

# Discovering Eating Routines in Context with a Smartphone App

Daniel Gatica-Perez

Idiap Research Institute and EPFL

Switzerland

gatica@idiap.ch

Joan-Isaac Biel

Amaris

Switzerland

joanisaac.biel@gmail.com

David Labbe and Nathalie Martin

Nestlé Research Center

Switzerland

david.labbe@rdls.nestle.com

nathalie.martin@rdls.nestle.com

## ABSTRACT

In everyday life, eating follows patterns and occurs in context. We present an approach to discover daily eating routines of a population following a multidimensional representation of eating episodes, using data collected with the Bites'n'Bits smartphone app. Our approach integrates multiple contextual cues provided in-situ (food type, time, location, social context, concurrent activities, and motivations) with probabilistic topic models, which discover representative patterns across these contextual dimensions. We show that this approach, when applied on eating episode data for over 120 people and 1200 days, allows describing the main eating routines of the population in meaningful ways. This approach, resulting from a collaboration between ubiquitous computing and nutrition science, can support interdisciplinary work on contextual analytics for promotion of healthy eating.

## CCS CONCEPTS

- Human-centered computing → Ubiquitous and mobile computing; Ubiquitous and mobile computing design and evaluation methods

## KEYWORDS

Mobile Crowdsensing; Smartphones; Eating Behavior; Routines

### ACM Reference Format:

Daniel Gatica-Perez, Joan-Isaac Biel, David Labbe and Nathalie Martin. 2019. Discovering Eating Routines in Context with a Smartphone App. In *Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2019 International Symposium on Wearable Computers (UbiComp/ISWC'19 Adjunct)*, September 9-13, 2019, London, United Kingdom. ACM, New York, NY, USA, 8 pages. <https://doi.org/10.1145/3341162.3349297>

## 1. INTRODUCTION

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [Permissions@acm.org](mailto:Permissions@acm.org).

*UbiComp/ISWC '19 Adjunct*, September 9-13, 2019, London, United Kingdom  
© 2019 Copyright is held by the owner/author(s). Publication rights licensed to ACM.

ACM ISBN 978-1-4503-6869-8/19/09...\$15.00  
<https://doi.org/10.1145/3341162.3349297>

Understanding patterns of food consumption in everyday life is fundamental to support healthy eating practices. This is critical given the increase of health problems worldwide related to overweight and obesity [20]. As other human activities, eating is structured around routines. Furthermore, eating is influenced by contextual factors including time, location, physical status, and social factors [5]. In nutrition science, research on eating routines has made progress towards understanding what these factors are and how they affect eating behavior [11], using small samples of participants and time-consuming methods to document eating practices, e.g. phone and face-to-face recall interviews. On the other hand, mobile computing has shifted practices in the behavioral sciences for field data collection and analysis. For food research, many mobile diary apps exist with increasingly analysis capabilities [21], [7]. In this paper, we present an approach to discover daily eating routines. Our contributions are the following. First, we build upon the eating episode framework originally proposed in nutrition science [5]. Individual episodes are represented holistically by integrating multiple contextual cues, including food type, time, location, social context, concurrent activities, and motivations. This data is captured through Bites'n'Bits, a mobile sensing app where people document their daily food intake, while context is captured through a combination of manual input and phone sensing [4]. Second, we use probabilistic topic models [6] as a flexible model to extract daily eating routines, where mobile data is used to represent patterns of context at the eating episode level. We show how this framework can extract different kinds of daily routines for 122 university students over 1208 days of daily life. The extracted routines are meaningful and could be used as a module of future tools for promotion of healthy eating.

The paper is organized as follows. We discuss previous work in Section 2. We introduce the Bites'n'Bits smartphone app and data in Section 3. The topic model framework for eating routine discovery is presented in Section 4. We present and discuss the results in Section 5, and conclude with final remarks in Section 6.

## 2. RELATED WORK

Eating is more than the food we consume. In nutrition science, this was conceptualized by [5] through *eating episodes*, a framework that resembles how context has been studied in ubiquitous computing [8]. Eating episodes are defined according to eight dimensions, including food/drink type and amount, time, location, social setting, concurrent activities, mental processes

like motivations, physical condition, and recurrence [8]. This holistic framework was developed to understand how individuals guide their own food choices according to personal and professional constraints. Methodologically, this work used a combination of face-to-face and phone interviews to obtain reports of eating episodes (24-hour recall) through manual transcription and content analysis of interviews. The methodology, while clearly time-consuming for researchers, demonstrated its utility to generate multifaceted descriptions of single eating episodes.

A second development in nutrition science was the *eating routine* framework [11], which builds upon eating episodes to add the regularity and adaptability of eating over time. Eating routines account for all dimensions of eating episodes in complex co-occurrence patterns. Routines involve the repeated consumption of certain foods in specific contexts (e.g. eating cereal daily in the early morning) or only in subsets of contexts (e.g. eating cereal in the early morning only when at home). They also involve the recurrence of certain contexts with variations of the food eaten (e.g. daily family dinner at 7pm with a varied menu), and the dynamic adaptation of eating to real life perturbations (e.g. switching family dinner to 8pm whenever work of one parent ends late). The eating routine framework is attractive for machine learning, as it conceptualizes eating practices as multidimensional sequences, possibly recurrent for individuals and groups of individuals, while allowing for within- and across-subject differences. We show that topic models can discover the eating routines of a population with an app in which instead of lengthy personal interviews about food recall, data is collected *in situ* by a combination of sensing and active contributions by app users.

