Classical machine learning models

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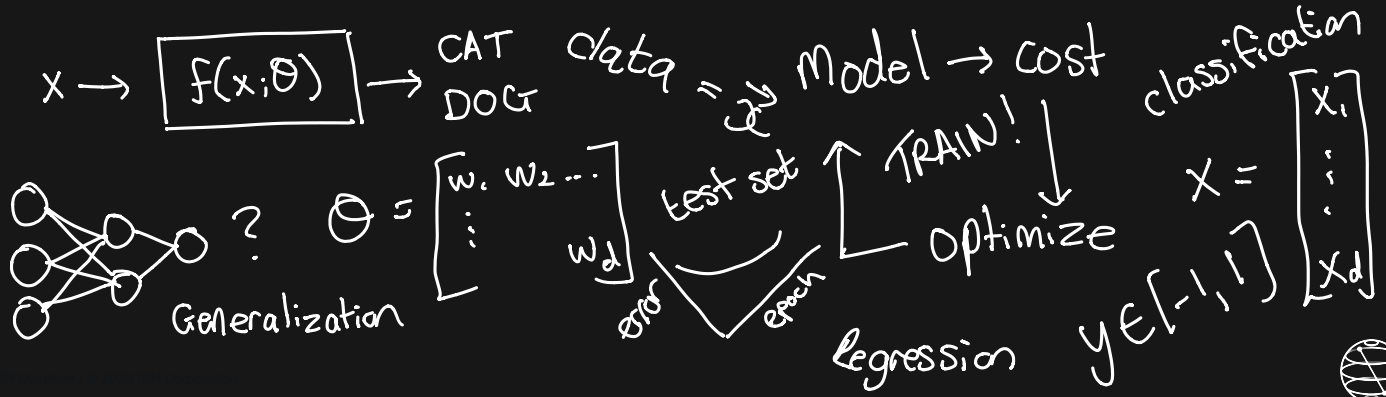
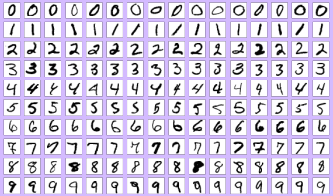
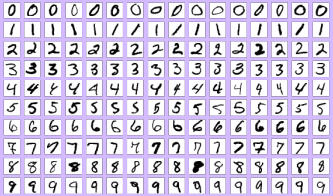


