# Overview of ImageCLEFlifelog 2018: Daily Living Understanding and Lifelog Moment Retrieval

Duc-Tien Dang-Nguyen[1], Luca Piras[2], Michael Riegler[3], Liting Zhou[1], Mathias Lux[4], and Cathal Gurrin[1]

[1] Dublin City University
zhou.liting2@mail.dcu.ie, {duc-tien.dang-nguyen, cathal.gurrin}@dcu.ie
[2] Pluribus One & University of Cagliari
luca.piras@diee.unica.it
[3] Simula Metropolitan Center for Digital Engineering
michael@simula.no
[4] ITEC, Klagenfurt University
mlux@itec.aau.at

**Abstract.** Benchmarking in Multimedia and Retrieval related research fields has a long tradition and important position within the community. Benchmarks such as the MediaEval Multimedia Benchmark or CLEF are well established and also served by the community. One major goal of these competitions beside of comparing different methods and approaches is also to create or promote new interesting research directions within multimedia. For example the *Medico* task at MediaEval with the goal of medical related multimedia analysis. Although lifelogging creates a lot of attention in the community which is shown by several workshops and special session hosted about the topic. Despite of that there exist also some lifelogging related benchmarks. For example the previous edition of the lifelogging task at ImageCLEF. The last years ImageCLEFlifelog task was well received but had some barriers that made it difficult for some researchers to participate (data size, multi modal features, etc.) The ImageCLEFlifelog 2018 tries to overcome these problems and make the task accessible for an even broader audience (e.g., pre-extracted features are provided). Furthermore, the task is divided into two subtasks (challenges). The two challenges are lifelog moment retrieval (LMRT) and the Activities of Daily Living understanding (ADLT). All in all seven teams participated with a total number of 41 runs which was an significant increase compared to the previous year.

## 1 Introduction

Lifelogging is a research field that gets more and more attention in the last years. This is not just due to the interesting challenges that this direction offers (huge amount of data, complex patterns, multi-modal learning, etc.) but also because of the availability of devices. A great amount of people used devices such as smart watches and other type of sensors. These sensors in combination with smartphones that are an almost natural companion for a person nowadays enable powerful and more insightful lifelogging.

The data collected using these different devices is called lifelogs. A lifelog is a digital record of a persons daily routines. Such a lifelog can look different for different people depending on their habits and devices they use. Some people might record the whole day with videos others rely more on sensors. Nevertheless of the composition of such a lifelog it is clear that the collected data reaches huge dimensions for each specific user. This calls for research with focus on systems that are able to analyze these huge amounts of data in a meaningful way. Such analysis can be manging fold and span from simple re-finding events task to summarization or information retrieval.

For example people that log their daily life want to recall certain things such as persons they saw during the day, products they found interesting in a shopping window while they were strolling trough the streets. Lifelogs can not only be used for the users need but hold also potential for other applications such as recommender systems. For example one could get recommendations based on items they focused on in a shopping window. Examples for events that a lifelogger might want to retrieve from their log can be seen in Figure 1.