In parallel, ubiquitous computing has developed detectors of *eating moments*, i.e., the ‘when’ and ‘what’ dimensions of an eating episode as defined in [5]. Two motivations have driven this research. The first one is the creation of tools to support *in-the-wild* research in nutrition, which in addition to recall interview techniques as described previously, has been complemented by food diaries [21], [7]. Recognizing eating moments could reduce human burden and non-compliance involved in food diaries. The second motivation is the development of personal systems to detect eating moments and take actions related to self-monitoring and promotion of behavioral change [1].

State-of-the-art methods for recognition of eating moments include the use of accelerometer and inertial sensors on custom-made devices or smartwatches to capture wrist activity [9], [17], and head activity [2]. These methods perform fine-grained temporal feature extraction and classification, defining the inference task as a binary, eating/non-eating moment classification problem. Other work uses combinations of audio and motion sensors placed on head and hands [14] or computer vision [13] to identify the food type. Recent work has also explored the recognition of the social context of eating during family meals [3], using motion and sound features derived from smartphones and smartwatches. In contrast, we are interested in automatically discovering daily eating routines following the

multidimensional representation of eating episodes, including food type, time, location, social context, concurrent activities, and motivations, which are provided by people at the moment of documenting their daily intake through the app. Our work could benefit in the future from the rapid progress on automatic recognition of the various contextual dimensions of eating.

### 3. THE BITES’N’BITS SMARTPHONE APP

We designed the Bites’n’Bits study, first presented in [4], to collect everyday eating data from a population of Swiss university students, through a smartphone application and a Fitbit Flex device (Figure 1). The app collected eating episodes as conceptualized in [5] for both iOS and Android smartphones. We asked participants to document all food and drink intake during 10 consecutive weekdays (no weekends). This included photos of consumed meals and snacks; a short survey for each meal or snack asking about location, social setting, concurrent activities, motivations for eating (only for snacks); and physical activity measures from the Fitbit wristband. The data was timestamped and geolocalized.



**Figure 1:** Top: The Bites’n’Bits app: *in-situ* collection of eating episodes. Center: Physical activity in the bag-of-words representation. Sedentary and lightly active are the predominant labels. Bottom: Eating occasion types (meals and snacks) in the bag-of-words representation.

People were free to define how to label their own food intake. We used a basic meal vs. snack binary categorization, rather than labels like breakfast, lunch, or dinner, as this construct itself has a contextual component [19], including factors like time and location [12]. For snack eating motivations, we used a shortened version of the Eating Motivation Survey (TEMS) listing motivations for eating (49 items) [15], and asked users to report when a snack was planned, and where/when it was bought.

The app was piloted through several iterations to find a tradeoff between user compliance and burden. In the app, users could also report forgotten meals/snacks at any time, and were asked to complete a short end-of-day survey. A day of data collection took on average 30 minutes. Finally, at the time of signup and exit, additional questionnaires were collected for each participant. This included demographic data; a battery of instruments used in nutrition science to characterize food intake frequency, taste preferences, and emotional factors for eating; and a few questions related to overall eating habits and experience with the phone app.

The data collection campaign was run with 122 EPFL students, who had a degree of homogeneity with respect to age (mean: 20.6 years-old, SD:1.69), background (participants were French speaking, with at least five years living in Switzerland), and with no dietary restrictions due to health conditions or eating regimes. Gender was imbalanced (35% female), reflecting the gender distribution of the technical university. The cohort produced a total of 1208 days of reported eating episodes, including 3414 meal episodes, 1034 snack episodes, 5097 photos, and 998 days of physical activity. Details can be found in [4] and <https://www.bitesnbits.org>. As a point of comparison, the original study on eating episodes and routines [5], [11] involved 42 subjects reporting their intake for seven consecutive days, for a total of 1448 eating/drinking episodes, so the Bites'n'Bits data contains roughly three times more participants and episodes collected in-situ. Finally, in a separate stage, all photos were manually coded using an online tool with respect to 14 food and drink categories (including beverages, bread & cereal, dairy products, eggs, fish, fruits, legumes & starches, meat, pastries, salty snacks, seasoning, sweets, vegetables).

## 4. PROBABILISTIC TOPIC MODELS TO DISCOVER EATING ROUTINES

### 4.1 TOPIC MODELS

Probabilistic topic models like Latent Dirichlet Allocation (LDA) are generative methods developed for text mining, i.e., to discover latent themes in an unstructured collection of documents based on word co-occurrence [6]. The idea behind LDA is that text documents represented by the standard bag-of-words model are mixtures of topics, i.e., of distributions defined over the dictionary of words available in the document collection. To generate document  $d$  in a collection of  $D$  documents, every word  $w_{d,n}$  in the document is produced by first drawing a topic  $z_{d,n}$  (from a set of  $K$  possible topics) from a per-document mixture over latent topics  $\theta_d$ , and then by sampling the conditional distribution of words for such topic,  $\beta_k$ . The joint

distribution is:  $p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1:K} p(\beta_i) \prod_{d=1:D} p(\theta_d) (\prod_{n=1:N} p(z_{d,n} | \theta_d) p(w_{d,n} | \beta_{1:K}, z_{d,n}))$ . Given the observed data ( $w_{d,n}$ ), LDA inference corresponds to approximating the posterior distribution of latent variables given the observations  $p(\beta_{1:K}, \theta_{1:D}, z_{1:D} | w_{1:D})$ . This is done via sampling methods or variational methods, which allows estimating the topic distributions and the per-document topic proportions.

