

Heroes of the Storm Balance Analysis

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Introduction

Is *Heroes of the Storm* balanced? Are there some characters that win significantly more often at all skill levels? Does Skill level or hero selection matter more in determining who wins a game? These are questions that many competitive players ask. In this document I will take a numerical approach to answer those questions using machine learning.

What is *Heroes of the Storm*

Heroes of the storm is a Multiplayer Online Battle Arena (MOBA) where two teams of five players take control of different characters in order to destroy the opposing team's base. Each character has different abilities and characteristics. Such as how much damage they can receive before dying and having to wait to join the game again, and how much damage they can deal out. The game tries to help players have competitive games and shoots for any given player to win 50% of their games.

The Data

The data used in this analysis comes from HotsLogs.com and can be found at <https://www.hotslogs.com/Info/API>. The data used in the analysis was downloaded on 3/2/2017 and has data up through 2/26/2017.

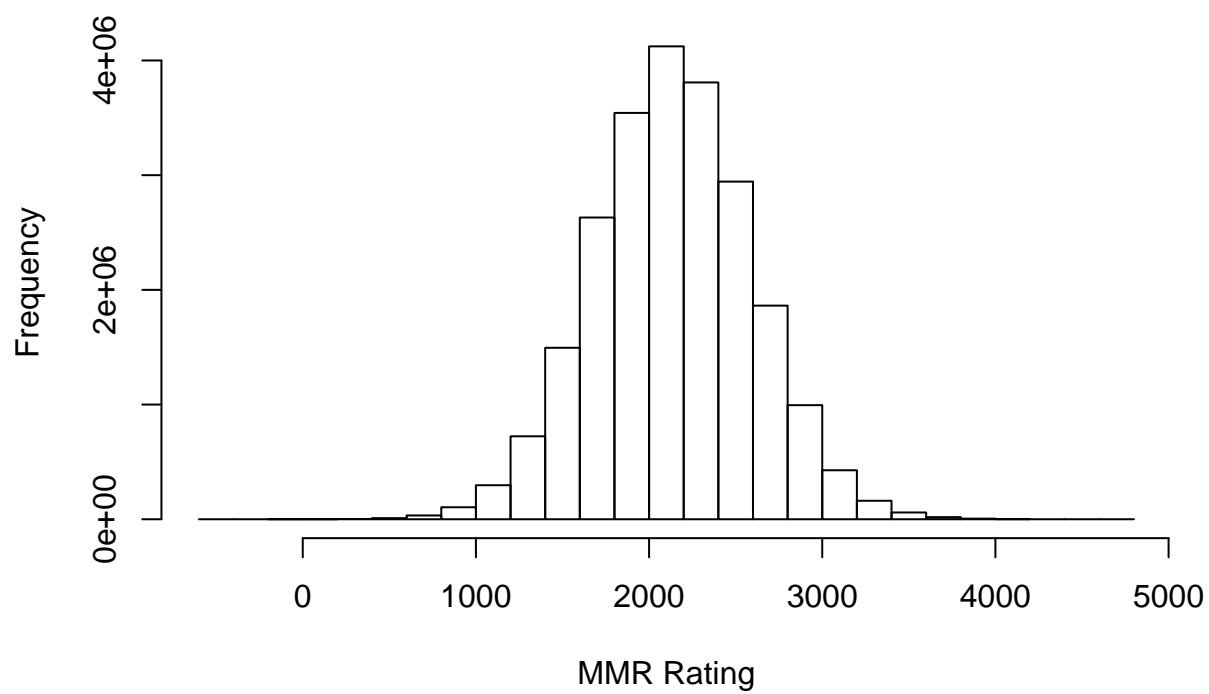
Hots logs gathers this data through voluntary submissions of replay files. Each replay file has data for all 10 players in that game. This includes What hero people played, what level that hero is for the player (an indication of overall time spent playing a specific hero), and an estimated MMR ranking for an individual and more.

The data used in the analysis was downloaded on 3/2/2017 and has data up through 2/26/2017, and has 23,242,890 records. Of particular note the data has an even split of 11,621,445 records of wins, and 11,621,445 of losses, with all characters being played between 70,736 and 928,234 times.

There is a nice distribution of players at different skill ratings (MMR), and using heroes at different varying levels.

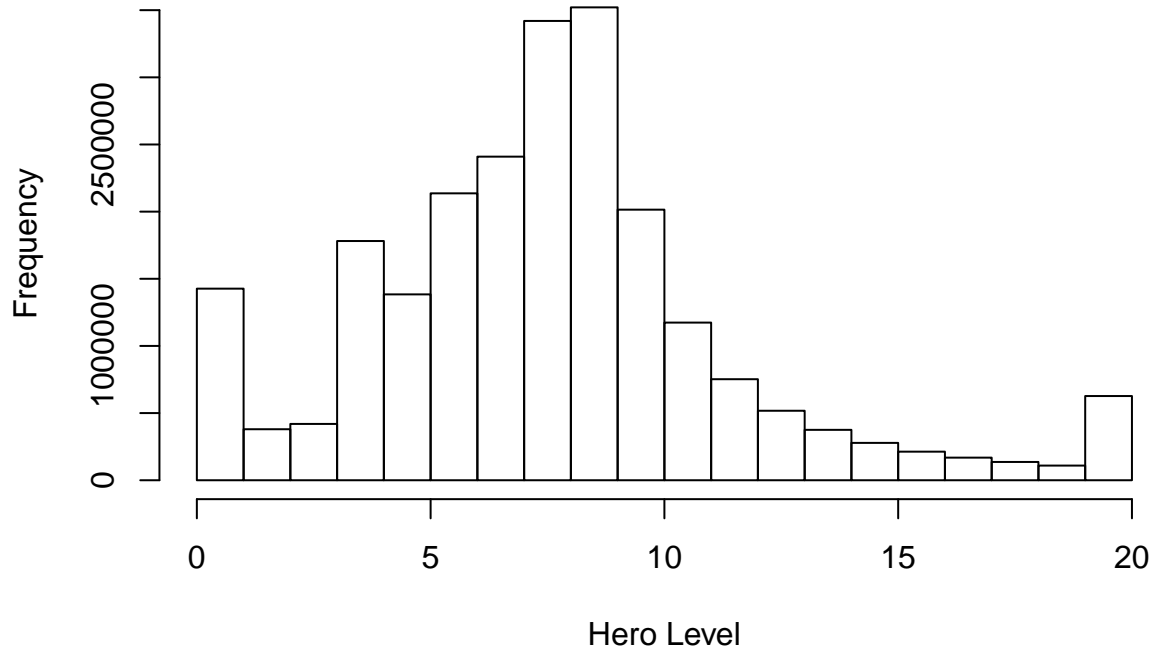
```
hist(graphs$MMR.Before, main = "Distribution of MMR Ratings", xlab = "MMR Rating")
```

Distribution of MMR Ratings



```
hist(graphs$Hero.Level, main = "Distribution of Hero level", xlab = "Hero Level")
```

Distribution of Hero level



The analysis

To answer the questions of is the game balanced, and what matters more for determining winning: Skill level or hero selection, We need to see what effect each Character has on a player's chance of winning a game, as well as what effect their skill has.

