Lecture 2 - Deep Neural Networks Compression

Efficacy and efficiency evaluation of machine learning models
Ph.D. Course

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Outline

1. The Need to Compress DNNs

2 Compressing for Pre-Trained Models

- 2.1 Structure-Preserving Compression Strategies
- `sHAM`
- 2.2 Structure-Altering Compression Strategies

3. Train Compressible Models

4. Exam Paper List

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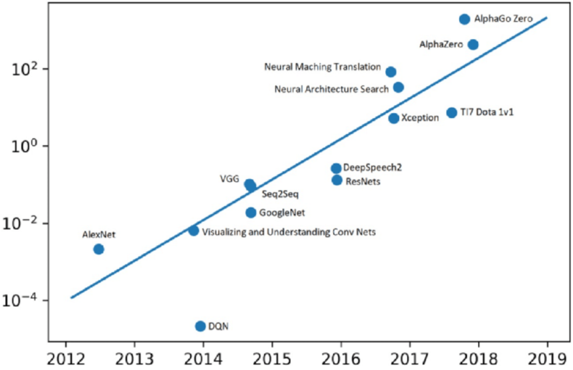
- Recalling the need for power-hungry hardware (petaflops/day, in 1e04)



Amodei, D. and Hernandez, D. Ai and compute. https://openai.com/index/ai-and-compute/ 2018.

Learning Issues with Too Large Models

- Overparameterization
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- In addition to the reduction of resource demand, compressing even in necessary in some contexts
  - e.g. when resources (RAM, battery, etc.) are limited (e.g., IoT devices)
  - low-power mobile/embedded systems

Allen-Zhu, Z.et *al*. Learning and generalization in overparameterized neural networks, going beyond two layers. Advances in Neural Information Processing Systems, 32, Curran Associates Inc, 2019.

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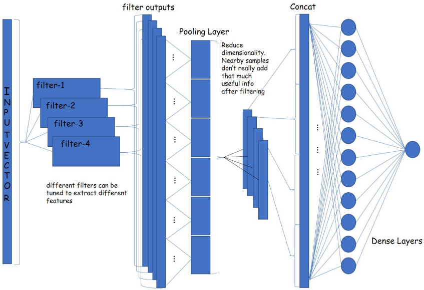

An illustration of Convolutional Neural Networks

Source: https://towardsdatascience.com/acomparisonof-dnncnnandlstmusingtfkeras2191f8c77bbe

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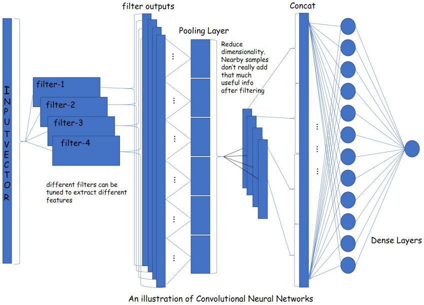

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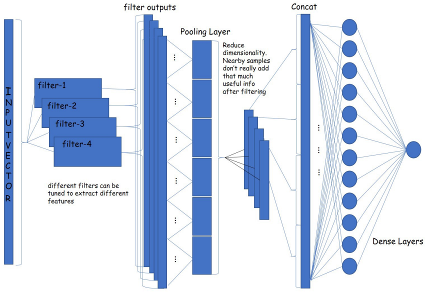

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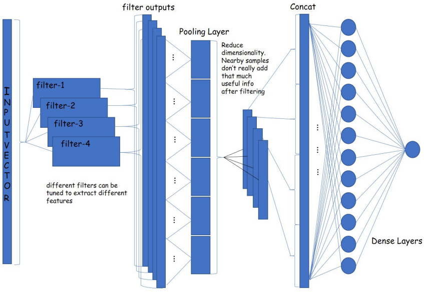

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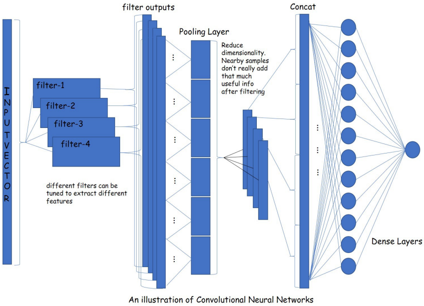

