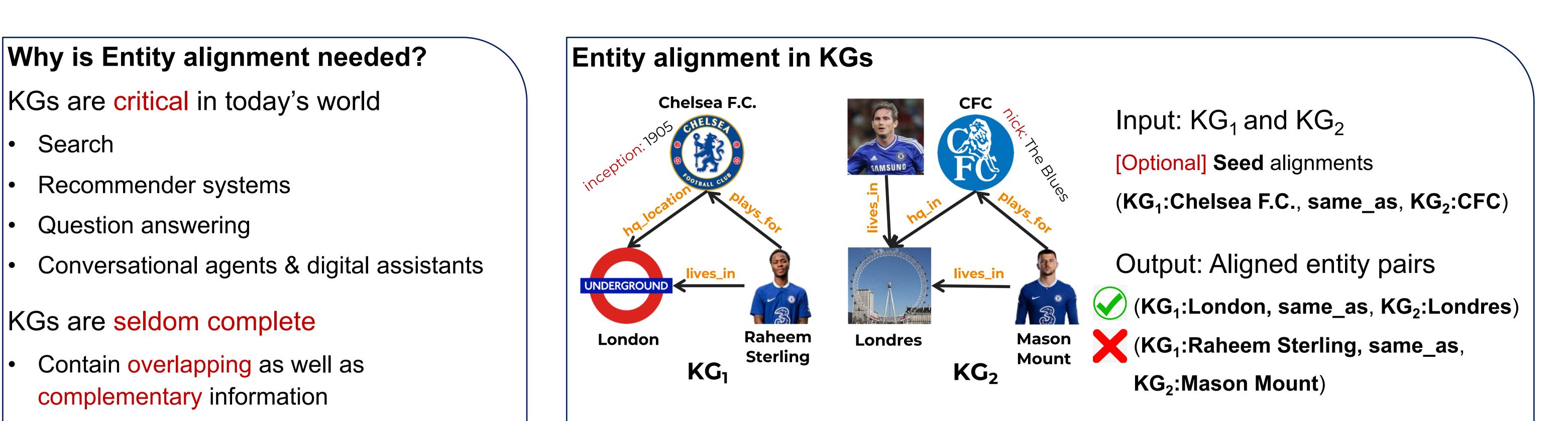
A Critical Re-Evaluation of Neural Methods for Entity Alignment Manuel Leone,* Stefano Huber,* <u>Akhil Arora</u>,* Alberto García Durán,* and Robert West Data Science Laboratory (DLAB), EPFL

