Test Time Adaptation

in Remote Sensing

Masters Thesis Phase-1

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Guide
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Outline

Problem Statement

- Foundational models like CLIP are transforming computer vision with strong zero-shot capabilities.
- CLIP has enabled powerful zero-shot recognition by aligning images and text in a shared embedding space.
  - Numerous improvements have further advanced prompt learning and model calibration.
- However, direct application of CLIP and its derivatives to Remote Sensing (RS) images faces challenges:
  - Domain gap between RS and natural images.
  - Poor calibration and reduced accuracy on RS benchmarks.
  - Limited labeled data and unique semantic classes in RS.
- Therefore, there is a need for Remote Sensing-specific foundational models and adaptation strategies that can deliver robust, calibrated performance in this domain.

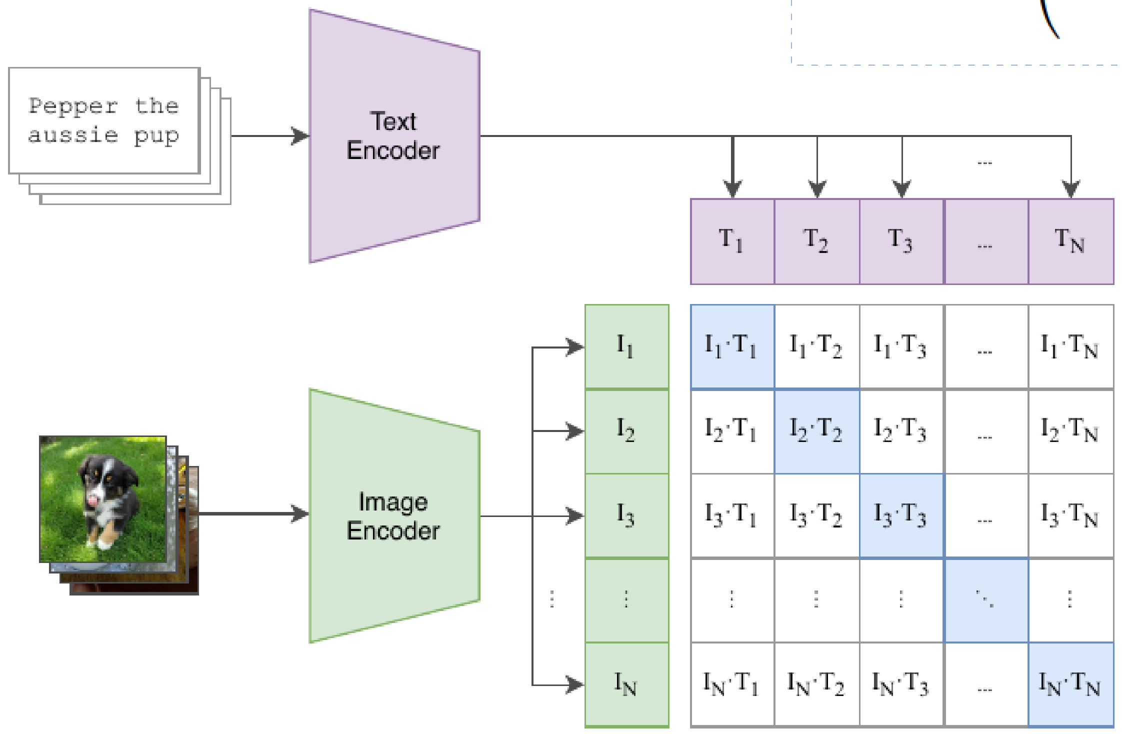
Literature Review

CLIP

Symmetric Cross-Entropy Loss
(a form of InfoNCE loss)

