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ABSTRACT
The way information is presented to users in online community platforms has an influence on the way the users create new information. This is the case, for instance, in question-answering fora, crowdsourcing platforms or other social computation settings. To better understand the effects of presentation policies on user activity, we introduce a generative model of user behaviour in this paper. Running simulations based on this user behaviour we demonstrate the ability of the model to evoke macro phenomena comparable to the ones observed on real world data.

Categories and Subject Descriptors
H.1 [**Models and Principles**]: Miscellaneous

General Terms
Model

Keywords
Generative Model, Discussion Forums, Online Community

1. INTRODUCTION
Users of online platforms are consumers and producers of information. They interact with each other by creating information items like messages, replies, questions and answers. Any information item the users add to the platform has a potential impact on the presentation of existing information items. The presentation of information items, in turn, affects the way users perceive them and thereby how they will react and respond to them. Thus, by creating information items each user is part of a feedback loop (Fig. 1) between herself and other users that is mediated by the online platform. This feedback loop influences the creation of content items in a way which still is not fully understood and described.

Related work in this field suggests explanations for the dependency between users and online community platforms. Salganik et.al [10] observed feedback effects for consumption of a synthetic media library. They did not take into account the creation of new content items. Nevertheless the results indicate that different alternatives for presenting information items influence the user actions on the micro level. Resulting self reinforcement processes can affect the distribution of reactions on the macro level. In work by Hogg and Lerman [6] the case of the community Digg has been investigated with the limitation of dealing with an unknown ranking algorithm. By investigating a community for support and discussion we provide insights into the generation processes that take place in discussion fora.

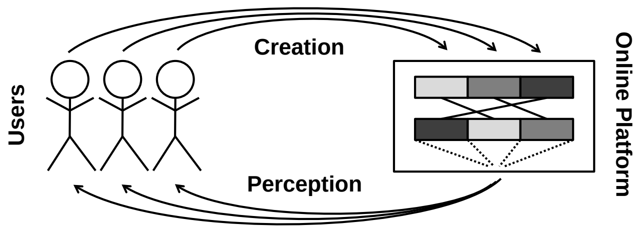

Figure 1: Feedback Loop

In this work we focus on the interdependence between user behaviour and functionality for content presentation. It is a common functionality of existing online platforms to support different types of filtering of available information items [11]. By filtering information items the platform also influences the users' perception of the information items. Furthermore, related work has shown that users are biased towards certain list entries based on their appearance and position [3].

Our hypothesis is that for better understanding and prediction of macro effects in content creation a model is required that comprises the presentation functionality as well as the user perception and interaction. Understanding the consequences of alternative presentation functionalities provides insights that community owner needs to be able to take the right design decisions.

The main contribution of this work is a generative model for the setting of collaborative creation of information items in online platforms. This model is evaluated on data of the SAP Community Network. In the proposed model different ways for perception of content items are considered. They comprise the application of different filters to an ordered list of information items. The model comprises a set of parameters that represent the particular system configuration. The set of parameters includes a.) the probability of applying one of the available filters to the list of information items; b.) the probability that one chooses the next information item on the list vs. continuing seeking further; c.) the probability to reply to existing content items instead of creating a new unconnected content item.

Estimating these few model parameters from observations on real data lets us adapt the model such that unforeseen data may be well mimicked by the model at the macro level. On the macro level we focus on structural properties of collections in community platforms, namely characteristic distributions of the size of collections of information items. We empirically show that our model reproduces these characteristics more accurately than alternative models for describing effects of attracting attention, such as preferential attachment.

The remainder of this paper is organized as follows. Section 2 explains the methodology of this paper. The observable properties of the SAP Community Network are collected in Section 3. In Section 4 we present a generative model of online communities and enact the model by estimating parameters from real world data in Section 5. The properties of real communities are compared with the simulated results of the community model in Section 6. In Section 7 we briefly discuss related work. Finally, Section 8 summarizes the key points and concludes this work.

2. METHODOLOGY

The goal of the following methodology is to create and to evaluate a model for the above mentioned feedback loop for content creation.

Such a model is characterized by properties of users and of the community platform. The resulting interdependencies between all components of the model interacting in the real world can be abstracted into an executable model for simulation (e.g. [10], [13]).

