Isolating Individual Skater Impact on Team Shot Quantity and Quality

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Introduction

Tired: Numbers
Wired: Pictures
Introduction

Tired: Numbers
Wired: Pictures

With Evgeni Malkin and Connor McDavid on the ice at 5v5 during 2017-2018, their teams generated 49 and 51 unblocked shots per hour, respectively; that is, 13% and 18% more than league average.
Malkin & McDavid *On-Ice* Offence

- Malkin: +19.9%
- McDavid: +24.5%
Malkin & McDavid *On-Ice* Defence

+4.1% Malkin

+4.6% McDavid
Aim

Isolate individual skater impact on team shots, both for and against.
New Thing

Treat maps as first-class objects, instead of single-numbers like rates or counts.
Isolation

Control for the most important aspects of play which are *outside* of a player’s control:

- Other skaters
  - Teammates
  - Opponents
- Zone usage
- The score (slyly sneaking in coaching, maybe)
Control for the most important aspects of play which are *outside* of a player’s control:

- Other skaters
  - Teammates
  - Opponents
    - Gonna settle this once and for all. For all!!

- Zone usage

- The score (slyly sneaking in coaching, maybe)
Bayesian Approach

Begin with an extremely simple estimate of player ability and update it slowly after every shot.
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*Before* the observations begin, what do we know about the players?
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They’re all NHL players.
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Take as prior that every player is a league average player.
Bayesian Approach

Begin with an extremely simple estimate of player ability and update it slowly after every shot.

*Before* the observations begin, what do we know about the players?

They’re all NHL players.

Take as prior that every player is a league average player. (With some sneakiness about players with very little icetime.)
Dessert First

How I did it:
Dessert First

How I did it: Later (math was implicated)
Dessert First

How I did it: Later (math was implicated)
For now, what is the good of it?
How I did it: Later (math was implicated)
For now, what is the good of it?
How I did it: Later (math was implicated)
For now, what is the good of it?
- The base layer of a “full-value” model (a war-like stat).
Dessert First

How I did it: Later (math was implicated)
For now, what is the good of it?
  ▶ The base layer of a “full-value” model (a war-like stat).
    ▶ Not interesting to me for the foreseeable future
Dessert First

How I did it: Later (math was implicated)
For now, what is the good of it?
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▶ Yes ok sure
▶ Understand which players are victims of circumstance and which the beneficiaries.
Dessert First

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For now, what is the good of it?
▶ The base layer of a “full-value” model (a war-like stat).
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▶ Understand which players are victims of circumstance and which the beneficiaries.
   ▶ Extremely satisfying but still one-dimensional.
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▶ Understand which players are victims of circumstance and which the beneficiaries.
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▶ Use it to see how different players affect how offence/defence moves through different parts of the ice.
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  ▶ Extremely satisfying but still one-dimensional.
▶ Use it to see how different players affect how offence/defence moves through different parts of the ice.
  ▶ VERY YES
  ▶ With tracking data we could work even more baroque and byzantine things into the same framework
To form summary statistics we weight shot maps according to league average shooting percentages from given locations to obtain threat.
Threat

To form summary statistics we weight shot maps according to league average shooting percentages from given locations to obtain threat.

Carefully avoiding shooting talent and goaltender talent.
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Carefully avoiding shooting talent and goaltender talent.

- Units of threat are goals per hour;
- Threat is like the worst xG model that is still worth writing down.
Malkin and McDavid Threat

With Evgeni Malkin and Connor McDavid on the ice at 5v5 during 2017-2018, their teams threatened 2.8 and 2.9 goals per hour, respectively; that is, 20% and 25% more than league average.
On-ice Observed Threat
On-ice Observed Threat
Teammates Distribution

Quality of Teammates, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)
Teammates Distribution

Quality of Teammates, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)
Competition Distribution

Quality of Competition, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)
Competition Distribution

Quality of Competition, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)

McDavid

Crosby

Malkin

Bad

Dull

Good

Fun
Score Impact

Score Impacts, 1718

-3* | -2 | -1 | 0 | +1 | +2 | +3*

+4.9% | +3.9% | +4.0% | -1.2% | -3.0% | -2.7% | -5.8%
Score Distribution

Score Affectedness, 2017-2018
Score Distribution

Score Affectedness, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)