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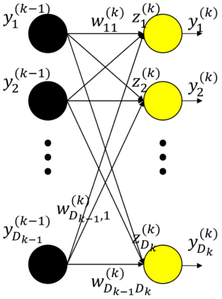
  - Preserving the topology means do not alter the input and the output size of layers
- In most architectures proposed, fully connected (dense) layers often cover the large majority of parameters (weights and biases)

Computation in Dense layers

The computation in dense layers is performed via vector-matrix products:



$$\mathbf{z}^{(k)} = \begin{bmatrix} z_1^{(k)} \\ z_2^{(k)} \\ \vdots \\ z_{D_k}^{(k)} \end{bmatrix} \qquad \mathbf{y}^{(k)} = \begin{bmatrix} y_1^{(k)} \\ y_2^{(k)} \\ \vdots \\ y_{D_k}^{(k)} \end{bmatrix}$$

$$\mathbf{W}^{(k)} = \begin{bmatrix} w_{11}^{(k)} & w_{21}^{(k)} & \vdots & w_{D_{k-1}1}^{(k)} \\ w_{12}^{(k)} & w_{22}^{(k)} & \vdots & w_{D_{k-1}2}^{(k)} \\ \cdots & \cdots & \ddots & \vdots \\ w_{1D_k}^{(k)} & w_{2D_k}^{(k)} & \cdots & w_{D_{k-1}D_k}^{(k)} \end{bmatrix} \qquad \mathbf{b}^{(k)} = \begin{bmatrix} b_1^{(k)} \\ b_2^{(k)} \\ \vdots \\ b_{D_k}^{(k)} \end{bmatrix}$$

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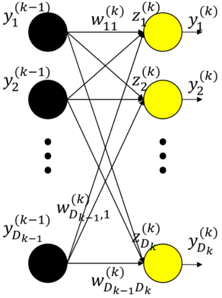

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For k-th layer, we have $\boldsymbol{y}^{(k)} = f_k(\boldsymbol{W}^k \cdot \boldsymbol{y}^{(k-1)})$ (casting the bias $\boldsymbol{b}^{(k)}$ into an additional input)

where

- $W^{(k)} \in \mathbb{R}^{D_k \times D_{k-1}}$ is the layer weight matrix
- f_k is the neuron activation function for this layer
- $\boldsymbol{y}^{(k)}$ is the output vector of k-th layer

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- For example, connection pruning and/or quantization of $\boldsymbol{W}$

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- Optimizing Compression Criteria during Network Training

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  3. Fine-tune the remaining connections (that is, retrain the network)

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- Binarization: extreme case where only two distinct weights are used (typically 0 and 1) [Hubara et *al.* 2016]

– Gamma, E. Helm, R. Johnson, R. and Vlissides, JM. Design Patterns: Elements of Reusable Object-Oriented Software. Addison Wesley, 1994

– I. Hubara, et al., Binarized neural networks. Advances in Neural Inf. Process. Syst. 2016.

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$$\overset{\bar{\mathbf{W}}}{\begin{bmatrix} 2 & 2 & 1 \\ 6 & 4 & 1 \\ 6 & 2 & 4 \end{bmatrix}} \Rightarrow \overset{\mathbf{C}}{\begin{bmatrix} 2 \\ 6 \\ 4 \\ 1 \end{bmatrix}} \quad \overset{\mathbf{M}}{\begin{bmatrix} 0 & 0 & 3 \\ 1 & 2 & 3 \\ 1 & 0 & 2 \end{bmatrix}}$$

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- Denoted by b and $\bar{b}$ the number of bits used to store one entry of $\overline{\boldsymbol{W}}$ and $\boldsymbol{M}$, respectively: the compression ratio is $\frac{bnm}{\bar{b}nm+kb}$.

S. Han, H. Mao, W.J. Dally. Deep compression: Compressing deep neural network with pruning, trained quantization and Huffman coding. ICLR 2015.

