Automated Bug Triaging to the Developers
A Machine Learning Approach

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- A dependency structure is formed over time for supervised learning from the fixed bugs.

Literature Survey

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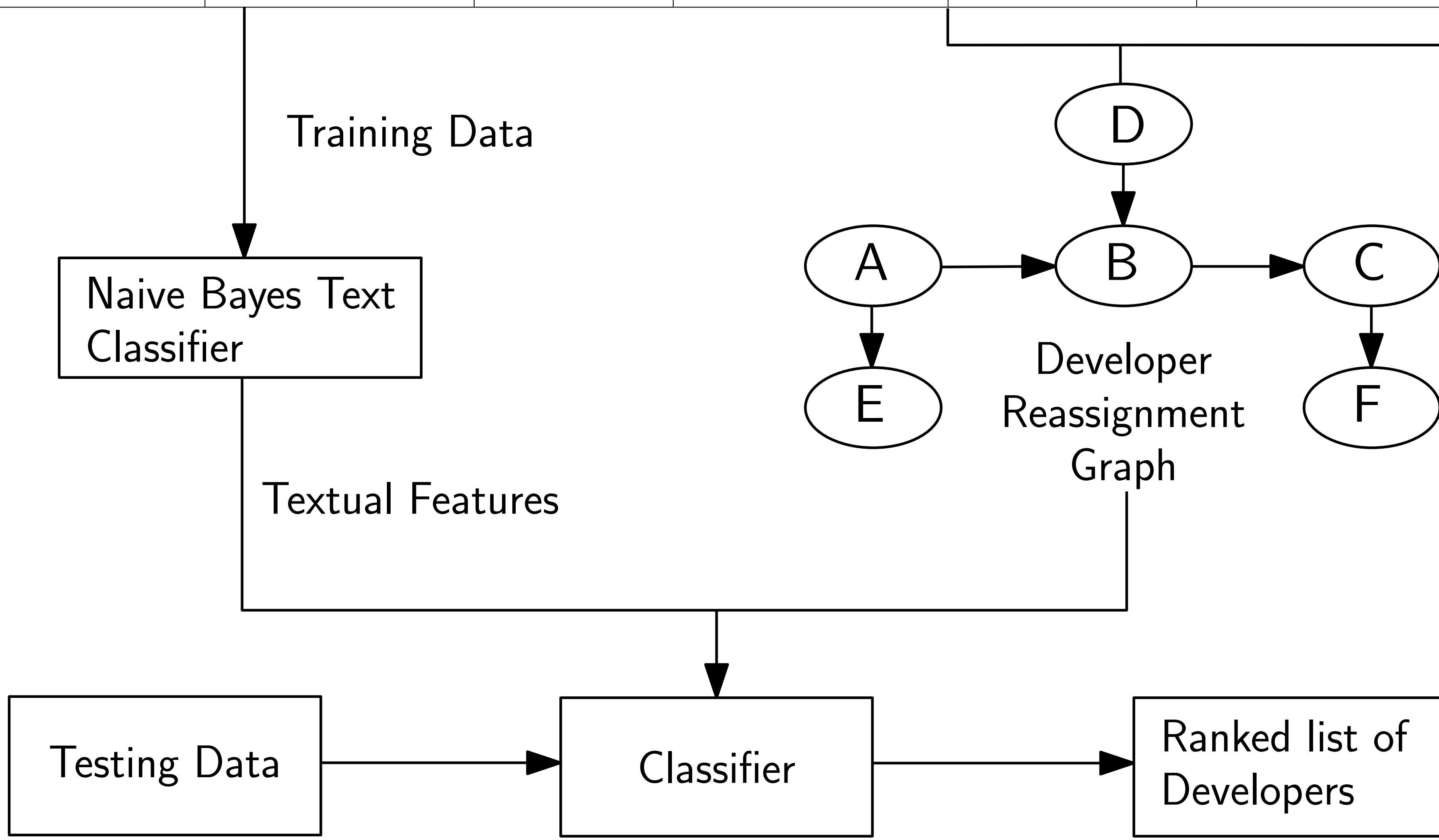
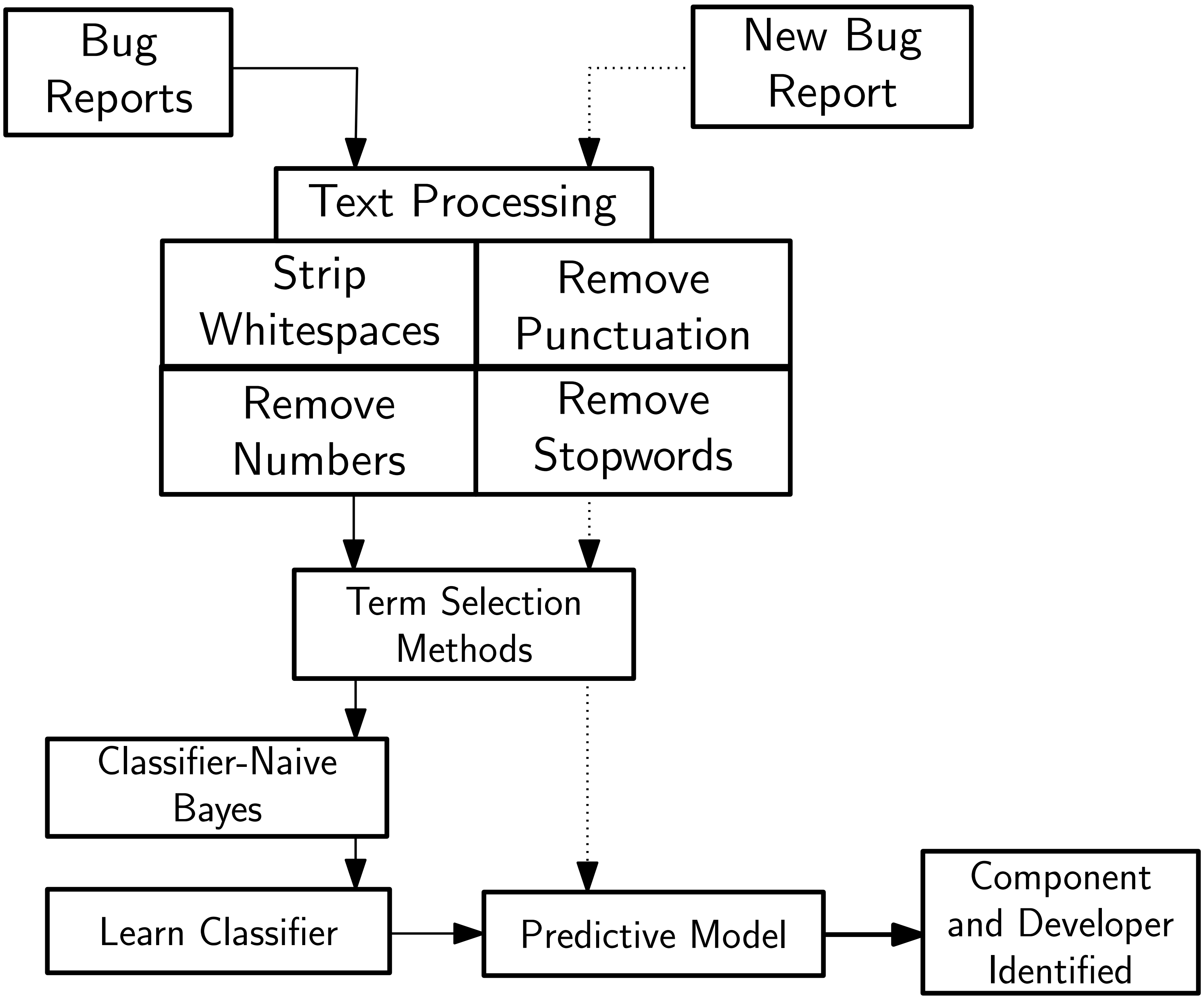
- Initially a training data set of fixed bugs that contains information regarding the developers to whom it was assigned and the reassignment to other developers.
- The system uses Naive Bayes classifier to classify the new bugs reported, and to calculate the probability of it belonging to a class.
- Graphs are used to predict the probability of reassignment of a bug to another developer.

