Identify Potential Diversification to Companies through Collaborative Filtering

Arnault Pachot, Adélaïde Albouy-Kissi, Benjamin Albouy-Kissi, Frédéric Chausse

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Arnault Pachot arnault.pachot@etu.uca.fr
Adélaïde Albouy-Kissi adelaide.kissi@uca.fr
Benjamin Albouy-Kissi benjamin.albouy@uca.fr
Frédéric Chausse frederic.chausse@uca.fr

Université Clermont-Auvergne, CNRS, SIGMA Clermont, Institut Pascal, F-63000 CLERMONT-FERRAND, FRANCE

The industrial fragility of European countries has been a major issue during the latest economic and health crises. Governments have become aware of the partial desertification of our industry but also of the astonishing capacity of the players to reinvent themselves, innovate to find solutions, and show resilience. Everywhere in our society, shaken from all sides, we have seen the emergence of diverse initiatives to overcome the shortages of necessities. In this study, we focus on the ability to diversify from the point of view of a company, which literature has shown to be a major factor in improving industrial resilience. We are interested in the proximity of industrial know-how between two product classes in the HS nomenclature, independent of the country or territory observed. Our goal is to evaluate the ability of a firm that produces product A to adapt its production to produce product B. We analyzed thousands of French companies' websites to label the products they manufacture. From the collected data we built a Recommender System (RS) for diversification based on collaborative filtering (CF). The results show that our Recommender System outperforms methods from macro data analysis, such as co-export analysis on the Product Space or semantic analysis of nomenclatures. We formalize an indicator of a company's agility based on its diversification capabilities. Finally, this work offers new perspectives on the formalization of a measurable Resilience Index (RI).

JEL Codes • L25 Firm Performance: Size, Diversification, and Scope

CCS CONCEPTS • Recommender systems • Network economics • Economics • Sustainability • Economic impact

Additional Keywords: Sustainable production • COVID19 and Economy • Econometric modeling • Resilience Index

1 INTRODUCTION

In this study, we focus on the ability to diversify from the point of view of a company, which appears in the literature to be a factor for improving industrial resilience (Agarwal et al., 2021; Martin, 2012).

To measure this adaptive capacity, we are interested in the proximity of industrial know-how between two classes of products in the HS nomenclature, regardless of the country or territory observed. We need to evaluate the ability of a company that produces product A to adapt its production to produce product B.

After presenting existing methods based on macro-economic approaches, we will describe a new methodology that exploits the observation of real co-productions of manufacturers to model proximities by collaborative filtering (CF). We will study the k-nn and matrix factorization approaches in a context of implicit data. We will compare the recommendations obtained with the state-of-the-art.

Finally, we formalize a new agility indicator that allows us to evaluate the diversification capacity of a given industrial company. We conclude with the perspectives offered by this indicator in the automatic measurement of a company's Resilience Index (RI).

2 PREVIOUS WORK

We will present the measures of proximity proposed in the literature. These measures are derived from macroeconomic data and are based on the analysis of exports by country or nomenclatures. We will then present the extent to which the literature considers the diversification capacity of firms in assessing their resilience.

2.1 Proximity in the Product Space

The work done by Hausmann et al. (Hausmann et al., 2011; Hausmann & Hidalgo, 2010) on economic complexity has defined a measure of proximity between products. This measure is based on a study of the export baskets of each country. A graph built with classes of products linked to each other according to their proximity is called the Product Space. The results obtained for each country can be consulted in the Atlas of Economic Complexity[1]. The proximity ϕ_{p_1,p_2} between the products p_1 and p_2 is calculated as follows.

Let X_{cp} be the exports of product p by country c, then the Revealed Competitive Advantage (RCA) that country c has for product p can be expressed as a function of exports according to the formula of (Balassa, 1965):

$$RCA_{\mathrm{cp}} = \left(\frac{\mathrm{X_{cp}}}{\sum_{\mathrm{c}} \mathrm{X_{cp}}}\right) / \left(\frac{\sum_{\mathrm{p}} \mathrm{X_{cp}}}{\sum_{\mathrm{c,p}} \mathrm{X_{cp}}}\right)$$

