COSTRIAGE: A Cost-Aware Triage Algorithm for Bug Reporting Systems

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Abstract

‘Who can fix this bug?’ is an important question in bug triage to “accurately” assign developers to bug reports. To address this question, recent research treats it as a optimizing recommendation accuracy problem and proposes a solution that is essentially an instance of content-based recommendation (CBR). However, CBR is well-known to cause over-specialization, recommending only the types of bugs that each developer has solved before. This problem is critical in practice, as some experienced developers could be overloaded, and this would slow the bug fixing process. In this paper, we take two directions to address this problem: First, we reformulate the problem as an optimization problem of both accuracy and cost. Second, we adopt a content-boosted collaborative filtering (CBCF), combining an existing CBR with a collaborative filtering recommender (CF), which enhances the recommendation quality of either approach alone. However, unlike general recommendation scenarios, bug fix history is extremely sparse. Due to the nature of bug fixes, one bug is fixed by only one developer, which makes it challenging to pursue the above two directions. To address this challenge, we develop a topic-model to reduce the sparseness and enhance the quality of CBCF. Our experimental evaluation shows that our solution reduces the cost efficiently by 30% without seriously compromising accuracy.

1 Introduction

Bug reporting (or issue tracking) systems play an important role in the software development process. Through bug reporting systems, many bug reports are posted, discussed, and assigned to developers. For example, a big software project like Mozilla receives more than 300 reports per day (Anvik 2007).

Running a bug reporting system thus has many challenges including, and bug triage is one of the main challenges. Yet most triage tasks including bug assignment heavily rely on manual effort, which is labor intensive and potentially error prone (Jeong, Kim, and Zimmermann 2009). For example, miss-assignment causes unnecessary bug reassignments and slows the bug fixing process (Jeong, Kim, and Zimmermann 2009; Guo et al. 2010).

For this challenge, a state-of-the-art approach (Anvik, Hiew, and Murphy 2006) treats bug triage as a recommendation problem and proposes a solution that can be viewed as an instance of content-based recommendation (CBR). We will denote this as PureCBR, which learns from previous bug assignment patterns and estimates each developer’s success possibilities for fixing reported bugs.

However, in a general recommendation problem, CBR is well-known to suffer from over-specialization. In other words, it recommends only the types of bugs that each developer has solved in the past. This problem is more critical in practice, as bug assignments will be skewed to few experienced developers, which will significantly delay the fix time for these bugs, as they will be assigned to overloaded developers. As an extreme example, consider a system that always assigns a bug to a single experienced developer who has fixed many types of bugs. This system would achieve high accuracy, but fail to delegate this load to other underutilized developers and thus slow down the bug fixing process.

This observation leads to two new goals: First, we need to reformulate the bug triage problem to optimize not only accuracy but also cost. Second, we need to consider a hybrid approach, more specifically, a content-boosted collaborative filtering (CBCF) approach (Melville, Mooney, and Nagarajan 2002), combining an existing CBR with a collaborative filtering recommender (CF). CBCF approach has been reported to perform better than either approach alone.

A key challenge in achieving both goals is sparseness. For the first goal of optimizing cost, we need to estimate the cost of developer $D$ fixing bug $B$. However, the past history only reports this cost for a single developer who solved $B$, that is, one bug is fixed by one developer. This makes it challenging to estimate the cost for the remaining developers. For the second goal of leveraging a CF, sparseness is also an obstacle, as CF requires the collection of information from developers who have worked on the same bug (collaborating), which cannot be done using past history. As only one developer was selected to work on each bug, this approach is essentially infeasible.

To overcome this sparseness problem, we propose a cost-aware triage algorithm, COSTRIAGE. COSTRIAGE models “developer profiles” to indicate developers’ estimated costs for fixing different types of bugs. “Types” of bugs are extracted by applying Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2003) to bug report corpora. This addresses
the sparseness problem and enhances the recommendation quality of CBCF.

Using developer profiles, whenever a new bug is reported, we first determine the type of the bug, and obtain each developer’s estimated cost for the bug. Then by combining the cost with the possibilities estimated by PureCBR, we rank the developers and assign the first developer to the bug.

