Assessement of Enterprise Interoperability Maturity Level through Generative and Recognition Models

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***Abstract* — In a globalized and networked society, enterprise interoperability is a key factor of success for enterprises in their effort to maximize their own added values and to exploit the market opportunities. The sustainable enterprise interoperability is a continuous challenge of the networked collaborative environment. By making business decisions, managers have to take into account the maturity level of their own enterprise and of others' with whom they get involved into businesses. Maturity level of enterprise interoperability has been defined by the Framework for Enterprise Interoperability (FEI), standardized by CEN EN ISO 11354. In this paper, we propose a novel approach to assess maturity levels of enterprise interoperability (MLEI) through latent factor analysis (LFA) and generative and recognition models applied to the categories and features defined by FEI. Given an enterprise interoperability maturity matrix we have trained a stochastic neural network, namely Restricted Bolzmann Machine (RBM) to learn the MLEI. Our research seeks to answer the following questions: whether the maturity level assessed by evaluators correlate with the maturity levels recognized by RBM trained in a supervised learning representation, and how to model recognition matrix of MLEI by using maturity level correlations between observed performances (inputs) and latent or hidden factors that influence the correct assessment. We considered a maturity level correlation matrix representing the enterprise features as defined in FEI in addition to a set of latent factors, representing the type of maturity level of each individual enterprise. Our proposal is based on a generative and a recognition model using deterministic non-linear functions in a Bayesian setting. The model has been tested on artificial data by training a RBM. Experiments on artificial data sets of enterprises proved that our proposal is a reliable approach that can be further developed into a methodology and extended for the design of adaptive learning agents. In the perspective of the Future Internet, such agents may successfully assist human evaluators in the tedious and time consuming process of the assessment of MLEI in real settings.**

Keywords* - *enterprise interoperability; maturity level of enterprise interoperability; generative and recognition models; Restricted Bolzmann Machine, latent factor analysis.

I. INTRODUCTION

The survival of traditional enterprises within the global economy relies on their ability to embrace new ideas and new organizational forms and to imagine new ways of delivering value to customers, new approaches to collaborating in a dynamic networked environment.

Organizations can only reach the full collaboration potential if the partnerships develop enhanced capabilities to seamless communicate, coordinate, cooperate, collaborate, and most importantly, interoperate in spite of different organizational structures, technologies or processes [1]. A broad definition of interoperability is referring to the ability of two or more systems to exchange information and use it accurately; consequently, the lack of it, disturbs the creation of new markets, networks, and diminish innovation and competitiveness of business groups [2]. Apart from being only a technical issue, interoperability challenges the enterprise at organizational and semantic level, underlying the need for patterns and solutions that support the seamless cooperation among ICT systems, information and knowledge, organizational structures and people [3].

In current practices, most organizations try to achieve interoperability by establishing peer-to-peer mappings with different partners, or in case of optimized networks, by using international standard models as the core for information sharing. The lack of interoperability as identified in several industrial sectors and in complex collaborative environments has a major cost, blocking the achievement of the time-to-market, demanded by today's competitive environment [4] [5].

This paper proposes a novel approach to assess maturity levels of enterprise interoperability (MLEI) through latent factor analysis (LFA) and generative and recognition models applied to the categories and features defined by FEI. The focus is given to the development of a generative and a recognition model using deterministic non-linear functions in a Bayesian setting. The model has been tested on artificial data by training a stochastic neural network, namely a Restricted Bolzmann Machine**.**

Measurements of the MLEI have been proposed from the perspective of interoperability potentiality, interoperability compatibility and interoperability performance. The calculation of metrics for interoperability potentiality and compatibility measurements has been done through human judgment and evaluation. Knowledge-based systems are mentioned to be built for these measures in the future [6].

Our research seeks to answer the following questions: whether the maturity level assessed by evaluators correlate with the maturity levels recognized by RBM trained in a supervised learning representation, and how to model recognition matrix of MLEI by using maturity level correlations between observed performances (inputs) and latent or hidden factors that influence the correct assessment.

