FAULT-PRONE FILTERING:

DETECTION OF FAULT-PRONE MODULES USING SPAM FILTERING TECHNIQUE

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THIS WORK: AT A GLANCE

- Objective: Fault-prone filtering
  - Development of simple and easy approach to detect fault-prone modules using generic text discriminator.
- Experiment
  - SPAM filter: CRM114 (generic text discriminator)
  - Data of fault-proneness from an OSS project (Eclipse)
  - 10-fold cross validation
- Result
  - Achieved good accuracy

OVERVIEW

- **Preliminary**
- Fault-Prone Filtering
- Experiments
  - 10-fold cross validation
  - Results
- Conclusions

PRELIMINARY:
FAULT-PRONE MODULES

- Fault-prone modules are:
  - Software modules (a certain unit of source code) which may include faults.
- In this study:
  - A software module:
    - Source code of a Java method
  - Fault-prone module:
    - Source code of a Java method which seems to include faults from the information of a bug tracking system.

PRELIMINARY:
SPAM E-MAIL FILTERING (1)

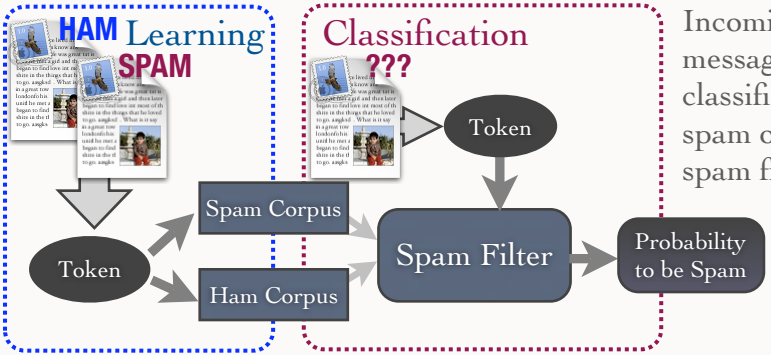
- Spam e-mail increases year by year.
  - About 94% of entire e-mail messages are Spam.

- Various spam filters have been developed.
  - Pattern matching based approach causes a rat race between spammers and developers.
  - Bayesian classification based approach has been recognized effective[1].

[1] P. Graham, Hackers and Painters: Big Ideas from the Computer Age, chapter 8, pp. 121-129, 2004.

PRELIMINARY:
SPAM E-MAIL FILTERING (2)

- All e-mail messages can be classified into
  - Spam: undesired e-mail
  - Ham: desired e-mail
- Tokenize and learn both spam and ham e-mail messages as text data and construct corpuses.



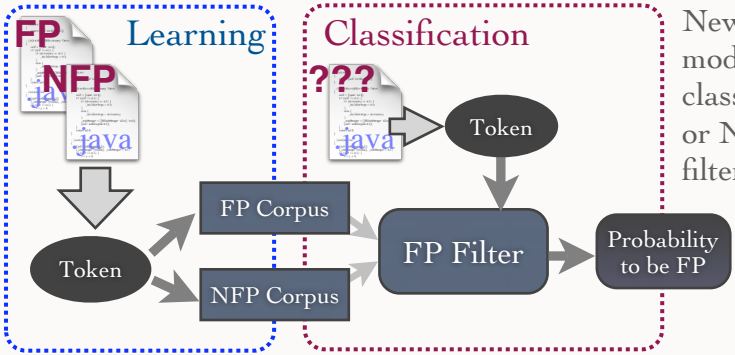
Incoming e-mail messages are classified into spam or ham by spam filter.

