Introduction to AI

February 6, 2019

Introduction examples

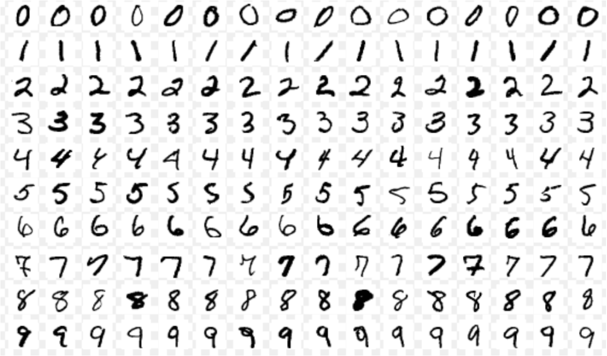

Figure: MNIST database [LeCun and Cortes, 2010]

Introduction examples

- Boston Dynamics robot (video)
- `https://www.youtube.com/watch?v=LikxFZZO2sk`
- `https://www.youtube.com/watch?v=g0TaYhjpOfo`

Introduction examples

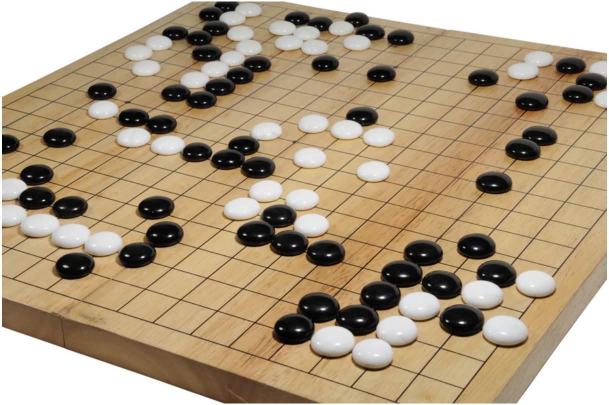

Figure: Go game, beaten by AlphaGo in 2017 [Silver et al., 2016]

Introduction examples

-
  - Boston Dynamics robot
  - MINST classification
  - AlphaGo
- All do different things but are gathered under the term "AI".

Introduction

- People doing "AI" can actually come from rather different scientific communities. Which ones according to you ?

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- People doing "AI" can actually come from rather different scientific communities:
  - Statistics

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  - Optimization

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  - Robotics

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  - Other mathematical fields : graph theory, combinatorics
  - Statistical physics
  - Robotics
  - Cognitive sciences / neuroscience / psychology

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- People doing "AI" can actually come from rather different scientific communities:
    - Statistics
    - Optimization
    - Other mathematic fields : graph theory, combinatorics
    - Statistical physics
    - Robotics
    - Cognitive sciences / neuroscience / psychology
- For instance, *data science* is mostly a mix between statistics, optimization, graph theory

Introduction

- It seems to be rather varied
- We will focus on *Machine Learning*, a term slightly more specific than "AI"
- In Machine Learning, some parameters are learned in an *automatic way* in order to solve a problem or to optimize a solution

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- It seems to be rather varied
- We will focus on *Machine Learning*, a term slightly more specific than "AI"
- In Machine Learning, some parameters are learned in an *automatic way* in order to solve a problem or to optimize a solution
- AI is not a recent research topic, it started with computer science. Machine Learning has been trendy for some years now because of some good performance on **some specific problems**

Introduction

In the three first examples, according to you which one is NOT a Machine Learning system ?

Introduction

- Alpha Go : Machine Learning (Reinforcement Learning)

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- MNIST : Machine Learning (Supervised Learning)

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- Alpha Go : Machine Learning (Reinforcement Learning)
- MNIST : Machine Learning (Supervised Learning)
- Boston Dynamics : no Machine Learning (just plain robotics)

Overview

The problem

- For a certain input x, you want to predict an output y
- To do so, you learn from a number of **labeled examples** (x_i, y_i)
- In the case where what you want to predict is a **class**, it is a **classification problem**
- In the case where what you want to predict is a general function $y = f(x)$, it is a **regression problem**

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- In the case where what you want to predict is a general function $y = f(x)$, it is a **regression problem**
- Example : MNIST (classification)
- Question : how do you choose and constrain your function f ?

