# Goals Above Replacement & Statistical Plus Minus

**RITSAC**

@EvolvingWild

# Single Number Metrics - A Brief History

- Baseball
  - Value Over Replacement Player (VORP), Wins Above Replacement
- Basketball
  - Adjusted Plus-Minus (APM)
  - Regularized Adjusted Plus-Minus (RAPM)
  - Real Plus-Minus (RPM)
  - Value Over Replacement Player (VORP)
- Hockey
  - WAR-On-Ice WAR, DTMAboutHeart WAR, Corsica.hockey WAR

- Metrics of interest:
  - APM / RAPM
  - Statistical Plus Minus (SPM) / Box-Plus Minus (BPM)

# Methodology / References

- Foundation
  - Adjusted Plus-Minus, Dan Rosenbaum 2004, Basketball
  - Regularized Adjusted Plus-Minus, Joseph Sill 2010, Basketball
  - Regularized Adjusted Plus-Minus, Brian MacDonald 2011-2012, Hockey
- Adaptations
  - Statistical Plus-Minus, Various, Basketball
  - Advanced Statistical Plus-Minus, Various, Basketball
  - Box Plus-Minus, Daniel Meyers, Basketball
  - Box Plus-Minus, Dawson Sprigings, Hockey

# Process Overview

- RAPM
  - 2007-2018 (11 year), per 60 skater coefficients/"ratings"
- Statistical Plus-Minus (per 60 rate)
  - Even-Strength Offense
  - Even-Strength Defense
  - Powerplay Offense
  - Shorthanded Defense
- Goals Above Average
  - Convert per 60 rate to "implied" goal totals
  - Penalty Goals (Taken and Drawn)
- Goals Above Replacement
  - Even-Strength
  - Powerplay
  - Shorthanded
  - Penalties

# RAPM Design Matrix - Explanation

- Shift-level weighted regularized linear regression
  - Observations: periods of play where no player substitutions occur
  - Target Variable: rate statistic (per 60), i.e. GF60
  - Weights: length of each shift
- Offense target variable = GF60
- Defense target variable = xGF60
- Regularization
  - L1 Regularization / LASSO Regularization
    - Feature selection removes players from consideration
    - Not Ideal
  - L2 Regularization / Ridge Regression
    - No feature selection
    - Ideal
  - Elastic Net Regularization
    - Ideal, but too computationally expensive

# RAPM Design Matrix - Visualization

| Play-By-Play Data | | | |
|---|---|---|---|
| **Home Skaters** | **Away Skaters** | **Home Goalie** | **Away Goalie** |
| 3-5 skaters | 3-5 skaters | 1 goalie | 1 goalie |
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| RAPM Regression Data | | | | | |
|---|---|---|---|---|---|
| **Target** | **Weights** | **Design Matrix / Features** | | | |
| **GF60** | **Shift Length** | **State Variables** | **Skaters – Offense** | **Skaters – Defense** | **[Goalies – Defense]** |
| 120.0 | 30 sec | 5 variables | 1187 columns | 1187 columns | 116 columns |
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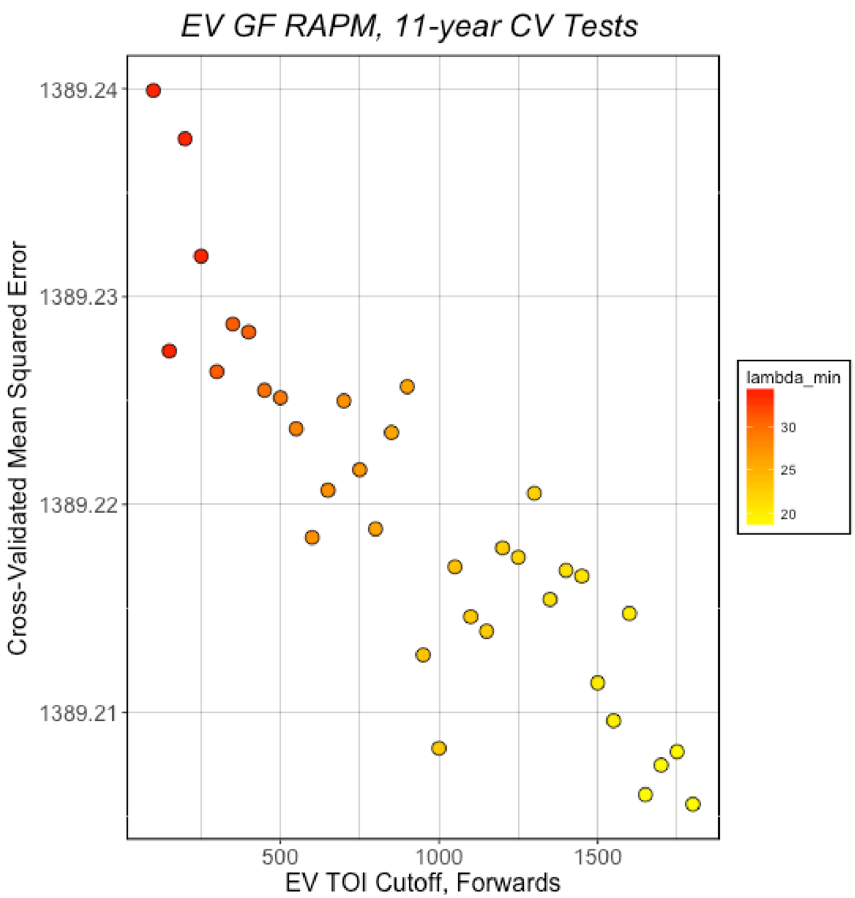
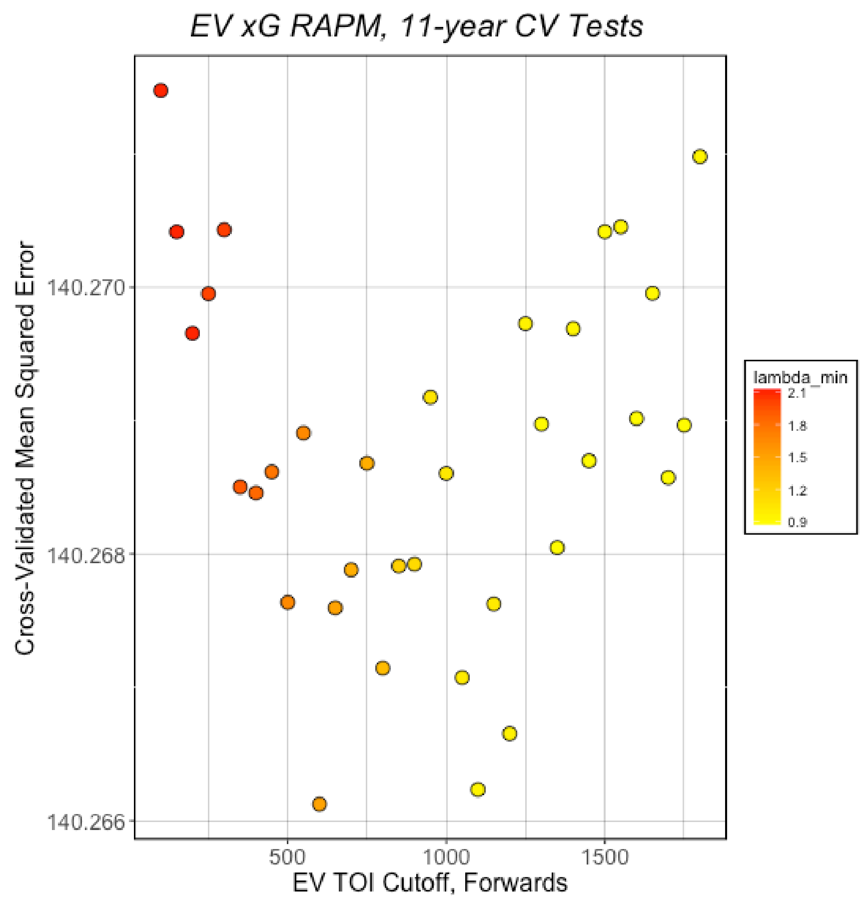
# RAPM Design Matrix - 11-year Figures

