

# DYNAMIC SEGMENTATION IN THE TRAVEL INDUSTRY

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## PREFACE

Even if consumers know what they want, they are often unable to select the product option that promises the highest expected utility, simply because their individual product conceptualization is incompatible with the product-centred "language" the provider is employing. One consequence of this confusion is a cautious buying behaviour most prominent in industries such as tourism, financial services or telecommunications. This paper presents a conceptual framework and a pragmatic implementation of an online matching algorithm based on an efficient self-correcting customer profiling technique that is empirically superior to many other approaches. The essence of the algorithm is that matching *per se* does not rely on a complex and industry-specific matching equation, but builds on a rather simple feedback loop of customer profile, selected offer and resulting satisfaction that can be easily transferred to many other industries where the product variety and/or complexity goes beyond the customer's cognitive capacity. In those cases, the customers are often unable to correlate the formal product features that are advertised by the provider with his individual needs that shall be satisfied with the offer.

## BASICS AND OBJECTIVES OF CUSTOMER SEGMENTATION

Segmenting customers involves identifying homogeneous groups from the totality of (potential) customers and treating them in accordance with their needs and customer value. The general objective is to more profitably address and take care of customers over the long term, for example by reducing the time and money expended on marketing, sales or service as

well as losses due to non-selective advertising.

In order to do this, segmentations must fulfill two key prerequisites: firstly, they must identify variables that define to what segment a specific customer belongs to (= "classification"). Secondly, these segments must have practical implications regarding what specific kind of marketing mix is most attractive to a certain customer segment (= "translation").

Customers can be segmented in along a wide variety of dimensions (for instance, customer value, sociodemographics, psychographics, or geography). There is no "correct" segmentation solution. In practice, however, the various solutions definitely differ in terms of how useful they are. The easier the classification variables can be measured and the clearer the practical implications that can be derived from the fact that a certain customer belongs to a specific segment, the better the segmentation. In fact, the key empirical basis of meaningful segmentation solutions is that there has to be a reliable link between the classification (independent variable) and the measures to be deduced from it (dependent variable), since purely circular segmentations ("We'll best reach customers who listen to the radio a lot (=classification) via radio advertising (=translation into measures)") are just as meaningless as non-differentiating measures ("Customers in every segment read the same newspapers – so we'll reach every segment equally well by using an advert in a specific newspaper").

## CLASSIC SEGMENTATION PROCEDURES AND THEIR LIMITATIONS

On the basis of customer data that is gathered ad hoc and/or already available within the company data

warehouse, segmentation solutions are developed via a sequence of multivariate analyses that build on one another and are to some extent carried out iteratively, and they are optimized to meet the above-mentioned criteria.

Naturally there are some inherent statistical issues, such as the just-mentioned simultaneous optimization of two independent criteria (unambiguous classification and segment specific translation), for which there is yet no seamless standard procedure. Besides that, there are some additional difficulties that are just as typical, but unlike the optimization problem, they can be avoided:

1. *Process validity*: segmentations are normally developed on the basis of data sets containing historical data about customers and their buying behavior. These data sets are frequently supplemented with primary surveys concerning needs, buying motivation or other psychographic characteristics. The data set that emerges from that combination is then evaluated ahistorically, i.e. the needs and reasons for buying as collected through the supplementing primary surveys are interpreted as the basis of the buying behavior that has already been previously recorded within the company's data warehouse. Because the chronological context of consumer behavior is illustrated and analysed in reverse order, it is impossible to use this as a basis for conclusions about cause and effect.

2. *Inflexible classification*: concomitant with ignorance of the actual process sequence, classic approaches to segmentation are also static inasmuch as if the classification variables once assigned customers to a specific segment, they finally belong to this segment "forever". Any alteration to the allocation, for example as a result of changing life circumstances or needs, is tied to a fresh gathering of data or new classification, and this only rarely happens in reality. The changes the customer undergoes thus often remain of no significance in terms of segment allocation, or only have an effect after a considerable time delay.

3. *Inflexible translation*: it is not only the classification of a customer as belonging to a segment that is static and based on historical data; the translation of segment membership into concrete measures that can be deduced from this is also inflexible. For example, it is impossible to take account of systematic changes in product preferences – which are particularly important in very complex or rapidly changing markets. Once a customer has been assigned to a specific segment, they are inflexibly associated with certain products or services they used to prefer in the past.

