#### Drafting Territories in the Board Game Risk

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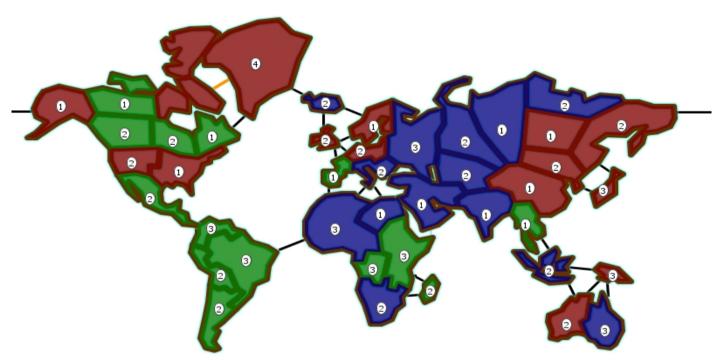




#### **Outline**

- Risk
  - Drafting territories
- How to draft territories in Risk?
  - UCT + machine-learned evaluation function
- Empirical results
- Conclusions + Future Work

#### Risk



http://sillysoft.net/lux

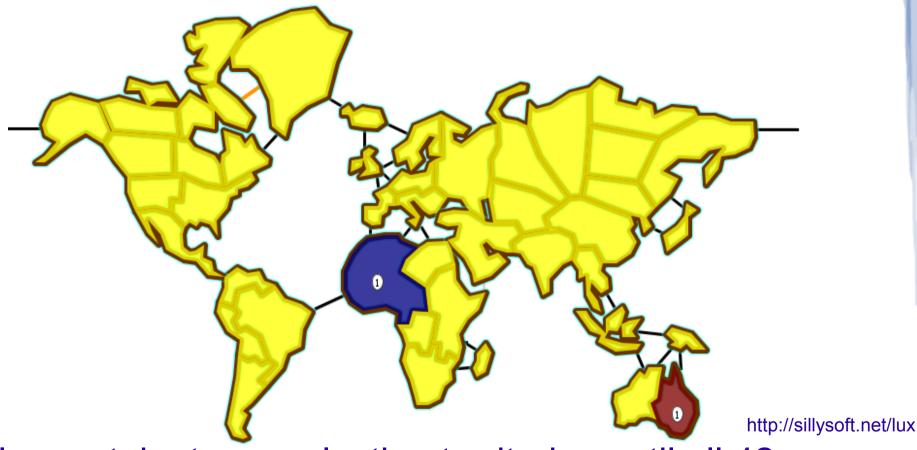
- Classic multi-player board game
- A number of computer implementations, including Lux Delux by Sillysoft Games
- Popular!

