Deep Unified Multimodal Embeddings for Understanding both Content and Users in Social Media Networks

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Abstract There has been an explosion of multimodal content generated on social media networks in the last few years, which has necessitated a deeper understanding of social media content and user behavior. We present a novel content-independent content-user-reaction model for social multimedia content analysis. Compared to prior works that generally tackle semantic content understanding and user behavior modeling in isolation, we propose a generalized solution to these problems within a unified framework. We embed users, images and text drawn from open social media in a common multimodal geometric space, using a novel loss function designed to cope with distant and disparate modalities, and thereby enable seamless three-way retrieval. Our model not only outperforms unimodal embedding based methods on cross-modal retrieval tasks but also shows improvements stemming from jointly solving the two tasks on Twitter data. We also show that the user embeddings learned within our joint multimodal embedding model are better at predicting user interests compared to those learned with unimodal content on Instagram data. Our work reveals that social multimedia content is inherently multimodal and possesses a consistent structure because in social networks meaning is created through interactions between users and content.

Keywords Social media networks · Deep learning · Multimodal learning · User behavior prediction · Representation learning · Joint embeddings · Cross-modal retrieval

1 Introduction

Social networks are today’s platform of choice for entities that want to exert influence, where the entities range from well organized groups such as companies and political organizations to amateur individuals [62,28,22,4]. All contemporary political and commercial marketing campaigns make skillful and extensive use of social multimedia platforms to engage in direct messaging to the public using advertising, opinion-analysis and news-facts [28,22,45]. On the geo-political front, extremist organizations have successfully recruited for and planned activities through social media [22]. Development of a computational framework for assessing the success of such efforts presents challenges that go beyond the state-of-the-art in both understanding the content and understanding the underlying user behavior and interaction. Social media content derives meaning through the structures and dynamics of interaction between the multimedia posting, the user who posted the content, and their followers on the social network, rather than as a stand-alone item to be understood in isolation. For example, a short clip featuring cowboys from a popular movie posted by the movie’s director would be seen as a promotion of the movie, but the same clip when posted by a fashion house that sells apparel that is featured in that clip would be seen as promoting that line of apparel (see Figure 3). The success of such influence has been consistently measured in terms of social connections such as the number of followers and re-tweet statistics [62,38,4,51], which does not take generally take the role of the posted content into account. Furthermore, the content on social media networks is highly unstructured with no constraints on the range of topics or even grammar, thus making
state-of-the-art approaches, based on training with curated datasets, unfit for understanding such content. The nature of the content in such leader-follower configurations has been studied only in genre specific fashion through investigations of phenomena such as detecting cyber-bullying [68], hate speech [59], pornographic material [67], and “rabble rousing” through politically persuasive content [66]. There has also been considerable work on sentiment detection in social media [81][1]. Such work mostly focuses on the literal meaning of the posted content rather than the intent behind it. Recently, [37] published initial work on identifying document intent in stand-alone Instagram postings based on the combination on image and its caption.

On the other hand, there has been extensive work on multimedia content analysis independently of social networks, covering detection and recognition of objects, scenes, activities, concepts, subjective attributes such as sentiment, visual question answering and topic discovering [76][71][73][20][11][38]. With recent breakthroughs in deep learning, the accuracy of the methods has gone up dramatically. However, such analysis has yet to be integrated into a unified social multimedia network analysis framework because of the challenges stemming from the lack of structure and grammar in posts, unconstrained topics, and heterogeneous data consisting of multiple modalities which might be missing content from certain modalities in posts depending on the nature of the social networks.

Prior works have also focused on discovering user behavior by learning low-dimensional embeddings either based on recommendation based models [83][70][19][71] or using social network graphs [56][26][27][74]. Despite their success in recommending items to users or predicting user behavior from the learned embeddings, these works have generally been restricted to social media networks with limited variability in content. Moreover, these approaches are generally only concerned with discovering user interests and not with content understanding in a joint manner. We believe that despite the “in-the-wild” nature of social media content, it is quite structured and it should be possible to exploit the relationship between multimodal content and users to enhance the understanding of each task. In other words, our aim is to gain a holistic understanding of the nature and propagation of influence in social networks. To that end, we both need to advance over state-of-the-art approaches so as to deal with the richness and complexity of social media, as well as to gain a fine-grained understanding of all the relationships between the various modalities and users.

In this paper, we propose a novel content-independent content-user-reaction model for social multimedia analysis. We embed users, images and text drawn from open social multimedia data in a common multimodal geometric space thereby enabling seamless (bidirectional) three-way retrieval between them. We are thus able to provide a generalized solution to both the problem of finding user interests and semantic understanding of multimodal content in a unified framework. We propose a deep learning based model, which uses modality-specific encoders and embeds their outputs into a common space (see Figure 1). The parameters of this model are learned using a novel loss formulation based on mixture of pair-wise loss functions designed to tackle the two tasks jointly. We show that our model is able to achieve the best performance jointly on the task of cross-modal retrieval between content-content pairs and content-user pairs on a multimodal corpus covering a wide range of topics collected from Twitter. As a result, our model is able to go beyond content/modality/genre specific recommendation models developed in previous state-of-the-art methods. Our results also demonstrate that the cross-modal retrieval between visual and textual content improves when training jointly to correlate users and content. This shows that user-content information is able to regularize the content understanding task due to the strong relationships between users and content. We then apply the features learned from our joint multimodal embedding to the task of predicting user interests on data collected from Instagram, and show consistent improvements compared to embeddings learned from either textual or visual content. We thus show that our model yields a general purpose framework for finding user affiliations based on content and without explicitly using social links as used in prior works [26][56]. We also show clusters emerging from the learned user embeddings, which seem to be not only grounded in multimodal content but also possess fine-grained distinctions. Our analysis reveals that social multimedia data is inherently multimodal and there is an underlying structure due to the social interactions between users and content.

Our specific contributions are listed below:

1. We propose a novel approach to simultaneously tackle the problems of modeling user behavior and semantic understanding of content from social multimedia data. Our approach embeds both content and users in a common geometric space that enables seamless multi-way retrieval between all modalities and users.
2. We propose a novel loss function based on mixture of ranking objectives that enables the above mentioned multi-way retrieval. Our loss function not only considers the correlations between users-content, as done in prior work, but also considers correlations between modalities in content. It has been carefully designed to cope with the distance between the three modalities - image, text and users. It thus enables a fine-grained component-wise understanding of the contribution of each modality to the influence of a piece of multimodal content.
3. We evaluate our approach on two real-world multimodal social media datasets, which capture the diverse topics and intent, levels of structure and grammar, and overall unconstrained nature of data shared on contemporary
social networks. The datasets are collected from Twitter (Multimodal Twitter Dataset) and Instagram (Fashion Instagram Dataset) to account for both text-focused and image-focused platforms.

4. We show consistent improvements on the task of cross-modal retrieval between multimodal content pairs and content-user pairs. We further show that our proposed loss function enables our model to perform zero-shot retrieval i.e. reason about modality pairs not seen during training. We also show that the proposed framework enhances content understanding when simultaneously learning to discover user interests within our model. We thus show that user-content interaction in social networks has a strong structure in spite of the completely unconstrained user subscription and content posting environment.

5. We show that the user embeddings learned within our proposed unified framework enable accurate prediction of user interests with the Instagram dataset especially when using all the modality pairs for training.

6. We show qualitative results that indicate that our framework helps uncover emergent structures (or clusters) in social media and their grounding in multimodal content. We find that the emergent clusters are notably consistent in their semantics.

7. We show qualitative results to highlight the ability of our model to understand content and ground fine-grained concepts in multimodal data while learning from noisy social media data.

8. We also show consistent improvements compared to competitive methods, based on prior state-of-the-art, on the combined task of content understanding and modeling user interests evaluated as cross-modal retrieval tasks.

9. Our overall approach enables a holistic understanding of the nature and propagation of influence in social networks, through fine-grained analysis of all the relationships between the data modalities including users. It thus helps deal with the richness and complexity of social multimedia data.

