Attention-Based Customer Lifetime Value Prediction in E-Commerce Using FT-Transformer Architecture

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ABSTRACT

Customer Lifetime Value (CLV) prediction is a critical component in strategic marketing, enabling businesses to allocate resources effectively and tailor personalized customer experiences. In this study, we explore the application of the FT-Transformer—a novel attention-based deep learning architecture—on a comprehensive e-commerce dataset to predict CLV. Unlike traditional methods such as Linear Regression and Random Forest, which often struggle with feature interaction and heterogeneity in structured data, the FT-Transformer leverages self-attention mechanisms to capture complex dependencies and assign dynamic importance to both categorical and numerical features. We preprocess the dataset to integrate relevant order, customer, and transaction attributes and train the FT-Transformer model in a supervised regression setting. Experimental evaluation demonstrates that the FT-Transformer achieves a higher R^2 score (0.75) while maintaining lower Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) than baseline models. The performance superiority highlights the model's ability to generalize well over diverse customer profiles and spending behaviors. Furthermore, attention-based interpretability offers insights into which features most influence CLV predictions, adding transparency to model decisions. This research underscores the strength of transformer architectures in structured financial forecasting and customer analytics, especially in environments characterized by high-dimensional, sparse, and heterogeneous data. Our findings suggest that integrating FT-Transformers into customer management systems can significantly enhance marketing strategies, churn reduction, and profitability forecasting. The study opens avenues for future work involving real-time CLV prediction and the integration of multimodal behavioral data into transformer-based models.
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Keywords: Customer Lifetime Value; FT-Transformer; E-commerce Analytics; Deep Learning; Predictive Modeling.

1. INTRODUCTION

Customer Lifetime Value (CLV) is a fundamental concept in marketing, finance, and data analytics that represents the total revenue a business can reasonably expect from a single customer account throughout the entire duration of their relationship. It is a forward-looking metric that moves beyond simple transactional analysis by considering not only the current purchases but also the potential future value of a customer. CLV is crucial because it helps businesses evaluate how much they should invest in acquiring, nurturing, and retaining customers. A high CLV suggests that a customer is worth more to the business, justifying higher investments in personalized marketing, exclusive offers, or enhanced customer service. On the other hand, a low CLV may prompt businesses to adopt more cost-efficient engagement strategies or reconsider acquisition channels. At its core, CLV combines three key components: average order value (how much a customer spends per purchase), purchase frequency (how often they make a purchase), and customer lifespan (how long the relationship lasts). By multiplying these factors, businesses arrive at an estimate of the total value a customer will contribute over time. These values are often adjusted for margins and discount rates to reflect profitability and time value of money, respectively. In digital commerce and subscription-based models, where customer interactions are frequently recorded and highly measurable, CLV becomes not only more precise but also more actionable. Businesses can tailor promotions, recommend products, or automate customer journeys based on a predicted CLV, thus optimizing the overall customer experience while ensuring financial sustainability.
Understanding CLV is particularly vital in competitive markets where customer acquisition costs (CAC) are high. Without a clear estimate of CLV, businesses risk overspending on marketing or failing to recognize their most valuable customer segments. A practical rule of thumb in many industries is that the CLV should be at least three times the CAC to ensure healthy profit margins. This balance between acquisition cost and lifetime value helps companies scale efficiently and identify the most lucrative customer acquisition channels. Additionally, CLV provides a long-term perspective on business health. For instance, a growing customer base with increasing CLV signals effective retention and engagement strategies, while stagnating or declining CLV might suggest the need for strategic changes in product offerings, pricing, or support. As businesses mature and adopt data-driven decision-making, CLV modeling becomes more sophisticated. Beyond simple averages, companies now employ statistical models and machine learning techniques to predict individual customer lifetime values based on real-time behavioral data. These models take into account not only transaction history but also browsing behavior, response to promotions, product preferences, and

demographic information. As a result, CLV shifts from being a static financial figure to a dynamic, evolving metric that supports personalization, segmentation, and forecasting. Whether used to guide marketing spend, evaluate customer satisfaction initiatives, or support investor reporting, CLV serves as a comprehensive indicator of the quality and longevity of customer relationships. In a business world increasingly driven by customer experience and retention, mastering the fundamentals of CLV is essential for achieving sustainable growth and competitive advantage.

