Novelty Assessment Report

Paper: PSP: Prompt-Guided Self-Training Sampling Policy for Active Prompt Learning

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Abstract

Active Prompt Learning (APL) using vision-language models (\textit{e.g.}, CLIP) has attracted considerable attention for mitigating the dependence on fully labeled dataset in downstream task adaptation. However, existing methods fail to explicitly leverage prompt to guide sample selection, resulting in the selected samples being ineffective in facilitating the prompt template's downstream task adaptation, while also overlooking valuable complementary information in the unselected samples. To fill this gap, we propose a novel Prompt-Guided Self-Training Sampling Policy (PSP) for APL, which integrates Soft Actor-Critic with a customized real-pseudo hybrid reward and vectorized critics to incorporate prompts in guiding sample selection toward those that facilitate the optimization of prompt template, by jointly considering both selected and unselected samples. Specifically, PSP comprises two prominent components: Vectorized Soft Actor-Critic Sampling Policy (VSSP) and Uncertainty Augmented Self-Training (UST) mechanism. VSSP customizes a real-pseudo hybrid reward based on learned prompts and image features, which is fed into vectorized critics to estimate Q-value for each sample and compute gradients that optimize the actor, allowing it to refine its sampling policy in an End-to-End manner to identify the most informative samples for prompt learning. Moreover, UST leverages the CLIP from the previous round to generate reliable pseudo-labeled data based on uncertainty and confidence of average predictions, thereby deepening the understanding of the overall data. Extensive experiments conducted on diverse real-world datasets validate the effectiveness of our PSP.

Core Task Landscape

This paper addresses: **Active Prompt Learning with Vision-Language Models**

A total of **50 papers** were analyzed and organized into a taxonomy with **23 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Active Sample Selection and Data Efficiency**
- **Prompt Optimization and Tuning Strategies**
- **Domain-Specific and Task-Specific Adaptations**
- **Robustness and Distribution Challenges**
- **Federated and Privacy-Preserving Learning**
- **Unsupervised and Low-Resource Learning**
- **Continual and Lifelong Learning**
- **Theoretical Foundations and Model Analysis**

Complete Taxonomy Tree

- Active Prompt Learning with Vision-Language Models Survey Taxonomy
- Active Sample Selection and Data Efficiency
  - Policy-Based Active Selection ★ (2 papers)
  - [0] PSP: Prompt-Guided Self-Training Sampling Policy for Active Prompt Learning (Anon et al., 2026) View paper
  - [1] Active Prompt Learning in Vision Language Models (Jihwan Bang, 2024) View paper
  - Uncertainty and Confidence-Based Selection (3 papers)
  - [2] Active Prompt Learning with Vision-Language Model Priors (Kim Hoyoung, 2024) View paper
  - [19] VeCAF: Vision-language collaborative active finetuning with training objective awareness (Rongyu Zhang, 2024) View paper
  - [36] Active Learning via Vision-Language Model Adaptation with Open Data (Wang Tong, 2025) View paper
  - Open-Set and Open-Vocabulary Active Learning (1 papers)
  - [34] OpenPath: Open-Set Active Learning for Pathology Image Classification via Pre-trained Vision-Language Models (Zhong Lanfeng, 2025) View paper
- Prompt Optimization and Tuning Strategies
  - Context and Text Prompt Learning (4 papers)
  - [3] Conditional Prompt Learning for Vision-Language Models (Kaiyang Zhou, 2022) View paper
  - [22] LASP: Text-to-Text Optimization for Language-Aware Soft Prompting of Vision & Language Models (Adrian Bulat, 2023) View paper
  - [26] Learning to Prompt for Vision-Language Models (Kai-yang, 2022) View paper
  - [28] Learning to Prompt for Open-Vocabulary Object Detection with Vision-Language Model (Yu Du, 2022) View paper
  - Visual and Multi-Modal Prompt Learning (6 papers)
  - [10] APoLLo : Unified Adapter and Prompt Learning for Vision Language Models (Chowdhury, 2023) View paper
  - [20] VaMP: Variational Multi-Modal Prompt Learning for Vision-Language Models (Silin Cheng, 2025) View paper
  - [25] MCPL: Multi-Modal Collaborative Prompt Learning for Medical Vision-Language Model. (Pengyu Wang, 2025) View paper
  - [35] Multi-Modal Prompt Learning on Blind Image Quality Assessment (Pan Wensheng, 2024) View paper

