EARWD: an Efficient Activity Recognition system using Web activity Data

A. M. Jehad Sarkar

Advisor: Prof. Sungyoung Lee, Ph.D.
Co-advisor: Prof. Young-Koo Lee, Ph.D.

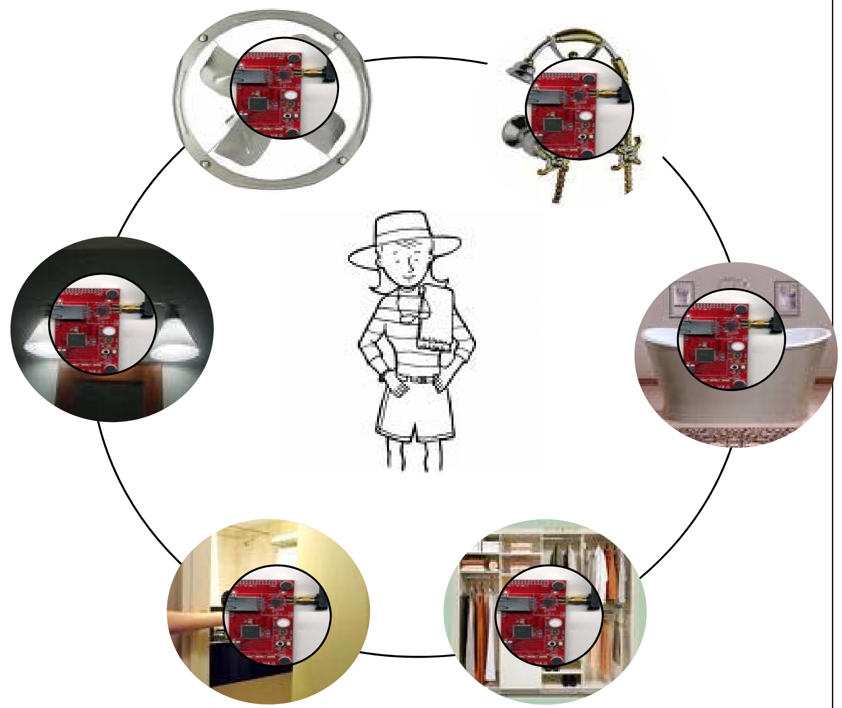
Department of Computer Engineering
Kyung Hee University
South Korea

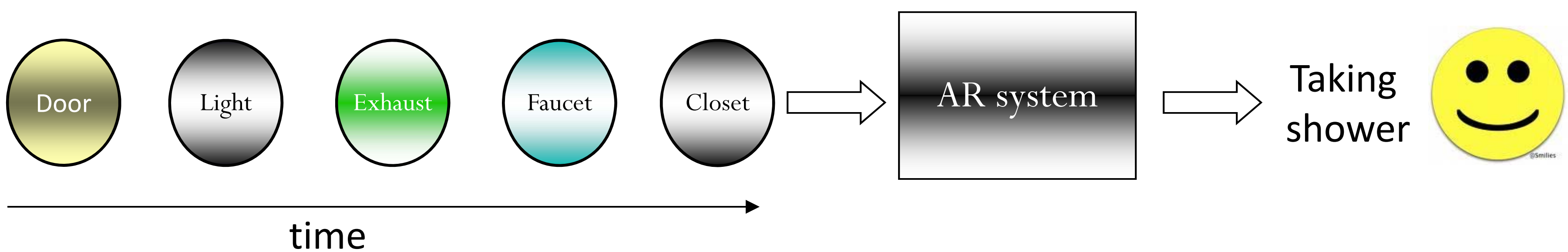
Agenda

- Introduction
  - Research background
  - Web helps to train an activity recognition system
- Related work
- Our approach
- Evaluation
- Conclusion & Future work

Research Background

- Recognition of Activities of Daily Livings (ADLs).
  - The things we normally do in daily living
  - Applications in healthcare (e.g. patient monitoring system)
- Recognition of ADLs using simple and ubiquitous sensor (Binary sensor)
  - ADLs are usually performed by interacting with a series of objects (e.g. door, light, exhaust fan, shower faucet…etc.)
  - Embed a set of small and simple state-change sensors to these objects
  - Recognize activity depending on the sensor activation (as user interact with the object) status





Training an AR system

- Two ways to train an AR system
  - Using real-world activity data
  - Using web activity data (our focus)

1. Select an environment (e.g. Home)
2. Select a set of objects and embed sensors
3. Select a set of activities
4. Assign participant and collect real-world activity data for a period of time (e.g. 30 days)
5. Train the system

Figure: An AR system trained from real-world activity data

1. Select an environment (e.g. Home)
2. Select a set of objects and embed sensors
3. Select a set of activities
4. Collect web activity data
5. Train the system

Figure: An AR system trained from web activity data

How to Make Bathing Safe For Independent Seniors

...

The simplest and most inexpensive remedy is to have a ***bath seat*** installed. This way, the user can have a seat in the ***bathtub*** for stability. The seat would be too high to take a bath, so the best way to bathe in this manner would be to use a hand-held shower head. Keep in mind the drawbacks for this method: The user still must step over the side of the tub to get in and out, and they will have to manually clean themselves with the shower head. If the user's mobility is not terribly restricted, just a little slow or unsteady, this method could easily work.

A ***bath lift*** would work better than a bath seat for someone with limited mobility. These mobility aids allow a user to sit comfortably before lowering them down into the bath. Once they are ready, the device lifts them back up to a sitting position. Often, they will feature a transfer bench so that the user can "slide" over the edge of the tub to get in or out. Bath lifts are more expensive than bath seats, but can restore privacy and independence even for seniors with moderately severe mobility restrictions.

Installing a tall walk-in bathtub in a separate area of the ***bathroom*** is probably the best way to guarantee safety for a senior with limited mobility. Walk-in ***bathtubs*** feature a ***doorway*** so that the user doesn't have to step over the side. While some walk-in bathtubs are meant to replace an ordinary ***bathtub*** as a permanent installation, I don't recommend those because they don't offer an easy way for the user to sit/stand and they will bring down the resale value of a house. Instead, opt for a tall walk-in bathtub with a bench. This type of walk-in tub can be removed from the ***bathroom*** when it's no longer needed. This way, the user can take a bath while sitting upright, similar to sitting in a ***hot tub***. There's no need to lower the body to ground level, and getting in and out is easy. Walk-in ***bathtubs*** are gaining in popularity for residential use as more and more people decide that they are worth the cost to maintain their privacy and independence.

...

Figure: a web page that describes an activity

Advantages of using web activity data

- Makes the system easily configurable
  - End-user with little expert knowledge would be able to configure the system
- The system becomes effortlessly scalable
  - Handle growing amounts of activities and objects in a graceful manner
  - No human is required to collect activity data to train the system
- A large number of data can be collected to train the classifier
- We would get information about almost all activities
- Inexpensive
- It would be applicable to a diverse set of environments

Agenda

- Introduction
- Related work
  - Proactive Activity Toolkit (PROACT) [3]
  - Unsupervised activity recognition [4]
  - Limitations
- Our approach
- Evaluation
- Conclusion & Future work

Proactive Activity Toolkit (PROACT) [3]

- Inference engine
  - Given models for activities, and sequences of sensor readings, returns the likelihood of current activities.
  - Sequential Monte Carlo (SMC) approximation to probabilistically solve for the most likely activities
- Mining engine
  - Extracts generic models automatically from text documents,

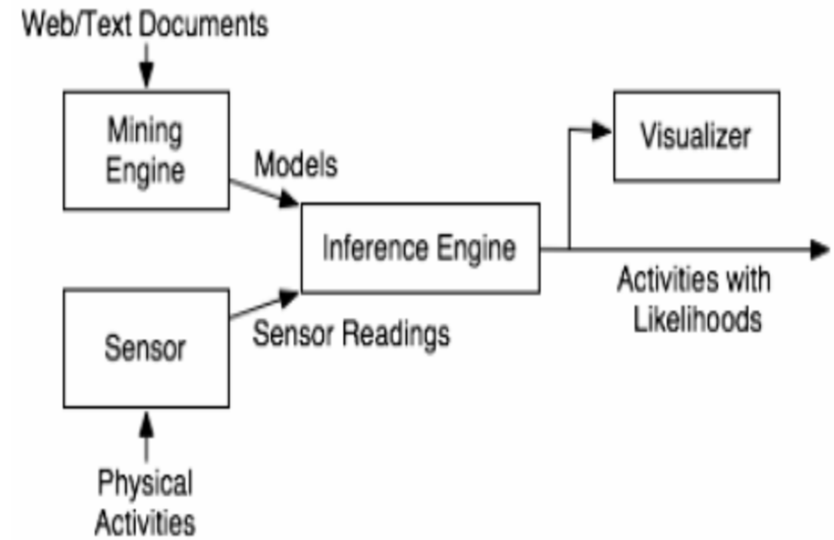


Figure: PROACT Overview

Making Tea:

1. Fill a **teapot** from the **faucet**. Place kettle on the **stove** and boil.
2. Pour hot **water** into a **cup**, filling ¾ of the cup. Immerse **teabag** in cup for two minutes and dispose of teabag.
3. Add **milk** and **sugar** to taste.

