# Bregman Neural Networks

Jordan Frecon<sup>1</sup>, Gilles Gasso<sup>1</sup>, Massimiliano Pontil<sup>2,3</sup>, Saverio Salzo<sup>2</sup>

 $^{\rm 1}$  LITIS - INSA Rouen Normandy  $^{\rm 2}$  CSML - Istituto Italiano di Tecnologia  $^{\rm 3}$  Dept. of Computer Science - University College London

♥litis









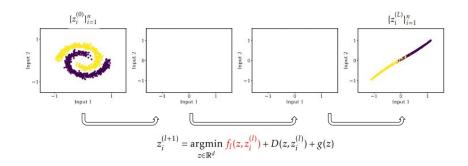
The Thirty-ninth International Conference on Machine Learning, Baltimore, USA

# Context: Representation Learning



Learn a representation linearly separable

## Bilevel Framework



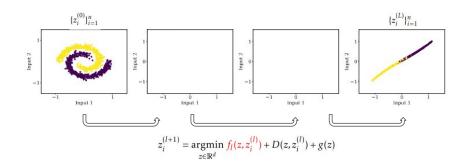
### Hyperparameter

•  $f_i$ : promotes the next representation depending on the previous one

#### **Fixed**

- D: divergence between two successive representations
- g: regularization

## Bilevel Framework



### Multi-layered Bilevel Problem

$$\min_{\psi,\{f_i\}_{i=0}^{L-1}} \sum_{i=1}^{n} \ell(\psi(z_i^{(L)}), y_i)$$
 s.c.

$$\min_{\psi,\{f_{i}\}_{i=0}^{L-1}} \sum_{i=1}^{n} \ell(\psi(z_{i}^{(L)}), y_{i}) \quad \text{s.c.} \quad \begin{aligned} z_{i}^{(0)} &= x_{i} \\ \text{for } I &= 0, 1, \dots L - 1 \\ z_{i}^{(l+1)} &= \operatorname*{argmin}_{z \in \mathbb{R}^{d}} f_{l}(z, z_{i}^{(l)}) + D(z, z_{i}^{(l)}) + g(z) \end{aligned}$$

## Connections with Neural Networks

#### Informal Theorem

For  $f_l$  bi-linear, D a quadratic distance and g a convex function:

## ⇒ Multilayer perceptron

 $abla f_l$   $\Leftrightarrow$  bias and weight  $W_l$  proximal operator of g  $\Leftrightarrow$  activation function ho

$$z^{(l)}$$
  $W_l$   $\rho$   $z^{(l+1)}$ 

## Connections with Neural Networks

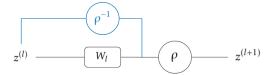
#### Informal Theorem

For  $f_l$  bi-linear, D a Bregman distance and g a convex function:

⇒ Bregman multilayer perceptron

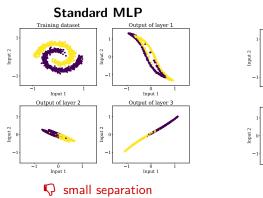
 $\nabla f_l$   $\Leftrightarrow$  bias and weight  $W_l$ 

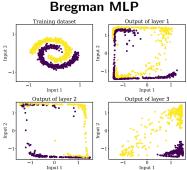
proximal operator of  ${\it g}$  with Bregman distance  $\Leftrightarrow$  activation function  $\rho$ 



# Numerical Experiments on Two-Spiral Dataset

### MLP with 3 layers and 2 neurons per layer

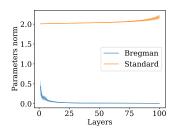




higher separation

# Numerical Experiments on Two-Spiral Dataset

MLP with 100 layers and 2 neurons per layer



#### Standard MLP

### **Bregman MLP**

decreasing impact with #layers slightly sensible to initialization

## Extension to other architectures

### ResNet

### BregmanResNet

$$z \leftarrow \text{ReLu}\left(z + \text{Conv2}\left[\text{ReLu}(\text{Conv1}[z])\right]\right) \qquad z \leftarrow \rho\left(\rho^{-1}(z) + \text{Conv2}\left[\rho(\text{Conv1}[z])\right]\right)$$

## Extension to other architectures

#### ResNet

### BregmanResNet

$$z \leftarrow \text{ReLu}\left(z + \text{Conv2}\left[\text{ReLu}(\text{Conv1}[z])\right]\right) \qquad z \leftarrow \rho\left(\rho^{-1}(z) + \text{Conv2}\left[\rho(\text{Conv1}[z])\right]\right)$$

	Test accuracy	$\ell_\infty$ -Robust accuracy	$\ell_2$ -Robust accuracy
BregmanResNet20 (atan)	89.11 (± 0.20)	33.86 (± 0.68)	50.56 (± 0.52)
BregmanResNet20 (tanh)	$89.28~(\pm~0.28)$	$35.29~(\pm~1.51)$	$51.68~(\pm~1.42)$
BregmanResNet20 (sigmoid)	89.75 ( $\pm$ 0.23)	$33.26~(\pm~1.47)$	$50.40~(\pm~1.46)$
BregmanResNet20 (softplus)	90.82 ( $\pm$ 0.12)	42.46 (± 1.25)	$53.13~(\pm~1.68)$
ResNet20	90.80 (± 0.18)	40.84 (± 0.71)	51.65 (± 1.32)

Residual networks on CIFAR-10

- Similar test accuracy
- Higher robust accuracies with Bregman variant

### Conclusion

# Thank You

### **BregmaNet: Bregman Neural Networks**



BregmaNet is a PyTorch library providing multiple Bregman Neural Networks. To date, implemented models cover Bregman variants of multi-layer perceptrons and various residual networks.

PyTorch library available at https://github.com/JordanFrecon/bregmanet