EPP: Elo-based predictive power score

Alicja Gosiewska
COSEAL, Potsdam, 26 August 2019

About me

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- Explainable Artificial Intelligence (XAI)
- Automated Machine Learning (AutoML)

MSc in Mathematics (Mathematical Statistics and Data Analysis)

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WARSAW UNIVERSITY OF TECHNOLOGY

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MI^2 Data Lab

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EPP: INTERPRETABLE SCORE OF MODEL PREDICTIVE POWER

A PREPRINT

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Available on arXiv from Tuesday.

What is wrong with AUC?

Weaknesses of most popular measures 1/2

1. What is the interpretation of a difference in performance for the two models?

	score
team	
Erkut & Mark,Google AutoML	0.618492
Erkut & Mark	0.616913
Google AutoML	0.615982
Erkut & Mark,Google AutoML,Sweet Deal	0.615858
Sweet Deal	0.615766

source: https://www.kaggle.com/antgoldbloom/analyzing-kaggledays-sf-competition-data

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Weaknesses of most popular measures 2/2

2. How to compare performances of models between data sets?

IEEE-CIS Fraud Detection

#	Team Name	Score
1	alijs	0.9562
2	7777777777777777777777777...	0.9559
3	ML Keksika	0.9546
4	krivoship	0.9544
5	2 old mipt dogs	0.9543

IEEE-CIS Fraud Detection
https://www.kaggle.com/c/ieee-fraud-detection/leaderboard

Springleaf Marketing Response

#	△pub	Team Name	Score
1	—	Asian Ensemble	0.80426
2	▲1	.baGGaj.	0.80393
3	▲1	Merging the Mundane and th...	0.80389
4	▼2	ARG eMMSamble	0.80367
5	—	n_m	0.80208

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diff = 0.0003

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Is 0.0003 the same increase for both data sets?

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- The gap in the IEEE-CIS Fraud Competition is larger as AUC is closer to 1.
  Therefore, relative improvement for **IEEE-CIS is larger** than relative improvement for Springleaf.

Weaknesses of most popular measures 2/2

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- Improvement for **Springleaf is larger** than for IEEE-CIS.
  The gap between first and second place for Springleaf is larger that the difference between the second and the third place. The opposite is true for IEEE-CIS Fraud detection.

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diff = 0.00004

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EPP:
Elo-based Predictive Power performance score

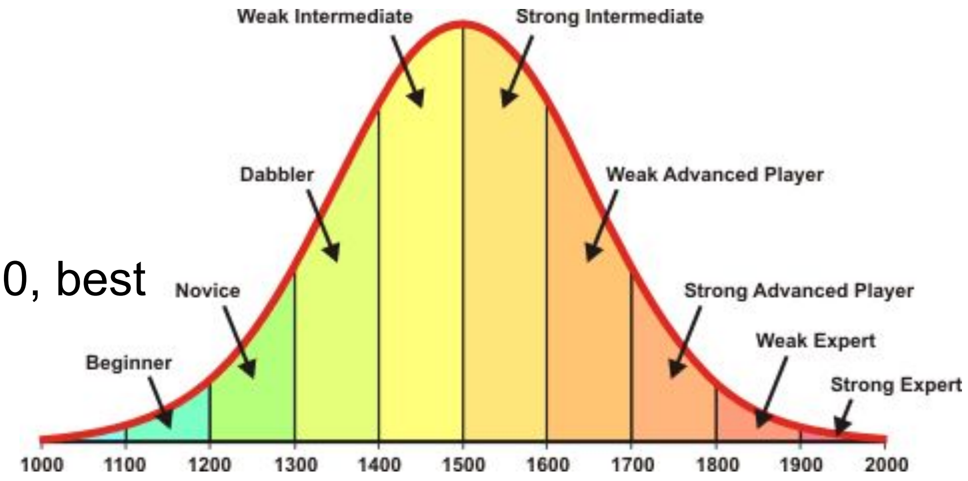
ELO rating system

https://www.365chess.com/players/Garry_Kasparov

http://www.stationgossip.com/2017/08/the-history-of-football-100-pics_9.html

ELO

- **Meaningful values.**
  An Average player have a rating of 1500, best players obtain rating over 2000.



