A Spatio-Temporal Category Representation for Brand Popularity Prediction

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ABSTRACT
Social media has become an important tool in marketing for companies to communicate with their consumers. Firms post content and consumers express their appreciation for the brand by following them on social media and/or by liking the firm generated content. Understanding the consumers’ attitudes towards a particular brand on social media (i.e., liking) is important. In this paper, we focus on a method for brand popularity prediction and use it to analyze social media posts generated by various brands during a specific period of time. Existing instance-based popularity prediction methods focus on popularity of images, text, and individual posts. We propose a new category based popularity prediction method by incorporating the spatio-temporal dimension in the representation. In particular, we focus on brands as a specific category. We study the behavior of our method by performing four experiments on a collection of brand posts crawled from Instagram with 150,000 posts related to 430 active brands. Our experiments establish that (1) we are able to accurately predict the popularity of posts generated by brands, (2) we can use this post-level trained model to predict the popularity of a brand, (3) by constructing category representations we are able to accurately predict the popularity of category specific content and use it for predicting the popularity of the category.

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Figure 1: We propose a spatio-temporal category representation to model the temporal behavior of category specific content and use it for predicting the popularity of the category.
for enhancing customer engagement and brand development. Remarkable research efforts show that social media has dramatically altered the way companies market their businesses. In [10], Mangold et al. state that social media as a new channel and context, is crucial in today’s marketing-mix. Zeng et al. in [22] describe how businesses profit from using social media as a source of information for business intelligence as well as an execution platform for product design and innovation, relationship management, and marketing. In [16, 17], the authors show the importance of analyzing social media from a business perspective. In [16], Risius et al. demonstrate the value of social media analytics for building brand loyalty. All these works [10, 16, 17, 22] use several statistics of user posts for analyzing different problems in business without analyzing their contents.

One of the interesting and challenging problems in the marketing and business community now is predicting the popularity of a brand based on the content of what they post. Brand popularity reflects a brand’s recognition on social media, which comes from positive experiences of consumers. Understanding the drivers behind the popularity, therefore enables brands to enhance social media strategies for establishing a better relationship with consumers. Recent research on predicting the popularity of a user post has focused on visual and textual content [1, 3, 6, 7, 9, 12, 13], with methods depending on the type of platform and social context. Elaborating on the success of recent post popularity prediction in social media [1, 3, 6, 7, 9, 12, 13] we continue the study by predicting the popularity of brands. We follow [12] for analyzing the content generated by brands. In this paper, for the study of brand popularity prediction, we use the content of posts generated by the brands themselves instead of user posts for representing brands.

Up to now, focal priority has been cross-sectional modeling of popularity based on users and the content they generate, however as indicated before temporal dynamics are also of importance as users’ interests change over time [8, 20]. Motivated by [8, 20], we propose a novel approach for incorporating the temporal dimension of content posted by brands to predict their popularity. In this paper we, therefore, incorporate the temporal dimension in the brand representation to account for changes over time in popularity that are not solely reflected by the content. We attempt to answer to the question: How do the spatial and temporal properties of the content generated by a brand affect its popularity? Figure 1 visualizes our proposal for representing a brand and how we utilize it for the brand popularity prediction problem.

Of course popularity depends on how users express their opinions and this varies over the different social media platforms. Among those platforms, Instagram is used for self-expression by images with a description through captions and hashtags. Unlike some other social media platforms, the content that is generated by the brands will always be visible for users. As a consequence Instagram allows for visual marketing that is not controlled. Moreover, the hashtags allow brands to target individuals and engage with them directly. Consequently, top brands on Instagram are seeing a per-follower engagement1 (i.e. likes per follower) rate of 4.21, which is 58 times higher than Facebook and 120 times higher than Twitter. These aspects make Instagram of particular interest in the research of brand popularity prediction. In this paper we, therefore, investigate brand popularity prediction on a dataset crawled from Instagram.

We make the following main contributions in this paper:

- We show the effectiveness of post popularity prediction on content generated exclusively by brands.
- We initiate the study of brand popularity prediction based on brand generated content on social media.
- We propose a spatio-temporal category representation for brand popularity prediction.
- We introduce a new dataset, for brand popularity prediction, obtained for free from Instagram by a simple crawling procedure.

