

Goal-based Performance Metrics for Ice Hockey Accounting for Goal Importance

Patrick Lambrix, Niklas Carlsson, Rasmus Säfvenberg

Linköping University, Sweden

Motivation for Niklas

Niklas
(and many others)
dream of:



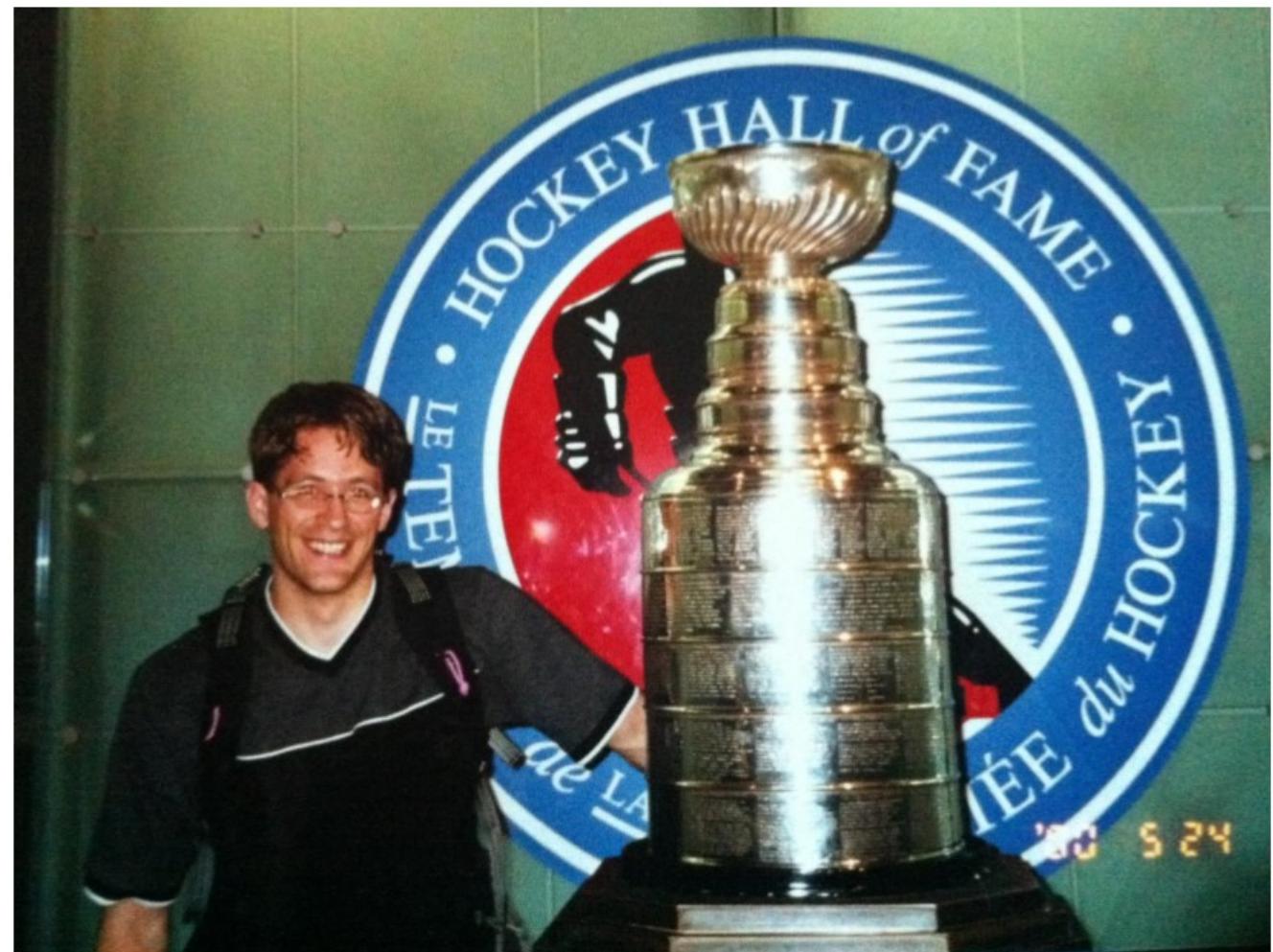
Motivation for Niklas

First try



Motivation for Niklas

A bit easier ...



Motivation for Niklas

Not completely
given up
first method

...



Motivation for Patrick

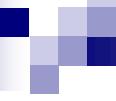


et
ke
Op
lang
wens
te dag
s bij-
mein
ische
natie is
om een
alleen
et alles
s, maar
termin-
n web-
forma-
nteren
werken
b. Een
en deel
e inter-
zelf al
en in de
et wor-
oor wel
g. Zo-

gen.
pees
met
en de
bedo-
den
naar
meer
gen.

Daa
ver
een
“Ik h
maar
zich
wete
finan
toek
der g
gena
zoek
land

Wa
eig
“Lin
200
Het
maar
dan
al be
Link
SAA
(ona
een
F-I
ech



Outline

- Motivation
- Methods and Results
- Conclusion

Performance metrics - traditional

RANK	SPELARE	NR	LAG	POS	GP	G	A	TP	PIM	GWG	PPG	SOG	HITS	BKS	+	-	+/-	TOI/GP
1	Ryan Lasch	81	 Frölunda	F	37	10	25	35	16	3	2	66	9	2	23	31	-8	19:02
2	Joakim Lindström	10	 Skellefteå	F	38	13	21	34	14	3	4	132	4	8	29	25	4	17:15
3	Derek Roy	9	 Linköping	F	39	5	29	34	22	0	2	74	4	20	29	20	9	17:15

- *Offensive:* G: goals, A: assists, TP: points, GWG: game winning goals, PPG: powerplay goals, SOG: Shots on goal
- *Defensive:* HITS: hits, BKS: blocked shots
- *+/-:* plus-minus
- *PIM:* penalty minutes
- *Time:* GP: games played, TOI: time on ice

Performance metrics - advanced

- **Corsi:** shots
- **xG** (Expected Goals): assigns a value to each shot, based on the likelihood of the shot resulting in a goal.
- Different **game scores**
- These metrics have made it into the ice hockey discourse

Performance metrics - advanced

Critique on advanced metrics: context

Some new approaches:

- Using Markov games
- THOR (Total Hockey Rating)

Motivation

Our goal: **Goal-based** metrics that take into account context

Variant 1

- Are variants on traditional metrics
- Are easy to understand for practitioners
- Take into account goal *importance*

Variant 2

- New metrics based on reinforcement learning
- Take into account actions leading to goals

Outline

- Motivation
- Methods and Results
- Conclusion

Data

- Play-by-play data from Sportlogiq
- Seasons 2007-2008 to 2013-2014
- Only regular season

Outline

- Motivation
- Methods and Results
 - Variant 1
 - Variant 2
- Conclusion

Defining a metric

- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

Defining a metric

- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

Observation:

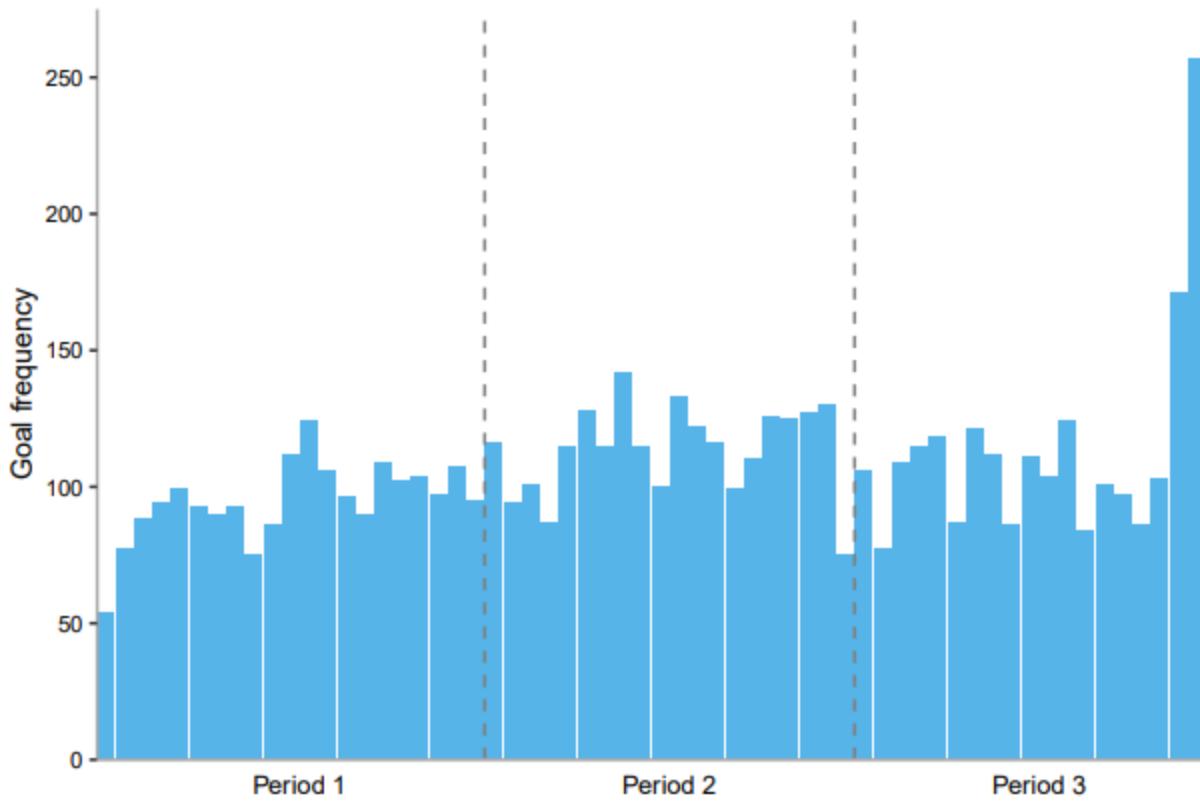


Fig. 1: Goal frequency for each minute of regulation time in the NHL during the 2013-2014 regular season.