In the following formulas, a country c is considered to export a product p if and only if RCA_{cp} is greater than 1. The calculation of the productive proximity between each product is done by looking for each pair of products $\{p_1; p_2\}$ exported together:

$$\mathrm{M_{cp}} = \begin{cases} 1 & \text{if } RCA_{cp} \geq 1 \\ 0 & \text{else} \end{cases}$$

$$\phi_{\mathrm{p_1,p_2}} = min\left(\frac{\sum_{\mathrm{c}} \mathrm{M_{cp_1}} \mathrm{M_{cp_2}}}{\sum_{\mathrm{c}} \mathrm{M_{cp_1}}}, \frac{\sum_{\mathrm{c}} \mathrm{M_{cp_1}} \mathrm{M_{cp_2}}}{\sum_{\mathrm{c}} \mathrm{M_{cp2}}}\right)$$

Product Space has been used to assess countries' diversification capabilities (Alshamsi et al., 2018; Boschma & Capone, 2015; Zhu et al., 2017) or with a view to diversifying companies (Pachot et al., 2021a), in particular to guide towards the production of greener products (Hamwey et al., 2013; Huberty & Zachmann, 2011; Mealy & Teytelboym, 2020; Perruchas et al., 2020).

2.2 Measurement of proximities between products based on the semantic analysis of nomenclatures

Natural Language Processing (NLP) techniques are used in the literature to perform automatic categorizations in HS nomenclature (He et al., 2021; Luppes, 2019; Spichakova & Haav, 2020). In a previous work, we built a vector space with Word2vec to characterize the semantic link between class descriptions of the HS nomenclature (Pachot et al., 2021b). Word2Vec represents each word in a distributed way as a vector. Learning is done from specialized neural networks (Bengio et al., 2003) or a similar approach (Collobert et al., 2011; Mikolov, Chen, et al., 2013; Mikolov, Sutskever, et al., 2013). The Word2Vec model can be used in two variants to make a context (skip-gram) or word (CBOW) prediction. In addition to capturing syntactic and semantic information, the vectors produced by Word2Vec have geometric properties (Mikolov, Sutskever, et al., 2013) which allow larger blocks of information (such as sentences and paragraphs) to be represented by combining vectors together. Word2Vec has also shown an amazing ability to capture word concepts by providing the ability to perform translations from simple linear transformations (Mikolov, Le, et al., 2013).

The Skip-gram method seeks to maximize the average logarithmic probability of prediction of words of the sequence $w_1, \dots w_n$ with respect to each other. Let k be the size of the learning window and n the size of the sequence. The function is defined as follows:

$$\frac{1}{n} \sum_{i=1}^{n} \left[\sum_{j=-k}^{k} \log p(w_{i+j} \mid w_i) \right]$$

In this model, each word w is associated with two vectors of learnable parameters, u_w and v_w. The probability of predicting w_i by knowing w_j is computed from u_w and v_w, in a softmax function, with V representing the vocabulary size:

$$p(w_i \mid w_j) = \frac{e^{u_{w_i} \cdot v_{w_j}}}{\sum_{l=0}^{V} e^{u_l \cdot v_{w_j}}}$$

This gives a minimization problem, solved by the hierarchical *softmax* (Morin & Bengio, 2005). In (Pachot et al., 2021b), the vector space was used to measure the proximities between the vectors of each product. Since

[1] https://atlas.cid.harvard.edu

nomenclatures are intended to standardize and structure information, special care was taken in writing the class descriptions to limit ambiguities. This makes them particularly suitable for automated semantic processing.

For each 5387 classes of the HS nomenclature, a vector v_p representing the product concept p in the vector space E was computed. The vector v_p is constructed from each vector word that appears in its class description in the HS nomenclature. The vector v_p is calculated by averaging the vectors of each word w_i that its class description contains. Thus, the distance between the products corresponds to the cosine similarity of their vectors in E. Let v_{p_i} and v_{p_j} be the vectors associated with the products p_i and p_j respectively, then we express the distance between these two products by the following equation:

$$\Psi_{p_i,p_j}(\tau) = \frac{v_{p_i} \cdot v_{p_j}}{\left|v_{p_i}\right| \left|v_{p_j}\right|}$$

2.3 Measuring the Resilience Index of a company

Organizational resilience is defined as the ability to bounce back from a disruption (Sheffi & Rice, 2005), the ability to return to the original or a new, more desirable state after experiencing a disruption (Carvalho et al., 2012), or the ability to cope with disruptions and contingencies in advance through strategic awareness and linked operational management of internal and external shocks (Annarelli & Nonino, 2016).

