Using Domain-specific Knowledge for Monte Carlo Tree Search in Go

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Contents

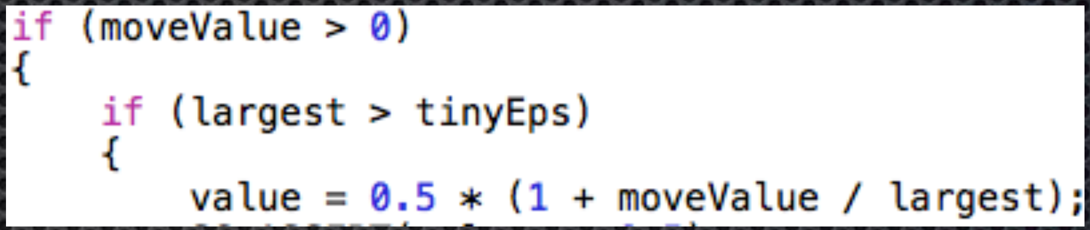
- Introduction - why use domain knowledge?
- Many kinds of knowledge in Go
- How to acquire
- How to use
- Research problems

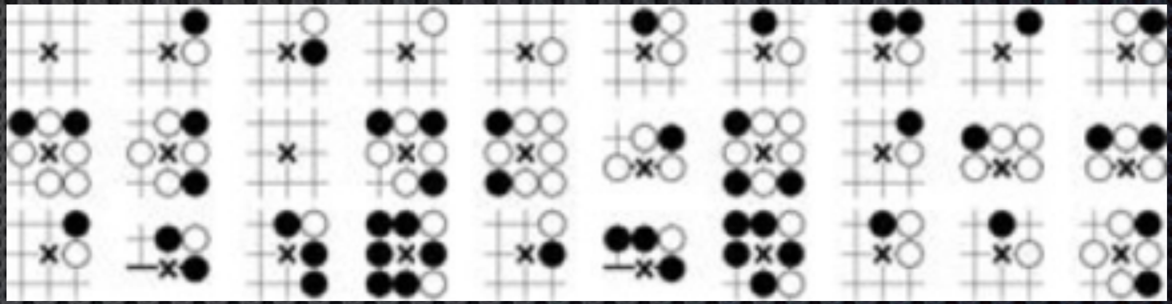
Format of Talk

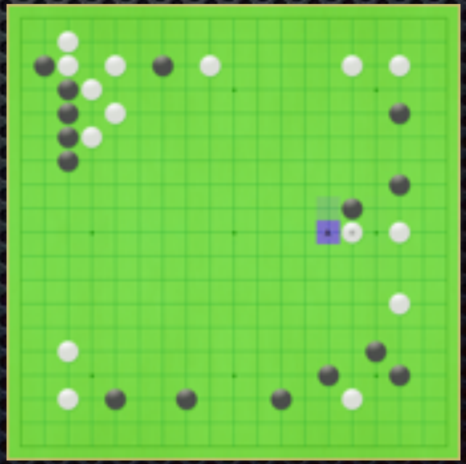
- Informal talk, much is unpublished, work in progress
- I have more questions than answers…
- I use our Fuego program as an example

Many Types of Knowledge in Go

- Rules, if-then-else…
- Patterns
- Deep neural networks
- Search control knowledge
- Exact knowledge, e.g. proven wins
- And more…