We experimentally evaluate COSTRIAGE using four real-life bug report corpora\(^1^,\) \(^2\), \(^3\), \(^4\), in comparison with two baselines: (1) PureCBR, and (2) CBCF. Our experimental results show that COSTRIAGE significantly reduces cost, without seriously significantly sacrificing accuracy.

## 2 Approach

To pursue the dual goals of accuracy and cost, we use two historical datasets \(\mathcal{H}_F\) and \(\mathcal{H}_C\). \(\mathcal{H}_F\) consists of the pairs of \((F(B), D)\), where \(F(B)\) is the feature vector of a given bug \(B\), and \(D\) is the developer who fixed \(B\). \(\mathcal{H}_C\) is an \(m\)-by-\(n\) matrix of costs for \(m\) developers and \(n\) fixed bugs. As a proof-of-concept, we use bug fix time as cost.

For a reported bug, using \(\mathcal{H}_F\), we identify who can fix the bug. Meanwhile, using \(\mathcal{H}_C\), we find how much it will cost for each developer to fix the bug. Finally, combining the both results, we rank the developers and choose one to be assigned.

### 2.1 Baseline I: PureCBR

Anvik’s algorithm (Anvik, Hiew, and Murphy 2006), PureCBR, considers bug triage as a multi-class classification problem, and utilizes only \(\mathcal{H}_F\). For each data record in \(\mathcal{H}_F\), \(F(B)\) is the set of keywords extracted from the title, descriptions, and other metadata contained in the bug report \(B\). The developer \(D\), who actually fixed this bug, is the class of this data record.

After training a multi-class classifier, when a new bug is reported, PureCBR estimates each developer’s score for the new bug by extracting its feature vector and applying the classifier. PureCBR simply picks the developer with the highest score to assign the reported bug. It thus neglects the costs of developers to fix the bug.

### 2.2 Baseline II: CBCF

Adopting PureCBR is a sufficient solution to utilize \(\mathcal{H}_F\), but it disregards \(\mathcal{H}_C\). We need to utilize both \(\mathcal{H}_F\) and \(\mathcal{H}_C\).

For a new reported bug \(B\), to be cost aware, we estimate each developer’s cost for fixing \(B\). Even though this problem seems to be related to CF problems, pure CF algorithms do not work for bug triage data, because we have no known cost for fixing \(B\). However, by training one classifier of cost for each developer, CBR or CBCF can be applied. We choose to apply CBCF because it outperforms CBR in general (Melville, Mooney, and Nagarajan 2002).

To combine CBCF-based cost estimation with PureCBR, we introduce the following four-step hybrid procedure:

1. For each developer, a support vector machine (SVM) classifier is trained using the bug features from the bugs fixed by the developers and the time spent to fix that as the class.
2. When a new bug \(B\) is reported, developers’ cost vector \(\mathcal{L}_C\) is estimated. An empty column for \(B\) is inserted to \(\mathcal{H}_C\), and each empty cell of \(\mathcal{H}_C\) is filled with the pseudo cost estimated by the corresponding classifier trained in the first step. We then apply column-column CF (developer-developer CF) to \(\mathcal{H}_C\), to revise the pseudo costs of \(B\).
3. PureCBR is performed to obtain the vector \(\mathcal{L}_S\) of developers’ success possibilities.
4. \(\mathcal{L}_C\) and \(\mathcal{L}_S\) are merged into one vector \(\mathcal{L}_H\). Developers are ranked in descending order of \(\mathcal{L}_H\), then the first developer is assigned to \(B\).

The first and the second steps of the procedure exactly follow Melville’s CBCF algorithm (Melville, Mooney, and Nagarajan 2002).

In the rest of the paper, we will denote this four-step approach as CBCF.

### Merging \(\mathcal{L}_C\) and \(\mathcal{L}_S\)

When we reach the last step, \(\mathcal{L}_C\) and \(\mathcal{L}_S\) are merged as follows. Formally, \(\mathcal{L}_C\) and \(\mathcal{L}_S\) are:

\[
\mathcal{L}_C = \{s_{c[1]}, s_{c[2]}, \ldots, s_{c[n]}\}, \quad \mathcal{L}_S = \{s_{s[1]}, s_{s[2]}, \ldots, s_{s[n]}\},
\]

where \(s_{c[i]}\) means the \(i\)th developer’s estimated cost to fix the given bug \(B\), and \(s_{s[i]}\) denotes the \(i\)th developer’s success possibility for fixing \(B\), obtained by PureCBR.

