CoditT5: Pretraining for Source Code and Natural Language Editing

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Pretraining + Code

- Language models pretrained on code and natural language
  - PLBART[1], CodeT5[2], Copilot[3]
- Impressive performance on generation tasks
- Does not capture the editing nature of software development
  - not designed for making edits
  - frequently copy the inputs without making edits (34.25% of the times)
  - make irrelevant edits

[1] Wasi A., Saikat C., Baishakhi R., and Kai-Wei C.. 2021. Unified Pre-training for Program Understanding and Generation. In Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies. 2655–2668.
[2] Yue W., Weishi W., Shafiq J., and Steven C.H. H.. 2021. CodeT5: Identifier-aware Unified Pre-trained Encoder-Decoder Models for Code Understanding and Generation. In Empirical Methods in Natural Language Processing. 8696–8708.
[3] https://github.com/features/copilot

CoditT5: Pretrained Model for Edits

- Pretrained objective that explicitly models edits
- CoditT5: designed for software-editing tasks

```java
public Integer getMinElement(List myList) {
    if (myList.size() >= 0) {
        return ListManager.getFirst(myList);
    }
    return 0;
}
```

edit →

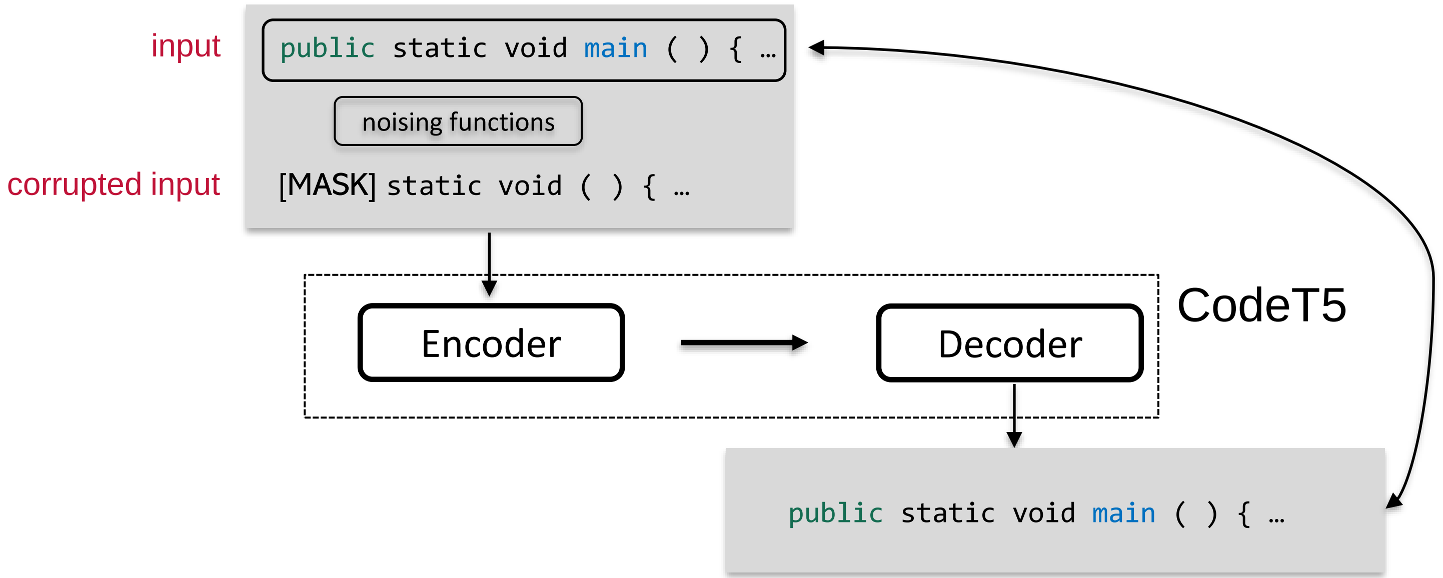
```diff
public Integer getMinElement(List myList) {
    if (myList.size() >= 0) {
-           return ListManager.getFirst(myList);
+           return ListManager.min(myList);
    }
-   return 0;
+   return null;
}
```

Our Contributions

- Propose a novel pretraining objective for editing tasks
- Build a large pretrained language model: CoditT5
- Evaluate on three downstream tasks
  - Comment updating
  - Bug fixing
  - Automated code review
- Combine CoditT5 with a standard generation model