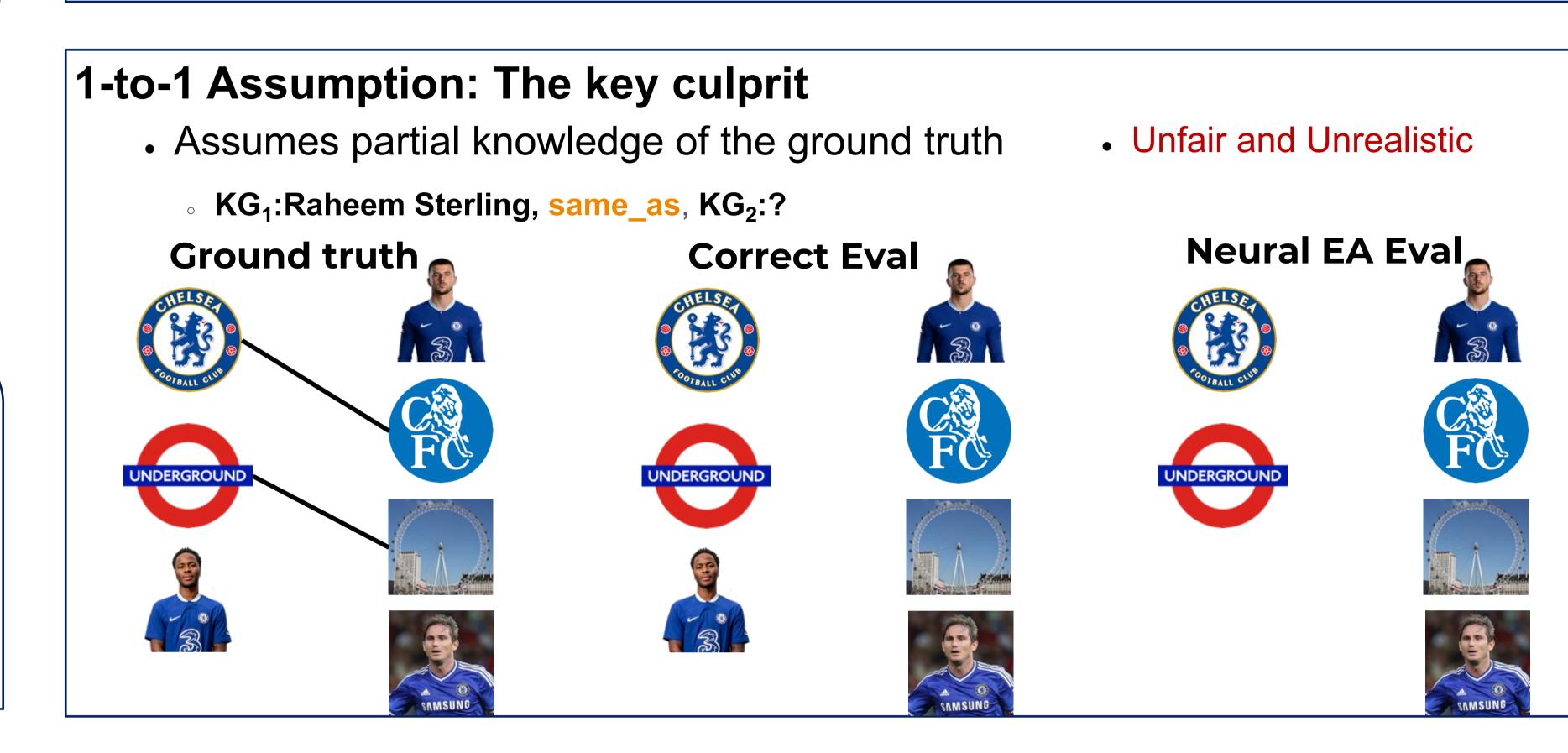


Why all the fuss?

- Hundreds of papers: semantic web, data management, NLP/IR/ML
- Endogamic comparisons!

Key research questions

- Is the evaluation setup employed by neural EA methods meaningful?
- What is the true progress achieved on account of neural EA?
- What lies in the future for neural EA?



Towards a realistic evaluation setup Approximate degree distribution Main Characteristics Туре Scope of original KGs OpenEA 1-to-1 assumption. Primary RealEA Primary no 1-to-1 assumption. No 1-to-1 assumption **XREALEA** no 1-to-1 assumption, cross-lingual. Primary Ablation no 1-to-1 assumption varying amount of supervision STIDREATEA

Datasets, datasets, datasets ...

	REALEA							
Dataset	DB-YG-15K	DB-WD-15K	DB-YG-100K	DB-WD-100K				
#Entities	19,865 - 21,050	20,038 - 19,581	126,145 - 136,211	129,847 - 137,721				
#Relations	290 - 32	306 - 214	386 - 32	456 - 329				
#Attributes	247 - 34	307 - 490	366 - 38	478 - 785				
#Rel. Triples	60,329 - 82,109	50,007 - 65,017	479,510 - 653,261	399,061 - 489,698				
#Att. Triples	129,330 - 392,845	85,331 - 112,786	677,721 - 1,427,545	566,073 - 668,925				
#Matchable Ent.	15,000	15,000	100,000	100,000				

SUPREALEA	Adiation	no 1-to-1 assumption, varying amount of supervision.
AttRealEA	Ablation	no 1-to-1 assumption, varying amount of attributes.
SpaRealEA	Ablation	no 1-to-1 assumption, sparser KG.
RealEA_NoObfs	Ablation	no 1-to-1 assumption, non-obfuscated URIs.
XREALEA_PURE	Ablation	no 1-to-1 assumption, purely cross-lingual.

