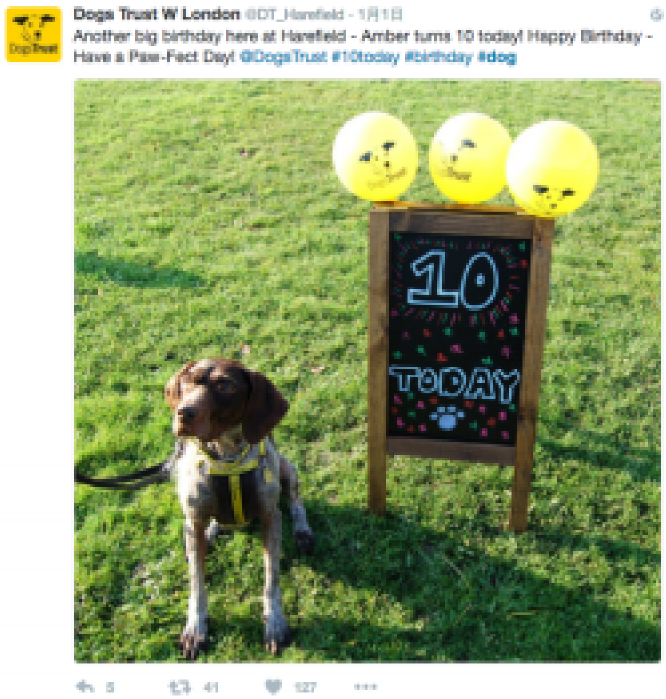
Multimodal Image inspired hashtag generator

PG Project

1 Abstract

The goal of this project is to generate hashtags given a multi-modal post on OSM (Online Social Media) like Instagram that may contain both images and text content. The user might also provide a set of few seed hashtags as input and the generated hashtags should be relevant to these hashtags as well. In the Figure 1, we are given an image, text content and certain hashtags (#dog, #birthday) as the inputs [1]. Our proposed method needs to utilize this data and suggest few other hashtags like #celebration, #party or #puppy for the same post. The project thus requires us to leverage the latest methods in computer vision such as Convolutional Neural Networks (Resnet50, Transfer learning) and in NLP such as glove embeddings, and word2vec to get a high precision/recall on the given task. We propose a two level hierarchical system where the predictions made by an image classifier are subsequently used by the corresponding text based approach. Our proposed approach shows significantly better results than the proposed baselines. To foster further research and to encourage reproducibility we release all our code and dataset respectively in our project page.



Dogs Trust W London @DT_Harefield · 1月1日

Another big birthday here at Harefield - Amber turns 10 today! Happy Birthday - Have a Paw-Fect Day! @DogsTrust #10today #birthday #dog

Figure 1: Predicting the correct hashtag: #dog is difficult without the image [16]

2 Related Work

The task of hashtag generation has been studied a lot in the past. One set of approaches use only the text data to predict relevant hashtags such as [9], [15] and [6]. Most of these approaches model the problem as either a classification or ranking task. Another set of approaches involve the use of topic modelling based methods such as LDA to generate relevant hashtags. [4] uses LDA to model the underlying topic assignment of language classified tweets. [7] improves upon the LDA based models by using a novel tweet pooling methods. However, none of these methods make use of

[1] There might be cases when any of these inputs is missing. The system should be able to take care of this as well

multimodal data such as both images and text for the task of hashtag recommendation / generation which is what we aim to solve.

There also exist works such as [10], [12] which predict the hastags using the images only. [10] uses zero-shot learning along with a novel loss function to predict the hashtags for a given image. [12] on the other hand uses a scene model and an object model trained on the MIT Places dataset and Imagenet dataset respectively to predict multiple hashtags for a given image. They use a binary cross entropy loss to train their problem in the multi-label setting. None of these approaches utilize multimodal data and as the problem is posed as a classification task, these approaches are not capable of generating new hashtags that are not a label in the dataset.

