Transformer-Based Semantic Self-Attention Regression for the Evaluation of Customer Satisfaction in Social Media Data

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ABSTRACT

A website that is optimized and has a high Search Engine Results Page (SERP) ranking is more likely to attract relevant users. As a result, there is a direct relationship between Search Engine Optimization (SEO) and user experience, and poor SEO makes it hard for a user to find the items he is looking for. The proposed Semantic Self-Attention Regression based on Transformer (SSAR-T) model uses four separate layers—tokenizing, embedding, encoding, and fine-tuning—to determine the degree of user experience satisfaction. Sample input text is fed to the tokenizing layer. The cosine Euclidean semantic similarity-based segment embedding is designed to help minimize the prediction error and training time. Self-attention-based encoder transformation is utilized with multiple attention heads, focusing on learning the context of surrounding words accurately and precisely. Non-linear regression-based fine-tuning is used for measuring customer satisfaction. KANO mapping functions are used to assess the model's precision. Compared to previous methods, the proposed SSAR-T model achieved improvements of 19%, 24% and 58% in precision and 9%, 14% and 12% in recall for SEO, Instagram influencer, and Twitter data samples, respectively.

Keywords-instagram; twitter; cosine euclidean semantic similarity; self attention-based encoder; non-linear regression; KANO; precision; recall

I. INTRODUCTION

Sentiment Analysis (SA) is a crucial field in various industries, including business, education, and politics, as it helps to analyze customer satisfaction, brand loyalty, and user feedback on products, improving quality and increasing sales. The study in [1] discussed various Machine Learning (ML) models that aim to assess the sentiment from users' opinions from large datasets. In [2], a two-step prediction method combined Deep Learning (DL) and conventional ML to examine Vietnamese e-commerce reviews. Using sophisticated DL techniques, such as the Bidirectional Gated Recurrent Unit (BiGRU) and the Bidirectional Encoder Representations from Transformer (BERT), aspect-based sentiments were first retrieved from the reviews. Transformer-based semantic self-attention regression was used to reduce error by utilizing cosine Euclidean semantic similarity-based segment embedding in the second layer.

In [3], a hybrid approach combined Particle Swarm Optimization (PSO) and Deep Reinforcement Learning (DRL), aiming to enhance product designs in ways that conventional techniques cannot. Recommendation algorithms, grouping, and predictive mechanisms offer valuable insights into consumer preferences, enabling the development of more personalized products. Using this multi-technique optimization strategy, both the design iteration time and user satisfaction scores significantly increased. Although training time demonstrated improvement, the accuracy and precision variables received little attention.

Digital marketing refers to the promotion of goods, services, or brands to a target audience using digital platforms, channels, and tactics. It uses a wide range of internet tools and techniques to communicate with prospective customers. One of the most crucial social media marketing strategies for this platform is SEO. In [4], DL methods were applied to the real estate website domain to improve services. However, existing marketing techniques are primarily based on manually produced content and struggle with content development. The introduction of generative Artificial Intelligence (AI) models revolutionized the creation of marketing content by addressing issues, such as the lack of creativity and uniqueness, simplifying the process of evaluating internet prospects [5]. However, it takes a long time to train DL algorithms, especially when using generative AI models.

II. LITERATURE SURVEY

In [6], speech tones were used to assess customer satisfaction, utilizing Long Short-Term Memory (LSTM) and Support Vector Machines (SVM). In [7], a comprehensive assessment of DL-based recommendation systems was carried out. In [8], a novel model to assess customer satisfaction used ML and Natural Language Processing (NLP). In [9], a customer satisfaction model used the structural equation modeling method to determine the link between consumer expectations and customer satisfaction. However, larger sample sizes produce more reliable results for the relationships being studied due to the complexity of the questionnaire and the number of variables evaluated. In [10], a comprehensive analysis of DL applications in sentiment analysis was carried out. However, many approaches cannot handle the negation, intensifier, or modifier clauses in sentences.

