

## Evidential Deep Learning

- **Evidential deep learning (EDL)**
  - a non-Bayesian approach to estimate aleatoric uncertainty (AU) and epistemic uncertainty (EU) by modeling the evidential prior of target distribution
- **Entropy-based classification EDL**
  - quantifies total uncertainty as predictive entropy
  - decomposes uncertainty by information theory
- **Variance-based classification EDL (ours)**
  - quantifies total uncertainty as predictive variance
  - decomposes uncertainty by law of total covariance

## Variance-Based Evidential Deep Learning

- **Classification problem notations**
  - $C$ : number of classes
  - $\mathbf{y}$ : target one-hot label vector
  - $\mathbf{p}$ : class probability vector
  - $\alpha$ : prior distribution parameters (model prediction)
- **Fundamental probability distribution assumptions**
  - $\mathbf{y} \sim \text{Multinomial}(1, \mathbf{p})$
  - $\mathbf{p} \sim \text{Dirichlet}(\alpha)$
- **Covariance matrix decomposition**

$$\text{Cov}[\mathbf{y}] := \mathbb{E}[(\mathbf{y} - \mathbb{E}[\mathbf{y}])(\mathbf{y} - \mathbb{E}[\mathbf{y}])^T] = \text{Diag}(\bar{\mathbf{p}}) - \bar{\mathbf{p}}\bar{\mathbf{p}}^T$$

$$\text{Cov}[\mathbf{y}]^{\text{alea}} := \mathbb{E}[\text{Cov}[\mathbf{y}|\mathbf{p}]] = \frac{\alpha_0}{\alpha_0 + 1} (\text{Diag}(\bar{\mathbf{p}}) - \bar{\mathbf{p}}\bar{\mathbf{p}}^T)$$

$$\text{Cov}[\mathbf{y}]^{\text{epis}} := \text{Cov}[\mathbb{E}[\mathbf{y}|\mathbf{p}]] = \frac{1}{\alpha_0 + 1} (\text{Diag}(\bar{\mathbf{p}}) - \bar{\mathbf{p}}\bar{\mathbf{p}}^T)$$

$$\alpha_0 := \sum_{i=1}^C \alpha_i \quad \bar{\mathbf{p}} := \mathbb{E}[\mathbf{p}] = \frac{\alpha}{\alpha_0}$$
- **Class-level evidential uncertainties**

$$U_i^{\text{alea}} := \text{Cov}[\mathbf{y}]_{i,i}^{\text{alea}} = \frac{\alpha_0}{\alpha_0 + 1} \bar{p}_i(1 - \bar{p}_i)$$

$$U_i^{\text{epis}} := \text{Cov}[\mathbf{y}]_{i,i}^{\text{epis}} = \frac{1}{\alpha_0 + 1} \bar{p}_i(1 - \bar{p}_i)$$
- **Sample-level evidential uncertainties**

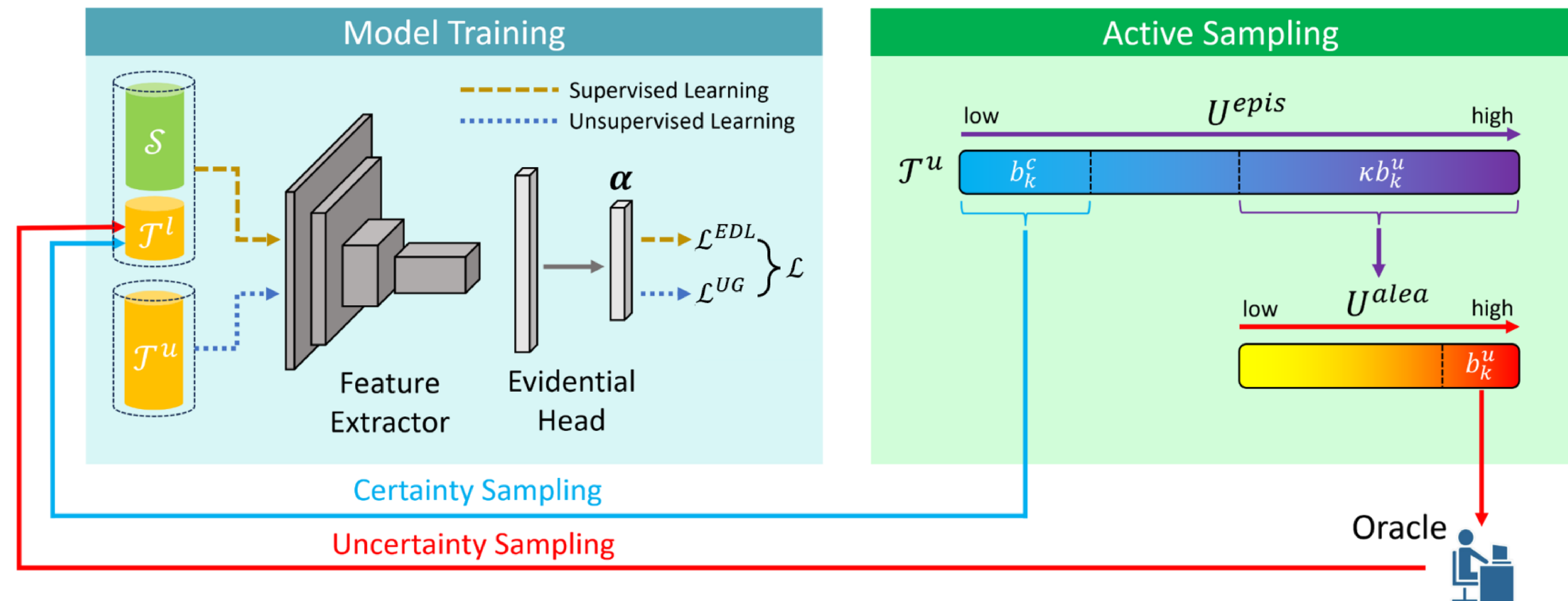
$$U^{\text{alea}} := \sum_{i=1}^C U_i^{\text{alea}} = \frac{\alpha_0}{\alpha_0 + 1} \left(1 - \sum_{i=1}^C \bar{p}_i^2\right)$$

