Weakly Supervised Learning through Rank-based Contextual Measures

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Introduction

- With the huge increase in multimedia collections and the lack labeled data in these scenarios;
- Creating methods capable of exploit the unlabeled data and work under weakly supervision in a crucial task;
- In this work, we propose a **rank-based model capable of exploit contextual information encoded in the unlabeled data**;
- This model can be used to perform **weakly supervised classification**.

Introduction

- The proposed model was evaluated considering several **rank-based correlation measures**, which can be used to identify strong similarity relationships between images, permitting to **expand the labeled set in an unsupervised manner**;
- The expanded labeled set in then used by a classifier to achieve better accuracy results.

Introduction

- This weakly supervised approach was evaluated with different combinations of rank correlation measures and classifiers;
- We used **four public image datasets** and different **features**;
- Positive gains were achieved in comparison with semi-supervised and supervised classifiers taken as baselines when trained with the same amount of labeled data.

Rank Based Weakly Supervised Learning

- A ranking provides an inherent contextual representation of data, which establish a **relationship between all elements** in each rank;
- With that in mind, the main hypothesis of this work is:
  - Contextual information encoded in ranked lists can be analyzed through **rank correlation** measures to identify **strong similarity relationships** between images;
  - Strong similarity relationships can be used to **expand small training sets**.

Rank Based Weakly Supervised Learning

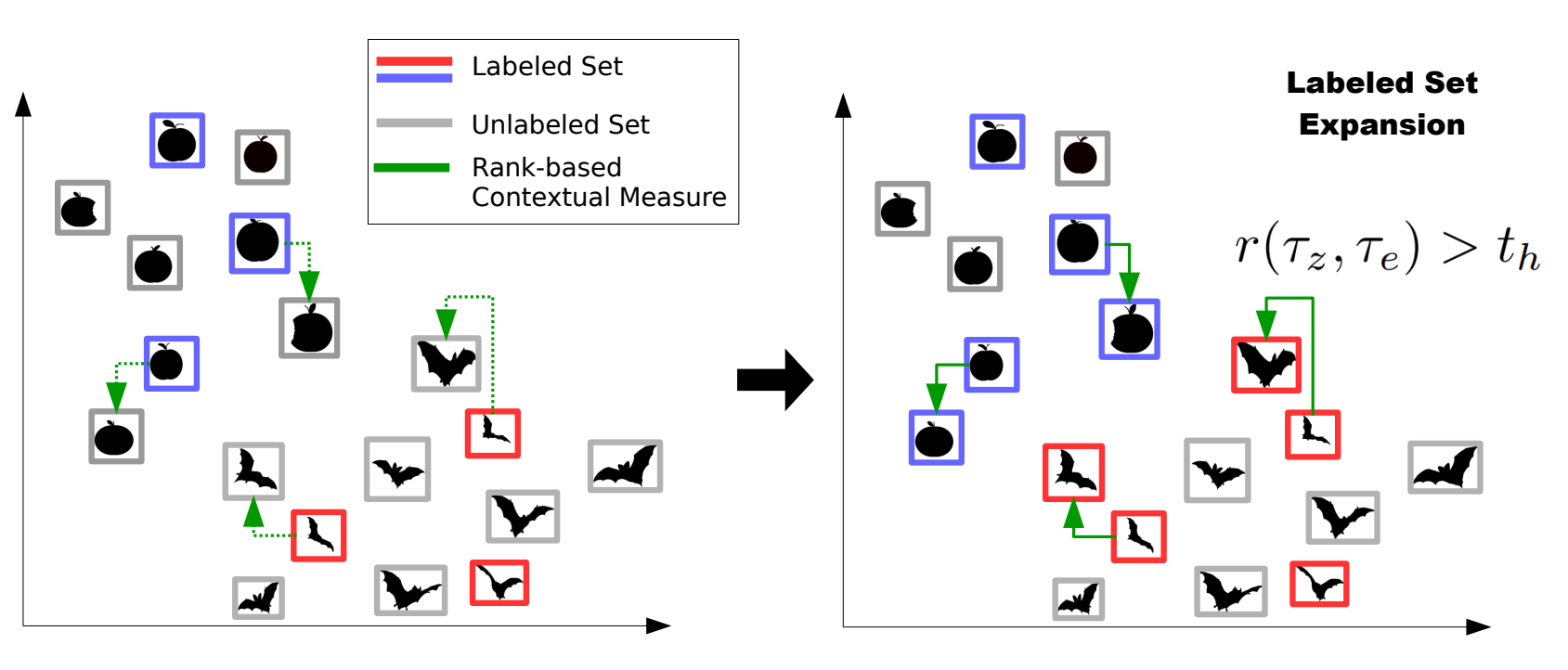


Figure 1: Weakly supervised learning based on contextual rank measures, represented by green lines and function $r(\tau_z, \tau_e)$.