In [11], a detailed comparison was presented between generative and traditional AI techniques. Online ratings and user reviews are two important factors that consumers utilize on most e-commerce websites to assess the reliability and quality of products. Reviews include customer feedback on their degree of satisfaction or dissatisfaction with the service, the reasons for negative evaluations, and the advantages of relevant products. However, more sophisticated techniques—weighted random forests and hybrid models—that deal with unstructured data were found to be unable to forecast client attrition. In [12], a DL method was proposed to classify customer evaluations and identify inconsistencies, but the consumer experience did not improve. Multiple Criteria Decision-Making (MCDM) models were used in [13] to improve search engine optimization. However, search engines did not update their machine learning techniques to eliminate low-value websites. In [14], a systematic review examined NLP-based automated responses to consumer inquiries. However, no empirical research on the opportunities and constraints associated with the application of NLP techniques in the customer service sector was carried out. In [15], an ANN technique was employed to predict the degree of user satisfaction with search engines, improving precision and accuracy. However, the results varied depending on the dataset, the training algorithm, the training function, the transfer function, and the neural network architecture.

III. METHODOLOGY

As shown in Figure 1, the proposed SSAR-T method consists of four layers to analyze the level of user satisfaction: the tokenizer, the segment embedding based on cosine Euclidean semantic similarity, the self-attention-based encoder transformation, and the non-linear regression-based fine-tuning.

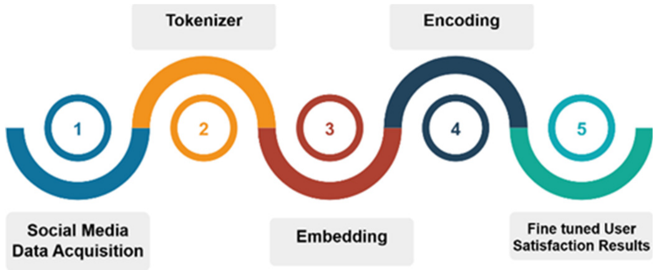

Fig. 1. Projected flow of the SSAR-T method.

A. *Tokenizer*

Three datasets were used to evaluate the proposed model. A website SEO sample dataset [16], and a pair of social media datasets, the Instagram influencer dataset [17] and the Twitter dataset [18], consisting of user opinions and tweets, respectively. In [19], a discretized recurrent DL classifier based on stochastic gradient ChatGPT was used on these datasets. The classifier is employed to identify potential keywords to identify and enhance the lead generation rate for various social media datasets. The tokenizer layer takes the input text from these three different sources, extracts the tokens, assigns a unique token ID, and then performs token embedding to generate the matching output text.

$$IT \rightarrow Tokens \rightarrow Token\ ID \rightarrow TE \rightarrow OT \quad (1)$$

The input text IT is divided into words or tokens. The relevant $TokenID$ is then generated for each token. Lastly, Token Embedding (TE) is performed to obtain the Output Text (OT).

B. *Cosine Euclidean Semantic Similarity-Based Segment Embedding*

The embedding, or token embedding, transforms the sequence of tokens into an array of real-valued vectors. More precisely, embedding indicates the conversion of discrete token types into a low-dimensional Euclidean space. This layer is composed of three elements: token embeddings, position embeddings, and segment embeddings. Since the token type is a typical embedding layer, it transforms a one-hot vector into a dense vector based on its token. Euclidean distance metrics are used to quantify distances and similarities between tokens. The tokens are transformed into a numerical vector, where each dimension corresponds to a token attribute. The coordinates of each token are now expressed as numerical vectors that reveal their semantic importance. Next, Euclidean distance metrics are used to determine how similar these vectors are to each other while evaluating semantic similarity. A greater distance indicates less semantic similarity, whereas a smaller distance indicates more semantic closeness. However, the location of the token determines the position of the position embedding. This segment embedding that employs the vocabulary of "0" or "1" yields dense output based on whether the token for analysis is associated with the first or second text segment.

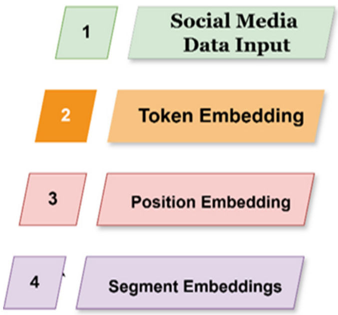

Fig. 2. Structure of cosine Euclidean semantic similarity-based segment embedding.