Existing pretraining objective

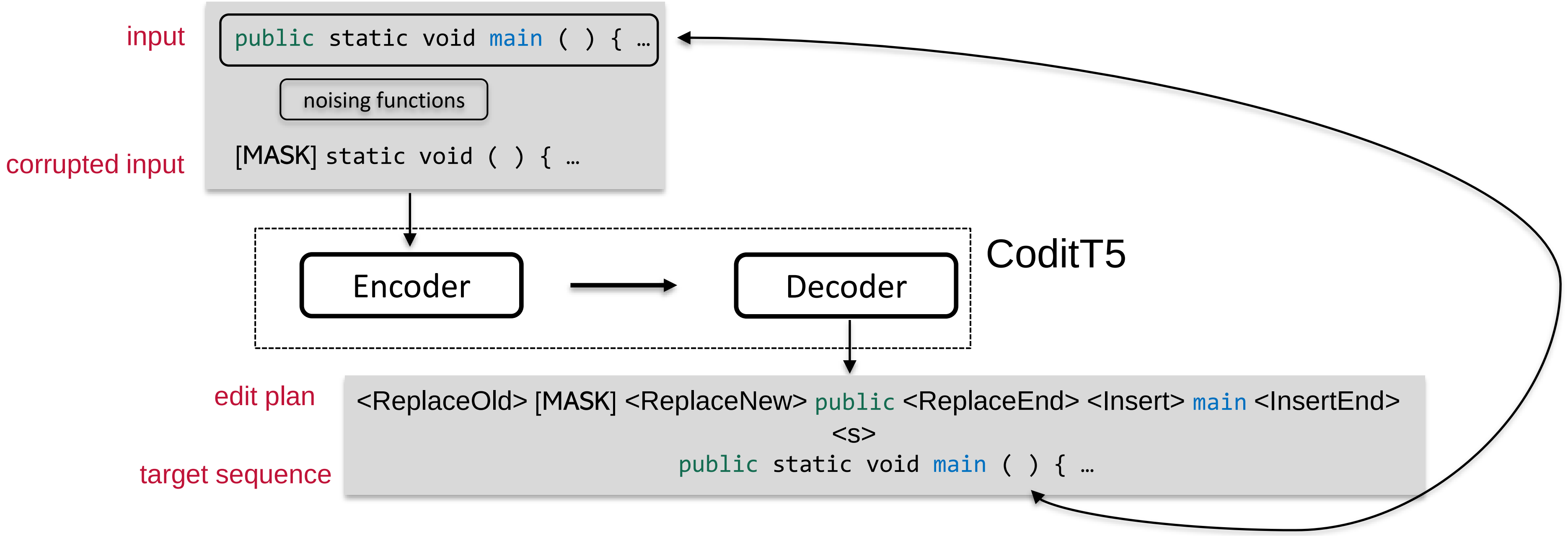
Denoising autoencoding



input
public static void main ( ) { …
noising functions
corrupted input
[MASK] static void ( ) { …
Encoder
Decoder
CodeT5
public static void main ( ) { …

CoditT5

- noising functions
- edit plan
- target sequence


input
public static void main ( ) { …
noising functions
corrupted input
[MASK] static void ( ) { …
Encoder
Decoder
CoditT5
edit plan
<ReplaceOld> [MASK] <ReplaceNew> public <ReplaceEnd> <Insert> main <InsertEnd>
<s>
target sequence
public static void main ( ) { …

Noising Functions

- Deleting random spans of tokens in the input

```
public static void main ( ) { …
```

```
public static void ( ) { …
```

- Inserting [MASK] token at random positions

```
public static void main ( ) { …
```

```
Public [MASK] static void main ( ) { …
```

- Randomly masking spans with the special [MASK] token

```
public static void main ( ) { …
```

```
[MASK] static void main ( ) { …
```

Noising Functions Cont’d

- Collect statistics from real-world edits:

	Code	Natural Language
Prob. Delete	0.50	0.07
Prob. Insert	0.21	0.11
Prob. Replace	0.30	0.82
Avg. # Tokens	6.50	3.00
Avg. # Spans	1.90	1.40