2 Related Works

Deep Multimodal Learning: We have witnessed significant progress in analyzing and understanding multimedia content in the last decade especially with the recent advances in deep learning [42, 36, 50, 60, 81, 78, 53, 6]. Recent works have tackled several problems requiring reasoning over multiple modalities such as visual question answering (VQA) [6, 47], visual caption alignment and generation [80, 36, 20, 2], language guided embodied navigational agents [14, 13], visual grounding [15, 12], multimodal sentiment analysis [50, 81, 66], and multimodal topic discovery [42, 58]. These problems require analyzing data from multiple modalities such as image, text, and speech and are also referred to as multi-view learning [58, 46, 75]. We refer interested readers to [7] for a detailed survey of approaches on multimodal machine learning. The progress has also been accelerated by the massive data generation on social media platforms such as Twitter, Instagram, and Facebook, where people not only post text but also upload images and videos. Despite such rapid progress, deep learning methods typically require large quantities of carefully curated data for solving the above tasks [83, 48]. Although this supervised paradigm is quite popular in deep learning research, it will not be sufficient for understanding noisy social multimedia content which is unconstrained in terms of the underlying concepts and topics. In contrast to works requiring massive amounts of labeled data, we need to understand multimodal content as well as the interests of the users posting such content by learning from the weak supervision available from the multimodal posts generated on these platforms.

Understanding Content and their Semantics from Social Media Data: In order to analyze and search the massive social multimedia content, it is important to develop tools for higher-level understanding of content across different modalities. For example, it is useful to be able to retrieve content relevant to a sentence or tag-level query across millions of documents [69, 65, 25, 58, 6, 71, 82]. This problem is also referred to as extracting semantics from content since it is generally concerned with understanding content in a form that is intelligible to a human [63]. The problem is challenging because of the diversity of topics/concepts, the lack of training data caused by one-off (sparsity) occurrence of much content, the multimodality of the data and the completely unconstrained in-the-wild content capture conditions. Prior works can be divided into supervised and unsupervised methods. Supervised approaches use human curated data for extracting semantic tags [73], descriptions [20] or subjective attributes (sentiments [9], sarcasm [61], metaphors [54]) from social media content. The most common practice is to annotate images by predicting multiple semantic tags by using classifiers trained for detecting objects, scenes, attributes etc [25, 73, 64, 85]. Despite their popularity, these approaches suffer from two critical drawbacks: (1) the number of tags is fixed and cannot be extended to new classes without re-training, and (2) these detectors generally do not take into account the semantic overlap between tags. Although recent works have tried to tackle these issues through zero-shot learning [23, 13, 8] or by modeling the relationships between tags for improving recognition [25, 73], the issues are far from solved. These drawbacks limit the applicability of such approaches in analyzing social multimedia data from multiple platforms at scale.
Image caption generation and alignment are other alternatives to solve the problem of understanding social multimedia content by describing/matching an image with a human level sentence \[31,20,35,78,15\]. This sentence is expected to describe the salient parts of an image such as scene, attributes, activities and interactions. Over the last three years we have seen significant progress in image captioning with the advances in vision and language based deep learning \[31\]. These methods generally rely on learning a joint metric space where images and sentences (or descriptions) are embedded together. Based on the application, the joint space can be tuned for for cross-modal matching or generating a caption in the image captioning task or answering a question in the VQA task. Despite promising results, current methods suffer from several limitations for downstream tasks, such as cross-modal retrieval, requiring understanding of social multimedia content. First, these methods require a well-structured training dataset e.g. MSCOCO \[44\] where humans are given a set of clear instructions for writing captions for given images. This is not only a time-consuming process but also the feasibility of obtaining factual and grammatically correct sentences from the data generated on social media platforms such as Twitter is limited \[53\]. Another key drawback is that these approaches are not known to work well for previously novel objects and scenes. Although there has been recent effort towards targeting captions for unseen objects \[5\], it is still an open problem. Our work addresses the problems with collecting large amounts of supervised data by proposing to learn the underlying semantics in multimodal data from large-scale multimodal data– visual and textual \[Figure 2\], while also modeling the users posting such content into account. Our algorithm is motivated by prior works utilizing joint multimodal spaces for aligning between multimodal entities e.g. images and text \[36\]. However, we also embed users posting such content in the same multimodal space leading to better performance on cross-modal retrieval task on social multimedia data.

Recently, several approaches have explored the use of data-free methods for understanding content. These approaches either use unsupervised approaches for discovering the underlying semantics and/or topics \[12,20,58\] or utilize the supervision available from the noisy tags for learning predictive models \[77,16,71,11\]. For example, \[58\] use topic modeling to automatically discover multimodal topics and opinion from disparate news sources and modalities. \[42\] propose to mine multimodal concepts relevant to specific events from collections of images and captions from sources such as news websites and Twitter. Works based on using supervision available from noisy user annotations, referred to as webly supervised learning \[11\], have focused on problems such as learning to predict hashtags \[82,71,16,77\], learning pre-trained models or visual features for downstream tasks \[48,11,33\], learning to predict visual concepts/descriptions \[53,24,79,86\]. Our work is closely related to \[71,16\], which focus on personalized hashtag prediction for a user. Specifically, they propose to learn models for predicting hashtags for an image conditioned on the user preferences- that can either be learned or obtained from the meta-data. The proposed work differs from the prior works in several aspects. First, our model directly associates images with sentences instead of individual tags, which leads to a richer semantic grounding to describe fine-grained concepts and is not restricted by a discrete vocabulary of the hashtags. For example, as shown in \[Figure 5\] our model is able to utilize the compositional nature of sentences and learn to differentiate between the semantics of two closely related compound concepts– “healthy food” and “unhealthy food”. This enables our model to better tackle the richness of social multimedia content. Second, compared to \[71,16\], which are restricted to learning associations between multimodal content, the proposed work learns to associate multimodal content as well as user interests within the same deep learning based framework. Another key difference is between the use of Instagram and Twitter social networks, used for evaluation in our work, which have completely different social dynamics in comparison to passive uploading sites such as Flickr as used in prior works \[71,16\]. Platforms such as Flickr serve as repositories for users to upload their photographs which are mostly related to personal and recreational pictures. On the other hand, content on Instagram and Twitter is predicated on provoking a response from the audience and can convey a multitude of intents based on the specific use of visual and textual modality \[37\] (see \[Figure 2\] and \[Figure 3\]). Moreover, the images are quite noisy, diverse and not restricted to specific genres. These images are often intimately associated with textual content and can be understood only in the context of a certain thread stemming from a hashtag.

User-Content Recommender Models: The proposed model is closely related to prior works on recommendation based models in which the task is to learn to recommend items to a user based on their past preferences, usage patterns etc. \[83,70\]. The models can be broadly divided into collaborative filtering, content based recommender system, and hybrid models \[70,83,55,10,21\]. Collaborative filtering exploits prior information about user-item interactions to learn a vector representations for users and items. These representations capture the attributes of content and users, and are used for recommendation \[60,30\]. While, content based recommendation methods directly use the features of items or users to recommend similar items \[55\]. Our work broadly falls into the category of hybrid recommendation systems \[10\], that combine both content representation and use of prior knowledge about user-item interaction (collaborative filtering).

Recent recommendation methods have also used neural networks due to their advantage in modeling non-linear inter-
Deep Unified Multimodal Embeddings for Understanding both Content and Users in Social Media Networks

actions and power of representation learning across different modalities. [21] [30] [18] [83]. [56] extend collaborative filtering to Neural Collaborative Filtering (NCF) by using neural networks to learn latent representations for users and items based on prior interaction data. They showed that NCF is able to surpass the performance of non-deep methods by a significant margin. [19] propose an extension of matrix factorization by using neural networks to replace the inner product operation and use it for collaborative filtering. Several methods have also explored the use of modality-specific deep encoders for learning joint representations for (heterogeneous) content and users, which can then be used for recommendations [16] [74]. [19] [40] [84] [32]. [19] proposed a cross-domain and multi-view recommendation system with multiple domain (news, app data, movie/TV usage) using neural networks. They learn a similarity function between a user and different views based on their interaction data. Despite solving the problem on handling data from different domains, there are noteworthy differences compared to our work. First, we work with distant domains (or modalities), namely visual and textual, that are very different from each other in comparison to the text-based domains used in [19]. Second, our loss function considers correlations not only between users-content, as done in [19], but also within content. Finally, [19] uses a single loss function to combine the scores from different user-domain pairs, while our loss function achieves it by using a mixture of objectives which is more efficient at handling missing and unbalanced data. Similarly, our work also differs from [84], who also propose to learn joint representations for different modalities and users based on product reviews. However, our work differs from this work in learning to associate not only user-content interactions but also content-content interactions. Our loss function is also different from [84], who merge the modalities into a single vector prior to optimizing a single objective function correlating merged content and user. Finally, as previously noted we evaluate our model on social networks such as Instagram and Twitter, whose content is more unconstrained and has a wider range of topics and semantics as compared to the dataset of product reviews used in [84]. Compared to most of these prior works, the proposed model aims to simultaneously address the problems of understanding content and user behavior from social multimedia data.