BAD

GOOD

DULL

McDavid

Crosby

Malkin

FUN
Zone Impact (Home Teams)
Zone Impact (Away Teams)
Zone Distribution

Zone Effects, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)
Zone Distribution

Zone Effects, 2017-2018

Offence (Threat, % of league average)

Defence (Threat, % of league average, inverted scale)

DULL

GOOD

BAD

FUN

Crosby

Malkin

McDavid
“Residue” Distribution

Residual between on-ice observed and magnus expected, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)
"Residue" Distribution

Residual between on-ice observed and magnus expected, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)

DULL
GOOD
Crosby
McDavid
Malkin
BAD
FUN
Isolated Individual Impact

Isolated Threat, 2017-2018

Defence (Threat, % of league average, inverted scale)

Offence (Threat, % of league average)
Isolated Individual Impact
Malkin & McDavid *Isolated* Offence
Malkin & McDavids *Isolated* Defence
As a whole, teammates have a much larger impact than competition; about five times as much. For some individual players; competition impact is still larger than teammate impact.
**Competition Dominates Context for Some Players**

For instance:

<table>
<thead>
<tr>
<th>Player</th>
<th>Team</th>
<th>Teammate Impact</th>
<th>Competition Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brandon Saad</td>
<td>CBJ</td>
<td>+0.2%</td>
<td>-6.4%</td>
</tr>
<tr>
<td>Nazem Kadri</td>
<td>TOR</td>
<td>-0.2%</td>
<td>-4.7%</td>
</tr>
<tr>
<td>Chris Thorburn</td>
<td>STL</td>
<td>+0.5%</td>
<td>+4.6%</td>
</tr>
</tbody>
</table>
Bayesian update as vaguely gestured at earlier can be implemented by (generalized) “ridge” regression. (Totally unrelated to the motivations of the people who first suggested it for totally technical reasons in situations not at all resembling ours, because math.)
Bayesian update as vaguely gestured at earlier can be implemented by (generalized) “ridge” regression. (Totally unrelated to the motivations of the people who first suggested it for totally technical reasons in situations not at all resembling ours, because math.) Take a linear model of the form

\[ Y = X\beta \]

where:

- \( Y \) is what you see on the ice.
- \( X \) is the design matrix (players (twice), zones, scores, intercepts)
- \( \beta \) is the estimates of the impact of each model feature.
Columns of $X$ correspond to model features - things that we imagine affect what happens. There are around 2,000.

Rows of $X$ correspond to slivers of hockey where none of those things change - “microshifts”. For a single season, around a million.

Values in $X$ are almost entirely indicators (zeros or ones).
Units of $\beta$ and $Y$

The only thing we need for $\beta$ (our estimate of ability/impact) and $Y$ (our “observations” of what happened on the ice) is to do is:

- have the same units;
- be things that can be added together and multiplied by numbers and;
- be things that have some notion of “size”.

(In fact any inner product space will do)
Units of $\beta$ and $Y$

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- Like a shot rate density map
Units of $\beta$ and $Y$

The only thing we need for $\beta$ (our estimate of ability/impact) and $Y$ (our “observations” of what happened on the ice) is to do is:

- have the same units;
- be things that can be added together and multiplied by numbers and;
- be things that have some notion of “size”.

(In fact any inner product space will do)

- Like a shot rate density map
  - Or a distribution of shot rate density maps...
  - Or a distribution of trajectories through a configuration space of all possible ways twelve hockey players can be placed and oriented on a hockey rink ............
How to *fit* the model

Given a model of the form $Y = X\beta$, where we know $X$ and $Y$, how do we find $\beta$?
How to *fit* the model

Given a model of the form $Y = X\beta$, where we know $X$ and $Y$, how do we find $\beta$?
We *could* simply find the $\beta$ with the smallest (total) deviation from the observations, like a chump. That is, minimize

$$(Y - X\beta)^T (Y - X\beta)$$

which is solved by

$$\beta = (X^T X)^{-1} X^T Y$$

For hockey, this will usually be overfit; that is, it will follow the chaos and noise of the data very closely (much too closely).
How to fit the model

