



**HAL**  
open science

# The counterintuitive mechanism of graph-based semi-supervised learning in the big data regime

Xiaoyi Mai, Romain Couillet

► **To cite this version:**

Xiaoyi Mai, Romain Couillet. The counterintuitive mechanism of graph-based semi-supervised learning in the big data regime. The 42nd IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2017), 2017, New Orleans, United States. 10.1109/icassp.2017.7952671 . hal-01957754

**HAL Id: hal-01957754**

**<https://hal.science/hal-01957754>**

Submitted on 19 May 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# THE COUNTERINTUITIVE MECHANISM OF GRAPH-BASED SEMI-SUPERVISED LEARNING IN THE BIG DATA REGIME

Xiaoyi MAI, Romain COUILLET

CentraleSupélec, Université Paris-Saclay, Gif-sur-Yvette, France

## ABSTRACT

In this article, a new approach is proposed to study the performance of graph-based semi-supervised learning methods, under the assumptions that the dimension of data  $p$  and their number  $n$  grow large at the same rate and that the data arise from a Gaussian mixture model. Unlike small dimensional systems, the large dimensions allow for a Taylor expansion to linearize the weight (or kernel) matrix  $W$ , thereby providing in closed form the limiting performance of semi-supervised learning algorithms. This notably allows to predict the classification error rate as a function of the normalization parameters and of the choice of the kernel function. Despite the Gaussian assumption for the data, the theoretical findings match closely the performance achieved with real datasets, particularly here on the popular MNIST database.

**Index Terms**— semi-supervised learning, graphs, performance analysis, random matrix theory

## 1. INTRODUCTION

Semi-supervised learning is one of the important legs of machine learning research. It is of great practical interest to combine labeled data and unlabeled data, especially for the classification problems where the collection of labeled data is expensive and time-consuming.

Graph-based methods constitute one of the main branches of semi-supervised learning. Let  $x_1, \dots, x_n \in \mathbb{R}^p$  be data vectors. Among them are  $n_{[l]}$  labeled data  $x_1, \dots, x_{n_l}$  and  $n_{[u]} = n - n_{[l]}$  unlabeled data  $x_{n_l+1}, \dots, x_n$ . Labeled and unlabeled data are considered as vertices in a weighted graph with edge weights  $W_{ij}$  reflecting the similarity between  $x_i$  and  $x_j$ , and defined through a kernel function  $f$ ; here  $W_{ij} = f(\|x_i - x_j\|^2/p)$ . There are several approaches to consider the semi-supervised learning problem on a graph, such as label propagation, random walk, electrical network, etc. [1] Inspired by [2] which introduces an energy-based approach to classify the unlabeled data, we formulate here the problem in terms of the minimization of a cost function derived from the graph, with the presence of a normalization term  $\alpha$  (as

detailed in Section 2). The adjustment of  $\alpha$  retrieves various known algorithms [3]. We propose here to identify the normalization which minimizes the classification error rate. The performance analysis is made difficult by the highly non-linear structure of the algorithm and of  $W$  itself. To cope with this strong technical limitation, we exploit the approach developed in [4] to linearize the weight matrix  $W$ . The main idea of this approach is that, under appropriate assumptions on the data model, as  $n$  and  $p$  grow large at the same rate, the key value  $\|x_i - x_j\|^2/p$  converges to a constant  $\tau$  for all  $i \neq j$ , thereby allowing for the linearization of  $W_{ij}$  around  $f(\tau)$ . This linearization turns  $W$  into a tractable random matrix from which the (asymptotic) output of the classification algorithms can be statistically retrieved, analyzed, and improved over their latent parameters (kernel function choice, normalization parameters, etc.).

Our main findings may be summarized as follows: we first observe that the classical cost function formulation is a priori not adapted to the large dimensional regime and is bound to lead to failing algorithms. This observation is theoretically confirmed but, surprisingly, for the case  $\alpha \simeq -1$ , the algorithm unexpectedly works. We analyze this case in depth and retrieve the limiting theoretical performance of classification.

## 2. OPTIMIZATION FRAMEWORK

Let  $x_1, \dots, x_n \in \mathbb{R}^p$  be  $n$  vectors classified in  $K$  classes  $\mathcal{C}_1, \dots, \mathcal{C}_K$ . The  $n_{[l]}$  data  $x_1, \dots, x_{n_{[l]}}$  are *labeled* in the sense that the classes for these data are known, while the  $n_{[u]} = n - n_{[l]}$  data  $x_{n_{[l]}+1}, \dots, x_n$  are kept *unlabeled*.