Figure: directions for Making Tea

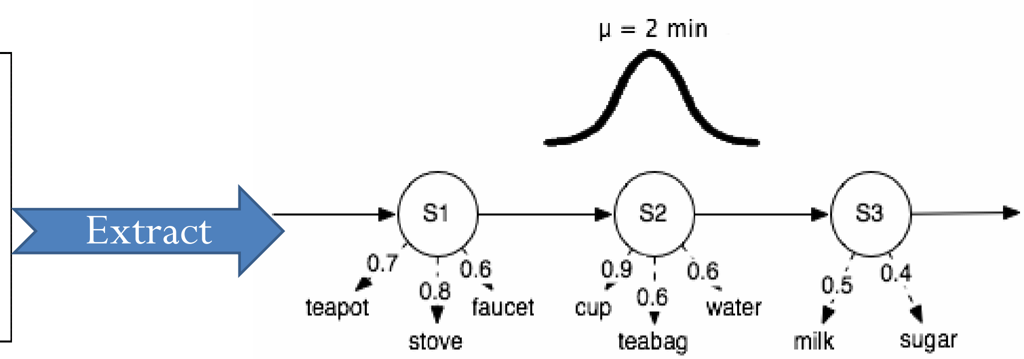


Figure: PROACT Model for Making Tea

PROACT mining engine

World Wide Web (WWW)

Select a set of websites like, http://www.ehow.com/, that describes activities, and understands the HTML structures

A set of websites

search for a page that describes an activity and extract the activity direction from this page

Activity direction

- set the title of the direction as the label of the activity,
- parse and extract the object phrases from the direction,
- remove the phrases that do not have noun sense

Set of objects

calculate the object-usage probability using the Google Conditional Probability (GCP)

GCP

$$GCP(O_i) = \frac{hitcount(object\ activity)}{hitcount(activity)}$$

Making Tea:

1. Fill a **teapot** from the **faucet**. Place kettle on the **stove** and boil.
2. Pour hot **water** into a **cup**, filling ¾ of the cup. Immerse **teabag** in cup for two minutes and dispose of teabag.
3. Add **milk** and **sugar** to taste.

Figure: directions for Making Tea

After Object Extraction:

T_1: {kettle, faucet, stove}

T_2: {water, cup, filling, teabag}

T_3: {milk, sugar}

After Noun Phrase Extraction:

O_1: {kettle, faucet, stove}

O_2: {water, cup, teabag}

O_3: {milk, sugar}

After Google Conditional Probabilities:

s_1: {(kettle, 0.11), (faucet, 0.01), (stove, 0.08)}

s_2: {(water, 0.50), (cup, 0.30), (teabag, 0.01)}

s_3: {(milk, 0.16), (sugar, 0.16)}

After Tagged Object Filtering:

$O_{deployed}$ = {kettle, stove, cup, teabag, milk}

t_1: {(kettle, 0.11) , (stove, 0.08)}

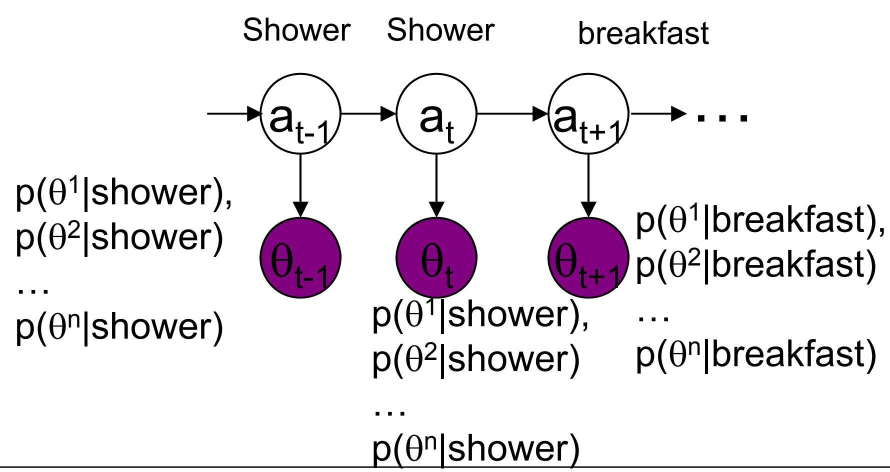
t_2: {(cup, 0.30), (teabag, 0.01)}

t_3: {(milk, 0.16)}

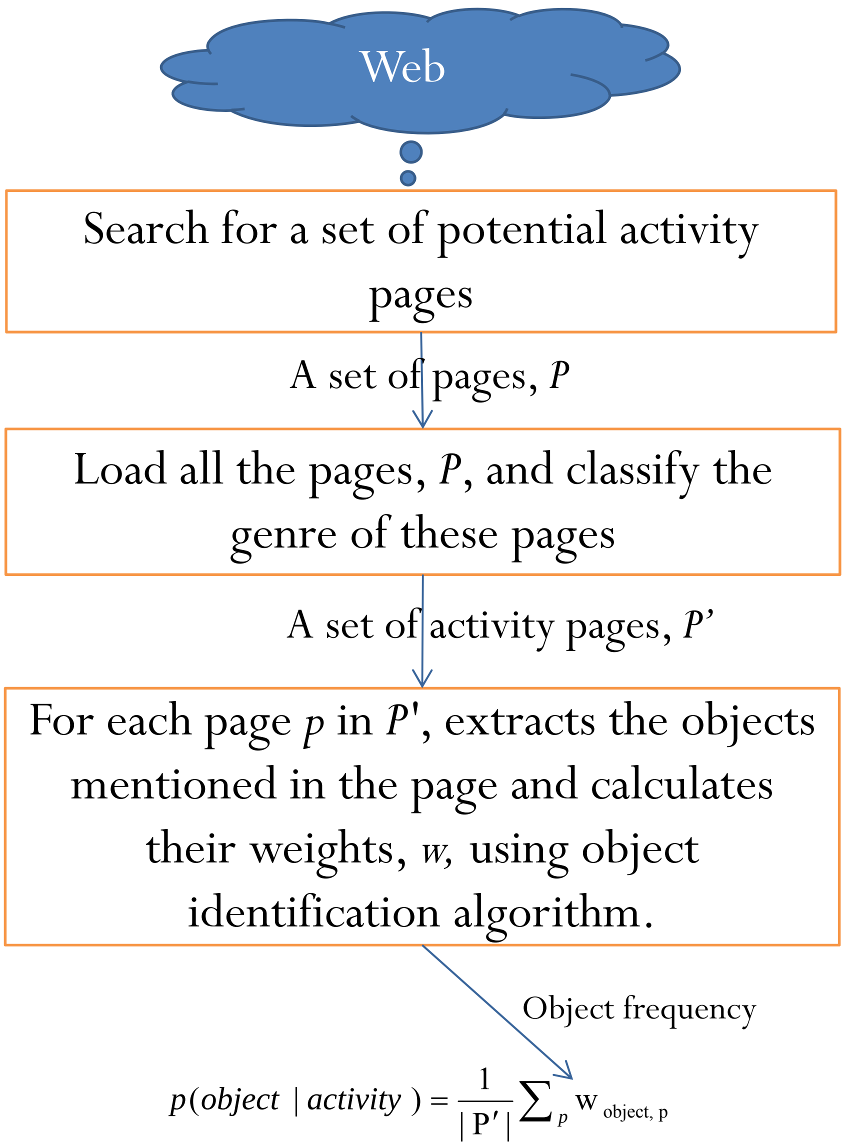
Figure: Steps in Mining the Directions for Making Tea

Unsupervised activity recognition [4]

- Wyatt et al. extends the idea of Perkowitz et al.[3]
- Activity models are not generic models, unlike [3],
  - Focused on a particular environment by taking inputs (e.g. activity names) from the environment.
- Activity models are based on hidden markov model $P(a,\theta) = \prod_{t=1}^{T} P(a_t|a_{t-1})P(\theta_t|a_t)$
  - the prior probabilities, π, is set to uniform distribution over activities,
  - the transition probability matrix T is set as,
    - self-transition probabilities are set to a fixed value (e.g. 0.75)
    - the remaining probability mass (e.g. 1 - 0.75 = 0.25) are distributed uniformly over all transitions to other activities
  - and the observation probability matrix B is mined from web



Mining engine [4]



- Document genre classifier
  - Search a set of pages through a search engine using a search criteria (e.g. bathing).
  - Load all the web pages and classify the genre of these pages
- Object identification algorithm
  - Extract the activity description from these pages (classified by the genre classifier)
  - Parse the activity description and search for the objects and determine the frequency of each object

Limitations of the existing systems[3][4]

- Low Accuracy
  - Only object-usage based model
    - There are cases where a set of objects could be used for different activities. It would hard for an AR to distinguish such activities.
- Complex and time consuming data collection methods (mining)
  - Document genre classifier
    - Load all the web pages and classify the genre of these pages
  - Object identification algorithm
    - Parse the activity description and search for the objects and determine the frequency of each object

Agenda

- Introduction
- Related work
- Our approach
  - Objective and challenges
  - Contributions
  - System overview
  - Activity classifier
  - Web activity data mining
- Evaluation
- Conclusion & Future work

Objectives

- Improve recognition system's accuracy
  - Use location information
    - It can provide important context, since group of activities are limited for a given location.

