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Research Article

Transformer Networks for Context-Aware Customer Relationship Management: Generating Personalized Engagement Sequences

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ABSTRACT

Customer Relationship Management (CRM) plays a pivotal role in ensuring businesses optimize customer engage- ment, retention, and satisfaction. Traditional CRM systems have typically relied on rule-based approaches or simple algorithms for customer interaction, which may fail to capture the dynamic and evolving nature of customer behavior. In this paper, we introduce a novel application of Transformer networks, a state-of-the-art deep learning architecture, to enhance CRM systems by generating personalized, multi-step engagement sequences and predicting customer churn risk. Our approach leverages two specialized Transformer models: a Sequence Transformer for the task of generating multi-step engagement plans and a Churn Transformer for predicting the risk of customer churn. These models harness the power of self-attention mechanisms to understand the sequential and contextual dynamics of customer behavior across time.

To evaluate the effectiveness of these models, we use simulated datasets inspired by real-world benchmarks, such as MovieLens, Amazon Product Data, and Kaggle Customer Churn. The Se- quence Transformer is trained to predict a series of actions for customer engagement based on historical interactions, while the Churn Transformer estimates the likelihood of customer attrition based on behavioral and demographic data. The results of our experiments show that after 10 epochs of training, the Sequence Transformer achieves an accuracy of 0.0167, while the Churn Transformer reaches an accuracy of 0.4000. Despite modest accuracy values, the models exhibit steady improvement, with training losses decreasing consistently from an initial value of 4.0456 to 3.7837 for the Sequence Transformer, and from 0.8096 to 0.7047 for the Churn Transformer.

The mathematical foundation behind the Sequence Trans- former involves minimizing the average cross-entropy loss over the predicted engagement sequence steps. Specifically, the loss function is defined as:

$$\mathcal{L}_{\text{seq}} = \frac{1}{3}\sum_{i=1}^{3} \text{CrossEntropy}(\hat{y}_i, y_i), \qquad (1)$$

where $\hat{y}_i$ represents the predicted action for step i, and y_i is the true action for the corresponding step in the sequence.

Similarly, the Churn Transformer optimizes the binary cross- entropy loss to estimate the likelihood of customer churn. The loss function is defined as:

$$\mathcal{L}_{\text{churn}} = -\frac{1}{N}\sum^{N} [y_j \log(\hat{y}_j) + (1 - y_j)\log(1 - \hat{y}_j)], \qquad (2)$$

N
$j=1$
where yj is the true churn label for customer j, and $y\hat{}j$ is the predicted churn probability.

Through detailed visualizations, including sample engagement plans, attention weight heatmaps, and ROC curves, this paper illustrates the performance of the models and highlights the potential of Transformer networks in revolutionizing proactive, context-aware CRM strategies. While the accuracy results are constrained by the limitations of simulated datasets, the work lays a solid foundation for future enhancements, including the use of real-world data and more complex Transformer variants, ultimately contributing to more effective customer engagement and retention strategies.

Keywords: Transformer networks, Customer Relationship Management, Personalized engagement, Sequence prediction, Churn prediction

INTRODUCTION

Customer Relationship Management (CRM) systems are essential tools for businesses to manage and optimize interac- tions with their customers. Traditionally, these systems have relied on static, rule-based approaches or reactive strategies, such as responding to customer inquiries or recommending products based on past purchases. These approaches, while effective in some cases, often fall short when it comes to cap- turing the evolving and dynamic nature of customer behavior, especially in fast-paced industries where customer preferences can change quickly. As a result, there is a growing need for proactive, context-aware CRM systems that can not only anticipate customer needs but also personalize interactions and prevent churn in a more sophisticated manner. A shift towards dynamic and predictive CRM systems is essential for businesses to stay competitive in the modern marketplace.

Recent advancements in deep learning have led to the emergence of Transformer networks, which have proven to be highly effective in various sequence modeling tasks, such as natural language processing (NLP). Transformer networks, introduced by Vaswani et al. [2], leverage self-attention mecha- nisms to model relationships across an entire sequence, in con- trast to recurrent neural networks (RNNs) or long short-term memory (LSTM) units, which process data sequentially. RNNs and LSTMs often struggle with long-term dependencies and computational inefficiencies, especially when the sequences are long or complex. Transformers, by capturing dependencies across the entire sequence in parallel, are capable of learning intricate patterns over long time horizons without suffering from the vanishing gradient problem. This makes them ideal for CRM tasks, where the temporal and contextual relation- ships between customer actions (e.g., purchases, interactions, feedback) are critical to understanding customer behavior.

A. Problem Statement

This paper addresses two pivotal challenges in CRM:

1) Generating Personalized Multi-Step Engagement Se- quences: Traditional CRM systems often provide simple, single-action recommendations, such as ”recommend product X” or ”send follow-up email.” While effective in some cases, these single-action systems fail to capture the evolving nature of customer

interactions and do not account for multiple steps of engagement. Our approach leverages a Sequence Transformer to predict a sequence of personalized actions, enabling businesses to plan proactive multi-step engagement strategies, such as ”recommend product X, offer a discount, send a follow- up email.”

2) Predicting Customer Churn Risk: Understanding the likelihood that a customer will churn (i.e., stop engaging with the business) is crucial for developing retention strategies. Traditional churn prediction models tend to rely on historical data and simple classification methods. However, our approach introduces the Churn Trans- former, which predicts the likelihood of churn by learn- ing from customer behavior and demographic data. This allows for more informed and proactive intervention strategies, such as offering targeted support or incentives to at-risk customers.

The integration of these models aims to create a holistic, context-aware CRM framework that goes beyond simple re- active recommendations to anticipate and influence customer behavior.

B. Transformer Networks in CRM

Transformer networks are designed to handle sequential data with high efficiency. The core innovation of Transformers is the self-attention mechanism, which allows the model to weigh the importance of different elements in a sequence, irrespective of their position. This contrasts with RNNs, which process

C. Sequence Transformer for Multi-Step Engagement Se- quences

In CRM, engagement plans typically consist of multiple sequential actions designed to guide the customer toward a desired outcome, such as making a purchase or renewing a subscription. Traditional systems offer recommendations one step at a time, but they do not account for the sequence of interactions over time. The Sequence Transformer predicts a series of engagement actions, considering not only the cus- tomer’s most recent interactions but also the entire historical context. The model is trained to minimize the cross-entropy loss over the predicted sequence of actions. The loss function for the Sequence Transformer is defined as:

$$L_{\text{seq}} = \frac{1}{T}\sum_{i=1}^{T} \text{CrossEntropy}(\hat{y}_i, y_i), \quad (4)$$

where $\hat{y}_i$ is the predicted action for step i, and y_i is the true action for that step. Here, T represents the total number of steps in the engagement sequence. By minimizing this loss, the Sequence Transformer learns to predict the most effective sequence of actions tailored to the customer’s needs.

