A Variational Bayesian Approach to Learning Latent Variables for Acoustic Knowledge Transfer

Hu Hu[1], Sabato Marco Siniscalchi[1,2], Chao-Han Huck Yang[1], Chin-Hui Lee[1]

[1]School of Electrical and Computer Engineering , Georgia Institute of Technology
[2]Computer Engineering School, University of Enna Kore

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Outline

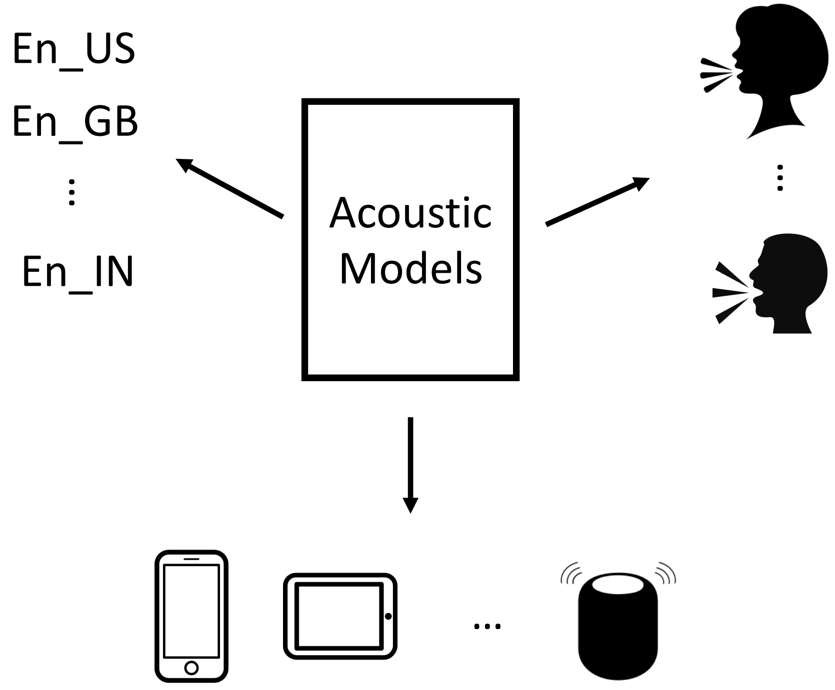
- Introduction
  - ➢ Acoustic mismatches and knowledge transfer
- Bayesian Adaptive Learning
  - ➢ Bayesian adaptive learning framework
  - ➢ Bayesian adaptation for speech processing systems
  - ➢ Challenges of Bayesian Adaptation for Deep Models
- Variational Bayesian Knowledge Transfer
  - ➢ Bayesian inference of deep latent variables
  - ➢ Variational Bayes based adaptive learning
  - ➢ Experimental evaluation

Acoustic Variabilities and Mismatches

- In production, acoustic models need to deal with different application scenarios.

- Acoustic variabilities:
  - ➢ Speakers: genders, accents, …
  - ➢ Recording devices: handsets, channels, …
  - ➢ Recording environments: scenes, noise types, reverberations, …
  - ➢ ….

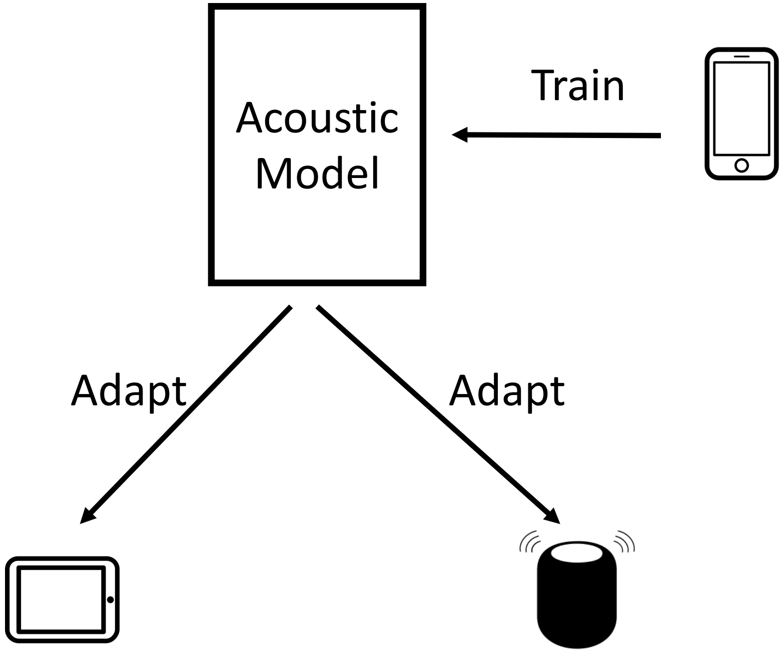
- Acoustic mismatches usually cause severe degradation in diverse testing conditions.
- Effective adaptation algorithms are required.



