Can One Modality Model Synergize Training of Other Modality Models?

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1. Introduction

Huge Success of recent Multimodal Learning

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- **Rise of *Foundation Models* (Large Models)**

Foundation Models

ResNet, LSTM, … → **Transformers, ViTs, CLIP, Diffusion Model, …**

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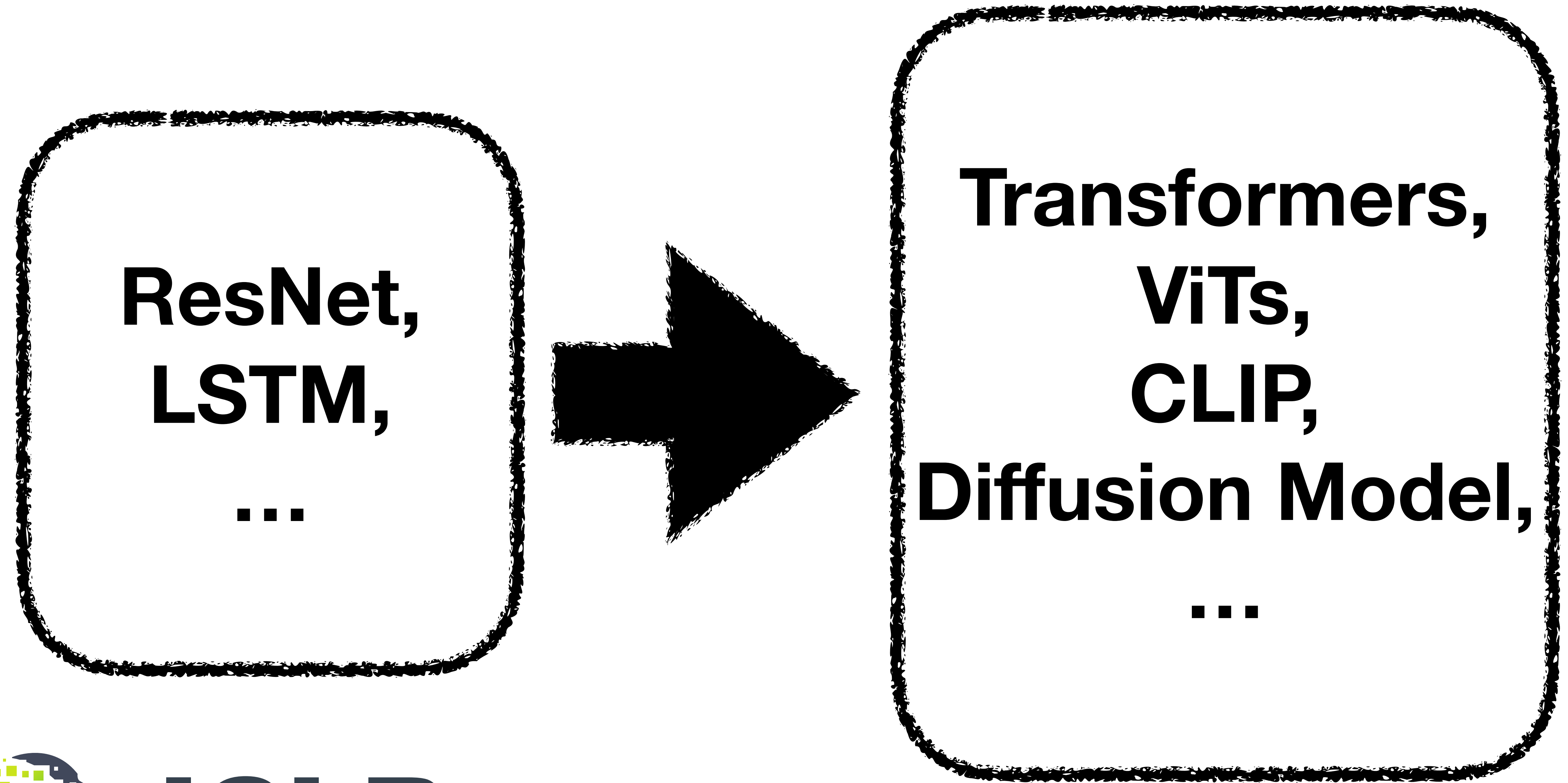
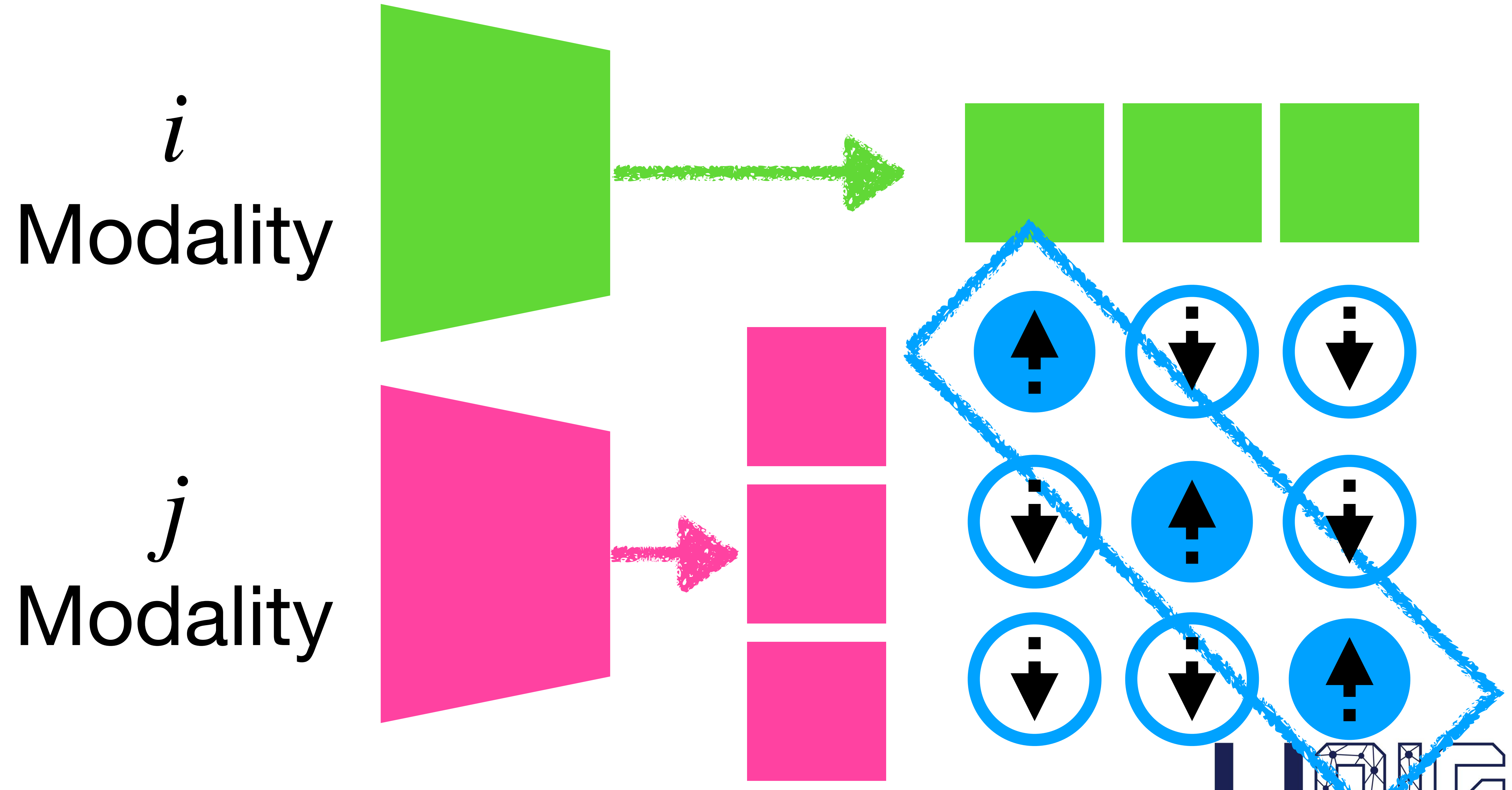
Huge Success of recent Multimodal Learning