Hence, classic segmentations are usually not learning systems. They refer to the past, and possess only minor flexibility with regard to classification and translation of segments into concrete measures. The following case study of a dynamic matching and segmentation algorithm is intended to demonstrate that this does not necessarily have to be so.

In this case study, the inherent flexibility of the dynamic and needs-based segmentation allows it to be deployed in a hitherto most unusual context, namely as the basis for a travel search engine that matches customer need profiles with specific offers. The special thing about it is that segmentation on the basis of a specific need profile neither rests on historical data or stable segment allocations, nor is the translation of segment membership in order to recommend a specific offer static; instead, it is based upon a learning feedback loop involving need segment, offer profile, and the satisfaction resulting from matching both.

#### CASE STUDY ON VALUE ADDED MATCHING AND DYNAMIC SEGMENTATION: HOW L'TUR ARRIVED AT M.O.P.S.

##### Objective

Travel is a product that is highly charged in terms of people's emotions. For many of them, their vacation is the highlight of the year, and for a long while they look forward to it with mounting excitement. At the same time, it is utterly impossible from a customer's perspective to gain an overview of the vast variety of

available offers. They range from a purely sun, sea and sand vacation through to city trips with an educational slant, and from a wellness weekend through to crossing the Alps by bike.

In contrast to the emotionality and individuality of this topic stands the dismal reality of "searching and booking" – this discrepancy becomes particularly evident among Internet-based travel agencies: here, you have to pass a formal search engine to get to your ideal vacation. The search engine is the key "gatekeeper" to all the thousands of wonderful offers that lie behind it.

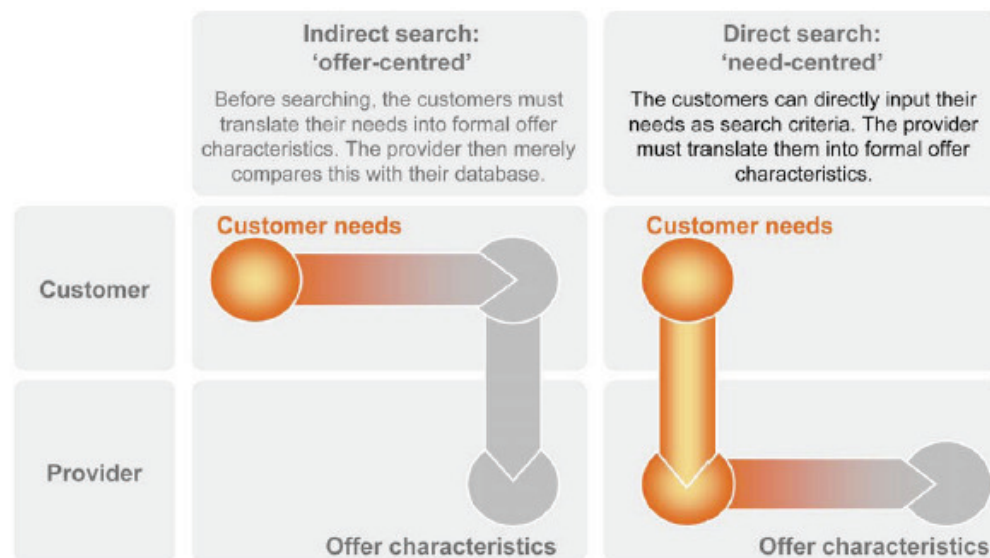
From the customer's perspective, every search engine in the tourism industry has hitherto been based upon an indirect allocation of demand and offer. "Indirect" in the sense that the customer first has to translate their needs into concrete and somewhat formal offer

characteristics (e.g. destination, hotel, departure airport, date or length of trip) so as to use this as a basis for starting the search. Using these criteria, the travel provider then searches through their database of offers (see figure 1). This thus entails a circular segmentation as defined in the first section, because classification and product criteria are identical – a translation from segment to measures does not take place.