$$U^{\text{epis}} := \sum_{i=1}^C U_i^{\text{epis}} = \frac{1}{\alpha_0 + 1} \left(1 - \sum_{i=1}^C \bar{p}_i^2\right)$$
- **Class correlation matrix**

$$\text{Corr}[\mathbf{y}] := \frac{\text{Cov}[\mathbf{y}]}{\sigma(\mathbf{y})\sigma(\mathbf{y})^T}$$

$$\sigma(\mathbf{y}) := \sqrt{\text{diag}(\text{Cov}[\mathbf{y}])}$$

## Active Domain Adaptation



EDL-based active domain adaptation (ADA) framework DUC with concurrent certainty and uncertainty sampling

- **Domain gap reduction**: model trained by uncertainties of unlabeled target dataset
- **Uncertainty sampling**: two-round sampling strategy based on evidential uncertainties
- **Certainty sampling**: certain samples identified by EU for semi-supervised learning

## Experiment Results and Analysis

- **Sample-level uncertainty quantification**

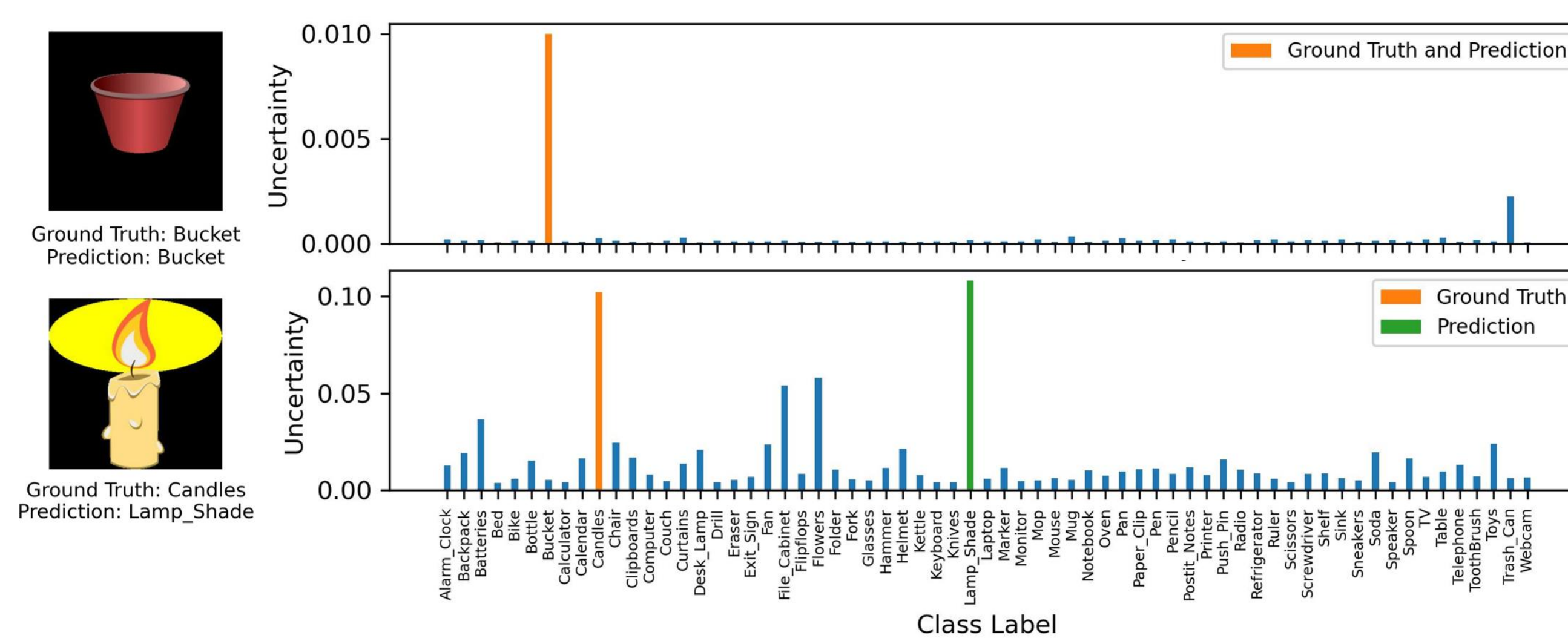
U	Office-Home		Visda-2017	
	w/o CS	w/ CS	w/o CS	w/ CS
Entropy	78.1	79.3	89.3	89.3
Variance	78.2	79.5	89.4	89.5

