Knowledge Graph Embedding for Detecting Brand Advocates in Online Social Networks

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***Abstract*— In the dynamic and ever-changing environment of social media, customer advocacy forms part of the key success factors that need to be monitored by brand teams. Focusing on the social media engagement aspect, this paper outlines a conceptual model that guides the evaluation of customer advocacy.The approach involves developing a Knowledge Graph (KG) that captures the complex connections among customers, brands, and even products. The KG is constructed based on state-of-the-art methods of entity and relationship Mining from social media text, backed by a highly layered structure with XLNet, BiLSTM, and CRF ensembles. The performance of the KG embedding models namely TransE, DistMult, ComplEx, HolE, and RotatE models are assessed with parameters such as Hits@k, Median Rank (MR), Mean Reciprocal Rank (MRR), and Mean Rank. The performance of RotatE framework to predict relationships within the KG and its accuracy have been shown by the experimental results. In this respect, the results reveal the importance of KG-based perspectives for investigating and resolving issues related to customer advocacy, as well as for developing relevant marketing strategies in contemporary environment..**

Keywords*— *Social Media Marketing; Online Brand Advocates Detection; Knowledge Graphs; KG Embedding; Social Media Analysis.

I. INTRODUCTION

With the advent of Web 2.0, online users have evolved from being mere consumers to active contributors, leading to a significant diversity in content quality. Online Social Networks (OSNs) have surfaced as a potent platform for disseminating information across a variety of domains. As a result, deciphering and understanding the content shared on OSNs has become a pivotal area of research. The process of identifying significant social content, while time-consuming, is of paramount importance in areas such as politics [1], e-commerce [2], e-learning [3], healthcare [4], travel [5], and more. In this context, online Customer Engagement (CE) has emerged as a key component of successful business strategies [6]. Online CE extends beyond understanding customer purchasing behavior and aims to grasp customers' attitudes towards a brand or company. By offering personalized experiences, businesses aim to transform customers into advocates through OSNs [7, 8]. These advocates share positive experiences, influencing others to become customers and potentially evolving into brand loyalists [9, 10]. This creates a cycle of advocacy and evangelism, where satisfied customers continually promote the brand to others. Businesses acknowledge the value of engaged customers and strive to harness positive feedback to convert content consumers into brand advocates and attract new customers [11, 12] [13] [14]. As a result, nurturing online advocacy and developing evangelists have become primary goals for businesses navigating the dynamic terrain of online CE.

Online customer advocacy has surfaced as a strategic method to foster beneficial and mutual relationships between businesses and their consumers, leading to organizational improvement [15, 16]. This concept is centered around motivating customers to actively endorse products or services to others, resulting in positive word-of-mouth (WOM). Despite its importance, the motivations driving consumer advocacy behaviors have not been thoroughly explored, and there is a scarcity of intelligent systems that can identify online advocates based on their social interactions with brands. This limitation underscores the need for innovative strategies to address this challenge. Knowledge Graphs (KGs) have attracted significant interest in both the industry and academic sectors due to their ability to provide structured and factual representations of human knowledge. This allows them to effectively address complex real-world challenges across various domains [17]. KGs have the potential to greatly enhance CE by providing a comprehensive understanding of customers, their preferences, and their interactions with a brand.

In response to the aforementioned challenges, this study aims to enrich the existing literature by introducing a framework that utilizes KG construction and embedding techniques to pinpoint brand advocates. By capitalizing on the capabilities of KG, the proposed framework aims to boost the precision and efficiency of identifying and understanding brand advocates, thereby providing valuable insights into the dynamics of customer advocacy in the digital sphere. While conventional graph representation methods, such as adjacency matrices, can be employed to address graph-related challenges, the approach of mapping the entire graph or its nodes into a vector space has garnered considerable interest in the scientific community [18]. As a result, we have implemented various state-of-the-art embedding techniques to project the KG into a low-dimensional vector space. To assess the effectiveness and performance of the integrated embedding models, we employed key evaluation metrics to measure their capabilities.

This paper is organized as follows: Section 2 provides a review of the literature relevant to the context of this study. Section 3 presents a detailed discussion of the overall methodology, shedding light on the proposed framework and its integral components. Section 4 elaborates on the experimental procedures conducted in this study, along with the evaluation mechanism and the tasks implemented. Lastly, Section 5 summarizes the conclusions derived from this research effort and outlines potential directions for future research in this field..

