



MODULE 4: INTRODUCTION TO DEEP LEARNING (DL)

BA713 - Machine Learning & AI

CONTENTS



WHAT IS DEEP LEARNING



WHY DEEP LEARNING



INTRODUCTION TO KERAS,
TENSORFLOW, & DNN

DEEP LEARNING (DL)

ARTIFICIAL INTELLIGENCE

Any technique that enables computers to mimic human behavior



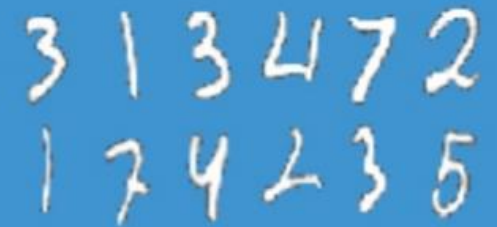
MACHINE LEARNING

Ability to learn without explicitly being programmed



DEEP LEARNING

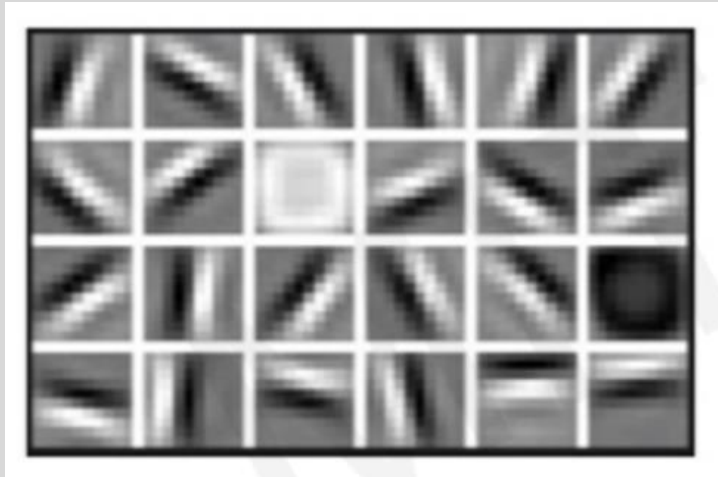
Extract patterns from data using neural networks



WHY DO WE NEED DEEP NEURAL NETWORKS?

- Increasing amount of data
- Increased features
- Time consuming → impractical

Low level features



Lines and Edges

Mid level features



Eyes and nose and ears

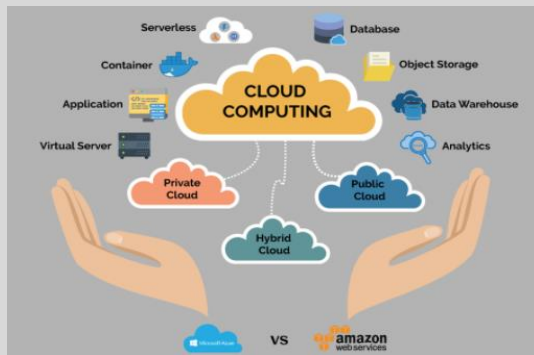
High level features



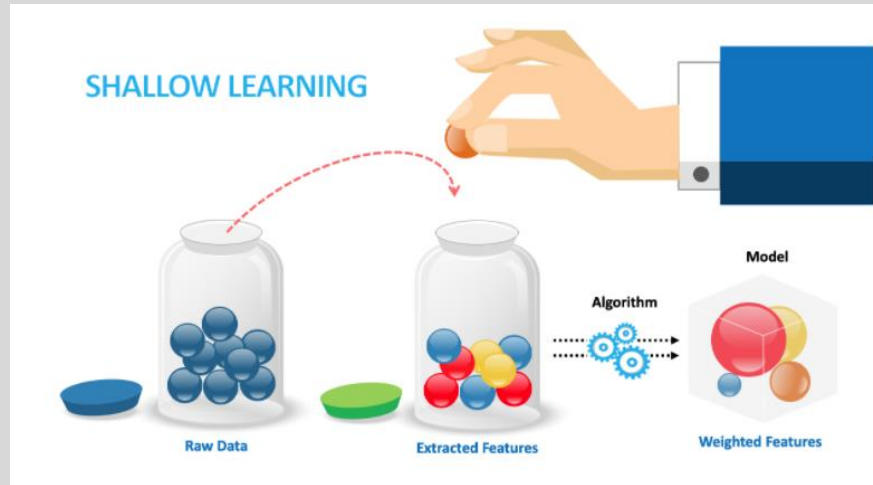
Facial Structure

WHY DEEP LEARNING (DL)?