Rank Based Weakly Supervised Learning

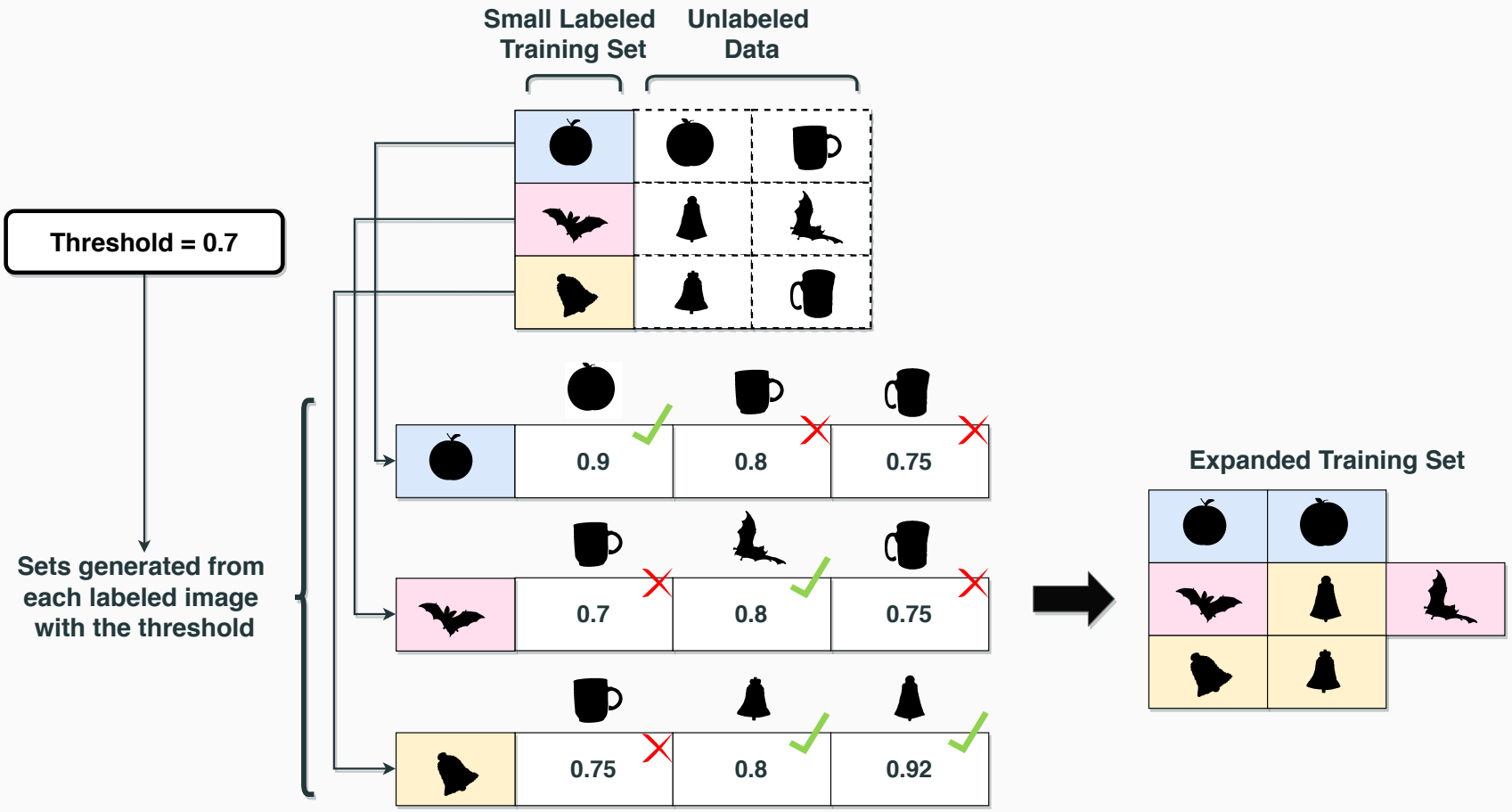


Figure 2: Weakly supervised learning based on contextual rank measures.

