# Rank-smoothed Pairwise Learning in Perceptual Quality Assessment

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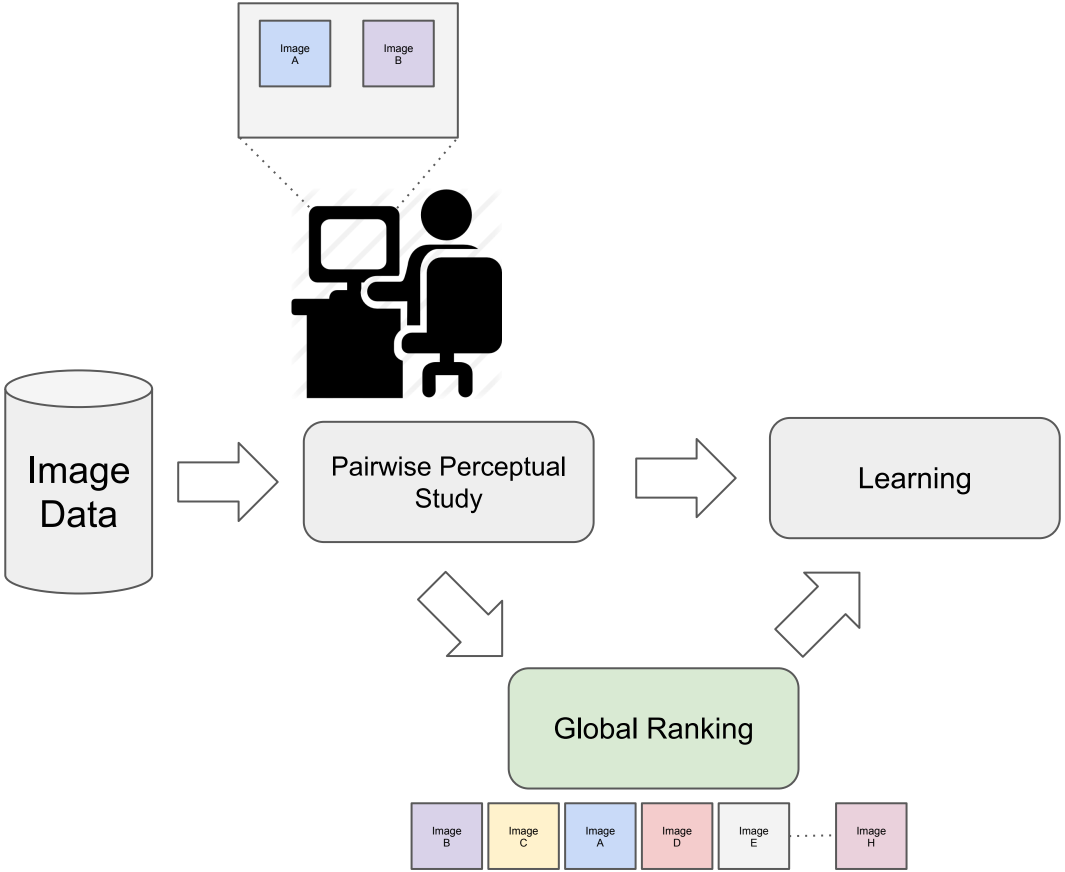
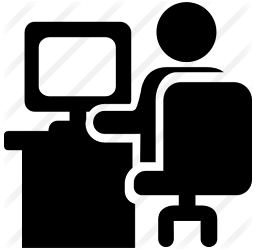
# Motivation

- Conducting pairwise comparisons is a widely used approach.
- Training on pairwise comparisons through mini-batch learning can be challenging.
- We propose a novel approach by incorporating **global ranking** into the pairwise training framework.



# Pairwise Perceptual Study



A

B

**Q**: Select the image with better quality?

# Pairwise Learning

- Comparisons are performed on a **subset** of all possible pairs of items (i, j).
  - Hence, we call them **local** comparisons
  - **Global** comparisons would take $O(N^2)$ with $N$ images
- The pairwise comparison is repeated multiple times across different evaluators.