https://bkgm.com/faq/Ratings.html

ELO

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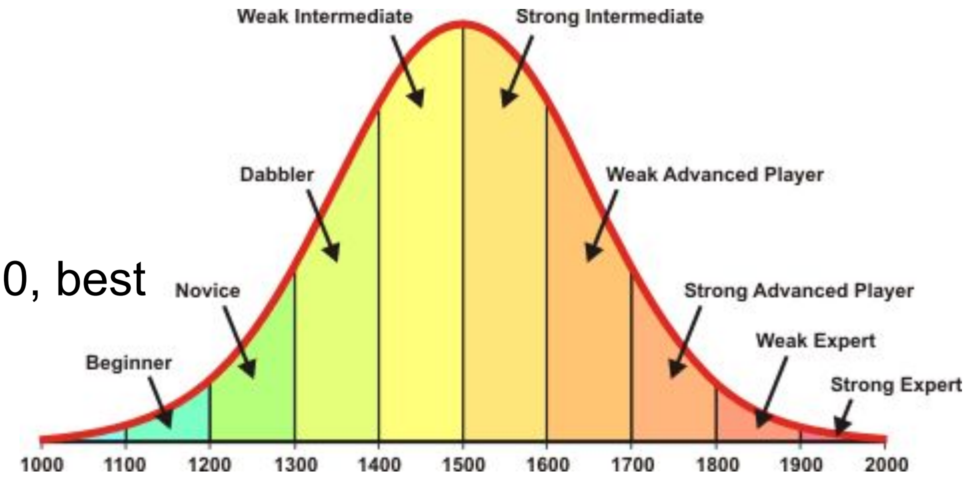
- **Probabilistic interpretation.**
  The difference between Elo scores of two players can be transferred into probabilities of winning when they play against each other.



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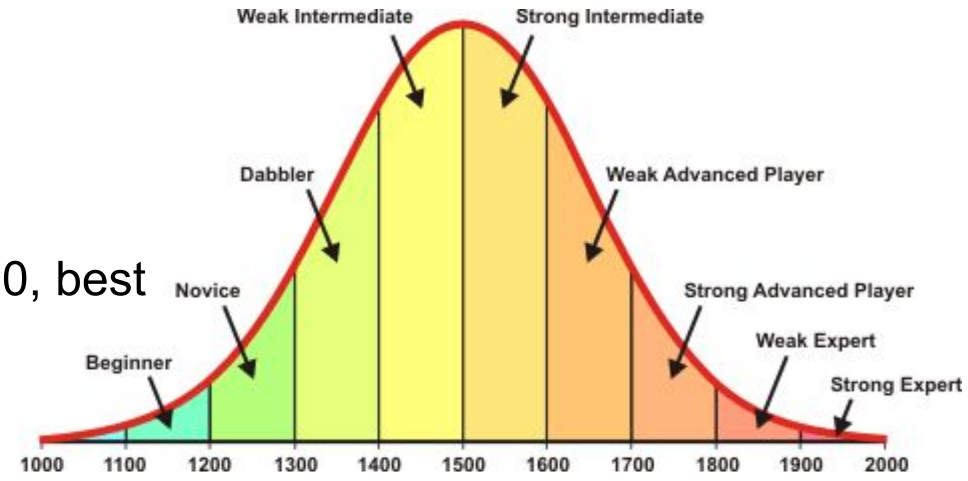

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- **Probabilistic interpretation.**
  The difference between Elo scores of two players can be transferred into probabilities of winning when they play against each other.

- **Partial results are enough.**
  It is not necessary for each player to play with each other player.

Elo-based Predictive Power score (EPP)

- There is an interpretation of differences in performance.