- [39] Unified Vision and Language Prompt Learning (Zang, 2022) View paper
- [42] Class-Aware Visual Prompt Tuning for Vision-Language Pre-Trained Model (Xing, 2022) View paper
- Dynamic and Conditional Prompt Adaptation (3 papers)
- [5] Consistency-guided Prompt Learning for Vision-Language Models (Roy Shuvendu, 2023) View paper
- [31] Adapting Pre-trained Language Models to Vision-Language Tasksvia Dynamic Visual Prompting (Shubin Huang, 2024) View paper
- [47] Foundations of Vision-Language Models: Concepts and Roadmap (Kaiyang Zhou, 2025) View paper
- Multi-Prompt and Ensemble Learning (4 papers)
- [15] GalLoP: Learning Global and Local Prompts for Vision-Language Models (Lafon, 2024) View paper
- [27] A Retrospect to Multi-prompt Learning across Vision and Language (Chen, 2023) View paper
- [29] Progressive multi-prompt learning for vision-language models (Jun Liu, 2025) View paper
- [48] Retaining and Enhancing Pre-trained Knowledge in Vision-Language Models with Prompt Ensembling (Donggeun Kim, 2024) View paper
- Regularization and Generalization Enhancement (3 papers)
- [12] Gradient-Regulated Meta-Prompt Learning for Generalizable Vision-Language Models (Jun-Cheng Li, 2023) View paper
- [30] AAPL: Adding Attributes to Prompt Learning for Vision-Language Models (Gahyeon Kim, 2024) View paper
- [40] Read-only Prompt Optimization for Vision-Language Few-shot Learning (Dongjun Lee, 2023) View paper