OVERVIEW

- Preliminary
- **Fault-Prone Filtering**
- Experiments
  - 10-fold cross validation
  - Results
- Conclusions

FAULT-PRONE FILTERING

- All software modules can be classified into
  - bug-detected (fault-prone: FP)
  - not-bug-detected (not-fault-prone: NFP)
- Tokenize and learn both FP and NFP modules as text data and construct corpuses



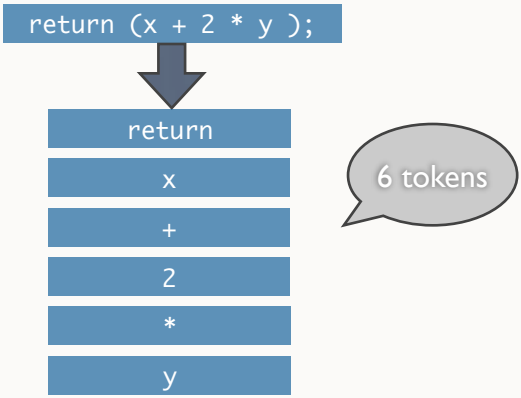
Newly developed modules are classified into FP or NFP by the FP filter.

FAULT-PRONE FILTERING:
SPAM FILTER: CRM114

- Spam filter: CRM114 (http://crm114.sourceforge.net/)
  - Generic text discriminator for various purpose
  - Generation of tokens
    - A token is a **combination of words**
    - 3 tokenization approaches: complex, simple, trivial
  - Classification techniques
    - Bayesian and Hyper-space distance
  - **4 classifiers** with different tokenization and classification
    - SBPH: Complex tokenization, Bayesian
    - OSB: Simple tokenization, Bayesian
    - BAYES: Trivial tokenization, Bayesian
    - HYPER: Simple tokenization, Hyper-space distance

FAULT-PRONE FILTERING:
TOKENIZATION: TRIVIAL

- Trivial tokenization
  - A token is generated from single word.
  - Conventional approach.



FAULT-PRONE FILTERING:
TOKENIZATION: COMPLEX

- Complex tokenization
  - Tokens are generated from combinations of at most 5 words

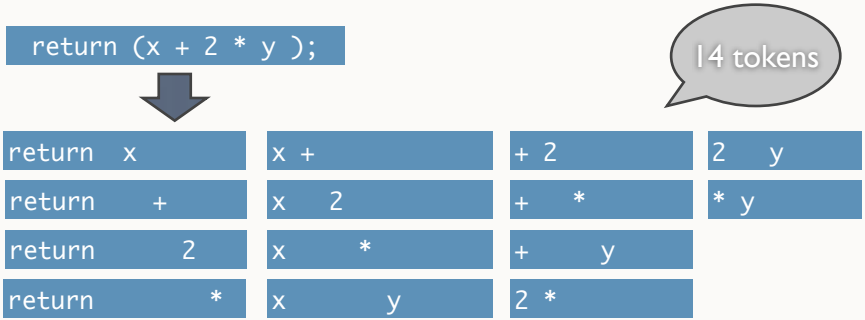
```
return (x + 2 * y);
```

41 tokens

return x	return 2 *	x y	x 2 * y	+ 2 * y
return +	return x + 2	x + 2	x + 2 y	2 *
return 2	return x + *	x + *	x + 2 * y	2 y
return *	return x 2 *	x + y	+ 2	2 * y
return x +	return + 2 *	x 2 *	+ *	* y
return x 2	return x + 2 *	x 2 y	+ y	
return x *	x +	x * y	+ 2 *	
return + 2	x 2	x + 2 *	+ * y	
return + *	x *	x + * y	+ 2 y	

FAULT-PRONE FILTERING:
TOKENIZATION: SIMPLE

- Simple tokenization
  - Tokens consisted of 2 words are selected from combinations of 5 words.



FAULT-PRONE FILTERING: CLASSIFICATION: BAYESIAN

- Calculate probability that a new module(T_{new}) is in FP corpus by Bayesian manner

