WELCOME TO THE

UCL x DeepMind lecture series

In this lecture series, leading research scientists from leading AI research lab, DeepMind, will give 12 lectures on an exciting selection of topics in Deep Learning, ranging from the fundamentals of training neural networks via advanced ideas around memory, attention, and generative modelling to the important topic of responsible innovation.

Please join us for a deep dive lecture series into Deep Learning!

#UCLxDeepMind

General information

Exits:

At the back, the way you came in

Wifi:

UCL guest

TODAY’S SPEAKER

Thore Graepel

Thore Graepel is a research group lead at DeepMind and holds a part-time position as Chair of Machine Learning at University College London. He studied physics at the University of Hamburg, Imperial College London, and Technical University of Berlin, where he also obtained his PhD in machine learning in 2001. After postdoctoral work at ETH Zurich and Royal Holloway College, University of London, Thore joined Microsoft Research in Cambridge in 2003. At DeepMind since 2015, Thore leads the multi-agent research team and contributed to AlphaGo, the first computer program to defeat a human professional player in the full-sized game of Go.

TODAY'S LECTURE

Introduction to Machine Learning and AI

In this lecture Thore will explain DeepMind's machine learning based approach towards AI. He will give examples of how deep learning and reinforcement learning can be combined to build intelligent systems, including AlphaGo, Capture-The-Flag, and AlphaFold. This will be followed by a short introduction to the different topics and speakers coming up in the subsequent lectures.

DeepMind

Introduction to Machine Learning and AI

Prof Thore Graepel

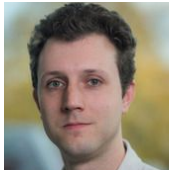
Chair of Machine Learning, UCL
Research Scientist, DeepMind

03/02/2020

Thanks to all these people (organisers)

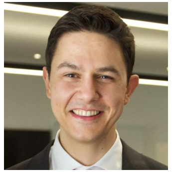

David Barber
UCL


Mark Herbster
UCL


Pontus Stenetorp
UCL


Sarah Hodkinson
DeepMind


Thore Graepel
DeepMind & UCL


George Kraev
DeepMind


Jon Fildes
DeepMind


Danielle Breen
DeepMInd


Dominic Barlow
DeepMind


Gaby Pearl
DeepMind

The lecturers

Thore
Graepel

Wojtek
Czarnecki

Sander
Dieleman

Viorica
Patraucean

James
Martens

Marta
Garnelo

Felix
Hill

Alex
Graves

Andriy
Mnih

Mihaela
Rosca

Irina
Higgins

Jeff
Donahue

Iason
Gabriel

Chongli
Qin

Plan for this Lecture

01

Solving Intelligence

02

AlphaGo & AlphaZero

03

Learning to Play Capture The Flag

04

Folding Proteins with AlphaFold

05

Overview of Lecture Series

1 Solving Intelligence

“

A human being should be able to change a diaper, plan an invasion, butcher a hog, conn a ship, design a building, write a sonnet, balance accounts, build a wall, set a bone, comfort the dying, take orders, give orders, cooperate, act alone, solve equations, analyze a new problem, pitch manure, program a computer, cook a tasty meal, fight efficiently, die gallantly. Specialization is for insects.

Robert A Heinlein

Science Fiction Author

What is Intelligence?

Intelligence measures an agent's ability to achieve goals in a wide range of environments

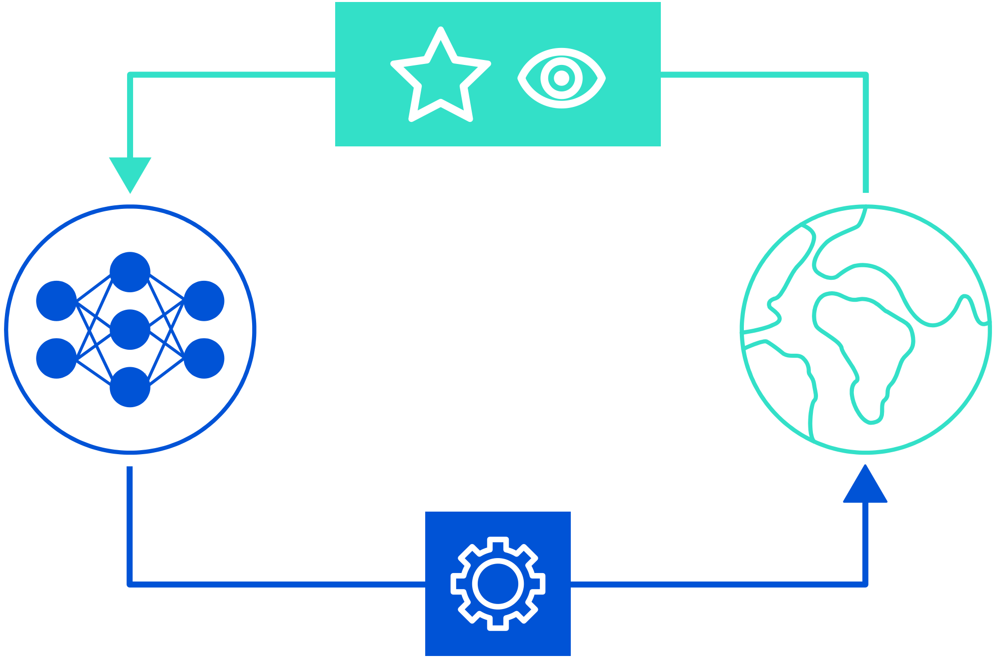
---

$$\underbrace{\Upsilon(\pi)}_{\text{Measure of Intelligence}} := \underbrace{\sum_{\mu \in E}}_{\text{Sum over environments}} \underbrace{2^{-K(\mu)}}_{\text{Complexity penalty}} \underbrace{V_{\mu}^{\pi}}_{\text{Value achieved}} .$$

Universal Intelligence: A Definition of Machine Intelligence, Legg & Hutter 2007

Reinforcement Learning

- General Purpose Framework for AI
- Agent interacts with the environment
- Select actions to maximise long-term reward
- Encompasses supervised and unsupervised learning as special cases
- Module Reinforcement Learning (UCL COMP0089)



Why use games to solve AI?

1

Microcosms of the real world

Games are a proving ground for real-world situations

2

Stimulate intelligence

By presenting a diverse set of challenges

3

Good to test in simulations

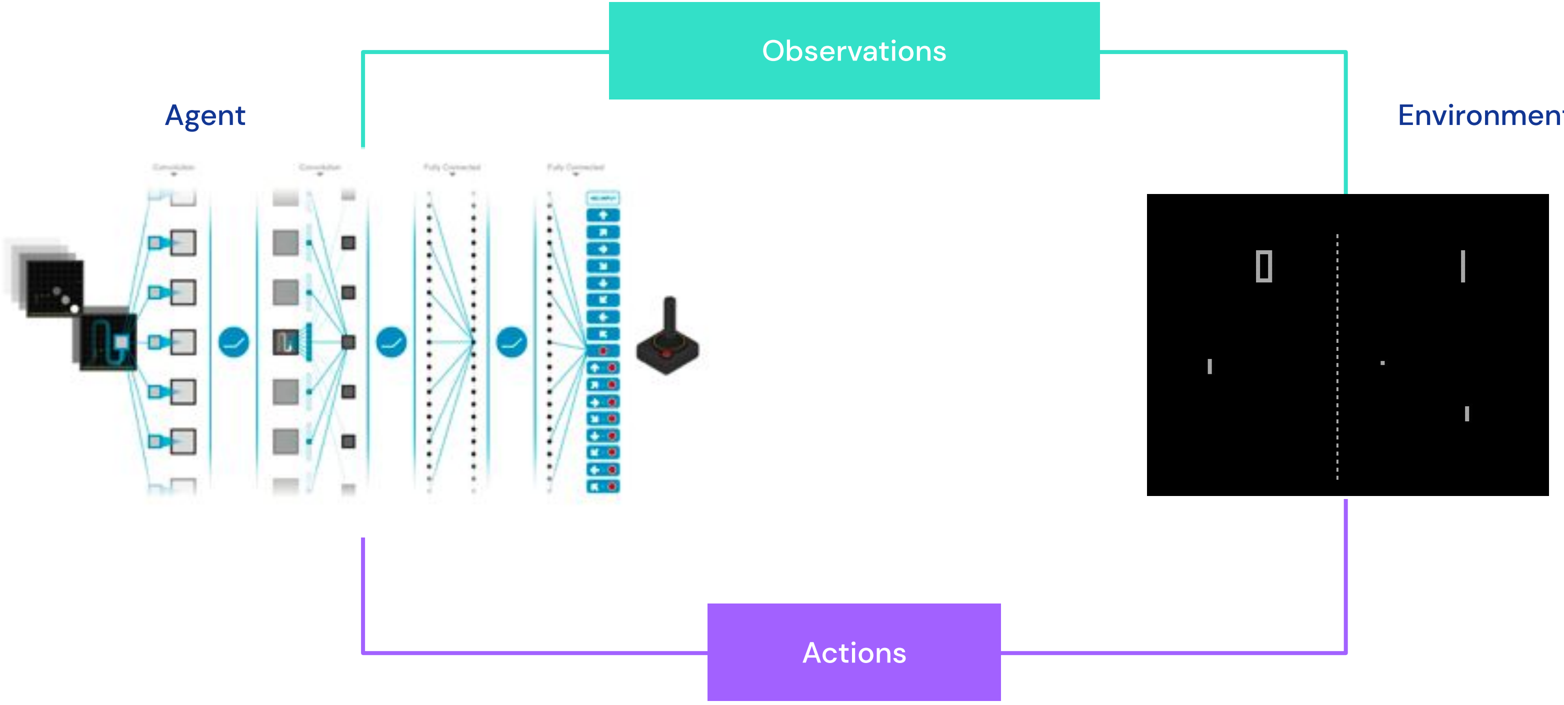
Efficient, run thousands in parallel, faster than real time

4

Measure progress and performance

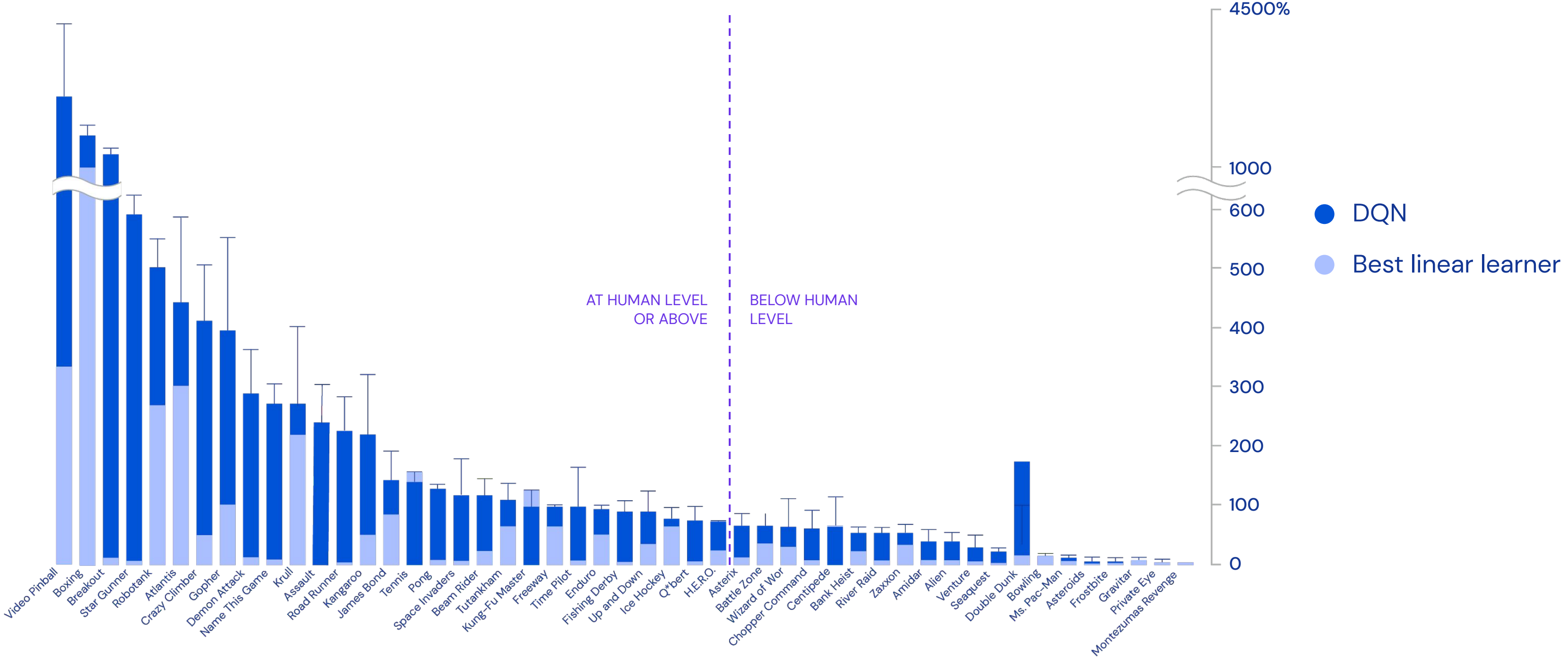
Measure progress and compare against human performance

Reinforcement Learning in Games



Superhuman Skill at Playing Atari Games

(Mnih et al, Nature 2015)



Why "Deep Learning"?

- Previous systems required feature engineering for every new problem
- Deep Learning enables end-to-end learning for a given loss and architecture
- Weak prior knowledge can be encoded via architecture (e.g. convolutions, recurrence)
- Deep Learning made possible by:
  - Greater computational power (GPUs, TPUs)
  - More available data (mobile devices, online services, distributed sensors, crowdsourcing)
  - Better understanding of algorithms and architectures

