What is the value of an action in ice hockey?
Deep Reinforcement Learning for Context-Aware Player Evaluation

Oliver Schulte
Guiliang Liu
Sport Analytics

Growth in Industry

• The Sports Analytics market is expected to grow from USD 123.7 Million in 2016 to USD 616.7 Million by 2021

• Commercial data providers include:
  • Sportlogiq
  • Stats

Source: MarketsandMarkets Analysis
Sport Analytics

Growth in academia

• MIT Sloan Sport Analytics Conference (held every year in Boston since 2007). Research and application papers.
• Journals
  • Journal Quantitative Analysis of Sports
  • Journal of Sports Analytics.
• Sports Analytics Group in SFU.
• Sports Analytics B.Sc. at Syracuse university
• Contributions to AI-related conferences (AAAI, IJCAI, UAI, KDD) in the recent years.

Coleman, B. J. “Identifying the players in sports analytics” Research Interfaces, 2012, 42, 109-118.
AI Meets Sports Analytics

AI

- modelling and learning game strategies
- multi-agent systems
- structured data (space, time)
- decision support for coaches, players, teams
  - identifying strengths and weaknesses ("gap analysis")
  - suggesting and identifying tactics
Our Approach: Sports Analytics as a major application area for Reinforcement Learning
Performance Evaluation: A Reinforcement Learning Approach
Evaluate players in the largest ice hockey league: National Hockey League (NHL)
Previous Approaches

- **Action Value Counts**
  - pass = +5
  - shot = +10

- **Value-Above-Replacement**
  - unifies

- **Reinforcement Learning Approach**

- **Latent Strength Models**
  - Chess: Elo Rating
  - Gaming: MS TrueSkills
Action Values: Current Approaches

- Like KPIs
- **Baseball Statistics**
- +/- Score in ice hockey
  - [nhl.com](http://nhl.com)
  - **Advanced Stats**
Problems with Action Counts

- How to combine counts for different actions into a single number?
  - e.g. passes + shots = ?
- Ignores context
  - e.g. goal at end of game is more valuable
- Does not capture medium-term impact: no look-ahead
- Illustration: Olympics 2010 Golden Goal
Solutions for Action Counts

• How to combine counts for different actions into a single number?
  ➢ Use expected utility as measurement scale
• Ignores context
  ➢ Make action value function of \textit{current match state}
• Does not capture medium-term impact: no look-ahead
  ➢ Estimate expected utility with respect to \textit{all future trajectories}
The Q-function

- The action-value function in reinforcement learning is just what we need.
- Called Q-function.
- Incorporates
  - context
  - lookahead
- Familiar in AI, very new in sports analytics!
- David Poole's Value Iteration Demo
- Q values for actual NHL play, not optimal policy.
1) Extract play dynamic from NHL dataset.
2) Estimate the $Q(s, a)$ with DRL model.
3) Define a novel Goal Impact Metric (GIM) to value each player.
A Markov Game Model for the NHL
• Transition graph with 5 parts:
  - Players/Agents $P$
  - States $S$
  - Actions $A$
  - Transition Probabilities $T$
  - Rewards $R$

• Transitions, Rewards depend on state and *tuple* of actions, one for each agent.

13 Action Types

<table>
<thead>
<tr>
<th>Action Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blocked Shot</td>
</tr>
<tr>
<td>Faceoff</td>
</tr>
<tr>
<td>Giveaway</td>
</tr>
<tr>
<td>Goal</td>
</tr>
<tr>
<td>Hit</td>
</tr>
<tr>
<td>Missed Shot</td>
</tr>
<tr>
<td>Shot</td>
</tr>
<tr>
<td>Takeaway</td>
</tr>
<tr>
<td>...</td>
</tr>
</tbody>
</table>
State Space

- At each time, we observe the following features
- Model also captures match history (more below)

Table 3: Complete Feature List. Values for the feature Manpower are EV=Even Strength, SH=Short Handed, PP=Power Play.

