Four Challenges for IML Designers: Lessons of an Interactive Customer Segmentation Prototype in a Global Manufacturing Company

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ABSTRACT

Interactive Machine Learning (IML) apps permeate all aspects of businesses, including sales. Customer segmentation is integral for sales, to identify customer groups to serve them appropriately. However, the novelty of such apps in a sales context raises the question: what challenges designers of such apps will face, in a sales context? To explore this question, we report our reflections on an IML study for customer clustering. We used data from a global manufacturing company to cluster customers using the Recency, Frequency, and Monetary (RFM) method. We applied a machine learning clustering model (K-Means) and discussed with seven seasoned sales managers the interaction with clusters. We report four challenges and foresee that designers of such systems will face, in the context of sales operations.

CCS CONCEPTS

• **Human-centered computing → Visualization application domains**; *Interaction design process and methods.*

KEYWORDS

Contextualization, Analytics, Customer Segmentation

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1 INTRODUCTION

Sales are at the heartbeat of every business. No matter whether a small to medium sized enterprise or a conglomerate, sales operations are arguably the most important ones for a company to survive and thrive. Likewise, understanding customers is paramount for sales operations. If performed expediently, customer segmentation enables companies to group customers, understand customers' needs, and subsequently increase customer retention and focus on operations and eventually revenues. Sales employees, responsible to deal with such a task, make decisions based on their experience, intuition, and nowadays descriptive statistics usually in the form of analytics (e.g., Tableau [24] or SAP's BOA [21] reports).

In the last decade, the advance of Data Science and Machine Learning (ML) is offering novel opportunities for a sales department, to tame subjective biases and offer novel insights. Although there is no ideal customer segmentation [7], a commonly used framework in sales is Recency, Frequency, and Monetary (RFM) analysis [13]. RFM segments customers into different groups based on their behavior. Recency and Frequency deal with a customer's last order and the number of orders, respectively. Monetary stands for the profit, of a certain customer. Such segmentation techniques can assist companies to tailor marketing and sales activities at strategic, tactical, and operational levels to optimize customer retention and relationship management [20].

Interactive Machine Learning (IML) is a domain of ML that involves the training of models by involving humans in the learning process [8]. Humans do not necessarily have to be knowledgeable about how learning models work but must be experts in the domain field to provide feedback to the learning system. We present an RFM segmentation using IML to support decision-making in the sales operations of a global manufacturing company of sustainable materials. We leverage sales data and calculate the RFM values on the customer base. Subsequently, we apply the unsupervised learning clustering model K-Means [22] to group customers on their RFM values.

We conducted seven in-depth interviews with seasoned sales managers, each with decades of experience. It is essential to gather feedback from people who have an in-depth understanding of sales and provide concrete experiences about how things are done rather than mere comparisons [5]. Based on the interview transcripts, we conducted a thematic analysis and present four challenges IML designers need to consider in the context of sales operations. Two unique aspects of our study include 1) an IML app based on a realistic dataset of thousands of customers of a global manufacturing company, and 2) in-depth interviews with a hard-to-get cohort: sales managers with decades of experience in sales operations.

2 RELATED WORK

Data mining and machine learning models positively impact the performance of customer segmentation [16, 19]. However, most

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cases lack interactivity, and feedback from expert users, inhibiting ML models and the validity of results. Involving expert users in an interactive machine-learning environment encourages analytical reasoning for experts to label clusters. A study [9] shows ML models integrated with visual analytics can help users to make sense of large datasets, validate results, and gather actionable insights. Interactive learning with feedback helps designers to understand flaws in models, build effective solutions, and enhance the model's explainability to end users.

Customer segmentation for identifying valuable customers has been well-established in academia and industry. Segmentation in Business-to-Business (B2B) settings is an understudied area in industrial and academic studies [4]. The segmentation for customers in B2B settings is more formalized and complex than in B2C contexts. Understandably so, contextual settings for a B2B environment are diverse, and recruiting participants from the industry in B2B settings is hard. Only a handful of studies have empirically tested the segmentation in a B2B context [4]. The RFM segmentation is quite diverse, and it can be applied with variations, by for example adding variables such as product type, time, or loyalty [16]. For instance, a modified RFM model using the product perspective is presented in [12] for a granular segmentation. Contextualizing customers to their product groups or distribution channels increases the predictive power of models with personalized filtering. The study shows a bifurcated version of RFM applied to product groups separately before aggregating the results. Still, it lacks interactive learning and external validity for clustering.