DeepMind

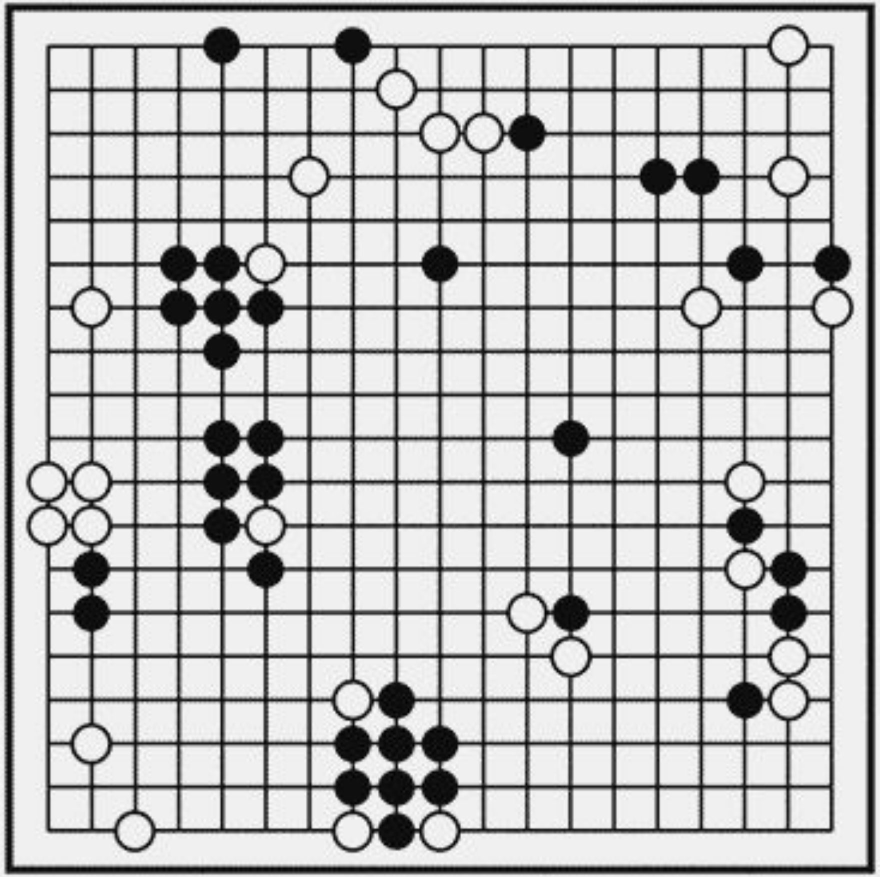
2 AlphaGo and AlphaZero

CASE STUDY

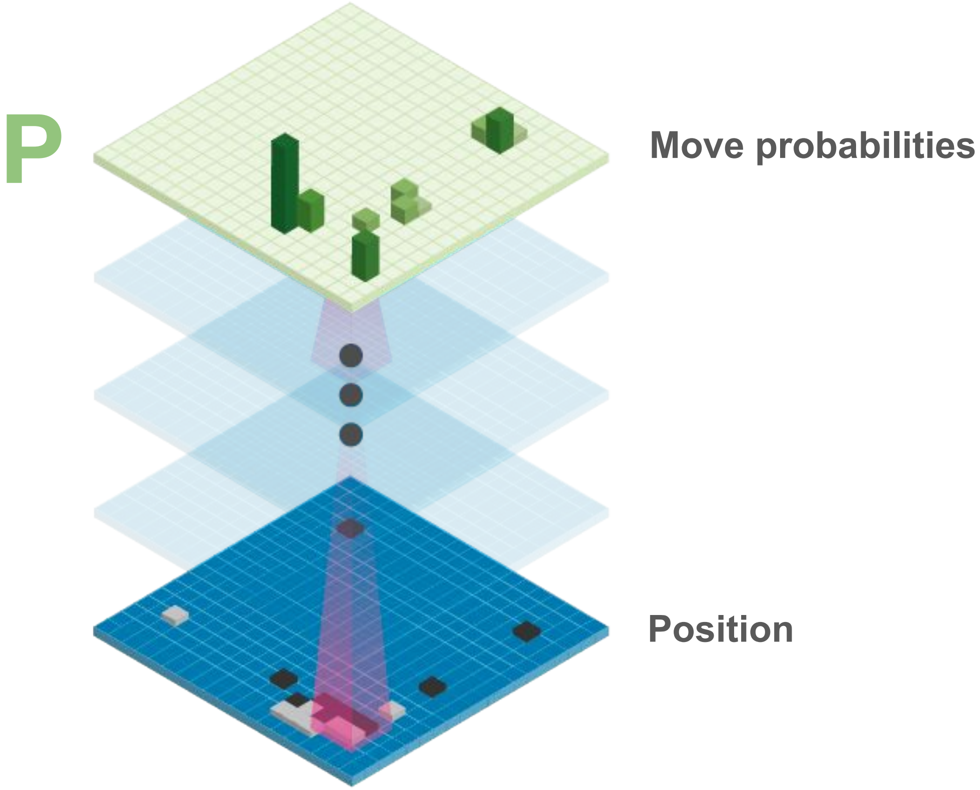
A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play learning

(Science, 2018)

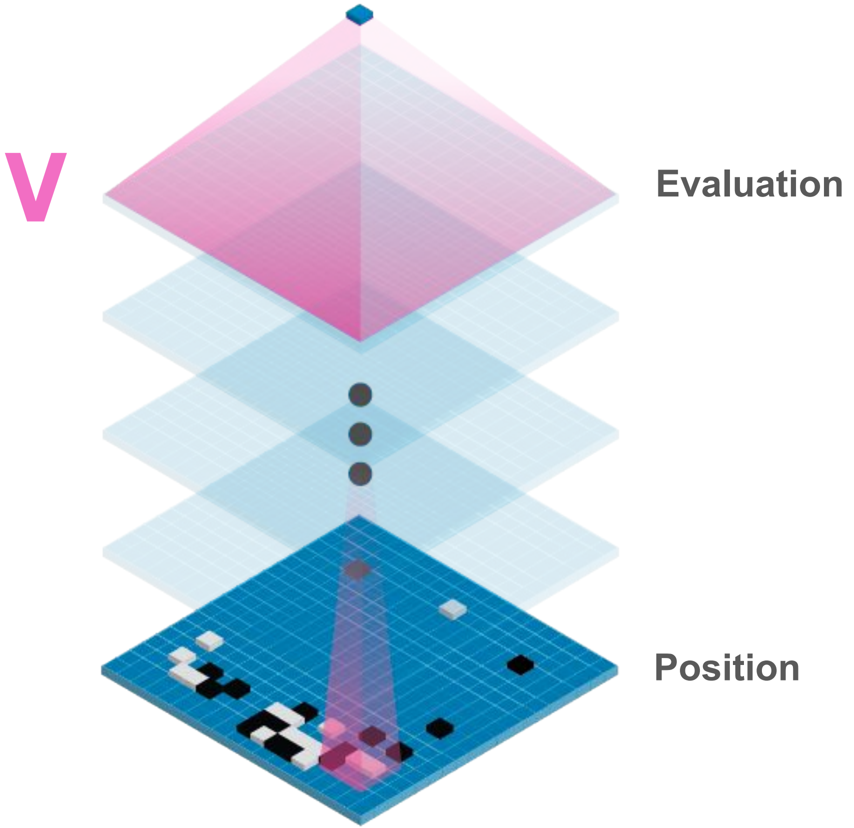
David Silver, Thomas Hubert, Julian Schrittwieser, Ioannis Antonoglou, Matthew Lai, Arthur Guez, Marc Lanctot, Laurent Sifre, Dharshan Kumaran, Thore Graepel, Timothy Lillicrap, Karen Simonyan, Demis Hassabis



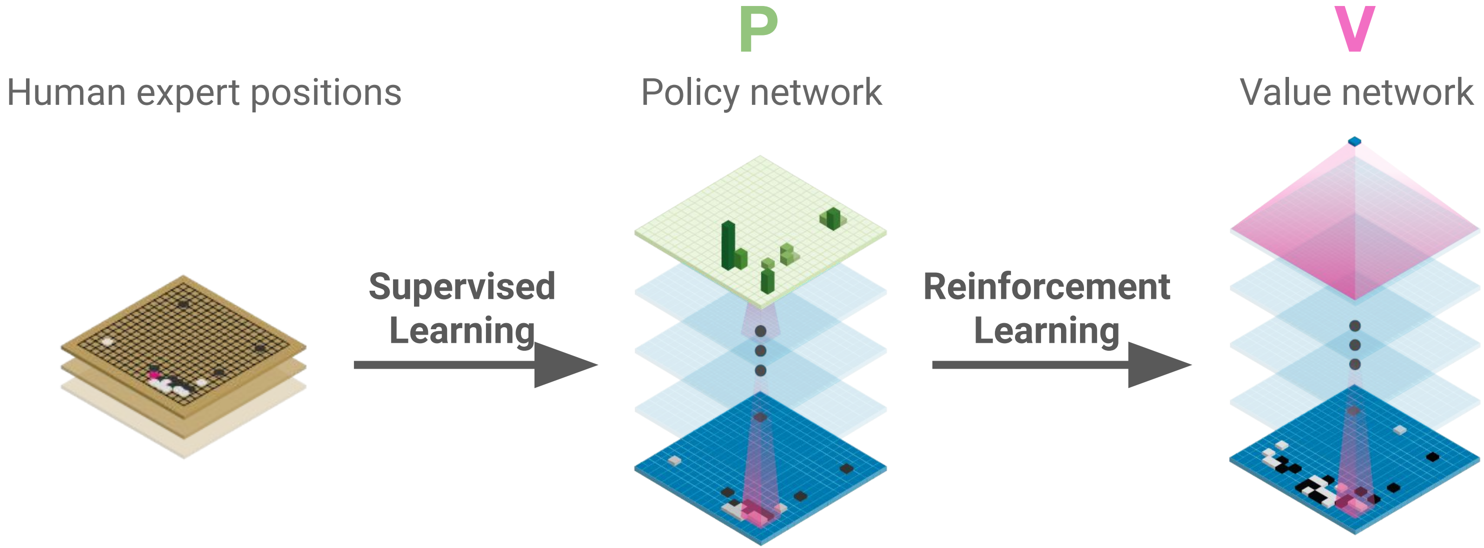
Deep Learning in AlphaZero: Policy Network



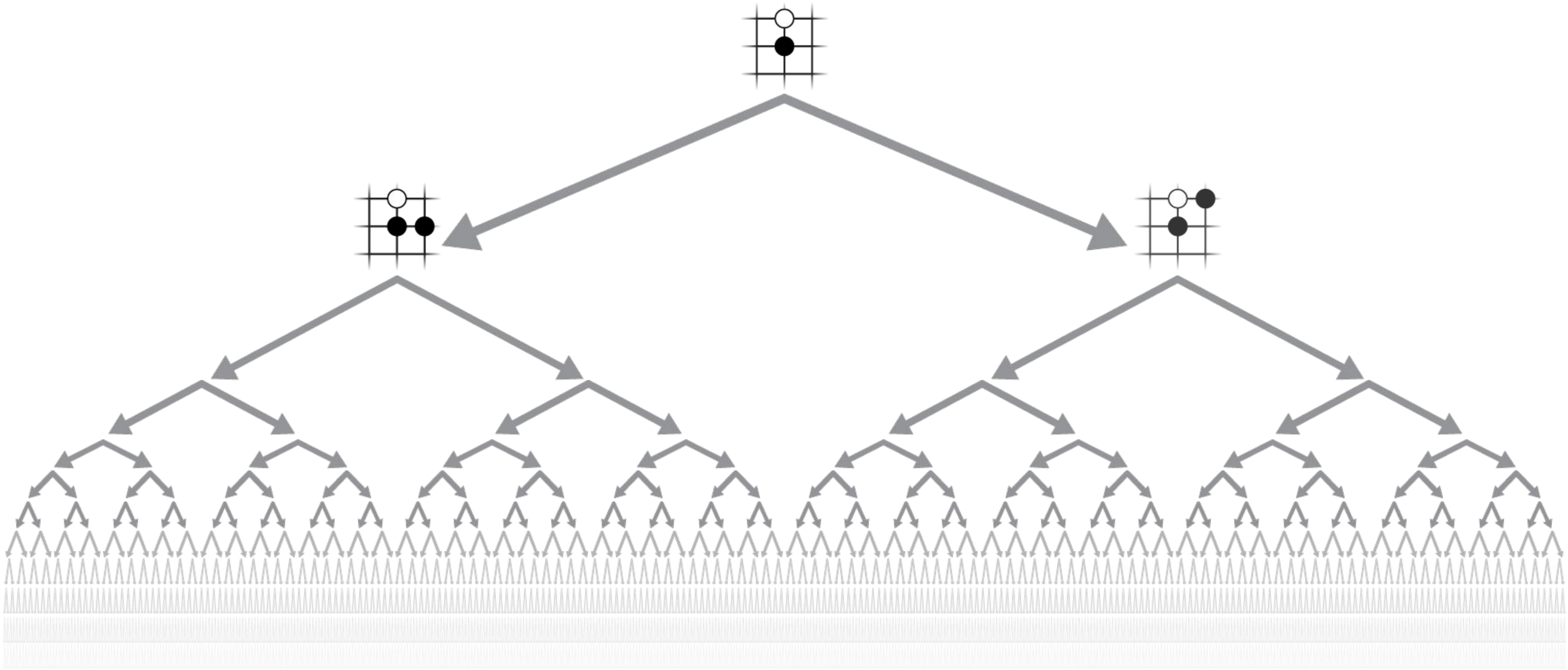
Deep Learning in AlphaZero: Value Network



