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

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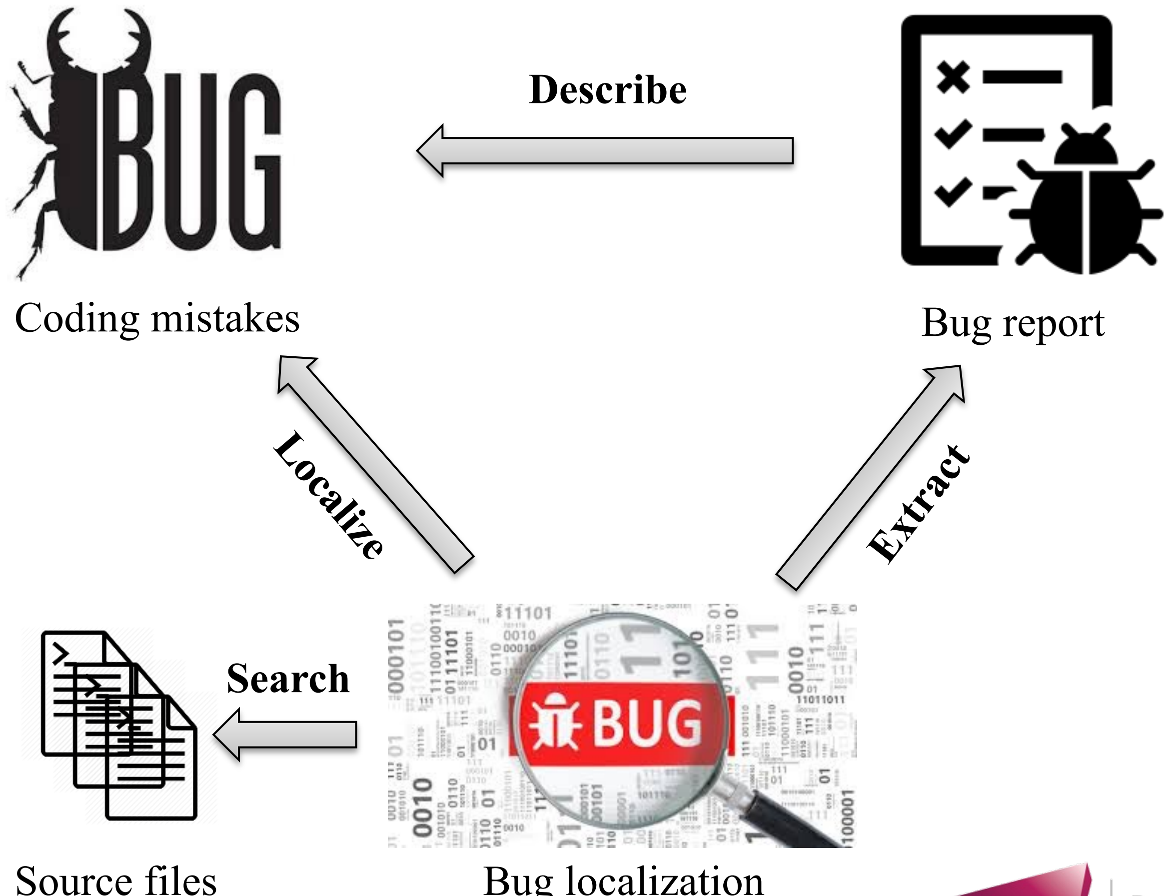
# Outline

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

# Background



Describe
Coding mistakes
Bug report
Localize
Extract
Search
Source files
Bug localization

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# 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 $\neq$semantics

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# 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.

