

Experimental Results On Compression Quality of aiNet

Special session : Foundations of Artificial Immune Systems

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Abstract—AiNet is an immune-inspired algorithm for data compression, i.e. the reduction of redundancy in data sets. In this paper we experimentally investigate the compression quality of aiNet. Therefore, a similarity measure between input set and reduced output set is presented. Four different artificially generated data sets are created and the compression quality is investigated. Experiments reveal that aiNet produced reasonable results on uniformly distributed data sets, but poor results on non-uniformly distributed data sets, i.e. data sets which contain dense point regions.

I. INTRODUCTION

The immune system provides from a technical point of view many problem oriented approaches for solving pattern recognition and clustering problems [1], [2]. A frequently applied immune-inspired algorithm for data reduction is aiNet (artificial immune network) [3]. AiNet is inspired by Jerne's postulated immune network theory and can be considered as a micro-evolutionary search algorithm. Roughly speaking, the aim of aiNet algorithm is to find a reduced set of points that closely represents the set of input points, or in other words, find a compressed input set representation with less redundancy. Once the reduced set is found, established clustering techniques like minimum spanning tree or k -means can be applied to determine a clustering result [3], [4]. The aiNet algorithm can therefore be considered as an immune-inspired search technique in the problem domain: given an input set of points, output a reduced set of points that closely represents the input set.

In this context two fundamental questions arise: *What does "closely represent" mean? How to measure the quality of the reduced output set?* We address these questions and organize as follows: In section II, Jerne's immune network theory is briefly summarized. In section III, the aiNet algorithm is outlined. In section IV, we briefly explain the nonparametric density estimation method and show a (known) probability density approach to measure the quality between input set and reduced output set by means of Parzen window estimators. In section V, the quality measure is experimentally investigated on different artificially generated data sets. In section VI, the obtained results are analyzed and discussed.

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II. IMMUNE NETWORK THEORY

The immune network theory proposed by Jerne¹ [6] postulates that the immune system consists of antibodies and antigens which form a regulated network. In Jerne's theory antibodies recognize not only antigens², but also other antibodies. As a result, the network is also regulated without antigenic influence. In addition to this new perspective, the network structure — i.e. the size and connectivity — is biased by *network stimulation* and *network suppression*. A network stimulation results in proliferation and memorization of antibodies, while a network suppression results in a reduction of maintained antibodies. According to Varela and Coutinho [7] three major immune network characteristics can be emphasized:

- *structure*: types of interactions among the antibodies and antigens, represented by matrices of connectivity
- *dynamics*: variation with time of the concentration and affinities of cells and molecules comprising the network
- *metadynamics*: continuous production of novel cells and death of non-stimulated and self-reactive cells.

The network structure is a result of the amount and connectivity strength of antibodies, and mirror the internal structure of the immune system. A foreign antigen causes a disturbance in this network structure and induces a restructuring and resizing of the previous structure. To accomplish the network restructuring and resizing, network stimulation and suppression are triggered. In the process of network stimulation, some antibodies are more strongly involved in recognizing and eliminating foreign antigens than other antibodies. These highly adapted antibodies are transformed into long-life memory antibodies. As the immune system continually produces novel antibodies, and since the total number of antibodies cannot be arbitrary large, non-stimulated and self-reactive antibodies are eliminated. This elimination and renewing process enables the immune system to adapt continually to arbitrary antigenic environments.

III. AI.NET ALGORITHM

The aiNet algorithm summarized in this section mimics the immune network characteristics, i.e. it is an abstracted implementation of the immune network theory explained above. The algorithm is proposed by de Castro

¹He received the Nobel Prize for this theory.

²This is the classical viewpoint of immunologists.

and von Zuben [8], [3] and has the general purpose of finding a compressed representation of the input set, by eliminating redundancy in the input set.

The pseudo-code of aiNet is presented below (see algorithm 1). For the sake of clarity the following notations and functions are used:

- \mathcal{B} collection of antibodies,
- \mathcal{G} collection of antigens,
- \mathcal{M} collection of memorized antibodies,
- \mathcal{H} collection of high affinity antibodies,
- \mathcal{C} collection of cloned antibodies,
- \mathcal{C}^* collection of cloned and mutated antibodies.

Members of each collection are l -dimensional points from \mathbb{R}^l and denoted in small bold letters, e.g. $\mathcal{H} = \{\mathbf{h}_1, \mathbf{h}_2, \dots, \mathbf{h}_{|\mathcal{H}|}\}$, where $|\mathcal{H}|$ is the cardinality of \mathcal{H} . Moreover, $r \in_R [0, 1]$ denotes a random value generated uniformly from the interval $[0, 1]$ and capital bold letters denote matrices, e.g. matrix \mathbf{D} with entries $\mathbf{D}_{ij} \forall i, j$. Additionally the following functions are used:

