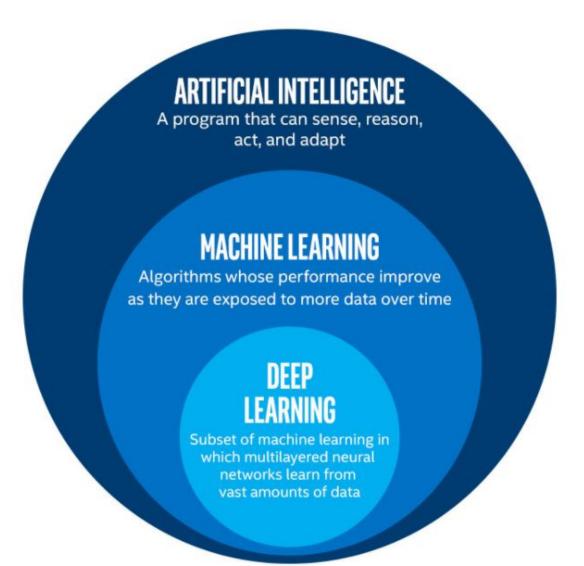
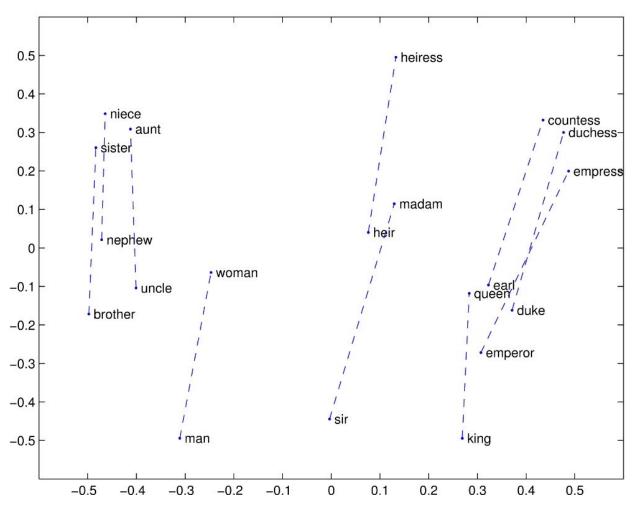
# Data Science and Artificial Intelligence Introduction

### What is Artificial Intelligence?



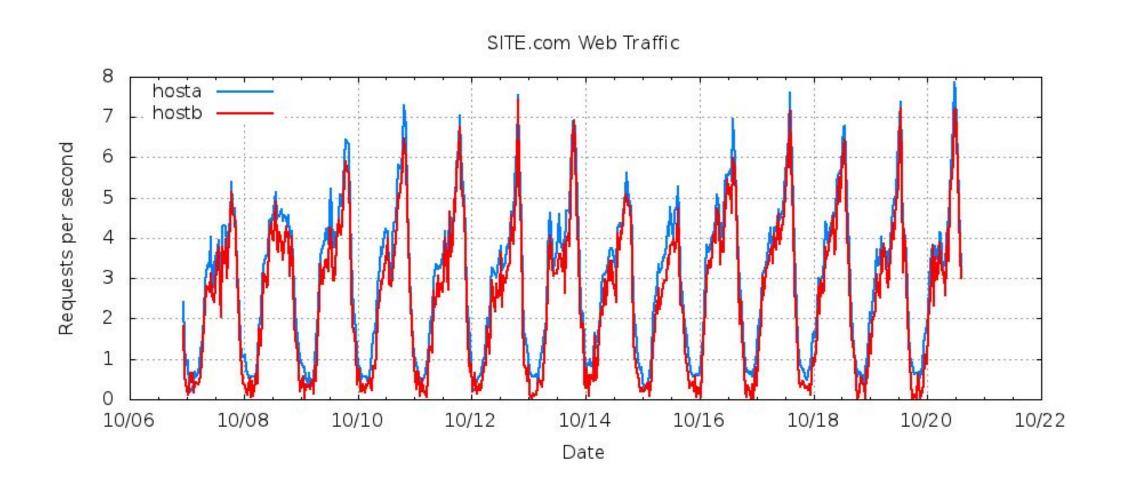
Al is not just machine learning, and machine learning is not just deep learning!

