DEEP LEARNING WITH KERAS

Themistoklis Diamantopoulos

Contents

INTRODUCTION TO MACHINE LEARNING

What is Machine Learning?

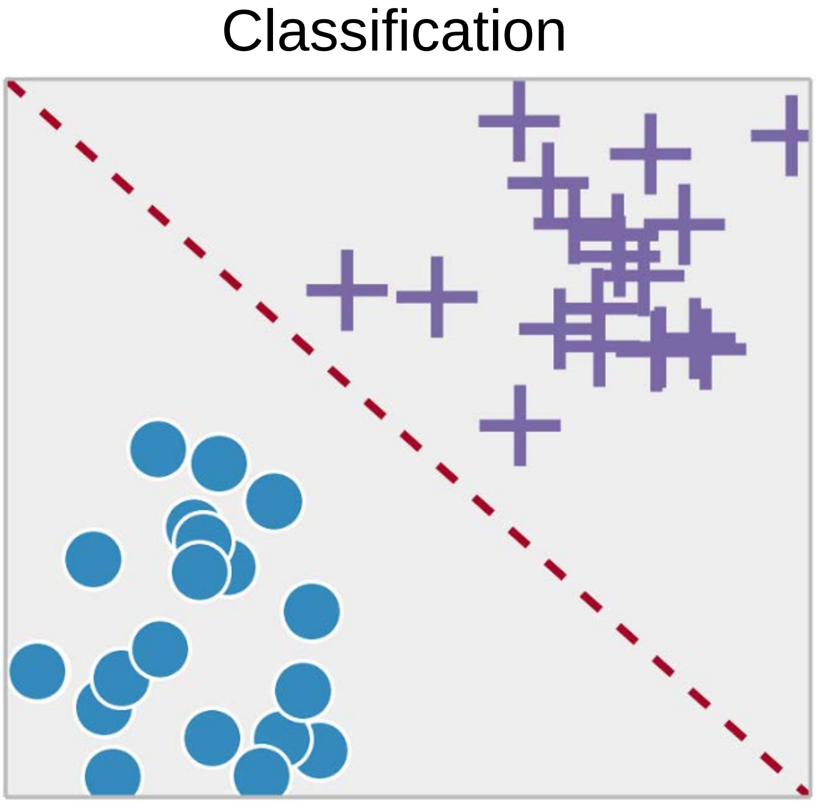
- Subfield of Artificial Intelligence
- Term coined in 1959 by Arthur Samuel

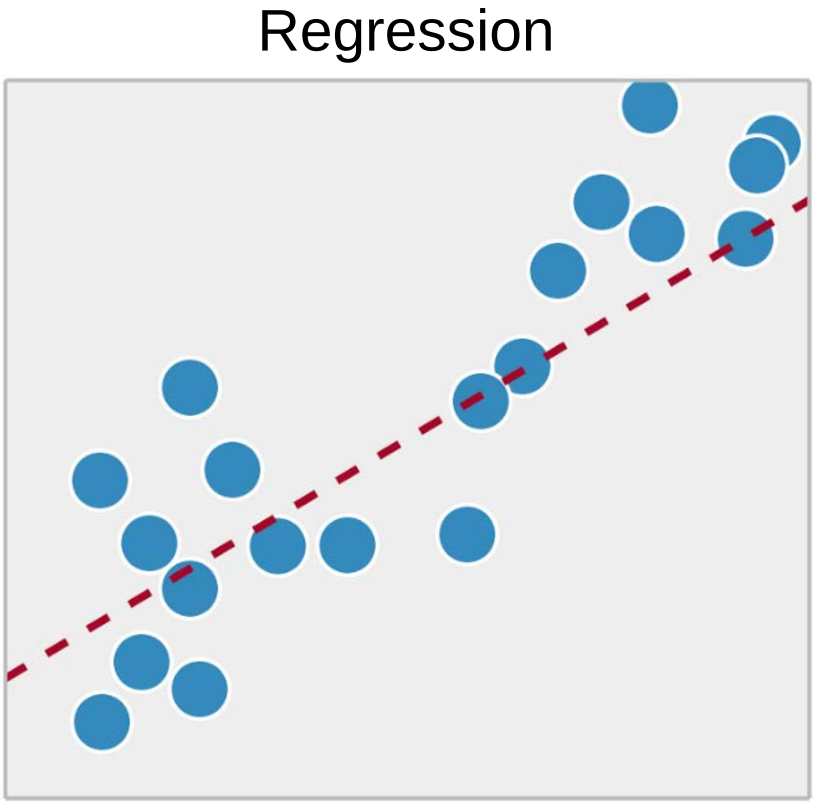
Progressively improve performance on a specific task with data, without being explicitly programmed

Types of Machine Learning tasks

- Supervised Learning
  - Learn output based on input data
- Unsupervised Learning
  - Find structure in given data
- Reinforcement Learning
  - Learn from the environment

Supervised Learning tasks



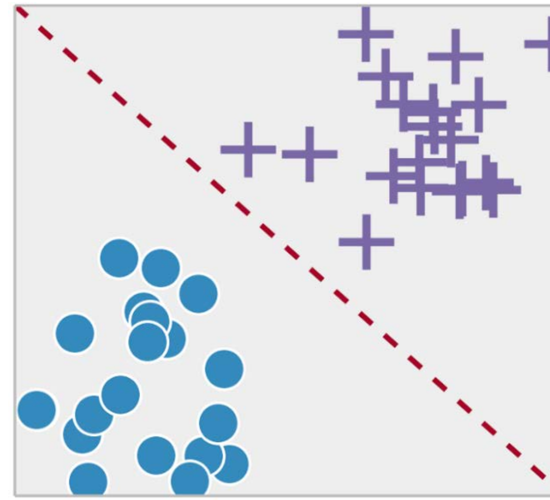


Source: https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68e32ea8d

Classification

- Classify data to 1, 2 or more classes
- Confusion Matrix

Predicted Class \ Actual Class	Positive	Negative
Positive	TP	FP
Negative	FN	TN
	P = TP + FN	N = FP + TN



- Evaluation Metrics
  - Accuracy = (TP + TN) / (P + N)
  - Precision = TP / (TP + FP)
  - Recall = TP / P

Bonus: Cross Entropy

$$H(y,\hat{y}) = \sum_i y_i \log \frac{1}{\hat{y}_i} = -\sum_i y_i \log \hat{y}_i$$

Source: https://rdipietro.github.io/friendly-intro-to-cross-entropy-loss/

Regression

- Build a model that fits the data
- Actual (y_i) and predicted values ($\hat{y}_i$)
  - Mean Absolute Error

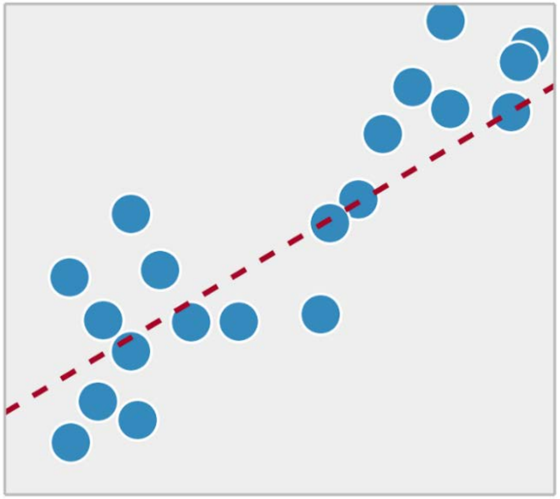
$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|\hat{y}_i - y_i\right|$$

