

MSDS 498

Final Presentation

Junior Hockey Player Recruiting Ranking

Northwestern

Group 1

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Team Introductions

- ❑ **Joseph 'Joe' Peedikayil**
Project management, analytics support and industry & customer analysis
- ❑ **Castan Sommer**
Technical/modeling lead and hockey expert
- ❑ **Jared Christensen**
Data acquisition, positioning/messaging and industry analysis
- ❑ **Nicholas 'Nikki' Pappacena**
Modeling lead and data analytics

Business Case

Situation Summary

- ❑ Current NCAA Ice Hockey recruiting is based on subjective viewer ratings, basic statistics like goals and assists, and networking with junior organizations and agents
- ❑ Companies like Neutral Zone and Puck Preps attempt to assist in rating junior hockey players, but the value of these tools is limited since they are based on averaging scout ratings
- ❑ There are no quantitative recruiting tools that leverage micro-statistics (i.e. player stats beyond simply goals and assists) that lead to goals and wins
- ❑ The impact of a given player's age and the competitiveness of the player's league is also overlooked leading to less accurate player assessments

Business Problem

- ❑ As a result, college recruiting teams don't have a sound analytical model to aid in player recruitment and are reliant on subjective/biased "expert judgement"
- ❑ This leads to schools spending millions of dollars in scholarship money each year without knowing the quantitative impact their recruits have had in junior hockey
- ❑ Without accurate player rankings, the performance of junior hockey players entering college is unpredictable and many college recruits are undervalued or overlooked
- ❑ Recruitment efforts are also less effective since recruiters are unable to focus on recruiting the best-fit player for their school based on team playing strategy

Proposed Solution

Solution

- ❑ Develop a data-driven junior hockey player recruiting model that leverages player micro-statistics to rank players based on skill and their individual impact on the game

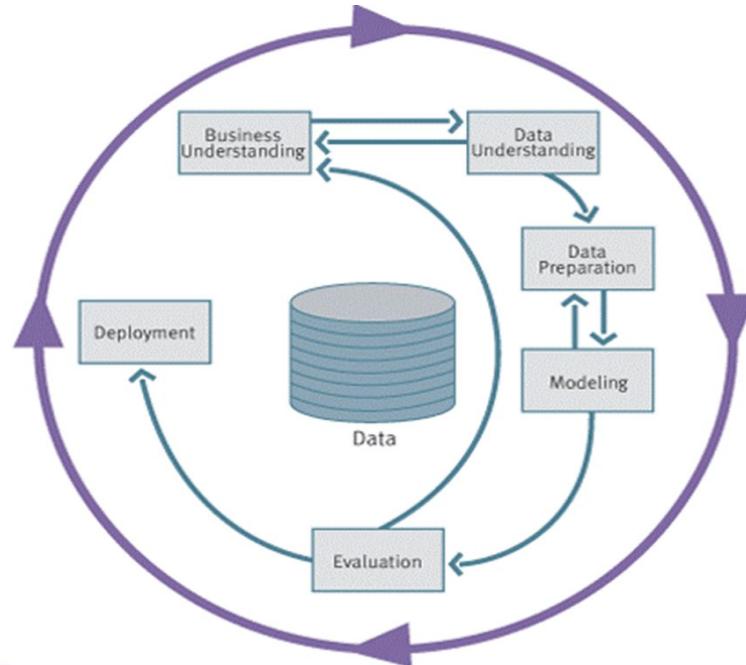
Benefits

- ❑ Improve player scholarship return-on-investment by supplementing existing recruiting tools with an objective, quantitative player ranking framework
- ❑ Identify overlooked and undervalued players that are a good fit with a given team's playing strategy
- ❑ Gain a recruiting advantage over schools that only use subjective player ratings

Project Management & Execution

Model Development & Analytics Project Plan

- ❑ Our modeling and Analytics project plan is based on the CRISP-DM principles adapted to facilitate our college recruiting player analytics and ranking model (see next 2 slides for detailed project plan)



Project Management Approach

- ❑ To ensure project timelines are met and accountability is measured, communication and tracking was our priority through the deliverable process.
- ❑ Scope, roles and responsibilities have been defined and properly assigned within the group. Each individual will have an assigned duty to mitigate overall risk and ensure all steps in our product development are addressed.
- ❑ A weekly meeting cadence ensured we had each other accountable and questions are gathered and discussed to identify any further steps that need to be taken or escalated.
- ❑ After each iteration of the model development process, UAT will be promptly done to guarantee validation and identify errors or faults in our logic.
- ❑ In the scenario we are not able to complete an analysis or gather sufficient insight, communication amongst the group will guarantee we address feasibility of our initial scope and adjust where appropriate to the overall end goal.

Resources Required

- ❑ Subscription to InStat (\$1,800 annually)
- ❑ Script or manual extract method to ingest data from InStat for model training
- ❑ NHL hockey player data for model validation
- ❑ Access to hockey experts familiar with the college recruiting landscape that can also provide context and insight on the underlying data and player statistics
- ❑ Open-source software programs and modules including pandas for data analysis and manipulation, scikit-learn for statistical modeling
- ❑ Tableau access for data visualization and dashboard creation
- ❑ Resources to perform 1) data acquisition, cleansing, and exploration and 2) model training, testing, and interpretation

Risks

- ❑ Developing a quantitative junior hockey player ranking model is dependent upon access to InStat, which is the primary data source for our model. Access to InStat data could be disrupted by either the service becoming unavailable, our access being revoked or the data itself becoming stale
- ❑ Similarly, we are reliant on the InStat data being accurate, comprehensive, and objective. Some level of human bias is involved in capturing player micro-stats. This human bias could negatively impact data reliability/accuracy
- ❑ Human bias also may negatively impact the accuracy of our player ranking model
- ❑ Limited historical data exists on junior hockey player micro-stats. This makes model validation and assessment of predictive power challenging
- ❑ The ability of our player ranking model to be somewhat accurate and perform well vs alternatives in the market.

