Metric-Oriented Pretraining of Neural Source Code Summarisation Transformers to Enable more Secure Software Development

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Abstract

Source code summaries give developers and maintainers vital information about source code methods. These summaries aid with the security of software systems as they can be used to improve developer and maintainer understanding of code, with the aim of reducing the number of bugs and vulnerabilities. However writing these summaries takes up the developers' time and these summaries are often missing, incomplete, or outdated. Neural source code summarisation solves these issues by summarising source code automatically. Current solutions use Transformer neural networks to achieve this. We present CodeSumBART - a $\text{BART}_{\text{BASE}}$ model for neural source code summarisation, pretrained on a dataset of Java source code methods and English method summaries. We present a new approach to training Transformers for neural source code summarisation by using epoch validation results to optimise the performance of the model. We found that in our approach, using larger n-gram precision BLEU metrics for epoch validation, such as BLEU-4, produces better performing models than other common NLG metrics.

1 Introduction

Software documentation, such as method summaries, aids developers and maintainers in understanding how a software system works. Venigalla and Chimalakonda (2021) report that "Software documentation aids better project comprehension and plays a major role in improving the popularity of the repository and also in increasing contributions to the repository. Software documentation is capable of aiding various phases of software development, and maintenance". Lin et al. (2021) note the importance of code comments for program comprehension for software maintenance.

The use of method summaries and other forms of code comment in reviewing code is vital for understanding that code. This review process can be used to find bugs and potential vulnerabilities in a codebase before they affect users. The United Kingdom's National Cyber Security Centre recommends both peer review as well as documenting and commenting code clearly as part of their recommended actions for secure development (National Cyber Security Centre, 2020). However, Rauf et al. (2021) note that "Secure code development requires cognitive effort, and under constraints of time and resources developers struggle to keep security at the top of their priority list", meaning that practices relating to secure development are often not a primary concern, even for security-conscious developers.

Neural Source Code Summarisation (NSCS) aims to reduce his cognitive load on developers by summarising source code methods without developer interaction, using neural network models. NSCS models require extensive training on large datasets of source code and related summaries to produce outputs with often low similarity to human-written summaries. Our training produces a model which produces better outputs while requiring no more training than other, similar-sized models. NSCS has grown in recent years with the development of new task-specific models, many of which build on Vaswani et al. (2017)'s Transformer architecture, such as NeuralCodeSum (Ahmad et al., 2020) and CodeBERT (Feng et al., 2020).

When training Transformer models for summarisation tasks, each epoch of training can be validated against a Natural Language Generation (NLG) metric. NLG metrics are often calculated alongside a loss metric or loss function, which is used to optimise the model during epoch validation. Our training method takes a different approach by removing the reliance on loss for validating a training epoch. As is usual in model training, we use Cross Entropy Loss during each training step to adjust model weights, but we opt not to use this in our epoch validation for early stopping, or for checkpointing. Validation with loss or NLG metrics al-

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lows for "checkpointing" where the improvement in outputs from each epoch of training can be compared to previous epochs and the training can be stopped early if the training is no longer improving. The use of early stopping and checkpointing prevents overfitting to a given dataset by ensuring the outputs remain generic. While loss is still used to generate model weights, our method only uses an NLG metric for validating each training epoch.

We train a BART Transformer model (Lewis et al., 2020) on a source code summarisation task using a variety of validation metrics. We present a method of optimising pretraining to provide better results by monitoring the validation metric used, and checkpointing the best performing epoch. When an epoch fails to improve, the model weights are reverted to the best performing epoch, and the training continues. After 5 training epochs have failed to improve and a minimum of 20 training epochs have taken place, training stops. We discuss this in detail in Section 3.

1.1 Research questions

RQ.1 Does pretraining on English language data improve model effectiveness for source code summarisation?

To answer this question, we fine-tune two pretrained transformer models commonly used for English summarisation tasks on our source code summarisation task. We then evaluate these against a suite of NLG metrics. Following this, we pretrain the same two models with randomly initialised weights on our source code summarisation task.

RQ.2 Does validating a model on LLM-based metrics improve the model's predictions over validating it on traditional, n-gram-based NLG metrics?

To answer this question, we compare the overall metric results of those models validated using n-gram-based metrics to those using BERTScore (Zhang et al., 2019) and FrugalScore (Kamal Eddine et al., 2022) to see if there is an improvement in model training provided by using LLM-based metrics. A measurable improvement caused by using LLM-based metrics for validation, rather than n-gram-based metrics shows that LLM-based metrics' improved ability to capture semantics allow them to aid in generating better models for automatic source code summarisation.

RQ.3 Does validating on a common NLG metric from Table 2 cause the model to perform better on NSCS?

We report whether any one metric is better for validation (producing a model that gives more accurate outputs) than others. Models such as NeuralCodeSum (Ahmad et al., 2020) use Smoothed BLEU-4 by default, but there is a wide variety of available metrics which can be used. A measurable improvement in the quality of outputs when the model is evaluated against a series of metrics means that this technique has the potential to be used in generating better models for automatic source code summarisation.

1.2 Contributions

We propose a new approach to the training and validation of Transformer models for NSCS tasks, which improves the quality of outputs, when compared to similar models, without a significant increase in the size or training time of a model. We present CodeSumBART, a $\text{BART}_{\text{BASE}}$ model, utilising this training approach to automatically summarise Java source code.