The problem

- From a large number of samples x_i, you want to retrieve information on their **structure**
- For instance you want to learn a **distribution**, or a **clustering** of your data.
- Examples : social networks

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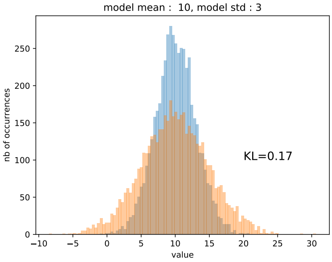

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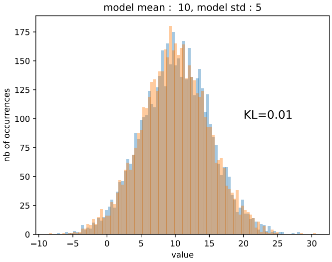

The problem

- From a large number of samples x_i, you want to retrieve information on their **structure**
- For instance you want to learn a **distribution**, or a **clustering** of your data.
- Question : how do you constrain your distribution to fit your data ?

The problem

- A **more general paradigm** that describes an **agent** in a **world**.
- The standard formalization was the one proposed by Richard Sutton [Sutton and Barto, 2016]
- At each time, the world is in a state s. An agent perfoms an **action** a according to a **policy** π. When performing an action, the agent receives an **reward** r.

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- Example : a Chessplayer, AlphaGo, a game AI, automatic vacuum cleaner

The problem

- At each time, the world is in a state s. An agent perfoms an **action** a according to a **policy** π. When performing an action, the agent receives an **reward** r.
- The agent wants to learn an **optimal policy**, meaning the policy that maximises its reward.

This paradigm has many variants

- State s, action a, policy π, reward r.
- Is the policy **deterministic** ? Is it **stochastic** ?
- Does the agent have a **model** of its environment ?
- How many steps ahead whould the agent look ?

This paradigm has many variants

- State s, action a, policy π, reward r.
- Is the policy **deterministic** ? Is it **stochastic** ?
- Does the agent have a **model** of its environment ?
- How many steps ahead should the agent look ?
- All these conditions change the way the problem should be addressed and solved. The **Bellman equations** rule the updates of the optimal policy.

Example problem

- Typical Machine Learning situation : should I explore my environment more or exploit what I have learnt so far ?
- Concept of ϵ-greedy policy

Final remark

- These paradigms can be mixed

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- Mosty, this means that
  - unsupervised learning can be used in a supervised learning problem (semi supervised learning)
  - unsupervised learning and supervised learning can be used in a reinforcement learning problem

Some famous methods

Let's look at some classical methods in ML

Linear separator

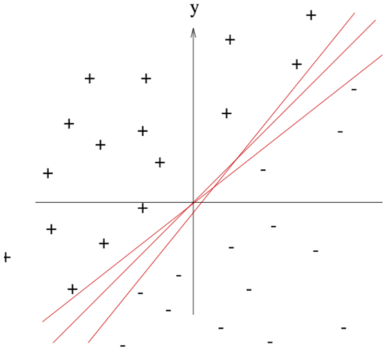
- Very favorable supervised learning case
- 

Figure: Linearly separable problem (image : wikipedia)

Linear separator

- Unfortunately, most problems are *not linearly separable*

K means clustering

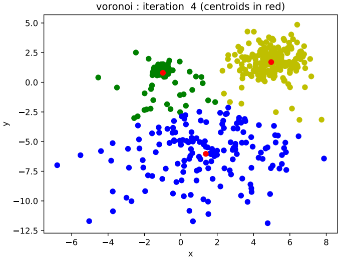
- A famous unsupervised clustering method
- 

Figure: K means clustering

Kmeans

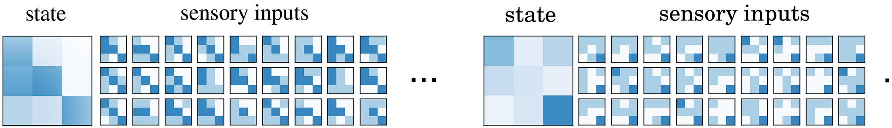


Figure: Other example of kmeans clustering, this time in 9 dimensions [Le Hir et al., 2018]

Kmeans : Esperance Maximisation algorithm

- Classical Machine Learning algorithm (EM)
- Blackboard
- What could be the drawbacks of this algorithm ?

Exercise 1 : Kmeans clustering

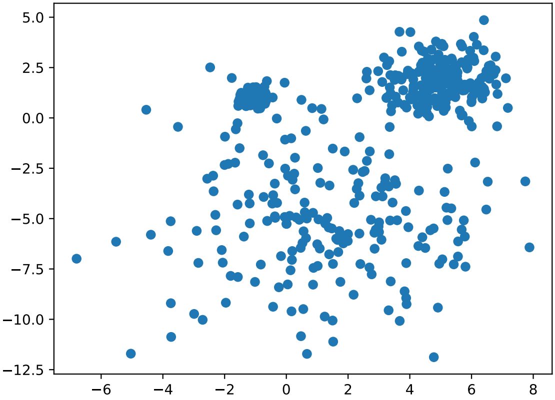


Figure: Data we want to cluster

Kmeans clustering

cd kmeans

- Modify the **kmeans_ex.py** file so that it performs the kmeans algorithm.
- There are **two mistake series** between lines 50 and line 82, you will need to fix them.

