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Dynamic Territory Management and Account Segmentation using Machine Learning: Strategies for Maximizing Sales Efficiency in a U.S. Zonal Network

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Abstract: In the context of Enterprise B2B sales, a company usually sells its products or services to large and diverse organizations (enterprises). Enterprise Customers often have global reach and complex hierarchical structure made up of several decision-making units. Consequently, Enterprise Customers comprise of several Customer Locations (offices, headquarters, production plants, stores etc.) to which the company sells its products or services. To maximize sales potential and other business objectives, it is suggested that each Enterprise Customer Location must be managed by the company and assigned a couple of relevant sales representatives. This activity is called Territory Management. Additionally, any company should have well-defined set of Customer Segmentation criteria that help identify the most valuable Customer Locations that need to have defined Territory Management strategy. The Customer Location Segmentation activity is done to deliver Territory Management configuration specific to each Customer Location and dedicated to small set of key products to one or couple of sales reps. In both cases (Territory Management and Segmentation), the number of supported markets is constantly increasing along with the volume of data. The current analytical task is not trivial and requires a significant computational power, as it takes into account various datasets and a lot of diversity. To address these problems, we share a robust in-depth methodological approach based on the Machine Learning methods. It is already implemented to solve CLS and Territory Management automation tasks for different types of B2B companies operating in various sectors on several datasets ranging from 10k to 2M of Customer Locations and Territory Management tasks have been repeatedly performed with up to 95% of accuracy and F1 score. The goal of this paper is to provide the best practices in Dynamic Territory Management and Customer Segmentation for Enterprise B2B companies willing to design the future of their enterprise segment to face the new challenges of the market and embrace the digital era.

Keywords: Dynamic Territory Management, Account Segmentation, Machine Learning, Sales Efficiency, Zonal Sales Network, U.S. Sales Territories, Predictive Analytics, Customer Segmentation, Sales Optimization, AI-driven Sales Strategies, Geospatial Analytics, Sales Force Automation, Market Potential Analysis, Demand Forecasting, Territory Realignment, Lead Scoring, Customer Lifetime Value (CLV), Sales Performance Metrics, Data-Driven Decision Making, Business Intelligence (BI), CRM Integration, Operational Efficiency, Resource Allocation, Territory Coverage Models, Clustering Algorithms (K-means, DBSCAN), Route Optimization, Sales Productivity, B2B Sales Strategy, Machine Learning Models (Random Forest, XGBoost), Territory Balancing

1. Introduction: Sales-oriented companies spend most of their efforts and budgets on customer acquisition. However, once customers are acquired, the cost of satisfying and retaining them is generally lower than negotiating with new customers. Therefore, proper segmentation and maintenance of the customer portfolio are vital for strategic decision-making. The territories are dynamic by nature: it is strategic to keep track of customer and prospect changes, from customer perception to sales, from nurturing to neglect, to take the correct actions. To support sales teams in this task, we present a statistical segmentation model that allows recognizing main changes in the customer role. We present a proposed dataset that allows statistically validating the proposed model and a tool that allows marketing managers to easily test their customer data and obtain results that will help them make important decisions.

Territory management is a broadly studied problem. It is mainly performed by using historical sales data to solve, or at least try to solve, sales inequality problems as unbalance or large differences among sales representatives in terms of sales generated. Companies often have to create such territories by establishing market areas around each sales representative. These areas are determined according to some selection criteria which usually include considering the lack of equality in workloads, the closeness to the customer, and territorial protection. Such zoning contains the necessary geographical information to perform segmentation tasks because it clears the access to public information. They also report data to study how customers evolve within territories. This movement needs to be noticed first. If the zones are static, researchers may only rely on historical customer data to estimate customer costs, revenues, and profitability.

2. Overview of Territory Management

Territory management is the process of assigning a defined set of accounts to a defined group of sales resources. Account segmentation is the statistical analysis of a customer base to identify groups of customers who have common characteristics. The results of account segmentation are used to define the relative priority of customers in various processes, including account planning, territory management, marketing, and sales. Account segmentation may be done to understand how customer groups differ along various dimensions other than value, motivation, or needs or to define the priority of customers based on value, motivation, or needs for use in areas such as marketing or sales funnel optimization. Sales territories are usually determined based on geography or workload balance. The traditional territory management process is either corporate defined or a field established using mapping software.

Sales are usually characterized by relatively high incentive structure and short selling cycles. This means that field reps' productivity is highly variable from month to month. Productivity is determined not only by the effort level of the rep but also by the attractiveness of the rep's customer accounts as defined by some combination of potential, fit, and relationship. Through a combination of account segmentation, territory optimization, and rep matching, companies can minimize demand or workload imbalances and increase territory management efficiency by increasing the likelihood that sales reps will be assigned to accounts with similar characteristics and sales potential.

In most large organizations, it is standard practice to assign a subset of existing and potential customers that share similar characteristics to a particular sales rep. Best-practice organizations invest significant effort in getting the process right because the sales rep play a crucial role in generating revenue. They need to be motivated to sell to the customers in their territory, year after year.

3. Importance of Account Segmentation

Account segmentation is the practice of splitting accounts into different groups based on similar characteristics. The aim is to allow the sales leader to apply different techniques or strategies

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to each group segment. Segmentations based on different assortments of key characteristics make sense for different organizations, industries and situations. Aside from general income and expenditure trends, which are uniform across entire businesses or business classes, there are other characteristics, which are unique to specific businesses and organizations in a particular industry or sector. Some businesses are highly dependent on special customers, while for others small accounts are a headache.

Fig 1 : Artificial Intelligence in Digital Marketing

Account segmentation is one of the fundamental decision criteria of sales optimization. Clear account segmentations provide a rational baseline for many critical sales decisions about how much to invest in business development, customer acceptability, sales force sizing, account coverage and support system design. Such segmentation must therefore also inform decisions whose primary objective is not segmentation, for example target setting, sales force incentive design, remote selling demand forecast, pipeline control and sales force compensation. It is also the basis for other activities including deployment, territory design, call planning and usage analytics. In short, segmentation drives a broad spectrum of decisions with a sales optimization objective or sales optimization component.