Recap



Recap

DATA

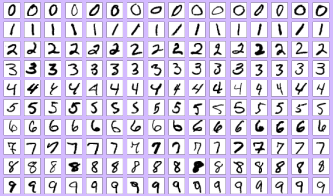


MODEL

$f(X_{train}; \vec{\theta})$

Recap

DATA



MODEL

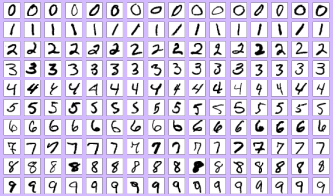
$$f(X_{train}; \vec{\theta})$$

COST

$$C(f(X_{train}; \vec{\theta}), y)$$

Recap

DATA



MODEL

$$f(X_{train}; \vec{\theta})$$

COST

$$C(f(X_{train}; \vec{\theta}), y)$$

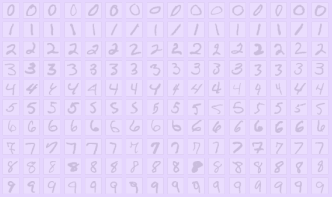
OPTIMIZATION

$$\frac{\partial C(f(X_{train}; \vec{\theta}),\ y)}{\partial \vec{\theta}}$$

Qiskit

Recap

DATA



MODEL

$f(X_{train}; \vec{\theta})$

COST

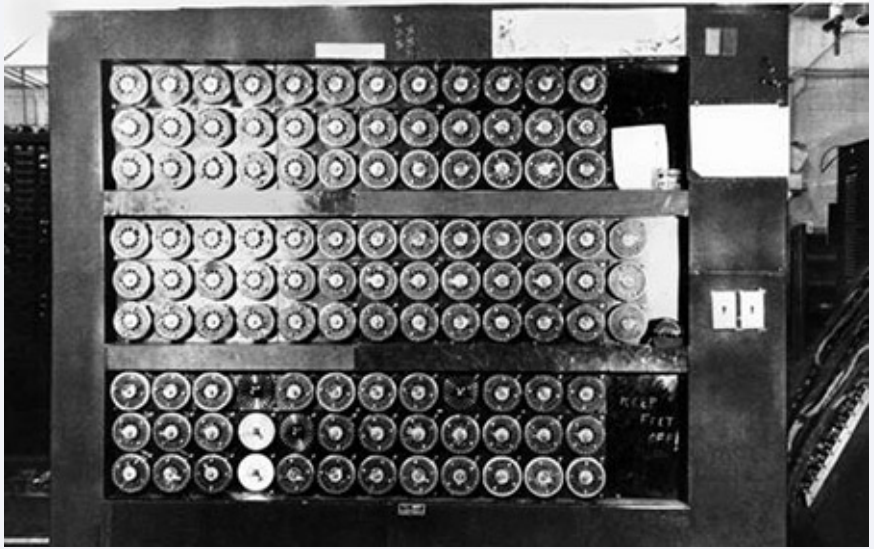
$C(f(X_{train}; \vec{\theta}), y)$

OPTIMIZATION

$$\frac{\partial C(f(X_{train}; \vec{\theta}), y)}{\partial \vec{\theta}}$$

History of machine learning

- 1950: Turing's Learning Machine

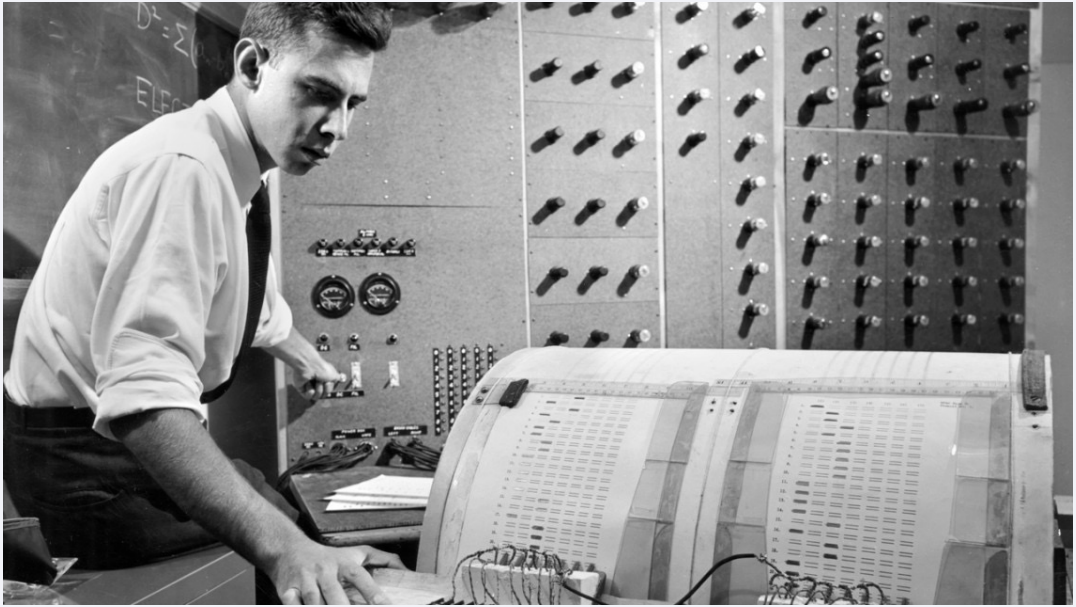


History of machine learning

- *Machine learning* was coined in 1952 by Arthur Samuel, an American IBMer

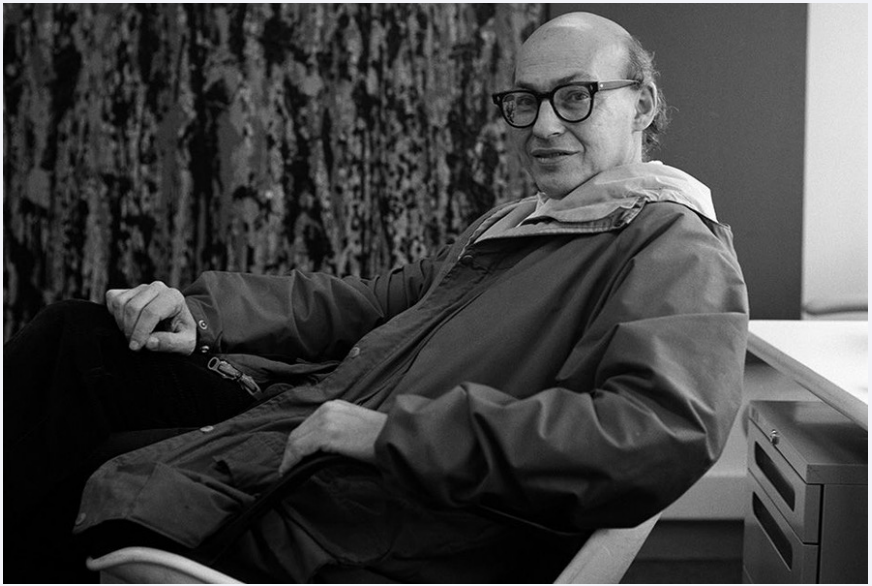
History of machine learning

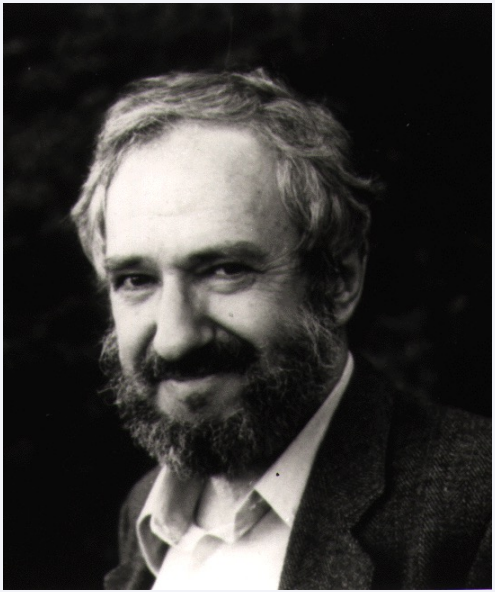
- 1957: Enter the perceptron model created by Frank Rosenblatt, Cornell