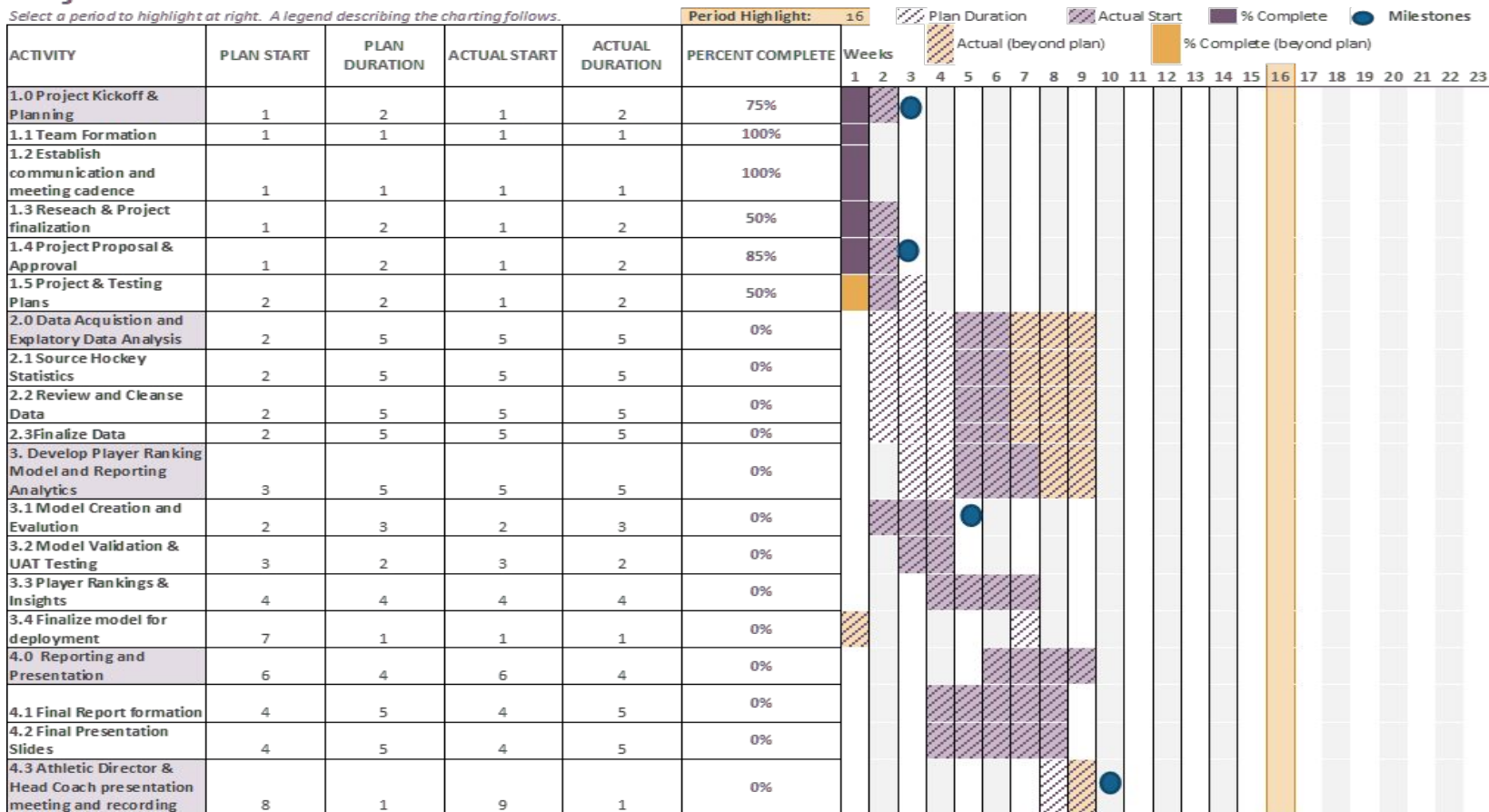
Status Reports

- ❑ Status reports were implemented following each week of model creation and adjustment in a consistent template.
- ❑ Characteristics measured will include:
 - Steps/tasks performed
 - Items that need escalation and further analysis
 - An honest reflection to determine whether we are on track or behind schedule with expected deliverables
 - Future steps that will be implemented for the following week

Project Timeline

Project Timeline

Select a period to highlight at right. A legend describing the charting follows.



EDA & Model Creation

Exploratory Data Analysis

- ❑ Import and clean college hockey commitment data from College Hockey Inc.
- ❑ A name dictionary was included in the cleaning process that needs to be updated as new players commit.
- ❑ Data from College Hockey Inc. has inaccuracies and many of those were fixed with manual 'loc' corrections.

```
#Import College commitment list from website

import requests
import pandas as pd

from IPython.display import display, HTML

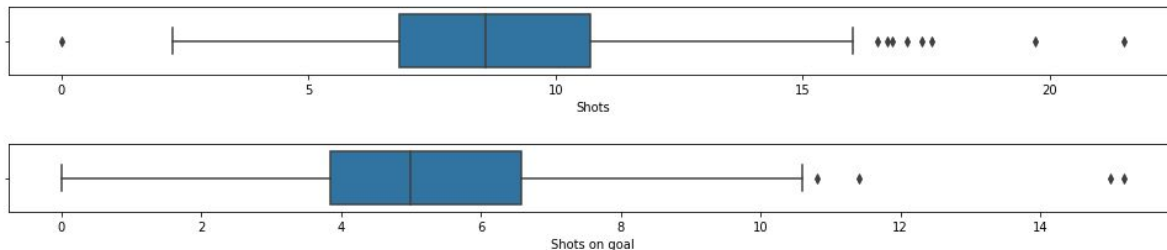
pd.options.display.max_columns = None
display(HTML("<style>.container { width:100% !important; }</style>"))

url = 'https://www.collegecommitments.com/CommitList.aspx?x7cq9=ALL'
html = requests.get(url).content
df_list = pd.read_html(html)
df = df_list[2]
df.head()
```

