

# PROJECT TOPIC

- **Goal:** Create a ELO Converter, converting Lichess Elo Ratings to Chesscom Elo Ratings. Chess has a Strength System called ELO, the higher it is the stronger you are. However, the Elo Systems are contained, so Elo on one website doesn't Translate 1:1 to the other. My goal here is to build a ML Model to translate the ELO from one site to the other.
- **Data:** I have a Dataset of more than 50k ELO Ratings from both website from people with the same username. This needs to be cleaned up as there are many false positives. I gathered this myself for another project and am looking to publish it on Kaggle or similar, however the full set has a lot of personal info, that I will need to check if that needs to be removed.
- **Machine Learning:** I will try K nearest neighbours and Linear Regression and see which works best for this problem. I will attempt different version of the KNN, to find the best parameters for me.

This project is inspired by some Data I gathered a while ago. I gathered the Dataset and wanted to do some ML on it, but never got around to it. So this is a perfect opportunity

## The Dataset

The Dataset are ELO Values for about 50k users on lichess and chesscom. I will create a predictor that predicts the rating for one rating to another.

## Loading the Data in

	li_bullet_rating	li_bullet_rd	li_blitz_rating	li_blitz_rd	li_rapid_rating	li_rapid_rd	ch_bullet_r
username							
garabomboelinvisible	1096	106	1043	52	1079	199	
antonym007	1196	45	1523	67	1587	102	
rilikva	1500	500	1411	342	2019	45	
pushydiscovery	2470	47	2424	96	2392	80	2
weaponizedspaghetti	1212	230	884	99	1153	53	

## Data Description

```
<class 'pandas.core.frame.DataFrame'>
Index: 118133 entries, garabomboelinvisible to abo01
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   li_bullet_rating      118133 non-null  int64
```

1	li_bullet_rd	118133	non-null	int64
2	li_blitz_rating	118133	non-null	int64
3	li_blitz_rd	118133	non-null	int64
4	li_rapid_rating	118133	non-null	int64
5	li_rapid_rd	118133	non-null	int64
6	ch_bullet_rating	59032	non-null	float64
7	ch_bullet_rd	59032	non-null	float64
8	ch_blitz_rating	78020	non-null	float64
9	ch_blitz_rd	78020	non-null	float64
10	ch_rapid_rating	77151	non-null	float64
11	ch_rapid_rd	77151	non-null	float64
12	ch_fide_rating	69432	non-null	float64

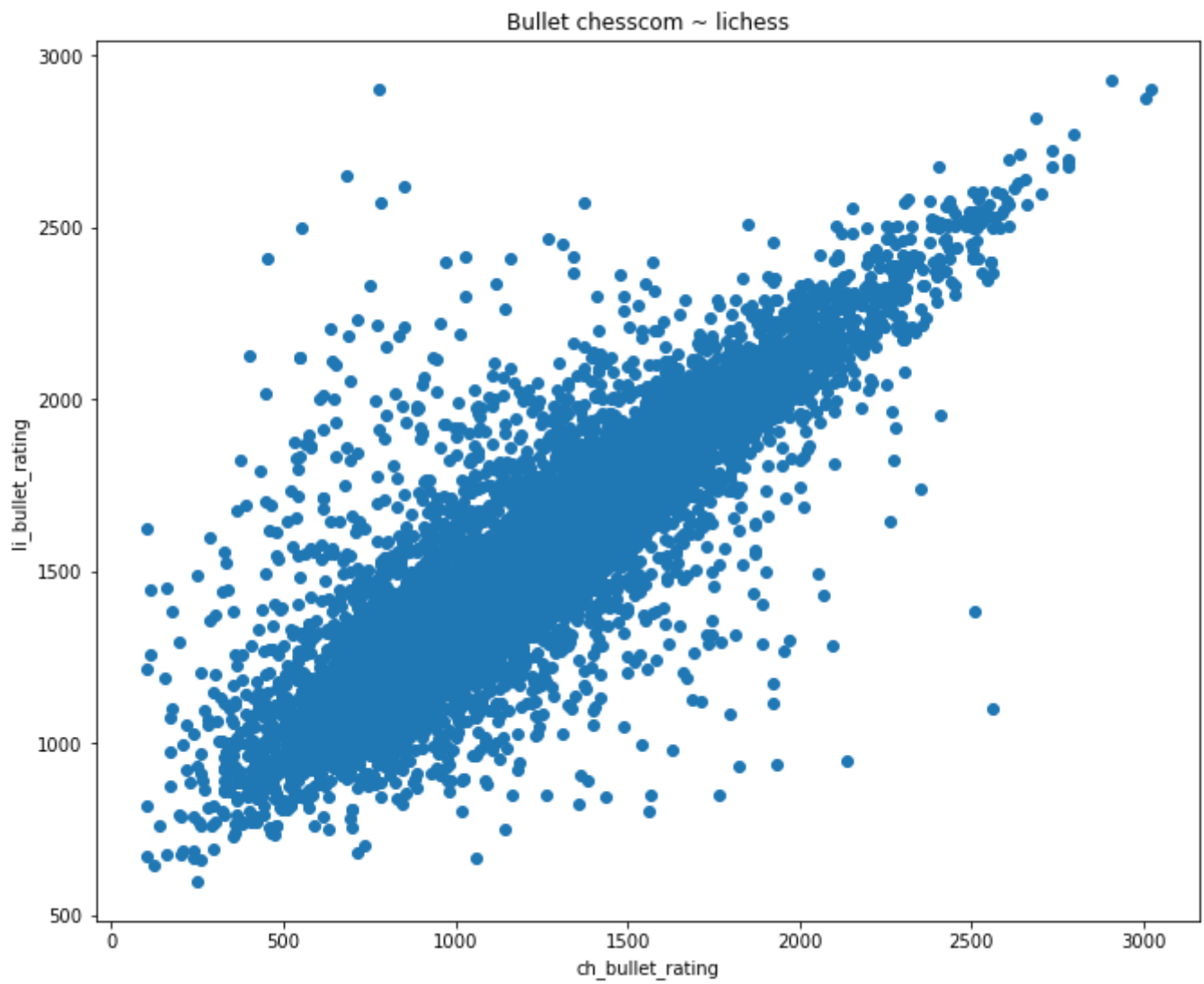
dtypes: float64(7), int64(6)  
memory usage: 12.6+ MB

- **RD is the *rating\_deviation***
  - **li prefix means lichess**
  - **ch prefix means chesscom**
- 
- **Bullet, Blitz and Rapid are game modes in Chess**