$$\text{diff} = EPP_A - EPP_B$$

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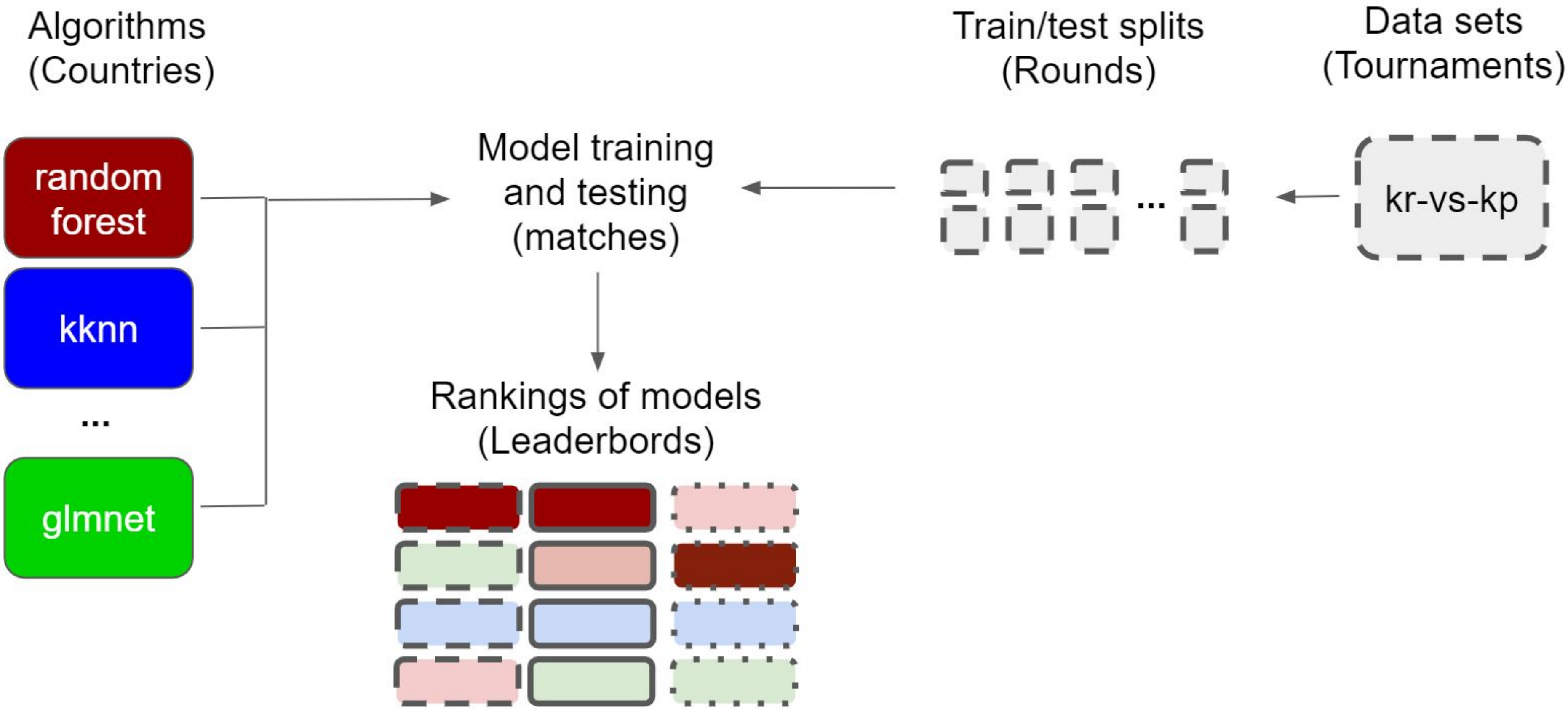
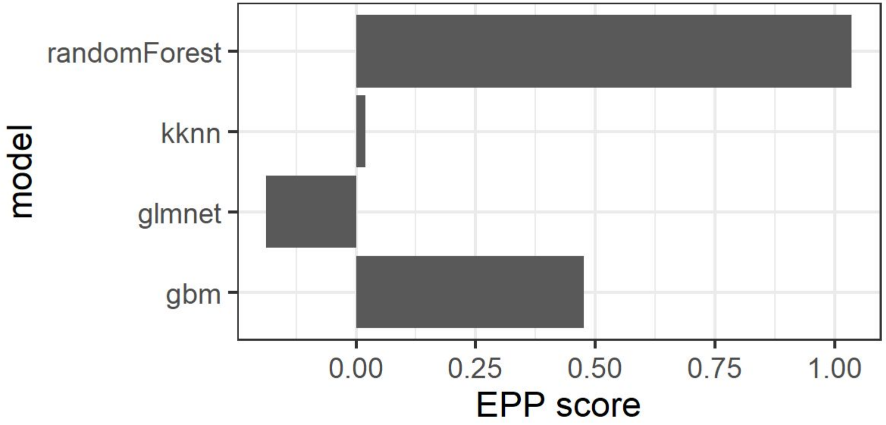
- One can compare performances between data sets.

The analogy between Elo and EPP



EPP scores are interpretable!



Model	EPP
randomForest	1.03
kknn	0.0195
glmnet	-0.187
gbm	0.476

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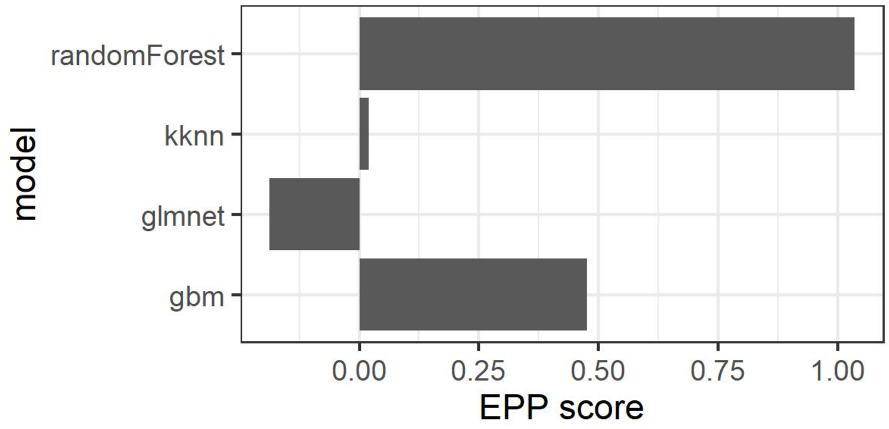