4. Machine Learning Fundamentals

To properly explore dynamic territory management and account segmentation using machine learning, this section presents some fundamentals of such algorithms. After defining machine learning, its general structure and some of the main ingredients of machine learning, we delve into the three main families of learning algorithms – supervised, unsupervised, and reinforcement learning – focusing on supervised and unsupervised.

Advances in computing power and the availability of large quantities of data have made machine learning and its applications available to most of the business areas. Machine learning algorithms enable estimating a function that maps from a feature space into a target space. The set of learning algorithms can be divided into those that need labels to train, which are supervised techniques, and those that do not require labels to perform the training, which are unsupervised techniques. There are additional algorithms, and we will present a bit in more detail training structures that fall within the family of reinforcement learning.

Drawing upon what has just been established, a high-level supervised learning procedure with discrete outcomes can be summarized in the following way: a data scientist uses data sampling techniques to prepare a training dataset of labeled data, collects a set of candidate functions from an appropriate function space, and uses a loss function quantifying the amount of difference between the predicted and actual output to evaluate the candidate functions. The function used will be the one that provides the smallest possible expected loss.

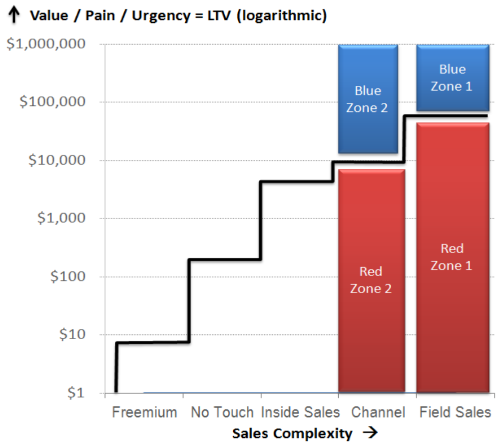

Fig : Sales Complexity Impacts your Startup's Viability - For Entrepreneurs

5. Data Collection and Preparation

The overall methodology described in this paper requires several sets of data. The first set contains general information regarding the accounts, including type, activity status, size, and geographic sectors. The second set collects information regarding the sales team. These data describe team organization, performance, geographic share, and performance by geographic sector. The last data set contains information collected on visits to the accounts conducted by salespeople during a specific period. This richness of information permits the identification of the main variables that drive salespeople to conclude or review an opportunity and permits segmentation of the accounts according to the behavior of salespeople.

Account information was collected from the system through two different processes. First, we obtained the relevant account attributes accessible through the account module. Those attributes were used to perform a clustering analysis through the K Means algorithm to obtain the type (or type grouping) of account to use as input for the algorithm. The K Means algorithm is an unconstrained, iterative method used to partition data into different non-overlapping subsets (clusters) such that each data point in each subset is more similar to the points in that subset than to those in the other subsets. The number of clusters must be specified in advance, and the algorithm is often interpreted as a method of reducing the large pool of data into centroids. After this first clustering process, we informed the rest of the account data set by assigning to each account the centroid of the cluster it belonged to.

Having performed clustering based on the first account attribute set, we decided to add specific attributes to the account attribute set; and knowing that those data would feed a supervised algorithm, we collected the internal account attributes that defined the periods of higher and lower sales for each account during a period of three years. Then, we updated the attributes of the already alpha numeric coded accounts linking these positive and negative attributes with the accounts already coded previously.

6. Feature Engineering Techniques

Feature engineering creates machine learning model input features from raw data, significantly impacting predictive performance. While labeled data is essential for supervised learning models, determining the features can be more complex than generating the labels, often requiring significant human expertise and time-consuming efforts. In context, we explore new feature production through evaluation of an extensive list of territory and account features, providing insight into what matters in territory tool prediction tasks. Shortening label production burden through unsupervised clustering expansion is compared to supervised territory tool training. More automated features are compared to those produced through explicit human design. Potential feature application is presented using an example case company. The random forest model is identified as the most versatile and generally performant, indicating territory model selection trustworthiness may improve results, particularly with this ensemble algorithm.

Feature engineering automates and accelerates the creation of machine learning model input features from raw data, greatly affecting the predictive performance of new models, and is often more important than model choice. Well-engineered inputs are capable of ameliorating issues stemming from small sample sizes and unsupervised learning without labeled examples. Selecting and optimizing features can require substantial model designer testing, as the same purely data-driven design process used to create features likely cannot be used to assess the final model goodness because of overfitting and poor generalization. Domain knowledge and experience can streamline the laborious process of assigning relevant, representative, and fast to calculate input variables for learning algorithms. Most predictive machine learning applications still rely on human-engineering feature sets, often using simple, readily explained concepts. Accounting, marketing, and sales typically have an extensive history of stakeholder knowledge accessible through metrics, but research herein additionally explores territory management tool specific elements, augmenting what and how this information might be accessed. Reduction of human feature selection burden is also completed through the use of established human designs alongside the discovery of new feature creation methods.

7. Predictive Modeling Approaches

The methodology discussed thus far involves a descriptive analysis of account characteristics, territories, and segmentations based on insight from historical data. Traditional descriptive analytical techniques such as an exploratory data analysis or visualizations are generally useful in accounting for existing segments. In addition to these techniques, it is also useful to take the modeling approach, i.e., to build an analytical model that predicts the segments in order to assess the relationships between account characteristics and predict the segment assignment for new accounts. While supervised modeling techniques allow analysts to evaluate historic relationships and predict the segmentations for new accounts, unsupervised techniques can automate the modeling so that segmentations are generated without the analyst's biases.

Additionally, territory/segment attributes generated from supervised models can be used as input features to improve the segmentation performance of unsupervised techniques.