Acoustic Knowledge Transfer

- Acoustic knowledge transfer:
  - Transfer knowledge from the source acoustic domain to the target ones related to testing conditions.
  - It is also referred to as the supervised domain adaptation.

- An example of device adaptation
  - Trained by data from iPhone (Source domain).
  - Adapted to iPad and HomePod (Target domains).



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Bayesian Adaptive Learning Framework

- Bayes' theory:

$$p(\lambda|\mathcal{D}) = \frac{p(\mathcal{D}|\lambda)p(\lambda)}{p(\mathcal{D})}$$

  - λ: model parameters; D: data; S: source domain; T: target domain.

- For adaptation setups:
  - Prior knowledge learnt from the source domain is encoded in prior distribution:

$$p(\lambda_T) = p(\lambda_S|\mathcal{D}_S)$$

  - The target domain posterior distribution:

$$p(\lambda_T|\mathcal{D}_T) = \frac{p(\mathcal{D}_T|\lambda_T)p(\lambda_S|\mathcal{D}_S)}{p(\mathcal{D}_T)}$$

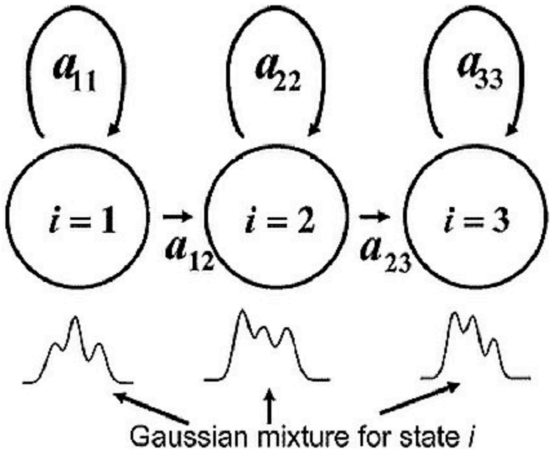
- The posterior is usually intractable and difficult to get.
  - An approximation is required: Maximum a posteriori (MAP), Variational Bayes (VB), …

MAP for GMM-HMM based ASR

- MAP shows good performance for GMM-HMM based ASR system to handle acoustic mismatches [Gauvian, 1994; Lee, 2000].

$$\lambda_T^* = \underset{\lambda_T}{argmax}\, p(\lambda_T|\mathcal{D}_T) = \underset{\lambda_T}{argmax}\, p(\mathcal{D}_T|\lambda_T)p(\lambda_T)$$

- Example: GMM and HMM parameters with conjugated prior distributions:
  - ➢ HMM parameters: Dirichlet distribution.
  - ➢ GMM parameters: Normal-Wishart distribution.



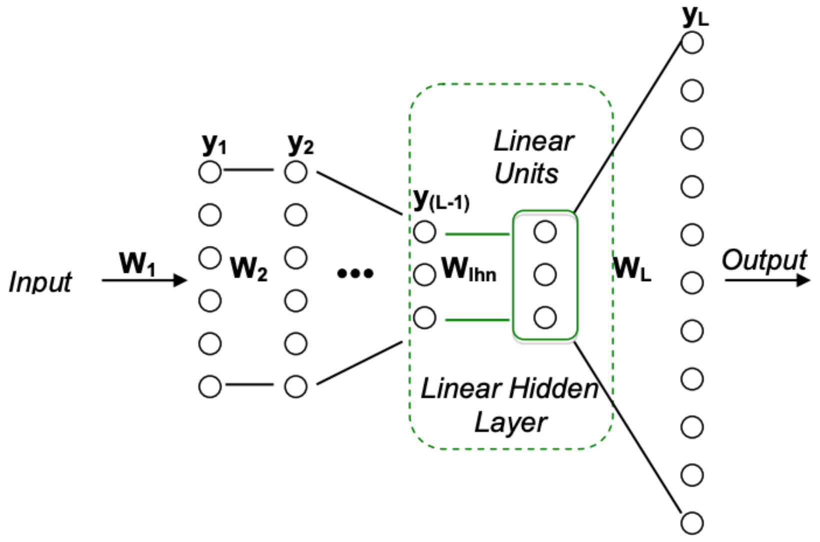
The GMM-HMM system.