In ubiquitous computing, topic models have been used to discover patterns in sequential data. This includes activities like walking or driving from accelerometer data [18], and recurrent patterns of place visits from mobile phone network data [10]. The successful use of LDA to extract routines depends on a careful definition of the different elements of the model. In our case, we first treat days of single users as documents; we then define a number of bag-of-words models in which the contextual cues from eating episodes are treated as the words of a document. Finally, with this definition, topics will correspond to eating routines.

### 4.2. FROM TOPICS TO EATING ROUTINES

With days in the lives of users as the unit of analysis, a key definition is the bag-of-words model to represent eating episodes in a day. One challenge is that episodes are sparse, as they occur only a few times a day. This is in contrast to other ubicomp datasets for each data is available at higher sampling rates [18].

Time	
Time slots (9)	<06:00; 06:00-08:30; 08:30-11:00; 11:00-13:30; 13:30-16:00; 16:00-18:30; 18:30-21:00; 21:00-23:30; >23:30
Eating occasion	
Occasion type (2)	meal; snack
Where (10)	home; EPFL; student residence; restaurant; etc.
With whom (4)	alone; alone in crowd; with someone; with a group
Social link (4)	friends; colleagues; partner; family
What else (18)	commuting; using phone; working; socializing; etc.
Physical activity	
Activity level (4)	sedentary; lightly active; mildly active; fairly active
Snacking	
Type of snack (5)	drink, fruit; pastries & sweets; bread; other
Where bought (7)	bakery; cafeteria; supermarket; snack machine; etc.
When bought (3)	now; yesterday; earlier
When planned (4)	now; yesterday; earlier; routine
Motivations (20)	convenience; habits; health; liking; pleasure; etc.

**Figure 2. Contextual data used for the creation of eating occasion words, physical activity words, and snacking words. The number of possible values for each attribute appears in parentheses. All words also include a time slot.**

We created a bag model using the data for all eating episodes in a user-day. We first divided the day in 9 timeslots as shown in Figure 2. This choice included typical meal periods: 06:00-08:30, 11:00-13:30, and 18:30-21:00, and other slots for the rest of the day. This time representation helps to compensate for variations in eating behaviors that tend to occur daily at similar times, e.g. "having a meal at 12:40" or "having a meal at 13:00" are considered as similar behaviors. In a second step, we created words by combining the contextual information of each eating occasion with the timeslot information for the different types of data. We defined three bag models that make use of different data types to study the variety of daily representations that can be expressed from eating episodes.

**Bag model 1: eating context words.** We created words for each eating occasion by concatenating the categorical responses associated to each contextual dimension with their corresponding timeslot. For example, for a snack taking place at 08:35 at EPFL, alone and while working, we created four words: *snack-08:30-11:00*, *alone-08:30-11:00*, *EPFL-08:30-11:00*, and *working-08:30-11:00*. Note that defining words in this way (instead of creating joint multiple-context words) allows generating documents with more words, which helps with data sparsity. Figure 1 (bottom) illustrates the distribution of meal and snack words for all timeslots. With this procedure, we created a collection of 1208 documents (one for each user-day) and a vocabulary of 250 words. The vocabulary size was reduced after discarding words appearing in less than 10 documents.

**Bag model 2: physical activity words.** We also created words considering the four physical activity levels estimated by Fitbit (sedentary, lightly active, fairly active, and very active). These values are directly provided by the device, and are available at the minute level. To avoid an explosion in the size of the vocabulary, we processed this data to create words with similar frequency to the eating episodes. First, we assigned an activity level representing each time slot as follows. For each of the 9 time slots, we added up the minutes spent on each activity level, discarding activity levels that lasted less than 15 minutes, and then choosing the activity level that lasted the longest. This procedure was chosen to improve the diversity of physical activity words, as the amount of time spent in sedentary activity in the Bites'n'Bits data is high. Second, we created one physical activity word per timeslot by concatenating the activity level with the corresponding timeslot. Finally, we considered physical activity words only for timeslots for which there was an eating episode. Figure 1 (center) shows the distribution of physical activity level words for all timeslots. Words *sedentary<06:00*, and *sedentary>23:00* were filtered as they typically correspond to sleeping.

**Bag model 3: snacking words.** We also created additional words from data only available to snacking occasions, including Type of snack, Where-bought, When-bought, When-planned, and Motivations. From the snack photo annotations, we choose the most frequent snacking types categories among the 14 food and drink categories (pastries and sweets (27%), drinks (30%), fruits (17%), bread (6%), and a fifth category for other snacks), to

create words. For Where-bought, When-bought, and When-planned, we considered the categorical responses of participants. For Motivations, we used the dimensions of our TEMS-modified survey to create one word per snack motivation.

**Inference and model selection.** For LDA inference, we used Gibbs sampling for approximate inference. Gibbs sampling requires specifying the parameters  $\alpha$  and  $\delta$  of the Dirichlet prior distributions (that control the priors for  $\theta$  and  $\beta$ ). Many works report using  $\alpha=50/K$  and  $\delta=0.1$ . However, by inspecting the likelihood of the trained models, the perplexity obtained through cross-validation, and the output of the models, we found it appropriate to use smaller  $\alpha$  values ( $\alpha = 0.5/K$ ) to modify the mean shape and sparsity of  $\theta$  [6]. The motivation for using a lower  $\alpha$  is guided by the assumption that days of users are composed of a small number of topics. The number of topics  $K$  was set by evaluating the perplexity of the model on held-out data, using cross-validation for a range of values of  $K$  and 1000 iterations of Gibbs sampling. This procedure results in a choice of  $K = 25$  for bag models 1 and 2, and  $K=16$  for bag model 3.

