

**World Cup Prediction** 





# Agenda

- 1. Problem Statement
- 2. Challenges
- 3. Datasets
- 4. Experiments
- 5. Results & Interpretations
- 6. Demo
- 7. Conclusion & Future Work





#### **Problem Statement**

#### Predict the outcome of a match given previous data









Modelling the Dataset

Data Collection (only FIFA?)

Data Integration (Different datasets)

Model: Classification VS Regression

Feature Engineering





Names from one dataset as **reference** 



DR Congo → Congo

Northern Ireland → Ireland

Dominican Republic → Dominica

England → United Kingdom



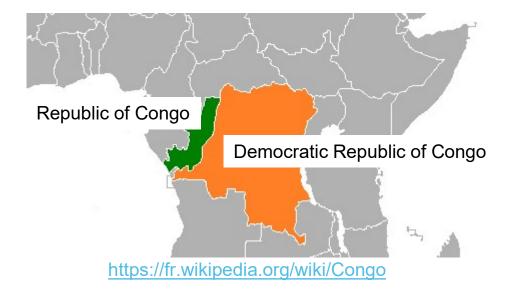


#### DR Congo → Congo

Northern Ireland → Ireland

Dominican Republic → Dominica

England → United Kingdom





DR Congo → Congo

Northern Ireland → Ireland

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X1;		Team1	Team2	Score1	Score2	Date/Time
Ę	50	Ireland	Northern Ireland	0	1	29.05.1999/00:00
413	37	Ireland	Northern Ireland	5	0	24.05.2011/20:45
863	33	Ireland	Northern Ireland	0	0	15.11.2018/20:45



DR Congo → Congo

Northern Ireland → Ireland

Dominican Republic → Dominica

England → United Kingdom



I was born in Dominica. Most people I meet, from all parts of the world, have no idea that Dominica exists. Growing up in Boston, the majority of people I meet just assume that I'm from the Dominican Republic when I tell them that I'm Dominican.

Dominica and the Dominican Republic are two completely different countries that are not related to each other in any way, other than being in the same region (the West Indies). https://www.quora.com/ Whats-the-differencebetween-Dominica-andthe-Dominican-Republic



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**England** → **United Kingdom** 



https://www.pinterest.com/pin/380343131002611548/





DR Congo → Congo

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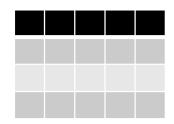
England → United Kingdom

Serbia and Montenegro → Yugoslavia





#### **Datasets**

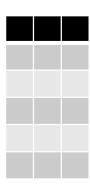


wide dataset → Features

data from Friendly & World Cup matches

from 1994

9071 \* 40



long dataset → **Observations** 

data from many **International tournaments** (Friendly, World Cup, African Cup of Nations, World Cup Quanlifications ...)

From 1872

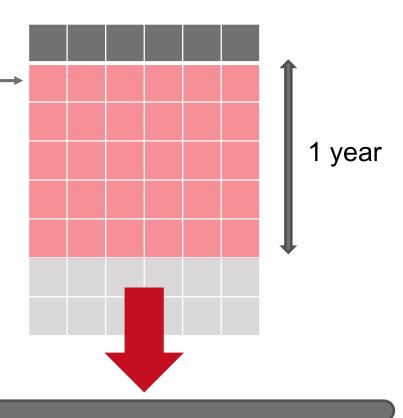
38900 \* 30



#### **Datasets**

i = 0

Teams + Scores + Date/Time



nb matches
nb & ratio goals
nb & ratio wins / losses / draws
nb & ratio win / losses / draws against opponent



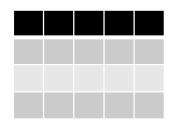
# Datasets i = 1 Sliding Window of width 1 year

nb matches
nb & ratio goals
nb & ratio wins / losses / draws
nb & ratio win / losses / draws against opponent