The indirect search may well make it easier for the provider to find a match, because there is no need to translate customer needs into offer characteristics; however, from the customer's perspective, this type of search is not very intuitive, because ultimately the customer is not buying offer characteristics, but first and foremost the satisfaction of their needs – whichever characteristics are necessary for this. Moreover, these

**FIGURE 1**  
THE INDIRECT SEARCH IS OFFER-CENTERED, WHILE THE DIRECT SEARCH IS NEED-CENTERED

**Need-oriented offer descriptions reduce uncertainty and make the search easier – the provider 'caters for' the customer**





formal criteria are frequently not yet set in stone, because the customer often wants to be inspired first, and get to know something new. It is not of primary importance here to adhere to a specific flight departure date, but to find the offer that is best tailored to individual needs.

A directly need or motive-oriented search would thus be far likelier to correspond to the customer's search logic. The search criteria should be precisely these needs and motives. Translating the needs into product characteristics would then no longer be the job of the customer, but of the provider. They can use the quality with which they fulfill this task to differentiate themselves within the competitive environment.

This initial consideration also helped to clearly define the project's strategic objective: LTUR, the largest last minute travel agency in Europe, wanted to be the first provider to offer its customers an alternative search and matching engine that works on the basis of a segmentation of personal needs and motives. This search engine should already turn the initial steps a customer takes into an experience, it should inspire and emotionalize. It should function within its own system of concepts and segments that forges long-term ties between customers and LTUR, even on the Internet – where competitors are just a click away.

#### Modular Procedure

The "Motive-Oriented Personal Search" (abbreviated to "M.O.P.S.") was developed within the framework of a market research project with a total of three stages that build upon one another. Both primary as well as secondary studies were carried out, their respective findings directly influencing the refinement of the search and matching algorithm – and this refinement process is still ongoing today.

##### *1<sup>st</sup> stage: Matching via ranking of motives*

The objective of matching customers to offers on the basis of personal vacation-related motives rendered it necessary as a first step to make a provisional categorization of precisely these motives. Studies that were already available internally as well as a multiplicity of

published research works made it possible to develop a range of reliable motive categories through secondary research (e.g. "simply relaxing", "getting to know the country and its people", "making use of a wellness offer", "doing sport", "making contacts" or "experiencing culture"). This was used as the basis for the development of a questionnaire that was able to gather data about how pronounced these motives were.

The questionnaire was divided into two parts (see figure 2): in the first half, customers were able to use "sliding scales" to give direct expression to their individual motive profile for the forthcoming vacation, as well as stating which life phase they were in (e.g. "single", "young family", etc.). In the secondary analyses and beyond, both the motive clusters used as well as the life phases proved to be extremely stable differentiation factors, and this is why the two questions formed the basis for the first matching algorithm.

The second part of the questionnaire used agreement scales, visual material and supplementary questions to record even more detailed information about needs and motives. This additional data was not used for the current matching process, but formed the empirical basis for the customer segmentation in Stage 2.

The second necessary prerequisite for a successful matching process is of course that not only the customers should characterize themselves, but that our offers should also be described in the same terms. To this end, the LTUR sourcing department characterized each offer in terms of how well the individual motives are satisfied there, and for which life phase the location or hotel is suitable.

The search algorithm in stage 1 then resulted in filtering out offers that on the one hand had the same motive ranking as the customer, and on the other hand were suitable for their individual life phase. Each offer was additionally provided with an index that stated how well the search profile fitted the offer.

During the first developmental stage, we continuously evaluated satisfaction with the search result and, if need

FIGURE 2  
SCREENPRINT OF QUESTIONNAIRE

The search questionnaire records the segmentation dimensions, plus additional aspects that served to refine the segments

1a) Motive profile (sliding scale)  
1b) Life phase (simple choice)

2) Data gathering as basis for segmentation in Phase 2

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be, reasons for breaking off the search. The huge success we thereby achieved among our customers is also reflected in the following key performance indicators:

- **Inspiration:** over 91% used M.O.P.S. as an opportunity to be inspired ( $n=254$ );
- **Satisfaction:** over 94% of users were already satisfied or very satisfied with M.O.P.S. in the first developmental stage ( $n=254$ );
- **Search results:** over 95% were of the opinion that M.O.P.S. delivers results that are more appropriate to the individual than the classic search ( $n=254$ );
- **Booking behavior:** the conversion rate from searching to booking was more than double that associated with the classic search ( $n>150,000$ );

- **Sales:** the average revenue per customer was 27% higher compared to the bookings through the classical search engine ( $n>15,000$ ).

