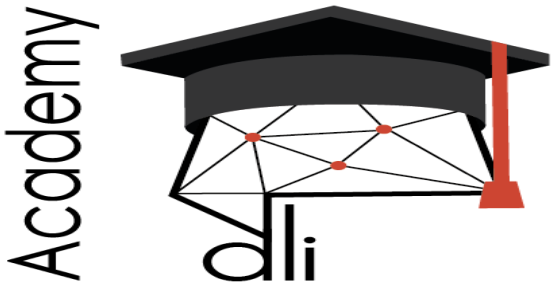

Deep Learning

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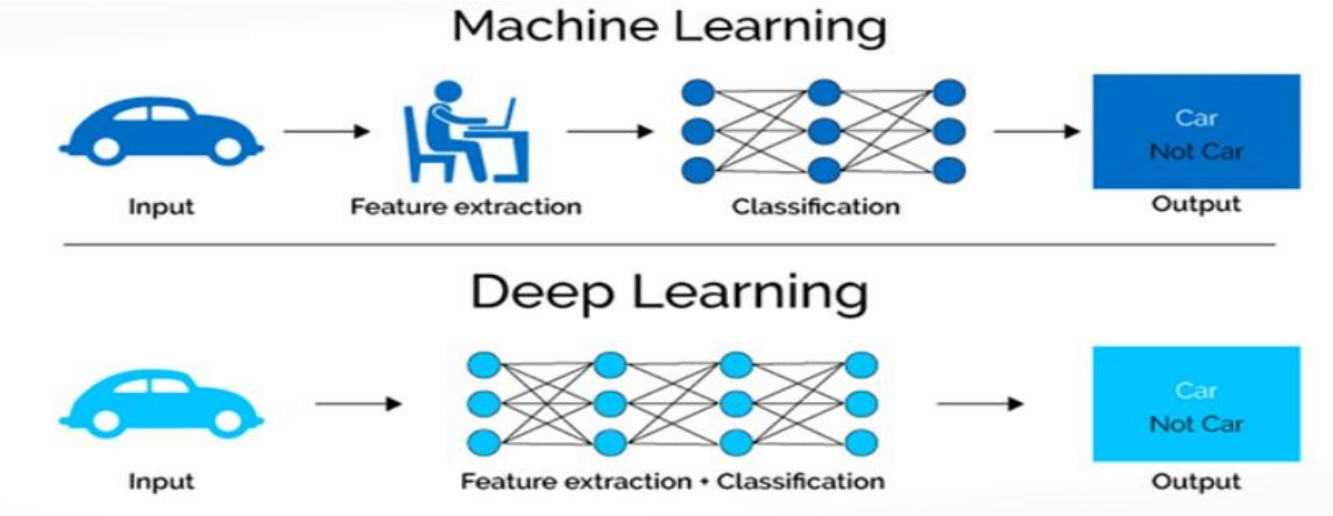
What is Deep Learning ?

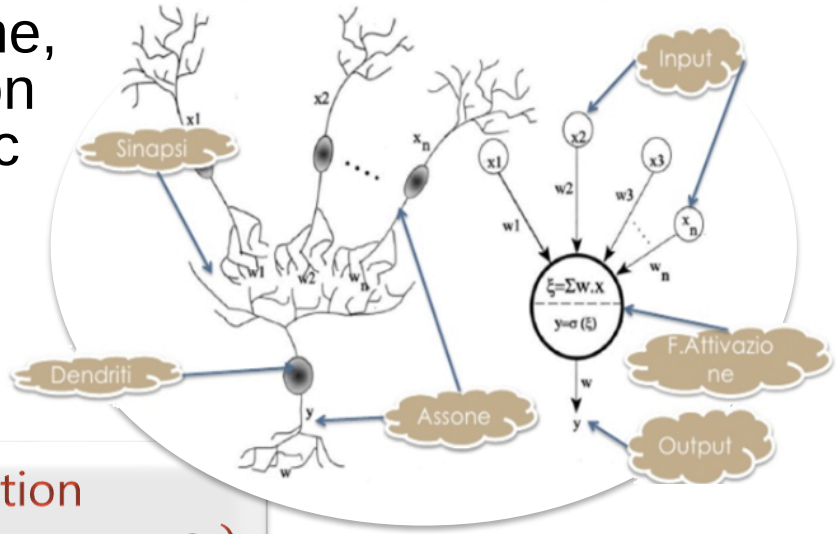
Deep Learning refers to algorithms that automatically ‘model’ high-level abstractions in data

i. here ‘model’ means: define, find, recognize and exploit
ii. here ‘automatically’ means: directly from data, without hinging upon handcrafted, task-specific features.



ARTIFICIAL NEURAL NETWORKS (ANNs)

ANNs were introduced, for the first time, by 1943, in a work on the formalization of neural activity in propositional logic form (*McCulloch & Pitts, 1943*).
We can define ANNs as a simple model of biological organisms' nervous system.



Neuron Activation

$$A_j = \sum_{i=1}^{N} w_{ij} X_i - \theta_i$$

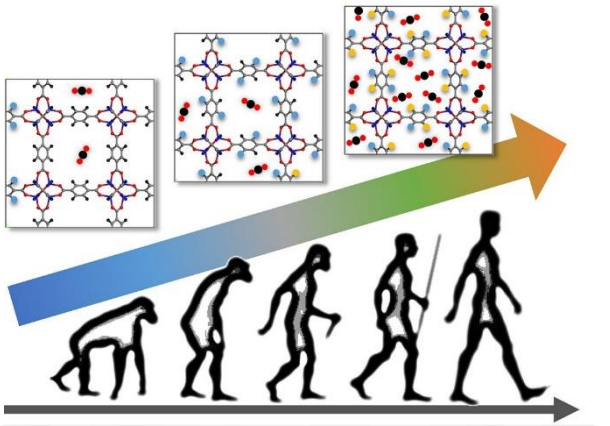
Activation function

$$y_j = \Phi(A_j) = \Phi\left(\sum_{i=1}^{N} w_{ij} X_i - \theta_i\right)$$

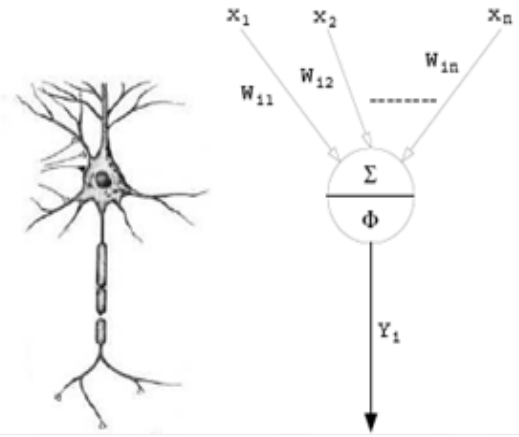
In data mining: Methods have been developed to produce comprehensible models and reduce training times:
1)Rule extraction: extraction of symbolic models from pre-trained neural networks.
2)Learn simple, easy-to-understand neural networks.

One traditional application ANN: Evolutionary robotics

In order to overcome the problems associated with the robotic system decomposition of traditional approaches (i.e. behavior-based robotics), evolutionary robotics can be used, where the robotic system is able to self-organize [*Nolfi, S., Floreano, D ., 2000*].

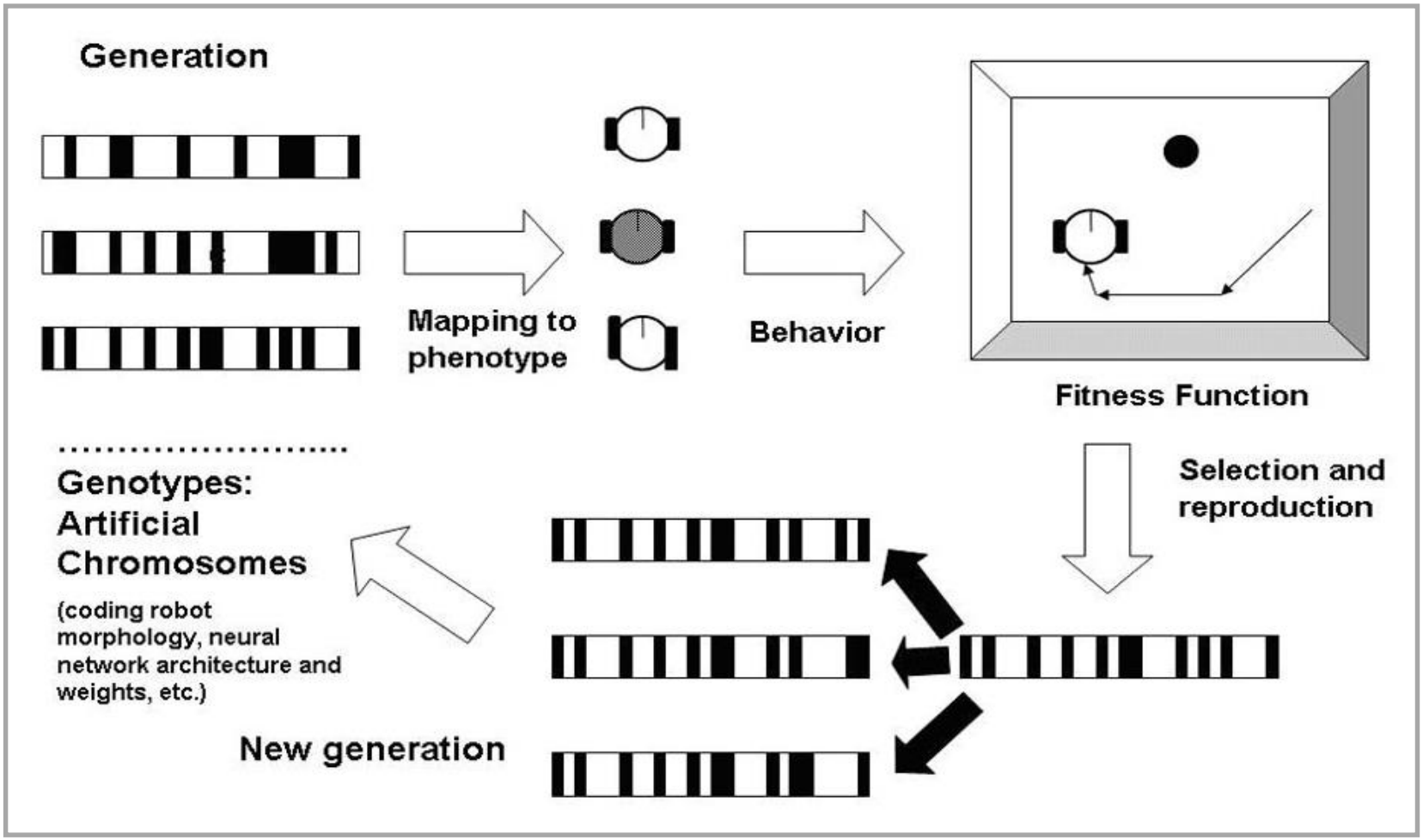


NeuroGenetic Algorithm



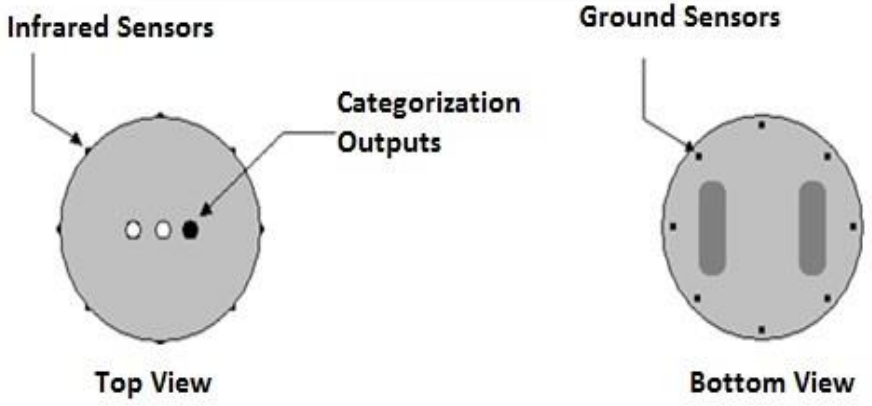
Control Neural Network

Evolutionary Robotics

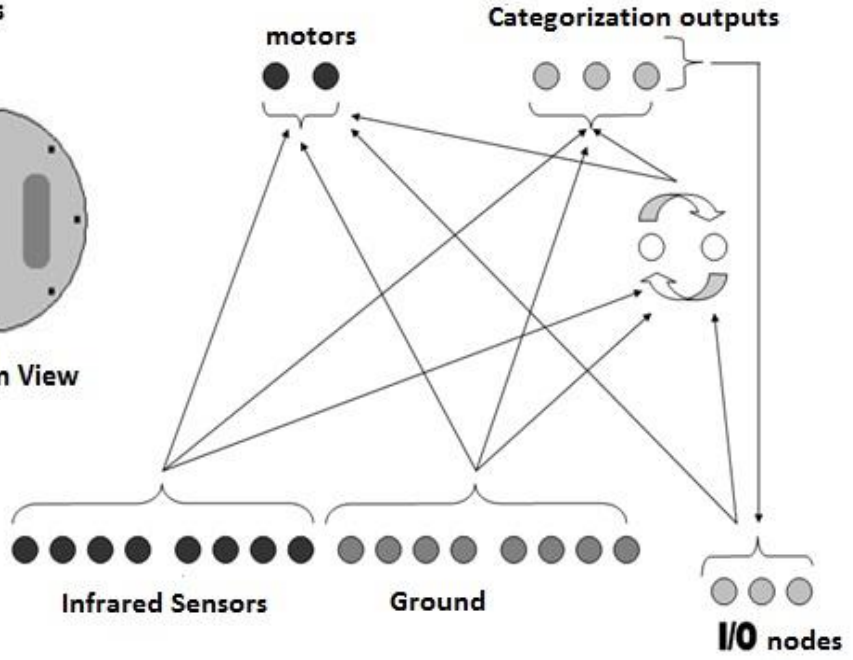


EXPERIMENTAL SETUP N.1

ROBOT'S CHASSIS



NEURAL NETWORK

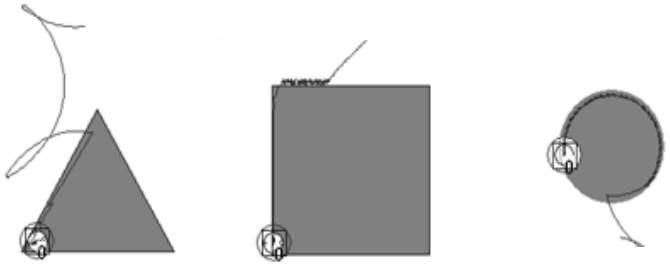


LEAKY Activation

$$A_j = t_j + \sum w_{ij} O_i \;,\; O_j = \delta_j O^{t-1} + (1 - \delta_j)\left(1 + \frac{1}{e^{A_j}}\right), 0 \le \delta_j \le 1$$