ADA accuracy (%) \*CS: certainty sampling

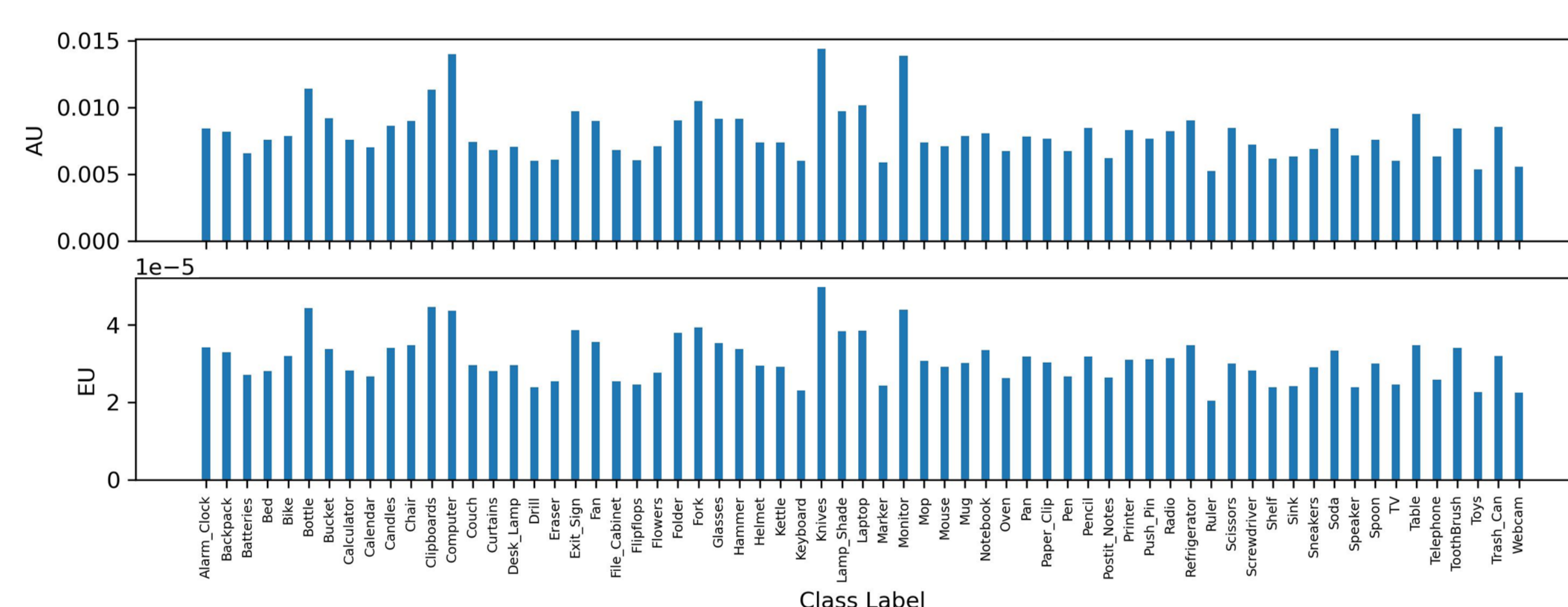
U	Office-Home		Visda-2017	
	AU	EU	AU	EU
Entropy	83.0	81.7	75.6	73.8
Variance	83.3	82.0	75.3	73.8

Misclassification detection AUC (%)

- **Class-level uncertainty quantification**



Class-level uncertainties of two Office-Home images



Class uncertainties of Office-Home Clipart

- **Between-class correlation quantification**

Class Pair		Corr
Computer	Monitor	-0.364
Bucket	Trash Can	-0.239
Desk Lamp	Lamp Shade	-0.226

Three most correlated class pairs in Office-Home Clipart

- **Compared with entropy-based EDL, the variance-based approach**

- achieves equivalent performance on sample-level uncertainty quantification
- provides class-level evidential uncertainties
- provides between-class correlations