Observation

- Goals are not equally important for winning/tying a game

scoring a goal leading 6-0

vs

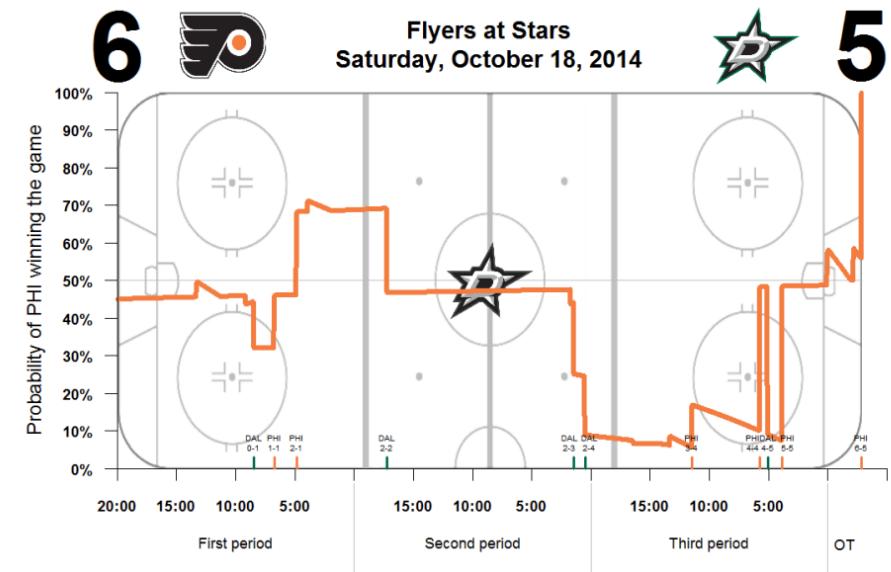
scoring a goal in last minute breaking a tie

Success probabilities

From Oliver Schulte's LINHAC 2022 talk:

- Success: An outcome (binary event) that a team wants to bring about
- Success probability ticker

- Pettigrew
(MIT SSAC 2015):



Success probabilities

- Success: Game points

- NHL: 2 GP for a win, 1 GP for an overtime loss

- Success probability ticker based on goal events

- Difference in success probability immediately before a goal and after a goal

Game Points Importance Value for a goal in a context

- Outcome in regulation time: win, tie, loss
- Context:
<time, goal differential, manpower differential>

$$P(\text{outcome} \mid \text{context}) = \frac{\text{Occ}(\text{context} \mid \text{outcome})}{\text{Occ}(\text{context})}$$

Game Points Importance Value for a context

Change of probability of winning the game by scoring the goal

$$\text{GPIV}_{\text{NHL}}^{\text{RT}}(\text{context BG})$$

$$= 2 \cdot [P(\text{win} \mid \text{context AG}) - P(\text{win} \mid \text{context BG})] \\ + 1 \cdot [P(\text{tie} \mid \text{context AG}) - P(\text{tie} \mid \text{context BG})].$$



Change of probability of the game ending in a tie by scoring the goal

Game Points Importance Value for a context

$\text{GPIV}_{\text{NHL}}^{\text{OT}}(\text{context BG}) = 0.5.$

GPIV vs Goal Differential

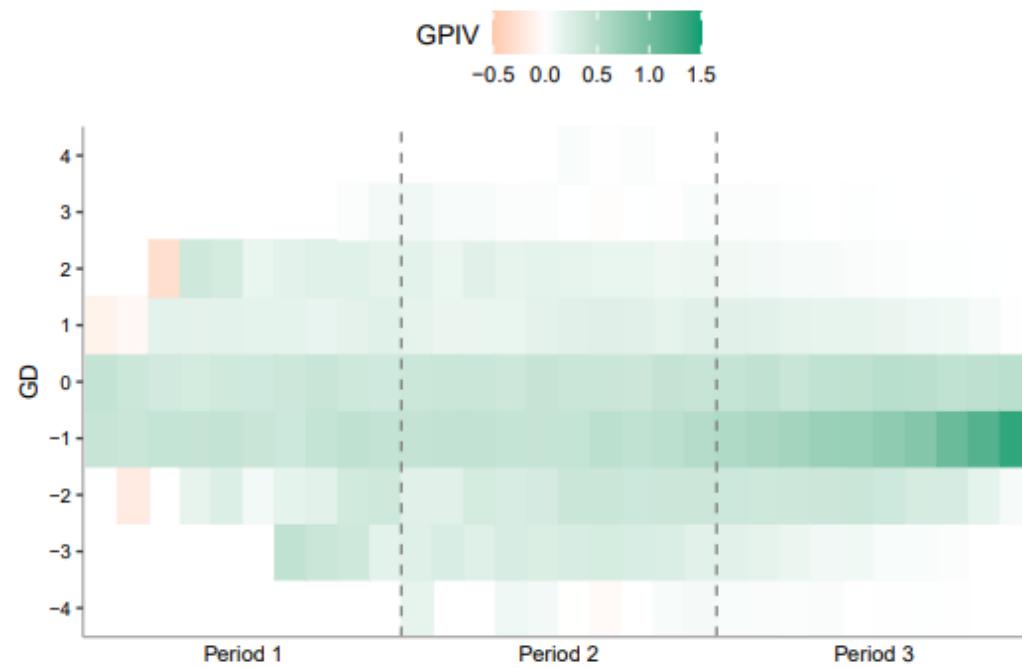


Fig. 2: GPIV versus GD for the 2013-2014 season. Each bin is two minutes. Less than two observations for each bin are left out.

GPIV vs Manpower Differential

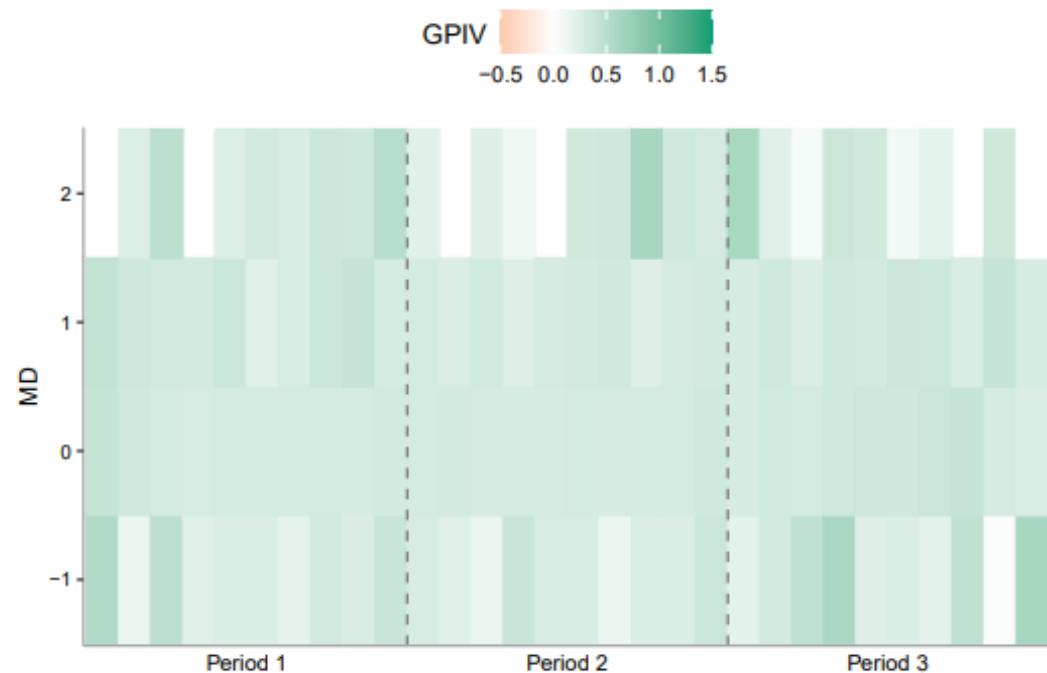


Fig. 3: GPIV versus MD for the 2013-2014 season. Each bin is two minutes. Less than two observations for each bin are left out.

Defining a metric

- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

New metrics

- Traditional metrics:
Goal contributes 1 directly (Goals, +/-) or indirectly (Assists)
- Variants of Goals, Assists, Points, +/-:
Goal contributes with its context-based GPIV

New metrics

- Variants of Goals, Assists, Points, +/-:
Goal contributes with its context-based GPIV

→GPIV-G, GPIV-A, GPIV-P, GPIV-+/-
 1. **Number** of goals in which the player is involved
 2. **Importance** of the goals in which the player is involved

Defining a metric

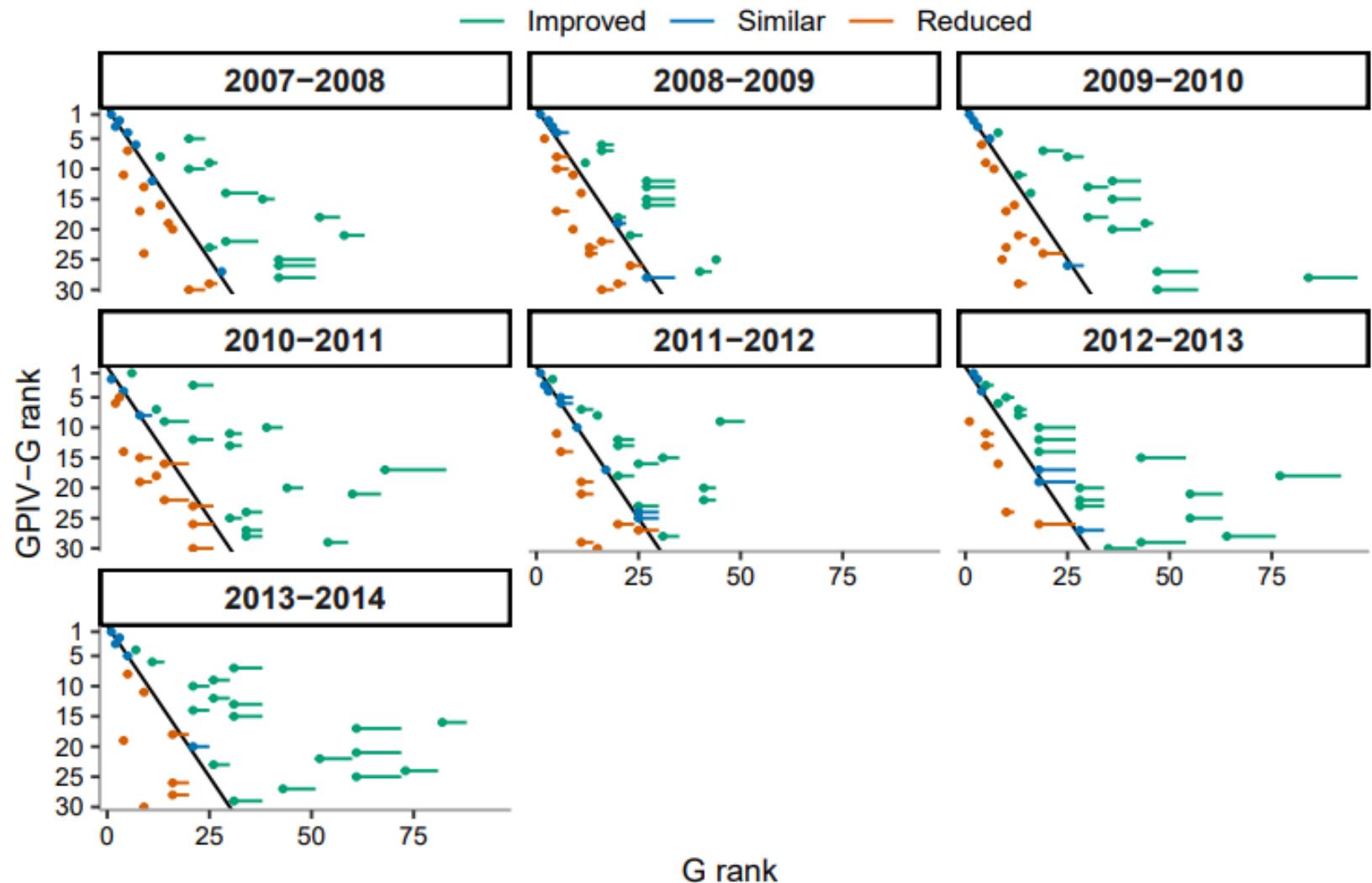
- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

Top 10 players for GPIV-P

Tab. 3: Top 10 players for GPIV-P for the 2013-2014 season.

