Comparative Analysis of Transformers for Modeling Tabular Data: A Casestudy using Industry Scale Dataset

Usneek Singh¹, Piyush Arora², Shamika Ganesan², Mohit Kumar², Siddhant Kulkarni², Salil R. Joshi²

¹BITS Pilani, India

²American Express AI Labs, India

usneeksingh1@gmail.com,{piyush.arora1,shamika.ganesan,mohit.kumar30,siddhant.r.kulkarni1,salilrajeev.joshi}@aexp.com

ABSTRACT

We perform a comparative analysis of transformer-based models designed for modeling tabular data, specifically on an industry-scale dataset. While earlier studies demonstrated promising outcomes on smaller public or synthetic datasets, the effectiveness did not extend to larger industry-scale datasets. The challenges identified include handling high-dimensional data, the necessity for efficient preprocessing of categorical and numerical features, and addressing substantial computational requirements.

To overcome the identified challenges, the study conducts an extensive examination of various transformer-based models using both synthetic datasets and the default prediction Kaggle dataset (2022) from American Express. The paper presents crucial insights into optimal data pre-processing, compares pre-training and direct supervised learning methods, discusses strategies for managing categorical and numerical features, and highlights trade-offs between computational resources and performance. Focusing on temporal financial data modeling, the research aims to facilitate the systematic development and deployment of transformer-based models in real-world scenarios, emphasizing scalability.

Keywords - transformers, tabular datasets, financial modeling

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1 INTRODUCTION

The Transformer model, introduced by Vaswani et al. (2017), has significantly impacted various domains, including Natural Language Processing (NLP), Computer Vision (CV), and audio processing. Built upon an encoder-decoder structure with an attention mechanism, the Transformer architecture proves adept at capturing sequence dependencies and learning hierarchical representations,

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making it effective for modeling sequential patterns. Currently, gradient boosted decision trees [3] are considered the state-of-the-art models for financial modeling. Although these models are intuitive, they come with certain limitations:.

1. reliance on manually derived features when dealing with continuous streaming data such as frequency features (e.g. how many months), statistical features (e.g. mean of spending)

2. do not effectively capture the dynamic relationships within time series data and instead rely on adhoc combinations of features such as minimum, maximum, sum, average, etc.

Transformers have gained attraction in the tabular domain due to their ability to generate contextual embeddings effectively and handle the limitations mentioned above as compared to tree based models [14, 15, 22], which we explore for modelling financial datasets.

Prior work cites synthetically generated data [23, 24], which differs significantly from real-world datasets. A significant challenge arises from the actual dimensionality of the datasets - real-world datasets exhibit 200-500 dimensions, whereas synthetic datasets only account for 10-15 dimensions [23]. Additionally, real-world financial datasets frequently suffer from noise such as out-of-range or missing values.

In this study, we leverage various transformer techniques to effectively model financial tabular series data. Our investigation involves comparison and analysis of different i) input processing techniques, ii) model architectures, and iii) training strategies for handling financial tabular data using transformers.

Specifically, our contributions are:

- Thorough analysis of different transformer architectures for tabular data based on different dimensions such as data preprocessing, training strategies etc.
- Comparative analysis of different transformer architectures for synthetic as well as finance industry datasets capturing realworld problems.

The paper is organized as follows: Section 2 presents related work on financial modeling & recent transformers based architectures, Section 3 provides an overview of architectures that we explore in this work. Section 4 presents our results on synthetic dataset, Section 5 showcases our results on industry based dataset. Section 6 talks about our findings in alternate regression tasks. Section 7 discusses lessons learned and Section 8 presents conclusion.

2 RELATED WORK

Traditional approaches for handling tabular data: Traditional machine learning models for handling financial tabular data include gradient boosted decision trees (GBDT) and recurrent neural network (RNN) models. GBDT, including XGBoost [3], LightGBM [18], and CatBoost [6], are commonly used for managing tabular data. To

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address the non-differentiability of decision trees, alternative methods with smooth decision functions have been proposed [13, 25]. Other techniques, such as Factorization Machines [11], provide insights into handling tabular data with regularization methods for deep learning models or simple multi-layer perceptron models [17]. However, these methods do not effectively capture sequential information and are less suitable for managing data with sequential tabular information. To address this, RNN-based models for handling tabular series, which capture temporal information in a limited sense contrasted to Transformer based approaches have been proposed [1, 7, 19].