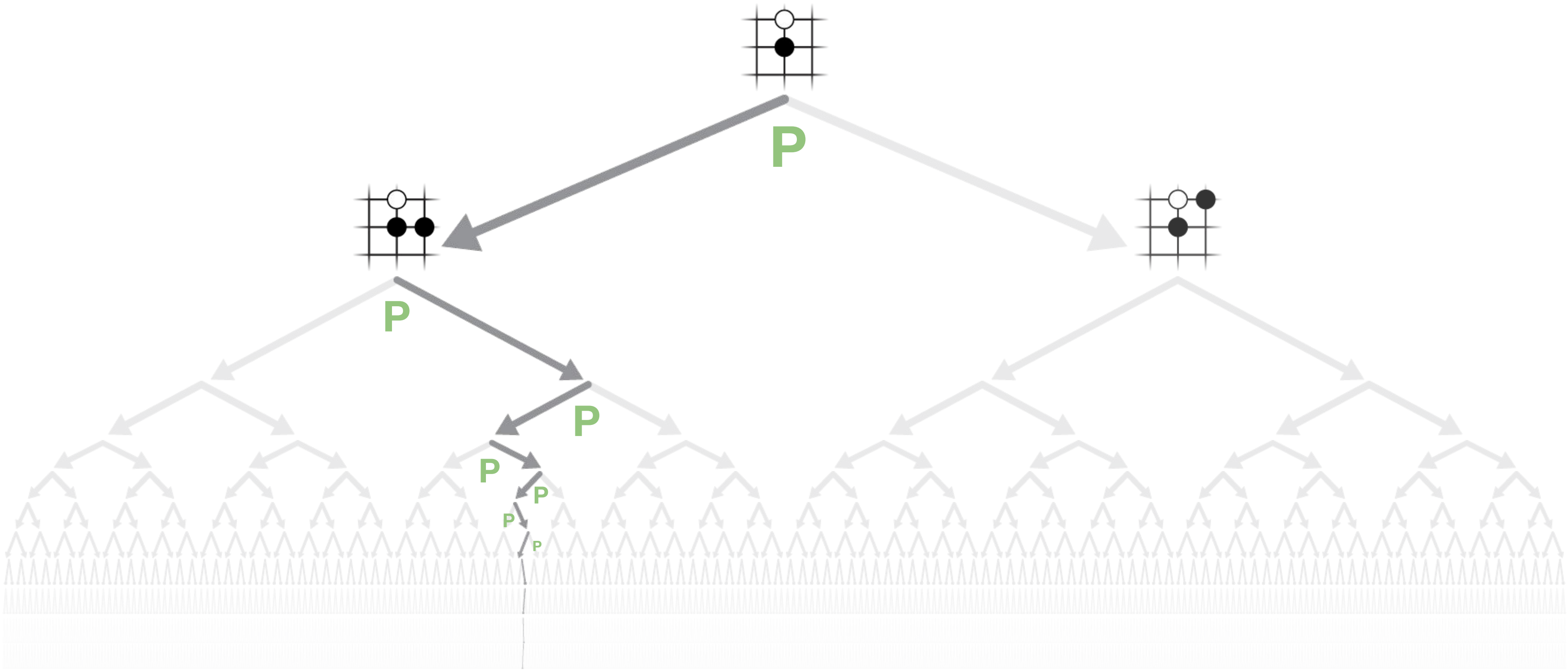
Training AlphaGo



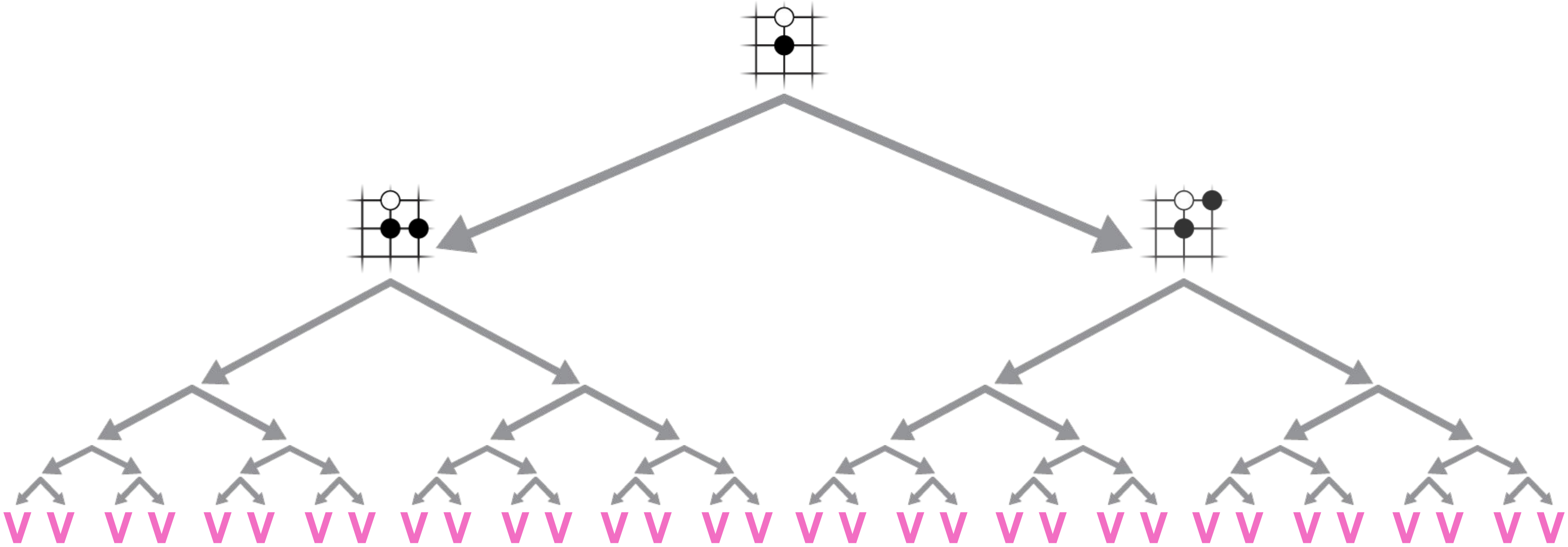
Exhaustive Search



Reducing breadth with the policy network



Reducing depth with the value network



AlphaGo vs Lee Sedol

Lee Sedol (9p): winner of 18 world titles

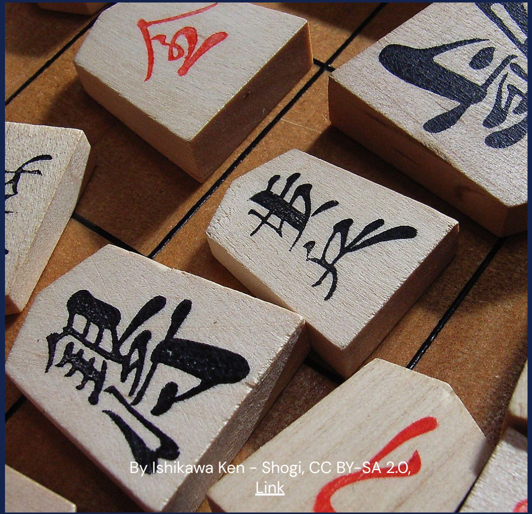
Match was played in Seoul, March 2016

No previous program had ever defeated a human professional player

AlphaGo won the match 4-1

AlphaZero: One Algorithm, Three Games

Chess



Shogi

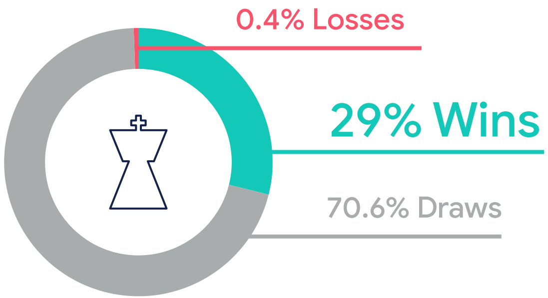
Go

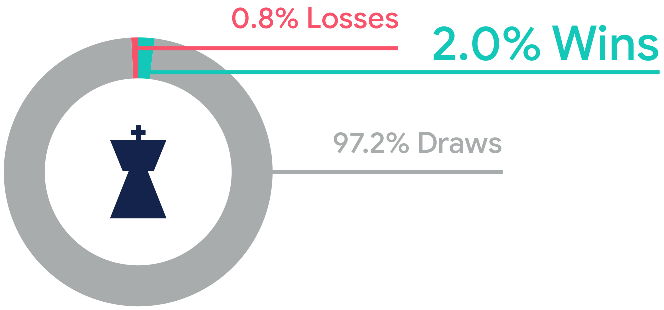
A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play, Science 2018, Joint work with: **David Silver**, **Thomas Hubert**, **Julian Schrittwieser**, Arthur Guez, Ioannis Antonoglou, Matthew Lai, Karen Simonyan, Marc Lanctot, Timothy Lillicrap, Laurent Siffre, Dharshan Kumaran, and Demis Hassabis

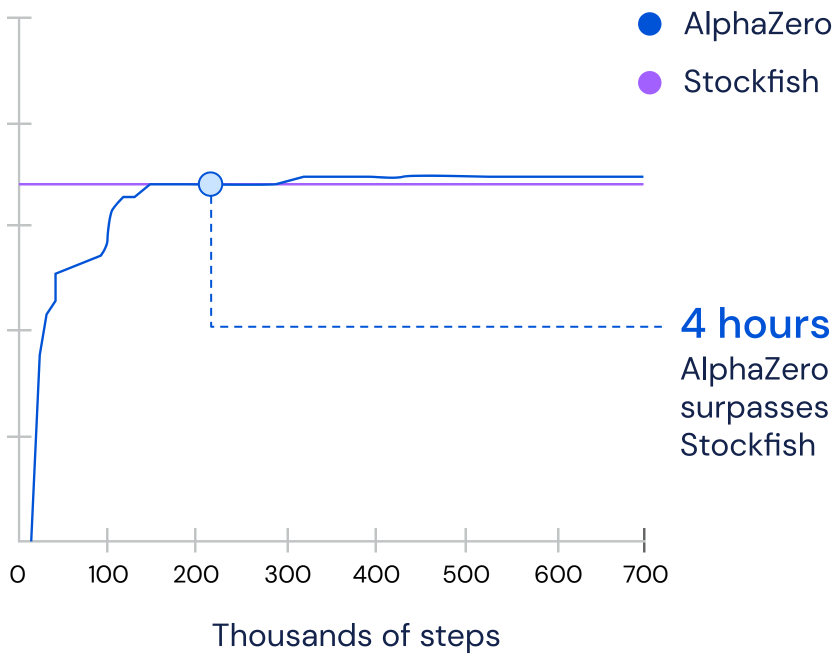
The Royal Game

Stefan Zweig

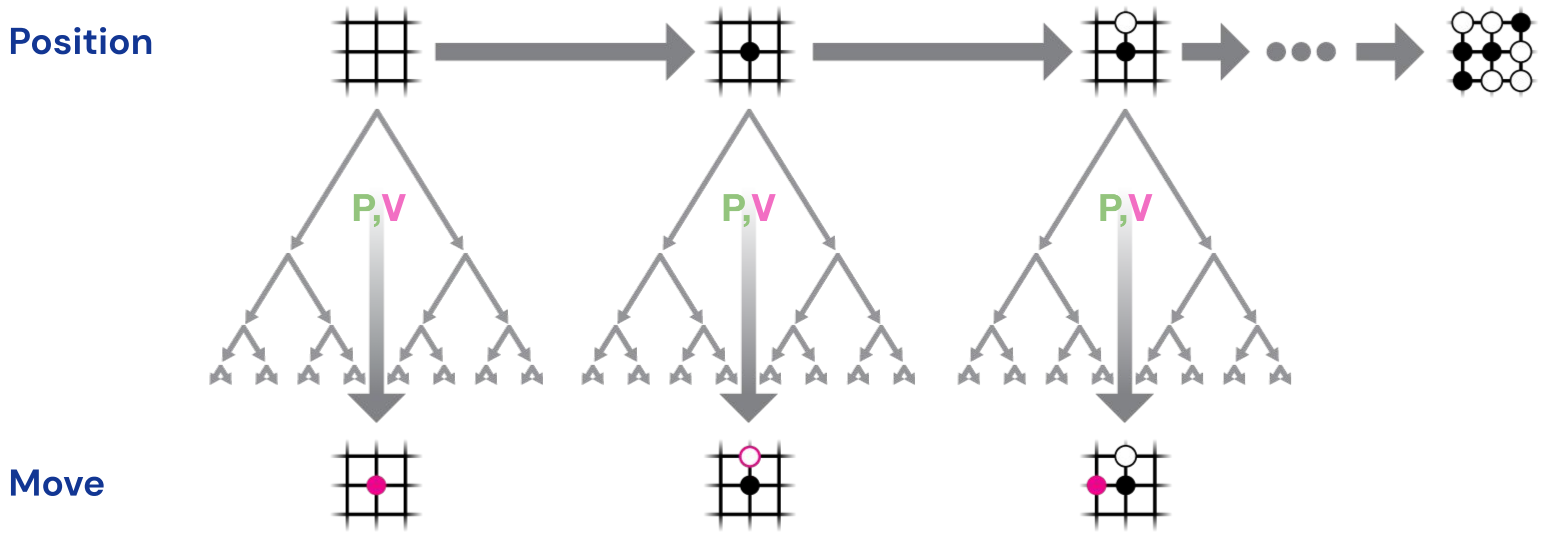

Wins of AlphaZero against Stockfish





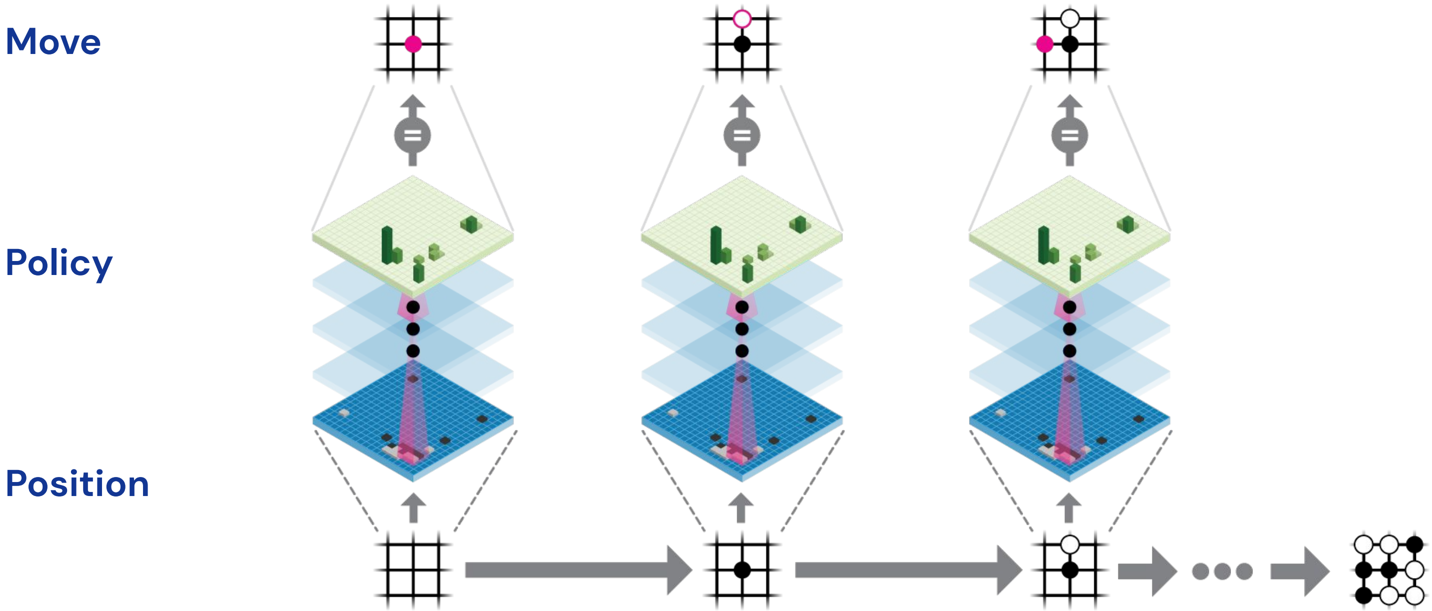


Reinforcement Learning in AlphaZero



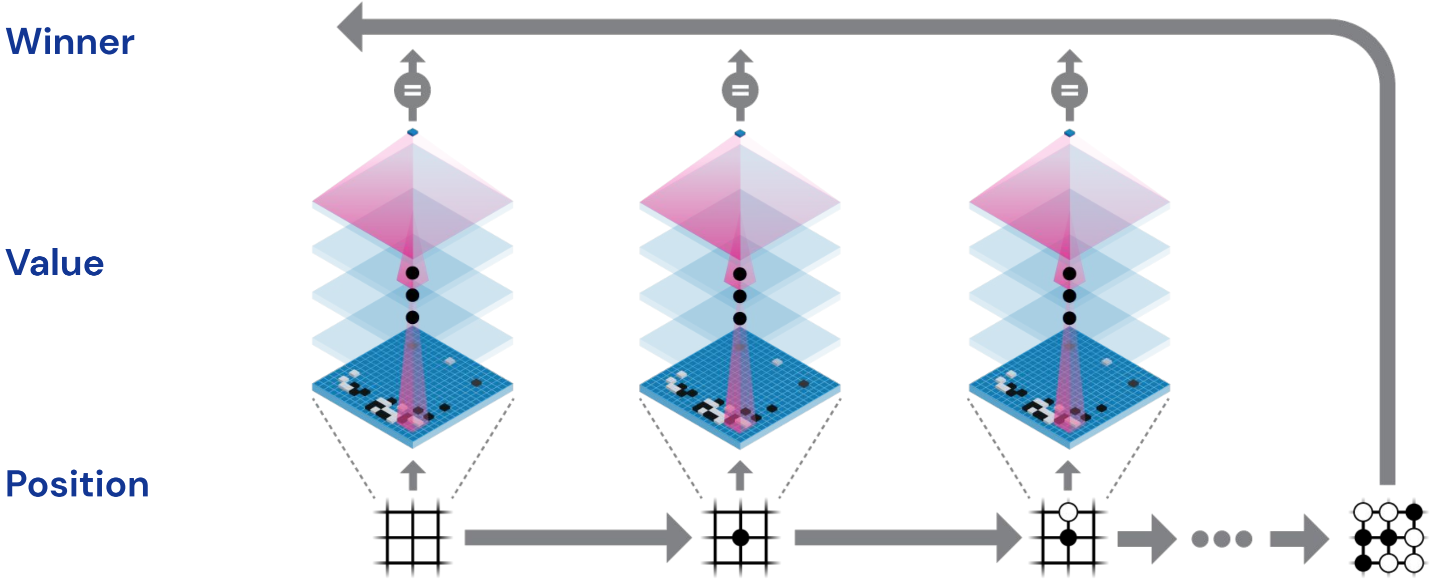
AlphaZero plays games against itself

Reinforcement Learning in AlphaZero



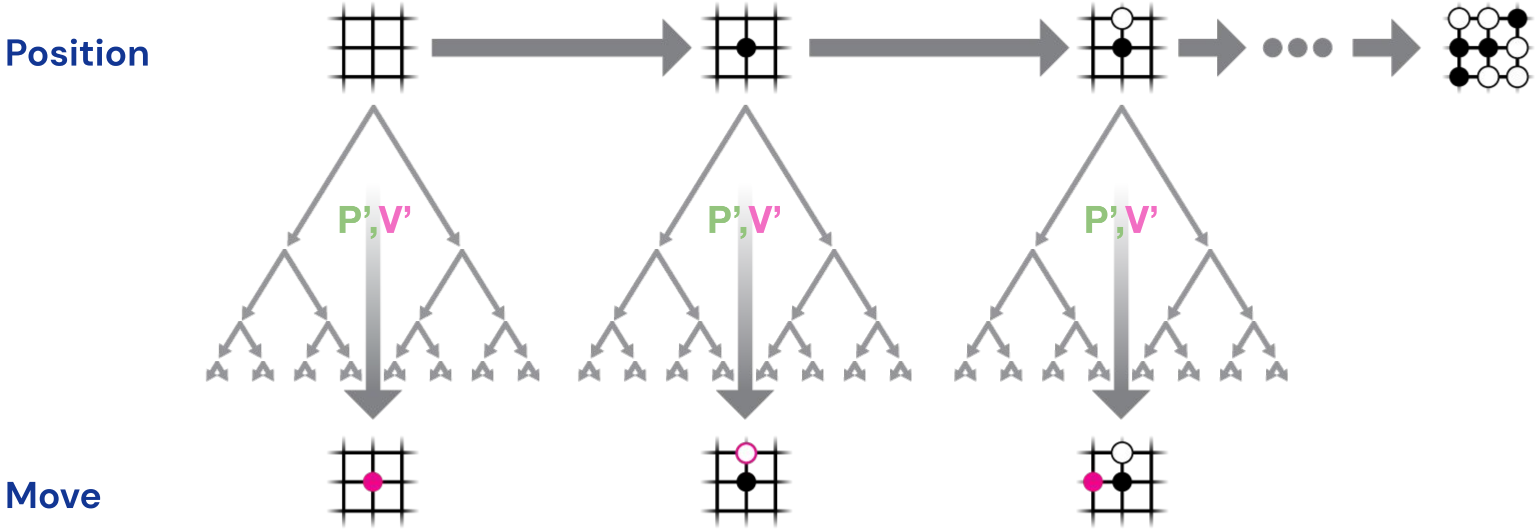
New policy network P' is trained to predict AlphaGo's moves

