

CoRet: Improved Retriever for Code Editing

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You



New Team



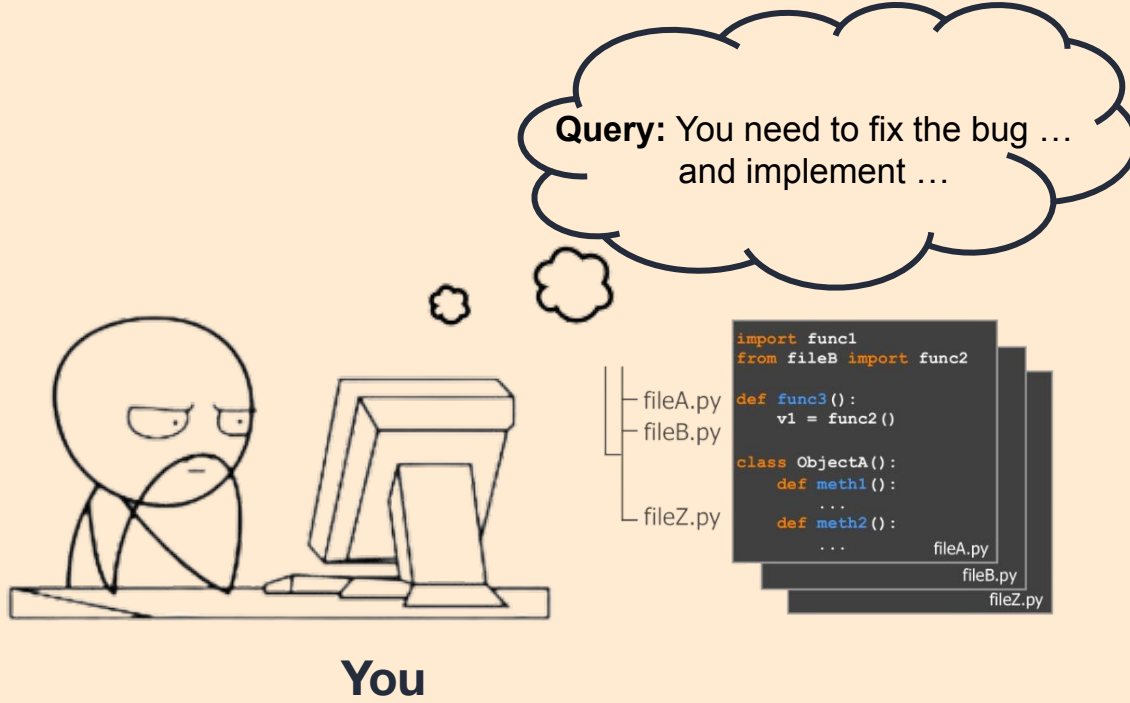
You

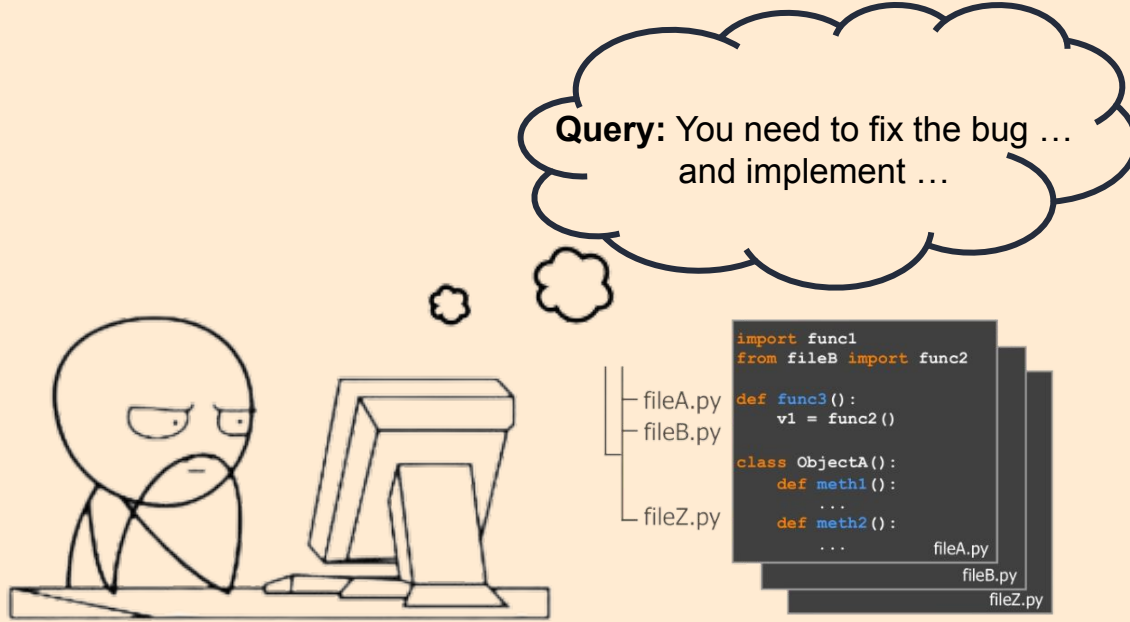
Query: You need to fix the bug ...
and implement ...

```
fileA.py  
fileB.py  
fileZ.py  
  
import func1  
from fileB import func2  
  
def func3():  
    v1 = func2()  
  
class ObjectA():  
    def meth1():  
        ...  
    def meth2():  
        ...  
fileA.py  
fileB.py  
fileZ.py
```



