基於智慧空間之銀髮族日常生活活動觀測照護系統

Activity of Daily Living-aware Healthcare for Elderly in Pervasive Environment

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Outline

- Introduction
- Activity Recognition
- Activity of Daily Living-aware Elderly Healthcare
- System Evaluation
- Conclusion and Future Work

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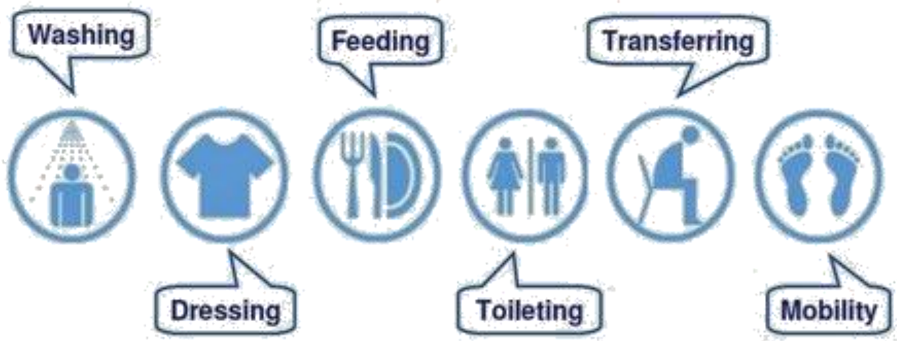
Activity of Daily Living

- With population aging, the aging in place is popular
  - Most elderly people prefer to live their own house
  - The inconvenient situations are still exist
    - Loss of autonomy
    - Dementia symptoms
- Activity of daily living(ADL) is an important factor to estimate the independency ability of elders



Motivation

- Monitoring the ADL of elders to measure their ability can improve the safe living conditions at home
- Most of the activity monitoring methods are still in the experimental stage
  - Both Ambient Intelligence (AmI) and mobile computing develop the techniques of activity recognition
  - The techniques of fusing both types of sensors is lacking
- Unfriendly human computer interaction
  - Most of activity recognition methods are supervised learning
  - All training data are required to be labeled

Objective

- We propose a system that helps caregivers recognize elders' ADL in their home
  - Monitoring elders activities in real-time
  - Discovering new activities
- Propose a model to categorize raw sensor data into fewer quantity of clusters
  - Labeling activity with fewer efforts

Challenge

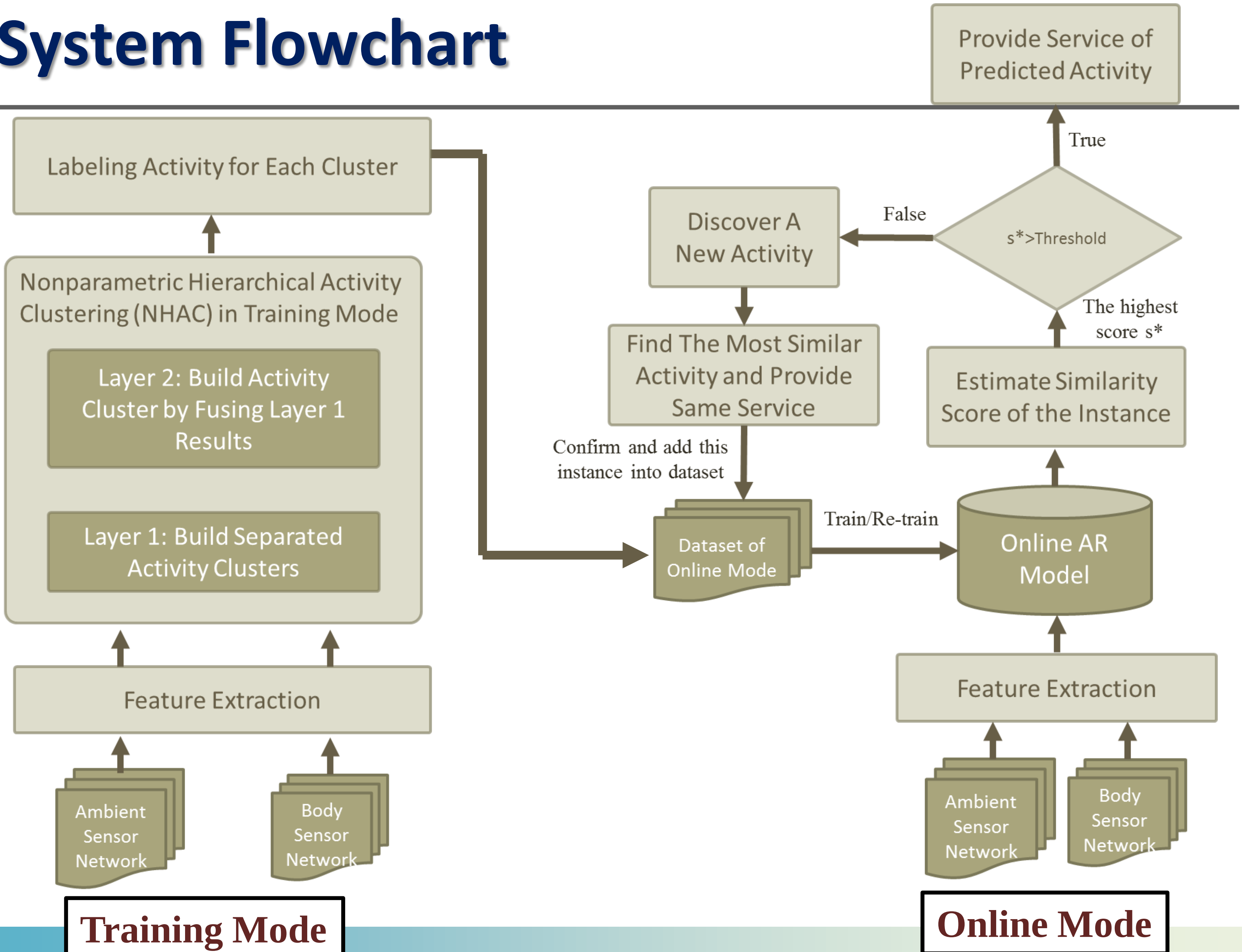
- Integrating data from both ambient and vital sign sensors
  - The difference methods of data analysis for Ambient Intelligence (AmI) and for mobile computing
- High cost on labeling activity
  - Ground truth of each instance in machine learning are necessary
- Adaptive learning of activity recognition
  - With aging, elderly people may have new lifestyles activities

Related Work

ADL-aware System	Sensor Network		Reduce the burden on labeling	Discover Unknown Activity
	Vital Sign	Ambient		
The proposed Model	✓	✓	✓	✓
Sun *et al*. [1]	✓		✓	
Yuan et al. [2]	✓			✓
Cheng et al. [3]	✓		✓	
Sanchez et al. [4]		✓		
Cook et al. [5]		✓	✓	✓
Zhang et al. [6]		✓		

[1] F.T. Sun, Y.T. Yeh, H.T. Cheng, C.c. Kuo, and M. Griss, "Nonparametric discovery of human routines from sensor data," in *IEEE International Conference on Pervasive Computing and Communications*, 2014, pp. 11-19.
[2] B. Yuan and J. Herbert, "Context-aware hybrid reasoning framework for pervasive healthcare,“ *Personal and ubiquitous computing,* vol. 18, pp. 865-881, 2014.
[3] H.T. Cheng, M. Griss, P. Davis, J. Li, and D. You, "Towards zero-shot learning for human activity recognition using semantic attribute sequence model," in *Proc. ACM international joint conference on Pervasive and ubiquitous computing*, 2013, pp. 355-358.
[4] D. Sanchez, M. Tentori, and J. Favela, “Hidden markov models for activity recognition in ambient intelligence environments,” in *Eighth Mexican International Conference on Current Trends in Computer Science*, 2007, pp. 33-40.
[5] D. J. Cook, N. C. Krishnan, and P. Rashidi, "Activity discovery and activity recognition: A new partnership," *IEEE Transactions on Cybernetics,* vol. 43, pp. 820-828, 2013.
[6] Q. Zhang, M. Karunanithi, R. Rana, and J. Liu, "Determination of Activities of Daily Living of independent living older people using environmentally placed sensors," in *2013 International Conference of the IEEE on Engineering in Medicine and Biology Society (EMBC)*, 2013, pp. 7044-7047.

System Flowchart



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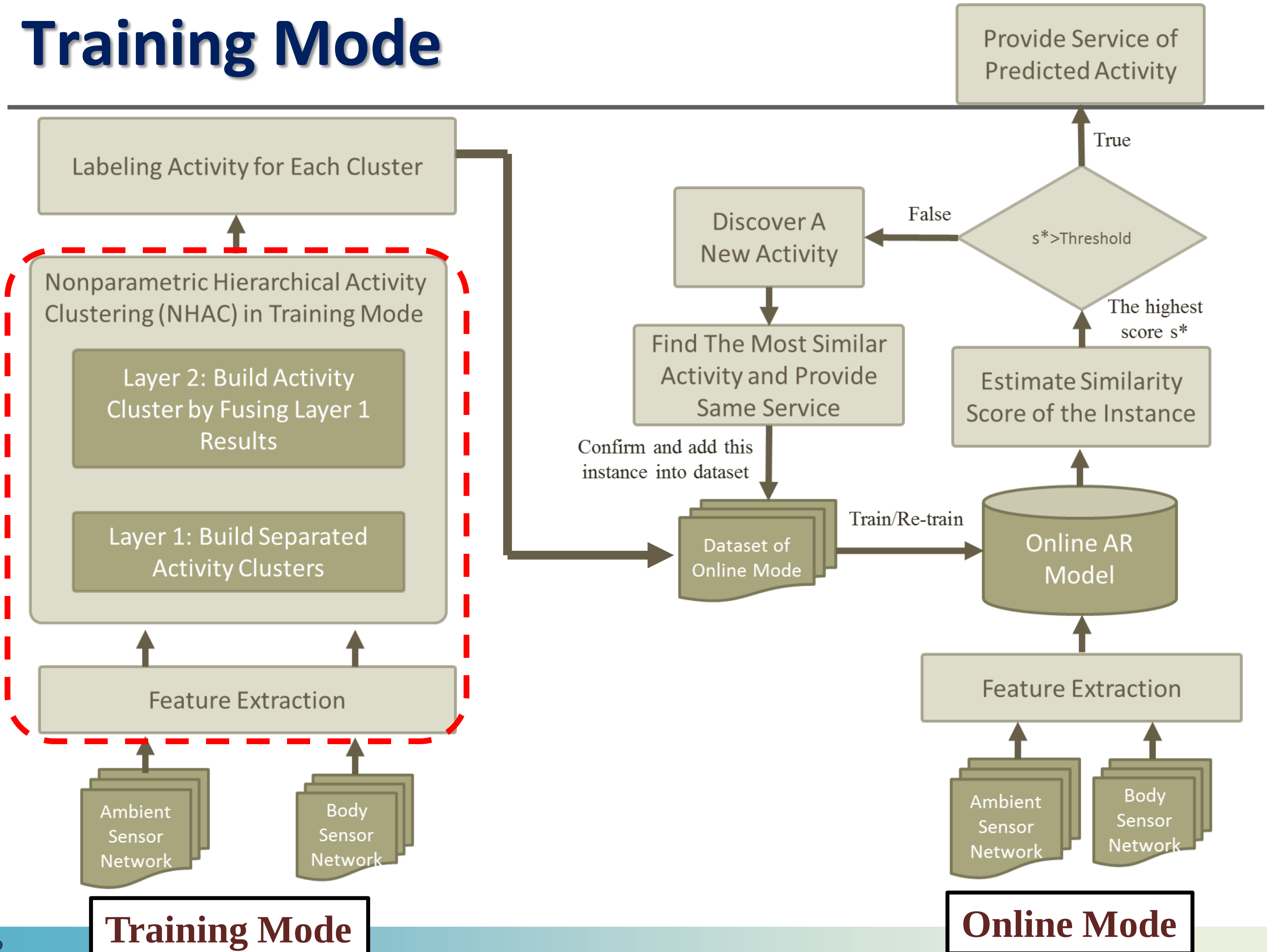
Architecture of Activity Recognition Model