	0	1	2	3	4	5
0	Date	Player Name	Pos.	College	Current Team	Starting Year
1	03/01/23	REPMANN, Christopher	RW	UMass Boston Beacons	New Hampshire Jr. Monarchs (NCDC)	2023-24
2	03/01/23	HOWARD, William	F	Augustana Univeristy Vikings	New Mexico Ice Wolves (NAHL)	2023-24
3	02/28/23	HOUGE, Simon	LD	U.S. Air Force Academy Falcons	Cretin/Derham Hall HS Raiders (MN-HS)	2024-25
4	02/28/23	DAVIS, Storm	LD	Framingham State University	Northern Cyclones Prem (USPL-P)	2023-24

Exploratory Data Analysis

- Statistical data comes from InStat and contains only junior hockey players from across nine North American leagues
- There are 29 stat columns from which the final rating will be created.
- Each data frame is cleaned, checked for duplicate player entries, and examined for outliers and themes using boxplots (For example, boxplots of USHL Shots and Shots on goal are shown below)
- Only players with 4+ games played and born from 2002 to 2006 are included



```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 449 entries, 11 to 673
Data columns (total 35 columns):
#   Column              Non-Null Count  Dtype
---  -
0   Player              449 non-null   object
1   Team                449 non-null   object
2   Date of birth       449 non-null   object
3   Position            449 non-null   object
4   Games played        449 non-null   int64
5   Goals               449 non-null   float64
6   First assist        449 non-null   float64
7   Second assist       449 non-null   float64
8   Points              449 non-null   float64
9   +/-                 449 non-null   float64
10  Puck touches        449 non-null   float64
11  Penalties drawn     449 non-null   float64
12  Faceoffs won, %     449 non-null   float64
13  Faceoffs won        449 non-null   float64
14  Hits                449 non-null   float64
15  Shots               449 non-null   float64
16  Shots on goal       449 non-null   float64
17  CORSI-              449 non-null   float64
18  CORSI+              449 non-null   float64
19  CORSI for, %        449 non-null   float64
20  Puck battles        449 non-null   float64
21  Puck battles won, % 449 non-null   float64
22  Passes              449 non-null   float64
23  Accurate passes     449 non-null   float64
24  Accurate passes, %  449 non-null   float64
25  Passes to the slot  449 non-null   float64
26  Pre-shots passes    449 non-null   float64
27  Scoring chances - total 449 non-null   float64
28  Inner slot shots - total 449 non-null   float64
29  Takeaways           449 non-null   float64
30  Entries via stickhandling 449 non-null   float64
31  Entries via pass     449 non-null   float64
32  Breakouts via stickhandling 449 non-null   float64
33  Breakouts via pass   449 non-null   float64
34  Birthyear           449 non-null   int64
dtypes: float64(29), int64(2), object(4)
```

Exploratory Data Analysis

Forward DFs

```
['Player',  
 'Team',  
 'Date of birth',  
 'Position',  
 'Games played',  
 'Goals',  
 'First assist',  
 'Second assist',  
 'Points',  
 '+/-',  
 'Puck touches',  
 'Penalties drawn',  
 'Faceoffs won, %',  
 'Faceoffs won',  
 'Hits',  
 'Shots',  
 'Shots on goal',  
 'CORSI for, %',  
 'Puck battles',  
 'Puck battles won, %',  
 'Passes',  
 'Accurate passes, %',  
 'Pre-shots passes',  
 'Scoring chances - total',  
 'Inner slot shots - total',  
 'Takeaways',  
 'Entries via stickhandling',  
 'Entries via pass',  
 'Birthyear',  
 'LeagueRate',  
 'League',  
 'AgeRate']
```

Defenseman DFs

```
['Player',  
 'Team',  
 'Date of birth',  
 'Position',  
 'Games played',  
 'Goals',  
 'First assist',  
 'Second assist',  
 'Points',  
 '+/-',  
 'Puck touches',  
 'Penalties drawn',  
 'Hits',  
 'Shots',  
 'Shots on goal',  
 'CORSI-',  
 'CORSI+',  
 'CORSI for, %',  
 'Puck battles',  
 'Puck battles won, %',  
 'Passes',  
 'Accurate passes',  
 'Accurate passes, %',  
 'Passes to the slot',  
 'Pre-shots passes',  
 'Scoring chances - total',  
 'Inner slot shots - total',  
 'Takeaways',  
 'Entries via stickhandling',  
 'Entries via pass',  
 'Breakouts via stickhandling',  
 'Breakouts via pass',  
 'Birthyear',  
 'LeagueRate',  
 'League',  
 'AgeRate']
```

- ❑ The dataframe for each league is split into forwards and defensemen, as different stats and different stat weights should be used for each position.
- ❑ For example, faceoff statistics are dropped from the D dataframes, as defensemen do not take faceoffs.