  - Mean Squared Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2$$

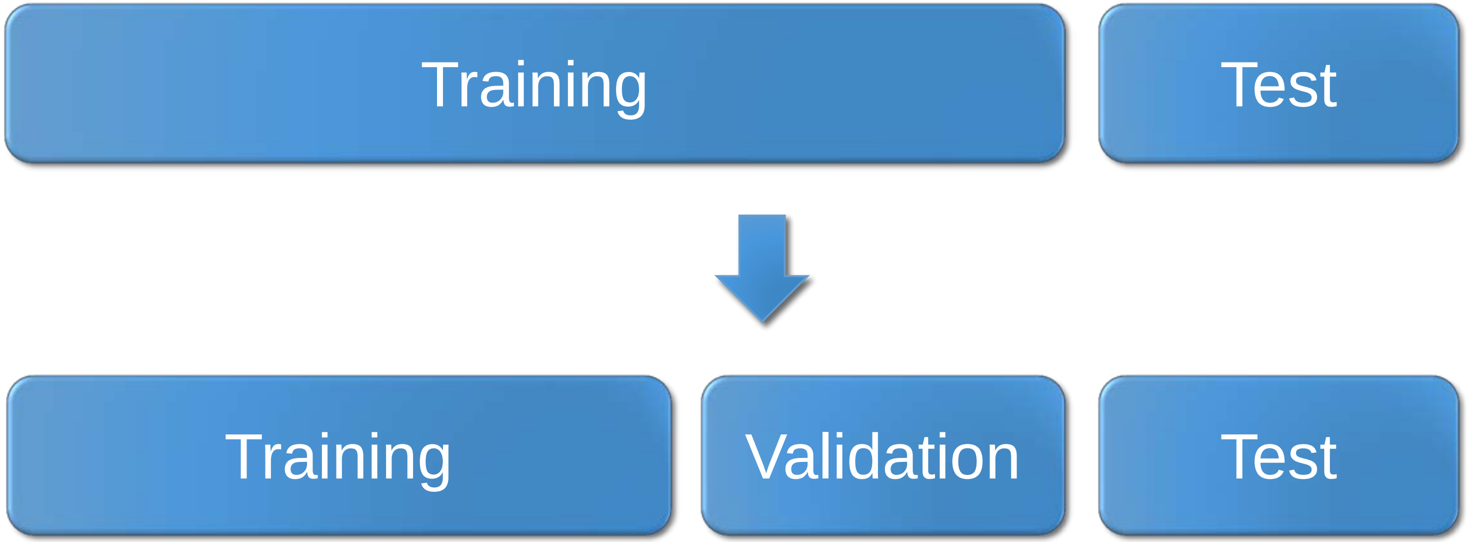
  - Coefficient of Determination

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad \text{where} \quad SS_{res} = \sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad \text{and} \quad SS_{tot} = \sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2$$



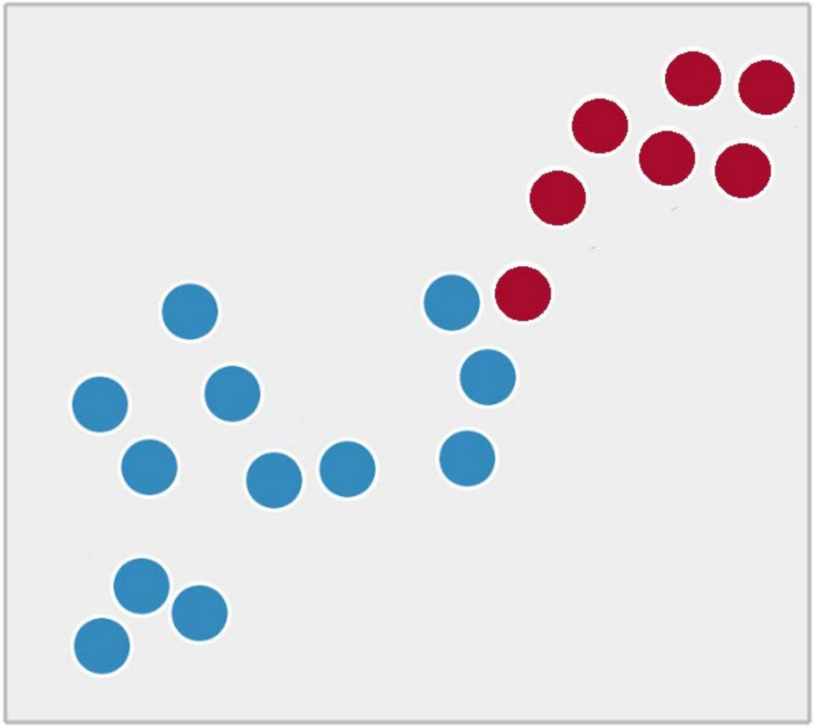
Data Splitting

- Use training data to train the model
  - Some data can be used to validate the model → validation set
  - Use folds of training data for validation → Cross-validation
- Evaluate the model on test data
  - Test set must not overlap with training data

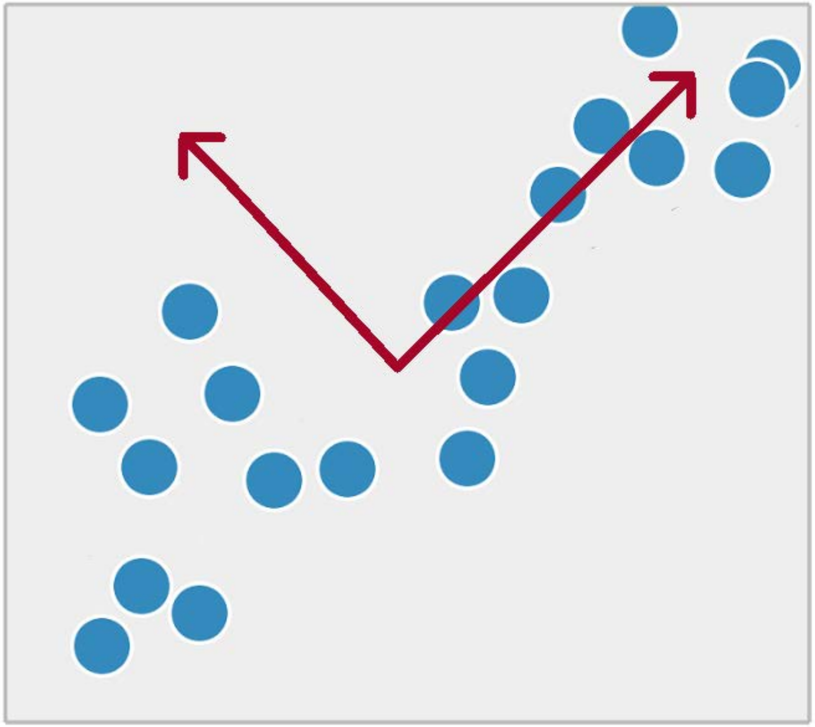


Unsupervised Learning tasks

Clustering



Dimensionality Reduction



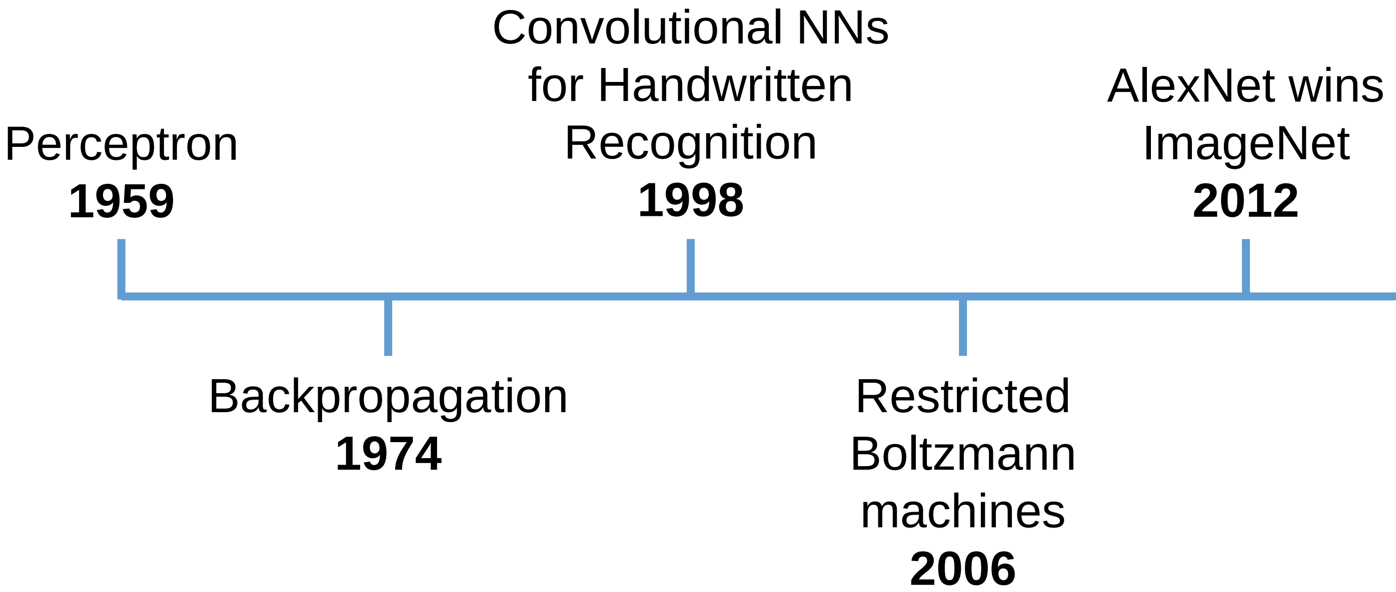
INTRODUCTION TO NEURAL NETWORKS

Why Neural Networks?

