# Who, What, When, and Where: Multi-Dimensional Collaborative Recommendations Using Tensor Factorization on Sparse User-Generated Data

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## ABSTRACT

Given the abundance of online information available to mobile users, particularly tourists and weekend travelers, recommender systems that effectively filter this information and suggest interesting participatory opportunities will become increasingly important. Previous work has explored recommending interesting locations; however, users would also benefit from recommendations for activities in which to participate at those locations along with suitable times and days. Thus, systems that provide collaborative recommendations involving multiple dimensions such as location, activities and time would enhance the overall experience of users.The relationship among these dimensions can be modeled by higher-order matrices called tensors which are then solved by tensor factorization. However, these tensors can be extremely sparse. In this paper, we present a system and an approach for performing multi-dimensional collaborative recommendations for Who (User), What (Activity), When (Time) and Where (Location), using tensor factorization on sparse user-generated data. We formulate an objective function which simultaneously factorizes coupled tensors and matrices constructed from heterogeneous data sources. We evaluate our system and approach on large-scale real world data sets consisting of 588,000 Flickr photos collected from three major metro regions in USA. We compare our approach with several state-of-the-art baselines and demonstrate that it outperforms all of them.

**Categories and Subject Descriptors**
H.3.3 [Information Search and Retrieval] : Information Filtering, Retrieval Models, Selection Process

**General Terms**
Algorithms; Design; Experimentation; Human Factors; Performance

**Keywords**
Recommender systems; Multi-dimensional recommendations; Collaborative recommendations; Tensor factorization

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## 1. INTRODUCTION

Today's smartphones come equipped with a multitude of sensors such as GPS and increasingly-powerful computational, storage and communication capabilities. These features have enabled smartphone applications to emerge across a variety of tourism-related areas such as travel recommendations, location-based services, and social suggestions. However, because information overload can be a problem for mobile users, it is important that only relevant and personalized information is presented. As a result, recommender systems that suggest items of interest to mobile users based on context and preferences have become increasingly popular.

Since the GPS embedded in smartphones can be used to accurately localize a user, *location* has become the basis of many recommender systems. These systems recommend interesting places or landmarks for visit to mobile users, particularly tourists and weekend travelers. However, in location recommendations, contextual information such as *time* often plays an important role as certain places are open only between fixed hours or can host certain activities at fixed times of a day or on fixed days in a week. In addition, users who want suggestions or recommendations for places to visit would also benefit from recommendations for *activities* to participate in at the location along with a suitable time of participation. Here, activities refer to human lifestyle and recreational activities such as shopping, dining, surfing etc. Users may even have specific *preferences* for activities such as preferring outdoor rather than indoor activities. For instance, at Pier 39 in San Francisco, a list of all possible things that a tourist can do includes shopping, eating seafood at the various restaurants, riding the Venetian carousel, watching the sea lions at the nearby dock or getting a view of the Fourth of July fireworks display. However, all these activities happen at specific locations in Pier 39 and either in specific months, on specific days or at specific hours. Thus, recommender systems that generate collaborative recommendations involving multiple dimensions such as location, time, activities, and user preferences etc., would enhance the overall experience of users and provide them with the most helpful recommendations.

As a simplest formulation, recommender systems model preferences of *users* for *items* in the form of a *utility matrix* where rows represent users, columns represent items and the values represent the users' ratings or preferences for those items on a scale of say, 1 to 5. The goal of the recommender system is then to impute the missing values based on observed values in the matrix [26, 35] using a standard approach such as collaborative filtering. User-based collaborative filtering determines a subset of users most similar to the current user and predicts the missing ratings based on a weighted combination of the ratings provided by those other users [26]. Likewise, item-based collaborative filtering [23] focuses on predicting the missing ratings for items based on a weighted com-

bination of the ratings given by the current user to similar items, where similarity between each pair of items is determined by the similarity of the ratings of those items provided by the users who have rated both items. Once the matrix has been completed (that is, all missing values have been imputed) by these neighborhood-based methods, a user can be given a recommendation list of ranked items ordered by descending predicted ratings.

An alternative powerful methodology that has been used with positive results in recommender systems is the latent factor model [21], an approach that emerged from research fueled by the Netflix prize[1]. Unlike neighborhood-based methods, latent factor models assume that similarity between users and items is simultaneously induced by some hidden lower-dimensional structure in the data. Some of the most successful realizations of latent factor models are based on matrix factorization, where users and items are simultaneously represented as unknown feature vectors (column vectors) along $k$ latent dimensions. These methods have become prominent in recent years because they combine scalability with high predictive accuracy. In addition, they offer more flexibility for modeling practical scenarios where the data is very sparse.

In case of recommendations along a single dimension, the 2-dimensional user $\times$ item matrix factorization model can be applied successfully. For instance, location recommendations can be modeled as a user $\times$ location matrix and can be solved using standard approaches to matrix factorization. However, to model collaborative multi-dimensional recommendations involving location, activity, time and other contextual information, the relationship among the various dimensions is represented by higher-order matrices called *tensors*. To address them, standard matrix factorization approaches need to be generalized to tensor factorization.

Another major challenge in recommender systems is that, in practice, most users provide interest ratings for only a subset of the recommended items. For instance, a user will provide ratings for only a subset of all possible locations. Moreover, as the number of dimensions increases, data sparsity increases and becomes a major concern for systems that generate multi-dimensional recommendations from real-world datasets.

In this paper, we address these challenges and present a system and an approach for performing multi-dimensional collaborative recommendations for Who (User), What (Activity), When (Time) and Where (Location), using tensor factorization on sparse user-generated data. Our contributions in this paper are:

- We address $n$-dimensional collaborative recommendations (where $n \geq 4$ and includes user, location, activity, time and any other contextual information) by fusing data from multiple sources such as Flickr (a photo sharing website), Foursquare (a location based social network), Yelp (a crowd-sourced reviews based website) and Viator (a travel website). While our approach can be extended to any number of dimensions, we make the work in this paper concrete by focusing on 4 dimensions and provide detailed discussion on how additional dimensionality can be addressed.
- While most of the prior efforts in multi-dimensional recommendations have been attempted using a single tensor, they suffer from tensor sparsity. We present a novel solution to this sparsity problem by formulating an objective function that simultaneously factorizes coupled tensors and matrices constructed from heterogeneous data sources. We then minimize this function using gradient descent.
- We evaluate our system and approach on large-scale real world data sets consisting of 588,000 Flickr photos collected from three major metro regions in the USA — the San Francisco Bay Area, Las Vegas and Chicago. From this data, we extracted over 4900 users, 6100 locations, 120 activities, and 96 time slots. The tensors constructed from these datasets are 99.999% sparse.
- We compare our approach with several state-of-the-art baselines and demonstrate that it outperforms all of them.
- Our approach also demonstrates an improvement in runtime without the need for sacrificing performance.

The rest of the paper is organized as follows: Section 2 reviews related work in location and activity recommendations and tensor factorizations applications to recommender systems. In Sections 3 and 4, we describe our datasets and the information inferred from them. We explain our approach in Section 5 and present its evaluation and comparison with baselines in Section 6. Finally, we conclude and outline future work in Section 7.

# 2. RELATED WORK

Since our work involves multi-dimensional recommendations for location, activity and time using tensor factorization on extremely sparse user-generated data, we have categorized the related work into different sections. The first section covers existing literature in location and activity recommendations while the second covers existing work in recommender systems using tensor factorization. We differentiate our work from them and identify their shortcomings.

## 2.1 Location and Activity recommendations

Most of the existing literature has focused on recommendations along one dimension (for instance, location). A few researchers have explored collaborative location and activity recommendations. To the best of our knowledge, none of the works have attempted collaborative location, activity and time recommendations.

### *2.1.1 Photos as a data source*

One of our main data sources for user locations are Flickr[2] photos. Many of the photos uploaded by users are geotagged, thereby providing a wealth of geospatial data. These photos have been used for many purposes, such as finding Point-of-Interest (POI) clusters [36], identifying the location of photos from visual, textual, and temporal features [9], determining when tourism is in season [12], and creating routes that are pleasing to the user [30].

