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Toward automatic forecasts for diffusion of innovations

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Abstract

The paper presents an automated framework for forecasting the diffusion of innovations. The framework utilizes existing diffusion information from any market areas or similar products introduced to the markets earlier. The existing data, be it little, enormous, or not present at all, defines a corresponding decision path in the model, and following the path generates a forecast by maximizing the available information. An information-processing technique called a self-organizing map, SOM, was used to generate a map of the economic, technological and social market characteristics that have been found to affect diffusion. This map is used as a basis for finding suitable analogies for predicting the diffusion of an innovation in a specific market. The framework is applied in the context of predicting the diffusion of cellular subscriptions and Internet use worldwide and, separately, in the European Union, including the new member states. In the experiments the model yielded significantly better results than a regression using the Bass model. The method allows analysts to concentrate on more qualitative issues and the system to perform complicated computing operations. Furthermore, the system is self-refining since its accuracy continuously improves when new and more up-to-date information is added to the database. The proposed framework and methods aim to move present theory toward more practical and automatic prediction tools for company analysts and diffusion researchers.

Keywords: Innovation; Diffusion; Forecast; Self-organizing map (SOM); Neural networks; Clustering

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1. Introduction

As Chatfield [1] noted in 1986, it is an academic challenge: "to find ways of making better use of existing [forecasting] methods and to find ways of communicating them to practitioners." The recent review by Martino [2] shows that there have been significant developments in technological forecasting methodology in the past decade. However, many of the existing and new methods require detailed know-how on the part of their users and are thus not readily adopted by business practitioners. Many studies have reported disappointing progress in getting forecasting developments implemented by business users (see, e.g., Ref. [3]). According to Fildes and Hastings [4], quantitative forecasting techniques are rarely used in organizations. Studies of business forecasting practice (e.g., Refs. [5,6]) reveal that only around 10% of the firms surveyed used quantitatively based forecasting techniques.

Sanders and Manroldt [6] studied the features practitioners considered most important or critical in forecasting software. The two what were rated most important were ease of use and the provision of easily understandable results. The significance of the latter is consistent with forecasters' arguments that a key feature of forecasting software is its ability to support forecasts and offer corporate executives a tool for persuasive presentation. In their review of automatic forecasting software packages [7], Tashman and Hoover found that they lacked the facility to foster this type of presentation. According to Ref. [6], some authors contend that many corporate analysts continue to use spreadsheets as their primary analysis tool and avoid forecasting software because they fear it would take too long to master. It has been believed that advances in software and computer technology would make complex algorithms accessible to practitioners [8], and automatic forecasting techniques may be efficient in certain businesses.

Interest in forecasting the diffusion of innovations in global markets has increased considerably in recent years. One of the disadvantages with studies addressing this issue is, however, the method applied. The Bass model [9] has been the one most often used in these cross-cultural diffusion studies, according to the review carried out by Mahajan, Muller and Wind [10].

The Bass model, whilst powerful as an ex-post explanation of diffusion, has limitations when applied to forecasting because of the limited data available to estimate its parameters [11]. Heeler and Hustad [12] have criticized its forecasting validity, since results obtained with international data have not been successful. They reported a poor fit of data to the model and also questioned its applicability when only short runs of data were available. Accurate predictions occurred only with at least 6 to 10 years of input data.

It is obvious that an accurate and easily applicable method for forecasting the diffusion of innovations would be an extremely beneficial tool for companies, especially when they need to estimate the diffusion of new-to-the-market products. It is crucial for a company seeking sustainable competitive advantage to anticipate future developments on its markets, i.e., at what kind of speed and intensity new products and services will be adopted by potential users in different market areas. It is relatively easy to make accurate short-term-demand forecasts for existing products in order to optimize operational-level decisions, but such forecasts would have only very limited use for more strategic purposes. Thus, attempts have concentrated more on long-term forecasts.

Long-term forecasts are important for newly introduced products and especially for completely new innovations when initial adoption levels are not available. General models, such as the Bass model, are helpful in this respect since they provide information about the overall behavior and nature of the diffusion process and its factors.

Many characteristics and properties must be considered if the Bass model alone is accepted as a general model of the diffusion process, despite its limitations (e.g., Ref. [13]) and the availability of other proposed models (e.g., Refs. [13–15]). For example, country characteristics such as wealth and culture (e.g., Refs. [16,17]) affect diffusion behavior as does the product or service type in question—the properties and characteristics typical of telecommunications in the assessment of products such as cellular subscriptions, for example [18]. The introduction of new and more specific factors and parameters to forecasting models has made them more accurate. It has also made them more specialized and complicated, and consequently more distant to company analysts, who should be the actual users of the forecasting knowledge. End-users lack easy-to-use, interpretable, and reliable applications that could be used as decision-making support tools in the marketing planning.

