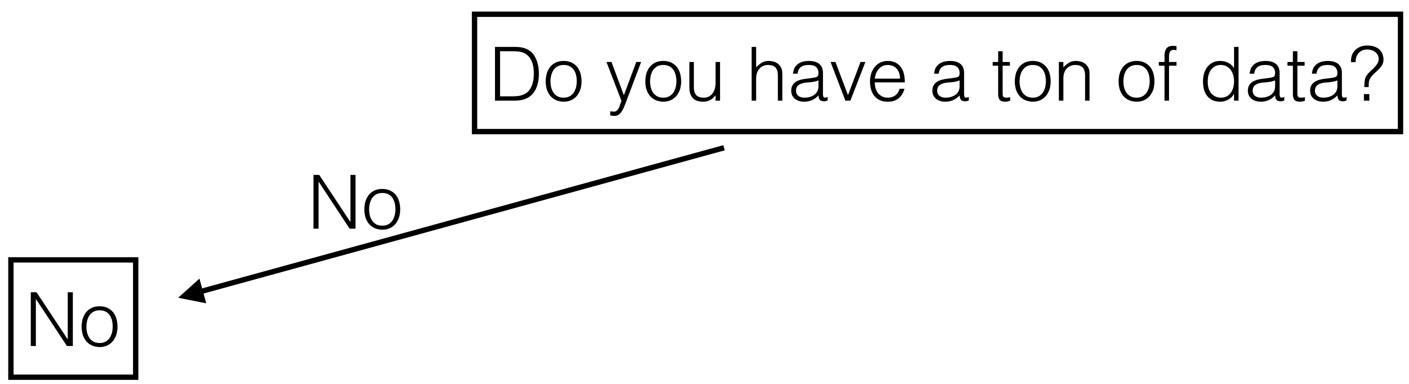

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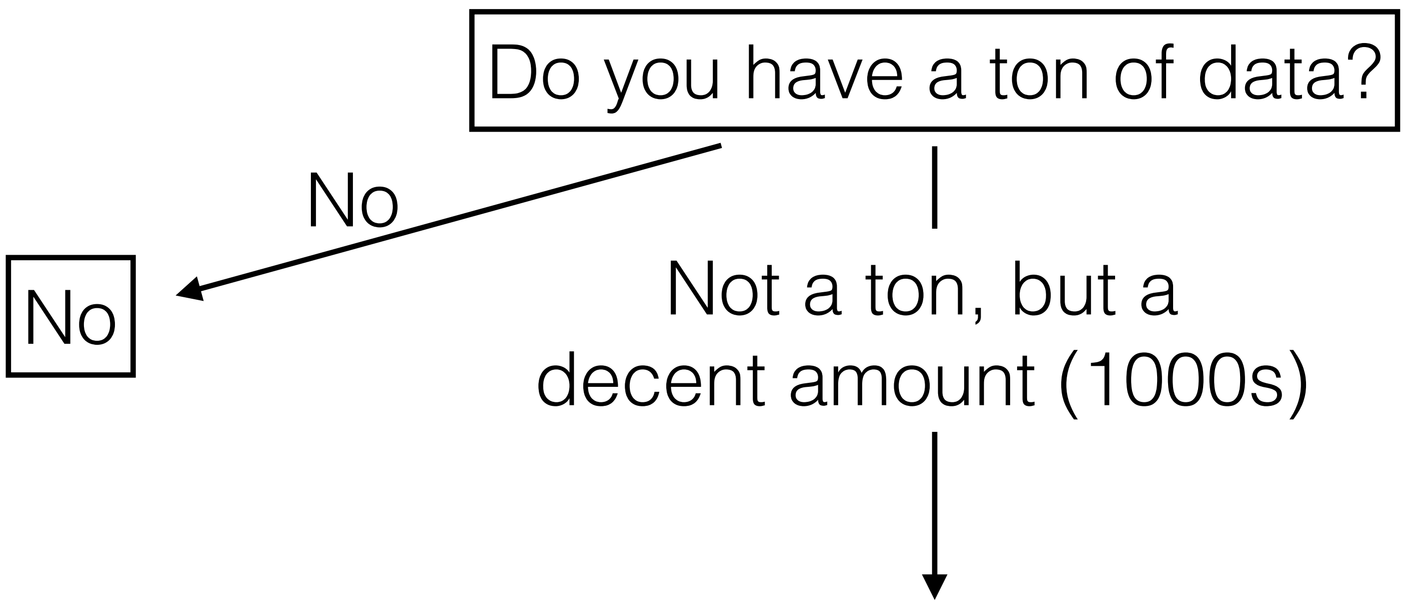