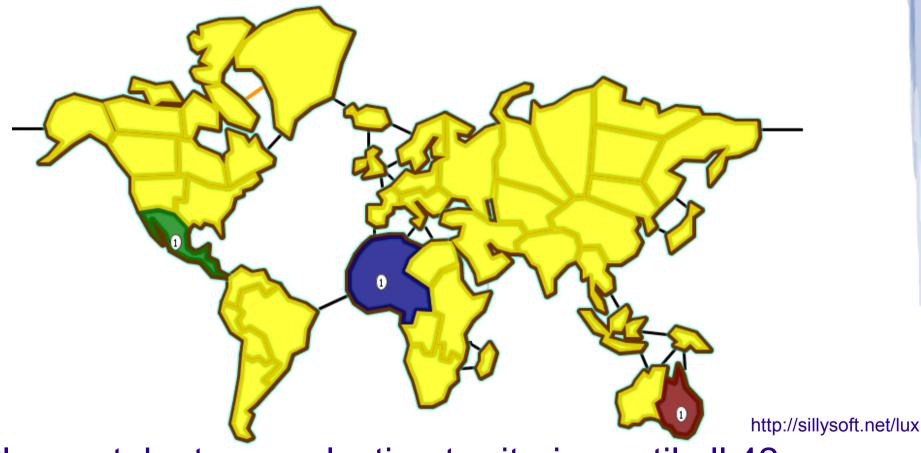
#### Risk

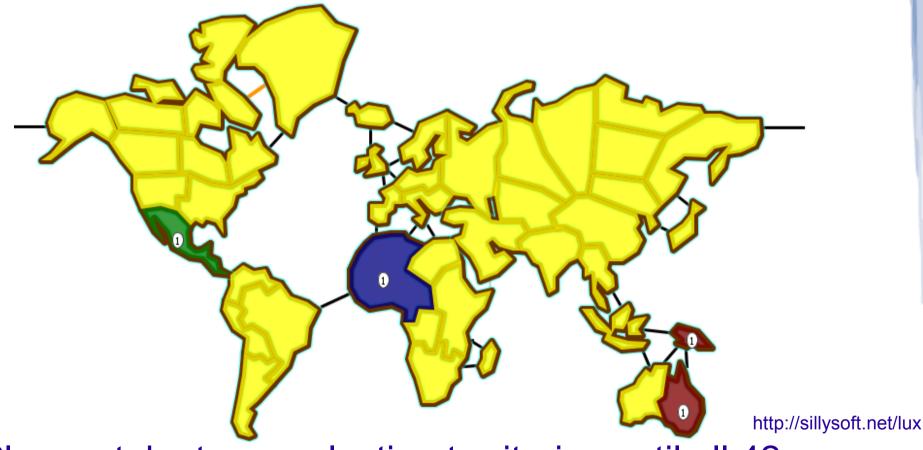
- Researchers are also interested:
  - Using multi-agent system technology in risk bots, Johansson and Olsson, 2006.
  - Mixing search strategies for multi-player games, Zuckerman, Felner, and Kraus, 2009.
- Both papers use non-standard variant where territories assigned randomly to begin the game.