2 Dataset

In order to train, validate, and evaluate the models, we use the filtered version of LeClair and McMillan (2019)'s Funcom dataset of Java source code method - English language summary pairs, as done in previous works by Mahmud et al. (2021) and Phillips et al. (2022). We clean the dataset following Phillips et al. (2022)'s approach, using their Java implementation of the dataset cleaning tool[1].

Phillips et al. (2022)'s method cleans the dataset using the matched pairs of Java source code and JavaDoc comments. The cleaning method uses JavaParser (van Bruggen et al., 2020) to select only compilable Java code and remove inline code comments. It then finds the method summaries from the JavaDoc by extracting the first line of text with more than eight characters. We then follow Phillips et al. (2022)'s steps: remove HTML and special characters (characters which are not alphanumeric, full-stops, apostrophes, or white space) from the summary and lowercase it. Repeated method-summary pairs are then removed from the dataset, which is trimmed from 1.2 million pairs to roughly 500,000 pairs and split randomly into 80% training, 10% validation, and 10% evaluation datasets. This is the same split used by Ahmad et al. (2020), Mahmud et al. (2021), and

[1] Phillips et al. (2022)'s dataset cleaning tool is found at github.com/phillijm/JavaDatasetCleaner

Phillips et al. (2022).

Training	Validation	Evaluation
399,999	49,999	49,999
80%	10%	10%

Table 1: Split of methods in the dataset.

Our dataset contains 499,997 method-summary pairs from multiple projects, split randomly into training, validation, and evaluation, as per Table 1.

3 Research methodology

We began by selecting the metrics we would use for validating models during training and evaluating models. The metrics chosen are as shown in Table 2: We selected BLEU-1 and BLEU-4, as well as Smoothed BLEU-4. BLEU-1 is a metric frequently used for evaluating summarisation, and Smoothed BLEU-4 is the metric employed for epoch validation by previous work by Ahmad et al. (2020) and Feng et al. (2020). METEOR can also be used used to evaluate source code summarisation, and is reported by Ahmad et al. (2020), Mahmud et al. (2021), and Phillips et al. (2022).

In addition to these common summarisation metrics, we measure FrugalScore and BERTScore, which utilise LLMs to compare if the meaning of a machine-generated text matches the meaning of a human-written one, rather than whether the language used matches. LLM-based metrics achieve this by capturing contextual embeddings. The forward step of the model training remains unchanged from the base model; during which Cross Entropy Loss is calculated and used in creating Model weights. During our model training, we validate each epoch of training on a given NLG metric from Table 2. We use this metric to better optimise the performance of our model to the task by checkpointing the best epoch and reverting epochs that did not show improvement. When an epoch shows improvement in the metric, it is checkpointed as the best model; when an epoch fails to show improvement in the metric, the model weights are reverted to the weights of the best performing epoch from these checkpoints before continuing training. We also use checkpoints for early stopping the model training. When a minimum threshold of 20 training epochs have taken place, if five consecutive epochs fail to provide any improvement to the model, we stop training in order to prevent overfitting. In this experiment, we also implemented a maximum of 200 training epochs for the same purpose, but did not reach this limit in any of our training.

Metric
BLEU-1 & 4 & SMOOTHED BLEU-4
METEOR
FrugalScore
BERTScore

Table 2: Metrics used.

Our training and validation process is shown in Figure 1. Our training dataset split of 399,999 method-summary pairs is used in the training step. As we validate our model, we use a validation split of 49,999 pairs. We use this data to calculate an NLG metric, then compare the average metric result to previous validation steps. If the model has improved in the last 5 epochs (early-stopping mechanism, x in Figure 1) and the model produced the highest average metric score this epoch, these model weights are saved as a checkpoint, and the next epoch of training begins unless the maximum number of training epochs (n in Figure 1) has been reached. If the model has shown improvement in the past 5 epochs, but has not improved in this training epoch, the model weights are reverted to the best scoring checkpoint. When this takes place, a small amount of noise is added to the weights in order to better prevent overfitting to the dataset and to prevent the model from generating the same model weights as the previous attempt. For this purpose, we added Gaussian noise multiplied by 0.001 to each of the model weights individually. If the model has not improved in the last 5 epochs, the early stopping mechanism is called. When the early stopping mechanism is called, or the maximum number of training epochs has been reached, we evaluate the model against all of the metrics, using the evaluation dataset split of 49,999 method-summary pairs. To ensure reliable results, we set a minimum of 20 training epochs. The results of our evaluation can be found in Tables 4, 5, and 6.

3.1 Methodology for RQ.1

We selected two transformer models commonly used for summarisation tasks: T5 (Raffel et al., 2020) and BART (Lewis et al., 2020). We selected these models due to their popularity, with each model having a high number of citations on Google Scholar and a high number of downloads on HuggingFace, and the availability of low resource usage