To measure a player's skill, I am going to use two variables. The first is the player's MMR before the game started. MMR is a skill rating given to a player by the game to assist in the match making process, and as such is a good approximator for the player's over all skill at the game. As the exact MMR is a number on an arbitrary scale I standardize this data point using Min Max standardization. In some cases the MMR value is blank; this is due to a lack of games played. As there is no way of knowing how skilled that player is at competitive MOBA Games I have set all null MMR Values to the median MMR Value.

As Players may or may not be equally skilled with every character in the game I will be using Hero Level to measure how skilled a player is with a given character. This is not a perfect measure however as players gain levels with a character based of the number of games they have played with that character, not on how good they are with them. However I believe that it is reasonable to assume as a player spends more time playing a character they will also become more skilled with that character.

I use a logistig regression algorithm to isolate the effect of these variables from one another and to build a predictive model for who will win and lose any given game. It is important to note that if any sort of accurate prediction can be made as to who will win a game then the game is not balanced properly.

Create base logistic model

```
Char_v_skill <- h2o.glm(  
  x=c("Name", "Hero Level", "MMR standardized"),  
  y="Is Winner",  
  training_frame = train_char,  
  validation_frame = test_char,  
  family="binomial"  
)
```

```
#summarize model and its preformance  
summary(Char_v_skill)
```

```
## Model Details:  
## =====  
##  
## H2OBinomialModel: glm  
## Model Key: GLM_model_R_1488850374422_1  
## GLM Model: summary  
##      family link                                regularization  
## 1 binomial logit Elastic Net (alpha = 0.5, lambda = 1.731E-5 )  
##   number_of_predictors_total number_of_active_predictors  
## 1                                64                                60  
##   number_of_iterations training_frame  
## 1                                2      train_char  
##  
## H2OBinomialMetrics: glm  
## ** Reported on training data. **  
##  
## MSE:  0.2489901  
## RMSE:  0.4989891  
## LogLoss:  0.6911222  
## Mean Per-Class Error:  0.5  
## AUC:  0.5354687  
## Gini:  0.07093733  
## R^2:  0.004039514  
## Null Deviance:  27388126  
## Residual Deviance:  27308113  
## AIC:  27308235  
##  
## Confusion Matrix for F1-optimal threshold:  
##      0      1      Error      Rate  
## 0      0  9877547 1.000000  =9877547/9877547  
## 1      0  9878810 0.000000  =0/9878810  
## Totals 0 19756357 0.499968  =9877547/19756357  
##  
## Maximum Metrics: Maximum metrics at their respective thresholds  
##  
##      metric threshold  value idx  
## 1      max f1  0.365527 0.666695 399  
## 2      max f2  0.365527 0.833351 399  
## 3      max f0point5  0.446687 0.556841 326  
## 4      max accuracy  0.498407 0.525577 191  
## 5      max precision  0.604114 0.697368  0  
## 6      max recall  0.365527 1.000000 399
```

```

## 7          max specificity 0.604114 0.999998 0
## 8          max absolute_mcc 0.496034 0.051434 199
## 9  max min_per_class_accuracy 0.500985 0.524443 183
## 10 max mean_per_class_accuracy 0.498407 0.525575 191
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
## H2OBinoialMetrics: glm
## ** Reported on validation data. **
##
## MSE: 0.2489897
## RMSE: 0.4989887
## LogLoss: 0.6911213
## Mean Per-Class Error: 0.4999888
## AUC: 0.5354678
## Gini: 0.07093557
## R^2: 0.004041114
## Null Deviance: 4833361
## Residual Deviance: 4819234
## AIC: 4819356
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      69 1743829 0.999960 =1743829/1743898
## 1      30 1742605 0.000017 =30/1742635
## Totals 99 3486434 0.500170 =1743859/3486533
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##      metric threshold  value idx
## 1      max f1 0.371927 0.666507 397
## 2      max f2 0.356043 0.833233 399
## 3      max f0point5 0.449254 0.556602 317
## 4      max accuracy 0.499303 0.525489 183
## 5      max precision 0.582017 0.632385 5
## 6      max recall 0.356043 1.000000 399
## 7      max specificity 0.601287 0.999995 0
## 8      max absolute_mcc 0.492095 0.051709 206
## 9  max min_per_class_accuracy 0.501157 0.524143 177
## 10 max mean_per_class_accuracy 0.499303 0.525497 183
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
##
##
## Scoring History:
##      timestamp  duration iteration negative_log_likelihood
## 1 2017-03-06 18:34:57 0.000 sec 0 13694063.11217
## 2 2017-03-06 18:34:59 2.091 sec 1 13654064.58247
## 3 2017-03-06 18:35:00 3.078 sec 2 13654056.26456
## objective
## 1 0.69315
## 2 0.69118
## 3 0.69118
##
## Variable Importances: (Extract with `h2o.varimp`)
## =====

