Knowledge Distillation

Intelligent Architectures (5LIL0)

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Knowledge Distillation

Definition: Knowledge Distillation (KD)

The transfer of knowledge from a large **teacher** network to a smaller **student** network.

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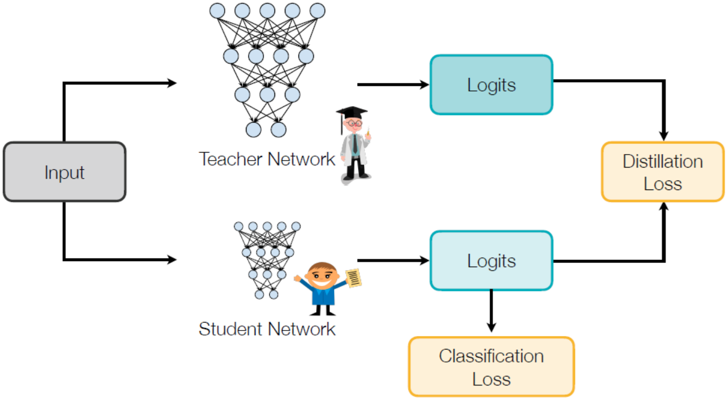

Prof. Song Han, "Knowledge Distillation" MIT 6.5940

Temperature

- Recall the softmax operation that produces output probabilities y_i:

$$y_i = \mathrm{softmax}(\mathbf{z}) = \frac{e^{z_i}}{\sum_{k=1}^{m} e^{z_k}}$$

- The outputs of the NN z_i are called **logits**

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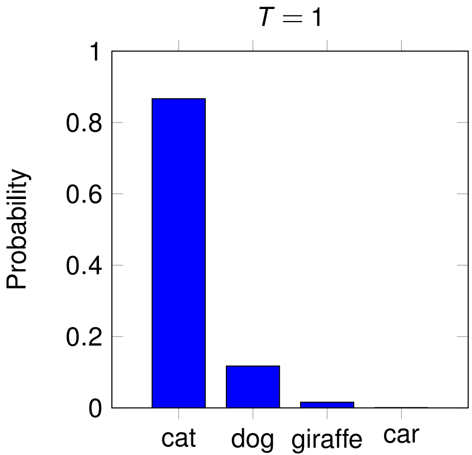
Definition: Softmax with temperature

$$y_i = \text{softmax}(\mathbf{z}, T) = \frac{e^{\frac{z_i}{T}}}{\sum_{k=1}^{m} e^{\frac{z_k}{T}}},$$

where T is the temperature parameter.

Why Temperature?

- Increasing T makes the output distribution more uniform



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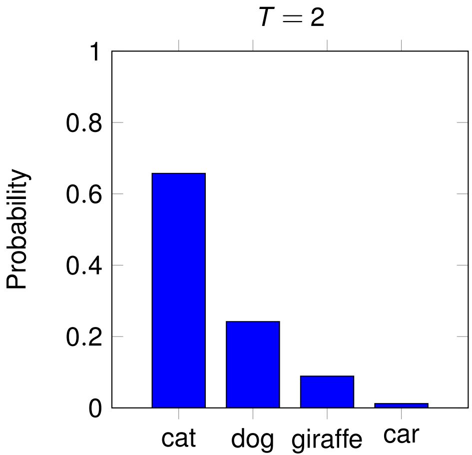

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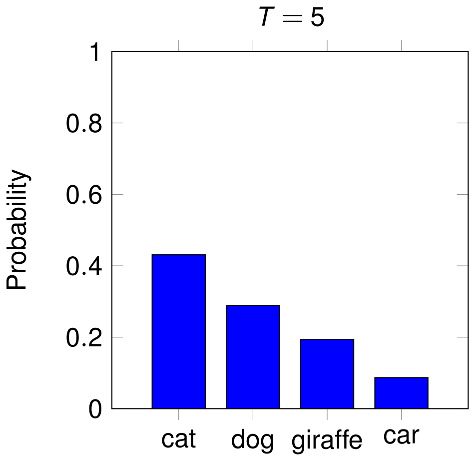

