Multiobjective recommendation for sustainable production systems*

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We present a recommendation system to help rebuild sustainable production systems. Our multi-objective system synergizes the public and private actors of a territory. From know-how proximities in the Product Space, we suggest productive jumps for companies in a territory that consider the expectations of companies not only in terms of diversification but also in terms of the expectations of local authorities who are anxious to build sustainable production systems. We formalize a multi-stakeholder recommendation that is applied to the sustainability of a territorial economy and we propose the following new objectives to consider:

(i) Economic growth, based on the concept of territorial economic complexity;
(ii) Productive resilience, defined rigorously from the theory of dynamic systems;
(iii) Food security and more generally basic necessities from an original approach based on Maslow's hierarchy of needs;
(iv) The need to develop greener productions that respect the environment.

The recommendation system that we propose incorporates territorial policy as a weighting of objectives. This "configuration" acts directly on the system to influence the recommended productive jumps. Each objective is defined to be computed directly from open data available for most countries without requiring external data.

CCS Concepts: • **Applied computing → Supply chain management**; • **Information systems → Recommender systems**.

Additional Key Words and Phrases: Multi-Objective Recommender Systems, Supply-chain resilience, Sustainable production system

1 INTRODUCTION

The Covid 19 crisis has shown the fragility of our European production systems. Years of externalizations have damaged our productive capacity. However, a general awareness has emerged following the crisis, and the public and private sector are now ready to collaborate to rebuild a sustainable production system. Financial support programs have been deployed to help companies relocate their production or reinforce their existing activities.

At the same time, companies have understood the importance of securing their supplies through local production units. This offers new business opportunities to suppliers to develop their production towards new products to overcome shortages. To support this effort, we imagined a recommender system whose goal is to suggest the development of new products to companies to ensure their commercial development, while taking into account territorial policies.

We will start by presenting the area of recommendation. Then, after describing the previous work in relation to the field of industry, we will introduce the public and private stakeholders. We will then detail how our multi-objective recommendation system works and we will present a first experimentation on a French territory.

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2 PREVIOUS WORKS

Recommendation systems are very successful in many areas. There are two types of these systems: content-based and collaborative filtering[6, 7]. Several recommendation systems are derived from the two main types, and it is usual to combine them before generating the list of recommended objects[10].

2.1 Multi-objective recommendation

Traditionally, recommendation systems are oriented towards the end-user and seek to optimize a single cost function. However, recommendation methods can be multi-objective when they aim to optimize several objectives. For example, by integrating diversity and novelty in the proposed products[4, 46, 48, 55]. Other uses concern the consideration of price in recommended products[15, 30]. Recommendation systems that seek to improve the fairness of results are also multi-objective recommendation systems[11, 40, 56]. The difficulty is to take into account each objective without significantly degrading the accuracy on the main objective.

Several approaches to this problem exist. The first approach draws its foundations from multi-objective optimization and seeks to optimize all of the objectives at the same time. This approach is based on Pareto concepts and the associated algorithms are of the evolutionary type[13, 17, 35, 41, 55, 57].

The second approach considers multi-objectives as a hybridization of methods in which the combination of results can be done in cascade[31, 36]: an objective refines the result of a previous objective (re-ranking), or mixing[46]. The multi-objective recommendation is then considered as a weighted hybridization of mono-objective functions.

2.2 Multistakeholder recommendation

Multistakeholder recommendation systems[2, 3, 5, 12] are derived from multi-sided platforms[16, 47] and reciprocal recommendation systems. The latter require us to take each stakeholder into account independently because their strategies, and therefore their objectives, are different.

2.3 Recommendation in the field of industry

Pachot et al. [43] have developed a recommendation system to recommend collaborative synergies between companies in the same territory based on the semantic analysis of product nomenclatures to find the productive link that exists (for example) between seed, wheat, flour and bread. A distribution of products in a vector space allows us to make recommendations.

The recommendations can be similar to client-supplier or co-production relationships. To improve the industrial resilience of a territory, it is appropriate to develop distributed manufacturing by encouraging the companies of a territory to work with each other.

The recommendation system integrates an alternative operation when no potential supplier is present on a territory, which suggests that suppliers are able to make "productive jumps" to produce the required goods. These productive jumps are made possible by the productive relationship between the classes of products. This relies on the data of productive proximity from the Product Space[27].