Diffusion models also require substantial experience with national sales if they are meant for forecasting [12]. However, there is no national sales history available for the forecasting model in a pre-launch analysis. Mahajan and Sharma [19] suggested methods for parameter estimation in such case. They obtained parameter estimates by using management judgments of market size, the time of the peak and the adoption level at the peak time. Lawrence and Lawton [20] suggested an estimation procedure when no prior data is available. Forecasts often incorporate judgmental consideration of the challenges imposed by the really new nature of the products [21], but judgment is also subject to bias and shortcomings (see, e.g., Refs. [22,23]). Judgments are considered less reliable when the task is more complex [23]—as it often is when it involves anticipating the future success of new products in turbulent markets such as information and communication technology (ICT). Many of the forecasting problems in the ICT industry occur in the category of really new products on which there are no data available [11], which also makes the use of statistical forecasting methods difficult or even impossible. Lilien et al. [24] developed software for generating diffusion forecasts for new-to-the-world innovations. This approach is based on analogies from existing products, thus requiring judgment-based assessment of product similarity. The application of the Lilien et al. approach as such in the telecommunications context might have some shortcomings: the data was mainly collected from the U.S. before the 1980s, and the products were mainly electrical appliances. Talukdar et al. [25] and others suggest that it would be misleading to draw analogies from rich to poor countries. There are also mixed results about whether product life cycles are getting shorter, and whether newer innovations have faster diffusion than old ones (e.g., Ganesh [26] and Bayus [27]). The network effects in the telecommunications industry result in lower p and higher q parameters than in many other innovation categories. This was also shown in Lilien et al. [24] (pp. 300–302), where the mean p and q values for other consumer products were put at 0.047 and 0.289, respectively, while the p for cellular telephones was 0.008 and the q 0.421.

The purpose of the present study was to develop an automatic model to help practitioners anticipate the future development of their new ICT innovations. Given the limitations of existing models, we aim at developing a forecasting procedure, which is easy to use, and which yields easily understandable results. One of our objectives was to ensure that the forecasting procedure would improve the accuracy of previous models, and that it would overcome some of the limitations of the Bass model in studies on the global diffusion of innovations. We aim to illustrate the accuracy of fit of the proposed framework by applying it to ICT innovations across global markets.

2. Forecasting the global diffusion of innovations

2.1. The Bass model

It has been shown that the diffusion of an innovation typically follows an S-shaped curve when the cumulative number of adopters is plotted against time. The earliest applications of diffusion modeling were mainly in empirical studies aimed at mathematically describing the development in the number of adopters of a specific product in a specific market area as a function of time. In the early 1970s more attention was paid to the behavioral theories behind innovation–adoption processes, and this is well presented in the diffusion model developed by Bass [9]. He concludes that the diffusion could be due to the spread of information between the adopters and from the mass media to the adopters. Mathematically, his model combines the logistic and exponential rise to maximum functions,

$$\frac{\mathrm{d}N(t)}{\mathrm{d}t} = p(m - N(t)) + q\frac{N(t)}{m}(m - N(t)) \tag{1}$$

where at any time t, $N(t)$ is the cumulative number of adopters and m is the total market potential for the new product. Bass calls the constants p and q the coefficients of innovation and imitation, respectively. Coefficient p captures the proportional adoptions due to the mass media, and coefficient q represents the adoptions due to interpersonal communications. The coefficients have also been called the coefficients of external and internal influence, respectively [10]. The Bass model is one of the most popular diffusion models, and was selected for this study on the basis of its simplicity and sound theoretical basis. Nevertheless, the forecasting framework proposed here is not restricted to the Bass model, and can be replaced with any other relevant model.

There are advantages and limitations in the prevailing diffusion models for predicting the success of new products and services; they are relatively easy to apply, and are applicable to a wide variety of academic disciplines and practical decision situations. Given an appropriate aggregation level and a long enough history of actual data (10 years of observations including the inflection point according to the recommendations put forward by Heeler and Hustad [12] and Schmittlein and Mahajan [28], 8 years of data according to Srinivasan and Mason [29]), diffusion models have been able to predict future demand and the timing of sales peaks quite accurately [30]. The problem with them in terms of predicting the diffusion of new products or services is that a reliable estimation of the parameters requires so many data points that when there is enough data the forecasts are no longer practically useful [13,31]. Their practical usefulness is also limited by the assumption that the diffusion process can be described with time as the only explanatory variable. In that case it is not possible for researchers and decision-makers to anticipate the effects of the marketing environment. Furthermore, most of the studies have concentrated on successful consumer durables in developed Western economies, and our knowledge of the diffusion of failed products and services, and of the diffusion in developing countries is very limited [32].

Of the fourteen international studies on diffusion reviewed by Mahajan et al. [10], nine [12,18,33–39] applied the Bass model, and three [40–42] used modified Bass model. However, some authors (e.g., Ref. [18]) have identified problems related to its application in the context of the global diffusion of innovations. The model has failed to estimate the diffusion parameters for a large number of countries (see, e.g., Ref. [18]). Dekimpe et al. [18] estimated Bass coefficients (the innovation coefficient and the imitation coefficient) across countries using nonlinear estimation for cellular subscriptions, and found that the Bass model yielded plausible parameter estimates only in 5% of cases—which incidentally were mainly European countries (Austria, Denmark, Finland, the Netherlands, Norway, Sweden, the UK and the U.S.).

Global-scale diffusion research is therefore needed in order to draw analogies from other products and other markets. Several authors have suggested using analogies by calculating estimates of the diffusion-model parameters and regressing these estimates against various factors, such as the macroeconomic and micro-level factors that are likely to affect the diffusion process [13,43]. The search for such empirical generalizations across products and social systems could guide forecasters already in the earliest phases of product planning [44].