II. Related Works

Artificial intelligence (AI) has markedly transformed Customer Engagement (CE) by optimizing interactions on social media platforms. By harnessing extensive social data, AI algorithms can perform large-scale analyses of customer dialogues, emotions, and preferences, providing brands with profound insights into consumer patterns and inclinations [19]. AI-enabled systems are capable of swiftly pinpointing recurring themes, tendencies, and nascent concerns from customer input, which empowers businesses to address customer issues and queries both quickly and proactively. Additionally, AI's ability to grasp the subtleties of each customer interaction allows for the customization of responses and suggestions, leading to a more impactful and individualized customer journey [20]. The incorporation of AI into customer-brand exchanges not only makes customer support more efficient but also bolsters customer fidelity and contentment [21, 22]. With ongoing advancements in AI, its influence on CE is poised to expand, redefining the dynamics of customer-brand relations and fostering innovation in social media marketing strategies [23].

In today's digitally connected world, brands have shifted their CE strategies to fully embrace the power of online social media platforms. These platforms serve as critical spaces where customers freely share their views, tastes, and feedback [24]. Brands are now keenly aware of the need to engage in these digital discussions and leverage the rich social data to forge enduring customer bonds. Consequently, numerous studies have been conducted to delve into the significance of social ties between consumers and brands. For instance, Nazir et al. [25] examined the determinants of consumer repurchase intentions within the hospitality sector, with a particular focus on the influence of AI technology, consumer engagement on social media, conversion rate optimization, and the overall consumer experience. Another study by Simay, Wei et al. [26] investigated the uptake of AI-driven color cosmetics applications by Chinese social media influencers and their intention to generate electronic word-of-mouth (e-WOM). This research concentrated on essential aspects like body esteem, price consciousness, social media dependency, and actual buying behavior to comprehend their effect on influencers' choices regarding AI color cosmetics. Additionally, Li, Lin et al. [27] explored a significant research void by assessing how AI can enhance the capabilities of Customer Relationship Management (CRM) systems and thus improve CRM performance. This study, which had not been extensively explored before, adopted an IT-enabled organizational capabilities framework to analyze the interplay between AI application, CRM capabilities, and CRM performance, with data gathered from 193 e-commerce firms in China to validate their hypothesis-driven research model and central thesis.

The fusion of AI and Knowledge Graphs (KGs) in shaping online customer advocacy has been pivotal in propelling a variety of research domains, offering key insights and methodologies for companies to improve Customer Engagement (CE), refine marketing initiatives, and elevate the overall customer experience [28-30]. The integration of these technologies is seen as a harbinger of progress in e-commerce and customer relationship management. For example, Yu et al. [31] developed the "FolkScope" framework, aimed at constructing a KG to understand the pattern of human intentions related to product purchases. The challenge lies in the extraction of knowledge, which is often implicit and not explicitly stated. To address this, the authors proposed a novel approach that semi-automatically generates the knowledge network by harnessing the capabilities of large language models (LLMs) with human-in-the-loop annotations. These LLMs generate intention assertions through e-commerce-specific prompts, which help in elucidating consumer behavior. Yan et al. [32] also advocated for the creation of a KG in the fashion industry, which helped mitigate the cold-start problem through the developed user-item KG. Further discussions on constructing KGs for recommender systems within the CE context have been explored in works by [33-35]

Shbita et al. [36] explored a method to enhance customer comprehension by formalizing the exchange between consumer demands and business offerings using Enterprise Knowledge Graphs (EKG). They crafted a system to extract customer needs from unstructured text and depict them through an EKG. In a separate study, Pai et al. [37] introduced an unsupervised technique for segmenting customers based on behavioral data, utilizing a dataset of 2.9 million beer reviews spanning 12 years to model beer consumption patterns as a KG. They applied KG embedding models to represent the data and cluster analysis to categorize distinct beer consumer segments. The use of KG technology in customer segmentation and clustering was further examined in studies by [38, 39].

Domain-specific KGs [17] are essential for understanding online customer behavior within niche markets [37]. Past research on customer advocacy mostly used social media numbers (likes, etc.) to measure engagement. This lacks depth; we need to analyze the actual conversations. Our study examines the text of brand-customer interactions using natural language processing and KGs. This lets us find brand advocates based on the deeper meaning of their words, not just simple metrics.

