Born Again Neural Networks

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Let's talk ML in Prague

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Prior work

Ensembles

Diverse models with similar validation performances can be often be combined to achieve predictive power superior to each of the constituent models. [3]

Born again trees

Learn a single tree that is able to recover the performance of a multiple-tree predictor. [4]

Knowledge distillation = model compression

Transfer knowledge acquired by a learned teacher model to a new simpler student model. [5]

Knolewdge distillation

Teacher

- high-capacity model
- good performance

Student

- more compact model
- not as good performance as the teacher but better than if it was trained without it

By transferring knowledge, one hopes to benefit from the student's compactness while suffering only minimal degradation in performance.

Knolewdge distillation

Teacher produces soft targets = probabilities of incorrect classes = the key to generalization outside of the training dataset.

Training student = minimize weighted average of:

- cross entropy with the soft targets
- cross entropy with the hard targets = labels

Knolewdge distillation results

System	Test Frame Accuracy	WER
Baseline	58.9%	10.9%
10xEnsemble	61.1%	10.7%
Distilled Single model	60.8%	10.7%

Figure: DNN acoustic models used in Automatic Speech Recognition. [5]

Born Again Networks (BANs)

- not compressing models
- students are parameterized identically to their parents
- students outperform teachers
- knowledge transfer between dense networks and residual networks of similar capacity

$$\min_{\theta_2} \mathcal{L}(y, f(x, \theta_2)) + \mathcal{L}(f(x, \arg\min_{\theta_1} \mathcal{L}(y, f(x, \theta_1))), f(x, \theta_2))$$

Figure: BAN loss function adding Kullback–Leibler divergence between the new model's outputs and the outputs of the original model. [1]

BAN Ensembles

Apply BANs sequentially with multiple generations of knowledge transfer. In each case, the k-th model is trained, with knowledge transferred from the $k-1$-th student:

$$\min_{\theta_k} \mathcal{L}(y, f(x, \theta_k)) + \mathcal{L}(f(x, \arg\min_{\theta_{k-1}} \mathcal{L}(y, f(x, \theta_{k-1}))), f(x, \theta_k))$$

Born Again Network Ensemble (BANE)

Averaging the prediction of multiple generations of BANs.

DenseNets reminder: Dense block

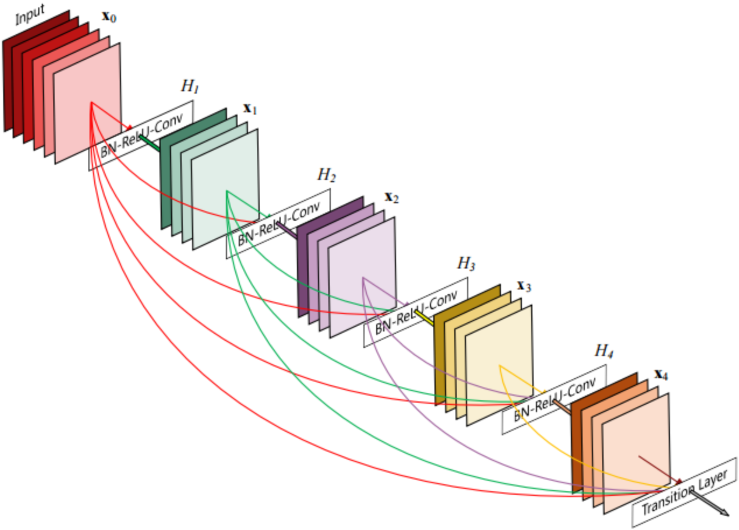

Figure 1: A 5-layer dense block with a growth rate of $k = 4$.

DenseNets reminder: Deep DenseNet

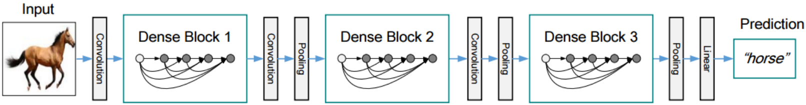

Figure: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling. [6]

BAN DenseNets Experiments

All experiments on: CIFAR-100 (100 classes each containing 600 32x32 colour images).

- DenseNet-BC-(depth)-(growth rate)
- BAN-1/2/3 = sequential training by previous BAN-(k-1)
- Ens*2/3 = ensembles of 2/3 BAN-x

Network	Parameters	Baseline	BAN-1	BAN-2	BAN-3	Ens*2	Ens*3
DenseNetBC-112-33	6.3 M	18.25	17.61	17.22	**16.59**	15.77	15.68
DenseNetBC-90-60	16.1 M	17.69	16.62	**16.44**	16.72	15.39	15.74
DenseNetBC-80-80	22.4 M	17.3	16.26	16.30	**15.5**	15.46	15.14
DenseNetBC-80-120	50.4 M	16.87	**16.13**	16.13	/	**15.13**	**14.9**

Figure: BAN training is clearly beneficial for DenseNets on CIFAR. [1]

ResNets reminder

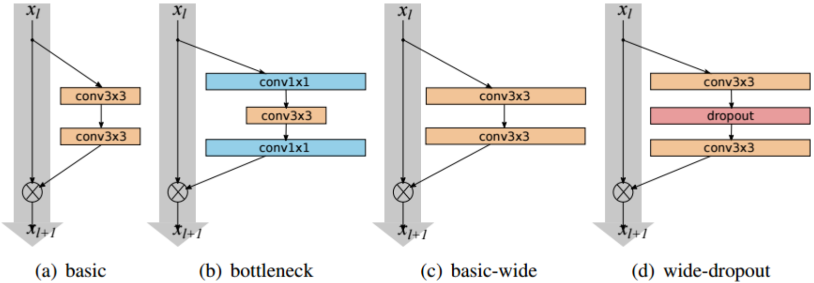

Figure: Various residual blocks used in the paper. Batch normalization and ReLU precede each convolution (omitted for clarity). [7]

BAN ResNets

BAN-ResNets:

- trained by DenseNet 90-60 teacher
- baseline = wide-ResNet28 [7]
- tested multiple nets with different number of units per block
- all benefit from BAN training

BAN-ResNets outperform:

- traditional counterparts
- equivalent ResNets trained without DenseNet teacher
- their DenseNet teacher

BAN Results

Single model non-ensemble SOTA on CIFAR 100 trained with SGD without any sort of shake-shake regularization:

- BAN-3-DenseNet-80-80
- 22M parameters
- 15.5% error

Ensemble SOTA under the same conditions:

- BAN-3-DenseNet-BC-80-120
- 150M parameters
- 14.9% error

Sources

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