- Domain-Specific and Task-Specific Adaptations
  - Biomedical and Medical Imaging (5 papers)
  - [8] Biomedcoop: Learning to prompt for biomedical vision-language models (Taha Koleilat, 2025) View paper
  - [18] Guiding Medical Vision-Language Models with Explicit Visual Prompts: Framework Design and Comprehensive Exploration of Prompt Variations (Qin, 2025) View paper
  - [21] Active prompting of vision language models for human-in-the-loop classification and explanation of microscopy images (Abhiram Kandiyana, 2024) View paper
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  - [46] Domain-Specific Interactive Prompting for Generalized Nuclei Classification (Binbin Zheng, 2025) View paper
  - Object Detection and Spatial Reasoning (2 papers)
  - [32] Openvidvrd: Open-vocabulary video visual relation detection via prompt-driven semantic space alignment (Liu Qi, 2025) View paper
  - [37] PEVL: Position-enhanced Pre-training and Prompt Tuning for Vision-language Models (Chen, 2022) View paper
  - Tracking and Temporal Tasks (1 papers)
  - [16] Learning Language Prompt for Vision-Language Tracking (Chengao Zong, 2025) View paper
  - Specialized Application Domains (2 papers)
  - [14] Pivot: Iterative visual prompting elicits actionable knowledge for vlms (Nasiriany, 2024) View paper
  - [43] Few-Shot Prompting with Vision Language Model for Pain Classification in Infant Cry Sounds (Anthony McCofie, 2025) View paper
- Robustness and Distribution Challenges
  - Noisy Labels and Data Quality (1 papers)
  - [9] NLPrompt: Noise-Label Prompt Learning for Vision-Language Models (Bikang Pan, 2025) View paper
  - Domain Adaptation and Shift (2 papers)
  - [33] Open Set Domain Adaptation with Vision-language models via Gradient-aware Separation (Chen, 2025) View paper
  - [38] Towards Dynamic-Prompting Collaboration for Source-Free Domain Adaptation (Yi Liu, 2024) View paper
  - Class Imbalance and Long-Tail Distribution (1 papers)
  - [41] Exploring Vision-Language Models for Imbalanced Learning (Yidong Wang, 2023) View paper
  - Missing Modalities and Incomplete Data (1 papers)
  - [17] Muap: Multi-step adaptive prompt learning for vision-language model with missing modality (Dai Ruiting, 2024) View paper
- Federated and Privacy-Preserving Learning
  - Federated Prompt Learning (2 papers)
  - [13] pFedPrompt: Learning Personalized Prompt for Vision-Language Models in Federated Learning (Tao Guo, 2023) View paper
  - [50] Privacy-preserving personalized federated prompt learning for vision-language models. (Yinan Wu, n.d.) View paper
- Unsupervised and Low-Resource Learning
  - Unsupervised Prompt Learning (1 papers)
  - [4] Unsupervised Prompt Learning for Vision-Language Models (Huang, 2022) View paper
  - Few-Shot and Low-Resource Adaptation (2 papers)
  - [23] A Good Prompt Is Worth Millions of Parameters: Low-resource Prompt-based Learning for Vision-Language Models (Chen, 2022) View paper
  - [45] Supporting vision-language model few-shot inference with confounder-pruned knowledge prompt. (Jiangmeng Li, 2025) View paper
- Continual and Lifelong Learning
  - Continual Multi-Modal Learning (1 papers)
  - [24] Decouple before interact: Multi-modal prompt learning for continual visual question answering (Zi Qian, 2023) View paper
- Theoretical Foundations and Model Analysis
  - Uncertainty Quantification and Probabilistic Modeling (1 papers)
  - [6] Post-hoc probabilistic vision-language models (Baumann, 2024) View paper
  - Counterfactual and Causal Analysis (1 papers)
  - [11] CPL: Counterfactual Prompt Learning for Vision and Language Models (He, 2022) View paper
  - Training-Free and Inference-Time Adaptation (2 papers)
  - [7] Controlmllm: Training-free visual prompt learning for multimodal large language models (Xinyue Cai, 2024) View paper
  - [49] Class-Specific Prompt Learning for Vision-Language Models. (Li Runhao, n.d.) View paper

Narrative

Core task: active prompt learning with vision-language models. The field has evolved into a rich ecosystem organized around several complementary themes. Active Sample Selection and Data Efficiency explores how to choose the most informative examples for prompt tuning, often employing policy-based or uncertainty-driven strategies to minimize annotation costs. Prompt Optimization and Tuning Strategies focuses on the mechanics of learning effective prompts, ranging from gradient-based methods like Conditional Prompt Learning[3] to ensemble and meta-learning approaches. Domain-Specific and Task-Specific Adaptations address tailoring prompts to specialized contexts such as medical imaging or open-vocabulary detection, while Robustness and Distribution Challenges tackle generalization under domain shift and out-of-distribution scenarios. Meanwhile, Federated and Privacy-Preserving Learning, Unsupervised and Low-Resource Learning, and Continual and Lifelong Learning branches investigate settings where data is decentralized, scarce, or arrives sequentially. Finally, Theoretical Foundations and Model Analysis provides deeper understanding of why and how prompts work.