Rank Based Weakly Supervised Learning

- Different contextual rank measures can be used to exploit contextual information, for example:,
  - **Intersection Measure**;
  - **Jaccard**;
  - **Jaccard**$_k$;
  - **Kendall** τ;
  - **Rank-Biased Overlap (RBO)**;

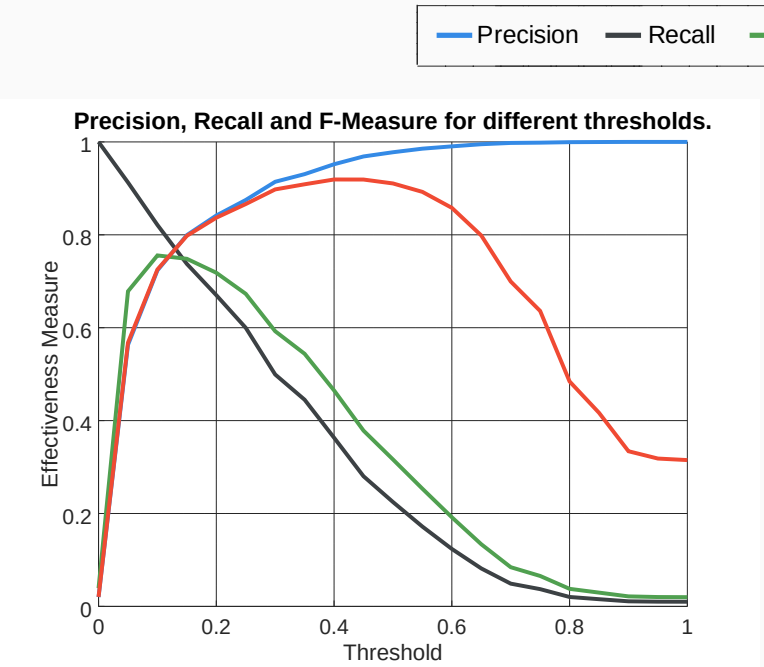
Experimental Evaluation

- 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**.

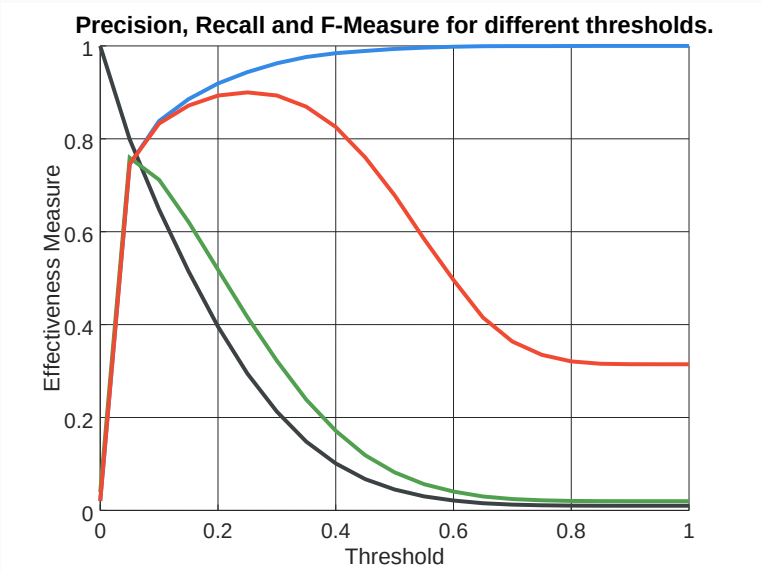
Experimental Evaluation

- The labeled set expansion works based on a specified threshold;
- If the **correlation measure** between a labeled image and an unlabeled image is greater of equal than the threshold, **the unlabeled image is then incorporated to the expanded labeled set**;
- It is imperative to find the **adequate threshold**, and to address that, an analysis of different effectiveness measures was conducted.