In supervised modeling tasks, the algorithm learns a mapping from a set of independent feature variables that represent the account attributes in order to predict a specific dependent variable. In account segmentation tasks, the dependent variable assigns the account to a specific segment. The advantage of supervised techniques for segmentation tasks is that they train from existing segment assignments to develop the prediction logic. This allows an analyst to become more focused on what features are useful, as the segments already exist. Logistic regression, naive bayes, hierarchical clustering, and neural networks are examples of supervised techniques that are used for account segmentation.

Equation 1 : Clustering for Account Segmentation (K-Means Algorithm)

$$\min_{C} \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \mu_i\|^2$$

- C_i: Cluster i
- x: Data point (account)
- μ_i: Centroid of cluster i
- k: Number of clusters (segments)

Unsupervised learning mitigates the need for external guidance, hence is used especially when labeled data is not available. Instead of segmenting new accounts based on historical information, unsupervised techniques such as clustering methods segment them based on their feature data similarity. The challenge of unsupervised techniques is tuning the appropriate parameter settings that affect the output performance. For example, the K-Means clustering algorithm requires specification of the number of clusters, which can affect the final results significantly. In contrast, the model assumptions used in supervised learning relax this requirement to an extent.

7.1. Supervised Learning In supervised learning, the model learns a function mapping input–output pairs such that given a new input sample, the model predicts a correct output. Supervised learning requires labeled data. Given a set of input variables, the model learns to predict an output using supervised learning methods such as regression or classification. The primary task of a machine learning model is to predict customer behavior in a certain period with respect to different business variables used as features. In territory management problems, model output labels or targets can be across three different areas of business. First, and the most common, is sales or revenue based label, in which the model learns to predict future sales or revenue targets from the input features. Inputs can be lagged values of sales or revenue, customer information such as segmentation score or product type, territory information such as territory health index, competitor activity such as presence in territory, periodic effects such as seasonality and special promotions, or other similar business features.

There is significant previous work on supervised learning based models for territory management. However, predicting business data with respect to time series or typical geographical data brings inherent difficulties. First, territories can be defined at the same level as the provided sales data, such as territory to zip code mapping, or at a coarser level that is different from the provided sales data. Building a model that can predict a time series variable is difficult when the input features are present at a different or coarser level. There are different methods to smooth results upwards or downwards for coarser levels. Hierarchical forecasting models, that forecast upward or downward with respect to time series or geographical population data, have been developed.

7.2. Unsupervised Learning In contrast to supervised learning, unsupervised learning algorithms do not require target values to be assigned to the training data. As a result, they can be applied with greater ease to larger samples and applied more widely, as unsupervised learning algorithms are more flexible than supervised variants. However, unsupervised algorithms are less efficient than supervised methods in terms of predictive performance. While many applications of dynamic territory management and account segmentation are focused on predicting responses, none are without desire of exploring the underlying structure of the data or interpretations of the profiles. We describe segmentation as the goal of unsupervised solutions.

Account segmentation has been implemented in a variety of ways. The most common method is use of clustering techniques that categorize accounts into 'similar' groups using their observed variable profiles. Some of the most well-known clustering solutions are reference-based methods, such as K-means and K-medoids, and partitioning algorithms – of which hierarchical clustering is the most well-known. With all of these approaches, the number of segments has to be determined prior to running the algorithm. Such refocus of H-clustering, K-medoids or K-means is not needed for other clustering techniques such as density-based or model-based methods. Density-based clustering originates from the concept of a cluster that contains groups of high-density data points among lower-density points. Both CLARA and DBSCAN have gained interest due to ability to find arbitrary cluster shapes, robustness in dealing with noise data and relaxes the size requirements of clustering numerous clusters. Model-based methods try to confirm a model-based probability distribution function which optimally fit the data in use to be clustered. The most common implementation of model-based techniques is Gaussian mixture model clustering or fitted mixtures of Gaussians.

Fig 2 : Digital Progress and Trends Report

8. Clustering Techniques for Segmentation

Segmentation allows a better understanding of the diverse customer base within a territory, resulting in more tailored offerings. The aim is to group customers with similar characteristics together and to differentiate them from other customer segments. Segmentation approaches may either be descriptive or normative. Descriptive segmentation involves identifying groups of customer accounts based on behavioral, performance or demographic characteristics. The goal is to find clusters of similar segment members, while allowing differences between other segment members. Normative segmentation, on the other hand, identifies different needs for very specific customer segments, allowing the development of strategies and specific marketing activities. Descriptive segmentation more frequently appears in the literature and is also the preferred method used in practice. Therefore, it is the approach we consider in this work.

The most frequently employed data mining techniques for customer segmentation purposes are clustering techniques. These techniques group customers with similar characteristics into clusters and maximize the dissimilarity between clusters. They allow for the discovery of hidden information from the database, as well as objectionable classifications. Clustering does not require any a priori knowledge about the underlying structure of the data, making it a non-supervised classification model. It is a relatively recent method and its use for sales territory management is limited in the literature. However, its frequent application in other scientific fields suggests a higher use in the near future. The availability of clustering techniques is expected to improve once segmentation becomes a persistent and quality practice of sales organization.

8.1. K-Means Clustering

K-means clustering is a partitioning method that divides a set of objects into a preset number of clusters. K-means clustering begins with a selection of k cluster centers. Variables are included to create a proximity function, one commonly used is the squared error function, which minimizes the distance from each object to its nearest cluster center:

This is an NP-hard problem but can be solved via a simple and efficient heuristic algorithm based on alternating optimization. Each variable is assigned to the nearest cluster point based on the proximity function, and the k cluster points are updated using

The algorithm terminates when the assignments no longer change. A notable drawback of the algorithm is that it is highly sensitive to initial cluster assignments. To circumvent this challenge, many methods have been proposed for selecting better values of the cluster centers in the initialization step. The most popular method is k-means plus plus, which reduces the sensitivity based on a cluster validity index. The K-means cluster validity index determines the spread and separation of clusters based on the average distance between samples in the same cluster compared to the average distance between samples in different clusters.