2.2. Country characteristics affecting diffusion

There appears to be no unified theory for incorporating marketing variables and exogenous factors into diffusion models [45]. However, some inferences can be drawn from existing empirical studies in the international context, which amount to more than 20 published studies (reviewed by, e.g., Ref. [46]). The predictors of diffusion used in previous studies have mainly been economic or socio-cultural factors but the timing of the adoption is also often used in attempts to explain the speed of diffusion within a social system. On the other hand, technological and political market characteristics are often ignored.

Several authors have argued that the diffusion rate in a society is related to its standard of living and stage of economic development [37,47–50]. Uncertainty and risk taking are assumed to affect individual adoption timing, and factors such as education and wealth reduce the perceived risk of adoption. Wealth and urbanization are also positively related to the ability to access the innovation [25]. In the telecommunications domain, Gruber and Verboven [51] studied the diffusion of mobile communications in Europe, and found that GDP and technology had stronger effects than the competitive situation. In this study we measured these characteristics using four indicators: GDP per capita, GDP per capita adjusted for purchasing power parity, the Human Development Index [52] (combining information about education, literacy, life expectancy, and wealth), and the urbanization percentage. Population and population growth (cf. Ref. [16]) are also included as indicators of market size and growth.

Diffusion theory predicts diffusion rates and patterns that vary by country because of differences in social-system characteristics [49]. Firstly, innovations diffuse more slowly in heterogeneous social systems [39,48,49]. Secondly, globalization and developments in information technology blur the boundaries between social systems, and their effects have been demonstrated in the findings of Gruber and Verboven [51]: European countries that adopted mobile communications later have caught up through faster diffusion rates. It has also been shown that countries adopting later will have faster diffusion especially in presence of network externalities [48,53]. Gatignon et al. also demonstrated the effects of intercultural communication [36]. They found that countries with a higher degree of cosmopolitanism show a greater propensity to innovate and a smaller propensity to imitate. In accordance with the studies mentioned above, we used the numbers of ethnic groups and languages as measures of homogeneity, and international telephone traffic per capita as an indicator of cosmopolitanism. We also included the timing of adoption among relevant country characteristics.

Some of the previous studies on international diffusion have included political variables. Dekimpe et al. [16,18] incorporated a dummy variable to indicate whether the country was communist or not. Tellis et al. [50] used membership in economic unions as an indicator of economic progressiveness, but found no effect on the timing of diffusion takeoff. Puumalainen and Sundqvist [54] found that political conditions did not seem to play a very significant role, except in poorer countries where a lower political risk was associated with a higher coefficient of innovation. In this study we included a political composite risk index and the level of inflation as indicators of the political conditions.

Diffusion models generally assume that the innovation in question is independent of other innovations. However, Peterson and Mahajan [55] proposed that interrelationships with other innovations can affect the adoption rate. They classified innovations as independent, complementary, contingent and substitute. Mahajan et al. [13] emphasize the need for the consideration of other innovations if the products are contingent or complementary. Dekimpe et al. [18] found that the number of competing cellular systems has a positive effect on the initial adoption level but not on the subsequent growth rate. In Refs. [48,51,56] the size of the installed fixed-line network was included in the study of the diffusion of digital phone switches and cellular subscriptions. The diffusion of telecommunications innovations is contingent upon the network infrastructure and terminal devices. We used the Technology Achievement Index [52] (combining information about patents, received license fees, the diffusion of old and new innovations, and education in science, mathematics and engineering) and telecom investments per capita as measures of the network infrastructure and the penetration of PCs as an indicator of the availability of terminal devices.

3. An automated diffusion forecasting framework

3.1. Decision paths

When the diffusion of an innovation in a specific market area—e.g., a country—is predicted, the forecast depends on area characteristics and the type and characteristics of the innovation (see, e.g., Refs. [16–18]). In the simplified case of a single country it is typically assumed that diffusion information is available, and a model (e.g., the Bass model) can be fitted based on the diffusion history: the longer the history, the more accurate is the fit and consequently also the forecast [10]. On the other hand, the longer the known history, the less we need forecasts. A new approach is needed to reflect a more complex situation in which no initial diffusion values, or only a few, are available. The bottom line is that diffusion values must be available for some countries, or at least there must exist similar products, but how should the forecast be performed in order to maximize the use of available information?

Different paths of information-maximizing-based forecasts were tracked during the research, and the corresponding framework is shown in Fig. 1. The initial problem is to find a forecast for a product P in a country C. Since the case in which product P has already been available in country C is trivial it is not considered in the framework. However, if the unreliability or the small number of historical diffusion values prevents the use of a diffusion model (e.g., Bass), the case would still fall within this framework. The next natural path is to start looking for analogies from other markets or products. Talukdar et al. [25] found that, while past experiences of other products in a country were relatively more useful in explaining the ultimate penetration level, past experiences in other countries in which a product had been introduced earlier were more useful in explaining the diffusion speed. Thus, the next decision in terms of product P is to find out whether it has been sold in other countries, and how well it has succeeded in other similar countries (not necessarily geographical neighbors). If it is a completely new-to-the-world innovation the only path is to consider other similar products P'. For example, Thomas [57] presented a comprehensive framework for assessing the similarity of products, and this could be incorporated in our