MAP for DNN-HMM based ASR

- MAP also shows good performance for DNN-HMM based ASR system for speaker adaptation [Huang, 2015; Huang 2017].

- Linear hidden network (LHN) is used to cast Bayesian assumption.

$$Loss_{MAP} = -\log p(\mathcal{D}_T|W) - \alpha \log p(W_{lhn})$$



DNN with linear hidden layer.

Challenges of Bayesian Adaptation for Deep Models

- Traditional Bayesian approaches usually focus on model parameters.
  - It works well for traditional statistic models like HMM, GMM, SVM, …

- For DNN, we have much more parameters than training samples.
  - # of para. >> # of data dimension * # of data [Sebastien, 2021].
  - Especially for the adaptation scenarios.

- Challenges and problems:
  - Difficult to get accurate estimations of model parameters by Bayesian approaches.
  - Curse of dimensionality.

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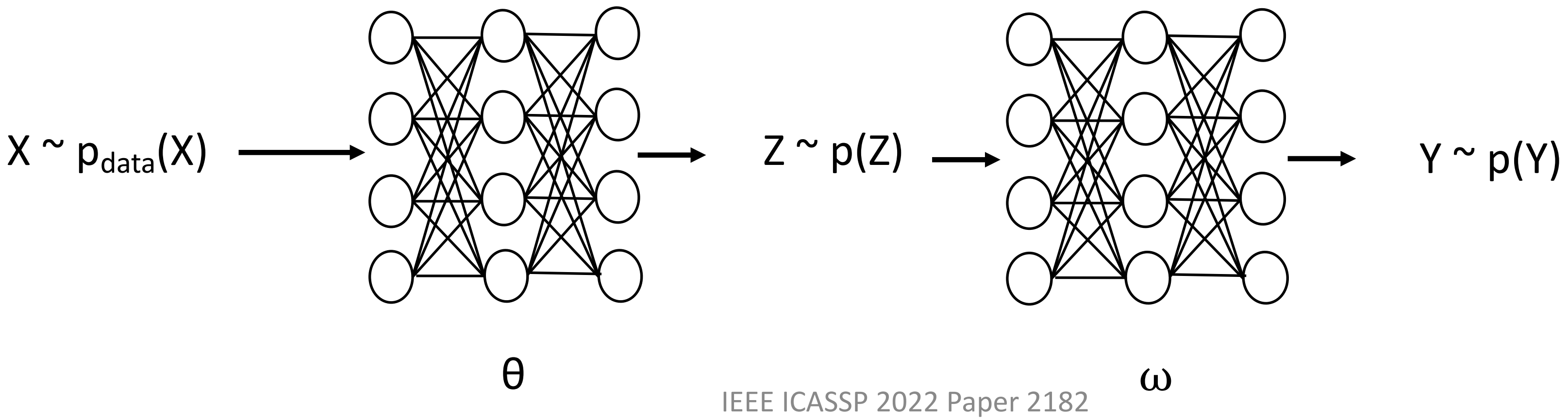
- Variational Bayesian Knowledge Transfer
  - ➢ Bayesian inference of deep latent variables
  - ➢ Variational Bayes based adaptive learning
  - ➢ Experimental evaluation

Deep Latent Variables

- We propose to perform Bayesian adaptive learning on **deep latent variables** rather than on DNN weights.
  - An unobservable representation of data, corresponding to intermediate hidden embedding from a specific layer of DNN.

