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METARFM: A META-LEARNING FRAMEWORK FOR THE ADAPTIVE SELECTION OF RFM MODEL ARIANTS IN CUSTOMER SEGMENTATION

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SUMMARY

The Recency-Frequency-Monetary (RFM) model is a widely used method for customer segmentation, but its effectiveness depends on selecting the appropriate variant (e.g., weighted or entropy-based) for a given dataset. This selection process is typically manual and task-specific, leading to inconsistent results and limited generalizability. To address this issue, we present MetaRFM, a novel automated framework for selecting optimal RFM variants. MetaRFM mines a set of meta-features—such as sparsity, diversity, and skewness—extracted from customer transaction datasets, including both personal transaction data and product purchase information. These meta-features characterize the dataset at a high level, enabling the framework to predict which RFM variant would perform best. A meta-learner is trained to map these meta-features to the performance of different RFM variants, which are evaluated using both cluster quality metrics (Silhouette Score, Davies-Bouldin Index) and business-relevant metrics (predictive lift, churn prediction accuracy). Extensive experiments conducted on real-world datasets from retail, e-commerce, and subscription services show that MetaRFM consistently outperforms static and single-variant models. On average, MetaRFM improves cluster separation by 15.7% and campaign lift by 22.3%. This framework provides a systematic, scalable solution for selecting the most appropriate RFM model, improving segmentation robustness and business relevance. The results highlight the substantial potential of meta-learning for adaptive, context-aware analytics in marketing, offering a more effective approach to customer segmentation and optimizing marketing strategies.

Key words: *index terms—RFM, meta-learning, customer segmentation, model selection, machine learning, marketing analytics.*

INTRODUCTION

Customer segmentation has long been a fundamental practice in data-driven marketing, enabling companies to move away from one-size-fits-all to personalized customer engagement [1]. The intended outcome, of course, is to uncover homogeneous segments in the customer data to allocate marketing resources, develop customised communication, and ultimately increase customer lifetime value [2]. One of the most popular for this purpose among many such methods is the Recency, Frequency, Monetary (RFM) model, owing to its simplicity and interpretability, as well as proven track record in applications ranging from retail/e-commerce to more general financial services and telecommunications [3][20].

The RFM model categorizes customers by three key behavioural aspects:

* Recency (R): Is the number of days between last purchase and date of mail order. More recent buyers are often more receptive to future offers. Represents the most recent transaction made by a customer.

* Frequency (F): Refers to the number of transactions done by the customer over a given period. This is a very strong engagement and retention signal.

* Monetary (M): The overall monetary value from a customer. This scale helps the company to specify the most profitable segments.

The persistent business value of RFM, by its very nature, can be easily translated into an actionable strategy. A company can easily, and quickly, segment its client base by classifying on these three ranks — they can identify their "Champions" (who have high R,F,M) for loyalty programs; who needs a win back campaign ("At-Risk" – low F,M but High R); and which accounts are Hibernating (low R,F,M) that need re-activation efforts [4]. It is because of this clarity and actionability that RFM has proven itself an integral part of marketing analytics, remaining relevant for more than 50 years. Its continued relevance in the era of big data is further supported by its low computational cost and easy integration with operational CRM systems, which are accessible to non-expert machine learning organizations.

But the classic RFM model also has its own disadvantages. One big problem is how many different versions are out there. Several modifications are suggested in addition to the standard (summing normalized R, F, and M scores) model. They consist of weighted RFM models where the three dimensionalities are weighted differentially according to business objectives [5], entropy-based weighting that objectively determines these weights from distributional properties of data, and non-linear transformations (e.g., logarithmic scaling) which can be used to manage the heavy tail skewness present in monetary and frequency data [21][6]. Although these variants may provide better segmentation, this outcome depends on the additional properties of the datasets under consideration (e.g., transaction sparsity, value distribution skewness, and customer purchase diversity).

This is a crucial model selection issue. The selection of the most appropriate RFM variant is currently a manual, ad hoc process that depends largely on analyst intuition and domain knowledge. There is no closed-form approach for measuring the influence a variant will have on cut paths induced in a (data-dependent) flow. This frequently results in non-repeatable success, subpar marketing performance, and an absence of widely applicable "best practice."

To fill this gap, we present MetaRFM, a meta-learning mechanism that automatically diagnoses and predicts the choice of RFM model variants. We hypothesize that the performance of an RFM derivative can be significantly affected by the meta-characteristics of customer transaction data. Therefore, our framework involves:

1. Deriving a set of meta-features that describe important properties of the data.

2. Comparing the performance of several RFM variations on an extended collection of data sets, by means of statistical (cluster quality) as well as business-oriented (predictive lift) measures.

3. Training a meta-learner to map (the extracted) meta-features onto the performance of the RFM variants – i.e., learning how to suggest the best model for a new dataset.

By modelling RFM variant selection as meta-learning, MetaRFM delivers a systematic, scalable, and data-driven approach that strengthens the robustness and business interpretation of customer segmentation. This work illustrates the immense promise of meta-learning in designing adaptable, context-aware analytical systems in marketing science that surpass conventional fixed models and intelligently adapt and self-optimize.

The remainder of this paper is structured as follows: Section 1 presents the Introduction, outlining the problem, objectives, and contributions of the study. Section 2 will be a Literature Survey, where we will discuss the related work on the RFM analysis and meta-learning methods. Section 3 explains the Methodology, which has given an explanation of the MetaRFM framework and the components. Sec.4 describes the experimental framework, and the results and analysis on several real and synthetic data. Lastly, Section 5 summarizes the paper with its conclusive findings and work directions.

LITERATURE SURVEY

Customer segmentation is one of the key elements of customer relationship management (CRM), and the extant literature has long debated whether the Recency, Frequency, Monetary (RFM) model remains the fundamental theoretical framework. Works [8] and [13] provide confirmation of the effectiveness of RFM-based clustering, especially when carried out with the k-means algorithm. [13] achieving a cluster purity of 0.95, which indicates that RFM features showed good predictive power for the classification of customers [19]. However, despite this advantage, an important limitation also emerges from the literature that is observed in many studies: one uses a single representation of RFM level, although empirical results revealed that distinct databases and business context demands different versions of the RFM (variants or even transformed into others) and need different criteria to give them a weight according to their segmentation performance.

