Beyond NDCG: Behavioral Testing of Recommender Systems with RecList

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ABSTRACT
As with most Machine Learning systems, recommender systems are typically evaluated through performance metrics computed over held-out data points. However, real-world behavior is undoubtedly nuanced: ad hoc error analysis and tests must be employed to ensure the desired quality in actual deployments. We introduce RecList, a testing methodology providing a general plug-and-play framework to scale up behavioral testing. We demonstrate its capabilities by analyzing known algorithms and black-box APIs, and we release it as an open source, extensible package for the community.

CCS CONCEPTS
• Software and its engineering → Acceptance testing; • Information systems → Recommender systems.

KEYWORDS
recommender systems, behavioral testing, open source

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1 INTRODUCTION
“A QA engineer walks into a bar. Orders a beer. Orders 0 beers. Orders 99999999999 beers. Orders a lizard. Orders -1 beers. Orders a nlekbksjldh. First real customer walks in and asks where the bathroom is. The

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1∗Patrick, Jacopo and Federico originally conceived and designed RecList together, and they contributed equally to the paper. Chloe and Brian added important capabilities to the package, and greatly helped in improving the paper as well.

... beyond NDCG alone fails to capture these nuances. This is particularly important in the world of RRs, given both the growing market for RRs\(^1\) and the role of RRs in shaping (often, narrowing \([\text{1]}\]) user preferences with potential harmful consequences \([\text{16]}\).

In recent years, recommender systems (hence RRs) have played an indispensable role in providing personalized digital experiences to users, by fighting information overload and helping with navigating inventories often made of millions of items [5, 9, 26, 36, 39]. RRs’ ability to generalize, both in industry and academia, is often evaluated through some accuracy score over a held-out dataset; however, performance given by a single number often fails to give developers and stakeholders a rounded view of the expected performances of the system “in the wild”. For example, as industry seems to recognize more than academia, not all inputs are created equal, and not all mistakes are uniformly costly; while these considerations are crucial to real-world success, reporting NDCG alone fails to capture these nuances. This is particularly important in the world of RRs, given both the growing market for RRs\(^1\) and the role of RRs in shaping (often, narrowing \([\text{1]}\]) user preferences with potential harmful consequences \([\text{16]}\).

Following the lead of [29] in Natural Language Processing, we propose a behavioral-based framework to test RRs across a variety of industries, focusing on the peculiarities of horizontal use cases (e.g. substitute vs complementary items) more than vertical domains. We summarize our main contributions as follows:

- we argue for the importance of a well-rounded and more nuanced evaluation of RRs and discuss the importance of scaling up testing effort through automation;
- we release an open-source package to the community – RecList. RecList comes with ready-made behavioral tests and connectors for important public datasets (Coveo Data Challenge [33], MovieLens [14], Spotify [40]) and an extensible interface for custom use cases;
- we demonstrate our methodology by analyzing standard models and SaaS offerings over a cart recommendation task.

While we developed RecList out of the very practical necessities involved in scaling RRs to hundreds of organizations across many industries\(^2\), as researchers, we also believe this methodology to be widely applicable in error analysis and thorough evaluation of new models: as much as we like to read about a new SOTA score on

\(^1\)E-commerce alone – arguably the biggest market for recommendations – is estimated to turn into a > 4 trillion industry by the end of 2021 [31].

\(^2\)Coveo is a multi-tenant provider of AI services, with a network of hundreds of deployments for customer service, e-commerce and enterprise search use cases.
MovieLens, we would also like to understand what that score tells us about the capabilities and shortcomings of the model.

2 AN INDUSTRY PERSPECTIVE

While quantitative metrics over standardized datasets are indispensable to provide an objective pulse on where the field is going, we often find that NDCG tells only one part of the performance story. As a very concrete example, while model performance depends mostly on what happens with frequent items, the final user experience may be ruined by poor outcomes in the long-tail [2]. Metrics such as coverage, serendipity, and bias [17, 19, 23] have been proposed to capture other aspects of the behaviors of RSs, but they still fall short of what is needed to debug RSs in production, and often do not provide any guarantee that a model will be reliable when released.