Within the Active Sample Selection branch, a handful of works have emerged that treat sample selection as a learnable policy problem, aiming to identify which examples yield the greatest improvement in prompt quality. PSP Prompt Sampling[0] sits squarely in this policy-based active selection cluster, emphasizing strategic sampling to boost data efficiency. It shares common ground with Active Prompt Learning[1] and Active Prompt Priors[2], both of which also prioritize intelligent example selection but may differ in their underlying selection criteria or integration with prompt optimization loops. Compared to broader prompt tuning methods like Conditional Prompt Learning[3] or Unsupervised Prompt Learning[4], PSP Prompt Sampling[0] places greater emphasis on the active curation of training samples rather than solely on the prompt representation itself. This positioning highlights an ongoing tension in the field: whether gains come primarily from better prompts or from better data, and how these two dimensions can be jointly optimized.

Related Works in Same Category

The following **1 sibling papers** share the same taxonomy leaf node with the original paper:

1. Active Prompt Learning in Vision Language Models

Authors: Jihwan Bang, Sumyeong Ahn, Jae-gil Lee | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Pre-trained Vision Language Models (VLMs) have demonstrated notable progress in various zero-shot tasks, such as classification and retrieval. Despite their performance, because improving performance on new tasks requires task-specific knowledge, their adaptation is essential. While labels are needed for the adaptation, acquiring them is typically expensive. To overcome this challenge, active learning, a method of achieving a high performance by obtaining labels for a small number of samples fro...

Relationship Analysis

Both papers belong to the Policy-Based Active Selection category, using reinforcement learning approaches to guide sample selection for prompt learning with vision-language models. The candidate paper (PCB) addresses class imbalance in active prompt learning by using VLM knowledge to balance labeling candidates before annotation, employing conventional sampling methods (Entropy, Coreset, BADGE) with a balance sampler. The original paper (PSP) differs by introducing a Soft Actor-Critic framework with vectorized critics and a real-pseudo hybrid reward that explicitly integrates learned prompts to guide the sampling policy, and additionally incorporates an uncertainty-augmented self-training mechanism to leverage pseudo-labeled data from unselected samples.

Contributions Analysis

Overall novelty summary. The paper proposes a Prompt-Guided Self-Training Sampling Policy (PSP) that combines reinforcement learning-based sample selection with self-training for active prompt learning. It resides in the 'Policy-Based Active Selection' leaf, which contains only two papers including this one. This is a notably sparse research direction within the broader taxonomy of 50 papers across 36 topics, suggesting that policy-based approaches to active sample selection in prompt learning remain relatively underexplored compared to other branches like prompt optimization strategies or domain-specific adaptations.

The taxonomy reveals that most active learning work in this field concentrates on 'Uncertainty and Confidence-Based Selection' (three papers) and 'Open-Set and Open-Vocabulary Active Learning' (one paper), while the broader 'Prompt Optimization and Tuning Strategies' branch is substantially more populated with methods focused on context learning, visual prompts, and regularization. The paper's integration of policy networks with prompt-guided rewards positions it at the intersection of active selection and prompt optimization, diverging from purely uncertainty-driven or heuristic selection methods that dominate neighboring leaves. This cross-cutting approach appears less common in the current landscape.

Among 21 candidates examined, the contribution-level analysis shows mixed novelty signals. The core PSP framework examined 10 candidates with no clear refutations, suggesting reasonable distinctiveness in its overall approach. The Vectorized Soft Actor-Critic component examined only 1 candidate with no refutation, though the limited search scope makes this less conclusive. The Uncertainty Augmented Self-Training mechanism examined 10 candidates and found 1 refutable match, indicating some overlap with existing self-training or uncertainty-based methods. The limited search scale means these findings reflect top-K semantic matches rather than exhaustive coverage.

