Conceptualization and Development of ML-based Recommender Systems for Software Engineering



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Università degli studi dell'Aquila / Italy XXXV Doctoral cycle a.a. 2021/2022

About me

> 2016-2018: Master degree at University of l'Aquila

- > 2018-2019: Research fellowship at Univaq
 - API recommendation by using code cloning techniques

> 2019-2023: Ph.D. in Computer Science

Hobbies: running, play tennis, writing novels 😳





Main research topics

Recommender system for software engineering

- Categorization of OSS repositories
- API function call recommendations
- Model-Driven engineering
 - Modeling assistants
 - MDE approach to design recommender systems

> Quality aspects in recommender systems

- Adversarial attacks
- Bias and fairness

Research group









Davide Di Ruscio Associate professor

Juri Di Rocco Assistant professor

Phuong T. Nguyen Assistant professor Riccardo Rubei Post-doc researcher

Collaborations









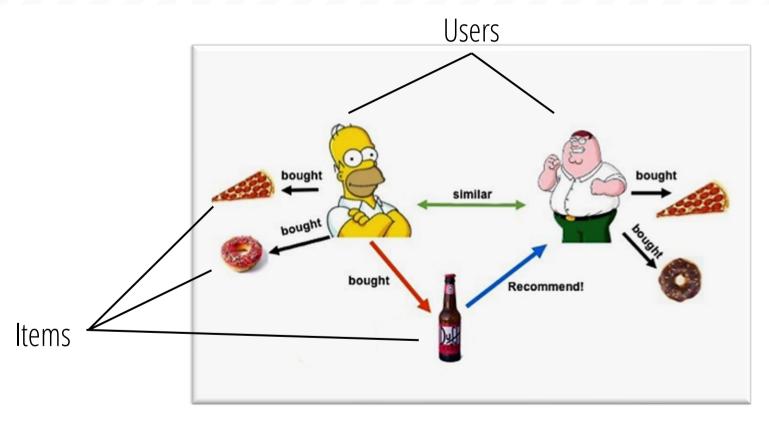
Massimiliano Di Penta Full professor University of Sannio

Cezar Sas Ph.D. student University of Gronigen

Andrea Capiluppi Associate professor University of Gronigen

Leonardo Mariani Full professor University of Milano-Bicocca

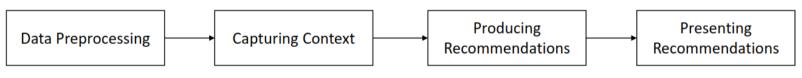
Recommender system in a nutshell



Recommender system for software engineering

Recommender systems* (RS) are complex software system that comes in handy to alleviate the burden of choice in different domains

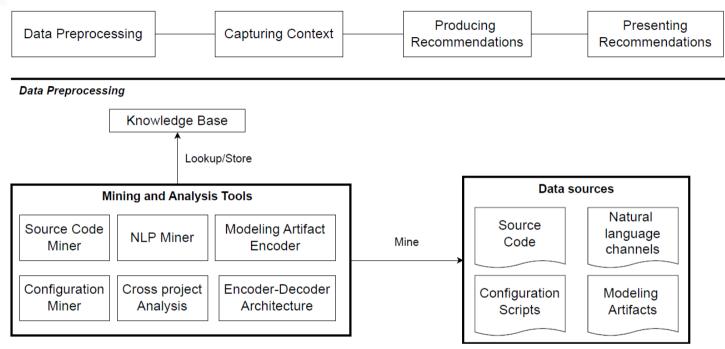
Recommender systems in software engineering** (RSSEs) has been defined



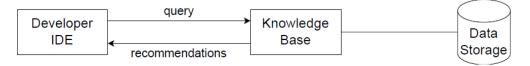
RSSE phases as described by Robillard et. al**

* Francesco Ricci, Lior Rokach, and Bracha Shapira. *Introduction to Recommender Systems Handbook*, pages 1–35. Springer US, Boston, MA, 2011. ISBN 978-0387-85820-3. ** M. Robillard, R. Walker and T. Zimmermann, *"Recommendation Systems for Software Engineering,"* in IEEE Software, vol. 27, no. 4, pp. 80-86, July-Aug. 2010, doi: 10.1109/MS.2009.161.

