

Reengineering IT Infrastructures:

A Method for Topology Discovery

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Abstract — ICT systems are made of software, middleware and hardware components and are usually distributed over a network. Middleware and hardware components are combined on what is usually designated an "IT Infrastructure (ITI)". It is upon that ITI that application software is run. The topology of that ITI poses constraints on software algorithms, data structures and software configuration, due to concerns such as fault tolerance, latency or synchronization. In large ITIs that topology evolves constantly. Therefore, when faced to the challenge of maintaining a legacy ICT system, it is important to use reengineering techniques to discover the ITI topology.

We propose a reengineering technique to discover the topology of a distributed IT infrastructure, based on a multinomial logistic regression model and a set of topology stereotypes. To demonstrate the feasibility of the approach we applied the model to several organizations with distributed ITIs and, among other aspects, we found that the most recurrent stereotypes are the *centralized* and *backbone* ones.

Keywords – Reengineering; IT infrastructures; Topology discovery; Logistic regression

I. INTRODUCTION

The concept of Information Technology Infrastructures (ITIs) is a coarse-grained one, since it embodies various components of Information Technology (IT) used to manage and process information in a networked organization. Currently most organizations have ITIs spanned from several locations (branch offices) and connected in a specific way (topology) to support the business. The problem is that most of these ITIs grow along with the organization and often that growth is uneven, driven as much by the conditions under the organization operates, as by the ITI model they aspire to. This growing process conducts to complex ITIs which in turns increase the effort and costs associated and decrease the capacity of ITIs to adapt to new businesses or new processes. Normally, the bigger and more intermeshed the infrastructure is, the more difficult is to manage it, with obvious higher costs. Since the ITI topology influences the level of complexity it is crucial to detect, understand and control it [1].

Detecting the topology especially in large distributed IT infrastructures can provide valuable information to business and IT professionals and is crucial to support their decisions regarding the growth of the infrastructures. Some of benefits that may arise from the detection of topologies are:

- (1) Help defining an ITI strategy, planning, architecture and optimization to meet business goals and objectives;
- (2) Defining and maintaining ITI operations and administrative policies according to the topology;
- (3) Better assessment of the impact of ITI changes;
- (4) Simplify ITI management in activities such as configuration, performance testing and fault detecting.

The previous benefits help to get more control over ITIs [2]. They are not always quantifiable, but are normally perceived as positive by internal and external stakeholders.

This study intends to investigate and analyze the relationship of multiple aspects in ITIs such as the size, locations, and relationships between objects with the goal of creating a reengineering method that can not only increase the knowledge of ITIs but also serve as a control mechanism to help IT decision makers, for instance to move from a distributed ITI available in a couple of locations to a distributed ITI available in hundreds or even thousands of locations in a controlled way. The main contributions of this paper is (i) the proposal of a model based on multinomial regression analysis to discover the topology in organizations with large distributed ITIs, and (ii) its application to ITI data collected from several organizations, thereby demonstrating its feasibility.

The structure of the paper is the following: In Section II, we describe a set of stereotypes that will be used for classifying the outcome of our topology discovery approach. In Section III we describe in detail how the method was created, how it was calibrated and we discuss its predictive success. In Section IV we apply the model to a sample of ITIs from distinct organizations and we discuss the results. Section V, we present the related work and finally, in Section VI, we conclude by presenting conclusions, as well as some directions for future work.

II. ITI TOPOLOGY STEREOTYPES

In terms of organization an ITI may be organized in different ways. In this paper we will consider the following four stereotypes for network topologies:

Backbone - In this topology stereotype all physical nodes are connected to a common transmission medium commonly referred as backbone or bus, which has two endpoints.

Ring - In this topology stereotype adjacent physical nodes are mutually connected, forming a ring;

Centralized - In this topology stereotype each physical node is connected to a physical central node with a point-to-point link in a 'hub' and 'spoke' fashion, the central node being the 'hub' and the other nodes that are attached to the central node being the 'spokes'. All data that is transmitted among nodes travels through this central node;

Fully meshed - In this topology stereotype all physical nodes are connected to all the others.

Figure 1 shows an example of these four different stereotypes each with five nodes.

