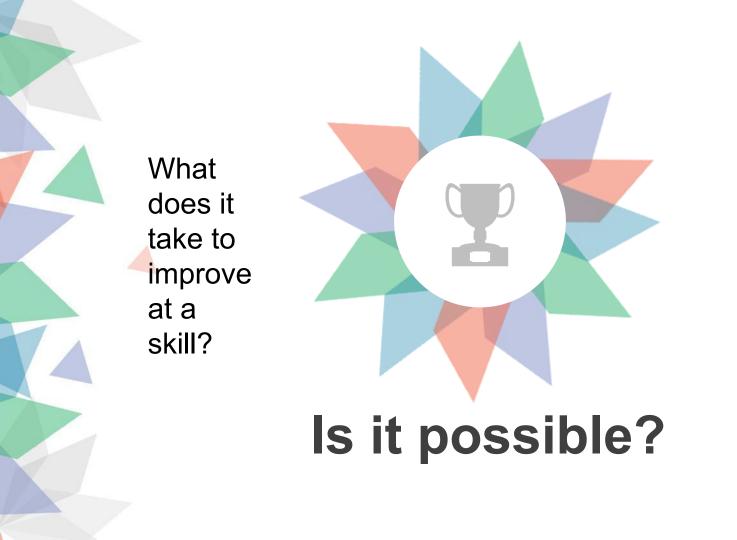
Quantifying Improvement

How to Get Good (with Data Science)





The Pillars of Improvement

1 Fundamentals

2 Raw Practice

Why LoL?