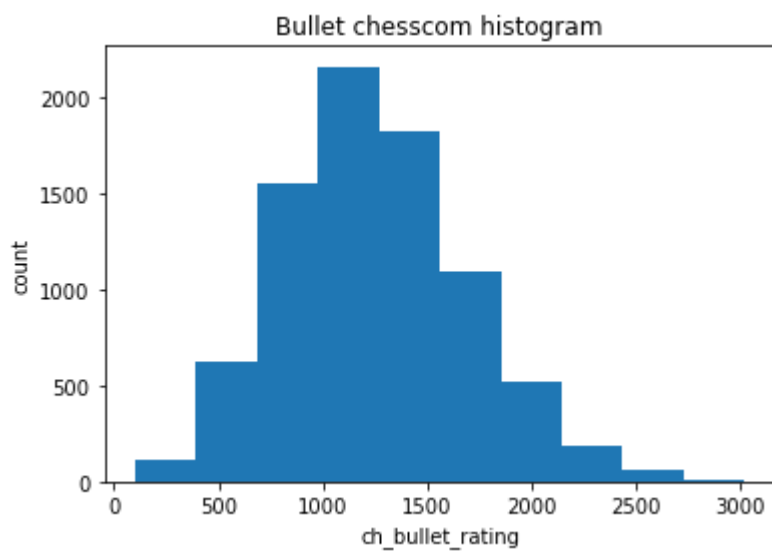
df now contains the interesting columns

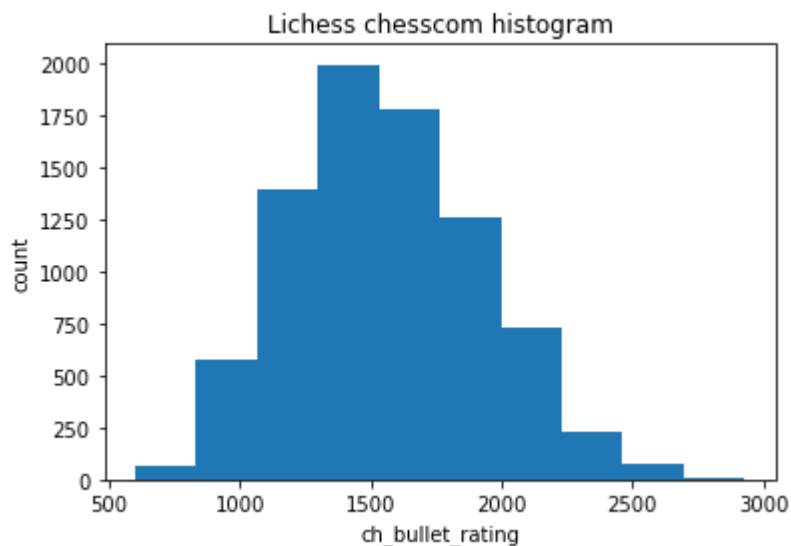
## Cleaning the Dataset

Now filter for an RD below 100 to remove untelling values.



there are some outliers but I will clean some up





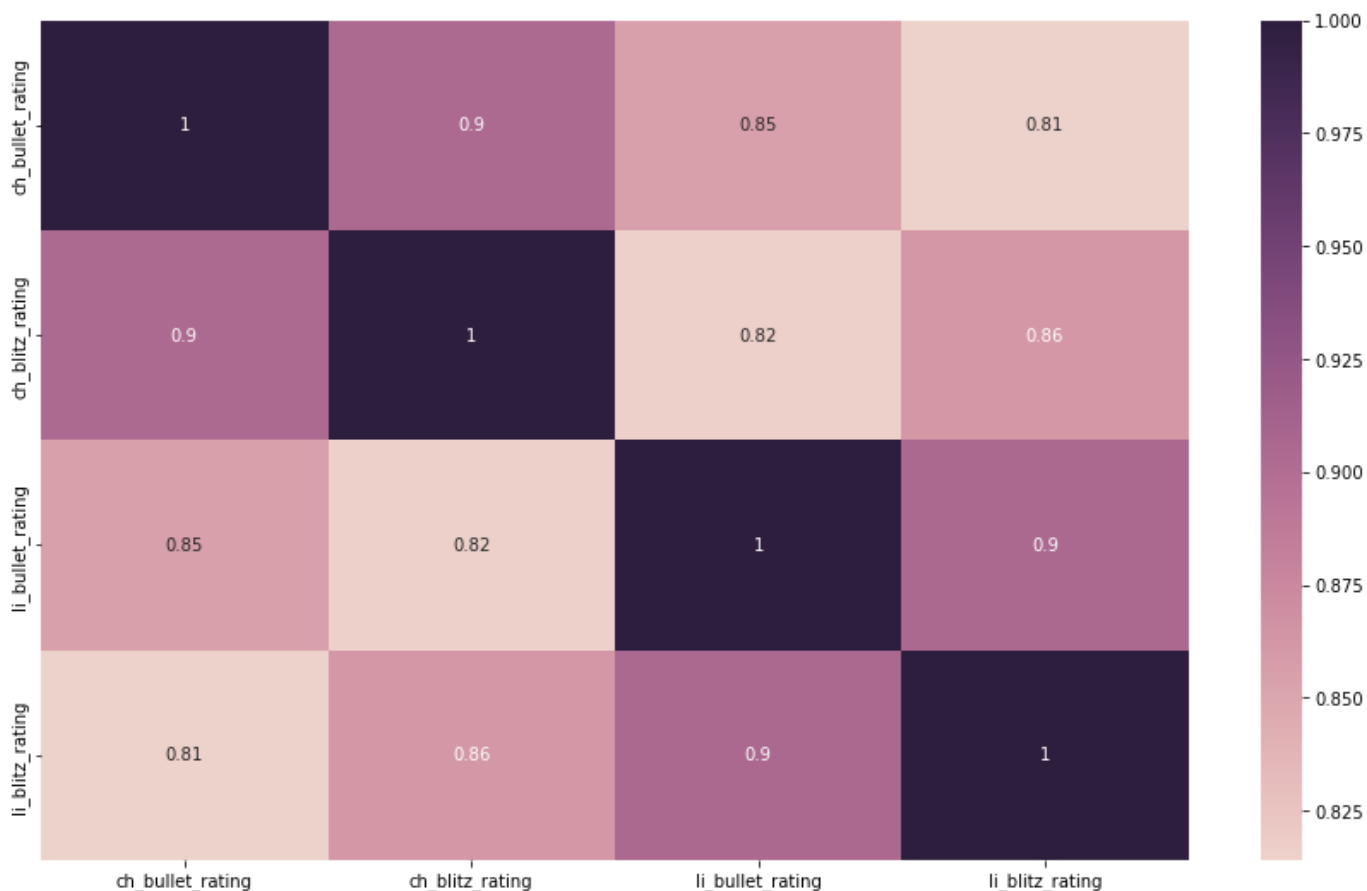
There is a heavy bias towards values between 1000-2000