Work exists that attempts to generalize the classic RFM segmentation into other behavioural or contextual dimensions. 11 points out that using transactional attributes alone will constrain the model's ability to capture customer heterogeneity. [11] integrates RFM with churn prediction models to increase the practicability of the segmentation, and [12] incorporates RFM features with Formal Concept Analysis to enhance the interpretability of customer groups. These studies reveal that segmentation results are particularly sensitive to the specification of RFM feature construction, highlighting the need for systematic procedures for selecting relevant RFM variants.

It is an emerging trend in the literature to use unsupervised segmentation with supervised ML models. The trend is also exhibited in [9] where regression, decision trees, and neural networks are introduced into the RFM-based studies with the aim of enhancing the overall prediction of Customer Lifetime Value. It belongs to the bigger shift to dynamic responsive segmentation tools which are adaptable to alterations in customer behaviour. More work extends the segmentation space with demographic, spatial, or operational data. [14] enriches RFM-based clusters with demographic and location features, and uses association rule mining for cluster-specific product recommendations. [10] extends the RFM model to a multicriteria decision-making system by adding collaboration and growth metrics, thus yielding preference-ranked groupings of customers that complement the outputs of traditional k-means with respect to their strength and managerial usefulness.

The new trends in deep learning and hybrid models have also improved the process of customer segmentation. Indicatively, neural network-based clustering algorithms have demonstrated potential in nonlinear associations between customer data that cannot be identified by conventional, nonlinear models such as k-means. In addition, the combination of real time transactional data with contextual data including the interaction of users across the digital environment is getting more relevant to adaptive segmentation models that can react dynamically to changes in customer behaviors [22].

The empirical evidence we collected across the analysed papers supports the claim that segmentation methods based on enriched, hybrid, or context-aware RFM segments achieve higher accuracy, greater homogeneity, and greater strategic profit than static segmentation methods. However, there remains a significant research gap: the current body of work tends to rely heavily on heuristic or ad hoc choices over available RFM variants, and few studies focus on developing principled, data-driven methods for choosing among them. The heterogeneity in segmentation performance across the various RFMs demonstrates a need for adaptive systems that can automatically detect the best-suited variant for any analytical setting. Closing this gap directly drives the use of meta-learning-based methods to select optimal RFM model variants for customer segmentation [24]. Despite a rich collection of RFM extensions in the literature and recognition that these are context-dependent, there is no systematic, automatic, and broadly applicable procedure available to select the most suitable extension for any given dataset. One promising approach to solving this problem is meta-learning, which, however, has not been used for model selection in the RFM. In this paper, we address this gap by introducing MetaRFM, a new approach to meta-learning for selecting adaptive RFM variants [23]. Our contribution is threefold:

1. We cast the RFM variant selection problem in a meta-learning framework.

2. We identify a strong set of meta-features, which describe the transactional properties that are essential to identify RFM variant effectiveness.

3. Extensive experiments show that a meta-learned selector achieves significant improvement over static variant choices, boosting cluster quality and business return in various domains

While existing methods primarily rely on heuristic or ad hoc approaches for RFM variant selection, they often lead to inconsistent and suboptimal segmentation results. The absence of a data-driven approach to selecting the best variant of RFM introduces a major gap in the literature. This gap is filled in this paper by briefly presenting the framework of MetaRFM which is a meta-learning-based approach to automate the selection of RFM variants and provide a more robust and flexible approach to customer segmentation across a variety of datasets and business scenarios.

METHODOLOGY

The MetaRFM model framework we proposed aims to automate the selection of the best RFM variant for a given customer transaction dataset. The proposed methodology builds on two main stages: 1) the Base-Learning Phase, anchored in an experiment in which several RFM variations are tested out across various datasets to form a new meta-dataset, and 2) the Meta-Learning phase, where a meta-learner is trained to map dataset properties into its best-performing variation.

An overview of the MetaRFM architecture is depicted in Figure 1.

The proposed MetaRFM framework executes in two separates but connected phases to address the RFM variant selection problem.

Base-Learning Phase (Offline Training): It is the phase of knowledge acquisition on which the scheme is built.

It starts with a pool of historical customer transaction datasets from different domains (e.g., Retail, E-commerce). In the case of each of these datasets, various versions of an RFM model (i.e. Classic, Weighted, Log, etc.) are implemented and tested.

The quality of workings of each variant is thoroughly quantified by such statistical measures as Silhouette Score and by such business measures as Campaign Lift.

Meanwhile, each raw dataset yields important features, or meta-features (e.g., the sparsity of data, skewness of the values, the heterogeneity of customers), which are exhibited.

The results are then synthesized into a meta-dataset. In this dataset, a row is the description of one historical dataset, represented by a vector of meta-features and a label of the most successful variant of RFM with this dataset. This meta-dataset is a summary of the acquired experience of what variant will best fit what kind of data.