The method we propose for modeling macro effects of user behavior in online communities comprises the following steps:

- Model Development: Based on assumptions on user behavior and on properties of a community platform we develop a model that is suitable for simulating micro effects and from these allow for measuring macro effects.
- Metric for Model Quality: We define a metric that allows us to compare the synthetic user behavior from the model with the behavior that was observed in existing communities.
- Parameter Learning: We employ a method for learning the model parameters for specific online communities.
- Simulation-based Validation: By simulating the model we create synthetic community activity. We compare this activity with the real observations of the community and quantify to which extent the model is sufficiently close to reality.

3. EVALUATION DATASET

The SAP Community Network[1] is a platform that hosts an online community settled around the products of SAP. It offers wikis, blogs, polls, document uploads, and forums. The community discusses a broad range of topics like usage, configuration, development, and other services related to the respective SAP product. Forums for different topics organize the discussions and question answering. An advantage of analyzing the SAP Community Network is that users have a professional interest in participating which results in low noise and rather consistent data. Therefore, we may model the underlying dynamics without further cleaning of the data from spam - unlike other communities (e.g. [5]). In the following we will focus our attention and our modeling efforts on these forums.

[1]http://www.sdn.sap.com/

Table 1: Statistics of all Analyzed Forums

Metric	Number of Threads	Number of Replies
max	37,042	144,086
min	1,481	3,432
average	9,474.4	30,874.8
median	4,902	15,689
sum	426,350	1,389,365

User Interface. The user interface for forums provides simple means to browse through the existing threads. The threads are presented in the form of an ordered list. The order is induced by the timestamp of the latest thread reply, beginning with the newest timestamp.[2] Additionally, the users can filter the list of threads. The list of implemented filters includes key-word based filtering or a constraint to threads that are tagged 'answered', tagged 'unanswered', or that are without any reply.

User Activity. The SAP Community Network dataset is covering user activity of all forums from 2003-12-15 until 2011-01-27. The number of registered users in this time period was 32,723. We restricted the analysis to the biggest forums that include 95 % of the available threads. This results in 45 forums to be analyzed comprising 426,350 threads and 1,389,365 replies. Summarizing statistics on all analyzed forums are shown in Table 1.

4. COMMUNITY MODEL

Our community model can be broken down into three parts: a.) an abstraction model of the content items, b.) a model for content presentation and c.) a model of the user behaviour that combines all model parts to an executable algorithm. This community model is as simplistic as possible to allow for generalization and to minimize the risk of overfitting.

4.1 Community Content Model

The original dataset of the SAP Community Network comprises a set of forums. Each forum consists of a set of threads. Each thread consists of content items in a tree structure whose directed links represent reply relationships. We consider each forum to be independent from all other forums. Since we are only interested in threadsize and timestamps of changes we simplify the original model by ignoring the actual contents as well as the topology of the tree-structure of the discussion thread.

[2]The user interface has been reworked in 2012. The new interface provides additional orderings that are not considered in this work because of lack of newer data.

Thus, we represent a thread as a triple $thread \in Timestamp \times Timestamp \times \mathbb{N}$, where the first timestamp corresponds to the *creation date* of the thread, the second timestamp represents the creation date of the *last reply* and the integer value represents the number of replies in the thread. For our model we are not interested in the exact reproduction of temporal aspects of reality. Therefore we model time as ordered events and timestamps t_i merely as discrete points in time. An obvious constraint is *creation date* $\leq$ *last reply*.

The community users create in each time step new content items. Therefore the content that exists in each forum differs between two different timestamps. The content available at timestamp $t \in Timestamp$ is a state C_t that consists of a set of threads: $C_t \subset Timestamp \times Timestamp \times \mathbb{N}$. This set of threads corresponds to the aggregation of all content items in threads up to the time t. We define $C_0 = \emptyset$. The transition from one state C_{t_i} to the next state $C_{t_{i+1}}$ depends on the user activity model which we introduce in Section 4.3.

4.2 Model of User Interface

The model of the user interface describes the different ways the community platform can present contents to the users. Therefore, we describe a user interface as a set of presentation modes M. Each presentation mode m is a combination of a ranking ρ and a filter σ.

A ranking $\rho : C \rightarrow \mathbb{R}$ assigns a score to each thread at time t. When presenting the threads to users, the threads are listed in descending order of their relevance score. In our setting we consider the ranking function that sorts threads by last activity, so $\rho(t_i, t_j, k) := t_j$.

