

AI驱动软件研发 全面进入数字化时代

Al⁺ software Development Digital summit

缺陷自动修复的"卡脖子"问题— 补丁正确性验证技术

文明 华中科技大学

科技生态圈峰会+深度研习 ——1000+技术团队的共同选择







文明 华中科技大学 副教授

文明博士主要聚焦软件安全、软件测试与分析、以及代码大模型安全等研究,在软件工程领域累计发表了CCF-A类推荐会议或期刊40余篇,其他高水平论文10余篇。 主持国家自然科学基金青年项目、面上项目、以及包括华为胡杨林基金系统软件专项在内的多项企业合作项目,参与湖北省重点研发项目等重要课题,担任了中国计算机学会系统软件、以及软件工程专委会委员。他常年担任TSE,TOSEM,TDSC 等CCF-A类国际期刊的审稿人,以及CCF-A/B类会议ASE 2021/2023,ESEC/FSE 2022/2024, SANER 2022, ISSRE 2022/2023的程序委员会委员。同时也荣获了 Internetware 2023杰出论文奖、ACM 新星奖 2023 (武汉)、以及入选了第七届中国科协青年人才托举工程计划。





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 2.基于表示学习的补丁验证
 3.基于缺陷定位的补丁排序

4. 总结与展望



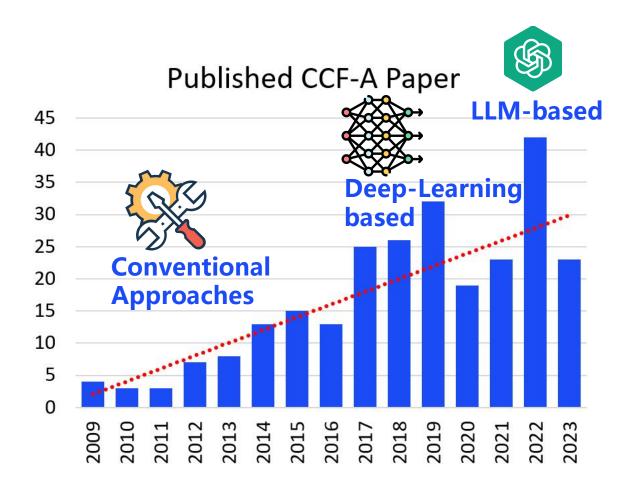
PART 01 程序自动修复与补丁正确性验证



The problem was first formulated in
 2005 [Jobstmann, CAV 05]

 Since GenProg [Weimer, ICSE 09] was proposed in 2009, APR has received huge research interests.

https://program-repair.org/bibliography.html





▶ 程序自动修复—工业界实践



Finding and fixing software bugs automatically with SapFix and Sapienz www.ogrelogic.com **Business Impact**

Technology

Review

MIT

A bot disguised as a human software developer fixes bugs

The automated programmer, called Repairnator, wrote patches good enough to fool actual human engineers.

by Emerging Technology from the arXiv October 23, 2018



"In this world nothing can be said to be certain, except death and taxes," wrote Benjamin Franklin in 1789. Had he lived in the modern era, Franklin may well have added "software bugs" to his list.

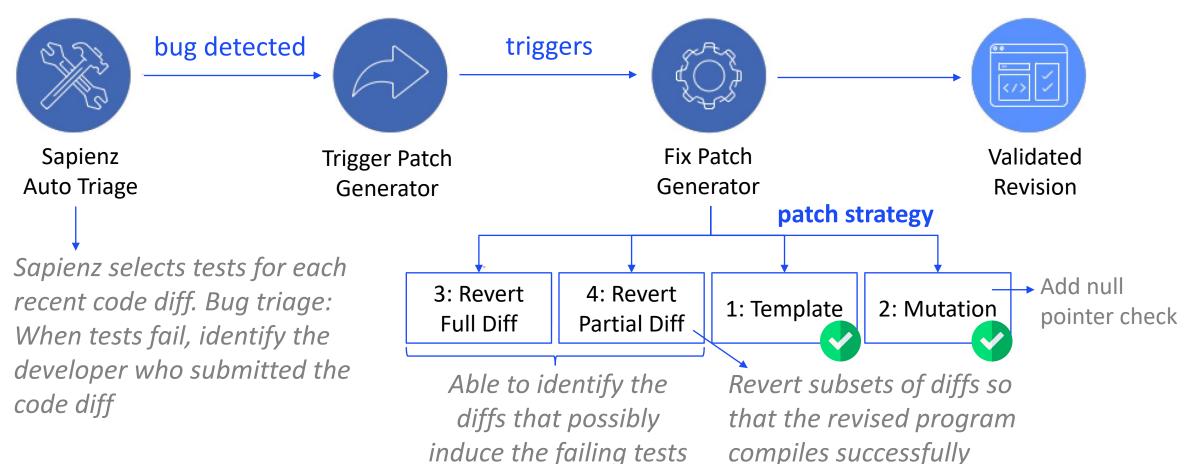


Logi

Topics+ The Down

▶ 程序自动修复— SapFix修复框架

Whether all tests are passed



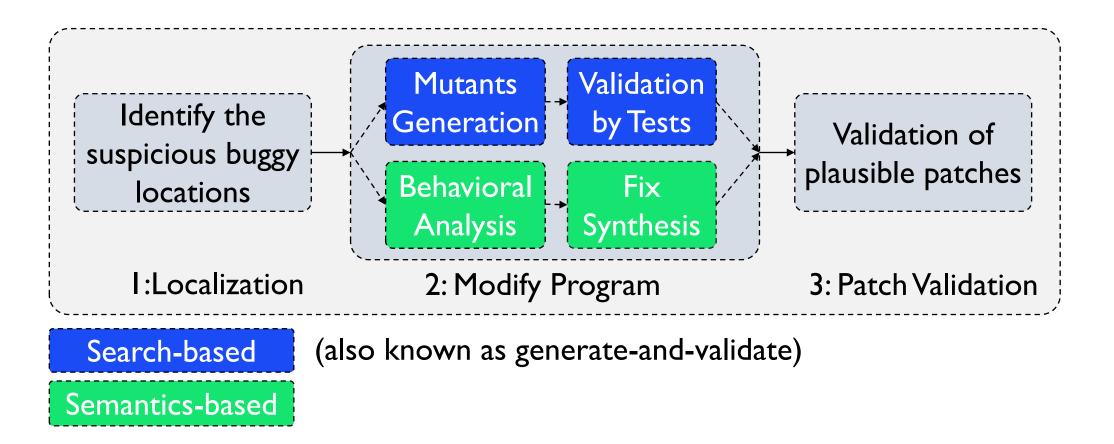
Credit: Facebook





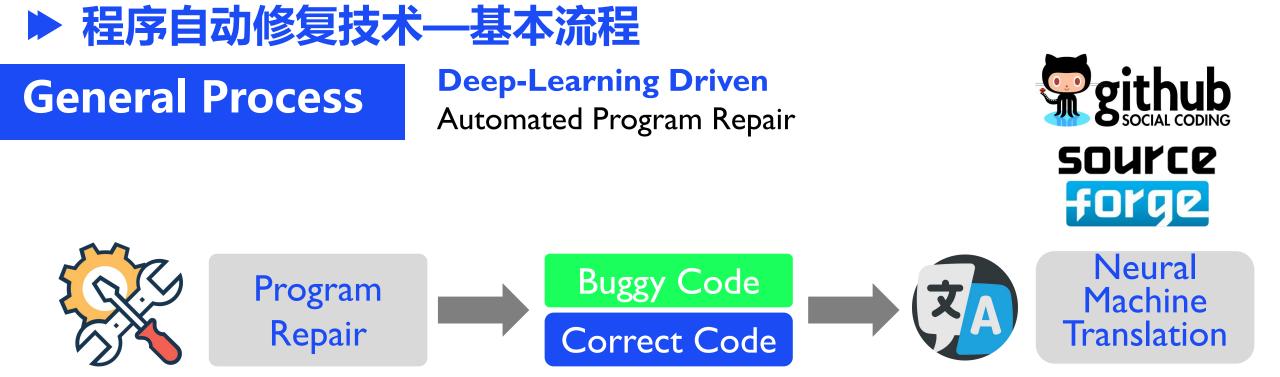
General Process

Conventional Automated Program Repair Approaches









 Lutellier, Thibaud, Hung Viet Pham, Lawrence Pang, Yitong Li, Moshi Wei, and Lin Tan. "Coconut: combining context-aware neural translation models using ensemble for program repair." In the 29th ACM SIGSOFT International Symposium on Software Testing and Analysis (ISSTA), pp. 101-114. 2020.