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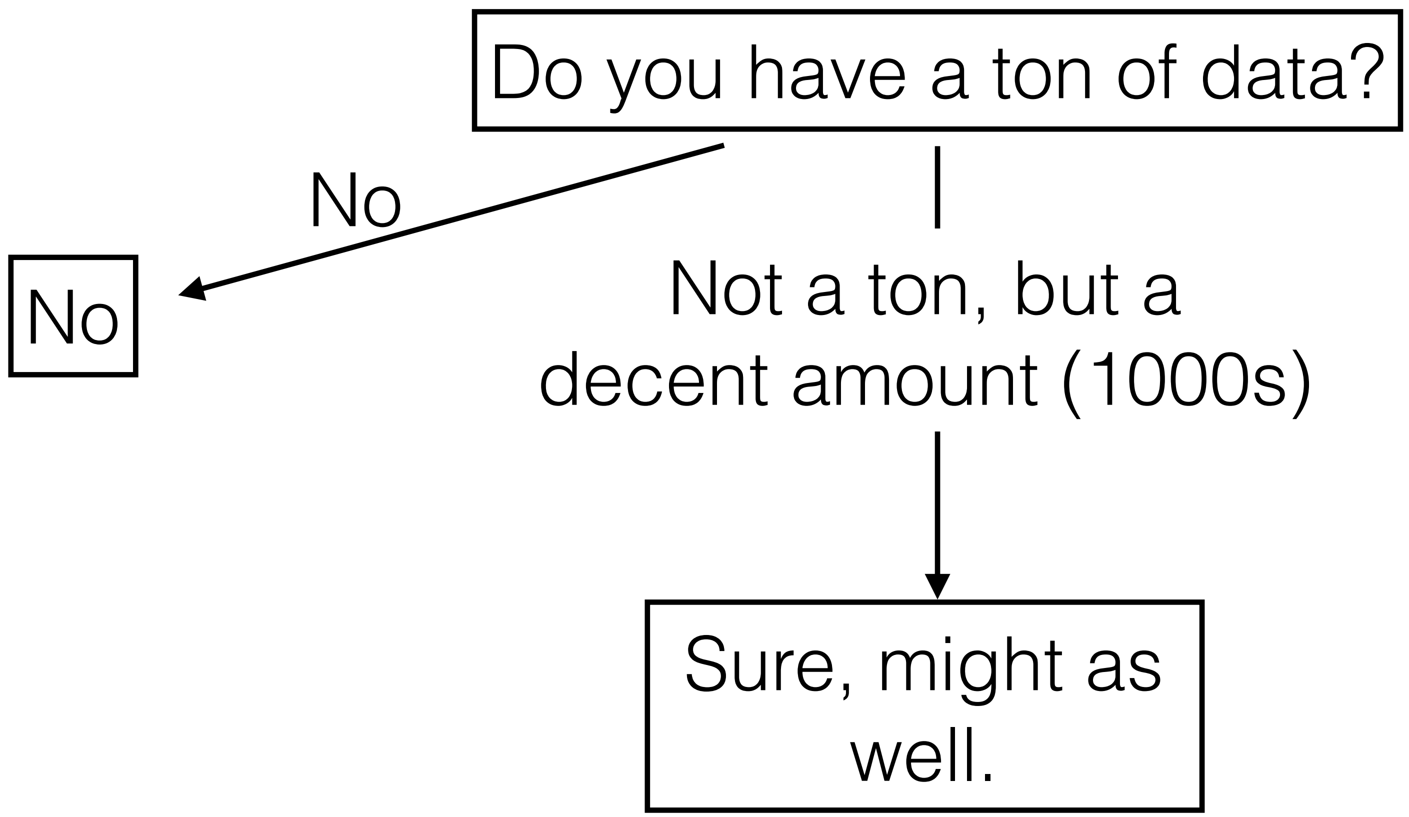