Exploratory Data Analysis

- ❑ Defining Player Ratings:
 - The process to rate players starts by first assigning each player a Z score for each statistic, as shown below, to normalize comparisons for players across each league
 - All Z-scores were added by 10 to have a positive baseline (CORSI- was subtracted by 10, as you do not want a high CORSI-)

```
#Apply zscores to each stat for each position in each league
import numpy as np
from scipy import stats
AJF[['Goals', 'First assist', 'Second assist', 'Points', '+/-', 'Puck touches', 'Penalties drawn', 'Faceoffs won, %', 'Faceoffs won', 'Hits', 'Shots', 'Shots on goal', 'CORSI for, %', 'Puck battles', 'Puck battles won, %', 'Passes to the slot', 'Pre-shots passes', 'Scoring chances - total', 'Inner slot shots - total', 'Takeaways', 'Entries via stickhandling', 'Entries via pass']] = AJF[['Goals', 'First assist', 'Second assist', 'Points', '+/-', 'Puck touches', 'Penalties drawn', 'Faceoffs won, %', 'Faceoffs won', 'Hits', 'Shots', 'Shots on goal', 'CORSI for, %', 'Puck battles', 'Puck battles won, %', 'Passes to the slot', 'Pre-shots passes', 'Scoring chances - total', 'Inner slot shots - total', 'Takeaways', 'Entries via stickhandling', 'Entries via pass']].apply(stats.zscore)
AJF.head()
```

	Player	Team	Date of birth	Position	Games played	Goals	First assist	Second assist	Points	+/-	Puck touches	Penalties drawn	Faceoffs won, %	Faceoffs won	Hits	Shots	Shots on goal	CORSI for, %	Puck battles	Puck battles won, %
11	BROCK SOUCH	Sherwood Park Crusaders	2006-10-11	Fwd	50	-0.461196	0.351459	0.054448	-0.078359	0.010555	-0.838740	-0.042481	-0.919610	-0.600090	-0.183188	-1.536018	-1.519257	-0.563039	-0.585009	-1.713572
19	NICHOLAS ANISIMOVICZ	Canmore Eagles	2006-08-31	Fwd	9	-1.322563	-1.297805	-1.041513	-1.835995	-1.807702	0.482944	0.626848	1.023767	2.414921	0.499049	-0.268558	-0.697925	-1.242513	0.106365	1.636637
28	OTTO HANSON	Blackfalds Bulldogs	2006-06-28	Fwd	31	-0.335143	-0.498162	0.021237	-0.454995	-0.336391	0.533363	-0.896944	0.839826	0.843056	1.166455	-0.085440	0.228142	0.279509	0.345687	1.694733
29	NATHAN FREE	Brooks Bandits	2006-06-23	Fwd	45	-0.650277	0.801258	1.050776	0.411268	0.575950	0.659409	-0.370025	-0.919610	-0.522115	-1.246093	-0.164432	-0.163232	0.727962	-0.452052	-1.248803
35	MAX SULLIVAN	Okotoks Oilers	2006-05-25	Fwd	5	-1.322563	1.800812	-1.041513	-0.279232	-1.415781	-0.057254	1.951266	-0.919610	-0.621131	-0.791268	2.004253	2.207058	0.157204	-1.808208	-2.062148

Exploratory Data Analysis

Defining Player Ratings Continued:

- **Attribute Multiplier:** The more important the stat measured, the higher the multiplier applied
- **Age Multiplier:** The younger the player, the higher the multiplier added
- **League Rating Multiplier:** The more difficult the league, the higher the multiplier applied
- Each stat is added up after the Attribute Multiplier is applied. That number is then multiplied by the Age and League Rating Multipliers

```
#Input League rating,
AJ['LeagueRate']=1.5
BC['LeagueRate']=1.7
CC['LeagueRate']=1.35
MJ['LeagueRate']=1.4
NA['LeagueRate']=1.6
NC['LeagueRate']=1.3
OJ['LeagueRate']=1.4
SJ['LeagueRate']=1.25
US['LeagueRate']=1.8
```

```
AJ['AgeRate'] = AJ['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
BC['AgeRate'] = BC['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
CC['AgeRate'] = CC['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
MJ['AgeRate'] = MJ['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
NA['AgeRate'] = NA['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
NC['AgeRate'] = NC['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
OJ['AgeRate'] = OJ['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
SJ['AgeRate'] = SJ['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
US['AgeRate'] = US['Birthyear'].map({2002: 1, 2003: 1.05, 2004: 1.15, 2005: 1.25, 2006: 1.35})
```

```
#Apply stat weights
AJF.loc[:, ['Goals']] *= 2
AJF.loc[:, ['First assist']] *= 1.7
AJF.loc[:, ['Second assist']] *= 1.5
AJF.loc[:, ['Points']] *= 1
AJF.loc[:, ['+/-'']] *= 1.05
AJF.loc[:, ['Puck touches']] *= 1.1
AJF.loc[:, ['Penalties drawn']] *= 1.4
AJF.loc[:, ['Faceoffs won, %']] *= 1.1
AJF.loc[:, ['Faceoffs won']] *= 1.15
AJF.loc[:, ['Hits']] *= 1.1
AJF.loc[:, ['Shots']] *= 1.05
AJF.loc[:, ['Shots on goal']] *= 1.15
AJF.loc[:, ['CORSI for, %']] *= 1.15
AJF.loc[:, ['Puck battles']] *= 1.15
AJF.loc[:, ['Puck battles won, %']] *= 1.05
AJF.loc[:, ['Passes to the slot']] *= 1.3
AJF.loc[:, ['Pre-shots passes']] *= 1.1
AJF.loc[:, ['Scoring chances - total']] *= 1.35
AJF.loc[:, ['Inner slot shots - total']] *= 1.5
AJF.loc[:, ['Takeaways']] *= 1.1
AJF.loc[:, ['Entries via stickhandling']] *= 1.3
AJF.loc[:, ['Entries via pass']] *= 1.1
```

#Add up stat columns, then multiply by the age rate and league rate

```
column_names = ['Goals', 'First assist', 'Second assist', 'Points', '+/-' , 'Puck touches', 'Penalties drawn', 'Faceoffs won, %', 'Faceoffs won', 'Hits', 'Shots', 'Shots on goal',
                'CORSI for, %', 'Puck battles', 'Puck battles won, %', 'Passes to the slot', 'Pre-shots passes', 'Scoring chances - total', 'Inner slot shots - total',
                'Takeaways', 'Entries via stickhandling', 'Entries via pass']
AJF['Rating'] = AJF[column_names].sum(axis=1)
AJF['Rating'] = AJF['Rating'] * AJF['AgeRate'] * AJF['LeagueRate']
```

Exploratory Data Analysis

- ❑ The 9 forward data frames and 9 defenseman data frames are combined into a single forward and a single defenseman data frame
- ❑ We only want 1 entry in the final output for each player, yet many players play in different leagues throughout the season. Ben Xiao helped develop a code that weights each player's rating based on the percentage of games that player played for each team
- ❑ In the output below, one sees that Aaron Neal and Adam Grenier need to be combined into a single entry.

