

parlando di scienza al cnr di pisa



con il patrocinio di



# ALPHAGO E RETI NEURALI



Fabrizio Falchi  
ISTI-CNR



ISTI-CNR  
 ΕΡΕΥΝΑ ΕΠΙΧΕΙΡΗΣΙΑΚΗ

# ΑΓΓΛΙΚΟ Ε ΒΕΤΙ ΜΕΥΒΑΓΙ

παράδοση της εκπαίδευσης της αριστείας



Εταιρεία Διακρίσεων και Διακρίσεων



con il patrocinio di



ΠΡΟΤΥΠΟ ΔΙ ΠΕΤ



Εταιρεία Διακρίσεων και Διακρίσεων

# DALLA TEORIA ALLA PRATICA



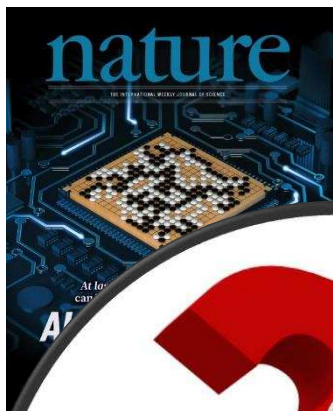
$$R_{\mu\nu} - \frac{1}{2}Rg_{\mu\nu} = 8\pi GT_{\mu\nu}$$



***A cosa serve?***



# DALLA PRATICA ALLA TEORIA



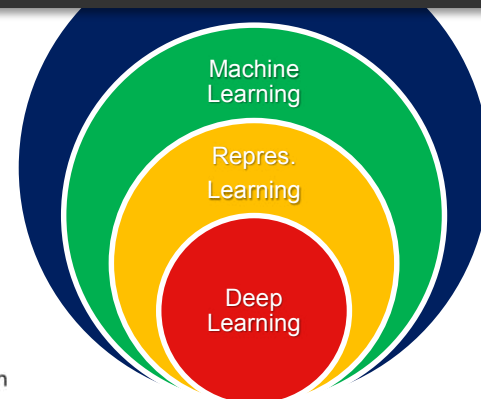
AlphaGo



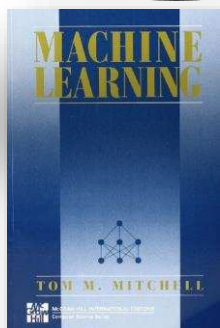
Google



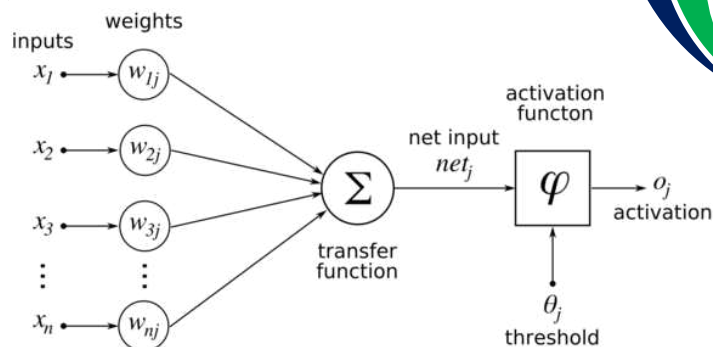
**Perché funziona?**



Nucleo



Estremità dell'assone



# PERCHÉ FUNZIONA?

## Quora

### How far along are we in the understanding of why deep learning works?



Yoshua Bengio, My lab has been one of the three that started the deep learning approach, bac...

10.9k Views • Upvoted by Tao Xu, [Built ML systems at Airbnb, Quora, Facebook and Microsoft.](#), Nikhil Garg, [I lead a team of Quora engineers working on ML/NLP problems](#), Alberto Bietti, [MS in machine learning, Ecole Normale Supérieure](#)

Yoshua is a Most Viewed Writer in Machine Learning.

Originally Answered: Yoshua Bengio: How far along are we in understanding why deep learning works?

Contrary to what some people think, I believe that we have already a good basic understanding of fundamentals about why deep learning works, e.g., \* We understand that distributed representations,... [\(more\)](#)



SANDY

Lake (Oneid)

173

CARNEGIE ROAD

CANNING

WILUNA

WONGAWOL

WONGAWOL ROAD

WONGAWOL

Windidda

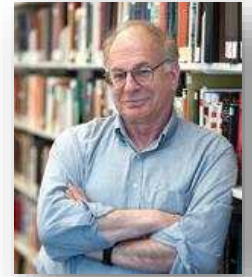
Lake Way

Windidda

Carclew Range

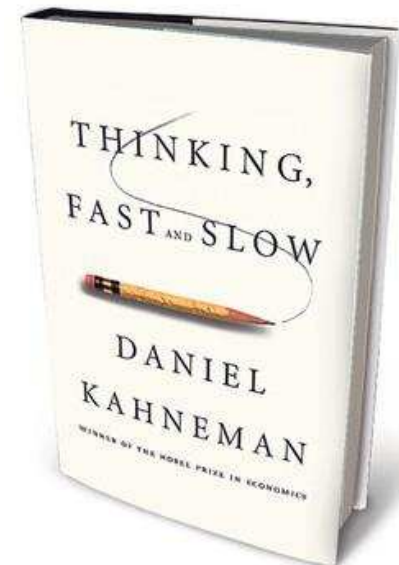
## Daniel Kahneman

- Psicologo
- Premio Nobel 2002 assieme a Vernon L. Smith per



*avere integrato risultati della ricerca psicologica nella scienza economica, specialmente in merito al giudizio umano e alla teoria delle decisioni in condizioni d'incertezza*

- ***Thinking, Fast and Slow (2011)***  
riassume molte delle sue ricerche  
best seller internazionale



Test



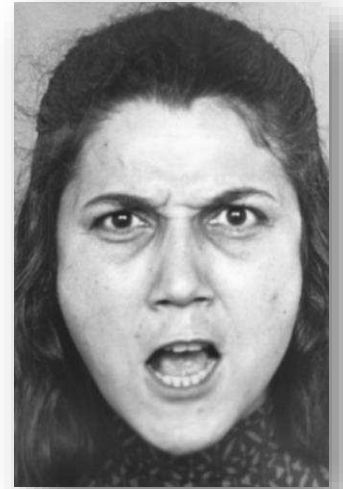


Avete probabilmente, intuitivamente, visto

- Donna, capelli neri, arrabbiata

Quello che avete visto si estende nel **futuro**:

- sensazione che stesse per dire parole molto scortesi, magari a voce alta e con tono stridulo.



**Non intendevate**

- valutare il suo stato d'animo o
- prevedere che azione potesse compiere.

$$17 \times 24 = ?$$

# 17x24=?

- è una moltiplicazione
- sapete che potete risolverla
- riconoscete che 12,609 e 123 sono poco plausibili
- escludere 586 è difficile

***Una soluzione precisa  
non vi è venuta in mente.***



***Vi siete chiesti  
se impegnarvi o no nel calcolo.***



# 17x24=?

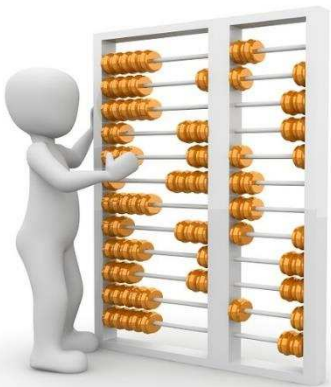
Procedete lungo una **sequenza di stadi**.



recuperate dalla memoria  
il **programma cognitivo** imparato a scuola



eseguire il calcolo è uno **sforzo**.



Sentite l'onere di conservare tanto  
materiale in **memoria**:

- il punto in cui eravate e
- quello in cui stavate andando
- il risultato intermedio.

# THINKING, FAST AND SLOW

- Il processo è consistito in un lavoro mentale, un lavoro riflessivo, impegnativo e ordinato, il prototipo del pensiero lento.
- Era coinvolto anche il **corpo**.  
I muscoli si sono tesi, la pressione del sangue e la frequenza cardiaca sono aumentate.  
Le puppille si sono dilatate.



# THINKING, FAST AND SLOW

Kahneman describe due modalità differenti di pensiero:

- **Sistema 1:**

- veloce, intuitivo, stereotipico, involontario

- **Sistema 2:**

- lento, conscio, infrequente, logico, calcolatore

A photograph of a Go board with black and white stones. The board is made of light-colored wood with a grid of lines. The stones are arranged in a pattern that suggests a game in progress. The word "ALPHAGO" is overlaid in white, bold, sans-serif font on the right side of the board.

**ALPHAGO**

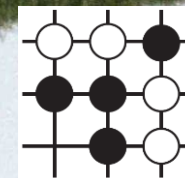
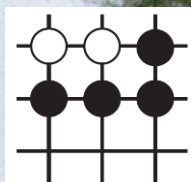
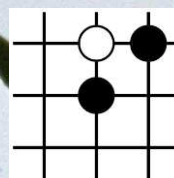
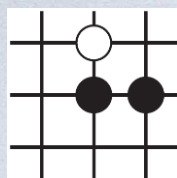
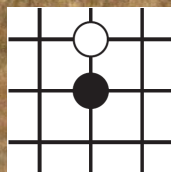
# ALBERO



Photo by: Stolz Gary M, U.S. Fish and Wildlife Service

# ALBERO DA ESPLORARE

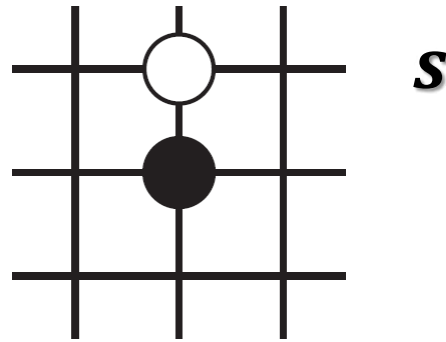
Stato corrente  
(radice)



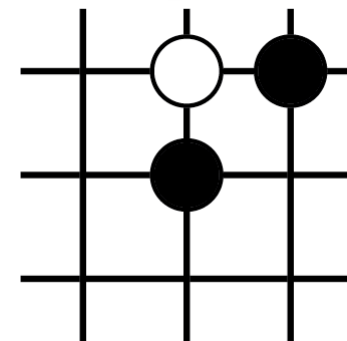
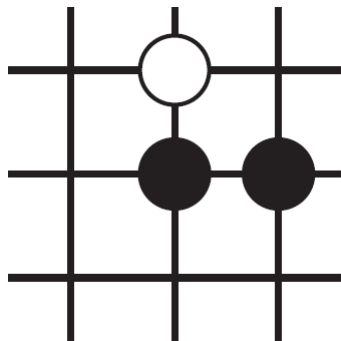
Esiti finali (foglie)

# SIMULAZIONE: QUALE PARTE ESPLORIAMO?

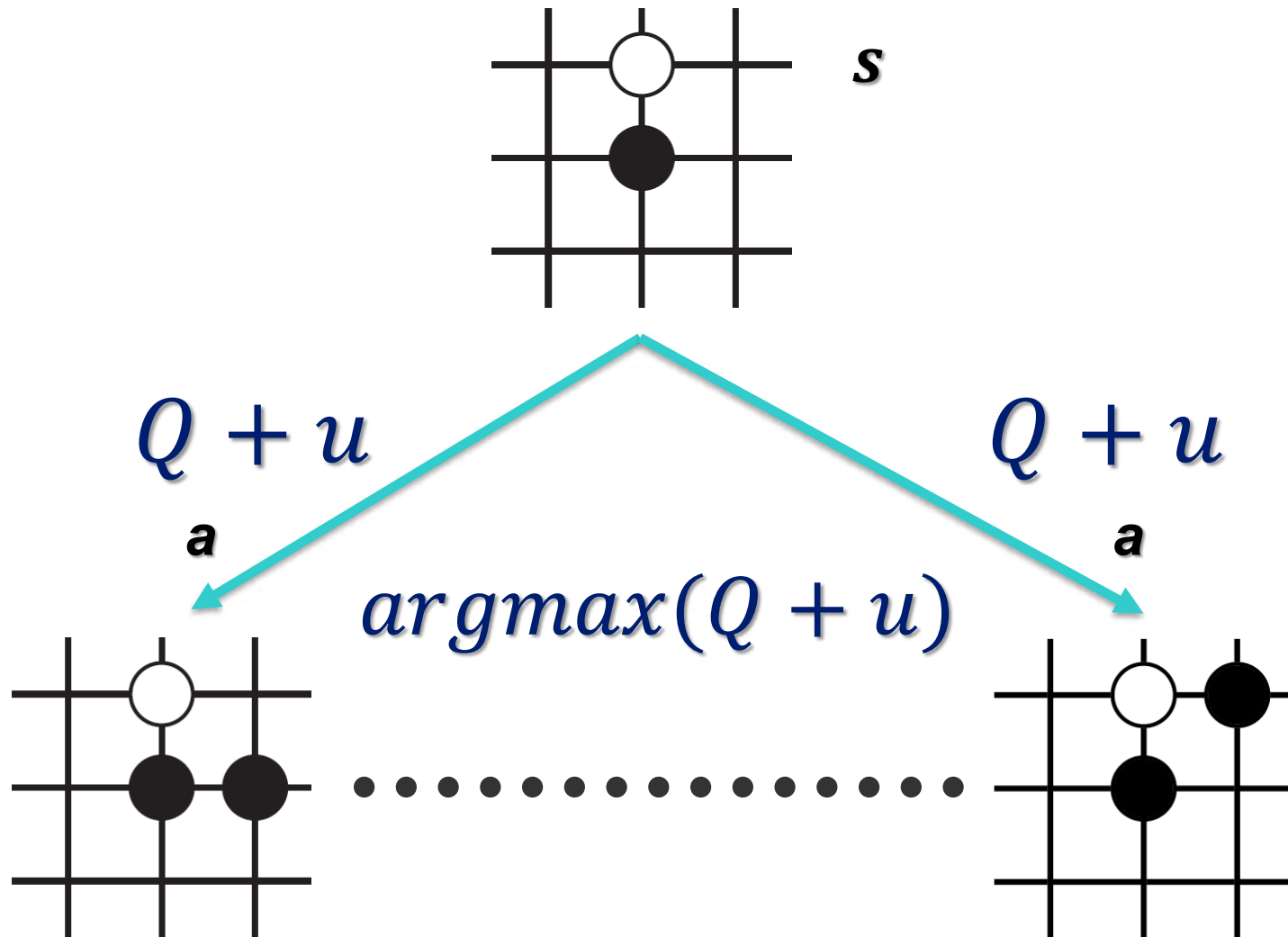
Stato attuale



*a*



# SIMULAZIONE: QUALE PARTE ESPLORIAMO?



# $Q + u$ : BONUS ESPLORATIVO ( $u$ )

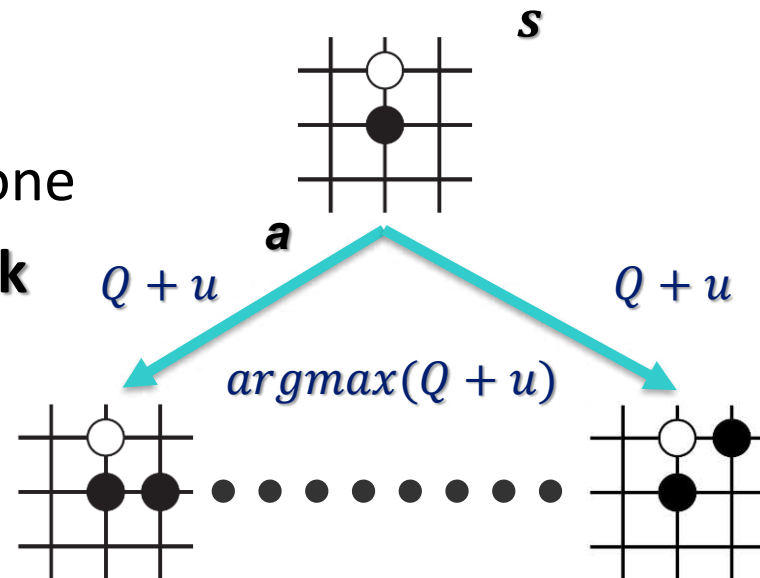
- $u$  è la componente esplorativa

$$u(s, a) \propto \frac{P(s, a)}{1 + N(s, a)}$$

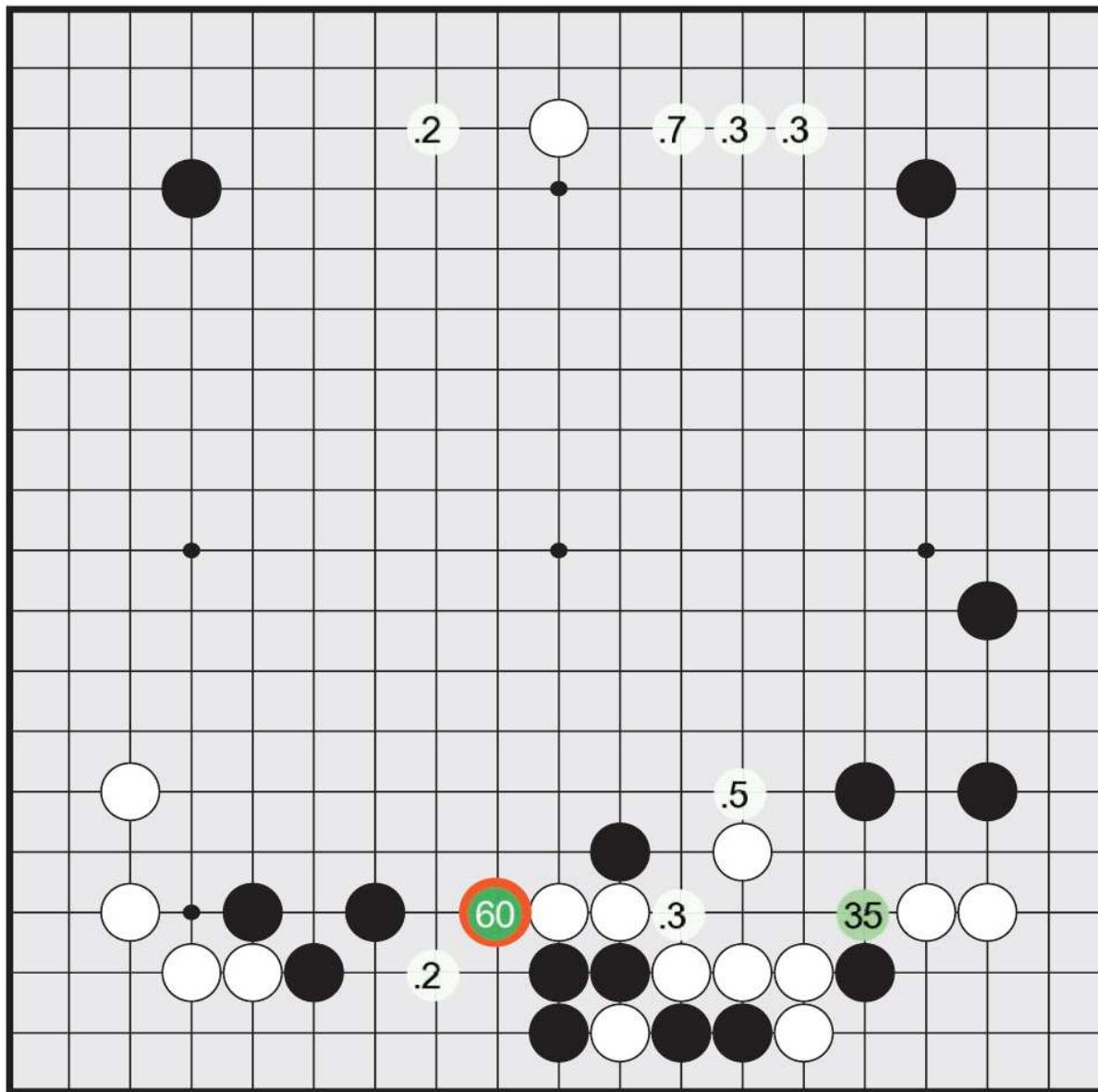
- $N(s, a)$  – n. passaggi sul ramo considerando tutte le simulazioni