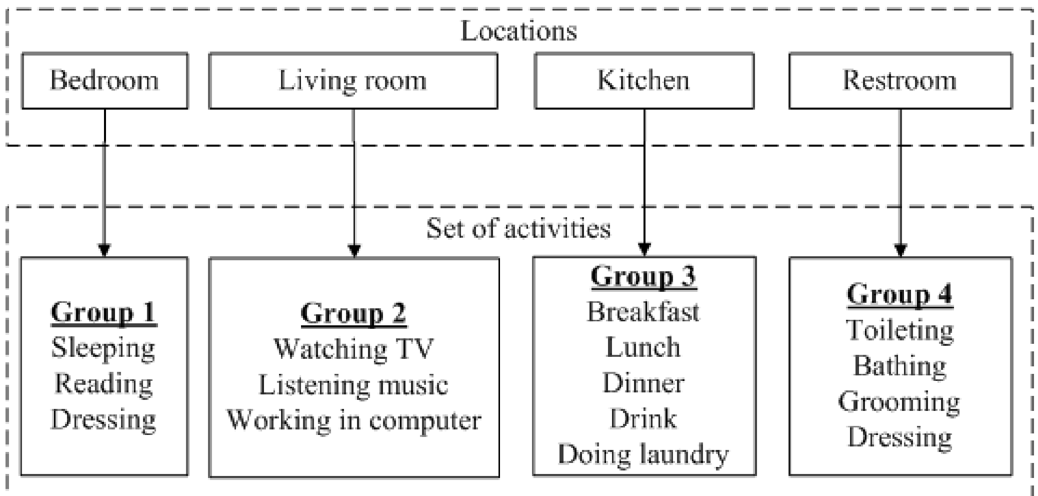


Figure: Location-specific activities

- Improve the data collection procedure
  - Introduce a efficient web mining method

Objectives and challenges

Objectives

- Improve recognition system's accuracy
  - Utilize location information
- Improve the data collection procedure
  - By introducing a efficient web mining method

Challenges

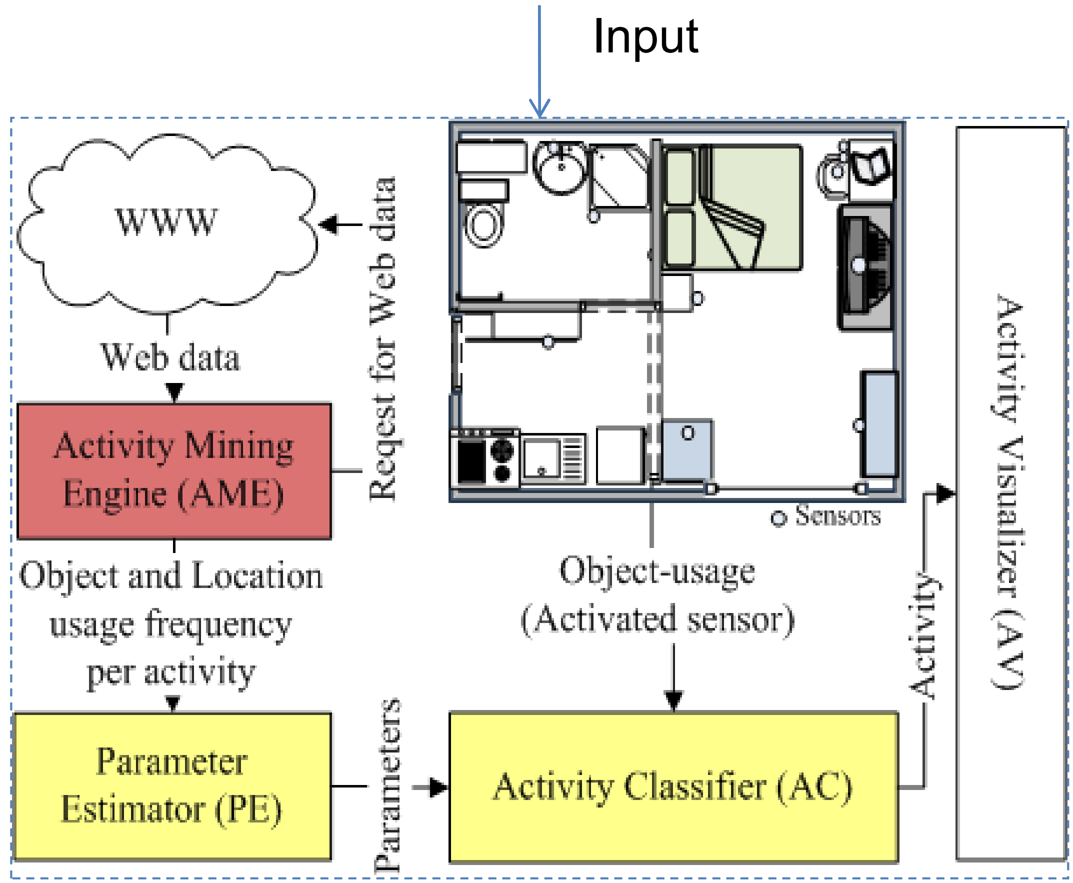
- Approach 1: use location and object-usage separately in multi-layer classifier
  - Model activities with no fixed location (e.g. dressing in bedroom or dressing in bathroom)
  - Model location-overlapping activities (e.g. moving back and forth from kitchen to living room while cooking)
- Approach 2: Integrate location with object-usage in one-layer classifier
  - Classify the activities with no specific location in general
  - Control the influence
  - Determine optimal degrees of influence
- Mining time

Contributions

- Efficient activity recognition system using web activity data
  1. High-accurate two-layer probabilistic classification integrating location and object-usage information
     - Location-and-object-usage based model in the first-layer
     - Object-usage based model in the second-layer
     - Deal with zero-probability problem
  2. Efficient and simple web activity data mining
     - Parameter estimation model using web activity data
     - Efficient implementation using advance operators of a search engine

System Overview

- Environment
  - A set of objects are attached with sensors
- Activity Mining Engine
  - Determine the object-usage and location-usage frequency per activity
- Parameter Estimator
  - Learns the model parameters
- Activity classifier
  - Classify activities based on object (e.g. Door) and location (e.g. Kitchen) usage based model
- Visualization
  - Web-based tool to monitor day-to-day activities



External input to the system

- The environment
  - Locations (e.g. bedroom, living room)
  - Objects/location (e.g. bed, TV) and corresponding sensors id.
- Activities to monitor and their group
  - Activities name/label (e.g. sleeping, watching TV)
  - Location(s) to perform an activity
  - The frequency of doing an activity per day.

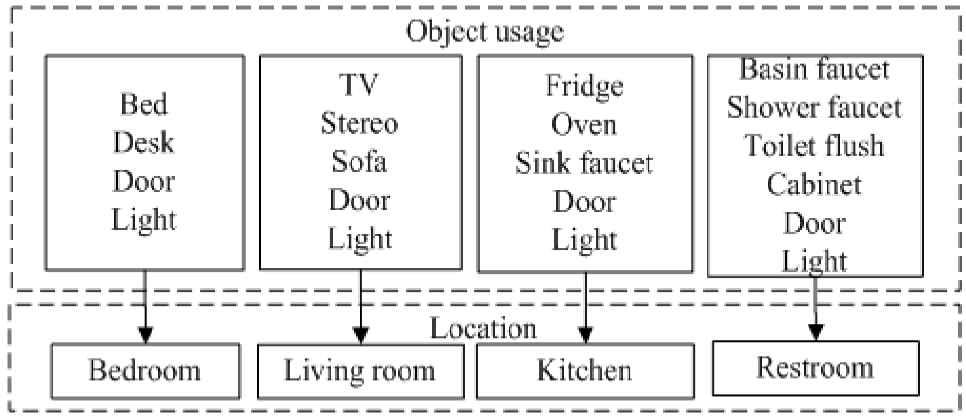


Figure: EARWD input Objects/location

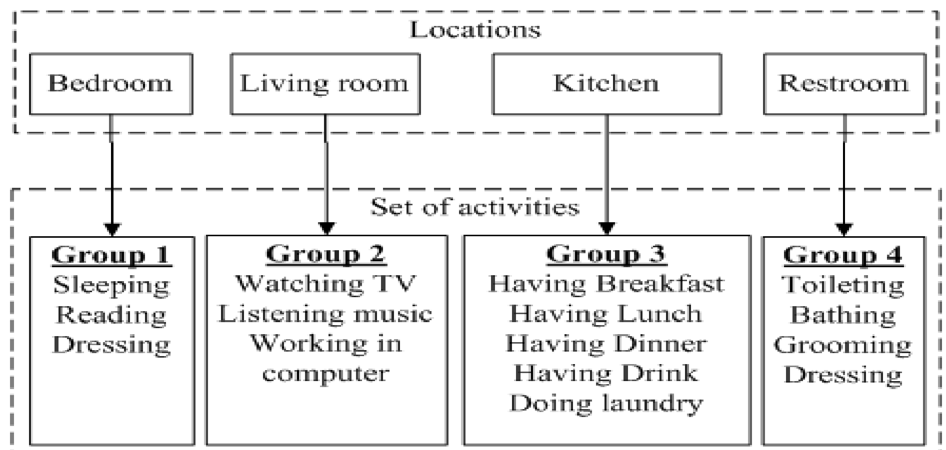


Figure: EARWD input - Location specific activities

Activity classifier

Contribution 1

Naïve Baysian based Two layer classifier

- Location-and-object-usage based model (LOBM) at the first layer classification
  - Classify a group of activities (e.g. kitchen activities)
  - Object with location to resolve any location-confusion.
- Object-usage based model (OBM) at the second layer classifier
  - Classify the actual activity from the activity group
  - For the activities with no specific location in general(e.g. Doing laundry)
  - Get the low level view of an activity