| RAPM TYPE | ROWS | COLUMNS |
|---|---|---|
| EV Full | 5,849,224 | 4,711 |
| EV Filtered | 5,849,224 | 2,504 |
| PP/SH Full | 982,906 | 7,665 |
| PP/SH Filtered | 982,906 | 2,972 |

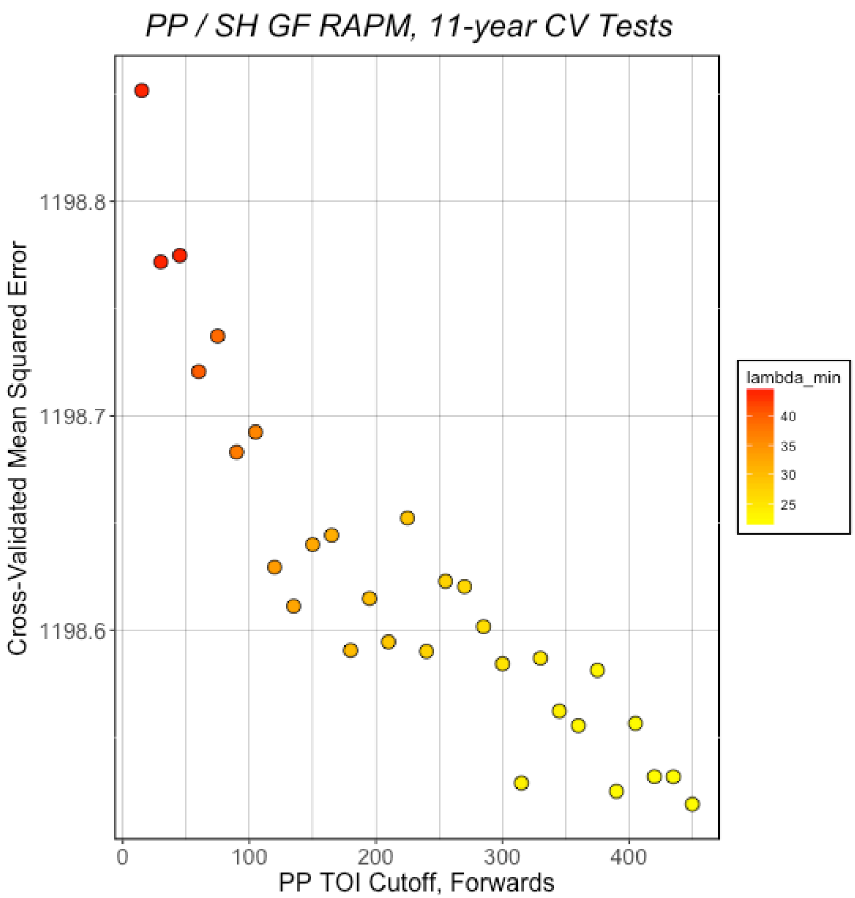
| RAPM TYPE | AVERAGE SHIFT LENGTH |
|---|---|
| EV filtered | 12.83 seconds |
| PP/SH filtered | 17.49 seconds |

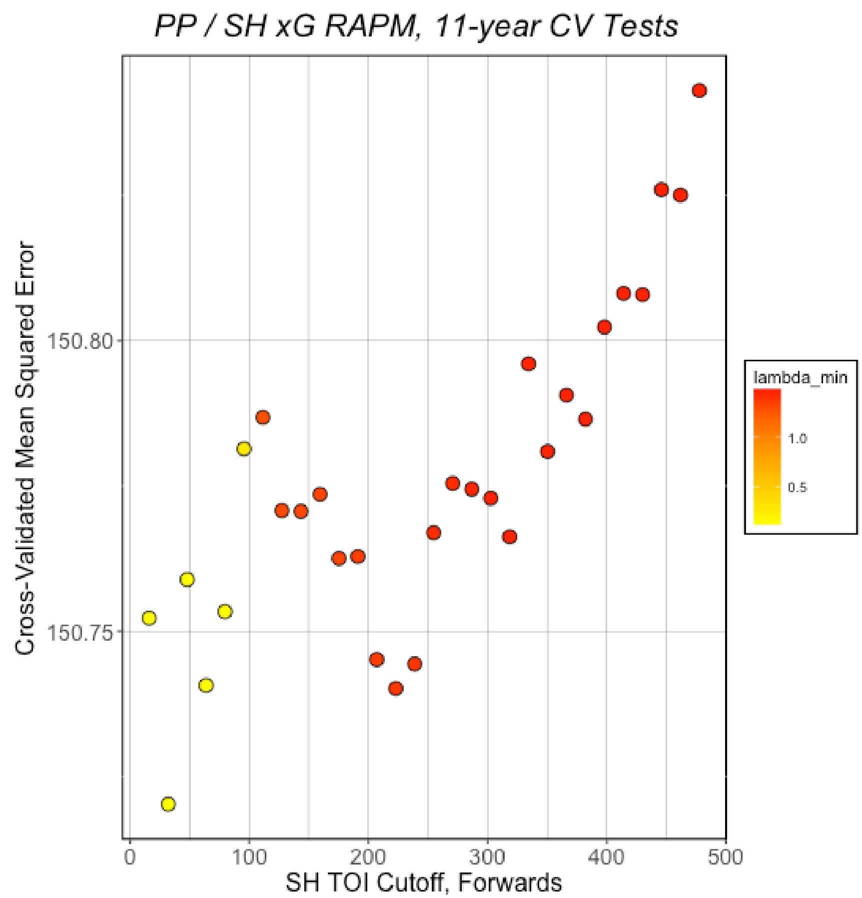
# Even-Strength RAPM: GF / xG Cross-Validation Testing



