Beyond Comparing Image Pairs: Setwise Active Learning for Relative Attributes

Lucy Liang and Kristen Grauman
University of Texas at Austin

Problem

Goal: Reliable relative attribute predictions

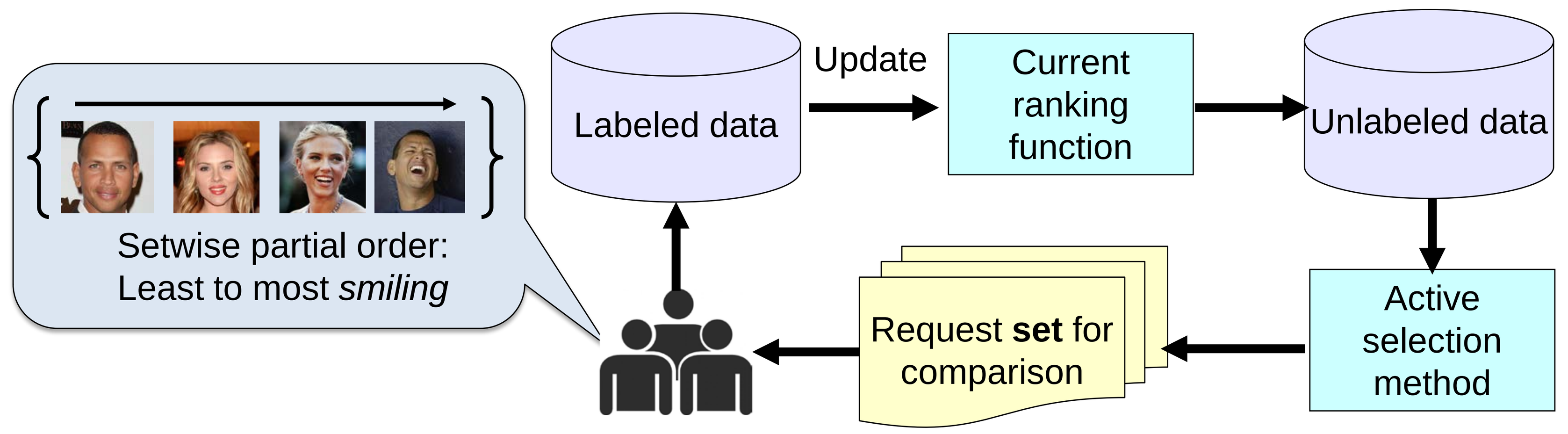
Challenge: Learning a ranking function is complex

- Supervision requires *comparisons*, not traditional labels.
- Subtle comparisons can be ambiguous to annotator.
- Expensive: quadratic number of possible training comparisons!

Which comparisons are most valuable for learning?

Our Idea

Actively select *setwise* comparisons to train a ranking function.

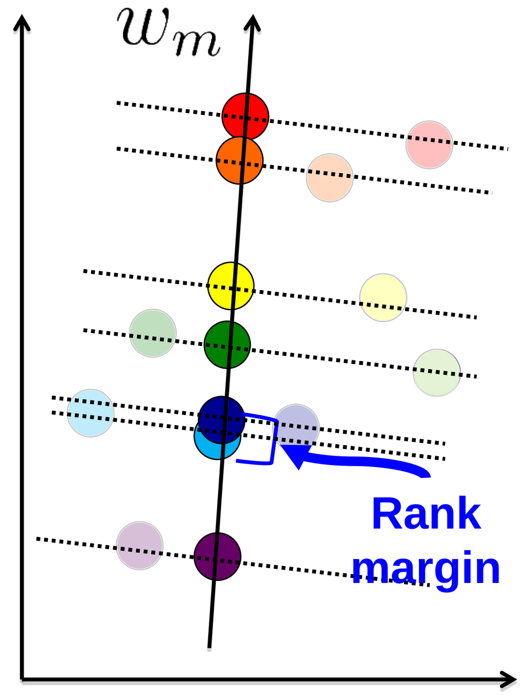


Background: Learning to Rank

1) Given ordered pairs $O_m = \{(i,j)\}$

2) For each attribute m, learn a ranking function $r_m(\boldsymbol{x}) = \boldsymbol{w}_m^T \boldsymbol{x}$ such that:

$$\forall (i,j) \in O_m : \boldsymbol{w}_m^T \boldsymbol{x}_i > \boldsymbol{w}_m^T \boldsymbol{x}_j$$



[Parikh and Grauman, ICCV 2011; Joachims KDD 2002]

Proposed Active Ranking Selection Criterion

We propose a Diverse Setwise Low Margin criterion, and show how to efficiently identify the most useful partial order to request from an annotator.

