Foz do Iguaçu - Brazil
SIBGRAPI'18
31st Conference on Graphics, Patterns and Images
October 29 – November 01

Semi-Supervised Learning with Interactive Label Propagation guided by Feature Space Projections

Bárbara C. Benato[1], Alexandru C. Telea[2], Alexandre X. Falcão[1]

[1] Institute of Computing, University of Campinas, Campinas, Brazil

[2] Department of Mathematics and Computing Science, University of Groningen, Groningen, the Netherlands

November 1, 2018

Introduction

Context: few supervised and many unsupervised samples

Problem: effective feature learning and design of high-quality classifiers.

Data supervision needs a specialist and is time-consuming.

However, machine learning solutions do not usually count on the user in the machine learning loop. [15][16]

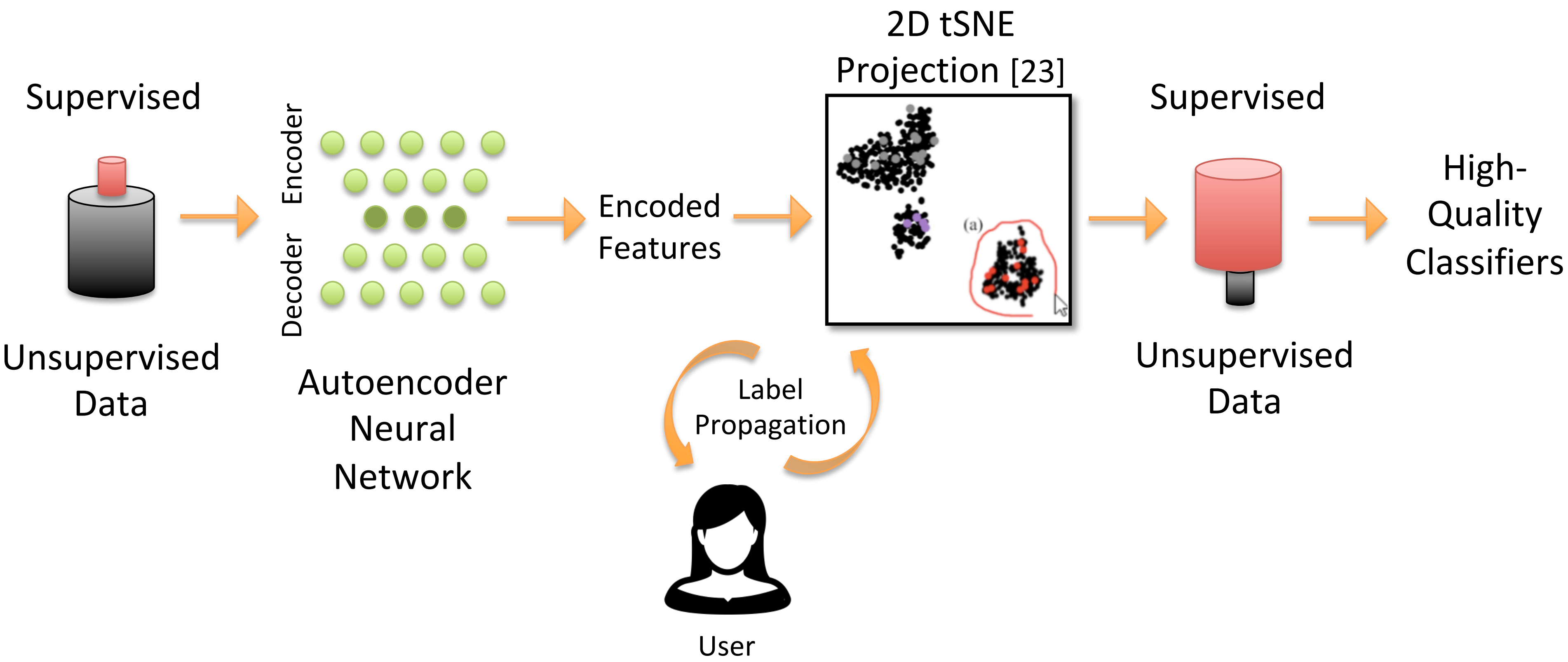
Objectives

In this work, we have as main intent to:

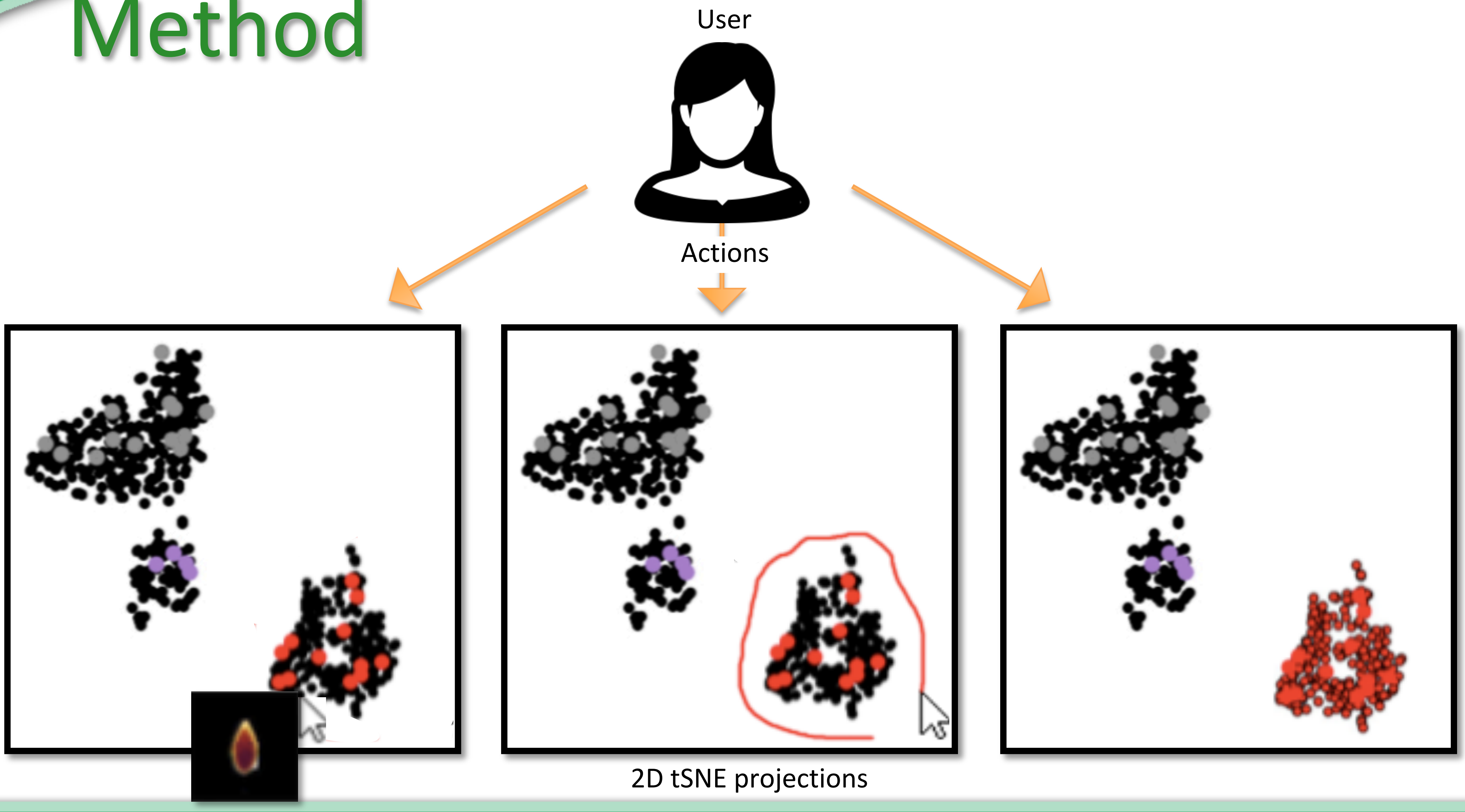
a) obtain large training set with accurately labeled samples;
b) keep at minimum the user effort;
c) incorporate the user in the semi-supervised learning process.

We propose a semi-supervised approach that exploits feature space projections and cognitive ability of humans to propagate labels.