- The maximum-likelihood estimate of the Bernoulli random variable that picks image i over j:

$$p_{ij}^{\text{local}} = \frac{n_{ij}}{n_{ij} + n_{ji}}$$

Empirical preference

Number of times image $i$ picked over image $j$

Number of times image $j$ picked over image $i$

# Pairwise Learning

- RankNet* is perhaps the most commonly used approach for learning to rank from pairwise comparisons.
- RankNet trains a network to extract a better representation for compared items.

$$C_{ij}^{\text{local}} := -p_{ij}^{\text{local}} \log(q_{ij}) - (1 - p_{ij}^{\text{local}}) \log(1 - q_{ij})$$

$$L(\Theta|\mathcal{P}) := \sum_{(i,j)\in\mathcal{P}} C_{ij}^{\text{local}}$$

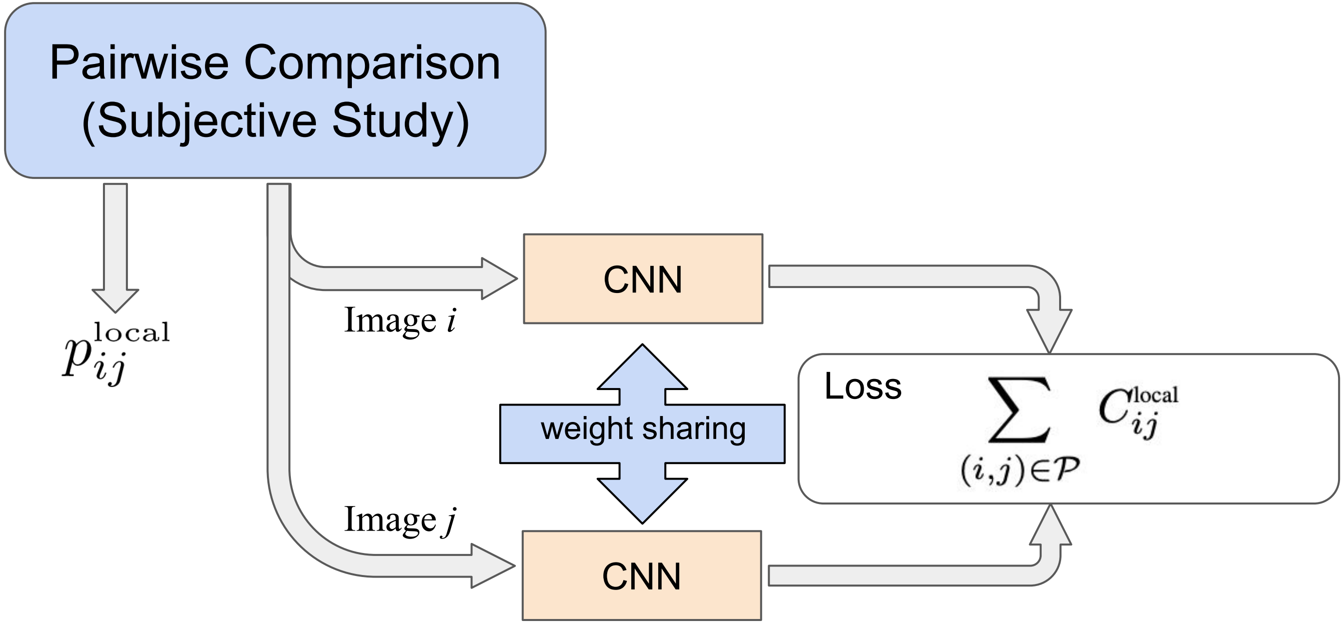
Cross-entropy loss

Predicted preference probability

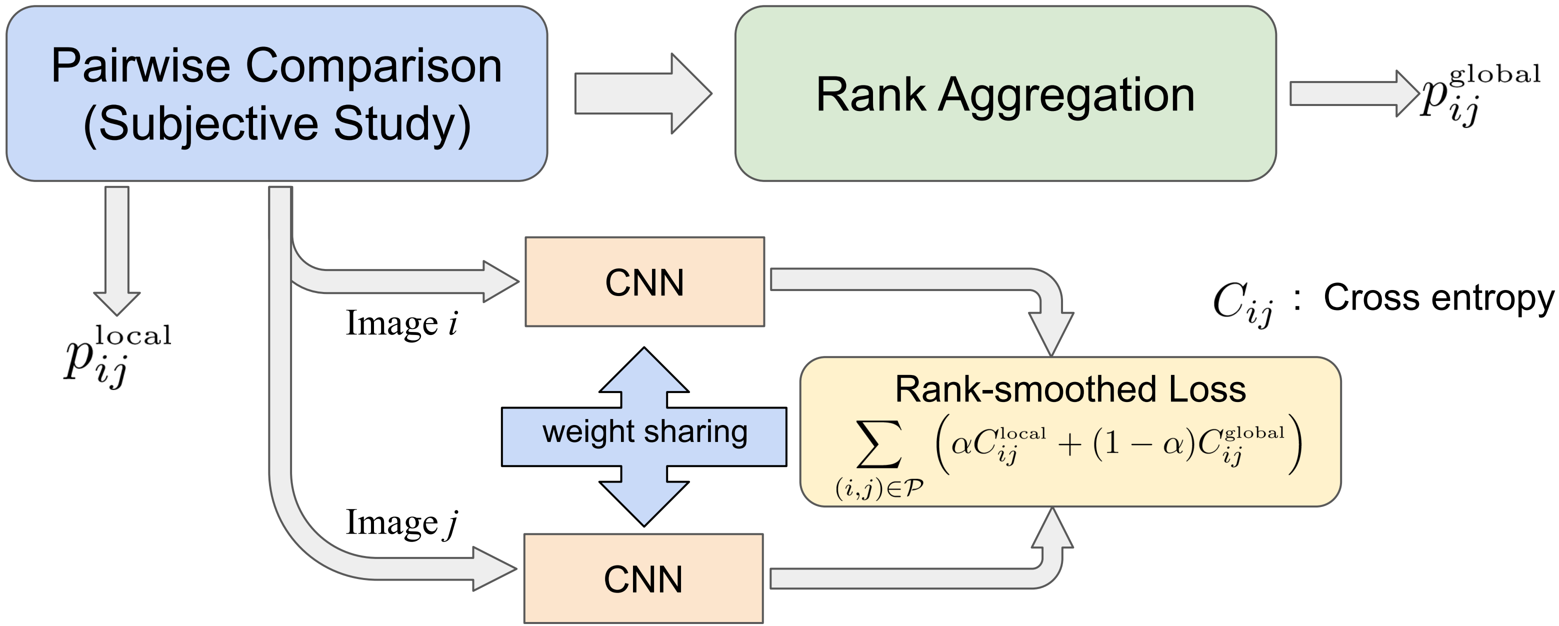
Parameters of a CNN

[*] Burges et al. “Learning to rank using gradient descent”, ICML 2005.

# Pairwise Learning



# Proposed Method



# Proposed Method: Rank-smoothed Learning

$$L(\Theta|\mathcal{P}) := \sum_{(i,j)\in\mathcal{P}} \left(\alpha\, C_{ij}^{\text{local}} + (1-\alpha)\, C_{ij}^{\text{global}}\right)$$