### *2.1.2 Location/Landmark/Venue recommendations*

Previous researchers have investigated the problem of making recommendations for geolocations that may be interesting to the user [7, 24, 32]. Such approaches use large bodies of collected geospatial data along with user preferences and then apply low-dimensional recommendation algorithms.

### *2.1.3 Activity Recommendations*

Even though users seek recommendations on what activities they can engage in when they visit a place or at a given time, the area of activity recommendation has not been researched extensively. Recent research has focused on diurnal activity recognition from smartphone sensory data [25] or from location [22]. Belotti et al. [5] explored the idea of serendipitous activity based discovery of venues and activities via the Magitti Mobile Leisure Guide. Ducheneaut et al. [11] experiment with several models such as collaborative filtering, preference-based, distance-based, and a weighted combination of these to provide activity recommendations via Magitti.

### *2.1.4 Collaborative Location and Activity recommendations*

Co-occurring location and activity collaborative recommendations were proposed by Zheng et al. in [38] where they addressed location recommendations given an activity, and activity recommendations given a location. They used Collective Matrix Factor-

[1] http://www.netflixprize.com/

[2] https://www.flickr.com/

| Data Source | Type of Data | Dimensions extracted | Volume of raw data extracted |
|---|---|---|---|
| Flickr | Geotagged and Timestamped Photos | User, Location, Activity, Time | 588,000 photos with 9 million words of text |
| Foursquare | Location and POI database | Location, Activity, Venue | 274,000 locations with POI or venue information |
| Yelp | Business and service reviews | Activity | 1060 service categories |
| Viator | Things to do in tourist spots | Activity | 60 things to do categories |

Table 1: Data fusion from heterogeneous data sources

ization (CMF) [33] to complete a sparsely populated 2-dimensional Location $\times$ Activity matrix and evaluated their approach on 162 users with recommendations for 5 activities. CMF takes advantage of correlations and sharing of information between data sets from multiple sources and simultaneously factorizes coupled matrices. It is shown to have achieved higher prediction accuracy than individual matrix factorization. Sattari et al. [31] used the same dataset as Zheng et al. in [38] but employed Singular Value Decomposition (SVD) in place of CMF to complete the Location $\times$ Activity matrix. Since SVD requires the matrix that needs to be decomposed to be fully populated, they padded it with zero values. They demonstrated an improvement in performance over [38].

Zheng et al. [37] modeled user, location and activity data as a 3-dimensional tensor and applied a regularized tensor and matrix factorization approach for location and activity recommendations. They formulated a CANDECOMP/PARAFAC (CP) [15, 8] decomposition style objective function and minimized it using gradient descent. This decomposition factorizes a tensor into a linear combination of component rank-one tensors. They evaluated their approach on a dataset of 164 users, 168 locations and 5 activities.

Our work stands out from the existing literature in several ways:

- We use large user-generated datasets which involves several thousand users and locations, and over a hundred popular lifestyle, recreational and tourist activities.
- We incorporate dimensions of user's context such as time in addition to location and activities.
- As opposed to the manual approach for activity inference from user comments that was employed in [38, 37], we propose an automated and unsupervised Natural Language Processing (NLP) based algorithm (Section 4.2) which is more robust and scalable to large real-world datasets.
- Moreover, a major limitation of using CP decomposition for tensors is that it is not suitable for very sparse tensors and demonstrates a sharp increase in error especially if more than 80% of the data is missing [2, 3]. Sparsity is a non trivial issue for us as our multi-dimensional data is 99.999% sparse. Hence, we propose our joint analysis and factorization based approach to solve the problem.

## 2.2 Other applications of Tensor Factorization to Recommender Systems

Symeonidis et al. [34] and Nanopoulos [28] applied Higher Order Singular Value Decomposition (HOSVD) [10] to a 3rd order tensor which represents users, items and tags in social tagging systems such as Last.fm and Bibsonomy. Karatzoglou et al. [18] address multi-dimensional recommendations by incorporating contextual information to model a User-Item-Context tensor. They utilize a sparse HOSVD style method that decomposes a D dimensional sparse tensor into D matrices and a D dimensional tensor. HOSVD is a generalization of the matrix SVD to a tensor. It assumes a dense tensor and is not suitable for very sparsely populated tensors. Moreover, unlike SVD, HOSVD may not provide the best low rank approximation of a tensor [20].

Hidasi and Tikk [17] apply an Alternating Least Squares (ALS) [19, 20] based tensor factorization approach for context-aware recommendations. ALS consists of three steps, each one being a conditional update of one of the factor matrices, given the others. However, it suffers from several drawbacks: It has poor convergence for sparse data [6] and is not scalable to large-scale data sets [2].

| Region | Photos | Users | Land Area ($km^2$) |
|---|---|---|---|
| San Francisco Bay Area | 280,045 | 7895 | 6053 |
| Las Vegas | 23,350 | 578 | 1818 |
| Chicago | 284,751 | 2423 | 1412 |

Table 2: Flickr.com raw dataset characteristics

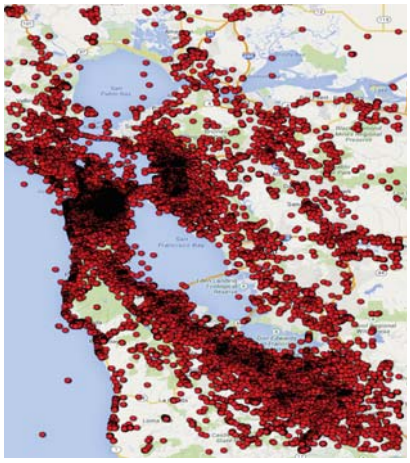
To address these limitations and perform multi-dimensional recommendations on large-scale and sparse user-generated datasets, we formulate our recommendation model via the Coupled Matrix and Tensor Factorization (CMTF) framework [1, 3]. CMTF is an approach similar to CMF and proposes joint analysis of a matrix and an $N^{th}$-order tensor with a common mode or dimension, where the tensor is factorized using an R-component CP model and the matrix is factorized by extracting R factors using matrix factorization. CMTF is shown to have achieved better performance than standard CP decomposition especially if more than 80% of the data is missing [2, 3]. A variant of the CMTF approach [1, 2] performs the joint analysis of the tensor and matrix by ignoring the missing entries and fitting the tensor and/or the matrix model to the known data entries only. This approach has been shown to easily scale to handle very large data sets with up to 99% missing entries [2].

To this end, we model our multi-dimensional recommendation problem as a joint analysis of a sparsely populated tensor with several matrices which share one or more common modes with the tensor. These tensors and matrices are constructed by fusing data for the various dimensions (users, locations, activities and time) from multiple data sources. This is a challenging task since data sets are often incomplete and heterogeneous. We then factorize these tensors and matrices simultaneously using a gradient descent-based algorithm. As we show later in Section 6.5, our approach outperforms standard CP decomposition, HOSVD and ALS.

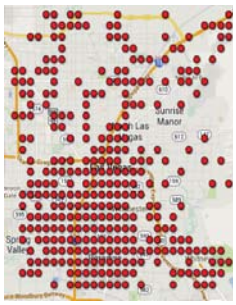
# 3. DATA

Table 1 summarizes the data sources, types of data, extracted dimensions and the volume of raw data from each source. Our primary dataset consists of 588,000 geotagged and timestamped publicly-available photos from Flickr.com, a popular photo-sharing website hosted in the USA. To obtain the data set, we searched specifically for photos taken with smartphones so that we could get the most accurate geospatial traces. Further, these photos spanned the time period of September 1, 2009, to September 1, 2013 and were taken from three major metro regions in the USA – the San Francisco Bay Area, Las Vegas and Chicago. Table 2 shows the characteristics of this dataset, while Figure 1 shows the geographical distribution of the photographs over the three regions. To improve legibility of the figure so that individual photo locations can be discerned, we sampled the number of photos down.