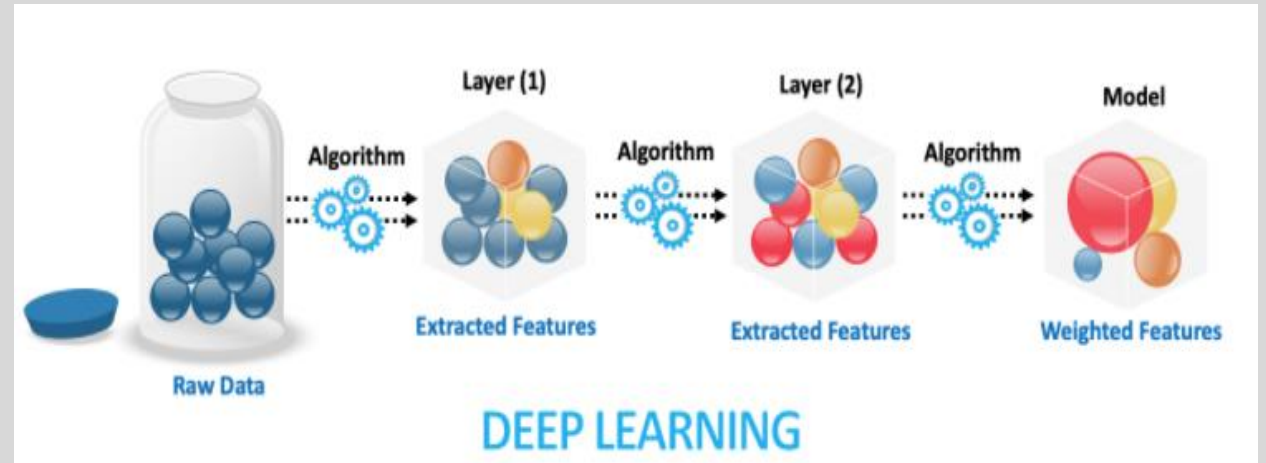
- **Big Data** → Cloud, AWS, Azure, etc
- **Hardware improvement** → Graphical Processing Units or GPUs, Parallel processing
- **Software Improvement** → improved techniques, toolkits, python, keras, pytorch, tensorflow, etc



SHALLOW LEARNING VERSUS DEEP LEARNING



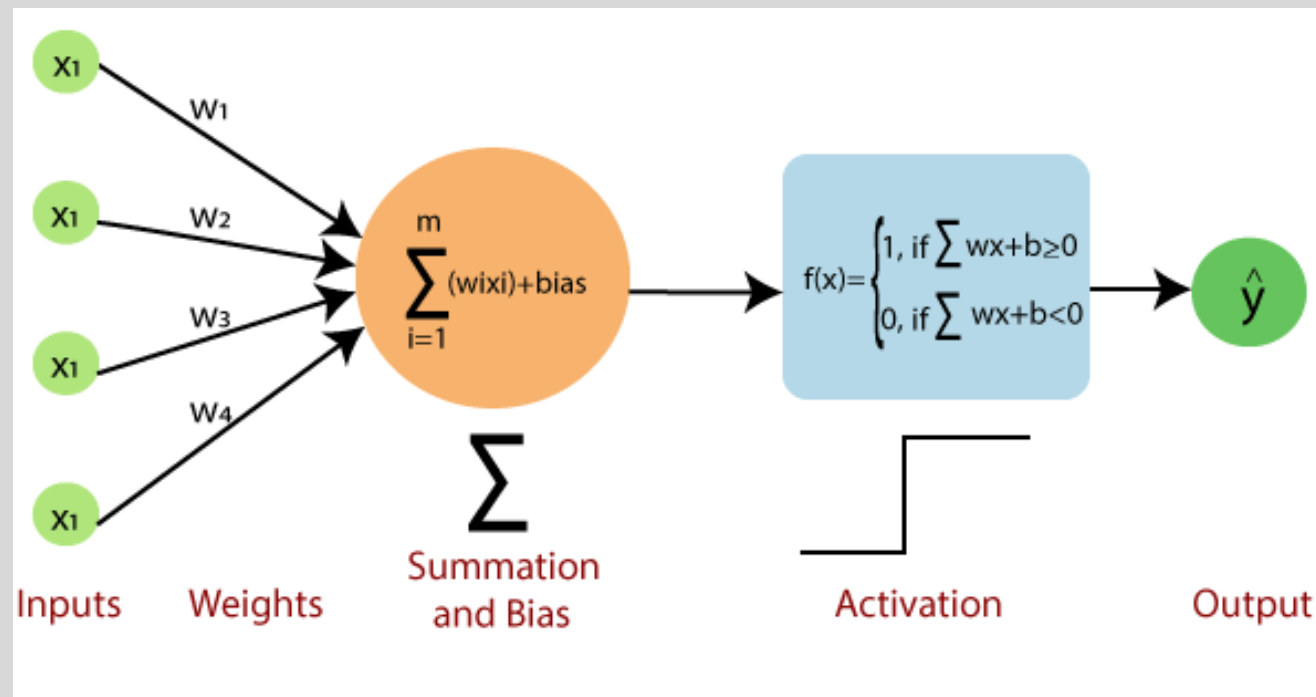
"**Shallow Learning**" is a type of machine learning where we learn from data described by pre-defined features.



A "**Deep learning**" algorithm automatically learns these features/patterns along with their weights.