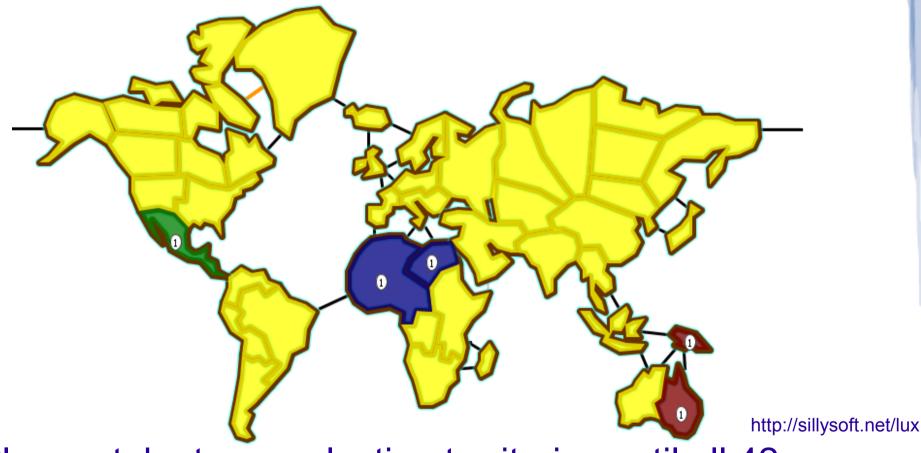


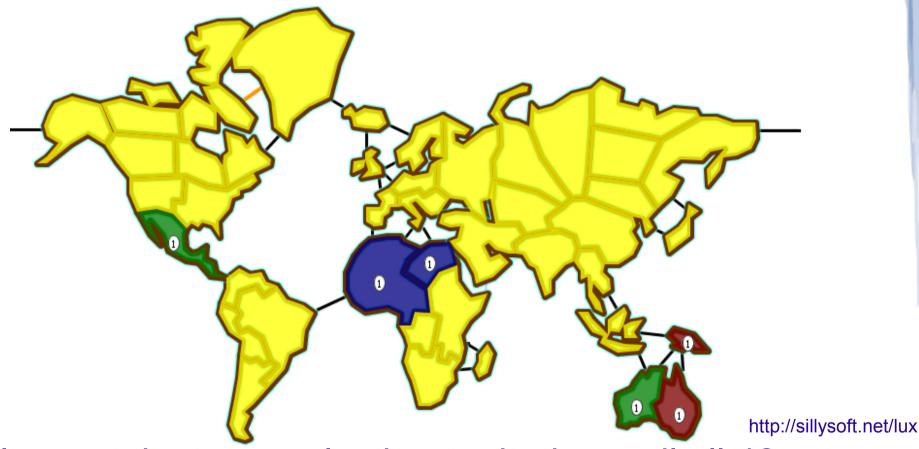




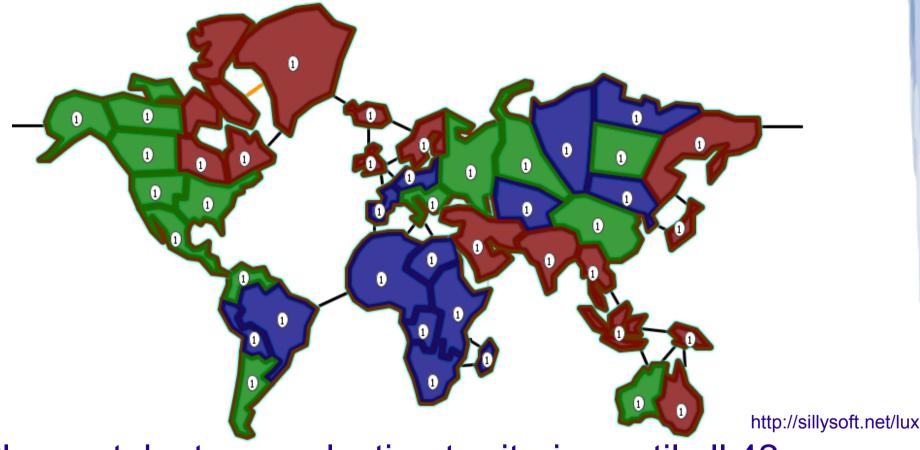












 Players take turns selecting territories until all 42 territories are owned.

Problem: How should we draft territories?

Does territory drafting even matter?



http://sillysoft.net/lux

Does territory drafting even matter?

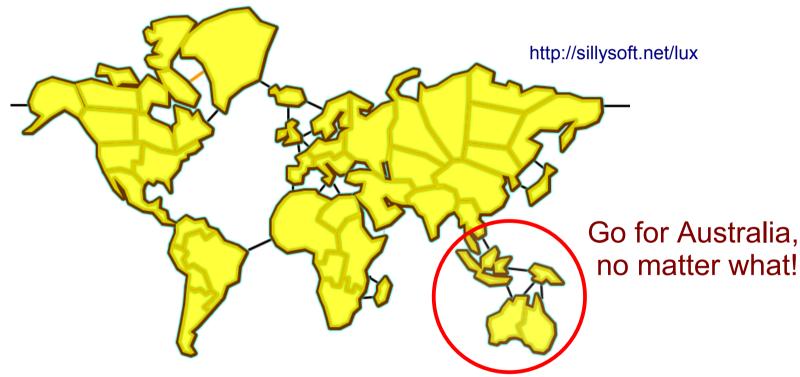


http://sillysoft.net/lux

Still, does territory drafting really matter?

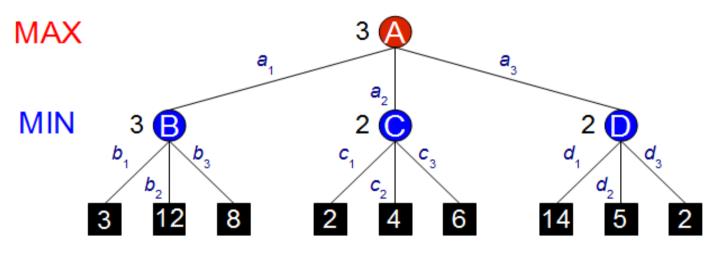
- What about the rest of the game after the draft?
  - Lux Delux provides several Risk bots.
  - We will use the "Quo" bot for all post-draft play and replace its drafting algorithm with our own.
- Others have worked on how to play the rest of the game, but all ignore the drafting phase.
  - Territory drafting is all we care about here.
- We are only going to play 3-player Risk.