The reminder of the paper is structured as follows: in Section II it is described the framework for Maturity level of Enterprise Interoperability (MLEI) and the model of the Latent Factor Analysis (LFA) for the categories and features identified in the FEI. Section III discloses the theoretical background for generative and recognition models. The discussion covers two aspects: (i) representational learning for internal model generation, (ii) expectation maximization. Section IV provides the implementation with stochastic neural networks - Restricted Bolzmann Machine in Python. Section V follows with conclusions by pointing to future works.

II. MATURITY LEVELS FOR ENTERPRISE INTEROPERABILITY (MLEI)

A. *The Framework for Enterprise Interoperability (FEI)*

Competitive markets are becoming increasingly complex and dynamic, with companies not surviving and prospering solely through their own individual efforts [5]. Each one's success depends on the activities and performance of others to whom they do business with, and hence on the nature and quality of the direct and indirect relations [7]. These involve a mix of cooperative and competitive elements, that to cope with them, organizations need to focus on their core competencies by improving their relationships with customers, streamlining their supply chains, and by collaborating with partners to create valued networks between buyers, vendors and suppliers [8]. This collaborative process may be described as coordinated and synchronous activities characterized by reciprocal interactions at high frequency that normally require the transfer of information among several organizations, i.e. knowledge sharing [9]. An emergent research challenge in seamless interoperability is rising. It focus on the sustainability within collaborative business networks, addressed by a wide complexity of interactions and a high probability of changing requirements, in the view that enterprises are complex, and adaptive systems (CAS), with factors that are making interoperability difficult to sustain over time [9]. The Framework for Enterprise Interoperability [10] defines three basic dimensions as follows:

- *Interoperability concerns*, defining the content of interoperation that may take place at various levels of the enterprise (data, service, process, business).
- *Interoperability barriers*, identifying various obstacles to interoperability in three categories (conceptual, technological, and organizational)
- *Interoperability approaches*, representing the different ways in which barriers can be removed (integrated, unified, and federated). The first two dimensions, interoperability concerns and barriers, constitute the problem space of enterprise interoperability. The intersection of a barrier and a concern is the set of interoperability problems having the same barrier and concern (Fig.1).

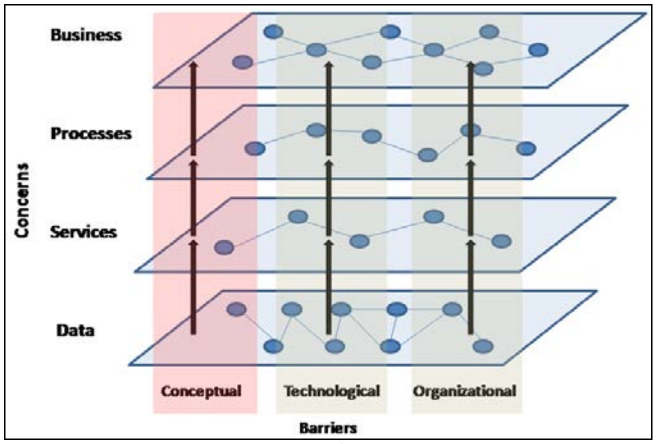

Fig. 1. Components of the problem space

The three dimensions together constitute the solution space of enterprise interoperability [11], [12], [13].

In our approach we assumed that intelligent agents are able to substantially assist humans involved in assessing the maturity level of the enterprise and provide reliable data concerning interoperability issues that can be represented in graphs for each layer of concern namely, data, services, processes and businesses.

Table I. Description of maturity levels

Maturity Level	Maturity Assessment	Interoperability Environment	Interoperability Degree
Level 4 Adapted	Dynamically accommodating with heterogeneous partner	**Federated** Dynamically adjust and accommodate	**Generalized** Full interoperability to any potential partners worldwide
Level 3 Organized	Meta modeling for mapping to interoperate with multiple heterogeneous partners	**Unified** Use of meta-models allowing heterogeneous systems to map one to others	**Extended** Many-to-many relation, multiple heterogeneous partners
Level 2 Aligned	Capable of making necessary changes to align to common formats or standards	**Integrated** Common format (or standard) for all partners to build there system components	**Restricted** Peer-to-peer relation, to use a common format or standard
Level 1 Defined	Capability of properly modeling and describing systems to	**Connected** Simple electronic exchange of information,	**Limited** With only some ad hoc interoperations

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	prepare interoperability	messaging, etc.	
Level 0 Unprepared	Not relevant: there is no capability for interoperation	**Isolated** Occasional and manual exchange of information (document, fax)	**Inexistent**

To handle the complex types of maturity level scenarios, we analyzed the most complex level of interoperability namely, "Level 4 - the *Adapted* level". This level corresponds to the highest level of interoperability maturity (universal) [12].