```

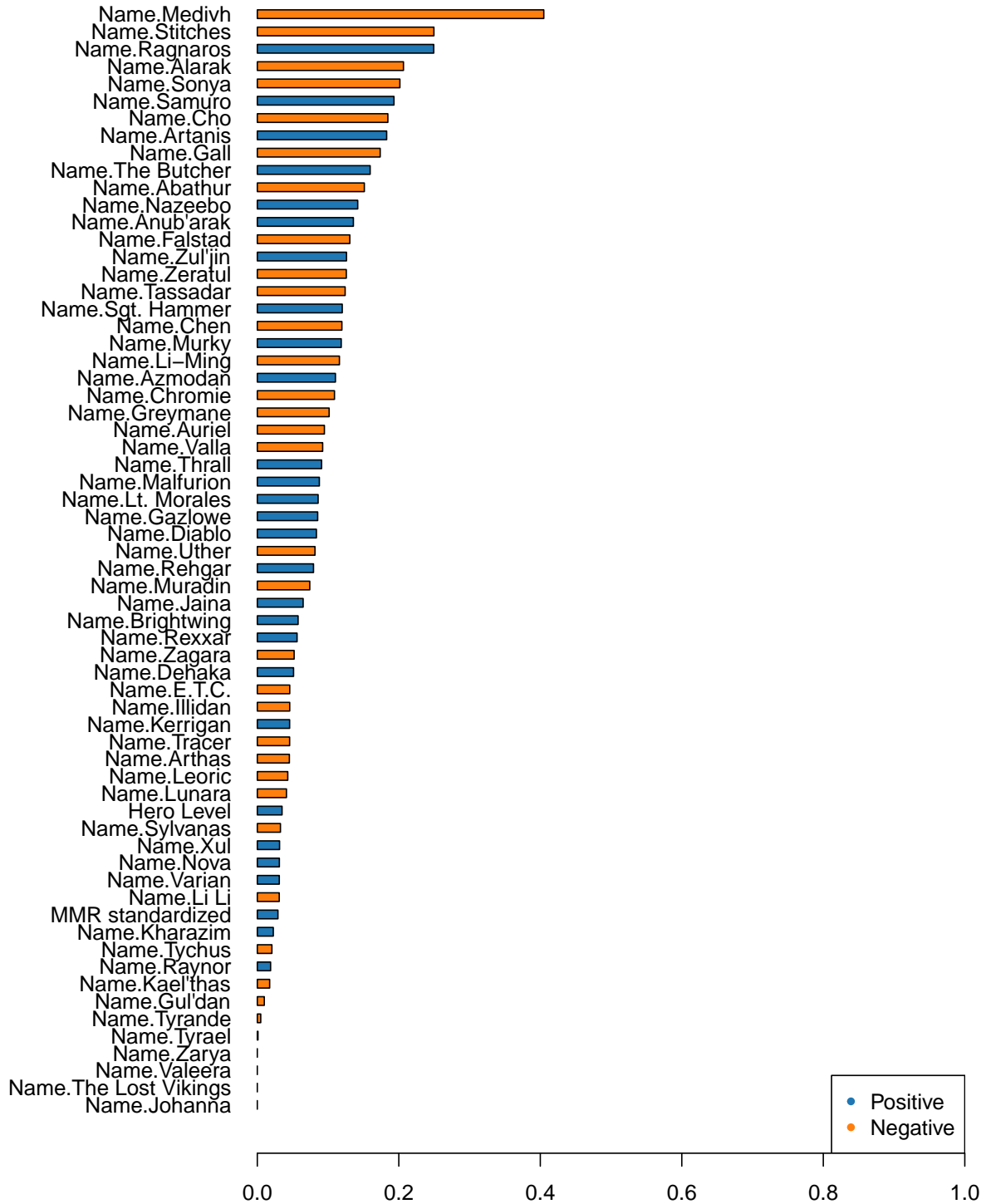
```
##
## Standardized Coefficient Magnitudes: standardized coefficient magnitudes
##      names coefficients sign
## 1  Name.Medivh      0.404929  NEG
## 2 Name.Stitches      0.249640  NEG
## 3 Name.Ragnaros      0.249367  POS
## 4  Name.Alarak       0.206601  NEG
## 5   Name.Sonya       0.201561  NEG
##
## ---
##      names coefficients sign
## 59      Name.Tyrande      0.004853  NEG
## 60      Name.Tyrael       0.001002  NEG
## 61      Name.Johanna      0.000000  POS
## 62 Name.The Lost Vikings  0.000000  POS
## 63      Name.Valeera      0.000000  POS
## 64      Name.Zarya       0.000000  POS
```

Looking at the summary of our model we can see that this model has almost no predictive power. With an “Area under the Curve” rating of just .53 and a mean error rate of .499 we see that this model can predict a win no better than a coin flip.

However, the variable importance and predicted win probability for each data point can still give us insights into the overall game balance of Heros of the Storm. Below we see a ranking of what data points effect our prediction the most. Orange bars indicate that the data point reduces a players change of wining, and a blue bar indicates that it increases a playrs chance to win.

```
h2o.varimp_plot(Char_v_skill)
```

Standardized Coef. Magnitudes



Below is a list of data points and how much they affect a player's chance of wining in descending order.

```
char_v_skill_prob <- exp(h2o.coef(Char_v_skill))/(exp(h2o.coef(Char_v_skill))+1)-.5
sort(char_v_skill_prob,decreasing = TRUE)
```

##	MMR standardized	Name.Ragnaros	Name.Samuro
##	0.0816466550	0.0620206187	0.0481412434
##	Name.Artanis	Name.The Butcher	Name.Nazeebo
##	0.0455885482	0.0397965805	0.0354277071
##	Name.Anub'arak	Name.Zul'jin	Name.Sgt. Hammer
##	0.0339047448	0.0314771500	0.0299805882
##	Name.Murky	Name.Azmodan	Name.Thrall
##	0.0296202658	0.0275766867	0.0227051748
##	Name.Malfurion	Name.Lt. Morales	Name.Gazlowe
##	0.0219172115	0.0214761507	0.0213267136
##	Name.Diablo	Name.Rehgar	Name.Jaina
##	0.0208726875	0.0198526657	0.0161944013
##	Name.Brightwing	Name.Rexxar	Name.Dehaka
##	0.0144095007	0.0140491460	0.0128142437
##	Name.Kerrigan	Name.Xul	Name.Nova
##	0.0114186417	0.0078684256	0.0077963208
##	Name.Varian	Name.Kharazim	Name.Raynor
##	0.0077689898	0.0056561825	0.0047009412
##	Hero Level	Name.Johanna	Name.The Lost Vikings
##	0.0021890927	0.0000000000	0.0000000000
##	Name.Valeera	Name.Zarya	Name.Tyrael
##	0.0000000000	0.0000000000	-0.0002505943
##	Name.Tyrande	Name.Gul'dan	Name.Kael'thas
##	-0.0012133570	-0.0024756501	-0.0043665187
##	Name.Tychus	Name.Li Li	Name.Sylvanas
##	-0.0051605891	-0.0077518195	-0.0081789429
##	Name.Lunara	Name.Leoric	Name.Arthas
##	-0.0103017188	-0.0107631069	-0.0113330081
##	Name.Tracer	Name.Illidan	Name.E.T.C.
##	-0.0114185197	-0.0114532257	-0.0114584412
##	Name.Zagara	Name.Muradin	Name.Uther
##	-0.0130070625	-0.0185327431	-0.0203730500
##	Name.Valla	Name.Auriel	Name.Greymane
##	-0.0230851620	-0.0236919868	-0.0253627496
##	Name.Chromie	Name.Li-Ming	Name.Chen
##	-0.0272422315	-0.0289850981	-0.0298549795
##	Name.Tassadar	Name.Zeratul	Name.Falstad
##	-0.0309984551	-0.0314068006	-0.0326425576
##	Name.Abathur	Name.Gall	Name.Cho
##	-0.0377516701	-0.0433154483	-0.0460029208
##	Name.Sonya	Name.Alarak	Name.Stitches
##	-0.0502203041	-0.0514673933	-0.0620879687
##	Intercept	Name.Medivh	
##	-0.0627499126	-0.0998713388	

