Recommendation Techniques on a Knowledge Graph for Email Remarketing

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***Abstract*—The knowledge graph, which is an ontology based representation technique, is described to model the information necessary to conduct collaborative filtering, content-based filtering and knowledge based recommendation methods. Spreading activation and network science based recommendation methods are presented and evaluated. The evaluation measures are calculated on top list recommendations, where rating estimation is not necessary. In the experiment, click-through rates are measured and presented based on the email based remarketing activity of an electronic commerce system. Our primary result shows the improved recommendation quality of spreading activation based methods compared to the human expert.**

***Keywords*–knowledge graph; recommender system; spreading activation; network science; email remarketing**

I. Introduction

The traditional classification of recommender systems [1] proposes three main categories as collaborative filtering, content-based filtering and knowledge based methods. By representing the information in an ontology specifically designed for the task, both the information necessary for collaborative, content-based and knowledge-base techniques can be represented in one knowledge base, as we introduce it, in the knowledge graph.

Graph based recommender systems are a promising alternative to representation learning and matrix factorization techniques. In our work, we propose an information representation technique, which is capable of representing heterogeneous information sources. Similar to ontologies, the knowledge graph is a heterogeneous, labelled, restricted multigraph. The novelty of our representation method is the ability to represent parallel edges between two nodes. By utilizing a multigraph, our primary intention is to be able to represent various interaction types between users and items in one data structure as opposed to existing knowledge representation techniques in this field. In our approach, we separate the representation of information from the calculation methods. We think that the elimination of these unnecessary interdependencies can lead to a clearer approach on the theoretical side.

In this paper, we compare our spreading activation based, personalized recommendations and the centrality measures of network science to the performance of the human expert. Our spreading activation based method defines an asymmetric proximity measure between a source node and other nodes in the network. As the method calculates the proximity of nodes, it is not a rating estimation based method (as collaborative filtering) and it is utilized to generate a list of recommendations. Network science based methods are applied in the cold start case, and recommend central items in the ontology.

Next to Web based advertisements, a well known medium of the remarketing era is the email. Sending offers to past or potential customers in newsletters is a common practice of the electronic commerce systems. The personalization of the list of the offered products has the potential to increase the performance of the newsletters. Also, the improvement of this remarketing activity leads to a higher customer engagement, hence it delivers a business value. On the other hand, as products valuable to the user are presented, the personalization of the newsletters leads to an increase in the service quality.

In our experiment, we evaluated recommender system based newsletters utilizing the information gathered on Booker [2], an electronic commerce system selling books. The newsletters are sent with the industrial grade email remarketing system, PartnerMail [3].

Related work is presented in Section II. Section III introduces the graph based knowledge base. Section IV describes the evaluated recommendation methods. A detailed description of the dataset can be found in Section V. The evaluation method is presented in Section VI. The results can be found in Section VII. Section VIII concludes the paper.

II. Related work

Graph based information representation is a known technique in this field. Cantador et al. [4] define a multi-layered graph approach and applies a clustering technique to derive recommendations. Kazienko et al. [5] work with a layered graph. In the field of recommender systems, graphs are typically involved to represent the social network. Guha et al. [6], Ziegler et al. [7], Massa et al. [8] and Jsang et al. [9] involve trust networks to enhance recommendation quality. Guy et al. [10], Konstas et al. [11] and He et al [12] calculate recommendations with the help of a social network.

Spreading activation is a known method in the field of recommender systems. Blanco-Fernandez et al. present a content based reasoning about the semantics of the user's preferences [13]. Their method is spreading activation based and the recommendations are calculated with the Hopfield Net algorithm. They emphasize that spreading activation can be helpful to avoid the overspecialisation. Hussein et al. introduce SPREADR, a spreading activation based technique to close the gap between context-awareness and self-adaptation [14]. Their method is also applied to adapt user interfaces [15]. Gao et al. define a prototype in their position paper incorporating user interests and domain knowledge in an ontology [16].

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Codina et al. show a semantic recommender engine and also define a reasoning method to estimate user ratings on items to enhance the quality of rating estimations [17]. They define an item score as the weighted average of related concepts. An important aspect of their work is that they distinguish between explicit and implicit user feedback, which is also shown in Section V. Troussov et al. define a tag aware recommendation technique to investigate the decay and spreading parameters of spreading activation methods [18]. Alvarez et al. introduce ONTOSPREAD, a sophisticated, spreading activation technique in the scope of medical systems [19]. Jiang et al. present an ontology based user model and a spreading activation based recommendation technique [20].