Let $DS[WS]$ represent the SEO sample data, $DS[Ins]$ represent the Instagram influencer data, and $DS[T]$ denote the Twitter data. The segment embedding generates dense output by employing the cosine Euclidean distance formula. It measures the distance between two vectors (considered for experimental purposes), providing a measure of their semantic similarity, represented as:

$$Cos\theta[WS] = \frac{WS[P].WS[Q]}{||WS[P]||.||WS[Q]||},$$
$$\text{where } P, Q \in DS[WS] \quad (2)$$

$$Cos\theta[Ins] = \frac{Ins[P].Ins[Q]}{||Ins[P]||.||Ins[Q]||},$$
$$\text{where } P, Q \in DS[Ins] \quad (3)$$

$$Cos\theta[T] = \frac{T[P].T[Q]}{||T[P]||.||T[Q]||},$$
$$\text{where } P, Q \in DS[Tw] \quad (4)$$

$$SS = \{Cos\theta[WS], Cos\theta[Ins], Cos\theta[T]\} \quad (5)$$

From (2-5), the cosine Euclidean distance-based semantic similarity (SS) for three datasets is derived based on the product of vectors P and Q and their magnitudes $|(|Ins[P]|)|$, $|(|Ins[Q]|)|$. By employing cosine Euclidean distance-based semantic similarity, more emphasis is placed on the vector orientation rather than its magnitude, making it suitable for text data.

C. Self-Attention-Based Encoder Transformation

The third layer is the encoder, where the output of the cosine Euclidean semantic similarity-based segment embedding is eventually utilized as input for the encoder transformer block. This model consists of 12 encoder transformation blocks, each with hidden layers $(L_1, L_2, \ldots, L_{12})$ and self-attention heads $(AH_1, AH_2, \ldots, AH_{12})$. Each block consists of four sub-layers: a feed-forward layer, a first normalization layer, a second normalization layer, and an attention layer. The input sequences go through multiple attention heads in each block, each focusing on comprehending the surrounding words' context. After processing the matching input sequences individually, each multiple attention head generates its output.

The output of these four sub-layers transforms the input text into contextual embeddings. The significance of each word in relation to the overall context of a text is assessed using the self-attention mechanism. Let's look at an example text called SS (semantic similarity function) that has been divided into a series of tokens called $SS_1, SS_2, \ldots, SS_N$, where each SS_i represents a flattened vector of dimension Dim_{in}. The parameters for the three layers are WQ, WK, and WV for query, key, and value, such that WQ, WK, $WV \in \mathbb{R}^{Dim_{in} * Dim_{attn}}$, with weights $W_0 \in R^{Dim_{attn} * Dim_{in}}$ and bias $B_0 \in R^{Dim_{in}}$, respectively. Then, the query, key, and value matrix vectors are formulated as:

$$Q = matmul(TE, WQ), \text{ where } Q \in \mathbb{R}^{N * Dim_{attn}} \quad (6)$$

$$K = matmul(TE, WK), \text{ where } K \in \mathbb{R}^{N * Dim_{attn}} \quad (7)$$

$$V = matmul(TE, WV), \text{ where } V \in \mathbb{R}^{N * Dim_{attn}} \quad (8)$$

From (6-8), the query Q, key K, and value V matrix vectors for the corresponding semantic similarity function result SS is obtained through the hyperparameter Dim_{attn} or the dimension of query, key, and value, respectively. Then, the attention matrix is computed as:

$$A = Att(Q, K, V) = Softmax\left(\frac{QK^2}{\sqrt{d_k}}\right), V, Q \in SS \quad (9)$$

The self-attention mechanism Att for weighing the semantic similarity function result (i.e., the significance of each word) is derived from (9) by using the dimension of the key vector d_k, the matrix representation of the input query vector Q, the matrix representation of the key vector K, and the matrix representation of the value vector V.

D. Non-Linear Regression-Based Fine-Tuning for Measuring Customer Satisfaction

The final phase uses data from Instagram influencers and Twitter to estimate customer satisfaction with a product using a non-linear regression algorithm. A semantic decision is made based on whether the emotion words included in the description text of each token are positive or negative.

