

# CyberMAGICS Workshop: Introduction to Machine Learning

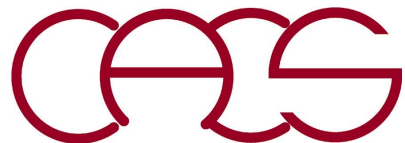
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University of Southern California*

Machine Learning hands-on: Anikeya Aditya, Nitish Baradwaj, Taufeq Razakh, Liquiu Yang



**Supported by National Science  
Foundation, Award OAC-2118061**

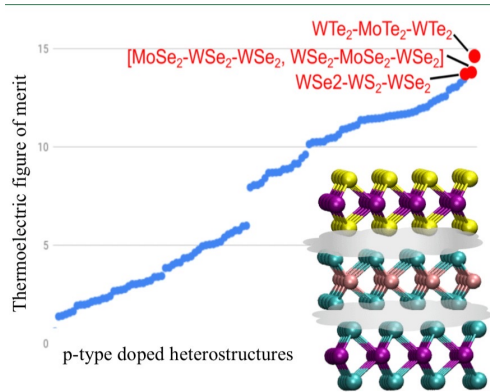


*CyberMAGICS Workshop, June 29, 2023*

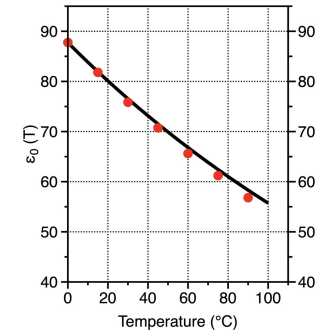
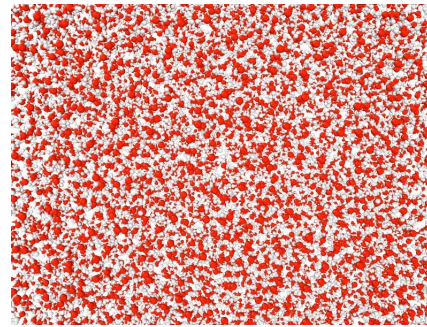


# Material Modeling with Machine Learning

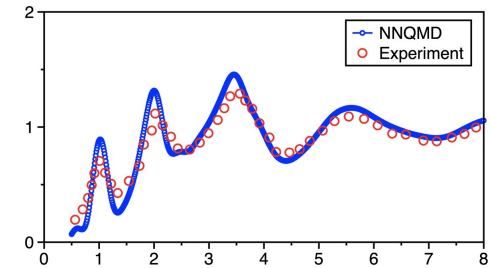
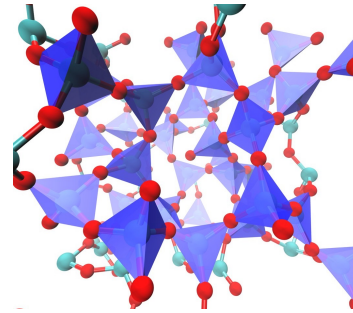
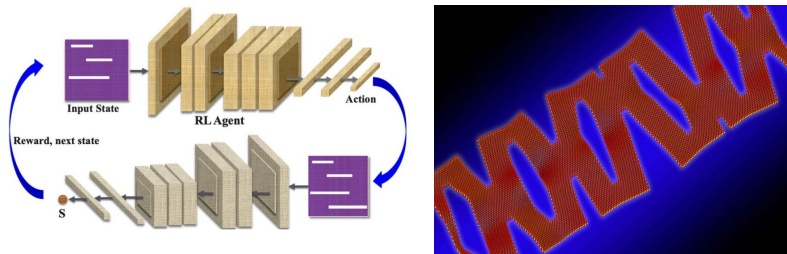
## Active learning for accelerated material design