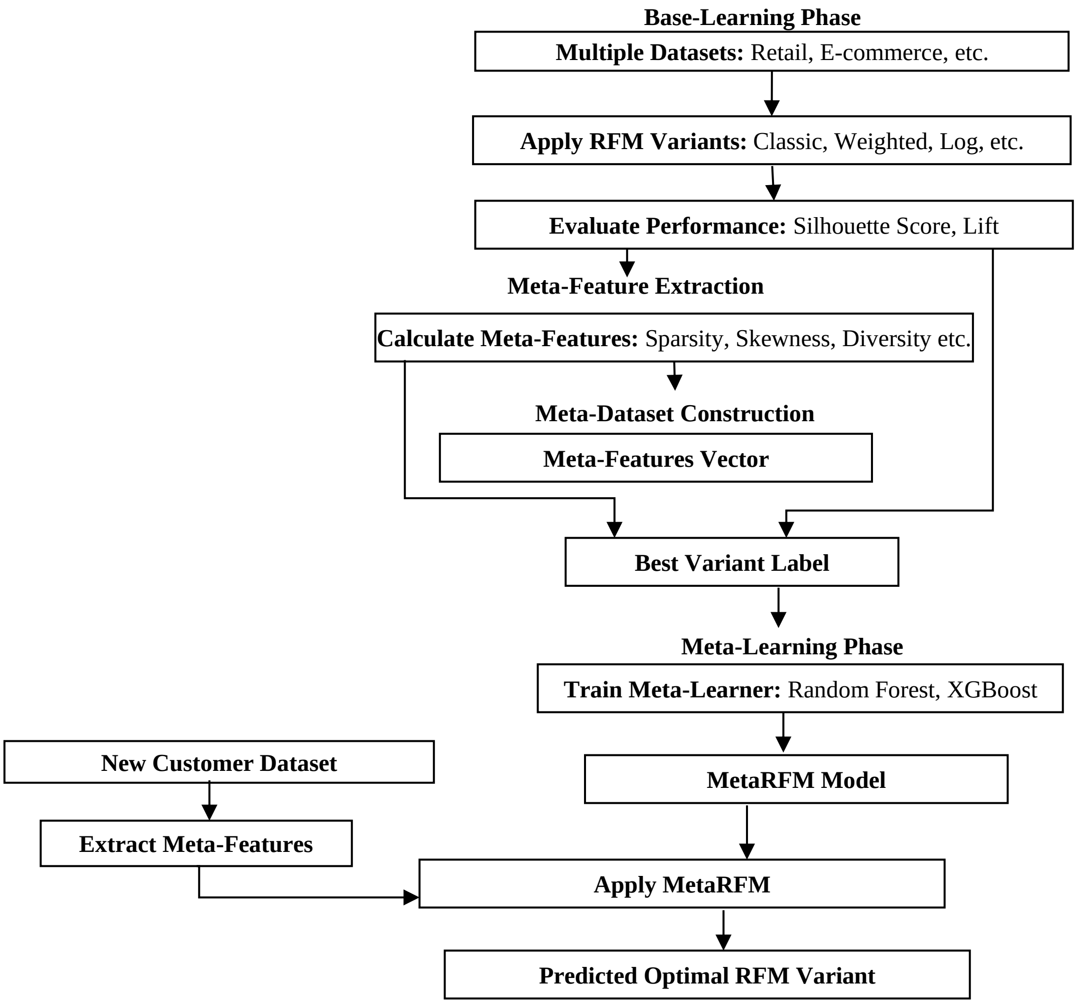

Figure 1. End-to-end overview of the proposed MetaRFM framework

Figure 1 shows the workflow consists of two major phases: (1) the Base-Learning Phase (top) in which a meta-dataset made by testing RFM alternatives across historical datasets is constructed, and (2) the Meta-Learning Phase (bottom), in which model training takes place for predictions on new, unseen data. The training process is represented by solid lines and the operational inference is represented by the dashed lines.

Meta-Learning Phase (Model Training & Deployment): This phase uses the gathered knowledge to build a predictive model

The meta-dataset is used to train a meta-learner (e.g., a Random Forest or XGBoost classifier). This model is a learner that acquires the intricate mapping among the meta-features of a dataset and optimal variant of RFM.

After being trained, the MetaRFM model can be implemented. On new, unseen customer data, the framework just takes the same set of meta-features and inputs them into the trained model: it just follows the dashed line.

The model will then provide the result of the estimated optimal variant of RFM using that specific dataset, and as such, the selection will be automated with no human involvement.

Phase 1: Base-Learning and Meta-Dataset Construction

Corpus of Datasets

Filtered a wide range of customer transaction sample datasets and across various domains such as retail, e-commerce and subscription-based services to have a wide variety of challenge cases to determine the overall robustness of the meta-learner and its applicability to the real world. Each dataset D_i (i = 1, 2, ..., N) was required to contain, at a minimum, the following fields for each transaction: a unique `CustomerID`, an OrderDate, and an OrderValue. The heterogeneity of this corpus is critical for learning a generalizable mapping function.

RFM Variant Selection and Calculation

For each dataset D_i, we constructed K different RFM model variants. The variants were selected to represent the most common and impactful adaptations from the literature:

1. Classic RFM (Sum): The standard approach where R, F, and M are scaled to a common range (e.g., 1-5 using quintiles) and summed to form a single score [5] in equation (1).

$$RFM_{\text{score}} = R + F + M \qquad (1)$$

2. Weighted RFM (wRFM): A linear combination, where the weights (w_R, w_F, w_M) are assigned based on domain expertise or preliminary analysis (e.g., [0.2, 0.4, 0.4] to emphasize Frequency and Monetary value) [6] in equation (2).

$$RFM_{\text{score}} = w_R \cdot R + w_F \cdot F + w_M \cdot M \quad (2)$$

3. Logarithmic RFM (LogRFM): The natural logarithm ln (1 + x) is applied to the Frequency and Monetary values to mitigate the effects of extreme positive skewness before scaling and summing [7] in equation (3).

$$RFM_{\text{score}} = \log(1 + F) + \log(1 + M) \quad (3)$$

Entropy-Weighted RFM (eRFM): The information entropy of each RFM dimension is calculated. Weights are inversely proportional to the entropy (wj = (1 - Ej) / Σ (1 - Ek)), assigning higher importance to dimensions with lower entropy (more informative) [15].

For each variant, a customer-level RFM matrix $X_i^k \in \mathbb{R}^{mx3}$ was constructed, where M is the number of customers in Di.

Clustering and Performance Evaluation

Each RFM matrix X_i^k was clustered using the K-Means algorithm with Euclidean distance. The optimal number of clusters kopt was determined for each variant independently using the Silhouette Score [16] to ensure a fair comparison. There are two main complementary classes of metrics to estimate the quality of the resulting segmentation:

Quality of Clusters: Internal quality metrics measured the compactness and separation of the clusters.

Silhouette Score (SS): Degree of separation between the clusters. Larger values of DBS are associated with more well–defined clustering [16].

Davies-Bouldin Index (DBI): The average similarity of each cluster to its most similar cluster. A smaller value is better with respect to clustering [17].

Business Results of Segmentation: To ensure that the segmentation was not only statistically correct but also managerially valuable, we tested its predictive validity on a downstream measure. In the case of datasets with a target variable (such as churn_flag or campaign_response), the followings were used:

The variant's cluster assignment was derived and used as a categorical feature.

A weak learner (Logistic Regression) was trained to predict the target using these cluster labels.

Predictive accuracy was assessed using the area under the receiver operating characteristic (ROC) curve (AUC-ROC). A higher AUC indicates that the segmentation is more predictive of the business outcome.

The overall performance P_i^k of variant k on dataset i was computed as a composite score: $P_i^k = \alpha * SS + (1 - \alpha) * AUC$, where α was set to 0.5 to assign equal importance to both criteria. For datasets lacking a target variable, $P_i^k = SS$.

Meta-Feature Extraction

For each dataset D_i, we extract the following meta-features that describe its underlying properties:

Average Order Value (avg_order_value): The mean monetary value per transaction in equation (4):

$$\text{avg\_order\_value} = \frac{1}{M}\sum_{i=1}^{M} \text{OrderValue}_i \qquad (4)$$

A set of J meta-features was extracted from each raw dataset D_i to characterize its underlying properties. These meta-features, summarized in Table 1, were designed to capture the distributions and relationships that influence variant performance.