## 5. RESULTS AND DISCUSSION

We now describe the routines extracted for each of the three bag models (eating context, physical activity, snacking), and discuss the implications and limitations of our work.

### 5.1 ROUTINES FROM BAG MODEL 1: EATING CONTEXT

By inspecting the most likely words of each topic (i.e., the most likely contextual dimensions), we can describe the main routines emerging from the data. Figure 3 summarizes the learned topic representation, and Figure 4 lists the top-10 most likely words sorted in descending order for three of the topics.

For example, Topic 1 reflects an eating routines of having 3 meals a day at 06.30-08.30, 11.00-13.00, 18.30-21.00, the three of them at home, but with differences regarding the social context ('alone-social-social' indicates alone in the morning meal, social in the midday meal, and social in the evening meal; a similar notation is used for the other topics).

Topics vary in the number of timeslots they involve. As shown in Figure 3 (column Timeslots), twelve topics correspond to sequences of three meal occasions at different timeslots. Topics 1, 2, and 3 differ by the specific combination of social setting for the three meals (alone or social), showing that LDA is capable of capturing these contextual differences. In addition, three topics correspond to sequences of two eating occasions at different timeslots: one of them corresponds to two meals, and the other two topics correspond to a mix of meal and snacks. Finally, ten topics correspond to single eating occasions (five for snacks and five for mixed meal and snack).

To further understand the discovered routines, we analyze the structure of the topics by computing the Jensen-Shannon distance between the term distributions of topics, and plotting the PCA decomposition of these differences with LDAVis [16]. Such visualization shows that semantically similar routines are brought together. Second, for each topic we compute the average ranking of the top three words related to each contextual

dimension as defined in Figure 2. We show these rankings in Figure 5. This procedure allows seeing what contextual features are more relevant for each topic. For instance, for Topic 1 the top rank (i.e., the lowest value) is for Eating Occasion Type (purple bar), while Where (blue bar) and With Whom (green bar) have the same rank.

Topic (P(z))	S	Description
1 (.07)	3	Meals @ 06:00-08:30, 11:00-13:30 & 18:30-21:00, home / alone-social-social
2 (.06)	3	Meals @ 06:00-08:30, 11:00-13:30 & 18:30-21:00, home / social-social-social
3 (.07)	3	Meals @ 06:00-08:30, 11:00-13:30 & 18:30-21:00, home / alone-social-alone
11 (.04)	3	Meals @ 08:30-11:00, 11:00-13:30 & 18:30-21:00, home / alone-social-social
19 (.03)	3	Meals @ 06:00-08:30, 11:00-13:30 & 18:30-21:00, student residence / alone-alone-alone
6 (.06)	3	Meals @ 08:30-11:00, 11:00-13:30 & 18:30-21:00, home / alone-alone-alone
4 (.06)	3	Meals @ 08:30-11:00, 11:00-13:30 & 18:30-21:00, home / alone-social-social
8 (.05)	3	Meals @ 08:30-11:00, 11:00-13:30 & 18:30-21:00, home / alone - EPFL / social - home /alone
9 (.05)	3	Meals @ 08:30-11:00, 11:00-13:30 & 18:30-21:00, home / alone-alone-social
5 (.06)	3	Meals @ 06:00-08:30, 11:00-13:30 & 21:00-23:30, home / alone-social-alone
10 (.04)	3	Meals @ 06:00-08:30, 11:00-13:30 & 21:00-23:30, home / alone-social-social
17 (.03)	3	Meals @ 06:00-08:30, 11:00-13:30 & 21:00-23:30, home / alone-alone-alone
13 (.04)	2	Meals @ 08:30-11:00, 11:00-13:30, social - EPFL / social
12 (.03)	2	Meal @11:00-13:30, Snack @ 16:00-18:30, EPFL / social-social
7 (.05)	2	Snack @ 08:30-11:00, Meal @ 11:00-13:30, EPFL / social-social
23 (.02)	1	Meal & Snack @ 21:00-23:30, home / alone
15 (.03)	1	Meal & Snack @ 21:00-23:30, home / social
24 (.02)	1	Snack @ 18:30-21:00, EPFL/social
25 (.02)	1	Snack @ 16:00-18:30, EPFL/alone, working
20 (.03)	1	Meal & Snack @ >23:30, home / alone
16 (.03)	1	Snack @ 16:00-18:30, EPFL/social
21 (.02)	1	Snack @ 16:00-18:30, home/alone
18 (.03)	1	Meal & Snack @ 13:30-16:00, alone
14 (.03)	1	Snack @ 13:30-16:00, EPFL/social
22 (.02)	1	Meal & Snack @ 13:30-16:00, socializing