New Team

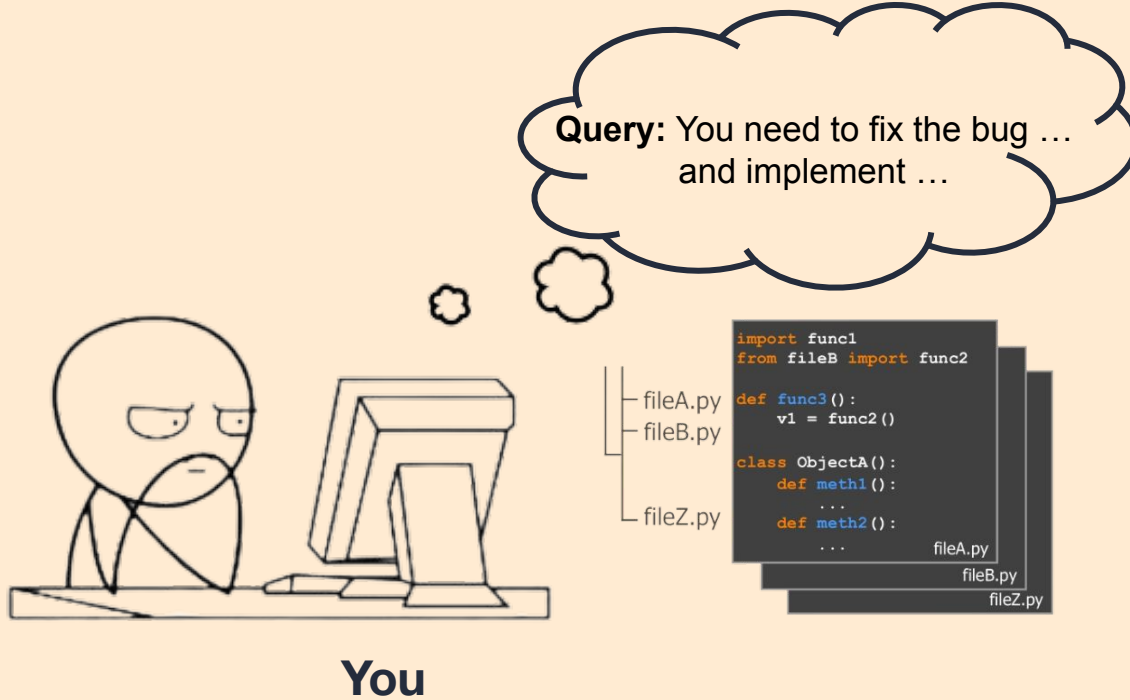




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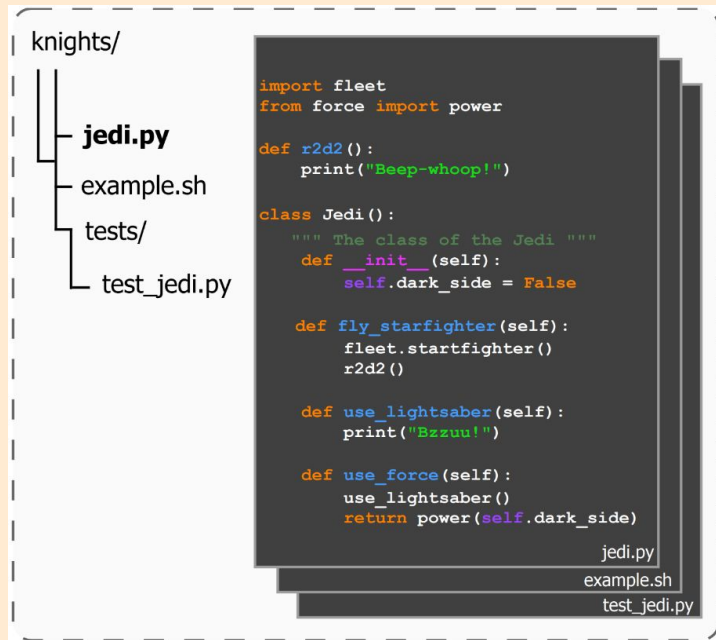
Which parts of the repo should you retrieve for editing?

Code Editing Retrieval Problem

