

# HINDBR: Heterogeneous Information Network Based Duplicate Bug Report Prediction

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Duplicate bug reports often exist in bug tracking systems (BTSs), leading to unnecessary maintenance effort such as repeatedly discussing the same bug.

Existing efforts on automatically detecting duplicate bug reports heavily rely on the text similarity calculated with information retrieval (IR) techniques (e.g., TF-IDF).

Modern BTSs introduce just-in-time (JIT) retrieval feature in their recent versions, e.g., Bugzilla 4.0.

The built-in JIT feature can suggest possible duplicates when a reporter is filling a bug (i.e., typing in the summary field).





With the advent of the just-in-time (JIT) retrieval feature in modern BTSs, textual-based approaches become ineffective in detecting after-JIT duplicate bug reports<sup>1</sup>.

The built-in JIT feature can suggest possible duplicates when a reporter is filling a bug (i.e., typing in the summary field), thereby reducing chances for submitting duplicate reports in the first place.

After JIT filtering, a substantial proportion of duplicate reports still exists in BTSs.

1. Rakha, M. S., Bezemer, C. P., & Hassan, A. E. (2018). Revisiting the performance of automated approaches for the retrieval of duplicate reports in issue tracking systems that perform just-in-time duplicate retrieval. Empirical Software Engineering, 23(5), 2597-2621.

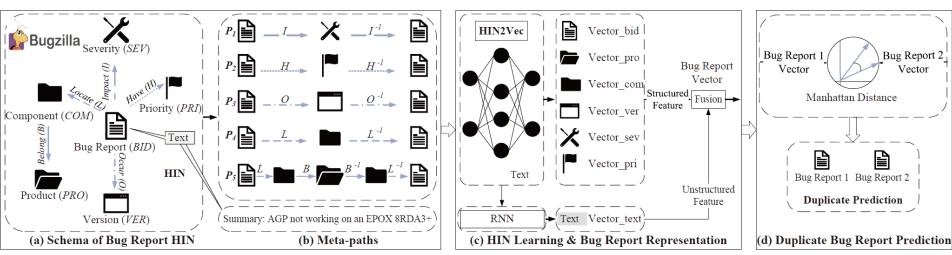


Fig. 1. Overview of HINDBR.

## A Motivating Example

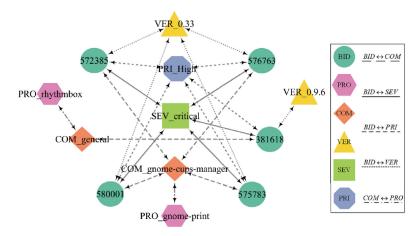


Fig. 2. An excerpt of a bug report HIN for the GNOME project.

# TABLE I Similarities of Duplicate and Non-Duplicate Pairs with HIN Vectors

Duplicate	Similarity	Non-Duplicate	Similarity	
(576763, 575783)	1	(381618, 576763)	2.14E-224	
(580001, 575783)	0.98	(201510 500001)	1515 005	
(576763, 572385)	0.96	(381618, 580001)	4.51E-225	
(572385, 575783)	0.76	(381618, 572385)	1.28E-225	
(580001, 572385)	0.51			
(580001, 576763)	0.41	(381618, 575783)	0	

## Background

#### **Duplicate Bug Report Prediction**

```
<bugzilla maintainer="helpdesk@kernel.org" urlbase="https://bugzilla.kernel.org/"</pre>
version="5.1.1">
<bug>
<br/>bug id>200389</br/>/bug id>
<creation ts>2018-07-02 01:59:58 +0000</creation ts>
<short desc>iwlmvm: 7265: stops working after kernel warning / trace</short desc>
product>Drivers
<component>network-wireless</component>
<version>2.5</version>
<br/>
<br/>
dug status>CLOSED</br/>
/bug status>
<re>olution>DUPLICATE</resolution>
<dup id>199967</dup id>
<priority>P1</priority>
<br/>
<br/>
bug severity>normal</br/>
bug severity>
</bug>
</bugzilla>
```

Fig. 3. Linux bug report ID-200389 (XML format).