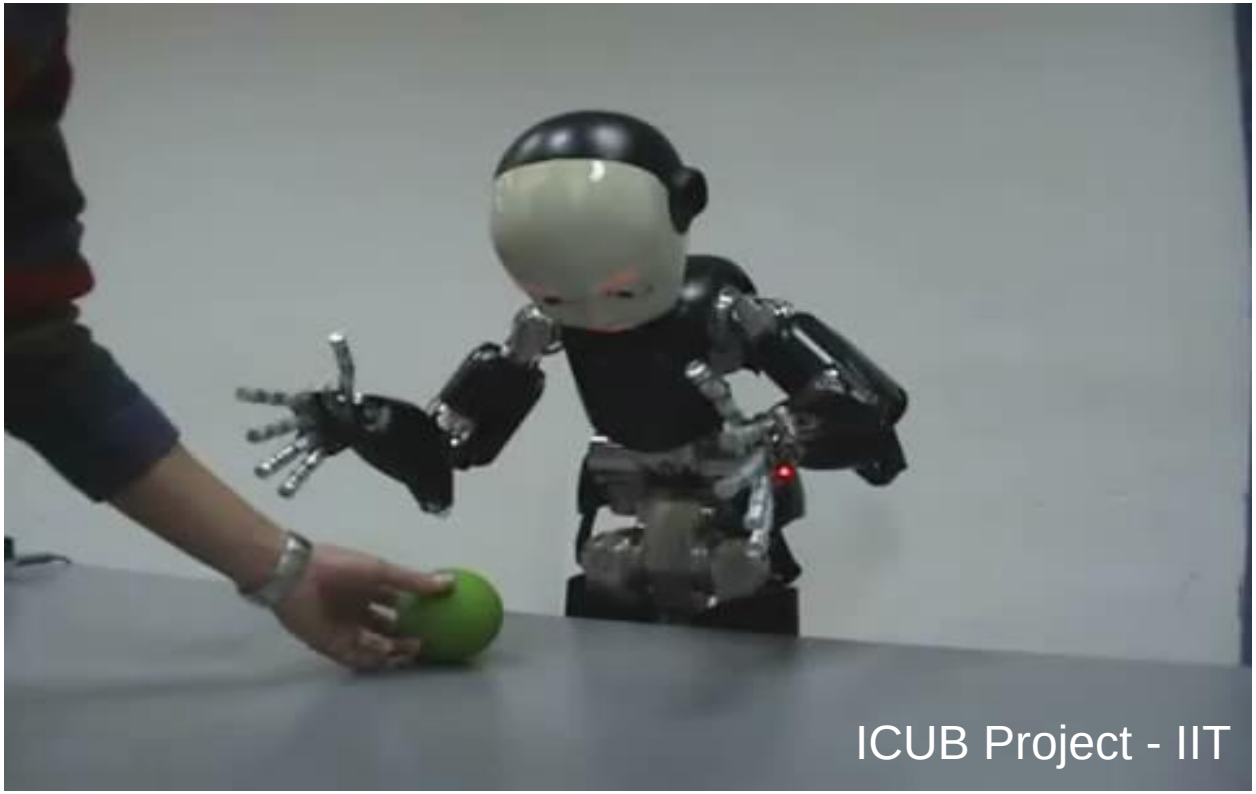
EXPERIMENTAL SETUP N.1

RESULTS



FITNESS CURVE

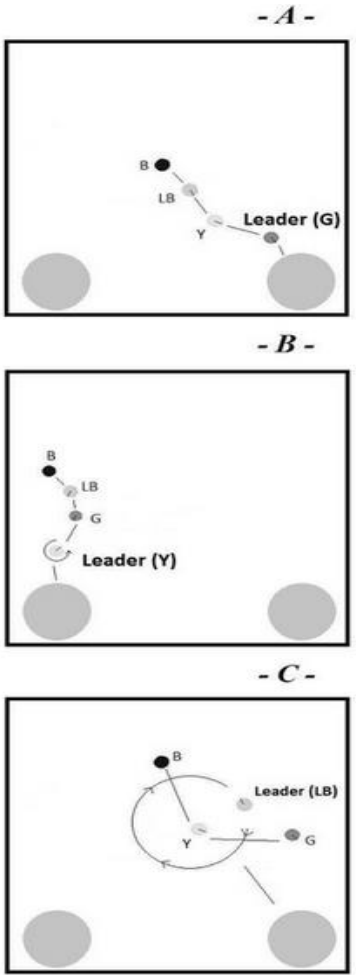
MAY Robotics help to understand social and psychological problems? (Cangelosi, & Riga, 2006)

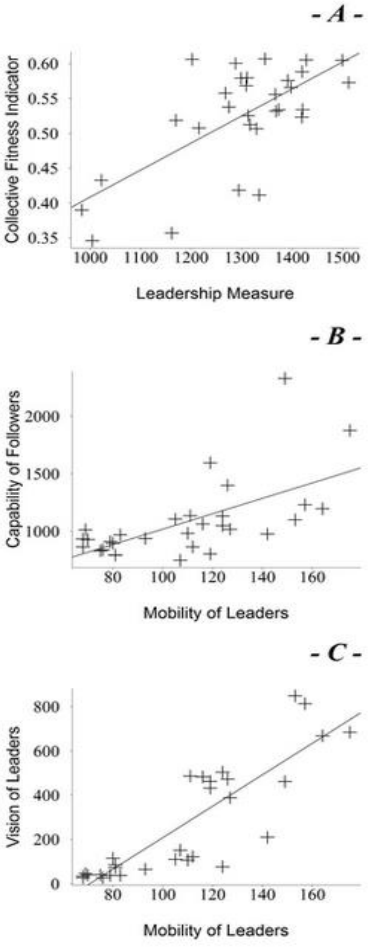


Emergence of Leadership in Robots (Pugliese, et al., 2015).

- Behavioural and quantitative analysis indicate that a form of leadership emerges
- Groups with a leader are more effective than groups without.
- The most skilled individuals in a group tend to be the leaders.
- Further analysis reveals the emergence of different “styles” of leadership (active and passive).

- A - Passive Leadership. - B - Weak Active Leadership. - C - Strong Active Leadership.





DEEP LEARNING: Neural Networks become more effective

In recent years **Deep Neural Networks** have achieved noticeably breakthroughs in research (*Bengio, 2009*). This new methodology dealing with deep neural networks and their training algorithms is called *"Deep Learning"*. **So far, in all the experiments, the resulting performances were many magnitudes better than other machine learning techniques available.**

GOOGLE DATACENTER

1,000 CPU Servers 2,000 CPUs • 16,000 cores	600 kWatts $5,000,000

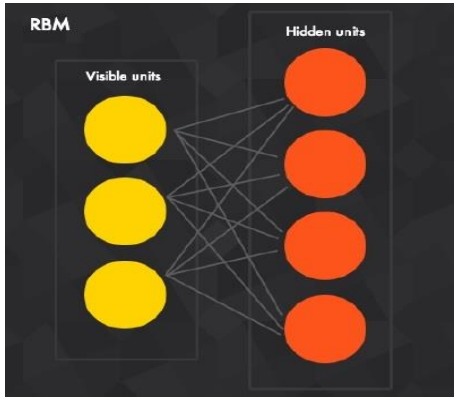
STANFORD AI LAB

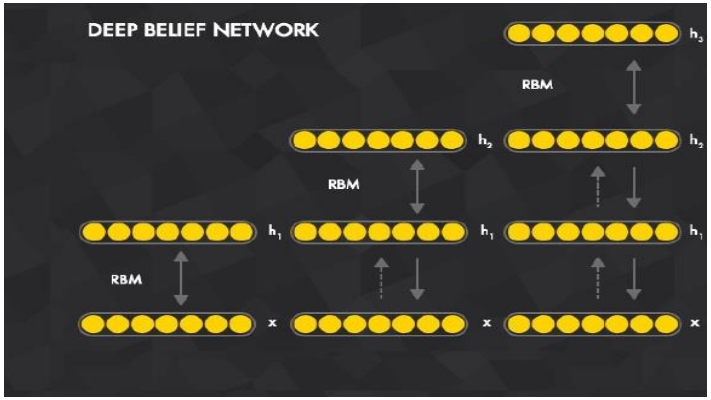
3 GPU-Accelerated Servers 12 GPUs • 18,432 cores	4 kWatts $33,000

DEEP LEARNING: a CUTTING-EDGE APPROACH to Big Data

Unsupervised Learning (generative model):

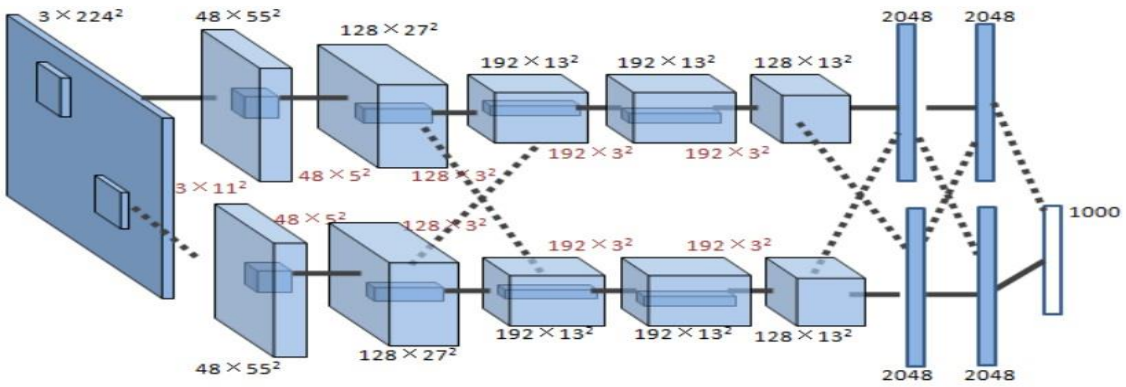
- Restricted Boltzman Machines (RBM)
- Deep Belief Networks (Hinton et al., 2006).
- *Contrastive Divergence*





Supervised Learning (discriminative model):

- Deep Convolutional Neural Networks (LeCun et al., 1989).
- *Back Propagation*



DEEP LEARNING: a cutting-edge approach to Computer Vision and NLP

GPU

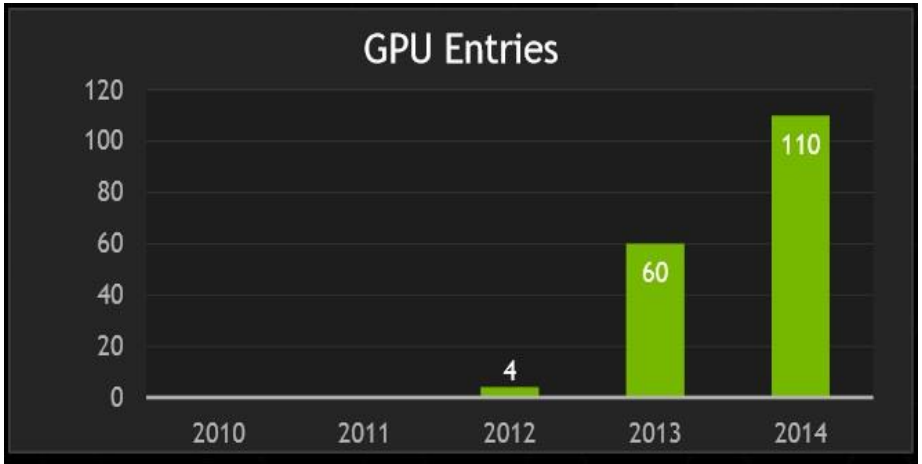
- The advent of GPUs makes possible the training of very large neural networks with even more than 150 millions of parameters.