A systematic review of research on Supply Chain (SC) resilience is presented by (Al Naimi et al., 2021). The level of resilience of a company is represented by the Resilience Index. Agility is an enabler having a positive influence over SC resilience (Christopher & Peck, 2004), and it is defined as the "Ability to sense the dynamic market changes and react quickly in order to meet customers' needs and prevent losses" (Agarwal et al., 2021; Ali & Gölgeci, 2019; Kumar & Anbanandam, 2019).

3 COLLABORATIVE FILTERING RECOMMENDER SYSTEM

We use the production data extracted from the websites of the manufacturers. We have a correspondence file indicating for each company c a list of m products $(p_1, \cdots, p_m)$ of the HS nomenclature observed on its website.

3.1 Building the data set

We have a list of 6519 French companies on which we have entrusted the ethical platform of data labelling Isahit[2] with the task of carrying out a manual labelling of each website. The task consisted of the following:

- On one hand, determine if a website of the company exists.
- If a website exists, consult the main pages, and choose, in the HS nomenclature (version 2017, on 4 digits), the products which are manufactured by the company.

The labelling was carried out on 6153 companies with a website. On each website, products were observed according to the following distribution:

Table 1: Number of products detected per website

Total	0	1	2	3	4	5	6	7	8
6153 companies	2059	3258	372	313	58	34	20	21	18

We constructed a sparce matrix of interactions by considering companies as users u_i, who interacted with products p_j corresponding to the list of products we detected on their website. We obtained 9133 unique interactions. The matrix covers 880 different product classes with a sparsity rate of 0.188%. The number of classes in the 2017 4-digit HS nomenclature is 1222, so our dataset covers 72.01% of the total nomenclature.

3.2 Measurement of proximities between products by Item-Item Nearest Neighbor

We first applied a k-nn method to construct a matrix of proximities between each product class. We reserved 20% of the data for cross-validation, and we measured *recall@k* prediction scores with $k \in [5,10]$. Our metric consists of counting the number of correct recommendations among the k recommended products. We obtained the following scores on the validation sample.

[2] https://fr.isahit.com

Table 2: Results Item-Item Nearest neighbor with $k \in [5,10]$

	recall@5 train	recall@5 test	recall@10 train	recall@10 test
Cosine	0.98848	0.96561	0.99934	0.95656
TFIDF	**0.98947**	**0.97104**	**0.99963**	**0.97828**
BM25	0.98809	0.96380	0.99901	0.96833

This RS is not adapted to perform online predictions because of complexity issue in $O(n^2)$, but it gives excellent prediction scores. This first experimentation allows us to have a robust measure of proximity between industrial know-how.

3.3 Matrix factorization recommender system

Matrix factorization (Koren et al., 2009) is a representation of the data in a latent reduced space, which will serve as a model for making predictions in this reduced space with constant dimensions. It is a model-based approach that consists of decomposing the sparce matrix of interactions into a product of several matrices.

Let I be the number of users, J the number of products, and K the number of latent factors. Let us suppose that we wish to carry out an approximation of the interaction's matrix R, called $\hat{R}$, in the form of a product of two matrices U of dimension $I \times K$ and V of dimension $J \times K$:

$$\hat{R} \approx U \cdot V^{\top}$$

Then a user's prediction about a product can be expressed as follows:

$$\widehat{r_{ij}} = u_{i_1} v_{j_1} + u_{i_2} v_{j_2} \dots u_{i_k} v_{j_k}$$

$$\widehat{r_{ij}} = \sum k = 1^K u_{i_k} v_{j_k} = u_i^{\top} v_j$$

Let u_i be the latent factor associated with user i, and v_j the latent factor associated with product j. We define u_{ik} as the affinity of a user i for the concept k, and v_{jk} as the affinity of a product j with the concept k. The principle of this method is to learn the values of the latent factor matrices U and V by comparing the actual interactions r_{ij} with the predicted values $\widehat{r_{ij}}$. Let $\Re$ be the set of interactions. We define the learning error of an interaction $e_{ij} = r_{ij} - \widehat{r_{ij}}$, and the average error with the quadratic error function J:

$$\mathrm{J} = \frac{1}{2} \sum_{(i,j)\in\Re} \left(e_{ij}\right)^2 = \frac{1}{2} \sum_{(i,j)\in\Re} \left(r_{i,j} - \sum_{k=1}^{K} u_{i_k} v_{j_k}\right)^2$$