## Looking at Correlations

FIDE, Bullet, Blitz, Rapid are the columns of interest

FIDE is our target value

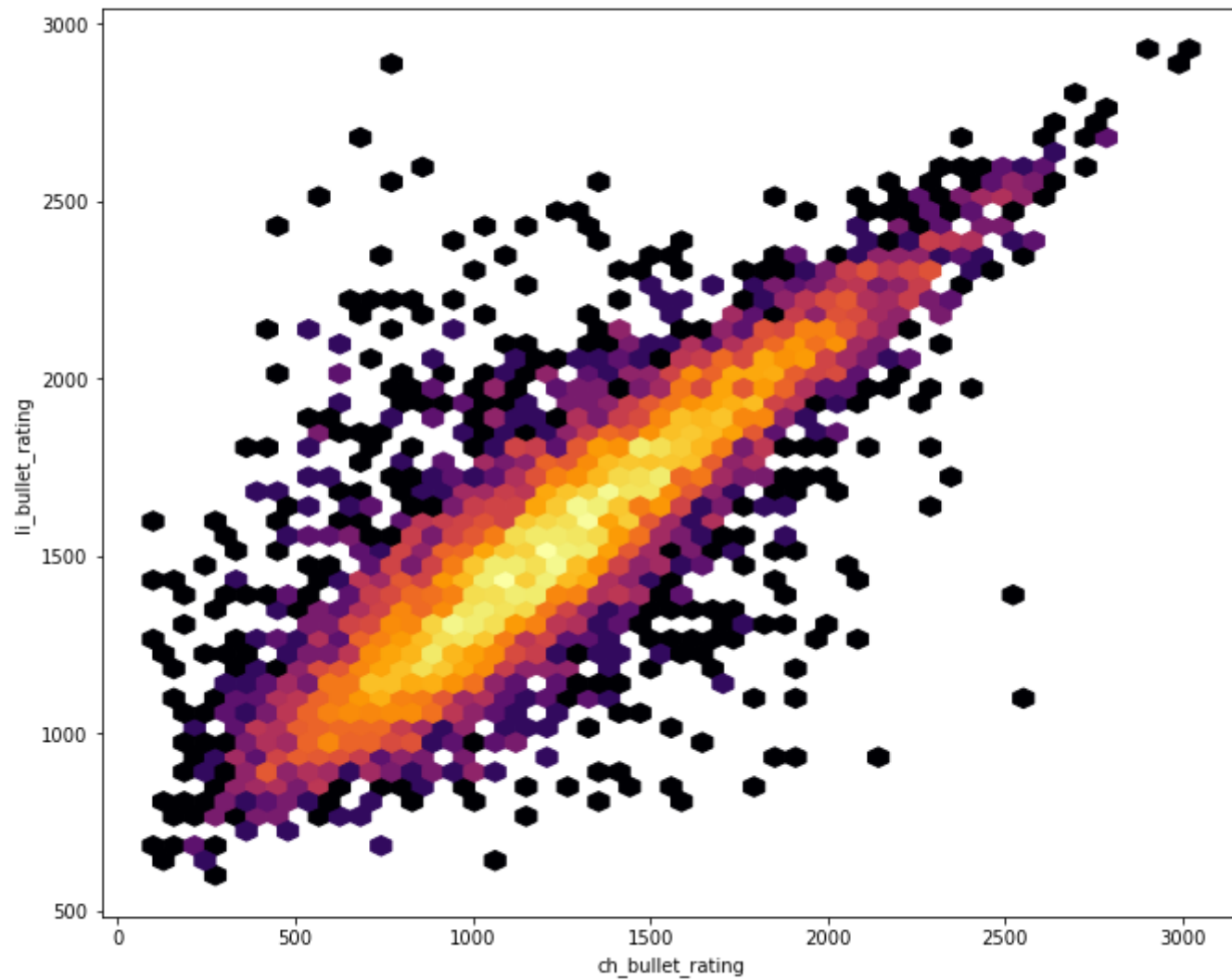
<AxesSubplot:>

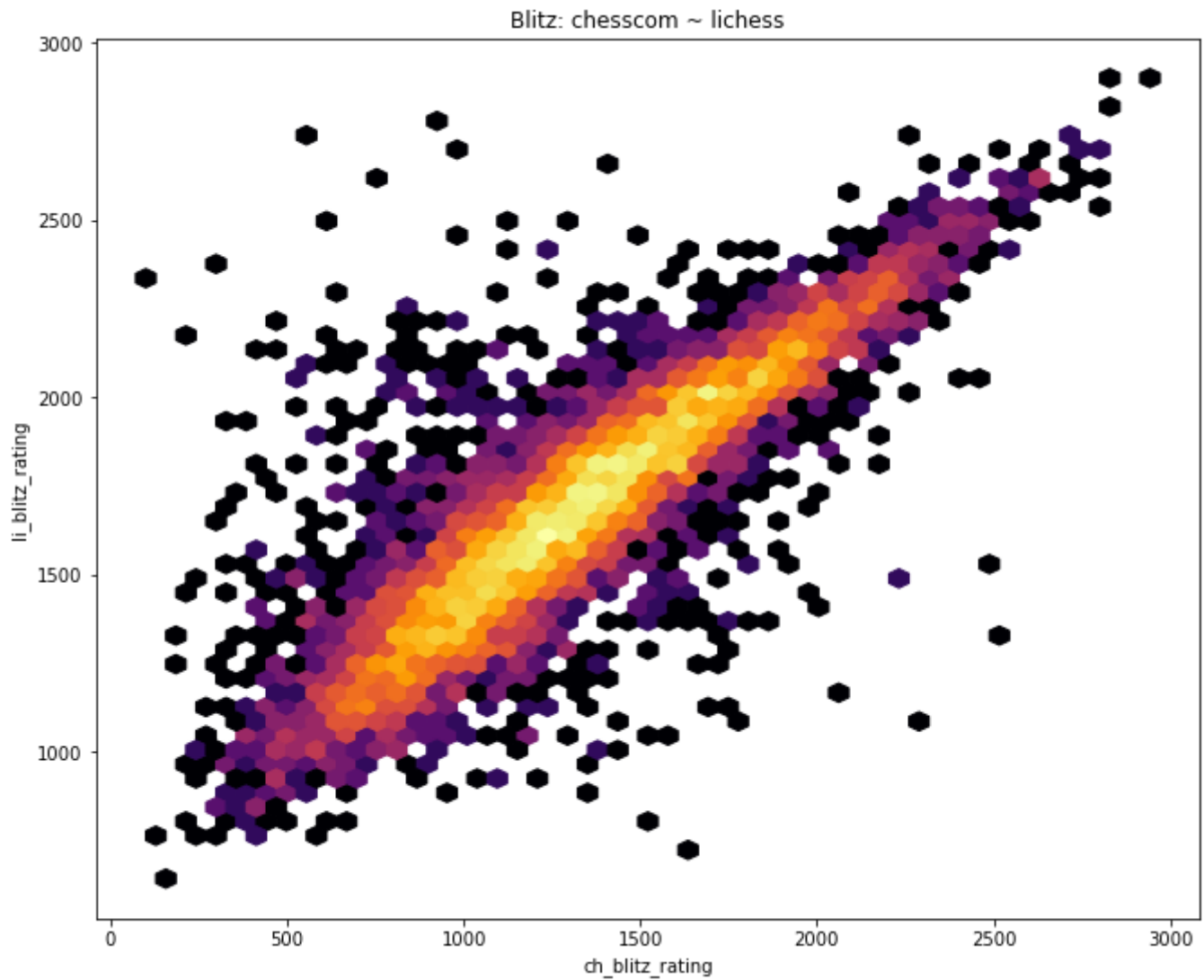


There is decent correlation here. I can see that chess\_bullet <-> chess\_blitz, lichess\_bullet <-> lichess\_blitz