**Structural information**

# 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.


**Semantic + Structural information**

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# CNN_Forest technique

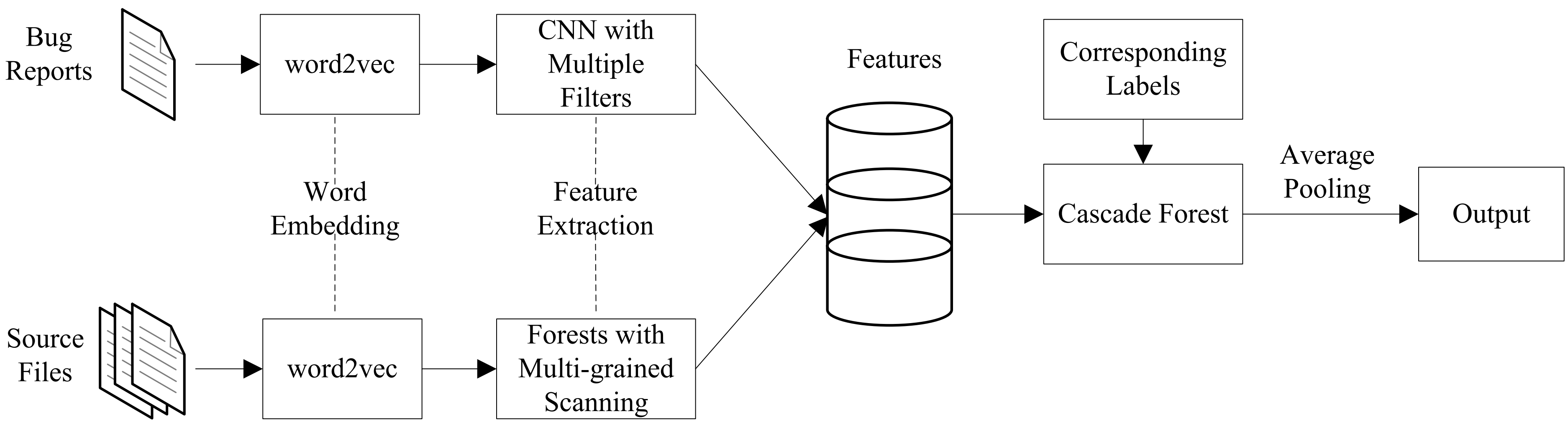
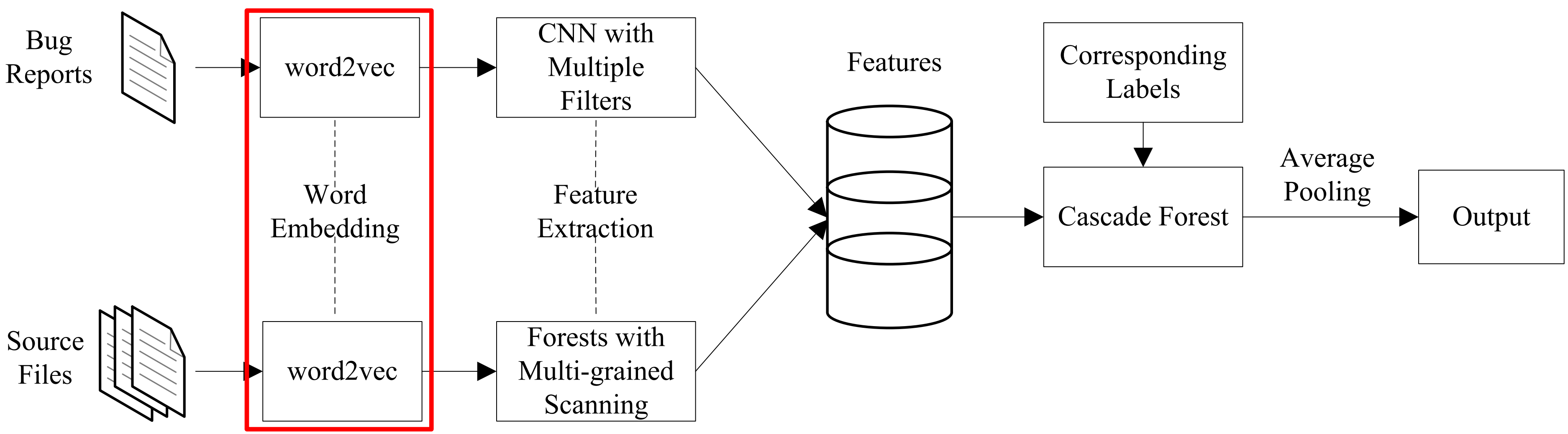



Figure 3: The Overall Workflow of CNN Forest.