Social Network Embeddings: Prior works have also looked into embedding users based on the social network graph or structure. A social network can be modeled as a graph with users as the nodes and edges as the connection between them such as friends, followers, commenters. These methods generally utilize the graph or neighborhood structure and embed users nodes into a low-dimensional embedding space capturing their structural similarities. Works such as [26] [72] [56] [27] use the local first or second order neighbourhood of nodes and convert the problem of learning node embeddings as an unsupervised representation learning problem. Similar to other areas, recent works have also used deep learning to improve the quality of the learned embeddings. For example, [56] treat a social network as a set of documents and propose an algorithm combining random walk and skip-gram model (used in learning unsupervised word representation). The learned embeddings can then be used for downstream tasks such as prediction of links between user or predicting their interests. We refer the interested reader to [27] for a detailed survey on these methods. A key limitation with the idea of learning user representations from social network graphs is that such information might not always be available from different social network platforms. In such cases, our approach provides an alternative mechanism to learn user interests (via embeddings) by relying on their posted content. Our approach also provides the benefit of being able to discover interests for isolated users in a network. We also believe that our approach can be combined with these approaches to gain from their relative complementary strengths in discovering user behavior.

3 Approach

In this section we describe our approach, Deep Unified User and Multimodal Content Embedding Model (DU2MCE), in detail. The proposed model meets the requirements of understanding multimodal content as well as discovering users’ affinity to such content (reaction) from open social media data in a common computational framework. We achieve this by learning to embed both multimodal content (visual and textual) and users in a common geometric space as shown in Figure 1. DU2MCE represents multimodal content as a semantic vector in the common embedding space. Each user in the given snapshot of the social media network is also represented as a vector in the common space. The learned vector implicitly captures the interests and behavior/affiliations of that user and can also be used to measure the reaction of that user to any content. Here, we refer to reaction as a measure of the user’s interest in certain content without any measure of polarity. The model learns to embed content and user in an unsupervised manner by utilizing the correlations between users and their multimodal posts.

We propose a novel end-to-end deep learning based approach that uses an innovative loss function based on multiple objectives to embed users and multimodal content in a common embedding space. We next describe our approach mathematically.
3.1 Deep Unified User and Multimodal Content Embedding Model (DU2MCE)

DU2MCE embeds users and multimodal content from a social media network in a unified geometric space. We denote the $j^{th}$ post $P_j$ as a triplet $P_j = (I_j, T_j, U_j)$, where $I_j \in \emptyset \cup \mathbb{R}^{M \times N \times 3}$ is the posted RGB image, $T_j \in \emptyset \cup \mathbb{S}$ is the posted text, and $U_i \in \mathbb{U}$ is the user who authored the post. $\mathbb{S}$ is the set of all strings and $\mathbb{U} = \{U_k\}_{k=1}^{K}$ is set of all $K$ users in the corpus. We use $\emptyset_I$ and $\emptyset_T$ to denote null elements for the case of missing data from image and text modalities respectively from a post. Being able to handle missing multimodal content in a post is an important requirement since users can author posts not containing either text or images. For example, users generally post more images than text on Instagram as compared to Twitter or Reddit.

We encode multimodal content by using modality-specific deep encoders. We denote the deep encoder for image and text modalities as $\phi_I$ and $\phi_T$. By the virtue of using a common geometric space for embedding content and users, we mathematically regard users as another modality such that each user $U_k$ is encoded as a fixed length vector by an encoder denoted as $\phi_U$. We describe each of these encoders below:

1. **Image encoder ($\phi_I$)** - we use a convolutional neural network (CNN), pre-trained for image classification, and remove the last layer and replace it by a fully-connected (FC) layer for projecting visual features into the common space. We denote the linear projection layer as $W_I \in \mathbb{R}^{D_I \times D}$, where $D_I$ and $D$ is the dimensionality of the image-features and the common embedding space respectively. We denote the output of this encoder for the image from post $P_j$ as $x_I^j = W_I \phi_I(I_j)$.

2. **Text encoder ($\phi_T$)** - we use a CNN based sentence encoder based on word based embeddings \cite{35} and use a FC for projecting features to the common embedding space. We denote the linear projection layer as $W_T \in \mathbb{R}^{D_T \times D}$, where $D_T$ is the dimensionality of the text-features. We denote the output of this encoder for the text from post $P_j$ as $x_T^j = W_T \phi_T(T_j)$.

3. **User encoder ($\phi_U$)** - we use an embedding matrix $U_e \in \mathbb{R}^{K \times D_u}$, whose $i^{th}$ row corresponds to the $i^{th}$ user in our corpus and $D_u$ is the dimensionality of the embeddings. We use a FC for projecting features to the final embedding space. We denote the linear projection layer as $W_U \in \mathbb{R}^{D_U \times D}$. We denote the output of this encoder for the user from post $P_j$ as $x_U^j = W_U \phi_U(U_j)$.

We learn the parameters of the above encoders and the projection layers by using a ranking based loss function that enforces co-occurring pairs of content/user to occur closer to each other in the embedding space and non-co-occurring pairs to be farther in the embedding space \cite{54}, \cite{36}. For example, we would expect the embeddings of content related to fashion and users interested in fashion to be close to each other.
other. Compared to prior works on cross-modal embeddings that generally handle data from a pair of modalities \[^{[36]}\] or a user-content pair from unimodal content \[^{[32]}\], we want to embed content from multiple modalities along with users.

We achieve this by proposing a loss function that uses a mixture of pair-wise objectives that jointly enforce the multimodal content and the user authoring this content, to be closer in the common embedding space. Specifically, the proposed loss optimizes the proposed DCNN architecture so as to push closer co-occurring pairs of multimodal content ((image, text) pairs) as well as the content-user pairs ((text, user) and (image, user) pairs). We denote the paired loss function for the (text, user) pairs as \(L_{T-U}\), (image, text) pairs as \(L_{I-T}\), and (image, user) as \(L_{I-U}\). The final loss is given as a convex combination of these losses:

\[
L = \frac{\lambda_1}{N_{T-U}} L_{T-U} + \frac{\lambda_2}{N_{I-T}} L_{I-T} + \frac{(1 - \lambda_1 - \lambda_2)}{N_{I-U}} L_{I-U}
\]

subject to \(\lambda_1, \lambda_2 \leq 1\) \((1)\)

where \(\lambda_1\) and \(\lambda_2\) are regularization parameters controlling the relative contribution of learning from different multimodal (or user) pairs. Here \(N_{T-U}\), \(N_{I-T}\), and \(N_{I-U}\) are the number of valid (text, user), (image, text), and (image, user) pairs respectively inside a minibatch. The regularization parameters can either be set empirically based on a validation set or chosen based on the ratio of the volume of visual modality and the volume of textual modality. Our work uses these pair-wise losses to generalize prior works on learning joint representations from heterogeneous sources \[^{[84]}\] by not only learning to associate user-content but also modalities within cross-modal content. The proposed loss function allows us to perform zero-shot retrieval on unseen modality pairs during training and also better handle missing data, in comparison to prior works because of the mixture based formulation (see Section 4.6).