Companies are able to dynamically adjust and accommodate 'on the fly' on the bases of some shared domain ontologies. At level 4 companies are able to interoperate with multi-lingual and multi-cultural heterogeneous partners. This level corresponds to the federated environment /approach defined in the Framework for Enterprise Interoperability [10].

At this level all information and interoperability itself becomes a subject of continuous improvement (evolution and adaptation). The problem space at level 4 is presented in Table II. All features, observed and un-observed have been modeled by latent factor analysis (LFA).

Table III. Description of the maturity level 4- Adapted

	Conceptual	Technological	Organizational
Business	**Continuous** Business/ IT alignment	**Reconfigurable** IT infrastructure / platform	**Agile** organization for on-demand business
Process	**Dynamic** process re-engineering	**Platform independent** dynamic and adaptive tools and engines for processes.	**Real-time monitoring** of processes Adaptive work procedures
Services	**On-demand/** adaptive service modeling	**Platform independent** reconfigurable services architecture for services composition	**Dynamic and on demand** allocation of resources to services
Data	**Adaptive data model** (both syntax and semantics)	**Direct database exchanges** capability and full data conversion tool	**Adaptive data** management rules and methods

B. *Model of Latent Factor Analysis (LFA)*

Latent factor models attempt to explain complex relations between several features by simple relations between the features and an underlying unobservable, i.e. latent structure. In our approach latent variables correspond to abstract concepts, like categories, behavioral or mental states, or data structures discussed in [10], [11].

Latent Factors model the maturity level of the enterprises by taking into consideration the features expressed through variables belonging to the categories defined in FEI, namely the barriers and concerns. Our hypothesis is that MLEI are key bottlenecks for an intelligent evaluator agent, who authors and performs automate discovery of maturity level models and data-driven revision of existing models via LFA.

Formally we have a collection $I = (i_1 . . . i_n)$ of manifest features which can be observed and expressed by n variables, and a collection $H = (h_1, . . . , h_m)$ of latent factors which are unobservable and 'explain' the dependence relationships between the manifest features. Here 'explaining' means that the manifest variables are assumed to be conditionally independent given the latent features.

The set of features depicted from barriers and concerns is represented for each enterprise in a matrix X, also some missing features have been taken into account as in Fig 2.a. and b.

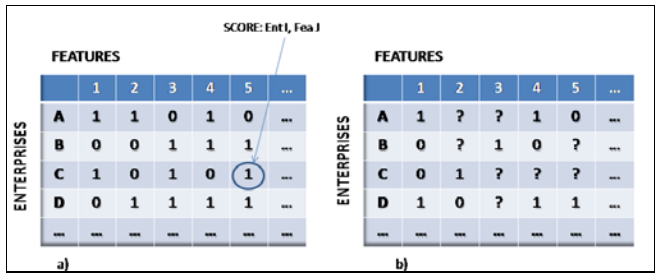

Fig. 2. a. Matrix of features and enterprises extracted from the problem space. b. Missing data