P-rank	GPIV-P rank	Rank change	Player	Position	P	GPIV-P	GPIV-P/P
1	1	0	Sidney Crosby	C	104	36.360	0.351
8-11	2	6	Alexander Ovechkin	R	79	30.415	0.385
8-11	3	5	Nicklas Bäckström	C	79	29.199	0.370
19-22	4	15	Blake Wheeler	R	69	29.114	0.422
8-11	5	3	Joe Pavelski	C	79	27.995	0.354
4	6	-2	Tyler Seguin	C	84	27.614	0.329
3	7	-4	Claude Giroux	C	86	27.440	0.319
19-22	8	11	Kyle Okposo	R	69	26.951	0.391
16-18	9	7	Anze Kopitar	C	70	26.327	0.376
6-7	10	-4	Phil Kessel	R	80	26.225	0.328

Rank changes P vs GPIV-P



Defining a metric

- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

P vs GPIV-P

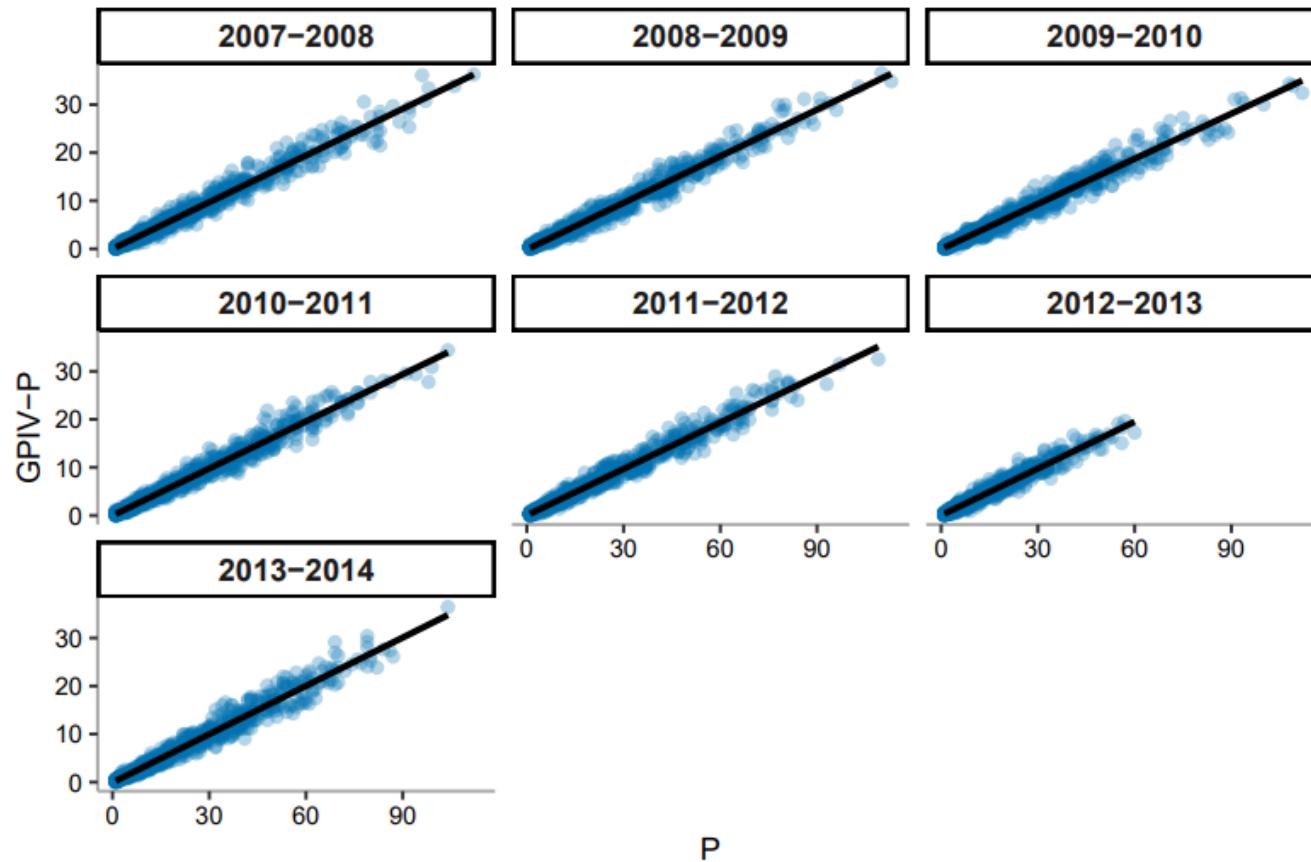


Fig. 10: Correlation traditional points and GPIV-points.

Defining a metric

- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

Multiple seasons

Tab. 7: Maximum values for the metrics. Notes below table.

Season	G	GPIV-G	A	GPIV-A	P	GPIV-P
2007-2008	65	20.333	67	24.762	112	36.243
2008-2009	56	17.126	78	24.234	113	(4) 36.549
2009-2010	51	15.554	83	23.515	112	(5) 34.359
2010-2011	50	(1) 13.529	75	24.401	104	34.382
2011-2012	60	18.889	67	(2) 23.175	109	32.507
2012-2013	29	10.656	43	(3) 13.808	60	(6) 19.668
2013-2014	51	19.731	68	22.481	104	36.460

Table notes:

- (1) Corey Perry 50/13.257 vs Patrick Marleau 36/13.529
- (2) Henrik Sedin 67/22.903 vs Joe Thornton 59/23.175
- (3) Martin St. Louis 43/13.289 vs Nicklas Bäckström 40/13.808
- (4) Evgeni Malkin 113/34.846 vs Alexander Ovechkin 110/36.549
- (5) Henrik Sedin 112/32.425 vs Alexander Ovechkin 108/34.359
- (6) Martin St. Louis 60/17.234 vs Steven Stamkos 57/19.668