Given a model of the form $Y = X\beta$, where we know $X$ and $Y$, how do we find $\beta$?
Instead, we could use our assumption that the players are NHL players and instead minimize:

$$\text{Error} = (Y - X\beta)^T(Y - X\beta) + \beta^T\Lambda\beta$$

where $\Lambda$ is a matrix which encodes our prior information that the players are all NHL players. This is zero-biased regression where we set our zero at league average.
Solved by:

$$\beta = (X^TX + \Lambda)^{-1}X^TY$$
Tuning

We get to choose $\Lambda$ since it encodes our *prior* information, before we examine the observations from the season. Choosing suitable values for its entries is a matter of skill and artifice (there is some guessing and eyeballing).

Much scope for very subtle priors if we want; I use a diagonal $\Lambda$ with entries:

1. $\lambda = 10,000$ for all players and zones and scores, and
2. $\lambda = 0.001$ for the intercepts, except:
3. $\lambda$ varying from 2,000 to 10,000 for low ice-time players.
Crowd Pleasers (Guys recently in strange situations)

Who was best/worst/weirdest in the last season?
### Best 5v5 Offensive Threat Performances, 2017-2018

(Thousand minute minimum)

<table>
<thead>
<tr>
<th>Player</th>
<th>Team</th>
<th>Isolated Threat Relative to League Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sidney Crosby</td>
<td>PIT</td>
<td>+21.7%</td>
</tr>
<tr>
<td>Connor McDavid</td>
<td>EDM</td>
<td>+21.3%</td>
</tr>
<tr>
<td>Roman Josi</td>
<td>NSH</td>
<td>+12.1%</td>
</tr>
<tr>
<td>John Klingberg</td>
<td>DAL</td>
<td>+11.5%</td>
</tr>
<tr>
<td>Kris Letang</td>
<td>PIT</td>
<td>+9.7%</td>
</tr>
<tr>
<td>Drew Doughty</td>
<td>L.A</td>
<td>+8.7%</td>
</tr>
<tr>
<td>Jeff Petry</td>
<td>MTL</td>
<td>+8.3%</td>
</tr>
<tr>
<td>Alex Radulov</td>
<td>DAL</td>
<td>+7.9%</td>
</tr>
<tr>
<td>Artemi Panarin</td>
<td>CBJ</td>
<td>+7.7%</td>
</tr>
<tr>
<td>Marc-Edouard Vlasic</td>
<td>S.J</td>
<td>+7.6%</td>
</tr>
</tbody>
</table>
### Best 5v5 Defensive Threat Performances, 2017-2018

(Thousand minute minimum)

<table>
<thead>
<tr>
<th>Player</th>
<th>Team</th>
<th>Isolated Threat Relative to League Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mikko Koivu</td>
<td>MIN</td>
<td>-17.9%</td>
</tr>
<tr>
<td><strong>Greg Pateryn</strong></td>
<td>DAL</td>
<td>-16.0%</td>
</tr>
<tr>
<td>Evgeni Dadonov</td>
<td>FLA</td>
<td>-14.4%</td>
</tr>
<tr>
<td><strong>Hampus Lindholm</strong></td>
<td>ANA</td>
<td>-12.9%</td>
</tr>
<tr>
<td>Carl Hagelin</td>
<td>PIT</td>
<td>-12.1%</td>
</tr>
<tr>
<td><strong>Colton Parayko</strong></td>
<td>STL</td>
<td>-12.0%</td>
</tr>
<tr>
<td>Radko Gudas</td>
<td>PHI</td>
<td>-10.0%</td>
</tr>
<tr>
<td>Brayden Point</td>
<td>T.B</td>
<td>-10.0%</td>
</tr>
<tr>
<td>Alex Iafallo</td>
<td>L.A</td>
<td>-9.9%</td>
</tr>
<tr>
<td><strong>Niklas Kronwall</strong></td>
<td>DET</td>
<td>-9.6%</td>
</tr>
</tbody>
</table>
### Best 5v5 Net Threat Performances, 2017-2018

(Thousand minute minimum)