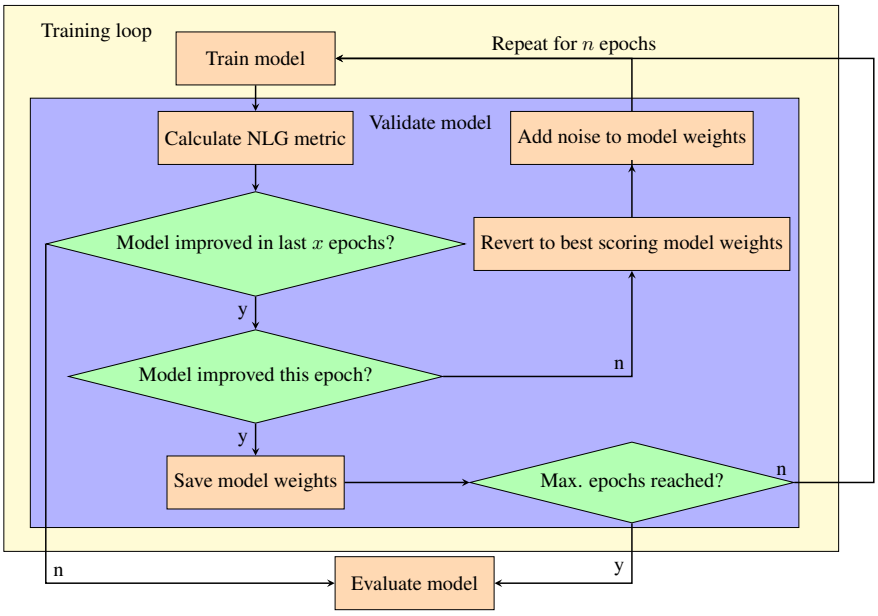

Figure 1: Epoch-based training with NLG metric orientation and early stopping

versions of the model, $T5_{SMALL}$ and $BART_{BASE}$, allowing us to train on machines which are commercially available with a low environmental impact.

The $T5_{SMALL}$ pretrained model is trained on the Colossal Clean Crawled Corpus (C4), proposed in the same paper as the T5 model (Raffel et al., 2020). C4 is a large English dataset, containing roughly 800GB of data extracted from the Common Crawl[2] archive of text mined by crawling the web. The $BART_{BASE}$ pretrained model is trained on a variety of tasks across several popular English datasets.

We fine-tuned these two pretrained models on our source code summarisation task as described in Section 3 and shown in Figure 1. We also trained models of the same model architecture, without English language pretraining and with randomly initialised weights, on the same task. We trained the models on a machine using an `Intel Xeon E5-2650 v4 CPU`, `94GB RAM`, and 4 `NVIDIA Tesla P100 GPUs` running Python 3.9.16 with the Open Cognitive Environment on Ubuntu 22.04.2 LTS. For RQ.1, we used BLEU-1 as our validation metric, due to its simplicity. We then compare these models to ascertain whether either model architecture is better for source code summarisation, and to observe the effect of English language pretraining on a model's ability to summarise source code.

3.2 Methodology for RQ.2

We selected the best performing model from the model training described in Section 3.1 ($BART_{BASE}$, with randomly initialised weights). Following the training method described previously, we trained a series of $BART_{BASE}$ models, each one validated on a different metric from Table 2. Once the models were trained, we evaluated each of them against the evaluation dataset split on our full list of NLG metrics in order to establish what effect, if any, the validation metric has had on our model.

In order to establish a baseline to compare our validation and training method against, we also trained the same $BART_{BASE}$ model on our dataset, but without any metric used for validation. In this baseline model, loss is calculated during the validation stage and used for checkpointing and early-stopping of the training, but model weights are not reverted based on the outcome of this loss. We again used a maximum of 200 training epochs, and a minimum of 20, with early stopping after 5 unsuccessful training epochs. The difference between this baseline training method and our own is the lack of adjusting model weights after validation to match those of the most successful training epoch.

We then compared the results of evaluating all of our models, highlighting the best results from our findings in Table 5. We sought to identify any patterns in the effect that the choice of validation metric had on our training method, as well as to identify whether using Large Language Model (LLM)-based NLG metrics in our approach is able to outperform traditional N-gram-based metrics.

3.3 Methodology for RQ.3

Following on from our findings in Section 4.2 relating to RQ.2, we identified any validation metric

[2] commoncrawl.org

which caused the model to outperform the models validated on other metrics by evaluating each model on the evaluation dataset split, using all metrics listed in Table 2. We present our best-performing model, compared to other popular models for NSCS to show the improvement our model presents compared to other solutions, in Table 6.

Training	Validation	Evaluation
164,775	5175	10,948
91%	3%	6%

Table 3: Split of methods in the CodeSearchNet dataset.

To test for overfitting to our dataset, We then compared our model to other models on a different dataset, CodeSearchNet (Husain et al., 2019). We cleaned the CodeSearchNet dataset, following the method Phillips et al. (2022) used for Funcom (LeClair and McMillan, 2019). We trimmed the dataset to valid Java methods only, then removed repeat entries. We then stripped HTML data from source code comments and extracted the method summaries from them. We then lowercased and removed special characters from the summaries and stripped out newline characters ("\n") from both methods and summaries. As the dataset is pre-split into testing, validation, and evaluation splits, we maintained these splits. The size of dataset splits for CodeSearchNet can be found in Table 3. We used the evaluation split of 10,948 method-summary pairs in our evaluation of the models.

The source code used to train each of our models can be found on GitHub[3]. Each model took between 2 - 4 days to run on one NVIDIA Tesla P100 GPU, with the exception of the model trained using METEOR, which took approximately a week, being constrained by file read/write speeds due to the nature of the script used to interface with the METEOR metric.

Once we had completed this evaluation, and compared our model to others within the domain of Neural Source Code Summarisation, we trained our model on the WMT 2016 DE-EN machine translation task (Bojar et al., 2016), and evaluated it against the same selection of metrics to gain insight into the generalisability of these methods when training models for tasks other than NSCS. For this task, we used the original split of data of 4,548,884 training pairs, 2168 validation pairs, and 2998 evaluation pairs as provided by the dataset, with results shown in Table 7.