	Player	Position	Birthyear	Date of birth	League	Team	Games played	Rating	GP_total
318	A.J. LACROIX	Fwd	2005	2005-04-25	BCHL	Chilliwack Chiefs	40	572.232191	40.0
535	A.J. VASKO	Fwd	2002	2002-10-29	BCHL	Alberni Valley Bulldogs	39	458.183073	39.0
1931	AARON ANDRADE	Fwd	2004	2004-05-24	OJHL	Georgetown	41	475.285981	41.0
1792	AARON CATRON	Fwd	2002	2002-02-04	NCDC	Junior Bruins	43	356.824584	43.0
557	AARON DAVIDSON	Fwd	2002	2002-06-10	BCHL	Chilliwack Chiefs	28	489.193964	28.0
513	AARON NEAL	Fwd	2003	2003-02-12	BCHL	Powell River Kings	15	462.547926	34.0
944	AARON NEAL	Fwd	2003	2003-02-12	MJHL	Dauphin Kings	19	395.337950	34.0
407	AARON SCHWARTZ	Fwd	2004	2004-03-22	BCHL	Surrey Eagles	37	552.883612	37.0
1122	ADAM ARMIJO	Fwd	2004	2004-02-26	NAHL	Odessa Jackalopes	36	477.726164	36.0
219	ADAM GRENIER	Fwd	2003	2003-01-27	AJHL	Drayton Valley Thunder	19	421.850554	23.0
522	ADAM GRENIER	Fwd	2003	2003-01-27	BCHL	Cowichan Valley Capitals	4	495.981234	23.0

Exploratory Data Analysis

- ❑ With the final rating for all players in hand, it is important to think about the final output for the end user. The rating has no set beginning or end, so how is one to interpret the results?
- ❑ A 0 to 5 'Star' scale of the Rating column is used. 0 being the lowest ranked player and 5 being the highest ranked player (for each position).

```
#Turn rating into 0 to 5 star rating to make more sense to viewer  
a, b = 0, 5  
x, y = FinalF.Rating.min(), FinalF.Rating.max()  
FinalF['Stars'] = (FinalF.Rating - x) / (y - x) * (b - a) + a  
FinalF.head()
```

	Player	Position	Date of birth	Birthyear	League	Team	Games played	Rating	Stars
0	A.J. LACROIX	Fwd	2005-04-25	2005	BCHL	Chilliwack Chiefs	40	572.232191	3.360020
1	A.J. VASKO	Fwd	2002-10-29	2002	BCHL	Alberni Valley Bulldogs	39	458.183073	2.079390
2	AARON ANDRADE	Fwd	2004-05-24	2004	OJHL	Georgetown	41	475.285981	2.271434
3	AARON CATRON	Fwd	2002-02-04	2002	NCDC	Junior Bruins	43	356.824584	0.941260
4	AARON DAVIDSON	Fwd	2002-06-10	2002	BCHL	Chilliwack Chiefs	28	489.193964	2.427604