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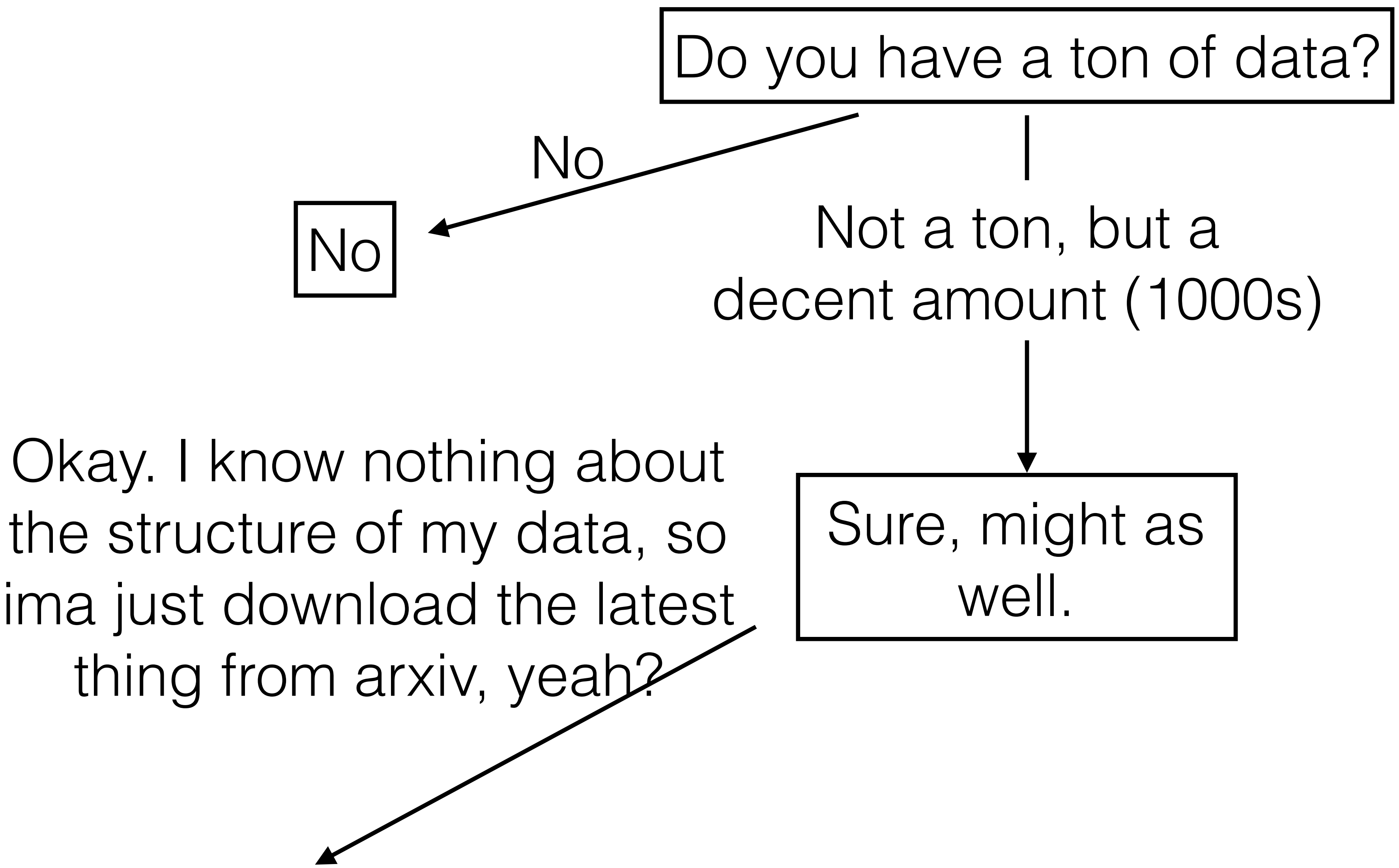

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