STRUCTURAL BUILDING BLOCK FOR DEEP NEURAL NETWORKS

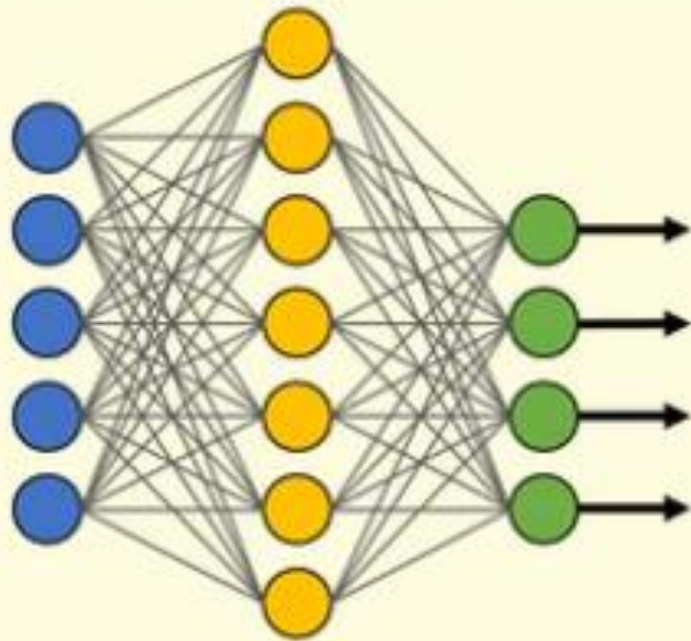
(Perceptron)



$$h_{\mathbf{W}, \mathbf{b}}(\mathbf{X}) = \phi(\mathbf{XW} + \mathbf{b})$$

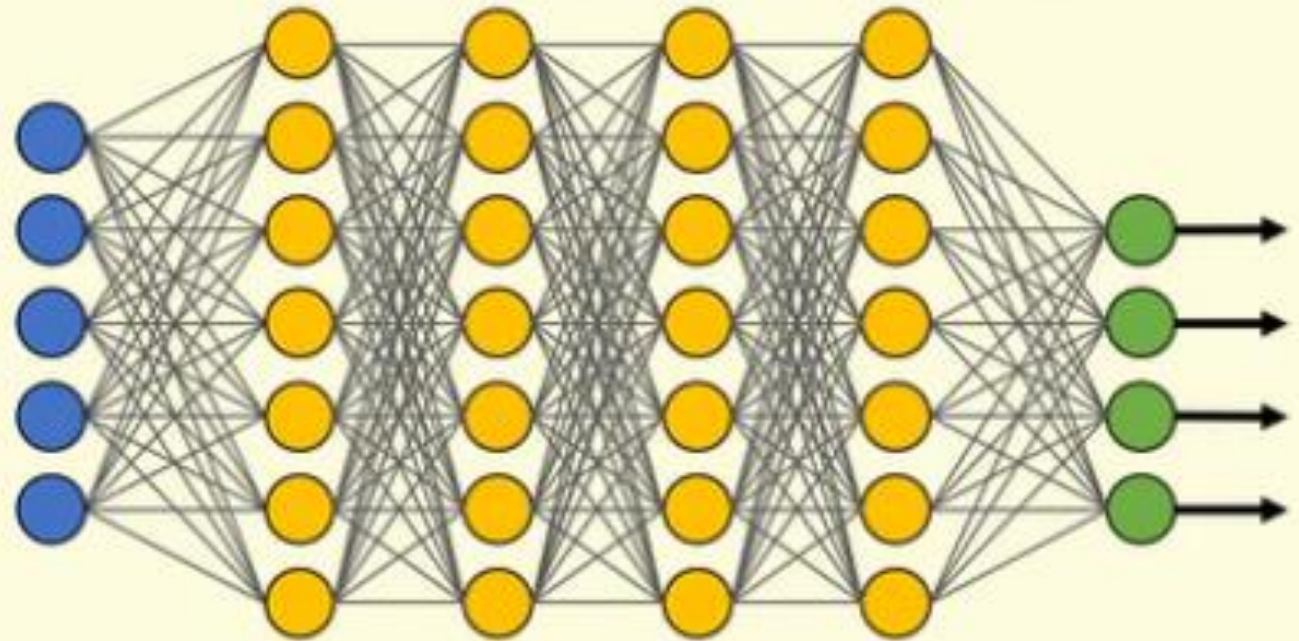
$\mathbf{W} \rightarrow$ Weight matrix
 $\mathbf{b} \rightarrow$ Bias vector
 $\mathbf{X} \rightarrow$ feature matrix
 $\phi \rightarrow$ non-linear activation function
 $h \rightarrow$ Output
 $\mathbf{XW} \rightarrow$ Linear combination of inputs
 $\mathbf{XW} = \sum_{i=1}^m x_i w_i$

Simple Neural Network



● Input Layer

Deep Learning Neural Network



● Hidden Layer

● Output Layer

KERAS & TENSORFLOW OVERVIEW

Keras:



- deep learning high-level API written in Python, running on top of the machine learning platform TensorFlow
- highly-productive interface
- provides essential abstractions and building blocks for developing DL solutions
- fast experimentation