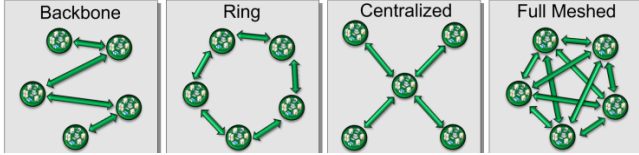


Figure 1 – Network topology stereotypes

III. A METHOD FOR TOPOLOGY DISCOVERY

A. Introduction

For an ITI with hundreds or even thousands of nodes spread all over the world, it is difficult to detect the topology. Since large ITIs often grew by merges of previously existing ITIs, most probably they do not comply with a single topology stereotype (i.e. they will have hybrid topologies), although one or two stereotypes may be dominant over the others. Since topology conveys important information for those performing ITI reengineering actions, we are interested in discovering the proneness of a given ITI to match each of the identified stereotypes. We will use two ITI complexity metrics, proposed and formalized in [3] and will show here that they are good predictors for classifying ITIs in terms of their underlying topology stereotypes. Since the explanatory variables (the complexity metrics) are defined in a ratio scale and the outcome variable (the stereotype) is nominal, with 4 categories, we can use the following logistic regression technique.

B. Multinomial logistic regression

Multinomial logistic regression is useful for situations in which we want to classify subjects based on values of a set of predictor variables [4]. This type of regression is similar to binary logistic regression, but is more general because the outcome variable is not restricted to two categories.

Logistic regression does not directly model the dependent variable (the topology in our case). Logistic regression transforms the dependent into a logit variable (natural log of the odds of Y occurring or not occurring, which is $\ln(p/1-p)$) and uses maximum likelihood estimation (MLE) to estimate the coefficients.

Though logistic regression is used for categorical variables, the output is a continuous function, an S-shaped curve that represents the probability associated with being in a particular category of the dependent variable.

Logistic regression has several similarities with linear regression. Logit coefficients are analogous to beta coefficients in the linear regression equation, the standardized logit coefficients are analogous to beta weights, and a pseudo R2 statistic is available to summarize the strength of the relationship.

Unlike other regression methods, logistic regression does not assume linearity of relationship between the explanatory variables and the outcome one, does not require normally distributed variables, does not assume homoscedasticity, and in general has less stringent requirements than linear regression. As a result, it is a very popular classification technique used in the area of predictive analytics [5].

Model formulation. For an outcome variable with K categories, consider the existence of K unobserved continuous variables $Z_1 \dots Z_k$, each of which can be thought of as the "propensity toward" a category (recall that categories are topology stereotypes in our case). Mathematically, the relationship between the Z 's and the probability of an outcome is described in equation (1) [6].

$$\pi_{ik} = \frac{e^{z_{ik}}}{e^{z_{i1}} + e^{z_{i2}} + \dots + e^{z_{iK}}} \quad (1)$$

where:

π_{ik} = probability the i^{th} case falls in category k
 z_{ik} = value of k^{th} unobserved continuous variable for i^{th} case

Z_k is assumed to be linearly related to the predictors, as described in equation (2).

$$Z_{ik} = b_{k0} + b_{k1}x_{i1} + b_{k2}x_{i2} + \dots + b_{kJ}x_{iJ} \quad (2)$$

where:

x_{ij} = j^{th} predictor for the i^{th} case
 b_{kJ} = j^{th} coefficient for the k^{th} unobserved variable
 J = number of predictors

If Z_k were observable, we could fit a linear regression to each Z_k . However if Z_k is unobserved, we must relate the predictors to the probability of interest by substituting for Z_k , thus obtaining equation (3).

$$\pi_i = \frac{e^{b_{k0} + b_{k1}x_{i1} + \dots + b_{kJ}x_{iJ}}}{e^{b_{i0} + b_{i1}x_{i1} + \dots + b_{iJ}x_{iJ}} + \dots + e^{b_{k0} + b_{k1}x_{i1} + \dots + b_{kJ}x_{iJ}}} \quad (3)$$

As it stands, if we add a constant to each Z , then the outcome probability is unchanged. This is the problem of non-identifiability [7]. To solve this problem, Z_k is (arbitrarily) set to 0. The K_{kth} category is called the reference category, because all parameters in the model are interpreted in reference to it. In other words, it is the "standard" category to which others will be compared.