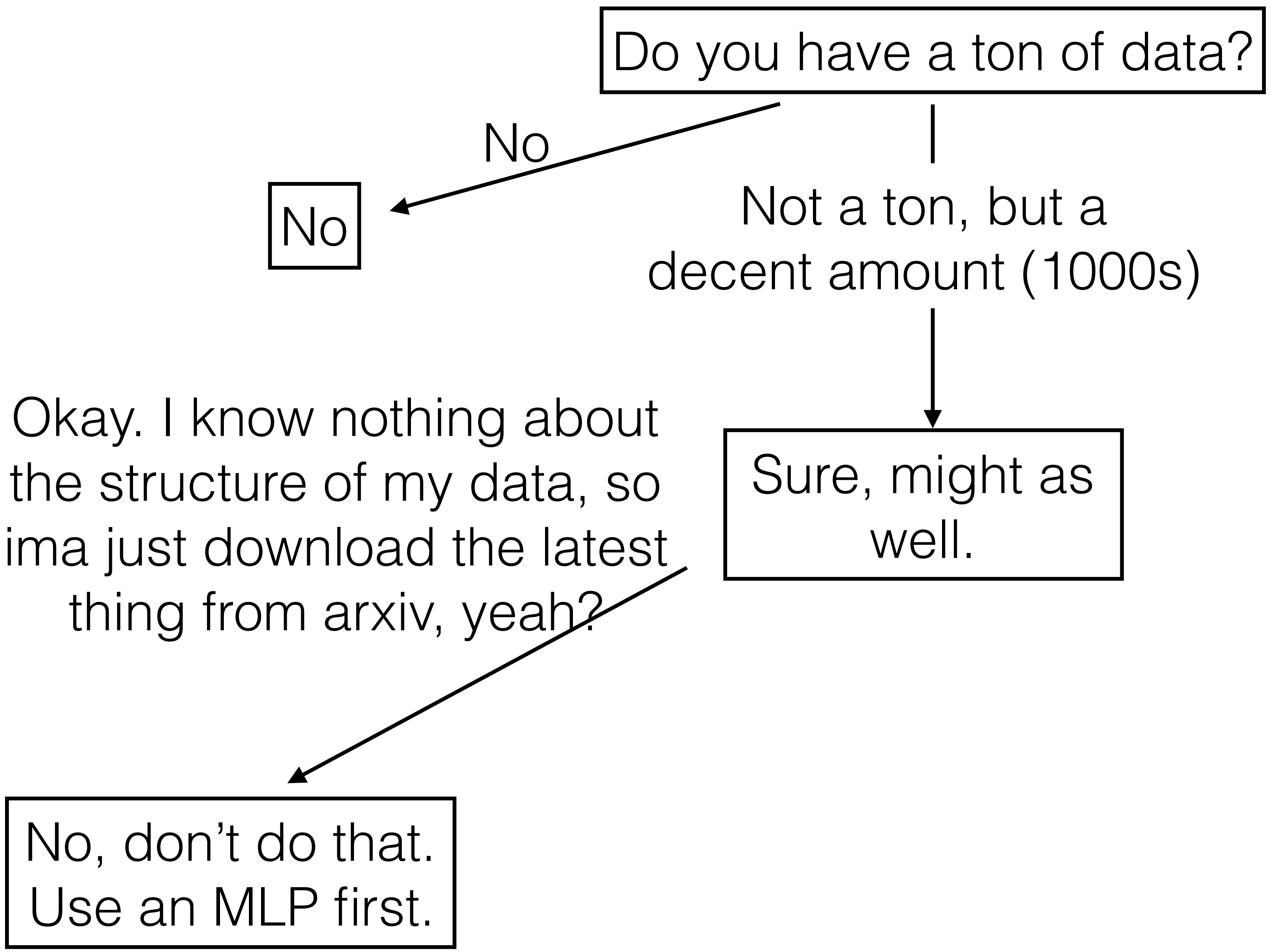

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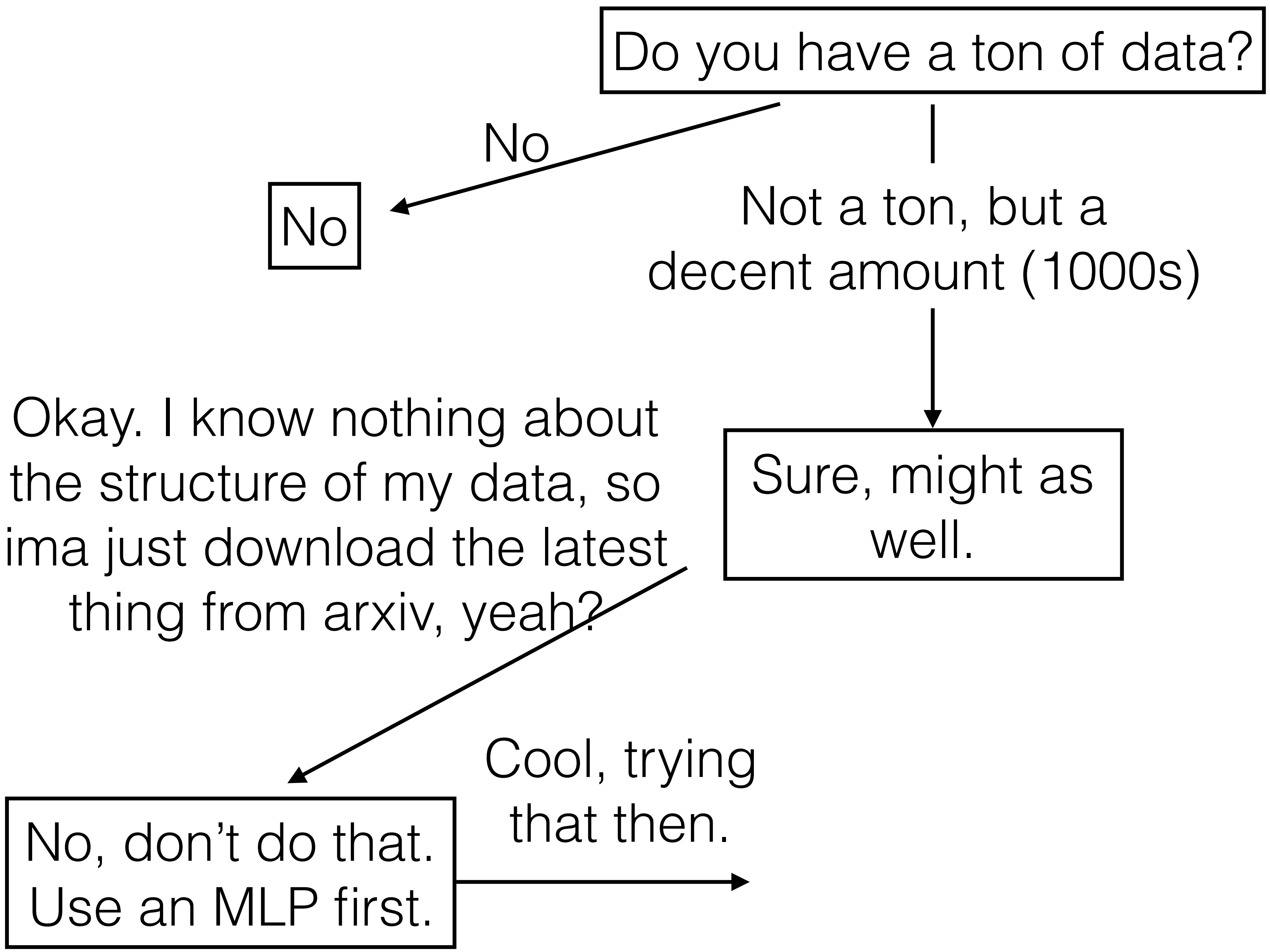