We organize the remainder of this paper as follows. We start by considering related work in Section 2. Section 3 describes our problem formulation and we define our brand representation for predicting the popularity of brand. We introduce the experimental setup on our dataset in Section 4. Results are presented in Section 5. Finally, Section 6 concludes with a summary of our findings and a discussion of several possible directions for future work.

## 2 RELATED WORK

In the past few years, extensive research has been done in analyzing the content generated by users on social media. In this section, we first review existing studies in post popularity prediction, then we explain those works that focus on post popularity prediction using temporal information.

### 2.1 Post Popularity Prediction

Popularity prediction of user generated posts in social media has recently received a lot of attention from the research community [1, 3, 6, 7, 9, 12, 13]. While some of the work has focused on predicting the popularity of textual content, such as messages or tweets on Twitter [1, 7], recent research focuses on the image content [3, 6, 9, 12, 13].

Notable examples of text based popularity prediction are [7] and [1]. In [7], Hong et al. predict the number of retweets on twitter using textual features extracted from tweets. They report the effect of combining textual features with contextual features of the user as well as temporal dynamics of retweet chains and suggest the importance of including a temporal dimension into popularity prediction. Bae et al. in [1] report the relation between the sentiment and popularity of tweets. These works successfully predict popularity of posts using textual data. However, visual content, which is rich in information, is not addressed.

In [3, 6, 9, 12, 13], the authors focus primarily on extracting different visual features from posts for predicting the popularity of an image and measuring the impact of these features on popularity. In [9], Khosla et al. report the results of image popularity prediction using simple image features, such as color, gist, gradient, texture, and low-level and high-level deep learning features as indicators for objects in images. They consider the problem of popularity prediction as a learning to rank problem. In [13], McParlane et al. learn a binary classifier for investigating the popularity of a post. They report the effect of social factors of each post such as

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1http://blogs.forrester.com/nate elliott/14 04 29 Instagram is the king of social engagement
how many followers a user has, the number of tags attached to the photo, and the length of the title. Moreover, they report the result of popularity prediction using content factors such as the number of faces in the images, analysis of the scene, and color features. Cappallo et al. in [3] learn a ranker by considering popular and unpopular latent factors. In [6, 12] the authors investigate the impact of sentiment analysis on the popularity of a post. Gelli et al. in [6] investigate the effect of visual sentiment analysis on images as well as contextual features used in [13]. They report the potential of predicting the popularity of images using visual sentiment scores as a feature, which was first introduced in [2] to detect sentiment in an image. Mazloom et al. in [12] initiate the problem of predicting popularity of brand-related user posts automatically in the business and marketing community. They further propose usage of an ensemble of cues, extracted from visual and textual channel of posts, which are important in analyzing brand popularity. All these works [3, 6, 9, 12, 13] don’t address the use of temporal dynamics in popularity prediction. Different from these works, we propose to incorporate the temporal dimension of brand generated posts since multiple factors of popularity are time sensitive [20]. Moreover, [3, 6, 9, 12, 13] are limited to popularity prediction of individual posts. We aim for popularity of categories based on multiple posts.

2.2 Temporal Post Popularity Prediction

In [21], Yang et al. analyze the temporal dynamics in social media content. They propose the k-spectral centroid algorithm for clustering time series to find patterns in social media. McParlane et al. in [13] utilize time, day and season in their representation of posts for predicting popularity. The time at which content is posted can be classified into time of day (i.e. morning, afternoon, evening, night), whether it is a week or a weekend day and also the season in which the content is posted. Wu et al. in [20] argue how time plays a crucial role in social media popularity. To capture the temporal dynamics of image popularity, they factorize popularity in the user-item context and the time-sensitive context. Different from these works [13, 20, 21] which focus on considering temporal dynamics on user generated post popularity prediction, we aim to incorporate the temporal dimension of posts generated by a brand to construct a category representation for predicting the popularity of a brand.

3 OUR PROPOSAL

In this paper, we aim to predict popularity of a category by introducing a category representation that incorporates temporal dynamics. To that end we consider each individual brand as a category throughout this work. Our category popularity prediction framework consists of two main parts, schematically illustrated in Figure 2. In the training phase, at first, we construct a category representation from a dataset of content generated by categories. We use the average number of likes of categories as labels. Second, in the prediction phase, we construct a representation of new categories and compute a popularity score. Before introducing the proposed framework for popularity prediction, the notation and key concepts will be formally introduced.

