WHO AND WHY?

An introduction to player evaluation

J. POHLKAMP-HARTT, NOV 20 2021

ANALYTICS SUPPORTS DATA-DRIVEN DECISIONS

INFORMATION

- DATA
- OPINIONS
- CONTEXT

PROCESS

- REPORTS
- DISCUSSION
- TECHNOLOGY

DECISIONS

- TARGETS
- PLAN
- COMMUNICATION

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EXAMPLE DECISION: SIGNING FREE AGENT CENTER

INFORMATION

- LAST 3 SEASONS METRICS
- SCOUTING REPORTS
- "WE NEED A PLAY DRIVING CENTER THAT IS RESPONSIBLE DEFENSIVELY"
- "WE ARE IN A WIN NOW MODE"

PROCESS

- SUMMARY REPORT OF METRICS AND SCOUTING OPINIONS FOR AVAILABLE PLAYERS
- ROUNDTABLE MEETING TO DISCUSS AND RANK PLAYERS
- APP OR SPREADSHEET TO PRESENT DATA , RECORD OPINIONS AND RANKINGS

DECISION

- "WE WILL TRY TO SIGN THE TOP RANKED PLAYERS IN ORDER, IF WE GET TO A PART OF THE LIST WHERE AGREEMENT WAS NOT COMPLETE WE WILL RECONVENE."

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  - Evolving with Feedback

PLAYER METRICS

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- Performance relative to team or linemates can indicate who drives play. Eg. Shot Share = Shots/Shots For WOI

EXAMPLE

WE ARE UP TO PICK AT THE DRAFT AND WE NEED TO DECIDE BETWEEN 2 USHL PLAYERS, WHO DO YOU WANT?

A

Stat	Value	League %	Team %
Goals	14	73.4	79.2
Assists	40	98.2	96.8
Corsi %	56.5	86.6	82.1
Shot Share	17.6	68.3	69.9
OZ Start %	72	91.6	98.3

B

Stat	Value	League %	Team %
Goals	23	92.9	88.4
Assists	29	90.6	93.2
Corsi %	50.9	66.8	60.2
Shot Share	28.7	93.4	95.5
OZ Start %	49	48.2	50

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- New advancements collect spatial data creating non-puck events. Eg. Screening a goalie.
  Some spatial metrics are not event based like player fitness or space occupied.

EXAMPLE

IT IS THE TRADE DEADLINE, WE WANT A SCORING WINGER TO COMPLIMENT OUR PLAY DRIVING CENTER.

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Stat	Value	League %	Team %
Slot Shots	3.93	84.3	88.9
Passes	11.86	44.4	50.1
Slot Shot Tendency	76.2	86.1	92.3
Defensive Touches	5.43	31.6	37.4
Possession Time	66.6	73.6	78.9

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Stat	Value	League %	Team %
Slot Shots	2.19	51.7	50
Passes	17.3	80.2	81.4
Slot Shot Tendency	48.5	49.7	47.6
Defensive Touches	9.65	76.9	79.1
Possession Time	74.6	87.4	87.8

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- These models can get quite complicated,
  It is important to understand how a model works before using it for player evaluation!
  Eg. expected possession value: EPV = P(goal in possession | current state)

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Stat	Value	League %	Team %
XPGF	0.964	61	55.5
XPGA	0.973	43.1	32.3
XPG%	49.8	53.6	48.9
iXG	0.429	85.9	93.9
A2E	0.175	85	94.5

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Stat	Value	League %	Team %
XPGF	1.23	94.3	100
XPGA	0.878	67.9	69.9
XPG%	62.9	84.6	80
iXG	0.286	59.7	48.7
A2E	-0.197	17.5	35

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- It is important to remember team/role fit for player recommendations.

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WAR	1.73	85.1	79.6
EPV	0.42	71.7	74.7
NHLe	7.82	95.4	95.8
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WAR	1.16	74.2	73.1
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  - Team needs
    Eg. If your team needs a bottom pair defenseman, don't only offer top pair players that are available (even if they are better).

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- Are the results logical?
  Eg. OZ Possession % does not correlate with higher iXG

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- People can contribute quickly with an opinion. To be involved in the conversation you need fast data recall.

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  - Be cognizant of accessibility: color blind friendly palettes and alt text are key!

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  - Lean on technology

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- Sometimes there are questions we cannot answer. Keep a record to guide future research.
- Always keep looking for new methods or data that can help.
  Lucky all you smart young people continue to push the envelope!

THANK YOU FOR PARTICIPATING AND ENJOY THE REST OF MSAM 2021!

JOIN US!

TWO ROLES CURRENTLY OPEN FOR APPLICATIONS:

DEVELOPER

DATA ENGINEER

GOOGLE SEARCH “BRUINS JOBS” FOR LINKS TO APPLY.