Architecture

Report ID	Description	Product	Component	Initial Dev	Reassigned
12784	. . .	JDT	Core	A	E



Modules


Bug Reports
New Bug Report
Text Processing
Strip Whitespaces
Remove Punctuation
Remove Numbers
Remove Stopwords
Term Selection Methods
Classifier-Naive Bayes
Learn Classifier
Predictive Model
Component and Developer Identified

Multinomial Naive Bayes Classifier

Feature Vector

$$W = (w_1,\ w_2,\ w_3,\ \ldots,\ w_n)$$

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Conditional Probability $\frac{\text{count}(w, D_k)+1}{\text{count}(D_k)+|V|}$

Multinomial Naive Bayes Algorithm

Algorithm 1: TRAIN MULTINOMIALNB - Text classification

Input: R: Training Corpus(List of bug reports)
D: List of Developers
Output: V-vocabulary,prior and condprob
$V \leftarrow$ extract Vocabulary
$N \leftarrow$ Count Bug Reports
foreach *Developer d in D* **do**
  $N_c \leftarrow$ Count bug reports of developer d from R
  prior(d) $\leftarrow \frac{|N_c|}{|N|}$
  $words_d \leftarrow$
  Collect all words from all bug reports of developer d
  foreach *word w in V* **do**
    $T_c \leftarrow$ Count occurences of w in $words_d$
    $T'_c \leftarrow$ Count words(d)
    condprob(w|d) $\leftarrow \frac{|T_c+1|}{T'_c+1}$
  end
end
return $V,\ prior\ and\ condprob$

Multinomial Naive Bayes Algorithm

Algorithm 2: APPLY MULTINOMIALNB - Text classification

```
Input: D: List of Developers
       V: Vocabulary
       prior
       condprob
       R: Bug Report
Output: d: The Developer with the highest probability to whom
           the bug will be assigned
W ← Extract words from Report R
foreach developer d in D do
    P(d|R) ← log(prior(d))
    foreach word w in W do
        freq = count(w,R)
        P(d|R) += freq * log(condprob(w|d))
    end
end
return argmax_d P(d|R)
```

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$$\text{tfidf(t,doc,DOC)} = tf(t, doc) \times idf(t, DOC)$$

Support Vector Machine

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- Multiclass SVM is implemented by reducing the single multiclass problem into multiple binary classification problems.(one-versus-all)