To merge the vectors and obtain a hybrid score vector \(\mathcal{L}_H\),

\[
\mathcal{L}_H = \{s_{h[1]}, s_{h[2]}, \ldots, s_{h[n]}\},
\]

a hybrid score \(s_{h[i]}\) of a developer is computed as a weighted arithmetic mean of the normalized \(s_{c[i]}\) and \(s_{s[i]}\):

\[
s_{h[i]} = \alpha \cdot \frac{s_{c[i]}}{\max(\mathcal{L}_C)} + (1 - \alpha) \cdot \frac{1/s_{s[i]}}{\min(\mathcal{L}_S)},
\]

where \(0 \leq \alpha \leq 1\). In Equation 1, we take the inverse of \(s_{c[i]}\) because a small \(s_{c[i]}\) value means high performance, i.e., short estimated time to fix \(B\). Both \(s_{c[i]}\) and \(1/s_{s[i]}\) are normalized to have a maximum value of 1. This hybrid computation involves one control parameter, \(\alpha\), to trade-off accuracy with cost.

### 2.3 Proposed Approach: COSTRIAGE

CBCF tries to utilize both accuracy and cost. However CBCF has room for improvement, because bug fix history is extremely sparse. We thus devise developer profiles, which are compact and unsparsely. Our new triage algorithm, COSTRIAGE, basically follows the four steps of CBCF, but we replace the first two steps with a new procedure using the developer profiles.

#### Constructing Developer Profiles

A developer profile is a numeric vector, in which each element denotes the developer’s estimated cost for fixing a certain bug type. The bug type means that if some bugs belong to the same type, these bugs share very similar features. More formally, a developer profile \(P_u\) is a \(T\)-dimensional vector of numeric scores \(p_u[i]\):

\[
P_u = \{p_u[1], p_u[2], \ldots, p_u[T]\},
\]
where \( p_{ui}[i] \) denotes the developer’s cost for \( i^{th}\)-type bugs and \( T \) denotes the number of bug types.

To model developer profiles, we need to address two major problems: (1) how to categorize bugs to determine bug types, and (2) how to obtain the profile of each developer.

- **Categorizing Bugs**: One naive way to define types of bugs is to assume that each reported bug belongs to its own specific type. This means that if \( N \) distinct bugs have been reported, \( N \) types of bugs exist, i.e., \( T = N \). Clearly, this approach is not desirable for our problem, because the dimensionality of the profiles would be both too large and unbounded. Therefore, we devise a method to define a small and limited number of bug types, adopting LDA.

The basic idea of LDA is that a document is a mixture of latent topics, and that each topic is characterized by a distribution of words. For a given number of topics \( T \) and a corpus of documents, where each document is a sequence of words, LDA extracts \( T \) topics from the corpus. After the topics are extracted, the LDA model of these topics can be used to determine the distribution of topics for each document.

To apply LDA, one main question is “what is the natural number of topics in a corpus?” Although it may be explicitly answered, obtaining such information is often difficult. To address this challenge, we adopt Arun’s divergence measure (Arun et al. 2010), because it has more robust behaviors than others (Cao et al. 2009; Zavitsanos et al. 2008).

In the context of bug reports, for using LDA, each bug report can be considered as a document, which consists of words that are explicitly stated in bug reports. Table 1 illustrates an LDA model of 48,424 Mozilla bug reports.

Each topic in an LDA model is represented as probabilities that words will occur in the report, and choose the topic with the most similar probability distribution. That is, for a given bug report \( \text{document} \), we compute probabilities that words will occur. For instance, Topic 1 of the LDA model of 48,424 Mozilla bug reports.