3.1 Problem Formalization

Given a specified category, popularity prediction of a category is the task of computing a score that shows how popular the category will be in comparison to other categories, based on the content that they generate. For consistency, we use $B_i$ to indicate the given category. We aim to construct a real-valued function $f(B_i)$ which produces a score for the popularity of $B_i$. By sorting all categories in a test set according to $f(\cdot)$ in descending order, a list of most popular categories will be obtained.

Let $B = \{(B_1, y_1), (B_2, y_2), ..., (B_m, y_m)\}$ be a set of $m$ categories, where $y_i$ is the popularity score of category $B_i$. Suppose category $B_i$ has been shared in total $n_i$ posts during the specific period of time; $B_i = \{P_{i_1}, P_{i_2}, ..., P_{i_{n_i}}\}$, where $P_{i_1}$ and $P_{i_{n_i}}$ are the first and last post shared by the category. Each post $P_{ij}, j = 1, ..., n_i$, has received a certain number of likes, $a_{ij}$, during a specific time which defines the popularity of post $P_{ij}$. Let $l_i = \{a_{i1}, a_{i2}, ..., a_{in_i}\}$ be the set of popularity scores of $B_i$ posts during the specific time period. We define $y_i = f(B_i) = \frac{1}{n_i} \sum_{j=1}^{n_i} a_{ij}$, the average number of likes of the category’s posts, as the popularity score of $B_i$.

The difficulty in constructing $f(B_i)$ largely depends on the representation of category $B_i$. We hypothesize that what makes a category become popular on the web, captured in the average number of likes a category will receive, depends on the content the category generates. The key idea of our proposal is to represent a category, based on the content shared on the web, as accurate as possible before predicting it’s popularity.

Next, we show in section 3.2 how to construct a spatio-temporal category representation based on content generated and posted by a category. For the ease of reference, Table 1 lists the main notation used throughout this work.

3.2 Category Representation

Let us now explain how a specific category $B_i$ can be represented using its generated content during a specific time. We propose to construct a category representation, $h(B_i)$, by a set of posts $P_{ij}, j = 1, ..., n_i$ generated and shared by $B_i$, $\alpha_{ij}$ the relative importance of $P_{ij}$ based on the number of likes users gave to $P_{ij}$, and $\gamma_{it}, t = 1,
We present three variants of category representation to capture changing interests in time of users. Depending on how a third component, a temporal dimension, with which we aim to take into account the relative importance of a category, we make use of the representation of category $B_i$. In addition, we use it for the problem of brand popularity prediction. Suppose $B = B_{TR} \cup B_{TE}$ is a set of $m$ brands with $B_{TR} = \{(B_1, y_1), (B_2, y_2), \ldots, (B_e, y_e)\}$ and $B_{TE} = \{(B_{e+1}, y_{e+1}), \ldots, (B_m, y_m)\}$ is a test set consisting of $e$ brands in $B$. By dividing the brands in a train and test set using the formulas explained in section 3.2, we define $B_{TR}$ and $B_{TE}$ as two matrix representations of all brands:

$$B_{TR} = \{h(B_1), h(B_2), \ldots, h(B_e)\}$$

$$B_{TE} = \{h(B_{e+1}), h(B_{e+2}), \ldots, h(B_{m})\}$$

Each row of $B_{TR}$ and $B_{TE}$ represents a brand. We train a brand popularity model on $B_{TR}$ and report the result of popularity prediction on $B_{TE}$.

Let $h(B_i)$ be the category representation of brand $B_i$ and $y_i$ show the popularity of $B_i$. The idea is to optimize $w$, parameter of function $f_w()$, on $B_{TR}$ to minimize the error between $y_i$ and $f_w(h(B_i)) = w^T h(B_i)$. We consider the problem of brand popularity prediction as a regression problem and try to optimize the following objective function:

$$y_i = f_w(h(B_i)) \rightarrow \min \sum_{i=1}^{e} (y_i - f_w(h(B_i))) - C \sum_{k=1}^{n} w_k^2$$

which can be formulated as

$$\arg \max_w \sum_{i=1}^{e} \log p(y_i|h(B_i), w) = -C \sum_{k=1}^{n} w_k^2$$

where $\log p(y_i|h(B_i), w) = \frac{1}{1 + e^{-w^T h(B_i)}}$.