### Different types of data: Text data

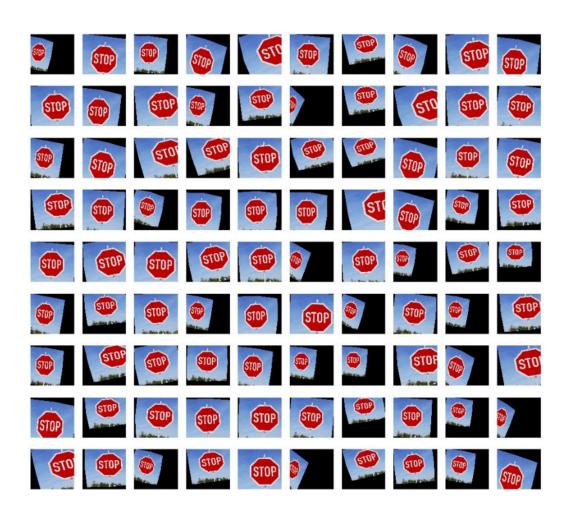


Source: <a href="https://nlp.stanford.edu/projects/glove/">https://nlp.stanford.edu/projects/glove/</a>

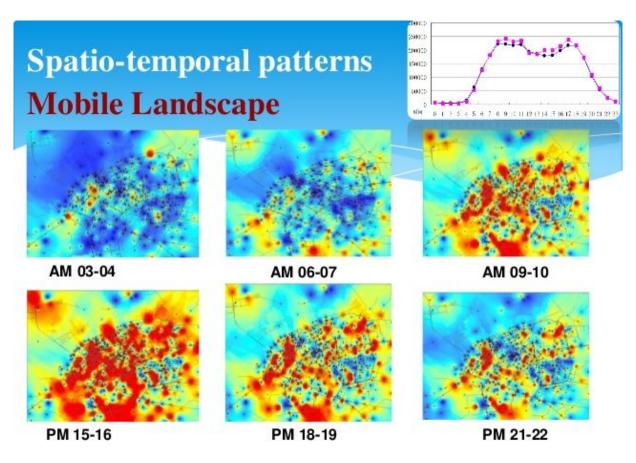
### Different types of data: Time Series Data



