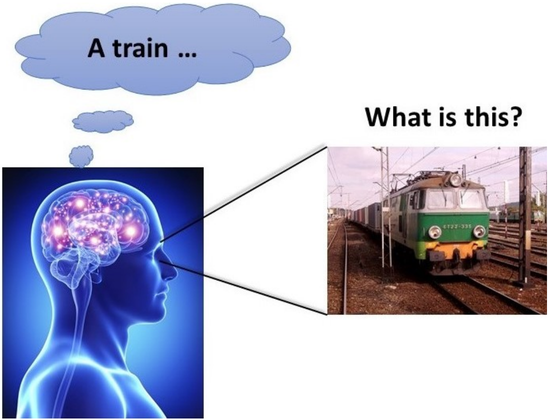
Introduction to
Artificial Intelligence and Machine Learning

Andrés Villa

Artificial Intelligence and Machine Learning

- Machine Learning is part of a broader field known as Artificial Intelligence.
- What is Artificial Intelligence?
  - Easy part: Artificial.
  - Hard part: Intelligence.

Taking inspiration on the biological world



Artificial World



What is Artificial Intelligence?

Study of computational models that allows a machine to perceive, reason, and act with great flexibility

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Study of computational models that allows a machine to acquire a level of understanding of its world.

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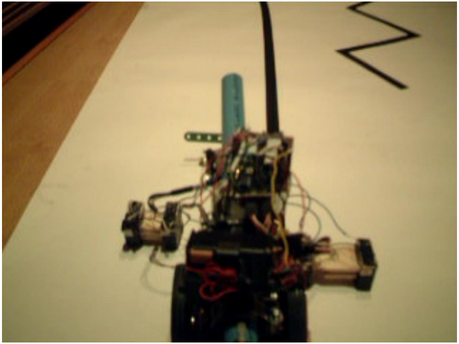
Understanding: Year 2001



Understanding: Year 2001

Understanding: Year 2019

Understanding: Year 2020

Understanding: Year 2020

Inductive learning

This bird can fly

This bird can fly

This bird can fly

This bird can fly

Can this bird fly ?

Inductive learning

This bird can fly

This bird can fly

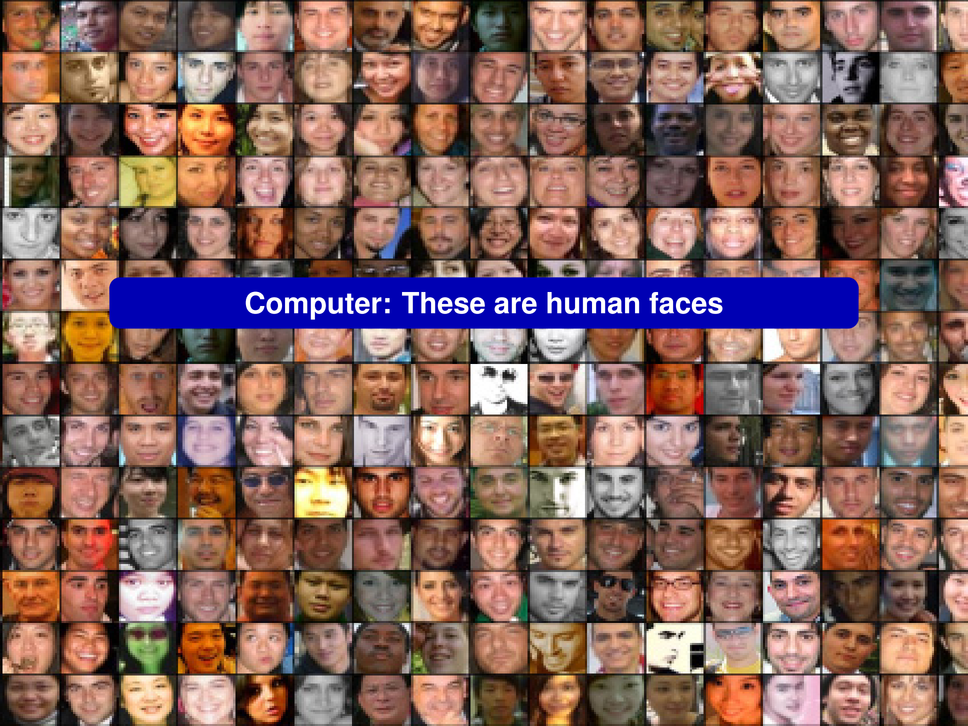
This bird can fly

This bird can fly

Can this bird fly ?

Machine Learning

Computational programs (algorithms) that learn from experience, i.e., data.


Computer: These are human faces


Computer: These are NOT human faces

Computer: Any human face?