# PP / SH RAPM: GF / xG Cross-Validation Testing



# Final 11-year RAPM Figures, EV & PP/SH

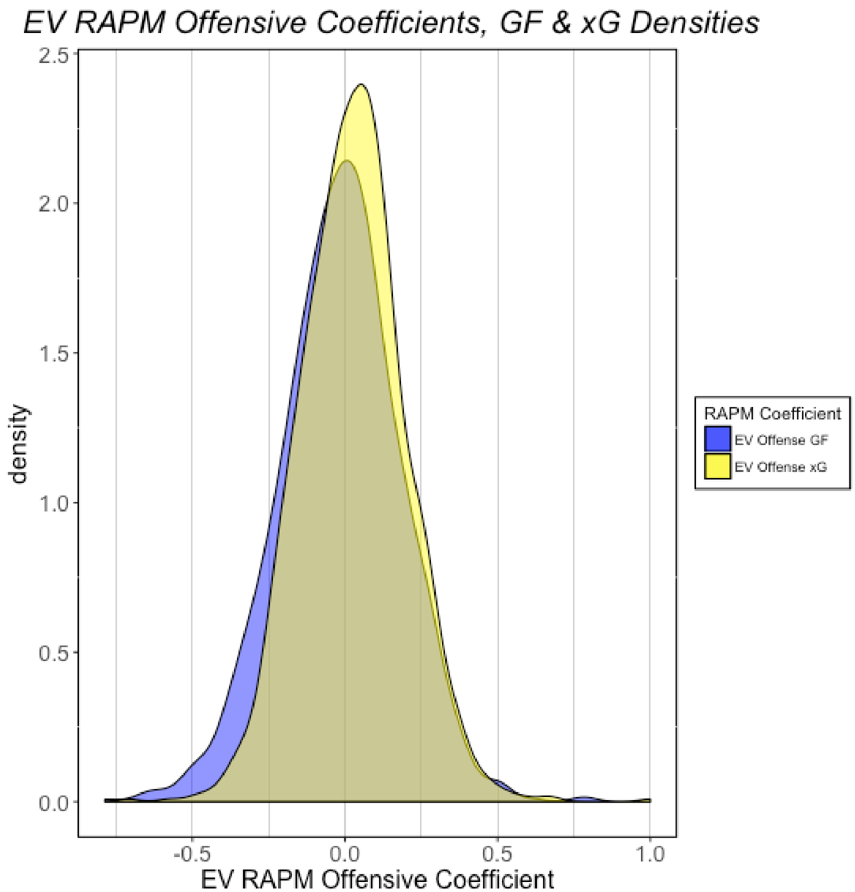
- Target Variable: Goals For (Offensive Components)

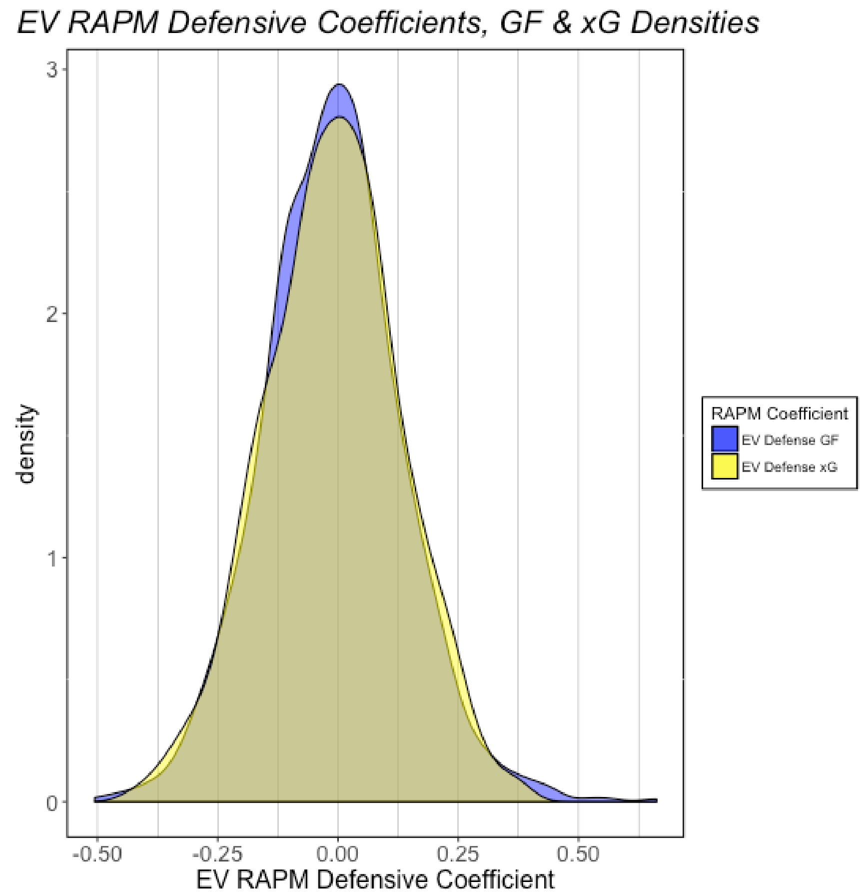
| STRENGTH | F TOI CUT | D TOI CUT | G TOI CUT | TOTAL F | TOTAL D | TOTAL G | CV MSE | LAMBDA MIN |
|---|---|---|---|---|---|---|---|---|
| EV | 1000 | 1287.2 | 1902.7 | 777 | 410 | 116 | 1389.208 | 22.89796 |
| PP/SH | 210 | 210 | 357.8 | 468 | 215 | 123 | 1198.595 | 28.65217 |

- Target Variable: Expected Goals For (Defensive Components)