Adjust model to improve predictive power

As the base model had little predictive power lets try to tune it to increase its power. To do this, I employ a grid search testing different coefficient penalty methods ranging from a pure ridge regression to a pure lasso regression.

```
hyper_parameters <- list(alpha = c(0,.2,.4,.6,.8,1))
```

```
#Creat lasso logit regression for all games
```

```
char_v_skill_grid <- h2o.grid(  
  algorithm = "glm",  
  grid_id = "char_v_skill",  
  hyper_params= hyper_parameters,  
  training_frame = train_char,  
  validation_frame = test_char,  
  x=c("Name","Hero Level", "MMR standardized"),  
  y="Is Winner",  
  lambda_search = TRUE,  
  family = "binomial"  
)
```

```
glm.sorted.grid <- h2o.getGrid("char_v_skill","auc")
```

```
best_model <- h2o.getModel(glm.sorted.grid@model_ids[[1]])
```

```
best_model
```

```
## Model Details:
```

```
## =====
```

```
##
```

```
## H2OBinomialModel: glm
```

```
## Model ID: char_v_skill_model_4
```

```
## GLM Model: summary
```

```
##      family link                                regularization
```

```
## 1 binomial logit Elastic Net (alpha = 0.8, lambda = 0.007456 )
```

```
##                                                                 lambda_search
```

```
## 1 nlambda = 100, lambda.max = 0.01082, lambda.min = 0.007456, lambda.1se = -1.0
```

```
##   number_of_predictors_total number_of_active_predictors
```

```
## 1                               64                               2
```

```
##   number_of_iterations training_frame
```

```
## 1                               5      train_char
```

```
##
```

```
## Coefficients: glm coefficients
```

```
##           names coefficients standardized_coefficients
```

```
## 1      Intercept    -0.071506             0.000128
```

```
## 2   Name.Abathur      0.000000             0.000000
```

```
## 3   Name.Alarak      0.000000             0.000000
```

```
## 4 Name.Anub'arak      0.000000             0.000000
```

```
## 5   Name.Artanis      0.000000             0.000000
```

```
##
```

```
## ---
```

```
##           names coefficients standardized_coefficients
```

```
## 60   Name.Zagara      0.000000             0.000000
```

```
## 61   Name.Zarya      0.000000             0.000000
```

```
## 62   Name.Zeratul      0.000000             0.000000
```

```
## 63   Name.Zul'jin      0.000000             0.000000
```

```
## 64      Hero Level      0.001757             0.007021
```

```
## 65 MMR standardized      0.111095             0.009833
```

```

##
## H2OBinomialMetrics: glm
## ** Reported on training data. **
##
## MSE: 0.2499394
## RMSE: 0.4999394
## LogLoss: 0.6930261
## Mean Per-Class Error: 0.5
## AUC: 0.5118171
## Gini: 0.0236342
## R^2: 0.0002422363
## Null Deviance: 27388126
## Residual Deviance: 27383340
## AIC: 27383346
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      0 9877547 1.000000 =9877547/9877547
## 1      0 9878810 0.000000 =0/9878810
## Totals 0 19756357 0.499968 =9877547/19756357
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##      metric threshold  value idx
## 1      max f1  0.485436 0.666695 399
## 2      max f2  0.485436 0.833351 399
## 3      max f0point5 0.490214 0.555591 391
## 4      max accuracy 0.499875 0.507869 217
## 5      max precision 0.515656 0.659091 0
## 6      max recall 0.485436 1.000000 399
## 7      max specificity 0.515656 0.999998 0
## 8      max absolute_mcc 0.498836 0.015828 248
## 9      max min_per_class_accuracy 0.499953 0.507804 215
## 10 max mean_per_class_accuracy 0.499875 0.507868 217
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
## H2OBinomialMetrics: glm
## ** Reported on validation data. **
##
## MSE: 0.2499388
## RMSE: 0.4999388
## LogLoss: 0.6930248
## Mean Per-Class Error: 0.5
## AUC: 0.511817
## Gini: 0.02363404
## R^2: 0.0002446734
## Null Deviance: 4833361
## Residual Deviance: 4832507
## AIC: 4832513
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      0 1743898 1.000000 =1743898/1743898
## 1      0 1742635 0.000000 =0/1742635
## Totals 0 3486533 0.500181 =1743898/3486533

```

```
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##
##      metric threshold    value idx
## 1      max f1  0.485474 0.666506 399
## 2      max f2  0.485474 0.833233 399
## 3      max f0point5 0.490973 0.555394 383
## 4      max accuracy 0.499465 0.507825 222
## 5      max precision 0.515106 0.727273  0
## 6      max recall  0.485474 1.000000 399
## 7      max specificity 0.515106 0.999995  0
## 8      max absolute_mcc 0.498530 0.016066 249
## 9      max min_per_class_accuracy 0.499963 0.506558 207
## 10     max mean_per_class_accuracy 0.499465 0.507847 222
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

Our best tuned model using a penatly factor turns out to have less predictive power than the base model, lending more credance to the idea that we cannot build an accurate predictive model. Of note however, is that when using a penalty factor on our variables to make sure the effects on a players win rate were significant, all but our MMR and Hero Level data points drop out of the model. This suggests that player skill, not certain characters, wins games.

