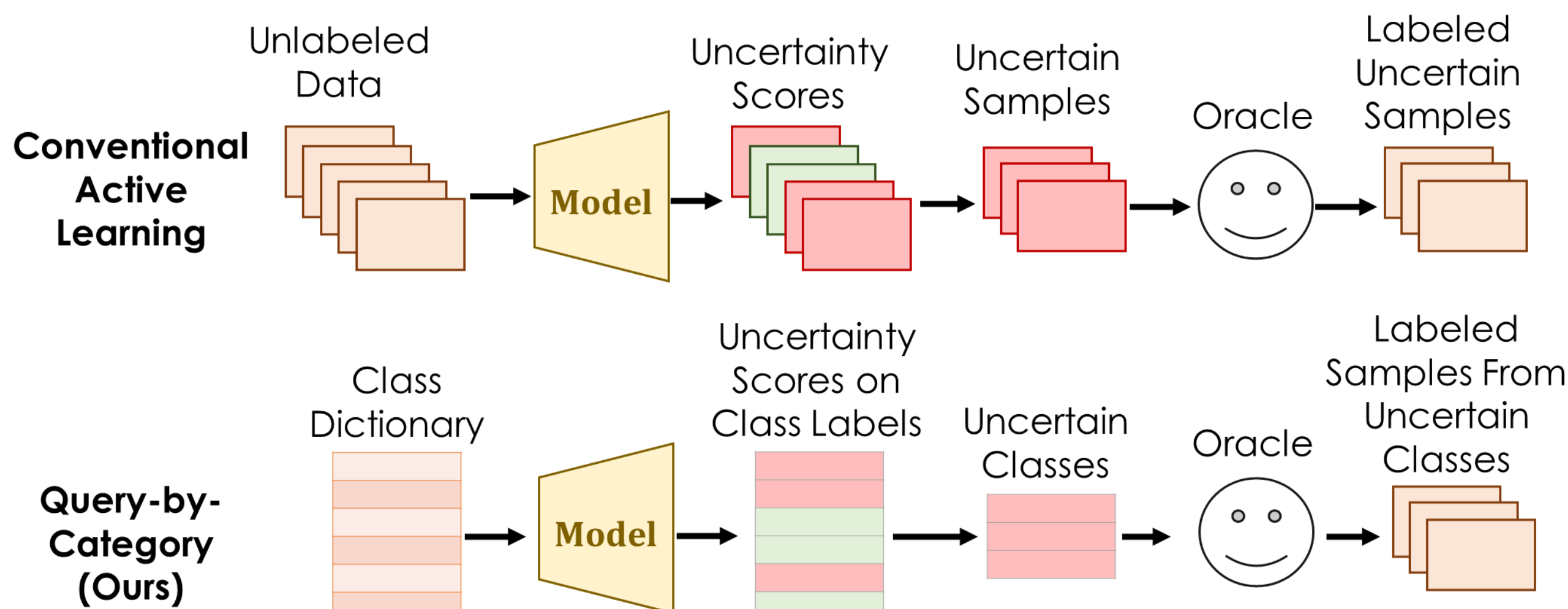


Overview

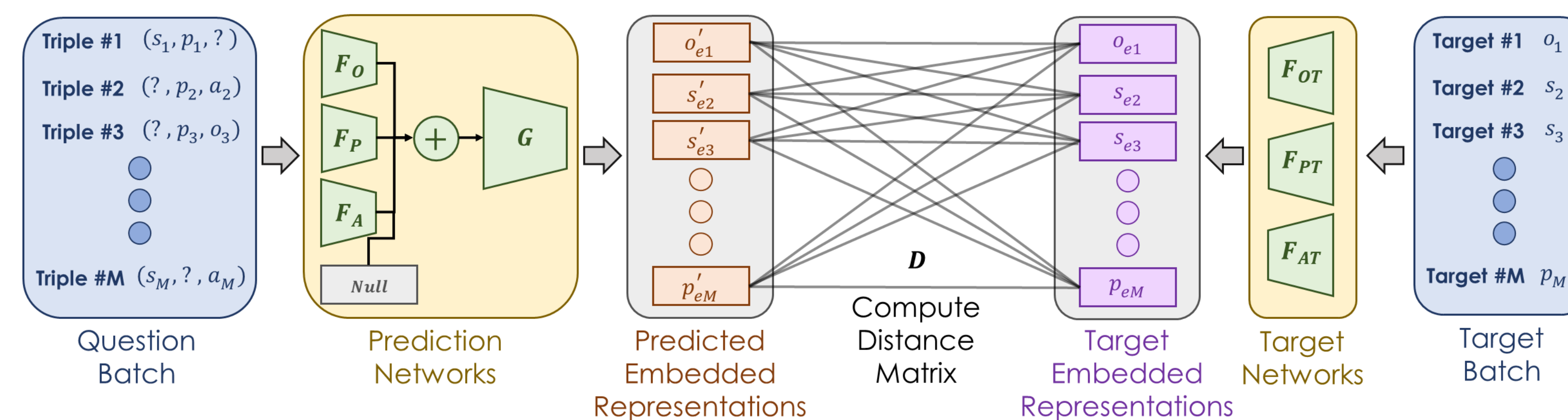
- An agent could better understand a scene by asking **questions** about particular **objects, attributes, or relationships** in a scene
- We introduce an active learning framework allowing agents to ask questions at the **category level** instead of the example level
- Challenge:** The distribution of attributes and relations in the natural world is **long-tailed**, causing overfitting
 - Problem is exacerbated in active learning settings
- Goal:** Train an agent to better understand visual scenes while minimizing the number of questions it asks an annotator