[3]GitHub: github.com/phillijm/CodeSumBART

4 Result analysis

4.1 Results relating to RQ.1

As shown in Table 4, $\text{BART}_{\text{BASE}}$ consistently outperforms T5_{SMALL} for our source code summarisation task. In answer to RQ.1: for BART, the model with randomly initialised weights outperformed the one with pretraining on a corpus of English data when trained and evaluated on our source code summarisation task. T5 showed improvement caused by pretraining with English language data, where BART showed improvement by not doing so - although both of these differences are small in comparison to the difference between the two model architectures.

We suspect this is due to a mixture of three factors. First: the nature of the language used to summarise source code, as technical and detailed language, which differs from much of the language used in pretraining, being news and conversational language. Also, the source code summarisation task requires the model to produce English outputs from a Java input text, whereas pretraining tasks on English language corpora require the model to produce English outputs from English inputs. Our results show that while English and Java share many words, the syntax and grammar of the language differ enough that pretraining models on English data does not aid models in understanding Java. Finally, the architecture of the models themselves: T5_{SMALL} makes use of 60 million parameters, whereas $\text{BART}_{\text{BASE}}$ uses 140 million.

4.2 Results relating to RQ.2

After training and validation were complete, we evaluated each of the models on our evaluation dataset split against the ten metrics. We found, from our evaluation results in Table 5, that training the model using BLEU-4 and Smoothed BLEU-4 provides the best-performing models on our dataset. The model trained using BLEU-1 in validation performs less well than the non-unigram BLEU metrics. Models trained using METEOR perform similarly, marginally outperforming BLEU-1.

Our results show that training models using BERTScore or FrugalScore as a validation metric in our training outperforms training without validation and optimisation, but does not perform as well as training using traditional non-unigram n-gram-based metrics for validation. Further work is yet to be done to ascertain why this appears to

Model	BLEU-1	BLEU-4	Sm. BLEU-4	METEOR	FrugalScore	BERTScore
Pretrained $T5_{SMALL}$	50.23	24.69	24.98	21.76	71.77	68.75
$T5_{SMALL}$*	49.39	23.48	23.78	50.95	71.21	67.97
Pretrained $BART_{BASE}$	51.87	26.22	26.50	23.28	72.50	70.23
$BART_{BASE}$*	52.74	27.33	27.59	23.84	73.12	70.75

* Models with weights randomly initialised

Table 4: Effects of English Pretraining

Metric	BLEU-1	BLEU-4	Sm. BLEU-4	METEOR	FrugalScore	BERTScore
None (Baseline)*	41.77	12.71	13.15	16.62	64.25	62.09
BLEU-1	52.74	27.33	27.59	23.84	73.12	70.75
BLEU-4	53.58	30.41	30.66	24.96	73.59	71.70
Smoothed BLEU-4	54.24	31.23	31.47	25.27	73.48	71.20
METEOR	53.29	29.35	29.61	24.59	73.42	71.15
FrugalScore	47.63	20.13	20.45	20.27	69.86	67.53
BERTScore	52.80	27.49	27.76	23.90	73.14	71.14

* loss is calculated during validation and used for early stopping, but model weights are not reverted.

Table 5: Comparison of Evaluation Metrics

be the case. We suspect that due to these metrics reliance on embeddings, rather than matching n-grams, key words and phrases may be neglected in generating summaries, leading to less accurate summaries being generated.

4.3 Results relating to RQ.3

We note, from Table 5, that validation using the BLEU-4 metric provides the best results on LLM-based metrics, while Smoothed BLEU-4 performs similarly and performs best on n-gram based metrics. From our testing, larger n-gram BLEU metrics in validation appear to produce more accurate results, however, further work is needed to determine the point at which this is no-longer the case.

In our evaluation, the model trained using METEOR in validation outperformed models trained using BERTScore and FrugalScore, but was similarly outperformed by BLEU-4.

We then evaluated our model validated using BLEU-4 against $BART_{BASE}$ and two NeuralCodeSum models; one pretrained following Ahmad et al. (2020)'s methodology, and one pretrained following Phillips et al. (2022)'s methodology, as well as CodeBERT (Feng et al., 2020) and GraphCodeBERT (Guo et al., 2021). We evaluated it against two NSCS tasks: our task, derived from the Funcom Dataset (LeClair and McMillan, 2019), and the evaluation task from Husain et al. (2019)'s CodeSearchNet dataset.

On our task, our model significantly outperformed both NeuralCodeSum models as well as CodeBERT, GraphCodeBERT, and $BART_{BASE}$ across all evaluation metrics.

We then processed the Evaluation split of the Java dataset from Husain et al. (2019)'s CodeSearchNet task. We processed this using Phillips et al. (2022)'s dataset cleaning tool. Evaluating these models against the CodeSearchNet task, we found our model consistently outperforms the NeuralCodeSum models and $BART_{BASE}$ (with the exception of NeuralCodeSum evaluated on BERTScore), and outperforms all models tested when evaluated on BLEU-4, with CodeBERT scoring highest on 4 metrics and GraphCodeBERT outperforming other models when evaluated on BLEU-1. These results can be seen in Table 6.

