Perceptron and Multilayer Perceptron

Pavlos Protopapas

Outline

1. Introduction to Artificial Neural Networks
2. Review of basic concepts
3. Single Neuron Network (‘Perceptron’)
4. Multi-Layer Perceptron (MLP)

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1. **Introduction to Artificial Neural Networks**
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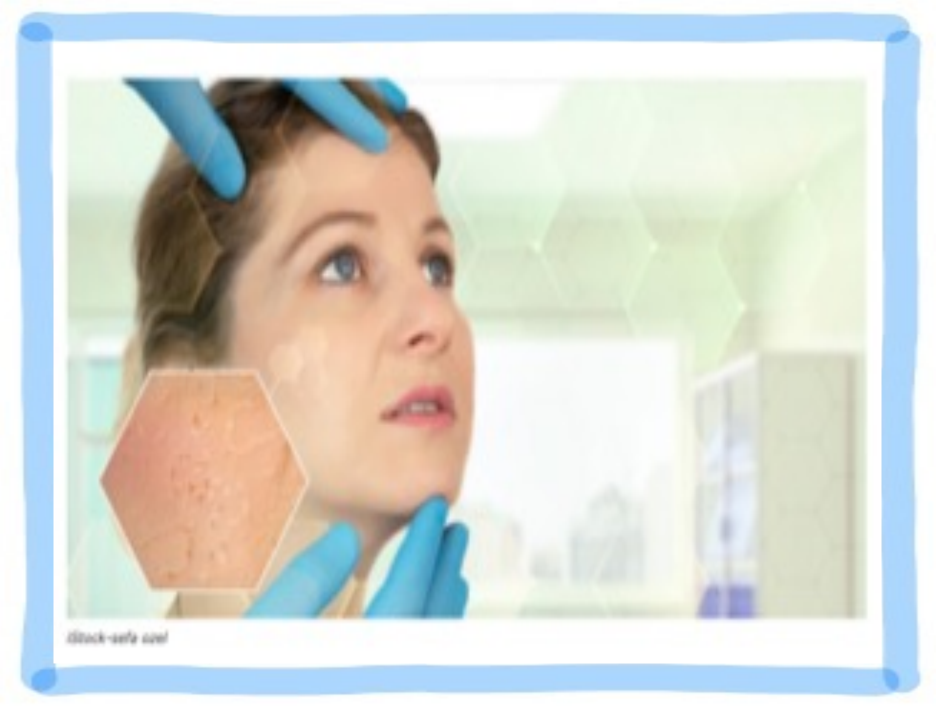
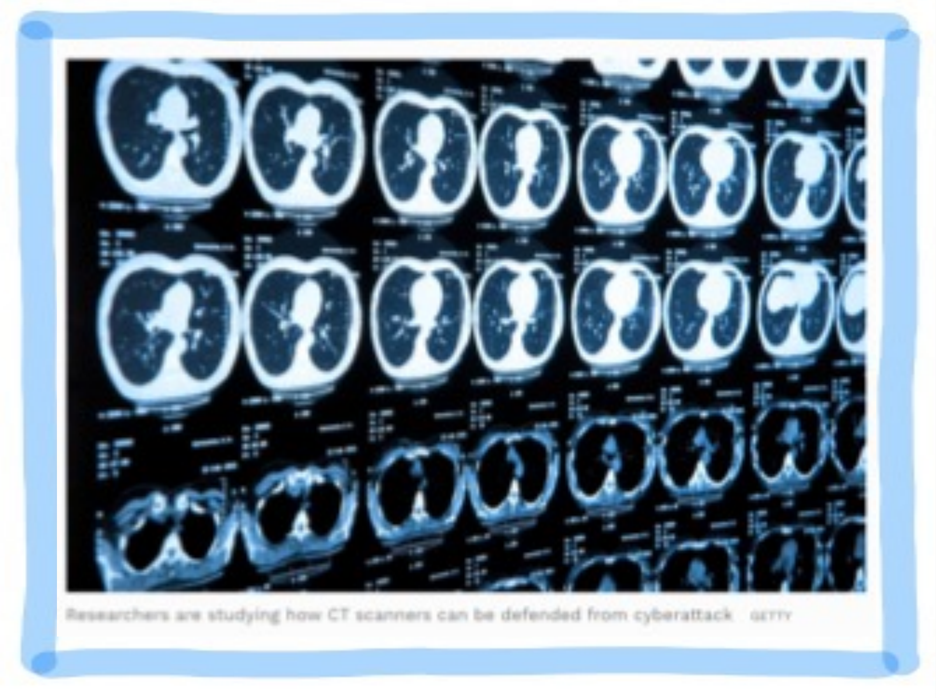
Today’s news

Skin Conditions



Using Deep Learning in diagnosing skin conditions

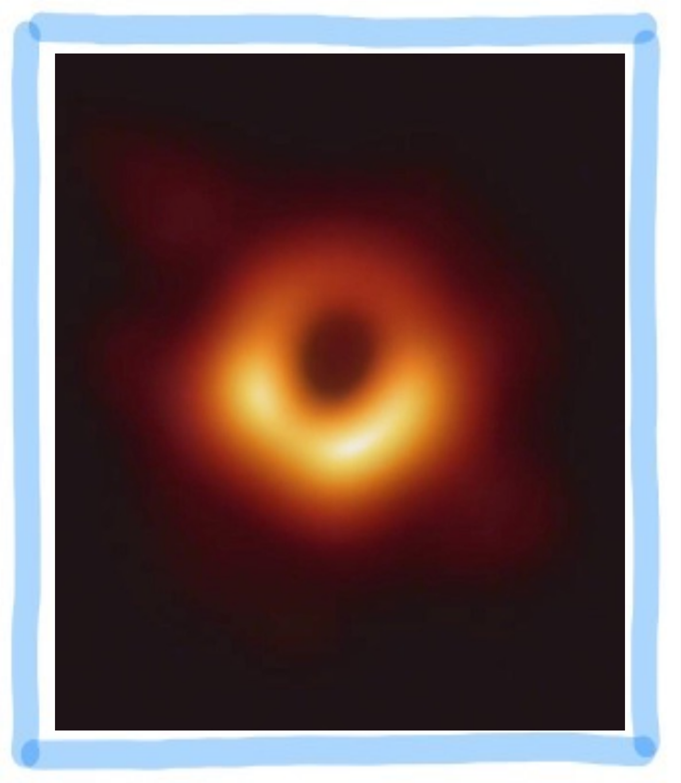
Stopping Cyberattacks



Detecting tampering with the diagnostic images, or quietly upped the radiation levels.

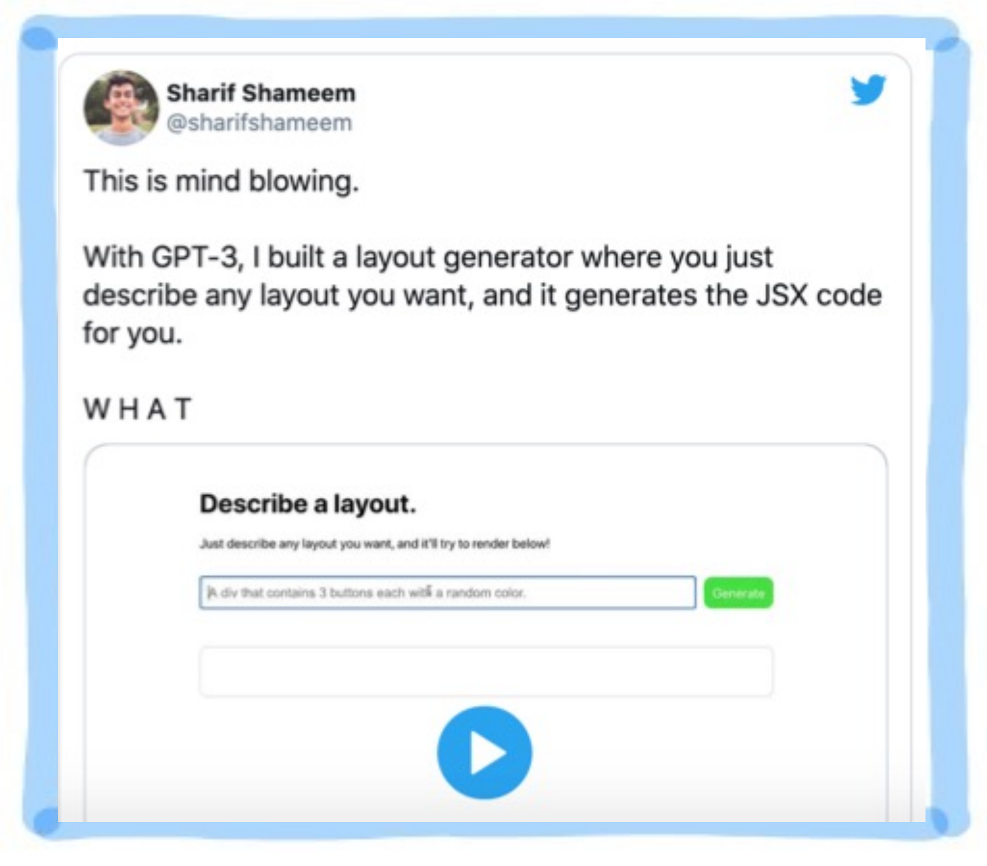
Today's news

Image generation



Katie Bouman's CHIRP produces the first-ever image of a black hole.