Experimental Evaluation

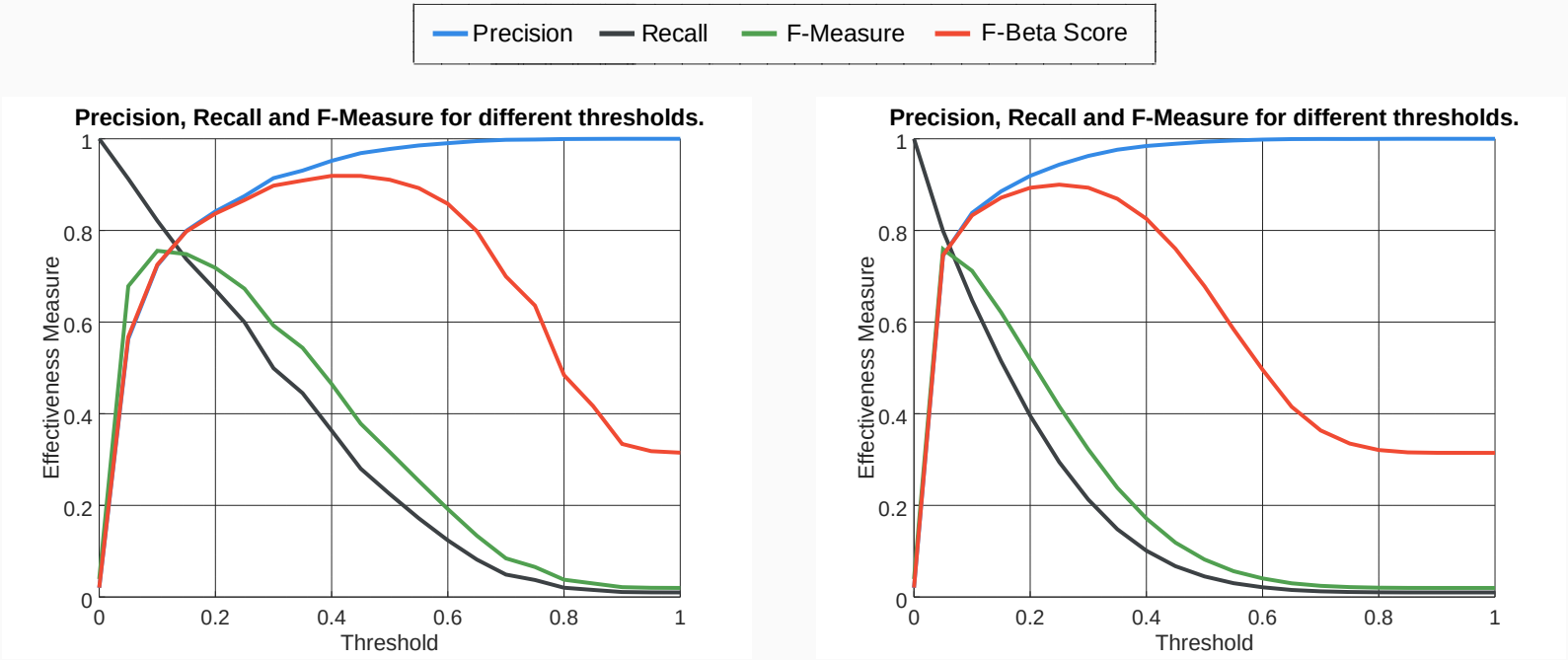


Corel5k+Resnet+Jaccard



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

Experimental Evaluation



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.

Experimental Evaluation

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

Experimental Evaluation

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%
Kendall$_\tau$	**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%

Experimental Evaluation

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

- We have presented a **rank-based model** applied to scenarios of weakly supervised learning;
- Our approach innovates by considering ranked lists contextual information to analyse manifold information and decide which data samples can be included in an **expanded labeled set**;
- Evaluated on four datasets, considering different features, various rank correlation measures, and classifiers;
- Very positive gains were achieved in most scenarios with gains up to $+60.72\%$.

Conclusions

- As future work, we intend to explore **automatic strategies** for the threshold definition;
- We also intend to investigate the automatic choice of the rank correlation measure and the use of other deep learning methods (CNN-Resnet and others) as final classifiers.

Acknowledgements

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