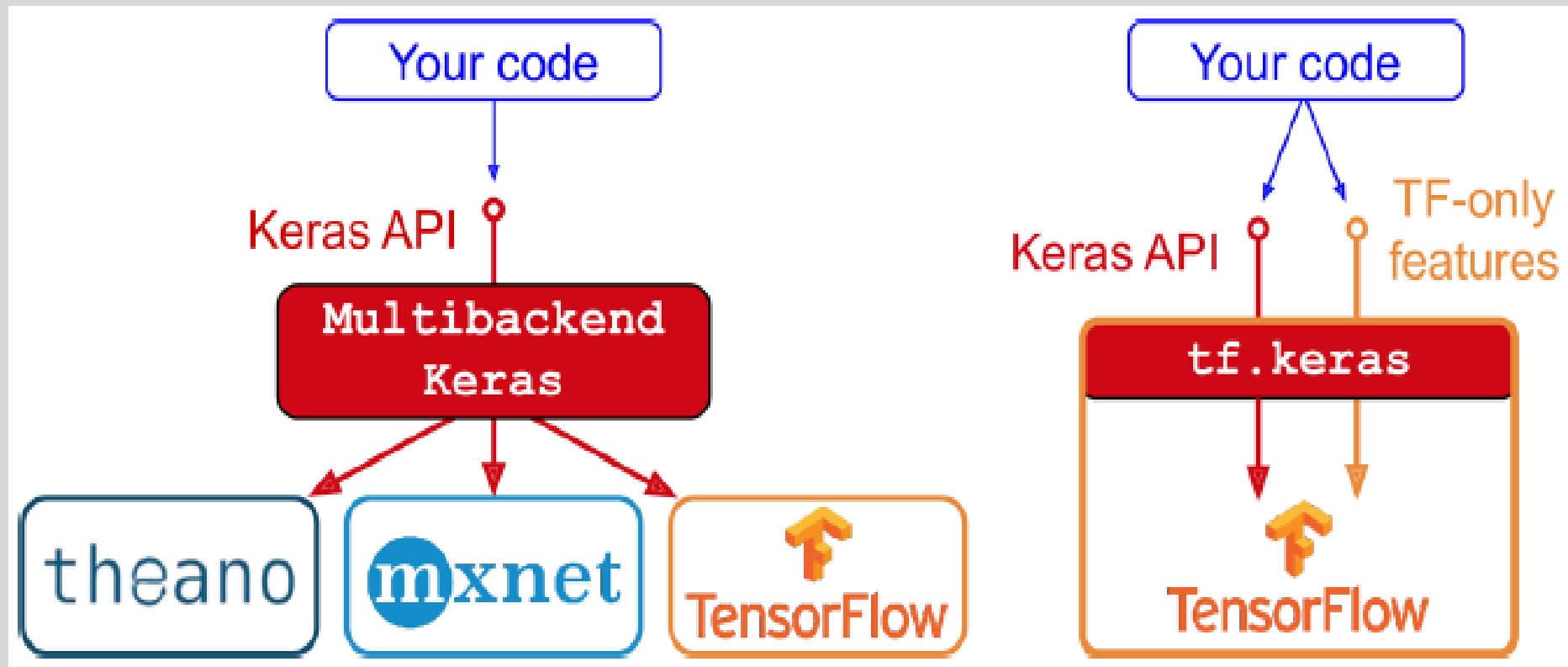
Tensorflow:



- end-to-end, open-source machine learning platform owned by Google
- infrastructure layer for Deep Learning programming
- Working with GPU/CPU/TPU
- with state-of-the-art tools, libraries, and community → build and deploy DL models
- Scaling computation to many devices → clusters of GPUs

IMPLEMENTATIONS OF THE KERAS API

- Keras is a high-level Deep Learning API that allows you to easily build, train, evaluate, and execute all sorts of neural networks.
- Its documentation (or specification) is available at <https://keras.io/>.



ANATOMY OF A DEEP NEURAL NETWORK (DNN)

- **Layers**, which are combined into a **network** (or **model**)
- The **input data** and corresponding **targets**
- The **loss function**, which defines the feedback signal used for learning
- The **optimizer**, which determines how learning proceeds