- **Rise of *Foundation Models* (Large Models)**
- ***Contrastively leverage information* across different modalities.**

Foundation Models



Train contrastively across modalities



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Problem Formulation - Limitations of recent Multimodal Learning

- However, ***significant limitations*** remain:

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  - ***Require high-quality data*** **describing each modality sufficiently.**

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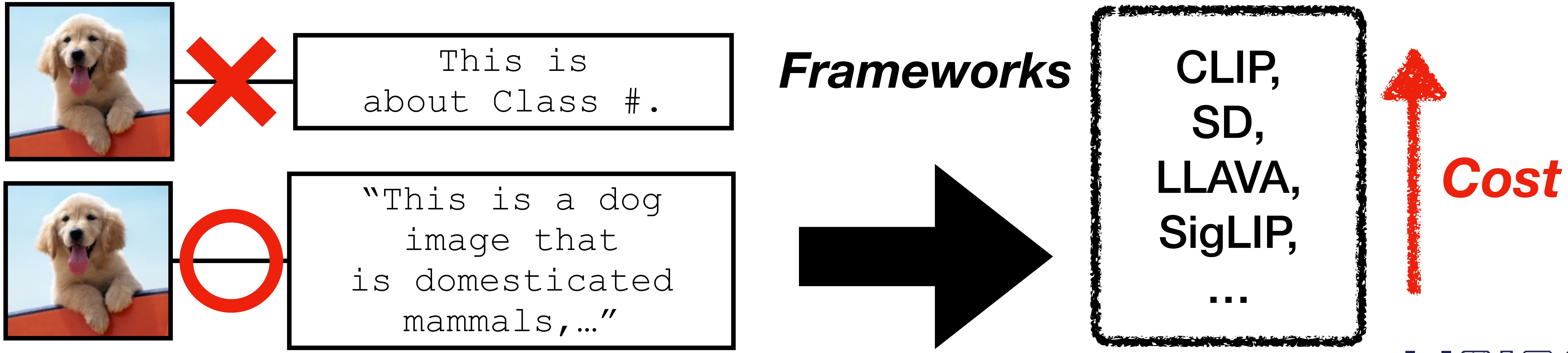
Problem Formulation - Limitations of recent Multimodal Learning

- However, ***significant limitations*** remain:
  - ***Require high-quality data*** **describing each modality sufficiently.**
  - Multimodal theoratical aspects focus ***when paired-datasets are available, where it requires high computational cost.***



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Our Approach: Synergistic Multimodal Learning in 2 Perspectives

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- ***Theoratical Perspective*: Derive how one modality can promote the training of other modality mathematically based on *2-Wasserstein distance between distribution of latent features of each modality*, where it reveals that it doesn't requires high quality of paired-datasets.**

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1. Introduction

Our Approach: Synergistic Multimodal Learning in 2 Perspectives

- ***Theoratical Perspective*****:** Derive how one modality can promote the training of other modality mathematically based on ***2-Wasserstein distance between distribution of latent features of each modality***, where it reveals that it doesn't requires high quality of paired-datasets.
- ***Empirical Perspective*****:** Demonstrates how a pretrained modality model can aid in training another modality, even with ***imperfect supervision between paired datasets***.

