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Real-time Recommender Systems in Multi-Domain Settings

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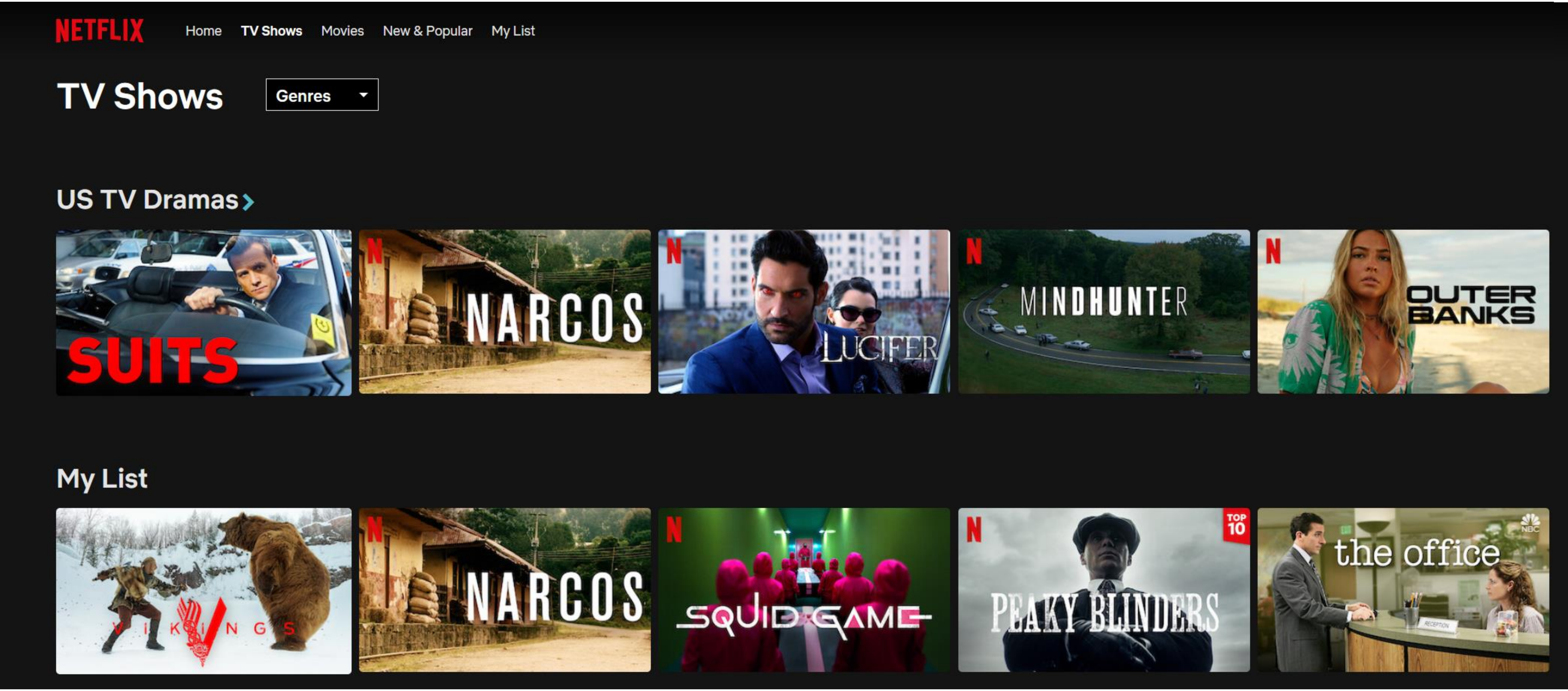
ISDS INSTITUTE OF INTERACTIVE SYSTEMS AND DATA SCIENCE

Know Center


NETFLIX
Home
TV Shows
Movies
New & Popular
My List
TV Shows
Genres
US TV Dramas
SUITS
NARCOS
LUCIFER
MINDHUNTER
OUTER BANKS
My List
NARCOS
SQUID GAME
TOP 10
PEAKY BLINDERS
the office

What if we want to provide recommendations in **multiple domains**?

E-COMMERCE	NEWS ARTICLES	ONLINE GAMING
MUSIC	TOURISM	E-LEARNING
HUMAN RESOURCES	VIDEO	EVENTS
HEALTH	FINANCE	INSURANCE

35%

Amazon

of what **consumers purchase** are a direct result from personalized recommendations

CONVERSION RATE

KPI

E-COMMERCE	NEWS ARTICLES	ONLINE GAMING
MUSIC	TOURISM	E-LEARNING
HUMAN RESOURCES	VIDEO	EVENTS
HEALTH	FINANCE	INSURANCE

Source:
www.freepik.com

Big Data – and now?

Need to support **frequent updates**

Demand for **real-time** data processing and recommendation

Many **different domain-specific** data features

- All potentially **useful** data sources!

Research Gap

Simultaneously deal with:

- Multiple domain-specific **requirements**
- Heterogenous information **sources**
- Frequent and diverse data **updates**
- Need for real-time **processing**

Lacic, E. (2016). **Real-Time Recommendations in a Multi-Domain Environment.** *In Extended Proceedings at Doctoral Consortium of the 27th ACM Conference on Hypertext and Social Media (HT'16)*

RQ1 — How does **combining** different **data** sources and recommender **approaches** impact the **robustness** of recommendations?

RQ2 — How can we address **customization**, **scalability** and **real-time** performance across **multiple** recommender systems **domains**?

RQ3 — How can we balance the **trade-off** between **accuracy** and **runtime** in real-time recommender systems?

RQ4 — How can we improve real-time recommendations **beyond accuracy**?

How does **combining** different **data** sources and recommender **approaches** impact the **robustness** of recommendations?

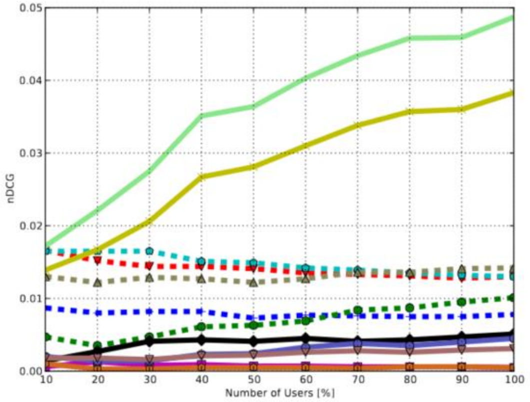
MP1

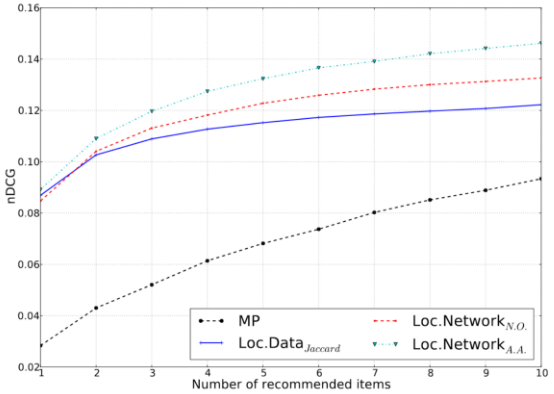
Lacic, E., Kowald, D., Eberhard, L., Trattner, C., Parra, D., and Marinho, L. B. (2015). **Utilizing online social network and location-based data to recommend products and categories in online marketplaces**. *In Mining, Modeling, and Recommending'Things' in Social Media (pp. 96-115). Springer.*

			Products			low-level categories			top-level Categories				
Sets			*nDCG@10*	*P@10*	*R@10*	*nDCG@10*	*P@10*	*R@10*	*nDCG@10*	*P@10*	*R@10*	*D@10*	*UC*
Most Popular			.0082	.0021	.0122	.0185	.0207	.0157	.2380	.2730	.2221	.5945	100.00%
Weighted Sum	Market	Content	.0158	.0107	.0145	.1109	.0933	.1085	**.5292**	**.4651**	.5251	.6389	99.79%
	Social	Content	.0029	.0018	.0024	.0527	.0433	.0572	.4216	.3264	.4495	.5589	81.65%
		Network	.1422	**.1188**	.1460	.1643	.1425	.1755	.3940	.3375	.4044	.4589	71.53%
		Combined	**.1427**	.1174	**.1465**	**.1821**	**.1531**	**.1968**	.5223	.4125	.5450	.6241	92.70%
	Location	Content	.0035	.0020	.0028	.0531	.0425	.0594	.5139	.3843	**.5583**	.6963	100.00%
		Network	.0015	.0007	.0010	.0330	.0283	.0377	.3535	.2670	.3766	.4864	70.59%
		Combined	.0031	.0021	.0030	.0537	.0439	.0601	.5152	.3883	.5563	.6932	100.00%
	Combined		.1477	.1206	.1515	**.2086***	.1740	**.2197***	**.5868***	.4734	**.5994***	.6630	100.00%
	Combined Top 3		**.1498***	**.1246***	**.1540***	.2078	**.1829***	.2174	.5696	**.4878***	.5809	.6521	100.00%

Utilizing **additional information sources** can lead to **more robust recommenders** with respect to accuracy, diversity, and user coverage

The use of **additional data** helps **mitigate** the **cold-start** problem, i.e., when a new user comes to the system.