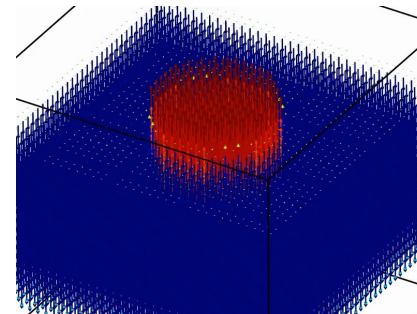
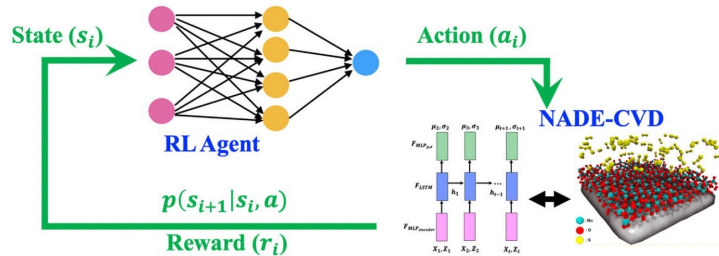
## Large-scale and long-time neural network QMD simulations



## Reinforcement learning for quantum materials synthesis

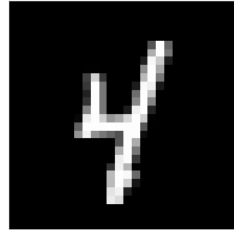


## Deep generative model for ferroelectrics

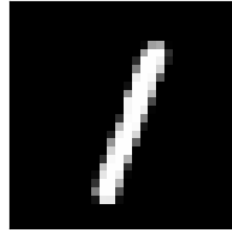


# What is Machine Learning?

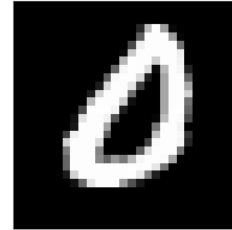
## Image classification using MNIST dataset



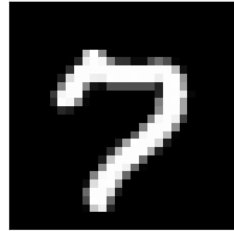
4 (4)



1 (1)



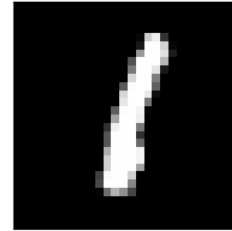
0 (0)



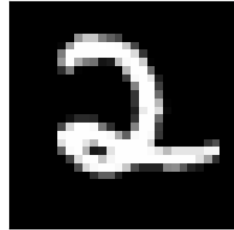
7 (7)



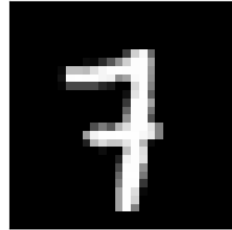
8 (8)



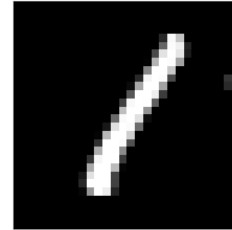
1 (1)



2 (2)



7 (7)



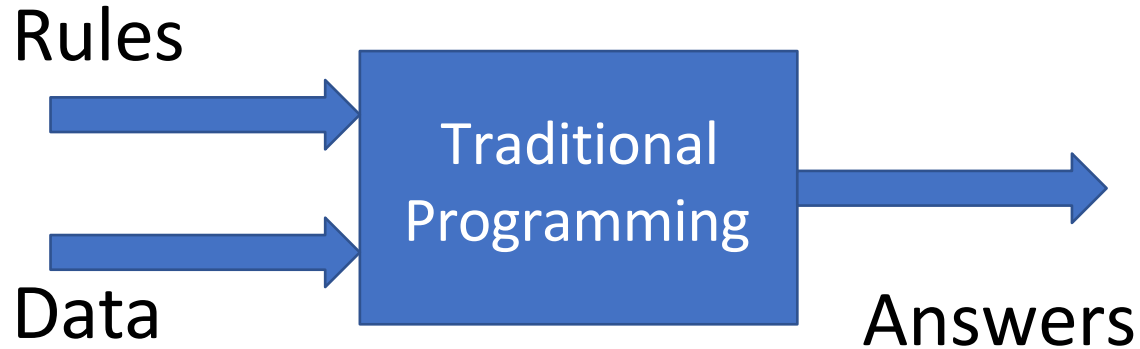
1 (1)

