Bug Localization with Semantic and Structural Features using Convolutional Neural Network and Cascade Forest

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Outline

• Background
• Main focus of existing techniques
• CNN_Forest technique
• Experimental results
• Conclusions and Future works
Background

Coding mistakes

Describe

Localize

Extract

Search

Source files

Bug report

Bug localization
Outline

• Background

• **Main focus of existing techniques**
  • CNN_Forest technique
  • Experimental results
  • Conclusions and Future works
Main focus of existing techniques

• Textual similarity
  transform the terms in bug reports and source files into textual representations (vectors) and then measure the textual similarity between them:
  
  ➢ Latent Semantic Indexing (LSI) represents code and queries as vectors, and estimates the similarity between their vector representations using the cosine similarity.
  
  ➢ Latent Dirichlet Allocation (LDA)-based approach measures the similarity between the descriptions of bug reports and the topics of source files estimated by LDA.
  
  ➢ Vector Space Model (VSM) transforms bug reports and source files into feature vectors and then measures the similarity between them.

Textual similarity ≠ semantics
Main focus of existing techniques

• The lexical mismatch problem
  ➢ There is a lexical mismatch problem between the texts in bug reports and code tokens in source files caused by the ignorance of the semantic information in them.
  ➢ Word embedding techniques are commonly applied to obtain vectors of words in bug reports and source files, and measures the similarity between them.
Main focus of existing techniques

• Lexical mismatch
  ➢ There is lexical mismatch problem between the texts in bug reports and code tokens in source files caused by the ignorance of the semantic information in them.
  ➢ Word embedding techniques are commonly applied to obtain vectors of words in bug reports and source files, and measures the similarity between them.

• Structural features
  ➢ Compared to natural languages, programs contain rich statistical properties and more stringent structural information.
  ➢ NP-CNN employs convolutional neural networks (CNNs) to extract structural features from both bug reports and source files, and uses a fully-connected network to fuse features.
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• Background
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• **CNN_Forest technique**
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CNN_Forest technique

Figure 3: The Overall Workflow of CNN Forest.
**CNN_Forest technique**

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CNN with Multiple Filters to Extract Features from Bug Reports

Figure 4: The Feature Extraction of Bug Reports using CNN.
CNN_Forest technique

Figure 3: The Overall Workflow of CNN Forest.
Ensemble of Random Forests with Multi-grained Scanning for Source Files

Figure 5: The Feature Extraction of Source Files using Ensemble of Random Forests.
Figure 3: The Overall Workflow of CNN Forest.
Figure 6: Cascade Forest to Further Extract Features and Learn the Correlated Relationships between Bug Reports and Source Files.
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• **Experimental results**
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Experimental Preparations

Table I Subject Projects

<table>
<thead>
<tr>
<th>Project</th>
<th>Time Range</th>
<th># of Bug Reports for Evaluation</th>
<th># of Bug Reports for Tuning</th>
<th># of Bug Reports for Training</th>
<th># of Bug Reports for Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>AspectJ</td>
<td>03/02-01/14</td>
<td>593</td>
<td>100</td>
<td>400</td>
<td>93</td>
</tr>
<tr>
<td>Eclipse UI</td>
<td>10/01-01/14</td>
<td>3,656</td>
<td>1,500</td>
<td>500</td>
<td>1,656</td>
</tr>
<tr>
<td>JDT</td>
<td>10/01-01/14</td>
<td>2,632</td>
<td>1,500</td>
<td>500</td>
<td>632</td>
</tr>
<tr>
<td>SWT</td>
<td>02/02-01/14</td>
<td>2,817</td>
<td>1,500</td>
<td>500</td>
<td>817</td>
</tr>
<tr>
<td>Tomcat</td>
<td>07/02-01/14</td>
<td>1,056</td>
<td>400</td>
<td>500</td>
<td>156</td>
</tr>
</tbody>
</table>

Metrics

\[
MRR = \frac{1}{Q} \sum_{i=1}^{Q} \frac{1}{first_i}
\]

\[
MAP = \frac{1}{Q} \sum_{i=1}^{Q} \sum_{r=1}^{R} \frac{(N_T(r)/r) \times ind(r)}{N_B(i)}
\]

1 http://eclipse.org/aspectj/
2 http://projects.eclipse.org/projects/eclipse.platform.ui
3 http://www.eclipse.org/jdt/
4 http://www.eclipse.org/swt/
5 http://tomcat.apache.org
Comparisons with other techniques

• validation set:
  - CNN_CNN uses the same strategy (CNN) to extract features from bug reports and source files.
  - Forest_Forest applies the same ensemble of random forests to extract features of bug reports and source files.