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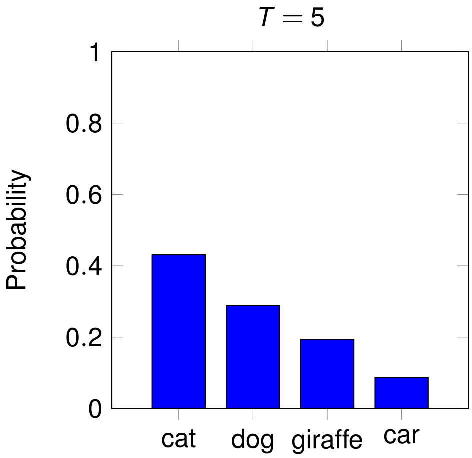

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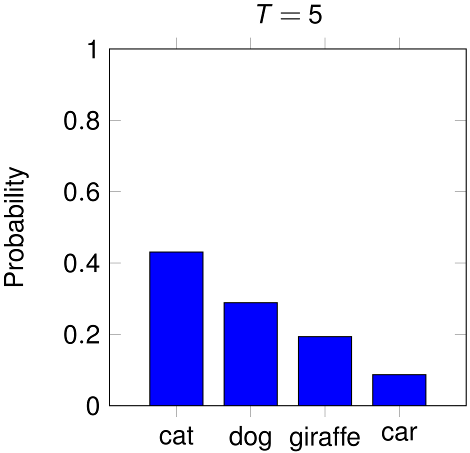

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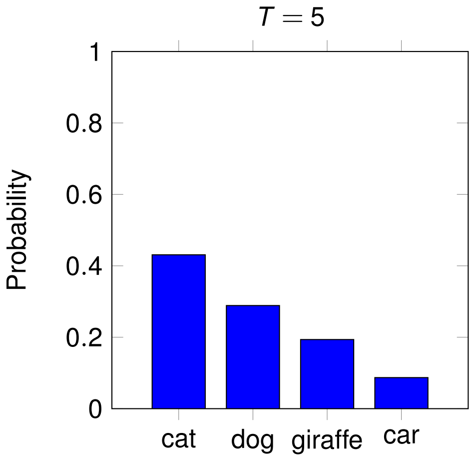
- A form of **regularization**!
- "Distillation" is refinement at high temperature (e.g., alcohol)



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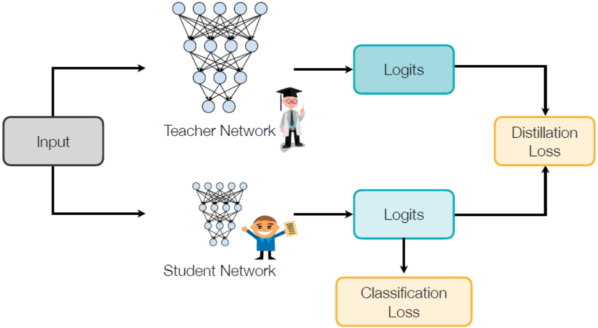
Student Training (1/2)

Let's define:

- Teacher output with $T > 1$: $\mathbf{y}_t$
- Student output with $T > 1$: $\mathbf{y}_s$
- Student output with $T = 1$: $\hat{\mathbf{y}}_s$
- Dataset label: $\mathbf{y}$



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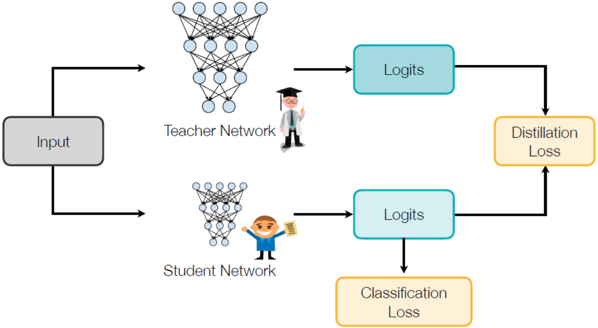