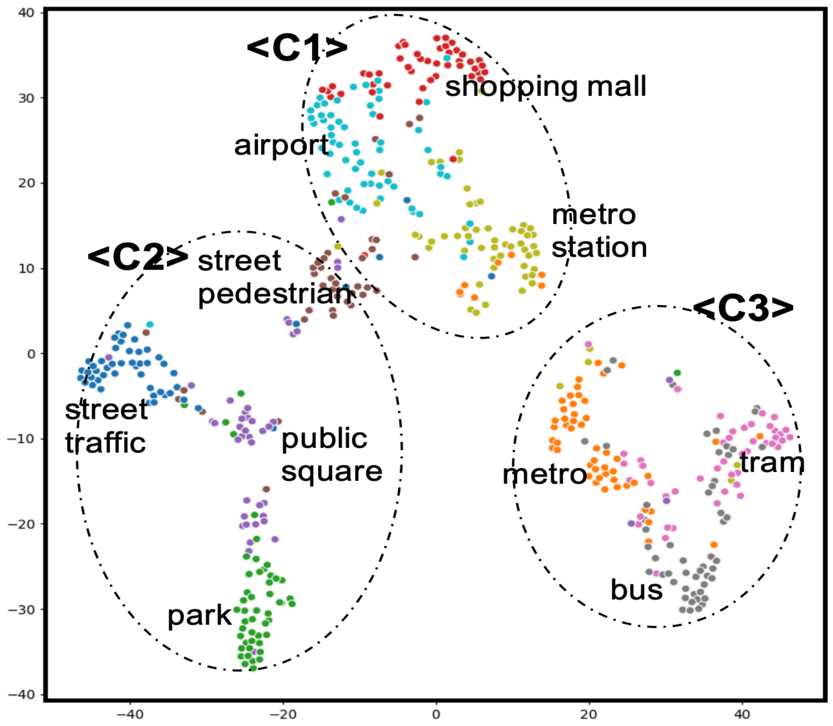
- An example of deep latent variables.
  - ➢ Z indicates the deep latent variables.
    - ➢ Prior: p(Z); Posterior: p(Z|X).
  - ➢ We decouple DNN weights to θ and ω.



Deep Latent Variables (Cont'd)

- Acoustic scene model embedding.
  - ➢ 10 different scene classes:
    - o Airport, metro, …
  - ➢ 3 general classes C1-C3:
    - o Indoor, outdoor, transportation.
  - ➢ Hidden embedding is generated by a DNN model and reduced to 2 dimensions.

- Deep latent variable has its own distribution form.
- Deep latent variable encodes structural relationships.

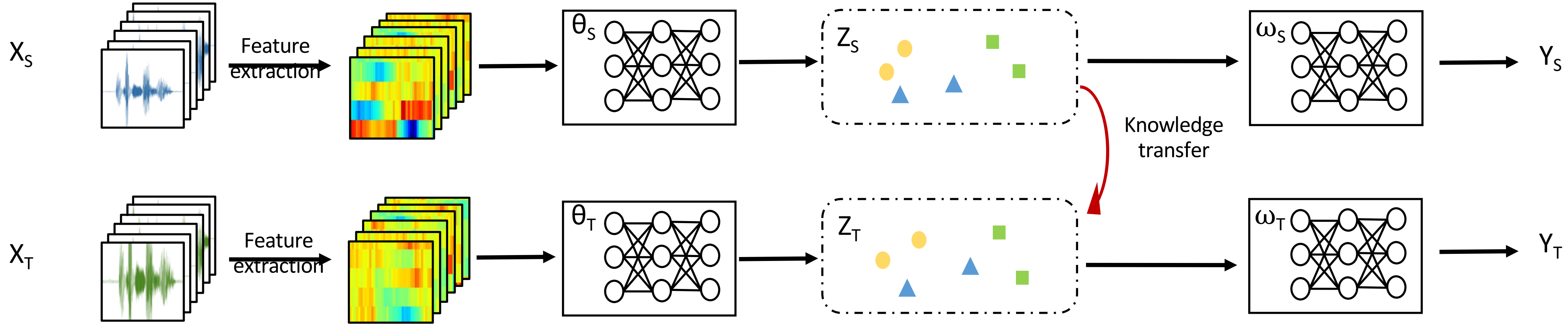


A visualization of deep latent variables [Hu, 2020].

Bayesian Inference of Deep Latent Variables

- Latent variables are introduced in addition to DNN weights.

$$p(\lambda) = p(Z, \theta, \omega) = p(Z|\theta)p(\theta)p(\omega)$$



Bayesian Inference of Deep Latent Variables (Cont'd)

- Prior knowledge for target model is learnt from the source domain

$$p(Z_T|\theta_T) = p(Z_S|\theta_S, \mathcal{D}_S)$$

- Posterior with latent variables:

$$p(\lambda_T|\mathcal{D}_T) = \frac{p(\mathcal{D}_T|\lambda_T)p(\theta_T)p(\omega_T)p(Z_S|\theta_S, \mathcal{D}_S)}{p(\mathcal{D}_T)}$$

- Variational Bayes (VB) based estimation way
  - Perform a distribution estimation to obtain the full posterior.