<table>
<thead>
<tr>
<th>Name</th>
<th>Type</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>X Coordinate of Puck</td>
<td>Continuous</td>
<td>[-100, 100]</td>
</tr>
<tr>
<td>Y Coordinate of Puck</td>
<td>Continuous</td>
<td>[-42.5, 42.5]</td>
</tr>
<tr>
<td>Velocity of Puck</td>
<td>Continuous</td>
<td>[-inf, +inf]</td>
</tr>
<tr>
<td>Time Remaining</td>
<td>Continuous</td>
<td>[0, 3600]</td>
</tr>
<tr>
<td>Score Differential</td>
<td>Discrete</td>
<td>(-inf, +inf)</td>
</tr>
<tr>
<td>Manpower</td>
<td>Discrete</td>
<td>{EV, SH, PP}</td>
</tr>
<tr>
<td>Event Duration</td>
<td>Continuous</td>
<td>[0, +inf)</td>
</tr>
<tr>
<td>Action Outcome</td>
<td>Discrete</td>
<td>{successful, failure}</td>
</tr>
<tr>
<td>Angle between puck and goal</td>
<td>Continuous</td>
<td>[−3.14, 3.14]</td>
</tr>
<tr>
<td>Home/Away Team</td>
<td>Discrete</td>
<td>{Home, Away}</td>
</tr>
</tbody>
</table>
Rewards

options for reward functions

episode

NBA: **Points** from Possession
Cervone et al. 2014
NFL: **Points** from Possession
nflscrapR Yurko et al. 2018
Chan and Puterman 2019
NHL: **Next Goal** *(our work)*

**final outcome**

NHL: **penalties**
Routley and Schulte 2015

**win probabilities**
AlphaGo
Canadian Tire
Hockey:
Pettigrew 2015
Schulte et al. 2017
Learning an Action-Value Function for the NHL
• Computer Vision Techniques: Video tracking

• Play-by-play Dataset

• Large-scale Machine Learning
Sports Data Types

- **Complete Tracking**: which player is where when. Plus the ball/puck. ★

- **Box Score**: Action Counts.

- **Play-By-Play**: Action/Event Sequence.
Tracking Data

- Basketball **SportsVU** since 2011
- New for **NFL Next Gen Stats**
- Coming to the NHL?
- Holy Grail: Tracking from Broadcast Video
- Sportlogiq, Stats
Oiliers vs. Canucks
Play-By-Play

- **Successive Play Sequences**
- **nhlscraper, nflscraper**
Our Play-By-Play Data

- Source: SportLogiq
- 2015-16
- Action Locations

<table>
<thead>
<tr>
<th>SportLogiq</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Teams</td>
<td>31</td>
</tr>
<tr>
<td>Players</td>
<td>2,233</td>
</tr>
<tr>
<td>Games</td>
<td>1,140</td>
</tr>
<tr>
<td>Events</td>
<td>3M+</td>
</tr>
</tbody>
</table>
DRL MODEL

- Recurrent LSTM network
- Dynamic trace back to previous possession change
Spatial Projection

Q-value for the action “shot” action over the rink.
Evaluating Player Performance
The Impact of an Action

\[ Q(s, a) = Q(s_t, a_t) - Q(s_{t-1}, a_{t-1}) \]
Goal Impact Metric

1. Apply the impact of an action to the player performing the action
2. Sum the impact of his actions over a game to get his net game impact.
3. Sum the net game impact of a player over a single season to get his net season impact.
Evaluation

• No ground truth for player ranking
• Compare with success metrics known to be relevant
• Other desiderata (consistency, predictive power) Franks et al. 2016
Rank players by GIM and identify undervalued players