# What is Machine Learning?



# What is Machine Learning?

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# Classification vs Regression

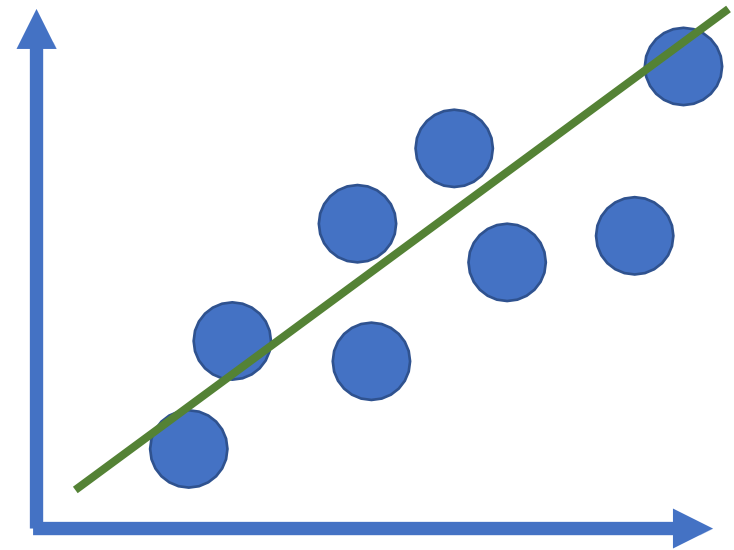
## Classification

Predict class label



## Regression

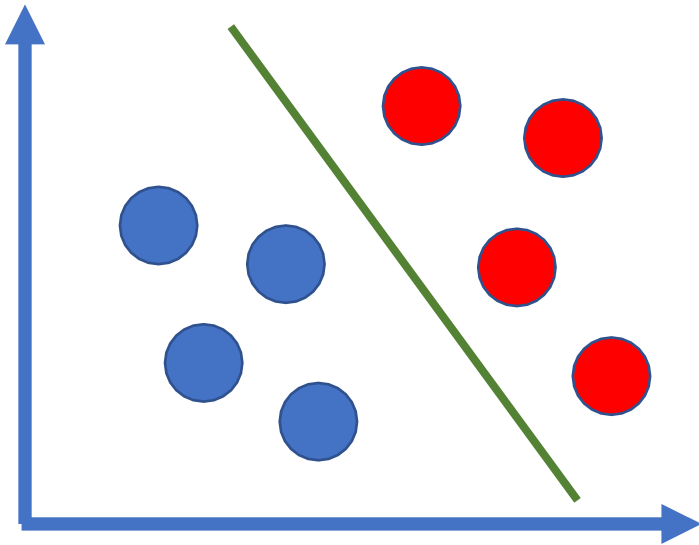
Predict real value



# Supervised vs Unsupervised

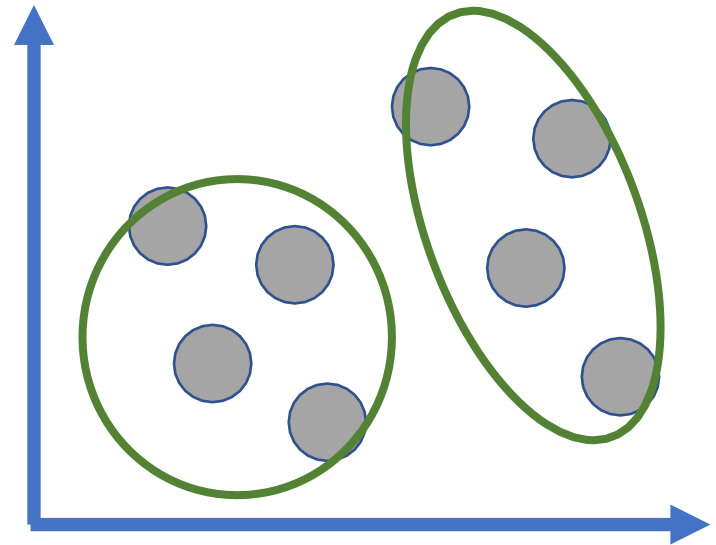
## Supervised:

Data are "labeled"  
classification, regression



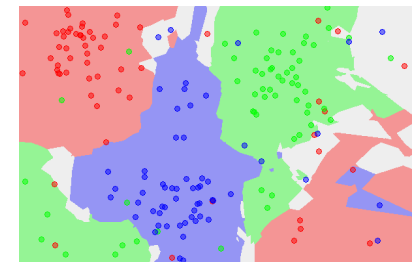
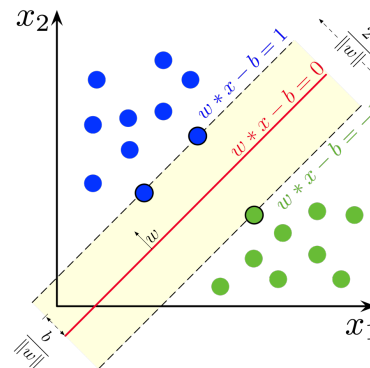
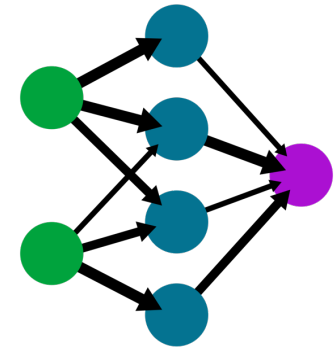
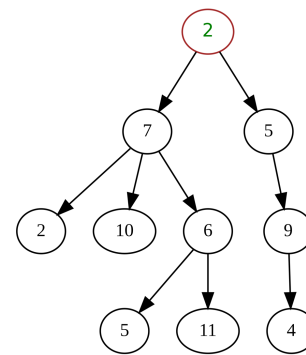
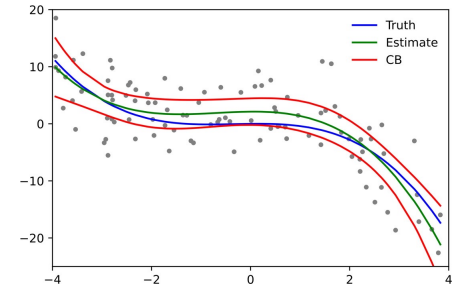
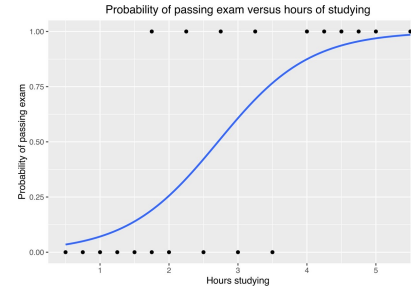
## Unsupervised:

Data are "not labeled"  
Clustering, dimensionality  
reduction



# ML Algorithms

- Linear/polynomial Regressions
- Logistic Regression
- K-Nearest Neighbors
- Decision Trees
- Random Forests
- Support Vector Machines
- Neural Networks
- Bayesian Networks
- PCA & t-SNE