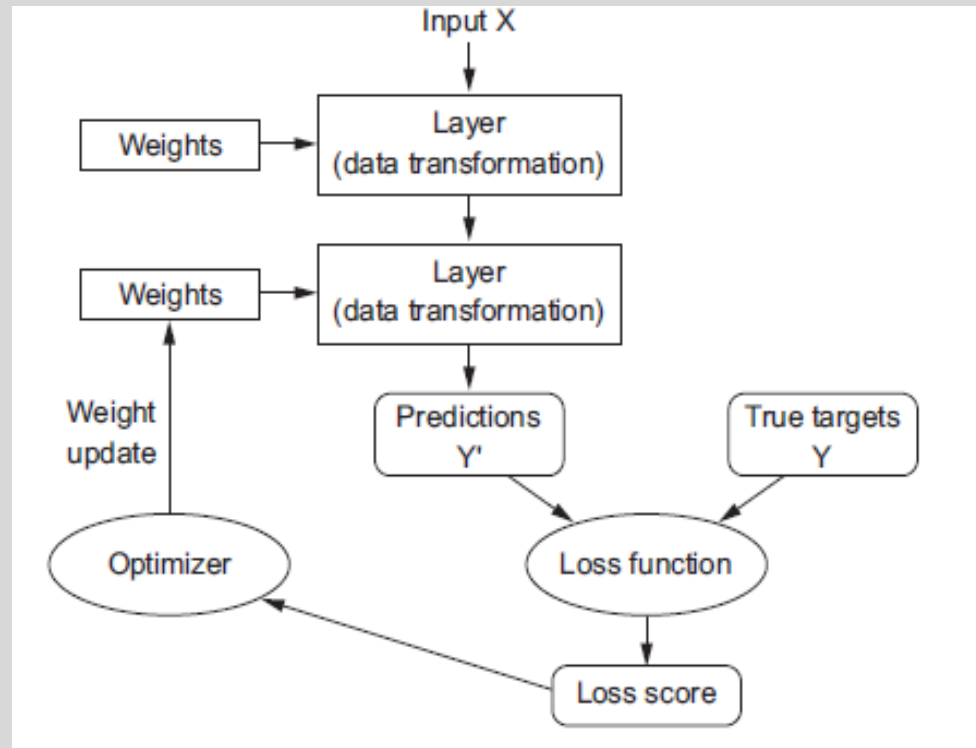


Figure: Relationship between the network, layers, loss function, and optimizer

Layers: the building blocks of deep learning

- data-processing module that takes as input one or more tensors and that outputs one or more tensors
- frequently layers have a state → the layer's **weights**, one or several tensors learned with stochastic gradient descent, which together contain the network's **knowledge**
- Densely/ Fully connected layers → **Dense** class in Keras
- **Simple vector data** → stored in 2D tensors → *(samples, features)* → DNN model
- **Sequence data** → 3D tensors → *(samples, timesteps, features)* → LSTM Model
- **Image data** → 4D tensors → *2D convolution layers (Conv2D)* → CNN Model

```
from keras import layers
```

```
layer = layers.Dense(32, input_shape=(784,))
```

A dense layer with 32
output units

Models: networks of layers

- linear stack of layers, mapping a single input to a single output
- Keras functional API → more complex
- Write models from scratch

```
from keras import models
from keras import layers

model = models.Sequential()
model.add(layers.Dense(32, activation='relu', input_shape=(784,)))
model.add(layers.Dense(10, activation='softmax'))
```

Simplest model type →
Sequential API

```
input_tensor = layers.Input(shape=(784,))
x = layers.Dense(32, activation='relu')(input_tensor)
output_tensor = layers.Dense(10, activation='softmax')(x)

model = models.Model(inputs=input_tensor, outputs=output_tensor)
```

Using Functional API

Loss functions and optimizers: configuring the learning process

Loss/objective function:

- minimize the loss/error → measure of success

Optimizer:

- Determines how the network will be updated based on the loss function
- variant of stochastic gradient descent (SGD).

```
from keras import optimizers
```

```
model.compile(optimizer=optimizers.RMSprop(lr=0.001),  
              loss='mse',  
              metrics=['accuracy'])
```

Optimizer RMSprop

Loss function-MSE

Network/Model training & evaluation

- Pass numpy array of input data and target label (x_train, y_train) into fit() method

```
# x_train and y_train are Numpy arrays  
model.fit(x_train, y_train, epochs=5, batch_size=32)
```

- Evaluate your test loss and metrics in one line:

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

- Or generate predictions on new data:

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

GRADIENT DESCENT OPTIMIZATION

- Deep Neural Networks learn through Gradient Descent Optimization

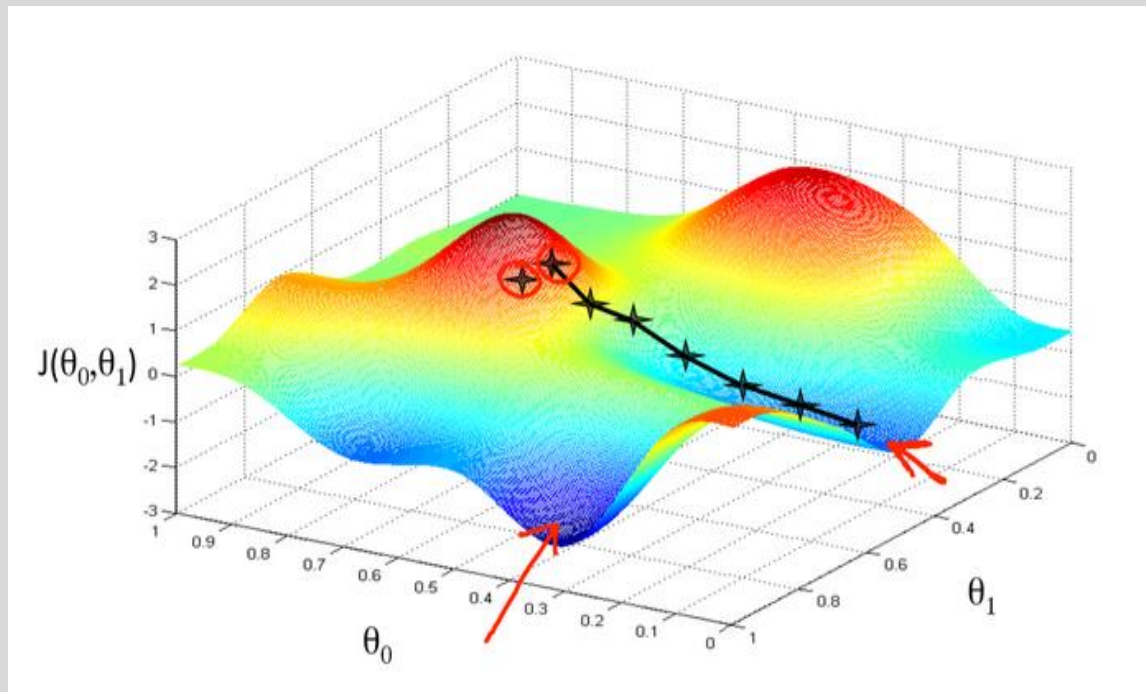


Figure a: Gradient Descent example

Gradient Descent Algorithms

1. Batch gradient descent
2. Stochastic gradient descent
3. Mini-batch gradient descent

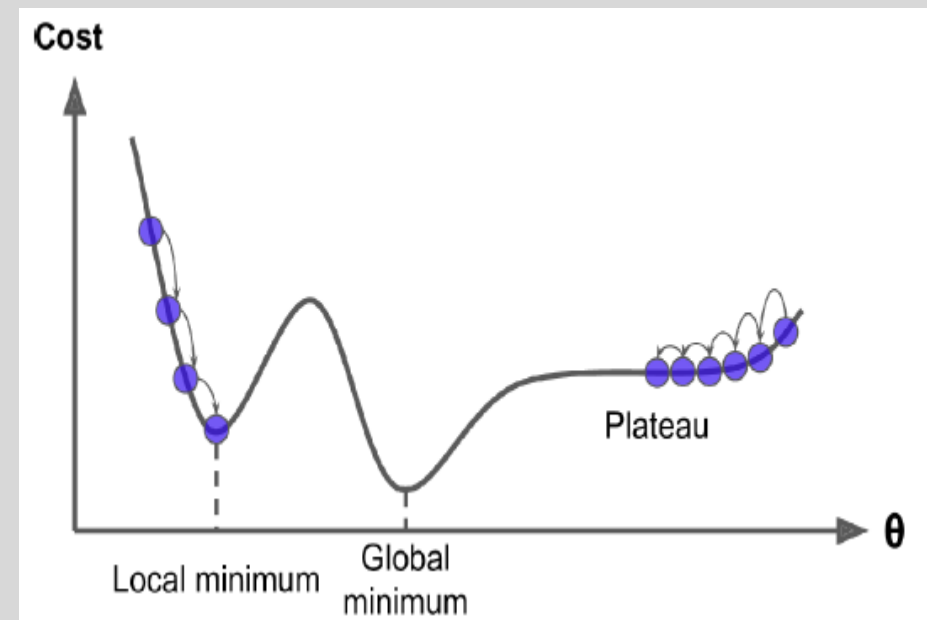


Figure b: Gradient Descent pitfalls

ADAPTIVE LEARNING RATES

- Adapt to the landscape
- Not fixed → can change based on the gradient
- Based on size of the weight
- Or Learning speed
- <https://keras.io/api/optimizers/>