We will therefore look for the values of U and V that minimize the loss function. To minimize the loss function, we apply a gradient descent after having randomly initialized the weights of the matrices U and V. At each step, the gradient descent will consist of performing two series of partial derivatives on the error $\frac{1}{2} e_{i,j}^2$, relative to U and V, to determine the gradient of the loss function at the point (i,j). Finally, we obtain two matrices U and V that allow us to predict the unknown value of an interaction, whatever the user and the product. The prediction of user i and product j is expressed as follows:

$$\widehat{r_{ij}} \approx u_i^{\top} v_j$$

The classical methods of matrix factorization must be adapted to deal with implicit data (Hu et al., 2008), which is our case. Indeed, we do not have a preference score between companies and products, but only Boolean information to indicate the presence or not of a product on the site of an industry. We use the *Implicit*[3] library to experiment with various implicit CF methods.

We follow the method described by Johnson (Johnson, 2014) as a factorization of the interaction matrix R into 2 lower-dimensional matrices $X_{n\times f}$ and $Y_{m\times f}$, with f as the number of latent factors.

Let l_{ui} represent the interaction of user u with product i, let β_i and β_j, respectively, be the biases on users and products, then the probability of l_{ui} is computed by the sum of the inner product of user and item latent factor vectors and user and item biases.

[3] https://implicit.readthedocs.io

$$p(l_{ui}|x_u, y_i, \beta_i, \beta_j) = \frac{exp(x_i y_j^T + \beta_u + \beta_i)}{1 + exp(x_u y_i^T + \beta_u + \beta_i)}$$

This minimization problem is solved by performing an alternating gradient ascent (Das et al., 2007). The partial derivatives for computing the user vectors and their biases are as follows:

$$\frac{\partial}{\partial x_u} = \sum_i \alpha r_{ui} y_i - \frac{y_i\,(1 + \alpha r_{ui} exp(x_u y_i^T + \beta_u + \beta_i)}{1 + exp(x_u x_i^T + \beta_u + \beta_i)} - \lambda x_u$$

$$\frac{\partial}{\partial \beta_u} = \sum_i \alpha r_{ui} - \frac{(1 + \alpha r_{ui} exp(x_u y_i^T + \beta_u + \beta_i)\}}{1 + exp(x_u x_i^T + \beta_u + \beta_i)}$$

3.4 Model learning

We use a grid system to determine the optimal hyper-parameters. Tables 3 and 4 show the results obtained with the Alternating Least Square (ALS), an approximate version (Annoy ALS), Logistical Matrix Factorization (LMF), and Bayesian Personalized Ranking (BPR) methods.

Table 3: Results of matrix factorizations with $k = 5$

	recall@15 train	recall@5 test	mse train	mse test
ALS	**0.74574**	**0.28416**	**0.00322**	**0.00221**
Annoy ALS	0.42775	0.17014	0.00326	0.00223
LMF	0.05929	0.05611	2.11817	2.11486
BPR	0.03207	0.03258	0.00405	0.00302

Table 4: Results of matrix factorizations with $k = 10$

	recall@10 train	recall@10 test	mse train	mse test
ALS	**0.79803**	**0.36290**	**0.00330**	**0.00225**
Annoy ALS	0.65597	0.27783	0.00330	0.00227
LMF	0.09016	0.09231	2.16010	2.15670
BPR	0.07067	0.07330	0.00365	0.00263

The ALS method obtains the best results. We see that the matrix factorization methods have lower performance than the k-nn methods presented above but have the advantage of being released online.

4 RESULTS

We presented three methods to measure the proximity between two classes of products, including a new one developed in this research work. The following table summarizes the proximity tables.