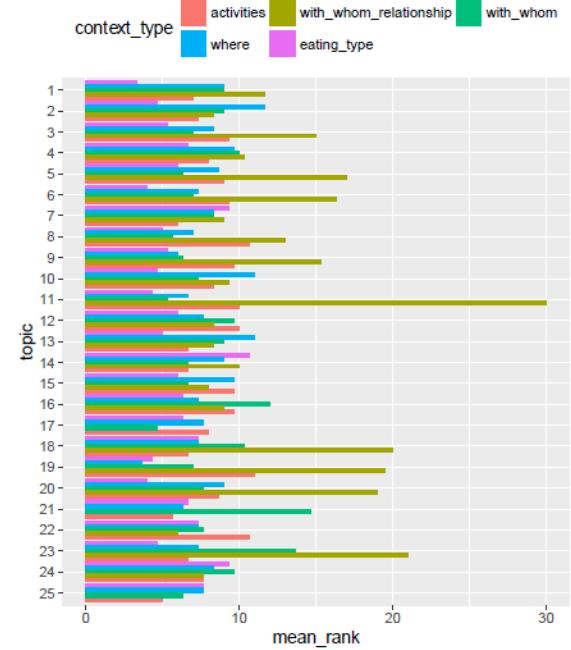
**Figure 3. Topics extracted for bag model 1 (eating context).** S denotes the number of time slots characteristic of the topic, and P(z) denotes the probability of each LDA topic.

Topics are mostly described by words associated to the Eating Occasion Type (meal or snack), the location (Where), and the social context (With Whom), and less so by words related to With Whom Relationship (olive green bar) or to What Else Activities (red bar). Words related to the Eating Occasion Type averaged 6.0 in the ranking of most likely words across all topics,

whereas words related to Where averaged 8.1; With Whom words averaged 8.3; With Whom Relationship averaged 12.0; and What Else Activities averaged 8.1. In the case of What Else, recomputing the ranking without considering ‘socializing’ (one of the What Else activities strongly associated to the social setting) gives an average rank of 13.0, showing that concurrent activities themselves do not drive much of the routine decomposition.

Topic	Top 10 words
1	meal@18:30-21:00; socializing@18:30-21:00; meal@06:00-08:30; alone@06:00-08:30; home@06:00-08:30; meal@11:00-13:30; home@18:30-21:00; socializing@11:00-13:30; with a group@18:30-21:00; with friends@11:00-13:30
17	alone@11:00-13:30; nothing else@11:00-13:30; meal@11:00-13; alone@06:00-08:30; home@06:00-08:30; meal@06:00-08:30; home@11:00-13:30; nothing else@06:00-08:30; alone@21:00-23:30; meal@21:00-23:30
19	student residence@18:30-21:00; student residence@06:00-08:30; meal@18:30-21:00; meal@06:00-08:30; alone@06:00-08:30; meal@11:00-13:30; alone@11:00-13:30; student residence@11:00-13:30; alone@18:30-21:00; nothing else@06:00-08:30

**Figure 4. Selected topics and top 10 words per topic for bag model 1 (eating context).**



**Figure 5. Average ranking of the top-3 words for each contextual dimension for each one of the 25 topics.**

The importance of each contextual dimension varies across topics. This result concurs with the key findings in [11] in that eating routines may be driven by few or many contextual dimensions. For example, as shown by combining Figure 3 and Figure 4, Eating Occasion Type words such as *meal18:30-21:00*,

*meal06:00-08:30*, or *meal11:00-13:30* have an average ranking of 3.3 in Topic 1, indicating that the topic is better described by this contextual dimension, compared to others such as Where or With Whom (both with average ranking 9.0). For Topic 19, words such as *student\_residence18:30-21:00*, *student\_residence06:00-08:30*, and *student\_residence11:00-13:30* have average ranking of 3.6, compared to Eating Occasion Type words (average ranking 4.3) and With Whom words (average ranking 7).

An attractive aspect of our framework is that individuals can be represented using their topic distribution. Figure 6 shows the ten days of one participant and the topic distribution of the latter and of another participant, obtained by averaging the distributions of topics across all days of each user. The participant on Figure 6 (top) shows consistency as two routines are needed to describe her/his days (Figure 6, center), compared to the participant on Figure 6 (bottom), whose days are represented as a mixture of several topics. To estimate the number of topics required to represent a day (resp. a person), we estimate the minimum number of topics accounting for 0.8 of the probability mass of the distribution associated to that day (resp. person). Figure 7 shows the histogram of topics required to describe all days and people. On average, two topics are needed to describe a day and seven topics to describe a person, respectively. An alternative measure is the entropy of each person. This is a first step towards future longitudinal studies in which the topic representation could be used to examine consistencies or variations of individual routines over longer time.

## 5.2 ROUTINES FROM BAG MODEL 2: PHYSICAL ACTIVITY

The description of topics for the model that incorporates physical activity to the eating context shows that 21 out of 25 topics are essentially equal to those of bag model 1, with the addition of patterns of light physical activity (not shown for space reasons). The occurrence of light physical activity could correspond to going for meals in campus or commuting time, which many students in the population do via public transportation. All topics show light physical activity; this is not surprising given the statistics of physical activity in Figure 1 (bottom), largely biased towards sedentary or light activity. We hypothesize that weekend periods (in addition to weekdays-only as done in the Bites'n'Bits data) could have resulted in more variability of physical activity to be captured by the topic representation.

## 5.3 ROUTINES FROM BAG MODEL 3: SNACKING

The topic distribution ( $K=16$ ) is shown in Figure 8. Topics are organized according to their timeslots, and then by the contextual cues, which include Snack Type, Where-bought, When-bought, When-planned, and Motivations, as described in Section 4, in addition to location and social context.

Topics capture the expected timing of snacking: four topics (1, 8, 4, 12) for the mid-afternoon (16:00-18:30); and two topics (2, 3)

for the early afternoon (13:30-16:00). There are other topics throughout the day. This is also visible in the temporal snacking statistics in Figure 1 (bottom right), where 16:00-18:30 and 13:30-16:00 are the most common times for snacking, yet other timeslots also contain snacking. Interestingly, the topics do not capture a differentiated pattern regarding the five snack categories defined in Section 4.