- $P(s, a) = p(a|s)$

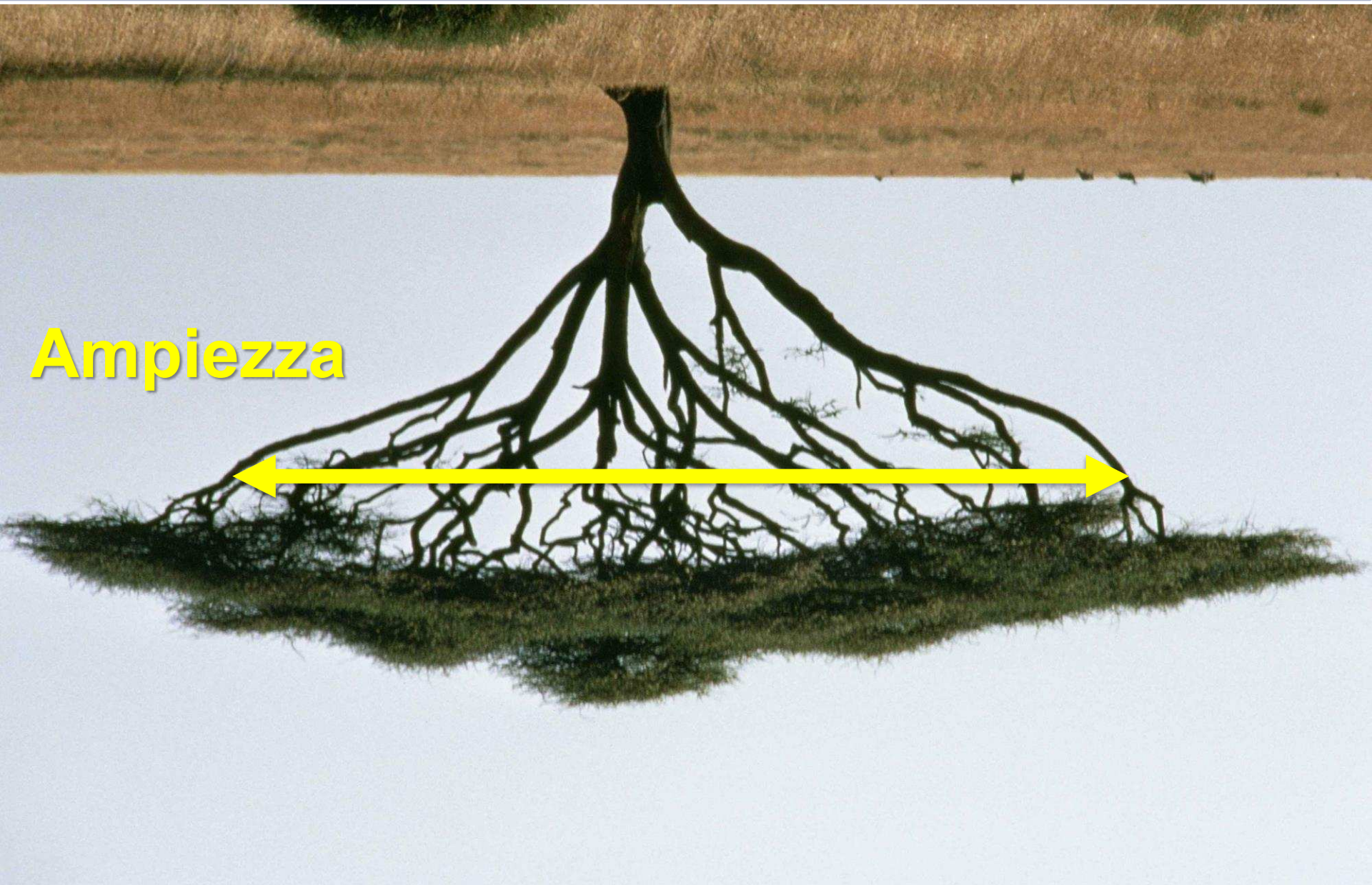
- non varia da simulazione a simulazione
- **Deep Convolutional Neural Network**  
(Policy Network)



# PROBABILITÀ A PRIORI (ESEMPIO) - $p(a/s)$



# ALBERO



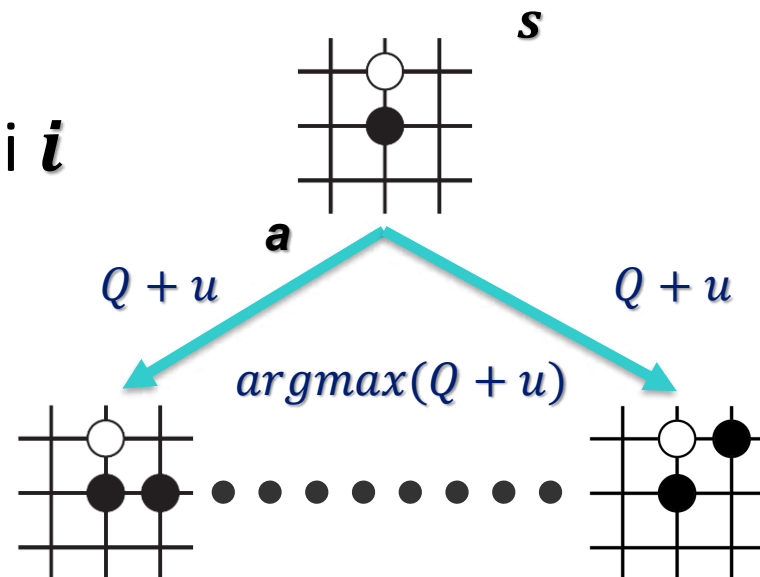
Ampiezza

# $Q + u$ : COMPONENTE DI VALUTAZIONE ( $Q$ )

- $Q(s, a)$  è la componente di valutazione

$$Q(s, a) = \frac{1}{N(s, a)} \sum_{i=1}^n 1(s, a, i) V(s_L^i)$$

- media le valutazioni  $V(s_L^i)$ 
  - di tutti gli stati **foglia**  $s_L^i$
  - raggiunti nelle varie simulazioni  $i$

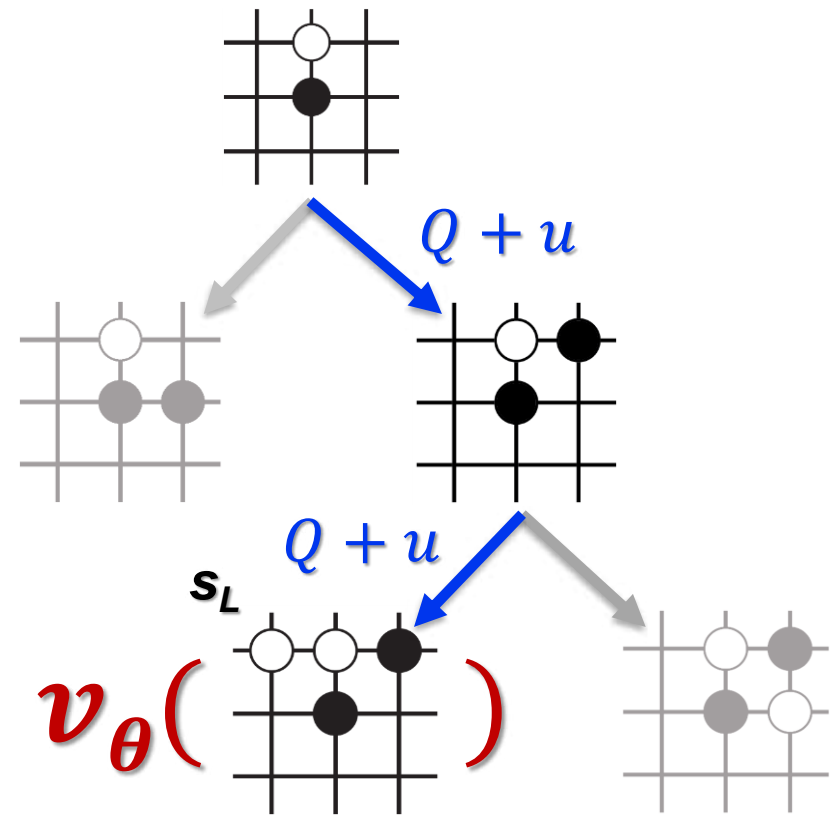


# VALUTAZIONE DEGLI STATI FOGLIA

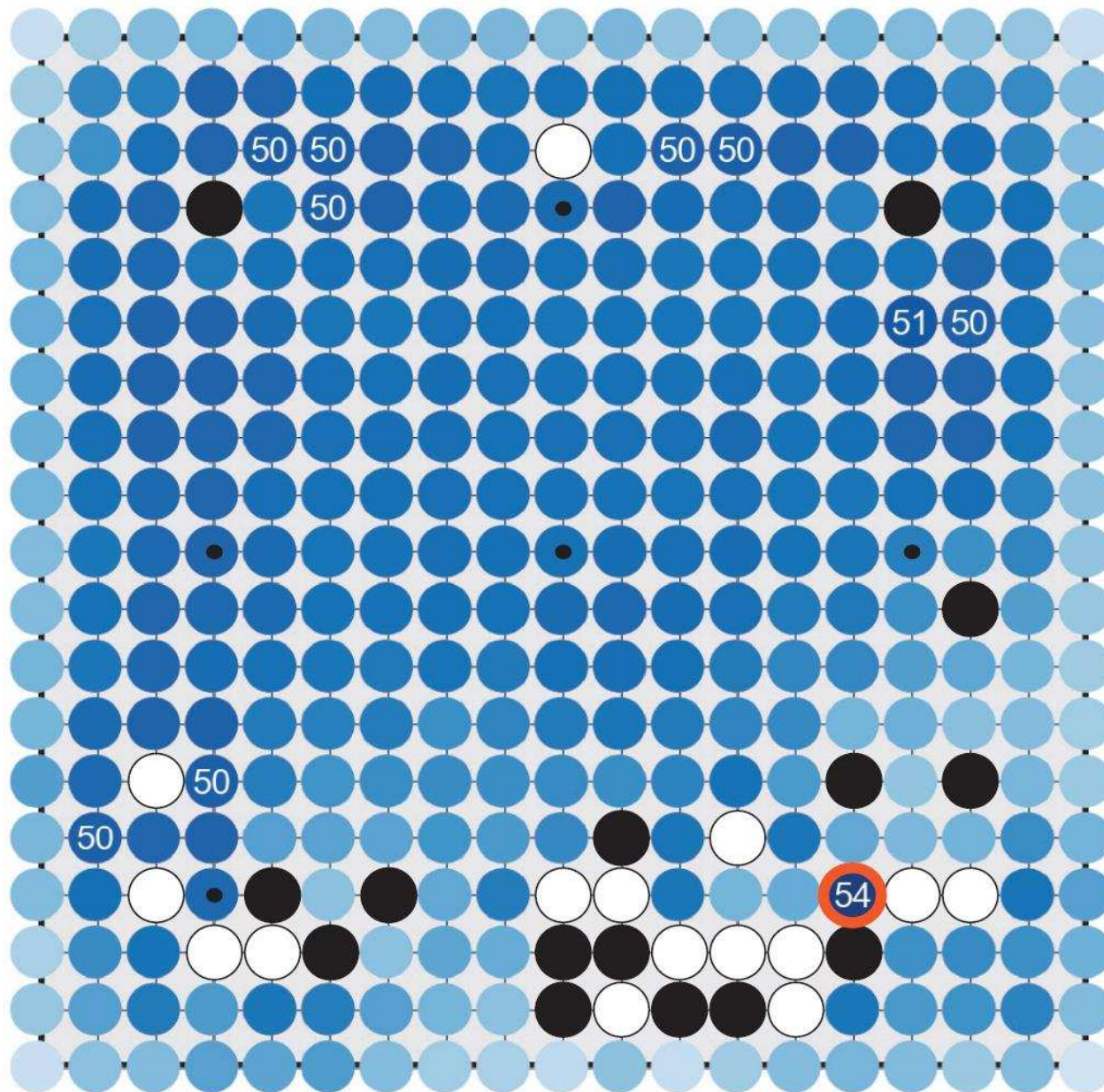
- Uno stato foglia ha valutazione

$$V(s_L) = (1 - \lambda)v_{\theta}(s_L) + \lambda z_L$$

- $v_{\theta}(s_L)$ 
  - Deep Convolutional Neural Network



# VALUTAZIONE DEGLI STATI CON $v_{\theta}(s_L)$



# VALUTAZIONE DEGLI STATI FOGLIA

- Uno stato foglia ha valutazione

$$V(s_L) = (1 - \lambda)v_{\theta}(s_L) + \lambda z_L$$

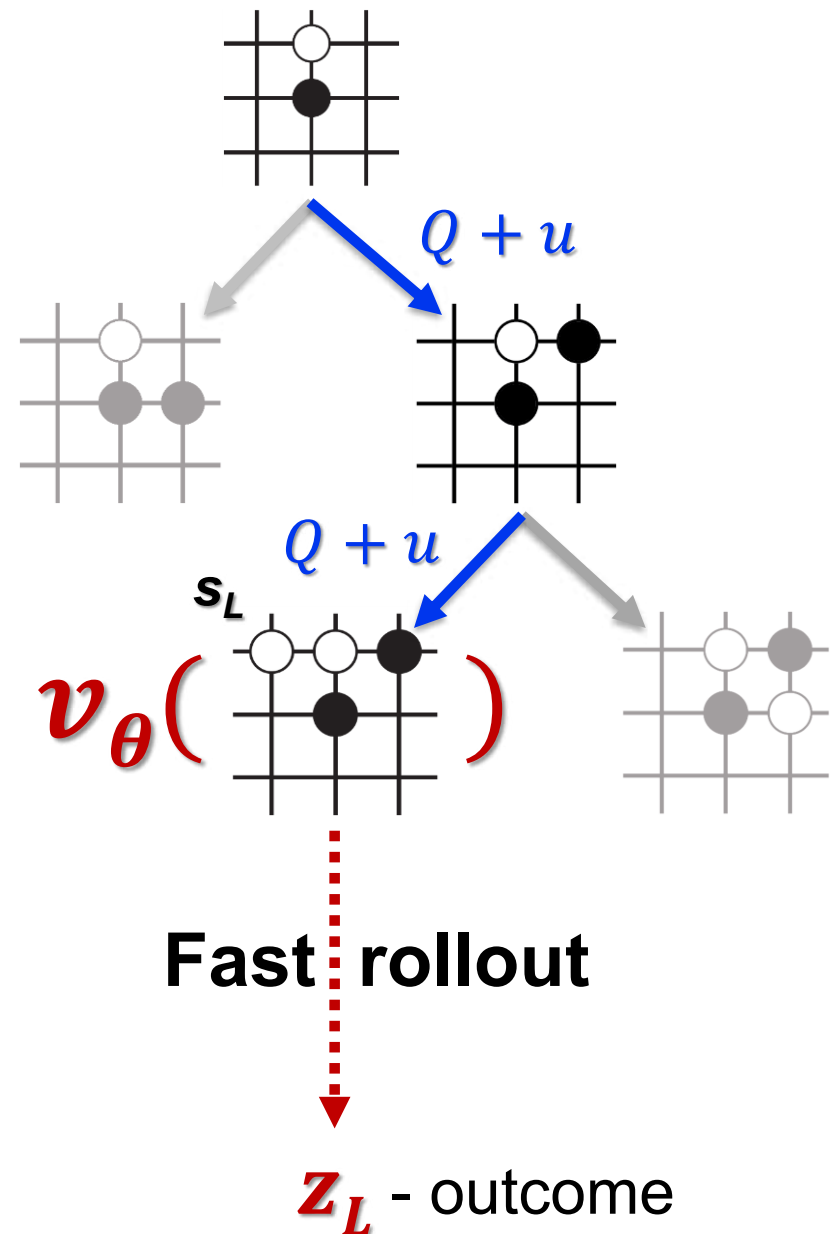
- $v_{\theta}(s_L)$

- **Neural Network**

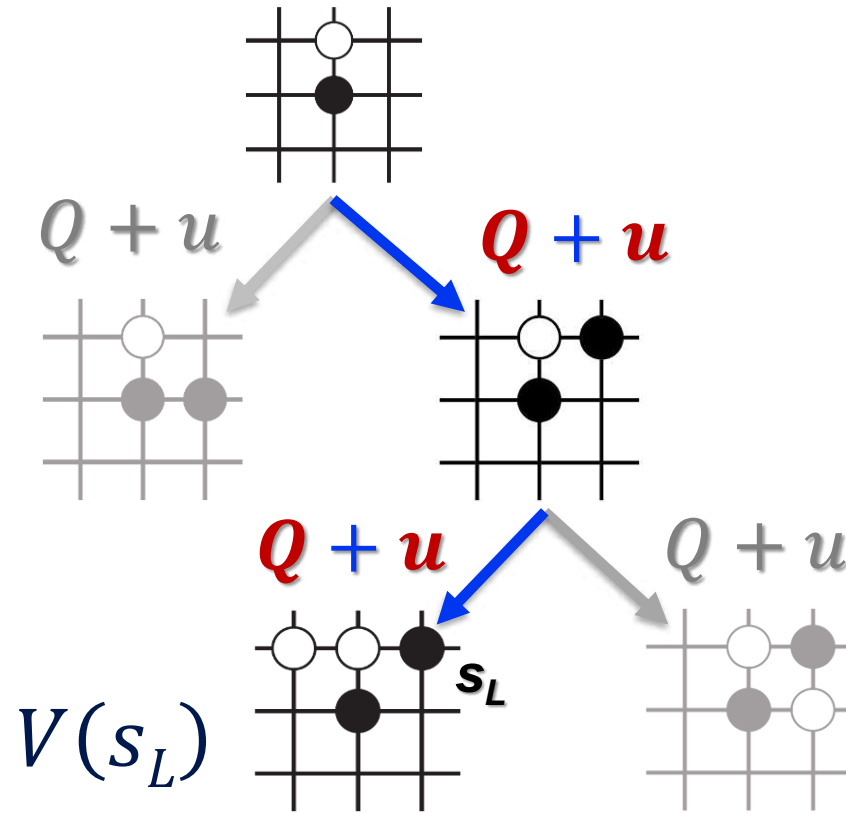
- $Z_L$  risultato finale

- **Fast rollout**

- linear softmax



# AGGIORNAMENTI

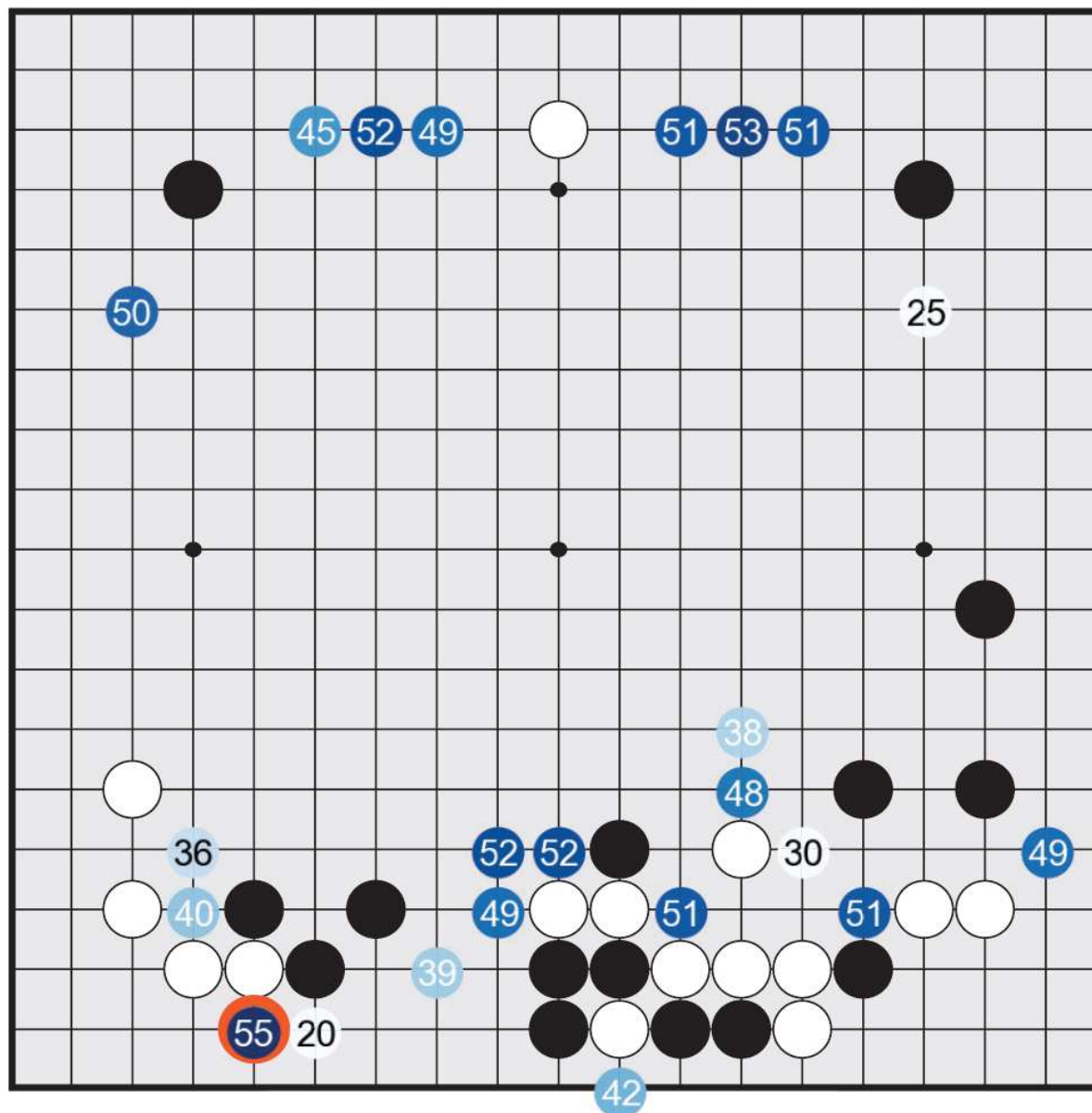


$$Q(s, a) = \frac{1}{N(s, a)} \sum_{i=1}^n 1(s, a, i) V(s_L^i)$$

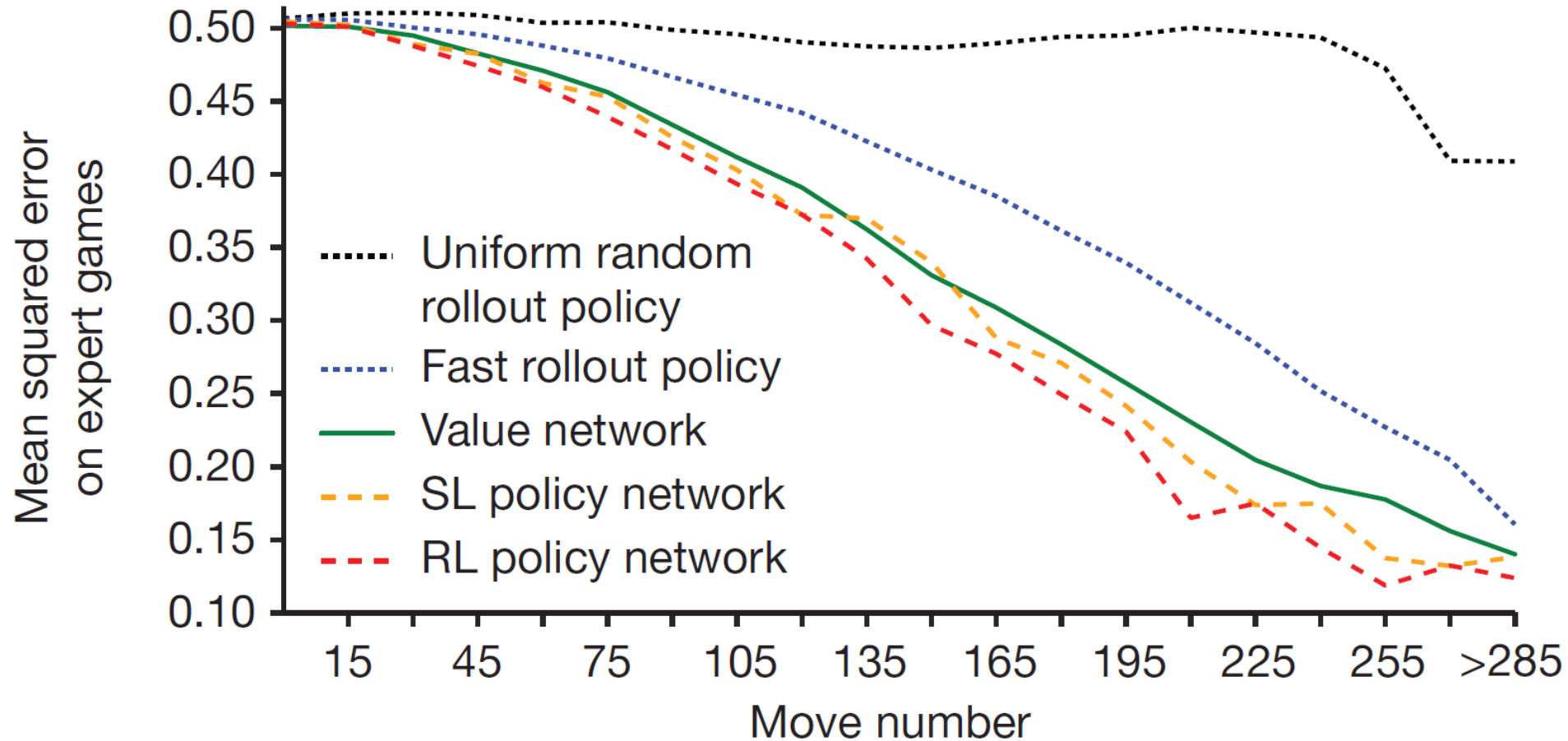
$$u(s, a) \propto \frac{P(s, a)}{1 + N(s, a)}$$