Recently, a few approaches have also been proposed that use multimodal data for image captioning and hashtag recommendation. [16] utilizes a novel co-attention mechanism to first predict relevant hashtags and then generate personalized recommendations. A few other approaches such as [2], [11] and [3] also deal with the task of hashtag generation / recommendation using multimodal data. However, unlike these methods, our approach is trained on a few specific topics of Instagram posts and is capable of generating a diverse set of relevant hashtags.

3 Dataset

A few datasets such as YFCC100M [14] and HARRISON dataset [12] deal with the task of hashtag generation using images. However, these datasets do not provide us with text data that is required for the training of our multimodal system. A few other datasets such as [1] deal with the task of personalized image captioning given text and image data along with prior user posts.

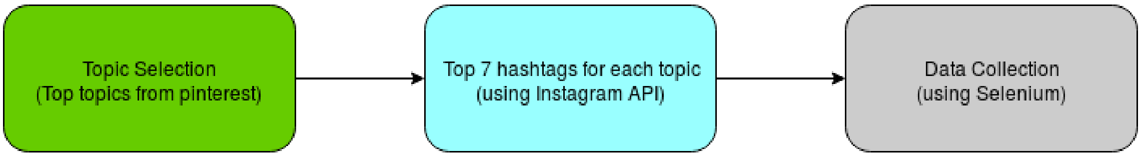


Figure 2: A brief description of our data collection pipeline

As the above datasets are not entirely relevant for our task, we collect our own dataset for this project. Figure 2 describes in detail the data collection process. We first choose a unique set of 8 topics using the Pinterest API and then collect the 7 most popular hashtags for each of these topics in Instagram using the Instagram API. With a seed set of around 56 hashtags, we scrape posts corresponding to these hastags using Selenium as the official Instagram API has rate limits. Our dataset consists of hashtags collected from a diverse set of 8 topics mentioned below:

1. Pets
2. Jewellery
3. Travel
4. Babies
5. Art
6. Food
7. Architecture
8. Nature

Table 1 provides a brief description of our dataset. For the purposes of training and evaluating our model, we split our data into a train, validation and test set with 70%, 15% and 15% of the data respectively. [2]

Description	
Number of Posts	60436
Number of Topics	8
Number of Hashtags	10983
Most used hashtag	#travel

Table 1: Description of the dataset

[2] The dataset can be found here: Dataset link

4 Architecture

Figure 3, shows the architecture of the model proposed by us. For a given Instagram post, we first separate out the images and text data. The image data is then pre-processed and passed on to an image classifier, which is basically a CNN such as Resnet50 [5]. The classifier is used to predict the topic corresponding to each image which is then passed on to our text based model for further processing. We simultaneously apply some pre-processing on the text as such as stemming and lemmatization to use it for further downstream tasks. In order to segment the given hastags into multiple hashtags, we utilize the Viterbi algorithm and this improves the accuracy of our approach significantly. Our text based approach consists of 8 word embeddings trained on the 8 topics mentioned earlier respectively. The pre-processed text data along with the topic predicted by the image classifier is then used to find the 10 most relevant hashtags for the given post based on a cosine similarity metric. We describe in detail the methodology for each task below.