Variational Bayes based Adaptive Learning

- Set a variational distribution to approximate the real distribution.
- Minimize the KLD between them, by

$$q^*(\lambda_T|\mathcal{D}_T) = \underset{q \in \mathcal{Q}}{argmin}\, \mathtt{KL}(q(\lambda_T|\mathcal{D}_T) \parallel p(\lambda_T|\mathcal{D}_T))$$

- Get a full VB expression with Z, θ and ω.
  - ➢ By taking a *non-informative prior* over θ and ω, we can arrive at the variational lower bound:

$$\mathcal{L}(\lambda_T; \mathcal{D}_T) = \mathbb{E}_{Z_T \sim q(Z_T|\theta_T, \mathcal{D}_T)} \log p(\mathcal{D}_T|Z_T, \theta_T, \omega_T) - \mathtt{KL}(q(Z_T|\theta_T, \mathcal{D}_T) \parallel p(Z_T|\theta_T))$$

Variational Bayes based Adaptive Learning (Cont'd)

- Gaussian mean-field variational inference (GMFVI) estimation is used:
  - Each hidden embedding is assumed to be sampled from individual Gaussians:

$$q(Z|\theta, \mathcal{D}) = \prod_{i}^{N_T} \mathcal{N}(Z^{(i)}; \mu^{(i)}, (\sigma^{(i)})^2 \boldsymbol{\mathcal{I}})$$

  - Final learning objective:

$$\mathcal{L}(\lambda_T; \mathcal{D}_T) = \sum_{i}^{N_T} \mathbb{E}_{z_T^{(i)} \sim \mathcal{N}(\mu_T^{(i)}, \sigma^2)} \log p(y_T^{(i)} | x_T^{(i)}, z_T^{(i)}, \theta_T, \omega_T) - \frac{1}{2\sigma^2} \sum_{i}^{N_T} \| \mu_T^{(i)} - \mu_S^{(i)} \|_2^2$$

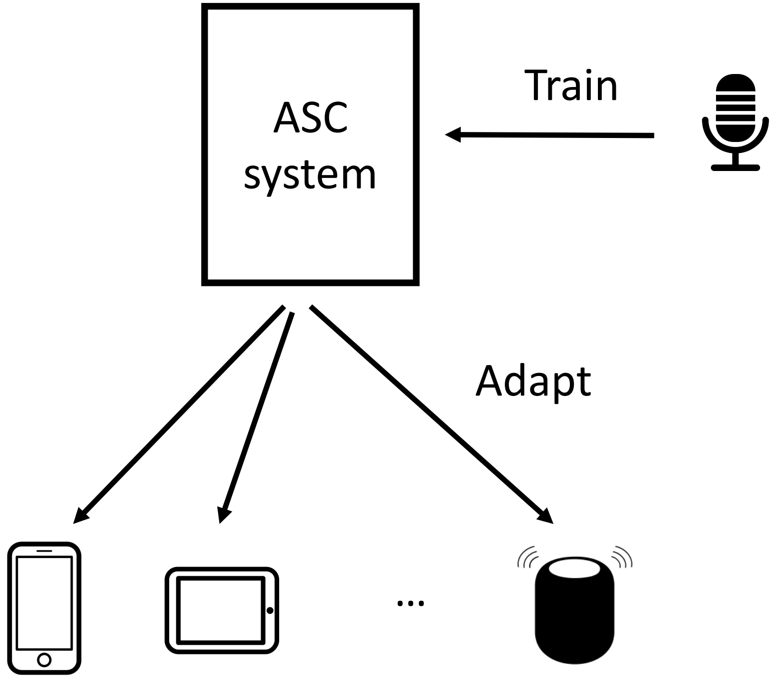
Experimental Setup of Acoustic Scene Classification

- Data set: DCASE 2020 ASC data set.
  - Code available: https://github.com/MihawkHu/ASC_Knowledge_Transfer

- Source domain data:
  - ➢ Recorded by a Zoom F8 audio recorder.
  - ➢ ~10K training audio clips.