Folding

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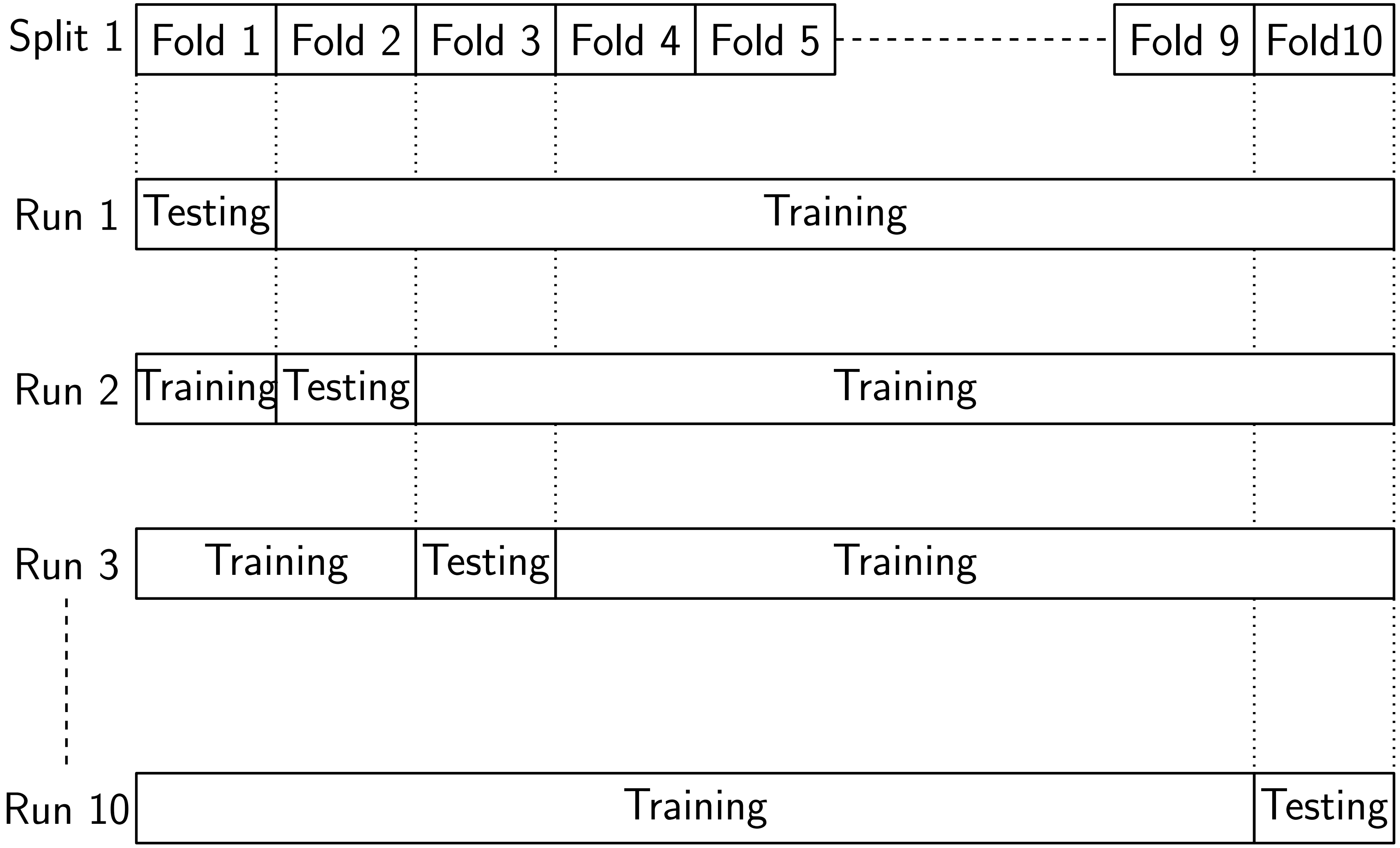
- In the n^{th} run, fold *n* is used as testing data and the remaining folds are used for training the classifier.

Folding



Split 1
Fold 1
Fold 2
Fold 3
Fold 4
Fold 5
Fold 9
Fold10
Run 1
Testing
Training
Run 2
Training
Testing
Training
Run 3
Training
Testing
Training
Run 10
Training
Testing

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- Tossing graphs are weighted directed graphs such that each node represents a developer, and each directed edge from D 1 to D 2 represents the fact that a bug assigned to developer D 1 was tossed and eventually fixed by developer D 2 .
- The weight of an edge between two developers is the probability of a toss between them, based on bug tossing history.

Tossing Graph [1]

Tossing paths
A→B→C→D
A→E→D→C
A→B→E→D
C→E→A→D
B→E→D→F

Developer who tossed the bug	Total tosses	Developer who fixed the bug					
		C		D		F	
		#	pr	#	pr	#	pr
A	4	1	0.25	3	0.75	0	0.00
B	3	0	0.5	2	0.67	1	0.33
C	2			2	1.00	0	0.00
D	2	1	0.50			1	0.50
E	4	1	0.25	2	0.50	1	0.25