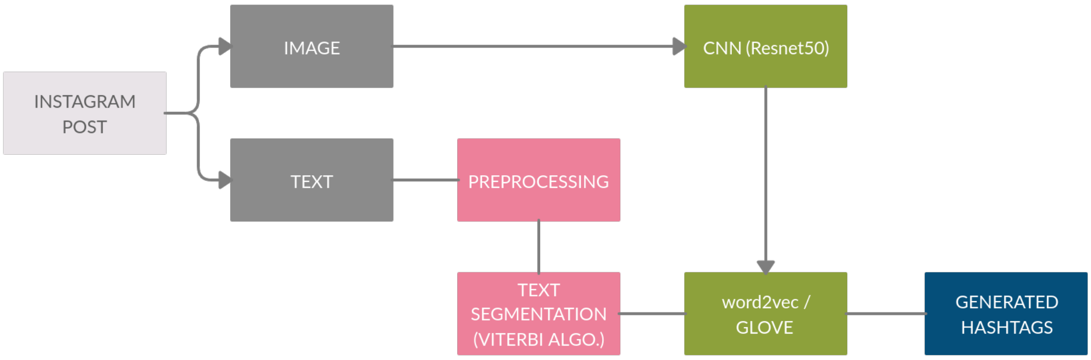


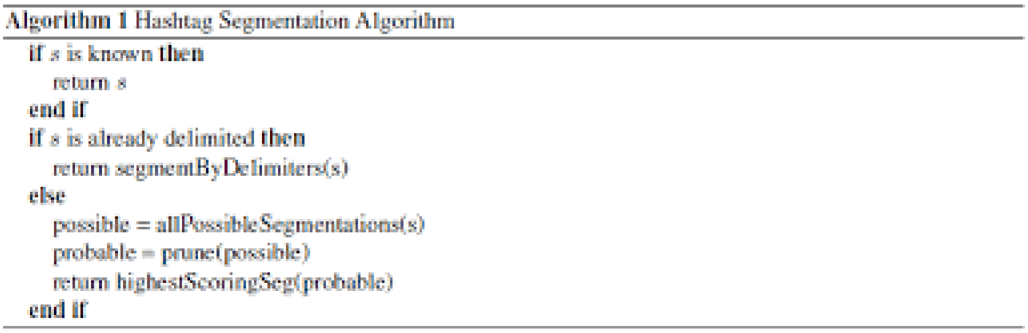
Figure 3: A brief description of our proposed architecture

4.1 Image Classifier

We train an image classifier such as Resnet-50 and Resnet-34 for the task of image classification. We model our problem as a multi-label classification problem and leverage transfer learning to finetune the model on our dataset. We train all our models using PyTorch and utilize the negative cross entropy loss for training. The optimizer used for training is the Adam optimizer with an initial learning rate of 0.01. We also leverage certain other approaches such as early stopping and cosine annealing along with data augmentations to improve the accuracy of the model. Our task is slightly ill posed as the labels provided for training is not annotated by humans. Rather, the labels are based on the topics provided by the user for an Instagram posts and are bound to have several mis-classifications.

4.2 Text Classifier

4.2.1 Pre-processing & Hashtag Segmentation



Algorithm 1 Hashtag Segmentation Algorithm

```
if $s$ is known then
    return $s$
end if
if $s$ is already delimited then
    return segmentByDelimiters(s)
else
    possible = allPossibleSegmentations(s)
    probable = prune(possible)
    return highestScoringSeg(probable)
end if
```

Figure 4

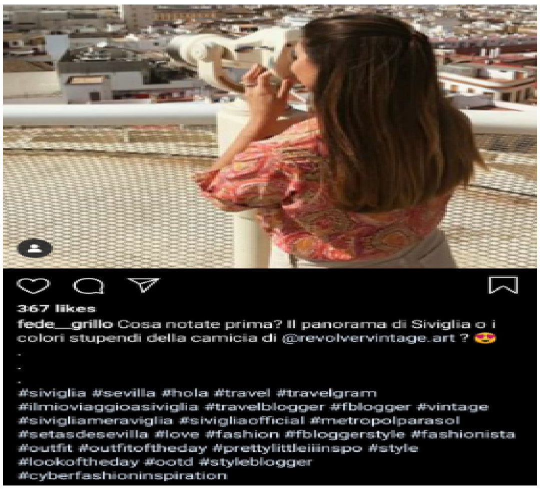
As a part of pre-processing, we have converted the input text into lower case and then removed special characters, emojis and other non-english words. There can be multiple words present in the input sentence without space (formed as one word) so, we have used segmentation to extract the words from a single word that can help us predicting hashtags.