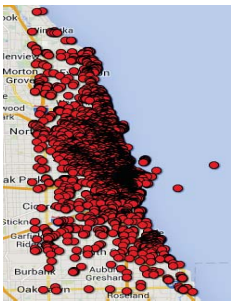
We extracted photos and their meta-content in JSON format using Flickr's public REST based API. Each photograph is marked with the user ID of the user who took it, geo-location in latitude and longitude format representing where it was taken, and an epoch timestamp representing when it was taken. We also extracted about 9 million words of user-generated text (including title, description, tags or comments) for these photos. Note that less than 50% of the photos are marked with any text. In addition, we also obtain POI or Venue information for 274,000 locations in the three geographical



(a) San Francisco Bay Area



(b) Las Vegas



(c) Chicago

Figure 1: Geographical distribution of photos from San Francisco Bay Area, Las Vegas and Chicago core regions. Map image tiles were provided by Google, and waypoint placement was performed using `http://www.gpsvisualizer.com/`.

regions from Foursquare[3]. Finally, we obtained information about popular activities from Yelp[4] and things to do in tourist spots from Viator[5]. We explain the inference and extraction of the various dimensions from the collected data in Sections 4 and 5.

# 4. INFERRING VARIOUS DIMENSIONS OF INFORMATION FROM FLICKR PHOTOS

As mentioned earlier, photos on Flickr have meta-data that includes a user ID, timestamp, location and text. We now infer the dimensions of user, location, activity and time from this meta-data.

## 4.1 Location Hashing

Our system relies on unique and discrete locations, but the Flickr geotags are stated as continuous floating-point latitude and longitude geocoordinate pairs. To discretize these values, we applied Cartographic Sparse Hashing, our O(1) algorithm (shown in Algorithm 1) that hashes a latitude and longitude pair into one of many virtual rectangular grid bins formed throughout the geocoordinate space. This algorithm takes as input (i) latitude and longitude as 64-bit floats and (ii) a bin resolution size *r* in meters as an integer. It then outputs a 64-bit integer key representing the final virtual bin. The algorithm leverages the fact that the latitude and longitude are expressed in decimal degrees, with the fifth decimal place corresponding roughly to 1 meter. Since this precision was acceptable to us, we truncated each value to five decimal places. The function then produces the resulting integer key with the longitude and latitude ending up in the high and low bits, respectively. This key

[3] `www.foursquare.com/`

[4] `www.yelp.com/`

[5] `www.viator.com/`

**Algorithm 1:** Cartographic Sparse Hashing (CASH) algorithm

**Input**: $latitude$ as 64-bit float, $longitude$ as 64-bit float, grid resolution $r$ in meters
**Output**: Hash value $hashResult$ as 64-bit integer
Trim $latitude$ digits past 5th decimal position;
$sigFig \leftarrow 10^5$;
$latitudeInt \leftarrow (int)(latitude \times sigFig)$;
Round down $latitudeInt$ to be divisible by $r$;
Repeat with $longitude$ to produce $longitudeInt$;
$hashResult \leftarrow shiftHigh(longitudeInt) + latitudeInt$;
**return** $hashResult$

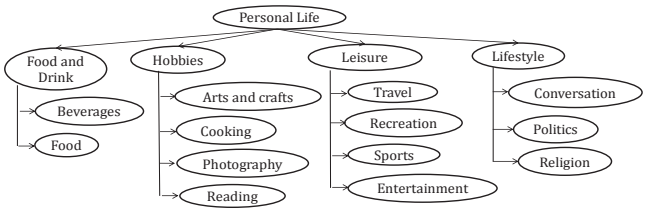



Figure 2: Partial view of the Activity Hierarchy showing all depth 1 nodes and a few depth 2 nodes

identifies a virtual bin approximately *r* meters per side, although the bin will be elongated north-to-south for regions further away from the equator due to the Earth's curvature.

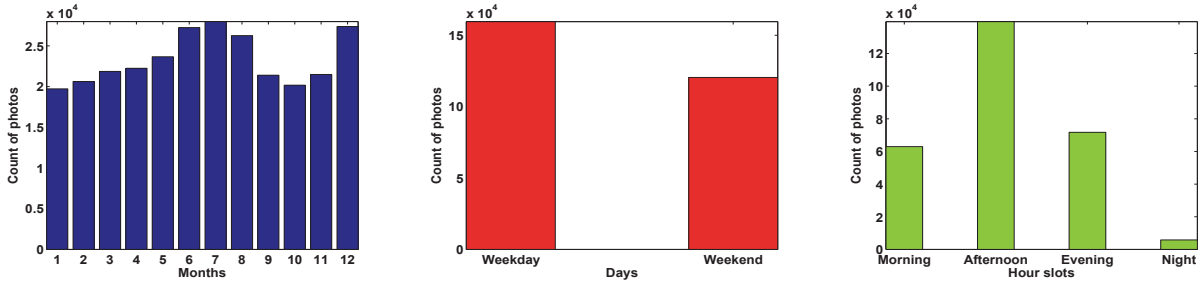
We experimented with 4 different location grid sizes - 300m, 500m, 700m and 1000m. These were determined based on the venue density in each grid as well as human walking distance (as people may often prefer to walk or use public transport). If the grid size is too large, recommendations beyond a certain walking distance will not be helpful to the user. On the other hand, if the grid size is too small, there may not be any venue or place to recommend in the grid. We explain the selection of the appropriate size based on performance in Section 6.3.

## 4.2 Activity Inference

Previous research in activity recognition [22, 25] focused on recognizing daily activities such as 'walking', 'driving', 'biking' etc. from smartphone sensors such as the accelerometer and GPS. However, a real world recommender system should be capable of recommending a diverse set of activities to users in addition to such diurnal activities. To address this, we employ an activity hierarchy which consists of lifestyle, recreational and tourist activities for activity recommendations.

Figure 2 shows a partial view of our Activity Hierarchy. We generated it by manually combining popular activities from the Yelp category list, Viator things to do list, and the FourSquare venue category hierarchy. Our hierarchy has a tree structure of depth 4 and contains 120 activity nodes including the root node 'Personal Life'. There are 4 high-level (depth 1) activities which branch out into 15 coarse-grained activities (depth 2). All the high-level and some of the coarse-grained activities that they include are shown in Figure 2. Some of the coarse-grained activities at depth 2 are further categorized into 28 fine-grained activities (depth 3) which are further categorized into 128 leaf node activities. For instance, the root node 'Personal Life' branches out into coarse-grained activities including 'Leisure' which is further categorized into fine-grained activities such as 'Entertainment' and Recreation' etc. 'Entertainment' is further categorized into leaf node activities such as 'Music', 'Movies' and 'Dance'. It is possible that a user is engaged in an activity which is not present in our hierarchy. To address this, we have a generic category 'Other' at each depth.

Inferring users' activities from our data set is non-trivial and challenging. Unlike previous research, we do not have labeled sen-




(a) Monthly distribution (b) Weekly distribution (c) Hourly distribution

Figure 3: Monthly, Weekly and Hourly distribution of photographs in the San Francisco Bay Area dataset

**Algorithm 2:** Activity inference from user-generated text

**Input**: Photo content items such as name, description, tag and comments and Activity Hierarchy
**Output**: Inferred Activities
Remove stop words from each photo content item;
Concatenate the content items to generate a search query;
Perform a web search using the search query and retrieve the text content of the top-most web search result;
Extract features such as named entities and types, document categories and social tags from the text content;
**foreach** *Activity in the Activity Hierarchy* **do**
  Compute SR scores between the features and the Activity;
  MaxSRScore for each activity ← arg max (SR Score between any of the features and the activity);
  **if** *MaxSRScore* < $SR_{threshold}$ **then**
    MaxSRScore ← 0.0;
**end**
MAXMaxSRScore ← arg max (MaxSRScore);
**if** *MAXMaxSRScore* ≠ *0* **then**
  MaxActivities ← Activities with MAXMaxSRScore;
**if** *MaxActivities* = ∅ **then**
  MaxActivities ← Propagated photo labels based on distance and time;
**return** *MaxActivities;*

sory data from users' phones. Though all the photos in our dataset are geotagged, a user could be engaged in several probable activities at a location. Also, less than 50% of the photographs are annotated with user-generated photo content such as a detailed name or a description, and even fewer photographs have tags or comments which can provide some indication of the activity occurring when the photograph was taken. In addition, crowd-sourcing the labeling of activities (as done in [38, 37]) is not feasible for 588,000 photos.

