AUTOMATIC NEURAL NETWORK SEARCH METHOD FOR OPEN SET RECOGNITION

Li Sun[1] , Xiaoyi Yu[1], Liuan Wang[1], Jun Sun[1], Hiroya Inakoshiy[2], Ken Kobayashiy[2] Hiromichi Kobashiy[2]

[1]Fujitsu R&D Center, Beijing, China; [2]Fujitsu Laboratories Ltd., Kawasaki, Japan

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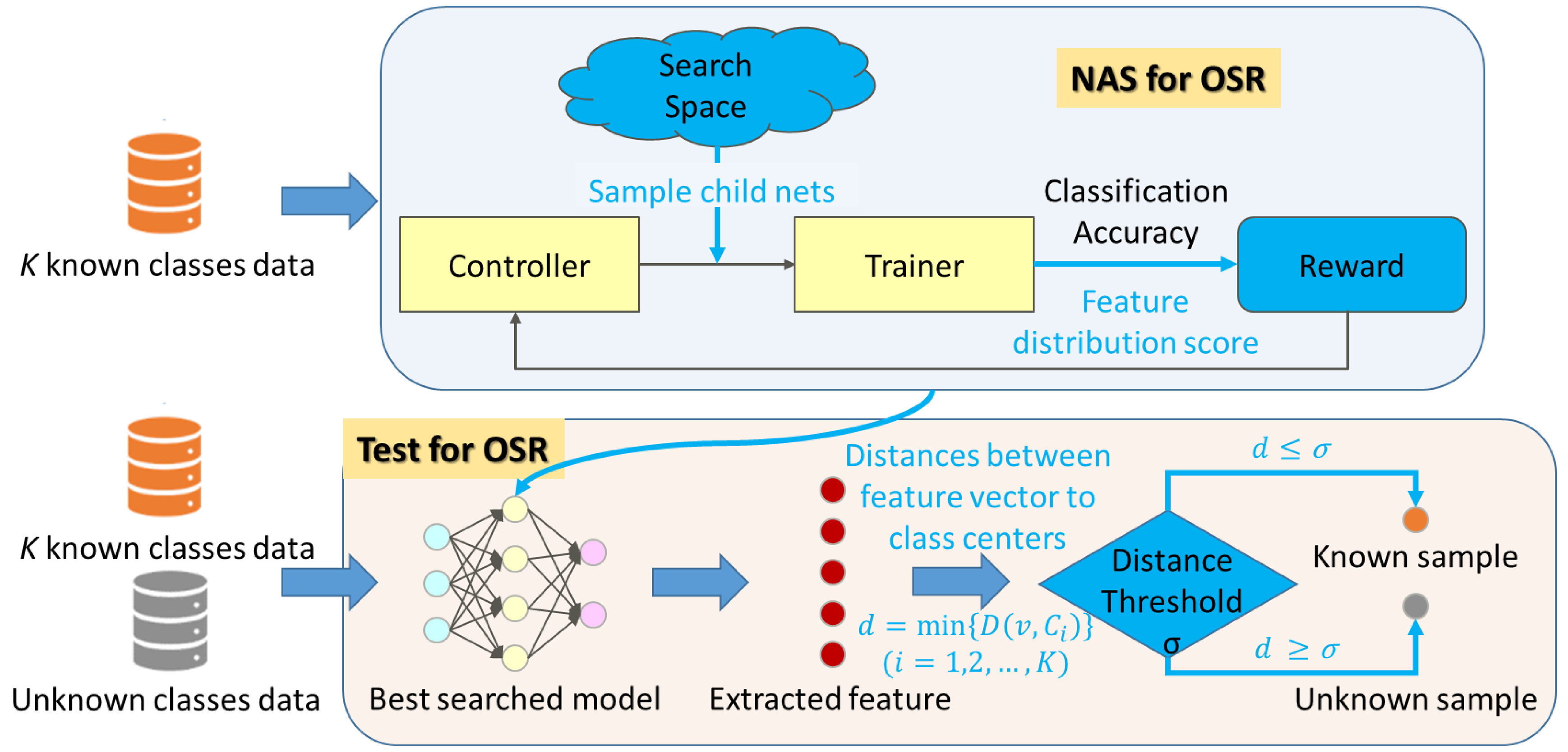
INTRODUCTION

