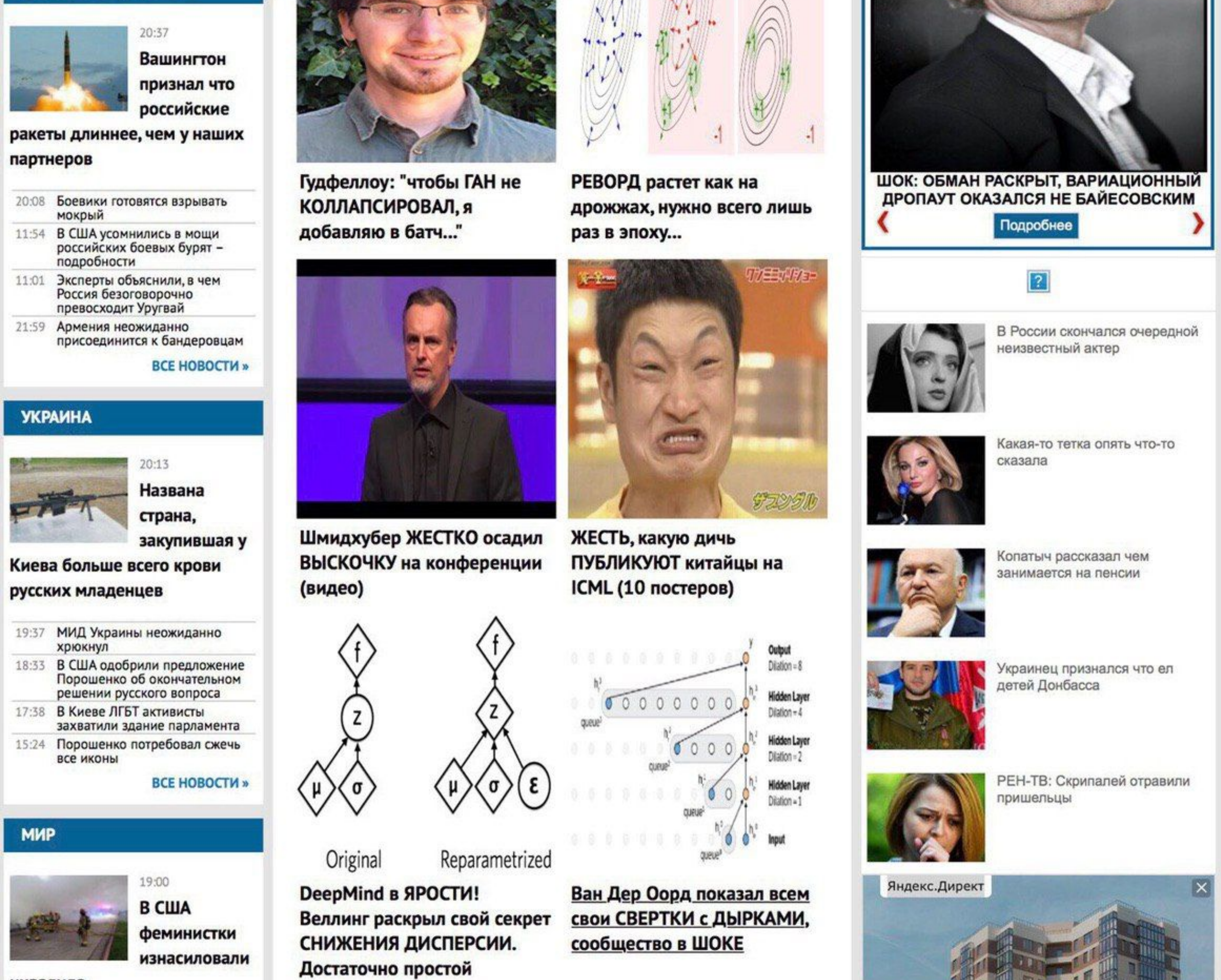
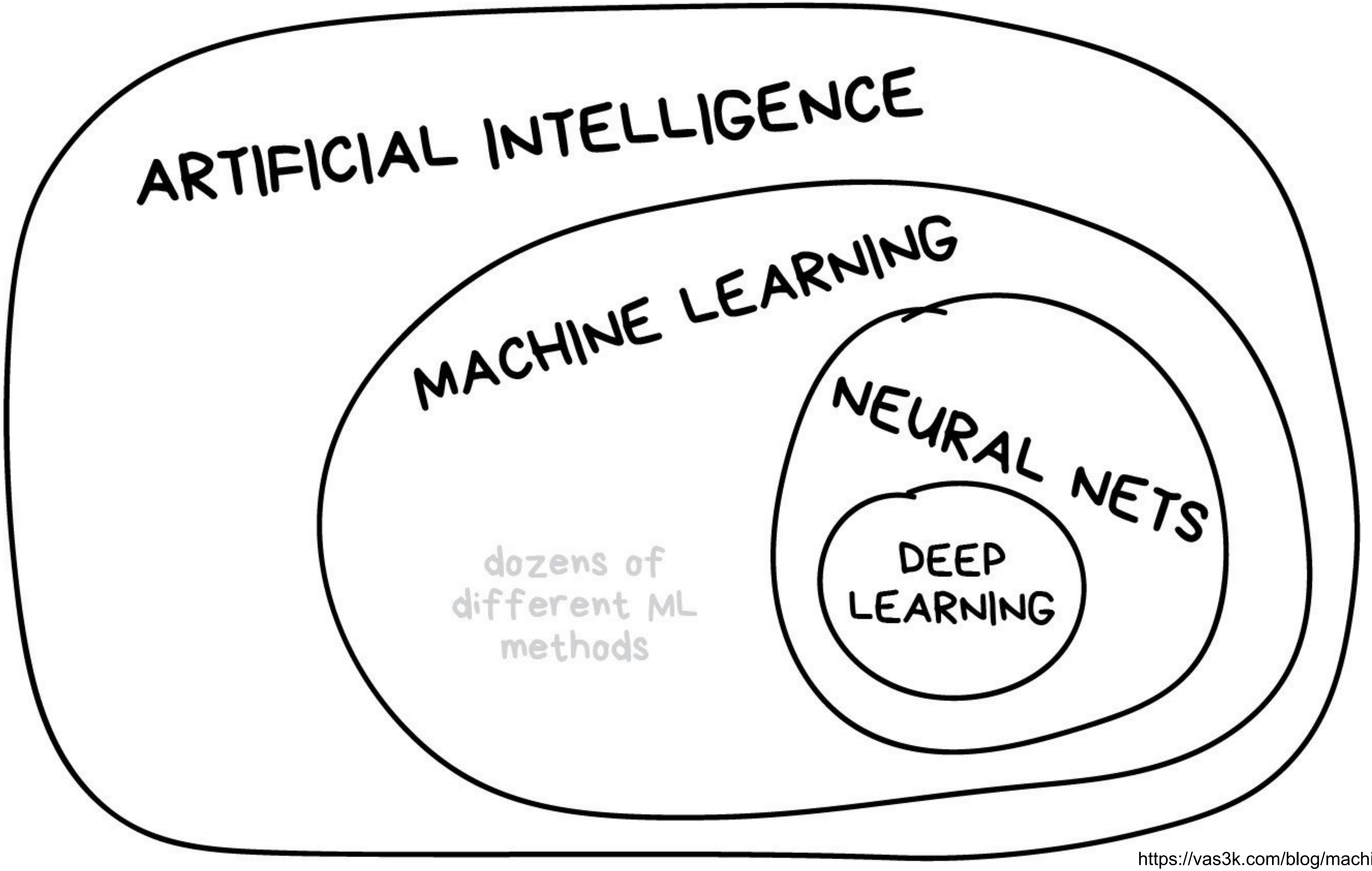


Classical Machine Learning Algorithms

Quick overview

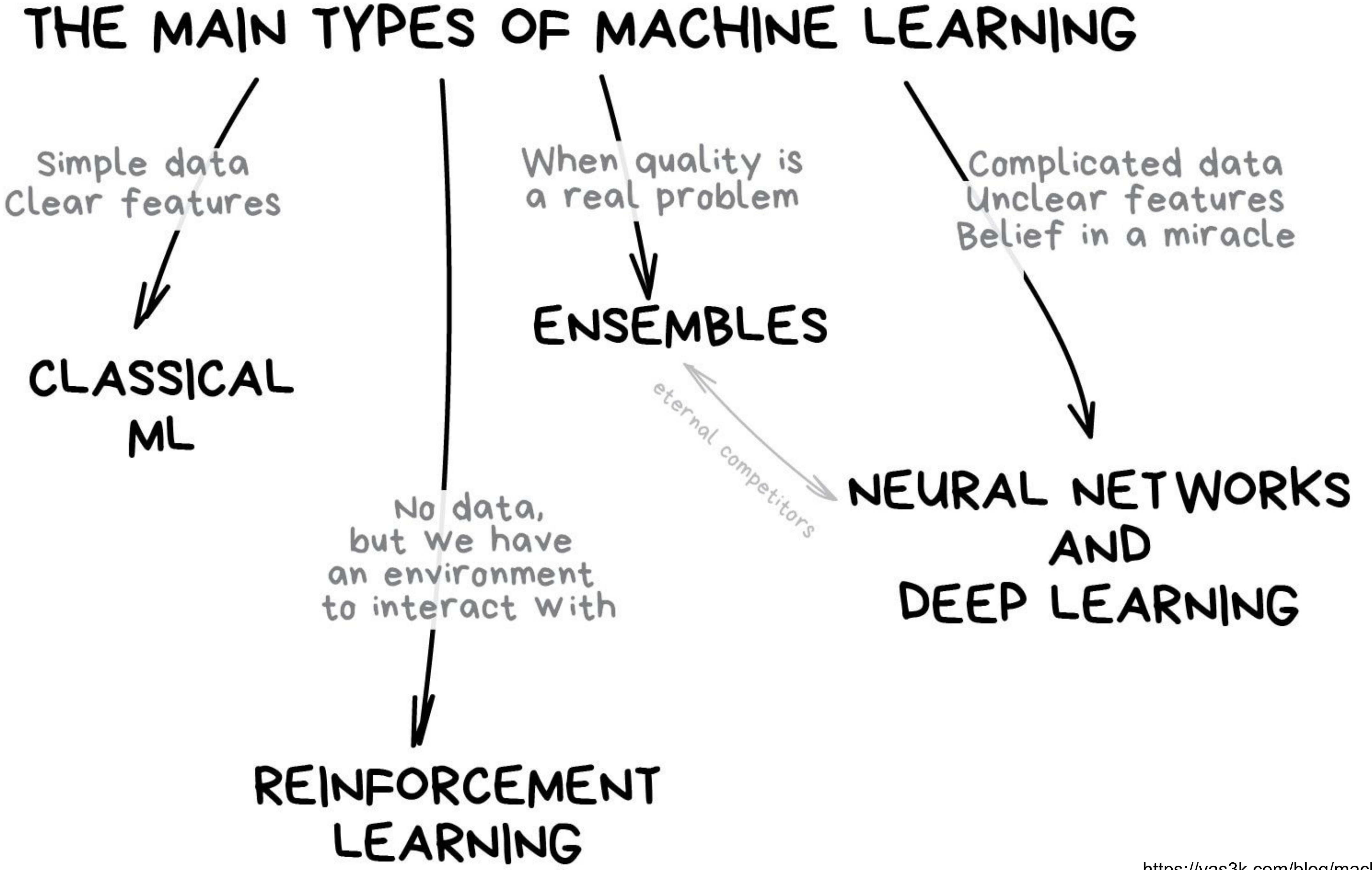
t.me/weirdreparametrizationtrick



https://vas3k.com/blog/machine_learning/

ML Paradigm

E	T	P
Experience	**Task**	**Performance measure**
Relevant data	Expected type of prediction	Metrics for prediction evaluation
Tabular data, labeled images, time series etc.	*Value, class, mask, representation*	*MSE, accuracy, IoU and many more*



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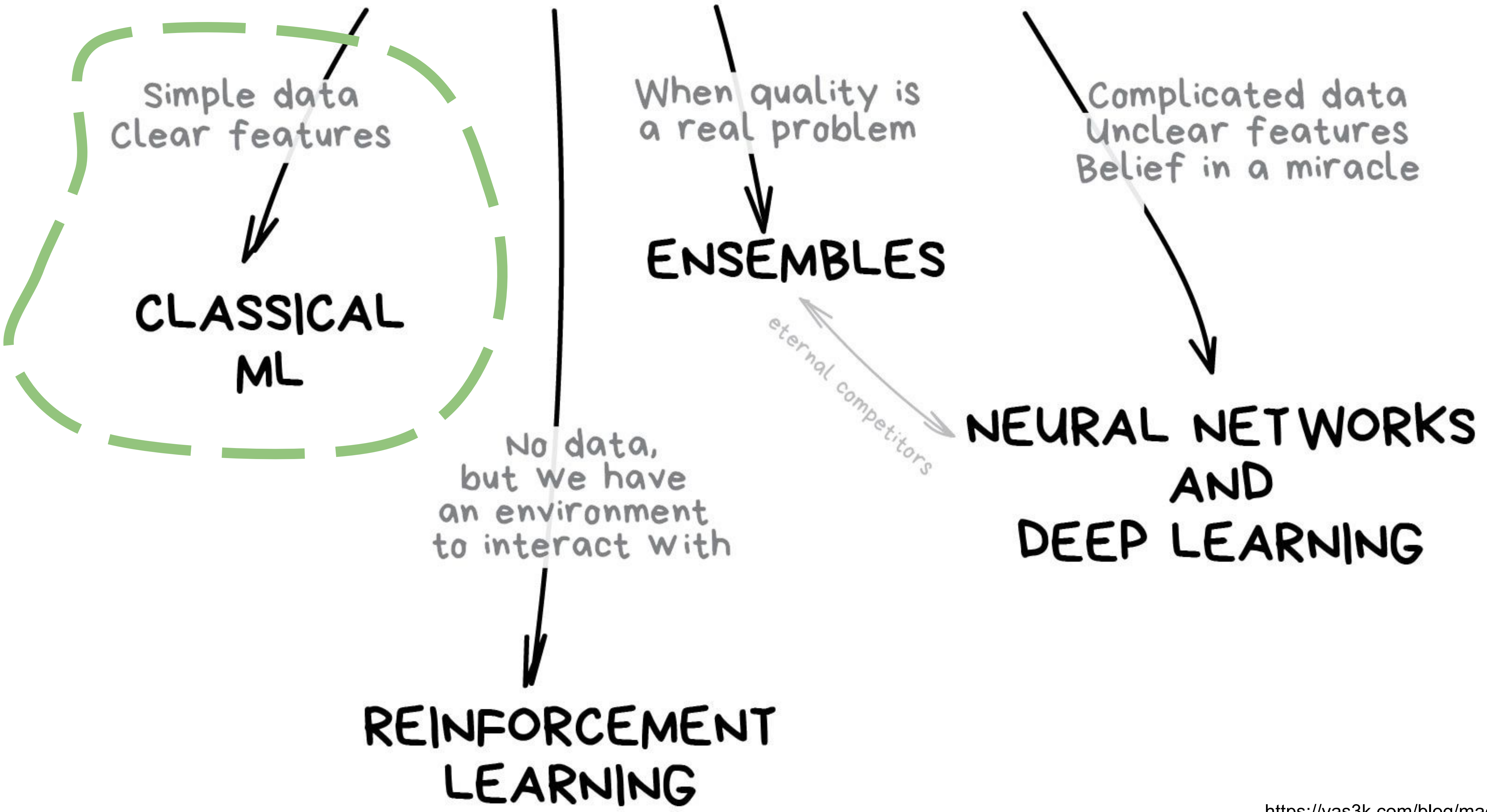
THE MAIN TYPES OF MACHINE LEARNING