$\text{dist}(\mathbf{x}, \mathbf{y})$	Euclidean distance between any two vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^l$
$\iota\text{-affinity}(\mathcal{X}, \mathcal{Y})$	return the inverse distance matrix $\mathbf{D}_{ij} = 1/\text{dist}(\mathbf{x}_i, \mathbf{y}_j) \forall i, j$
$\text{select}(\mathcal{S}, \mathbf{D}, n)$	select n elements from collection \mathcal{S} which have the largest distance in $\mathbf{D}_{ij} \forall i, j$
$\text{rnd}(\cdot)$	rounding function which gives the nearest integer value
$\text{clone}(\mathbf{e}, n)$	duplicate element \mathbf{e} , n times
$\text{mutate}(\mathbf{e}_1, \mathbf{e}_2)$	change ³ element \mathbf{e}_1 according to $\mathbf{e}_1 \leftarrow \mathbf{e}_1 + \alpha(\mathbf{e}_2 - \mathbf{e}_1)$, where $\alpha \leftarrow r \cdot 1/\text{dist}(\mathbf{e}_1, \mathbf{e}_2)$ and $r \in_R [0, 1]$
$\sigma_s\text{-remove}(\mathcal{E}, \sigma)$	remove all elements from collection \mathcal{E} whose $\text{dist}(\mathbf{e}_i, \mathbf{e}_j) < \sigma \forall i, j$
$\sigma_d\text{-remove}(\mathcal{E}, \mathbf{a}, \sigma)$	remove all elements from collection \mathcal{E} whose $\text{dist}(\mathbf{e}_i, \mathbf{a}) > \sigma \forall i$
$\text{concat}(\mathcal{E}_1, \mathcal{E}_2)$	concat collection \mathcal{E}_1 with \mathcal{E}_2

IV. NONPARAMETRIC DENSITY ESTIMATION

In this section we briefly introduce the concept of nonparametric density estimation and show a quality measure in the context of density estimation for data sets proposed by Fukunaga and Hayes [10].

³As we performed our experiments with the existing aiNet implementation taken from [9], the presented mutation function is for the sake of conformity derived from the Matlab source code. The aiNet mutation function presented in [3], [8] is a local guided greedy search, without any random influence, whereas the aiNet mutation function presented in [5] contains a random component. The same with the function for calculating the number of clones. Line (9) is formulated according to [3], [5]. However, in the Matlab source code, $|\mathcal{B}|$ is replaced with a fixed value $c = 10$. We used this fixed value in our experiments.

Algorithm 1: aiNet

```

input :  $\mathcal{G} = \{\mathbf{g}_1, \mathbf{g}_2, \dots, \mathbf{g}_{|\mathcal{G}|}\} \in \mathbb{R}^l$ ,
         $N$  (number of maintained antibodies)
         $\sigma_s$  (suppression threshold),
         $\sigma_d$  (natural death threshold),
         $n$  (number of best-matching antibodies),
         $\zeta$  (% of antibodies to be selected as
            memory),
         $\text{max}_g$  (number of maximum generations)
output:  $\mathcal{M} = \{\mathbf{m}_1, \mathbf{m}_2, \dots, \mathbf{m}_{|\mathcal{M}|}\} \in \mathbb{R}^l$ 
1 begin
   //initialize randomly set  $\mathcal{B}$ 
2  $\mathcal{B} \leftarrow \{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_N\} \in_R [0, 1]^l$ 
3 repeat
   //for each antigen
4   for  $i \leftarrow 1$  to  $|\mathcal{G}|$  do
     //determine inverse distance from
     //antigen  $\mathbf{g}_i$  to each antibody  $\mathbf{b}_j$ 
5      $\mathbf{D} \leftarrow \iota\text{-affinity}(\{\mathbf{g}_i\}, \mathcal{B})$ 
     //select  $n$  antibodies from  $\mathcal{B}$  with
     //the smallest distances to  $\mathbf{g}_i$ 
6      $\mathcal{H} = \{\mathbf{h}_1, \dots, \mathbf{h}_{|\mathcal{H}|}\} \leftarrow \text{select}(\mathcal{B}, \mathbf{D}, n)$ 
     //determine number of clones for each
     //antibody in  $\mathcal{H}$  and create this
     //amount of clones
7      $\mathcal{C} \leftarrow \emptyset$ 
8     for  $j \leftarrow 1$  to  $|\mathcal{H}|$  do
9        $n_c \leftarrow \text{rnd}(|\mathcal{B}| - 1/\mathbf{D}_{ij} \cdot |\mathcal{B}|)$ 
10       $\mathcal{C} \leftarrow \mathcal{C} \cup \text{clone}(\mathbf{h}_j, n_c)$ 
     //mutate each clone with a rate
     //proportional to the inverse
     //distance of its parent antibody
11      $\mathcal{C}^* \leftarrow \emptyset$ 
12     for  $j \leftarrow 1$  to  $|\mathcal{C}^*|$  do
13        $\mathcal{C}^* \leftarrow \mathcal{C}^* \cup \text{mutate}(\mathbf{c}_j^*, \mathbf{g}_i)$ 
     //determine inverse distance from
     //antigen  $\mathbf{g}_i$  to each cloned antibody  $\mathbf{c}_j^*$ 
14      $\mathbf{D}^* \leftarrow \iota\text{-affinity}(\{\mathbf{g}_i\}, \mathcal{C}^*)$ 
     //select from  $\mathcal{C}^*$ ,  $\xi\%$  of the antibodies
     //with largest distances in  $\mathbf{D}^*$  and
     //store them in  $\mathcal{M}$ 
15      $\mathcal{M} \leftarrow \text{select}(\mathcal{C}^*, \mathbf{D}^*, \text{rnd}(|\mathcal{C}^*| \cdot \xi/100))$ 
     //eliminate those memory clones from
     // $\mathcal{M}$  whose distances  $> \sigma_d$ 
16      $\sigma_d\text{-remove}(\mathcal{M}, \mathbf{g}_i, \sigma_d)$ 
     //eliminate those memory clones whose
     //distance  $< \sigma_s$ 
17      $\sigma_s\text{-remove}(\mathcal{M}, \sigma_s)$ 
     //concatenate antibody collection
     //with resultant memory clones coll.
18      $\mathcal{B} \leftarrow \text{concat}(\mathcal{B}, \mathcal{M})$ 
   //eliminate those antibodies whose
   //distance  $< \sigma_s$ 
19    $\sigma_s\text{-remove}(\mathcal{B}, \sigma_s)$ 
   //generate randomly new antibodies
20    $\mathcal{B}_{\text{diversity}} \leftarrow \{\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_{N-|\mathcal{B}|}\} \in_R [0, 1]^l$ 
   //concatenate old antibody collection with
   //new diverse antibody collection
21    $\mathcal{B} \leftarrow \text{concat}(\mathcal{B}, \mathcal{B}_{\text{diversity}})$ 
22    $\text{iter} \leftarrow \text{iter} + 1$ 
23 until  $\text{iter} = \text{max}_g$ 
24 return  $\mathcal{M}$ 
25 end