# Background

#### **Duplicate Bug Report Prediction**

TABLE II
AN EXAMPLE OF BUG GROUP IN GNOME PROJECT

Type	Bug ID	Summary
Master	572385	crash in Printing: Just clicked the gnome-c
	575783	crash in Printing:
Duplicates	576763	crash in Printing: launching gnome-cups-man
	580001	crash in Printing: Checking to see why I co

# Background

HIN2Vec: a Network Representation Learning for HIN

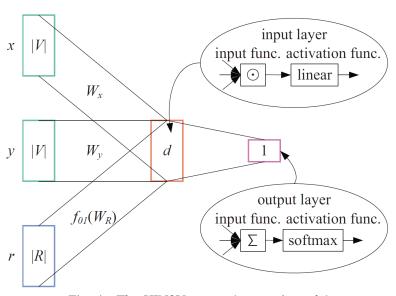


Fig. 4. The HIN2Vec neural network model.



#### Constructing HIN for Bug Reports

Six Nodes: BID, COM, PRO, VER, PRI, SEV

Five Relations: R1: Bug-Component

R2: Component-Product

R3: Bug-Version

R4: Bug-Priority

R5: Bug-Severity



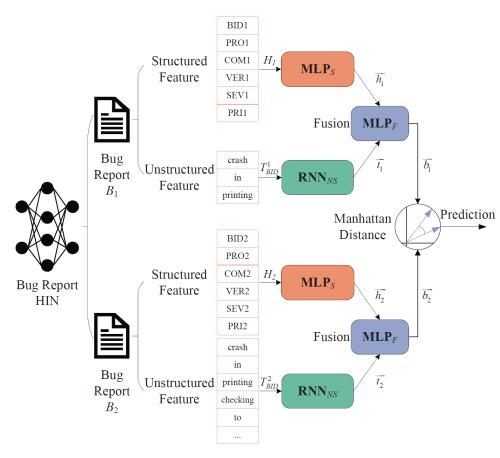


Fig. 5. Detailed structure of HINDBR.

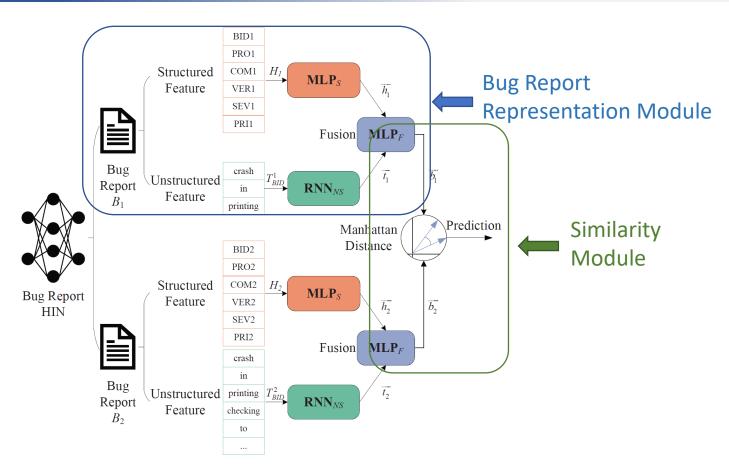


Fig. 5. Detailed structure of HINDBR.

#### **Bug Report Representation Module**

Structured Feature: MLP<sub>s</sub>

$$h = tanh(W^H H),$$

Unstructured Feature: RNN<sub>NS</sub>

$$t_i = tanh(W^T[x_i, t_{i-1}]), \forall i = 1, 2, \dots, N_T,$$

Feature Fusion: MLP<sub>F</sub>

$$b = tanh(W^B[h, t]),$$

#### Similarity Module

Manhattan Distance

$$S(b_1, b_2) = exp(-||b_1 - b_2||_1),$$

Model Training: Training Instance  $\langle B_1, B_2 \rangle$ . Label: 1 for duplicate

Loss Function: binary cross entropy loss

$$\mathcal{L}(\theta) = -(ylog(\hat{y}) + (1 - y)log(1 - \hat{y})),$$

Similarity Threshold: 0.5

$$\hat{y} = \begin{cases} 1, & S(B_1, B_2) \ge 0.5 \\ 0, & S(B_1, B_2) < 0.5 \end{cases},$$