It is crucial to measure the impact of ML-enabled tools to support companies' needs for customer segmentation. A study [3], although carried out in a B2C environment, shows how machine learning can support eliminating classification errors and increasing accuracy. An integral factor in segmentation is to identify the right number of clusters for customer groups. Clustering methods, e.g., K-Means, provide flexibility to group customers into predefined clusters. Validation and quality of the clusters are also essential and various methods to internally validate the results of clustering algorithms using K-Means are described in [10]. Choosing the optimal number of clusters is also studied in [6] with different clustering algorithms and their compactness score. Likewise, a case study [23] in the B2B settings shows a two-stage cluster analysis of B2B customers based on their characteristics. Internal validity methods help to find an optimal number of clusters. However, studies lack the involvement of end users (business experts) for segmentation and validation purposes. Literature does demonstrate the RFM applicability towards customer segmentation, but most cases have B2C context and lack validity in real scenarios [18, 19].

Based on the existing research, it is evident that the use of the learning algorithms with the RFM analysis improves the quality of segmentation. However, to what extent the ML-enabled apps affect B2B segmentation involving external user validation and conclude meaningful labels is unclear. Overall, ML-based segmentation has been studied but, it lacks real-world B2B scenarios. Also, we find IML has limited applications for sales activities for B2B global companies. This provides an opportunity to lay the foundation to understand sales employees' perspective with the IML, contextualized cluster labeling, and personalization of clustering parameters to make sales teams more effective.

3 METHOD

3.1 Process & Participants

We interviewed, over MS Teams, seven highly experienced sales managers, with decades of experience in sales, management, and customer service. We recruited participants from our funding organization and industry partner, a global manufacturing company with sales operations in more than 150 countries. Our participants (Table 1) covered a customer base of more than 50 countries across three continents (North and South America, and Europe). Participants were given consent forms with extensive data usage, storage, and privacy information. Prior to the interview, we emailed a brief questionnaire to gather their preconceptions about customer segmentation and RFM in specific. Before formally starting the interview, we asked for the participant's consent to record the interview and use it for our note-taking. In the interview session, participants were given a brief description of our prototype and how to use it. We asked participants to provide feedback on the prototype and its: 1) relation to their daily work contexts; and 2) impact on strategic and tactical decision-making. We concluded the interviews with a post-study questionnaire asking participants to provide their feedback on the prototype they experienced. Interviews lasted almost an hour (average: 53 minutes, SD: 23 mins). Three examples of questions we asked are:

- Are the cluster labels relatable?
- Given such a segmentation, what are some of the actions you would take?
- What is the ideal number of clusters for your context?

We used MS Teams' automatic transcription and, wherever necessary, we listened carefully back to the recording to correct the transcription. We used open coding of participant interviews and performed a qualitative analysis using Affinity Diagramming [15] and performed a Thematic Analysis [2]. By examining the transcripts, we identified the relevant codes and used the Miro [17] visual whiteboard for completing the analysis. Once we concluded the coding phase, we further refined our thematic analysis using patterns in individual constructs to categorize and group issues (e.g., prototype explanations, for instance, respective codes were high-level observations, rather than concrete explanations). This was also complemented by reviewing the coded extracts by cross-analyzing the interview transcripts. The cross-analysis helped to focus and identify themes that are consistent across the participants. This is also critical to spot the differences between participants. The process ascertained whether any additional codes had been missed during the coding stage. Once we were confident that our thematic analysis is rigorous and addressed our context, we substantiated higher-level themes and concluded our analysis process.