```

Nonparametric density estimation is a method for estimating an unknown probability density $p(\cdot)$. Given samples $\mathcal{N} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\} \in \mathbb{R}^l$ drawn independently from $p(\cdot)$, the aim is to find an estimator $\hat{p}_N(\cdot)$ which approximates $p(\cdot)$. Parzen window (also called kernel estimator) is defined as

$$\hat{p}_N(\mathbf{x}) = \frac{1}{N} \sum_{i=1}^N K(\mathbf{x} - \mathbf{x}_i) \quad (1)$$

and is one feasible approach⁴ to estimate $p(\cdot)$. A kernel function must satisfy the condition

$$\int_{-\infty}^{\infty} K(\mathbf{x}) d\mathbf{x} = 1 \quad (2)$$

and therefore the (multivariate) Gaussian kernel function is frequently employed

$$K(\mathbf{x}) = \frac{1}{(2\pi)^{l/2} h^l} \exp\left(-\frac{\|\mathbf{x}\|^2}{2h^2}\right). \quad (3)$$

The window width (also called bandwidth) h controls the *smoothness*, i.e. the influence of the surrounding points \mathbf{x}_i , whereas the kernel function $K(\cdot)$ determines the *shape*.

A. A Quality Measure for Reduced Parzen Window

The Parzen window estimation method is computationally expensive, because all stored samples $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$ are used to estimate $\hat{p}_N(\mathbf{x})$. Fukunaga and Hayes [10] proposed a data reduction algorithm for finding a reduced sample set $\mathcal{R} = \{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_r\} \subset \mathcal{N}$, such that the Parzen density estimates over sample sets \mathcal{N} and \mathcal{R} are as close as possible. The density at \mathbf{x} is then estimated by the reduced sample set as follows

$$\hat{p}_r(\mathbf{x}) = \frac{1}{r} \sum_{i=1}^r K(\mathbf{x} - \mathbf{y}_i). \quad (4)$$

To measure the similarity between $\hat{p}_N(\mathbf{x})$ and $\hat{p}_r(\mathbf{x})$ Fukunaga and Hayes suggested to use the entropy

$$\mathfrak{J} = \int \ln \left[\frac{\hat{p}_r(\mathbf{x})}{\hat{p}_N(\mathbf{x})} \right] \hat{p}_N(\mathbf{x}) d\mathbf{x}. \quad (5)$$

If the equality $\hat{p}_N(\mathbf{x}) = \hat{p}_r(\mathbf{x})$ holds, then $\mathfrak{J} = 0$; otherwise $\mathfrak{J} < 0$ [10]. Hence a larger entropy implies that \hat{p}_r is closer to \hat{p}_N . A closer look at (5) reveals, that by interchanging numerator with denominator one obtains the well known Kullback-Leibler divergence with a negative sign

$$- \int \ln \left[\frac{\hat{p}_N(\mathbf{x})}{\hat{p}_r(\mathbf{x})} \right] \hat{p}_N(\mathbf{x}) d\mathbf{x} = \int \ln \left[\frac{\hat{p}_r(\mathbf{x})}{\hat{p}_N(\mathbf{x})} \right] \hat{p}_N(\mathbf{x}) d\mathbf{x}. \quad (6)$$

The Kullback-Leibler divergence [11] (also called relative entropy) is a distance⁵ measure between two probability distributions.

