

What is the Value of an Action in Ice Hockey? Learning a Q-function for the NHL

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Big Picture: Sports Analytics meets Reinforcement Learning

- ▶ Reinforcement Learning: Major branch of Artificial Intelligence (*not* psychology).
- ▶ Studies *sequential decision-making under uncertainty*.
- ▶ Studied since the 1950s
 - Many models, theorems, algorithms, software.

Reinforcement
Learning



on-line intro text
by Sutton and Barto



Markov Game Models

Markov Game

- ▶ Fundamental model type in reinforcement learning: Markov Decision Process.
- ▶ Multi-agent version: Markov Game.
- ▶ Models dynamics: e.g. given the current state of a match, what event is likely to occur next?
- ▶ Application in this paper:
 1. value actions.
 2. compute player rankings.

Markov Game Dynamics Example

Home = Colorado

Away = St. Louis

Differential = Home - Away

Initial State

Goal

Differential = 0,

Manpower

Differential = 2,

Period = 1

face-off(
Home,Offensive Zone)



0,2,1
[face-
off(Home,Off.)]

Time in
Sequence
(sec)

0 sec
Alexander Steen
wins Face-off in
Colorado's
Offensive Zine

Markov Game Dynamics Example



GD = 0, MD = 2, P = 1

0,2,1
[face-off(Home,Off.)]

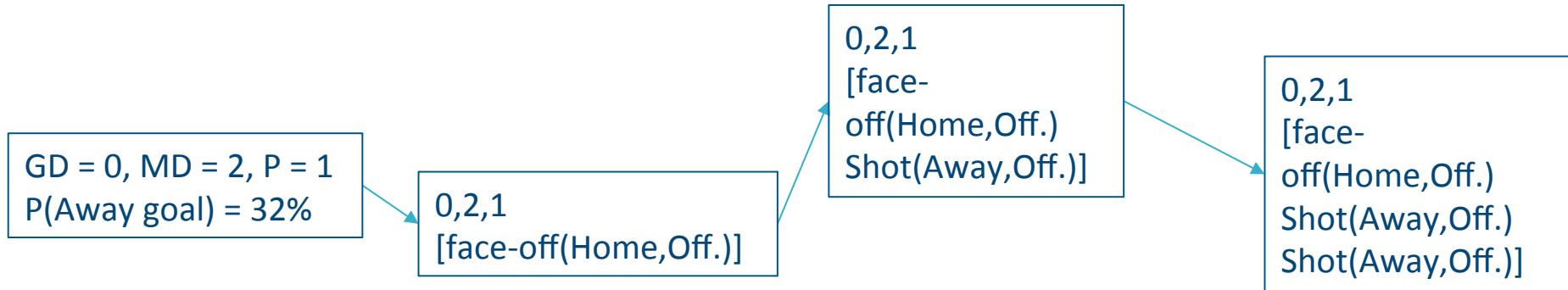
0,2,1
[face-off(Home,Off.)
Shot(Away,Off.)]

Time in
Sequence (sec)

