Brand Content Optimization: A Major Challenge for Sellers on Marketplaces

Richardson Ciguene*, Bertrand Marron, and Nicolas Habert

***Abstract*—Today, more and more consumers are purchasing their products and services online. At the same time, the penetration rate of very small and medium-sized businesses on marketplaces continues to increase, which has the direct impact of intensifying competition between sellers, thus, only the best-optimized deals are ranked well by algorithms and are visible to consumers. However, it is almost impossible to know all the Brand Content rules and criteria established by marketplaces, which is essential to optimizing their product sheets, especially since these rules change constantly. In this paper, we propose to detail this question of Brand Content optimization by taking into account the case of Amazon, in order to capture the scientific dimension behind such a subject. In a second step, we will present the genesis of our research project, DEEPERFECT, which aims to set up original methods and effective tools, in order to help sellers, present on marketplaces, in the optimization of their branded content.**

***Index Terms*—E-commerce, scoring, marketplace, Amazon, Brand content, product sheets**

I. Contextualization

A. Introduction

According to Banque Publique d'Investissement of France (Bpifrance Creation, 2019; The Documentation Center Economy Finance, 2020), around 250,000 companies were created in the 4th quarter of 2020, making a total number of 850,000 companies created during the year 2020. During this same period, marketplaces experienced a historic penetration rate by sellers, about +80%, because, whether in the sale of products or services, more than a trend, it is an obligation for small and medium-sized enterprises to have an effective presence on the internet. However, Web Retailer (2022) and Kunst (2020) have shown that these companies are not always satisfied with their online performance, and technically, this is highly correlated with poor quality of their branded content on these platforms.

Indeed, a very small percentage of product sheets respects the marketplace optimization requirements. This concerns the choice of category, descriptive textual content of the products, photos of the products, etc. Thus, all these products are penalized by the ranking and recommendation algorithms, which constitutes a considerable loss of turnover on each of them. So, it is more than obvious that these sellers today need intelligent methods and tools, capable of guiding them on a daily basis in optimizing their offer, in order to stand out from the competition.

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B. The Existing and Its Limits

In the e-commerce market, certain tools to help optimize product sheets exist and they are mainly of two types. The first type are functionalities already integrated into marketplace platforms which offer sellers performance indices on their product sheets. These features have some weak points such as: weak scientific basis, which means that certain indices are not precise enough, or even completely decorrelated from reality; variation in requirements from one marketplace to another, so the work becomes tedious for a seller who is positioned on several marketplaces at the same time; variation in requirements from one product category to another, which requires special attention to each product and for each marketplace; simplicity of recommendations for improvement, to say that the seller is rarely entitled to clearly defined suggestions;

The second type of existing support tools are mainly product sheet scoring solutions that are developed by specific agencies (e.g., Seller App Help & Knowledge-Base). The main weaknesses of such tools are: not deep enough analyzes and not precise enough optimization recommendations; the rules, criteria, and algorithms of marketplaces vary so often that it becomes impossible for them to stay up to date in their methods of analysis; the tendency to develop this kind of tools only for internal use in agencies, therefore no direct opening to sellers; generally mono-platform (e.g., Amazon at a time).

From a scientific research point of view, there are a number of works that are close to this subject. They are mainly presented around the subject of analysis and scoring of customer opinions like Zhang and Balaji (2006); Sohail and Jamshed *et al.* (2014). These works mainly focus on user sentiment analysis (Zhao and Bing *et al.*, 2010; Feldman, 2013), but do not necessarily go in the direction of optimizing Brand Content. Overall, let's remember that there are already a lot of methods and tools to help analyze marketplace offer sheets in order to optimize them. However, the subject remains quite complex, because it is mainly impossible to know all the optimization rules imposed by the marketplaces (Goettsche Partners, 2011; Cdiscount Marketplace Powered by OCTOPIA; Tasset, 2019). Moreover, even if we managed to detect them all, it would be painful to follow them daily, because they vary constantly and are quite different from one platform to another. For all these reasons, there are hardly any fairly reliable and cross-platform audit tools like the DEEPERFECT project offers.

Another limitation found in almost all existing tools is the inefficiency of measuring certain criteria, as this would require the use of certain artificial intelligence approaches. For example, it would take image analysis (Wu and Li, 2015) to detect whether the size of the object (product) in the main

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photo occupies a certain dimension as required by Amazon, or whether its background is a specific color as required by Cdiscount and Fnac Darty.