Based on the available signals from 21 examined candidates, the work appears to occupy a relatively novel position by combining policy-based selection with prompt-guided rewards, though the self-training component shows some prior overlap. The sparse population of its taxonomy leaf and the cross-cutting nature of its approach suggest potential novelty, but the limited search scope prevents definitive conclusions about how thoroughly the space of policy-based active prompt learning has been explored.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Prompt-Guided Self-Training Sampling Policy (PSP) for Active Prompt Learning

Description: The authors introduce PSP, a framework that combines Soft Actor-Critic with a tailored real-pseudo hybrid reward and vectorized critics to explicitly leverage prompts for guiding sample selection in active prompt learning. This approach bridges sample selection and prompt learning by jointly considering both selected and unselected samples.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. RLS3: RL-Based Synthetic Sample Selection to Enhance Spatial Reasoning in Vision-Language Models for Indoor Autonomous Perception

URL: View paper

Brief Assessment

RLS3[67] focuses on RL-guided synthetic data generation for VLM fine-tuning in spatial reasoning tasks, not on active prompt learning with sample selection policies for vision-language models.

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2. Toward Ambulatory Vision: Learning Visually-Grounded Active View Selection

URL: View paper

Brief Assessment

Ambulatory Vision[70] focuses on active view selection in 3D environments for embodied visual question answering, not on active learning with reinforcement learning for sample selection in prompt-based vision-language models. The candidate addresses viewpoint optimization for VQA tasks, while the original addresses sample selection for prompt learning.

3. Vl-rethinker: Incentivizing self-reflection of vision-language models with reinforcement learning

URL: View paper

Brief Assessment

VL Rethinker[62] focuses on incentivizing self-reflection in vision-language models through reinforcement learning for multimodal reasoning tasks, not on active learning sample selection for prompt learning. The technical approaches and problem domains are fundamentally different.

4. Improving vision-language-action model with online reinforcement learning

URL: View paper

Brief Assessment

Improving VLA Online[65] focuses on improving vision-language-action models for robotic control through online reinforcement learning, not on active learning sample selection for prompt-based vision-language models. The technical domains are fundamentally different.

5. Reason-rft: Reinforcement fine-tuning for visual reasoning of vision language models

URL: View paper

Brief Assessment

Reason-RFT[64] focuses on reinforcement fine-tuning for visual reasoning in vision-language models using GRPO, not on active learning sample selection guided by prompts for downstream task adaptation.

6. Few-Shot Vision-Language Reasoning for Satellite Imagery via Verifiable Rewards

URL: View paper

Brief Assessment

Satellite Verifiable Rewards[66] focuses on few-shot reinforcement learning for satellite imagery reasoning tasks using verifiable rewards, not on active learning sample selection for prompt-based vision-language models. The candidate addresses vision-language reasoning in remote sensing with minimal examples, while the original contribution concerns active prompt learning with sample selection policies guided by prompts.

7. Fine-tuning large vision-language models as decision-making agents via reinforcement learning

URL: View paper

Brief Assessment

Finetuning VLM RL[63] focuses on fine-tuning vision-language models with reinforcement learning for multi-step decision-making tasks in interactive environments, not on active learning with sample selection for prompt-based models. The technical approaches and problem domains are fundamentally different.

8. VRAG-RL: Empower Vision-Perception-Based RAG for Visually Rich Information Understanding via Iterative Reasoning with Reinforcement Learning

URL: View paper

Brief Assessment

VRAG-RL[68] focuses on vision-based retrieval-augmented generation for visually rich documents using reinforcement learning, not active learning for sample selection in prompt-based vision-language models. The candidate addresses a different problem domain (RAG for document understanding) rather than active prompt learning with sample selection policies.

9. Rl-vlm-f: Reinforcement learning from vision language foundation model feedback

URL: View paper

Brief Assessment

RL VLM Feedback[61] focuses on using vision-language models to generate reward functions for reinforcement learning tasks through preference labeling, not on active learning sample selection for prompt optimization. The candidate addresses reward engineering in RL, while the original addresses sample selection in active prompt learning - fundamentally different problem domains.

10. WeThink: Toward General-purpose Vision-Language Reasoning via Reinforcement Learning

URL: View paper

Brief Assessment

WeThink[69] focuses on general-purpose vision-language reasoning through reinforcement learning for multimodal question-answering tasks, not on active learning with sample selection for prompt-based models. The technical approaches and problem domains are fundamentally different.