0 sec
Alexander
Steen wins
Face-off

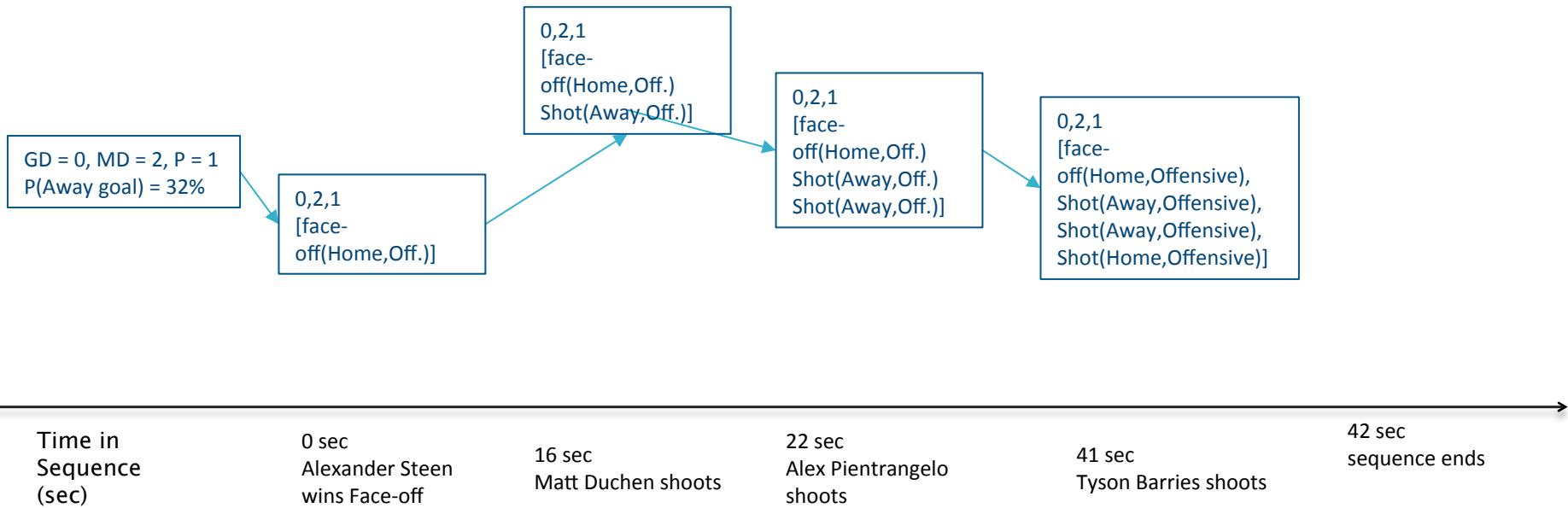
16 sec
Matt
Duchen
shoots

Markov Game Dynamics Example

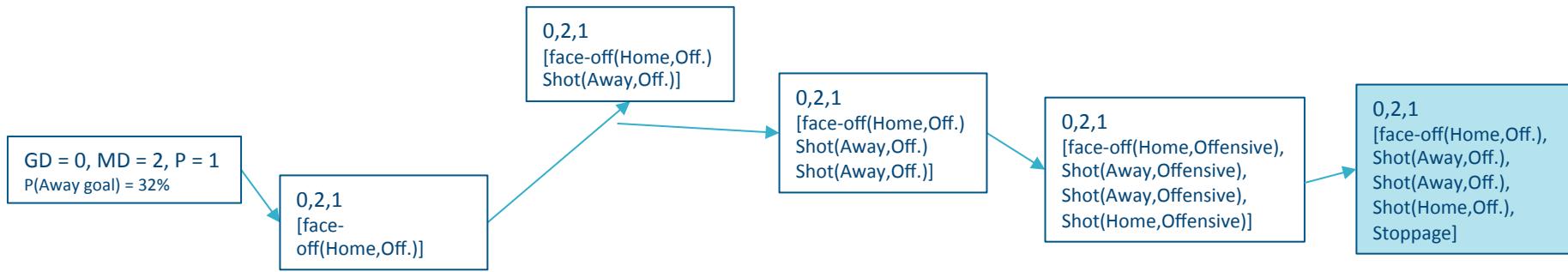


Time in Sequence (sec)	0 sec	16 sec	22 sec	41 sec	42 sec
	Alexander Steen wins Face-off	Matt Duchen shoots	Alex Pientrangel o shoots	Tyson Barries shoots	sequence ends

Markov Game Dynamics Example



Markov Game Dynamics Example



Time in Sequence (sec)

