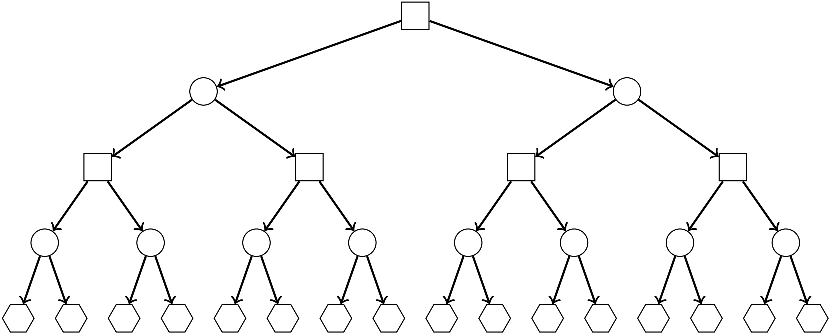
Artificial Intelligence for Perfect Information Games

Thibault Gauthier

November 8, 2017

Solving a game



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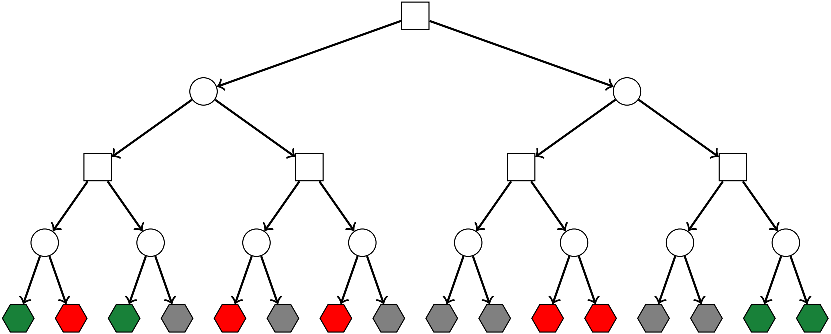
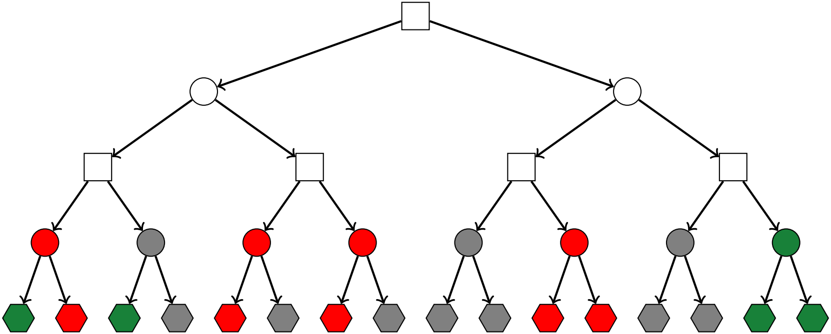


: win, : lose, : draw

Solving a game



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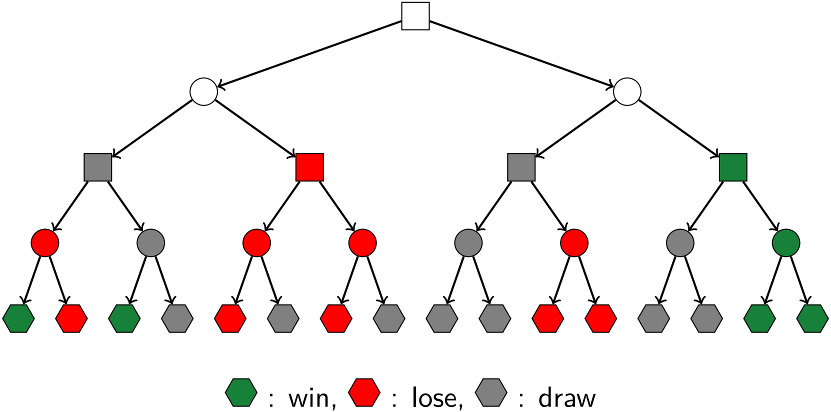