Computer Code Generation



The Potential of Data Science

Gender Bias

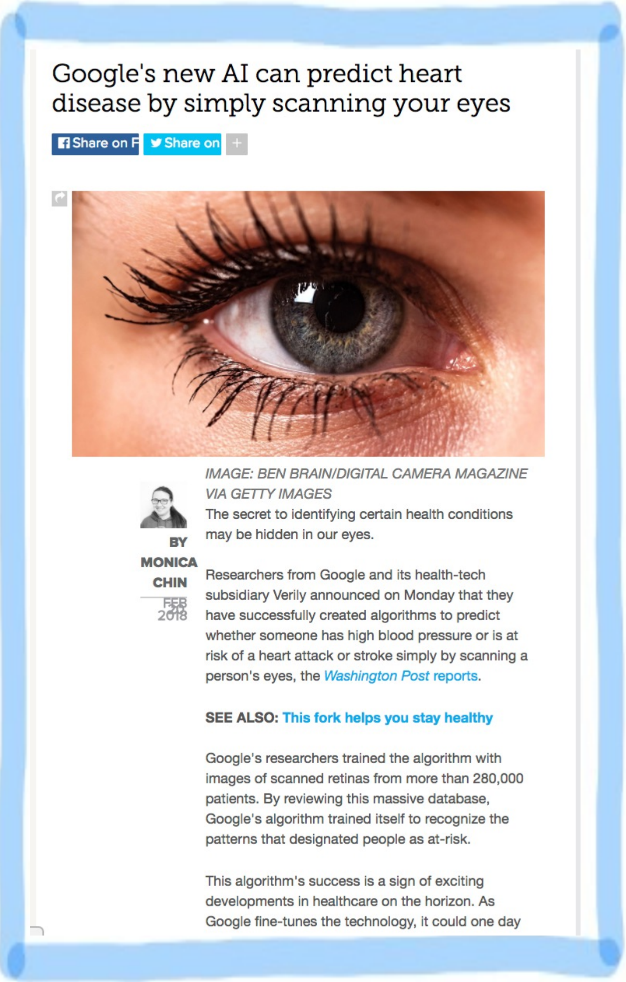
Some DS models for evaluate job applications show bias in favor of male candidate

Racial Bias

Risk models used in US courts have shown to be biased against non-white defendants

Historical Trends

Disease prediction



Google's new AI can predict heart disease by simply scanning your eyes

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IMAGE: BEN BRAIN/DIGITAL CAMERA MAGAZINE VIA GETTY IMAGES

BY MONICA CHIN

FEB 2018

The secret to identifying certain health conditions may be hidden in our eyes.

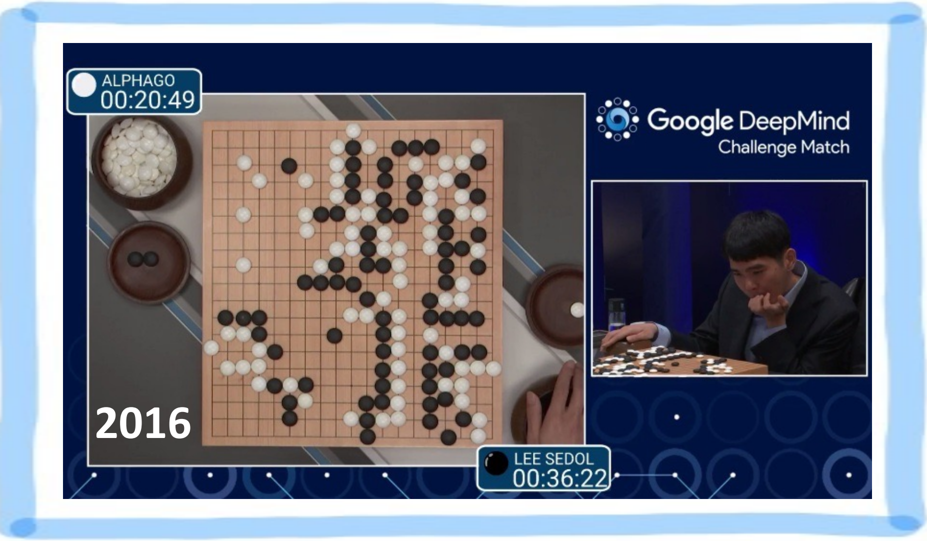
Researchers from Google and its health-tech subsidiary Verily announced on Monday that they have successfully created algorithms to predict whether someone has high blood pressure or is at risk of a heart attack or stroke simply by scanning a person's eyes, the *Washington Post* reports.

SEE ALSO: This fork helps you stay healthy

Google's researchers trained the algorithm with images of scanned retinas from more than 280,000 patients. By reviewing this massive database, Google's algorithm trained itself to recognize the patterns that designated people as at-risk.

This algorithm's success is a sign of exciting developments in healthcare on the horizon. As Google fine-tunes the technology, it could one day

Game strategy



DeepMind

AlphaZero AI beats champion chess program after teaching itself in four hours

Google's artificial intelligence sibling DeepMind repurposes Go-playing AI to conquer chess and shogi without aid of human knowledge

Natural Language Processing

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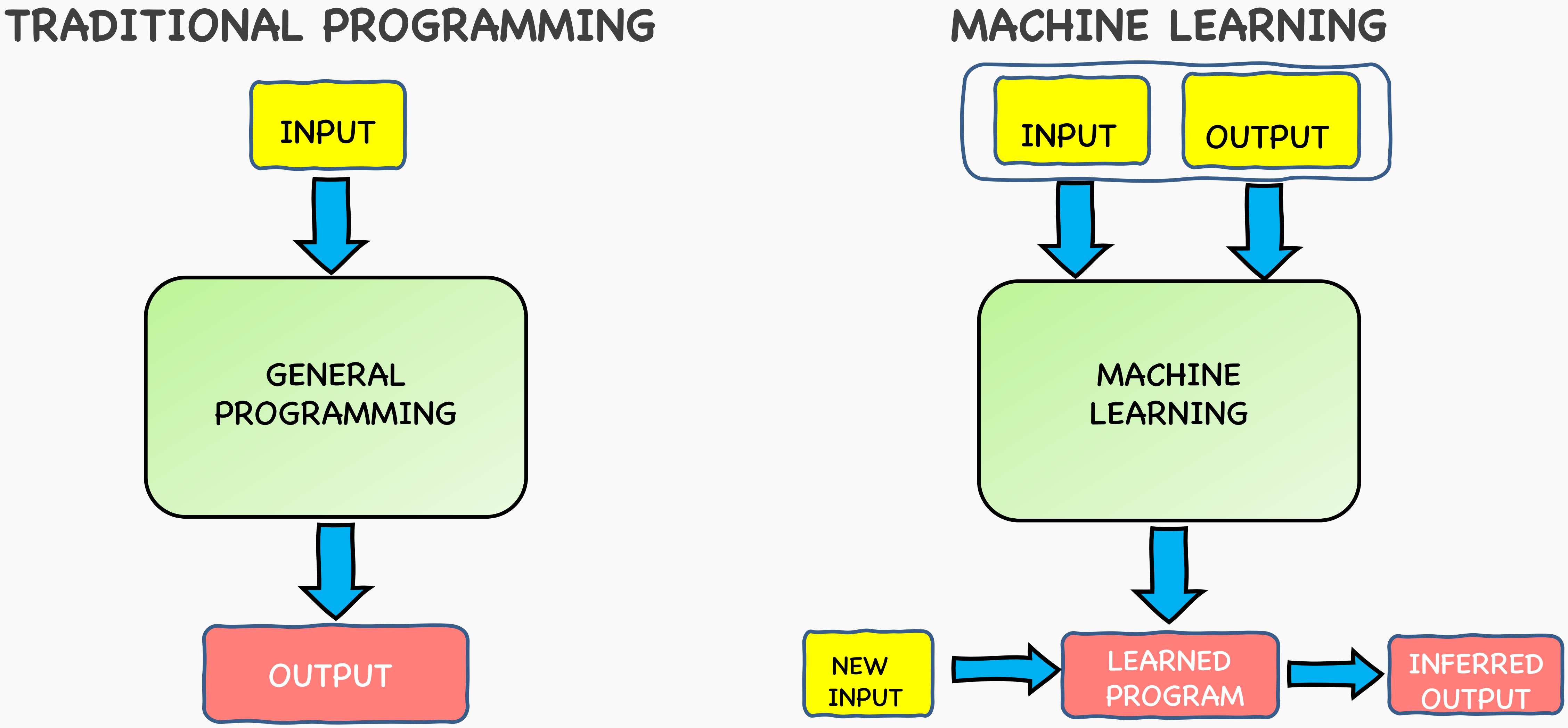
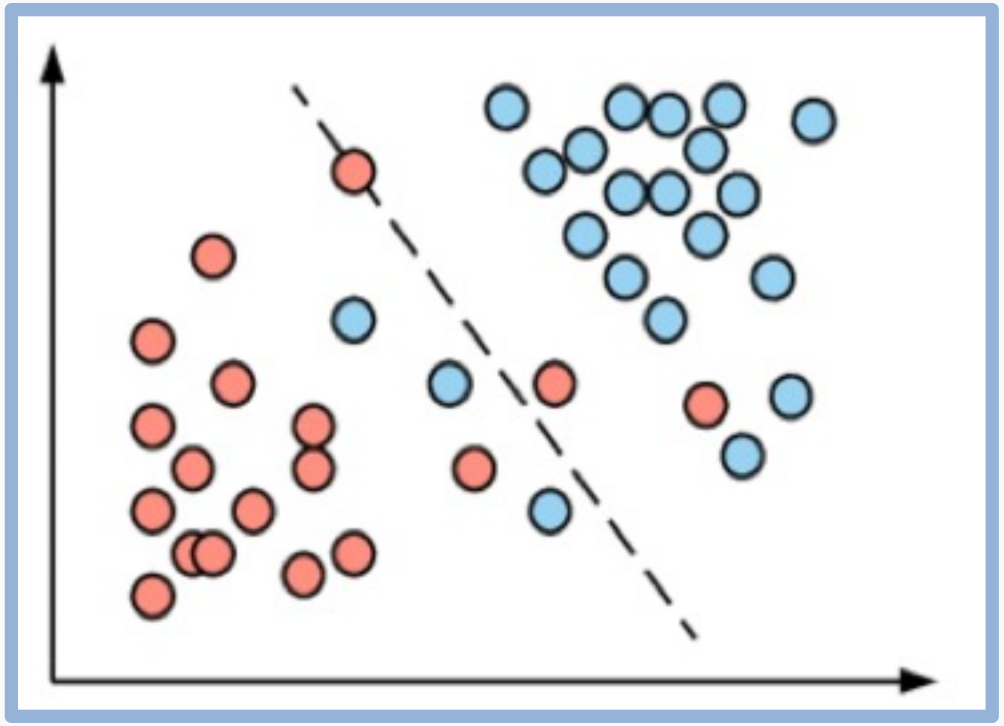
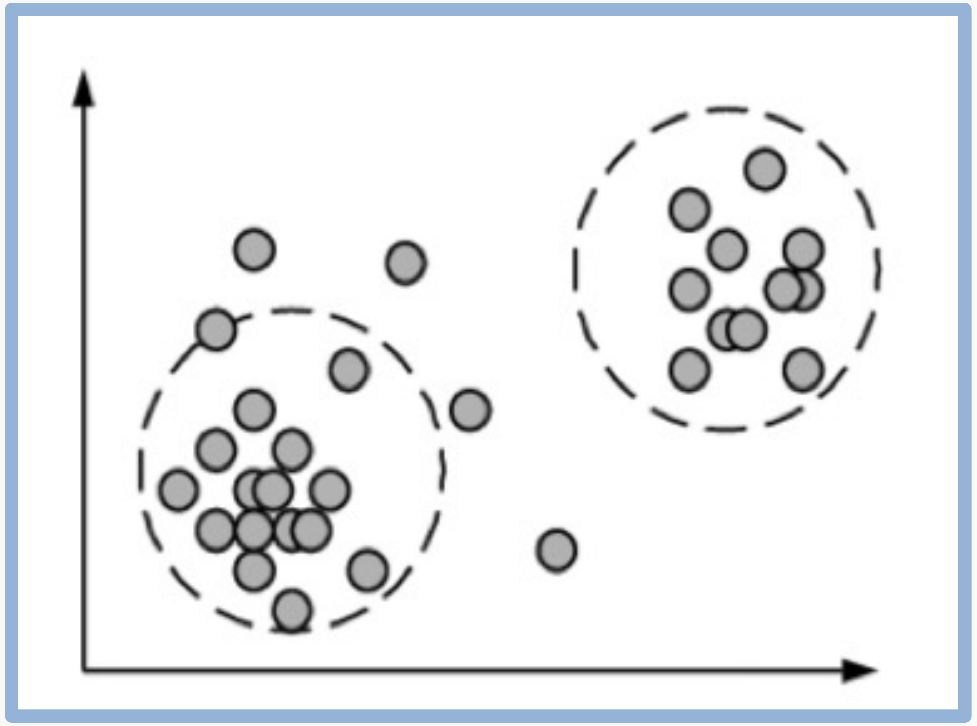
What is Machine Learning?