FP Corpus (T_{FP})

x ++	* fact
x x	fact ++
* ++	fact x
* x	++ x

NFP Corpus (T_{NFP})

x --	* fact
x x	fact --
* --	fact x
* x	-- x

Tokens (T_{new})

x ++	+ sigma
x x	sigma ++
+ ++	sigma x
+ x	++ x

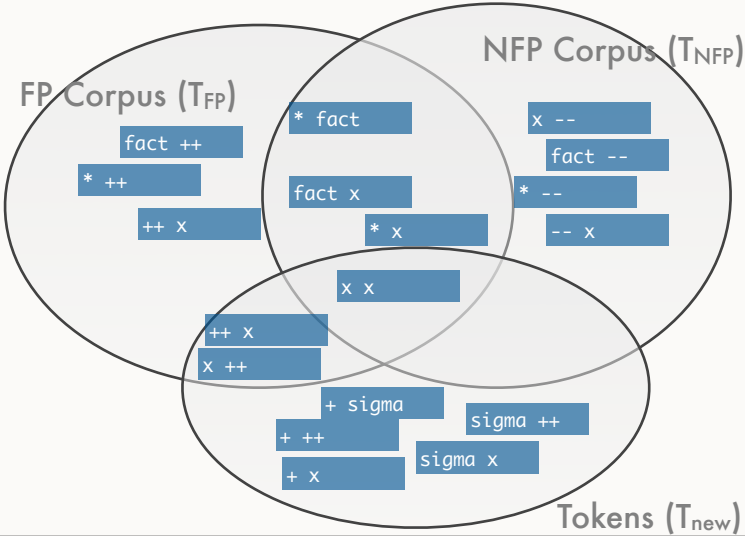
$$P(T_{FP}|T_{new}) = \frac{P(T_{new}|T_{FP})P(T_{FP})}{P(T_{new}|T_{FP})P(T_{FP}) + P(T_{new}|T_{NFP})P(T_{NFP})}$$

$$= \frac{\frac{3}{8} \times \frac{1}{2}}{\frac{3}{8} \times \frac{1}{2} + \frac{1}{8} \times \frac{1}{2}}$$

$$= 0.75$$

FAULT-PRONE FILTERING:
CLASSIFICATION: DISTANCE

- Calculate distances to both tokens, and choose nearest one

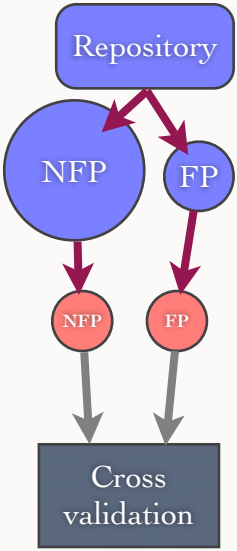


OVERVIEW

- Preliminary
- Fault-Prone Filtering
- **Experiments**
  - **10-fold cross validation**
  - **Results**
- Conclusions

EXPERIMENT: PROCEDURE

- Collect FP and NFP modules from target project.
- Sample randomly FP and NFP modules for 10-fold cross validation from all collected FP and NFP modules.
  - To adjust balance of data between FP and NFP.
- Apply 4 classifiers to sampled modules using 10-fold cross validation.
  - To see which classifier is appropriate for Fault-Prone Filtering.



EXPERIMENT: COLLECTING FP & NFP MODULES

- Track FP modules from CVS log based on an algorithm by Sliwerski, et. al[2].
- [2] J. Sliwerski, et. al., When do changes induce fixes? (on fridays.). In Proc. of MSR2005, pp. 24-28, 2005.
  - Search terms such as
    - “issue”, “problem”, or “#”, and bug id (numbers)
    - “fixed”, “resolved”, or “removed”
    - i. e. “Issue #100 is fixed.”

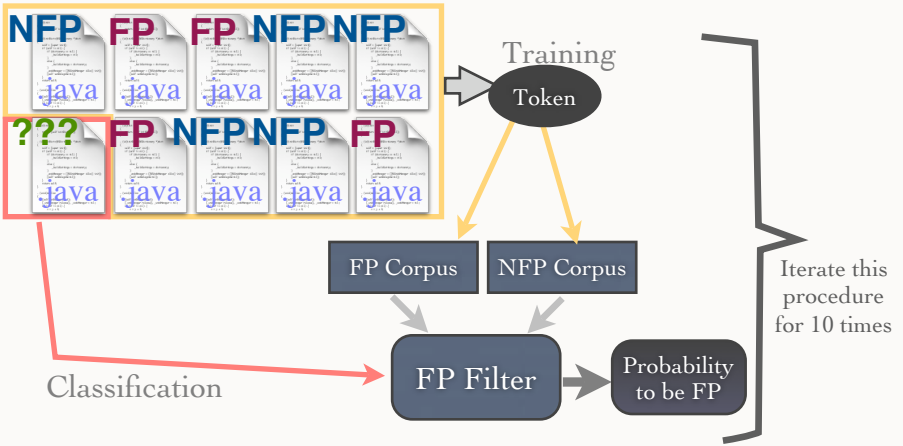
    from CVS log, then identify a revision the bug is removed.
  - Get difference from the previous revision and identify modified modules.
  - Track back repository and identify modules that have not been modified since the bug is reported.
    - They are FP modules.