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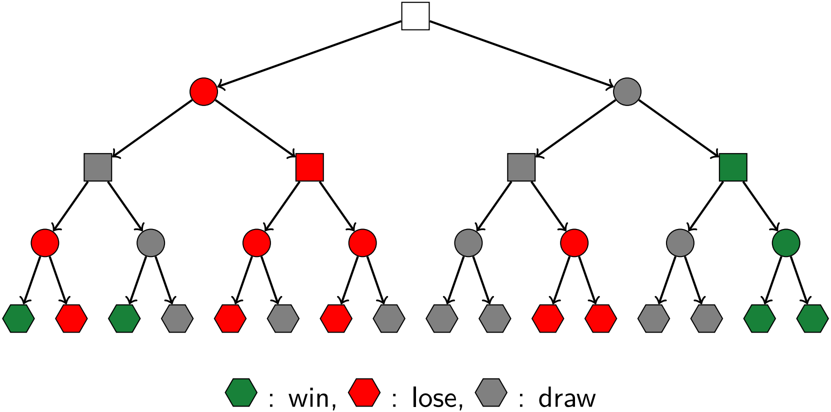

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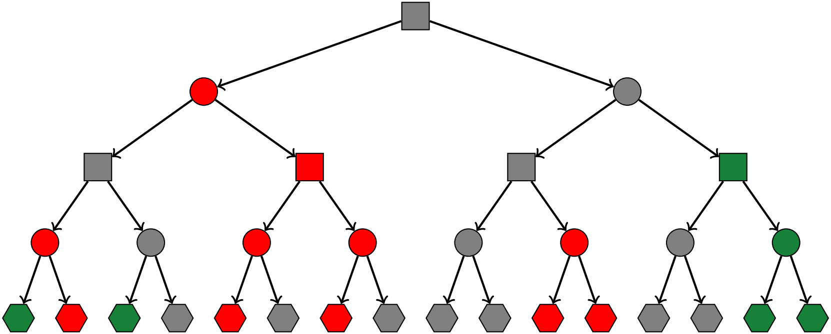

: win, : lose, : draw

Game complexity

Game	Moves	Length	Positions	Solved
Tic-Tac-Toe	4	9	10^3	
Checkers	2.8	30	10^{20}	
Chess	35	70	10^{47}	
Go	250	150	10^{170}	

Game complexity

Game	Moves	Length	Positions	Solved
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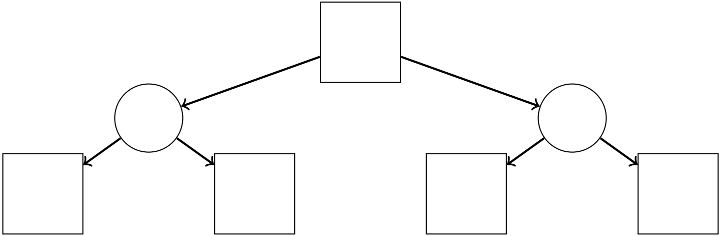
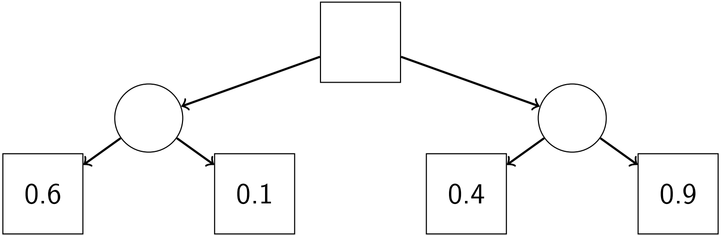
Minimax algorithm



Minimax algorithm



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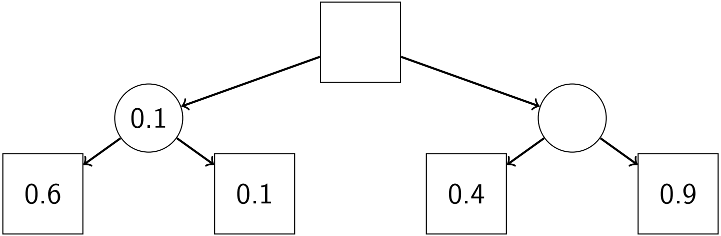

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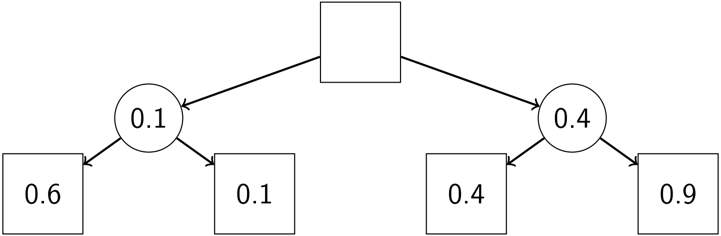