- Cognitive features
- Inspired by the brain
  - 10^{11} neurons
  - 0.001 sec switching time
  - $>10^4$ connections per neuron
  - 0.1 sec for scene recognition

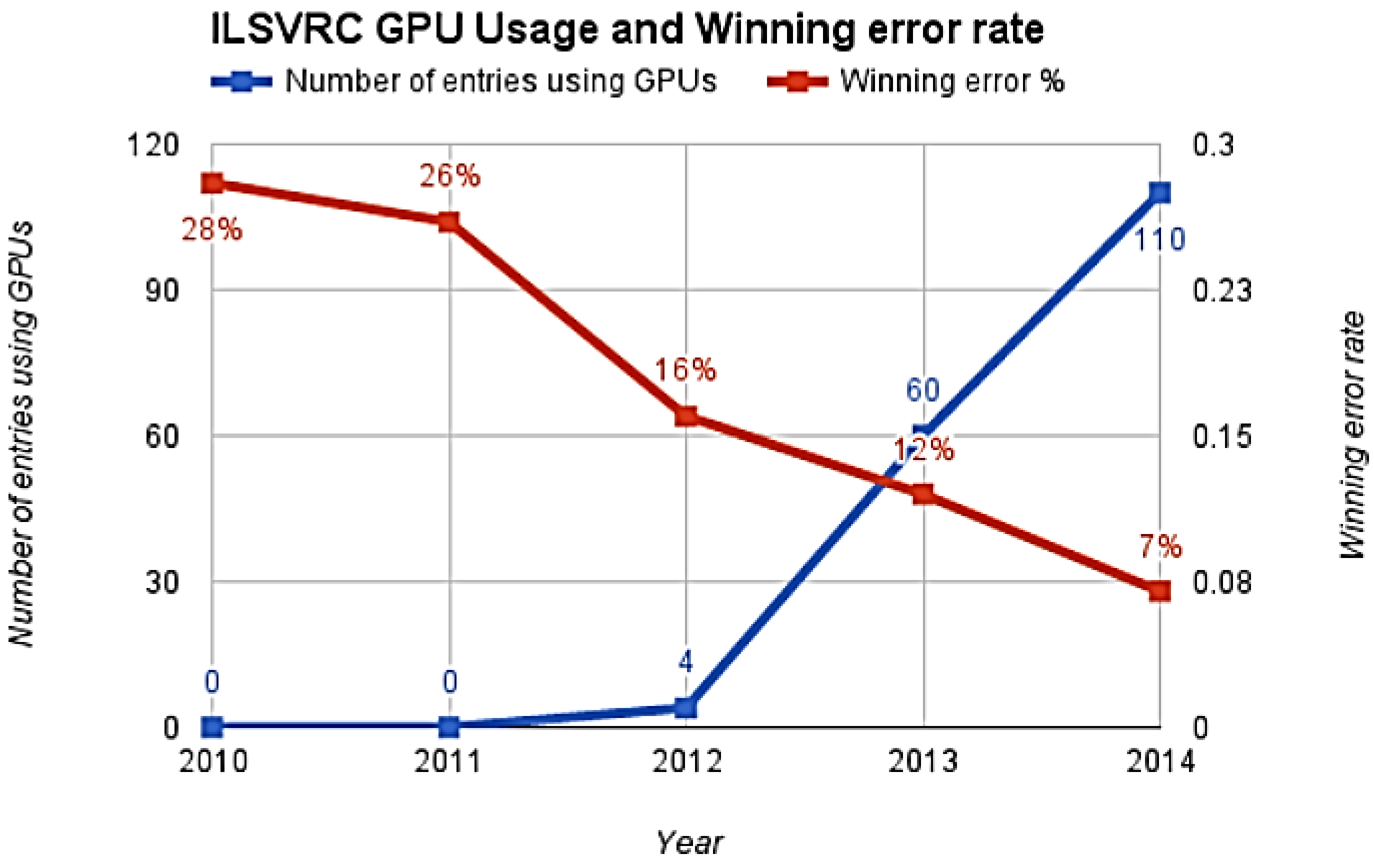
A brief history course

- From the perceptron to deep learning
- AI Winter 1969 – 1986



The first breakthrough

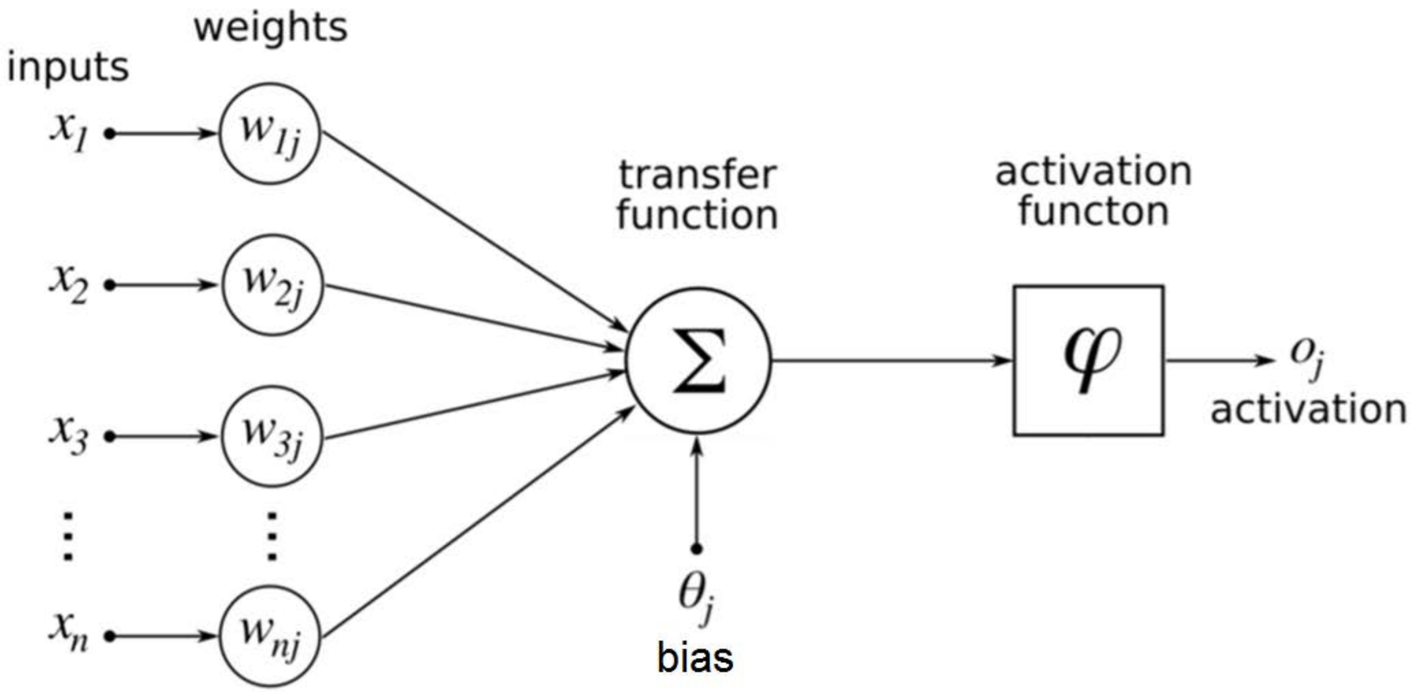
- ImageNet image recognition challenge



Source: https://beamandrew.github.io/deeplearning/2017/02/23/deep_learning_101_part1.html

The perceptron - where it all started

- Invented in 1959 by Frank Rosenblatt
- Practically also the first Neural Network

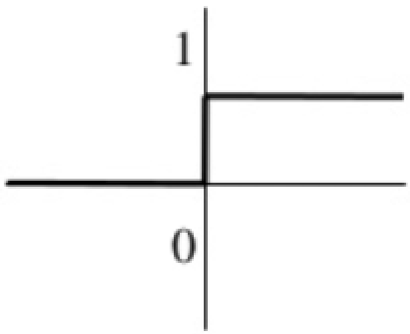


Source: https://commons.wikimedia.org/wiki/File:ArtificialNeuronModel_english.png

Activation functions

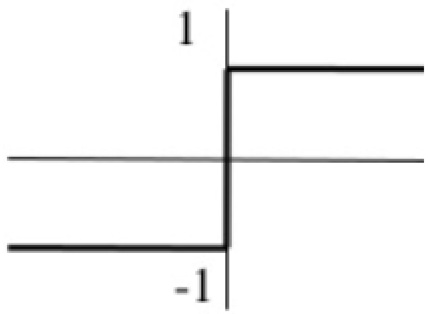
- Different types of functions

Step function



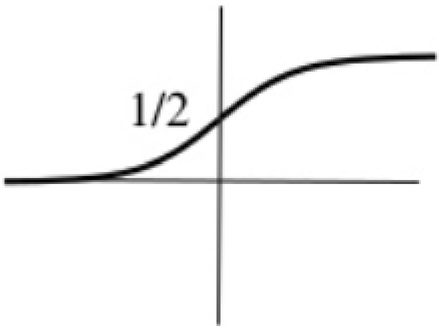
$$step_t(x) = \begin{cases} 1 & x > t \\ 0 & otherwise \end{cases}$$