Reinforcement Learning in AlphaZero

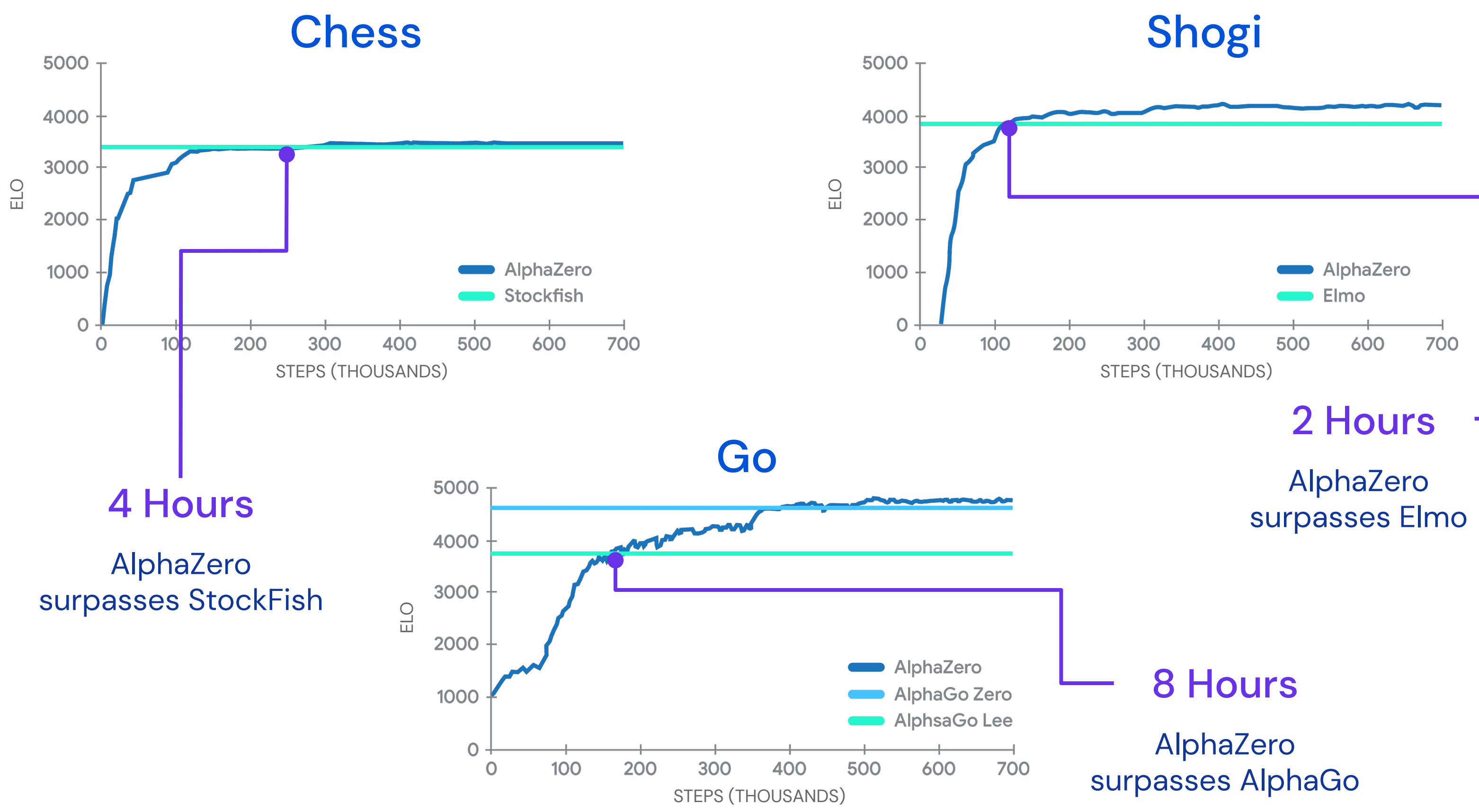


New value network V’ is trained to predict winner

Reinforcement Learning in AlphaZero



New policy/value network is used in next iteration of AlphaGo Zero



Chess
5000
4000
3000
2000
1000
0
ELO
0
100
200
300
400
500
600
700
STEPS (THOUSANDS)
AlphaZero
Stockfish
Shogi
AlphaZero
Elmo
Go
AlphaZero
AlphaGo Zero
AlphsaGo Lee
4 Hours
AlphaZero
surpasses StockFish
2 Hours
AlphaZero
surpasses Elmo
8 Hours
AlphaZero
surpasses AlphaGo

Amount of search per decision

State-of-the-Art
Chess Engine

10,000,000's
OF POSITIONS

AlphaZero

10,000's
OF POSITIONS

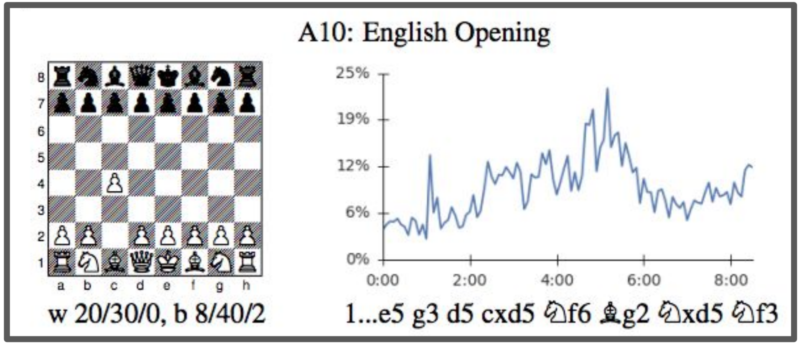
Human
Grandmaster

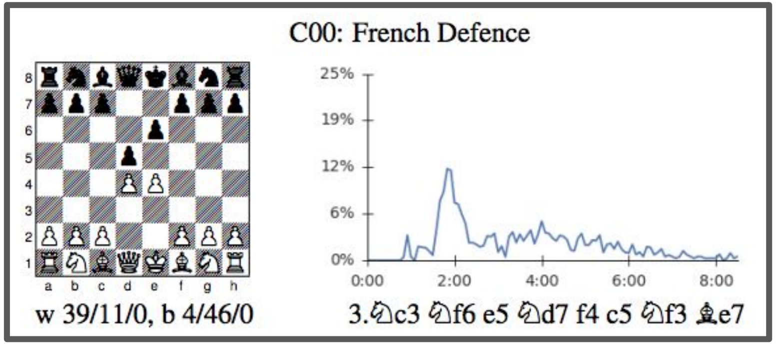
100's
OF POSITIONS

1000 x
more than

100 x
more than

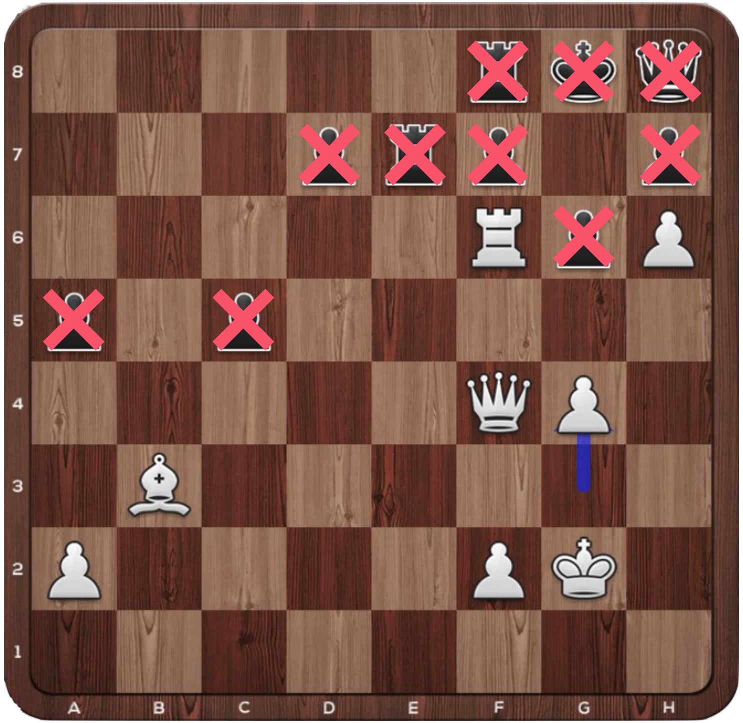
Discovering Chess Opening Theory





The immortal Zugzwang game

- Stockfish
- Alphazero



AlphaZero Conclusions

- Deep Learning enables us to search the huge search space of complex board games
- Self-play produces large amounts of data necessary for training the deep neural networks
- Self-play provides an automatic curriculum, starting from simple opponents to stronger and stronger opponents.
- System discovers new knowledge
- New directions: Learn rules of the game, more than two players, imperfect information, larger action spaces etc.

Additional Resources about AlphaGo and AlphaZero

AlphaGo

DeepMind AlphaGo website

Nature paper: “Mastering the Game of Go with Deep Neural Networks and Tree Search”

AlphaZero

DeepMind AlphaZero website

Nature paper: “Mastering the Game of Go without human knowledge”

Science paper: “Mastering Chess and Shogi with Self-Play Reinforcement Learning”

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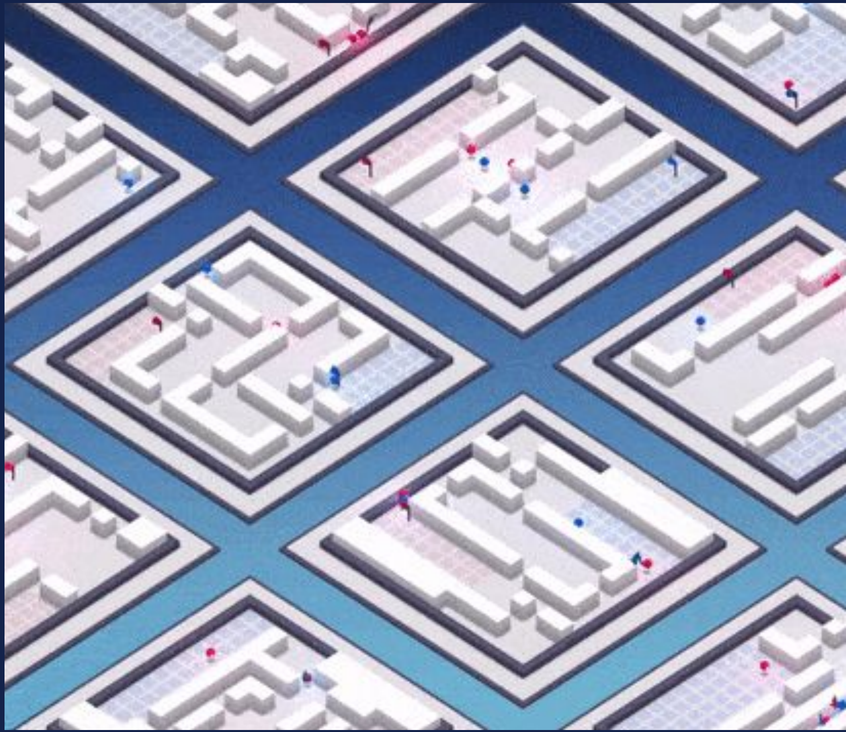
3 Learning to Play Capture the Flag

CASE STUDY

Human-level performance in 3D multiplayer games with population-based reinforcement learning

(Science, 2018)

Max Jaderberg, **Wojciech M. Czarnecki**, **Iain Dunning**, Luke Marris, Guy Lever, Antonio Garcia Castaneda, Charles Beattie, Neil C. Rabinowitz, Ari S. Morcos, Avraham Ruderman, Nicolas Sonnerat, Tim Green, Louise Deason, Joel Z. Leibo, David Silver, Demis Hassabis, Koray Kavukcuoglu, and Thore Graepel



Capture the Flag

Large-scale decentralised multi-agent learning, scalable computational architectures.

Population based training
Internal reward evolution,
Hierarchical temporal policies.

Agents exceed human-level,
as both teammates and opponents.

Rich emergent representation
and behaviour.

Agent observation
raw pixels

Outdoor
map overview

Rules of Capture the Flag

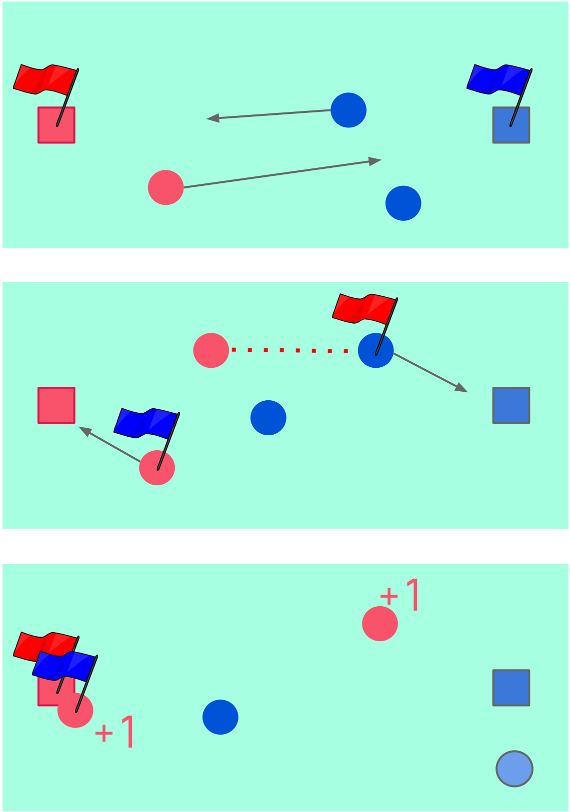
Multiplayer team game e.g. 2 vs 2.

Run to opponent base, and pick up flag.

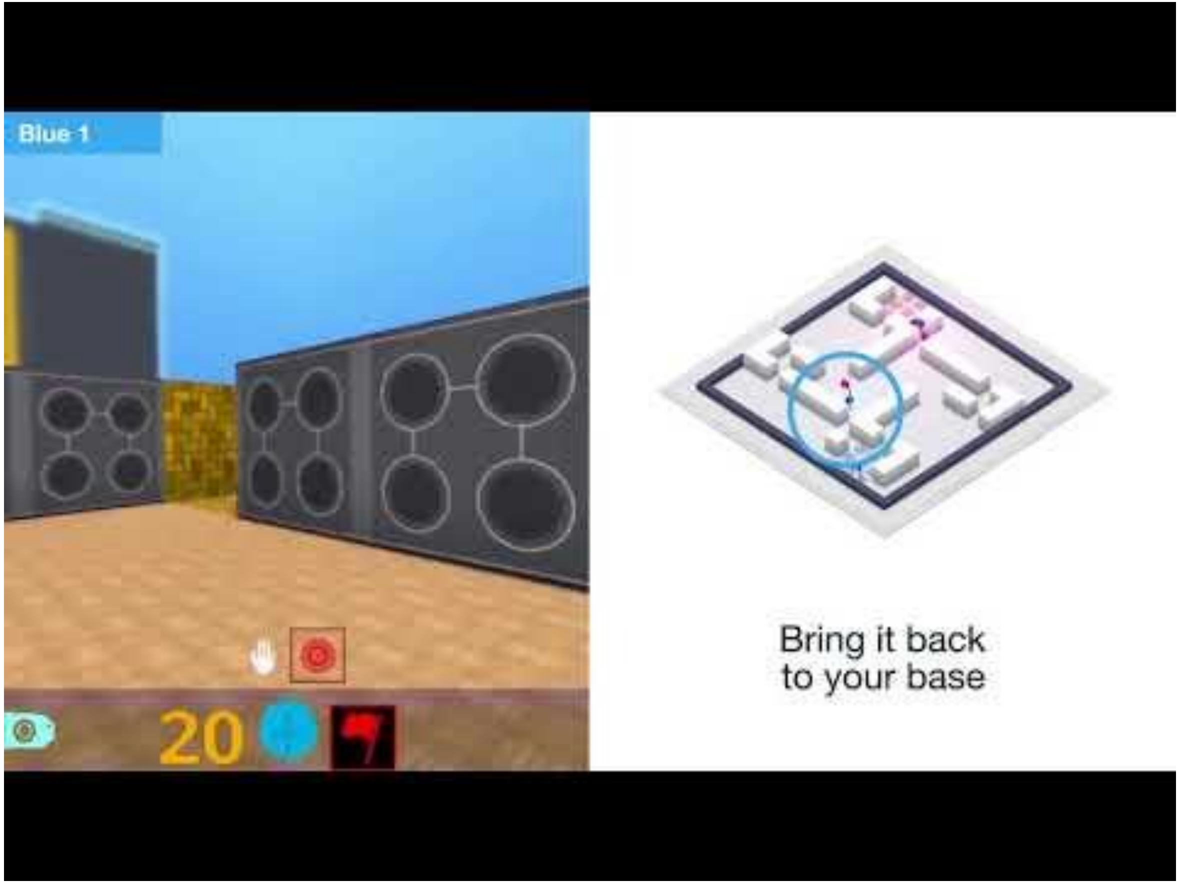
Bring opponent flag back to your base.