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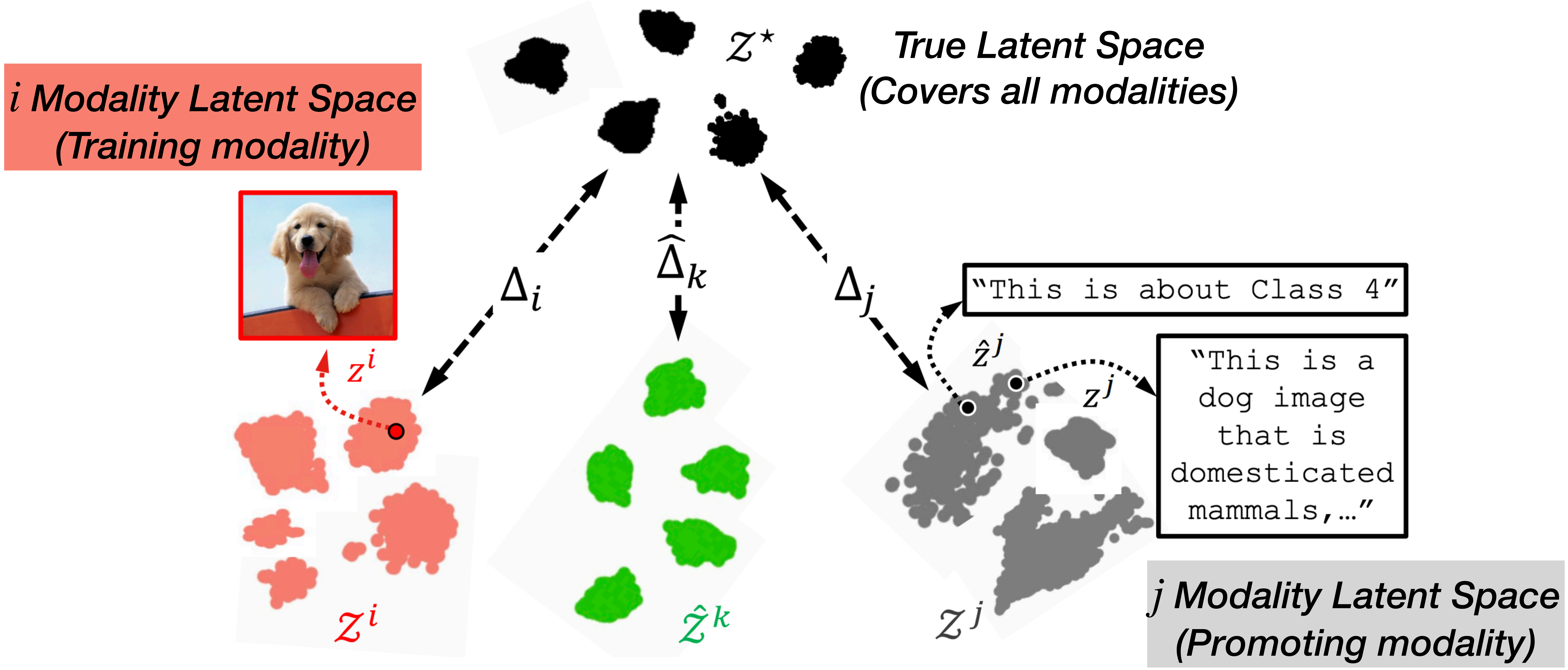
2. Motivation (Theoratical Perspective)

Skeptual Concept *based on Our Hypotheses*



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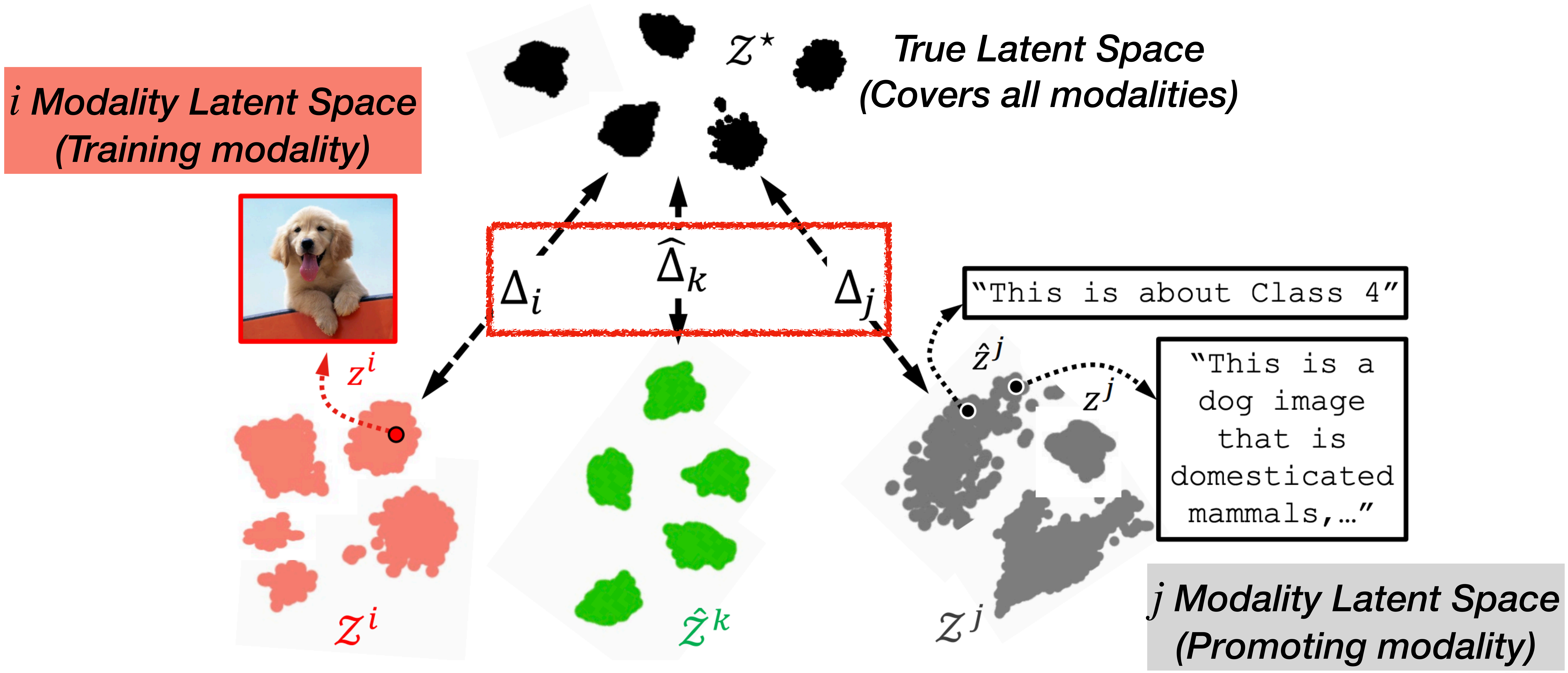
***Skeptual Concept** based on Our Hypotheses*