⁴The other popular method is k -nearest neighbor estimator.

⁵The Kullback-Leibler divergence is not a *true metric* because it satisfies not all metric properties and therefore is often termed divergence instead of distance.

In order to discretize and simplify (5), Fukunaga and Hayes used the expectation of (5) taken with respect to $\hat{p}_N(\mathbf{x})$, i.e.

$$\mathbb{E} \left[\ln \left[\frac{\hat{p}_r(\mathbf{x})}{\hat{p}_N(\mathbf{x})} \right] \right] \approx \sum_{i=1}^N \ln \left[\frac{\hat{p}_r(\mathbf{x}_i)}{\hat{p}_N(\mathbf{x}_i)} \right] \underbrace{\hat{p}_N(\mathbf{x}_i)}_{\rho}. \quad (7)$$

By replacing ρ by $1/N$ one obtains a simplified approximation of (5), i.e.

$$\tilde{J} = \frac{1}{N} \sum_{i=1}^N [\ln \hat{p}_r(\mathbf{x}_i) - \ln \hat{p}_N(\mathbf{x}_i)]. \quad (8)$$

Finally by substituting (1) and (4) in (8) one obtains

$$J =$$

$$\frac{1}{N} \sum_{i=1}^N \left[\ln \frac{1}{r} \sum_{j=1}^r K(\mathbf{x}_i - \mathbf{y}_j) - \ln \frac{1}{N} \sum_{j=1}^N K(\mathbf{x}_i - \mathbf{x}_j) \right]. \quad (9)$$

They noticed that $J \leq 0$ (and also $\tilde{J} \leq 0$) is no longer guaranteed, but argued [10] that J represents a significantly simplified closeness measure. Furthermore they reported good and reasonable experimental results, when applying this closeness measure.

In our experiments we will use (9) as a closeness measure between the input data set and the aiNet output data set. To be more precise, the probability densities $\hat{p}_N(\cdot)$ and $\hat{p}_r(\cdot)$ are estimated by means of a Parzen window estimator over the input set \mathcal{N} and output set \mathcal{R} , respectively. The closeness between $\hat{p}_N(\cdot)$ and $\hat{p}_r(\cdot)$ is then determined by means of term (9) and gives a measure on the reduction quality of input set and output set. The larger the value of J , the closer $\hat{p}_r(\cdot)$ to $\hat{p}_N(\cdot)$ and consequently the more similar (in a probabilistic sense) input set to output set.

V. DATA SETS AND EXPERIMENTS

In order to quantify and measure the closeness between input set and aiNet output set \mathcal{M} , four artificially generated (input) data sets with different characteristics are created (see figures 3(a),4(a),5(a),6(a)). Each data set contains 400 points, sampled from different probability distributions. The data sets are generated with the open source program *R* [12]. Since some data sets are intricate to characterize, we have shown the *R* source code used⁶ (see Fig. 1), but also give a brief description. Data set (1) is generated from a two dimensional Gaussian distribution (μ, I) , where

$$\mu = (0, 0) \text{ and } I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

Data set (2) is generated by a mixture of six Gaussian distributions with different mean vectors and covariance matrices. Data set (3) is generated by a mixture

⁶Source code of functions `dataset2` and `dataset3` is from [13].

of two Gaussian distributions. The first has the same parameters as distribution of data set (1), the second the parameters $1/4(\mu, I)$, i.e. it is a “dense” Gaussian inside a Gaussian. Data set (4) contains of points which are consecutively calculated from a sine/cosine function. Additionally to each sampled point, noise in the form of a Gaussian distribution with $\mu = 0$ and $\sigma = 0.2$ is added.

```
#####
dataset1 <- function(m) {
  x <- c(rnorm(m), rnorm(m))
  y <- c(rnorm(m), rnorm(m))
  return(data.frame(x,y));
}
#####
dataset2 <- function(m){
  z<- c(rbinom(1,m,1/3))
  z[2]<-rbinom(1,m-z[1],1/2)
  v<- c(rbinom(1,m,1/3))
  v[2]<-rbinom(1,m-v[1],1/2)
  x <- c(rnorm(z[1])/2+2, rnorm(z[2])+6,
        rnorm(m-z[1]-z[2])/2+3,
        rnorm(v[1])/1+4, rnorm(v[2])/3+1,
        rnorm(m-v[1]-v[2])+8)
  y <- c(rnorm(z[1])/2+1, rnorm(z[2])/3+1,
        rnorm(m-z[1]-z[2])/2+1.5,
        rnorm(v[1])/3+2, rnorm(v[2])/3+2,
        rnorm(m-v[1]-v[2])/3+1.5)
  return(data.frame(x,y))
}
#####
dataset3 <- function(m){
  x <- c(rnorm(m)/4, rnorm(m))
  y <- c(rnorm(m)/4, rnorm(m))
  return(data.frame(x,y))
}
#####
dataset4 <- function(m,noise=0.2) {
  x <- c(1:2*m);
  y <- c(1:2*m);
  for (i in 1:m) {
    x[i] <- (i/m) * pi;
    y[i] <- sin(x[i]) + rnorm(1,0,noise);
  }
  for (j in 1:m) {
    x[m+j] <- (j/m + 1/2) * pi;
    y[m+j] <- cos(x[m+j]) + rnorm(1,0,noise);
  }
  return(data.frame(x,y))
}
```