<table>
<thead>
<tr>
<th>Topic 1</th>
<th>Topic 2</th>
<th>Topic 3</th>
<th>Topic 4</th>
<th>Topic 5</th>
<th>Topic 6</th>
<th>Topic 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>c</td>
<td>0.058</td>
<td>mozilla</td>
<td>0.047</td>
<td>js</td>
<td>0.028</td>
<td>window</td>
</tr>
<tr>
<td>line</td>
<td>0.058</td>
<td>firefox</td>
<td>0.024</td>
<td>error</td>
<td>0.018</td>
<td>page</td>
</tr>
<tr>
<td>cpp</td>
<td>0.040</td>
<td>add</td>
<td>0.014</td>
<td>mozilla</td>
<td>0.019</td>
<td>click</td>
</tr>
<tr>
<td>int</td>
<td>0.032</td>
<td>version</td>
<td>0.010</td>
<td>file</td>
<td>0.014</td>
<td>menu</td>
</tr>
<tr>
<td>src</td>
<td>0.026</td>
<td>thunderbird</td>
<td>0.010</td>
<td>function</td>
<td>0.011</td>
<td>open</td>
</tr>
<tr>
<td>const</td>
<td>0.023</td>
<td>file</td>
<td>0.008</td>
<td>as</td>
<td>0.010</td>
<td>text</td>
</tr>
<tr>
<td>bytes</td>
<td>0.019</td>
<td>added</td>
<td>0.007</td>
<td>chrome</td>
<td>0.009</td>
<td>select</td>
</tr>
<tr>
<td>builds</td>
<td>0.018</td>
<td>install</td>
<td>0.007</td>
<td>content</td>
<td>0.009</td>
<td>search</td>
</tr>
</tbody>
</table>

Table 2 shows example profiles constructed from Mozilla bug reports. On average, developer \( D_1 \) took 14.28 days to fix \( 4^{th}\)-type bugs, and 5.44 days to fix \( 6^{th}\)-type bugs. In contrast, \( D_2 \) took 1.75 days to fix \( 4^{th}\)-type bugs, and 12.90 days to fix \( 6^{th}\)-type bugs. This suggests that these developer profiles clearly reveal the differences between developers.

Table 2: Sparserness of developer profiles obtained from bug reports for Mozilla project. There are many blanks in the profiles, and this may incur some overspecialization problems. The \( 2^{nd}\)-type bugs will always be assigned to Developer \( D_1 \). Likewise, to \( D_4 \), only \( 6^{th}\) or \( 7^{th}\)-type bugs are assigned.

<table>
<thead>
<tr>
<th>Bug types</th>
<th>Dev</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>( D_1 )</td>
<td>7.73</td>
<td>1.71</td>
<td>8.59</td>
<td>14.28</td>
<td>7.54</td>
<td>5.44</td>
<td>8.45</td>
<td></td>
</tr>
<tr>
<td>( D_2 )</td>
<td>8.18</td>
<td>-</td>
<td>3.50</td>
<td>1.75</td>
<td>4.00</td>
<td>12.90</td>
<td>13.18</td>
<td></td>
</tr>
<tr>
<td>( D_3 )</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>( D_4 )</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: An LDA model of bug reports for Mozilla. \( T = 7 \). Top-10 representative words with the highest probabilities.
The similarity between two profiles is computed as their cosine similarity:

\[ S(P_u, P_v) = \frac{P_u \cdot P_v}{\|P_u\| \|P_v\|} \times \omega(P_u, P_v), \]

(4)

where \( \| \cdot \| \) denotes its \( L^2 \) norm (Euclidean length). To compute the dot product, \( P_u \cdot P_v \), and the \( L^2 \) norms, \( \|P_u\| \) and \( \|P_v\| \), we only consider dimensions in which the values exist in both profiles.

In Equation 4, \( \omega(P_u, P_v) \) is a significance weighting factor, which is a simple but very effective way to prevent over estimation of the similarities (Herlocker, Konstan, and Riedl 2002; Ma, King, and Lyu 2007). The significance weighting factor is computed as:

\[ \omega(P_u, P_v) = \min \left( \frac{|P_u \cap P_v|}{\Theta}, 1 \right), \]

(5)

where \( \Theta \) is a given threshold, and \( |P_u \cap P_v| \) denotes the number of dimensions in which both profiles have known values. If only a small number of dimensions have values in both profiles, considering only those dimensions would devalue the similarity between two profiles.