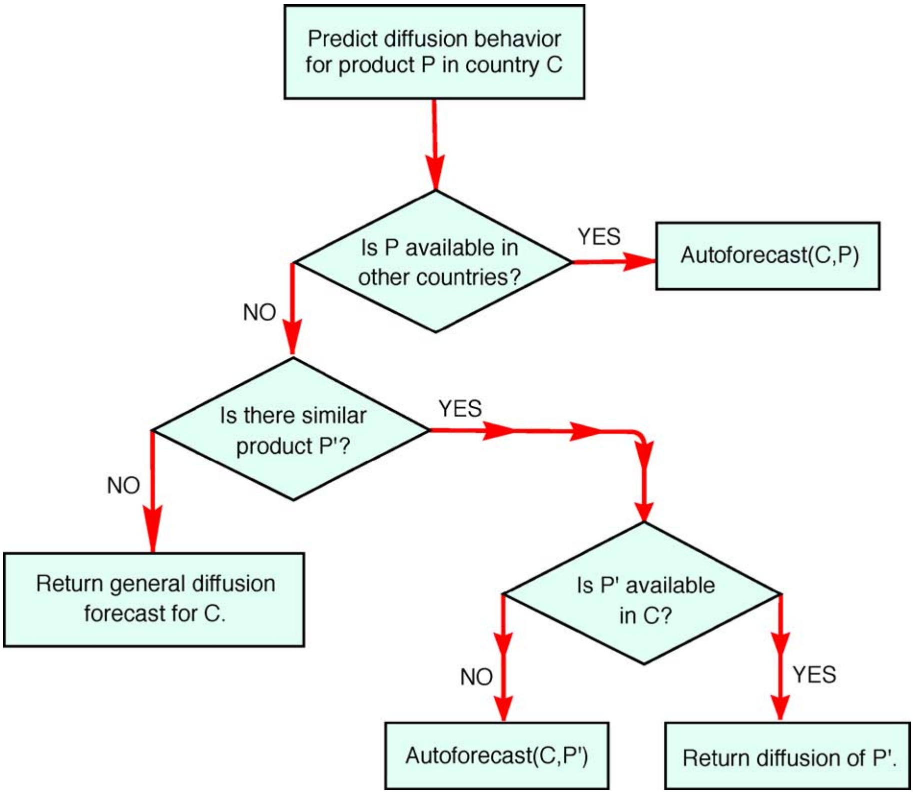

Fig. 1. A framework for describing decision-making in diffusion forecasting.

framework. However, Thomas' approach requires the collection of data from consumers, which is often impractical for managers aiming at international markets. If the innovation is of the most difficult kind in that it is completely new and of a completely new type, then only a general forecast can be given, which could include the average diffusion curve in country C. However, if similar product P' is available in country C we are reduced to the first branching question, but again, if it is not available the forecast can be made only by estimating it with the help of data on other similar countries.

An advantage of the framework presented in Fig. 1 is that its bottlenecks can be detected and their significance evaluated, and the different modules can be separately studied and further improved. These improvements will be considered in the future, but in this study a special consideration is given in this study to the function Autoforecast(C, P), which can estimate the diffusion of a product P for a country C. Since the idea is to find similar countries based on country characteristics and to utilize the existing diffusion values from the similar countries, the forecasting is reduced to the problem of how to perform the task automatically.

3.2. Finding similar countries and combining their diffusion information

The search for similar countries can be done manually, but since the aim in this study is to automate the forecasting process as extensively as possible an automatic method for this sub-task is considered next. In order to find the most similar countries, all countries must first be organized so that the most similar ones are located as neighbors. The organization should be based on the country characteristics relevant to the diffusion, and a method by which this kind of multi-dimensional data is put in a relational order would be preferred.

The very task of organizing lends itself to one of the most popular methods, the self-organizing map (SOM), developed by Kohonen [58,59], which is also referred to as the Kohonen map. It organizes countries according to their country characteristics and those with similar country parameters are located near each other; it is a hierarchy-preserving non-linear mapping. SOM has many beneficial properties, such as tolerance for incomplete and missing data (see, e.g., Ref. [60] for more details), and it has been successfully used in similar tasks, such as in forecasting bankruptcies, future prices, workplace behavior, and energy use [61,62].

A SOM-based method that computes an automatic forecast for a given country and product is sketched in Algorithm 1, in which there are two things to be defined: (1) how many neighbors (N) should be used and (2) how the diffusion information of N neighbors can be combined. The second problem is more analytical, but it has to tolerate two forms of incompleteness: there are often only a few initial diffusion values available for new innovations, and those from different countries may be from varying time durations and of different lengths. To guarantee a proper Bass model fit a certain minimal amount of diffusion numbers is required, and according to Ref. [12], at least six data points were required in this study. Furthermore, in order to combine diffusion numbers a Bass model fit must first be made separately for all neighbors and the Bass curves combined to form a mean Bass curve, which is the forecast. The problems associated with different time durations and data vector lengths are eliminated by the separate Bass models. The first problem concerning the number of neighbors N is more problem-specific, but a general solution can be found by inspecting the results over all existing products. In carrying out this experiment, three telecommunications products (the Internet, cellular subscriptions, and ISDN) were selected and their error behavior was inspected in order to find an averagely good N. Fig. 2 shows the mean errors over all countries where neighbors have been used to generate the diffusion as advocated in Algorithm 1. The figure shows that values $N \geq 5$ provide the best results on average. $N=5$ was therefore selected for this study.