- An activity recognition model is proposed to real-time recognize elder's activity of daily living
- To achieve fewer efforts on labeling, the model has two modes
  - Training mode
    - Categorizing raw data into a number of clusters
    - Reducing the number of labeling data
  - Online mode
    - Real-time recognizing elders' activity
    - Discovering unknown activity

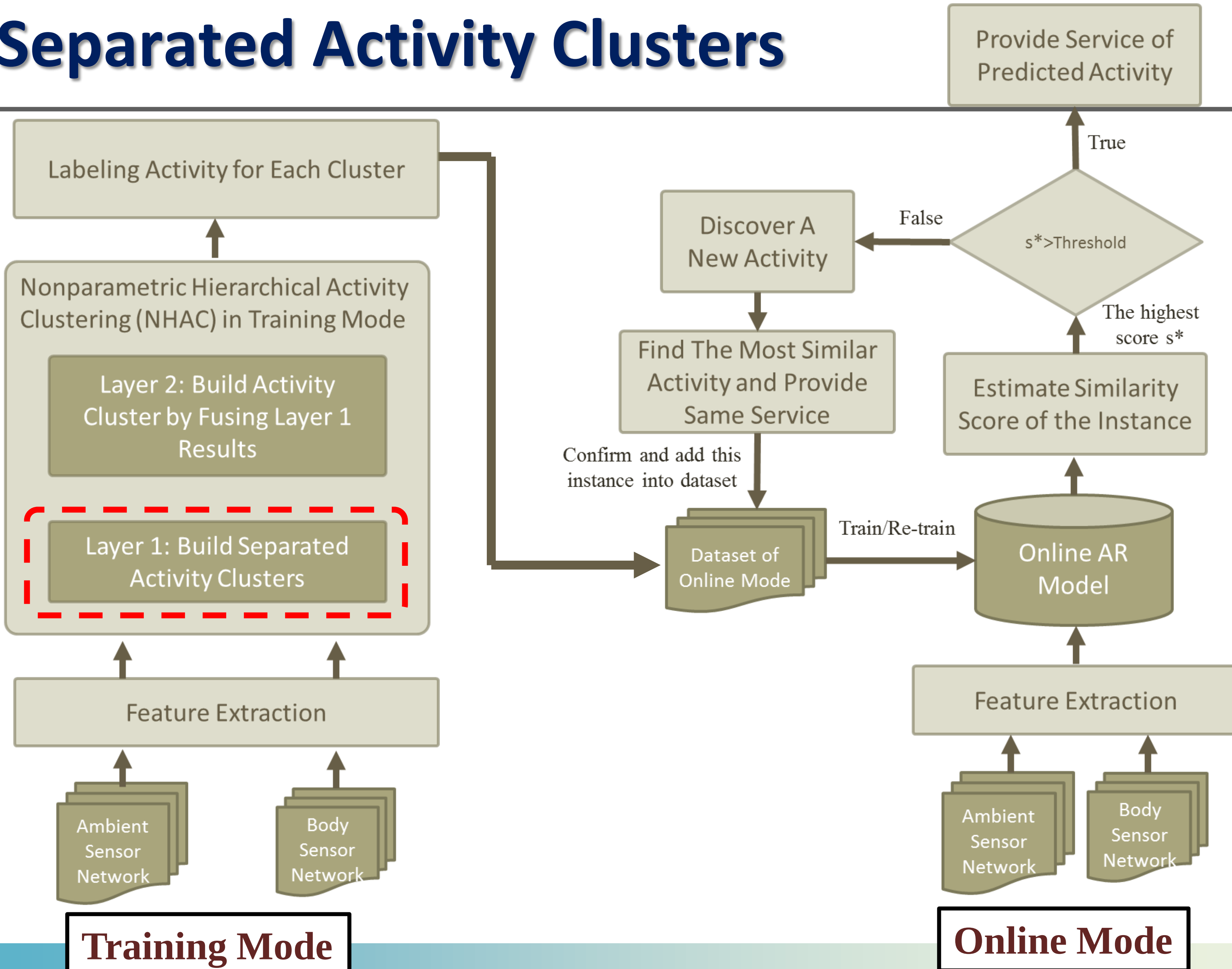
Training Mode



Activity Clustering in Training Mode

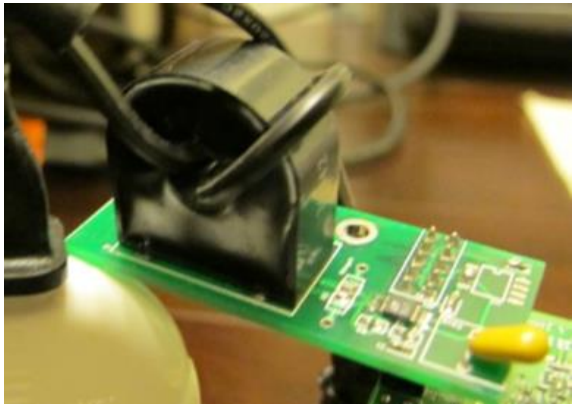
- To achieve fewer efforts on labeling, training mode should not require prior knowledge
  - Supervised learning needs to give ground truths on data
  - Some unsupervised learning requires prior knowledge, *e.g.*, K-means should give a specific number *k*
- The proposed activity clustering is a Non-Parametric Hierarchical Activity Cluster(NHAC)
  - Non-parametric unsupervised AC models do not need to set a specific number *k*

Separated Activity Clusters

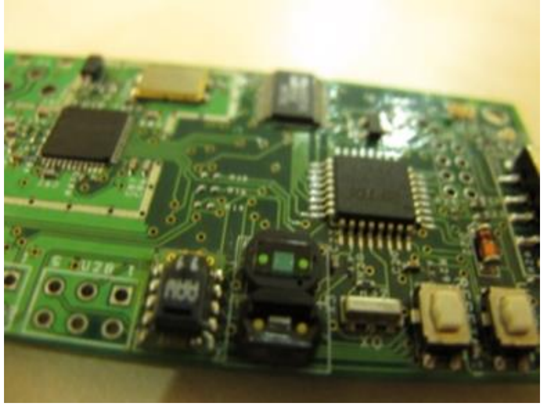


Activity Clustering from Ambient Sensor Data

- We are monitoring environment state by current sensors, lumen sensor and switch sensors
- Because ambient sensors are triggered by human activity, their data extracts as binary values



Current Sensor



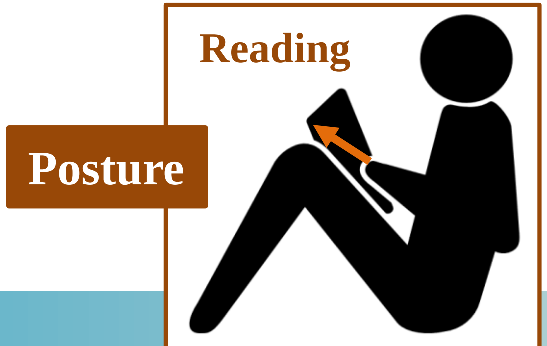
Lumen Sensor

Activity Clustering from Ambient Sensor Data

- Clustering of data instances depend on time-frequency (TF) of each data instance
  - Data instance is a feature vector whose dimension equals number of sensors
  - If a TF of data instance is higher than 1%, that data instance forms the head of cluster
- Using k-nearest neighbor (KNN) to cluster rest instances whose TFs are lower than 1%

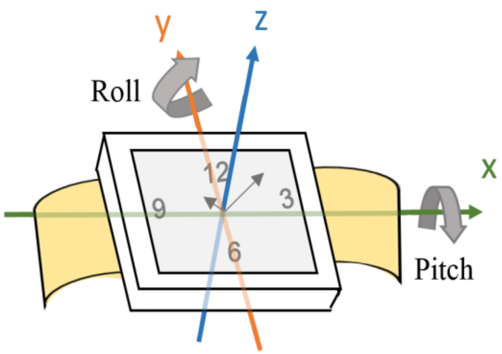
Activity Clustering from Vital Sign Sensor data

- A wearable device “ZenWatch” is used to monitor human’s behavioral activities
  - The sensors on ZenWatch are accelerometer and gyroscope
- The activity of human can be categorized to two types: static and dynamic
  - We consider each are “posture type” and “motion type”
  - Posture: hand is usually turning to a fixed direction
  - Motion: hand is always moving in reasons but not turning in a fixed direction



Activity Clustering from Vital Sign sensor data

- To detect posture and motion types by monitoring the device's orientation and acceleration variable
  - Orientation is captured from accelerometer and gyro
  - Condensing the raw data as mean and variance

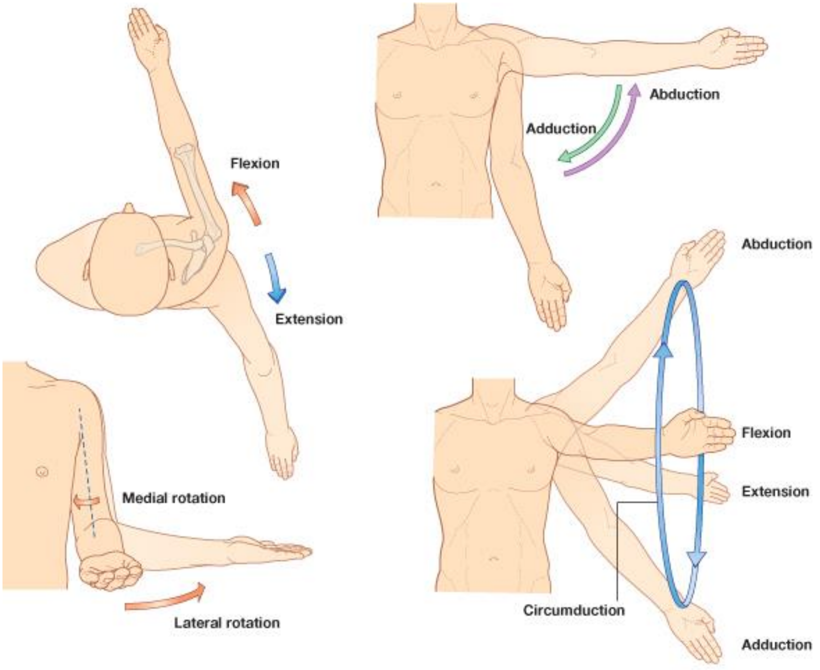


Orientations	Accelerations
Mean of Pitch	Mean of Accelerations
Mean of Roll	Variance of Accelerations
Pitch variation	Magnitude
Roll variation	

