Impact of Evaluation Methodologies on Code Summarization

Pengyu Nie, Jiyang Zhang, Junyi Jessy Li, Raymond J. Mooney, Milos Gligoric
The University of Texas at Austin

Introduction

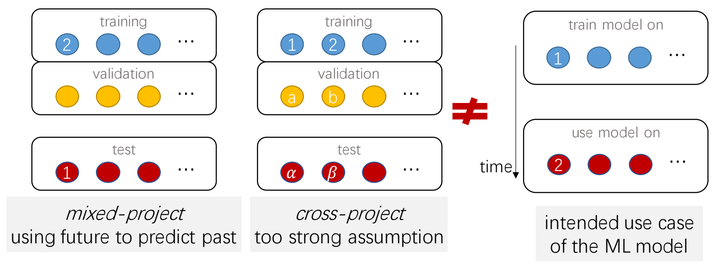
Temporal relations are not explicitly modeled in the evaluation of machine learning (ML) models for code summarization. This may lead to evaluations inconsistent with the intended use cases.

① written in 2018

```
/** Returns total number of connections in the pool. */
public synchronized int connectionCount() {
  return connections.size();
}
```

② written in 2019

```
/** Returns the number of idle connections in the pool. */
public synchronized int idleConnectionCount() {
  int total = 0;
  for (RealConnection connection : connections) {
    if (connection.allocations.isEmpty()) total++;
  }
  return total;
}
```



Our contributions

- Study the evaluation methodologies in prior work: mixed-project and cross-project
- Propose a **time-aware** methodology: time-segmented
- Empirically experiment the three methodologies

Use Cases

We argue that evaluation methodology should be designed according to the intended use case of the ML model. Results obtained in batch-mode could be very different from those obtained in continuous-mode.

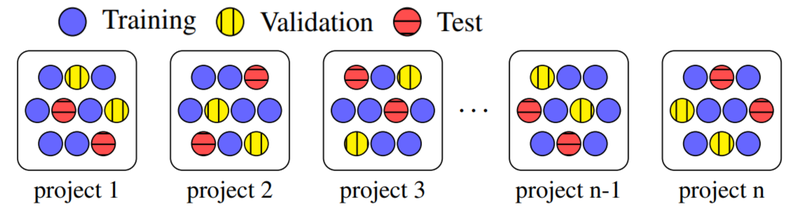
methodology	use case
mixed-project	in-project batch-mode
cross-project	cross-project batch-mode
time-segmented	continuous-mode

- does not consider software evolution (temporal relations among samples)
- only happen once in the lifecycle of a project

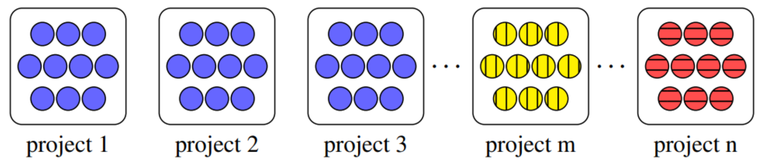
- train on past samples and use on new samples
- may be more practical in the context of continuously developing software

Evaluation Methodologies

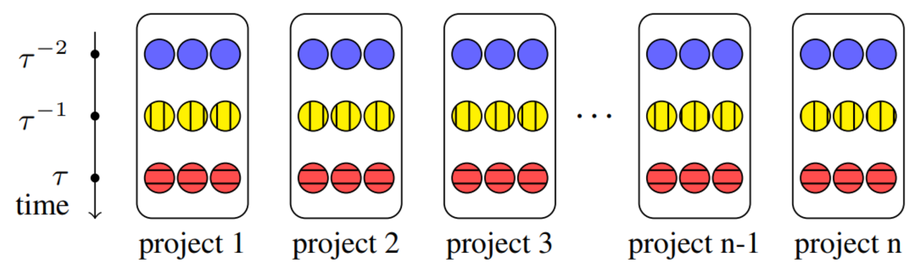
The *mixed-project* methodology randomly shuffles the samples and splits them into training, validation, and test sets.



The *cross-project* methodology randomly shuffles the projects and splits them into training, validation, and test sets.



The *time-segmented* methodology is time-aware: the samples in the training set were available in the projects before the samples in the validation set, which were in turn available before the samples in the test set.