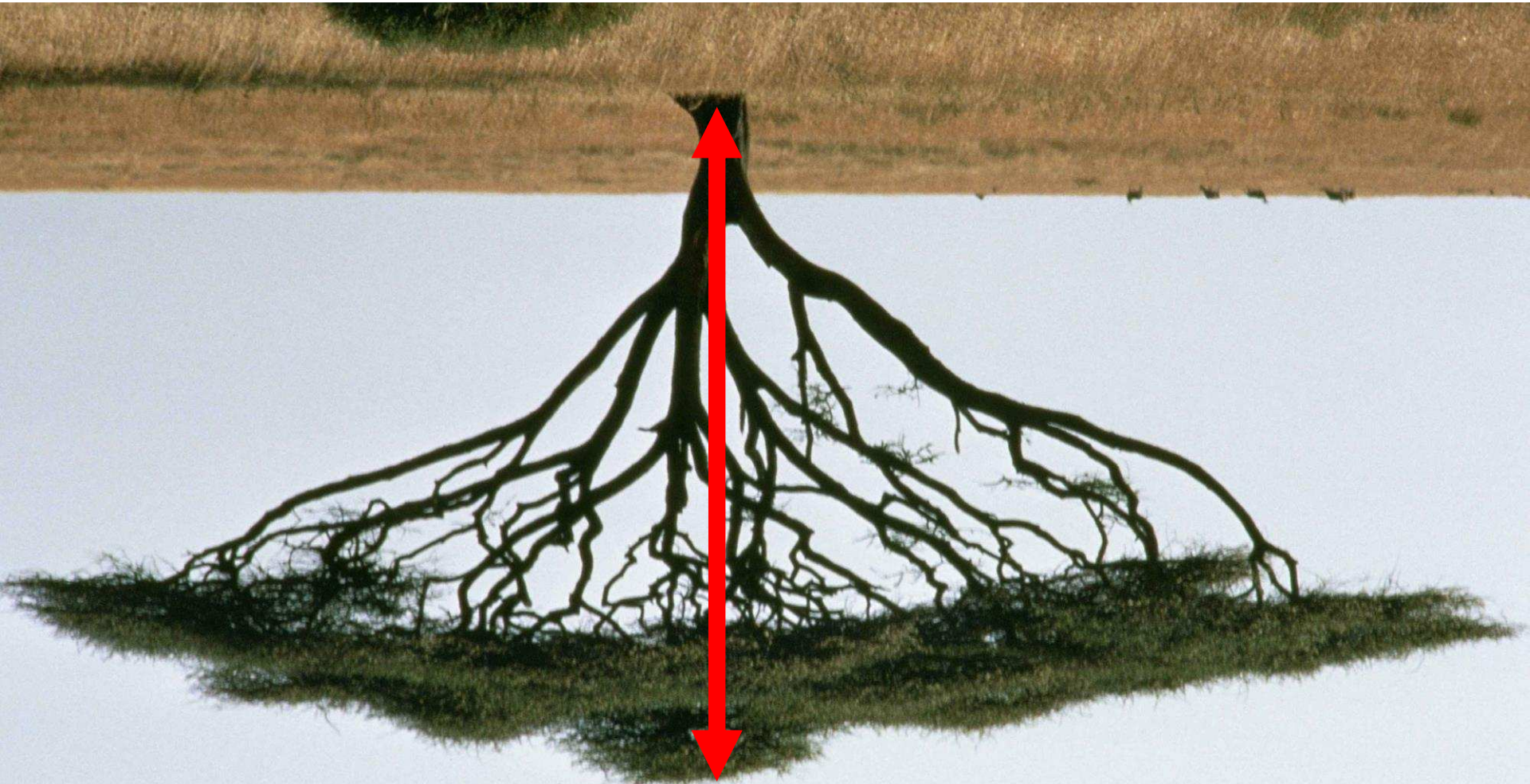
# $Q(s, a)$ USANDO SOLAMENTE $Z_L$



# VALUE NETWORK VS ROLLOUTS

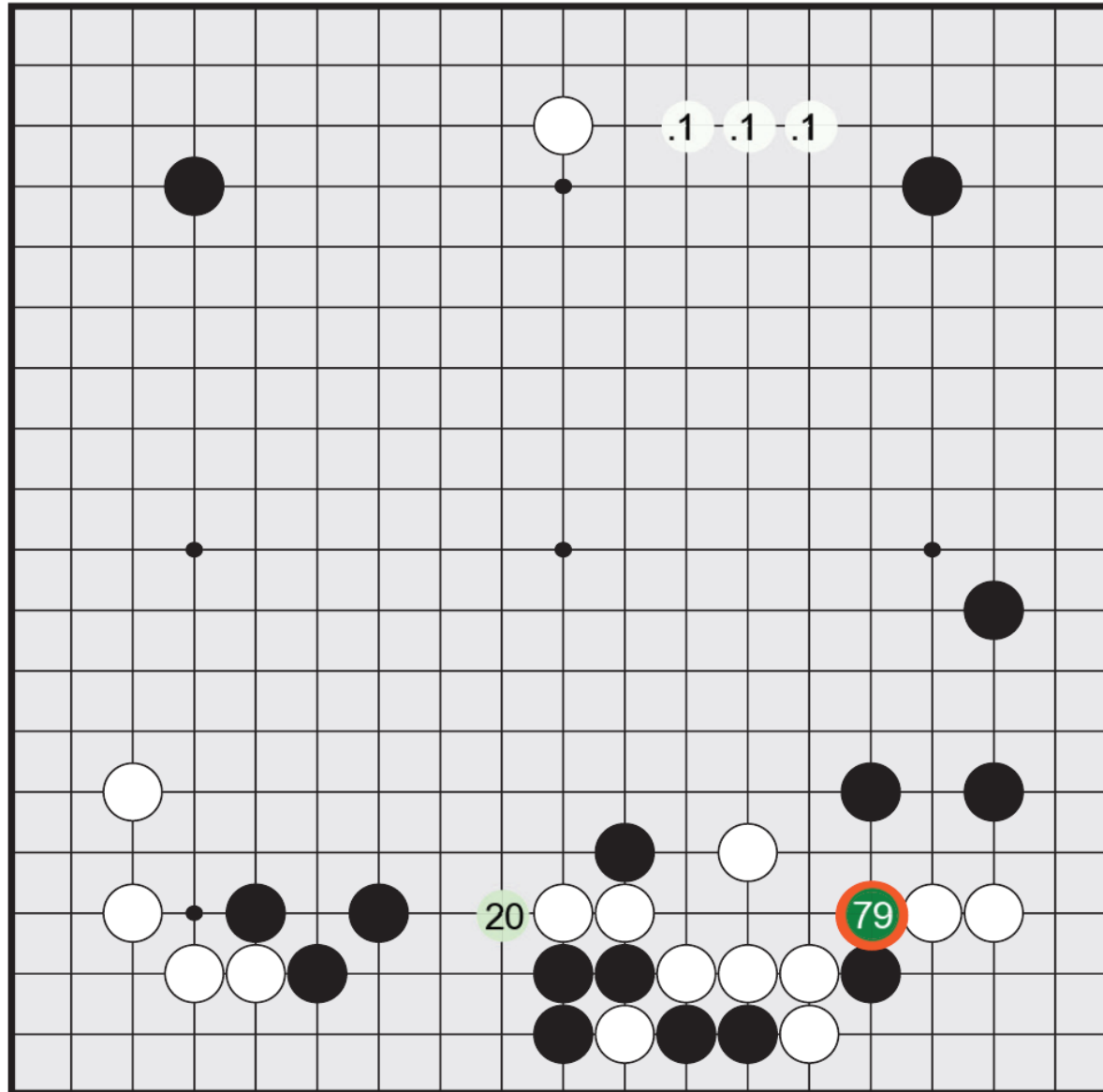


# ALBERO



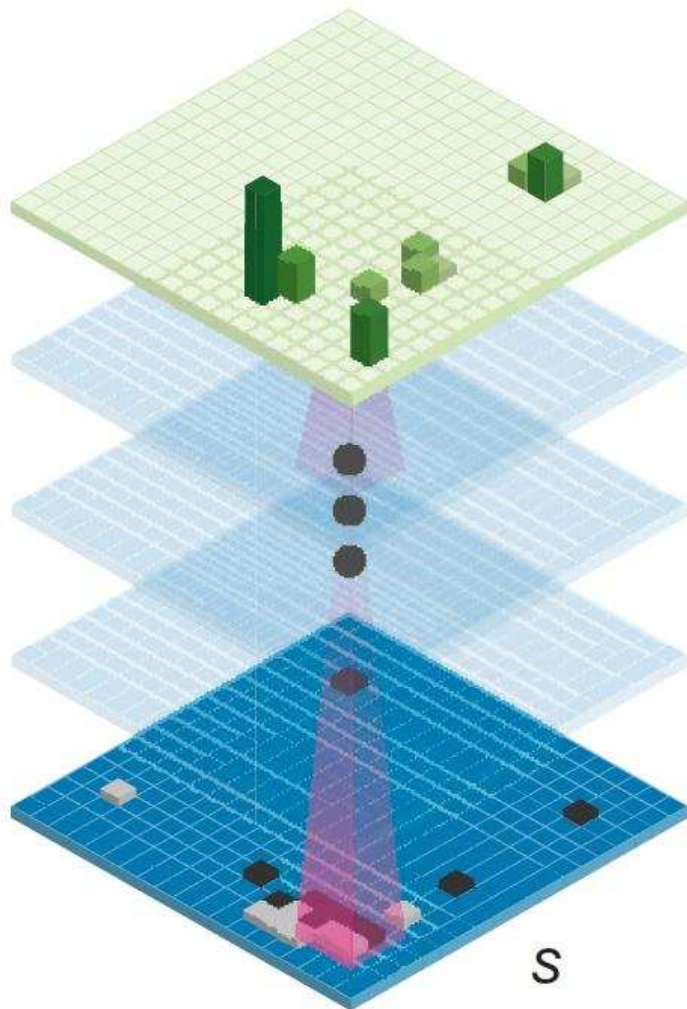
**Profondità**

# PERCENTUALE DI SIMULAZIONI $N(s, a)/n$



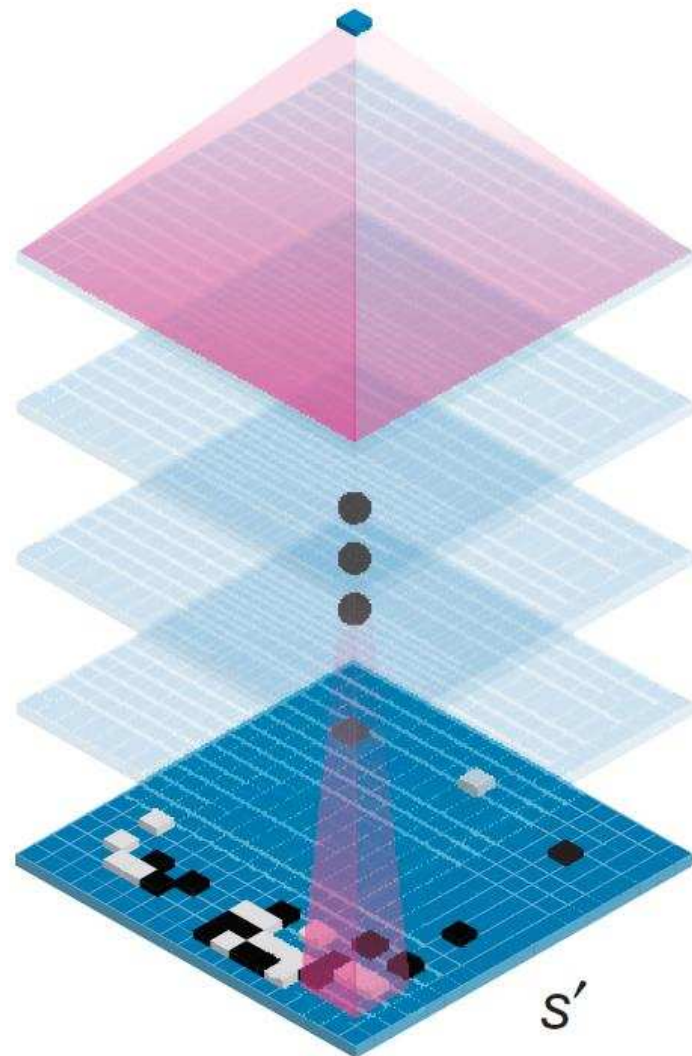
# Policy network

$$p_{\sigma/\rho}(a|s)$$



# Value network

$$v_{\theta}(s')$$



# DEMIS HASSABIS

## Short Bio

Before embarking on my research career, I was previously a well-known UK videogames designer and AI programmer. I started my professional games career at the age of 16 working at the legendary Bullfrog Productions, and then after getting my degree at Cambridge, I joined the newly founded Lionhead Studios. In 1998 I founded and ran my own 60-person development studio, called Elixir Studios, producing games for Microsoft and Vivendi Universal, and have contributed to many best-selling and award-winning games over a successful 10-year career including: Syndicate (1993), Theme Park (1994), Black & White (2001), Republic (2003), and Evil Genius (2004).

I also play many games to an accomplished level including chess, shogi and poker and won the World Games Championships at the Mind Sports Olympiad a record 5-times before retiring from competitive play in 2003. You can find further information about my past from [here](#).



*Playing at the World Series of Poker  
(hence the silly glasses)*

## Academic History

### 2005–2009

- PhD in Cognitive Neuroscience, **Wellcome Trust Centre for Neuroimaging** (WTCN), UCL, UK
- Thesis: "**The neural processes underlying episodic memory**" (supervisor: Prof **Eleanor Maguire**) (viva committee: Prof **John O'Keefe**, Prof **Lynn Nadel**)

### 1994–1997

- BA (First) in Computer Science, Queens' College, Cambridge University





## Sn. Staff Research Scientist

Google DeepMind

February 2014 – Present (1 year 4 months) | London, United Kingdom



## Co-founder & Chief Science Officer

DeepMind Technologies

February 2011 – January 2014 (3 years) | London, United Kingdom

## Research Associate

Gatsby Computational Neuroscience Unit, UCL

February 2009 – December 2010 (1 year 11 months)



## Post Doc in Finance

University of Lugano

June 2007 – October 2008 (1 year 5 months)

Portfolio choice theory and behavioural finance models



## PhD Student

IDSIA

April 2003 – May 2007 (4 years 2 months)



## Senior Software Engineer

Adaptive Intelligence Inc.

January 2002 – October 2002 (10 months) | Wellington, New Zealand

## Senior Software Engineer

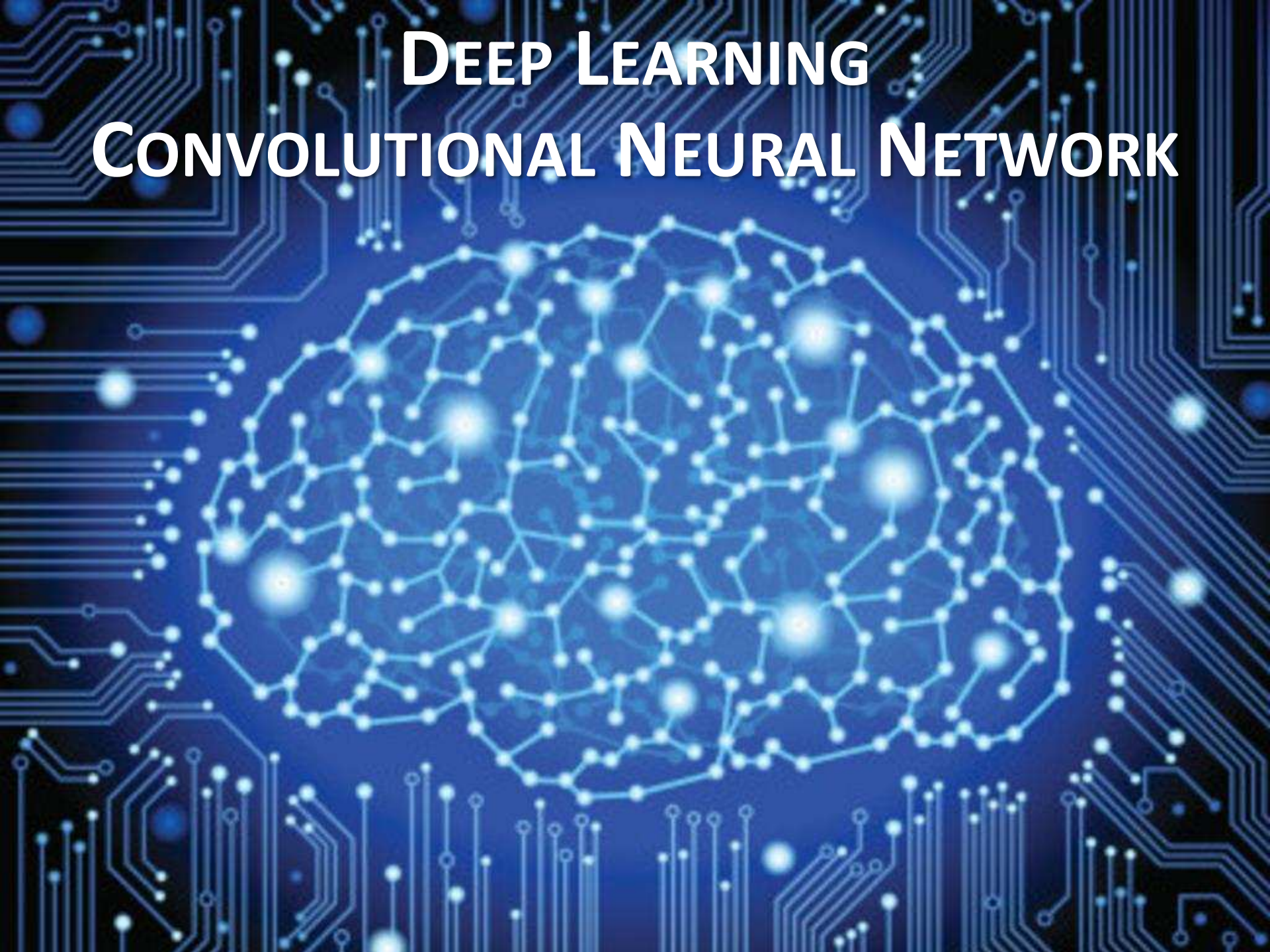
Webmind

September 1999 – May 2001 (1 year 9 months)