Semantics free Entity URIs

Appropriate metrics: Prec/Rec/F1

instead of Hits@k/MRR

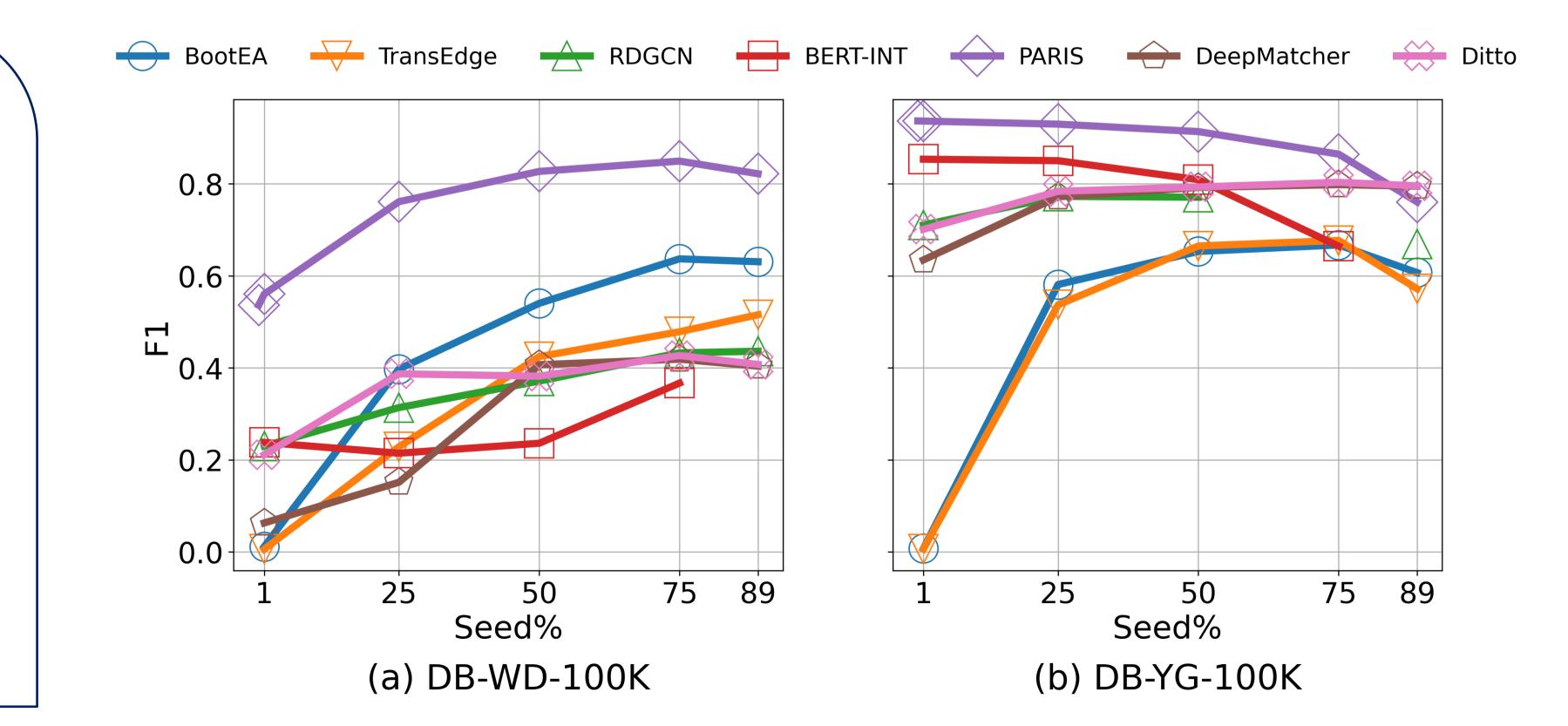
Results: RealEA

		DB-YG-15K (RealEA)		DB-WD-15K (REALEA)		DB-YG-100K (REALEA)			DB-WD-100K (REALEA)				
Category	Method	Precision	Recall	F_1 -score	Precision	Recall	F_1 -score	Precision	Recall	F_1 -score	Precision	Recall	F_1 -score
Neural (EA)	ВоотЕА	0.459 ± 0.008	0.313 ± 0.009	0.372 ± 0.007	0.609 ± 0.007	0.280 ± 0.009	0.383 ± 0.008	0.671 ± 0.005	0.487 ± 0.004	0.565 ± 0.003	0.548 ± 0.008	0.272 ± 0.007	0.363 ± 0.006
Neural (EA)	RDGCN	0.822 ± 0.003	0.709 ± 0.004	0.761 ± 0.003	0.583 ± 0.012	0.242 ± 0.009	0.342 ± 0.011	0.846 ± 0.001	0.708 ± 0.002	0.771 ± 0.001	0.538 ± 0.003	0.203 ± 0.001	0.295 ± 0.001
Neural (EA)	BERT-INT	0.817 ± 0.001	0.827 ± 0.004	0.822 ± 0.002	0.604 ± 0.030	0.075 ± 0.006	0.134 ± 0.010	0.841 ± 0.001	0.865 ± 0.006	0.853 ± 0.003	0.698 ± 0.009	0.120 ± 0.002	0.206 ± 0.003
Neural (EA)	TransEdge	0.335 ± 0.025	0.203 ± 0.017	0.253 ± 0.020	0.589 ± 0.126	0.183 ± 0.034	0.279 ± 0.054	0.566 ± 0.011	0.438 ± 0.018	0.494 ± 0.016	0.339 ± 0.041	0.147 ± 0.012	0.205 ± 0.018
Neural (RL)	DMATCH	0.851 ± 0.023	0.787 ± 0.014	0.821 ± 0.012	0.234 ± 0.009	0.162 ± 0.011	0.186 ± 0.013	0.878 ± 0.008	0.691 ± 0.007	0.773 ± 0.012	0.048 ± 0.021	0.344 ± 0.000	0.092 ± 0.014