Defining a metric

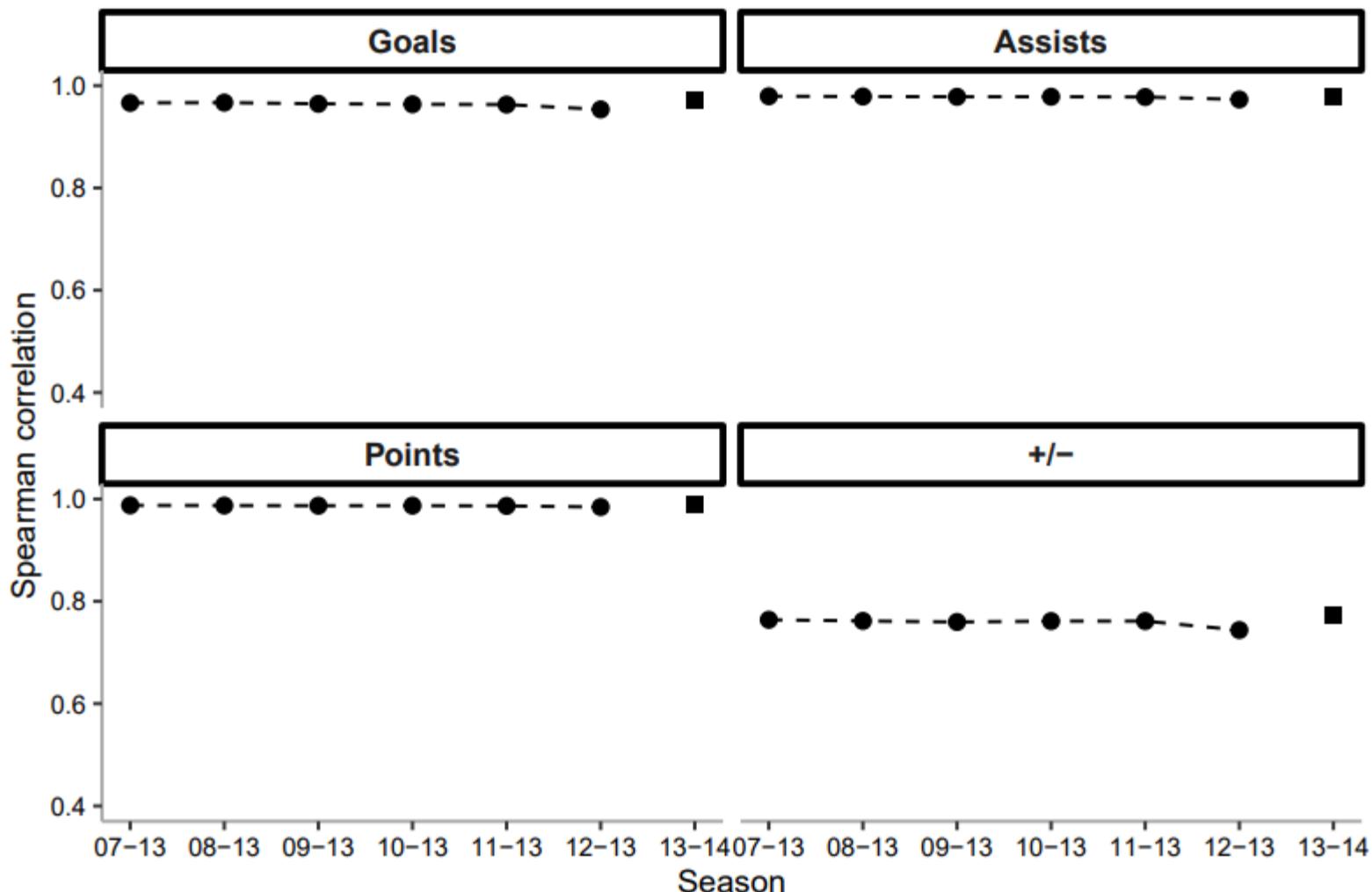


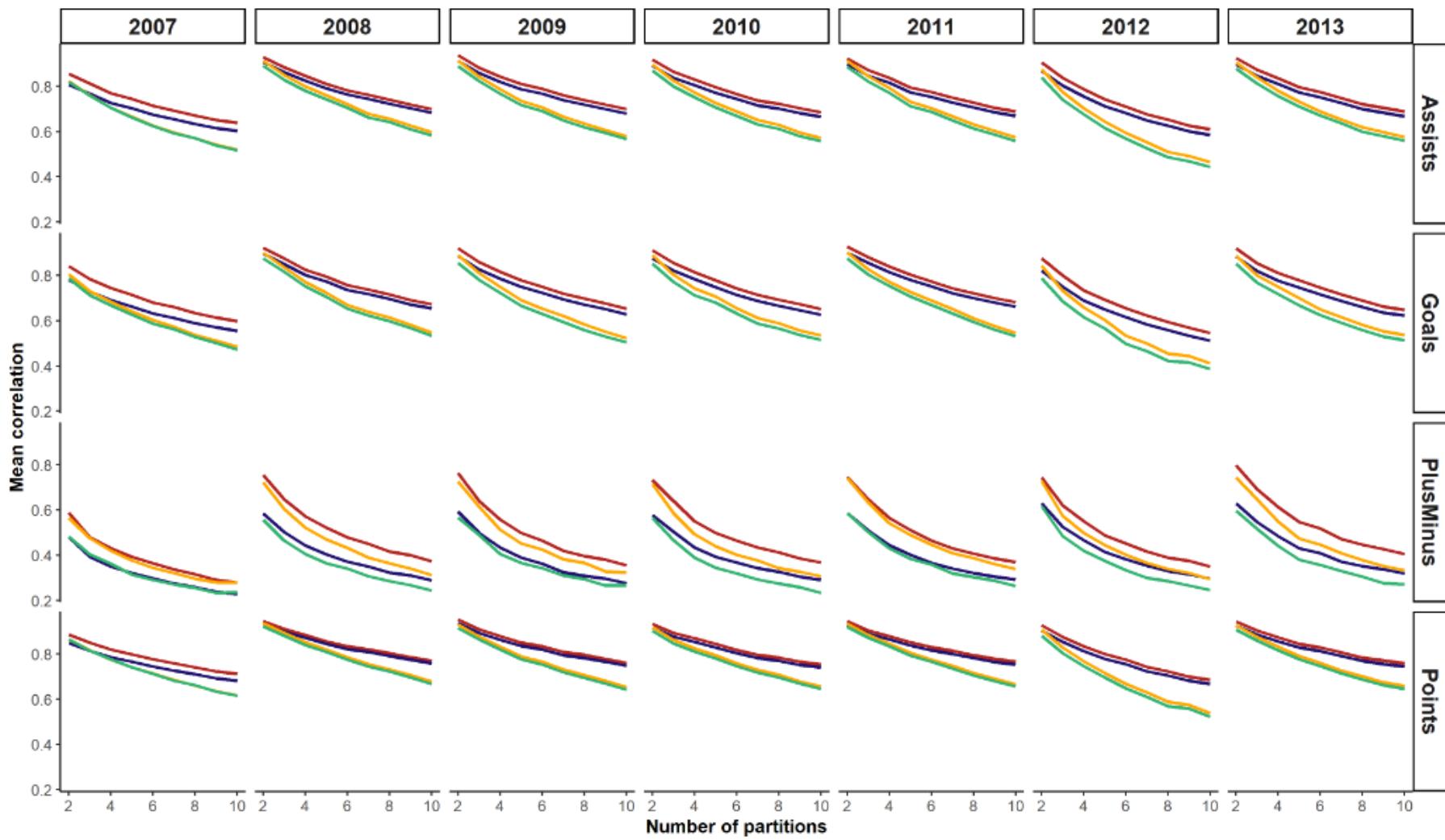
Fig. 12: Correlation between traditional and GPIV metrics during the 2013-2014 season based on occurrences from multiple seasons.

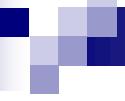
Defining a metric

- What are the intuitions behind the metric?
- How is the metric defined?
- Does it pass the eye test?
- Are there correlations with existing metrics?
- Is the metric stable?
- Can one predict the value of the metric at the end of a season based on data for part of the season?

Correlation for different partitions and seasons for Pearson

— Generalized traditional vs. traditional — Generalized GPIV vs. GPIV
— Generalized traditional vs. GPIV — Generalized GPIV vs. traditional





Playoffs

Playoffs

$$\text{GPIV}_{\text{NHL}}^{\text{RT (playoffs)}}(\text{context BG}) = P(\text{win} \mid \text{context AG}) - P(\text{win} \mid \text{context BG})$$

$$\text{GPIV}_{\text{NHL}}^{\text{OT (playoffs)}}(\text{context BG}) = 0.5$$

Playoffs

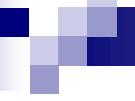
Tab. 10: Top 10 players for GPIV-P for the 2013-2014 playoffs. GP = Games played.

P-rank	GPIV-P rank	Rank change	Player	Position	GP	P	GPIV-P	GPIV-P/P
2	1	1	Justin Williams	R	26	25	4.705	0.188
1	2	-1	Anze Kopitar	C	26	26	4.301	0.165
7-8	3	4	Jonathan Toews	C	19	17	3.988	0.235
6	4	2	Drew Doughty	D	26	18	3.944	0.219
5	5	0	Patrick Kane	R	19	20	3.923	0.196
4	6	-2	Marian Gaborik	R	26	22	3.805	0.173
14-19	7	7	P.K. Subban	D	17	14	3.539	0.253
2	8	-6	Jeff Carter	C	26	25	3.297	0.132
28-33	9	19	Duncan Keith	D	19	11	3.111	0.283
10-13	10	0	Brent Seabrook	D	16	15	3.096	0.206

Playoffs

Tab. 11: Top 10 players for GPIV-P/P with minimum 5 P for the 2013-2014 playoffs. GP = Games played.

P-rank	GPIV-P rank	Rank change	Player	Position	GP	P	GPIV-P	GPIV-P/P
59-77	20	39	Daniel Briere	C	16	7	2.282	0.326
78-94	33	45	Dany Heatley	L	11	6	1.918	0.320
59-77	26	33	Mikko Koivu	C	13	7	2.048	0.293
34-45	13	21	Nathan MacKinnon	C	7	10	2.844	0.284
95-114	55	40	Marc Staal	D	25	5	1.421	0.284
28-33	9	19	Duncan Keith	D	19	11	3.111	0.283
59-77	30	29	Ryan Suter	D	13	7	1.971	0.282
52-58	21	31	Nick Bonino	C	13	8	2.247	0.281
78-94	44	34	Jared Spurgeon	D	13	6	1.637	0.273
95-114	60	35	Matt Nieto	L	7	5	1.366	0.273



Pairs of players

Pairs of players – direct impact

Tab. 12: Top 10 direct pairs for the 2013-2014 season. Player position in parentheses (L for left wing, R for right wing, C for center).

Rank	Player pair	Team	GPIV-G-DP (G-DP)	GPIV-G-DP-1 (G-DP-1)	GPIV-G-DP-2 (G-DP-2)
1	Jamie Benn (L), Tyler Seguin (C)	DAL	13.96 (45)	7.42 (23)	6.54 (22)
2	Chris Kunitz (L), Sidney Crosby (C)	PIT	12.92 (39)	6.63 (26)	6.29 (13)
3	Corey Perry (R), Ryan Getzlaf (C)	ANA	12.30 (39)	8.66 (25)	3.64 (14)
4	Alex Ovechkin (R), Nicklas Backstrom (C)	WSH	12.27 (35)	10.61 (29)	1.66 (6)
5	Phil Kessel (R), James van Riemsdyk (L)	TOR	11.56 (34)	5.88 (17)	5.68 (17)
6	Andrew Ladd (L), Bryan Little (C)	WPG	11.05 (29)	5.98 (15)	5.07 (14)
7	Paul Stastny (C), Gabriel Landeskog (L)	COL	9.65 (24)	5.15 (14)	4.50 (10)
8	Claude Giroux (C), Jakub Voracek (R)	PHI	9.50 (29)	5.74 (14)	3.75 (15)
9	Kyle Okposo (R), John Tavares (C)	NYI	8.98 (24)	5.95 (14)	3.03 (10)
10	David Krejci (C), Milan Lucic (L)	BOS	8.78 (27)	4.47 (10)	4.31 (17)

Pairs of players – on ice

Tab. 13: Top 10 indirect pairs for the 2013-2014 season. Player position in parentheses (L for left wing, R for right wing, C for center).

Rank	Player pair	Team	GPIV-GD-IP (GD-IP)	GPIV-GF-IP (GF-IP)	GPIV-GA-IP (GA-IP)
1	Sidney Crosby (C), Chris Kunitz (L)	PIT	27.39 (79)	40.60 (117)	13.21 (38)
2	Claude Giroux (C), Jakub Voracek (R)	PHI	22.68 (52)	35.74 (98)	13.05 (46)
3	Joe Pavelski (C), Joe Thornton (C)	SJS	20.64 (57)	27.95 (77)	7.31 (20)
4	Wayne Simmonds (R), Scott Hartnell (L)	PHI	20.16 (42)	23.54 (60)	3.39 (18)
5	Tyler Seguin (C), Jamie Benn (L)	DAL	19.87 (56)	32.23 (101)	12.36 (45)
6	Wayne Simmonds (R), Claude Giroux (C)	PHI	19.03 (33)	21.22 (53)	2.19 (20)
7	Wayne Simmonds (R), Jakub Voracek (R)	PHI	18.51 (33)	19.45 (46)	0.94 (13)
8	Sidney Crosby (C), Matt Niskanen (D)	PIT	18.39 (49)	22.09 (63)	3.70 (14)
9	Ryan Getzlaf (C), Corey Perry (R)	ANA	18.21 (58)	31.66 (102)	13.46 (44)
10	Jakub Voracek (R), Kimmo Timonen (D)	PHI	18.11 (41)	23.07 (56)	4.96 (15)

Conclusions – variant 1

- Introduced new goal-based performance metrics for ice hockey players
- Strong correlation for G, A, P between new and traditional metrics
- Pass the eye test
- Data from previous season can be used to approximate new metrics for regular season
- Predict using data from part of a season

Outline

- Motivation
- Methods and Results
 - Variant 1
 - Variant 2
- Conclusion

Action Impact Model

- Based on the work by Routley and Schulte 2015*
- Idea:
 - Define state $s = \langle c, ps \rangle$
where c is a context and ps is a play sequence
 - Actions are performed in states
 - Define impact of action in a state
 - Define player impact based on action impacts

*Schulte's group presented a more extended model at IJCAI 2018.