Algorithm 1. Autoforecast(C,P)

(1) Generate an organized country map by passing all available country parameters to the SOM.
(2) Find N closest neighbors of C from the generated map.
(3) Combine diffusion information of the neighbors for product P and return a Bass model fit.

There is one more issue to be considered. The approach presented assumes that innovation diffusion is similar in countries with similar country characteristics, but this assumption may fail if the diffusion of a specific product depends only on some of the characteristics. Product-specific diffusion parameters were not available during this research, so we generated an artificial situation by adding the product-specific diffusion values to the country data in the SOM; SOM maps are product-specific and they must be generated separately for all products. In this case the Bass model was not needed as the diffusion values could be found directly from the generated SOM, thus also allowing inspection of the Bass bias in the proposed model. These two approaches are referred to in the experiments as

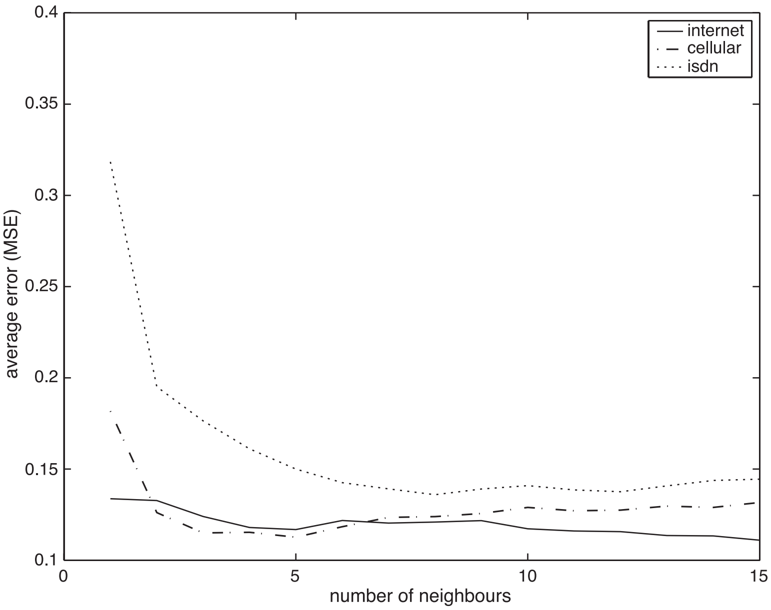

Fig. 2. Mean squared error between actual country specific diffusion and diffusion generated using neighbors as a function of number of neighbors N for different products.

SOM1 for the standard method and SOM2 for the method in which the product-specific information was used in the SOM.

4. Methodology

It is evident that the success of the proposed framework depends on the performance of the proposed automatic forecasting method. Experiments were conducted using real diffusion and country data to evaluate the performance. Internet usage and cellular subscriptions were chosen as the innovations in question. These enabling services are of particular interest since the telecommunications business is currently undergoing massive change and there are many related innovations that are still in the early diffusion stages.

4.1. Data description

Diffusion data was collected from the International Telecommunications Union (ITU) database of World Telecommunication Indicators and consisted of annual statistics from 113 countries each with a population of more than one million inhabitants. Since a minimum of six observations was required the diffusion patterns of cellular usage were reliable only for 96 countries and those for Internet usage for 80 countries. The diffusion numbers were normalized by dividing them by the population of each country, yielding values between [0, 1]. Other normalizing factors were also considered but without any significant effect [60].

The country characteristics were obtained from ITU (penetrations of cellular subscription, PC and Internet use, population, GDP per capita, international telephone traffic and telecom investments per capita), the CIA World Factbook (PPP adjusted GDP per capita, urbanization, population growth, inflation, numbers of ethnic groups and languages), the PRS Group (political risk index), and the UNDP (human-development index and technology-achievement index). The country characteristics were also normalized to the magnitude [0, 1], which is a standard SOM procedure (see Ref. [60] for more details in this particular case).

4.2. Measuring performance

Measuring performance is an important consideration since it provides the basis on which to determine whether a method outperforms another or not. It is typical in this kind of experiment to use the leave-one-out testing method, meaning in this case that one country at a time was left out and its diffusion forecast using information from the others. The test is repeated for all countries and the errors are summed. This is not the situation in practice, but the diffusion typically begins at approximately the same time in many countries; when it is not available for one of them it is not available for the others either. The leave-one-out method must be considered optimistic in terms of time-dependent data when results are conditional upon the available amount of data; if the diffusion numbers were removed from the other countries the forecast accuracy would also decrease. This more realistic analysis makes the testing procedure significantly more complex and since the aim of this study is to present the framework and report the first preliminary results the analysis of realistic predictive validity was left for future research. All tests were performed using the optimistic leave-one-out procedure in which the diffusion data is removed from the country under scrutiny and all data is available for the other countries.

As a result, the framework returns a Bass curve for that country which must be compared to the real existing diffusion values in the accuracy measurements. There are many different error measures that can be used, such as the mean squared error (MSE), the mean absolute error (MAE), correlation, and Euclidean distance. The MAE and MSE measures are the most popular ones and they are also analytically compatible with the Bass model. Thus, MSE was selected as the error measure to describe the mean squared vector distance between the forecast and the actual diffusion numbers.

Reporting errors separately for each country would be difficult to interpret and on the other hand a cumulative error would not provide any practical evidence of the method quality. In order to obtain a better interpretation the forecasting error was measured for the European Union (EU) as it was pre-2004, the enlarged EU, and for all countries separately. Within each country group the accuracy was measured as a proportion of countries for which a specific error level was achieved; an optimal method would have MSE=0 for 100% of countries, thus providing a curve that rapidly climbs to 100 at the origin.