- Orientation helps to detect "Posture type" activity
- Acceleration helps to detect "Motion type" activity

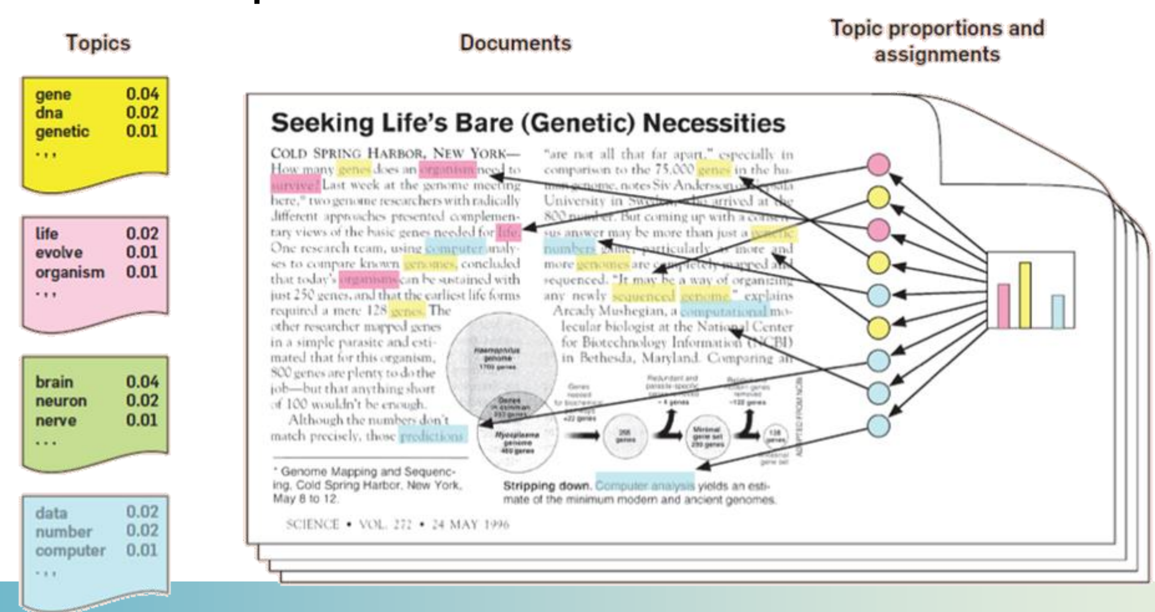
Activity Clustering from Vital Sign sensor data

- An instance over one second is considered as hand's movement
  - The number of consecutive hand's movements are usually associated with a specific activity



Activity Clustering from Vital Sign sensor data

- The topic model is used to detect topics from different documents
  - Each vocabulary belongs to a specific topic
  - One document has several vocabularies
  - According to the vocabularies distribution, the topic model can find the topic of one document



Activity Clustering from Vital Sign sensor data

- We modified the topic model to our activity cluster
  - The features are considered as "word", so one vocabulary is constructed by one instance's features

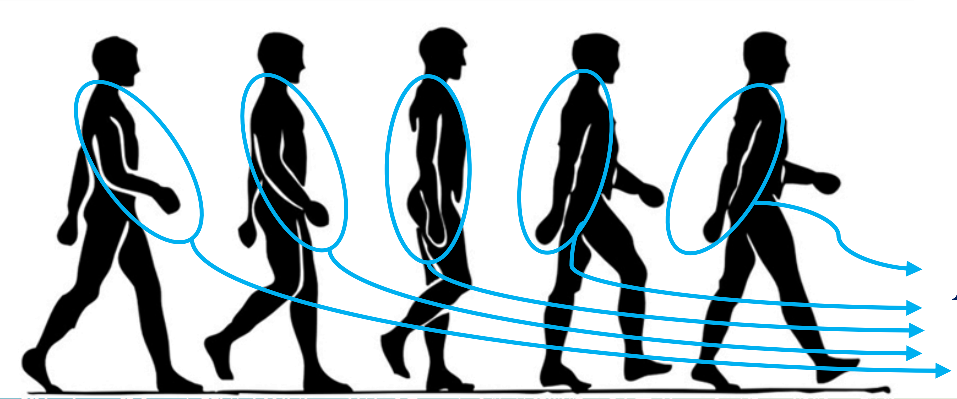
Hand's movement = $\{\mu_{Pitch}, variation_{Pitch}, \mu_{Roll}, variation_{Roll}, \mu_x, \sigma_x^2, \mu_y, \sigma_y^2, \mu_z, \sigma_z^2, magnitude\}$

Vocabulary **Words**

  - An activity consists a series of hand's movements
  - An activity belongs to one specific ADL

Walk

Topic

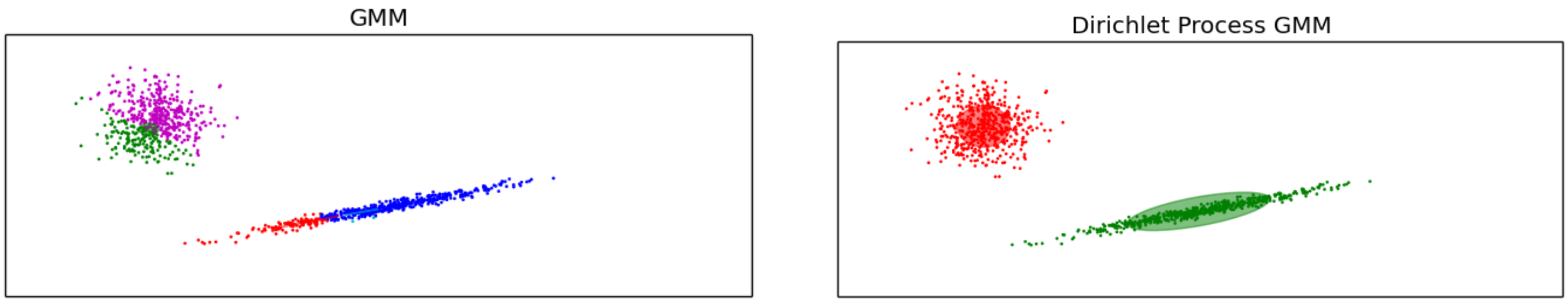


Vocabularies

A series of hand's movements

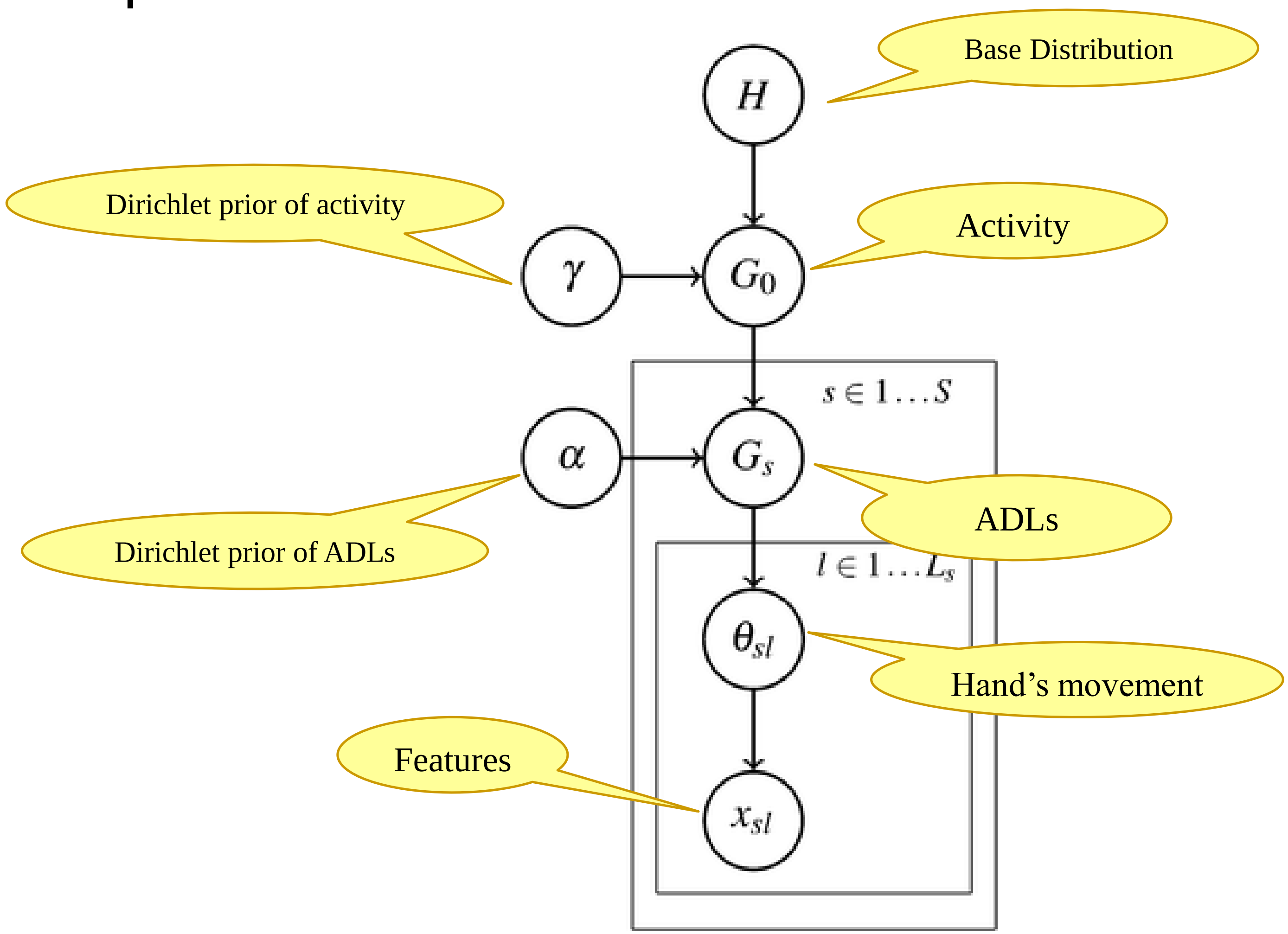
Activity Clustering from Vital Sign sensor data

- The topic model is constructed by Two Layer Dirichlet process mixture model (2LDPMM)
  - First Layer recognizes hand’s movements
  - Second Layer recognizes activity by concatenating 60 successive hand’s movements
  - This method can find different kinds of hand’s movements from raw data without giving a specific number
- DPMM is a infinite mixture model

