Topic-aware staff learning material generation in complaint management systems

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Abstract: In this paper, a topic-aware staff learning material generation approach is proposed in complaint management systems. Historical processing logs are extracted to form a complaint space. Complaint processing skills of staff members are assessed in terms of quantity, efficiency and quality on various topics. Similar staff members are clustered according to their behavioural characteristics. A resource recommendation algorithm is proposed to recommend complaint processing records from highly skilled colleagues in the cluster for the staff member to learn. Preliminary experiment results show good performance of the proposed method.

Keywords: user modelling; staff learning; user clustering; complaint management system.


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1 Introduction

As the development of major modern companies, the scales of their customers grow fast and the businesses become much complex. Complaint management has become one of the most important tasks in order to ensure quality service (Hunt et al., 2005). Partially due to the rapid turnover of staff, the skills of staff members for processing customer complaints can be varied. Personalised and targeted learning has therefore become an important way for staff members to improve their skills.

Traditional learning material generation methods are teacher-centric, not learner-centric, since they do not sufficiently take into account the different characteristics of different learners (Liu et al., 2006). In order to find learning materials that are suitable for a staff member to learn, a user model has to be established to assess his/her skills on various topics. In online systems, users’ interaction records with the system are a handy source for user modelling, from which behavioural patterns can be extracted to map their interests/knowledge to a topic ontology (Kim and Chan, 2008; Barradas et al., 2016).

In this paper, a personalised recommendation approach for staff learning in complaint management systems is proposed. Complaint processing logs are extracted to form a complaint space. Skills of staff members are assessed in terms of quantity, efficiency and quality on various topics. Similar staff members are clustered according to their behavioural characteristics. A learning material recommendation algorithm is presented to recommend complaint processing records for the staff members to learn.

The rest of the paper is organised as follows. Section 2 introduces the related work. Section 3 presents our topic-aware staff learning material generation method. Experiment results are described in Section 4. Possible applications are introduced in Section 5. The conclusion is drawn in Section 6.
2 Related work

There has been extensive work on user modelling for learners in intelligent tutoring systems (Xie et al., 2014; Desmarais and Baker, 2012). A machine learning approach is used to construct a student model to learn how long a student costs to solve a problem (Beck and Woolf, 2000). The model of problem difficulty is learnt in two phases. Data from all the students are used to train a neural network. The output of the neural network is adjusted to better fit individual students’ performance. Anitha and Deisy (2013) propose a method to dynamically generate learning path in an e-learning environment using genetic algorithm. A learning agent is constructed to model how likely a student is to answer a problem correctly and how long time he/she takes (Beck and Woolf, 1998). The agent is trained using historical records from the system. Predictions can be made for the time required to generate a response. User models can also be constructed for task generation in e-learning systems (Zou et al., 2014). The load of various incidental word learning tasks is measured from the perspective of involvement load hypothesis to constructed load-based learner profiles. A task generation method is proposed based on the load-based learner profile to increase the effectiveness of word learning and motivate learners.

A lot of work has been done for topic-aware resource recommendation in online systems (Dolog et al., 2004; Wang et al., 2015). Content-based filtering and collaborative filtering are widely used approaches (Adomavicius and Tuzhilin, 2005). Besides, folksonomy can also be used for community-based personalised recommendation and search (Xie et al., 2012). A collaborative tagging system provides users an environment to annotate resources, and assist users in searching their interested resources by using semantic tags. Three different strategies are presented to discover user communities. A personalised search approach is proposed that combines switching fusion and a revised needs-relevance function to optimise personalised resource ranking. A hybrid approach is proposed for personalised recommendation of news on the web (Wen et al., 2012). Web pages are classified using weights of terms. A user’s interest and preference are generated by analysing his/her browsing history. Recommendations are made to pages that the user is likely to be interested in and is related to the user’s preferred topics.

Existing approaches focus on general purpose web applications. Little work has been done for personalised recommendation for staff learning purpose in complaint management systems. In this paper, we propose a topic-aware staff learning material generation approach in complaint management systems.

3 Topic-aware learning material generation

The basic principle of the learning material generation approach is that people are easy to learn from those who are highly skilled and are similar to them in terms of behavioural characteristics. In this section, the workflow of the complaint management system is introduced and detailed steps of the topic-aware learning material generation procedure are described.
3.1 The workflow of the complaint management system

The system architecture and main workflow of the complaint management system are briefly introduced. Figure 1 shows the overall workflow of the complaint management system.