These results, together with the enormous media response, led to LTUR beginning to successively install M.O.P.S. terminals in over 150 stores throughout Europe. Searching via M.O.P.S. shortens the waiting time there, and helps our customers to gain an initial impression of suitable offers, even before their personal advice session.

#### 2<sup>nd</sup> stage: Matching via motive segments

With each search process, the M.O.P.S. search engine aggregated information about the specific needs of LTUR customers. It was thus possible within the

course of a few months to gather way over  $n > 25,612$  fully completed search questionnaires, both online and offline. They were the basis of a hierarchical multivariate motive segmentation; we used factor analyses to check methodological assumptions, hierarchical cluster and cluster-centre analyses in an iterative segmentation process, and finally discrimination analyses to validate the segment solutions. From this emerged five main motive clusters with a total of 12 motive segments (see figure 3). Because of the large number of respondents, it was possible to reliably differentiate a relatively large number of segments.

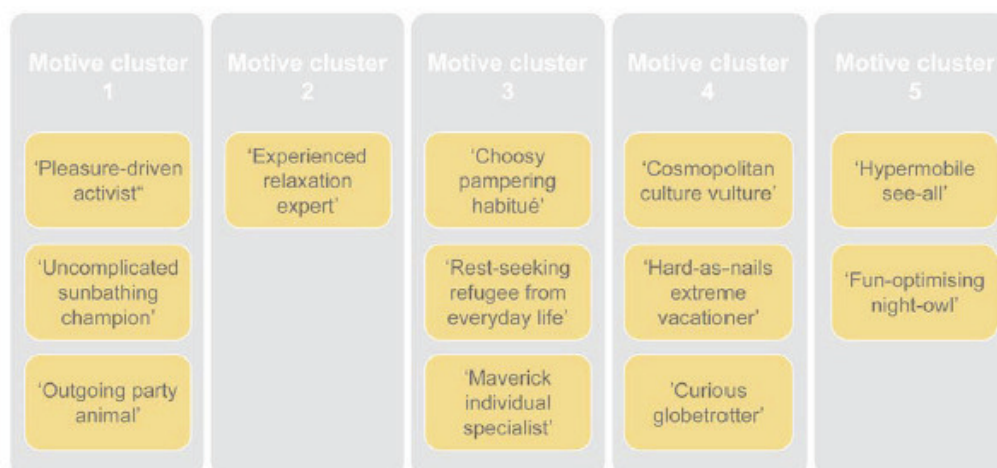
The motive segments formed the basis for the matching algorithm in the second stage: customers and offers were now no longer allocated to one another in a purely logical manner, resting upon matching motive rankings, but based upon empirically founded motive segments: on

the basis of their responses, users were assigned to one of the twelve segments. The offers, which had already been rated internally in the first phase using identical motive categories and life phases, were now likewise allocated to a segment, using analogous segmentation rules. The matching algorithm thus delivered as a result those travel offers allocated to the segment to which the searching customer also belonged. The search algorithm was further supplemented with some additional filter options that facilitated an even more accurate search (e.g. price range).

Motive segmentation as the foundation for the matching algorithm immediately had three positive consequences: firstly, it was now possible to work with far fewer (12 instead of 144), but more appropriate segments, because their number was now determined empirically, and no longer a result of combining motive rankings and

**FIGURE 3**  
12 MOTIVE SEGMENTS AS ONE RESULT OF STAGE 2

**On the basis of  $n > 25,000$  respondents, it was possible to statistically differentiate 12 distinct segments**





life phases (number of possible motive rankings (4!) multiplied by the number of life phases (6);  $4! \times 6 = 144$  logical segments in stage 1). It was thus secondly possible to also increase the number of suitable search results per segment. Moreover, it was thirdly possible to shorten the search questionnaire by 35%, because questions that were statistically redundant and/or irrelevant to the segmentation were cut. With the conclusion of the second phase, it was thus possible to implement an algorithm that represented a significant improvement in quantitative as well as qualitative respects.

*3<sup>rd</sup> stage: Matching via motive satisfaction*

Parallel to the second phase, an ongoing satisfaction survey was already being implemented, via which every LTUR customer is surveyed following their return from vacation ("welcome back survey").