EXPERIMENT: MODULE COLLECTION

- Extracted bugs from Bugzilla database of Eclipse
  - Conditions:
    - Type of faults: Bugs
    - Status of faults: Resolved, Verified, or Closed
    - Resolution of faults: Fixed
    - Severity: Blocker, Critical, Major, or Normal
  - Total # of faults: *40,627*
- Result of collection
  - # of faults found in CVS log: 21,761 (52% of total)
    - # of fault-prone(FP) modules: 65,782
    - # of not-fault-prone(NFP) modules: 1,113,063
  - For experiments, we randomly chose about 20,000 modules from both FP and NFP modules.

EXPERIMENT:
10-FOLD CROSS VALIDATION

- Divide all modules into 10 subsets randomly
- Each subset classified once.



EXPERIMENT:
EVALUATION MEASUREMENTS

- Accuracy
  - Overall accuracy of prediction
  - (N1+N4) / (N1+N2+N3+N4)
- Recall
  - How much actual FP modules are predicted as FP.
  - N4 / (N3+N4)
- Precision
  - How much predicted FP modules include actual FP modules
  - N4 / (N2+N4)
- Type-I error: N2
- Type-II error: N3 (Should be avoided)

Result of prediction		Predicted	
		NFP	FP
Actual	NFP	N1	N2
	FP	N3	N4

EXPERIMENT:
RESULT OF CROSS VALIDATION

SBPH		Predicted	
		NFP	FP
Actual	NFP	11,073	8,269
	FP	2,979	16,236

Precision: 0.663 Recall: **0.844**
Accuracy: **0.708**

OSB		Predicted	
		NFP	FP
Actual	NFP	12,249	7,093
	FP	2,972	16,243

Precision: 0.696 Recall: **0.845**
Accuracy: **0.739**

BAYES		Predicted	
		NFP	FP
Actual	NFP	10,514	8,828
	FP	1,955	17,260

Precision: 0.662 Recall: **0.898**
Accuracy: **0.720**

HYPER		Predicted	
		NFP	FP
Actual	NFP	14,995	4,347
	FP	6,354	12,861

Precision: **0.747** Recall: 0.669
Accuracy: **0.722**

EXPERIMENT: DISCUSSION

- OSB classifier is appropriate for fault-prone filtering.
  - Both high accuracy and high recall
- Others are also good.
  - Bayesian approaches tend to have high recall.
  - Distance based approach has high precision.
- High recall implies high coverage of faults.
- High precision implies high cost-effectiveness of testing.
  - Balance of recall and precision is required.
  - Changing threshold of determining FP and NFP enables to control cost-effectiveness of testing.

OVERVIEW

- Preliminary
- Fault-Prone Filtering
- Experiments
  - 10-fold cross validation
  - Results
- **Conclusions**

THREATS TO VALIDITY

- Construction validity
  - Collection of fault-prone modules from OSS projects.
  - We could not cover all faults in bugzilla database.
- Internal validity
  - 10-fold cross validation cannot deal with important information on fault-prone detection:
    - Order of creation or modification of modules
    - Application to time series data is effective
- External validity
  - Generalizability of the results

CONCLUSIONS

- Summary
  - We proposed the new approach to detect fault prone modules
    using spam filter.
  - The case study showed that our approach can predict fault prone modules with high accuracy.
- Future works
  - Using differences between revisions as an input of Fault-prone filtering
    - Seems more reasonable...
  - Application to industrial data

THE END

FAULT-PRONE FILTERING:

DETECTION OF FAULT-PRONE MODULES USING SPAM FILTERING TECHNIQUE

Thank you!