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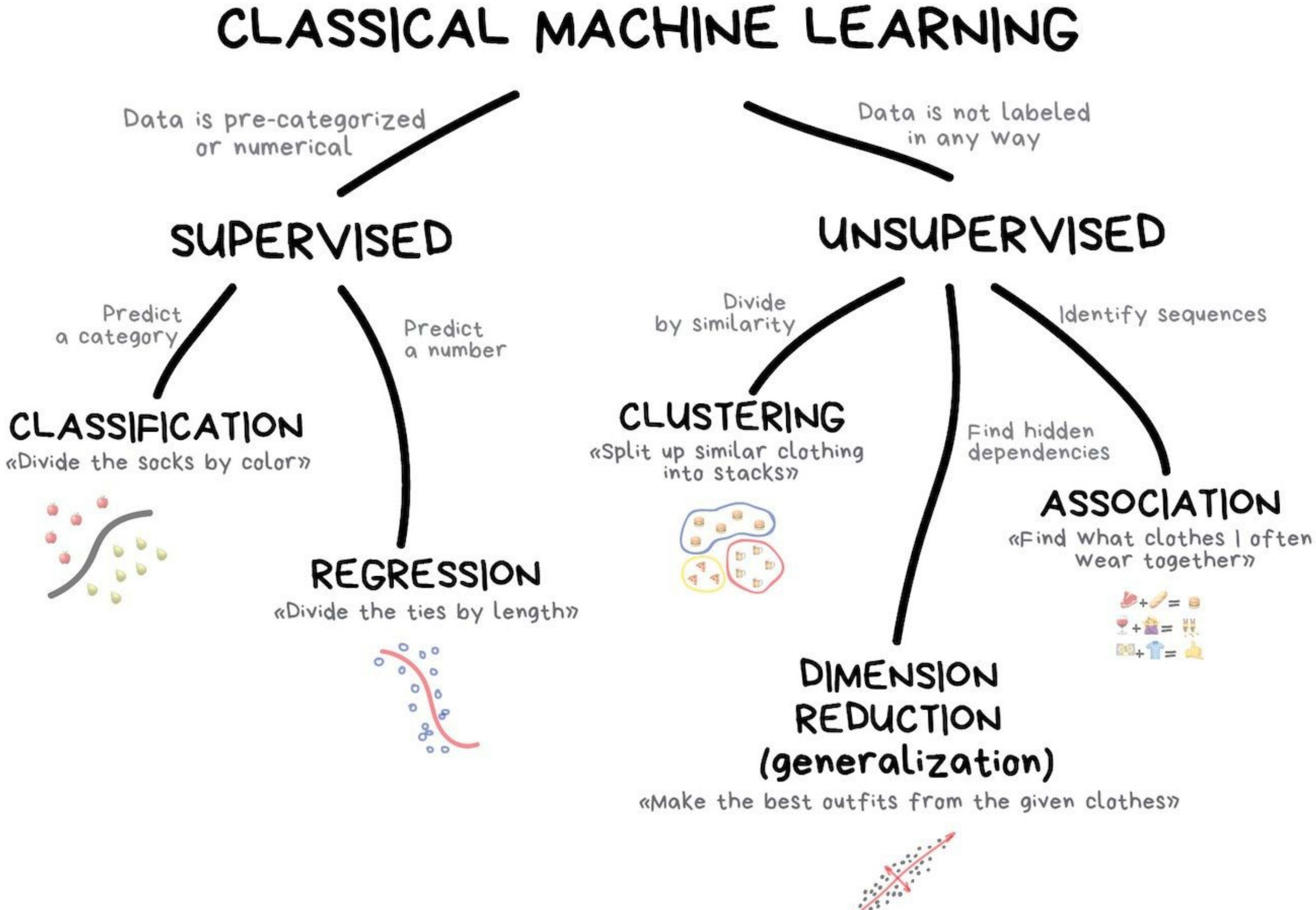

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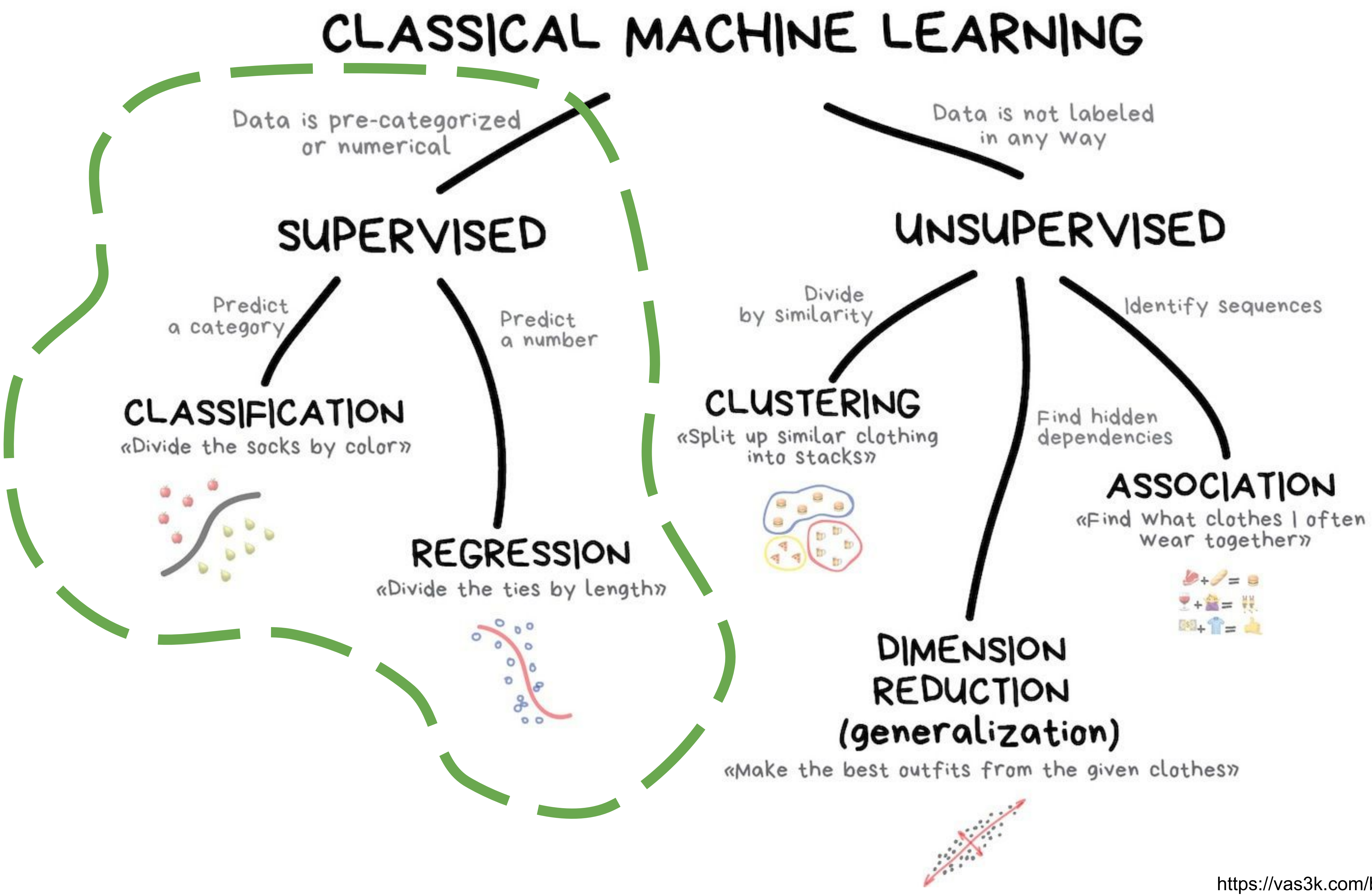

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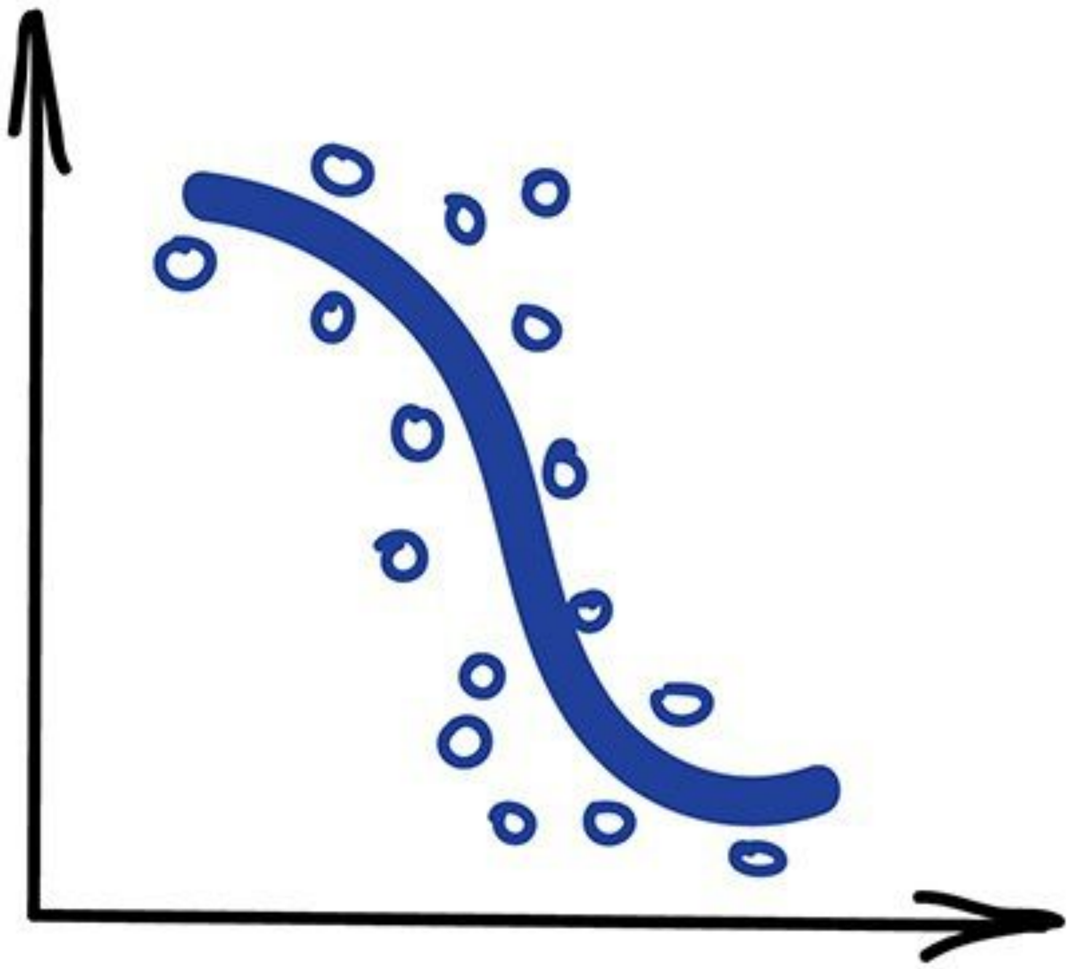

Regression

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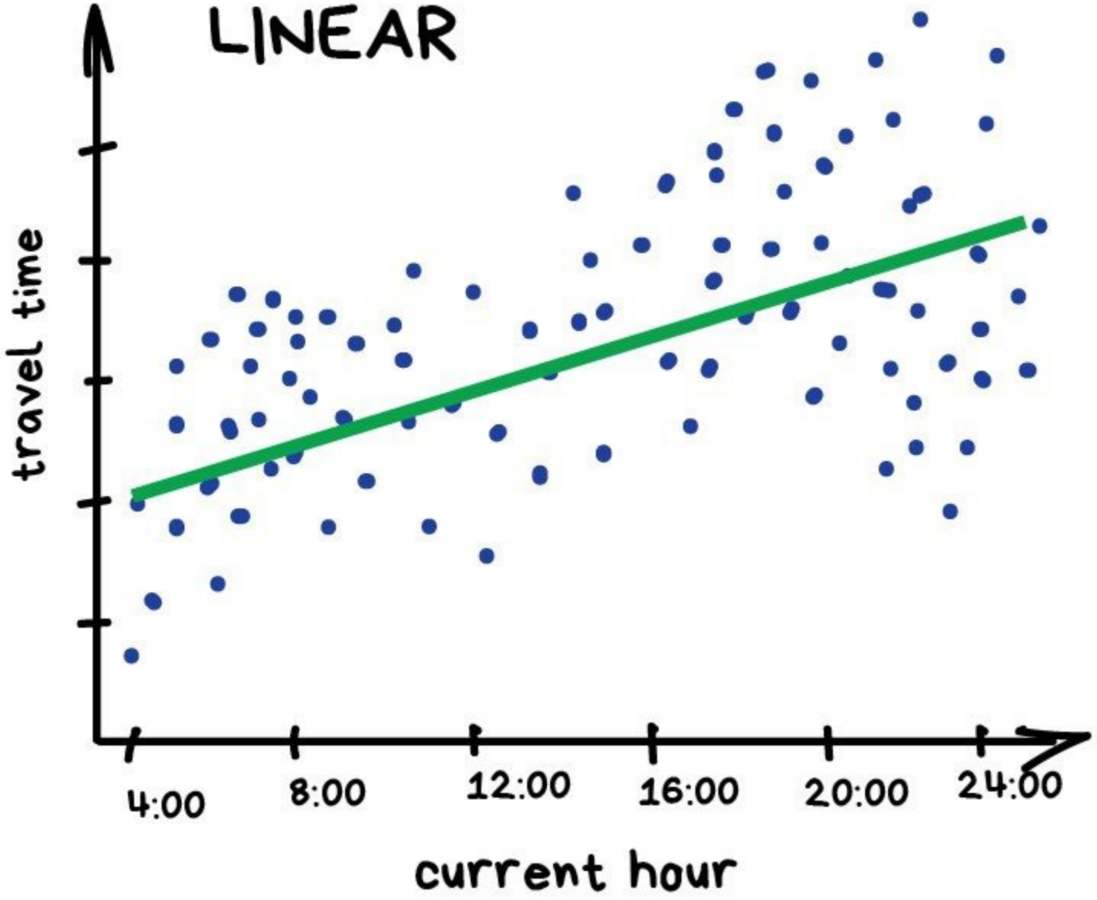
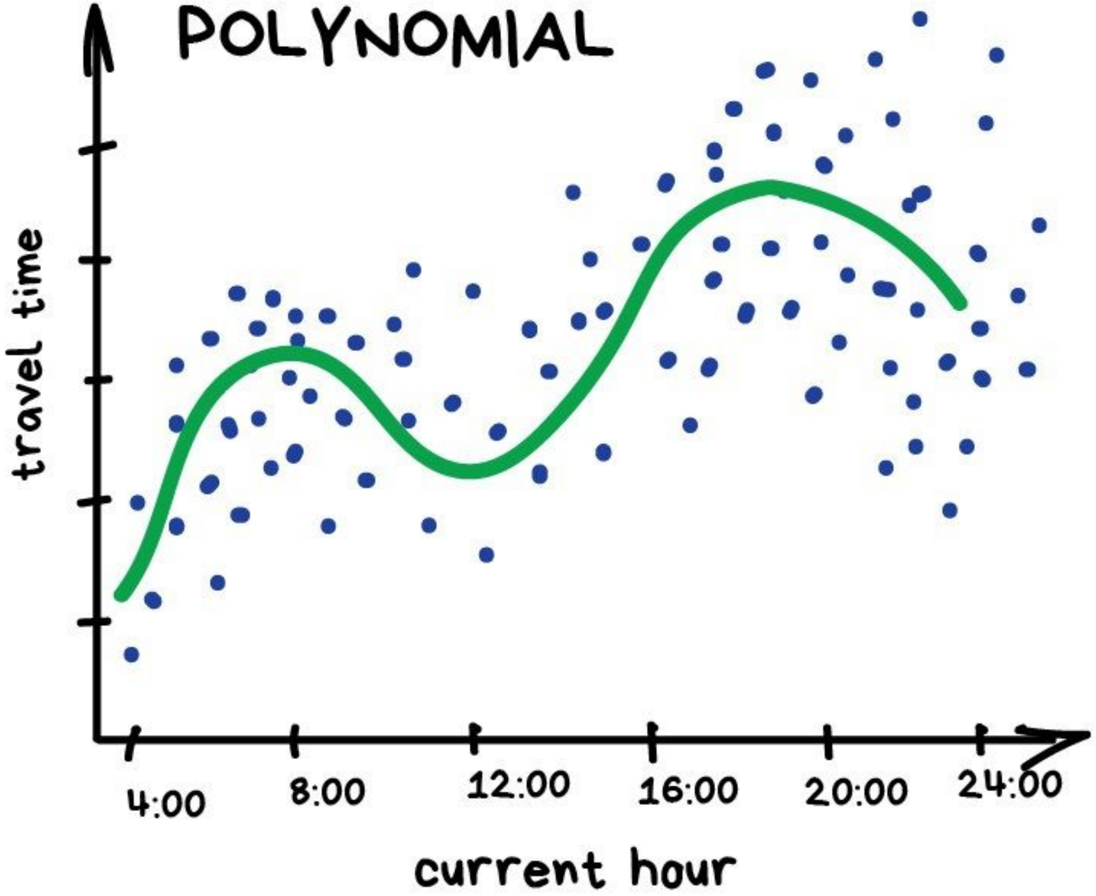
PREDICT TRAFFIC JAMS