Loss

$$C_{ij}^{\text{global}} := -p_{ij}^{\text{global}} \log(q_{ij}) - (1 - p_{ij}^{\text{global}}) \log(1 - q_{ij})$$

$$q_{ij}^{\star} = \alpha\, p_{ij}^{\text{local}} + (1-\alpha)\, p_{ij}^{\text{global}}, \quad (i,j) \in \mathcal{P}$$

➔ The parameter $0 \leq \alpha \leq 1$ controls the trade-off between the local and the global loss.

# Proposed Method

$$L(\Theta | \mathcal{P}) := \sum_{(i,j)\in\mathcal{P}} \left( \alpha\, C_{ij}^{\text{local}} + (1-\alpha)\, C_{ij}^{\text{global}} \right)$$

Loss

$$C_{ij}^{\text{global}} := -p_{ij}^{\text{global}} \log(q_{ij}) - (1 - p_{ij}^{\text{global}}) \log(1 - q_{ij})$$

Approximated by Rank Aggregation method*

[*] Negahban, et al. "Iterative ranking from pairwise comparisons", NIPS, 2012.

# Rank Aggregation

- The algorithm of Negahban et al (Rank Centrality) constructs a **Markov chain** transition matrix $\mathbf{\Pi}$:

$$\Pi_{ij} = \begin{cases} \frac{1}{d_{\max}(i)} p_{ij}^{\text{local}} & i \neq j \\ 1 - \frac{1}{d_{\max}(i)} \sum_{k:\,(i,k)\in\mathcal{P}} p_{ik}^{\text{local}} & i = j \end{cases}$$

➔ $d_{\max}(i)$ denotes the maximum out-degree of node i.