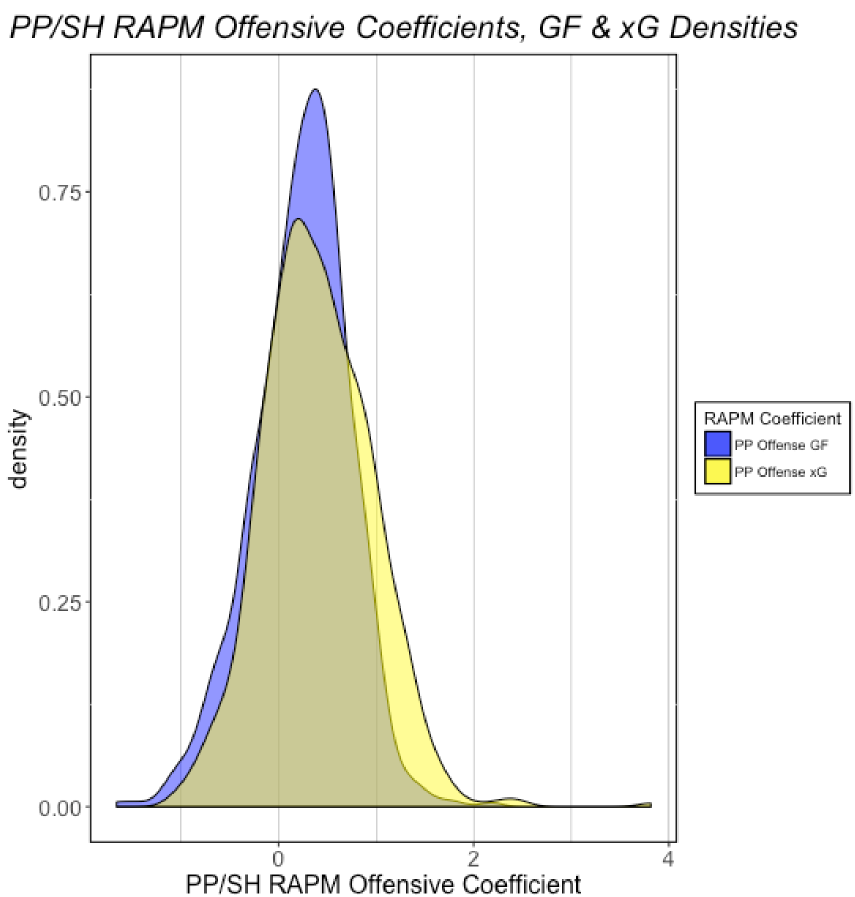
| STRENGTH | F TOI CUT | D TOI CUT | TOTAL F | TOTAL D | CV MSE | LAMBDA MIN |
|---|---|---|---|---|---|---|
| EV | 1000 | 1287.2 | 777 | 410 | 140.2686 | 1.033051 |
| PP/SH | 223 | 269.6 | 379 | 293 | 150.7401 | 1.372727 |

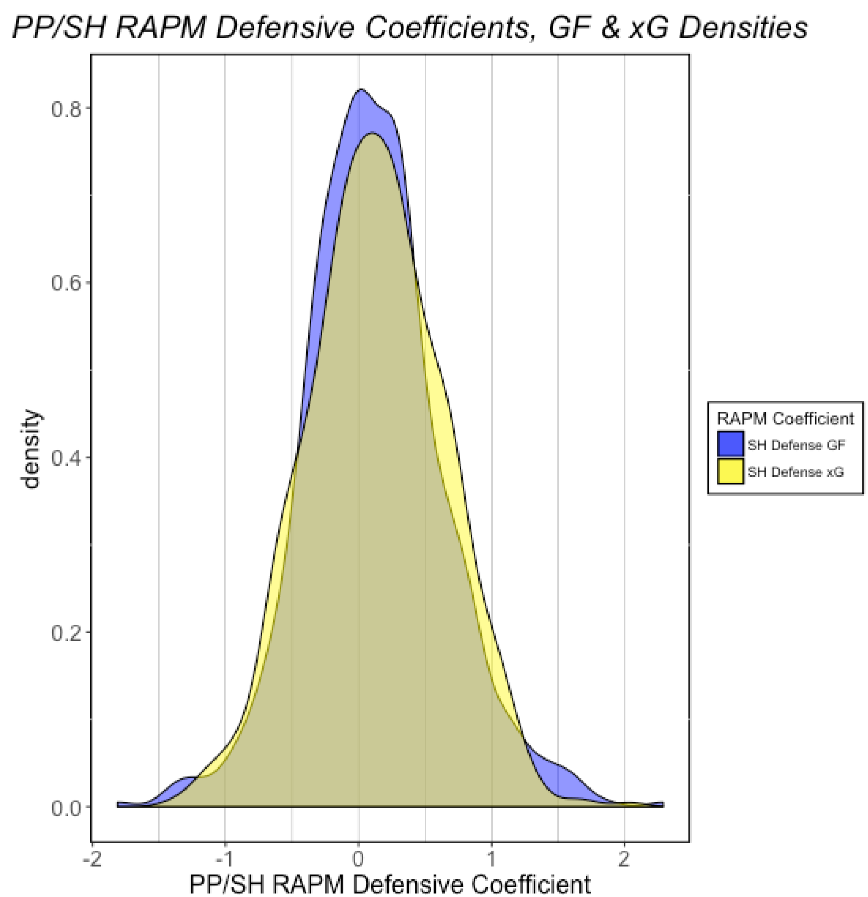
# EV RAPM: Goals vs. Expected Goals, Densities