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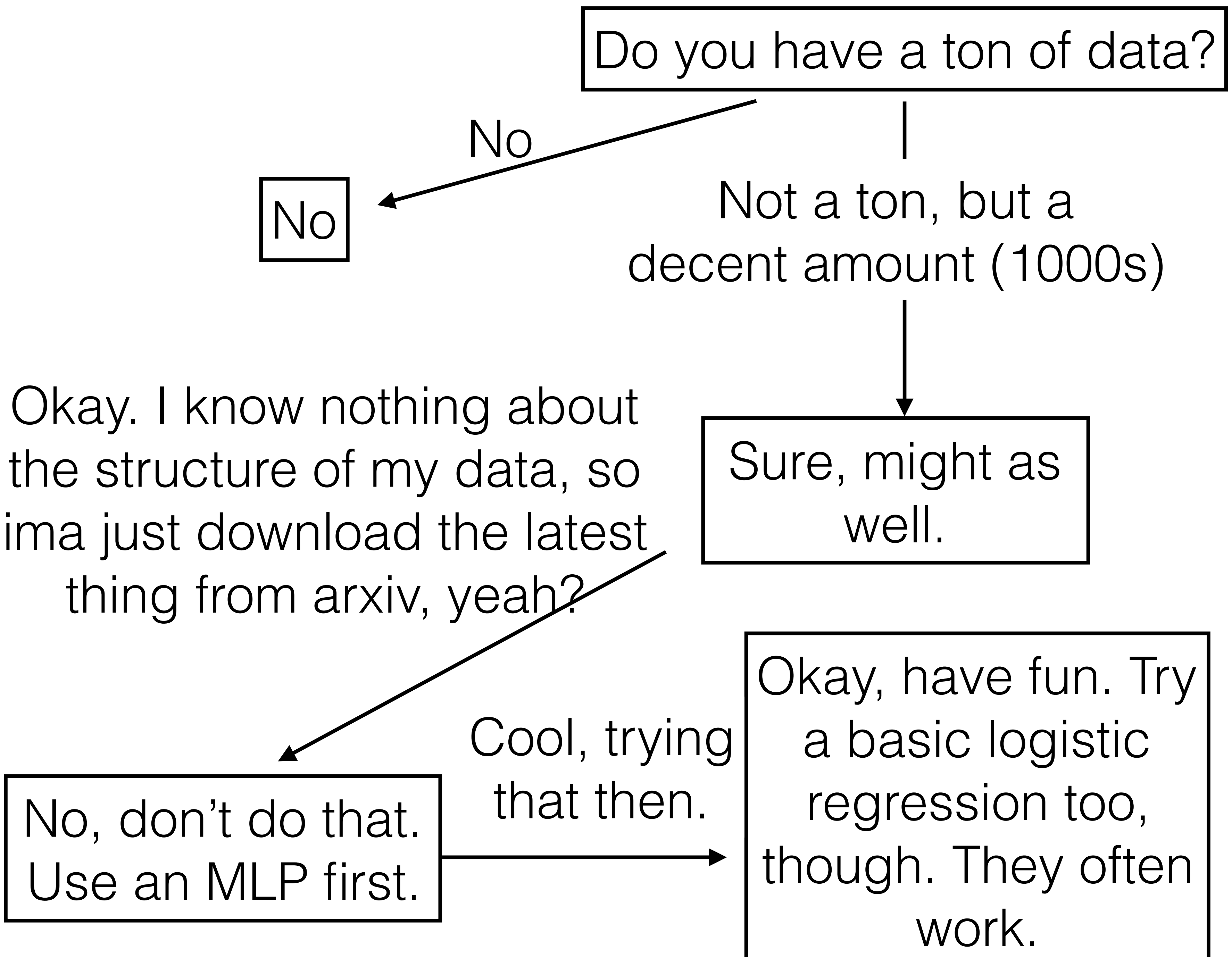