You should obtain something like this:

Kmeans

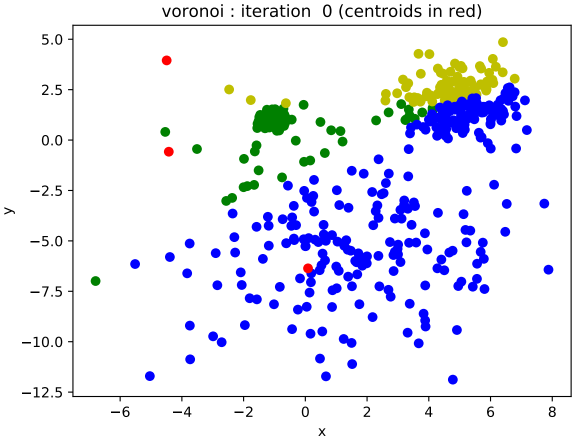


Figure: Voronoi 0th iteration

Kmeans

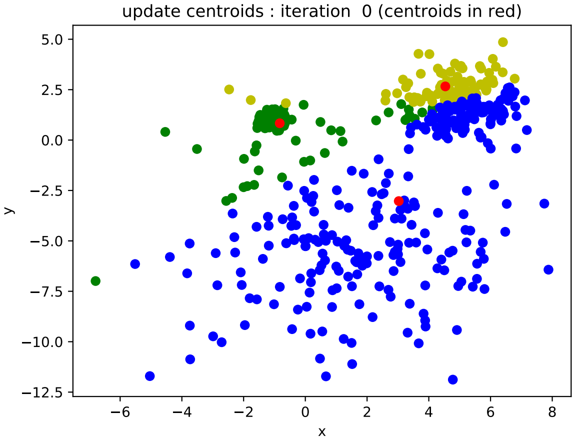
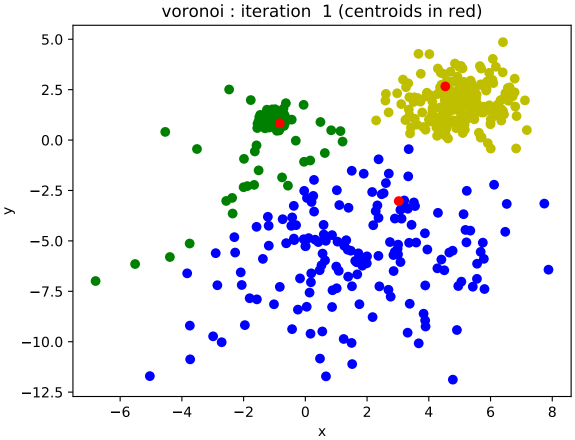


Figure: Centroids 0th iteration

Kmeans



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Kmeans

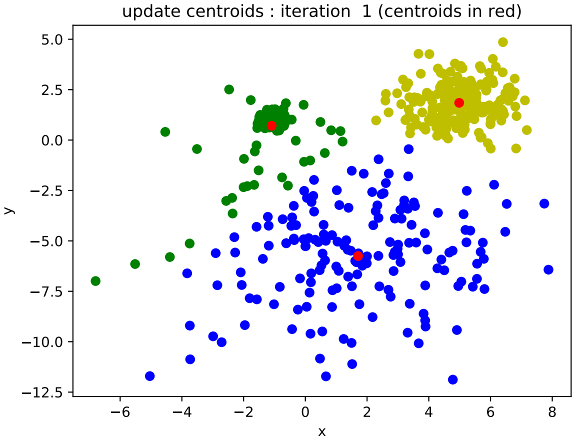


Figure: Centroids 1st iteration

Kmeans : Esperance Maximisation algorithm

- What would you do if the algorithm falls in a local optimum ?