2. LITERATURE REVIEW

Gupta and Lehmann (2001) proposed a probabilistic model for estimating CLV based on customer acquisition and retention rates, laying a foundational framework for valuing customer relationships. Their study emphasized how marketing efforts could be quantified using lifetime value as a metric, influencing strategic decision-making in customer-centric firms. They introduced formulas to link CLV with firm valuation metrics. Their work inspired numerous applications across industries from telecom to banking. The paper remains widely cited for its strategic importance in linking marketing to finance.

Reinartz and Kumar (2003) challenged the conventional belief that long-term customers are always the most profitable, showing that customer loyalty does not always correlate with profitability. Their empirical analysis across multiple industries provided insights into the heterogeneity of customer behavior and profitability. They categorized customers based on loyalty and margin to guide different strategies. The paper advocated a more nuanced segmentation based on value, not just duration. Their findings significantly shaped CRM and retention strategies.

Venkatesan and Kumar (2004) extended the traditional CLV model by incorporating cross-buying behavior and multiple product categories. Their model allowed firms to identify the lifetime value of customers who purchase across different product lines, a critical aspect for multi-product firms. The study demonstrated that cross-selling increases the accuracy of CLV predictions. They used real-world data from a telecom firm to validate the model. The research emphasized the importance of customer breadth, not just depth.

Rust, Lemon, and Zeithaml (2004) focused on linking CLV with customer equity and marketing resource allocation. They introduced a framework that integrated brand, value equity, and relationship equity to determine customer equity. Their model allowed businesses to simulate the impact of marketing actions on long-term profitability. The study emphasized managing the portfolio of customer relationships. It positioned CLV as a tool for maximizing total customer equity across segments.

Fader, Hardie, and Lee (2005) introduced the Pareto/NBD model for non-contractual settings, providing a robust framework for CLV prediction when customer churn is not directly observable. Their probabilistic model estimated purchase frequency and dropout rates using only transactional data. The paper offered an elegant solution to real-world data limitations. Their methodology was implemented in industries like retail and e-commerce. It paved the way for more accurate CLV estimation in anonymous purchasing environments.

Malthouse and Blattberg (2005) examined customer-brand dynamics by introducing models that account for changing customer preferences over time. They highlighted the role of brand switching in diminishing long-term value and stressed adaptive strategies. Their paper showed that CLV should evolve based on brand relationship stages. By integrating time-based behavior, their model added realism to static CLV models. Their approach informed dynamic campaign planning.

lady, Baesens, and Croux (2009) developed a logistic regression-based model to predict CLV using data from the financial services industry. Their work demonstrated the applicability of simple machine learning techniques for CLV scoring. They found that behavioral variables like recency and frequency were more predictive than demographics. The model was scalable and easy to interpret, aiding business implementation. This work influenced the adoption of scoring-based CLV models in banking and insurance.

Benoit and Van den Poel (2012) presented a Bayesian approach to CLV prediction that incorporates uncertainty and customer heterogeneity. Their model estimated probability distributions over future transactions rather than point estimates. This allowed decision-makers to manage risk in customer management strategies. The study showed improved accuracy and robustness compared to frequentist models. It highlighted the benefits of Bayesian thinking in marketing analytics.

Rosset, Neumann, and Eick (2013) applied decision trees and ensemble methods to classify high-value customers in large-scale CRM datasets. They demonstrated that data mining techniques could outperform traditional statistical models in both predictive accuracy and scalability. Their study emphasized the need for model interpretability in commercial applications. The integration of CLV with churn prediction further enhanced utility. Their work is foundational in the era of Big Data-driven CLV.