Hashtags are complex structures with multiple words combined into single words. (eg : #picoftheday). For training purposes, we segment such complex hashtags into multiple words using the 'Viterbi algorithm' to find the most likely sequence of hidden states. An example is "foodnature" = ["food", "nature"]. We also apply stemming after hashtag segmentation as further pre-processing. The Viterbi algorithm used by us has been shown in Figure 4 above.

4.2.2 Training

We have trained a word embedding approach like Word2Vec [8] and Glove embeddings [13] on our corpus and used distance measures such as cosine similarity to get the most relevant hashtags. The approach is detailed below.

A sample post representing the typical posts on Instagram has been shown in Figure 5.



367 likes

fede__grillo Cosa notate prima? Il panorama di Siviglia o i colori stupendi della camicia di @revolvervintage.art ? 😍

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#siviglia #sevilla #hola #travel #travelgram #ilmioviaggioasiviglia #travelblogger #fblogger #vintage #sivigliameraviglia #sivigliaofficial #metropolparasol #setasdesevilla #love #fashion #fbloggerstyle #fashionista #outfit #outfitoftheday #prettylittleiiinspo #style #lookoftheday #ootd #styleblogger #cyberfashioninspiration

Figure 5: There is a lack of sufficient text

Typically a post consists of the following:

1. A photo
2. A caption of 2-3 lines
3. A bunch of hashtags

From above it is clear that the amount of text present is very less and therefore using only the text for training our model won't be enough. We tackle the above problem using below 2 approaches:

- Assuming the hashtags that appear together are semantically related to each other we can also convert them to text and include them in our training corpus. Using the above assumption we prepare our corpus by first preprocessing (removing non-english texts, emoticons, etc.) and then training two different models on the prepared corpus.
  - **Word2Vec**: Using 30 epochs and window size of 5 we trained the model to create 300 dimensional word embeddings.
  - **GloVe**: Using 30 epochs for training we trained the model to create 300 dimensional word embeddings.
- To better capture the semantic relationship between words we use pre-trained word embeddings for a corpus size of 400K words trained on wikipedia data. We train our word2Vec model with our corpus on top of it which helps to capture the context of the instagram corpus. Therefore our vocabulary is able to cover more words and is able to capture both the generic and insta-specific meaning of a word.

Based on the above mentioned points, we propose three main methods of training as specified below:

1. **Topic based Glove Model**:- We have used glove embedding to find similarity between words. Here for each topic, we have one model that is trained on its corresponding topic's corpus.

2. **Topic based Word2vec Model**:- We have used word2vec embedding to find similarity between words. Here for each topic we have one model that is trained on corresponding topic's corpus plus pre trained wikipedia glove embedding.

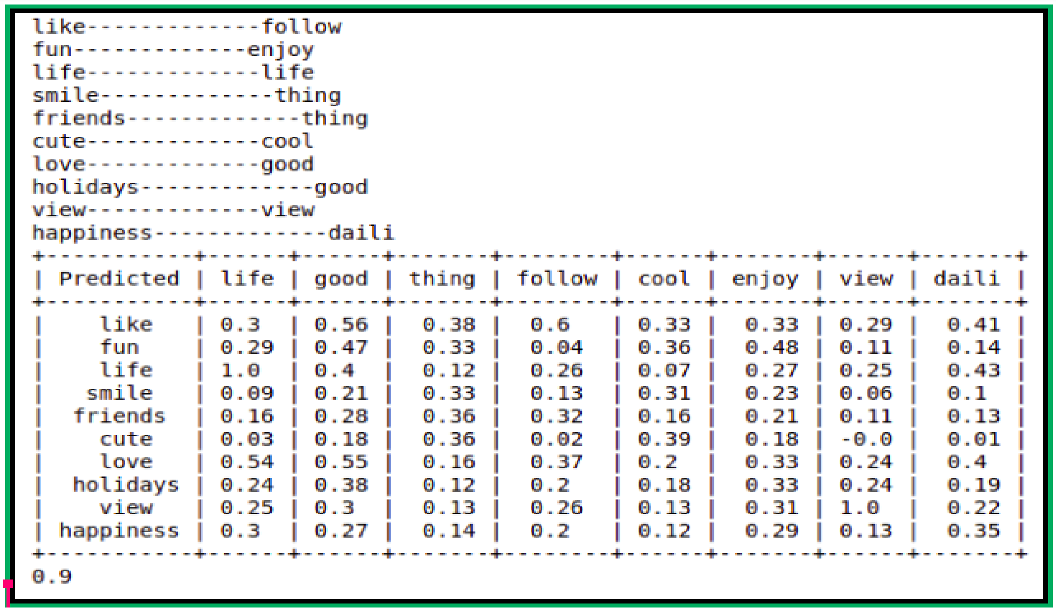
3. **Global word embeddings**:- We have trained one global model irrespective of topic that is trained on complete corpus plus pre trained wikipedia glove embedding.

