Formulation

Experiments

Dynamics in Classifier

intern

Multimedia Laboratory @ CUHK

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Background

- How Imagenet1k is cleaned
 - 671 leaf nodes, 329 internal nodes
 - Classse are balanced
- Difficulty to classify on ImageNet22k (Deng et al. 2009) comes from
 - Fine-grained classed with few instance to train

Experiments

Hierachical Prediction

Feature of a sample \mathbf{x}_i . Ground truth label $\mathbf{y}_i = c_i$, i.e. $y_i^{c_i}$.

$$P(y_i^{c_i}|\mathbf{x}_i) = \sum_{c_k \in PAR(c_i)} P(y_i^{c_i}|y_i^{c_k}, \mathbf{x}_i) P(y_i^{c_k}|\mathbf{x}_i)$$

$$= P(y_i^{c_i}|y_i^{PAR(c_i)}, \mathbf{x}_i) P(y_i^{PAR(c_i)}|\mathbf{x}_i)$$

Genralize to atribute depth *d*:

$$P(y_i^{c_i}|y_i^{\operatorname{PAR}(c_i,d)},\mathbf{x}_i)P(y_i^{\operatorname{PAR}(c_i,d)}|\mathbf{x}_i)$$

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Prediction at depth d

$$P(y_i^{\text{Par}(c_i,d)}|\mathbf{x}_i) = \frac{\sum_{j \in \text{FIND}(c_i,0,d)} e^{f_j}}{\sum_{j \in AII} e^{f_j}}$$

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Prediction conditioned by depth d

$$P(y_i^{\operatorname{Par}(c_i,d)}|\mathbf{x}_i) = \frac{e^{f_{c_i}}}{\sum_{j \in \operatorname{FIND}(c_i,d,-1)} e^{f_j}}$$

Experiments

Hierachical Loss

E.g. For Cifar100, given logits \mathbf{f} and ground truth label y_i

$$\begin{array}{lcl} L_i^{100} & = & -\log\left(\frac{\Sigma_{j\in \mathrm{FIND}(y_i,2,2)}\mathrm{e}^{f_j}}{\Sigma_{j\in \mathrm{FIND}(y_i,0,2)}\mathrm{e}^{f_j}}\right) \\ L_i^{20} & = & -\log\left(\frac{\Sigma_{j\in \mathrm{FIND}(y_i,1,2)}\mathrm{e}^{f_j}}{\Sigma_{j\in \mathrm{FIND}(y_i,0,2)}\mathrm{e}^{f_j}}\right) \\ L_i^{group} & = & -\log\left(\frac{\Sigma_{j\in \mathrm{FIND}(y_i,2,2)}\mathrm{e}^{f_j}}{\Sigma_{j\in \mathrm{FIND}(y_i,1,2)}\mathrm{e}^{f_j}}\right) \end{array}$$

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Statistic Info of ImageNet

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Samples/Class

ImgNet	imgs	imgs/cls	histogram	distribution
~1k	~1.4M	~1.4K ¹	200 200 200 200 200 200 200 200 200 200	17 200 del 400 del 1500
~10k	~28.96M	~2.8K	9 3 200 200 400 500 600 700 600	30° 30°
~17k	9.4M	545	600 600 200 1 50 350 256 260 260 360	10° di griss unios trina traine train

 $^{^{1} \}rm images/class$ of ILSVR2012 competition $= 1.3 \rm k$ for all most all classes. We download the latest dataset.

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Statistic Info of ImageNet

Hierachical Categories

All sub-datasets are sampled from ImageNet, and 1K covers most of 22k, thus, it is observed that characteristic of categories' distribution are similar.

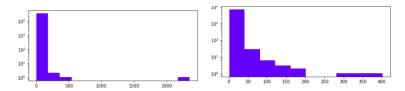


Figure 1: Left: Distribution of nodes' child number, Right: Igonore outliers

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Statistic Info of ImageNet

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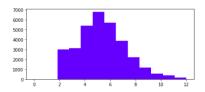


Figure 2: Distribution of nodes' depth

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Learning Curve

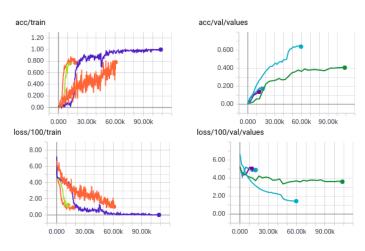


Figure 3

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Learning Curve

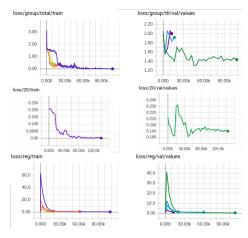


Figure 4: The initial value of loss100 is 5, loss group is 1.6 and loss20 0.27.

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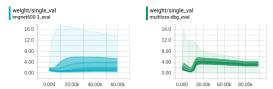


Figure 5: The distribution of weight matrix's sinlge value. It is a common trading on different dataset that the class codes to a concentrating into a subspace

Orthogonality

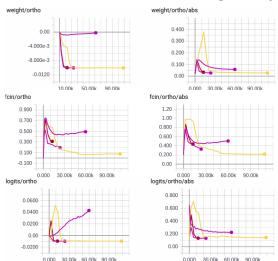


Figure 6: $logits=weight^T \cdot fcin$. The logits of imagenet become positive may because the reference sample do not cover the whole validation dataset and there are many instance of similar classes.

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Reflections

- Generalize to WordNet Tree
 - Key Obstacle: The number of child of node is not same, i.e. function FIND cannot feed with fix-length matrix and return matrix. Hostile for gpu matrix operation.
- Structure Code for Feature

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Deng, Jia et al. (2009). "Imagenet: A large-scale hierarchical image database." In: Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. IEEE, pp. 248–255.