To address these challenges, we propose an automated and unsupervised NLP based algorithm (Algorithm 2) to infer a user's activity from user-generated text such as the photo content items. As shown, we first remove all stop words from each photo content item and concatenate the items. We then perform a web search query to elucidate the meaning of the concatenated items and retrieve the content of the top-most web search result. From this content, we extract features such as named entities, document categories and tags. These features are extracted using three NLP techniques:

- Named Entity Recognition - a subtask of information extraction that identifies names of persons, organizations etc. in a given text or sentence
- Document Categorization - a task that classifies the subject or topic of the text, and
- Social Tagging - the practice of generating tags or keywords by users rather than experts to describe online content.

For this feature extraction, we employ a tool called OpenCalais[6] which can recognize up to 39 entities from the text. It also categorizes the text into one or more 18 document categories such as Finance, Entertainment etc. In addition, it associates one or more social tags with it. The use of these techniques ensures that a large amount of world knowledge is exploited for feature extraction.

We then compute the Semantic Relatedness (SR) scores between each activity and each feature extracted from the web content. SR [14] is a metric for determining the similarity of two documents or phrases based on their semantic meaning. It is normalized to a value between 0 (little to no relatedness) and 1 (extremely high relatedness). While there are several techniques and systems available for computing SR, we employ the Semantic Textual Similarity (STS) system [13] for computing SR scores. STS is based on Latent Semantic Analysis (LSA) along with WordNet knowledge and is trained on the LDC Gigawords and Stanford Webbase corpora.

For each activity, we store the maximum SR score (MaxSRScore) between any of the features and the activity. If the MaxSRScore for an activity is less than a threshold, we set it to 0.0, thereby reducing noise and false positives. Since SR is a cosine similarity measure, a threshold of 0.293 (1 - cos 45 °) is generally considered an appropriate threshold, and we use that in our current implementation. Finally, we iterate over all the activities and select those with the highest MaxSR scores. If a photo has no labeled activities, we apply a simple label propagation technique to label it based on its nearest neighbors (with respect to location and time). This approach is intuitive because if two consecutive photos are close in time and location, it is highly probable that the user was performing the same activity in both.

To illustrate Algorithm 2 better, consider a photo which has been tagged as 'Brazen Wildcat Half' by the user. This phrase by itself does not convey any meaningful information about the user's activity, but a web search for it reveals content such as 'Brazen Wildcat Half Marathon Racing...'. From the web content text, we get features such as 'Trail Run', 'Athletics' and 'Recreation' etc. Algorithm 2 then maps these features to the activities: Sports, Running and Recreation. From this, we can infer that the user was engaged in these activities when the photo was taken.

## 4.3 Time hashing

Since each photo has a unique timestamp, the number of timestamps in our dataset is huge. To address this, we perform feature hashing to hash the value of each timestamp to a timeslot. In order to determine the granularity of timeslots, we analyzed the monthly, weekly, daily and hourly distribution of photographs.

Figure 3(a) shows the distribution of photographs in the San Francisco Bay Area dataset for months in a year (1= January until 12 = December). As evident, the number of photos varies with each month. Clearly, July and December have the highest photo counts as these months have the typical vacations of July 4th and Christmas. We also analyzed the differences in weekdays and weekends.

[6] http://www.opencalais.com/

| Grid Size *r* (m) | # of unique hashed locations | | |
|---|---|---|---|
| | San Francisco | Las Vegas | Chicago |
| 300 | 7869 | 2747 | 5082 |
| 500 | 5565 | 1932 | 3665 |
| 700 | 4222 | 1475 | 2855 |
| 1000 | 2999 | 1058 | 2070 |

Table 3: Number of unique hashed locations in our 3 datasets

As shown in Figure 3(b), weekdays have a higher photo count.

We further considered the distribution of photographs at different hours in a day. To this end, we divided a day into 4 hourly slots:

- Morning - hours between 6 am and 12 pm
- Afternoon - hours between 12 pm and 6 pm
- Evening - hours between 6 pm and 12 am
- Night - hours between 12 am and 6 am

As seen in Figure 3(c), the highest count of photographs is taken in the afternoo.n Intuitively, the least number (5834) were taken at night. Based on this analysis, we generated buckets of hashed time slots. Since there are 12 months in a year, 2 types of days in a week - weekday and weekend, and each day has 4 hourly slots, the total number of hashed timeslots is 96. For each photo, we first convert its epoch timestamp to a standard date time format which is then hashed to a timeslot. For instance, a photo taken on August 19, 2013 at 2 pm will be hashed to 'WeekDay_8_Afternoon'.

# 5. OUR JOINT ANALYSIS AND FACTORIZATION BASED APPROACH

## 5.1 Data Modeling of various dimensions

After inferring the user, location, activity and time information from the Flickr photos, the data in each dataset needs to be modeled along the various dimensions of our multi-dimensional tensor. These dimensions are:

- Location dimension - We first apply data filtering to reduce noise. We retain only those unique hashed locations that have been visited by at least $u_t$ users (where $u_t$ = 5), Thus, for each unique hashed location present in our 3 datasets, we determine the number of unique users from that dataset who visited that location. We remove all locations that have $\leq 5$ unique users. We perform this thresholding mainly to eliminate locations that can be residences of users or random spots such as roads. Table 3 shows the final count of locations in our datasets. The number of locations for each dataset varies with the hashed grid size, where we note that we discern at least 6127 locations in all with the largest grid size (1000m). These correspond to the Location dimension of our tensor.
- User dimension - Once the final set of locations for each dataset has been obtained, we use only those photographs which have been taken at these locations. The corresponding user IDs for these photographs represent the User dimension of our tensor. Our final set of users consists of 2498 unique users in the San Francisco Bay Area, 573 unique users in Las Vegas and 1850 unique users in Chicago.
- Activity dimension - The 120 activities in our activity hierarchy represent the Activity dimension of our tensor.
- Time dimension - The 96 hashed time slots represent the Time dimension of our tensor.

## 5.2 Constructing the tensors and matrices

We now construct a 4 dimensional tensor from these dimensions.

### 5.2.1 *User × Location × Activity × Time tensor*

The four dimensional (User, Location, Activity and Time) data modeled from each of the Flickr datasets can be represented as a sparse tensor $X \in \mathbb{R}^{u \times l \times a \times t}$ where $u$ is # of users, $l$ is # of locations, $a$ is # of activities and $t$ is # of time slots. The ratings placed into this tensor should represent the user's interest for performing a certain activity at a certain location at a certain time. However, in our data set, users do not provide any explicit ratings. Hence, we derive an implicit feedback [29] value normalized over [0.0, 1.0]. Each cell value of the tensor represents the frequency of the current user being at the current location performing the current activity at the current time. The counts are further normalized based on the total number of data points (photographs) for each user.

Moreover, each user typically visits a small subset of the possible locations at only a few of all the possible times and performs a fraction of all the activities possible. Hence, our tensor is very sparse and any given fiber will have only a few non-empty entries. After this construction, the tensors from the 3 datasets have a density of the order of $10^{-3}\%$. Thus, the tensors are 99.999% sparse.

To supplement the sparse 4 dimensional tensor, we further construct various 2-dimensional matrices which are *coupled* with the tensor i.e. they involve one or more of these dimensions and thus, share at least one mode in common with the tensor. We construct them using data obtained from various other data sources.