III. Method

This section covers the main modules that are part of this the course of study. After providing an overview of the collected data, the techniques employed for KG creation and KG embedding are showcased. Figure 1 presents a schematic representation of the proposed framework.

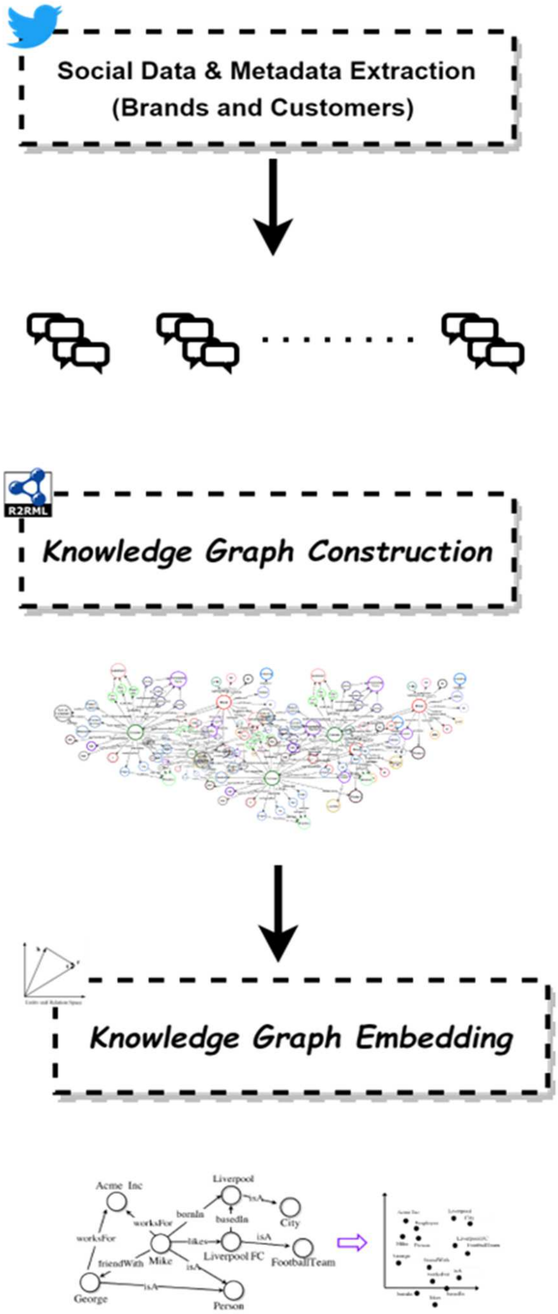

Figure 1: A diagram of the proposed model

A. Data Collection and Preparation

Figure 1 outlines our process for gathering social data and metadata about brands and customers. We begin by targeting reputable Australian brand Twitter accounts. The Twitter API helps us collect tweets from these brands, from which we extract conversations between the brands and their customers. We carefully filter these conversations to focus on those with meaningful interactions, ensuring our analysis works with the most relevant data. Next, we collect the Twitter accounts of the customers in those conversations. This gives us their social data (their tweets) and their metadata (account details). To refine our results, we manually check the content of customer tweets to identify brand advocates – those who express positive views. These advocates are influential through word-of-mouth, impacting how others perceive the brand.

B. KG Construction

KG construction aims to model customer advocates by building a KG that maps out how customers, brands, and products relate to each other. This KG provides a much richer understanding of why customers become advocates and how that advocacy impacts a brand's reputation and strategic decisions. The KG also includes details about the social aspects of customers, brands, and products.

In the world of customer advocacy, entity extraction is essential for finding and isolating the most important information hidden within unstructured text. It automatically finds and labels relevant items – company names, products, customer identities, emotions, and other essential details. This gives businesses an immediate understanding of how customers feel, what they say about the brand, and their overall experiences. Relationship extraction goes a step further: it reveals the connections between the entities found in the text. Applied to customer advocacy, this might expose how brands and customers interact, how customers feel about certain products, or how influential brand supporters are. Companies can then use these insights to make smarter decisions and build stronger customer advocacy programs.