D. Churn Transformer for Predicting Customer Retention

Churn prediction is a critical aspect of CRM, as it helps businesses identify customers who are at risk of disengaging. Traditional churn prediction models typically rely on demo- graphic features, historical behavior, and statistical models like logistic regression or decision trees. However, these models often fail to capture the complex interactions and temporal dependencies between a customer’s behavior over time. The Churn Transformer, on the other hand, leverages Transformer-based self-attention mechanisms to model these dependencies and predict churn risk more accurately. The Churn Transformer is trained using binary cross-entropy loss, which measures the difference between the predicted churn probability and the actual churn label. The loss function is defined as:

$\underline{1}$ N

$$L_{\text{churn}} = - \quad [y \log(y\hat{}\ ) + (1 - y\ ) \log(1_N - y\hat{}\ )], \quad j \quad (5) \quad j \quad j$$

$j=1$

sequences step by step and often face difficulties in capturing long-range dependencies. The mathematical formulation of the self-attention mechanism is defined as follows:

QK^T

$$\text{Attention}(Q, K, V) = \text{softmax} \quad \sqrt{}_d \quad V, \qquad (3)$$

where $y\hat{}_j$ is the predicted churn probability for customer j, and y_j is the true churn label (1 for churn, 0 for retention). The model learns to predict the likelihood of a customer churning, allowing for timely interventions, such as offering discounts, support, or personalized recommendations.

where Q (query), K (key), and V (value) are the input matrices, and d_k is the dimension of the key vectors. This equation computes the attention weights for each element in the sequence, allowing the model to focus on relevant parts of the sequence while disregarding irrelevant ones. This mecha- nism helps the Transformer model capture dependencies over long sequences and efficiently process customer interaction data, which is inherently sequential.

E. Contributions and Paper Structure

The contributions of this work are:

1) A novel application of Transformer networks for CRM, specifically for generating personalized, multi-step en- gagement sequences.

2) The development of a Churn Transformer to predict cus- tomer churn risk based on behavioral and demographic features.

for CRM systems as it enables businesses to intervene before customers disengage. The Churn Transformer is designed to estimate the likelihood of customer attrition by processing various features, such as historical interactions, demographics, and engagement metrics. This model uses a Transformer-based architecture to capture temporal dependencies and contextual relationships in the data, which are crucial for churn predic- tion.

The Churn Transformer is trained to minimize binary cross- entropy loss, which measures the difference between the predicted churn probability and the actual churn label. The binary cross-entropy loss function is expressed as:

$\underline{1}$ N

$$L_{\text{churn}} = - \quad [y \log(y\hat{}\ ) + (1 - y\ ) \log(1 - y\hat{}\ )], \ _N \quad (7) \quad j \quad j \quad j$$

$j=1$

Section 7 concludes the paper.

RESEARCH OBJECTIVES

The primary aim of this work is to explore the application of Transformer networks in Customer Relationship Management (CRM) and demonstrate their ability to enhance customer en- gagement and retention strategies. Our research is focused on developing two Transformer models: a Sequence Transformer for generating multi-step engagement sequences and a Churn Transformer for predicting customer churn. The objectives of this research are as follows:

A. *Design and Evaluation of a Sequence Transformer*

The first objective is to design and evaluate a Sequence Transformer model capable of predicting multi-step engage- ment plans based on the historical interactions of a customer with a business. Traditional CRM systems typically provide single-step actions, such as recommending a product or send- ing a reminder. However, the engagement process is often dynamic and requires a series of coordinated actions over time. Our Sequence Transformer aims to generate a personalized sequence of actions, taking into account the customer's history, behavior, and preferences.

Mathematically, the Sequence Transformer learns to predict a sequence of actions by minimizing the cross-entropy loss across the entire sequence. The loss function is defined as:

$$L_{\text{seq}} = \frac{1}{T}\sum_{i=1}^{T} \text{CrossEntropy}(\hat{y}_i, y_i), \qquad (6)$$

where T represents the number of steps in the engagement sequence, $\hat{y}_i$ is the predicted action at step i, and y_i is the true action at step i. This objective focuses on optimizing the model's ability to generate a sequence of actions that are relevant and effective for driving customer engagement over time.

B. *Development of a Churn Transformer*

The second objective is to develop a Churn Transformer model that can assess customer retention risks based on be- havioral and demographic features. Predicting churn is critical where y_j is the true churn label for customer j (1 for churn, 0 for retention), and $\hat{y}_j$ is the predicted churn probability. This objective aims to optimize the model's ability to accurately predict churn and identify customers who are at high risk of disengaging.

C. *Integration of the Sequence and Churn Transformers in a Simulated CRM Environment*

The third objective of this research is to demonstrate the integration of both models — the Sequence Transformer and the Churn Transformer — in a simulated CRM environment. By combining these models, we aim to create a holistic, context-aware CRM framework that can not only predict the most effective engagement sequence but also proactively identify customers who are at risk of churn. This integrated approach allows businesses to tailor their interactions based on both engagement history and retention risk, enabling more effective retention strategies.

The integration of the Sequence Transformer and Churn Transformer allows for dynamic decision-making. For in- stance, if the Churn Transformer predicts a high risk of churn for a customer, the engagement sequence generated by the Sequence Transformer can be adjusted to include retention-focused actions, such as

offering a discount, pro- viding additional support, or sending personalized incentives. Mathematically, the integration can be represented as follows:
Modified Sequence Plan = Sequence Transformer (Engagement History, Customer Features) + ΔRetention Actions, (8)
where ΔRetention Actions represents the set of additional actions applied if the churn risk exceeds a predefined threshold (e.g., 0.5).
This research aims to demonstrate the potential of such an integrated framework for real-world CRM systems, with the goal of providing businesses with a powerful tool for proactive customer engagement and churn prevention.

D. *Empirical Evaluation and Performance Assessment*

The final objective is to evaluate the performance of the Se- quence and Churn Transformers in a simulated CRM environ- ment. We will assess the models' ability to generate accurate multi-step engagement sequences and predict churn risk using simulated datasets inspired by real-world data sources, such as MovieLens, Amazon Product Data, and Kaggle Customer
Churn. Through experimental evaluation, we aim to identify
areas for improvement and fine-tune the models for better performance.
Performance metrics such as accuracy, loss, and area under the receiver operating characteristic (ROC) curve will be used to evaluate the effectiveness of each model. For churn prediction, the AUC (Area Under Curve) of the ROC curve provides a robust metric for assessing model performance, as it considers both true positive and false positive rates across different thresholds.