➔ The **stationary distribution** of $\mathbf{\Pi}$ approximates global ranking probabilities:

$$p_{ij}^{\text{global}} := \frac{\pi_i}{\pi_i + \pi_j}$$

# Smoothing Probability Estimates

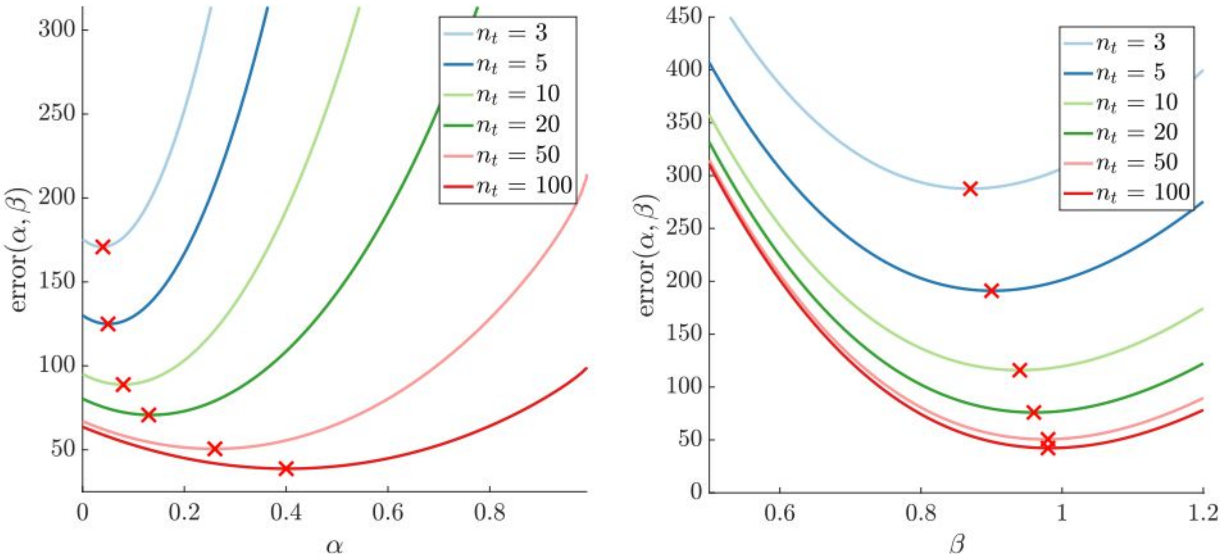
- In many applications such as word embedding, smoothing the estimated probabilities of the items results in an improved performance.
- Our $\beta$-smoothed version with parameter $\beta \geq 0$:

$$p_{ij}^{\text{global}} := \frac{\pi_i^\beta}{\pi_i^\beta + \pi_j^\beta}$$

- $\beta = 0 \rightarrow$ uniform distribution
- $\beta = 1 \rightarrow$ identity mapping
- $\beta > 1 \rightarrow$ skewed distributions towards popular items

# Results (Synthetic Data)

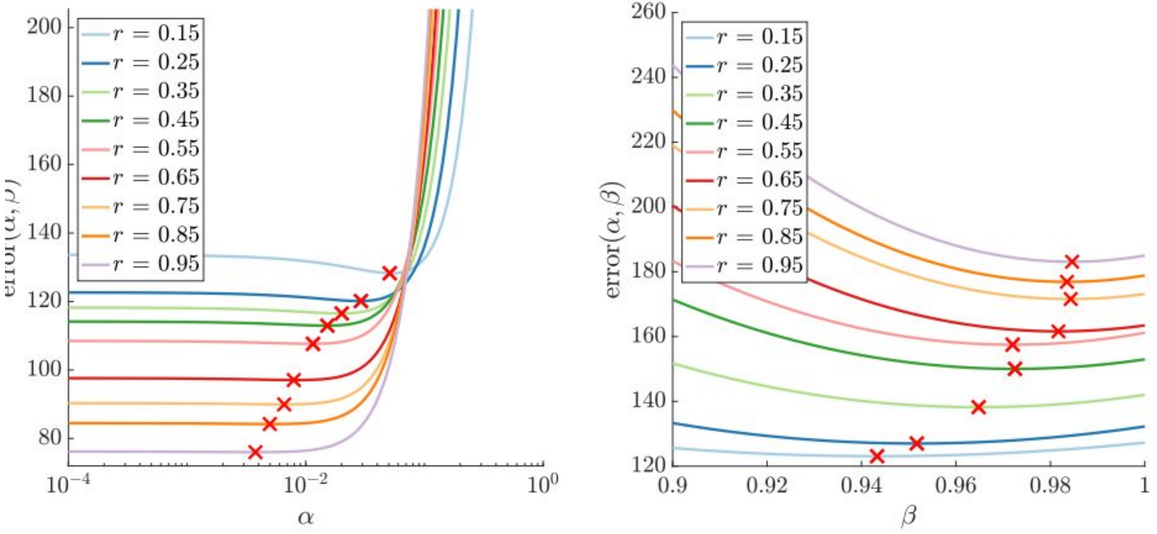
- ➔ Random samples ($N$=500) from random power-law distribution
- ➔ The number of comparisons per pair ($n_t$) ↑ ⇒ optimal $\alpha$ ↑
    - ◆ Local comparisons becomes more accurate