5 Evaluation Mechanism and Results

Evaluation mechanisms like precision and recall (with exact keyword match) cannot be used for the problem of hashtag prediction because even though the predicted hashtag might be contextually similar to the ground truth hashtag but the above mechanisms will label it as misclassification. Therefore for our problem we use a 'Similarity Confusion Matrix' for finding the accuracy (based on K-means clustering algorithm).

For each post, we keep predicted hashtags as rows and ground truth hashtags as the columns and then calculate the cosine similarity for each pair. For each predicted hashtag (row), we consider the ground truth hashtag (column) which has the maximum cosine similarity with our predicted hashtag. If the cosine similarity score corresponding to this maximum value is above a certain threshold (0.5), then it is considered to be a correctly predicted hashtag [3]. We perform the above for all of our predicted hashtags (10) and compute the number of correctly predicted hashtags out of 10. This provides us the accuracy of our predictions for each post.

For each ground truth hashtag (column) we take the maximum row and claim that the predicted hashtag corresponding to that row is the closest (or most appropriate) to the original hashtag. And if the similarity metric is above a certain threshold, it is considered as correctly predicted. A brief example of the computation of our metric for a given post is provided in Figure 6.



```
like-------------follow
fun-------------enjoy
life-------------life
smile-------------thing
friends-------------thing
cute-------------cool
love-------------good
holidays-------------good
view-------------view
happiness-------------daili
+-----------+------+------+-------+--------+------+-------+------+-------+
| Predicted | life | good | thing | follow | cool | enjoy | view | daili |
+-----------+------+------+-------+--------+------+-------+------+-------+
|    like   | 0.3  | 0.56 |  0.38 |  0.6   | 0.33 |  0.33 | 0.29 |  0.41 |
|    fun    | 0.29 | 0.47 |  0.33 |  0.04  | 0.36 |  0.48 | 0.11 |  0.14 |
|    life   | 1.0  | 0.4  |  0.12 |  0.26  | 0.07 |  0.27 | 0.25 |  0.43 |
|   smile   | 0.09 | 0.21 |  0.33 |  0.13  | 0.31 |  0.23 | 0.06 |  0.1  |
|  friends  | 0.16 | 0.28 |  0.36 |  0.32  | 0.16 |  0.21 | 0.11 |  0.13 |
|    cute   | 0.03 | 0.18 |  0.36 |  0.02  | 0.39 |  0.18 | -0.0 |  0.01 |
|    love   | 0.54 | 0.55 |  0.16 |  0.37  | 0.2  |  0.33 | 0.24 |  0.4  |
|  holidays | 0.24 | 0.38 |  0.12 |  0.2   | 0.18 |  0.33 | 0.24 |  0.19 |
|    view   | 0.25 | 0.3  |  0.13 |  0.26  | 0.13 |  0.31 | 1.0  |  0.22 |
| happiness | 0.3  | 0.27 |  0.14 |  0.2   | 0.12 |  0.29 | 0.13 |  0.35 |
+-----------+------+------+-------+--------+------+-------+------+-------+
0.9
```