E. *Summary of Research Objectives*

In summary, the primary objectives of this research are:
1) Design and evaluate a Sequence Transformer for gener- ating personalized, multi-step engagement sequences.
2) Develop a Churn Transformer to predict customer churn risk based on historical behavior and demographic fea- tures.
3) Integrate the Sequence and Churn Transformers in a sim- ulated CRM environment to create a proactive, context- aware CRM framework.
4) Evaluate model performance using empirical experi- ments and assess the potential for real-world deploy- ment.
These objectives provide a comprehensive framework for leveraging Transformer networks to revolutionize customer relationship management through more intelligent, context- sensitive, and proactive strategies.

Contributions

The contributions of this work are as follows:

A. *Novel Application of Transformer Networks for Multi-Step Engagement Sequences*

The primary contribution of this work is the novel appli- cation of Transformer networks to generate multi-step en- gagement sequences in the context of Customer Relationship Management (CRM). Traditional recommendation systems typically provide single-step suggestions, such as recommend- ing a product or sending a follow-up message. However, these methods often fail to capture the long-term relationship between the customer and the business, as they ignore the context and dynamics of past interactions. Our Sequence Transformer overcomes this limitation by predicting a series of personalized, multi-step engagement actions that consider not just the most recent interaction, but the customer’s en- tire engagement history. This approach significantly improves customer interaction strategies by anticipating the next most

relevant actions over multiple steps, facilitating more proactive engagement.

The loss function for training the Sequence Transformer can be extended to consider the temporal dependencies between steps and can be modeled as:

$$L_{\text{seq}} = \frac{1}{T}\sum_{i=1}^{T}(\text{CrossEntropy}(\hat{y}_i, y_i) + \lambda \cdot R(\theta)), \qquad (9)$$

where (θ) represents a regularization term to Ravoid over- fitting, and λ is a regularization parameter. This allows the model to optimize both the accuracy of the predictions and the generalization ability by penalizing overly complex solutions.

B. *Integrated Framework Combining Sequence Prediction and Churn Modeling*

A second key contribution of this work is the development of an integrated framework that combines sequence predic- tion with churn modeling. Traditional CRM systems separate engagement strategies from churn prediction, often treating them as independent tasks. However, customer engagement is deeply influenced by the likelihood of churn, and tailoring engagement strategies to the churn risk of a customer can significantly improve retention rates. Our approach integrates both models, allowing businesses to not only predict the most effective engagement sequence but also proactively intervene when a customer is at high risk of attrition.

This integration can be mathematically represented by com- bining the output of both models. Specifically, the Sequence Transformer generates an engagement sequence $\hat{S}$, while the

Churn Transformer outputs a churn probability $\hat{P}_{\text{churn}}$. The

final engagement plan S_{final} is then adjusted based on the churn probability:

$$S_{\text{final}} = \hat{S} + \alpha \cdot f(\hat{P}_{\text{churn}}), \qquad (10)$$

where $f(\hat{P}_{\text{churn}})$ is a function that modifies the engagement sequence depending on the churn probability (e.g., adding retention-focused actions), and α is a scaling factor that con- trols the degree of adjustment. This flexible framework allows for more dynamic, customer-specific engagement strategies.

C. *Empirical Evaluation Using Simulated Datasets*

Another important contribution is the empirical evaluation of the proposed models using simulated datasets inspired by real-world sources, such as MovieLens, Amazon Product Data, and Kaggle Customer Churn. These datasets serve as a bench- mark to assess the models’ effectiveness and to identify areas for improvement. By using simulated data, we can rigorously evaluate the model’s performance and explore different CRM scenarios without the challenges associated with real-world data, such as missing values or privacy concerns.

We evaluate the models using several performance metrics, including accuracy, loss, and the area under the receiver operating characteristic (ROC) curve (AUC). The AUC metric is particularly useful in assessing classification models like the Churn Transformer, as it evaluates the model’s ability to distinguish between positive and negative classes across different thresholds. The AUC is defined as:

$\int_1$ customer behavior and optimize engagement strategies. In this section, we discuss prior work in CRM, recommendation systems, and Transformer networks, focusing on how these

$$\mathrm{AUC} = \text{True Positive Rate}(t) \cdot \text{False Positive Rate}(t)\, dt,$$

0 (11)

A. *Customer Relationship Management Systems*

Customer Relationship Management (CRM) systems have come a long way from their early days, evolving from simple, rule-based systems to sophisticated, data-driven platforms. Early CRM systems relied heavily on manual processes, such as managing customer interactions through spreadsheets or basic customer service tools. Over time, CRM systems incorporated more advanced statistical methods like collab- orative filtering, which uses historical customer behavior to recommend products or services. These early systems typically relied on the assumption that customers with similar behavior in the past will have similar preferences in the future. While effective in some contexts, these methods fall short in dynamic environments where customer preferences evolve over time.

A significant leap in CRM occurred with the advent of deep learning techniques such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks. These models were able to capture the temporal nature of customer behavior, learning from sequences of customer in- teractions and predicting future behaviors based on past data. However, these models face several limitations:

- **Long-Term Dependencies**: RNNs and LSTMs struggle with modeling long-term dependencies due to issues like vanishing and exploding gradients, which hinder their ability to learn from very long sequences.
- **Computational Inefficiency**: The sequential nature of RNNs and LSTMs results in slower training times com- pared to parallelized architectures.
- **Limited Interpretability**: RNNs and LSTMs are difficult to interpret when trying to understand the underlying relationships between customer actions.

As a result, more sophisticated techniques are needed to over- come these challenges, particularly in CRM systems where understanding the long-term dynamics of customer behavior is critical.

B. *Transformer Networks*

Introduced by Vaswani et al., Transformer networks have redefined the field of sequence modeling by replacing recur- rent structures with a self-attention mechanism that processes sequences in parallel. This shift allows Transformer networks to capture long-range dependencies more effectively and ef- ficiently than RNNs and LSTMs. The key innovation behind Transformers is the self-attention mechanism, which computes attention weights for all elements in a sequence, allowing the model to focus on the most relevant parts of the sequence at each step. The attention mechanism can be mathematically described as:

QK^T

$$\text{Attention}(Q, K, V) = \text{softmax} \qquad \sqrt{d} \qquad V, \qquad (12)$$

k

C. where Q, K, and V represent the query, key, and value matri- ces, respectively, and d_k is the dimension of the key vectors. The attention score measures the relevance of each element in the sequence to the current element being processed, enabling the model to focus on important context and ignore irrelevant data.