When developing RecList, we started from popular use cases that represent the most widely adopted strategies for recommendation systems:

1. similar items: when shown running shoes, users may want to browse for another pair of running shoes — in other words, they are looking for substitutable products [9]; similarly, in entertainment [22, 26] RSs may suggest content similar to a previous viewing;
2. complementary items: when a TV has been added to the cart, shoppers may want to buy a complementary product (e.g. a cable). This type of recommendation is typical of e-commerce scenarios and exhibits a characteristic asymmetry (Figure 1);
3. session-based recommendations: real-time behavior has been recently exploited to provide session-based personalization [7, 13, 15, 37], which captures both preferences from recent sessions and real-time intent; a typical session-based RS ingests the latest item interactions for a user and predicts the next interaction(s).

From these use cases, we identified three main areas of behavioral intervention:

1. enforce per-task invariants: irrespective of the target deployment, complementary and similar items satisfy formal relations which are different in nature. In particular, similar items need to be interchangeable, while complementary items may have a natural ordering (See Fig. 1). We operationalize these insights by joining predictions with item metadata: for example, we can use price information to check for asymmetry constraints;
2. being less wrong: if the ground truth item for a movie recommendation is "When Harry met Sally", hit-or-miss metrics won’t be able to distinguish between model A that predicts "Terminator" and model B that suggests "You’ve got mail". In other words, A and B are not wrong in the same way: one is a terrible suggestion and one is reasonable mistake. RSs are a major factor in boosting user experience (which translates to revenues, loyalty, etc.); in a recent survey, 38% of shoppers said they would stop shopping if shown non-relevant recommendations [21];

Figure 1: Examples of behavioral principles for RSs: in (1) we observe the asymmetry desired when recommending complementary items, while (2) exemplifies that model mistakes (i.e. missing the ground truth item) may degrade the shopping experience in different ways.

3. data slices: in real-world RSs, not all inputs are created equal. In particular, we may tolerate a small decrease in overall accuracy if a subset of users we care about is happier. For a practical example, consider a multi-brand retailer promoting the latest Nike shoes with a marketing campaign: other things being equal, this retailer would want to make sure the experiences of users landing on Nike product pages are particularly well curated. Aside from horizontal cases (e.g. cold-start items), the most interesting slices are often context-dependent, which is an important guiding principle for our library.

Building RecList requires us to solve two problems: operationalize behavioral principles in code whenever possible, and provide an extensible interface when domain knowledge and custom logic are required (Section 4).

3 RELATED WORK

This work sits at the intersection of several themes in the research and industrial communities. We were initially inspired by behavioral testing for NLP pioneered by [29]: from this seminal work we took two lessons: first, that black-box testing [3] is a source of great insights when added to standard metrics; second, that this methodology goes hand-in-hand with software tools, as creating, maintaining, and analyzing behavioral tests by manual curation is a time-consuming process. On the other hand, RecList needs to

3 In case the reader is too young to know better, suggesting "Terminator" in this context is way worse than suggesting "You’ve got mail".
consider the peculiarities of RSs, as compared to NLP: in particular, the concept of generic models does not apply, as RSs are deployed in different shops and domains: the same pair of running shoes can be popular in Shop X and not Shop Y, and categorized as sneakers in one case, running shoes in the other.

From the A/B testing literature [18], we take the important lesson that not all test cases are created equal: in particular, just as a careful A/B test cares both about the aggregate effect of treatment and the individual effects on specific data slices, a careful set of RS testing should worry about the overall accuracy as well as the accuracy in specific subgroup-of-interests: in ML systems, as in life, gains and losses are not always immediately interchangeable.