DEMO

This is a chair

This is a chair

Most times a difficult problem

This is a chair

What are these?

Artificial Intelligence: Modern View (Russell and Norvig)

An intelligent agent (or intelligent machine) corresponds to an agent able to perceive, reason, and act with great flexibility.

Machine learning perspective

An intelligent agent corresponds to an agent able to learn from experience.

This course perspective

An intelligent agent is able to acquire a level of understanding of its world.

Learning from experience

Gaining knowledge from data in order to:

- Make predictions, take decisions, . . . , and in general build useful representations to understand its world.

- Machine learning techniques operate over multidimensional data.
- Every data example or instance is given by a set of relevant measurements or attributes.

Examples: Datasets from UCI repository (`http://archive.ics.uci.edu/ml`):

Wine Data Set

Download: Data Folder, Data Set Description

Abstract: Using chemical analysis determine the origin of wines

Data Set Characteristics:	Multivariate	**Number of Instances:**	178	**Area:**	Physical
Attribute Characteristics:	Integer, Real	**Number of Attributes:**	13	**Date Donated**	1991-07-01
Associated Tasks:	Classification	**Missing Values?**	No	**Number of Web Hits:**	573523

Bank Marketing Data Set

Download: Data Folder, Data Set Description

Abstract: The data is related with direct marketing campaigns (phone calls) of a Portuguese banking institution. The classif

Data Set Characteristics:	Multivariate	**Number of Instances:**	45211	**Area:**	Business
Attribute Characteristics:	Real	**Number of Attributes:**	17	**Date Donated**	2012-02-14
Associated Tasks:	Classification	**Missing Values?**	N/A	**Number of Web Hits:**	248768

The dataset used to learn a model using a machine learning technique is known as: Training set.

Age	Job	Marital	Education	Debt	Balance (Euros)	Housing	Loan	Contact	Day	Month	Contact duration (secs)	Campaign	Previous contacts	Subscribe deposit
30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	0	no
33	services	married	secondary	no	4789	yes	yes	cellular	11	may	220	1	4	no
35	management	single	tertiary	no	1350	yes	no	cellular	16	apr	185	1	1	no
30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	0	no
59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	0	no
35	management	single	tertiary	no	747	no	no	cellular	23	feb	141	2	3	no
36	self-employed	married	tertiary	no	307	yes	no	cellular	14	may	341	1	2	no
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41	entrepreneur	married	tertiary	no	221	yes	no	unknown	14	may	57	2	0	no
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43	admin.	married	secondary	no	264	yes	no	cellular	17	apr	113	2	0	no
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41	management	married	tertiary	no	5883	no	no	cellular	20	nov	182	2	0	no

Attributes, dimensions, variables or features

Class or Label

Instances

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- Every training example can be considered as a vector that lies in a feature space.

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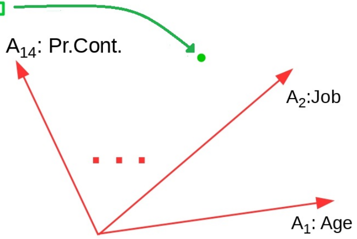

Generalization: The ultimate goal

Training set used during the learning process.

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New instances unknown to the model.

20	student	single	secondary	no	502	no	no	cellular	30	apr	261	1	0	?
31	blue-collar	married	secondary	no	360	yes	yes	cellular	29	jan	89	1	1	
40	management	married	tertiary	no	194	no	yes	cellular	29	aug	189	2	0	
56	technician	married	secondary	no	4073	no	no	cellular	27	aug	239	5	0	

Can we measure generalization capabilities?

Training set.

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Test Set: instances with known label, but not included during training. They are used to evaluate generalization capabilities of the resulting model (why?).

20	student	single	secondary	no	502	no	no	cellular	30	apr	261	1	0	?
31	blue-collar	married	secondary	no	360	yes	yes	cellular	29	jan	89	1	1	
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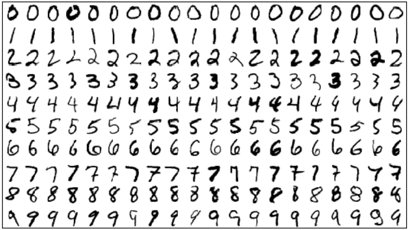
1. (i) Traing set: used to train the main model.
2. (ii) Test set: used to measure the performance that can be expected from a machine learning model.
3. (iii) Validación set: used to adjust hyperparameters, ex. number of iterations, model structure, etc.

Rule of thumb: from the available data, reserve 60-80% for training, 10-20% for test, and 10-20% for validation.