To solve the problem and find the optimal value of $w$ we use L2 regularized L2 loss Support Vector Regression, as used in [9, 12], from the LIBLINEAR package [5]. After training the model and finding the optimum value of $w$ on $B_{TR}$, we use it for prediction of brand popularity on $B_{TE}$ and report the rank correlation between the predicted scores and grand truth.

### Experimental Setup

We investigate the effectiveness of our proposal for predicting popularity of a brand by performing a series of experiments on a dataset crawled from Instagram.
4.1 Dataset

Since there is no existing dataset for predicting the popularity of a brand, we created one by crawling the content brands post on Instagram. A grand variety of brands have adopted Instagram for the means of visual marketing. Unlike other social media platforms, the content that is generated by the brands will always be visible by users. Moreover, the hashtags allow brands to target certain individuals and engage with them directly. This makes our Instagram dataset especially relevant for the research on brand popularity prediction. Our dataset consists of 150,000 posts generated by 430 active brands, such as Expedia, Ford, Nike and McDonald’s, across 27 different industries like Travel, Automotive, Sports and Fast Food. All the content is generated between 01/05/2015 and 30/04/2016 and the brands behind the content are considered active, which means that they at least generate content every week. Figure 3 shows examples of posts with the number of likes generated by three highly popular brands.

The dataset is split into two parts, where two thirds are used for training the model and one third is used as a test set for evaluation of the model.

4.2 Implementation details

Feature extraction To represent a post in our dataset we use the following state of the art features:

Textual features We use the textual features used in [12]:

- **W2V** A trained deep neural network proposed in [14], which computes a 300 dimension vector by mapping each tag onto its Word2Vec representation. A post is then represented by average pooling of the W2V representation of all tags in the post.
- **Textual Sentiment** Represented by making use of SentiStrength [19]. First the stop words are removed and stemming is performed. The sentiment value of each tag is computed using SentiStrength to generate positive (ranging from 1 to 5) and negative (ranging from -1 to -5) sentiment scores.
- **Terms** a sparse representation with a length of 5250, where the length of the vector equals the number of unique tags generated by three highly popular brands.

Visual features We use the visual features as used in [12]:

- **CNN-Pool5** As low-level visual features, we used the 1024-dimensional features from pooling the last fully connected layer of the Deep Net in [18] which is trained on ImageNet [4]
- **Concepts** we extract the convolutional neural network features, initially proposed in [18] and trained to identify those 15,293 ImageNet [4] concept categories, for which at least 200 positive examples are available. We represent the image of each post by the 15,293-dimensional output of the softmax layer of the network as an effective representation has been shown in [11].
- **Visual Sentiment** A feature based on the Visual Sentiment Ontology which was first introduced in [2] to detect sentiment in an image. The sentiment ontology representation
4.3 Experiments

**Experiment 1: Post popularity prediction** In this experiment we evaluate the popularity of the brand generated posts. We train a post level popularity model over all posts in the training set and use it for predicting the popularity of a post in the test set. We report the result of post popularity prediction using different visual and textual features, which we mentioned in section 4.2, on our test set. We also report the result of fusing visual and textual features, by an average pooling scenario, for predicting the popularity of brand generated post. The combination of features creates an overview of the current state of the art prediction methods on content generated exclusively by brands.

**Experiment 2: Baseline: Brand popularity by post level training model** We create and evaluate a baseline for brand popularity prediction using a post level training model. We use this model to predict the popularity score for each post of a brand in the test set. We obtain a popularity score for a brand in the test set by averaging the predicted score of each post of a brand. Then we report the rank correlation between the predicted scores and ground truth as a popularity of a brand. We also report the result of the brand popularity prediction using different visual and textual features and their fusion by average pooling.