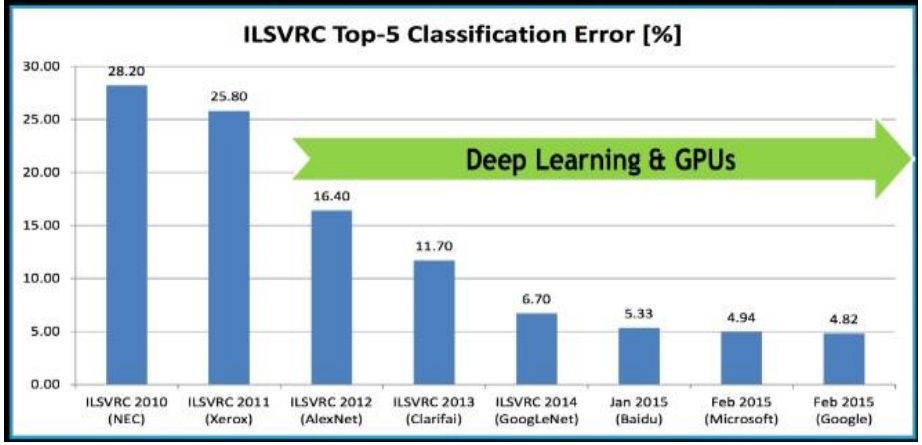
BIG DATA

- A new generation of larger training and test sets.

DROPOUT

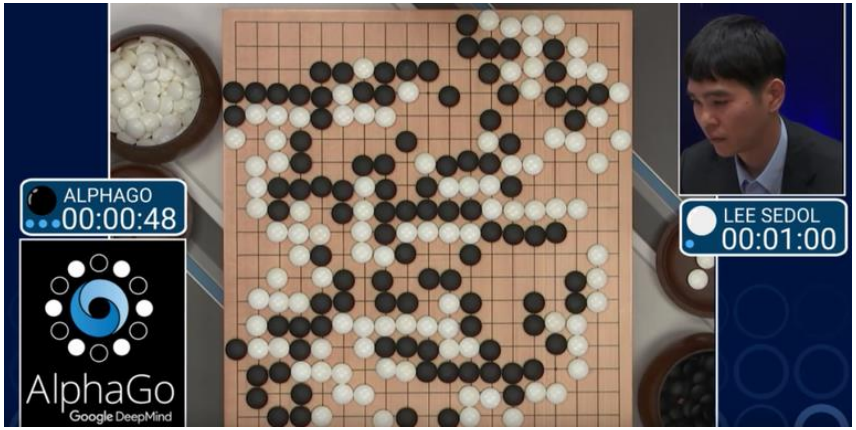
- Better model regularization techniques have been discovered such as ***"Dropout"*** or ***"Data Augmentation"***





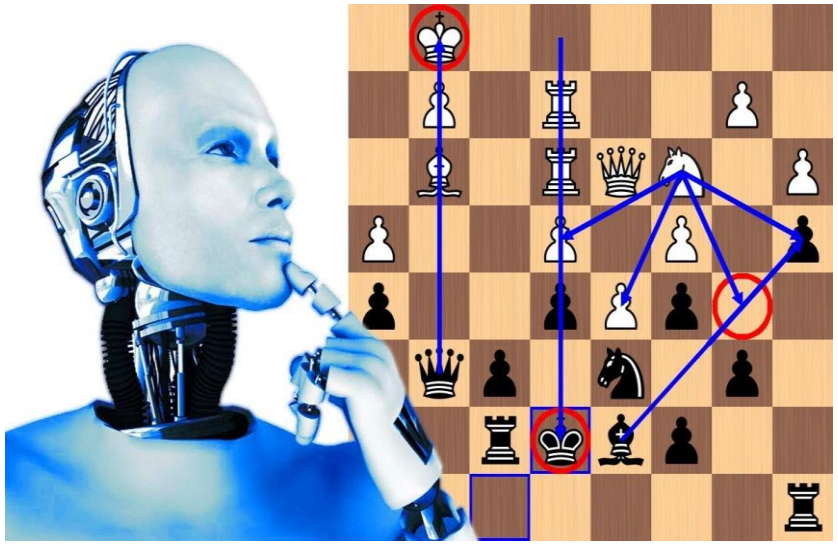
Why Deep Learning over-performed traditional statistics models?

- "Deep Learning" approaches can be **end-to-end trained** without a task-specific feature engineering.
- **These model are scalable**: adding GPUs they can be trained faster.
- **"Deep Learning is killing every problem in AI"** (*Elizabeth Gibney, 2016*)
- **Basically, statistics is not able to deal with very high dimensionalities of data as Deep Learning does**.



Alpha Zero: Mastering the games of Go and Chess without Human Knowledge

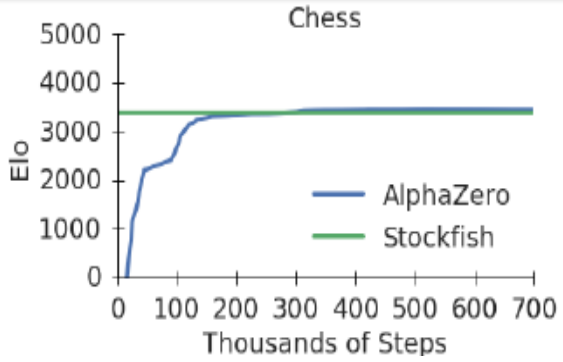
- **In Just 4 Hours, Google's AI Mastered All The Chess Knowledge in History**
- **"I always wondered how it would be if a superior species landed on Earth and showed us how they played chess. Now I know." grandmaster Peter Heine Nielsen.**

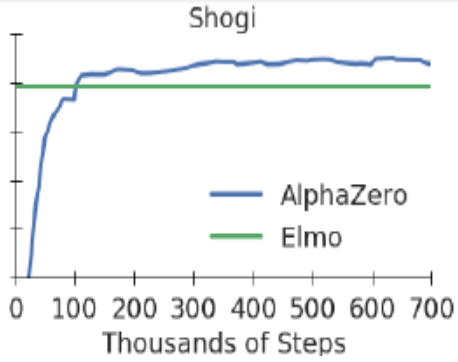


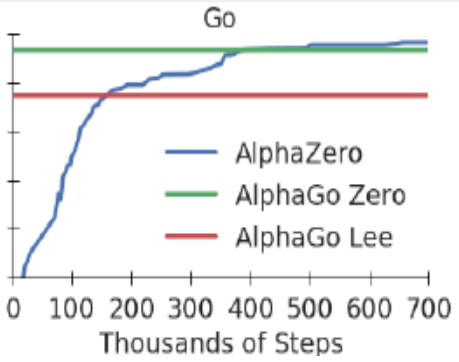
- **Google's AlphaZero Destroys Stockfish In 60 Game Matches**

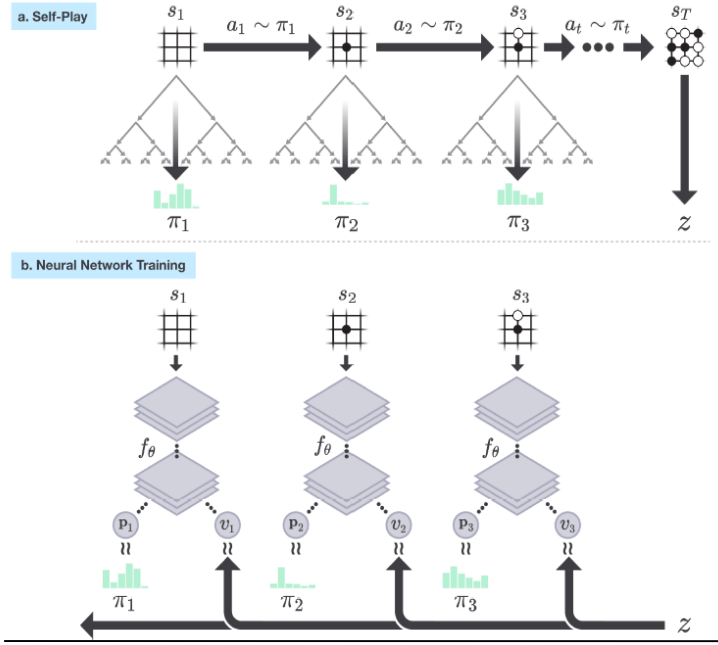
"This algorithm could run cities, continents, universes."
***PETER DOCKRILL* (*Senior Writer*)**

Alpha Zero IS an Artificial Intelligence, it IS NOT just a Chess Engine..

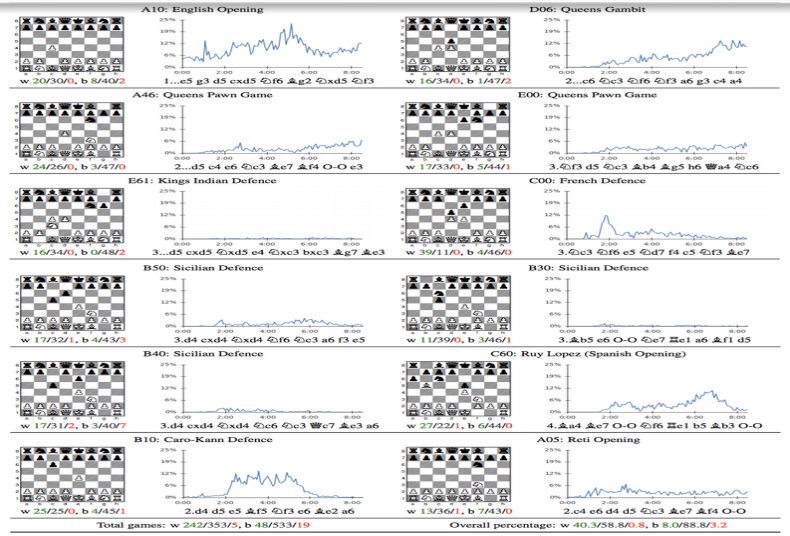






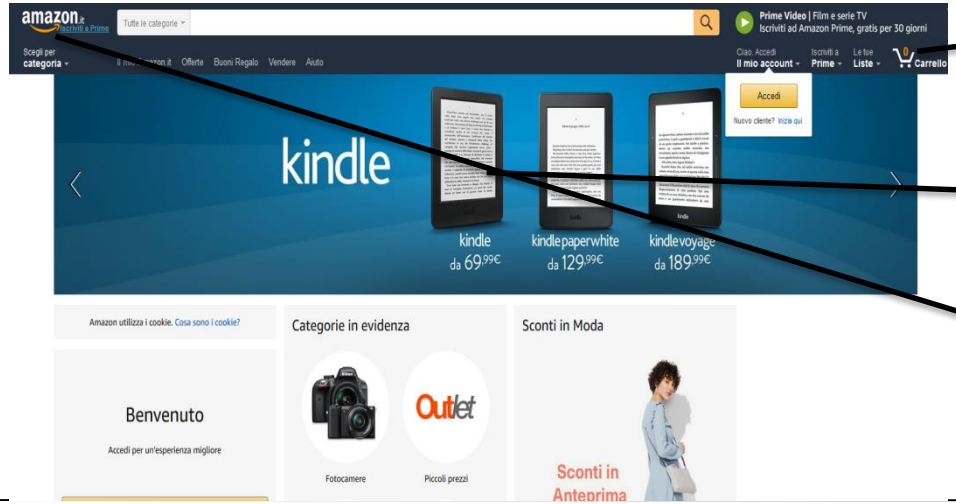


12 Chess Openings Discovered by Alphazero



Web-Site classification by Images Approach

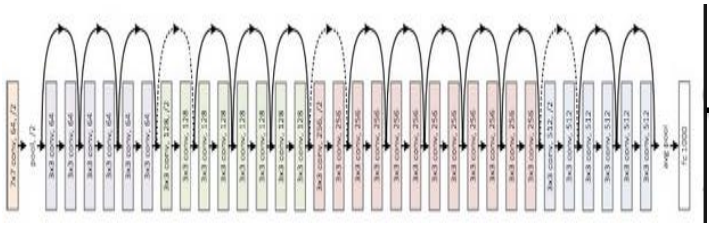
- According to the **False Positive Reduction** technique we exploit the inner images segmentation of a Web-site in order to train an evolved ConvNet (ResNet) model onto the single websites images segments.
- **ConvNet** is trained in **“Transfer Learning”** mode, which means taking advantage of a pre-trained model onto well-know datasets such as Imagenet (1000 image classes, 1.2 mln images)



Web-Site classification by Images Approach

Positive Set (E-commerce)

Residual Neural Network



1 - E-commerce

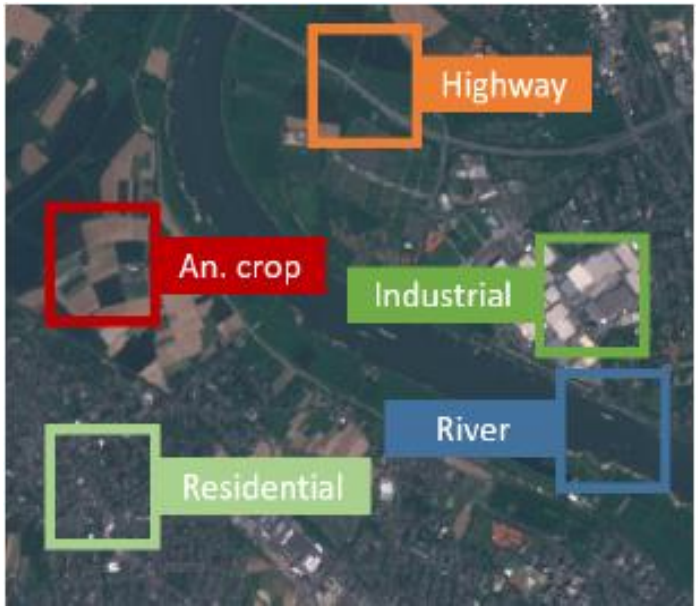
0 – Non E-commerce

Negative Set (Non E-commerce)

- In test stage, on a **Test Set,** Web-site images are still segmented and the label of the image with higher probability is assigned to the web-site itself.