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$$\mathrm{diff} = EPP_{RF} - EPP_{GMB} = 1.03 - 0.476 = 0.554$$

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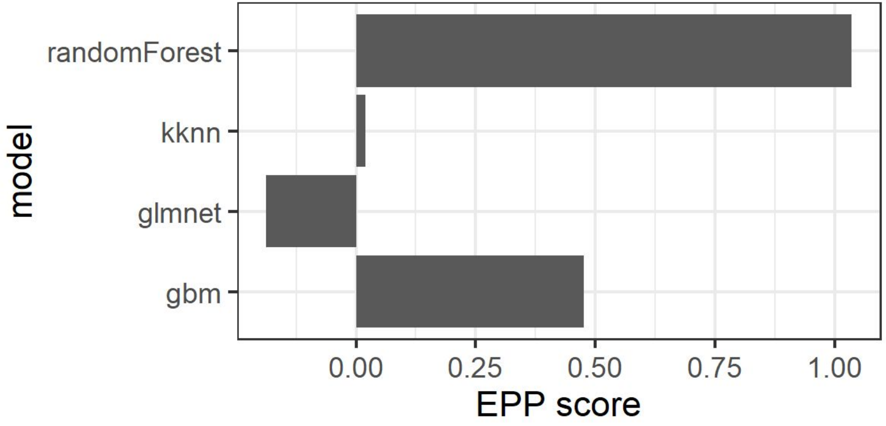

