Non parametric multi-task relative attribute learning
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Abstract
Relative attribute ranking aims at ranking images given an attribute (Per example tasty, natural ...etc). Motivated by the fact that several attributes might be related, we introduce a new multi-task learning (MTL) formulation for relative attribute ranking.

Motivation
- A person can not give a numerical value for how present an attribute is in an image (i.e how ‘Sporty’ this shoe is).
- Several attributes share the same properties, MTL can help in this situation.
- Having a framework that allows the combination of several different architectures for each attribute, hence the non parametric formulation.

Problem
- If $x_i$ has more of attribute $l$ than $x_j$, then we want a mapping $f$ such that $f(x_i) > f(x_j)$.
- We want to discover relationships between tasks and use them to improve the generalization performance of each predictor individually.

Methodology
- The input labels are pairwise preference informations.
- We train separately several different architectures (Neural networks, Svm).
- We choose the best predictor per attribute then we stack the predictions across the entire dataset for all the attributes in $P$.
- Task relationships are discovered by minimizing the rank of the prediction matrix $F$, or equivalently by minimizing its trace norm.

Formulation

**Objective:**

$$\min_F \frac{1}{T} \sum_{l=1}^{T} \frac{1}{n_l} \max(0, 1 - F'A(l))^2 + \beta ||F - P||^2_F + \lambda ||F||_*$$

Objective

- $T$ is the number of tasks, $N$ is the number of data points. $n_l$ is the number of pairwise comparisons given as input for task $l$.
- $P \in \mathbb{R}^{N \times N}$ is the predictors matrix, each row contain the predictions across the entire dataset for a specific task.
- $A(l) \in \mathbb{R}^{N \times n_l}$ is the preference matrix. Each column of $A$ is a vector of size $N$ containing exactly one 1 and one -1. If $A(l)(i) = 1$ and $A(l)(j) = -1$, it means that data point $i$ contains more of attribute $l$ than data point $j$.
- $F(l)$ is the predictor for task $l$, i.e. row number $l$ of $F$.
- $||.||_F$ is the Frobenius norm and $||.||_*$ is the trace norm.
- $\beta, \lambda$ are regularization parameters.

Results

OSR dataset: 2688 images, 6 attributes: Natural, Open, Perspective, Large-objects, Diagonal-plane, Close-depth.

- Five training configurations. Training with 20, 40, 60, 80, 100 pairwise preferences.
- For each of this configurations we take 10 different splits.
- Parameters to tune: $\lambda, \beta$ (via validation set).

On display bellow are the mean ranking accuracies for each attribute of OSR dataset over the 10 splits and for all the 5 training configurations.

Conclusion

- We present a new multi-task learning method for relative attribute ranking.
- Our regularization strategy allows the combination of non parametric predictors, independently of their feature space or their origin (i.e.it could be a human predictor, an artificial neural network or a Gaussian process...etc).
- We demonstrate the abilities of our algorithm on OSR dataset, and achieve higher performance than several MTL algorithms baselines on almost all the attributes.

References