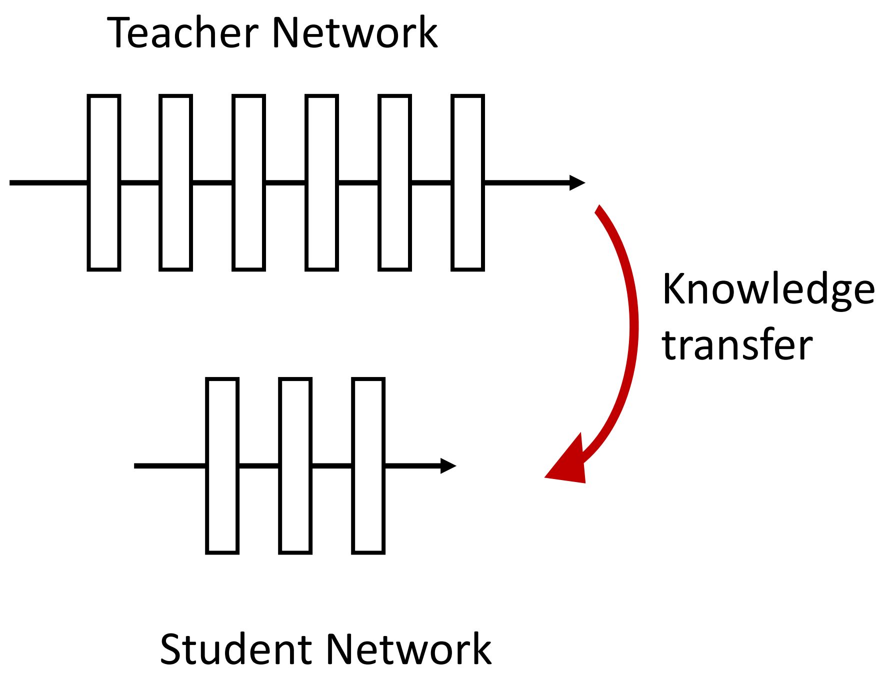
- Target domain data:
  - ➢ Recorded by 8 different devices:
    - o iPhone SE, Samsung Galaxy S7, …
  - ➢ Each has 750 training audio clips.

- Two state-of-the-art models [Hu, 2020] are used: RESNET and FCNN.



Teacher-Student Learning Family

- Teacher-student learning (TSL) is used as a comparison.
  - ➢ Transfers knowledge from the teacher network to the student network.
  - ➢ The basic approach is to minimize the KLD between outputs of teacher model and student model.



- Point estimation vs. distribution estimation.

Teacher-Student Learning Family (Cont'd)

- 13 recent cut-edging knowledge transfer methods compared in our experiments:
  - TSL: Teacher-student learning [Li, 2014; Hinton, 2015].
  - NLE: Neural label embedding [Meng, 2020].
  - Fitnets: Hints for thin nets [Romero, 2014].
  - AT: Attention transfer [Zagoruyko, 2016].
  - AB: Activation boundaries [Heo, 2019].
  - VID: Variational information distillation [Ahn, 2019].
  - FSP: Flow of solution procedure [Yim, 2017].
  - COFD: Comprehensive overhaul feature distillation [Heo, 2019].
  - SP: Similarity preserving [Tung, 2019].
  - CCKD: Correlation congruence knowledge distillation [Peng, 2019].
  - PKT: Probabilistic knowledge transfer [Passalis, 2018].
  - NST: Neuron selectivity transfer [Huang, 2017].
  - RKD: Relational knowledge transfer [Park, 2019].

- All above are implemented and compared. Some are presented in the next few slides.

Experimental Results on Acoustic Scene Classification (1/5)

Method	RESNET avg% ± std	FCNN avg% ± std
Source.	37.70	37.13
No transfer	54.29 ± 0.76	49.97 ± 2.70
One-hot	63.76 ± 0.59	64.45 ± 0.51
TSL	68.04 ± 0.34	66.27 ± 0.46
NLE	65.64 ± 0.53	64.47 ± 0.59
AT	63.73 ± 0.81	64.16 ± 0.49
SP	64.57 ± 0.76	65.74 ± 0.37
RKD	65.28 ± 0.81	65.63 ± 0.22
VBKT-GMFVI	**69.58 ± 0.49**	**69.96 ± 0.13**

- Accuracies on source device data:
  - RESNET: 79.09 %, FCNN: 79.70 %.

