Knowledge Distillation

TODO: Reorganize the format
Knowledge distillation is the process of lossy transfer from a model to another while attempting to retain the accuracy and decreases model complexity.

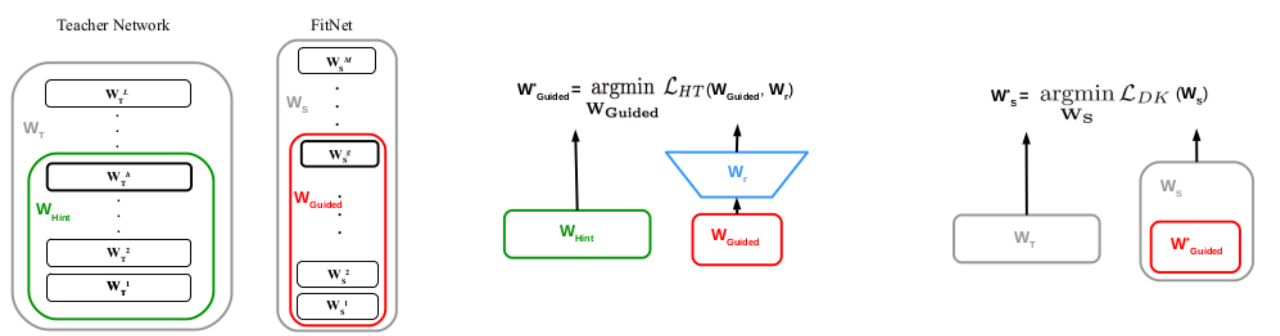
Papers

[Distilling the Knowledge in a Neural Network]()

- Distillation by training the student model with soft targets produced from teacher model
  - Soft targets are produced by increasing "Temperature" of the softmax function, Higher "Temperature" produces softer distributions
  - $q_i = \dfrac{exp(z_i/T)}{\sum_j exp(z_j/T)}$
- $L = \frac{T^2 CE(soft) + CE(hard)}{2}$

[FitNets: Hints for Thin Deep Nets]()

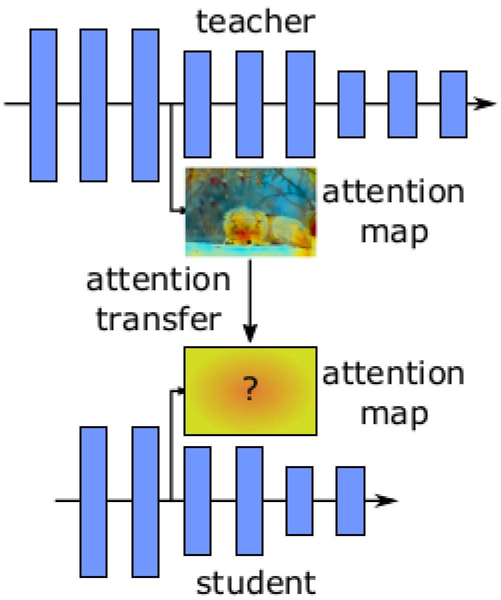
- Uses intermediate-level hints from the teacher hidden layers to guide the training process of the student