![Workflow of the complaint management system](image)

From the figure we can see that the system includes functions for complaint issuing, complaint processing, problem solving, complaint archiving, learning material generation, and staff learning. It also contains databases for complaint processing, complaint archiving, and learning materials. Firstly, a customer issues a complaint, which initiates the complaint management workflow. After receiving the complaint, a complaint processing staff member processes it and assigns a problem solving staff member if needed before sending it to the complaint processing database. After the problem is solved, the result is returned to the database before it can be reported to the customer. Processed complaints are archived periodically into the complaint archive database. The learning material generation function reads historical records from the archive database and recommends complaints that are suitable for a given complaint processing staff member. The generated materials are stored in the learning material database. The staff learning function organises the learning materials and presents them to a complaint processing staff member in various forms in a learning session.
3.2 Complaint space

Complaints in a company can be classified into various topics. Skills of customer service staff should be assessed for each topic, respectively. We define a topic ontology that represents the hierarchical structure of the topics. Each complaint is classified into a certain topic according to its content.

A complaint space is built from the historical complaint repository to describe the features of complaints. The complaint space is defined as a five-tuple in (1).

\[
C_{space} = (PS, US, US, f_u, f_s)
\]

where \( PS = \{p\} \) is the set of complaints in the company, \( US = \{u\} \) is the set of customer service staff that handle complaints, \( CS \) is the set of complaint topics, \( \forall c \in CS, c \) is a set of complaints whose topics are \( c \), \( f_u : PS \rightarrow US \) is a function from \( PS \) to \( US \), \( f_s(p) \) is the customer service staff member that handles complaint \( p \), \( f_s \) is a function, \( \forall u \in US \) and \( \forall c \in CS \), \( f_s(u, c) \) is the skill assessment result of staff member \( u \) on complaint topic \( c \).

3.3 Staff skill assessment

With the complaint space \( C_{space} \) established, staff members’ skills can be assessed using the accumulated historical data. For a particular topic \( c \), a staff member’s skills are assessed in 3 aspects, i.e., quantity (\( N \)), efficiency (\( E \)), and quality (\( Q \)). Each aspect is assessed according to several features extracted from \( C_{space} \). Formally, the assessment of staff member \( u \) on topic \( c \) is represented as a three-tuple in (2).

\[
f_i(u, c) = (f_N(u, c), f_E(u, c), f_Q(u, c))
\]

where \( f_N, f_E \) and \( f_Q \) are the assessment results in terms of quantity, efficiency and quality, respectively.

\[
f_i(u, c) = \frac{1}{1 + e^{-\sum_{i \in X} (R_i(u, c) - \bar{R}(c))}}
\]

where \( X = \{N, E, Q\} \) is the set of aspects that are assessed, \( R_i(u, c) \) is staff member \( u \)’s rating for feature \( i \) on topic \( c \), and \( \bar{R}(c) \) represents the mean value of \( R_i(u, c) \) for all staff members. All the feature ratings are normalised before used.

A sigmoid function is used in (3) to map the assessment results to interval (0, 1) so that assessment results of different aspects are equally treated in the learning material recommendation algorithm. \( \bar{R}(c) \) is used to identify the ratings of ordinary staff members for feature \( i \) on topic \( c \). The assessment result of a staff member with all the features equal to the average on topic \( c \) is 0.5. Higher ratings for features lead to higher assessment results.
3.4 Finding similar staff

Staff members are clustered using the k-means algorithm. The feature vector of a staff member \( u \) that represents his/her behavioural characteristics is defined in (4).

\[
BS(u) = (N, R_{E_1}, R_{E_2}, \ldots, R_{E_m}, R_{Q_1}, R_{Q_2}, \ldots, R_{Q_n})
\]

where \( N \) represents the number of complaints processed by staff member \( u \), \( R_{E_1}, R_{E_2}, \ldots, R_{E_m} \) are staff member \( u \)'s ratings for features regarding processing efficiency, and \( R_{Q_1}, R_{Q_2}, \ldots, R_{Q_n} \) are staff member \( u \)'s ratings for features regarding processing quality.

The distance function used in the clustering algorithm is the squared Euclidean distance as shown in (5). It is a frequently used distance function in optimisation problems as well as clustering. Progressively greater weights are placed on objects that are farther apart.

\[
dist(u_1, u_2) = \left\| BS(u_1) - BS(u_2) \right\|^2_2
\]

After clustering similar staff members according to their behavioural characteristics, we can find highly skilled colleagues in the same cluster as the current staff member for whom we want to recommend learning materials.