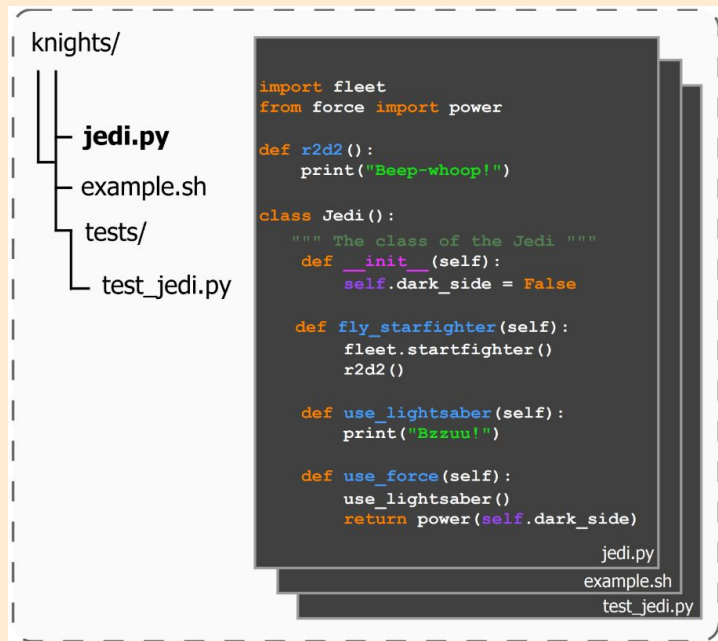


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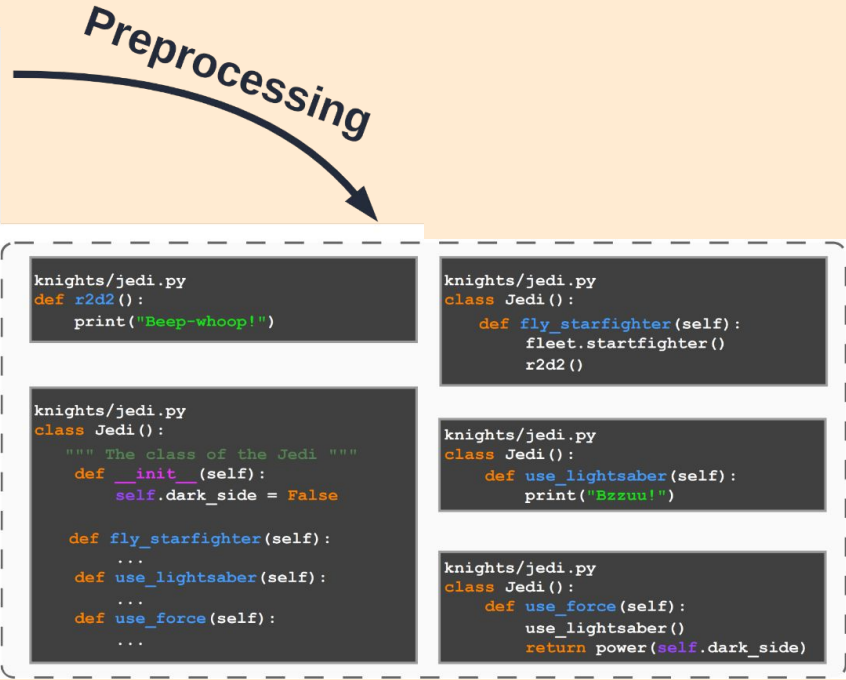
Train a light-weight **code retriever** including **semantics** and **structure** across a repo.



