It’s Time to Consider ‘Time’ when Evaluating Recommender-System Algorithms [Proposal]

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ABSTRACT
In this position paper, we question the current practice of calculating evaluation metrics for recommender systems as single numbers (e.g. precision \( p=0.28 \) or mean absolute error \( MAE = 1.21 \)). We argue that single numbers express only average effectiveness over a usually rather long period (e.g. a year or even longer), which provides only a vague and static view of the data. We propose that recommender-system researchers should instead calculate metrics for time-series such as weeks or months, and plot the results in e.g. a line chart. This way, results show how algorithms’ effectiveness develops over time, and hence the results allow drawing more meaningful conclusions about how an algorithm will perform in the future. In this paper, we explain our reasoning, provide an example to illustrate our reasoning and present suggestions for what the community should do next.

KEYWORDS
recommender systems, evaluation, time series, metrics

1 INTRODUCTION
Recommender-system evaluation is an actively discussed topic in the recommender-system community. Discussions include advantages and disadvantages of evaluation methods such as online evaluations, offline evaluations, and user studies [1–4]; the ideal metrics to measure recommendation effectiveness [5–8]; and ensuring reproducibility [9–11]. Over the last years, several workshops about recommender-system evaluation were held and journals published several special issues [11–14].

An issue that has not been addressed by the community, is, to the best of our knowledge, the question for which intervals the metrics should be calculated, and how to present them. Typically, researchers calculate a few metrics for each algorithm (e.g. precision \( p \), normalized discounted cumulative gain \( nDCG \), mean absolute error \( MAE \), coverage \( c \), or serendipity \( s \)). For each metric, they present a single number such as \( p = 0.38, MAE = 1.02, c = 97\% \), i.e. the metrics are calculated based on all data available. Hence, the metrics express how well an algorithm performed on average over the period of data collection, which is often rather long. For instance, the data in the MovieLens 20m dataset was collected over ten years [15]. This means, when a researcher reports that an algorithm has e.g. an MAE of 0.82 on the MovieLens dataset, the algorithm had that MAE on average over ten years.

2 THE PROBLEM: SINGLE-NUMBER METRICS
We argue that presenting a single number that expresses the overall average is problematic as an average provides only a broad and static view of the data. If someone was asked how an algorithm had performed over time – i.e. before, during, and after the data collection period, the best guess, based on a single number, would be that the algorithm had the same effectiveness all the time.

Consider the following example: A researcher aims to compare the effectiveness of algorithms A and B. She receives 12-months usage data from a recommender system in which the two algorithms have been used. The researcher calculates for algorithms A and B a metric (e.g. precision) to express the algorithms’ effectiveness (a real researcher would probably calculate more than one metric but to illustrate our point, one metric is sufficient). The outcome of such an evaluation would be a chart as presented in Figure 1. The chart shows the effectiveness for algorithm A (0.48) and for algorithm B (0.67). A typical interpretation of these results would be that algorithm B is more effective than algorithm A, and algorithm B should be used in a recommender system rather than algorithm A.

1 We use the term ‘effective’ to describe how ‘well’ a recommender system achieves its objective, which could be, for example, to maximize user satisfaction (measured e.g. through user ratings) or revenue. However, for this paper, it is not important what the actual objective of the recommender system is or how it is measured.

2 Please note that for our argument, it would not matter if data is used from a real-world recommender system that implements the algorithms (as in our example), or if a researcher uses a dataset like the MovieLens dataset.
If someone was asked how algorithms A and B had performed in the past, and will perform in the future, the best guess would be that the algorithms’ effectiveness was stable and will remain stable over time. This assumption is illustrated in Figure 2 (the time during which data was collected are months M1 to M12, the time before the data collection period are months M-1 and M-2, and the time after the data collection period, i.e. the future, are months M13 and M14).