0 sec
Alexander Steen wins Face-off

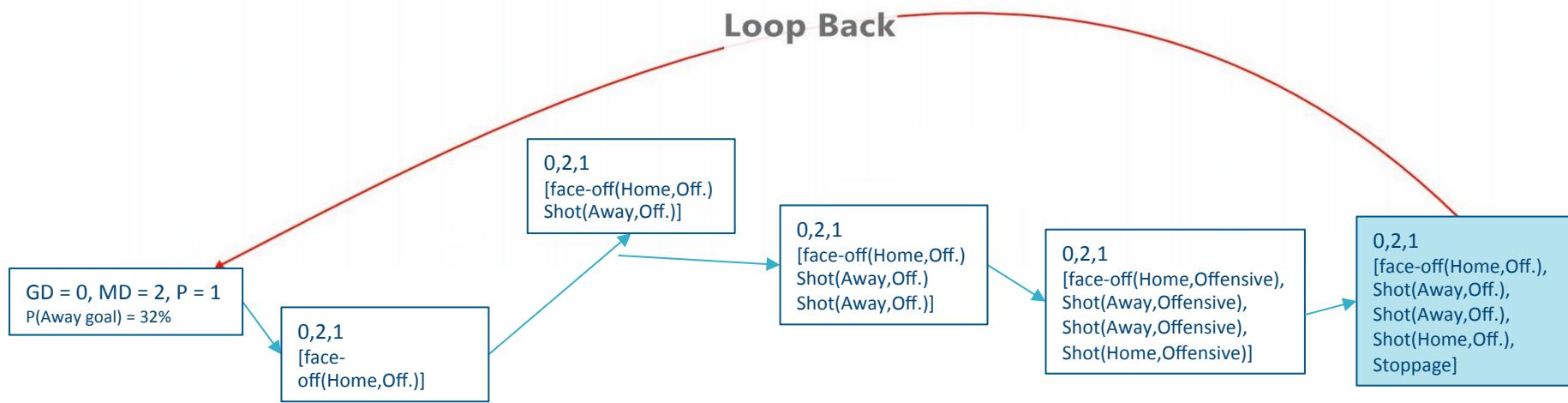
16 sec
Matt Duchen shoots

22 sec
Alex Pientrangelo shoots

41 sec
Tyson Barries shoots

42 sec
sequence ends

Markov Game Dynamics Example



Time in Sequence (sec)

0 sec
Alexander Steen wins Face-off

16 sec
Matt Duchen shoots

22 sec
Alex Pientrangelo shoots

41 sec
Tyson Barries shoots

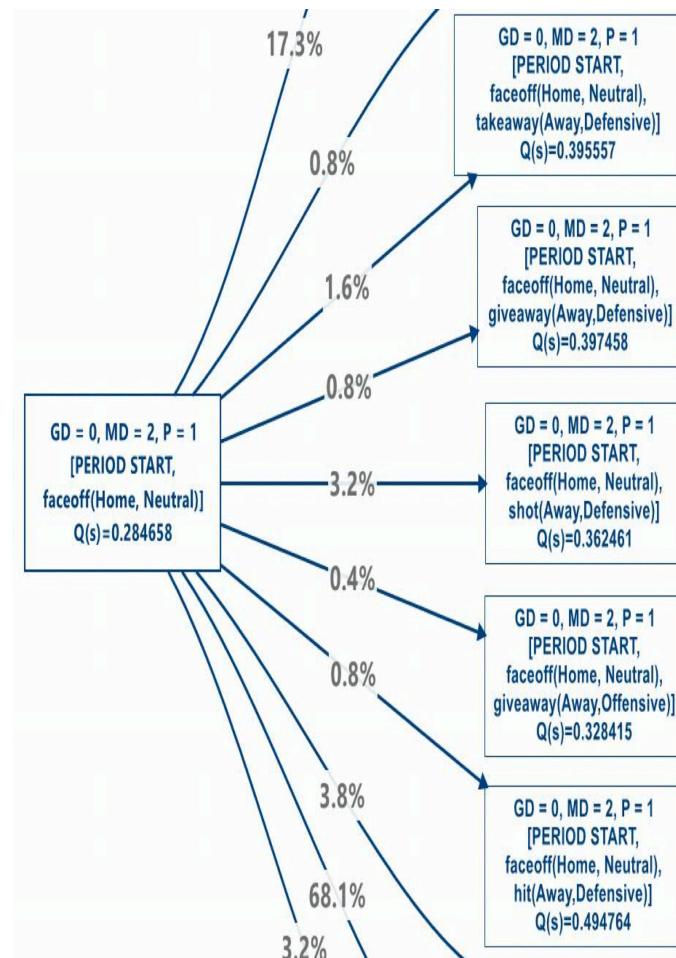
42 sec
sequence ends

Markov Game Description

- ▶ Two agents, Home and Away.
- ▶ Zero-sum: if Home earns a reward of r , then Away receives $-r$.
- ▶ Rewards can be
 - win match
 - **score goal**
 - receive penalty (cost).