Code Repository

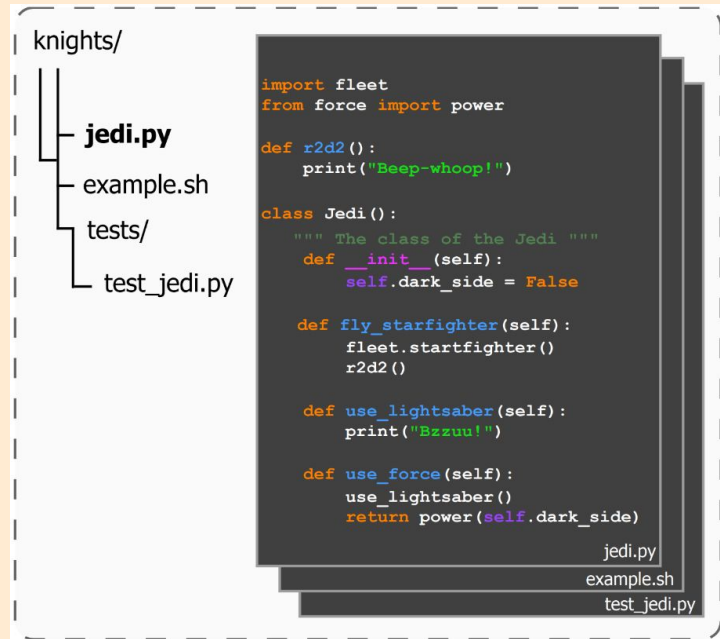


Code Repository

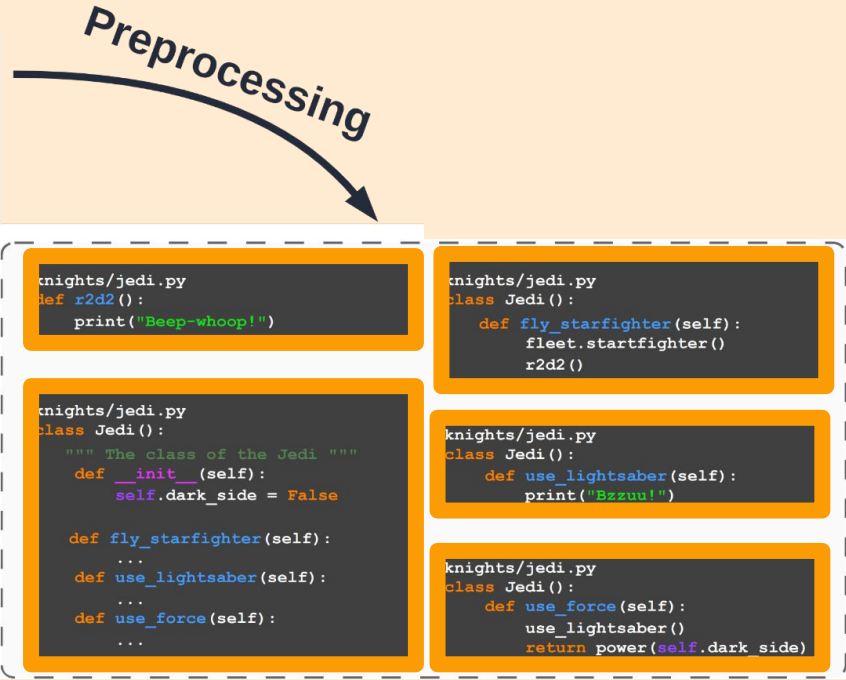


Code Chunks

Code Chunks

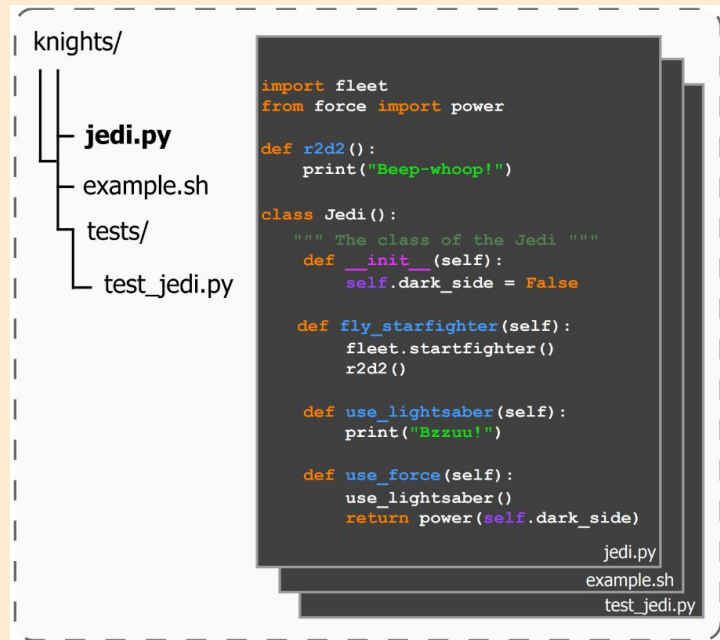


Code Repository