1. **Distillation loss:**
   - Kullback-Leibler divergence loss: $L_{\text{KL}}(\mathbf{y}_t, \mathbf{y}_s) = \mathbf{y}_t^\top \log\left(\frac{\mathbf{y}_t}{\mathbf{y}_s}\right)$

G. Hinton, O. Vinyals, J. Dean, "Distilling the Knowledge in a Neural Network," 2015.

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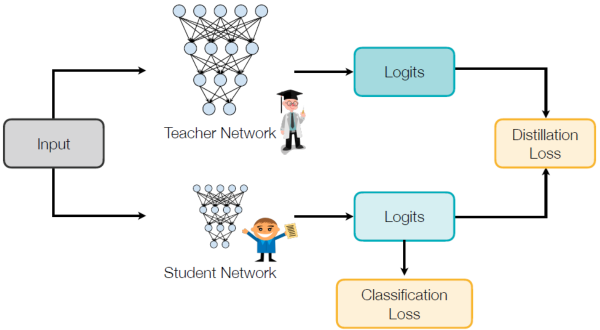

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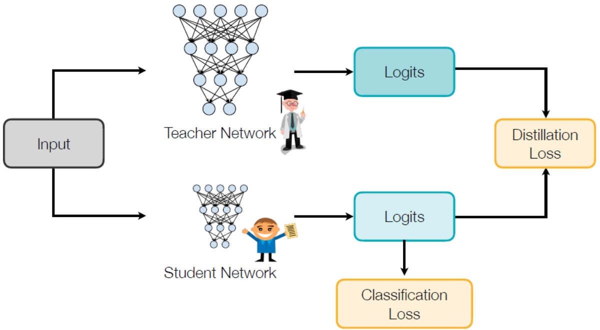

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2. **Classification loss:**
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Kullback-Leibler Divergence Loss vs Cross-Entropy Loss

- General relationship between KL and CE:

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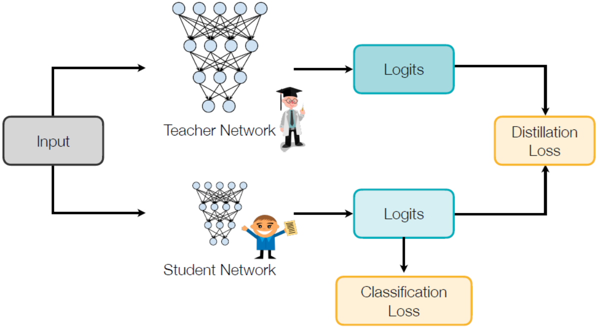
- In knowledge distillation, **y** are soft labels and $L_{\mathrm{KL}}(\mathbf{y},\hat{\mathbf{y}}) \neq L_{\mathrm{CE}}(\mathbf{y},\hat{\mathbf{y}})$
- **However:** $\frac{\partial H(\mathbf{y})}{\partial \hat{\mathbf{y}}} = 0$, so $L_{\mathrm{CE}}(\mathbf{y},\hat{\mathbf{y}})$ and $L_{\mathrm{KL}}(\mathbf{y},\hat{\mathbf{y}})$ are interchangeable for training!

Student Training (2/2)

Knowledge distillation:

1. Pre-train teacher
2. Fix teacher weights
3. Train student



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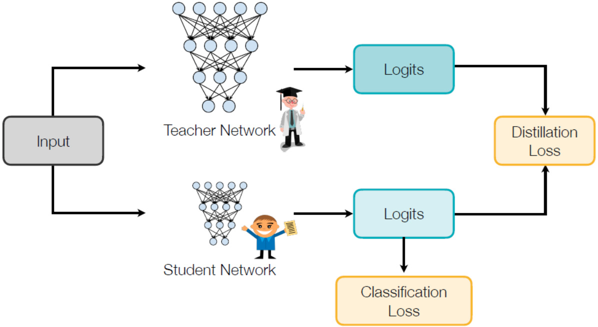