Action Impact Model

Context

Notation	Name	Range
GD	Goal Differential	[-8,8]
MD	Manpower Differential	[-3,3]
P	Period	[1,7]

Action Impact Model

Events

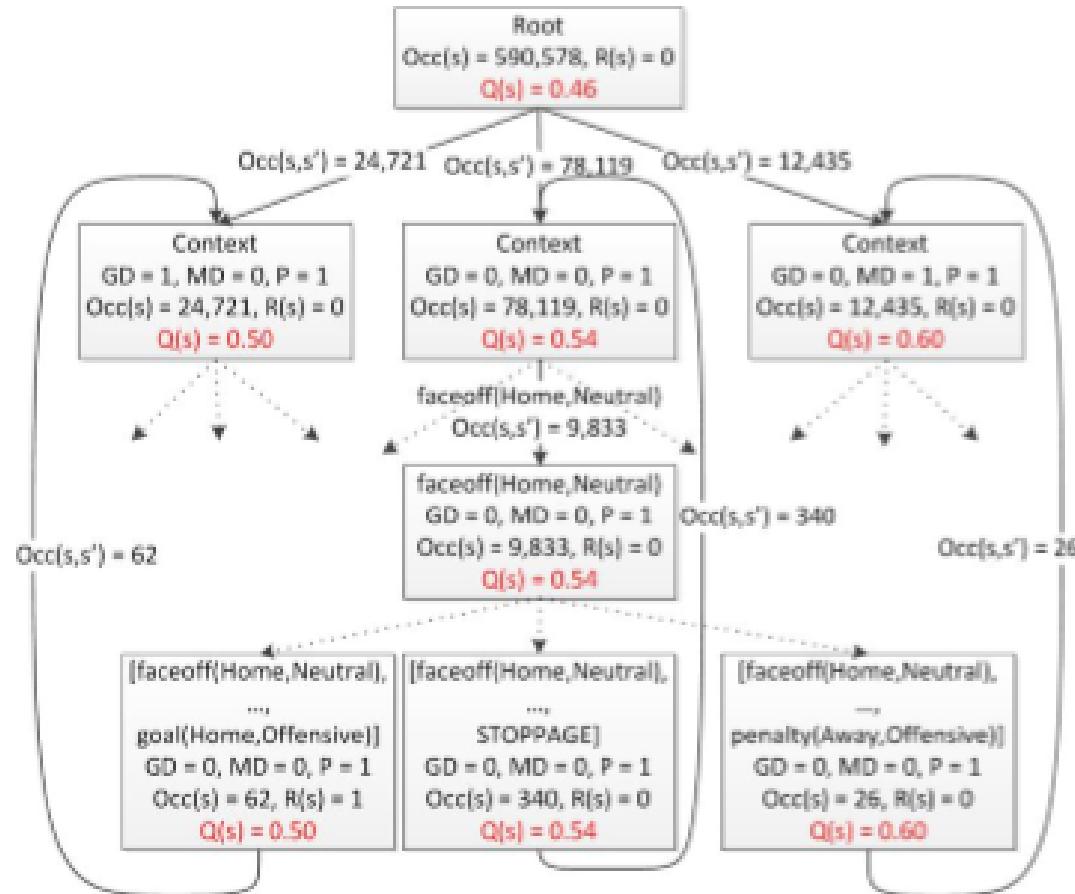
Action Event	Start/End Event
Faceoff	Period Start
Shot	Period End
Missed Shot	Early Intermission Start
Blocked Shot	Penalty
Takeaway	Stoppage
Giveaway	Shootout Completed
Hit	Game End
Goal	Game Off
	Early Intermission End

Action Impact Model

A play sequence is defined as

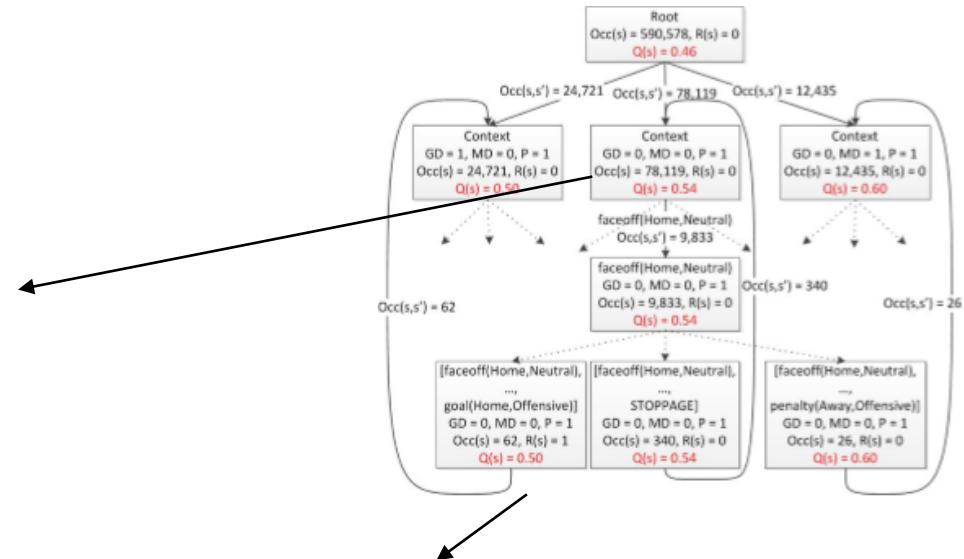
- the empty sequence or
 - a sequence of events
 - first event: start marker
 - (possible) next events: action events
 - (possible) last event: end event
- (→complete sequence)

Action Impact Model



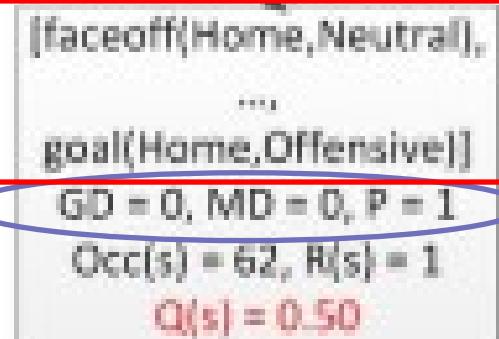
Action Impact Model

State $s = \langle c, ps \rangle$



Context

Play sequence



Action Impact Model

- Actions are performed in states

$\langle c, ps \rangle * a =$

$\langle c, append(ps, a) \rangle$ if state has no end event
(add action to play sequence, e.g., shot)

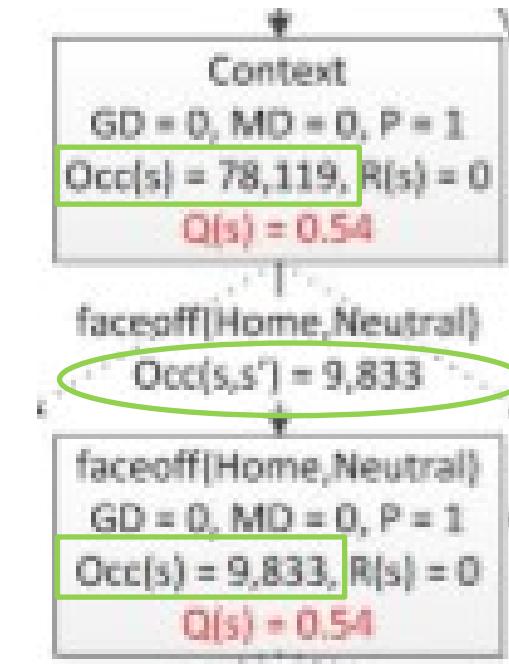
$\langle c', empty-set \rangle$ if state has end event
(change context, e.g., after a goal)

Action Impact Model

Based on play-by-play data:

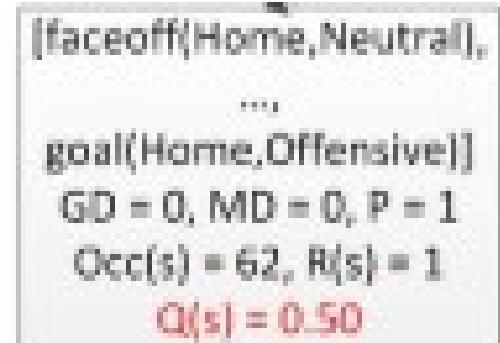
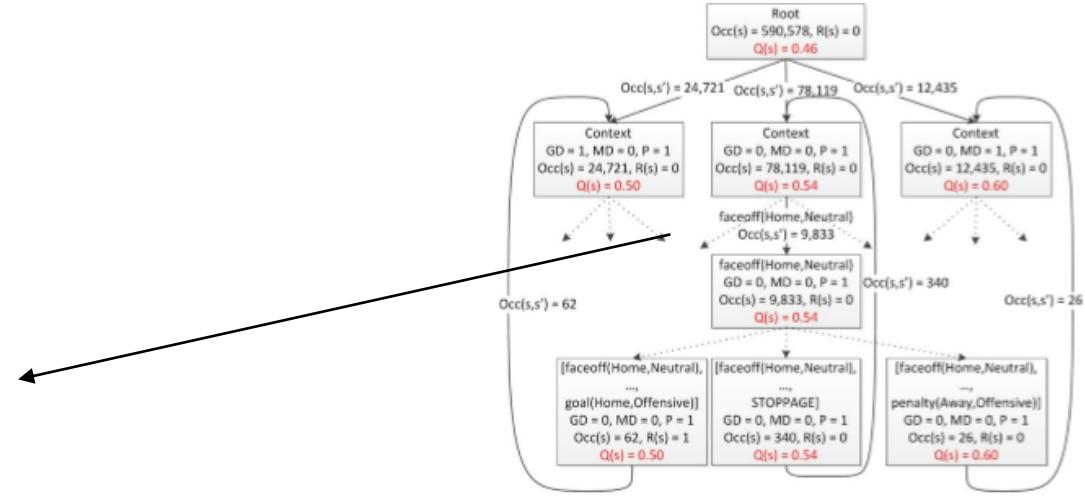
- Occurrences of state s : $Occ(s)$
- Occurrences of state s immediately followed by state s' : $Occ(s,s')$
- Transition probability $T(s,s') = Occ(s,s') / Occ(s)$

Action Impact Model



Occurrences

Occurrences



Action Impact Model

Value iteration algorithm → Q-values

Reward function: goal states receive reward 1

(In single player experiments
also goal against reward -1)