### 5.2.2 *Location × Activity Matrix*

Knowing what activities occur in a given location can enable inference of the activity a user is engaged in when he is at the location. As mentioned earlier, even though all the photographs have a geolocation, more than 50% of the photographs do not have any photo content to indicate what activity the user could be engaged in. Hence, this location-activity information can enable inference of the most likely activity a user could be engaged in at a location.

To obtain this relationship for each activity in our hierarchy, we query the Foursquare location database to find all the locations, in each of our datasets, where that particular activity can occur. Thus, for each location $l_i$ in a dataset, we get an n-dimensional frequency vector $c_i$ = [$c_1$, $c_2$ ... $c_n$] for n activities (where n = 120). Each $c_{i,j}$ is normalized as $\frac{c_{i,j}}{\sum_{j=1}^{n} c_{i,j}}$. From this information, we construct a Location × Activity matrix $Y \in \mathbb{R}^{l \times a}$ which contains normalized counts for the activities that occur in each location.

### 5.2.3 *Location × Venue Matrix*

Activities typically occur at a venue or a POI such as a restaurant, shopping mall, etc. For instance, a user would 'Eat' at a 'Restaurant' or 'Shop' at a 'Shopping Mall' in a location. Hence, the knowledge of venues that are present in a location can be leveraged to enable the inference of the user's activity.

For each location in each of our datasets, we also obtain the counts of different venues (from the Foursquare location database) that are present in it. The venues belong to the Foursquare venue hierarchy that includes 470 different types of venues such as restaurants, movie theaters etc. Thus, for each location $l_i$ in a dataset, we get an m-dimensional frequency vector $v_i$ = [$v_1$ ... $v_m$] for m venues (m = 470). Each $v_{i,j}$ is normalized as $\frac{v_{i,j}}{\sum_{j=1}^{m} v_{i,j}}$. From this information, we construct a Location × Venue matrix $J \in \mathbb{R}^{l \times v}$ which contains normalized counts for venues in each location.

### 5.2.4 *Location × Location Similarity Matrix*

The locations that have similar type and count of venues will host similar activities. Hence, we employ the Location × Venue matrix to compute the location similarity information. For each pair of locations $l_i$ and $l_j$ in each dataset, we calculate the cosine similarity between the venues vectors as sim($l_i$,$l_j$) = $\frac{v_i \cdot v_j}{\|v_i\| \|v_j\|}$ where $0 \leq$ sim($l_i$,$l_j$) $\leq 1$. Using the location similarity information, we construct a symmetric Location × Location matrix $Z \in \mathbb{R}^{l \times l}$.

### 5.2.5 *Activity × Activity Correlation Matrix*

Users may often have preferences for activities that are similar and correlated. For instance, a user who likes sports might engage in several different types of outdoor sports such as basketball, tennis, etc. Hence, this knowledge of correlation between activities can be exploited easily to further boost the information about the kinds of activities a user could be interested in.

We use the SR metric (from Section 4.2) to compute correlation between all the activities present in our hierarchy. For each pair of activities $a_i$ and $a_j$ in our Activity hierarchy, we calculate the SR score between their descriptions to get sim($a_i$,$a_j$). For instance, SR score between 'Sailing' and 'Surfing' is 0.63, indicating that they are correlated. This is intuitive as both are water sports. From this correlation information, we construct a symmetric Activity × Activity matrix S $\in \mathbb{R}^{a \times a}$.

## 5.3 Objective function formulation

We now perform joint analysis of the constructed tensor and matrices. We formulate an objective function that simultaneously factorizes the main 4-dimensional tensor and the four 2-dimensional coupled matrices that contain additional information. The tensor is factorized using a CP model while the matrices are factorized using matrix factorization. As discussed earlier, such an approach achieves better performance than standard CP decomposition for extremely sparse tensors. The objective function for our multi-dimensional recommendation problem is:

$F = \frac{1}{2}\|W \times (X - U \circ L \circ A \circ T)\|^2 + \frac{\lambda_1}{2}\|Y - LA^\top\|^2 + \frac{\lambda_2}{2}\|S - AA^\top\|^2 + \frac{\lambda_3}{2}\|Z - LL^\top\|^2 + \frac{\lambda_4}{2}\|TR\|^2 + \frac{\lambda_5}{2}(\|U\|^2 + \|L\|^2 + \|A\|^2 + \|T\|^2)$

Thus, the objective function comprises six summands and can be written in the form F = $F_1$ + $F_2$ + $F_3$ + $F_4$ + $F_5$ + $F_6$. The six summands and the terms and symbols that they include are:

- $F_1$ - The weighted least squares error term for the decomposition of the 4 dimensional tensor X into the factor matrices U $\in \mathbb{R}^{u \times k}$, L $\in \mathbb{R}^{l \times k}$, A $\in \mathbb{R}^{a \times k}$ and T $\in \mathbb{R}^{t \times k}$ where *k* is the number of factors. W is a weight tensor $\in \mathbb{R}^{u \times l \times a \times t}$ and indicates the missing entries in X such that:
  $w_{u,l,a,t} = \begin{cases} 1 & \text{if } x_{u,l,a,t} \text{ is known} \\ 0 & \text{if } x_{u,l,a,t} \text{ is missing} \end{cases}$
  This term tries to minimize the loss in only the known entries of the tensor.
- $F_2$ - The least squares error term for the decomposition of the 2-dimensional matrix Y (containing the Location - Activity information) into factor matrices L $\in \mathbb{R}^{l \times k}$ and A $\in \mathbb{R}^{a \times k}$.
- $F_3$ - The least squares error term for the decomposition of the 2-dimensional symmetric matrix S (containing the Activity - Activity correlation information) into the factor matrices A $\in \mathbb{R}^{a \times k}$ and its transpose $A^\top \in \mathbb{R}^{k \times a}$.
- $F_4$- The least squares error term for the decomposition of the 2-dimensional symmetric matrix Z (containing the Location - Location correlation information) into the factor matrices L $\in \mathbb{R}^{l \times k}$ and its transpose $L^\top \in \mathbb{R}^{k \times l}$.
- $F_5$ - Regularization term for temporal smoothing. It leverages the fact that human behavior in successive time periods will be similar and will have a gradual variation. Hence, it tries to reduce the error between consecutive time slots. R is a bi-diagonal matrix $\in \mathbb{R}^{k \times k}$ with 1 on the main diagonal and -1 on the diagonal above it.
- $F_6$ - Regularization term to avoid overfitting.
- $\lambda_1$ - $\lambda_5$ are model parameters.
- $\|\|^2$ denotes the Frobenius norm, ∘ denotes the outer product

In general, there is no closed form solution for F, so we use numerical methods, such as gradient descent, to solve this problem. By using the representations in [19], we take the first order derivatives of F with respect to each of the factors to get the following:

**Algorithm 3:** Gradient descent based algorithm

**Input**: Sparse tensor X$\in \mathbb{R}^{u \times l \times a \times t}$, 2 D matrices Y $\in \mathbb{R}^{l \times a}$, Z $\in \mathbb{R}^{l \times l}$, S $\in \mathbb{R}^{a \times a}$, *k* and convergence criteria
**Output**: Complete tensor M $\in \mathbb{R}^{u \times l \times a \times t}$
**for** *n = 1:size(X)* **do**
  Initialize U, L, A, T;
**end**
Initialize F, $\nabla_U$F, $\nabla_L$F, $\nabla_A$F and $\nabla_T$F;
Set *i* = 0;
**while** *not converged* **do**
  Compute step length $\alpha_i$;
  Compute the gradients $\nabla_U F_i$, $\nabla_L F_i$, $\nabla_A F_i$, $\nabla_T F_i$;
  $U_{i+1} = U_i - \alpha_i \nabla_U F_i$, $L_{i+1} = L_i - \alpha \nabla_L F_i$, $A_{i+1} = A_i - \alpha \nabla_A F_i$, $T_{i+1} = T_i - \alpha \nabla_T F_i$;
  Compute $F_{i+1}$;
**end**
M ← U ∘ L ∘ A ∘ T;
**return** *M;*

