



# Photo-Z redshift reconstruction using a constructive multilayer perceptron

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#### Motivations : Photo-Z redshift reconstruction

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#### On the realistic validation of photometric redshifts, or why Teddy will never be Happy

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#### Challenge ?

- Lack of spectroscopic coverage in feature space (e.g. colours and magnitudes)
- Mismatch between photometric error distributions associated with the spectroscopic and photometric samples.

#### Motivations : Photo-Z redshift reconstruction

- Regression task
  - Techniques :
    - Decision tree, IBL, Bayesian networks, Lattice-based,
    - SVM, Artificial Neural Networks (ANN), ...
- Different models of ANN:

  - Multilayer perceptron
  - ...
- Choice of the ANN structure ?
   Application to photo-Z redshift reconstruction

#### Motivations

This story might be apocryphal, but it doesn't really matter. It is a perfect illustration of the biggest problem behind neural networks. **Any** automatically trained net with more than a few dozen néurons is virtually impossible to analyze and understand. One can't tell if a net has memorized inputs, or is 'cheating' in some other way. A promising use for neural nets these days is to predict the stock market. *Even though initial results are extremely good,* investors are leery of trusting their money to a system that nobódy understands

Neil Fraser [2003]

## Problem : Settings

#### Multilayer perceptron

#### process



Output layer (m neurons)

- Choose a topology
- Choose an activation function (sigmoïd, ...)
- Initialize the connection weights
- Train the neural network (BackPropagation, ...)

Input layer (n neurons)

### Problem : Settings

#### Multilayer perceptron topology



## Problem : Background

Assumptions :

- MLP Feedforward networks are universal approximators
  - K. Hornik, M. Stinchcombe, and H. White, Neural Networks, vol. 2, pp 359-366, 1989

## Problem : Background

- Existing approaches
  - Adhoc approach
    - One hidden layer: number of units equal to the average between the number of output units and the number of input units
    - **-** ....
  - Automatic approaches
    - Dynamic construction of ANN from the training set
    - Use of an apriori domain knowledge (set of rules)
    - Concept-lattice based ANN

Problem : our contribution

Propose an automatic approach of defining interpretable ANN architecture when the domain knowledge is not available

- E. Mephu Nguifo et al., M-CLANN: Multiclass Concept Lattice-Based Artificial Neural Network. Constructive Neural Networks 2009: 103-121.
- Lauraine Tiogning Kueti et al., Boolean factors based Artificial Neural Network. IJCNN 2016: 819-825
- Norbert Tsopzé et al., Towards a generalization of decompositional approach of rule extraction from multilayer artificial neural network. IJCNN 2011: 1562-1569

## Our proposal

#### Architecture of ANN :

- Input layer = input data
  - One (neuron) unit for each attribute [+ bias]
- Hidden layer : one
  - One neuron = one Boolean factor
  - Input layer are fully connected to hidden layer
- Output = one neuron (Regression)

## Experimentations

Jeu de données	Nombre d'objets	Taille (après prétraitement)	Nombre de bandes
PHAT2	316	52 Ko	18
PHAT1	515	84 Ko	18
PHAT0	1984	328 Ko	18
SDSS DR9 Data 1	5000	621 Ko	10
SDSS DR9 Data 2	12000	1477 Ко	10
Deep2 DR4 _sans_1	10838	735 Ko	6
Deep2 DR4 _sans_0_1	11784	677 Ko	6
SDSS DR10 Data 1	300 000	32 119 Ko	10
SDSS DR10 Data 2	500 000	53 536 Ko	10

### Experimentations





## Experimentations





#### Experimentations (Results)





#### Experimentations (Results in the Literature)

	class	$std(\Delta z_{norm})$	$bias(\Delta z_{norm})$	$ \Delta z_{norm}  > 0.15$
[2]	galaxies	0.041	-0.003	0.99%
[3]	galaxies	$\sigma_{68} = 0.03$	-0.001	1.56%
[9]	galaxies	$\sigma_{68} = 0.0248$	0.0008	0.73%
[13]	quasars	0.15	0.032	> 0.3 : 6.53%
[7]	galaxies	0.0490	-0.0081	7.6%
[10]	galaxies	0.024	0.0	1.51%
[6]	galaxies	0.0205	0.00005	4.11%

#### Conclusion

- BF-ANN, new approach to find interpretable
   ANN architecture when domain knowledge is not available
  - Semantic of neuron
  - Two variants
  - Preliminary validation seems promising

Next :

Rules extraction (Tsopze et al. IJCNN 2011)

#### Thanks !