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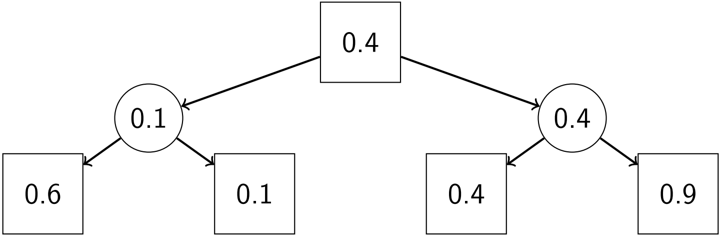
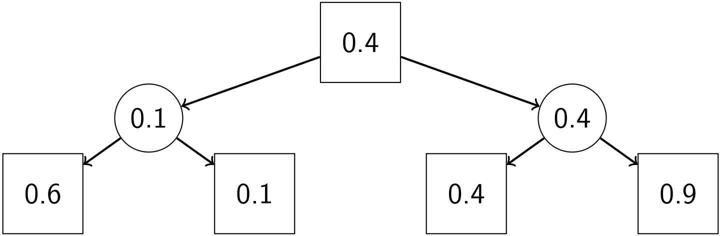


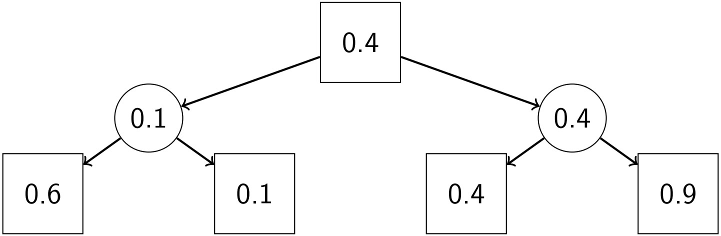
Evaluation and policy



$$Evaluation: \quad Position \to \mathbb{R}$$
$$Policy: \quad Position \to \mathbb{R}^{Move}$$

$$Evaluation(root) =$$
$$Policy(root) =$$

Evaluation and policy



$Evaluation: \ \ Position \rightarrow \mathbb{R}$
$Policy: \ \ Position \rightarrow \mathbb{R}^{Move}$

$Evaluation(root) = 0.4$
$Policy(root) = Left\ 0\%\ Right\ 100\%$

Heuristics

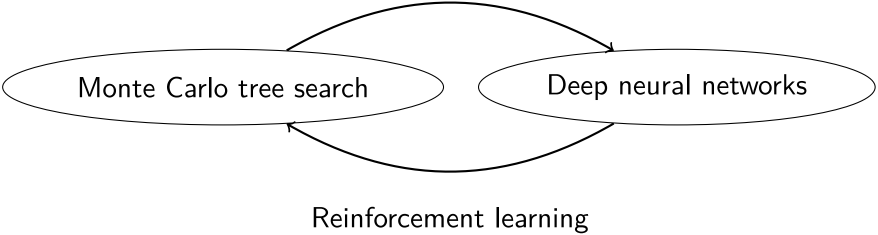
In chess:

- Evaluation: value of pieces, king's safety, pawn doubling, . . .
- Policy: derived from evaluation
- Search: minimax + alpha-beta pruning + . . .

In go (before 2016):

- Evaluation: random playouts
- Policy: statistics on good shapes
- Search: Monte Carlo tree search

AlphaGo



[2] Mastering the Game of Go without Human Knowledge
David Silver, Julian Schrittwieser, Karen Simonyan et al.
Nature 550, 354–359, 2017

Monte Carlo tree search with priors

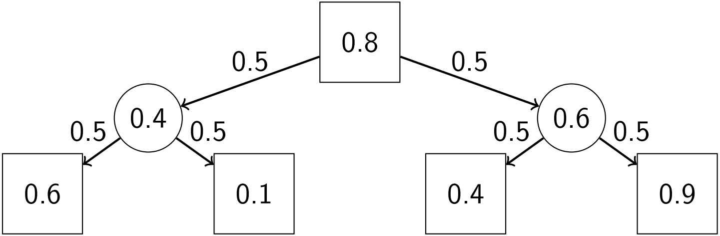
Let P_{prior} be a fixed policy and E_{prior} be a fixed evaluation.
MCTS computes a "better" evaluation $E_{average}$ and policy $P_{average}$.