Following classical works [2, 3], we define an overall cost function

$$C(F) = \sum_{k=1}^K \sum_{1 \leq i, j \leq n} W_{ij} \|D_i^\alpha F_{ik} - D_j^\alpha F_{jk}\|^2$$

with  $F_{ik}$  containing the (soft if  $F_{ik} \in \mathbb{R}$  or hard if  $F_{ik} \in \{0, 1\}$ ) score for  $x_i$  to belong to class  $\mathcal{C}_k$ ,  $W_{ij} = f(\|x_i - x_j\|^2/p)$  for some kernel function  $f$ ,  $D_i = \sum_j W_{ij}$  and  $\alpha \in \mathbb{R}$  a tuning parameter. In unsupervised learning, the value of  $F$  is determined by minimizing  $C(F)$  [5]. In semi-supervised learning, since some data classes are known, we additionally impose the values of  $F_i$ , for  $1 \leq i \leq n_{[l]}$ , thereby leading to

This work is supported by the ANR Project RMT4GRAPH (ANR-14-CE28-0006).

the following constrained optimization problem:

$$\min_{F \in \mathbb{R}^{n \times K}} C(F) \text{ s.t. } F_{ik} = \delta_{x_i \in \mathcal{C}_k}, 1 \leq i \leq n_{[l]}, 1 \leq k \leq K \quad (1)$$

which has the explicit solution

$$F_{[u]} = (I_{n_u} - D_{[u]}^{-1-\alpha} W_{[uu]} D_{[u]}^\alpha)^{-1} D_{[u]}^{-1-\alpha} W_{[ul]} D_{[l]}^\alpha F_{[l]} \quad (2)$$

where  $F = \begin{bmatrix} F_{[l]} \\ F_{[u]} \end{bmatrix}$ ,  $W = \{W_{ij}\}_{i,j=1}^n = \begin{bmatrix} W_{[ll]} & W_{[lu]} \\ W_{[ul]} & W_{[uu]} \end{bmatrix}$

and  $D = \begin{bmatrix} D_{[l]} & 0 \\ 0 & D_{[u]} \end{bmatrix}$ . The final (hard) decision consists in classifying  $x_i$  in  $\mathcal{C}_a$  for  $a = \max_{k \in \{1, \dots, K\}} F_{ik}$ .

The performance of the classification algorithm can be highly dependent on the value of  $\alpha$ . In the literature, there are three common choices for  $\alpha$  corresponding to three different methods [3], as listed below:

$$\begin{cases} \alpha = 0, & \text{Standard Laplacian method} \\ \alpha = -\frac{1}{2}, & \text{Normalized Laplacian method} \\ \alpha = -1, & \text{PageRank method.} \end{cases}$$

### 3. MODEL AND THEORETICAL RESULTS

#### 3.1. Model and assumptions

To obtain quantitative classification performance after the hard-decision step following (2), we assume that the data  $x_i$  are retrieved from a mixture of  $K$  Gaussian (corresponding to the classes) and let  $n, p \rightarrow \infty$ . Specifically, for  $k \in \{1, \dots, K\}$ ,  $x_i \in \mathcal{C}_k$  corresponds to  $x_i \sim \mathcal{N}(\mu_k, C_k)$ . There are  $n_k$  instances in  $\mathcal{C}_k$ , among which  $n_{[l]k}$  are labeled and  $n_{[u]k}$  are unlabeled.

When the number of data points  $n$  and their dimension  $p$  grow simultaneously large, in order to ensure that the classification problem we study here is non trivial, in the sense that the asymptotic error rate is neither 0 nor 1,  $\mu_k$  and  $C_k$  are chosen to behave in a prescribed manner, as described in [4] for the unsupervised scenario.<sup>1</sup>

**Assumption 1** (Growth Rate). *As  $n \rightarrow \infty$ ,  $\frac{p}{n} \rightarrow c_0 > 0$ ,  $\frac{n_k}{n} \rightarrow c_k > 0$ , and  $\frac{n_{[l]}}{n} \rightarrow c_{[l]} > 0$ . Besides,*

1. For  $\mu^\circ \triangleq \sum_{k=1}^K \frac{n_k}{n} \mu_k$  and  $\mu_k^\circ \triangleq \mu_k - \mu^\circ$ ,  $\|\mu_k^\circ\| = O(1)$ .
2. For  $C^\circ \triangleq \sum_{k=1}^K \frac{n_k}{n} C_k$  and  $C_k^\circ \triangleq C_k - C^\circ$ ,  $\|C_k^\circ\| = O(1)$  and  $\text{tr} C_k^\circ = O(\sqrt{n})$ .
3. As  $n \rightarrow \infty$ ,  $\frac{2}{p} \text{tr} C^\circ \rightarrow \tau$ .