Any questions?

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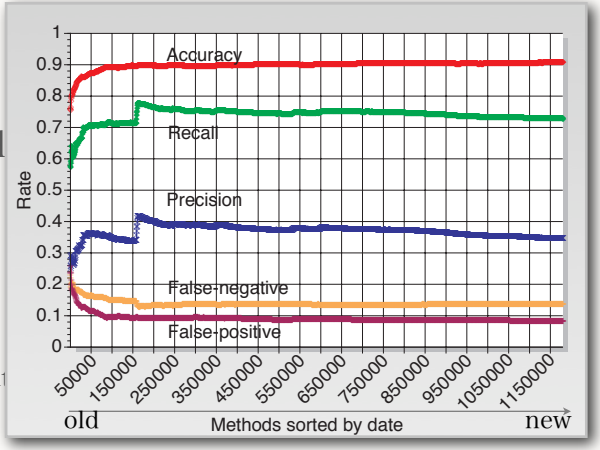
RESULT OF EXPERIMENT (TRANSITION OF RATES)

- All extracted modules are sorted by date, and applied FP filter one by one from the oldest one.
- Observation
  - The prediction result become stable after 50,000 modules classification.



EXPERIMENT:
CHANGING THRESHOLD

- Threshold of probability (t)
  - A threshold to determine FP or NFP from given probability. Usually set as 0.5.

- Changing threshold contributes accuracy of the model.

OSB t=0.8		Predicted	
		NFP	FP
Actual	NFP	14,436	4,906
	FP	4,802	14,413

Precision: 0.746
Recall: 0.750
Accuracy: 0.748

OSB t=0.5		Predicted	
		NFP	FP
Actual	NFP	12,249	7,093
	FP	2,972	16,243

RELATED WORKS

- Much research has been done so far.
  - Logistic regression
  - CART
  - Bayesian classification
  - and more.
- Most of them use software metrics
  - McCabe, Halstead, Object-oriented, and so on.
- Intuitively speaking, our approach uses a new metric, “frequency of tokens”.

EXPERIMENT:
CHANGING THRESHOLD

HYPER		Predicted	
		NFP	FP
Actual	NFP	732	297
	FP	297	665

Precision: **0.691**
Recall: **0.691**
Accuracy: **0.702**

EXPERIMENT: TARGET PROJECT

- Target: argoUML project
  - Written in Java
    - "Methods" in Java classes are considered as modules
  - Large CVS repository (about 900MB)
  - Faults are recorded precisely

EXPERIMENT: COLLECTING FP & NFP MODULES

- Track FP modules from CVS log based on an algorithm by Sliwerski, et. al[2].
- [2] J. Sliwerski, et. al., When do changes induce fixes? (on fridays.). In Proc. of MSR2005, pp. 24-28, 2005.

  - Search terms such as “issue”, “problem”, “#”, and bug id as well as “fixed”, “resolved”, or “removed” from CVS log, then identify a revision the bug is removed.
  - Get difference from the previous revision and identify modified modules.
  - Track back repository and identify modules that have not been modified since the bug is reported.
    - They are FP modules.

EXPERIMENT: MODULE COLLECTION

- Extracted bugs from bugzilla database of argoUML
  - Conditions:
    - Type of faults: Bugs
    - Status of faults: Resolved, Verified, or Closed
    - Resolution of faults: Fixed
    - Severity: Blocker, Critical, Major, or Normal
  - Total # of faults: 1,058
- Result of collection
  - # of faults found in CVS log: 396 (37% of total)
    - # of fault-prone(FP) modules: 962
    - # of not-fault-prone(NFP) modules: 331,488
      - For experiments, we randomly chose 1,029 modules from 331,488 modules.