Supervised v/s Unsupervised Machine Learning

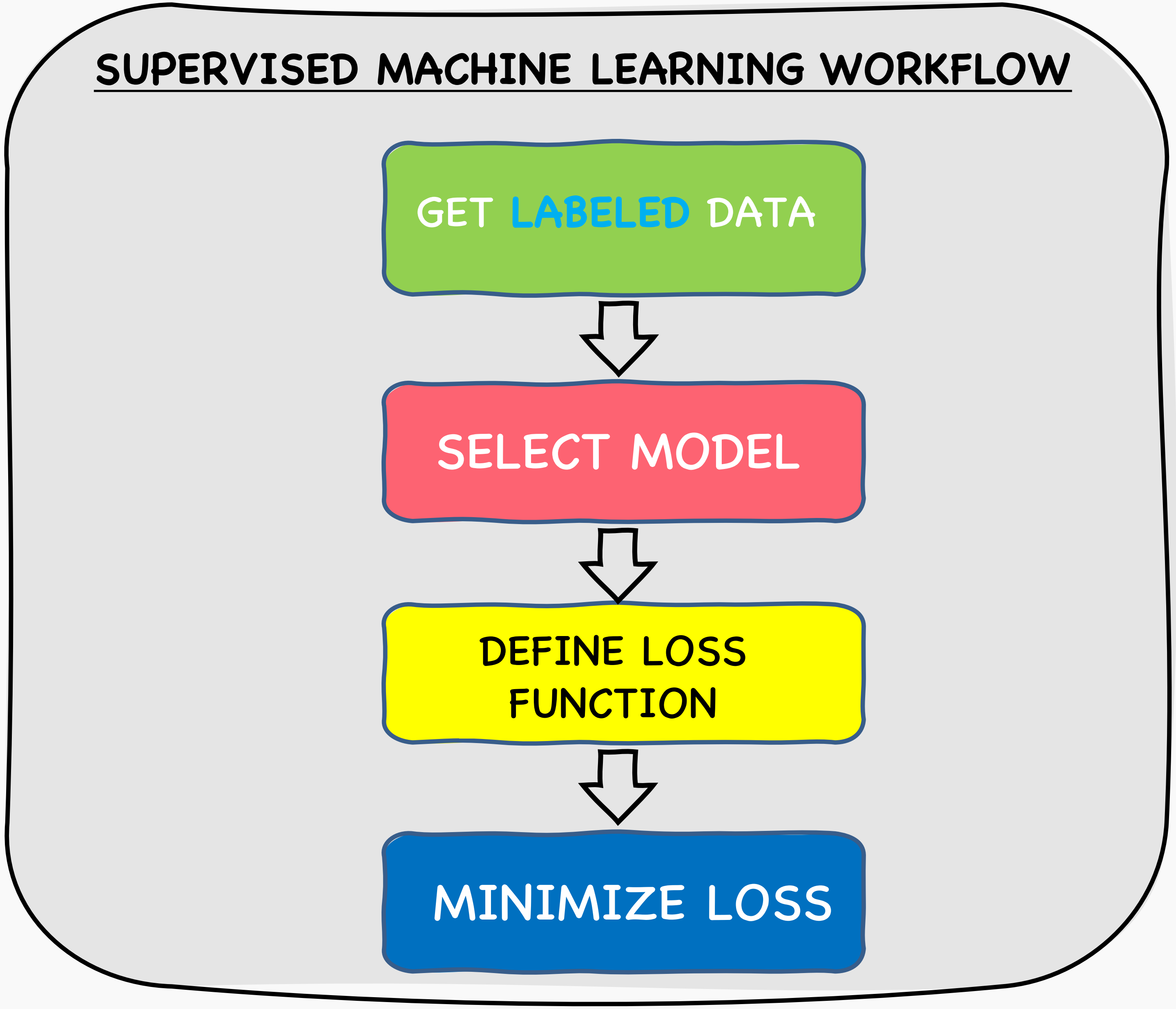


Supervised Learning: Learns with “labeled” data



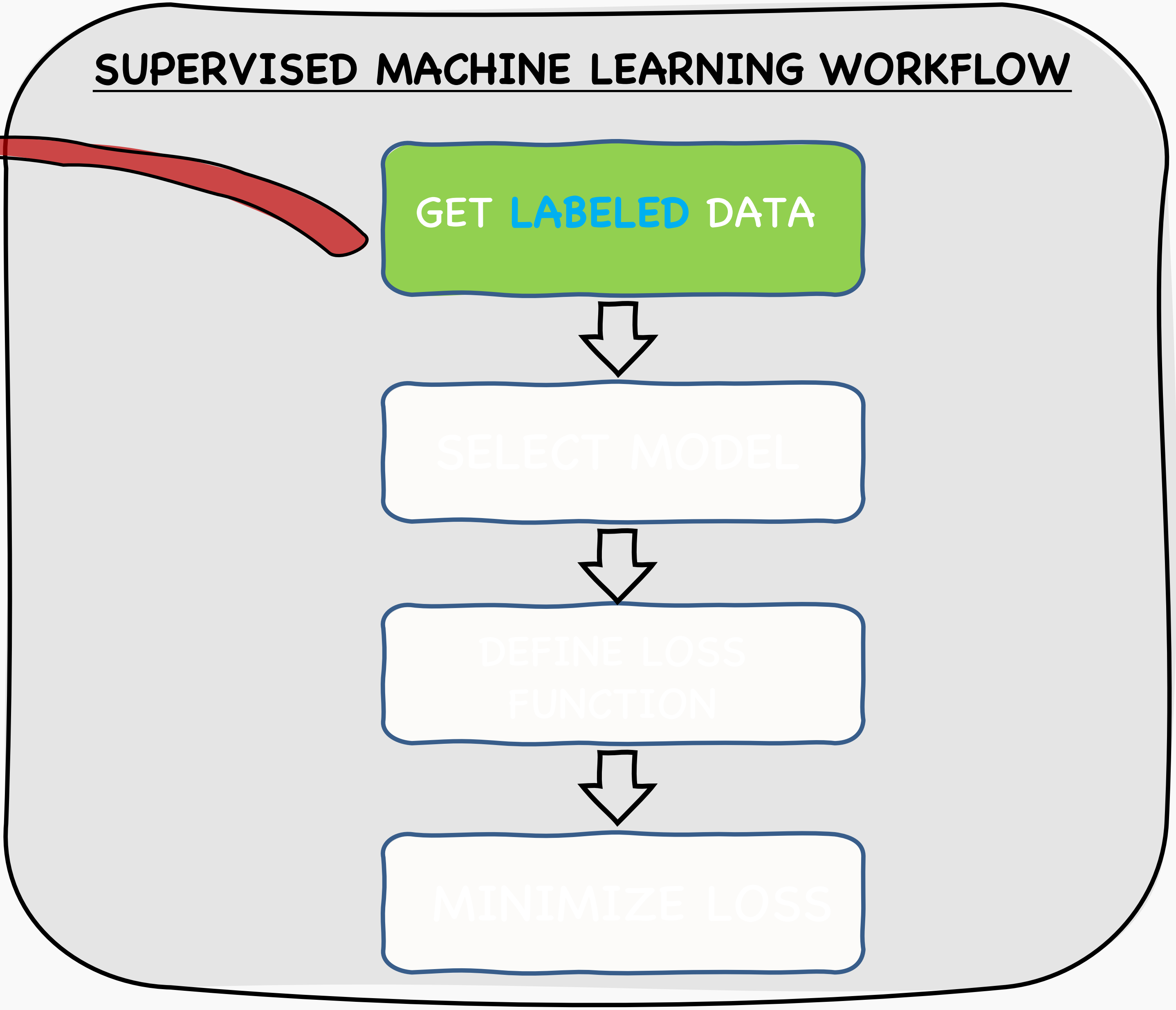
Unsupervised Learning: Learns by clustering or association

Building blocks of **supervised** machine learning



Building blocks of **supervised** machine learning

Sales vs Advertising budget,
Patient history vs heart disease
(Response & Predictor variables)



Response vs. Predictor Variables

$X = X_1, \dots, X_p$

$X_j = x_{1j}, \dots, x_{ij}, \dots, x_{nj}$

predictors

features

covariates

response variable ***Y***

is continuous

$Y = y_1, \dots, y_n$

outcome

response variable

dependent variable

TV	radio	newspaper	sales
230.1	37.8	69.2	22.1
44.5	39.3	45.1	10.4