KL divergence ◄······ $$\mathrm{error}(\alpha, \beta) = \sum_{(i,j)\in\mathcal{P}} p_{ij} \log \frac{p_{ij}}{q^\star_{ij}} - p_{ij} + q^\star_{ij}$$

# Results (Synthetic Data)

- ➔ Random samples ($N$=500) from random power-law distribution
- ➔ The number of pairs ($r$) ↑ ⇒ optimal $\alpha \to 0$
  - ◆ Local comparisons become less important than global ranking

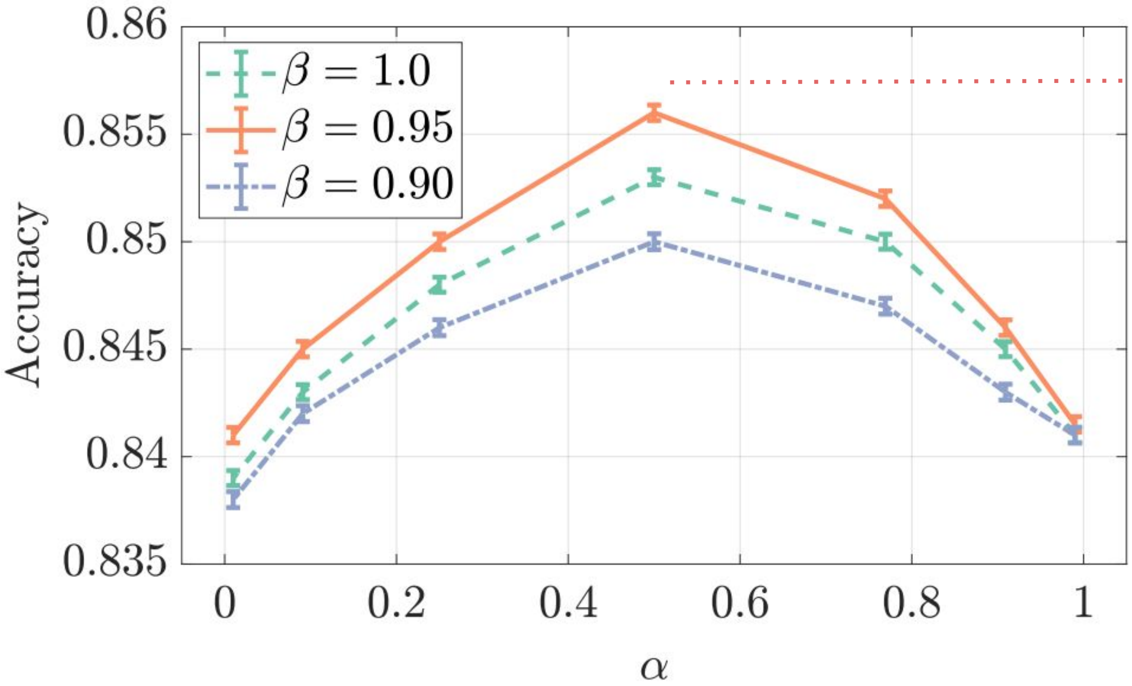



KL divergence ◄······

$$\mathrm{error}(\alpha, \beta) = \sum_{(i,j)\in\mathcal{P}} p_{ij} \log \frac{p_{ij}}{q^{\star}_{ij}} - p_{ij} + q^{\star}_{ij}$$