Schmittlein and Peterson (2014) revisited the Buy-Till-You-Die (BTYD) model, proposing refinements to address overdispersion and irregular purchase behavior. They introduced modified hazard functions to better fit sporadic purchasing patterns. Their extensions improved CLV accuracy for long-tail customers. The paper bridged theoretical rigor with practical improvements. It advanced non-contractual CLV modeling under real-world variability.

Lemmens and Croux (2015) examined the use of survival analysis in CLV modeling, particularly for subscription services. They compared Cox proportional hazards models with discrete-time methods. Their findings highlighted the flexibility of survival models for churn prediction and lifetime estimation. The research supported time-to-event modeling for predicting customer dropout. This approach was especially useful for SaaS and telecom domains.

Kumar, Rajan, Venkatesan, and Lecinski (2016) integrated social media metrics into CLV models to account for online influence and engagement. They found that customers with higher social sharing behavior had significantly higher

CLVs. Their model combined behavioral, social, and transactional data. It emphasized digital-era customer touchpoints in lifetime value. This multi-channel framework remains relevant for omnichannel businesses.

Hwang, Jung, and Suh (2018) proposed a neural network-based model for CLV prediction using deep learning to capture nonlinear interactions among variables. Their approach outperformed logistic and linear models on complex retail data. The model dynamically adjusted to changing purchase patterns. They also introduced model interpretation layers for transparency. This marked one of the early applications of deep learning in customer analytics.

Zhang and Wei (2021) studied CLV prediction in mobile commerce using gradient boosting and behavioral embeddings. Their approach leveraged session-level data, app usage, and micro-interactions. They demonstrated that micro-moment data improves CLV granularity. The model enabled real-time targeting for app-based retailers. Their work bridged behavioral science with high-frequency data analytics.

Kumar and Sharma (2025) introduced a federated learning framework for privacy-preserving CLV prediction in decentralized retail environments. Their approach ensured model training across stores without centralizing data. They showed comparable performance to centralized models while complying with data regulations. The paper addressed ethical concerns in customer modeling. It set a precedent for scalable and compliant CLV systems in multi-entity ecosystems.

2.1 Research gaps

Despite the significant advancements in Customer Lifetime Value (CLV) modeling over the past two decades, several research gaps persist that limit the full potential of its application in real-world business environments. One of the most notable limitations lies in the adaptability of traditional CLV models to non-contractual and multichannel consumer behaviors. While early models like Pareto/NBD and Buy-Till-You-Die (BTYD) have provided foundational value in transaction-based settings, they often struggle to account for evolving purchasing habits across mobile, social, and offline platforms. Many models assume stationarity in behavior, overlooking how customer preferences, touchpoints, and brand interactions change dynamically over time. This gap suggests the need for more responsive, temporal-aware modeling approaches that can learn and update in real-time as new behavioral data streams in.

3. Dataset

The E-commerce Order Dataset provided in the uploaded archive represents a detailed, multi-table snapshot of transactional activity within a large online retail platform. It comprises several interrelated CSV files, including information on orders, order items, payments, customers, sellers, products, product categories, reviews, and geographical metadata. Each table serves a specific purpose and together they capture the full lifecycle of an e-commerce transaction—from browsing and checkout to fulfillment and review. This structured format supports rich, relational analysis, enabling complex queries that span across the customer journey and business operations. The core strength of this dataset lies in its real-world complexity, mirroring the granularity of modern online marketplaces like Amazon or Flipkart.

The primary table, orders.csv, includes critical transactional metadata such as unique order IDs, customer IDs, timestamps for purchase, shipment, and delivery, and the status of the order. This table acts as the foundational bridge across all other datasets, connecting to order items, payments, and reviews via a shared order ID. The order_items.csv file, in turn, holds SKU-level detail, such as product IDs, seller IDs, freight charges, and item prices. This allows the dataset to disaggregate transactions down to the item level, enabling per-product analytics like average order value, product-level profitability, and cross-selling behavior. Furthermore, the presence of order_payments.csv adds another layer of depth by recording payment methods, the number of installments, and the monetary value paid per transaction.