We argue that such assumptions are naïve, as many algorithms’ effectiveness is not stable over time. It is well known that the effectiveness of many recommendation algorithms depends on the number of users, items, and ratings as well as known as algorithm’s parameters such as neighbourhood size or user model size [21-24]. As the numbers of users etc. are likely to change over time, also the effectiveness of the algorithms will change over time. We have observed this effect in our own recommender systems Docear [16] and Mr. DLib [17]. Middleton, Shadbolt, & De Roure observed a similar effect [18], while Jack from Mendele reports that precision increased from 0.025 when they launched their recommender system to 0.4 after six months [19]. Also Netflix emphasizes the importance of considering time in recommender systems [20].

3 OUR PROPOSAL: TIME-SERIES METRICS

We propose that, instead of a single number, recommender-systems researchers should present metrics for time series, i.e. each metric should be calculated for a certain interval of the data collection period, e.g. for every day, week, or month. This will allow to gain more information about an algorithm’s effectiveness over time, identify trends, make better predictions on how an algorithm will perform in the future, and hence to make more meaningful conclusions on which algorithms to deploy in a recommender system.

Calculating effectiveness for each month would lead to a chart like in Figure 3, given the data from the previously introduced example. The chart shows that effectiveness of algorithm A improves over time from 0.14 in the first month of the data collection period to 0.90 in the last month. In contrast, the effectiveness of algorithm B decreases from 0.83 to 0.53. Most importantly, the chart shows that algorithm A outperformed algorithm B from month 9 onwards.

Even though Figure 1 and Figure 3 are based on the same (hypothetical) data, Figure 3 is more meaningful than Figure 1. Based on Figure 1, one would conclude that algorithm B is more effective than algorithm A. Based on Figure 3, a more differentiated conclusion can be drawn, namely that algorithm B was only more effective during the first months, but after month 9, algorithm A was more effective and looking at the trend it seems likely that algorithm A will continue to be the more effective algorithm in the future.

We therefore propose that recommender-system researchers should calculate their metrics for time-intervals of the data collection period, and present them in line plots as shown in Figure 3. Similarly, reviewers and organizers of conferences and journals should encourage the submitting authors to present their results as time series, when possible. Also, researchers who publish datasets should include time information such as when a user registered or when a rating was made.

We are aware that, in some cases, researchers already present data that shows how algorithms react to changes in the algorithms’ parameters or the number of items and users in a dataset [21,24]. They present, for instance, how effective an algorithm is with a neighborhood size of two, three, four, etc. or how effectiveness changes based on the number of data points. While these information certainly is relevant, no one currently knows, how many and which variables affect an algorithm’s effectiveness [16]. Therefore, it is not possible to present a comprehensive analysis of all variables effecting an algorithm’s effectiveness. We consider ‘time’ to be a good aggregate, and we think that knowing how an algorithm’s effectiveness changes over time is at least meaningful.
equally important as knowing how it changes based on variations in e.g. neighborhood size, user model size or the number of users.

4 NEXT STEPS

We used a hypothetical example to demonstrate the need for time-based evaluation metrics. To identify if and to what extent the need really exists, more research is needed. We suggest to analyze existing datasets such as MovieLens [25], RARD [25], Docear [16] or other datasets e.g. from https://kaggle.com. The analyses should calculate metrics for different algorithms over time, to see if and how strong the effectiveness of algorithms changes. It will be particularly interesting to see how often the change is so strong that the conclusions about which of two algorithms is more effective will change.

To further quantify the problem, a literature survey could be conducted to find out how many researchers currently present single-number metrics, and how often time-series metrics might make sense. A suitable corpus to analyze would be the full papers from the previous ACM Recommender Systems conferences (see appendix).

If the research confirms our assumptions, specific time-series metrics need to be created. One option would be, as done in the example, to calculate each metric e.g. per month and plot the results in a chart. However, in some cases, space restrictions might prevent researchers from presenting numbers for each interval. In such cases, it might be sensible to present the min, max, and average values for the intervals as well as standard deviation; or the values for the first and last month and/or a trend function. The community should also agree on notations for the time-series metrics. For instance, to express precision $p$ in interval $i$, the metric could be labelled $p@i$ (e.g. p@m5 to express average precision in the fifth month).

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FILE HISTORY

- 2017-08-30: Moved list of RecSys papers to appendix; Added reference to Netflix paper that mentions the importance of time; adjusted the header of the document.
- 2017-08-28: First version