Rule-based:



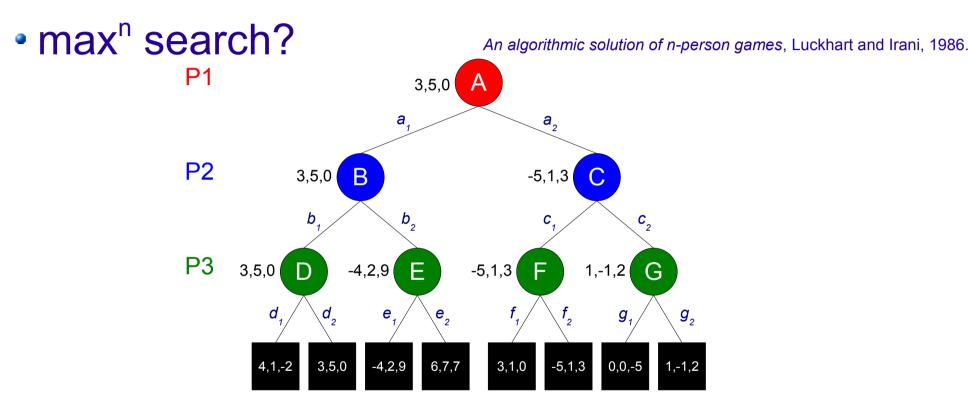
 All bots supplied with Lux Delux are rulebased drafters.

• Minimax search?



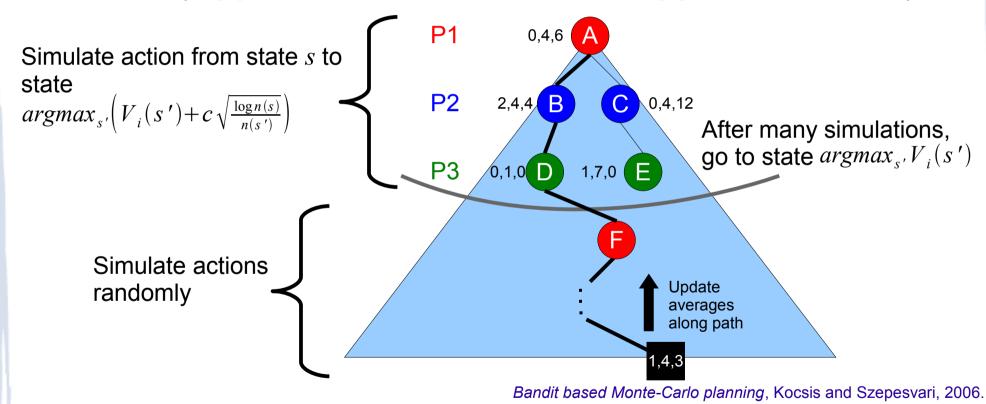
Artificial Intelligence: A Modern Approach, Russell and Norvig, 2003.

Really only applies to 2-player games...

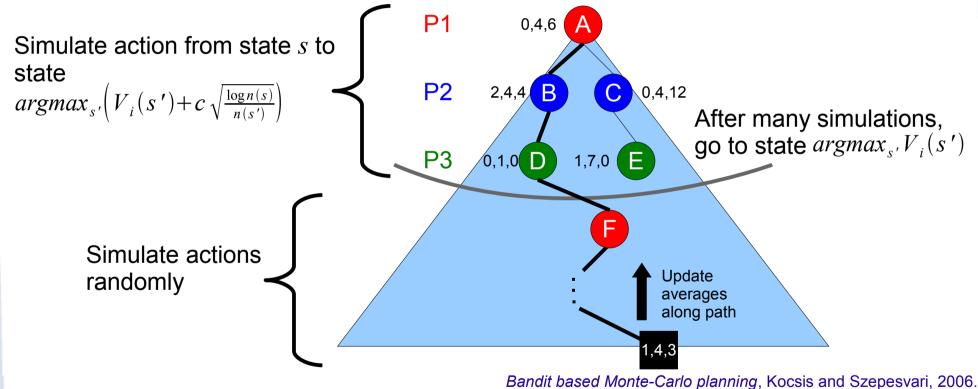


- Large branching factor (42, then 41, then 40, etc.)
- Would require good evaluation function of all draft states

UCT? (Upper Confidence Bounds applied to Trees)