The modeling of the companies' productions is based on a statistical analysis of the productions associated with their economic activity code. A first experiment was carried out on French companies.

We also find recommendation systems dedicated to the supply chain, specifically for distribution[14, 29] or to promote the use of waste in the context of industrial symbiosis[54].

Table 1. Stakeholders in the recommender system

Stakeholders	Strategies	Objectives	Function
Companies	Business strategy	Diversification	a_1
		Competitive advantage	a_2
Local authorities	Territorial policy	Economic growth	a_3
		Productive resilience	a_4
		Securing basic necessities	a_5
		Green production	a_6

To our knowledge, no study has aimed at the construction of a multi-objective recommendation system in the field of industrial production, and in particular with the aim of favoring the construction of sustainable production systems.

3 DESCRIPTION OF STAKEHOLDERS

3.1 Companies

Companies produce manufactured goods or raw materials. Their production units are located on a territory and carry out an economic activity. Firms collaborate with each other within a territory, or import goods or raw materials from other territories or countries.

Companies follow a commercial strategy that not only encourages them to develop their commercial portfolio by seeking new customers but also encourages them to diversify their production by favoring the production of goods that give them a better competitive advantage. At the same time, they seek to secure their supplies by diversifying their suppliers and giving preference to local suppliers. For several years, companies have also been encouraged to improve their social and environmental impact.

3.2 Local authorities

Building a sustainable ecosystem requires active collaboration between the private and public sectors. We would like to integrate local authorities into our recommendation system, which through their financial aid, taxation or thanks to their teams on the ground have a certain number of levers to help build such ecosystems.

The territorial policy that is associated with local authorities is defined by several objectives related to economic growth, food security, industrial resilience, and environmental aspects. We consider territorial policy as a "configuration" of the recommendation system in which local authorities indicate their priorities on each of the objectives.

4 FORMALIZATION

We design a recommendation system for the companies of a territory, whose object is the recommendation of new products to be developed. These production units have a know-how that offers them the possibility to make "productive jumps"; that is, to move from the production of one kind of product to another when the "proximity of know-how" between the two products is relatively strong.

There is naturally a propensity for companies to adapt their offer to seize new commercial opportunities, but we propose to set up a recommendation system that also takes into account territorial policy. As mentioned earlier, the territorial policy consists in weighing the different objectives of the referral system. The public authorities thus have the possibility of influencing the functioning of the system by choosing the objectives that are most important to them.

Let $\{a_1, a_2, \ldots, a_n\}$ be the list of algorithms associated with each objective. The territorial policy $\mathcal{P}$ on the territory τ is defined as follows:

$$\mathcal{P}(\tau) = \{w_{a_0}, w_{a_1}, \ldots, w_{a_n}\} \tag{1}$$

We start by listing the achievable production jumps for a production unit that correspond to the first objective for companies: diversifying their production. To do this, we first calculate the current production associated with each production unit. In this task, we rely on a correspondence table that makes the link between the economic activity code of the production unit and the associated production (product codes in the HS nomenclature).

We then directly use the Product Space developed by the Growth Lab of Harvard University[24] to identify the opportunities for productive jumps for each of the products that the production unit manufactures. The Product Space is a graph of products in which each node corresponds to a product class (from the HS classification) and the weighting of the edges corresponds to the proximity of know-how between two product classes. For a given production unit u, we obtain a list of new products $\mathcal{A} : \{x_0, x_1, \ldots, x_n\}$, which are ranked in descending order with respect to the level of productive relatedness. We choose an additional objective for companies that consists in increasing the competitive advantage and four objectives for territorial authorities that make sense with the development of sustainable systems[42]. They take into account economic aspects, resilience, security of basic goods and environment:

- Economic growth: we integrate the objective of developing the economic growth of the territory. This is a wealth creator, and is essential to ensure economic prosperity and job creation. To identify the products that are the most effective in creating economic growth, we will take into account their level of economic complexity, which is a measure that has been shown to be highly correlated.
- Productive resilience: we integrate an objective to improve the level of resilience of a territory. Given the fragility of our production systems, which have been damaged by various economic or health crises, we absolutely must build more robust production systems. We are going to integrate a theoretical measure of resilience of a territory.
- Securing basic necessities: we also want to give the possibility to favor the basic necessities (e.g., food and pharmaceuticals) over other products. To do so, we have followed an original approach inspired by Maslow's hierarchy to distinguish "vital" products.
- Green production: finally, we take into account the environmental dimension of production, aware of the importance of repositioning production systems towards the production of greener goods.