REGRESSION

https://vas3k.com/blog/machine_learning/

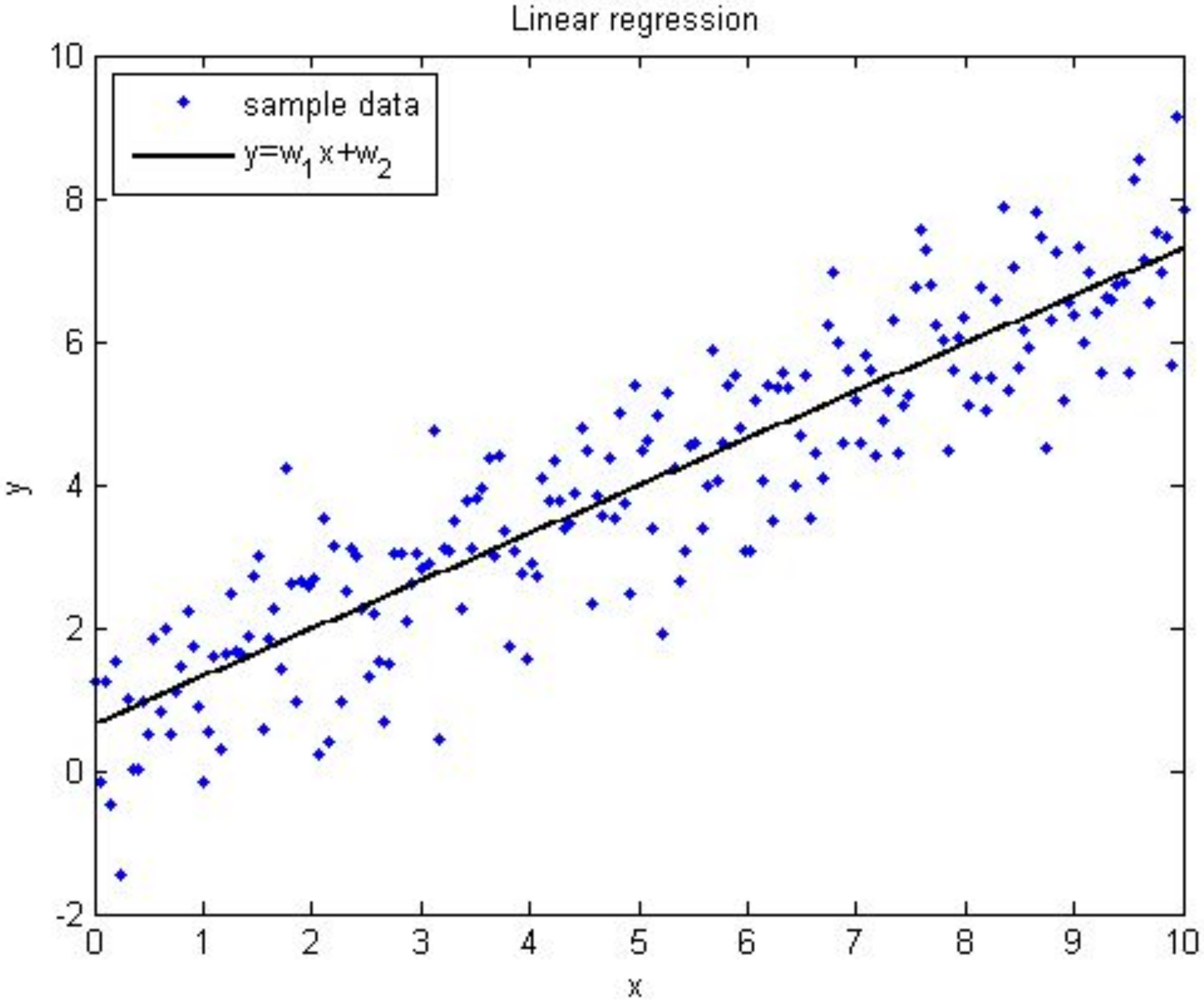
Simple linear regression

$x \in \mathbb{R}$ – input

$y \in \mathbb{R}$ – target

$w_0, w_1 \in \mathbb{R}$ – weights

$\hat{y} = w_0 + w_1 x$



Simple linear regression

given data

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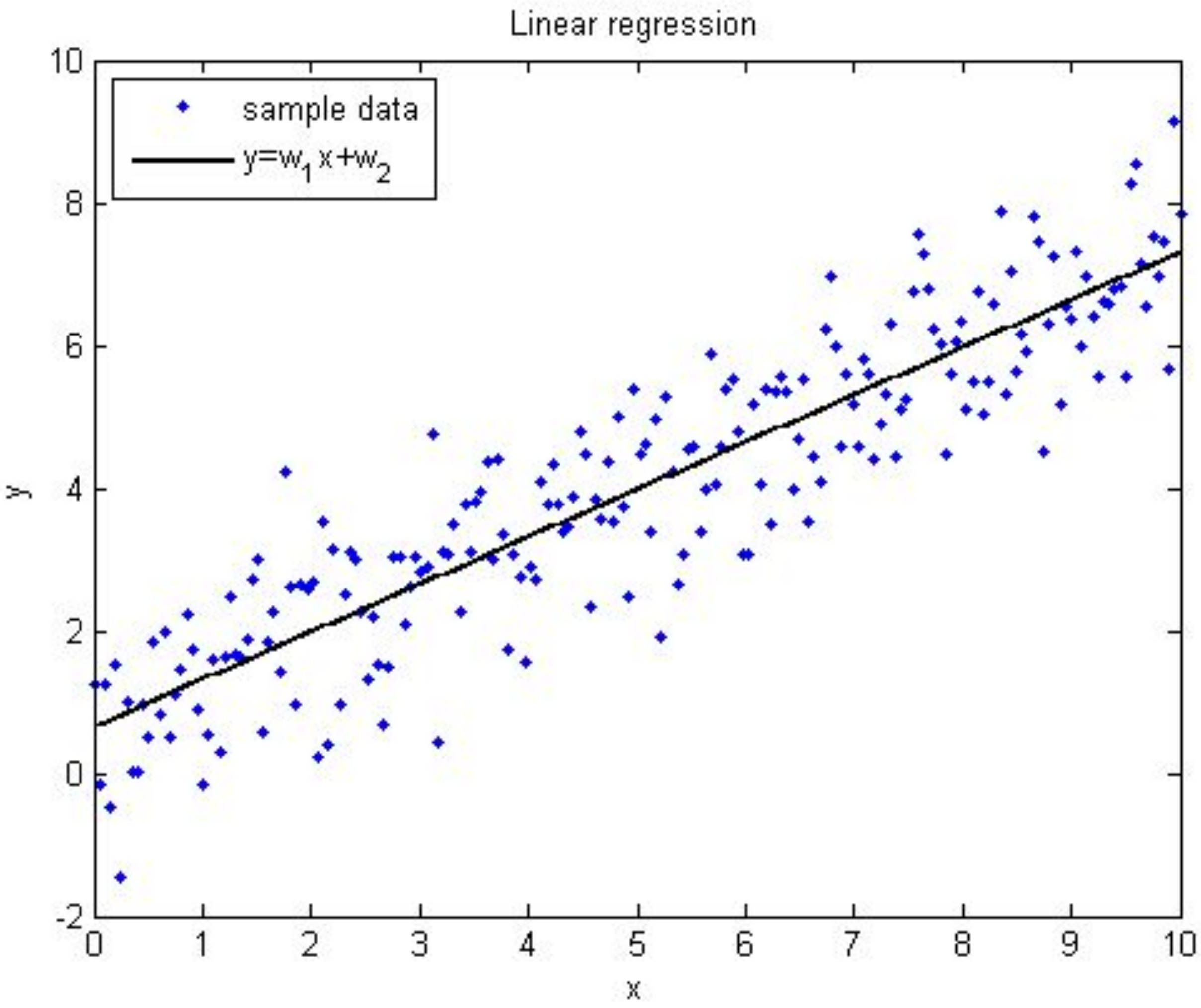

Simple linear regression

given data

$x \in \mathbb{R}$ – input

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trainable coefficient

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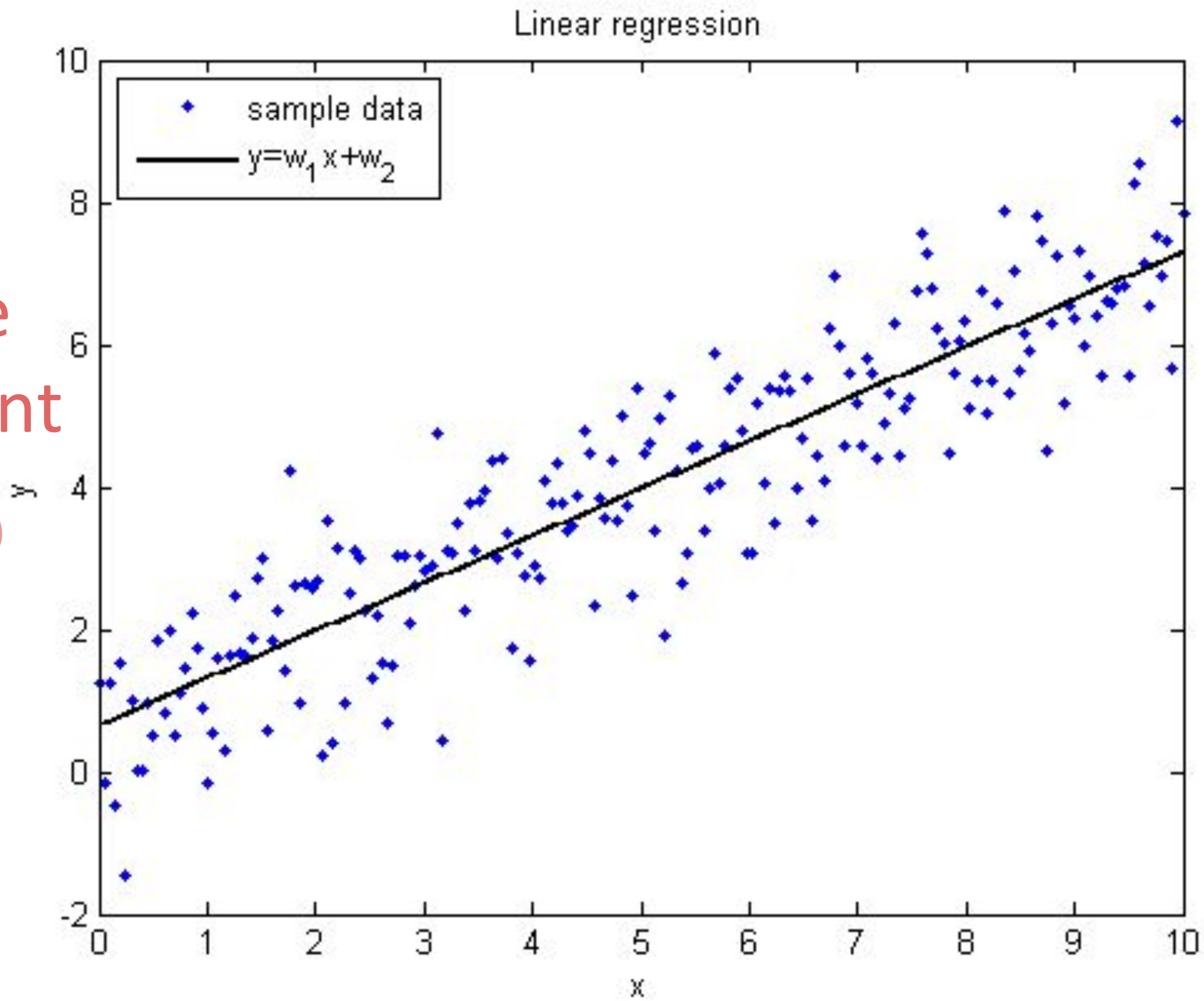


Multiple linear regression

housing.csv (1.36 MB) 10 of 10 columns

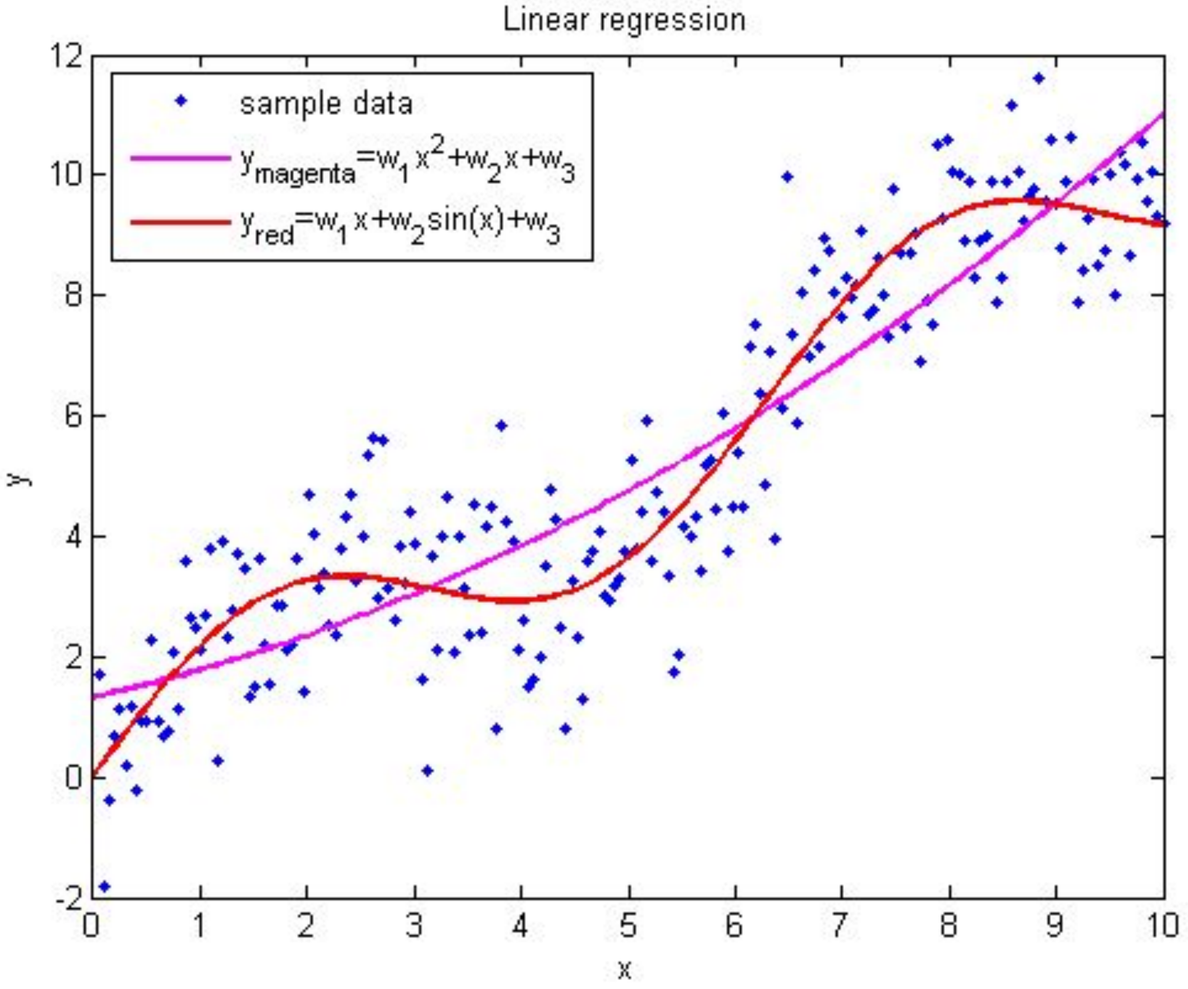
	# longitu...	# latitude	# housin...	# total_ro...	# total_b...	# populat...	# househ...	# median...	# median...	A ocean_...
1	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
2	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
3	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
4	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
5	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY
6	-122.25	37.85	52.0	919.0	213.0	413.0	193.0	4.0368	269700.0	NEAR BAY
7	-122.25	37.84	52.0	2535.0	489.0	1094.0	514.0	3.6591	299200.0	NEAR BAY
8	-122.25	37.84	52.0	3104.0	687.0	1157.0	647.0	3.12	241400.0	NEAR BAY
9	-122.26	37.84	42.0	2555.0	665.0	1206.0	595.0	2.0804	226700.0	NEAR BAY
10										AY