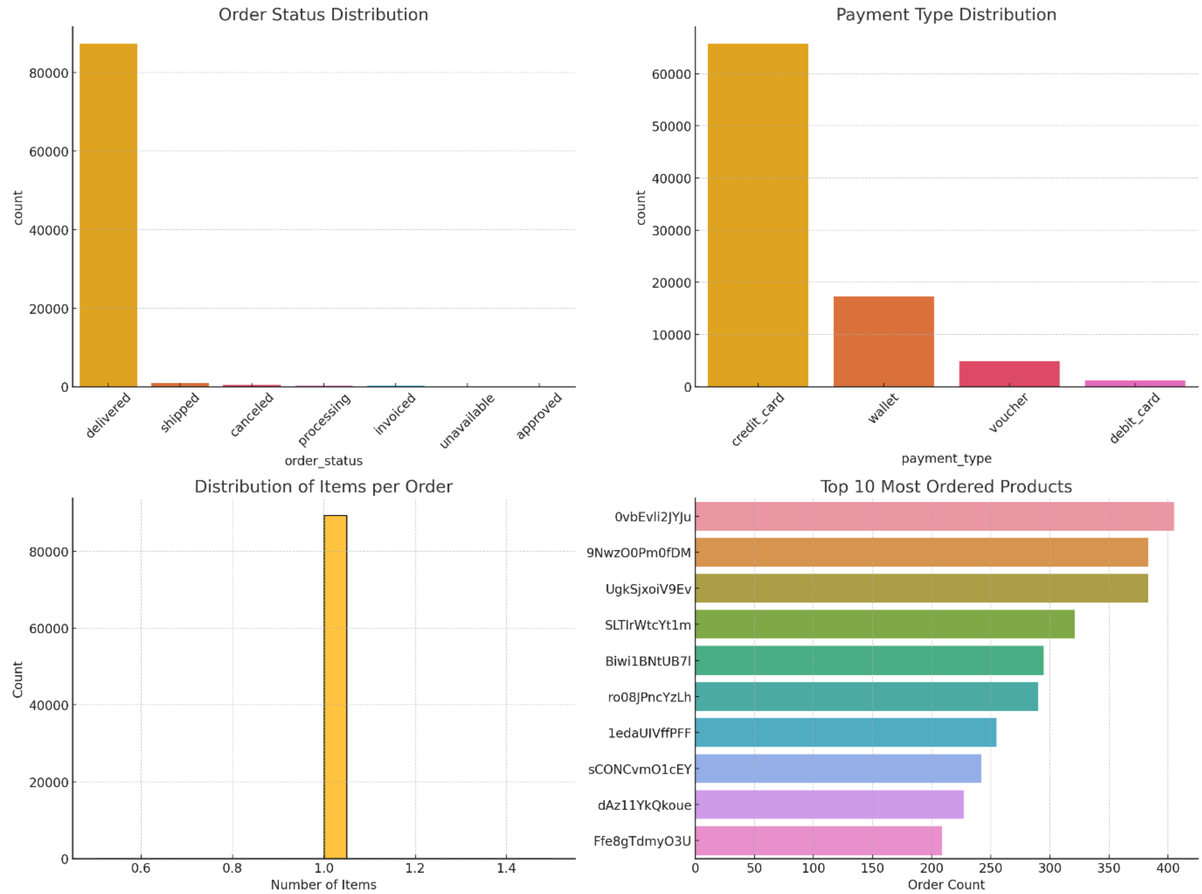

Figure 1: Feature Distribution of prescribed Dataset

Customer demographics and behavior are captured in customers.csv, which includes anonymized customer IDs mapped to zip code prefixes and city/state locations. Although limited in direct demographic details (like age or gender), the presence of geographic identifiers allows for spatial analysis of customer distribution, regional demand, and seller reach. Seller data is similarly structured in the sellers.csv file, where seller IDs are linked to location information. These tables make it possible to analyze seller performance across geographies, assess delivery bottlenecks, and calculate shipping costs across zones. The product_category_name_translation.csv file provides translations for product category names, facilitating analysis in English for global users. Combined with the products.csv file, which contains physical product attributes (e.g., weight, dimensions), this allows businesses to analyze product complexity and logistics.