Case example: MNIST dataset

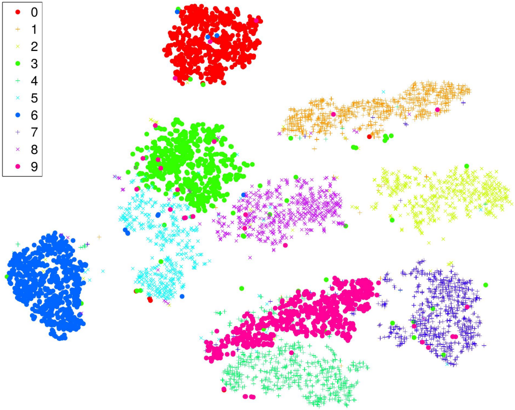


- MNIST is a dataset of images corresponding to handwritten digits.
- Each image displays a single digit from 0 to 9. Images are binary with a resolution of 28x28 pixels.
- Goal: Build a classifier that can recognize the digit in each image.
- Dataset consists of 60.000 training examples and 10.000 test cases.

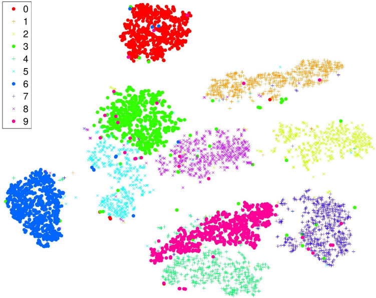
What size is the feature space of the MNIST dataset?

Ej. MNIST dataset

- It is not possible to provide a direct representation of the MNIST feature space using a 2D visualization.
- However, we can use dimensionality reduction techniques such as t-SNE (`http://lvdmaaten.github.io/tsne`) to obtain a suitable approximation:



Ej. MNIST dataset



- This visualization illustrates the complexity of the target classifier.

Resulting confusion matrix after applying a K-nearest neighbors classifier over the MNIST test set.

Prediction

Real

	0	1	2	3	4	5	6	7	8	9
0	972	1	1	0	0	1	3	1	0	0
1	0	1129	3	0	1	1	1	0	0	0
2	7	6	992	5	1	0	2	16	3	0
3	0	1	2	970	1	19	0	7	7	3
4	0	7	0	0	944	0	3	5	1	22
5	1	1	0	12	2	860	5	1	6	4
6	4	2	0	0	3	5	944	0	0	0
7	0	14	6	2	4	0	0	992	0	10
8	6	1	3	14	5	13	3	4	920	5
9	2	5	1	6	10	5	1	11	1	967

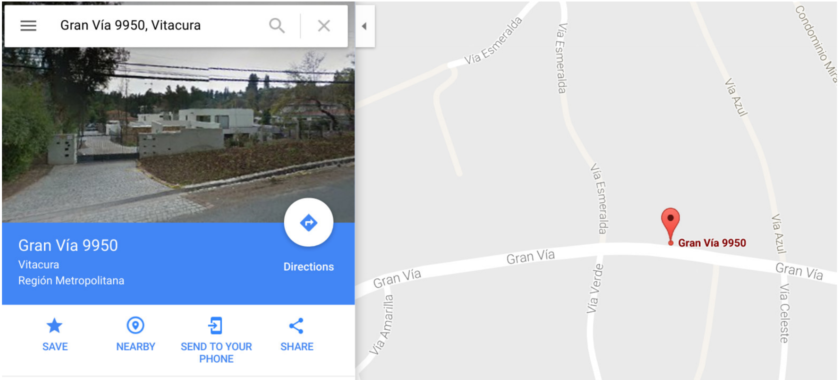
These results are based on K=1 using Euclidean distance in the space of 784 dimensions (why 784?).

- As we discussed, Machine Learning is about learning from data.
- Currently, Big Data is a great ally.
- By providing large sources of data, Big Data is increasing the accuracy of machine learning techniques.
- The synergistic combination between machine learning and big data is a key element to the current success of AI.

Good experience, i.e. data, is key to learn.

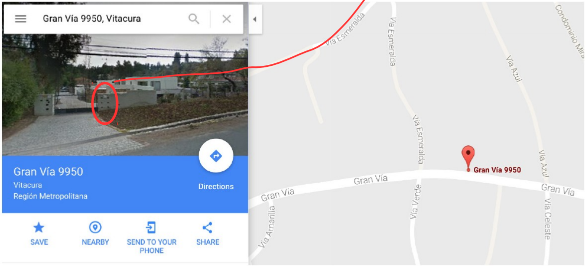
Experience is key

Example: Google Street View.