Our model-generated outputs have a high mean Word Error Rate (WER) (Popović and Ney, 2007) of approximately 56.6, despite a high BLEU-4. A high WER, (in turn, derived from Levenshtein distance) (Levenshtein et al., 1966), shows that while BLEU shows our model has generated key 4-gram phrases which match the human-written summaries of a method, the structuring of the sentence is unique. Previous work by El-Haj et al. (2014) used WER as a metric to compare pairs of texts as a measure of similarity between two texts. We use

Evaluated against Funcom (LeClair and McMillan, 2019)						
Model	BLEU-1	BLEU-4	Sm. BLEU-4	METEOR	FrugalScore	BERTScore
CodeSumBART	**53.58**	**30.41**	**30.66**	**24.96**	**73.59**	**71.70**
$BART_{BASE}$	3.16	0.07	0.28	4.83	43.80	31.60
NeuralCodeSum	24.07	2.67	2.67	8.75	53.28	59.95
NeuralCodeSum*	33.71	20.30	20.30	19.11	64.66	69.02
CodeBERT	23.06	1.93	19.33	15.72	60.86	67.30
GraphCodeBERT	24.04	1.89	19.35	13.84	60.75	66.78
Evaluated against CodeSearchNet (Husain et al., 2019)						
Model	BLEU-1	BLEU-4	Sm. BLEU-4	METEOR	FrugalScore	BERTScore
CodeSumBART	27.52	**5.02**	5.71	10.85	60.20	56.97
$BART_{BASE}$	3.08	0.09	0.23	5.14	47.65	30.18
NeuralCodeSum	19.96	2.02	2.02	7.64	52.83	58.98
NeuralCodeSum*	2.49	0.71	0.71	5.71	50.73	52.79
CodeBERT	24.30	3.94	**17.96**	**12.55**	**62.23**	**68.37**
GraphCodeBERT	**38.42**	3.22	17.50	12.31	62.19	68.15

* A NeuralCodeSum model pretrained following Phillips et al. (2022)'s methodology.

Table 6: Comparison of Source Code Summarisation Models Using two Datasets

WER to compare prediction and reference texts for source code summaries. Example outputs and WERs can be seen in Appendix A.

Metric	Result
BLEU-1	66.67
BLEU-4	36.57
Smoothed BLEU-4	36.66
METEOR	35.82
FrugalScore	83.37
BERTScore	80.10

Table 7: CodeSumBART trained on WMT 2016 DE-EN dataset

When we trained our model on the WMT 2016 DE-EN translation task (Bojar et al., 2016), we found that our model provided results (seen in Table 7) which are similar to our model when trained and evaluated on our NSCS task. These results suggest that our methods can be applied to model training in other domains, outside of NSCS.

4.4 Statistical correlation of results

Using the evaluation metrics from Table 2, we evaluated each output our model produced on the evaluation split from our dataset. We then used Spearman's Rank Correlation Coefficient, ρ, to check the correlation between each metric. We found a strong, positive correlation between all metrics even when the sample size is reduced to a 1% random sample of the data. The lowest value of Spearman's rank correlation coefficient was 0.71 between BERTScore and BLEU-4, this pair also provided our largest p-value: $8.87{*}10^{-}71$ - suggesting a statistically significant result. These results can be seen in Appendix B. The high correlation shows agreement between the metrics; predictions rated highly by one metric are rated highly by the others, suggesting that these metrics are approximately equally capable of evaluating NSCS tasks.

5 Related work

In 2021, Rauf et al. (2021) analysed ten years of research into developer behaviour regarding secure coding practices, with regards to developer psychology, discovering barriers developers face to secure coding. Later, Khan et al. (2022) identify an extensive list of security risks in practice, including a lack of secure development or coding.

Similarly, Rindell et al. (2021) conducted a study of security practices in agile development. They found that while security is implemented in various ways in agile environments, models such as SSDLC for ensuring secure development are rarely implemented in their entirety. They also note a positive correlation between increased agility and increased security engineering practices.

The Transformer neural network model was introduced by Vaswani et al. (2017) as a general-

purpose neural network. Since then, the Transformer has become a ubiquitous model for many NLP tasks. Much work has been done to advance the Transformer model; BART (Lewis et al., 2020) uses an architecture which combines both bidirectional and auto-regressive transformers to build a model. Raffel et al. (2020) introduced T5, a simple transformer model, which treats all tasks as text-to-text problems, using transfer learning.

Optimising model training by optimising a model's parameters with respect to evaluation metrics is a concept initially developed by Shen et al. (2016) in the form of Minimum Risk Training (MRT). MRT aims to optimise model parameters by minimising loss in terms of evaluation metrics. Norouzi et al. (2016) present an alternative algorithm, Reward Augmented Maximum Likelihood (RML). RML builds on maximum likelihood estimation, adding a step where log-likelihood is optimised on rewards for possible outputs.

Recent works have applied the Transformer model architecture to NSCS. CodeBERT (Feng et al., 2020) and NeuralCodeSum (Ahmad et al., 2020) use Transformer-based models to summarise source code, with CodeBERT being a bidirectional Transformer model. Mahmud et al. (2021) compare these two Transformer models, as well as Code2Seq (Alon et al., 2018) on the Funcom dataset (LeClair and McMillan, 2019). Phillips et al. (2022) establishes a method of cleaning Funcom to allow for better training and evaluation of a NeuralCodeSum model, as well as introducing the use of an LLM-based metric for evaluating NSCS. Recent work by Haque et al. (2023) focuses on altering the training process to produce better models for NSCS tasks by using label smoothing. Zhou et al. (2023) propose an alternative improved training approach for models for NSCS tasks by using "meta-learning" to transform the training process into a few-shot deep learning task. Mastropaolo et al. (2024) propose a model, STUNT, built on $T5_{SMALL}$, for NSCS tasks. STUNT's training relies on a comment classification model, SALOON, for generating training data as it is trained on snippets of code and related summaries found in code comments, not methods and method summaries.