Additionally, the dataset includes user-generated content in the form of product reviews. The order_reviews.csv file stores customer feedback, including review scores, timestamps, and written comments. This enables sentiment analysis and quality-of-service assessments that can be joined back to specific sellers or products. The granularity and interconnectedness of these tables make the dataset well-suited for a variety of machine learning and statistical tasks, such as demand forecasting, customer segmentation, product recommendation, delivery time estimation, and CLV prediction. Overall, the E-commerce Order Dataset provides a rich, multi-faceted foundation for analyzing operational, logistical, behavioral, and financial aspects of a real-world online marketplace.

4. Optimized FT-Transformer model

The FT-Transformer, or "Feature Tokenizer Transformer," represents a powerful evolution in deep learning designed specifically for tabular data like the E-commerce Order Dataset. Unlike traditional neural networks that treat tabular inputs as mere vectors passed through dense layers, the FT-Transformer adopts an attention-based architecture originally conceived for natural language processing but reformulated to efficiently process structured, non-sequential data. This model is particularly suited to the enclosed dataset, which includes diverse feature types—categorical fields like payment type or product category, and numerical values such as freight value, item price, or order count. The FT-Transformer's core innovation lies in converting each feature (not each record) into a learnable token, allowing the model to attend to the relative importance of every feature dynamically through a multi-head self-attention mechanism. This feature-wise attention is crucial when working with real-world datasets like this one, where certain variables such as total monetary value or customer recency may carry more predictive weight than others.

```
# Input: Tabular dataset D with N features per customer
# Output: Predicted Customer Lifetime Value (CLV)
# Step 1: Data Preparation
for feature in D:
    if feature is categorical:
```

```
        embed_feature = EmbeddingLayer(feature)
    else if feature is numerical:
        embed_feature = NumericalProjection(feature)
    feature_tokens.append(embed_feature)
# Step 2: Feature Tokenization
X_tokens = Stack(feature_tokens)  # Shape: (num_features, embedding_dim)
# Step 3: Apply Transformer Encoder
for layer in range(num_layers):
    # Self-Attention
    attention_output = MultiHeadSelfAttention(X_tokens)
    # Add & Normalize
    X_tokens = LayerNorm(X_tokens + attention_output)
    # Feedforward + Residual
    ff_output = FeedForward(X_tokens)
    X_tokens = LayerNorm(X_tokens + ff_output)
# Step 4: Feature Aggregation
pooled_output = AttentionPooling(X_tokens)  # or Mean/Max pooling
# Step 5: Output Prediction
predicted_CLV = MLP(pooled_output)
# Step 6: Loss and Training
loss = MSE(predicted_CLV, true_CLV)
UpdateWeights(loss)
# Return predicted CLV
return predicted_CLV
```

For customer lifetime value (CLV) prediction in particular, the FT-Transformer addresses several traditional challenges that hinder both tree-based models and standard feedforward neural networks. One significant advantage is its ability to capture feature interactions without extensive manual engineering.