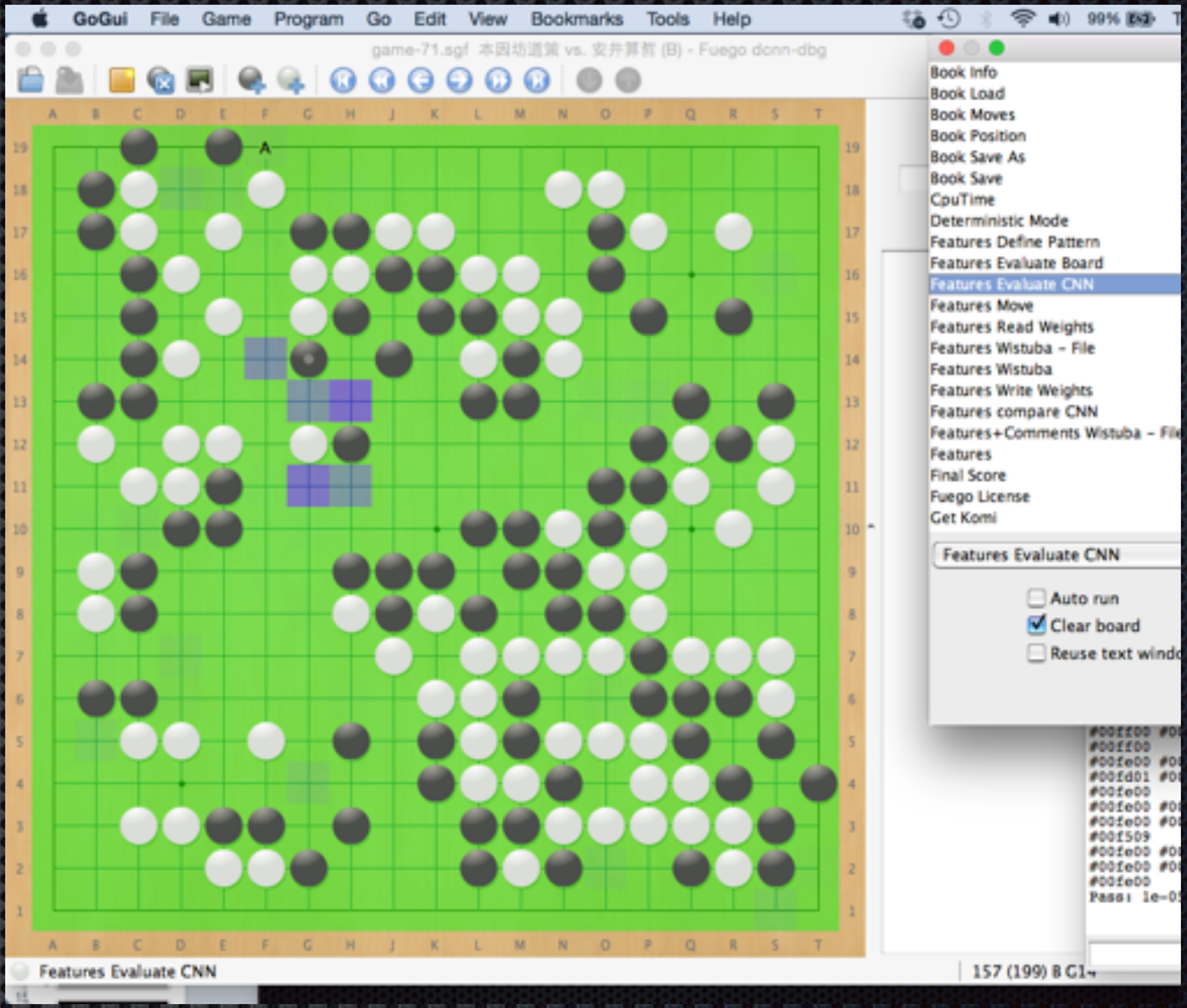




Credits: sciencedaily.com

About Fuego

- Fuego is:
  - A Game-independent MCTS framework
  - A Go program
  - Open source
  - Mostly developed at University of Alberta
- Many other programs use Fuego as basis (e.g. MoHex)
- Many researchers have used Fuego for experiments



The Fuego Go Program

- Developed since 2008, based on older Go program Explorer
- Uses Monte Carlo Tree Search (MCTS), RAVE, prior knowledge
- MoGo-style rule-based simulations (+ some changes)
- Lock-free multithreading
- In 2009, won 9x9 game on even vs Chou Chun-Hsun
- Won the 2009 Computer Olympiad 9x9 and 2010 UEC Cup (19x19)
- MP-Fuego: massively parallel version (TDS-df-UCT, Yoshizoe) uses up to 2000 cores
- Strength: Fuego on good PC about 1 dan, MP-Fuego maybe 3 dan

Types of Knowledge in Fuego

- Part 1: Simulations (very short here)
- Part 2: In-tree knowledge (a lot)
  - Rules, features, “Greenpeep” patterns
- Part 3: “Slow” knowledge (some)
  - DCNN
  - Tactical search
- [Part 4: Exact knowledge - not today]

Part 1: Simulations

- Fuego: Rule-based, as in MoGo
  - Select move from highest-ranked rule that produces at least one move
- Alternative: probability-based, as in Crazy Stone
  - Weight map over all legal moves
- Used to select the next move to play in simulation
- Speed about 1,000,000 moves/second/core

Research Questions

- What works in simulations?
  - Right now, we still mostly use trial-and-error
- How to design an effective playout policy?
- How to evaluate a policy? (without playing thousands of test games)
- What distinguishes a good from a bad policy?

Part 2: In-Tree Knowledge

- Evaluated for each node in the game tree
- Used in UCT formula to select best child in tree
- Big influence on shape of tree
- Speed goal: about 1000 nodes/second/core

Using In-Tree Knowledge

- Assume you have some knowledge. What do you do with it?
- Three main approaches in the literature
- Two are used in Fuego
  - Initialize playout statistics with “fake” wins and losses
  - Add a third term to the UCB formula: mean + exploration + knowledge

Third Way: Iterative Widening

- Consider only N best moves
- Increase N over time
- Never tried in Fuego

Fuego’s In-Tree Knowledge

1. Oldest: hand-coded rules,
   “fake” wins and losses

2. Next: “Greenpeep” patterns,
   additive knowledge

3. Recent: Feature learning using
   Latent Factor Ranking

1. Handcoded Rules

- Simple, crude rules (from 2008)
  - Bonus for moves in corner and on 3rd line
  - Bonus for moves in low-liberty situations (e.g. ladders)
  - Bonus for moves from the simulation policy
- Weights (number of wins/losses) tuned manually

2. “Greenpeep” Patterns

- Greenpeep was the name of a Go program by Chris Rosin
- Greenpeep used 12 point diamond-shaped patterns with extra knowledge (liberty counts)
- Chris developed a machine learning technique based on self play to train weights
- “Additive” knowledge in Fuego, about 130 Elo improvement (about 2010)
- Theory: C. Rosin, Multi-armed bandits with episode context, ISAIM 2010

3. Feature Learning Using Latent Factor Ranking

- Work on feature learning
  - Remi Coulom, Computing Elo Ratings of Move Patterns in the Game of Go, 2007
  - Later improved by Coulom and Aja Huang
  - Wistuba and Schmidt-Thieme,
    Move Prediction in Go – Modelling Feature Interactions Using Latent Factors, KI 2013

From Coulom to Wistuba

- Main change:
- Model pairwise interactions between features
- Example: A and B may be OK features by themselves, but A and B together is really good