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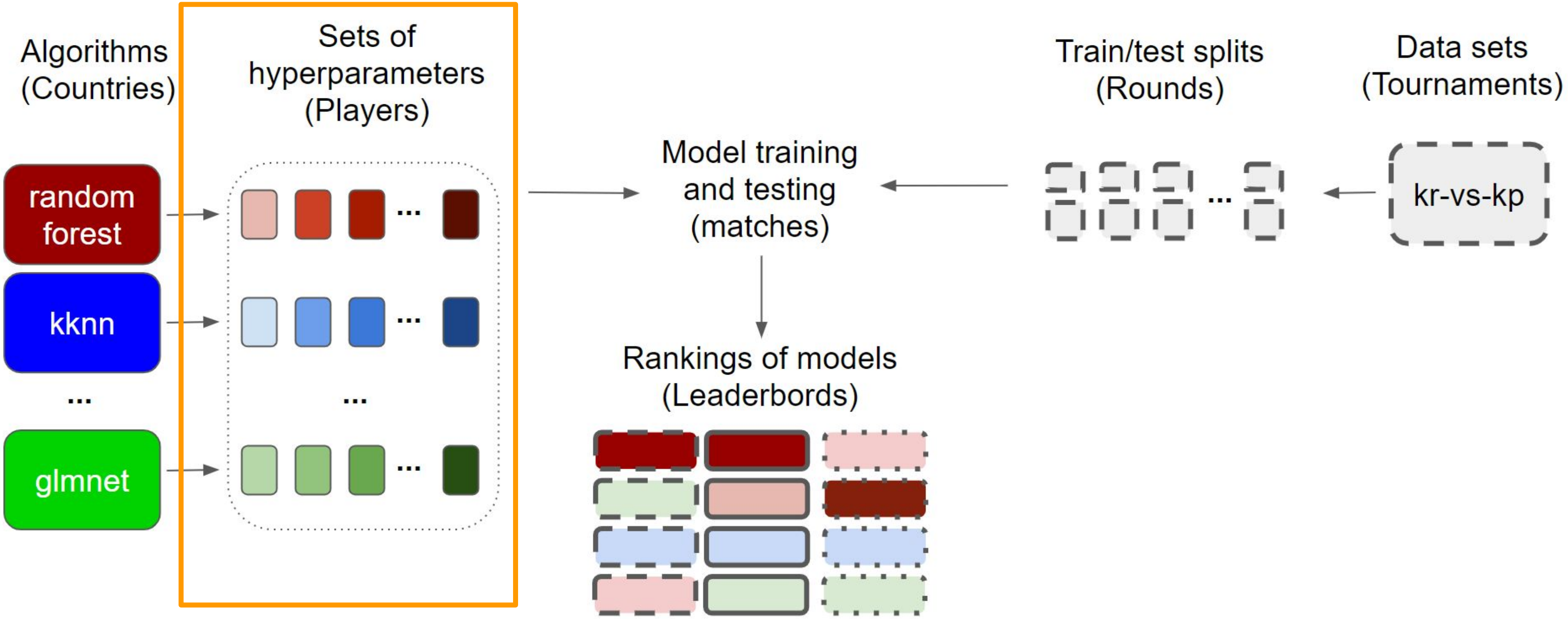
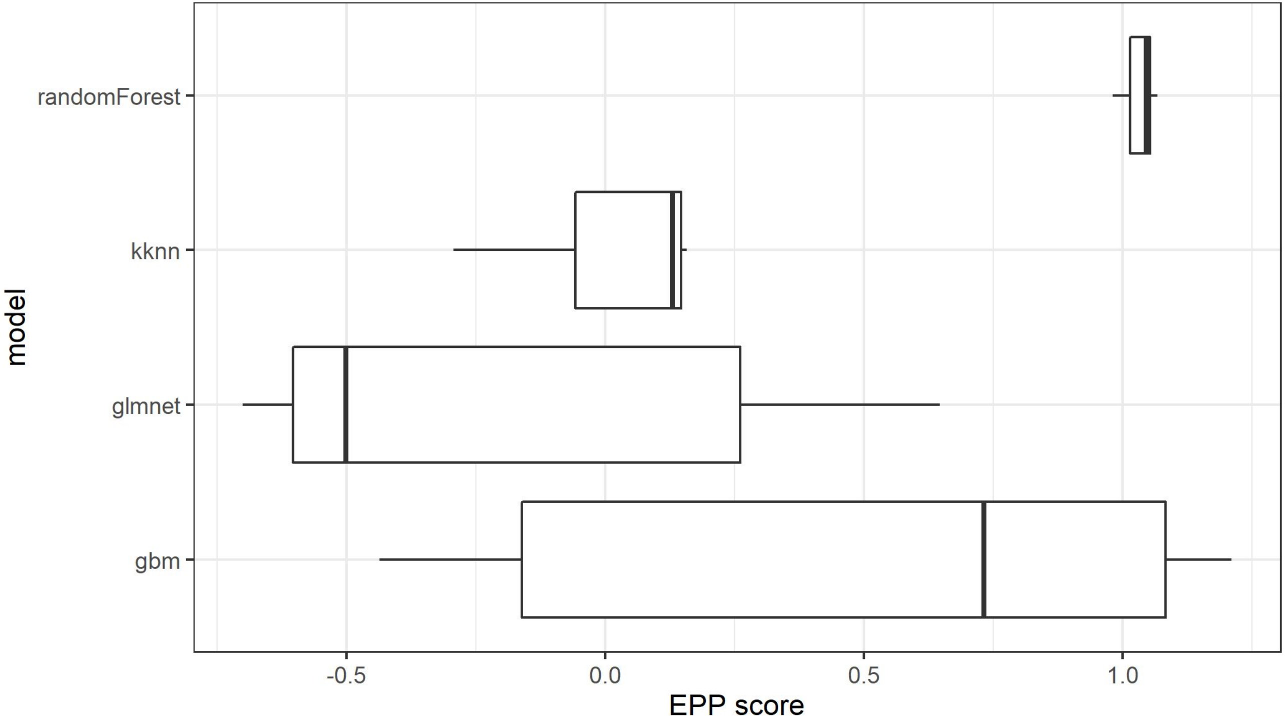
$$P\left(\begin{array}{c}\text{randomForest}\\ \text{wins with gbm}\end{array}\right) = invlogit(\text{diff}) = \frac{e^{\text{diff}}}{1+e^{\text{diff}}} = \frac{e^{0.554}}{1+e^{0.554}} = 0.635$$