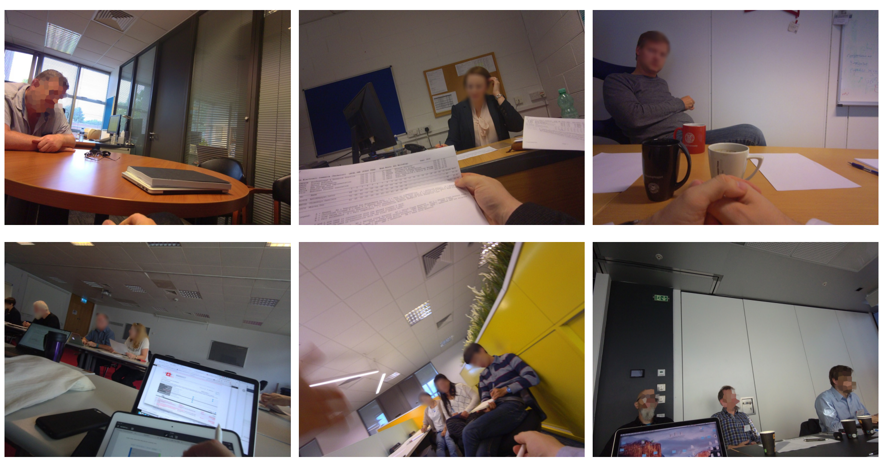

**Fig. 1.** An example lifelogging information need: 'Show me all meeting moments'.

The ImageCLEF2018lifeLog task is the second edition of it. The first lifeLog task was performed in 2017 [2] and was inspired by the image annotation and retrieval tasks that were part of ImageCLEF for more than a decade (since 2003). With the lifeLogging task at ImageCLEF the focus lies on multi-modal analysis of large data collections. This is following the general evolution of ImageCLEF (the focus changed of pure image retrieval to a more multi-modal approach including concept localization and natural language description of images [11,13,15,14]. In the last three editions [5,6,7]).

This paper provides an overview of the second edition of the ImageCLEFlifelog task which is again part of the overall benchmark campaign organized every year by ImageCLEF [8] under the CLEF initiative[1]. The overview paper is organized as following: In section 2 we provide a detailed task description. This includes rules, data and resources. In the following section 3 submissions and results are presented and discussed. In he final section 4 the paper is concluded and final remarks and future work are discussed.

## 2 Overview of the Task

### 2.1 Motivation and Objectives

The main goal of the task is to make use of lifelogging data and explore the possibilities that come with it. As discussed in the introduction there are several interesting and useful applications that can emerge from this data. To limit the scope for the 2018 version of the task two sub-tasks are proposed. This makes it easier for the participants to focus on a specific outcome and participants were also allowed to submit only for one of the subtasks.

The two subtasks focus on two different topics. The first one Lifelog moment retrieval (LMRT) asks the participants to retrieve a specific moment in the daily life of a logger. Specific queries are provided that should be answered. The second subtask, Daily Living understanding (ADLT), targets understanding of daily living over a period of time and for specific concepts. In the following the two subtasks are described in more detail.

### 2.2 Challenge Description

**Lifelog moment retrieval (LMRT)**
The participants have to retrieve a number of specific moments in a lifeloggers life. We define moments as semantic events, or activities that happened throughout the day. For example, they should return the relevant moments for the query "Find the moment(s) when I was shopping for wine in the supermarket." Particular attention should be paid to the diversification of the selected moments with respect to the target scenario. The ground truth for this subtask was created using manual annotation.
**Daily Living understanding (ADLT)**
Given a period of time, e.g., "From 13 August to 16 August" or "Every Saturday", the participants should analyse the lifelog data and provide a summarisation based on the selected concepts (provided by the task organizers) of Activities of Daily Living (ADL) and the environmental settings / contexts in which these activities take place.

[1] http://www.clef-initiative.eu

| | |
|---|---|
| Size of the Collection | **18.854** GB |
| Number of Images | **80,440** images |
| Number of Known Locations | **135** locations |
| Concepts | Fully annotated (by Microsoft Computer Vision API) |
| Biometrics | Fully provided ($24 \times 7$) |
| Human Activities | Provided |
| Number of ADLT Topics | **20** (10 for devset, 10 for testset) |
| Number of LMRT Topics | **20** (10 for devset, 10 for testset) |

**Table 1.** Statistics of ImageCLEFlifelog2018 Dataset.

Some examples of ADL concepts: "Commuting (to work or another common venue)", "Traveling (to a destination other than work, home or another common social event)", "Preparing meals (include making tea or coffee)", "Eating/drinking", and contexts: "In an office environment", "In a home", "In an open space". Appendix A provides the full ontology of the concepts and contexts. The summarisation should be described as the number of times and the spending time the queried event happened. For example:

- ADL: "Eating/drinking: 6 times, 90 minutes", "Traveling: 1 time, 60 minutes"
- Context: "In an office environment: 500 minutes", "In a church: 30 minutes"

### 2.3 Dataset

The task will be split into two related subtasks using a completely new multimodal dataset which consists of 50 days of data from a lifelogger, namely: images (1,500-2,500 per day from wearable cameras), visual concepts (automatically extracted visual concepts with varying rates of accuracy), semantic content (semantic locations, semantic activities) based on sensor readings (via the Moves App) on mobile devices, biometrics information (heart rate, galvanic skin response, calorie burn, steps, etc.), music listening history. The dataset is built based on the data available for the NTCIR-13 - Lifelog 2 task. Table 1 summarises the data collection.