4.3. Linear regression method as benchmark

A benchmark method was needed to determine whether the proposed framework could produce any advantage over current practices in companies. Given its simplicity and popularity in similar forecasting schemes, linear regression was used as a benchmark method (e.g., Ref. [46]). Any standard statistical software can be used for the linear regression to find linear dependence between country characteristics and the parameters of the Bass model. This may be done separately for all products, and a diffusion curve for product P in country C generated based on the Bass parameter estimates calculated from the country characteristics. As a standard tool that is available to all analysts, this approach may provide some evidence of the lower bound accuracy achieved in practice.

5. Results

As mentioned above, the bias set by the selection of the Bass model needs to be examined in order to verify that the accuracy is not limited by the model itself. The bias can be estimated by fitting the Bass model to the existing diffusion values since no forecasting method based on it can achieve better results than this, i.e., the bias is considered optimal in terms of reference results. Furthermore, the model selection should not be a critical consideration until the forecast converges close to the bias.

A generated country map using all country characteristics is shown in Fig. 3. This map is only a sub-task in the automatic forecasting using Algorithm 1, but here the results are briefly interpreted in order to clarify its importance to the success of the whole framework. For example, the map in Fig. 3 shows Canada (CAN) and the USA (USA) as neighbors, and similarly Norway (NOR) and Denmark (DNK), and Finland (FIN) and Sweden (SWE) are located near each other. These results are not surprising, and an inexperienced analyst would achieve the same. What is more interesting is the revelation of some less straightforwardly explainable similarities for other countries, such as Turkey (TUR) and Brazil (BRA), which are located near each other on the map. Moreover, it should be emphasized that the identification

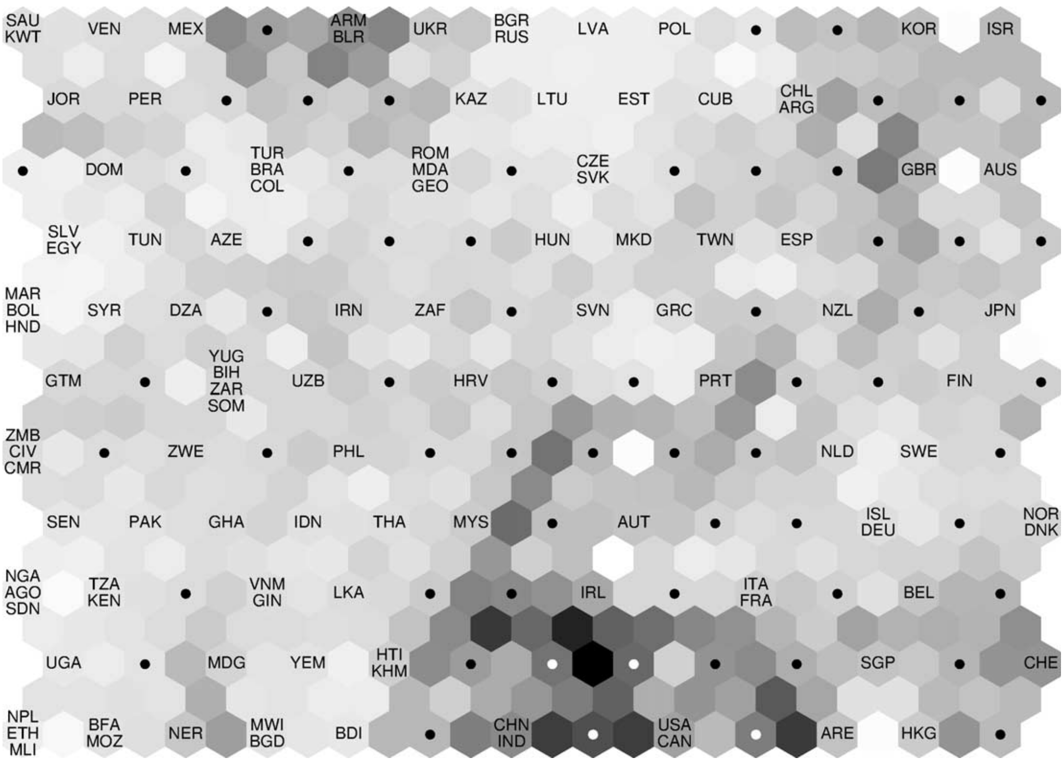

Fig. 3. Organized country map generated by SOM using country parameters.

of neighbors, while of course still being interesting, is not the main advantage, which is the automatic generation of this map. Furthermore, as new information is added to databases, the map can be automatically regenerated to refine forecasting accuracy.

The method described in Algorithm 1 and leave-one-out testing were used to compute forecasts for Internet usage and cellular subscription diffusion separately for EU countries pre-2004, the new EU countries, and for all countries. The results are shown in Figs. 4–6. One further consideration should be the mean squared error (MSE) and the minimal MSE level at which forecasts have any practical use. This consideration is postponed, however, since the proposed framework was analyzed only quantitatively and no qualitative evaluations were made; these results are applicable to method comparison not to evaluation. Finally, it can be concluded from the results of all of the conducted experiments that the two proposed methods SOM1 and SOM2 were significantly more accurate than simple linear regression (see Figs. 4–6). Furthermore, the SOM2 method outperformed SOM1 which indicates that the inclusion of product-specific data and the removal of model bias may improve the forecast for example, as shown in Fig. 4(a), SOM2 achieved an error level of MSE≤0.2 for over 70% of EU countries and SOM1 for over 60%, while the linear regression achieved the same level of error for less than 30% of EU countries. There may still be improvements that can be made, and factors to be considered before the methods converge to the bias curve that represents the ultimate achievable goal.