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</thead>
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</tr>
<tr>
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<td>PIT</td>
<td>+24.0%</td>
</tr>
<tr>
<td>Connor McDavid</td>
<td>EDM</td>
<td>+23.4%</td>
</tr>
<tr>
<td>Brendan Gallagher</td>
<td>MTL</td>
<td>+23.4%</td>
</tr>
<tr>
<td>Pierre-Luc Dubois</td>
<td>CBJ</td>
<td>+23.1%</td>
</tr>
<tr>
<td><strong>Colton Parayko</strong></td>
<td>STL</td>
<td>+17.6%</td>
</tr>
<tr>
<td>Jordan Eberle</td>
<td>NYI</td>
<td>+17.5%</td>
</tr>
<tr>
<td><strong>Torey Krug</strong></td>
<td>BOS</td>
<td>+17.2%</td>
</tr>
<tr>
<td>Derek Ryan</td>
<td>CAR</td>
<td>+17.1%</td>
</tr>
<tr>
<td>Brayden Point</td>
<td>T.B</td>
<td>+17.1%</td>
</tr>
</tbody>
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Worst 5v5 Net Threat Performances, 2017-2018

(thousand minute minimum)

<table>
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<tr>
<th>Player</th>
<th>Team</th>
<th>Isolated Threat Relative to league average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haydn Fleury</td>
<td>CAR</td>
<td>-27.5%</td>
</tr>
<tr>
<td>Justin Braun</td>
<td>S.J</td>
<td>-23.1%</td>
</tr>
<tr>
<td>Brooks Orpik</td>
<td>WSH</td>
<td>-19.3%</td>
</tr>
<tr>
<td>Dion Phaneuf</td>
<td>OTT &amp; L.A</td>
<td>-18.9%</td>
</tr>
<tr>
<td>Viktor Arvidsson</td>
<td>NSH</td>
<td>-18.5%</td>
</tr>
<tr>
<td>Mattias Janmark</td>
<td>DAL</td>
<td>-17.7%</td>
</tr>
<tr>
<td>Mike Green</td>
<td>DET</td>
<td>-17.6%</td>
</tr>
<tr>
<td>Michael Del Zotto</td>
<td>VAN</td>
<td>-17.5%</td>
</tr>
<tr>
<td>Vladimir Sobotka</td>
<td>STL</td>
<td>-17.1%</td>
</tr>
<tr>
<td>Jonathan Drouin</td>
<td>MTL</td>
<td>-16.6%</td>
</tr>
</tbody>
</table>
## Most Painful 5v5 Minutes, 2017-2018

(eight-hundred minute minimum)

<table>
<thead>
<tr>
<th>Player</th>
<th>Team</th>
<th>Context Threat Relative to league average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brandon Sutter</td>
<td>VAN</td>
<td>-27.7%</td>
</tr>
<tr>
<td>Devante Smith-Pelly</td>
<td>WSH</td>
<td>-23.1%</td>
</tr>
<tr>
<td>Carl Soderberg</td>
<td>COL</td>
<td>-22.9%</td>
</tr>
<tr>
<td>Jean-Gabriel Pageau</td>
<td>OTT</td>
<td>-22.8%</td>
</tr>
<tr>
<td><em>Marc-Edouard Vlasic</em></td>
<td>S.J</td>
<td>-22.2%</td>
</tr>
</tbody>
</table>
Most Sheltered 5v5 Minutes, 2017-2018

(eight-hundred minute minimum)

<table>
<thead>
<tr>
<th>Player</th>
<th>Team</th>
<th>Context Threat Relative to league average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brayden Schenn</td>
<td>STL</td>
<td>+25.3%</td>
</tr>
<tr>
<td><em>Mikhail Sergachev</em></td>
<td>T.B</td>
<td>+22.1%</td>
</tr>
<tr>
<td>Tyler Bozak</td>
<td>TOR</td>
<td>+22.0%</td>
</tr>
<tr>
<td>Jake Guentzel</td>
<td>PIT</td>
<td>+21.4%</td>
</tr>
<tr>
<td>Tomas Plekanec</td>
<td>MTL &amp; TOR</td>
<td>+20.8%</td>
</tr>
</tbody>
</table>
Future Work

For shot density isolation itself:

- Non-linear effects. (Chemistry!)
- More subtle priors (including joint priors)

For a broader evaluation scheme:

- Special Teams (same machinery should work!)
- Goalies and shooting talent (totally different)
Thanks!