Query-by-Category (QBCat) Framework



Model Architecture

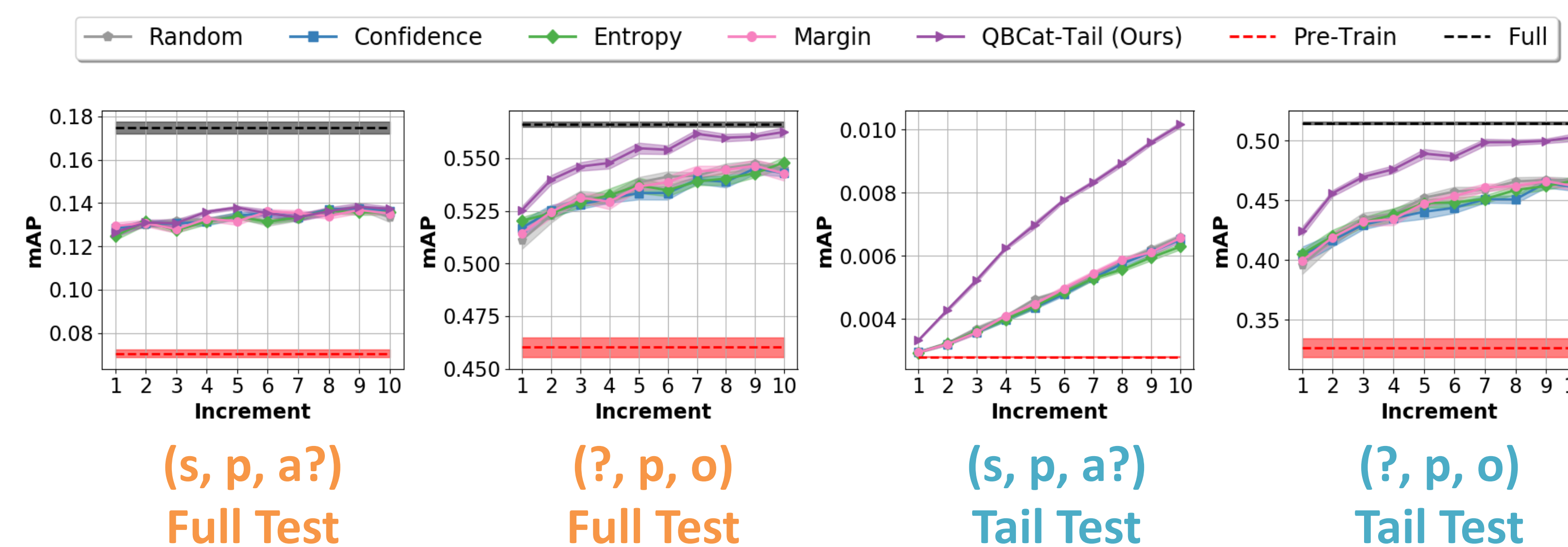
- We perform **Visual Triple Completion** where an agent is provided with two elements in a triple, and it must predict the missing element
- We use a Neighborhood Component Analysis Loss (Metric Learning) for training