17.2	45.9	69.3	9.3
151.5	41.3	58.5	18.5
180.8	10.8	58.4	12.9

n observations

p predictors

Heart Data

These data contain a binary outcome AHD for 303 patients who presented with chest pain.

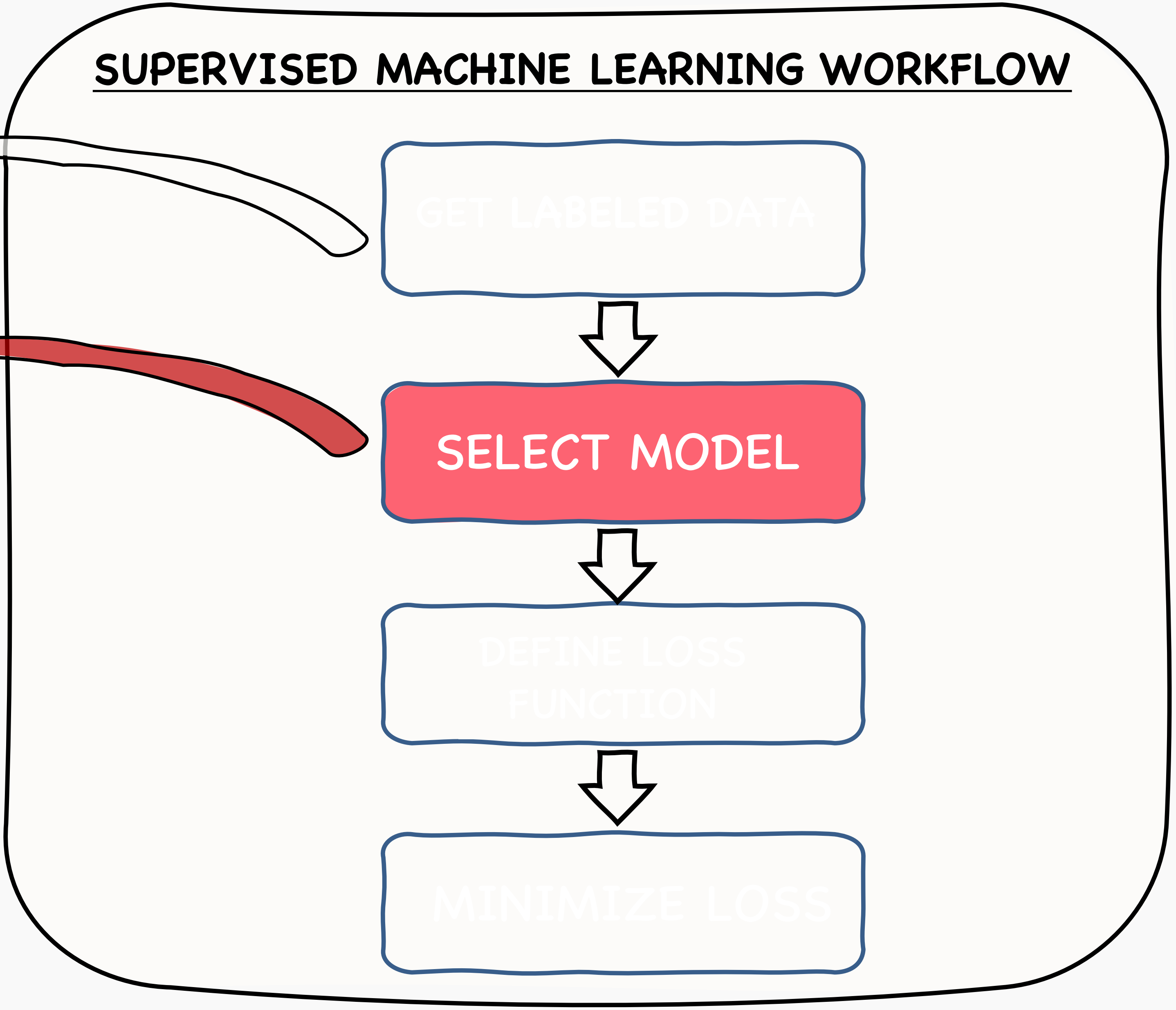
response variable ***Y*** is Yes/No

Age	Sex	ChestPain	RestBP	Chol	Fbs	RestECG	MaxHR	ExAng	Oldpeak	Slope	Ca	Thal	AHD
63	1	typical	145	233	1	2	150	0	2.3	3	0.0	fixed	No
67	1	asymptomatic	160	286	0	2	108	1	1.5	2	3.0	normal	Yes
67	1	asymptomatic	120	229	0	2	129	1	2.6	2	2.0	reversable	Yes
37	1	nonanginal	130	250	0	0	187	0	3.5	3	0.0	normal	No
41	0	nontypical	130	204	0	2	172	0	1.4	1	0.0	normal	No

Building blocks of **supervised** machine learning

Sales vs Advertising budget,
Patient history vs heart disease
(Response & Predictor variables)