Popular Adaptive Keras Optimizers

1. **Adagrad**
2. **Adadelta**
3. **RMSprop**
4. **Adam**

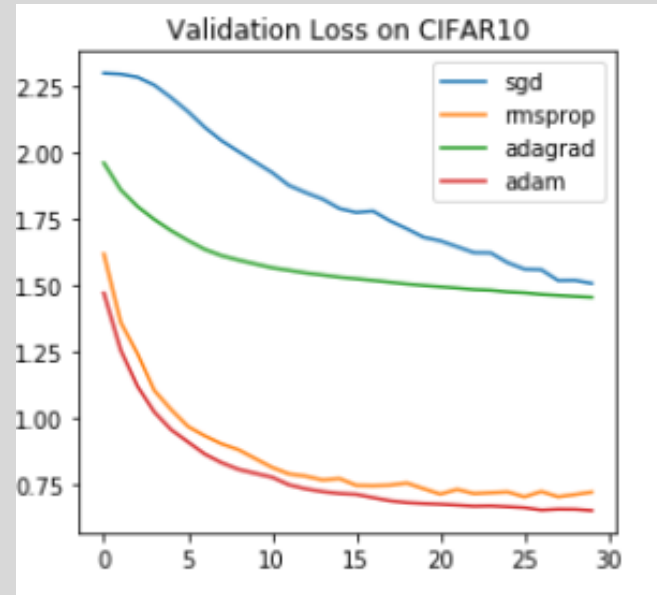
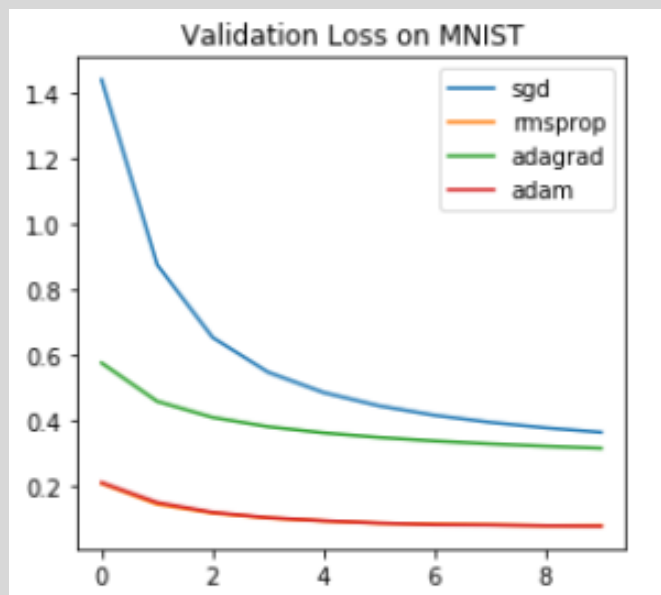
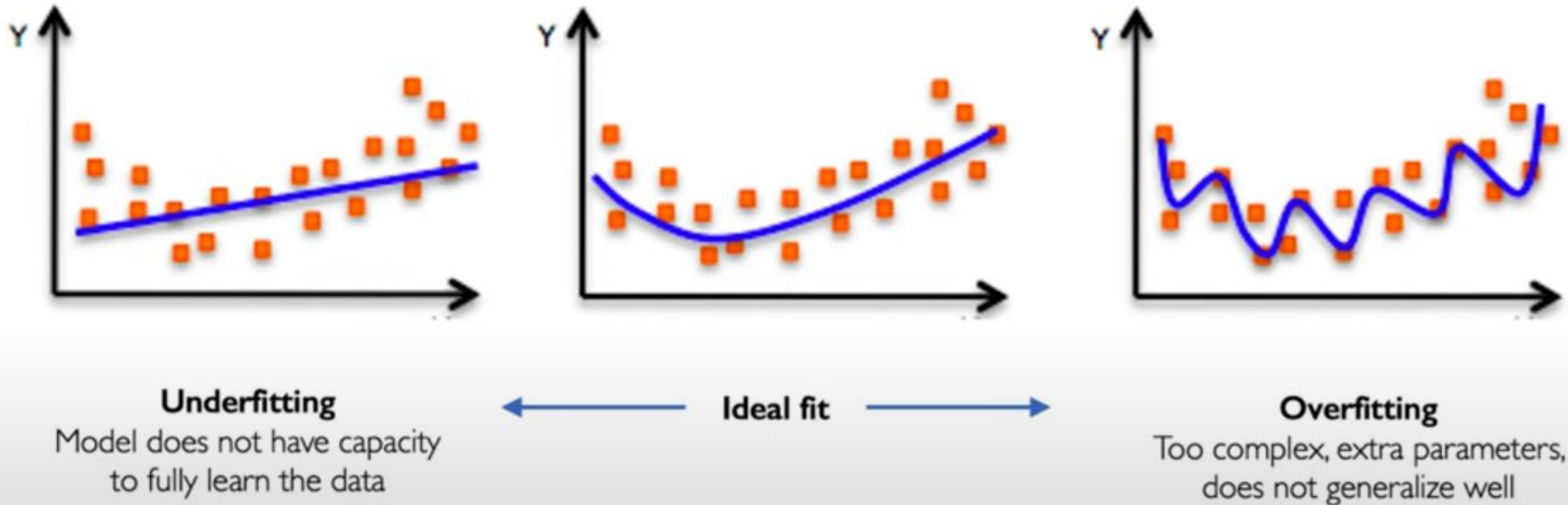