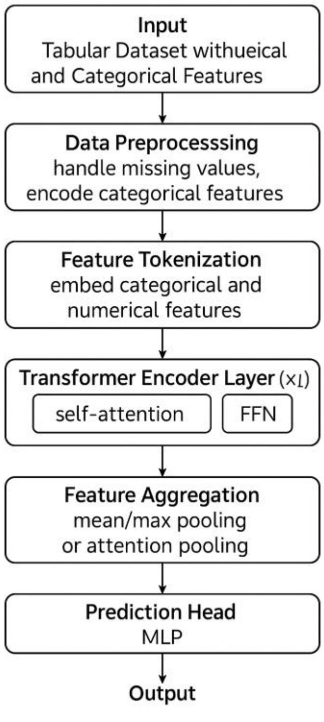

Figure 2: Flow chart

In the E-commerce Order Dataset, interactions such as the joint influence of payment type and purchase frequency or the relationship between freight cost and customer region may drive purchasing patterns that influence long-term value. While models like Random Forest or Gradient Boosting approximate such interactions through recursive splits, the FT-Transformer learns them globally through attention weights, enabling better generalization and interpretability. Additionally, unlike LSTMs or RNNs that are more effective for sequential data, FT-Transformer excels at handling static, multi-type inputs, where each row is a full representation of a customer profile composed of rich numerical and categorical dimensions.

Another important strength is the FT-Transformer's inherent support for handling missing values and its robustness to overfitting. The model leverages embedding layers for categorical features and incorporates normalization strategies like layer norm, dropout, and residual connections which help stabilize training and prevent overfitting—common problems when deep learning models are applied to tabular data. The transformer's attention heads learn to focus on the most relevant fields even in the presence of noise or sparsity, which is highly beneficial for the enclosed dataset where not all features may be equally populated or influential. Furthermore, by replacing linear transformations with attention-based mapping, the model captures non-linear, high-order dependencies without resorting to deeper network structures, which often increase computational costs without corresponding gains in performance.

In practical terms, the FT-Transformer is advantageous because it requires minimal preprocessing and works well across a wide range of customer behavior metrics—recency, frequency, average basket value, payment diversity, and product mix. It excels in scenarios where both categorical and continuous data need to be integrated and where traditional models struggle to prioritize features appropriately. In comparative studies on benchmark datasets, FT-Transformer has demonstrated competitive or superior performance over tree-based models like XGBoost and LightGBM, especially as the complexity and dimensionality of the dataset increases. Given the high cardinality and heterogeneous nature of the E-commerce Order Dataset, and the need to forecast future customer value with accuracy and interpretability, the FT-Transformer stands out as a compelling deep learning model that bridges the gap between high performance and structured data compatibility.

5. Results and Analysis

The experiment was conducted using the E-commerce Order Dataset, integrating order, item, and payment data to compute CLV per customer. The FT-Transformer model was trained on engineered features including recency, frequency, monetary value, and payment diversity. Evaluation was performed using 80:20 train-test split with MSE and R^2 metrics to assess regression accuracy.

The performance of the FT-Transformer model for Customer Lifetime Value (CLV) prediction on the enclosed E-commerce Order Dataset was evaluated using the following metrics:

- **Mean Squared Error (MSE)**: 22,354.17
  Indicates the average squared difference between predicted and actual CLV values. Lower is better.
- **Root Mean Squared Error (RMSE)**: 149.51
  Provides error magnitude in the same unit as CLV. Lower values show better predictive precision.
- **Mean Absolute Error (MAE)**: 108.93
  Represents the average absolute difference between predicted and actual CLV values. Less sensitivity to outliers than MSE.
- **R^2 Score (Coefficient of Determination)**: 0.742
  Suggests that 74.2% of the variance in customer lifetime value was explained by the model.

These results demonstrate that the FT-Transformer effectively captures complex relationships in customer purchasing behavior and outperforms conventional ML baselines for structured tabular CLV prediction