C. Predictors

We have proposed and shown in [3] that the following metrics could be obtained with the meta-modeling based measuring approach (M2DM) proposed in [8]:

Infrastructure Meshing Factor (IMF $\in [0, 1]$) – is a metric of connectivity that corresponds to the total number of connections divided by the maximum number of connections for a given number of nodes.

Infrastructure Topology Factor (ITF $\in [0, 1]$) – is a metric of ITI centrality that corresponds to the connectivity (sum of fan-in and fan-out) of the most connected node, divided by the maximum possible connectivity of that node. A ITI with at least 1 node connected to all others has ITF=1.

D. Training sample

Any regression model requires calibration, that is, its coefficients must be calculated for a sample data set where both the values of the explanatory variables and of the outcome variable are known.

TABLE I. SAMPLE EXTRACT

Topology Stereotype	N. nodes (sites)	N. links (site links)	ITF	IMF
Backbone (3)	3	4	1,00	0,67
Ring (3)	3	6	1,00	1,00
Centralized (3)	3	4	1,00	0,67
Fully Meshed (3)	3	6	1,00	1,00
Backbone (4)	4	6	0,67	0,50
Ring (4)	4	8	0,67	0,67
Centralized (4)	4	6	1,00	0,50
Fully Meshed (4)	4	12	1,00	1,00
(...)	(...)	(...)	(...)	(...)
Backbone (99)	99	196	0,02	0,02
Ring (99)	99	198	0,02	0,02
Centralized (99)	99	196	1,00	0,02
Fully Meshed (99)	99	9702	1,00	1,00
Backbone (100)	100	198	0,02	0,02
Ring (100)	100	200	0,02	0,02
Centralized (100)	100	198	1,00	0,02
Fully Meshed (100)	100	9900	1,00	1,00

We generated such a training sample, with almost an hundred cases. Each case represents an ITI with a different number of nodes (sites) ranging from 3 to 100. A small subset of that sample, representing an ITI with 3, 4, 99 and 100 nodes, is represented in TABLE I. The cases in this training data set represent 100% “pure” ITIs, that is, each case corresponds to a stereotypical ITI, to allow exact classification, as required to calibrate the model. For instance, for an ITI with 4 sites we need 12 connections to have each node connected to all the others, thus matching the “fully meshed” stereotype. The equations for the number of site links for a stereotypical ITI are easy to infer from Figure 1, and are represented in TABLE II.

TABLE II. SITE LINKS AS $F(\text{STEREOTYPE}, \text{SITE NODES})$

Topology Stereotype	Number of nodes (sites)	Number of links (site links)
Backbone	N	$2*(N-1)$
Ring	N	$2*N$
Centralized	N	$2*(N-1)$
Fully Meshed	N	$N*(N-1)$

E. Model parameters

Based upon the previously described training data set, we determined the regression coefficients by using the SPSS statistical tool. The latter can be found in “B” column in TABLE III. An illustration of the use of those parameters will be presented later in this paper.

We used the *centralized* network topology stereotype as the reference category since, from our experience, this stereotype is one of the most commonly found in ITIs.

TABLE III. MODEL PARAMETERS

Topology Recode ^a	B	Std. Error	Wald	df	Sig.	Exp(B)	95% Confidence Interval for Exp(B)	
							Lower Bound	Upper Bound
Backbone	Intercept	4,733	1,087	18,947	1	,000		
	ITF	-9,914	1,547	41,091	1	,000	4,95E-005	2,39E-006
	IMF	7,689	2,511	9,376	1	,002	2183,495	15,915
Fully Meshed	Intercept	2,959	1,475	4,026	1	,045		
	ITF	-7391,574	2,565	8306533	1	,000	,000	,000
	IMF	7395,863	,000		1		^b	
Ring	Intercept	9,690	1,373	49,849	1	,000		
	ITF	-36139,2	2,576	2E+008	1	,000	,000	,000
	IMF	36133,452	,000		1		^b	

^a-The reference category is: Centralized.