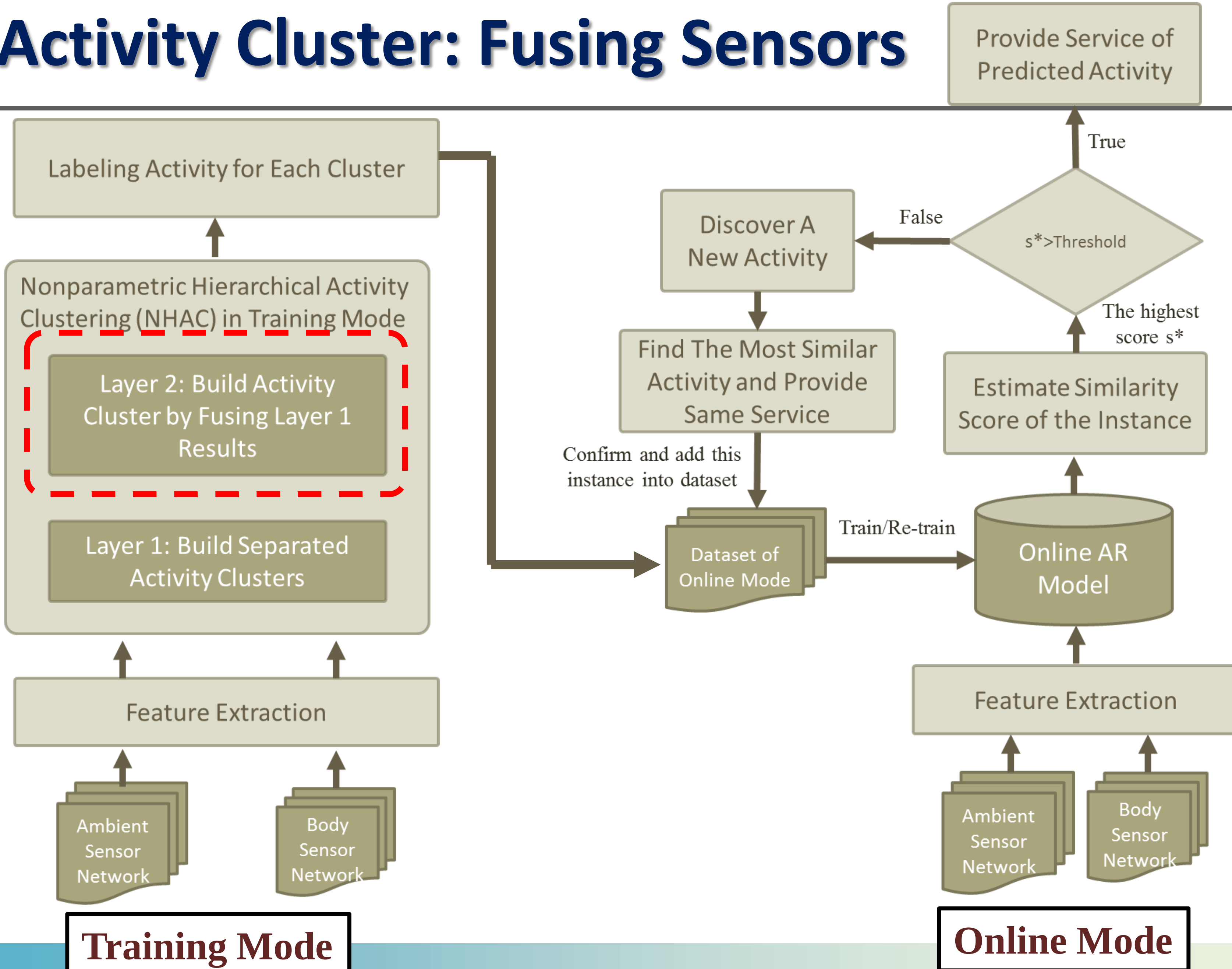


Activity Clustering from Vital Sign sensor data

- The plate notation of 2LDPMM

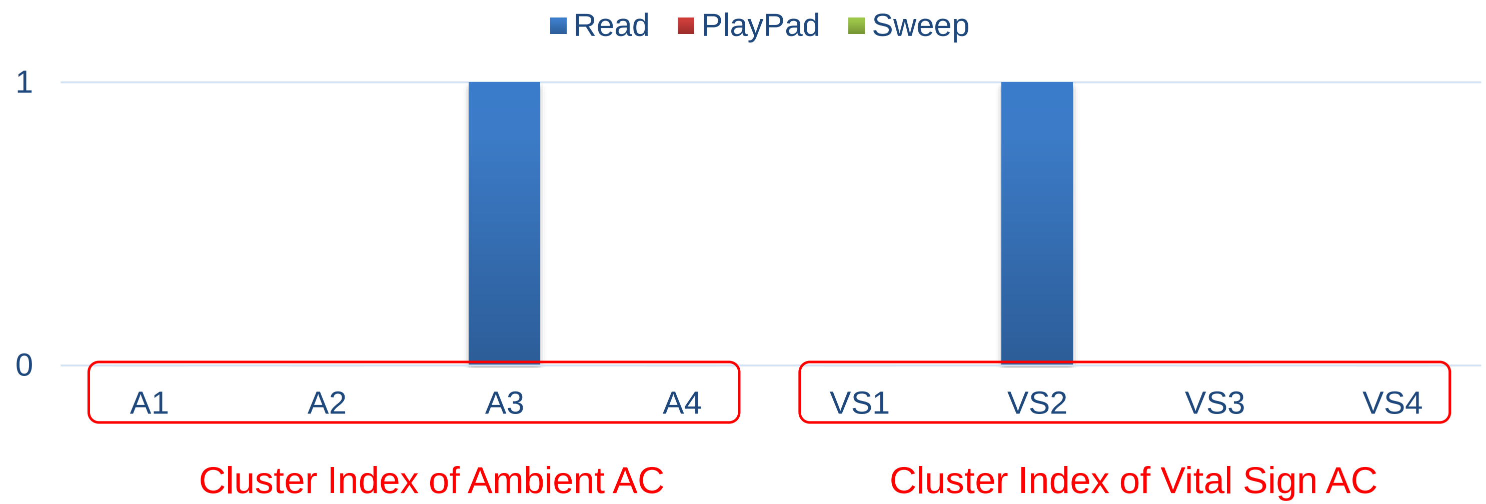


Activity Cluster: Fusing Sensors



Activity Clustering From Fuse Data Both Sensors

- Fusing ambient and vital sign information to detect living activities more precisely
  - Considering each cluster as a sensor from the 1st layer NHAC
  - Each sensor is used to sensing a specific activity
- If an instance's TF are higher than 1 %, the instance forms the head of cluster



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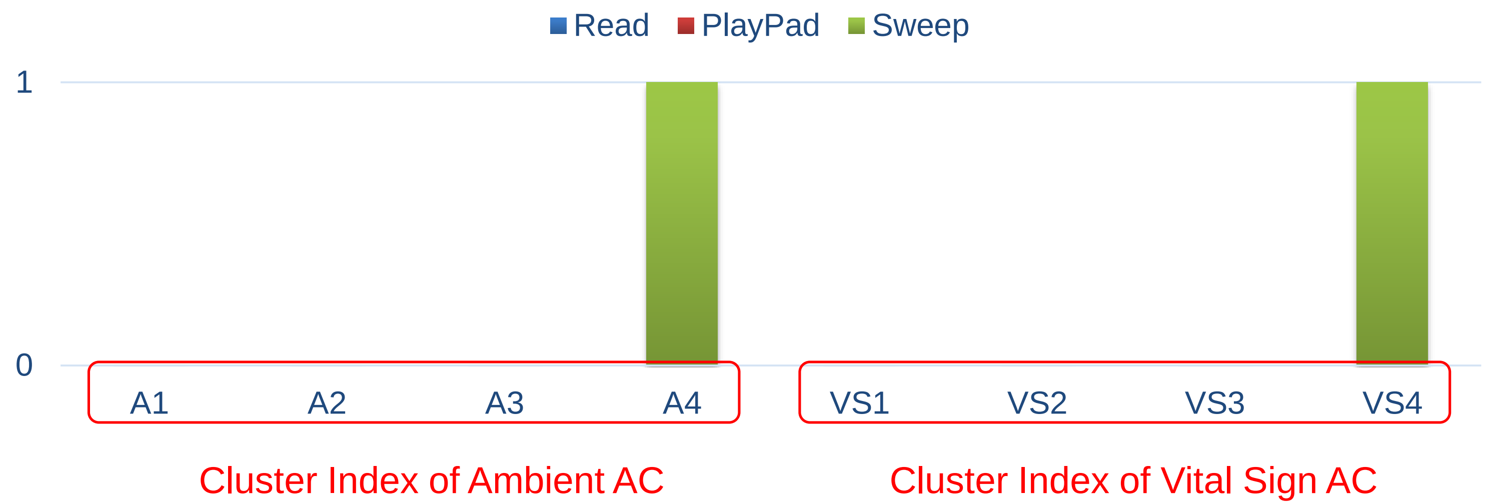
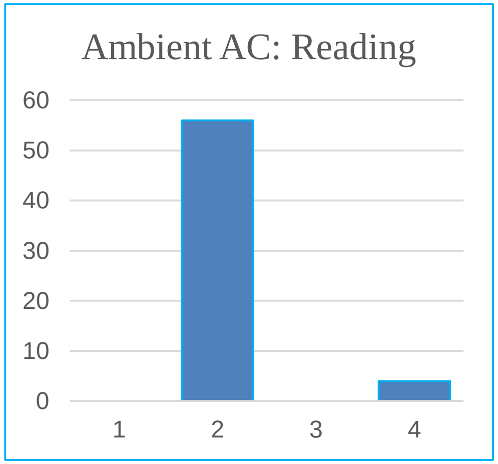


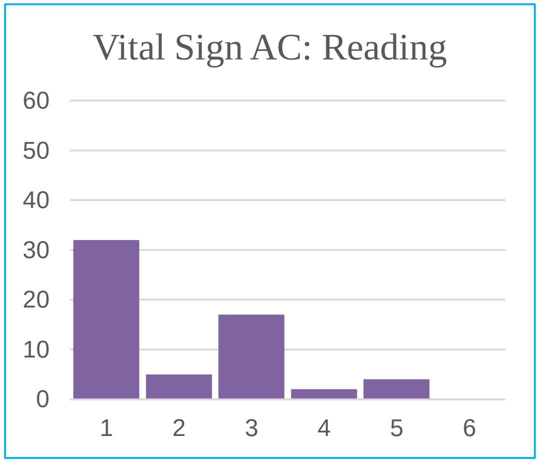
Activity Clustering From Fuse Data Both Sensors

- Using KNN to cluster rest instances
  - The occurrence time of each cluster in one minute from the 1st layer NHAC
  - Finding nearby neighbors by Manhattan distance