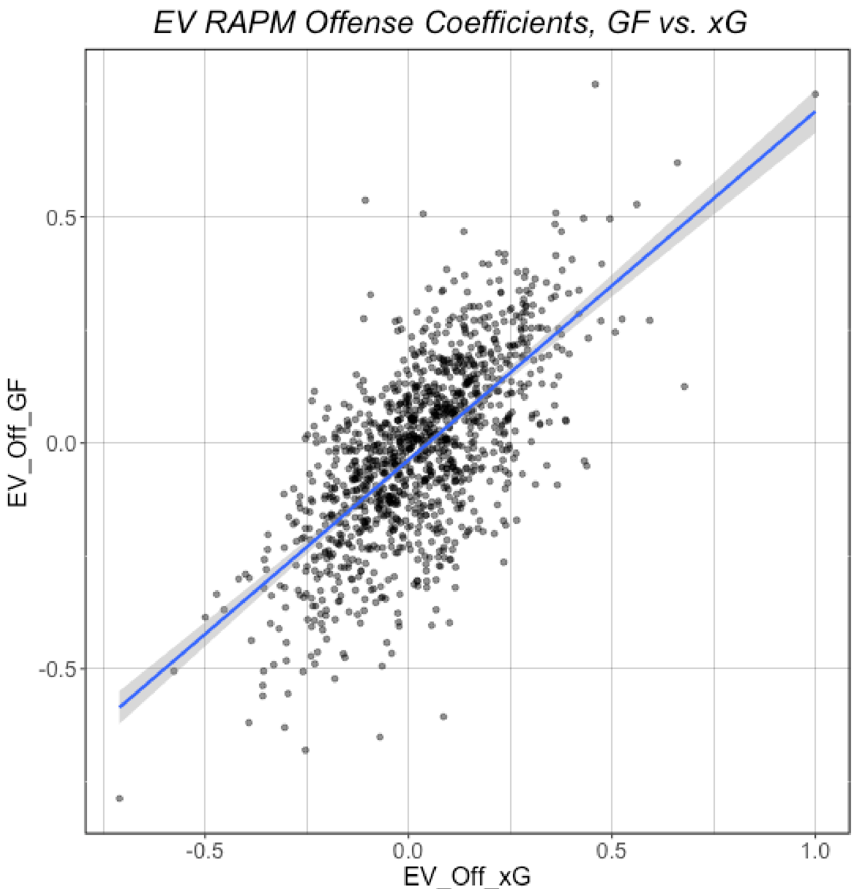



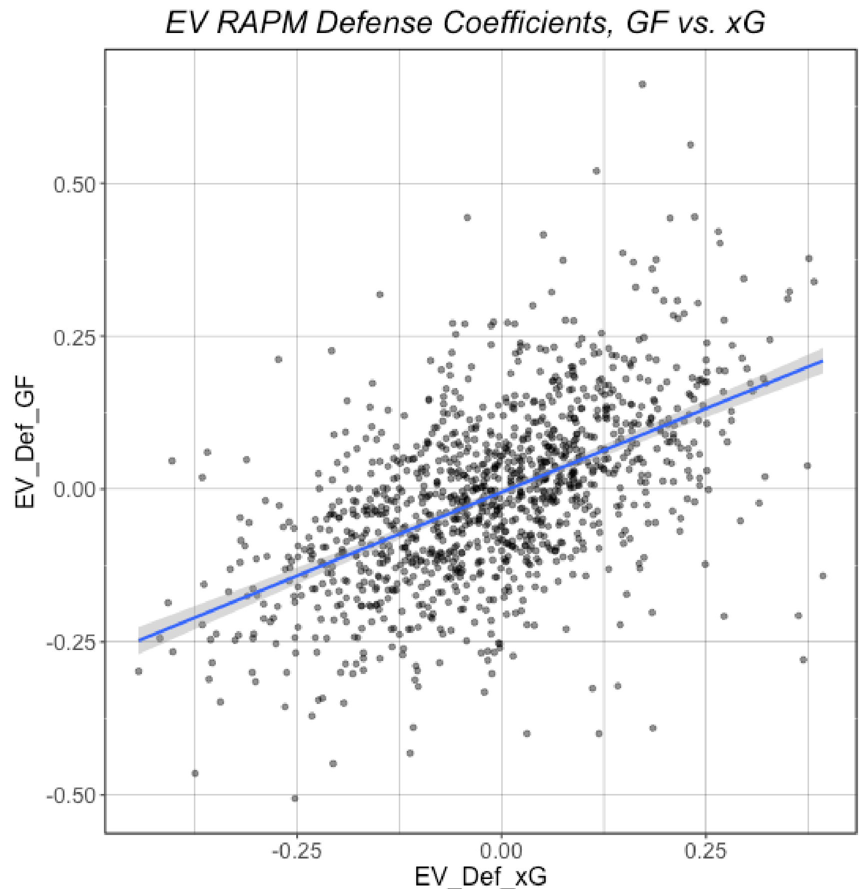
# PP/SH RAPM: Goals vs. Expected Goals, Densities



# EV RAPM: Goals vs. Expected Goals, Comparison



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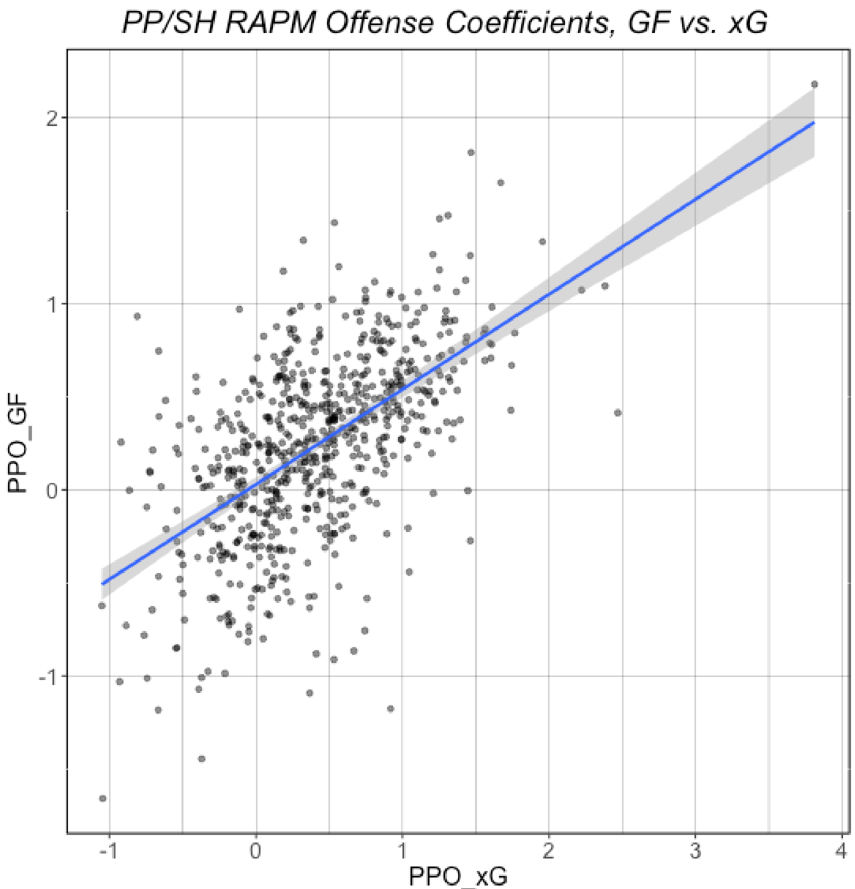