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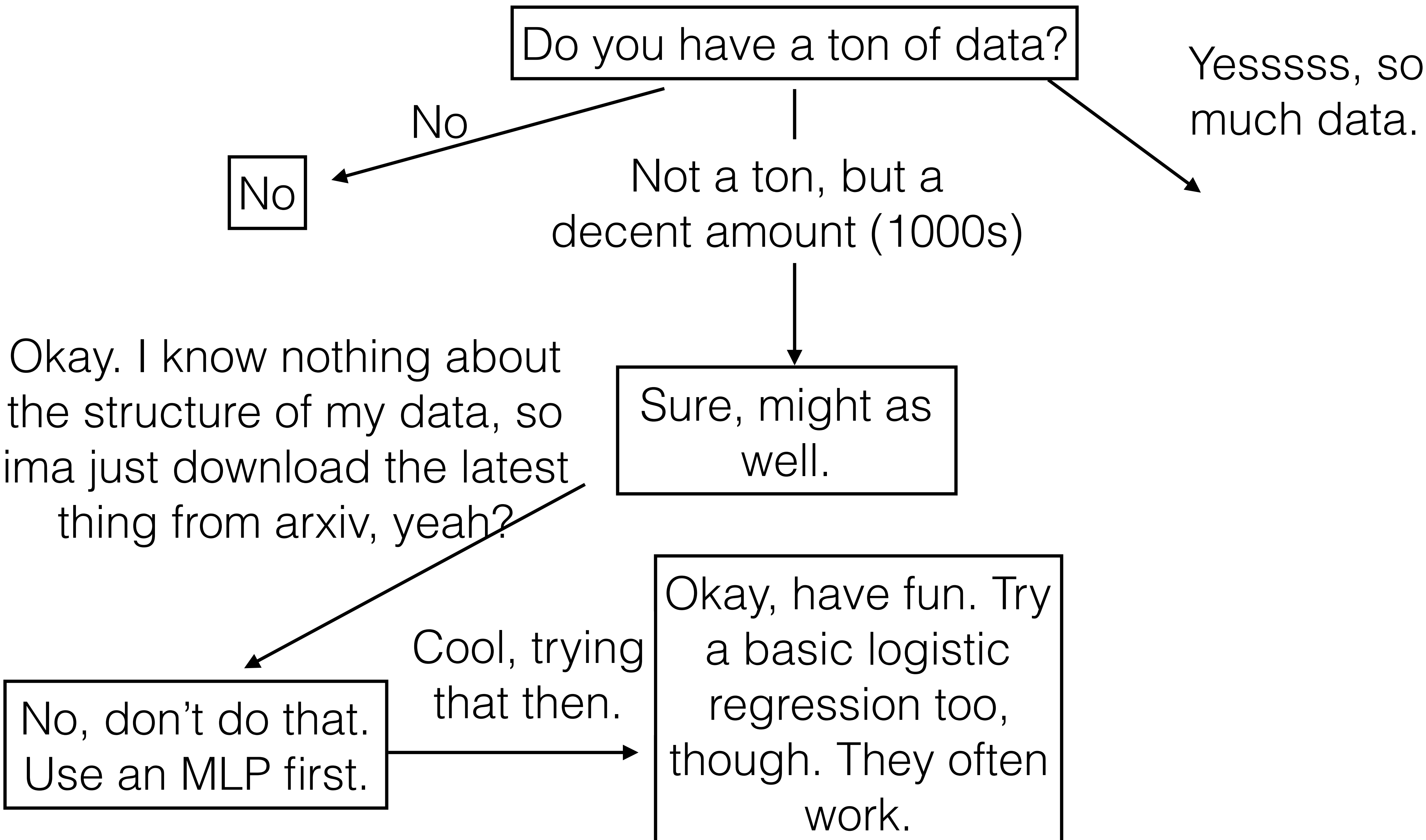

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