$$\hat{y} = w_0 + w_1 x_1 + \ldots + w_N x_N = \sum_{j=0}^{M} w_j x_j$$

Also linear regression

$$\hat{y} = \sum_{j=0}^{M} w_j g(x_j)$$

$$g(x) = x \Rightarrow \hat{y} = \sum_{j=0}^{M} w_j x_j$$



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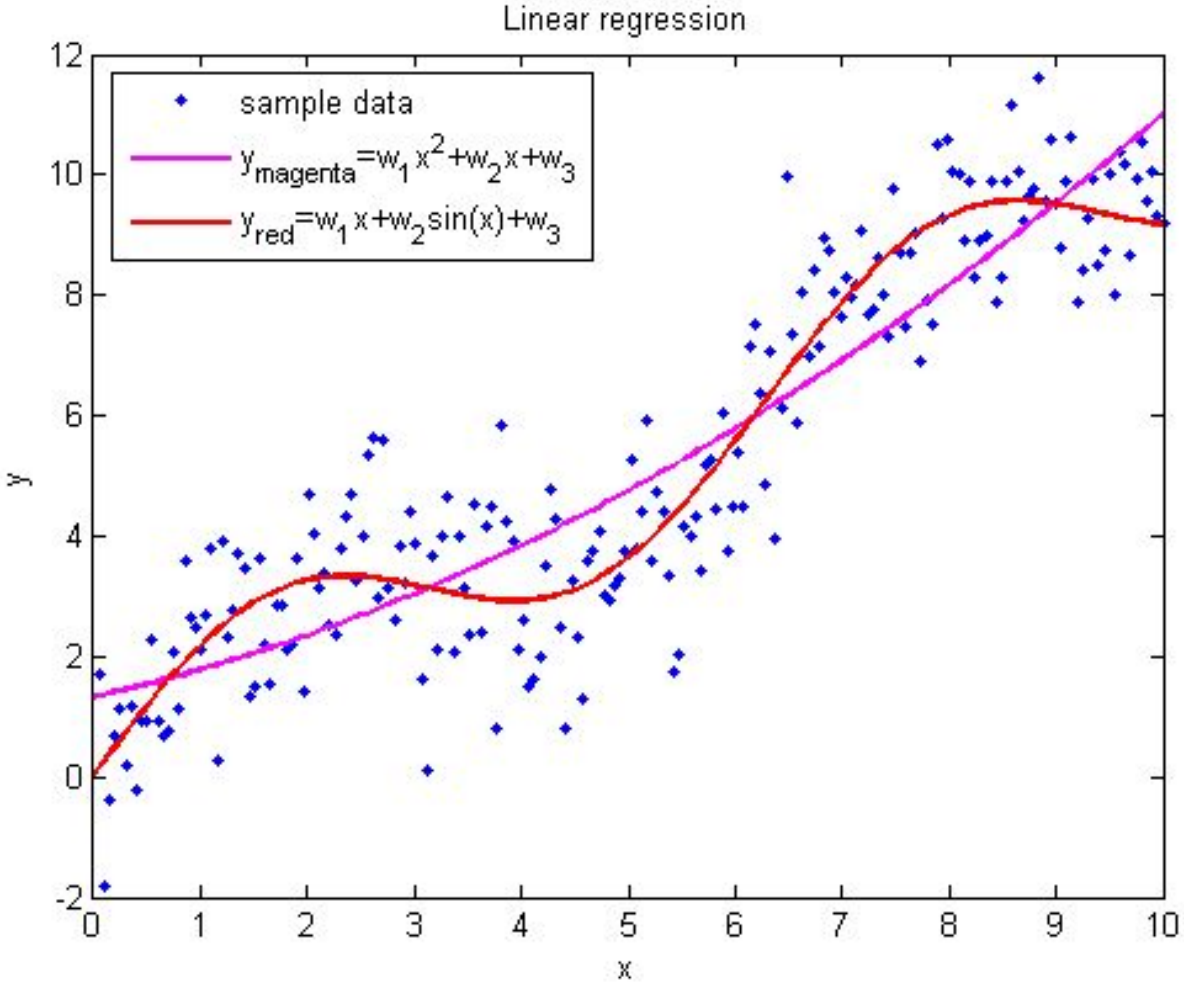
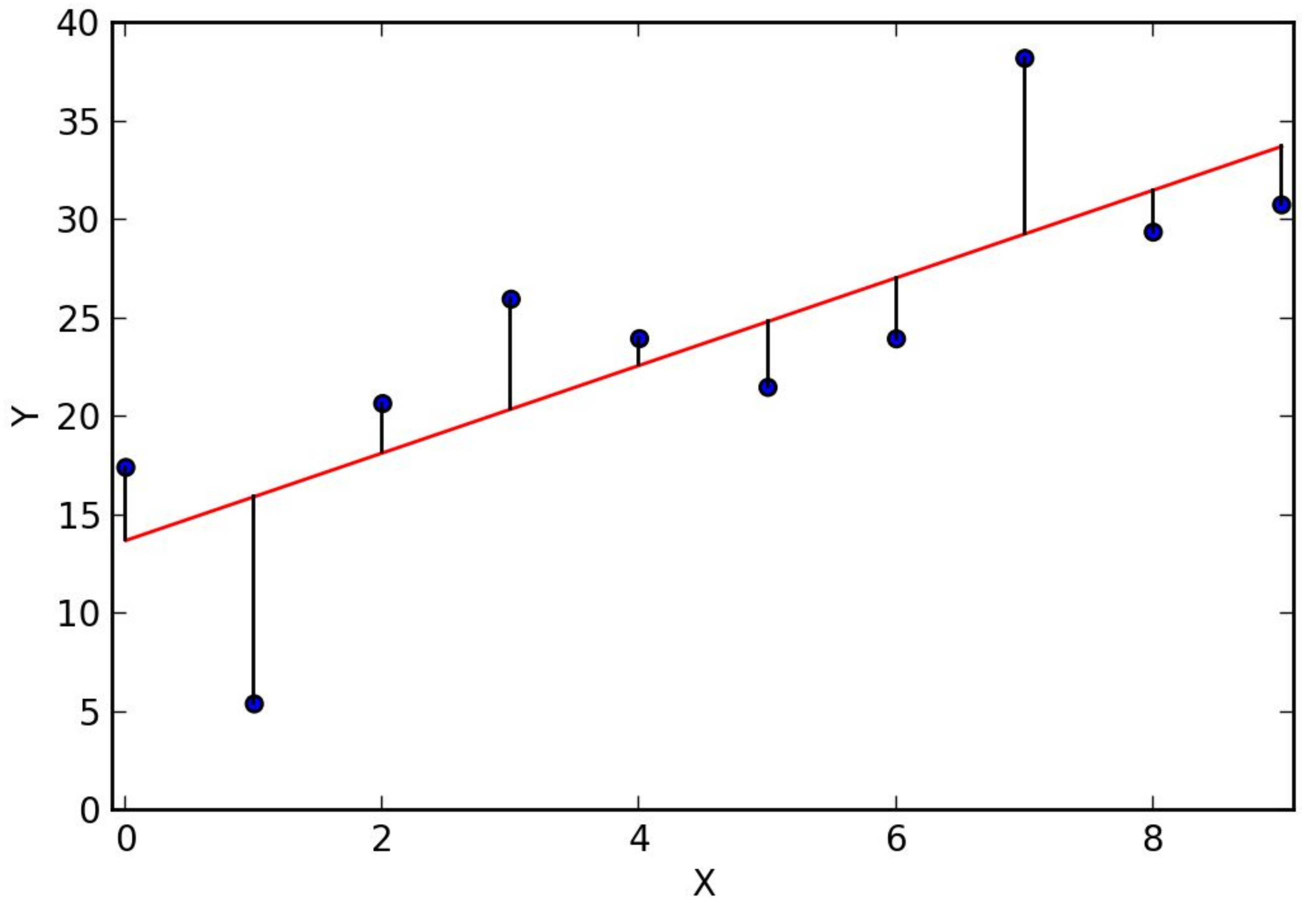


Evaluating prediction

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

y – target
$\hat{y}$ – prediction



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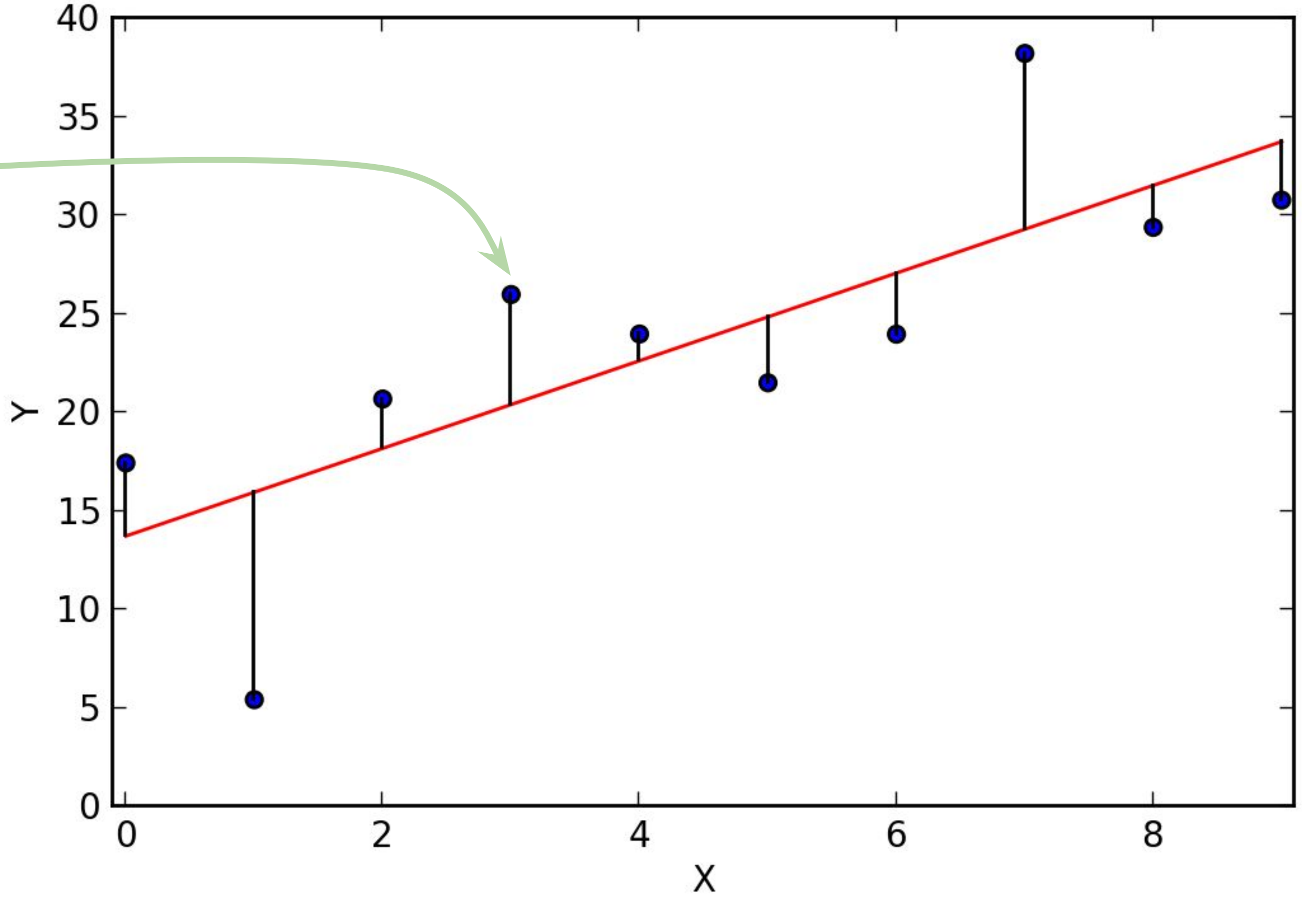

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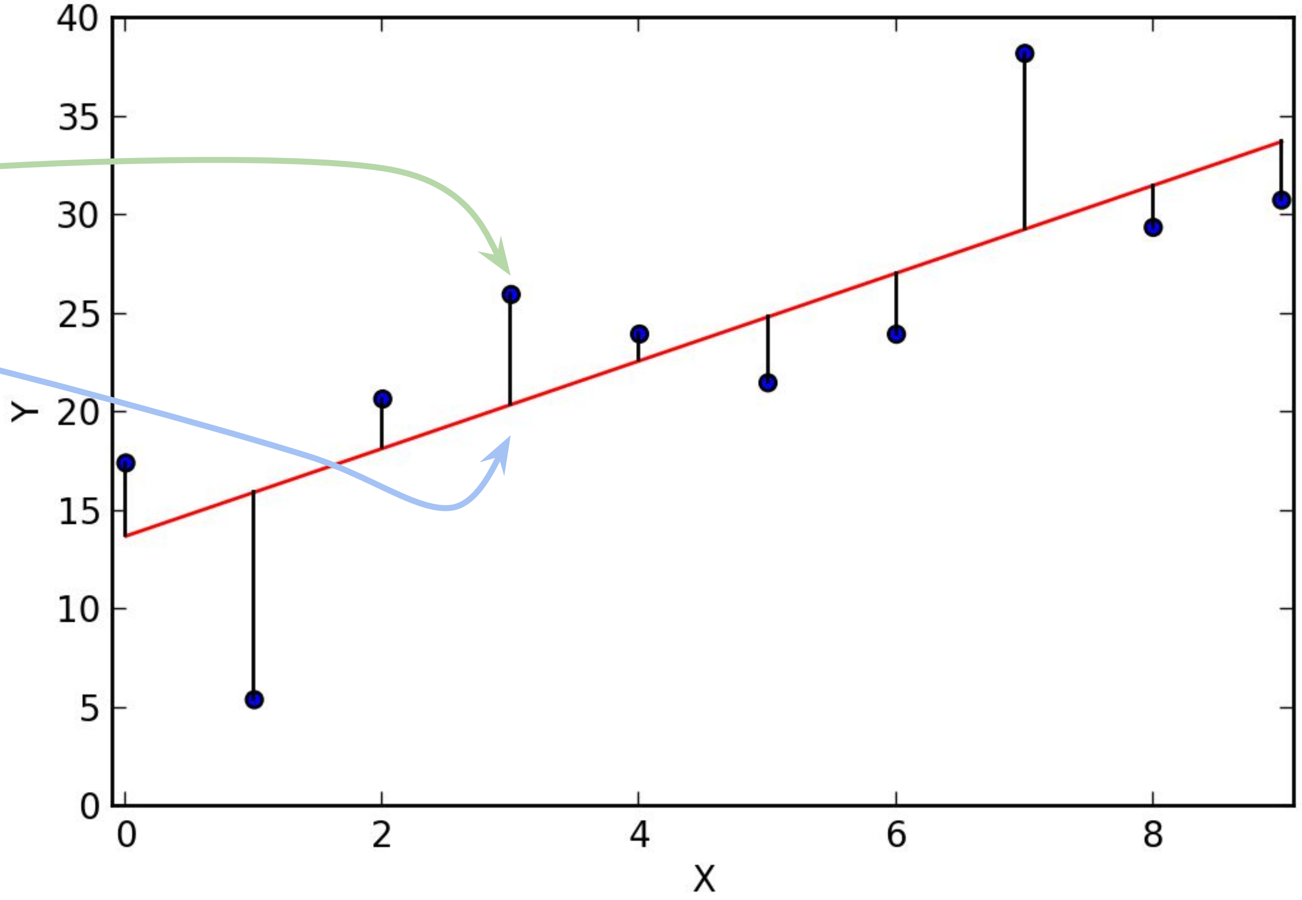