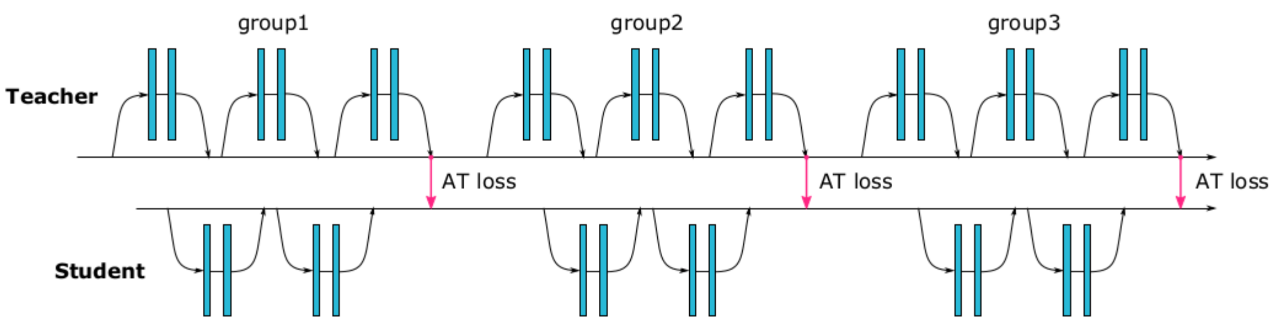


(a) Teacher and Student Networks (b) Hints Training (c) Knowledge Distillation

[Paying More Attention to Attention: Improving the Performance of CNN via Attention Transfer]()

- Uses Attention map (activation based and gradient based) to transfer knowledge





[A Gift From Knowledge Distillation: Fast Optimization, Network Minimization and Transfer Learning]

- Flow of solution procedure (FSP) captures relationship between feature maps from different layers. It is calculated using the inner product of features, similar to Gram matrix used for texture representation

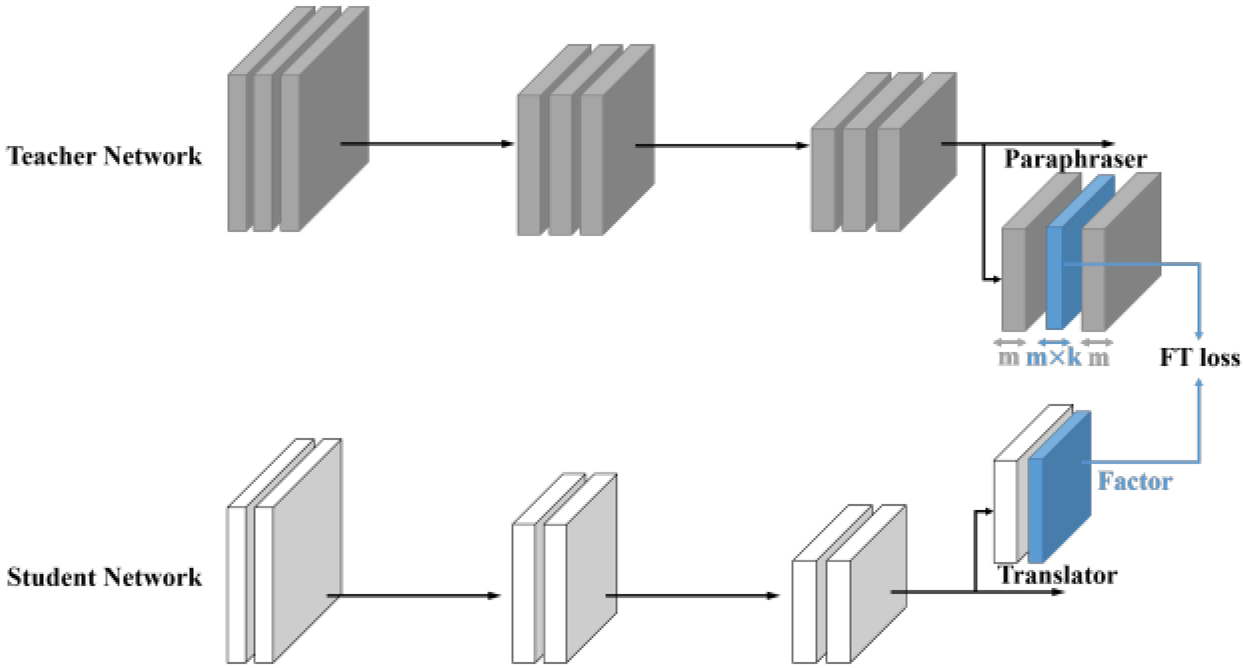
[Learning Deep Representations with Probabilistic Knowledge Transfer]

- Probabilistic KT(PKT): matching probability distributions of data within their respective feature spaces

[Paraphrasing Complex Network: Network Compression via Factor Transfer]