Regression,
Classification, Object
Detection



Supervised Machine Learning examples

SUPERVISED MACHINE LEARNING

response variable Y
is categorical e.g. Yes/No

CLASSFICATION

- FRAUD DETECTION
- EMAIL SPAM DETECTION
- IMAGE CLASSIFICATION

response variable Y
is continuous

REGRESSION

- RISK ASSESSMENT
- SCORE PREDICTION
- HOUSING PRICES

Building blocks of **supervised** machine learning

Sales vs Advertising budget,
Patient history vs heart disease
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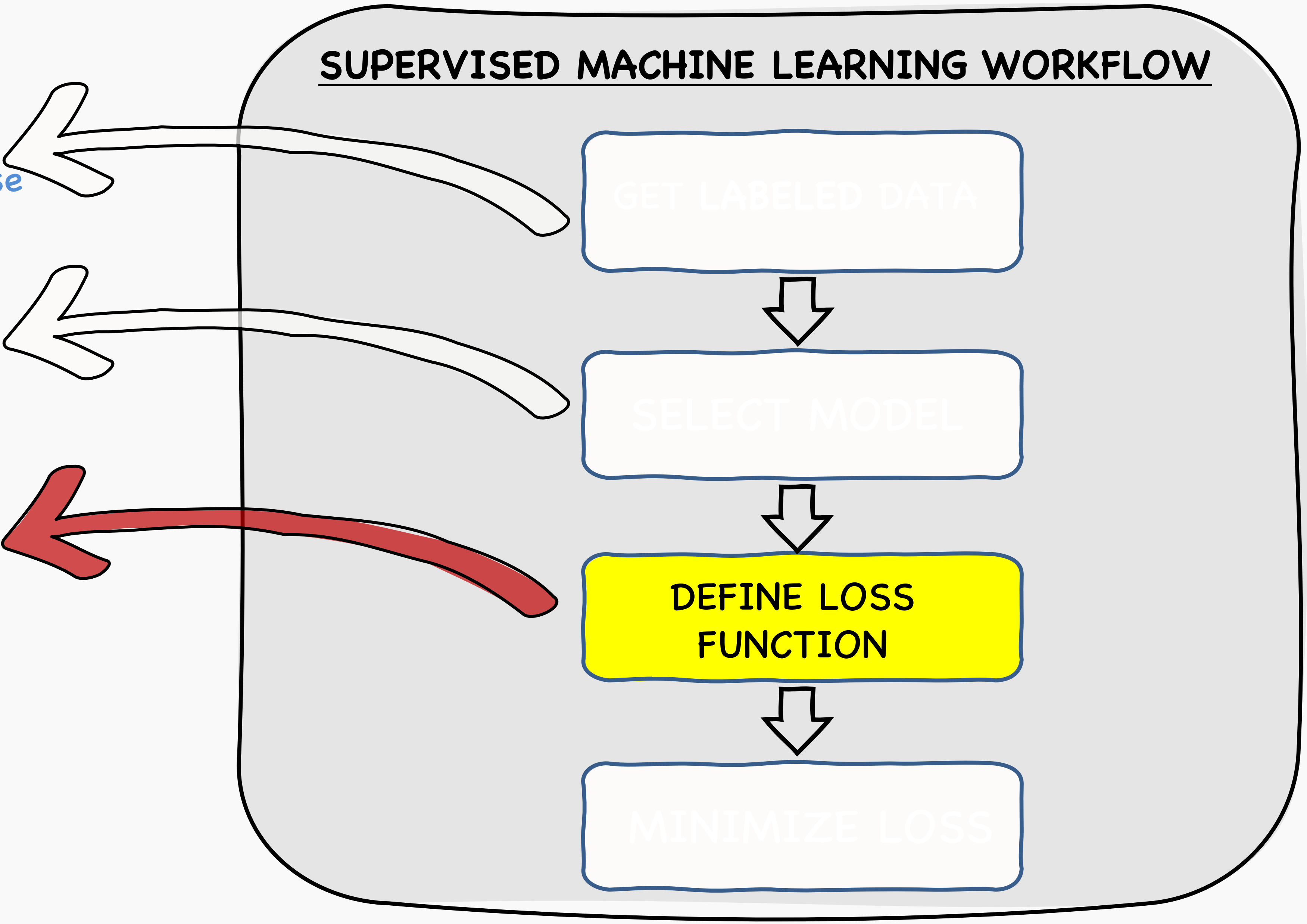
Regression,
Classification, Object
Detection

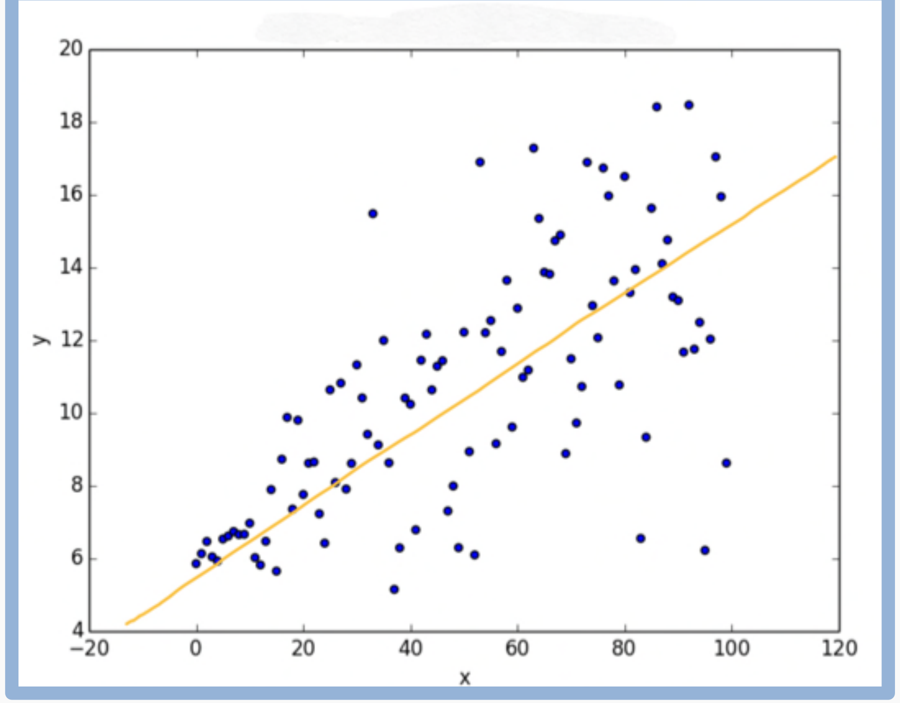
Mean Squared Error,
Binary Cross Entropy,
Categorical Cross
Entropy, Hinge Loss



Loss for linear regression

MSE as the **loss function**,

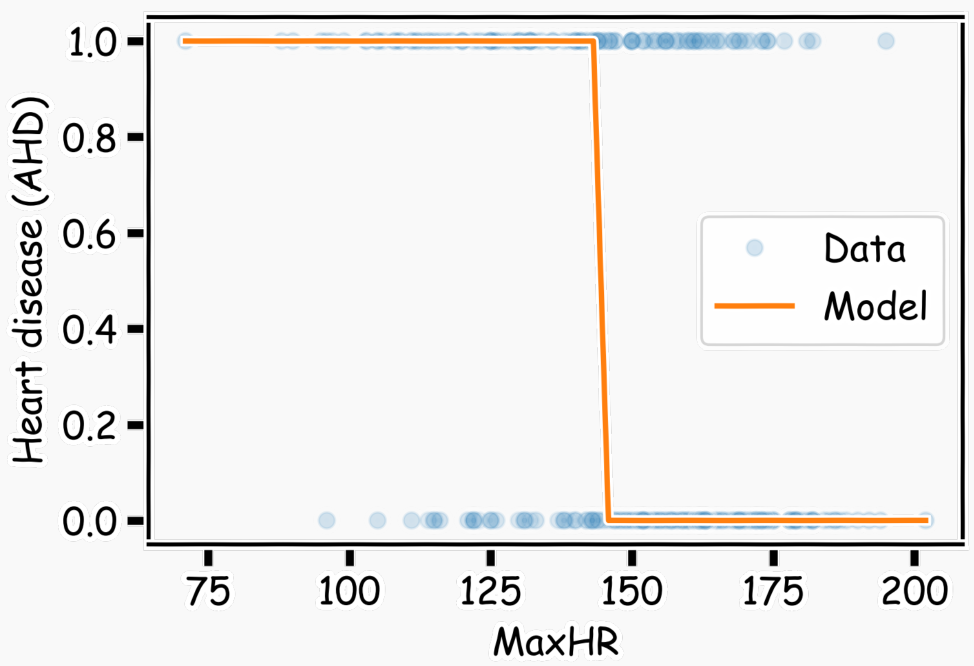
$$L(\beta_0, \beta_1) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 = \frac{1}{n}\sum_{i=1}^{n}[y_i - (\beta_1 X + \beta_0)]^2 .$$