<table>
<thead>
<tr>
<th>Name</th>
<th>GIM</th>
<th>Assists</th>
<th>Goals</th>
<th>Points</th>
<th>Team</th>
<th>Salary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taylor Hall</td>
<td>96.40</td>
<td>39</td>
<td>26</td>
<td>65</td>
<td>EDM</td>
<td>$6,000,000</td>
</tr>
<tr>
<td>Joe Pavelski</td>
<td>94.56</td>
<td>40</td>
<td>38</td>
<td>78</td>
<td>SJS</td>
<td>$6,000,000</td>
</tr>
<tr>
<td>Johnny Gaudreau</td>
<td>94.51</td>
<td>48</td>
<td>30</td>
<td>78</td>
<td>CGY</td>
<td>$925,000</td>
</tr>
<tr>
<td>Anze Kopitar</td>
<td>94.10</td>
<td>49</td>
<td>25</td>
<td>74</td>
<td>LAK</td>
<td>$7,700,000</td>
</tr>
<tr>
<td>Erik Karlsson</td>
<td>92.41</td>
<td>66</td>
<td>16</td>
<td>82</td>
<td>OTT</td>
<td>$7,000,000</td>
</tr>
<tr>
<td>Patrice Bergeron</td>
<td>92.06</td>
<td>36</td>
<td>32</td>
<td>68</td>
<td>BOS</td>
<td>$8,750,000</td>
</tr>
<tr>
<td>Mark Scheifele</td>
<td>90.67</td>
<td>32</td>
<td>29</td>
<td>61</td>
<td>WPG</td>
<td>$832,500</td>
</tr>
<tr>
<td>Sidney Crosby</td>
<td>90.21</td>
<td>49</td>
<td>36</td>
<td>85</td>
<td>PIT</td>
<td>$12,000,000</td>
</tr>
<tr>
<td>Claude Giroux</td>
<td>89.64</td>
<td>45</td>
<td>22</td>
<td>67</td>
<td>PHI</td>
<td>$9,000,000</td>
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<tr>
<td>Dustin Byfuglien</td>
<td>89.46</td>
<td>34</td>
<td>19</td>
<td>53</td>
<td>WPG</td>
<td>$6,000,000</td>
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<tr>
<td>Jamie Benn</td>
<td>88.38</td>
<td>48</td>
<td>41</td>
<td>89</td>
<td>DAL</td>
<td>$5,750,000</td>
</tr>
<tr>
<td>Patrick Kane</td>
<td>87.81</td>
<td>60</td>
<td>46</td>
<td>106</td>
<td>CHI</td>
<td>$13,800,000</td>
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<tr>
<td>Mark Stone</td>
<td>86.42</td>
<td>38</td>
<td>23</td>
<td>61</td>
<td>OTT</td>
<td>$2,250,000</td>
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<tr>
<td>Blake Wheeler</td>
<td>85.83</td>
<td>52</td>
<td>26</td>
<td>78</td>
<td>WPG</td>
<td>$5,800,000</td>
</tr>
<tr>
<td>Tyler Toffoli</td>
<td>83.25</td>
<td>27</td>
<td>31</td>
<td>58</td>
<td>DAL</td>
<td>$2,600,000</td>
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<tr>
<td>Charlie Coyle</td>
<td>81.50</td>
<td>21</td>
<td>21</td>
<td>42</td>
<td>MIN</td>
<td>$1,900,000</td>
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<tr>
<td>Tyson Barrie</td>
<td>81.46</td>
<td>36</td>
<td>13</td>
<td>49</td>
<td>COL</td>
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<tr>
<td>Jonathan Toews</td>
<td>80.92</td>
<td>30</td>
<td>28</td>
<td>58</td>
<td>CHI</td>
<td>$13,800,000</td>
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<tr>
<td>Sean Monahan</td>
<td>80.92</td>
<td>36</td>
<td>27</td>
<td>63</td>
<td>CGY</td>
<td>$925,000</td>
</tr>
<tr>
<td>Vladimir Tarasenko</td>
<td>80.68</td>
<td>34</td>
<td>40</td>
<td>74</td>
<td>STL</td>
<td>$8,000,000</td>
</tr>
</tbody>
</table>

- Mark Scheifele drew salaries **below** what his GIM rank would suggest.
- Later he received a $5M+ contract in 2016-17 season
EMPIRICAL EVALUATION

Comparison Metric:
- Plus-Minus (+/-)
- Goal-Above-Replacement (GAR)
- Win-Above-Replacement (WAR)
- Expected Goal (EG)
- Scoring Impact (SI)
- GIM-T1
Comparison Metric:
- Plus-Minus (+/-)
- Goal-Above-Replacement (GAR)
- Win-Above-Replacement (WAR)
- Expected Goal (EG)
- Scoring Impact (SI)
- GIM-T1

Correlations with standard Success Measures:
- Compute the correlation with 14 standard success measures:

<table>
<thead>
<tr>
<th>methods</th>
<th>Point</th>
<th>SHP</th>
<th>PPP</th>
<th>FOW</th>
<th>P/GP</th>
<th>TOI</th>
<th>PIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>+/-</td>
<td>0.237</td>
<td>0.159</td>
<td>0.089</td>
<td>-0.045</td>
<td>0.238</td>
<td>0.141</td>
<td>0.049</td>
</tr>
<tr>
<td>GAR</td>
<td>0.622</td>
<td>0.226</td>
<td>0.532</td>
<td>0.16</td>
<td>0.616</td>
<td>0.323</td>
<td>0.089</td>
</tr>
<tr>
<td>WAR</td>
<td>0.612</td>
<td>0.235</td>
<td>0.531</td>
<td>0.153</td>
<td>0.605</td>
<td>0.331</td>
<td>0.078</td>
</tr>
<tr>
<td>EG</td>
<td>0.854</td>
<td>0.287</td>
<td>0.729</td>
<td>0.28</td>
<td>0.702</td>
<td>0.722</td>
<td>0.354</td>
</tr>
<tr>
<td>SI</td>
<td>0.869</td>
<td>0.37</td>
<td>0.707</td>
<td>0.185</td>
<td>0.655</td>
<td>0.955</td>
<td>0.492</td>
</tr>
<tr>
<td>GIM-T1</td>
<td>0.902</td>
<td>0.384</td>
<td>0.736</td>
<td>0.288</td>
<td>0.738</td>
<td>0.777</td>
<td>0.347</td>
</tr>
<tr>
<td>GIM</td>
<td>0.93</td>
<td>0.399</td>
<td>0.774</td>
<td>0.295</td>
<td>0.749</td>
<td>0.835</td>
<td>0.405</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>methods</th>
<th>Assist</th>
<th>Goal</th>
<th>GWG</th>
<th>OTG</th>
<th>SHG</th>
<th>PPG</th>
<th>S</th>
</tr>
</thead>
<tbody>
<tr>
<td>+/-</td>
<td>0.236</td>
<td>0.204</td>
<td>0.217</td>
<td>0.16</td>
<td>0.095</td>
<td>0.099</td>
<td>0.118</td>
</tr>
<tr>
<td>GAR</td>
<td>0.527</td>
<td>0.633</td>
<td>0.552</td>
<td>0.324</td>
<td>0.191</td>
<td>0.583</td>
<td>0.549</td>
</tr>
<tr>
<td>WAR</td>
<td>0.516</td>
<td>0.652</td>
<td>0.551</td>
<td>0.332</td>
<td>0.192</td>
<td>0.564</td>
<td>0.532</td>
</tr>
<tr>
<td>EG</td>
<td>0.783</td>
<td>0.834</td>
<td>0.704</td>
<td>0.448</td>
<td>0.249</td>
<td>0.684</td>
<td>0.891</td>
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<tr>
<td>SI</td>
<td>0.869</td>
<td>0.745</td>
<td>0.631</td>
<td>0.411</td>
<td>0.27</td>
<td>0.591</td>
<td>0.898</td>
</tr>
<tr>
<td>GIM-T1</td>
<td>0.873</td>
<td>0.752</td>
<td>0.682</td>
<td>0.428</td>
<td>0.291</td>
<td>0.607</td>
<td>0.877</td>
</tr>
<tr>
<td>GIM</td>
<td>0.875</td>
<td>0.878</td>
<td>0.751</td>
<td>0.465</td>
<td>0.345</td>
<td>0.71</td>
<td>0.912</td>
</tr>
</tbody>
</table>
Round-by-Round Correlations:

- How *quickly* a metric acquires predictive power for the season total.
- For a metric (EG, SI, GIM-T1, GIM), measure the *correlation* between
  a) Its value computed over the **first n round**.
  b) The value of the three main success measures, assists, goals, points and its value computed over the **entire season**.
Round-by-Round Correlations:

- How quickly a metric acquires predictive power for the season total.
- For a metric (EG, SI, GIM-T1, GIM), measure the correlation between
  a) Its value computed over the first n round.
  b) The value of the three main success measures, assists, goals, points computed over the entire season.