The linking of the motive profile from the M.O.P.S. search with the actual booked offer and people's satisfaction with this offer forms the basis of the matching algorithm for the third and last generation (see figure 4).

In two steps, the customers and offer are matched in the algorithm in stage 3: in the first step, the customer is allocated to a segment, still using the questionnaire from Stage 2. However, they subsequently do not get the offers that LTUR has classified as belonging to this segment, but instead in the second step they receive the offers with which customers sharing the identical motive profile were de facto most satisfied – this is formally done via a simple selection routine (i.e. "select the offer with the highest conditional overall satisfaction index given the customers belonging to the same segment as the searching customer").

FIGURE 4  
DEVELOPMENT OF STAGE 3

**Segment-specific and/or offer-specific satisfaction data has been gathered continuously since the implementation of the second phase**

**Stage 3: Feedback loop involving segment, offer, and satisfaction**



- a. **Data gathering:** everyone who books travel via M.O.P.S. is asked about their level of satisfaction after returning from holiday.
- b. **Refinement of the matching algorithm (=translation):** based on the segmentation data and the segmentation data of many travellers, the search result now received by each new traveller who completes the search questionnaire (and thus assigns themselves to a segment) consists of proposed **trips that most satisfied other travellers with the same need profile**.
  - The translation of the need profile into offer characteristics is now no longer the responsibility of the provider, but depends upon the totality of customers with a corresponding profile and concrete experiences of the offer – to this extent, this matching algorithm is based upon condensed peer recommendations.

Each customer thus deliberately benefits from the collective experiences of all the customers in their segment. As a provider, LTUR actually does nothing further in the future than define the segments and make the satisfaction data implicitly available to all its customers in the form of this self-learning matching algorithm. With the conclusion of this last phase, LTUR is thus the first provider to have installed a segment-specific recommendation system that also constantly refines and updates itself via the constant dataflow of the ongoing satisfaction survey and its automated evaluation. This is not merely hitherto unique in the tourism industry, but also goes far beyond the otherwise customary and very successfully deployed recommendation systems one is familiar with from, for example, amazon.com, where we can see what other customers also bought – but we do not know whether they liked it; or where we see how a book is rated but we do not know whether our

expectations are matching the ones of the evaluating reviewer.

Looking back, M.O.P.S. was developed in three stages in which the above mentioned two prerequisites of customer segmentations – the classification of individuals and the translation into measures – were alternatingly evolved (see figure 5).

### CONCLUSION AND BASIC NOTION

Apart from the immense strategic added value that the dynamic matching brings to LTUR in relation to customer advice, optimization of direct marketing, making adjustments in the hotel buying department, and the establishment of community functionalities, etc., this case study makes clear that it is possible to dynamize segmentations and thereby create differentiating added value for customers and companies (see figure 6).

FIGURE 5  
THREE STAGES OF M.O.P.S.

**M.O.P.S., the Motive-Oriented Personal Search was constantly refined in three development stages that built upon one another**