Fig. 1. R source code for generating data sets from different probability distributions

As the cardinality of the output set of aiNet is controlled by parameter σ_s [3], the experiments are performed with different parameter settings $\sigma_s =$

$\{0.2, 0.1, 0.05, 0.01, 0.005\}$ for obtaining different output set reductions. The other algorithm parameters are set as follows:

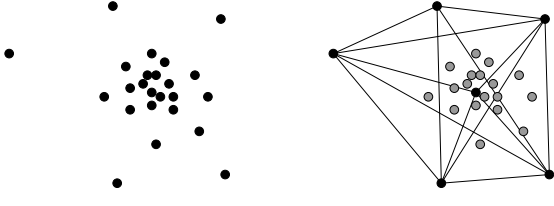
$$\sigma_d = 1, \quad n = 4, \quad N = 10, \quad \zeta = 20\%, \quad \max_{gen} = 10.$$

These parameter values are chosen, because reasonable and good results on the compression quality for different data sets is reported in [3] when using these parameter settings. For the sake of the completeness, we have to report that the min-max normalization component from the aiNet algorithm was removed, as the optimal kernel bandwidth $h = 0.96$ is derived for two dimensional unscaled data sets [14].

In the performed experiments, 400 points from each of the four probability distributions are sampled, and used as the input data set. Since aiNet is a non-deterministic randomized algorithm, we performed 50 runs on each input set for each parameter σ_s . After all simulation runs are completed, the entropy values according to (9) are computed for each σ_s and each associated input/output set. The mean (denote as J_μ) and standard deviation (denote as J_σ) of the entropy value over all runs is finally computed. Moreover, the cardinality of each computed output set is determined and likewise averaged (denoted as $|\mathcal{M}|_\mu$ and $|\mathcal{M}|_\sigma$). As it is difficult to quantify the magnitude of J_μ — (recall: a larger entropy implies that probability density \hat{p}_r is closer to \hat{p}_N , but how “good” is a certain magnitude of J_μ) — a *reference* value is computed. This is straightforward, because we know the underlying probability distributions (see figure 1). More specifically, $|\mathcal{M}|_\mu$ many points from each probability distribution are sampled and the entropy value for each associated input set is computed. This process is also repeated 50 times for obtaining comparative reference values denote as J_μ^{ref} (mean) and J_σ^{ref} (standard deviation). According to (9) these reference values must be close zero, because the sampled points in the input/output set are generated from the same probability distribution and therefore the estimated densities should be nearly identical. This fact can be verified in table I (see J_μ^{ref} row of each data set).

VI. RESULTS

The obtained simulation results are shown in table I and figures (3)-(6). First, one can notice, for parameter values $\sigma_s = \{0.01, 0.005\}$ the output set contains more points than the input set. That means, one has to choose a suitable parameter σ_s for obtaining the proper cardinality (compression quantity) of the output set — a similar result is reported in [3]. Second, one can see that aiNet outputs unsatisfiable results for $\sigma_s = 0.2$, on data sets (1)-(3). These data sets contain “dense” point regions which are not properly captured by aiNet (see figures 3(b), 4(b), 5(b)). This can also be verified by means of results shown in table I. The difference between J_μ and J_σ is significantly high especially for data set (3),



(a) Given some points from an unknown probability distribution (b) The final output set \mathcal{M} satisfies the criterion that all points in \mathcal{M} have neighborhood distances $\geq \sigma_s$

Fig. 2. aiNet optimization criterion

moreover this is also clear identifiable when comparing figures 5(a) and 5(b).

This large dissimilarity between input set and output set can be explained by investigating the dependency of parameter σ_s and the optimization criterion of aiNet. The aiNet optimization criterion is guided by the three functions:

$$\begin{aligned} &1: \mathbf{D}^* \leftarrow \iota\text{-affinity}(\{\mathbf{g}_i\}, \mathcal{C}^*) \\ &2: \mathcal{M} \leftarrow \text{select}(\mathcal{C}^*, \mathbf{D}^*, \text{round}(|\mathcal{C}^*| \cdot \xi/100)) \\ &3: \sigma\text{-remove}(\mathcal{M}, \sigma_s) \end{aligned} \quad (10)$$