have the strongest correlations. But all have good relations to eachother.

## Visualize Correlations

Bullet: chesscom ~ lichess





## Model Training

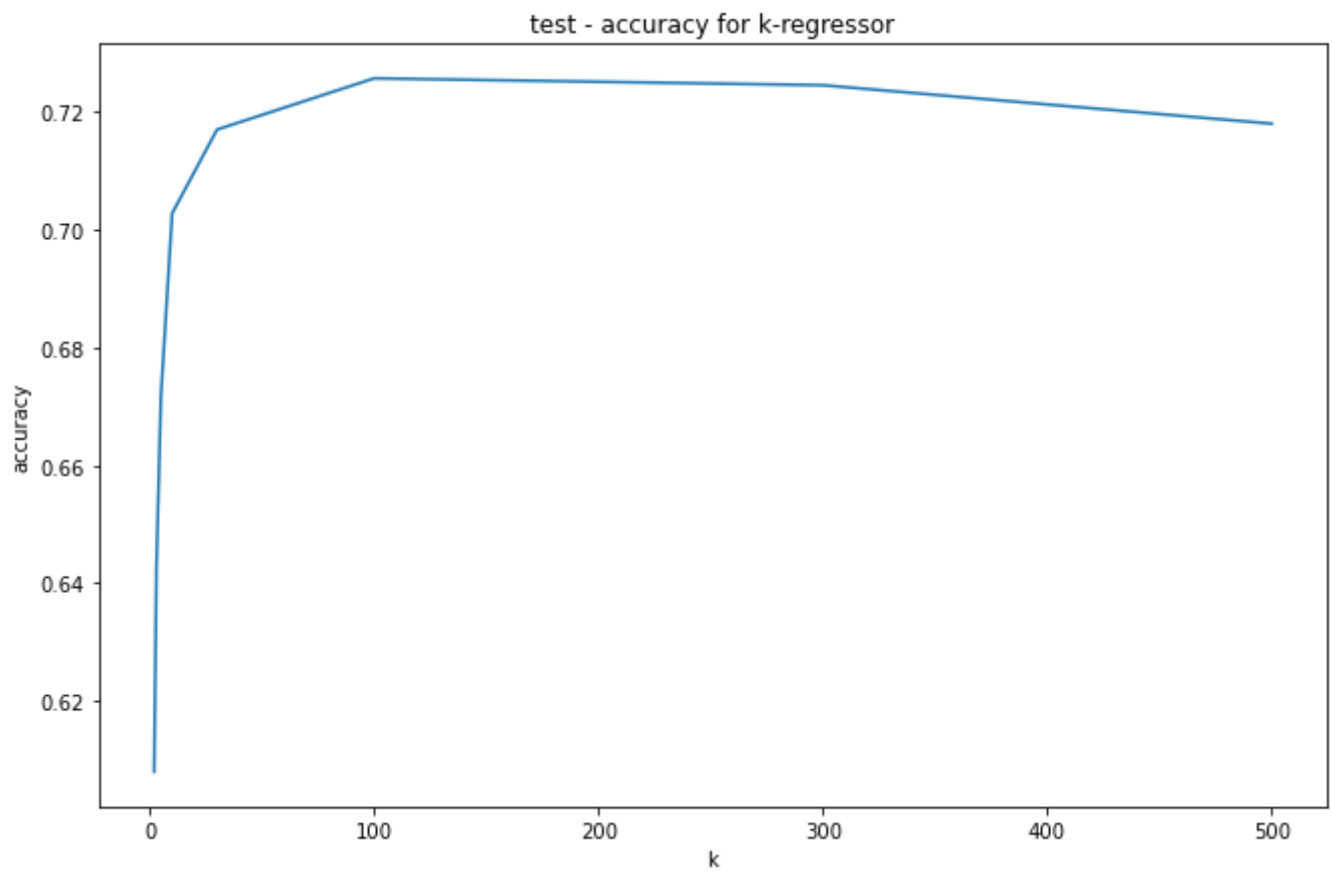
train, test, validation 70,20,10 split

```
length of  
Dataset: 8123  
train_set: 5686  
test_set: 1624  
val_set: 813
```