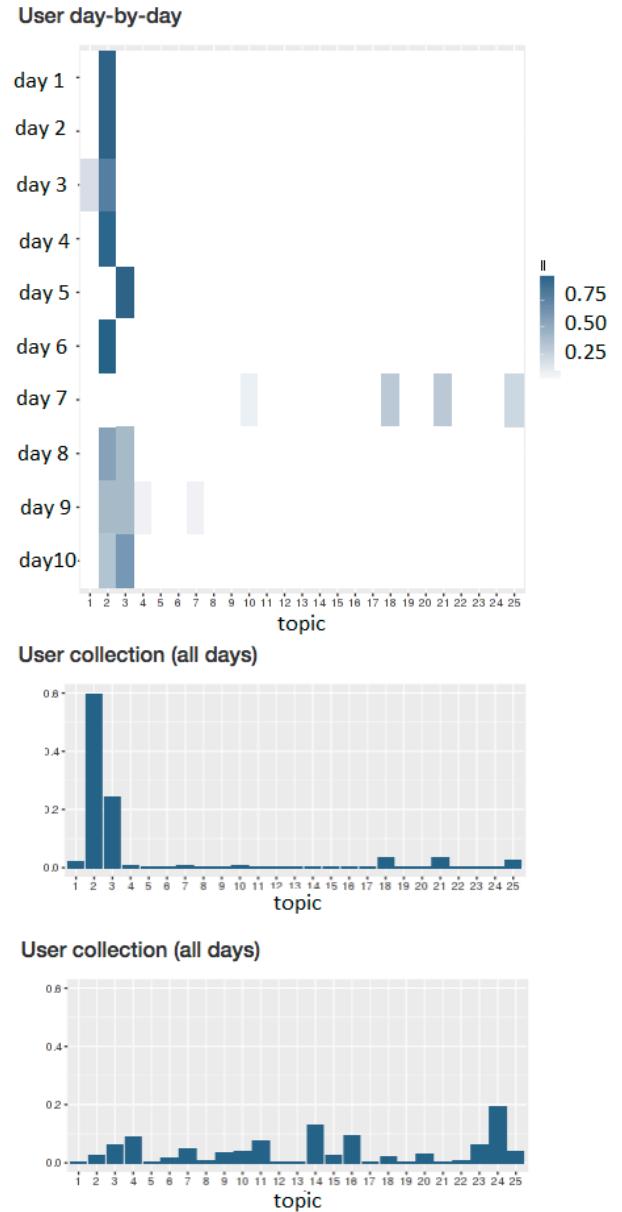
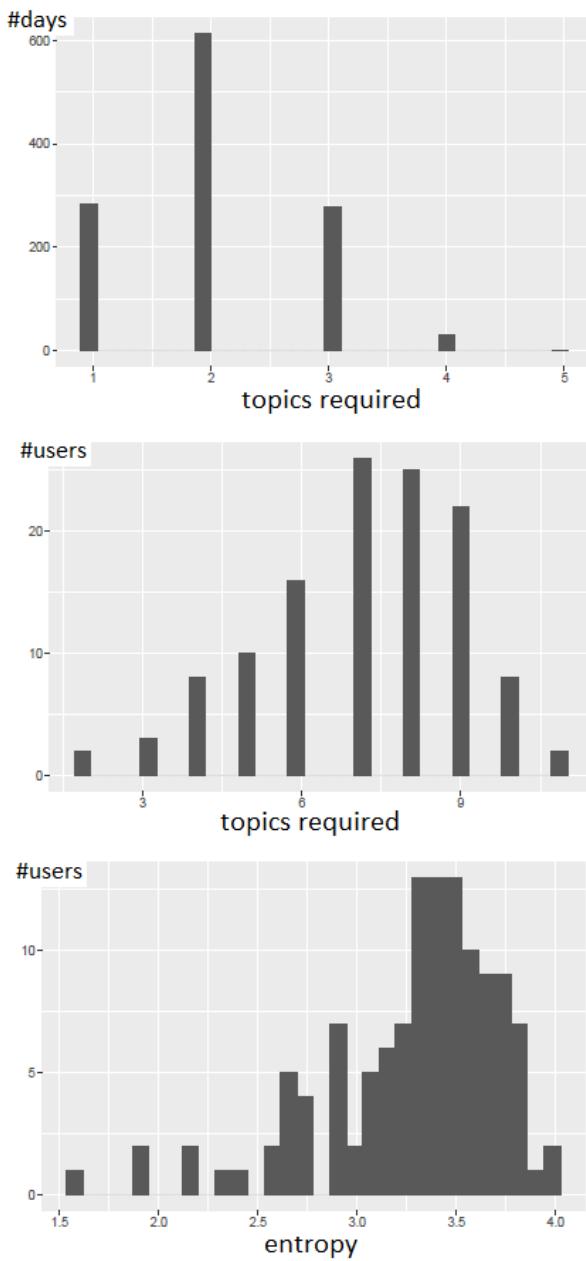


Figure 6. (Top): Topic distribution per day for a Bites'n'Bits user over 10 days; probability values are shown in blue. (Center): Topic distribution for the same user. The user is represented by a few routine topics (Bottom): Topic distribution of a second user, whom requires a larger number of topics. The first user displays more routine eating behavior.