Neural network

- A **neuron** is a simple elementary function
- A neural network a more complex function built with several neurons

Neural networks

- A **neuron** is a simple elementary function
- A neural network a more complex function built with several neurons
- A **Deep Neural Network** is a big neural networks ont more than two stacked layers of neurons

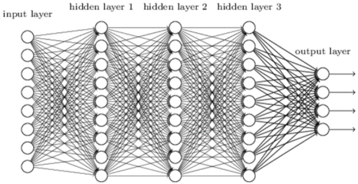


Figure: A deep neural network : source
`https://datawarrior.wordpress.com/2017/10/31/interpretability-of-neural-networks/`

AlexNet

- **AlexNet** [Krizhevsky et al., 2012] is an example of Deep Neural Network : famous for a good performance at the ImageNet recognition challenge. Is is a **Convolutional Neural Network**

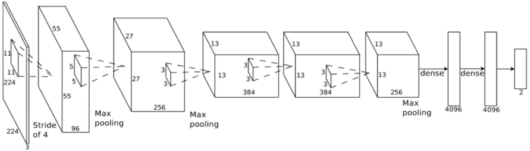
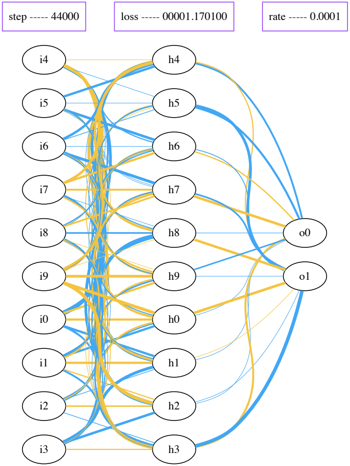


Figure: AlexNet

Neural Networks

We will do exercises on neural networks tomorrow.



Spectral Clustering

- How can you cluster data if you do not have a **distance** between them ?

Spectral Clustering

- How can you cluster data if you do not have a **distance** between them ?
- A **Similarity** is a more general notion that allows you to compare data
- It can be used in unsupervised learning contexts [Le Hir et al., 2018]

Research and problems in AI

What makes AI a hard problem ?

Curse of dimensionality

- First aspect : algorithmic complexity
- The objects considered are in high dimensional spaces, and in high number
- Even "simple" situations grow very complex (Atari games)

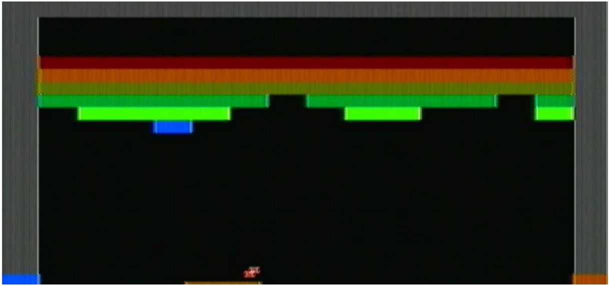


Figure: One Atari game

Curse of dimensionality

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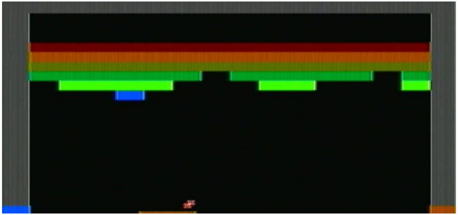

Figure: One Atari game

- Especially true for reinforcement learning
- If it is algorithmically hard to solve an Atari game, how hard would a real world problem be ?

Non convexity, non linearity

- We try to optimize crazy functions : in extremely high dimensional spaces, with crazy shapes. (blackboard)
- So the power of the mathematical tools si limited and **experimentation** is needed.
- So there lacks **grounding** to the results

Overfitting

- What could be the drawbacks of using a very simple model (very few parameters) ?

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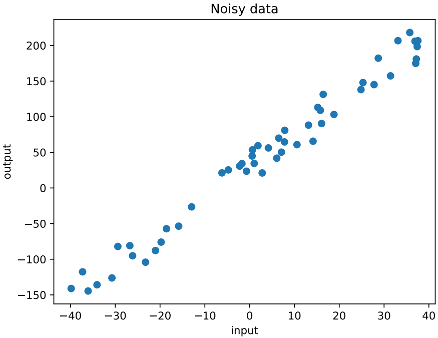
Overfitting

- What could be the drawbacks of using a very simple model (very few parameters)
  - Weak expressive power
- What could be the drawbacks of having a very complex model (that contains a very large number of parameters, e.g. millions as in a very deep neural network) ie a very high expressive power ?
  - Harder to optimize
  - Harder to interpret
  - Can **overfit**

Exercise 2

- We will learn a model of the following data :



- We want to perform supervised learning in order to be able to predict the output y for a new sample x.