History of machine learning

- 1969: Limitations of neural networks, Marvin Minsky & Seymour Papert



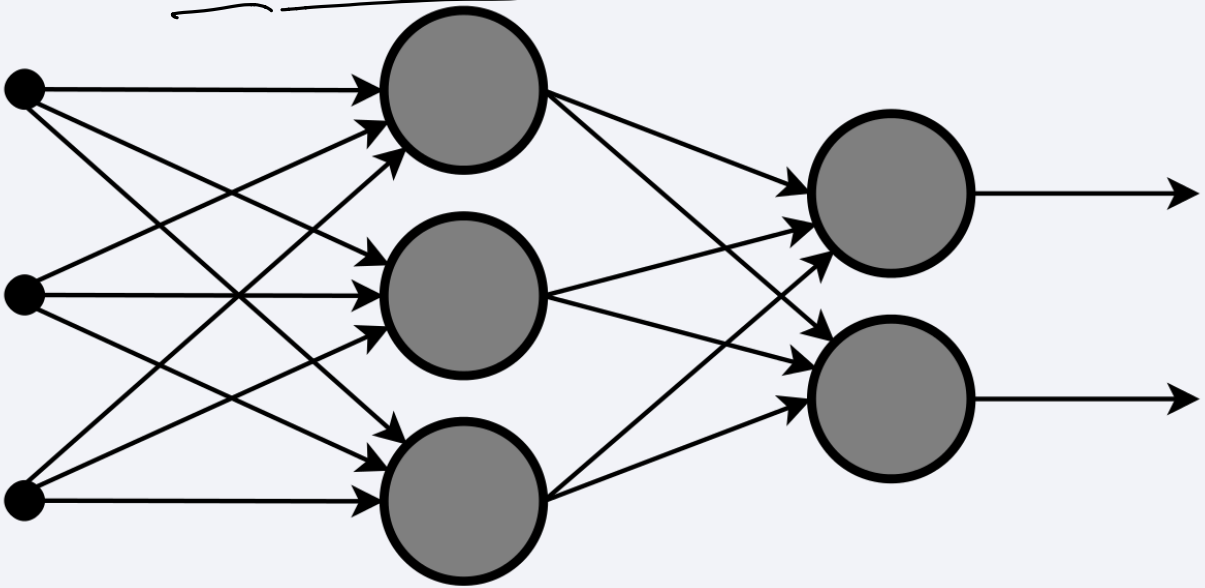


History of machine learning

- 1970’s: AI winter

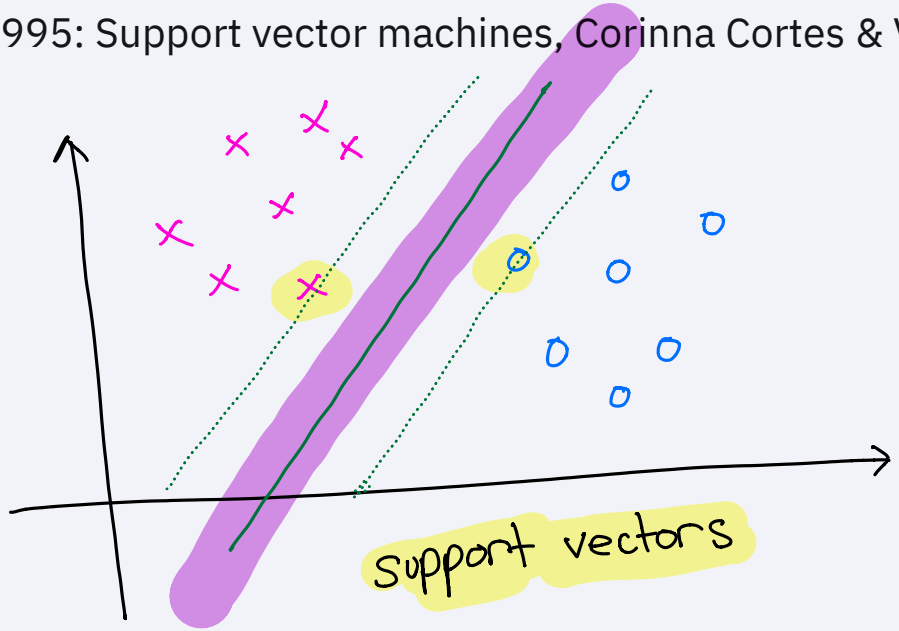
History of machine learning

- 1970 & 1986: Backpropagation, Seppo Linnainmaa & Geoffrey Hinton



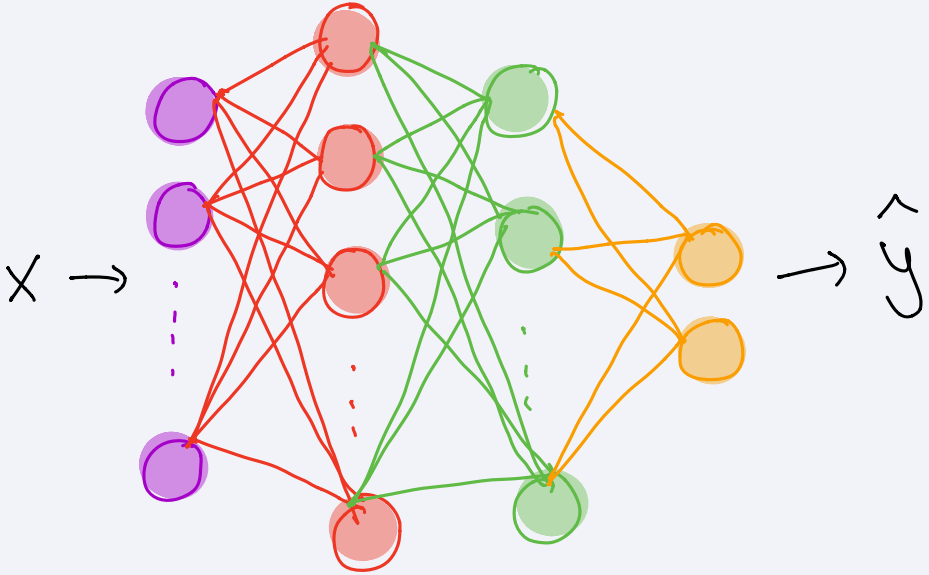
History of machine learning

- 1995: Support vector machines, Corinna Cortes & Vladimir Vapnik



History of machine learning

- 2010s: Deep learning became feasible in practice



Qiskit

Linear models

Linear models

Linear models

1-dimensional data, regression problem

$\vec{x}_1 = [-]$ dataset $= (\vec{x}_1, \ldots, \vec{x}_n)$

d- dimensiond data

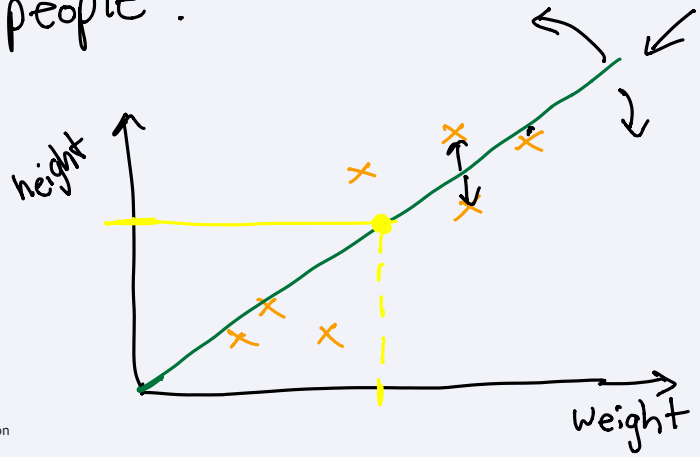
$\vec{x}_1 = \begin{bmatrix} \\ \\ \vdots \\ \\ d \end{bmatrix}$ $d \rightarrow$ features