Occurrence Time



Cluster Index of Ambient AC

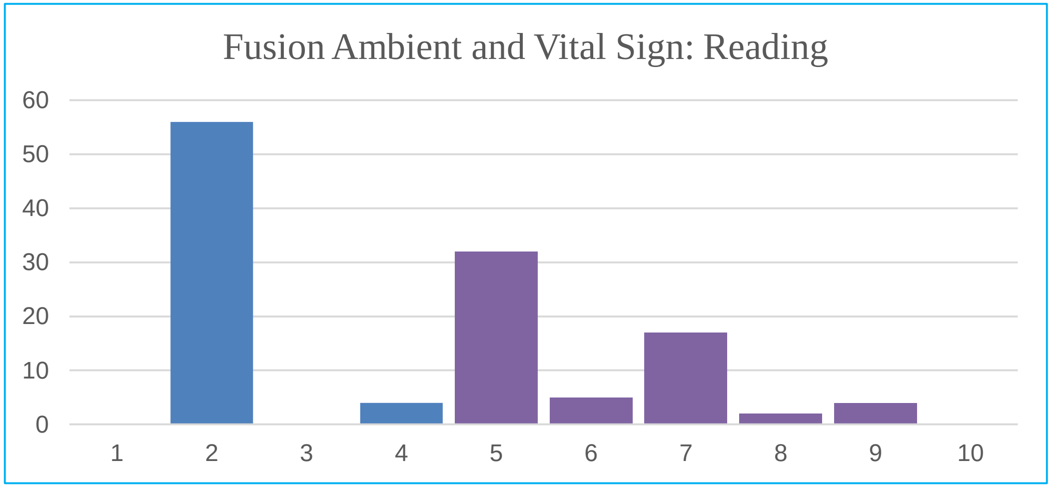


Cluster Index of Hand's Movements

Activity Clustering From Fuse Data Both Sensors

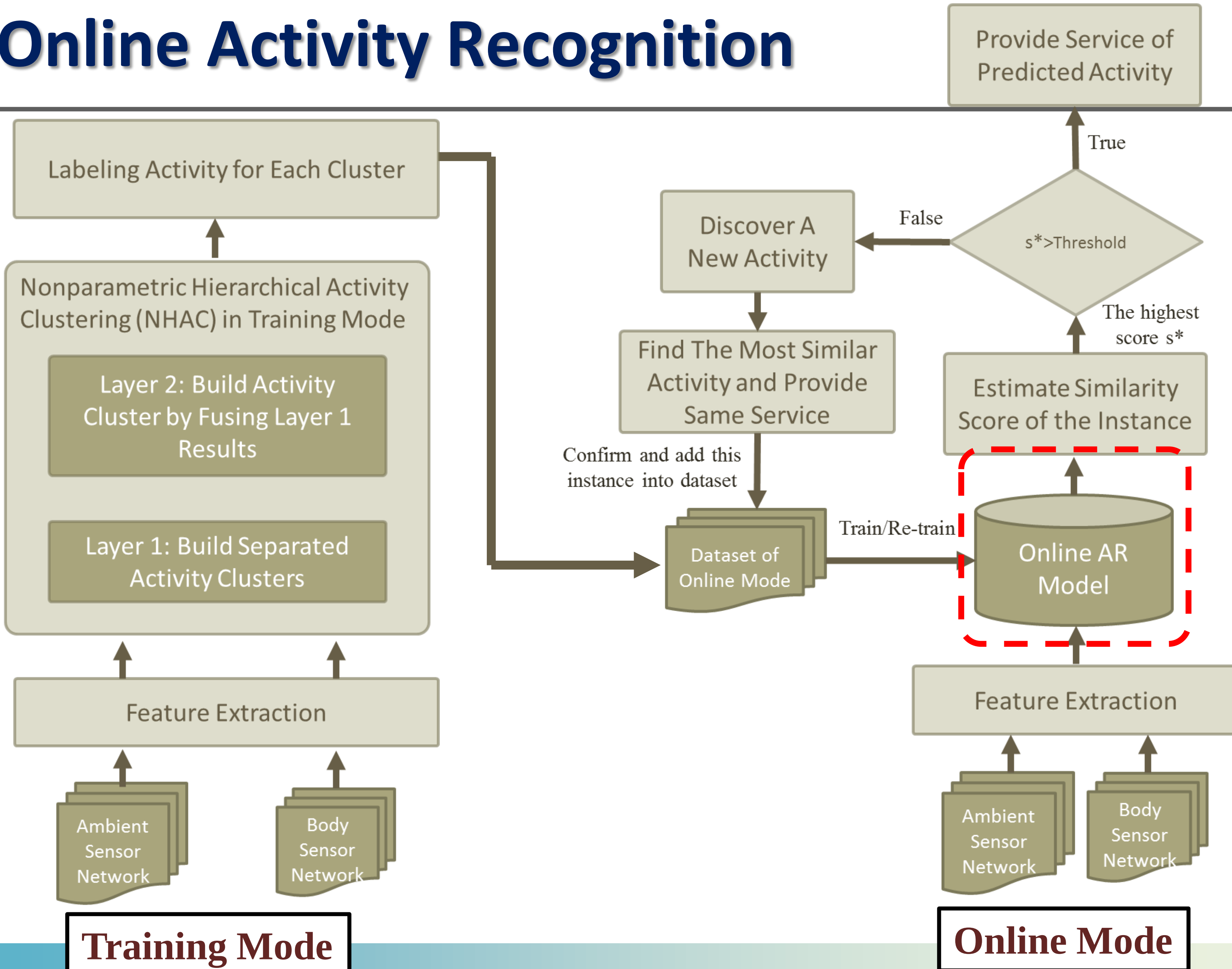
- Using KNN to cluster rest instances
  - The occurrence time of each cluster in one minute from the 1st layer NHAC
  - Finding nearby neighbors by Manhattan distance

Occurrence Time



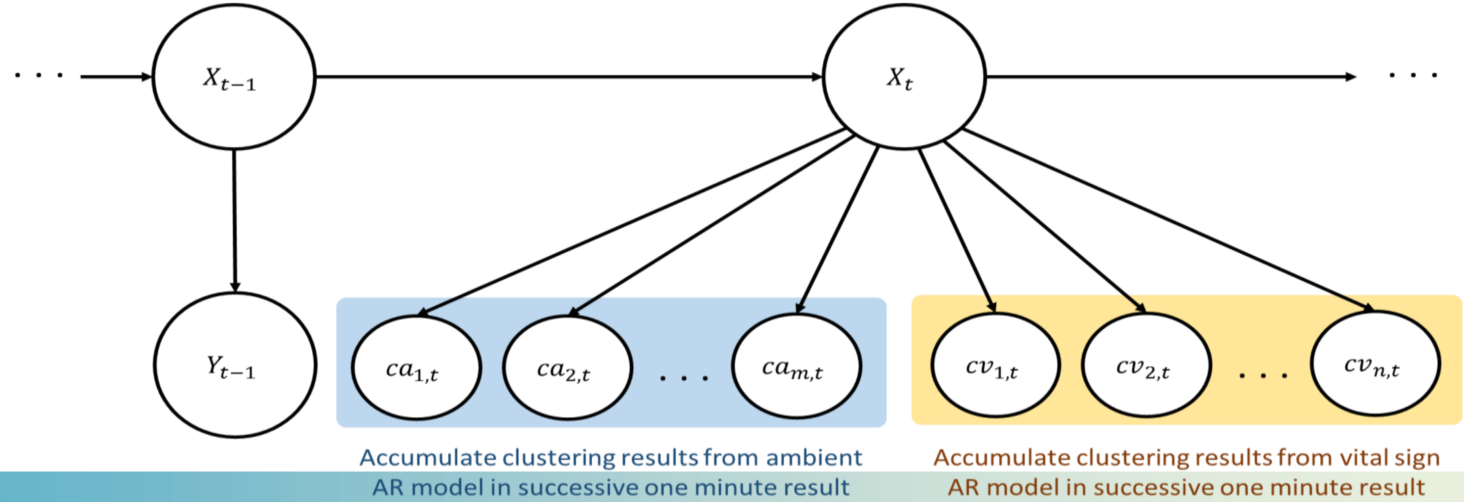
Index of KNN Features

Online Activity Recognition



Activity Recognition Model in Online Mode

- Using Dynamic Bayesian Network (DBN) to build online mode AR model
  - Because user can label data in training mode, the online mode uses an supervised learning method
- DBN determines activity using the instance's observations and the previous state
  - The training mode is regardless temporal information



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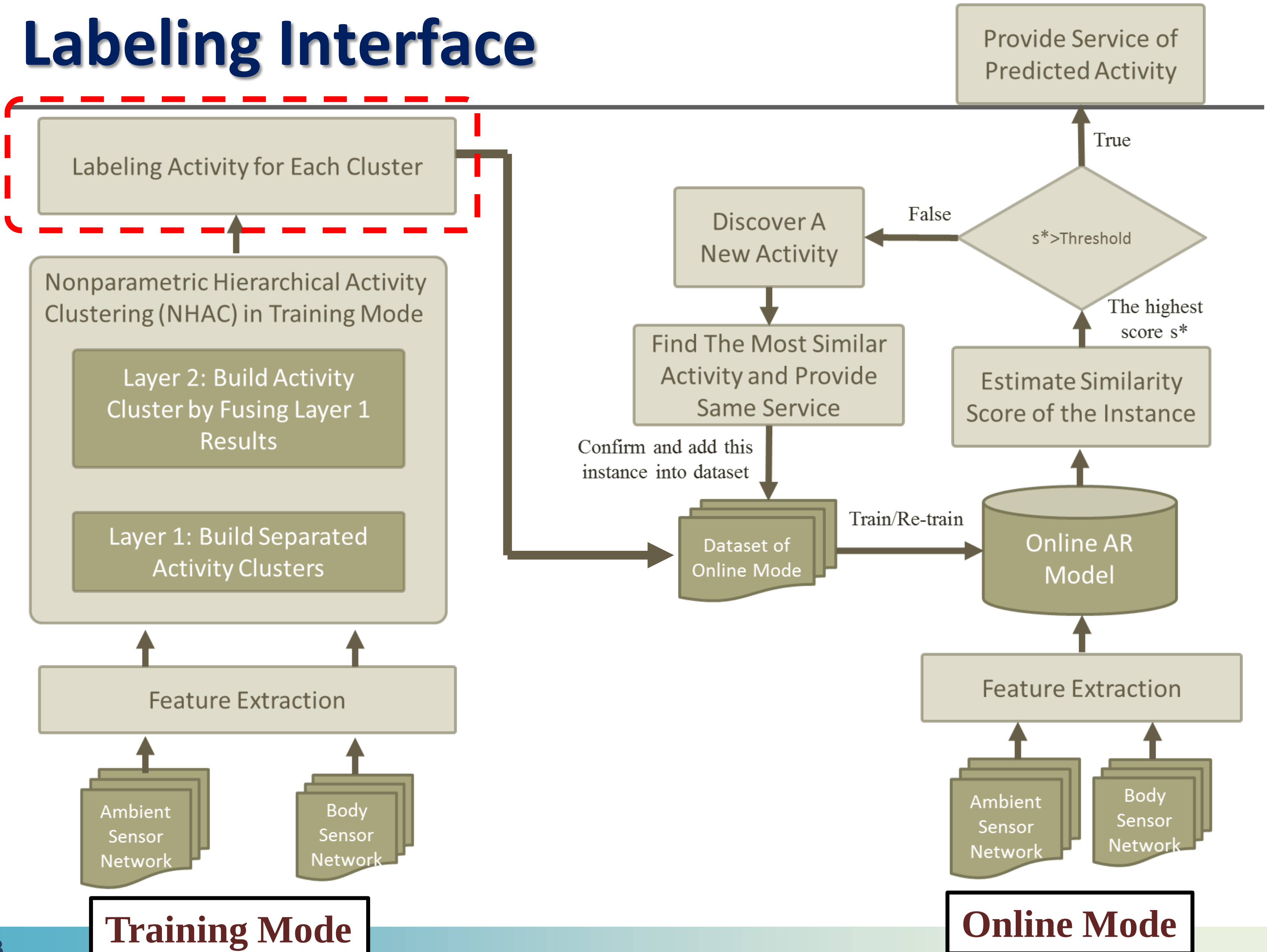
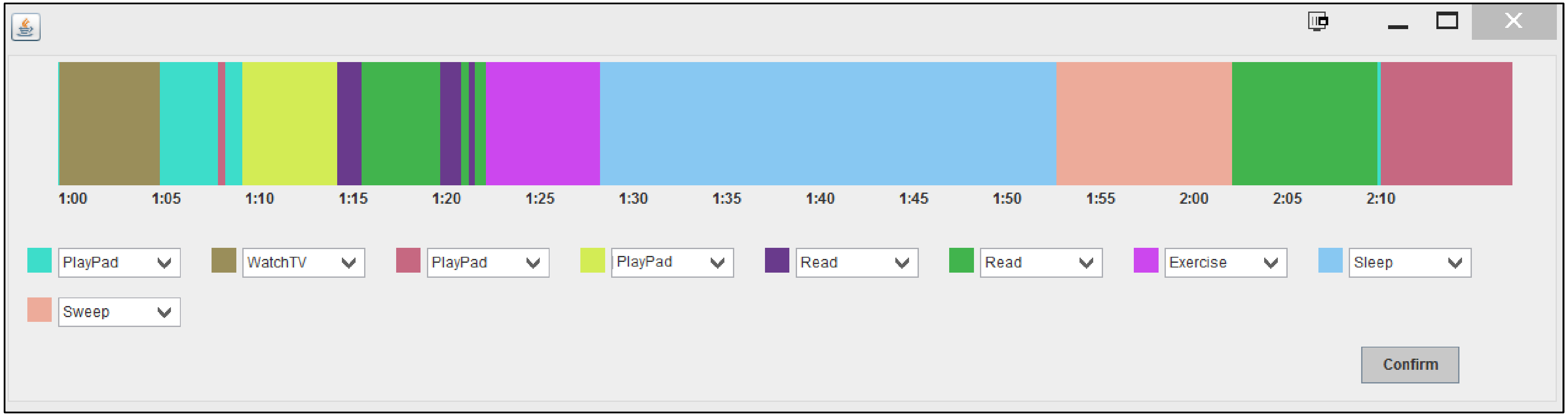
Labeling Interface