- Impact of action a in state s : $Q_T(s * a) - Q_T(s)$

Action Impact Model

Algorithm 1 Dynamic Programming for Value Iteration

Require: Markov Game model, convergence criterion c ,
maximum number of iterations M

```
1: lastValue = 0
2: currentValue = 0
3: converged = false
4: for  $i = 1; i \leq M; i \leftarrow i + 1$  do
5:   for all states  $s$  in the Markov Game model do
6:     if converged == false then
7:        $Q_{i+1}(s) =$ 
8:       
$$R(s) + \frac{1}{Occ(s)} \sum_{(s,s') \in E} (Occ(s,s') \times Q_i(s'))$$

9:     end if
10:   end for
11:   if converged == false then
12:     if  $\frac{currentValue - lastValue}{currentValue} < c$  then
13:       converged = true
14:     end if
15:   end if
16:   lastValue = currentValue
17:   currentValue = 0
18: end for
```

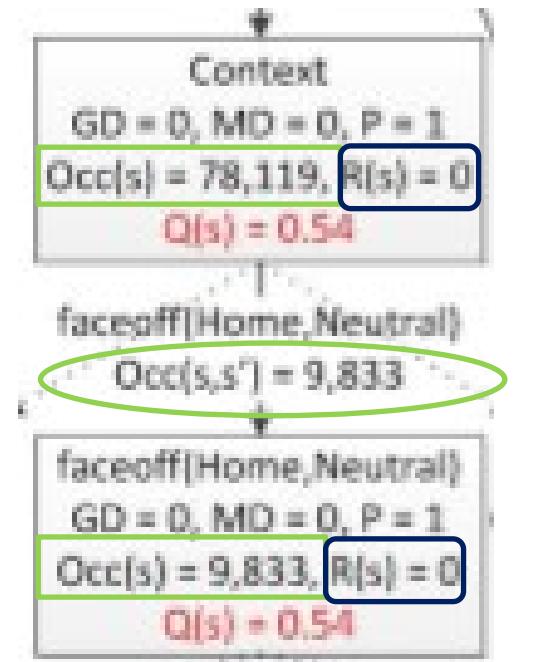
Action Impact Model

7:

$$Q_{i+1}(s) = R(s) + \frac{1}{Occ(s)} \sum_{(s,s') \in E} (Occ(s, s') \times Q_i(s'))$$

Compute separate Q-values for Home and Away teams

Action Impact Model

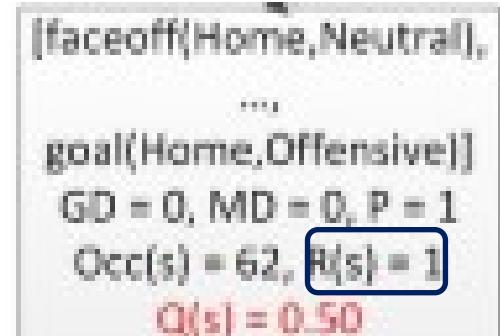
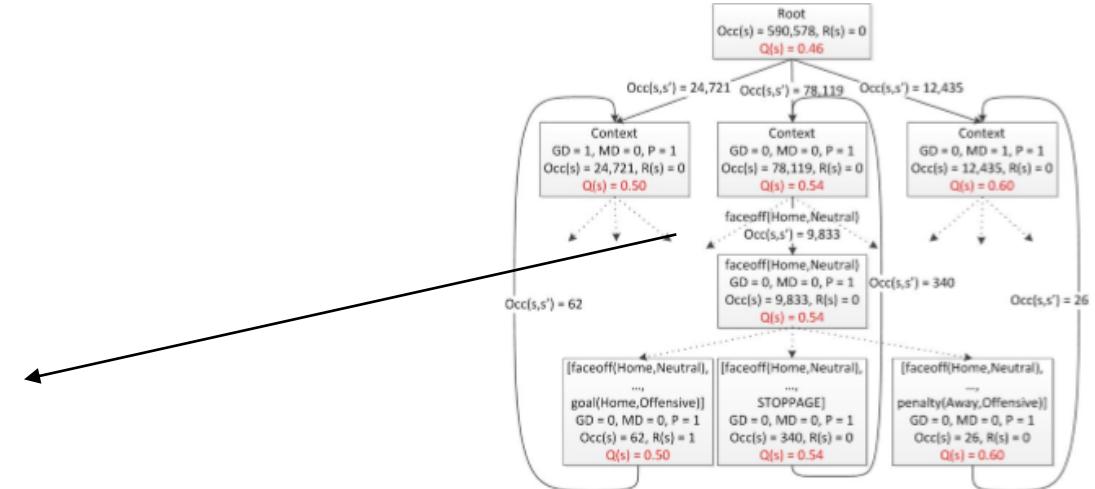


Occurrences

Occurrences

Reward

Q-value



Player Impact

Sum of action impacts

1. Based on all actions performed by the player
(direct goal-based impact)
2. Based on actions when the player is on the ice
(on-ice goal-based impact)

Variants normalized by time

Player Pair Impact

Sum of action impacts when both players are on the ice (on-ice goal-based impact)

Variants normalized by time

Top players 2007-2008 and 2008-2009 for direct impact

PlayerName	Position	Age	Salary	GP	G	GA	PlusMin	Points	Direct	Directh	On-ice	On-iceh
2007												
Alex Ovechkin	F	22	3.83	82	65	47	28	112	71.96	182.65	232.56	588.85
Dion Phaneuf	D	22	0.94	82	17	43	12	60	59.22	134.05	246.12	559.67
Rick Nash	F	23	5.50	80	38	31	3	69	59.01	181.80	158.82	485.99
Jarome Iginla	F	30	7.00	82	50	48	27	98	58.94	161.92	204.12	560.88
Dustin Brown	F	23	1.18	78	33	27	-13	60	53.78	156.41	171.40	501.48
Brenden Morrow	F	28	4.10	82	32	42	23	74	51.15	146.62	171.59	504.57
Zdeno Chara	D	30	7.50	77	17	34	14	51	50.74	117.69	203.78	468.89
Trent Hunter	F	27	1.55	82	12	29	-17	41	50.31	167.65	153.36	508.27
Mike Green	D	22	0.85	82	18	38	6	56	48.26	122.63	219.72	545.08
Pavel Datsyuk	F	29	6.70	82	31	66	41	97	48.22	134.68	198.44	559.41
2008												
Alex Ovechkin	F	23	9.00	79	56	54	8	110	75.93	194.34	239.89	612.23
Dustin Brown	F	24	2.60	80	24	29	-15	53	59.76	177.60	178.34	540.84
Shea Weber	D	23	4.50	81	23	30	1	53	53.14	136.10	201.19	511.36
Evgeni Malkin	F	22	3.83	82	35	78	17	113	50.76	134.92	220.41	591.75
Dion Phaneuf	D	23	7.00	79	11	36	-11	47	50.34	122.64	240.57	532.49
Vincent Lecavalier	F	28	7.17	77	29	38	-9	67	49.46	143.99	188.17	549.37
Sheldon Souray	D	32	6.25	81	23	30	1	53	49.38	125.86	203.08	514.73
Jeff Carter	F	24	4.50	82	46	38	23	84	48.88	141.78	189.35	548.30
Rick Nash	F	24	6.50	78	40	39	11	79	48.88	145.11	171.59	498.26
Martin St. Louis	F	33	5.00	82	30	50	4	80	47.82	135.55	204.19	569.06

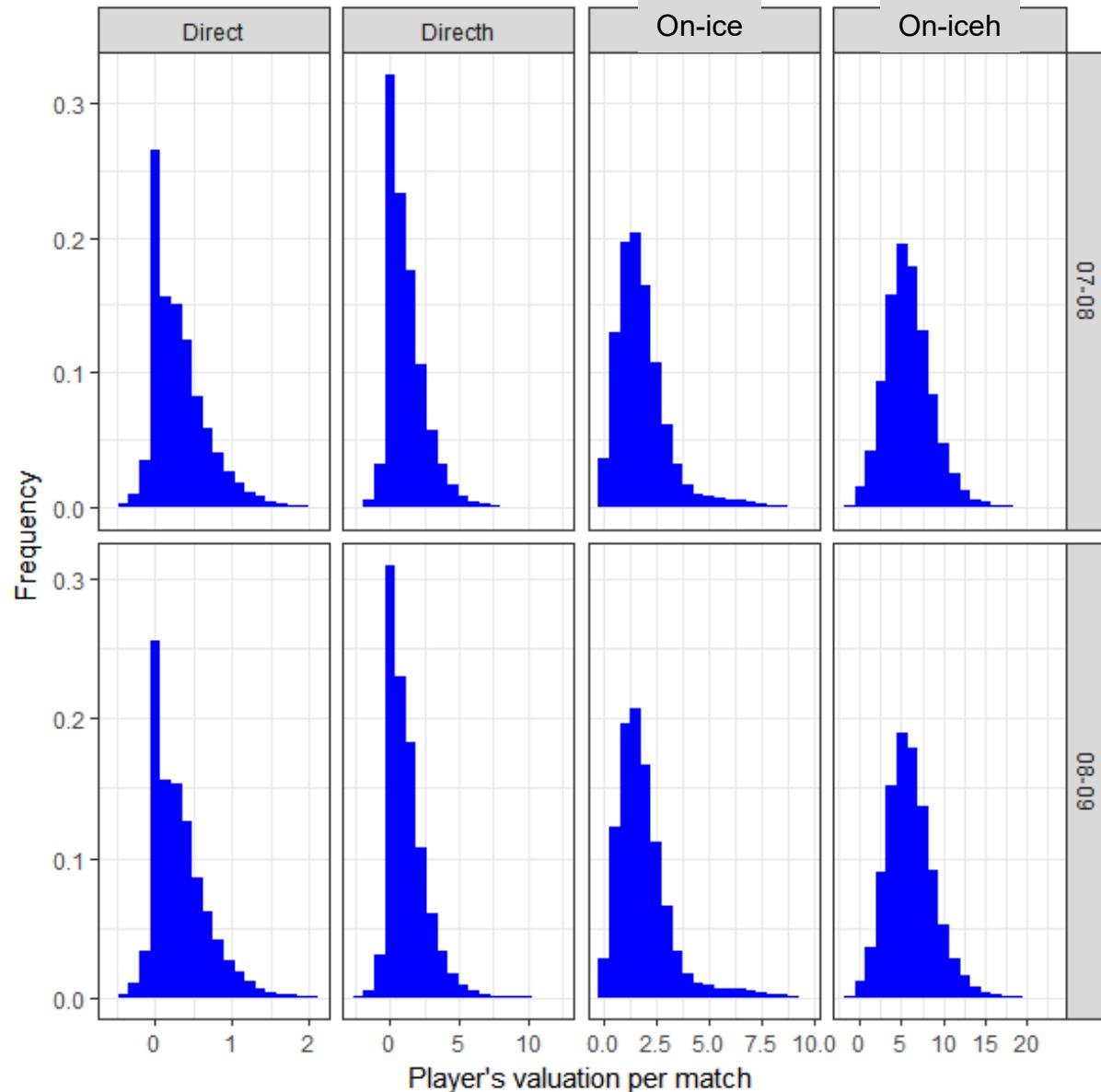
Table 5.1: Top 10 Players performance for 2007-2008 and 2008-2009 for the Direct metric.