Experience is key

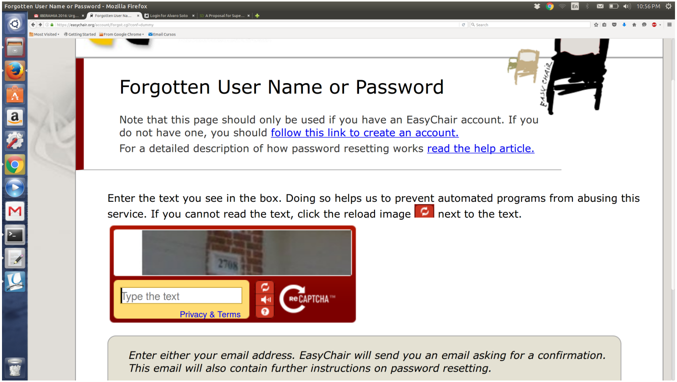
Example: Google Street View.



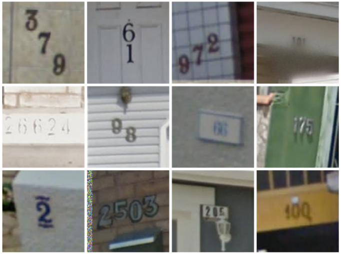
How can they do this?

Experience is key

Example: Google Street View.

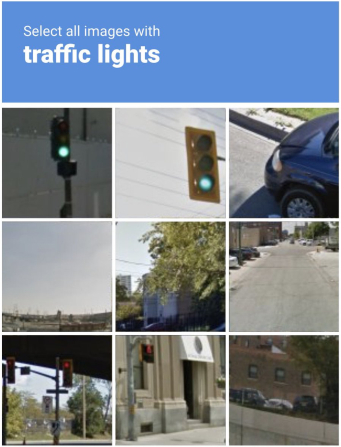


Experience is key: Training Data

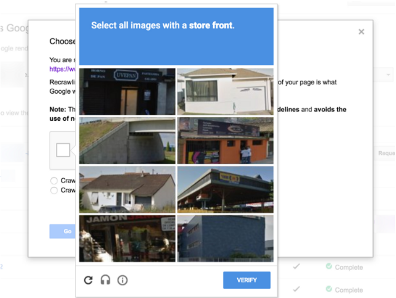


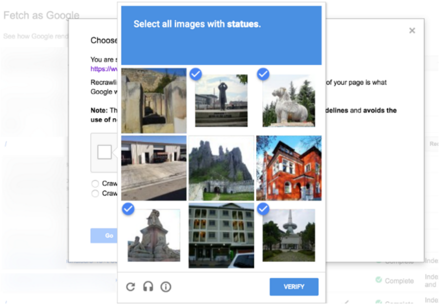
http://research.google.com/pubs/pub42241.html

Experience is key: Training Data

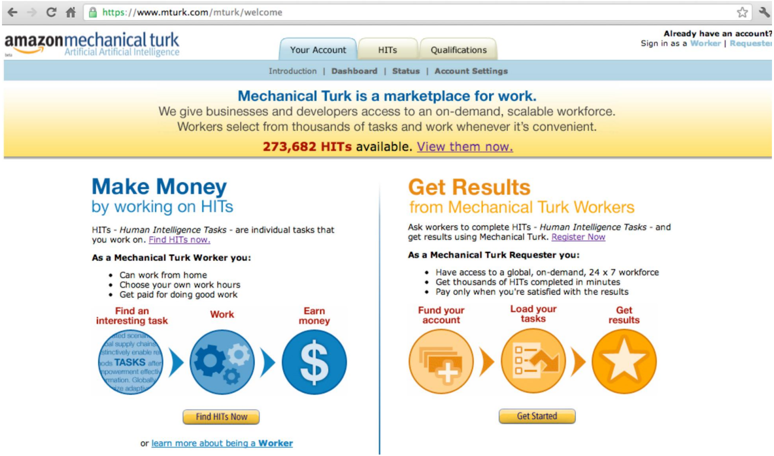


Experience is key: Training Data





Experience is key: Crowdsourcing and Human Computation



Experience is key: Crowdsourcing and Human Computation

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- Chatbot training data

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What is chatbot training data?