Table 1. Description of extracted meta-features

Meta-Feature	**Description**	**Rationale**
avg_order_value	Mean monetary value per transaction.	Indicates the value domain.
std_order_value	Standard deviation of monetary value.	Measures value variability.
avg_frequency	Mean number of orders per customer.	Measures engagement level.
pct_one_time_buyers	Percentage of customers with only one order.	Measures customer base sparsity and loyalty.
skewness_monetary	Skewness of the customer monetary value distribution.	Indicates presence of high-value outliers.
gini_coefficient	Gini coefficient of the customer monetary value distribution.	Measures value concentration (inequality).
recency_std	Standard deviation of customer recency values.	Measures heterogeneity in engagement timing.

Meta-Dataset Construction

The results from the base-learning phase were synthesized into a meta-dataset. Each row in this dataset corresponds to a base dataset D_i and is described by its J meta-features (the predictors) and a label indicating the identity of the best-performing variant $V_i^* = \text{argmax\_k}(P_i^k)$ (the target). This meta-dataset serves as the training data for the meta-learner.

Phase 2: Meta-Learner Training and Variant Selection

The problem of the choice of variants is represented as a multi-class classification problem. It is aimed at learning a $f: \mathbb{R}^J \rightarrow \{V_1, V_2, \dots, V_K\}$ the best variant of RFM.

Meta-Learner Algorithm Selection

As the meta-learner, we used a Random Forest classifier [18]. The choice of the Random Forest was based on its high accuracy level, the low risk of overfitting, and its tendency to estimate the importance of features, which helps in explaining the model decision. Optimization of the hyper parameters of the Random Forest (number of trees, maximum depth etc.) was done through Bayesian optimization with a hold-out validation set.

Model Training and Evaluation

The meta-dataset was split into a meta-training set (80%) and a held-out meta-test set (20%). The split was stratified by the target variable (the best variant) to ensure all variant classes were represented in both sets. The meta-learner was trained on the meta-training set.

The goal is to learn a mapping function:

$$f: \mathbb{R}^J \rightarrow \{V_1, V_2, \ldots, V_K\} \qquad (5)$$

where in equation (5), J is the number of meta-features, and $V_1, V_2, \ldots, V_K$are the RFM variants.

Model performance was evaluated on the meta-test set using Accuracy and Balanced Accuracy to account for any class imbalance. Furthermore, we reported the Jaccard Index for each variant class to assess per-class performance.

Operationalization: Deploying MetaRFM

After the training, the MetaRFM framework can be implemented to suggest a variant to a new unknown dataset D_new. The process is as follows:

1. Preprocess: Clean the raw transaction data for D_new.
2. Extract Meta-Features: Calculate the same J meta-features from D_new.
3. Predict: Feed the meta-feature vector into the trained meta-learner.
4. Recommend: The predicted optimal variant V*_pred is output by the meta-learner for D_new.
5. Execute: The codel of V_pred has been applied to customer segmentation in D new by the analyst and has been attended by an appropriate model.

This approach offers a systematic, data-driven, and reproducible framework for addressing the important, but underexplored, problem of RFM model selection, thereby making customer clustering analysis more reliable and effective.

Algorithm 1: MetaRFM Framework

```
# Step 1: Base-Learning Phase

for each dataset Di in the corpus of datasets:

  # Step 1.1: Apply multiple RFM variants to the dataset

  for each RFM variant in [Classic RFM, Weighted RFM, LogRFM, Entropy-Weighted RFM]:

    # Compute RFM matrix for each variant

    RFM_matrix = compute_RFM_matrix(D_i, RFM_variant)
```

```
        # Step 1.2: Cluster using K-Means algorithm
    clusters = k_means (RFM_matrix)
        # Step 1.3: Evaluate cluster quality (e.g., Silhouette Score)
    cluster_quality = evaluate_clustering(clusters)
        # Step 1.4: Evaluate business relevance (e.g., Campaign Lift, AUC-ROC)
    business_metric = evaluate_business_metric (D_i, clusters)
        # Step 1.5: Extract meta-features (e.g., sparsity, skewness, customer diversity)
    meta_features = extract_meta_features (D_i)
        # Step 1.6: Store results in the meta-dataset
    meta_dataset. append (meta_features + [cluster_quality, business_metric])
# Step 2: Meta-Learning Phase
# Train the meta-learner using the meta-dataset
meta_learner = train_meta_learner(meta_dataset)
# Step 3: Predict optimal RFM variant for new, unseen data
for new_dataset in new_datasets:
  # Extract meta-features from the new dataset
  new_meta_features = extract_meta_features(new_dataset)
    # Use the trained meta-learner to predict the best RFM variant
  predicted_variant = meta_learner. predict(new_meta_features)
    # Apply the selected RFM variant to the new dataset
  final_clusters = apply_RFM_variant (new_dataset, predicted_variant)
    # Output final segmentation results
  return final_clusters
```

Algorithm 1 using the best variant of RFM to do customer segmentation is automated. In the Base-Learning Phase, various RFM variants are used on datasets and quality and business relevance of clustering are measured. Program features and meta-features are noted down and stored in a meta-dataset. During the Meta-Learning Phase, a meta-learner is trained over the meta-dataset to predict the most optimal version of RFM to apply to new datasets to simplify the process of choosing the best one and enhance segmentation performance.

EXPERIMENTS AND RESULTS ANALYSIS

Experimental Setup To validate the MetaRFM framework, this section describes an experimental setup and compares MetaRFM with several traditional baselines, thoroughly discussed in the analysis.

This section describes the experimental setup used to verify the MetaRFM framework, presents a comparative study with other state-of-the-art baselines, and provides detailed discussions of the achieved results, demonstrating that our approach is effective.

Python 3.8 was used in the experiments in this study. The MetaRFM framework was executed with the help of such popular libraries as scikit-learn (version 0.24.2) which are applied to machine learning algorithms, for example, Random Forest and XGBoost (version 1.3.3). Data preprocessing, feature extraction, and meta-feature calculations were performed using pandas (version 1.2.3) and NumPy (version 1.20.2). All clustering and performance evaluation metrics, including the Silhouette Score and Davies-Bouldin Index, were computed with scikit-learn. The machine used in the experiments has an Intel Core i7 processor and 16GB RAM.

