



Wrocław University of Technology

# Various applications of restricted Boltzmann machines for bad quality training data

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20.06.2014





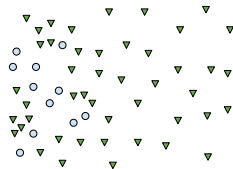
# Veracity of Data

Typical problems with data - training context

- **Imbalanced data problem.** One class dominates another in the training data.
- **Noisy labels problem.** Some of the examples in training data contain incorrectly assigned labels.
- **Missing values issue.** Values of some features are unknown.
- **Unstructured data.** The data is represented in unprocessed form: images, videos, documents, XML structures.
- **Semi-supervised data.** Some portion of training data is unlabelled.



Example of imbalanced data



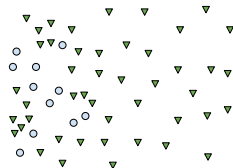
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# Methods

## Restricted Boltzmann Machines (RBM)

- **RBM** is a **bipartite Markov Random Field** with **visible** and **hidden** units.
- The **joint distribution** of visible and hidden units is the **Gibbs** distribution:

$$p(\mathbf{x}, \mathbf{h}|\boldsymbol{\theta}) = \frac{1}{Z} \exp(-E(\mathbf{x}, \mathbf{h}|\boldsymbol{\theta}))$$

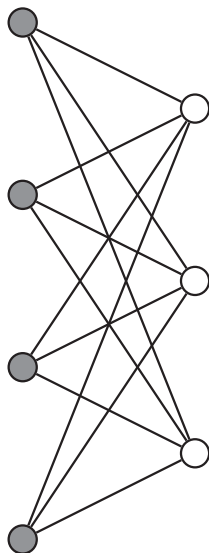
- For **binary visible**  $\mathbf{x} \in \{0, 1\}^D$  and **hidden** units  $\mathbf{h} \in \{0, 1\}^M$  the energy function is as follows:

$$E(\mathbf{x}, \mathbf{h}|\boldsymbol{\theta}) = -\mathbf{x}^\top \mathbf{W} \mathbf{h} - \mathbf{b}^\top \mathbf{x} - \mathbf{c}^\top \mathbf{h},$$

- Because of **no visible to visible**, or **hidden to hidden** connection we have:

$$p(x_i = 1|\mathbf{h}, \mathbf{W}, \mathbf{b}) = \text{sigm}(\mathbf{W}_{i \cdot} \mathbf{h} + b_i)$$

$$p(h_j = 1|\mathbf{x}, \mathbf{W}, \mathbf{c}) = \text{sigm}((\mathbf{W}_{\cdot j})^\top \mathbf{x} + c_j)$$



# Methods

## RBM for imbalanced data

- Train the model on **examples** from **minority** class by application of **MLL** (scaled):

$$\frac{1}{N} \log (p(\mathcal{X}_{n=1}^N | \theta)) = \frac{1}{N} \sum_{n=1}^N \log \left( \sum_{\mathbf{h}} p(\mathbf{x}_n, \mathbf{h} | \theta) \right)$$

- Generate artificial examples  $\bar{\mathcal{X}}_{m=1}^M$  using Synthetic Oversampling TEchnique (**SMOTE**).
- For each of the newly created example  $\mathbf{x}_m$  apply **Gibbs** sampling:

$$\mathbf{h}_m \sim p(\mathbf{h} | \bar{\mathbf{x}}_m, \theta)$$

$$\tilde{\mathbf{x}}_m \sim p(\mathbf{x} | \mathbf{h}_m, \theta)$$

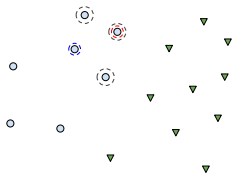
- Label newly created example  $\tilde{\mathbf{x}}_m$  and store in training data.

# Methods

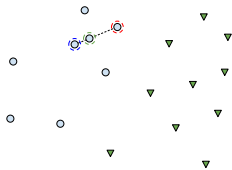
## RBM for imbalanced data - example

SMOTE procedure:

A



B



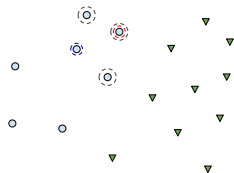


# Methods

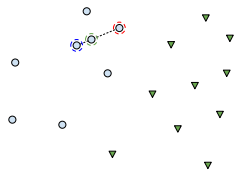
## RBM for imbalanced data - example

SMOTE procedure:

A



B



Generating artificial examples on MNIST data:

EXAMPLE 1          

EXAMPLE 2          

SMOTE          

SMOTE RBM          

## RBM for other raw data issues

- Problem of **missing values**.
  - **RBM** is trained for **each of the classes** separately.
  - **Gibbs** sampling is applied to **uncover** unknown values.
  - RBM models are iteratively **updated** while new training **example is completed**.
- Problem of **noisy labels**.
  - **RBM** is trained for **each of the classes** separately.
  - Each of the trained models is used as an **oracle** to detect **uncorrected labelled data**.
  - **Reconstruction** error is used to determine **unlabelled examples**.
- Problem of **unstructured data**.
  - **RBM** is used as domain-independent **feature extractor** that transforms raw data into **hidden units**.