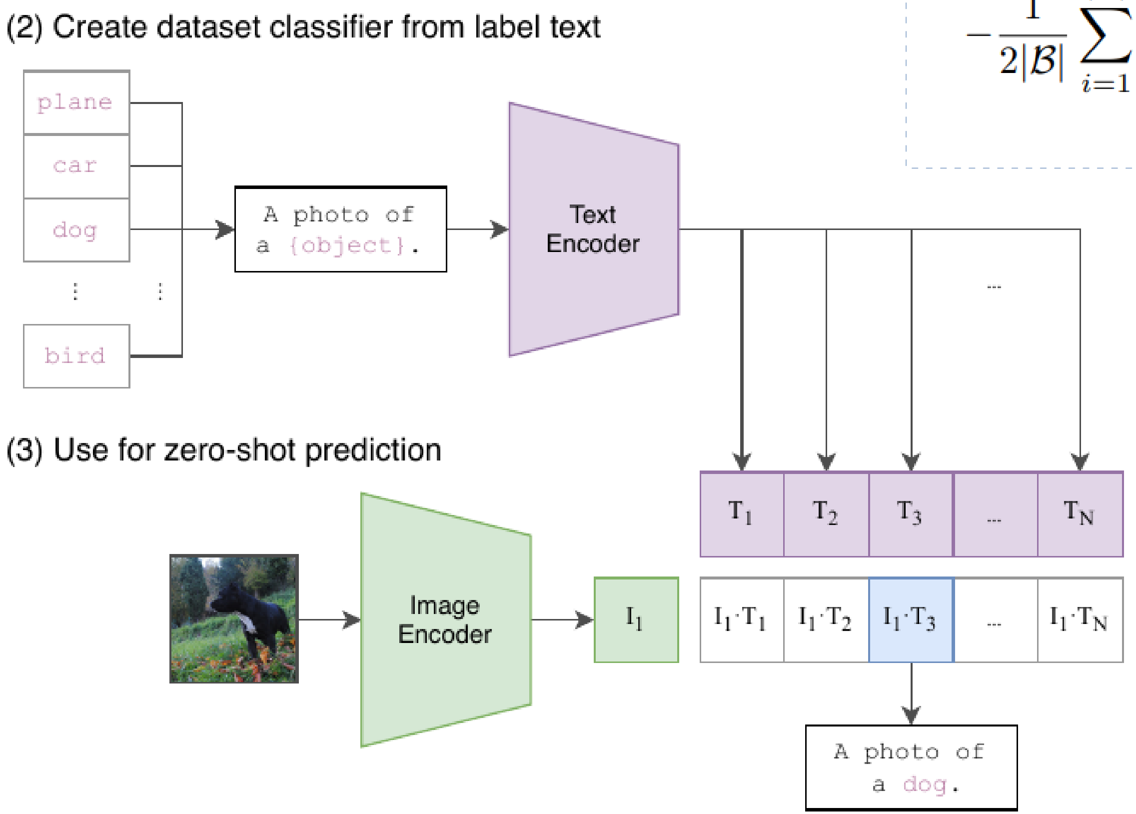
$$-\frac{1}{2|\mathcal{B}|}\sum_{i=1}^{|\mathcal{B}|}\left(\overbrace{\log\frac{e^{t\mathbf{x}_i\cdot\mathbf{y}_i}}{\sum_{j=1}^{|\mathcal{B}|}e^{t\mathbf{x}_i\cdot\mathbf{y}_j}}}^{\text{image}\rightarrow\text{text softmax}}+\overbrace{\log\frac{e^{t\mathbf{x}_i\cdot\mathbf{y}_i}}{\sum_{j=1}^{|\mathcal{B}|}e^{t\mathbf{x}_j\cdot\mathbf{y}_i}}}^{\text{text}\rightarrow\text{image softmax}}\right)$$

(1) Contrastive pre-training



Literature Review

CLIP



Symmetric Cross-Entropy Loss
(a form of InfoNCE loss)

$$-\frac{1}{2|\mathcal{B}|}\sum_{i=1}^{|\mathcal{B}|}\left(\overbrace{\log\frac{e^{t\mathbf{x}_i\cdot\mathbf{y}_i}}{\sum_{j=1}^{|\mathcal{B}|}e^{t\mathbf{x}_i\cdot\mathbf{y}_j}}}^{\text{image}\to\text{text softmax}}+\overbrace{\log\frac{e^{t\mathbf{x}_i\cdot\mathbf{y}_i}}{\sum_{j=1}^{|\mathcal{B}|}e^{t\mathbf{x}_j\cdot\mathbf{y}_i}}}^{\text{text}\to\text{image softmax}}\right)$$

Limitations :

Manually handwritten, hand-crafted prompts (suboptimal)

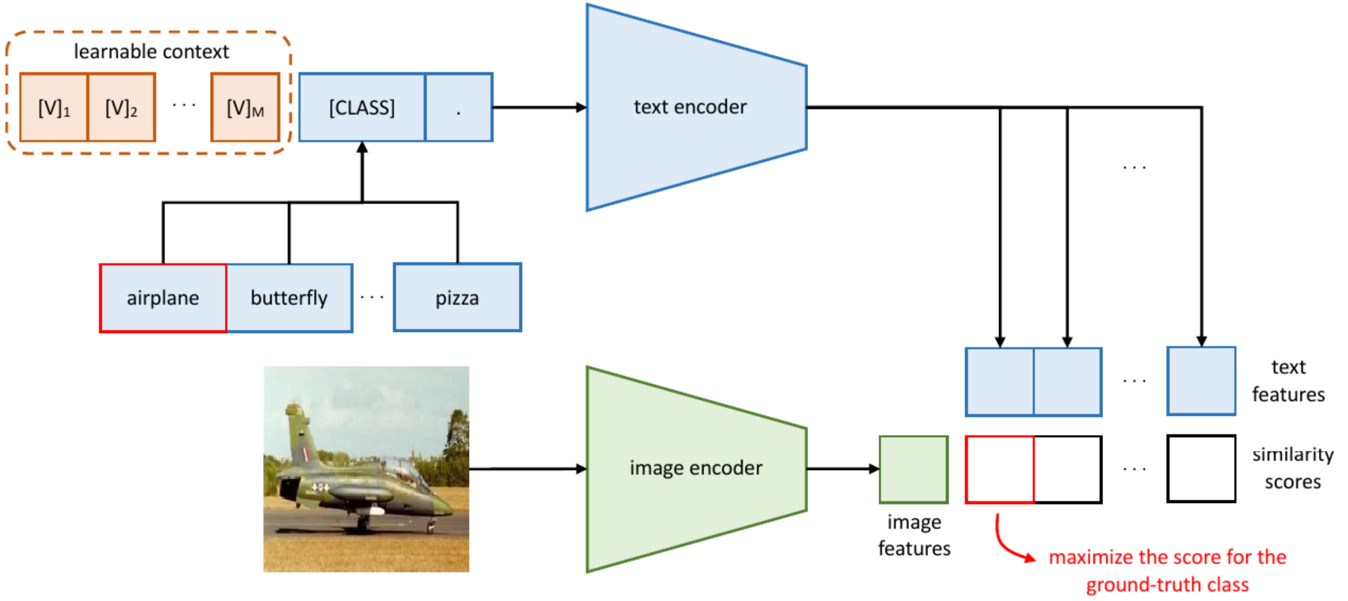
Small change in wording could cause a significant drop in performance