In the process of building the Knowledge Graph (KG), we adhere to our previously established and validated framework [40]. A key aspect of this process is entity extraction in customer advocacy, which is made possible by a complex architecture that integrates XLNet, BiLSTM, and CRF layers. XLNet, a transformer-based language model, offers bidirectional context information and semantic representations of the input text [41]. It improves upon the limitations of BERT by incorporating permutation-based training and the Transformer-XL architecture. The XLNet model processes the input sentence and generates token-level embeddings that encapsulate the semantic meaning of each term. Built atop the XLNet encoding layer, the BiLSTM layer captures contextual dependencies in both forward and backward directions [41]. It excels at capturing long-term dependencies in sequential data, making it particularly suited for tasks like entity recognition in customer advocacy. The hidden states from both the forward and reverse layers are merged to create a comprehensive representation of the input sequence. This allows the model to effectively capture dependencies and make accurate predictions based on the sequential nature of the data. The CRF layer models the sequential dependencies among entity labels. It assigns the most probable label sequence for the input tokens, taking into account the dependencies between neighboring labels and input features. By explicitly capturing label dependencies, the CRF layer ensures coherent and consistent predictions, leading to more accurate entity extraction results..

C. Knowledge Graph Embedding Models

Knowledge Graph Embedding (KGE) involves converting the components of a KG - entities and relationships - into a lower-dimensional space that maintains semantic continuity. In the realm of KGE, existing research typically categorizes embedding techniques into two primary groups: translation distance models and semantic matching models [42]. Translation distance models strive to evaluate the validity of a specific fact by calculating the distance between two entities. Conversely, semantic matching models aim to assess the validity of facts by examining the underlying semantics of entities and relationships within their low-dimensional representations. This study includes a selection of the most widely used KG embedding models from the broad array proposed in the literature, with the goal of examining their effectiveness. Table 1 shows the list of incorporated KGE, along with their descriptions and formulas.

Table 1:Incorporated KGE models

Model	Description	Equation
TransE [43]	TransE acquires the conceptual representation of both entities and relations as vectors within the same low-dimensional semantic space.	$f_{TransE} = -\lVert e_h + e_r - e_t \rVert_n$
DistMult [44]	Depicts the interaction between entities and relations as a bilinear product of their respective vectors.	$f_{DistMult} = r^T (h \odot t)$
ComplEx [45]	Expands DistMult into the complex space, where each vector is depicted as a complex number.	$f_{\text{ComplEx}} = \text{Re}(\langle e_r, e_h, \bar{e}_t \rangle)$
HolE [46]:	Attempts to represent the interaction between entities and relations by calculating the circular correlation of their embedding vectors.	$f_{\text{HolE}} = w_r \cdot (e_h \otimes e_t) = \frac{1}{k} \text{F}(w_r) \cdot \left(\overline{F(e_h)} \odot F(e_t)\right)$
RotatE [47]	RotatE depicts entities and relations as vectors with complex values. Each entity and relation is linked to a vector in the complex plane, which is composed of a real component and an imaginary component.	$\mathbf{e}_t = \mathbf{e}_h \odot \mathbf{r}_r$

D. Knowledge Graph Embedding Model Evaluation

In this section, we provide a brief on the performance metrics incorporated in this study to measure the performance of the KG Embedding models. The following learning-to-rank metrics are commonly used in the literature to measure the performance of KG Embedding models. This evaluation is crucial as it measures the model's effectiveness in accurately capturing and predicting relationships within a KG. Table 2 demonstrates the incorporated evaluation metrics.

Table 2:Incorporated KGE evaluation metrics.

Metric	Description	Formula
Mean Reciprocal Rank (MRR)	This refers to a function that calculates the average of the reciprocals of the elements contained in a ranking vector. It serves as a metric to assess the performance of a system in relation to the elements it retrieves.	$\text{MRR} = \frac{1}{\lvert T \rvert} \sum_{i=1}^{\lvert Q \rvert} \frac{1}{rank(s,p,o)_i}$
Mean Rank (MR)	This refers to the average rank of the correct test facts or triples, as represented in a vector of rankings (i.e., the mean of the predicted ranks).	$\text{MR} = \frac{1}{\lvert T \rvert} \sum_{i=1}^{\lvert Q \rvert} rank(s,p,o)_i$
Adjusted Mean Rank (AMR):	This metric is computed by adding up the product of the reciprocal of the rank and the reciprocal of the number of correct tail entities for each individual query.	$AMR = 1/N * \Sigma\, (1/rank\_i)$
Hits@N	This refers to the count of elements in the ranking vector, retrieved from the model, that are placed within the top 'N' positions.	$\text{Hits@N} = \begin{cases} \sum_{i=1}^{\lvert Q \rvert} 1, & if\ rank(s,p,o)_i \leq N \\ 0, & otherwise \end{cases}$