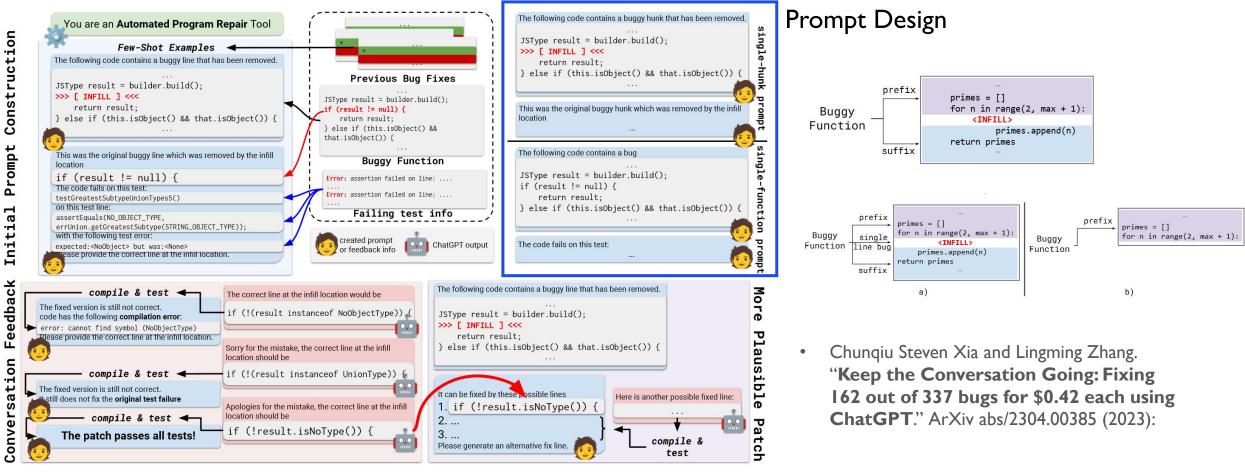
• Jiang, Nan, Thibaud Lutellier, and Lin Tan. "CURE: Code-aware neural machine translation for automatic program repair." In the 43rd International Conference on Software Engineering (ICSE), pp. 1161-1173. IEEE, 2021.



▶ 程序自动修复技术—基本流程

General Process

Large-Language Model based Automated Program Repair

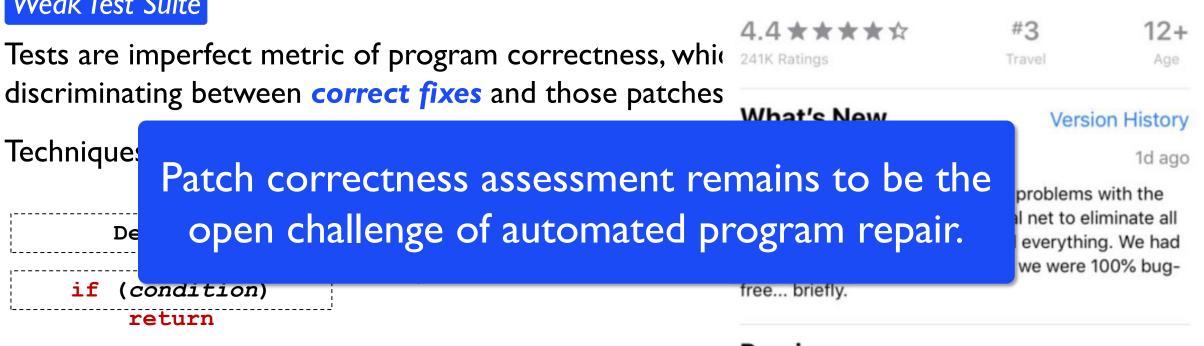


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▶ 程序自动修复技术—补丁过拟合

Overfitting

Weak Test Suite

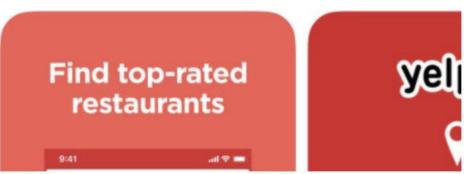


Many of the patches generated by existing approaches function deletion.

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Preview

yelp



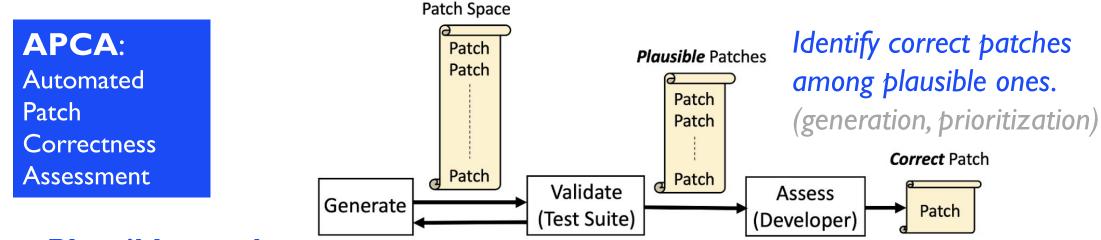
Yelp: Local Food

Restaurant & Delivery Finder

& Services

UPDATE

▶ 补丁正确性验证技术—基本定义



Plausible patch: a patch that passes the test suite is a plausible patch;

Correct patch: a plausible patch that indeed fixes the target bug is deemed correct;

Overfitting patch: a plausible patch that actually does not fix the target bug.

"APR techniques generate more overfitting patches than correct ones on real bugs" – [1][2]

"Patches overfit to the test suite, often breaking undertested functionality." – [3]

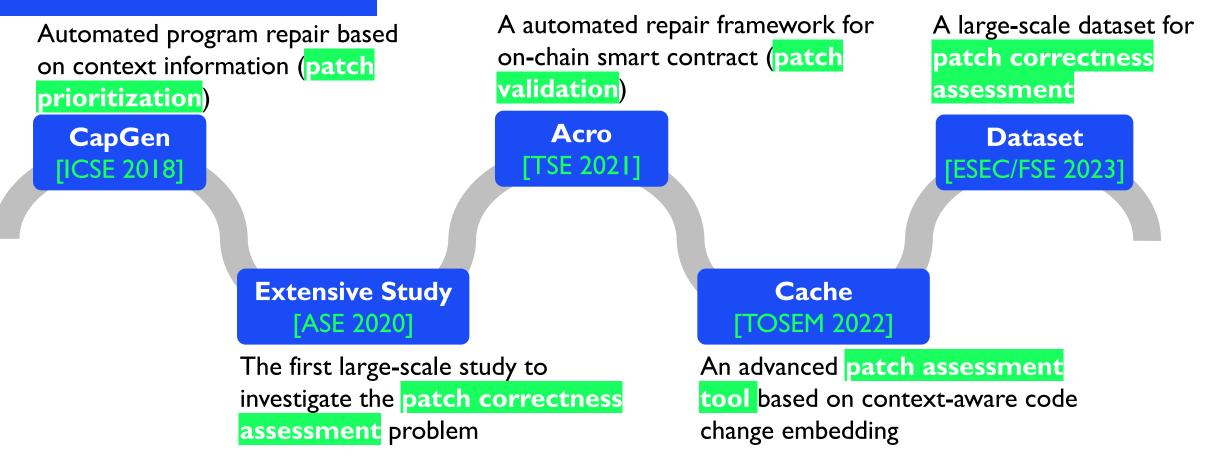
[1] Zichao Qi, Fan Long, Sara Achour, and Martin Rinard. 2015. An analysis of patch plausibility and correctness for generate-and-validate patch generation systems. In Proceedings of the 24th International Symposium on Software Testing and Analysis (ISSTA). ACM, 24–36.

[2] Xuan Bach D.Le, FerdianThung, David Lo,and Claire Le Goues. 2018. Overfitting in semantics-based automated program repair. Empirical Software Engineering 23, 5 (2018), 3007–3033.
 [3] Edward K Smith, Earl T Barr, Claire Le Goues, and Yuriy Brun. 2015. Is the cure worse than the disease? overfitting in automated program repair. In Proceedings of the 10th Joint Meeting on Foundations of Software Engineering. ACM, 532–543.