1. Choose a sequence of moves leading to a position s based on:

$$E_{average} + \frac{P_{prior}}{P_{average}}$$

2. Extend the tree by applying all possible moves from s.
3. Evaluate s using E_{prior}.
4. Update $E_{average}$ and $P_{average}$ for all ancestors of s.

Monte Carlo tree search with priors



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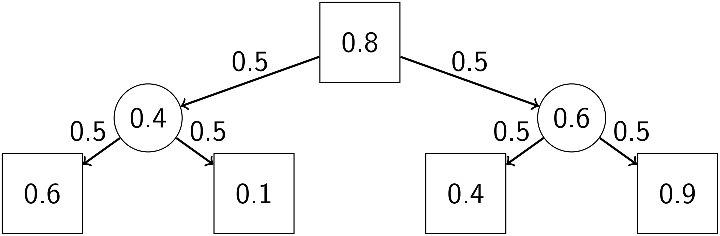

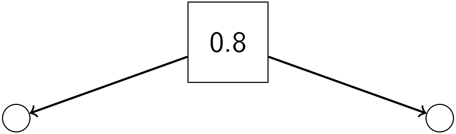

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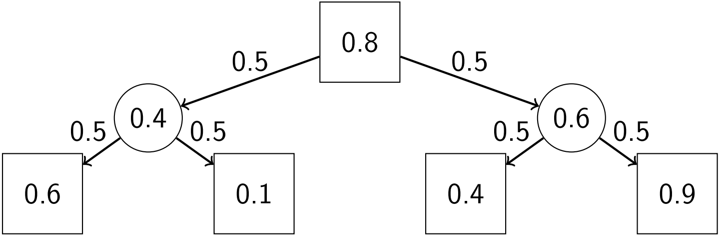

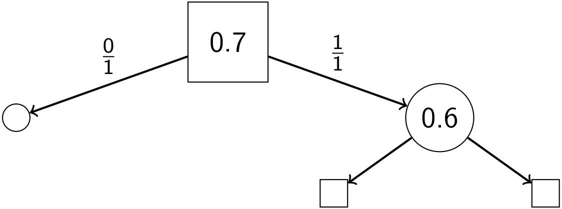

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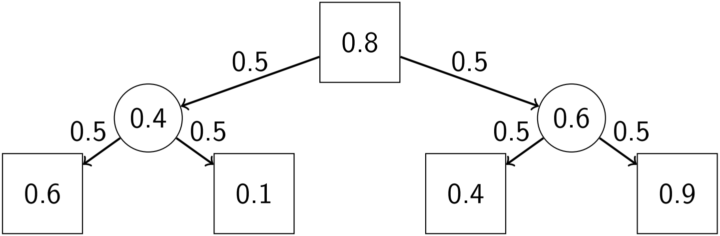