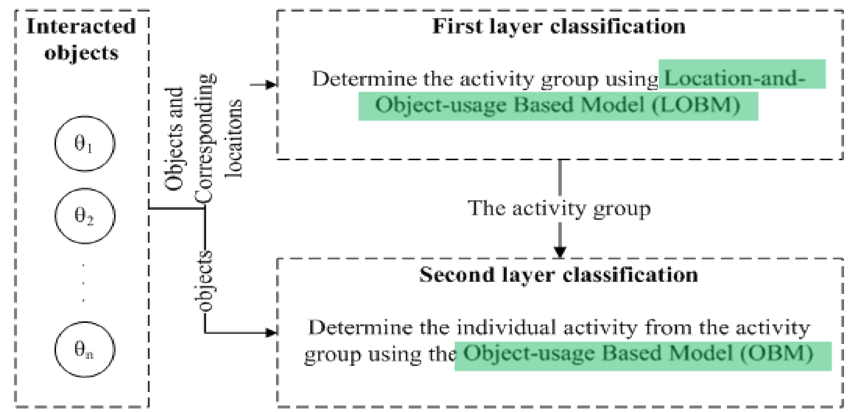


Figure: Overview of the two-layer classifier

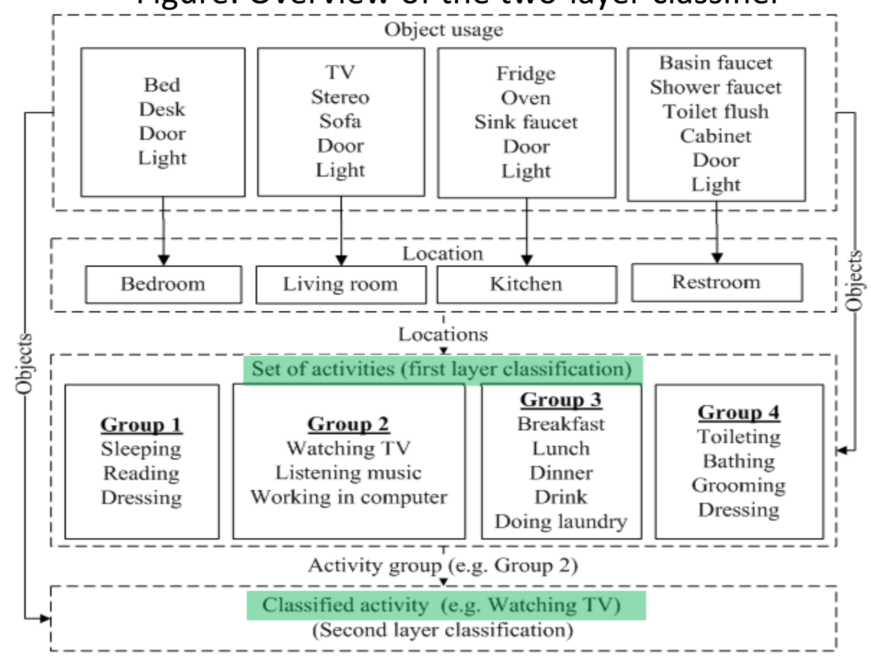


Figure: Two-layer classification: an example for activity watching TV

Location-and-object-usage based model

- Location-and-object-usage based model (LOBM)

$$P_{LOBM}(A_j \mid \Theta) \propto \prod_{k=1}^{|\Theta|} (\alpha P(l_{\theta_k} \mid A_j) + (1-\alpha) P(\theta_k \mid A_j))$$

  - A_j, is an activity group , Θ, is the set of object-usage and $P(l_{\theta_k} \mid A_j)$, $P(\theta_k \mid A_j)$ are the probabilities of using a location and an object given an activity group respectively
  - $0 < \alpha < 1$, is the influential Coefficient (IC) to control the influence of location and object.

Table: An example of object-usage frequency

Activity		Objects		
		Oven	Door	Faucet
Grp 1	Bathing	5	4	60
	Toileting	1	2	100
Grp 2	Going out	7	100	1
Grp 3	Breakfast	70	2	2
	Dinner	90	5	10

Table: An example of location-usage frequency

Activity		Locations		
		Kitchen	Hallway	Toilet
Grp 1	Bathing	10	4	80
	Toileting	2	3	90
Grp 2	Going out	4	90	1
Grp 3	Breakfast	60	7	3
	Dinner	50	6	2

Object-usage based model

- Object-usage based model (OBM)

$$P_{OBM}(a_i \mid \Theta) \propto P(a_i)\prod_{k=1}^{|\Theta|}(\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda)P(\theta_k \mid M_c))$$

  - a_i ε A_j is an activity, $P(\theta_k \mid M_{a_i})$, $P(\theta_k \mid M_c)$ is the probabilities of using a an object given an activity model (AM), M_{a_i} and the activity collection (CM), M_c
  - $0 < \lambda < 1$, is the **Smoothing Coefficient (SC)**to control the influence of an object given an activity and the activity collection.

Why smoothing

- Naïve bayes model $P(a_i \mid \Theta) \propto P(a_i) \prod_{k=1}^{|\Theta|} P(\theta_k \mid a_i)$
- OBM $P_{OBM}(a_i \mid \Theta) \propto P(a_i) \prod_{k=1}^{|\Theta|} (\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda) P(\theta_k \mid M_c))$
- Zero-probability of unseen object
  - calculated probability would be zero for the unseen object for an activity (during training)
  - will wipe out all information in the other probabilities when they are multiplied (during testing)
- to overcome zero probability problem we develop a smoothing technique

Activity model (AM) and Collective Model (CM)

- OBM $$P_{OBM}(a_i \mid \Theta) \propto P(a_i)\prod_{k=1}^{|\Theta|}(\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda)P(\theta_k \mid M_c))$$
- An Activity Model (M_{a_i}) = $\{v_1, v_2, \ldots v_n\}$ is an observation vector of *n* number of objects for an activity, a_i. Where, v_i, being the observed frequency of i^{th} object for an activity.
- A Collective Model (M_c) = $\{M_{a_1}, M_{a_2}, \ldots, M_{a_m}\}$ is a collection of observation vectors of *m* number of activities. Where, M_{a_i}, being the activity model for i^{th} activity.

Table: An example of object-usage frequency

Activity	Objects		
	Oven	Door	Faucet
Bathing	5	4	60
Toileting	1	2	100
Going out	7	100	1
Breakfast	70	2	2
Dinner	90	5	10

Model parameter estimation

- *Models:*
  - *LOBM:*

$$P_{LOBM}(A_j \mid \Theta) \propto \prod_{k=1}^{|\Theta|} (\alpha P(l_{\theta_k} \mid A_j) + (1-\alpha) P(\theta_k \mid A_j))$$

  - *OBM:*

$$P_{OBM}(a_i \mid \Theta) \propto P(a_i) \prod_{k=1}^{|\Theta|} (\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda) P(\theta_k \mid M_c))$$

- *During training we estimate,*

$$P(\theta_k \mid A_j) = \frac{\sum_{a_k \in A_j} freq(\theta_k \mid a_k)}{\sum_{a_k \in A_j, o_c \in O} freq(o_c \mid a_k)} \qquad P(\theta_k \mid M_{a_i}) = \frac{freq(\theta_k \mid a_i)}{\sum_{o_c \in O} freq(o_c \mid a_i)}$$

$$P(l_{\theta_k} \mid A_j) = \frac{\sum_{a_k \in A_j} freq(l_{\theta_k} \mid a_k)}{\sum_{a_k \in A_j, l_c \in L} freq(l_c \mid a_k)} \qquad P(\theta_k \mid M_c) = \frac{\sum_{a_i \in A} freq(\theta_k \mid M_{a_i})}{\sum_{a_k \in A, o_c \in O} freq(o_c \mid M_{a_k})}$$

➢ O and L are the set of all objects and locations respectively.