Method


Supervised
Unsupervised Data
Encoder
Decoder
Autoencoder Neural Network
Encoded Features
2D tSNE Projection [23]
(a)
Label Propagation
User
Supervised
Unsupervised Data
High-Quality Classifiers

Method



Experimental Setup

Exploit different levels of difficulty:

- MNIST dataset [36]:
  - 10 classes
- Parasites dataset (in-house):
  - Helminth larvae:
    - 1 class + 1 impurity class
  - Helminth eggs:
    - 8 classes + 1 impurity class
  - Protozoan cysts:
    - 6 classes + 1 impurity class

Parasites

Impurities

Experimental Setup

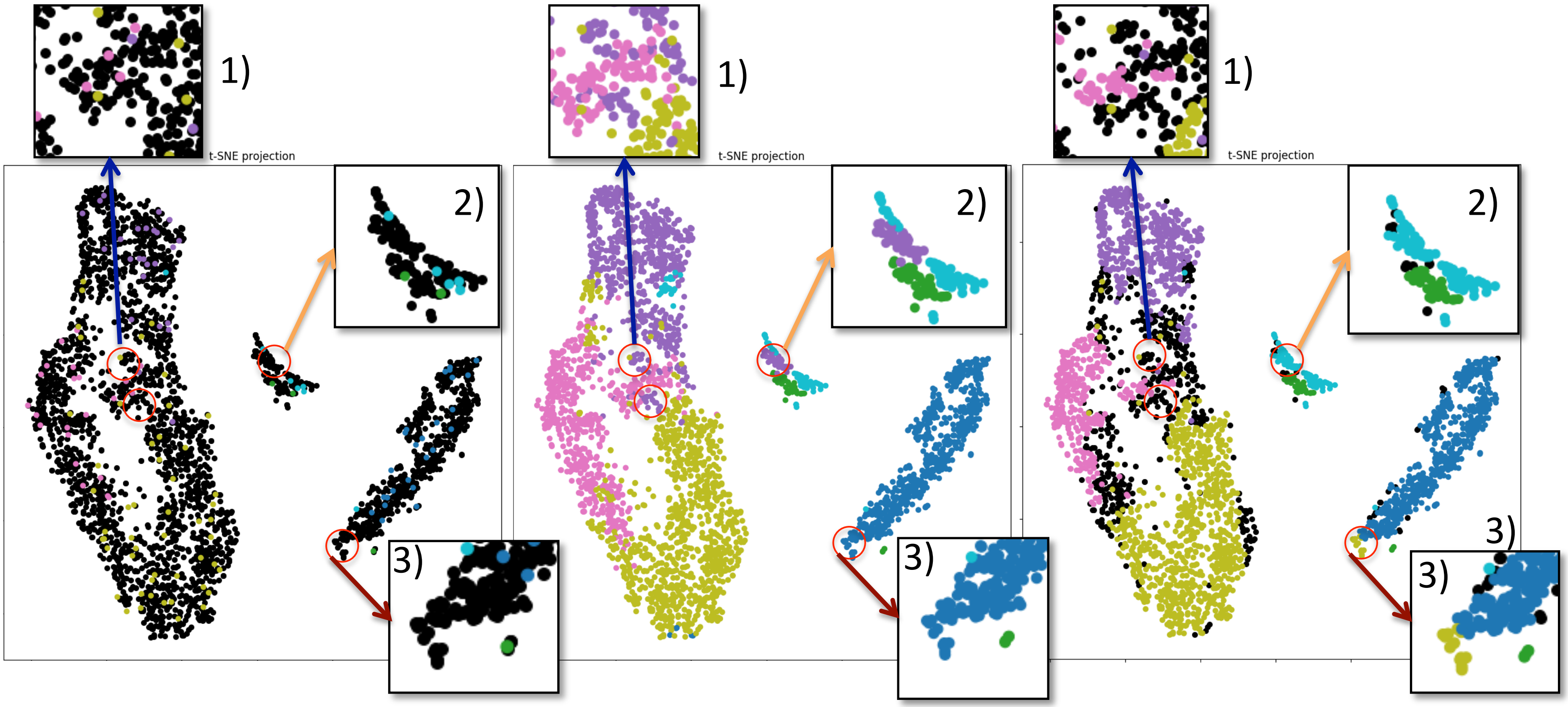
Compared the Interactive Label Propagation (ILP) with two automatic methods:

- *Laplacian Support Vector Machines* (LapSVM) [1]
- *Semi-Supervised Optimum Path Forest* (OPF-Semi) [2]

With the labeled dataset, we trained classifiers:

- *Support Vector Machines* (SVM) [24]
- *Optimum-Path Forest* (OPF) [25]

Results and Discussion

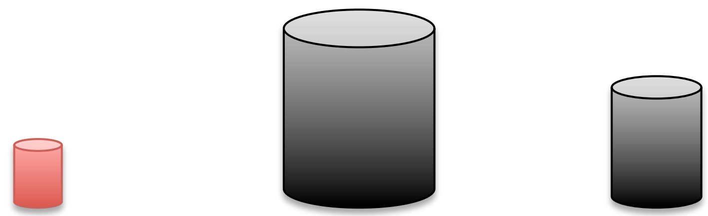


a) No label propagation

b) Automatic (OPF-Semi)

c) ILP (proposed)

Results and Discussion



	Supervised	Unsupervised	Test
baseline	3%	-	30%
LapSVM	3%	67%	30%
OPF-Semi	3%	67%	30%
ILP	3%	? %	30%

$\underbrace{\hspace{6em}}_{\text{Training set}}$

Training set

Results and Discussion

- Best results

Dataset	Technique	Labeled Samples	Propagation Accuracy	Kappa (SVM)	Kappa (OPF)
Helminth Larvae	baseline	–	–	0.375378	0.531080
	LapSVM	67%	0.882613	0.121253	0.173416
	OPF-Semi	67%	0.920696	–	0.600475
	ILP	59%	**0.981273**	**0.727843**	**0.723049**
Protozoan cysts	baseline	–	–	0.823106	0.762682
	LapSVM	67%	0.521598	0.346761	0.371770
	OPF-Semi	67%	0.802238	–	0.729438
	ILP	52%	**0.947177**	**0.851948**	**0.841023**

Conclusion

We incorporate the user in the semi-supervised learning process by letting the feature space projection guide the label propagation actions of the user.

The VA technique used to propagate labels is very simple, and the results are surprisingly good.

Even subject to errors done by the human user, the ILP achieves consistent and better classification performance than two modern automatic label propagation methods and two different classifier techniques.

References

[1] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, "Backpropagation applied to handwritten zip code recognition," *Neural Comput.*, vol. 1, no. 4, pp. 541–551, 1989.

[2] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in Neural Infor- mation Processing Systems 25*, F. Pereira, C. J. C. Burges, L. Bottou, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2012, pp. 1097–1105.

[3] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org.

[14] P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio, and P. Manzagol, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," *Journal of Machine Learning Research*, vol. 11, pp. 3371–3408, December 2010.

[15] D. Kingma and M. Welling, "Auto-encoding variational bayes," 2013.

[16] J. Masci, U. Meier, D. Cires¸an, and J. Schmidhuber, "Stacked convolutional auto-encoders for hierarchical feature extraction," in *Artificial Neural Networks and Machine Learning (ICANN 2011: 21st Interna- tional Conference on Artificial Neural Networks, Proc. Part I)*. Berlin, Heidelberg: Springer, 2011, pp. 52–59.

[17] Y. Wang, H. Yao, and S. Zhao, "Auto-encoder based dimensionality reduction," *Neurocomputing*, vol. 184, no. C, pp. 232–242, April 2016.

[21] L. V. D. Maaten and G. Hinton, "Visualizing high-dimensional data using t-sne," *J. Mach. Learn. Res.*, vol. 9, no. 1, pp. 2579–2605, 2008.

[22] P. Joia, D. Coimbra, J. A. Cuminato, F. V. Paulovich, and L. G. Nonato, "Local affine multidimensional projection," *IEEE Trans. Vis. Comp. Graph.*, vol. 17, no. 12, pp. 2563–2571, Dec 2011.

[23] L. V. D. Maaten, "Accelerating t-SNE using tree-based algorithms," *Journal of Machine Learning Research*, vol. 15, no. 1, pp. 3221–3245, 2014.

[24] P. Rauber, A. Falcão, and A. Telea, "Visualizing time-dependent data using dynamic t-sne," in *Proceedings of the Eurographics / IEEE VGTC Conference on Visualization: Short Papers*, ser. EuroVis '16, 2016, pp. 73–77.