RSSEs: Conceptual framework



Capturing Context, Producing Recommedations, Presenting Recommendations Phases





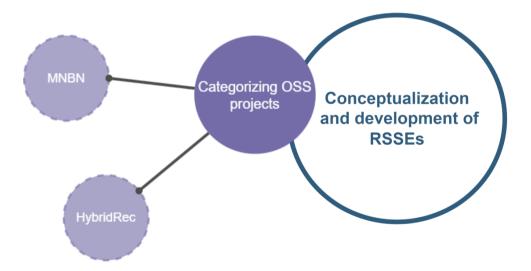




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Conceptual map





Setting the context



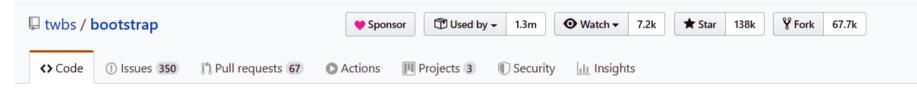
In 2017, GitHub introduced *topics* to help developers increase the reachability of their repositories

> Assigning wrong labels can compromise the discoverability*

As first attempt, we develop an automatic approach based on Multinomial Naive Bayesian network (MNBN)**

[*] Hudson Borges, André C. Hora, and Marco Tulio Valente. Understanding the Factors That Impact the Popularity of GitHub Repositories. In 2016 IEEE International Conference on Software Maintenance and Evolution, ICSME 2016, Raleigh, NC, USA, October 2-7, 2016, pages 334—344. IEEE Computer Society
[**] Claudio Di Sipio, Riccardo Rubei, Davide Di Ruscio, and Phuong T. Nguyen. A multinomial naïve bayesian (mnb) network to automatically recommend topics for github repositories. In Proceedings of the Evaluation and Assessment in Software Engineering, EASE '20

Motivating example

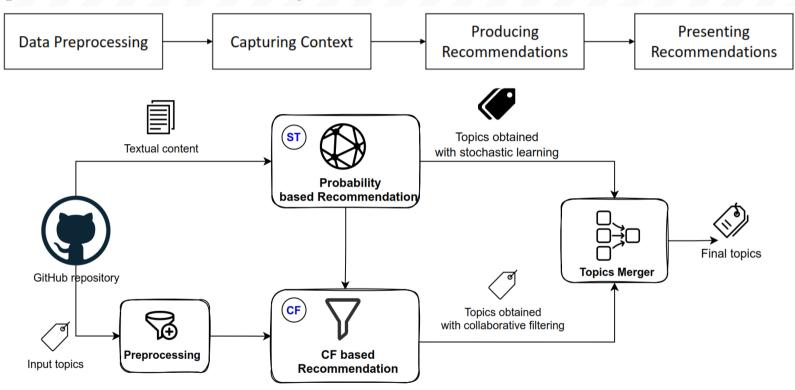


The most popular HTML, CSS, and JavaScript framework for developing responsive, mobile first projects on the web. https://getbootstrap.com

CSS	bootstrap	javascript	html	SCSS	css-framework	Sass

Bootstrap GitHub projects and its topics

Proposed solution: HybridRec*



*Di Rocco, J., Di Ruscio, D., <u>Di Sipio, C</u>., Nguyen, P.T., and Rubei, R., *HybridRec: A recommender system for tagging GitHub repositories.* Applied Intelligence (2022). DOI: https://link.springer.com/article/10.1007/s10489-022-03864-y