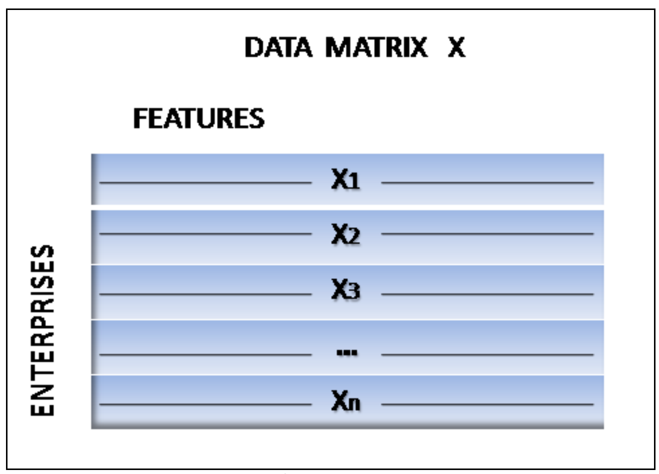

Fig. 3. Matrix X for each evaluated enterprise

Latent factor analysis reduces the dimensionality of data. A large number of observable features can be aggregated in a model to represent an underlying concept, making it easier to understand the data. At the same time, latent factors link observable ("sub-symbolic") data in the real world to symbolic data in the modeled world. The observed inputs I, are represented by the total number of assessed features, the total number of latent variables are referring to the hidden variables belonging to the enterprise h_e and the hidden variables belonging to the features h_f as in Fig. 4.

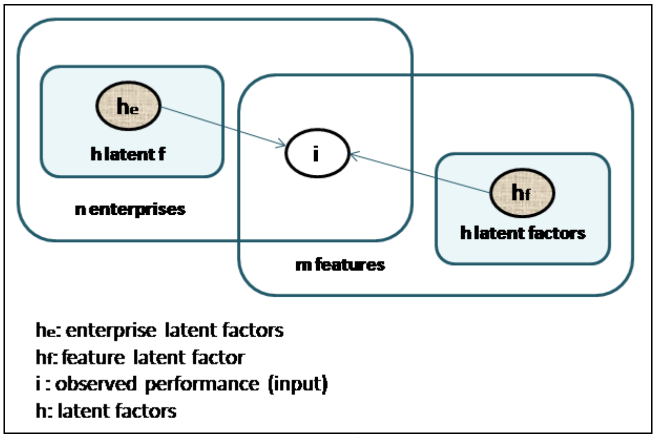

Fig. 4. Model for LFA

The available data are represented by the repeated observations of the vector H = (h1, . . . ,h_m) of manifest variables. Categorical variables can either be ordinal or nominal, and metrical variables can either be discrete or continuous. Latent variable models are perfectly suitable for the Expectation Maximization EM-algorithm. The E-step involves numerical integration and the M-step needs in principle iterative methods as well [14].

III. Generative and Recognition Models

A. Representational learning for internal model generation

Representational leaning in a supervised context can be achieved by generative models. Such forms of generative models range from conventional statistical models (e.g. factor and cluster analysis) to those applying Bayesian inference and learning [15], [16], [17] [18]. The goal of generative models is "to learn representations that are economical to describe but allow the input to be reconstructed accurately" [17]. Representational learning is framed in terms of estimating probability densities of the features, hereby the barriers and concerns presented in fig. 1. This is referred to as posterior density analysis in the estimation literature and posterior mode analysis if the inference is restricted to estimating the most likely feature (barrier or concern). The mode of a distribution is the location of its maximum.

Let us frame the problem of representing features from the problem space (barriers and concerns) in terms of a deterministic non-linear generative function

$$i = F(v,\theta) \tag{1}$$

Where, v is a vector of features (matrix X) of underlying barriers and concerns in the enterprise environment (ex. heterogeneous data format and structure, meaning of terms used to express business issues, order of operations in business processes, etc) and *i* represents observed inputs. $F(v,\theta)$ is a function that generates inputs from the barriers and concerns defined by FEI [10]. θ are the parameters of the generative model. Unlike the features extracted from barriers and concerns, θ are fixed quantities that have to be learned. Non-linearities in Eq. (1) represent interactions among the barriers and concerns. Second-order interactions are formally identical to interaction terms in conventional statistical models of observed data. These can often be viewed as contextual effects, where the expression of a particular feature depends on the context established by another. These contextual effects are profound and must be discounted before the representations of the underlying barriers (conceptual, organizational or conceptual) can be considered true. In probabilistic learning, one allows for stochastic (i.e. random) components in the generation of inputs and recognizing a particular feature becomes probabilistic. Here the issue of deterministic invertibility is replaced by the existence of an inverse conditional probability (i.e. recognition) density that can be parameterized. We will show that one needs separate (approximate) recognition and generative models that induces the need for both forward and backward influences. Separate recognition and generative models resolve the problem caused by generating processes that are difficult to invert [18].