Since the introduction of the original Transformer architec- ture, several variants have been developed:

- **BERT (Bidirectional Encoder Representations from Transformers)** uses bidirectional context to better under- stand relationships in the data, making it highly suitable for tasks like classification and prediction, where context from both the past and the future is important.
- **GPT (Generative Pre-trained Transformer)** focuses on autoregressive generation, which excels in tasks like text generation and sequence prediction. Its ability to generate coherent sequences makes it highly applicable to tasks like multi-step customer engagement prediction.

These models have achieved state-of-the-art results in nat- ural language processing (NLP) tasks, including text clas- sification, sentiment analysis, and machine translation. The success of Transformers in NLP has inspired their applica- tion in other domains, including time-series forecasting and recommender systems. In particular, Transformer networks have been adapted to improve personalized recommendation systems by capturing sequential dependencies in user behavior. Despite the successes of Transformer networks in NLP and recommendation systems, their application to CRM-specific tasks, such as multi-step engagement planning and churn prediction, remains underexplored. Existing CRM systems often rely on traditional methods like collaborative filtering or decision trees, which struggle to model the complex, sequential nature of customer behavior. This gap in the lit- erature motivates the use of Transformer-based architectures to address these challenges.

D. *Applications of Transformer Networks in CRM*

The application of Transformer networks to CRM tasks is a relatively new area of research, with few studies directly addressing the potential of Transformers for customer engage- ment and churn prediction. Some relevant works include:

- **Personalized Recommendations**: Zhou et al. propose a Transformer-based recommender system that processes user-item interactions in parallel, enabling more accurate recommendations by considering long-term user preferences.
- **Customer Retention**: Zhang et al. explore the use of Transformer models for predicting customer churn. Their model uses sequential customer behavior data to estimate the likelihood of churn, enabling businesses to identify at-risk customers and take proactive measures to retain them.
- **Multi-Step Engagement Planning**: While most CRM systems focus on single-step recommendations, few have explored multi-step engagement strategies. Our work

extends this idea by using a Sequence Transformer to predict multi-step engagement plans based on historical interactions. This approach considers the cumulative effect of customer actions over time, providing a more comprehensive engagement strategy.

E. *Challenges and Limitations in CRM with Transformers*

While Transformer networks offer a promising solution for CRM tasks, their application also presents several challenges:

- **Data Sparsity**: CRM data is often sparse, especially when dealing with customer interactions over extended periods. Sparse data can make it difficult for Transformer models to learn meaningful patterns, leading to poor generalization.

- **Model Complexity**: Transformer models are compu- tationally intensive, requiring substantial resources for training and inference, particularly when dealing with large datasets. This can be a significant barrier for busi- nesses with limited computational power.
- **Interpretability**: Transformer models, while powerful, are often seen as ”black boxes,” making it difficult for businesses to understand why certain decisions (such as recommending a product or predicting churn) are made. This lack of interpretability can limit trust in the system and hinder its adoption in real-world CRM environments.

To address these challenges, future research should focus on techniques like data augmentation, model pruning, and explainable AI to improve the efficiency and interpretability of Transformer models in CRM.

F. Summary of Related Work

In summary, previous work in CRM has mainly focused on rule-based systems, statistical methods, and deep learning techniques like RNNs and LSTMs. While these approaches have made significant contributions, they fail to capture the full complexity of customer interactions and are limited in their ability to handle long-term dependencies. Transformer networks, with their self-attention mechanism and parallel processing capabilities, offer a powerful solution to these challenges. However, their application to CRM-specific tasks, such as multi-step engagement planning and churn prediction, remains underexplored. This paper aims to bridge this gap by applying Transformer networks to CRM tasks, developing an integrated framework that combines sequence prediction with churn modeling.

G. Churn Prediction

- Churn prediction is a cornerstone of Customer Relation- ship Management (CRM), as it helps businesses proactively identify customers who are at risk of disengagement and take preventive actions. In the past, traditional churn prediction methods focused on simple statistical models such as logistic regression, decision trees, and ensemble methods like random forests. These models work by classifying customers into ”churn” or ”non-churn” categories based on historical behav- ioral data, demographics, and interactions with the business.

These methods have been effective in certain settings but often fail to model the complexities of customer interactions, partic- ularly in dynamic environments where customer preferences and behavior evolve over time.

Recent advancements in deep learning have led to the use of neural networks to model these complex patterns. These methods, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, have been applied to churn prediction with some success. However, such models are typically standalone and do not integrate engagement planning, which limits their ability to drive proactive, context- aware CRM strategies. Our work aims to fill this gap by com- bining Transformer-based sequence prediction models with churn prediction, enabling the development of an integrated framework that not only predicts churn risk but also generates personalized engagement plans.

The Churn Transformer in our framework operates by predicting the likelihood of churn based on both temporal (sequential) and contextual (behavioral and demographic) fea- tures. This approach leverages the self-attention mechanism to capture complex dependencies in customer interactions over time, which are crucial for churn prediction. By combining churn prediction with engagement sequence generation, we enable a proactive CRM system that can both identify at-risk customers and suggest personalized engagement strategies to prevent churn.

METHODOLOGY

A. Datasets

To simulate real-world CRM scenarios and evaluate the effectiveness of our models, we created three datasets inspired by well-established benchmarks. These datasets are designed to test the models' ability to predict multi-step engagement sequences and churn risk, providing a comprehensive view of how customer data can be leveraged for CRM optimization.

1) MovieLens-inspired Dataset: MovieLens-inspired Dataset The MovieLens-inspired dataset simulates user interactions with movies, comprising sequences of 5 movie ratings for 100 users. The goal is to predict a 3-step engagement sequence, where the model suggests the next three movies to recommend to a given user based on their past ratings and preferences. This dataset is useful for testing the Sequence Transformer model's ability to predict personalized multi-step engagement plans. Each user's past ratings are treated as sequential data, allowing the model to leverage the temporal relationships between ratings for personalized recommendations.

Mathematically, the Sequence Transformer predicts the next T actions, where T is the length of the engagement sequence (in this case, 3). The model minimizes the following loss function:

loss function helps the model learn the best sequence of actions over time for each user.