3.2 Prototype: CustomerRadar

We developed CustomerRadar, an IML prototype using RFM segmentation to support decision-making in sales. This interactive app allows users without knowledge of ML models to visualize customer segments. The prototype provides each user with a personalized dashboard to reflect on segment interpretations. We use K-Means as an initial clustering model to segment the customers into groups based on calculated Euclidean distance on recency, frequency, and

Table 1: Participants' demographics

ID	Function	Region	Years of Experience	Expertise
P1	Major Market Account Manager	North America	15+	NA
P2	Sales Manager	Europe	30+	Tableau, BOA
P3	Sales Manager - paper and packaging solutions	Europe	10+	Salesforce
P4	Head of Sales - dye sublimation	Europe	20+	Salesforce
P5	Head of Sales - the packaging	Europe	10+	Salesforce
P6	VP Sales	North America	30+	NA
P7	Director of Global Marketing	North America	15+	NA

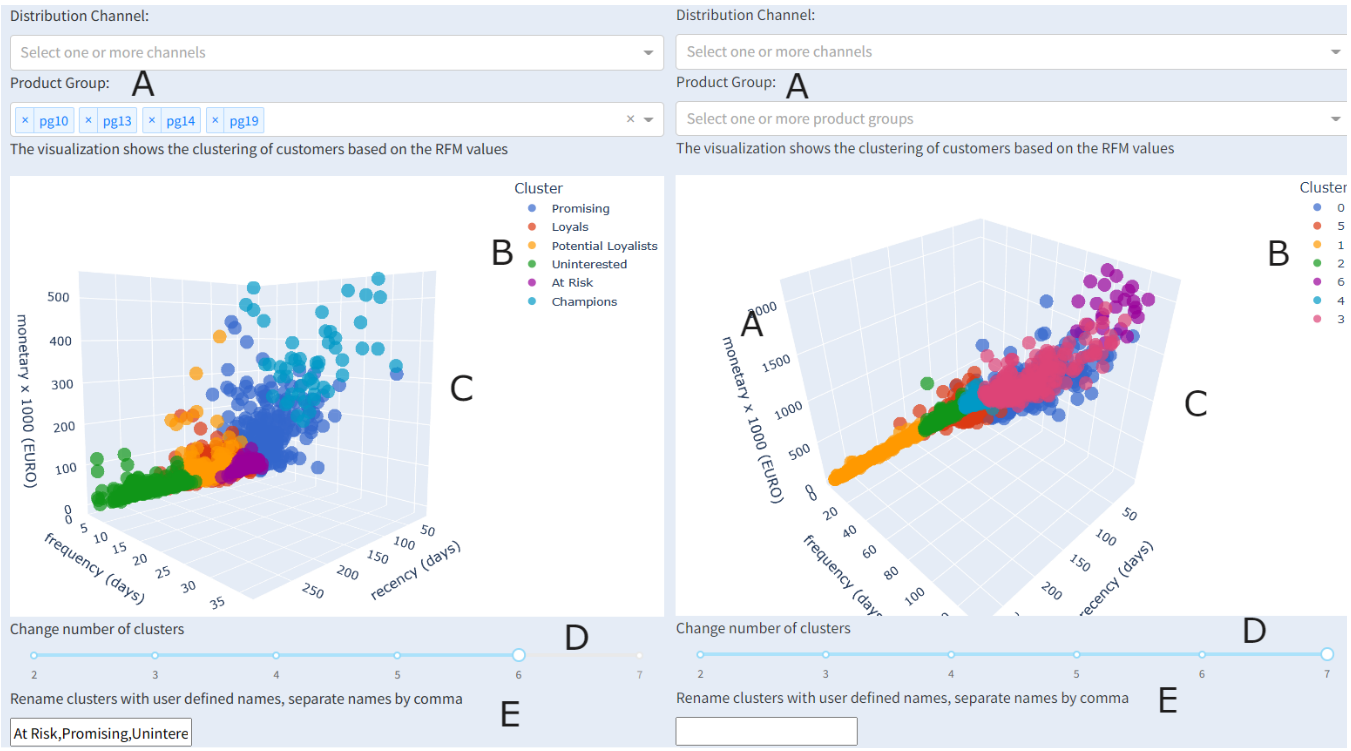

Figure 1: Interactive cluster (left: six, right: seven) analysis. Users can: (A) Filter distribution channels and product groups. (B) Filter clusters for selective/granular analysis. (C) Visualize and interact with clusters visually. (D) Change the number of clusters (range:2-7) for a contextualization of the customer groups. (E) Re-label the clusters. For confidentiality, the visualization is based on fictional data.