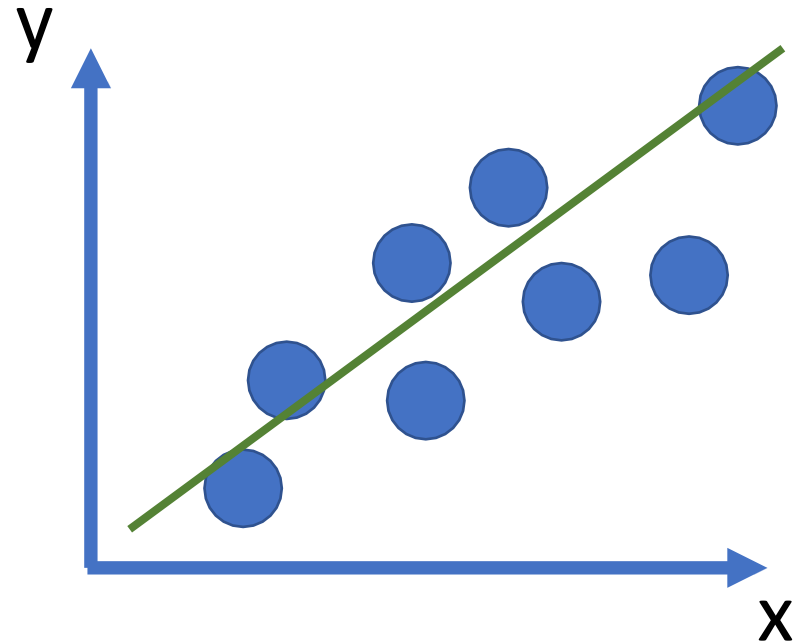




# Linear Regression

- Assumes a linear relationship between the input variable(s) and the output variable (y)
- Can be univariate, multivariate, polynomial, logarithmic, ...
- Coefficients ( $b_i$ ) are obtained by minimizing the sum of the difference between all data and line

$$\hat{y} = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n = \mathbf{x}_i^T \boldsymbol{\beta}$$

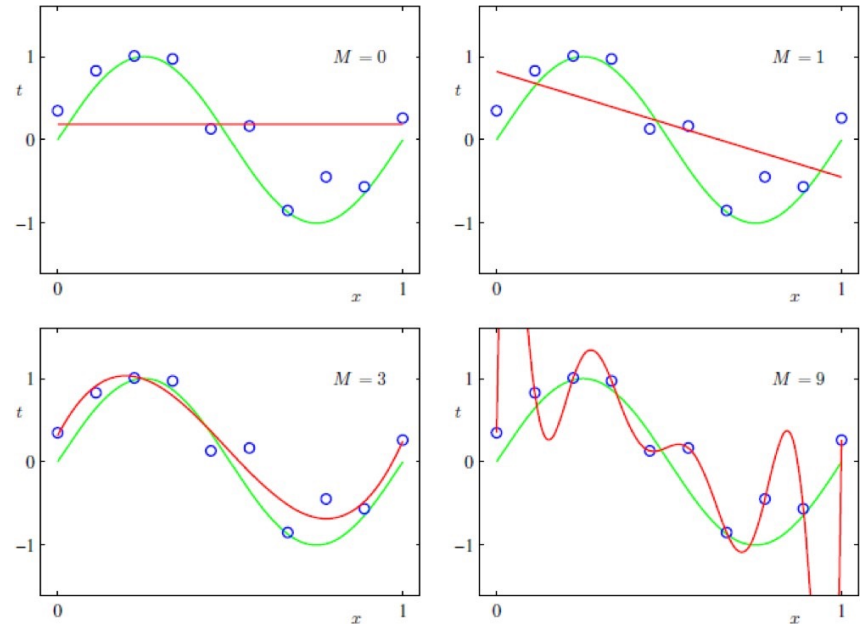


$$L = \frac{1}{N} \sum_{i=1}^N (\hat{Y}_i - Y_i)^2$$

# Overfitting and Regularization

- A good ML model should accurately predict existing training data as well as “unseen” (out-of-sample) data
- A model with many parameters tends to pick up noise in data and poorly perform on unseen data, i.e. overfitting
- Regularizations, such as Ridge and LASSO

$$\hat{y} = \beta_0 + \beta_1 x_1 + \dots + \beta_n x_n = \mathbf{x}_i^T \boldsymbol{\beta}$$