Statement in line 1 and 2 causes the finding of all points in \mathcal{M} which are close (with regard to the Euclidean distance) to points in the input set. Statement in line 3 causes the removal of all points in \mathcal{M} whose neighborhood⁷ distance is $< \sigma_s$. That means, the final output set \mathcal{M} , consists only of points whose distance is $\geq \sigma_s$ to all points (see figure 2). The parameter σ_s not only controls the compression ratio, but also the neighborhood distances of each point in the output set. It is obvious that, the smaller σ_s the more points aiNet will find, which satisfies criterion (10). For a very small σ_s , e.g. $\sigma_s = 0.005$, all points from the input set are satisfying the criterion and therefore one obtains a nearly identical input set. Furthermore, one can also verify (see figures 3(f), 4(f), 5(f), 6(f)) that for such a small σ_s the output set contains several points that overlap, because this is the only way to satisfy criterion (10) with more points in the output set than in the input set. From this insight it is now clear, why aiNet outputs good and reasonable results on data set (4). Recall, data set (4) contains of sampled points without any dense point regions. As aiNet finds points, all which have to satisfy criterion (10), and points in data set (4) properly satisfy this criterion because they are uniformly distributed, one obtains good and reasonable results, especially for $\sigma_s = 0.2$. Furthermore, results in table I reveal that the difference between J_μ and J_μ^{ref} for $\sigma_s \rightarrow 0$ tends to

⁷Distance to adjacent points.

be zero. However for very small values of σ_s the output set contains more points than the input set and this consequently results in a data expansion rather than in a compression. Moreover for very small values of σ_s , the aiNet algorithm outputs nearly the identical input set (with many overlapping points). That means, aiNet seems to be inappropriate as a technique to sample points from an estimated probability distribution [15].

To summarize, aiNet guided its search of finding the reduced output set by means of the optimization criterion (10). The criterion, however, is inappropriate for non-uniformly distributed data sets, because it induces the finding of points whose distance to adjacent points must be greater-equal than a pre-defined threshold. It is clear, that this criterion is best to satisfiable when the input set is uniformly distributed.

TABLE I

aiNET RESULTS OF ENTROPY VALUES AND CARDINALITY OF THE OUTPUT SET

data set 1					
σ_s	0.2	0.1	0.05	0.01	0.005
J_μ	-0.117852	-0.031902	-0.016569	-0.010274	-0.009244
J_σ	0.006373	0.002765	0.002818	0.003604	0.003484
$ \mathcal{M} _\mu$	130.04	284.12	379.94	470.84	484.74
$ \mathcal{M} _\sigma$	4.69	4.92	5.33	7.48	9.44
J_μ^{ref}	-0.004868	-0.002365	-0.005553	-0.003208	-0.000568
J_σ^{ref}	0.018443	0.011041	0.012714	0.011754	0.011975

data set 2					
σ_s	0.2	0.1	0.05	0.01	0.005
J_μ	-0.072474	-0.019583	-0.009615	-0.003313	-0.002143
J_σ	0.008152	0.001887	0.002239	0.002914	0.002816
$ \mathcal{M} _\mu$	144.66	293.26	388.48	483.08	500.36
$ \mathcal{M} _\sigma$	4.39	3.85	6.76	10.02	11.84
J_μ^{ref}	-0.004136	-0.006214	-0.005241	-0.003856	-0.005415
J_σ^{ref}	0.007414	0.010635	0.007737	0.007215	0.009109

data set 3					
σ_s	0.2	0.1	0.05	0.01	0.005
J_μ	-0.235993	-0.133765	-0.076392	-0.024572	-0.024088
J_σ	0.008587	0.004041	0.005003	0.003903	0.003718
$ \mathcal{M} _\mu$	100.48	197.58	287.90	432.04	445.72
$ \mathcal{M} _\sigma$	3.08	3.64	5.20	10.06	7.78
J_μ^{ref}	-0.004953	-0.003212	-0.000835	0.000213	-0.000147
J_σ^{ref}	0.015143	0.013324	0.011609	0.009977	0.010159

data set 4					
σ_s	0.2	0.1	0.05	0.01	0.005
J_μ	-0.014436	-0.002651	-0.003337	0.001812	0.003771
J_σ	0.008660	0.002786	0.002448	0.002337	0.002043
$ \mathcal{M} _\mu$	49.66	168.70	305.20	432.44	454.04
$ \mathcal{M} _\sigma$	3.66	4.70	6.57	6.76	8.73
J_μ^{ref}	0.000599	-0.001215	-0.000293	0.000213	-0.000147
J_σ^{ref}	0.004204	0.002903	0.002378	0.009977	0.010159

VII. CONCLUSIONS

We have experimentally investigated the compression quality of the aiNet algorithm. A closeness measure between input set and compressed output set was presented. This closeness measure is based on the Kullback-Leibler divergence. Experiments reveal that aiNet produced reasonable results on the uniformly

distributed data set, but poor results on the non-uniformly distributed data sets, i.e. data sets which contain dense point regions. This unsatisfactory result on non-uniformly distributed data sets was caused by the optimization criterion of aiNet.