Literature Review
CLIP + CoOp

Cross-Entropy Loss

$$\mathcal{L}_{\text{CoOp}} = -\sum_{i=1}^{M} \mathbf{y}_i \log(p(\mathbf{y}_i|\mathbf{x}_i))$$

$$p(\mathbf{y}_k|\mathbf{x}) = \frac{\exp(\text{sim}(f(\mathbf{x}), g(\mathbf{t}_k))/\tau)}{\sum_{j=1}^{K} \exp(\text{sim}(f(\mathbf{x}), g(\mathbf{t}_j))/\tau)}$$



Limitations :

Learns a static set of context vectors shared by all classes

Not generalizable to unseen (new) classes

Overfitting the base classes

Literature Review

CLIP + CoCoOp

Cross-Entropy Loss

$$\mathcal{L}_{\text{CoOp}} = -\sum_{i=1}^{M} \mathbf{y}_i \log(p(\mathbf{y}_i|\mathbf{x}_i))$$

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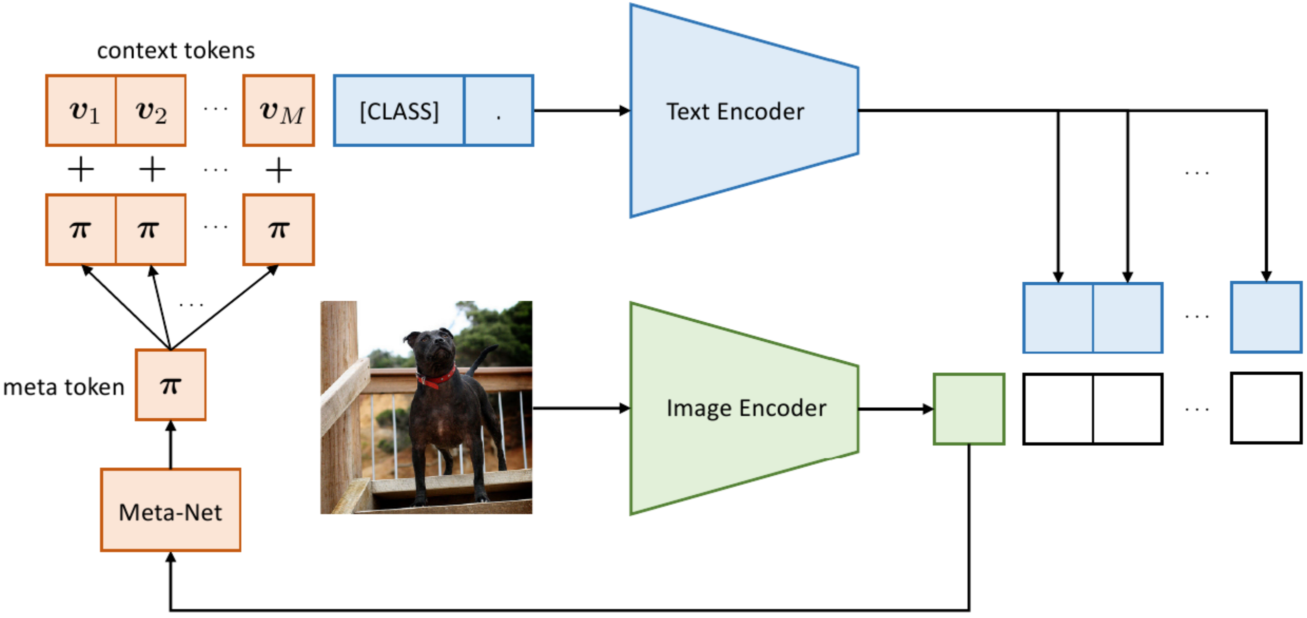


Limitations :