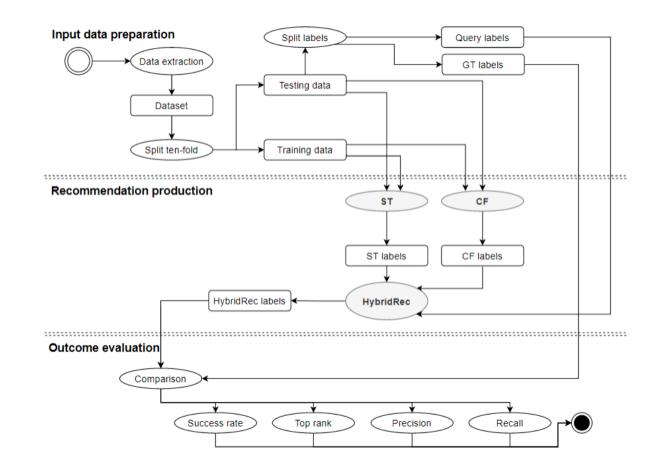
Evaluation metrics

success rate@N =
$$\frac{count_{p \in P}(|GT(p) \cap (\cup_{r=1}^{N} REC_{r}(p))| > 0)}{|P|}$$

$$precision@N(p) = \frac{\sum_{r=1}^{N} |GT(p) \cap REC_r(p)|}{N} \qquad recall@N(p) = \frac{\sum_{r=1}^{N} |GT(p) \cap REC_r(p)|}{|GT(p)|}$$

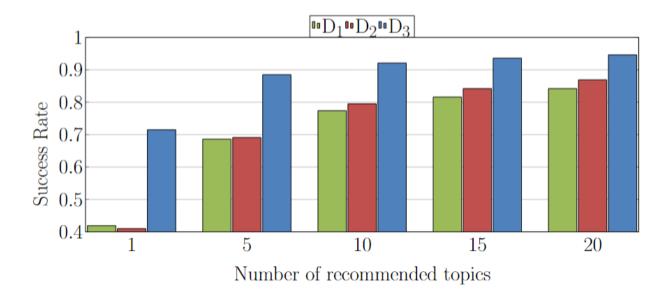
$$Top \ rank = \frac{TpRank(r)}{|R|} \times 100\% \qquad coverage @N = \frac{\left|\bigcup_{p \in P} \bigcup_{r=1}^{N} REC_r(p)\right|}{|I|}$$

Evaluation process



Results

	D ₁	D ₂	D ₃
# of artifacts	11,694	6,253	5,620
# of topics	19,337	455	6,442
Avg. number of topics	8.24	6.70	8.60
Avg. frequency of topics	16.13	42.10	29.90



HybridRec: Contributions and limitations

Contributions

- 네 It works also for MVN projects
- ☆ Combining different approaches increases the performances
- ☆ It can cover all the types of GitHub topics

Limitations

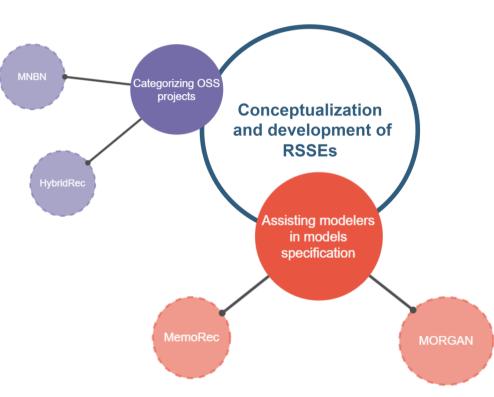
- ✓ No comparison with a baseline
- ✓ Not able to analyze the source code

Assisting modelers in specifying models and metamodels





Conceptual map



Setting the context



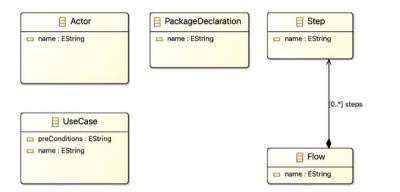
- MDE employs models as first-class artifacts to facilitate the overall development lifecycle*
- Recently, intelligent modeling assistants (IMAs) have been proposed to automatize their specification**