#### **Datasets**

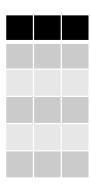


wide dataset → Features

data from Friendly & World Cup matches

from 1994

+ FIFA Score, FIFA Ranking, Population, Surface, Density



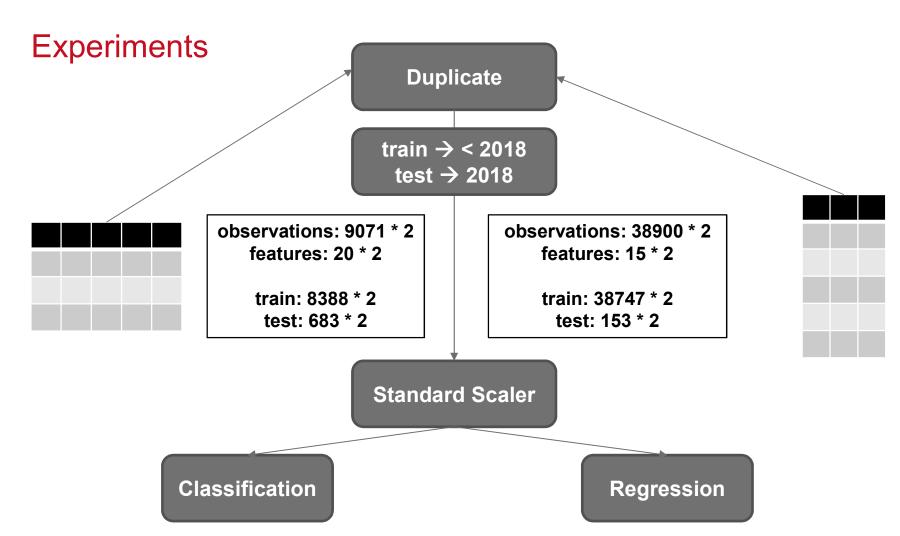
long dataset → **Observations** 

data from many **International tournaments** (Friendly, World Cup, African Cup of Nations, World Cup Quanlifications ...)

From 1872









# Results (Classification)

Classifier	Accuracy Score
Dummy Classifier	36,82 %
Random Forest	48,17 %
Bernoulli NB	46,92 %
Extra Trees	41,58 %
KNN	39 %
MLP	44,66 %
Nearest Centroid	48,61 %
Ridge Classifier	48,76 %
SVC	49,04 %

Classifier	Accuracy Score
Dummy Classifier	36,27 %
Random Forest	36,6 %
Bernoulli NB	41,5 %
Extra Trees	38,56 %
KNN	34,64 %
MLP	45,42 %
Nearest Centroid	39,22 %
Ridge Classifier	41,18 %
SVC	42,48 %

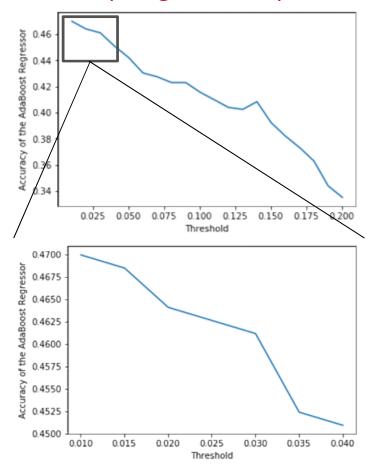


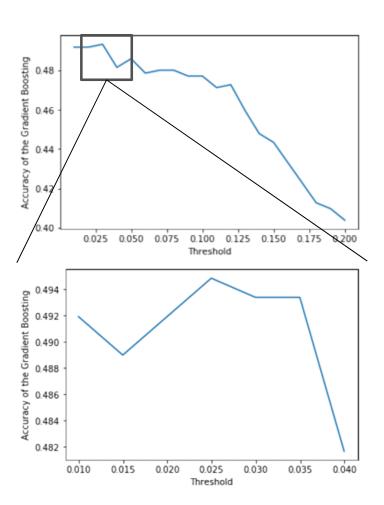
Regressor	Accuracy Score	Accuracy (threshold = 0,03)			
MLP Regressor	45,82 %	46,41 %			
Gradient Boosting	48,76 %	49,34 %			
Random Forest	45,24 %	42,17 %			
AdaBoost	48,02 %	43,19 %			
Bagging Regressor	44,22 %	45,39 %			
Transformed Target	48,90 %	48,02 %			