**Figure 7. Histogram of topics per day (top) and per person (center), and histogram of entropy per person (bottom).**

For a given time, topics can capture differences in social context: compare *home alone* in topic 4 vs. *social* in topic 8; or the same pattern for topics 5 (*social*) and 9 (*home alone*), but for a different time than for topics 4 and 8. Topics 7 and 13 capture a pattern on late snacking at home (after 21:00). On the other hand, Topic 15 captures a pattern of early morning snacking (06:00-08:30). We hypothesize that this could be due to how people chose to label their own intake using context [19], [12]. For instance, some people could have labeled a pastry in this timeslot as breakfast, while other people could have labeled it as a snack.

Regarding Where-bought, the supermarket option dominates the representation. Regarding When-bought, different patterns are captured for the same timeslot, e.g. *bought\_yesterday* in Topic 4 vs. *bought\_now* in Topics 1 and 8. With respect to When-planned patterns, we see that the *planned\_now* appears in 11 out of the 12 topics for which planning words are representative. The exception is Topic 12, where *planned\_routine* appears with both *bought\_yesterday* and *habits* motivation, which suggests a rather different trend.

Finally, regarding motivations, *liking* is represented in 13 topics; *pleasure* and *health* are represented in 5 and 4 topics, respectively; *habits* is represented in 2 topics; and *need* and *convenience* are represented in 1 topic each. Unsurprisingly, for all 5 topics for which *pleasure* appears as a top word, *liking* also appears as a top one. Topic 10 includes *health* with a possible element of planning (*bought\_yesterday*). Finally, a distinct topic is Topic 14, represented mainly by motivations. Overall, these results illustrate the versatility of the topic formulation.

Topic	Timeslots & Description
1	16:00-18:30; planned now; bought in supermarket; pleasure; liking; bought now
8	16:00-18:30; bought in supermarket; liking; planned now; bought now; social
4	16:00-18:30; alone; bought in supermarket; bought yesterday; planned now; home
12	16:00-18:30; pleasure; habits; liking; bought yesterday; planned routine
2	13:30-16:00; planned now; EPFL; liking; bought in supermarket
3	13:30-16:00; bought in supermarket; bought yesterday; liking; pleasure; health; planned now
10	08:30-11:00; bought in supermarket; planned now; alone; bought yesterday; health
6	08:30-11:00; bought in supermarket; planned now; EPFL; liking; bought now
5	18:30-21:00; liking; bought in supermarket; pleasure, social
9	18:30-21:00; bought in supermarket; home; planned now; alone; liking
7	21:00-23:30; liking; bought in supermarket; home; pleasure
14	21:00-23:30; habits; liking; need; convenience; health
15	06:00-08:30; liking; bought in supermarket; planned now; bought now; alone
13	>23:30; alone; home; liking; planned now
11	11:00-13:30; liking; planned now; bought in supermarket; health; social
16	11:00-13:30; EPFL; bought earlier; bought in supermarket; social

**Figure 8. Summary description of topics extracted for bag model 3 (snacking).**

## 5.4 IMPLICATIONS AND LIMITATIONS

At a time when commercial food diary phone apps are flourishing, (MyFitnessPal, SeeHowYouEat, or MyPlate to name a few), it is pertinent to ask what routine representations can bring in terms of added value. One of the main advantages of the topic model formulation is its inherent interpretability. One could envision a routine representation running on top of individual episodes, offering contextualized information about eating with respect to time, location, social context, and motivations, and supporting users in their reflective and decision-making processes. Importantly, discovering routines requires longitudinal data. We showed that two weeks of data per individual allowed learning basic routine models for the cohort. Individual-based models would require collecting data over longer periods, and thus call for engagement mechanisms, which is a well-known challenge of food diary apps [21], [7].

Regarding limitations of our work, a first one comes from having collected weekday-only data. Weekend periods could have resulted in larger variability of both physical activity (e.g. outdoor sports) and eating practices. We observed that besides indicating light physical activity, the extracted bag model 2 routines were the same as the routines extracted for bag model 1. A second inherent limitation has to do with extracting routines that correspond to university students. This is a main difference with respect to the original studies on eating episodes and eating routines, which researched other adult populations [5] [11]. This said, our methodology is general and we expect it to be applicable to data from diverse populations. Finally, LDA is the simplest model in a family of methods that could infer more detailed aspects. For instance, we could use Hierarchical Dirichlet Processes to estimate automatically the number of routines as part of the learning process, which in LDA is done in a separate step. An empirical comparison of the routines extracted by LDA and other methods would be necessary.

## 6. CONCLUSIONS

Based on a collaboration between ubiquitous computing and nutrition science, we presented a framework to discover daily eating routines from real-world data collected from 122 university students via the Bites'n'Bits smartphone app. Following a multidimensional representation of eating episodes, including eating occasion type, time, location, social context, concurrent activities, and motivations, LDA was used to extract daily routine patterns for three bag-of-word models: context, context and physical activity, and a contextual description of snacking episodes. The discovered routines are meaningful, consisting of two daily meals and three daily meals at specific time slots, locations, and social context, along with other patterns specialized on snacks or mixed meal/snack consumption. The results illustrate how topic models can help operationalize the extraction of eating routines in a flexible way, appealing to conceptual models of real-life eating behavior from nutrition science, and formalizing everyday eating as a probabilistic mixture of routine patterns, capable of accommodating variations of time and context for days and people. Future work could investigate the use of automatic

inference of context from phone sensing to complement or replace some of the manual input needed in our framework; and the application of the framework to larger and more diverse populations, using the same app-in-the-wild strategy.