Linear models

1-dimensional data, regression problem

Task: predict the height of a person, based on their weight

$n = 10$ samples, we know heights (y_i) and weights (x_i) of 10 people.



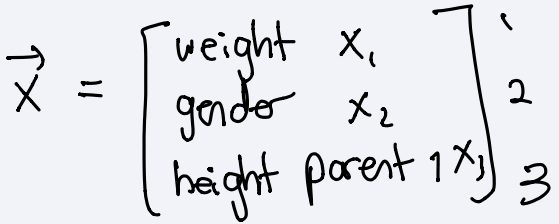
$$\hat{y}_i = \theta x_i$$

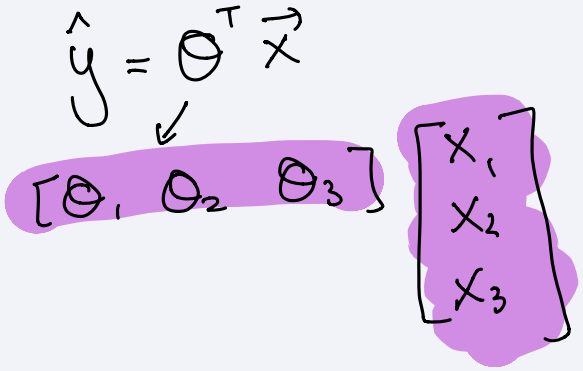
$$\text{MSE}: \frac{1}{10} \sum_{i=1}^{10} (\hat{y}_i - y_i)$$

Linear models

Higher dimensional data, regression problem

Task: predict the height of a person, based on their weight, gender, height of their parents, etc.



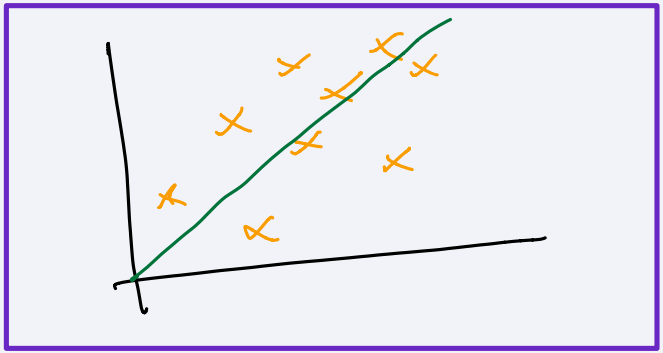


Linear models

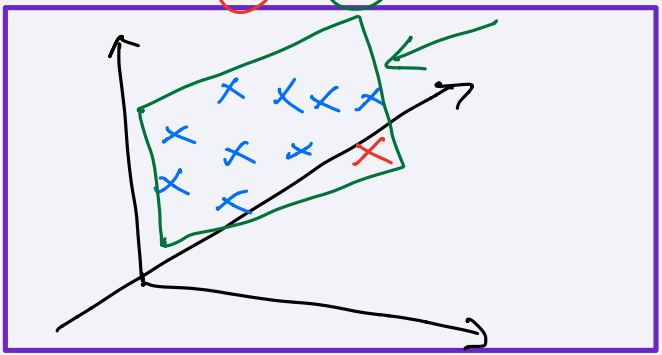
Higher dimensional data, regression problem

Task: predict the height of a person, based on their weight, gender, height of their parents, etc.

$$\hat{y} = \theta x$$



$$\hat{y} = \vec{\theta}^{\mathrm{T}} \vec{x}$$



Qiskit

Neural networks

Neural networks

2-dimensional data, classification

$$\vec{x}_i = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \qquad \hat{y}_i \rightarrow 1, -1$$