Transformer based approaches for handling tabular data: Various transformer-based approaches have been developed for handling tabular data, each with different input processing, model architectures, and training mechanisms. TabTransformer [15] utilizes a simple transformer model trained with Masked Language Modeling to generate contextual embeddings for categorical and numerical values. SAINT [27] modifies the transformer block to create embeddings at the single-row level for both categorical and numerical values. TabBERT [24] introduces a hierarchical transformer that captures the hierarchy in sequence data by converting numerical values into categorical form. Liu et al. [22] propose a supervised learning mechanism with two parallel towers to capture attention across time and dimension, presenting a direct approach without intermediate embeddings. Han et al. [12] develop a framework that separately handles categorical and numerical values using a pretrained transformer with a joint loss for each category. TARNet [4] incorporates knowledge from the end task by alternating between masked language modeling and supervised downstream tasks during pre-training. Crossformer [28] captures attention across both dimensions similar to Liu et al., and its architecture resembles that of TabBERT. Each transformer-based approach outlined above possesses its own advantages and disadvantages, catering to different requirements and exhibiting varying performance in handling tabular data. Most of these approaches are tried out on synthetic tabular data alone.

3 METHODOLOGY

In our exploration of transformer techniques for tabular series data, we carefully selected architectures to align with our research objectives. We categorized our training techniques into two main groups: direct supervised training and decoupled pre-training & fine-tuning (described in section 3.2). For direct supervised training, we considered CrossFormer [28], Gated Transformer (Twin Tower) [22], and TARNet [4]. We opted for Twin Tower due to its accessibility and robust performance. Within the category of decoupled pre-training & fine-tuning strategies, we explored various models, including TabBERT [24], LUNA [12], and UniTTab [23]. TabBERT [24] became our standard choice due to its widespread recognition and effectiveness in handling tabular series data. While UniTTab [23] and LUNA [12] share similar techniques with TabBERT, we retained LUNA for its unique approach to enhancing numerical reasoning within language models, a crucial aspect of our research. While our study didn't encompass all available models, our selection was deliberate, aiming to provide representation from each category.

TabBERT introduces a hierarchical transformer that captures the hierarchy in sequence data, where each row is further divided into attributes. Twin Tower propose a supervised learning mechanism, employing an architecture with two parallel towers to capture attention across time and dimension, without learning intermediate embeddings. LUNA propose a framework that separately handles categorical and numerical values. We provide an objective comparison of these three models in Table 1.

To understand the time complexity of the above models in terms of input size, we assume that each sequence consists of N rows:- $[r_1, r_2, ..., r_N]$ and each row consists of M attributes: $[k_1, k_2, ..., k_M]$. For a transformer with a sequence of length N, due to multi-headed attention in encoder and decoder layers time complexity is $O(N^2)$. Since in hierarchical transformers such as TabBERT, for each row encoder attention is also computed at the attribute level the time complexity becomes:

$$T(r_i, k_i) = O(N^2 * M^2)$$
(1)

For Twin Tower, attention is parallel computed for different dimensions (across time and attributes). Then the outputs are combined using a gating channel $(f(O_1, O_2) = W_1 * O_1 + W_2 * O_2)$. Hence the time complexity can be expressed as:

$$T(r_i, k_i) = O(N^2 + M^2)$$
(2)

Next, we discus various techniques for handling input data and training process.

3.1 Data prepocessing

Financial dataset comprises a combination of categorical and numerical (continuous) values. Various approaches can be employed to handle these values:

- Converting numerical values to categorical values: Pretraining transformers using a cross-entropy loss requires converting continuous or numerical values into categorical values. Techniques like binning/quantization or frequency encoding have been proposed for this conversion [23, 24].
- **Converting categorical values to numerical values:** For direct supervised training, categorical values can be treated as continuous values and directly passed to the transformer's embedding layer. Methods like binary encoding, one-hot encoding, or label encoding are used to convert categorical values into numerical values [4, 22].
- Treating numerical and categorical values separately: A modified loss proposed by Han et al. [12] treats numerical and categorical values separately during pre-training. This approach uses separate loss terms for regression (numerical) and cross-entropy (categorical) values, eliminating the need for value conversion and preventing information loss.

These different approaches provide flexibility in adapting the preprocessing step to the specific characteristics and requirements of the financial dataset.