Sign function



$$sign(x) = \begin{cases} +1 & x \geq 0 \\ -1 & otherwise \end{cases}$$

Sigmoid function



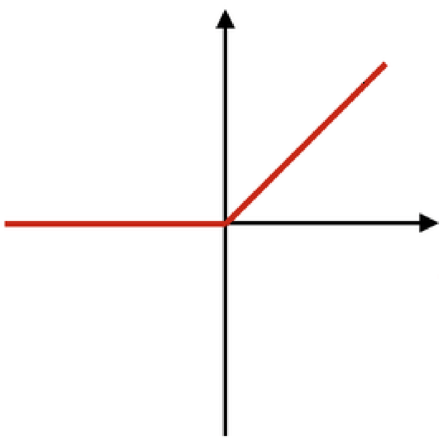
$$sigmoid(x) = \frac{1}{1+e^{-x}}$$

Useful Resource: https://en.wikipedia.org/wiki/Activation_function

Activation functions (continued)

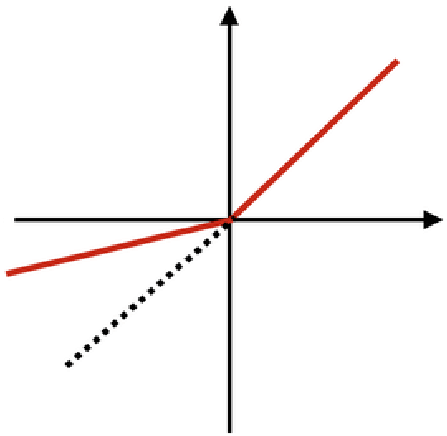
- Different types of functions

ReLU
(Rectified Linear Unit)



$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$$

PReLU
(Parametric ReLU)



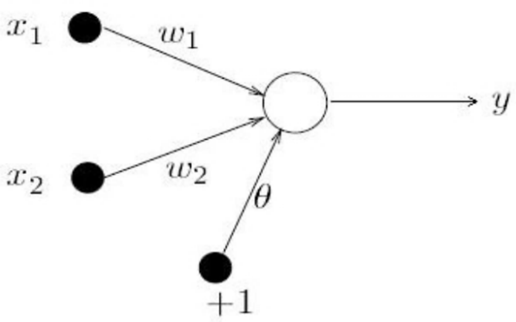
$$f(\alpha, x) = \begin{cases} \alpha x & \text{for } x < 0 \\ x & \text{for } x \geq 0 \end{cases}$$

Softmax
(similar to Sigmoid - generalized logistic function used for multiclass classification problems

Useful Resource: https://en.wikipedia.org/wiki/Activation_function

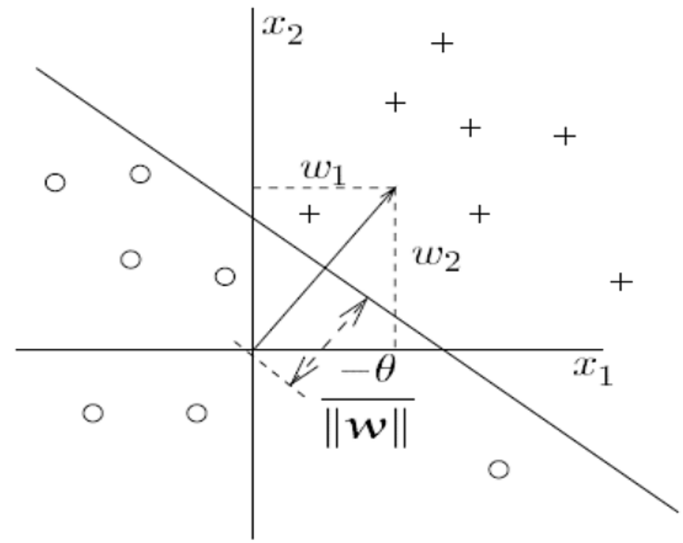
Example use of perceptron

- Bias → Offset from the origin
- Weights → Slope of the line



$$w_1 x_1 + w_2 x_2 + \theta = 0$$

$$x_2 = -\frac{w_1}{w_2} x_1 - \frac{\theta}{w_2}$$



$$y = \operatorname{sgn}\left(\sum_{i=1}^{2} w_i x_i + \theta\right)$$

$$\operatorname{sgn}(s) = \begin{cases} 1 & \text{if } s > 0 \\ -1 & \text{otherwise.} \end{cases}$$

$$d(n) = \begin{cases} +1 & \text{if } x(n) \in \text{set } A \\ -1 & \text{if } x(n) \in \text{set } B \end{cases}$$

REPEAT

1. Select random sample from training set
2. If classification is correct, do nothing
3. If classification is incorrect, modify w:

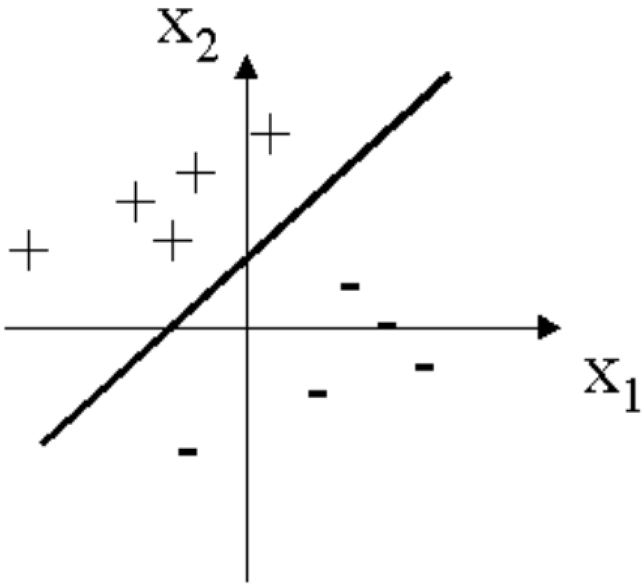
$$w_i = w_i + \eta d(n) x_i(n)$$

Source: http://aass.oru.se/~lilien/ml/seminars/2007_02_01b-Janecek-Perceptron.pdf

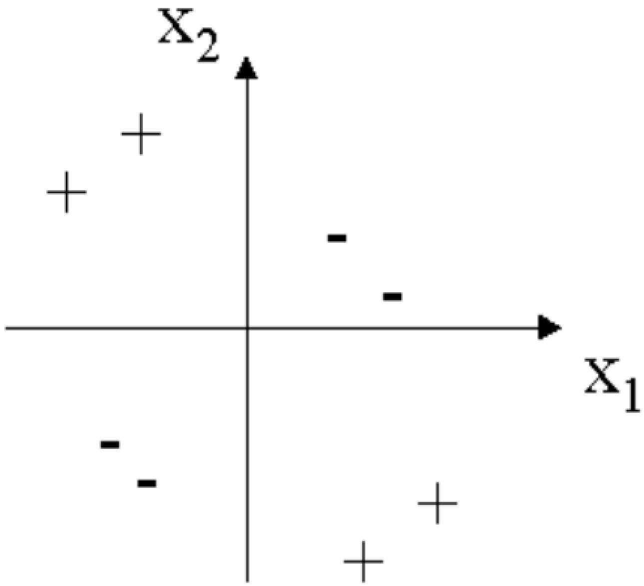
Limitations of perceptron

- Can be used only for Linearly Separable Data

Linearly Separable



Not Linearly Separable

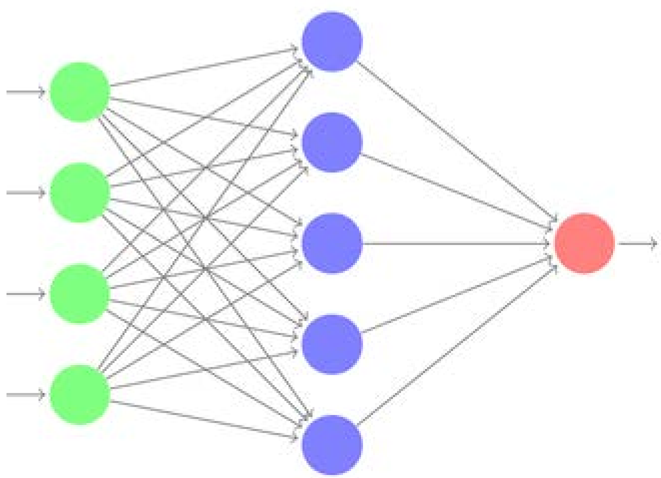


Source: http://aass.oru.se/~lilien/ml/seminars/2007_02_01b-Janecek-Perceptron.pdf