Neural networks

Qiskit

Formula representation

Linear model $\hat{y} = \theta^T \vec{x} + b$

Perceptron $\hat{y} = \sigma(\theta^T \vec{x})$ activation fn

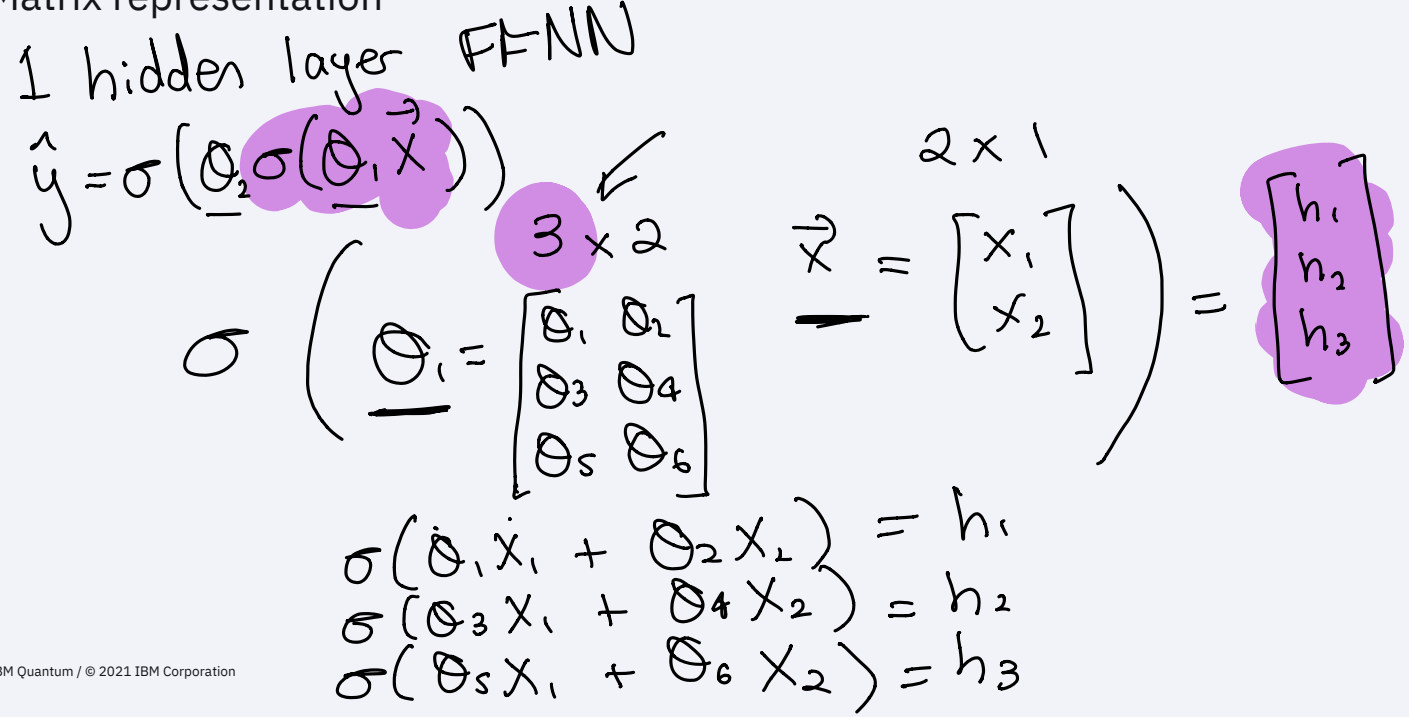
Feed forward NNs $\hat{y} = \sigma(\theta_2 \sigma(\theta_1^T \vec{x}))$ perceptron

$\hat{y} = \sigma(\theta_3 \sigma(\theta_2 \sigma(\theta_1 \vec{x})))$ ←

Neural networks

Qiskit

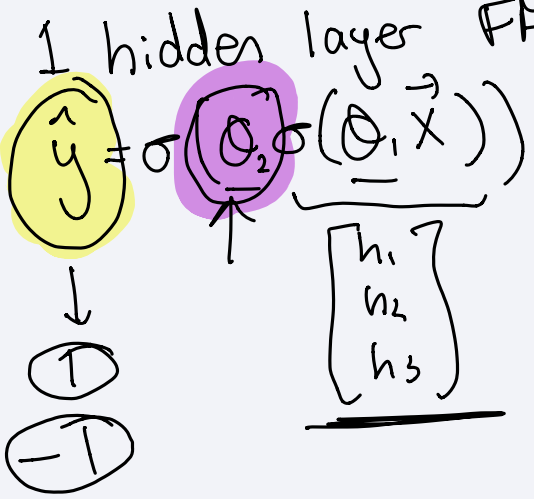
Matrix representation



Neural networks

Qiskit

Matrix representation



$$\hat{y} = \sigma(\theta_2 \sigma(\theta_1 \vec{x}))$$

$1 \times 3 \quad 3 \times 1$

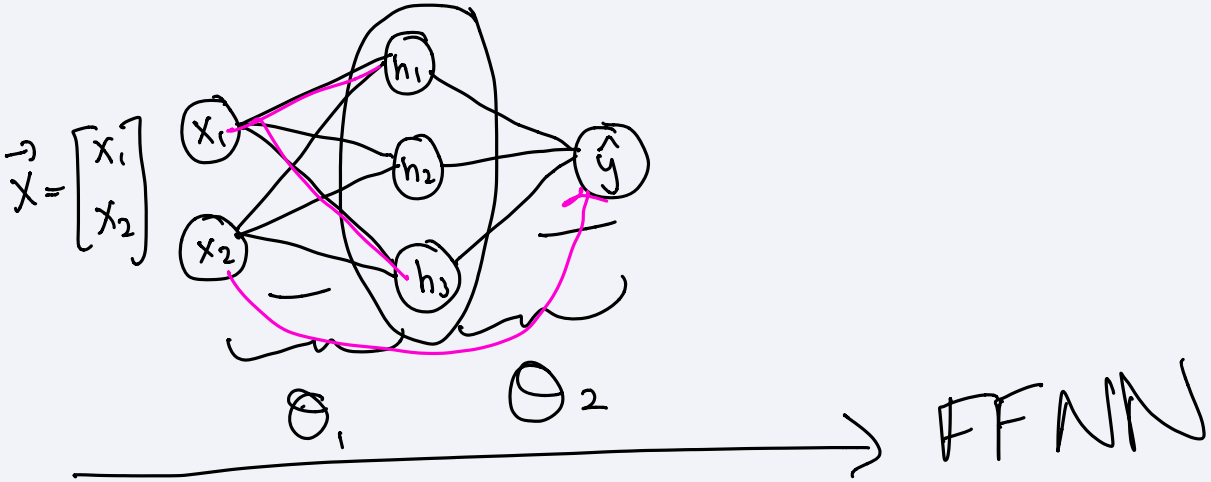
$$\theta_2 = [\theta_1' \ \theta_2' \ \theta_3'] \begin{bmatrix} h_1 \\ h_2 \\ h_3 \end{bmatrix} \leftarrow \text{neurons}$$

$$\hat{y} = \sigma(\theta_1' h_1 + \theta_2' h_2 + \theta_3' h_3)$$

Neural networks

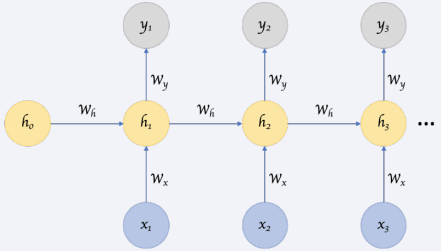
Qiskit

Graphical representation



Neural networks

The success of neural networks



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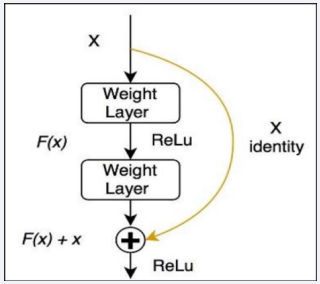