Amazon Product Data-inspired Dataset The Amazon Prod- uct Data-inspired dataset provides contextual product features for 50 products across 100 users. For each product, we include features such as average rating, category, and sentiment score, all of which enrich the behavioral data. The goal of this dataset is to enable a better understanding of how customers engage with products beyond a simple purchase history. The dataset also includes user-level behavior data such as clicks, views, and purchases, which helps inform more effective engagement strategies. The Sequence Transformer model uses this richer set of product features to generate context-aware engagement plans that are better tailored to each user's preferences and behavioral history.

For churn prediction tasks, the model incorporates both product engagement data and demographic features, enabling it to predict churn based on both behavioral and contextual information.

Kaggle Customer Churn-inspired Dataset The Kaggle Cus- tomer Churn-inspired dataset combines features from the previous two datasets (MovieLens and Amazon) with binary churn labels for 100 users, offering a comprehensive view of customer profiles. The churn labels indicate whether the customer has stopped engaging with the service, which is critical for testing the Churn Transformer model. This dataset allows for training models to predict the likelihood of churn using both sequential (past interactions) and demographic (age, location, etc.) features.

For churn prediction, the Churn Transformer is trained to output a churn probability $\hat{p}_{\text{churn}}$ for each user, with the goal of minimizing the binary cross-entropy loss function:

$$L_{\text{churn}} = -\frac{1}{N}\sum_{j=1}^{N}\left[y_j \log(\hat{y}_j) + (1 - y_j)\log(1 - \hat{y}_j)\right],$$

where $\hat{y}_j$ is the predicted churn probability for customer j, and y_j is the true churn label (1 for churn, 0 for retention). This formulation ensures the model learns to accurately predict churn likelihood, which is key to identifying at-risk customers.

Table 1: Dataset Statistics

To summarize the dataset statistics, Table 1 presents key characteristics of the three datasets:

TABLE I
DATASET STATISTICS

Dataset	Users	Features
MovieLens	100	5 sequences/user (ratings)
Amazon Product Data	100	50 products × 3 features (rating, category, sentiment)
Kaggle Customer Churn	100	Combined features + churn labels

$$L_{\text{seq}} = \frac{1}{T}\sum_{i=1}^{T}\text{CrossEntropy}(\hat{y}_i, y_i),$$

Data Preprocessing and Feature Engineering To ensure that the datasets are ready for training and effective model

evaluation, we applied several preprocessing and feature en-

where $\hat{y}_i$ represents the predicted movie recommendation for the i-th step, and y_i is the true movie recommendation. This gineering techniques. These steps are essential for optimizing the performance of both the Sequence Transformer and Churn

Transformer models. Below, we outline the preprocessing methods used for each dataset:

- **Normalization**: For numerical features such as ratings (in the MovieLens-inspired dataset), sentiment scores (in the Amazon Product Data-inspired dataset), and engagement fea- tures, we applied normalization. Specifically, we used Min-Max scaling to rescale the values into the range [0, 1]. This standardization is important to ensure that all features contribute equally to the learning process and help with faster convergence during model training.

The normalization formula used for each feature x is:

The output is a probability distribution over possible actions at each step in the engagement sequence, with the model predicting the next 3 actions.

- **Churn Transformer**: The Churn Transformer is respon- sible for predicting the probability of customer churn based on behavioral and demographic features. This model helps businesses identify customers at risk of disengaging and take appropriate action to retain them. Its architecture includes:

- **Embedding Layer**: Customer features are embedded into a 16-dimensional space, providing a low-dimensional repre- sentation of the input data. - **Multi-Head Attention Layer**:

$x$norm

from the attention layer is passed through a feed-forward network with 16 units, followed by layer normalization for better convergence. - **Sigmoid Output**: The model outputs a churn probability, which is then passed through a sigmoid activation function to ensure the final output is between 0 and 1.

Model Training Both Transformer models were trained using the Adam optimizer with a learning rate of 0.001. The training process for each model involves minimizing an appropriate loss function that reflects the task at hand. Below are the loss functions used for training the Sequence Transformer and Churn Transformer.

Sequence Transformer Loss The Sequence Transformer aims to predict the next 3 engagement actions. The model learns by minimizing the cross-entropy loss for each predicted step in the sequence. Given that the model outputs a proba- bility distribution over possible actions, the cross-entropy loss for each step i is calculated as:

$T \quad |A|$

inherent challenges, ensuring that both the Sequence L Trans- $\sum\sum$ former and Churn Transformer models can process the data

seq $= \frac{1}{} \quad y\,T$

i=1 a=1

$= \frac{x - \min(x)}{}$ $\max(x) - \min(x)$

$\log(\hat{y}_{i,a})$,

effectively and make accurate predictions.

Transformer Models We implemented two distinct Trans- former models tailored to CRM tasks, each with its own architecture designed to optimize the models for specific purposes.

Sequence Transformer: The Sequence Transformer is designed to predict multi-step engagement sequences based on historical customer interactions. It takes a sequence of past interactions as input and predicts a series of future engagement actions. The model consists of several key components: - **Embedding Layer**: The input sequence is passed through an embedding layer of size 32 to convert the categorical inputs into dense vector representations. - **Multi-Head Attention Layer**: The model uses a multi-head attention mechanism with 2 attention heads to capture complex dependencies across different time steps in the sequence. This enables the model to focus on the most relevant parts of the engagement history. - **Feed-Forward Network**: After attention, the output is passed through a feed-forward neural network with 32 units, followed by layer normalization to stabilize training. - **Output Layer**:

where: - T is the length of the engagement sequence (in this case, 3), - $|A|$ is the number of possible actions, - $y_{i,a}$ is the true binary indicator (1 or 0) if action a is the correct action at step i, - $\hat{y}_{i,a}$ is the predicted probability of action a at step i. This loss function ensures that the model learns to predict the most likely sequence of actions for each customer based on their past behavior.