Weight sharing: Main approaches

- **CWS** (*Clustering Weight Sharing*) exploits k-Means and maps the weights to the respective centroid
- **PWS** (*Probabilistic Weight Sharing*) is a probabilistic approach that maps the weights to representative values using a probability distribution on representatives based on their 'distance' to the weight to be quantized
- **UQ** (*Uniform Quantization*) selects representative weights uniformly in a variable size interval centered around the weight to be quantized
- **ECSQ** (*Entropy Constrained Scalar Quantization*) learns C_i and c_i by optimizing jointly distortion and entropy of the resulting distribution of representative weights

For a survey, see Marinò, G.C. et *al*. Deep neural networks compression: A comparative survey and choice recommendations. Neurocomputing, 2023, 520, pp. 152–170.

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- Exploits low-rank factorization of rank q via truncated SVD of $\boldsymbol{W}$, i.e. $\boldsymbol{W} \simeq \boldsymbol{U}\boldsymbol{\Sigma}\boldsymbol{V}^T$, $\boldsymbol{U} \in \mathbb{R}^{n\times q}$, $\boldsymbol{\Sigma} \in \mathbb{R}^{q\times q}$, and $\boldsymbol{V} \in \mathbb{R}^{m\times q}$

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- No retraining needed

S. Swaminathan, D. Garg, R. Kannan, et al., Sparse low rank factorization for deep neural network compression, Neurocomputing 398 (2020) 185–196

Lossless representation of the layer

Once 'simplified' the layer matrix, lossless format supporting the dot product can be leveraged:

1. E.g. CSC, CSR, CER, CSER, Index Map, SLR, HAM, sHAM

HAM - Huffman Address Map

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- $\mathtt{HAM}(\overline{\boldsymbol{W}})$ is split into $\left\lceil \frac{|\mathtt{HAM}(\overline{\boldsymbol{W}})|}{B} \right\rceil$ integers (B word size)

- To decompress we also need to store the inverse Huffman code

Marinò, G.C. et *al.* Efficient and Compact Representations of Deep Neural Networks via Entropy Coding. IEEE Access, 2023, 11, pp. 106103–106125

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- Then compress the CSC vector containing the non-zero values with `HAM` format
- More efficient than `HAM` for very sparse input matrices

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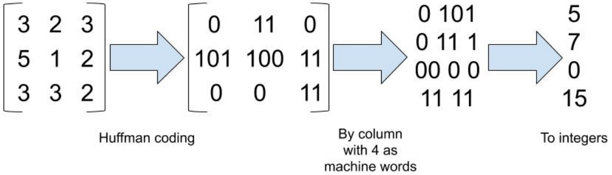
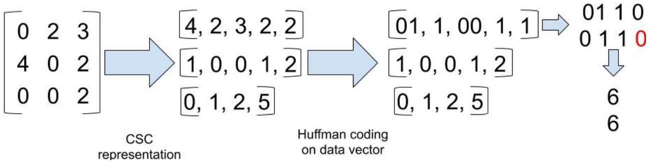
HAM/sHAM – Example

Example of HAM format



Example of sHAM format



Outline

1. The Need to Compress DNNs

2 Compressing for Pre-Trained Models

- 2.1 Structure-Preserving Compression Strategies
- sHAM
- 2.2 Structure-Altering Compression Strategies

3. Train Compressible Models

4. Exam Paper List

Knowledge Distillation (KD) in Deep Neural Networks

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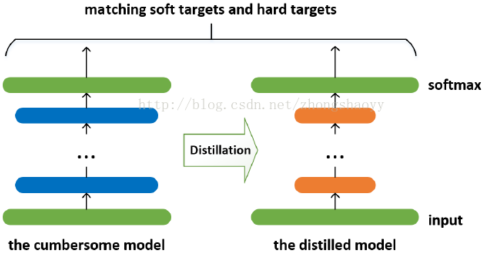