Selecting a proper encoding scheme and suitable data is still open challenges

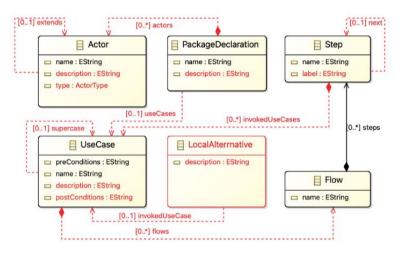
[*] Marco Brambilla, Jordi Cabot, and Manuel Wimmer. *Model-driven software engineering in practice*. Synthesis lectures on software engineering, 3(1):1–207, 2017. [**] Gunter Mussbacher, Benoit Combemale, Jörg Kienzle, Silvia Abrahão, Hyacinth Ali, Nelly Bencomo, Márton Búr, Loli Burgueño, Gregor Engels, Pierre Jeanjean, Jean- Marc Jézéquel, Thomas Kühn, Sébastien Mosser, Houari Sahraoui, Eugene Syriani, Dániel Varró, and Martin Weyssow. *Opportunities in intelligent modeling assistance*. Software and Systems Modeling, 19(5):1045–1053, September 2020.

Motivating example



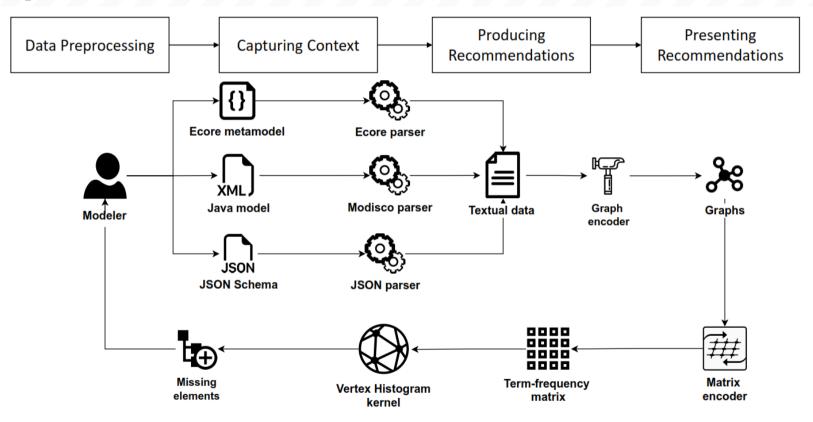


Partial metamodel



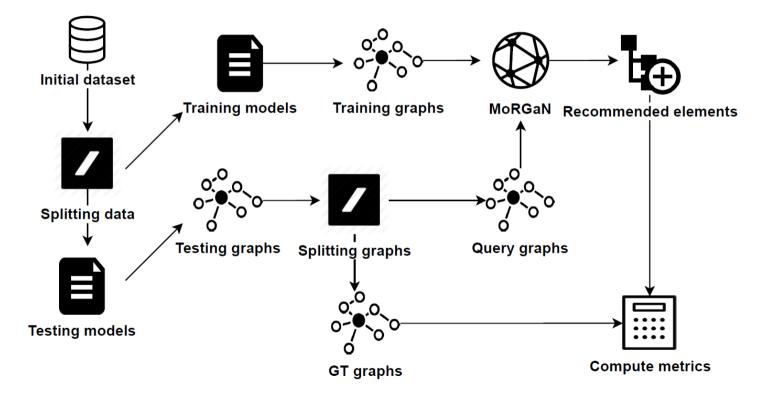
Complete metamodel

Proposed solution: MORGAN*



*Di Sipio, C., Di Rocco, J., Di Ruscio, D., Nguyen, P. T., *MORGAN: An intelligent modeling assistant based on kernel similarity and graph neural networks*, Journal of Software and Systems Modeling, 2023, DOI: <u>https://doi.org/10.1007/s10270-023-01102-8</u>