Top players 2007-2008 and 2008-2009 for on-ice impact

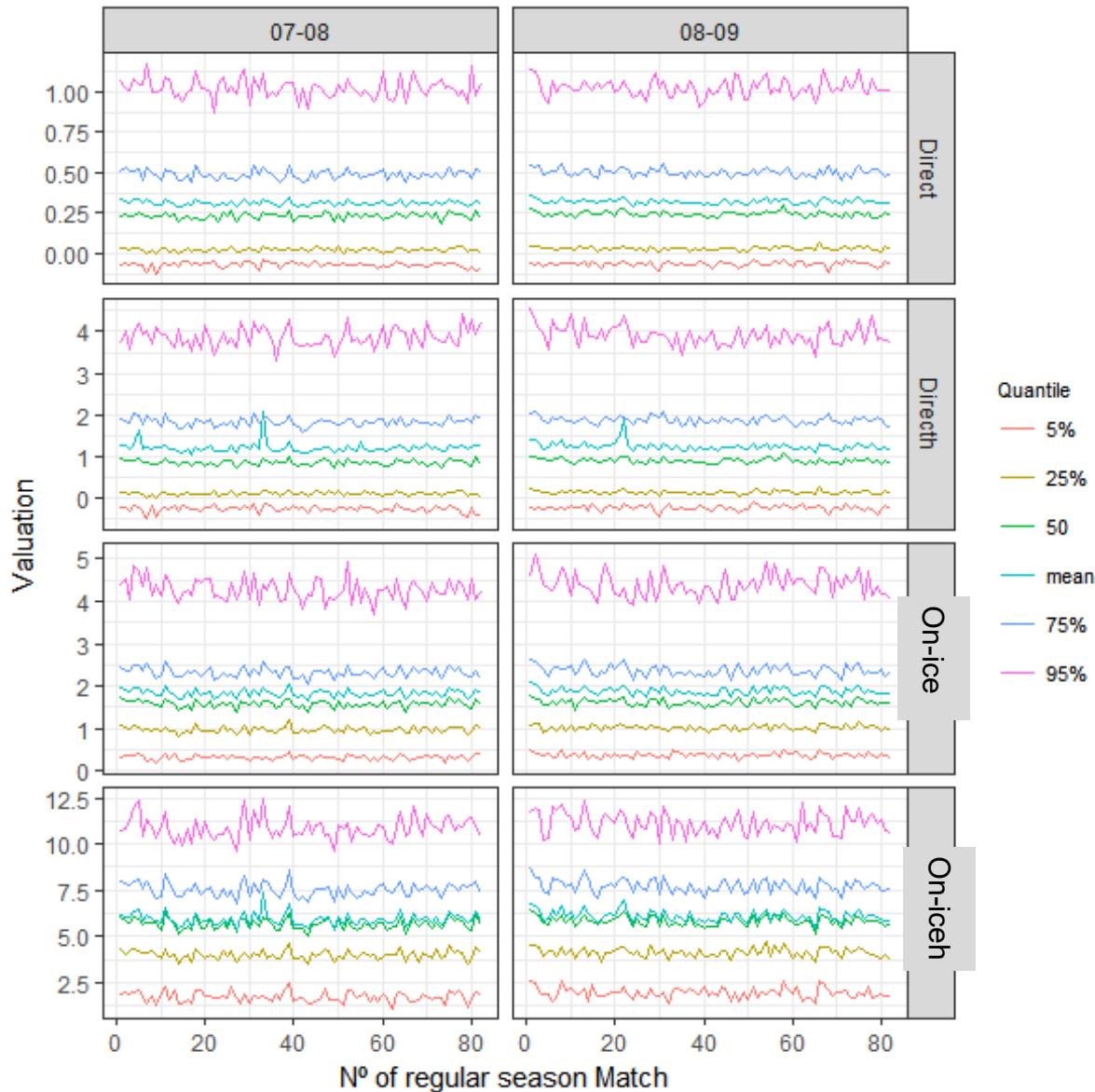
PlayerName	Position	Age	Salary	GP	G	GA	PlusMin	Points	Direct	Directh	On-ice	On-iceh
2007												
Dion Phaneuf	D	22	0.94	82	17	43	12	60	59.22	134.05	246.12	559.67
Alex Ovechkin	F	22	3.83	82	65	47	28	112	71.96	182.65	232.56	588.85
Tomas Kaberle	D	29	4.25	82	8	45	-8	53	38.32	93.36	221.93	551.72
Mike Green	D	22	0.85	82	18	38	6	56	48.26	122.63	219.72	545.08
Andrei Markov	D	29	5.75	82	16	42	1	58	42.37	105.18	213.81	530.37
Nicklas Lidstrom	D	37	7.60	76	10	60	40	70	29.04	66.41	205.68	480.18
Jarome Iginla	F	30	7.00	82	50	48	27	98	58.94	161.92	204.12	560.88
Zdeno Chara	D	30	7.50	77	17	34	14	51	50.74	117.69	203.78	468.89
Lubomir Visnovsky	D	31	2.05	82	8	33	-18	41	32.64	83.52	201.34	523.00
Roman Hamrlik	D	33	5.50	77	5	21	7	26	37.79	93.89	201.29	509.39
2008												
Dion Phaneuf	D	23	7.00	79	11	36	-11	47	50.34	122.64	240.57	532.49
Alex Ovechkin	F	23	9.00	79	56	54	8	110	75.93	194.34	239.89	612.23
Evgeni Malkin	F	22	3.83	82	35	78	17	113	50.76	134.92	220.41	591.75
Dan Boyle	D	32	6.67	77	16	41	6	57	36.11	88.65	219.94	539.81
Chris Pronger	D	34	6.25	82	11	37	0	48	43.40	99.89	217.92	503.72
Mike Green	D	23	6.00	68	31	42	24	73	46.41	106.62	214.33	493.09
Nicklas Backstrom	F	21	2.40	82	22	66	16	88	37.12	111.83	214.19	630.43
Braydon Coburn	D	23	1.20	80	7	21	7	28	40.78	100.10	211.64	516.12
Andrei Markov	D	30	5.75	78	12	52	-2	64	38.03	96.17	209.18	527.62
Mark Streit	D	31	4.10	74	16	40	6	56	39.38	97.60	206.59	504.31

Table 5.4: Top 10 players performance for 2007-2008 and 2008-2009 for the On-ice metric without goalkeeper positions