K-means is easy to interpret and efficient. However, clusters detected by K-means will have low variance and high distance from the nearest centers. K-means assumes spherical clusters of equal volumes, and clusters from its detection are highly separable. This means that K-means clustering does not produce clusters of varying shapes and sizes. K-means can work well with very large data sizes; it is also sensitive to outliers and noise. These algorithms can also discover clusters in circular shape. Due to the long list of advantages and disadvantages, K-means is not often relied on alone. Rather, K-means is often used as an exploratory tool in conjunction with other methods.

8.2. Hierarchical Clustering At first, the Hierarchical Clustering algorithm creates a tree-like structure called dendrogram. The root of the dendrogram contains all the data and the leaves represent all data points. The Hierarchical Clustering algorithm is one of two basic approaches to clustering. In the bottom-up approach, first, each data point forms a separate cluster. Then, two closest clusters are merged into a new cluster. This continues until all clusters are merged into one cluster containing all data points, or until a termination condition is fulfilled. The top-down approach starts with one cluster containing all data points. The cluster is recursively split into two new clusters until a termination condition is fulfilled. Dendrograms can be used to visualize and explore cluster hierarchies. Dendrograms visualize which clusters were combined or split at the time and what other clusters were combined or split at the same time. This hierarchical structure of clusters can be exploited for segmentation. For example, we can extract one segmentation by visual inspection of the dendrogram or post-processing the dendrogram.

Hierarchical clustering algorithms differ in the choice of the proximity measure, the proximity matrix data structure, and the cluster join/split strategy. The most basic idea is to reduce the number of distance calculations. These speedups use the concept of locality. Hierarchical clustering algorithms using the nearest neighbor or max-link proximity measures cannot be speeded up in a way that does not influence the clustering results. Hierarchical clustering using the average-link or group-average measures can be speeded up, while neighbor-joining is a speedup for a specific hierarchical clustering algorithm. Finally, hierarchical clustering is mostly used to create a dendrogram of low-dimensional data items and initially create a clustering of high-dimensional data items that can be refined with another clustering algorithm.

9. Sales Efficiency Metrics

In any study considering sales operations, sales efficiency is the first area to investigate. Because unlike other drivers of business growth including marketing, product, or pricing, there is no buyer's journey associated with sales, the job of driving revenue is 100% a cost-driven endeavor. Companies will often experience growth-growth years that are fueled by mentioned demand drivers. Until they don't. When growth slows these companies have to re-evaluate their strategies and usually revert to a sales-centric effort. But during the growth years, they're not focused on sales efficiency.

A common mistake is measuring arbitrary metrics like profit per sales employee, and concluding from there that more efficiency is better. Sometimes it is. But often it is a result of corner-cutting, which becomes even more obvious when growth resumes and the relative "inefficiency" is employed to support accelerated growth. Companies should structure their sales functions so that they are optimally efficient during normal times or mild recessions, with a view to being able to leverage any sales function inefficiencies to weather an economic storm.

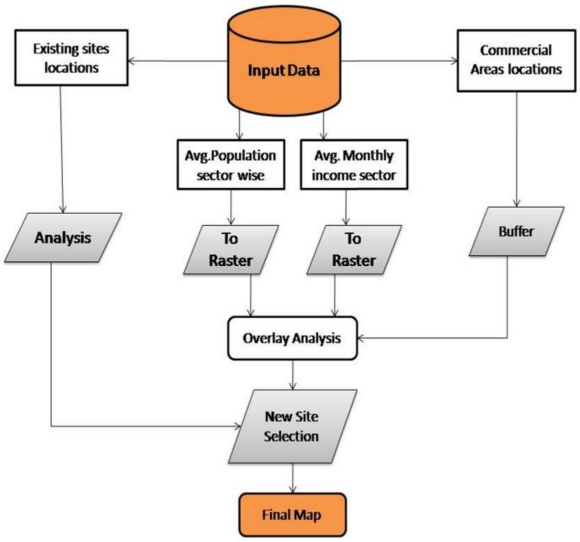

Fig 3 : Innovative GIS techniques for identifying

How sales teams are compensated, including incentives, plays a huge role in overall company sales efficiency, or inefficiency. Some roles are purely quota-carrying, others are meant to support account-based marketing, prospecting, or client management roles with capturing scope. For instance, are salespeople compensated primarily with a percentage of fees generated, a fixed amount with claw-back provisions for losses that exceed goodwill, or a combination of both?

10. Dynamic Territory Assignment Strategies

While the concept of territory assignment is useful, territories are seldom fixed for long. Credit risk, for example, changes, customers develop new needs, buying patterns shift, or new customers are added. These changes can easily result in neglected customers, representing lost sales opportunities, or over-served customers, creating excessive costs and eliminating margins. Both situations cannot simply occur; a client's willingness to accept an unresponsive supplier, or of suppliers imposing excessive costs upon a customer is finite. Both situations coalesce into an uncomfortable position for a supplier: rapid share loss and falling profitability, while at the same time facing increasing pressure for cost reductions. It is thus obvious that territory assignment is not a static process but one requiring frequent check-ups, more commonly referred to as Dynamic Territory Management.

Dynamic Territory Management, in the classic sense, traditionally serves the purpose of reflecting changes in resource allocation based on predefined customer clusterings. Automated response systems mainly allow for one type of action: moves between existing account clusters. Probabilistic models can be used to highlight risk clients, minimizing the incidence of missed acceptable risk clients; however, the models used to do so are static ones, constrained by insufficient measurement technology delivering timely and sufficiently detailed data to calculate account ratings directly from changing purchasing behavior.

Dynamic Territory Management can thus simply be summarized as a continuous updating of account ratings and their probabilities indicating a change in supplier response. Such a simplistic model, while being valid, is also very restrictive. An obvious extension of Dynamic

Territory Planning would be a simulation and forecasting model, helping policymakers both in marketing and at corporate level assessing future impact of decisions taken today.