Experimental Results on Acoustic Scene Classification (2/5)

Method	RESNET avg% $\pm$ std	FCNN avg% $\pm$ std
Source.	37.70	37.13
No transfer	54.29 ± 0.76	49.97 ± 2.70
One-hot	63.76 ± 0.59	64.45 ± 0.51
TSL	68.04 ± 0.34	66.27 ± 0.46
NLE	65.64 ± 0.53	64.47 ± 0.59
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VBKT-GMFVI	$\mathbf{69.58 \pm 0.49}$	$\mathbf{69.96 \pm 0.13}$

- Accuracies on source device data:
  - RESNET: 79.09 %, FCNN: 79.70 %.
- Device mismatches causes huge degradations when directly applying the source model.

Experimental Results on Acoustic Scene Classification (3/5)

Method	RESNET avg% ± std	FCNN avg% ± std
Source.	37.70	37.13
No transfer	54.29 ± 0.76	49.97 ± 2.70
One-hot	63.76 ± 0.59	64.45 ± 0.51
TSL	68.04 ± 0.34	66.27 ± 0.46
NLE	65.64 ± 0.53	64.47 ± 0.59
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RKD	65.28 ± 0.81	65.63 ± 0.22
VBKT-GMFVI	$\mathbf{69.58 \pm 0.49}$	$\mathbf{69.96 \pm 0.13}$

- Accuracies on source device data:
  - RESNET: 79.09 %, FCNN: 79.70 %.
- Device mismatches causes huge degradation when directly applying the source model.
- Fine-tuning with target data can help ease the mismatch issue.

Experimental Results on Acoustic Scene Classification (4/5)

Method	RESNET avg% ± std	FCNN avg% ± std
Source.	37.70	37.13
No transfer	54.29 ± 0.76	49.97 ± 2.70
One-hot	63.76 ± 0.59	64.45 ± 0.51
TSL	68.04 ± 0.34	66.27 ± 0.46
NLE	65.64 ± 0.53	64.47 ± 0.59
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VBKT-GMFVI	**69.58 ± 0.49**	**69.96 ± 0.13**

- Accuracies on source device data:
  - RESNET: 79.09 %, FCNN: 79.70 %.
- Device mismatches causes huge degradation when directly applying the source model.
- Fine-tuning with target data can help ease the mismatch issue.
- Knowledge transfer algorithms show advantages over simply fine-tuning.

Experimental Results on Acoustic Scene Classification (5/5)

Method	RESNET avg% $\pm$ std	FCNN avg% $\pm$ std
Source.	37.70	37.13
No transfer	54.29 ± 0.76	49.97 ± 2.70
One-hot	63.76 ± 0.59	64.45 ± 0.51
TSL	68.04 ± 0.34	66.27 ± 0.46
NLE	65.64 ± 0.53	64.47 ± 0.59
AT	63.73 ± 0.81	64.16 ± 0.49
SP	64.57 ± 0.76	65.74 ± 0.37
RKD	65.28 ± 0.81	65.63 ± 0.22
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- Accuracies on source device data:
  - RESNET: 79.09 %, FCNN: 79.70 %.
- Device mismatches causes huge degradation when directly applying the source model.
- Fine-tuning with target data can help ease the mismatch issue.
- Knowledge transfer algorithms show advantages over simply fine-tuning.
- Our proposed VBKT method improves performance on target devices and outperforms all others.