In the rest of this paper, we will present the DEEPERFECT project in detail as well as the results of the first experiments which were carried out mainly on Amazon product sheets. At the end of the article, we present our main perspectives for the medium and long term.

II. Genesis of These Works

A. Presentation of the Overall Project

The main objective of the DEEPERFECT project is to develop innovative methodologies and approaches for audits, scoring and automatic recommendations, in order to better support marketplace sellers in improving their Brand Content (specifically their product sheets). These methods are based on the most advanced requirements of the ranking algorithms of these marketplaces (Ex: How to rank your products for Amazon A10 algorithm) and will make use of certain artificial intelligence techniques (Pallathadka and Ramirez-Asis *et al.*, 2021) to audit the contents of the sheets with precision. We aim to be able to offer personalized optimization recommendations for the brand content of each existing offer on the marketplaces.

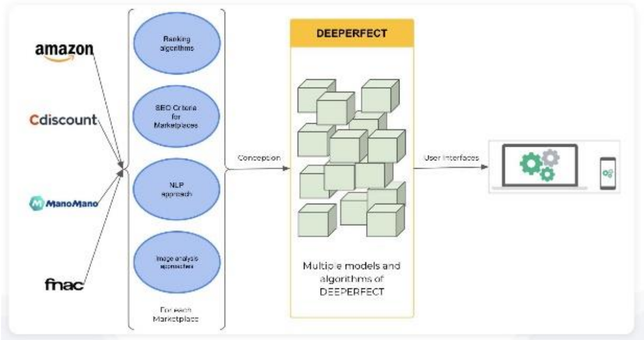

Fig. 1. Summary figure of the project.

As shown in Fig. 1, the first phase of the project wants to take into account four of the main marketplaces including Amazon, CDiscount, ManoMano and Fnac Darty. In addition to the popularity of these marketplaces, they were chosen because we will more easily have the data necessary for the project thanks to certain partnerships already established. Thus, for each of these platforms, we rely on their ranking algorithms, their natural referencing criteria, some natural language processing techniques (Chowdhury, 2003) and image analysis (Fomalont, 1999), to help optimize branded content. Indeed, thanks to these information, we will set up a set of scoring and AI models, to allow us to effectively audit the contents of any product sheet, and to provide automatic optimization recommendations to sellers. From a more application point of view, Fig. 2 shows the usage scenario of DEEPERFECT functionality and its practical advantages.

Technically, one of the main difficulties is the implementation of the necessary process allowing to capture the changes in the rules and criteria of optimization of the sheets, because these vary continuously. Also, from a research point of view, another obstacle will be the intelligent use of artificial intelligence approaches adapted, or even re-adapted to the extent of a few criteria. Admittedly, AI is more than necessary in such a subject, but it is generally quite resource-intensive methods. This is even more the case in this project where certain criteria require the use of very specific approaches such as image processing to analyze the photos or even clustering to study the relevance of the category where the product is listed. In addition, since we are targeting several marketplaces, it is necessary to see if the AI models will be generic to them or if specific models will have to be developed. Trivially, we already know that there is a question of compromise because a generic model should be inefficient but less expensive, unlike specific models which would have to be more efficient and more expensive.

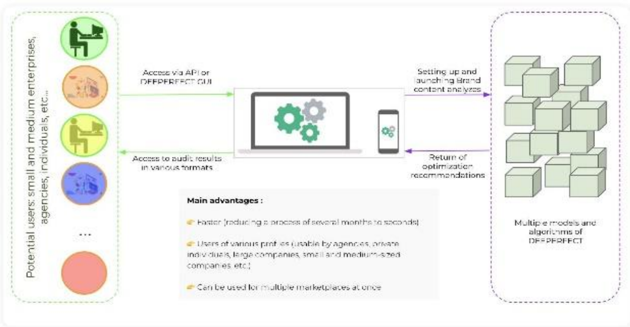

Fig. 2. Scenario of use of DEEPERFECT functionality and its practical advantages.

B. First Approach Formalization

We start from the fact that the qualification of a product page on a marketplace can only be done based on a set of well-defined criteria. So, we have started with evaluating a product sheet, by basing ourselves on a set of criteria which revolve mainly around the photos of the product, its title, its description and its rating. For the moment, a total of 23 criteria are identified, although for the moment, we will only take into account 13 criteria. These criteria are chosen by Bizon marketplace experts and are common to the majority of marketplaces, even if the focus is currently on Amazon.