Real-world recognition or classification tasks in computer vision are not apparent in controlled environments and often get involved in open set. Previous research work on real-world recognition problem is knowledge- and labor-intensive to pursue good performance for there are numbers of task domains. Auto Machine Learning (AutoML) approaches supply an easier way to apply advanced machine learning technologies, reduce the demand for experienced human experts and improve classification performance on close set. This paper proposes an automatic neural network search method for designing effective convolution neural network (CNN) models for open set recognition (OSR). Feature distribution information is explicitly incorporated into the main objective. So during the search process, the sampled models will enlarge inter-class differences and reduce intra-class variations. We design a flexible search space based on classic CNN models to diversify neural architectures and also add some search principles to limit the size of the search space. Experimental results on CIFAR-10 and Dunhuang historical Chinese datasets show that our approach improves performances on both close and open set. Comparing with the other two OSR algorithms, our method also achieves the best performance.

OVERVIEW



INNOVATIONS

- **Optimization objective**
  - Both close set accuracy and feature distribution of output features are under consideration
  - The feature distribution is scored by Euclidean distances. We want to find the model which can obtain separable inter-class differences and compact
- **Flexible search space, limited sample principles**
  - We design a flexible search space based on classic CNN models to explore as much as possible architectures for OSR.
  - We add some empirical principles to limit search space size and improve search efficiency.

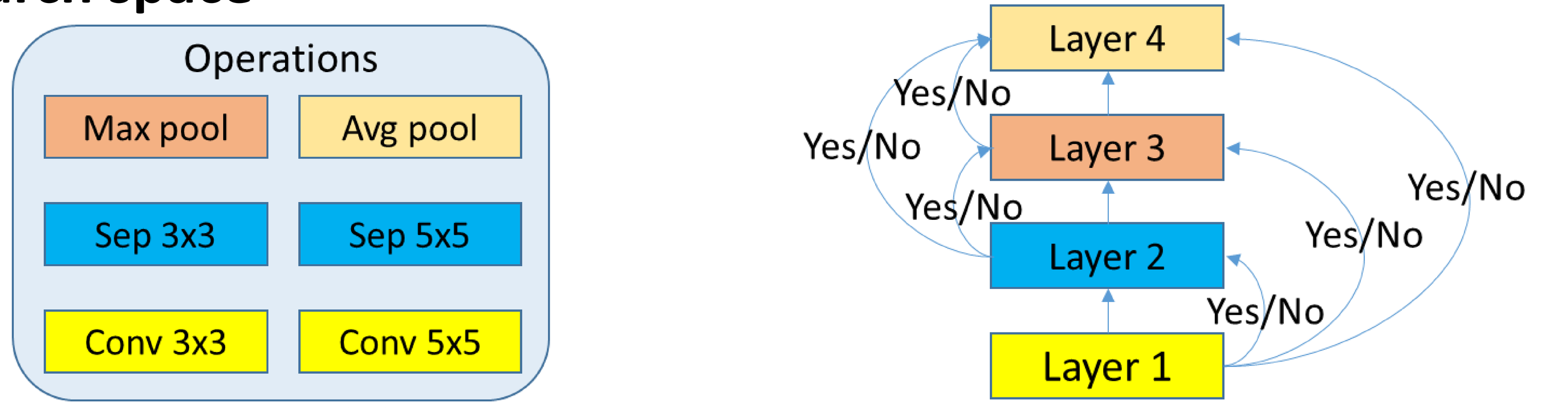
METHOD

- **Formulate optimization objective**
  - We formulate the objective consists of two parts, close set accuracy and feature distribution information. Our purpose is to find the model achieving separable inter-class differences and compact intra-class variations.