# CNN_Forest technique

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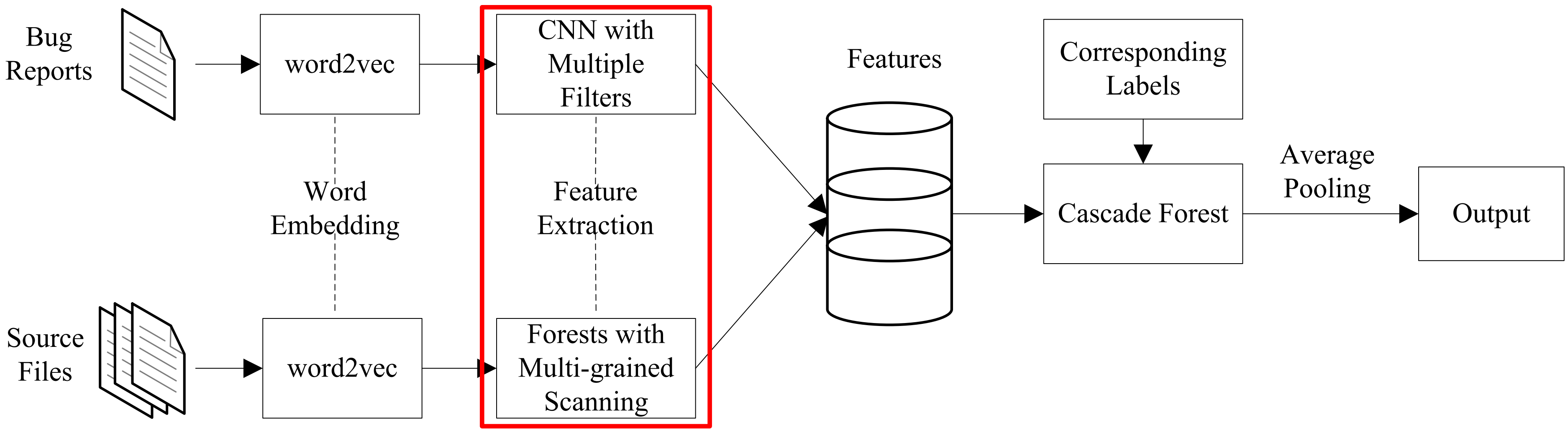
# CNN_Forest technique

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# CNN_Forest technique

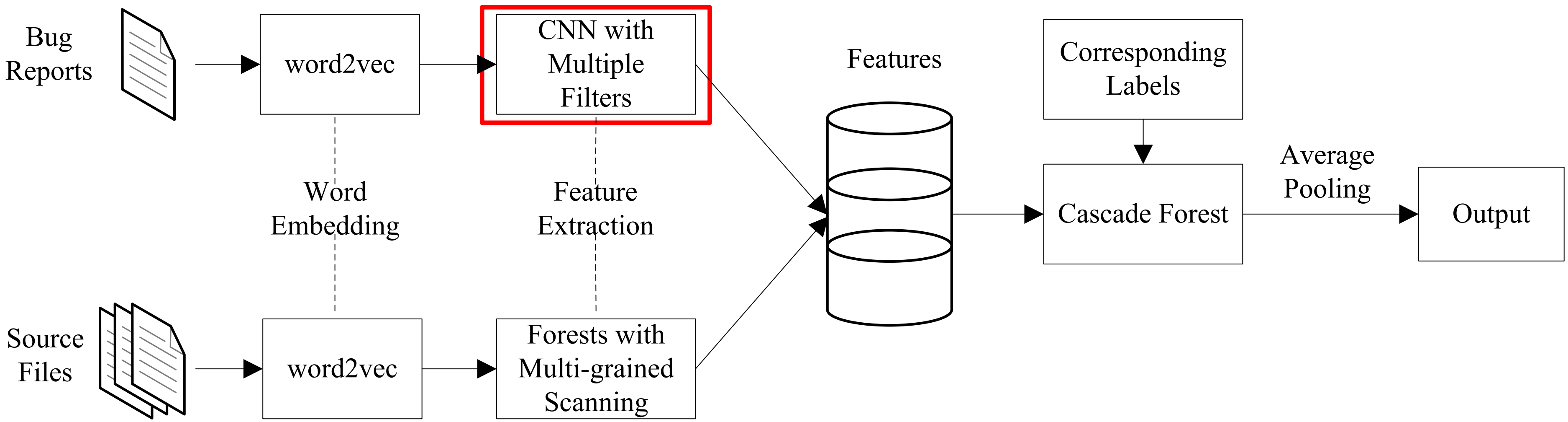


Figure 3: The Overall Workflow of CNN Forest.