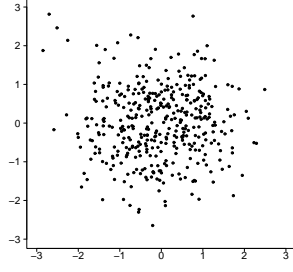
As aiNet is an algorithm whose search is guided in an evolutionary fashion, it should be feasible to modify the old optimization criterion according to term (9) to overcome this problem.

ACKNOWLEDGMENTS

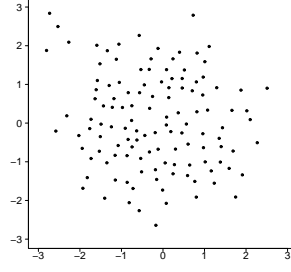
Work reported in this paper is supported in part by AFOSR's grant, FA9550-04-1-0159.

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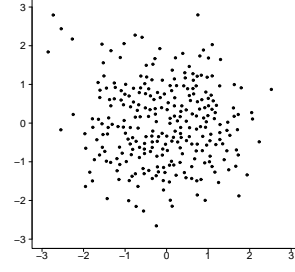
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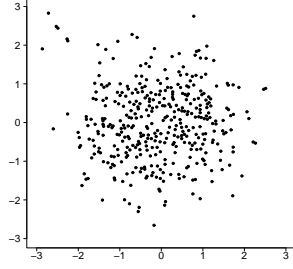
(a) data set (1) consists of 400 points sampled from a Gaussian distribution $\mu = (0, 0)$ and unit matrix I



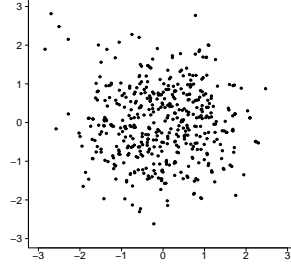
(b) aiNet output of simulation run 10, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 126$



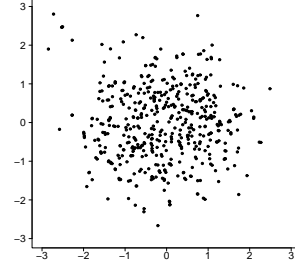
(c) aiNet output of simulation run 10, with $\sigma_s = 0.1$ and resulting output $|\mathcal{M}| = 276$



(d) aiNet output of simulation run 10, with $\sigma_s = 0.05$ and resulting output $|\mathcal{M}| = 386$

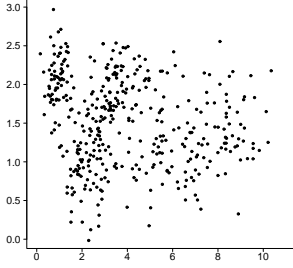


(e) aiNet output of simulation run 10, with $\sigma_s = 0.01$ and resulting output $|\mathcal{M}| = 471$

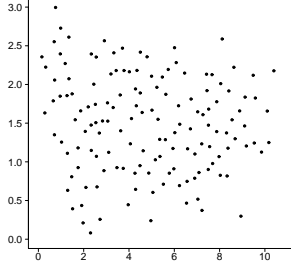


(f) aiNet output of simulation run 10, with $\sigma_s = 0.005$ and resulting output $|\mathcal{M}| = 496$

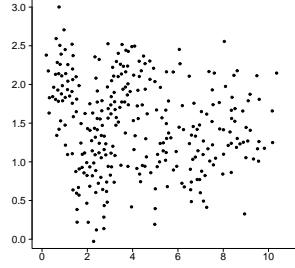
Fig. 3. Data set (1) and the resulting aiNet output data sets with different parameter settings σ_s



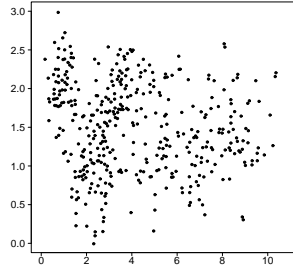
(a) data set (2) consists of 400 points sampled from mixtures of Gaussian distributions with different mean vectors and covariance matrices



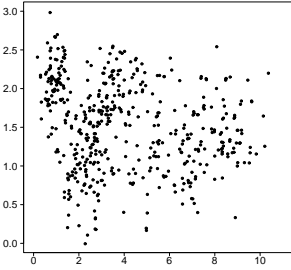
(b) aiNet output of simulation run 23, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 144$



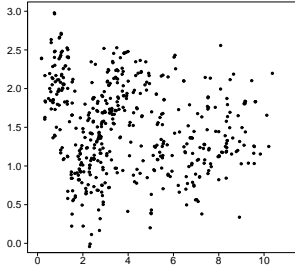
(c) aiNet output of simulation run 23, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 296$



(d) aiNet output of simulation run 23, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 401$

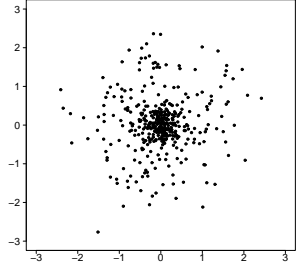


(e) aiNet output of simulation run 23, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 491$