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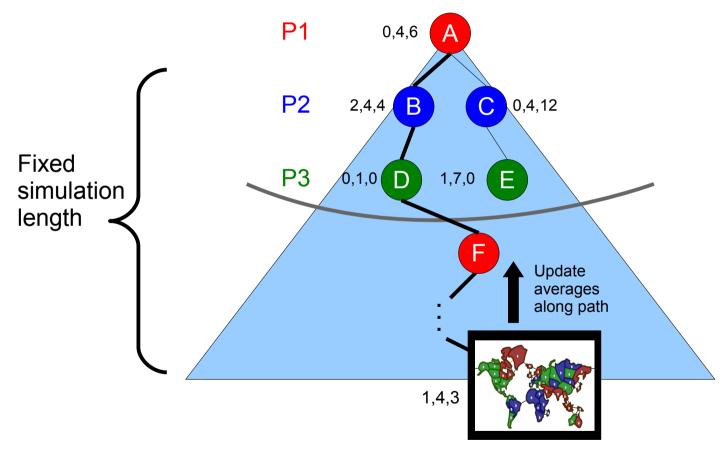
- Better at handling large branching factor
- Typically requires no evaluation function

# Applying UCT to Risk Drafting

- Typically with UCT, the more simulations that are run to completion, the more informative the decision.
- Big Problem: Risk can be a very long game
  - Game may never end through random play, and so we may not even complete one simulation.

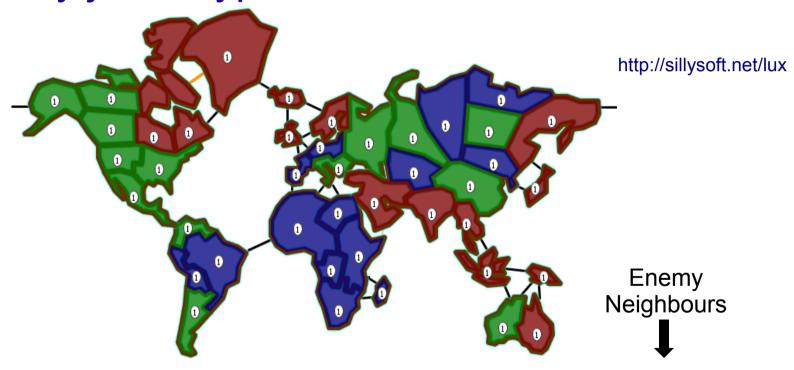
# Applying UCT to Risk Drafting

Solution: Terminate simulations at draft end.



• All terminal states are "simple" => easier to evaluate

• For any draft outcome, define feature set  $S_i$  for player i by just 4 types of features:



 $S_2 = (Aus-0, SA-2, Afr-6, NA-0, Eur-2, Asia-4, Pos-2, 13, 15)$ 

Continent counts

Turn order

Friendly Neighbours

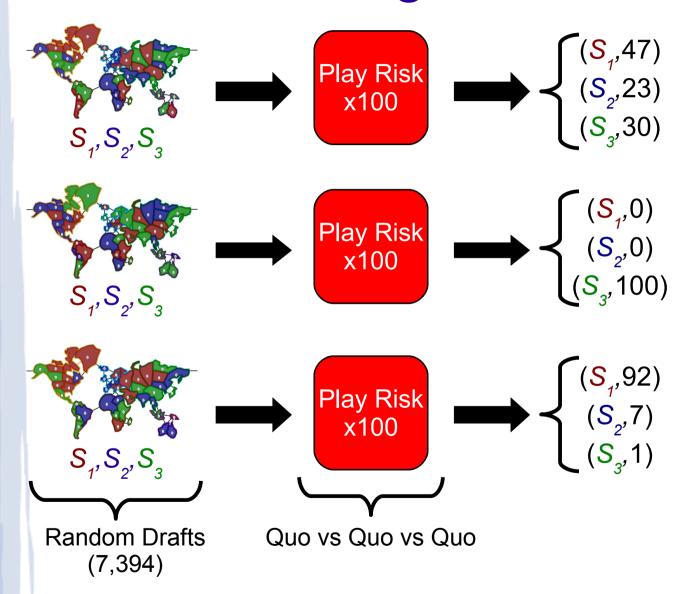
- For any draft outcome, define feature set  $S_i$  for player i by just 4 types of features:
  - The number of territories owned in each continent
  - The player's position in the turn order
  - The number of distinct enemy neighbours
  - The number of friendly neighbours