▶ 补丁正确性验证技术

Our Contribution





▶ 补丁正确性验证技术—补丁排序

Patch Prioritization

Intuition

A fixing ingredient should be applied to the location with similar contexts compared with the location where it is extracted

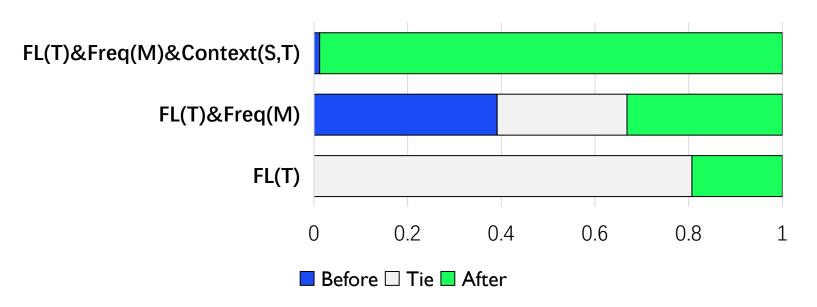
Variable Context	Genealogy Context	Dependency Context
Variable Usage Similarity	Tree Structure Similarity	Semantic Similarity
Ancestor Nodes		Dependent Nodes



▶ 补丁正确性验证技术—补丁排序

Patch Prioritization

$Correctness\ Score(< T, M, S >) = FL(T) * Freq(M) * Context(S, T)$



The relative ranks of the incorrect plausible patches

 Our context-aware prioritization strategies can rank of the correct patches in prior to 98.78% of the incorrect plausible ones





Overview APCA: Automated Patch Correctness Assessment



"A correct patch is often syntactically and semantically proximate to the original program"

Anti-patterns

[FSE 2016]

Check if the code change in the patch violates predefined rules.

ssFix [ASE 2017]

- TokenStrct: similarity of structural tokens
- TokenConpt: similarity of conceptual tokens

S3 [FSE-2017]

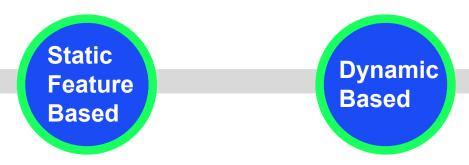
- ASTDist: number of changed AST nodes
- ASTCosDist: distance of distinct AST node types
- VariableDist: distance of locations of variables and constants

CapGen [ICSE-2018]

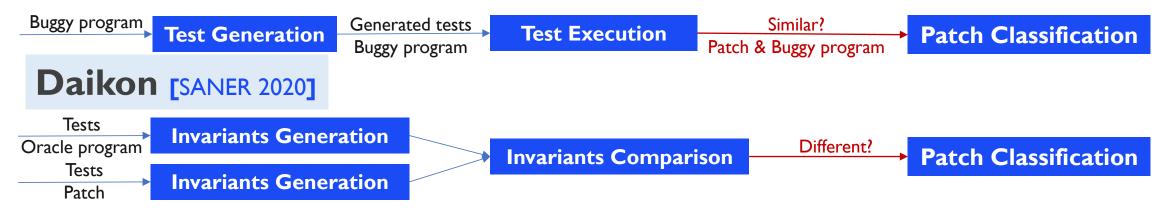
- VariableSimi: similarity of variables
- SyntaxSimi: similarity of syntactic structures
- SemanticSimi: similarity of contextual nodes



Overview APCA: Automated Patch Correctness Assessment

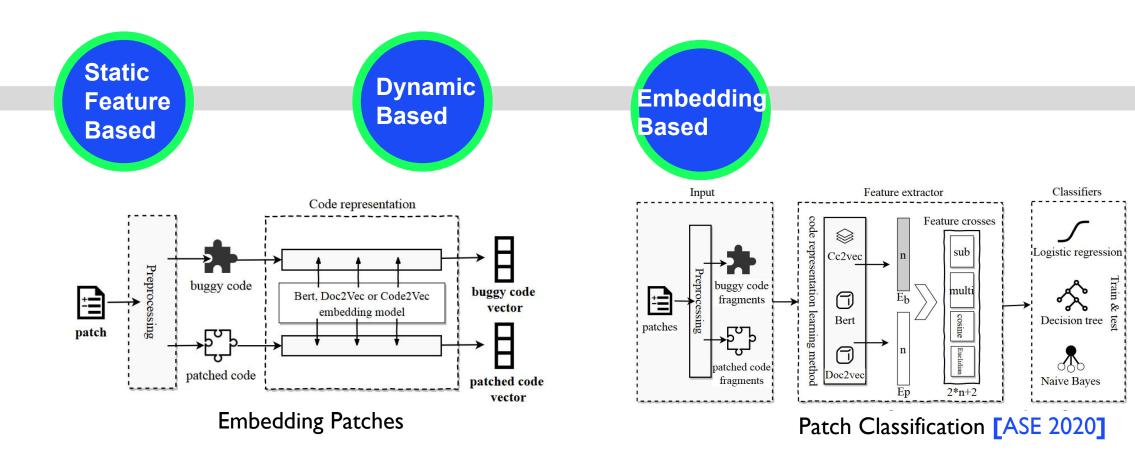


DiffTGen [ISSTA 2017] Opad [FSE 2017] Patch-Sim [ICSE 2018]





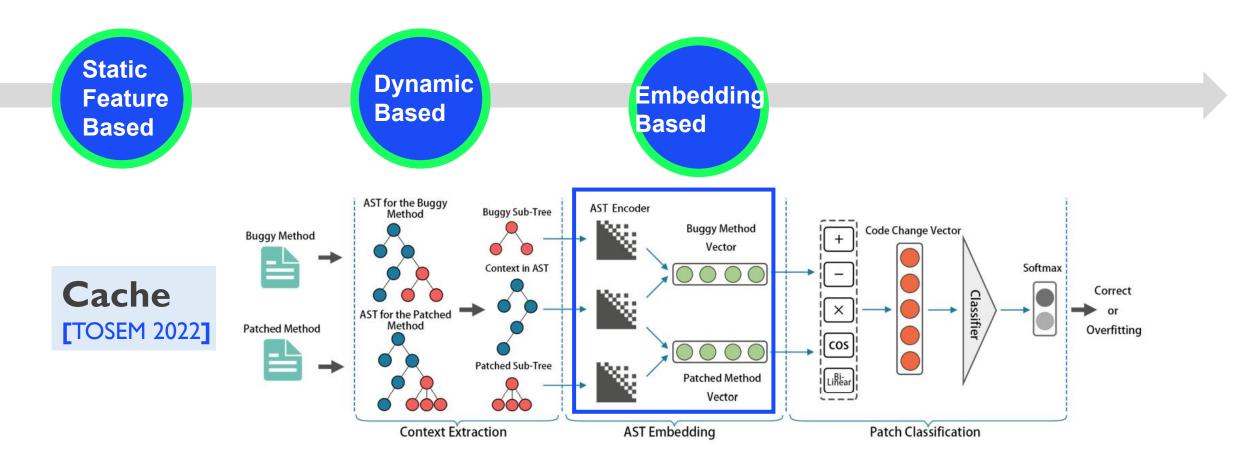
Overview APCA: Automated Patch Correctness Assessment





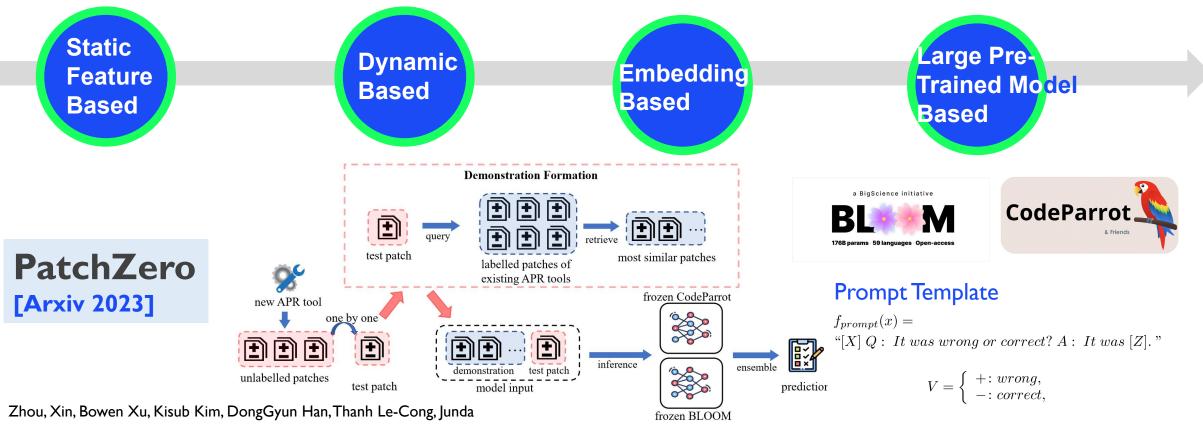
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Overview APCA: Automated Patch Correctness Assessment