True function

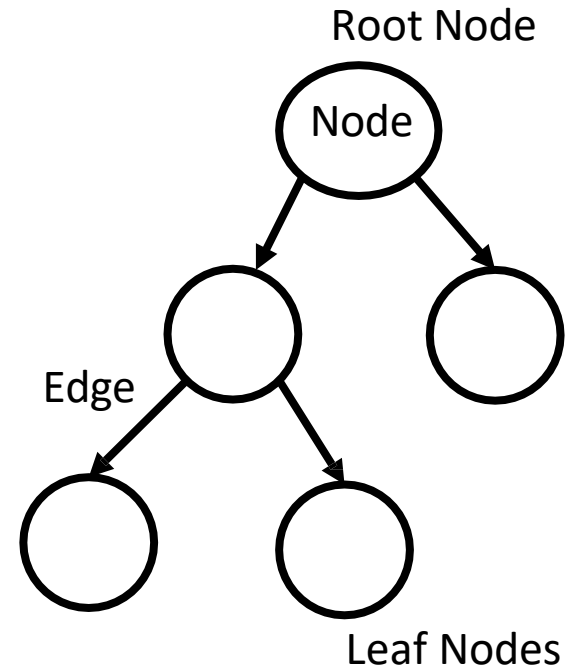
Training data with noise

Model predictions

$$\min_{\beta, \beta_0} \left\{ \frac{1}{N} \|y - X\beta\|^n \right\} \text{ with } \|\beta\| \leq t \text{ or } \|\beta\|^2 \leq t$$

# Decision Tree and Random Forest

- Used for classification or regression
- Starting from root node, “ask a question and select an answer” until a leaf node is reached
- Tree construction based on information theory
  - Gini index/entropy for classification
  - Variance/RMSE for regression
- Easy to construct and interpret, but also overfit



$$I_{Gini} = 1 - \sum_j p_j^2$$

$$I_{entropy} = -\sum_j p_j \log(p_j)$$

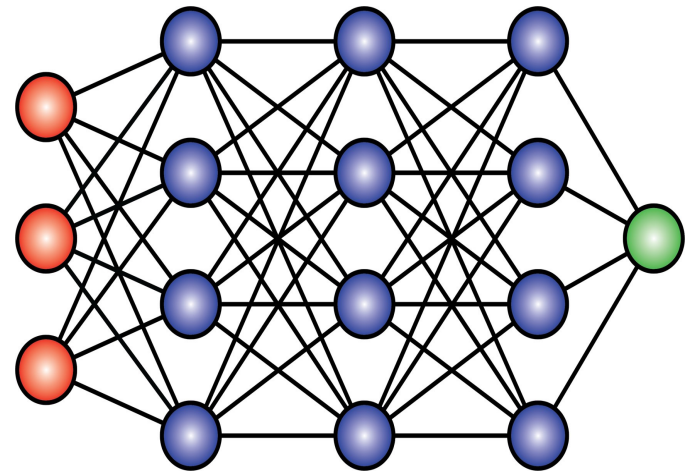
# Decision Tree and Random Forest

- **Ensemble of decision trees**
- **Aggregate predictions from each tree as the model prediction**
- **Good prediction accuracy, generalizability, robust to overfitting**
- **Less interpretability to single decision tree**