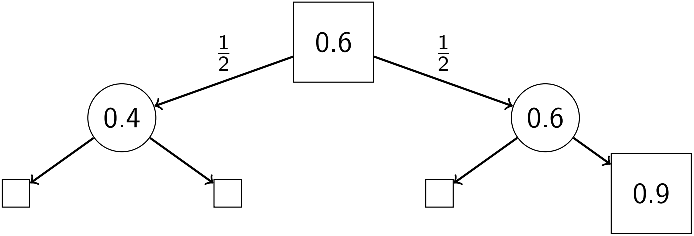

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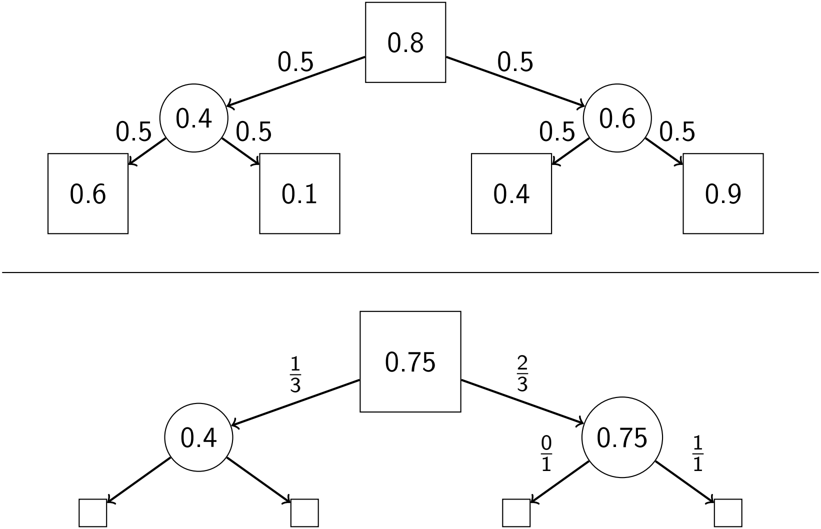
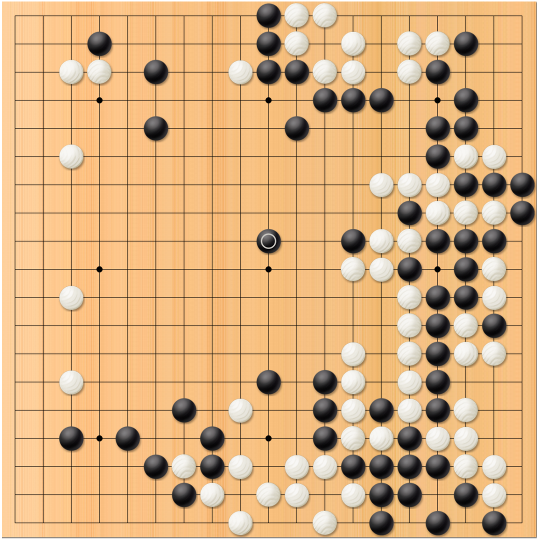


Monte Carlo tree search with priors: summary

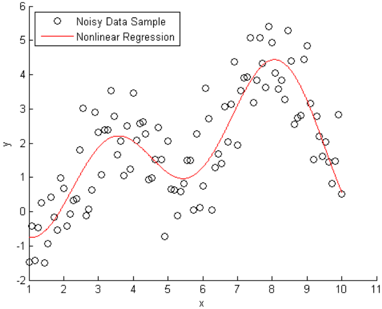
1. Input: Prior evaluation, policy.
2. Simulations from a starting position s_{start}
3. Output: Example of a better evaluation and policy for s_{start}
4. Repeat the process with different starting position for more examples.

Go is mostly a pattern recognition game



Machine learning

From data points (training examples), to generalization and compression of information.



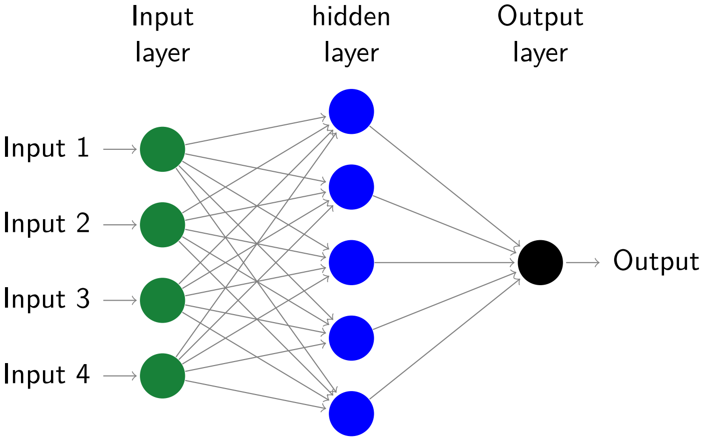
`https://datascience.stackexchange.com/questions/9529/how-to-select-regression-algorithm-for-noisy-scattered-data/9535`

Machine learning for pictures input: Convolutional neural networks

- 2012: Distinguishing cats from dogs in pictures.
- 2015: Predicting the next played move with 57% accuracy high amateur games at the game of Go.

Neural networks

Each arrow is associated with a weight use to multiply its input.



The hidden layer is fully-connected.

