Towards Employing Recommender Systems for Supporting Data and Algorithm Sharing

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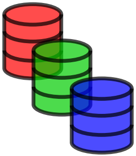
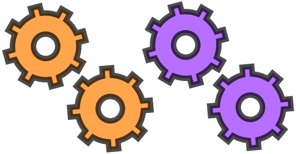
ACM SIGCOMM Data Economy Workshop 2022

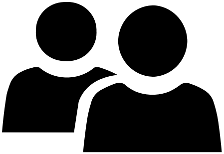
Motivation

- Data and algorithm sharing important for a data and AI-driven economy
- E.g., a company gains access to a dataset to enhance its AI pipeline
- Three key-players: Data Providers, Algorithm Providers, and Users
- Many datasets + many algorithms = Choice Overload

  $\Rightarrow$ **Recommender Systems for Data and Algorithm Sharing**

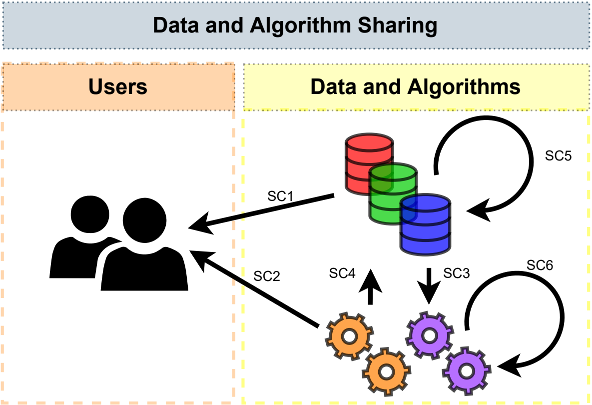






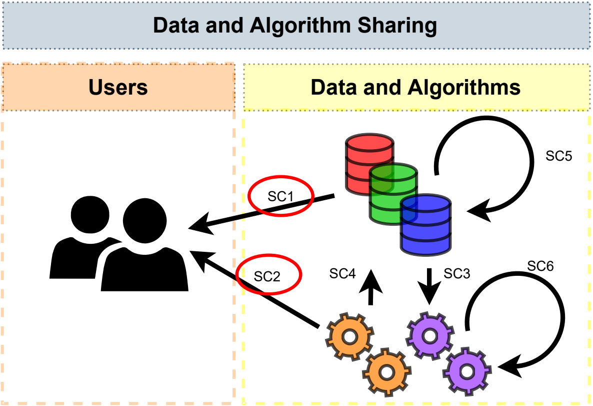
Data and Algorithm Sharing Platforms

- Comprises users and items (i.e., datasets and algorithms)
- Item-to-user and item-to-item recommendations possible



Six Recommendation Scenarios

- **Datasets to Users (SC1), Algorithms to Users (SC2)**
- Datasets to Algorithms (SC3), Algorithms to Datasets (SC4)
- Datasets to Datasets (SC5), Algorithms to Algorithms (SC6)



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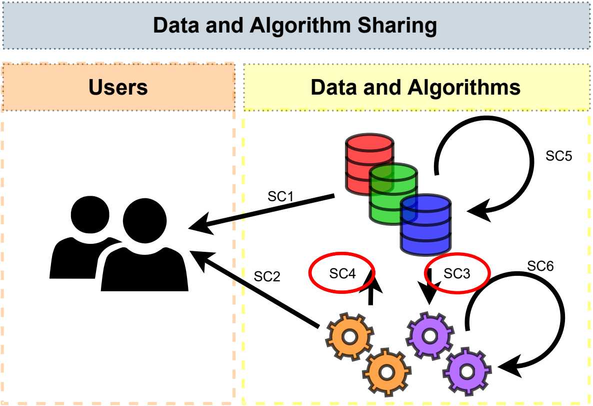