```
h2o.varimp_plot(best_model)
```

Standardized Coef. Magnitudes



```
char_v_skill_grid_prob <- exp(h2o.coef(best_model))/(exp(h2o.coef(best_model))+1)-.5
sort(char_v_skill_grid_prob,decreasing = TRUE)
```

##	MMR standardized	Hero Level	Name.Abathur
##	0.0277451378	0.0004392831	0.0000000000
##	Name.Alarak	Name.Anub'arak	Name.Artanis
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Arthas	Name.Auriel	Name.Azmodan
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Brightwing	Name.Chen	Name.Cho
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Chromie	Name.Dehaka	Name.Diablo
##	0.0000000000	0.0000000000	0.0000000000
##	Name.E.T.C.	Name.Falstad	Name.Gall
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Gazlowe	Name.Greymane	Name.Gul'dan
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Illidan	Name.Jaina	Name.Johanna
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Kael'thas	Name.Kerrigan	Name.Kharazim
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Leoric	Name.Li Li	Name.Li-Ming
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Lt. Morales	Name.Lunara	Name.Malfurion
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Medivh	Name.Muradin	Name.Murky
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Nazeebo	Name.Nova	Name.Ragnaros
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Raynor	Name.Rehgar	Name.Rexxar
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Samuro	Name.Sgt. Hammer	Name.Sonya
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Stitches	Name.Sylvanas	Name.Tassadar
##	0.0000000000	0.0000000000	0.0000000000
##	Name.The Butcher	Name.The Lost Vikings	Name.Thrall
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Tracer	Name.Tychus	Name.Tyrael
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Tyrande	Name.Uther	Name.Valeera
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Valla	Name.Varian	Name.Xul
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Zagara	Name.Zarya	Name.Zeratul
##	0.0000000000	0.0000000000	0.0000000000
##	Name.Zul'jin	Intercept	
##	0.0000000000	-0.0178688712	

Do we get the same results when casual games are removed

As game balance is most important for competitive games I will recreate the same models as above but for only games played competitively.

```

Char_split_comp <- h2o.splitFrame(Characters[Characters[["GameMode(3=Quick Match 4=Hero League 5=Team L
ratios = .85,
destination_frames = c("train_char", "test_char"),
seed = 444)

train_char <- Char_split_comp[[1]]
test_char <- Char_split_comp[[2]]

Char_v_skill_comp <- h2o.glm(
  x=c("Name", "Hero Level", "MMR standardized"),
  y="Is Winner",
  training_frame = train_char,
  validation_frame = test_char,
  family="binomial"
)

```

```
Char_v_skill_comp
```

```

## Model Details:
## =====
##
## H2OBinomialModel: glm
## Model ID: GLM_model_R_1488850374422_18
## GLM Model: summary
##   family link                      regularization
## 1 binomial logit Elastic Net (alpha = 0.5, lambda = 3.377E-5 )
##   number_of_predictors_total number_of_active_predictors
## 1                          64                          60
##   number_of_iterations training_frame
## 1                      2      train_char
##
## Coefficients: glm coefficients
##           names coefficients standardized_coefficients
## 1      Intercept    -0.359699          -0.022025
## 2   Name.Abathur    -0.283849          -0.283849
## 3   Name.Alarak     -0.168640          -0.168640
## 4 Name.Anub'arak     0.129634           0.129634
## 5   Name.Artanis     0.232347           0.232347
##
## ---
##           names coefficients standardized_coefficients
## 60   Name.Zagara     -0.108651          -0.108651
## 61   Name.Zarya       0.112318           0.112318
## 62   Name.Zeratul    -0.115476          -0.115476
## 63   Name.Zul'jin     0.136043           0.136043
## 64      Hero Level     0.021277           0.073232
## 65 MMR standardized    0.255320           0.025055
##
## H2OBinomialMetrics: glm
## ** Reported on training data. **
##
## MSE:  0.2488968
## RMSE: 0.4988956
## LogLoss: 0.690936

```

```

## Mean Per-Class Error:  0.4997748
## AUC:  0.5377323
## Gini:  0.07546468
## R^2:  0.004412783
## Null Deviance:  8421823
## Residual Deviance:  8394957
## AIC:  8395079
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      2401 3035113 0.999210 =3035113/3037514
## 1      1033 3036514 0.000340  =1033/3037547
## Totals 3434 6071627 0.499772 =3036146/6075061
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##      metric threshold  value idx
## 1      max f1  0.388636 0.666694 390
## 2      max f2  0.356566 0.833335 399
## 3      max f0point5 0.453140 0.556830 320
## 4      max accuracy 0.498928 0.527074 200
## 5      max precision 0.616917 0.673469  0
## 6      max recall  0.356566 1.000000 399
## 7      max specificity 0.616917 0.999989  0
## 8      max absolute_mcc 0.490665 0.054800 224
## 9      max min_per_class_accuracy 0.501064 0.526058 193
## 10     max mean_per_class_accuracy 0.498928 0.527074 200
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/F>)`
## H2OBinoMialMetrics: glm
## ** Reported on validation data. **
##
## MSE:  0.2489081
## RMSE:  0.4989069
## LogLoss:  0.6909584
## Mean Per-Class Error:  0.4997584
## AUC:  0.5373456
## Gini:  0.07469124
## R^2:  0.004367708
## Null Deviance:  1486065
## Residual Deviance:  1481372
## AIC:  1481494
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      501 535500 0.999065  =535500/536001
## 1      242 535726 0.000452  =242/535968
## Totals 743 1071226 0.499774  =535742/1071969
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##      metric threshold  value idx
## 1      max f1  0.390570 0.666660 389
## 2      max f2  0.356802 0.833325 399
## 3      max f0point5 0.451750 0.556927 324
## 4      max accuracy 0.495346 0.526841 210