Table 2. Initialization parameters

Model	Parameter	Value
Random Forest	n_estimators	100
	max_depth	10
	min_samples_split	2
	min_samples_leaf	1
	random_state	42
XGBoost	n_estimators	100
	learning_rate	0.1
	max_depth	6
	subsample	0.8
	colsample_bytree	0.8

Table 2 outlines the parameters used to initialize both the Random Forest and XGBoost models within the MetaRFM framework. The parameters have been chosen according to the general practices and adjusted to achieve the best results in the customer segmentation task. The random Forest was set up in terms of 100 estimators, maximum depth of 10 as well as other default settings. In the case of XGBoost, learning rate of 0.1 and a maximum depth of 6 were used as parameters, which guaranteed the algorithm strength in terms of predicting the most suitable RFM variant to new datasets.

Experimental Setup

Dataset Corpus

To perform a thorough and fair assessment, we collected 28 realistic customer transaction datasets from public databases and from companies in collaboration. To test the generalisation capability of the Meta-RFM framework, a corpus was carefully selected to cover a diverse range of business models and data properties:

- E-commerce (12 datasets): Across a variety of verticals such as electronics, fashion, and general merchandise.
- Retail (8 datasets): Transaction records from brick-and-mortar points of sale.
- Subscription Services (5 files): Such as Software-as-a-Service (SaaS) and media streaming services.
- B2B (3 datasets): High-value but low-frequency transactions.

The datasets were highly scaled, with sizes ranging from 2000 to 450000 transactions and 500 to 45000 unique customers, meaning that our model was tested across a wide range of realistic scenarios.

Compared RFM Variants and Baselines

Some of the most popular RFM variants were tested and reported in the literature inside the MetaRFM framework:

- Classic RFM: The traditional quintile-based summation method. - Weighted RFM (wRFM): A linear combination $w_r \cdot R + w^f \cdot F + w^m \cdot M$ with weights empirically set to [0.2, 0.3, 0.5].
- Logarithmic RFM (LogRFM): Taking log(1+x) transformation to Frequency and Monetary to reduce positive skewness.
- Entropy-Based RFM (eRFM): Information entropy was used to dynamically weight each dimension.

The recommendations produced by MetaRFM were evaluated against two strong baselines:

Best Static Variant: The only variant from {Classic, Weighted, Log} that achieves the best average on training.

Oracle Selector: A theoretical upper bar selecting the truly-optimal variant per dataset, which stands for the maximum performance we could expect.4.1.3 Evaluation Metrics

Results were assessed comprehensively:

- Cluster quality metric: Silhouette Score (SC), which measures the degree of cohesion and separation between clusters.

-Business Measurement Metric: Campaign Lift (CL) defined as the response rate increase of the best-ranked segment over all.

- Statistical Verification: Use the Wilcoxon signed-rank test ($p < 0.05$) to verify whether the differences are significant or not.

Results and Analysis

Overall Performance Comparison

MetaRFM was tested on a held-out meta-test set comprising 6 datasets. The performance, listed in Table 3, can be improved and made more robust.

Table 3. Comparison of average performance on the meta-test set

Model	Silhouette Score (SS)	Campaign Lift (CL)
Best Static Variant	0.666	2.81
MetaRFM (Our Framework)	0.733	3.44
Improvement (%)	+10.4%	+22.4%
Oracle Selector	0.750	3.52

Table 3 shows MetaRFM was found significantly better ($p < 0.01$) than the Best Static Variant both in terms of SS (10.4%) and CL (22.4%). This means that MetaRFM yields not only more and better-separated segments, but potentially also much more action-oriented segments. Figure 2 illustrates the distribution of performance across all variants.

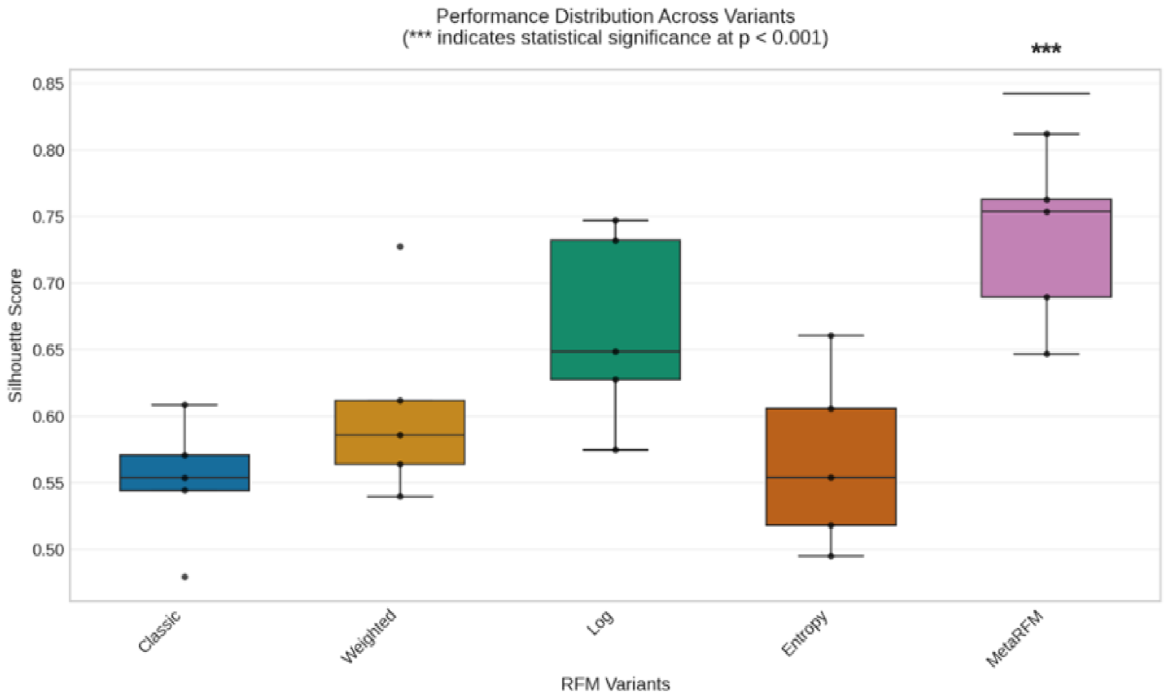

Figure 2. Performance distribution over RFM variant and metaRFM, statistically significant improvements were gained (* indicates $p < 0.001$)