**Format of the metadata.** The metadata is stored in an .xml file, which is a simple aggregation of all users data. It is structured as follows:

The root node of the data is the USERS tag. Each user element contains all the data of that user (u1 or u2). Each user has a tag USER that contains the user ID as an attribute, example: [user id=u1]. For this year, only user u1 is considered. Inside the USER element, is his/her data:

Following that there is a tag DAYS, this tag contains the lifelogging information of that user organised per day, each day is included in a tag DAY that has the data (a tag DATA), the relative path to the directory that contains the images captured in that particular day (the tag IMAGES-DIRECTORY), then the minutes of of that day under a root tag called MINUTES.

At the start of each day there is a set of daily metatdata for that user. This data is of three forms; BIOMETRICS, ACTIVITIES & PERSONAL LOGS. The biometrics contains WEIGHT, FAT MASS, HEART RATE, SYSTOLIC blood pressure & DIASTOLIC blood pressure, which were readings taken after waking up each day. The activities contains summary activities: STEPS taken that day, DISTANCE walked in meters that day & ELEVATION climbed in meters that day. The personal logs contain HEALTH LOGS, including the TIME of reading, GLU Glucose levels in the blood, BP Blood Pressure, HR Heart Rate, MOOD manually logged every morning and sometimes a COMMENT, as well as DRINK LOGS and FOOD LOGS which were manually logged throughout the data.

Following that, the days data is organised into minutes. The MINUTES element, contains exactly 1440 child elements (called MINUTE), each child has an ID (example: [minute id=0], [minute id=1], [minute id=2] etc.), and it represent one minute in the day ordered from 0 = 12:00 AM, to 1439 = 23:59PM.

Each minute contains: 0 or 1 location information (LOCATION tag), 0 or one activity information (ACTIVITY tag), biometrics, 0 or more captured images (IMAGES tag with IMAGE child element (each element has has a relative path to the image and a unique image ID), and 0 or 1 MUSIC tag giving details of the music listened to at that point in time.

The location information is captured by Moves app (https://www.moves-app.com/), and they represent to semantic locations (Home, Work, DCU Computing building, GYM, Name of a Store, etc), or to landmark locations registered by Moves. This tag can contain information in several languages. For locations that are not (HOME) or (WORK), the GPS locations are provided.

### 2.4 Performance Measures

**Metrics LMRT.** For assessing performance, classic metrics are deployed. These metrics are:

- Cluster Recall at X (CR@X) - a metric that assesses how many different clusters from the ground truth are represented among the top X results;
- Precision at X (P@X) - measures the number of relevant photos among the top X results;
- F1-measure at X (F1@X) - the harmonic mean of the previous two.

Various cut off points are to be considered, e.g., X=5, 10, 20, 30, 40, 50. Official ranking metrics is the F1-measure@10, which gives equal importance to diversity (via CR@10) and relevance (via P@10).

Participants are allowed to undertake the sub-tasks in an interactive or automatic manner. For interactive submissions, a maximum of five minutes of search time is allowed per topic. In particular, the organizers would like to emphasize methods that allow interaction with real users (via Relevance Feedback (RF), for example), i.e., beside of the best performance, the way of interaction (like number of iterations using RF), or innovation level of the method (for example, new way to interact with real users) are encouraged.