The RS literature exploited already insights contained in RecList, typically as part of error analysis [30], or as performance boost for specific datasets [12]. For example, “being less wrong” is discussed in [34], while cold start performance is often highlighted for methods exploiting content-based features [35]. Our work builds on top of this scattered evidence, and aims to be the one-stop shop for behavioral analysis of RSs: RecList provides practitioners with both a common lexicon and working code for scalable, in-depth error analysis.

Finally, as far as standard metrics go, the literature is pretty consistent: a quick scan through recent editions of RecSys and SIGIR highlights the use of MRR, ACCURACY, HITS, NDCG as the main metrics [8, 20, 25, 28, 38]. To ease the comparison with research papers on standard KPIs, we made sure that these metrics are computed by RecList as well, together with behavioral results.

4 RECLIST (A.K.A. CHECKLIST FOR RECS)

RecList is behavioral testing applied to RSs, and available as a plug-and-play open-source package that can be easily extended to proprietary datasets and models. Following [29], we decouple testing from implementation: our framework treats RSs as a black box (through an extensible programming interface), allowing us to test RSs for which no source code is available (e.g. SaaS models). To strengthen our exposition of the methodology, we offer here a high-level view of the logical architecture and capabilities of RecList as a package. However, please note the code is actively evolving as a community project: the reader is encouraged to check out our repository4 for up-to-date documentation, in-depth explanation of available tests and practical examples over popular datasets and baseline models.

4.1 Abstractions

RecList is a Python package built over these main abstractions:

- **RecTask**: the recommendation use case (Section 2).
- **RecModel**: the model we are testing – as long as a simple prediction-based interface can be implemented, any model can be represented in RecList. For example, a SaaS model would make an API call to a service and let RecList handle the analysis.
- **RecDataset**: the dataset we are using – the class provides standard access to train/test splits and item metadata. RecList comes with ready-made connectors for popular datasets.

4.2 Capabilities

While we refer readers to our repository for an up-to-date list of available RecLists, RecModels and RecDatasets, we wish to highlight some key capabilities:

- **leveraging representation learning**: word embeddings for behavioral testing in NLP are replaced by representation learning per dataset. By unifying access to items and metadata (e.g. brands for products, labels for music), RecList provides a scalable, unsupervised flow to obtain latent representation of target entities, and uses them to generate new test pairs, or supply similarity judgment when needed (Figure 2). RecList ships with prod2vec over session-like data [6, 24], but the same idea would work with other representational techniques (e.g. zero-shot representations [27], BERT-based embeddings [7]):

- **merging metadata and predictions**: RecList’s tests provide a functional interface that can be applied to any dataset by supplying the corresponding entities. For example, asymmetry tests can be applied to any feature exhibiting the desired behavior (e.g. price for complementary items); in the same vein, data slices can be specified with arbitrary partitioning functions, allowing seamless reporting on important subsets;

- **injecting domain knowledge when needed**: RecList allows to easily swap default similarity metrics with custom ones (or, of course, write entirely new tests): for example, if a practitioner is working in a domain with a very accurate taxonomy, he could define a new distance between predictions and labels, supplementing out-of-the-box unsupervised similarity metrics.

| Test                          | P2V   | GOO   | S1    |
|-------------------------------|-------|-------|-------|
| HR@10                         | 0.197 | 0.199 | 0.094 |
| MRR@10                        | 0.091 | 0.102 | 0.069 |
| Coverage@10                   | 1.01e-2 | 1.99e-2 | 3.00e-3 |
| Popularity Bias@10            | 9.91e-5 | 1.41e-4 | 1.20e-4 |
| Cos Distance (Brand)          | 0.411 | 0.483 | 0.540 |
| Cos Distance (Misses)         | 0.564 | 0.537 | 0.577 |
| Path Length (Category)        | 1.13  | 1.59  | 1.91  |

4Note that we use RecList to indicate the class or its instances, and RecList to indicate the package as a whole.
Figure 2: Sample workflow for behavioral tests. Starting with shopping data (left), the dataset split (orange) and model training (blue) mimic the usual training loop. RecList creates a latent space to measure the relationships between inputs, ground truths and predictions, such as how far misses are from ground truths (violet) (see Fig. 3 for a real-world example). Since a session can be viewed as a sequence of items or features (brands), RecList can re-use skip-gram to create embeddings for different tests.