As for the kernel function, it follows the assumption below.

<sup>1</sup>Since semi-supervised learning is simpler than unsupervised learning, the algorithms ought to perform at least as well under these conditions.

**Assumption 2** (Kernel function). *The kernel function  $f : \mathbb{R}^+ \rightarrow \mathbb{R}^+$  is three-times continuously differentiable in a neighborhood of  $\tau$ .*

The constant  $\tau$  introduced in the third point of Assumption 1 is important as  $\|x_i - x_j\|^2/p \rightarrow \tau$  almost surely and uniformly on all  $i \neq j \in \{1, \dots, n\}$ , which implies that all data points  $x_i$  are almost equally far away from each other whether or not they belong to the same class. As a consequence, the  $W_{ij}$ 's, which are supposed to reflect the similarity between  $x_i$ 's, are asymptotically the same for all  $i \neq j$ , thus do not exert its expected effect in the cost function  $C(F)$ , as they do for small dimensional data. For that reason, we do not expect the classification algorithm to work in our case, but contrary to our intuition, it shall in fact work if and only if  $\alpha \simeq -1$ , as explained in the subsection below.

#### 3.2. Principle and results

As  $\|x_i - x_j\|^2/p \rightarrow \tau$  almost surely, the off-diagonal entries of  $W$  can be Taylor-expanded around  $f(\tau)$ , which allows for the decomposition of  $W$  and  $D$  into a series of tractable random matrices. However, to access  $F_{[u]}$  in (2), this leaves us with the complicated inverse of the matrix  $I_{n_u} - D_{[u]}^{-1-\alpha} W_{[uu]} D_{[u]}^\alpha$  to handle. Fortunately, after decomposition, we find that

$$W_{[uu]} = f(\tau) 1_{n_{[u]}} 1_{n_{[u]}}^T + O(n^{\frac{1}{2}})$$

$$D_{[u]} = n f(\tau) I_{n_{[u]}} + O(n^{\frac{1}{2}})$$

where  $O(\cdot)$  is with respect to the matrix operator norm, and similarly for  $W_{[ul]}$  and  $D_{[l]}$ , which then leads to

$$D_{[u]}^{-1-\alpha} W_{[uu]} D_{[u]}^\alpha = \frac{1}{n} 1_{n_{[u]}} 1_{n_{[u]}}^T + O(n^{-\frac{1}{2}}).$$

Therefore,  $(I_{n_{[u]}} - D_{[u]}^{-1-\alpha} W_{[uu]} D_{[u]}^\alpha)^{-1}$  can be Taylor-expanded around

$$\left( I_{n_{[u]}} - \frac{1}{n} 1_{n_{[u]}} 1_{n_{[u]}}^T \right)^{-1} = I_{n_{[u]}} + \frac{1}{n_{[l]}} 1_{n_{[u]}} 1_{n_{[u]}}^T.$$

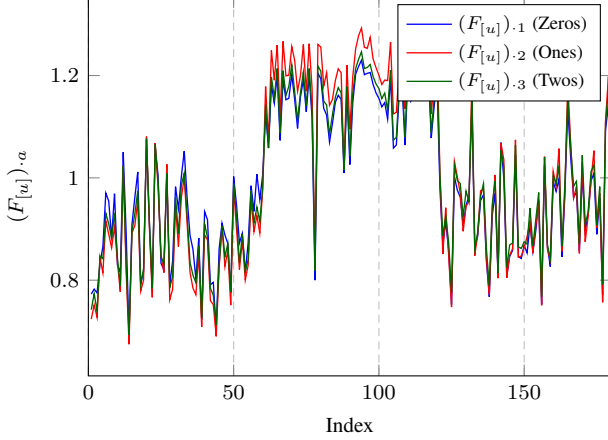
After explicit computation of the various  $O(\cdot)$  terms above (the full derivation is left to an extended version of the article), we are able to analyze (2).