# CNN with Multiple Filters to Extract Features from Bug Reports

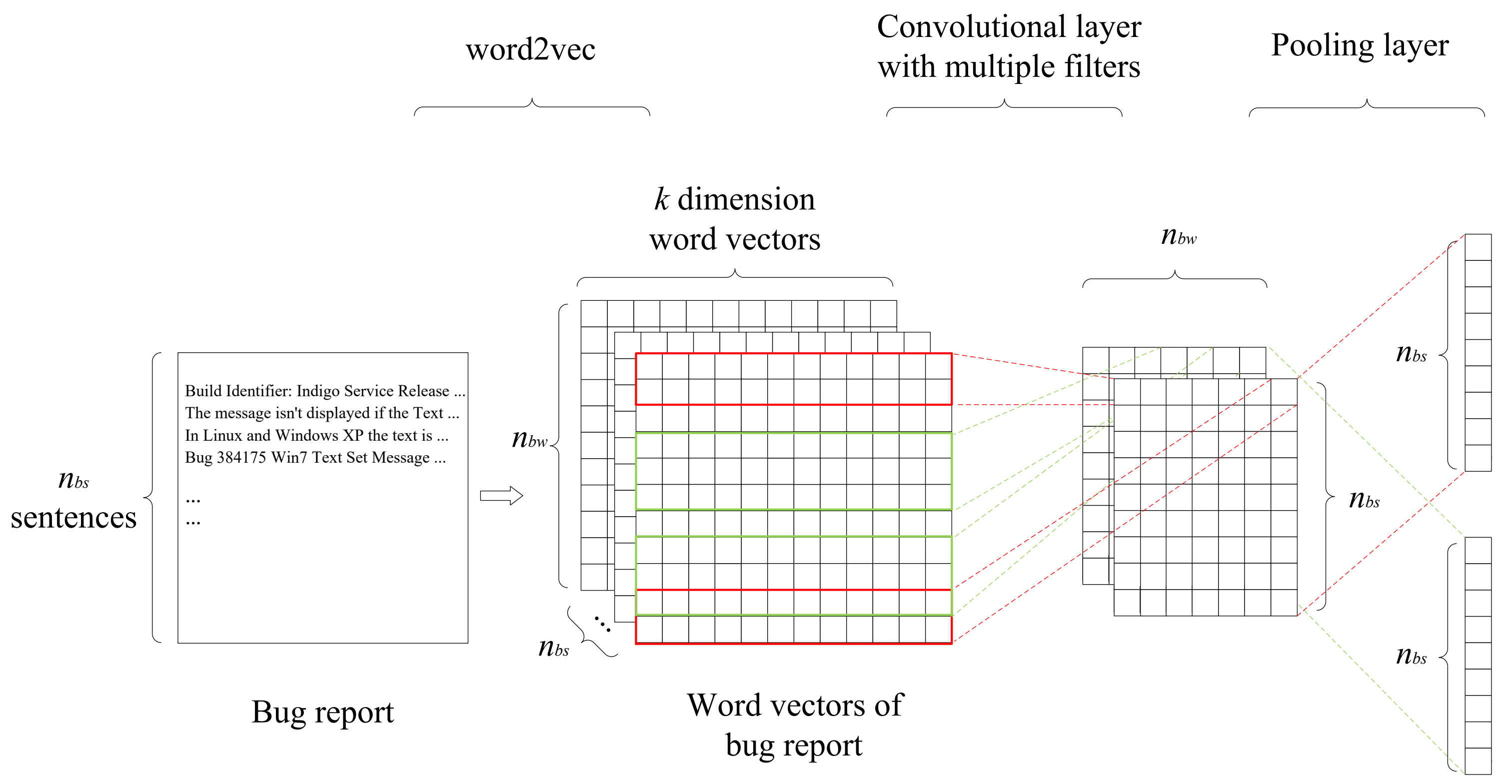


Figure 4: The Feature Extraction of Bug Reports using CNN.