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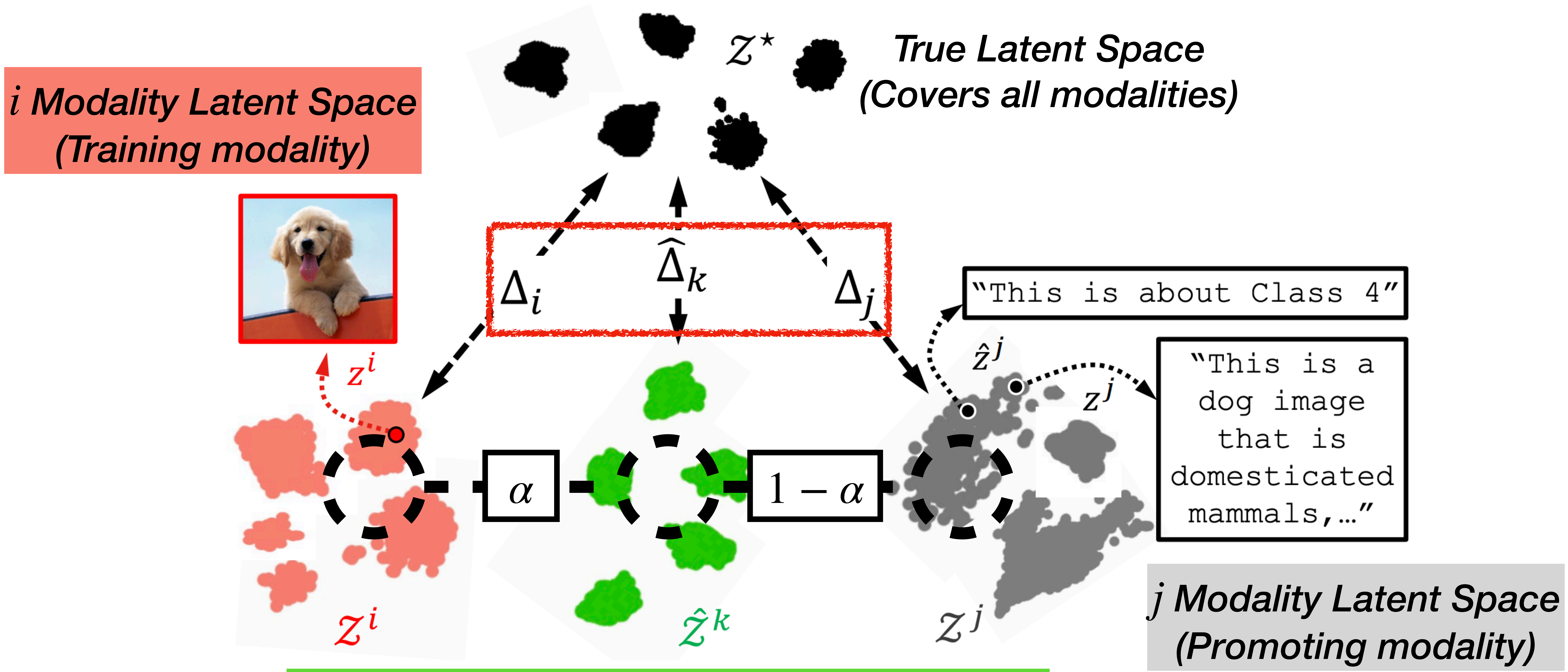

Interpolated between Z^i and Z^j with Coef. α

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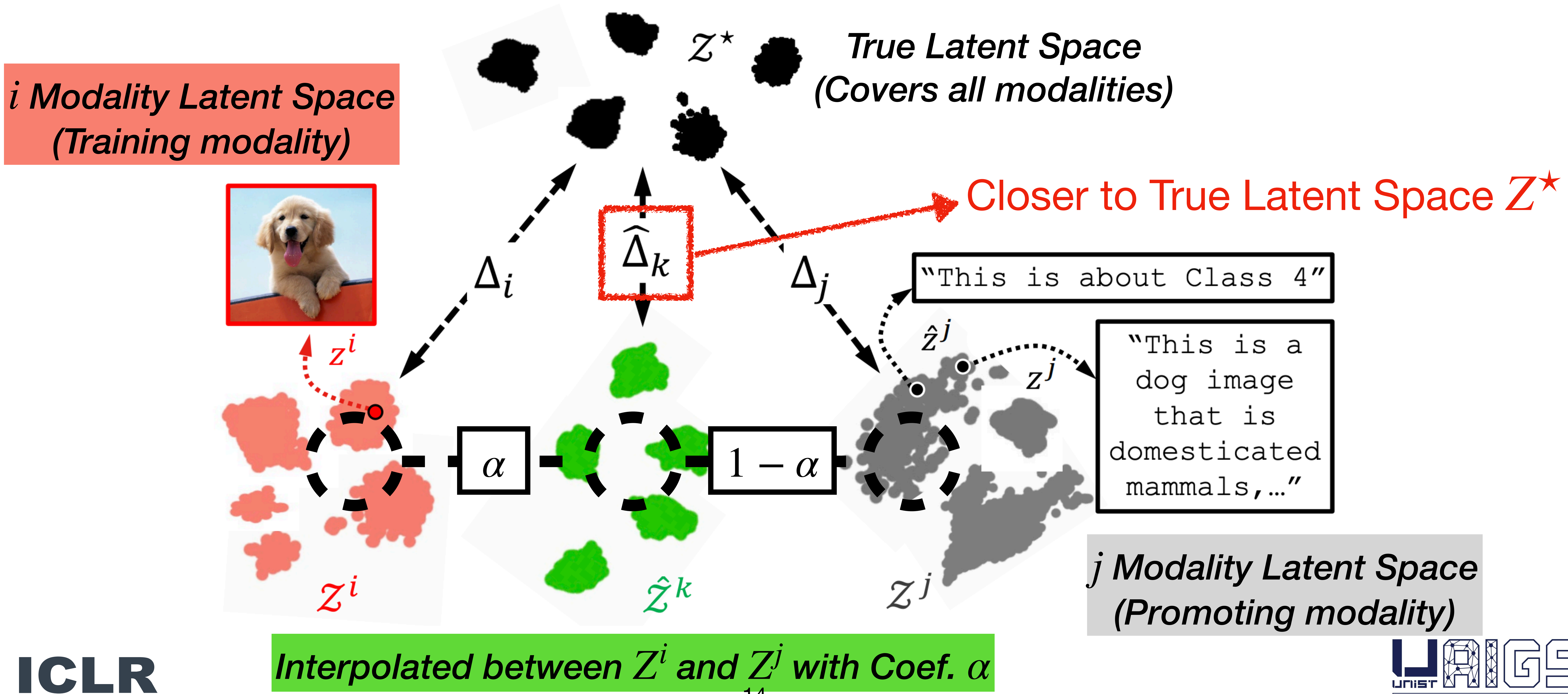