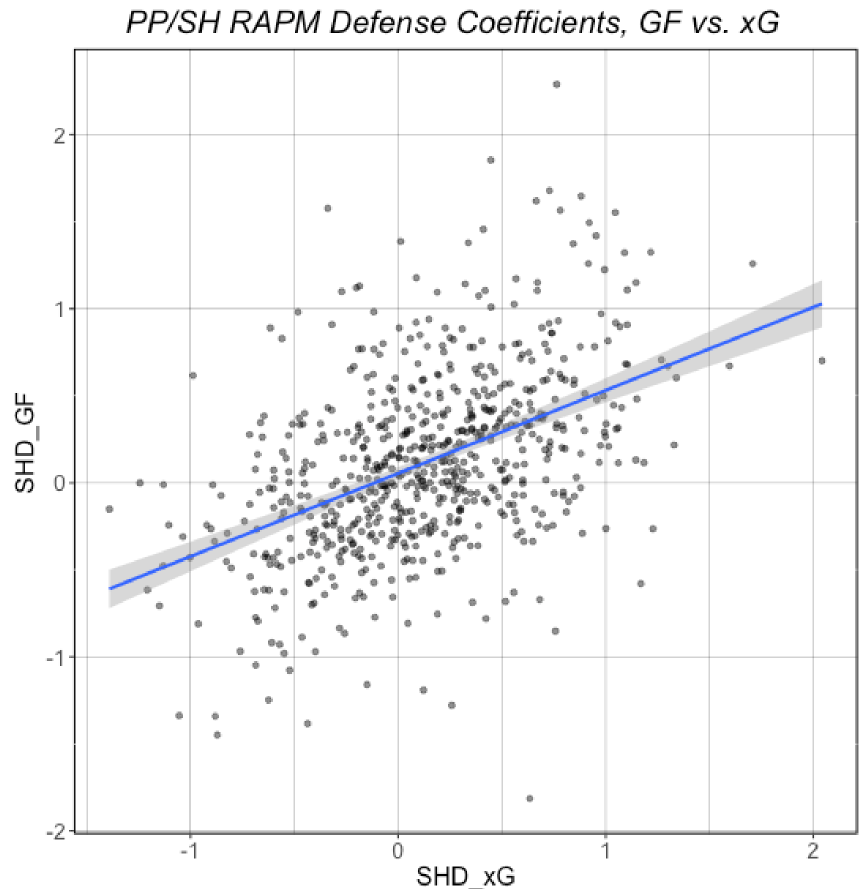

# Statistical Plus-Minus

- Basketball
  - APM / RAPM / SPM / ASPM / BPM / RPM / etc.
  - Our approach is very similar to Daniel Myers' Box Plus-Minus
- Process/outline:
  - Long-term RAPM regression coefficients used as the target variable(s)
  - Corresponding long-term (career sum) play-by-play derived metrics are the feature variables
  - We then train the individual models for each component with above data
  - These models are used to "predict" / generate single season per 60 values
  - We "expand" these per 60 values to GAA/GAR/WAR [(per60 / 60) * TOI]
- Additionally
  - Historical data / comparison is not our concern
  - Algorithms other than linear regression are used

# Process Overview (Reminder)

- RAPM
  - 2007-2018 (11 year), per 60 skater coefficients/"ratings"
- Statistical Plus-Minus (per 60 rate)
  - Even-Strength Offense
  - Even-Strength Defense
  - Powerplay Offense
  - Shorthanded Defense
- Goals Above Average
  - Convert per 60 rate to "implied" goal totals
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  - Even-Strength
  - Powerplay
  - Shorthanded
  - Penalties

# Data Setup

- The base training sets
  - Even-Strength Offense: 11-year EV GF RAPM Coefficient (GF60)
  - Even-Strength Defense: 11-year EV xG RAPM Coefficient (xGA60)
  - Powerplay Offense: 11-year PP/SH GF RAPM Coefficient (GF60)
  - Shorthanded Defense: 11-year PP/SH xG RAPM Coefficient (xGA60)
- Split into two groups per training set:
  - Forwards
  - Defensemen
  - (goalies are excluded)
- 8 total "training" sets are used to construct the SPM models
  - Each includes the RAPM values + all selected pbp-derived metrics

# All Offense Features (EV & PP)

- TOI_perc, TOI_GP
- G, A1, A2, Points
- G_adj, A1_adj, A2_adj, Points_adj
- iSF, iFF, iCF, ixG, iCF_adj, ixG_adj
- GIVE_o, GIVE_n, GIVE_d
- GIVE, GIVE_adj
- TAKE_o, TAKE_n, TAKE_d
- TAKE, TAKE_adj
- iHF_o, iHF_n, iHF_d
- iHF, iHF_adj
- iHA_o, iHA_n, iHA_d
- iHA, iHA_adj
- OZS_perc, NZS_perc, DZS_perc
- FO_perc, r_FO_perc
- rel_TM_GF60, rel_TM_xGF60, rel_TM_SF60, rel_TM_FF60, rel_TM_CF60
- rel_TM_GF60_state, rel_TM_xGF60_state, rel_TM_SF60_state, rel_TM_FF60_state, rel_TM_CF60_state

# All Defense Features (EV & SH)

- TOI_perc, TOI_GP
- iBLK, iBLK_adj
- GIVE, GIVE_adj, GIVE_o, GIVE_n, GIVE_d
- TAKE, TAKE_adj, TAKE_o, TAKE_n, TAKE_d
- iHF, iHF_adj, iHF_o, iHF_n, iHF_d
- iHA, iHA_adj, iHA_o, iHA_n, iHA_d
- OZS_perc, NZS_perc, DZS_perc
- FO_perc, r_FO_perc
- rel_TM_SA60, rel_TM_FA60, rel_TM_CA60, rel_TM_xGA60
- rel_TM_SA60_state, rel_TM_FA60_state, rel_TM_CA60_state, rel_TM_xGA60_state

# A Note on Relative to Teammate Metrics

- Relative to Teammate **Original** Calculation:

    - Player CF60 - weighted average of all Teammates on-ice CF60 without Player (weighted by Player TOI% with Teammate)

- Relative to Teammate **New** Calculation:

    - Player CF60 - weighted average of all Teammates on-ice CF60 (weighted by Player TOI% with Teammate)

- The new method was used for all of the Rel TM metrics throughout the model
- Both the "low-TOI" and team adjustments are not used
- The new version is more stable (less issues with Sedin-like players)
- Computation time is significantly reduced

# Feature and Model Selection

- Utilize algorithms other than Linear Regression:
  - Basketball APM/ variants use Linear-type models (Ridge)
  - Given the amount of options and the complex nature, why limit?
  - Well... because linear regression does a great job with this problem
    - The training dataset is VERY Gaussian
- Employ an ensemble of algorithms to fit our model(s):
  - Caret package used, which makes testing many algorithms relatively easy
  - GBM / Neural Network / Various kernels / etc.
  - Linear Regression and Its Cousins - very good
- 5 total algorithms after much testing:
  - Linear Regression
  - Elastic Net Regression (`glmnet` package in R)
  - Support Vector Machines (w/ linear kernel from `kernlab`)
  - Cubist (`Cubist` package in R)
  - Bagged Multiple Adaptive Regression Splines (MARS, `bagEarth` package in R)
- For each component, only 3 algorithms were used

# Final Features: Even-Strength

| COMPONENT | LINEAR MODEL FEATURES | MACHINE LEARNING FEATURES |
|---|---|---|
| **EVO_F** | TOI_perc, G, GIVE_d, TAKE_o, TAKE_n, TAKE_d, iHF_d, iHA_o, OZS_perc, NZS_perc, r_FO_perc, rel_TM_GF60, rel_TM_SF60 | TOI_perc, G, iSF, GIVE_o, GIVE_n, GIVE_d, TAKE_o, TAKE_n, TAKE_d, iHF_n, iHF_d, iHA_o, OZS_perc, NZS_perc, r_FO_perc, rel_TM_GF60, rel_TM_xGF60, rel_TM_SF60 |
| **EVO_D** | A1, iCF, GIVE_d, TAKE_o, iHA_n, NZS_perc, DZS_perc, rel_TM_GF60, rel_TM_SF60 | TOI_perc, A1, iCF, GIVE_o, GIVE_d, TAKE_o, TAKE_d, iHF_o, iHF_d, iHA_o, iHA_d, NZS_perc, DZS_perc, rel_TM_GF60, rel_TM_SF60 |
| **EVD_F** | `Not Used` | TOI_perc, iBLK, GIVE_o, GIVE_d, TAKE_o, TAKE_n, iHF_o, iHF_d, iHA_o, iHA_d, NZS_perc, DZS_perc, rel_TM_xGA60_state |
| **EVD_D** | TOI_perc, iHA_n, OZS_perc, DZS_perc, rel_TM_xGA60_state | TOI_perc, iBLK, GIVE_o, GIVE_d, TAKE_n, iHF_n, iHF_d, iHA_n, iHA_d, OZS_perc, DZS_perc, rel_TM_xGA60_state |