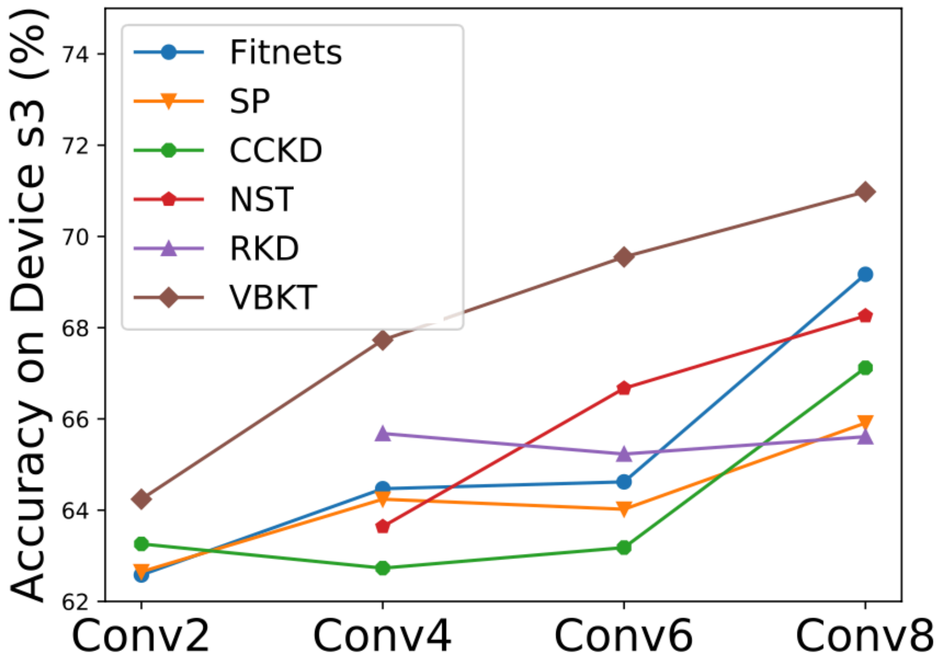
Appendix: More Results and Analysis

- Effects of Hidden Embedding Depth
  - Methods use only one hidden layer are compared.

- Last layer (Conv8) shows best results than others.

- Layers closer to output show better results.
  - Better transferable properties.

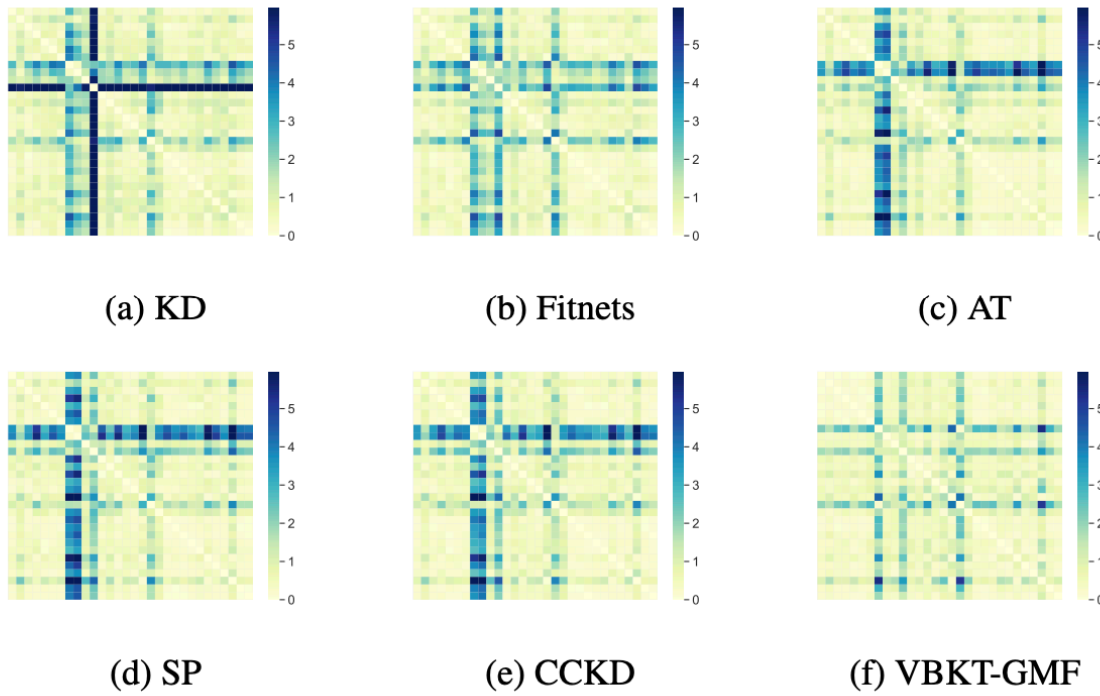
- The proposed method consistently outperforms all others.



Appendix: More Results and Analysis

- Visualization of intra-class discrepancy
  - 30 samples from the same class are randomly selected.
  - L2 distance between model outputs are computed and visualized.
  - Darker color means bigger intra-class discrepancy.

- The proposed method has consistent smaller intra-class discrepancy than others.
  - It has more discriminative information and better cohesion of instances.



Thank you~