Table 5: Summary of the proximity tables between products

	Méthode	Type
ϕ_1	Co-exports analysis	Macro
ϕ_2	Semantic analysis of nomenclatures	Macro
ϕ_3	Products on the websites	Micro

To compare the proximity tables, we convert them into graphs in order to calculate their distances. The *NetComp*[4] library developed by (Wills & Meyer, 2020) allows us to measure their spectral distances. Let G and G' be two graphs of size n with λ_i^A and $\lambda_i^{A'}$ their respective adjacency spectra. Considering a norm l_2 as a measure of the distance between the two spectra, the spectral adjacency distance between the two graphs is defined as follows (Wills & Meyer, 2020):

$$d_A(G, G') \stackrel{\text{def}}{=} \sqrt{\sum_{i=1}^{n} (\lambda_i^A - \lambda_i^{A'})^2}$$

[4] https://github.com/peterewills/NetComp

In our case, we use the normalized Laplace distance l_L which can be used to compare graphs of different sizes. In Table 6, we present the spectral distance obtained between the three methods.

Table 6: Spectral distances between the different proximity measurements

	ϕ_1	ϕ_2	ϕ_3
ϕ_1	0		
ϕ_2	12.74	0	
ϕ_3	9.69	6.86	0

Comparison of proximity measures based on recommendations

From each proximity table, we can make predictions of the k nearest neighbors of each product. Thus, for each product p of the HS nomenclature we obtain a set E with a maximum of k nearest products $E_{\phi_i}(p) = \{p_1, \cdots, p_k\}$. Indeed, the number of neighbors can be less than k.

We carry out this operation for each of the three measures $\{\phi_1, \phi_2, \phi_3\}$. We count the number of common elements between the sets obtained from the three proximity measures.

Table 7: Identical recommendation scores across measures, avec $k = 5$

	ϕ_1	ϕ_2	ϕ_3
ϕ_1	1		
ϕ_2	0	1	
ϕ_3	0	0.0685	1

We note that the Harvard measure on co-export analysis has no common recommendation with the other two methods. The method ϕ_2,which relies on semantic proximities in nomenclatures, obtains a score of 7%. We thus show that the macroeconomic methods fail to predict the diversification of firms. This is in contrast to our measure which obtains a score > 96% using a *recall@5* type metric.

5 MEASURING THE AGILITY OF A COMPANY

We propose to analyze the ability of companies to diversify their production rapidly by analyzing productive proximities. We are interested in the products that each company would be able to produce quickly by slightly adapting its production tool.

To do this, we will evaluate the productive opportunities for e, in the sense of the new product classes that e can produce. We define a threshold l of maximum proximity between two product classes below which a productive jump is possible. In our experiments we consider $l = 0.8$.

Let $L_e: (p_1, \cdots, p_n)$ be the list of the production of e and $(\lambda_1, \cdots, \lambda_n)$ their respective weights. Let L_{hs} be the total list of product classes of the HS 2017 nomenclature on 4 digits. Let $\phi(p_1, p_2)$ be our proximity measure between p_1 and p_2. We define P_i, the list of products close to p_i, as follows:

$$P_i: q_i \in L_{\text{hs}}, \phi(q_i, p_i) < l, q_i \neq p_i, p_i \in L_e$$

We then obtain the formulation of Agility:

$$\text{Agility}(e) = \sum_{i=0}^{n} \lambda_i max(1, |P_i|)$$

Thus, our function evaluates the diversification capacity of each of the products manufactured by e while considering their respective importance in the production of e.

6 CONCLUSION AND PERSPECTIVES

In this experiment, we presented a new method to propose diversification opportunities to a company. In cross-validation, our method obtained high *recall@5* scores, > 96%, outperforming the scores obtained with macro-economic methods. The measurement of proximities between product classes offers interesting perspectives in the automatic evaluation of a company's agility score, for which we have proposed a formalization.

However, macro-economic methods and our CF methods are not to be opposed. In the case of the analysis of co-exports, for example, there is an interest in identifying "new diversification paths", whereas our method will be satisfied with presenting existing diversifications. With the objective of developing a recommendation system for companies or territories, we could consider combining the different methods to provide a more varied recommendation. A system able to evaluate the relevance of the recommendations on a collaborative platform intended for companies, integrating serendipity in the results, could improve knowledge of the expectations of companies and thus contribute to enrich the models by integrating real user's ratings.

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