Automatic Extraction of Statistics from Satellite Imagery: Land Use and Land Cover Classification (Helber, et al.,)

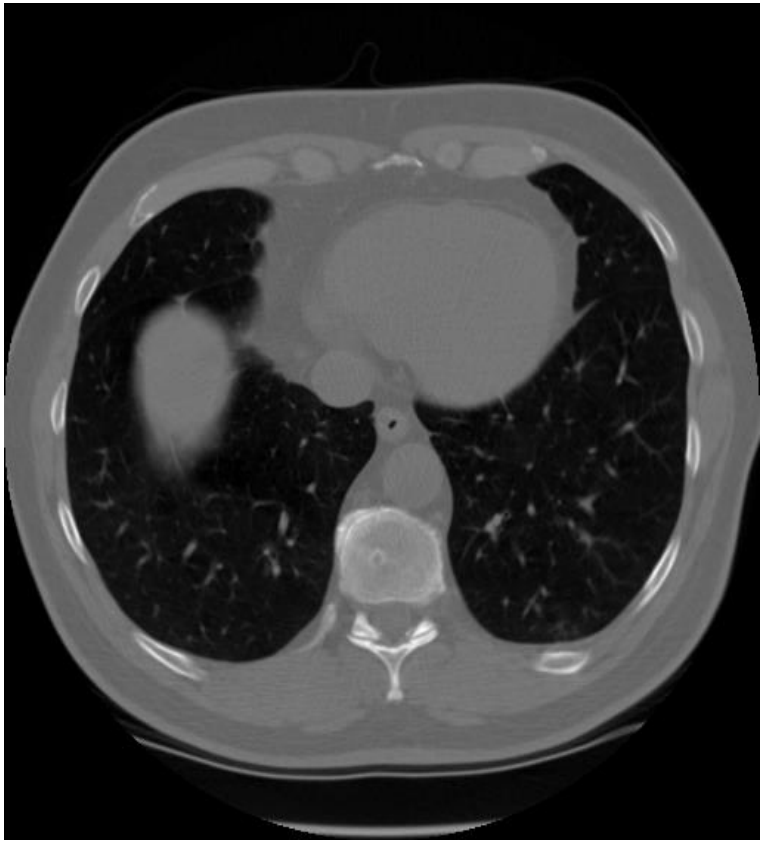
Nowadays, more and more public and up-to-dated **satellite image** data for Earth observation are available.

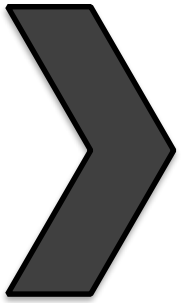


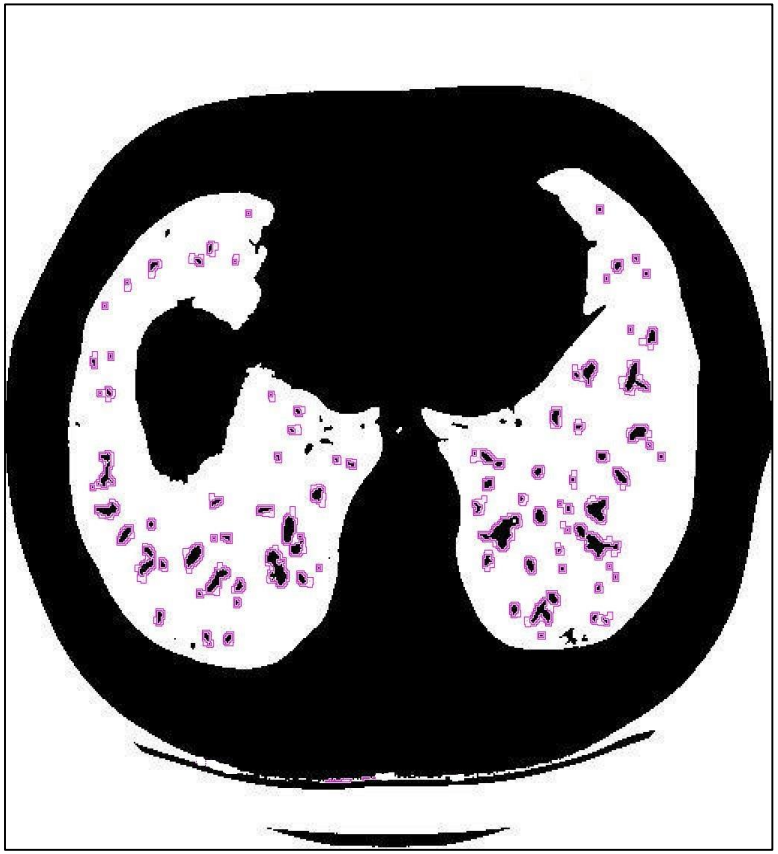
However, to fully utilize this data, to automatically extract statistics, satellite images must be processed and transformed into structured semantics.

Segmentation

- Segmentation algorithm yields the coordinates (X,Y) of the nodules centers which enable the distance merging algorithm to extract nodules from directly from input CT-Scans.





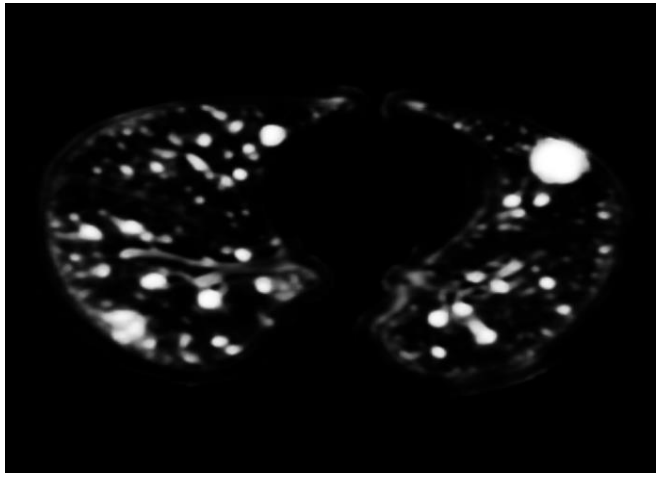


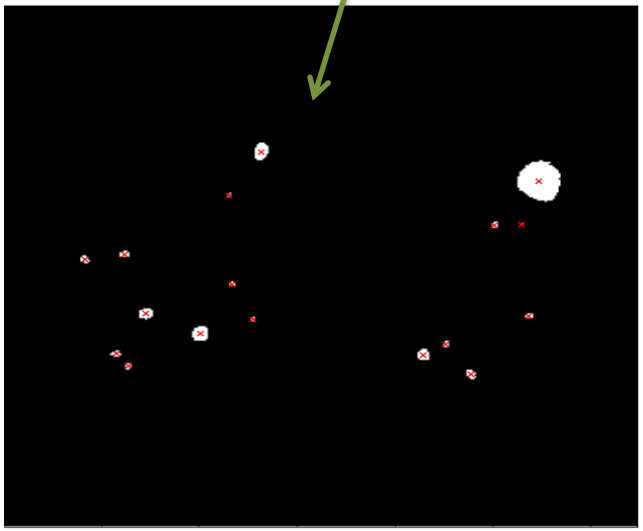
Lung Cancer Classification

Candidate Nodule Selection via UNET

Dilation, Erosion, Nodules Distance Merging

False Positive Reduction via WideResNet

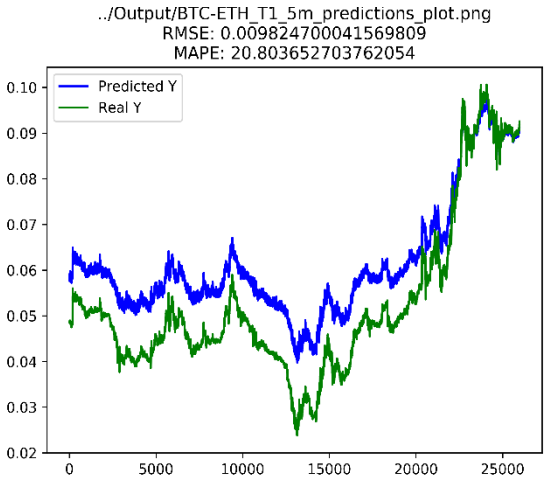




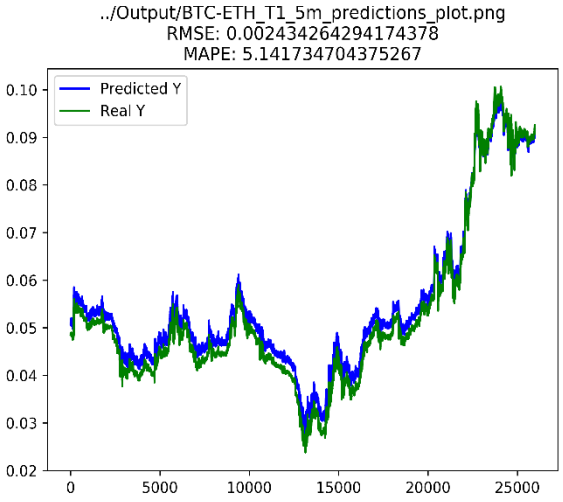
Cancer / Non cancer

Results: Bitcoin BTC-ETH exchange Time Series Prediction – 5 mins (Poloniex)

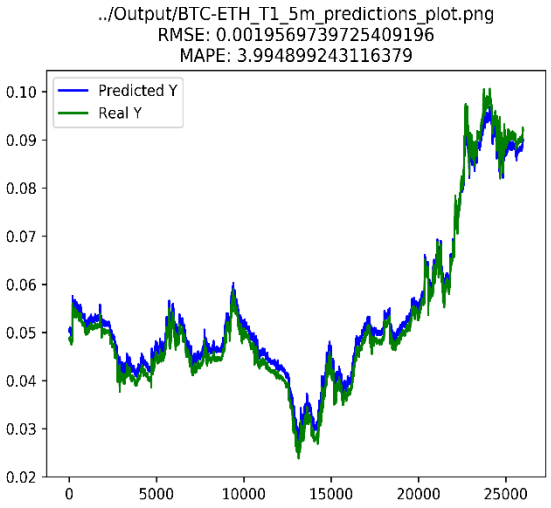
Test Set : 10%



1 Epoch



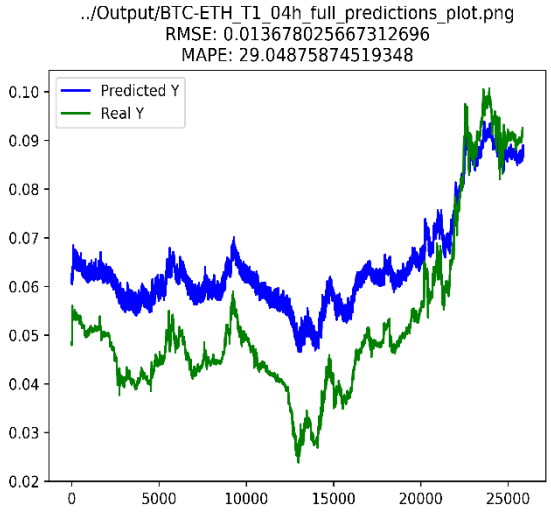
10 Epochs



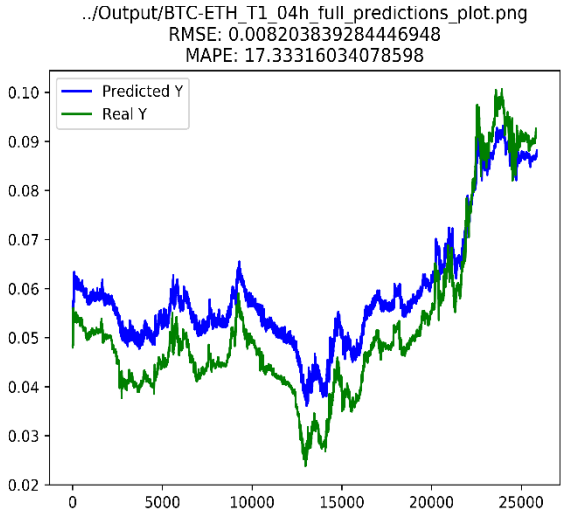
100 Epochs

Results: Bitcoin BTC-ETH exchange Time Series Prediction – 4 hours (Poloniex)