Here, sentiment class A is used as an input variable and customer satisfaction Res is an output variable. The satisfaction levels are given as:

$$SL = \{extremely\ negative, very\ negative, negative, positive, very\ positive, extremely\ positive\}$$

and:

$$Res = \{extremely\ low, very\ low, low, high, very\ high, extremely\ high\}.$$

Identifying the input-output variables is the initial stage in a non-linear regression system. Assuming the values of positive and negative sentiment on token i are TE_i^+ and TE_i^-, a crisp set is turned into a non-linear regression set. The goal of the suggested non-linear regression model is to identify a customer's level of satisfaction. If users or customers have positive feelings towards token i, then, $TE_i^+ = 1, TE_i^- = 0$, and in contrast, if users or customers have negative feelings $TE_i^- = 1, TE_i^+ = 0$. The sample input text is finally decided using the KANO utility mapping function. Customers' positive and negative feelings about each sample input text are used to indicate token performance, and their degree of satisfaction is shown by the star rating. The definition of the utility function is initially represented as stated below.

$$Res = \alpha + \sum_{i=1}^{13}(\beta_i^+ TE_i^+ + \beta_i^- TE_i^-) \quad (10)$$

where Res measures the level of user satisfaction employing the positive TE_i^+ and negative TE_i^- sentiment of token i via the coefficients of positive sentiment β_i^+ and negative sentiment β_i^-, respectively. The KANO mapping rules are designed based on β_i^+ and β_i^- as measured by the above utility function. Figure 3 shows the structure of the non-linear regression-based fine-tuning for measuring customer satisfaction. As shown in Figure 3, using the utility function and star rating reflecting the level of customer satisfaction through KANO mapping rules based on the regression coefficients, six different class results are defined. Classification rules are listed in Table I, where γ and δ are two positive hyperparameters greater than zero. Here, γ is set to measure the significance of β_i^+ and β_i^-. When β is lower than γ, it is close to zero. On the other hand, δ measures the similarity between the influence of positive and negative attribute performances on customer satisfaction, namely, β_i^+ and β_i^-.

TABLE I. THE KANO MAPPING RULES

	Mapping Rule	**Satisfaction level**
1	$\boldsymbol{\beta^+ > \gamma\ (\&\&)\beta^- > \gamma(\&\&)\beta^- > \frac{1}{\delta}\beta^+(\&\&)\beta^- < \delta\beta^+}$	Extremely -ve
2	$\boldsymbol{\beta^+ < -\gamma(\&\&)\beta^- < \gamma; -\gamma < \beta^+ < \gamma(\&\&)\beta^- < -\gamma}$	Very -ve
3	$\boldsymbol{\beta^+ > \gamma(\&\&)\lvert\beta^-\rvert < \gamma;\ \beta^{Neg} > \gamma(\&\&)\beta^- < \frac{1}{\delta}\beta^+}$	-ve
4	$\boldsymbol{\lvert\beta^+\rvert < \gamma(\&\&)\lvert\beta^-\rvert > \gamma; \beta^+ > \gamma(\&\&)\beta^- > \delta\,\beta^+}$	+ve
5	$\boldsymbol{\lvert\beta^+\rvert < \gamma(\&\&)\lvert\beta^-\rvert < \gamma}$	Very +ve
6	$\boldsymbol{\beta^+ < -\gamma(\&\&)\beta^- > \gamma; \beta^+ > \gamma(\&\&)\beta^- < -\gamma}$	Extremely +ve

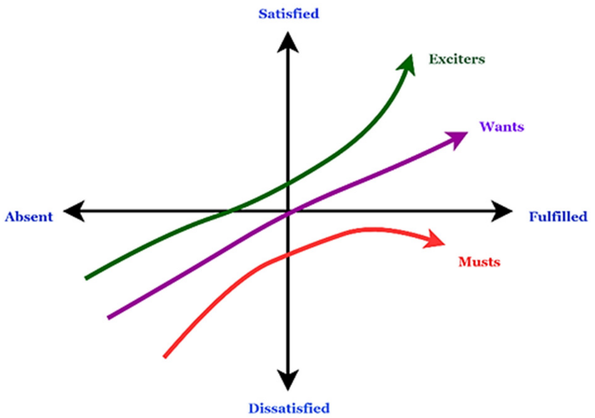

Fig. 3. KANO Model.