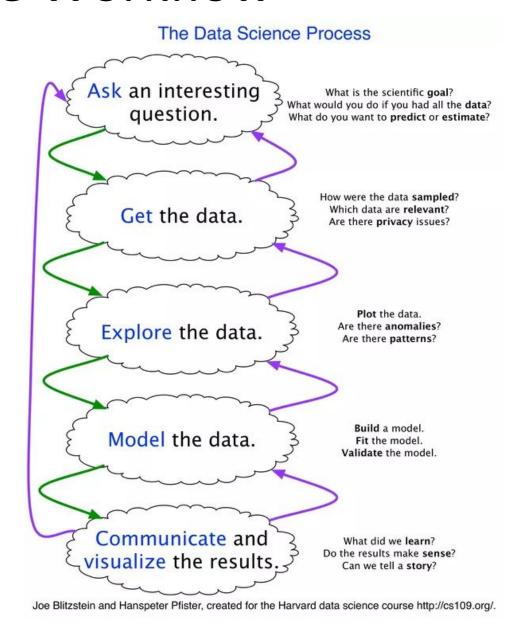
## Different types of data: Image Data



# Different types of data: Spatio-temporal Data



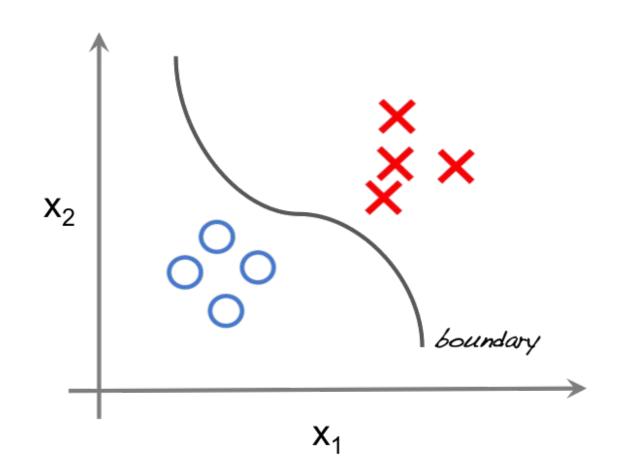
#### Data Science Workflow

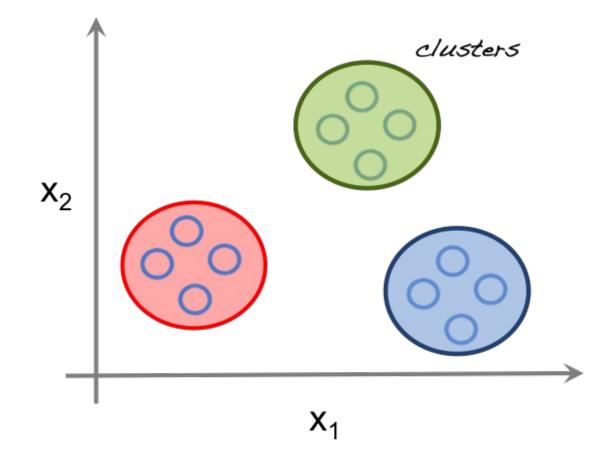


# Supervised vs Unsupervised Learning

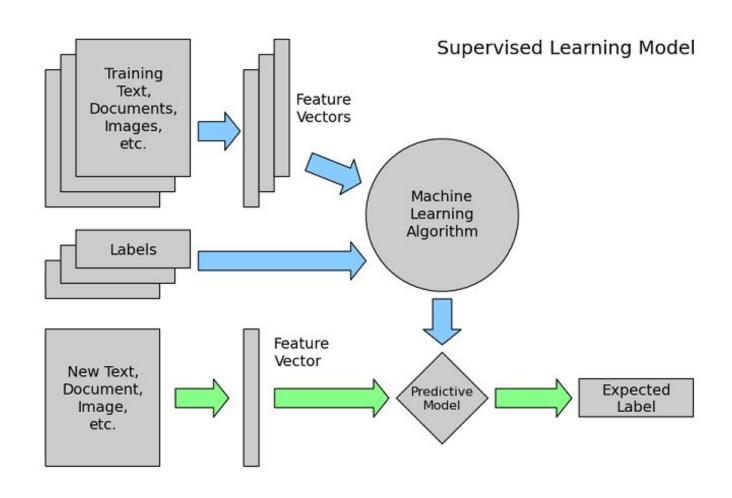
Supervised learning

Unsupervised learning





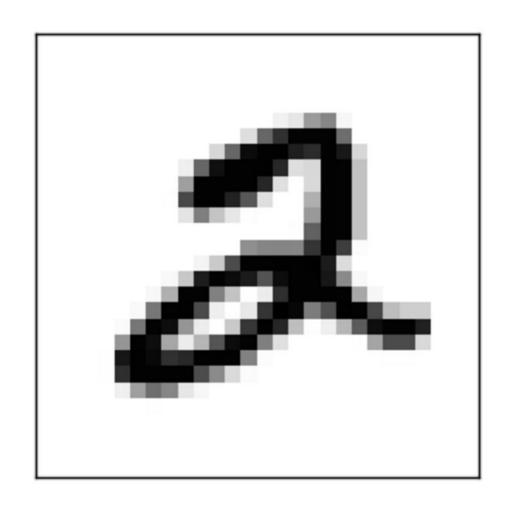
## **Supervised Learning Process**



# Working example – Simple Image Classification

The MNIST database of handwritten digits
(<a href="http://yann.lecun.com/exdb/mnist/">http://yann.lecun.com/exdb/mnist/</a>) has a training set of 60,000 examples, and a test set of 10,000 examples.

# Image as input



#### Loss function in a softmax classifier

#### **Cross-entropy loss**

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_j}}\right)$$
 or equivalently  $L_i = -f_{y_i} + \log\sum_j e^{f_j}$ 

#### Softmax function

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^K e^{z_k}}$$
 for  $j = 1, ..., K$ .

# Minimizing the loss function – Gradient Descent

- Compute the best direction along which we should change our weight vector that is mathematically guaranteed to the direction of steepest descent
- This direction is based on the gradient of the loss function we update the weights in the negative direction of the gradient, since we want to minimize the loss function

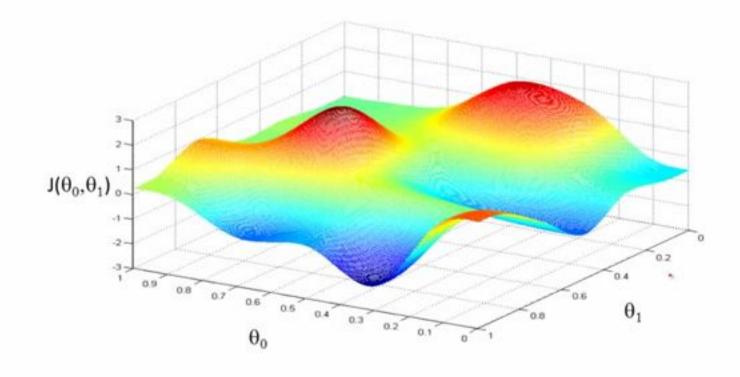
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