3.5 Learning material recommendation

The learning material recommendation algorithm takes several factors into consideration. The topic distribution for the recommended complaints is consistent with the target staff member \( u_0 \)'s processing record. Recommendations for each topic include complaints that aim to improve \( u_0 \)'s efficiency skills and those that aim to improve his/her quality skills. Efficiency targeted complaints are from the colleagues who are highly skilled in terms of efficiency and so are quality targeted ones. The numbers of the two kinds of complaints are inversely proportional to \( u_0 \)'s assessment scores for the two types of features.

Algorithm 1. Learning material recommendation

INPUT: CSpace, staff member \( u_0 \), number of recommended complaints \( num \)

OUTPUT: a set of complaints \( PS_{recommend}(u_0) \subset PS \) to be recommended to \( u_0 \)

1. \( PS_{recommend}(u_0) \leftarrow \Phi \)
2. Let \( US(u_0) \subset US \) be the set of users that are in the same cluster as \( u_0 \)
3. \( N(u_0) \leftarrow \sum_{c} N(u_0, c) \) is the total number of complaints processed by \( u_0 \)
4. for each topic \( c \in CS \) do
5. Get top-rated users \( u \in US_{E}(u_0, c) \subset US(u_0) \) for \( f_E(u, c) \)
6. Get top-rated users \( u \in US_{Q}(u_0, c) \subset US(u_0) \) for \( f_Q(u, c) \)
7. Get complaints \( PS_E(u_0, c) \) and \( PS_Q(u_0, c) \) processed by \( US_{E}(u_0, c) \) and \( US_{Q}(u_0, c) \) in \( c \) so that \( |PS_E(u_0, c)| / |PS_Q(u_0, c)| = f_E(u_0, c)/f_Q(u_0, c) \)
8. \( PS(u_0, c) \leftarrow PS_E(u_0, c) \cup PS_Q(u_0, c) \)
9. Randomly select \((N(u_0, c) \times num)/N(u_0)\) complaints from \( PS(u_0, c) \) into \( PS(u_0, c) \)
10. \( PS_{recommend}(u_0) \leftarrow PS_{recommend}(u_0) \cup PS(u_0, c) \).
The purpose of the learning material recommendation algorithm is to recommend complaint processing records from those who are highly skilled and are similar to $u_0$ in terms of behavioural characteristics. As we can see in Algorithm 1, initially the recommendation set $PS_{recommend}(u_0)$ is empty. For each of the topics in the complaint management system, highly skilled users in terms of efficiency and quality who are similar to $u_0$ are selected and their processed complaints are retrieved, respectively. The numbers of retrieved complaints are specifically designed so that the weaker aspect of skills is given more chance to learn. On the other hand, the total number of complaints recommended for the topic is chosen according to $u_0$’s own topic distribution of processing record so that more practice can be done on assigned or favourite topics for the user. All the topics are processed sequentially and selected complaints are added to the recommendation set $PS_{recommend}(u_0)$. Finally, the complaint processing records in $PS_{recommend}(u_0)$ are recommended to $u_0$ for his/her learning purpose.

4 Experiments

Preliminary experiments are conducted for the evaluation of the proposed method. The complaint management system in China Mobile Group Guangxi Company Limited is used as the complaint management platform in the experiment.

Historical complaint processing records of 1,000 staff members are extracted from the system, which are classified into ten topics, as shown in Table 1. The ten topics are defined according to the business of the company. The corresponding staff members are clustered according to their behavioural characteristics and their skills are assessed. Five staff members (A to E) are randomly selected from them and learning materials are recommended to them according to Algorithm 1. A survey is carried out for the staff members to self-assess their skills on the topics, as well as their feedback to the recommended complaint records for them to learn from.