---

**Correlation with assist**

- EG
- SI
- GIM-T1
- GIM

---

**Correlation with Goal**

- EG
- SI
- GIM-T1
- GIM

---

**Correlation with Point**

- EG
- SI
- GIM-T1
- GIM

---

**Auto Correlation**

- EG
- SI
- GIM-T1
- GIM
GOAL IMPACT AND SALARY

Predicting Players' Salary:

• A good metric is positively related to players' future contract.

\[
\begin{array}{|c|c|c|}
\hline
\text{methods} & \text{2016 to 2017 Season} & \text{2017 to 2018 Season} \\
\hline
\text{Plus Minus} & 0.177 & 0.225 \\
\text{GAR} & 0.328 & 0.372 \\
\text{WAR} & 0.328 & 0.372 \\
\hline
\text{EG} & 0.587 & 0.6 \\
\text{SI} & 0.609 & 0.668 \\
\text{GIM-T1} & 0.596 & 0.69 \\
\text{GIM} & 0.666 & 0.763 \\
\hline
\end{array}
\]

• Many underestimated players in 16-17 season. (high GIM, low salary).
• This percentage decreases in 17-18 season. (from 32/258 to 8/125).
## RELATED WORK

### Markov Value Function Based Players Evaluation

<table>
<thead>
<tr>
<th>Year</th>
<th>Venue</th>
<th>Authors</th>
<th>Name</th>
<th>Sports</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>IJCAI</td>
<td>Guiliang Liu and Oliver Schulte</td>
<td>Deep reinforcement learning in ice hockey for context-aware player evaluation</td>
<td>Ice Hockey</td>
</tr>
<tr>
<td>2015</td>
<td>UAI</td>
<td>Kurt Routley and Oliver Schulte</td>
<td>A Markov game model for valuing player actions in ice hockey.</td>
<td>Ice Hockey</td>
</tr>
<tr>
<td>2014</td>
<td>MIT Sloan</td>
<td>Dan Cervone, Alexander, et al.</td>
<td>Pointwise: Predicting points and valuing decisions in real time …</td>
<td>Basketball</td>
</tr>
</tbody>
</table>
• “We assert that most questions that coaches, players, and fans have about basketball, particularly those that involve the offense, can be phrased and answered in terms of EPV [i.e. the value function].” Cervone, Bornn et al. 2014.

• We have seen how the action-value function can be used to rank players

• Can also be ranked to give decision advice to coaches (e.g. Wang et al. 2018)
Future Work

Supported by a Strategic Project Grant with SportLogiq

Pascal Poupart
Waterloo

Greg Mori
SFU

Luke Bornn
SFU, Sacramento Kings
Increasing Realism and Accuracy

accuracy

number of parameters

realism

Routley and Schulte 2015

Liu and Schulte 2018
Increasing Realism and Accuracy: Hierarchical Models

- Current Model pools data from all players and teams ➔ average team/player
- How can we capture patterns specific to players/teams?
- Current sports analytics: Use a hierarchical model
  - aka shrinkage, multi-level, random effects
- How can we represent individual patterns in a decision process model?
  - In a deep decision process model?

Interpretation

• Goal: Explain why the neural net assigns high/low values to some states

1. Mimic Learning (Liu and Schulte 2018)
2. Likely Future Trajectories (Khan, Poupart et al. 2011)

What-if scenarios?

Learning at Higher Scales

• Intuitively, players and coaches think in terms of plays (maneuvers).
• Related to RL concepts
  • Options
  • Task hierarchies
• Common Example in Sports Analytics: Trajectory Clustering

NFL Example: Route Types as Higher-Scale Options

0 – Hitch
1 – Out
2 – Slant
3 – Fade
4 – Corner
5 – Post
6 – Comeback

Figure due to Chu et al. 2019
Conclusion

• Modelling ice hockey dynamics in the NHL
• A new context-aware method for evaluating actions and players
• A configurable and scalable Markov Game model that incorporates context and long-term effects of all actions
• Learning an action-value function is a powerful AI-based approach to supporting decisions in sports
THANK YOU!

Github link: https://github.com/Guiliang/DRL-ice-hocke