Learning Markov Game Parameters

Markov Game Transition Probabilities = Parameters



Big Data: Play-by-play
2007–2015

Number of Teams	32
Number of Players	1,951
Number of Games	9,220
Number of Sequences	590,924
Number of Events	2,827,467

Big Model: 1.3 M states

Action Values

Player Performance Evaluation

Expected rewards

- ▶ Key quantity in Markov game models: the **total expected reward** for a player given the current game state.
 - Written $V(s)$.
- ▶ Looks ahead over all possible game continuations.

transition
probabilities

dynamic
programming



total
expected
reward of
state s

Q-values and Action Impact

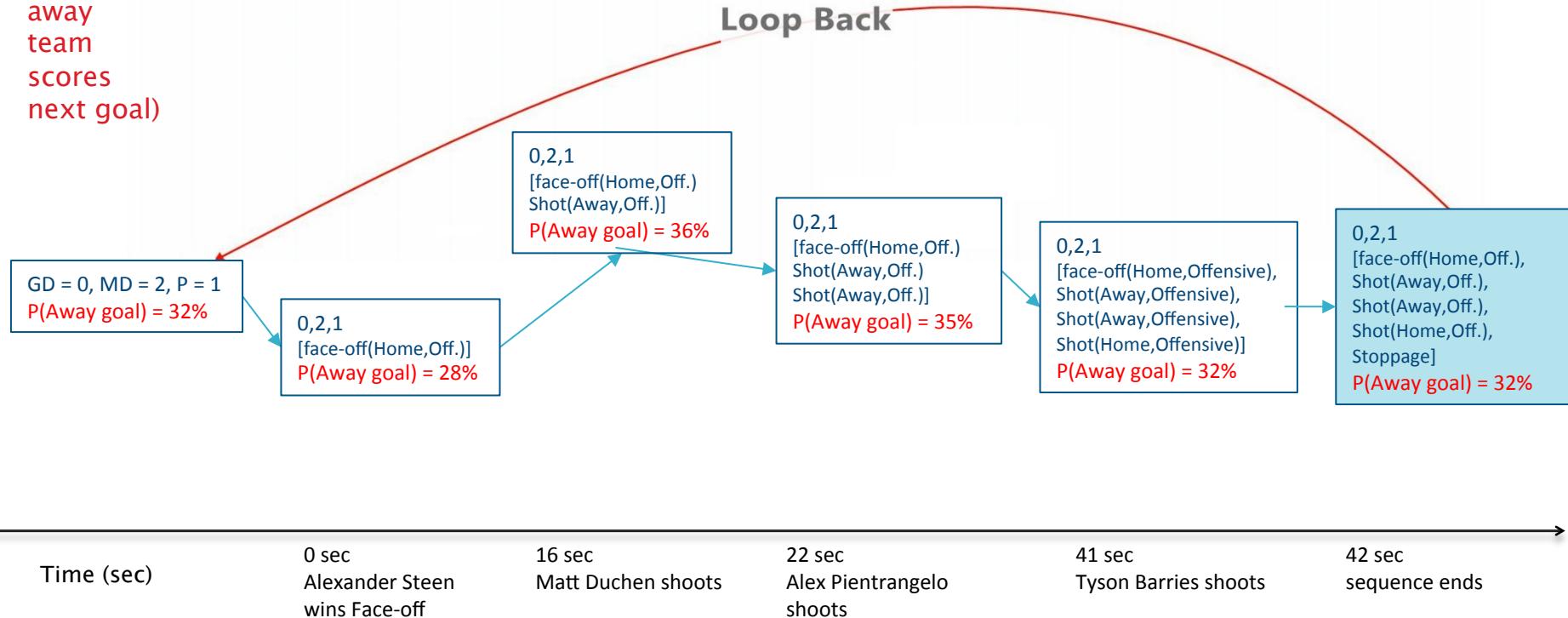
- ▶ $Q(s,a)$ = the expected total reward if action a is executed in state s .
- ▶ The **action-value function**.