Tunability of the algorithms

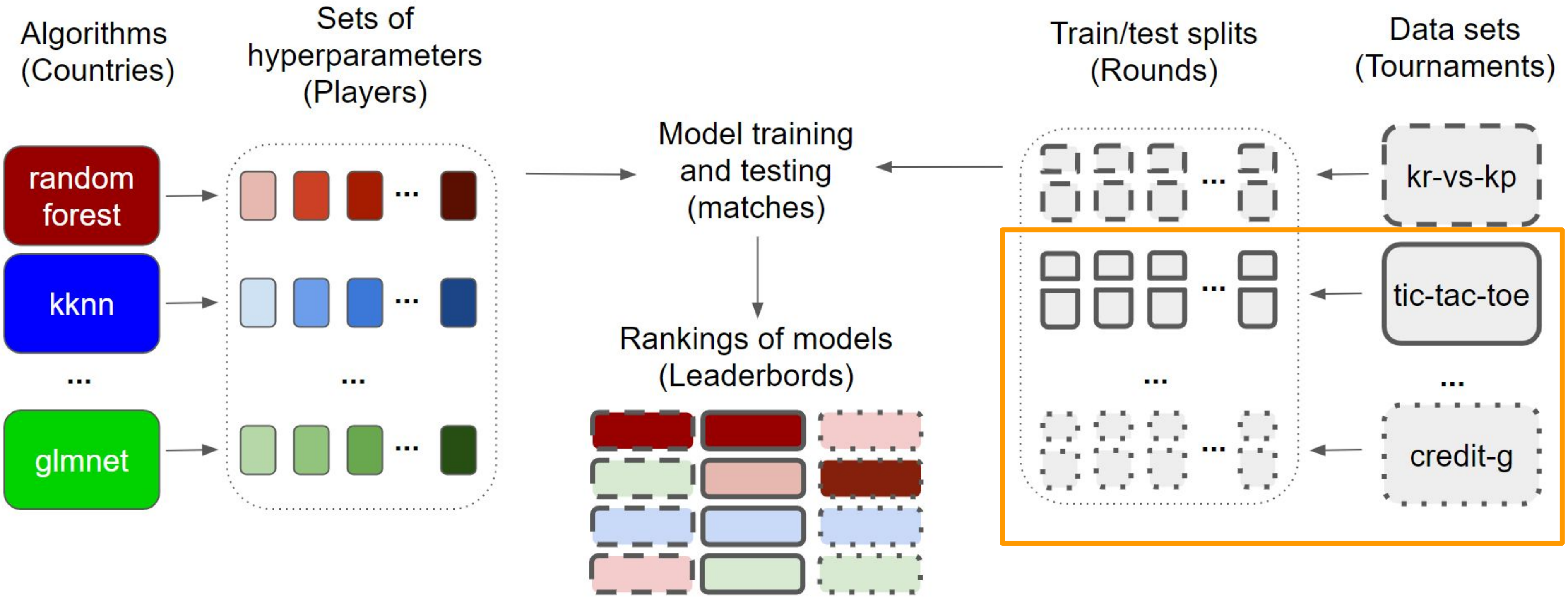


Tunability of the algorithms

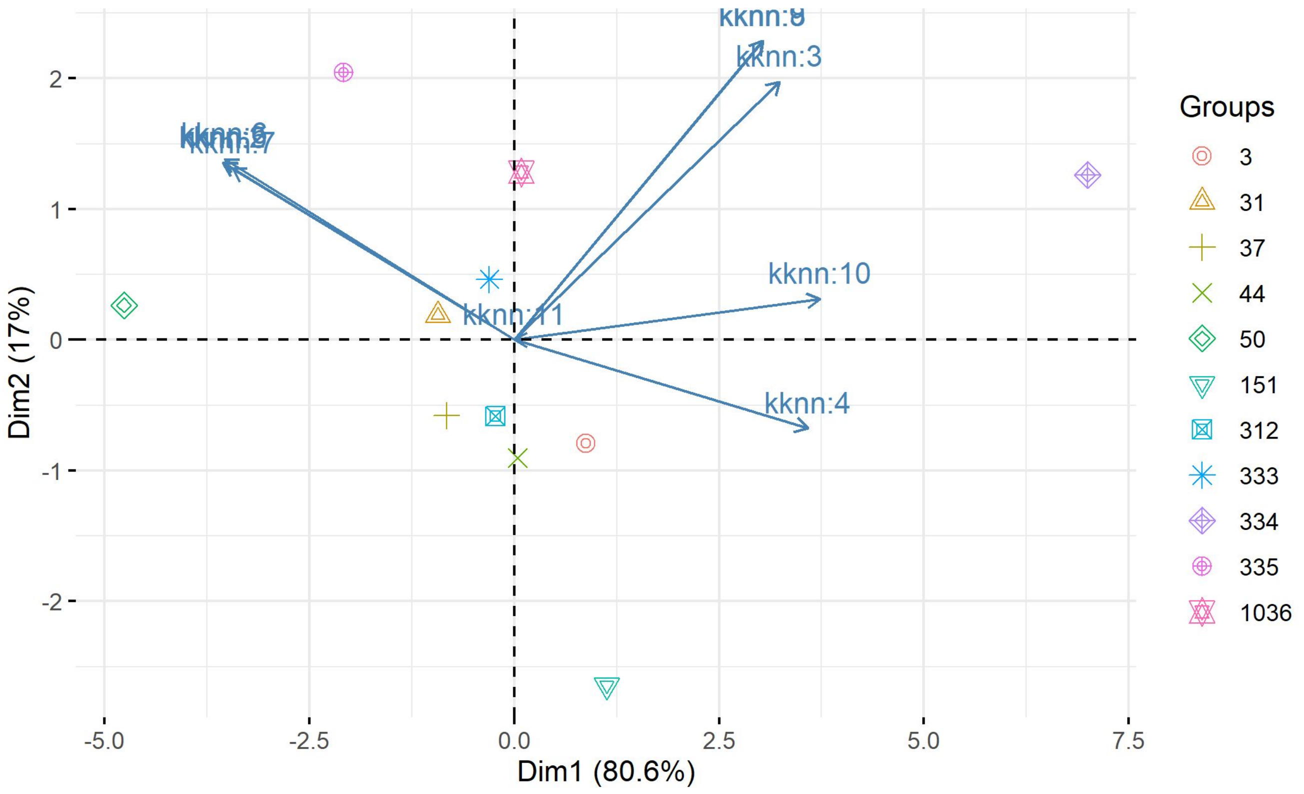
EPP scores for different hyperparameters