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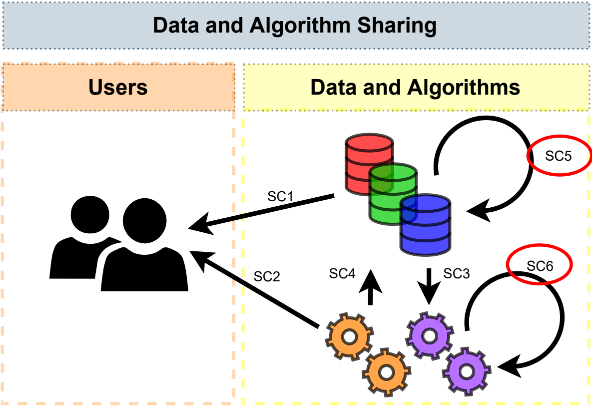
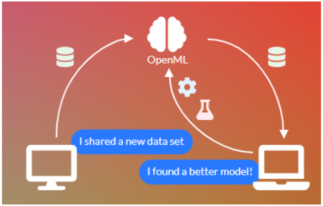


OpenML Dataset

- Retrieved from dataset and algorithm sharing platform OpenML[1]
- Interactions: User u applied algorithm a to dataset d
- Many (new) datasets and algorithms without interactions
- We want to predict interactions!



Users	512
Algorithms	1,307
Datasets	573
$\text{Algorithms}_{w/o\ Int.}$	11,037
$\text{Datasets}_{w/o\ Int.}$	2,104

} 10,945 Interactions

[1] https://www.openml.org/

Evaluation Procedure

Recommendation Algorithms

- *Most Popular (MP)*: Recommends the most popular items
- *Collaborative Filtering (CF)*: Recommends preferred items of similar target entities, i.e., those who get the recommendation
- *Content-based Filtering (CB)*: Recommends items similar to the ones the target entity prefers

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Evaluation Criteria

- Accuracy: How satisfied the target is with the recommendations
- Popularity Bias (Exploration Potential): How well the available items can be explored through recommendations

Results: Recommendation Accuracy

- CF generates the most accurate recommendations
- MP and CB perform poorly

Recommendation Scenario	Method	P@1	R@10	nDCG@10	Cov@10	RecPop@10
SC1 (Datasets to Users)	MP	0.00	0.22	0.08	0.01	593.79
	CF	**0.26**	**0.34**	**0.30**	0.06	181.50
	CB	0.05	0.05	0.04	**0.12**	**10.25**
SC2 (Algorithms to Users)	MP	0.03	0.11	0.07	0.00	265.75
	CF	**0.12**	**0.26**	**0.18**	0.02	90.51
	CB	0.02	0.06	0.03	**0.03**	**9.25**
SC3 (Datasets to Algorithms)	MP	0.00	0.12	0.04	0.01	555.20
	CF	**0.33**	**0.39**	**0.35**	0.06	143.36
	CB	0.00	0.13	0.09	**0.14**	**7.07**
SC4 (Algorithms to Datasets)	MP	0.01	0.29	0.18	0.00	270.62
	CF	**0.52**	**0.56**	**0.51**	0.01	97.56
	CB	0.01	0.03	0.02	**0.03**	**12.75**
SC5 (Datasets to Datasets)	MP	0.00	0.02	0.01	0.00	650.23
	CF	**0.17**	**0.44**	**0.28**	0.09	55.74
	CB	0.05	0.12	0.08	**0.28**	**14.88**
SC6 (Algorithms to Algorithms)	MP	0.01	0.02	0.01	0.00	278.32
	CF	**0.07**	**0.24**	**0.14**	0.02	55.01
	CB	0.04	0.12	0.07	**0.04**	**7.87**

Results: Recommendation Accuracy

- Highest accuracy for SC4: Many more algorithms (i.e., 1307) than datasets (i.e., 573) ⇒ accurate recommendations
- Lowest accuracy for SC6: Sparse/Large interaction space ⇒ poor recommendations

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Results: Recommendation Accuracy

- SC2 and SC4 have same item catalog and same no. of targets ($\approx$ 500 users, $\approx$ 600 datasets), but accuracy for SC2 is smaller than for SC4
- Reason: Users have larger profiles than datasets $\rightarrow$ more difficult to generate accurate recommendations

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Results: Popularity Bias (Exploration Potential)

- CB recommends most and least popular items
- Harder to explore larger item catalogs (i.e., algorithms)
- Many items remain unexplored

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Summary

Our findings

- Six recommendation scenarios between users, datasets, and algorithms
- CF produces accurate recommendations, CB covers most items
- Not all datasets and algorithms can be explored!
- Recommendation scenarios are different recommendation problems!

Future Work

- Monetization and financial constraints
- Privacy-related, legal, or economical concerns

Thank you!

OpenML Dataset

zenodo.org/record/6517031

Contacts

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