- Factor Transfer(FT): trains the student to replicate "factors", which are paraphrased knowledge extracted from the teacher network

- Paraphraser extracts "teacher factors" from the teacher using convolutional layers
- Translator extracts "student factors" and mimics the teacher factors



- Limitations:
  - additional parameters

[Knowledge Transfer via Distillation of Activation Boundaries Formed by Hidden Neurons]

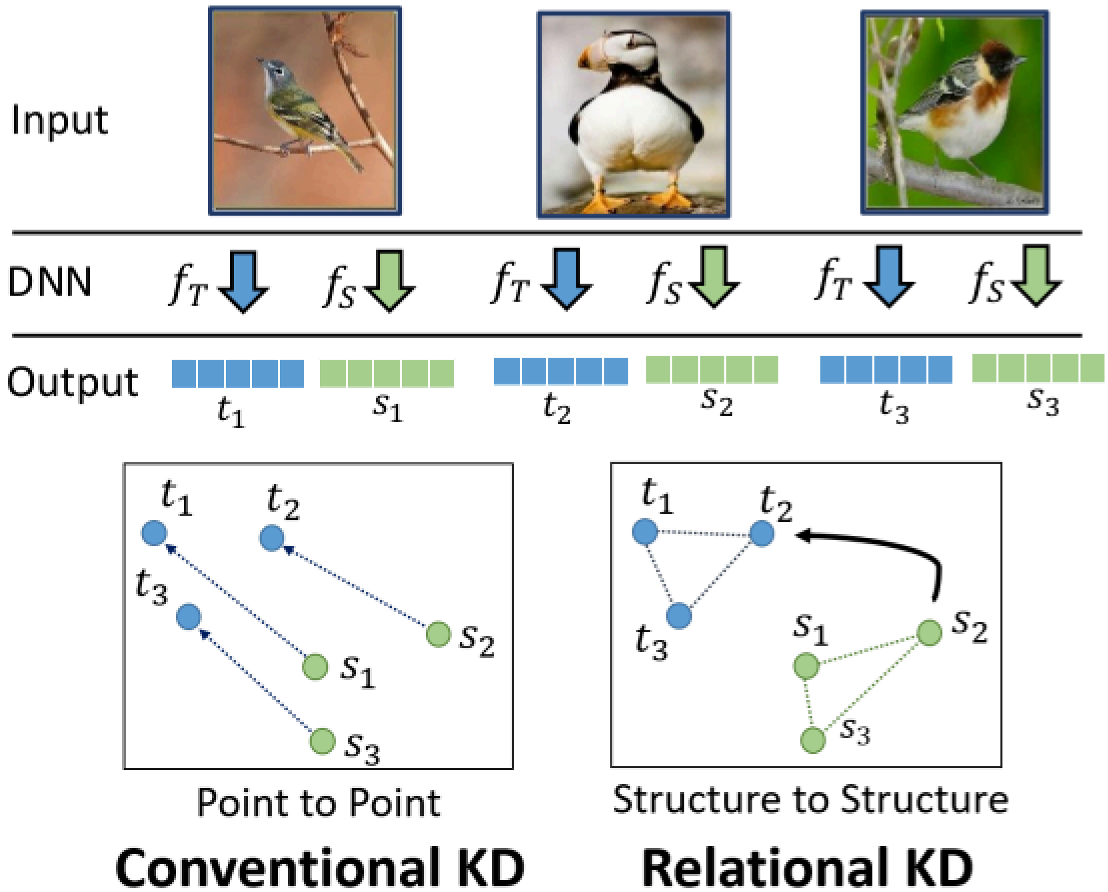
- Distilling the activation boundaries formed by the hidden neurons in a teacher network to a student network
- Activation Transfer Loss: minimizes the difference in neuron activations between teacher and student, regardless of the magnitude of the response
- Piecewise Differentiable Loss: To overcome the non-differentiability of the activation transfer loss, a hinge loss-inspired alternative loss is proposed, enabling gradient-based optimization