Figure 6: A sample image showing the computation of our metric for a given post. Here, the columns are the ground truth hashtags and the rows are the hashtags predicted by us. As the similarity between the ground truth hashtags and our predicted hashtags is more than 0.5 for 9 out of 10 hashtags, the accuracy for this post is 0.9

[3] The threshold is decided based on the maximum similarity we found for a pair of dissimilar words according to our model.

For the image classifier, we simply use accuracy as a metric to evaluate the performance of our approach. We do not use any other metric such as F1 score or precision and recall as our dataset is pretty balanced with equal number of images for each category.

We propose 2 baselines and evaluate our approach against them and an oracle model:

1. **Top K Baseline**:- For each post, we first predict the topic based on the image or using the ground truth itself and return the top 10 hashtags for this topic

2. **Global word2vec**:- We train a single text model on the whole corpuse and then predict the top 10 most similar words based on the sentence embeddings. This baseline does not use any image data or topic specific corpus

3. **Pretrained Wikipedia word2vec embeddings**:- In this model, we use word embeddings pretrained model on a Wikipedia corpus and finetune on our dataset. This is another form of global embedding approach.

4. **Topic based word2vec & Glove embeddings**:- We train 8 separate glove and word2vec embeddings on the corpus for each topic. During test time, we first predict the topic for a post using the image classifier and then predict hashtags using the particular topic specific word embeddings.

5. **Oracle**:- Similar to the above approach but we assume access to the ground truth topics for a given post.

6 Results

Table 2 shows the performance of our image classifier on the given dataset. The resnet-50 model performs the best followed by the resnet-34 model. The model clearly performs well on our semi-labelled dataset and gets an accuracy of upto 73%. This is a pretty decent accuracy for the given data as a single image might actually belong to multiple classes as well.

Model	Accuracy
resnet-34	71.2
resnet-50	72.8

Table 2: Image classifier results

Table 3 shows the performance of our approach with respect to the baselines and the oracle approach. We also evaluate the importance of our hashtag segmentation step by computing the accuracy with and without the hashtag segmentation as shown in Table 4. We release all our code and the dataset used for this project in our project page. The link to the GitHub code and the YouTube video are given here and here respectively.

Model	Accuracy
Top K Baseline	41.829%
word2vec + wikipedia glove embeddings	87.558%
Global model (word2vec)	63.040%
Global model (glove)	74.18%
Our approach (glove with topics)	96.172%
Oracle	96.525%

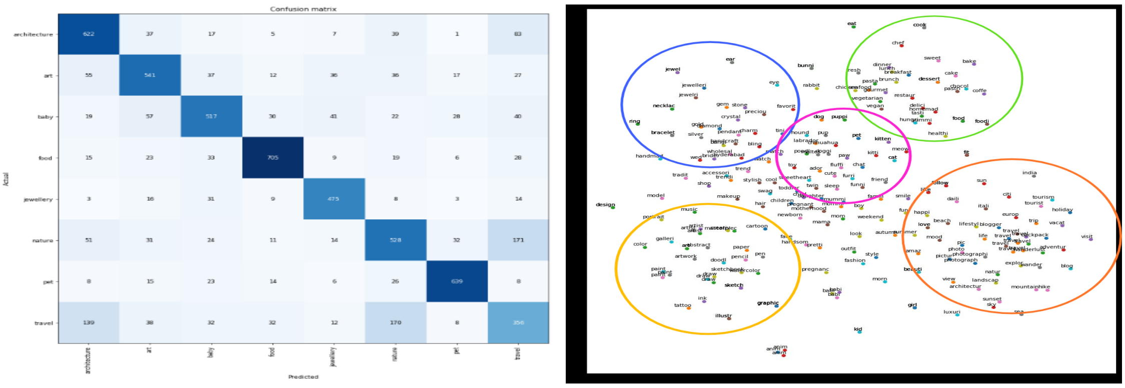
Table 3: Results for our proposed approach

