Statistical Machine Learning

Phase1 :

Open-set recognition and Non-parametric Bayesian

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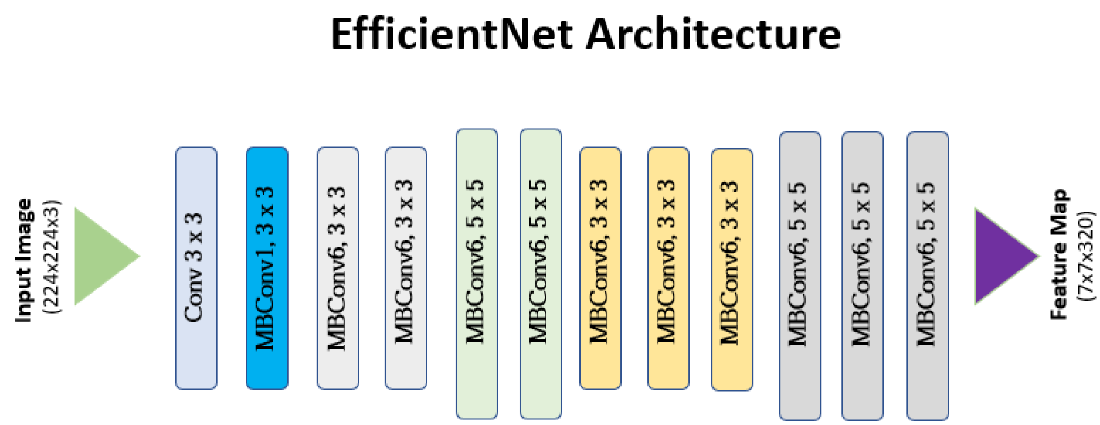
In this project we Comprehensive Framework to address both Openset recognition and determine the label/cluster of new unseen classes.

Our model consists of two different part, in first part we try to utilize deep neural network to extract more generizable embedding from Input data. And also separate the seen classes (and classify it) from unseen new class. In second part we try to cluster the unseen new classes with Non-Parametric Bayesian models to achieve more accurate result in test time. In next paragraphs we will dive into technical details of each block.

In first module we use EfficientNet[1] structure as a base model. EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient. This network has an architecture as follow :



This convolution block follows a fully connected layer (which first layer size is the desired embedding size used in next block) to learn to classify the class label (from seven seen class).

In this block we do some tricks to have more generalization:

1) We use learning rate scheduler while training model
2) We use RandAug augmentation to make some diverse sample for our model. [2]
3) We also use label smoothing to make more robust features [3]

The classification accuracy for seen class while training and testing is as follows:

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Training accuracy while training: 93.81
Valdation accuracy while training: 98.18
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Openset detection accuracy: 82.61
Openset best separator accuracy: 88.59
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In first block we separate the seen class from open set and pass the unknown data into our supervised Contrastive Kmeans Dirichlet Process Gaussian Mixture Model , or SCKDPGMM.

In SCKDPGMM we use a semi Expectation Maximization Algorithm, which in expectation phase we try to find the best fit clustering for a desired embedding and in maximization step we find most separate embedding for desired clustering with supervised contrastive learning algorithm, and continue this training procedure until convergence (or iterate until max_epoch).

Algorithm SCKDPGMM

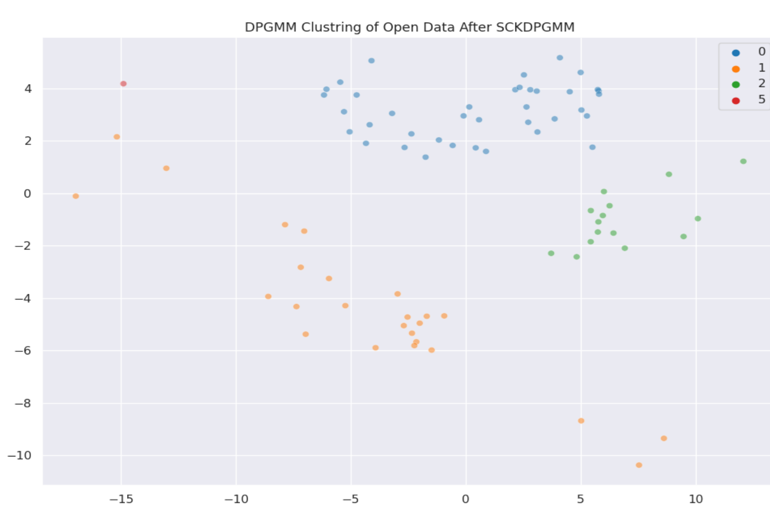
Initialization step : For initialization of cluster number we use a self supervised contrastive algorithm in [4] and after initialization step we go to main loop of our algorithm :