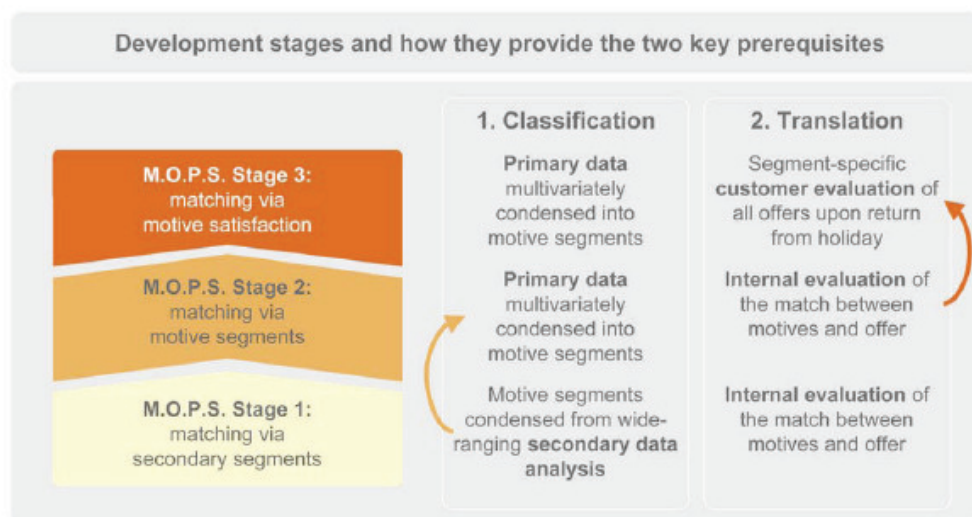
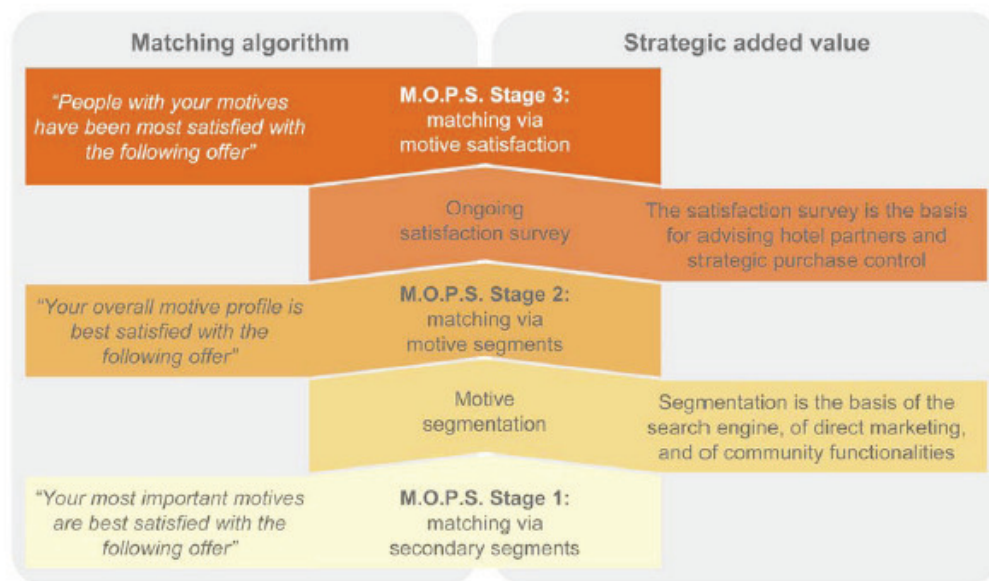




FIGURE 6  
M.O.P.S. AND ITS STRATEGIC ADDED VALUE

Understanding the links between need, offer, and satisfaction guarantees L'TUR numerous competitive advantages



The feedback process and combination of customer segmentation, customer choice and satisfaction research within the framework of a learning system fully exploit the benefits of customer segmentation, without entailing the typical disadvantages that go hand in hand with classic approaches to segmentation:

- *Up-to-dateness and dynamism*: the segmentation is neither based on historical data or stable segment assignments, nor is the translation of segment membership (so as to recommend a travel offer) static. Instead it is based upon a learning feedback loop involving need segment, offer profile, and segment-specific and offer-specific satisfaction.
- *Cause and effect*: given the segment-specific customer evaluation of all the offers, the segment-description

itself does not any longer carry any crucial information. The implications of belonging to a specific customer segment are no longer derived from the static segment description but from the dynamically combined information of segment, selected offer and resulting satisfaction. The segment becomes the mere 'label' whose meaning only develops through this dynamic link that illustrates the connection between cause (segment and selected offer) and effect (resulting satisfaction). The problem of "translating needs into offers", the key problem of classic approaches to segmentation, is thus elegantly sidestepped because the segments no longer have to be "interpreted"; instead, this interpretation is 'left to' the feedback loop, and hence to the intelligence of the collective customer experience – in that respect, M.O.P.S. is genuine "Web 2.0" feature.

- *Validity and relevance:* the direct link with actual purchase behaviour continually validates the dynamic segmentation.

Besides that, the underlying idea of a dynamic matching and segmentation is not restricted to the travel industry. It can generally be implemented in all industries where the product range or profile is too complex to be easily overseen by the customers (e.g. IT: "which laptop is most appropriate to my needs?"; financial services: "what portfolio fits my individual purpose?"). Here, the approach of motive-oriented direct matching serves the inherent customer need to easily select between potential options. The basic notion is that it is not the customer that should learn to understand the companies offering but the company has to learn the customer's language and understand their product conceptualisation.

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