### Table 1 Complaint topics in the system

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Service setup</td>
<td>B1</td>
</tr>
<tr>
<td>2</td>
<td>Website service</td>
<td>B2</td>
</tr>
<tr>
<td>3</td>
<td>3G service</td>
<td>B3</td>
</tr>
<tr>
<td>4</td>
<td>Refund not needed</td>
<td>B4</td>
</tr>
<tr>
<td>5</td>
<td>Refund needed</td>
<td>B5</td>
</tr>
<tr>
<td>6</td>
<td>Charges and billing</td>
<td>B6</td>
</tr>
<tr>
<td>7</td>
<td>Outbound calling</td>
<td>B7</td>
</tr>
<tr>
<td>8</td>
<td>Promotional SMS opt-out</td>
<td>B8</td>
</tr>
<tr>
<td>9</td>
<td>Supporting systems</td>
<td>B9</td>
</tr>
<tr>
<td>10</td>
<td>Internal feedback</td>
<td>B10</td>
</tr>
</tbody>
</table>

Four features are taken into account for the assessment of staff members’ complaint processing skills, which are shown in Table 2. Among the feature ratings, on-site solved rate (E1) and first contact solved rate (E2) are those regarding processing efficiency, and
dispatching accurate rate (Q1) and archive accurate rate (Q2) are those regarding processing quality.

Table 2  
Skill assessment features

<table>
<thead>
<tr>
<th>No.</th>
<th>Feature</th>
<th>Symbol</th>
<th>Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>On-site solved rate</td>
<td>E1</td>
<td>Efficiency</td>
</tr>
<tr>
<td>2</td>
<td>First contact solved rate</td>
<td>E2</td>
<td>Efficiency</td>
</tr>
<tr>
<td>3</td>
<td>Dispatching accurate rate</td>
<td>Q1</td>
<td>Quality</td>
</tr>
<tr>
<td>4</td>
<td>Archive accurate rate</td>
<td>Q2</td>
<td>Quality</td>
</tr>
</tbody>
</table>

Figure 2  
Overall characteristics of the topics (see online version for colours)

Figure 2 shows the overall characteristics of the topics in terms of feature ratings of staff members and the number of complaints. From the figure we can see that the numbers of complaints vary between more than 500 and less than 5,000. Topic service setup (B1) gets the most complaints while internal feedback (B10) gets the least. For efficiency and quality related features, E2 consistently gets higher ratings than E1 for all the topics while Q2 gets higher ratings than Q1. Especially, the ratings of E1 for B3 and Q1 for B10 get rather low values compared to others.

Experiment results for skill assessment and learning material recommendation are as follows. Comparison of computed and self-assessment for different types of features is shown in Figure 3. From the figure we can see that the computed feature scores are consistent with the staff members’ self-assessments in terms of overall trends. Especially, for efficiency features, the computed scores are higher than self-assessed values for five topics, and are lower for the other five topics. However, for quality features, self-assessed values are higher than computed ones for eight topics.
Figure 3  Comparison of computed and self-assessment for different types of features (see online version for colours)

Figure 4  Difference between computed and self-assessments (see online version for colours)

Figure 4 shows the difference between computed and self-assessments. From the figure we can see that the differences of efficiency and quality skills both remain at a low level. The quality difference for staff member D and efficiency difference for E are a little higher, but are still reasonable. This indicates that the assessment of staff skills is accurate.

The staff members are asked in the survey to state whether they think the recommended learning materials are helpful to improve their skills. The results are shown in Figure 5. From the figure we can see that staff members give positive feedback to the recommendations and think that the recommended materials are helpful to improve their skills. Among the topics, recommendations of website service (B2) and out-bound calling (B7) are most helpful to them.
5 Applications

The proposed approach is used to generate learning materials in complaint management systems. Some characteristics can be found in this kind of systems. The main objective of the systems is that users collaborate to finish some tasks. A certain task requires knowledge on a specific topic. The skills of users to finish the tasks can be divided into various aspects. The learning goal is to improve the skills of users to handle the tasks. Learning material generation in these systems is achieved based on the principle that people are easy to learn from those who are highly skilled and are similar to them.

We argue that the proposed method is applicable to other collaborative application platforms which have similar characteristics, which may include collaborative editing systems, and collaborative computing systems. The proposed approach may also be applied to general intelligent tutoring systems with specific adjustments, which is subject to further study and verification.

6 Conclusions

A topic-aware staff learning material generation approach in complaint management systems is proposed in this paper. The idea is that people are easy to learn from those who are highly skilled and are similar to them in terms of behavioural characteristics. The overall workflow of the complaint management system is introduced. A complaint space is built to describe the features of complaints. Skills of staff members are assessed in three aspects, namely quantity, efficiency, and quality. Similar staff members are clustered according to their behavioural characteristics. A learning material recommendation algorithm is presented to recommend complaint processing records. Experiments show good performance of the method.
References