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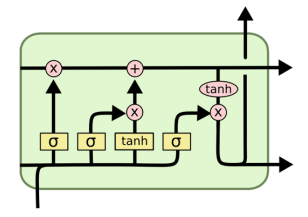

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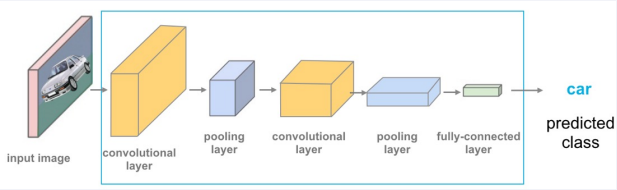
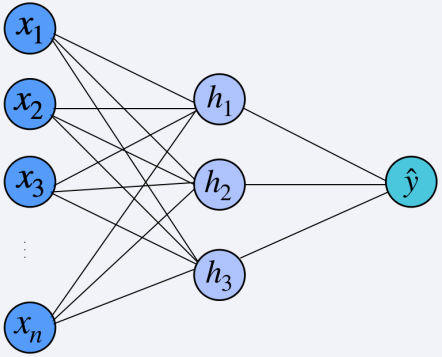


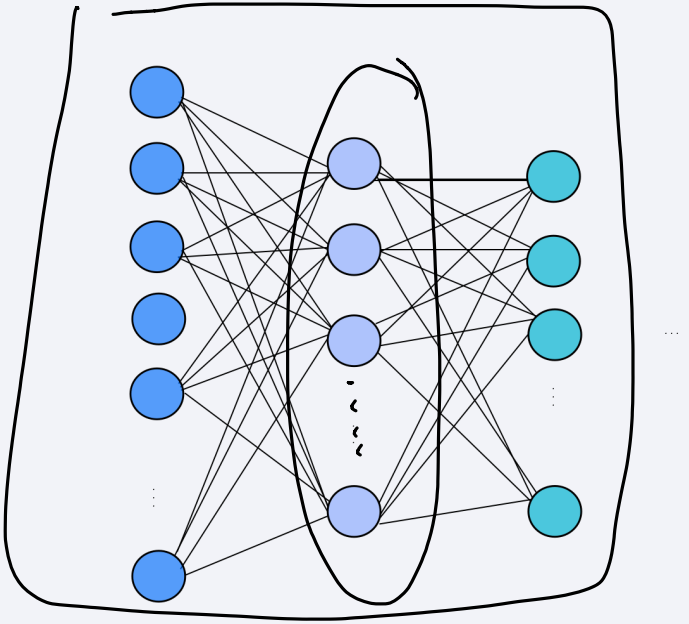
Krizhevsky et al."Imagenet classification with deep convolutional neural networks." Communications of the ACM 60.6 (2017): 84-90.

Neural networks

The success of neural networks



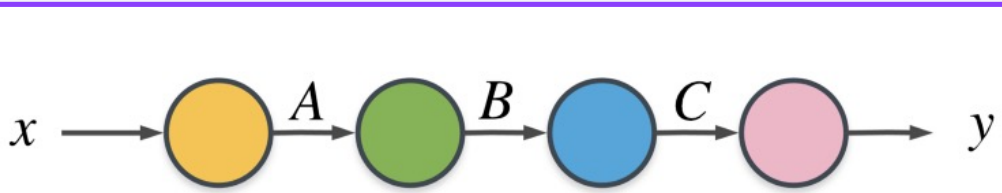
Hornik et al. "Multilayer feedforward networks are universal approximators." Neural networks 2.5 (1989): 359-366.



Michael Nielsen - https://www.youtube.com/watch?v=Ijqkc7OLenI

Neural networks

- 1970 & 1986: Backpropagation, Seppo Linnainmaa & Geoffrey Hinton



$$\frac{\partial y}{\partial x} = \frac{\partial y}{\partial C} \times \frac{\partial C}{\partial B} \times \frac{\partial B}{\partial A} \times \frac{\partial A}{\partial x}$$