## K-nearest-neighbours

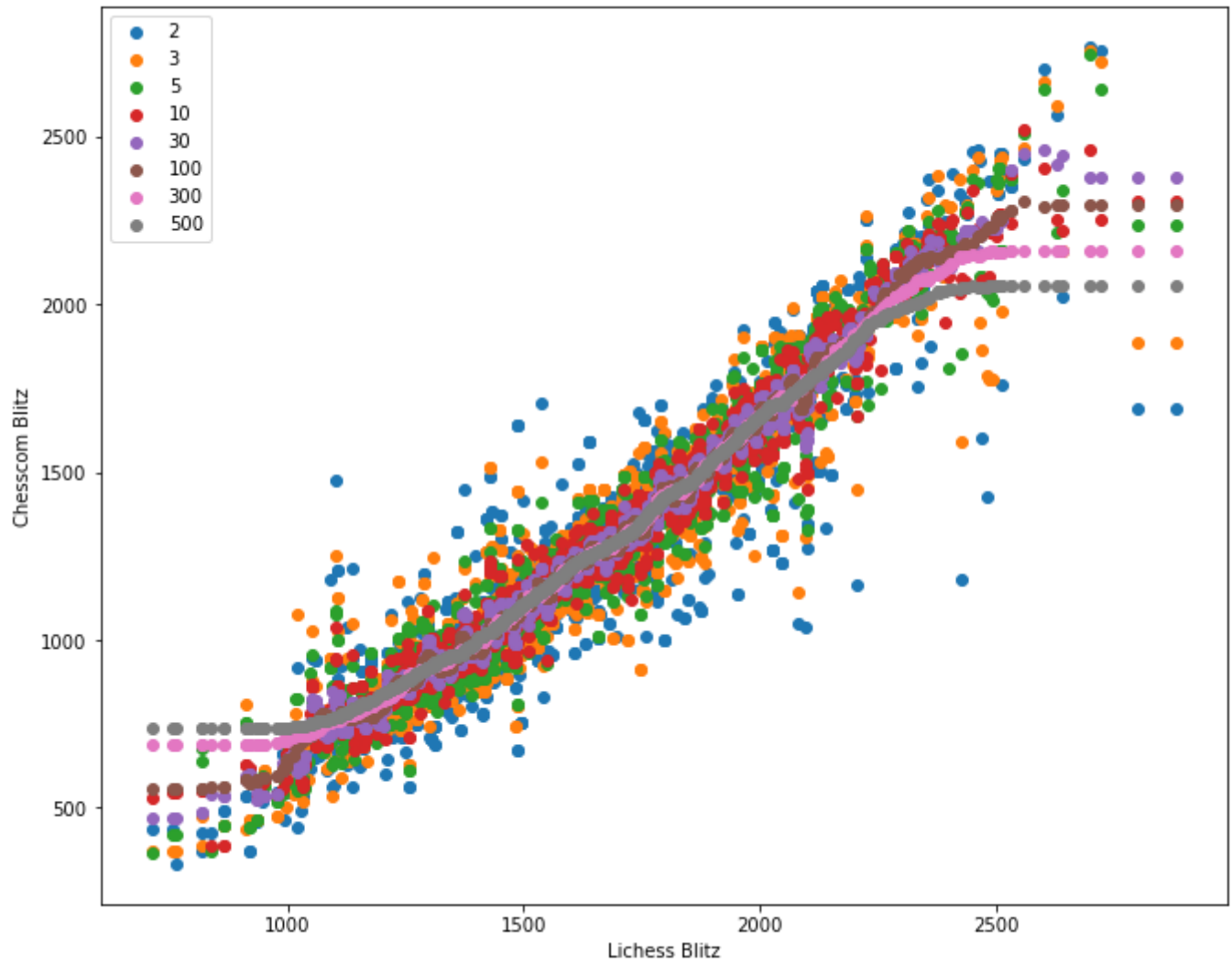
K=2,5,10,30,100,300,500

```
k2 0.6079834524076553  
k3 0.6425789977252938  
k5 0.6716768201397763  
k10 0.7027723435737401  
k30 0.7169990987858982  
  
k100 0.7257000668551719  
k300 0.724533049090944  
k500 0.7180013561487815
```

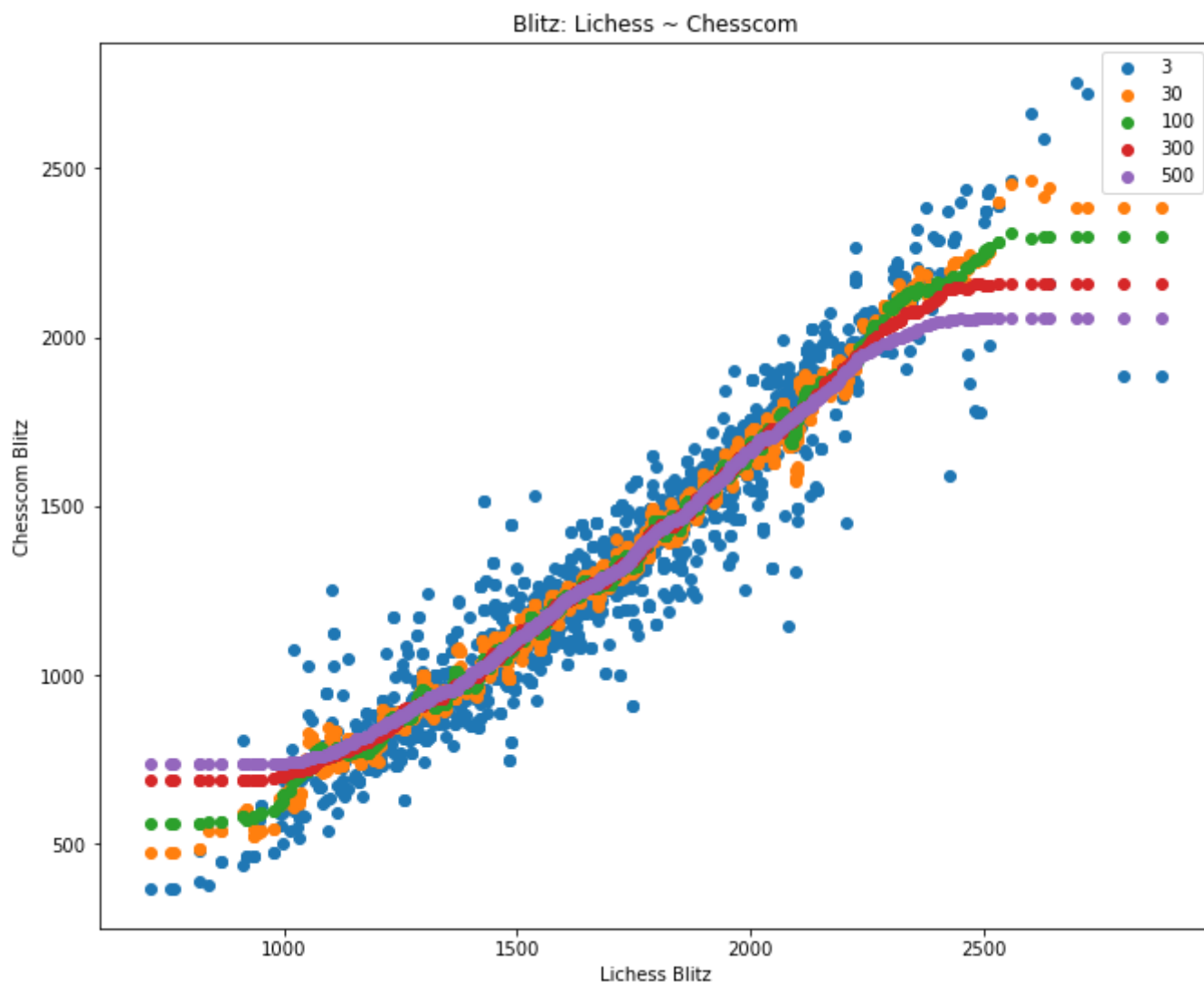


K=100 seems to be the best

Blitz: Lichess ~ Chesscom







Due to the lack of data for the high values there is some overfitting going on for high k