- **Student loss function:**

$$L(\mathbf{y}, \hat{\mathbf{y}}_s, \mathbf{y}_s, \mathbf{y}_t) = \alpha L_{\mathrm{CE}}(\mathbf{y}, \hat{\mathbf{y}}_s) + (1-\alpha) T^2 L_{\mathrm{CE}}(\mathbf{y}_t, \mathbf{y}_s), \quad \alpha \in [0, 1]$$

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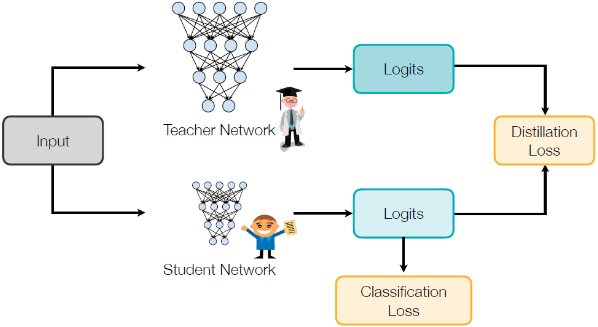

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- Due to the use of softmax$(\mathbf{z}, T)$, $L_{\text{CE}}(\mathbf{y}_t, \mathbf{y}_s)$ is T^2 times smaller than $L_{\text{CE}}(\mathbf{y}, \hat{\mathbf{y}}_s)$

G. Hinton, O. Vinyals, J. Dean, "Distilling the Knowledge in a Neural Network," 2015.

A Surprising Result

- **Experiment:** Remove all instances of “3” from the training set of the student

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A Surprising Result

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- **Result:** 87% of threes in the test set are classified correctly [1]!

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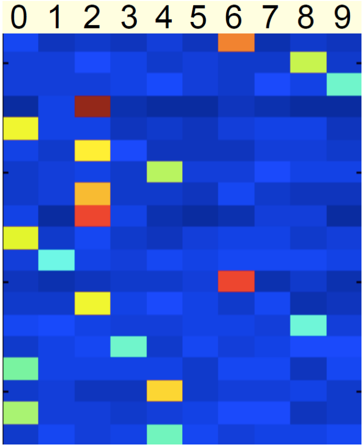
A Surprising Result

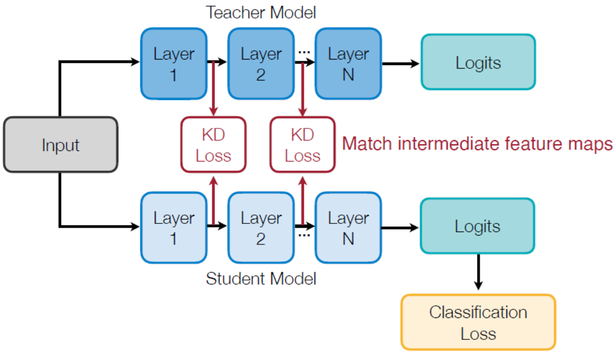
- **Experiment:** Remove all instances of “3” from the training set of the student
- **Result:** 87% of threes in the test set are classified correctly [1]!
- **How can this be?** The teacher’s “**dark knowledge**” [2] becomes accessible!



[1] G. Hinton, O. Vinyals, J. Dean, “Distilling the Knowledge in a Neural Network,” 2015.
[2] G. Hinton, O. Vinyals, J. Dean, “Dark knowledge,” TTIC Distinguished Lecture Series, 2014.