Main Ideas in Feature Learning

- Moves are described by a set of features, e.g. pattern, tactics, location, distance
- Assign Weights to features to maximize “move prediction”:
- Try to guess which move was played by a strong human player

Feature Details

features_move O3

FE_EXTENSION_NOT_LADDER

FE_LINE_3

FE_DIST_PREV_3

FE_GOUCT_ATARI_DEFEND

FE_GOUCT_PATTERN

FE_POS_6

FE_GAME_PHASE_3

FE_CFG_DISTANCE_LAST_2

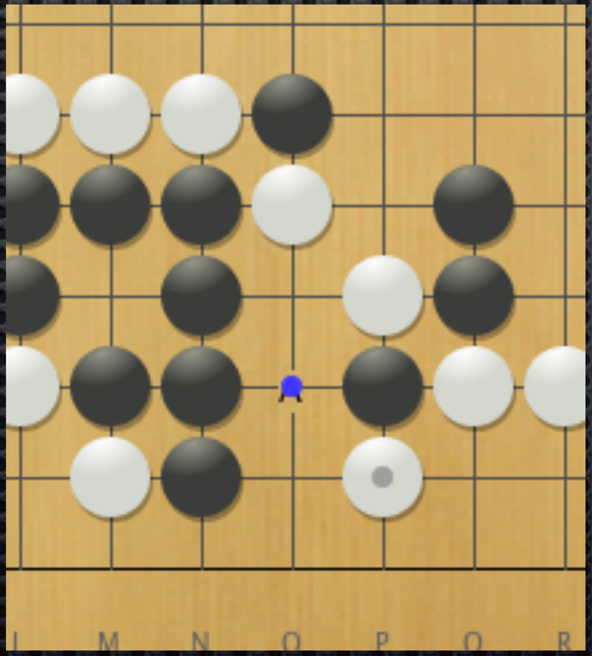
FE_CFG_DISTANCE_LAST_OWN_4_OR_MORE

FE_SAVE_STONES_1

WBW

EEE

BBB



features_move K2

FE_ATARI_LADDER

FE_LINE_2

FE_DIST_PREV_10

FE_POS_10

FE_GAME_PHASE_3

FE_CFG_DISTANCE_LAST_4_OR_MORE

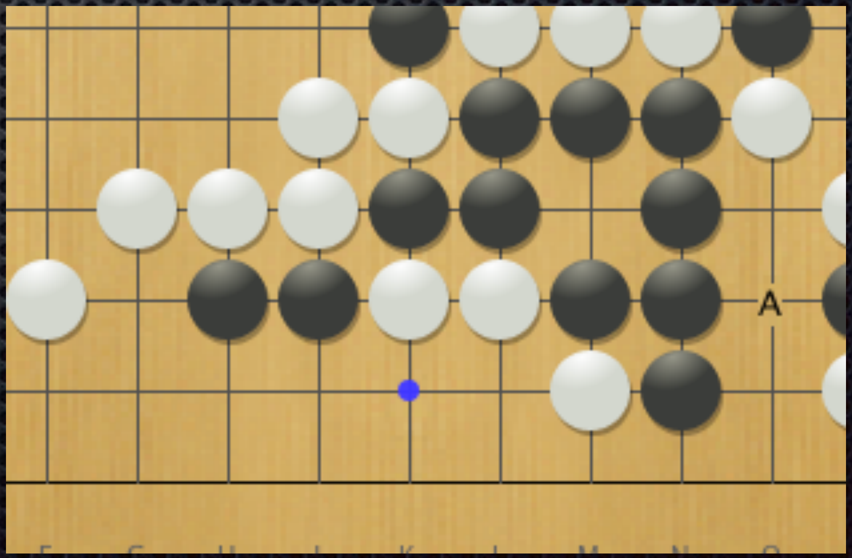