Table: An example of object-usage frequency

Activity		Objects		
		Oven	Door	Faucet
Grp 1	Bathing	5	4	60
	Toileting	1	2	100
Grp 2	Going out	7	100	1
Grp 3	Breakfast	70	2	2
	Dinner	90	5	10

Table: An example of location-usage frequency

Activity		Locations		
		Kitchen	Hallway	Toilet
Grp 1	Bathing	10	4	80
	Toileting	2	3	90
Grp 2	Going out	4	90	1
Grp 3	Breakfast	60	7	3
	Dinner	50	6	2

Influential coefficient estimation

- LOBM $$P_{LOBM}(A_j \mid \Theta) \propto \prod_{k=1}^{|\Theta|} (\alpha P(l_{\theta_k} \mid A_j) + (1-\alpha) P(\theta_k \mid A_j))$$
- Influential coefficient (α)
  - *0 < α < 1, is the* ***influential Coefficient (IC)***.
  - how much influence would be optimal (or nearly optimal) for a given dataset?
  - calculate the importance of the locations for all the activity groups
  - the sum of average number of times the locations appeared in the activity dataset

$$\alpha = \frac{\sum_{i=1}^{q} \frac{\sum_{a_k \in A_i, l_c \in L} freq(l_c \mid a_k)}{\sum_{a_k \in A_i} freq(a_k)}}{q}$$, q is the number of activity groups

  - *L* is the set of locations in the environment, l_c ε *L*

Smoothing coefficient

- OBM

$$P_{OBM}(a_i \mid \Theta) \propto P(a_i) \prod_{k=1}^{|\Theta|} (\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda) P(\theta_k \mid M_c))$$

- Smoothing coefficient (λ)
  - *0 < λ < 1, is the* ***Smoothing Coefficient (SC)***.
  - smoothing is proportional to the number of zero-frequencies
  - the more zero-frequencies we have in a dataset, the more smoothing is required.
  - the average of the average number of objects with zero-frequencies in each activity

$$\lambda = \frac{\sum_{a_i \in A} \frac{\sum_{o_c \in O} \delta(freq(o_c \mid a_i))}{t}}{m} \qquad \delta = 1 \text{ if } freq(o_c \mid a_i) == 0, 0 \text{ otherwise}$$

  - *m* and t are the number of activities and objects respectively
  - *O* is the set of objects in the environment, o_c ε *O*

Activity mining engine (AME)

Contribution 2

- Goal
  - provide enough **activity knowledge**
    - object-usage and location-usage frequency for an activity such that PE can compute the followings.

$$P(\theta_k \mid A_j) = \frac{\sum_{a_k \in A_j} freq(\theta_k \mid a_k)}{\sum_{a_k \in A_j, o_c \in O} freq(o_c \mid a_k)} \qquad P(\theta_k \mid M_{a_i}) = \frac{freq(\theta_k \mid a_i)}{\sum_{o_c \in O} freq(o_c \mid a_i)}$$

$$P(l_{\theta_k} \mid A_j) = \frac{\sum_{a_k \in A_j} freq(l_{\theta_k} \mid a_k)}{\sum_{a_k \in A_j, l_c \in L} freq(l_c \mid a_k)} \qquad P(\theta_k \mid M_c) = \frac{\sum_{a_i \in A} freq(\theta_k \mid M_{a_i})}{\sum_{a_k \in A, o_c \in O} freq(o_c \mid M_{a_k})}$$

  - efficient and simple

Table: An example of object-usage frequency

Activity		Objects		
		Oven	Door	Faucet
Grp 1	Bathing	5	4	60
	Toileting	1	2	100
Grp 2	Going out	7	100	1
Grp 3	Breakfast	70	2	2
	Dinner	90	5	10

Table: An example of location-usage frequency

Activity		Locations		
		Kitchen	Hallway	Toilet
Grp 1	Bathing	10	4	80
	Toileting	2	3	90
Grp 2	Going out	4	90	1
Grp 3	Breakfast	60	7	3
	Dinner	50	6	2

Types of activity pages in the web

- Explicit Activity Catalog Page (EACP)
- Implicit Activity Catalog Page (IACP)

Explicit Activity Catalog Page (EACP)

- Provides instructions in detail, like how to perform an activity.
- Has a title, which in most cases contains the activity name.
- Has a body, which provides detail descriptions of how to perform the activity
- Contains information regarding object-usage and location-usage for that activity

Implicit Activity Catalog Page (IACP)

- It does not directly defines how to perform the activity but instead provides the instructions that would influence the activity or
- Provides required objects and/or location for the activity
- It has similar characteristics as EACP

AME: Example activity pages

Bathing in Style - The Art of Bathing Well

...

The perfect length of a bath is 10-15 minutes. After that your skin starts to wrinkle and your water gets cold. It is always good to have a bottle of water available since a warm or hot bath can be dehydrating. Be sure to sip water if you feel the need. Some people prefer a glass of red wine, champagne or port to help relax. Or you can have a cup of green tea or even chamomile tea to help you relax. Lock your ***door***, turn the ***lights*** off and light as many candles as you can (candles are essential as they affect your mood). Support your head with a bath pillow or a folded up towel. Pick a nice relaxing ***CD***, close your eyes and enjoy your peace and quiet.

...

Figure: Example of an explicit activity catalog page (EACP)

IS20_Toileting.pdf

…

A child is ready for independence when he shows signs that he knows he needs to go tothe toilet. These maybe by jiggling around, going quiet, or by moving to a particular area inthe house or backyard where you know he often 'does his business'.

Begin training for independence as part of your toilet training program. When you giveyour child the cue "toilet", also using the sign and/or COMPIC picture, get him to eithersay the word, point to the picture, with you helping him to point if necessary, or help himmake the sign. Make sure your COMPIC picture of the toilet is handy so that you don'thave to hunt around for it each time. You may want to have a few around on the fridge,the ***bedroom*** door, the **lounge room** door, and the **toilet** door.

...

Figure: Example of an Implicit Activity Catalog Page (IACP)

How to Make Bathing Safe For Independent Seniors

...

The simplest and most inexpensive remedy is to have a ***bath seat*** installed. This way, the user can have a seat in the ***bathtub*** for stability. The seat would be too high to take a bath, so the best way to bathe in this manner would be to use a hand-held shower head. Keep in mind the drawbacks for this method: The user still must step over the side of the tub to get in and out, and they will have to manually clean themselves with the shower head. If the user's mobility is not terribly restricted, just a little slow or unsteady, this method could easily work.

A ***bath lift*** would work better than a bath seat for someone with limited mobility. These mobility aids allow a user to sit comfortably before lowering them down into the bath. Once they are ready, the device lifts them back up to a sitting position. Often, they will feature a transfer bench so that the user can "slide" over the edge of the tub to get in or out. Bath lifts are more expensive than bath seats, but can restore privacy and independence even for seniors with moderately severe mobility restrictions.

Installing a tall walk-in bathtub in a separate area of the ***bathroom*** is probably the best way to guarantee safety for a senior with limited mobility. Walk-in ***bathtubs*** feature a ***doorway*** so that the user doesn't have to step over the side. While some walk-in bathtubs are meant to replace an ordinary ***bathtub*** as a permanent installation, I don't recommend those because they don't offer an easy way for the user to sit/stand and they will bring down the resale value of a house. Instead, opt for a tall walk-in bathtub with a bench. This type of walk-in tub can be removed from the ***bathroom*** when it's no longer needed. This way, the user can take a bath while sitting upright, similar to sitting in a ***hot tub***. There's no need to lower the body to ground level, and getting in and out is easy. Walk-in ***bathtubs*** are gaining in popularity for residential use as more and more people decide that they are worth the cost to maintain their privacy and independence.

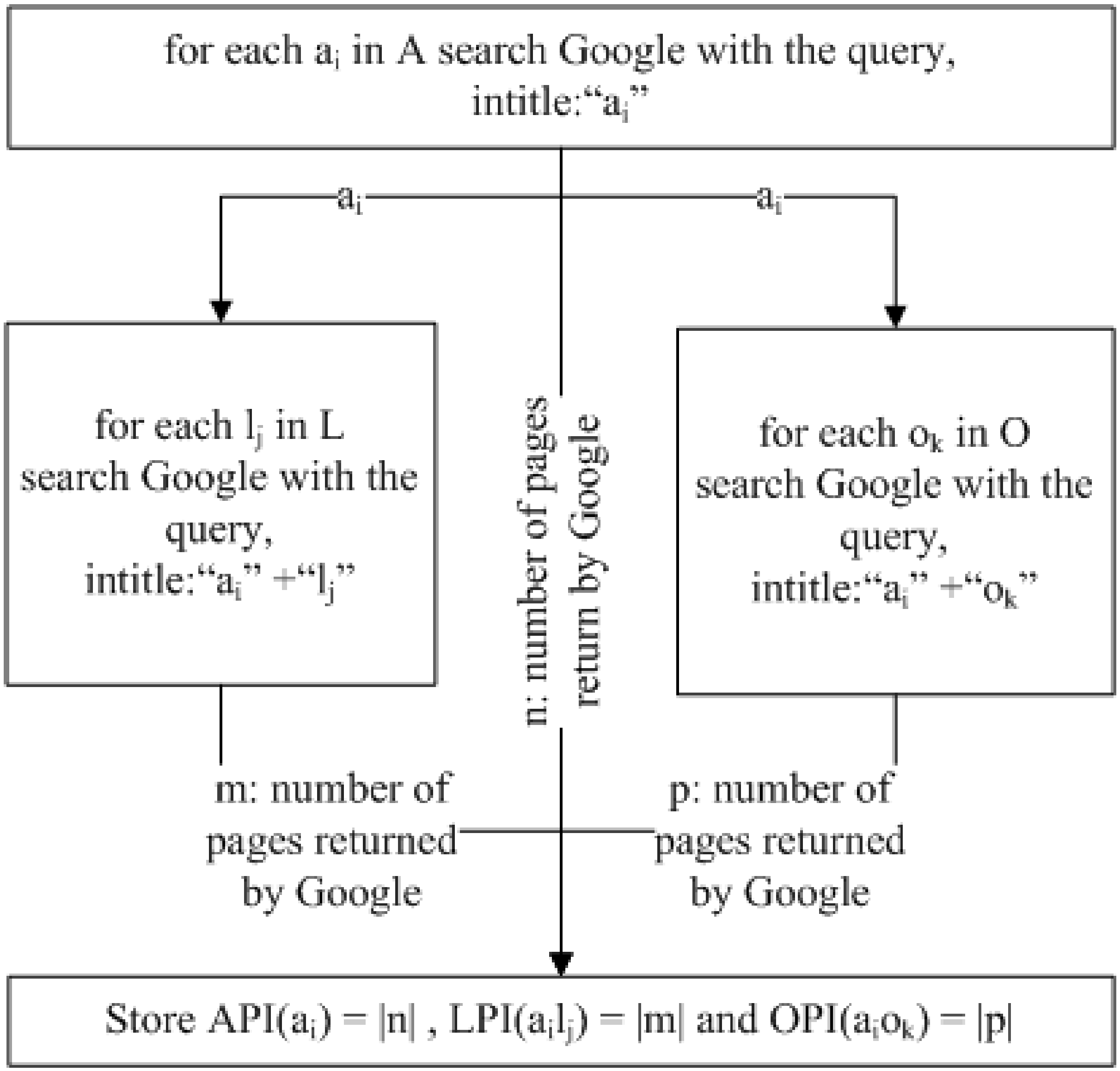
...