The maximal accuracy of the Bass model was assessed by measuring the discrepancies between the true existing diffusion values and the Bass model values. Of course the errors represent the capability of the Bass model to explain history rather than the forecasting, which is quite the opposite. However, a forecast cannot outperform historical information, and thus the historical fit could be seen as maximal approachable accuracy. The error can be interpreted as a bias of the Bass model itself, and as long as forecasts remain significantly worse than the Bass fit, it can be assumed that the difference is due to missing explanatory factors rather than to the model in question. It was evident from the

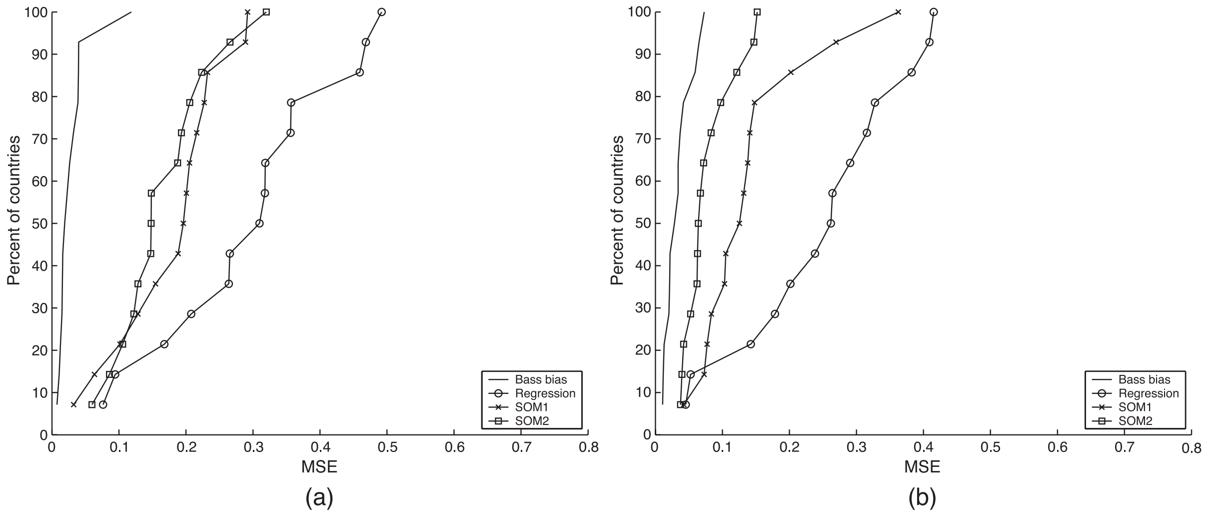

Fig. 4. Forecasting error in the pre-2004 EU countries using linear regression, SOM1 and SOM2 forecasts, and the Bass model bias curve: (a) Internet users; (b) cellular subscriptions.

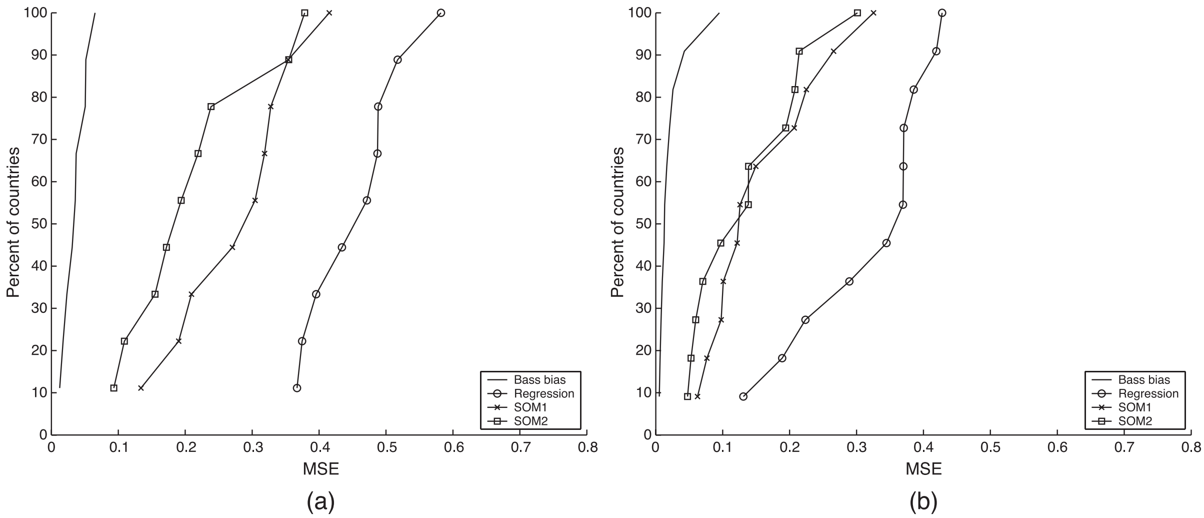

Fig. 5. Forecasting error in the new EU countries using linear regression, SOM1 and SOM2 forecasts, and the Bass model bias curve: (a) Internet users; (b) cellular subscriptions.