Contribution 2: Vectorized Soft Actor-Critic Sampling Policy (VSSP)

Description: VSSP is a component that customizes a real-pseudo hybrid reward using learned prompts and image features, which is then fed into vectorized critics to estimate Q-values for each sample and compute actor gradients. This enables the actor to refine its sampling policy in an end-to-end manner to identify the most informative samples for prompt learning.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Decentralized policy gradient method for mean-field linear quadratic regulator with global convergence

URL: View paper

Brief Assessment

Decentralized Policy Gradient[71] focuses on mean-field linear quadratic regulator problems in multi-agent reinforcement learning with decentralized policy updates over communication networks, not on active learning with hybrid rewards and vectorized critics for sample selection in vision-language models.

Contribution 3: Uncertainty Augmented Self-Training (UST) mechanism

Description: UST is a mechanism that leverages the teacher CLIP model to generate reliable pseudo-labeled data by evaluating uncertainty and confidence of average predictions across multiple augmentations. This mechanism extracts complementary information from unselected samples to deepen understanding of the overall data distribution.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. An uncertainty-guided tiered self-training framework for active source-free domain adaptation in prostate segmentation

URL: View paper

Brief Assessment

Uncertainty Tiered Self[54] focuses on medical image segmentation (prostate MRI) with source-free domain adaptation, while the original paper addresses active prompt learning for vision-language models. The technical approaches differ fundamentally in their application domains and methodologies.

2. Rice Panicle Segmentation using Multi-Stage Pseudo-labeling and Active Learning

URL: View paper

Brief Assessment

Rice Panicle Pseudo[58] focuses on rice panicle segmentation using entropy-based uncertainty for active learning sample selection, not on generating pseudo-labels through uncertainty evaluation of multiple augmentations for vision-language model prompt learning.

3. nnFilterMatch: A Unified Semi-Supervised Learning Framework with Uncertainty-Aware Pseudo-Label Filtering for Efficient Medical Segmentation

URL: View paper

Brief Assessment

nnFilterMatch[60] focuses on medical image segmentation using entropy-based pseudo-label filtering within a single-pass training framework, whereas the original paper's UST mechanism is designed for active prompt learning with vision-language models (CLIP). The technical contexts and application domains differ substantially.

4. Semi-supervised active learning for object detection

URL: View paper

Brief Assessment

Semi Supervised Active[55] focuses on object detection with classification and localization stability for uncertainty measurement, while UST targets vision-language prompt learning using CLIP model predictions across augmentations. The technical domains and uncertainty evaluation approaches differ fundamentally.

5. Exploiting completeness and uncertainty of pseudo labels for weakly supervised video anomaly detection

URL: View paper

Brief Assessment

Completeness Uncertainty Pseudo[51] focuses on video anomaly detection using uncertainty-based pseudo-label selection with Monte Carlo dropout for filtering reliable samples. The original paper applies uncertainty-based self-training to active prompt learning with CLIP models for image classification tasks, representing a fundamentally different application domain and technical approach.

6. Uncertainty-guided never-ending learning to drive

URL: View paper

Prior Art Analysis

Uncertainty Never Ending[52] demonstrates prior work that leverages uncertainty-based pseudo-labeling with teacher-student frameworks for self-training in vision tasks. The candidate paper presents a comprehensive system where an ensemble of inverse dynamics models generates pseudo-labels with epistemic uncertainty estimates, which are then filtered based on confidence and uncertainty thresholds. This approach of using uncertainty to evaluate and select reliable pseudo-labeled data from unselected samples predates the original paper's UST mechanism, which similarly uses teacher CLIP models to generate pseudo-labels by evaluating uncertainty and confidence across multiple augmentations.