[Knowledge Adaptation for Efficient Semantic Segmentation]

- Distillation for Semantic Segmentation
- Efficiency-Accuracy Trade-off: Reducing feature map resolution via subsampling increases efficiency but compromises accuracy
- Knowledge Translation: A pre-trained autoencoder rephrases the teacher's knowledge into a compact representation

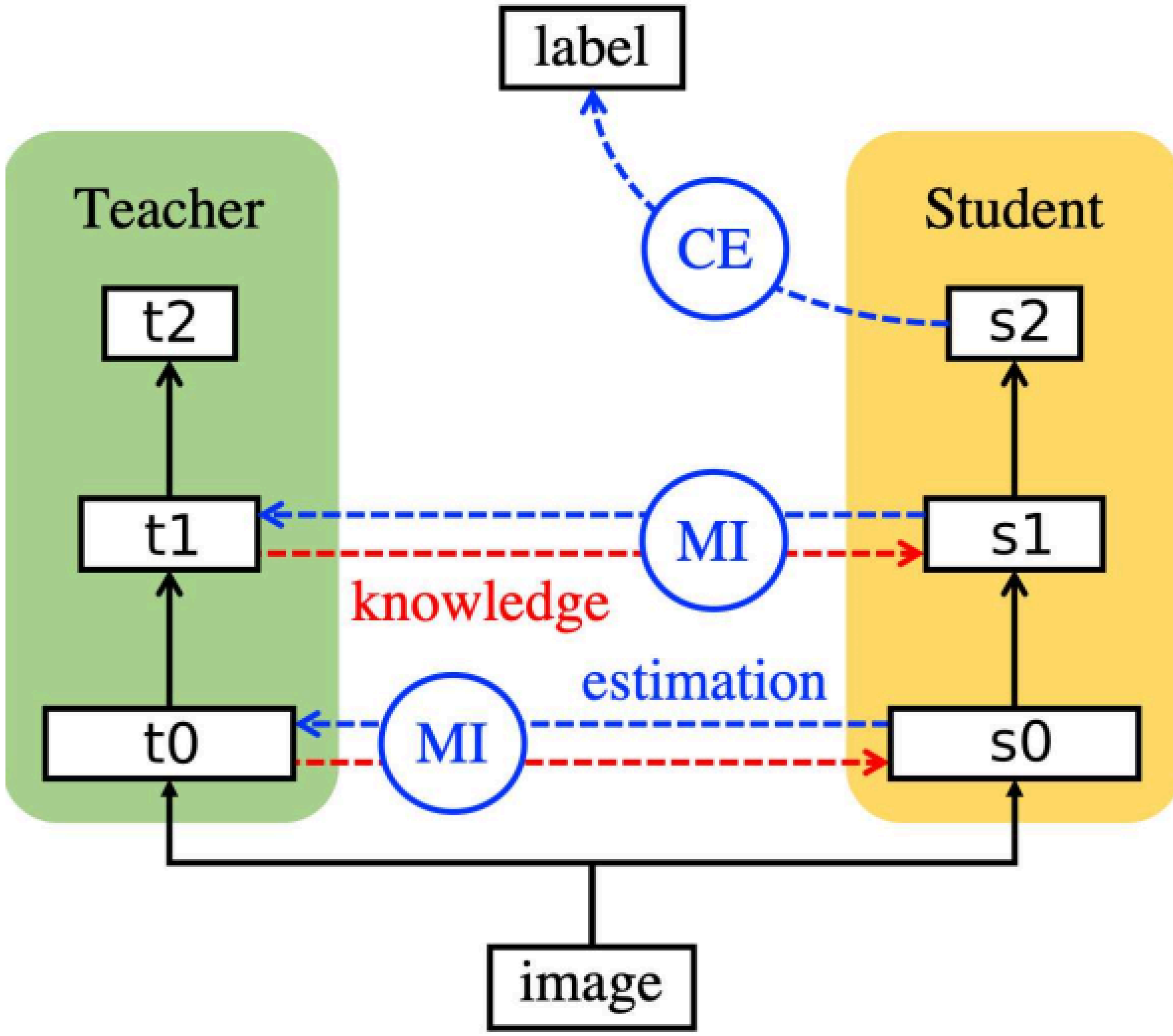
[Relational Knowledge Distillation]*

- Relational Knowldge Distillation (RKD): Transfer mutual relations of data examples instead with distance-wise and angle-wise distillation losses that penalize structural differences