## Analyst Programmer

Freightways Information Services

# DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK



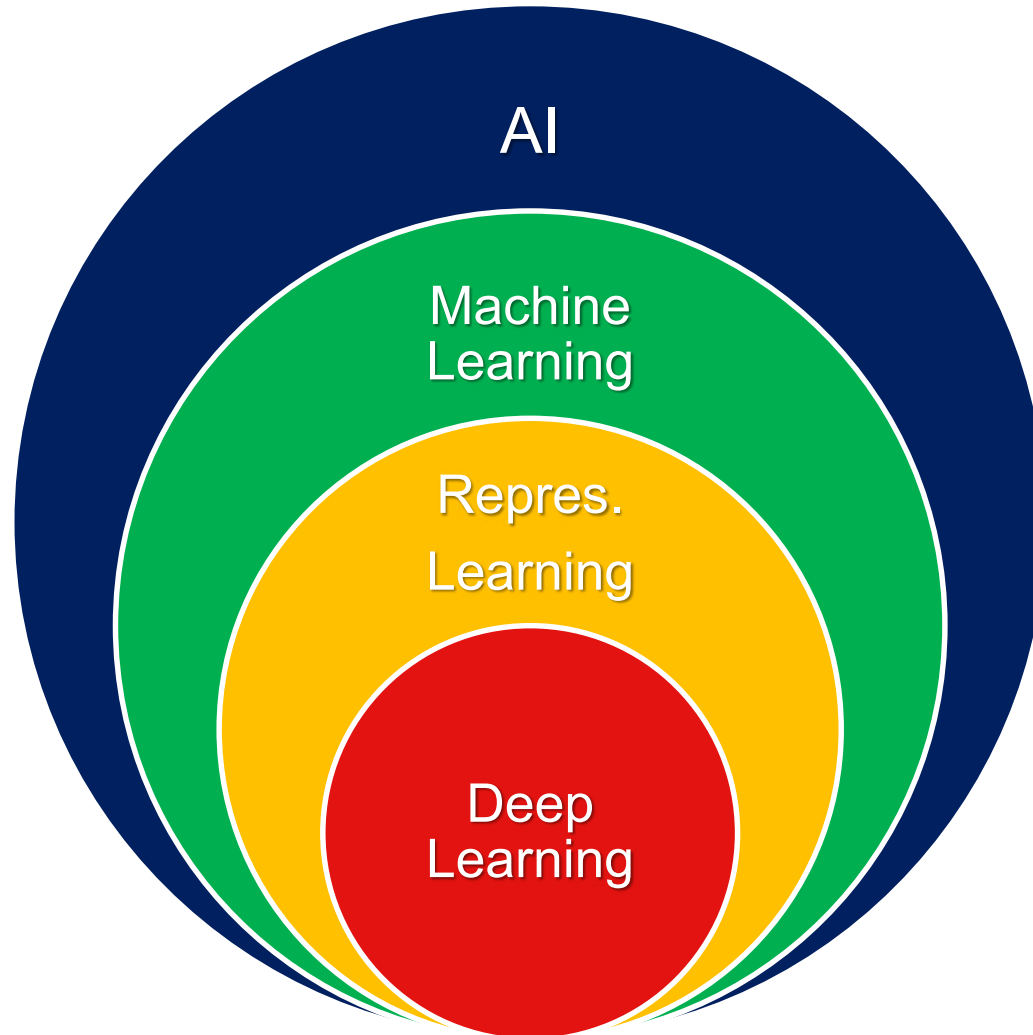
# DEEP LEARNING (FROM NATURE)

**nature**

International weekly journal of science

Archive > Volume 521 > Issue 7553 > Insights > Reviews > Article

Yann LeCun, Yoshua Bengio & Geoffrey Hinton



# CNN AND DEEP LEARNING

## C'è voluto tempo



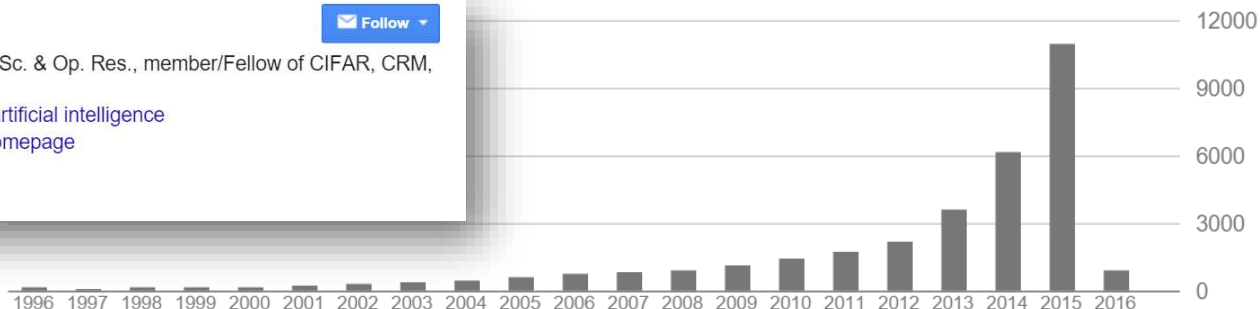
**Yoshua Bengio**

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Professor, U. Montreal, Computer Sc. & Op. Res., member/Fellow of CIFAR, CRM, REPARTI, GRSNC, CIRANO

[Machine learning](#), [deep learning](#), [artificial intelligence](#)

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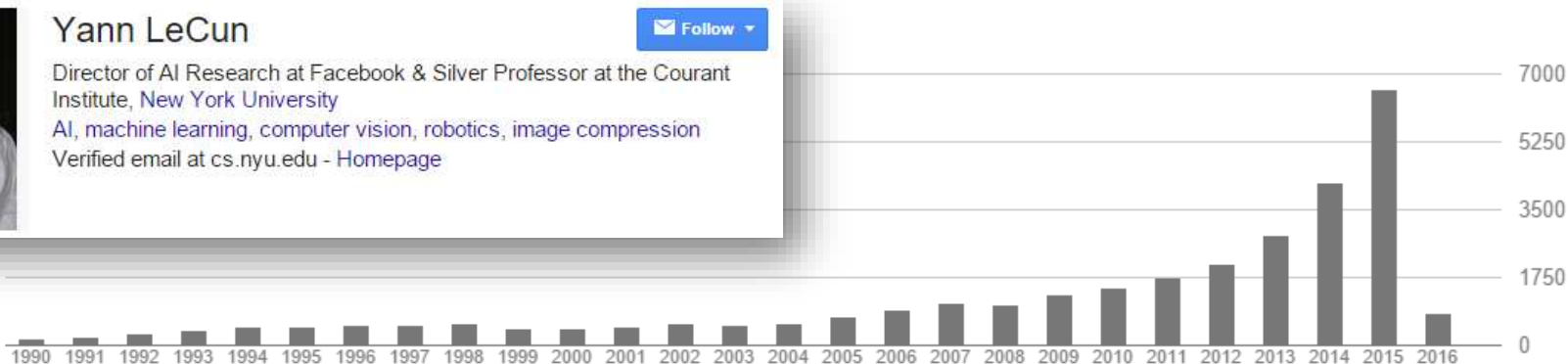
**Yann LeCun**

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Director of AI Research at Facebook & Silver Professor at the Courant Institute, New York University

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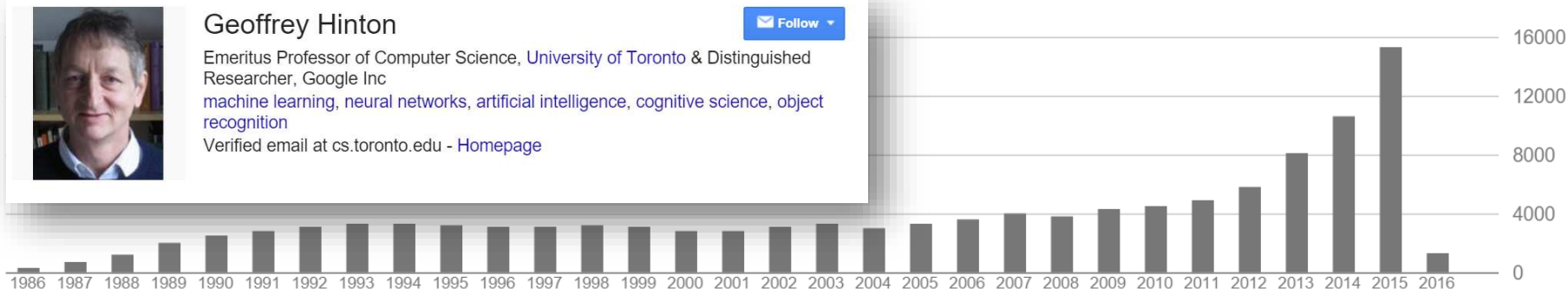
**Geoffrey Hinton**

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[machine learning](#), [neural networks](#), [artificial intelligence](#), [cognitive science](#), [object recognition](#)

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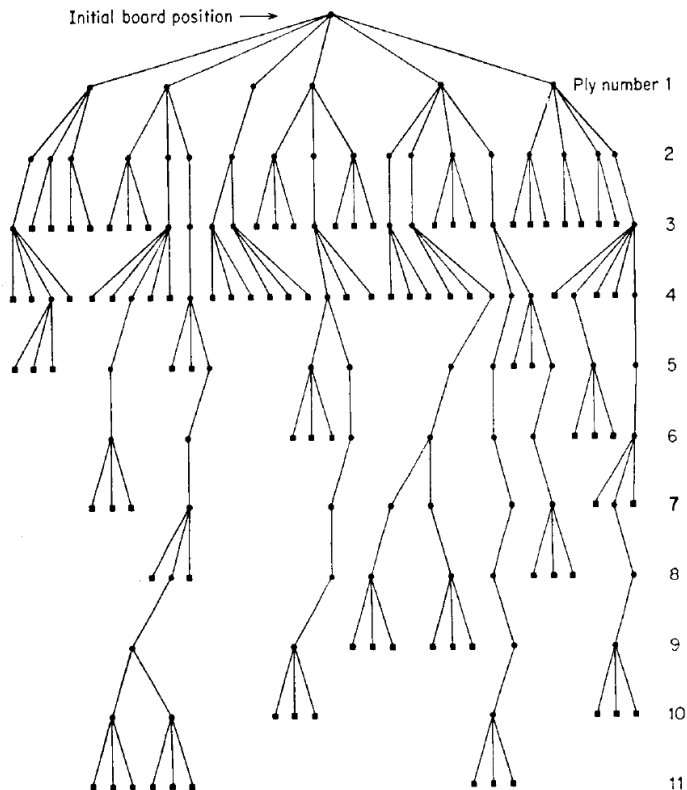
# MACHINE LEARNING

*Field of study that gives computers the ability to learn without being explicitly programmed.*

Arthur Samuel (1959)

Some studies in machine learning using the game of checkers

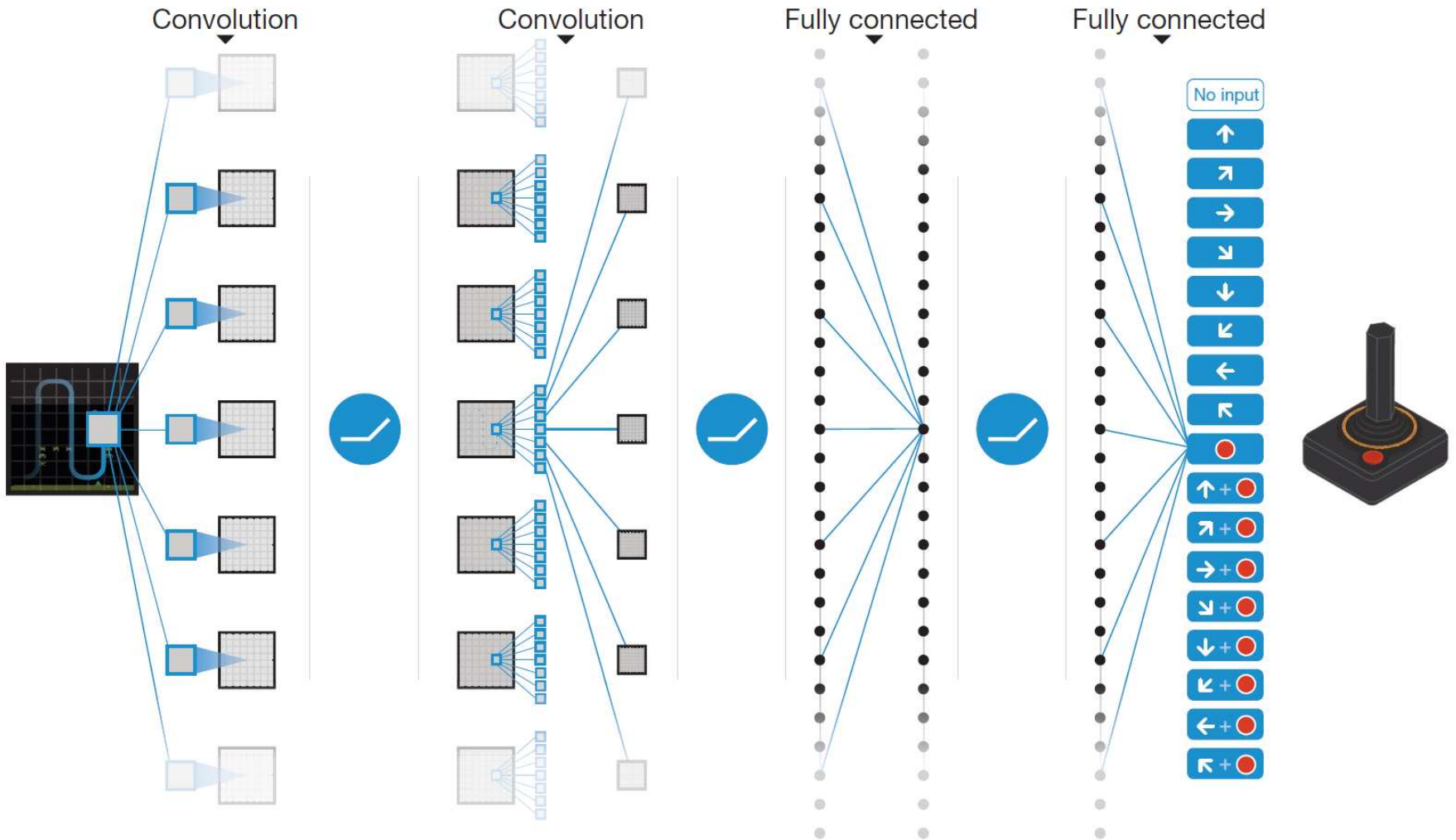
IBM, J Res Dev 3:210–229



# DEEPMIND PLAYING ATARI

<https://www.youtube.com/watch?v=Q70uIPJW3Gk>

# DEEPMIND PLAYING ATARI



# MACHINE LEARNING

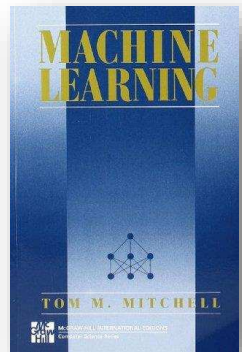
*The field of machine learning is concerned with the question of how to construct programs that automatically improve with experience.*

*A computer program is said to **learn**:*

- from experience **E***
- with respect to some task **T***
- and some performance measure **P***

*if its performance*

- on the task **T***
- as measured by **P***
- **improves** with experience **E***



**Tom M. Mitchell**  
*Machine Learning*  
McGraw-Hill, 1997

# ALPHAGO: EXPERIENCE

## 1. 30 milioni di stati da **Kiseido Go Server**

- Game server established in 2000 for people to play Go.



## 2. Policy Gradient **Reinforcement Learning**

- Partite giocate dalla rete attuale  
con se stessa a uno dei passi precedenti (casuale)

## 3. 30 million posizioni distinte da partite giocate con se stesso

# DEEP LEARNING (FROM NATURE)

**nature**  
International weekly journal of science

Archive > Volume 521 > Issue 7553 > Insights > Reviews > Article

Yann LeCun, Yoshua Bengio & Geoffrey Hinton

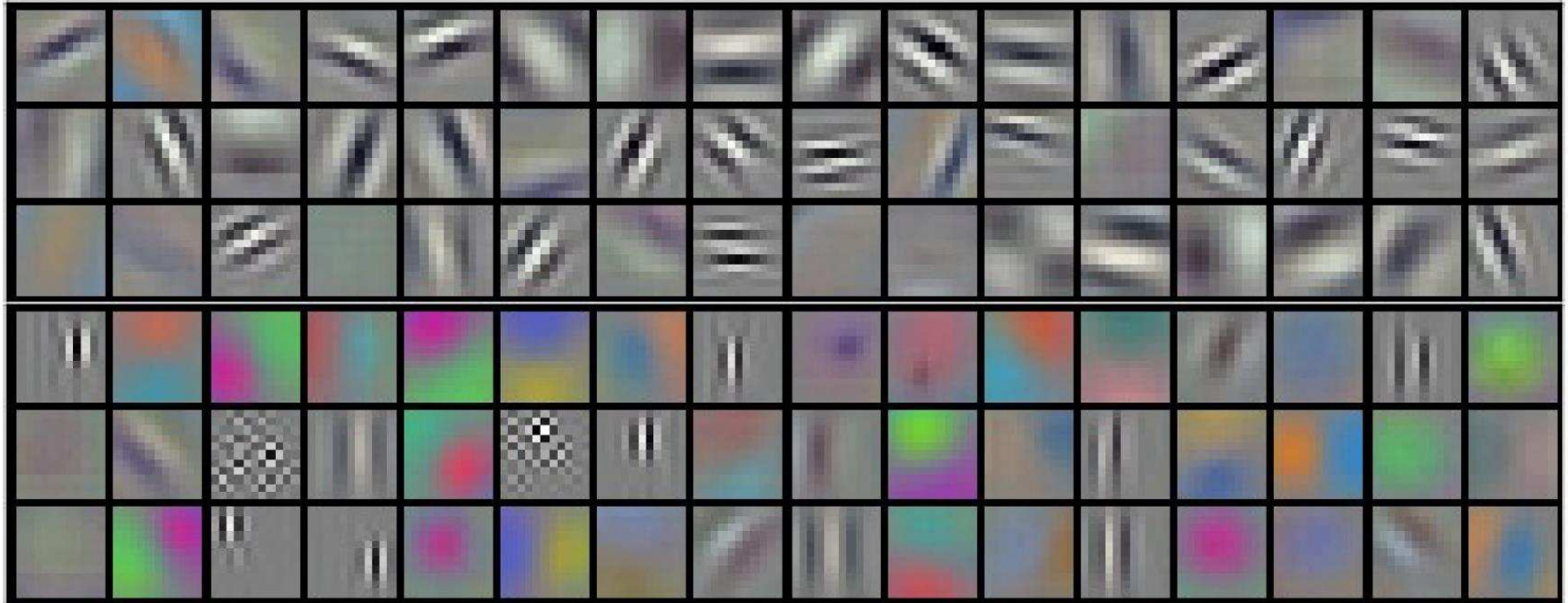
## Representation learning methods that

allow a machine to be fed with raw data and to automatically discover the representations needed for detection or classification.

## Deep-learning are representation learning methods

- with **multiple levels** of representation, obtained by
- composing simple but **non-linear modules** that each
- transform the representation at one level into a representation at a higher, slightly more abstract level.

## 96 learned low-level filters

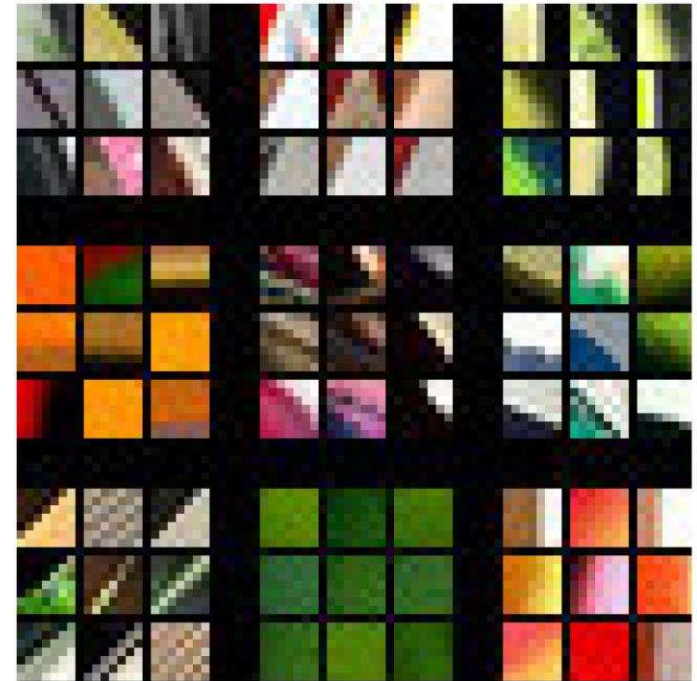


# VISUALIZING CONVOLUTIONAL NETWORKS

- 9 feature maps and top 9 activations for each of them across validation data



Layer 1



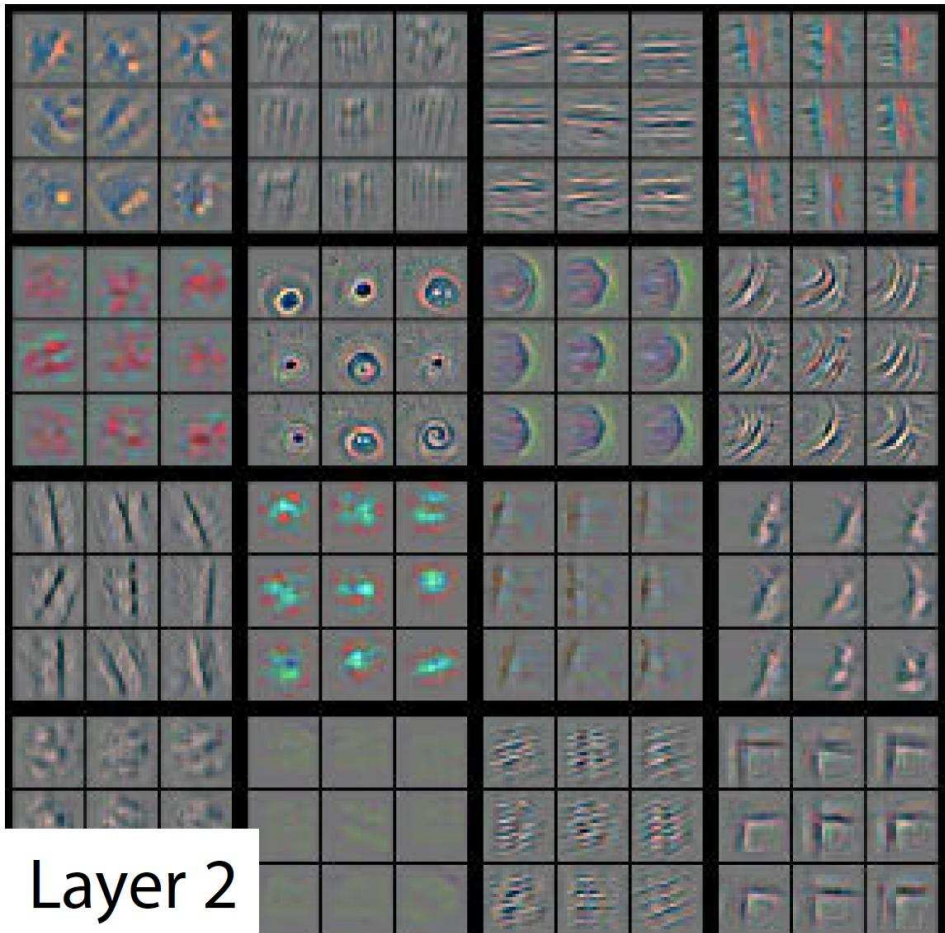
[\*Visualizing Convolutional Networks\*](#)

Zeiler, Matthew D., and Rob Fergus.