Chatbots are applications that turn raw, unstructured data into a conversation. A chatbot needs training data for two reasons: to understand what people are saying, and how to respond. A truly intelligent chatbot needs to be fed data that:

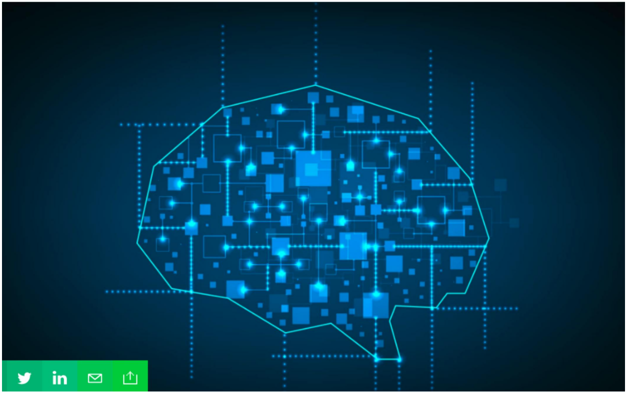
- **Is extremely large volume.** The more data you can use to train your bot, the higher the rate of confidence in intent detection.
- **Maintains a high level of quality.** Especially in the case of text data, this means tagging your text corpora well. Though a dull and time consuming task, it's necessary as quality of data is key to a successful conversation.

Experience is key: Crowdsourcing and Human Computation

Appen acquires Figure Eight for up to $300M, bringing two data annotation companies together

Anthony Ha @anthonyha / 4 hours ago

Comment



10/03/2019

Experience is key: Training Data

Example: Xbox human pose recognition.

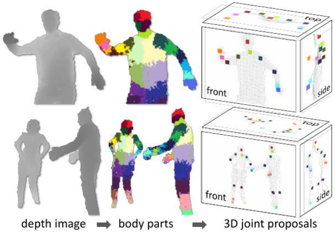
Real-Time Human Pose Recognition in Parts from Single Depth Images

Jamie Shotton Andrew Fitzgibbon Mat Cook Toby Sharp Mark Finocchio
Richard Moore Alex Kipman Andrew Blake
Microsoft Research Cambridge & Xbox Incubation

Abstract

We propose a new method to quickly and accurately predict 3D positions of body joints from a single depth image, using no temporal information. We take an object recognition approach, designing an intermediate body parts representation that maps the difficult pose estimation problem into a simpler per-pixel classification problem. Our large and highly varied training dataset allows the classifier to estimate body parts invariant to pose, body shape, clothing, etc. *Finally we generate confidence-scored 3D proposals of several body joints by reprojecting the classification result and finding local modes.*

The system runs at 200 frames per second on consumer



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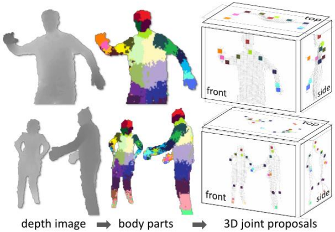

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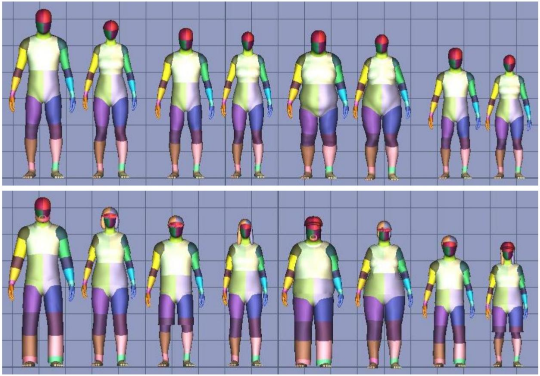

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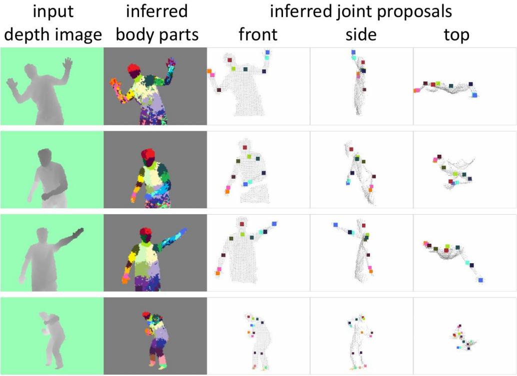


Experience

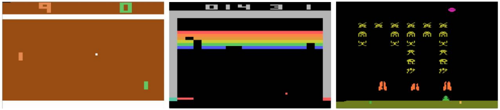
So far we have been focusing on a learning paradigm known as: Supervised learning. However, depending of the type of training data available and the goals of the learning process, we can find several popular learning paradigms:

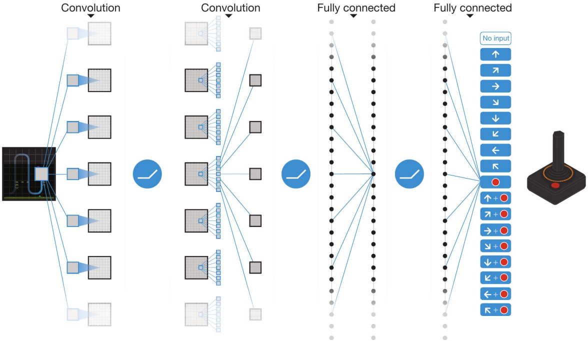
- Supervised learning.
- Reinforcement learning.
- Unsupervised learning.
- Self-supervised learning.
- Semi-supervised learning.
- Active learning.
- Structural learning.
- Instance based learning.
- ...