Variational Information Distillation for Knowledge Transfer

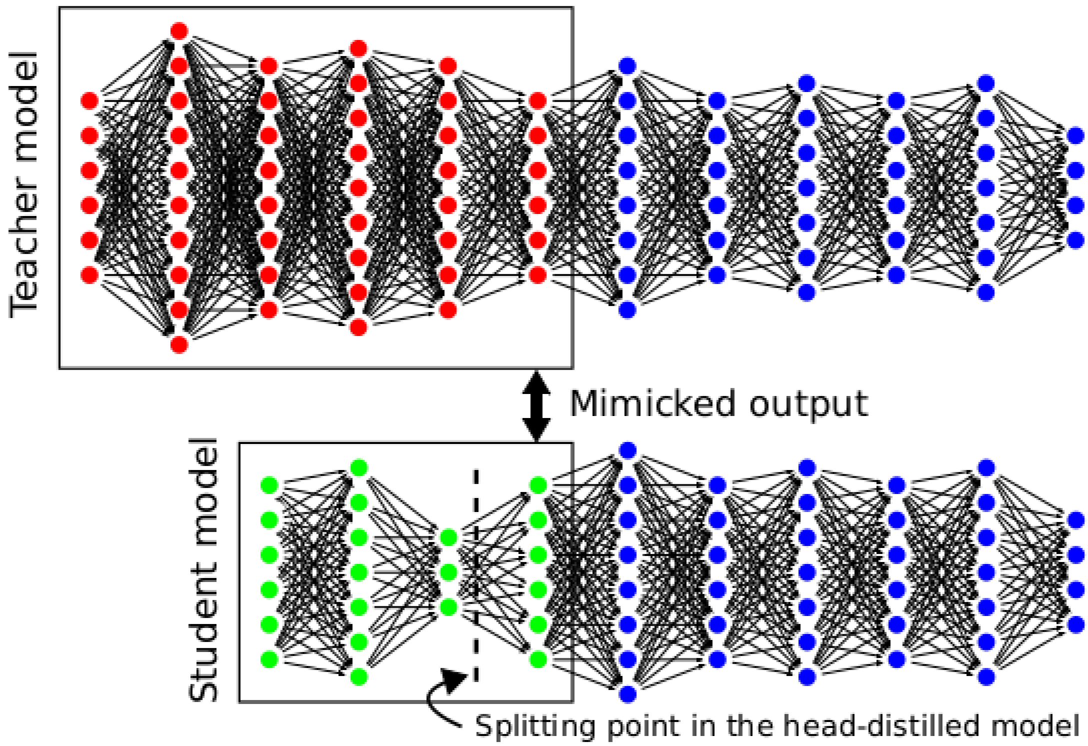
- Minimizing CE loss while retaining high mutual Information (MI) with the teacher network.
    - MI is maximized by learning to estimate the distribution of the activations in the teacher network