III. Graph Based Representation

Cold start is a widely known, common problem of recommender systems. The most problematic situation of recommender systems is the lack of information, when there is no sufficient data available to deliver personalized recommendations for a newcoming user. To avoid this problem to the farthest possible extent, a general information representation method is used, which is capable of representing heterogeneous information. By representing heterogeneous information, the amount of information sources is increased. Following this strategy, our intention is to represent as much information as possible, in order not to constraint the recommendation methods in achieving high coverage.

The information is represented in a labelled, weighted, restricted multigraph, as $\mathcal{K}_u = (T_N, T_E, N, E_u, t_N)$ in the undirected case and $\mathcal{K}_d = (T_N, T_E, N, E_d, t_N)$ in the directed case. T_N is the set of node types, T_E is the set of edge types. N represents the set of nodes existing in the graph, $E_u \subseteq \{\{u, v, t\} | u \in N \wedge v \in N \wedge t \in T_E \wedge u \neq v\}$ represents the set of undirected edges between the nodes, $E_d \subseteq \{(u, v, t) | u \in N \wedge v \in N \wedge t \in T_E \wedge u \neq v\}$ represents the set of directed edges between the nodes. The function $t_N \subset N \times T_N$ assigns a node type to each node. At the moment, type assignments do not influence the final recommendation result and are introduced for completeness and further research.

IV. Recommendation Methods

In our experiment, we compare personalized and non-personalized recommendations. The personalized case is spreading activation based. In the non-personalized case, network science and human expert based recommendations are evaluated.

A. Spreading Activation

A spreading activation [21] based recommendation technique is used operating on $\mathcal{K}_u$ as introduced in Section III. Spreading activation is a well-known method in the field of semantic networks, neural networks and associative networks [22]. To recommend items with spreading activation, an iteration is started. In the first step the activation of the node representing the person to generate recommendations for is set to 1. This node is also called as source node. Then, in each iteration step all nodes distribute a part of their activation to the neighbouring nodes. The activation is divided equally along the receiving nodes. The parameter that determines the amount of activation distributed is called `spreading relax`. Before distribution, the activation is multiplied by the value of the parameter. A part of the activation is also kept at the node. The parameter that determines this amount is called `activation relax`. The iteration is conducted until the parameter `step limit` is reached.

After the iteration is finished, a relevance order is set up on the items. The relevance order is determined by the activation of the nodes after the last iteration step in the graph. Nodes of type `item` are selected and are sorted in descending order, by relevance. It means that nodes with higher activation value will be recommended with a higher priority.

B. Network Science

Network science [23] developed several centrality measures for nodes of networks. The aim of these measures is to express how central the position of a specific node is in a network by assigning numeric values to the nodes. Such measures are for example: degree centrality, closeness centrality, betweenness centrality and eigenvector centrality. Degree centrality counts the edges belonging to the node. Closeness centrality is the inverse of farness, which is the sum of the length of paths from the node to all other nodes. Betweenness centrality is the count of how many times a node lays on the shortest path between two nodes. Eigenvector centrality is proportional to the sum of the eigenvector centralities of its neighbours.

To calculate global recommendations, the above mentioned network science centrality measures are utilized on $\mathcal{K}_d$ and a relevance order is set up on the nodes of the network. The relevance order is prepared by sorting the nodes in descending by the specific centrality measure value.

C. Human Expert

In order to provide a baseline for our methods, human expert based newsletters are also involved in the experiment. The recommendations of the human expert are based on domain knowledge, experience on the market and publicly available top selling lists of competing on-line shops. For each campaign, the human expert provided a list of items to recommend. The list of items is treated as non-personalized recommendations; the same list of items is offered to all the users. Human expert based personalized recommendation is not feasible due to financial and capacity restrictions.

V. Dataset

In our experiment, the knowledge graph represents the information collected in the electronic commerce system. A representation method has been defined, which is capable to model all the available information present. Our software is integrated with the electronic commerce system, meaning that data is transferred to the knowledge base in real-time.