Requires labeled data

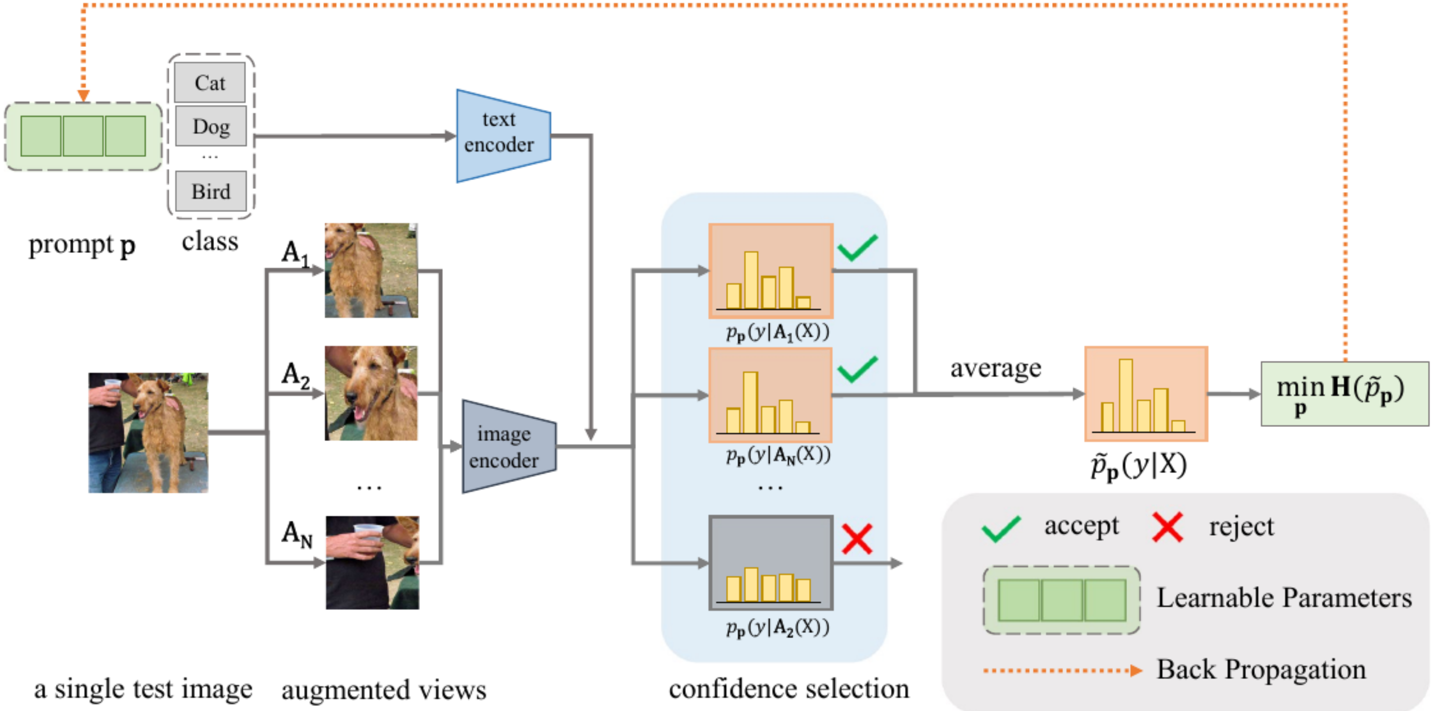
This restriction limits the generality of the underlying foundation models like CLIP

Literature Review
CLIP + TPT

$$p^* = \arg\min_{p} - \sum_{i=1}^{K} \tilde{p}_{p}(y_i|X_{\text{test}}) \log \tilde{p}_{p}(y_i|X_{\text{test}}),$$

Cross-Entropy Loss

$$\tilde{p}_{p(y|X_{\text{test}})} = \frac{1}{\rho N} \sum_{i=1}^{N} \mathbb{1}[\mathbf{H}(p_i) \leq \tau] p_{p}(y|\mathcal{A}_i(X_{\text{test}})),$$



Limitations :

Intrinsically leads to overconfident predictions and consequently increases the Expected Calibration Error (ECE) (i.e., poor calibration)

Compromised the model's reliability

Literature Review

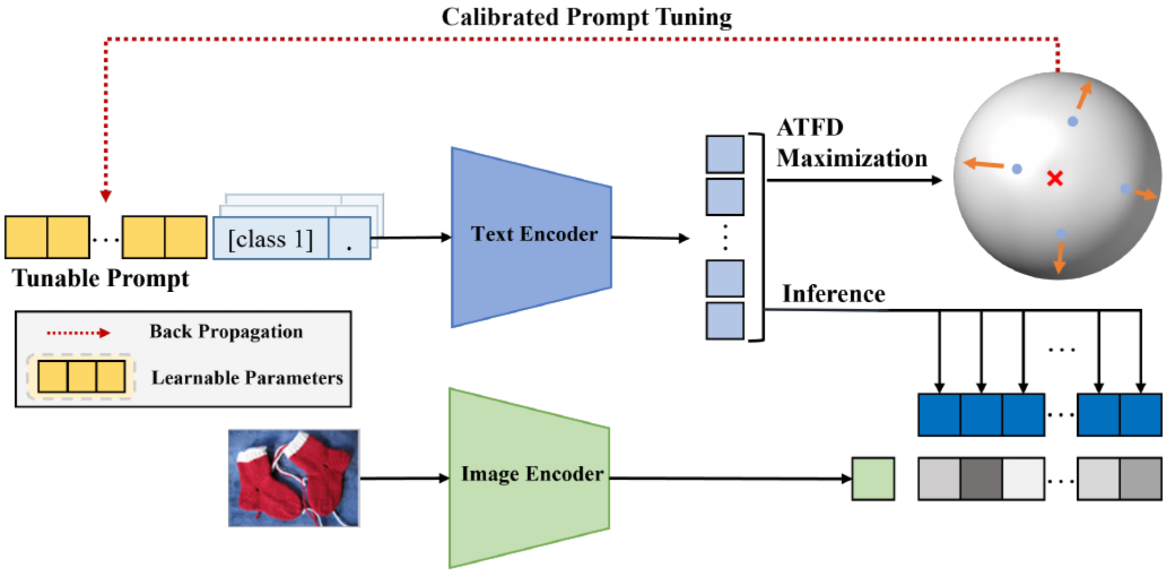
CLIP + C-TPT

$$\mathrm{ECE} = \sum_{m=1}^{M} \frac{|A_m|}{N} \left| \mathrm{acc}(A_m) - \mathrm{conf}(A_m) \right|,$$

Cross-Entropy Loss + AFTD Maximization

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} [\mathcal{L}_{\text{TPT}} + \lambda \cdot \mathcal{L}_{\text{C-TPT}}(\mathbf{t}_{[\mathbf{p};y_1]}, \mathbf{t}_{[\mathbf{p};y_2]}, \ldots, \mathbf{t}_{[\mathbf{p};y_N]})],$$

$$\mathrm{ATFD}(\mathbf{t}_{[\mathbf{p};y_1]}, \mathbf{t}_{[\mathbf{p};y_2]}, \ldots, \mathbf{t}_{[\mathbf{p};y_N]}) = \frac{1}{N} \sum_{i=1}^{N} ||\mathbf{t}_{\text{centroid}} - \mathbf{t}_{[\mathbf{p};y_i]}||_2.$$