Evaluation process

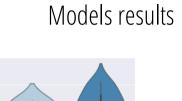


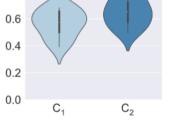
Results

1.0

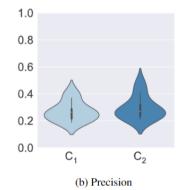
0.8

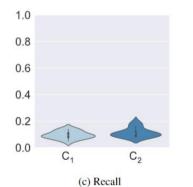


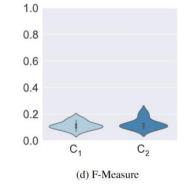




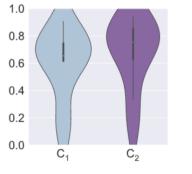




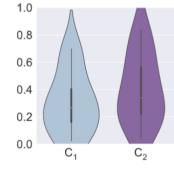




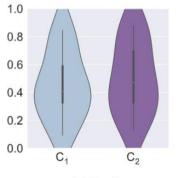
Metamodels results

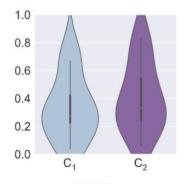


(a) Success rate



(b) Precision





(c) Recall

(d) F-Measure

MORGAN: Contributions and limitations

Contributions

Lt was the first approach using graph kernel similarity to support modeling activities

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🖞 It can support both metamodel and model completion

Limitations

- ✓ Scalability issue when large datasets are considered
- ✓ No user evaluation

Automating the design and the deployment of RSSEs

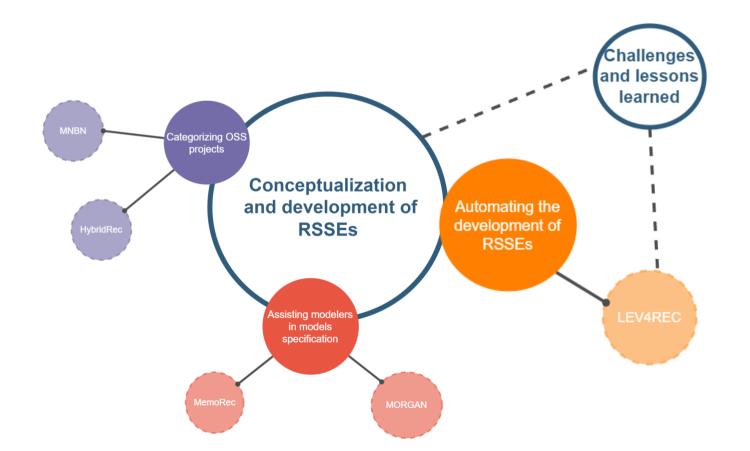
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Conceptual map





Lessons learned from developed RSSE

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Requirements

#R1: Importance of a clear requirement definition process

#R2: Users skepticism

Development

#D1: Selecting the right representation can be of paramount importance

#D3: Start first with the techniques you already know and move on from there

#D2: Do not pretend to immediately find the optimal solution (move on iteratively)

Evaluation

#E1: Candidate baselines might not be reusable

#E2: User studies are cumbersome, and they can take a long time to be conducted and completed

#E3: In certain contexts, the k-fold cross-validation technique is a good alternative to user studies

Setting the context



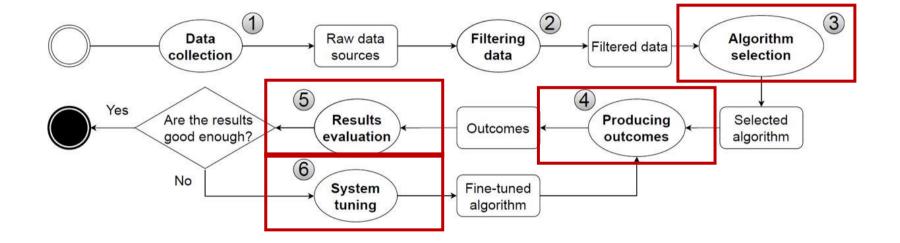
Several frameworks have been proposed to automatize the development of RS^{*,**}