^b-Floating point overflow occurred while computing this statistic. Its value is therefore set to system missing.

F. Internal validation

Due to the exploratory nature of statistical analysis, we constructed and analyzed several logistic regression models, with a different number of explanatory variables. The results presented herein correspond to the best non over-specified model we were able to identify.

Notice that (in TABLE III) the Wald statistic allows us to consider all effects (*intercept*, *ITF* and *IMF*) as significant when adopting a confidence level of 95%.

Model fitting analysis. The first step in model validation is analyzing whether the regression model fits the data better than a null model (a model that only considers the intercept parameter). Formally speaking, we are concerned with the following hypotheses:

H_0 The model does not have a statistically significant different outcome than another model that only considers the intercept parameter.

H_1 The model does have a statistically significant different outcome than another model that only considers the intercept parameter.

The Chi-Square likelihood ratio test can be used to test the preceding hypotheses. The likelihood ratio is a function of log likelihood used in significance testing in multinomial logistic regression. A "likelihood" is a probability, specifically the probability that the observed values of the dependent variable may be predicted from the observed values of the independent variables. Like any probability, the likelihood varies from 0 to 1. The log likelihood (LL) is its log, this varying from 0 to minus infinity. LL is calculated through iteration, using maximum likelihood estimation. Because $-2LL$ has approximately a Chi-Square distribution, it can be used for assessing the significance of logistic regression.

TABLE IV. LIKELIHOOD RATIO TEST FOR THE FULL MODEL

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	1078,118			
Final	,000	,000	4	,000

Taking a confidence level of 95% (test significance $\alpha = 5\%$) and upon the information in TABLE IV, we can reject the null hypothesis and accept the alternate one that our model is better than a null model.

The Chi-Square likelihood ratio test can also be used to assess the adequacy of each model effect (the intercept parameter and each explanatory variable) individually, that is, blocking the variation in the other effects. In this case the Chi-Square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The latter is formed by omitting an effect from the final model. The null hypothesis is that the coefficient of that effect is 0.

TABLE V. LIKELIHOOD RATIO TESTS FOR EACH EFFECT

Effect	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	380,561	313,813	3	,000
ITF	690,879	624,132	3	,000
IMF	613,685	546,938	3	,000

Based upon TABLE V and again taking a confidence level of 95%, we can reject the null hypothesis for each of the three effects individually and therefore conclude that all of them have a statistically significant impact on the outcome variable and therefore should be kept in the model. The likelihood ratio test of individual parameters is a better criterion than the alternative Wald statistic, mentioned earlier, when considering which variables to drop from the logistic regression model.

Goodness-of-fit coefficients. To analyze data with a logistic regression, an equivalent statistic to R-squared

goodness of fit coefficient does not exist. A wide variety of pseudo-R-squares measures (e.g. *Cox and Snell's*, *Nagelkerke's*, and *McFadden's*) have been proposed to evaluate the goodness-of-fit of logistic models. The name "pseudo" is due to the fact that these coefficients look like R-squared in the sense that they are on a similar scale, ranging from 0 to 1 with higher values indicating better model fit. The *Cox and Snell's* coefficient is an attempt to imitate the interpretation of multiple R-Square based on the log likelihood of the final model vs. log likelihood for the baseline model, but its maximum can be (and usually is) less than 1.0, making it difficult to interpret. The *Nagelkerke's* coefficient is a modification of the *Cox and Snell* one to assure that it can vary from 0 to 1. That is, *Nagelkerke's R2* divides *Cox and Snell's* by its maximum in order to achieve a measure that ranges from 0 to 1. Therefore, *Nagelkerke's R2* will normally be higher than the *Cox and Snell* measure. Lastly, the *McFadden's* coefficient is a less common pseudo-R2 variant, based on log-likelihood kernels for the full, versus the intercept-only, models.

TABLE VI. PSEUDO-R SQUARE COEFFICIENTS

Cox and Snell	,922
Nagelkerke	,984
McFadden	,921

Based upon TABLE VI, where the values of the three previously described goodness-of-fit coefficients are reproduced, we can conclude that the model is very well fit. We can confirm this fitness by using the model to predict the values of the outcome variable in our training set.