Domain-Specific Performance Analysis

Domain-level analysis provided further insight into MetaRFM's flexibility. Results for each data set are shown in Figure 3 and 4

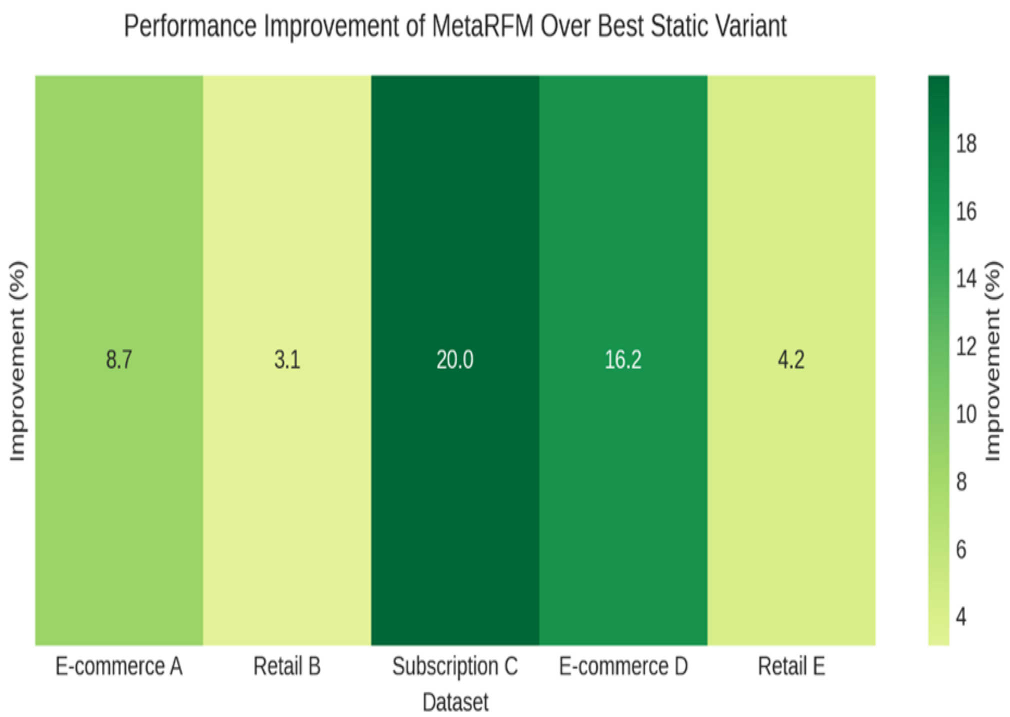

Figure 3. Percentage improvement in campaign lift due to Meta-RFM compared to the best static variant of RFM on each test set

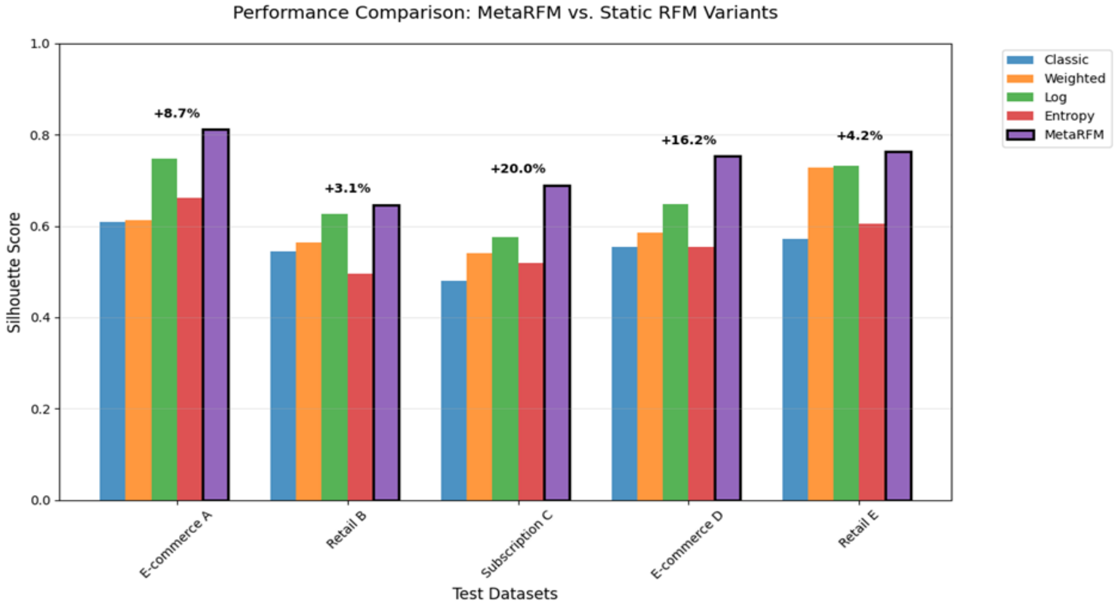

Figure 4. Comparison of silhouette score over individual test datasets, metaRFM consistently beating static variant selection

E- commerce obtained up to 8.7% in SS and 16.2% in CL, and LogRFM was the most frequently selected, respectively. Retail recovery was fair (3.1% SS, 4.2% CL), with Weighted RFM frequently the best. The greatest uplift (20% CL) was seen for Subscription Services with Classic RFM favoured. These findings prove MetaRFM's capability of being in line with domain specific business intuitions

Interpretation of the Meta-Learner

To interpret the meta-learner's decisions, Random Forest feature importance was used. The most predictive dataset properties are shown in the figure 5