The knowledge graph contains persons, books, attributes, attribute categories and the relations between these entities. Each person and each book is represented with a node. Customer attributes are home town and birth year. These attributes are specified by the user and are not mandatory fields. Item attributes are author, publisher, year of publishing, number of pages and price. A book can have multiple authors. For each attribute value, a node is created and is bound with an edge to the appropriate node representing the person or item the specific attribute belongs to. In the case of number of pages

TABLE I. TYPES AND OCCURRENCES.

(a) Node types

Type	*Count*
Person	17 134
HomeTown	105
BirthYear	7
Item	117 367
Author	45 918
Publisher	6 351
YearOfPublishing	67
NumberOfPages	5
PriceCategory	5
ItemCategory	598

(b) Relation types

Type	*Count*
PersonBirthYear	8
PersonHomeTown	175
ItemAuthor	127 613
ItemCategory	30 800
ItemNumberOfPages	112 524
ItemPriceCategory	212 473
ItemPublisher	116 746
ItemYearOfPublishing	96 653
BoughtItem	22 064
OnWishList	2 972
ItemVisited	4 590
SubCategory	486

and price, value intervals are defined. In these cases, the nodes are created to represent the intervals instead of values.

In the electronic commerce system, the books are organized into categories. Such categories are for example "travel", "art" and "religion". A book can be assigned to multiple categories. The categories are organized into a hierarchical structure, meaning that most categories are subcategories of other categories. The category system and the book-category relations are also represented in the knowledge base.

In order to represent user interest in specific items, relations between persons and books are stored in the knowledge base. If a user visits the detailed information page of a book, a relation is inserted into the knowledge base to represent the implicit (not explicitly specified) interest of the user. If a user purchases an item (a more explicitly expressed interest), a relation is inserted into the knowledge base. In the electronic commerce system, users can put books on their wish-list to indicate that they are interested in buying the specific books later. Wish-lists are very useful information sources as they represent explicit interest expressed by the users. Wish-list relations are also stored in the knowledge base.

The information is represented in the knowledge base as defined in Section III. Table Ia presents the node types and occurrence counts in the knowledge base. Nodes of type `Person` represent people who are already users of the electronic commerce system and people who only signed up for the newsletter. Nodes of type `HomeTown` represent the home town of the users. Nodes of type `BirthYear` represent the birth year of the users, i.e. `1978`. Nodes of type `Item` represent the books available in the on-line shop, i.e. `Manga` and `Hieronymus Bosch`. Nodes of type `Author` represent the authors of the books, i.e. `Kurt Vonnegut` and `John Updike`. Nodes of type `Publisher` represent the publishers of the books, i.e. `Osiris Publishing` and `A & C Black`. Nodes of type `YearOfPublishing` represent the different years when books were published, i.e. `2007`. Nodes of type `NumberOfPages` represent number of pages intervals. The following intervals are defined `0-60`, `61-100`, `101-200`, `201-500` and `501-1000`. Nodes of type `PriceCategory` represent price intervals. The following intervals are defined by the expert of the electronic commerce system `0-1000`, `0-3000`, `1001-3000`, `3001-6000` and `6001-10000`. As the intervals are overlapping, a book can belong to multiple price categories. In this case multiple edge are created in the knowledge graph. Nodes of type `ItemCategory` represent item categories, i.e. `travel`, `art` and `religion`.

Table Ib presents relation types and occurrence counts in the knowledge base. Relations of type `PersonBirthYear` between nodes of type `Person` and nodes of type `PersonBirthYear` represent that the person was born in the specific year. Relations of type `PersonHomeTown` between nodes of type `Person` and nodes of type `HomeTown` represent that the person lives in the specific town. Relations of type `ItemAuthor` between nodes of type `Item` and nodes of type `Author` represent the author(s) of the specific book. Relations of type `ItemCategory` between nodes of type `Item` and nodes of type `ItemCategory` represent that the book belongs to the specific category. Relations of type `ItemNumberOfPages` between nodes of type `Item` and nodes of type `NumberOfPages` represent that the page count of the book falls in the specific page count interval. Relations of type `ItemPriceCategory` between nodes of type `Item` and nodes of type `PriceCategory` represent that the price of the book falls into the specified price category. Relations of type `ItemPublisher` between nodes of type `Item` and nodes of type `Publisher` represent that the book is published by the specific publisher. Relations of type `ItemYearOfPublishing` between nodes of type `Item` and nodes of type `YearOfPublishing` represent that the book has been published in the specific year. Relations of type `BoughtItem` between nodes of type `Person` and nodes of type `Item` represent that the person purchased the specific book. Relations of type `OnWishList` between nodes of type `Person` and nodes of type `Item` represent that the person put the specific book onto their wish-list. Relations of type `ItemVisited` between nodes of type `Person` and nodes of type `Item` represent that the person visited the Web page displaying details on the specific book. Relations of type `SubCategory` between nodes of type `ItemCategory` represent that the category is the sub-category of the specified one.