FE_CFG_DISTANCE_LAST_OWN_4_OR_MORE

FE_KILL_STONES_2

EEE

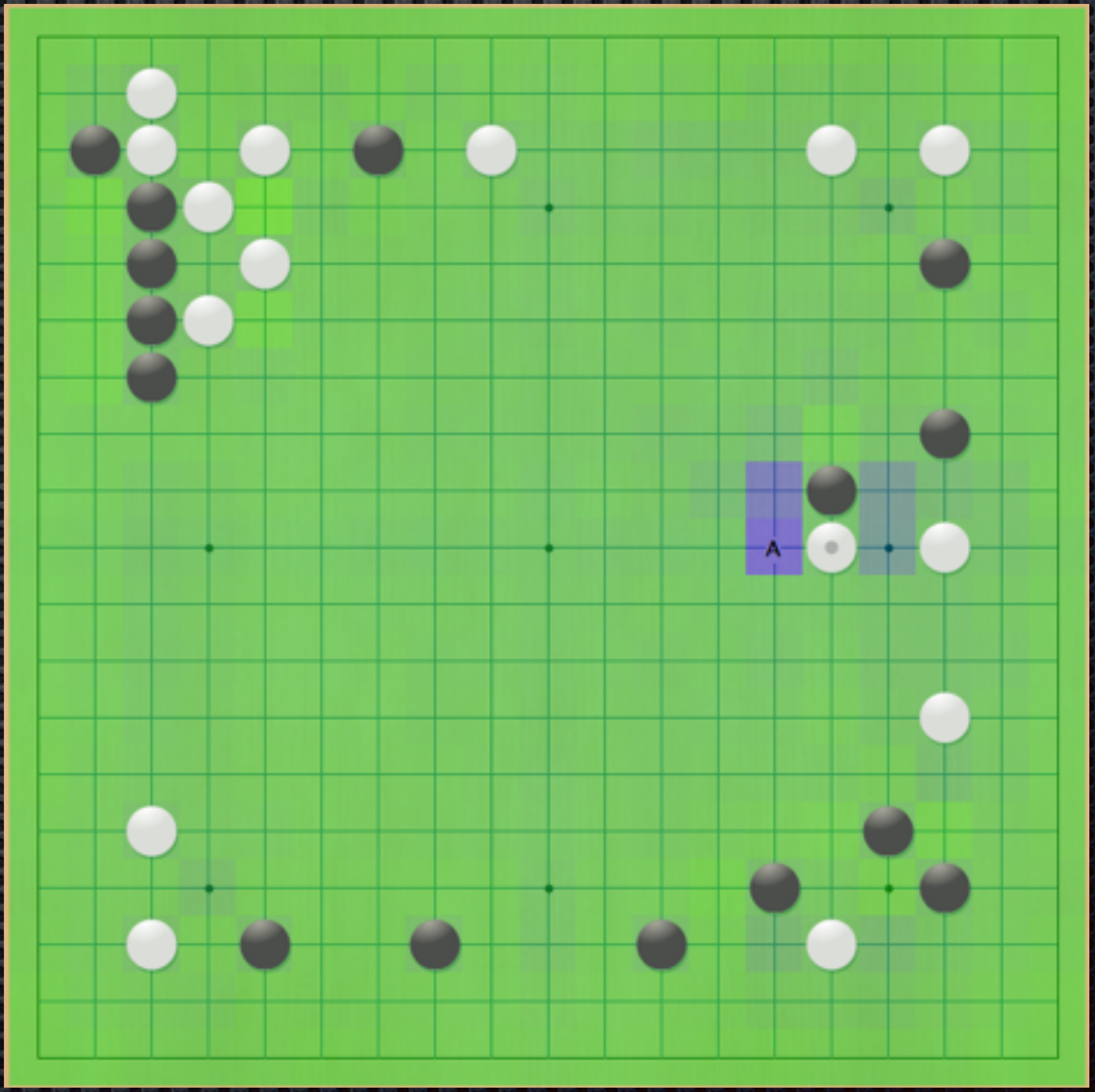
EEE

BWW



Example in Fuego

- Simple features
  + 3x3 patterns
- Trained weights with 20000 master games
- blue = good
- green = bad



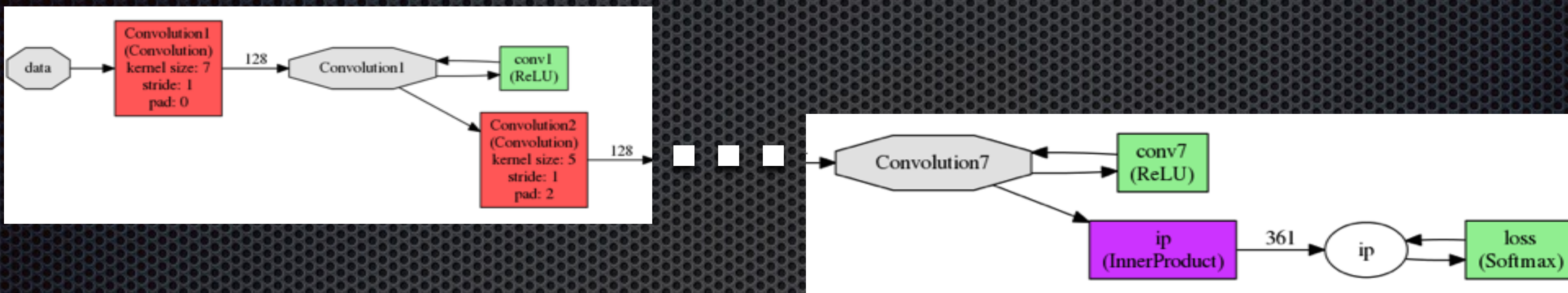
Current Work on Features in Fuego

- By Chenjun Xiao
- Add large patterns, not just 3x3
  - Almost done…
- New algorithm for training
  - (Slightly) better results than Wistuba
  - Produces probabilities for moves being best, not just “some numbers”

Part 3: Slow Knowledge

- Too slow to compute at every node in the search
- Can still be useful
- Two Examples:
  - Deep neural network
  - Tactical search