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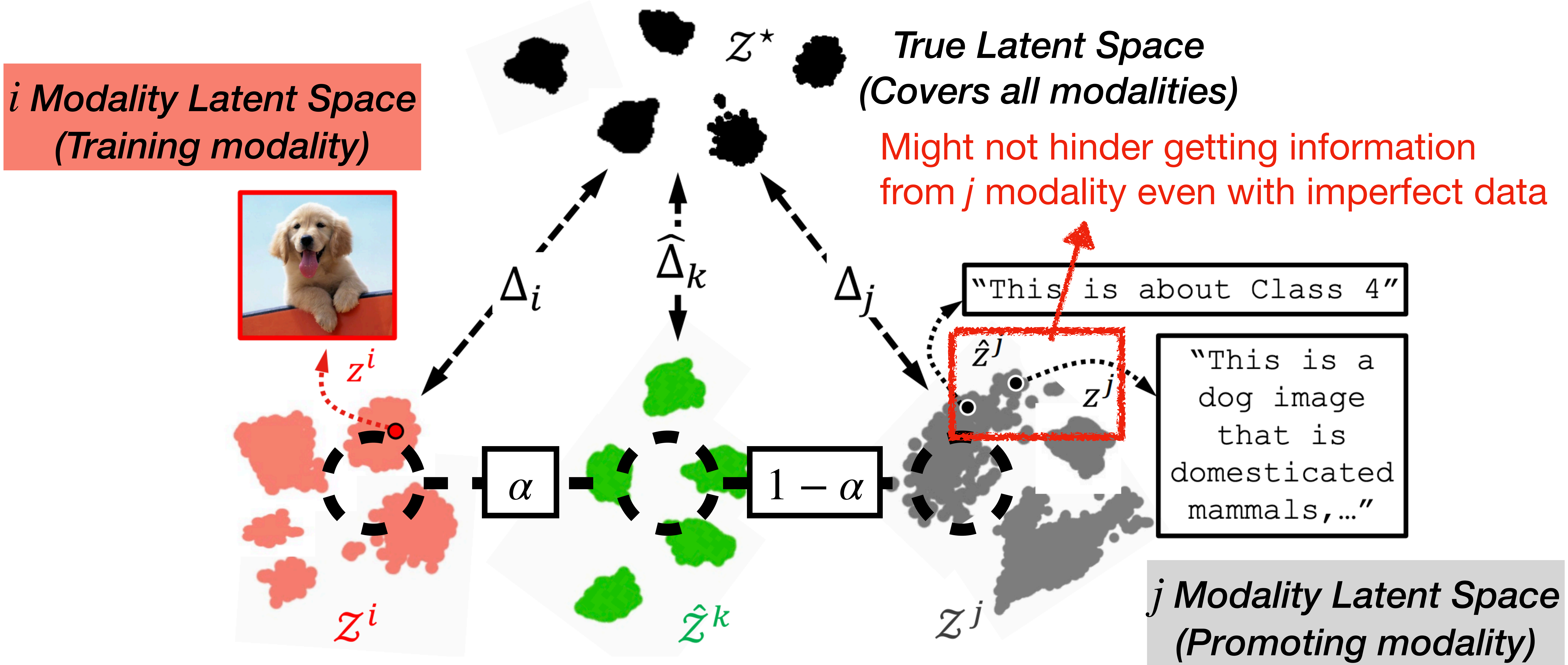
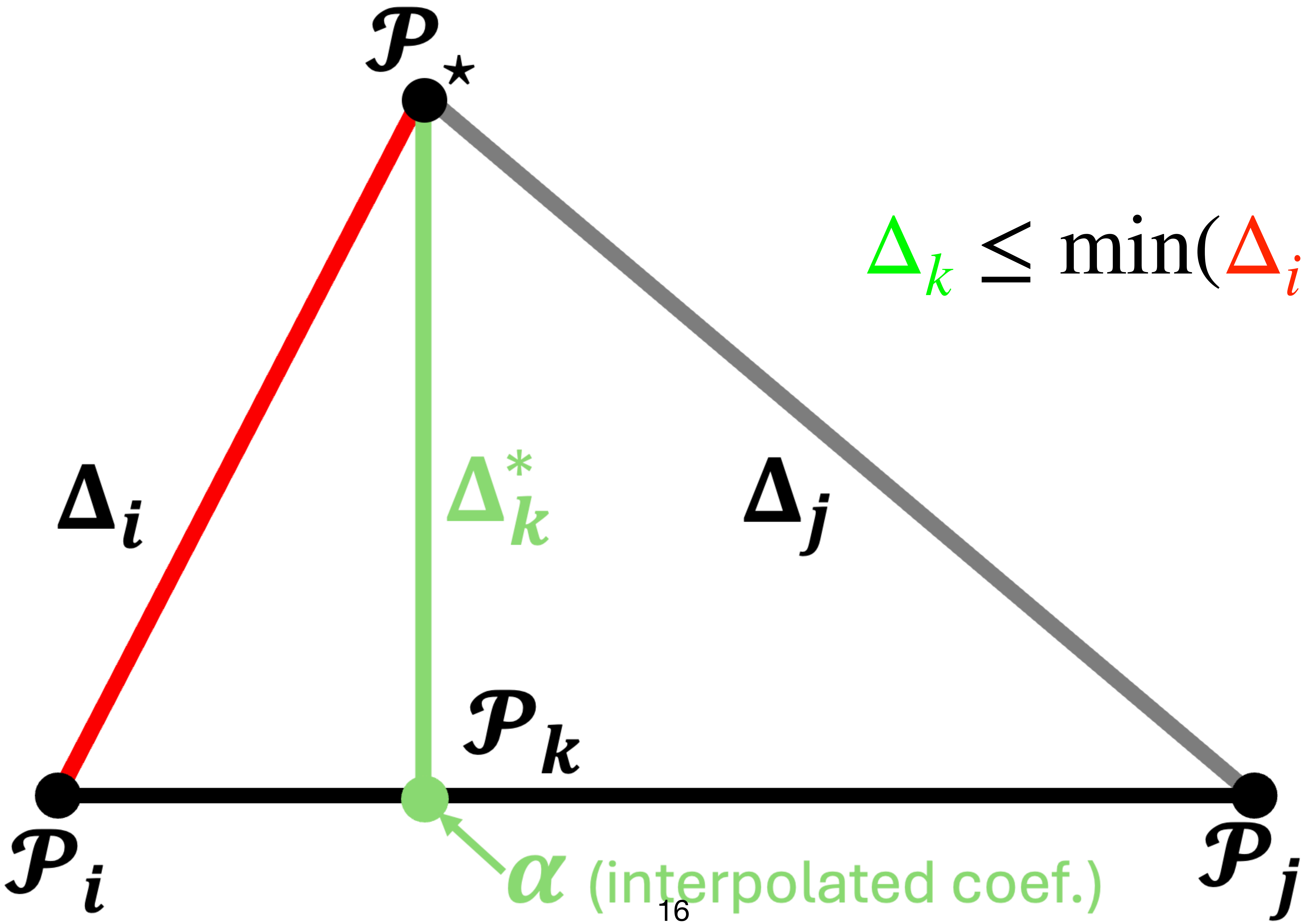