We present below the technical details of the measurement of each of these objectives. We perform a weighted hybridization[46] from the different objectives to re-rank the list $\mathcal{A}$.

For each production unit u we compute the scores $\{\hat{p}_{a_1}(x_i|u), \hat{p}_{a_2}(x_i|u), \ldots, \hat{p}_{a_n}(x_i|u)\}$ of each product $x_i \in \mathcal{A}$ for each algorithm $\{a_1, a_2, \ldots, a_n\}$. All scores must be normalized. Then we perform a weighted sum of each score to obtain a final score for each product:

$$\hat{p}(x_i|u) = \sum_{j=1}^{n} \hat{p}_{a_j}(x_i|u) \times w_{a_j} \tag{2}$$

4.1 Objective 1: Diversify production

Our system makes a recommendation of productive jumps, which are repositioning or industrial diversification opportunities for companies. As presented in Pachot et al. [43], the Product Space developed by Hausmann and Klinger [25] provides a model to make recommendations.

To make the correspondence between a production unit and the products it manufactures, we use a correspondence table[1]. The productive proximity between product classes is based on the study of country co-exports. From a large-scale analysis of the types of products exported by country, Hidalgo et al. [27] computed the proximity of productive know-how (called "productive kinship") between each type of product and construct a graph of the productive space.

The measurement of the productive proximity between each product is done by looking for the percentage of times that product p_1 is co-exported with product p_2:

$$\phi_{p_1,p_2} = min \left\{ \frac{\sum_c M_{cp_1} M_{cp_2}}{\sum_c M_{cp_1}} \middle| \frac{\sum_c M_{cp_1} M_{cp_2}}{\sum_c M_{cp2}} \right\} \tag{3}$$

We consider that a product p is exported by a country c when it grants the country a revealed competitive advantage (RCA) according to the formula of Balassa [8]. Let X_{cp} be the exports of product p by country c, then the revealed competitive advantage that country c has for product p can be expressed as a function of exports:

$$RCA_{cp} = \frac{X_{cp}}{\sum_c X_{cp}} / \frac{\sum_p X_{cp}}{\sum_{c,p} C_{cp}} \tag{4}$$

We consider that a country c exports a product p if RCA_{cp} is greater than 1.

$$M_{cp} = \begin{cases} 1 & si\ RCA_{cp} \geq 1; \\ 0 & else \end{cases} \tag{5}$$

From the data of productive kinship available in open data[53], we build a function $a_1(u)$ that for each production unit u will associate a list $\mathcal{A}$ of products and their associated scores of productive proximity.

4.2 Objective 2: Increase the competitive advantage

Now we need to consider the commercial interest for each firm. Some products are more advantageous for a production unit than others and we have the *RCA* formula to allow us to rank the productive opportunities according to the competitive advantage that they would grant to the production unit.

We define a modified version of *RCA* applied to the products of a sub-national territory. We compare the share of an activity in a territory with the share of that activity on a global scale. This prevents the more developed regions of a country from appearing to have a comparative advantage in each product[9, 45]:

$$RCA_{cp}^{local} = \frac{X_{cp}^{local} / X_c^{local}}{X_p^{world} / X^{world}} \tag{6}$$

We define a function $a_2(u, \tau)$, which for each production unit u of a territory τ will associate a list of products $\in \mathcal{A}$ and their associated score of RCA.

4.3 Objective 3: Improve economic performance

Several studies have confirmed the strong relationship between a country's economic complexity and its growth rate: regions specializing in the manufacture of more complex products experience faster economic growth[18, 27]. Therefore, we choose to use the economic complexity indicator (ECI) as a target to improve the growth of a territory.