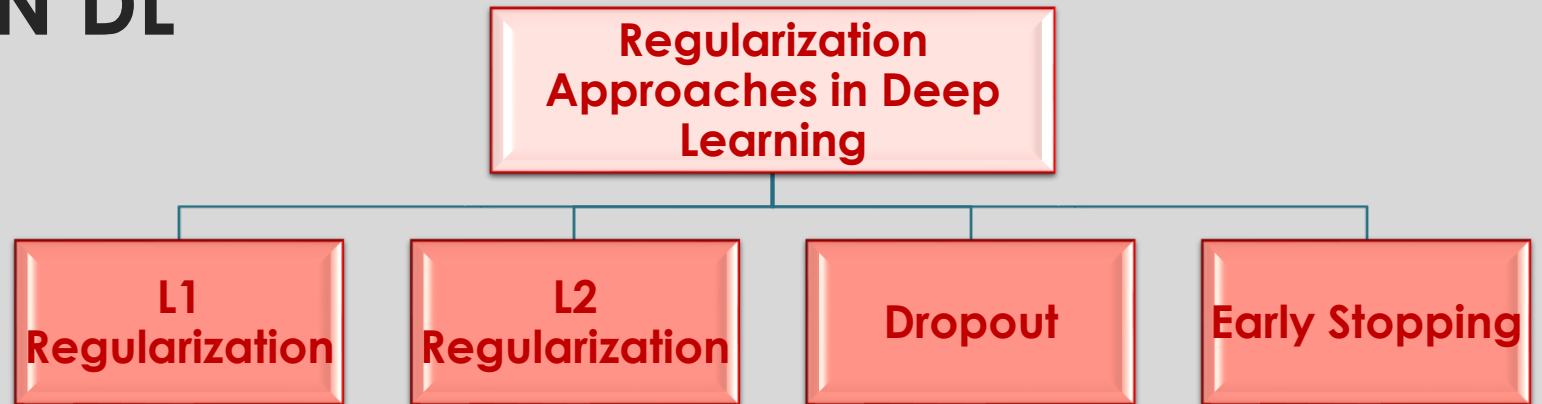
Image source: <https://heartbeat.fritz.ai/an-empirical-comparison-of-optimizers-for-machine-learning-models-b86f29957050>

OVERFITTING PROBLEM IN A DNN MODEL



REGULARIZATION IN DL

- Put constraints on optimization problem
- Reduce model complexity
- Improves generalization on unknown test data



L1 & L2 Regularization

- Update the cost function by adding regularization term
- Cost function = Loss (e.g., binary cross entropy) + Regularization term

```
from keras import regularizers
model.add(Dense(64, input_dim=64,
                kernel_regularizer=regularizers.l2(0.01))
```

For L2

$$\text{Cost function} = \text{Loss} + \frac{\lambda}{2m} * \sum \|w\|^2$$

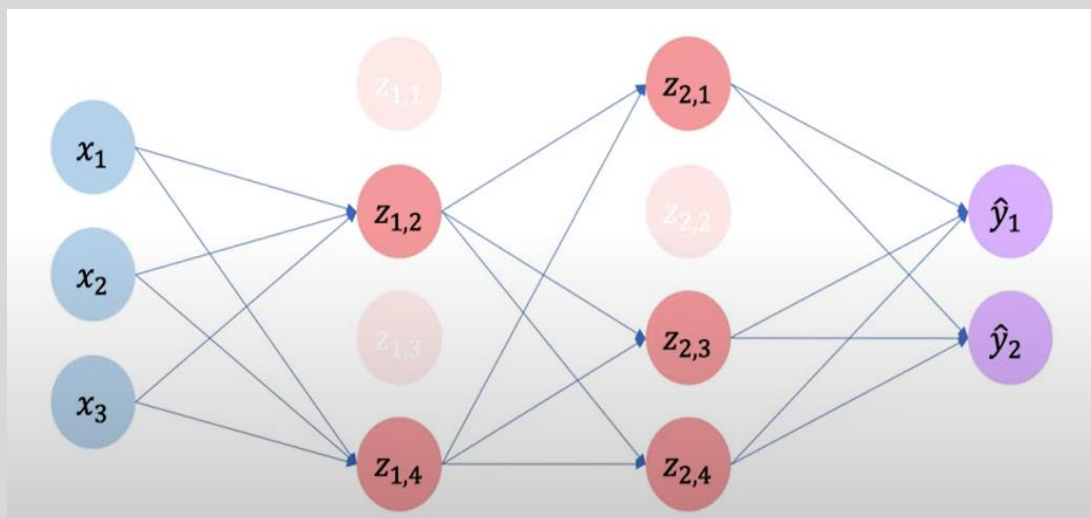
For L1

$$\text{Cost function} = \text{Loss} + \frac{\lambda}{2m} * \sum \|w\|$$

$\lambda \rightarrow$ Regularization parameter
 $w \rightarrow$ weights

Dropout

- Randomly drop some activations → results of some nodes
- Normally 50%
- Rely on only the other set of nodes left
- Dropout layer → between existing layers
- applies to outputs of the prior layer that are fed to the subsequent layer



Source: introtodeeplearning.com

```
# example of dropout between fully connected layers
from keras.layers import Dense
from keras.layers import Dropout
...
model.add(Dense(32))
model.add(Dropout(0.5))
model.add(Dense(1))
...
```

Source: <https://machinelearningmastery.com/>

Early Stopping

- Stop training a DL model before it overfits

```
from keras.models import Sequential
from keras.layers import Dense
from keras.callbacks import EarlyStopping
```

```
# simple early stopping
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1)
```

```
# fit model
history = model.fit(trainX, trainy, validation_data=(testX, testy), epochs=4000, verbose=0, callbacks=[es])
```



Source: introtodeeplearning.com



THANKS!

Do you have any
questions?