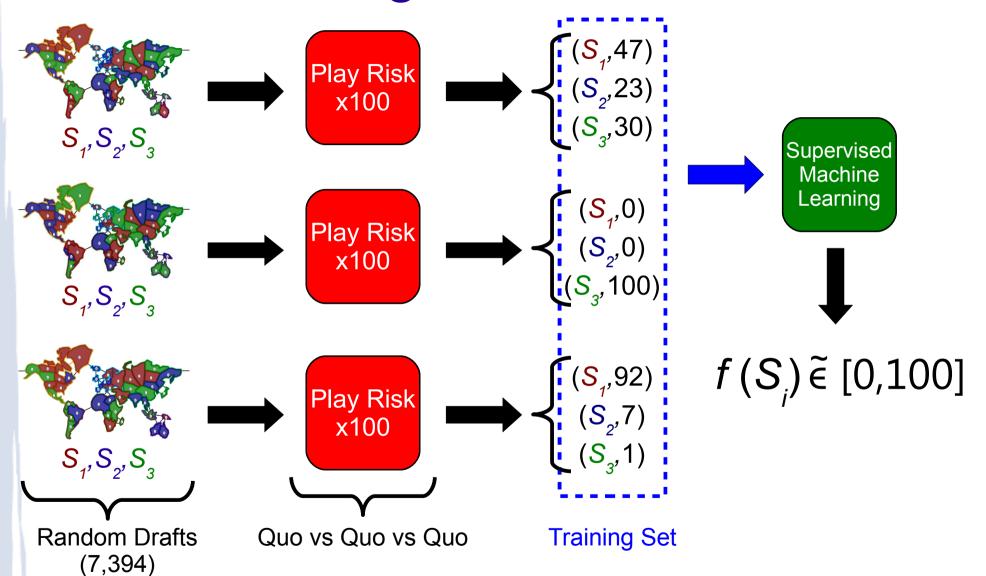






Random Drafts (7,394)



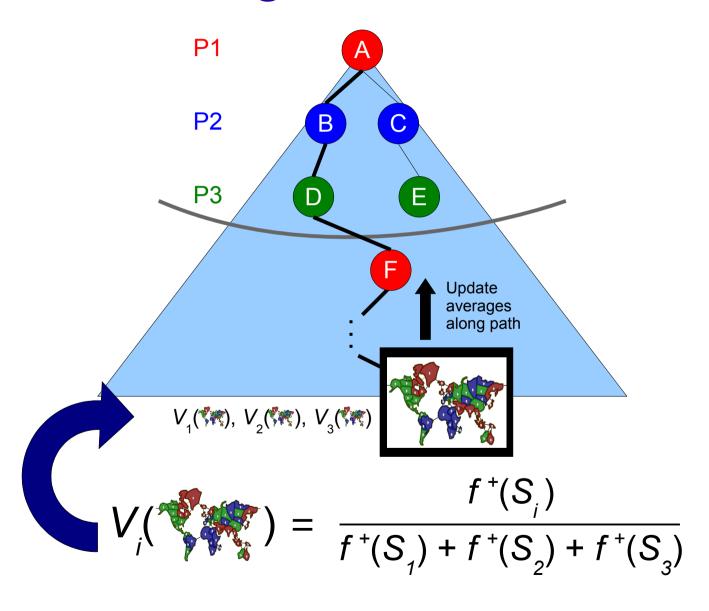


Adapted from Automated action set selection in Markov decision processes, Lee, 2004.