$\nabla_U$F= ($W^{(1)}$ - $X^{(1)}$)(T ∗ A ∗ L) + $\lambda_5$U

$\nabla_L$F= ($W^{(2)}$ - $X^{(2)}$)(T ∗ A ∗ U) + $\lambda_1$( $LA^\top$ - Y)A + $\lambda_3$(- Z - $Z^\top$ + 2L$L^\top$)L + $\lambda_5$L

$\nabla_A$F= ($W^{(3)}$ - $X^{(3)}$)(T ∗ L ∗ U) + $\lambda_1$( $LA^\top$ - Y)$^\top$L + $\lambda_2$(- S - $S^\top$ + 2A$A^\top$)A + $\lambda_5$A

$\nabla_T$F= ($W^{(4)}$ - $X^{(4)}$)(A ∗ L ∗ U) + $\lambda_4$TR + $\lambda_5$T

where $W^{(i)}$ and $X^{(i)}$ denotes the mode-$i$ tensor unfolding or matricization [7] of W and X such that $W^{(1)}$ and $X^{(1)} \in \mathbb{R}^{u \times lat}$, $W^{(2)}$ and $X^{(2)} \in \mathbb{R}^{l \times uat}$, $W^{(3)}$ and $X^{(3)} \in \mathbb{R}^{a \times ult}$, and $W^{(4)}$ and $X^{(4)} \in \mathbb{R}^{t \times ula}$, and ∗ denotes the Khatri-Rao product.

## 5.4 Minimizing the objective function

We employ Algorithm 3, which uses gradient descent, to minimize F and its gradient G. We implemented it in MATLAB using the Tensor Toolbox [4]. As input, the algorithm takes the incomplete sparse tensor (X), the low dimensional matrices (Y, Z, and S), the number of factors (*k*) as well as the stopping or convergence criteria. The individual components (U, L, A, T) are initialized using the n-mode singular vectors of X which span the subspace of the mode-n fibers i.e. the left singular vectors of the n-mode matricization of X. In each iteration, we first compute the step length using the More-Thuente line-search method [27]. We then compute the values of the gradients for the objective function and the components, and update the objective function value by taking a step in the direction of the gradient. The convergence criteria are set as:

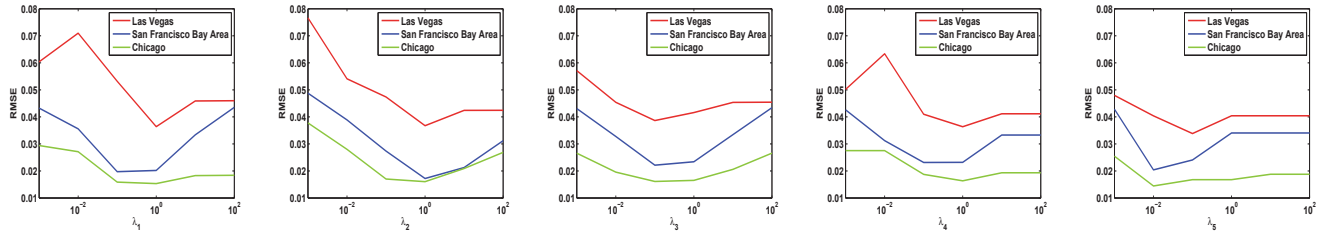
- Relative change in Function Value i.e. $\frac{F_{i+1} - F_i}{F_i} \leq 10^{-10}$
- Relative change in Gradient Value i.e. $\frac{G_{i+1} - G_i}{G_i} \leq 10^{-10}$
- Number of iterations $i \leq 10^5$

Finally, when the algorithm converges, we obtain the complete tensor M $\in \mathbb{R}^{u \times l \times a \times t}$ by taking the outer product of the individual components U, L, A and T.

## 5.5 Extending to N > 4 Dimensions

We note that while we have focused on N=4 dimensions for concreteness, we can extend the model to accommodate additional dimensions, without loss of generality, by performing data engineering and modifying the objective function. For instance, if we add another contextual dimension such as users' purchases, we can supplement the sparse tensors and matrices with User × Purchases or Location × Purchases matrix obtained from another data source.

[7] Matricization is generation of the matrix representation of a tensor in which all column or row matrices are stacked one after another.




(a) RMSE variation for $\lambda_1$ (b) RMSE variation for $\lambda_2$ (c) RMSE variation for $\lambda_3$ (d) RMSE variation for $\lambda_4$ (e) RMSE variation for $\lambda_5$

Figure 4: Variation of RMSE for different values of $\lambda_1$ - $\lambda_5$ on the validation sets

We can then modify the objective function to include the purchases dimension and employ Algorithm 3 to minimize it.

# 6. EVALUATION

## 6.1 Methodology

To evaluate the recommendations produced by our system, we used the following methodology: we randomly split each of the three datasets (from San Francisco Bay Area, Las Vegas and Chicago) into training and testing sets with a 7:3 ratio, where we use the training set for training and tuning the model parameters. We use the held-out test set for computing the performance metrics over the predicted and ground truth values. More formally, we define $P$ to be a test dataset containing $n$ values. For each held out value $\in P$, $y_i$ denotes ground truth value and $\hat{y_i}$ denotes predicted value.

## 6.2 Metrics

We use three standard performance metrics [16] for evaluating the performance of our approach on a test set $P$:

- Root Mean Squared Error (RMSE) - RMSE is computed as $\sqrt{\frac{\sum_{i=1}^{n}(\hat{y_i}-y_i)^2}{n}}$. However, RMSE can be susceptible to large errors and often places more emphasis on them. Hence, we compute Mean Absolute Error (MAE) as well to evaluate the performance of our approach.
- Mean Absolute Error (MAE) - MAE is computed as $\frac{\sum_{i=1}^{n}|\hat{y_i}-y_i|}{n}$. However, both RMSE and MAE may be less appropriate for tasks where a ranked result is returned to the user, who then only views items at the top of the ranking. For this, we compute Normalized Discounted Cumulative Gain (nDCG).
- Normalized Discounted Cumulative Gain (nDCG) - nDCG is commonly used in information retrieval to measure a search engine's performance. A higher nDCG value for a list of search results indicates that more relevant items were ranked higher in the list. In particular, nDCG@p measures the relevance of top p results and is defined as:

  $\text{nDCG@p} = \frac{\text{DCG@p}}{\text{iDCG@p}}$ where $\text{DCG@p} = rel_1 + \sum_{i=2}^{p}\frac{rel_i}{\log_2 rel_i}$,

  iDCG@p is the DCG@p value of ideal ranking list and $\text{rel}_i$ is a relevance value. nDCG ranges from 0 to 1. The higher the nDCG value is, the better a ranking result list is.

## 6.3 Parameter Tuning

We performed parameter tuning via parameter-sweeping experiments on the different training sets. We randomly split each training set into training and validation sets with a 4:1 ratio. We held out the validation set and constructed the model using the training set with different values for the model parameters, $\lambda_1$ - $\lambda_5$, # of factors ($k$) and location grid size $r$. We computed RMSE on the held out validation sets and picked the parameter values that minimized it.

| Grid Size $r$ (m) | RMSE | | |
|---|---|---|---|
| | San Francisco | Las Vegas | Chicago |
| 300 | 0.0217 | 0.0378 | 0.0170 |
| 500 | **0.0213** | **0.0376** | **0.0162** |
| 700 | 0.0222 | 0.0392 | 0.0175 |
| 1000 | 0.0224 | 0.0437 | 0.0186 |

Table 4: RMSE on validation set for various location grid sizes

### 6.3.1 *Impact of model parameters*

For tuning each individual parameter, we set the remaining parameters as 0.00001 in order to reduce their impact on the model performance. We then ran the parameter-sweeping experiments 5 times for each parameter value and averaged the RMSE. Figure 4 shows the variation of RMSE for different values of the model parameters for the 3 validation sets. As evident, the RMSE first increases and later decreases as value of each parameter ( $\lambda_1$ - $\lambda_5$) increases. This is because when a parameter value is too small, the model cannot fully utilize the information from the corresponding matrix. On the other hand, if it is too large, then the information from the matrix will dominate the objective function. After this tuning, we set $\lambda_1 = 1.0$, $\lambda_2 = 1.5$, $\lambda_3 = 0.5$, $\lambda_4 = 1.0$ and $\lambda_5 = 0.02$.