**Metrics ADLT.** The final score is computed as the percentage of similarity between the ground-truth and the submitted values, measured as average of the number of times and minutes differences, as follows:

$$ADL_{score} = \frac{1}{2}\left(max(0, 1 - \frac{|n-n_{gt}|}{n_{gt}}) + max(0, 1 - \frac{|m-m_{gt}|}{m_{gt}})\right)$$

where $n, n_{gt}$ are the submitted and ground-truth values for how many times the events occurred, respectively, and $m, m_{gt}$ are the submitted and ground-truth values for how long (in minutes) the events happened, respectively.

### 2.5 Ground Truth Format

Ground truth is provided in two individual txt files: one file for the cluster ground truth and one file for the relevant image ground truth.

In the cluster ground-truth file each line corresponds to a cluster where the first value is the topic id, followed by cluster id number, followed by the cluster user tag separated by comma. Lines are separated by an end-of-line character (carriage return). An example is presented below:

- 1, 1, Badger & Dodo Cafe
- 1, 2, Costa coffee
- 
- 2, 1, Airport Restaurant
- 2, 2, Arnotts Department Store
- 

In the relevant ground-truth file the first value on each line is the topic id, followed by a unique photo id, and then followed by the cluster id number (that corresponds to the values in the cluster ground-truth file) separated by comma. Each line corresponds to the ground truth of one image and lines are separated by an end-of-line character (carriage return). An example is presented below:

- 1, u1_2016-09-17_124915_1, 1
- 1, u1_2016-09-17_125300_1, 1
- 1, u1_2016-09-17_125332_2, 1
- 1, u1_2016-08-27_070424_1, 2
- 1, u1_2016-08-27_070456_2, 2
- 1, u1_2016-08-27_070528_1, 2
- 
- 2, u1_2016-08-27_133126_1, 1
- 2, u1_2016-08-27_133158_2, 1
- 2, u1_2016-08-27_133230_1, 1
- 2, u1_2016-08-17_121617_1, 2
- 2, u1_2016-08-17_121704_1, 2
- 

## 3 Evaluation Results

### 3.1 Participating Groups and Runs Submitted

This year the number of participants was considerably higher with respect to 2017: we received in total 41 runs: 29 (21 official, 8 additional) for LMRT and 12 (8 official, 4 additional) for ADLT, from 7 teams from Brunei, Taiwan, Vietnam, Greece-Spain, Tunisia, Romania, and a multi-nation team from Ireland, Italy, Austria, and Norway. The received approaches range from fully automatic to fully manual, from using a single information source provided by the task to using all information as well as integrating additional resources, from traditional learning methods (e.g. SVMs) to deep learning and ad-hoc rules. Submitted runs and their results are summarized in Tables 2 and 3.

### 3.2 Results for ADLT and LMRT Tasks

In this section we provide a short description of all submitted approaches followed by the official result of the task.

The organiser team participated in both tasks [16]. The idea was to provide a baseline using only provided data. For both subtasks LIFER was used. LIFER is a interactive lifelog search engine that is able to solve different lifeloggin challenges.

The CIE@UTB [3] authors propose a content-context-based method to automatically create summaries for the ADLT task. The two main concepts used are a daily-normal environment panorama image which is used to detect events in known environments and a daily-abnormal environment taxonomy which is used to detect events in pre-defined taxonomy. The team only participated in the ADLT task.

CAMPUS-UPB [4] focused on LMRT. In their methods they analysed visual information, textual information and metadata. Visual concepts are extracted using a convolutional neural network (CNN) approach. Visual features are then clustered using K-means and reranked using the concepts and queried topics.

AILab-GTI [9] proposed a weakly supervised learning method for LMRT. The method consists of three different strategies. The Two-class strategy, is based on deep learning and presents each topic by two classes one described by the topic and the other by the absence of it. The second strategy, Ten-class strategy, considers all classes at the same time. The final strategy, called Eleven-Class strategy is similar to the previous one with one additional class for topics not belonging the the challenge.

The NLP-Lab [10] team tackled both subtask of the ImageCLEFlifeloggin task. The main idea was to reduce user involvement during the retrieval by using natural language processing. For both tasks specific approaches were presented based on the same methodology. Visual concepts are extracted from the images and combined with textual knowledge to get rid of the noise. For ADLT the images are ranked by time and frequency, whereas for LMRT ranking is performed exploiting similarity between image concepts and user queries.