Eq. (1) relates the unknown space of barriers and concerns *v* and some unknown parameters θ to observed inputs *i*. The objective is to make inferences about the features and to learn the parameters. Inference may be simply estimating the most likely features and it is based on the products of learning.

The goal of learning is to acquire a recognition model for inference that is effectively the inverse of a generative model. The generative model creates data from features and the inverse model recognizes features from data [18] [19].

Learning a generative model corresponds to making the density of inputs, implied by a generative model $p(i;\theta)$ as close as possible to those observed $p(i)$. The generative model is specified in terms of a prior distribution over the features $p(v;\theta)$ and the generative distribution or likelihood of the inputs given the features $p(i|v;\theta)$. Together, these define the marginal distribution that has to be matched to the input distribution

$$p(i;\theta) = \int p(i|v;\theta)\, p(v;\theta) dv \tag{2}$$

Once the parameters of the generative model have been learned, through this matching, the posterior density of the features, given the inputs is given by the recognition model, which is defined in terms of the recognition distribution.

$$p(v|i;\theta) = \frac{p(i|v;\theta)\, p(v;\theta)}{p(i;\theta)} \tag{3}$$

The final goal of learning is the acquisition of a useful recognition model that can be applied to observed inputs *i*. One solution is to posit an approximate recognition distribution $q(v;i,\phi)$ that is consistent with the generative model and that can be learned at the same time. The approximate recognition distribution is represented by some parameters ϕ.

B. Expectation Maximisation in representational learning

The objective is to estimate the parameters of an approximate recognition density $q(v;i,\phi)$ for the generative model. This objective can be split into two steps. Firstly, the scope is to ensure that the recognition density is consistent with the generative model, observing that one is the inverse of the other's. Secondly, the aim is to adjust the parameters of the generative model to fully account for the data. These two steps correspond to the expectation and maximization steps, respectively. The objective function is the function of the parameters and specifies how 'good' such parameters are. The objective function embodies both the internal consistency of the recognition and generative models and the likelihood of the data given the generative model. In density learning, representational learning has two components that are framed in terms of expectation maximization [20].

Iterations of an E-step ensure the recognition approximates the inverse of the generative model and the M-step ensures that the generative model can predict the observed inputs.

Probabilistic recognition uses $q(v;i,\phi)$ to determine the probability that *v* featured the observed inputs. EM provides a useful procedure for density estimation that helps relate many different models within a framework that has direct connections with statistical mechanics. Both steps of the EM algorithm involve maximizing a function of the densities that corresponds to the negative free energy in physics [19].

$$\begin{aligned} D &= \langle d(i) \rangle_i \\ d &= \int q(v;i,\phi) \ln \frac{p(v,i;\theta)}{q(v;i,\phi)} dv \\ &= \langle \ln p(v,i;\theta) \rangle_q - \langle \ln q(v;i,\phi) \rangle_q \\ &= \ln p(i;\theta) - KL\{q(v;i,\phi), p(v|i;\theta)\} \end{aligned} \quad (4)$$

This objective function comprises two terms. The first is the expected log likelihood of the inputs under the generative model. The second term is the Kullback–Leibler (KL) divergence calculated between the approximating and true recognition densities. The KL term is always positive, rendering D a lower bound on the expected log likelihood of the inputs. Maximizing D encompasses two components of representational learning: (i) it increases the likelihood of the inputs produced by the generative model and (ii) minimizes the discrepancy between the approximate recognition model and that implied by the generative model. The E-step increases D with respect to the recognition parameters ϕ; ensuring a veridical approximation to the recognition distribution implied by the generative parameters θ. The M-step changes θ enabling the generative model to reproduce the inputs. E is ϕ =max D M is θ =max D. There are a number of ways of motivating the free energy formulation in Eq. (4). A useful one, in this context, rests upon the problem posed by non-invertible models. This problem is finessed by assuming it is sufficient to match the joint probability of inputs and causes under the generative model $p(i,v;\theta) = p(i|v;\theta)p(v;\theta)$ with that implied by recognizing the causes of inputs encountered $p(i,v;\phi) = q(v;i,\phi)p(i)$. Both these distributions are well defined even when $p(v|i;\theta)$ is not easily parameterized. This matching minimizes s the divergence

$$\begin{aligned} & KL\{p(v,i;\phi), p(v,i;\theta)\} \\ &= \int q(v;i,\phi)p(i) \ln \frac{q(v;i,\phi)p(i)}{p(v,i;\theta)} dvdi \\ &= -D - H(i) \end{aligned} \quad (5)$$