Distilled Split Deep Neural Networks for Edge-Assisted Real-Time Systems

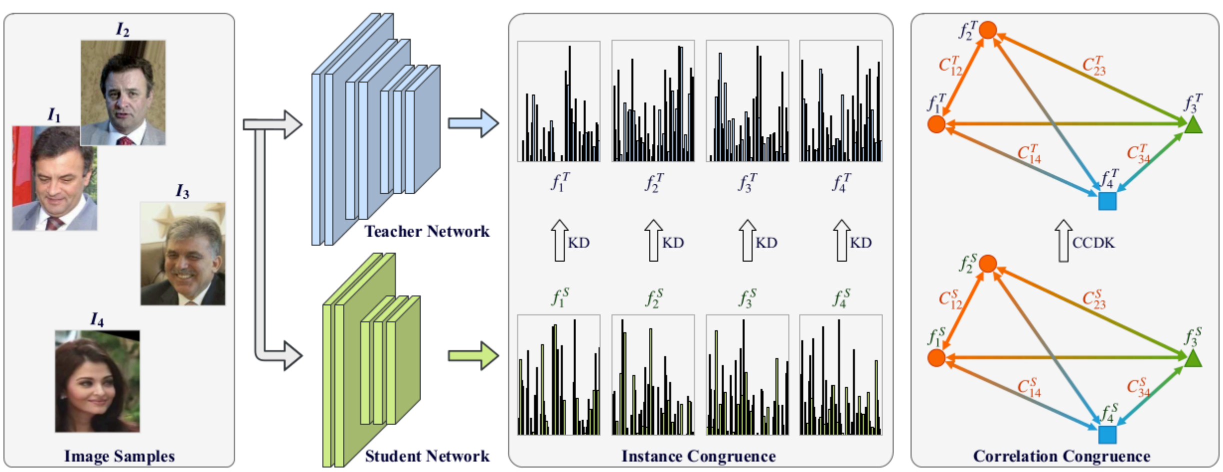
- Split DNN models into head and tail models, where the two sections are deployed at the mobile device and edge servers

- The head model is distilled from the teacher model to mimic its output



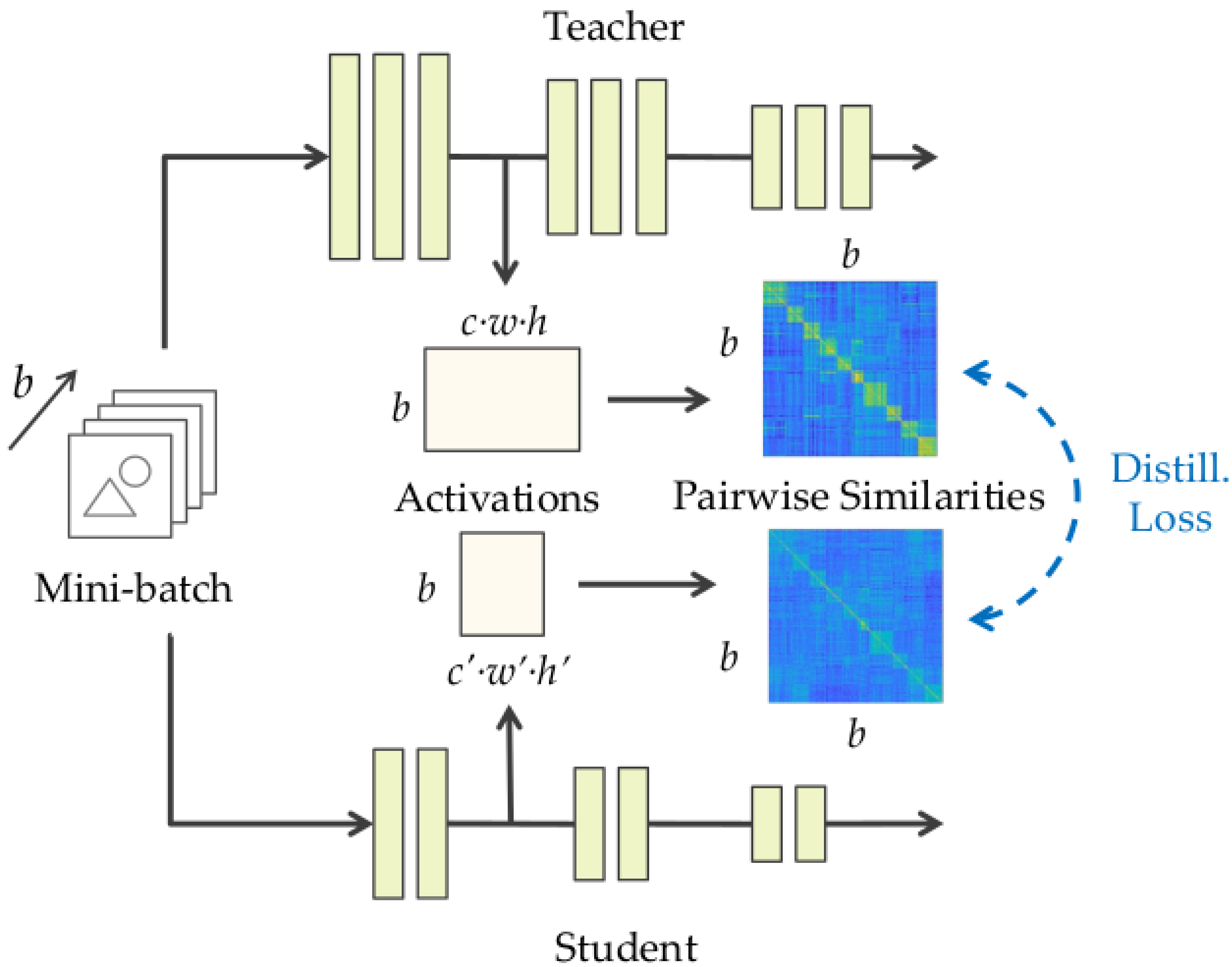
Correlation Congruence for Knowledge Distillation