11. Integration with CRM Systems

Perhaps the best part of having invested time developing expertise in drawing optimal territory maps, and developing specific patterns of quota assignment, is that this proprietary know-how can be embedded into the everyday workflow of users, thus increasing the impact. To that end, we had talked about integrating our machine learning algorithms into CRM systems. CRM vendors are already offering highly configurable platforms to allow companies to achieve their unique processes, and sitting on top, are various tools which execute individual functionalities. Several of these functionalities would benefit from doing more, e.g., dynamic account segmentation would feed into lead scoring, lead assignment and opportunity pipelines; quota assignment would improve forecasting accuracy to feed into pipeline management; and pipeline management would recommend how to alter specific opportunities to improve probability to close.

From a business perspective, instead of building separate demand-generation capabilities, it is easier for CRM vendors to acquire functionality, to become a one-stop-shop, reducing friction costs of the user adopting integrated solutions. Workflows were built around CRMs, and therefore, it is natural for any cognitive extension of commercial relationships to reside on these platforms. Building proprietary extensions on existing integrations speeds up deployment time and reduces maintenance work for clients. It also minimizes operational friction since the appropriate data is readily available. Clients have unique data that their customers share over long periods of time. These data are then used to build models which help companies undertake proactive actions that improve outcomes. Third-party extensions provide clients with tools which assist users in completing their work smoothly. It makes sense for vendors to build modules that add cognitive complexity to these mundane tasks. The third-party tools are add-ons to existing platforms.

12. Case Studies in U.S. Zonal Networks

In this section we present results from our experience with using concurrent Zone Profiling Models to create a dynamic view of geographic market potential for a set of accounts in two dissimilar illustrative business applications relevant to a U.S. zonal network. One application is in the Retail Industry where the challenges are to identify a relevant subset of stores for promotional targeting, while providing a strategic location for stores, and to ensure that promotional campaigns to boost store performance are aligned with market demand. The second application is in the Technology Services industry, with the challenge being to optimize territory infrastructure in order to boost support for managed service users, boost market activity, and increase sales. In both cases concurrent multi-account multi-zone profiling models are applied over different data segments to create a more dynamic view of zone and sector activity that is then used in segmentation and validation, and the zone maps are then updated with this zonal information analysis. We offer three different insights from the application of zoning activity in profiling model updates. First, we clarify how zoning can impact activity generation in both positive and negative manner, and how different accounts can generate different levels of activity in the same zone. Second, we provide a set of segmentation and validation metrics that balance inter-account differences in geographically-assigned responsibilities as well as differences in small area activity. Finally, we demonstrate how Zone Positioned Models can be created that maintain the true spatial geographical market contacts these zone optimizations imply.

The profiling dependencies that these model updates imply provide a dynamic view of activity at the geographic zones for a set of accounts and allow concurrent fund allocation or distribution optimization both for the pricing, promotional as well as marketing resource allocation needs of assigned zones, as well as concurrent stock allocation planning to disparate warehouses for balanced market service and customer satisfaction optimization.

12.1. Case Study 1: Retail Sector Common applications of the zonal networks are found in the retail sector. Ranked store lists of virtually any retail outlet are generated by accounting or marketing teams for reporting purposes. Advertisements and promotional mailings are created using lists of stores that are ranked according to the amount of candy sold, or by a percentage-share basis relative to the total dollar sales in each zone. Other lists are generated using a geometric algorithm and are ranked by novelty or seasonality in the product sold. These lists form part of a mass-mailing marketing operation. Response to the marketing effort is measured by increasing product sales in the various market areas served by these stores. The overall effectiveness of a company's marketing operation is measured in terms of the increase in sales per store after deducting the company's marketing expenses. Obviously, different product lines contribute differently to the overhead. The overhead is minimized if the shares of product inventory by each store are the same. If they are not, the marked-up price should vary inversely with the share percentage. Seasonal and novelty accounts may have to be given special treatment.

The case study illustrates how dynamic territory management can be applied in the retail sector. A comparison is made using a well-known static approach and a dynamic approach. The former is based on the insight that a compromise on the assignment of each zone to the closest store will minimize the expected error in the zoning solution. Assuming that the number of territories is fixed, the total error is the sum of aggregated weighted levels in excess of a threshold for all the zoned stores. The latter uses a fuzzy-layered multilayer perceptron to recommend an assignment of store zone. The study is concerned with how effectively the recommended assignment predicts the likely need for a spatial adjustment to the territory structure as the information is received, which would improve prediction performance. The hot-start approach used during stage one minimizes the Doptimal criterion for an individual store. The second stage then merges adjacent store territories according to the Doptimal criterion.

12.2. Case Study Here we describe a case study on a zonal network from the technology sector involving three products (software, hardware, services) and revenue forecasting at the four-digit Standard Industry Classification (SIC) level. We begin with a description of the data used to make an initial static zonal network.

optimal service center

The Technology Supplier (TS) sells a full stock arrangement comprising software, computer hardware which includes servers, input and output devices, and services. Its customers are made up of related establishments in Standard Industrial Classification (SIC) groups 737 (computer service and custom programming), 702 (hotels and other lodging), 701 (theatrical producers and services), and 799 (amusement and recreation services). Customer establishments account for 24% of revenues for 737, 7% for 702, 5% for 701, and 2% for 799.

TS provides a number of related products, and the nature and configuration of these products delivered affect the product prices, delivery time, and service quality. Demand, and thus revenue, is somewhat predictable from either the product market or the customer establishment perspective. Demand is hard to project accurately for any one data point on either dimension, but support can be found at the zonal market for demand prediction and thus zonal revenue contributions can help revenue predictions. Actual zonal revenues can then be fed back into the forecasts of revenues at individual establishments so as to make realistic and internally consistent revenue forecasts.

13. Challenges in Implementation

The primary challenge faced during the implementation of the adoption of dynamic territory management and account segmentation practice is the data quality issue. The accuracy, depth, and granularity of the data directly influence the algorithms used in machine learning-based and AI-based dynamic territory management and account segmentation. In our case, the closest hit of lost customers and churned customers was between twelve to twenty months. Further, the customer attributes were either missing or incorrect in terms of which stage of lifecycle it was and whether the customer is both a customer as well as a competitor. During variable selection, it was found that clear "Triggered variable" like "New launch" was either missing or vague within the customer attributes. This type of executive-level decision being made from an array of missing customer pro forma analysis calls for a correct algorithm and exact engineering of databases. Further, the number of lost churned customers increases if exponential growth happens within a period after dynamic territory management and account segmentation adoption, which worsens the clarity and visibility of these data-based management decisions.