Matching Features

- **Distillation loss:** squared error/cross-entropy between teacher and student features



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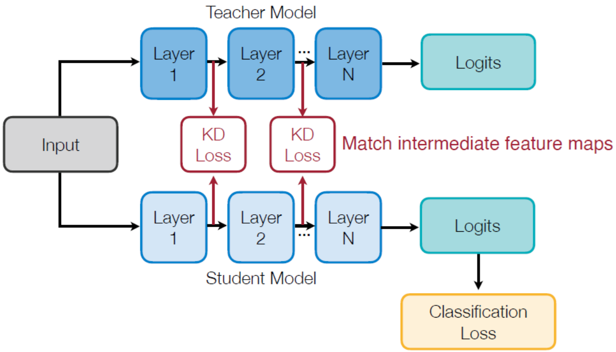

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- **Distillation loss:** squared error/cross-entropy between teacher and student features
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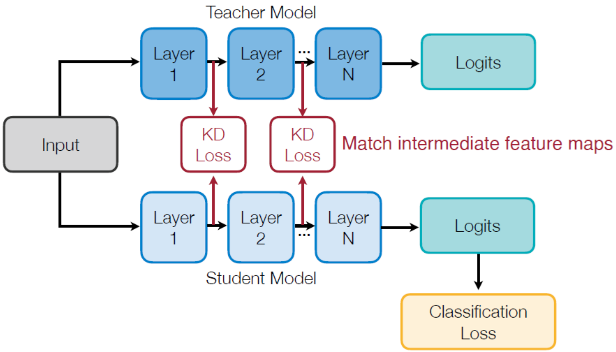

[1] A. Romero, N. Ballas, S. Ebrahimi Kahou, A. Chassang, C. Gatta, Y. Bengio, "FitNets: Hints for Thin Deep Nets," ICLR 2015

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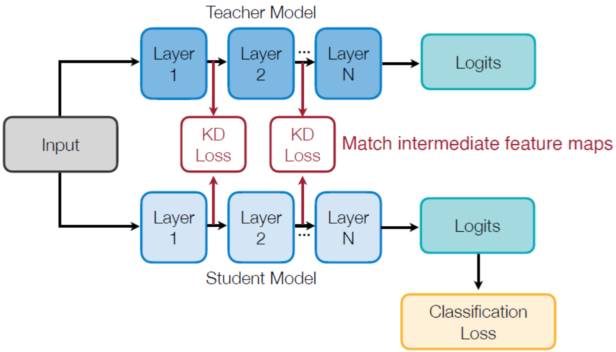

- It is also possible to match weights, gradients, sparsity patterns, and more [2]

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[2] J. Gou, B. Yu, S. J. Maybank, D. Tao, "Knowledge Distillation: A Survey," IJCV 2021

Online Distillation

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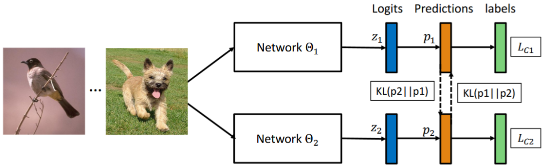

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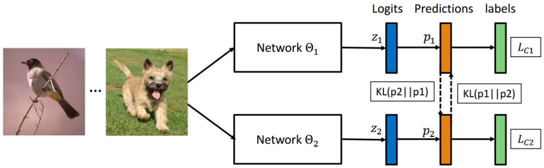

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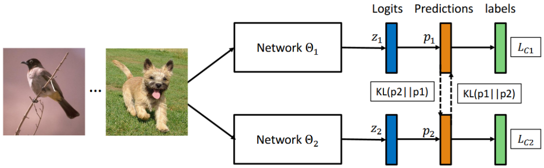

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	Net1	Net 2	Net 1	Net 2
CIFAR-100	WRN-28-10	ResNet-32	78.69	68.99
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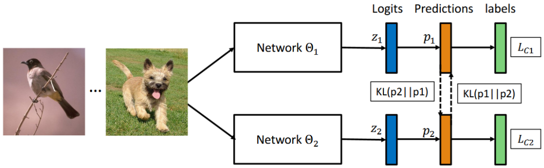

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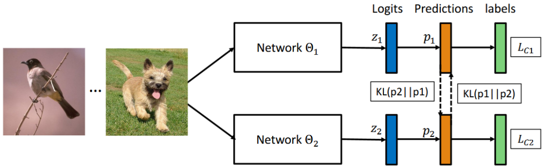