A filter $\sigma : C \rightarrow \{\textit{true, false}\}$ assigns a boolean value to each thread, indicating whether or not it should be displayed to the user. Examples for filters motivated by our use case are to display only threads which have no reply, i.e. $\sigma_{noReply}(t_i, t_j, k) := \textit{true}, \textit{if } k \leq 1, \textit{otherwise false}$, or to show all threads which have at least one reply, i.e. $\sigma_{reply}(t_i, t_j, k) := \textit{true}, \textit{if } k \geq 2, \textit{otherwise false}$.

Finally, there is the option of not using a filter. This corresponds to a presentation mode $m \in M$ where the filter function $\sigma_{showAll}$ assigns a *true* value to all threads.

4.3 Model of User Activity

The model of user activity describes how the state of a forum changes based on how the users create new content items. When creating content items, users are influenced by the presentation of existing content items, i.e. the model of the user interface.

The model of user activity defines the state transition how to get from C_{t_i} to $C_{t_{i+1}}$. There are two possible high level activities a user can choose from: a.) to create a new thread with probability u or b.) to add a reply with probability $1 - u$.

- If a new thread is created, we set $C_{t_{i+1}} = C_t \cup \{(t_{i+1}, t_{i+1}, 1)\}$. This means we extend the set of threads with one new thread which has been created at time t_{i+1} and consists of a single content item. Obviously, also the time of the last activity coincides with the creation time.
- If a reply is added, we assume the user to select an existing thread (t_i, t_j, k) and update it to $(t_i, t_{i+1}, k + 1)$. This means, the length of the thread is incremented by one entry and the time of the last activity is set to the current time t_{i+1}. The state of the community then changes as follows: $C_{t_{i+1}} = C_t \setminus \{(t_i, t_j, k)\} \cup \{(t_i, t_{i+1}, k + 1)\}$.

To identify the thread a user selects for adding an answer, we assume the user to choose a content presentation mode $m \in M$ from the user interface model. The choice of presentation mode follows an empirically given, but unobserved and hence unknown distribution which models user preferences in interacting with the system. Based on this presentation mode the user is shown a ranked and potentially filtered list of threads from C_{t_i}. We will denote this list with $m(C_{t_i})$ and use $|m(C_{t_i})|$ as the length of this list.

Once the presentation form has been selected, the user needs to identify the thread she will respond to. Also this selection is a stochastic process. We model the selection process by a random variable X that provides us the number of the selected entry in the list $m(C_t)$. Following the results in [3], we assume X to follow a geometric distribution. Accordingly the user selects the item at rank k with probability:

$$P(X = k) = (1 - q)^k \cdot q \qquad (1)$$

with q as the probability of stopping at each item while going through the list of ranked content items.

If $X > |m(C_{t_i})|$ (which happens with probability $(1 - q)^{|m(C_{t_i})|}$) we restart the process from the point where we decide whether to add a thread or to create a reply[3].

All three models may be brought together into a simulation algorithm that is presented in Alg. 1.

5. LEARNING MODEL PARAMETERS

The simulation has the following parameters:

- u, the probability $[0, 1]$ of a user to create a new thread instead of replying to an existing thread
- q, the probability $(0, 1]$ of a user to select the current thread for replying when traversing the ranked list of existing threads
- $p_{filterShowHasReply}$, the probability $[0, 1]$ of a user to display only threads that have at least one reply
- $p_{filterShowNoReply}$, the probability $[0, 1]$ of a user to display only threads that have no reply
- $p_{filterShowAll}$, the probability $[0, 1]$ of a user to display all threads

Please note that the probabilities for using a particular filter sum up to 1. Therefore not all possible combinations of these probabilities are valid.

For learning the parameters for our models two methods are applied. In cases where parameters can be determined directly from the data this is done. This applies to the parameter u that is calculated by counting the occurrences of threads and replies in the

[3]We assume that a user that has not found any thread to answer restarts the entire process of creating a content item