How can we address **customization**, **scalability** and **real-time** performance across **multiple** recommender systems **domains**?

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MP4

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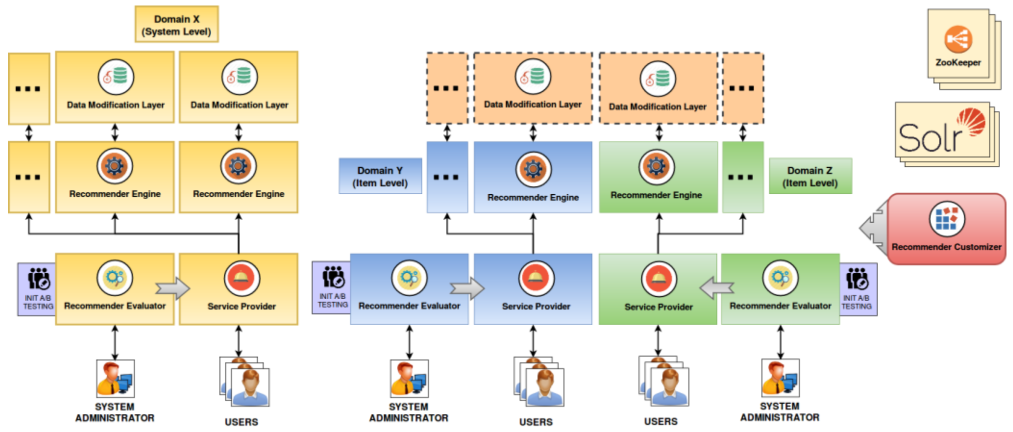
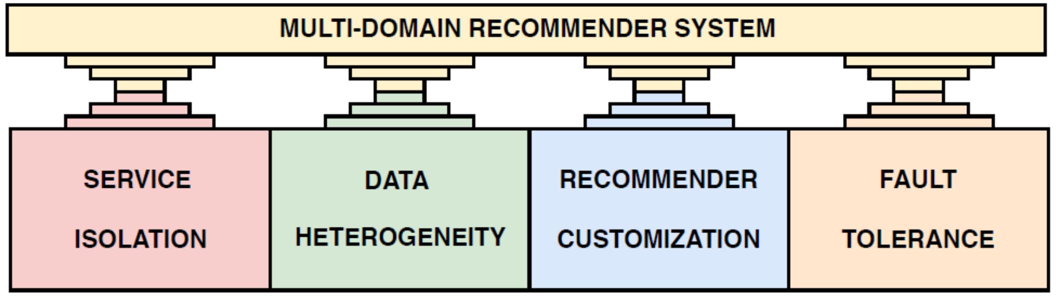
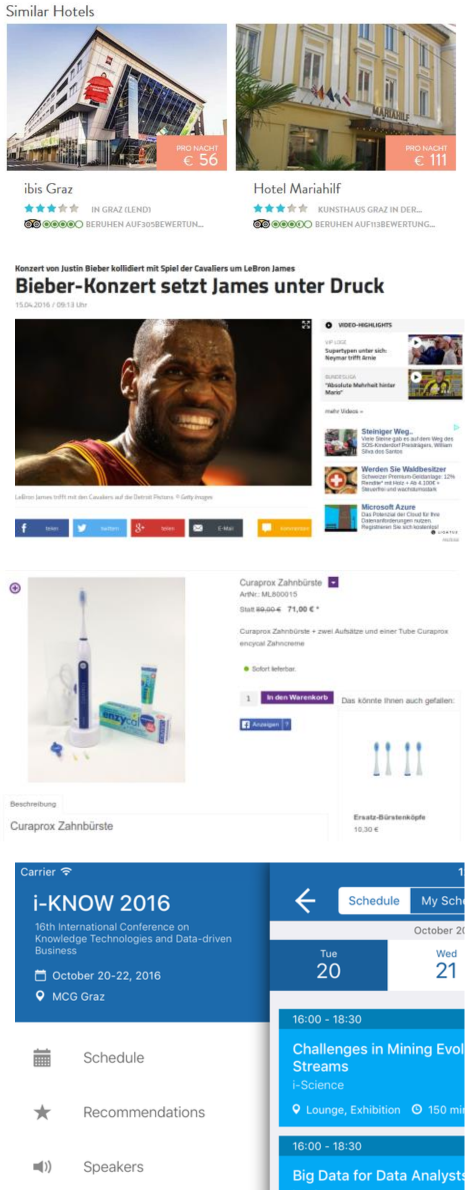
SocRecM → Scalable Recommendations-as-a-Service (ScaR)

- Suited for providing recommendations in an environment where multiple domains need to be simultaneously supported in real-time
- **Design principles** and **architecture** that is easily adapted for different recommendation scenarios







How can we balance the **trade-off** between **accuracy** and **runtime** in real-time recommender systems?

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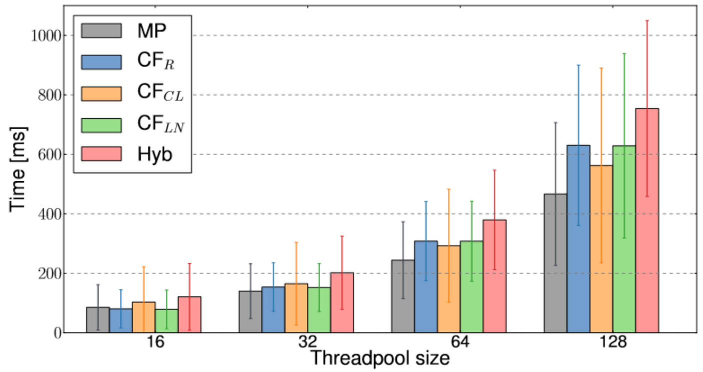
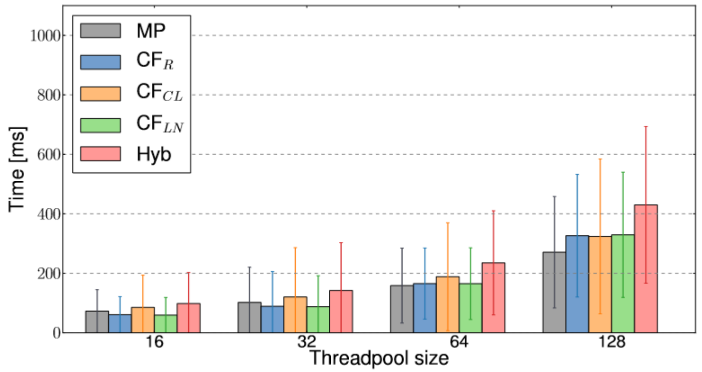
MP4 — **Lacic, E.** (2016). **Real-Time Recommendations in a Multi-Domain Environment**.*In Extended Proceedings at Doctoral Consortium of the 27th ACM Conference on Hypertext and Social Media (HT'16)*

MP5 — **Lacic, E.**, Reiter-Haas, M., Duricic, T., Slawicek, V. and Lex, E. (2019). **Should we Embed? A Study on the Online Performance of Utilizing Embeddings for Real-Time Job Recommendations**. *In Proceedings of the 13th ACM Conference on Recommender Systems (RecSys'2019). ACM*

- Efficient data handling and horizontal **scaling** to support the desired number of recommendation requests
  - i.e., minimize the impact on the runtime performance of individual algorithms