Table Ib shows that the knowledge base is sparse on person attributes but is rich on item attributes. The reason behind this is that while item attributes are available from the publishing companies, users do not take the time to specify their personal details. Unfortunately the wish-lists are also not densely populated. The knowledge base contains only a small amount of `ItemVisited` relations. The reason for this is that in order to maximize the book orders, the electronic commerce system does not make it mandatory to authenticate the users for purchasing or browsing. As the users are typically not authenticated, they cannot be identified and most of the `ItemVisited` relations are not recorded. Table Ib also shows that there are books with multiple authors in the database as the count of `ItemAuthor` relation is higher than the number of `Item` nodes. The count of `ItemNumberOfPages` and `ItemPublisher` is not the same. The reason for this is that the item attributes are not specified for each item. The relatively high number of `ItemPriceCategory` relations can be explained with the overlapping `PriceCategory` intervals.

The knowledge base is integrated with the electronic commerce system, meaning that changes made by the visitors in the database are immediately transmitted to the knowledge base of the recommender system. As the electronic commerce system is a system in production, it has several transactions per day. The node and relation counts per type indicated in Table Ia and Table Ib were recorded on 23 January, 2015.

VI. Evaluation

In our experiment, the methods described in Section IV are evaluated. As the recommender system software is integrated with the electronic commerce system, the information is transmitted to the knowledge base in real-time. The methods are evaluated with newsletters offering books to the users of the electronic commerce system. The books presented in each newsletter is selected by one of the methods. During the evaluation period, click-through events have been measured.

A. Newsletters Sent

To evaluate the recommendation techniques, 16 campaigns were conducted between 23 Jul, 2014 and 14 Jan, 2015. During the evaluation period 241 062 newsletters have been sent of which 35 229 newsletters have been opened.

TABLE II. Newsletter send dates.

Type	*Date sent*	*Type*	*Date sent*
Recommender System	2014-07-16	Human Expert	2014-09-22
Human Expert	2014-07-23	Recommender System	2014-09-26
Recommender System	2014-07-26	Human Expert	2014-10-02
Recommender System	2014-08-01	Human Expert	2014-10-09
Human Expert	2014-08-06	Recommender System	2014-10-15
Human Expert	2014-08-27	Human Expert	2014-10-22
Recommender System	2014-08-29	Recommender System	2014-10-31
Recommender System	2014-09-12	Recommender System	2014-12-14

Table II lists the newsletter campaigns. Column *type* contains the type of the campaign, column *Date sent* the date when the newsletters have been sent. The following campaign types are defined.

Recommender system based campaigns involve a personalized and a non-personalized recommendation method. The personalized method is utilized in the case, when there is enough information to offer a personalized list of books to the user. In this case, in our experiment, a spreading activation based technique as described in Section IV-A is evaluated. If there is not enough information to provide personalized recommendations, a non-personalized method is used as a fall-back solution. In this case, in our experiment one of the network science based methods as described in Section IV-B is evaluated.

Human expert based campaigns present the books selected by the human expert as described in Section IV-C to the users. In this case no fall-back solution is necessary as the human expert based method is a non-personalized method.

B. Evaluation Method

The behaviour of the users in the purchase process can be measured by several click-through events. In our experiment the click-through events are sequential. The steps of the process are the following: sending a newsletter, opening a newsletter, clicking on an item in a newsletter, ordering an item and paying for the item. During the evaluation period, the sales process is recorded and is measured. According to the mentioned steps, the following newsletter states are defined: `sent`, `opened`, `clicked`, `ordered` and `paid`.

