

Neural Program Repair: Systems, Challenges and Solutions

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What is NPR (Neural Program Repair)?

- APR (Automated Program Repair) aims to fix bugs automatically.
- NPR is an emerging direction of APR that apply neural models.
- Generally, NPR frames APR as a bug-to-patch translation.



end-to-end



Recently, more and more researchers are paying attention to NPR.

- Advantages of NPR techniques
 - Remarkable performance
 - Accessible resources for training



However, understanding NPR systems is not easy.

• Requires expertise in both APR and Deep Learning field

What we provide in this paper

- An in-detail review of previous NPR systems
- To make NPR systems more understandable,
 - decompose NPR systems into a 4-phase pipeline.
- To mine potential improvements,
 - analyze design choices on each phase.
 - identify three challenges, discuss the current solutions.



Time	System	Publication Channel	Evaluated Language
2020	ICSE	DLFix	Java
2021	ICSE	CURE	Java
2022	ICSE	RewardRepair	Java
2021	PMLR	TFix	JavaScript
2020	ICML	DrRepair	C, C++
2019	TOSEM	Tufano	Java
2019	TOSEM	CODIT	Java
2019	TSE	SequenceR	Java
2020	ICLR	Hoppity	JavaScript
2019	ICLR	Vasic	C#,python
2020	ASE	PatchEdits	Java
2020	ISSTA	CoCoNut	Java, C, Python
2021	MSR	CodeBERT-ft	Java
2021	ACL(Findings)	Grammar-Transformer	Java
2017	AAAI	DeepFix	С
2021	FSE	Recoder	Java

16 systems in total

Compile Error: 2 Common Error: 14

Java: 11 C: 3 JavaScript: 2 Python: 2 C#: 1 C++: 1





Generally, NPR approaches can be decomposed into 4 phases:

- Preprocessing
 - transform original programs into forms that are acceptable by neural models
- Input Representation
 - encode processed input into vectors
- Output Searching
 - estimate the probability of patches
- Patch Ranking
 - reduce the size of candidates





NPR Systems – Summary of Design Choices

System	Context	Abstraction	Tokenization	Input	Encoder	Decoder	Output	Rank Strategy
CoCoNut	Method	Literal	Lexical+Camel	Code	FConv-context	FConv	Code	Beam Search
CODIT	Node Ancestor	\	Lexical	Code	Bilstm	BiLSTM+copy	Code	-Beam Search
				CFG Rule	Bilstm	BiLSTM+copy	CFG Rule	
Cure	Method	Literal	Camel+BPE	Code	PT-GPT+Fconv-context	PT-GPT+Fconv	Code	Code-aware
CodeBERT	Node Ancestor	λ	BPE	Code	CodeBERT	Transformer Dec.	Code	Beam Search
DeepFix	Method	λ	Lexical	Code	GRU	GRU	Code	Beam Search
DLFix	Method	Literal	Lexical	AST	Tree-LSTM	Tree-LSTM	Node	DL-based
DrRepair	Method	λ	Lexical	Code, NL	LSTM	LSTM+copy	Code	Beam Search
Hoppity	Method	λ	Lexical	Graph	GNN	Edit Operator	Node Edit	Beam Search
PatchEdits	Line	١	BPE	Code	Transformer Enc.	Transformer Dec. +copy	Code Edit	Beam Search
Recoder	Method	Identifier	Lexical	Code, AST	Hybrid Reader	Modified TreeGen	Node Edit	Beam Search
RewardRepair	Class	λ	BPE	Code	PT-T5	PT-T5	Code	Beam Search
Tufano	Method	Identifier,Literal	Lexical	Code	Bilstm	BilstM	Code	Beam Search
SequenceR	Class	λ	Lexical	Code	Bilstm	BiLSTM+copy	Code	Beam Search
TFix	Neighbor Lines	λ	BPE	Code, NL	PT-T5	PT-T5	Code	Beam Search
Tang	Method	Identifier	-Lexical	Code	Transformer Enc.	-Grammar Decoder CFG		Beam Search
		String		CFG Rule	Transformer Enc.			
Vasic	Method	\	Lexical	Code	LSTM+copy	Linear	Positon+Code	Beam Search



What are motivations of various design choices?









Limit use of code-related information

Finding 1: The introduction of grammar rules is helpful for generating compilable patches.

Example: CODIT, Recoder, Tang

Limitation: Existing methods of introducing grammar rules are to model the input and output as CFG rules, not a human-like way.

Future direction: Let the model learn how to follow the syntax rules when outputting code tokens.



short code text may produce a lo sequence of CFG rules



Limit use of code-related information

Finding 2: Structural models can be more precise at encoding structural inputs such as the AST. *Example:* DLFix, Recoder, Hoppity *Limitation:* Using structural models may decrease the applicability *Future direction:* Investigating the performance differences between structured input and sequential input.





The OOV problem

Finding 1: Abstraction of source programs can efficiently reduce the size of the vocabulary, thus mitigating the OOV problem.

Limitation: Abstraction of codes may decrease the recall rate of the NPR model.

Future Direction: More balanced abstraction methods





The OOV problem

Finding 2: BPE-based tokenization also works for mitigating the OOV problem. *Limitation:* BPE produces long inputs and long outputs, which are not handled well by neural network models.

Future Direction: A combination of word-level tokenization and BPE



stream . flush (); length: 6



Large search space

Finding 1: The number of candidates is not *the more, the better. Reason:* Since NPR models are a kind of probability-estimation model, a larger candidate set will have a higher probability to contain a correct patch. However, the time and cost price of large candidate sets are usually ignored.

Future Direction: Investigating the performance-cost balance from an empirical perspective





- A decompose of previous NPR systems.
- An exploration of the design space.
- A summary of major challenges.
- Discussions of current solutions and possible improvements.

Future Work

- More rules when generating patches.
- Explicable NPR models.
- Multi-perspective evaluation.



•Thank you!

Q&A