Training a neural network

Type of examples:

neural network	input-output
policy network	position-policy
value network	position-evaluation

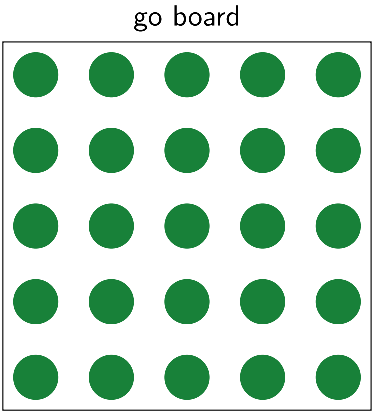
Generating examples:

- from professional games
- from self-play

Training algorithm:

- modification of the weights by gradient descent (backpropagation)

A convolution of 256 filters of kernel size 3x3 with stride 1



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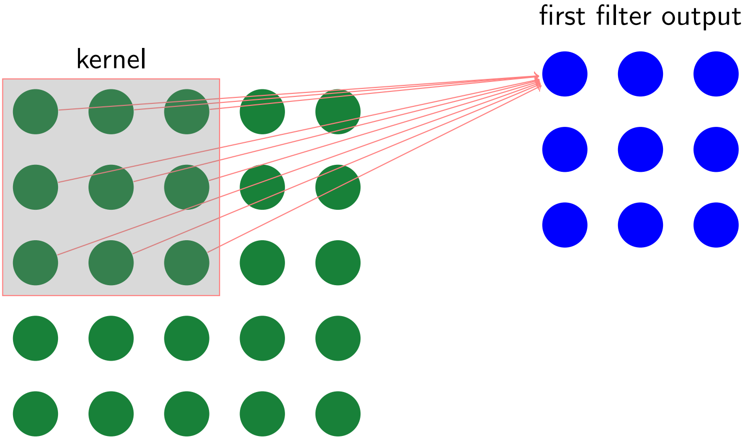

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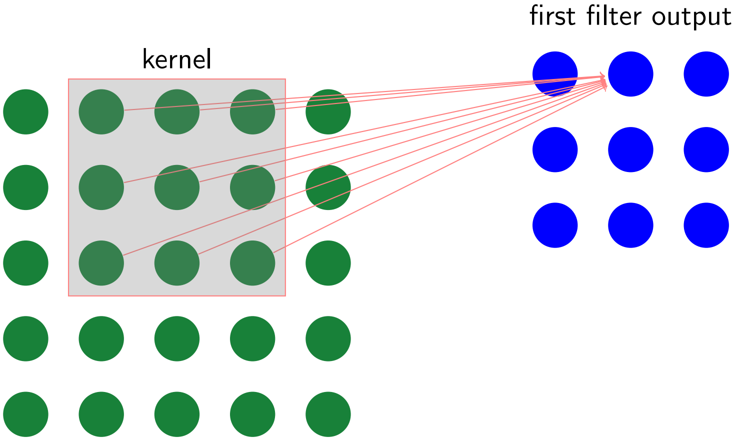

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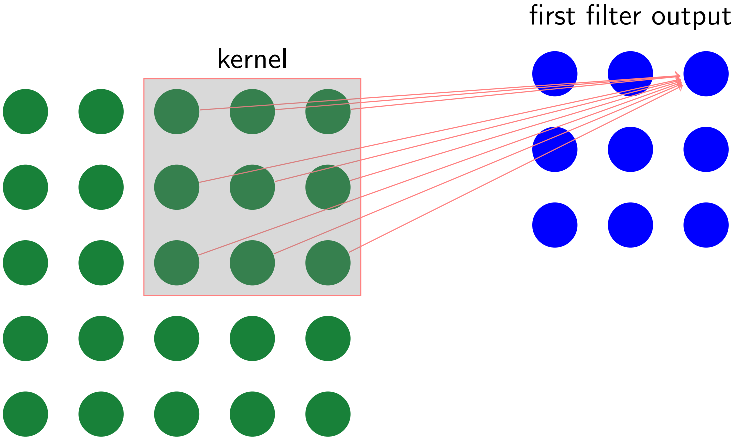