[1]There are several correspondence tables according to the nomenclatures used for the classes of economic activities. For example, for the USA, ISIC-HS (https://unstats.un.org/unsd/classifications/Econ) or NAF-CPF, equivalent to NACE-CPA for Europe (https://www.insee.fr/fr/information/2399243). See Pachot et al. [43] for details

The calculation of economic complexity presented by Hausmann et al. [24] is based on two measures: productive diversity and ubiquity. Diversity illustrates the variety of different products exported by a country. Ubiquity is an indication of the number of countries that export the same product. Let M be a matrix of products exported by country, such that $M_{cp} = 1$ if country c exports product p:

$$\begin{aligned} Diversity: \quad & k_{c,0} = \textstyle\sum_p M_{cp} \\ Ubiquity: \quad & k_{p,0} = \textstyle\sum_c M_{cp} \end{aligned} \tag{7}$$

From the measures of diversity $k_{c,0}$ and ubiquity $k_{p,0}$, we can recursively define the variables $k_{c,N}$ and $k_{p,N}$ corresponding to the average ubiquity and diversity of products exported by a country c.

$$\begin{aligned} k_{c,N} &= \tfrac{1}{k_{c,0}} \textstyle\sum_p M_{cp} \,.\, k_{p,N-1} \\ k_{p,N} &= \tfrac{1}{k_{p,0}} \textstyle\sum_c M_{cp} \,.\, k_{c,N-1} \end{aligned} \tag{8}$$

We wish to express $k_{c,N}$ as a function of $k_{c,0}$. To do this, we replace $k_{p,N-1}$ by $\frac{1}{k_{p,0}} \sum_c M_{cp} \,.\, k_{c,N-2}$ and then simplify the equation:

$$\begin{aligned} k_{c,N} &= \tfrac{1}{k_{c,0}} \textstyle\sum_p M_{cp} \tfrac{1}{k_{p,0}} \textstyle\sum_{c'} M_{c'p} \,.\, k_{c',N-2} \\ &= \textstyle\sum_{c'} k_{c',N-2} \textstyle\sum_p \tfrac{M_{c'p}\, M_{cp}}{k_{c,0}\, k_{p,0}} \end{aligned} \tag{9}$$

We consider the matrix $\widetilde{M}_{c,c'}$ as a weighted (and normalized) diversification similarity matrix. This matrix reflects the extent to which the types of products exported from two countries are similar[38]:

$$\widetilde{M}_{c,c'} \equiv \sum_p \frac{M_{c'p}\, M_{cp}}{k_{c,0}\, k_{p,0}} \tag{10}$$

Let us rewrite the equation:

$$k_{c,N} = \sum_{c'} \widetilde{M}_{c,c'} \,.\, k_{c',N-2} \tag{11}$$

We note that $k_{c,N} = k_{c,N-2} = 1$ satisfies this equation when the eigenvector of $\widetilde{M}_{c,c'}$ is associated with the largest eigenvalue. Since this eigenvector is a vector composed only of 1, it does not contain any information. Therefore, it is better to look at the eigenvector that is associated with the second largest eigenvalue. This is the eigenvector that captures the most variance in the system and is therefore a relevant measure of economic complexity. We denote $\vec{K_i}$ as the i-th eigenvector of $\widetilde{M}_{c,c'}$, which is associated with the i-th eigenvalue of $\widetilde{M}_{c,c'}$, ordered in a decreasing order[22]:

$$\widetilde{M}_{c,c'} \,.\, \vec{K_2} = \lambda_2 \vec{K_2} \tag{12}$$

The economic complexity index ECI[26] is obtained by normalizing the eigenvector of $\widetilde{M}_{c,c'}$ associated with its second largest eigenvalue. $< \vec{K_2} >$ corresponds to the mean of $\vec{K_2}$ and $stdev(\vec{K_2})$ to its standard deviation.

$$ECI_c = \frac{\vec{K_2} - < \vec{K_2} >}{stdev(\vec{K_2})} \tag{13}$$

In the same way, the complexity of a product (PCI) is defined by the following formula, with $\vec{Q}$ the eigenvector of $\widetilde{M}_{p,p'}$ constructed on the same principle as $\widetilde{M}_{c,c'}$, but exchanging the c countries with the p products:

$$PCI_p = \frac{\vec{Q}_2 - <\vec{Q}_2>}{stdev(\vec{Q}_2)} \tag{14}$$

We now wish to calculate the economic complexity of a sub-national territory. We must use a modified version of the equation 13, which combines PCIs calculated using international trade data with local data:

$$ECI_c^{local} = \frac{1}{M_c}\sum_p M_{cp}^{local} PCI_p \tag{15}$$

Where M_{cp}^{local} is calculated in the same way as equation 5 but using RCA_{cp}^{local} instead of RCA_{cp}:

$$M_{cp}^{local} = \begin{cases} 1 & si\ RCA_{cp}^{local} \geq 1; \\ 0 & else \end{cases} \tag{16}$$

A pre-calculated table with the complexities associated with each Harmonized System (HS) product class is available in open data[2]. We choose to retain the values for the latest available year (i.e., 2019).