Edit Plan

Concrete edit actions to be applied to the input

- Example:

corrupted input	[MASK] `static void ( ) { …`
edit plan	<ReplaceOld> [MASK] <ReplaceNew> `public` <ReplaceEnd> <Insert> `main` <InsertEnd>
Input	`public static void main ( ) { …`

Edit Plan Formats

- Delete

  <Delete> [span of tokens] <DeleteEnd>

- Insert

  <Insert> [span of tokens] <InsertEnd>

- Replace

  <ReplaceOld> [span of old tokens]

  <ReplaceNew> [span of new tokens] <ReplaceEnd>

Target Sequence

The final edited sequence after applying the edit plan

- Why?
  - can not always derive the target sequence deterministically
  - maintaining fluency and coherency of the edited sequence

corrupted input	[MASK] `static void ( ) {` …
edit plan	<ReplaceOld> [MASK] <ReplaceNew> `public` <ReplaceEnd> <Insert> `main` <InsertEnd>

Pretraining Data

- CodeSearchNet[1]:
  - 6 programming languages: Python, Java, Ruby, Php, Go, JavaScript
  - natural language comments
- 5.9M methods and 1.6M comments after preprocessing

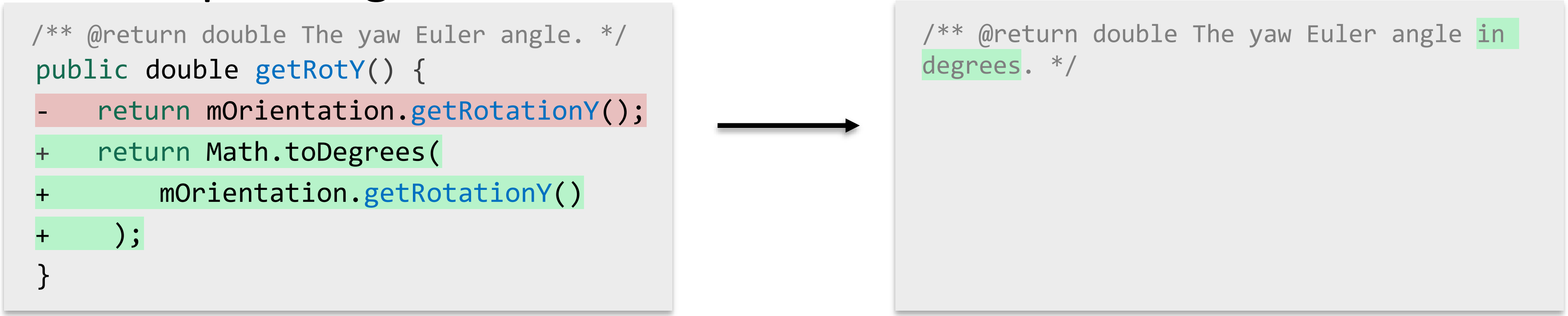
[1] Hamel H., Ho-Hsiang W., Tiferet G., Miltiadis A., and Marc B.. 2019. Codesearchnet challenge: Evaluating the state of semantic code search. arXiv preprint arXiv:1909.09436 (2019)

Downstream Tasks

- Comment Updating
- Bug Fixing
- Automated Code Review

Comment Updating

- Updating a natural language comment to reflect changes in the corresponding body of code
- Dataset[1]: Java method changes paired with changes in the corresponding comments



```
/** @return double The yaw Euler angle. */
public double getRotY() {
-    return mOrientation.getRotationY();
+    return Math.toDegrees(
+        mOrientation.getRotationY()
+    );
}
```

$\longrightarrow$

```
/** @return double The yaw Euler angle in
degrees. */
```

[1] Panthaplackel, S., Nie, P., Gligoric, M., Li, J. J., & Mooney, R. (2020, July). Learning to Update Natural Language Comments Based on Code Changes. In Annual Meeting of the Association for Computational Linguistics.1853–1868
[2] Lin, B., Wang, S., Liu, Z., Xia, X., & Mao, X. (2022). Predictive Comment Updating with Heuristics and AST-Path-Based Neural Learning: A Two-Phase Approach. IEEE Transactions on Software Engineering.