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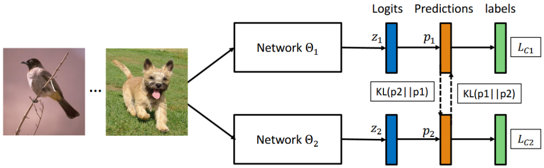

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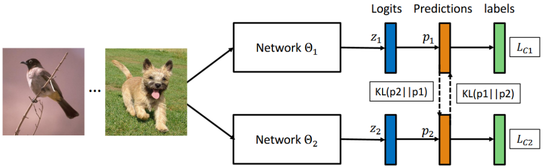

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- **Intuition:** Different prior knowledge (i.e., different initializations) → different soft labels

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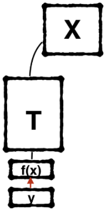
Self-Distillation

- A single neural network [1]:
    1. **Step 0**: train only on dataset



Step 0

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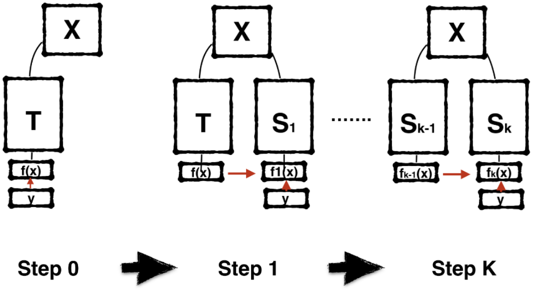

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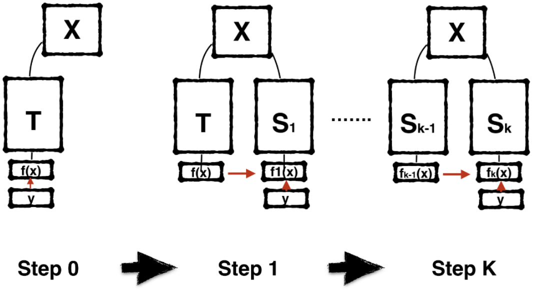
- A form of **self-regularization**!



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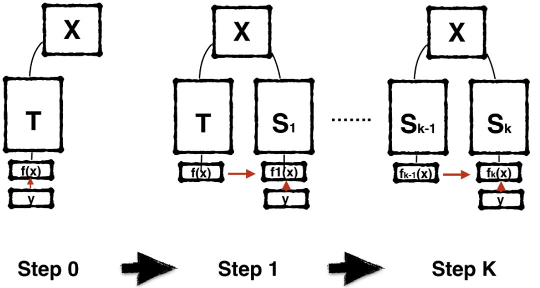

- A form of **self-regularization**!

- **Alternative:** Split network into parts, train early parts with output of later parts with KD

[1] T. Furlanello, Z. Lipton, M. Tschannen, L. Itti, A. Anandkumar, "Born Again Neural Networks," ICML 2018

Self-Distillation

- A single neural network [1]:
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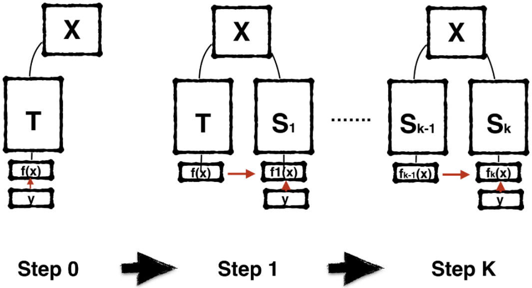

- A form of **self-regularization**!
- **Alternative:** Split network into parts, train early parts with output of later parts with KD
- **Advantage:** Can use only subset of network for performance-complexity trade-offs [2]

[1] T. Furlanello, Z. Lipton, M. Tschannen, L. Itti, A. Anandkumar, "Born Again Neural Networks," ICML 2018
[2] L. Zhang, J. Song, A. Gao, J. Chen, C. Bao, K. Ma, "Be Your Own Teacher: Improve the Performance of Convolutional Neural Networks via Self Distillation," ICCV 2019

