Weakly Supervised Learning through Rank-based Contextual Measures

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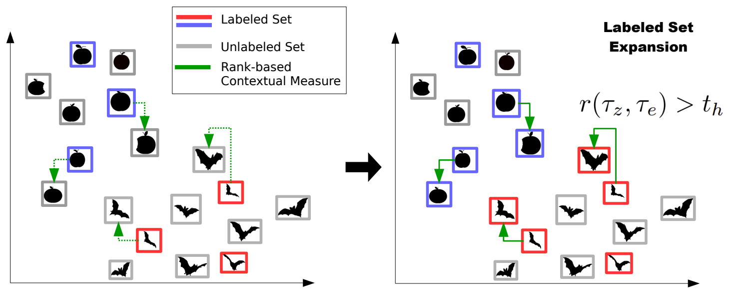
Introduction

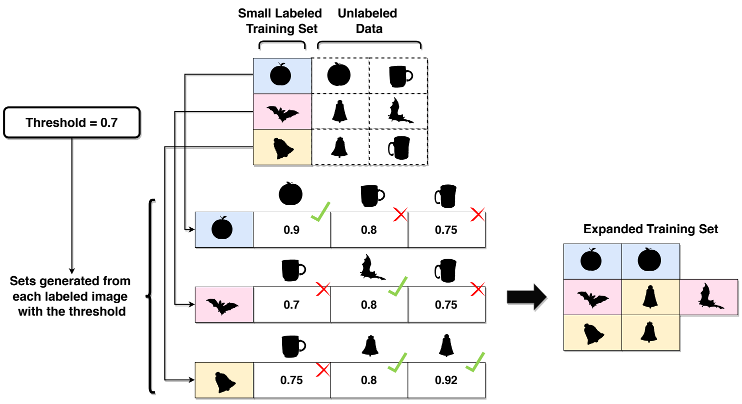
Due to the huge increase in multimedia data collections and the lack of labeled data in these scenarios, creating methods capable of exploit the unlabeled data and operate under weakly supervision is a crucial task. In this work, we propose a **rank-based model capable of exploit contextual information encoded in the unlabeled data** in order to perform weakly supervised classification. We evaluated several rank-based correlation measures in order to identify strong similarity relationships and **expand the labeled set in an unsupervised manner**. The expanded labeled set is then used by a classifier to achieve better accuracy results. We evaluated this weakly supervised approach with different combinations of rank correlation measures and classifiers. In our experiments, we used four public image datasets and different features. Positive gains were achieved in comparison with semi-supervised and supervised classifiers taken as baselines considering the same amount of labeled data.

Rank-Based Weakly Supervised Learning

A ranking provides an inherent contextual representation which establish a relationship among all elements in each rank. Therefore, the main hypothesis of this work can be highlighted as:

- The contextual information encoded in ranked lists can be analyzed through **rank correlation** measures to identify **strong similarity relationships** between images;
- Once identified, strong similarity relationships can be used to **expand small training sets**.





Different contextual rank measures can be used to exploit contextual information:

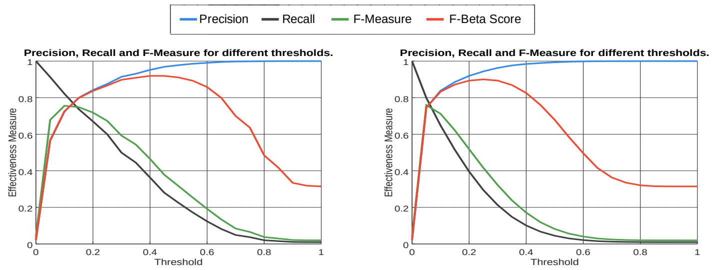
- **Intersection Measure**;
- **Jaccard**;
- **Jaccard**$_k$;
- **Kendall** τ;
- **Rank-Biased Overlap (RBO)**;

Experimental Evaluation

Experiments were conducted considering four public image datasets with size ranging from 1360 to 70000 images, and for each dataset we used different features:

- **MPEG-7** (1400 images): **ASC - Aspect Shape Context** and **CFD - Contour Features Descriptor**;
- **Flowers** (1360 images): **ACC - Auto Color Correlogram** and **CNN-Resnet**;
- **Corel5k** (5000 images): **ACC - Auto Color Correlogram** and **CNN-Resnet**;
- **MNIST** (70000 images): **CNN-Resnet**.

The labeled set expansion works based on a specified threshold. If the correlation measure between a labeled and an unlabeled image is greater or equal than the threshold, the unlabeled image is then incorporated to the expanded labeled set. Thus, it is imperative to find the **adequate threshold**. An analysis of different effectiveness measures was conducted in order to find the optimal threshold for each scenario.