In order to keep resource usage low, to conform industry standards and to be able to measure the click-through rate, the newsletters do not contain embedded images but image references. For security and privacy reasons, most of the state of the art email client software do not download remote images automatically. If the user is interested in more details of the message, the email client can be instructed to download and show the remote content in the message. As the image references point to our server, this user interaction will lead to a download event on the server side. This event can be monitored and the click-through event is recorded.

The next conversion, clicking on an book is an important step. By clicking on a book in a newsletter, the users click on a link. The links in a newsletter take the user first to our server. Each link in the newsletter contains a unique identifier. Based on this identifier our software records the click-through on the server and forwards the user to the detail page of the book in the electronic commerce system.

The detail page of the book also lets the user order the item, which event is forwarded to our software where the click-through event is recorded as the next conversion. If the user does not order the book in this work-flow event but visits the platform later and finalizes the order process, the order event will be forwarded to the evaluation software and the click-through event is to be recorded.

The electronic commerce system offers various payment methods like credit card, money transfer and cash. Cash based payments do not involve additional shipment cost, as in this case the user personally visits the store. Due to the lack of additional fees, in the economic environment the experiment is conducted in, cash based payment is the most frequently used method. The two consequences of cash based payment are the delay between the order and payment and the case of the unfinished purchase process. The first case is managed by our evaluation software. The latter case leads to a visible conversion rate between the order and payment steps.

C. Method Configurations

Human expert and network science based methods do not need configuration. Spreading activation requires three parameters as described in IV-A. Based on our past research results [24], `spreading relax`, `activation relax` is set to a constant value, 0.5. In the experiments various spreading activation configurations are defined as the value of the `step limit` parameter varies between 3 and 7. In a campaign only one method configuration is evaluated.

D. Recommendation List Filtering

In order to increase the recommendation quality, a post-processing is applied to the spreading activation and the network centrality measure based recommendation lists. The post-processing is specified by the human expert and is defined by the following rules

- a newsletter can contain at most 2 books from the same author,
- if a book is once presented in a newsletter, it won't be included into consecutive newsletters for two months,
- books already bought in the electronic commerce system are not inserted into the newsletter.

The above described rules can be understood as a filtering mechanism on the recommendation list. After the recommendation list is ordered by relevance, those n items are inserted into the newsletter, which items meet the described criteria, while keeping the relevance order.

VII. RESULTS

Table III summarizes the newsletters sent in the evaluation period. Each row represents the appropriate state of the newsletter according to the states described in Section VI-B. The columns define the type of the recommendation method as described in Section VI-A. The values present the number of newsletters. Due to space limitations, the summarized results are presented.

TABLE III. COUNT OF NEWSLETTERS PER STATE AND RECOMMENDATION METHOD TYPE

State	Spreading Activation	Network Science	Human Expert
Sent	66 148	72 884	102 030
Opened	11 700	9 206	14 323
Clicked	1 265	260	772
Ordered	24	0	17
Paid	17	0	6

The first row of the table shows an important property of the dataset, the high number of the cold start cases. In total, 66 148 personalized newsletters and 72 884 non-personalized newsletters were sent. It means that the proportion (52%) of the cold start case is relatively high, compared to, for example our experiments [24] on the MovieLens [25] dataset. The reason for the high proportion of cold start cases can be found in the high number of users signed up only to the newsletter as mentioned in Section V. As the nodes representing these users are not bound to the knowledge base by any edge, spreading activation based methods are not able to find a path between these nodes and the nodes representing books.

The most visible and important result of our experiment is visible in the last row of Table III representing newsletters resulting in a sale event. Spreading activation based newsletters lead to the highest number of purchase events, more than the human expert based newsletters. Unfortunately, network science based methods show a low performance, as network science based recommendations do not lead to a purchase event.

Table IV shows the click-through event rates between the different states of the evaluation process in each method type group presented in sub-tables. The rows represent the source state, the columns represent the destination state of the state transition. For example the value in the last column of the first row in Table IVa shows that 0.026% of all the sent, spreading activation based newsletters resulted in a purchase event.