Interpolated between Z^i and Z^j with Coef. α

2. Motivation (Theoratical Perspective)

Skeptual Concept *based on Our Hypotheses* ***(Easier verison)***



$$\Delta_k \leq \min(\Delta_i, \Delta_j)$$

3. Experiment (Empirical Perspective)

Experimental Settings for Synergistic Multimodal Learning

- **Imperfect Supervision:**
  - Conducting ***imperfectly paired datasets***, where paired data provide only partial or insufficient descriptions of each other.
  - Ex). *[*  *, "This is about class #."]* ⇒ ***Imperfect (Vision, Text)***

3. Experiment (Empirical Perspective)

Experimental Settings for Synergistic Multimodal Learning

- **Imperfect Supervision:**
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  - Ex). [🐕‍🦺 , *"This is about class #."*] ⇒ ***Imperfect (Vision, Text)***
- **Matching modalities at Latent Feature Space (or Subspace):**
  - Each modality is analyzed and compared within the latent feature space, extracted from the each modality model. ⇒ ***Need new loss functions***

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3. Experiment (Empirical Perspective)

Loss Functions

Classification Loss: $\mathcal{L}_{cls} = \underset{(\mathbf{x}_m^i, y_m^i) \sim \mathcal{S}^i}{\mathbb{E}} \left[\mathcal{L}_{CE} \left(h \circ g(\mathbf{x}_m^i), y_m^i \right) \right]$

Latent Loss: $\mathcal{L}_z = \underset{(\mathbf{x}_m^i, y_m^i, \hat{z}_m^i) \sim \mathcal{S}^i \times \hat{Z}^j}{\mathbb{E}} \left[|| g(\mathbf{x}_m^i) - \hat{z}_m^i ||_2^2 \right]$

$\Rightarrow$ **Total Loss:** $\mathcal{L}_{\textbf{total}} = (1 - \alpha)\mathcal{L}_{\textbf{cls}} + \alpha \mathcal{L}_{\mathbf{z}}$

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3. Experiment (Empirical Perspective)

Experimental Settings of $\hat{z}^j$ (imperfect supervision)

Datasets & Cases	**Implementation of $\hat{z}^j_m$**
ImageNet-1k [**L**→**V**]	**[L]** $\Rightarrow$ `This is about Class #.`†
IEMOCAP [**L**→**A**]	**[L]** $\Rightarrow$ `This is about Emotion #.`†
IEMOCAP [**A**→**L**]	**[A]** $\Rightarrow$ Add Gaussian Noise: $\xi \sim \mathcal{N}(0, \lambda I)^{\dagger\dagger}$ & Random Shuffling
AVMNIST [**V**→**A**]	**[V]** $\Rightarrow$ Random Shuffled Image (mismatch paired sets)
AVMNIST [**A**→V]	**[A]** $\Rightarrow$ Add Gaussian Noise: $\xi \sim \mathcal{N}(0, \lambda I)^{\dagger\dagger}$ & Random Shuffling

†: # is a random number that does not directly correspond to the actual label.
††: λ is a parameter that controls the variance of the Gaussian noise. We applied $\lambda = 10^{-3}$

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3. Experiment (Empirical Perspective)

Empirical Results: Vision-Langauge

Table 1: Classification results on ImageNet-1K and evaluation benchmarks (OOD and robustness)

Model [L→V]	IN	V2	Rend.	Sketch	A	Style.	C (↓)
ResNet-50 (reproduced)	77.83	66.20	39.28	27.35	6.44	8.59	66.01
+ **BERT** (Devlin et al., 2018)	78.41	67.10	40.38	28.19	**8.47**	**9.64**	**64.96**
+ **RoBERTa** (Liu et al., 2019)	**78.54**	**67.30**	**40.92**	**28.78**	8.25	9.19	65.32
ViT-B/32 (reproduced)	75.04	62.02	40.31	27.34	9.23	16.56	55.45
+ BERT (Devlin et al., 2018)	76.59	63.37	41.28	28.53	11.31	18.11	53.28
+ **RoBERTa** (Liu et al., 2019)	**76.75**	**64.00**	**41.81**	**29.50**	**11.55**	**18.75**	**52.95**
ViT-B/16 (reproduced)	80.07	68.60	44.72	31.22	24.20	18.81	51.21
+ **BERT** (Devlin et al., 2018)	81.62	70.07	**45.72**	33.13	25.12	**20.31**	49.27
+ **RoBERTa** (Liu et al., 2019)	**81.90**	**70.55**	45.41	**33.19**	**26.89**	19.93	**48.51**

3. Experiment (Empirical Perspective)

Empirical Results: Language-Audio, Vision-Audio

Table 2: Classification results on IEMOCAP and AVMNIST datasets on each cases of $[M_j \rightarrow M_i]$.

Datasets	Model [L→A]	Accuracy	Model [A→L]	Accuracy
IEMOCAP††	Wav2Vec2† (Ravanelli et al., 2021)	59.46	BERT (Devlin et al., 2018)	55.81
	+ BERT-B (Devlin et al., 2018)	60.44	+ **Wav2Vec2-B** (Baevski et al., 2020)	**56.49**
	+ **BERT-L** (Devlin et al., 2018)	**61.20**	+ Wav2Vec2-L (Baevski et al., 2020)	56.05
Datasets	**Model [V→A]**	**Accuracy**	**Model [A→V]***	**Accuracy**
AVMNIST	Audio Model (Li et al., 2023)	41.28	Vision Model (Li et al., 2023)	65.18
	+ ResNet-18 (He et al., 2016)	42.08	+ Wav2Vec2-B (Baevski et al., 2020)	66.37
	+ **ResNet-34** (He et al., 2016)	**42.44**	+ **Wav2Vec2-L** (Baevski et al., 2020)	**66.69**

†: SpeechBrain (Ravanelli et al., 2021) experimented with 4 out of 6 labels; we used the all labels.
††: Owing to transformer-type model requires numerous data, we fine-tuned the pretrained model.
*: Since the audio data in AVMNIST is based on spectrograms, we use the original raw audio data prior to its conversion into spectrogram.