Can only score if own flag is at base. Need to tag opponent flag carrier to return your flag to base.

Winner is team which scores most flag captures after five minutes.



Capture the Flag in Action

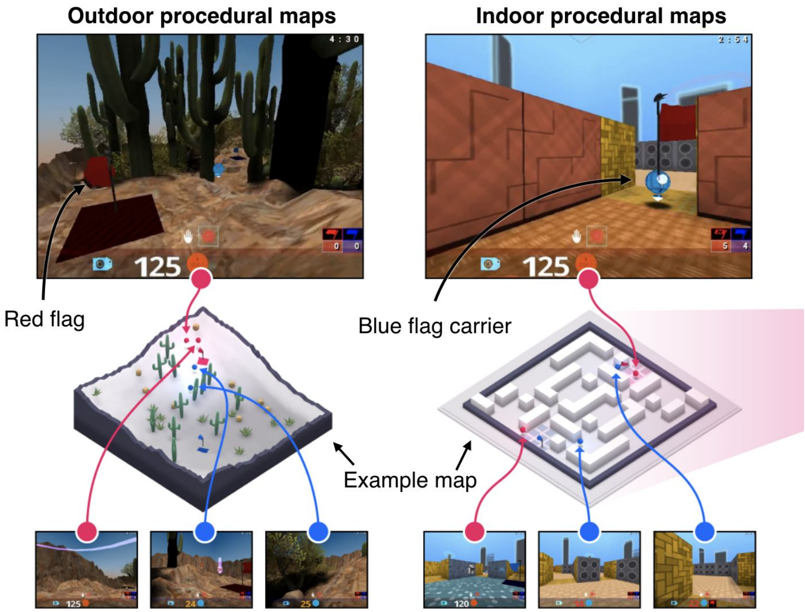


Capture the Flag environments

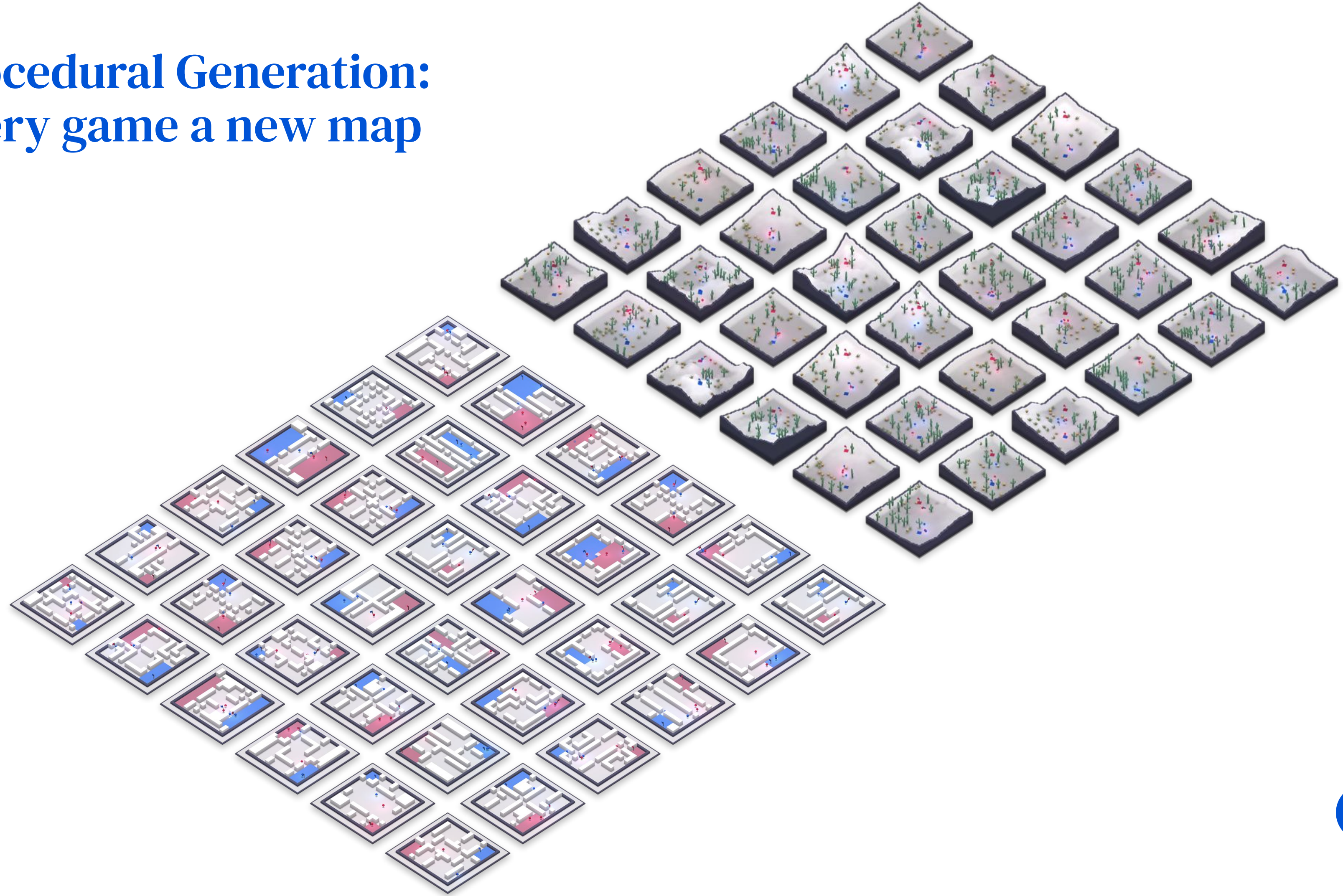
Based on DMLab (Quake III Arena).

Train agents on two style of maps, outdoor and indoor.

Maps are procedurally generated every game.

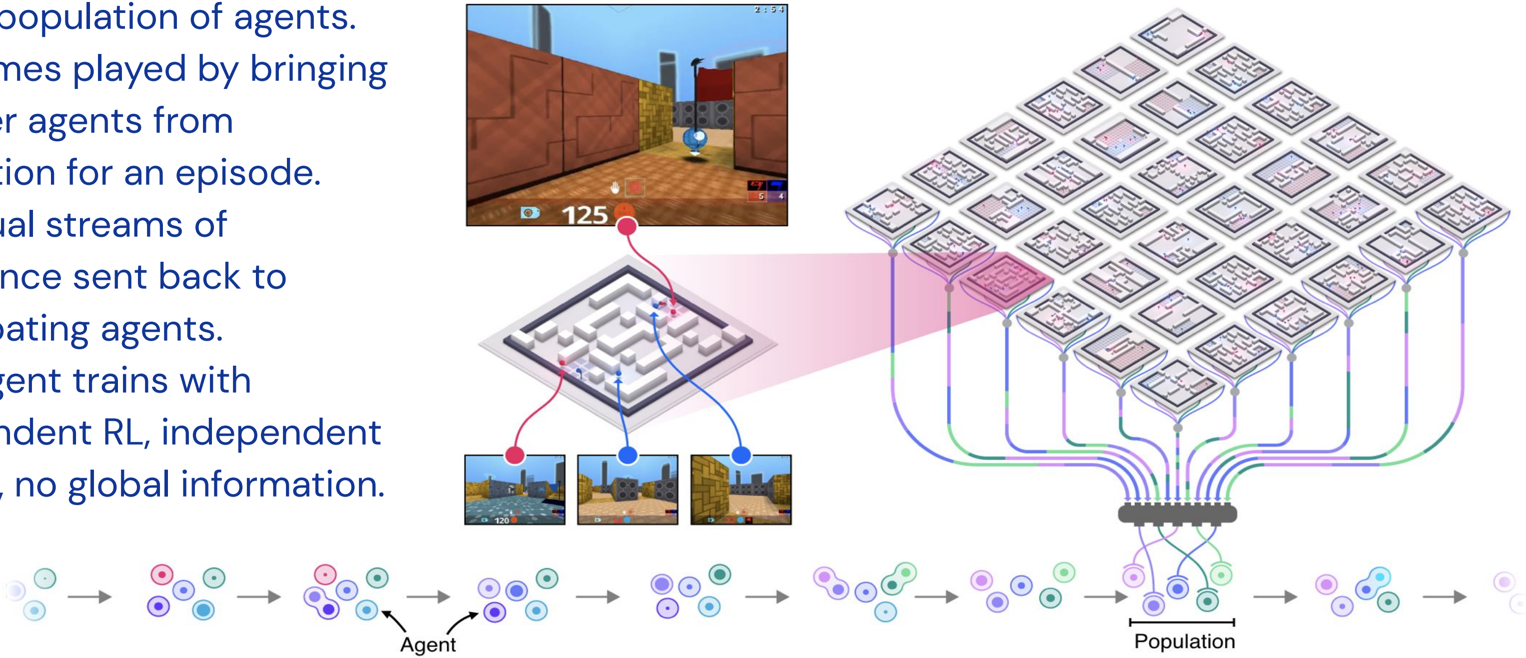


Procedural Generation: Every game a new map



Training Procedure

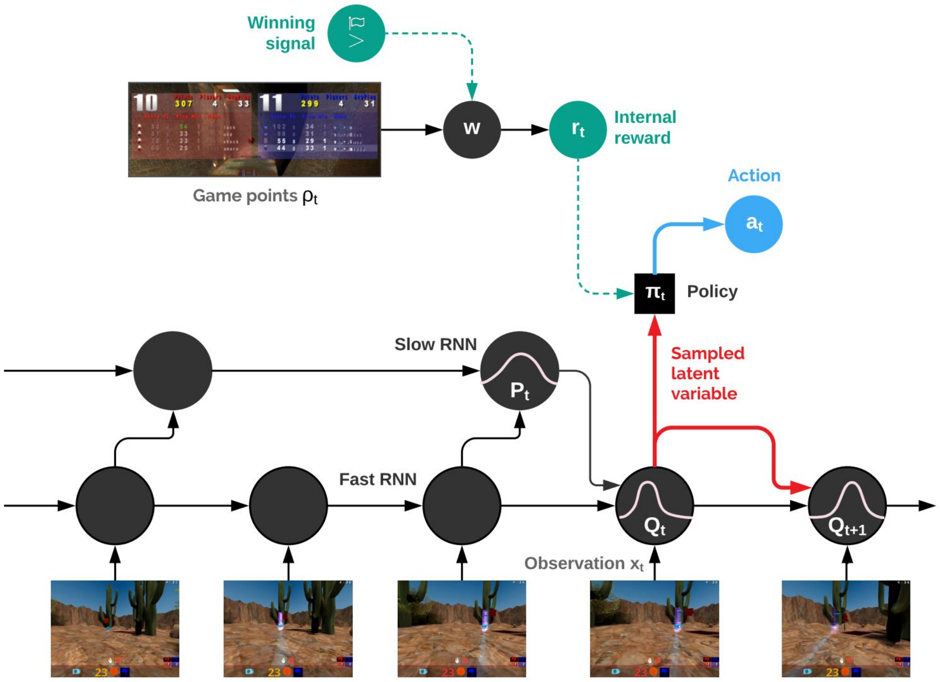
- Train a population of agents.
- CTF games played by bringing together agents from population for an episode.
- Individual streams of experience sent back to participating agents.
- Each agent trains with independent RL, independent actions, no global information.



Neural Network Architecture of FTW

Hierarchy of recurrent neural networks at two time scales: Slow RNN and Fast RNN

Internal rewards based on game events learned at even slower time scale

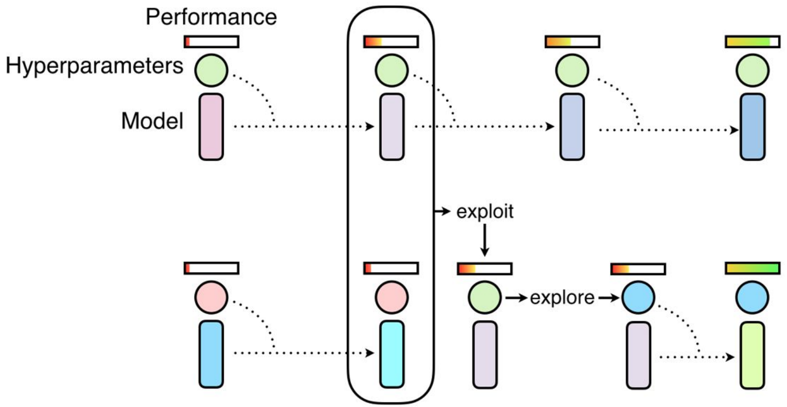


Population based Training

Population of agents serves two purposes.

Provides diverse teammates and opponents: robust multi-agent training without collapses found with naive self-play.

Provides meta-optimisation of agents: using population based training [Jaderberg '17]. Used for model selection, hyperparameter adaptation, internal reward evolution.



Population based Training

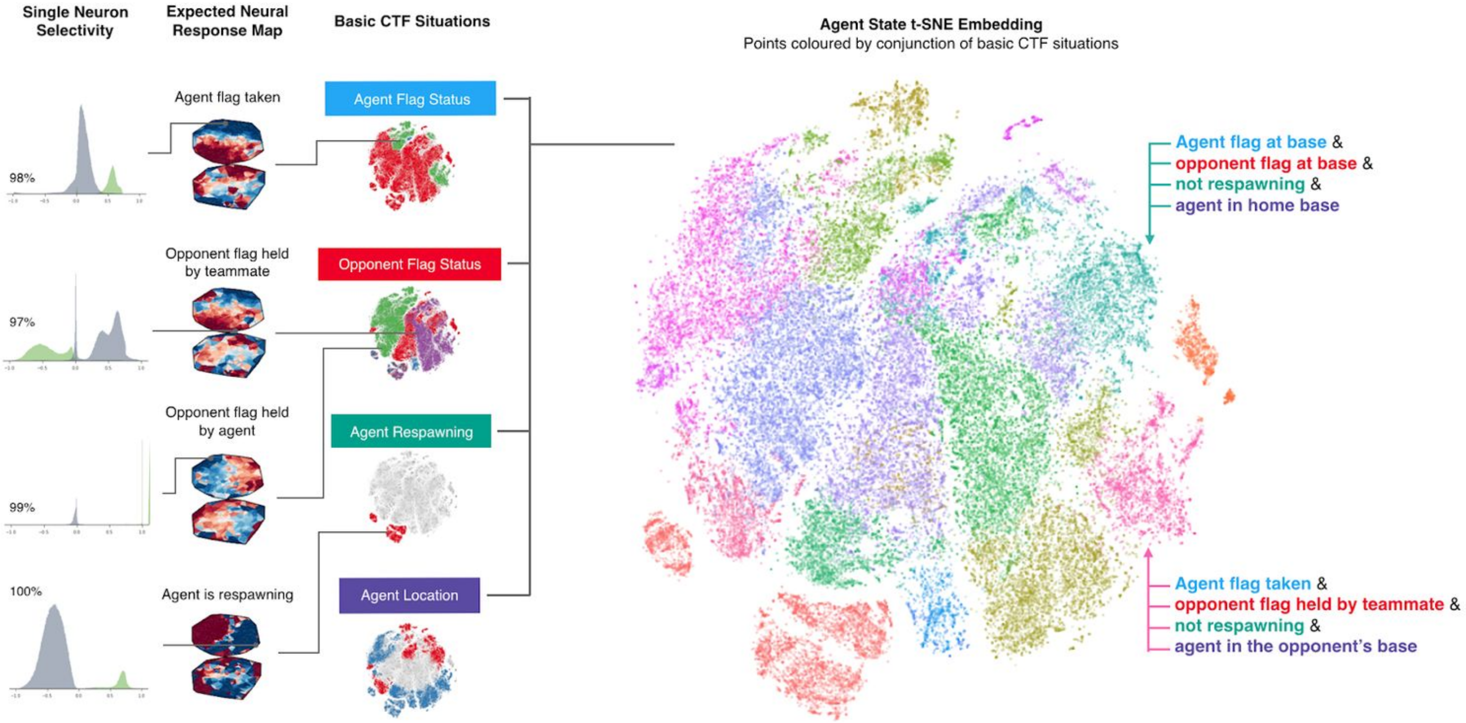
FTW agent is far stronger than baseline agents (UNREAL [Jaderberg '16]).