We compute each of the paired loss functions by using a max-margin based ranking loss formulation that samples an anchor sample from one modality and a positive and negative sample from another modality. We describe the formulation of the loss with an example for computing the loss for a (text, user) pair from post \(P_j\) i.e. \(L_{T-U}(T_j, U_j)\). We first extract text and user features from post \(P_j\) as \(x^T_j\) and \(x^U_j\) respectively. We then sample negative user pairs \(U_n = \{U_n\}_{n=1}^N \) s.t. \(U_n \neq U_j\). We use a cosine similarity function to compute the similarities between text and user pairs as they are embedded in the same space by the proposed deep encoders. The loss and the similarity metric are computed as:

\[
S(x^T_j, x^U_n) = \frac{x^T_j x^U_n}{\|x^T_j\|_2 \|x^U_n\|_2}
\]

\[
\mathcal{L}_{U-T}(T_j, U_j) = \sum_{U_n \in U} [0, m - S(x^T_j, x^U_n) + S(x^T_j, x^U_n)]^+
\]

where \([a]_+ = \max(a, 0)\) \(\forall a\) and \(m\) is the margin. We sample the negatives \(U_n\) in an online fashion from a sampled minibatch. We handle the case of missing data from either modality by summing \(\text{Eq. 2}\) over pairs available from non-missing samples and then normalizing the loss components appropriately. The above formulation guides the model to increase the similarity between pairs from the same post and vice-versa. We use the same formulation and similarity metric for \(L_{I-T}\) and \(L_{I-U}\).

4 Experiments

We now describe the experiments used for performance evaluation. We begin by outlining the datasets used to evaluate our approach. Since there were no prior public datasets that capture the complexity of multimodal content and users on current social media networks, we collect two datasets from Twitter \((\text{Multimodal Twitter Corpus})\) and Instagram \((\text{Fashion Instagram Corpus})\). We then provide information regarding the tasks and corresponding metrics used for evaluation. This is followed by information regarding implementation details. Thereafter, we describe the empirical results. In particular, we first evaluate the performance of our model directly on cross-modal retrieval tasks for content understanding and recommending content to users based on their interests. We then evaluate the ability of the user embeddings learned from our model on a downstream task of predicting user interests on the Fashion Instagram Corpus. We then provide qualitative results to show the salient (multimodal) topics captured by the user clusters derived from the learned user embeddings on the Multimodal Twitter Corpus. We finally compare our model with some competitive methods and baselines on cross-modal retrieval tasks on the Multimodal Twitter Corpus.

4.1 Datasets

In order to perform a comprehensive evaluation, the datasets should mirror the challenges associated with unconstrained and noisy (multimodal) content and user behavior on social media platforms. We meet these requirements by using two datasets from popular social networks for evaluation. The first dataset, referred to as the Multimodal Twitter Corpus, contains popular content as guided by the 100 most popular Twitter hashtags. The second dataset, referred to as the
Fig. 2: This figure shows some images and their corresponding tweets from the proposed Multimodal Twitter Corpus. These examples depict the in-the-wild nature of social multimedia content. It also shows how users use both images and captions to convey specific meaning from their posts [37]. For example, for the second image in first row, showing some raw food items, it is difficult to establish that the intent conveyed by the user is not about food but rather about their perception of news media solely based on the image.

Fig. 3: This figure shows some posts from the proposed Fashion Instagram Corpus. These images demonstrate the strong visual nature of social media posts on Instagram platform as compared to Twitter. Similar to other multimodal social media networks, users use both captions and images to create specific meaning or intent from their posts [37]. For example, despite the two posts on the second row being about fashion, they convey different intents. The first is about spreading general information about a product while the second is about showing off or exhibiting personal preferences.
Fashion Instagram Corpus, contains content from users who follow some popular fashion, hospitality, and shoe brands on Instagram. These datasets also allow us to study the performance of our model on network with different content characteristics e.g., Twitter has more textual content than visual content, which is the opposite for Instagram. We next describe the methodology for collecting these datasets followed by pre-processing and creation of train-test splits for evaluating our model. The statistics for these datasets are reported in Table 1.

Multimodal Twitter Corpus: We collected this dataset by first creating a list of 100 most popular hashtags on Twitter e.g., #love, #beautiful, #me, #cute, #nature, #amazing etc. These hashtags were then used to crawl an initial list of ~ 110K accounts from Twitter. We then downloaded the tweets– text and posted images (if available) from these accounts. Since our aim is to gauge user behavior from multimodal content only and not social connections, we do not use any user metadata such as location, followers for learning our model. Due to the wide variety in the initial hashtags, this dataset contains content and users interested in diverse topics such as nature, art, international events, fashion, sports, movies etc. We have shown some examples from the dataset in Figure 2. It is evident from these examples that this dataset contains noisy image-caption pairs, where they seem to be interacting to convey a specific meaning [37]. For example, for the second image in first row in Figure 2 showing some raw food items, it is difficult to establish that the intent conveyed by the user is not about food but rather about news media, solely based on the image. We believe that it is important to work with such examples to understand the multitude of user interests on present social media platforms. Prior to pre-processing, we include accounts with more than 20 tweets resulting in ~ 40K users. As shown in Table 1 the final dataset after pre-processing has 39808 images and includes around 9.45M posts of which all of the posts have text and only 1.26M posts have images. The relative ratio of different modalities is a function of the social interactions and nature of the social media networks. For example, platforms such as Instagram and Snapchat are more visual as compared to Twitter or Reddit. We use this dataset for the cross-modal retrieval experiments.

Fashion Instagram Corpus: We collected this dataset by first using a list of 23 popular brands strongly focused on one of the three categories- “shoes”, “fashion”, and “hospitality”. We then retrieve a few hundred posts from these brands. We first expanded the user set by retrieving posts from users who made a comment on these posts. We also added additional data from users who followed these brands but were not included in the original list. This dataset only includes a subset of users since we are restricted by the Instagram API. We have shown some samples from the dataset in Figure 3 which clearly shows the visual nature of content employed by users for self-expression. As shown in Table 1 the final dataset after pre-processing has 2900 users and includes around 796K posts of which almost all the posts have images and around 722K posts have captions. This is in contrast to the previous dataset where the ratio of images to text was 1 : 10. We use this dataset by employing the user embedding learned by our model for the downstream task of predicting user interests.

Pre-Processing and Training/Test Splits: We focus on embedding multimodal content and users in the joint embedding space. As mentioned in Section 2 the proposed model exploits correlations between pairs of multimodal content as well as content-user pairs. Due to the disparate nature of different modalities e.g. equivalence between content is different in images and text, and the requirement of evaluating the tasks of both semantic understanding of content and user interests within the same framework, we have to be extremely careful about creation of training/validation/testing splits. We proceed by first preprocessing the data in separate steps for textual and visual modalities.

For the textual modality, we first clean the tweets with a basic text processing pipeline that includes removal of non-alphanumeric characters and stopwords, followed by lemmatization. We use off-the-shelf tools from the StanfordNLP toolkit for this step [57]. We currently retain the hashtags but remove the emoticon embeddings in tweets to simplify our pipeline. In the future, it would be interesting to see the benefits of directly using this additional information e.g. using hashtags as another modality within our framework. We then use the cleaned text to create a vocabulary (words with at least 5 occurrences) and learn word-based word2vec embeddings [51]. We then use the vocabulary to filter the textual posts for out-of-vocabulary words. In the multimodal corpora, we found several accounts to be posting content that was either exact duplicates or similar except for the ordering of one or two words. In order to avoid similar content to be part of both training and test sets, we remove these duplicates by using a simple procedure based on measuring the percentage of overlapping words between textual components of two posts along with checking for exact duplicates for the image components. We next pre-process the visual components of the tweets.

We observe in both corpora that several posted images were exact or near duplicates. This was the case since there could be re-tweets or a picture could have become viral and different users posted their own interpretations of that image. We thus begin by creating an index of all the unique images in a corpus. We found standard tools (such as fdupes) based on image hashes to be ineffective and thus created our own pipeline by using CNN based features for images. To handle a large number of images, we create a searchable index of all the images in a corpus by using an efficient KD-Tree based implementation [52]. We then identify nearest neighbors for all the images in the set and iterate over them to create an
we maximize the training samples by using only 20% we use
Twitter Corpus is collected from Twitter and is used for the cross-modal retrieval experiments for evaluating both the tasks of content understanding and discovering user interests. The Fashion Instagram Corpus, collected from Instagram, is used to evaluate the task of predicting user interests from the user embeddings learned by our model. We have shown examples from these datasets in Figure 2 and Figure 3.