# Final Features: Powerplay Offense and Shorthanded Defense

| COMPONENT | LINEAR MODEL FEATURES | MACHINE LEARNING FEATURES |
|---|---|---|
| **PPO_F** | Not Used | TOI_perc, A1, A2, ixG, GIVE_all, TAKE_all, iHF_all, iHA_all, OZS_perc, DZS_perc, r_FO_perc, rel_TM_GF60, rel_TM_CF60 |
| **PPO_D** | TOI_perc, G, A1, A2, OZS_perc, DZS_perc, rel_TM_GF60 | TOI_perc, G, A1, A2, ixG, GIVE_all, TAKE_all, iHF_all, iHA_all, OZS_perc, DZS_perc, rel_TM_GF60, rel_TM_xGF60 |
| **SHD_F** | Not Used | TOI_perc, GIVE_all, TAKE_all, iHA_all, OZS_perc, DZS_perc, r_FO_perc, rel_TM_CA60, rel_TM_xGA60 |
| **SHD_D** | Not Used | TOI_perc, GIVE_all, TAKE_all, iHF_all, iHA_all, OZS_perc, DZS_perc, rel_TM_CA60, rel_TM_xGA60 |

# EV Offense - Forwards: Linear Model Summary

| COEFFICIENTS | ESTIMATE | STD. ERROR | T VALUE | PR(>T) |
|---|---|---|---|---|
| (Intercept) | 0.4346170 | 0.0384309 | 11.309 | < 2e-16 *** |
| TOI_perc | -0.0037883 | 0.0006178 | -6.132 | 1.56e-09 *** |
| G | 0.0267679 | 0.0114637 | 2.335 | 0.019867 * |
| GIVE_d | 0.0081214 | 0.0067971 | 1.195 | 0.232613 |
| TAKE_o | 0.0278472 | 0.0077146 | 3.610 | 0.000332 *** |
| TAKE_n | 0.0340725 | 0.0112527 | 3.028 | 0.002566 ** |
| TAKE_d | -0.0219583 | 0.0088086 | -2.493 | 0.012937 * |
| iHF_d | 0.0041621 | 0.0020055 | 2.075 | 0.038377 * |
| iHA_o | 0.0095549 | 0.0014097 | 6.778 | 2.88e-11 *** |
| OZS_perc | -0.0033895 | 0.0004790 | -7.077 | 4.08e-12 *** |
| NZS_perc | -0.0086026 | 0.0006778 | -12.691 | < 2e-16 *** |
| r_FO_perc | 0.0249220 | 0.0083611 | 2.981 | 0.002991 ** |
| rel_TM_GF60 | 0.6220178 | 0.0074231 | 83.794 | < 2e-16 *** |
| rel_TM_SF60 | -0.0023535 | 0.0010684 | -2.203 | 0.027975 * |

# Feature Importance Example: EVD - Defensemen

| -- | GLMNET (LASSO) | -- | LM | -- | CUBIST | -- |
|---|---|---|---|---|---|---|
| 1 | rel_TM_xGA60_state | 0.928910696 | rel_TM_xGA60_state | 46.515970 | rel_TM_xGA60_state | 50 |
| 2 | TOI_perc | 0.007767517 | TOI_perc | 9.771783 | TOI_perc | 50 |
| 3 | DZS_perc | 0.014528579 | DZS_perc | 10.073346 | DZS_perc | 50 |
| 4 | OZS_perc | 0.005626670 | OZS_perc | 5.370464 | OZS_perc | 50 |
| 5 | iHA_n | 0.048740394 | iHA_n | 4.872459 | iHA_n | 25 |
| 6 | iHA_d | 0.002764914 | -- | -- | iHA_d | 5 |
| 7 | TAKE_n | 0.036359107 | -- | -- | -- | -- |
| 8 | GIVE_d | 0.008029687 | -- | -- | -- | -- |
| 9 | iHF_n | 0.006040686 | -- | -- | -- | -- |
| 10 | iBLK | 0.003132787 | -- | -- | -- | -- |
| 11 | iHF_d | 0.000000000 | -- | -- | -- | -- |
| 12 | GIVE_o | 0.000000000 | -- | -- | -- | -- |

# Ensemble Models & Performance

| COMPONENT | 1 | 2 | 3 | WEIGHTS (%) | RMSE | $R^2$ |
|---|---|---|---|---|---|---|
| EVO_F | lm | bagEarth | svmLinear | 25.2 / 34.5 / 40.3 | 0.03446 | 0.9759 |
| EVO_D | lm | cubist | svmLinear | 37.9 / 32.1 / 30.0 | 0.02950 | 0.9536 |
| EVD_F | bagEarth | svmLinear | glmnet | 41.4 / 29.8 / 28.8 | 0.05552 | 0.8490 |
| EVD_D | lm | cubist | glmnet | 36.9 / 27.4 / 35.7 | 0.05219 | 0.8591 |
| PPO_F | cubist | bagEarth | svmLinear | 37.9 / 36.5 / 25.6 | 0.1015 | 0.9567 |
| PPO_D | lm | svmLinear | glmnet | 39.7 / 35.2 / 25.1 | 0.09035 | 0.9625 |
| SHD_F | cubist | bagEarth | svmLinear | 31.0 / 34.3 / 34.7 | 0.1731 | 0.8601 |
| SHD_D | cubist | bagEarth | glmnet | 28.2 / 44.4 / 27.4 | 0.1614 | 0.8613 |

- Evaluation metrics (RMSE / $R^{2)}$ produced from 300 runs of 80/20 train/test split
- Model Occurrences: svmLinear: 6, bagEarth: 5, Cubist: 5, LM: 4, glmnet: 4
- Areas for improvement... MORE TIME

# Penalty Goals, Team Adjustment, Replacement Level, WAR

- Penalty goals calculation:
  - Goal value derived from the change in GF60/GA60 from one strength state to the next
  - Not a regression technique
- Team adjustment process:
  - Based on the method used in Daniel Myers' BPM
- WAR: Goals to Win conversion
  - Pythagenpat method developed used in baseball
  - Adjusts for goal scoring environment per season
  - ~5.1 goals per win