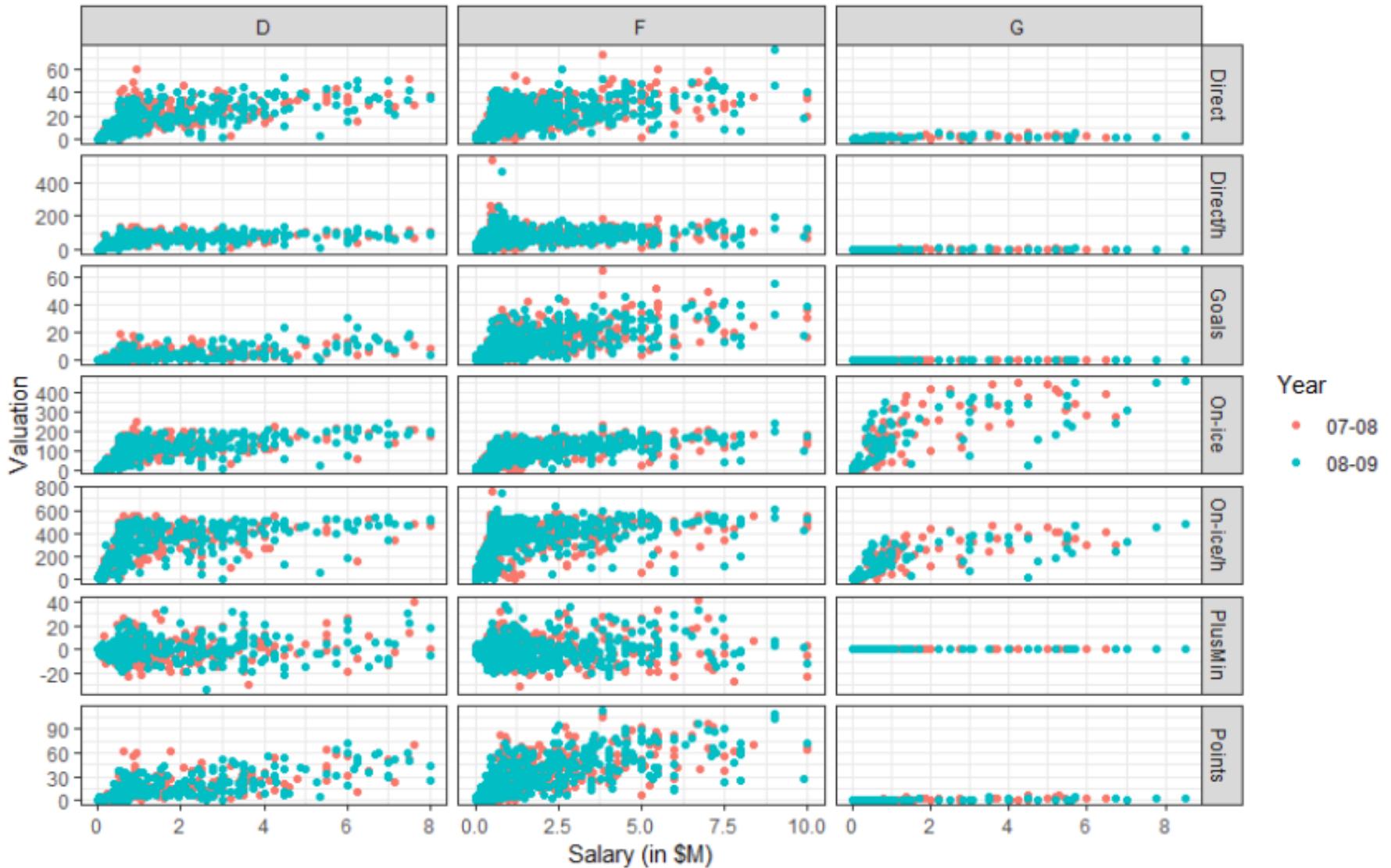
Distribution of impact values



Quantiles per game



Impact vs salary per position

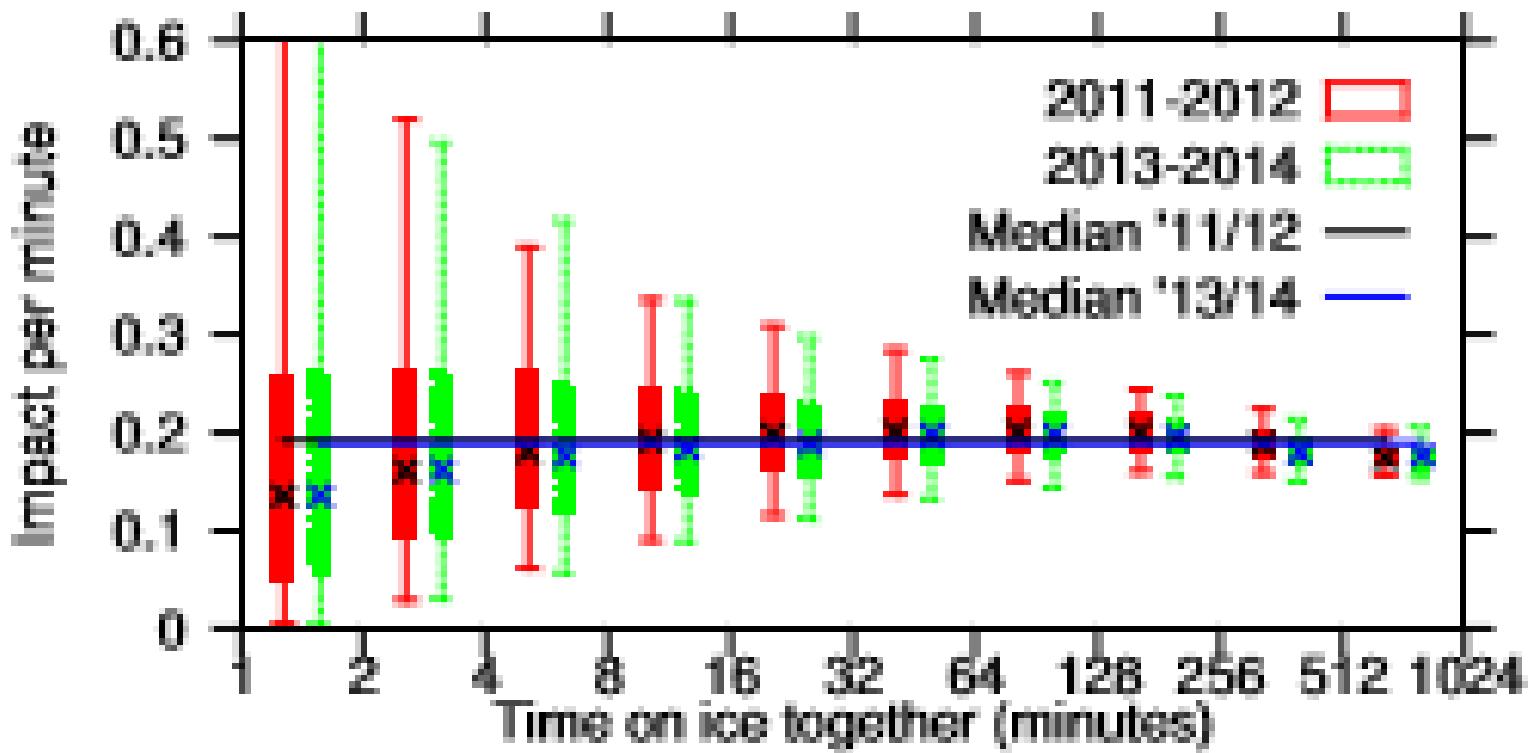


Top pairs 2011-2012

Table 3. Top pairs 2011-2012 according to team impact.

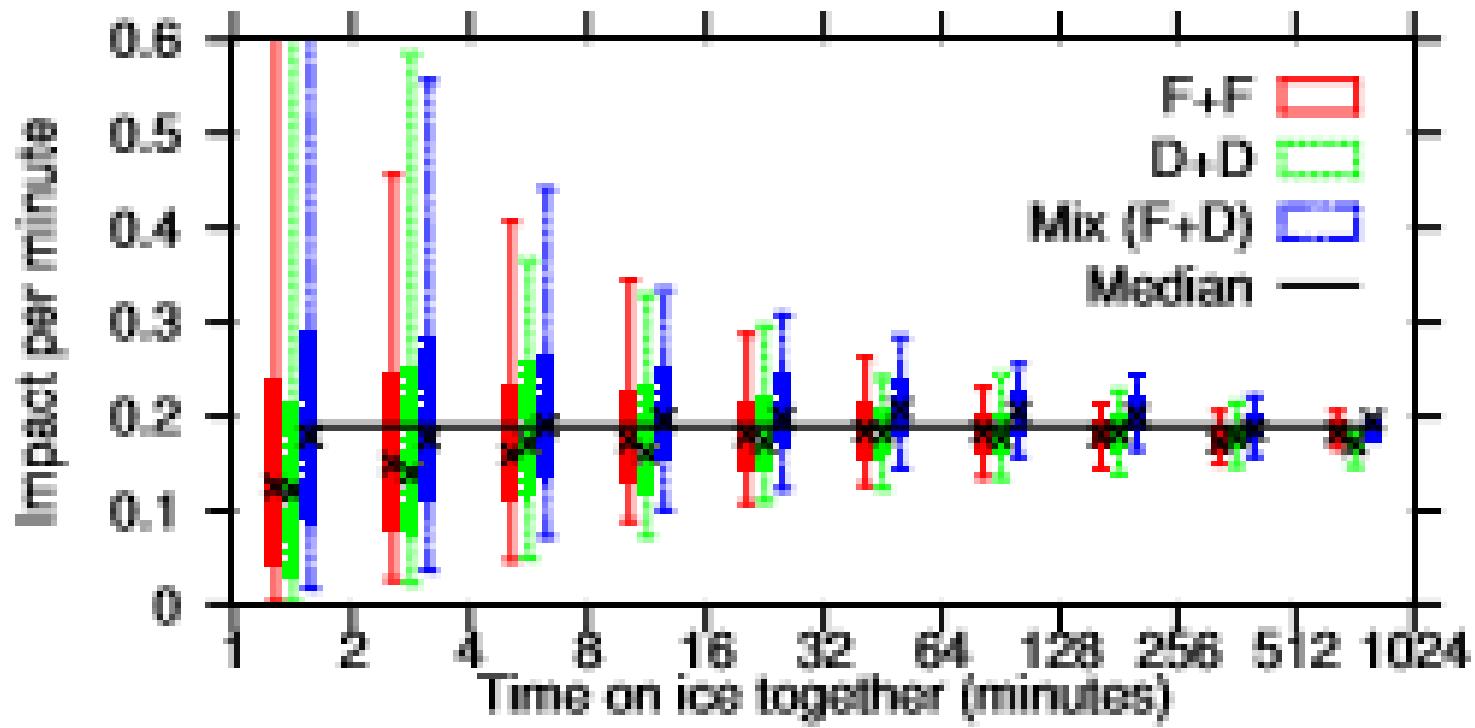
		Player 1				Player 2				Pair stats			
	Name	Pos	G	A	+/-	Name	Pos	G	A	+/-	Team	Impact	TOI
Forwards	Ilya Kovalchuk	R	37	46	-9	Zach Parise	L	31	38	-5	NJD	121.17	40,163
	Ryan O'Reilly	C	18	37	-1	Gabriel Landeskog	L	22	30	+20	COL	115.74	39,021
	Joe Pavelski	C	31	30	+18	Joe Thornton	C	18	59	+17	SJS	112.65	39,353
	Steven Stamkos	C	60	37	+7	Martin St. Louis	R	25	49	-3	TBL	111.77	35,941
	Milan Michalek	L	35	25	+4	Jason Spezza	C	34	50	+11	OTT	111.73	36,689
Defenders	Dan Girardi	D	5	24	+13	Ryan McDonagh	D	7	25	+25	NYR	155.28	55,911
	Filip Kuba	D	6	26	+26	Erik Karlsson	D	19	59	+16	OTT	134.74	47,985
	Francois Beauchemin	D	8	14	-14	Cam Fowler	D	5	24	-28	ANA	125.54	45,795
	Josh Gorges	D	2	14	+14	P.K. Subban	D	7	29	+9	MTL	125.16	44,390
	Carl Gunnarsson	D	4	15	-9	Dion Phaneuf	D	12	32	-10	TOR	123.06	36,181
Mixed	Jason Spezza	C	34	50	+11	Erik Karlsson	D	19	59	+16	OTT	110.58	35,990
	Joe Pavelski	C	31	30	+18	Dan Boyle	D	9	39	+10	SJS	106.04	35,612
	Joe Thornton	C	18	59	+17	Dan Boyle	D	9	39	+10	SJS	102.96	35,160
	Tomas Fleischmann	L	27	34	-7	Brian Campbell	D	4	49	-9	FLA	98.08	31,804
	Stephen Weiss	C	20	27	+5	Brian Campbell	D	4	49	-9	FLA	96.79	32,995

Impact per minute



Variation decreases when more joint TOI
Medians highest in 16-256 minutes joint TOI

Impact per minute



Mixed pairs may have higher impact

Further Reading

Papers available at the
LiU Sports Analytics Group page:

<https://www.ida.liu.se/research/sportsanalytics/>

Currently working on / Future work

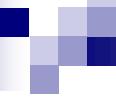
- Combine variant 1 and 2 by using GPIV as the reward function in variant 2
- Game prediction and season simulation
- Roles of ice hockey players
- Importance of powerplay

Linköping Hockey Analytics Conference - LINHAC

LINHAC aims to bring together professionals and academics with an interest in hockey analytics. LINHAC will feature the latest research in hockey analytics in academia and companies, panel discussions with analysts, coaches, GMs and players, industry sessions with the latest hockey analytics products, and an analytics competition for students.

LINHAC 2022: recordings available

LINHAC 2023 – June 7-9, 2023



Thanks to our students

- Carles Sans Fuentes
- Dennis Ljung
- Jon Vik
- Min-Chun Shih
- Rabnawaz Jan-Sher
- Sofie Jörgensen
- Haris Kozlica
- Timmy Lehmus Persson