SCALE-UP



- Improvements can be done on an algorithmic level
  - e.g., a **user pre-filtering step** to build a smaller set of candidate neighbors in a greedy manner for Collaborative Filtering

	Approach	$\overline{T}$ (ms)	σ (ms)	$P@10$	$R@10$	$nDCG@10$	UC
	Most Popular	78.59	20.00	.0285	.0285	.0232	**100%**
CF	CF_{Full}	2,053.45	9,600.63	.0611 (.0918)	.0527 (.0792)	.0316 (.0475)	66.56%
CF	$CF_{OV=20}$	**59.56**	**60.08**	.0586 (.0890)	.0541 (.0821)	.0318 (.0483)	65.87%
CF	$CF_{OV=40}$	65.47	69.61	.0689 (.1042)	.0645 (.0974)	.0378 (.0571)	66.21%
CF	$CF_{OV=60}$	74.62	85.83	**.0724 (.1095)**	**.0678 (.1026)**	**.0396 (.0599)**	66.10%
CF	$CF_{OV=80}$	82.40	102.75	.0707 (.1077)	.0661 (.1007)	.0386 (.0588)	65.62%
CF	$CF_{OV=100}$	87.38	115.17	.0693 (.1055)	.0646 (.0983)	.0373 (.0568)	65.70%

How can we improve real-time recommendations **beyond accuracy**?

MP5

Lacic, E., Reiter-Haas, M., Duricic, T., Slawicek, V. and Lex, E. (2019). **Should we Embed? A Study on the Online Performance of Utilizing Embeddings for Real-Time Job Recommendations**. *In Proceedings of the 13th ACM Conference on Recommender Systems (RecSys'2019). ACM*

MP6

Lacic, E., Reiter-Haas, M., Kowald, D., Dareddy, M. R., Cho, J. and Lex, E. (2020). **Using Autoencoders for Session-based Job Recommendations**. In the Journal of *User Modeling and User-Adapted Interaction (UMUAI). Springer*

Goals:

Investigate the trade-off between **accuracy** and **beyond-accuracy** in an:

- Offline setting
- Online setting

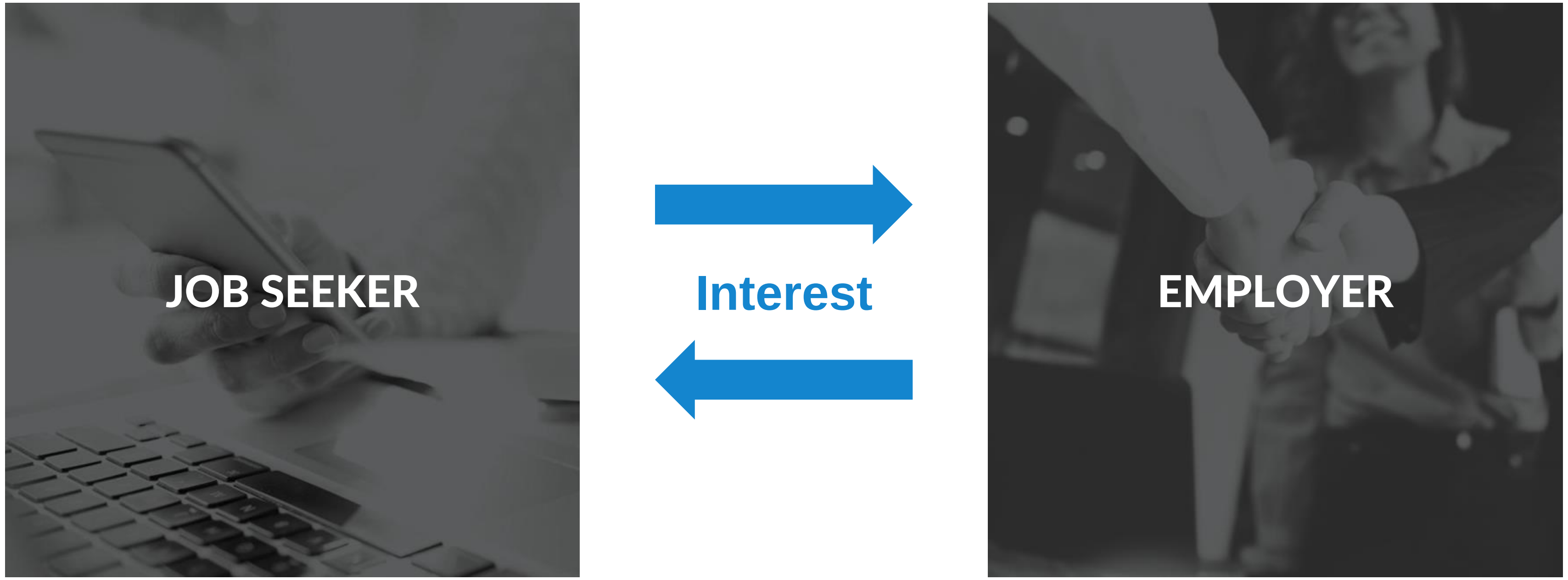
Optimize on **beyond-accuracy** for anonymous user sessions:

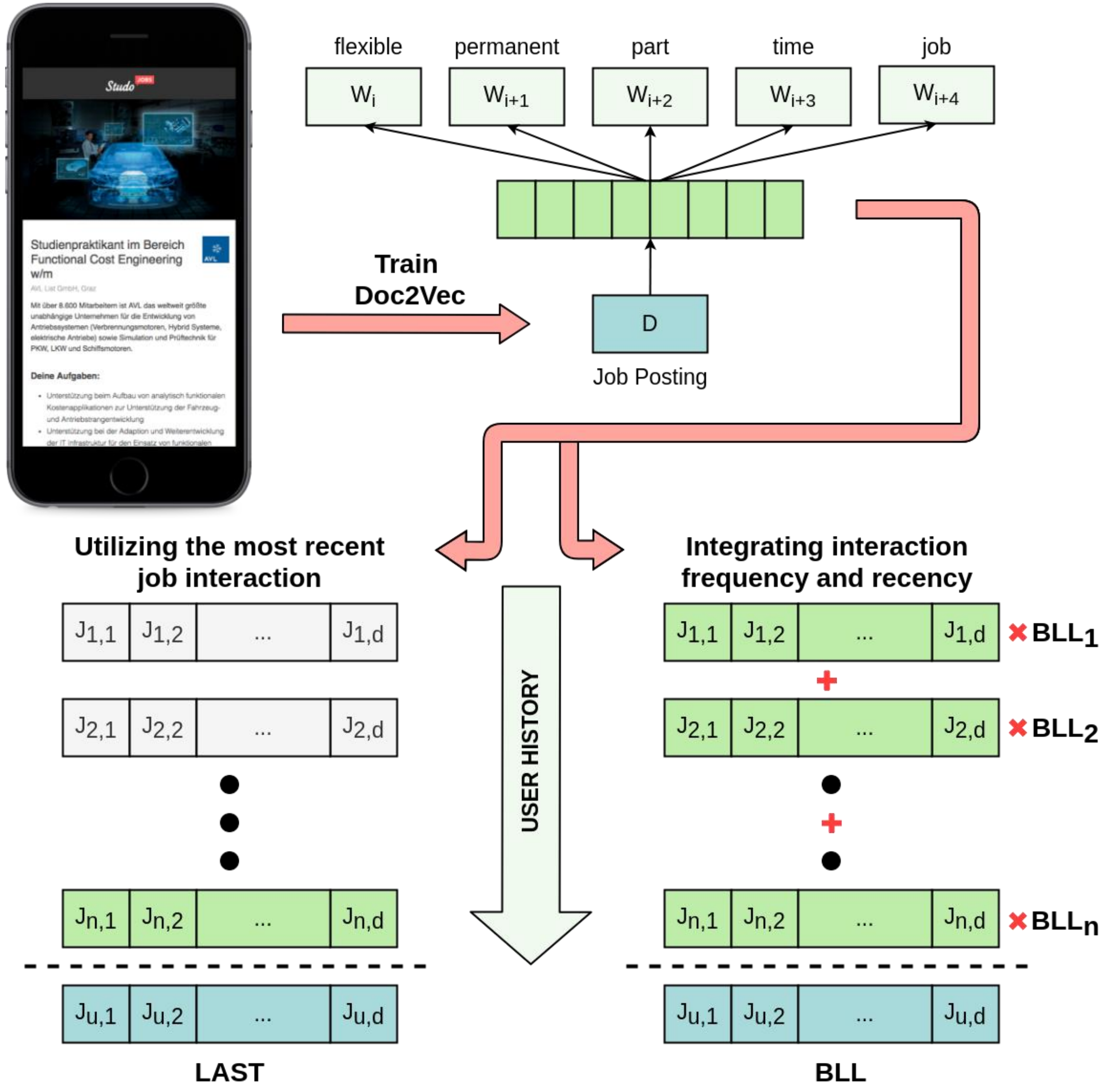
- Frequent scenario for real-time recommender systems in the real world