**Experiment 3: Brand popularity prediction using brand category representation** In this experiment we evaluate the three category representation methods we explained in section 3.2 for predicting the popularity of a brand. We represent each brand in the train and test set using our proposal which is explained in section 3.3 and train a model on the train set and predict the popularity of a brand in the test set. We evaluate the effect of different visual and textual features for representing a brand category in brand popularity prediction. We also report the result of fusing all features by average pooling.

**Experiment 4: Popularity prediction on an off-line collection** In this experiment we evaluate the effect of our proposal for selecting those images from an off-line collection of images of a brand which are expected to get a high number of likes. For this purpose we randomly select 100 posts of each brand from the test set and use only the visual data. We extract the visual features per test image and apply the pre-trained models of experiment 1 to compute a popularity score. Then, we rank the images of the brand from the test set based on their popularity score and select the top p images as most promising for sharing in social networks. We evaluate the selection, by defining the popularity ratio as average number of matches between images selected by our method and images from the ground truth ranking. The value of the popularity ratio shows the quality of the approach for selecting images to be shared in social networks. Proximity of the popularity ratio to 1 indicates a better image selection. We report the accuracy of selecting popular images using different visual features by selecting 10, 20, 30, ..., 100 images for sharing in social networks. We also repeat this procedure by selection images of brands randomly. We repeat the random selection of images for 50 times and report the average of the results.

5 RESULTS

5.1 Post Popularity Prediction

We report the result of this experiment in Table 2. Starting with the textual features, the results show the 0.346, 0.481 and 0.145 rank correlation as a popularity of a brand generated post using W2V, Terms, and Textual Sentiment features respectively. Using an average pooling for fusing these textual features, the result reaches 0.494. The results in Table 1 also show the importance of visual features in predicting the popularity of a post where the results reach 0.341, 0.287, 0.293 and 0.366 rank correlation using CNN-Pool5, Concepts, Visual Sentiment and fusion of them respectively. The results depict that Concepts and Sentiment present in the image of a post holds information on the popularity of a post. People may respond to concepts in images positively or negatively and a post that contains those positive concepts generally attains more likes. At the end the result in Table 1 shows the significant improvement in predicting the popularity of a brand generated post by combining the textual and visual features. The result of rank correlation reaches 0.520.

The results of experiment 1 confirm that visual and textual features are complementary for predicting the popularity of a brand generated post. Moreover, in general, we are able to predict popularity of brand generated content.

5.2 Baseline: Brand popularity by post level training model

Table 3 shows the results of Experiment 2, where we use a post-level training model on predicting popularity of a brand. It shows the rank correlation reaches 0.474, 0.133, 0.143, and 0.479 using W2V, Terms, Textual Sentiment, and fusion of visual features respectively. The Table 3 also mention to the effect of visual feature on brand popularity, where the rank correlation reaches 0.408, 0.299, 0.399 and 0.411 using CNN-Pool5, Concept, Visual Sentiment, and fusion of visual features respectively. All visual features have a significant positive impact on brand popularity. Table 3 also confirms complementarity of the visual and textual features for brand popularity prediction by training a post-level popularity model, where the result reaches 0.500 rank correlation.

The results of experiment 2 show the ability of predicting the popularity of a brand using a trained model based on the content they generated. Again, the results confirm that visual and textual features are complementary for predicting the popularity of a brand.
5.3 Brand Popularity prediction by category representation

We show the result of experiment 3 in Table 4. Table 4 describes the result of brand popularity using our proposal for brand representation using visual, textual, and fusing of them.

Using NCR as a brand representation the result reaches 0.517, 0.141, 0.154 and 0.527 when we use W2V, Terms, Sentiment, and fusion them respectively. On the other hand using visual features for the NCR representation of a brand, the result of brand popularity reaches 0.441, 0.322, 0.445 and 0.479 when we use CNN-Pool5, Concepts, Sentiments, and fusion of all visual features respectively. Combining visual and textual features in the NCR representation of a brand, the rank correlation reaches 0.544.

The results in Table 4 also show the efficiency of using WCR as a method for brand representation in comparison with NCR method. We observe that the rank correlation using all textual and visual features reaches 0.526, 0.167, 0.174, 0.464, and 0.365, and 0.461 where features are W2V, Terms, Sentiment, CNN-Pool5, Concepts, and Visual Sentiment respectively. By fusing textual features, visual features, and combining visual and textual features the rank correlation reaches to 0.532, 0.497, and 0.579 respectively. We observe 5% relative improvement in brand popularity prediction compared to NCR, showing the effect of considering the importance per week inside the week representation.