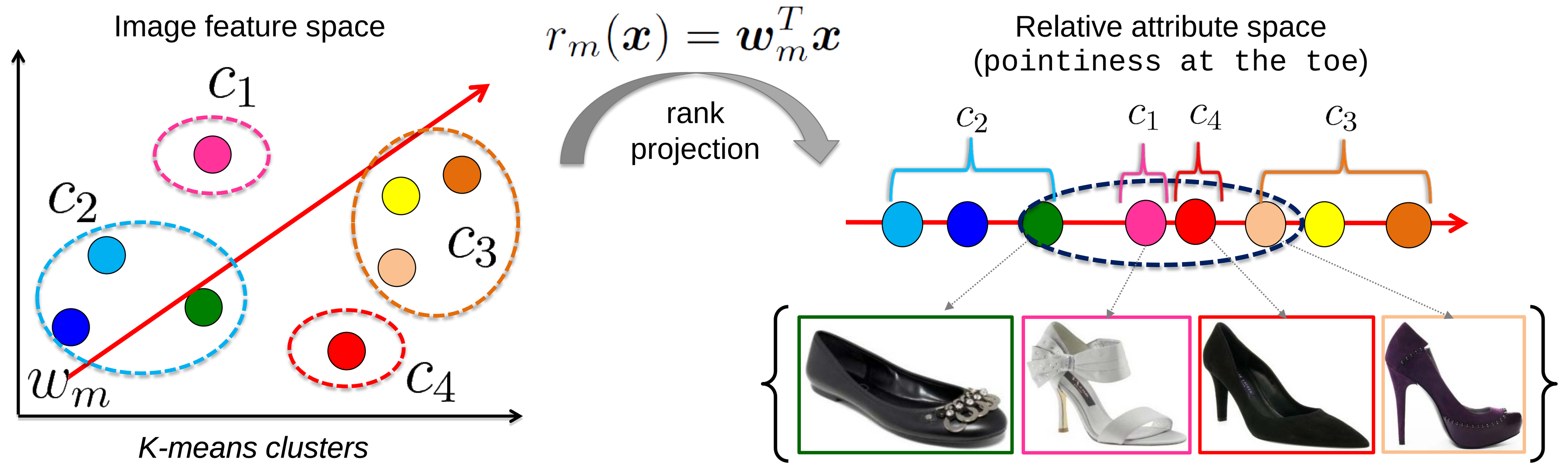
Objective:

$$\mathcal{S}^* = \underset{\mathcal{S} \subseteq \mathcal{P}}{\operatorname{argmin}} \sum_{(i,j) \in \mathcal{S}} |\boldsymbol{w}^T \boldsymbol{x}_i - \boldsymbol{w}^T \boldsymbol{x}_j|,$$

Mutually low margins in attribute space → Uncertainty

$$s.t. \quad c_i \neq c_j, \forall i \neq j,$$

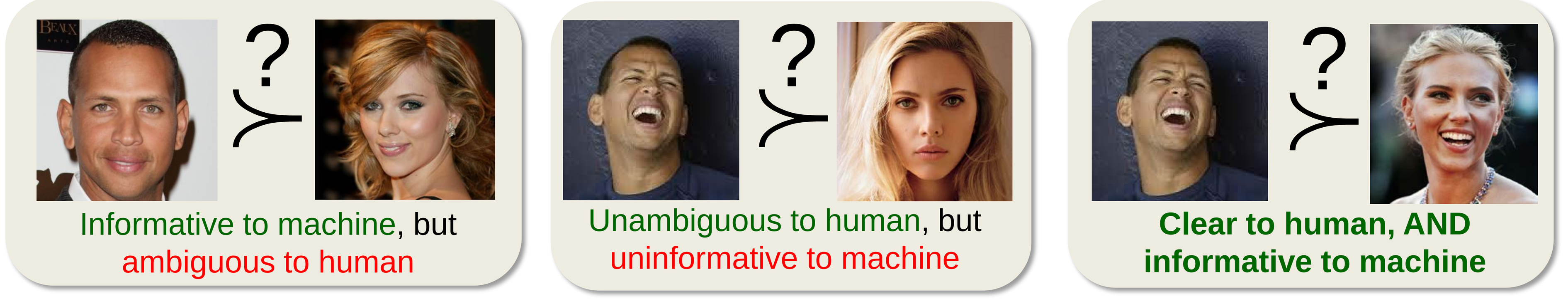
Cluster separation in image feature space → Diversity