Based on this similarity notion, to determine the set \( N_u \) of neighborhood profiles, we pick the top-k most similar profiles to \( P_u \). Then by aggregating \( N_u \), we can fill up the blanks in \( P_u \). To illustrate, Table 3 shows the example profiles introduced in Table 2, after we fill up the blanks using CF.

Table 3: Developer profile examples introduced in Table 2. Missing values were filled up using CF.

<table>
<thead>
<tr>
<th>Dev</th>
<th>Bug types</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 7.73 1.71 8.59 14.28 7.54 5.44 8.45</td>
</tr>
<tr>
<td>2</td>
<td>8.18 6.40 3.50 1.75 4.00 12.90 13.18</td>
</tr>
<tr>
<td>3</td>
<td>13.18 12.99 10.97 11.41 15.14 22.40 20.75</td>
</tr>
</tbody>
</table>

After we fill up all blanks in the profiles, for a given bug report, we can find out all developers’ estimated costs, \( L_C \), by determining the most relevant topic using the LDA model. Then PureCBR is also performed to obtain \( L_S \), and we merge \( L_C \) and \( L_S \) into \( L_H \), in the same way of CBCF.

3 Experimental Results

In this section, we discuss our experimental setup and present our results. We design our experiments to address two research questions:

**Q1** How much can our approach improve cost (bug fix time) without sacrificing bug assignment accuracy?

**Q2** What are the trade-offs between accuracy and cost (bug fix time)?

3.1 Setup

We evaluate our approach using bug reports from four open source projects: Apache, Eclipse, Linux kernel, and Mozilla.
it is important to select the “optimal” value. To choose $T$, we adopt the divergence measure proposed in (Arun et al. 2010), as we discussed in Section 2.3. The optimal $T$ minimizes the divergence between the document-word matrix and the topic-word matrix. Formally:

$$T = \arg\min_k KL_{\text{Divergence}}(t) \quad (7)$$

Such $T$ corresponds to the lowest $KL_{\text{Divergence}}$ value. In our experiments, the optimal $T$ are 19, 17, 7, and 7 for Apache, Eclipse, Linux kernel, and Mozilla projects’ bug report corpora respectively.

After determining the optimal number of topics, $T$, of each bug report corpus, we identify the bug type of each valid bug report. We evaluate the scores of each topic in a report, and then determine the report’s bug type as the topic which has the highest score. Scores are the sum of extracted word distributions related to each topic respectively, from the title and the description in the bug report. For bug reports which have no topic words, we assign the reports’ bug types randomly.

We then model the developer profiles of active developers. We first evaluate each developer profile (Table 2). However, we could not compute all values, because some developers had never been assigned certain types of bugs as mentioned in Section 2.3. In this case, we predict missing values using CF and complete modeling profiles of active developers (as illustrated in Table 3).

To evaluate the effectiveness of our profile modeling, we compute the relative error of expected bug fix time, using the four corpora. COSTRIAGE generally outperforms CBCF, especially for the case of the Apache corpus (Table 5).

### Evaluation

To evaluate the algorithms, we use two measures: \textit{Accuracy} = $\frac{|W|}{N}$, and

\[
\text{Average bug fix time} = \frac{\sum_{w_i \in W} \{\text{bug fix time of } w_i\}}{|W|},
\]

where $W$ is the set of bug reports predicted correctly, and $N$ is the number of bug reports in the test set. Because the “real” fix time for mismatched bugs is unknown, we only use the fix time for correctly matched bugs to compute the average fix time for a given set of bugs.

We use the first 80% of bug reports as a training set and the remaining 20% as a test set to conduct our experiments.

### 3.2 Results

This section presents our experimental results and addresses the research questions raised at the beginning of this section.

#### Improving Bug Fix Time

We apply COSTRIAGE, CBCF, and PureCBR to our subjects, and compare accuracy and bug fix time of the three approaches.

Table 6 shows the comparison results. Using PureCBR, the accuracy is 69.7% for Apache. On average, a developer takes 32.3 days to fix one bug for Apache. By controlling the parameter $\alpha$ for each of CBCF and COSTRIAGE, we match the accuracy of both CBCF and COSTRIAGE, to fairly compare their cost savings. For the Apache corpus, in one setting, both CBCF and COSTRIAGE sacrifice about 5.5% of accuracy, i.e., the both methods show 65.9% accuracy, but COSTRIAGE significantly outperforms CBCF in terms of cost. While CBCF only reduces the cost by 2.2%, COSTRIAGE reduces it by more than 30%.