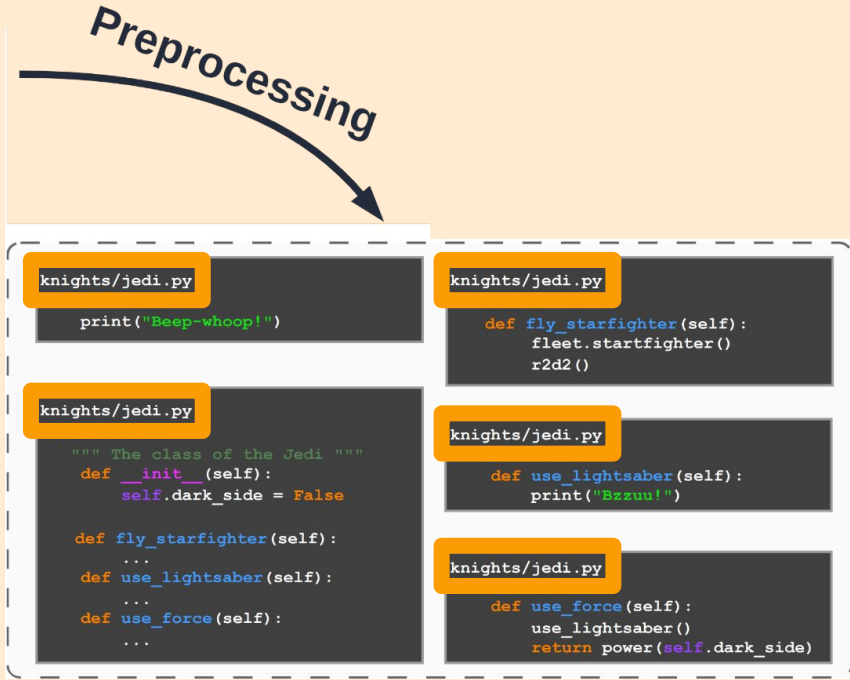


Code Chunks

Code Chunks with Repo-Hierarchy



Code Repository



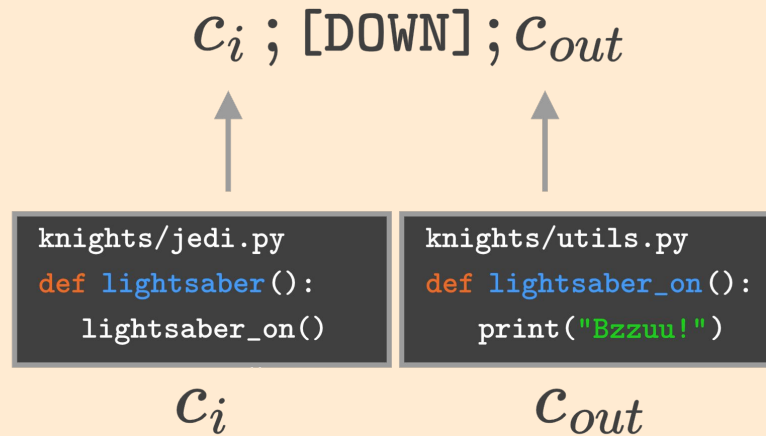
Code Chunks

```
knights/jedi.py  
def lightsaber():  
    lightsaber_on()
```