experiments that although the proposed forecasting outperformed a linear regression with the Bass model there is still a gap between the bias curve and the forecasting results, and thus the conditions for selecting the Bass model here can be relaxed. In addition, the proposed framework was implemented without any model, but by allowing the free non-linear construction of diffusion values when improvements were achieved in all of the experiments. However, the difference between the framework utilizing the Bass model and the one not utilizing any model is not dramatic. Moreover, the improvement is somehow artificial due to the experimental setup, in which it was assumed that data was missing from one country while it was available for all others: the generalization power of

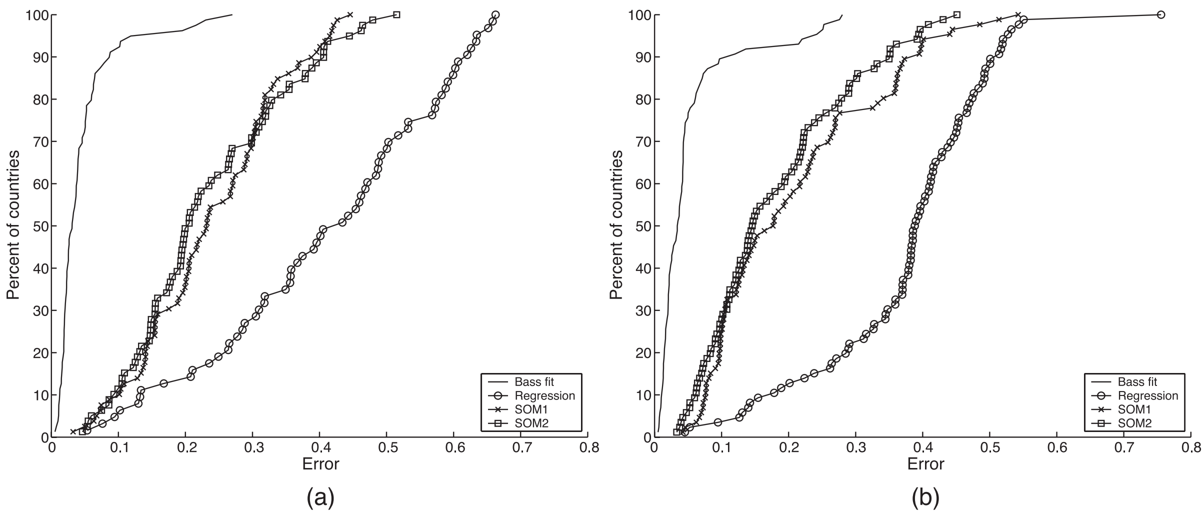

Fig. 6. Forecasting error in all countries using linear regression, SOM1 and SOM2 forecasts, and the Bass model bias curve: (a) Internet users; (b) cellular subscriptions.

models is needed in more realistic situations in which only a very limited amount of data is available in order to prevent unnatural forecasts.

6. Discussion

The aim of this research was to automate forecasts of the diffusion of innovations by performing all possible computational tasks automatically and leaving only qualitative decisions to users. In this case, an example of a qualitative decision would be to analyze characteristics of a new innovation and search for similar existing products—tasks that should be natural to business analysts in their own business area. The first step in the automation was the definition of the tree-structure framework. The second step was to use a self-organizing map for finding diffusion analogies. Finally the framework was tested using real diffusion data. The results of our experiments show that the proposed framework outperformed the benchmark method (the Bass model combined with linear regression).

The framework has several distinct features. First, it overcomes some of the limitations of previous diffusion models, as it incorporates country and product parameters. Second, the model is not that sensitive to the number of observations (i.e., the amount of historical data) in the market area of interest. The framework also yields reliable diffusion curves for innovations with limited historical data. Third, it is very easy to use. As the literature reveals, many forecasting models are not applied because very few people understand them. The proposed automated diffusion modeling framework does not require expertise in forecasting methods on the part of the users, which, it is to be hoped, will encourage practitioners to apply it. Fourth, the proposed model is more accurate than the benchmark method.

Our study is not free of limitations. The forecasting accuracy may be limited by the choice of country characteristics. The characteristics for this framework were chosen on the basis of existing research on international diffusion, in which the empirical settings are often consumer durables in developed Western economies. The effects of these country characteristics are not necessarily generalizable to all types of products and/or countries. Furthermore, the SOM application gives equal weight to all characteristics in defining similarity, while the effect on diffusion may actually vary between them, and the parameters themselves may at least to some extent be product-specific.

Future tests should test the predictive validity of the proposed framework by splitting the existing diffusion data into separate modeling and validation periods. Cultural information should also be included in the country characteristics, given recent findings (e.g., Refs. [17,50]) that, for example, uncertainty avoidance is an important predictor of diffusion in international settings. Furthermore, the method could be further improved by generating country maps separately for all products: by utilizing product-specific diffusion information and maps generated from the country characteristics it may be possible to achieve non-linear regression between the country characteristics and the product types, and consequently, the maps could be separately optimized for different products. Since we claim user-friendliness for users it would also be interesting to assess the ease of usage and applicability of our framework as perceived by practitioners.

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