Fig 4 : Ultimate Guide on Customer Relationship Management

Most sales organizations are traditional in their go-to-market strategies and are accustomed to the territory mapping and account segmentation processes, tools, and templates followed for decades based on intuition, experience, and gut feel of the impaneled sales managers. Change is resisted and responsibilities for going against the grain are rare to find. However, in this case, the sales organizations need to face the new dimension of a territory sales approach. Further, such an adoption by the sales organization has to be at scale, and the buy-in owners need to be a designated group with a charter describing the intention of such exhaustive strategic decision-making and describe the accountability and ownership.

13.1. Data Quality Issues Data quality can be a problem for any data science project. Although the models we provide are quite robust, the better the data quality, the better the models. It is likely that your organization already has well-established data governance procedures, but that may or may not permeate down to the account metadata level, especially in large cases. Data quality issues can also arise from the increase of non-transactional data, which typically has less governance associated with it. Here are some broad categories of potential data quality issues:

- Missing data. This is one of the most common problems associated with data. It can occur for a variety of reasons: the information could not be collected, it could have been discarded or lost, or it could violate some business rule and thus be null. While there are several statistical methods to deal with missing data, such as imputation or using only complete cases, these widen uncertainty intervals around predictions and move estimated results away from point estimates. This is resultant from the loss of information. These methods do not work when large amounts of data are missing or when data is missing not at random.

Equation 2 : Territory Workload Balancing

$$\text{Workload}_t = \sum_{i \in T_t} w_i \quad \forall t \in \{1, \ldots, T\}$$

- T_t: Set of accounts assigned to territory t
- w_i: Weight of account i (e.g., effort, revenue potential)
- Goal: $\text{Workload}_t \approx \text{Workload}_{t'}$

- Rounding. This situation is often the result of data being collected by humans, as they frequently round their estimates. This alters the distribution of values and inflates the variance, thus restricting prediction accuracy and precision.

- Codification problems. This refers to changes in the codification of categorizations at some point in time. For example, if the country field previously had the value "United States," and now has "USA," you might accidentally treat the values as two distinct countries. Another common case is when new codes are introduced, which can lead to inconsistencies in the classification of some entities across time. In time series analysis, the fact that classification across time is non-stationary can lead to spurious predictions and results.

13.2. Resistance to Change When reevaluating the preordained segmentation rules or the focus of customer engagement within an organization, the categorical feedback is overwhelmingly positive. However, introducing a new segmentation methodology that allows for dynamic modifications during the engagement cycle is often met with trepidation from the organization. Reassuring clients that traditional market segmentation rules and principles, such as ensuring that a client's account is serviced adequately, and that observing local customs and global policy does not become a disposable choice during this process, is imperative before employing a methodology or framework for account segmentation. By achieving satisfactory segmentation results, client attrition and churn are ensured for only the most unsatisfactory accounts, thus overcoming this degree of resistance. Forming validation arrangements with experienced actors in the company's internal communication is of utmost importance for changing the engagement model towards an account and toward the segments in particular.

Despite these inherent obstacles during the preparation of our model outputs, there are additional risks associated with the validation and engagement reinforcement processes which may surface. Our validation phases, such as geographic zone segregation, temporal testing, and resource allocation reinforcement methods, can be tested many times. Moreover, the core tests, such as hyperparameter tests, and k-fold or bootstrapped testing, can be employed without fear of future citation. The risks of loss lie mainly with the resource allocation methods post validation and its implementation in its after-performance phases during the engagement optimization and client communication strategy, if not properly conceived and validated accordingly. Specific improvement ratios for segment recurrency and client expectation resolution can be adopted if wished. Hence, prior to testing the impact of weights and ratios on outgoing contact costs and required results.

14. Best Practices for Machine Learning in Sales

Several baby steps are required to successfully apply machine learning to sales. Many sales organizations will apply machine learning models to sales tasks for the first time. Luckily, most of these tasks are not mission critical and models can be built, rolled-out, and monitored when they do good, and fixed when they do bad. But on the way to mature model usage, numerous missteps can tempt teams deploying their first models into failure, including high expectations, shortcuts during data preparation, picking the least effort models, too advanced models, careless rollouts and a lack of maintenance of deployed models.

The crippling of business growth by poor segmentation may tempt sales leaders to select the most complex models available, but this may be a mistake. They may also expect those models to do the best job. While deep learning is a fashionable term nowadays, most users may not even be aware of the fact that many times, intermediary models available for a fraction of the computational cost in much shorter timeframes may yield better results. But we are not only talking about deep learning. Besides neural networks, there are many other advanced algorithms that leverage ensemble classifiers, but their heavy lifting will be less needed in sales than in other areas. The reason is simple: in sales, we have limited data. As a consequence, the brain may not be all that useful at learning about the basic factors. If modelers have a good knowledge of the business problem and a rather engineered input set, machine learning should be able to do a decent job after a little bit of tuning.

15. Future Trends in Territory Management

In this chapter, we extracted key trends regarding territory management and account segmentation. They have been mainly summarized from recent reports by leading technology companies in sales-oriented tools.A specific area of growth is Account-Based Sales Development (ABSD). This model recognizes that not all accounts can or should be sold to in the same way. Sales development can be aligned according to the importance or standing of the strategic account, with the highest-value accounts using both marketing and sales resources more heavily. The ultimate goal of especially working strategic accounts is to drive deeper relationships across multiple contacts. For sales development for both low- and medium-priority accounts, established processes can be used to improve the efficiency of prospecting and pipeline generation. Research is suggesting that the tiered approach to account segmentation can allow firms to heighten the focus on key target accounts to ensure that maximum resources are available in these accounts.