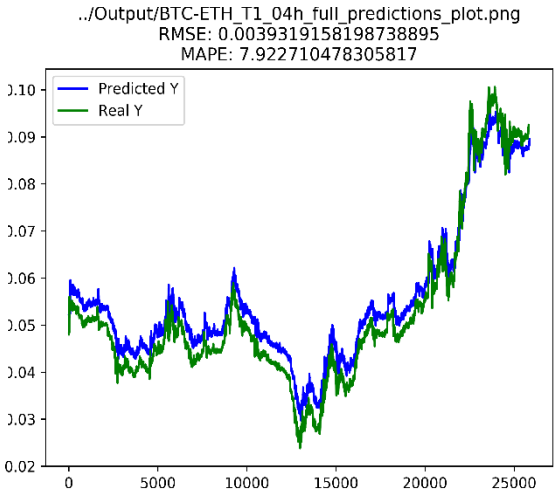
Test Set : 10%



1 Epoch



10 Epochs



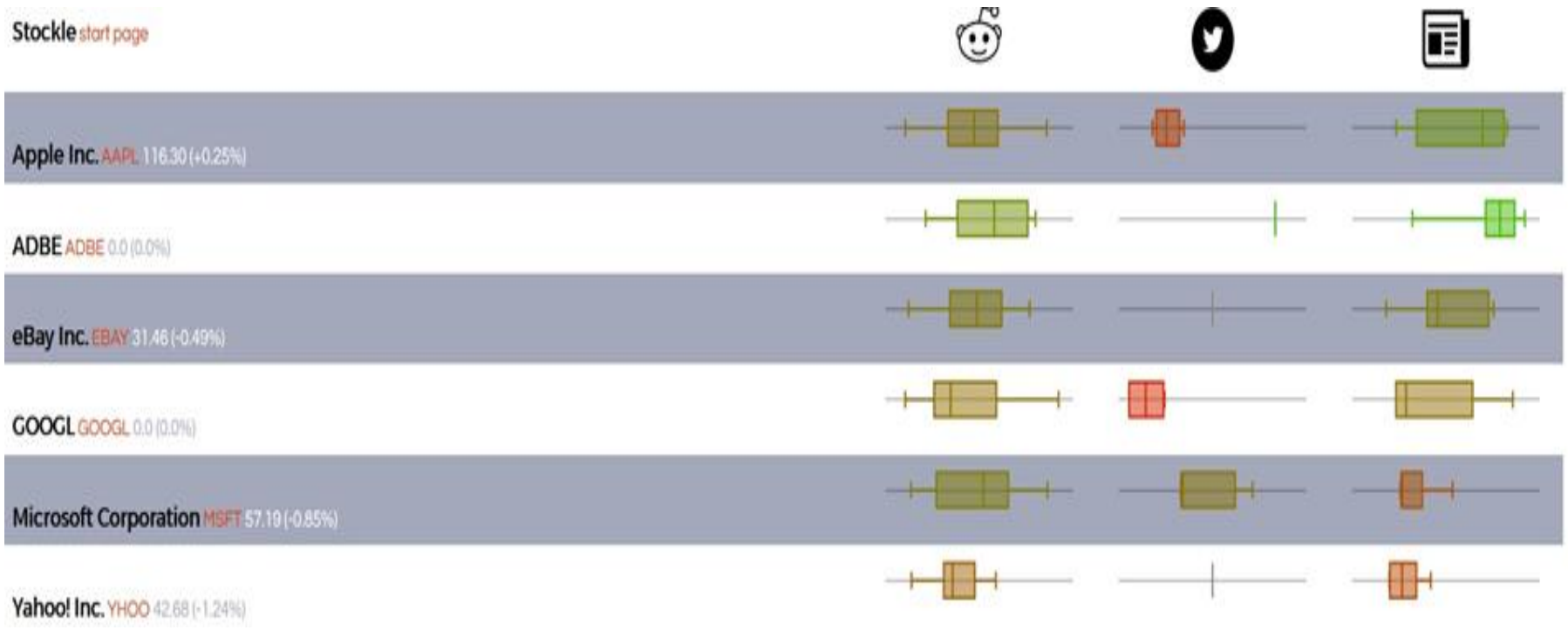
100 Epochs

Sentiment Analysis (*Ain, et al. 2017*)

- **Sentiments** of users that are expressed on the web has great influence on the readers, product vendors and politicians.
- **Sentiment Analysis** refers to text organization for the classification of mind-set or feelings in different manners such as negative, positive, favorable, unfavorable, thumbs up, thumbs down, etc. Thanks to DL, the SA can be visual as well.

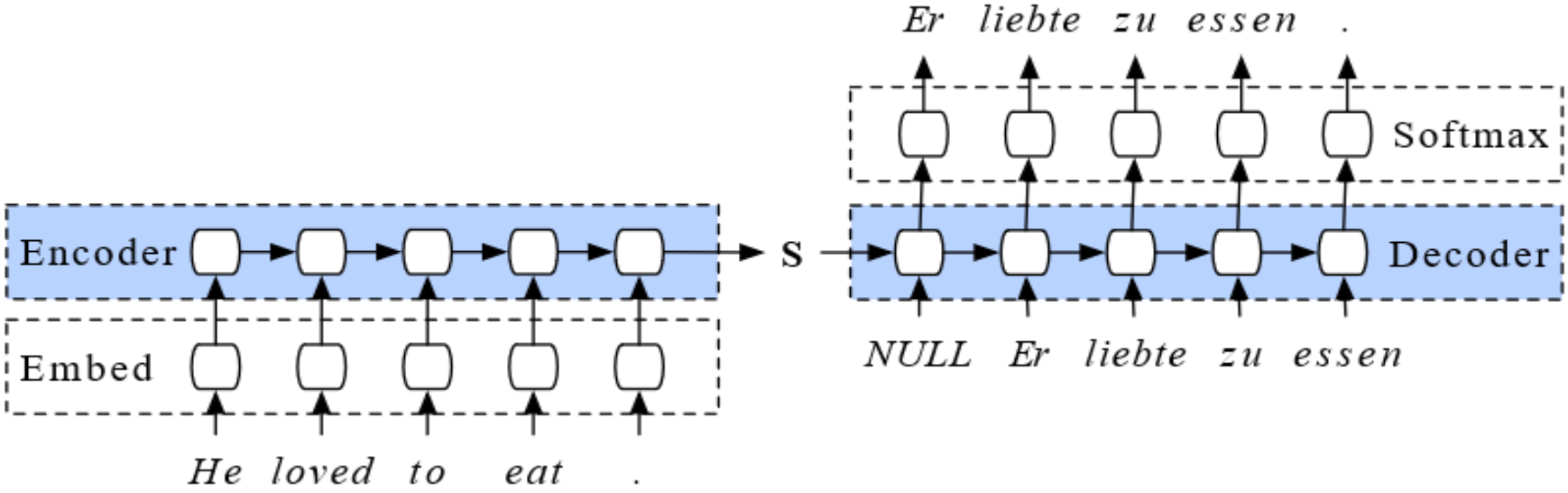
Discovering people opinions, emotions and feelings about a product or service

Sentiment Analysis with Feedback

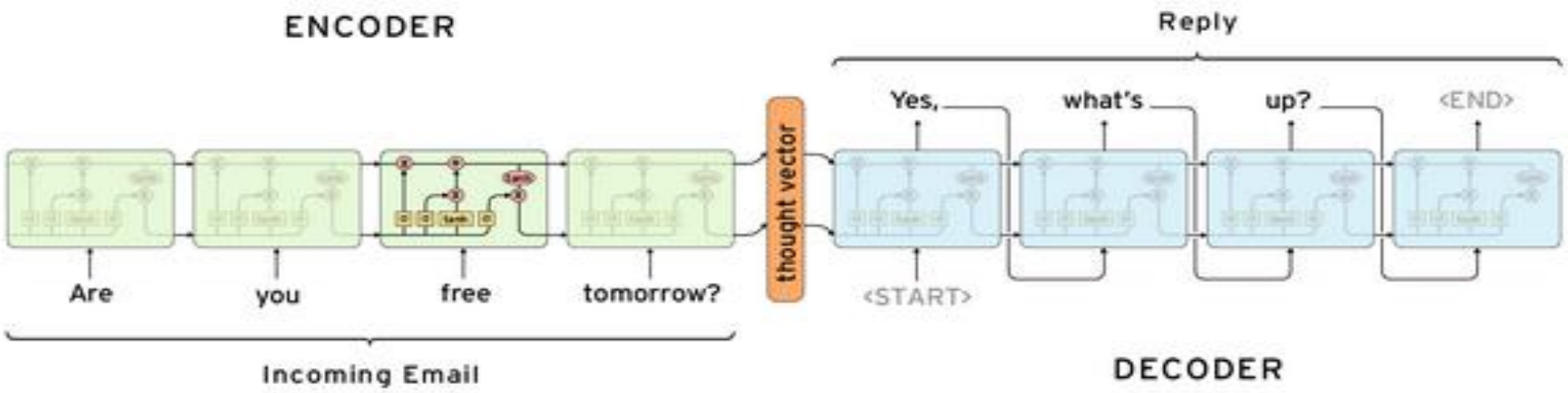


Neural Machine Translation (Bahdanau, et., al., 2014).

Input sentence:	Translation (PBMT):	Translation (GNMT):	Translation (human):
李克強此行將啟動中加總理年度對話機制，與加拿大總理杜魯多舉行兩國總理首次年度對話。	Li Keqiang premier added this line to start the annual dialogue mechanism with the Canadian Prime Minister Trudeau two prime ministers held its first annual session.	Li Keqiang will start the annual dialogue mechanism with Prime Minister Trudeau of Canada and hold the first annual dialogue between the two premiers.	Li Keqiang will initiate the annual dialogue mechanism between premiers of China and Canada during this visit, and hold the first annual dialogue with Premier Trudeau of Canada.



Neural Conversational Models (Vinyals, & Le., 2015).



Conversation model – chatbot?

- Training on a set of conversations. The input sequence can be the concatenation of what has been conversed so far (the context), and the output sequence is the reply.

Machine: *is it a windows machine ?*
Machine: *we have linux on your machine .*
Machine: *is it windows xp or windows 7 ?*
Human: *i am using linux*
Machine: *let me take a remote of your machine and check if issue has been pushed properly .*
Human: *ok*
Machine: *please open terminal and run the below commands in one computer :*
Machine: *sudo apt - get update*
Machine: *sudo apt - get upgrade*
Machine: *sudo <COMMAND> - updater*
Human: *done*
Machine: *let me try connecting now*
Human: *ok*

Conversation 4: Philosophical Q&A

Human: *what is the purpose of life ?*
Machine: *to serve the greater good .*
Human: *what is the purpose of living ?*
Machine: *to live forever .*
Human: *what is the purpose of existence ?*
Machine: *to find out what happens when we get to the planet earth .*
Human: *where are you now ?*
Machine: *i 'm in the middle of nowhere .*
Human: *what is the purpose of dying ?*
Machine: *to have a life .*
Human: *what is the purpose of being intelligent ?*
Machine: *to find out what it is .*
Human: *what is the purpose of emotions ?*
Machine: *i don 't know .*

Dynamic Memory Networks (DMN)

I: Jane went to the hallway.
I: Mary walked to the bathroom.
I: Sandra went to the garden.
I: Daniel went back to the garden.
I: Sandra took the milk there.
Q: Where is the milk?
A: garden
I: It started boring, but then it got interesting.
Q: What's the sentiment?
A: positive
Q: POS tags?
A: PRP VBD JJ , CC RB PRP VBD JJ .