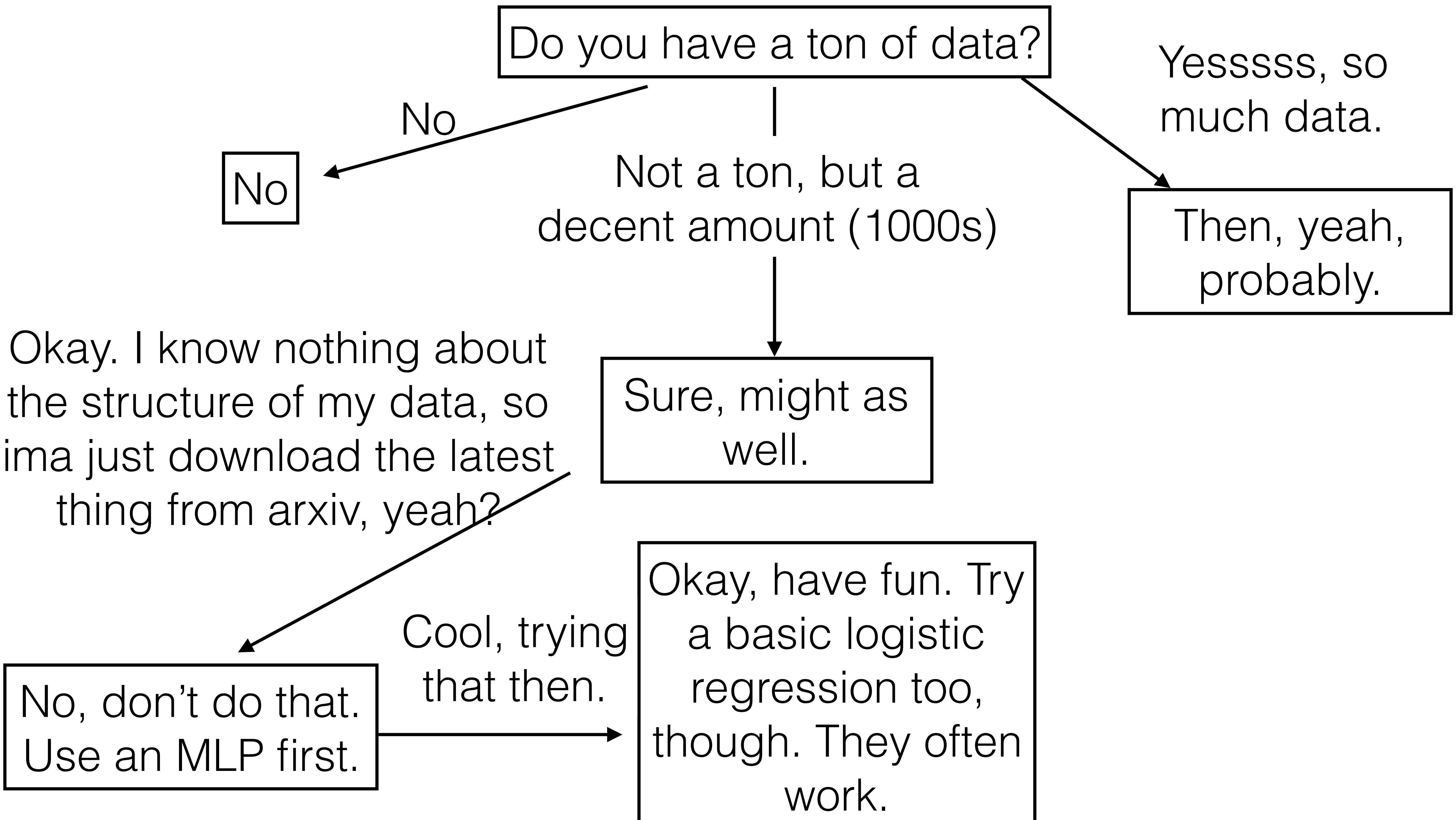

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