**Proposition 1.** *The columns of  $F_{[u]}$  can be expressed as<sup>2</sup>*

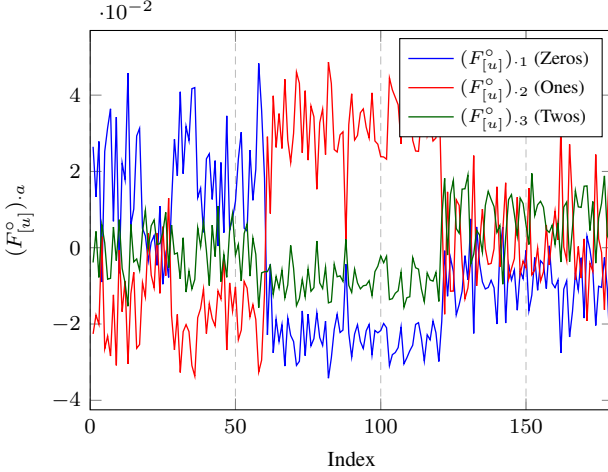
$$(F_{[u]})_{\cdot a} = \underbrace{\frac{n_{[l]a}}{n} v}_{O(1)} + (1+\alpha) \left[ \underbrace{\kappa \frac{\text{tr} C_a^\circ}{p} 1_{n_{[u]}}}_{O(n^{-\frac{1}{2}})} + \underbrace{\phi_a 1_{n_{[u]}}}_{O(n^{-1})} \right] + O(n^{-1}) \quad (3)$$

for some constant  $\kappa$  and a random vector  $v$ , both independent of  $a$  and of entries of order  $O(1)$ , and  $\phi_a$  a random variable of order  $O(1)$ . Here  $1_n$  is the vector of ones of size  $n$ .

<sup>2</sup>The  $O(\cdot)$  terms below are understood entry-wise.



**Fig. 1.** Vectors  $(F_{[u]})_{\cdot a}$  for 3-class MNIST data (zeros, ones, twos),  $n = 192$ ,  $p = 784$ ,  $n_{[l]}/n = 1/16$ ,  $n_{[l]1} = n_{[l]2} = n_{[l]3}$ ,  $n_{[u]1} = n_{[u]2} = n_{[u]3}$ , Gaussian kernel,  $\alpha = -1$ .



**Fig. 2.** Centered vectors  $(F_{[u]}^o)_{\cdot a} = (F_{[u]})_{\cdot a} - \sum_{b=1}^K \frac{n_{[l]b}}{n_{[l]}} (F_{[u]})_{\cdot b}$  for 3-class MNIST data (zeros, ones, twos),  $n = 192$ ,  $p = 784$ ,  $n_l/n = 1/16$ ,  $n_{[l]1} = n_{[l]2} = n_{[l]3}$ ,  $n_{[u]1} = n_{[u]2} = n_{[u]3}$ , Gaussian kernel,  $\alpha = -1$ .

The three curly-bracketed terms in the right-hand side of (3) do not contain relevant information about the classes, which is solely contained within the tailing term  $O(n^{-1})$  (see the extended version of the article for a full characterization of  $v$  and  $\phi_a$ ). More importantly, the first two are fatally harmful to the classification as they induce strong biases of higher order than the information terms. Our first conclusion is then that, for the classification algorithm to behave correctly in the large dimensional regime, we need to:

(i) Adapt the hard decision step from comparing  $(F_{[u]})_{\cdot a}$  to comparing  $(F_{[u]})_{\cdot a}/n_{[l]a}$  so as to eliminate the bias induced by the first term (by making it the same for every column of  $F_{[u]}$ );

(ii) Impose  $\alpha = -1 + O(n^{-\frac{1}{2}})$  if  $\text{tr}C_a^o$  is not the same for all  $a \in \{1, \dots, K\}$  in order to degrade the bias due to the second term.

Even when  $\text{tr}C_a^o$  is the same for all  $a \in \{1, \dots, K\}$  (something a priori unknown), it is still in our interest to take  $\alpha = -1 + O(n^{-\frac{1}{2}})$  because of the existence of the third term. While it might not be fatal to the classification as it is of the same order as the information terms, it induces uncontrollable randomness. By taking  $\alpha = -1 + O(n^{-\frac{1}{2}})$ , we render it negligible compared to the information terms.