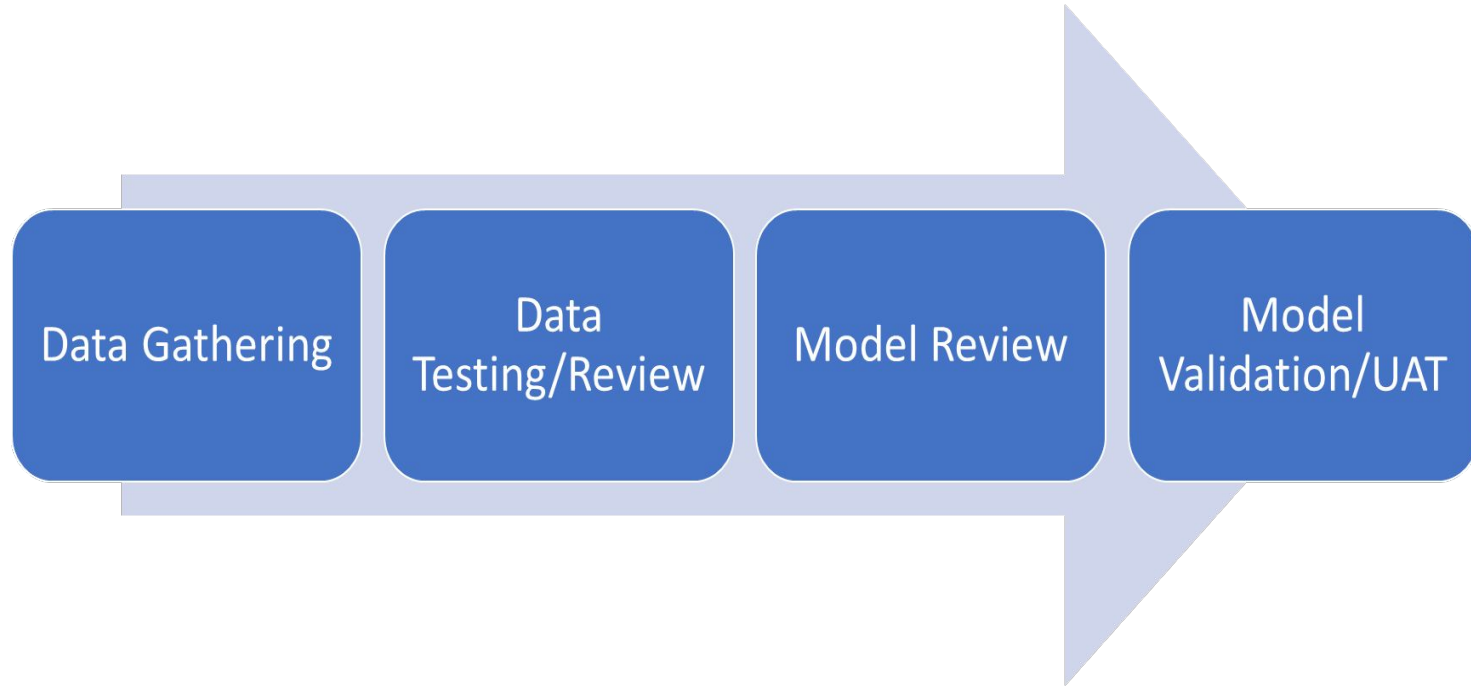
Exploratory Data Analysis

- ❑ The final forward and defenseman data frames are combined.
- ❑ The final stat data frame and the original data frame of college commitments are merged.
- ❑ Cleaning is performed on duplication issues and redundant columns, and players who did not play junior hockey this year are removed from the data frame.
- ❑ Both 'Date of birth' and 'Birthyear' are kept in the data frame, as 'Date of birth' is important in player identification, and 'Birthyear' is important when analyzing the output.
- ❑ The final result is exported to Excel.

	Player	Position	College	Date of birth	Birthyear	League	Team	Games played	Rating	Stars
4	CONNOR PELC	Fwd	Mercyhurst University Lakers	2003-04-28	2003	USHL	Des Moines	15.0	492.314229	2.462640
10	MICHAEL YOUNG	Fwd	Princeton University Tigers	2002-08-28	2002	NAHL	New Jersey Titans	34.0	468.139928	2.191193
11	NICHOLAS O'HANISAIN	Def	Bowling Green State University Falcons	2002-02-09	2002	NAHL	Minot Minotauros	34.0	470.484382	1.707275
12	BRYCE BOLLMAN	Fwd	Bowdoin College	2002-06-23	2002	NCDC	New Hampshire Jr. Monarchs	38.0	353.794018	0.907231
13	ALEXANDER THUNDERCLOUD	Def	Milwaukee School of Engineering	2002-01-04	2002	NCDC	Wilkes-Barre Scranton Knights NCDC	21.0	479.359896	1.802718

Model Validation

Testing Plan Overview



Testing Plan Requirements

- ❑ Data Gathering: The primary steps in our groups journey will be to establish secure web connections to pull data for the following categories
 - Junior Hockey Player hockey data and statistics via scouts and data aggregator companies (InStat, Rivals etc.)
 - College and NHL hockey player data (ESPN, NCAA etc)
- ❑ Model Creating and testing: With the data requirements met, modelling will be performed using the following software tools to assist with insight creation
 - Model development tools (R, Python etc.)
 - Microsoft Office tools to assist with organizational practices
 - Review models outputs
 - Check for player scoring and ranking reasonableness
- ❑ UAT Planning: User testing will be implemented on the following basis
 - Model validation process will be performed on the chosen model
 - Analysis, exploratory data analysis, model development and report production will be core actions performed during the validation and output review process.

Model Validation & UAT Testing Plan

- ❑ Extract the same variables used in the junior hockey dataset for an InStat NHL dataset
- ❑ Run the NHL dataset through the junior hockey model to find player ratings of NHL players
- ❑ Pull the top 100 players from the resulting NHL player rating dataset
- ❑ Compare our results to *The Athletic's* top 100 NHL players (as of January 19, 2023)
- ❑ Adjust variable weights in the model until X% of the forwards and defencemen are found in our model and *The Athletic's* list

The Top 100 NHL Players													MID-SEASON UPDATE
Tier 1	1A	Connor McDavid											
	1B	Nathan MacKinnon, Auston Matthews											
	1C	Cale Makar, Sidney Crosby, Leon Draisaitl, Nikita Kucherov, David Pastrnak, Adam Fox, Victor Hedman											
Tier 2	2A	Jack Hughes, Kirill Kaprizov, Mitch Marner, Mikko Rantanen, Jason Robertson, Matthew Tkachuk											
	2B	Charlie McAvoy, Aleksander Barkov, Petric Bergeron, Brad Marchand, Brayden Point											
	2C	Miro Heiskanen, Roman Josi, Sebastian Aho, Jack Eichel, Artemi Panarin, Mark Stone, Tage Thompson, Erik Karlsson, Rasmus Dahlin											
Tier 3	3A	Kyle Connor, Rogan Hertz, Nico Hischier, Alex Ovechkin, Elias Pettersson											
	3B	Hampus Lindholm, Jacob Savin, Shea Theodore, Devin Toews, Mikko Zibanejad, Nikolaj Ehlers, Johnny Gaudreau, Gabriel Landeskog, William Nylander, Steven Stamkos											
	3C	Drew Doughty, Dougie Hamilton, Josh Morrissey, Alex Petrangola, Matthew Barzal, Pierre-Luc Dubois, Filip Forsberg, Jake Guentzel, Andrei Svechikov, John Tavares, Brady Tkachuk, John Carlson, Thomas Chabot, Quinn Hughes, Jared Spurgeon											
Tier 4	4A	Jasper Bratt, Alex DeBrincat, Kevin Fiala, Jonathan Huberdeau, Patrick Kane, Dylan Larkin, Elias Lindholm, Timo Meier, Joe Pavelski, Robert Thomas											
	4B	Rasmus Andersson, Aaron Ekblad, Morgan Rielly, Moritz Seider, Mikhail Sergachev, MacKenzie Weegar, Matty Beniers, Pavel Buchnevich, Tomas Hertl, Zach Hyman, Chris Kreider, Evgeni Malkin, Tim Stütgen, Matej Zuparek											
	4C	Jonas Brodin, Kris Letang, Daniel Nurse, Zach Werenski, Phillip Danault, Joel Eriksson Ek, Bo Horvat, Nazem Kadri, Anze Kopitar, Martin Necas, Valeri Nichushkin, Mark Scheffle, Carter Verhaeghe, Brent Burns, Jakob Chytrek, Adam Peltch											