Baselines & Metrics: Comment Updating

- Baselines:
  - PLBART
  - CodeT5
  - RNN edit model[1]
- Metrics (from 0 to 100):
  - xMatch: pct. of the predictions exactly matches the ground truths
  - GLUE, SARI: edit actions overlap
  - BLEU, METEOR: token-level overlap

[1] Panthaplackel, S., Nie, P., Gligoric, M., Li, J. J., & Mooney, R. (2020, July). Learning to Update Natural Language Comments Based on Code Changes. In Annual Meeting of the Association for Computational Linguistics.1853–1868

Eval: Comment Updating

	xMatch	SARI	GLEU	BLEU	METEOR
RNN Edit Model	33.33	56.23	51.88	56.55	52.26
PLBART	35.33	52.83	54.75	62.04	56.79
CodeT5	38.00	58.80	58.84	**65.20**	59.63
CoditT5	**43.33**	**61.41**	**59.53**	64.56	**60.75**

CoditT5 achieves higher performance for most of the metrics, highlighting the benefit of explicitly modeling edits for the editing tasks

Bug Fixing

- Generating a fixed code snippet given buggy code snippet
- Dataset[1]: Java BugFixPairs-Small ($B2F_S$) and BugFixPairs-Medium ($B2F_m$) datasets with buggy code snippet, fixed code

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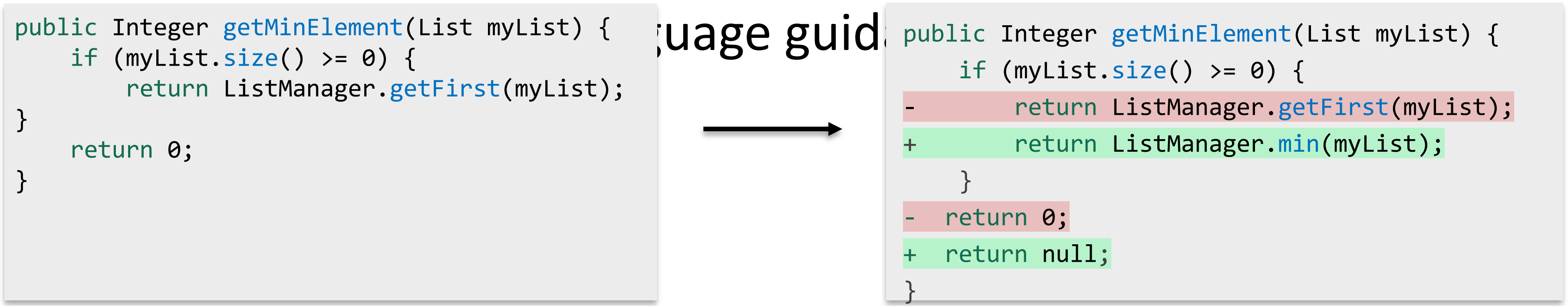

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```diff
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    if (myList.size() >= 0) {
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+       return ListManager.min(myList);
    }
-  return 0;
+  return null;
}
```

[1] Chakraborty, S., & Ray, B. 2021. On Multi-Modal Learning of Editing Source Code. In Automated Software Engineering. 443–455
[2] Dawn D., Chen W., Alexey S., and Neel S. 2021. Generating bug-fixes using pretrained transformers. In nternational Symposium on Machine Programming. 1–8
[3] Antonio M., Simone S., Nathan C., David N. P., Denys P., Rocco O., and Gabriele B.. 2021. Studying the usage of text-to-text transfer transformer to support code-related tasks. In International Conference on Software Engineering. 336–347.

Baselines & Metrics: Bug Fixing

- Baselines:
  - MODIT[1] (PLBART)
  - CodeT5
- Metrics:
  - xMatch: pct. of the predictions exactly matches the ground truths

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Eval: Bug Fixing

	xMatch	
	B2F$_s$	**B2F$_m$**
PLBART	31.09	24.18
CodeT5	34.81	26.66
CoditT5	**37.52**	**29.96**

CoditT5 is better than baselines on xMatch

Automated Code Review

- Generating the revised code snippet, given a code snippet under review and a brief natural language sentence prescribing code edits
- Dataset[1]: Java methods (before and after the review) paired with pu