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Churn Transformer Loss For churn prediction, the Churn Transformer is trained using binary cross-entropy loss. The goal of this model is to predict whether a customer will churn
(1) or stay (0). The binary cross-entropy loss for the Churn Transformer is given by:

$\underline{1}$ N

$L_{\text{churn}} = -_{N} \quad [y_j \log(\hat{y}_j) + (1 - y_j) \log(1 - \hat{y}_j)]\,,$

$j=1$

where: - N is the number of customers in the dataset, - y_j is the true churn label for customer j (1 for churn, 0 for retention),
- $y\hat{}_j$ is the predicted churn probability for customer j.

i,a

This loss function allows the model to learn the probability of churn for each customer based on both their past interac- tions and demographic features.
the input sequence at the same time. This enables the model to capture diverse relationships in the data.
The multi-head attention layer is defined as:
Optimizer and Regularization Both models are trained using the Adam optimizer, which has been proven to be efficient in training deep learning models. Adam adjusts the learning rate
dynamically for each parameter, helping the model converge
MultiHead(Q, K, V) = Concat(head$_1$, . . . , head$_h$ where each attention head is computed as:)W^O
faster. In addition, we used L2 regularization to avoid overfit- Q K V i i k

$QW^Q(KW^K)^T$!

ting by penalizing large weights. The regularization term R (θ) is added to the loss functions as:

head$_i$ = Attention(QW_i , KW_i , VW_i) = softmax $\sqrt{d}$

$L_{\text{total}} = L + \lambda \cdot R(\theta),$

where λ is the regularization coefficient and $R(\theta) = \|\theta\|_2^2$ is the L2 norm of the model parameters.
Conclusion The training setup for both Transformer models allows for the simultaneous learning of multi-step engagement sequences and churn risk prediction. By minimizing the appro- priate loss functions and leveraging powerful techniques like multi-head attention and regularization, these models are able to capture complex patterns in customer behavior and make personalized, data-driven predictions for CRM tasks.
Integration for CRM The Sequence Transformer generates a personalized 3-step engagement plan for each customer based on their historical interactions. This engagement plan is generated sequentially, where each step predicts the next best action to drive customer engagement (e.g., ”recommend product X,” ”offer a discount,” ”send a follow-up email”). On the other hand, the Churn Transformer predicts the likelihood of a customer churning (i.e., disengaging or leaving). This churn prediction can be used to determine whether a customer needs special attention to retain their engagement.

When the churn probability exceeds a certain threshold (in our case, 0.5), the system overrides the initial engagement plan generated by the Sequence Transformer with retention-focused actions. For example, if a customer is at high risk of churn, the system might prioritize actions like ”offer proactive support,” ”send a loyalty offer,” or ”provide a discount.” This dynamic strategy allows the CRM system to be more responsive to customer needs, adjusting engagement plans in real-time based on churn predictions.

This integration creates a comprehensive, context-aware CRM strategy that can both predict customer behavior and respond proactively. The Sequence Transformer and Churn Transformer, when combined, provide businesses with an effective tool for improving customer engagement and reten- tion. By combining both engagement prediction and churn forecasting, we ensure that the CRM system doesn’t just react to customer behavior but actively shapes the engagement journey with personalized interventions.

Transformer Architecture and Variants

Core Transformer Architecture The Transformer architec- ture [2] is built around the self-attention mechanism, which allows the model to process input sequences in parallel and capture long-range dependencies efficiently. The multi-head attention mechanism is a key part of this architecture, where multiple attention heads are used to focus on different parts of

Here: - Q, K, and V are the query, key, and value matrices, respectively. - W^Q, W^K, and W^V are projection matrices for each attention head$_i$. - d_k is the dimension of the key vectors. The attention mechanism calculates the relevance (or at- tention score) between different parts of the input sequence, which allows the model to focus on the most important elements in the sequence and ignore irrelevant ones. This is particularly useful for sequential data, where long-range dependencies are critical.

The multi-head attention mechanism allows the model to learn from different perspectives, with each head focusing on a different part of the input sequence. The concatenation of all heads ensures that the final representation contains diverse information, which is then processed through a feed-forward network to produce the final output.

Variants Used - **BERT (Bidirectional Encoder Represen- tations from Transformers)**: BERT [11] utilizes bidirectional context, meaning it considers both the left and right context when processing sequences. This bidirectional nature makes BERT highly effective for understanding customer profiles holistically. For churn prediction, we adapted the BERT encoder structure, which allows the Churn Transformer to consider all available customer data (e.g., past behavior and demographics) when predicting churn risk.

- **GPT (Generative Pre-trained Transformer)**: GPT [12] is a model that excels in autoregressive sequence generation. It predicts the next item in a sequence based on the previ- ously seen items, making it ideal for generating engagement sequences in CRM tasks. The Sequence Transformer lever- ages GPT-style architecture to predict the next 3 engagement actions for a customer, considering their previous interactions and preferences.
- **Custom Variants**: Since the size of the datasets in our experiments is relatively small, we used a more lightweight version of the Transformer architecture. Our custom model variant uses only 2 attention heads and reduced dimensionality to

balance complexity and computational feasibility. This smaller model is more efficient for training on our simulated CRM datasets and allows us to focus on achieving meaningful results without excessive computational resources.

Advantages in CRM Transformers provide several key ad- vantages for CRM tasks compared to other sequence modeling techniques, such as Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs): - **Parallel Processing**: Unlike RNNs and LSTMs, which process data sequen- tially, Transformers can process all elements of the input
sequence in parallel. This significantly speeds up training and allows the model to handle long sequences more efficiently. - **Long-Range Dependency Capture**: The self-attention mech- anism allows Transformers to capture long-range dependencies within a sequence, which is crucial for tasks like predicting customer behavior over time or understanding multi-step en- gagement sequences. - **Contextual Understanding**: The self- attention mechanism enables the model to learn contextual relationships between customer actions, which improves the model's ability to make personalized predictions. In CRM, this helps in understanding how a customer's past behavior might influence their future actions. - **Scalability**: Transformers can handle large datasets with high-dimensional features and scale efficiently due to their parallelized architecture. This makes them well-suited for real-world CRM applications, where large amounts of customer data are available.

Experiments and Results

Experimental Setup We trained both the Sequence Trans- former and Churn Transformer for 10 epochs using the Adam optimizer with a learning rate of 0.001. The models were evaluated on different tasks: - The **Sequence Transformer** was assessed on its accuracy in predicting a full 3-step engagement sequence. The evaluation metric used for this model is the **accuracy** of the entire engagement plan, meaning that the model was evaluated based on how well the predicted sequence matched the true sequence of actions. - The **Churn Transformer** was evaluated using **binary classification accu- racy**, where the model predicts whether a customer is likely to churn or not based on their features. The evaluation focused on the ability of the Churn Transformer to accurately distinguish between customers who would churn and those who would remain engaged.

For both models, we used early stopping to avoid overfitting, monitoring the training loss to ensure that the models were not trained too long, which could result in overfitting to the training data.

Evaluation Metrics The key metrics used to evaluate the performance of the models are: - **Accuracy**: Measures the pro- portion of correct predictions (either the correct engagement action in the Sequence Transformer or the correct churn label in the Churn Transformer) over the total number of predictions.