Computer vision – ECCV 2014 (cited by 639)

# VISUALIZING CONVOLUTIONAL NETWORKS

- Top 9 activations for some random feature maps across the validation data

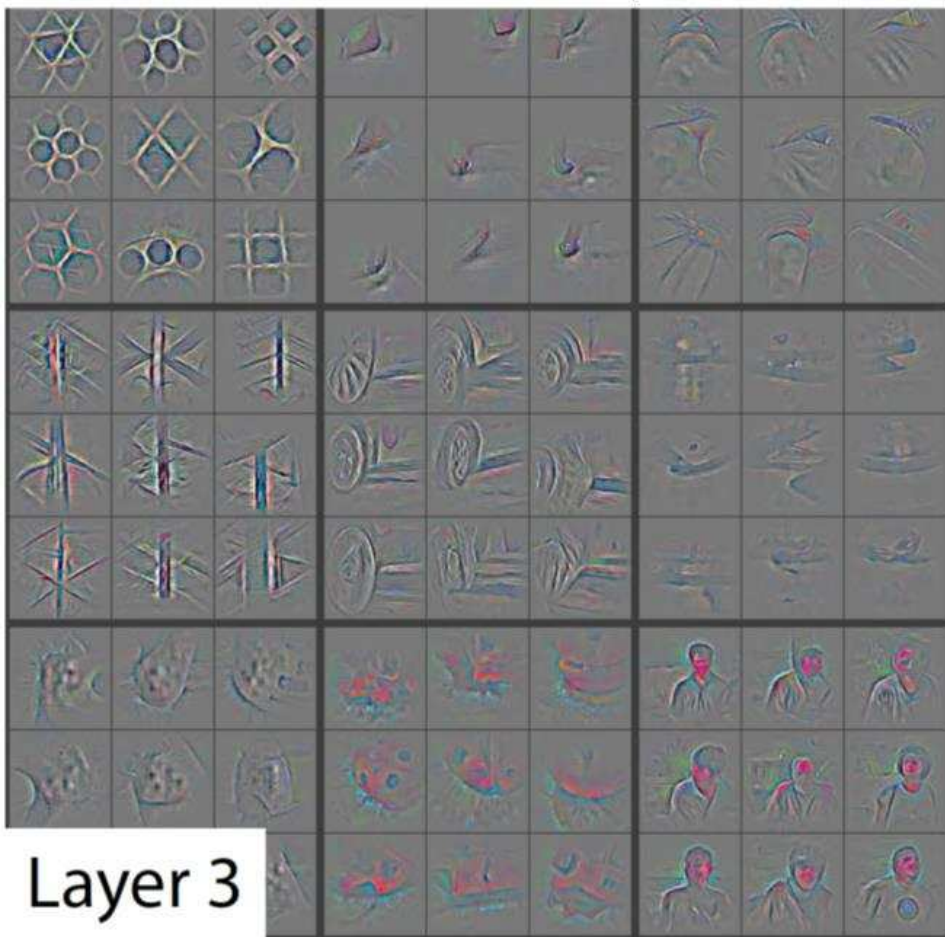


[Visualizing Convolutional Networks](#)

Zeiler, Matthew D., and Rob Fergus.

Computer vision – ECCV 2014 (cited by 639)

# VISUALIZING CONVOLUTIONAL NETWORKS

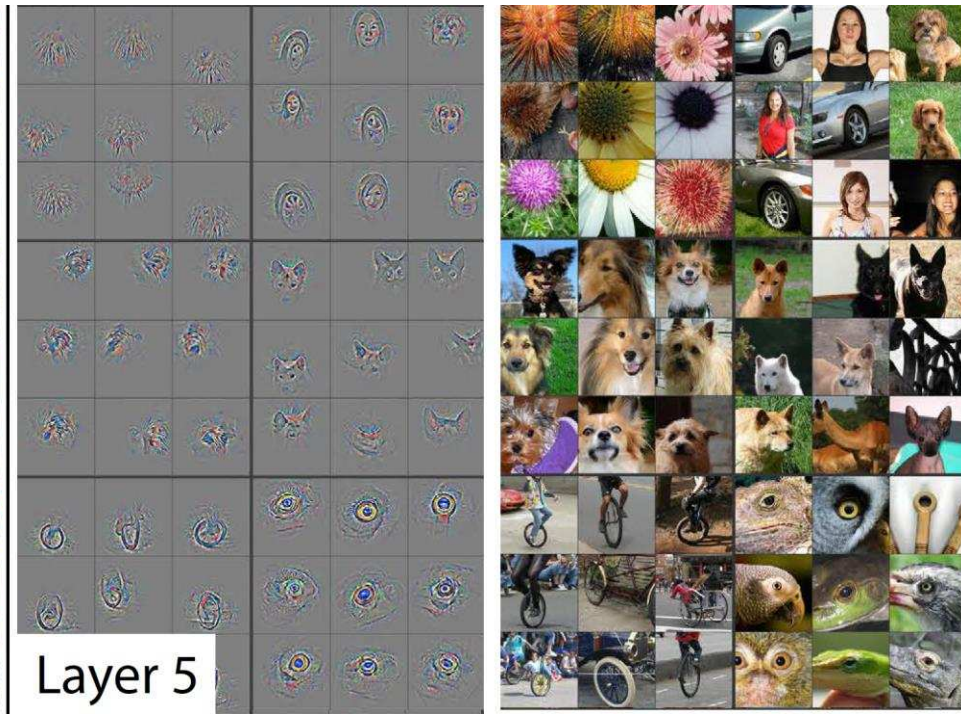
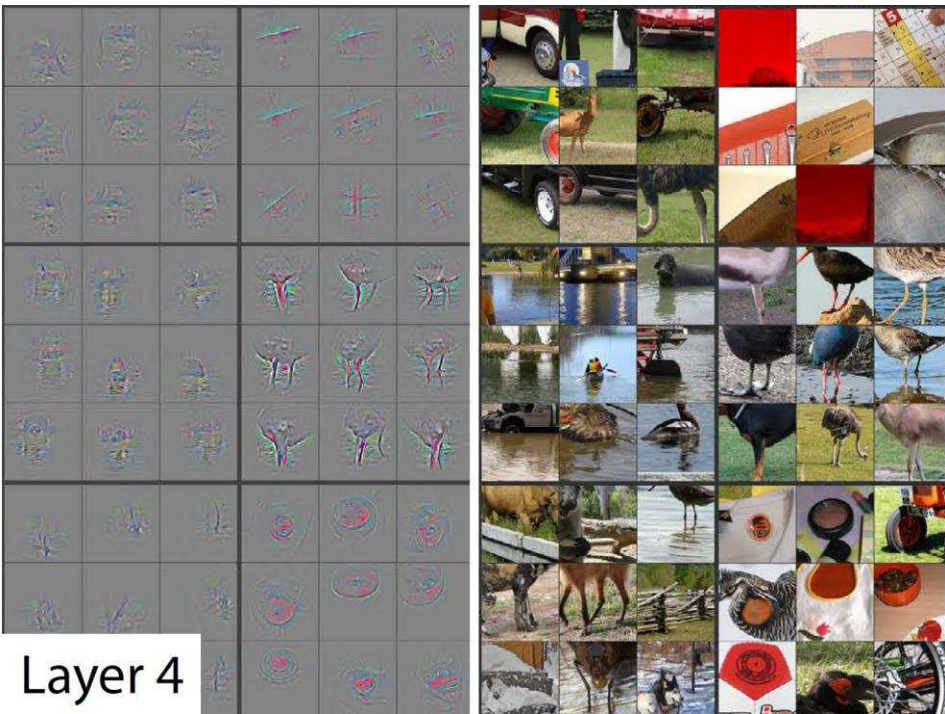


[Visualizing Convolutional Networks](#)

Zeiler, Matthew D., and Rob Fergus.

Computer vision – ECCV 2014 (cited by 639)

# VISUALIZING CONVOLUTIONAL NETWORKS



[\*Visualizing Convolutional Networks\*](#)

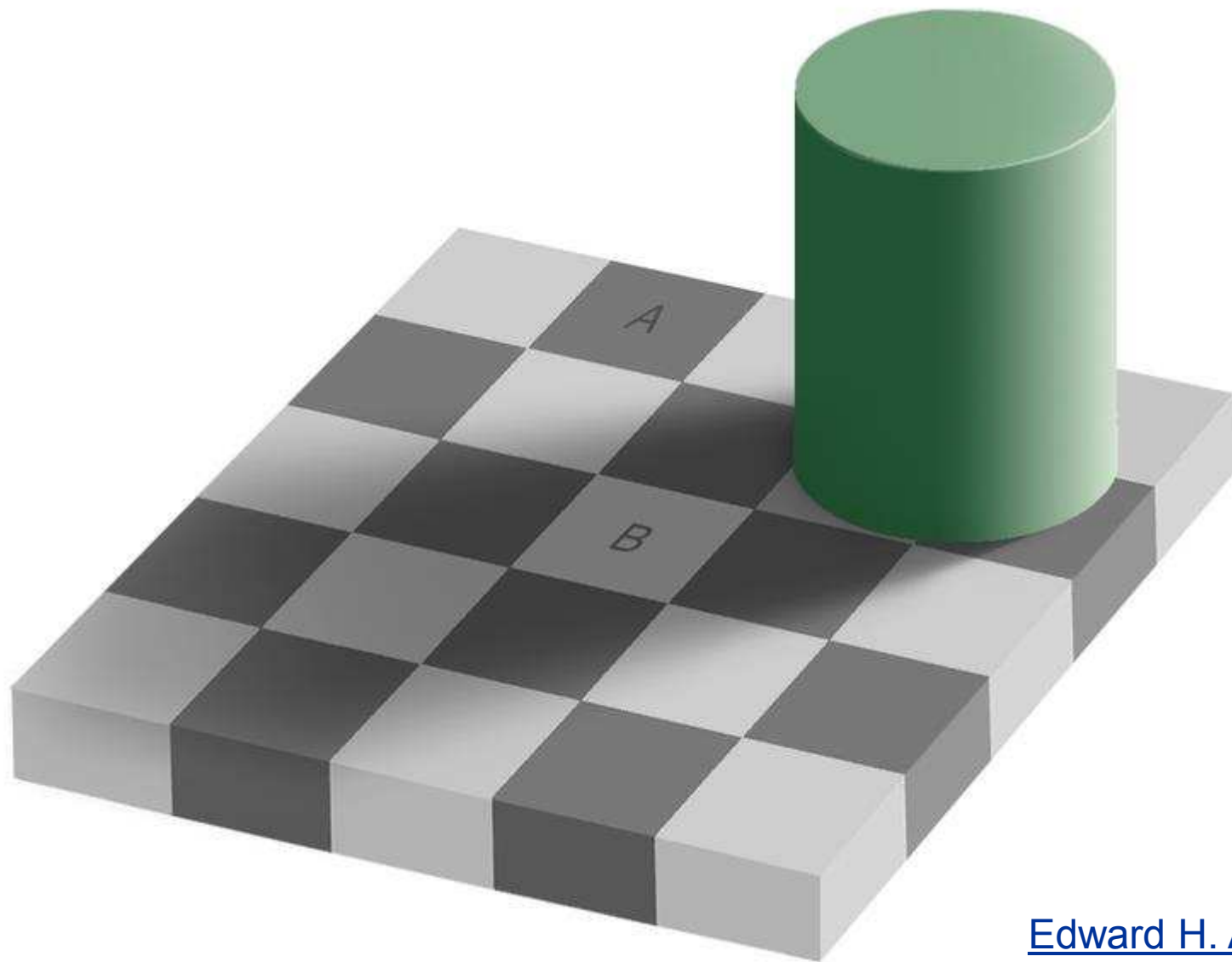
Zeiler, Matthew D., and Rob Fergus.

Computer vision – ECCV 2014 (cited by 639)



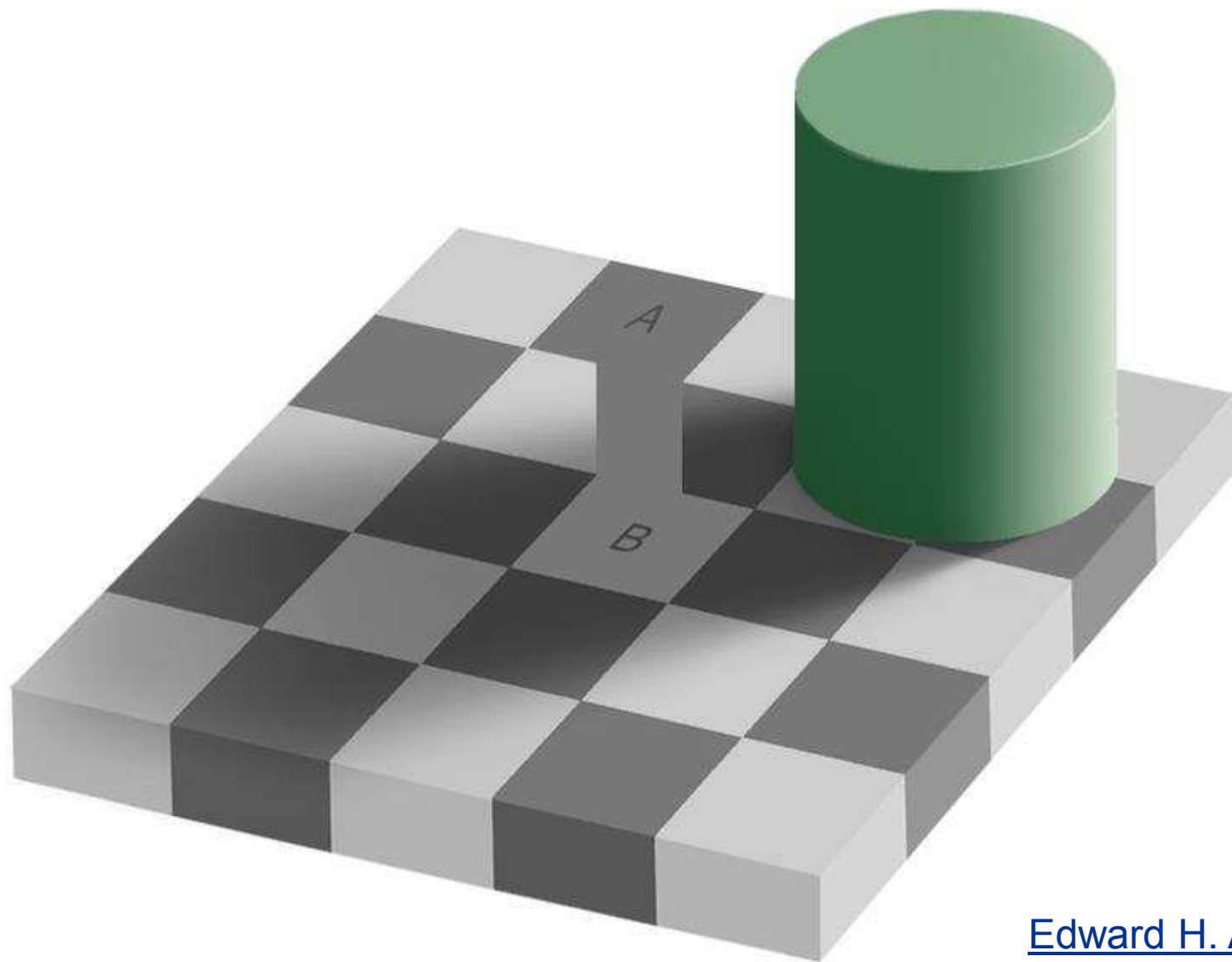


# ILLUSIONI

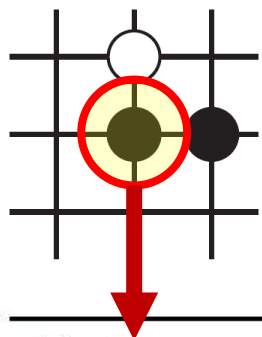


Edward H. Adelson

# ILLUSIONI



Edward H. Adelson



## Cosa “vede” AlphaGo Deep CNN?

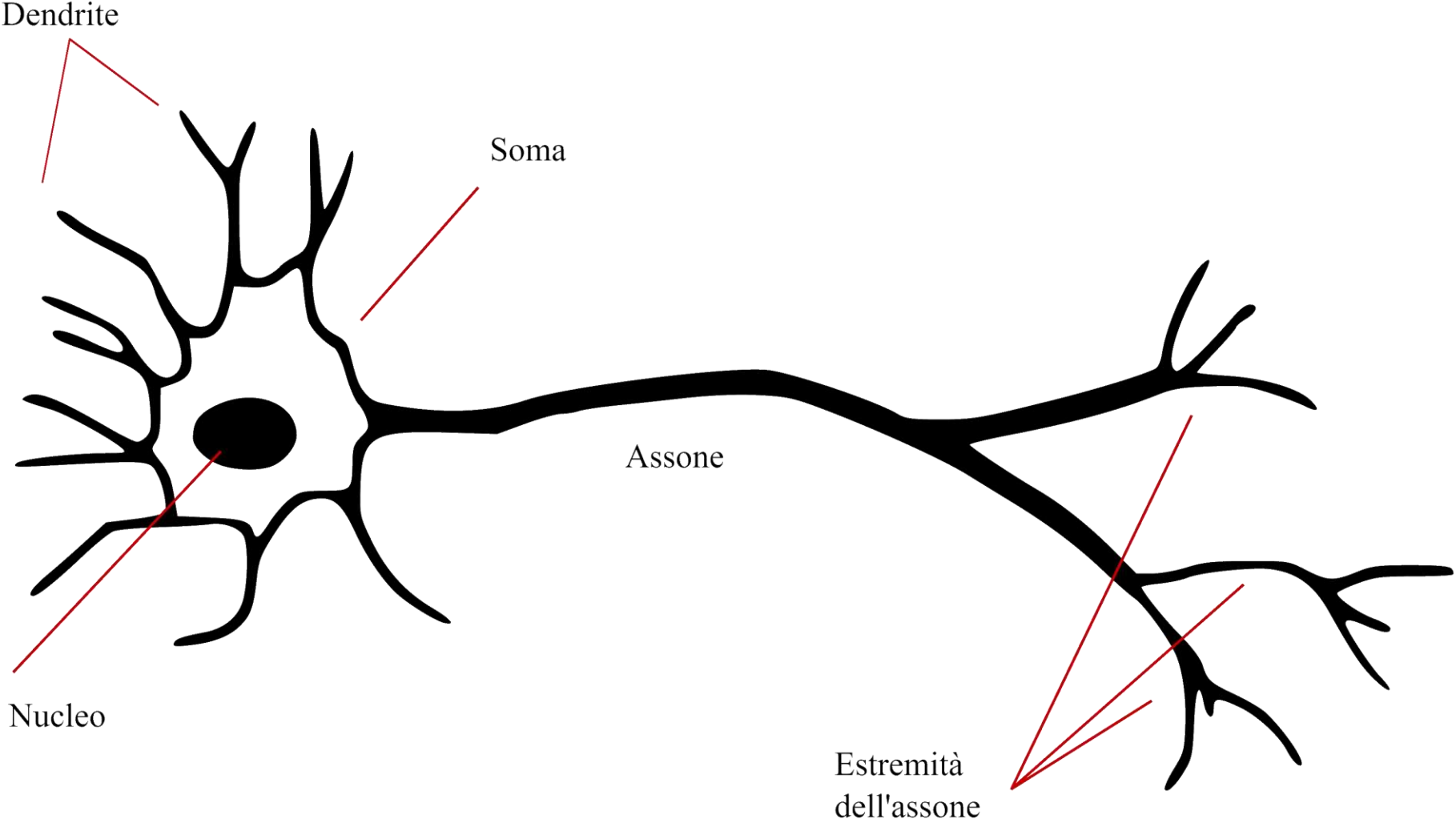
Feature	# of planes	Description
Stone colour	3	Player stone / opponent stone / empty
Ones	1	A constant plane filled with 1
Turns since	8	How many turns since a move was played
Liberties	8	Number of liberties (empty adjacent points)
Capture size	8	How many opponent stones would be captured
Self-atari size	8	How many of own stones would be captured
Liberties after move	8	Number of liberties after this move is played
Ladder capture	1	Whether a move at this point is a successful ladder capture
Ladder escape	1	Whether a move at this point is a successful ladder escape
Sensibleness	1	Whether a move is legal and does not fill its own eyes
Zeros	1	A constant plane filled with 0
Player color	1	Whether current player is black

Feature planes used by the policy network (all but last feature) and value network (all features).