In terms of scoring, various methods exist in the literature and the objective was to find and draw inspiration from one of these methods or adapt it as best as possible to our context. When we talk about adaptation, we mean answering the question: what is the best way to merge the weights and values of our criteria to obtain a fairly representative overall score? Is a sum sufficient? …a multiplication? …a weighted average? …or go to mathematically more advanced scoring functions such as the surface of area units under the curve represented by a reference function?

For this first work we have empirically chosen to start with the calculation of a reference function (reference score) which we prefer to keep secret, if not to say that this function is a sensible combination of the values and weights of the criteria. However, the final score that is assigned to the analyzed product sheet is a calculation of the integral of the reference function over a defined interval, for the moment, empirically. Thus, thanks to this way of doing things, the reference function will be able to evolve over time to better adapt to our constraints without this greatly influencing our way of calculating the final score.

More formally, in some places in the paper, we will use the symbol c to designate a criterion (for example, the notation n

$l = [c_0, c_1, \ldots, c_{21}, c_{22}]$ means a list of 23 criteria). Based on the recommendations of our experts, we were able to allocate a weight s_i to each criterion c_i. Once the weights of the criteria are determined, as we said earlier, we calculate the value of the reference function with the s_i, the result represents our reference score, $f(x)$. For illustration, if the reference function were the sum of the weights of the criteria, it would be represented as follows:

$$f(x) = \sum_1^e \quad (s_i)$$

where e corresponds to the quantity of criteria taken into account.

For the moment, our $f(x)$ is a discrete function which can only take a value on the interval [1,100]. That is to say, a product sheet which is 100% bad on all the criteria will have a score $f(x) = 1$ and conversely, if it is 100% excellent on all the criteria, it will have an $f(x) = 100$. We will understand later in this section why the minimum value is fixed at 1, but not at 0. Below is a graphical representation of the gradation of $f(x)$.

Fig. 3. Gradation of $f(x)$.

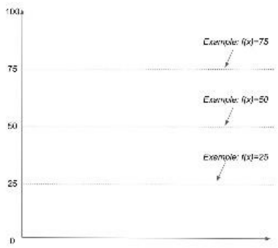

Fig. 4. Examples of straight lines of $f(x)$.

As specified in Fig. 3 and Fig. 4, the value of $f(x)$ in no way represents the final score of the form. To better respond to our context, we thought of creating a metric based around integration calculations (about the same type as the Narkhede, 2018 score). To explain it formally, if we plot the line/curve represented by our function $f(x)$, being a continuous function on the interval $[m, n]$ (a fictitious minimum bound m, and a fictitious maximal bound n), our final score is: "the area in units of area which is located between our straight line of $f(x)$, the abscissa axis and the two straight lines with equation $x = m$ and $x = n$". Thus, the formula for calculating this surface is therefore the integral of $f(x)$ over the continuous interval m and n.

$$Final\ Score = \int_m^n \quad f(x)dx$$

$$or\ more\ simply \int_m^n \quad adx \text{ (for: } f(x) = a,\ min = m \text{ and } max = n)$$

The benefit is that if for some reason the shape of $f(x)$ should change/evolve, such as going from a polynomial function to an exponential function, it doesn't impact how the score is calculated final because it will suffice to calculate its antiderivative to have its integral over the interval $[m, n]$ (Lacroix, 1797).

III. Experimentation, Results and Validation

Once the criteria analysis methods had been defined and validated by a team of three marketplace experts, we set up our first experimentation protocol.

A. Experiment Protocol

We chose to conduct this wave of experimentation only with data from Amazon and took into account only 13 criteria among the 23 that were defined by the experts. The objective is to rotate the values and weights of the criteria in order to find the results that allow the observation of results as close as possible to reality. Note that here the expression "close to reality" perfectly retains its subjective meaning because there are currently no rules identifying a product sheet as being perfect.

Thus, we scrapped a dataset, consisting of 192 Amazon product sheets, from the MyHomeBoutique store in Bizon. This sample makes it possible to have a mix of good and bad quality sheets but also, has made it possible to remain generic in the sense that these results can be valued for the three other marketplaces. For each sheet, a process is set up to extract the necessary information and score it by referring to the weightings predefined by the experts. For example, we scored: image rules (quantity and quality); the existence of a video in the file; the character quantity of the title; the presence of the brand name in the title; the amount of bullet points in the description; the amount of characters per bullet point; if the bullet points start with a capital letter; the amount of characters in the description; the existence of an A+ page; the existence of a range table; linking the shop with the product sheet; the product rating and reviews. Once a score is assigned to each criterion, we determine the overall weight ($f(x)$).