-iterate until convergence

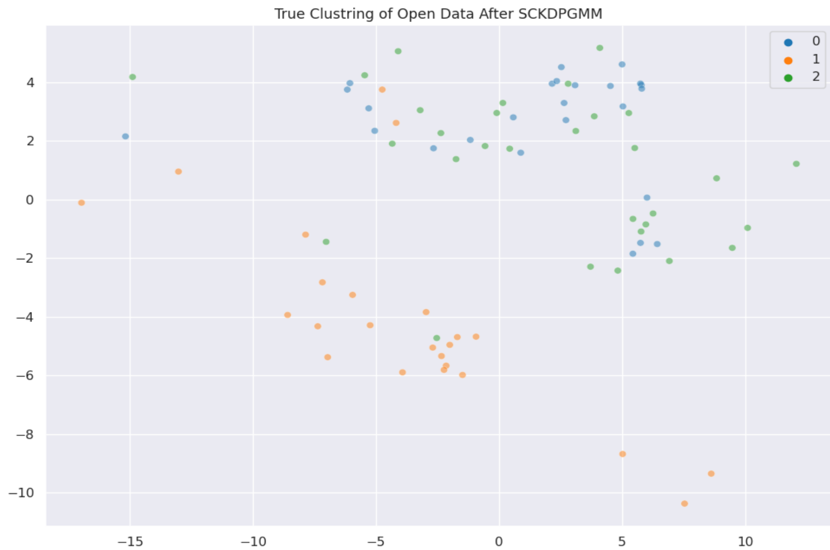
1**. expectation step**: we apply a kmeans clustering with a really big cluster number (here we use 12) and after that concatenate this label into input embedding and pass it into LDA algorithm to project data into 2 dimension. now we bring these features into Dirichlet Process Gaussian Mixture Model, To finally cluster the open data.

2. **Maximization step** : we pass the computed label into supervised contrastive learning algorithm [5] to have more accurate and separate embedding .

The final accuracy of this part is 63% . the visualization of the clustering output of our model on test is as follow:



The real label of classes are as follow :



As can be seen, class 1 separates very good with our algorithm. But the class 0 and 2 which have overlap in our feature space, have some misclustering.

References

[1] Koonce, B. and Koonce, B., 2021. EfficientNet. Convolutional Neural Networks with Swift for Tensorflow: Image Recognition and Dataset Categorization, pp.109-123.

[2] Cubuk, E.D., Zoph, B., Shlens, J. and Le, Q.V., 2020. Randaugment: Practical automated data augmentation with a reduced search space. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops (pp. 702-703).

[3] Vaze, S., Han, K., Vedaldi, A. and Zisserman, A., 2021. Open-set recognition: A good closed-set classifier is all you need. arXiv preprint arXiv:2110.06207.

[4] Jaiswal, Ashish, Ashwin Ramesh Babu, Mohammad Zaki Zadeh, Debapriya Banerjee, and Fillia Makedon. "A survey on contrastive self-supervised learning." Technologies 9, no. 1 (2020): 2.

[5] Khosla, Prannay, Piotr Teterwak, Chen Wang, Aaron Sarna, Yonglong Tian, Phillip Isola, Aaron Maschinot, Ce Liu, and Dilip Krishnan. "Supervised contrastive learning." Advances in neural information processing systems 33 (2020): 18661-18673.