Algorithm 1: User Model

```
Input: Set of threads C_{t_i} at time t_i, thread creation probability u, thread selection probability q,
multinomial distribution θ over presentation modes in M.
Output: Set of threads C_{t_{i+1}} at time t_{i+1}
// Decide whether to create a new thread or a new reply to an existing thread
A ← UNIFORMRANDOM(0, 1);
if A ≤ u then
    // Add a new thread
    C_{t_{i+1}} = C_{t_i} ∪ {(t_{i+1}, t_{i+1}, 1)};
else
    // Decide which filter to use
    i ← MULTINOMIALRANDOM(θ);
    // Apply filter to obtain filtered and ranked list of threads
    m(C_{t_i}) ← FILTER(m_i, C_t);
    // Select a thread to reply to
    k ← 0;
    repeat
        B ← UNIFORMRANDOM(0, 1);
        k ← k + 1;
    until B ≤ q OR |R| < k;
    // Proceed only if the selected position in the thread list does not exceed its length
    if |m(C_{t_i})| ≥ k then
        // Update modification time and thread size
        thread ← m(C_{t_i})[k];
        thread' ← (threadCreationTimestamp(thread), t_{i+1}, size(thread) + 1));
        C_{t_{i+1}} = (C_{t_i} \ {thread}) ∪ {thread'};
```

training data. In all other cases the parameters are fitted to minimize the quality metric (cf. Section 6.2). This procedure applies to all other parameters: q, $p_{filterShowHasReply}$, $p_{filterShowNoReply}$, and $p_{filterShowAll}$.

The strategy of fitting the parameters was to cover the whole parameter space. In pretests we found out that an interval of 0.05 is sufficiently fine grained. This resulted in 4620 valid parameter combination that we tested on hold out training data.

6. EVALUATION

For each of the investigated forums the model parameters are extracted or fitted on hold out training data. Subsequently the parameterized models are executed and their results are compared to the properties that have been observed in the respective forums on separate test data.

6.1 Baseline

To be able to judge the benefit of our method we compare it to alternative approaches for explaining the observed macro-effects. The distribution of thread length observed in the data sets suggests a power law distribution. Given the generative character of the setting, a simple preferential attachment model [1] might explain the data as well.

Thus, we use as baseline method a preferential attachment model where a user chooses to interact with a content item proportional to the number of interactions it has previously received. The motivation for such an interpretation is the assumption that certain content items attract more attention than others due to their attractiveness. In turn a high number of interaction increases the perceived attractiveness of a content item.

6.2 Testing Model Quality

We compare if the distribution of thread sizes observable in the real online communities is the same distribution as in the simulated online communities. We consider both distributions as describing two independent random samples. These properties allow the application of suitable statistical tests for testing the hypothesis that the thread sizes resulting from the simulation has the same distribution as observed in the real online community.

A suitable test for this hypothesis under the given assumptions is the Smirnov Test [2]. This test is a two sample version of the Kolmogorov Test and therefore often called Kolmogorov-Smirnov two-sample test. For the Smirnov Test the test statistic is defined as follows: Let $S_r(x)$ be the empirical cumulative distribution function of the tread sizes observable in the real community and $S_s(x)$ be the empirical cumulative distribution function of the thread sizes of a simulation run. Then the two-sided statistic test is defined as the greatest vertical distance between the two cumulative distributions functions $T = \sup_x |S_r(x) - S_s(x)|$. The hypothesis H_0 is that two samples of sizes m and n are drawn from the same distribution. This hypothesis can be rejected at the significance level $\alpha = 0.05$ for sample sizes $n, m > 40$ if $T > 1.36\sqrt{\frac{m+n}{mn}}$.

6.3 Model Parameters

For learning the parameters two methods are applied. In cases where parameters can be determined directly from the data this is done. This applies to the parameter u that is calculated by counting the occurrences in the training data. In all other cases the parameters are fitted according to minimize the test statistics for the Smirnov Test. This procedure applies to all other parameters: q, $p_{filterShowHasReply}$, $p_{filterShowNoReply}$, and $p_{filterShowAll}$. Since the latter three parameters are dependent on each other all pa-

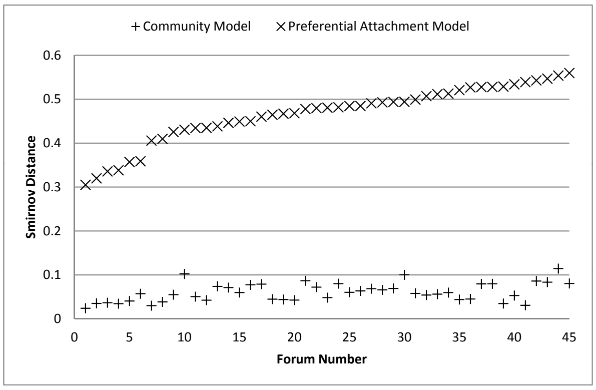

Figure 2: Evaluation Results for Filter Model and Preferential Attachment Model

rameters can be reduced to three parameters that have to be fitted.