Source: https://796t.com/content/1548498443.html

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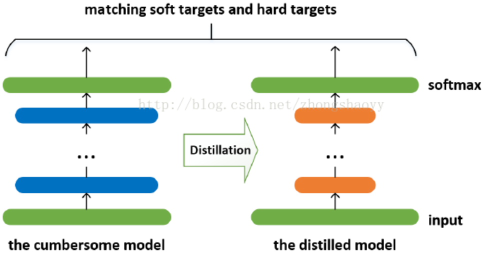

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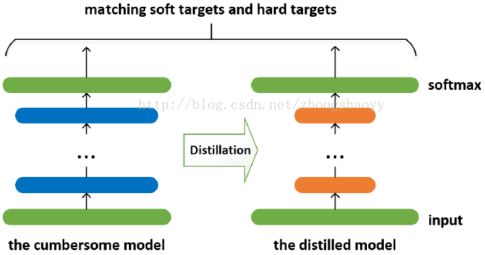

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– Soft targets (probabilities) from the teacher guide the student's learning.

– Soft Targets: Instead of using the teacher's hard class labels (e.g., "cat"," dog"), we use soft targets–probability distributions over classes

Hinton, G.E., Vinyals, O., and Dean, J. (2015). Distilling the Knowledge in a Neural Network. ArXiv, abs/1503.02531.

Distillation Process

- For each training input, the teacher provides a vector of class probabilities
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- The goal is for the student to learn not only which class is correct but also the confidence associated with it

Temperature

- The soft targets are often scaled using a temperature parameter (usually denoted as T)
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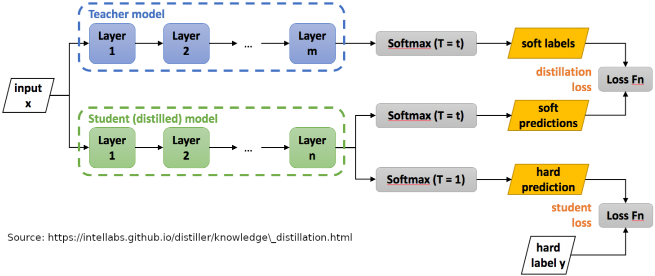
- Higher T values make the probabilities more uniform, lower T values sharpen the probabilities (more peaky)
- The overall loss combines the KD and the task-specific losses, using two values for T: $t > 1$ for teacher and student KD loss output, and $T = 1$ for student classification (same logits for both student losses)



Source: https://intellabs.github.io/distiller/knowledge_distillation.html

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- Choice of Teacher Models: The accuracy of student models depends on the choice of teacher models
- Accuracy Degradation: Student models may not consistently achieve the same high accuracy as teacher models during inference

Other structure-Altering Compression Strategies: Channel/filter pruning

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- Filter Pruning is set as an Optimization Problem

Luo, J.H. et *al.* ThiNet: A Filter Level Pruning Method for Deep Neural Network Compression. 2017. arXiv:1707.06342.

ThiNet

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- Solving point 3 is NP-hard, thus authors adopt a greedy approximate solution growing the set of r filters one at a time, adding the one having the smallest objective values

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- Penalty terms are included into the loss, each for every compression scheme
- Supports different schemes, including pruning and quantization
- Alternated training and compression steps to reduce the complexity and tackle intractable problems

M. Á. Carreira-Perpiñán, Y. Idelbayev. Model compression as constrained optimization, with application to neural nets. 2017. arXiv:1707.04319

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List of papers about DNN compression to discuss for the exam

- https://dl.acm.org/doi/10.1145/3617688. Smart-DNN+: A Memory-efficient Neural Networks Compression Framework for the Model Inference;
- https://dl.acm.org/doi/abs/10.5555/3491440.3491534. Channel pruning via automatic structure search;
- https://arxiv.org/abs/2012.03096. Parallel Blockwise Knowledge Distillation for Deep Neural Network Compression;
- https://dl.acm.org/doi/10.1145/3459637.3482005. LC: A Flexible, Extensible Open-Source Toolkit for Model Compression;
- Link. ECC: Platform-Independent Energy-Constrained Deep Neural Network Compression via a Bilinear Regression Model.