Corel5k+Resnet+Jaccard (b) **Corel5k+Resnet+Jaccard**$_k$

For each one of these analysis, the threshold obtained at the maximum F-beta was considered as optimal and used in our classification experiments. Several supervised and semi-supervised classifiers were used in our experiments, in which they were evaluated considering a 10-Fold cross validation (10% training/90% test sets in each fold).

- **Supervised/Semi-Supervised Methods**:
  - **Optimum Path Forest (OPF)**;
  - **Support Vector Machines (SVM)**;
  - **k-Nearest Neighbors (kNN)**.
  - **Learning Discrete Structures for Graph Neural Networks (LDS-GNN)**;
  - **Label Spreading**;
  - **Pseudo-Label with SGDClassifier**.

Table 1: Accuracy for each dataset and measure before and after our weakly supervised approach using **OPF**.

		MPEG-7		Flowers		Corel5k		Mean
		ASC	CFD	ACC	Resnet	ACC	Resnet	
OPF		82.95%	67.75%	30.54%	71.77%	40.21%	83.56%	62.80%
Intersection	WS-OPF	85.56%	81.28%	30.69%	75.05%	41.69%	89.11%	67.23%
	Gain	+2.6%	+13.52%	+0.16%	+3.28%	+1.48%	+5.55%	+4.43%
Jaccard	WS-OPF	84.45%	77.56%	31.2%	76.95%	41.15%	88.44%	66.63%
	Gain	+1.5%	+9.81%	+0.66%	+5.18%	+0.94%	+4.88%	+3.83%
Jaccard$_k$	WS-OPF	**86.74%**	81.63%	31.97%	79.08%	**41.92%**	89.19%	68.42%
	Gain	**+3.79%**	+13.88%	+1.43%	+7.3%	**+1.71%**	+5.64%	+5.63%
Kendallτ	WS-OPF	85.67%	**82.63%**	**32.12%**	78.5%	41.77%	88.84%	68.26%
	Gain	+2.71%	**+14.88%**	**+1.58%**	+6.72%	+1.56%	+5.29%	+5.46%
RBO	WS-OPF	**86.75%**	82.2%	30.62%	**81.09%**	41.5%	**89.42%**	**68.60%**
	Gain	**+3.79%**	+14.44%	+0.08%	**+9.32%**	+1.29%	**+5.87%**	**+5.80%**
Spearman	WS-OPF	85.56%	81.28%	31.91%	78.21%	41.69%	89.11%	67.96%
	Gain	+2.6%	+13.52%	+1.37%	+6.44%	+1.48%	+5.55%	+5.16%

Table 2: Weakly supervised results in comparison with supervised and semi-supervised classifiers in isolation. Weakly supervised results consider the best rank measure with each classifier and **RBO for MNIST** dataset. Label Spreading and Pseudo-Label are reported as additional baselines.

		MPEG-7		Flowers		Corel5k		MNIST	Mean
		ASC	CFD	ACC	Resnet	ACC	Resnet	Resnet	
Supervised	kNN	13.92%	12.39%	28.47%	63.67%	34.05%	76.8%	89.04%	45.48%
	OPF	82.95%	67.75%	30.54%	71.77%	40.21%	83.56%	88.71%	66.50%
	SVM	83.12%	68.56%	37.5%	80.65%	45.27%	88.33%	84.89%	69.70%%
Semi-Supervised	Label Spreading	84.94%	71.90%	33.37%	72.65%	**46.52%**	82.32%	70.08%	65.97%
	LDS-GNN	2.55%	5.14%	28.69%	55.69%	24.66%	60.01%	-	29.46%
	Pseudo-Label+SGD	20.26%	19.39%	28.8%	80.89%	32.52%	87.35%	**92.21%**	51.63%
Proposed Weakly Supervised	WS-KNN	74.64%	66.67%	32.98%	80.02%	40.04%	89.01%	89.81%	67.60%
	WS-OPF	86.75%	82.63%	32.12%	81.09%	41.92%	89.42%	89.37%	71.9%
	WS-SVM	**87.15%**	**84.44%**	37.75%	84.06%	45.6%	**91.22%**	86.96%	**73.88%**
	WS-LDS	5.1%	17.81%	**46.03%**	**85.86%**	46.32%	88.8%	-	48.32%

Conclusions

In this work, we have presented a rank-based model applied to scenarios of weakly supervised learning. Our approach innovates by considering ranked lists contextual information to analyze manifold information and decide which data samples can be included in an expanded labeled set. The proposed method was evaluated on four datasets, considering different features, various rank correlation measures, and classifiers. The obtained results indicated very positive accuracy gains in most scenarios with gains up to +60.72%. As future work, we intend to explore automatic strategies for threshold definition. We also intend to investigate the automatic choice of the rank measure and the use of other deep learning methods (CNN-Resnet and others) as final classifiers.

Acknowledgements

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