Figure: Example of an Implicit Activity Catalog Page (IACP)

AME: Google advance operators

Name	Description
“”	The quotes forces Google to search for the exact phrase. For example, the query [“Preparing dinner”] would find the pages containing the exact phrase “Preparing dinner”.
intitle	If we include [intitle:] in our query, Google would return all the web pages containing the word in the title of the web pages. For instance, the query [intitle:``Preparing dinner''] would find all the web pages that have ``Preparing dinner'' in their title.
+	By attaching a + immediately before a word, we can instruct Google to match that word precisely (without including synonyms). For instance, the query [intitle:``Preparing dinner'' +``Butler pantry'' would find all the pages containing the phrase ``Preparing dinner'' in their title and containing the exact phrase ``Butler pantry'' in their text.

AME :Mining algorithm



Mining example

Figure: An example of Activity Page Indexed (API).

Figure: An example of Location Page Indexed (LPI)

Figure: An example of Object Page Indexed (OPI)

Mining time complexity

- Let *m, t, q* be the total number of activities, objects, and locations respectively.
- Total number of queries required by the mining engine is, $r = m + m(q + t)$;
- Time complexity = $O(r)$.
- Example:
  - if we consider an environment where 20 objects (embedded with sensors) in 5 different locations and there are 10 activities to monitor. To mine the model parameters, the AME would need 260 queries in total.
  - If google takes 0.5 seconds/query, total mining time will be 130 seconds appx.

Agenda

- Introduction
- Related work
- Our approach
- **Evaluation**
- Conclusion & Future work

Evaluation objectives

- Validate the performance of the EARWD
- Three experiments
  - evaluate the classifier's performance in classifying activities
  - compare different classifiers in terms of their classification accuracy and compare the performance of mining
  - analyze the impact of the coefficients (α and λ) to classifier's performance

Experimental setup

- Setup for mining
  - The AME uses the site, http://ajax.googleapis.com/ instead of http://google.com/ (original site would not allow robot)
    - For example, to mine the API for ``Cooking'', the AME would send a query as http://ajax.googleapis.com/ajax/services/search/web?v=1.0&q=intitle:Cooking
- Setup for evaluating system's performance
  - Three Datasets
    - PlaceLab (MIT) datasets (subject 1, subject 2) [4]
    - Intelligent Systems Lab Amsterdam (ISLA) dataset [5]
  - Evaluation mathodologies
    - Timeslice accuracy
      - N is the number of activity instances
    - Class accuracy
      - C is the number of classes
      - N_c is the number of activity instances in class c

$$\frac{\sum_{i=1}^{N} recognized_i == true}{N}$$

$$\frac{1}{C}\sum_{c=1}^{C}\left\{\frac{\sum_{i=1}^{N_c} recognized_i == true}{N_c}\right\}$$

Experiment 1: Efficiency of the system

- Activity recognition accuracy
- Performance comparison of the two-layer classifier with the one-layer classifier
  - Two layer models
    - $LOBM_{tl}$
    - OBM_{tl}

$$P_{LOBM}(A_j \mid \Theta) \propto \prod_{k=1}^{|\Theta|} (\alpha P(l_{\theta_k} \mid A_j) + (1-\alpha) P(\theta_k \mid A_j))$$

$$P_{OBM}(a_i \mid \Theta) \propto P(a_i) \prod_{k=1}^{|\Theta|} (\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda) P(\theta_k \mid M_c))$$

  - One layer model ($LOBM_{ol}$)

$$P_{LOBM_{ol}}(a_i \mid \Theta) \propto P(a_i) \prod_{k=1}^{|\Theta|} (\alpha P(l_{\theta_k} \mid a_i) + (1-\alpha)(\lambda P(\theta_k \mid M_{a_i}) + (1-\lambda) P(\theta_k \mid M_c)))$$

$$\alpha = \frac{\sum_{i=1}^{m} \frac{\sum_{l_c \in L} LPI(l_c \mid a_i)}{API(a_i)}}{m}$$

Experiment 1: Accuracies per class

- Two-layer classifier performs better for the activities with no specific locations because of location specific activity grouping.

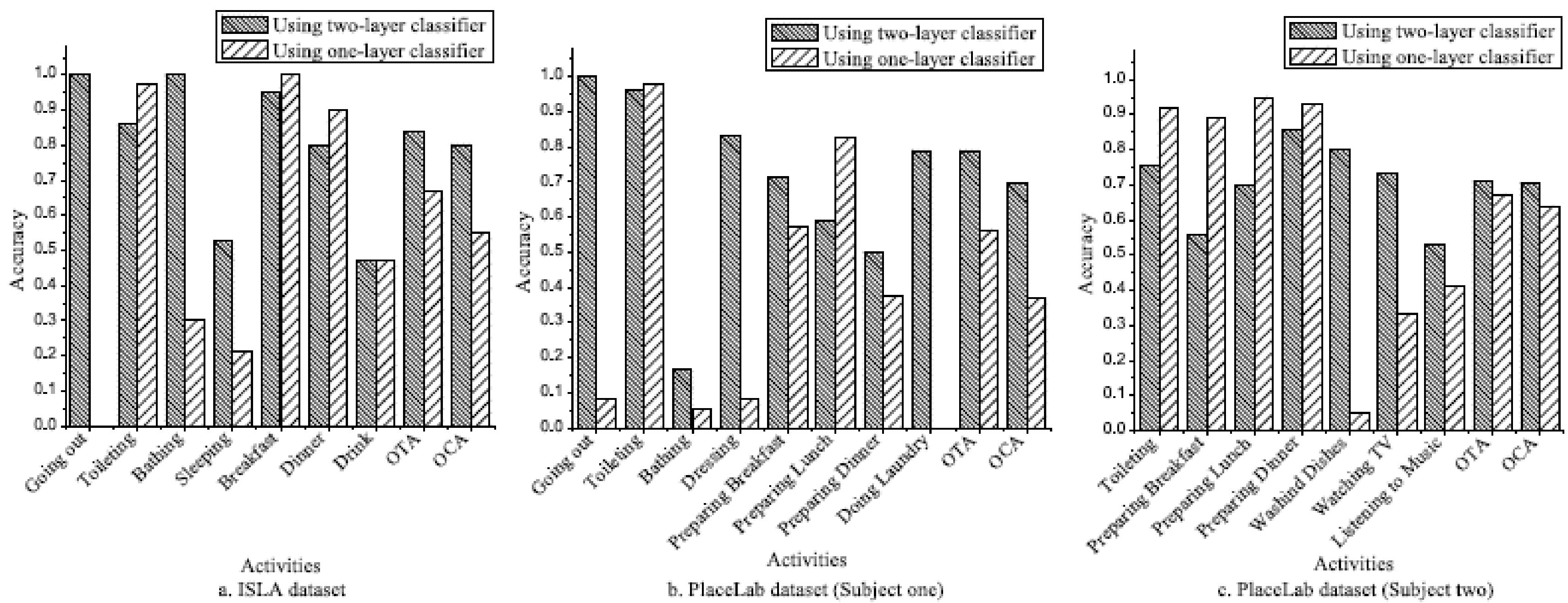
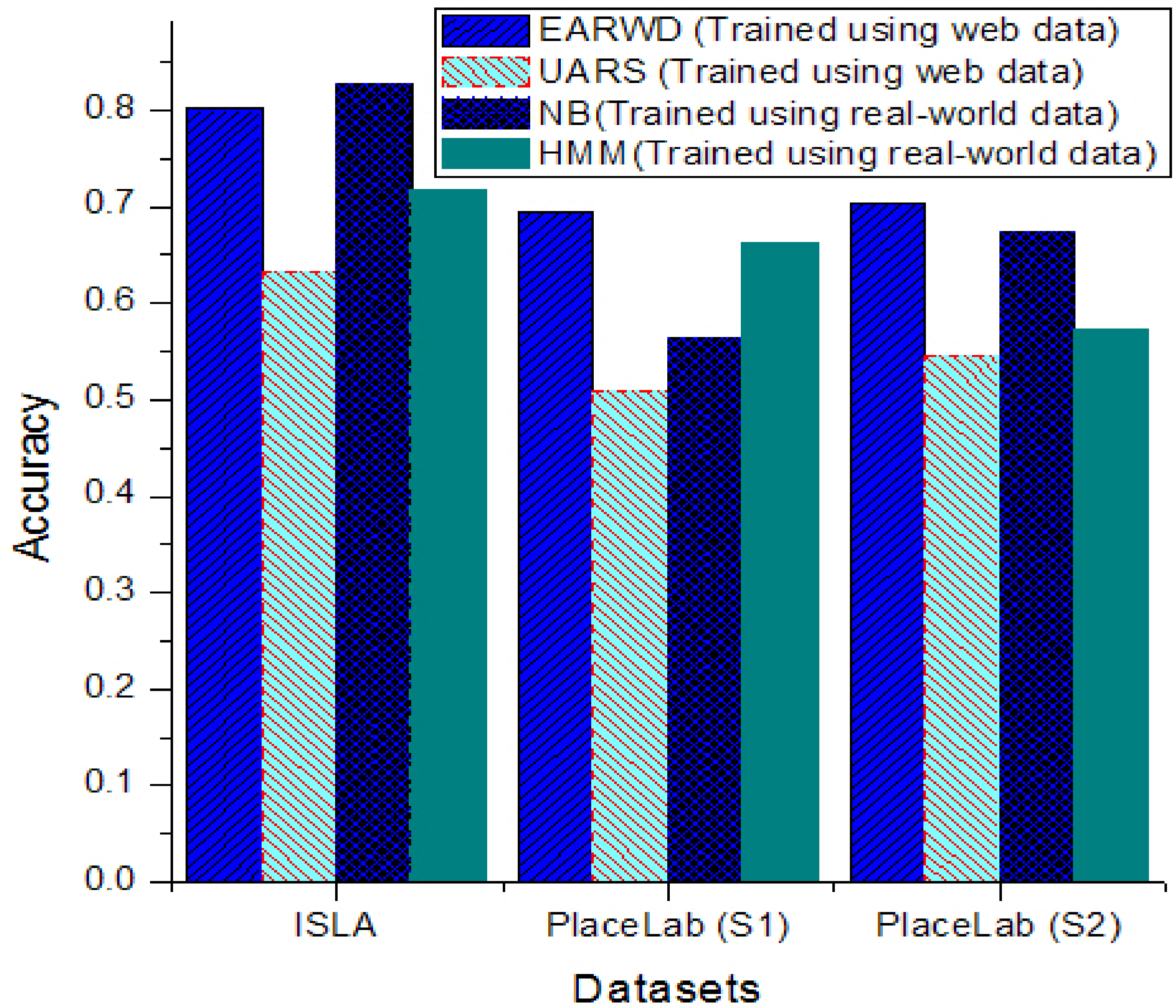