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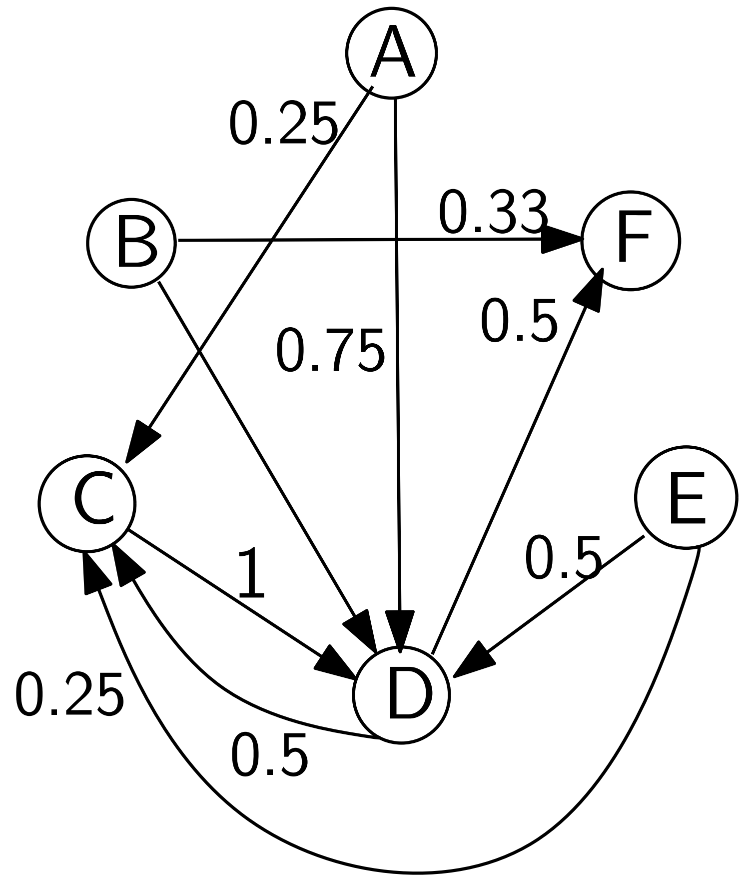
- For example, developer A has tossed four bugs in all, three that were fixed by D and one that was fixed by C, hence $P\ r(A \to D) = 0.75$, $P\ r(A \to C) = 0.25$, and $P\ r(A \to F\ ) = 0$.

Tossing Graph [2]

- In the above table we provide sample tossing paths and show how toss probabilities are computed.
- For example, developer A has tossed four bugs in all, three that were fixed by D and one that was fixed by C, hence P r(A $\rightarrow$ D) $=$ 0.75, P r(A $\rightarrow$ C) $=$ 0.25, and P r(A $\rightarrow$ F) $=$ 0.
- The developers who did not toss any bug (e.g., F) do not appear in the first column, and developers who did not fix any bugs (e.g., A) do not have a probability column

Tosssing graph built using tossing path



Output

```
Terminal
File  Edit  View  Search  Terminal  Help
sags@sags-HP-630-Notebook-PC ~/Project/Review1 $ python review2.py
Training dataset : 53379
Testing Dataset : 13344
The accuracy for MultinomialNB is :  0.770353717026
[0.78239922074029677, 0.7633673010639892, 0.78629551925670615, 0.778597122302158
27, 0.7732014388489209, 0.76540767386091124, 0.77919664268585132, 0.785941247002
39809, 0.76211031175059951, 0.78219424460431652]
The accuracy for Kfold MultinomialNB Classifier is :  0.786295519257
The accuracy using pipeline for LinearSVM is :  0.800554556355
The predicted developer is : platform-debug-inbox@eclipse.org
Predicted Developer ID is : 9
Tossing possibilities in the decreasing order of probability ---
9 -> 14 Probability : 0.291666666667
9 -> 7 Probability : 0.25
9 -> 4 Probability : 0.125
9 -> 18 Probability : 0.125
9 -> 42 Probability : 0.125
9 -> 9 Probability : 0.0416666666667
9 -> 24 Probability : 0.0208333333333
9 -> 178 Probability : 0.0208333333333
sags@sags-HP-630-Notebook-PC ~/Project/Review1 $
```

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- An accuracy of 78.63% is achieved using Multinomial Naive Bayes Classifier for a dataset containing approximately 68000 tagged bug reports.

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- The same feature vectors are used to train the Multiclass SVM Classifier and an accuracy of 80.05% is achieved.
- The learning time of the classifier is drastically reduced by using sparse representation of the word counts.
- The efficiency of the classifier was further improved by using tf-idf weights and extracting only important features and using them.

References

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2 J. Anvik, L. Hiew, G. C. Murphy, Who should fix this bug?, in: ICSE, 361370, 2006.
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Thank You.