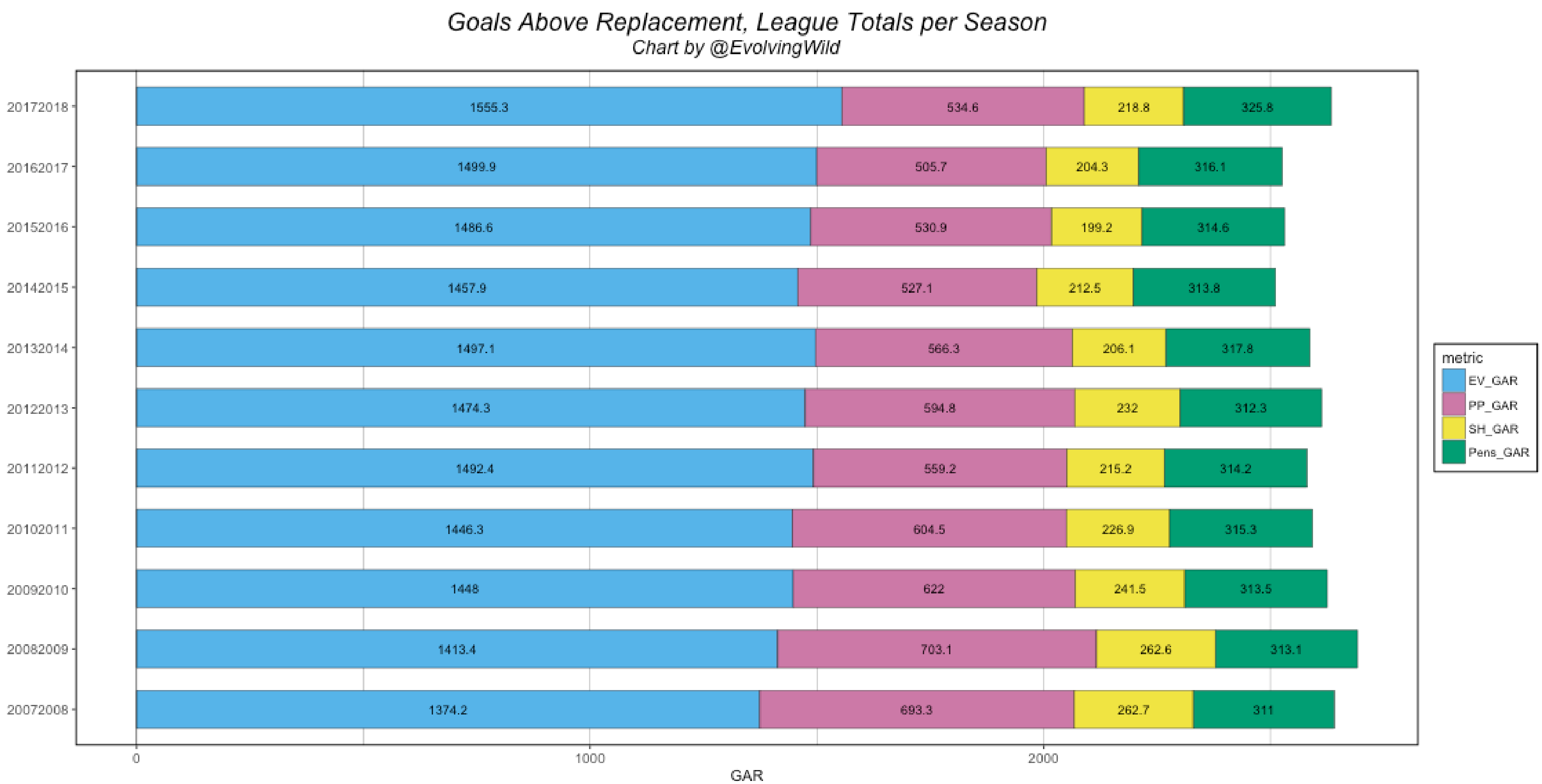
# 11-year Leaders: Forwards

| PLAYER | TOI_ALL | EV_GAR | PP_GAR | SH_GAR | PENS_GAR | GAR | WAR |
|---|---|---|---|---|---|---|---|
| Pavel Datsyuk | 11724.4 | 108.4 | 31.3 | 6.5 | 31.6 | 177.7 | 34.1 |
| Sidney Crosby | 14722.6 | 106.9 | 37.8 | 1.5 | 24.4 | 170.2 | 32.7 |
| Anze Kopitar | 17791.7 | 101.2 | 25.3 | 3.3 | 34.0 | 163.9 | 31.4 |
| Evgeni Malkin | 14226.2 | 92.1 | 44.9 | 0.4 | 19.0 | 156.5 | 30.0 |
| Jonathan Toews | 15616.2 | 100.6 | 29.7 | 4.8 | 19.7 | 154.8 | 29.9 |
| Alex Ovechkin | 17500.7 | 84.4 | 48.6 | 0.0 | 22.3 | 155.3 | 29.8 |
| Joe Thornton | 15790.5 | 91.4 | 38.9 | 2.2 | 19.9 | 152.4 | 29.4 |
| Joe Pavelski | 16014.0 | 90.8 | 33.5 | 2.6 | 25.7 | 152.5 | 29.2 |
| Nicklas Backstrom | 16005.4 | 85.1 | 58.3 | 1.9 | 0.2 | 145.7 | 27.9 |
| Ryan Getzlaf | 16131.6 | 107.4 | 31.6 | 4.2 | -9.1 | 133.8 | 25.6 |

# 11-year Leaders: Defensemen

| PLAYER | TOI_ALL | EV_GAR | PP_GAR | SH_GAR | PENS_GAR | GAR | WAR |
|---|---|---|---|---|---|---|---|
| Zdeno Chara | 20073.3 | 83.3 | 20.2 | 12.7 | 4.8 | 120.9 | 23.3 |
| Mark Giordano | 16143.0 | 82.9 | 18.6 | 7.3 | 2.1 | 110.9 | 21.4 |
| Ryan Suter | 21939.0 | 76.0 | 23.5 | 5.4 | 1.3 | 106.3 | 20.5 |
| Marc-Edouard Vlasic | 17870.3 | 71.9 | 3.3 | 4.1 | 25.4 | 104.6 | 20.1 |
| Kris Letang | 15976.1 | 44.0 | 29.5 | 7.2 | 20.1 | 100.8 | 19.4 |
| Shea Weber | 18930.1 | 60.9 | 27.5 | 6.2 | 6.5 | 100.7 | 19.4 |
| Brian Campbell | 17873.3 | 46.8 | 20.2 | 8.5 | 25.0 | 100.4 | 19.2 |
| Alex Pietrangelo | 15238.7 | 51.4 | 12.1 | 7.9 | 22.2 | 93.5 | 17.9 |
| Dan Boyle | 14285.1 | 43.3 | 29.5 | 11.2 | 9.1 | 93.1 | 17.9 |
| Victor Hedman | 14341.6 | 71.3 | 11.2 | 9.1 | 1.0 | 92.3 | 17.8 |

# Season Total Goals Above Replacement



# Questions?

- Where you can find us:
    - Twitter: @EvolvingWild
    - Hockey Graphs
    - Our website / shiny app (https://evolvingwild.shinyapps.io/hockey/)

Thank you!