The results in Table 4 emphasize the efficiency of considering the temporal behaviour of popularity of contents generated by a brand inside the brand representation. Using STCR, the rank correlation reaches 0.532, 0.197, 0.204, 0.540 using W2V, Terms, Textual Sentiment, and fusion them respectively. By visual feature to construct STCR the rank correlation reaches 0.487, 0.394, 0.471, 0.511 where the features are CNN-Pool5, Concepts, Visual Sentiment, and fusion respectively. The Table 4 show the best result of brand popularity reaches 0.598 where we fused the visual and textual features represented by STCR. By comparing the result of STCR by NCR and WCR we find that incorporating the importance of brand per week and importance of post inside the week, we reach to more accurate brand representation.

The STCR addresses not only the weekly importance of certain images but also assigns weights to images within the week. It emphasises specifically the images of importance for the brand and combines it with the importance of a certain week in the brand popularity over time.

By comparing the result of our category representations with the baseline, experiment 2, we find 10%, 16%, and 20% relative improvement in brand popularity prediction when we use NCR, WCR, and STCR respectively.

The results of experiment 3 confirm that brand popularity prediction accuracy profits from constructing a representation of a brand. Moreover it depicts that a brand representation in which temporal behavior is incorporated is more representative for popularity prediction.

5.4 Popularity prediction on off-line collection

We show the results of experiment 4 in Figure 4. The results demonstrate the effectiveness of using different visual features for selecting those images from an offline collection which have the potential of getting more likes and becoming more popular. Figure 4 shows the result of image selection using our proposal always much better than random selection. When we request to select 30 images we reach 0.125 accuracy in popularity ratio using Random selection, whilst using Concepts, Sentiments, CNN-Pool5 and Fusion of all visual features reach 0.280, 0.328, 0.371, and 0.410. The result shows that by considering fusion of all visual features, we come to an accurate set of selected images which depicts each type of visual features capture different aspects of popularity of a post.

We also observe from Figure 4 that the presence of Visual Sentiment for all brands has a positive effect on the predicted popularity. We further investigate which particular ANPs correlate most with the number of likes in different industries. In order to evaluate the correlation of visual sentiment with popularity, we compute the SVR weights separately for two industries, Food and Fashion, and industry.

<table>
<thead>
<tr>
<th>Features</th>
<th>W2V Terms Sentiment Fusion</th>
<th>CNN-Pool5 Concept Sentiment Fusion</th>
<th>Multimodal Fusion</th>
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<td>NCR</td>
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<td>0.441 0.322 0.445 0.479</td>
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<tr>
<td>WCR</td>
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<tr>
<td>STCR</td>
<td>0.532 0.197 0.204 0.540</td>
<td>0.487 0.394 0.471 0.511</td>
<td>0.598</td>
</tr>
</tbody>
</table>
of helping brands in selecting the content they should share on their page on social media.

6 CONCLUSION

In this paper we study the prediction of popularity of brands. We investigate how the visual and textual contents of brand generated posts impact their popularity. Different from existing works which focus more on predicting the popularity of user generated posts, we are the first to study brand popularity prediction. We incorporate the spatio-temporal behavior of the popularity of the posts generated by brand for representing brand. We study the behavior of our proposal for predicting the popularity of brands on a dataset crawled from Instagram.

The results of experiment 1 confirm complementarity of visual and textual features for predicting post popularity. In addition, it shows how we are able to accurately predict the popularity of content that is generated and posted exclusively by brands. The results of experiment 2 show that by using the post level training model we have the ability to predict the popularity of the brand. Experiment 3 displays that prediction of brand popularity is more accurate when a brand is represented as a category representation. Moreover, incorporation of the temporal dimension into the representation increases the predictability of brand popularity. Finally, experiment 4 reveals that using our proposal, where all channels are fused, we have the ability of selecting a set of off-line images of a brand likely to become more popular.

We conclude that for category popularity prediction it is beneficial to construct a category representation in which spatio-temporal dynamics are considered.

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