Limitations :

Underutilized the textual feature space, leading to suboptimal calibration

Overlooked the critical correlation between angular separation (cosine similarity) and calibration performance

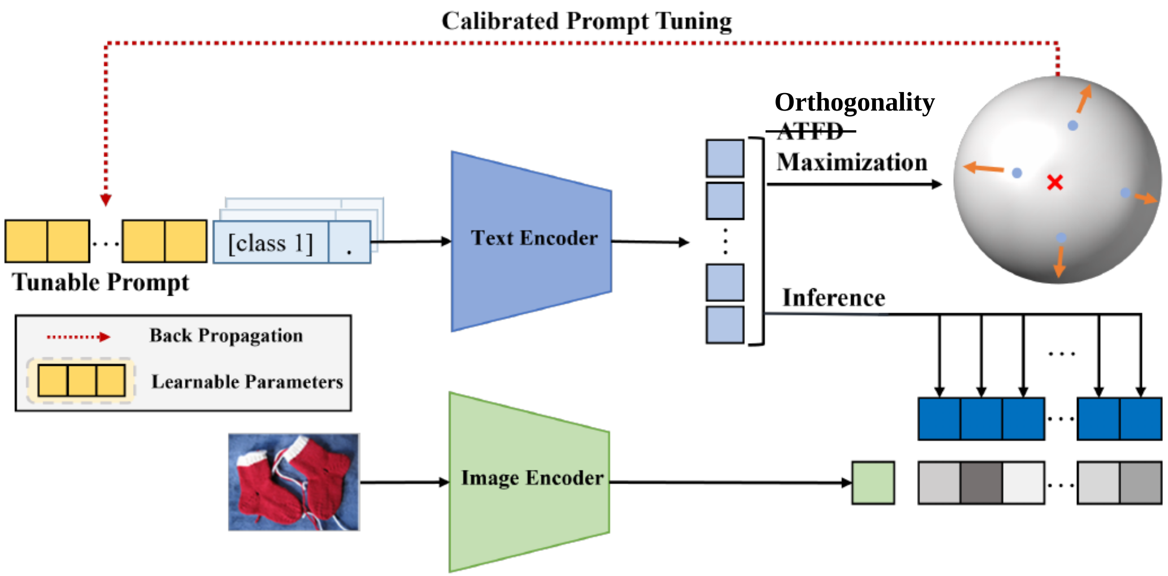
Literature Review

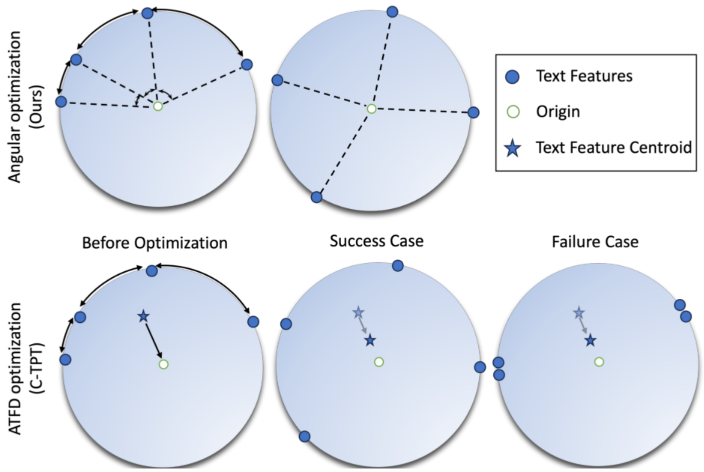
CLIP + O-TPT

Cross-Entropy Loss + Orthogonality Maximization

$$\mathbf{t}^* = \arg\min_{\mathbf{t}} (L_{TPT} + \lambda \|\mathbf{E}\mathbf{E}^T - I_C\|_2^2)$$

$$\text{ECE} = \sum_{m=1}^{M} \frac{|A_m|}{N} \left| \text{acc}(A_m) - \text{conf}(A_m) \right|,$$