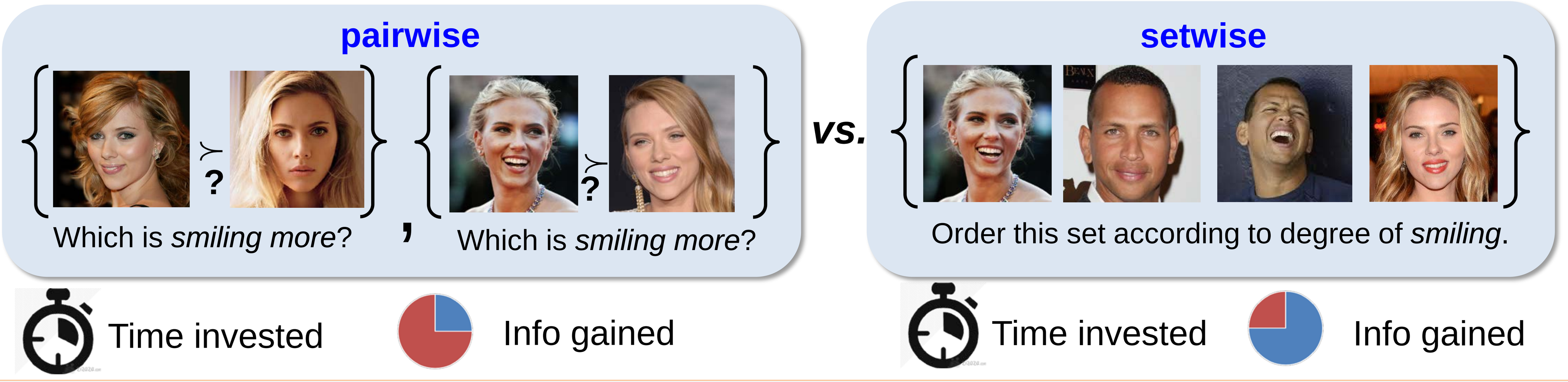
Optimization: Exploit 1D ordering in attribute space to efficiently identify contiguous min-margin set, then perturb to satisfy diversity constraint.

Key properties:

1. **Account for ambiguities to both machine and human**



2. **Amortize effort by identifying *mutually informative* comparisons**



Experimental Setup

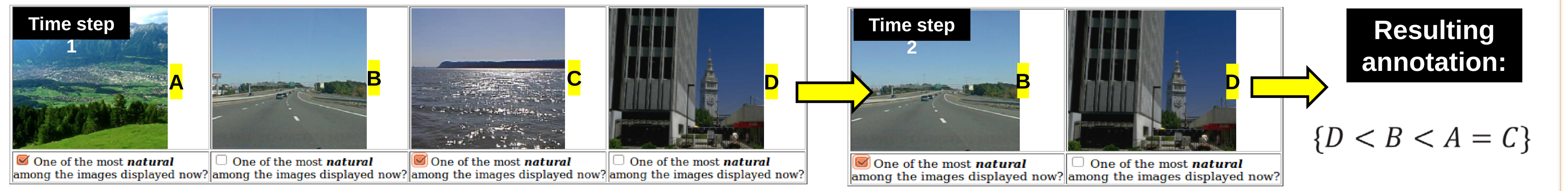
Datasets:

Shoes [Kovashka12]: 10 attributes

PubFig [Kumar09]: 11 attributes

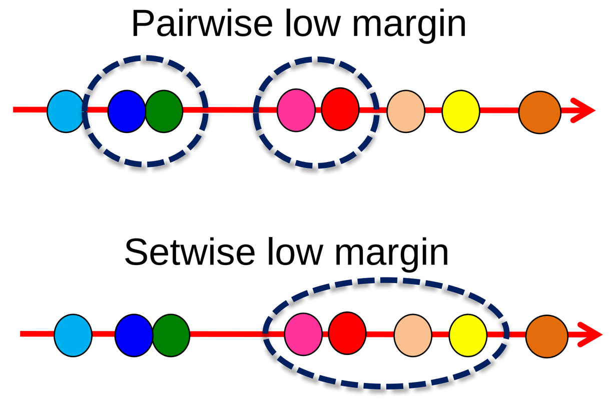
Scenes [Oliva01]: 6 attributes

Cascading partial order annotation interface:



Methods compared: Each method selects a set of k=4 items

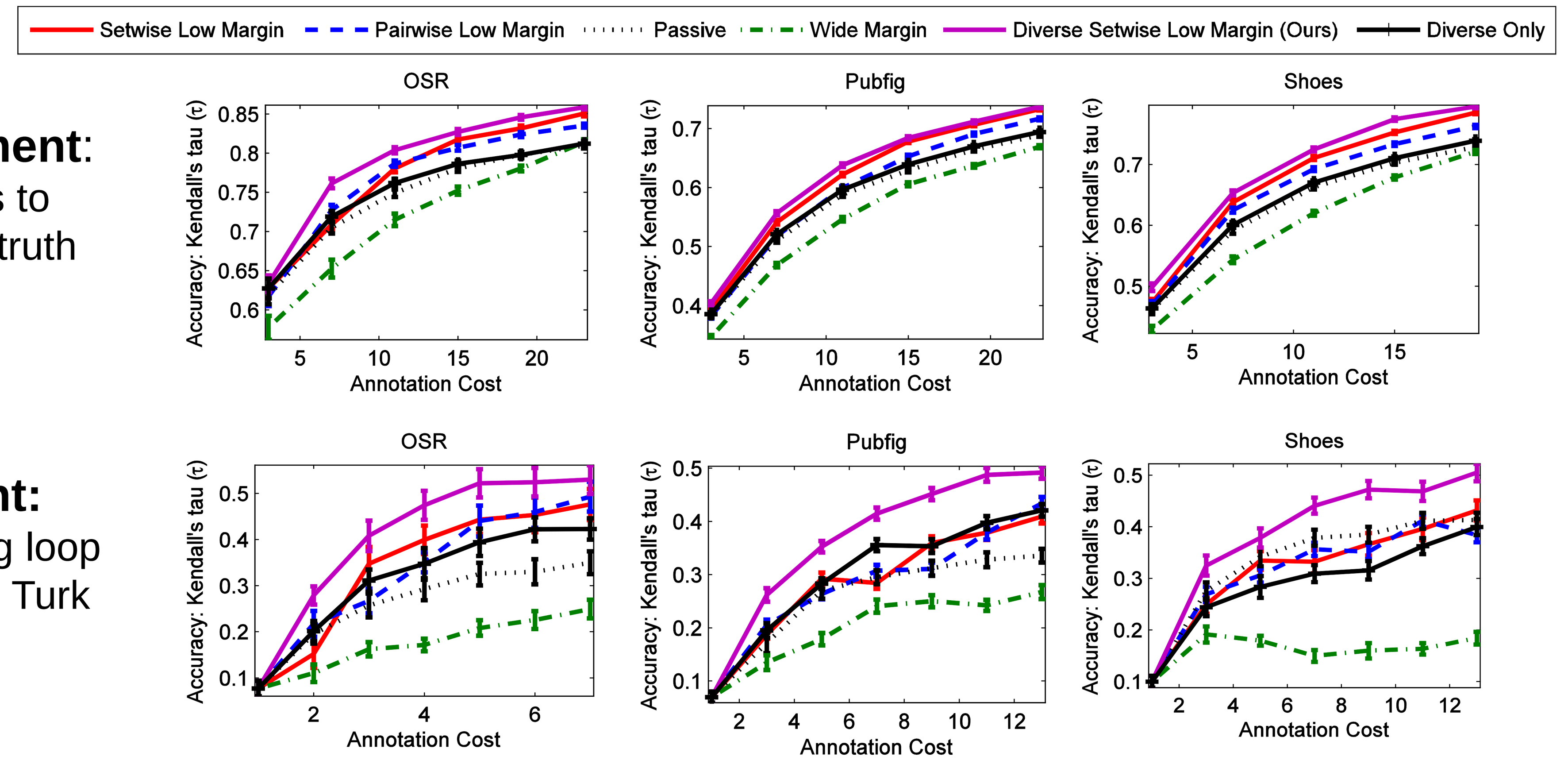
- **Passive** – Select set at random (status quo).
- **Diverse only** – Select set from different clusters, but ignore margins.
- **Wide margin** – Select set with widest, rather than lowest, margins.
- **Pairwise low margin** – Select k/2 pairs with pairwise lowest margin
- **Setwise low margin** [Yu, KDD05] – Select set with lowest *mutual* margin



Results

Offline experiment: Use existing labels to determine ground truth

Live experiment: Run active learning loop live on Mechanical Turk



We reduce annotation costs by 39% compared to standard passive approach!