IV. Experimental Results

A. Dataset Exploration

Figure 1 shows how we carefully analyzed collected tweets to find meaningful conversations between the brand and customers. We removed short or irrelevant conversations to ensure our model focuses on the most engaged customers. These customers' Twitter accounts (including their tweets and profile information) were then studied by hand to identify advocates— people who actively promote the brand's products or services. To ensure our labeling was reliable, we used Cohen's kappa. This metric compares how often our experts agreed on labels, correcting for the possibility of chance agreement. Cohen's kappa ranges from -1 to 1, with higher numbers meaning stronger agreement.

B. XLNet-BiLSTM-CRF

The XLNet-BiLSTM-CRF model described in our earlier study [40] was carefully tuned for optimal performance. We started by using a larger XLNet-Base variant (24 layers, 1024 hidden units, 16 attention heads) for deeper, richer pattern recognition. The increased max-seq-length of 256 provides additional contextual information. Larger batch sizes of 64 improve efficiency and accuracy. A learning rate of 1e-5, along with adjusted dropout rates (0.2 for XLNet, 0.5 elsewhere), helps find an optimal solution and reduces overfitting. Static and contextualized embeddings work together for better input, and 100 training epochs ensure the model fully learns the data.

C. KG Embedding Experimental Results

We use the advanced PyKEEN™ version 1.10.1, built on PyTorch, as our backend framework for performing KGE on a carefully built domain KG. This allows us to leverage PyTorch's deep learning and automatic differentiation capabilities. Our experiments are powered by the high-performance Australian Pawsey supercomputing infrastructure. For thorough evaluations, we divide the domain KG into training, test, and validation sets (70%, 20%, and 10% respectively). We fine-tune the hyperparameters of various KG embedding models using a random search strategy, which has shown its effectiveness over the traditional grid search approach, especially when dealing with a large number of parameters. By using these sophisticated methods, we aim to generate accurate and informative KG embeddings that will enhance knowledge representation and reveal insightful patterns and relationships within the domain KG.

The hyperparameters for the KGE models are optimised using Gridsearch strategy. Table 3 presents the optimized hyperparameters for various knowledge graph embedding models. Each row corresponds to a specific model, including ComplEx, TransE, DistMult, RotatE, and HolE. The optimized hyperparameters include settings such as batch size, number of epochs, embedding dimensionality (k), learning rate (eta), loss function type, regularization method, optimizer, and early stopping epoch. These hyperparameters were fine-tuned to maximize the performance of each model on the task of knowledge graph completion. The table provides a concise summary of the key settings required to reproduce the optimized performance of each model.

Table 3:Hyperparameter Settings

Model	Optimised Hyperparmeter
ComplEx	{'batches_count': 50, 'epochs': 500, 'k': 50, 'eta': 10, 'loss': 'pairwise', 'loss_params': {'margin': 20.0, 'alpha': 0.5}, 'regularizer': 'LP', 'regularizer_params': {'p': 2, 'lambda': 0.0001}, 'optimizer': 'adam', 'verbose': True, 'early_stopping_epoch': 300}
TransE	{'batches_count': 10, 'epochs': 300, 'k': 100, 'eta': 10, 'loss': 'nll', 'loss_params': {'margin': 0.5, 'alpha': 0.5}, 'regularizer': 'LP', 'regularizer_params': {'p': 2, 'lambda': 1e-05}, 'optimizer': 'adam', 'verbose': True, 'early_stopping_epoch': 270}
DistMult	{'batches_count': 100, 'epochs': 200, 'k': 50, 'eta': 5, 'loss': 'nll', 'loss_params': {'margin': 20.0, 'alpha': 0.5}, 'regularizer': 'LP', 'regularizer_params': {'p': 2, 'lambda': 0.0001}, 'optimizer': 'adam', 'verbose': True, 'early_stopping_epoch': 150}
RotatE	{'batches_count': 10, 'epochs': 300, 'k': 100, 'eta': 10, 'loss': 'nll', 'loss_params': {'margin': 0.5, 'alpha': 0.5}, 'regularizer': 'LP', 'regularizer_params': {'p': 2, 'lambda': 1e-05}, 'optimizer': 'adam', 'verbose': True, 'early_stopping_epoch': 210}
HolE	{'batches_count': 50, 'epochs': 200, 'k': 100, 'eta': 10, 'loss': 'pairwise', 'loss_params': {'margin': 0.5, 'alpha': 0.5}, 'regularizer': None, 'regularizer_params': {'p': 2, 'lambda': 1e-05}, 'optimizer': 'adam', 'verbose': True, 'early_stopping_epoch': 200}