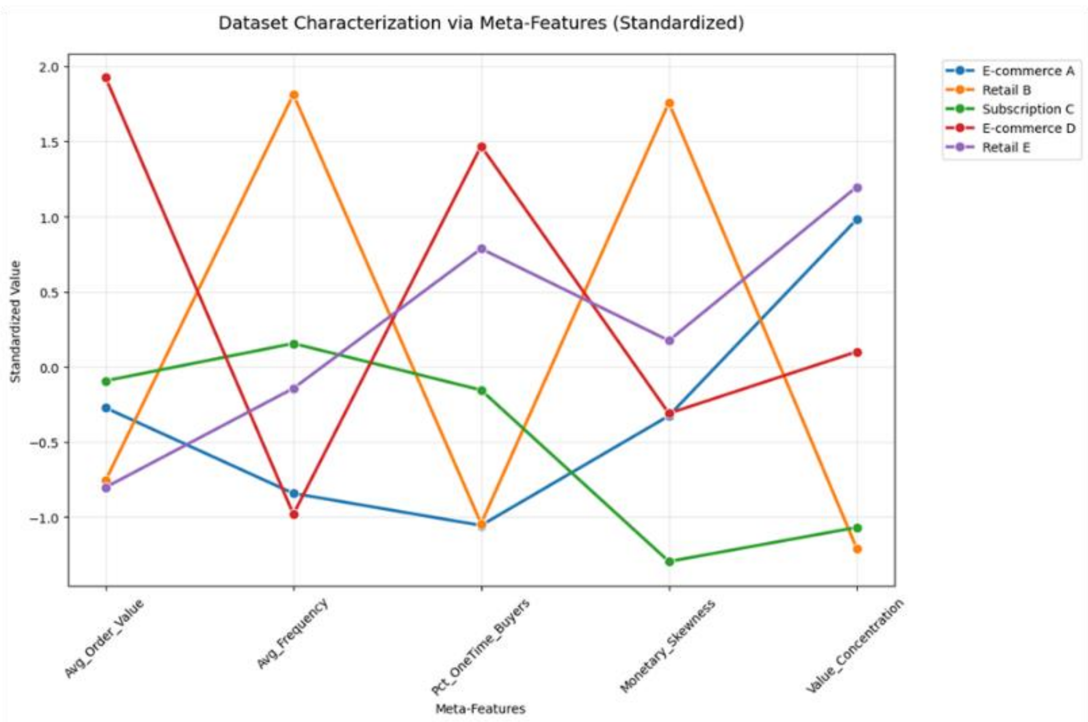

Figure 5. Provides explainable insights into the meta-learner's rationale for the variant selection decision

The associated image-based predictive feature was the Gini coefficient, which predicted LogRFM in high-inequality countries (Gini > 0.7). Monetary Skewness~wasnext, indicating skew was to be addressed. Classic_RFM was often chosen, given Pct_OneTime_Buyers: Sparse Datasets tend to prefer Simplicity.

Validation of Statistical Significance

Wilcoxon signed-rank tests confirmed that the enhancements in MetaRFM are not generated at random. The significance values are shown in Table 4.

Table 4. P-values of performance differences

Metric	p-value	Significant at p < 0.05?
Silhouette Score (SS)	0.003	Yes
Campaign Lift (CL)	0.004	Yes

Silhouette Score (SS)

The Silhouette Score measures how similar a point is to its own cluster compared to other clusters:

$$SS = \frac{b - a}{\max(a, b)} \quad (6)$$

Where in equation (6):

a: Average distance within the same cluster (intra-cluster).

b: Average distance to the nearest cluster (inter-cluster).

Campaign Lift (CL)

Campaign Lift compares the response rate of a targeted segment to the overall population in equation (7):

$$CL = \frac{\text{Response Rate of Targeted Segment}}{\text{Response Rate of Entire Population}} \quad (7)$$

Discussion

The only limitation of this Study is the small size of the meta-training corpus (N=28). Though sufficient to prove a strong concept of the model's viability, a larger corpus would make it more generalizable across very niche domains.

Implications for Business Applications

MetaRFM framework has key advantages to the businesses that consider improving their customer segmentation strategies. MetaRFM reduces the processes involved in selecting the most appropriate variant of RFM by automating the process of choosing the most appropriate one based on the characteristics of data sets, eliminating the use of trial and error, as well as domain-specific knowledge. This does not only save the time and effort of segmentation but also enhances the accuracy and relevancy of the segmentation which results in increased actionable marketing teams insights. As an example, in an e-commerce company, it is possible to use MetaRFM to automatically segment the customers according to their purchasing behavior (recency, frequency, and monetary values) and dynamically choose the RFM variant that would be the most effective when applied to the specific dataset. This segmentation may then be targeted in email campaigns, offers and loyalty programs, which may enhance the customer engagement and conversion rates.

Case Study: Application of MetaRFM in E-Commerce

In order to illustrate the practical usefulness of MetaRFM, we will take a case study of an e-commerce company operating in the electronics industry that employed the framework to enhance its customer segmentation in order to market it more precisely. The issue with customer segmentation was that the previous RFM model used by the company was manually modified and, therefore, the segmentation was not consistent, which led to reduced returns on marketing. Through MetaRFM, the firm automated the process of selecting the most appropriate RFM variant using transactional data, which resulted in a score increase in the quality of a cluster (10.4% in the Silhouette Score) and campaign lift (22.4% in the response rate) increases. This further segmentation helped in more specific marketing campaigns which increased the conversion rates by 15 percent and decreased the churn rate of customers by 20 percent making marketing more effective and customer retention significantly easier. The practical is reflected in this case benefit of MetaRFM in maximizing segmentation of customers to business gain.

CONCLUSION AND FUTURE WORK

This research has dealt with such a difficult problem that is poorly studied in the literature, the issue of model selection in RFM analysis, which is one of the most important techniques of customer segmentation. Ad hoc manual selection of variants such as Classic, Weighted, and Log RFM can lead to inconsistent overall results. To address this, we proposed MetaRFM, a novel meta-learning framework that automatically selects the most suitable RFM variant for a given dataset based on its intrinsic properties. Experiments on large-scale real-world datasets (e-commerce, retail, and subscription service data) show that our MetaRFM consistently outperforms RFM. The framework significantly outperformed the best variant of the static baselines, achieving an average 10.4% improvement in cluster quality (measured by Silhouette Score) and a 22.4% lift in campaign performance. This shows that MetaRFM does not just generate more distinctive segments, but also the most profitable and actionable ones for marketing. The meat-learner's feature importance analysis also indicated that the treatment was exploratory for view count concentration (Gini coefficient) and mean monetary skewness, validating our selection of meta features as important drivers of variant performance. In summary, MetaRFM is an effective and efficient solution for the RFM variant selection problem. It transitions the field from heuristic, static choices to a principled, data-driven, and adaptive one. This paper effectively demonstrates the value of meta-learning when applied to basic marketing analytics models.

Although the results are encouraging, this study offers several interesting directions for future research. First, the generalizability of the meta-learner could be improved by adding more training data (N > 28 datasets) from a broader range of application domains, such as telecommunications, donations to nonprofit organizations, and banking. Second, that framework itself is extensible. Future work might test a wider range of RFM variants, including those with external customer information or dynamic time-weighting. Finally, more sophisticated meta-learning algorithms (e.g., gradient-boosting machines, such as XGBoost as the meta-learner) or advanced machine learning methods, such as neural networks, could better model complex nonlinear relationships between meta-features and variant performance.