### Mini-batch gradient descent

- In most deep learning models, you have training data with millions of examples —> very slow to compute the loss function over all the training data, just to perform a single parameter update
- This term sometimes used interchangeably with Stochastic gradient descent (SGD), but to be precise, SGD refers to doing a parameter update with **each** training example

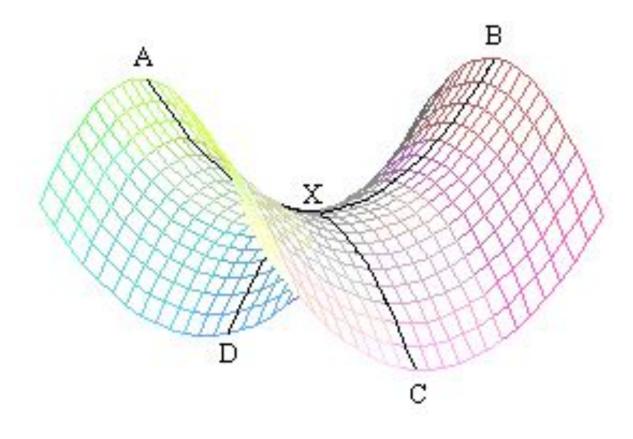
# Problems faced with optimizing gradient descent

 Vanilla gradient descent is susceptible to local minima in non-convex functions



Source: Andrew Ng, Stanford CS229

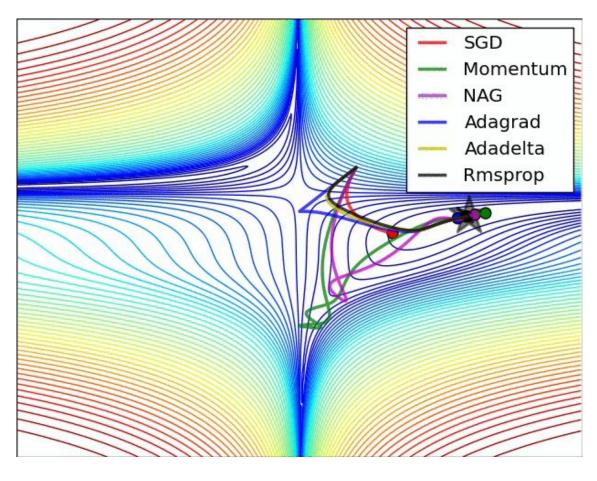
# Problems faced with optimizing gradient descent



# Different gradient descent optimization algorithms

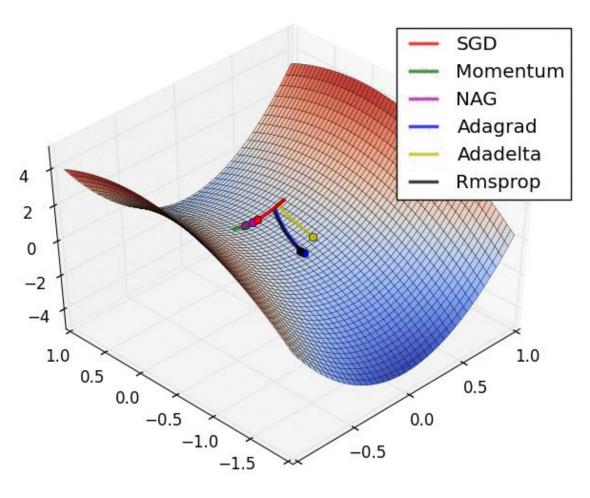
- Momentum adds a fraction of the update vector of the previous time step to the current update vector
- **Nesterov accelerated gradient** using the momentum term to approximate the next position of the parameters, giving prescience to where the parameters are going to be
- Adaptive learning rate methods eg. Adagrad (adapts the learning rate to the parameters, performing larger updates for infrequent parameters and smaller updates for frequent parameters), Adadelta, RMSprop and Adam

# Optimizing gradient descent



Source: Alec Radford

# Optimizing gradient descent



Source: Alec Radford