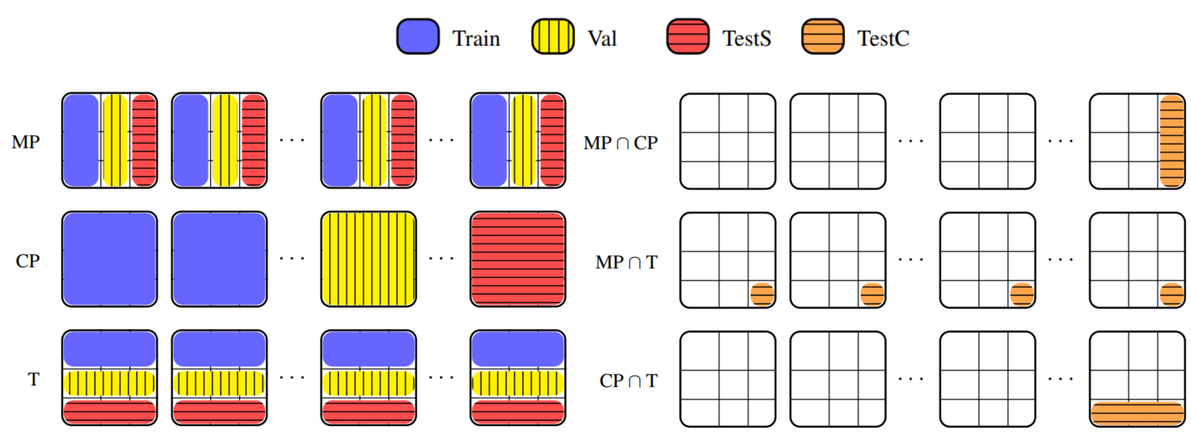
We studied 18 recent papers on developing new ML models for code summarization: 15 used the mixed-project methodology, 4 used the cross-project methodology, but none used the time-segmented methodology.

Experiments

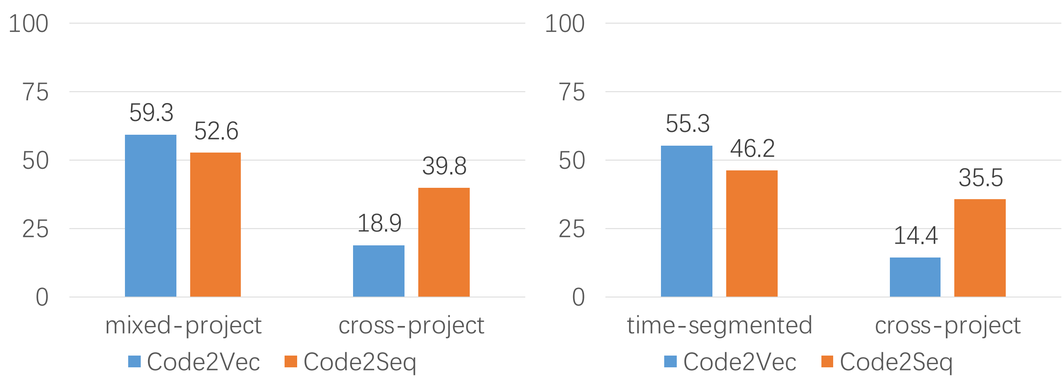
We run several existing ML models using different methodologies to understand their impact on automatic metrics, which are commonly used to judge the performance of models. We focus on the two most studied code summarization tasks: comment generation and method naming. For each task, we select several well-studied, representative, publicly available models, and use automatic metrics that are frequently reported in prior work.

Task	comment generation	method naming
Models	DeepComHybrid Hu et al. ESE'20 Transformer Seq2Seq Ahmad et al. ACL'20	Code2Vec Alon et al. POPL'19 Code2Seq Alon et al. ICLR'19
Metrics	BLEU METEOR ROUGE-L EM (exact match)	Precision Recall F1 EM (exact match)