Once the modalities have been pre-processed, we now focus on creating splits for evaluation. The cross-modal retrieval task demands evaluation of three retrieval tasks- text-to-user, image-to-text, and image-to-user. To perform unbiased evaluation, we would like to careful about not mixing images/text in the train and validation splits. We do so by first creating training/validation/test splits from the visual modality (randomly) by using the list of (unique) images and captions created earlier. This step ensures that there is no overlap between images between the train and validation/test splits for evaluating the image-to-image and image-to-user retrieval task. In order to create splits for the tasks involving textual modality, we first consider posts with no posted images. We then create validation and test sets for evaluating text-to-user retrieval task. We finally create the training set by merging all the tweets that (i) did not have an image and were not included in the previous validation/test splits for text-to-user retrieval, and (ii) the tweets with images but not part of the validation/test splits for retrieval tasks involving images. For all the retrieval tasks on the Multimodal Twitter Corpus, we use 20% data for testing, 2% for model validation, and rest for training. We follow prior works on image-caption matching and use 5000 image-caption pairs for testing the image-to-text retrieval task [20]. Since our motive for using the Fashion Instagram Corpus is to highlight the effectiveness of the learned user embeddings in predicting user interests, we maximize the training samples by using only 10000 posts for the validation set (which is used for finding the test checkpoint). The final statistics for both the datasets are reported in Table 1.

| Multimodal Twitter Corpus | Fashion Instagram Corpus |
|---------------------------|--------------------------|
| # Tweets                  | 9.45M                    |
| # Images                  | 1.26M                    |
| # Users                   | 39808                    |
| Training Set (Multimodal Embeddings) | |
| # Tweets                  | 7.10M                    |
| # Images                  | 981K                     |
| Testing Set (Cross-Modal Retrieval) | |
| # User-Text pairs         | 1.89M                    |
| # Image-Text pairs        | 5K                       |
| # Image-User pairs        | 251K                     |
| # Posts                   | 796K                     |
| # Images                  | 796K                     |
| # Captions                | 722K                     |
| # Users                   | 2000                     |

Table 1: Statistics for the two Multimodal social media Corpora used to evaluate the proposed algorithm. The Multimodal Twitter Corpus is collected from Twitter and is used for the cross-modal retrieval experiments for evaluating both the tasks of content understanding and discovering user interests. The Fashion Instagram Corpus, collected from Instagram, is used to evaluate the task of predicting user interests from the user embeddings learned by our model. We have shown examples from these datasets in Figure 2 and Figure 3.

index of unique images. We then use this index to create a list of unique image and corresponding captions, that will be used for creating splits and also evaluating the image-to-text retrieval task [20].

4.2 Evaluation Metrics and Tasks

We evaluate the joint user and content embeddings learned by our model on two tasks— (i) cross-modal retrieval, and (ii) prediction of user interests as a multi-class classification problem.

We select three cross-modal retrieval tasks to evaluate the learned embeddings for the task of semantic understanding of content (image-to-caption) and discovering user interest relative to different content modalities (image-to-user retrieval and text-to-user retrieval). Compared to prior works in recommendation based methods that only evaluate the task of understanding user interests, we evaluate both the tasks simultaneously. Although several metrics exist for evaluating retrieval tasks such as recall, precision, normalized discounted cumulative mean, we use the mean median rank metric due to its clear interpretation [49]. This metric is calculated by first sorting the retrieval results for a query based on their scores and then computing the median rank of the ground-truth sample. The median ranks across all query examples are averaged to report the mean median rank. We use the ground-truth available from the paired content and user information inside a multimodal post. The best achievable performance for this metric is 1 when the model always retrieves the correct result as per the ground-truth.

We evaluate the task of predicting users interests from the user embeddings learned within our joint embeddings as a multi-class classification problem for three broad classes— “shoes”, “fashion”, and “hospitality”. In this experiment, we aim to investigate the quality of the learned user embeddings for the downstream task of predicting user behavior. We annotate the users against the three classes by setting a label for a user and an interest to 1 if the user either commented on or followed the brands within that interest group else 0 (see Section 4.1). For this evaluation, we remove the user embeddings for the 23 initial brands resulting in 2877 users. The distribution of the users for each class is shown
We found that such initialization helps with faster convergence and recall from the binary predictions made by the classifier. Since our primary aim is to establish the quality of the user embeddings for predicting user behavior, we use a simple linear SVM classifier with \( C = 1 \) for evaluating the embeddings from different models. The performance will generally show the effectiveness of the user embeddings, learned in an unsupervised manner within our model, in capturing user behavior from their social media content.

### 4.3 Implementation Details

We use a ResNet-152 network \cite{29} as the image encoder \( \phi_I \). We use the features \( D_I = 2048 \) from a network pre-trained on ImageNet classification task with the last layer removed and do not fine-tune the network during learning. We encode a sentence into a stream of vectors by using \( D_s \) word-based embeddings that were learned separately for the cleaned sentences for each corpus using the Gensim library\footnote{https://radimrehurek.com/gensim/}. We restrict the length of sentences to 20 words and pad sentences which length is less than 20 words with a pad token. For the text encoder \( \phi_T \), we use a CNN, on the word embedding, with three parallel convolutional blocks with different stride lengths \((2, 3, 4)\) and number of filter \((512, 256, 256)\) \cite{35}. The outputs from these blocks are concatenated and used as text features. Recently, there has been a significant improvement in pre-trained approaches for several NLP tasks that encode sentences using deeper and more efficient pipelines e.g. BERT and ELMo \cite{17}. However, since our primary focus was on jointly embedding multimodal content and users in a common geometric space, we opted to keep our architecture simple and focus more on the core learning method. We set the dimensionality of the common embedding space as \( D = 1024 \). We use 300 dimensional embeddings for users, which are initialized using the average of word2vec embeddings (learned previously) of all the tweets posted by a user. We found that such initialization helps with faster convergence. For training our model, we use an Adam optimizer with a learning rate of 0.0005, which is dropped by a factor of 10 after every 10 epochs. We use a batch size of 1000 posts and the margin is set to \( m = 0.2 \) in all of our experiments. We select model checkpoints for evaluation on the test set based on the performance on the validation set. Since we evaluate our model on 3 different cross-modal retrieval tasks simultaneously, we use a cumulative metric based on the addition of normalized mean median ranks on the three tasks for selecting the best checkpoint. We add the normalized ranks for those retrieval tasks where the regularization parameter is non-zero \( \lambda > 0 \).

### 4.4 Quantitative Results

#### 4.4.1 Cross-Modal Retrieval

Since our objective is to simultaneously address the problems of semantic understanding of content and discovering user interests in a joint framework, we evaluate our model on three cross-modal retrieval tasks on the Multimodal Twitter Corpus as shown in Table 2. We divide the results into three blocks based on the number of modality pairs being used for training. Due to the flexibility provided by the proposed loss function, we are able to control the relative strength of the different modality pairs\footnote{We refer to users also as a modality in this section.} for training the joint embedding space by controlling the respective regularization parameters \( \lambda_1 \) for \((text, user)\) pairs, \( \lambda_2 \) for \((text, image)\) pairs and, \( \lambda_3 \) for \((image, user)\) pairs (see Eq. \ref{eq:2}). We can also remove the contribution of a modality pair from training by setting the corresponding \( \lambda_i = 0 \). We observe from the results in the first block (Single Modality Pair) that the model performs significantly better than random for the modality pair being used for training. For example, for the case of training with \((text, user)\) pair i.e. \((\lambda_1, \lambda_2, \lambda_3) = (1, 0, 0)\), the median rank achieved by DU2MCE on text-to-user retrieval task is 371 compared to the random performance of 19904. Similarly the performance of the model while training with \((text, image)\) and \((image, user)\) is 149 and 1407 respectively. In the single modality pair case, the model does not perform well on other modality pairs that have not been used for training. Although this may seem obvious, it highlights the disadvantage of prior models (see Section 2) that are either concerned with content understanding \cite{20, 17, 15} or discovering user interests from a single modality \cite{8, 3, 21}. As a result, they generally require separate models for handling each task.