**Table 2.** Submitted runs for ImageCLEFlifelog2018 ADLT task.

| Team | Run Name | Score (similarity) |
|---|---|---|
| Organizers [16] | Run 1* | 0.816 |
| | Run 2*,† | 0.456 |
| | Run 3*,† | 0.344 |
| | Run 4*,† | 0.481 |
| | Run 5*,† | 0.485 |
| CIE@UTB [3] | Run 1 | **0.556** |
| NLP-Lab [10] | Run 1 | 0.243 |
| | Run 2 | 0.285 |
| | Run 3 | 0.385 |
| | Run 4 | 0.459 |
| | Run 5 | 0.479 |
| HCMUS [12] | Run 1 | 0.059 |

Notes: * submissions from the organizer teams are just for reference.
† submissions submitted after the official competition.

HCMUS [12] proposed a method based on visual concept fusion and text-based query expansion for both sub tasks. First concepts are extracted from the images. In addition textual descriptions of the images are created. These information are then combined in an inverted index for retrieval. To determine the similarity between words and phrases word embedding is used. Based on this and the users provided queries semantically similar concepts are recommended to the users.

The Regim Lab [1] team decided to work on the LMRT task. Combinations of visual features, textual features and a combination of both were used. For the visual features fine tuned CNN architectures were utilized. For the combination of visual and textual features the best visual run was combined with XQuery FLOWR results.

As mentioned before, for the ADLT task, four teams have been participated: CIE@UTB [3], NLP-Lab [10], HCMUS [12] and the Organisers team [16].

The official results are summarised in Table 2. The best run was submitted by CIE@UTB with a score of 0.556 which is also outperforming the organizers baseline approaches.

For LMRT, six teams have participated: AILab-GTI [9], Regim Lab [1], NLP-Lab [10], HCMUS [12], CAMPUS-UPB [4] and the Organisers team [16]. The results are presented in Table 3. The best results were achieved by AILab-GTI with an F110 of 0.545. Major of the teams outperform the organisers baseline approaches.

## 4 Discussions and Conclusions

We learned that multi-modal data analysis has been explored and exploited this year, with the majority of the approaches combining visual, textual, location

**Table 3.** Submitted runs for ImageCLEFlifelog2018 LMRT task.

| Team | Run Name | Score (F1@10) |
|---|---|---|
| Organizers [16] | Run 1* | 0.077 |
| | Run 2* | 0.131 |
| | Run 3*,† | 0.407 |
| | Run 4*,† | 0.378 |
| | Run 5*,† | 0.365 |
| AILab-GTI [9] | Subm#1 | 0.504 |
| | Subm#2 | **0.545** |
| | Subm#3 | 0.477 |
| | Subm#4 | 0.536 |
| | Subm#5 | 0.477 |
| | Subm#6 | 0.480 |
| | exps5 | 0.512 |
| | Subm#0† | 0.542 |
| Regim Lab [1] | Run 1 | 0.065 |
| | Run 2 | 0.364 |
| | Run 3 | 0.411 |
| | Run 4 | 0.411 |
| | Run 5 | 0.424 |
| NLP-Lab [10] | Run 1 | 0.177 |
| | Run 3 | 0.223 |
| | Run 4 | 0.395 |
| | Run 5 | 0.354 |
| HCMUS [12] | Run 1 | 0.355 |
| | Run 2 | 0.479 |
| CAMPUS-UPB [4] | Run 1 | 0.216 |
| | Run 2† | 0.169 |
| | Run 3† | 0.168 |
| | Run 4† | 0.166 |
| | Run 5† | 0.443 |

Notes: * submissions from the organizer teams are just for reference.
† submissions submitted after the official competition.

and other information to solve the task. This was quite different from last year when often only one type of data was analysed. Furthermore, we learned that many approaches are based on deep neural networks, from standard CNN to specifically designed deep networks for lifelogging tasks. However, there are still rooms for improvement, since the best results are coming from the fine-tuned queries, which means we need more advanced techniques to bridging the gap between the abstract understanding of human needs and the multi-modal data. Furthermore, automatically "translate" the query into the retrieval criteria is still a challenge which requires further studies. Regarding the number of the signed-up teams and the submitted runs, we received a significant improvement compared to last year. This shows how interesting and challenging lifelog data is and that it holds much research potential. As next steps we do not plan to enrich the dataset but rather provide richer data and narrow down the application of the challenges (e.g., extend to health-care application).

