別紙様式８

研　究　主　論　文　抄　録

論文題目

Machine Learning Optimization using Evolutionary Algorithm for Text Classification

（テキスト分類のための進化的アルゴリズムを用いた機械学習最適化）

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主論文要旨

Machine learning methods involve optimization in several parts, i.e., features selection, hyperparameter optimization, and neural architecture search. Several strategies are used for the optimization ranging from manual tuning to more sophisticated methods such as grid search, random search, bayesian, or evolutionary algorithm (EA). This thesis investigates ways to optimize machine learning methods using EA for text classification tasks. As an initial effort, we apply a variable length chromosome genetic algorithm to select features in naive bayes (VLCGA-NB). This method produces only features that have major contributions and reduces the number of selected features by 24.5%. Our next strategy is employing a genetic algorithm to optimize hyperparameters of a convolutional neural network (GA-CNN). We define 20 hyperparameters and conduct experiments with different number of hyperparameters and different number of optimized hyperparameters. Our GA-CNN shows better performance than other methods and proves that a larger number of hyperparameter and layer-specific hyperparameter values are important. Despite the good results, the architecture of the CNN is static, and the parameters of the GA are determined manually. Moreover, GA is also often trapped into a local optimum. Then, we propose a method called the “diversity-guided genetic algorithm-convolutional neural network (DGGA-CNN).” This method uses adaptive parameter control and random injection to facilitate the search process and preserve population diversity. Within the same approach, we also propose a dynamic architecture search of CNN using a novel finite state machine (FSM). Our experimental results exhibit that the DGGA-CNN is superior to the other methods in terms of fitness values, handling of premature convergence, and efficiency. Up until this point, we optimize a large number of hyperparameters for the

CNN. We optimized all the hyperparameters simultaneously, including the unimportant ones. The important hyperparameters may have a higher contribution towards improvement in the performance of machine learning algorithms. Therefore, we also propose an automatic selection of important hyperparameters using functional ANOVA and optimize them throughout the generation of GA. Our experiments show that optimizing important hyperparameters can improve the performance of CNN.