monetary values. The K-Means separates the data into a defined number of clusters maintaining a high intra-class similarity. It iteratively calculates the K-centroids and moves data into different clusters based on the distance from those centroids. We provide visual interaction to users to vary the number of clusters, filter customers, and semantically label them, as described in Figure 1 (A-E). It is possible to filter customers on market segments or product groups. It is possible to observe a customer in an interactive segmentation by tweaking the parameters and using historical data. We start with six clusters by default and allow control to the user to modify clusters to observe how the customers and cluster settings change visually. The change of labels for customer groups by sales experts contextualizes the customer groups intuitively and supports interactive learning. Users visually interact with learning models and experience analytics on real data and provide feedback for the improvement of segmentation models. This leverages IML capabilities to alter the decision-making process of sales. For instance, sales experts can cross-check their subjective impression of which customers are the most valuable. In a sales context, it is important to know which customers are most valuable to express gratitude to and check whether one offers the best-in-class service.

4 FINDINGS: FOUR CHALLENGES FOR IML DESIGNERS (IN SALES OF A GLOBAL B2B COMPANY)

We identify four core challenges for designers of Interactive Machine Learning (IML) systems, in the context of the sales operations of a global B2B company based on our study. We posit that these four challenges would apply to the sales operations of other similar companies. We illustrate these four challenges in our participants' own words.

4.1 Challenge 1: Think of Meaningful Customers' Cluster Labels, from the Onset

We quickly realized, from pilots with two sales managers, that labeling the clusters with meaningful labels was important. That is because sales already had a preconceived knowledge of dividing their customers into different groups based on their experience and intuition. Therefore, providing users with labels they can associate with, from the very first time they interact with the prototype, creates a link to their cognitive model. Hence, we first labeled the default screen, which presents six clusters, but then had to find meaningful labels for the other cluster settings. In the case of six clusters, the labels were: "Champions", "Loyals", "Promising", "At Risk, "Potential Loyals", and "Uninterested". The labels were chosen based on the RFM average values of each cluster. For example, the "Champions" cluster includes customers with high FM and low R. Whereas, the "Promising" cluster includes customers with low R, who have bought more than once, and not the lowest M. Based on those six clusters we then accordingly labeled the five, four, three and two clusters. For example, for the two clusters, we decided on the labels: "Strategic" and "Transactional". These labels were initially chosen by us but were discussed and confirmed with our participants.

The automated cluster labels were much appreciated and triggered a conversation about current customer segmentation in the company. Participants emphasized the importance of contextual labeling which eventually would help them to make strategic decisions. For instance, P2 said *"But I like how you have used the labels ... That'll help drive some strategic decisions"*. P1 praised the segmentation, *"It has good data, that would help to better understand the market(s)"*. P5 stresses the value of labels, *"We could use this to identify strategies which customers are best to follow"*.

Designers must take into account that when the number of clusters changes, the labels of clusters need to dynamically change. This dynamic aspect makes it challenging to personalize cluster labels to match users' cognitive models. Therefore, it is essential to provide users an option to re-label initial labels, to match their internal vocabulary. As P6 highlighted, *"The **Promising** might be a **Prospect** and the **Potential Loyalists** might be **Targets**"*. Moreover, different sales teams might need different labels as P1 questioned, *"I couldn't quite see what made them look promising. So, I want to have better definitions"*. Hence, such IML systems need to allow different participants (or teams) to have their definitions of cluster labels and change labels as they wish. The differences between the definitions could be justified if they are visible and annotated with explanations for the choice of labels, in the IML system itself.

4.2 Challenge 2: Provide Users Validation Mechanisms

The second important challenge for IML designers we identify is to provide users the ability to check and validate instances in clusters. For example, why would a sales manager think of a customer as *Strategic*? This implies the explainability of dividing criteria for the under-the-hood learning model. It is crucial for the success of an IML model in segmentation tasks to have both internal and user validity. By internal validation, we refer to the quality of the clusters while user validation is referred to as providing a rationale behind the clustering choice. There is a challenge to define a clearer rationale behind a clustering choice. From a holistic perspective, a criterion or threshold is needed to rationale customers from a certain cluster as P6 argued, *"I'm assuming, behind this, there's a metric that says you are **Transactional**"*. The validity measure was also important among other participants as P5 pointed out *"I think the tool of categorizing where that customer pool lies is important"*. User validation also includes the cross-validation between the sales colleagues (experts), for instance, P2 called for discussion on differences: *"So it should open up the discussion at least"*. In another instance of cross-validation, P4 summarized the differences of interpretation to classify a customer at risk by *"Not straightforward to cluster as **At Risk**"*.