All digital

Is a skill

Lots of relevant data recorded

Methodology

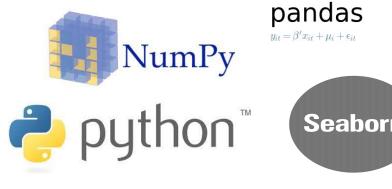
Sources

Op.gg (LoL stats)
Wol.gg (# hours spent)
Riot API

Model

OLS Linear Regression

Tools



Features



Avg. CS, Avg. Dmg To Champs + 7 more

02

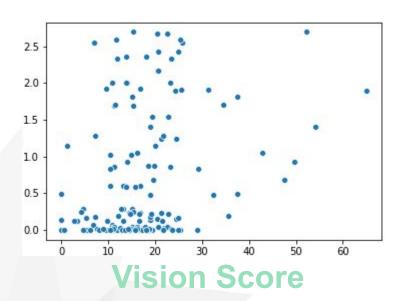
Raw Practice
Hours Played

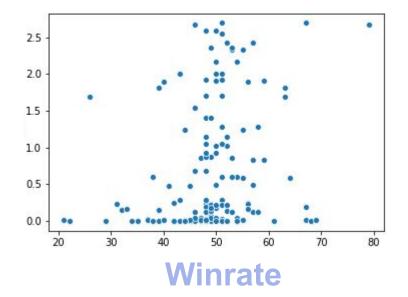


Bands of Performance

4

X vs. Rank

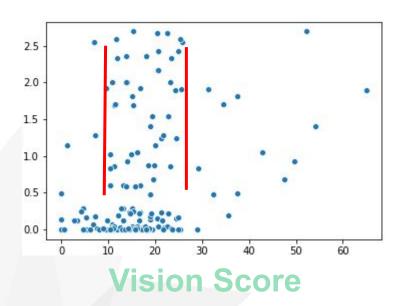


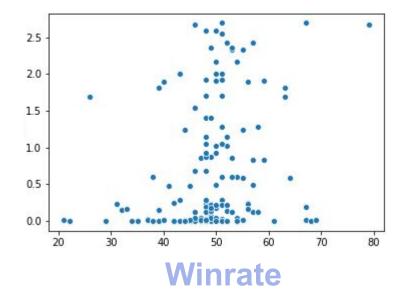


Bands of Performance

4

X vs. Rank

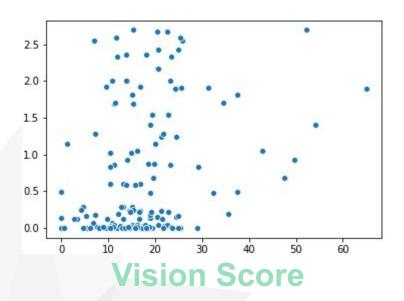


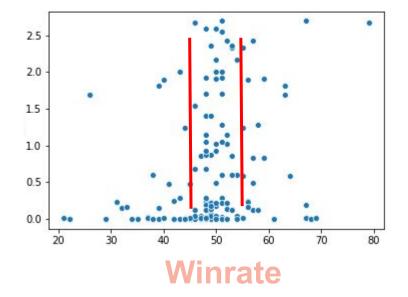


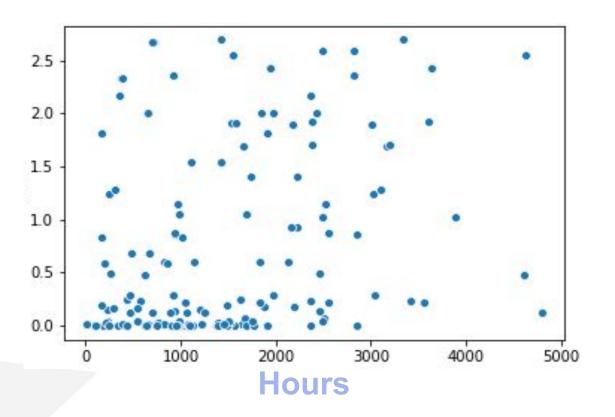
Bands of Performance

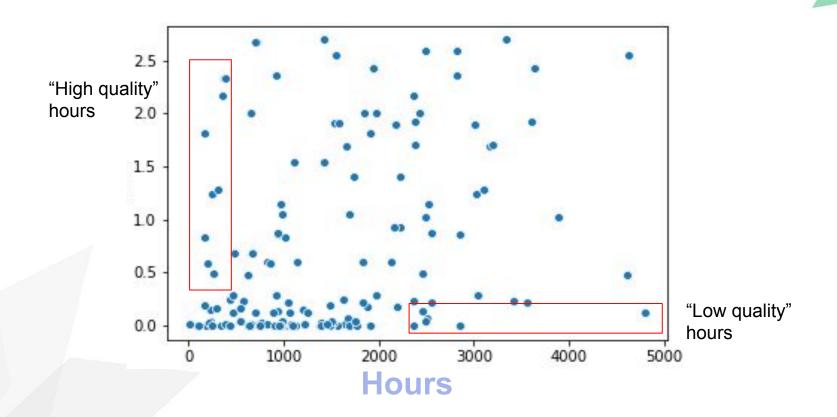
4

X vs. Rank















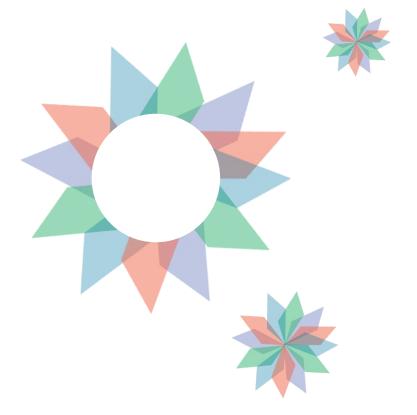




Recommendations

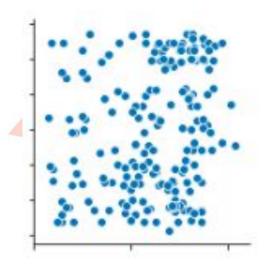
Perfect practice makes perfect Be patient, but critical







Thank you!

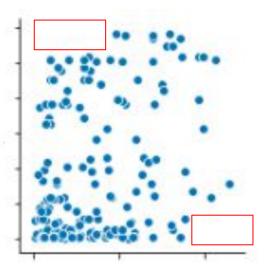


Avg CS vs Rank from larger dataset w/ unscaled rank, from an intermediate unsaved dataset

Rank scaling formula: ((total number of users on leaderboard + 1) - (actual rank))^3

Reason for scaling: Attempt to reflect uneven distributions of playerbase across rank and to show that, after a certain point, the same numeric increase in rank requires a much larger increase in skill compared to before.