The Athletic

NHL Player Rankings vs. Model Prediction

- ❑ Individual player stats were procured from [Hockey Reference](#) for the 2022 NHL season
- ❑ Junior hockey recruiting model was tested against the NHL dataset to determine a “Star” rating for each player
- ❑ Test results validate our recruitment model, as NHL player ratings were accurately identified with a significant change in “Star” valuation between Tier 1, 2 and 3 players as predicted by *The Athletic’s* list

Tier	Stars
Tier 1 Average Stars:	3.96
Tier 2 Average Stars:	3.24
Tier 3 Average Stars:	3.15

NHL Player	Tier (The Athletic)	Stars (Model)
Connor McDavid	Tier 1	4.959
Nathan Mackinnon	Tier 1	4.149
Auston Matthews	Tier 1	5.000
Cale Makar	Tier 1	4.006
Sidney Crosby	Tier 1	3.755
Leon Draisaitl	Tier 1	4.618
Nikita Kucherov	Tier 1	2.782
David Pastrnak	Tier 1	3.782
Adam Fox	Tier 1	2.842
Victor Hedman	Tier 1	3.757
Jack Hughes	Tier 2	2.156
Charlie McAvoy	Tier 2	3.456
Kirill Kaprizov	Tier 2	4.423
Mitch Marner	Tier 2	3.858
Mikko Rantanen	Tier 2	4.000
Jason Robertson	Tier 2	3.173
Matthew Tkachuk	Tier 2	4.449
Aleksander Barkov	Tier 2	3.990
Patrice Bergeron	Tier 2	4.316

(Complete list of Tier 1, 2 and 3 players on next slide)

Player Tiers (*The Athletic*) and Model “Star” Valuation

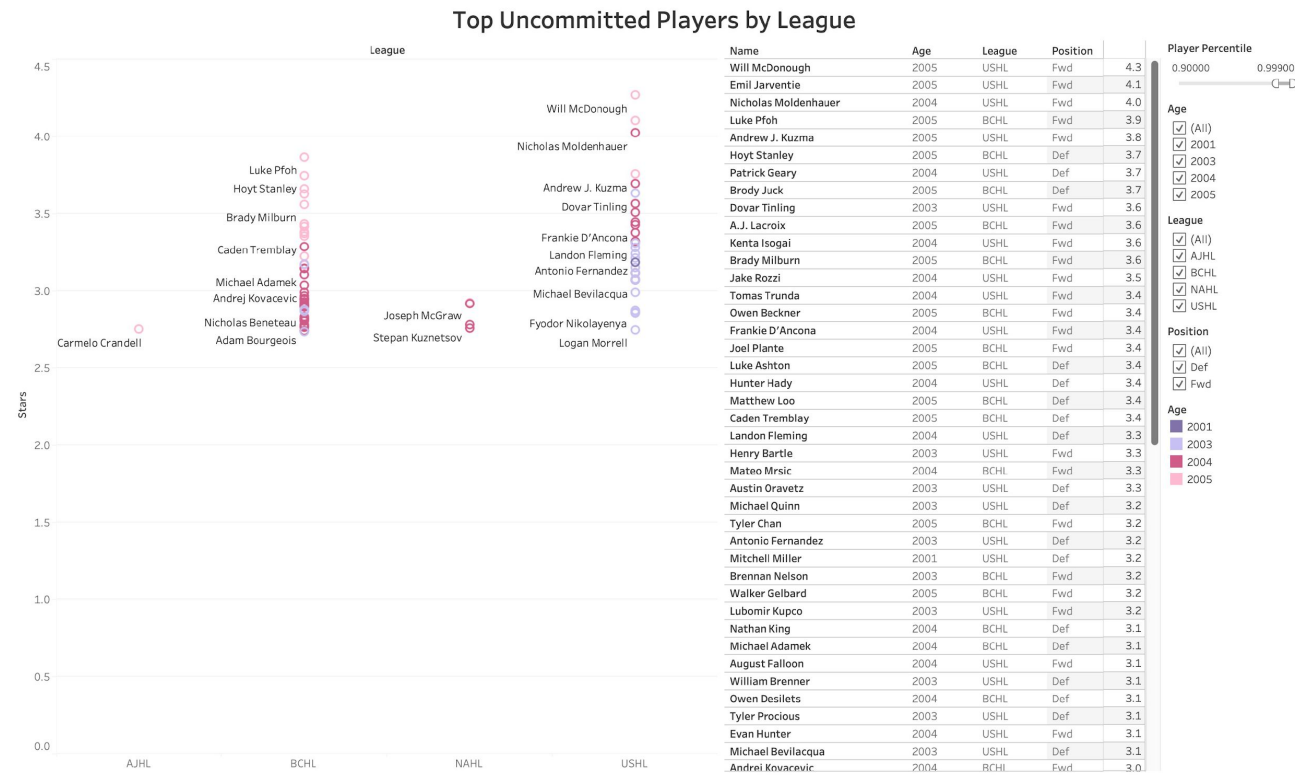
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Connor McDavid	Tier 1	4.959
Nathan Mackinnon	Tier 1	4.149
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Patrice Bergeron	Tier 2	4.316