5 A WORKED-OUT EXAMPLE: CART RECS

To showcase RecList in a real-world setting, we test three RSs on a complementary items task: a prod2vec-based recommender [6] (hence P2V); Google Recommendation APIs (GOO) [10]; and one popular SaaS model (S1). We use data from a “reasonable scale” [32] e-commerce in the sport apparel industry, where 1M product interactions have been sampled for training from a period of 3 months in 2019, and 2.5K samples from a disjoint time period for testing. The main take-away of this experiment is simple: models (GOO and P2V) that are close when point-wise metrics are reported (Table 1) may have a very different behavior, when analyzed through RecList. In particular, we discuss three insightful RecTests we performed:

- **Product Popularity**: we compare model hits across item popularity (i.e. how accurate the prediction is, when the target is very / mildly / poorly popular). P2V can be seen to perform better on rare items by 40% over GOO. On the other hand GOO outperforms P2V by 200% on the most frequently-viewed items.

- **“Being Less Wrong”**: we compute the cosine-distance (over a prod2vec space) between query and ground truth, and query and prediction for missed predictions (Figure 3). We observe that GOO’s prediction distribution better matches the label distribution, suggesting that its predictions are qualitatively more aligned to the complementary nature of the cart recommendation task.

- **Slice-by-Brand**: we measure hits across various brands. While P2V and GOO have very similar overall performance, P2V is particularly performant on asics, compensating for a slightly lower result on nike: without behavioral testing, this bias in P2V would have been hard or time-consuming to catch.

Additional RecTests are included in Table 1: in particular, “Being Less Wrong” can be operationalized over brand affinity as well (CosDist (Brand)), capturing the intuition that an Adidas product is closer to a Nike one than a Lacoste one. Conversely, Path Length goes for a discrete approach and measures distance as the path length between input and prediction based on a product tree (longer suggests greater diversity, better for cart recommendations).

6 CONCLUSION

We introduced RecList, a package for behavioral testing in recommender systems. RecList aims to both provide a shared lexicon to explicitly discuss RSs trade-offs, and a convenient API for scaling and re-use behavioral tests. Our alpha already provides out of the box support for popular datasets and common tests; not dissimilarly from Lego blocks, existing lists can be extended with new tests, tests can be re-assembled for different purposes, and – as long as “blocks” implement the proper interface – entirely new RecLists can be created. We are indeed aware that RecList is, by nature, a never-ending and continuously improving project: behavioral testing needs to constantly evolve as our understanding of RSs improves and their capabilities and reach change: by open sourcing...
RecList, we hope to help the field go beyond “leaderboard chasing”, and to empower practitioners with better tools for analysis, debugging, and decision-making.

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REFERENCES

[1] Panagiotis Adamopoulos and Alexander Tuzhilin. 2014. On Over-Specialization and Concentration Bias of Recommendations: Probabilistic Neighborhood Selection in Collaborative Filtering Systems. In Proceedings of the 8th ACM Conference on Recommender Systems (Foster City, Silicon Valley, California, USA) (RecSys ’14). Association for Computing Machinery, New York, NY, USA, 153–160. https://doi.org/10.1145/2645710.2645752

[2] Nikhil Arora, Daniel Esmens, Lars Fredler, Wei Wei Liu, Kelley Robinson, Eli Stein, and Gustavo Schuler. 2021. The value of getting personalization right—or wrong—is multiplying. Retrieved November 15, 2021 from https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/the-value-of-getting-personalization-right—or-wrong—is-multiplying