As we will discuss in this course, all these learning frameworks are just different ways to provide semantic to the learning process (grounding).

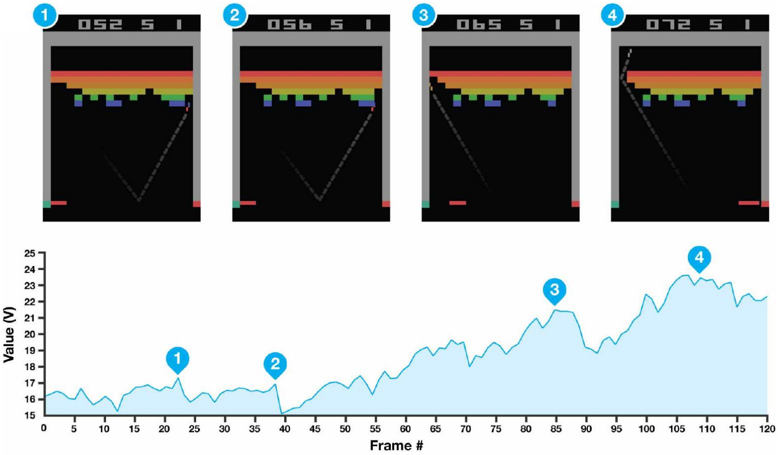
Reinforcement learning

Learning to play Atari games (Mnih et al., NIPS-2014)

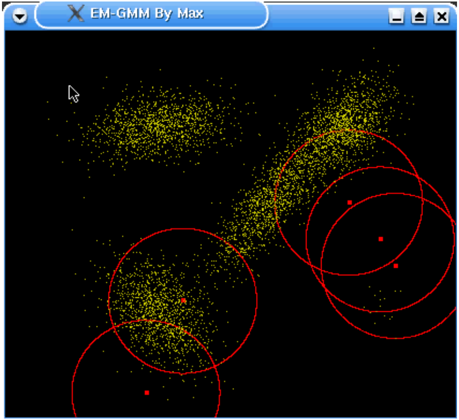




Reinforcement learning



Unsupervised Learning



Self-supervised Learning

Machine Learning

Any computer program that improves its performance at some task through experience.

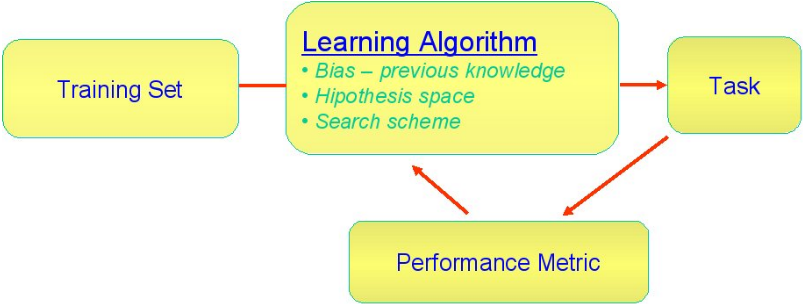
A computer program is said to learn from experience E with respect to some class of task T and performance measure P, if its performance for tasks in T, as measured by P, improves with experience E.

Key assumption of Inductive Machine Learning

Any hypothesis that approximates a target function well over a sufficiently large set of training examples will also approximate this target function well over unobserved examples.

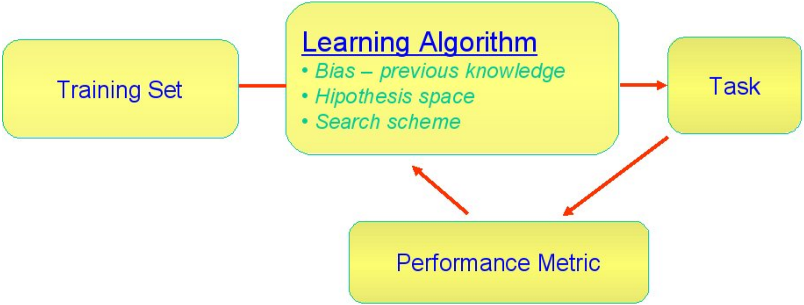
- $\boxed{\text{OJO}}$ The previous assumption requires that the training data must be representative of the target concept or function.

Learning involves searching through a space of possible hypotheses to find a hypothesis that provides a suitable (best) fit to the available training data and prior constraints (previous knowledge).



$\boxed{\text{OJO}}$ There is a new element: previous knowledge. . . Any comment?