Taviss et al. (2023)'s Asm2Seq model is designed to generate natural language summaries of x86 and AMD64 assembly code for the purpose of aiding in vulnerability analysis.

Stapleton et al. (2020) take a human approach to evaluating source code summarisation. Stapleton et al. (2020) found that "data suggests that participants did not see a clear difference in quality between human-written and machine generated comments"; finding developers' ratings to be an unreliable predictor of how much a summary helps them - and that developer intuition may be poor at assessing the relevancy of information.

Large Language Models have increasingly been used to generate metrics for NLG tasks. BERTScore (Zhang et al., 2019) and MoverScore (Zhao et al., 2019) being two examples of these metrics. These are large models, with a sizeable environmental impact when implemented at large scale. Kamal Eddine et al. (2022)'s FrugalScore seeks to solve this by reducing the number of parameters used while retaining accuracy. FrugalScore learns from the internal mapping of LLMs to produce a smaller language model with similar accuracy.

6 Conclusion

We present CodeSumBART, an improved Transformer model for automatic source code summarisation. Our model uses a new training method to achieve a high degree of accuracy by validating the results of each training epoch against an NLG metric and using that validation performance to revert model weights from under-performing training epochs to those from the best-performing epoch.

Our findings show that our training provides an improved method of training transformer models for automatic source code summarisation. CodeSumBART outperforms state-of-the-art models in evaluation across several metrics and produces outputs comparable to human-written summaries to within a high degree of accuracy in two Java source code summarisation tasks. This model can be applied to Java source code methods to aid in the secure development process by reducing the cognitive load on developers. The model and training method we have created could be used to enable more secure software development through integration into developer tools to summarise new source code methods as they are written, and summarise legacy code methods for easier maintenance.

Following this work, we intend to continue to investigate the role that NSCS models can play in cybersecurity, focussing on the potential application of NSCS on bug and vulnerability patch data, using human evaluation alongside NLG metrics.

7 Limitations

In this paper, we have only used a dataset for the summarisation of Java source code in English. Further research is required to establish the validity of our results in the setting of other languages, particularly our findings for RQ.1, with respect to whether transformer models pretrained on English data perform better or worse on tasks summarising source code in different languages.

Our work also only focused on small Transformer models. While our models can be run on most commercially available workstations with little environmental impact, larger scale Transformers and LLMs present exciting opportunities for source code summarisation, which we have not investigated as part of this paper.

We also chose to evaluate our results against a suite of traditional and LLM-based NLG metrics. While these metrics are all designed with the aim of complementing and being comparable to human expert evaluation, future work could be done to compare these metrics to human evaluation in the domain of source code summarisation.

8 Ethics statement

The first ethical consideration of our research is the environmental impact of our research. We have taken steps to minimize this impact by choosing to training small models on commercially available workstation machines. Any future research into whether larger models are capable of outperforming the results we have achieved will have a larger environmental impact.

We also considered the dataset we have used. The data itself is comprised of publicly available Java source code, and the primary dataset we have used was compiled by LeClair and McMillan (2019). We also used data from the CodeSearchNet dataset (Husain et al., 2019), which is derived from open source projects on GitHub with licenses which permit the re-distribution of parts of code.

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A CodeSumBART example predictions

```
Selected Summaries (5 longest, 5 shortest, 5 mean.)

Shortest Summaries longer than 2 tokens:
        Source: public hashtable get hash ( ) { return attributes ; }
        Prediction: returns the entireable of contains guaranteed to filter the
            attribute. this .
        Reference: returns the hashtable that is used to store the attributes of
            this object
        WER: 0.615

        Source: public void close ( ) { _ disconnect ( ) ; }
        Prediction: closeoses the connectionagramrovider. creates connection  the
            chatacle thread.
        Reference: closes the dataprovider and the connection to the oracle database
        WER: 0.7

        Source: public responses get addressing responses ( ) { return addressing
            responses ; }
        Prediction: getss value of addressing to to addressing
        Reference: return the type of responses required by addressing.
        WER: 0.875

        Source: public int get colon pos ( ) { return colon pos ; }
        Prediction: gets position of   code   token token token  or  1 if not
            present
        Reference: returns position of   code     token  or  1 if not present.
        WER: 0.4

        Source: public chord node get successor ( ) { return this . successor ; }
        Prediction: returns the successor of this chord.
        Reference: returns the successor of this peer.
        WER: 0.167


Longest Summaries:
        Source: public void test clg07 ( ) throws exception { assert equals ( 0 ,
            test utilities . bool search ( " ( cccc . cc . cccn ) . n . c " , "
            ccccc . cccn " ) ) ; assert equals ( 0 , test utilities . bool search (
            " ( cl . cccc . cc . ccccn ) . n . c " , " ccccc . cccn " ) ) ; assert
            equals ( 1 , test utilities . bool search ( " ( cccc . cc ) . ( cccn ) .
             n . c " , " ccccc . cccn " ) ) ; assert equals ( 0 , test utilities .
            bool search ( " ( cc br . ccn ) . ( occ ) " , " br ccccc . cccn . occc "
             ) ) ; assert equals ( 1 , test utilities . bool search ( " ( cc br ) .
            ( ccn ) . ( occ ) " , " br ccccc . cccn . occc " ) ) ; assert equals ( 1
             , test utilities . bool search ( " ( cc [ br , cl ] ) . ( ccn ) . ( occ
             ) " , " br ccccc . cccn . occc " ) ) ; }
        Prediction: finds the virtualpoint for the reference reference the reference
             reference to
        Reference: returns a virtual point on the line between the point closest
            geographically to
        WER: 0.769

        Source: public void test clg07 ( ) throws exception { assert equals ( 0 ,
            test utilities . bool search ( " ( cccc . cc . cccn ) . n . c " , "
            ccccc . cccn " ) ) ; assert equals ( 0 , test utilities . bool search (
            " ( cl . cccc . cc . ccccn ) . n . c " , " ccccc . cccn " ) ) ; assert
            equals ( 1 , test utilities . bool search ( " ( cccc . cc ) . ( cccn ) .
             n . c " , " ccccc . cccn " ) ) ; assert equals ( 0 , test utilities .
            bool search ( " ( cc br . ccn ) . ( occ ) " , " br ccccc . cccn . occc "
             ) ) ; assert equals ( 1 , test utilities . bool search ( " ( cc br ) .
            ( ccn ) . ( occ ) " , " br ccccc . cccn . occc " ) ) ; assert equals ( 1
             , test utilities . bool search ( " ( cc [ br , cl ] ) . ( ccn ) . ( occ
             ) " , " br ccccc . cccn . occc " ) ) ; }
        Prediction: sets the the check the the class    is not if that the
        Reference: set how to compare to this conditionfactor. value is true implies
             match for
        WER: 0.923
```