3.2 Training mechanisms

Transformers in the language domain are typically trained through decoupled unsupervised pre-training and supervised fine-tuning due to the large vocabulary size. In the tabular domain, training Comparative Analysis of Transformers for Modeling Tabular Data: A Casestudy using Industry Scale Dataset

Table 1: Comp	oarative Analysis	s of Transformer	Architectures: E	xploring Key	y Factors for	Selecting the O	ptimal Architecture
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Model	TabFormer (TabBERT)	Gated Transformer (Twin Tower)	LUNA
Required Pre-training	Yes	No	Yes
Pretraining method	Masked Language Modeling (MLM)	No	MLM (with regression loss)
Prediction level	Series (Multiple Rows)	Series (Multiple Rows)	Series (Multiple Rows)
Categorical values	As embeddings	As numerical values	As embeddings
Numerical values	As embeddings of categorical values	As numerical values	As numerical values
Architecture	Hierarchical Transformer	Twin tower	Hierarchical Transformer
Dataset Tested	2 datasets, artificially generated	13 datasets	1 public dataset
Prone to Overfitting	No	Yes	No
Training Time	High	Least	Medium
Data Pre-Processing	Data Quantization, Bulky Vocabulary	Easy Processing e.g. categorical encoding	Vocabulary creation for categorical values
Similar architectures	UniTTab, LUNA	CrossFormer, TARNet	Numerical reasoning based architecture

can also be conducted using direct supervision or the decoupled approach similar to language models. Our exploration examines two training mechanisms:

- **Decoupled pre-training and fine-tuning:** Separate pre-training and fine-tuning processes are used for tabular transformers [12, 15, 24]. It is particularly useful when labeled data is limited or when the same corpus is utilized for multiple downstream tasks.
- **Direct supervised training:** For specific problems with ample labeled data, direct supervised training is employed. Transformer based approaches such as Liu et al. [22] and Zhang et al. [28] use this approach.

TabBERT follows the approach of converting numerical values to categorical values and employs decoupled pre-training and finetuning. Twin Tower converts categorical values to numerical values and uses direct supervised training. LUNA modifies the loss function during pre-training to handle numerical values separately.

4 SYNTHETIC DATA BASED STUDY

This section describes our experimental evaluation on a public synthetic dataset.

4.1 Credit Fraud Prediction

The fraud prediction dataset, [24], comprises a diverse set of transactions generated artificially, involving various users. Each transaction is labeled as either fraudulent or non-fraudulent and includes multiple attributes, categorized as either categorical (e.g., 'use chip') or numerical (e.g., 'amount') (as illustrated in Figure 1). The primary goal is to predict whether a user is engaged in fraudulent activity based on a sequence of their transactions. The adopted approach follows the original problem definition [24], where, given a window of N consecutive transactions, if at least one is classified as fraudulent, the entire sequence is labeled as fraudulent.

It is crucial to note that the data distribution is highly imbalanced. Out of a total of 24 million transactions, only approximately 30,000 transactions belong to the fraudulent category. By applying the aforementioned labeling strategy with a window size of 10 (N=10), we obtain a mere 9,000 fraud sequences within a vast dataset of 2.4 million data points. We show the data distribution in Table 2.

4.2 Performance comparison

We focus on three models: TabBERT, Twin Tower, and LUNA. We also include the baseline scores of a standard vanilla architecture

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Figure 1: A snapshot of credit fraud prediction dataset

Table 2: Data Distribution of the credit fraud problem

	Transact	ion wise	Sample wise			
	Train	Test	Train	Test		
Fraudulent	23996	5761	7229	1797		
Non-Fraudulent	19485524	4871619	1943723	485940		

(the left tower in Twin Tower architecture discussed in the subsection 4.3) trained via direct supervised training. We upsampled the data to equalize the frequency of fraudulent and non-fraudulent class using SMOTE [26] library. The evaluation metric is the binary F1 score on the fraudulent class. We do not use accuracy score as accuracy is not a suitable metric for evaluating tasks with imbalanced class ratios. We report precision, recall, and F1 score for these models in Table 3.

 Table 3: Performance comparison of different transformer architectures on credit fraud problem.