We now discuss the results reported in the second block (Two Modality Pairs), where we use two modality pairs for training by setting one of the \( \lambda_i \) to be always zero. The fact that we are able to control the modality pairs being used to learn the joint embedding model highlights the generalized nature of our model as compared to prior works that work with either single or two modality pairs and also do not focus on content understanding. For simplicity we do not tune the regularization parameters on the validation set and fix them to 0.5 for the modality pairs being used. The median ranks for text-to-user and image-to-text retrieval tasks for the case of \((text, user)\) and \((text, image)\) pairs, i.e. \((\lambda_1, \lambda_2, \lambda_3) = (0.5, 0.5, 0)\), are 420 and 154 respectively. Both of these numbers are slightly lower as compared to their counterparts with single modality pairs (420 versus 371 on image-to-text retrieval task for the single modality case). One can expect such a result since we are handling distant content modalities that are disparate and thus a dedicated...
(modality-specific) geometric space might be more optimal for retrieval.

It is interesting to note that the performance on the image-to-user retrieval (2455) tasks is much better than random (19004) despite not using that modality pair for training. We believe this happens since the joint embedding space is indirectly able to associate images and users by learning to correlate (text, user) pairs along with (image, text) pairs. The textual space is able to act as a bridge between users and images. This is a significant outcome since it highlights the ability of our model to discover joint representations that can reason about a modality pair without ever having seen it during training. This is also an example of zero-shot retrieval\(^3\)\[23\]13, where we are able to retrieve samples from unseen modality pair(s) during testing. Interestingly, we also make a similar observation for the case of training with (text, user) and (image, user) modality pairs \((\lambda_1, \lambda_2, \lambda_3) = (0.5, 0.5, 0.5)\). The performance on the image-to-text retrieval task, for which no modality pairs have been observed during training, is 239, which is noticeably better than random performance of 2500. This result highlights that users are not merely a separate or disconnected entity in a social media network in comparison to the content. Rather, they seem to be acting as anchors (or topics) in the embedding space that enhance the semantic understanding of multimodal content in this space. This is a promising result for future research on learning user behavior and content semantics in social media network since it shows that despite the unconstrained nature of the content and user subscription, the data is in fact quite structured. As a result, the joint understanding of content and users can be used to improve parallel research on multimodal content understanding.

We also note in the two modality pair case that for \(\lambda_3 \neq 0\), the model performs quite well on the image-to-user retrieval task as compared to using only (image, user) pairs for training. For example, the median ranks for \((\lambda_1, \lambda_2, \lambda_3) = (0.5, 0.5, 0.5)\) and \((\lambda_1, \lambda_2, \lambda_3) = (0, 0.5, 0.5)\) are 664 and 1181 respectively as compared to 1407 of \((\lambda_1, \lambda_2, \lambda_3) = (0, 0.1)\). We believe this happens because the image-to-user retrieval task is generally harder as compared to text-to-user retrieval owing to the complexity of the visual modality and also because the training data is smaller as compared to the latter case (the ratio for volume of image to text content is approximately 1 : 10). In this case, being able to utilize correlation information from other modality pairs is helpful, as has been observed in prior works on multi-task learning with several multimodal tasks\[24\], where information from additional modalities is able to regularize tasks with limited data or higher complexity. Such multi-task learning is more useful when learning along with (text, user) pairs since the task is directly related to understanding user interests and retrieving them based on the content. Interestingly, we also note that learning to associate content from multimodal content pairs i.e. (image, text) pairs, also aids in discovering user interests.

We show results for training the model with all the modality pairs in the third block (All Modality Pairs) in Table 2. We show results with three different combinations of the regularization parameters. The first combination \((\lambda_1, \lambda_2, \lambda_3) = (0.33, 0.33, 0.33)\) gives equal weights to all the regularization parameters. While the second and third combination give a lower weight to \(\lambda_1\), which corresponds to (text, user) modality pair- which has a larger number of samples compared to modality pairs involving images, the third combination \((\lambda_1, \lambda_2, \lambda_3) = (0.1, 0.45, 0.45)\) performs best on all the tasks based on a combined metric that computes the sum of normalized median ranks for the three tasks. First, we observe for \((\lambda_1, \lambda_2, \lambda_3) = (0.33, 0.33, 0.33)\) that our model performs quite well on all the cross-modal retrieval tasks. For example, the performance on user-to-text, image-to-text, image-to-user is 450, 144, and 980 respectively. Although these numbers are slightly lower as compared to the best performance recorded in the previous case, the performance is still quite competitive given that we are using joint representations from a single multimodal space to tackle three retrieval tasks with distant modalities. To the best of our knowledge, such an observation has not been shown in any prior work working with multiple domains\[19\]\[33\]. While training our model with the third combination \(((\lambda_1, \lambda_2, \lambda_3) = (0.1, 0.45, 0.45))\), the model performs best on the image-to-text retrieval task (127 compared to previous best of 138 for \((\lambda_1, \lambda_2, \lambda_3) = (0, 0.5, 0.5))\). We also notice the performances on text-to-user and image-to-user retrieval tasks are at par or better compared to the case of training the model with individual modality pairs. For example, the performance on image-to-user with training using all modality pairs \(((\lambda_1, \lambda_2, \lambda_3) = (0, 0.1, 45, 0.45))\) and only (Image, User) pairs \(((\lambda_1, \lambda_2, \lambda_3) = (0, 0, 1))\) is 785 and 1407 respectively. This highlights the strength and advantages of our model DU2MCE, which learns to jointly embed multimodal content and users in the common embedding space.

These findings are important to the research community since they clearly show that content understanding and discovering user behavior from social multimedia data can be tied together in a single optimization problem. This is possible due to the underlying structure of users, their behavior, and the posted content on social media networks. We believe that we observe better performance on content understanding (image-to-text) while using information from users’ textual and visual posts since the users serve as anchor points, in the embedding space, that are connected with specific content semantics. Such anchors act as regularizers to improve performance on tasks with limited training data. We also note the performance improvement on the image-to-user retrieval task while using information from either (image, text) pairs or (text, user) pairs or both for training. The proposed model is
a generalization of prior works that either use single modality pairs for training or train with multiple domains from a single modality (generally textual) without associating content from multiple domains. We argue that this work will help merge content understanding with modeling user behavior for future research. Moreover, the proposed model is general enough to handle other modalities such as speech, hashtags, emoticons.

4.4.2 Predicting User Interests

The results presented in the previous section show that our model is able to perform well on retrieval tasks related to both content understanding and discovering user interests. We previously evaluated the task of understanding user interest by using two cross-modal retrieval tasks to retrieve users from either text or images. We now try to ascertain the quality of the learned user embeddings directly for predicting user behavior/interests. The experiments are conducted on the Fashion Twitter Corpus and the results are presented in Table 3. We first report results with two baselines where the user embeddings are obtained by averaging the word embeddings of their posts (Avg-Text) and the image embeddings of their posted images (Avg-Image). We observe that the image based embeddings (F1-score=0.40) outperform the text based embeddings (F1-score=0.45). We believe this happens because these experiments are conducted on a dataset collected from Instagram, which is a highly visual social network. As a result, images are generally more representative of a user behavior as compared to their posted text. We also show results with the proposed model for different combinations of modality pairs being used for training. These combinations (in sequence) use (text, user) pairs, (image, user), and all content/user pairs for training the joint embeddings within the proposed framework (see Section 4.4.1). We use \((\lambda_1, \lambda_2, \lambda_3) = (0.33, 0.33, 0.33)\) for training the model with all content/user pairs since the ratio of text to images is almost the same for this dataset.

The general performance trends seem to be similar to those presented in the cross-modal retrieval experiments. The model using (text, user) pairs for training seems to perform worse as compared to the model using (image, user) pairs (F1-score of 0.47 vs. 0.49). This trend is expected due to the visual nature of Instagram posts as also seen for the baseline models. We also observe the advantage of learning these user embeddings within our model instead of naively computing them by averaging, as done for the baseline. For example, our model using (image, user) pairs has a F1-score of 0.49 compared to 0.45 of the baseline model Avg-Image that also uses image posts from the users. The proposed model while using all the modality pairs for learning achieves the best performance on this task (F1-score=0.52 compared to previous best of 0.49 for (image, user)\(^4\)). This result highlights the fact the joint understanding of content along with user behavior allows our model to learn stronger representations for each user that effectively capture their underlying behavior. Being able to learn user embeddings that are informed by multimodal content understanding seems to provide an alternative and can also be used in combination with methods utilizing information about social connections such as followers, friends, [26,43,39] for improving the understanding of user behavior.