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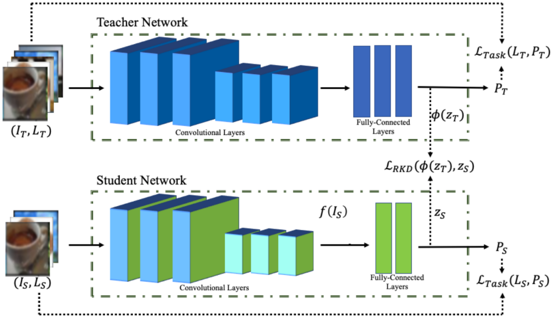

[1] L.-Y. Wang, A. Rhodes, W.-C. Feng, “Class Specialized Knowledge Distillation,” ACCV 2022

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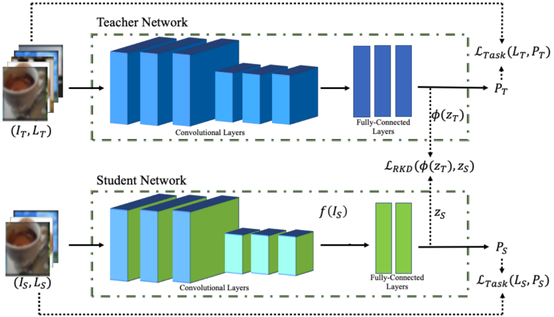

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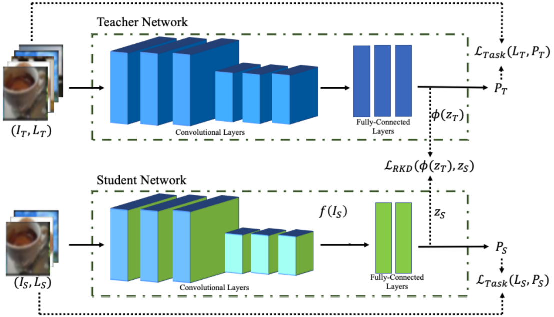

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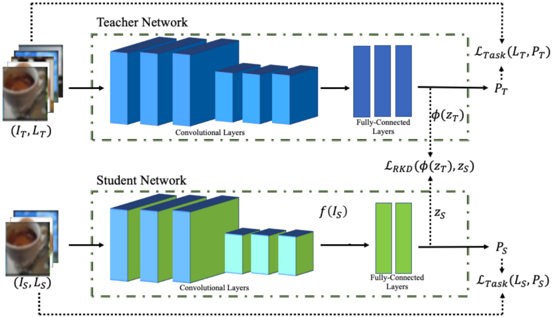

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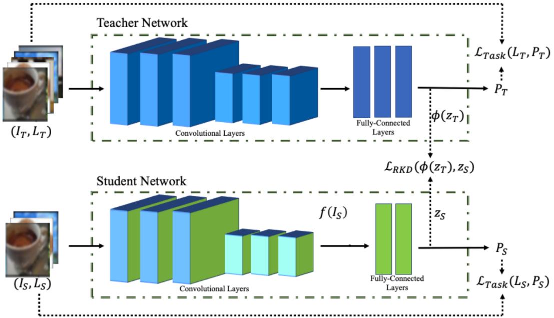

- Train with subset of dataset and all outputs? **Dark knowledge** uses student capacity!
- **Better solution:**
  1. Take a subset of teacher outputs z_T (denoted $\phi(z_T)$ in [1]) to align with z_S
  2. Renormalize $\phi(z_T)$ with temperature-based softmax and apply distillation loss

[1] L.-Y. Wang, A. Rhodes, W.-C. Feng, “Class Specialized Knowledge Distillation,” ACCV 2022

Conclusion

Summary:

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Next Time (After Carnival):

- NXP guest lecture (dr Willem Sandberg): Neural architecture search

TU/e