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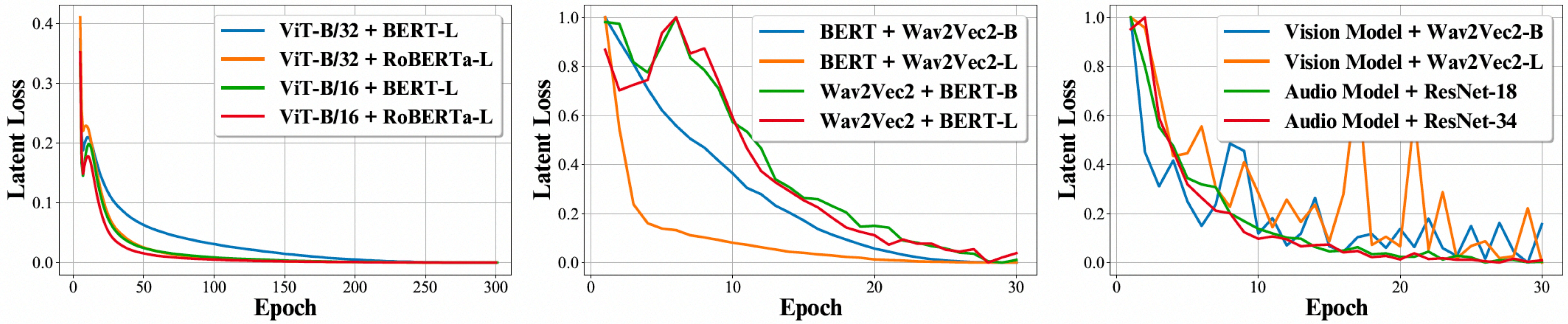
4. Analysis

Convergence of Latent Loss (Magnitude of Losses)



(a) ImageNet-1K $\mathcal{L}_z$ (b) IEMOCAP $\mathcal{L}_z$ (c) AVMNIST $\mathcal{L}_z$

⇒ All cases converges almost to, but not exactly to, zero due to interpolation.

4. Analysis

Wasserstein Distance between Paired Modalities

IEMO. [L→A]	WD
$W_2(\mathcal{P}_A, \hat{\mathcal{P}}_k)$	0.494
$W_2(\hat{\mathcal{P}}_L, \hat{\mathcal{P}}_k)$	0.141
$W_2(\mathcal{P}_A, \hat{\mathcal{P}}_L)$	**0.977**

IEMO. [A→L]	WD
$W_2(\mathcal{P}_L, \hat{\mathcal{P}}_k)$	0.965
$W_2(\hat{\mathcal{P}}_A, \hat{\mathcal{P}}_k)$	0.460
$W_2(\mathcal{P}_L, \hat{\mathcal{P}}_A)$	**1.005**

AVMN. [V→A]	WD
$W_2(\mathcal{P}_A, \hat{\mathcal{P}}_k)$	0.025
$W_2(\hat{\mathcal{P}}_V, \hat{\mathcal{P}}_k)$	0.754
$W_2(\mathcal{P}_A, \hat{\mathcal{P}}_V)$	**0.790**

AVMN. [A→V]	WD
$W_2(\mathcal{P}_V, \hat{\mathcal{P}}_k)$	0.908
$W_2(\hat{\mathcal{P}}_A, \hat{\mathcal{P}}_k)$	0.502
$W_2(\mathcal{P}_V, \hat{\mathcal{P}}_A)$	**0.954**