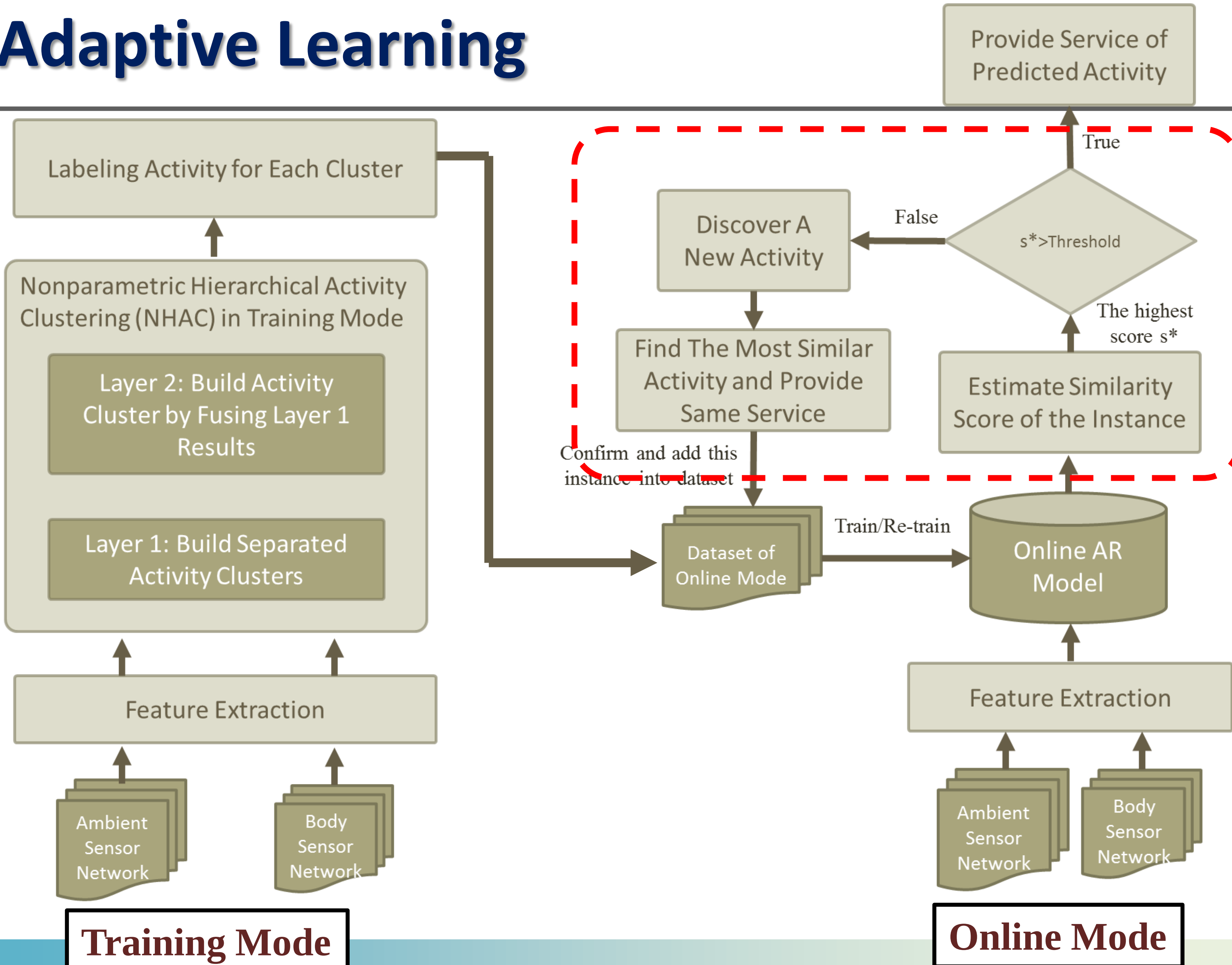


The Interface of Labeling Data

- After building NHAC in training mode, training data are categorized into clusters
  - Each cluster represents an living activity
  - Labeling all clusters to regenerate training data with label
- A GUI is designed for user labeling clusters



Adaptive Learning

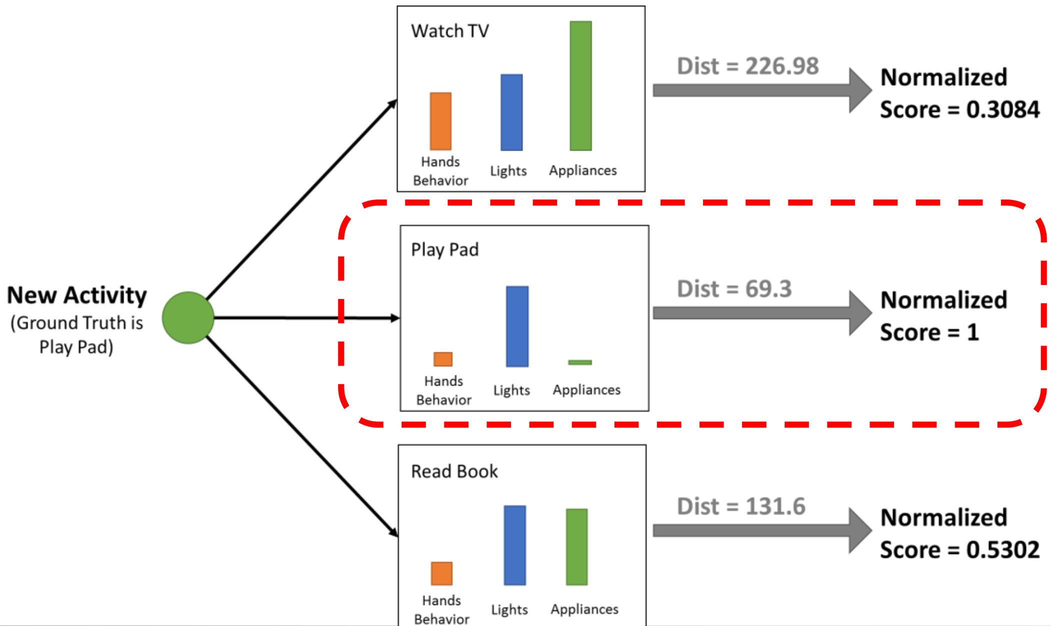


Adaptive Learning in Online Mode

- To achieve the function of discovering unknown activity, adaptive learning is necessary for AR model
- We design a similarity function for detecting whether the input instance is known activity or not
  - The similarity function calculates the similarity scores of all activities
  - If the highest score is lower than threshold *T*, this input instance may be an unknown activity

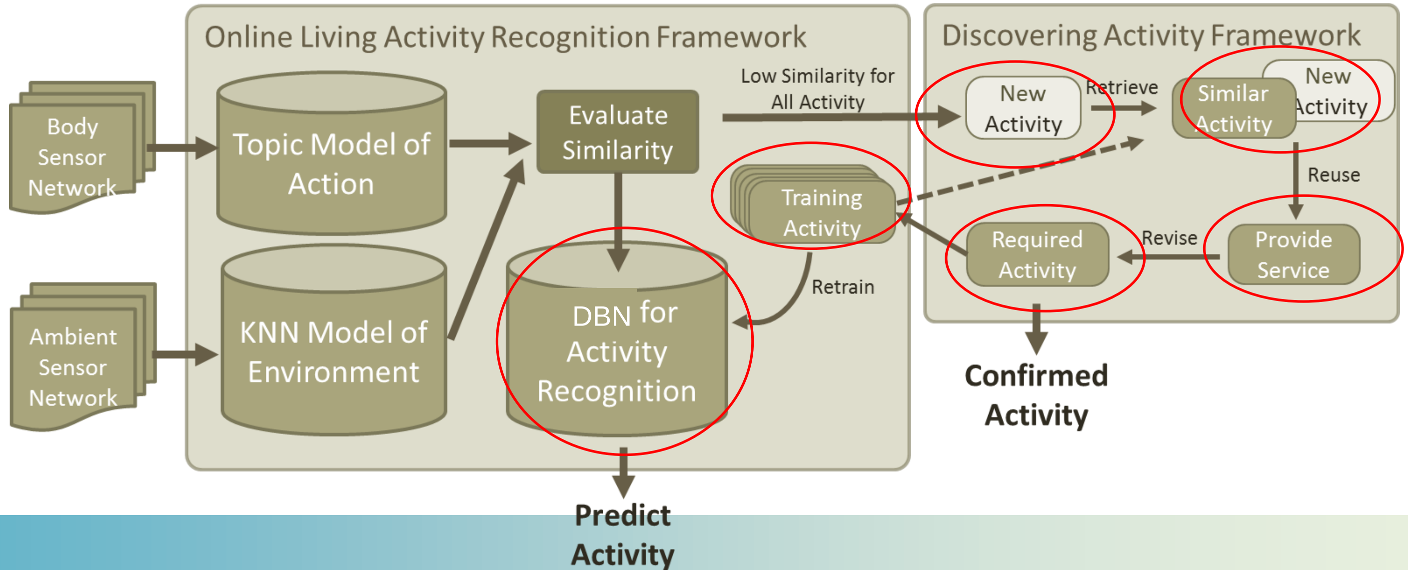
Adaptive Learning in Online Mode

- Adaptive learning can discover new activity and learn it
  - We test one new activity: playing iPad on the bed
- The similarity function computes all known ADLs' similarity score
  - The highest score of ADL is "Play pad"