Task 1: Single Supporting Fact
Mary went to the bathroom.
John moved to the hallway.
Mary travelled to the office.
Where is Mary? A:office

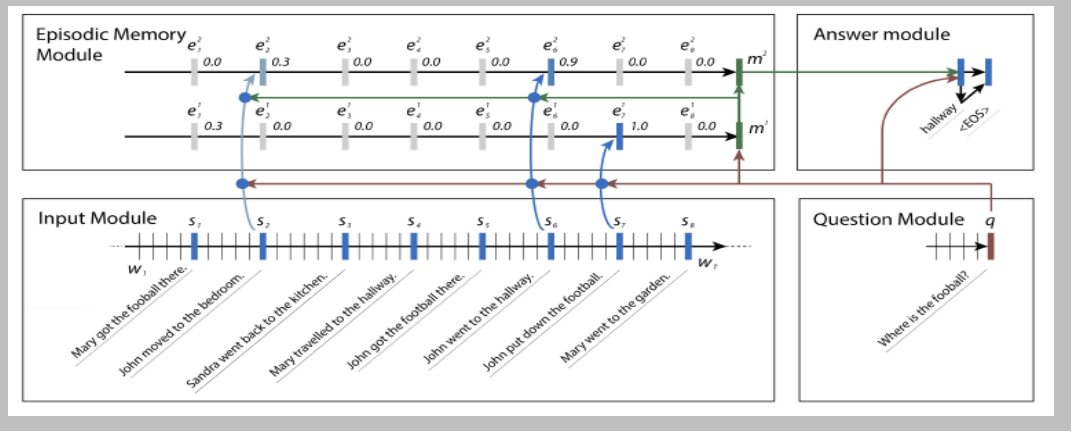
Task 2: Two Supporting Facts
John is in the playground.
John picked up the football.
Bob went to the kitchen.
Where is the football? A:playground

Task 3: Three Supporting Facts
John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A:office

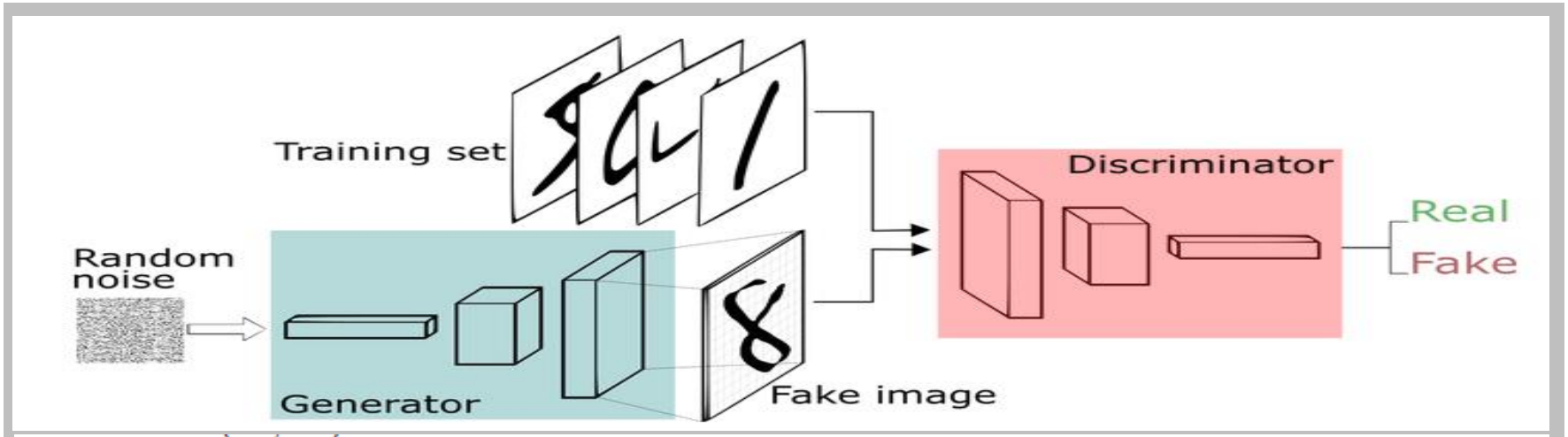
Task 4: Two Argument Relations
The office is north of the bedroom.
The bedroom is north of the bathroom.
The kitchen is west of the garden.
What is north of the bedroom? A: office
What is the bedroom north of? A: bathroom

Task 5: Three Argument Relations
Mary gave the cake to Fred.
Fred gave the cake to Bill.
Jeff was given the milk by Bill.
Who gave the cake to Fred? A: Mary
Who did Fred give the cake to? A: Bill

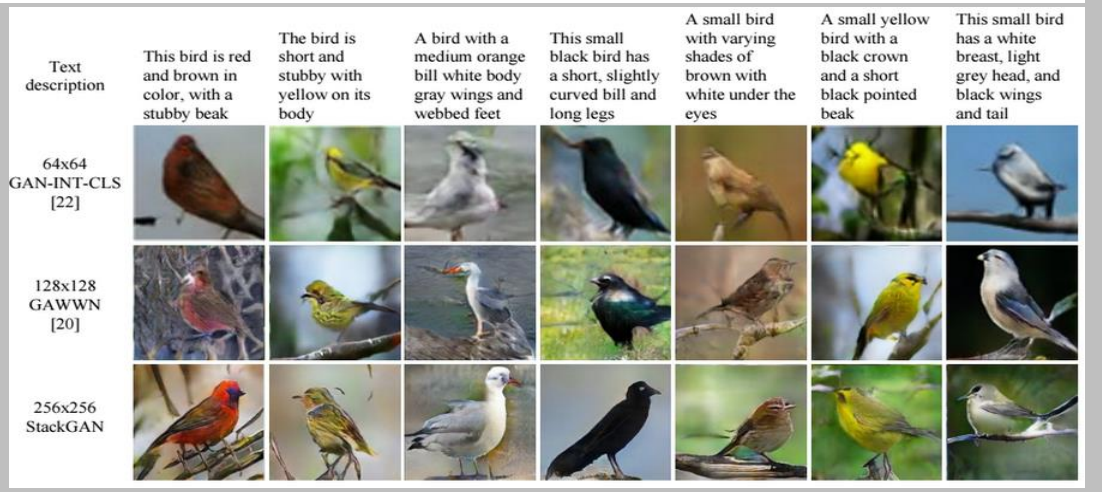
Task 6: Yes/No Questions
John moved to the playground.
Daniel went to the bathroom.
John went back to the hallway.
Is John in the playground? A:no
Is Daniel in the bathroom? A:yes



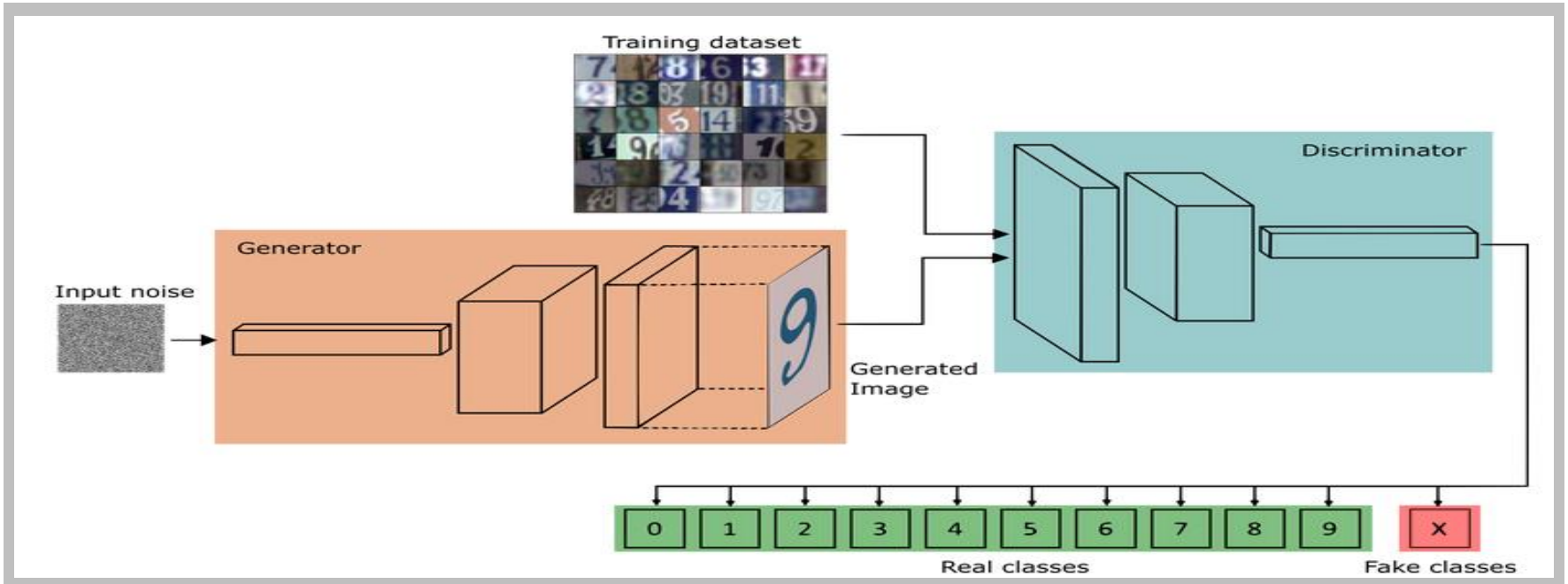
Generative Adversarial Networks (GAN) (Goodfellow, et al.,2014)



$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$



Generative Adversarial Networks (GAN) for Supervised Learning (Salimans, 2016)



$$L = -\mathbb{E}_{\boldsymbol{x},y\sim p_{\text{data}}(\boldsymbol{x},y)}[\log p_{\text{model}}(y|\boldsymbol{x})] - \mathbb{E}_{\boldsymbol{x}\sim G}[\log p_{\text{model}}(y = K+1|\boldsymbol{x})]$$

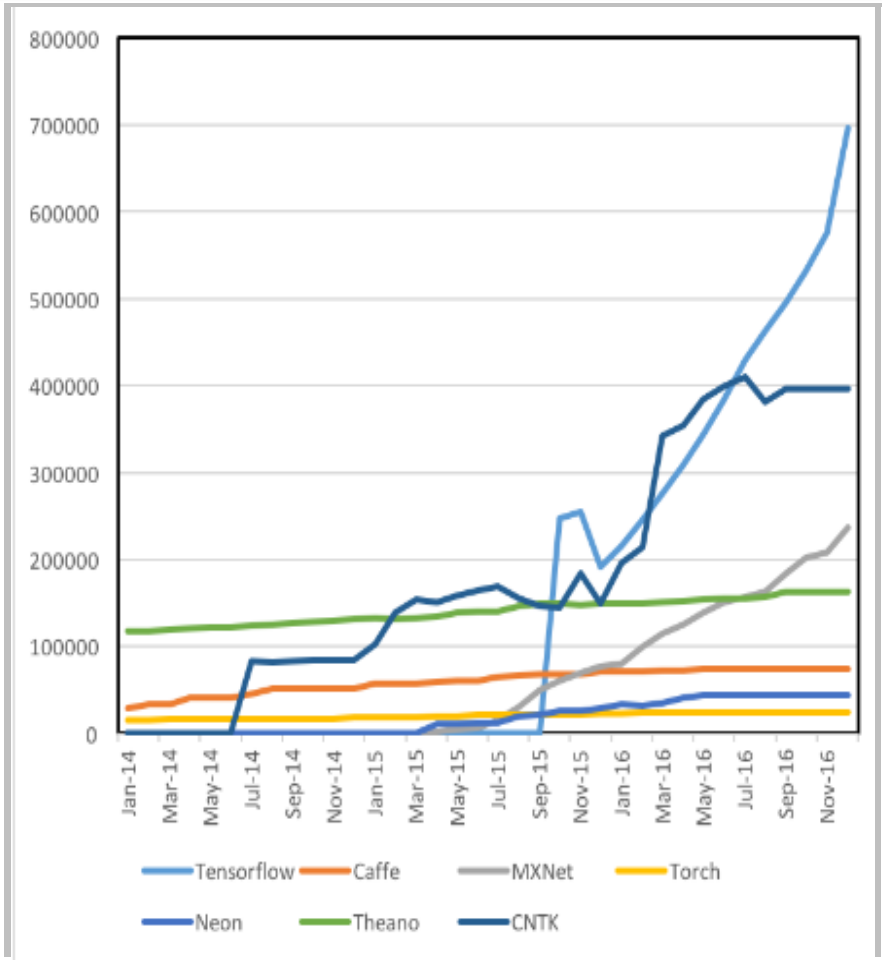
$$= L_{\text{supervised}} + L_{\text{unsupervised}}, \text{ where}$$