Architecture	Precision	Recall	F_1 score
Vanilla	0.96	0.74	0.836
Twin Tower	0.95	0.76	0.844
TabBERT	0.97	0.81	0.886
LUNA	0.98	0.80	0.880

Furthermore, when considering the practical applicability of these models in an industry setting, factors such as training time and space requirements become important metrics for assessing their efficiency. To provide a more quantitative analysis of the training time for these models, we present the relevant information in Table 4. We use Nvidia V100 16GB GPUs for our experiments. Refer Appendix A.1 for more details on the hyperparameters.

Table 4: Training Time Comparison of different transformer architectures on credit fraud problem

Approach	# epochs	Total time (Hrs)
Vanilla	20	3.6
Twin Tower	50	27.5
TabBERT	3	90 (pre-train) + 3 (fine-tuning)
LUNA	3	62 (pre-train) + 3 (fine-tuning)

4.3 Ablation study - Time Dependence vs Dimension Dependence

During the experimentation with the Twin Tower architecture, a notable observation is made regarding the importance of attention weights across time steps and attribute dimensions. In the Twin Tower architecture, where the left tower focuses on interaction across time steps (referred to as the *Vanilla* approach) and the right tower attends to interaction across features, we assess the significance of feature interactions in isolation. (Refer to A.3 for more details on the architecture). An experiment is conducted by selectively masking one tower during training. The findings reveal that the isolated performance of the left tower closely resembles that of the complete Twin Tower model. However, the isolated performance of the right tower is poor, suggesting that, in the dataset used, temporal information holds more importance compared to interactions across features. To summarize the outcomes of this study, we present the results in Table 5.

 Table 5: Performance scores with attention captured along different dimensions

Method	Precision	Recall	F_1 score
Time interaction tower (Vanilla)	0.96	0.74	0.84
Feature interaction tower	0.38	0.19	0.26

5 INDUSTRY DATA BASED STUDY

We next report the experimental investigation on industry data. Credit default prediction is crucial for robust risk modeling, enabling the identification of customers who might fail to repay debts, thereby preventing significant financial losses. The task involves predicting a binary variable based on a customer's performance within an 18-month window after their latest credit card statement. A default event is recorded if the customer fails to pay the due amount within 120 days after the statement date.¹

Table 6 provides details on the data distribution for the train, val & test set respectively. The dataset comprises approximately 190 features for each record, extracted from various thematic categories such as Delinquency, Spend, Payment, Balance, and Risk-based variables. This extensive customer information over a temporal nature poses a complex challenge due to the sheer volume of data.

Dealing with missing values in industry datasets is a notable challenge, about 122 features have missing values. During data

¹https://www.kaggle.com/competitions/amex-default-prediction/

analysis we observed that there are two main broader categories of missing values: i) features missing few values for a single month across 13 months, ii) for about 15 features more than 50% of the total records were missing. In literature there has been multiple methods recommended for handling imputation for missing values, using mean, mode, median, max, min etc., [5] or dropping the feature all together [10] depending on the nature of variables. As such transformers have shown to handle missing values and noise, in prior research [8]. Hence, in our explorations we went with replacing missing values with zero (0), for the model to learn signals to capture the representation of missing values and noise in data better using attention mechanism. However, this is an interesting area of exploration for future extension to identify trade-offs with different imputations while working with large feature sets and that too for industry datasets on the scale of 5-10M records.

Table 6: Data distribution

Data Type	Records	Customers
Train Data	5.8M	460K
Val Data	5.7M	470k
Test Data	5.6M	460k

Given that tree-based models are commonly employed for modeling financial datasets, the baseline model for this study utilizes a LightGBM-based approach. The results of various transformer models and the baseline scores are presented in Table 7. The evaluation metric M for this problem is the mean of two rank-ordering measures: the Normalized Gini Coefficient (G) and the default rate captured at 4% (D). The default rate captured at 4% represents the percentage of positive labels (defaults) captured within the highestranked 4% of predictions and serves as a Sensitivity/Recall statistic.

$$M = 0.5 * (G + D)$$
(3)

The metric M has a maximum value of 1.0. Both sub-metrics G and D assign a weight of 20 to negative labels to account for downsampling. Additionally, F1 score evaluation is provided for better comparison with synthetic data studies. Given the similarities in training mechanisms and performance between LUNA and TabBERT observed in the credit fraud problem, the analysis focuses exclusively on TabBERT for the credit default problem. TabBERT was pre-trained on AWS p3.8xlarge, equipped with 4 V100 GPUs, maximum memory of 244GB. The entire process of pre-training and fine-tuning TabBERT took approximately 2.5 days, while Twin Tower and LightGBM took 2.5 hrs and 4 hrs, respectively. More details on hyperparameters can be referred in section A.2.