Predictive success analysis. The predictive success of logistic regression can be assessed by looking at the classification table. The latter shows the number of cases classified correctly and incorrectly for each category (stereotype) of the dependent variable (ITI topology).

TABLE VII. CLASSIFICATION TABLE

Observed	Predicted				
	Centralized	Backbone	Fully Meshed	Ring	Percent Correct
Centralized	98	0	1	0	99,0%
Backbone	2	97	0	0	98,0%
Fully Meshed	0	0	99	0	100,0%
Ring	0	0	2	97	98,0%
Overall Per.	25,3%	24,5%	25,8%	24,5%	98,7%

The classification table shows both the observed versus predicted responses. The columns are the predicted values of the dependent variable, while the rows are its observed (actual) values. In a perfect model the main diagonal will be fitted with 100% value and all other cells filled with 0%.

Based upon the classification table represented in TABLE VII, we can predict the network topology stereotypes with an overall precision of 98,7% what can be considered as a very high predictive power.

IV. THE MODEL AT WORK

In this section we will apply our multinomial logistic regression model to ITI data collected from several organizations and interpret the results.

A. Real-world sample

TABLE VIII presents a summary of the relevant information collected from 8 ITIs, each belonging to a different organization ranging from a few locations (e.g. organizations 6 and 7) to ones with branch offices spread all over the world (e.g. organizations 1, 2 and 3). To preserve the anonymity of the involved organizations we represent each ITI with a sequence number.

TABLE VIII. ITI DATA COLLECTED FROM 8 ORGANIZATIONS

ITI	Sites	Sitelinks	ITF	IMF
1	212	486	0,011	0,322
2	44	102	0,053	0,325
3	39	104	0,070	0,421
4	29	60	0,073	0,571
5	11	24	0,272	0,218
6	7	12	0,285	1,000
7	8	16	0,285	1,000
8	26	48	0,073	0,960

B. Topology discovery

To illustrate the whole process of topology discovery, we will use data from ITI 1. Recall that the *centralized* topology stereotype was chosen as the reference category.

To compute the propensity of ITI 1 being of *centralized*, *backbone*, *ring* or *fully meshed* stereotypes, we first determine the value of Z_k as described in equation (2). The calculation of Z_k for the *backbone* topology stereotype is described in the following equation:

$$\begin{aligned} Z_{ITI1 backbone} &= 4,733 + (-9,914 \times 0,322) \\ &\quad + (7,689 \times 0,011) \\ &= 1,621 \end{aligned} \quad (4)$$

The B_{kj} coefficients are taken from the *backbone* row and column B in TABLE III. The x_{ij} predictors are taken from the data available for ITI1 which corresponds to the first row of TABLE VIII. The computation of Z_k for the *fully meshed* and *ring* topology stereotypes is likewise:

$$\begin{aligned} Z_{ITI1 FullyMeshed} &= 2,959 + (-7391,574 \times 0,322) \\ &\quad + (7395,863 \times 0,011) \\ &= -2298,805 \end{aligned} \quad (5)$$

$$\begin{aligned} Z_{ITI1 Ring} &= 9,690 + (-36139,200 \times 0,322) \\ &\quad + (36133,451 \times 0,011) \\ &= -11244,486 \end{aligned} \quad (6)$$

$$Z_{ITI1 Centralized} = 0 \quad (7)$$

Now by substituting the Z_k for each topology stereotype in the corresponding instantiations of equation (3), we obtain the desired propensities, expressed as probabilities:

$$\begin{aligned} \text{Probability}_{ITI1 Centralized} &= \\ &= \frac{0^1}{1 + e^{-11244,486} + e^{-2298,805} + e^{1,621}} = 16,5\% \end{aligned} \quad (8)$$

$$\begin{aligned} \text{Probability}_{ITI1 Backbone} &= \\ &= \frac{e^{1,621}}{1 + e^{-11244,486} + e^{-2298,805} + e^{1,621}} = 83,5\% \end{aligned} \quad (9)$$

$$\begin{aligned} \text{Probability}_{ITI1 FullyMeshed} &= \\ &= \frac{e^{-2298,805}}{1 + e^{-11244,486} + e^{-2298,805} + e^{1,621}} = 0\% \end{aligned} \quad (10)$$

$$\begin{aligned} \text{Probability}_{ITI1 Ring} &= \\ &= \frac{e^{-11244,486}}{1 + e^{-11244,486} + e^{-2298,805} + e^{1,621}} = 0\% \end{aligned} \quad (11)$$

Based on the previous equations we can say that there is a **15,5%** probability that ITI 1 implements the *centralized* stereotype, a **83,5%** probability that implements the *backbone* stereotype and a null probability of implementing the *fully meshed* or the *ring* stereotypes.