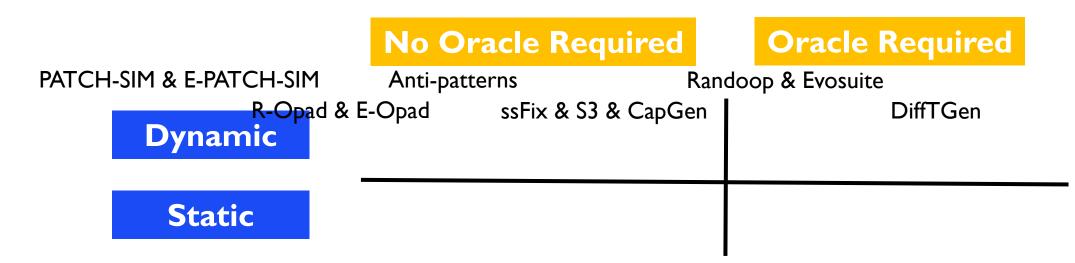


Overview APCA: Automated Patch Correctness Assessment



He, Bach Le, and David Lo. "Patchzero: Zero-shot automatic patch correctness assessment." arXiv preprint arXiv:2303.00202 (2023).





Which types of technique are more effective in identifying correct patches? Are existing techniques complementary to each other?

Empirical Investigation

Technique 9 different techniques and 3 heuristics based on 8 static code features
 Patch 902 patches automatically generated by 21 APR tools from 4 different categories

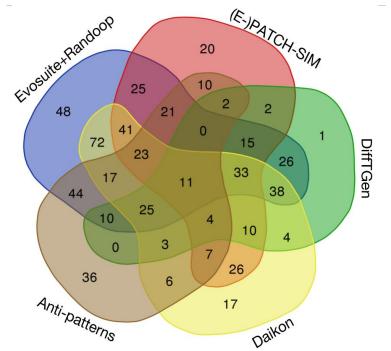


Oracle required	red Effectiveness of each APCA Technique						
	APCA	TP	FP	TN	FN	Precison	Recall
	Evosuite	350	3	245	304	99.15%	53.52%
	Randoop	221	6	242	433	97.36%	33.79%
	DiffTGen [†]	184	5	232	417	97.35%	30.62%
Dynamic —	Daikon [†]	337	38	166	120	89.87%	73.74%
	R-Opad	67	0	248	587	100.00%	10.24%
	E-Opad	92	0	248	562	100.00%	14.07%
	PATCH-SIM [†]	249	51	186	392	83.00%	38.85%
	E-PATCH-SIM [†]	166	36	202	477	82.18%	25.82%
	Anti-patterns	219	37	211	435	85.55%	33.49%
Static	S3	516	135	113	138	79.26%	78.90%
	ssFix	515	138	110	139	78.87%	78.75%
Heuristics	CapGen	506	140	108	148	78.33%	77.37%

• Dynamic APCA techniques with oracles can generate a fewer number of false positives than those without oracles.

- Opad can achieve 100% precision while the recall is rather low.
- Heuristics based on static features can achieve higher recalls but are less precise.





Existing APCA techniques are highly **complementary** to each other;

Distribution of the overfitting patches identified by different APCA techniques.

- Only **I** overfitting patches are detected by all the displayed techniques.
- Substantial overfitting patches are detected exclusively by specific techniques.
- 610 unique overfitting patches (93.3%) can be detected by at least one technique.



Target Integrate static features and dynamic techniques for effectiveness enhancement.

Step 1: integrate the eight static features via learning

- six classification model: Random Forest, Decision Table, J48, Naive Bayes, Logistic Regression, SMO.
- patch benchmark separation.
- 10-fold cross validation.

Step 2: combine trained model with existing techniques via majority voting

- without oracle: <u>PATCH-SIM + Anti-patterns + Model</u> ^C patch validation.
- with oracle: Evosuite + Randoop + Model^② [∽] patch evaluation.

Integration Results with and without the Oracle

	Strategy	TP	FP	Precision	Recall
it	PATCH-SIM	249	51	83.00%	38.85%
non	Anti-patterns	219	37	85.55%	33.49%
Anti-patterns Integration with the Learned Model PATCH-SIM + F-PATCH-SIM + Anti-patterns		343	30	91.96%	52.45%
≥ PAT	PATCH-SIM + E-PATCH-SIM + Anti-patterns	182	38	82.73%	27.83%
	Evosuite	350	3	99.15%	53.52%
with	Randoop	221	6	97.36%	33.79%
	Integration with the Learned Model	435	4	99.10%	66.51%
	Evosuite + Randoop + Daikon	295	3	98.99%	45.11%

Under both scenarios, the integration results significantly outperform existing techniques.

The learned model makes contributions for performance enhancement.





PART 02 基于表示学习的补丁验证

▶ 基于表示学习的补丁验证

Wang, Shangwen, Ming Wen, Bo Lin, Hongjun Wu, Yihao Qin, Deqing Zou, Xiaoguang Mao, and Hai Jin. "Automated patch correctness assessment: How far are we?." In Proceedings of the 35th IEEE/ACM International Conference on Automated Software Engineering, pp. 968-980. 2020.

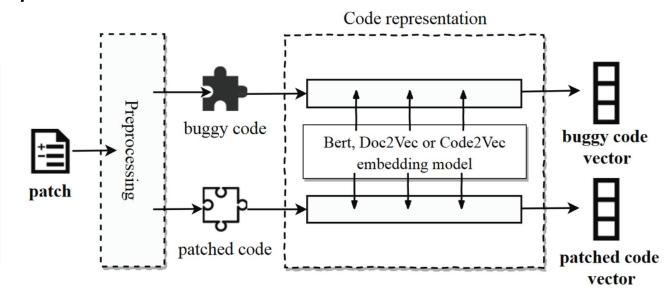
Dynamic Techniques

Static Techniques

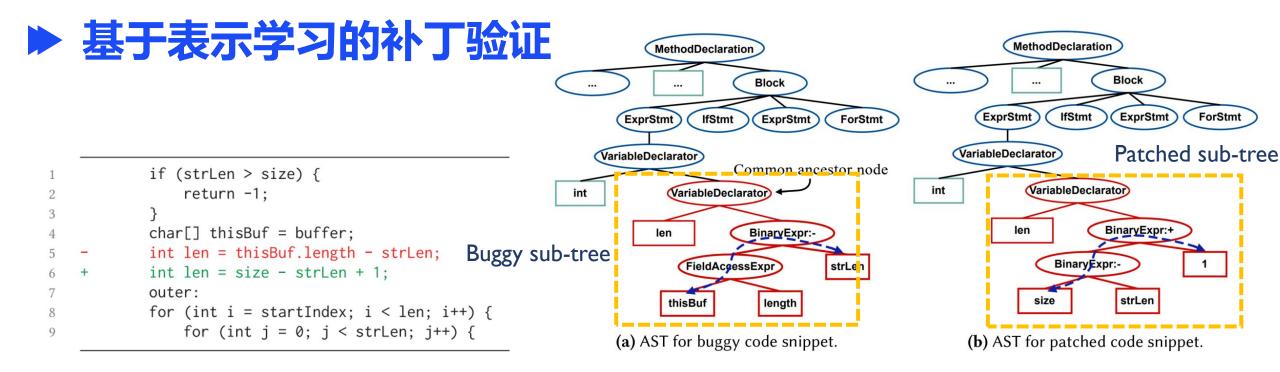
Time-consuming to generate and execute tests

More efficient while less precise. Relying on manually designed features.