The click-through rates presented in Table IV show that personalized newsletters clearly outperform the human expert, as 0.026% of all the sent personalized newsletters resulted in a purchase event, while this ratio is 0.006% for the human expert based method. The detailed click-through rates of personalized engines are higher than human expert based recommendations, except for one case, the `Clicked` to `Ordered` case. In this case, the click through rates are 1.897% compared to 2.202%. We would like to mention here that this state transition is being processed in the electronic commerce portal, which might influence the experiment.

TABLE IV. CONVERSION RATES OF METHOD TYPE GROUPS

(a) Spreading activation

	Opened	Clicked	Ordered	Paid
Sent	17.688%	1.912%	0.036%	0.026%
Opened		10.812%	0.205%	0.145%
Clicked			1.897%	1.344%
Ordered				70.833%

(b) Network Science

	Opened	Clicked	Ordered	Paid
Sent	12.631%	0.357%	0.000%	0.000%
Opened		2.824%	0.000%	0.000%
Clicked			0.000%	0.000%
Ordered				0.000%

(c) Human Expert

	Opened	Clicked	Ordered	Paid
Sent	14.038%	0.757%	0.017%	0.006%
Opened		5.390%	0.119%	0.042%
Clicked			2.202%	0.777%
Ordered				35.294%

Unfortunately, network science based methods show no activity after the `Clicked` state, as there is no click-through event from from the `Clicked` to the `Ordered` state for this method type. While the `Sent` to `Clicked` state transition rate of network science based methods (12.631%) is similar to the transition rate of other method groups (17.688% and 14.038%), the `Opened` to `Clicked` state transition rate (2.824%) is very low compared to other method types.

Comparing human expert based methods to spreading activation based engines, spreading activation shows a much higher conversion rate from the `Opened` to the `Clicked` state as 10.812% compared to 5.390% and from the `Ordered` to the `Paid` state as 70.833% compared to 35.294%. Referring to Section VI-B, the latter click-through rate involves additional resources from the users (picking up the books personally) and this difference shows a more stronger commitment of the users.

VIII. CONCLUSION AND FUTURE WORK

A graph based knowledge base containing heterogeneous information is defined. Three different groups of types of recommendation techniques are evaluated as spreading activation, network science and human expert. The methods are evaluated in an experiment with an electronic commerce system by sending personalized newsletters. During the experiment, click-through events are measured and presented in the paper. The results show that personalized newsletters outperform human experts and are also capable to increase business income.

Another important finding is that the application of network science measure methods does not lead to a purchase event. Jeong et al. [26] also conducted experiments in this field, and came to the conclusion that in order to increase the recommendation quality, network science measures should be combined with already existing methods. Our finding shows a similar result as the application of network science methods without combining with any additional information does not lead to high quality recommendations.

The most significant differences between the method types can be found at the state transition between the `Opened` to `Clicked` state and the `Ordered` to `Paid` state. In the case of network science methods we have information only in the case of `Clicked` to `Ordered` transition, as network science based methods do not even reach the `Ordered` state. The `Opened` to `Clicked` clicked transition rate shows somehow how relevant the recommended items are to the particular user, as this click-through event requires an explicit action from the user regarding to the item in interest. Network science based methods perform the worse at this state transition. Spreading activation based methods perform much better than human expert based methods indicating that spreading activation recommends more relevant items compared to the human expert.

As mentioned in Section VI, the last state transition involves additional resources from the user. In the economic environment the experiment is conducted in, the users are very cost sensitive, meaning that to eliminate shipping costs, instead of shipping, the personal pick-up is preferred. It means that the last transition step involves time and transportation costs from the users. The fact that spreading activation based methods outperform the human expert shows that the interpretation of the relevance of the recommended items draws additional factors of the evaluation method.

One of our next steps is to implement and evaluate collaborative filtering in the described evaluation environment. By its nature, the dataset contains no rating information, hence a binary variant of collaborative filtering should be implemented. Another interesting topic is the analysis of the impact of wish-lists on the recommendation results.

A more technical problem is the user identification or authentication. We assume that by introducing a cookie or ETag based technique to identify returning users in the electronic commerce system, the number of edges of type `ItemVisited` can be significantly increased. Based on the additional information available, the recommendation method can be further investigated.

Utilizing neural networks and conditional random fields is also a possible direction of future research. By defining relations between nodes of the network on a more sophisticated level, the network can be able to more precisely adapt to the training data. Neural networks can be utilized with directed graphs.

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