Table 7: Transformer results on industry based dataset

Architecture	Metric M	Gini	Capture Rate	F ₁ Score
LightGBM	79.29	91.87	66.72	0.783
Vanilla	79.43	91.95	66.91	0.792
Twin Tower	79.86	92.17	67.56	0.795
TabBERT	71.70	88.56	54.89	0.708

Comparative Analysis: The TabBERT model, which performed well on synthetic datasets, demonstrates significant under performance on an industrial dataset. The model struggles to effectively learn embeddings for the extensive vocabulary present in financial Comparative Analysis of Transformers for Modeling Tabular Data: A Casestudy using Industry Scale Dataset

datasets. Converting numerical features into categorical ones results in information loss, diminishing discriminative power, and relying on arbitrary cutoff points due to data quantization mechanism. This approach overlooks the similarity between closely related numbers assigned to different categories, which is crucial for problems sensitive to small input variations [9]. In contrast, the Twin-Tower approach, which employs a direct supervised training approach, proves to be effective and efficient for this use case, closely followed by the Vanilla approach.

6 EXPERIMENTS WITH REGRESSION TASKS

The findings and lessons explored in this work for the different transformer modeling approaches, are not limited to these two classification datasets but is also applicable to other classification datasets on structured data as well as for different regression tasks. We share some findings and analysis on the explorations conducted on regression problem for synthetic and industry scale datasets.

6.1 Synthetic Dataset

For comparing performance of these different transformer approached on a regression task, we experimented with Pollution prediction dataset [2]. Task is to predict PM2.5 and PM10 air concentration for 12 monitoring sites, each containing around 35k entries (rows). This is a commonly used public dataset for regression prediction on a multi-variate time series based data and have been used as a benchmark for evaluating transformer models for regression tasks [23, 24]. Dataset has about 400k data points, every row has 11 fields with both numerical and categorical values. For a detailed description of the data, please refer [20]. Data has missing values, and we replace missing data with zero (0), in our experiments. Table 8 present the results of different transformer models.

Table 8: Performance comparison of different transformer architectures on public dataset for regression problem. ⁺ as per the results reported in [24]

Architecture	RMSE
Vanilla	53.6
Twin Tower	54.2
TabBERT ⁺	32.8

6.2 Industry dataset

We experiment with a very common problem in finance industry know as spend prediction [16]. The problem is quite known but have not been explored in-depth due to lack of proper industry scale real datasets. Given consumer data records comprising of different features such as their credit card spend behaviors for last 12 months or so, credit bureau scores, etc., task is to predict their future spend. This model forms a foundational model for marketing and other incentives offered to a consumer. This data consisted of 200k customer data with 1 record per month from 13 months data for each customer so total data points amounting to 2.6M records. Each data point has 148 feature attributes ². We used 70% of the data for training and 15% for validation and 15% for testing. Table 9 presents the results of different transformers for spend prediction.

 Table 9: Different transformer results on industry based

 dataset for regression

Architecture	RMSE
LightGBM	25618
Vanilla	25370
Twin Tower	24471
TabBERT	66126

In this work, we've noticed a similar trend in how regression models perform compared to the classification models we discussed earlier in this paper. Direct supervised techniques like Twin Tower work work well with large and complex datasets while decoupled pre-training and fine-tuning techniques like TabBERT have some limitations dealing with them. We find that these techniques can be used for different types of tasks involving tabular understanding. Importantly, our findings can be applied to a wide range of tablerelated tasks, not limited to specific tasks we tested.

7 LESSONS LEARNED

We present the key insights gained from the experimentation discussed in Sections 3, 4, and 5.

• **Upsampling effect:** Fraud prediction and finance-related datasets often show class imbalance but at the same time use unweighted evaluation metrics. For fraud prediction using a synthetic dataset, we employed the SMOTE library, which generates artificial data points using a nearest neighbor algorithm. Notably, we observe significant performance improvements with SMOTE-based upsampling with the techniques such as Twin Tower as shown in Table 10. Without upsampling F1 score is 0.608 and with upsampling it increased to 0.844.