Benchmarked by playing tournaments against humans.

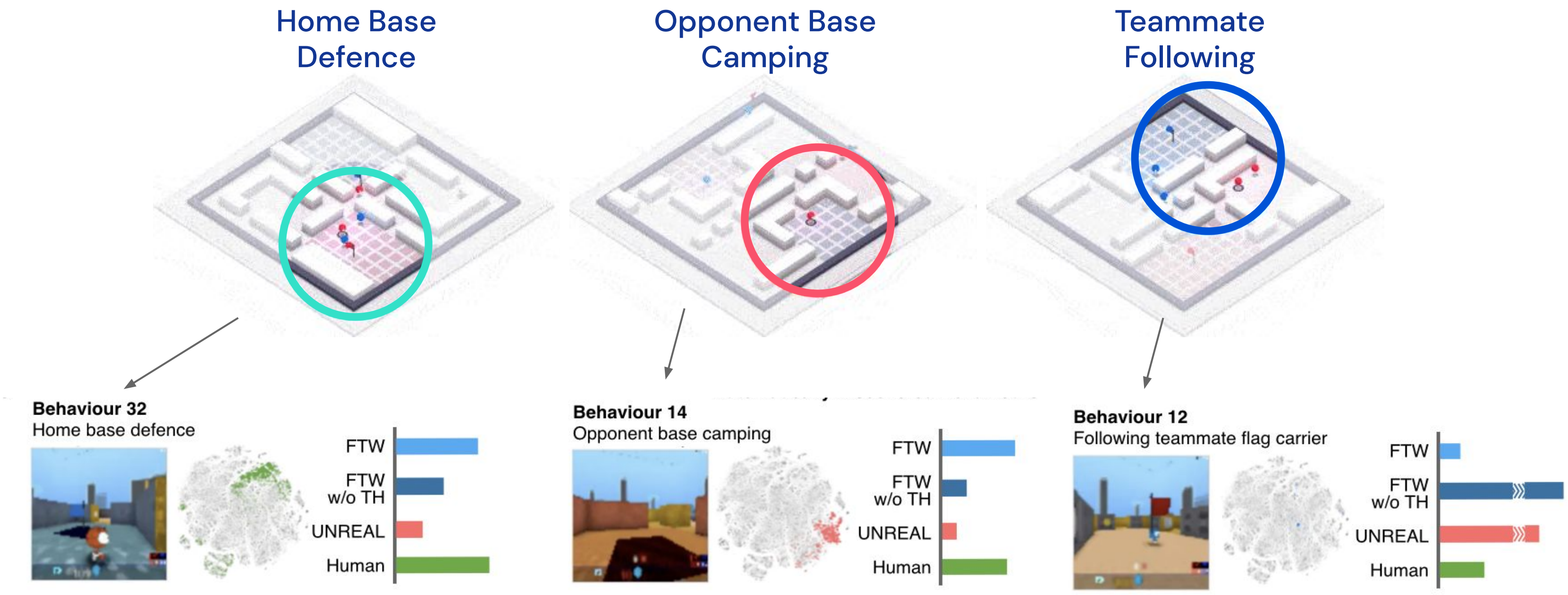
Humans only win against agents when playing with an agent teammate.

Humans rated FTW agent as most collaborative!

Internal Representation of Neural Network Activity



Agent Behaviour: Playing similar to Humans



Capture The Flag Conclusions

- Deep Reinforcement Learning can now learn to play complex multi-player video games at human level
- Train populations of agents to enable optimisation and generalisation.
- Use procedurally generated environments to produce robust, generalisable behaviours.
- We can now begin to understand how agents behave and why.
- Extra resources: blog post, arXiv paper

DeepMind

4

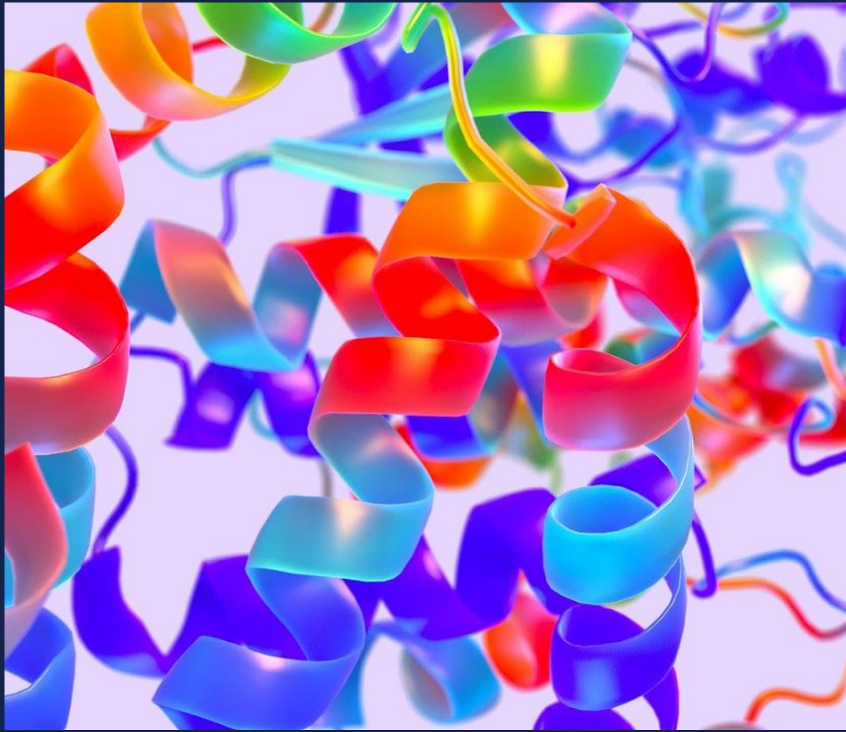
Beyond Games: AlphaFold

CASE STUDY

AlphaFold: Improved proteins structure prediction using potentials from deep learning

(Nature, 2020)

Andrew Senior, **Richard Evans**, **John Jumper**, **James Kirkpatrick**, **Laurent Sifre**, Tim Green, Chongli Qin, Augustin Zidek, Alexander W. R. Nelson, Alex Bridgland, Hugo Penedones, Stig Petersen, Karen Simonyan, David T. Jones, Pushmeet Kohli, Steve Crossan, David Silver, Koray Kavukcuoglu, Demis Hassabis



Proteins - Fundamental Building Blocks of Life

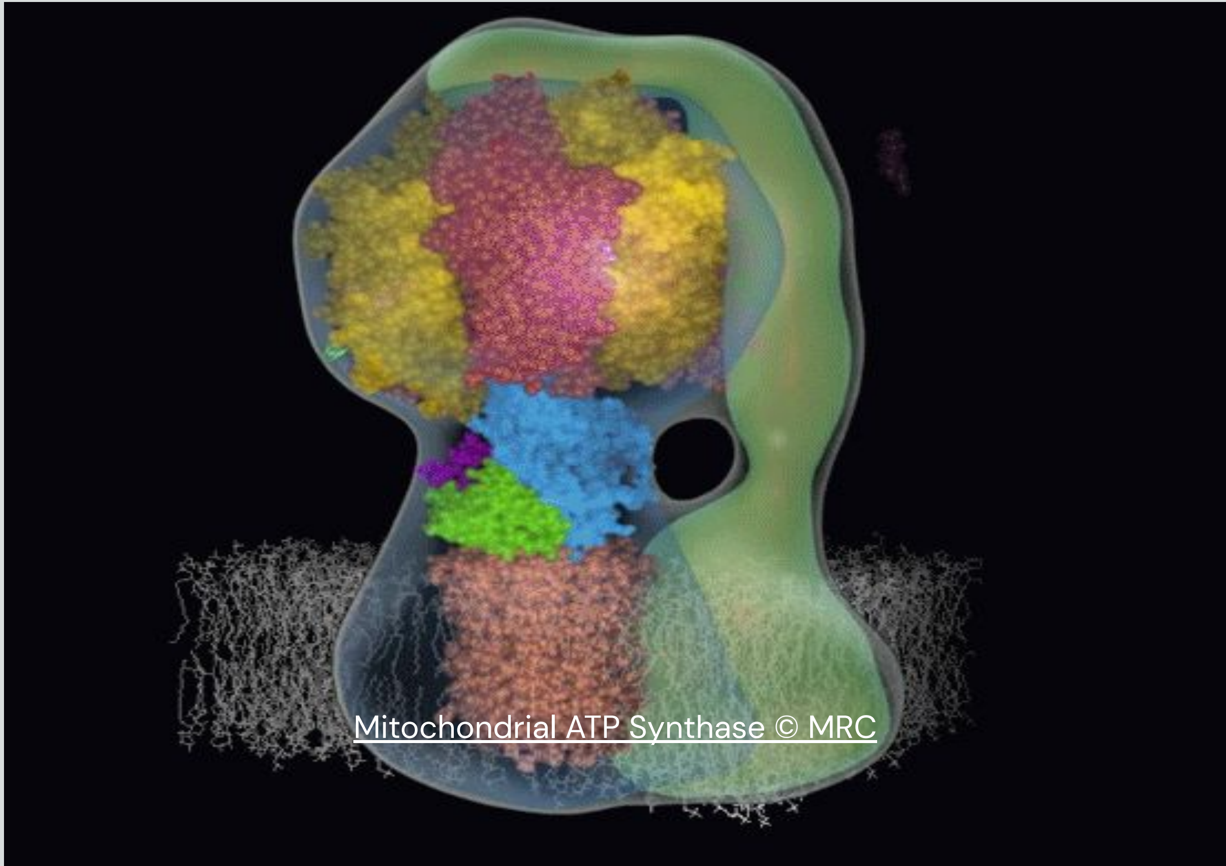
Proteins carry out all kinds of functions in living organisms:

- Catalysing reactions
- Transducing signals across the cell membrane
- Gene regulation
- Cellular transport
- Antibodies

Proteins are target of many drugs.

Proteins are a class of drugs

The shape of proteins tells us about their function



“

I think that we shall be able to get a more thorough understanding of the nature of disease in general by investigating the molecules that make up the human body, including the abnormal molecules, and that this understanding will permit…the problem of disease to be attacked in a more straightforward manner such that new methods of therapy will be developed.

Linus Pauling, 1960

Nobel Prize Chemistry 1954

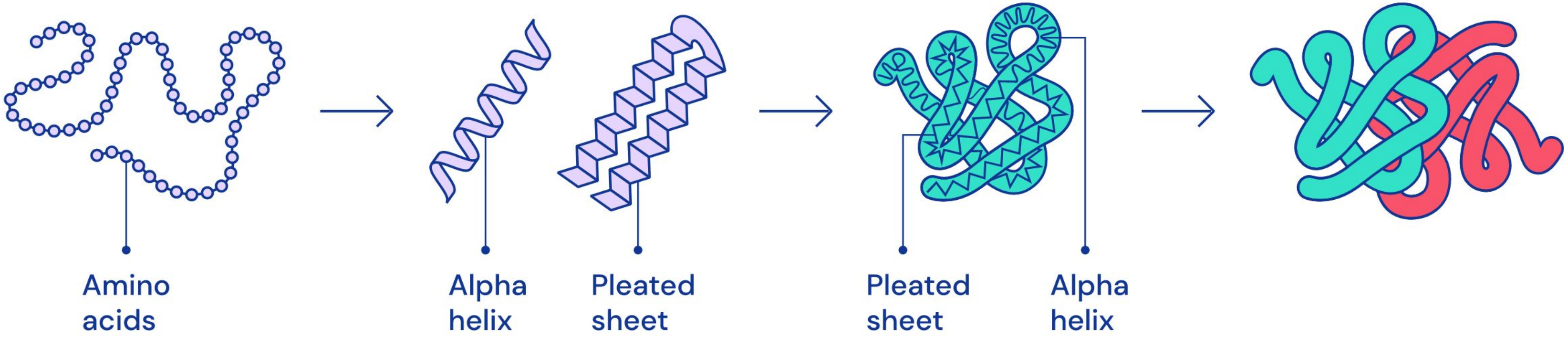
Complex 3D shapes emerge from a string of amino acids

Every protein is made up of a sequence of amino acids bonded together

These amino acids interact locally to form shapes like helices and sheets

These shapes fold up on larger scales to form the full three-dimensional protein structure

Proteins can interact with other proteins, performing functions such as signalling and transcribing DNA



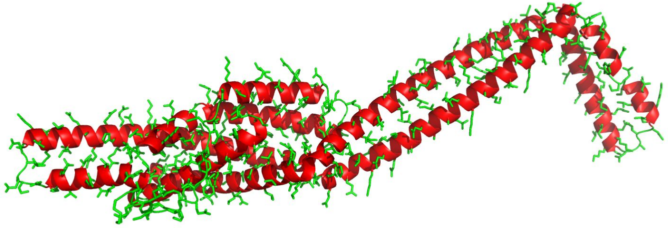
Protein Structure Prediction

- Amino acid residues connected in a chain with a repeating -N-C-C- backbone
- Side chains connected to the C-alpha determine structure
- Structure can tell us about the function of a protein

Target amino acid sequence

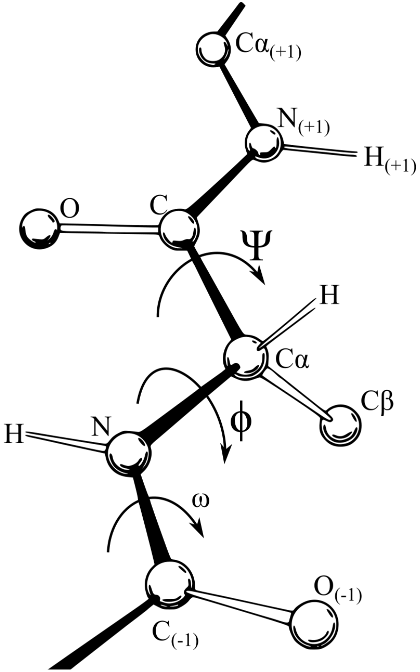
MSEIITFPQQTVVYPEINVKTLSQAVKNIWRLSHQQKSGIEIIQEKTLR
ISLYSRDLDEAARASVPQLQTVLRQLPPQDYFLTLTEIDTELEDPELD
DETRNTLLEARSEHIRNLKKDVKGVIRSLRKEANLMASRIADVSNVVI
LERLESSLKEEQERKAEIQADIAQQEKNKAKLVVDRNKIIESQDVIRQ
YNLADMFKDYIPNISDLDKLDLANPKKELIKQAIKQGVEIAKKILGNIS
KGLKYIELADARAKLDERINQINKDCDDLKIQLKGVEQRIAGIEDVHQI
DKERTTLLLQAAKLEQAWNIFAKQLQNTIDGKIDQQDLTKIIHKQLDF
LDDLALQYHSMLLS

3D structure (atom coordinates)



Protein Structure Prediction - Parameters

- Goal is to predict the coordinates of every atom, particularly the backbone
- Torsion angles (ϕ, ψ) for each residue are a complete* parameterisation of backbone geometry
- 2N degrees of freedom for chains of length N



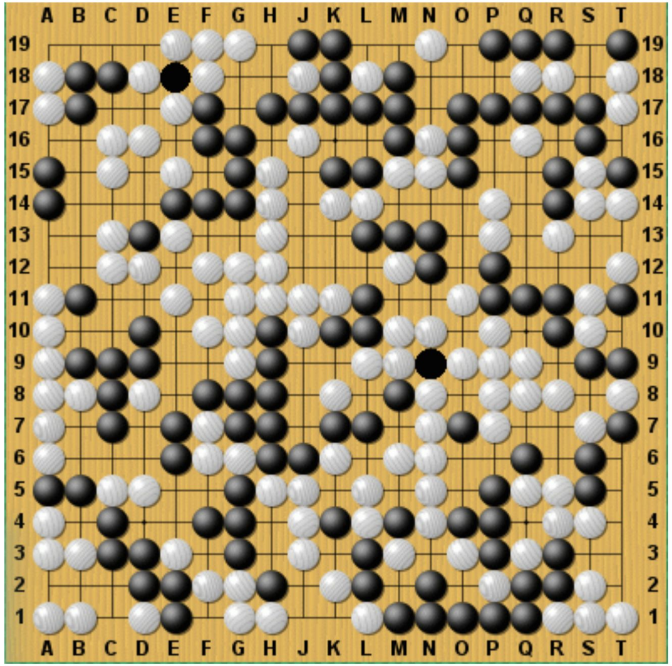
Dcrjsr CCBY3.0
wikipedia.org/Dihedral_angle

Levinthal’s Paradox

“Many naturally-occurring proteins fold reliably and quickly to their native state despite the astronomical number of possible configurations”

Example: protein of 361 amino acids

- $3^{361} = 2 \times 10^{172}$ configurations
- Assume protein can sample 10^{13} new configurations per second or 3×10^{20} per year
- It would take 10^{152} years to sample them all
- Similar number of configurations as there are legal Go positions!