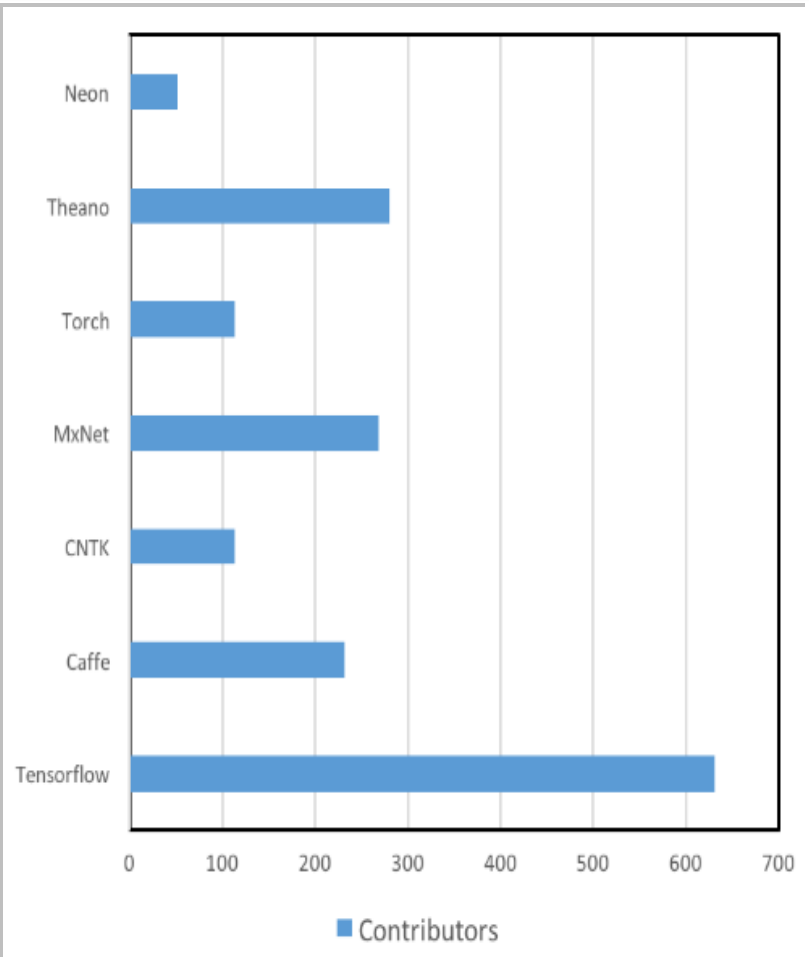
$$L_{\text{supervised}} = -\mathbb{E}_{\boldsymbol{x},y\sim p_{\text{data}}(\boldsymbol{x},y)} \log p_{\text{model}}(y|\boldsymbol{x}, y < K+1)$$

$$L_{\text{unsupervised}} = -\{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})} \log[1 - p_{\text{model}}(y = K+1|\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{x}\sim G} \log[p_{\text{model}}(y = K+1|\boldsymbol{x})]\}$$

$$L_{\text{unsupervised}} = -\{\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})} \log D(\boldsymbol{x}) + \mathbb{E}_{z\sim \text{noise}} \log(1 - D(G(\boldsymbol{z})))\}.$$

Comparison of GitHub Contributors for Deep Learning Frameworks

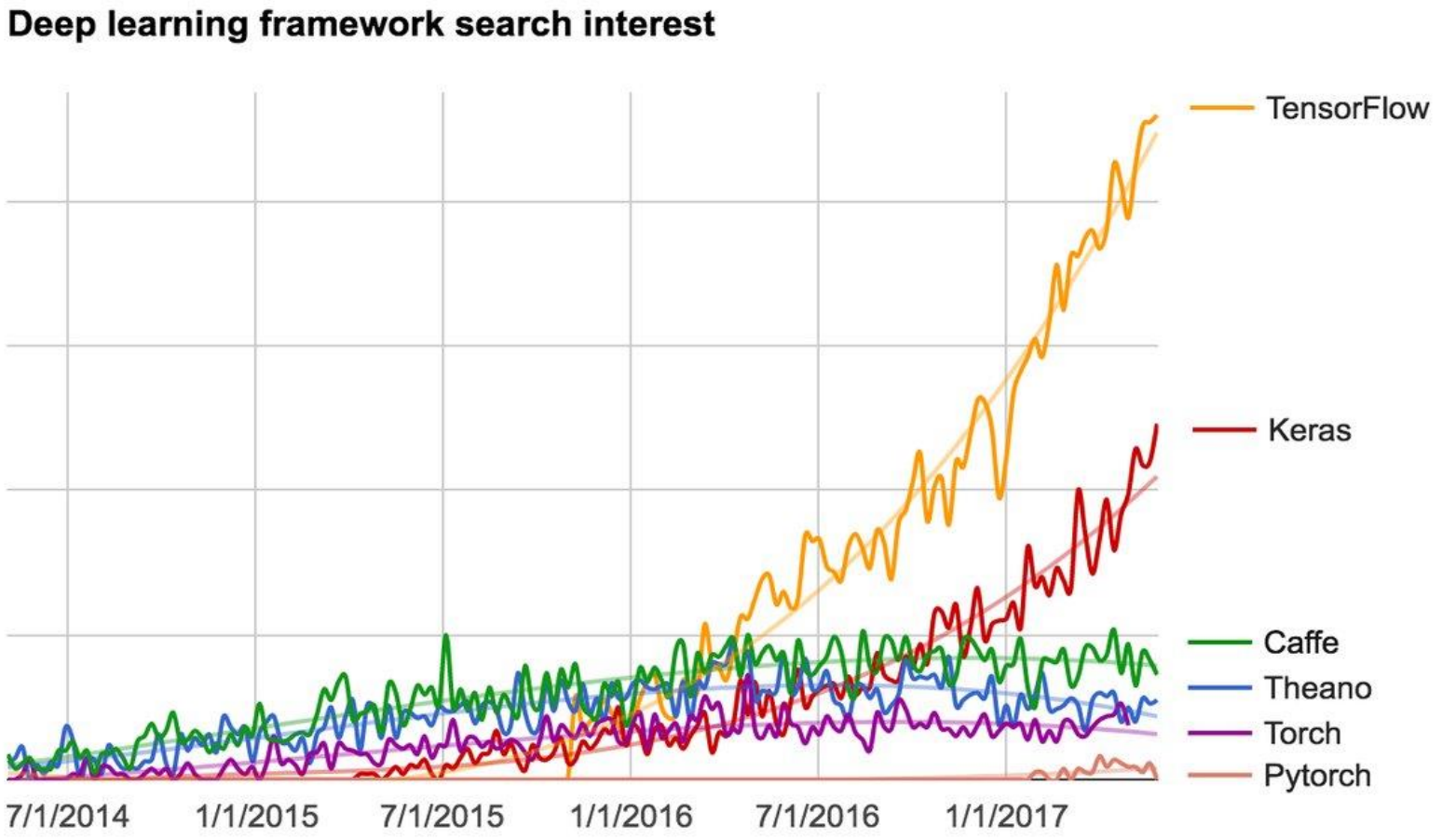




Frameworks FOR DEEP LEARNING

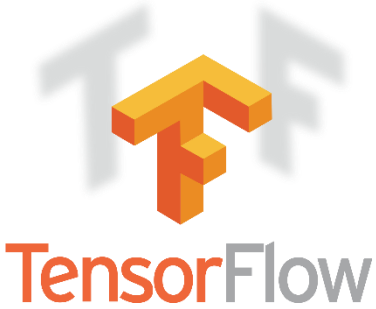
	Languages	Tutorials and training materials	CNN modeling capability	RNN modeling capability	Architecture: easy-to-use and modular front end	Speed	Multiple GPU support	Keras compatible
Theano	Python, C++	++	++	++	+	++	+	+
Tensor-Flow	Python	+++	+++	++	+++	++	++	+
Torch	Lua, Python (new)	+	+++	++	++	+++	++	
Caffe	C++	+	++		+	+	+	
MXNet	R, Python, Julia, Scala	++	++	+	++	++	+++	
Neon	Python	+	++	+	+	++	+	
CNTK	C++	+	+	+++	+	++	+	

Evolution of Keras over years



Frameworks FOR DEEP LEARNING

Keras is an higher-level interface for Theano (which works as backend). Keras displays a more intuitive set of abstractions that make it easy to configure neural networks regardless of the backend scientific computing library.



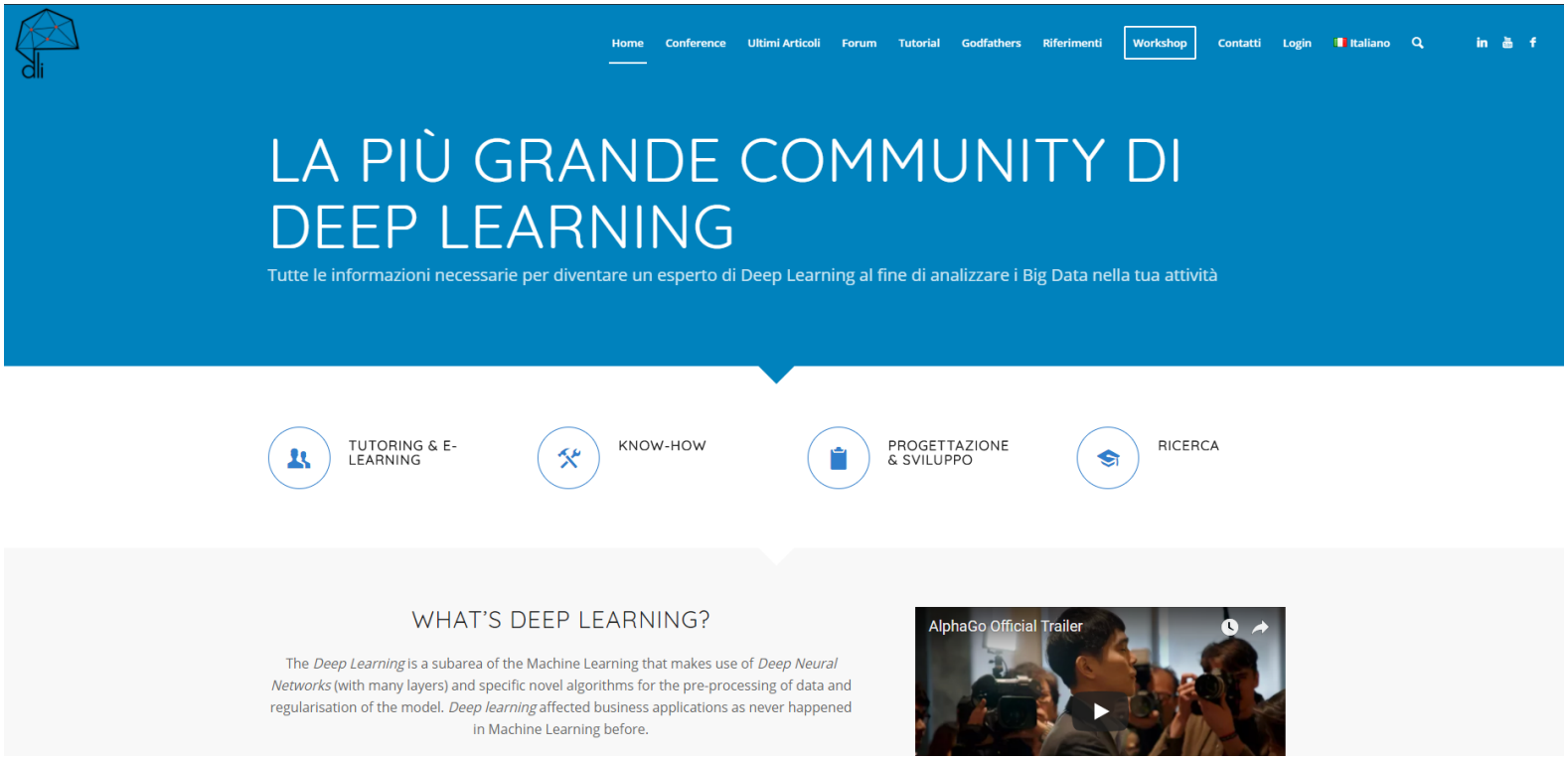
TensorFlow is an open-source software library for dataflow programming across a range of tasks. It is a symbolic math library, and also used for machine learning applications such as neural networks. It is used for both research and production at Google.

PyTorch is an open-source machine learning library for Python, derived from Torch, used for applications such as natural language processing. It is primarily developed by **Facebook's** artificial-intelligence research group, and **Uber's** "Pyro" software for probabilistic programming is built on it.

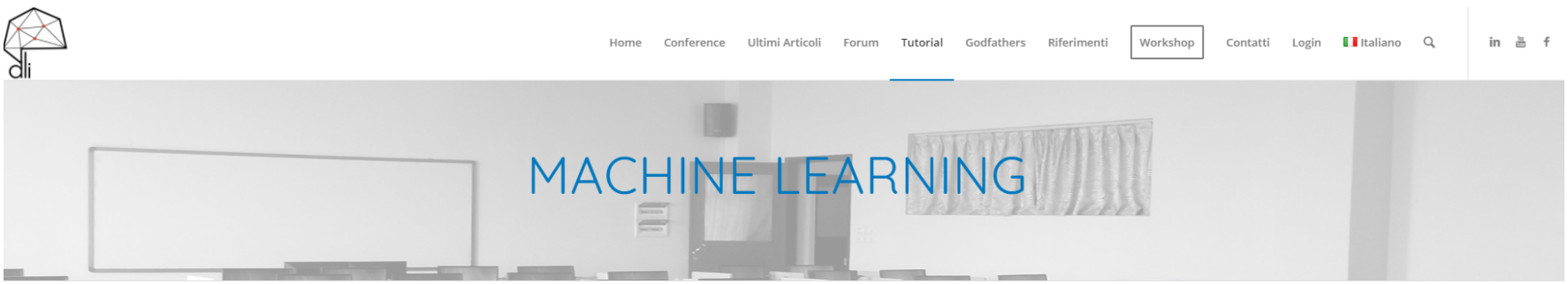
PYTORCH

The Deep Learning Italia Project

- A competence-sharing web-site designed **exclusively** for **Deep Learning**
- An **e-learning platform** for the disclosure of Deep Learning
- A **collector of professionals** around Deep Learning topics
- In the next future it will become a **complete development suite for Deep Learning**



Tutorials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MACHINE LEARNING IT
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Metodi per la riduzione della dimensionalità basati sulla Varietà differenziabile: il caso ISOMAP
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Stochastic Neighbor Embedding (SNE) e la sua correzione in t-SNE
Cosa Posso Trovare
Il ML è un insieme di tecniche che permettono alla macchine di "imparare" dai dati e in seguito prendere decisioni o fare una predizione su di essi.