OFFLINE SETTING

ONLINE SETTING

ANONYMOUS SESSIONS


JOB SEEKER
Interest
EMPLOYER

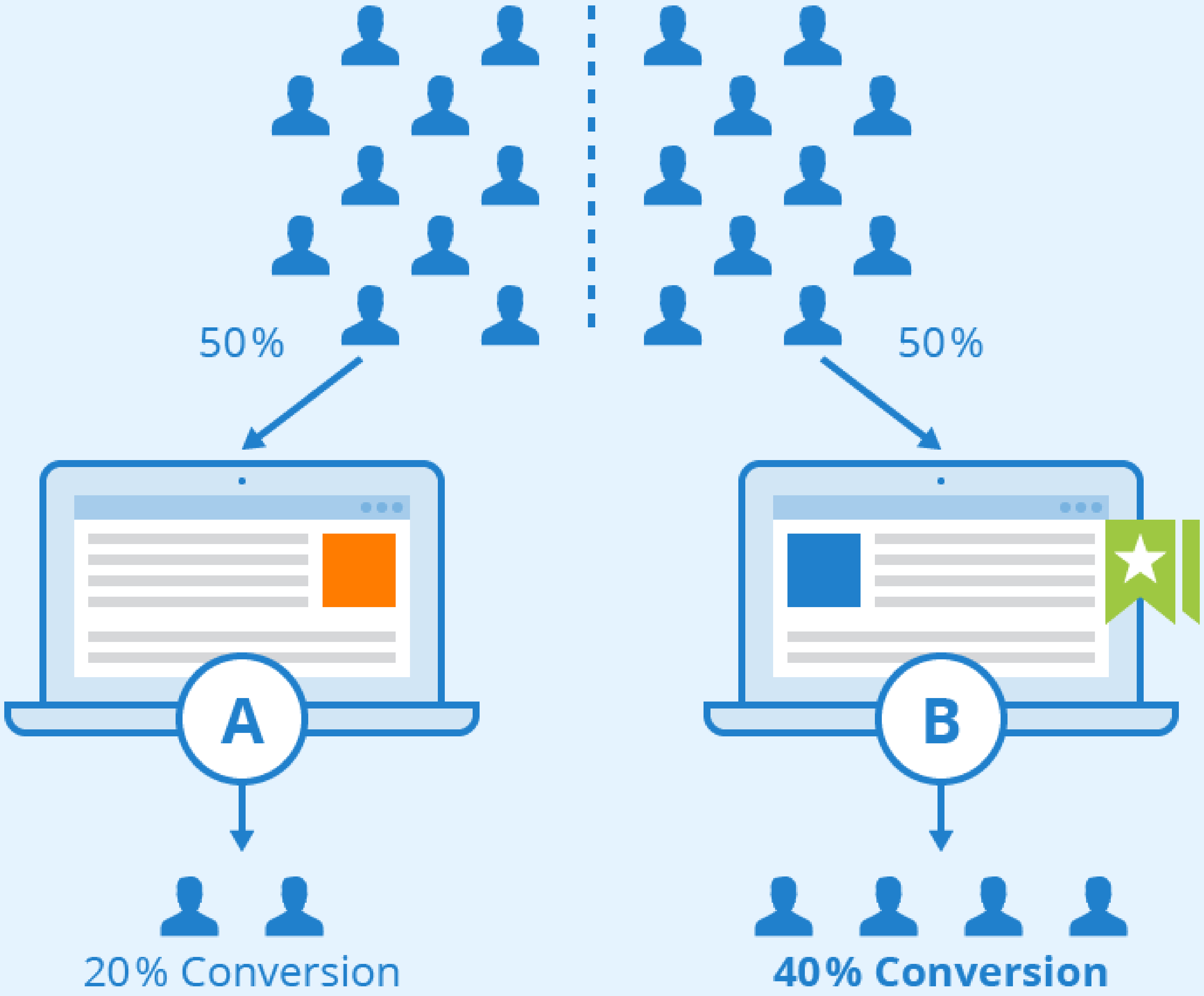


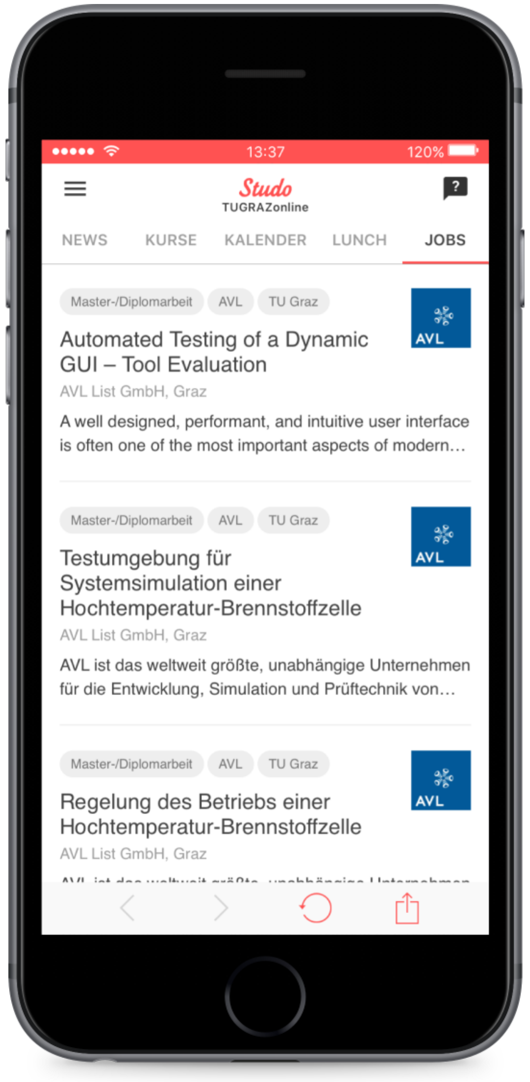
Integrating frequency and recency on item embeddings provides a good **trade-off** between **Novelty**, **Diversity** and **Accuracy**

			Novelty	Diversity	nDCG
Doc2Vec	LAST	d=100	.7469	.4845	.0170
		d=200	.7389	.5091	.0182
		d=300	.7352	.5163	.0177
	AVG	d=100	.7525	.6929	.0107
		d=200	.7870	.7455	.0099
		d=300	.8085	.7439	.0091
	BLL	d=100	.7300	.5974	.0156
		d=200	.7516	.6408	.0146
		d=300	.7609	.6388	.0144

BEYOND ACCURACY:

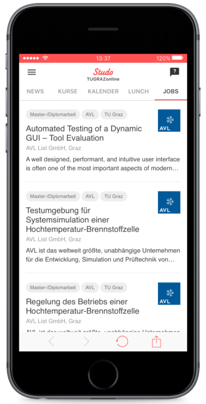
ONLINE SETTING

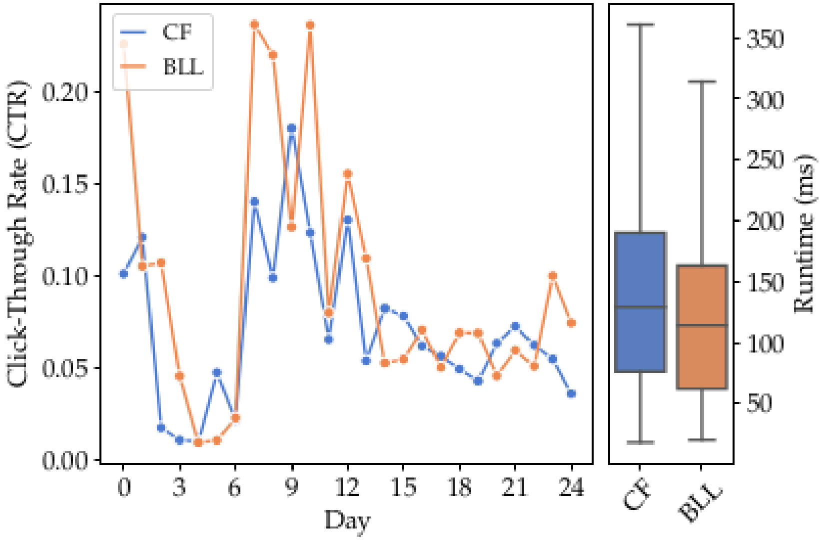

50%
50%
A
B
20% Conversion
40% Conversion



HOMEPAGE PERSONALIZATION

Location Context: Homepage

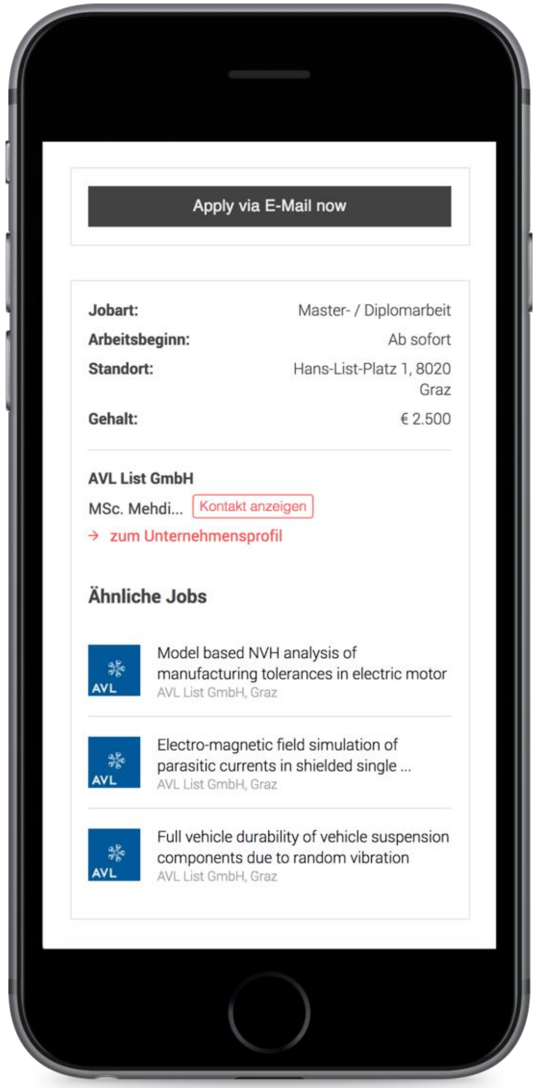




 # Days: 25
 # Distinct Users: 9,620
 # Recommendation Requests: 26,334

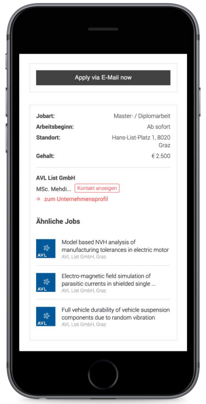
Approach	CTR	↗	Runtime (ms)	↘
BLL	**0.0671***	15.69%	**114****	13.64%
CF	0.0580		132	

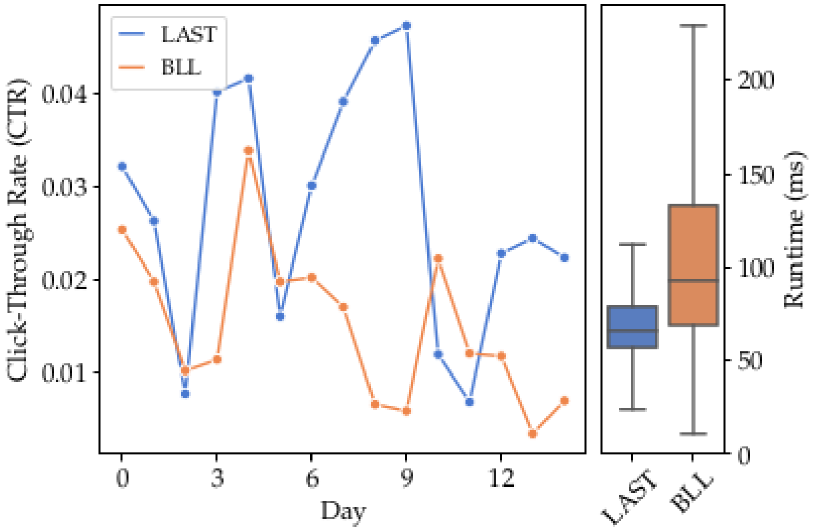
By combining embeddings with BLL we can improve both the **user acceptance** and **runtime** performance.



DETAILS PAGE PERSONALIZATION

Location Context: Details Page



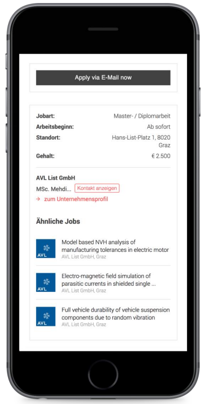


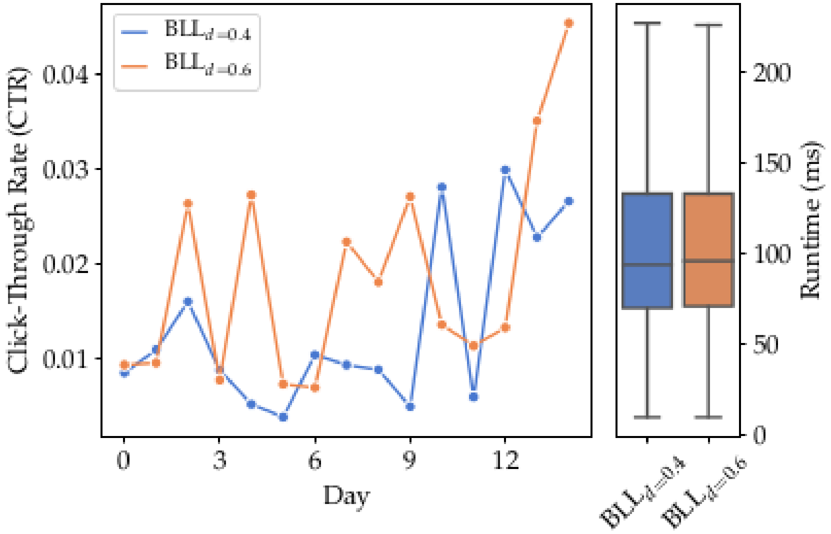
 # Days: 15
 # Distinct Users: 4, 715
 # Recommendation Requests: 18, 464

Approach	CTR	↗	Runtime (ms)	↘
LAST	**0.0249****	75.35%	**67****	28.72%
BLL	0.0142		94	

The much **simpler** and **runtime efficient** LAST strategy exhibits a **better user acceptance** when recommending similar jobs.

Location Context: Details Page





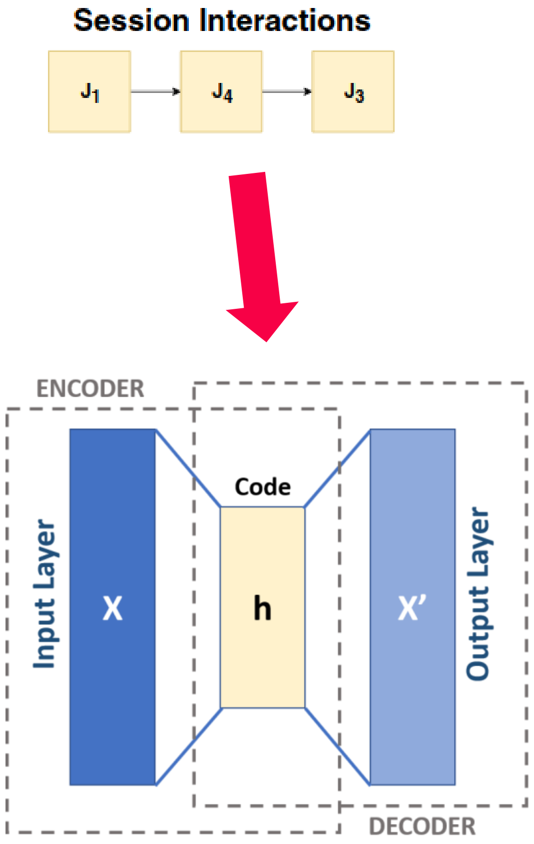
 # Days: 15
 # Distinct Users: 3, 375
 # Recommendation Requests: 11, 992