The IML must be adaptive enough to cater to the internal and user validity measures. The validation also applies at the semantic level (or external validation), for example, having most of the positive indicators does not guarantee an overall correct placement of data points in the cluster. For instance, in the case of customer segmentation having high values of recency and frequency does demonstrate a strong link to the company, but does that make a customer strategic? One must include other factors such as serving costs associated with a very frequently returning customer. We tackle the problem of internal validity by providing users to choose between various clustering methods and understand and compare their internal validity based on cluster quality measures. For that reason, our prototype provides several features to control the personalization of clusters. Users can redefine a contextual cluster and reflect upon that.

4.3 Challenge 3: List Actionable Insights

We find that in the context of sales operations, an essential component of IML models is to go beyond clustering and provide some actionable insights. For example, we find that clustering a bunch of customers is not enough; listing top customers within a cluster is necessary. For instance, P1 alluded to shortlisting customers in case of a full order book: *"I don't have enough tons; I have to decide which of those 10 customers looks the best"*. Furthermore, identifying customers to cross-sell products that they are currently not buying but might be interested in, is another actionable insight like P6 pointed, *"Product mix is we want to pursue harder ... to be more of the loyalist as opposed to the promising"*. P1 also advocated *"I understand you bought our product. Help me with other products we have that you can buy"*. With our prototype users could filter customers based on product and market, which can then provide actionable insights to them. This way they can follow up with customers for further investigation and lead to a successful business as P5 mentioned *"we could use this to identify strategies of which customers are best to follow"*. The ability to interact with cluster visualizations engaged the users to zoom in on the clusters where they need really to focus. This is more feasible when combined with the comparison between different markets and different product groups.

4.4 Challenge 4: Offer Flexibility in Clustering Parameters

IML needs to incorporate variations in company standards for segmentation. For instance, in the sales context, various parameters such as contribution per ton, contribution across products, costs to serve, and business diversity are important considerations. This is a deeper challenge as it seems as if different companies may have their standards and IML must effectively adapt to those. For our study, participants express the need to have diverse comparison measures for the customer's contribution. For instance, a precise measure could be the contribution per product or units sold e.g., P6 mentioned *"Present the C1 per ton rather than the total. I think that would be helpful"*. In a B2B environment, companies have a diverse customer base. Therefore, handling such scenarios is essential for effective segmentation. For instance, P5 highlighted one difference between customers: *"We split between the volume business and margin business"*. Likewise, P2 mentioned: *"If you have a distributor (merchant). Their frequency and recency figures will be different"*. It is also important to balance out the size of the customer. Big customers don't need to be always best customers as P7 noted that they require a high cost to serve *"their contribution never factors in the cost to serve"*.

In real scenarios, salespeople use their knowledge with some data support from a stack of reports to make decisions about customer segments. However, they want to, but find it difficult to base on a data-driven approach due to the limitations of existing tools. As P3 pointed out, *"not all the customers who are shouting loud are those who pay best"*. Although participants voiced the need for objectivity, they did not rule out the importance of the subjective factor. As P2 mentioned *"Because this is just broad data, this doesn't have emotion involved. It doesn't have a human contact aspect"*. It becomes even more challenging for IML systems to focus on objective, data-based clustering and somehow cater to the subjective aspect of sales, e.g., on customers with whom there is a desire to develop a long-term relationship. Hence, there is a need to build IML systems to capture the complexities of sales in B2B settings to provide a meaningful UX.

5 DISCUSSION

Our discussion will follow the structure of our findings. We will discuss the challenges of trying to label clusters automatically; validating clusters; supporting actionable insights; including more variables in clustering.