With the emerging of code embedding techniques, patches can be easily transferred to vectors, thus facilitating the utilization of deep learning techniques







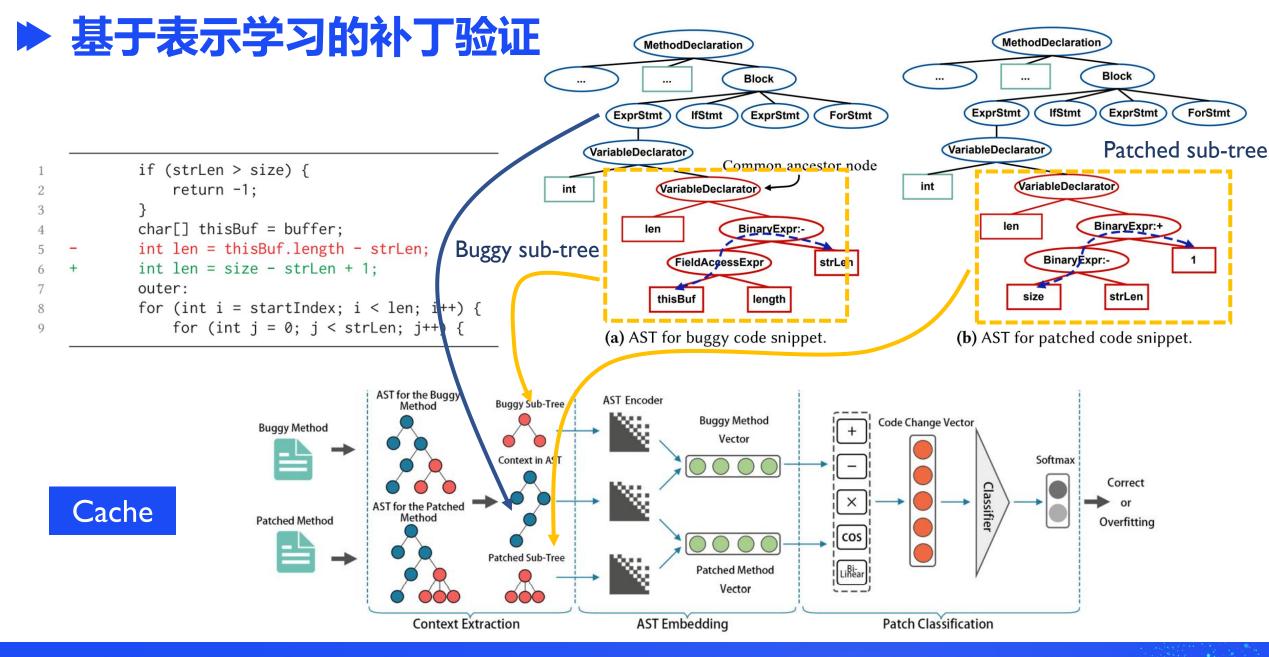
Missing Contexts

Treating the added and deleted lines separately by considering the whole line as a token sequence and embedding each single token. { int, len, =, thisBuf, length, -, strLen }

Missing Structures

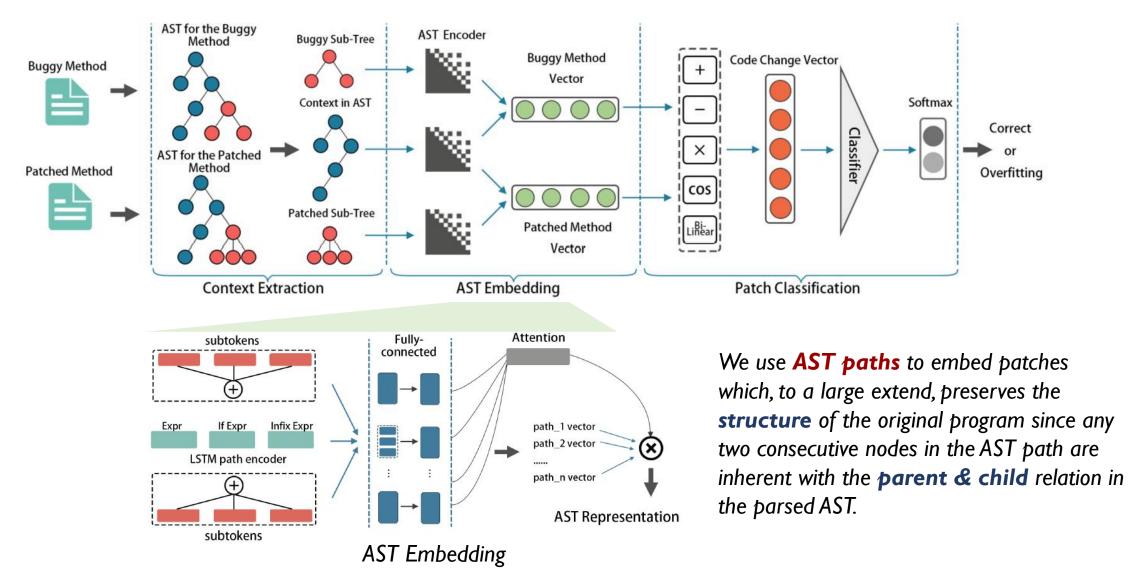
Treating **keywords** in a program in the same way with other **tokens** (e.g., variable names), thus overlooking the program's inherent structures.















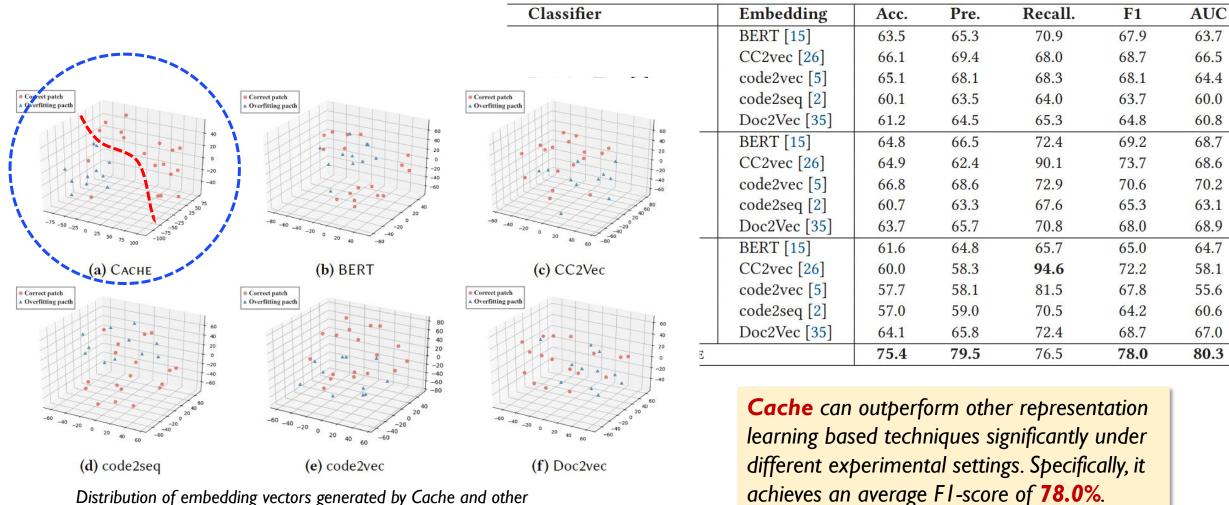
Dataset

Table 1. Datasets Used in Our Experiments

Datasets	Subjects	# Correct patches	# Overfitting patches	Total
Small	Tian et al. [76]	468	532	1,000
	Wang et al. [81]	248	654	902
	Filtered	535	648	1,183
Large	ManySStuBs4J [30]	51,433	0	51,433
	RepairThemAll [16]	900	63,393	64,293 [†]
	Filtered	25,589	24,105	49,694



▶ 基于表示学习的补丁验证—实验结果



Distribution of embedding vectors generated by Cache and other Representation Learning Techniques

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Effectiveness of Cache Compared with Other Representation Learning Techniques

▶ 基于表示学习的补丁验证—实验结果

APCA	Acc.	Prec.	Recall.	F1
Evosuite [23]	65.9	99.1	53.5	69.5
Randoop [65]	51.3	97.4	33.8	50.2
DiffTGen [85]	49.6	97.4	30.6	46.6
Diff TGen [85] Daikon [20]	76.1	89.9	73.7	81.0
R-Opad [91]	34.9	100.0	10.2	18.5
E-Opad [91]	37.7	100.0	14.7	25.6
PATCH-SIM [87]	49.5	83.0	38.9	53.0
E-PATCH-SIM [81]	41.7	82.1	25.8	39.3
Anti-patterns [74]	47.6	85.5	33.5	48.1
S3 [37]	69.7	79.3	78.9	79.0
Anti-patterns [74] S3 [37] ssFix [86]	69.2	78.9	78.8	78.8
CapGen [82]	68.0	78.3	77.4	77.8
Random Forest [25]	72.5	87.0	89.1	88.0
ODS [92]	<mark>88.</mark> 9	90.4	94.8	92.5
Сасне	90.8	92.9	94.5	93.7

Effectiveness of Cache Compared with Other APCA Techniques

denotes techniques that require the oracle information. The bold name means the technique is dynamic.