Approach	CTR	↗	Runtime (ms)	↘
$\mathrm{BLL}_{d=0.6}$	**0.0174***	35.94%	97	2.06%
$\mathrm{BLL}_{d=0.4}$	0.0128		**95**	

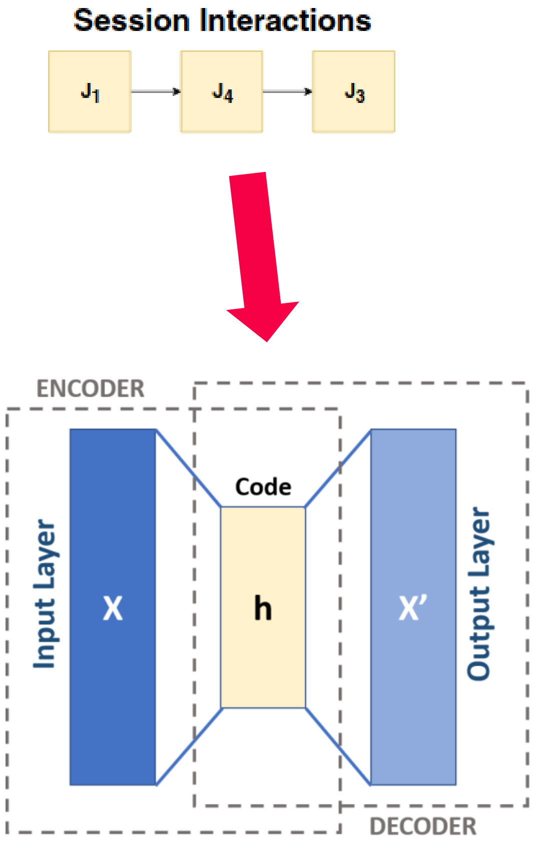
Location context matters with respect to what kind of recommendations the user expects!
Users expect recommendations that are related to the **recent history** (i.e., less exploration).

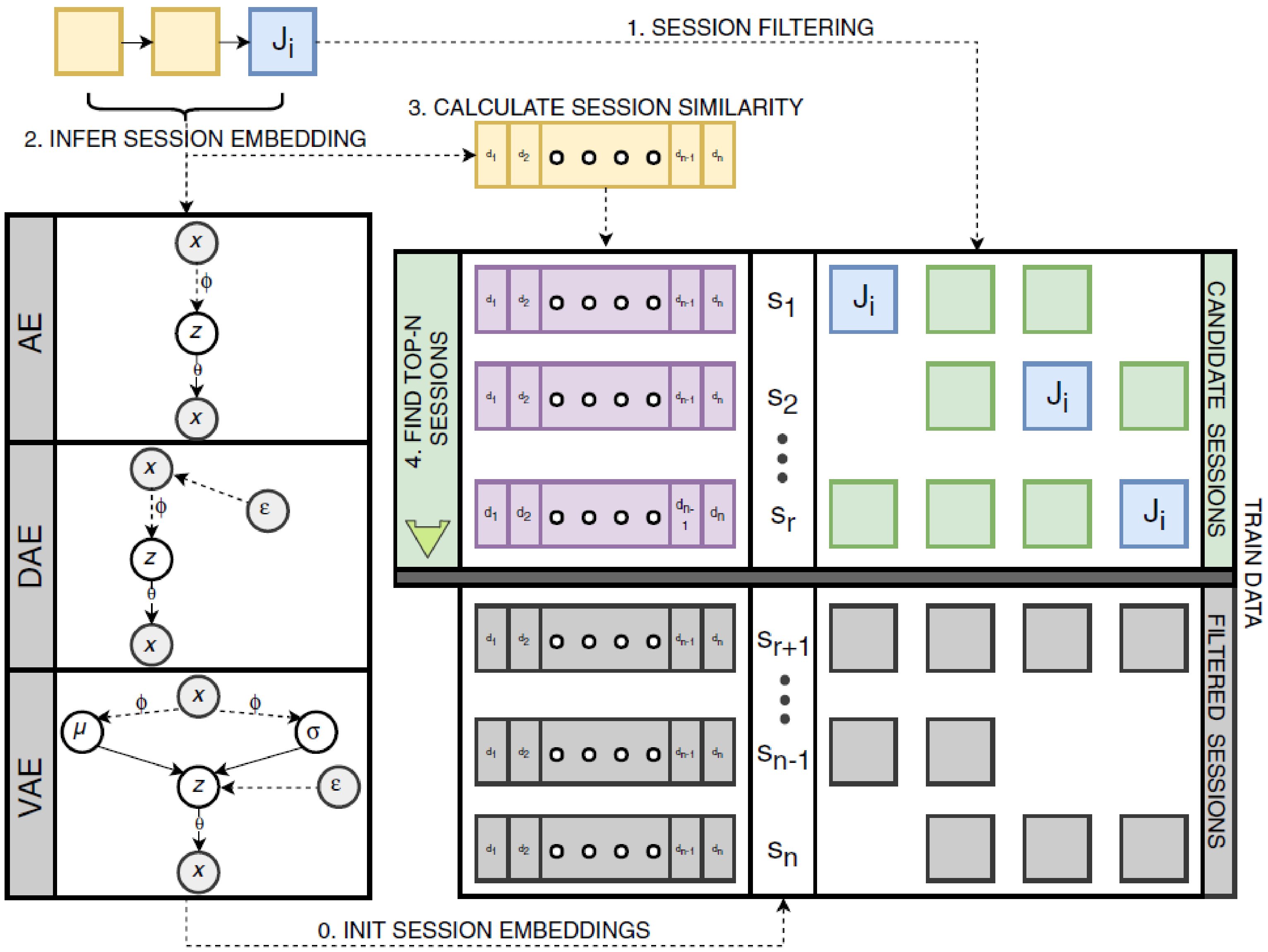
BEYOND ACCURACY:

ANONYMOUS USER SESSIONS



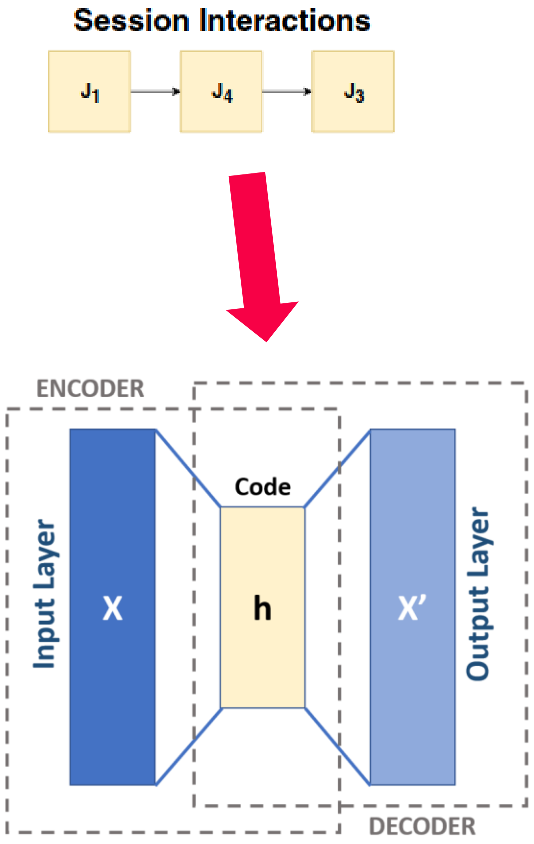
A novel method that uses **neural autoencoders** to infer **session embeddings** which are utilized in a **kNN** manner