4.5 Qualitative Results

4.5.1 Discovered Multimodal User Clusters

In order to gain further insight into the learned user embeddings and how they relate to multimodal content, we analyze them using unsupervised clustering. To do so, we first cluster the user embeddings learned for all the users from the Multimodal Twitter Corpus using k-means into 50 clusters. We use the embeddings from the best performing model in Table 2 using all the modality pairs \((\lambda_1, \lambda_2, \lambda_3) = (0.1, 0.45, 0.45)\). In order to ground these clusters within the visual and textual social multimedia content, we create a frequency table of all the words present in the posts corresponding to the users within each cluster. From these word-frequency tables, we remove the most common 200 words in the corpus. The word-frequency tables are then used to create wordclouds, where the size of each word is dependent on its frequency. In order to select the representative images for each cluster, we use the property that images and cluster centroids—calculated as average of the embeddings of the users in that cluster, are embedded in the same space. We select the top images based on their proximity to the cluster centroids in the embedding space. We have shown the wordclouds and top images for six clusters in Figure 4.

These clusters clearly show that the clusters emerging from the learned user embeddings are naturally grounded in the multimodal content. The learned clusters seem to be generally pure and represent semantically meaningful topics. For example, cluster-1 seems to correspond to fashion, shoes etc., while cluster-2 corresponds to technology, gadgets etc. It is also interesting to note that our model is also able to discover slightly abstract topics such as cluster-5 which corresponds to motivational post quotes. We also observe two clusters (1 and 8) with semantically close concepts related to fashion. Cluster-1 seems to represent to vintage fashion, clothing etc., while cluster-8 represents cosmetic products. Being able to discriminate between semantically close concepts shows the ability of our model in being able to successfully discover semantics from in-the-wild social multimodal data. These visualizations highlight the strength of our model in being able to not only establish content understanding but also discover user interests grounded in those semantics. We believe that
Table 2: Table shows the performance on cross-modal retrieval tasks when training the proposed model with a single modality pair, two modality pairs, and all modality pairs on the Multimodal Twitter Corpus. For each row, we also show the regularization parameters used for the proposed loss function (Eq. 2) that control the contribution of different modality pairs for training our model. The cross-modal retrieval task measures the performance for both the tasks of content understanding (Image-To-Text) and discovering user interests (Text-To-User and Image-To-User). *: Denotes the model that performs cumulatively best on all the tasks based on the sum of normalized mean median ranks for the three tasks (see Section 4.4.1).

Table 3: Table showing results on the downstream task of predicting user interests from the user embeddings learned by our model on the Fashion Instagram Corpus (see Section 4.4.2).

such an understanding also provides a powerful tool to index and search large-scale social multimedia data for different topics.

4.5.2 Semantic Cross-Modal Retrieval Examples

We now try to gain insights into the ability of our model to understand multimodal content. We refer to content understanding as the ability to automatically associate high-level or semantic meaning described using textual modality with visual modality (see Section 2). We show top retrieved images for few closely related textual queries in Figure 5 for the model learned using all the modality pairs \((\lambda_1, \lambda_2, \lambda_3) = (0.1, 0.45, 0.45)\) on the Multimodal Twitter Corpus. We observe that our model is able to effectively discriminate between semantically close concepts such as “sports car” and “vintage cars” or “healthy food” and “unhealthy food”. Such a result shows the strength of our model in being able to understand highly unstructured multimodal content from social media data. At the same time, it also shows the advantage over prior works utilizing discrete hashtags for describing images due to their restriction by the given hashtag vocabulary [71]. On the other hand, the proposed model is able to utilize the compositional nature of language to discover new meanings in the visual modality. We believe that this will encourage further research on learning to describe content by learning from weakly/weably supervised and massive social multimedia data. As shown in Table 2, the ability to understand content is also enhanced by joint learning of user embeddings which seem to act as anchors that act as regularizers. This shows that content and user behavior are well connected in social multimedia networks.

4.6 Comparison with Competing Methods

We compare our model on the tasks of cross-modal retrieval with a simple baseline and two competing approaches using the Multimodal Twitter Corpus in Table 4. In this experiment, we want to establish that the proposed model is able to perform well together on the tasks of user behavior discovery and understanding user content. The former task is evaluated using content-to-user retrieval tasks (image-to-user and text-to-user), while the latter task is evaluated using content-to-content retrieval tasks (image-to-image), as described in Section 4.4.1. The combined performance on all these tasks is computed by adding their normalized (using
Fig. 4: This figure shows the multimodal user clusters discovered by our model. For each user cluster we also show the wordcloud for the top words corresponding to the users in that cluster as well as the images closest to the centroid of these clusters in the common embedding space (see Section 4.5.1).

the total number of retrievable samples) mean median ranks. We first implement two baseline approaches—Avg-Text and Avg-Image, where the user embeddings are computed by averaging the word embedding of their tweets and the image embeddings of the posted images respectively. We use a random vector for users having no image content. Since these methods only yield embeddings for content-user pairs in their respective cases, their performance can only be computed for text-to-user and image-to-user retrieval tasks. The other two approaches are based on prior recommendation based methods that either learn from a single modality [29,21] or multiple modalities without any understanding of content [19,84]. The first approach is based on extending previous recommendation methods that learn joint embeddings for single modality-user pairs to handle content understanding between multiple modalities along with user behavior. We refer to this approach as Bridging-Modality, where the idea is to first learn content-user embedding space for a single modality and then use that modality as a bridge to connect the other modality and the user embeddings. We achieve this by training our method first with only (text, user) pairs \((\lambda_1, \lambda_2, \lambda_3) = (1, 0, 0)\). Thereafter, we fix the encoders for the text and the user modality and learn the model with (image, text) pairs \((\lambda_1, \lambda_2, \lambda_3) = (0, 1, 0)\). Since we had earlier constrained the joint embedding space by fixing the networks for user and text modalities, we are now able to associate images and users implicitly by using the text modality as a bridge to connect them. The second approach, referred to as Merged-Modality is based on [19,84], where the features from the two modalities are merged together and a single loss function is using for embedding the merged content and users in a common space. In this case, we merged the image and textual content by fusing them with sum pooling after they are embedded in the same space. We handle the case of missing data for image modality by using an embedding vector filled with zeros. We allow a fair comparison by using the same learning settings and ranking loss formation as used in our model.

The results in Table 4 reveal that the proposed model DU2MCE outperforms the baseline methods and the methods based on prior state-of-the-art methods on the combined task of understanding content and discovering user behavior by a noticeable margin. Our model is able to surpass the baseline on both the image-to-text retrieval tasks (1372 of baseline versus 785 of DU2MCE) and text-to-user retrieval task (1963 of baseline versus 551 of DU2MCE). This highlights the benefits of using learning based paradigms for learning recommendation models as compared to static approaches. We also observe that our model outperforms the Bridging-Modality based method on the image-to-text (238 of Bridging-Modality versus 127 of DU2MCE) and the image-to-user (2083 of Bridging-Modality versus 785 of DU2MCE) retrieval tasks by a non-trivial margin. Although the performance of our model on the text-to-user retrieval (551) task is slightly lower as compared to Bridging-Modality (372), it outperforms the latter method on the normalized mean rank metric measuring the joint performance.

\[\text{The metric is normalized mean median rank and thus lower value is better.}\]
on all the tasks (0.042 of DU2MCE versus 0.062 of Bridging-Modality). This result highlights the ability of our model to effectively handle heterogeneous content from social media networks that can occur in different proportions due to the specific nature of the social media network. For example, networks such as Twitter and Reddit are more text-focused compared to Instagram. Moreover, the performance improvements on the image-to-user retrieval task demonstrates that Bridging-Modality based model is unable to effectively utilize the relationship between content and user interests to enhance the performance on both the tasks, as achieved within our model (see Section 4.4.1). We also observe that our model performs significantly better than does the Merged-Modality based method, which merges different modalities together and uses a single loss function for correlating content and users [84]. Both of these methods—Bridging-Modality and Merged-Modality, seem to be doing well on the text-to-user retrieval tasks, which has more data, but perform poorly on image related retrieval tasks. These results demonstrate the strength of our model in tackling a key limitation in prior works that focused solely on discovering user interests and did not address content understanding in a holistic manner. A key insight in these results is that social media networks, despite their unconstrained nature, are a structured ecosystem where content and users interact together to produce meaning.