EPP-based embeddings of data sets



PCA on EPP scores across data sets



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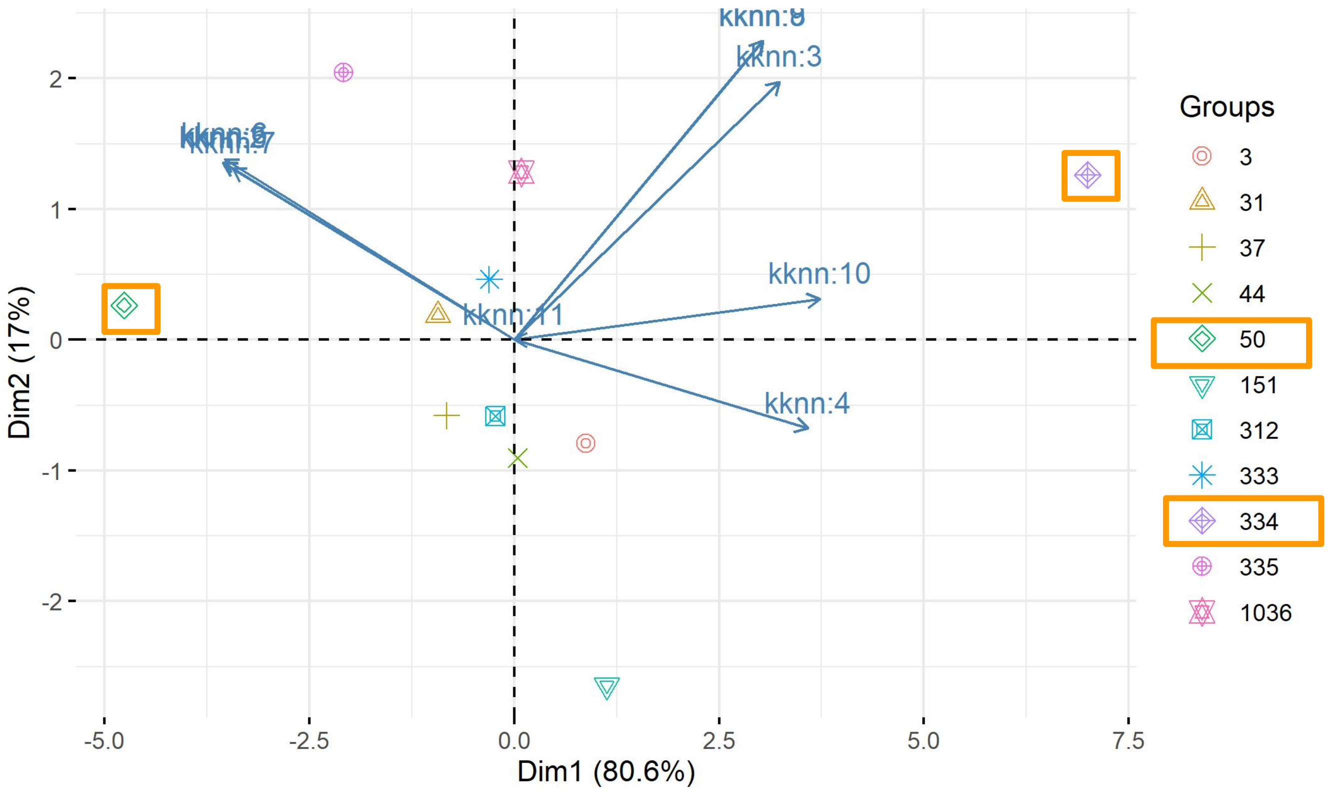
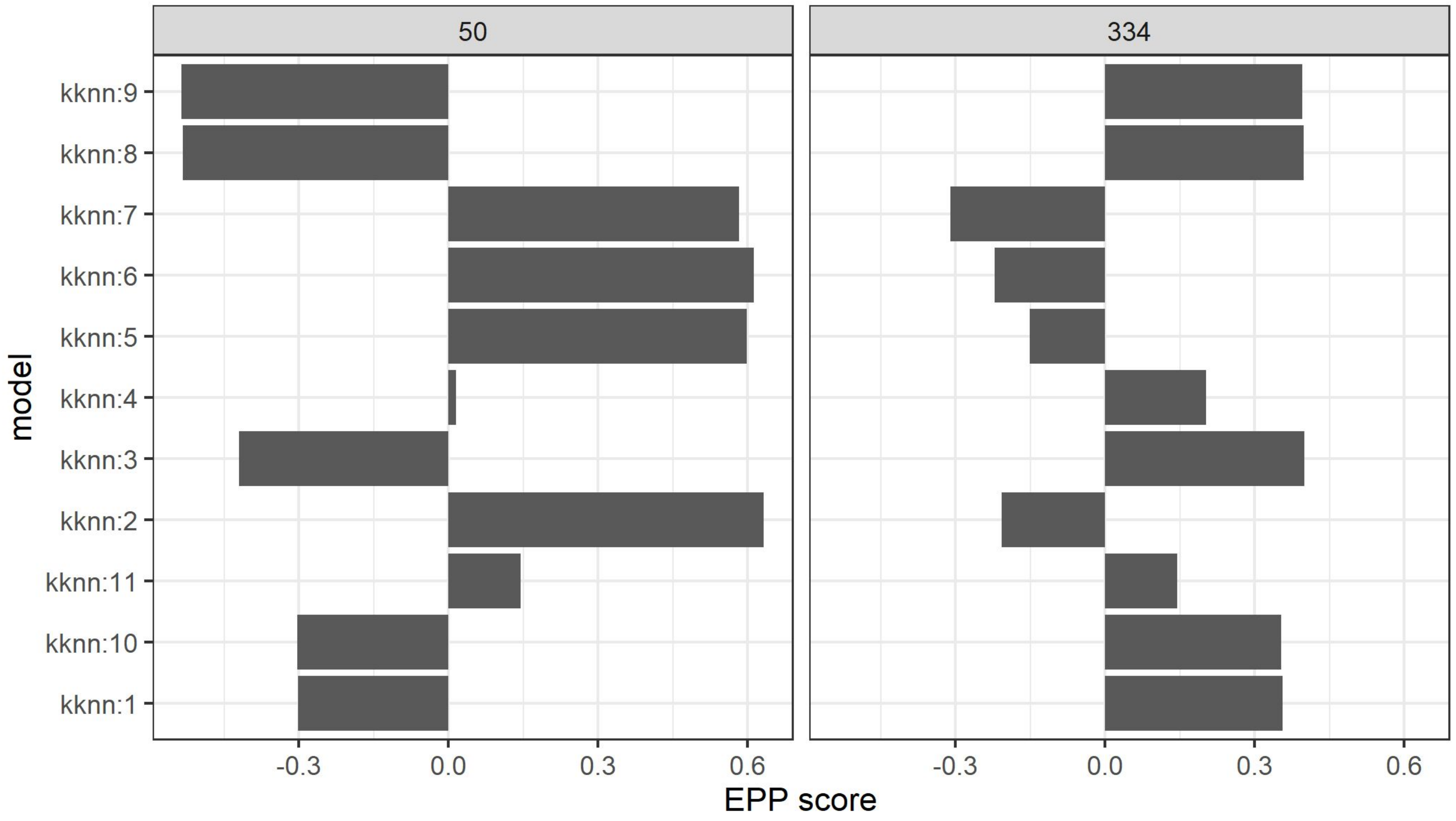


EPP scores for different hyperparameter settings



Takeouts

Takeouts

EPP: Elo-based Predictive Power score:

1) There is a probabilistic interpretation of differences in performance.

2) You can use EPP score to compare models across different hyperparameters and different data sets.

EPP: INTERPRETABLE SCORE OF MODEL PREDICTIVE POWER

A PREPRINT

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Weaknesses of most popular measures 3/3

3. How stable is the performance for different CV folds?

k	AUC AutoML_1	AUC AutoML_2
1	0.8	0.9
2	0.8	0.78
3	0.8	0.78
4	0.8	0.78
Mean AUC	**0.8**	**0.81**

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Mean AUC	**0.8**	**0.81**

Comparing just means across folds creates false impression that the AutoML_2 model is better than the AutoML_1.

Yet, we can see that AutoML_1 wins in 3 out of 4 folds.