Training parameters

$$\hat{y} = w_0 + w_1 x$$

$$L(y, \hat{y}) = (y - \hat{y})^2$$
$$= (y - w_1 x - w_0)^2$$

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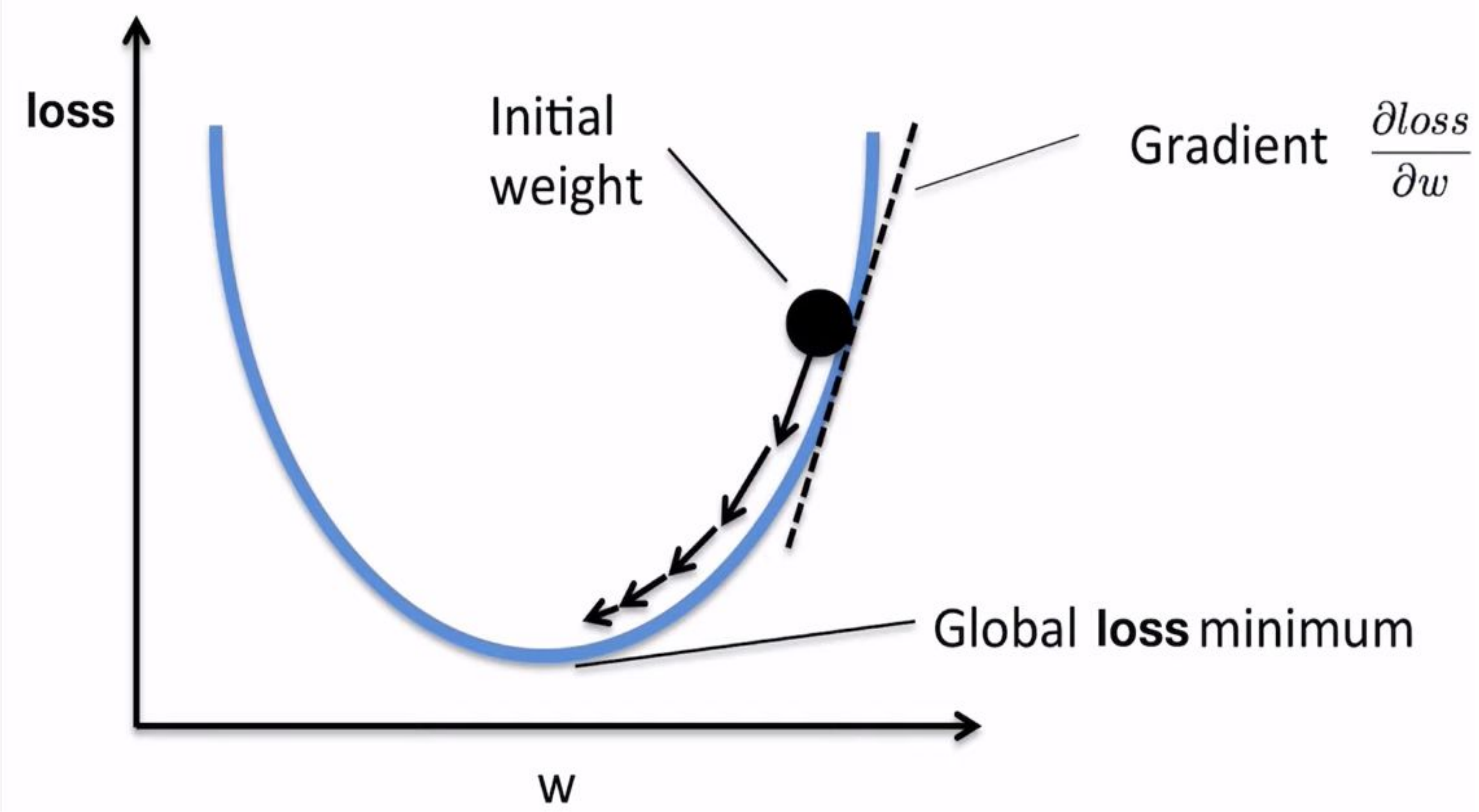

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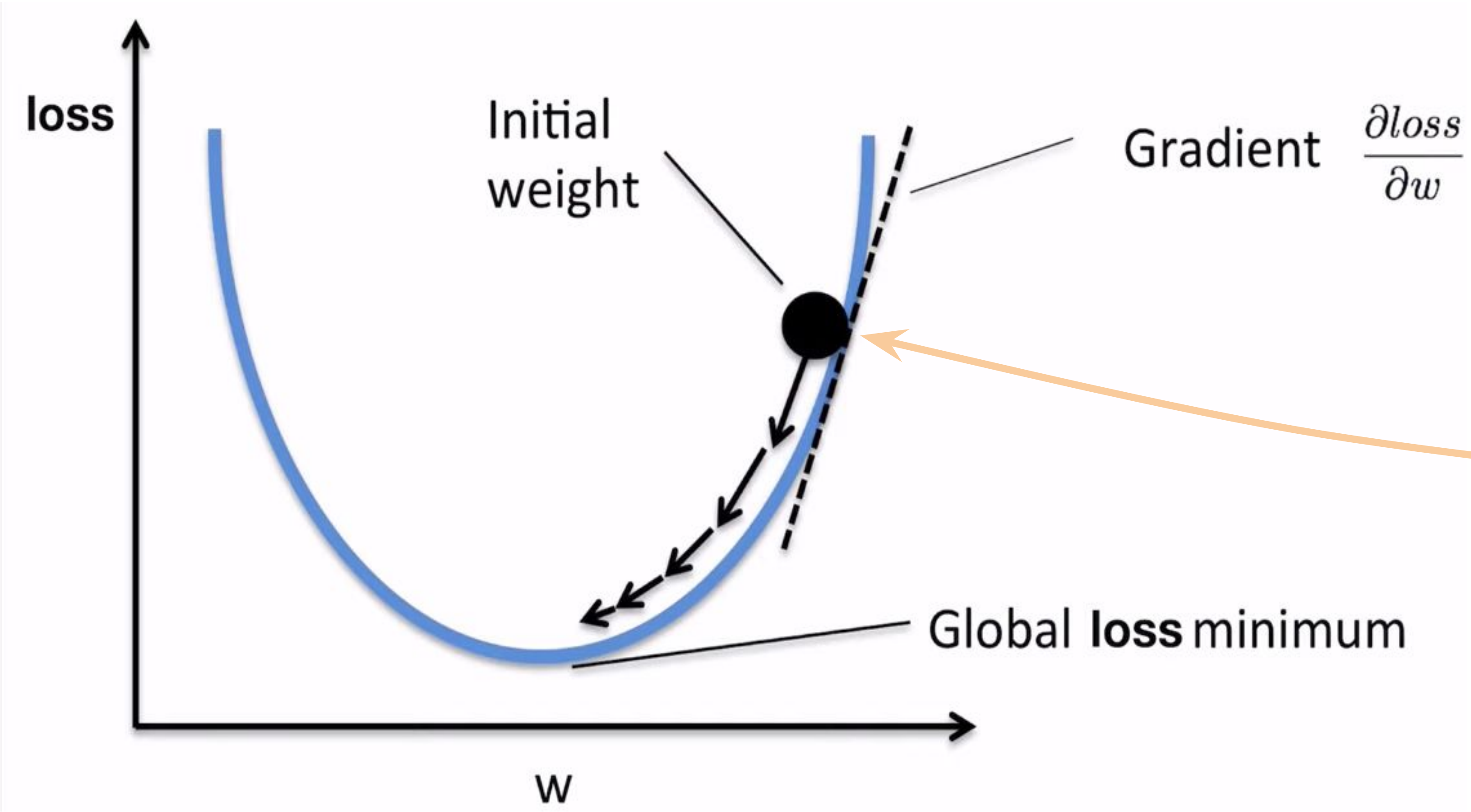

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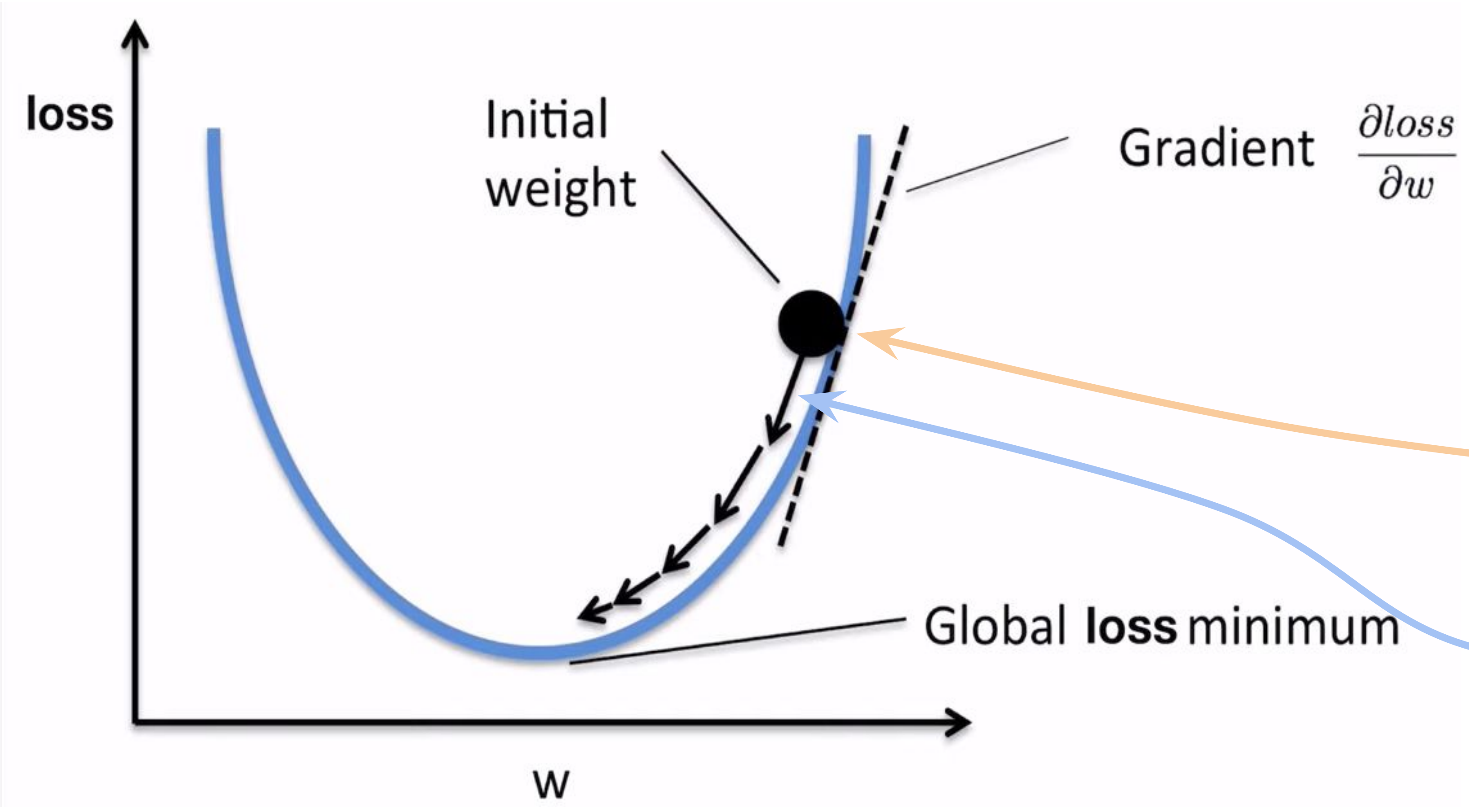

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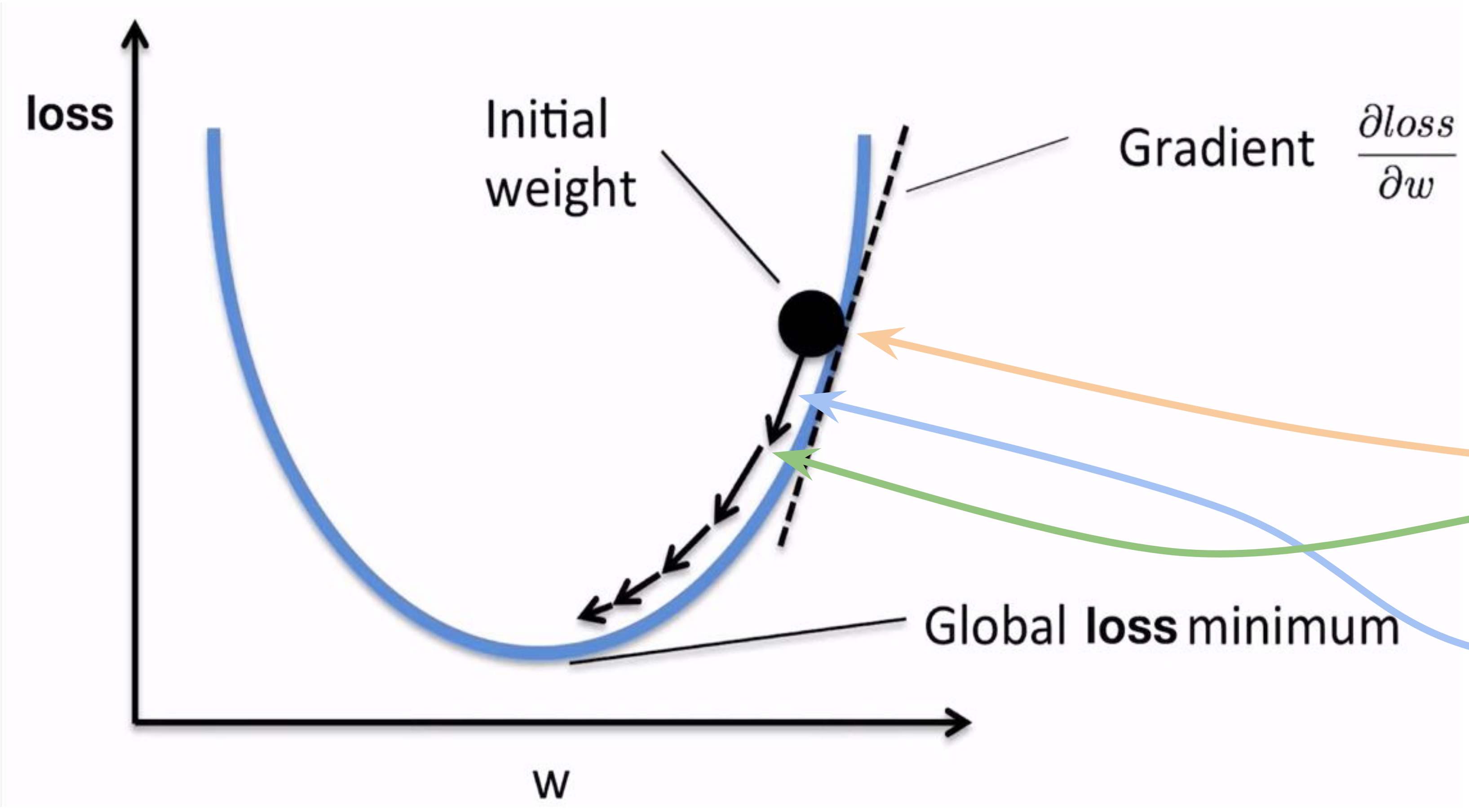