- CCKD: Transfers not only the instance-level in formation but also the correlation between instances
  - by introducing a correlation congruence constraint, it aims to match the correlation matrix of the student network's feature representations with that of the teacher netowork



Similarity-Preserving Knowledge Distillation

- Preserve the pairwise similarities derived from the activations of the teacher and student networks for a given mini-batch of inputs



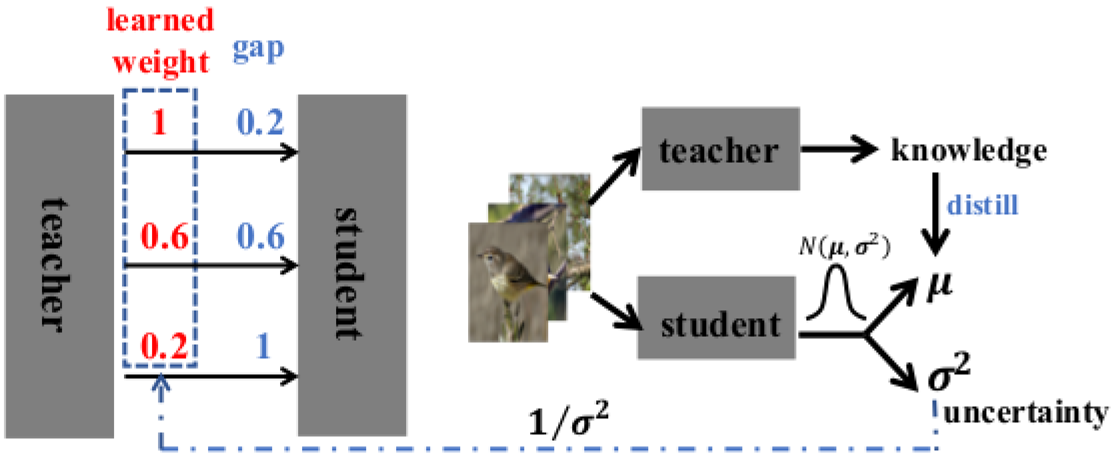
Contrastive Representation Distillation

- Transferring structural knowledge between teacher and student models by maximizing the mutual information between their representations
  - maximizing a lower bound on the mutual information between teacher and student representations

Prime-Aware Adaptive Distillation

- Learn from the obvious
- Hard samples have detrimental effect on the training of the student model
- Modeling knowledge distillation with data uncertainty (the student model Generates a mean a.k.a. the prediction and a variance, the lower the variance the higher the confidence hence