Adaptive Learning in Online Mode

- If discovering an unknown activity, the mechanism of adaptive learning is triggered
  - The adaptive learning is built by case-based reasoning (CBR)
- CBR is the process of solving new problems based on the solutions of similar past problems
  - The system provides a service of the most similar activity



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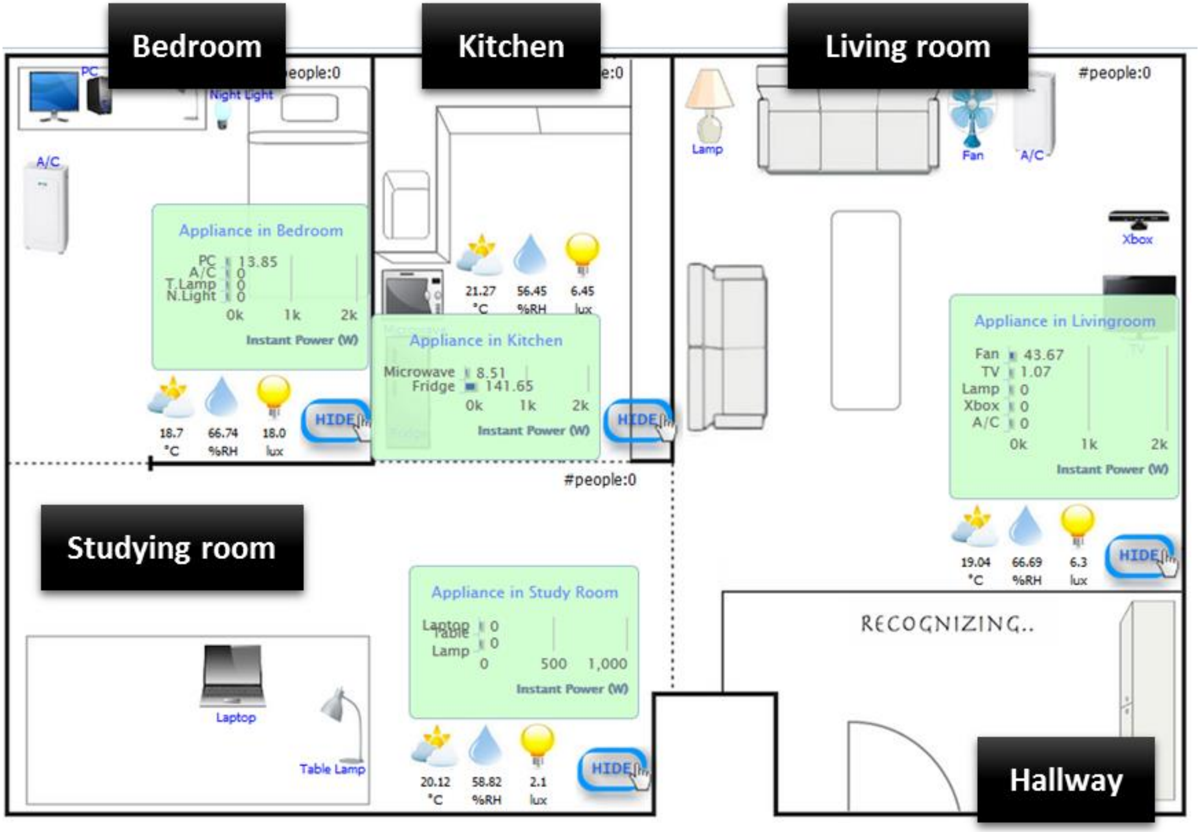
Experiment Setting

- Layout of experimental environment



Testing Activity of Daily Living

- Single-user Activity
  - 3 individual users with 2 hours of daily life routine
  - 10 types of ADLs

Activity list in the simulated home

Location	Activity	Location	Activity
Living Room	Watch TV	Study Room	Read book
	Do exercise		Play pad
	Read newspaper		Sweep
	Meal	Kitchen	Wash dishes
Bedroom	Sleeping	Hallway	Go out

Activity Clustering: Only Ambient

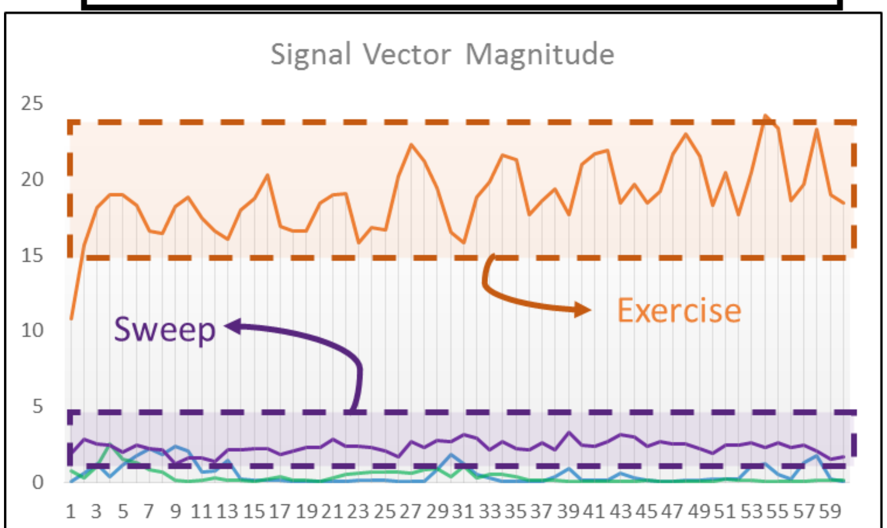
- The ambient part AR model finds 8 clusters, and each cluster represents one to two activities.

Subject 1	C1	C2	C3	C4	C5	C6	C7	C8
Watch TV	69	0	0	0	0	0	0	0
Read Newspaper	0	62	0	0	0	0	0	0
Exercise	0	0	114	0	0	0	5	0
Meal	0	0	220	0	0	0	5	0
Play Pad	0	0	0	133	4	0	0	0
Read Book	0	0	0	0	126	0	0	0
Sweep	2	0	0	0	63	1	0	0
Sleep	0	0	0	0	0	293	0	6
Wash Dishes	6	0	0	0	0	0	166	0
Go Out	0	0	0	0	0	0	0	59
Other	8	0	0	4	0	0	0	3

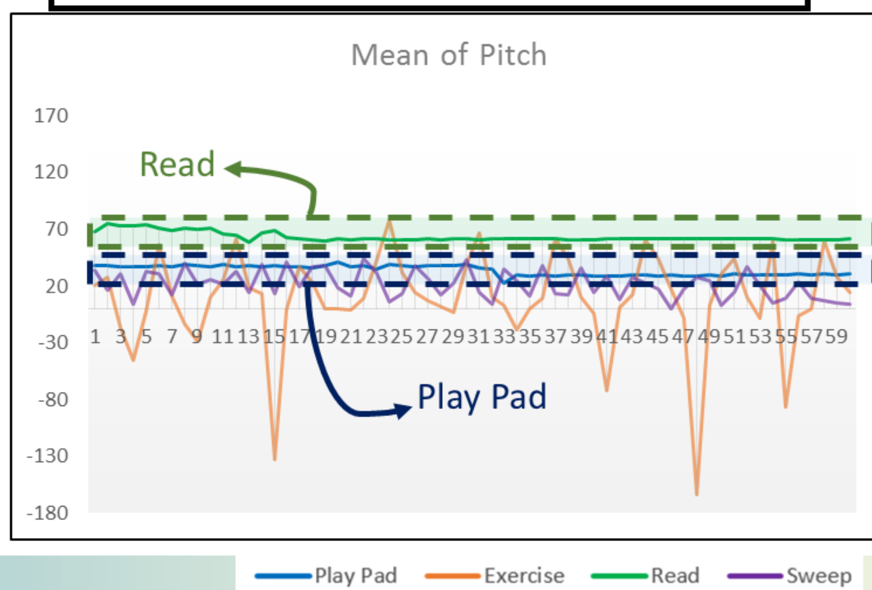
Activity Clustering: Only Vital Sign

- Feature extraction:
  - Find the physical meaning
  - Reduce the quantity of data
- Distinguish “Posture” and ”Motion”
  - Acceleration and Orientation

Detecting Motion Actions by Acceleration



Detecting Posture Actions by Orientation



Activity Clustering: Only Vital Sign

- The result of First Layer 2LDPMM
  - Find 56 kinds of clusters (hand’s movements)
- One activity may have many kinds of hand’s movements
  - In other words, one kind of hand’s behavior may occur in different activities

Subject1	h1	h2	h3	h4	h5	h6	h7	h8	h9	h10	h11	…	h54	h55	h56
Watch TV	129	229	0	0	0	0	0	0	0	0	0	…	0	0	0
Read Newspaper	2	268	0	0	0	0	0	0	0	0	0	…	0	0	0
Exercise	0	0	0	151	19	87	67	13	235	25	13	…	0	0	0
Meal	184	78	2	0	0	0	0	0	0	0	0		2	124	170
Play Pad	541	103	0	0	0	0	0	0	0	0	0	…	0	8	5
Read Book	24	575	1	0	0	0	0	0	0	0	0	…	0	5	0
Sweep	0	1	1	0	0	0	0	0	0	0	0	…	0	1	0
Sleep	0	0	31	0	0	0	0	0	0	0	0	…	0	0	0
Wash Dishes	0	0	0	0	0	0	0	0	0	0	0	…	54	14	0
Go Out	0	0	1	0	0	0	0	0	0	0	0	…	0	1	0
Other	0	0	0	0	0	0	0	0	0	0	0		0	0	0

Activity Clustering: Only Vital Sign

- The result of Second Layer 2LDPMM
  - Find 16 kinds of clusters (activities)
- One activity may have many kinds of actions
  - Having meal has different activities(Drinking, Eating, tec.)