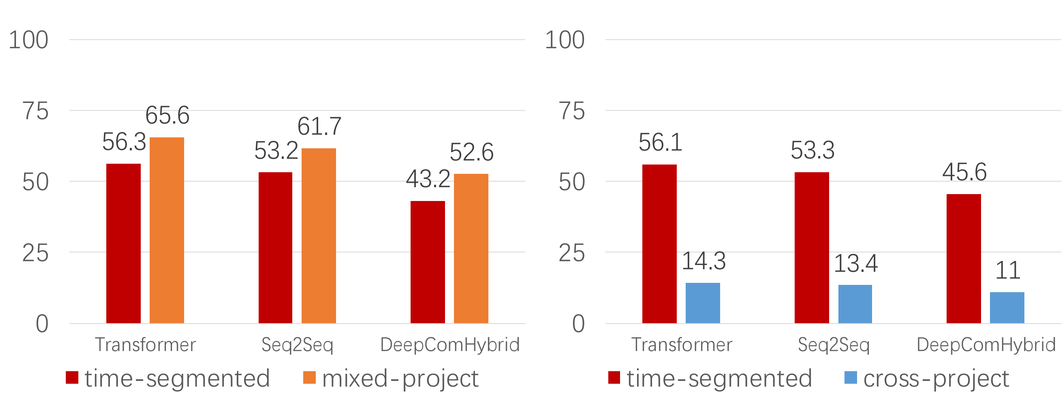
We collect a dataset of (code, comment) samples **with timestamps** from open-source Java projects on GitHub. We split the dataset to get training (Train), validation (Val), and standard test (TestS) sets for each methodology (MP = mixed-project, CP = cross-project, T = time-segmented), and a common test (TestC) set for each pair of methodologies.



Finding 1: different methodologies may lead to conflicting evaluation results. For example, Code2Vec is better than Code2Seq under the mixed-project and time-segmented methodologies, but is worse under the cross-project methodology.



Finding 2: absolute values for automatic metrics vary widely across the three methodologies. Results under the mixed-project methodology are inflated, and results under the cross-project methodology may be an under-estimation of the more realistic continuous-mode use case.



Conclusion

- We need to more **diligently choose evaluation methodology** and report results of ML models according to the **intended use cases**.
- **Time-segmented** evaluation methodology should be adopted in the evaluation of ML models for code summarization.

data and code: github.com/EngineeringSoftware/time-segmented-evaluation
preprint: arxiv.org/abs/2108.09619
Pengyu Nie pynie@utexas.edu

Objectives

The evaluation methodologies of prior work on developing ML models for code summarization **do not consider the timestamps of code and comments**, which may lead to misunderstanding if a model might be useful once adopted. In this work, we investigate a **time-aware** evaluation methodology for code summarization and empirically study the impact of different methodologies.

- Study two evaluation methodologies used in prior work: mixed-project and cross-project
- Propose a time-aware evaluation methodology: time-segmented
- Experiment several ML models using the methodologies

Introduction

There has been a growing interest in developing machine learning (ML) models for code summarization tasks, e.g., comment generation and method naming. Despite substantial increase in the effectiveness of ML models, the evaluation methodologies, i.e., the way people split datasets into training, validation, and test sets, were not well studied. Specifically, **no prior work on code summarization considered the timestamps of code and comments during evaluation**. This may lead to evaluations that are inconsistent with the intended use cases. In this work, we introduce the **time-segmented evaluation methodology**, which is novel to the code summarization research community, and compare it with the mixed-project and cross-project methodologies that have been commonly used.

Task	comment generation	method naming
Models	DeepComHybrid Hu et al. ESE'20 Transformer Seq2Seq Ahmad et al. ACL'20	Code2Vec Alon et al. POPL'19 Code2Seq Alon et al. ICLR'19
Metrics	BLEU METEOR ROUGE-L EM (exact match)	Precision Recall F1 EM (exact match)

Use Cases

We argue that evaluation methodology should be designed according to the intended use case of the ML model. We defined the *in-project and cross-project batch-mode* use cases (see paper for definition) which can be evaluated by the mix-project and cross-project methodologies, but they do not consider **software evolution**. As such, we define a more practical *continuous-mode* use case which can be evaluated using the time-segmented methodology: training the model with code available at a timestamp, and using the model on new code after that timestamp.

methodology	use case
mixed-project	in-project batch-mode
cross-project	cross-project batch-mode
time-segmented	continuous-mode

- does not consider software evolution (temporal relations among samples)
- only happen once in the lifecycle of a project
- train on past samples and use on new samples
- may be more practical in the context of continuously developing software