The trend toward increased customization in territory design is also increasing, both toward more specific design to avoid segmentation error and increased demand for increased temporal design to take into account the growing dynamic nature of the external marketplace. Additionally, some companies are eager to diversify their sales focus and access new segments of customers. These trends place new and varying demands on the demand-facing processes of enterprises and change the way we must think about territory as a potential source of value for the enterprise. Despite recent improvements in the tools available for commercial use, the key elements of territory management remain grounded in traditional economic factors: increasing sales productivity, decreasing overall selling costs, and improving revenue growth.

16. Ethical Considerations in Machine Learning

Effective marketing relies on the ability of marketers to receive, analyze, and act on customer information. The explosion of marketing technology has shifted this responsibility to machine learning algorithms, which automate the collection, integration, and modeling of consumer information. These advances, however, pose ethical challenges. This chapter reviews existing ethical frameworks for ML systems and discusses how they can be applied to marketing contexts. It proposes the integration of human-centric design principles as an additional source of ethical guidance in marketing ML and highlights six marketing-related areas of concern: Algorithmic Inefficiencies and Failures, Algorithmic Decision-Making Risks, Equity and Fairness, Group Influence, Privacy and Security, and Structural Market Forces. The chapter concludes with a discussion of the future ethical considerations for ML in marketing.

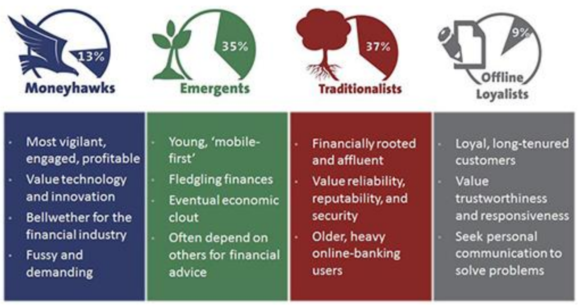

Fig 5 : Segmentation Strategies for Retail Banking

Machine learning enables organizations to enhance their marketing processes by predicting critical consumer-related variables from data. By optimizing relevant functions such as customer clustering, account segmentation, and objective setting, organizations can increase marketing efficiency as well as effectiveness. Yet, while products that leverage machine learning proliferate, their reliance and dominance over specific functions makes their manipulation and abuse both more likely and, in economic terms, more desirable. The same artifacts that allow these systems to magically create new value can also be exploited with harmful consequences for individuals as well as society as a whole. This rapid deployment of machine learning in marketing makes our domain well positioned to further the discussion on what constitutes human-centered, ethically and morally sound artifacts.

17. Conclusion

In order to make the most appropriate decisions in their business environments, companies must visually see their entire business landscape and recognize where their resources are located. They have to understand what is happening in each area represented by an account or geographical territory, identify why some areas are not performing as desired and what can be done to improve results. As a company's portfolio of business opportunities changes, the efforts and investments in pre-built systems and procedures need to become more focused. Machine learning can rapidly model markets at detailed levels and manage dispensation of appropriate actions at the local market level in a way which is adaptive and flexible to the changing market dynamics triggering a positive financial outcome.

Equation 3 : Predictive Sales Model

$$\hat{y} = f(x) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \epsilon$$

- $\hat{y}$: Predicted sales value
- x_i: Input features (territory size, number of accounts, etc.)
- β_i: Model parameters
- ϵ: Error term

Dynamic territory management enables companies to efficiently allocate field sales and service resources to where they have maximum financial impact, capturing the most revenue within a spending portfolio maximized for incentive compensation. Although it is most often referred to in the context of geography, territory could also be understood to apply to products or customer types. Dynamic account segmentation helps companies balance their demand for service and order taking, product push, customer relationship upkeep, and collection with the associated revenue generation opportunity. Interventions could be managed through matrixed organizations in which regional management deploys people having certain specific skills for training, education, product push, product awareness updates, order taking, technical services, collecting, etc. Scheduling of such interventions is over a short time interval, and should follow the rapid response changing market environment insights. Recognizing that changes will happen, market activity must move their customer from the segmented relationship service level back to their default states. This refreshing of relationships through sort assignments must be efficient, effortless, and occur over short periods.

References:

[1] Nuka, S. T., Chakilam, C., Chava, K., Suura, S. R., & Recharla, M. (2025). AI-Driven Drug Discovery: Transforming Neurological and Neurodegenerative Disease

Treatment Through Bioinformatics and Genomic Research. American Journal of Psychiatric Rehabilitation, 28(1), 124-135.

[2] Annapareddy, V. N. (2025). The Intersection of Big Data, Cybersecurity, and ERP Systems: A Deep Learning Perspective. Journal of Artificial Intelligence and Big Data Disciplines, 2(1), 45-53.

[3] Recharla, M., Chakilam, C., Kannan, S., Nuka, S. T., & Suura, S. R. (2025). Revolutionizing Healthcare with Generative AI: Enhancing Patient Care, Disease Research, and Early Intervention Strategies. American Journal of Psychiatric Rehabilitation, 28(1), 98-111

[4] Kumar, B. H., Nuka, S. T., Malempati, M., Sriram, H. K., Mashetty, S., & Kannan, S. (2025). Big Data in Cybersecurity: Enhancing Threat Detection with AI and ML. Metallurgical and Materials Engineering, 31(3), 12-20.

[5] Chava, K. . (2025). Dynamic Neural Architectures and AI-Augmented Platforms for Personalized Direct-to-Practitioner Healthcare Engagements. Journal of Neonatal Surgery, 14(4S), 501–510. https://doi.org/10.52783/jns.v14.1824.

[6] Manikandan, K., Pamisetty, V., Challa, S. R., Komaragiri, V. B., Challa, K., & Chava, K. (2025). Scalability and Efficiency in Distributed Big Data Architectures: A Comparative Study. Metallurgical and Materials Engineering, 31(3), 40-49.

[7] Suura, S. R. (2025). Integrating genomic medicine and artificial intelligence for early and targeted health interventions. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 2(1).