$$impact(s,a) = Q(s,a) - V(s)$$

Expected reward after action Expected reward before action

Q-value Ticker

Q-value
=
P(that
away
team
scores
next goal)

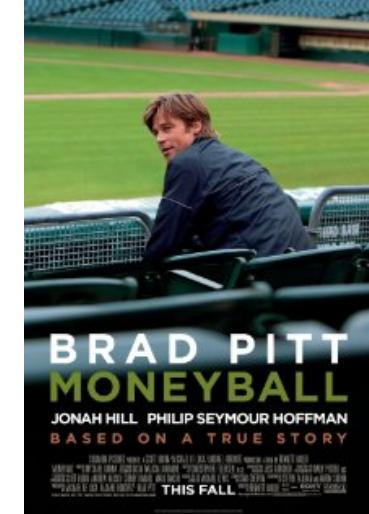


Advantages of Impact Value

- ▶ Context-Aware.
 - e.g. goals more valuable in ties than when ahead.
- ▶ Look Ahead:
 - e.g. penalties → powerplay → goals but not immediately.

Computing Player Impact

1. From the Q-function, compute impact values of state-action pairs.
2. For each action that a player takes in a game state, find its impact value.
3. Sum player action impacts over all games in a season. (Like + / -).



Results 2014-2015 1st half

- The Blues' STL line comes out very well.
- Tarasenko is under-valued, St. Louis increased his salary 7-fold.



Name	Position	Goal Impact	Goals	Points	+/-	Takeaways	Salary
Jori Lehtera	C	17.29	8	25	13	21	\$3,250,000
Henrik Zetterberg	LW	14.54	7	30	-1	21	\$7,500,000
Jason Spezza	C	14.33	6	25	-11	25	\$4,000,000
Vladimir Tarasenko	RW	12.78	20	37	18	20	\$900,000
Jonathan Toews	C	12.60	13	29	9	19	\$6,500,000
Joe Pavelski	C	12.22	16	29	5	22	\$6,000,000
Kyle Okposo	RW	11.79	8	29	-4	18	\$3,500,000
Brent Burns	D	11.56	10	27	-3	16	\$5,760,000
Gustav Nyquist	RW	11.47	14	22	-7	15	\$1,050,000
Joe Thornton	C	11.44	8	30	2	28	\$6,750,000
Ryan Kesler	C	10.99	12	27	-1	20	\$5,000,000
Tomas Plekanec	C	10.50	10	23	6	15	\$5,000,000
Sidney Crosby	C	10.43	10	37	12	18	\$12,000,000
Patrick Marleau	LW	9.96	7	27	-2	19	\$7,000,000
Martin Hanzal	C	9.76	6	17	1	16	\$3,250,000
Jaden Schwartz	LW	9.57	11	27	10	21	\$2,000,000
Pavel Datsyuk	C	9.51	13	25	4	16	\$10,000,000
Steven Stamkos	C	9.44	16	33	-2	14	\$8,000,000
Alex Ovechkin	RW	9.43	16	28	5	18	\$10,000,000
Rick Nash	LW	9.35	23	36	16	32	\$7,900,000
Sean Monahan	C	8.92	11	22	6	23	\$925,000
Phil Kessel	RW	8.70	17	38	-4	14	\$10,000,000
Jaromir Jagr	RW	8.68	5	20	-12	25	\$3,500,000
Frans Nielsen	C	8.64	6	17	-1	23	\$3,000,000
Nikita Kucherov	RW	8.60	14	31	20	13	\$743,000