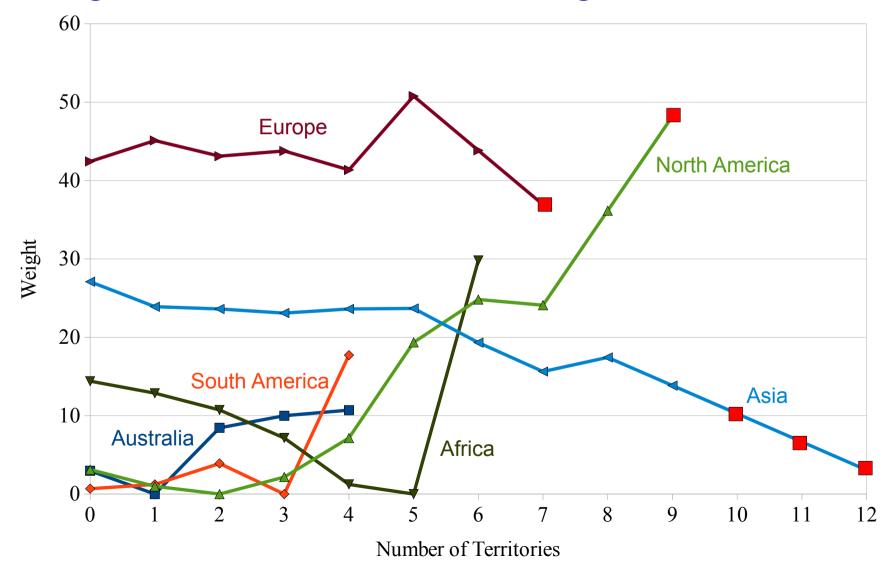
- Used linear regression to obtain f
- Final evaluation function:

$$V_{i}(S_{i}) = \frac{f^{+}(S_{i})}{f^{+}(S_{1}) + f^{+}(S_{2}) + f^{+}(S_{3})}$$

where 
$$f^+(S_i) = \max\{0, f(S_i)\}$$



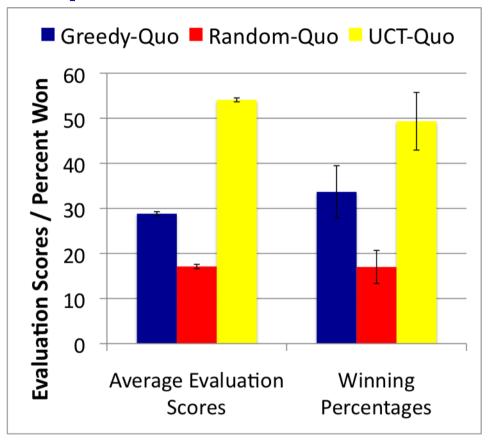
Weights of features from linear regression:



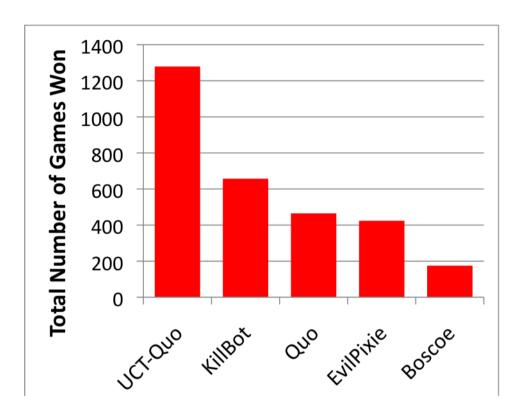
Weights of features from linear regression:

Feature	Weight
First to play	13.38
Second to play	5.35
Third to play	0.00
Enemy neighbours (multiplier)	-0.07
Friendly neighbours (multiplier)	0.48

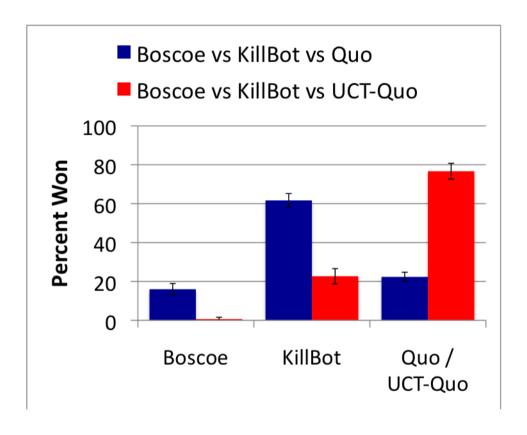
- The good guy:
  - UCT-Quo: UCT + ML evaluation function → Quo
- The bad guys (most difficult bots in Lux Delux):
  - Killbot: Directs attacks/defence at viable continents
  - Quo: Tries to slowly expand a cluster of territories
  - EvilPixie: Similar to Killbot, different parameters
  - Boscoe: Similar to Quo, plus targets runaway leaders
- Some other guys:
  - Greedy-Quo: 1-ply max<sup>n</sup> + ML evaluation function → Quo
  - Random-Quo: Drafts randomly → Quo