Labeling without contextual information is challenging in a dynamic clustering application where end-users can personalize clusters. By changing the number of clusters, the data may move between clusters changing the context. Automated clustering employs supervised learning methods like multi-layer perceptron [6] to automatically label clusters. This is achieved through feature importance by training a classification algorithm for each cluster and assigning the label with the most important feature observed in data points inside a specific cluster. Alternatively, the calculation of feature metrics can be used as customer segmentation for labeling [23]. Feature metrics let designers create segments of customers and group them through a comparative analysis between cluster features. Customers with a higher level of frequency and monetary (FM) are more likely to be loyal and valuable. However, our experiments with sales experts prove customers who are shouting louder are not always the best ones. A detailed (yet static) method is to use RFM to Customer Lifetime Value (CLV) correlation to label and rank segmentation [1]. This relies on making quartiles to segment customers into pre-defined groups. Based on the significance of a quartile score, a CLV label could be assigned. We use a combination of feature metrics and correlational methods to initially label the clusters and then enabled the expert users to modify the labels based on their understanding. We embed this functionality inside an interactive machine-learning environment so that it can capture user feedback. We notice that, without an expert opinion, it is difficult to label clusters as the system dynamics change across teams and markets.

If the user is not able to validate the clusters, the labeling is useless. Without the true labels of clusters known, internal and external validity becomes imperative. Interval validity is based on an index measure (e.g., silhouette) which defines the quality of clusters [11]. This only ensures the internal intricacies of data objects like homogeneity or separation of clusters. External validation requires making use of information that is not part of clustering itself. For instance, examples with true labels can be used to determine the validity or a human may intervene to validate the actual clusters. The other methods of validation: stability (determining the number of clusters) or visual (appearance) are also effective [25] which we embed in our interactive app. We use the elbow (the inflection point) and silhouette (cluster cohesion and separation) methods for internal validity. For external validation, we perform a soft-behavioral micro-segmentation [4] of customers with highly expert salespeople. We aim to support coordination across teams, as we extend to validate segmentation by human experts of the domain. Without knowing the true labels, experts contextualize and validate the clusters based on their experience.

Models are effective when the end users can identify what actions to take. Analytics must respond to customers in a dynamic environment with actionable insights [14]. This aims to customize learning models and identify a variety of customer behavior. With our prototype, users have flexibility in clustering and personalizing visualizations that provide actionable decisions to sales employees. For instance, what customers are at risk? or which are the best customers to follow for a new business? This can lead to making valuable strategies to target the needs of segments. However, it is essential to provide visual interfaces that match the user's perception of users across businesses. Excessive information and contextual limits often hinder the user's ability to intercept insights. Hence, we see a potential to augment interfaces to provide clear and actionable insights.

B2B segmentation systems are highly fragmented due to the complexity of the problem and the needed validity [4]. We observed that there are several criteria to capture the diversity of B2B segmentation in such an environment. Essentially, how variables across companies influence segment interpretation, access, or response varies considerably. The flexibility to adapt interactive segmentation models to cater varying needs of different companies requires efficacious integration. Literature apart, we understand the practical limitations of incorporating customized segmentation. Besides, there are omniscient challenges to fathom the factors that could influence B2B transactions. Through our prototype and study, we lay the foundations to incorporate the customization challenges in an interactive learning environment. We believe that including a variety of custom parameters with continuous corrective feedback from expert users will greatly improve the performance of our segmentation prototype.

In the future, we will analyze and incorporate findings from expert feedback and literature for the missing features in our prototype. For instance, it is paramount to work on approaches to label clusters contextually. By making machine learning more interactive in this context, we aim to generalize our results and invite other researchers to bridge the gap between academia and industry.

6 CONCLUSION

We conducted an interview study with seven sales managers using an interactive machine-learning prototype for customer clustering based on RFM. We provided seven seasoned sales managers of a global manufacturing company with a prototype to experience, observe and interact with customer clusters by tweaking parameters, models, labeling, and changing the number of clusters. We showcased how interactive machine learning complemented with visualization can support user experience (UX) in sales contexts. Designing an effective customer segmentation framework has several challenges for designers, four of which we present in this paper. We present practical considerations to build effective interactive applications supporting users' validation, insight accessibility, and uniform applicability across companies.

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