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# A The Lifelog Ontology

They are the activities/facets of daily life and the environmental settings / contexts in which these activities take place. For the ADLT task, we selected a subset of ten of these activities and settings for evaluation.

## A.1 Activities / Facets of Life Activity

- Commuting (to work or other common venue)
- Travelling (to a destination other than work, home or some other common social event)
- Preparing meals (include making tea or coffee)
- Eating/drinking
- Taking care of children / playing with children
- Sleeping
- Praying / worshipping / meditating
- Socialising / casual conversation
- Relaxing / meditation
- Reading
  - reading a book
  - reading digital content
- Gardening
- Shopping
  - retail shopping and purchasing
  - browsing for items in store
  - online shopping
- Work meeting/interaction (one or more people)
  - face-to-face
  - online meeting
- Watching (TV)
- Playing computer games
- Using desktop computer / laptop computer
- Using mobile device / tablet
- Physical activities / sports
  - walking
  - running
  - cycling
  - other sports/exercise
- Searching / Information Seeking
  - WWW
  - media seeking
  - files
  - locations (map)
- Organising things
  - papers
  - boxes

  - other
- Packing bags/suitcases
- Cleaning
  - home cleaning
  - vacuuming
  - dish washing
- Hygiene & make-up
  - hands
  - face
  - teeth
  - make-up
  - other personal hygiene
- Artistic endeavours
  - writing
  - drawing / painting
  - playing music instruments

### A.2 Settings/Context (the physical environment)

- In an office environment
- In a home
  - in a kitchen
  - in a living room - in a bedroom
  - in a garden
- In a publicly-accessible building
  - in a shop / mall
  - in a restaurant
  - in a hospital
  - in a school / college - in a church
  - in a tourist site
  - other
- In an open space
  - street
  - public green-space
  - by the sea
- In a vehicle (as a driver or passenger - inside)
  - car (driver)
  - car (passenger)
  - bus
  - train / tram
  - airplane
  - boat
  - other vehicle

## B Topics List 2018

Table 4: Description of topics for the development set in ADLT.

| |
|---|
| **T.001 Public transportation**<br>ADL: commuting<br>Span: 2016-08-15 to 2016-08-19<br>Description: Find how many times and how long the user commuted from 15th Aug to 19th Aug |
| **T.002 Eating and Drinking**<br>ADL: Eating/Drinking<br>Span: 2016-08-29 to 2016-09-04<br>Description: Find how many times and how long the user was eating or drinking from 29th Aug to 4th Sep |
| **T.003 Watching (TV)**<br>ADL: Watching (TV)<br>Span: 2016-09-26 to 2016-10-02<br>Description: Find how many times and how long the user was watching the TV from 26th Sept to 2nd Oct |
| **T.004 Shopping Grocery**<br>ADL: Shopping<br>Context: Grocery shops<br>Span: 2016-09-19 to 2016-09-25, 16: 00 to 20: 00<br>Description: Find how many times and how long the user was shopping in the grocery shops from 19th Sept to 25 Sept |
| **T.005 Socialising**<br>ADL: Socialising<br>Context: Public place<br>Span: Weekends<br>Description: Find how many times and how long the user was socialising with his friends in the public place (coffee shop, bar, restaurant, etc.) on weekend days. |
| **T.006 Using laptop or desktop**<br>ADL: Using laptop or desktop computer<br>Description: Find how many times and how long the user was using his laptop on weekend days. |
| **T.007 In Office**<br>ADL: Exclude meetings<br>Context: In office environment<br>Span: 2016-09-05 - 2016-09-09<br>Description: Find how many times and how long the user was working (exclude meetings) in office environment from 5th Sept to 9th Sept. No matter which office the user was working in. |

**T.008 In A Vehicle**
Context: In a Vehicle
Span: 2016-09-01 - 2016-09-30
Description: Find how many times and how long the user was in a vehicle from 15th Aug to 21st Aug, from 10: 00 to 17: 00.