### 6.3.2 *Impact of number of factors*

We varied the number of latent factors ($k$) from 10 to 50. However, we observed that the RMSE did not exhibit significant variation which implies that changing the number of factors did not have a significant impact on performance, as also reported by Zheng et al. [37, 38]. For our experiments, we set $k = 30$.

### 6.3.3 *Impact of location grid size*

Table 4 shows the RMSE for the 3 validation datasets for different location grid sizes. The grid size of 500m has the lowest RMSE for all the validation sets and hence we use that for our experiments. This is also intuitive because recommended locations within a distance of 500m can be easily reached on foot.

Henceforth, all experiments will use the tuned parameter values.

## 6.4 Comparison with Baselines

We compare our approach with 7 state-of-the-art baselines.

### 6.4.1 *Collaborative Filtering baselines*

These baselines exploit similarity on each of the individual dimensions to complete the tensor. They take only the 4 dimensional tensor as input. We implemented 4 CF baselines:

- User-User Collaborative Filtering baseline (UCF) - This baseline exploits the user-user similarity information to fill in the missing entries of the sparse tensor X. In particular, for UCF, we consider CF on each user $\times$ location matrix with respect to each activity and each time slot, on each user $\times$ activity matrix with respect to each location and each time slot, and on each user $\times$ time matrix with respect to each location and

each activity independently. To this end, we matricize X in Mode 1 to generate matrix $X^{(1)} \in \mathbb{R}^{u \times lat}$. We then use Pearson correlation coefficient between the vectors in the matrix to compute pairwise user similarity information. For each user, we compute the weighted average of the top N similar users to predict the missing values.

- Location-Location Collaborative Filtering baseline (LCF) - Similarly, the LCF baseline exploits the location-location similarity information to fill in the missing entries of X. We matricize X in Mode 2 to generate matrix $X^{(2)} \in \mathbb{R}^{l \times uat}$. We use Pearson correlation coefficient between the vectors in the matrix to compute pairwise location similarity information. For each location, we then compute the weighted average of the top N similar locations to predict the missing values.
- Activity-Activity Collaborative Filtering baseline (ACF) - The ACF baseline exploits the activity-activity similarity information to fill in the missing entries of X. We matricize X in Mode 3 to generate matrix $X^{(3)} \in \mathbb{R}^{a \times ult}$. We use Pearson correlation coefficient between the vectors in the matrix to compute pairwise activity similarity information. For each activity, we then compute the weighted average of the top N similar activities to predict the missing values.
- Time-Time Collaborative Filtering baseline (TCF) - Finally, the TCF baseline exploits the time- time similarity information to fill in the missing entries of X. We matricize X in Mode 4 to generate matrix $X^{(4)} \in \mathbb{R}^{t \times ula}$. We use Pearson correlation coefficient between the vectors in the matrix to compute pairwise time similarity information. For each time slot, we then compute the weighted average of the top N similar time slots to predict the missing values.

In these experiments, we set N = 10, since the prediction results do not depend on N significantly as suggested by Zheng et al. [37]

### 6.4.2 Model based baselines

We implemented the standard CP decomposition model which, when applied to our multi-dimensional recommendation problem, has an objective function of the form:

$F = \frac{1}{2}\|X - U \circ L \circ A \circ T\|^2 + \frac{\lambda_5}{2}(\|U\|^2 + \|L\|^2 + \|A\|^2 + \|T\|^2)$

Thus, it takes only the 4 dimensional tensor as input and its objective function has only the tensor decomposition term along with the regularization term. This can be obtained by setting $\lambda_1$ - $\lambda_4$ = 0 in our objective function (see Section 5.3) and replacing the weighted least squares error term with the standard least squares error term in summand $F_1$. We then minimize this objective function using the gradient descent based Algorithm 3.

### 6.4.3 Algorithmic baselines

The 2 algorithmic baselines that we employ are:

- Higher Order Singular Value Decomposition (HOSVD) - We implement the HOSVD approach proposed by Lathauwer et al. [10]. This approach also takes only the 4 dimensional tensor as input. It first matricizes the 4 dimensional User $\times$ Location $\times$ Activity $\times$ Time tensor X along each of the 4 modes to get the matrices $X^{(1)}$, $X^{(2)}$, $X^{(3)}$ and $X^{(4)}$. On each matrix, SVD is applied to compute the low rank approximation: $X^{(i)} = U^{(i)} \cdot S^{(i)} \cdot V^{(i)\top}$ where $1 \leq i \leq 4$.
  The core tensor S is then constructed as:
  $S = X \times_1 {U_{c_1}}^{(1)\top} \times_2 {U_{c_2}}^{(2)\top} \times_3 {U_{c_3}}^{(3)\top} \times_4 {U_{c_4}}^{(4)\top}$
  where ${U_{c_1}}^{(1)\top}$, ${U_{c_2}}^{(2)\top}$, ${U_{c_3}}^{(3)\top}$, and ${U_{c_4}}^{(4)\top}$ are the transpose of the $c_1$-dimensionally reduced $U^{(1)}$, $c_2$ - dimensionally reduced $U^{(2)}$, $c_3$-dimensionally reduced $U^{(3)}$, and $c_4$-dimensionally reduced $U^{(4)}$ matrices respectively.
  Finally, the completed matrix M is obtained as:
  $M = S \times_1 {U_{c_1}}^{(1)} \times_2 {U_{c_2}}^{(2)} \times_3 {U_{c_3}}^{(3)} \times_4 {U_{c_4}}^{(4)}$

| Approach | RMSE | | |
|---|---|---|---|
| | San Francisco | Las Vegas | Chicago |
| Our approach | **0.0197** | **0.0339** | **0.0153** |
| UCF | 0.0324 | 0.0486 | 0.0293 |
| LCF | 0.0336 | 0.0430 | 0.0311 |
| ACF | 0.0333 | 0.0433 | 0.0317 |
| TCF | 0.0319 | 0.0484 | 0.0315 |
| Standard CP | 0.0224 | 0.0427 | 0.0178 |
| HOSVD | 0.0227 | 0.0405 | 0.0175 |
| ALS | 0.0222 | 0.0389 | 0.0173 |

Table 5: RMSE for our approach and baselines on the 3 test sets

| Approach | MAE | | |
|---|---|---|---|
| | San Francisco | Las Vegas | Chicago |
| Our approach | **0.0076** | **0.0179** | **0.0049** |
| UCF | 0.0104 | 0.0314 | 0.0062 |
| LCF | 0.0102 | 0.0310 | 0.0066 |
| ACF | 0.0105 | 0.0323 | 0.0069 |
| TCF | 0.01 | 0.0354 | 0.0065 |
| Standard CP | 0.0095 | 0.0228 | 0.0058 |
| HOSVD | 0.0098 | 0.0239 | 0.0061 |
| ALS | 0.0093 | 0.0218 | 0.0054 |

Table 6: MAE for our approach and baselines on the 3 test sets

  where $c_1$, $c_2$, $c_3$ and $c_4$ are set empirically. Based on the experiments of Nanopoulos [28], we preserve 30% of the information in each matrix.
- Alternating Least Squares (ALS) - In ALS, the objective function is a standard CP formulation and the idea is to solve for each factor matrix, leaving all other factors fixed. We implement the ALS algorithm proposed by Kolda and Bader [19, 20] for the standard CP decomposition (see Section 6.4.2) of our multi-dimensional recommendation problem.