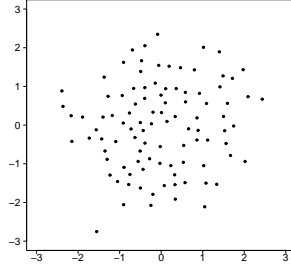


(f) aiNet output of simulation run 23, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 503$

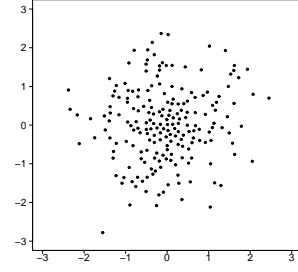
Fig. 4. Data set (2) and the resulting aiNet output data sets with different parameter settings σ_s



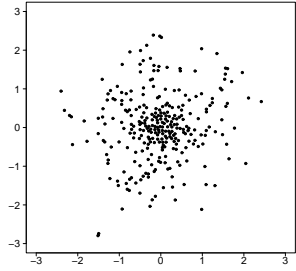
(a) data set (3) consists of 400 points sampled from a “dense” Gaussian distribution inside a Gaussian distribution



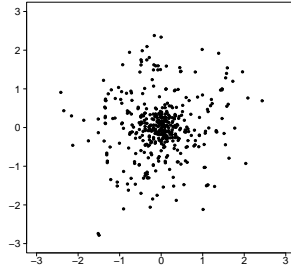
(b) aiNet output of simulation run 17, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 99$



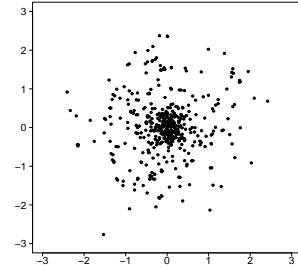
(c) aiNet output of simulation run 17, with $\sigma_s = 0.1$ and resulting output $|\mathcal{M}| = 200$



(d) aiNet output of simulation run 17, with $\sigma_s = 0.05$ and resulting output $|\mathcal{M}| = 286$

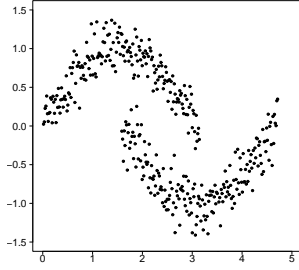


(e) aiNet output of simulation run 17, with $\sigma_s = 0.01$ and resulting output $|\mathcal{M}| = 420$

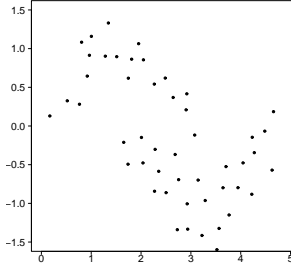


(f) aiNet output of simulation run 17, with $\sigma_s = 0.001$ and resulting output $|\mathcal{M}| = 436$

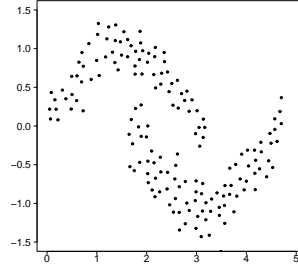
Fig. 5. Data set (3) and the resulting aiNet output data sets with different parameter settings σ_s



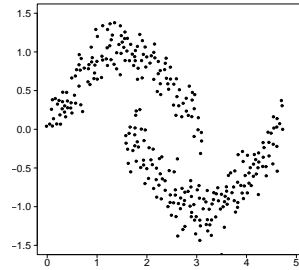
(a) data set (4) consists of 400 points sampled consecutively from a sinus/cosine function, with added noise in form of a Gaussian distribution with $\mu = 0$ and $\sigma = 0.2$



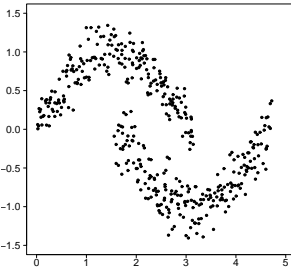
(b) aiNet output of simulation run 25, with $\sigma_s = 0.2$ and resulting output $|\mathcal{M}| = 49$



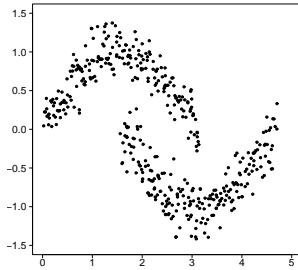
(c) aiNet output of simulation run 25, with $\sigma_s = 0.1$ and resulting output $|\mathcal{M}| = 164$



(d) aiNet output of simulation run 25, with $\sigma_s = 0.05$ and resulting output $|\mathcal{M}| = 306$



(e) aiNet output of simulation run 25, with $\sigma_s = 0.01$ and resulting output $|\mathcal{M}| = 431$



(f) aiNet output of simulation run 25, with $\sigma_s = 0.005$ and resulting output $|\mathcal{M}| = 451$

Fig. 6. Data set (4) and the resulting aiNet output data sets with different parameter settings σ_s