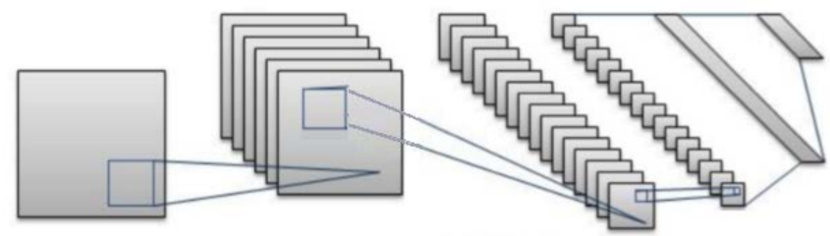
Neural Network Topologies

- Used for different types of problems

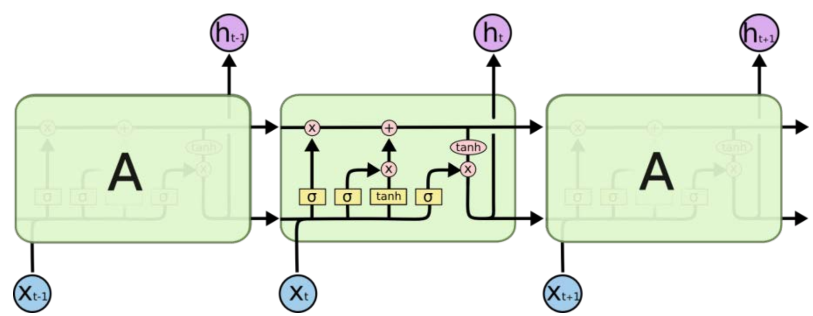
Multi-Layer Perceptron



Convolutional Neural Network



Recurrent Neural Network

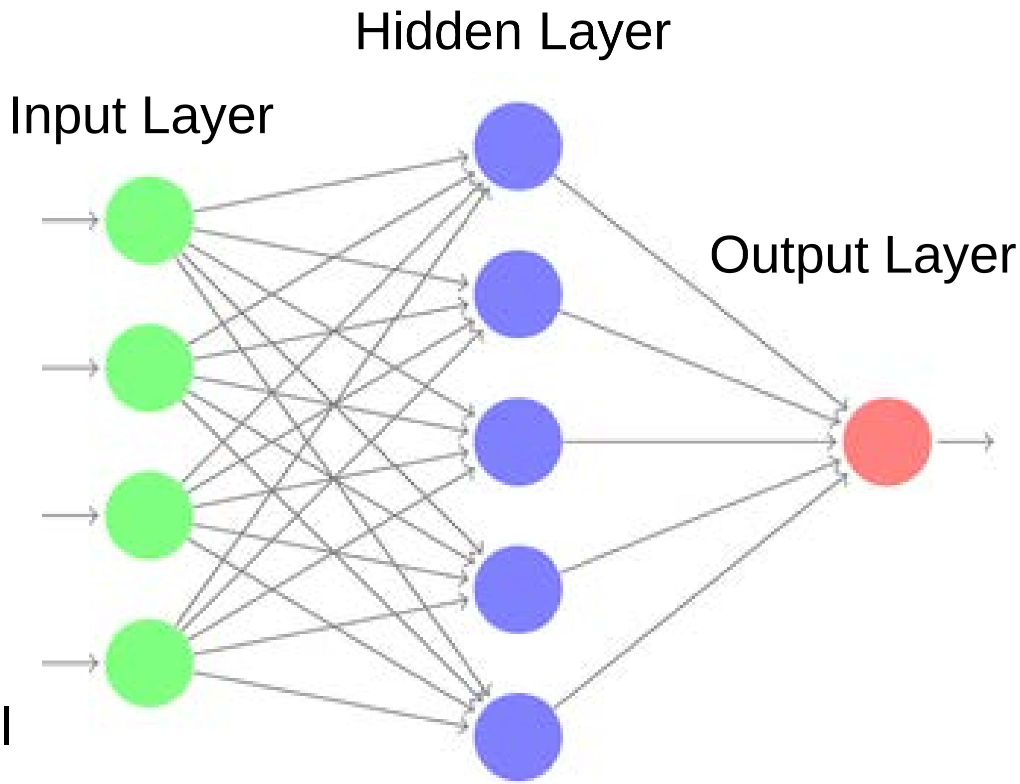


Useful Resource: https://towardsdatascience.com/the-mostly-complete-chart-of-neural-networks-explained-3fb6f2367464

MULTI-LAYER PERCEPTRON

Training a Multi-Layer Perceptron

- Gradient Descent
  - Start with some initial parameters θ
  - Update them using:
    $$\theta \leftarrow \theta - \eta \cdot \nabla_{\theta} E(\mathrm{x}, \theta, \mathrm{y})$$
    where:
    - η: learning rate
    - $E(x, \theta, y)$: error
  - Continue until error is small