According to the above KANO mapping rules based on the regression coefficients of positive and negative sentiment and employing the results of the utility function, the satisfaction level of the customer is said to be investigated in an accurate and precise manner.

IV. PERFORMANCE EVALUATION

The performance of the proposed method was evaluated using the precision and recall metrics. During the evaluation phase, precision and accuracy were calculated and compared for the proposed SSAR-T, Bidirectional Encoder Representations from Transformer (BERT) with Bidirectional Gated Recurrent Unit (BiGRU) (BERT-BiGRU), and Particle Swarm Optimization (PSO) with Deep Reinforcement Learning (DRL) (PSO-DRL) techniques to determine their efficiency in analyzing user satisfaction level. The detailed analysis was performed for sample sizes varying from 1000 to 10,000.

$$Pre = \frac{TP}{TP+FP} \quad (11)$$

The higher the precision, the more efficient the method is, and vice versa. Table II presents a comparison of precision for the proposed SSAR-T and two existing methods, BERT-BiGRU and PSO-DRL, based on SEO, Instagram influencer, and Twitter sample data. Table II depicts the observed values for precision for various sample sizes. Recall is mathematically represented as:

$$Rec = \frac{TP}{TP+FN} \quad (12)$$

Similar to precision, recall (Rec) was also measured for sample sizes ranging from 1,000 to 10,000 over the three datasets. Table III shows the recall results for all three methods.

TABLE II. PRECISION COMPARISON

Samples	**Precision**								
	SEO			**Instagram influencer**			**Twitter**		
	SSAR-T	**BERT-BiGRU**	**PSO-DRL**	**SSAR-T**	**BERT-BiGRU**	**PSO-DRL**	**SSAR-T**	**BERT-BiGRU**	**PSO-DRL**
1000	0.97	0.95	0.92	0.96	0.94	0.92	0.96	0.94	0.91
2000	0.95	0.85	0.8	0.94	0.86	0.76	0.94	0.9	0.8
3000	0.93	0.83	0.78	0.91	0.79	0.69	0.9	0.86	0.76
4000	0.91	0.81	0.76	0.87	0.79	0.69	0.88	0.84	0.74
5000	0.89	0.79	0.74	0.83	0.75	0.65	0.85	0.81	0.71
6000	0.86	0.76	0.71	0.8	0.72	0.62	0.81	0.77	0.67
7000	0.88	0.78	0.73	0.82	0.74	0.64	0.83	0.79	0.69
8000	0.9	0.8	0.75	0.84	0.76	0.66	0.85	0.81	0.71
9000	0.92	0.82	0.77	0.86	0.78	0.68	0.87	0.83	0.73
10000	0.9	0.8	0.75	0.88	0.8	0.7	0.9	0.86	0.76

TABLE III. RECALL COMPARISON

Samples	**Recall**								
	SEO			**Instagram influencer**			**Twitter**		
	SSAR-T	**BERT-BiGRU**	**PSO-DRL**	**SSAR-T**	**BERT-BiGRU**	**PSO-DRL**	**SSAR-T**	**BERT-BiGRU**	**PSO-DRL**
1000	0.99	0.99	0.99	0.99	0.99	0.98	0.99	0.99	0.98
2000	0.97	0.94	0.89	0.94	0.89	0.84	0.84	0.79	0.76
3000	0.94	0.89	0.86	0.95	0.85	0.78	0.81	0.76	0.73
4000	0.92	0.89	0.84	0.89	0.84	0.76	0.79	0.74	0.71
5000	0.89	0.86	0.84	0.86	0.82	0.73	0.76	0.71	0.66
6000	0.86	0.84	0.79	0.83	0.76	0.69	0.73	0.68	0.63
7000	0.89	0.84	0.79	0.8	0.75	0.68	0.7	0.65	0.62
8000	0.9	0.87	0.82	0.83	0.78	0.7	0.73	0.68	0.63
9000	0.92	0.89	0.84	0.85	0.8	0.72	0.75	0.7	0.67
10000	0.94	0.9	0.81	0.86	0.84	0.73	0.76	0.71	0.68

Figures 4 and 5 show the recall and precision results while investigating the satisfaction level of the user experience using the proposed SSAR-T and three existing methods, BERT-BiGRU and PSO-DRL, and GSAL-BERT on the three datasets. To ensure a fair comparison, the same datasets were used to validate the efficiency of the four methods.