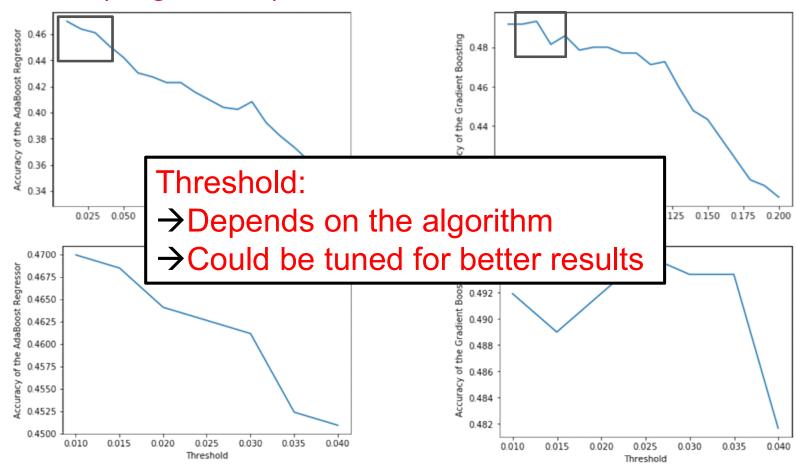
Regressor	Accuracy Score	Accuracy (threshold = 0,05)	
MLP Regressor	43,79 %	44,44 %	
Gradient Boosting	41,83 %	43,14 %	
Random Forest	37,91 %	34,64 %	
AdaBoost	39,87 %	39,87 %	
Bagging Regressor	39,22 %	37,25 %	
Transformed Target	41,18 %	41,38 %	





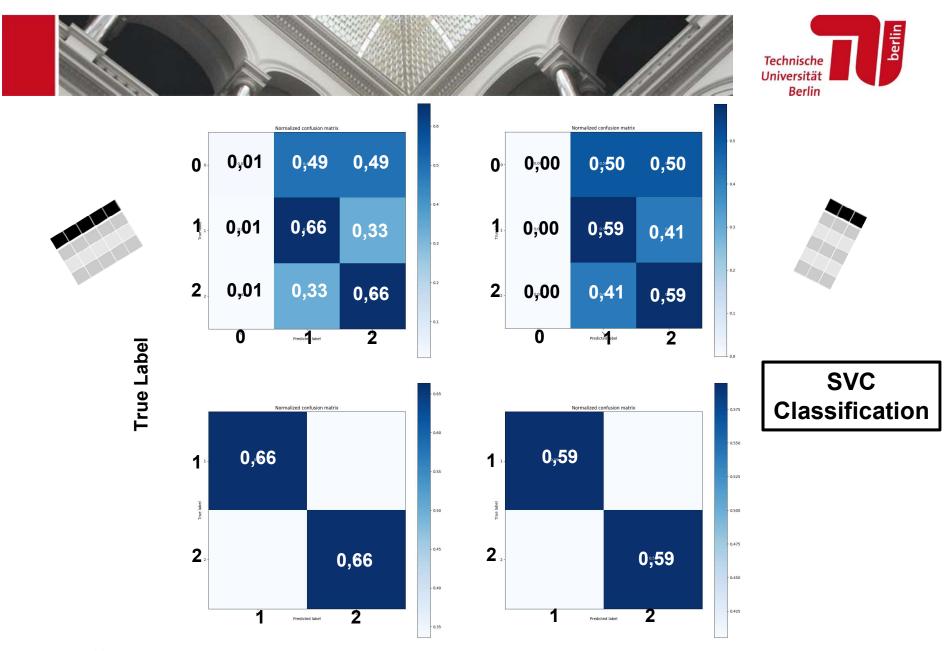








Model	Class	Precision	Recall	F1-Score
	0	0.38	0.02	0.03
svc	1	0.49	0.66	0.56
	2	0.49	0.66	0.56
Dondom	0	0.31	0.04	0.07
Random Forest	1	0.49	0.64	0.55
	2	0.49	0.64	0.55
Negrost	0	0.33	0.26	0.29
Nearest Centroid	1	0.53	0.57	0.55
	2	0.53	0.57	0.55
Didae	0	0.00	0.00	0.00
Ridge Classifier	1	0.49	0.66	0.56
	2	0.49	0.66	0.56