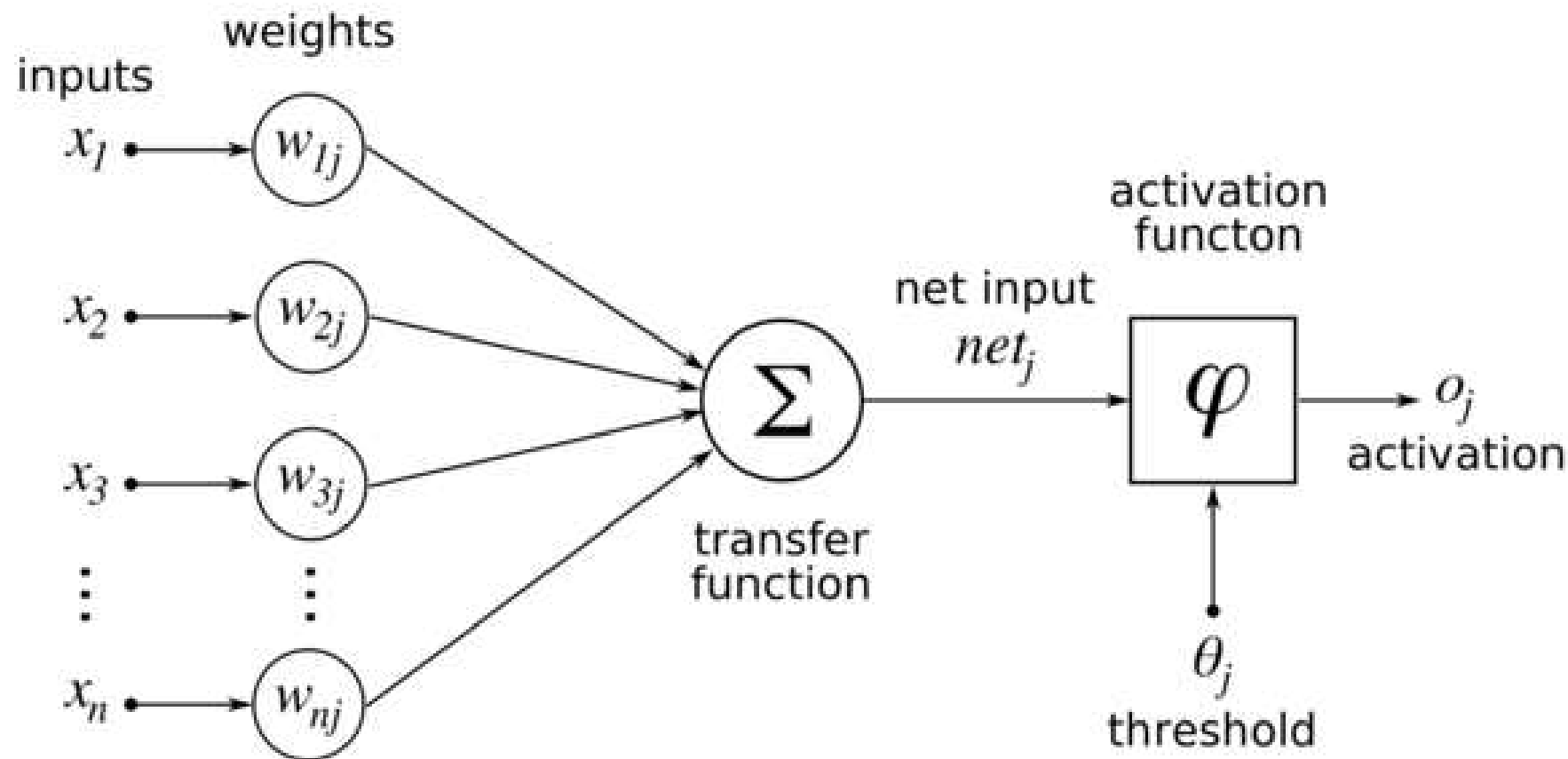


# BUILDING BLOCKS

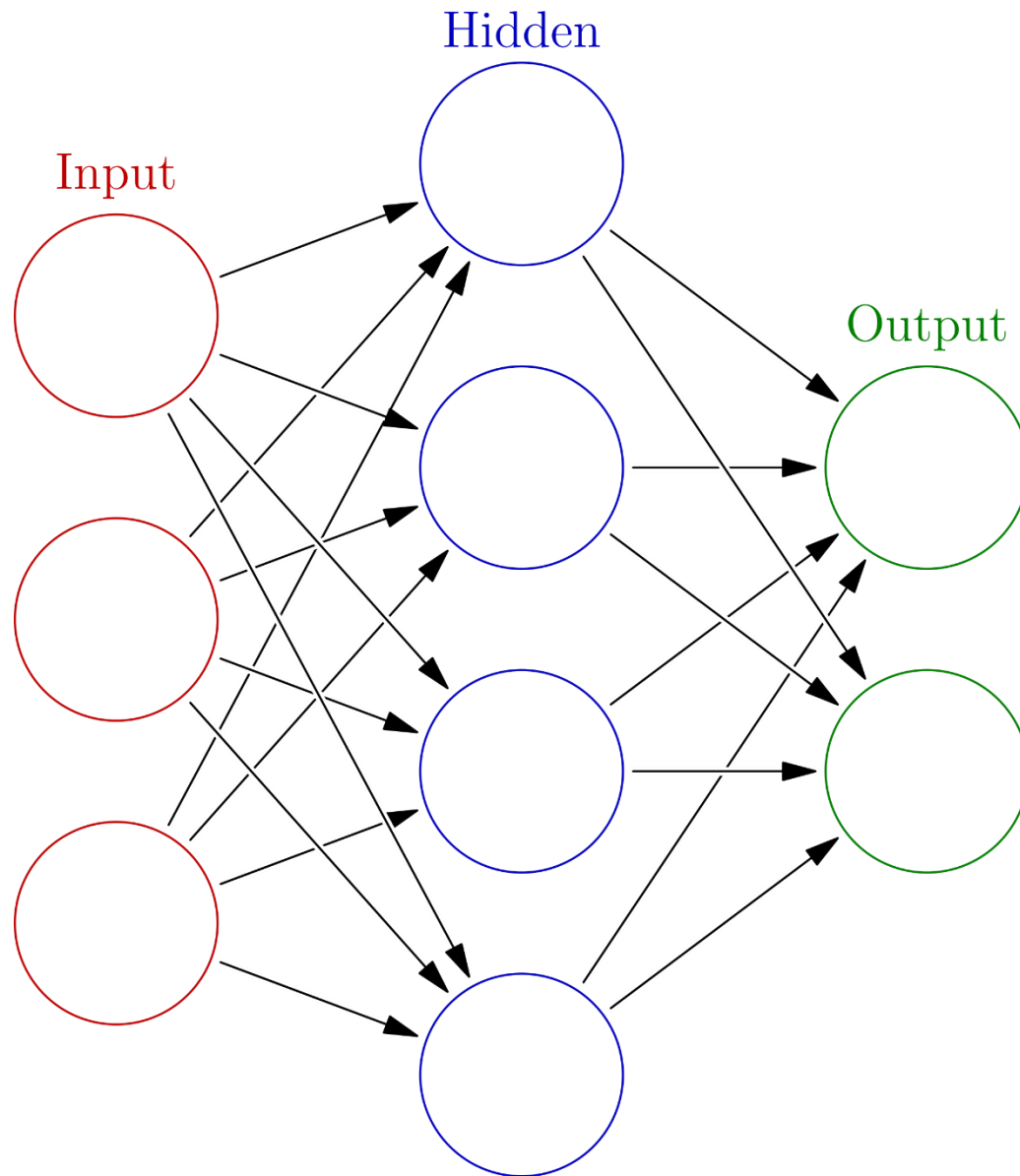
# NEURONE



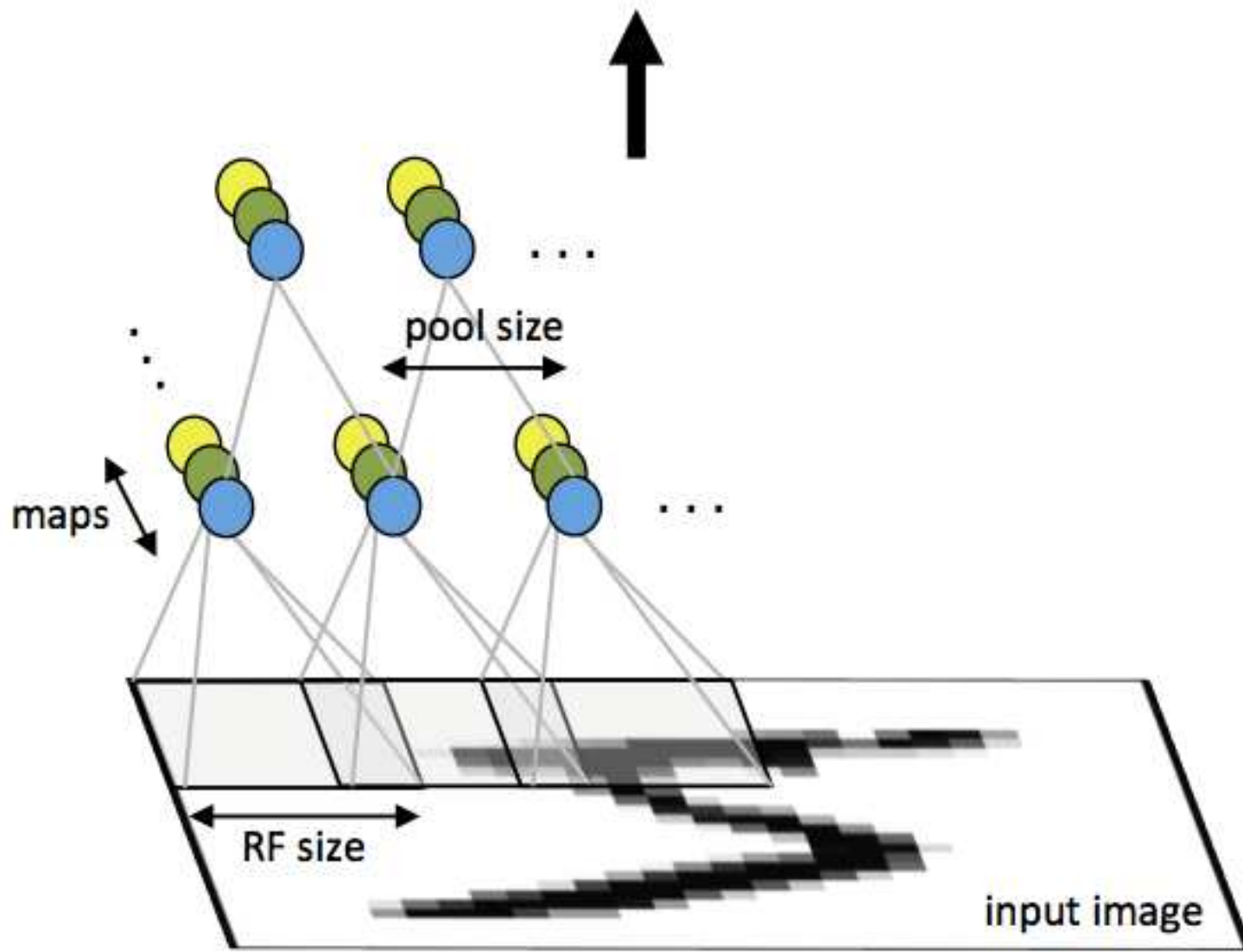
# NEURONE



# RETE NEURONALE (CLASSICA)



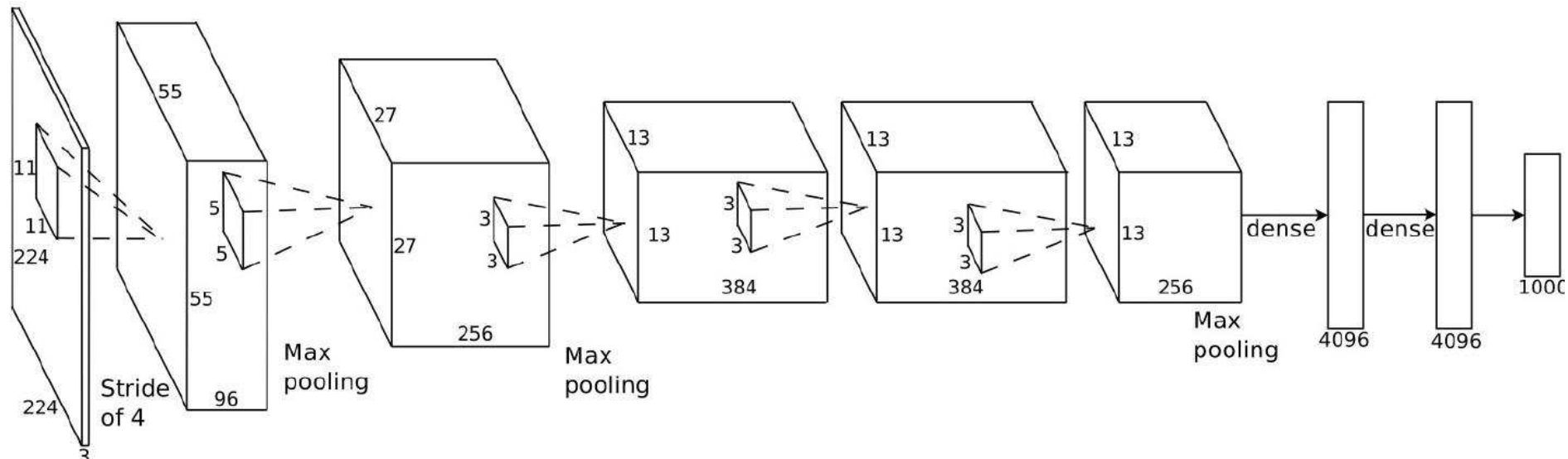
# CONVOLUTIONAL NEURAL NETWORK



<http://ufldl.stanford.edu/tutorial>

From Tutorial by: Andrew Ng, Jiquan Ngiam, Chuan Yu Foo, Yifan Mai, Caroline Suen, Adam Coates, Andrew Maas, Awni Hannun, Brody Huval, Tao Wang, Sameep Tandon

# ALEXNET 2012

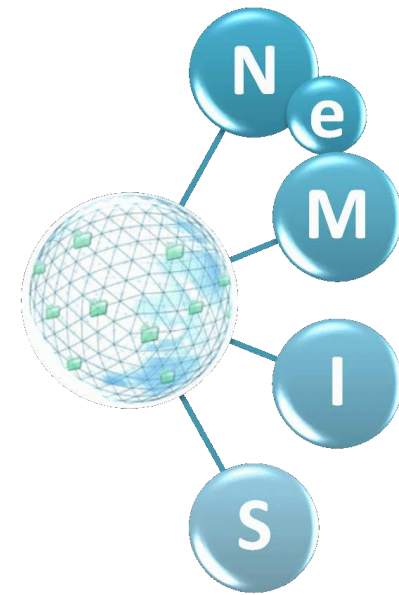


- Livelli: 6
- Filtri: 96, 256, 384, 384, 256
- Neuroni: 650,000
- Valori da imparare: 60,000,000
- AlphaGO: 13 livelli, 196 filtri per layer

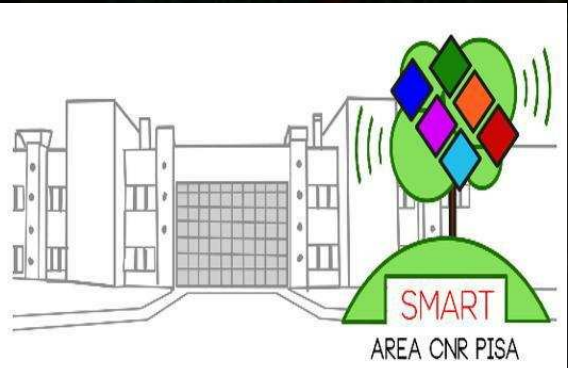
# COSA FACCIAMO NOI



Istituto di Scienza e Tecnologie  
dell'Informazione "A. Faedo"



Dir: Fausto Rabitti



**Giuseppe Amato**  
**Fabio Carrara**  
**Fabrizio Falchi**  
**Claudio Gennaro**  
**Claudio Vairo**

01/03/2016, 06:39



# europeana

eagle project

Giuseppe Amato  
Fabrizio Falchi  
Lucia Vadicamo

pool5, FV256



(pool5 → 1,024), (FV256 → 4,096)



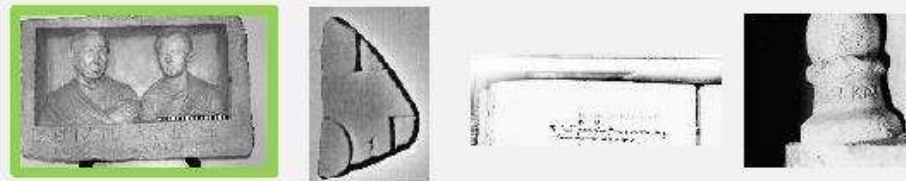
pool5 → 2,048



FV256 → 4,096



VLAD256



# SEARCHING IN 100M PHOTOS



0.000000



0.091064



0.093994



0.096680



0.101318



0.101318



0.102051



0.102539



0.104004



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0.105713



0.107178



0.107422



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0.107910



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0.109131



0.109131



0.109619



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0.111816



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0.112305



0.112549



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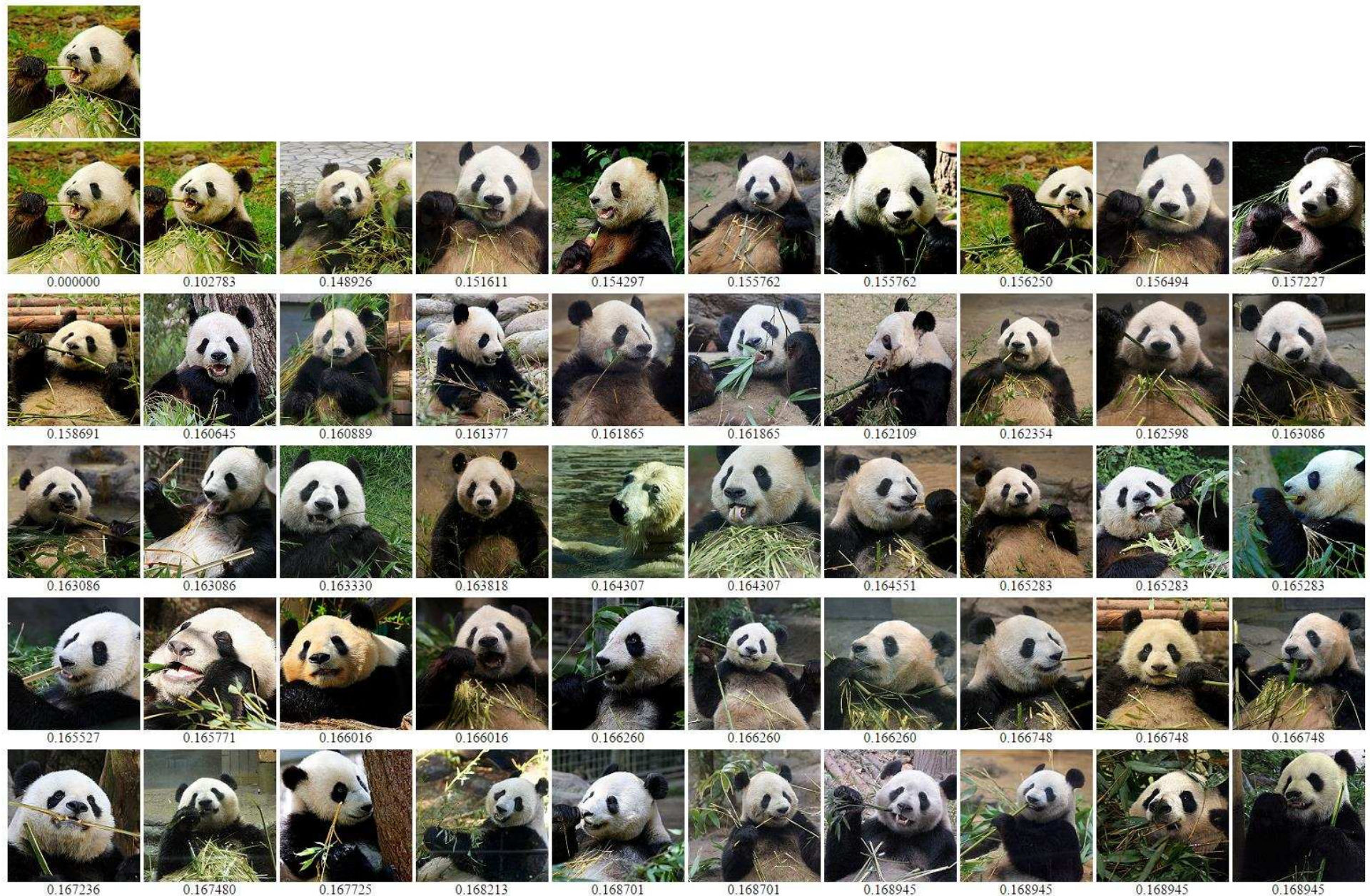


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# SEARCHING IN 100M PHOTOS



# SEARCHING IN 100M PHOTOS



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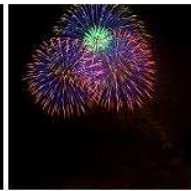
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0.165527