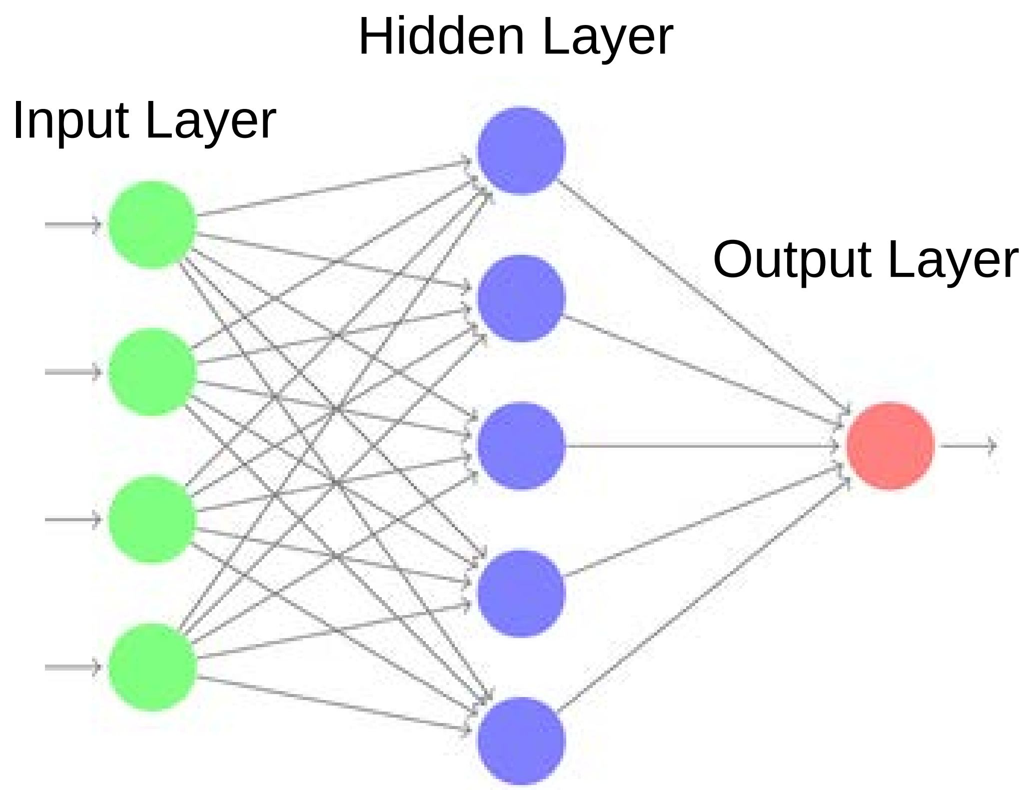


Training a Multi-Layer Perceptron

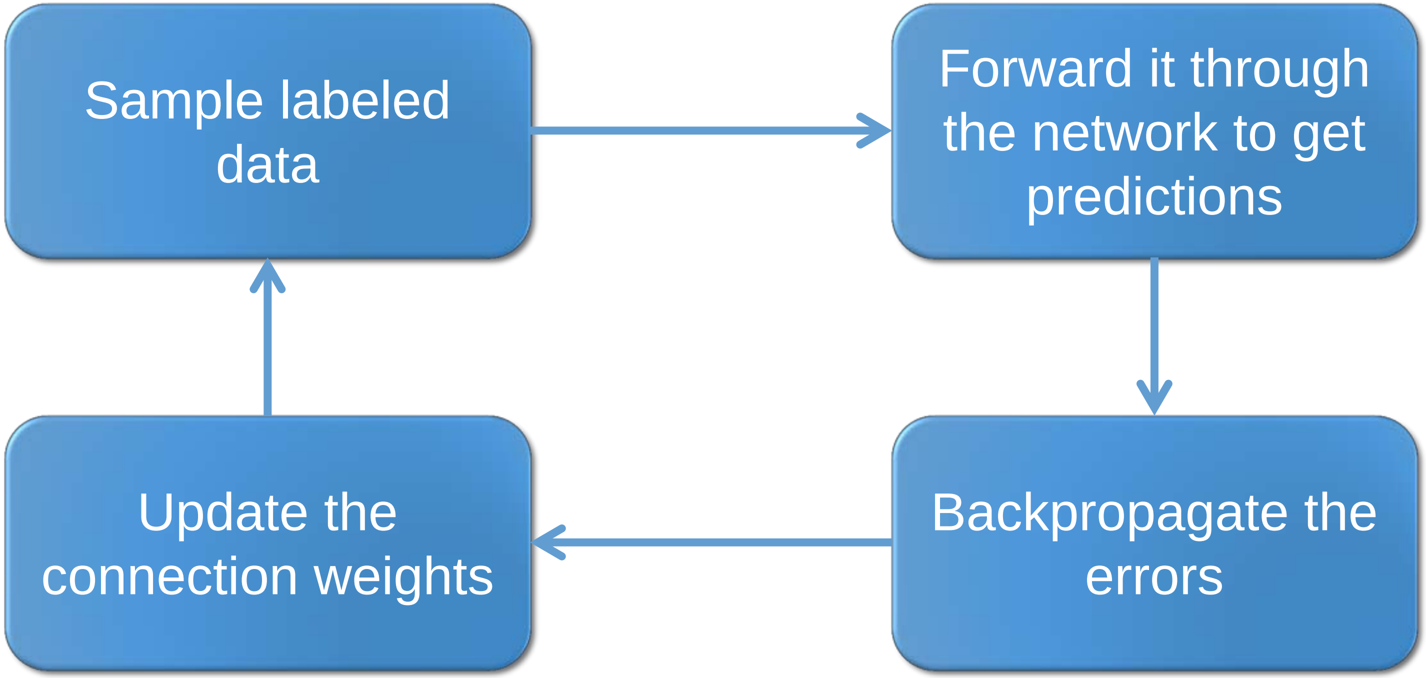
- Gradient Descent

$$\theta \leftarrow \theta - \eta \cdot \nabla_{\theta} E(\mathrm{x}, \theta, \mathrm{y})$$

- Backpropagation
  - Easy way to compute $\nabla_{\theta} E(\mathrm{x}, \theta, \mathrm{y})$



Training a Multi-Layer Perceptron

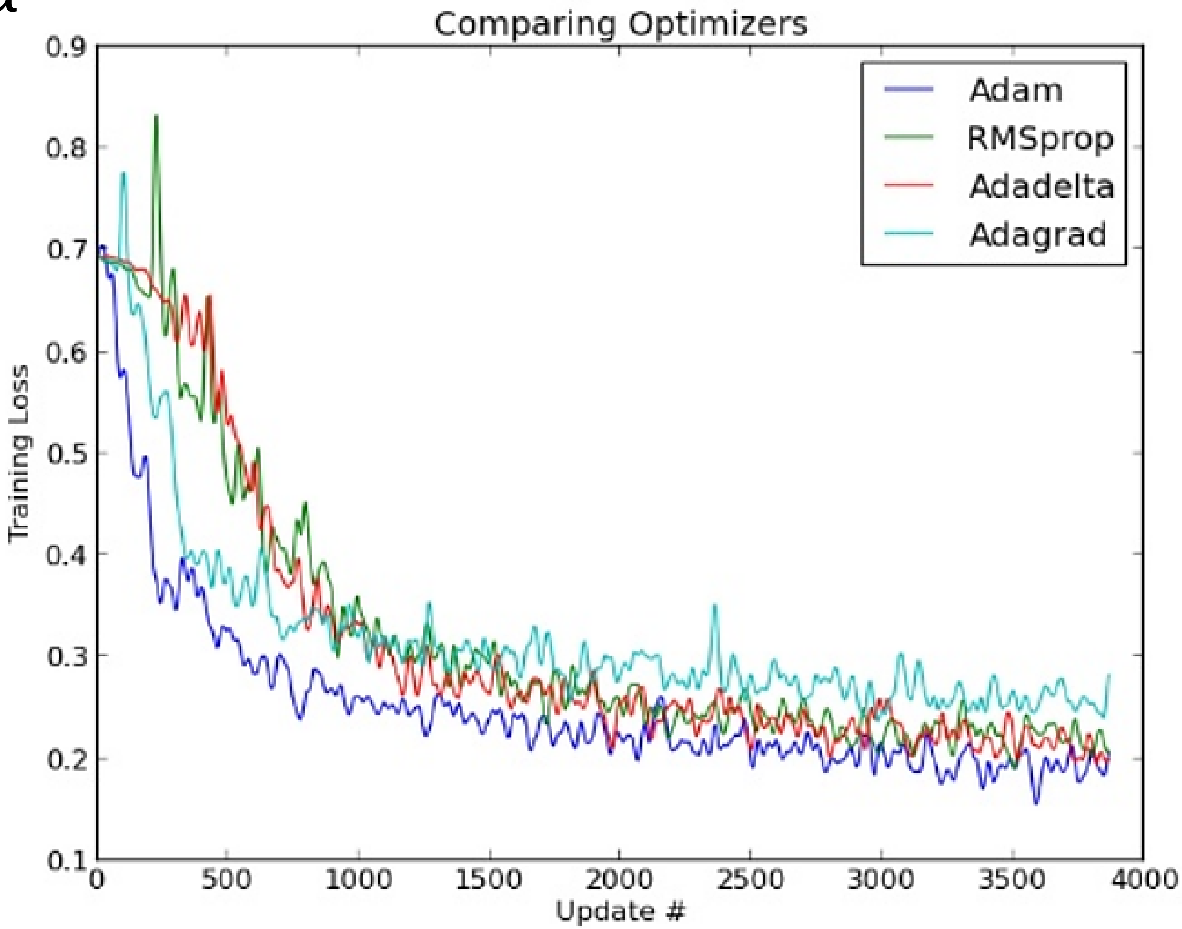


Generate an error signal that measures the difference between the predictions of the network and the desired values and then use this error signal to change the weights so that predictions get more accurate

Source: https://www.slideshare.net/LuMa921/deep-learning-a-visual-introduction

Gradient Descent Optimizers

- RMSprop, Adadelta
  - Better later convergence
- Adagrad
  - Early optimization speed
- Adam
  - Combines the advantages of the above



Source: https://www.slideshare.net/indicods/general-sequence-learning-with-recurrent-neural-networks-for-next-ml

INTRODUCTION TO DEEP LEARNING

What is Deep Learning?

- Subfield of Machine Learning
- Practical definition:

Imitates the workings of the human brain in processing data and creating patterns for use in decision making

What are Deep Neural Networks?

- Simple answer:

  Neural Networks with many layers

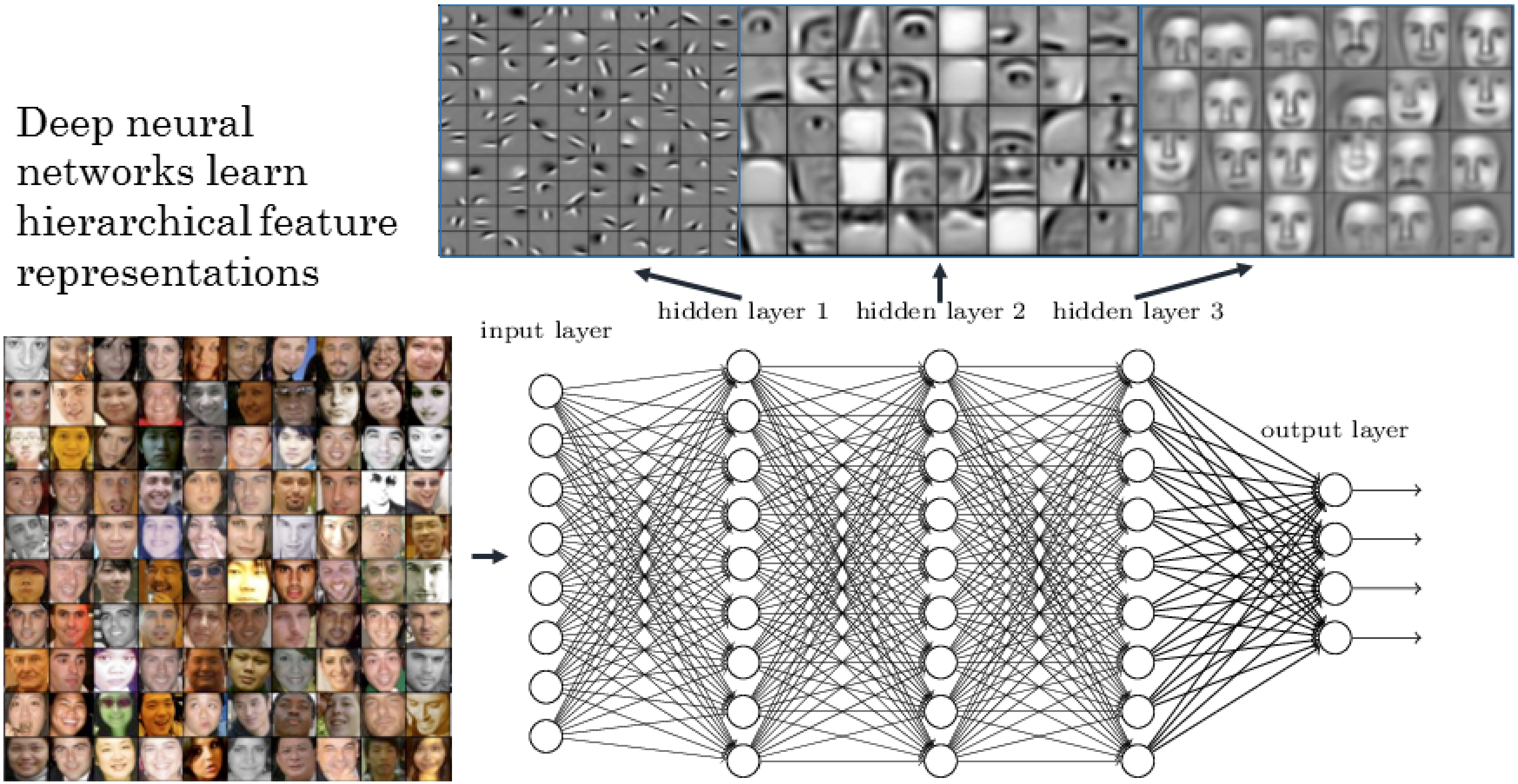
- Practical answer:

  Neural Networks with more than one hidden layer

- Elaborate answer:

  Neural Networks that train on a distinct set of features in each layer → Feature Hierarchy

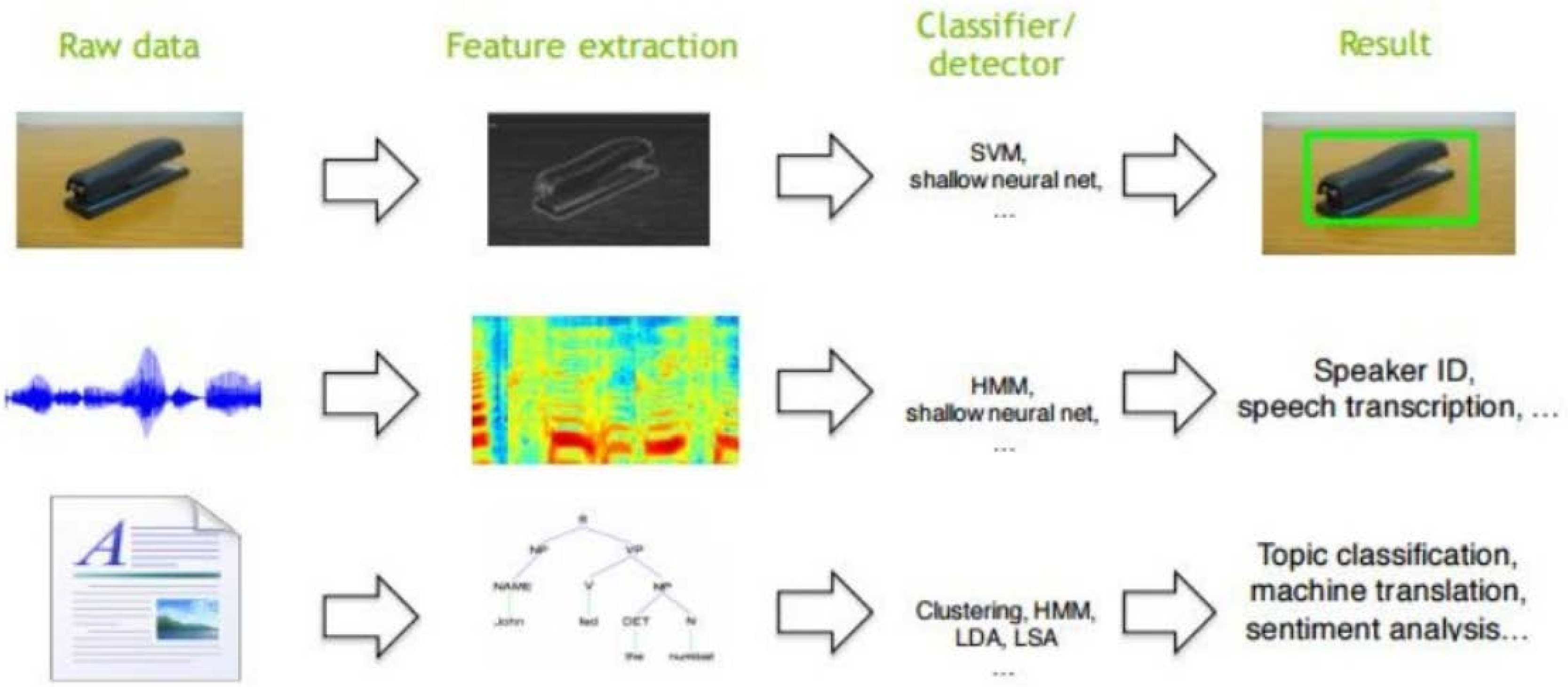
Feature Hierarchy



Source: https://www.strong.io/blog/deep-neural-networks-go-to-the-movies

Traditional Machine Perception

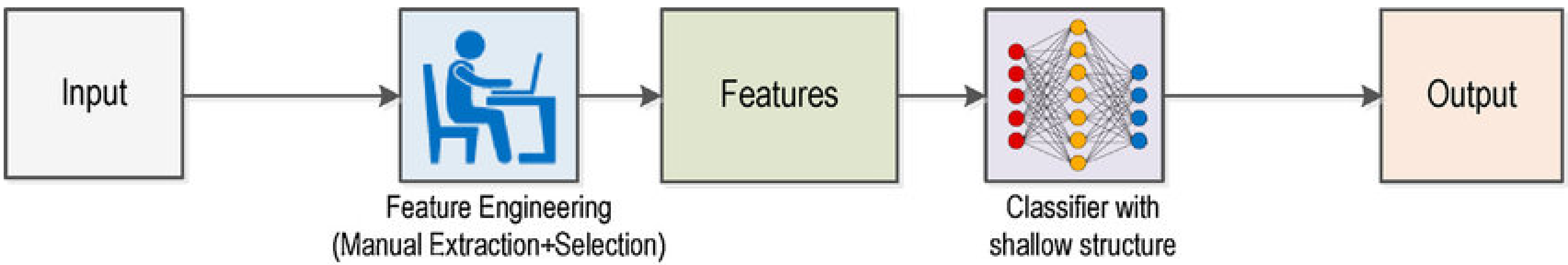
- Hand-crafted Feature Extraction



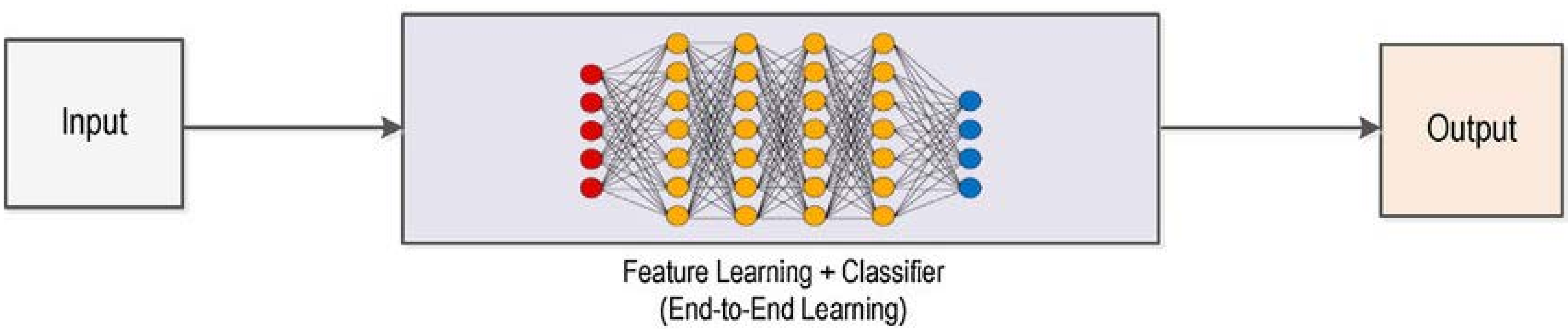
Source: https://www.slideshare.net/kuanhoong/big-data-malaysia-a-primer-on-deep-learning