# CNN_Forest technique

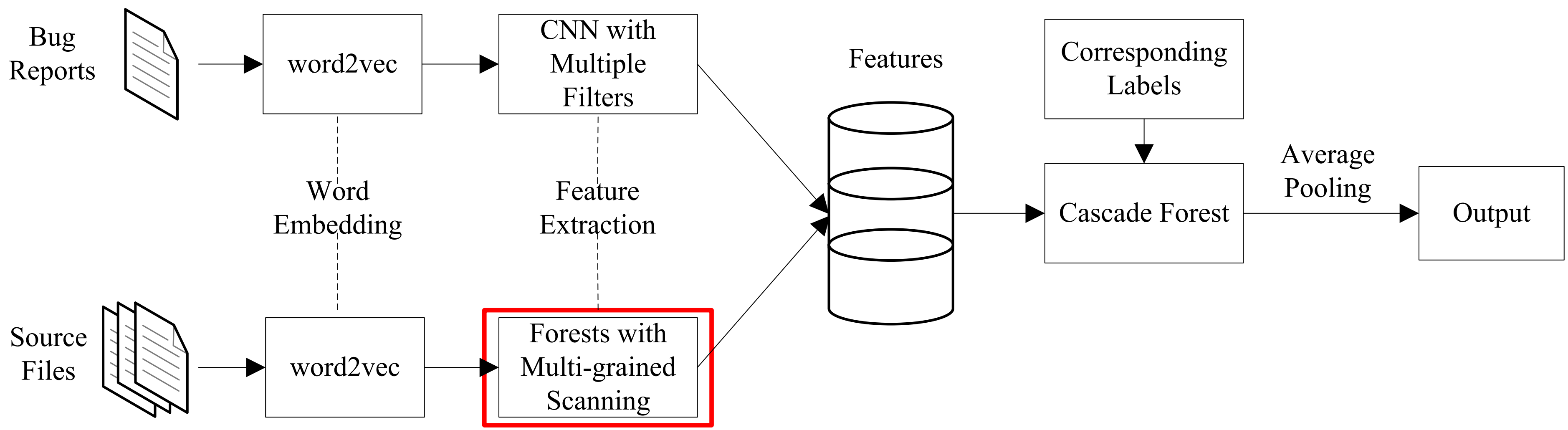


Figure 3: The Overall Workflow of CNN Forest.

