To Compare the Performance of Labeled Data in Computer Science

Charles Dickens*

Department of Social Sciences, University of Cambridge, United Kingdom

charles222@gmail.com

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Description

Models based on deep learning are relatively large, making it difficult to deploy such models to resource-constrained devices such as mobile phones and embedded devices. One possible solution is knowledge distillation. In this method, a small model (student model) is trained using information from a larger model (teacher model). This article presents a perspective of knowledge distillation techniques applied to deep learning models. To compare the performance of different techniques, we propose a new metric, called the distillation metric, that compares different knowledge-based distillation solutions based on model size and accuracy score. Based on this investigation, some interesting conclusions were drawn and presented in this paper, including current challenges and possible research directions. Models of lifetimes for individual lines of source code or tokens can estimate maintenance requirements, guide preventive maintenance, and more broadly identify factors that improve software development efficiency. We present methods and tools that allow us to track the birth and death of each lineage or token. Through them, we analyze the lifetime events of 3.3 billion source code elements in 89 revision control repositories. Statistical analysis shows that lines of code are persistent, with a median lifespan of about 2.4 years, and young lines are more likely to be modified or deleted if they follow a Weibull distribution, and the associated hazard rate is over time. Decrease over time. This behavior appears to be independent of any particular characteristic of the line or token, as we were unable to identify any factors that significantly impacted the longevity of the project as a whole. We found that programming language, developer tenure, and experience were not significantly correlated with line or token lifetimes, while project size and project age were barely correlated.

Labeled data is the main component of classification tasks. Dates marked are not always available and free. Semi-supervised learning uses heuristics to solve the problem of labeling unlabeled instances. Self-training is one of the most popular and understandable approaches to labeling data. In this paper, a new approach called self-training using associative classification with Ant Colony Optimization (ST-AC-ACO) is proposed to label and classify unlabeled data instances and provide improved self-training classification accuracy by associating (term) and between a set of term and class designations of identified instances. We used Ant Colony Optimization (ACO) to create associative classification rules based on labeled and pseudo-labeled instances. Experiments demonstrate the superiority of the proposed associative self-training approach over competing conventional self-training approaches.

Conclusion

Modern software development and operations rely on monitoring to understand how systems are performing in production. Application logs and data provided by the runtime environment are essential for detecting and diagnosing undesirable behavior and improving system reliability. Researchers and practitioners have actively addressed a variety of protocol-related challenges, including: B. How developers can effectively provide better tooling support for logging decisions, effectively process and store log data, and extract insights from log data. A holistic view of research efforts on logging practices and automated log analysis is key to providing guidance and disseminating the latest techniques for technology transfer. This white paper examines 108 research papers, 24 peer-reviewed journals, and 12 industry papers in various domains (machine learning, software engineering, systems, etc.) and organizes research areas in terms of log data life cycle. Our analysis shows that logging is a challenge not only for open source projects, but also for the industry. Machine learning is a promising approach to enable contextual analysis of source code for log recommendations, but further research is needed to assess the practical usability of these tools. Very little research has addressed efficient log data persistence, and published methods for analyzing applications. Record logs and evaluate state-of-the-art log analysis techniques in a DevOps context.

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Conflict of Interest

The author has declared no conflict of interest.