0.165527



0.165771



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0.167236



0.167725



0.167725



0.167969



0.168213



0.168213



0.168213



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0.168945



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0.170410



0.170654



0.170654



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0.171875



0.172119



0.172119



0.172119



0.172119

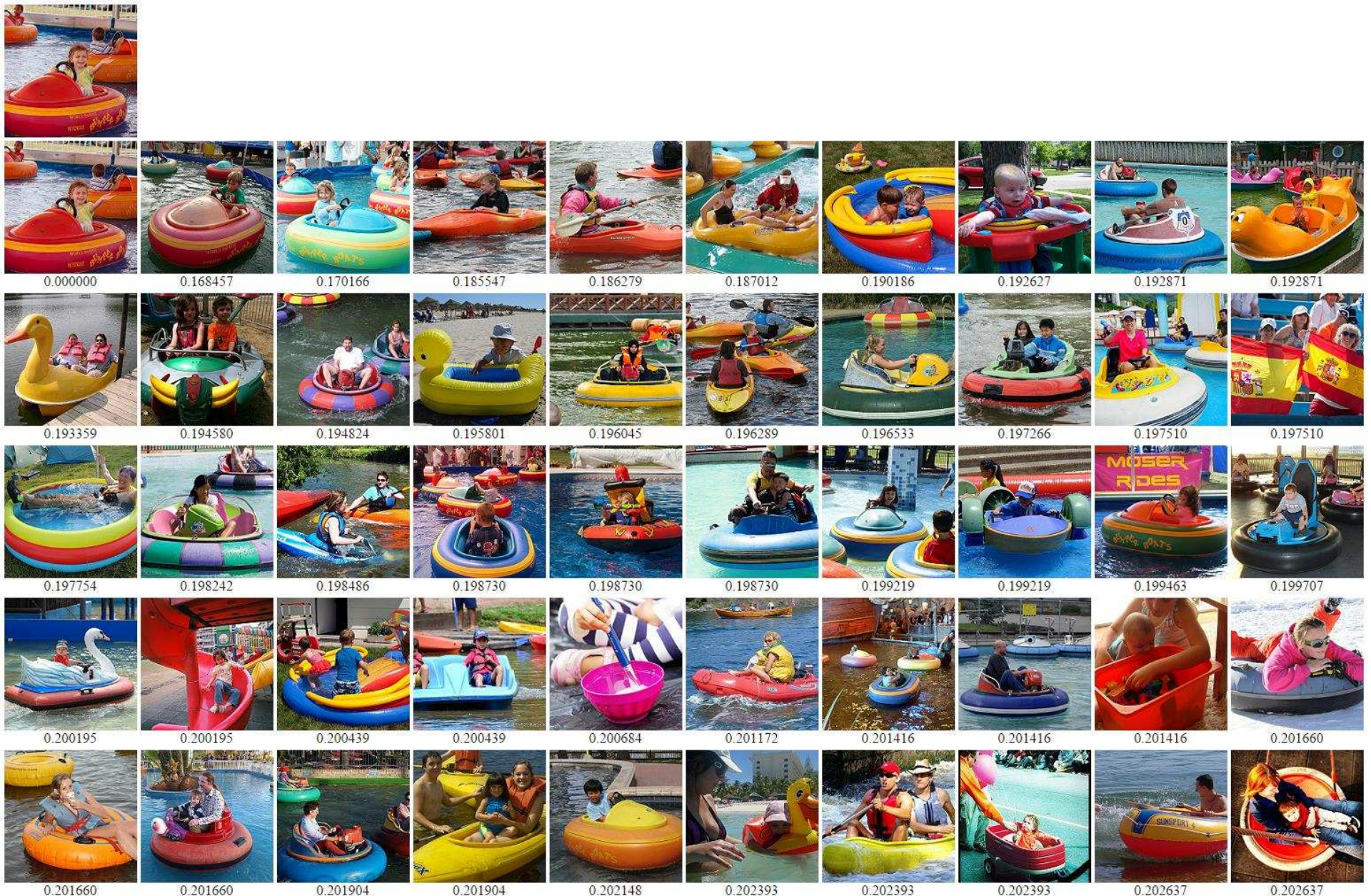


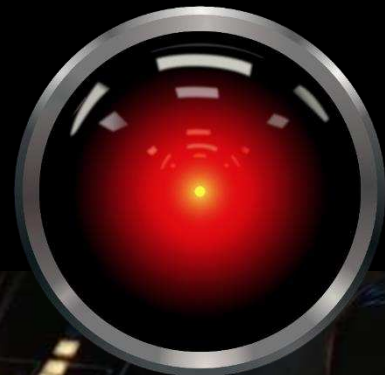
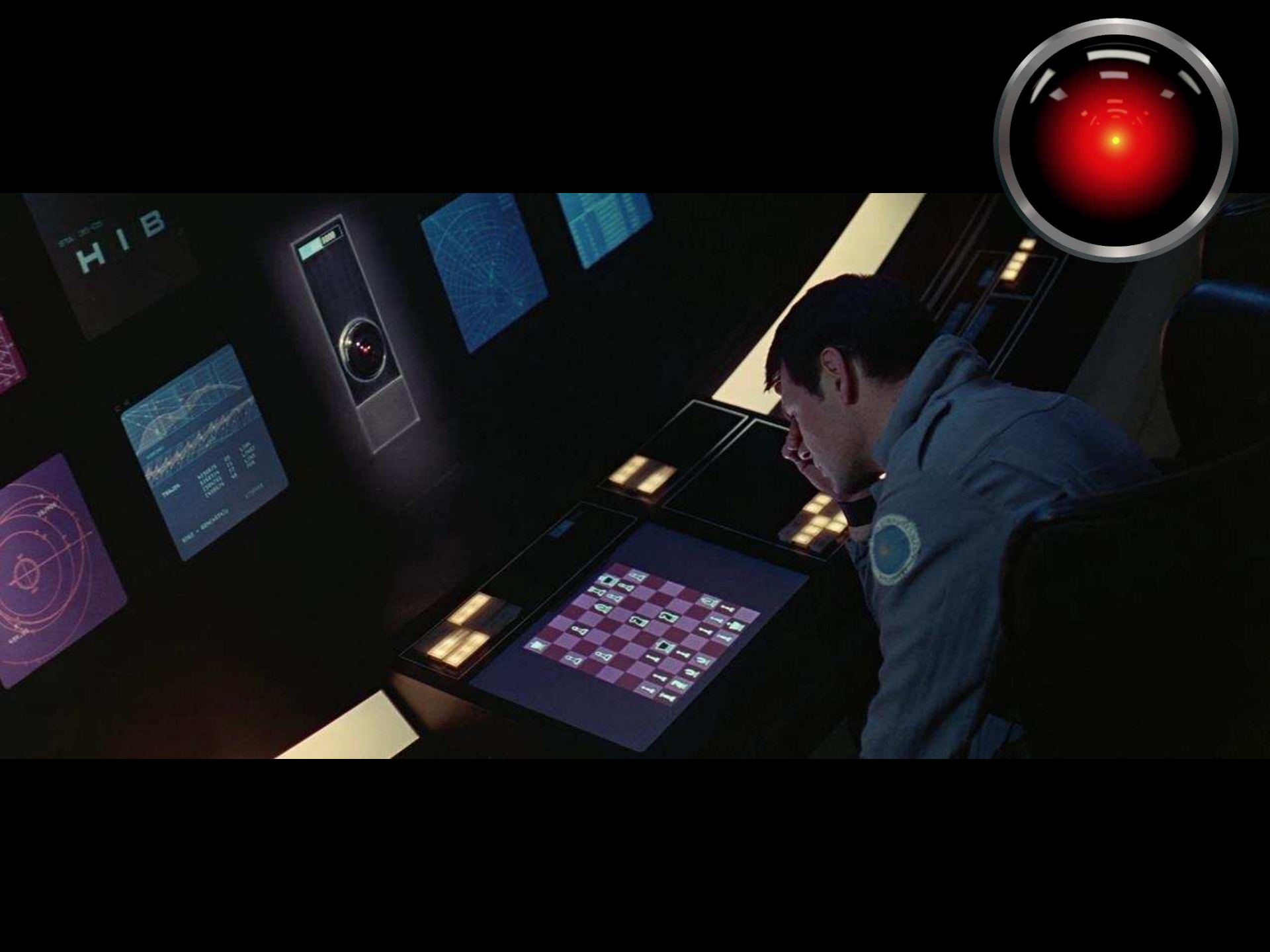
0.172119



0.172119

# SEARCHING IN 100M PHOTOS



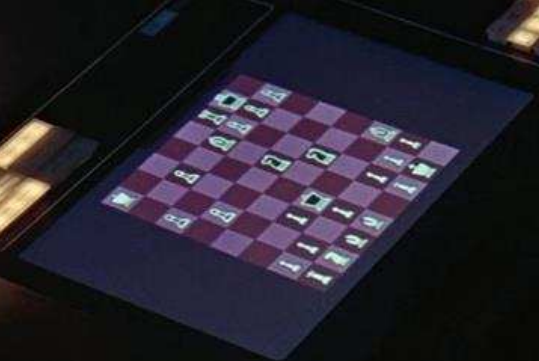


H I B

THREAT

MINOR	100
MAJOR	200
Critical	300
Severe	400

1000







nature

International weekly journal of science

Archive

Volume 529

Issue 7587

Editorial

Article

*As shown by its results, the moves that AlphaGo selects are invariably correct. But the interplay of its neural networks means that a **human can hardly check its working**, or verify its decisions before they are followed through. As the use of deep neural network systems spreads into everyday life — they are already used to analyze and recommend financial transactions — it raises an interesting concept for humans and their relationships with machines. The machine becomes an **oracle**; its pronouncements have to be believed.*

# Præludium 2

Das Wohltemperierte Klavier I, BWV 847

Johann Sebastian BACH  
(1685-1750)

The first system of the musical score for Præludium 2, BWV 847. It consists of two staves: a treble clef staff and a bass clef staff. The key signature is two flats (B-flat and E-flat), and the time signature is common time (C). The music features a continuous eighth-note pattern in both hands, with a melodic line in the treble and a supporting bass line in the bass.

The second system of the musical score, starting at measure 4. It continues the eighth-note pattern from the first system. The treble staff shows a melodic line with some chromatic movement, while the bass staff provides a steady accompaniment.

The third system of the musical score, starting at measure 7. The eighth-note texture remains consistent, with the treble staff leading the melodic development and the bass staff providing harmonic support.

The fourth system of the musical score, starting at measure 10. This system shows the continuation of the piece's rhythmic and melodic motifs, maintaining the characteristic eighth-note flow of the prelude.

# BACH - PRELUDIO



# Præludium 2

Das Wohltemperierte Klavier I, BWV 847

Johann Sebastian BACH  
(1685-1750)

The image displays the musical score for Præludium 2, BWV 847 by Johann Sebastian Bach. The score is written for two staves (treble and bass clef) and is in G minor (two flats) and 2/4 time. The piece consists of six systems of two staves each. The first system starts with a treble clef and a bass clef. The second system starts with a treble clef and a bass clef. The third system starts with a treble clef and a bass clef. The fourth system starts with a treble clef and a bass clef. The fifth system starts with a treble clef and a bass clef. The sixth system starts with a treble clef and a bass clef. A red circle highlights a specific note in the final system, which is a G4 note in the bass clef.

# BACH - PRELUDIO



Staatsbibliothek zu Berlin, D-B Mus. ms. Bach P 202  
middle of the 18th century (ca. 1740–1759)

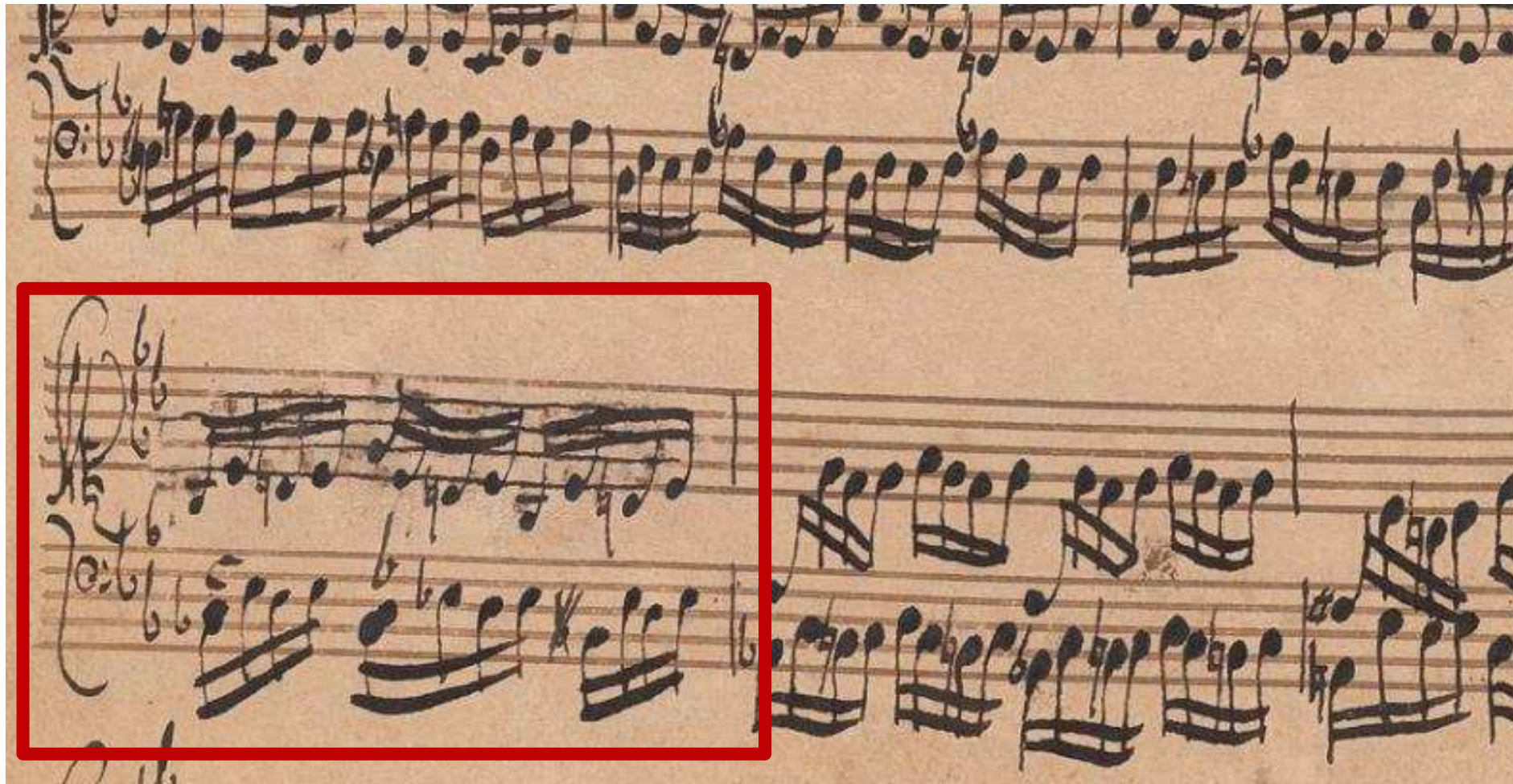
# BACH - PRELUDIO



Staatsbibliothek zu Berlin, D-B Mus. ms. P 415

Autograph, 1720-22

# BACH - PRELUDIO



Yale Music Music Deposit 31  
W. F. Bach's Klavierbüchlein (1720)

# SOFTWARE & RESOURCES

```
function(scope, element, attr, ngSwitchController) {  
  var switchExpr = attr.ngSwitch || attr.on,  
      selectedTranscludes = [],  
      selectedElements = [],  
      previousElements = [],  
      selectedScopes = [];  
  
  scope.$watch(watchExpr, function ngSwitchWatchAction(value) {  
    // ...  
    previousElements.length = 0;  
  
    for (i = 0, ii = selectedScopes.length; i < ii; ++i) {  
      var selected = selectedElements[i];  
      selectedScopes[i].$destroy();  
      previousElements[i] = selected;  
      animate.leave(selected, function() {  
        // ...  
      });  
    }  
  
    selectedElements.length = 0;  
    selectedScopes.length = 0;  
  
    if ((selectedTranscludes = ngSwitchController.cases['!' + value]) ||  
        scope.$eval(attr.change);  
    forEach(selectedTranscludes, function(selectedTransclude) {  
      var selectedScope = scope.$new();  
      selectedScopes.push(selectedScope);  
      selectedTransclude.$compile(selectedTransclude, selectedScope);  
    });  
  });  
}
```

# GOOGLE TENSORFLOW

- November 9, 2015
- White paper: <http://www.tensorflow.org/whitepaper2015.pdf>
- API
  - Python (preferred) and C++
  - (Go, Java, JavaScript, Lua R) community is invited to work on this using SWIG
- “Google’s goal with TF seems to be recruiting”
- is about more than deep learning



# GOOGLE DEEP LEARNING COURSE


[Nanodegree](#)[Catalog](#)[Sign In](#)[Sign Up](#)

## Deep Learning

Taking machine learning to the next level



■■■ Advanced

 **Approx. 3 months**

Assumes 6hrs/wk (work at your own pace)

Built by 

 **Join 61,607 students**

### Course Summary



**Machine learning** is one of the fastest-growing and most exciting fields out there, and **deep learning** represents its true bleeding edge. In this course, you'll develop a clear understanding of the motivation for deep learning, and design intelligent systems that learn from complex and/or large-scale datasets.

### Start Free Course

[START FREE COURSE](#)

 **Free**

#### You get

-  Instructor videos
-  Learn by doing exercises and view project instructions

# GOOGLE CLOUD VISION API

## CLOUD VISION API FEATURES

Derive insight from images with our powerful Cloud Vision API

### Label Detection

Detect broad sets of categories within an image, ranging from modes of transportation to animals.

### Explicit Content Detection

Detect explicit content like adult content or violent content within an image.

### Logo Detection

Detect popular product logos within an image.

### Landmark Detection

Detect popular natural and manmade structures within an image.

### Image Attributes

Detect general attributes of the image, such as dominant color.

### Optical Character Recognition

Detect and extract text within an image, with support for a broad range of languages, along with support for automatic language identification.

### Face Detection

Detect multiple faces within an image, along with the associated key facial attributes like emotional state or wearing headwear.

**Facial Recognition is not supported.**

### Integrated REST API

Access via REST API to request one or more annotation types per image. Images can be uploaded in the request or integrated with [Google Cloud Storage](#).

## Caffe

---

build **passing** license BSD

Caffe is a deep learning framework made with expression, speed, and modularity in mind. It is developed by the Berkeley Vision and Learning Center (BVLC) and community contributors.

Check out the [project site](#) for all the details like

- [DIY Deep Learning for Vision with Caffe](#)
- [Tutorial Documentation](#)
- [BVLC reference models](#) and the [community model zoo](#)
- [Installation instructions](#)

and step-by-step examples.

gitter **join chat**

Please join the [caffe-users group](#) or [gitter chat](#) to ask questions and talk about methods and models. Framework development discussions and thorough bug reports are collected on [Issues](#).

Happy brewing!

## License and Citation

---

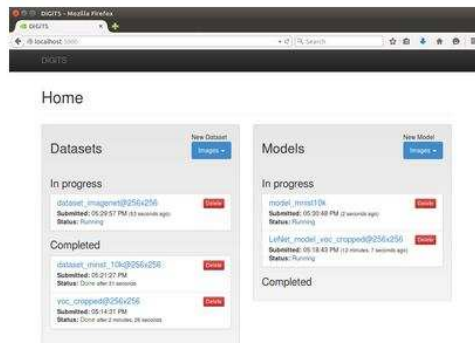
Caffe is released under the [BSD 2-Clause license](#). The BVLC reference models are released for unrestricted use.

## NVIDIA® DIGITS™ – Interactive Deep Learning GPU Training System

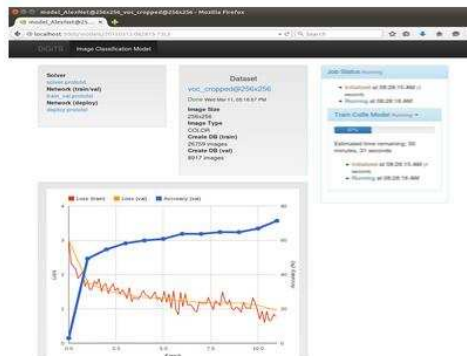
The NVIDIA Deep Learning GPU Training System (DIGITS) puts the power of **deep learning** in the hands of data scientists and researchers. Quickly design the best deep neural network (DNN) for your data using real-time network behavior visualization. Best of all, DIGITS is a complete system so you don't have to write any code. Get started with DIGITS in under an hour.

*DIGITS makes it way easier to design the best network for the job. The DIGITS interface makes it super easy to track key diagnostics during training. The field will definitely benefit from having tools like this for configuration and introspection.*

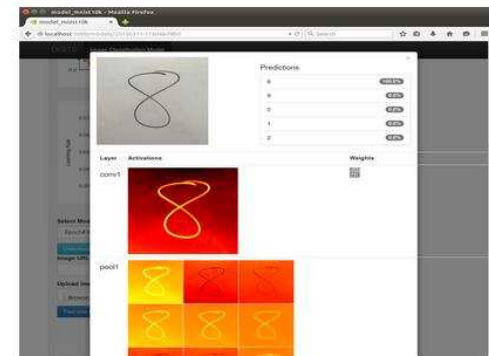
— Simon Osindero, AI Architect at Flickr



DIGITS training multiple DNNs and building a new dataset in parallel.