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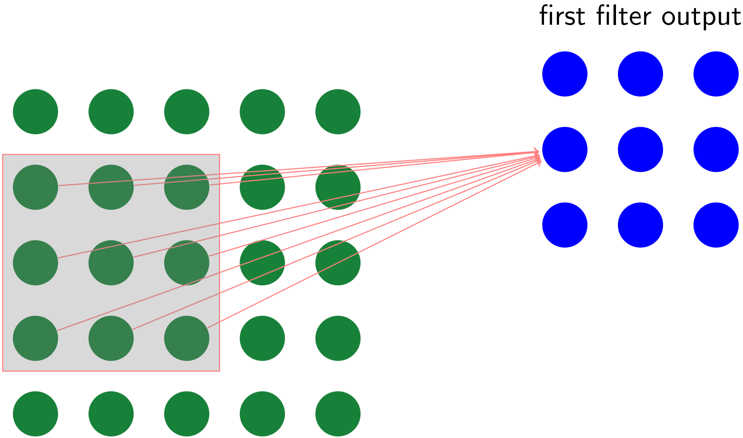

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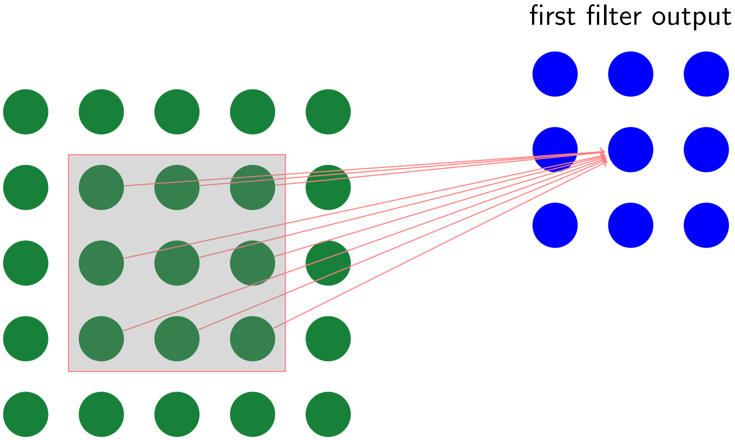

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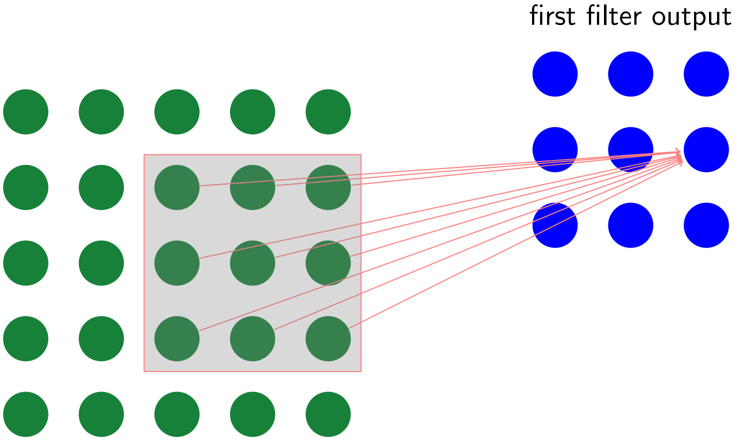

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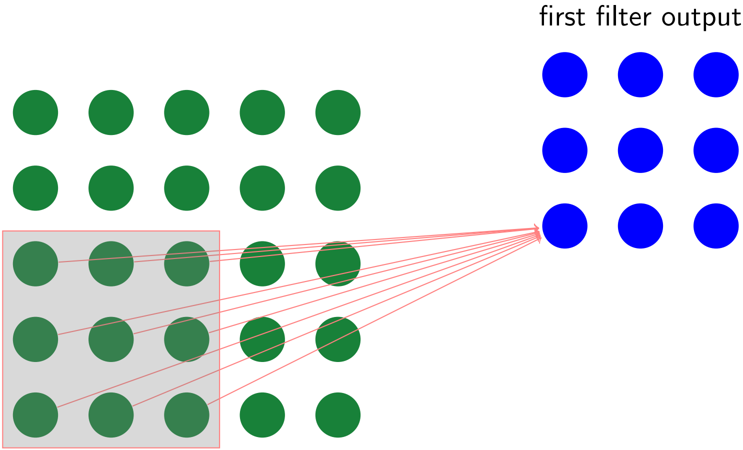