[3] B. Becker and J. Wiley. 1996. Black Box Testing. Techniques for Functional Testing of Software and Systems. IEEE Software 13, 5 (1996), 96–. https://doi.org/10.1109/ MS.1996.536464

[4] David Berg, Ravi Kiran Chiruvuri, Romain Cledat, Savin Goyal, Ferras Hammad, and Ville Tuulos. 2019. Open-Sourcing Metaflow, a Human-Centric Framework for Data Science. https://netflixtechblog.com/open-sourcing-metaflow-a-human-centric-framework-for-data-science-fa27fa45a9

[5] Rahul Bhagat, Srevarasat Muralidharan, Alex Lobzhanidze, and Shankar Vishwanath. 2018. Buy It Again: Modeling Repeat Purchase Recommendations. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (London, United Kingdom) (KDD ’18). Association for Computing Machinery, New York, NY, USA, 62–70. https://doi.org/10.1145/3219819.3219891

[6] Federico Bianchi. J. Tagliabue, Bingjing Yu, Luca Bigon, and Ciro Greco. 2020. Fantasy Embeddings and How to Align Them: Zero-Shot Inference in a Multi-Shop Scenario. ArXiv abs/2007.14096 (2020).

[7] Federico Bianchi, Bingjing Yu, and Jacopo Tagliabue. 2021. BERT Goes Shopping: Comparing Distributional Models for Product Representations. In Proceedings of The 4th Workshop on e-Commerce and NLP. Association for Computational Linguistics, Online, 1–12. https://doi.org/10.18653/v1/2021.ercnlp-1.1

[8] Renqin Cai, Jibang Wu, Aidan San, Chong Wang, and Hongning Wang. 2021. You Do Not Need a Bigger Boat: Recommendations at Reasonable Scale in a (Mostly) Serverless and Open Stack Data Science. CoRR abs/2107.05124 (2021).

[9] Lei Gao, Hongzhi Yin, Qinyong Wang, Tong Chen, Alexander Zhou, and Nguyen Quoc Viet Hung. 2019. Streaming Session-Based Recommendation. In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (Anchorage, AK, USA) (KDD ’19). Association for Computing Machinery, New York, NY, USA, 1569–1577. https://doi.org/10.1145/3292500.3330839

[10] F. Maxwell Harper and Joseph A. Konstan. 2015. The MovieLens Datasets: History and Context. ACM Trans. Recomm. Syst. 5, 4, Article 19 (Dec. 2015), 19 pages. https://doi.org/10.1145/2827872

[11] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Dominoskos Tikk. 2016. Session-based Recommendations with Recurrent Neural Networks. CoRR abs/1511.06939 (2016).

[12] Kartik Hosanagar, Daniel Fleder, Dongyu Lee, and Andreas Buja. 2014. Will the Global Village Fracture Into Tribes? Recommender Systems and Their Effects on Consumer Fragmentation. Management Science 60 (04 2014), 805–825. https://doi.org/10.1287/mnsc.2013.1808

[13] Dietmar Jannach and Malte Ludewig. 2017. When recurrent neural networks meet the neighborhood for session-based recommendation. In Proceedings of the Eleventh ACM Conference on Recommender Systems. 306–310.

[14] Ron Kohavi, Alex Deng, Brian Frasca, Roger Longbotham, Toby Walker, and Ya Xu. 2012. Trustworthy Online Controlled Experiments: Five Puzzling Outcomes Explained. In Proceedings of the 18th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (Beijing, China) (KDD ’12). Association for Computing Machinery, New York, NY, USA, 786–794. https://doi.org/10.1145/2339530.2339653

[15] Denis Kotkov, Jari Veijalainen, and Shuajiang Wang. 2016. Challenges of Serendipity in Recommender Systems. In WEBIST.

[16]Application and User-Adapted Interaction 28, 4-5 (2018), 331–390.