The strategy of fitting the parameters was to cover the whole parameter space. In prior testes we found out that an interval of 0.05 is sufficiently fine grained. This resulted in 4620 valid parameter combination that have been tested.

6.4 Results

From all forums we have randomly chosen 10% of the threads and refer to them as Sample A. The remainder is used for testing the model in Sample B. For finding the best parameter combination for our model we simulated the space of the parameters. This resulted in 4620 parameter combinations for the proposed filter model. We performed a parameter fitting as well for the baseline model *Preferential Attachment* Subsequently we computed the average Smirnov Distance between 100 runs with the fitted parameters and the threads from Sample B.

The results for each forum are plotted in Fig. 2, ordered by distance to the baseline model. The plot shows that the *Community Model* that has been presented in this paper is better suitable to explain the observed distribution that the compared baseline *Preferential Attachment Model* for each of the investigated forums.

7. RELATED WORK

Lampe et al. [7] analysed how Slashdot users make use of personalised filter and ranking functions to modify the presentation of comments. Their analysis is based on a log file analysis. The obtained insights are proposed as basis for automatically setting the filters also for those users who are not aware of these mechanisms or reluctant to use them.

Wilkinson [14] investigate macroscopic effects in online collaborative platforms. He observed a power law distribution regarding the number of items produced by individual community members and a log normal distribution of activity per topic. However, while these macroscopic observation were made across four different platforms, the impact of presentation layers in platforms was not considered explicitly. Ren and Kraut [9] used an agent-based simulation to identify the impact of topical breadth, information overload and different styles of moderation on online communities. The moderation style corresponded to global or personalised filters in this setting. However, the aim of the investigation was to analyse benefits for users on a macro scale and not the impact on content perception.

Most similar to our analysis is the work by Hogg and Lerman [6]. They investigate a stochastic model of user interaction with content items to predict the popularity of individual items. Collective voting mechanism for content items affect their prominent appearance in the user interface which makes it more likely other users react to them. However, the focus of this model is to predict the popularity of a single document from early observations in the interactions. The Community Activity framework of van Oostendorp and van Varik [12] provides an agenda on how to stimulate activity in a community. A literature survey, analysis of real world communities as well as a life experiment showed that also the presentation of certain types of user information affect the level of interaction. None of the described methods, however, analysed the impact of how content items are presented.

Salganiak et al. [10] consider the impact of popularity information and presentation modes of music on the users' choice of items. The popularity information was conveyed by providing download statistics for the individual. The presentation modes covered listing the items in a ranking according to decreasing popularity or in a checkerboard way with random positions of the items. They observed that both has an impact on the user behaviour: the availability of information about the popularity of an item as well as the presentation mode. This not only affected the choice of items, but also the overall inequality in the item choice distribution.

Structured after the two aspects creation and perception of information items. Such feedback loops at the micro level of individuals and the macroscopic effects have been studied before in the general context of online community networks. For instance, several generative models have been proposed to explain the degree distribution as one fundamental property of information networks, such as the World Wide Web or citation networks [1, 8].

Dellschaft et al. [4] investigated the influences that produce the power law distributions observed in tag streams of Del.icio.us. They argue that the background knowledge of users is a required model component for accurate generation of the observable tag distributions. Weng et al. [13] provide a generative model for the spread of memes in the Twitter community. For Twitter they identify the social network of users as an important parameter of the model. The model is capable of accurately simulating macro effects as distributions for breadth of user attention and meme popularity.

8. CONCLUSION

In this work we have presented a generative model for forums in an online community. This model takes into account parameters for user behaviour and the functionality of the community platform for presenting the threads that already exist. The evaluation of this model on a data set of the SAP Community Network showed that our model is more accurate in simulating the distributions of thread lengths than the baseline preferential attachment. By explaining the activity of the user base with the functionality of the community platform, designers of community platforms have a tool for evaluating the effects of changes in functionality.

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APPENDIX

A. DATA SETS

At `http://userpages.uni-koblenz.de/~schwagereit/data/scn-data.zip` we provide an anonymized data set of the forum data that is used in this paper.

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