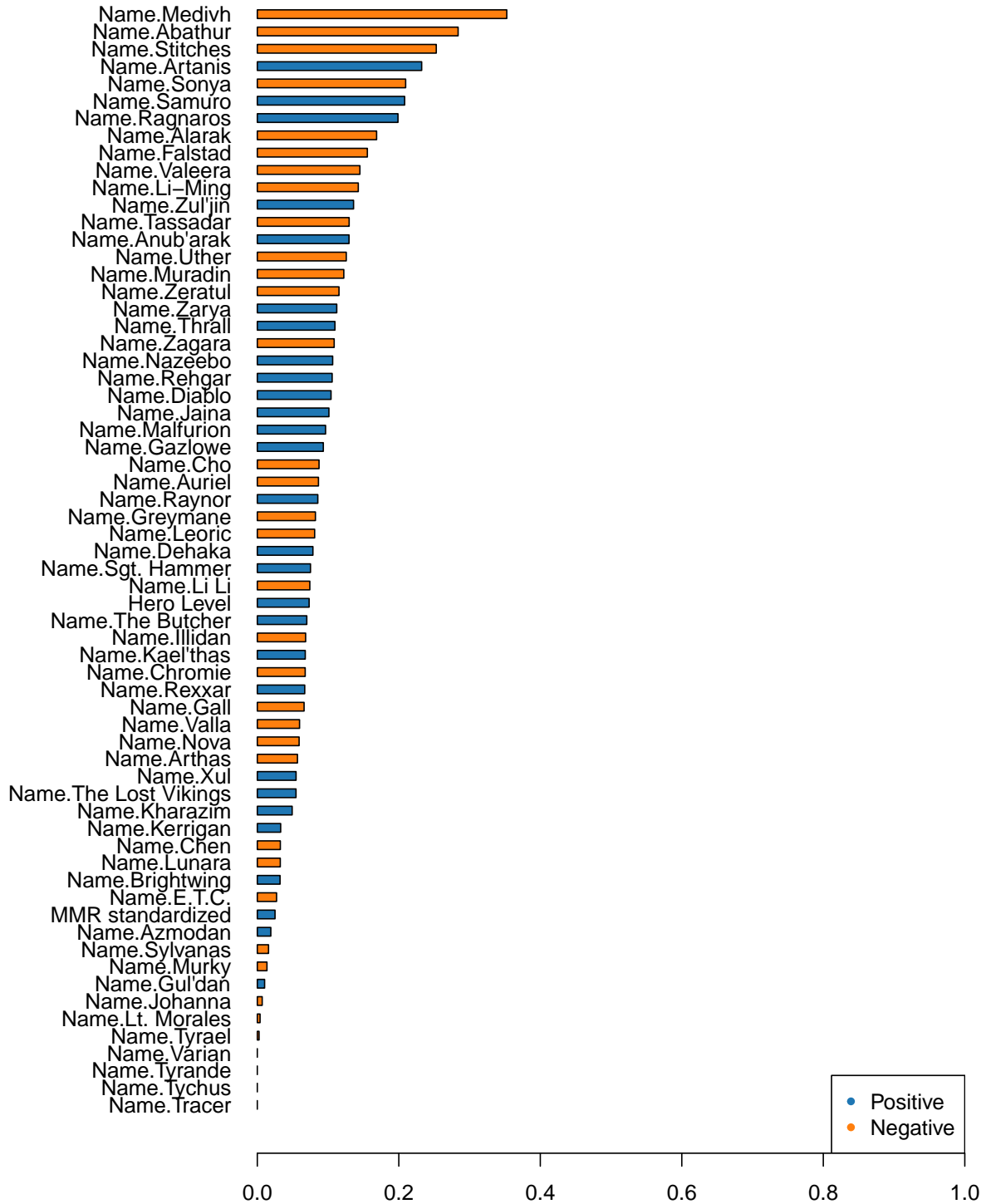
```

```
## 5          max precision 0.615123 0.727273 1
## 6          max recall 0.356802 1.000000 399
## 7          max specificity 0.618669 0.999993 0
## 8          max absolute_mcc 0.488356 0.054251 231
## 9  max min_per_class_accuracy 0.501064 0.526029 193
## 10 max mean_per_class_accuracy 0.495346 0.526843 210
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
```

Again, the base model gives us an AUC of just .53

```
h2o.varimp_plot(Char_v_skill_comp)
```


Standardized Coef. Magnitudes



```
comp_prob <- exp(h2o.coef(Char_v_skill))/(exp(h2o.coef(Char_v_skill))+1)-.5
sort(comp_prob,decreasing = TRUE)
```

##	MMR standardized	Name.Ragnaros	Name.Samuro
##	0.0816466550	0.0620206187	0.0481412434
##	Name.Artanis	Name.The Butcher	Name.Nazeebo
##	0.0455885482	0.0397965805	0.0354277071
##	Name.Anub'arak	Name.Zul'jin	Name.Sgt. Hammer
##	0.0339047448	0.0314771500	0.0299805882
##	Name.Murky	Name.Azmodan	Name.Thrall
##	0.0296202658	0.0275766867	0.0227051748
##	Name.Malfurion	Name.Lt. Morales	Name.Gazlowe
##	0.0219172115	0.0214761507	0.0213267136
##	Name.Diablo	Name.Rehgar	Name.Jaina
##	0.0208726875	0.0198526657	0.0161944013
##	Name.Brightwing	Name.Rexxar	Name.Dehaka
##	0.0144095007	0.0140491460	0.0128142437
##	Name.Kerrigan	Name.Xul	Name.Nova
##	0.0114186417	0.0078684256	0.0077963208
##	Name.Varian	Name.Kharazim	Name.Raynor
##	0.0077689898	0.0056561825	0.0047009412
##	Hero Level	Name.Johanna	Name.The Lost Vikings
##	0.0021890927	0.0000000000	0.0000000000
##	Name.Valeera	Name.Zarya	Name.Tyrael
##	0.0000000000	0.0000000000	-0.0002505943
##	Name.Tyrande	Name.Gul'dan	Name.Kael'thas
##	-0.0012133570	-0.0024756501	-0.0043665187
##	Name.Tychus	Name.Li Li	Name.Sylvanas
##	-0.0051605891	-0.0077518195	-0.0081789429
##	Name.Lunara	Name.Leoric	Name.Arthas
##	-0.0103017188	-0.0107631069	-0.0113330081
##	Name.Tracer	Name.Illidan	Name.E.T.C.
##	-0.0114185197	-0.0114532257	-0.0114584412
##	Name.Zagara	Name.Muradin	Name.Uther
##	-0.0130070625	-0.0185327431	-0.0203730500
##	Name.Valla	Name.Auriel	Name.Greymane
##	-0.0230851620	-0.0236919868	-0.0253627496
##	Name.Chromie	Name.Li-Ming	Name.Chen
##	-0.0272422315	-0.0289850981	-0.0298549795
##	Name.Tassadar	Name.Zeratul	Name.Falstad
##	-0.0309984551	-0.0314068006	-0.0326425576
##	Name.Abathur	Name.Gall	Name.Cho
##	-0.0377516701	-0.0433154483	-0.0460029208
##	Name.Sonya	Name.Alarak	Name.Stitches
##	-0.0502203041	-0.0514673933	-0.0620879687
##	Intercept	Name.Medivh	
##	-0.0627499126	-0.0998713388	

The Variable importance and probabilities are about the same as for our model using all games played, with some differences in character ordering.