Description	Accuracy
Our approach without segmentation	65.34%
Our approach with segmentation	96.172%

Table 4: Ablation study on the importance of hashtag segmentation

7 Analysis of results

From the above tables, we can see that the image classifier performs well for the given dataset. We also create a confusion matrix to find the topics in which the classifier gets confused the most as shown in Figure 7(a). We find that the model confuses between certain classes a bit more such as travel and architecture, travel and nature and so on. We believe that modelling our problem as a multi-label task instead of a simple multi-class & single label task would improve the accuracy further. We can also notice that the word embeddings have semantics associated with them. On applying LDA on the word embeddings followed by TSNE, we can see that the hashtags related to a given topic get clustered together as can be seen in Figure 7(b).

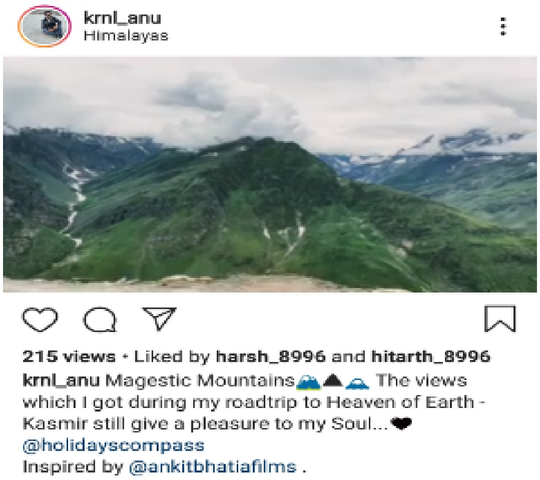


Actual \ Predicted	architecture	art	baby	food	jewellery	nature	pet	travel
architecture	622	37	17	5	7	39	1	83
art	55	541	37	12	36	36	17	27
baby	19	57	517	30	41	22	28	40
food	15	23	33	705	9	19	6	28
jewellery	3	16	31	9	475	8	3	14
nature	51	31	24	11	14	528	32	171
pet	8	15	23	14	6	26	639	8
travel	139	38	32	32	12	170	8	356

Figure 7: (a) Confusion matrix of image classifier, (b) Clustering of word embeddings

From the results of Table 4, we can see that the use of segmentation in our approach improves the accuracy of our model significantly. This shows that, there exists several hashtags in our dataset which contain two or more sub-hashtags which provide more context when segmented out.

We also show the sample hashtags predicted by our approach for a given post in Figure 8. From this image, we can see that the hashtags predicted by our model are very relevant and are semantically related. Thus, the model can be deployed to predict Instagram hashtags in the wild. From the Table 3, we can also see that the use of predictions made by the image classifier instead of the ground truth (oracle) does not significantly reduce the performance of our approach. This implies that our image classifier performs pretty decently.



krnl_anu
Himalayas

215 views • Liked by harsh_8996 and hitarth_8996
krnl_anu Magestic Mountains🏔▲🏔 The views which I got during my roadtrip to Heaven of Earth - Kasmir still give a pleasure to my Soul...❤
@holidayscompass
Inspired by @ankitbhatiafilms .

Figure 8: **Predicted Hashtags**: #view #mountain #world #amazing #ig

8 Conclusion

We propose a hierarchical approach to predict hashtags for a multi-modal data such as Instagram posts. We collect over 60,000 posts and train an image and text based approach for the same. We propose a new metric for computing the relevance of the predicted hashtags and provide an algorithm to compute the same. We then evaluate our model against some baselines as well as an oracle approach and show that the approach performs significantly better than the baselines and only slightly worse than the oracle.

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