Neural (RL)	Ditto	0.873 ± 0.012	0.821 ± 0.014	0.838 ± 0.003	0.339 ± 0.017	0.214 ± 0.004	0.262 ± 0.002	$\textbf{0.916} \pm \textbf{0.011}$	0.682 ± 0.001	0.784 ± 0.011	0.757 ± 0.012	0.248 ± 0.009	0.376 ± 0.008
Non-neural (EA)	Paris+	$\textbf{0.906} \pm \textbf{0.000} ~^{\dagger}$	$0.931\pm0.001^\dagger$	$\textbf{0.918} \pm \textbf{0.001}$	$0.928\pm0.002^\dagger$	$0.551\pm0.004^\dagger$	$0.691\pm0.003^\dagger$	$0.923\pm0.000^\dagger$	$0.939\pm0.000^\dagger$	$0.931\pm0.000^\dagger$	$0.927\pm0.001^\dagger$	$0.615\pm0.001^\dagger$	$\textbf{0.740} \pm \textbf{0.001}$

Takeaways

PARIS+ is the **best** EA method till date

- Statistically significantly better in quality
- Several orders of magnitude faster

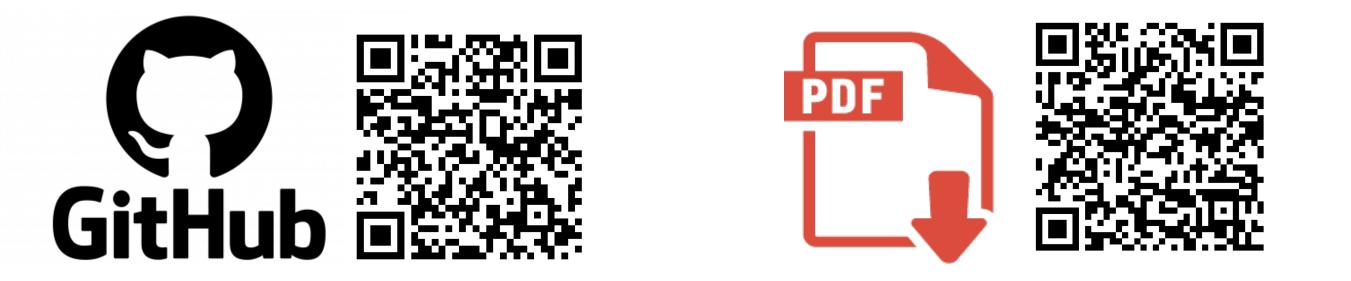


- ER/RL methods can perform EA reasonably well
- Not as good as PARIS+, but competitive to neural EA

Neural EA methods need to be repositioned to showcase their true potential

Broader Impact

- A nudge towards the end of endogamic comparisons
- Encouraging other communities to follow suit!





This work was presented at the 48th International Conference on Very Large Databases (VLDB), September 5–9, 2022, Sydney, Australia.