DIGITS real-time monitoring of DNN model training



DIGITS visualizing a test image

# MICROSOFT CNTK

- January 25, 2016 (academic licens since April 2015)
- one of the advantages of CNTK is its ability to run on a single core, as well as on a large cluster of GPU-based machines
- C++

## Computational Network Toolkit

Production-quality, Open Source,  
Multi-machine, Multi-GPU,  
Highly efficient RNN training,  
Speech, Image, Text

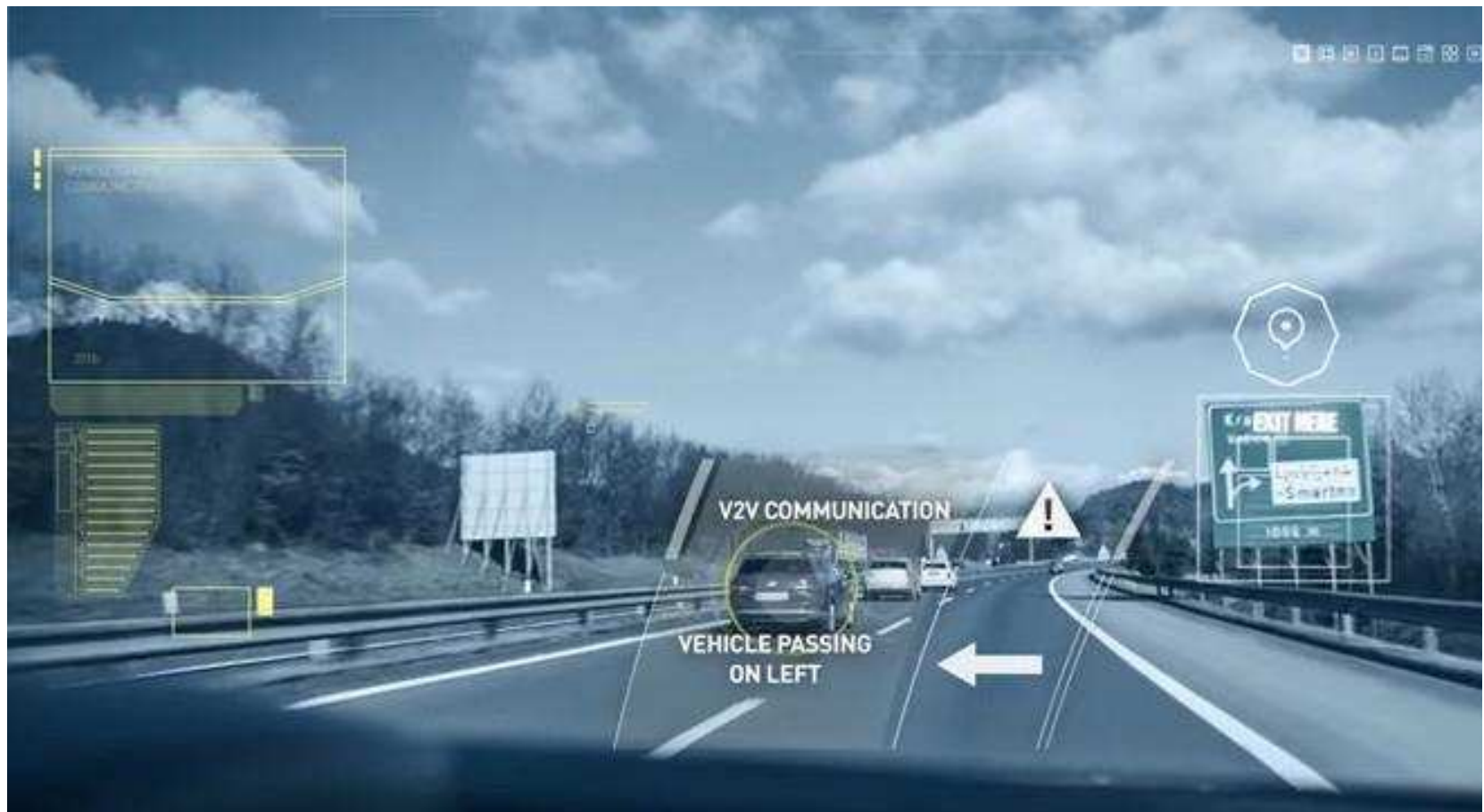
[Get from Github](#)

[Get Started](#)



# QUALCOMM SNAPDRAGON 820 AND 80A

- January 2016
- Snapdragon 820 is a phone
- Snapdragon 820A is a chip for cars and drones



# MIT EYERISS GPU

- 10 times as efficient as a mobile GPU could allow mobile devices to run artificial intelligence algorithms locally, without a major drain to the phone's battery
- “This work is very important, showing how embedded processors for deep learning can provide power and performance optimizations that will bring these complex computations *from the cloud to mobile devices.*”, Mike Polley
- Funded by Defense Advanced Research Projects Agency (**DARPA**)

nature

International weekly journal of science

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[Archive](#) > [Volume 529](#) > [Issue 7587](#) > [News](#) > [Article](#)

NATURE | NEWS



## Google AI algorithm masters ancient game of Go

Deep-learning software defeats human professional for first time.

[Elizabeth Gibney](#)

27 January 2016

An aerial photograph of a massive, curling ocean wave. The water is a deep, vibrant blue, and the crest is breaking into white foam. The wave is curling over, creating a tunnel-like structure. The sky is a clear, bright blue.

# THE DEEP LEARNING BIG WAVE

## Compare Search terms ▾

deep learning

Search term

artificial intelligence

Search term

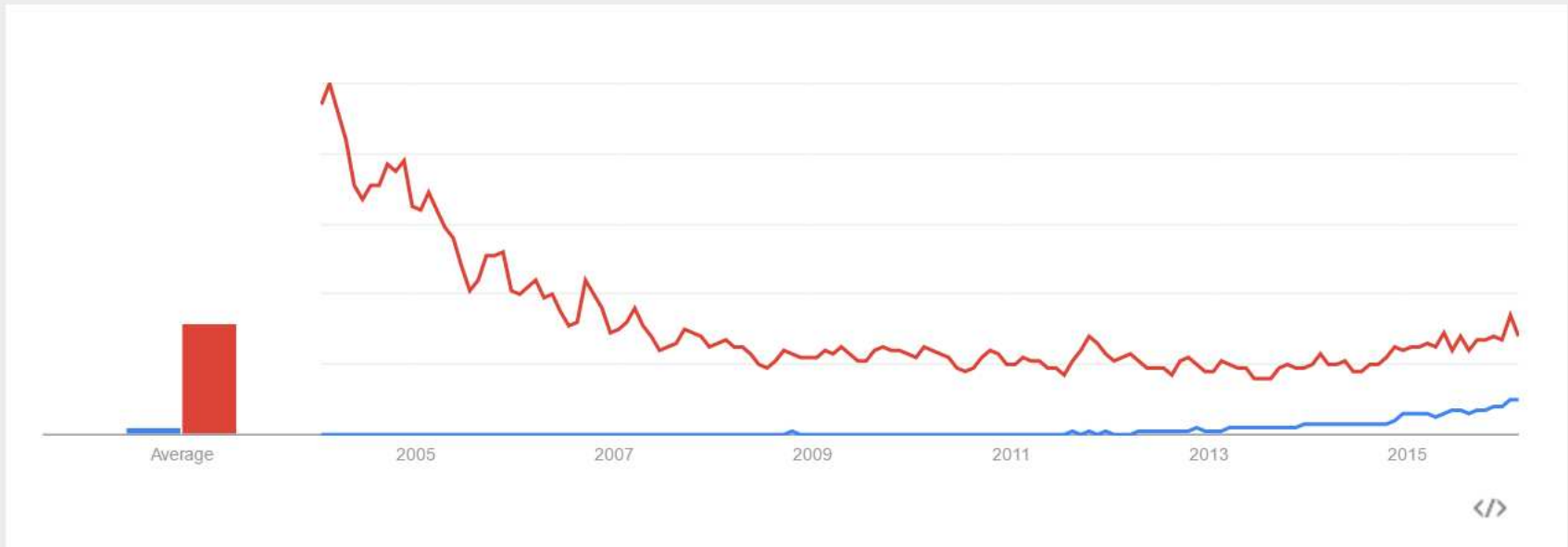
+ Add term

## Interest over time ?

Compare to category ?

News headlines ?

Forecast ?



# GOOGLE TRENDS IN SCIENCE - WEB SEARCH

Worldwide ▾

Jan. 2012 - Feb. 2016 ▾

Science ▾

Web Search ▾

Compare Search terms ▾

Deep Lear... ×  
Search term

Big Data ×  
Search term

Computer ... ×  
Search term

Multimedia  
Search term

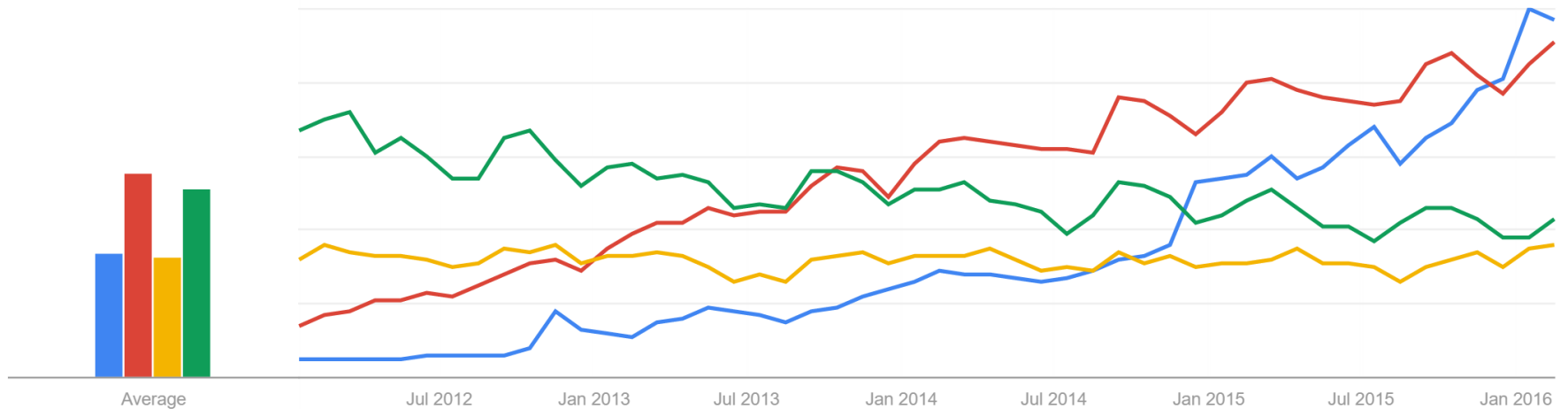
+ Add term

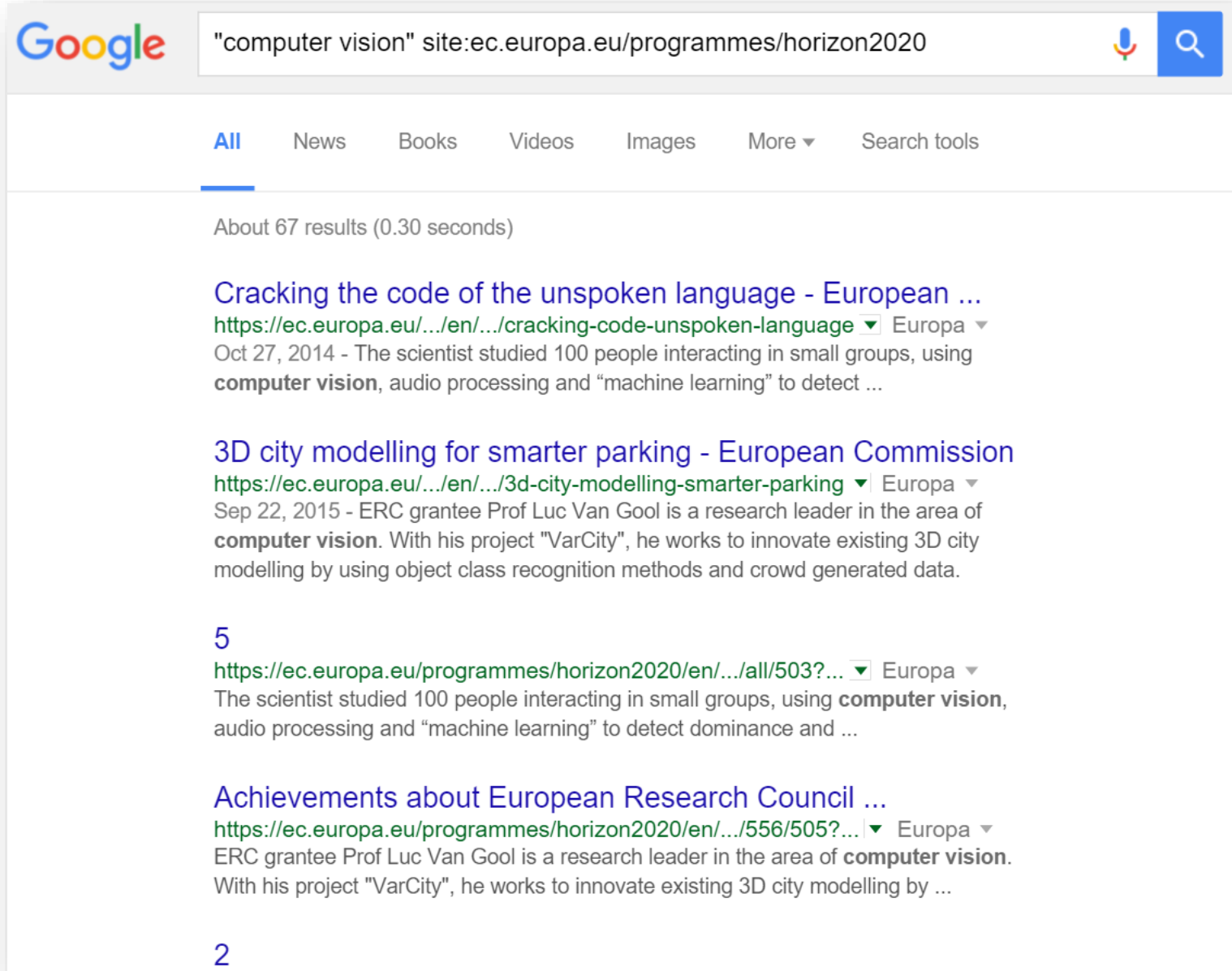
Interest over time ?

Compare to category ?

News headlines ?

Forecast ?





The image shows a Google search interface. The search bar contains the query: "computer vision" site:ec.europa.eu/programmes/horizon2020. The search results are filtered to show only results from the domain ec.europa.eu. The first result is titled "Cracking the code of the unspoken language - European ..." and is dated Oct 27, 2014. The second result is titled "3D city modelling for smarter parking - European Commission" and is dated Sep 22, 2015. The third result is titled "Achievements about European Research Council ..." and is dated 5. The fourth result is titled "5" and is dated 2. The search results are displayed in a list format with blue links and green text for the URL and date. The search bar includes the Google logo, a microphone icon, and a search icon. The navigation menu includes "All", "News", "Books", "Videos", "Images", "More", and "Search tools".

Google "computer vision" site:ec.europa.eu/programmes/horizon2020

All News Books Videos Images More Search tools

About 67 results (0.30 seconds)

[Cracking the code of the unspoken language - European ...](#)  
<https://ec.europa.eu/.../en/.../cracking-code-unspoken-language> Europa  
Oct 27, 2014 - The scientist studied 100 people interacting in small groups, using **computer vision**, audio processing and "machine learning" to detect ...

[3D city modelling for smarter parking - European Commission](#)  
<https://ec.europa.eu/.../en/.../3d-city-modelling-smarter-parking> Europa  
Sep 22, 2015 - ERC grantee Prof Luc Van Gool is a research leader in the area of **computer vision**. With his project "VarCity", he works to innovate existing 3D city modelling by using object class recognition methods and crowd generated data.

5  
<https://ec.europa.eu/programmes/horizon2020/en/.../all/503?...> Europa  
The scientist studied 100 people interacting in small groups, using **computer vision**, audio processing and "machine learning" to detect dominance and ...

[Achievements about European Research Council ...](#)  
<https://ec.europa.eu/programmes/horizon2020/en/.../556/505?...> Europa  
ERC grantee Prof Luc Van Gool is a research leader in the area of **computer vision**. With his project "VarCity", he works to innovate existing 3D city modelling by ...

2

# HORIZON 2020



"big data" site:ec.europa.eu/programmes/horizon2020/



All News Videos Images Books More ▾ Search tools

About 187 results (0.52 seconds)

## [Big Data and Media & Content Workshop - European ...](#)

<https://ec.europa.eu/.../en/.../big-data-and-media-content-worksho...> ▾ Europa ▾

Jun 29, 2015 - The Converging Media and Content Unit will hold a workshop on **Big Data** and Media&Content on 24 September 2015. This workshop will ...

## [\[PDF\] Draft Horizon 2020 Work Programme 2016-2017 in ... - E...](#)

[https://ec.europa.eu/.../05i.%20LEIT-ICT\\_2016-2017\\_pre-public...](https://ec.europa.eu/.../05i.%20LEIT-ICT_2016-2017_pre-public...) ▾ Europa ▾

Oct 20, 2015 - ICT-15-2016-2017: **Big Data** PPP: Large Scale Pilot actions in sectors ...  
ICT-16-2017: **Big data** PPP: research addressing main technology ...

## [\[PDF\] Draft Horizon 2020 Work Programme 2016-2017 in ... - E...](#)

[ec.europa.eu/.../08.%20SC1-Health%202016-2017\\_pre-pub.pdf](ec.europa.eu/.../08.%20SC1-Health%202016-2017_pre-pub.pdf) ▾ Europa ▾

Sep 11, 2015 - SC1-PM-18–2016: **Big Data** supporting Public Health policies  
..... 34. SC1-PM-19–2017: PPI for uptake of standards for the ...

## [Using big data for the future of personal transportation ...](#)

<https://ec.europa.eu/.../using-big-data-future-personal-transportati...> ▾ Europa ▾

Nov 26, 2014 - Using **big data** for the future of personal transportation: DATASIM - The EU Framework Programme for Research and Innovation.

## [CEEDS: new ways of exploring big data - European ...](#)

<https://ec.europa.eu/.../en/.../ceeds-new-ways-exploring-big-data> ▾ Europa ▾

# HORIZON 2020



"deep learning" site:ec.europa.eu/programmes/horizon2020



All News Videos Books Images More Search tools

1 result (0.27 seconds)

## RE.WORK Future Technology Summit - European ...

<https://ec.europa.eu/programmes/.../rework-technology-summit-1> Europa

Mar 20, 2015 - WORK Future Technology Summit will take place in London, along a standalone **Deep Learning** Summit and tracks on Future Cities, Robotics ...

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## HORIZON 2020

The EU Framework Programme for Research and Innovation

European Commission > Horizon 2020

Home | What is Horizon 2020? | Find Your area | How to Get funding? | News, Events & Publications | Projects

### RE.WORK Future Technology Summit

Published by [newsroom editor](#) on 20/03/2015

**Event date:** From 24/09/2015 to 25/09/2015  
**Venue:** London (UK)

The RE.WORK Future Technology Summit will gather experts to learn about future technologies and discuss their impact on science and society. The Future and Emerging Technologies unit of the European Commission will be part of the discussion.

The 3rd annual RE.WORK Future Technology Summit will take place in London, along a standalone **Deep Learning Summit** and tracks on Future Cities, Robotics & AI and Future Healthcare. The event will bring together over 500 attendees including CTOs, engineers, scientists, designers and innovators to explore how rapidly advancing technologies will impact and solve challenges in business and society. Topics explored will include, 3D printing, smart materials, drones, pattern recognition, image processing, sensors, nanotechnology and advanced artificial intelligence.



Search

#### #H2020

[NCP H2020 in Brussels](#)  
@NCP\_Brussels

Tips & Tricks - Easme - Eureka - insider's view  
[#H2020](#) [#eurostars](#)  
[@EUREKA\\_NETWORK](#)  
[@Innoviris](#) [@EuropeBrux](#)  
<pic.twitter.com/8dlqZXkjQ>

YOUR FEEDBACK

- Instead of exactly prescribing which feature we want the network to amplify, we can also let the network make that decision.
- In this case we simply feed the network an arbitrary image or photo and let the network analyze the picture.
- **We then pick a layer and ask the network to enhance whatever it detected.**
- Each layer of the network deals with features at a different level of abstraction, so the complexity of features we generate depends on which layer we choose to enhance.
- For example, lower layers tend to produce strokes or simple ornament-like patterns, because those layers are sensitive to basic features such as edges and their orientations.



# BENGIO ON “WHY DEEP LEARNING WORKS”

Quora



- We understand that distributed representations, depth, and elements of the convolutional architecture and recurrent architectures correspond to
  - preferences in the space of functions (or informally, **priors**)
- and we have theory explaining why some of these preferences can buy an important (sometimes exponential) **statistical advantage** (in the sense of needing less data to achieve some level of accuracy);
- more details in my book, pointing to some of the recent papers, my favourite being
  - "On the Number of Linear Regions of Deep Neural Networks" (NIPS'2014).

# BENGIO ON “WHY DEEP LEARNING WORKS”

Quora



- We understand better why the **optimization** problem involved in training deep networks is probably not as intractable as was previously believed, in the sense that the **vast majority of local minima** would actually correspond to very **good solutions**. Two good papers on the subject:
  - Identifying and attacking the saddle point problem in high-dimensional non-convex optimization (NIPS'2014)
  - The loss surface of multilayer networks (AISTATS'2015).

**Neural network architecture.** The input to the policy network is a  $19 \times 19 \times 48$  image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a  $23 \times 23$  image, then convolves  $k$  filters of kernel size  $5 \times 5$  with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a  $21 \times 21$  image, then convolves  $k$  filters of kernel size  $3 \times 3$  with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size  $1 \times 1$  with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used  $k = 192$  filters; Fig. 2b and Extended Data Table 3 additionally show the results of training with  $k = 128, 256$  and 384 filters.

# DEEP LEARNING (FROM NATURE)

An **image**, for example, comes in the form of an array of pixel values, and

1. the learned features in the first layer of representation typically represent the presence or absence of **edges** at particular orientations and locations in the image.
2. The second layer typically detects **motifs** by spotting particular arrangements of edges, regardless of small variations in the edge positions.
3. The third layer may assemble motifs into larger combinations that correspond to **parts** of familiar objects, and subsequent layers would detect objects as combinations of these parts.
4. The key aspect of deep learning is that these layers of features are not designed by human engineers: they are learned from data using a **general-purpose learning** procedure.

# nature

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## Digital intuition

A computer program that can outplay humans in the abstract game of Go will redefine our relationship with machines.

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