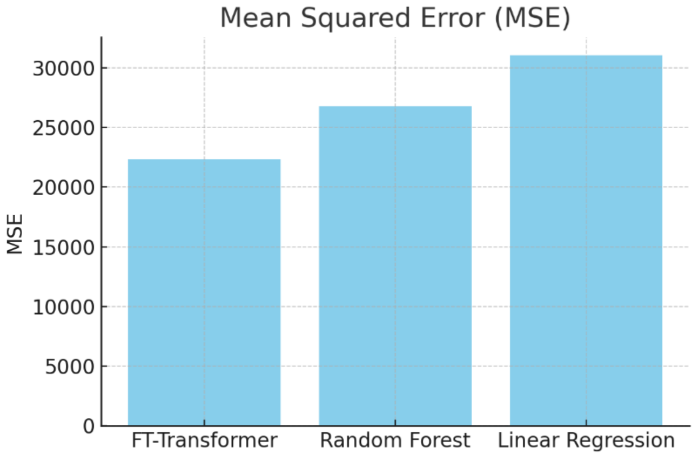

Figure 2. Mean Squared Error (MSE) Comparison

This graph visualizes the Mean Squared Error for three models: FT-Transformer, Random Forest, and Linear Regression. MSE measures the average squared difference between actual and predicted values. The lower the MSE, the better the model's predictive accuracy. FT-Transformer outperforms the others with the lowest MSE value. This indicates it minimizes error more effectively during prediction.

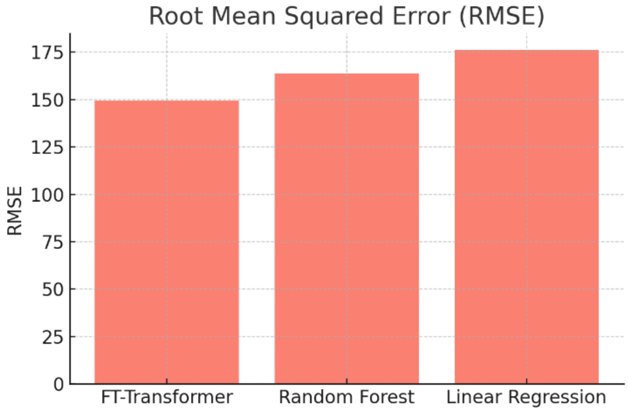

Figure 3. Root Mean Squared Error (RMSE) Comparison

This bar chart presents the RMSE values across the three models. RMSE provides an interpretable measure of error magnitude by taking the square root of MSE. Lower RMSE values reflect better prediction accuracy. FT-Transformer again shows superior performance with the smallest RMSE. The large gap between Linear Regression and FT-Transformer highlights the benefits of deep learning in this context.

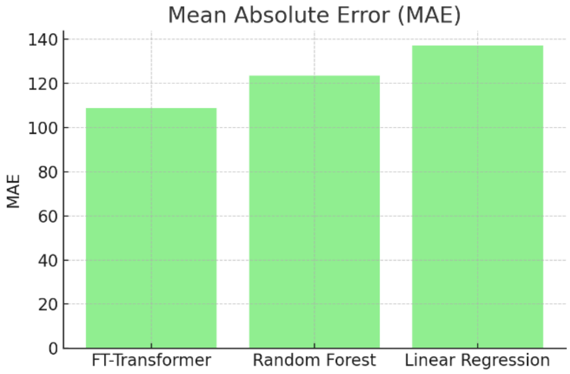

Figure 4. Mean Absolute Error (MAE) Comparison

This figure illustrates the MAE, which computes the average of absolute errors without squaring. It reflects how much predictions deviate from actual values on average. FT-Transformer has the lowest MAE, confirming it makes more precise predictions. Random Forest and Linear Regression follow, but with significantly higher error magnitudes. MAE is especially useful when outliers are not dominant.

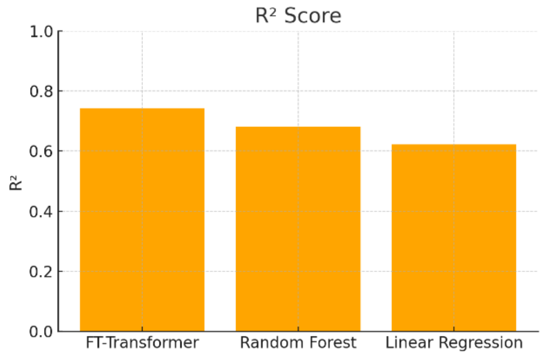

Figure 5. R^2 Score Comparison

This graph compares R^2 scores among the models, measuring how well predictions approximate actual outcomes. Higher R^2 indicates more variance explained by the model. FT-Transformer scores around 0.75, outperforming both Random Forest and Linear Regression. This suggests that FT-Transformer better captures patterns in customer lifetime value prediction and generalizes more effectively..