As observed in Figure 1,  $(F_{[u]})_{\cdot a}$  are indistinguishable at the first order for MNIST data. This is unsettling at first sight because  $(F_{[u]})_{\cdot a}$  do not behave at all like  $(F_{[l]})_{\cdot a}$ , which is the purpose of the algorithm. This unexpected behavior of  $(F_{[u]})_{\cdot a}$  is again due to the large dimensional effect of data and is consistent with our analysis. A detailed calculus in fact reveals that the classification algorithm works nonetheless with  $\alpha \simeq -1$  thanks to the information terms contained within the tailing term  $O(n^{-1})$  of (3), which allow for the separation of classes, as shown in Figure 2.

With these remarks in mind and with some further calculus (available in the extended version of the article), we are in position to provide the main result of the article:

**Theorem 1.** For  $x_i \in \mathcal{C}_b$  unlabeled, let  $\hat{F}_{ia} = \frac{np}{n_{[l]a}} F_{ia}$  and  $\alpha = -1 + \frac{\beta}{\sqrt{p}}$ . Then, under Assumptions 1–2,  $\hat{F}_i - G_b \rightarrow 0$  weakly, with  $G_b \sim \mathcal{N}(M_b, \Sigma_b)$ , where

$$(M_b)_a = -\frac{2f'(\tau)}{f(\tau)} \tilde{\mu}_a^o \tilde{\mu}_b^o + \frac{f''(\tau)}{f(\tau)} \frac{\text{tr}\tilde{C}_a^o}{\sqrt{p}} \frac{\text{tr}\tilde{C}_b^o}{\sqrt{p}} + \frac{2f''(\tau)}{f(\tau)} \frac{\text{tr}(\tilde{C}_a \tilde{C}_b)}{p} - \frac{f'(\tau)^2}{f(\tau)^2} \frac{\text{tr}C_a^o}{\sqrt{p}} \frac{\text{tr}C_b^o}{\sqrt{p}} + \frac{n\beta}{n_{[l]}} \frac{f'(\tau)}{f(\tau)} \frac{\text{tr}C_a^o}{\sqrt{p}} + B_b \quad (4)$$

$$(\Sigma_b)_{a_1 a_2} = \left( \frac{f'(\tau)^2}{f(\tau)^2} + \frac{f''(\tau)}{f(\tau)} \right)^2 \frac{2\text{tr}C_b^2 \text{tr}C_{a_1}^o \text{tr}C_{a_2}^o}{p^2} + \frac{4f'(\tau)^2}{f(\tau)^2} \left[ \mu_{a_1}^{oT} C_b \mu_{a_2}^o + \delta_{a_1}^{a_1} \frac{\text{tr}C_b C_{a_1}}{n_{[l]a_1}} \right] \quad (5)$$

where  $B_b$  is a constant bias of order  $O(n)$ ,  $\tilde{\mu}_a^o = \mu_a^o - \sum_{d=1}^K \frac{n_{[l]d}}{n_{[l]}} \mu_d^o$ ,  $\tilde{C}_a^o = C_a^o - \sum_{d=1}^K \frac{n_{[l]d}}{n_{[l]}} C_d^o$  and  $\tilde{C}_a = C_a - \sum_{d=1}^K \frac{n_{[l]d}}{n_{[l]}} C_d$ .

Since  $\hat{F}_i$  is asymptotically a Gaussian vector, we easily access the asymptotic misclassification rate for the unlabeled data. In particular, for  $K = 2$ , we have:

**Corollary 1.** Under the conditions of Theorem 1, and with  $K = 2$ , we have, for  $a \neq b \in \{1, 2\}$ ,

$$P(x_i \rightarrow \mathcal{C}_a | x_i \in \mathcal{C}_b) - Q\left(\frac{(M_b)_b - (M_b)_a}{\sqrt{\hat{\beta}^T \Sigma_b \hat{\beta}}}\right) \rightarrow 0 \quad (6)$$

where  $j = [1 - 1]^T$  and  $Q(x) = \frac{1}{2\pi} \int_x^\infty \exp(-t^2/2) dt$ .

From (4) and (5), we see that  $f(\tau)$ ,  $f'(\tau)$ ,  $f''(\tau)$  and  $\beta$  are the parameters influencing the output of the classification algorithm. When  $K = 2$ , some interesting conclusions for these parameters are readily drawn. From Corollary 1, we deduce that for the classification algorithm to perform better than random, we need to ensure that  $(M_b)_b - (M_b)_a > 0$ .