We define a function $a_3(u)$, which for each production unit u will associate a list of products $\in \mathcal{A}$ and their associated score of PCI ranked in decreasing order.

4.4 Objective 4: Improve the resilience of the production system

Resilience is defined as the ability to recover quickly after a disruptive shock. For a production system, this corresponds to the ability of a system to quickly recover its production level or a higher level.

To measure the resilience indicator of a territorial production system, we start from an approach derived from the theory of dynamic systems[49–51]. In particular, the studies of Kharrazi [32], Kharrazi et al. [33, 34] focus on the definition of a theoretical resilience indicator built from the analysis of imports, while the exports of a territory are of particular interest to us. The theoretical resilience of a dynamic system is proposed based on two measures: efficiency and redundancy. Kharrazi et al. [34] have conducted a study on the behavior of the production systems of countries between 1996 and 2012, including the economic crisis of 2009, confirming the relevance of the theoretical indicator of resilience. The measure of a territory's efficiency (also called ascendancy) can be considered as the degree of articulation or constraint of flows in a production system[34]. The more specialized a system is, the more optimized its connections are, the more efficient it is, and the less resilient it is. The theoretical measure of efficiency is as follows:

$$Efficiency = \sum_{i,j} \frac{T_{ij}}{T_{..}} \log \frac{T_{ij}T_{..}}{T_{i.}T_{.j}} \tag{17}$$

Where T_{ij} is a product export value from country i to country j, $T_{i.} = \sum_j T_{ij}$ is the total exports leaving country i, $T_{.j} = \sum_i T_{ij}$ is the total imports entering country j and $T_{..} = \sum_{ij} T_{ij}$ is the sum of all exports in the system [21].

Conversely, a redundant system has many connections, and will therefore be "more flexible in re-rooting its flows and maintaining critical functions"[32]. Redundancy can be defined as the "degree of freedom or overhead of flows in a network"[32]. It is measured from the conditional entropy:

$$Redundancy = -\sum_{i,j} \frac{T_{ij}}{T_{..}} \log \frac{T_{ij}^2}{T_{i.}T_{.j}} \tag{18}$$

[2] https://atlas.cid.harvard.edu/rankings/product

From the efficiency and redundancy measures of a system, we can then measure the theoretical resilience level:

$$\begin{aligned}\alpha &= \mathit{Efficiency}/(\mathit{Efficiency} + \mathit{Redundancy}) \\ \mathit{Resilience} &= -\alpha \log(\alpha)\end{aligned} \tag{19}$$

We seek to recommend new products to be developed to companies in a territory that can help to improve the resilience score. We compute the contribution of a each product x to the resilience. We define a function $a_4(u)$ which for each production unit u will associate a list of products $\in \mathcal{A}$ and their associated score of their contribution to the resilience of the territory.

4.5 Objective 5: Secure the production of essential goods

We consider that products can be ordered according to their contribution to the needs of individuals. To do so, we propose an approach based on the hierarchy of needs of Maslow [37].

Genkova [20] provides a table of correspondence between the categories of needs of Maslow's pyramid and the categories of products in the CPC nomenclature. All of the indirect products that are necessary for the production of the goods of each category are also associated.

We weight each product inversely to its corresponding level in Maslow's pyramid and we obtain a function $a_5(u)$, which for each production unit u will associate a list of products $\in \mathcal{A}$ and their associated score of their contribution to the needs.

4.6 Objective 6: Promote the production of environmental products

We want the recommendation system to take the environmental impact of products into account. As a priority, we propose the productive jumps towards products with a lower environmental impact. Several studies have been carried out to integrate this dimension into the Product Space [19, 23, 28, 39, 44].

Initiatives exist to list green products[1, 19]. We retain the list provided by APEC[3], which is defined as products "that directly and positively contribute to green growth and sustainable development objectives".