#### Trade-off between Accuracy and Bug Fix Time

In this section, we observe the trade-offs between bug assignment accuracy and bug fix time using COSTRIAGE compared to CBCF.

We apply COSTRIAGE and CBCF to the four subjects with varying $\alpha$ to observe the trade-offs between accuracy and average bug fix time. Figure 1 shows the relation graphs

### Table 4: Subject systems

<table>
<thead>
<tr>
<th>Projects</th>
<th># Fixed bug reports</th>
<th># Valid bug reports</th>
<th># Total developers</th>
<th># Active developers</th>
<th># Bug types</th>
<th># Words</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Apache</td>
<td>13,778</td>
<td>656</td>
<td>187</td>
<td>10</td>
<td>19</td>
<td>6,915</td>
<td>2001-01-22 - 2009-02-09</td>
</tr>
<tr>
<td>Eclipse</td>
<td>152,535</td>
<td>47,862</td>
<td>1,116</td>
<td>100</td>
<td>17</td>
<td>61,515</td>
<td>2001-10-11 - 2010-01-22</td>
</tr>
<tr>
<td>Linux kernel</td>
<td>3,082</td>
<td>968</td>
<td>270</td>
<td>28</td>
<td>7</td>
<td>71,878</td>
<td>2002-11-14 - 2010-01-16</td>
</tr>
<tr>
<td>Mozilla</td>
<td>162,839</td>
<td>48,424</td>
<td>1,165</td>
<td>117</td>
<td>7</td>
<td>71,878</td>
<td>1998-04-07 - 2010-01-26</td>
</tr>
</tbody>
</table>

### Table 5: The relative error of expected bug fix time. We use the first 80% of bug reports in the four corpora as a training set and the rest as a test set to compute the error.

<table>
<thead>
<tr>
<th></th>
<th>Apache</th>
<th>Eclipse</th>
<th>Linux</th>
<th>Mozilla</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBCF</td>
<td>51.23</td>
<td>10.62</td>
<td>25.31</td>
<td>10.67</td>
</tr>
<tr>
<td>COSTRIAGE</td>
<td>19.18</td>
<td>16.66</td>
<td>9.25</td>
<td>8.76</td>
</tr>
</tbody>
</table>

### Table 6: Average bug fix time and accuracy using PureCBR, CBCF, and COSTRIAGE.

<table>
<thead>
<tr>
<th></th>
<th>PureCBR</th>
<th>CBCF</th>
<th>COSTRIAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Project</td>
<td>Time</td>
<td>Acc</td>
<td>Time</td>
</tr>
<tr>
<td>Apache</td>
<td>32.3</td>
<td>69.7</td>
<td>-2.2%</td>
</tr>
<tr>
<td>Eclipse</td>
<td>17.9</td>
<td>40.4</td>
<td>-5.6%</td>
</tr>
<tr>
<td>Linux</td>
<td>55.3</td>
<td>30.9</td>
<td>-24.9%</td>
</tr>
<tr>
<td>Mozilla</td>
<td>11.3</td>
<td>64.3</td>
<td>-4.4%</td>
</tr>
</tbody>
</table>
We proposed a new bug triaging technique, Costriage, by (1) treating the bug triage problem as a recommendation problem optimizing both accuracy and cost and (2) adopting CBCF combining two recommender systems. A key challenge to both techniques is the extreme sparseness of the past bug fix data. We addressed the challenge by using a topic-model to reduce the sparseness and enhanced the quality of CBCF. Our experiments showed that our approach significantly reduces the cost without significantly sacrificing accuracy. Though we used a proof-of-concept implementation by using bug fix time as cost, our developer profile model is general enough to support other code indicators such as interests, efforts, and expertise to optimize for both accuracy and cost for automatic bug triage.

Our algorithm is not restricted to only bug triage problems. Any recommendation techniques involving two objectives can potentially adopt our algorithm. For example, identifying experts for a question in QA (Question & Answer) system is a problem of matching a question to an expert, and our algorithm can utilize both side needs of questioner and answerer.

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