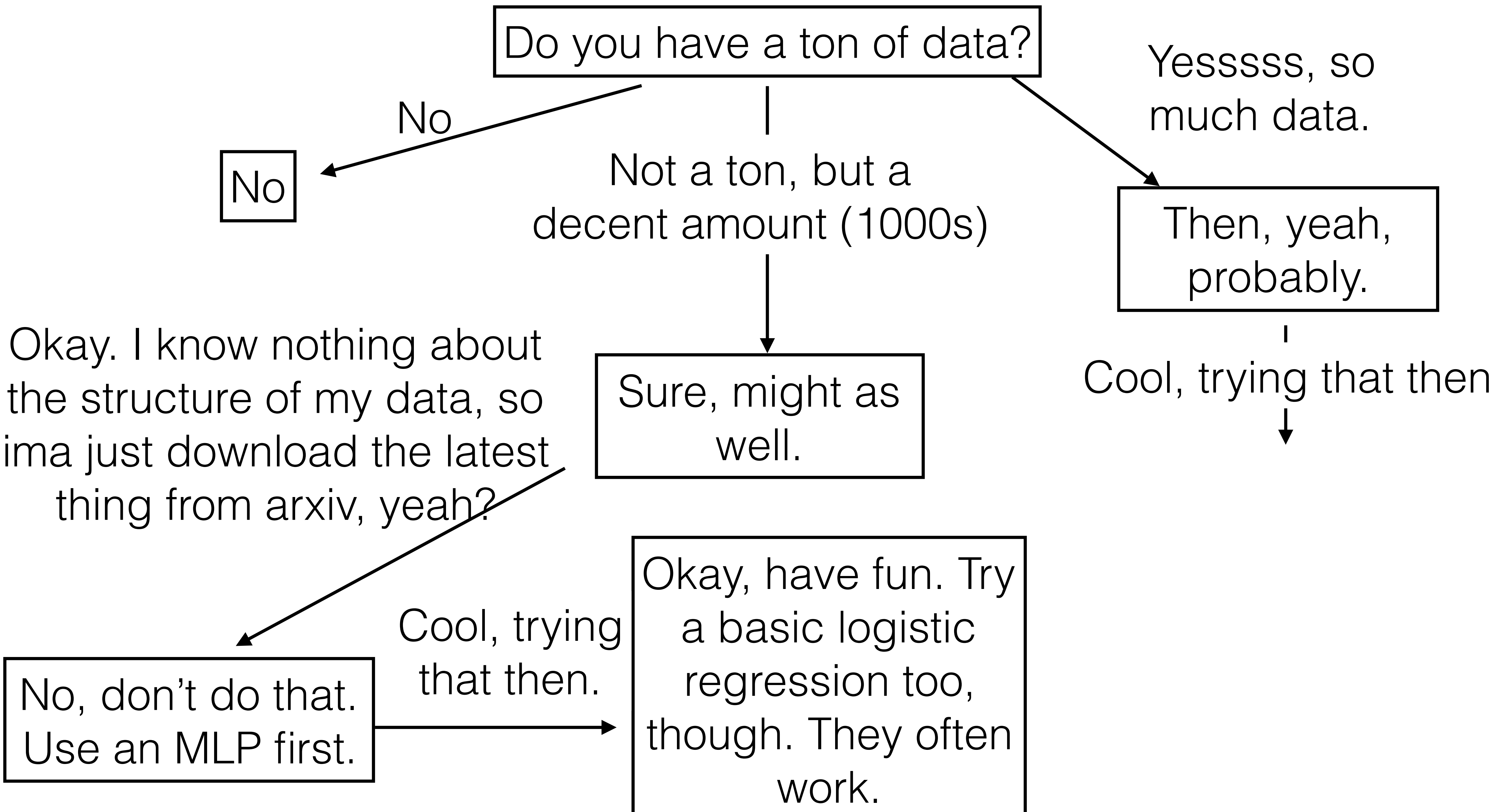

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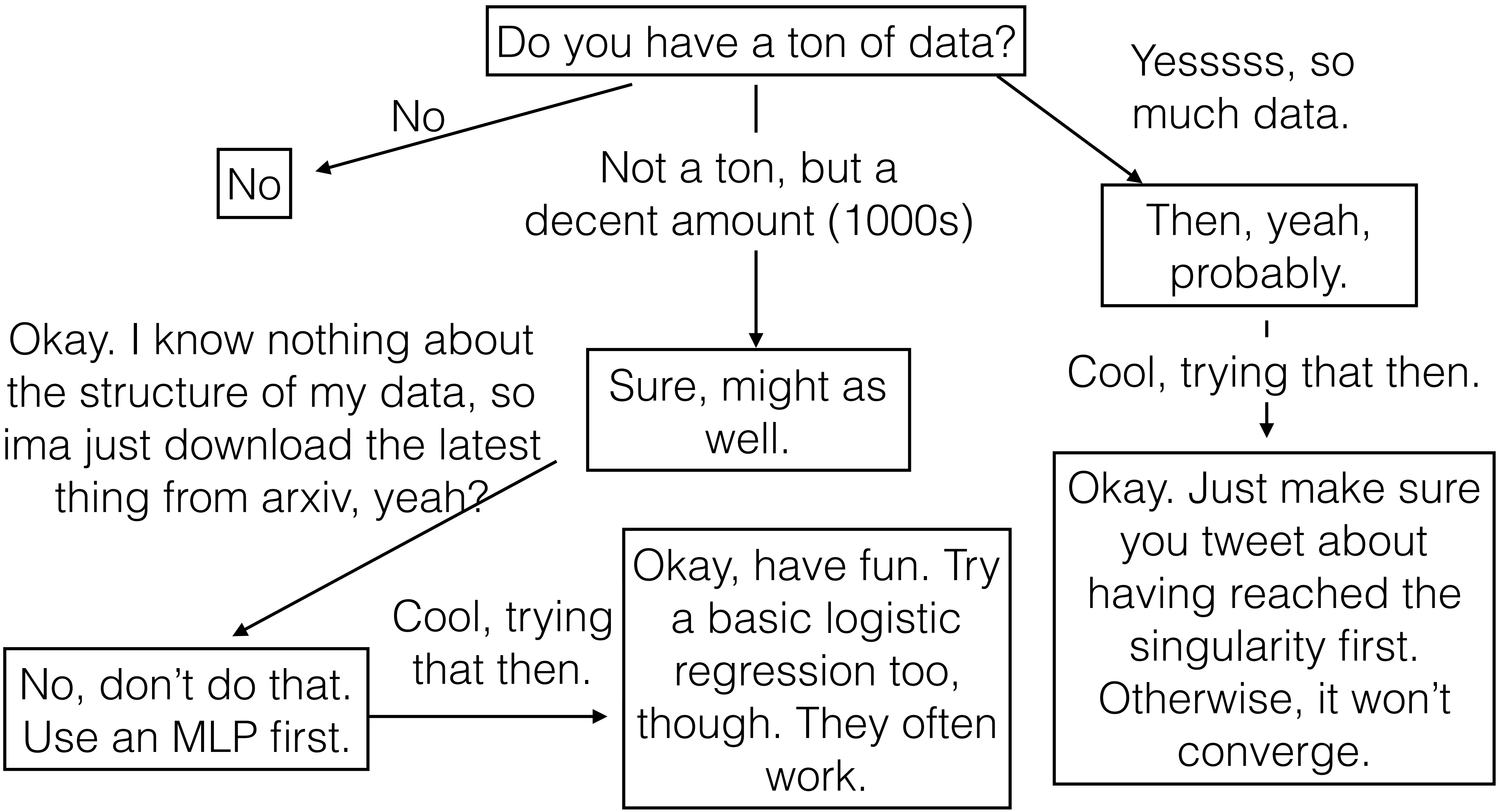

bye :)