## ACKNOWLEDGMENTS

This work was supported by EPFL Integrative Food and Nutrition Center (IFNC), through the *Understanding Eating Routines in Context* project. D. Gatica-Perez also acknowledges the support of the EC H2020 project *WeNet: The Internet of Us*.

## REFERENCES

- [1] O. Amft and G. Troster, 2009. On-body sensing solutions for automatic dietary monitoring. *IEEE Pervasive Computing*, 8(2):62-70.
- [2] A. Bedri, R. Li, M. Haynes, R. P. Kosaraju, I. Grover, T. Prioleau, M. Y. Beh, M. Goel, T. Starner, and G. Abowd, 2017. EarBit: Using Wearable Sensors to Detect Eating Episodes in Unconstrained Environments. *PACM on Interactive, Mobile, Wearable, and Ubiquitous Technologies (IMWUT)*, 1(3), Sep.
- [3] C. Bi, G. Xing, T. Hao, J. Huh, W. Peng, and M. Ma, 2017. FamilyLog: A mobile system for monitoring family mealtime activities, in *Proc. IEEE Int. Conf. on Pervasive Computing and Communications (PerCom)*, Hawaii, Mar.
- [4] J.-I. Biel, N. Martin, D. Labbe, and D. Gatica-Perez, 2017. Bites'n'Bits: Eating Behavior in Context from Mobile Data, *PACM on Interactive, Mobile, Wearable, and Ubiquitous Technologies (IMWUT)*, 1(4), Dec.
- [5] C. A. Bisogni, L. W. Falk, E. Madore, C. E. Blake, M. Jastran, J. Sobal, and Carol M. Devine, 2007. Dimensions of everyday eating and drinking episodes. *Appetite*, 48(2):218–231, Mar.
- [6] D. Blei, 2012. Probabilistic topic models. *Communications of the ACM*, 55(4):77–84.
- [7] F. Cordeiro, E. Bales, E. Cherry, and J. Fogarty, 2015. Rethinking the Mobile Food Journal: Exploring Opportunities for Lightweight Photo-Based Capture, in *Proc. ACM Conf. on Human Factors in Computing Systems*, Seoul, pp. 3207-3216, Apr.
- [8] A.K. Dey, Context-Aware Computing. In J. Krumm (ed.) 2010. *Ubiquitous Computing Fundamentals*, Chapman & Hall/CRC Press, Boca Raton.
- [9] Y. Dong, J. Scisco, M. Wilson, E. Muth, and A. Hoover, 2014. Detecting periods of eating during free-living by tracking wrist motion. *IEEE Journal of Biomedical and Health Informatics*, 18(4):1253-1260, Jul.
- [10] K. Farrahi and D. Gatica-Perez 2011. Discovering Routines from Large-Scale Human Locations using Probabilistic Topic Models, *ACM Transactions on Intelligent Systems and Technology*, 2(1).
- [11] M. M. Jastran, C. A. Bisogni, J. Sobal, C. Blake, C. M. Devine, 2009. Eating routines. Embedded, value based, modifiable, and reflective, *Appetite*, 52(1):127-136, Feb.
- [12] D. Marshall and R. Bell, 2003. Meal construction: exploring the relationship between eating occasion and location. *Food Quality and Preference*, 14(1):53–64.
- [13] A. Meyers, N. Johnston, V. Rathod, A. Korattikara, A. Gorban, N. Silberman, S. Guadarrama, G. Papandreou, J. Huang, and K. Murphy, 2015. Im2Calories: towards an automated mobile vision food diary. In *Proc. IEEE Int. Conf. on Computer Vision*, pp. 1233–1241.
- [14] M. Mirtchouk, C. Merck, and S. Kleinberg, 2016. Automated estimation of food type and amount consumed from body-worn audio and motion sensors, in *Proc. ACM Int. Joint Conf. on Pervasive and Ubiquitous Computing*, Heidelberg, pp. 451-462.
- [15] B. Renner, G. Sproesser, S. Strohbach, and H. T. Schupp, 2012. Why we eat what we eat. The Eating Motivation Survey (TEMS). *Appetite*, 59(1):117–128.
- [16] C. Sievert and K. E. Shirley, 2014. LDAvis: A method for visualizing and interpreting topics. In *Proc. ACL Workshop on Interactive Language Learning, Visualization and Interfaces*. pp. 63–70.
- [17] E. Thomaz, I. Essa, and G. D. Abowd, 2015. A practical approach for recognizing eating moments with wrist-mounted inertial sensing. In *Proc. ACM Int. Joint Conf. on Pervasive and Ubiquitous Computing*, Osaka, pp.1029-1040.
- [18] T. Huynh, M. Fritz, and B. Schiele. Discovery of activity patterns using topic models, 2008. In *Proc. ACM Int. Conf. on Ubiquitous Computing*, Seoul, Sep.
- [19] B. Wansink, C. R. Payne, and M. Shimizu, 2010. “Is this a meal or snack?” Situational cues that drive perceptions. *Appetite*, 54(1):214–216.
- [20] World Health Organization, 2018. Obesity and Overweight Key Facts. <https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight>.
- [21] L. Zepeda and D. Deal, 2008. Think before you eat: photographic food diaries as intervention tools to change dietary decision making and attitudes. *International Journal of Consumer Studies*, 32(6):692-698.