Ideal curve: stepwise function with a higher exponent after a certain rank, and a gradual plateau beginning near the top 100/top 200 players



Boxes show no player of highest caliber has less than some amt of hrs, no low enough ranked player has more than some amt of hrs

Hours played vs rank unscaled, from an intermediate unsaved dataset

```
['summoner_name',
'rank',
'champ_pool',
'winrate',
'avg_kda',
'avg_cs',
'hours_played',
'avg_dmg_obj',
'avg_gold_spent',
'avg_cc_score',
'avg_dmg_champs',
'avg_dmg_taken',
'avg_vision_score',
'avg_dps']
```

Dep. Variable:	rank	R-squared:	0.342
Model:	OLS	Adj. R-squared:	0.286
Method:	Least Squares	F-statistic:	6.145
Date:	Fri, 19 Jul 2019	Prob (F-statistic):	4.60e-08
Time:	03:11:27	Log-Likelihood:	-6037.3
No. Observations:	142	AIC:	1.210e+04
Df Residuals:	130	BIC:	1.213e+04
Df Model:	11		
Covariance Type:	nonrobust		

		coef	std err	t	P> t	[0.025	0.975]
Intercept	-2.166e+18		5.93e+17	-3.653	0.000	-3.34e+18	-9.93e+17
champ_pool	-5.643	e+15	7.33e+16	-0.077	0.939	-1.51e+17	1.39e+17
winrate	1.644e+16		8.41e+15	1.956	0.053	-1.89e+14	3.31e+16
avg_kda	3.885e+16		7.25e+16	0.536	0.593	-1.05e+17	1.82e+17
avg_cs	4.579	e+15	1.65e+15	2.781	0.006	1.32e+15	7.84e+15
hours_played	2.164e+14		6.31e+13	3.427	0.001	9.15e+13	3.41e+14
avg_dmg_obj	-1.967	e+13	1.76e+13	-1.116	0.266	-5.45e+13	1.52e+13
avg_gold_spent	7.096	e+13	5.98e+13	1.187	0.237	-4.73e+13	1.89e+14
avg_cc_score	-2.588	e+15	8.47e+15	-0.306	0.760	-1.93e+16	1.42e+16
avg_dmg_taken	-1.111	e+13	1.56e+13	-0.713	0.477	-4.2e+13	1.97e+13
avg_vision_score	3.291	e+16	8.07e+15	4.076	0.000	1.69e+16	4.89e+16
avg_dps	2.463	e+15	1.76e+15	1.398	0.164	-1.02e+15	5.95e+15
Omnibus:	9.928	28 Durbin-Watson:		1.325			
Prob(Omnibus):	0.007	007 Jarque-Bera (JB):		10.744			
Skew:	0.670		Prob(JB):	0.00	464		

Cond. No. 2.64e+05

Kurtosis: 2.862

		coef	std err	t	P> t	[0.025	0.975]
Intercept	-2.16	6e+18	5.93e+17	-3.653	0.000	-3.34e+18	-9.93e+17
champ_pool	-5.643e+15		7.33e+16	-0.077	0.939	-1.51e+17	1.39e+17
winrate	1.644e+16		8.41e+15	1.956	0.053	-1.89e+14	3.31e+16
avg_kda	3.88	5e+16	7.25e+16	0.536	0.593	-1.05e+17	1.82e+17
avg_cs	4.579e+15		1.65e+15	2.781	0.006	1.32e+15	7.84e+15
hours_played	2.16	4e+14	6.31e+13	3.427	0.001	9.15e+13	3.41e+14
avg_dmg_obj	-1.96	7e+13	1.76e+13	-1.116	0.266	-5.45e+13	1.52e+13
avg_gold_spent	7.09	6e+13	5.98e+13	1.187	0.237	-4.73e+13	1.89e+14
avg_cc_score	-2.58	8e+15	8.47e+15	-0.306	0.760	-1.93e+16	1.42e+16
avg_dmg_taken	-1.11	1e+13	1.56e+13	-0.713	0.477	-4.2e+13	1.97e+13
avg_vision_score	3.29	1e+16	8.07e+15	4.076	0.000	1.69e+16	4.89e+16
avg_dps	2.46	3e+15	1.76e+15	1.398	0.164	-1.02e+15	5.95e+15
Omnibus:	9.928 Durbin-Watson:		1.	325			
Prob(Omnibus):	0.007	Jarqu	e-Bera (JB):	10.	744		

Prob(JB):

Cond. No. 2.64e+05

0.00464

Skew: 0.670

Kurtosis: 2.862