For each sheet analyzed, for each criterion, our process returned three results that correspond to: its score; its color code (if for the criterion in question the product is in the red, orange or green zone); and a personalized remark/suggestion by for the status of the criterion in question. Here is an illustration in the code snippet below in Fig. 5 for the product rating criteria.

```
# 12 -------- Note du produit
def note_produit(notation_moyenne):
    if (notation_moyenne) <= 3.1:
        return 2, "rouge", "Saviez-vous qu'une fiche de produit noté à moins de 3.1 étoiles n'est pas bien vue par Ama
    elif (notation_moyenne > 3.1) and (notation_moyenne <= 3.5):
        return 5, "orange", "Votre produit à une note de plus de 3.1. Cela n'est pas suffisant par rapport aux exigenc
    elif (notation_moyenne > 3.5) and (notation_moyenne <= 3.8):
        return 7, "orange", "Votre produit à une note de plus de 3.5. C'est déjà assez bien, mais loin d'être suffisan
    elif (notation_moyenne > 3.8) and (notation_moyenne <= 4.8):
        return 9, "vert", "Votre produit à une note de plus de 3.8. C'est très bien par rapport aux exigences d'Amazon
    elif (notation_moyenne) > 4.8:
        return 10, "vert", "Bravo, votre produit est très bien noté par rapport aux exigences d'Amazon. Faites votre r
```

Fig. 5. Code snippet that shows an example of the three returned values (french).

To determine the final score, we empirically assigned values to the bounds m = 2 and n = 10. Then, as simulated in the table in Section I.-B., we expect the worst record ($f(x)$= 1) receives a score of 8/1000 and conversely, the best receives a score of 800/1000.

B. Results

Once the criteria are scored, the reference function and the global score are calculated for 192 products. To illustrate the results, we have extracted two examples of analyzed files (among the set of 192 files) from the experiment log that we show below.

Overall, the results seem very relevant. By visiting the links of the analyzed product sheets and comparing each score to that of the others, we can see that there is a kind of scoring fairness. Thus, just the 13 criteria used at the moment and our measurement approach already allow us to have a fairly relevant scoring tool. Fig. 6 is an example of an analysis result for a product (noting that the contents of this product page must have evolved since these experiments).

Fig. 6. Example of product sheet analyzed: https://www.amazon.fr/dp/B07HH55PJD. Score: 446/1000

Notes and Suggestions

- ➔ Strong points
  - ◆ *Congratulations, your product sheet has more than four images. This quantity is perfect compared to Amazon's requirements.*
  - ◆ *Bravo, you had thought of adding the name of your brand in the title of your product sheet. This is one of the key criteria for a product sheet to be well optimized.*
  - ◆ *Congratulations, your product description contains the amount of bullet points recommended by Amazon. This will play a positive role in optimizing your product sheet.*
  - ◆ *Well done, your product is highly rated against Amazon's requirements. Do your best to keep this rating at this level.*
- ➔ Average points
  - ◆ *Your product title is slightly too short compared to the average. It contains less than ninety-nine characters. A well-crafted title of normal size greatly optimizes the product sheet.*
  - ◆ *Your bullet points have on average 50 to 85 characters. This amount of characters is quite little compared to what Amazon recommends.*
  - ◆ *Your product sheet contains a description, that's good, but not enough, because it is made of less than a thousand characters. It would be nice to table greatly optimizes your product sheet? We would advise you to work on this aspect.*
  - ◆ *We would advise you to link your shop to the product sheet. This can significantly optimize your product page. give your description a little more detail.*
  - ◆ *Your listing already has some customer reviews. That's good enough, but you need even more for it to have an even more positive impact on the quality of your listing.*
- ➔ Weak points
  - ◆ *Did you know that it is possible to add a video to your product sheet. This could significantly increase the quality of your product listing.*
  - ◆ *Did you know that Amazon recommends starting bullet points with capital letters? This would increase the optimization of your product listing.*
  - ◆ *Did you know you can create an A+ page for your product? This would greatly optimize your listing.*
  - ◆ *Did you know that the presence of a range table greatly optimizes your product sheet? We would advise you to work on this aspect. We would advise you to link your shop to the product sheet. This can significantly optimize your product page.*

C. Validation, Deployment and Initial Findings

Once the experimental phase was over, and the results validated by our experts (those who had defined the criteria and their values), our team of developers proceeded with the creation of an API used to retrieve information from product sheets and then process and analyze them. Thus, data such as title, description, images, bullet points, etc., are scrapped each time, to be analyzed by our method. This API is now used in various services of the agency, in particular: in the free audit tool which is accessible to everyone from our site; in our monthly reporting tools to provide more transparency to our customers; by our account managers and salespeople to analyze product catalogs simultaneously for their customers.