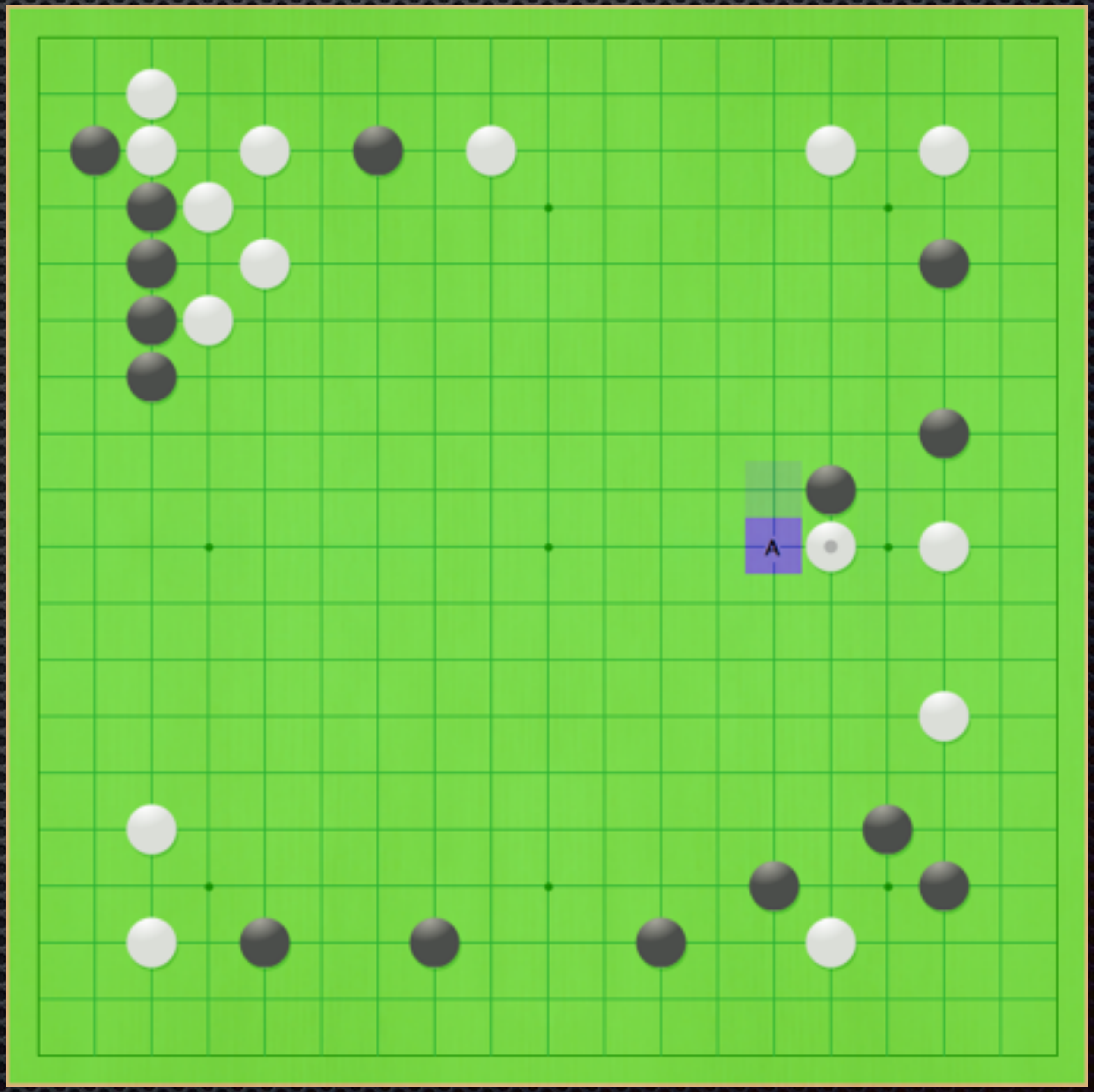
Deep Convolutional Neural Networks (DCNN)



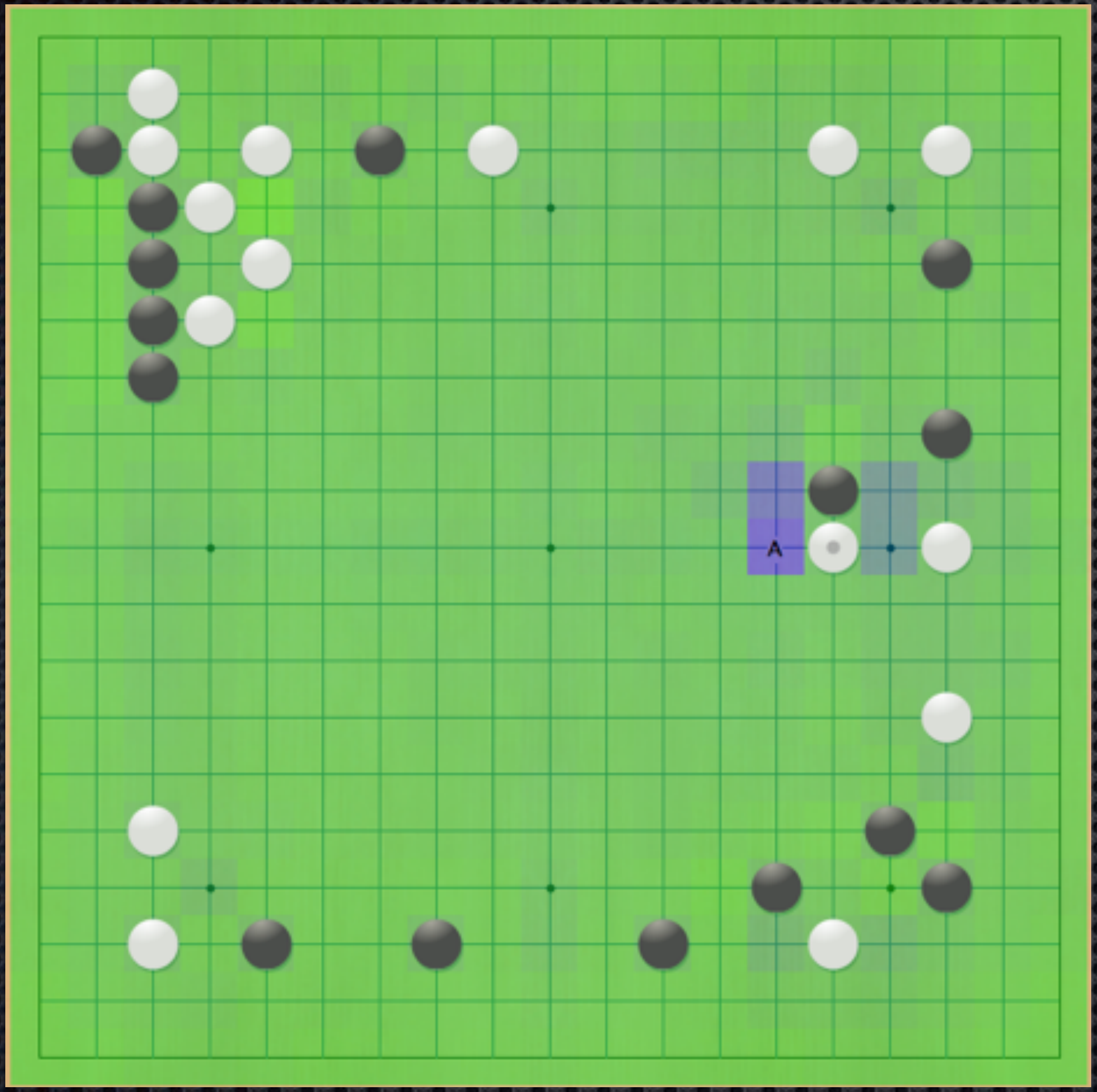
- Introduced for Go in two recent publications
  - Clark and Storkey, JMLR 2015
  - Maddison, Huang, Sutskever and Silver, ICLR 2015
- Very strong move prediction rates, 55.2% (Maddison et al)
- Slow to train and use (even with GPU)

