

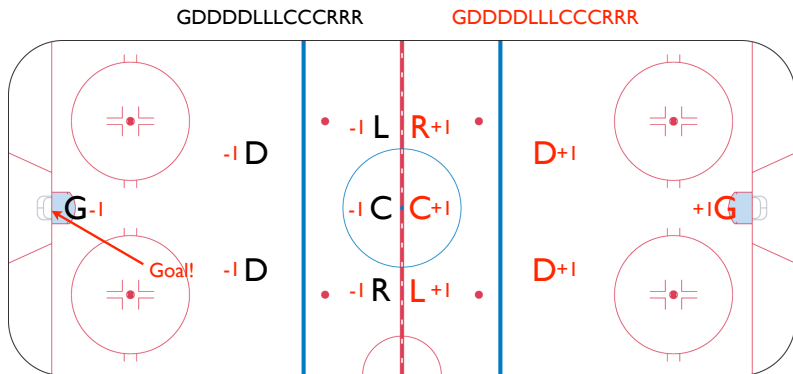
# Regularized Estimation of Player Performance

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## Plus-Minus

PM is a running count of, for every goal, a +1 for those on the scoring team and -1 for those on the team scored upon.



It doesn't quite measure player quality, as we haven't controlled for the effects of teammate and opponent quality (or anything else).

## A Regression version of PM

Set up a 'response' variable:

$y_i = +1$  for a *home* team goal,

$y_i = -1$  for an *away* team goal.

We're interested in how individual players affect

$$q_i = p(y_i = 1) = p(\text{home team scored goal } i)$$

The standard model for such problems is logistic regression, say

$$\log \left[ \frac{q_i}{1 - q_i} \right] = \alpha + \beta_{HG} + \beta_{HD} \dots + \beta_{HR} - \beta_{AG} - \dots - \beta_{AR}$$

where  $\beta_{HG}$  is Home-Goalie and  $\beta_{AR}$  is Away-Right-wing, etc.

Then, for player  $j$  and given a goal was scored,  $e_j^\beta$  is the multiplier on odds that it was scored by his team if he's on the ice.

We actually use a larger regression model:

$$\log \left[ \frac{q_i}{1 - q_i} \right] = \alpha + \mathbf{u}_i' \boldsymbol{\gamma} + \mathbf{v}_i' \boldsymbol{\varphi} + \mathbf{x}_i' \boldsymbol{\beta}_0 + (\mathbf{x}_i \circ \mathbf{s}_i)' (\boldsymbol{\beta}_s + p_i \boldsymbol{\beta}_p)$$

where

- ▶  $\mathbf{u}_i$  holds indicators for each team-season,
- ▶  $\mathbf{v}_i$  holds indicators for various special-teams scenarios,
- ▶  $\mathbf{x}_i$  contains player-presence indicator,

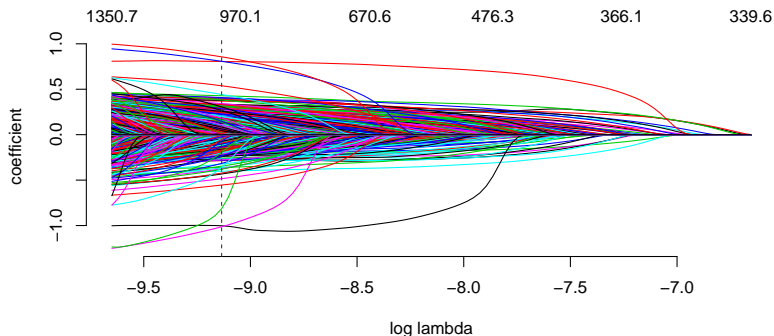
All of these indicators are +1 for home and -1 for away.

Then  $\beta_j$  measures player effect after **controlling** for team strength (e.g., coach or schedule) and on-ice scenarios (e.g., PP or PK).

We also allow deviations in the player effects for specific seasons ( $s_{it}$ ) and in the playoffs ( $p_{it}$ ), but these are seldom 'significant'.

## Regularization

Instead of minimizing deviance, we minimize deviance *plus penalty*  $\lambda|\beta_j|$  on the size of each  $\beta_j$  estimates.



Enumerate a 'path' of models for different  $\lambda$ , and use the one that predicts best out-of-sample. **This is how modern stats/ML works.**