After six months of use, we have consolidated the traces of use of the tool to make an initial analysis of the market in terms of Brand Content. It shows that overall, the average score for all the analyzes is 549. In 45% of the cases, the sheets had a score lower than 500 and in 75% of the cases, the sheets had a score lower than 700. The maximum and minimum scores reached are respectively 936 and 55. Below we present the Top five countries compared to the average scores in Table I. The USA comes first and France is in fifth place. The worst average score observed is that of the United Arab Emirates which is 281.

TABLE I: TOP FIVE COUNTRIES IN TERMS OF BRAND CONTENT ON AMAZON

Top 1	697	USA
Top 2	609	Germany
Top 3	600	UK
Top 4	582	Italie
Top 5	548	France

Since 89% of products come from the France marketplace, here we zoom in on the main statistics for France. Knowing that the average score is 548, only 25% of the analyzes had a score higher than 700 and the maximum score obtained was 936. Also, this dataset concerned 1895 unique categories, and Table II is the Top ten of the average scores for these categories.

TABLE II: TOP TEN AMAZON CATEGORIES IN TERMS OF BRAND CONTENT

Top 1	834	*Auto and Motorcycle / Oils and liquids / Greases and lubricants /*
Top 2	799	*Beauty and Fragrance / Skin care / Face /*
Top 3	789	*Office supplies / Small supplies / Boards and presentation accessories / Magnetic boards /*
Top 4	785	*Office supplies / School supplies / School supplies / Lunch boxes and water bottles / Water bottles /*
Top 5	784	*Auto and Motorcycle / Oils and liquids / Oils / Car engine oils /*
Top 6	768	*Office supplies / Writing / Pens and refills / Fountain pens /*
Top 7	768	*Hygiene and Health / Vitamins, minerals and supplements / Herbal supplements / Spirulina /*
Top 8	760	*Watches / Men / Wristwatches /*
Top 9	747	*Auto and Motorcycle / Oils and liquids / Oils / Motorcycle engine oils /*

Note when in this first step of the Top ten, a parent category such as "Office supplies" comes up three times. This could be explained by the fact that the three product groups belong to the same brand.

IV. Conclusion, Insights and Talks

In this paper we have addressed the issue of Brand Content on Marketplaces, which is a main lever for sellers. We understood that despite everything, it is not necessarily easy to manage because the rules are multiple and vary constantly, not to mention the fact that they are often different from one market place to another. In this sense, we presented our DEEPERFECT project, which aims to help sellers by creating innovative tools and methods for optimizing Brand Content. A method for analyzing the content of Amazon products has been developed and tested on a set of products, and the resulting tool is currently open for use by the general public and Bizon experts.

For now, this tool has some limitations. For example, we are currently only analyzing a dozen criteria, whereas Amazon's optimization rules are of the order of a few dozen. Moreover, certain criteria such as the relevance of the card in relation to the category where it is listed or the detection of the white background in the main image require processes based on artificial intelligence, which we do not take into account. account at the moment.

As a result, an analysis of the first traces of use of the scoring tool allowed us to have an overall idea of its use and the state of brand content on Amazon's marketplaces. However, there are certain subtleties to remember, such as the fact that the majority of the data comes from internal use. Because, remember that every month we generate reports for our customers, which involves a complete analysis of their catalogs monthly. It also happens that our consulting service needs to analyze entire catalogs during certain market studies. Although the tool is accessible to the general public from the Bizon site, this source does not constitute more than 5% of the overall dataset used for this work.

In short, even if these results provide new information, even knowledge, it is important to put things into perspective because for the moment, they are mainly data from customers that we support. Of course, in a while, we will have consolidated enough data to be able to bring out a more faithful and precise reflection of the real market.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

R. Ciguene and N. Habert conducted the research; R. Ciguene and B. Marron analyzed the data; R. Ciguene wrote the paper; all authors had approved the final version.

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