DCNN in Fuego

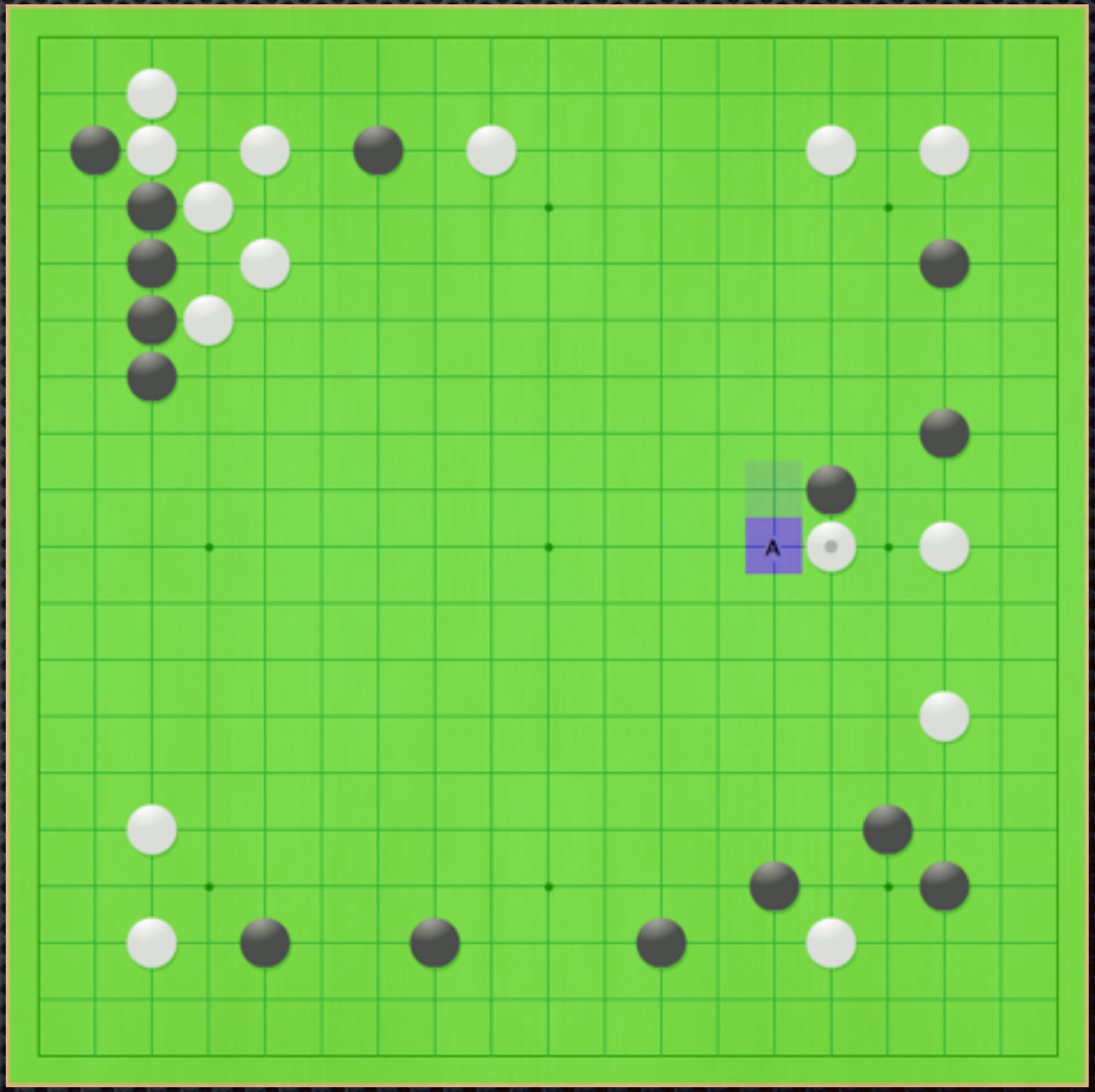
- We use networks trained by Storkey and Henrion (Storkey's new student)
- Integrated in Fuego by Andrew Jacobsen (my student)