This is equivalent to maximizing D because the entropy of the inputs H (i) is fixed. The E-step adjusts the recognition parameters to match the two joint distributions, while the M-step does exactly the same thing but by changing the generative parameters. The dependency of the generative parameters, on the input distribution, is imediated vicariously in the M-step through the recognition.

In the setting of invertibility, where $q(v;i,\phi) = p(v|i;\theta)$ the divergence in Eq. (6) reduces to $KL\{p(i), p(i;\theta)\}$.

As above, the M-step then finds parameters that allow the model to simply match the observed input distribution (i.e. maximize the expected likelihood).

IV. Implementation with Restricted Bolzmann Machine

A. Supervised learning

Supervised learning refers to the simplest problem in which the parameters of the generative model are known, allowing one to generate simulated sensory inputs from features with a known prior distribution. This is because their supervised aspect means the generative model is already known. From the point of view of expectation maximization, only the first step is required to find the parameters of the recognition density. In supervised schemes the generative model is pre-specified and only the recognition parameters need to be learned. The generative model is known in the sense that any feature determines the input, either deterministically or stochastically. In this case only the E-step is required in which the parameters ϕ that specify $q(v;i,\phi)$ change to maximize ***D***. The only term in Eq. (4) that depends on ϕ is the divergence term, such that learning reduces to minimizing the expected difference between the approximate recognition density and that required by the generative model.

$$\textbf{E} \quad \phi = \max_{\phi} D = \min_{\phi} \left\langle KL(q(v;i,\phi), p(v|i;\theta)) \right\rangle_i \tag{6}$$

Supervised learning, of this sort, is equivalent to non-linear function approximation, a perspective that can be adopted on all supervised learning of deterministic mappings with neural nets.

B. Implementation with Restricted Bolzmann Machines

Restricted Boltzmann Machines (RBMs) have been used as generative models of various types of data, including labeled or unlabeled images [21], groups of words that represent documents [22] and user ratings of movies [23].

In our approach we used RBM to learn maturity levels of enterprise interoperability. A RBM can be regarded as a probabilistic model consisting of a set of visible units *v* and a set of hidden units *h* which form a bipartite graph. The visible units of an RBM correspond to the input variables of the data that is to be modeled. The hidden units capture correlations between visible units. RBM as a feature extractor, uses the values of visible units to infer the hidden units. RBM has binary-valued of hidden and visible units, and consists of a matrix of weights $W = (w_{i,j})$ associated with the connection between hidden unit h_j and visible unit v_i, as well as bias weights a_i for the visible units and b_j for the hidden units as in fig. 5.

An RBM can be characterized by an energy function $E(v,h)$ as in eq. (7).

$$E(v,h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_i \sum_j h_j w_{i,j} v_i \tag{7}$$

or, in vector form,

$$E(v,h) = -a^T v - b^T h - h^T W v \tag{8}$$

The joint probability distribution over all units defined by the model is given by:

$$P(v,h) = Z^{-1} \exp(-E(v,h)) \tag{9}$$

where $Z = \int_{v,h} \exp(-E(v,h))$ is a partition function.

The marginal probability of a visible (input) vector is the sum over all possible hidden layer configurations:

$$P(v) = \frac{1}{Z} \sum_h e^{-E(v,h)} \tag{10}$$

Because there are no connections between pairs of visible units or pairs of hidden units, but every visible unit is connected to every hidden unit, for m visible units and n hidden units we have,

$$P(v|h) = \prod_{i=1}^{m} P(v_i | h) \tag{11}$$

$$P(h|v) = \prod_{j=1}^{n} P(h_j | v) \tag{12}$$

and the individual activation probabilities are given by

$$P(h_j = 1 | v) = \sigma(b_j + \sum_{i=1}^{m} w_{i,j} v_i) \tag{13}$$

$$P(v_i = 1 | h) = \sigma(a_i + \sum_{j=1}^{n} w_{i,j} h_j) \tag{14}$$

where σ denotes the logistic function σ (x) = 1/1+exp(-x).