Number of legal Go positions
as ternary number on Go board

(John Tromp, 2016)

Why deep learning for protein folding?

Experimental techniques are expensive and time-consuming

- Cryo-electron microscopy,
- Nuclear magnetic resonance
- X-ray crystallography

Hard to model long and short range interactions explicitly

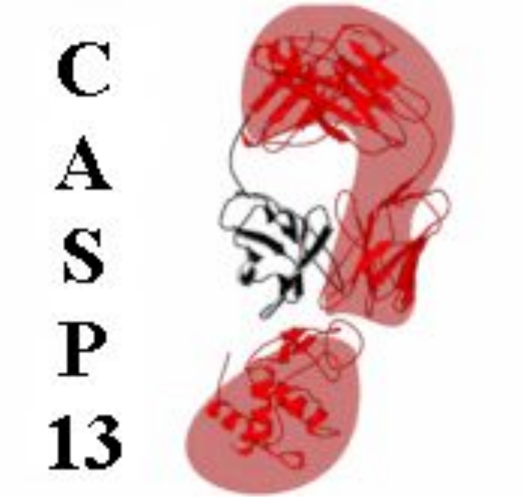
Data available from experiments:

- 150,000 proteins in Protein Data Bank (since 1971)
- But: much less data than for speech or image recognition

CASP assessment provides a benchmark with well-defined goals

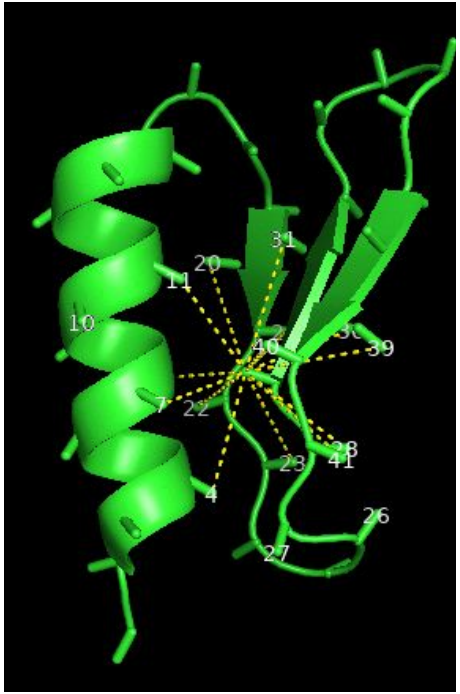
RCSB PDB PROTEIN DATA BANK

159881 Biological Macromolecular Structures Enabling Breakthroughs in Research and Education



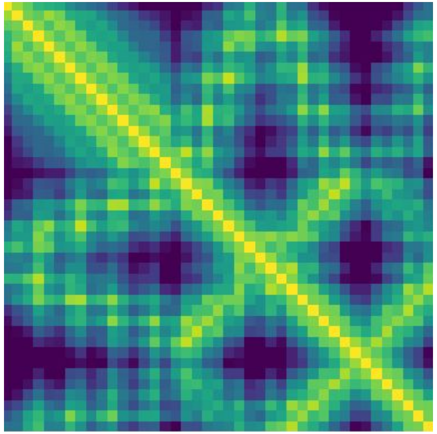
Blind biennial assessment
of structure prediction algorithms

What to predict?
Pairwise distances between residues!



distance (i,j)

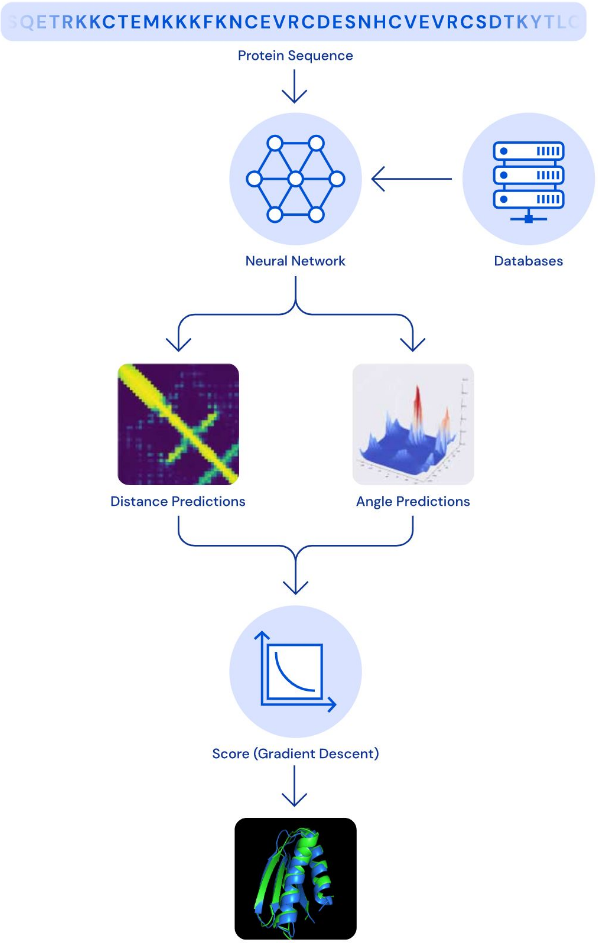
residue i →



residue j →

AlphaFold System

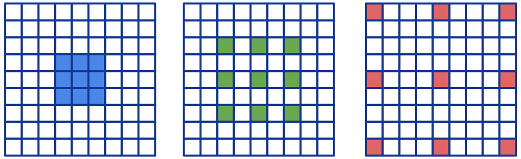
- Combine sequence with data from protein database with coevolutionary information
- Predict pairwise distances and configuration angles
- Run gradient descent on resulting score function to obtain configuration estimate
- Code is available on github: https://github.com/deepmind/deepmind-research/tree/master/alphafold_casp13

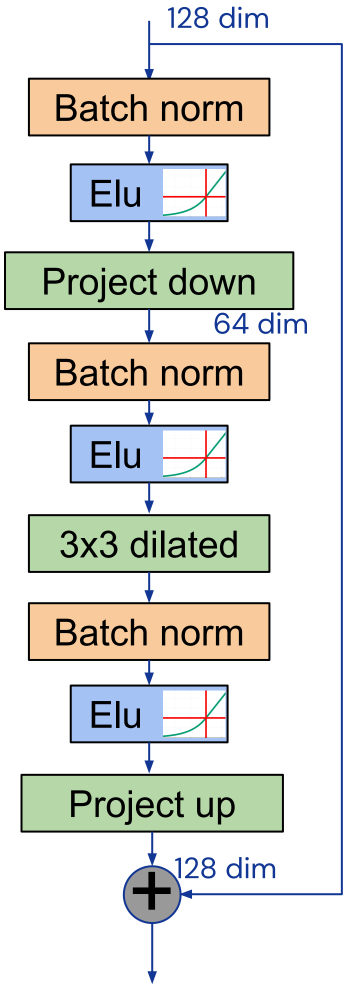


Deep Dilated Convolutional Residual network

One residual block
Modifies a 64x64x128 representation from the previous block

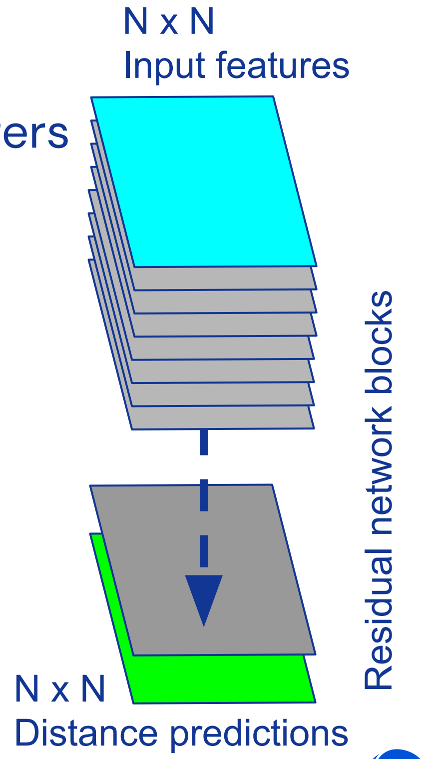
Dilated convolutions
Efficient long-range interaction





Repeat 220 times, cycling through dilations 1, 2, 4, 8

21 million parameters



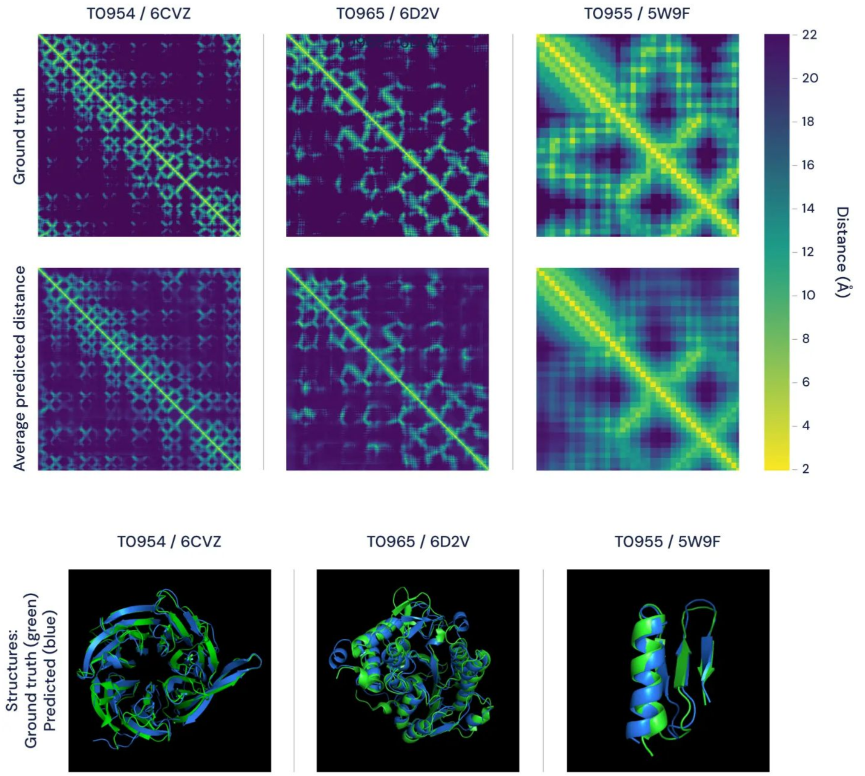
Accuracy of AlphaFold's predictions

Top: Distance matrices for three proteins – the brighter the pixel the closer the pair.

- Top row: real experimentally determined distances.
- Bottom row: average of AlphaFold's predicted distances
- Good match on both local and global scales

Bottom: Same comparison using 3D models.

- Blue: AlphaFold's predictions
- Green: ground truth data



Optimise potential with gradient descent

- Repeated small steps always decreasing the potential
- Repeat the optimization to find multiple local minima
- Initialize from torsion predictions, later from corruptions of best results

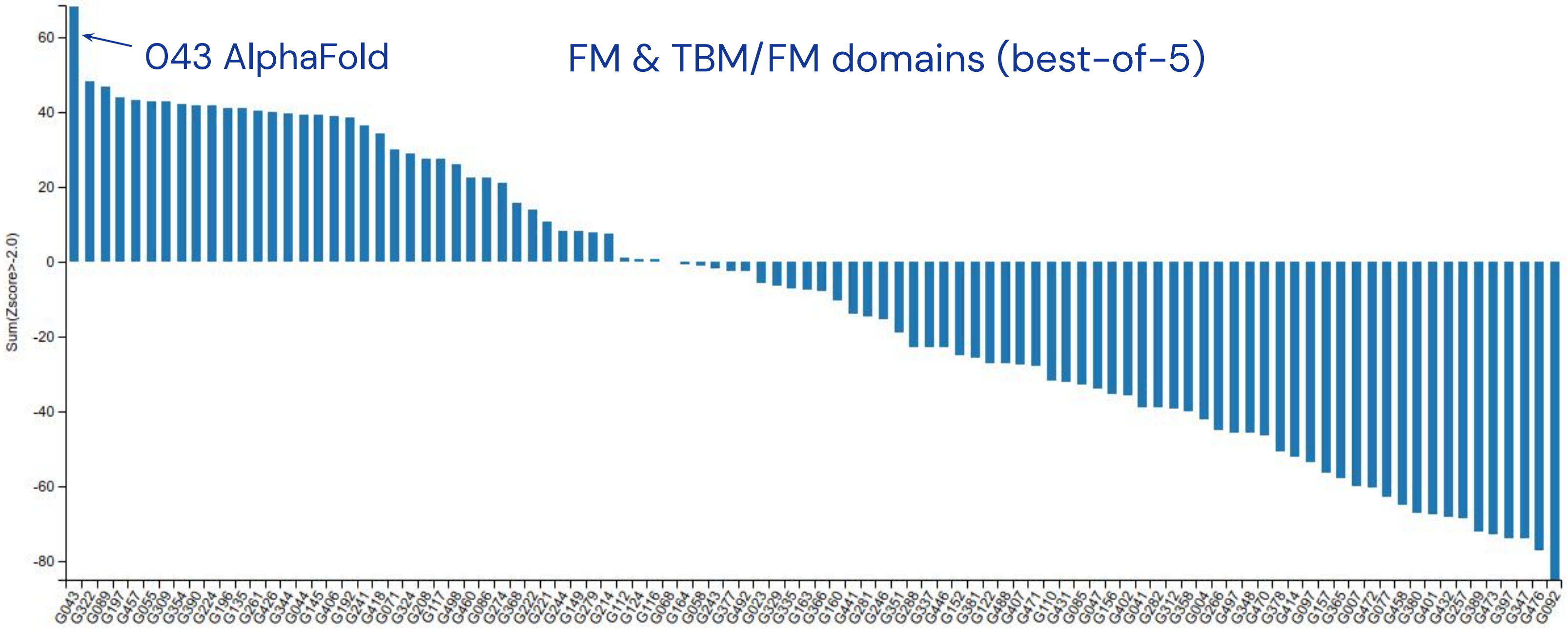
CASP13: Critical Assessment of Techniques for Protein Structure Prediction (est. 1994)

Biannual global competition for protein structure prediction

- Blind structure prediction of 82 chains - sequestered newly-solved structures
- May-August 2018 ~1 chain per day
- For each chain, 3 weeks to return up to 5 structure predictions
- 90+ groups from labs around the world
- Post-hoc scoring relative to ground truth with metrics chosen post-hoc based on backbone alignment metric GDT_TS

We are indebted to decades of prior work by the CASP organisers, as well as to the thousands of experimentalists whose structures enable this kind of assessment.

CASP13 Results



Conclusions AlphaFold

→ Deep learning-based distance prediction...