Machine learning, 3 main ingredients:
Representation + Performance + Optimization.



Machine learning, 3 main ingredients:
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Machine learning problem

$$f^* = \arg\min_{f \in \mathcal{H}} \mathcal{L}(f(x)) = \arg\min_{f \in \mathcal{H}} \int_{x_i \in T} \mathcal{L}(f(x_i)) d_T$$

We usually approximate this using a training set Tr:

$$f^* \approx f^*_{Tr} = \arg\min_{f \in \mathcal{H}} \frac{1}{N} \sum_{x_i \in Tr}^{N} \mathcal{L}(f(x_i))$$

$\mathcal{H}$: hypothesis space.
$\mathcal{L}$: loss function
f^*: optimal hypothesis in $\mathcal{H}$ under $\mathcal{L}$.

Generic machine learning loss

$$f^* \approx f^*_{Tr} = \arg\min_{f \in \mathcal{H}} \frac{1}{N} \sum_{x_i \in Tr}^{N} \mathcal{L}(f(x_i))$$

Supervised learning

$$f^*_{Tr} = \arg\min_{f \in \mathcal{H}} \tfrac{1}{N} \sum_{x_i, y_i \in Tr}^{N} \mathcal{L}(f(x_i), y_i)$$

Hypothesis space

- Models have limits (suitable representation?).
- Search in complex spaces (non-lineal or convex) is usually a hard and exhausting process (right optimization tool and performance metric?).

- If the hypothesis space is too flexible, there is a higher risk to converge to misleading hypothesis (suffer overfitting problems).
- If the search tool is too limited, there is a higher risk to being unable to find a good hypothesis (converge to local optimals).

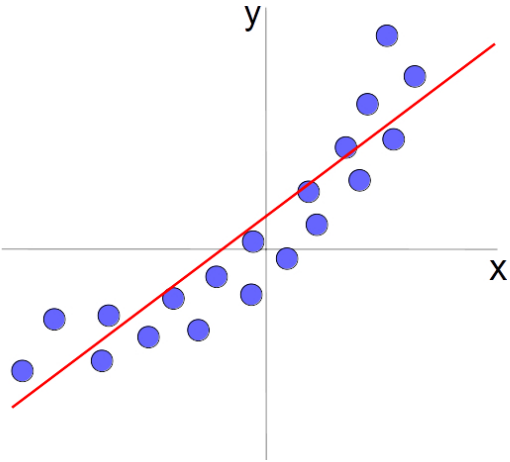
Overfitting?

- When one applies a ML technique, one is interested in the generalization capabilities of the resulting model, why?.
- Generalization? $\rightarrow$ Inductive learning.
- In other words, one is interested in obtaining good predictions for new instances of the target domain.

Overfitting: It is a situation when a ML model starts to memorize (overfit) the traininig data, decreasing its capability to correctly predict new instances.

Jorge Luis Borges: ``Funes el memoriozo".
``...Había aprendido sin esfuerzo el inglés, el francés, el portugués, el latín. Sospecho, sin embargo, que no era muy capaz de pensar. Pensar es olvidar diferencias, es **generalizar, abstraer**. En el abarrotado mundo de Funes no había sino detalles, casi inmediatos."

Underfitting, Overfitting, Good fit



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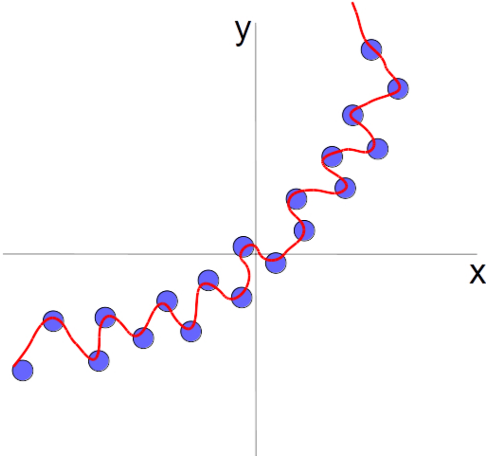

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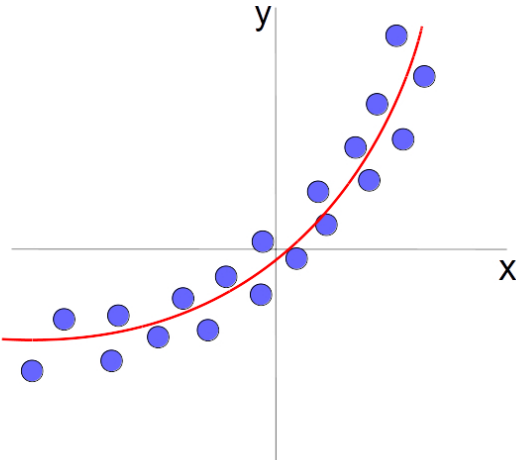