[17] Tomas Mikolov, Kui Chen, Gregory S. Corrado, and Jeffrey Dean. 2013. Efficient Estimation of Word Representations in Vector Space. In ICML.

[18] Theo Moinis, Daniel Aloise, and Simon J. Bianchard. 2020. RecSeats: A Hybrid Convolutional Neural Network Choice Model for Seat Recommendations at Reserved Seating Venues. In Fourteenth ACM Conference on Recommender Systems (Virtual Event, Brazil) (RecSys ’20). Association for Computing Machinery, New York, NY, USA, 140–149. https://doi.org/10.1145/3383313.3342235

[19] Krista Garcia. 2018. The Impact of Product Recommendations. Retrieved November 9, 2021 from https://www.emarketer.com/content/the-impact-of-product-recommendations

[20] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[21] Malte Ludewig and Dietmar Jannach. 2018. Evaluation of session-based recommendation algorithms. User Modeling and User-Adapted Interaction 28, 4-5 (2018), 331–390.

[22] Marco Tilló Ribeiro, Tongzhouqiang (Sherry) Wu, Carlos Guzman, and Sameer Samat. 2021. Reserve Seating Venues. In Fourteenth ACM Conference on Recommender Systems (Virtual Event, Brazil) (RecSys ’21). Association for Computing Machinery, New York, NY, USA, 590–591. https://doi.org/10.1145/3466031.3476620

[23] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[24] Malte Ludewig and Dietmar Jannach. 2018. Evaluation of session-based recommendation algorithms. User Modeling and User-Adapted Interaction 28, 4-5 (2018), 331–390.

[25] Krista Garcia. 2018. The Impact of Product Recommendations. Retrieved November 9, 2021 from https://www.emarketer.com/content/the-impact-of-product-recommendations

[26] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[27] Malte Ludewig and Dietmar Jannach. 2018. Evaluation of session-based recommendation algorithms. User Modeling and User-Adapted Interaction 28, 4-5 (2018), 331–390.

[28] Marco Tilló Ribeiro, Tongzhouqiang (Sherry) Wu, Carlos Guzman, and Sameer Samat. 2021. Reserve Seating Venues. In Fourteenth ACM Conference on Recommender Systems (Virtual Event, Brazil) (RecSys ’21). Association for Computing Machinery, New York, NY, USA, 590–591. https://doi.org/10.1145/3466031.3476620

[29] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[30] Malte Ludewig and Dietmar Jannach. 2018. Evaluation of session-based recommendation algorithms. User Modeling and User-Adapted Interaction 28, 4-5 (2018), 331–390.

[31] Krista Garcia. 2018. The Impact of Product Recommendations. Retrieved November 9, 2021 from https://www.emarketer.com/content/the-impact-of-product-recommendations

[32] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[33] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[34] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[35] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[36] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.

[37] Sudarshan Lankhede and Christoph Körler. 2021. Recommendations and Results Optimization in Netflix Search. In RecSys ’21: Fifteenth ACM Conference on Recommender Systems.
[37] Shoujin Wang, Longbing Cao, and Yan Wang. 2019. A Survey on Session-based Recommender Systems. ACM Computing Surveys (CSUR) 54 (2019), 1 – 38.

[38] Xiang Wang, Xiangzun He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural graph collaborative filtering. In Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval. 165–174.

[39] Yixin Wang, Dawen Liang, Laurent Charlin, and David M. Blei. 2020. Causal Inference for Recommender Systems. In recsys2020.

[40] Hamed Zamani, Markus Schell, Paul Lamere, and Ching-Wei Chen. 2019. An Analysis of Approaches Taken in the ACM RecSys Challenge 2018 for Automatic Music Playlist Continuation. ACM Trans. Intell. Syst. Technol. 10, 5, Article 57 (Sept. 2019), 21 pages. https://doi.org/10.1145/3344257