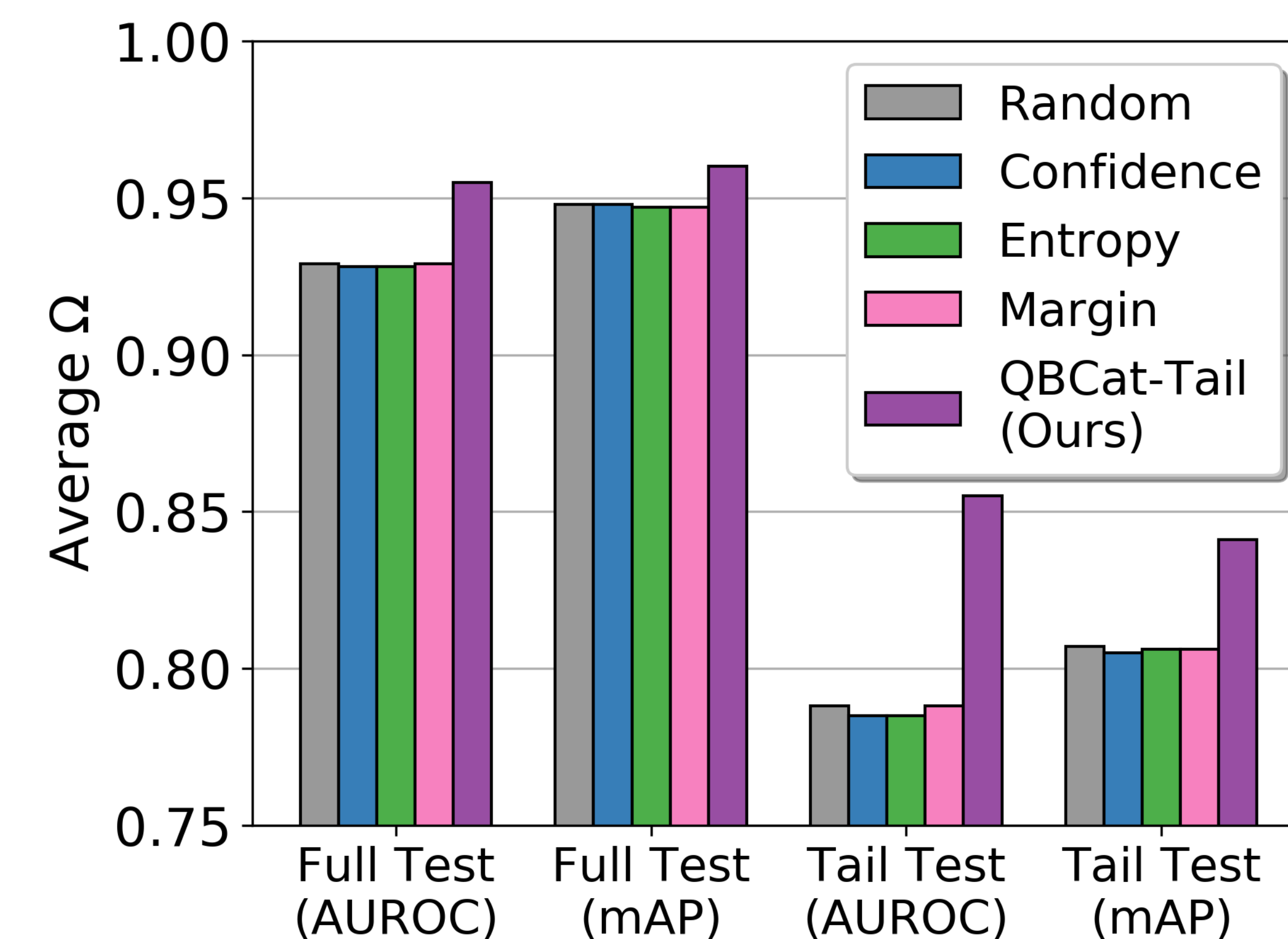
Experimental Setup

- We propose the **QBCat-Tail** active sampling method that selects data from **tail classes uniformly at random**
- We compare QBCat-Tail to four conventional active learning baselines: **Random, Confidence, Entropy, and Margin**
- We perform incremental active learning over 10 increments
- We compare performance on the **Visual Genome** dataset using a **full test set** and a **tail test set**

Incremental Results



Overall Results



- QBCat-Tail has **strong performance on tail data** without sacrificing performance on the natural data distribution
- QBCat-Tail **outperforms all baselines**
- Performance differences among conventional active learners are **minimal**

Summary

- We introduced the **Query-by-Category** framework to train agents to predict objects, predicates, and attributes in **visual scenes**
- We introduced a simple yet effective active sampling approach (**QBCat-Tail**) that asks for examples from tail classes
- We demonstrated the effectiveness of QBCat-Tail on the Visual Genome dataset compared to active learning baselines

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