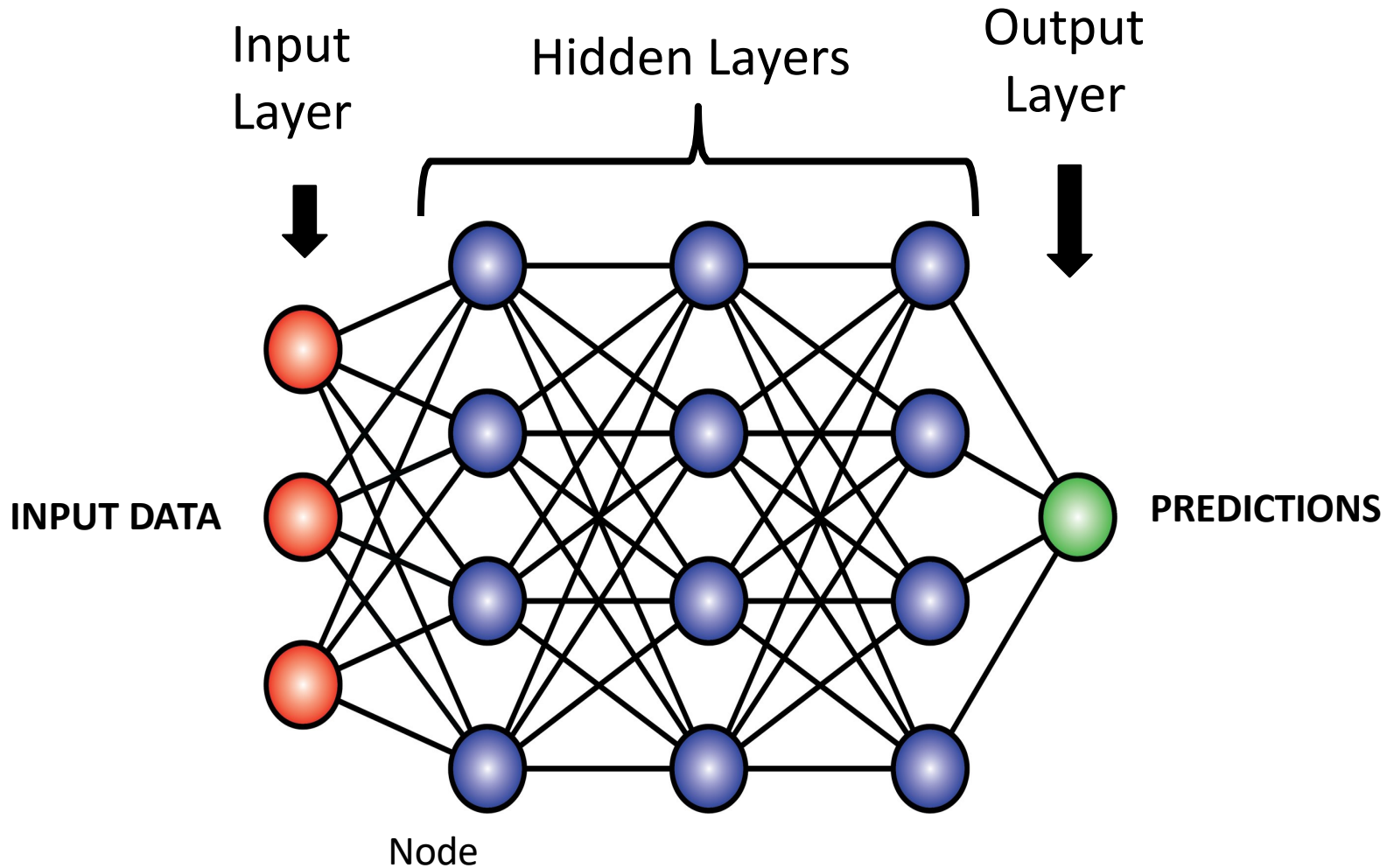


# Neural Network

- **Inspired by biological brain**
- **A universal function approximator**
- **A key component in other deep learning algorithms**
- **Hyperparameters**
  - **Number of nodes**
  - **Degree of connectivity of nodes**
  - **Number of layers in network**

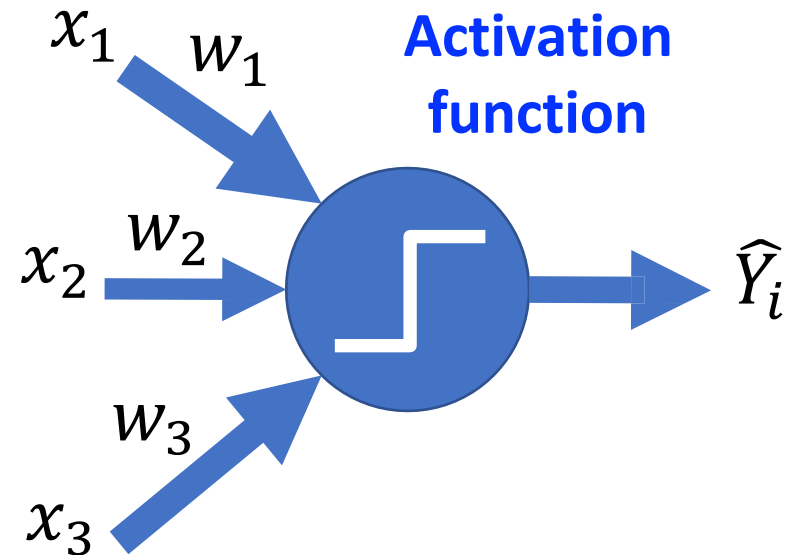


# Neural Network



# Neural Network

- On each node, outputs ( $x$ ) from previous layer are aggregated with weights ( $w$ )
- A non-linear activation function transforms the aggregated inputs and pass it to next layer
- Compute Loss function (difference between model prediction and given true value) after the output layer