```
comp_grid <- h2o.grid(
  algorithm = "glm",
  grid_id = "comp_grid",
  hyper_params= hyper_parameters,
```

```

training_frame = train_char,
validation_frame = test_char,
x=c("Name","Hero Level", "MMR standardized"),
y="Is Winner",
lambda_search = TRUE,
family = "binomial"
)

glm.sorted.grid <- h2o.getGrid("comp_grid","auc")
best_model <- h2o.getModel(glm.sorted.grid@model_ids[[1]])
best_model

## Model Details:
## =====
##
## H2OBinomialModel: glm
## Model ID: comp_grid_model_2
## GLM Model: summary
##      family link                      regularization
## 1 binomial logit Elastic Net (alpha = 0.4, lambda = 0.02201 )
##
##                                     lambda_search
## 1 nlambda = 100, lambda.max = 0.04221, lambda.min = 0.02201, lambda.1se = -1.0
##  number_of_predictors_total number_of_active_predictors
## 1                               64                               1
##  number_of_iterations training_frame
## 1                               8      train_char
##
## Coefficients: glm coefficients
##      names coefficients standardized_coefficients
## 1      Intercept      -0.086316              0.000014
## 2   Name.Abathur       0.000000              0.000000
## 3   Name.Alarak       0.000000              0.000000
## 4 Name.Anub'arak      0.000000              0.000000
## 5   Name.Artanis      0.000000              0.000000
##
## ---
##      names coefficients standardized_coefficients
## 60   Name.Zagara      0.000000              0.000000
## 61   Name.Zarya      0.000000              0.000000
## 62   Name.Zeratul    0.000000              0.000000
## 63   Name.Zul'jin    0.000000              0.000000
## 64      Hero Level    0.008922              0.030709
## 65 MMR standardized    0.000000              0.000000
##
## H2OBinomialMetrics: glm
## ** Reported on training data. **
##
## MSE:  0.2497997
## RMSE:  0.4997997
## LogLoss:  0.6927466
## Mean Per-Class Error:  0.5
## AUC:  0.5205985
## Gini:  0.04119708
## R^2:  0.0008010076

```

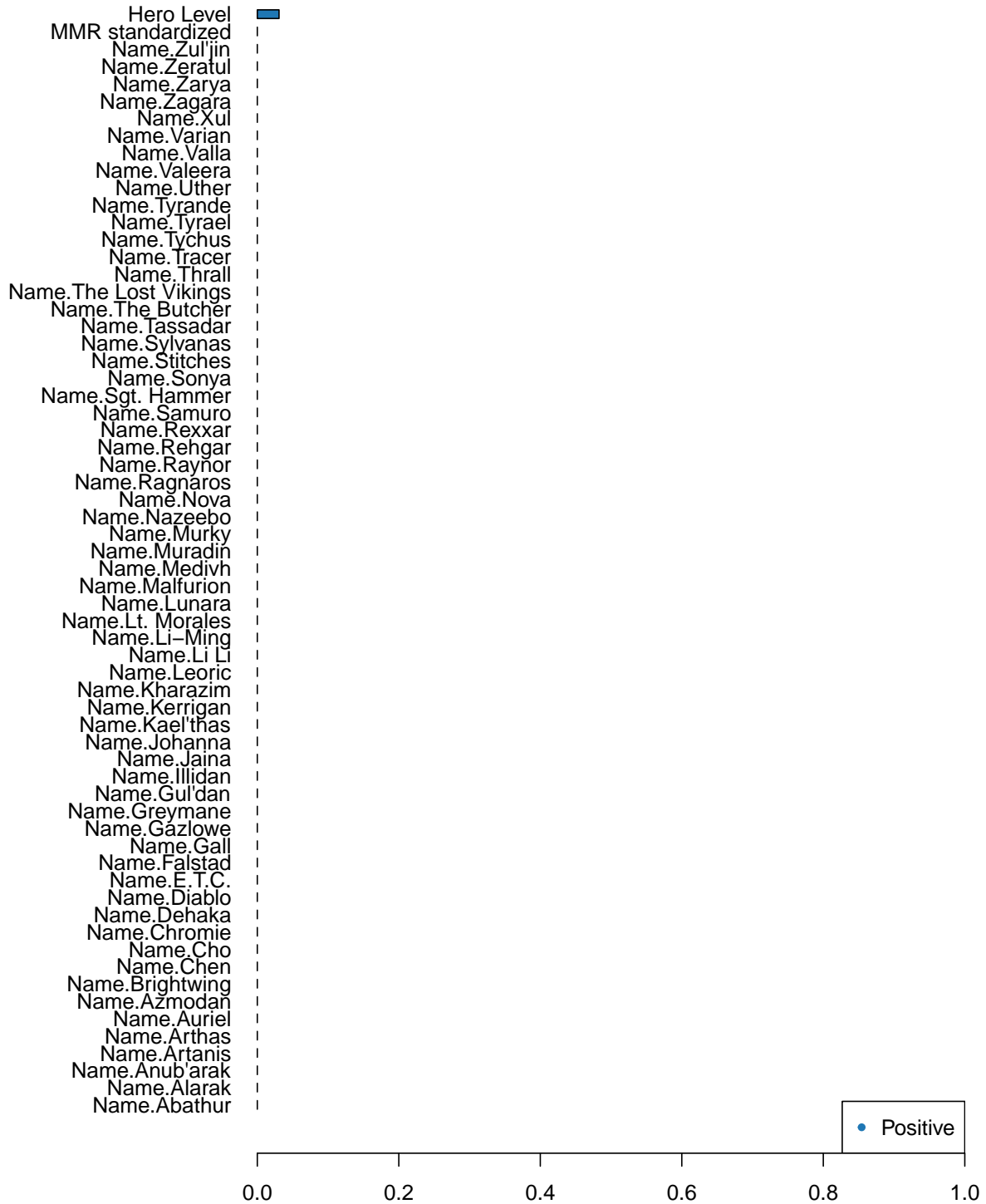
```