Source: public void test clg07 ( ) throws exception { assert equals (0 , test utilities . bool search (" (cccc . cc . cccn) . n . c " , " ccccc . cccn ")) ; assert equals (0 , test utilities . bool search (" (cl . cccc . cc . ccccn) . n . c " , " ccccc . cccn ")) ; assert equals (1 , test utilities . bool search (" (cccc . cc) . (cccn) . n . c " , " ccccc . cccn ")) ; assert equals (0 , test utilities . bool search (" (cc br . ccn) . (occ) " , " br ccccc . cccn . occc ")) ; assert equals (1 , test utilities . bool search (" (cc br) . (ccn) . (occ) " , " br ccccc . cccn . occc ")) ; assert equals (1 , test utilities . bool search (" (cc [br , cl]) . (ccn) . (occ) " , " br ccccc . cccn . occc ")) ; }
Prediction: constructbometricometric cumulative chart cumulative option
Reference: hypergeometric bar chart with cumulative option
WER: 0.5

Source: public void test clg07 ( ) throws exception { assert equals (0 , test utilities . bool search (" (cccc . cc . cccn) . n . c " , " ccccc . cccn ")) ; assert equals (0 , test utilities . bool search (" (cl . cccc . cc . ccccn) . n . c " , " ccccc . cccn ")) ; assert equals (1 , test utilities . bool search (" (cccc . cc) . (cccn) . n . c " , " ccccc . cccn ")) ; assert equals (0 , test utilities . bool search (" (cc br . ccn) . (occ) " , " br ccccc . cccn . occc ")) ; assert equals (1 , test utilities . bool search (" (cc br) . (ccn) . (occ) " , " br ccccc . cccn . occc ")) ; assert equals (1 , test utilities . bool search (" (cc [br , cl]) . (ccn) . (occ) " , " br ccccc . cccn . occc ")) ; }
Prediction: test test checks fail a xpath elements returned returns fail x
Reference: this test will perform an xpath query which will return
WER: 0.9

Source: public void test clg07 ( ) throws exception { assert equals (0 , test utilities . bool search (" (cccc . cc . cccn) . n . c " , " ccccc . cccn ")) ; assert equals (0 , test utilities . bool search (" (cl . cccc . cc . ccccn) . n . c " , " ccccc . cccn ")) ; assert equals (1 , test utilities . bool search (" (cccc . cc) . (cccn) . n . c " , " ccccc . cccn ")) ; assert equals (0 , test utilities . bool search (" (cc br . ccn) . (occ) " , " br ccccc . cccn . occc ")) ; assert equals (1 , test utilities . bool search (" (cc br) . (ccn) . (occ) " , " br ccccc . cccn . occc ")) ; assert equals (1 , test utilities . bool search (" (cc [br , cl]) . (ccn) . (occ) " , " br ccccc . cccn . occc ")) ; }
Prediction: set the line. to draw origin shape.
Reference: sets the line used to label this series.
WER: 0.75

Mean Summaries:
Source: private void fire waypoints available (gps unit event evt) { for (iterator it = _ listeners . iterator ( ) ; it . has next ( ) ;) { gps unit event listener l = (gps unit event listener) it . next ( ) ; l . waypoints available (evt) ; } }
Prediction: resetets all properties to their. for the. requests
Reference: resets all fields to values valid for validation.
WER: 0.75

Source: public void test assign graph pool ( ) { o data manager . assign graph pool ( ) ; assert true (o data manager . o dex . is open ( ) & & o data manager . o graph pool . is open ( )) ; o data manager . close db ( ) ; }
Prediction: sets the bindings are not files types are be .
Reference: whether internal bindings or and external binding should be used.
WER: 0.8