As a static technique, Cache achieves the optimum overall performance compared with existing APCA techniques with a **high F1-score** reaching **93.7%**. Furthermore, it can even achieve a higher precision than certain **dynamic techniques**, e.g., PATCH-SIM.

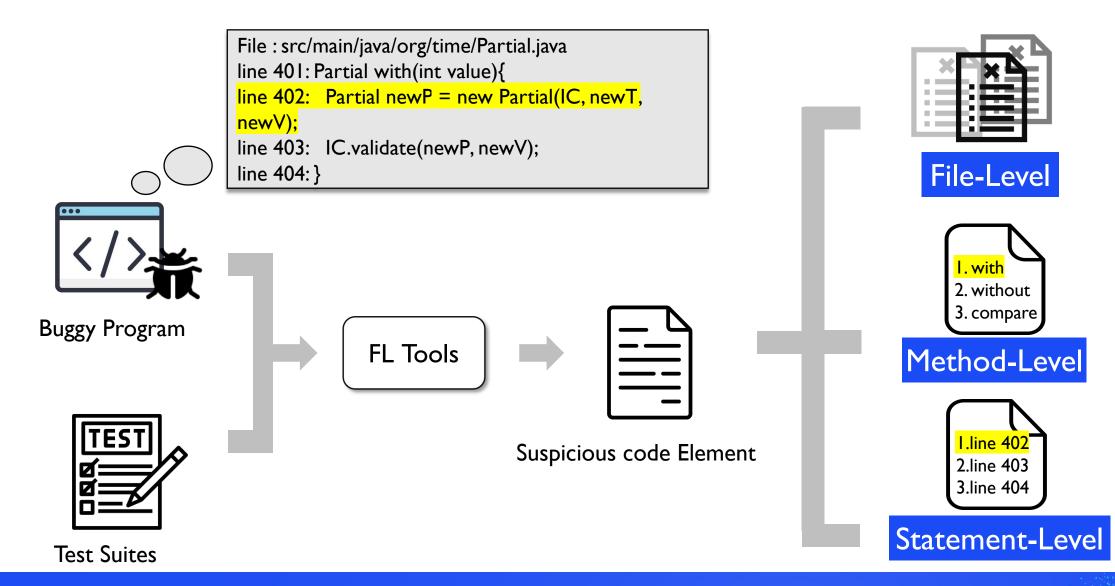
Lin, Bo, Shangwen Wang, Ming Wen, and Xiaoguang Mao. "**Context-aware code change embedding for better patch correctness assessment**." *ACM Transactions on Software Engineering and Methodology* (*TOSEM*) 31, no. 3 (2022): 1-29.





PART 03 基于缺陷定位的补丁排序

▶ 基于缺陷定位的补丁排序—背景





▶ 基于缺陷定位的补丁排序—动因

Developers look for variable-level FL approaches

- Monitoring variable are widely used in practice
- Variables values are useful to understand the **root cause** of the bug



Community comments

All	Comments	Work Log	History	Activity	Transitions	1

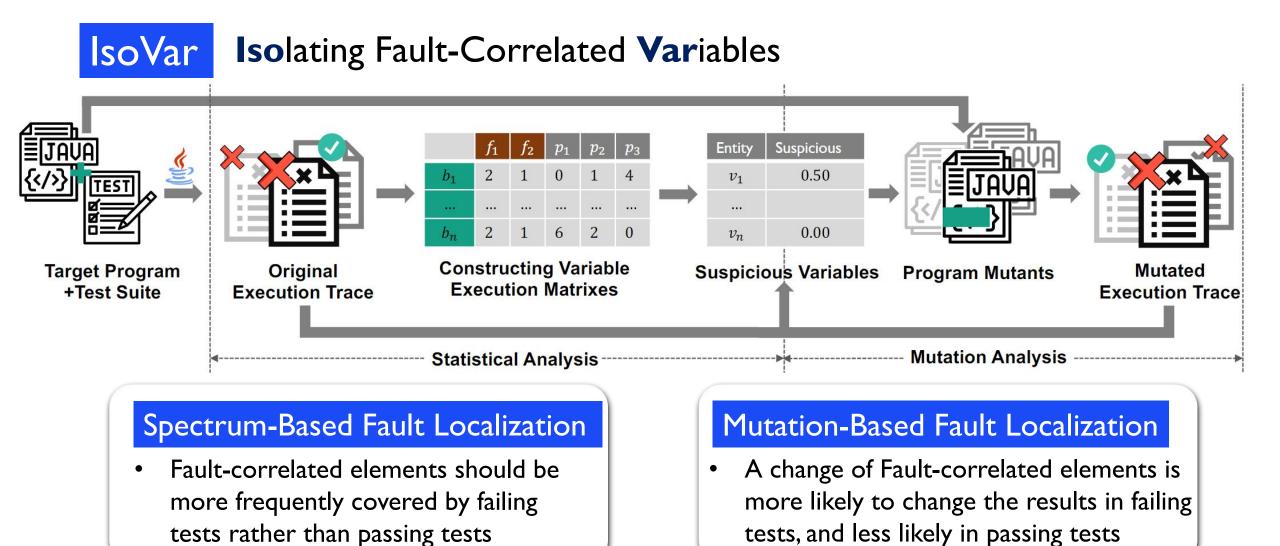
Jesse Pelton added a comment - 01/Jun/04 15:01

So gTranscoder is getting reset or overwritten at some point. Try setting a breakpoint on the variable (use the "Data" tab on VS.Net's "New Breakpoint" dialog) to see when it gets changed. I'd probably set a breakpoint in XMLString::initString, let gTranscoder get initialized, then set the data breakpoint and run until the breakpoint gets tripped.

Reference URL: https://issues.apache.org/jira/browse/XERCESC-1222



▶ 基于缺陷定位的补丁排序—框架



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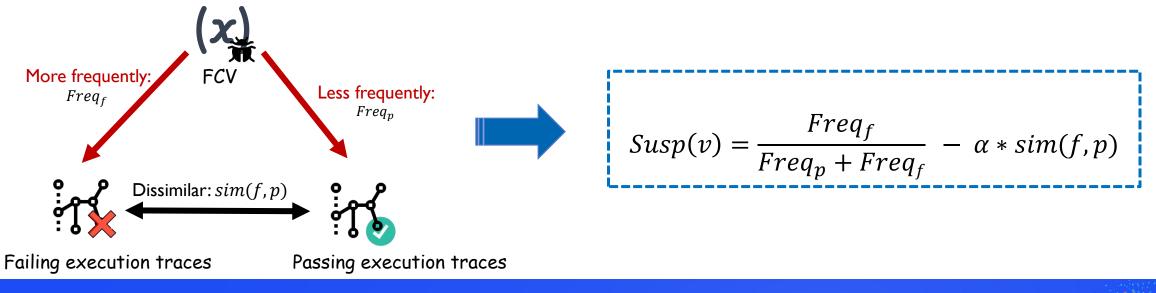
NIDD AI+ 软件研发数字峰会 AI* software Development Digital summit

▶ 基于缺陷定位的补丁排序—方法

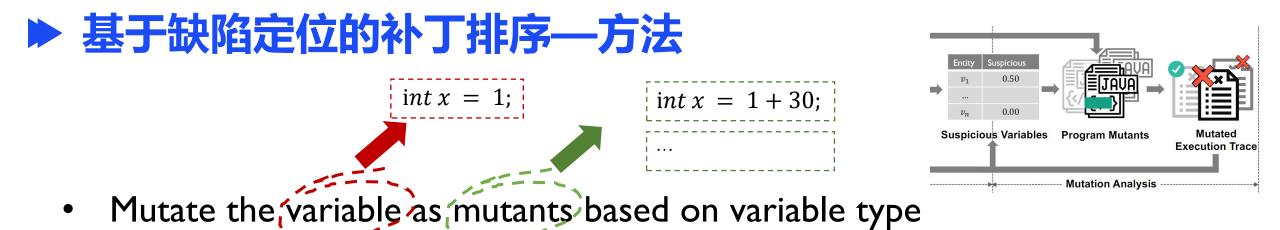
			Failing ₁	Failing ₂	Passing ₁	Passing ₂	Passing ₃	
		BB_1	2	1	0	0	0	
	Variable	BB ₂	2	0	0	1	0	
	valiable	BB ₃	2	1	0	0	0	
 Build <u>variable execution matrix</u> 		BB ₄	2	0	6	2	4	-