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Linear regression overview

special case: $\hat{y} = w_1 x + w_0$

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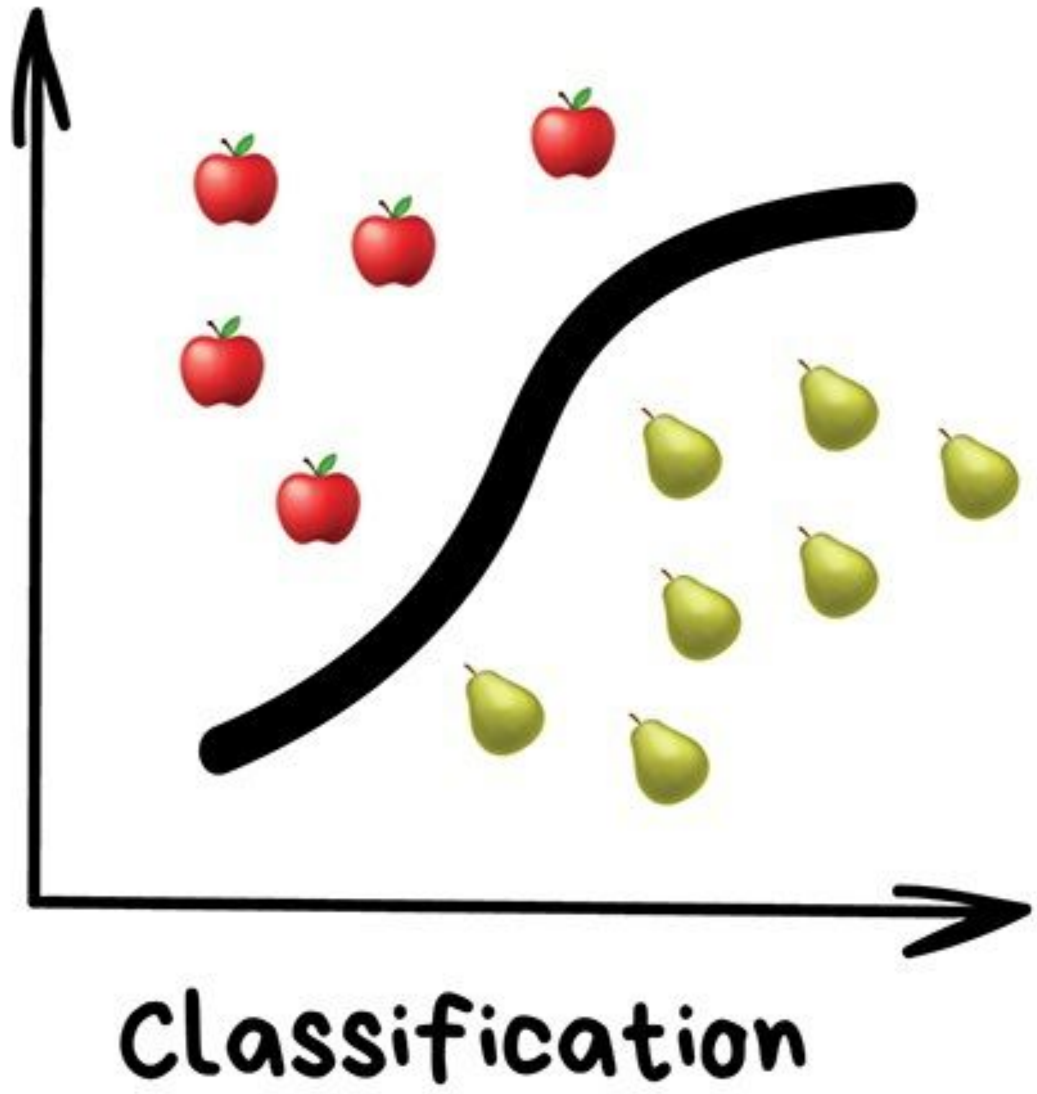

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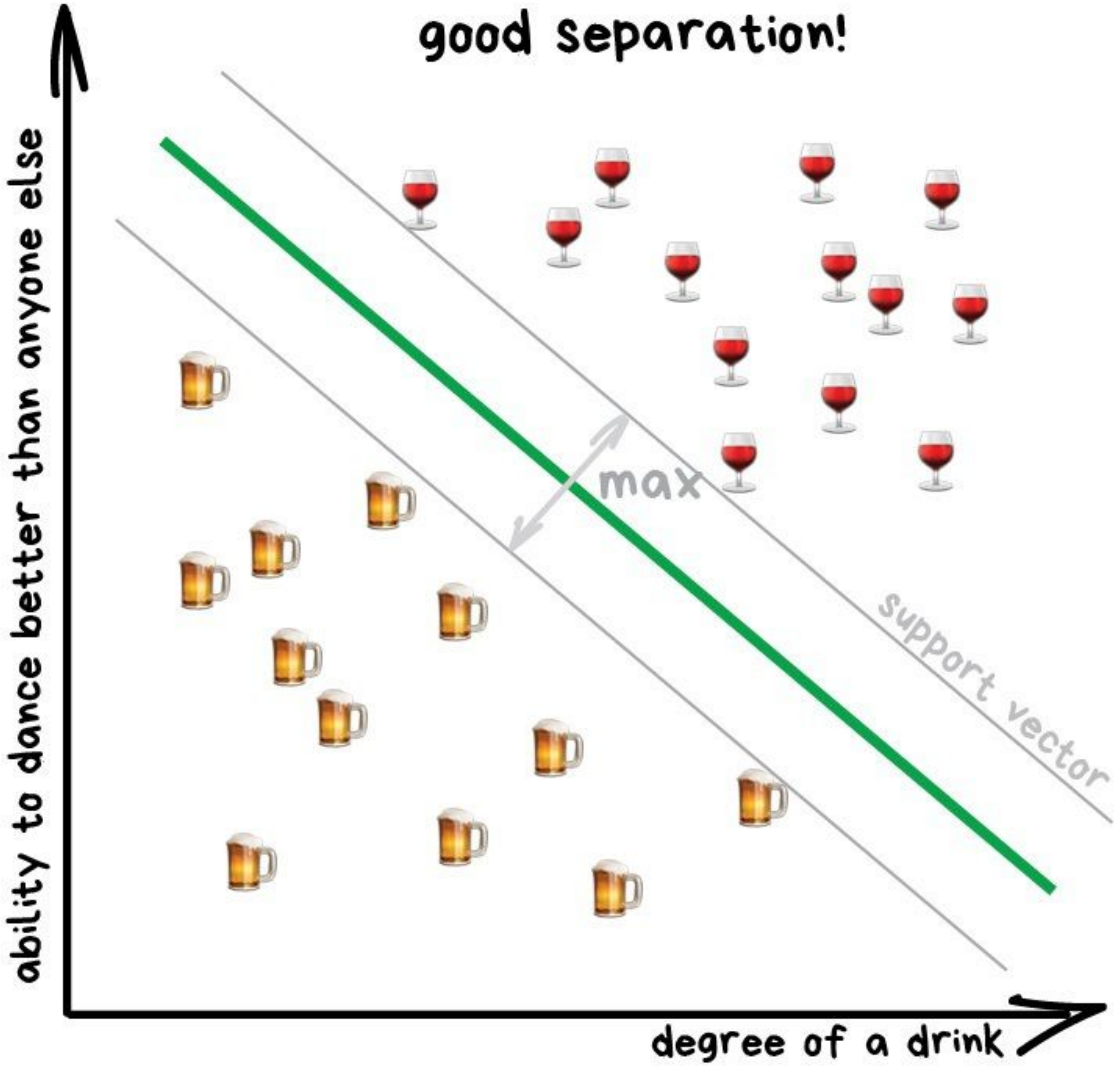
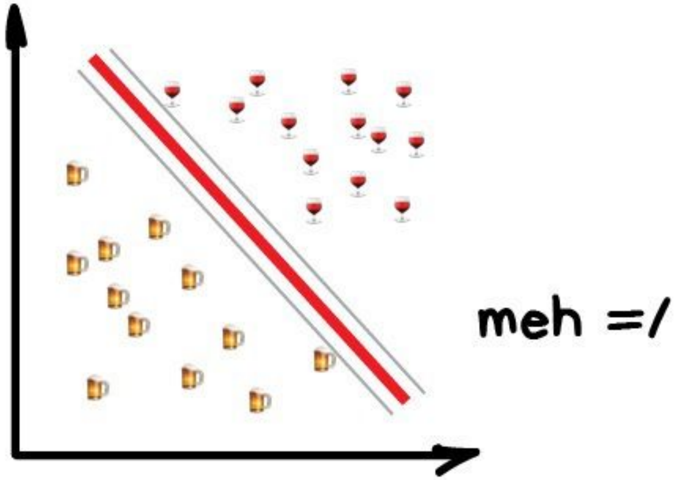
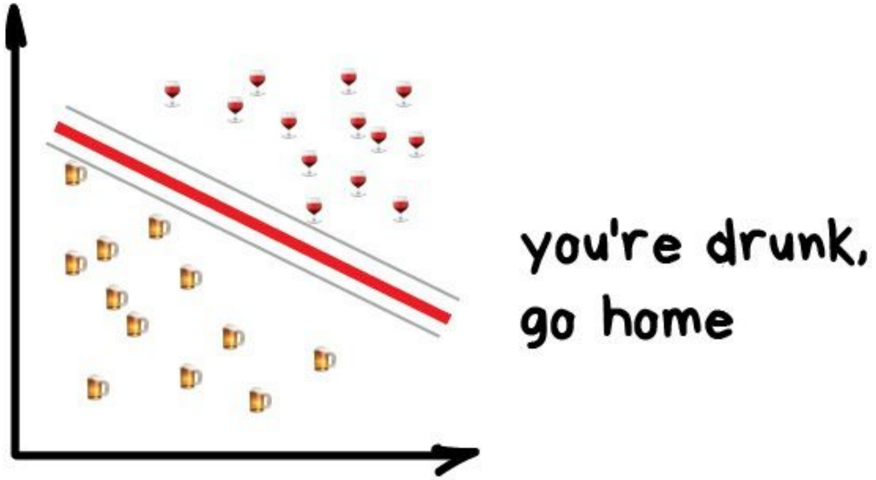
SEPARATE TYPES OF ALCOHOL







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Logistic regression

$x_1, x_2 \in \mathbb{R}$ – inputs
$y \in \{0, 1\}$ – target

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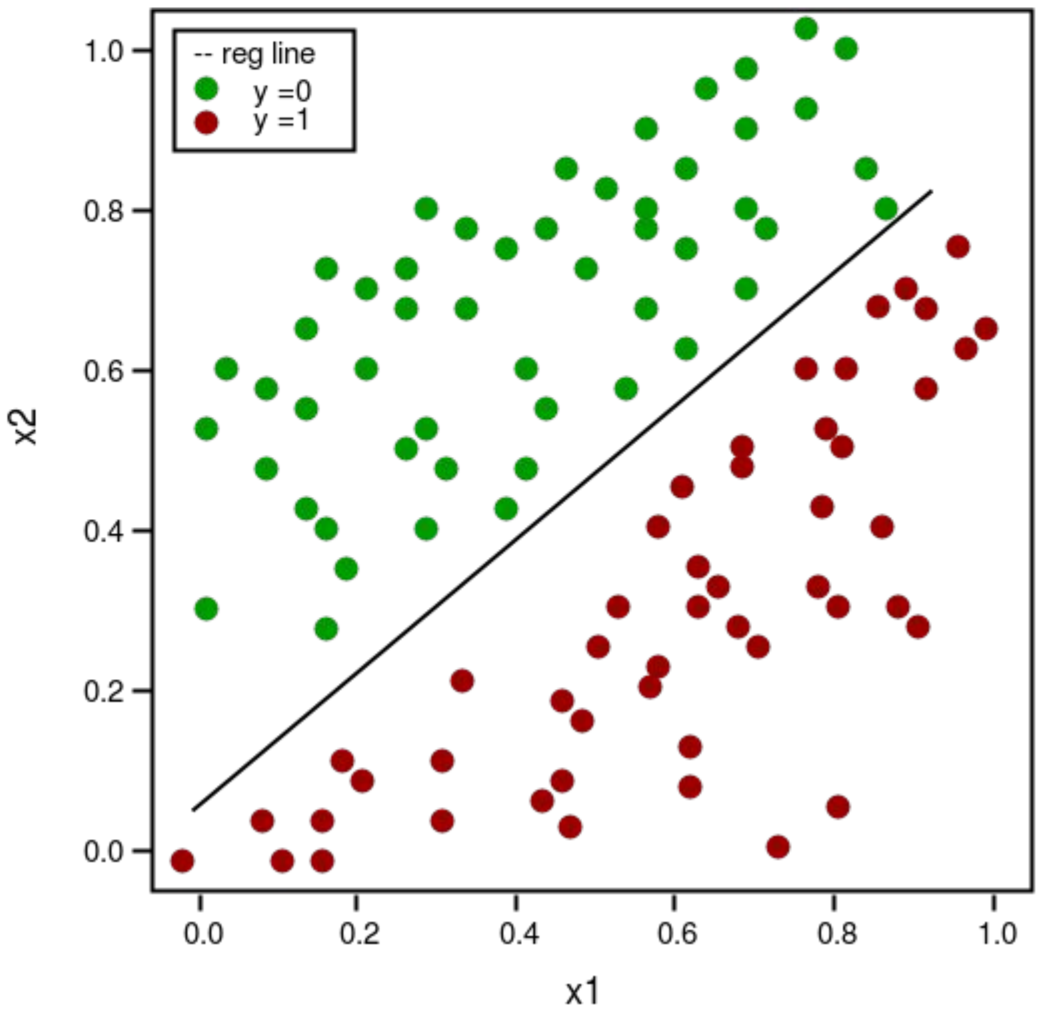

