Introduction

Here I intend to document all my findings and reasoning on an experiment to create a prediction model for the NCAA lacrosse tournament. The goal is for this document to grow organically, each section being added as the results are done, with the thought process being written down throughout.

Initial Data and Current State of the Field

The only data we are starting with is the 2013-2017 regular seasons' game results. Explicitly a home-away team and how many goals each team scored. Further box results for each game can be found on the ncaa.org site, but will only be added later if/when needed. We also have access to a csv file that contains the NCAA tournament seedings and the results.

Currently there are some analyses available for lacrosse games. Inside Lacrosse has a rudimentary predictor, and laxpower also contains a great deal of team statistics. lacrosseanalytics.com also contains some basic evaluation metrics such as strength of schedule and adjusted offensive efficiency.

Lacrosse doesn't yet get the attention analysts have devoted to baseball or basketball prediction. Predictions are only a rough estimate about how likely a team is to win or score points, but they can also be seen as a tool to show which aspects of the game are keys to victory.

Lacrosse Primer for the Uninitiated

It is not unreasonable to assume (though unfortunate) that the reader isn't familiar with the game of lacrosse. Without going into too much depth, a few details are worth pointing out to be able to put the resulting analysis into context.

- Lacrosse is a semi-continuous game, played in four quarters. Semi-continous here means there are few breaks in action, save for referee interventions (timeouts, goals, penalties, injuries). Defensive to offensive transition can occur without a stoppage like in football.
- Generally speaking, a goal leads to a faceoff (similar to ice hockey). Meaning a team that just scored can regain possession of the ball and go on another offensive attempt without the other team ever having control of the ball.
- NCAA lacrosse does not have ties. Overtime periods continue until a goal is scored and thus a winner emerges.

First Pass Through Data

An initial exploration through the data shows the following:

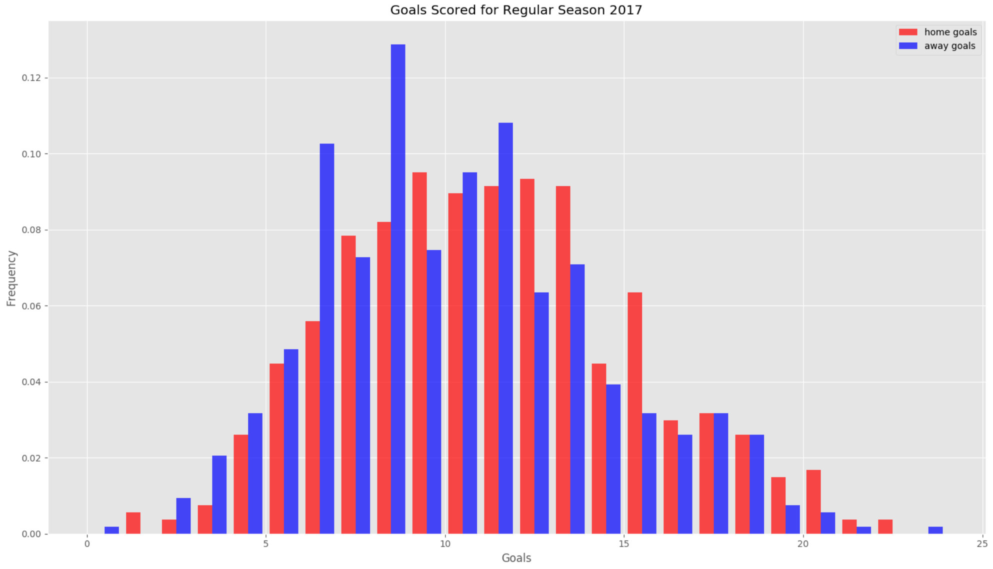
year	home goals	away goals	games played	average home goals	average away goals
2013	5128	4692	477	10.75	9.84
2014	5478	4922	511	10.72	9.63
2015	5652	5052	522	10.83	9.68
2016	5688	5095	533	10.67	9.56
2017	5822	5325	537	10.84	9.92