1) Models Embedding Evaluation Results

Table 4 shows a comparison of various KG embedding models based on their performance metrics. The models were evaluated on a specific dataset using common evaluation metrics such as Hits@k, Mean Reciprocal Rank (MRR), Mean Rank (MR), and Adjusted Mean Rank (AMR). The results provide insights into the ranking capabilities and accuracy of the models in predicting correct answers within the KG. For example, RotatE performs exceptionally well across all metrics in the table. It has the highest Hits@1, Hits@3, Hits@5, and MRR scores, and the second-lowest MR and AMR scores. This indicates that RotatE is often able to rank the true entity very highly among its predictions, which is reflected in its high Hits@k and MRR scores. Furthermore, its low MR and AMR scores suggest that, on average, the true entity is ranked close to the top of its predictions. These characteristics make RotatE a very effective model for this task. The strength of RotatE lies in its ability to capture and model complex relationships in the knowledge graph. It does this by representing entities as complex vectors and relations as rotations in the complex vector space. This allows it to model asymmetric relations, which is a common characteristic in real-world knowledge graphs. On the other hand, TransE has the lowest Hits@1, Hits@3, Hits@5, and MRR scores, and the second-highest MR and AMR scores. This suggests that TransE often ranks the true entity relatively low among its predictions, which is reflected in its low Hits@k and MRR scores. Its high MR and AMR scores indicate that, on average, the true entity is ranked quite far from the top of its predictions. These characteristics make TransE less effective for this task compared to the other models. TransE represents entities as vectors and relations as translations in the vector space. While this approach is simple and intuitive, it has limitations. For example, it struggles to model complex and asymmetric relations, which are common in real-world knowledge graphs. This could explain its lower performance compared to the other models.

Table 4: Performance comparison using different evaluation metrics.

Model	Hits@1	Hits@3	Hits@5	Hits@10	MRR	MR	AMR
ComplEx	0.197	0.426	0.513	0.613	0.392	22.529	0.029
TransE	0.112	0.220	0.317	0.410	0.227	45.795	0.069
DistMult	0.015	0.399	0.416	0.432	0.168	105.151	0.158
RotatE	0.757	0.869	0.892	0.910	0.821	5.012	0.008
HolE	0.657	0.769	0.792	0.814	0.721	15.012	0.018

The effectiveness of embedding models is typically evaluated based on their suitability for various practical tasks. The subsequent sections examine how the developed approach can be applied to tasks such as link prediction, clustering, and visualization, highlighting its usefulness in these areas.

2) Advocates and Customers Projection in 3D Space

TensorBoard [1] a web-based visualization tool provided by TensorFlow, is designed to aid researchers and developers in understanding, debugging, and optimizing machine learning models. One of its key features is the "Projector", which visualizes high-dimensional data in 3D projections. This is achieved by projecting high-dimensional data points into a 3D space using dimensionality reduction techniques such as t-SNE (t-distributed stochastic neighbor embedding) or PCA (principal component analysis). The 3D Projections feature enables users to project high-dimensional data, like embeddings, into a 3D space, simplifying the exploration and understanding of complex relationships between data points. This is especially beneficial when dealing with data that cannot be directly visualized in 2D, such as word embeddings, graph embeddings, or other feature representations used in machine learning models. For instance, Figure 2 presents a 3D visualization of the implemented KG embeddings. This visualization aids in identifying already labeled advocates, such as “Advocate746”, and in pinpointing customers who show proximity to this advocate, such as Customer1248, Customer1008, Customer1251, etc. These customers could potentially be brand advocates who were not explicitly labeled as such in the original dataset. By leveraging TensorBoard's 3D Projections feature, businesses can unearth valuable insights into the customer-brand relationship and identify potential advocates that might have been overlooked in the conventional dataset. This model is crucial in deciphering complex network relationships and identifying key influencers, which can be instrumental for marketing strategies and influence analysis in sophisticated datasets.