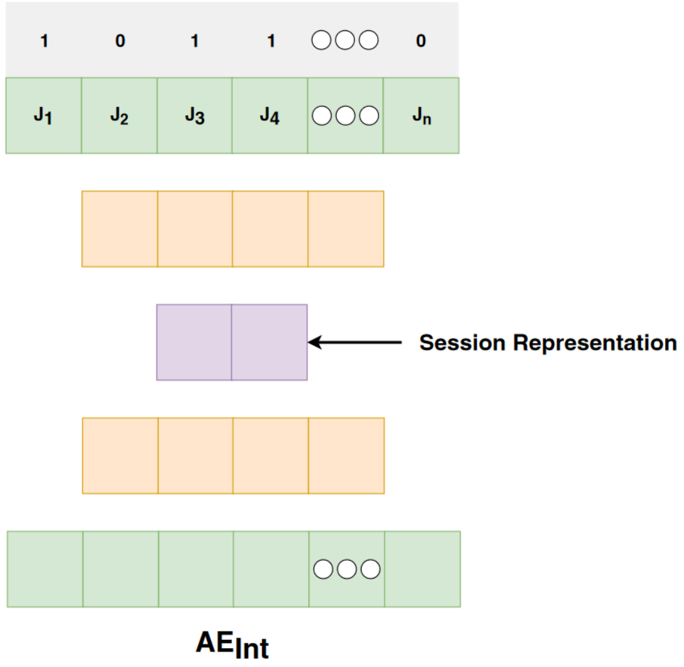

Session Interactions
J1
J4
J3
ENCODER
Input Layer
X
Code
h
X'
Output Layer
DECODER

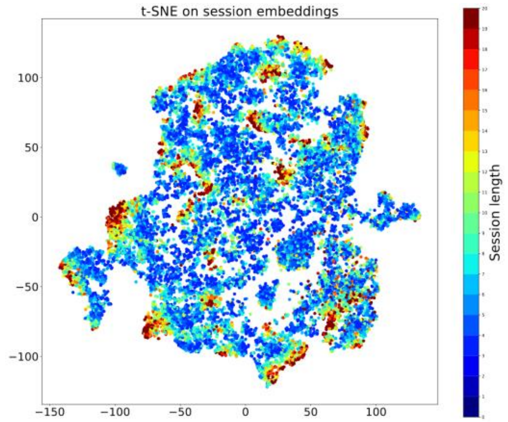

Ji
1. SESSION FILTERING
2. INFER SESSION EMBEDDING
3. CALCULATE SESSION SIMILARITY
AE
DAE
VAE
x
z
ϕ
θ
ε
μ
σ
4. FIND TOP-N SESSIONS
s1
s2
sr
sr+1
sn-1
sn
CANDIDATE SESSIONS
FILTERED SESSIONS
TRAIN DATA
0. INIT SESSION EMBEDDINGS

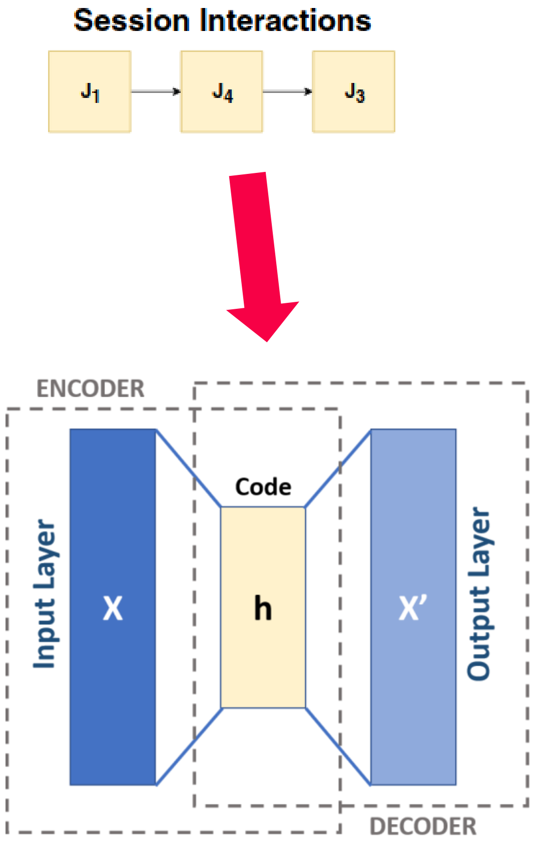
Either by:

1) Only considering **user interactions**



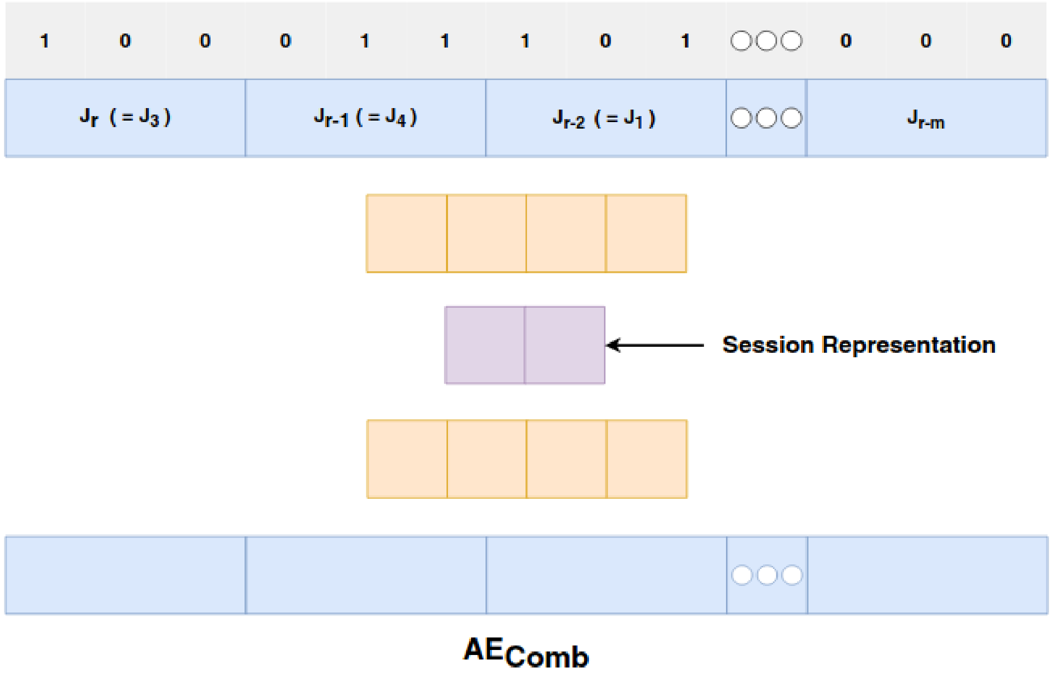


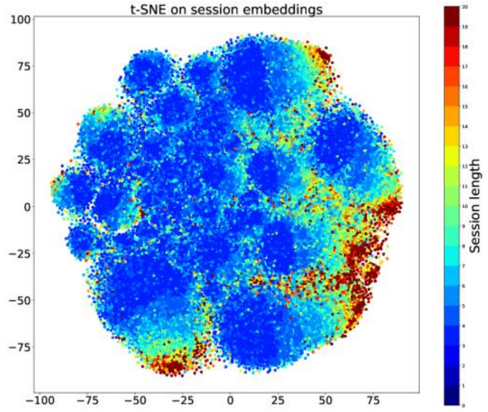




Either by:

1) Only considering **user interactions**
2) Adding 1-hot **encoded content features** for every job interaction





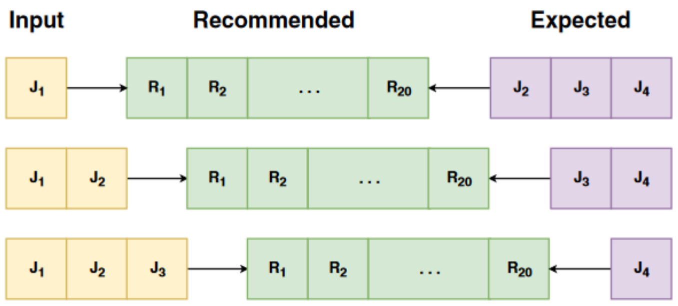
$$sKNN(s_t, j_i) = \sum_{i=1}^{n} sim(s_t, s_i) \times 1_{s_i}(j_i)$$

Beyond Accuracy Optimization

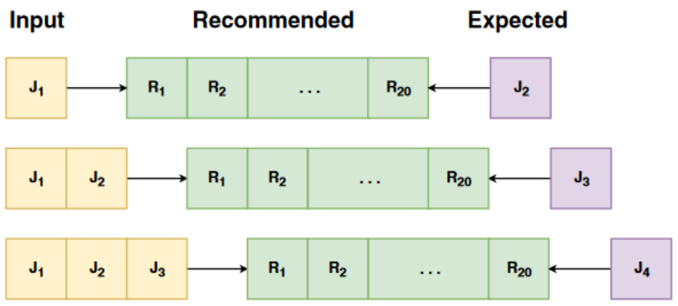
System-based novelty
- Introduce job postings that have not been (frequently) experienced before in the system