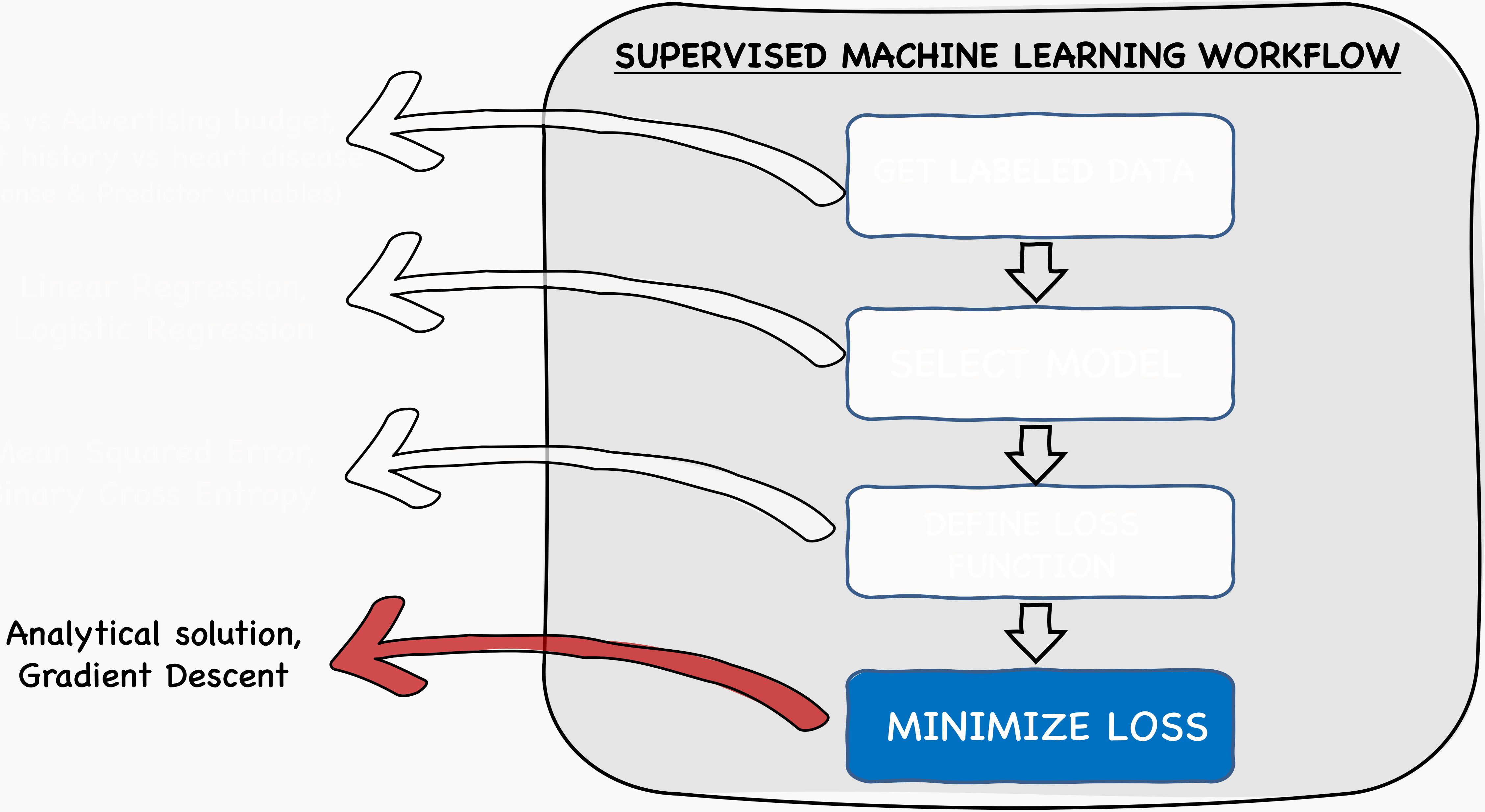
Loss function for Logistic Regression

Cross Entropy as a loss function

$$\mathcal{L}(\beta_0, \beta_1) = -\sum_i [y_i \log p_i + (1 - y_i)\log(1 - p_i)]$$

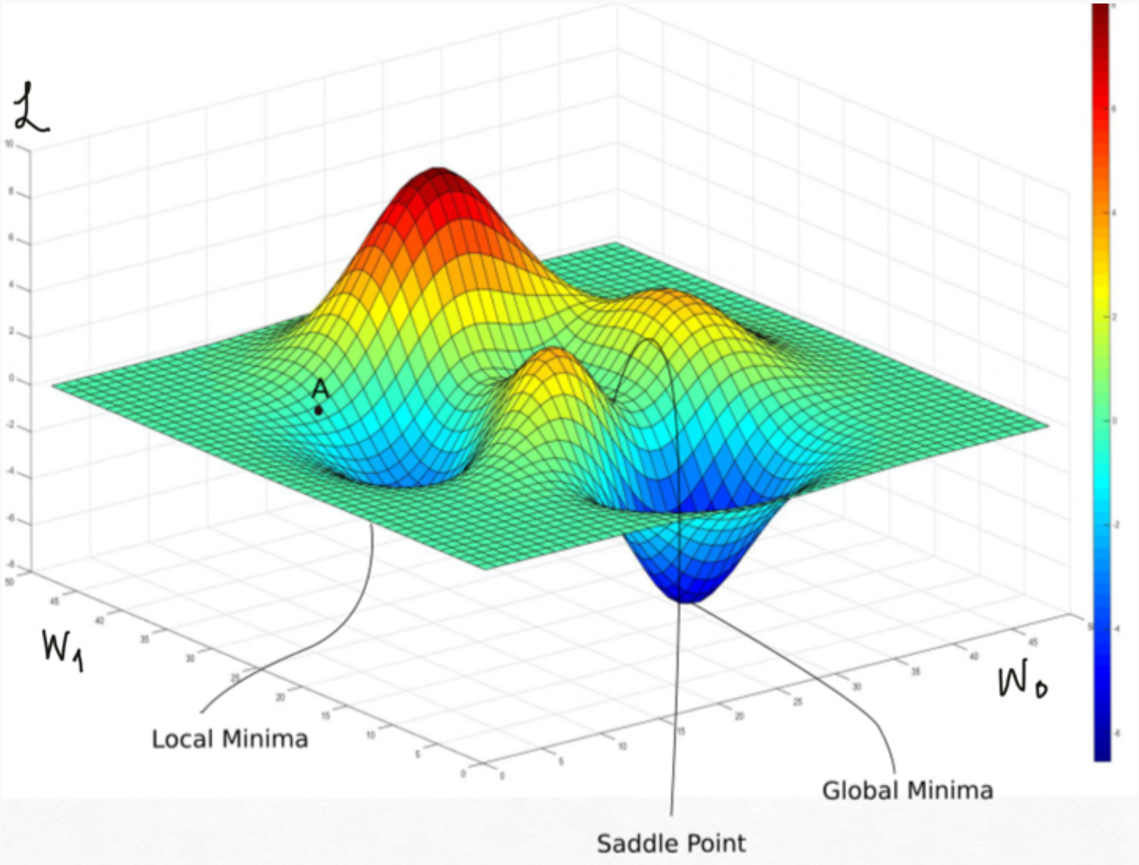


Building blocks of **supervised** machine learning



Optimization

How does one minimize a loss function?



Minima or maxima of $L(\beta_0, \beta_1)$ must occur at points where the gradient (slope)

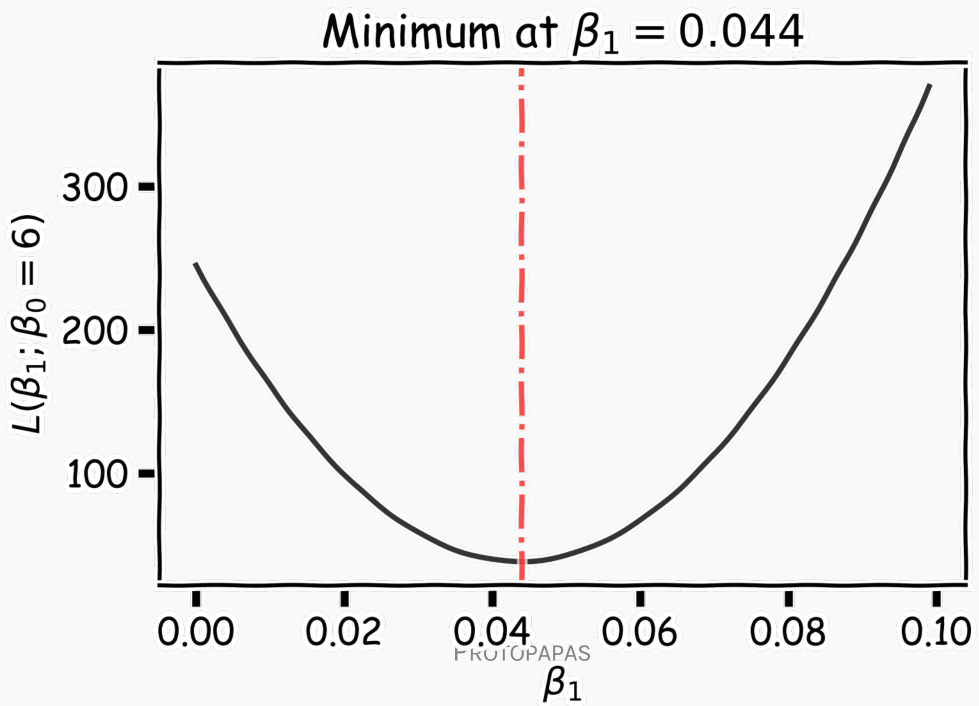
$$\nabla L = \left[\frac{\partial L}{\partial \beta_0}, \frac{\partial L}{\partial \beta_1}\right] = 0$$

- Brute Force: Try every combination
- Exact: Solve the above equations
- Greedy Algorithm: Gradient Descent

Optimization: Brute force

A way to estimate $\text{argmin}_{\beta_0,\beta_1} L$ is to calculate the loss function for every possible β_0 and β_1. Then select the β_0 and β_1 where the loss function is minimum.