None of the existing approaches consider constraints at the design time

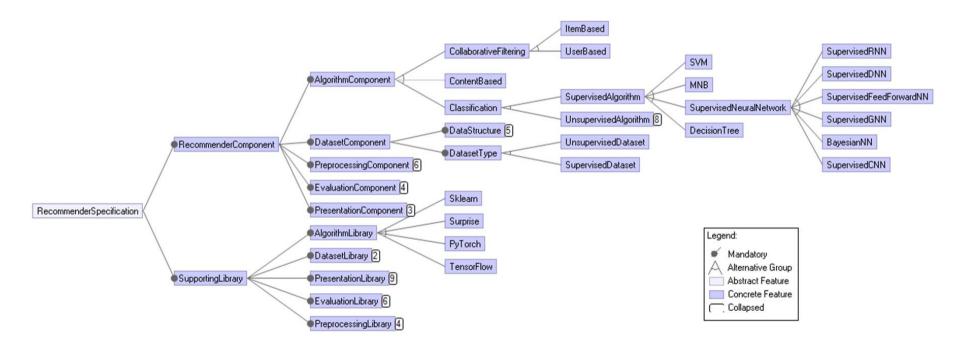
*Almonte, L., Perez-Soler, S., Guerra, E., Cantador, I., de Lara, J.: Automating the Synthesis of Recommender Systems for Modelling Languages p. 14 (2021) **Anelli, V.W., Bellogin, A., Ferrara, A., Malitesta, D., Merra, F.A., Pomo, C., Donini, F.M., Di Noia, T.: Elliot: A comprehensive and rigorous framework for re producible recommender systems evaluation. In: Proceedings of the 44th International ACM SIGIR Confer ence on Research and Development in Information Re trieval, SIGIR '21, p. 2405–2414. Association for Computing Machinery, New York, NY, USA (2021).

Motivating example

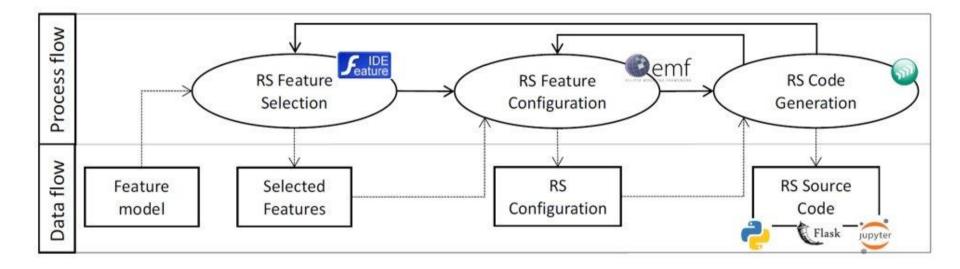




Feature model



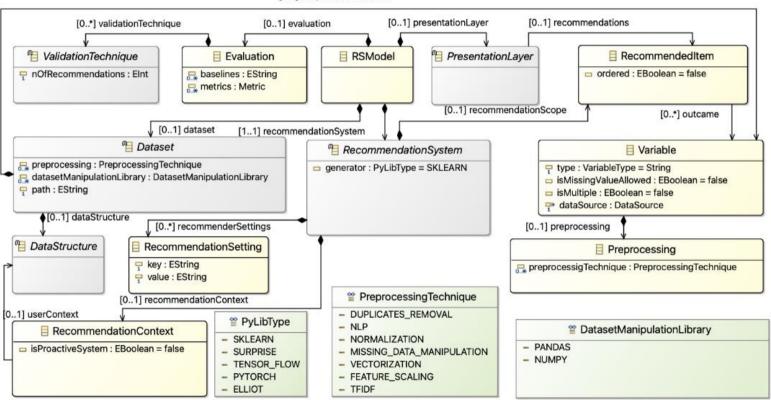
Proposed solution: LEV4REC*,**



*Di Sipio, C., Di Ruscio, D., and Nguyen, P.T. *Democratizing the development of recommender systems by means of low-code platforms*, In Proceedings of the 23rd ACM/IEEE International Conference on Model Driven Engineering Languages and Systems: Companion Proceedings, MODELS '20, New York, NY, USA, 2020. Association for Computing Machinery. ISBN 9781450381352. DOI: https://doi.org/10.1145/3417990.3420202

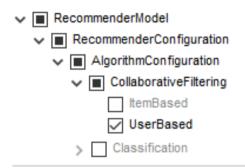
** Di Sipio, C., Di Rocco, J., Di Ruscio, D. and, Nguyen, P.T., 2021. *A Low-Code Tool Supporting the Development of Recommender Systems*. In Fifteenth ACM Conference on Recommender Systems (RecSys '21). Association for Computing Machinery, New York, NY, USA, 741–744. DOI: https://doi.org/10.1145/3460231.3478885