For each variable, IsoVar record the spectrum of the basic blocks containing that variable

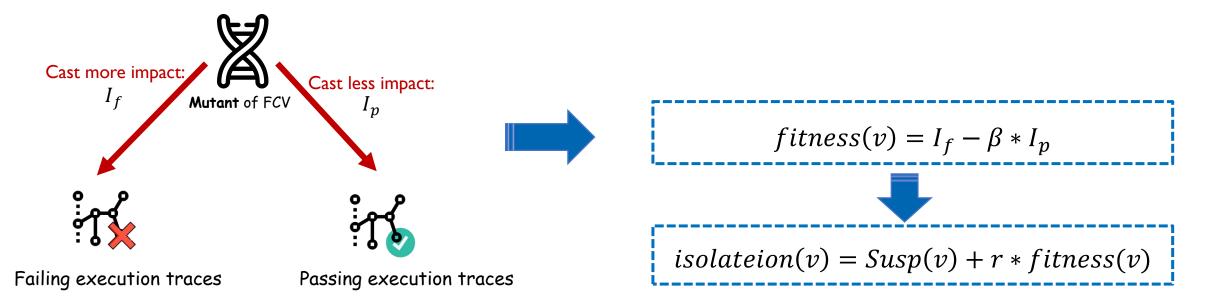
• Fulfill the insights from spectrum-based fault localization





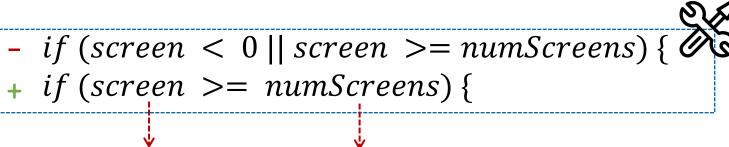


• Fulfill the insights from mutation-based fault localization





▶ 基于缺陷定位的补丁排序—实验结果



Refine Patch Priority Score by IsoVar outputs

Insight correct patches should involve more fault-correlated variables

TABLE 3: Patch Prioritization for Existing APR Techniques

APR	Cardumen	jMutRepair	NPEFix	Nopol	Arja	DynaMoth	GenProg	JGenProg	jKali	RSRepair	Kali	PraPR	TBar	SimFix	Summary
#CP	3	4	4	3	774	2	45	3	2	43	3	39	80	33	1,034
#CPBP	3	4	0	3	764	2	3	3	2	13	3	17	55	29	901
#CPBP ^b	3	4	1	3	767	2	36	3	2	20	3	19	56	31	950

Enhance 14 automated program repair techniques to rank the correct patches. The precision improvement is 69.6%-79.9%

prioritize 49 more correct patches

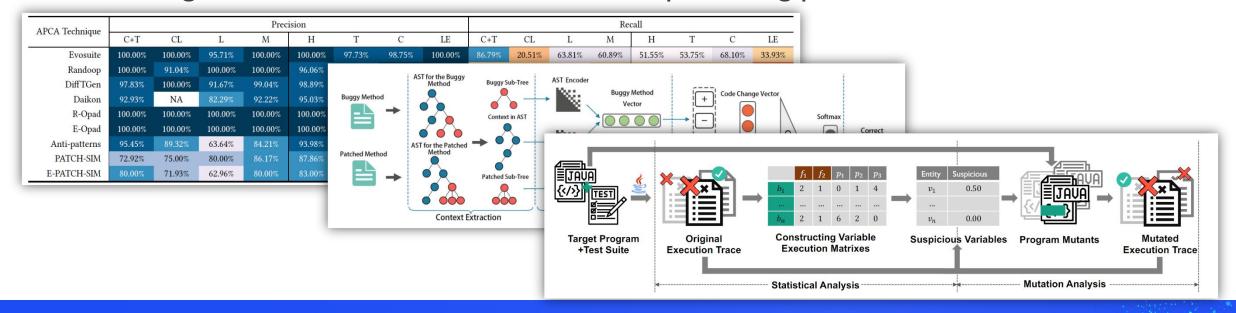




PART 04 总结与展望



- Automated program repair is important, especially in the large language model era.
- Precise patch correctness assessment (PCA) is the key for practical automated program repair.
- Existing PCA efforts are yet insufficient. Our proposed static analysis based, and learning based methods have demonstrated promising performance.





Direction How to better represent a patch?

Code-Change-Oriented Pre-Trained Model

Original Code Change:

Old Token Seq.	this	<u>.</u>	remove	Things		<null></null>	Things);	
New Token Seq.	this	<u> </u>	add	Things		New	Things);	
Edit Action Seq.	equal	equal	replace	equal	equal	Insert	equal	equal	J

Masked Code Change:

6-		F					
Old Token Seq.	MASK .	MASK	MASK		<null></null>	Things);
New Token Seq.	MASK .	add	Things	MASK	MASK	Things);
Edit Action Seq.	MASK equal	replace	equal	equal	Insert	MASK	MASK

Transformer Encoder Layers

Reconstruct Masked Code/Edit:

Masked Unit Prediction	Masked Old Token	Masked New Token	Masked Edit Action		
	Prediction	Prediction	Prediction		
MASK MASK MASK this this equal	MASK MASK + (remove) Things	MASK MASK (New	MASK MASK equal equal		

Pre-training Objectives

CCBERT: Self-Supervised Code Change **Representation Learning**, Arxiv 2023

Pre-training **Unit Prediction Action Prediction** Token Prediction **Token Prediction** Objectives | h_{i-1} Hidden States h_0 h_i h_{i+1} h_L ... Feature **Transformer Encoder Layers** extraction layers Input Repre. $x_0 | \cdots | x_{i-1}$ x_{i+1} x_i x_L ••• Code Token Edit Action Position Input Layer Embedding Embed. Embed Embed Edit Old New Position Token Action Token Pre-processing | t_{i+1} | **Code Tokens** t_0 t_{i-1} ••• t_L ti A Code Change Hunk

Masked Old

Masked New

Masked Token

Overview of CCBERT



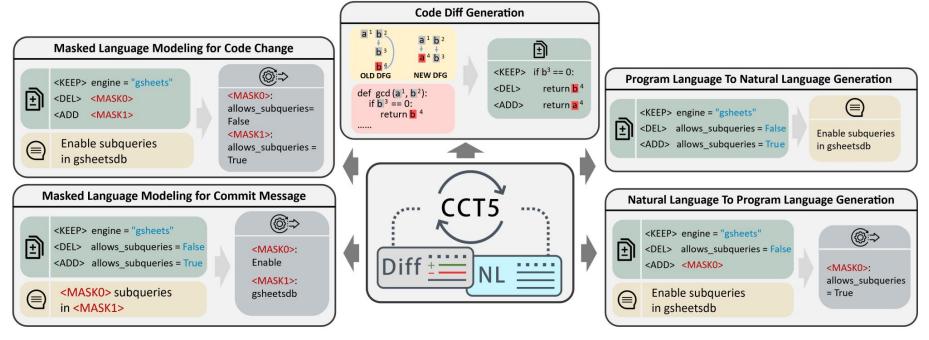


Masked Edit



Direction How to better represent a patch?

Code-Change-Oriented Pre-Trained Model



Overview of CCT5

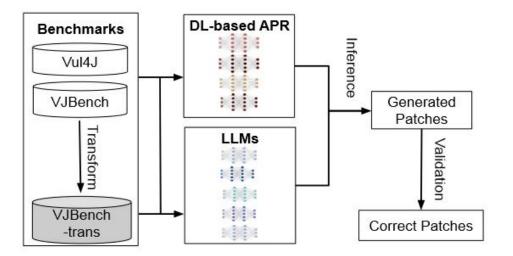
Lin, Bo, Shangwen Wang, Zhongxin Liu, Yepang Liu, Xin Xia, and Xiaoguang Mao. "CCT5: A Code-Change-Oriented Pre-Trained Model." ESEC/FSE (2023).





Direction How to design better prompts?