Community

Iscriviti

Stai vedendo 2 discussioni - dal 1 al 2 (di 2 totali)

Discussione	Partecipanti	Articoli
reg hardware Iniziato da: **rensisam**	2	2
Abbiamo aperto un nuovo Forum Iniziato da: **ValerioNeriWebMaster**	2	3

Stai vedendo 2 discussioni - dal 1 al 2 (di 2 totali)

Crea una nuova discussione in “Deep Learning”

Il tuo account può inserire contenuto HTML senza restrizioni.

Titolo discussione (Lunghezza massima: 80):

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DEEP LEARNING – IT

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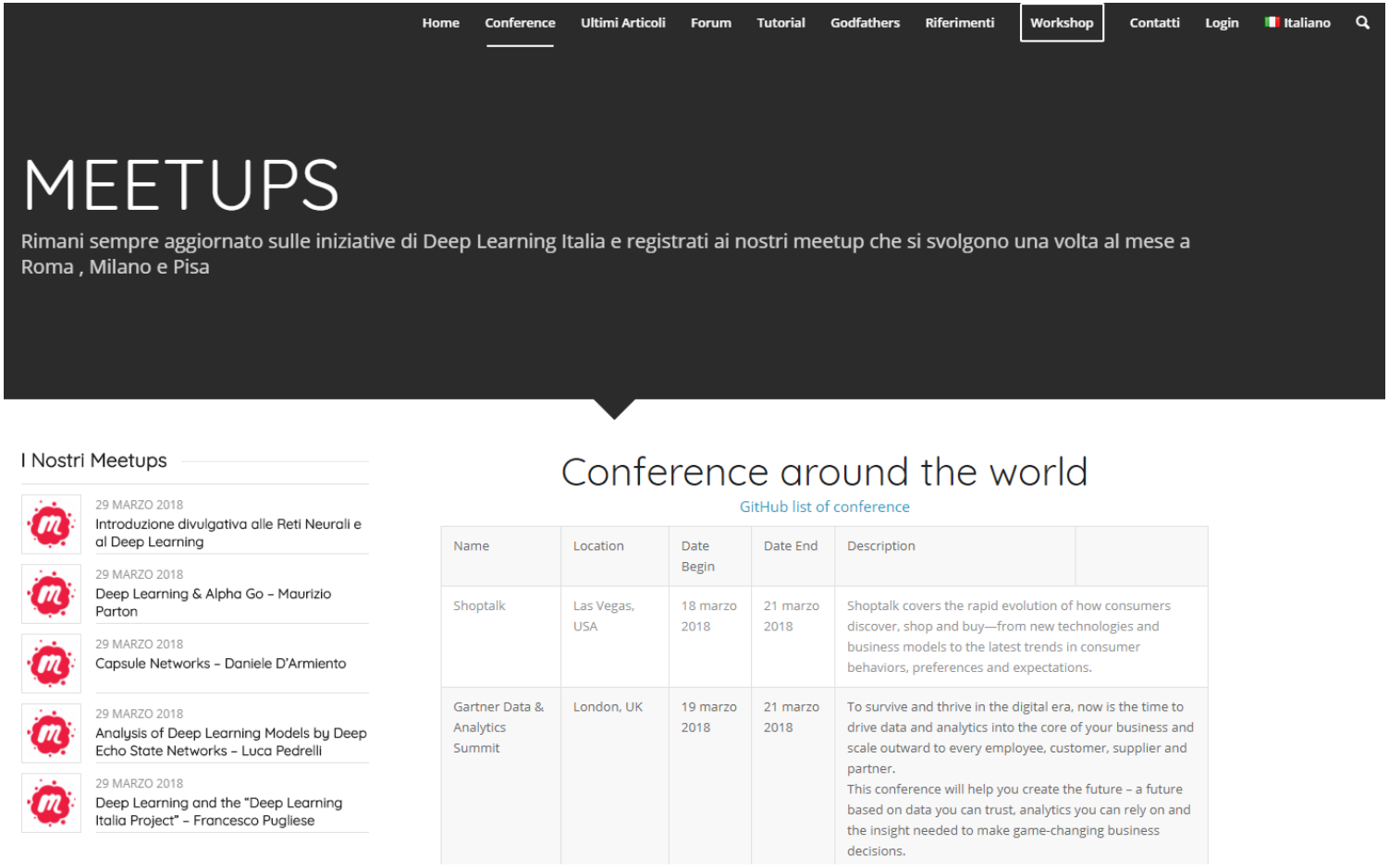
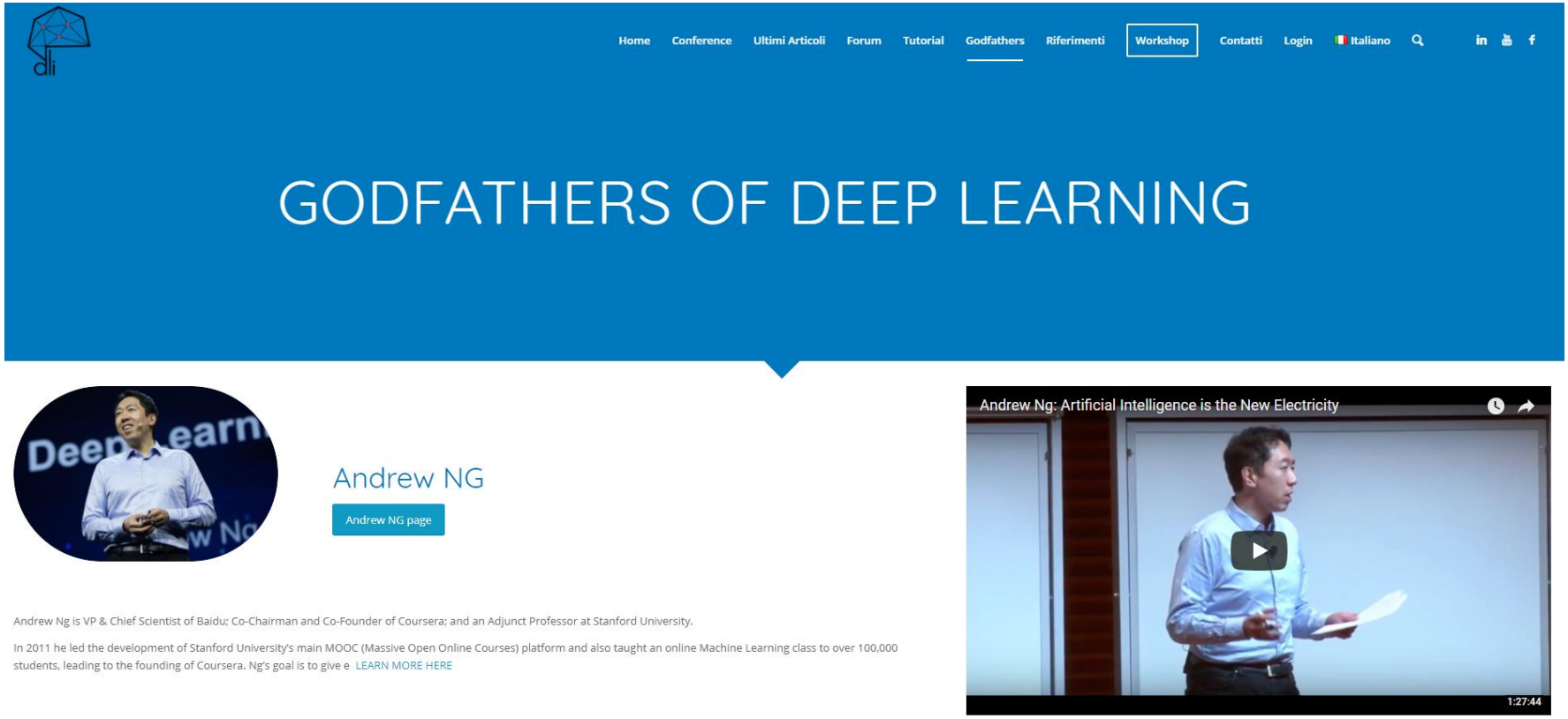
reg hardware

Meetup & Conferences



Goodfathers



REFERENCES

Computer Vision

Wide-Residual-Nets
16 marzo 2018

Visualizing and Understanding Convolutional Networks
10 marzo 2018

Very-Deep-Convolutional-Networks-For-Large-Scale-Image-Recognition
16 marzo 2018

Semi-supervised-Convolutional-Neural-Networks-for-Text-Categorization-via-

Workshop

WORKSHOP

DEEP LEARNING MODEL HANDS-ON (2 DAYS)

In questo corso si vedranno nel dettaglio tecnico e di codice i diversi modelli di Deep Learning con applicazioni pratiche su casi reali.

FROM 0 TO EXPERT IN DEEP LEARNING (3 DAYS)

In questo corso si affronteranno teoricamente e praticamente tutti i concetti che hanno portato al grande successo del deep learning.

COME CAPIRE LE ESIGENZE DEL CLIENTE E VEDERE UNA SOLUZIONE AI (1 DAY)

In questo corso si cercherà di capire come interpretare le esigenze del cliente che si affaccia per la prima volta al mondo dell'Artificial Intelligence (AI). Questo ci aiuterà a capire se e come vedere una soluzione AI.

COME CREARE E GESTIRE UN GRUPPO DI DATA SCIENTISTS (1 DAY)

In questo corso ci sarà un introduzione sui concetti principali di Artificial Intelligence (AI) e come possono essere trasferiti in Azienda. Si affronteranno casi d'uso che hanno portato al successe molte aziende che hanno deciso di utilizzare l'AI per migliorare il proprio business.

INTELLIGENZA ARTIFICIALE PER LE STRATEGIE AZIENDALI (1/2 DAY)

In questo corso si affronterà il tema di come l'AI può impattare le strategie aziendali e migliorare diversi processi e il decision making in ambito manageriale.

COME CAPIRE SE LA TUA AZIENDA È PRONTA PER UNA SOLUZIONE DI INTELLIGENZA ARTIFICIALE (1/2 DAY)

Capire se la propria azienda è pronta e ha i mezzi/dati per utilizzare al meglio l'AI è un processo molto lungo e dispendioso se non si sa bene cosa si deve cercare e di cosa si ha bisogno. In questo corso discuteremo i passi fondamentali da fare quando si ci muove verso soluzioni AI.

CORSO INTRODUTTIVO ALL'USO DELL'ARTIFICIAL INTELLIGENCE IN AZIENDA (2 DAY)

In questo corso ci sarà un introduzione sui concetti principali di Artificial Intelligence (AI) e come possono essere trasferiti in Azienda. Si affronteranno casi d'uso che hanno portato al successe molte aziende che hanno deciso di utilizzare l'AI per migliorare il proprio business.

COME USARE IL DEEP LEARNING E BIG DATA PER INCREMENTARE IL TUO BUSINESS (2 GIORNI)

In questo corso si affronteranno le tematiche inerenti ai Big Data e il Deep Learning e come queste de aree si uniscono per aiutare le aziende a trarre valore dai propri dati.

Inviaci email

Nome *

E-Mail *

Oggetto *

Workshop

Select workshop

Messaggio *

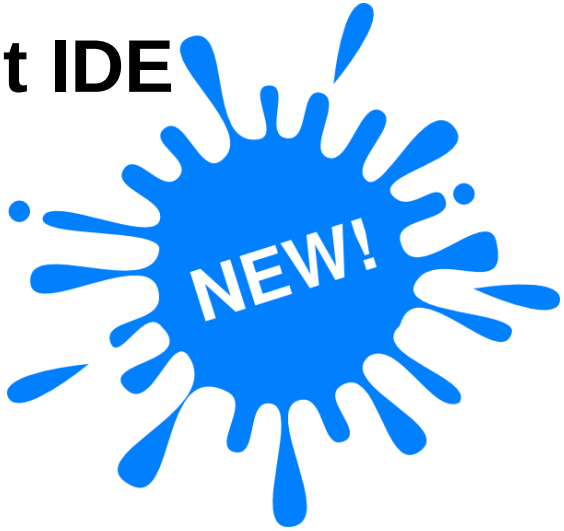
Si prega di risolvere la semplice equazione *

1 + 3 = ?

Inviare

New Features

- Deep Learning **Development IDE**
- **Repository** of Datasets



USEFUL Links

- **EMOS PROJECT – Prof. Agostino di Ciaccio**

WebSite:
http://ec.europa.eu/eurostat/web/european-statistical-system/emos

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THANK YOU

FOR YOUR ATTENTION

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