# Ensemble of Random Forests with Multi-grained Scanning for Source Files

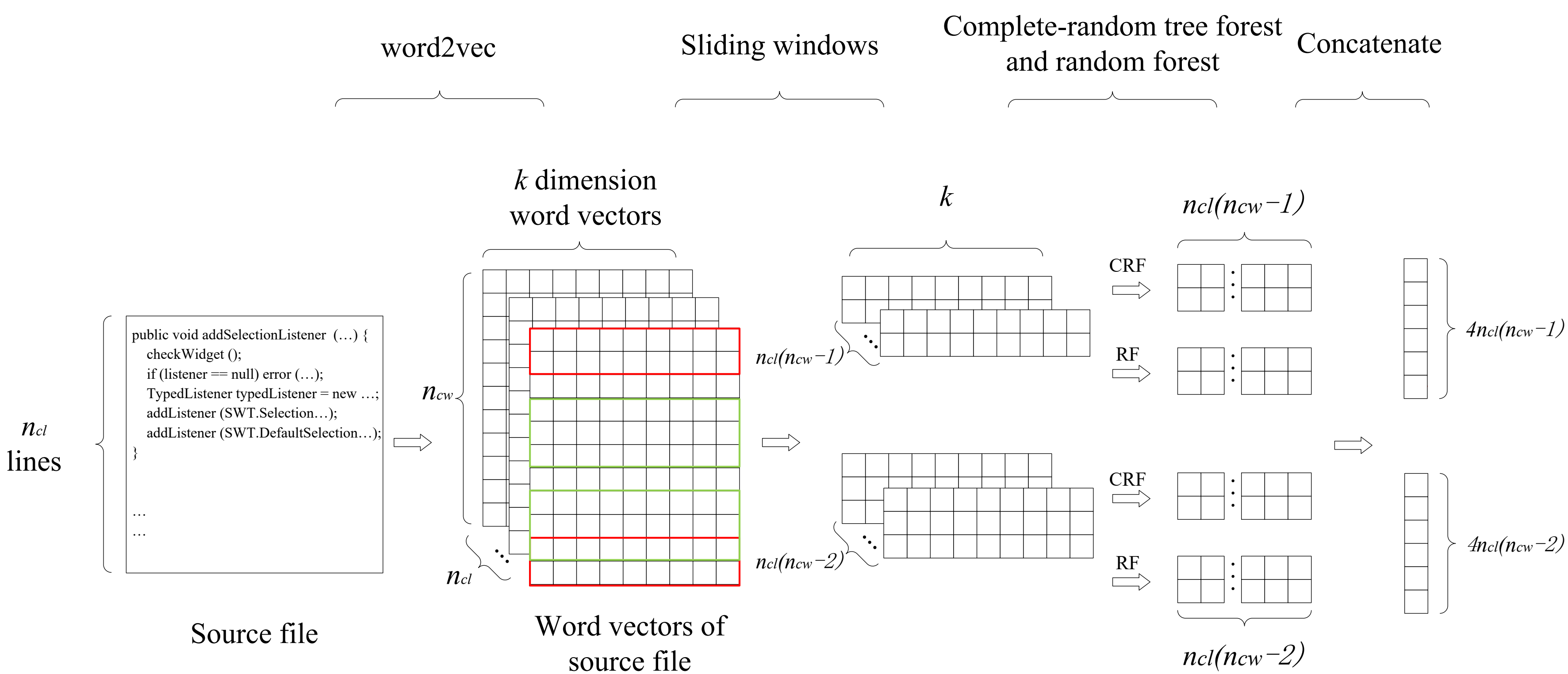


Figure 5: The Feature Extraction of Source Files using Ensemble of Random Forests.

# CNN_Forest technique

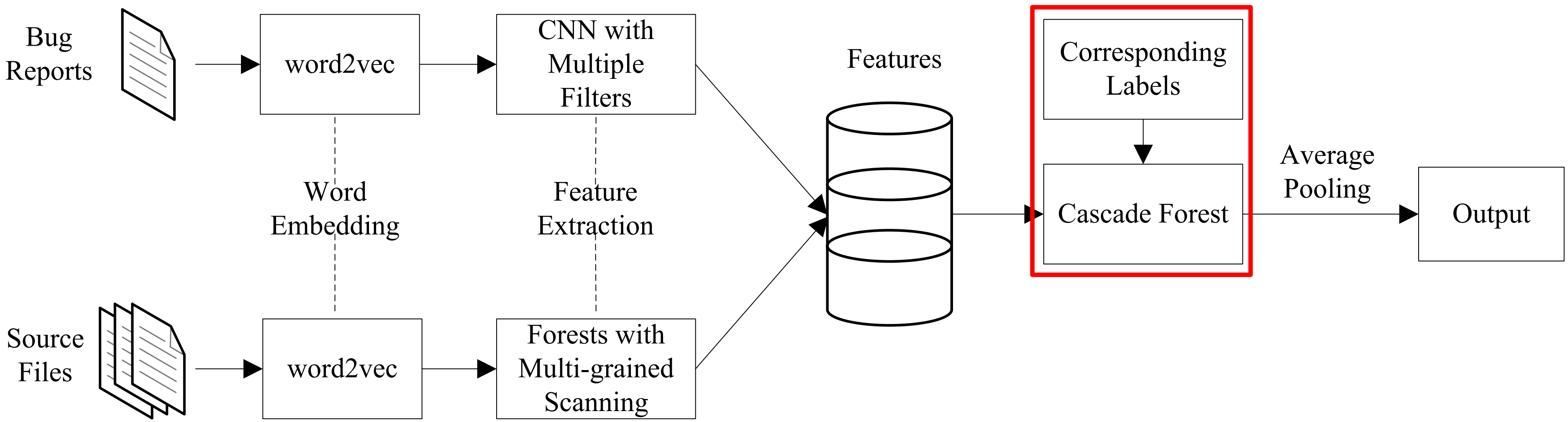


Figure 3: The Overall Workflow of CNN Forest.