**T.009 At home**
Context: At home
Span: Weekends, from 19: 00
Description: Find how many times and how long the user was staying at home in weekend evenings (from 19: 00).

**T.010 At the Seaside**
Context: At the Seaside
Description: Find how many times and how long the user was spending time at the seaside.

Table 5: Description of topics for the test set in ADLT.

**T.001 Coffee at work**
ADL: Drinking (coffee)
Context: Office
Description: Find how many times and how long the user having coffee in the office. Having coffee at the bars at the workplace is not considered.

**T.002 Shopping after work**
ADL: Shopping
Span: 2016-08-15 to 2016-09-15 18: 00 - 20: 00
Description: Find how many times and how long the user went for shopping after work from 15th Aug to 15th Sep.

**T.003 Preparing meals**
ADL: Preparing meals
Context: Home
Span: before 9: 00
Description: Find how many times and how long the user preparing meal at home before going to work.

**T.004 Watching TV**
ADL: Watching TV
Context: Home
Span: 2016-09-01 to 2016-09-30, 06: 00 to 07: 00
Description: Find how many times and how long the user was watching TV early morning in September.

**T.005 Attending Presentation**
ADL: Listening/Watching
Context: Work
Span: 2016-09-01 to 2016-09-30

Description: Find how many times and how long the user was attending presentation at the workplace in September.

**T.006 Using phone in a vehicle**
ADL: Using mobile phone/tablet
Context: In a vehicle
Description: Find how many times and how long the user was using his phone or tablet inside his car as a driver or as a passenger.

**T.007 In Office**
ADL: Exclude using desktop/laptop computers
Context: In office environment
Span: 2016-09-05 - 2016-09-09
Description: Find how many times and how long the user was working (exclude using computer) in office environment from 5th Sept to 9th Sept. No matter which office the user was working in

**T.008 Walking down the Street**
ADL: Walking
Context: On the Street
Span: 2016-09-01 - 2016-09-30
Description: Find how many times and how long the user was walking on the street in September.

**T.009 In a Church**
Context: In a Church
Span: Weekends
Description: Find how many times and how long the user was spending time inside a church in the weekends.

**T.010 Party**
ADL: Socialising/Eating/Drinking
Context: In a restaurant
Description: Find how many times and how long the user having a party (including lunch and dinner) at a restaurant, no matter where and when.

Table 6: Description of topics for the development set in LMRT.

**T.001 Public transportation**
Description: Find the moments when I was taking public transportation
Narrative: Moments in which the user was was taking any public transportation.

**T.002 Eating Lunch**
Description: Find the moments when I was eating lunch from 11: 00am to 3: 00pm
Narrative: Moments in which the user was eating lunch are relevant regardless of where the lunch is eaten. Time is relevant