This indicates home-field advantage of about one goal. Does this hold for all teams? Let's grab the top seeded team, middle ranked team, and lowest ranked team, according to laxpower, for each year to compare:

year	team	games played (home-away)	avg goals scored (home-away)	avg goals allowed (home-away)
2013	Syracuse	15-5	11.13-12.6	8.67-9.8
2013	Army	7-7	10.43-9.71	7.29-8.29
2013	Wagner	8-5	9.5-7.2	14.5-15.6
2014	Duke	14-6	15.5-13.33	9.43-10.17
2014	Saint Joseph's	7-8	11.43-10.88	7.86-8.5
2014	Wagner	8-5	7-6.8	12.63-12
2015	Notre Dame	10-5	12.9-14	9.4-9.2
2015	Fairfield	8-7	10-9.14	7.38-7.57
2015	VMI[1]	9-6	5.56-4.5	13.78-17.83
2016	Maryland	12-8	12.58-10.13	8.66-7.88
2016	Drexel	6-9	9-8.89	8.33-10.22
2016	VMI [2]	6-10	8.83-4.3	12-15.1
2017	Maryland	11-8	12.91-11.88	8.36-9.38
2017	Cornell	6-7	13-10.57	11-15.57
2017	NJIT [3]	6-9	5.83-7.67	10.67-13.56

With some exceptions, there does seem to be a trend of teams scoring more at home and giving up more goals when away.

Now let's see the distribution of goals scored. Let's plot both home and away goals on the same plot.



Looking at this plot, it seems to be a normal distribution. The results for years 2013-2016 look similar. Arguing a bit, one could say it looks a bit more like a skew normal distribution. With the limited sample size, we could probably fit a Poisson, Weibull or some other more distribution to the data.

However, a much more interesting distribution to know would be an individual team's scoring distribution. Which any layman will tell you could be largely dependent on their opponent. This means we need more data for each team.

NCAA.org Data

The NCAA hosts a website at ncaa.org where individual game statistics are available. In particular this allows us access to a finer granularity of data for each team. With data like goals, assists, groundballs, turnovers, faceoffs, penalties, saves and clears. Now each team can have their play evaluated off of a number of variables, with goals given up and goals scored being the values to predict.

Another option is giving a team a single value score, or a multiple value. Analogous to a chess player's ELO rating, which we can give to the team as a whole, or to their respective units (offense, defense and face-offs). This could be more useful in allowing us to predict a match's results.

Accessing this data is relatively simple. The website uses GET parameters to get the individual team's statistics, so decyphering these parameters and their meaning will allow a scraper to go over the site and save the data locally.

Once the data is available locally, we can attempt a number of different methods to develop our rating and evaluate the matchups.

Initial Thoughts For Matchup Predictor

Having read how a number of the NCAA March Madness predictors work, it seems like adding a few data columns to the aggregated data will help us combine relevant data without having to pass the entire dataset through the model. Three different approaches present themselves for evaluation

Autoencoder

Using an autoencoder we could throw the raw data into the autoencoder and allow it to spit out as many latent variables as we desire (one, three, ten, etc). Then we could connect this encoder to an evaluation function, which takes the output of the encoder for two teams playing one another and evaluates the result, backpropagating any errors to have the network learn. Since this is a neural network architecture, we can later decouple the various stages and have the autoencoder give us team ratings and predict future matchup success.

Team Probability Distributions

Using the data, we could create a probability distribution of each team's results. Allowing for some weighting with the other team's Strength of Schedule (SOS, a variable we can calculate), the result of the game could be the weighted average of the results. This has the advantage of being simple to calculate, and we could use a Monte Carlo simulation (a fancy way of saying running it a lot of times) to generate an outcome probability.

Deep Learning

As seems to be all the rage these days, we could create a large and deep network, throw each team's statistics into it and let the network figure it all out. With just over 2500 games presently available (we could probably get a few more seasons worth of data), there is some doubt if we have enough data to make a truly deep learning network converge on a satisfactory solution.

Other Regression Methods

There are other regression methods that are available and possibly appropriate for these methods. In theory adding a naive bayes classifier, a support vector machine, and a random forest classifier, we could then take the results of all these models and stack them together to give a prediction. We may explore these options if the first two (or three, let's be honest, we could probably get away with a simple MLP for that).