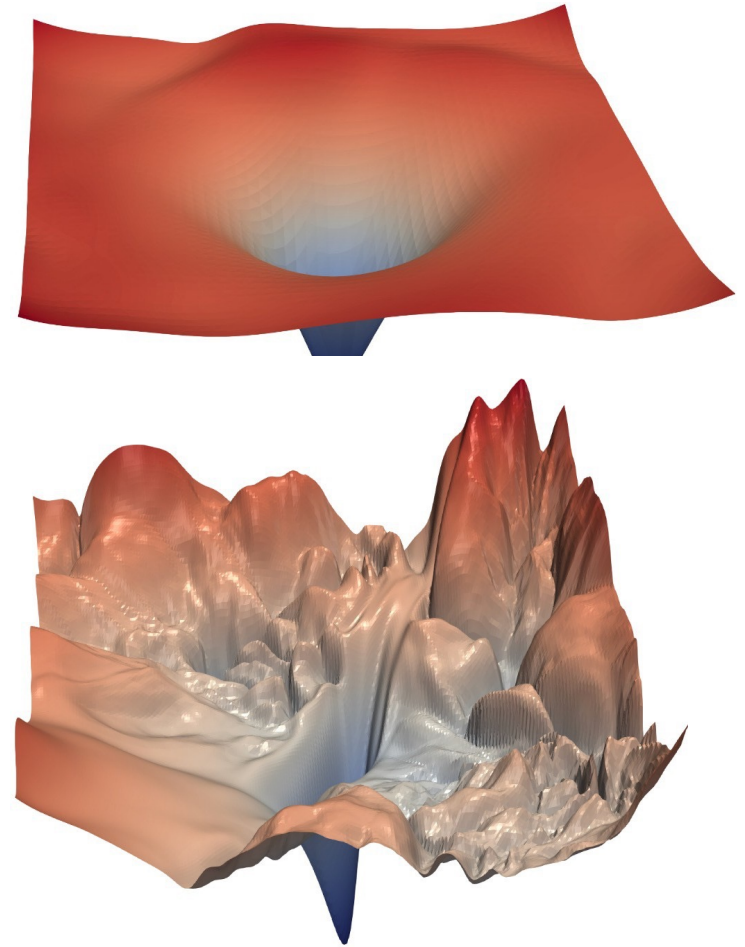
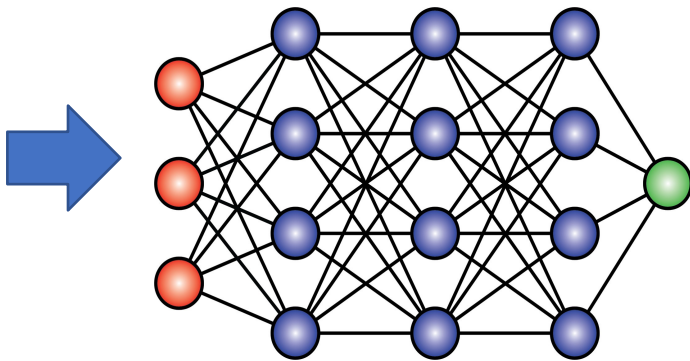


$$L = \frac{1}{N} \sum_{i=1}^N (\hat{Y}_i - Y_i)^2$$

# Neural Network Training

- Network parameters are “trained” by minimizing loss function
- Stochastic gradient descent is commonly used

$$\Delta w = -\partial L / \partial w$$



Loss function landscape



# Moving Forward

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- **Linear algebra, Statistics & Probability, Python**

- **Online courses**

<https://www.coursera.org/browse/data-science/machine-learning>

- **Textbooks**

Deep Learning

Ian Goodfellow and Yoshua Bengio and Aaron Courville

<https://www.deeplearningbook.org/>

The Elements of Statistical Learning

Trevor Hastie, Robert Tibshirani, Jerome Friedman

<https://hastie.su.domains/ElemStatLearn/>

- **Python Programming**

Scikit-learn <https://scikit-learn.org>

Pytorch <https://pytorch.org>

Tensorflow <https://www.tensorflow.org>