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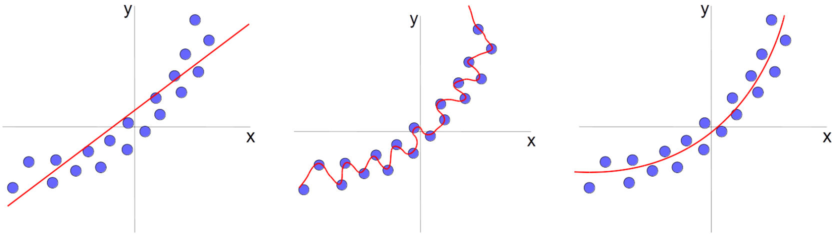
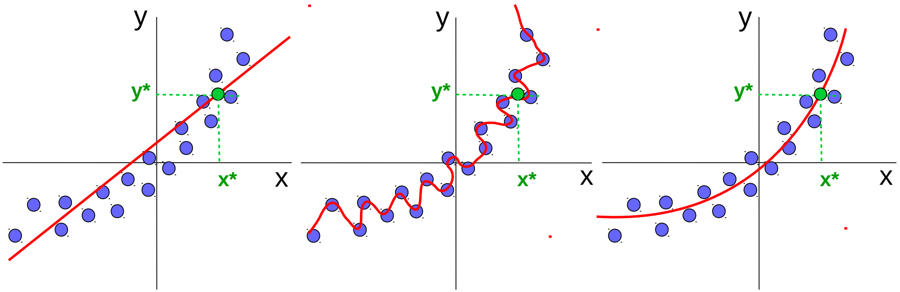
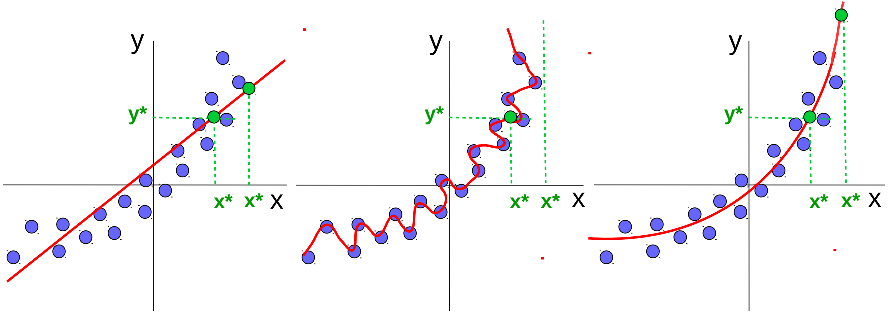


Generalization



Generalization



Concepts that you should know about ML.

- Classical AI and ML views.
- Generic view of ML.
- Main elements of a ML technique: Representation + Performance + Optimization.
- Supervised and unsupervised ML.
- Overfitting.
- Training, test, validation sets.

- Recommended reading: “A Few Useful Things to Know About Machine Learning” by Pedro Domingos.

Tapping into the "folk knowledge" needed to advance machine learning applications.

BY PEDRO DOMINGOS

A Few Useful Things to Know About Machine Learning

MACHINE LEARNING SYSTEMS automatically learn programs from data. This is often a very attractive alternative to manually constructing them, and in the last decade the use of machine learning has spread rapidly throughout computer science and beyond. Machine learning is used in Web search, spam filters, recommender systems, ad placement, credit scoring, fraud detection, stock trading, drug design, and many other applications. A recent report from the McKinsey Global Institute asserts that machine learning (a.k.a. data mining or predictive analytics) will be the driver of the next big wave of innovation.[15] Several fine textbooks are available to interested practitioners and researchers (for example, Mitchell[16] and Witten et al.[24]). However, much of the "folk knowledge" that is needed to successfully develop machine learning applications is not readily available in them. As a result, many machine learning projects take much longer than necessary or wind up producing less-than-ideal results. Yet much of this folk knowledge is fairly easy to communicate. This is the purpose of this article.

» key insights

- **Machine learning algorithms can figure out how to perform important tasks by generalizing from examples. This is often feasible and cost-effective where manual programming is not. As more data becomes available, more ambitious problems can be tackled.**
- **Machine learning is widely used in computer science and other fields. However, developing successful machine learning applications requires a substantial amount of "black art" that is difficult to find in textbooks.**
- **This article summarizes 12 key lessons that machine learning researchers and practitioners have learned. These include pitfalls to avoid, important issues to focus on, and answers to common questions.**

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