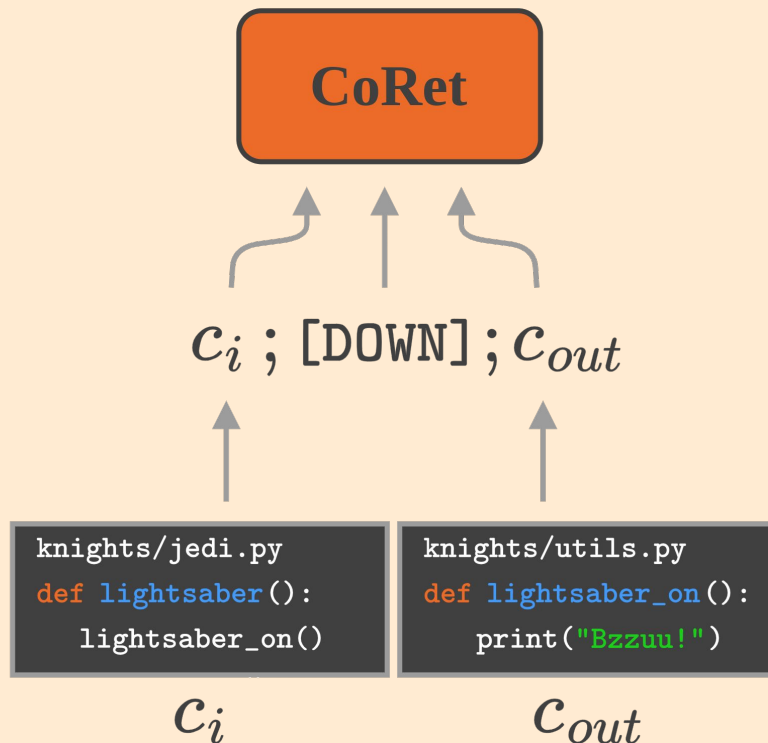
\mathcal{C}_i

```
knights/utils.py  
def lightsaber_on():  
    print("Bzzuu!")
```

\mathcal{C}_{out}



Embedding with Call Graph Context



Training

$$\mathcal{L}(\theta)$$

Training

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_i^N$$

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Training with Likelihood Loss

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Data & Model

SWE-Bench (Verified subset)



Data & Model

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LCA (Bug localisation task)



Data & Model

SWE-Bench (Verified subset)



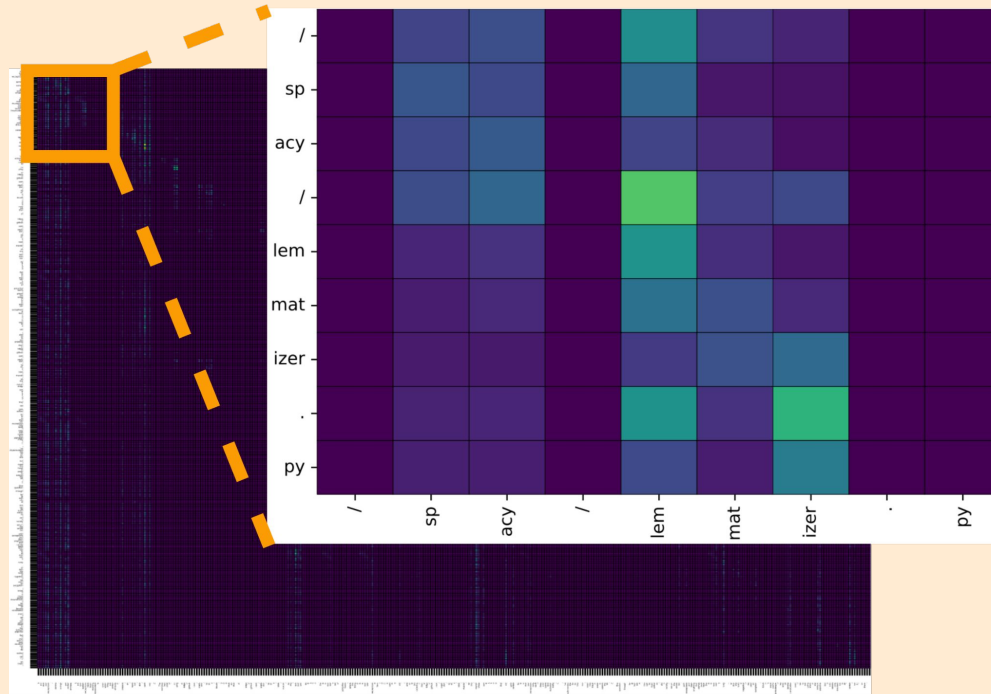
LCA (Bug localisation task)