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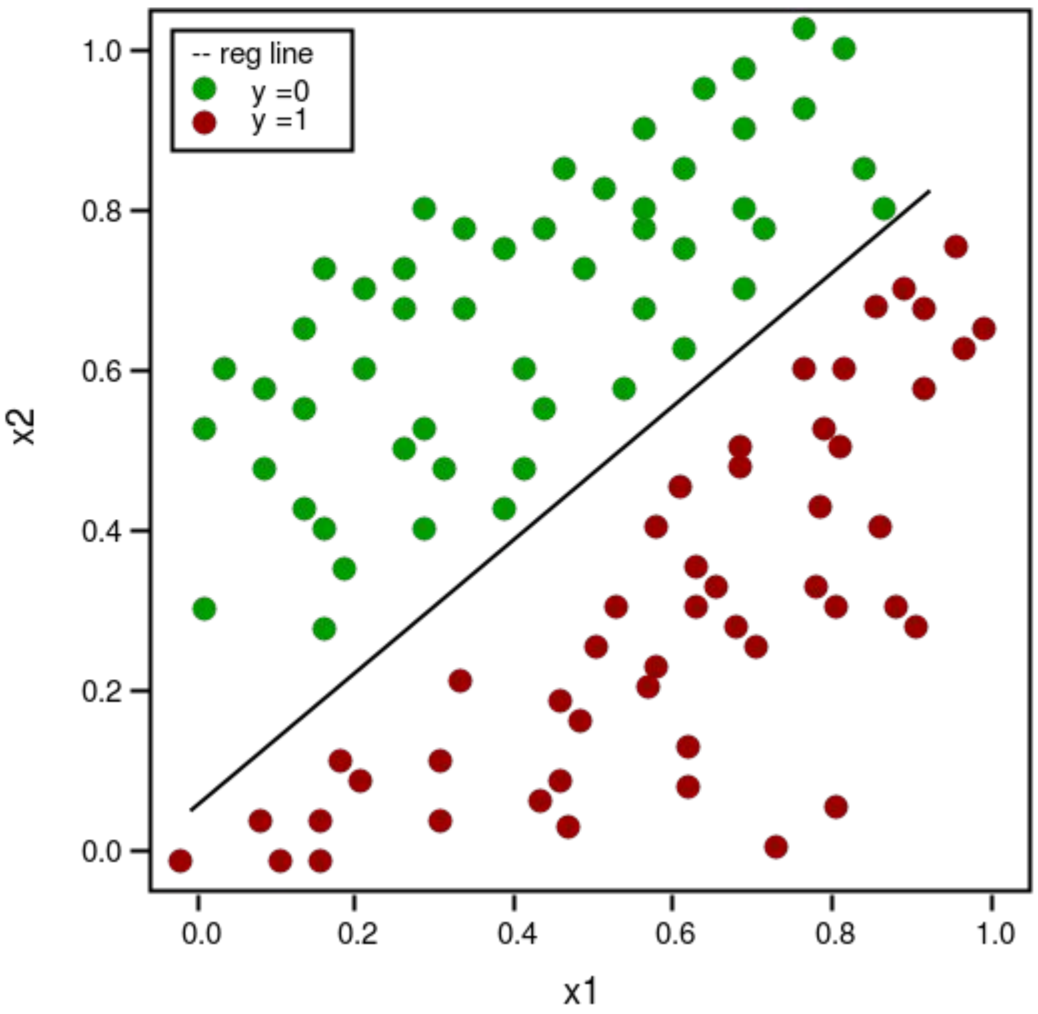
$w_0, w_1, w_2 \in \mathbb{R}$ – weights

$$\hat{y} = w_0 + w_1 x_1 + w_2 x_2$$



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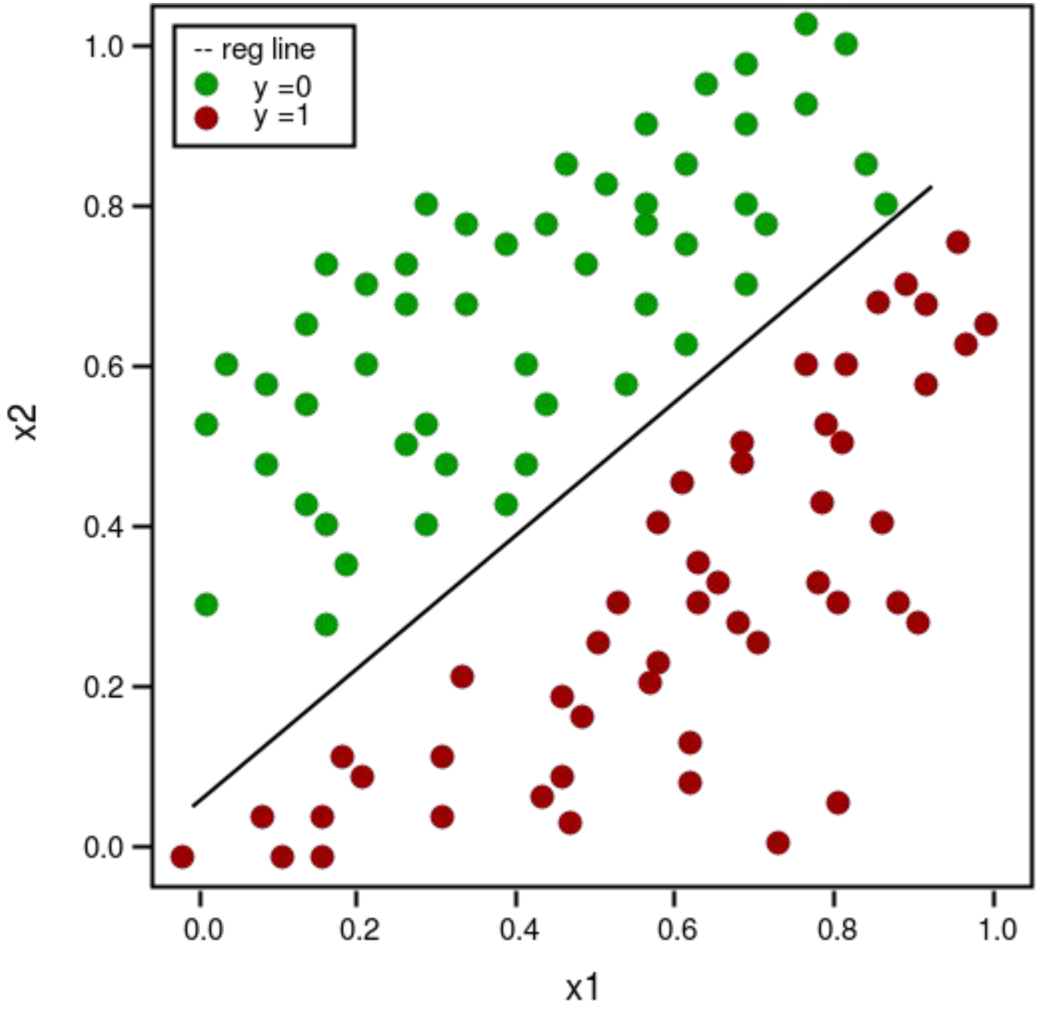

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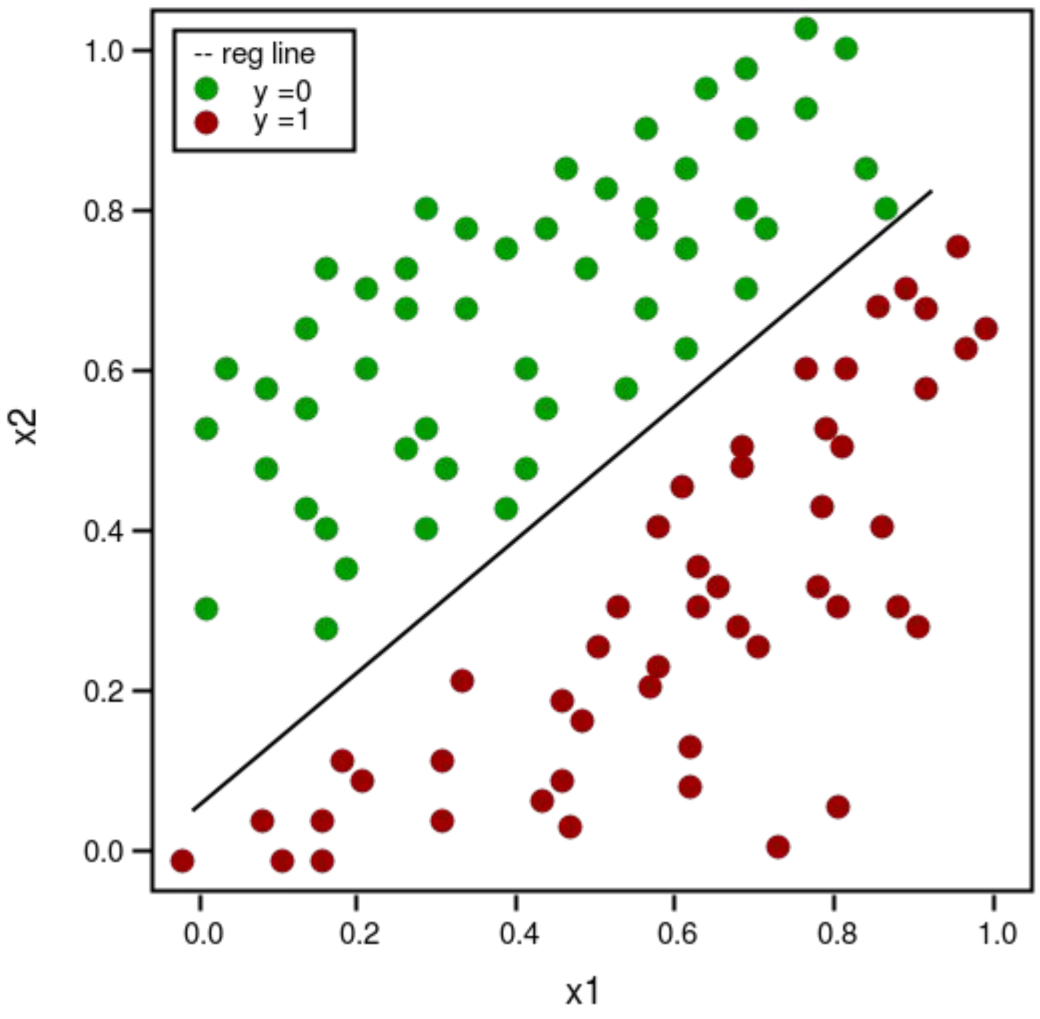
$\hat{y} = f(w_0 + w_1 x_1 + w_2 x_2)$



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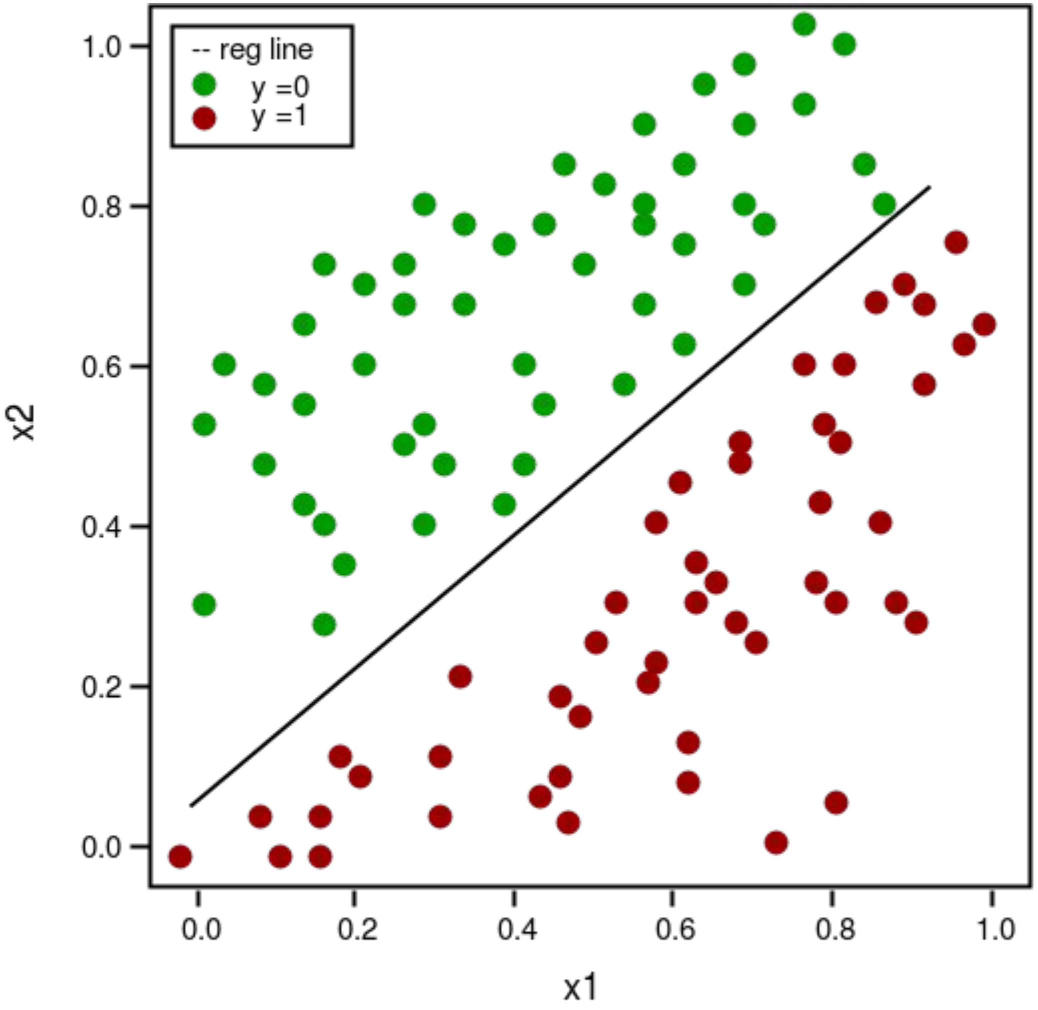
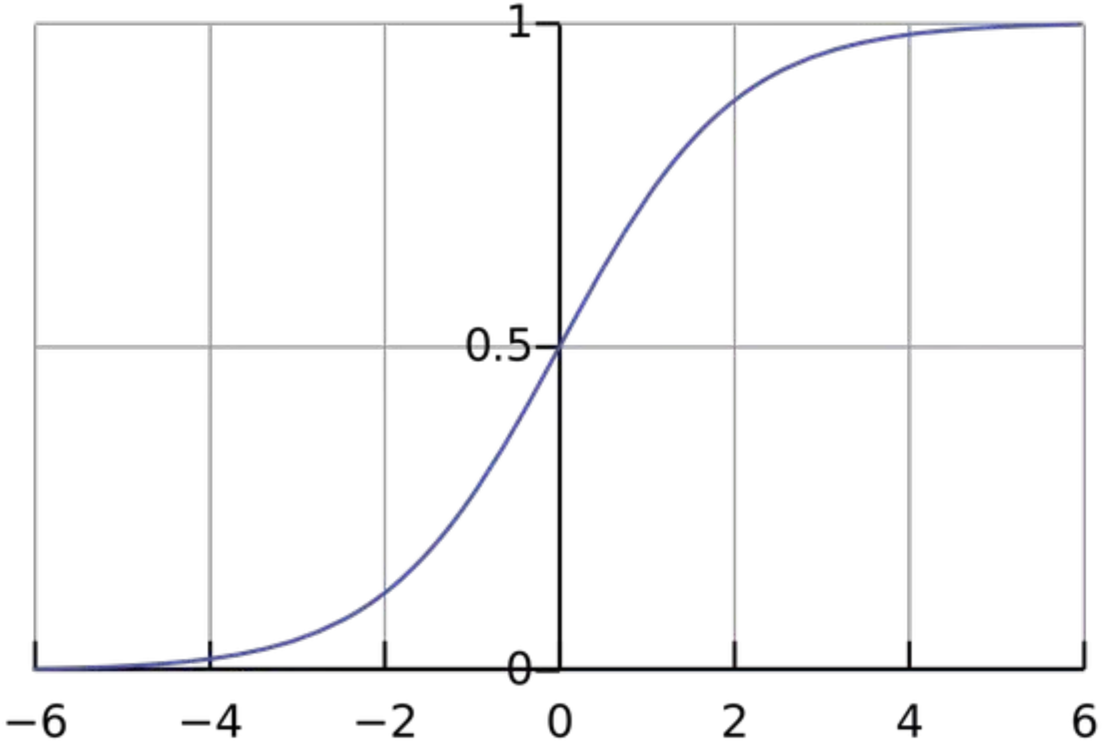
$$f(\cdot) : \mathbb{R} \longmapsto (0, 1)$$



