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- PhD student at the Vrije universiteit Amsterdam
- Research is mainly about job recommender systems and recruitment websites



- In this study we wish to address the problem of recognizing unique users from session data.
- Recognizing users from session data is typically an interplay between cookies and log-in.
- 20% of the internet users may delete their cookie at least once a week ¹.
- We study this problem by: 1) proposing a click simulation model,
 2) studying how effective (H)DBSCAN*-type algorithms are to this problem.

¹Dasgupta et al. Overcoming browser cookie churn with clustering. Proceedings of the fifth ACM international conference on Websearch and data mining, pages 83–92. ACM, 2012

- Introduction
- Literature
- Click simulation model
- \cdot MS-(H)DBSCAN* algorithms for session clustering
- Results and conclusion

- Specific type of entity/identity resolution problem ²
- $\cdot\,$ ICDM³ and CIKM 4 cross-device matching competitions
- Ambiguity in the literature:
 - Problem is addressed under different names (user stitching, visitor stitching, automatic identity linkage)
 - Problem is addresses from single and multiple website perspective

²Di et al. "node2bits: Compact Time-and Attribute-aware Node Representations", 2019
 ³ICDM 2015: Drawbridge Cross-Device Connections, 2015.

(https://competitions.codalab.org/competitions/11171)

⁽https://www.kaggle.com/c/icdm-2015-drawbridge-cross-device-connections)

⁴CIKM Cup 2016 Track 1: Cross-Device Entity Linking Challenge, 2016.

Research objective

We assume:

- Single website (a search engine)
- Homogeneous queries, but with different utility functions

Interested in:

- What simulation model should we use to obtain realistic simulated datasets, without making the simulation model overly complex?
- How effective are (H)DBSCAN*-type algorithms on clustering sessions compared to using cookies, in terms of multiple website statistics?
- Sensitivity of (H)DBSCAN*-type algorithms on the underlying dataset.

Why simulation?

- Have an actual ground truth (problem of unary classification).
- Sensitivity of clustering algorithm under different simulation settings.
- Quite some literature on models explaining website behavior on search engines ⁵.
- Most public data sets originate from large search engines/large advertisers. How generalizable are these for other websites?

⁵Chuklin et al. "Click models for web search." Synthesis lectures on information concepts, retrieval, and services 7.3 (2015): 1-115.

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- Users' item preferences: Fleder-Hosanagar model⁶.
- Interaction with search engine: Simplified Dynamic Bayesian Network click model⁷.
- **Cookie churn**: 1) modeling cookie lifetime, 2) allowing users to use multiple devices (with different cookie-IDs).

⁶Fleder et al. "Blockbuster culture's next rise or fall: The impact of recommender systems on sales diversity. Management science", 55(5):697–712, 2009

⁷Chapelle et al. "A dynamic bayesian network click model for web search ranking." Proceedings of the 18th international conference on World wide web. 2009.

Simulation summary

- Draw items V and users U and compute each user's attraction and satisfaction over all items using Fleder's model;
- ² for $u \in \mathcal{U}$ do
- 3 Draw initial device, cookie lifetime;
- 4 Set t and t_{start} to arrival time of u, draw user lifetime T_{u}^{user} ;
- 5 $i \leftarrow 1;$

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6 while t \leq t_{start} + T_u^{user} do
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- Simulate clicks for query session *i* according to SDBN, items are presented according to a popularity recommender:
 - Draw $T_{\mu i}^{abs}$ and update t;

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Update device and cookies;
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10 i \leftarrow i + 1
```

11 end

12 end

7

8

9

User (u) 1	Query- session (i)	Cookie (o)	Device (d)	List position	Item (v)	t	Click/ skip
1	1	1	1	1	12	12	1
1	1	1	1	2	13	12	0
1	1	1	1	3	44	12	0
1	1	1	1	10	84	12	0
2	1	1	2	1	5	12	0
312	32	2	2	1	871	16	0

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Results

		APE	KL-div.			New
		unique	session	KL-div		user
Model	Dataset	users	count	conversion	ARI	accuracy
MS-DBSCAN	train	15	0.55	0.13	0.0012	0.56
MS-DBSCAN _P	train	77	0.74	0.092	0.14	0.5
DBSCAN-RAND	train	0.011	1	0.096	0.0002	0.42
MS-HDBSCAN*+	train	10	0.75	0.15	0.00079	0.52
MS-HDBSCAN*-	train	10	0.75	0.15	0.00079	0.52
MS-HDBSCAN*	train	0.011	0.9	0.11	0.092	0.46
MS-HDBSCAN*	train	0.011	0.9	0.11	0.1	0.46
OBS	train	15	0.017	0.0032	0.91	0.95
MS-DBSCAN	valid	60	0.11	0.0026	0.0022	0.56
MS-DBSCAN _P	valid	6.8	1.4	0.13	0.0015	0.4
DBSCAN-RAND	valid	40	0.32	0.015	0.00046	0.5
MS-HDBSCAN*+	valid	53	0.16	0.0042	0.002	0.55
MS-HDBSCAN*-	valid	53	0.16	0.0042	0.002	0.55
MS-HDBSCAN* ⁺ _P	valid	7.2	1.4	0.13	0.0015	0.4
MS-HDBSCAN*	valid	7.2	1.4	0.13	0.0015	0.4
OBS	valid	51	0.1	0.0076	0.91	0.95

Conclusion

- We presented a click simulation model with cookie censoring and illustrated its usage and advantages on the problem of uncovering users from their web sessions.
- Usage of cookie-IDS as clusters outperforms MS-(H)DBSCAN*-type algorithms on the homogeneous query case;
- Of the MS-(H)DBSCAN*-type algorithms, MS-DBSCAN significantly outperformed other MS-(H)DBSCAN* type algorithms in terms of ARI, including DBSCAN-RAND;
- Increasing ARI or new user accuracy also seems to increase the unique user average percentage error;
- Increasing the signal (e.g.,by increasing the number of clicks) improved the results, but slightly.

- What happens if we move to a multi-query case?
- Adjust clustering approaches using supervised methods s.t. they are less prone to overfitting.
- Holistic research on cookie (censoring) models.