Codesage S (128M parameters)



Repo-Hierarchy is important



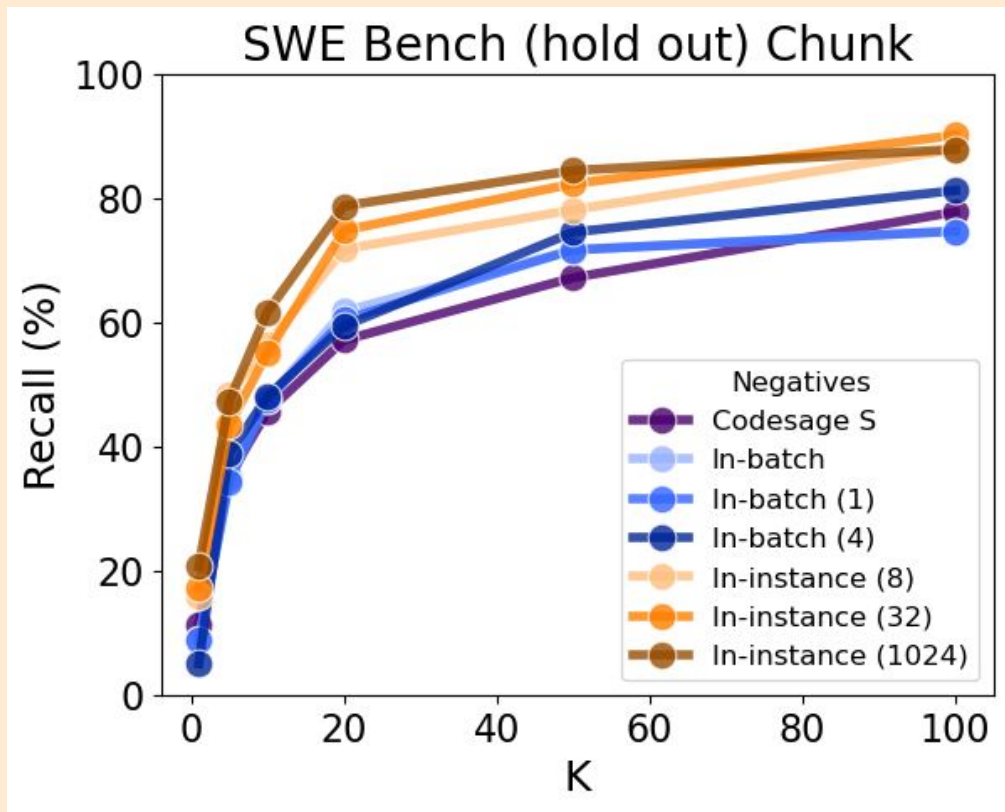
Call graph improves multi-chunk retrieval

Model	SWE Verified			LCA		
	@5	@20	MRR	@5	@20	MRR
CodeSage S	0.34	0.51	0.35	0.26	0.34	0.28
CoRet – CG	0.52	0.69	0.52	0.32	0.41	0.45
CoRet – CG + file	0.54	0.69	0.52	0.29	0.38	0.44
CoRet	0.54	0.71	0.53	0.32	0.47	0.47