## 6.5 Results

For testing experiments, we held out the test dataset and generated the completed tensor using the training dataset with the tuned parameter values, number of factors *k* (30) and for the optimal grid size (500m). We then computed the RMSE and MAE between the predicted and the ground truth held out values of the test set.

Since we do not have human supplied relevance rankings, we compute nDCG on the held-out known values. We calculated nDCG with respect to each recommendation dimension by fixing the remaining dimensions and computing nDCG on the current dimension. Thus, for each of the held out values in the test set, we first fixed user, location and activity and ranked the time slots in the completed tensor. This ranking was used to calculate DCG (refer to Section 6.2) for time. To compute iDCG for time, we determined the ranking for the ground truth time values. We then calculated nDCG@p (with p = 5) for time. Finally, we averaged the values for all user, location and activity combinations to generate an averaged nDCG@5 for the time dimension. Similarly, we fixed user, location and time values and ranked activities to compute nDCG@5 for the activity dimension and fixed user, activity and time to compute nDCG@5 for the location dimension.

Tables 5, 6, and 7 show the results achieved by our approach as well as the baselines on the 3 test datasets for the 3 performance metrics: RMSE, MAE and nDCG@5. For RMSE and MAE, a lower value signifies superiors performance while for nDCG, a higher value signifies superior performance. For each metric, we ran all algorithms 5 times on each test dataset and averaged the result. Clearly, our approach outperforms these baselines.

| Approach | nDCG@5 for location | | |
|---|---|---|---|
| | San Francisco | Las Vegas | Chicago |
| Our approach | **0.898** | **0.835** | **0.821** |
| UCF | 0.691 | 0.523 | 0.693 |
| LCF | 0.71 | 0.514 | 0.682 |
| ACF | 0.702 | 0.582 | 0.695 |
| TCF | 0.735 | 0.593 | 0.701 |
| Standard CP | 0.685 | 0.453 | 0.651 |
| HOSVD | 0.890 | 0.815 | 0.798 |
| ALS | 0.798 | 0.722 | 0.748 |
| Approach | nDCG@5 for activity | | |
| | San Francisco | Las Vegas | Chicago |
| Our approach | **0.869** | **0.827** | **0.798** |
| UCF | 0.452 | 0.465 | 0.467 |
| LCF | 0.457 | 0.477 | 0.485 |
| ACF | 0.440 | 0.458 | 0.412 |
| TCF | 0.391 | 0.34 | 0.401 |
| Standard CP | 0.341 | 0.314 | 0.393 |
| HOSVD | 0.829 | 0.817 | 0.714 |
| ALS | 0.770 | 0.737 | 0.692 |
| Approach | nDCG@5 for time | | |
| | San Francisco | Las Vegas | Chicago |
| Our approach | **0.833** | **0.832** | **0.807** |
| UCF | 0.581 | 0.612 | 0.605 |
| LCF | 0.563 | 0.605 | 0.567 |
| ACF | 0.541 | 0.609 | 0.575 |
| TCF | 0.593 | 0.632 | 0.582 |
| Standard CP | 0.578 | 0.605 | 0.563 |
| HOSVD | 0.812 | 0.82 | 0.798 |
| ALS | 0.732 | 0.725 | 0.656 |

Table 7: nDCG (for location, activity and time) for our approach and baselines on the 3 test sets

## 6.6 Discussion of Results

As evident from the results, the neighborhood-based Collaborative Filtering baselines exhibit poor performance with respect to all the 3 performance metrics. There are two possible reasons for this result. First, these approaches employ only the User $\times$ Location $\times$ Activity $\times$ Time tensor. Since the tensor is extremely sparse, computing similarity along any dimension will be error prone as most of the entries are missing. Hence, our approach which supplements the sparse tensor with additional information from external sources overcomes this hurdle. Second, each of these baselines predicts the missing values based on similarity along one dimension only, ignoring the other dimensions. Since our problem involves collaborative recommendations along multiple dimensions, it is important to employ all the dimensions for recommendations as we do.

The model based and algorithmic baselines such as Standard CP, HOSVD and ALS also utilize only the sparse tensor as input. As pointed out in Section 2, the standard CP approach demonstrates an increase in error if the data is extremely sparse. Similarly, ALS has poor convergence if the data is sparse and does not scale to large datasets. Moreover, HOSVD and ALS have high space complexity. On the other hand, our approach overcomes the sparsity of the data by supplementing the sparse tensor with coupled matrices and also scales to large datasets. Hence, it outperforms these baselines.

Also, we note that the nDCG values for location varies greatly for each dataset for each algorithm while the nDCG values for activity and time do not exhibit such a high variation. This is possibly because the number of locations in each of the dataset varies significantly while the number of activities and time slots are constant for each dataset. In addition, the nDCG values for location are higher in general for most of the algorithms and datasets, as compared to activity and time. This indicates that location is the most important dimension for recommendation, followed by time and activity. This is also intuitive because in our datasets, each photo has a location and timestamp but $< 50\%$ photos have meta data to enable activity inference. Hence, the activity data is sparser than for location and time. This would affect the performance of all the baselines since they use the sparse tensor as the only input. However, in our approach, we supplement this sparse tensor with additional matrices involving Location, Activity and Time. We also perform regularized temporal smoothing. Hence, the nDCG for Activity and Time are higher and comparable to that of Location for our approach.

| Approach | Time (in seconds) | | |
|---|---|---|---|
| | San Francisco | Las Vegas | Chicago |
| Without weighting | 12000 | 2465 | 10500 |
| With weighting | 9600 | 1180 | 8580 |

Table 8: Runtime comparison

## 6.7 Runtime Comparison

Since our data is very sparse, we performed a weighted decomposition of the tensor which minimizes the error in only the known entries of the tensor. We also experimented without the weighting imposed on the tensor i.e. minimize the error in all the entries of the tensor. In this case, our objective function is:

$F = \frac{1}{2}\|X - U \circ L \circ A \circ T\|^2 + \frac{\lambda_1}{2}\|Y - LA^\top\|^2 + \frac{\lambda_2}{2}\|S - AA^\top\|^2 + \frac{\lambda_3}{2}\|Z - LL^\top\|^2 + \frac{\lambda_4}{2}\|TR\|^2 + \frac{\lambda_5}{2}(\|U\|^2 + \|L\|^2 + \|A\|^2 + \|T\|^2)$

We minimized it using Algorithm 3. Both approaches have the same performance with respect to RMSE, MAE and nDCG@5. However, they differ in their runtime. As shown in Table 8, the weighted approach is faster as it minimizes the loss on only the known entries of the tensor. All experiments were run on a 64 bit Windows machine with core i7 processor and 16 GB RAM.

# 7. CONCLUSION AND FUTURE WORK

In this paper, we presented a system and an approach for performing multi-dimensional collaborative recommendations for Who (User), What (Activity), When (Time) and Where (Location), using tensor factorization on sparse user-generated data. To address the problem of sparsity for multi-dimensional recommendations, we modeled this problem as a joint analysis of a sparsely populated User $\times$ Location $\times$ Activity $\times$ Time tensor along with several matrices which share one or more common modes with the tensor. These tensors and matrices were constructed by fusing data for the various dimensions (users, locations, activities and time) from multiple heterogeneous data sources, namely Flickr, Foursquare, Yelp and Viator. We factorized these tensors and matrices simultaneously using a gradient descent-based algorithm. We evaluated our system and approach on our primary large-scale real-world data set consisting of 588,000 Flickr photos collected from three major metro regions in the USA — San Francisco Bay Area, Las Vegas and Chicago. We compared our approach with several state-of-the-art baselines and demonstrated that it outperforms all of them. Our approach also demonstrated an improvement in runtime without the need for sacrificing performance.

We now plan to create a Hadoop-based pipeline for performing multi-dimensional analytics. We will also work on scaling this approach to larger and more complex real-time datasets. In addition, we plan to analyze the space-time complexity of our algorithms and parallelize them to run on higher-dimensional data. We will also compare our approach more closely with other standards such as CMF and CMTF and evaluate our system's runtime performance against them.

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