Source: public int get int (string key) { int i = 0 ; try { i = integer . parse int (props . get property (key)) ; } catch (throwable t) { logger . log (level . warning , " could not parse integer value " , t) ; } return i ; }
Prediction: sets the audio renderer. use this of these
Reference: set the audio renderer to use. one of
WER: 0.75

```
        Source: public void work on ( assembly a ) { composite node new node = new
            composite node ( name ) ; for ( int i = 0 ; i < number nodes ; i + + ) {
             component node node = ( component node ) a . pop ( ) ; new node .
            insert ( node ) ; } a . push ( new node ) ; }
        Prediction: getss filterconfig. for this filter.
        Reference: return the filter configuration object for this filter.
        WER: 0.625

        Source: public void set active ( final boolean active ) { if ( ( mode ! =
            mode . server ) & & ( ! in applet ) ) { if ( active ) { status . set
            sort mode ( sort mode . remote , " remote " ) ; } else { status . set
            sort mode ( sort mode . no _ sort , " no sort " ) ; } } }
        Prediction: inv be be called for
        Reference: must not be called.
        WER: 1.0


Mean Word Error Rate: 0.566
Mean Word Error Rate (Shortest 100 summaries): 0.520
Mean Word Error Rate (Mean 100 summaries): 0.521
Mean Word Error Rate (Longest 100 summaries): 0.562
```

B Correlation for evaluation metrics

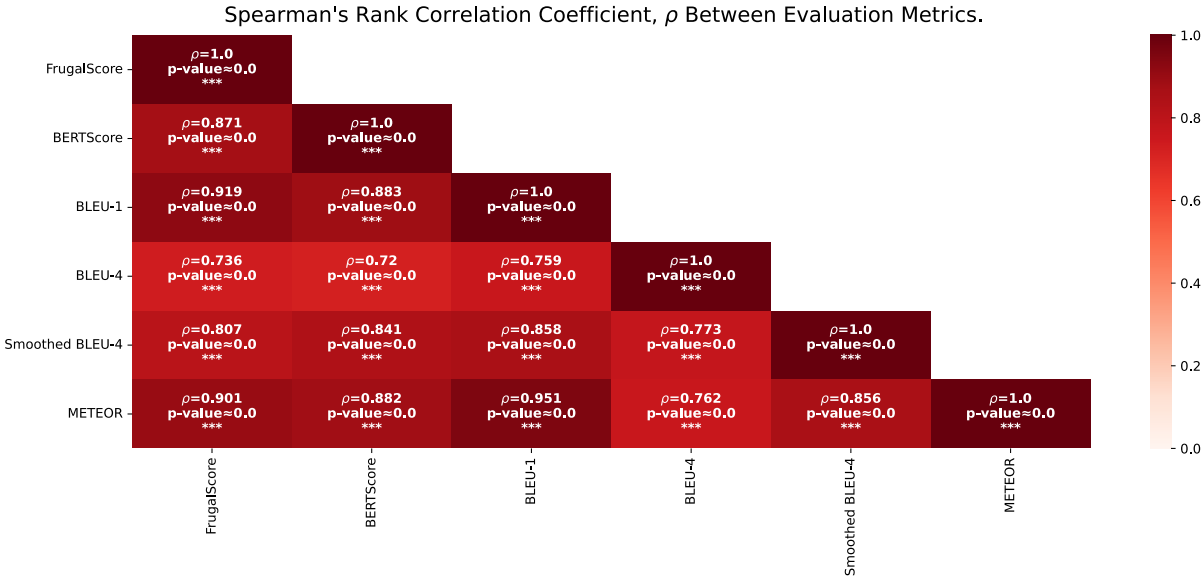

Figure 2: Spearman's Rank Correlation Coefficient, using 100% of the Evaluation Split

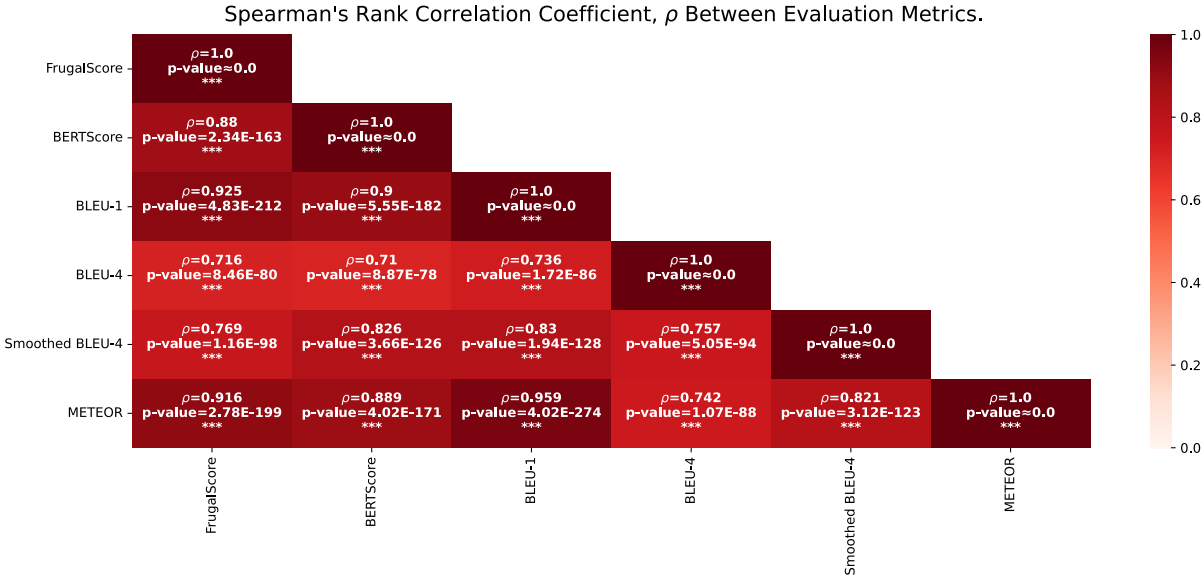

Figure 3: Spearman's Rank Correlation Coefficient, using 1% of the Evaluation Split