RS Metamodel



[0..*] indipendentVariables

CrossRec* use case



Configuration statistics
 Number of selected features: 31
 Number of manually selected features: 8

Number of unselected features: 47

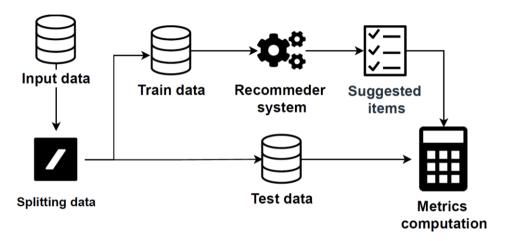
Feature specification

- A RS Model CrossRec
 - Supervised Dataset crossRecData.csv
 - Variable GithubProject
 - Variable LibraryDependence
 - 🔸 🔶 Graph Graph
 - Web Application
 - ✓ ♦ Evaluation
 - > 🔶 Cross Validation Ten Fold
 - > 🔶 Filtering RS CollaborativeFiltering

Property	Value		
Library			
Name	🖃 Ten Fold		
NOf Recommendations	10 回答		
Number Of Fold	10 回答		
Model fine-tuning			

*Phuong T. Nguyen, Juri Di Rocco, Davide Di Ruscio, and Massimiliano Di Penta. *CrossRec: Supporting software developers by recommending third-party libraries*. Journal of Systems and Software, 161:110460, 2020. ISSN 0164-1212. doi: https://doi.org/10.1016/j.jss.2019.110460. URL https://www.sciencedirect.com/science/article/pii/S0164121219302341

Results: Quantitative analysis



	Collaborative filtering		Classification	
Avg. metrics	CROSSREC	LEV4REC	Aurora	LEV4REC
Precision	0.623	0.634	0.945	0.950
Recall	0.622	0.552	0.938	0.949
F1	0.623	0.590	0.942	0.949

Qualitative evaluation: Focus group*

Participant	Recommender	Low-code	Software	Model-driven
	Systems	Engineering	Product Lines	Engineering
P1	Expert	Outsider	Outsider	Outsider
P2	Good Knowledge	Good Knowledge	Good Knowledge	Good Knowledge
P3	Expert	Expert	Expert	Expert
P4	Familiar	Good Knowledge	Familiar	Expert
P5	Expert	Expert	Expert	Expert

Pro

- 🗅 Decent degree of automation
- 습 Generalizability

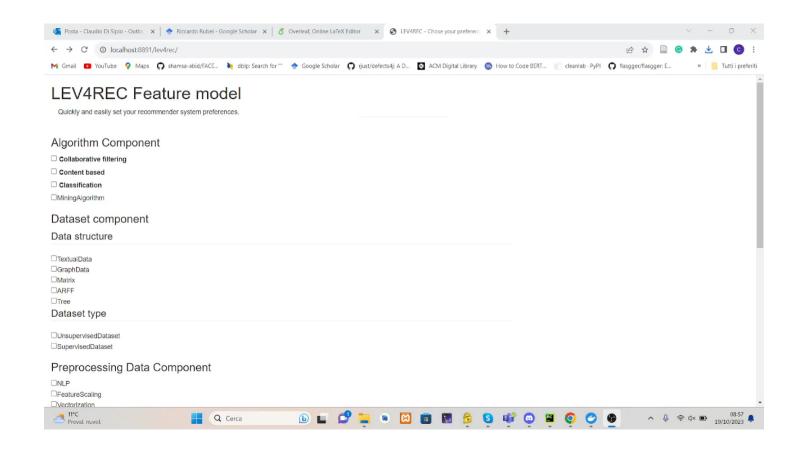
Cons

- Usability, i.e., improving the user interface
- ✓ Extensibility, i.e., providing dedicated extension point

*J. Kontio, L. Lehtola, and J. Bragge. Using the focus group method in software engineering: obtaining practitioner and user experiences. In Proceedings. 2004 International Symposium on Empirical Software Engineering, 2004. ISESE '04., pages 271–280, 2004. doi: 10.1109/ISESE.2004.1334914.