## Null Deviance: 8421823
## Residual Deviance: 8416956
## AIC: 8416960
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      0 3037514 1.000000 =3037514/3037514
## 1      0 3037547 0.000000 =0/3037547
## Totals 0 6075061 0.499997 =3037514/6075061
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##      metric threshold  value idx
## 1      max f1  0.480661 0.666669 19
## 2      max f2  0.480661 0.833335 19
## 3      max f0point5 0.482889 0.555563 18
## 4      max accuracy 0.498496 0.514500 11
## 5      max precision 0.523016 0.533240 0
## 6      max recall 0.480661 1.000000 19
## 7      max specificity 0.523016 0.966129 0
## 8      max absolute_mcc 0.498496 0.029603 11
## 9      max min_per_class_accuracy 0.500727 0.430056 10
## 10 max mean_per_class_accuracy 0.498496 0.514499 11
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/>
## H2OBinoMialMetrics: glm
## ** Reported on validation data. **
##
## MSE: 0.2497982
## RMSE: 0.4997981
## LogLoss: 0.6927434
## Mean Per-Class Error: 0.5
## AUC: 0.5208652
## Gini: 0.04173037
## R^2: 0.0008073219
## Null Deviance: 1486065
## Residual Deviance: 1485199
## AIC: 1485203
##
## Confusion Matrix for F1-optimal threshold:
##      0      1      Error      Rate
## 0      0 536001 1.000000 =536001/536001
## 1      0 535968 0.000000 =0/535968
## Totals 0 1071969 0.500015 =536001/1071969
##
## Maximum Metrics: Maximum metrics at their respective thresholds
##      metric threshold  value idx
## 1      max f1  0.480661 0.666653 19
## 2      max f2  0.480661 0.833325 19
## 3      max f0point5 0.485117 0.555561 17
## 4      max accuracy 0.498496 0.515060 11
## 5      max precision 0.523016 0.534807 0
## 6      max recall 0.480661 1.000000 19
## 7      max specificity 0.523016 0.966127 0
## 8      max absolute_mcc 0.498496 0.030752 11

```

```
## 9    max min_per_class_accuracy  0.500727 0.430557  10
## 10 max mean_per_class_accuracy  0.498496 0.515063  11
##
## Gains/Lift Table: Extract with `h2o.gainsLift(<model>, <data>)` or `h2o.gainsLift(<model>, valid=<T/
h2o.varimp_plot(best_model)
```

Standardized Coef. Magnitudes



```
comp_grid_prob <- exp(h2o.coef(best_model))/(exp(h2o.coef(best_model))+1)-.5
sort(comp_grid_prob, decreasing = TRUE)
```

##	Hero Level	Name.Abathur	Name.Alarak
##	0.002230567	0.000000000	0.000000000
##	Name.Anub'arak	Name.Artanis	Name.Arthas
##	0.000000000	0.000000000	0.000000000
##	Name.Auriel	Name.Azmodan	Name.Brightwing
##	0.000000000	0.000000000	0.000000000
##	Name.Chen	Name.Cho	Name.Chromie
##	0.000000000	0.000000000	0.000000000
##	Name.Dehaka	Name.Diablo	Name.E.T.C.
##	0.000000000	0.000000000	0.000000000
##	Name.Falstad	Name.Gall	Name.Gazlowe
##	0.000000000	0.000000000	0.000000000
##	Name.Greymane	Name.Gul'dan	Name.Illidan
##	0.000000000	0.000000000	0.000000000
##	Name.Jaina	Name.Johanna	Name.Kael'thas
##	0.000000000	0.000000000	0.000000000
##	Name.Kerrigan	Name.Kharazim	Name.Leoric
##	0.000000000	0.000000000	0.000000000
##	Name.Li Li	Name.Li-Ming	Name.Lt. Morales
##	0.000000000	0.000000000	0.000000000
##	Name.Lunara	Name.Malfurion	Name.Medivh
##	0.000000000	0.000000000	0.000000000
##	Name.Muradin	Name.Murky	Name.Nazeebo
##	0.000000000	0.000000000	0.000000000
##	Name.Nova	Name.Ragnaros	Name.Raynor
##	0.000000000	0.000000000	0.000000000
##	Name.Rehgar	Name.Rexxar	Name.Samuro
##	0.000000000	0.000000000	0.000000000
##	Name.Sgt. Hammer	Name.Sonya	Name.Stitches
##	0.000000000	0.000000000	0.000000000
##	Name.Sylvanas	Name.Tassadar	Name.The Butcher
##	0.000000000	0.000000000	0.000000000
##	Name.The Lost Vikings	Name.Thrall	Name.Tracer
##	0.000000000	0.000000000	0.000000000
##	Name.Tychus	Name.Tyrael	Name.Tyrande
##	0.000000000	0.000000000	0.000000000
##	Name.Uther	Name.Valeera	Name.Valla
##	0.000000000	0.000000000	0.000000000
##	Name.Varian	Name.Xul	Name.Zagara
##	0.000000000	0.000000000	0.000000000
##	Name.Zarya	Name.Zeratul	Name.Zul'jin
##	0.000000000	0.000000000	0.000000000
##	MMR standardized	Intercept	
##	0.000000000	-0.021565623	

The model with the penalization factors for competitive games also performed about the same as the model with all the data. Interestingly when only using data for competitive games, the only data point that remains is Hero Level.

Conclusion

Given the extremely low predictive power of all the models created we should reject the idea that a prediction can be made for who will win a game based of individual characters played. This is not to say that there is not some combinations of characters that can be used to predict which players will win. This would require further testing, likely using association data techniques.

Furthermore given that the effect of each character on a player's win probability dropped to 0 when penalized for significant, we can conclude that a players skill, not chosen characters, is what will carry them to victory.