## Linear- and Multilinear Regression

### Multilinear for target: FIDE on Blitz and Bullet

#### OLS Regression Results

Dep. Variable:	ch_blitz_rating	R-squared:	0.871
Model:	OLS	Adj. R-squared:	0.871
Method:	Least Squares	F-statistic:	1.085e+04
Date:	Sun, 11 Sep 2022	Prob (F-statistic):	0.00
Time:	21:25:06	Log-Likelihood:	-31200.
No. Observations:	4841	AIC:	6.241e+04
Df Residuals:	4837	BIC:	6.243e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-185.1669	12.117	-15.281	0.000	-208.922	-161.411
li_blitz_rating	0.6730	0.015	44.027	0.000	0.643	0.703
li_bullet_rating	-0.3016	0.016	-18.679	0.000	-0.333	-0.270
ch_bullet_rating	0.6725	0.010	69.114	0.000	0.653	0.692

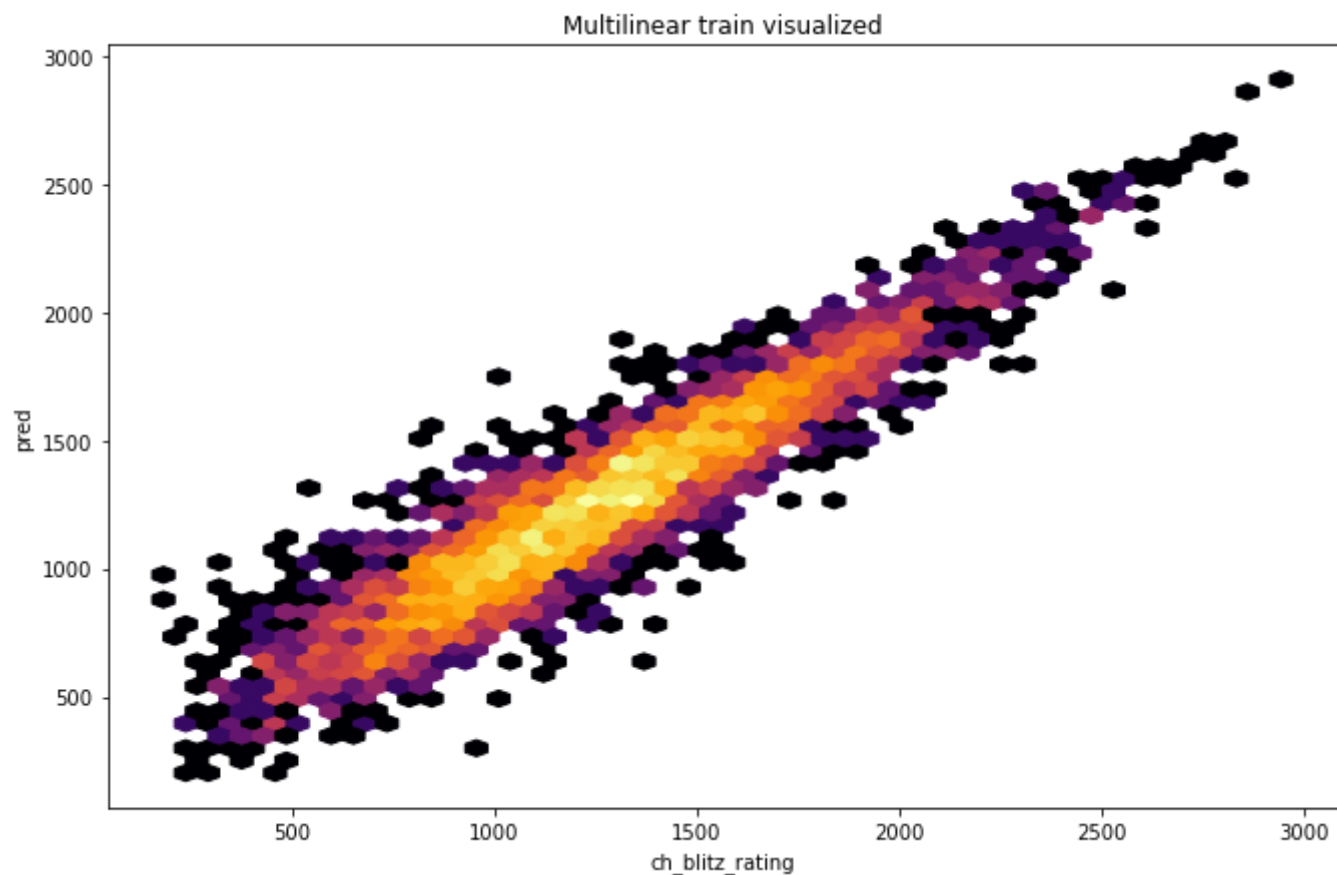
  

Omnibus:	270.163	Durbin-Watson:	1.993
----------	---------	----------------	-------

Prob(Omnibus):	0.000	Jarque-Bera (JB):	671.843
Skew:	-0.324	Prob(JB):	1.29e-146
Kurtosis:	4.706	Cond. No.	1.44e+04

### Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.  
 [2] The condition number is large, 1.44e+04. This might indicate that there are strong multicollinearity or other numerical problems.