In our approach, we have modeled the MLEI by an RBM that uses a layer of binary hidden units (maturity levels) to model the higher-order correlations between assessed enterprises.

The matrix *W* (weights) and the vectors a_i and b_j (biases) are the parameters of the model.

1) Training algorithm

RBM was trained to maximize the product of probabilities assigned to a training set V (a matrix, each row of which is treated as a visible vector v),

$$\arg\max_W \prod_{v \in V} P(v) \tag{15}$$

to maximize the expected log probability of V :

$$\arg\max_W \mathrm{E}\,[\sum_{v \in V} \log P(v)] \tag{16}$$

The algorithm used to train the RBM, namely to optimize the weight vector W, is the contrastive divergence (CD) algorithm [24] which is the difference between two Kullback - Leibler divergences. The algorithm performs Gibbs sampling and is used inside a gradient descent procedure to compute weight update [24]. The procedure for single-step contrastive divergence (CD-1) for a single sample means:

1. Sampling and computing of the probabilities of the hidden units and a hidden activation vector h from this probability distribution for training sample v
2. Computing of the *positive gradient* of v and h.
3. Sampling from h, a reconstruction v' of the visible units, then a re-sampling of the hidden activations h' from this.
4. Computing of the *negative gradient* of v' and h'.

Let the weight update to $w_{i,j}$ be the positive gradient minus the negative gradient, times some learning rate.

For traning the RBM we used a set of 6 evaluators (Ev1, Ev2, Ev3, Ev 4, Ev 5, Ev6) that have been assessed the maturity level for a set of 6 enterprises (A, B, C, D, F, G). The assessed enterprises correspond to the visible units of the RBM because their states are observed and the feature detectors (maturity levels) correspond to hidden units as in fig. 5.

RBMs perform a *binary* version of factor analysis. Instead of evaluators assessing a set of concerns and barriers on a continuous scale, they include it in one maturity level (maturity level 4 – *Adapted* or Maturity level 3- *Aligned*). The RBM will try to discover latent factors that can explain the activation of these maturity level choices. Each visible unit is connected to the hidden units (this connection is undirected, so each hidden unit is also connected to all the visible units), and the bias units are connected to all the visible units and to all the hidden units. In the network no visible unit is connected to any other visible unit and no hidden unit is connected to any other hidden unit (fig. 5).

In our example implemented in Phyton, we supposed to have a set of six enterprises and we asked evaluators to tell their maturity level assessment. The aim was to learn two latent units underlying concerns and barrier features corresponding to maturity level 4 - *Adapted* and maturity level 2 – *Aligned*.

```
rbm = RBM(num_visible = 6, num_hidden = 2)
training_data =
np.array([[1,1,1,0,0,0],[1,0,1,0,0,0],[1,1,1,0,0,0],[0,0,1,1,1,0],
[0,0,1,1,0,0],[0,0,1,1,1,0]]) # A 6x6 matrix where each row is a
training example and each column is a visible unit.
r.train(training_data, max_epochs = 1000)
```

The evaluators have evaluated the enterprises as follows: that are evaluated in enterprises as follows enterprises:
The prediction ist that the latent units will correspond to these categories then our RBM would match to this predictions:

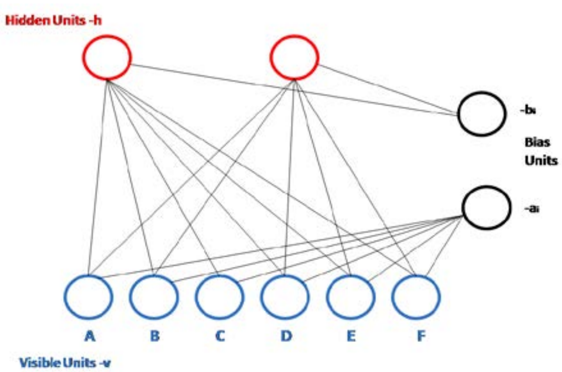

Fig. 5. RBM representation

Ev 1: (A = 1, B = 1, C = 1, D = 0, E=0, F=0) ML4 - Adapted
Ev 2: (A = 1, B = 0, C = 1, D = 0, E=0, F=0) ML4 - Adapted
Ev 3: (A = 1, B = 1, C = 1, D = 0, E=0, F=0) ML2 - Adapted
Ev 4: (A = 0, B = 0, C = 1, D = 1, E=0, F=0) ML2 - Aligned
Ev 5: (A = 0, B = 0, C =1, D = 1, E=1, F=0) ML4 - Aligned
Ev 6: (A = 0, B = 0, C = 0, D = 1, E=1, F=0) ML2 - Aligned

The network learned the following weights:

Table III. Weights for the hidden units

Enterprise ID	Hidden unit 1	Hidden unit 2
A	- 1.08987705	4.96606654
B	- 5.18354129	2.27197472
C	- 2.51720193	4.11061383
D	6.78633901	-4.12505343
E	2.25474524	-3.75606165
F	4.81563804	-2.90950988

The learning weights have been monitored at 50 epochs, 150 epochs and 200 epochs.

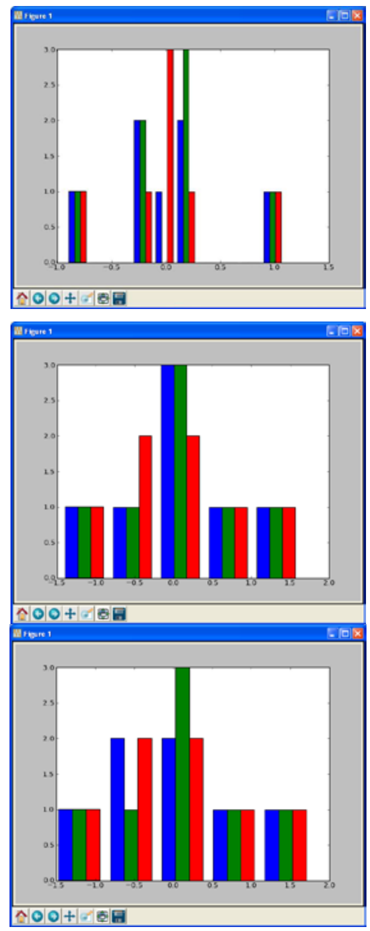

Fig. 6. Histogram of learning weights at 50 epochs, 150 epochs and 200 epochs

The first hidden unit corresponds to the Maturity level 2- *Aligned* and the second hidden unit corresponds to the Maturity level 4 – *Adapted* as we have supposed (Table III).
A new evaluator Ev7 assessment has been introduced. Ev 7 has evaluated the enterprises as follows (A = 0, B = 0, C= 0, D = 1, E = 1, F = 0). The RBM turned the maturity level 2 *Aligned* unit on and not the maturity level 4 *Adapted*, correctly guessing that Ev 7 has evaluated the enterprise as of Maturity level 2- *Aligned*. Based on our training

examples, the conclusion is that the generated assessments do match with those of the evaluators that have assessed as maturity level 4 – *Adapted* .

The values of numerical meta-parameters such as the learning rate, the momentum, the weight-cost, the sparsity target, the initial values of the weights have not been discussed, being beyond the scope of this paper.

V. CONCLUSIONS AND FUTURE WORK

In this paper we proposed a novel approach to assess the maturity level with regard enterprise interoperability. This approach was based on generative and recognition models that can be implemented by stochastic neural nets and further can be integrated with intelligent learning agents. The hypothesis that MLEI are key bottlenecks for an intelligent evaluator agent who authors and perform automate discovery of maturity level models and data-driven revision of existing models via latent factor analysis was true and the generated assessments do match with those of the evaluators that have assessed maturity level 4 – *Adapted* for enterprises.

Such learning agents may assess automatically the maturity level of interoperability and further on, may support humans in decision makings.

Future work outlooks: (i) The research will focus on optimization of the RBM by studying types of units to be used, updates of the states of the hidden units for each training case. (ii) We will also continue to asses the generality of our implementation by extending it into a methodology and then assess its correctness in real settings, by empirical methodology validation in several collaborative networked environments.

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