Table 10: Twin Tower results for credit fraud prediction with and without upsampling

Method	Precision	Recall	F_1 score
Without Upsampling	0.74	0.51	0.608
With Upsampling	0.95	0.76	0.844

- Architectures for tabular series: The study focuses on architectures for modeling sequential tabular data, emphasizing attention across both attribute dimensions and time steps. The ablation study in Section 4 demonstrates the crucial importance of attention across time steps for the model's performance. The findings suggest that simplifying the architectures to prioritize attention across time steps provides a practical solution for working with large datasets under resource and space constraints.
- Hyper Parameter Optimization: Selecting the right parameters is crucial for achieving optimal model performance. Parameters such as the number of attention heads, hidden layer dimensions, learning rate, optimizer, etc., can be effectively chosen using libraries such as RayTune [21]. The study showcases performance enhancements in credit default prediction achieved by fine-tuning hyperparameters, as detailed in Table 11.

²Due to privacy reasons, this dataset cannot be released.

 Table 11: Performance scores with and without hyperparameter optimization on credit default prediction problem

Architecture	Metric M	Gini	Capture Rate	F ₁ Score
Twin Tower	79.53	92.07	66.99	0.792
Twin Tower (with HPT)	79.86	92.17	67.56	0.795

• Infrastructure and compute resources : As discussed in Section 5, training models such as TabBERT for credit default prediction poses challenges due to memory constraints. Industry datasets often present large scale and high dimensionality. Therefore, simpler architectures for models are preferred, as they can offer comparable performance to pre-training-based models while consuming fewer resources.

8 CONCLUSION

This study provides a thorough analysis of transformer techniques for financial tabular series, covering input processing, architecture, training mechanisms, and upsampling. Evaluation on both artificial and real-world industry datasets highlights the Twin Tower model as a suitable choice for industry-scale datasets, offering reduced space requirements and competitive F1 scores. The findings emphasize the importance of considering essential factors in model selection. The study aims to advance transformer applications in financial analysis, offering guidance for researchers and enhancing practical usability. Future work aims to improve interpretability and address challenges with missing and noisy data.

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Comparative Analysis of Transformers for Modeling Tabular Data: A Casestudy using Industry Scale Dataset

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A APPENDIX

A.1 Hyperparameters for Credit Fraud Prediction

For the credit fraud problem, we share the list of hyperparameters (refer Table 12) for our experiments described in section 4.

Architecture	TabBERT	Twin Tower	LUNA
Learning Rate	5e-5	4.35e-5	5e-5
Optimiser	Adam	Adam	Adam
Dropout	0.1	0.134	0.1
Attention heads	12	8	12
Hidden units	768	256	768
Window size	10	10	10
Stride	5	1	10
Batch size	8	256	8
MLM Probability	0.15	-	0.15

Table 12: Hyperparameter values for Credit Fraud Problem

A.2 Hyperparameters for Industry Based Study -Credit Default Prediction

For the credit default problem, we share the list of hyperparameters (refer Table 13 and 14) for our experiments described in section 5.

Table 13: LightGBM Hyperparameter values for Credit De-fault Prediction

LightGBM model	Values
No. of leaves	100
Min data in leaf	2
No. of boosting rounds	2000
Early stopping rounds	50
Learning Rate	0.01
Seed	42
Max depth	default (-1)

 Table 14: Hyperparameter values for Credit Default Prediction

Architecture	TabBERT	Twin Tower
Learning Rate	0.01	1e-4
Optimiser	Adam	Adam
Dropout	0.1	0.1
Attention heads	12	12
Seed	9	42
Hidden units	768	512
Window size	12	12
Batch size	16	512
MLM Probability	0.15	NA

Additionally, we present a loss convergence plot during the training of TabBERT for the credit default problem. As mentioned in section 5, our analysis reveals that TabBERT's performance is sub-optimal compared to direct supervised training methods such as Twin Tower when applied to real industry-scale datasets.



Figure 2: MLM loss convergence for TabBERT pre-training

A.3 Twin Tower architecture of the Gated Transformer

As discussed in section 3, the Gated Transformer by [22] consists of two parallel transformer blocks. The left block captures attention across different time steps whereas the right transformer captures attention across attribute dimension. The output from both the blocks are combined using a gated channel. We present a study to independently assess the contribution of each tower in combined performance of the model via ablation study presented in subsection 4.3.



Figure 3: Image describing the architecture of Gated Transformer (referred from Liu et al. [22]). The left tower captures attention across time step while right tower captures attention across attribute dimension.