Literature Review

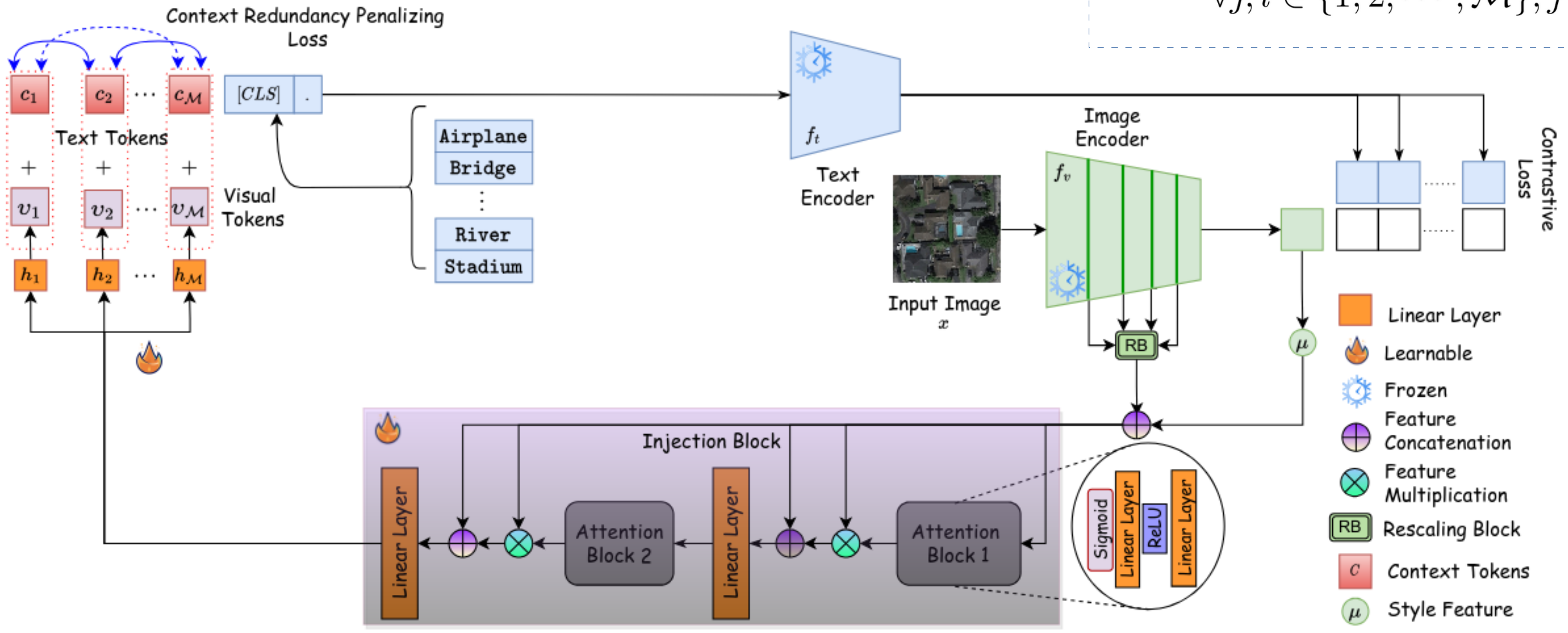
APPLENet

Cross-Entropy Loss + Context Redundancy Penalizing Loss

$$\mathbf{L}_{\mathbf{total}} = \underset{\mathcal{B}_{\phi},\{h_m\}}{\arg\min}[\mathbf{L}_{\mathbf{ce}} + \lambda * \mathbf{L}_{\mathbf{CRP}}]$$

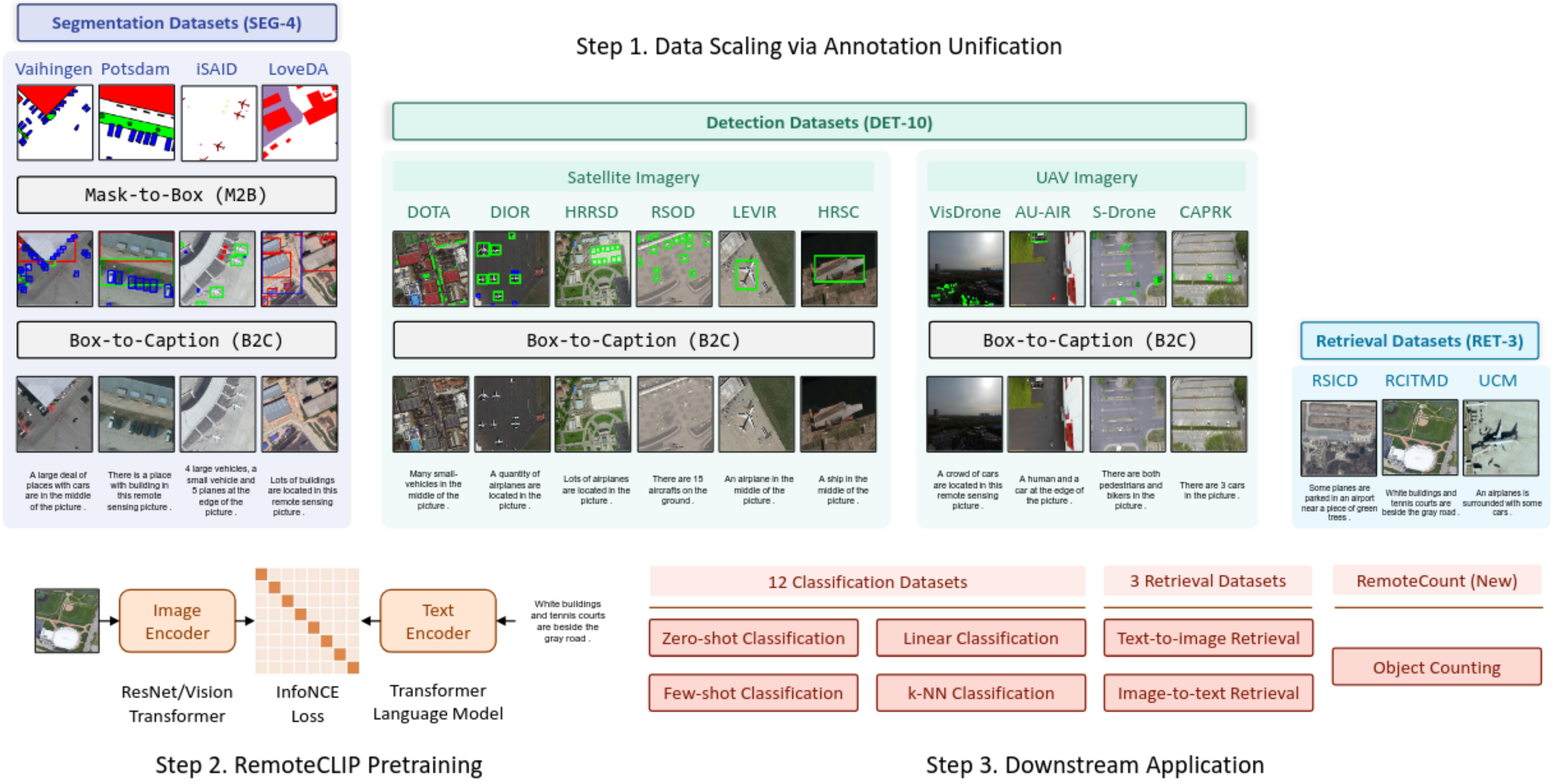
$$\mathbf{L}_{\mathbf{CRP}} = \underset{\mathcal{B}_{\phi},\{h_m\}}{\arg\min} \underset{(x,y)\in\mathcal{P}(\mathcal{D}_s)}{\mathbb{E}} \left|c'_j(x) \cdot c'_l(x) - \mathcal{I}\right|,$$