# Results (Large scale perceptual comparisons)

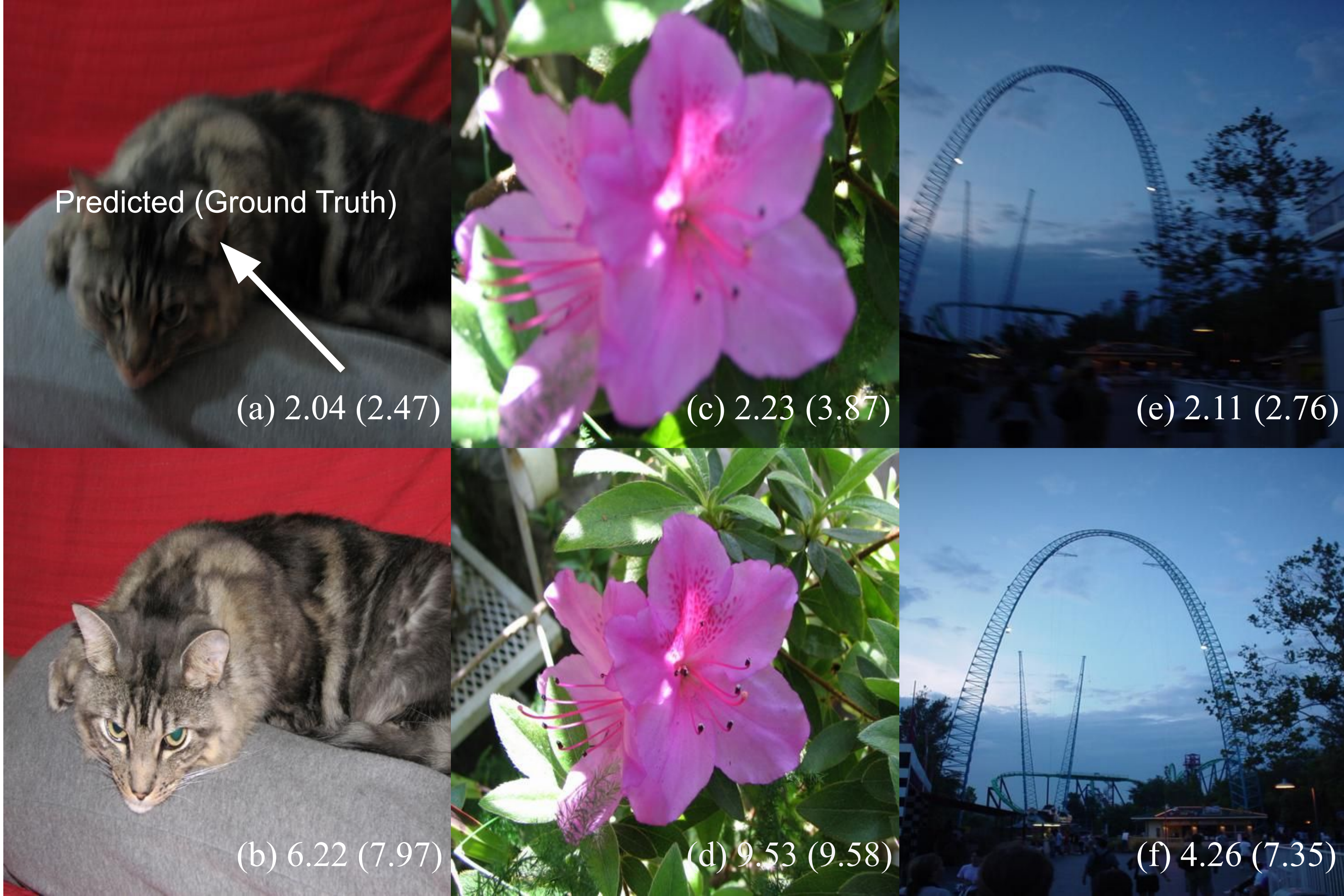
- Dataset: ~17M pairwise comparisons from 250K images
  - 5 human raters per pair
  - A minimum of 13 pairs per image
- Trained multiple Inception-v2 CNNs




α = 0.5

Local comparisons and global ranking are equally important

# Results


Predicted (Ground Truth)
(a) 2.04 (2.47)
(c) 2.23 (3.87)
(e) 2.11 (2.76)
(b) 6.22 (7.97)
(d) 9.53 (9.58)
(f) 4.26 (7.35)

# Conclusions

- We proposed a method for a more efficient learning from image pair comparisons.
- Combining the pairwise empirical comparisons with global ranking of images leads to better learning.
- Note that our approach is tested on generic synthesized data, implying that it can be employed beyond the scope of image quality assessment.

Thanks!