C. Results

The values in TABLE IX result from the application of our model to each organization.

TABLE IX. DISCOVERED ITI TOPOLOGY STEREOTYPES

ITI	Prob.	Prob.	Prob.	Prob.	Detected Topology
	Centralized	Backbone	Fully Meshed	Ring	
1	16,5%	83,5%	0,0%	0,0%	Backbone
2	12,8%	87,2%	0,0%	0,0%	Backbone
3	25,0%	75,0%	0,0%	0,0%	Backbone
4	59,0%	41,0%	0,0%	0,0%	Centralized
5	2,4%	97,6%	0,0%	0,0%	Backbone
6	95,2%	4,8%	0,0%	0,0%	Centralized
7	95,2%	4,8%	0,0%	0,0%	Centralized
8	98,5%	1,5%	0,0%	0,0%	Centralized

Based upon the last column of TABLE IX we concluded that most topologies are of type *centralized* and *backbone*, which is in accordance with our expectations. Notice that ITI4 is an interesting case because his dominant stereotype is *centralized* (**59%**) but there is a relatively high probability (**41%**) of matching the *backbone* stereotype. These numbers can be due to the fact that this organization was involved in acquisitions and merger processes. Therefore it is natural that the resulting ITI is hybrid.

V. RELATED WORK

MLR is a parametric classification method. There are other parametric, non-parametric and recursive partitioning methods that could be used, as well, to solve the same problem of topology discovery. Other parametric techniques covered include linear regression, generalized linear regression and discriminant analysis. Recursive partitioning algorithms are usually tree-based. Non-parametric methods include neural networks, genetic algorithms or k-nearest neighbor techniques.

Several authors have proposed techniques to discover basic ITI information such as its nodes and links. They do it by means of probing and detecting active devices and collecting topology data from those devices [1, 9-11]. However, we weren't able to find none applying classification techniques to the problem of discovery of ITI topology stereotypes.

VI. CONCLUSIONS AND FUTURE WORK

A. Conclusions

Topology discovery is an important step to support ITI reengineering actions. In this paper we propose and validate a model to discover IT infrastructures topology based on a *Multinomial Logistic Regression (MLR)* model. ITI topology, the outcome variable, is classified according to a set of topology stereotypes (*centralized, backbone, ring and fully meshed*). Several ITI complexity metrics were explored as explanatory variables and we were able to construct a MLR model that is accurate enough with just two predictors. In fact, the model classifies correctly the ITI topology in almost 99% of the cases. Due to space constraints, the metrics collection process is not described in this paper, but it can be found in [3].

The MLR model further allows understanding the current level of ITI topology hybridization by providing the marginal propensities for matching each of the topology stereotypes. Notice that although we have used only 4 stereotypes, the model can be generalized to a larger number.

We have demonstrated the feasibility of our approach by applying it to several real-world IT infrastructures ranging from medium to large size, so scalability is not an issue. Those case studies only matched the *centralized* and *backbone* topology stereotypes. From our experience those are indeed the most frequently adopted stereotypes, so this was not a surprise. Also expected was the absence of cases matching the *fully meshed* stereotype. The latter is very expensive since it maximizes the number of links and is only adopted in extreme situations (usually with a low number of nodes) where reliability is a must.

B. Future work

The larger the training set, the better is expected to be the power of prediction, so we have provisions for extending that set.

To reinforce the external validation of our approach we plan to progress in two directions:

- enlarging the number of cases in our ITI sample, namely by adding cases that cover the ring topology.
- using some non-parametric classification techniques with the same case studies and compare the results.

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