$$\forall j,l \in \{1,2,\cdots,\mathcal{M}\}, j \neq l, c'_j = c_j + v_j$$



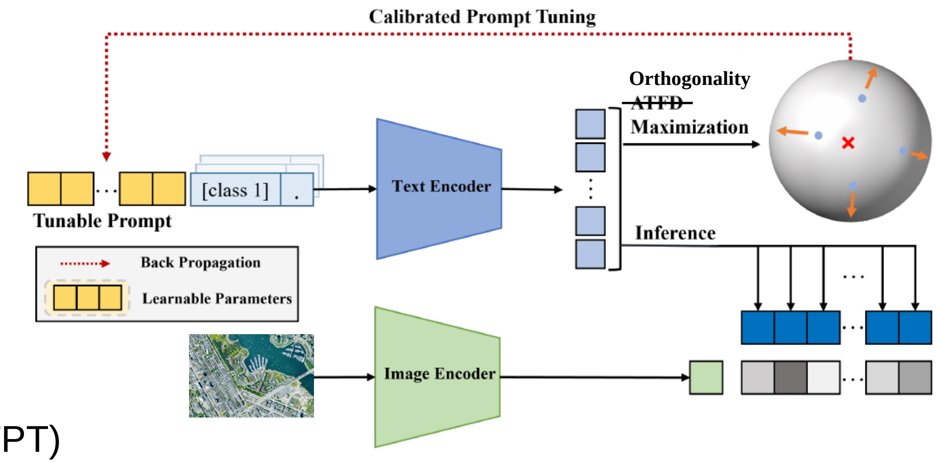
Literature Review

RemoteCLIP



Proposed Design

RemoteCLIP + O-TPT



Backbone:

RemoteCLIP (ViT-B/32) for remote-sensing domain priors

Head:

CLIP-style text prompts with learnable context (O-TPT)

Adaptation:

Test-time prompt tuning (entropy minimization + orthogonality regularization)

Evaluation:

Single-view inference (center-crop). Temperature scaling optional

Datasets:

AID, UCM, WHU-RS19, NWPU-RESISC45, EuroSAT, PatternNet

Metrics :

| Accuracy | ECE (Expected Calibration Error) |

Dataset	Model	Accuracy	ECE
UCM	openCLIP	72.380 %	4.614
	openCLIP + O-TPT	68.761 %	12.163
	RemoteCLIP	90.904 %	3.454
	RemoteCLIP + O-TPT	**91.095 %**	**3.348**
AID	openCLIP	66.600 %	5.541
	openCLIP + O-TPT	63.866 %	9.942
	RemoteCLIP	**87.833 %**	5.206
	RemoteCLIP + O-TPT	87.433 %	**1.998**
WHU-RS19	openCLIP	86.447 %	3.658
	openCLIP + O-TPT	77.631 %	8.525
	RemoteCLIP	**93.552 %**	5.070
	RemoteCLIP + O-TPT	92.763 %	**1.998**
NWPU-RESISC45	openCLIP	66.555 %	7.371
	openCLIP + O-TPT	61.266 %	13.914
	RemoteCLIP	65.822 %	**6.482**
	RemoteCLIP + O-TPT	**66.844 %**	7.865
EuroSAT	openCLIP	42.900 %	21.883
	openCLIP + O-TPT	48.500 %	**16.172**
	RemoteCLIP	34.099 %	18.9075
	RemoteCLIP + O-TPT	**35.499 %**	26.192
PatternNet	openCLIP	**58.95 %**	9.379
	openCLIP + O-TPT	54.447 %	10.476
	RemoteCLIP	51.578 %	**12.724**
	RemoteCLIP + O-TPT	54.736 %	13.578