Features vs DCNN

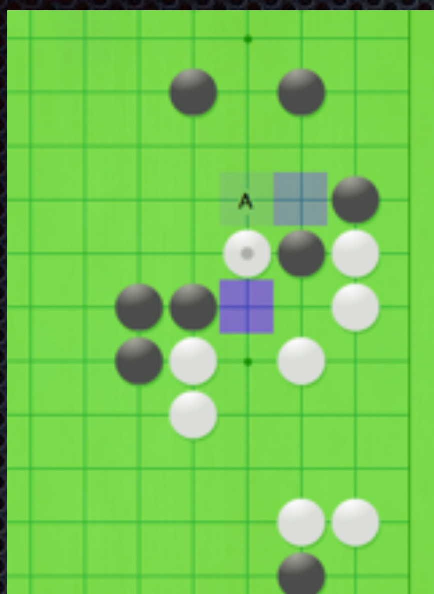


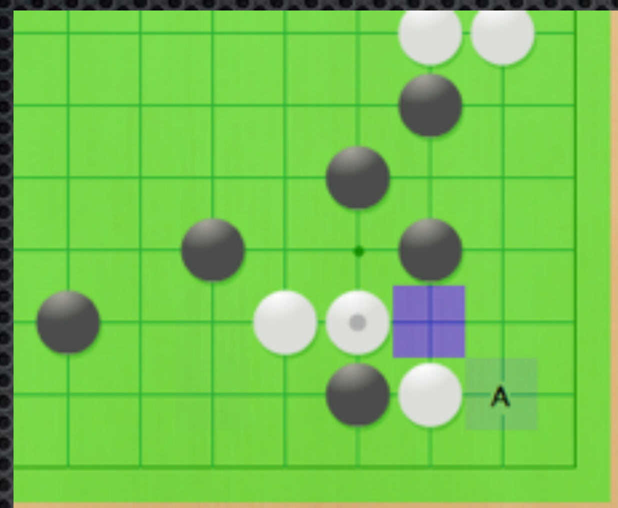
Feature Knowledge

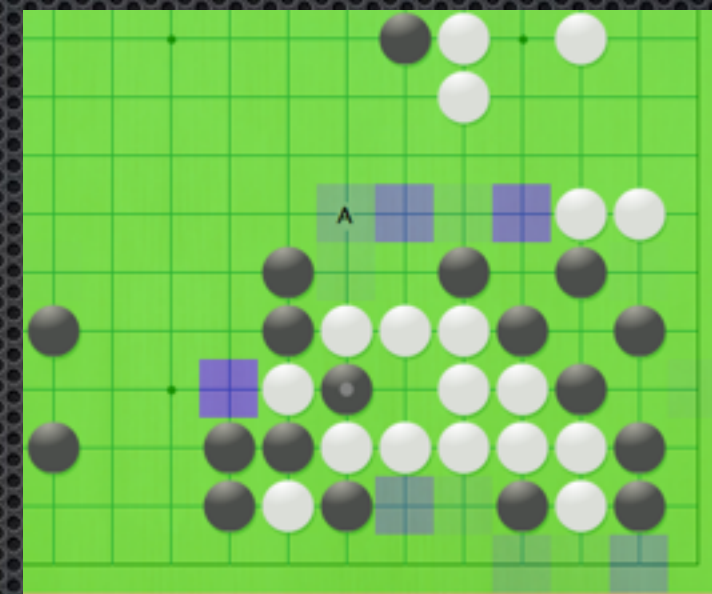


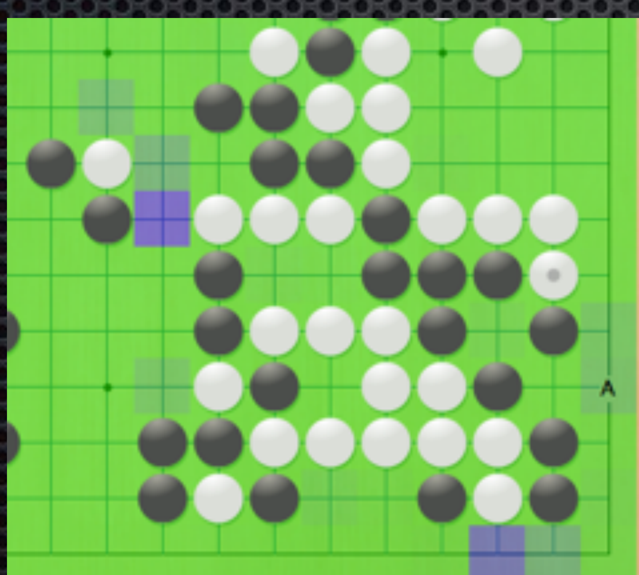
DCNN Evaluation

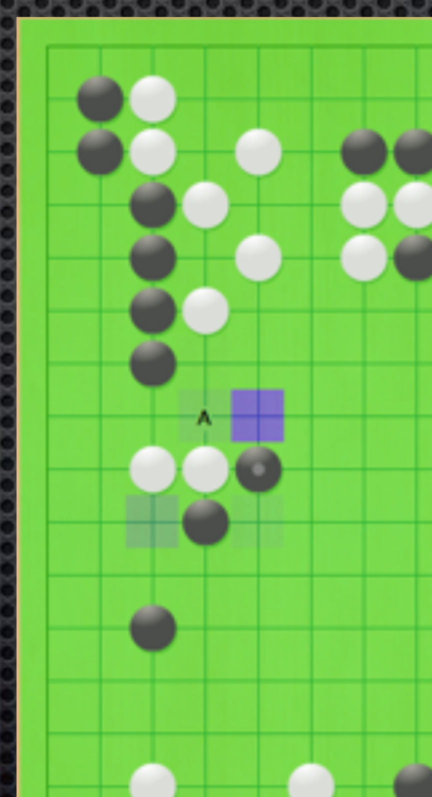
Some Examples of Bad DCNN Moves

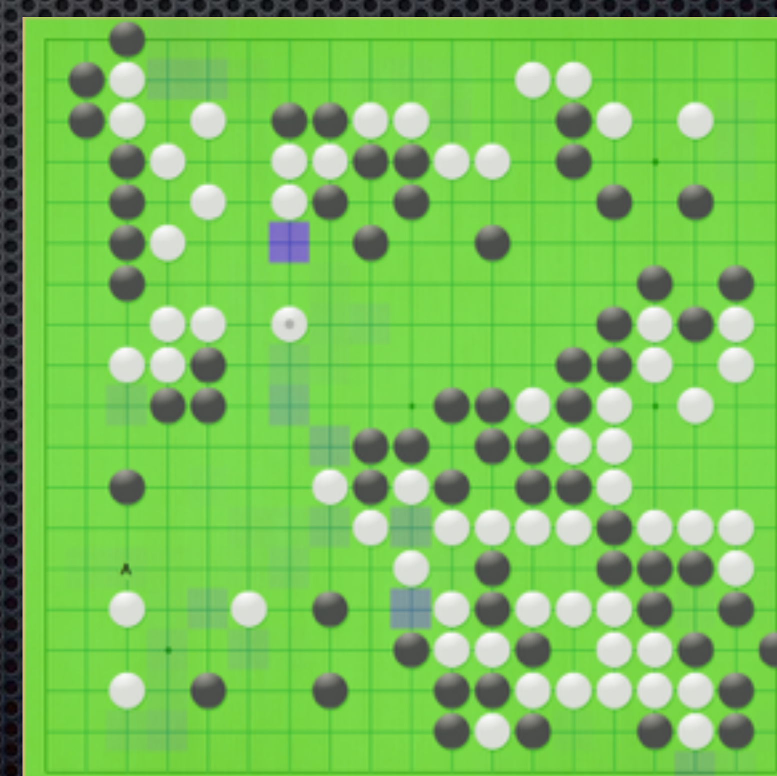












Research Questions

- How to learn when:
  - Move is usually bad, but good here (e.g. empty triangle example)
  - Move is usually good, but bad here (e.g. cut example)
- Training based on statistics of “similar” examples cannot help - unless definition of “similar” is *extremely* good
- How to catch these cases by exploration in MCTS

How to use Slow Knowledge?

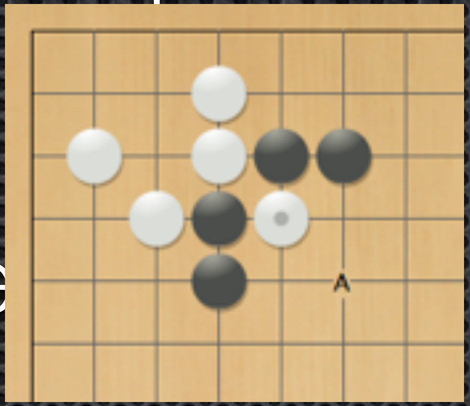
- Solution in Fuego
  - Threshold N, e.g. N=200
  - Call slow knowledge for all nodes that reach N simulations
  - For large N, this is a very small percentage of all nodes
  - Can do something expensive

Discussion

- Problem: knowledge is only called after many simulations
- MCTS may not be changed much
- How to balance?
- Better call right away? But for which nodes?
- Our DCNN-Fuego prototype calls DCNN first, but only at root

Tactical Search

- Observation: Fuego often makes simple tactical mistakes
  - Example: “geta”, capture by ne



- Can be solved by a small tactical search
- Our old program Explorer contains such a search
- Use as slow knowledge, give bonus to moves that save or capture
- About 70-80 Elo improvement for simple implementation

Other Ideas for Knowledge

(not implemented in Fuego)

- Local Life and Death search
- Semeai (capturing races)
- Prove safety, or invade/defend territories
- Local searches to filter which moves make sense locally

Discussion

- Many kinds of knowledge used in Go
- Old programs were mostly about encoding knowledge
- First MCTS programs used very little, but it is all coming back
- Want to use machine learning to deal with large amounts of knowledge
- Self-play or learn from human master games

Discussion (2)

- Simulation policies are still “magic”
- Probably the biggest differences between top programs and open source programs are in this area
- Need scientific principles to design better policies

Discussion (3)

- Integrating “slow” knowledge is a big challenge
- How to “mix” it with a MCTS?
- We have only crude solutions (threshold, root-only)
- Can we predict which nodes are important, so we can call slow knowledge immediately?

Summary

- Reviewed knowledge in MCTS Go programs, especially Fuego
- Many imperfect, incomplete solutions
- Many different but overlapping approaches
- Can we unify them based on a good theory?
- Still much work to be done to understand and improve
- What we do in Go can help other applications