Session-based novelty
- Represents how surprising or unexpected the recommendations are for a specific session

Coverage
- How many jobs a recommender approach can cover with its predictions



Testing for the Remaining Jobs in a Session



Testing for the Next Job in a Session

Beyond Accuracy Optimization

System-based novelty
- Introduce job postings that have not been (frequently) experienced before in the system

Session-based novelty
- Represents how surprising or unexpected the recommendations are for a specific session

Coverage
- How many jobs a recommender approach can cover with its predictions

"++" indicates best, "+" good, "o" average, "-" low and "- -" the worst ranking with respect to (1) accuracy (i.e., nDCG and MRR), (2) beyond-accuracy (i.e., EPC and EPD) and (3) coverage

	Accuracy	Beyond Accuracy	Coverage
VAE_{Int}	++	++	++
VAE_{Comb}	+	++	++
sKNN	+	o	+
V-sKNN	++	+	++
S-sKNN	++	+	+
GRU4Rec	++	+	+
pRNN	- -	- -	- -
Bayes	- -	- -	o
iKNN	o	-	+
BPR-MF	-	- -	++
POP	- -	- -	- -

Notable **improvement** on **beyond accuracy** measures while achieving **comparable accuracy** results wrt. state-of-the-art session-based recommendation approaches.

Contributions:

RQ1

- Utilizing **additional information sources** leads to **more robust recommenders**
- Especially helpful in **mitigating the cold-start** problem

RQ2

- Four different **design principles** for a multi-domain recommender system
- A **scalable** and **customizable architecture** adapted to multiple domains (**ScaR framework**)

RQ3

- Runtime performance can be improved by **adapting** the **underlying algorithms**
- **Scaling** helps in achieving the **trade-off** between accuracy and real-time performance

RQ4

- Important to **improve beyond accuracy** when assessing the **true utility** of real-time recommenders
- Novel method based on **neural autoencoders** that improves the beyond-accuracy performance of **anonymous user sessions**

Future Work

- Extending the beyond accuracy evaluation with different methods on **identifying** and **removing biases** from the utilized information sources

- Investigate in more detail the **topic of privacy** in a multi-domain setting
    - E.g., different domains may have different requirements wrt. sharing and controlling their data

- Modelling **interest shifts** in **real-time** as there is a huge potential for more sophisticated approaches which combine both, the **short-term** and **long-term** preferences of a user

- Tackle the problem of **approximating the online performance** (e.g., CTR) of a recommender algorithm before it is put in production

6 Main Publications

RQ1	MP1	**Lacic, E.**, Kowald, D., Eberhard, L., Trattner, C., Parra, D., and Marinho, L. B. (2015). **Utilizing online social network and location-based data to recommend products and categories in online marketplaces**. *In Mining, Modeling, and Recommending'Things' in Social Media (pp. 96-115). Springer.*
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RQ2 RQ3	MP4	**Lacic, E.** (2016). **Real-Time Recommendations in a Multi-Domain Environment**.*In Extended Proceedings at Doctoral Consortium of the 27th ACM Conference on Hypertext and Social Media (HT'16)*
RQ3 RQ4	MP5	**Lacic, E.**, Reiter-Haas, M., Duricic, T., Slawicek, V. and Lex, E. (2019). **Should we Embed? A Study on the Online Performance of Utilizing Embeddings for Real-Time Job Recommendations**. *In Proceedings of the 13th ACM Conference on Recommender Systems (RecSys'2019). ACM*
RQ4	MP6	**Lacic, E.**, Reiter-Haas, M., Kowald, D., Dareddy, M. R., Cho, J. and Lex, E. (2020). **Using Autoencoders for Session-based Job Recommendations**. In the Journal of *User Modeling and User-Adapted Interaction (UMUAI). Springer*

12 Additional Publications

RQ1	AP1	**Lacic, E.**, Kowald, D., Traub, M., Luzhnica, G., Simon, J., and Lex, E. (2015). **Tackling Cold-Start Users in Recommender Systems with Indoor Positioning Systems**. *In Proceedings of the 9th ACM Conference on Recommender Systems (RecSys'15)*
RQ1	AP2	Duricic, T., **Lacic, E.**, Kowald, D., and Lex, E. (2018). **Trust-Based Collaborative Filtering: Tackling the Cold Start Problem Using Regular Equivalence**. *In Proceedings of the 12th ACM Conference on Recommender Systems (RecSys'18)*
RQ1	AP3	**Lacic, E.**, Kowald, D., Seitlinger, P., Trattner, C., and Parra, D. (2014). **Recommending items in social tagging systems using tag and time information**. *In Proceedings of the 1st International Workshop on Social Personalisation co-located with the 25th ACM Conference on Hypertext and Social Media (HT'2014)*
RQ1	AP4	Reiter-Haas, M., Slawicek, V. and **Lacic, E.** (2017). **Studo Jobs: Enriching Data With Predicted Job Labels**. *In Workshop on Recommender Systems and Social Network Analysis (RS-SNA'17) co-located with the 17th International Conference on Knowledge Technologies and Data-driven Business (i-KNOW'17)*
RQ1 RQ2	AP5	**Lacic, E.**, Kowald, D., and Trattner, C. (2014). **Socrecm: A scalable social recommender engine for online marketplaces**. *In Proceedings of the 25th ACM Conference on Hypertext and Social Media (HT'14), pp. 308-310.*
RQ2 RQ3	AP6	Traub, M., Kowald, D., **Lacic, E.**, Schoen, P., Supp, G., and Lex, E. (2015). **Smart booking without looking: providing hotel recommendations in the TripRebel portal**. ,p. 50. ACM. (best demo honourable mention) *In Proceedings of the 15th International Conference on Knowledge Technologies and Data-driven Business (i-KNOW'15)*
RQ2 RQ3	AP7	Kowald, D., **Lacic, E.**, Theiler, D., and Lex, E. (2018). **AFEL-REC: A Recommender System for Providing Learning Resource Recommendations in Social Learning Environments**. *In the Social Interaction-Based Recommender Systems (SIR'18) Workshop co-located with the 27th International Conference on Information and Knowledge Management (CIKM'18)*
RQ2	AP8	**Lacic, E.**, Traub, M., Kowald, D., Kahr, M., and Lex, E. (2016). **Need Help? Recommending Social Care Institutions**. *In Workshop on Recommender Systems and Big Data Analytics (RSBDA'16) co-located with the 16th International Conference on Knowledge Technologies and Data-driven Business (i-KNOW'16)*
RQ2 RQ3	AP9	**Lacic, E.**, Traub, M., Kowald, D., and Lex, E. (2015). **ScaR: Towards a Real-Time Recommender Framework Following the Microservices Architecture**. *In Workshop on Large Scale Recommender Systems (LSRS'15) co-located with the 9th ACM Conference on Recommender Systems (RecSys'15)*
RQ3	AP10	**Lacic, E.**, Kowald, D., and Lex, E. (2018). **Neighborhood Troubles: On the Value of User Pre-Filtering To Speed Up and Enhance Recommendations**. *In the International Workshop on Entity Retrieval (EYRE'18) co-located with the 27th International Conference on Information and Knowledge Management (CIKM'18)*
RQ4	AP11	**Lacic, E.**, Kowald, D., Reiter-Haas, M., Slawicek, V. and Lex, E. (2018). **Beyond Accuracy Optimization: On the Value of Item Embeddings for Student Job Recommendation**. *In the International Workshop on Multi-dimensional Information Fusion for User Modeling and Personalization (IFUP'2018) co-located with WSDM'2018*
RQ4	AP12	**Lacic, E.**, Kowald, D., Theiler, D., Traub, M., Kuffer, L., Lindstaedt, S., and Lex, E. (2019). **Evaluating Tag Recommendations for E-Book Annotation Using a Semantic Similarity Metric**. *In REVEAL Workshop co-located with ACM Conference on Recommender Systems (RecSys'2019)*

Thank you for listening! Questions?

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