Traditional vs Deep Learning

Traditional Learning



Deep Learning

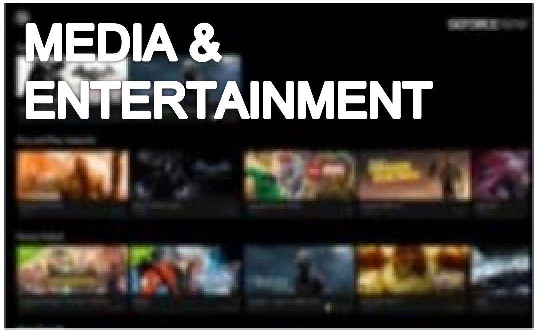


Source: https://www.researchgate.net/publication/322325843

Deep Learning Applications

Cancer Cell Detection
Diabetic Grading
Drug Discovery

Image Classification
Speech Recognition
Language Translation



Video Captioning
Video Search
Real Time Translation

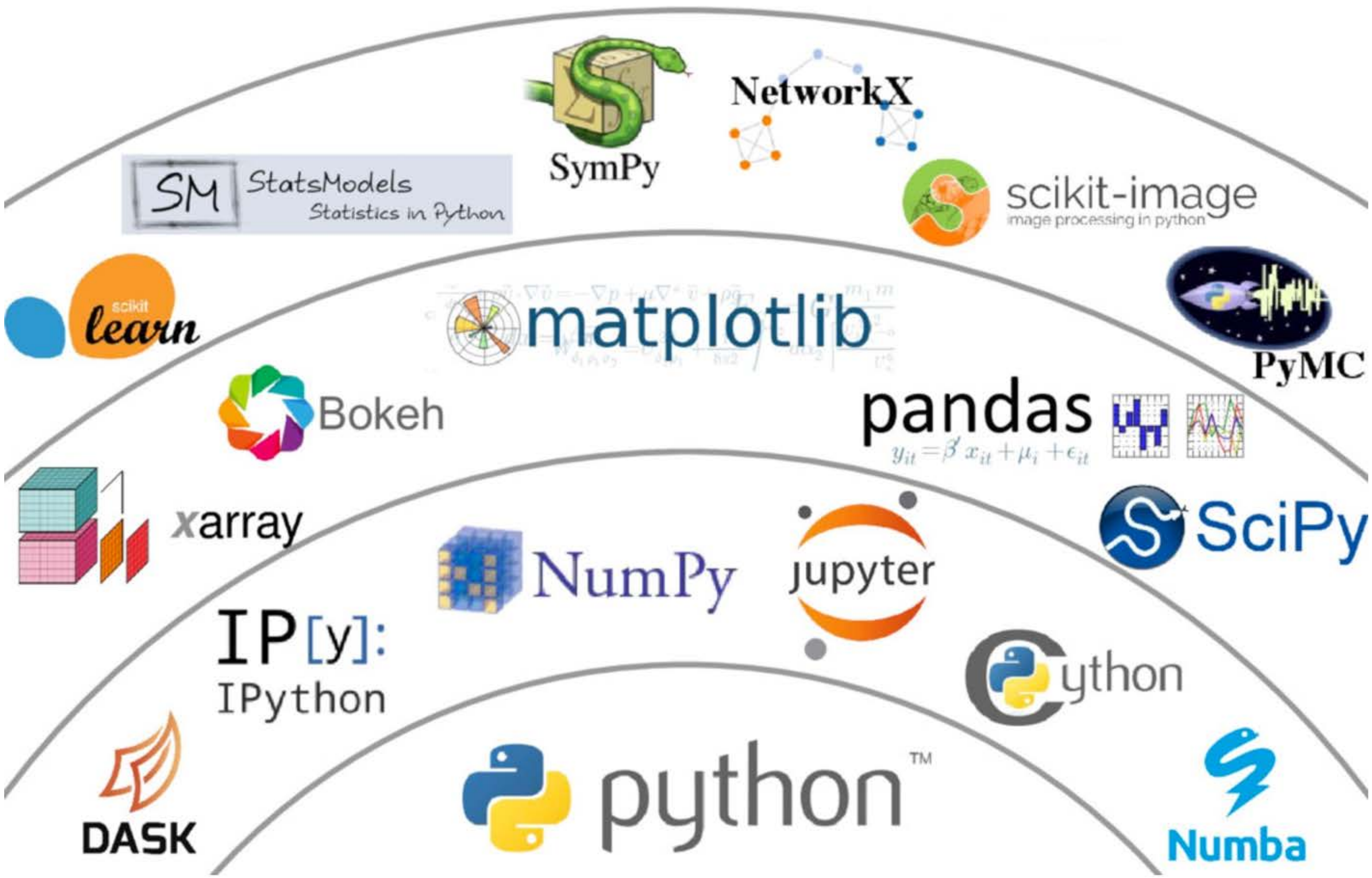
Face Detection
Video Surveillance
Satellite Imagery

Pedestrian Detection
Lane Tracking
Recognize Traffic Sign

Source: https://www.slideshare.net/insideHPC/tesla-accelerated-computing-platform

DEEP LEARNING WITH PYTHON

Set of Powerful Libraries



Source: https://www.datacamp.com/community/blog/python-scientific-computing-case

Machine Learning Libraries

- numpy
  - Arrays: universal point of reference in the python ML world
- pandas
  - Data manipulation made easy
- scipy
  - Basis of scientific computing
- scikit-learn
  - (Almost) all machine learning algorithms you will ever need
- matplotlib
  - Plot all of the above

… and all of these are seamlessly connected!

Deep Learning with Python

- Multiple options
- All equivalent but all different
- Hard to port solutions

theano

TensorFlow

Microsoft CNTK

Source: https://www.slideshare.net/kuanhoong/big-data-malaysia-a-primer-on-deep-learning

Deep Learning with Keras

- One framework to rule them all
- Easier to code and read
- Can harness CPU and GPU

theano

TensorFlow

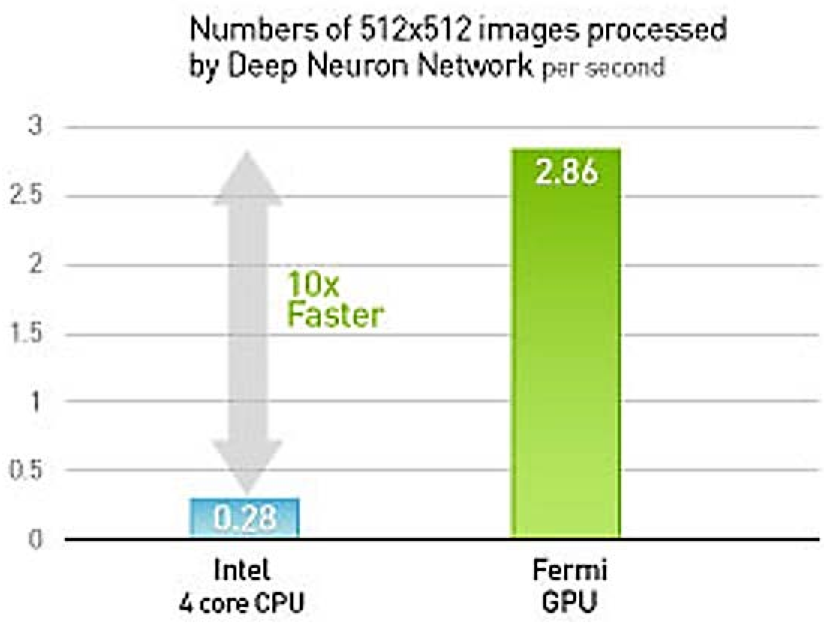
Microsoft CNTK

Keras

Source: https://www.slideshare.net/kuanhoong/big-data-malaysia-a-primer-on-deep-learning

Keras Requirements

- An up-to-date python distribution
- The python numpy-scipy-scikit stack
- A fast CPU or GPU



If possible,
use a GPU!

… although your CPU will
do for simple applications!

Source: http://www.gpurendering.com/technology/learningMachinesGpuVsCpu.html

Neural Networks with Keras

```
model = Sequential()
model.add(Dense(units=64, activation='relu', input_dim=100))
model.add(Dense(units=10, activation='softmax'))
```

Create Model

```
model.compile(loss='categorical_crossentropy',
              optimizer='sgd', metrics=['accuracy'])
```

Configure Learning

```
model.fit(x_train, y_train, epochs=5, batch_size=32)
```

Train the model

```
metrics = model.evaluate(x_test, y_test, batch_size=128)
```

Get metrics

```
classes = model.predict(x_test, batch_size=128)
```

Make predictions

Source: https://keras.io/

Time for hands-on!