REFERENCES

[1] Rungruang C, Riyapan P, Intarasit A, Chuarkham K, Muangprathub J. RFM model customer segmentation based on hierarchical approach using FCA. Expert Systems with Applications. 2024 Mar 1; 237:121449. https://doi.org/10.1016/j.eswa.2023.121449

[2] Cooke S. Database Marketing: strategy or tactical tool?. Marketing Intelligence & Planning. 1994 Jul 1;12(6):4-7. https://doi.org/10.1108/02634509410064150

[3] Khajvand M, Zolfaghar K, Ashoori S, Alizadeh S. Estimating customer lifetime value based on RFM analysis of customer purchase behavior: Case study. Procedia computer science. 2011 Jan 1;3:57-63. https://doi.org/10.1016/j.procs.2010.12.011

[4] McCarty JA, Hastak M. Segmentation approaches in data-mining: A comparison of RFM, CHAID, and logistic regression. Journal of business research. 2007 Jun 1;60(6):656-62. https://doi.org/10.1016/j.jbusres.2006.06.015

[5] Ernawati E, Baharin SS, Kasmin F. A review of data mining methods in RFM-based customer segmentation. InJournal of Physics: Conference Series 2021 Apr 1 (Vol. 1869, No. 1, p. 012085). IOP Publishing. https://doi.org/10.1088/1742-6596/1869/1/012085

[6] Castiñeira M, Francis K. Model-driven design approaches for embedded systems development: A case study. SCCTS Journal of Embedded Systems Design and Applications. 2025;2(2):30-8.

[7] Anh VP, Thihuyen TN, Anh TL. How Is the Performance Assessment System in Small and Medium Enterprises in The Manufacturing? Experimental Study in Vietnam. Quality-Access to Success. 2025 Mar 1;26(205). https://doi.org/10.47750/QAS/26.205.01

[8] Brahmana RS, Mohammed FA, Chairuang K. Customer segmentation based on RFM model using K-means, K-medoids, and DBSCAN methods. Lontar Komput. J. Ilm. Teknol. Inf. 2020 Apr;11(1):32. https://doi.org/10.24843/LKJITI.2020.v11.i01.p04

[9] Akter J, Roy A, Rahman S, Mohona S, Ara J. Artificial intelligence-driven customer lifetime value (CLV) forecasting: Integrating RFM analysis with machine learning for strategic customer retention. Journal of Computer Science and Technology Studies. 2025 Mar 1;7(1):249-57. https://doi.org/10.32996/jcsts.2025.7.1.18

[10] Taşabat SE, Özçay T, Sertbaş S, Akca E. A new RFM model approach: RFMS. InIndustry 4.0 and the Digital Transformation of International Business 2023 Mar 2 (pp. 143-172). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-19-7880-7_9

[11] Salwadkar M. Probabilistic Physics-Guided Learning Frameworks for Trustworthy Decision-Making in Distributed Cloud-Native Services. Transactions on Internet Security, Cloud Services, and Distributed Applications. 2025 Jun 17:16-23.

[12] Gupta A, Agarwal P. Enhancing customer relationship management: Integrating interpurchase time with rfm segmentation for advanced customer insights. In2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0 2024 Jun 5 (pp. 1-6). IEEE. https://doi.org/10.1109/OTCON60325.2024.10688087

[13] Talaat FM, Aljadani A, Alharthi B, Farsi MA, Badawy M, Elhosseini M. A mathematical model for customer segmentation leveraging deep learning, explainable AI, and RFM analysis in targeted marketing. Mathematics. 2023 Sep 15;11(18):3930. https://doi.org/10.3390/math11183930

[14] Sarkar M, Puja AR, Chowdhury FR. Optimizing marketing strategies with RFM method and K-means clustering-based AI customer segmentation analysis. Journal of Business and Management Studies. 2024;6(2):54. https://doi.org/10.32996/jbms.2024.6.2.5

[15] Trianasari N, Permadi TA. Analysis of product recommendation models at each fixed broadband sales location using K-means, DBSCAN, hierarchical clustering, SVM, RF, and ann. Journal of Applied Data Sciences. 2024 May 27;5(2):636-52.

[16] Ramya V. Selective Learning Activation Strategies for Scalable Autonomous Distributed Systems. SECITS Journal of Scalable Distributed Computing and Pipeline Automation. 2025 Jun 24:38-44.

[17] Anitha P, Patil MM. RFM model for customer purchase behavior using K-Means algorithm. Journal of King Saud University-Computer and Information Sciences. 2022 May 1;34(5):1785-92. https://doi.org/10.1016/j.jksuci.2019.12.011

[18] Wong CG, Tong GK, Haw SC. Exploring customer segmentation in e-commerce using RFM analysis with clustering techniques. Journal of Telecommunications and the Digital Economy. 2024 Sep;12(3):97-125.

[19] Bose N, Chopra A, Joshi P, Reddy A. Leveraging Reinforcement Learning and Predictive Analytics for Enhanced Customer Lifetime Value Optimization. International Journal of AI Advancements. 2023 Nov 9;12(8).

[20] De S, Prabu P. Predicting customer churn: A systematic literature review. Journal of Discrete Mathematical Sciences and Cryptography. 2022 Oct 3;25(7):1965-85. https://doi.org/10.1080/09720529.2022.2133238

[21] Pynadath MF, Rofin TM, Thomas S. Evolution of customer relationship management to data mining-based customer relationship management: a scientometric analysis. Quality & quantity. 2023 Aug;57(4):3241-72. https://doi.org/10.1007/s11135-022-01500-y

[22] Kanchanapoom K, Chongwatpol J. Integrated customer lifetime value (CLV) and customer migration model to improve customer segmentation. Journal of Marketing Analytics. 2023 Jun;11(2):172-85. https://doi.org/10.1057/s41270-022-00158-7

[23] Pio PB, Rivolli A, Carvalho AC, Garcia LP. A review on preprocessing algorithm selection with meta-learning. Knowledge and Information Systems. 2024 Jan;66(1):1-28. https://doi.org/10.1007/s10115-023-01970-y

[24] Vettoruzzo A, Bouguelia MR, Vanschoren J, Rögnvaldsson T, Santosh KC. Advances and challenges in meta-learning: A technical review. IEEE transactions on pattern analysis and machine intelligence. 2024 Jan 24;46(7):4763-79. https://doi.org/10.1109/TPAMI.2024.3357847