Python

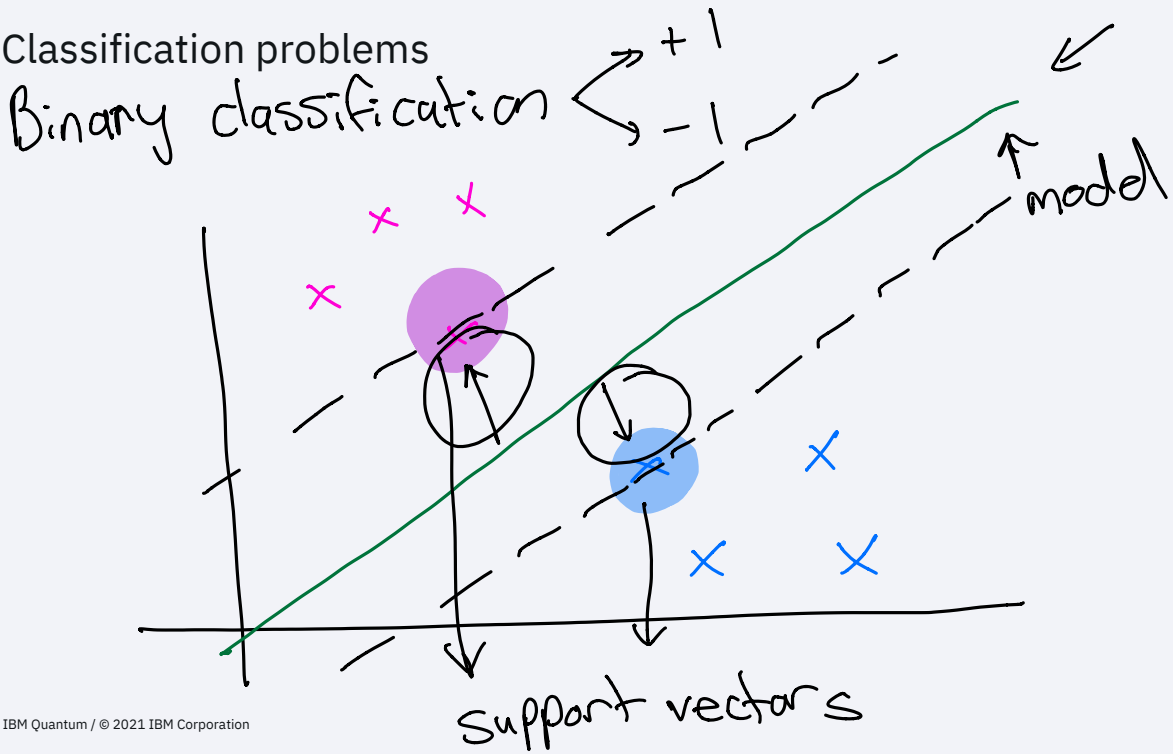
Qiskit

Support vector machines

Support vector machines

Qiskit

Classification problems



Support vector machines

Qiskit

Classification problems

Linear classifier

$y_i \in [-1, 1]$

$f(x) = \theta^T \vec{x} + b$

$\theta \in \mathbb{R}^d$

d-dimensional

→ quadratic opt.

- Primal formulation

Support vector machines

Qiskit

Classification problems

$$f(x) = \theta^T x + b$$

- Dual formulation

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i (x_i^T x) + b$$

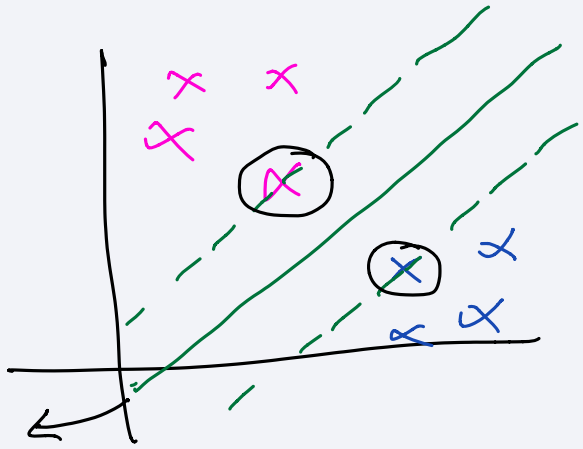
inner product

x_i x

Why?

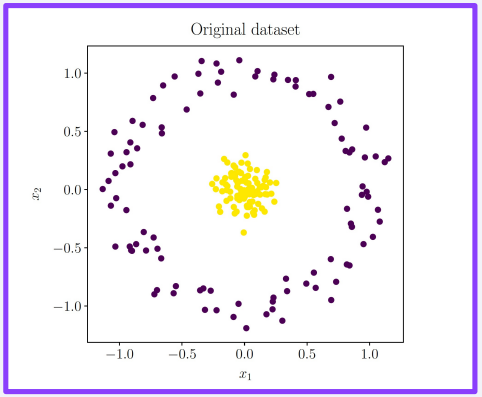
most $\alpha_i = 0$

$\#\alpha_i \neq 0 \rightarrow$ #support vectors



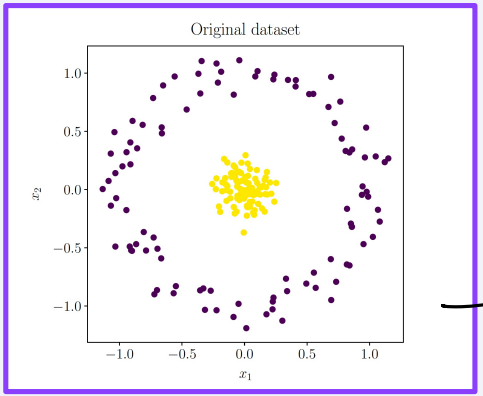
Support vector machines

Classification problems – data not linearly separable?



Support vector machines

Classification problems – data not linearly separable? Apply a **feature map**



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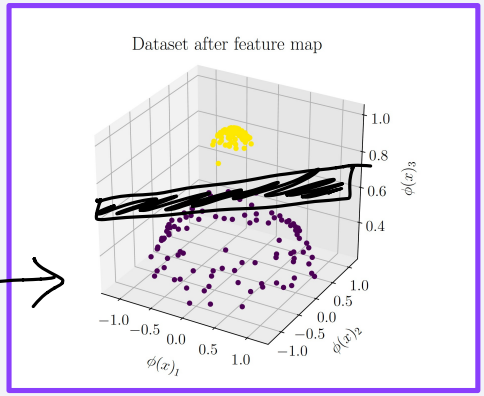


