Circuit Recognition with Convolutional Neural Networks

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Abstract

Identifying decisive properties (features) of circuits and performing proper treatment are crucial for solving various computer-aided design problems. Convolutional neural networks (CNNs) have been used extensively in the machine learning community because pre-defined features are not highly required. The networks are capable of learning concealed structures of objects during training. This paper proposes a new circuit representation and applies CNNs to recognize circuit functionalities. Experiments demonstrate the effectiveness of the proposed method for circuit classification and functional operator detection.

CNNs for Image Processing

![Convolution Layers](image)

A convolutional neural network is a type of artificial neural network inspired by the mechanism of the animal visual system. The major advantage of CNNs is the lack of dependence on the human efforts in designing and selecting features. A typical CNN is a feed-forward network mainly composed of convolution layers, pooling layers and fully connected layers.

Operator Classification

As a comparison for the CNN approach, we take all entries of input matrices as features and use SVM methods implemented in scikit-learn to classify circuits. We prepare three classes of circuits, multipliers, dividers and modulo operators with varying bit-widths. Then we train CNNs with different training dataset sizes (the number of cases in each class) and test the prediction accuracy.

Circuit Representation for CNN

CNNs expect all circuits are represented as fixed size matrices filled with real numbers. Consider an And-Inverter Graph (AIG), it can be expressed with (1) an adjacent matrix or (2) a dependency matrix similar to AIGER: each row indicates input literals for each signal.

![Figure 4: An And-Inverter Graph (AIG)](image)

Hence we devise a convolution operation for circuits and a corresponding pooling operation to represent circuits for CNNs.

Operator Detection

All cases are randomly generated with m arithmetic operators of varying bit-widths, where at most one operator is a multiplier. These circuits are classified as absence or presence of multipliers. Then we examine how the total number of operators (m) influences the accuracy of the prediction. The size of the training dataset of each class is fixed at 330.

Pooling Layers

To reduce the amount of parameters, it is usual to insert a pooling layer after a convolution layer. In a pooling layer, an input feature map is partitioned into small regions and shrunk by a certain operator, such as MAX, average. Pooling layers also lessen the overfitting issue of CNNs by ignoring small disturbances. A fully connected layer takes all output features computed by the previous layer to determine each of its output values.

Conclusion

This paper proposed a framework for recognizing circuit properties based on CNNs. Experimental results demonstrated that the proposed methods can be effective in operator classification and detection. Future work includes, but not limited to: (1) revise the convolution and pooling operations on circuits to improve operator detection, (2) apply the trained models to real circuits to assist reverse engineering, (3) use the proposed framework to recognize other combinational circuit properties, and (4) develop other convolution operators to describe circuits for other circuit learning problems, including sequential circuits. The ultimate goal is a general framework which assists in learning and characterizing essential properties of circuits for their own applications.