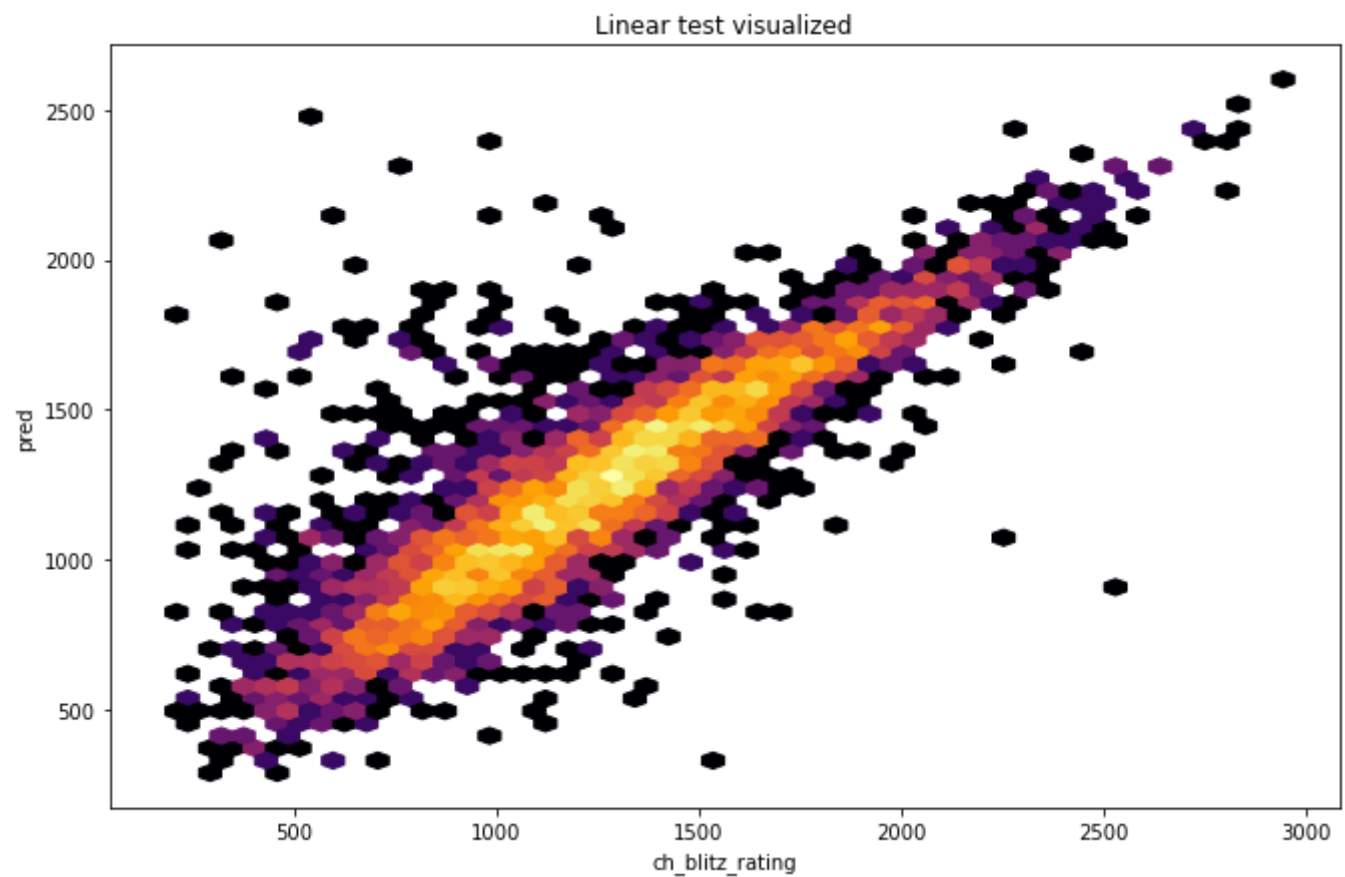
## Linear for target: FIDE on Blitz

OLS Regression Results						
Dep. Variable:	ch_blitz_rating	R-squared:	0.736			
Model:	OLS	Adj. R-squared:	0.736			
Method:	Least Squares	F-statistic:	1.350e+04			
Date:	Sun, 11 Sep 2022	Prob (F-statistic):	0.00			
Time:	21:25:07	Log-Likelihood:	-32925.			
No. Observations:	4841	AIC:	6.585e+04			
Df Residuals:	4839	BIC:	6.587e+04			
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
Intercept	-536.9158	15.774	-34.038	0.000	-567.840	-505.992
li_blitz_rating	1.0896	0.009	116.179	0.000	1.071	1.108
Omnibus:	1892.213	Durbin-Watson:	1.973			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	20615.396			
Skew:	-1.554	Prob(JB):	0.00			
Kurtosis:	12.620	Cond. No.	8.48e+03			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large,  $8.48\text{e}+03$ . This might indicate that there are strong multicollinearity or other numerical problems.