Evidence

Evidence 1 - **Rationale**: Both papers use ensemble models to estimate uncertainty for pseudo-label generation, though the candidate uses inverse dynamics models while the original uses CLIP models. - **Original**: UST leverages the teacher CLIP from the previous round to generate reliable pseudo-labeled data based on uncertainty and confidence of average predictions across multiple augmentations. - **Candidate**: we propose to learn an ensemble of models and aggregate predictions from each model to improve accuracy... ensembling models effectively estimates well-calibratedepistemic uncertainty... we compute the disagreement ut = std({ˆym t }m m=1) as epistemic uncertainty among the ensemble models

Evidence 2 - **Rationale**: Both approaches filter pseudo-labels based on uncertainty and confidence metrics to obtain reliable training data. - **Original**: ust employs the teacher clip model from round t - 1 to generate reliable pseudo-labels by evaluating the uncertainty and confidence of the average predictions - **Candidate**: for the high uncertainty samples (ˆxt, ˆyt) ∈ n, we propose to apply temporal consistency smoothing to further purify each waypoint... we propose an adaptive filtering mechanism that contains a confidence-based filter to remove samples with potentially deprecated images

Evidence 3 - **Rationale**: Both papers use threshold-based filtering on uncertainty and confidence to select reliable pseudo-labeled samples, demonstrating similar mechanisms for pseudo-label quality control. - **Original**: bpls selects samples where gc i exceeds the prediction confidence threshold τc and gu i is below the prediction uncertainty threshold τu - **Candidate**: we use the two-component gaussian mixture model (gmm) to fit the uncertainties of all samples in the video. given sample ˆxt and its uncertainty ut, its low uncertainty probability is the posterior probability pgmm(g|ut)... c = {(ˆxt, ˆyt) ∈ u: pgmm(g|ut) ≥ ϵa} n = {(ˆxt, ˆyt) ∈ u: pgmm(g|ut) < ϵa}

Evidence 4 - **Rationale**: Both methods use averaging across multiple predictions (augmentations in original, temporal windows in candidate) to obtain more reliable pseudo-labels. - **Original**: ust begins by employing the same data augmentation to sample xu i from remaining unlabeled data du{xs i }ns i=1 to generate l augmentations of each unlabeled sample {xu,l i }l l=1... ust calculates the average of the logits zavg i to obtain the average prediction ˆyu i - **Candidate**: we propose to set a time window with size l and leverage those adjacent waypoints in the window to re-estimate the waypoint ˆyk... ˜yk = pl/2 i=1 yk -i + pl/2 i=1 yk i l where we denote ˜yk as the purified waypoint

7. Incremental Pedestrian Attribute Recognition via Dual Uncertainty-Aware Pseudo-Labeling

URL: View paper

Brief Assessment

Incremental Pedestrian Uncertainty[59] focuses on multi-label continual learning for pedestrian attribute recognition with incomplete labels, not active prompt learning with CLIP models for general vision tasks.

8. Uncertainty-aware Pseudo Label Refinery for Domain Adaptive Semantic Segmentation

URL: View paper

Brief Assessment

Uncertainty Pseudo Refinery[53] focuses on domain adaptive semantic segmentation with pixel-level pseudo labels, while UST targets active prompt learning for vision-language models using image-level classification with multiple augmentations and CLIP-based confidence evaluation.

9. A Facial Expression Recognition Method Integrating Uncertainty Estimation and Active Learning.

URL: View paper

Brief Assessment

Facial Expression Uncertainty[56] focuses on facial expression recognition tasks with uncertainty estimation for active learning, not on vision-language model prompt learning with pseudo-labeling for general vision tasks.

10. Active uncertainty representation learning: Toward more label efficiency in deep learning

URL: View paper

Brief Assessment

Active Uncertainty Representation[57] focuses on ensemble-based self-training for self-supervised learning baselines, not on pseudo-labeling guided by teacher CLIP models for active prompt learning in vision-language tasks.

Appendix: Text Similarity Detection

Textual similarity detection checked 22 papers and found 2 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Active Prompt Learning in Vision Language Models

Detected in: Core Task (sibling)

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

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