Figure: The accuracies per class for three datasets, two-layer classifier (left), one-layer classifier (right). The rightmost two pairs of bars compare the overall timeslice accuracy (OTA) and the overall class accuracy (OCA).

Experiment 2: Performance comparison with the other classifiers



Experiment 2: Mining time comparison

- EARWD
  - It uses search engine's advance operators
    - to determine an activity page and
    - to count the frequency of an object-usage for an activity .
- UARS
  - Additional genre classifier
    - Determine an activity page
  - Object identification algorithm
    - Count the frequency of an object-usage for an activity

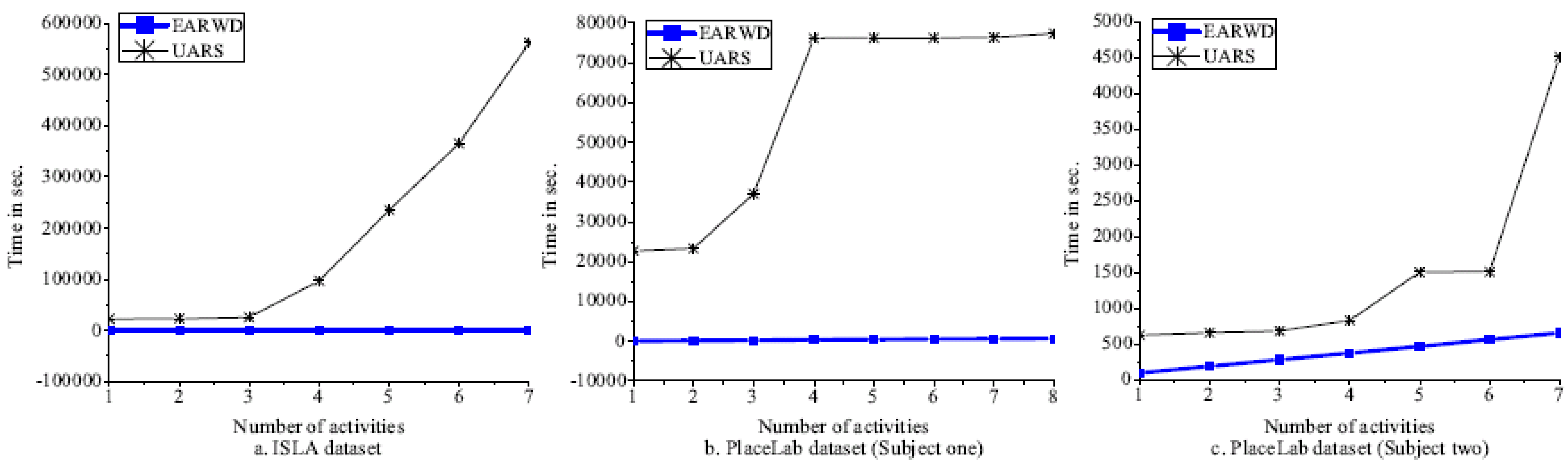


Figure: Mining time comparison between the our system and the UARS [4]

Experiment 3: Varying model coefficients

- Analyze the impact of the coefficients
- Multi-layer classifier using Location and object provides better accuracy
- Smoothing provide better result

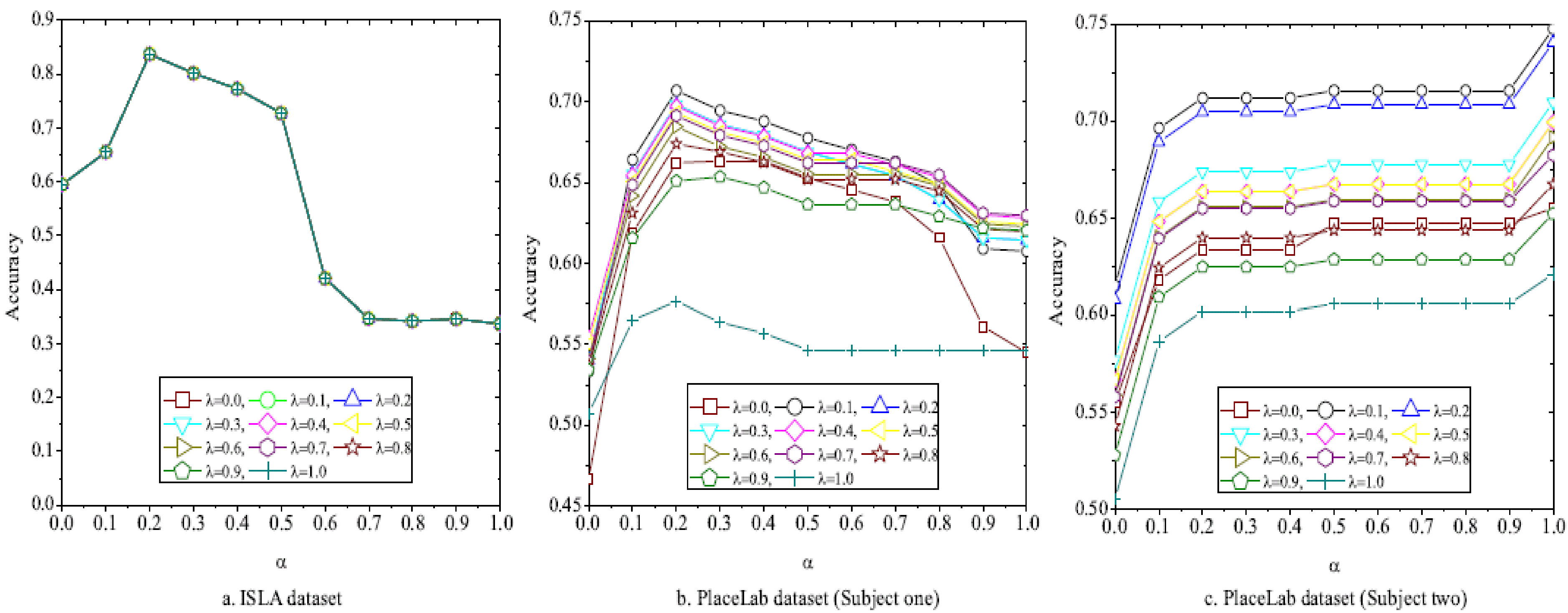


Figure: Activity recognition accuracy with different α and λ settings.