Prompt Design



Model	Input Format
Codex	Comment buggy lines (BL) with hint "BUG:" and "FIXED:" Prefix prompt: Beginning of the buggy function to BL comment Suffix prompt: Line after BL comment to end of the buggy function
CodeT5	Mask buggy lines with <extra_id_0> and input the buggy function</extra_id_0>
CodeGen	Input beginning of the buggy method to line before buggy lines
PLBART	Mask buggy lines with <mask> and input the buggy function</mask>
InCoder	Mask buggy lines with <mask> and input the buggy function</mask>
Tuned LLMs	Comment buggy lines and input the buggy function

Wu, Yi, Nan Jiang, Hung Viet Pham, Thibaud Lutellier, Jordan Davis, Lin Tan, Petr Babkin, and Sameena Shah. "**How Effective Are Neural Networks for Fixing Security Vulnerabilities**." (ISSTA 2023).



▶ 总结与展望—拥抱大模型

Direction How to design better prompts?

Correctly Repaired Vulnerabilities. (X/Y: X denotes correct patches while Y denotes plausible patches)

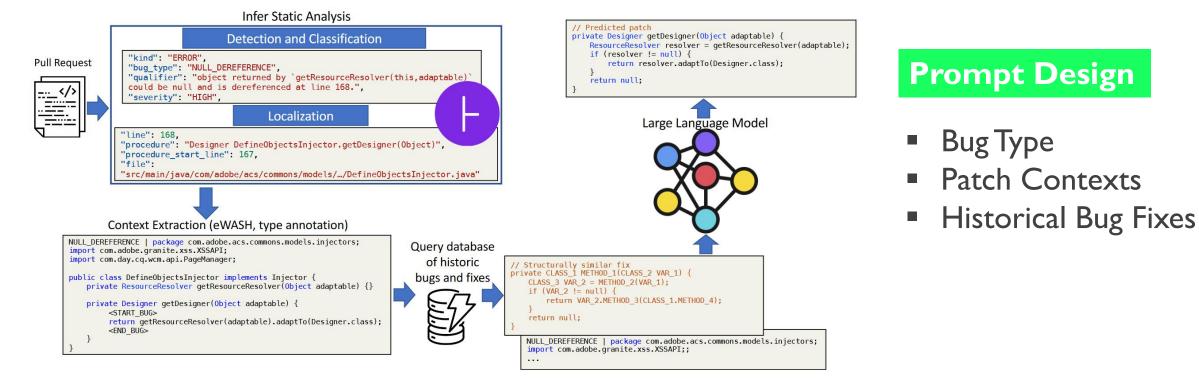
		LLMs		Fine-Tu	ned LLMs		APR models						
	Codex	CodeT5	CodeGen	PLBART	InCoder	CodeT5	CodeGen	PLBART	InCoder	CURE	Recoder	RewardR	KNOD
VJBench (15) Vul4J (35)	4.0 / 4.6 6.2 / 10.9	0/0 2/2	1/2 1/6	2/3 0/4	2/2 3/4	3/4 2/7	3/4 5/8	2/3 2/6	3/4 6/9	0/1 1/4	1/2 0/4	2/3 0/2	0/0 1/1
Total (50)	10.2 / 15.5	2/2	2/8	2/7	5/6	5/11	8/12	4/9	9/13	1/5	1/6	2/5	1/1
Compilation Rate (%)	79.7	6.4	35.8	47.8	65.2	46.8	47.2	45.2	55.2	24.5	57.6	37.7	37.3

- Existing LLMs and APR models **fix very few Java vulnerabilities.** Codex fixes 10.2 (20.4%) vulnerabilities on average, exhibiting the best fixing capability.
- Manually examine whether a patch is correct, and 44.9% of the patches are **plausible** but **incorrect**. It calls for action to design better APCA techniques.
- Model fine-tuning can enhance the repair performance. It calls for action to create larger vulnerability repair training datasets, and fine-tune LLMs with such data.





Direction How to design better prompts?

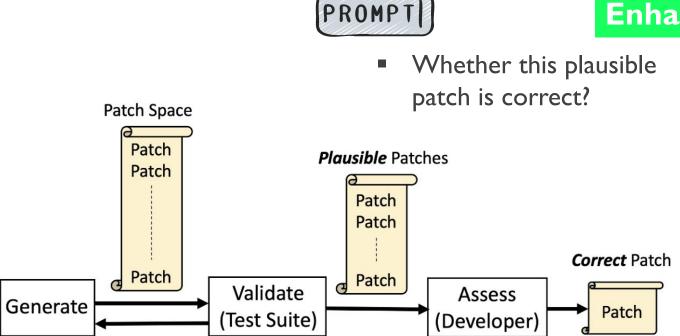


Jin, Matthew, Syed Shahriar, Michele Tufano, Xin Shi, Shuai Lu, Neel Sundaresan, and Alexey Svyatkovskiy. "Inferfix: End-to-end program repair with LLMs." arXiv preprint (2023).





Direction How to design better prompts?



Enhanced (PROMPT)

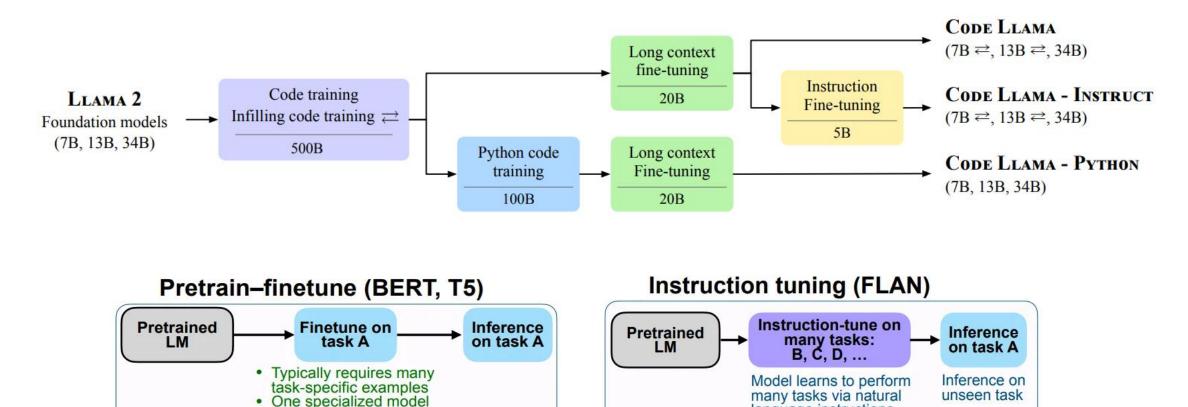
- Whether this plausible patch is correct?
 - Bug Type Static Analysis
 - Patch Contexts
 - Historical Bug Fixes
 -

Data Mining





Direction How to fine-tune an specified LLM model?



AI驱动软件研发全面进入数字化时代

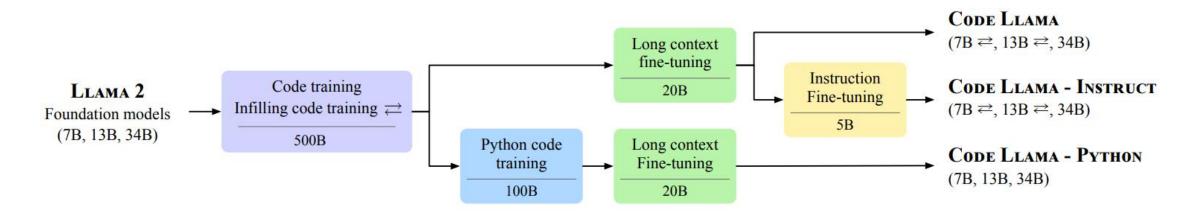
for each task



language instructions

▶ 总结与展望—微调大模型

Direction How to fine-tune an specified LLM model?



"instruction": "Detect whether the following code contains

vulnerabilities.",

"input": "static struct pktcdvd_device

*pkt_find_dev_from_minor(int dev_minor)\n{\n\tif
(dev_minor >= MAX_WRITERS)\n\t\treturn
NULL;\n\treturn pkt_devs[dev_minor];\n}",

"output": "I"

"instruction": "Detect whether the following code contains vulnerabilities.",

"input":"static struct pktcdvd_device *pkt_find_dev_from_minor(int dev_minor)\n{\n\tif (dev_minor >=
MAX_WRITERS)\n\t\treturn NULL;\n\treturn pkt_devs[dev_minor];\n}",

"output": "vulnerable. The sign of 'dev_minor' is not checked, which could permit a negative integer to bypass the 'dev_minor >= MAX_WRITERS' check. This can allow an invalid memory access to occur when 'dev_minor' is used as an index for 'pkt_devs', leading to sensitive information leaks or system crashes. "





THANKS



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