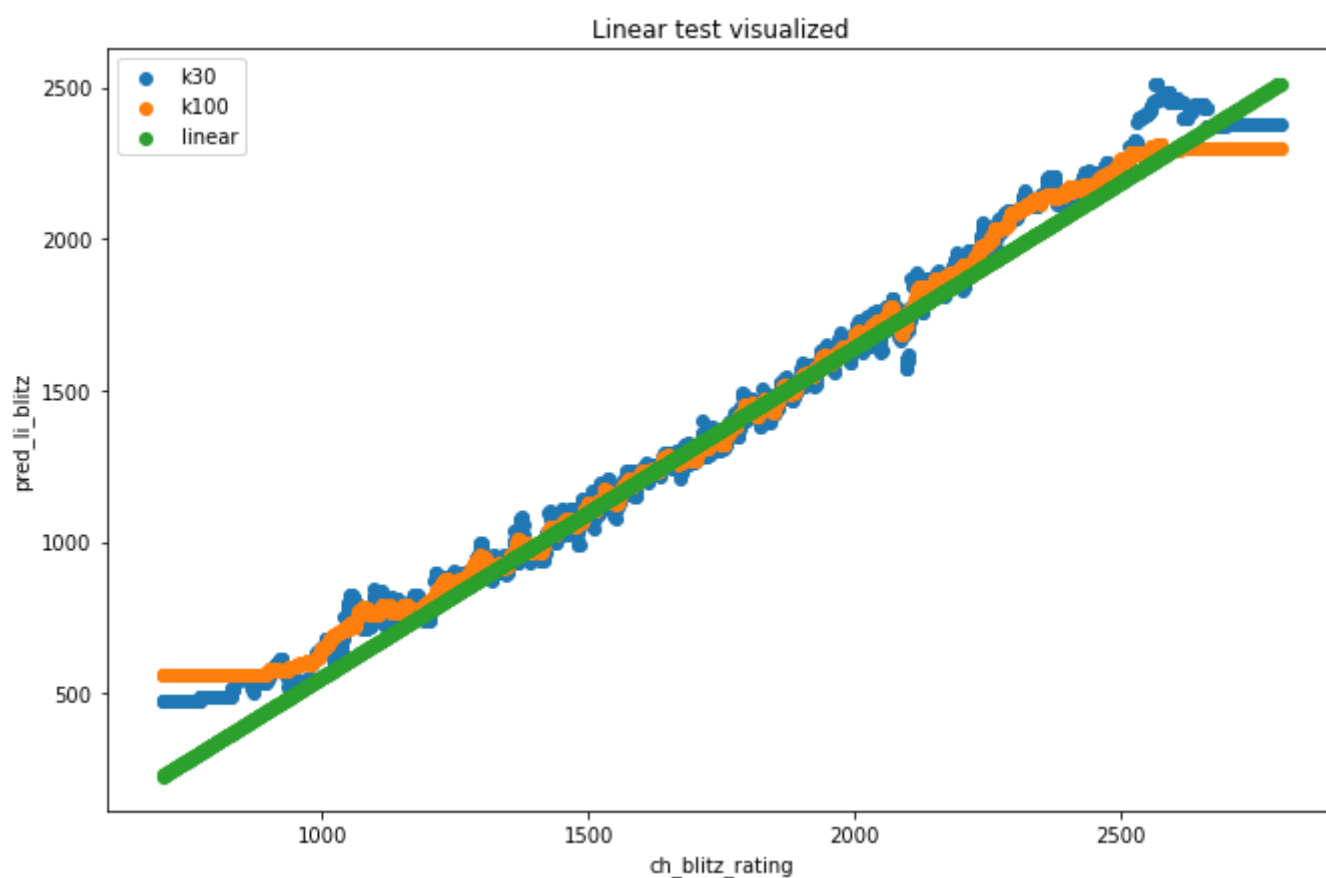
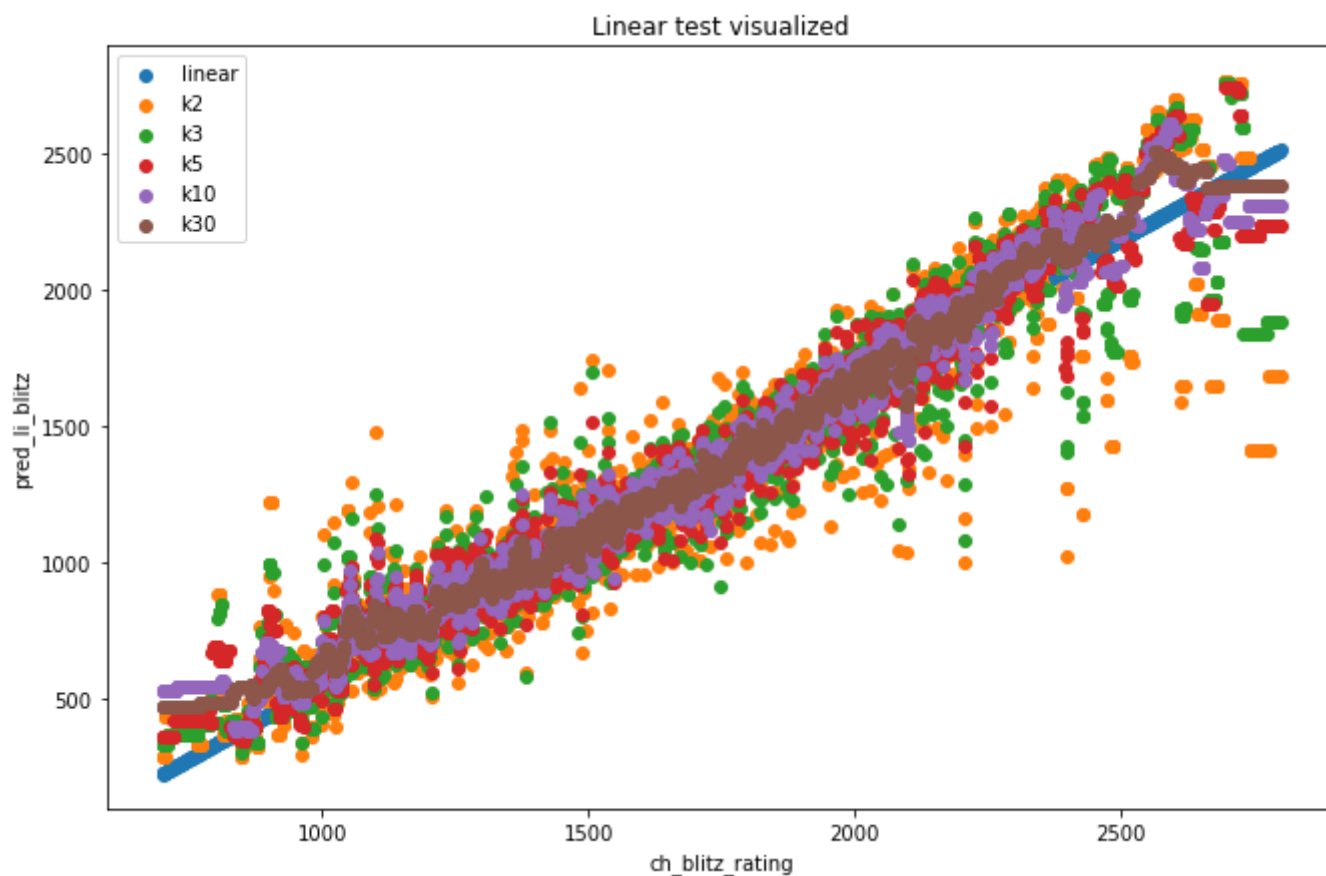
## Accuracies

r\_squared\_accuracy of

MultiLinear: 0.7750097278913504

Linear: 0.6819650681539863

Export the data



r-squared accuracies  
k30 0.7169990987858982  
k100 0.7257000668551719  
k300 0.724533049090944  
k500 0.7180013561487815  
Linear 0.6819650681539863

~75 r-squared accuracy is decent for the Dataset at hand. K100 is the one I am most happy with.

## Conclusion

K-nearest-neighbours with  $k=100$  is my Model of choice. It gives the best r-squared accuracy. The only issues is has it that for very low and very high Elos we have don't have very good accuracy. However, most people lie within 700 and 2500 Elo, for which is it extremely accurate.

$k=30$  is almost as good and can also be used, it is a little better near the edges and almost as good as  $k=100$  for the rest, but a little bit too much variance, leading to illogical results.

Multilinear regression is the best Model, however it depends on more than just one input variable, so if we have more information from the Users, except just one Elo. Then it is the most powerful, however the information gain does not move the needle a lot. We get 5% more accuracy, but require 300% more data.