Results 2013-2014 Season

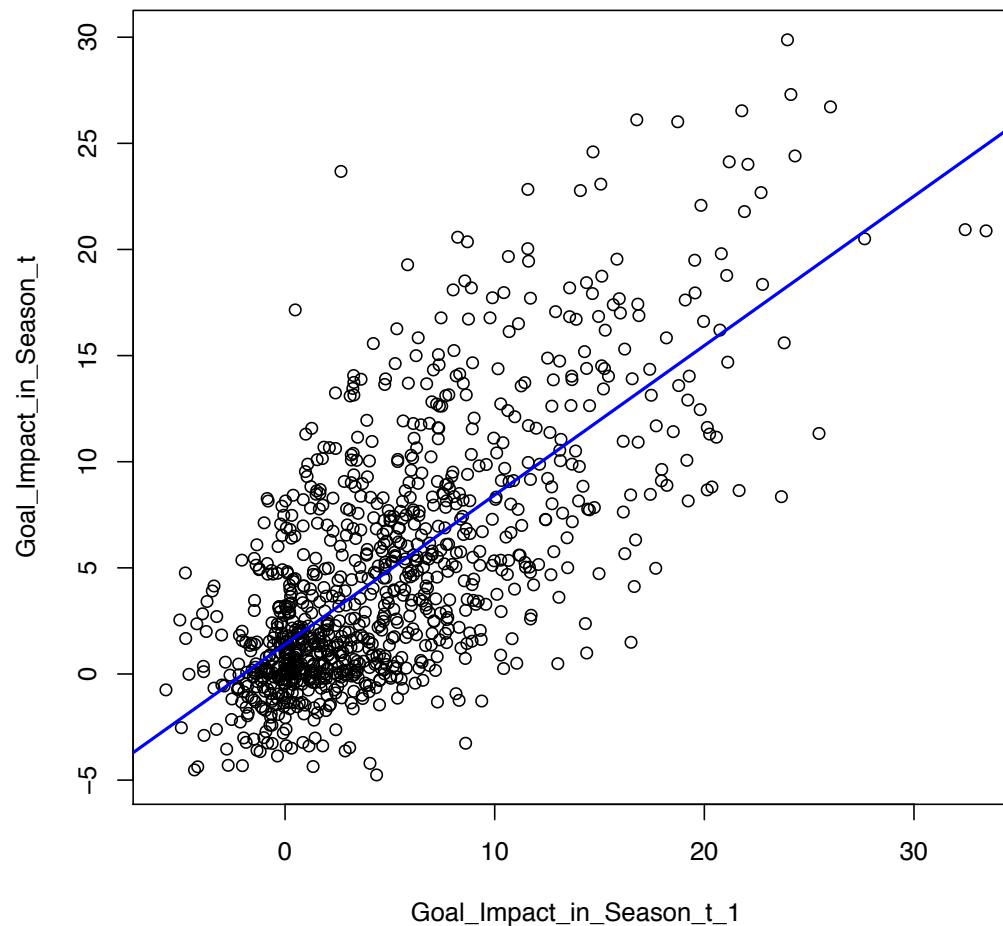


Name	Goal Impact	Points	+/-	Salary
Jason Spezza	29.64	66	-26	\$5,000,000
Jonathan Toews	28.75	67	25	\$6,500,000
Joe Pavelski	27.20	79	23	\$4,000,000
Marian Hossa	26.12	57	26	\$7,900,000
Patrick Sharp	24.43	77	12	\$6,500,000
Sidney Crosby	24.23	104	18	\$12,000,000
Claude Giroux	23.89	86	7	\$5,000,000
Tyler Seguin	23.89	84	16	\$4,500,000

Jason Spezza: high goal impact, low +/-.

- plays very well on poor team (Ottawa Senators).
- Requested transfer for 2014–2015 season.

Consistency Across Seasons



Correlation coefficient = 0.703
Follows Pettigrew(2015)

Related Work

- ▶ Routley and Schulte, UAI 2015
 - Values of Ice Hockey Actions, compares with THoR (Schuckers and Curro 2015).
 - Ranks players by impact on goals and *penalties*.
- ▶ Pettigrew, Sloan 2015.
 - reward = win.
 - estimates impact of goal on win probability given score differential, manpower differential, game time.
- ▶ Cervone et al., Sloan 2014.
 - Conceptually similar but for basketball.
 - our impact function = their EPVA.
 - uses spatial tracking data.

Conclusion

- ▶ Reinforcement Learning → Model of Game Dynamics.
- ▶ Connects advanced machine learning with sports analytics.
- ▶ Application in this paper:
 - use Markov game model to **quantify impact** of a player's action (on expected reward).
 - use total impact values to rank players.
- ▶ Impact value
 - is aware of context.
 - looks ahead to game future trajectory.
- ▶ Total impact value is consistent across seasons.