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**Predicted Label** 





#### Investigating the Results



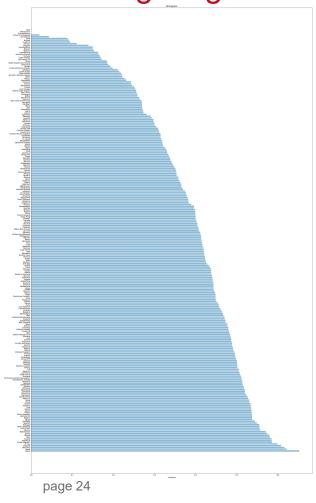
Regressor	Accuracy Score	threshold = 0,03	Accuracy (2 classes)
MLP Regressor	45,82 %	46,41 %	62,62 %
Gradient Boosting	48,76 %	49,34 %	65,20 %
Random Forest	45,24 %	42,17 %	63,22 %
AdaBoost	48,02 %	43,19 %	54,67 %
Bagging Regressor	44,22 %	45,39 %	62,82 %
Transformed Target	48,90 %	48,02 %	66,60 %

→ Draw matches are usually more difficult to predict (even for humans) !!





## Investigating the Results



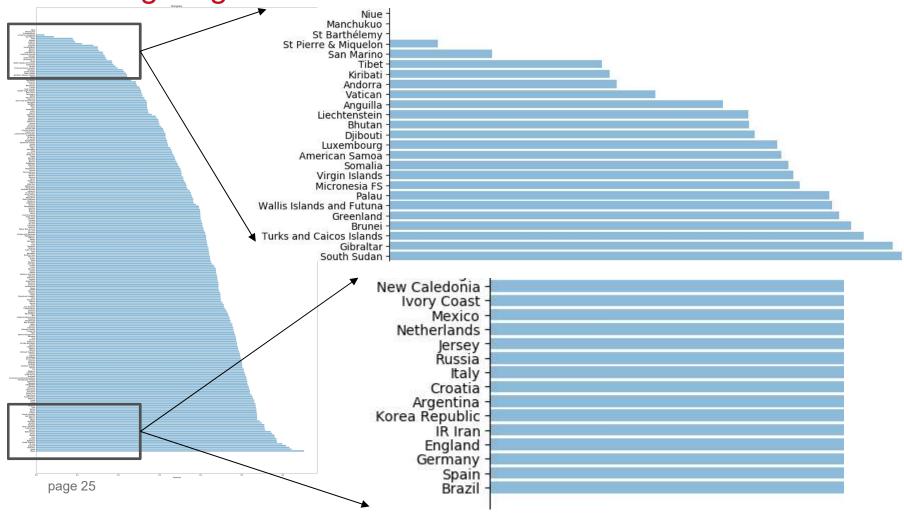
strength (teami) =

average 
$$\frac{score(team_i)}{score(team_i) + score(opponent_i)}$$





## Investigating the Results







## Demo

# <u>DEMO</u>



#### **Future Work**

Features > Observations

 Focus on adding more features rather than more data

Regression > Classification

- Allows us to model the strength of a team, rather than only the winner
- 6-1 VS 2-1  $\rightarrow$  0,86 VS 0,67

Model

• Tune the threshold, accordingly to the model

**Draw Matches** 

- Online Learning
- User implication





#### Resources

https://www.flashscore.com/football/world/friendly-international/archive/

https://www.fifa.com/

https://ourworldindata.org/

http://en.fifaranking.net/ranking/

https://data.worldbank.org/

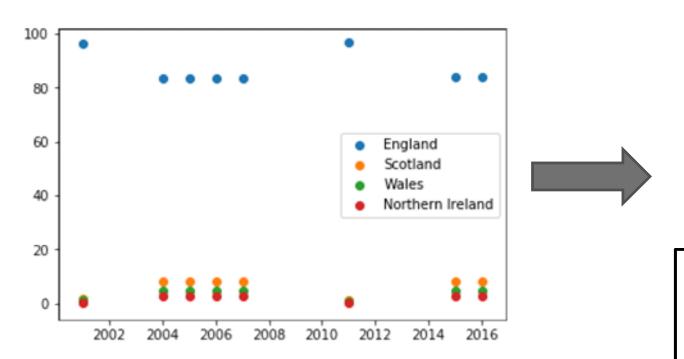
http://projectbritain.com/population.html

http://www.worldometers.info/world-population



# **⊕** Thank you for Your Attention **⊕Questions** ?







England: 84% Scotland: 8.3%

Scotiand: 8.3% Wales: 4.8%

Wales. 4.0%

Northern Ireland: 2.9%