#### **Data Collection**

TABLE III
COLLECTED BUG REPORTS

Project Type	Project	Time Frame	JIT Year	# of Reports
Davidannant	Eclipse	10/10/01 - 09/30/18	2011 [29]	528,862
Development Tool	GCC	08/03/99 - 09/30/18	2011 [30]	81,463
1001	LLVM	10/07/03 - 09/30/18	Unknown	38,107
Desktop	Freedesktop	01/09/03 - 09/30/18	2011 [31]	106,065
Environment	GNOME	02/05/99 - 09/30/18	Unknown	673,301
	KDE	01/21/99 - 09/30/18	2012 [32]	388,711
Office Suite	LibreOffice	08/03/10 - 09/30/18	Unknown	62,029
	OpenOffice	10/16/00 - 09/30/18	2012 [33]	127,797
Operating System	Linux kernel	11/06/02 - 09/30/18	2012 [34]	32,340
	2,038,675			

#### **Feature Extraction**

- HIN Construction
- Text Extraction

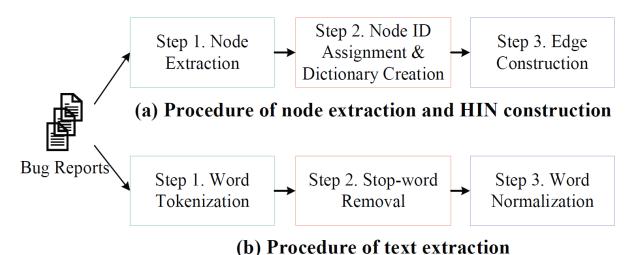


Fig. 7. Procedure of constructing HIN and extracting text.



Bug Pairs Generation: Model Training and Testing

TABLE IV
NUMBER OF BUG PAIRS FOR MODEL TRAINING AND TESTING

Project	Duplicate Pair	Non-Duplicate Pair	Pair
Eclipse	54,742	218,968	273,710
Freedesktop	11,316	45,264	56,580
GCC	7,819	31,276	39,095
GNOME	69,381	277,524	346,905
KDE	41,094	164,376	205,470
LibreOffice	6,771	27,084	33,855
Linux kernel	2,998	11,992	14,990
LLVM	3,093	12,372	15,465
OpenOffice	12,821	51,284	64,105
Total	210,035	840,140	1,050,175

Bug Pairs Generation: Before-JIT & After-JIT Evaluation

 $\begin{tabular}{ll} TABLE\ V\\ Number\ of\ Bug\ Pairs\ for\ Before-JIT\ and\ After-JIT\ Evaluation \end{tabular}$ 

Project	Be	fore-JIT	After-JIT		
Troject	Duplicate	Non-Duplicate	Duplicate	Non-Duplicate	
Eclipse	5,474	21,896	5,474	21,896	
Freedesktop	1,131	4,524	1,131	4,524	
GCC	781	3,124	781	3,124	
KDE	4,109	16,436	4,109	16,436	
Linux kernel	299	1,196	299	1,196	
OpenOffice	1,282	5,128	1,282	5,128	

## Implementation Details

#### **Settings of Pre-trained Embeddings**

• Word2Vec:  $d_1 - 100$ 

• HIN2Vec:  $d_2 - 128$ 

#### Settings of Neural Networks in HINDBR

- Text
- HIN1 (no Text)
- HIN2 (with Text)

## Implementation Details

Settings of Model Training: Keras, Dell Precision Tower, RTX2080Ti

- Training Parameters: epochs 100; batch size 128;
- Stratified Cross-Validation Evaluation: 5-fold cross-validation
- Dealing with Imbalanced Data: SMOTE + TL

#### **Evaluation Metrics**

- Accuracy
- Precision
- Recall
- F1 Score



#### **Comparison Method**

DLDbr: Text feature (Long: CNN + Short: LSTM)
 Structure feature (Numerical Vectors)

#### Research Questions (RQs)

- RQ1: HINDBR Effectiveness
- RQ2: Impacts of Feature Settings
- RQ3: Impacts of Before-JIT and After-JIT Duplicates