Experiment 3: Estimated vs. optimal α and λ values

- The estimated coefficient, α , for the ISLA dataset and for the PlaceLab dataset (Subject One) are near their optimal values.
- The estimated coefficient, α , is not near to the optimal value for the PlaceLab dataset (Subject One).
  - Switching between locations (by the user) while doing an activity was relatively less.

Table: Estimated vs. optimal α and λ values

Datasets	α		λ	
	Estimated	Optimal	Estimated	Optimal
ISLA	0.3343	0.2	0.0051	-
PlaceLab (Subject one)	0.1529	0.2	0.1475	0.1
PlaceLab (Subject two)	0.3643	1	0.1224	0.1

Conclusion

- Efficient activity recognition system using web activity data
    - Easily configurable
    - Effortlessly scalable
    - High-accurate two-layer probabilistic classification integrating location and object-usage information
        - Location-and-object-usage based model in the first-layer to classify a group of activity
        - Object-usage based model in the second-layer to classify the actual activity
        - Deal with zero-probability problem
    - Efficient and simple web activity data mining
        - Parameter estimation model using web activity data
        - Efficient implementation using advance operators of a search engine (we use Google for our experiment)
- We performed three experiments to validate the performance of the system

Future work

- Sensor-based, multi-user activity recognition
- Challenges
  - How to determine who uses the object?
    - Wearable sensor?
    - Or RFID sensors (could be expensive)
  - How to recognize a collective effort

References

1. E. M. Tapia, S. S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," in *Pervasive, ser. Lecture Notes in Computer Science, A. Ferscha and* F. Mattern, Eds., vol. 3001. Springer, 2004, pp. 158–175.
2. T. van Kasteren, A. Noulas, G. Englebienne, and B. Kr¨ose, "Accurate activity recognition in a home setting," in UbiComp '08: Proceedings of the 10th international conference on Ubiquitous computing. New York, NY, USA: ACM, 2008, pp. 1–9.
3. M. Perkowitz, M. Philipose, K. Fishkin, and D. J. Patterson, "Mining models of human activities from the web," in *WWW '04: Proceedings of the 13th international conference on World Wide Web. New York, NY, USA: ACM, 2004, pp. 573–582.*
4. D. Wyatt, M. Philipose, and T. Choudhury, "Unsupervised activity recognition using automatically mined common sense," in AAAI'05: Proceedings of the 20th national conference on Artificial intelligence. AAAI Press, 2005, pp. 21–27.
5. S. S. Intille, J. Rondoni, C. Kukla, I. Ancona, and L. Bao. A context-aware experience sampling tool. In Proceedings of the Conference on Human Factors and Computing Systems: CHI '03 extended abstracts on Human factors in computing systems, pages 972–973, 2003.
6. S. S. Intille, E. M. Tapia, J. Rondoni, J. Beaudin, C. Kukla, S. Agarwal, L. Bao, and K. Larson. Tools for studying behavior and technology in natural settings. In Proceedings of UBICOMP, pages 157–174, 2003.
7. D. J. Patterson, L. Liao, D. Fox, and H. A. Kautz, "Inferring high-level behavior from low-level sensors," in Proc. Ubicomp, ser. Lecture Notes in Computer Science, A. K. Dey, A. Schmidt, and J. F. McCarthy, Eds., vol. 2864. Springer, 2003, pp. 73–89.
8. F. Jelinek and R. L. Mercer, "Interpolated estimation of Markov source parameters from sparse data," in Proceedings, Workshop on Pattern Recognition in Practice, E. S. Gelsema and L. N. Kanal, Eds. Amsterdam: North Holland, 1980, pp. 381–397.

List of publications

International Journal Papers:

[1] **Jehad Sarkar**, La The Vihn, Young-Koo Lee, Sungyoung Lee. GPARS: a general-purpose activity recognition system. Accepted for publication at the Journal of Applied Intelligence (available online). DOI 10.1007/s10489-010-0217-4 (SCI).

[2] **Jehad Sarkar**, Young-Koo Lee, Sungyoung Lee. A Smoothed Naive Bayes-Based Classifier for Activity Recognition. IETE Technical Review 27(2), 107119 (2010). DOI 10.4103/0256-4602.60164 (SCIE).

International Conference Papers:

[3] **Jehad Sarkar**, Young-Koo Lee, Sungyoung Lee. ARHMAM: an activity recognition system based on Hidden Markov minded activity model. The Fourth International Conference on Ubiquitous Information Management and Communication (ICUIMC'10), pp: 484-492, 2010, SKKU, Suwon, South Korea.

[4] **Jehad Sarkar**, Kamrul Hasan, Young-Koo Lee, Sungyoung Lee, Salauddin Zabir. Distributed activity recognition using key sensors. 11th International Conference on Advanced Communication Technology, pp: 2245-2250, 2009, Phoenix Park, South Korea.

[5] **Jehad Sarkar**, Phan Tran Ho Truc, Young-Koo Lee and Sungyoung Lee. statistical language modeling approach to activity recognition. In Proceedings of the 5th International Conference on Ubiquitous Healthcare, pp: 148-152, 2008,, Busan, South Korea.

[6] Khandoker Tarik-ul Islam, **Jehad Sarkar**, Kamrul Hassan, Mohammad Rezwanul Huq, Andrey Gavrilov, Sungyoung Lee, and Young-Koo Lee. A framework for smart object and Its collaboration in smart environment. 10th International Conference on Advanced Communication Technology, pp:852-855, 2008, Phoenix Park, South Korea.

Domestic Conference Papers:

[7] Syed Khairuzzaman Tanbeer, **Jehad Sarkar**, Byeng-Soo Jeong,, Young-Koo Lee and Sungyoung Lee. I-Tree: A frequent patterns mining approach without candidate generation or support constraint. In Proceedings of the 27th KIPS (Korean Information Processing Society) conference, pp:31-33 Kyung won University, Korea, May 11-12, 2007.

Appendix

Naïve Bayes classifier for activity recognition

- Assumes that the effect of an object on a given activity is independent of the other object (i.e. independent assumption)
- For classification, the classifier computes the posterior probability, $P(a_i \mid \Theta)$, using the Bayes rule: $P(a_i \mid \Theta) \propto P(a_i)\prod_{k=1}^{|\Theta|} P(\theta_k \mid a_i)$
  - Θ, is the set of object-usage for a given time, $\Theta_k \varepsilon\, \Theta$
  - $P(a_i)$ is the prior probability of an activity, a_i,
  - $P(\Theta_k \mid a_i)$, is the probability of an object given an activity
- In order to classify the activity label of Θ, $P(a_i \mid \Theta)$ is evaluated for each activity, a_i.
- The classifier predicts that the activity label of vector, Θ, is the activity a_i if and only if, $P(a_i \mid \Theta) > P(a_j \mid \Theta)$ *for* $1 \le j \le m,\ j \ne i$
  - m, is the number of activities

Mining challenges

- Identifying a web document that is related to an activity
- Object and location extraction from the document
- Mining time

AME: Mining algorithm

Algorithm 4.1: AME(A, O, L). The activity mining engine to mine activity knowledge from the web.

Data: List of activities A, List of objects O, List of locations L

Result: Activity Pages Indexed (API), Location Pages Indexed (LPI) and Object Pages Indexed (OPI)

for $i \leftarrow 1$ **to** $length(A)$ **do**

  $API_i = \texttt{this} \leftarrow SG(\text{“}intitle:\text{“}a_i\text{”}\text{”})$; `/* SG (Search Google) would return the number of pages indexed by Google for the given query */;`

  for $j \leftarrow 1$ **to** $length(L)$ **do**

    $LPI_{ij} = \texttt{this} \leftarrow SG(\text{“}intitle:\text{“}a_i\text{”} + \text{“}l_j\text{”}\text{”})$;

  end

  for $k \leftarrow 1$ **to** $length(O)$ **do**

    $OPI_{ik} = \texttt{this} \leftarrow SG(\text{“}intitle:\text{“}a_i\text{”} + \text{“}o_k\text{”}\text{”})$;

  end

end

- A, O, L is the set of activities, objects and locations respectively
- API: Number of pages indexed by google for an activity, a_i (i.e. $freq(a_i)$)
- LPI: Number of pages indexed by google for a location, $l\theta_k$, given an activity, a_i (i.e. $freq(l\theta_k | a_i)$)
- OPI: Number of pages indexed by google for an object , θ_k, given an activity, a_i (i.e. $freq(\theta_k | a_i)$)

Experiment 1: Estimated α and λ

Table: Calculated α and λ

Datasets	α		λ
	Two-layer	One-Layer	
ISLA	0.3343	0.5663	0.0051
PlaceLab (Subject one)	0.1529	0.5116	0.1475
PlaceLab (Subject two)	0.3643	0.4775	0.1224

Experiment 3: Estimated vs. optimal α and λ values

- The estimated coefficient, α , for the ISLA dataset and for the PlaceLab dataset (Subject One) are near their optimal values.
- The estimated coefficient, α , is not near to the optimal value for the PlaceLab dataset (Subject One).
  - Switching between locations (by the user) while doing an activity was relatively less.

Table: Estimated vs. optimal α and λ values

Datasets	α		λ	
	Estimated	Optimal	Estimated	Optimal
ISLA	0.3343	0.2	0.0051	-
PlaceLab (Subject one)	0.1529	0.2	0.1475	0.1
PlaceLab (Subject two)	0.3643	1	0.1224	0.1