```
"Generally better to qualify than making static import"
public List<Pattern> getExcludedResponseHeaderPatterns() {
-    return emptyList();
+    return List.emptyList();
}
```

[1] Rosalia T., Luca P., Michele T., Denys P., and Gabriele B. 2021. Towards Automating Code Review Activities. In International Conference on Software Engineering. 163–174
[2] Zhiyu L., Shuai L, Daya G., Nan D., Shailesh J., Grant J., Deep M., Jared G., Alexey S., Shengyu F., et al. 2022. CodeReviewer: Pre-Training for Automating Code Review Activities. arXiv preprint arXiv:2203.09095 (2022).
[3] Rosalia T., Simone M., Antonio M., Luca P., Denys P., and Gabriele B.. 2022. Using Pre-Trained Models to Boost Code Review Automation. In International Conference on Software Engineering. 2291–2302

Baselines & Metrics: Automated Code Review

- Baselines
  - PLBART
  - CodeT5
- Metrics:
  - xMatch: pct. of the predictions exactly matches the ground truths
  - BLEU: token-level overlap

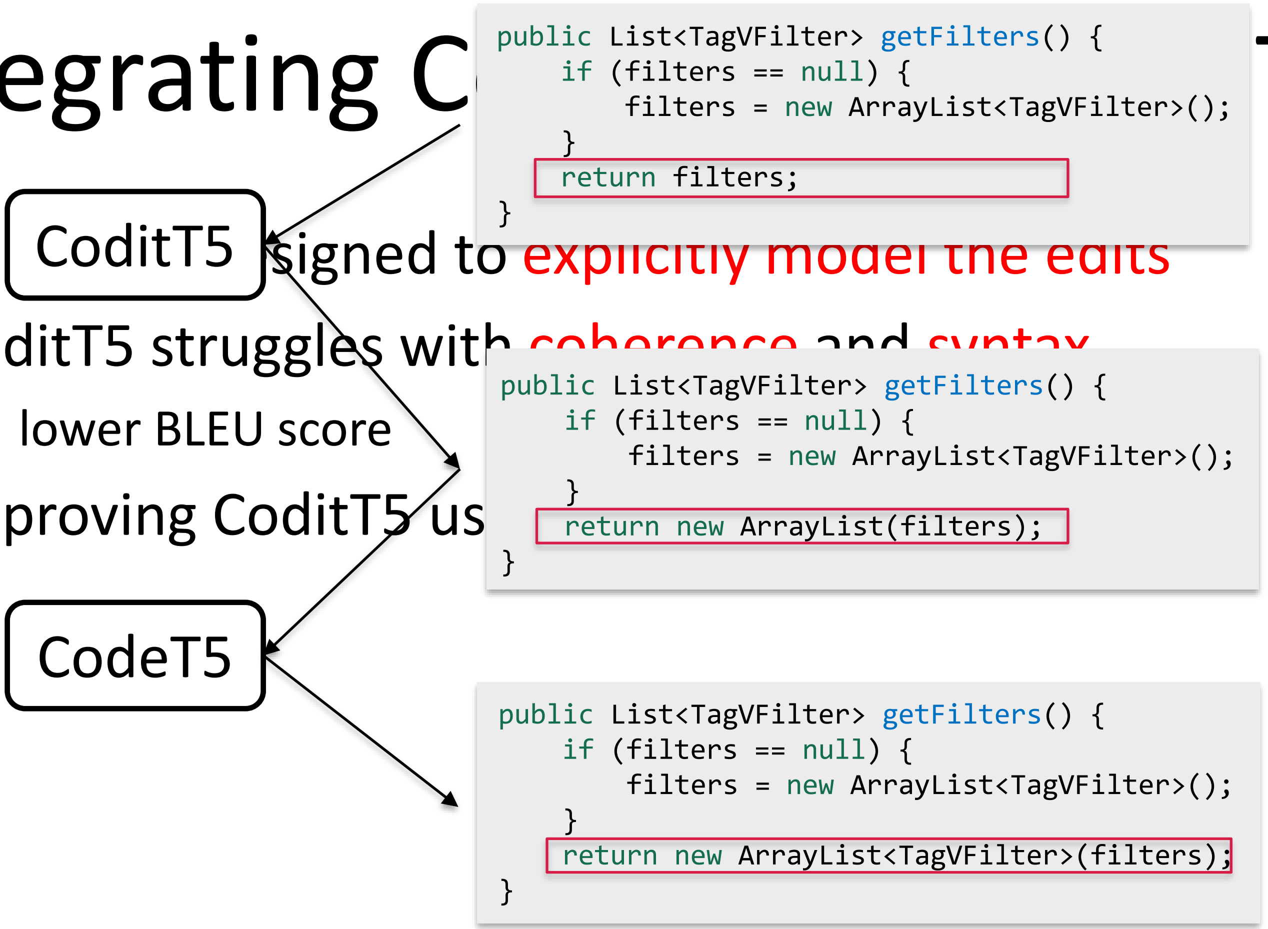
Eval: Automated Code Review

	xMatch	**BLEU**
PLBART	26.78	79.38
CodeT5	34.98	**83.20**
CoditT5	**37.19**	80.50

CoditT5 has better performance on xMatch

Integrating C T5

- Co signed to explicitly model the edits
- CoditT5 struggles with coherence and syntax
  - lower BLEU score
- Improving CoditT5 us