[8] Chabok Pour, J., Kalisetty, S., Malempati, M., Challa, K., Mandala, V., Kumar, B., & Azamathulla, H. M. (2025). Integrating Hydrological and Hydraulic Approaches for Adaptive Environmental Flow Management: A Multi-Method Approach for Adaptive River Management in Semi-Arid Regions. Water, 17(7), 926.

[9] Burugulla, J. K. R. (2025). Enhancing Credit and Charge Card Risk Assessment Through Generative AI and Big Data Analytics: A Novel Approach to Fraud Detection and Consumer Spending Patterns. Cuestiones de Fisioterapia, 54(4), 964-972.

[10] Peruthambi, V., Pandiri, L., Kaulwar, P. K., Koppolu, H. K. R., Adusupalli, B., & Pamisetty, A. (2025). Big Data-Driven Predictive Maintenance for Industrial IoT (IIoT) Systems. Metallurgical and Materials Engineering, 31(3), 21-30.

[11] Recharla, M., Chakilam, C., Kannan, S., Nuka, S. T., & Suura, S. R. (2025). Harnessing AI and Machine Learning for Precision Medicine: Advancements in Genomic Research, Disease Detection, and Personalized Healthcare. American Journal of Psychiatric Rehabilitation, 28(1), 112-123.

[12] Kumar, S. S., Singireddy, S., Nanan, B. P., Recharla, M., Gadi, A. L., & Paleti, S. (2025). Optimizing Edge Computing for Big Data Processing in Smart Cities. Metallurgical and Materials Engineering, 31(3), 31-39.

[13] Kannan, S. (2025). Transforming Community Engagement with Generative AI: Harnessing Machine Learning and Neural Networks for Hunger Alleviation and Global Food Security. Cuestiones de Fisioterapia, 54(4), 953-963.

[14] Sriram, H. K. (2025). Leveraging artificial intelligence and machine learning for next-generation credit risk assessment models. European Advanced Journal for Science & Engineering (EAJSE)-p-ISSN 3050-9696 en e-ISSN 3050-970X, 2(1).

[15] Chakilam, C., & Rani, P. S. Designing AI-Powered Neural Networks for Real-Time Insurance Benefit Analysis and Financial Assistance Optimization in Healthcare Services.

[16] Chakilam, C., Kannan, S., Recharla, M., Suura, S. R., & Nuka, S. T. (2025). The Impact of Big Data and Cloud Computing on Genetic Testing and Reproductive Health Management. American Journal of Psychiatric Rehabilitation, 28(1), 62-72.

[17] Suura, S. R. (2025). Integrating Artificial Intelligence, Machine Learning, and Big Data with Genetic Testing and Genomic Medicine to Enable Earlier, Personalized Health Interventions. Deep Science Publishing

[18] Kumar Kaulwar, P. (2025). Enhancing ERP Systems with Big Data Analytics and AI-Driven Cybersecurity Mechanisms. Journal of Artificial Intelligence and Big Data Disciplines, 2(1), 27-35.

[19] Suura, S. R. (2025). Agentic AI Systems in Organ Health Management: Early Detection of Rejection in Transplant Patients. Journal of Neonatal Surgery, 14(4s).

[20] Dodda, A., Polineni, T. N. S., Yasmeen, Z., Vankayalapati, R. K., & Ganti, V. K. A. T. (2025, January). Inclusive and Transparent Loan Prediction: A Cost-Sensitive Stacking Model for Financial Analytics. In 2025 6th International Conference on Mobile Computing and Sustainable Informatics (ICMCSI) (pp. 749-754)..

[22] Challa, S. R. The Intersection of Estate Planning and Financial Technology: Innovations in Trust Administration and Wealth Transfer Strategies. GLOBAL PEN PRESS UK.

[23] Nuka, S. T. (2025). Leveraging AI and Generative AI for Medical Device Innovation: Enhancing Custom Product Development and Patient Specific Solutions. Journal of Neonatal Surgery, 14(4s).

[24] Annapareddy, V. N. (2025). Connected Intelligence: Transforming Education and Energy with Big Data, Cloud Connectors, and Artificial Intelligence. Deep Science Publishing.

[25] Mashetty, S. (2025). Securitizing Shelter: Technology-Driven Insights into Single-Family Mortgage Financing and Affordable Housing Initiatives. Deep Science Publishing.

[26] Sriram, H. K. (2025). Generative AI and Neural Networks in Human Resource Management: Transforming Payroll, Workforce Insights, and Digital Employee Payments through AI Innovations. Advances in Consumer Research, 2(1).

[27] Challa, K., Chava, K., Danda, R. R., & Kannan, S. EXPLORING AGENTIC AI Pioneering the Next Frontier in Autonomous DecisionMaking and Machine Learning Applications. SADGURU PUBLICATIONS.

[28] Challa, S. R. (2025). Advancements in Digital Brokerage and Algorithmic Trading: The Evolution of Investment Platforms in a Data Driven Financial Ecosystem. Advances in Consumer Research, 2(1).

[29] Ganti, S., Vankayalapati, R. K., Krishnamoorthy, P., Thakare, P. S., Nayak, U. A., & Vignesh, P. (2025, February). Enhancing IoT-Driven Smart Home Security and Automation with a GCN Model. In 2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS) (pp. 1-6). IEEE.

[30] Syed, S., Nampalli, R. C. R., Nikam, M., Krishnan, T., & Perada, A. (2025, February). IoT-Driven Environmental Pollution Monitoring with a Deep Attentional Hybrid Transformer Model. In 2025 International Conference on Emerging Systems and Intelligent Computing (ESIC) (pp. 356-361). IEEE.

[31] Nampalli, R. C. R., Syed, S., Bansal, A., Vankayalapati, R. K., & Danda, R. R. (2024, December). Optimizing Automotive Manufacturing Supply Chains with Linear Support Vector Machines. In 2024 9th International Conference on Communication and Electronics Systems (ICCES) (pp. 574-579). IEEE.