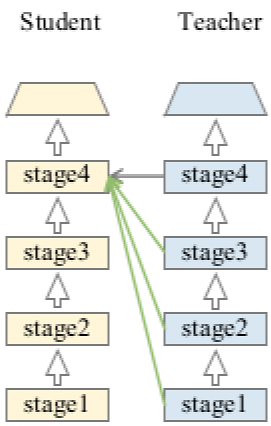
the prime samples are assigned larger learned weights)



Prime-Aware Adaptive Distillation

Distilling Knowledge via Knowledge Review

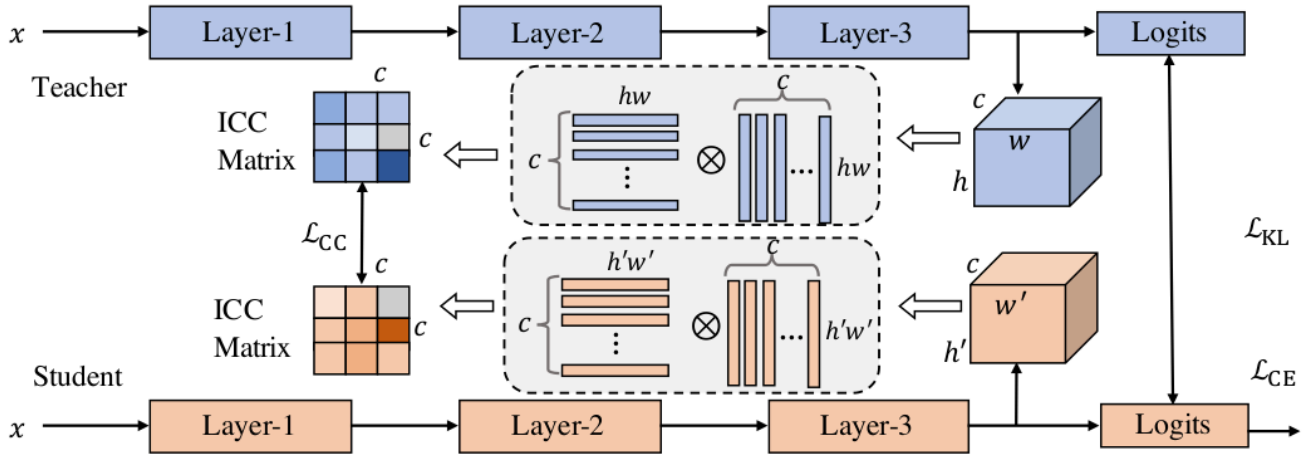
- Use low-level features in the teacher network to supervise deeper features for the student



- Attention Based Fusion (ABF): Dynamically aggregates features from different levels using attention maps, enabling adaptive integration of diverse information
- Hierarchical Context Loss (HCL): Employs spatial pyramid pooling to distill knowledge at different levels of contextual abstraction, facilitating more comprehensive knowledge transfer

Exploring Inter-Channel Correlation for Diversity-Preserved Knowledge Distillation

- Student mimics teacher's ICC matrix



Knowledge Distillation from A Stronger Teacher

- Proposes to preserve the relations between predictions rather than matching the exact values
  - Uses Pearson correlation coefficient as a metric to measure the relationship between the teacher and student predictions
  - preserving the preference by the teacher, instead of recovering the absolute values accurately

Understanding the Role of the Projector in Knowledge Distillation

- Projection layer, often used for dimension matching, plays a much more crucial role in KD
- While larger projectors can theoretically encode more information, they tend to decorrelate input-output features, potentially harming the distillation process.

Logit Standardization in Knowledge Distillation

- Shared Temperatures have its limitations:
  - forces the student to match the teacher's logits precisely, hindering the student's ability to learn within its capacity constraints
  - lead to misleading evaluations of student performance
- Z-score Logit Standardization applies to both teacher and student logits before the softmax function
  - Allows the student to learn and preserve the relative relationships between logits without requiring a strict magnitude match

#TrainingStrategy