```
public List<TagVFilter> getFilters() {
    if (filters == null) {
        filters = new ArrayList<TagVFilter>();
    }
    return filters;
}
```

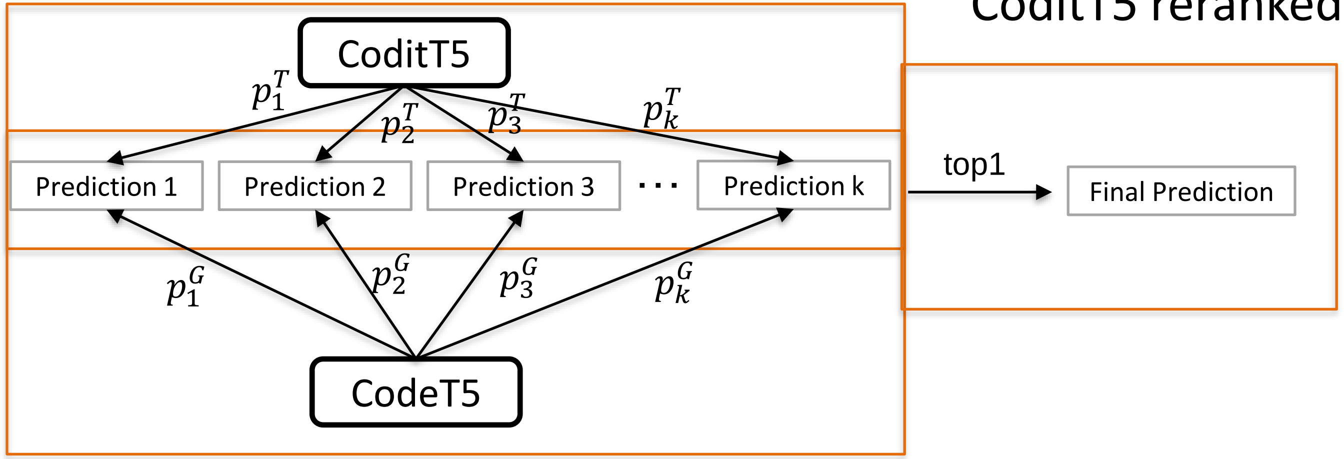
```
public List<TagVFilter> getFilters() {
    if (filters == null) {
        filters = new ArrayList<TagVFilter>();
    }
    return new ArrayList(filters);
}
```

```
public List<TagVFilter> getFilters() {
    if (filters == null) {
        filters = new ArrayList<TagVFilter>();
    }
    return new ArrayList<TagVFilter>(filters);
}
```

Integrating CoditT5 and CodeT5

- Combine two models using simple likelihood-based reranking strategies at test time

CoditT5 reranked w/ CodeT5



Eval: Combination

	Comment Update		$B2F_s$	$B2F_m$	Code Review	
	xMatch	BLEU	xMatch		xMatch	BLEU
CodeT5	38.00	65.20	34.81	26.66	34.98	83.20
CoditT5	43.33	64.56	37.52	29.96	37.19	80.50
CoditT5 reranked w/ CodeT5	**45.33**	**66.80**	**40.22**	32.06	40.98	**84.12**
CodeT5 reranked w/ CoditT5	44.00	65.58	39.56	**32.24**	**43.42**	83.92

Summary

- Novel pretraining objective that explicitly models edits
- CoditT5: a large pretrained model for software editing tasks
- Combining our edit-based model with a standard generation model through simple reranking strategies
- Evaluate on three downstream tasks

https://github.com/EngineeringSoftware/CoditT5

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