E.g. the loss function for different β_1 when β_0 is fixed to be 6:



Very **computationally expensive** with many coefficients

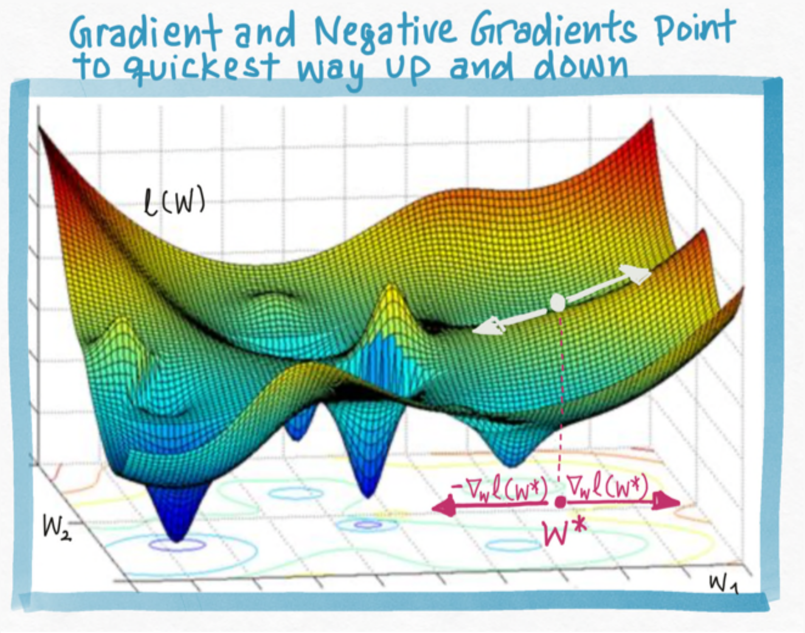
Gradient Descent

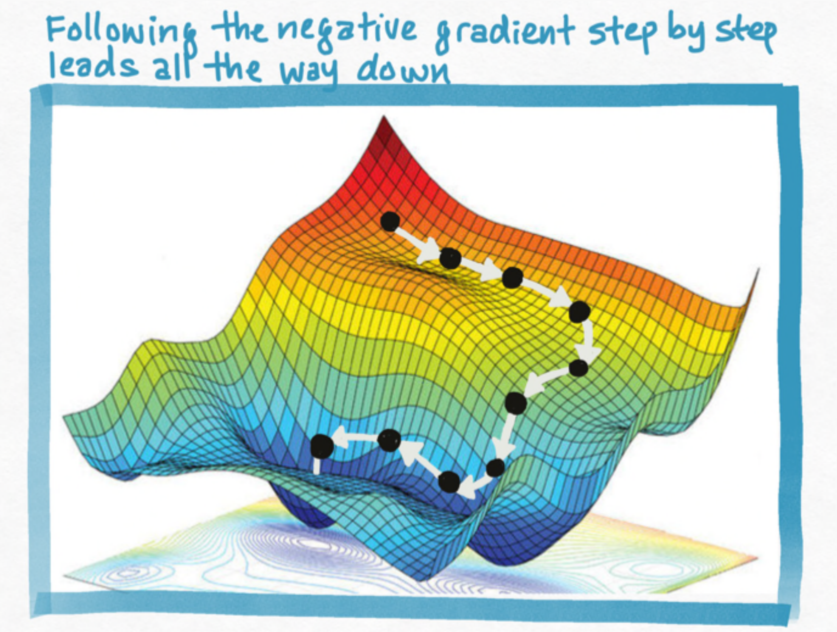
When we can't analytically solve for the stationary points of the gradient, we can still exploit the information in the gradient.

The gradient ∇L at any point is the direction of the steepest increase. The negative gradient is the direction of steepest decrease.

By following the –ve gradient, we can eventually find the lowest point.

This method is called Gradient Descent





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Logistic Regression Revisited

True y

$x_1 \longrightarrow$ Affine $\longrightarrow h_1 = \beta_0 + \beta_1 x_1 \longrightarrow$ Activation $\longrightarrow p_1 = \dfrac{1}{1 + e^{-h_1}} \longrightarrow$ Loss Fun $\longrightarrow \mathcal{L}_1(\beta) = -y_1 \ln(p_1) - (1 - y_1)\ln(1 - p_1)$

Logistic Regression Revisited

$$x_1 \rightarrow \boxed{\text{Affine}} \rightarrow h_1 = \beta_0 + \beta_1 x_1 \rightarrow \boxed{\text{Activation}} \rightarrow p_1 = \frac{1}{1 + e^{-h_1}} \rightarrow \boxed{\text{Loss Fun}} \rightarrow \mathcal{L}_1(\beta) = -y_1 \ln(p_1) - (1 - y_1)\ln(1 - p_1)$$

$$x_2 \rightarrow \boxed{\text{Affine}} \rightarrow h_2 = \beta_0 + \beta_1 x_2 \rightarrow \boxed{\text{Activation}} \rightarrow p_2 = \frac{1}{1 + e^{-h_2}} \rightarrow \boxed{\text{Loss Fun}} \rightarrow \mathcal{L}_2(\beta) = -y_2 \ln(p_1) - (1 - y_2)\ln(1 - p_2)$$

Logistic Regression Revisited

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$\vdots$ $\vdots$ $\vdots$

Logistic Regression Revisited

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$\vdots \qquad \vdots \qquad \vdots$

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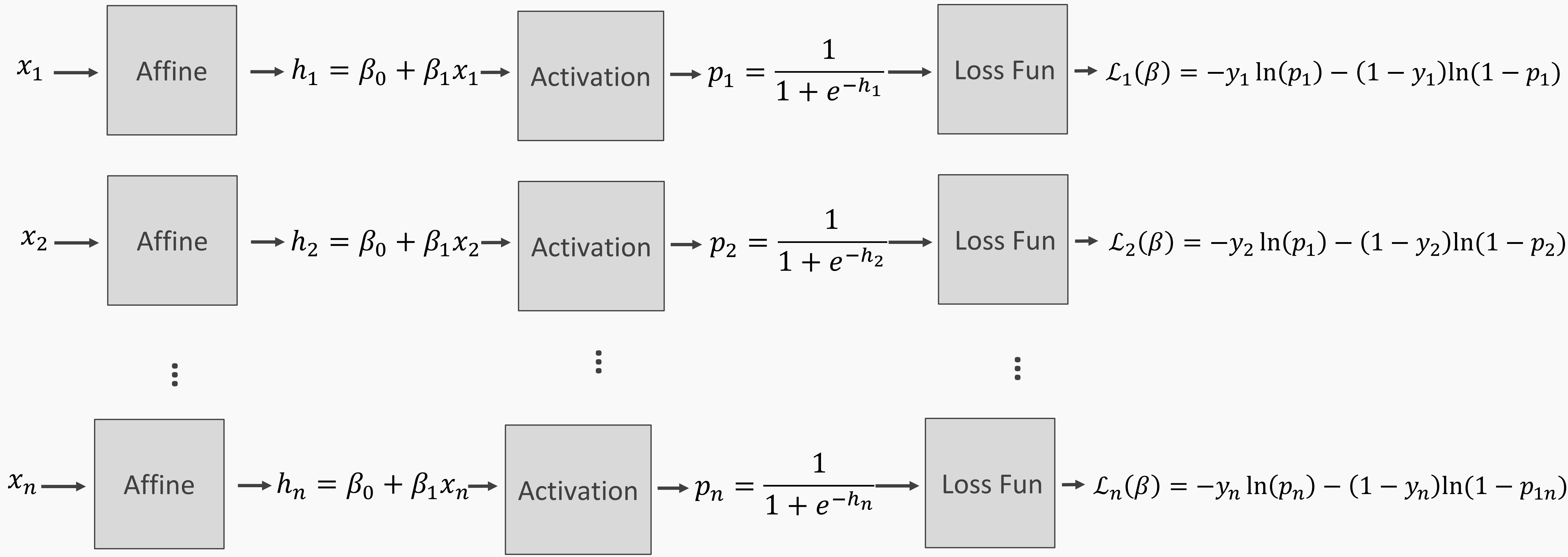
Logistic Regression Revisited

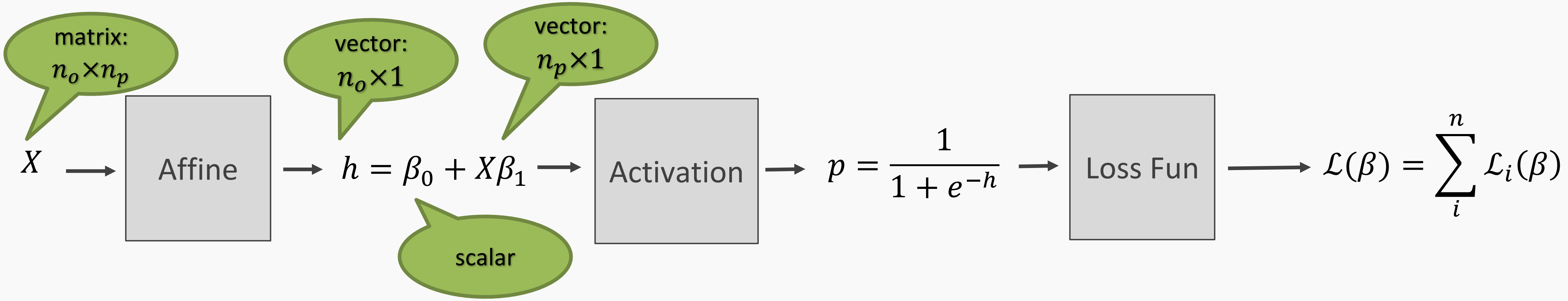


$$\boxed{\mathcal{L}(\beta) = \sum_i^n \mathcal{L}_i(\beta)}$$

Build our first ANN

n_p: number of predictors

n_o: number of observations



Build our first ANN

$$X \longrightarrow \boxed{\text{Affine}} \longrightarrow h = \beta_0 + X\beta_1 \longrightarrow \boxed{\text{Activation}} \longrightarrow p = \frac{1}{1 + e^{-h}} \longrightarrow \boxed{\text{Loss Fun}} \longrightarrow \mathcal{L}(\beta) = \sum_{i}^{n} \mathcal{L}_i(\beta)$$

$$X \longrightarrow \boxed{\text{Affine}} \longrightarrow h = XW + b \longrightarrow \boxed{\text{Activation}} \longrightarrow \hat{y} = \frac{1}{1 + e^{-h}} \longrightarrow \boxed{\text{Loss Fun}} \longrightarrow \mathcal{L}(\beta) = \sum_{i}^{n} \mathcal{L}_i(\beta)$$