• testing set:
  - NP-CNN applies CNN to learn unified features from natural and programming languages.
  - LR+WE enhances their previously-proposed learning-to-rank model (LR) by adding new features obtained by word embedding (WE) techniques.
  - DNNLOC combines deep learning techniques with the information retrieval techniques to localize the buggy files for bug reports.
  - BugLocator measures the textural similarity between the texts in bug reports and source files using the revised Vector Space Model (rVSM).
## Intrinsic Evaluation

**Table 2: Performance Comparison for Intrinsic Evaluation.**

<table>
<thead>
<tr>
<th>Project</th>
<th>Metrics</th>
<th>CNN_Forest</th>
<th>CNN_CNN</th>
<th>Forest_Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>AspectJ</td>
<td>MAP</td>
<td>0.458</td>
<td>0.449</td>
<td>0.430</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.563</td>
<td>0.560</td>
<td>0.549</td>
</tr>
<tr>
<td>Eclipse UI</td>
<td>MAP</td>
<td>0.460</td>
<td>0.441</td>
<td>0.465</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.590</td>
<td>0.561</td>
<td>0.588</td>
</tr>
<tr>
<td>JDT</td>
<td>MAP</td>
<td>0.448</td>
<td>0.448</td>
<td>0.435</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.517</td>
<td>0.502</td>
<td>0.492</td>
</tr>
<tr>
<td>SWT</td>
<td>MAP</td>
<td>0.462</td>
<td>0.415</td>
<td>0.439</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.530</td>
<td>0.507</td>
<td>0.512</td>
</tr>
<tr>
<td>Tomcat</td>
<td>MAP</td>
<td>0.627</td>
<td>0.623</td>
<td>0.604</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.681</td>
<td>0.669</td>
<td>0.647</td>
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</tbody>
</table>
## Extrinsic Evaluation

Table 3: Performance Comparison of the State-of-the-Art Techniques.

<table>
<thead>
<tr>
<th>Project</th>
<th>Metrics</th>
<th>CNN_Forest</th>
<th>NP-CNN</th>
<th>LR+WE</th>
<th>DNNLOC</th>
<th>BugLocator</th>
</tr>
</thead>
<tbody>
<tr>
<td>AspectJ</td>
<td>MAP</td>
<td>0.436</td>
<td>0.402</td>
<td>0.302</td>
<td>0.323</td>
<td>0.278</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.519</td>
<td>0.487</td>
<td>0.454</td>
<td>0.475</td>
<td>0.364</td>
</tr>
<tr>
<td>Eclipse UI</td>
<td>MAP</td>
<td>0.432</td>
<td>0.429</td>
<td>0.398</td>
<td>0.413</td>
<td>0.332</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.534</td>
<td>0.529</td>
<td>0.461</td>
<td>0.514</td>
<td>0.383</td>
</tr>
<tr>
<td>JDT</td>
<td>MAP</td>
<td>0.423</td>
<td>0.405</td>
<td>0.417</td>
<td>0.342</td>
<td>0.290</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.514</td>
<td>0.463</td>
<td>0.516</td>
<td>0.452</td>
<td>0.367</td>
</tr>
<tr>
<td>SWT</td>
<td>MAP</td>
<td>0.394</td>
<td>0.371</td>
<td>0.381</td>
<td>0.369</td>
<td>0.269</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.482</td>
<td>0.466</td>
<td>0.446</td>
<td>0.445</td>
<td>0.312</td>
</tr>
<tr>
<td>Tomcat</td>
<td>MAP</td>
<td>0.550</td>
<td>0.529</td>
<td>0.503</td>
<td>0.523</td>
<td>0.425</td>
</tr>
<tr>
<td></td>
<td>MRR</td>
<td>0.614</td>
<td>0.585</td>
<td>0.556</td>
<td>0.604</td>
<td>0.481</td>
</tr>
</tbody>
</table>
Why does CNN_Forest work best?

• Word embedding
  ➢ Convert the texts in bug reports and source files into word vectors.

• CNN with multiple filters
  ➢ CNN has performed excellently in natural language processing because of convolving filters.

• Ensemble of random forests with multi-grained scanning
  ➢ Source files are composed of code tokens that involve more stringent structural information.

• Cascade forest
  ➢ Correlated relationships between bug reports and source files are learned by the alternate cascade structure that is similar to the layer-structure in deep learning.
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Conclusions

• This paper proposed CNN_Forest, a new CNN and random forest-based model for bug localization.

• Two **different techniques** are leveraged to extract features respectively from bug reports and source code files *automatically* according to the **differences** between natural languages and programming languages.

• Both **semantic and structural information** of bug reports and source files are extracted. The ensemble of random forests is applied to detect the structural information from the source code. The alternate cascade forest works as the **layer-structure** in deep learning to learn the correlated relationships between bug reports and source files.
Future works

• Fine-tune the proposed model to further improve its process automation and prediction performance for bug localization.
  ➢ evaluation on other kinds of random forest techniques (e.g., extra-trees) to enhance diversity.
• Focus on projects written in other programming languages.
• Extend the model to aforementioned projects for bug localization with other performance metrics to evaluate their performances.
  ➢ Accuracy@k
  ➢ Area Under the receiver operator characteristic Curve (AUC)
• Examine the performance of the proposed model in other applications of software engineering
  ➢ defect prediction
Thank you for your attention!