Softmax function

$$\sigma(\cdot) : \mathbb{R} \longmapsto (0, 1)$$

$$\sigma(z) = \frac{1}{1 + exp(-z)}$$



Loss function: cross-entropy

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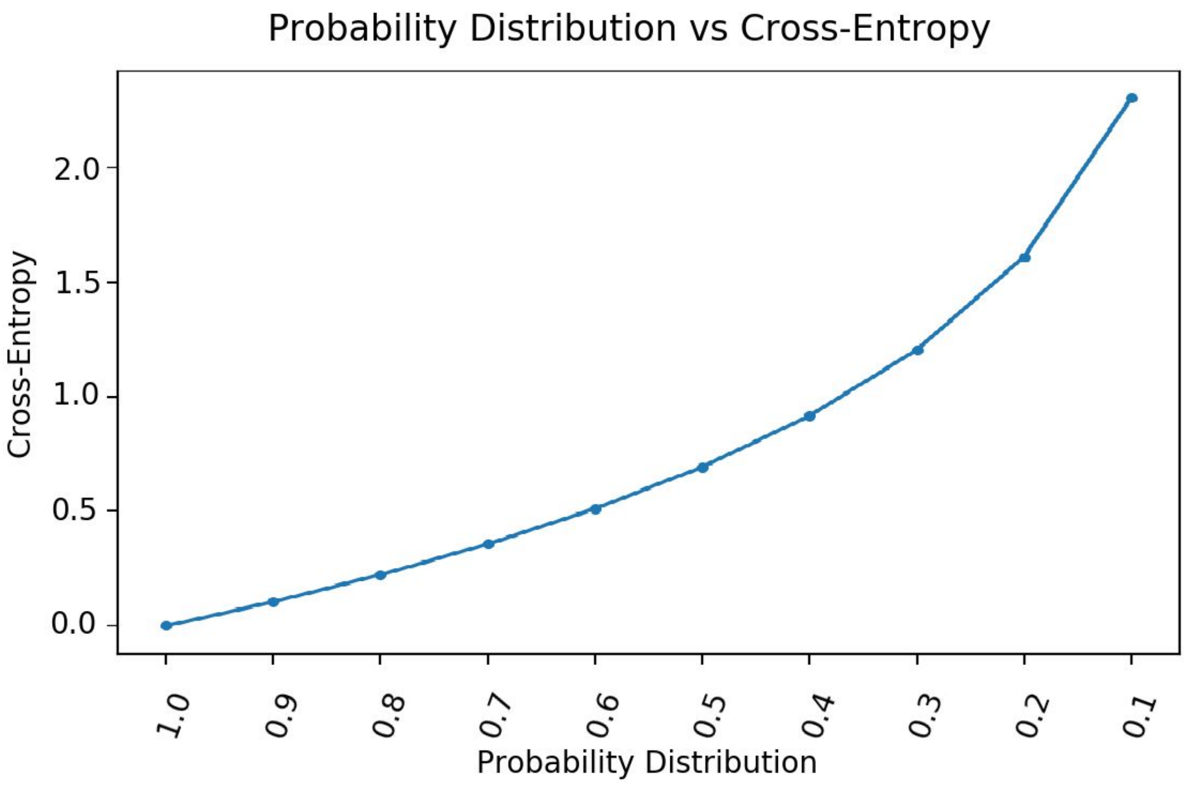

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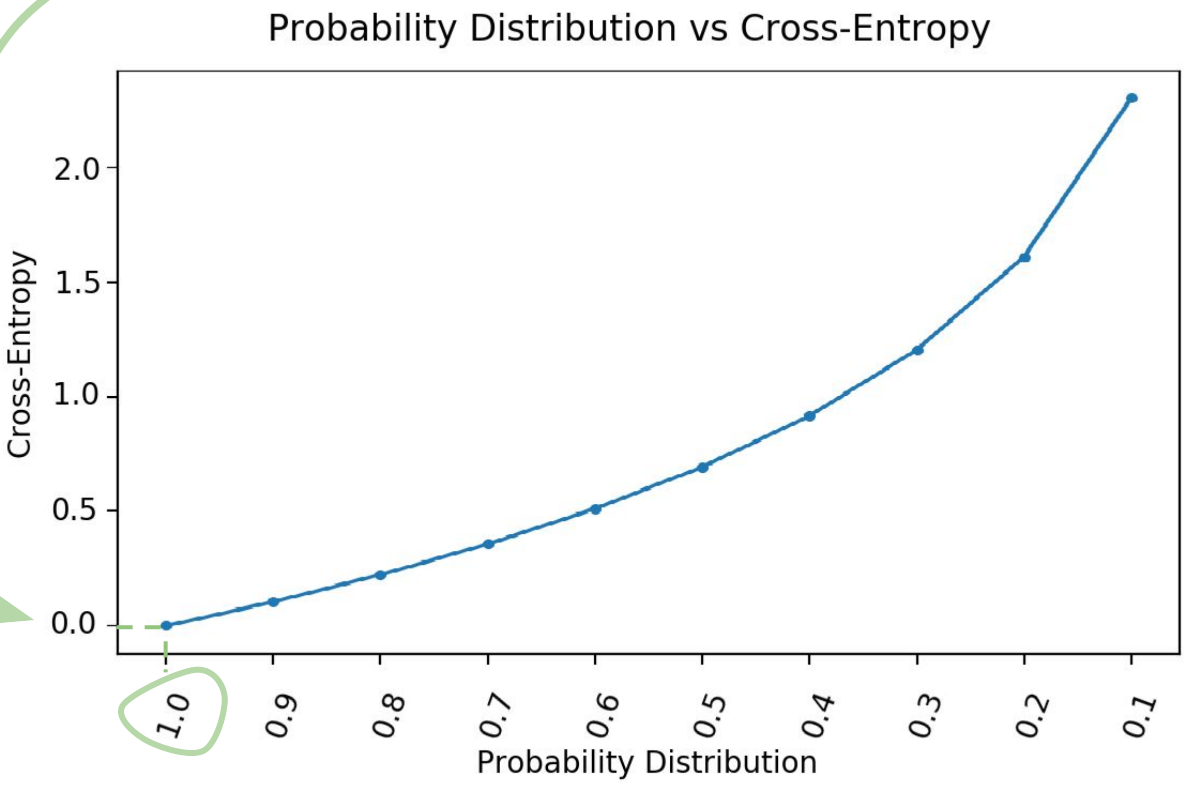

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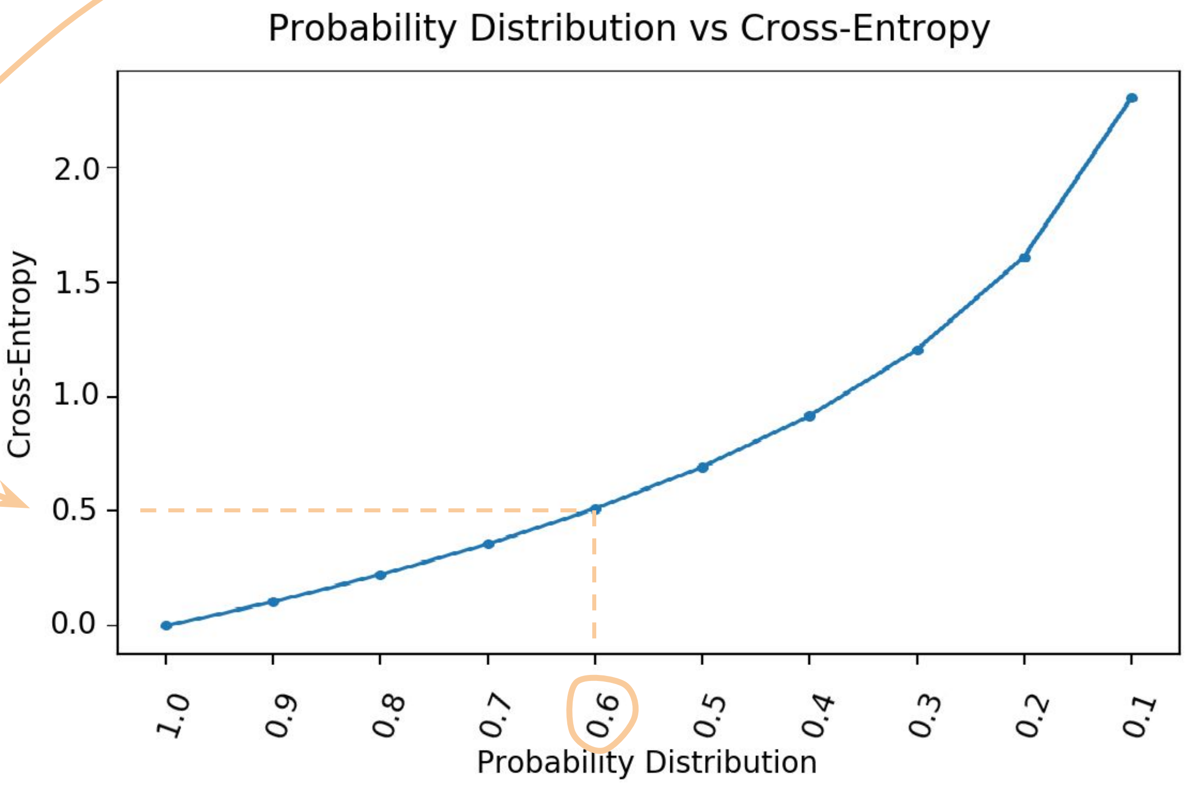

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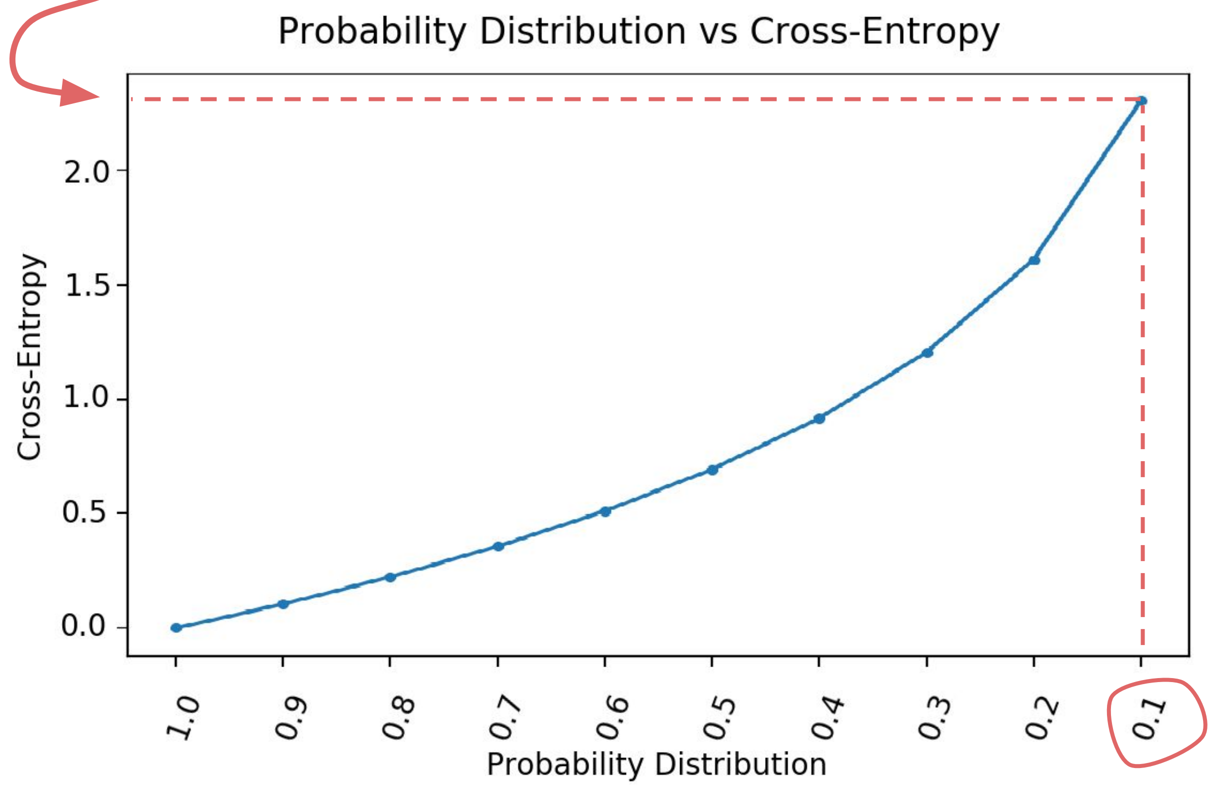
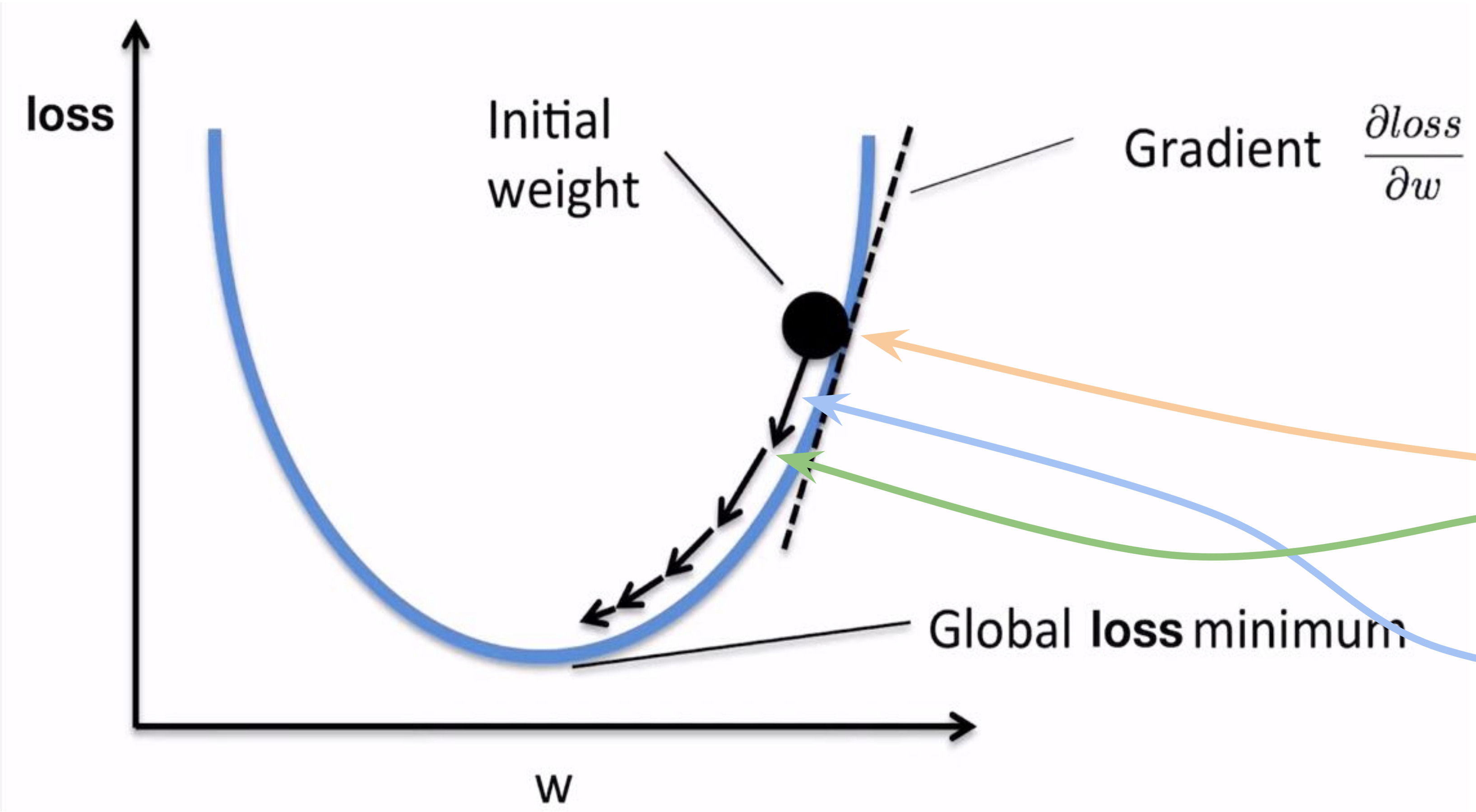


Training process: gradient descent



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model equation: $$\hat{y} = \sigma\Big(\sum_{j=0}^{M} w_j g(x_j)\Big)$$

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https://xkcd.com/1838/