$$Reward = ACC \times FDS$$
$$FDS = \frac{1}{1+L_c} + 1$$

FDS: Feature distribution score

- **Search strategy**
  - We employ a gradient-based reinforcement learning approach to find optimal objective.
- **Search space**



- **Open set recognition**
  - During the open set recognition process, we use the minimum Euclidean distance between this sample's feature vector and each known-class center
    $d = \min(D(v, C_i)), i = 1,2,\dots,K$, C_i is the i^{th} class center and there are total K known classes

EXPERIMENTS

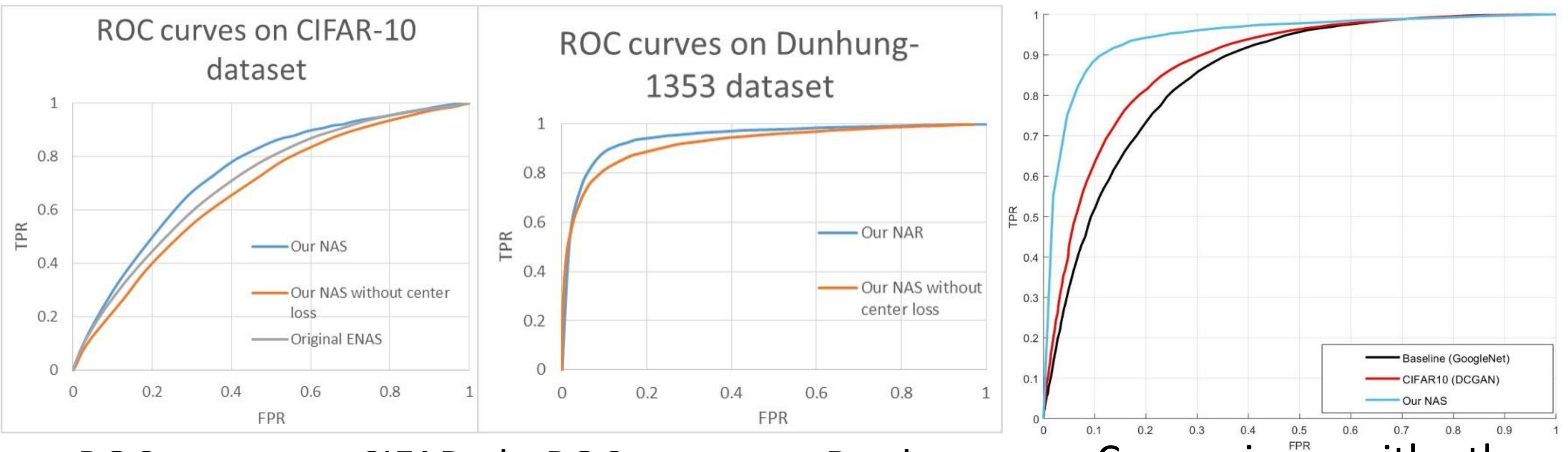
- **Performance on CIFAR-10 dataset**

Table.1 Experiment setting of CIFAR dataset

Procedure	Training NAS	OSR TEST
Number of known classes	5	5
Number of unknown classes	0	5
Number of total samples	25000	10000

Table.2 Close set classification results on CIFAR-5 dataset

Types of NAS	Our NAS	Our NAS (No center loss)	Original ENAS
Parameters with 12 layers	1.4M	1.1M	2.5M
Evaluation-softmax	0.9560	0.9498	0.9548
Evaluation-CenterDistance	0.9614	0.9500	0.9548



a. ROC curves on CIFAR b. ROC curves on Dunhuang c. Comparisons with other open set methods

- **Performance on DunHuang historical Chinese dataset**

Table.3 Experiment setting of Dunhuang dataset

Procedure	Training NAS	OSR TEST
Number of known classes	300	300
Number of unknown classes	0	1053
Number of total samples	22449	19008

Table.4 Close set classification results on Dunhuang-300 dataset

Types of NAS	Our NAS	Our NAS (No center loss)
Parameters with 24 layers	7.6M	7.2M
Evaluation-softmax	0.9650	0.9592
Evaluation-CenterDistance	0.9655	0.9476