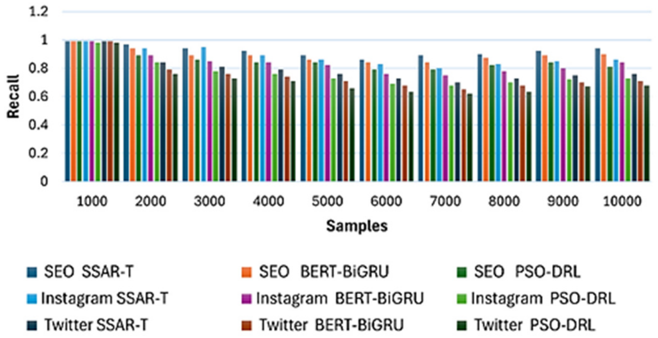

Fig. 4. Recall comparison for various Models.

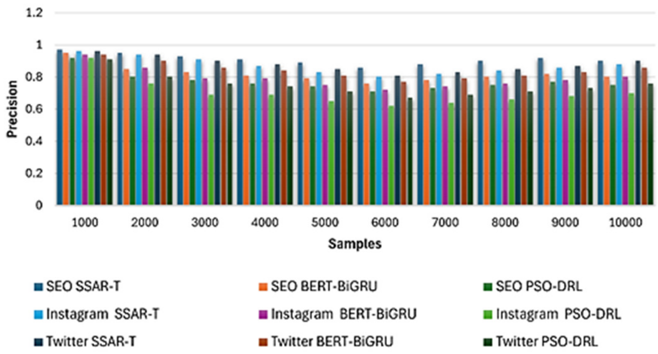

Fig. 5. Precision comparison for various Models.

Three inferences were made from the evaluation results. First, using the proposed SSAR-T method, precision was found to be better than the three existing methods, BERT-BiGRU, PSO-DRL, and GSAL-BERT. Second, precision and recall on the SEO sample dataset were found to be better than those on the two social media datasets. Third, precision was not found to be proportional or inversely proportional to the samples used for simulation. The reason behind the improvement in precision and recall using SSAR-T is due to the application of the self-attention-based encoder transformation in the third layer. This layer calculates attention scores by acquiring the dot product of the query vector to that of the key vector, ascertaining how much attention the current feature or word should pay to each feature or word in the sequence. Based on the attention scores, efficient attention on the most relevant feature or word in the sequence is emphasized. This improves the overall precision in the proposed SSAR-T method by 11%, 18%, and 29% using SEO samples, 10%, 25%, and 37% using Instagram samples, and 5%, 18%, and 35% using Twitter samples. The recall when employing the proposed SSAR-T method was improved by 4%, 9%, and 14% using SEO samples, 6%, 16%, and 21% using Instagram samples, and 6%, 12%, and 17% using Twitter samples.

V. CONCLUSION

Analysis of the satisfaction level of user experience using text and sentiment analysis is one of the most popular research areas that may assist in determining the degree to which a customer is happy with a product or service, and hence aid in improving the overall retention rate. Previous research works determined the level of user experience satisfaction using distinct traditional and non-traditional methods, including ML and DL. The proposed SSAR-T method was used to investigate the satisfaction of user experience by employing tokenization, embedding, encoding, and fine-tuning. First, samples acquired from three datasets, SEO, Instagram influencer, and Twitter, were provided as input to the tokenization process, which, in turn, splits the input text into tokens along with the generation of a unique token ID for further processing. Second, cosine Euclidean semantic similarity-based segment embedding is performed, which, along with token embedding and position embedding, translates a one-hot vector into a dense vector based on its token. Third, self-attention-based encoder transformations are applied with multiple attention heads, focusing on learning the context of surrounding words. Fourth, non-linear regression function-based fine-tuning is performed for measuring customer satisfaction with minimal prediction errors. The proposed SSAR-T method was developed in Python. The experimental results validated that the SSAR-T method achieves better results in performance metrics such as precision and recall. Other metrics, such as accuracy, prediction error, training time, and return on investment, will be evaluated in the future.

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