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$$X = \begin{bmatrix} 1 & X_{11} & \dots & X_{1p} \\ 1 & \vdots & \dots & \vdots \\ 1 & X_{o1} & \dots & X_{op} \end{bmatrix} \quad \mathrm{W} = \begin{bmatrix} b \\ W_1 \\ \vdots \\ W_p \end{bmatrix}$$

Build our first ANN

$$X \longrightarrow \boxed{\text{Affine}} \longrightarrow h = XW \longrightarrow \boxed{\text{Activation}} \longrightarrow \hat{y} = \frac{1}{1+e^{-h}} \longrightarrow \boxed{\text{Loss Fun}} \longrightarrow \mathcal{L}(W) = \sum_{i}^{n} \mathcal{L}_i(W)$$

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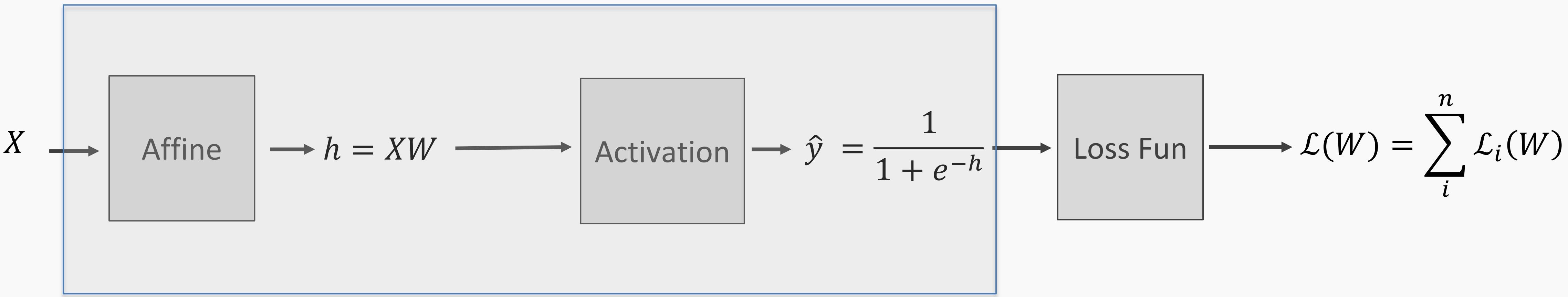

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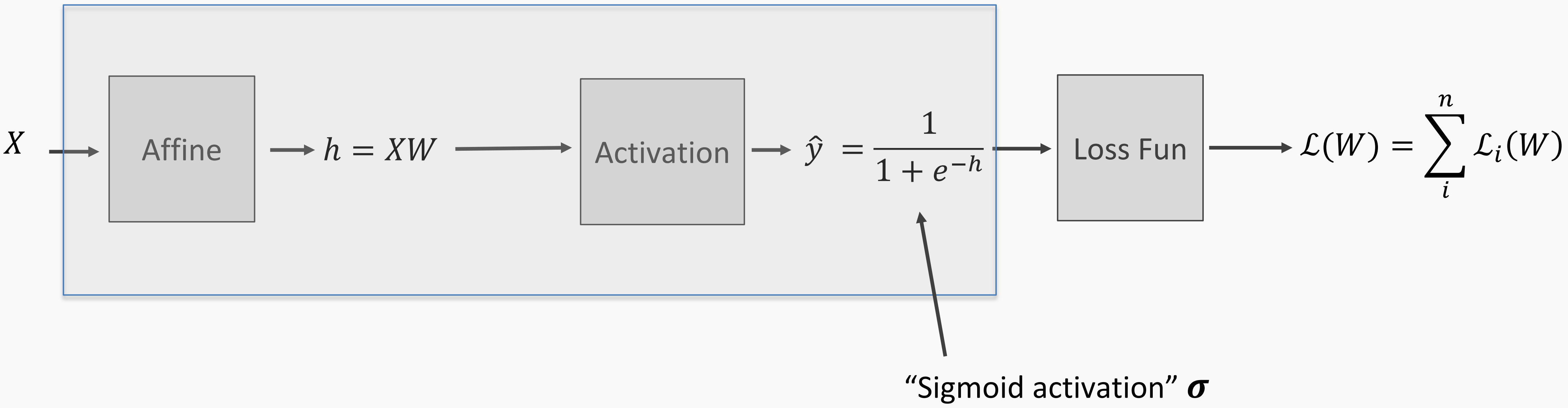

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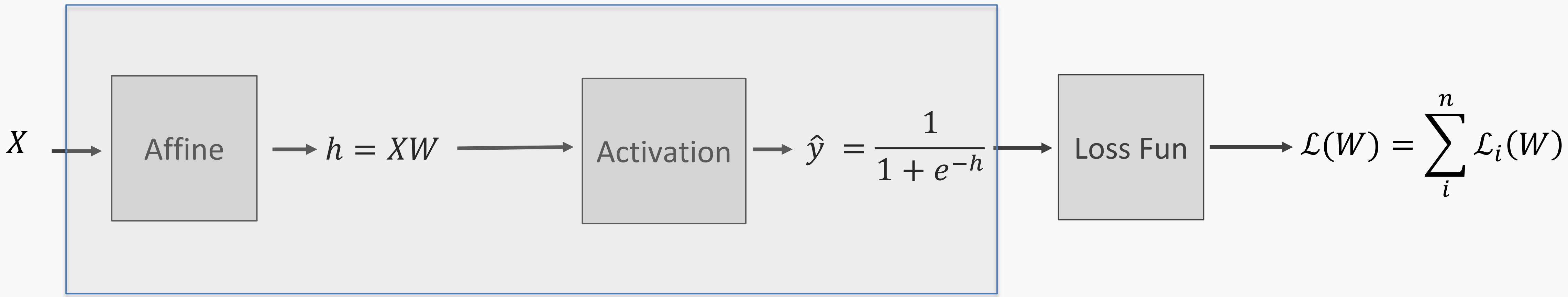

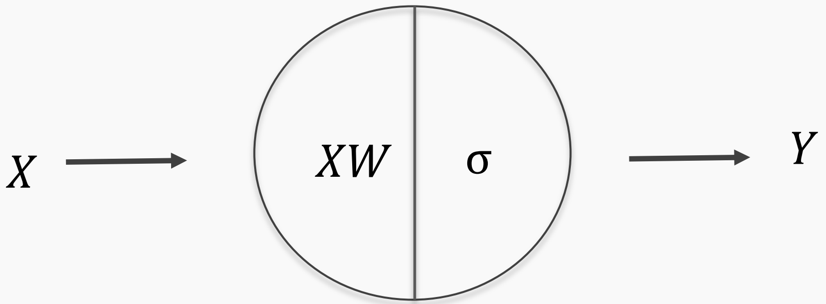

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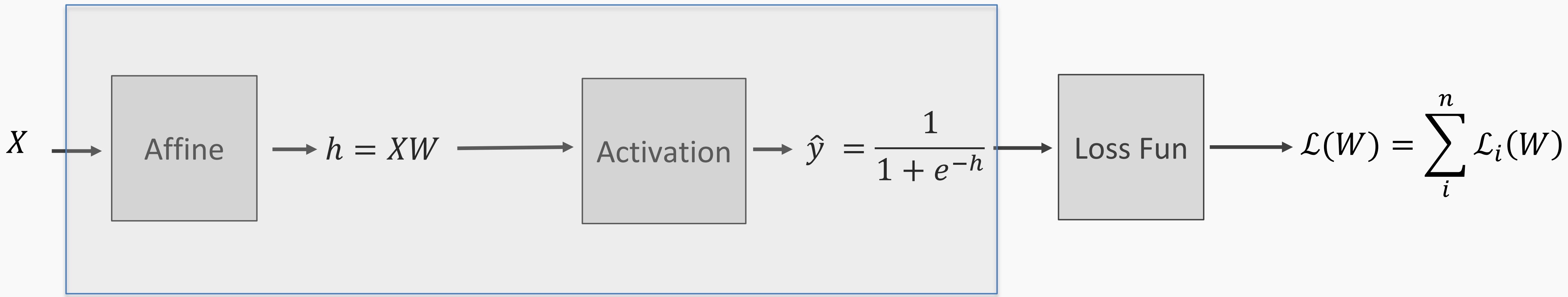

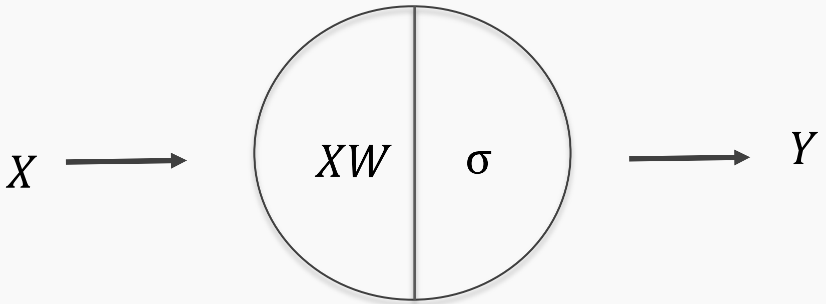

Single Neuron Neural “Network”