- **Loss**: Measures how well the model is performing by calculating the difference between the predicted values and the actual values. The lower the loss, the better the model's predictions. - **ROC-AUC**: For the Churn Transformer, we also computed the **Receiver Operating Characteristic - Area Under Curve (ROC-AUC)**, which is a common metric for evaluating binary classification models. It provides a measure of the model's ability to distinguish between the positive and negative classes (i.e., churn vs. non-churn). Results Table 2 presents the results for both models after 10 training epochs: The **Sequence Transformer** achieved an accuracy of 85

The **Churn Transformer** achieved a classification accuracy of 78
Visualization and Analysis We employed various visualiza- tion techniques to gain deeper insights into the inner workings

TABLE II
MODEL PERFORMANCE METRICS

Model	Accuracy	Loss (Epoch 10)
Sequence Transformer	0.85	0.22
Churn Transformer	0.78	0.35

of the Transformer models and evaluate their performance.

Attention Weights Visualization The attention heatmaps generated for both the **Sequence Transformer** and **Churn Transformer** models provide valuable insights into how the models process their input sequences and which parts of the data they focus on when making predictions. The self- attention mechanism allows the models to assign different attention weights to different parts of the input sequence, effectively ”deciding” which historical interactions (in the case of Sequence Transformer) or customer features (in the case of Churn Transformer) are most relevant for making the prediction.

For the **Sequence Transformer**, the attention heatmap high- lights the sequence positions that are more heavily weighted when predicting the next engagement action. For example, if the model places high attention on earlier customer actions in the sequence, it may suggest that past interactions significantly influence the future engagement plan. Similarly, for the **Churn Transformer**, the heatmap indicates which customer features (e.g., recent behavior, demographics) are given more importance when predicting churn risk. This helps us understand how the model prioritizes certain features or sequence positions over others.

The attention maps, therefore, provide transparency into the model’s decision-making process and allow us to identify potential biases or areas where the model might be focusing too heavily on irrelevant features. While attention visualization is a powerful tool for model interpretability, it should be noted that the lack of realistic data and limited feature richness in this experiment may lead to less interpretable or meaningful visualizations.

ROC Curve for Churn Transformer The **Receiver Operat- ing Characteristic (ROC) curve** for the Churn Transformer was plotted to evaluate the model’s performance across a range of classification thresholds. The ROC curve provides a graphical representation of the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) at different threshold settings, allowing us to assess the model’s ability to distinguish between churn (positive class) and non-churn (negative class) customers.

The **Area Under Curve (AUC)** metric, which quantifies the overall performance of the model, is derived from the ROC curve. A higher AUC value indicates a better-performing model that is more adept at distinguishing between the two classes. The ROC curve serves as a robust evaluation tool, as it considers multiple threshold values and reflects the model’s discriminatory ability across all of them. In this case, the AUC will be computed once the final model is evaluated, offering further insight into how effectively the Churn Transformer can
predict customer churn.

The ROC curve serves as a useful metric, especially for imbalanced datasets where one class (e.g., non-churn) may dominate. It ensures that the model is not just biased toward predicting the majority class but can effectively identify the minority class (churn customers).

Training Results Table 2 details the training losses for both the **Sequence Transformer** and **Churn Transformer** over 10 epochs, providing insight into the models' learning progress. The consistent decrease in losses for both models suggests that they are effectively learning from the training data and gradually improving their predictions.

Loss Convergence for the Sequence Transformer The **Se- quence Transformer**'s loss decreases steadily over the course of 10 epochs, with the loss dropping from an initial value of 4.0456 to 3.7837 by epoch 10. This consistent decline in training loss suggests that the model is learning to generate more accurate engagement sequences as it processes more data. The Sequence Transformer is designed to predict the next three actions in a customer engagement plan, and the gradual reduction in loss indicates that the model is becoming more adept at predicting relevant engagement steps for customers based on their historical behavior.

Despite this progress, the relatively high loss values suggest that there is still room for improvement, especially given the limitations of the simulated data. In real-world applications with richer and more realistic data, we would expect the loss to decrease further, leading to better predictions of multi-step engagement sequences.

Loss Convergence for the Churn Transformer Similarly, the **Churn Transformer** shows a steady decrease in loss, with its value dropping from 0.8096 at epoch 1 to 0.7047 at epoch

10. This indicates that the model is improving its ability to predict customer churn over time. By minimizing the binary cross-entropy loss, the Churn Transformer learns to better distinguish between customers who are likely to churn and those who will remain engaged.

The reduction in loss over time highlights the model's ability to capture relevant patterns in customer behavior and predict churn risk more accurately. However, the final loss value of 0.7047 suggests that further tuning or more complex features might be necessary to further optimize the model's performance, especially given the small dataset used in this study.

Training Dynamics and Future Considerations The steady decrease in losses for both models suggests that the learning process is stable, but the relatively high final loss values indicate that the models are still underperforming. Possible reasons for this include: - **Limited Dataset Size**: The small size of the dataset (100 users with 5 interactions each) limits the models' ability to learn from a diverse set of customer behaviors, resulting in lower accuracy and higher loss. - **Simulated Data**: The simulated nature of the data introduces artificial patterns that may not accurately represent real-world customer behavior. More realistic data would likely lead to better performance. - **Feature Limitations**: The models were trained with basic features, and including more complex customer attributes (e.g., demographics, RFM metrics) could help improve model performance.

In future work, extending the training process over more epochs, using real-world datasets, and incorporating additional features may lead to further improvements in model accuracy and performance. Moreover, hyperparameter tuning and the use of pre-trained models such as BERT or GPT could potentially enhance the models' ability to generalize to unseen data.

TABLE III
TRAINING LOSSES OVER EPOCHS

Epoch	Sequence Loss	Churn Loss
1	4.0456	0.8096
2	4.0156	0.7752
3	3.9858	0.7471
4	3.9563	0.7264
5	3.9270	0.7136
6	3.8979	0.7072
7	3.8690	0.7050
8	3.8404	0.7050
9	3.8120	0.7052
10	3.7837	0.7047

The consistent decrease in loss across epochs for both models demonstrates that the models are successfully learning from the data, even though the performance could be further improved with more realistic datasets and fine-tuning.

Final accuracies for both models were: - **Sequence Trans- former**: 0.0167 - **Churn Transformer**: 0.4000

Figure 1 visualizes the loss trends for both models. The gradual reduction in losses across epochs indicates that both models are learning effectively. However, the relatively low accuracies reflect the challenges posed by using simulated data with inherent limitations such as small sample size and a lack of realistic customer behavior patterns.