NHL Player	Tier (The Athletic)	Stars (Model)
Brad Marchand	Tier 2	3.552
Brayden Point	Tier 2	3.022
Miro Heiskanen	Tier 2	2.224
Roman Josi	Tier 2	3.964
Sebastian Aho	Tier 2	3.884
Jack Eichel	Tier 2	1.967
Artemi Panarin	Tier 2	3.191
Mark Stone	Tier 2	1.485
Tage Thompson	Tier 2	3.453
Erik Karlsson	Tier 2	1.513
Rasmus Dahlin	Tier 2	2.809
Kyle Connor	Tier 3	3.701
Hampus Lindholm	Tier 3	2.199
Roope Hintz	Tier 3	3.740
Jacob Slavin	Tier 3	2.670
Nico Hischier	Tier 3	3.025
Shea Theodore	Tier 3	2.702
Alex Ovechkin	Tier 3	4.616
Devon Toews	Tier 3	2.851

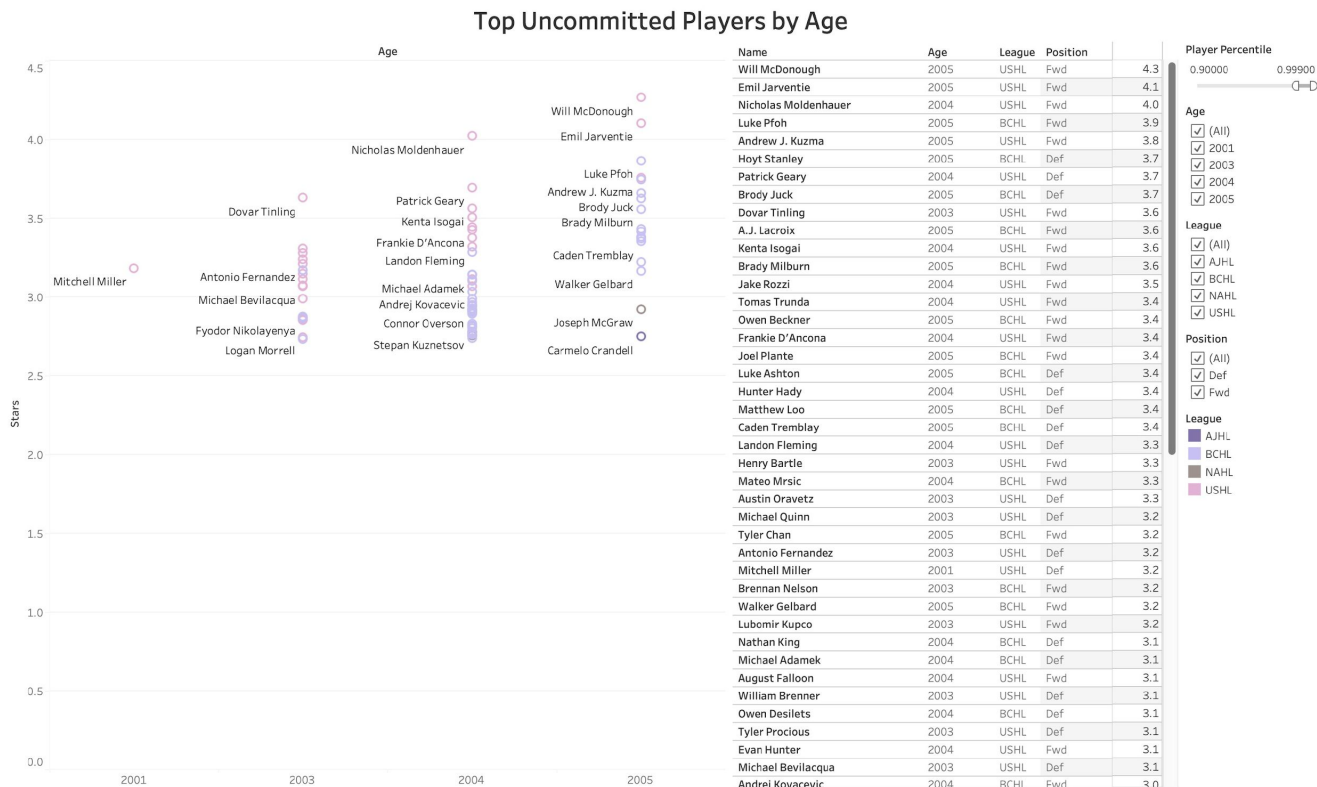
NHL Player	Tier (The Athletic)	Stars (Model)
Elias Pettersson	Tier 3	3.161
Nikolaj Ehlers	Tier 3	3.134
Drew Doughty	Tier 3	1.671
Johnny Gaudreau	Tier 3	4.441
Dougie Hamilton	Tier 3	2.364
Gabriel Landeskog	Tier 3	3.151
Josh Morrissey	Tier 3	2.941
William Nylander	Tier 3	3.309
Alex Pietrangelo	Tier 3	3.043
Steven Stamkos	Tier 3	4.461
Mathew Barzal	Tier 3	2.537
John Carlson	Tier 3	3.186
Pierre-Luc Dubois	Tier 3	3.696
Thomas Chabot	Tier 3	2.355
Filip Forsberg	Tier 3	4.126
Quinn Hughes	Tier 3	2.416
Jake Guentzel	Tier 3	3.855
Jared Spurgeon	Tier 3	2.208
Andrei Svechnikov	Tier 3	3.938

Junior Hockey Recruiting (JHR) Dashboard

Top Uncommitted Players by League



Top Uncommitted Players by Player Age



Dashboard Demo

THANK YOU