**RQ1: HINDBR Effectiveness** 

TABLE VI
PREDICTION RESULTS OF HINDBR COMPARED WITH BASELINE APPROACH DLDBR

Project	Accuracy		Precision		Recall		F1 Score					
	DLDBR	HINDBR	Impro.	DLDBR	HINDBR	Impro.	DLDBR	HINDBR	Impro.	DLDBR	HINDBR	Impro.
Eclipse	0.8910	0.9489	6.51%	0.8196	0.9005	9.87%	0.7930	0.8374	5.60%	0.8037	0.8671	7.89%
Freedesktop	0.9161	0.9621	5.01%	0.8503	0.9184	8.01%	0.8519	0.8891	4.36%	0.8504	0.9035	6.24%
GCC	0.9061	0.9587	5.81%	0.8523	0.9205	8.01%	0.8306	0.8721	5.01%	0.8392	0.8957	6.73%
GNOME	0.9843	0.9883	0.42%	0.9620	0.9709	0.93%	0.9769	0.9707	-0.63%	0.9693	0.9708	0.15%
KDE	0.9639	0.9834	2.02%	0.9363	0.9651	3.08%	0.9312	0.9508	2.11%	0.9333	0.9579	2.64%
LibreOffice	0.8440	0.9277	9.91%	0.7708	0.8538	10.76%	0.7022	0.7703	9.69%	0.7259	0.8096	11.53%
Linux kernel	0.8943	0.9578	7.10%	0.8242	0.8961	8.72%	0.8321	0.8925	7.26%	0.8274	0.8942	8.08%
LLVM	0.8388	0.9296	10.82%	0.7500	0.8423	12.31%	0.7033	0.7903	12.38%	0.7115	0.8154	14.61%
OpenOffice	0.8432	0.9487	12.51%	0.7508	0.8969	19.45%	0.7464	0.8369	12.13%	0.7454	0.8658	16.16%

#### **RQ2: Impacts of Feature Settings**

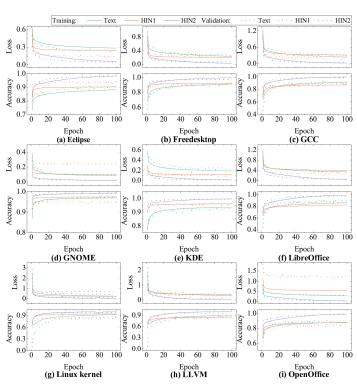


Fig. 8. Comparison of training history under different feature settings.

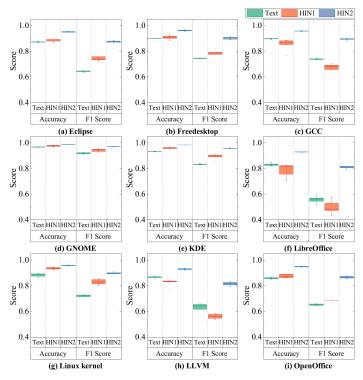


Fig. 9. Comparison of performance under different feature settings.



#### **RQ2: Impacts of Feature Settings**

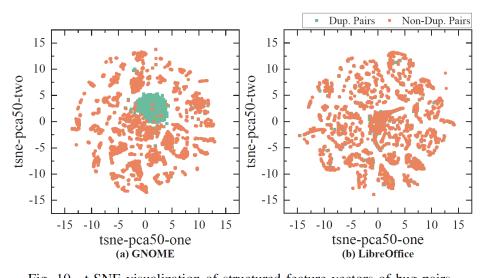


Fig. 10. t-SNE visualization of structured feature vectors of bug pairs.

#### RQ3: Impacts of Before-JIT & After-JIT Duplicates

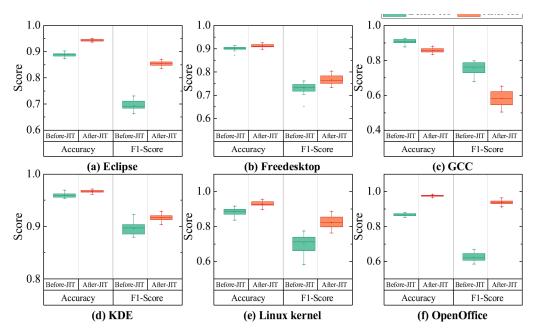


Fig. 11. Comparison of performance on before-JIT and after-JIT datasets.



# Thank you for your listening!

Q&A