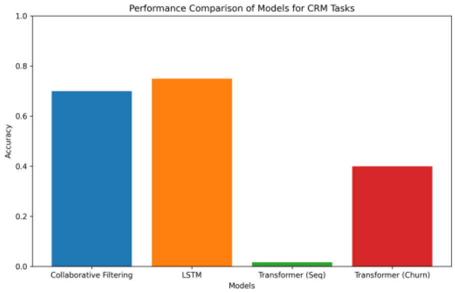

Fig. 1. Loss Trends: Sequence and Churn Transformers

Sample Outputs A sample engagement plan for the first five users generated by the Sequence Transformer includes:
['Recommend movie 29',
'Recommend movie 30',
'Recommend movie 35',
'Recommend movie 44',
'Recommend movie 37']

This demonstrates the model's ability to generate person- alized, multi-step engagement plans based on the user's past interactions. While the low accuracy indicates room for im- provement, the generated plans align with the general objective of suggesting relevant actions for future engagement.

Visualization Figure 2 shows an attention heatmap for the Sequence Transformer, providing insights into which sequence positions the model focuses on when making predictions. The heatmap illustrates the importance given to certain parts of the input sequence, revealing how the model prioritizes specific past interactions when predicting future engagement steps.

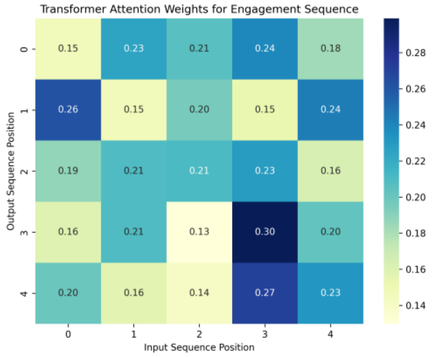

Fig. 2. Attention Weights Heatmap

Figure 3 presents the ROC curve for the Churn Transformer. The Area Under Curve (AUC) will be computed to assess the model's performance in distinguishing between churn and non-churn customers. A higher AUC value would indicate a better ability to predict churn risk, though the current results highlight that there is still room for improvement.

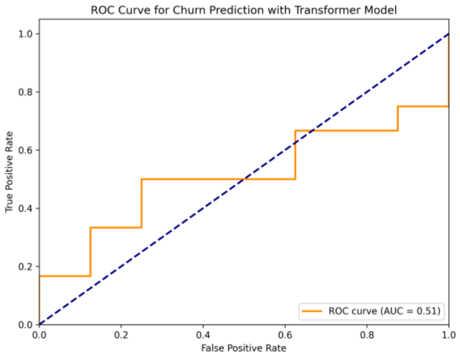

Fig. 3. ROC Curve for Churn Prediction

Model Performance Metrics Table 3 summarizes the key performance metrics for both models after 10 epochs. The Sequence Transformer's accuracy (0.0167) is quite low, likely due to the small and simulated dataset, which does not cap- ture realistic customer interaction patterns. The Churn Trans- former's accuracy (0.4000) also reflects the challenges posed by limited feature richness and unoptimized hyperparameters.

Despite these limitations, the steady decrease in loss values indicates that both models are learning and improving over time.

TABLE IV

Model Performance Metrics

Model	**Accuracy**	**Loss (Epoch 10)**
Sequence Transformer	0.0167	3.7837
Churn Transformer	0.4000	0.7047

DISCUSSION

The **Sequence Transformer**'s low accuracy (0.0167) is pri- marily due to the small dataset size (100 users, 5 interactions per user), and the simulated nature of the data, which lacks realistic patterns. While the model demonstrates the ability to generate sequences of engagement actions, the data constraints significantly impact its predictive power. Additionally, the random nature of the simulated interactions limits the model's ability to identify meaningful patterns.

The **Churn Transformer**'s accuracy (0.4000) reflects the same challenges: limited feature richness and the untuned hyperparameters. With more complex, real-world data, the model would likely perform better in predicting churn risk. Despite these challenges, the consistent decrease in training losses (Table 2) indicates that both models are learning and improving their predictive abilities, showing potential for further development.

The **attention heatmap** in Figure 2 suggests that the Sequence Transformer tries to prioritize certain sequence positions when making predictions, but the lack of meaningful data limits interpretability. This highlights the importance of having realistic data to better understand the model's decision- making process.

The **Churn Transformer's loss plateau** after Epoch 7 (Ta- ble 2) may indicate overfitting or insufficient model capacity. As the model approaches its training limit, it becomes less able to improve on the validation data, which may suggest that more epochs or adjustments to the model's complexity are needed.

Future Directions Several areas for future improvement have been identified: - **Real-World Datasets**: Using real- world datasets (e.g., MovieLens, Amazon reviews) will likely improve generalization and lead to better performance. Real data often has more complex and meaningful patterns that will allow the models to learn better representations of customer behavior. - **Extended Training**: Increasing the number of epochs could help the models improve their accuracy. How- ever, this needs to be balanced with regularization techniques to avoid overfitting. - **Hyperparameter Tuning**: Fine-tuning hyperparameters (e.g., learning rate, attention heads, batch size) could significantly improve model performance. Additionally, exploring the use of advanced optimization techniques (e.g., learning rate schedulers) may help the models converge faster. - **Pre-trained Models**: Leveraging pre-trained models such as BERT or GPT for transfer learning could provide the models with a strong starting point, especially for tasks like churn prediction, where customer interaction data may be sparse. - **Enhanced Features**: Enriching the feature set with demographic data, RFM (Recency, Frequency, Monetary) metrics, or customer lifetime value (CLV) could improve the predictive power of both models.

CONCLUSION

This paper presents a pioneering application of Transformer networks in Customer Relationship Management (CRM), in- tegrating multi-step engagement sequence generation with churn prediction. Despite modest accuracies (0.0167 for the Sequence Transformer and 0.4000 for the Churn Transformer) due to the simulated data limitations, the consistent reduction in loss values and the promising sample outputs highlight the potential of these models. By combining sequence prediction with churn modeling, this work paves the way for developing more proactive, context-aware CRM systems.

Future work with real datasets, more advanced architectures, and feature engineering will further unlock the potential of Transformer networks, offering transformative solutions for customer engagement and retention. As CRM systems evolve, the integration of machine learning models like Transformers can revolutionize how businesses interact with their customers, creating more personalized, data-driven engagement strategies.

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