LEV4REC demo





LEV4REC: Conclusion

Contributions

- An MDE-based environment to specify recommender systems
- ☆ It can cover additional languages apart from Python, e.g., Java, C++
- 🗠 Each component can be extended by modifying the two models

Limitations

- ✓ User interface needs improvement
- ✓ Provide dedicated extension point
- ✓ Only a subset of features has been implemented

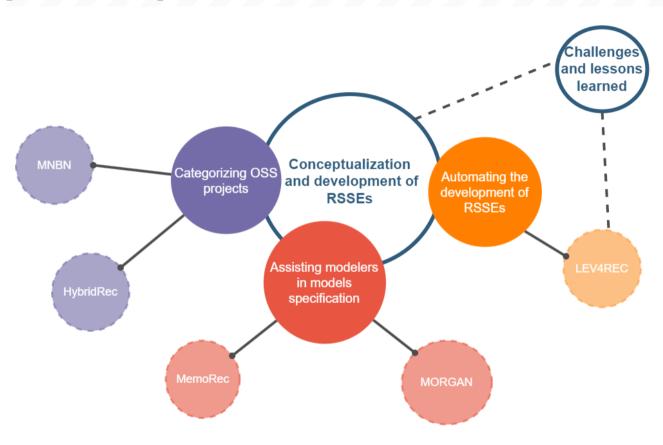
Conclusion





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Conceptual map



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Categorizing Github



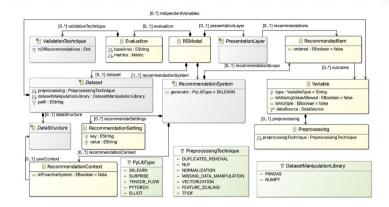


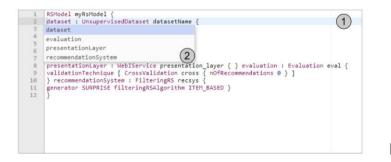
Repository	Real topics	Featured topics	Recommended topics
a1studmuffin/SpaceshipGenerator	python,blender-scripts, spaceship, procedural-generation, game- development, 3d	python, 3d	shell, terminal, 3d , opengl, python
0xAX/go-algorithms	golang, algorithm, data-structures, go, sort, tree-structure	algorithm, data- structures, go	data-structures, al- gorithm, twitter, li- brary, go

Context	Recommended item			
Step	<i>attribute</i> finalState:EString <i>reference</i> continuation:Step <i>reference</i> initialState:initState <i>reference</i> finalStates:FinalState			
Flow	<i>attribute</i> finalizeFlow:EBoolean <i>attribute</i> eventPat- ternId:EString <i>reference</i> initialState:initState <i>reference</i> finalStates:FinalState			
Step	metaclass StepAlternative:EClass metaclass Automaton metaclass FSM metaclass mFSM			

Automating the design of RSSEs







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Future work in RSSEs

Embody user feedback in an agnostic way*

RSSEs for IoT application domain**

Investigate qualitative aspects in RSSEs, e.g., fairness***, trustworthiness, explainability

*Rubei, R., <u>Di Sipio, C</u>., Di Rocco, J., Di Ruscio, D., and Nguyen, P.T., Endowing third-party libraries recommender systems with explicit user feedback mechanisms, 2022 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER), 2022, pp. 817-821, DOI: 10.1109/SANER53432.2022.00099
 **Di Rocco J. and <u>Di Sipio C.</u>, *ResyDuo: Combining data models and CF-based recommender systems to develop Arduino projects*, 5th International Workshop on Multi-Paradigm Modeling for Cyber-Physical Systems (MPM4CPS'23)
 **Nguyen P.T, Rubei R., Di Rocco J, <u>Di Sipio C</u>., Di Ruscio D., Di Penta M, *Dealing with Popularity Bias in Recommender Systems for Third-party Libraries: How far Are We?*, The 20th Mining Software Repositories (MSR 2023).