Keeping this in mind, we now take a closer look at each term of (4):

(i) Evidently,  $\tilde{\mu}_b^o \tilde{\mu}_b^o \geq \tilde{\mu}_a^o \tilde{\mu}_b^o$ . So for the first term, in order to have  $-\frac{2f'(\tau)}{f(\tau)} \tilde{\mu}_b^o \tilde{\mu}_b^o \geq -\frac{2f'(\tau)}{f(\tau)} \tilde{\mu}_a^o \tilde{\mu}_b^o$ , we need  $f'(\tau) < 0$  since  $f(\tau) > 0$  according to Assumption 2. The same reasoning for the second and third terms induces  $f''(\tau) > 0$ .

(ii) Since  $\text{tr}C_b^o \text{tr}C_b^o \geq \text{tr}C_a^o \text{tr}C_b^o$ , for the fourth term, we always have  $-\frac{f'(\tau)^2}{npf(\tau)^2} \frac{\text{tr}C_b^o}{\sqrt{p}} \frac{\text{tr}C_b^o}{\sqrt{p}} \geq -\frac{f'(\tau)^2}{npf(\tau)^2} \frac{\text{tr}C_a^o}{\sqrt{p}} \frac{\text{tr}C_b^o}{\sqrt{p}}$  for any  $f'(\tau)$ . So this term is harmful, working in the opposite direction to  $(M_b)_b - (M_b)_a > 0$ .

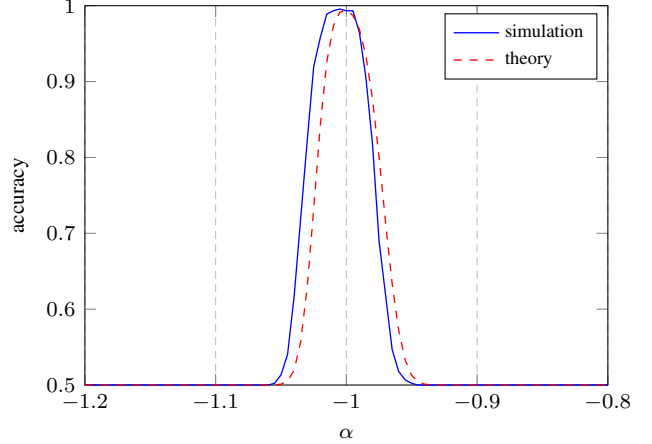
(iii) For the fifth term, we have  $\frac{n\beta}{n_{[l]}} \frac{f'(\tau)}{f(\tau)} \frac{\text{tr}C_b^o - \text{tr}C_a^o}{\sqrt{p}}$  for  $(M_b)_b - (M_b)_a$  and  $\frac{n\beta}{n_{[l]}} \frac{f'(\tau)}{f(\tau)} \frac{\text{tr}C_a^o - \text{tr}C_b^o}{\sqrt{p}} = -\frac{n\beta}{n_{[l]}} \frac{f'(\tau)}{f(\tau)} \frac{\text{tr}C_b^o - \text{tr}C_a^o}{\sqrt{p}}$  for  $(M_a)_a - (M_a)_b$ . It is a balance term in the sense that, if it increases  $(M_b)_b - (M_b)_a$ , it decreases inevitably  $(M_a)_a - (M_a)_b$ . As it is the only term containing  $\beta$  in (4) and (5), it allows to decrease  $P(x_i \rightarrow \mathcal{C}_a | x_i \in \mathcal{C}_b)$  at the expense of  $P(x_i \rightarrow \mathcal{C}_b | x_i \in \mathcal{C}_a)$  or the other way around through the adjustment of  $\beta$ .