2-d

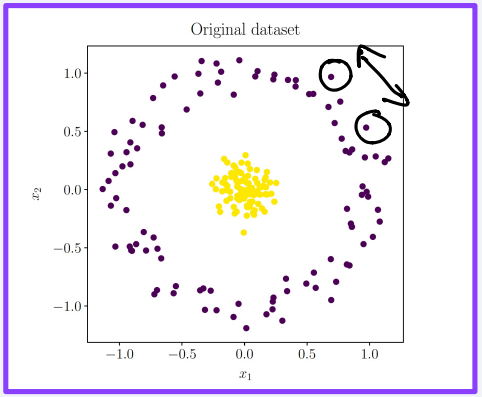
3d

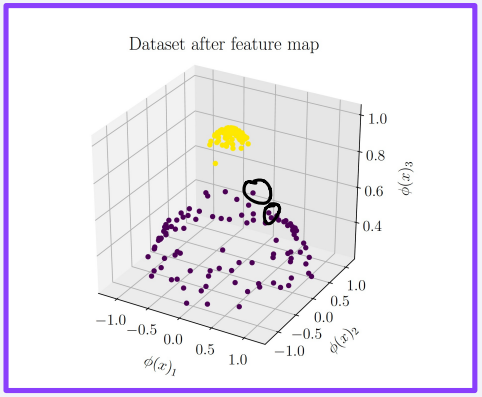
$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

$\phi(\vec{x}) = \begin{bmatrix} x_1 \\ x_2 \\ x_1 x_2 \end{bmatrix}$

Support vector machines

Classification problems – data not linearly separable? Apply a **feature map**





$x_i^T x_j$ similarity

$\phi(\vec{x})$

$\phi(x_i)^T \phi(x_j)$ similarity

Support vector machines

Qiskit

Classification problems

$$f(x) = \sum_i \alpha_i y_i (x_i^T x) + b$$

$$f(x) = \theta^T x + b$$

$$f(x) = \sum_i \alpha_i y_i (\phi(x_i)^T \phi(x)) + b$$

inner product

$$f(x) = \theta^T \phi(x) + b$$

kernel

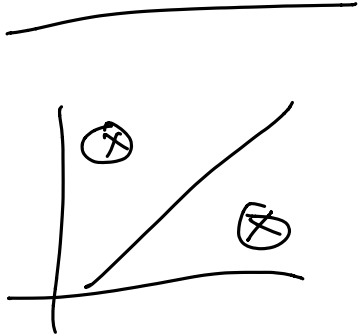
Recap

Linear models

$\hat{y} = \theta^T x + b$

Neural networks

Support vector machines



Quantum machine learning

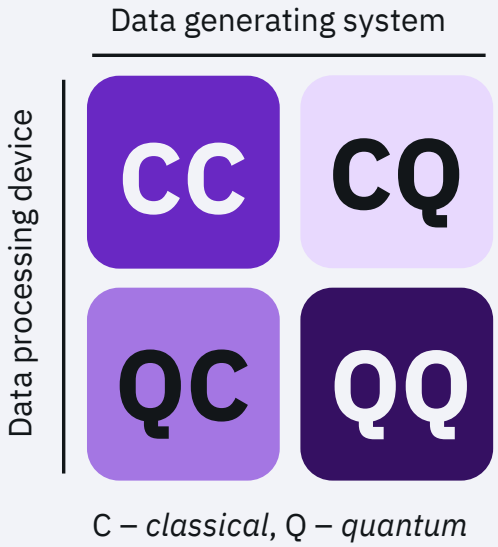
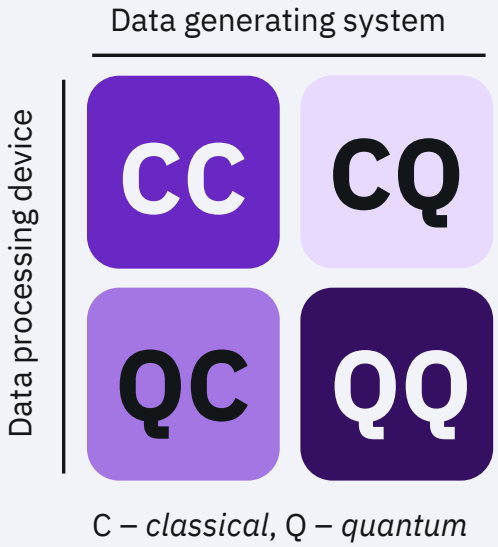


Image credit: *Maria Schuld and Francesco Petruccione. Supervised learning with quantum computers. Vol. 17. Springer, 2018.*

Quantum machine learning



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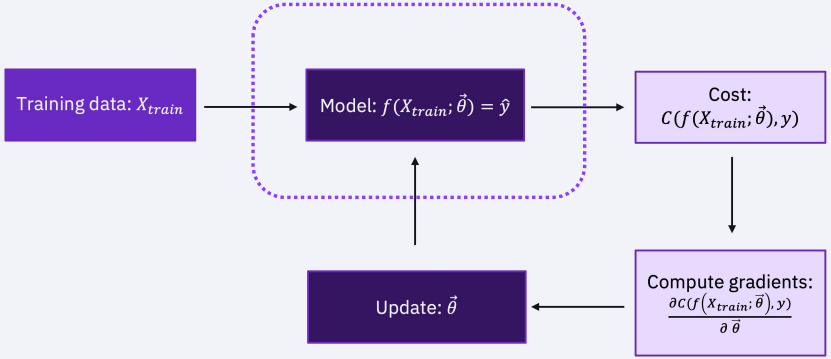


For the next lectures

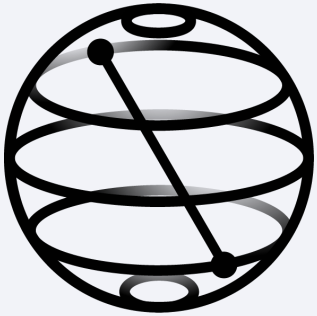
Qiskit

For the next lectures, brush up on classical ML and intro to QC concepts.

In particular:

- Linear algebra basics (vectors, matrices, tensors)
- Dirac notation (bra-ket notation, measurement operators)
- Circuit notation (gates)
- Cost function minimization (backpropagation, gradient descent)
- Support vector machines (data, feature maps, kernels)

Thank you!



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