Let $\mathcal{G}$ be the list of green products, we define a function $a_5(u)$, which for each production unit u will associate a list of products $x \in \mathcal{A}$ and an associated score s such that if $x \in \mathcal{G}$ then $s = 1$ else $s = 0$.

5 EXPERIMENTATION

We tested the recommender system using open data on French companies: production units, import and export amounts by French department and by product class. We made available the pre-calculated rankings associated with each objective, as well as a first experimentation on a French department[4].

5.1 Datasets

We relied on the SIRENE[5] dataset that is available history of French production units since 1973. It provides information for every company, relating them to their connected production unit, their NACE economic sector, their workforce group, and their postal address. We choose the HS nomenclature limited to 4 digits as the reference nomenclature for

[3] APEC List of Environmental Goods: https://www.apec.org/meeting-papers/leaders-declarations/2012/2012_aelm/2012_aelm_annexc.aspx
[4] https://github.com/apachot/Multiobjective-recommendation-for-sustainable-production-systems
[5] https://www.sirene.fr/sirene/public/static/acces-donnees

Table 2. Example of recommendations for a production unit located in Haute-Loire in France (NACE activity code 29.32: Manufacture of other parts and accessories for motor vehicles).

Code	Description	Score	a_1	a_2	a_3	a_4	a_5	a_6
HS8406	Turbines; steam and other vapour turbines	3.76	0.61	0.001	0.74	0.41	1	1
HQ8514	Industrial or laboratory electric furnaces and ovens (including those functioning by induction or dielectric loss); other industrial or laboratory equipment for the heat treatment of materials by induction or dielectric loss	3.71	0.67	3.7e-06	0.89	0.16	1	1
HS8503	Electric motors and generators; parts suitable for use solely or principally with the machines of heading no. 8501 or 8502	3.69	0.68	1.37e-05	0.70	0.31	1	1
HS8419	Machinery, plant (not domestic), or laboratory equipment; electrically heated or not, (excluding items in 85.14) for the treatment of materials by a process involving change of temperature; including instantaneous or non electric storage water heaters	3.67	0.72	0.00024	0.78	0.17	1	1
HS8417	Furnaces and ovens; industrial or laboratory, including incinerators, non-electric	3.54	0.58	1.8e-05	0.74	0.21	1	1

the products. By resorting to a combination of correspondence tables between activities and products (NACE → CPA→ HS)[6], we associate each NACE class with HS classes.

We use datasets from global trade[52], as well as local datasets from each French department[7]. These datasets provide us for a given territory or country, the amount of exports of each product class, for each country or french department. We use the year 2019 and convert the French data (French CPF nomenclature) into the HS nomenclature.

5.2 Recommender System

We retrieve the list of production units on a territory. From their activity code, our system is able to determine which product classes are manufactured by this production unit. We then use a proximity table between the product classes to determine which products are the closest in the sense of know-how. These products represent the potential production jumps.

At each productive jump we compute a global score from the weighted average of 6 pre-computed rankings, associated to the 6 objectives of our recommendation system. We then propose a list of 5 classes of products whose productive jump has obtained the highest score. You will find in table 2 an example of recommendation for a production unit located in Haute-Loire in France, that manufactures parts and accessories for motor vehicles.

6 CONCLUSION

The expectations of the different actors in a territory often come up against the complexity of the production systems. Stakeholders whose strategies are sometimes opposed can find a solution in a recommendation system that takes their

[6]We parse the NAF to CPF correspondence document (https://www.insee.fr/fr/statistiques/fichier/2399243/Nomenclatures_NAF_et_CPF_Reedition_2020.pdf) to obtain a NACE 2 to CPF 2.1 CSV file. NACE is obtained from NAF code by removing the last letter. CPF and CPA are identical in version 2.1. Matching between CPA 2.1 and HS 2017 is done using the CPA 2.1 to NC 2017 correspondence table (https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_REL) because HS code equivalent to the sixth first digits of the related NC code.
[7]https://www.data.gouv.fr/fr/datasets/statistiques-regionales-et-departementales-du-commerce-exterieur/

objectives into account. We explored the fields of recommendation, information theory and economics to find objectives that can be integrated, and we formalized a first version of a multi-objective recommendation system. We will continue our work by validating the system on a territory. We also consider a Pareto-efficient hybridization to guide the local authorities in setting the weights of the system.

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