Interpolated representation are both smaller than WD between modalities

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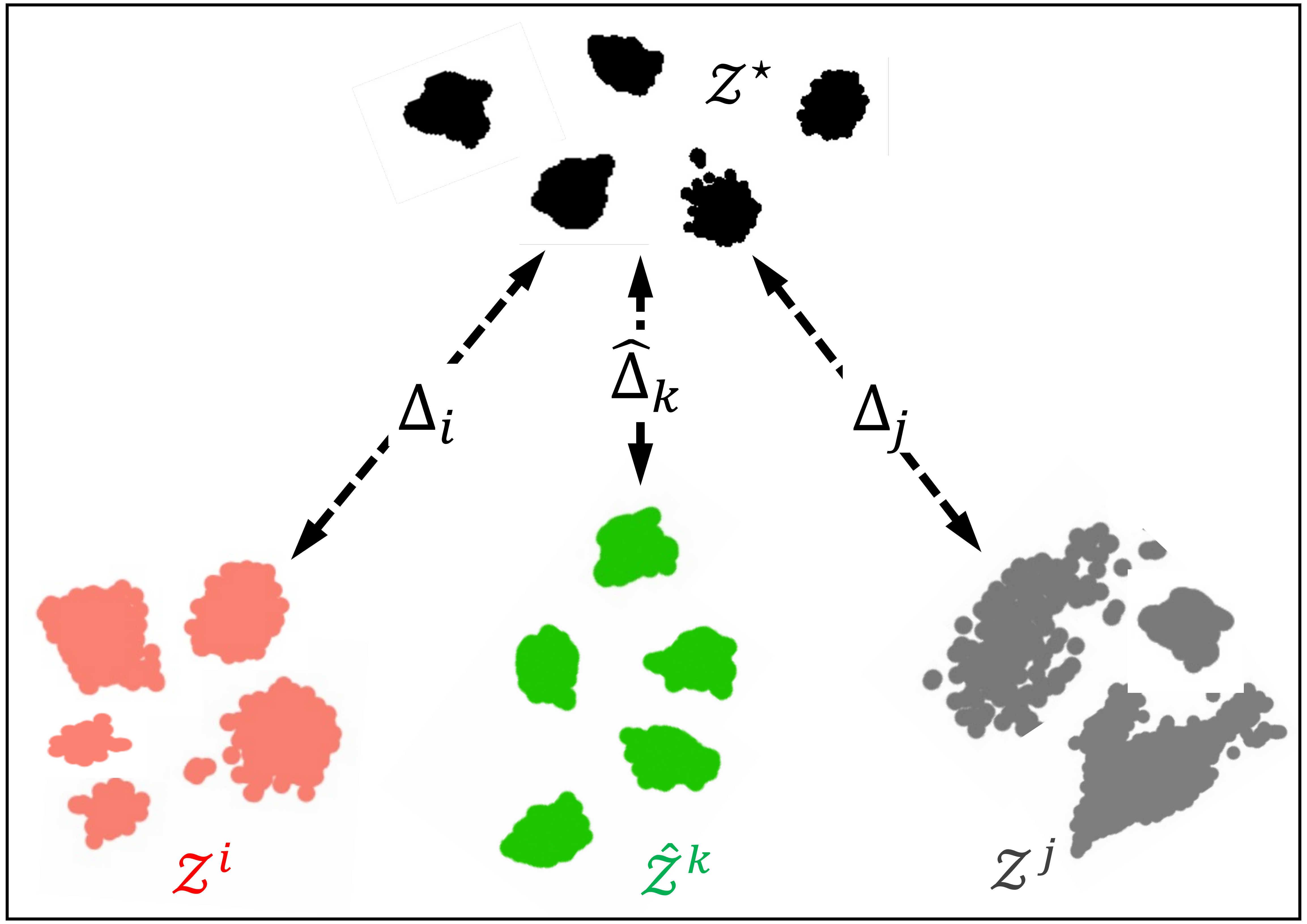
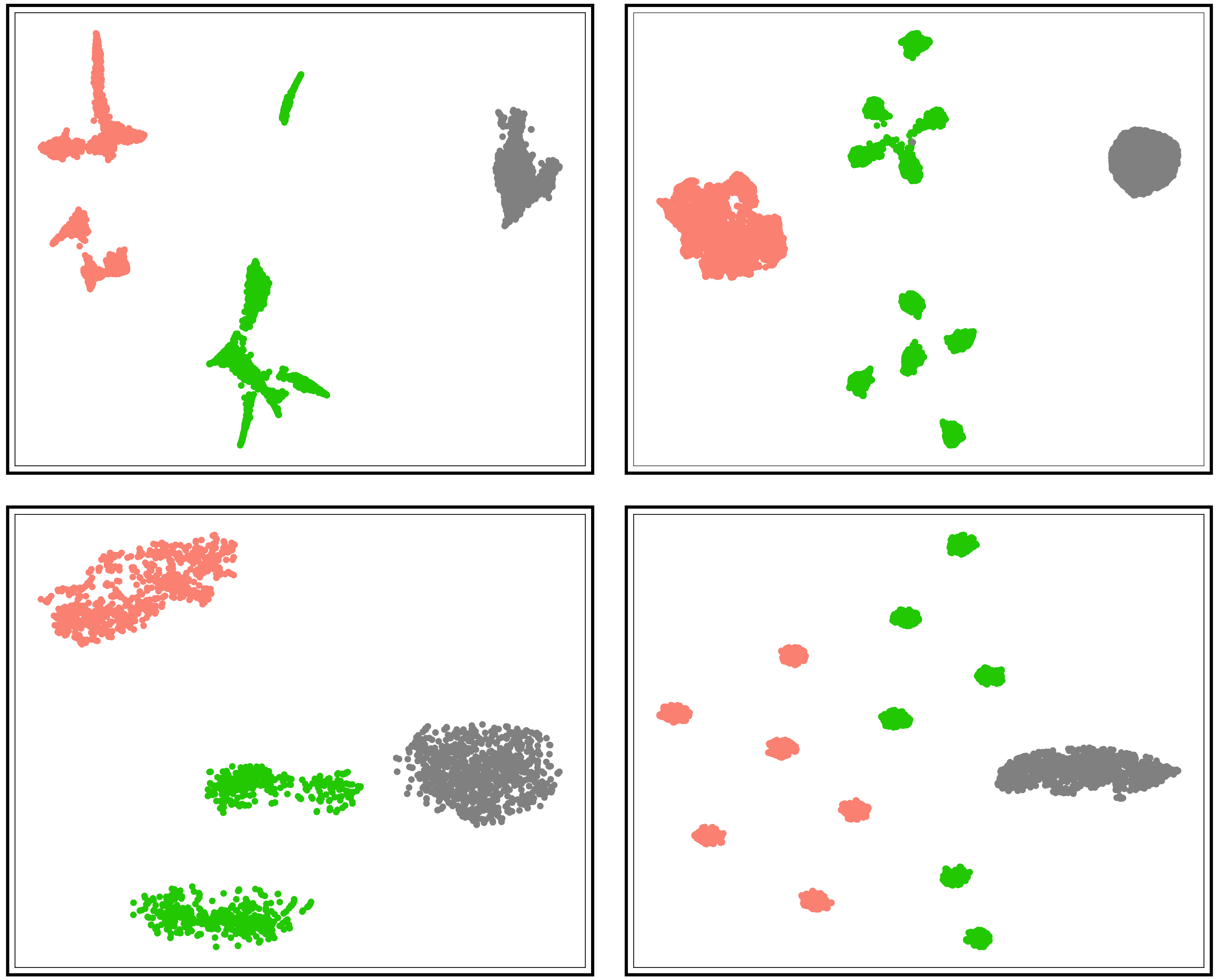
4. Analysis

Wasserstein Distance between Paired-Modalities



Our Hypothesis



Our Results (t-SNE Visualizations)

4. Analysis

Ablation Studies: Usage of Paired Supervision z^j vs. $\hat{z}^j$

Model [L→V]	$\hat{z}^j$	z^j
ResNet-50 + RoBERTa	78.54	78.61 (+0.07)
ViT-B/32 + RoBERTa	76.75	76.99 (+0.24)
ViT-B/16 + RoBERTa	81.90	82.54 (+0.64)

Slightly improved but minimal gains

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5. Conclusion

- Our paper demonstrate that **a modality can enhance learning in another**, even with **weakly related or mismatched supervision,**
- Both **theoretical and empirical frameworks** support this finding, reinforcing its validity.
- Exploring more complex multimodal settings, incorporating additional modalities, and scaling to larger models for further advancements.

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Thank you!