#### 4. SIMULATIONS

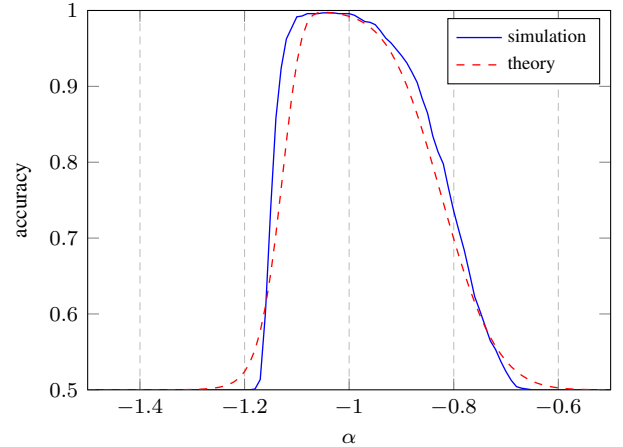
We provide in this section two simulations conducted respectively on Gaussian data as defined in Assumption 1 and on the real-world MNIST database [6]. Here, for the theoretical comparison, we handle the MNIST data as if they were Gaussian with means and covariances empirically obtained from the full set of 13 007 images. In those simulations, we display the actual classification accuracy as a function of  $\alpha$ , and the theoretical curve obtained by applying Corollary 1. We find that our theoretical results match extremely well the reality not only for Gaussian data (Figure 3), but, quite surprisingly, also for MNIST data (Figure 4) which are evidently not Gaussian. This suggests that most of the image information is retrieved from its first order (empirical) moments.

#### 5. CONCLUDING REMARKS

This article has proposed a novel (random matrix-based) framework of semi-supervised learning analysis. The linearization of (2) led to theoretical results providing direct access to the performance of the classification algorithm in the large data regime. From the theoretical results, we deduced several important conclusions concerning the latent



**Fig. 3.** Theoretical and empirical accuracy as a function of  $\alpha$  for 2-class Gaussian data,  $n = 512$ ,  $p = 1024$ ,  $n_{[l]}/n = 1/8$ ,  $n_{[u]1} = n_{[u]2}$ , Gaussian kernel.



**Fig. 4.** Theoretical and empirical accuracy as a function of  $\alpha$  for 2-class MNIST data (zeros, ones),  $n = 1024$ ,  $p = 784$ ,  $n_{[l]}/n = 1/16$ ,  $n_{[u]1} = n_{[u]2}$ , Gaussian kernel.

parameters of the algorithm: (i)  $\alpha$  should be taken around  $-1$ . (ii) When  $K = 2$ , the kernel function  $f$  should be chosen so that  $f'(\tau) < 0$ ,  $f''(\tau) > 0$  in order to ensure the good working of the classification algorithm.

An important non-trivial extension of this work would be to handle discrete kernel matrices such as the popular k-nearest neighbor approach. More importantly, the advent of new semi-supervised learning approaches arising from the sparse big data [7] and signal processing on graph [8, 9] fields calls for a development of our random matrix tools to encompass these novel approaches.

## 6. REFERENCES

- [1] Xiaojin Zhu, John Lafferty, and Ronald Rosenfeld, *Semi-supervised learning with graphs*, Carnegie Mellon University, language technologies institute, school of computer science, 2005.
- [2] Xiaojin Zhu, Zoubin Ghahramani, John Lafferty, et al., “Semi-supervised learning using gaussian fields and harmonic functions,” in *ICML*, 2003, vol. 3, pp. 912–919.
- [3] Konstantin Avrachenkov, Paulo Gonçalves, Alexey Mishenin, and Marina Sokol, “Generalized optimization framework for graph-based semi-supervised learning,” *arXiv preprint arXiv:1110.4278*, 2011.
- [4] Romain Couillet and Florent Benaych-Georges, “Kernel spectral clustering of large dimensional data,” *arXiv preprint arXiv:1510.03547*, 2015.
- [5] Ulrike Von Luxburg, “A tutorial on spectral clustering,” *Statistics and computing*, vol. 17, no. 4, pp. 395–416, 2007.
- [6] Yann LeCun, Corinna Cortes, and Christopher JC Burges, “The mnist database of handwritten digits,” 1998.
- [7] Mahdi Soltanolkotabi, Ehsan Elhamifar, Emmanuel J Candes, et al., “Robust subspace clustering,” *The Annals of Statistics*, vol. 42, no. 2, pp. 669–699, 2014.
- [8] Aliaksei Sandryhaila and José MF Moura, “Discrete signal processing on graphs,” *IEEE transactions on signal processing*, vol. 61, no. 7, pp. 1644–1656, 2013.
- [9] Aliaksei Sandryhaila and Jose MF Moura, “Discrete signal processing on graphs: Frequency analysis,” *IEEE Transactions on Signal Processing*, vol. 62, no. 12, pp. 3042–3054, 2014.