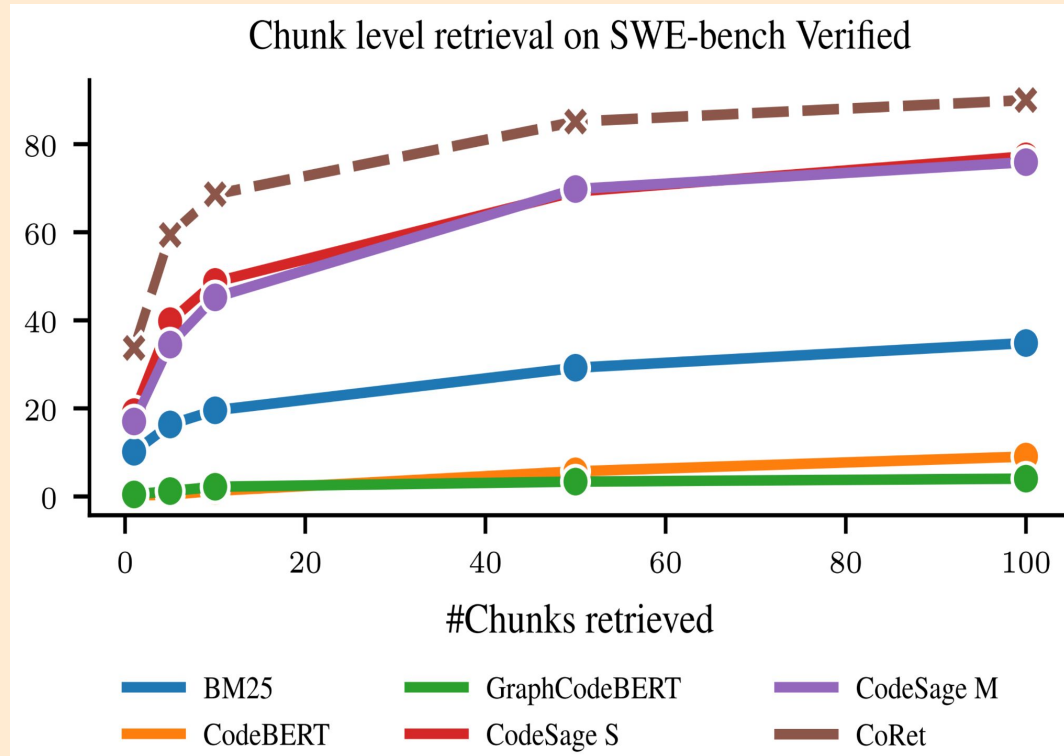
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Negatives from the same repo are best



Recall +15 percentage points!

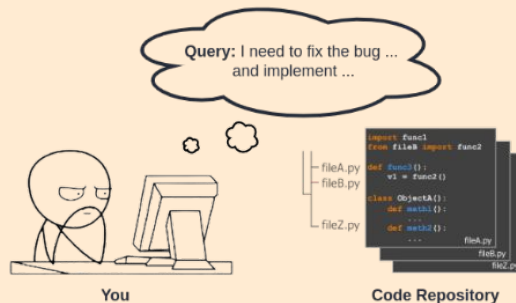


Train a light-weight **code retriever** including **semantics** and **structure** across a repo.

Paper

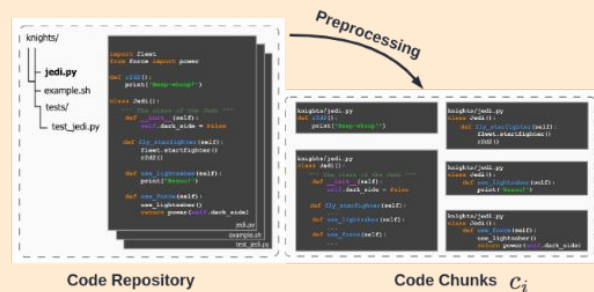


Code Editing Retrieval Problem



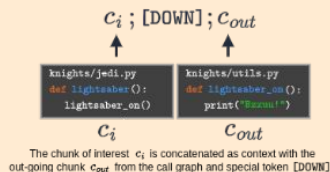
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Code Chunks with Repo-Hierarchy



The code repo is split into semantically succinct unit we called code chunks. We include **repo-hierarchy** structure by including the file path string.

Embedding with Call Graph Context

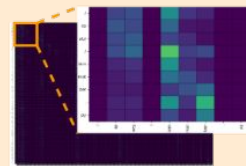


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CoRet: Fine-tuned CodeSage S (130M parameters).
SWE Verified: Software Engineering Benchmark (Verified subset).
LCA: Long Code Arena (Bug localisation task).

Repo-hierarchy is important

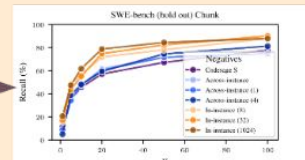


Training with Likelihood Loss

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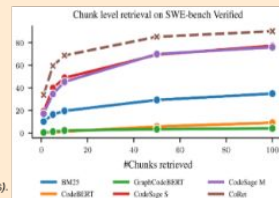
N = Number of repo instances i , C_i^* = Set of ground truth code chunks c^* , q = Natural Language query.
 \mathcal{B} = Random negative sample in the same repo instance.

Negatives from the same repo are best



Training with negatives from the same repo instance improve over negatives across repo instances (standard in-batch negatives).

Recall +15 percentage points



Takeaways