- 50 rounds played, 6 games per round (all 3! orderings)
- UCT runs 3000 simulations with exploration constant c = 0.01 in less than 1 second on personal laptop



- Round robin tournament (all 10 3-player match-ups), 50 rounds per match-up, 6 games per round (all 3! orderings)
- UCT runs 3000 simulations with exploration constant
   c = 0.01 in less than 1 second on personal laptop



- 50 rounds played, 6 games per round (all 3! orderings)
- UCT runs 3000 simulations with exploration constant c = 0.01 in less than 1 second on personal laptop

#### Conclusions

- Simple machine-learned evaluation function can generalize fairly well
- Combining UCT with a machine-learned evaluation function works well for drafting territories in Risk
  - Our UCT-Quo bot outperforms all of the strongest bots supplied with Lux Delux
- Territory drafting is an important stage in Risk
- Our approach could be appealing to commercial Risk Al programmers
  - Makes good decisions very quickly

#### **Future Work**

- Generalize the evaluation function to more players
- Adapt to other types of games, perhaps those that involve drafting-type scenarios
- In particular, apply to drafting in sports leagues
  - Real-life rookie / waiver / expansion drafts
  - Video games
  - Fantasy sports

#### Real-Life Sports League Drafts



Wikimedia Commons – Alexander Laney

- Teams take turns selecting players from a pool
- Create an automated draft assistant?
- Mock drafts against automated opponents?

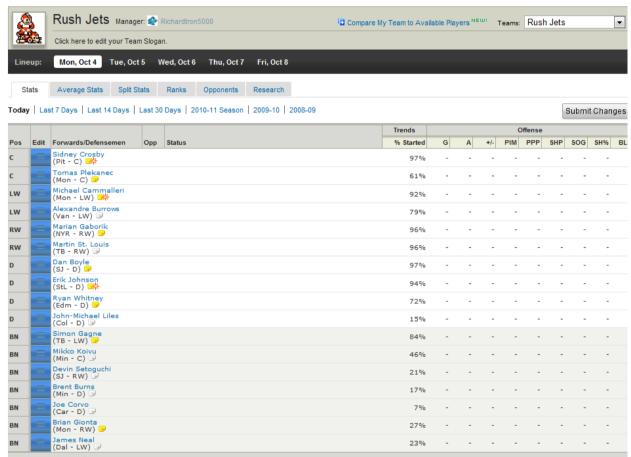
# Drafting in Video Games



EA Sports "NHL 10"

 Create more intelligent computer opponents to draft against?

# **Fantasy Sports Drafts**



Yahoo! Sports Fantasy Hockey

- Fantasy sports are a multi-billion dollar business
- Implement a drafting coach?

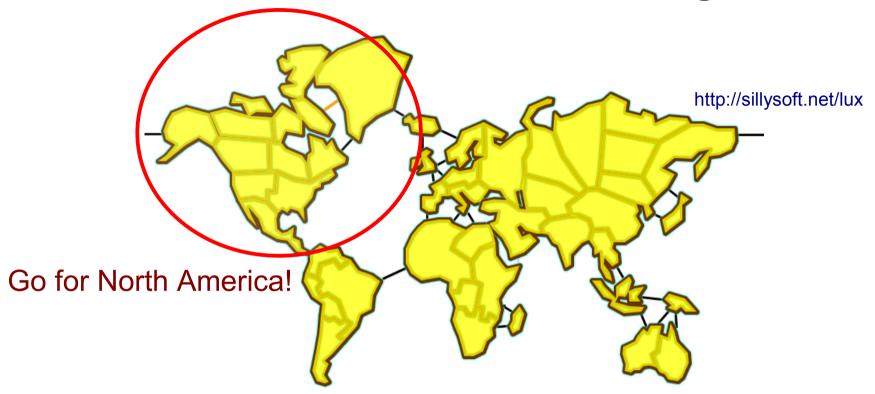
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# Thanks for Listening!



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