# Cascade Forest

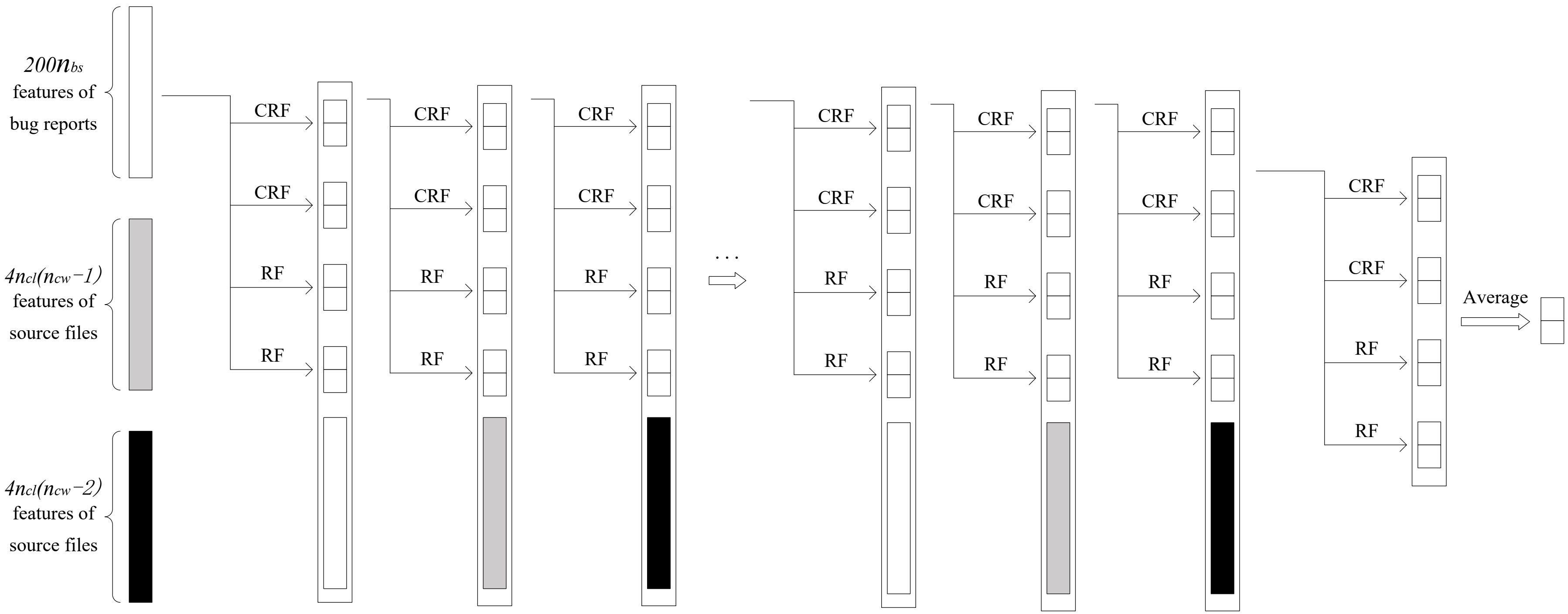


Figure 6: Cascade Forest to Further Extract Features and Learn the Correlated Relationships between Bug Reports and Source Files.

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# Experimental Preparations

Table I Subject Projects

| Project | Time Range | # of Bug Reports for Evaluation | # of Bug Reports for Tuning | # of Bug Reports for Training | # of Bug Reports for Testing |
|---|---|---|---|---|---|
| AspectJ[1] | 03/02-01/14 | 593 | 100 | 400 | 93 |
| Eclipse UI[2] | 10/01-01/14 | 3,656 | 1,500 | 500 | 1,656 |
| JDT[3] | 10/01-01/14 | 2,632 | 1,500 | 500 | 632 |
| SWT[4] | 02/02-01/14 | 2,817 | 1,500 | 500 | 817 |
| Tomcat[5] | 07/02-01/14 | 1,056 | 400 | 500 | 156 |

[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

Metrics

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

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

# 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.

| Project | Metrics | CNN_Forest | CNN_CNN | Forest_Forest |
|---|---|---|---|---|
| AspectJ | MAP | **0.458** | 0.449 | 0.430 |
| | MRR | **0.563** | 0.560 | 0.549 |
| Eclipse UI | MAP | 0.460 | 0.441 | **0.465** |
| | MRR | **0.590** | 0.561 | 0.588 |
| JDT | MAP | **0.448** | **0.448** | 0.435 |
| | MRR | **0.517** | 0.502 | 0.492 |
| SWT | MAP | **0.462** | 0.415 | 0.439 |
| | MRR | **0.530** | 0.507 | 0.512 |
| Tomcat | MAP | **0.627** | 0.623 | 0.604 |
| | MRR | **0.681** | 0.669 | 0.647 |

# Extrinsic Evaluation

Structural

Semantic Textual

Textual similarity

Table 3: Performance Compa… the State… rt Techn…

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

# 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 aforementined 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!

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