5 Conclusion and Future Work

We presented a novel content-independent content-user-reaction model for social multimedia that embeds users, images and text drawn from open social media in a common multimodal geometric space, thereby enabling seamless multi-way retrieval. Our approach is able to simultaneously tackle the two problems of semantic understanding of multimodal content and modeling user interest within a unified mathematical
Deep Unified Multimodal Embeddings for Understanding both Content and Users in Social Media Networks

Table 4: Comparison of proposed model with different competing approaches on cross-modal retrieval task on the Multimodal Twitter Corpus. The joint performance is computed by adding the normalized (using the total number of retrievable samples) mean median ranks across the three tasks.

| Method                | Mean Rank | Median Rank | Joint-Performance |
|-----------------------|-----------|-------------|-------------------|
|                       | Text-User | Image-Text  | Image-User        |
| Random                | 19904     | 2500        | 19904             |
| Baseline (Avg-Text)   | 1963      | –           | –                 |
| Baseline (Avg-Img)    | –         | 1372        | –                 |
| Bridging-Modality     | 372       | 238         | 2083 0.062        |
| Merged-Modality       | 514       | 601         | 2405 0.148        |
| DU2MCE (Proposed)     | 551       | 127         | 785 0.042         |

Our model uses a novel loss function that allows us to handle the complexities associated with the unconstrained nature of social multimedia data. We established the validity of our approach by achieving consistent improvements beyond prior art on several cross-modal retrieval tasks on a real-world multimodal dataset collected from Twitter. We showed that our model is able to exploit the relationships between content and user behavior on social media networks to not only improve the performance on retrieval tasks for modalities with limited data but also perform zero-shot retrieval. We applied user embeddings learned from our joint multimodal embedding to the task of predicting user interests in an Instagram based dataset, and showed that the best results are obtained by the joint image-text-user embedding compared to all other combinations of modalities. Since our solution is based on learning a similarity measure between modalities, it yields a general purpose framework for finding user affiliations without the use of linking data from the social network. Our framework is able to deal with the inherent lack of explicit structure and grammar and unconstrained subject matter of social media.

Our results showed that the best retrieval performance on the combined tasks of content understanding and user interest discovery is achieved when all modalities are used which in turn shows that social media content is inherently multimodal even when a social network lends itself best to a single modality, such as text for Twitter and images for Instagram. Despite the lack of explicit structure in social network membership and content, our work reveals emergent structures in content-user relationships, as well as in content-content relationships within and across modalities. The clusters of content that emerge are remarkably consistent in their semantics. Our framework sets up the possibility of systematically understanding the relative significance of each modality in exerting influence.

The proposed framework is highly scalable and also lends itself to seamless incorporation of additional modalities. We have some early results with embedding sentiment and document intent that indicate that we can get a richer understanding of the influence exerted by a piece of multimedia content than we do currently. The proposed three way retrieval sets up the possibility of generating content to better suit the interests of a certain group by enabling modality wise exploration and retrieval of more suitable content, as well as achieve better coherence in the generated content. Moreover, our framework can be combined with methods that explicitly use social network graph for learning user representation. Finally, our multimodal embeddings based features are general purpose since they can be used to drive a variety of event detectors on other downstream tasks. Our framework thus offers rich possibilities for further work in social media content understanding and generation.

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References

1. Agarwal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, R.: Sentiment analysis of twitter data. In: Workshop on Language in Social Media, pp. 30–38 (2011)
2. Anderson, P., He, X., Buehler, C., Teney, D., Johnson, M., Gould, S., Zhang, L.: Bottom-up and top-down attention for image captioning and visual question answering. In: Conference on Computer Vision and Pattern Recognition, pp. 6077–6086 (2018)
Deep Unified Multimodal Embeddings for Understanding both Content and Users in Social Media Networks

45. Lipsman, A., Mudd, G., Rich, M., Bruich, S.: The power of “like”: How brands reach (and influence) fans through social-media marketing. Journal of Advertising research 52(1), 40–52 (2012)

46. Liu, A.A., Xu, N., Wong, Y., Li, J., Su, Y.T., Kankanhalli, M.: Hierarchical & multimodal video captioning: Discovering and transferring multimodal knowledge for vision to language. Computer Vision and Image Understanding 163, 113–125 (2017)

47. Lu, J., Yang, J., Batra, D., Parikh, D.: Hierarchical question-image co-attention for visual question answering. In: Neural Information Processing Systems, pp. 289–297 (2016)

48. Mahajan, D., Girshick, R., Ramanathan, V., He, K., Paluri, M., Li, Y., Bharamee, A., van der Maaten, L.: Exploring the limits of weakly supervised pretraining. In: European Conference on Computer Vision, pp. 181–196 (2018)

49. Manning, C., Raghavan, P., Schütze, H.: Introduction to information retrieval. Natural Language Engineering 16(1), 100–103 (2010)

50. Mathews, A.P., Xie, L., He, X.: Senticap: generating image descriptions with sentiments. In: AAAI Conference on Artificial Intelligence, pp. 1606–1610 (2016)

51. Mikolov, T., Chen, K., Corrado, G., Dean, J.: Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781 (2013)

52. Muja, M., Lowe, D.G.: Scalable nearest neighbor algorithms for high dimensional data. Transactions on Pattern Analysis and Machine Intelligence 36(11), 2227–2240 (2014)

53. Ordonez, V., Kulkarni, G., Berg, T.L.: Im2text: Describing images using 1 million captioned photographs. In: Neural Information Processing Systems, pp. 1143–1151 (2011)

54. Qi, P., Dozat, T., Zhang, Y., Manning, C.D.: Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781 (2013)

55. Perozzi, B., Al-Rfou, R., Skiena, S.: Deepwalk: Online learning of social representations. In: SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 701–710. ACM (2014)

56. Qi, P., Dozat, T., Zhang, Y., Manning, C.D.: Universal dependency parsing from scratch. In: CoNLL Shared Task: Multilingual Parsing from Raw Text to Universal Dependencies, pp. 160–170. Association for Computational Linguistics, Brussels, Belgium (2018). URL https://nlp.stanford.edu/pubs/qi2018universal.pdf

57. Ribeiro, M.H., Calais, P.H., Santos, Y.A., Almeida, V.A., Meira Jr, W.: Characterizing and detecting hateful users on twitter. In: International Conference on Web and Social Media (2018)

58. Sarwar, B.M., Karypis, G., Konstan, J.A., Riedl, J., et al.: Item-based collaborative filtering recommendation algorithms. International Conference on World Wide Web 1, 285–295 (2001)

59. Shchianova, R., de Juan, P., Tetreault, J., Cao, L.: Detecting sarcasm in multimodal social platforms. In: International Conference on Multimedia, pp. 1136–1145. ACM (2016)

60. Siddiquie, B., Chisholm, D., Divakaran, A.: Exploiting multimodal affect and semantics to identify politically persuasive web videos. In: International Conference on Multimodal Interaction, pp. 203–210. ACM (2015)

61. Singh, M., Bansal, D., Sofat, S.: Behavioral analysis and classification of spammers distributing pornographic content in social media. Social Network Analysis and Mining 6(1), 41 (2016)

62. Serrat, O.: Social network analysis. In: Knowledge solutions, pp. 113–125 (2017)

63. Sheu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

64. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

65. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

66. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

67. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

68. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

69. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

70. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

71. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

72. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

73. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

74. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

75. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

76. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

77. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

78. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

79. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

80. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

81. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

82. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

83. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

84. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)

85. Shu, P.C.Y.: Semantic computing. Semantic computing, pp. 1–9 (2010)
86. Zhuang, B., Liu, L., Li, Y., Shen, C., Reid, I.: Attend in groups: a weakly-supervised deep learning framework for learning from web data. In: Conference on Computer Vision and Pattern Recognition, pp. 1878–1887 (2017)