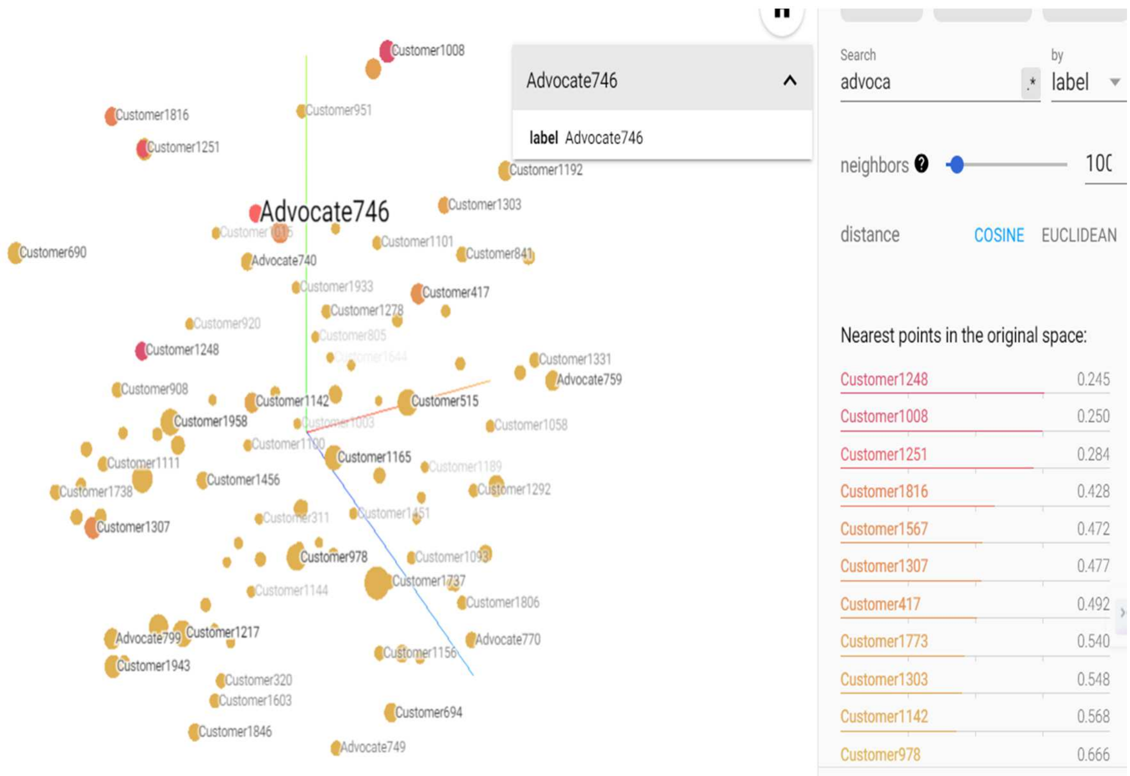

Figure 2: 3D visualisation of the constructed KG embedding demonstrating Advocate746 entity as well its closest entities.

[1] https://www.tensorflow.org/tensorboard

V. Conclusion

this paper presents a comprehensive framework for understanding customer advocacy within the realm of social media marketing through the lens of knowledge graph construction and embedding. Leveraging advanced techniques in data collection, KG construction, and KG embedding, our proposed methodology offers a systematic approach to uncovering nuanced relationships between brands and customers in the digital landscape. Through empirical evaluations using various KG embedding models, we demonstrate the effectiveness of our approach in capturing complex interactions and predicting customer advocacy behavior.

However, despite the promising results, our study has several limitations. Firstly, the reliance on Twitter data may introduce biases inherent to the platform, limiting the generalizability of our findings. Additionally, the manual curation of brand advocates may introduce subjectivity and potential labeling errors. Furthermore, the scalability of our framework to larger datasets and diverse social media platforms warrants further investigation. Future research directions include expanding the scope of our framework to incorporate additional social media platforms and data sources, such as Instagram and Facebook, to provide a more comprehensive understanding of customer advocacy behavior. Additionally, exploring novel techniques for entity and relationship extraction, as well as enhancing the interpretability and scalability of KG embedding models, are crucial avenues for further investigation. Lastly, integrating sentiment analysis and natural language processing techniques to capture the nuanced emotions and sentiments expressed by customers in social media interactions can provide deeper insights into brand-customer relationships.

Acknowledgment *(Heading 5)*

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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