**T.003 Coffee**
Description: Find the moment(s) when I was drinking coffee in a cafe.

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| Narrative: Moments that show the user consuming coffee or tea in a cafe (outside of home or office) are considered relevant. The coffee can be hot in a cup or paper cup, or cold coffee in a plastic or paper cup. |
| **T.004 Sunset & Sunrise**<br>Description: Find the moments when I was outside at sunset and sunrise.<br>Narrative: To be considered relevant, the moment must show the sun setting or rising. This can be at night time and morning time, or can be when the sun is disappearing and appearing behind a mountain in the evening. |
| **T.005 Presenting/Lecturing**<br>Description: Find the moments when I was lecturing to a group of people in a classroom environment.<br>Narrative: A lecture can be in any classroom environment and must contain more than one person in the audience, who are sitting down. A classroom environment has desks and chairs clearly visible. Discussion or lecture encounters in which the audience are standing up, or outside of a classroom environment are not considered relevant. |
| **T.006 Grocery Shopping**<br>Description: Find all the moments when I was grocery shopping.<br>Narrative: Any moment when the user was in a grocery store and visibly interacting with products is considered relevant. |
| **T.007 Cooking**<br>Description: Find the moments when I was cooking at home.<br>Narrative: Cooking at home includes preparation of ingredients and cooking of the food. To be considered relevant the user must be seen to be preparing food. Eating food at home is not considered relevant. |
| **T.008 Having Beers in a Bar or restaurant**<br>Description: Find the moment when I had beer in a bar or in a restaurant.<br>Narrative: To be considered relevant, the user must be clearly in a bar and having more than one drink. Black and light beers were consumed in this moment. |
| **T.009 Working in a Coffee Shop**<br>Description: Find the moments in which I was working in a coffee shop.<br>Narrative: To be considered relevant the user must be seen working with a laptop in a coffee shop. Relevant moments must show coffee on the table beside the laptop. Working in any place besides a coffee shop is not considered relevant. Socialising or relaxing in a coffee shop is not considered relevant if there is no laptop being used. |
| **T.010 Eating Pasta**<br>Description: Find the moments when I was eating Pasta.<br>Narrative: The user was eating pasta, either sitting at a table, an office desk or in a corridor outside an office. Sometimes pasta eating occurred with another person, sometimes it was in solitude. |

Table 7: Description of search topics for the test set in LST.

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| **T.001 Preparing Salad**<br>Description: Find the moments when I was preparing salad.<br>Narrative: To be considered relevant, the moments must show the lifelogger preparing a salad, in a kitchen or in an office environment. Eating salad is not considered relevant. Preparing other types of food is not considered relevant. |
| **T.002 VR Experiments**<br>Description: Find the moments when I was doing Virtual Reality (VR) experiments or seeing someone else doing VR experiments.<br>Narrative: To be considered relevant, the moments must show a VR device in use by the lifelogger. |
| **T.003 My Presentations**<br>Description: Find the moments when I was giving a presentation to a large group of people.<br>Narrative: To be considered relevant, the moments must show more than 15 people in the audience. Such moments may be giving a public lecture or a lecture in the university. |
| **T.004 Interviewed by a TV presenter**<br>Description: Find all the moments when I was interviewed by TV presenter.<br>Narrative: The moment must show the cameras or cameramen in front of the lifelogger. The interviews can occur at the lifelogger's home or in the office environment. |
| **T.005 Dinner at Home**<br>Description: Find the moments when I was having dinner at home.<br>Narrative: Moments in which the user was having dinner at home are relevant. Dinner in any other location is not relevant. Dinner usually occurs in the evening time |
| **T.006 Assembling Furniture**<br>Description: Find the moments when I was assembling a piece of furniture.<br>Narrative: To be considered relevant, the moments must show some parts of the furniture being assembled. |
| **T.007 Taking a coach/bus in foreign countries**<br>Description: Find the moments when I was taking a road vehicle in foreign countries.<br>Narrative: To be considered relevant, the user must be taking road transport in a different country (i.e. not Ireland). Taking airplane, train or boat is not considered relevant. |
| **T.008 Costa Coffee with friends**<br>Description: Find the moments when I was with friends in Costa coffee.<br>Narrative: To be considered relevant, the moment must show at least a person together with the lifelogger in any Costa Coffee shop. Moments that show the user alone are not considered relevant. |
| **T.009 Using mobile phone or tablets in a vehicle** |

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| Description: Find the moments in which I was using my mobile phone or tablets in a vehicle.<br>Narrative: To be considered relevant the user must be seen using with a mobile phone or a tablet in a vehicle, as a driver or as a passenger. |
| **T.010 Graveyard**<br>Description: Find the moments when I was at a graveyard.<br>Narrative: The user must be in a graveyard or inside a church inside a graveyard. Passing or standing outside of the graveyard is not considered relevant. |