- Gives more accurate predictions of contact between residues
- A richer source of information than contact prediction
- Constructs a smooth potential that is easy to optimise

→ Limitations:

- Accuracy still limited
- Method depends on finding homologous sequences
- Only predicts backbone, side chains filled by external tool (Rosetta)

→ Work builds on decades of experimental and computational work of other researchers

→ Deep learning can deliver solutions to science & biology problems

5 The future lectures

The lectures

No.	Lecture Title
01	Introduction to Machine Learning and AI
02	Neural Networks Foundation
03	Convolutional Neural Networks for Image Recognition
04	Vision beyond Imagenet – Advanced models for Computer Vision
05	Optimization for Machine Learning
06	Sequences and Recurrent Networks
07	Deep Learning for Natural Language Processing
08	Attention and Memory in Deep Learning
09	Generative Latent Variable Models and Variational Inference
10	Frontiers in Deep Learning: Unsupervised Representation Learning
11	Generative Adversarial Networks
12	Responsible innovation

LECTURE 02

Neural Networks Foundations

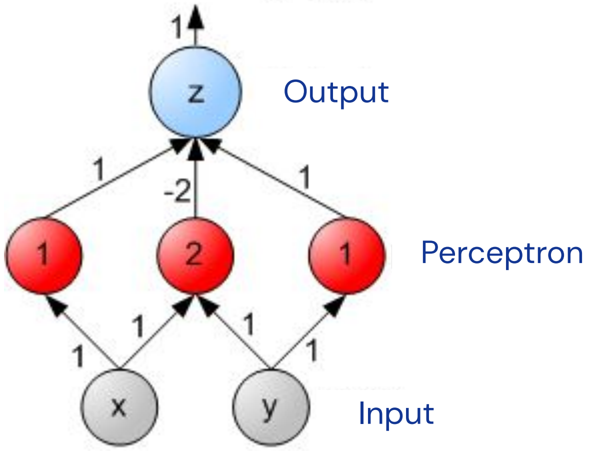
Wojtek Czarnecki

Neural Networks Foundations

(Wojtek Czarnecki)

- What are Neural Networks?
- What kinds of functions can they represent?
- How are they trained?
- What are their limitations?

$z = \text{XOR}(x, y)$



LECTURE 03

Convolutional Neural Networks for Image Recognition

Sander Dieleman

Convolutional Neural Networks for Image Recognition

(Sander Dieleman)

- How can we build prior knowledge into our architectures?
- Convolutional Neural Networks encode spatial priors
- Revolutionised image recognition
- Now part of any vision based machine learning application

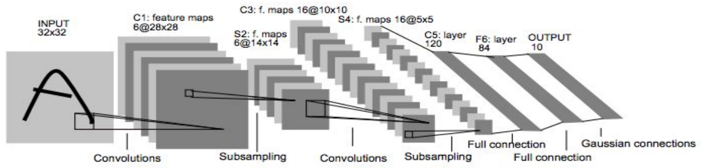


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Architecture of LeNet 5 Gradient-based learning applied to document recognition
(Lecun et al, 1998)

Size normalised examples from the MNIST dataset
Architecture of LeNet 5 Gradient-based learning applied to document recognition
(Lecun et al, 1998)

LECTURE 04

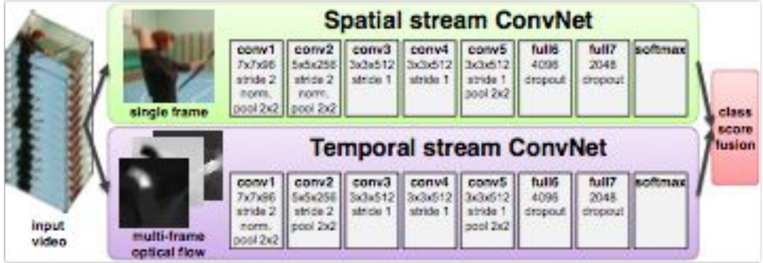
Vision beyond Imagenet - Advanced models for Computer Vision

Viorica Patraucean

Vision beyond Imagenet - Advanced models for Computer Vision

(Viorica Patraucean)

- Object detection, semantic segmentation, estimation of optical flow
- Moving images: analysing videos for action recognition and tracking
- Self-supervised learning, also using additional modalities such as audio
- Computer vision for building intelligent agents



Two-Stream Convolutional Networks for Action Recognition in Videos, Simonyan & Zisserman, 2014

LECTURE 05

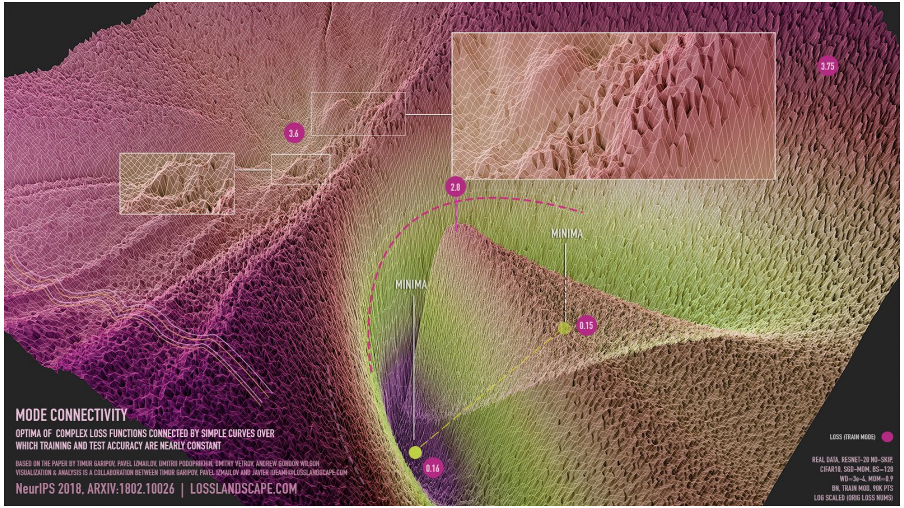
Optimization for Machine Learning

James Martens

Optimization for Machine Learning

(James Martens)

- Optimization methods are the engines underlying neural networks that enable them to learn from data.
- Fundamentals of gradient-based optimization methods, and their application to training neural networks.
- Gradient descent, momentum methods, 2nd-order methods, and stochastic methods.



Mode connectivity in loss landscape,
Garipov et al, NeurIPS, 2018.
Also see https://losslandscape.com/

LECTURE 06

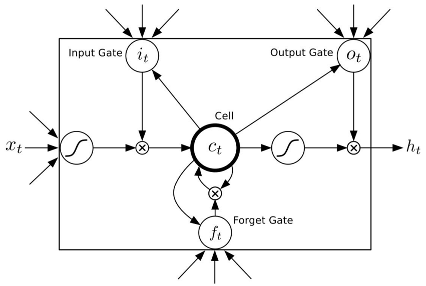
Sequences and Recurrent Networks

Marta Garnelo

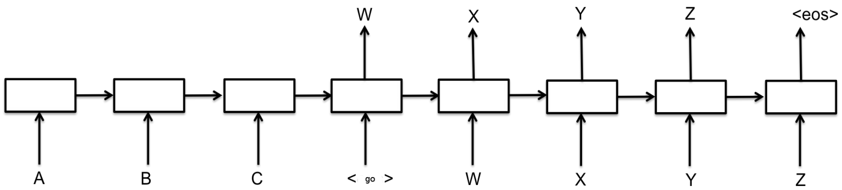
Sequences and Recurrent Networks

(Marta Garnelo)

- Almost all data is sequential : text, DNA, video, audio
- How can we process such data using machine learning
- Fundamentals of sequence modeling including Recurrent Neural Networks and Long-Short Term Memory (LSTMs)
- Mapping sequences to sequences as in machine translation



LSTM cell (Long-short term memory, Hochreiter & Schmidhuber, Neural Computation 1997)



Sequence to sequence learning with neural networks (Sutskever et. al, NIPS 2014)

LECTURE 07

Deep Learning for Natural Language Processing

Felix Hill

Deep Learning for Natural Language Processing

(Felix Hill)

- Why Deep Learning for language?
- Simple recurrent networks to Transformers.
- Unsupervised / representation learning for language. From Word2Vec to BERT.
- Situated language understanding. Grounding. Embodied language learning.

SYSTEM PROMPT (HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION (MACHINE-WRITTEN, 10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

GPT-2 Language Model, OpenAI Blog post, Better Language Models and Their Implications, 2019

LECTURE 08

Attention and Memory in Deep Learning

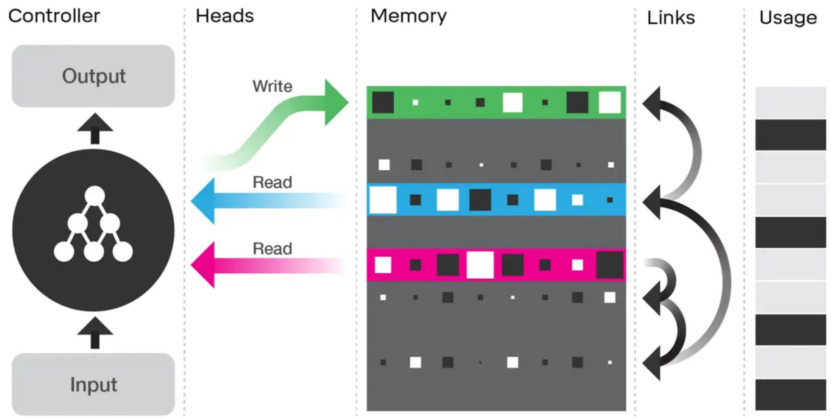
Alex Graves

Attention and Memory in Deep Learning

(Alex Graves)

- Attention and memory: two vital new components of deep learning.
- Implicit attention, discrete and differentiable variants of explicit attention.
- Networks with external memory, attention for selective recall.
- Variable computation time, which can be seen as a form of 'attention by concentration'.

Illustration of the Differentiable Neural Computer
Hybrid computing using a neural network with dynamic external memory



Hybrid computing using a neural network with dynamic external memory (Graves et al, Nature, 2016)

LECTURE 09

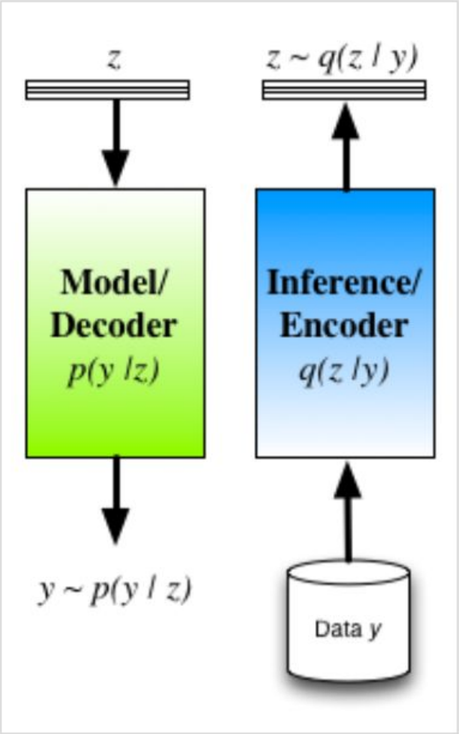
Generative Latent Variable Models and Variational Inference

Andriy Mnih

Generative Latent Variable Models and Variational Inference

(Andriy Mnih)

- Unsupervised Learning
- Latent variable modelling and the central role of inference
- Flow-based models which combine high expressive power with tractable inference
- Variational inference for efficient training of intractable models
- VAE modelling framework



Encoder-decoder view of inference in latent variable models.

Image: The Spectator, Shakir's Machine Learning Blog, 2015

LECTURE 10

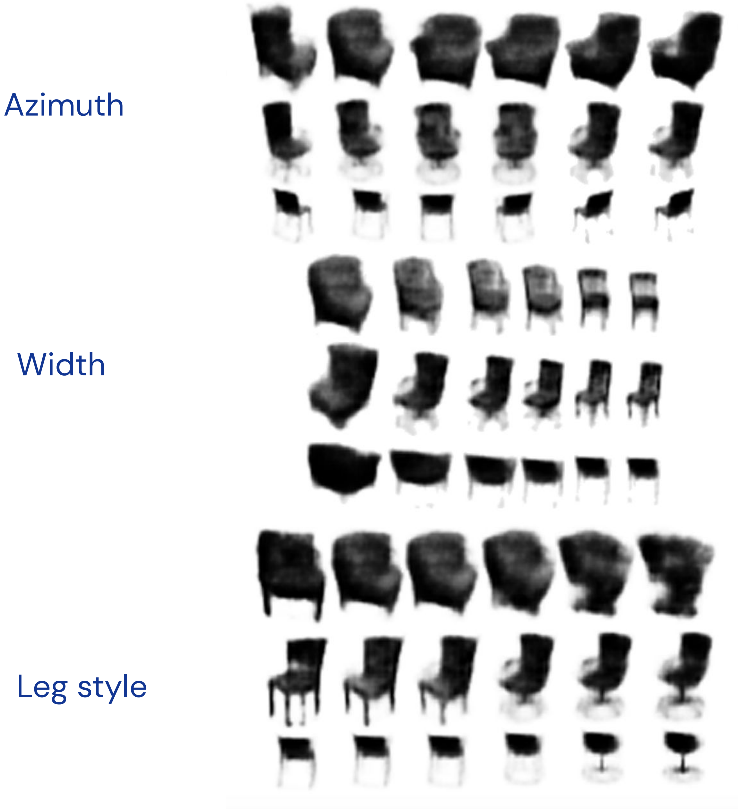
Frontiers in Deep Learning: Unsupervised Representation Learning

Mihaela Rosca & Irina Higgins

Frontiers in Deep Learning: Unsupervised Representation Learning

(Mihaela Rosca & Irina Higgins)

- What is a good representation?
- Unsupervised learning has potential to address open problems like data efficiency, generalisation, robustness, fairness etc
- Different approaches such as disentangling, CPC, VQ-VAE, Bert, auxiliary losses for RL



β-VAE: Learning basic visual concepts with a constrained variational framework, (Higgins et al, ICLR 2017)

LECTURE 11

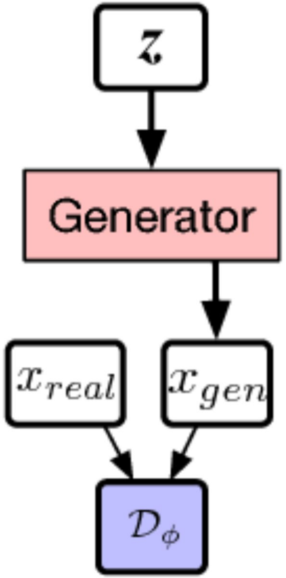
Generative Adversarial Networks

Mihaela Rosca & Jeff Donahue

Generative Adversarial Networks

(Mihaela Rosca & Jeff Donahue)

- Generative adversarial networks (GANs, Goodfellow et al. 2014) promising approach to generative modeling
- Two "competing" networks: a generator tries to fool a discriminator with synthesised data
- Variations, e.g., CycleGAN, VAE-GAN hybrids, bidirectional GAN
- Domains, such as video and speech synthesis



Variational Approaches for Auto-Encoding Generative Adversarial Networks
(Mihaela Rosca et al 2017)

LECTURE 12

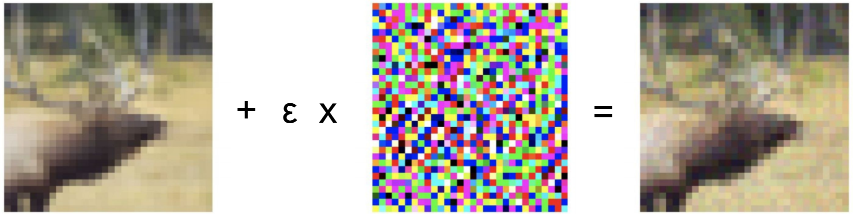
Responsible Innovation

Iason Gabriel & Chongli Qin

Responsible Innovation

(Iason Gabriel & Chongli Qin)

- AI provides powerful tools that are shaping our lives and society
- With great power comes great responsibility
- How to build safe, robust, and verified AI systems that do exactly what we expect of them
- How to think about the ethical consequences of building and deploying AI systems



The Three Laws of Robotics (Asimov, 1942):

1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey the orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Laws.

Thank you

Questions