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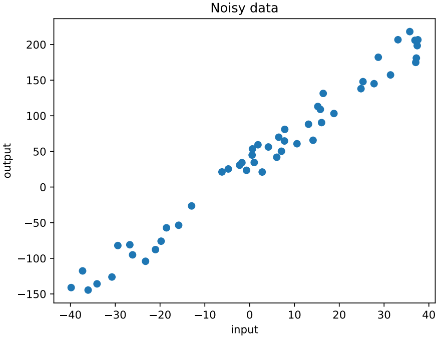

- To illustrate the problem of overfitting, we will use **polynoms** as models.

Exercise 2

- **cd overfitting**. Use the dataset contained in **linear_noisy_data.csv**, load it from **fit_data_ex.py** in order to assess the impact of the **degree** of the polynom on overfitting.
- You just need to use the functions written in the file (no modification needed)

Exercise 2

- The higher the degree of the polynom, the more parameters it has and the better it can fit the training points :

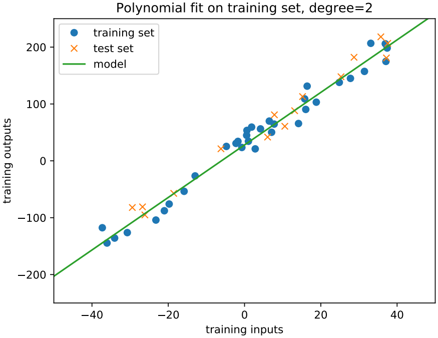

Figure: degree 2

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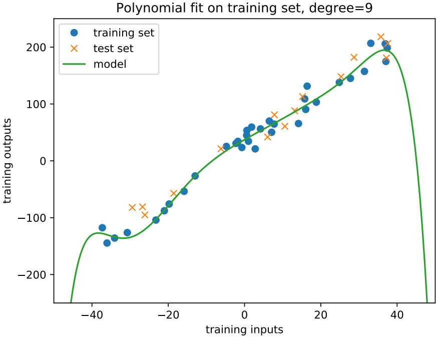

Figure: degree 9

Exercise 2

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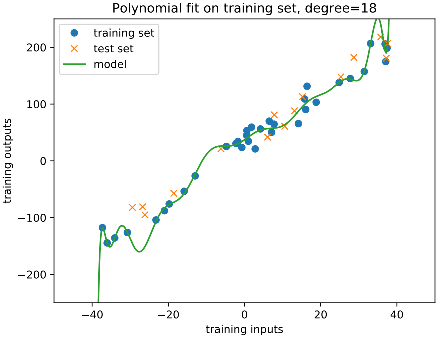

Figure: degree 19

Exercise 2

- However, the error on the test set increases and the model looses **signification**

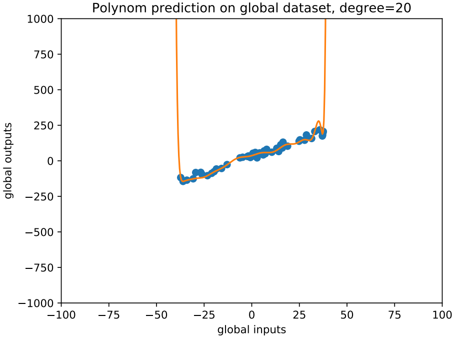

Figure: Useless solution

Exercise 2

- In that case the best solution should be a very simple polynom (degree 1)

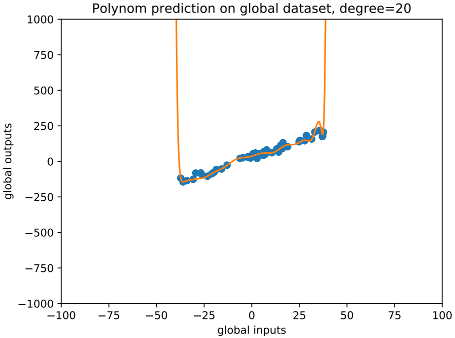

Figure: Useless solution

Trying to prevent overfit

- The problem of overfitting is linked to that of **generalisation** : to what extent are we allowed to extrapolate the knowledge obtained on the training samples to new samples ?
- To improve generalisation, one can use :
  - a **validation set**
  - **regularization**

Regularization methods

- Penalize the magnitude of the weight in a neural network
- Remove neurons in a neural network (pruning)
- use smooth functions (continuous)

Deep learning

- Deep learning is powerful for some situations but is subject to the above shortcomings
- Some researchers try to have a better understanding of their behavior. Some famous ones are Yoshua Bengio (Montral), Geoffrey Hinton (Toronto), Stphane Mallat (Paris)

The End

References

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