EXPERIMENT:
EVALUATION MEASUREMENTS

Result of prediction		Predicted	
		NFP	FP
Actual	NFP	N1	N2
	FP	N3	N4

- Accuracy
  - Overall accuracy of prediction
  - (N1+N4) / (N1+N2+N3+N4)
- Recall
  - How much actual FP modules are predicted as FP.
  - N3 / (N3+N4)
- Precision
  - How much predicted FP modules include actual FP modules
  - N2 / (N2+N4)

EXPERIMENT:
RESULT OF CROSS VALIDATION

SBPH		Predicted	
		NFP	FP
Actual	NFP	601	428
	FP	189	773

Precision: 0.643 Recall: **0.803**
Accuracy: 0.690

OSB		Predicted	
		NFP	FP
Actual	NFP	546	483
	FP	156	806

Precision: 0.625 Recall: **0.838**
Accuracy: 0.674

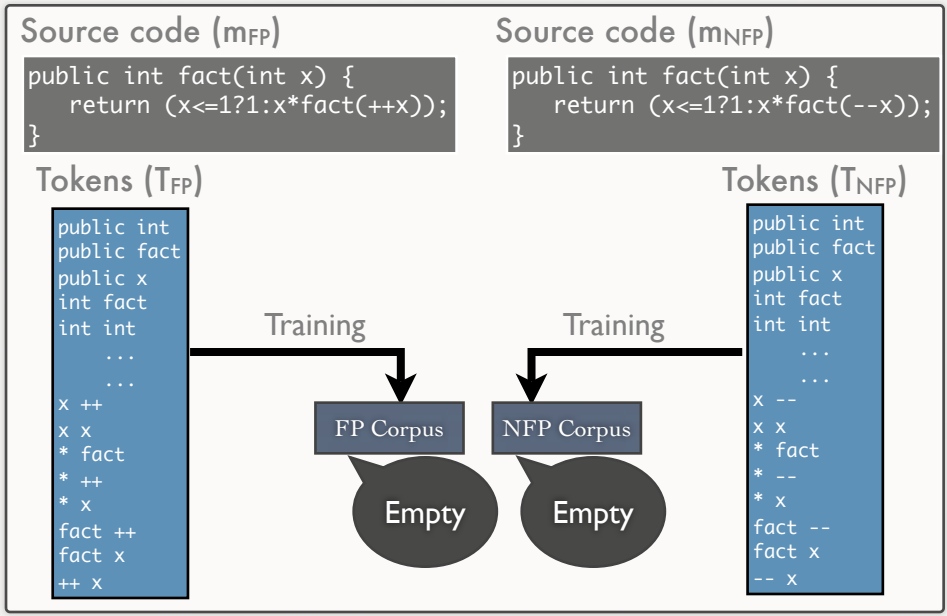
BAYES		Predicted	
		NFP	FP
Actual	NFP	236	793
	FP	29	933

Precision: 0.540 Recall: **0.970**
Accuracy: 0.587

HYPER		Predicted	
		NFP	FP
Actual	NFP	786	243
	FP	352	610

Precision: **0.715** Recall: 0.634
Accuracy: **0.701**

FAULT-PRONE FILTERING:
FAULT-PRONE TRAINING



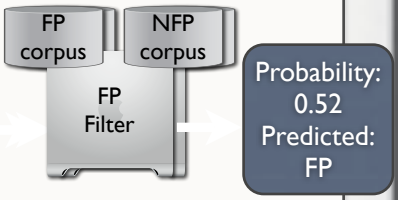
FAULT-PRONE FILTERING:
FAULT-PRONE CALCULATION

Source code (m_{new})

```
public int sigma(int x) {
   return (x<=0?0:x+sigma(++x));
}
```

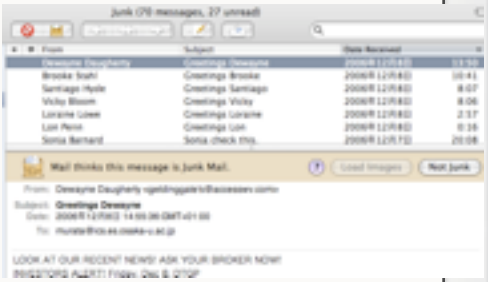
Tokens (T_{FP})	Tokens (T_{new})	Tokens (T_{NFP})
public int	public int	public int
public fact	public sigma	public fact
public x	public x	public x
int fact	int sigma	int fact
int int	int int	int int
...	...	...
...	...	...
x ++	x ++	x --
x x	x x	Prediction
* fact	+ sigma	* fact
* ++	+ ++	* --
* x	+ x	* x
fact ++	sigma ++	fact --
fact x	sigma x	fact x
++ x	++ x	-- x

m_{new} is predicted as FP because T_{FP} has more similarity than T_{NFP}.