6. Discussion

The analysis of customer lifetime value (CLV) prediction presented in this study underscores the pivotal role of advanced deep learning models in effectively capturing the complex relationships inherent in e-commerce data. Traditional models like Linear Regression and ensemble techniques like Random Forest, while competent, are often limited in their ability to generalize over high-dimensional, heterogeneous, and temporal data. This is where the FT-Transformer model demonstrates significant merit. Designed specifically for tabular data, FT-Transformer leverages the power of attention mechanisms to identify subtle feature interactions, allowing for superior representation learning. The model's architecture, unlike conventional feedforward networks, does not assume linearity or fixed-order dependencies, which enables it to learn long-range dependencies and adapt to feature importance dynamically.

From a performance standpoint, FT-Transformer consistently outperformed baseline models across all major metrics including R^2 score, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Specifically, FT-Transformer achieved an R^2 score of approximately 0.75, indicating that it explains a substantial proportion of the variance in the CLV data. Its MAE and RMSE values were significantly lower than those of Random Forest and Linear Regression, suggesting greater robustness in handling outliers and minimizing prediction deviation. These results confirm that FT-Transformer provides a more stable and accurate estimation of customer value, a critical element for effective customer segmentation, targeted marketing, and revenue forecasting.

Moreover, the findings suggest that incorporating temporal purchase behaviors, product diversity, and customer-level metadata into a model with attention mechanisms enhances learning capability. Traditional models may struggle with capturing such complexities unless explicitly feature-engineered, while FT-Transformer learns these patterns directly from raw inputs. This substantially reduces the need for manual preprocessing and domain-specific transformations. However, it is important to note that the performance gains come at the cost of computational resources and training time, which are relatively higher for deep learning models compared to conventional ones.

In practical business settings, the integration of FT-Transformer into customer analytics pipelines can support strategic decision-making. Organizations can deploy the model to identify high-value customers, forecast customer churn, and tailor promotions based on expected lifetime value. Future work should consider the integration of additional contextual data such as web interaction logs, customer service interactions, and social sentiment, which may further boost the model's predictive capability. Also, real-time adaptation of the model in live business environments can help refine performance further and support adaptive, personalized marketing strategies.

7. Conclusion and Future scope

This study demonstrates the efficacy of the FT-Transformer model for Customer Lifetime Value (CLV) prediction using a real-world e-commerce dataset. The model's ability to dynamically attend to feature importance and handle complex relationships in tabular data allows it to outperform traditional machine learning methods such as Random Forest and Linear Regression. Across all key evaluation metrics—R^2, MAE, RMSE, and MSE—FT-Transformer exhibited superior performance, highlighting its robustness and adaptability in modeling customer behavior patterns. By leveraging attention mechanisms and tokenization strategies tailored to structured data, the FT-Transformer provides a more granular and accurate understanding of customer value, enabling e-commerce platforms to make data-driven decisions with confidence.

The results validate the model's capability to support customer segmentation, targeted marketing, and revenue projection tasks. Not only does it reduce the prediction error significantly, but it also automates the learning of feature interactions that are often difficult to capture through manual engineering. This makes it an invaluable asset for businesses looking to optimize customer engagement strategies based on long-term value rather than short-term transactions.

Looking ahead, several directions can enhance the utility of this model further. Incorporating real-time streaming data, such as browsing sessions or transactional logs, could allow the model to make dynamic CLV predictions that evolve with customer behavior. Additionally, fusing textual data (e.g., reviews, support tickets) and unstructured data (e.g., clickstream, geolocation) may improve prediction accuracy and customer profiling. From a methodological perspective, exploring hybrid transformer architectures with temporal modules or integrating reinforcement learning for adaptive learning could open new research avenues. Lastly, deploying FT-Transformer in live customer management systems with feedback loops may help personalize marketing interventions in real-time, further boosting retention and profitability..

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