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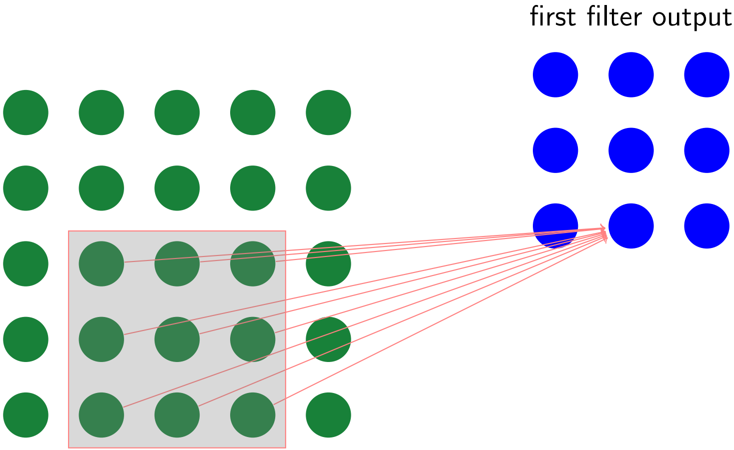

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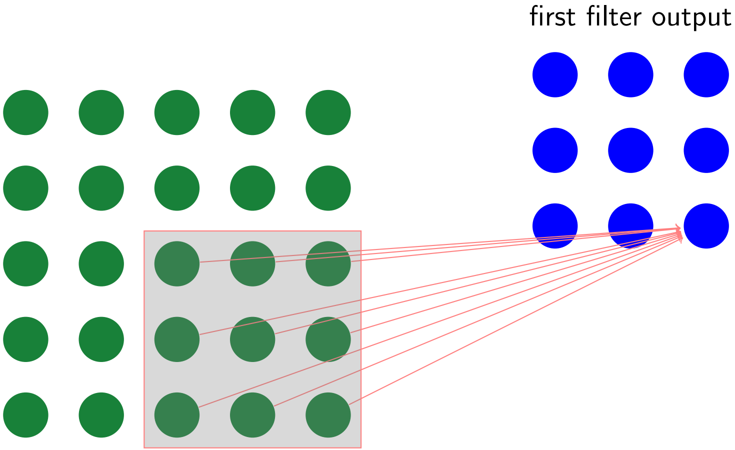

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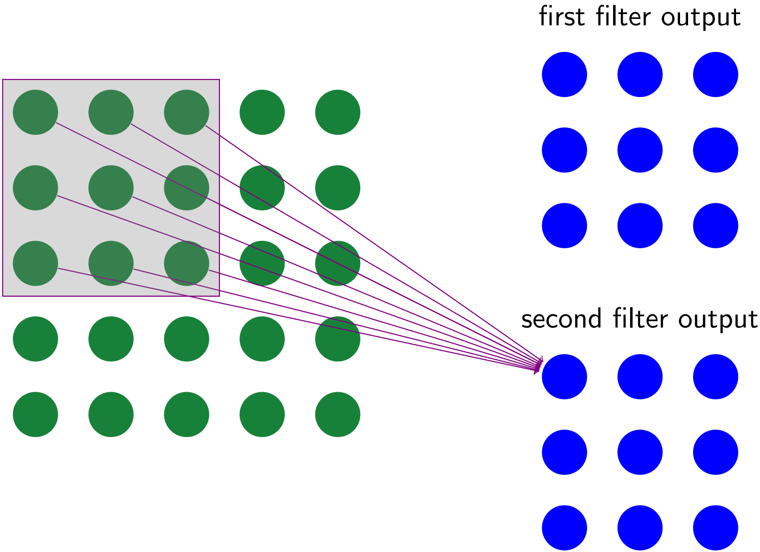

Neural network architecture

- Input: Go position.
- Neural network
  - 79 convolutional layers
  - Batch normalizations
  - Residual connections
- Output
  - policy: 2-fully connected layer
  - evaluation: 3 fully-connected layer

Self-learning system

1. Start with random prior policy and prior evaluation.
2. Self-play using Monte-Carlo Tree Search with 1600 simulations.
3. Create better examples position-policy and position-evaluation.
4. Generalize and compress by training the neural network architecture.
5. Better policy and evaluation becomes prior policy and evaluation.
6. Loop to 2.

Performance and legacy

- Beat the best human player at go:
  Go is easy.
- Rediscover human go knowledge through self-learning:
  With suitable algorithms, complex strategies can be build by accumulating small improvements.