TRAINING ONLY ERRORS PROCEDURE

- In Spam filtering:
  - Apply e-mail messages to spam filter in order of arrival.
  - Only misclassified e-mail messages are trained in corpuses.
  - You may do this procedure in daily e-mail assorting.



- In Fault-prone filtering:
  - Apply software modules to fault-prone filter in order of construction and modification.
  - Only misclassified modules are trained in corpuses.

RESULT OF CROSS VALIDATION

- Result for Eclipse BIRT plugin
- 10-fold cross validation

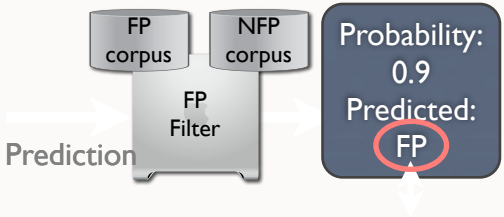
Cross Validation OSB		Predicted	
		NFP	FP
Actual	NFP	70,369	16,011
	FP	2,039	7,501

- Precision: 0.319
- Recall: 0.786
- Accuracy: 0.811

- Recall is important for quality assurance.
- Precision implies the cost for finding FP modules.

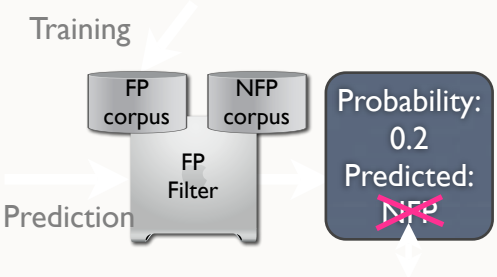
Recall is rather high, and precision is rather low.

TRAINING ONLY ERRORS PROCEDURE



FP

TRAINING ONLY ERRORS PROCEDURE

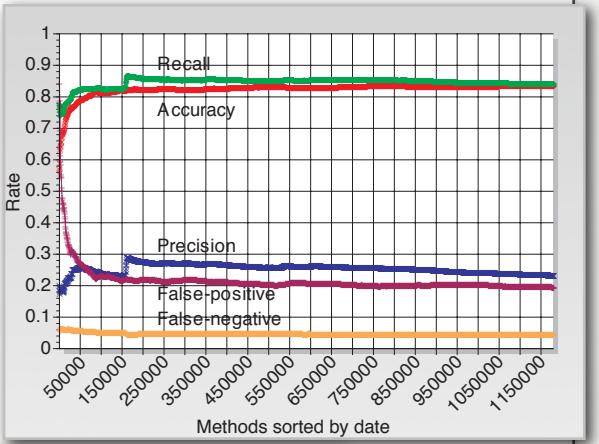


PROCEDURE OF EXPERIMENT

- Two experiments with different thresholds of probability (t_{FP}) to determine FP and NFP.
  - Changing t_{FP} may achieve higher recall
- Experiment 1:
  - TOE with OSB classifier, t_{FP}=0.5
- Experiment 2:
  - TOE with OSB classifier, t_{FP}=0.25
  - Predict more modules as FP than Experiment 1

RESULT OF EXPERIMENT (OSB, T_{FP} = 0.25)

- Comparison with threshold = 0.50
  - Precision becomes lower.
    - Only 1/4 of FP predicted modules hits actual faulty modules.
  - Recall becomes much higher.
    - 83% of actual faulty modules can be detected.



TOE - final OSB		Predicted	
		NFP	FP
Actual	NFP	930,218	182,845
	FP	10,592	55,190

- Precision: 0.232
- Recall: 0.839
- Accuracy: 0.835