Limitations

- Scene ambiguity in RS imagery
  - Single-label scenes often contain multiple semantic regions (e.g., residential + agriculture)
- Entropy-only adaptation signal can be brittle
  - Confident views may disagree on class; entropy of the mean remains high, driving noisy updates
- Variance across runs
  - Random crops is causing metric jumps

```
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```
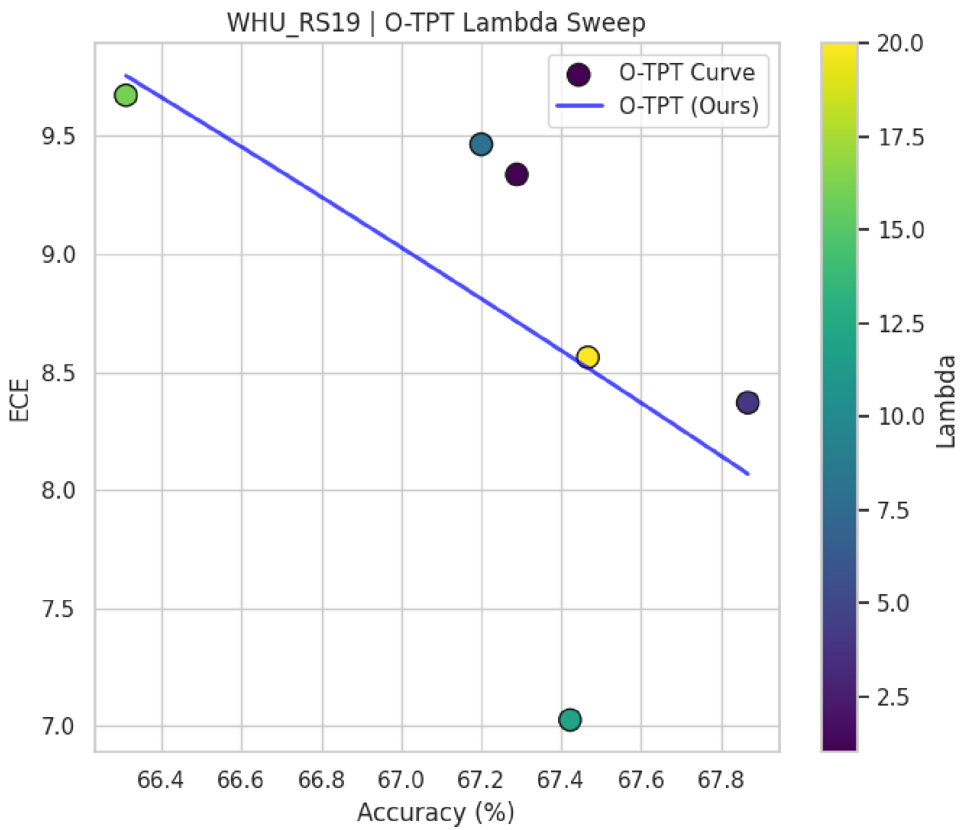
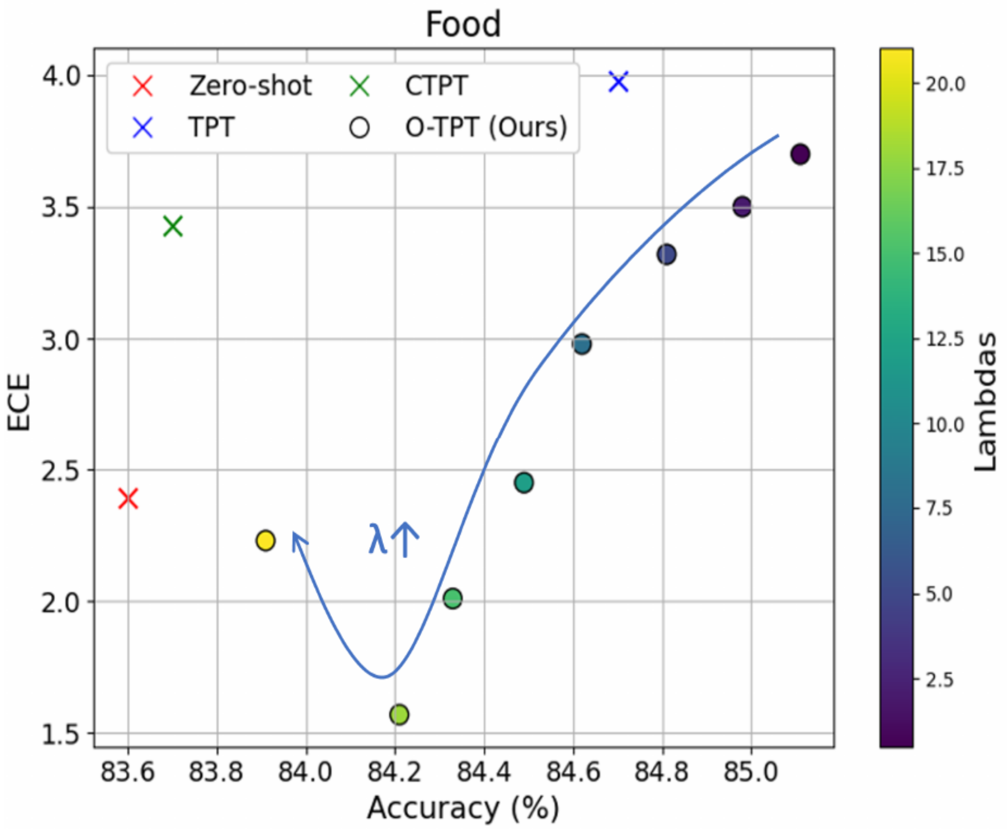

Limitations (Hypothesis)

- Assumption violation:
  TPT/O-TPT assumes label invariance across augmented views of the same image
- RS scenes break this:
  - Some crops show only agriculture, others residential, others mixed - each “rightfully” yields different class predictions
- Resulting dynamics:
  - Many low-entropy (confident) views but with different classes
  - Averaged prediction becomes multi-modal → high H(mean), inconsistent gradients
  - Leads to noisy λ trends and limited gains

Limitations (Hypothesis)





Future Work

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Thank You!