Subject1	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
Watch TV	0	0	0	7	0	0	0	21	41	0	0	0	0	0	0	0
Read Newspaper	0	2	0	2	0	0	0	0	54	4	0	0	0	0	0	0
Exercise	115	3	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Meal	0	0	9	76	12	26	101	1	0	0	0	0	0	0	0	0
Play Pad	0	0	0	40	0	0	0	87	4	3	0	0	0	3	0	0
Read Book	0	2	0	9	0	0	0	0	108	3	0	0	0	0	0	0
Sweep	0	0	0	0	0	0	0	0	0	10	56	0	0	0	0	0
Sleep	0	0	0	0	0	0	0	0	0	0	0	13	286	0	0	0
Wash Dishes	0	0	4	0	0	0	0	0	0	0	0	0	0	4	164	0
Go Out	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	56
Other	0	1	2	2	0	0	0	1	0	5	0	3	0	1	0	0

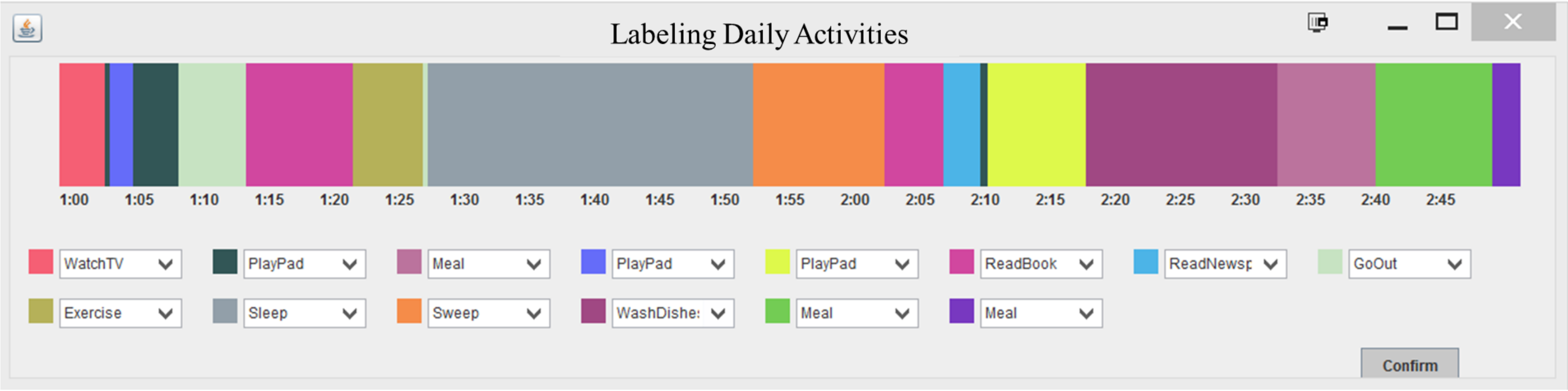
AC Results: Fusion Ambient and Vital Sign

- The result of Non-parametric Hierarchical Activity Recognition Model
  - Find 14 kinds of clusters (behaviors of different ADLs)
- One activity may have many kinds of behaviors

Subject1	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
Watch TV	21	42	0	0	0	0	0	0	6	0	0	0	0	0
Read Newspaper	0	0	62	0	0	0	0	0	2	0	0	0	0	0
Exercise	0	0	0	119	0	0	0	0	0	0	0	0	0	0
Meal	0	0	0	0	26	107	90	0	0	0	0	0	2	0
Play Pad	0	0	0	0	0	0	0	89	45	3	0	0	0	0
Read Book	0	0	0	0	0	0	0	0	2	124	0	0	0	0
Sweep	0	0	0	0	0	0	0	0	0	0	64	0	0	2
Sleep	0	0	0	0	0	0	0	0	0	0	0	297	0	2
Wash Dishes	0	0	0	0	0	0	0	0	0	0	0	0	172	0
Go Out	0	0	0	0	0	0	0	0	0	0	0	0	0	59
Other	1	0	0	2	0	0	0	1	3	0	1	1	2	4

AC Results: Fusion Ambient and Vital Sign

- The labeling interface for building ADL-aware healthcare system
  - According to 14 kinds of recognized clusters, each cluster represent one ADL
  - One color represents one cluster



AC Results: Fusion Ambient and Vital Sign

- Accuracies of each ADL and all ADLs

$$\text{Accuracy} = \frac{(TruePositive + TrueNegative)}{All\ instances}$$

  - That the TP of each cluster is its dominated ADL
  - The accuracy of fusion result is up to 97.4846%

Activity	Watch TV	Read Newspaper	Exercise	Meal	Play Pad	Read Book	Sweep	Sleep	Wash Dishes	Go Out
Accuracy	0.9844	1	0.9834	1	0.9054	0.9764	0.9846	0.9966	0.9773	0.9403
Average Accuracy		0.974846								

- The accuracies of only ambient and only vital sign:
  - Only ambient data is 83.6175%
  - Only vital sign data is 83.7175%

Performance of Online Activity Recognition

- Testing 10 folds cross-validation of online AR model
  - Using labeling data from NHARM
  - 3 individual subjects for single-user activity experiments
  - The precision each subject are 97.8%, 98.7%, 96.5%
  - Average precision is up to 97.67%

Activity	Subject 1		Subject 2		Subject 3	
	Precision	Recall	Precision	Recall	Precision	Recall
Watch TV	100%	97.6%	99.4%	98.9%	99.3%	100%
Play Pad	95.7%	84.6%	99.7%	99.2%	88.9%	99.0%
Meal	100%	99.6%	97.7%	100%	94.6%	99.0%
Read Book	98.4%	97.4%	100%	100%	100%	83.1%
Read Newspaper	91.4%	94.4%	91.7%	100%	97.3%	100%
Go out	91.5%	97%	-	-	87.1%	100%
Exercise	97%	100%	95.2%	100%	95.9%	100%
Sweep	97.6%	99.2%	99.4%	98.9%	98.1%	100%
Sleep	100%	99%	99.0%	99.8%	100%	100%
Wash Dishes	97.2%	100%	97.6%	100%	96.9%	100%
Overall	**97.8%**	**97.8%**	**98.7%**	**99.4%**	**96.5%**	**97.6%**

Outline

- Introduction
- Activity Recognition
- Activity of Daily Living-aware Elderly Healthcare
- Evaluation
- **Conclusion and Future Work**

Conclusion

- We have proposed a healthcare system to monitor the activities of daily living for elders in their home
- The proposed ADL-aware system is more appropriate for real life environment
  - Precisely detecting activities by fusing ambient and vital sign sensor data
  - Reducing the burden on labeling data by non-parametric hierarchical activity clustering (NHAC)
  - Discovering new activity and retraining the AR model by case-based reasoning (CBR)
- The experiment result shows the performance of activity recognition is up to 97.67% by fusing sensors

Q & A

Future works

- A more friendly interface for elderly user
  - We can invite some elderly people use our system and give some feedbacks
  - Base on those feedbacks to improve the labeling interface
- Developing more applications based on the activity-aware system
  - The service is simple that we only give alert message when the system monitors the abnormal activity labeled by user
  - There are more useful applications can imply in the our healthcare system based on the real-time monitoring activity

Appendix

Activity Recognition of Ambient Part

- Let $T = \{x_1, \dots, x_N\}$ be the training set, where $x_i \in R^m$
- The similarity measurement uses Hamming distance

$$dist(x_i, x_j) = \sum_{k=1}^{m} |x_{i,k} - x_{j,k}|$$

- The identity function

$$\delta(\mathrm{c}, f_i(x)) = \begin{cases} if\ c = f_i(x), then\ it\ is\ 1 \\ otherwise, then\ it\ is\ 0 \end{cases}$$

  - Where $f_i(x)$ is the cluster head for i^th neighbor of x
- The number of neighbors with cluster c

$$\mathrm{g(c)} = \sum_{i} \delta(\mathrm{c}, f_i(x))$$

Activity Recognition of Ambient Part

- The function of weight voting is used to determine one instance belongs to which cluster

$$w_i = \frac{1}{dist}$$

- The instance will belong to the closet cluster c^*

$$c^* = \arg\max_c \sum_i w_i \, \delta\big(c, f_i(x)\big)$$

Activity Recognition of Vital Sign Part

- The topic model is constructed by Two Layer Dirichlet process mixture model (2LDPMM)
- 2LDPMM is a non-parametric unsupervised learning inference model
  - It's hard to define the specific number of kinds of hand's waving motions
  - 2LDPMM is a data-driven method, so it can find different kinds of hand's waving motion from raw data without given a specific number

Dirichlet Process Mixture Model

- Dirichlet distribution is the conjugate prior of multinomial distribution
- Binomial distribution

$$P(X = x|n, p) = \binom{n}{x} p^x (1-p)^{n-x}$$

- Multinomial distribution

$$P(x_1, \ldots, x_k|n, p_1, \ldots, p_k) = \frac{N!}{\prod_{i=1}^{k} x_i!} p_i^{x_i}$$

  - Where $\sum_i x_i = N$, and $x_i \geq 0$

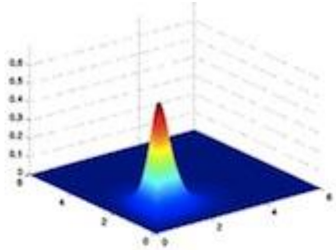
Dirichlet Process Mixture Model

- Dirichlet distribution is the conjugate prior of multinomial distribution

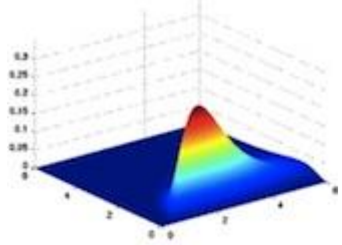
$$p(P = \{p_i\}|\alpha_i) = \frac{\prod_i \Gamma(\alpha_i)}{\Gamma(\sum_i \alpha_i)} \prod_i p_i^{\alpha_i - 1}$$

  - Where $\sum_i p_i = 1$ and $p_i \geq 0$

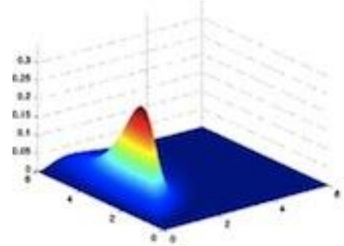
- Two parameters
  - Concentration $\sigma = \sum_i \alpha_i$
  - Base measure $(\alpha_1', \ldots, \alpha_k')$ that $\alpha_i' = \frac{\alpha_i}{\sigma}$



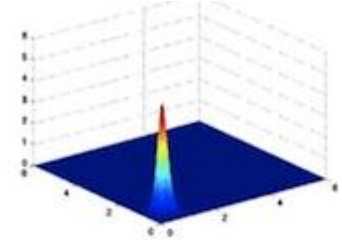
$\alpha_1 = 3.5\ \alpha_2 = 3.5\ \alpha_2 = 3.5$



$\alpha_1 = 10\ \alpha_2 = 3.5\ \alpha_2 = 3.5$



$\alpha_1 = 3.5\ \alpha_2 = 10\ \alpha_2 = 3.5$

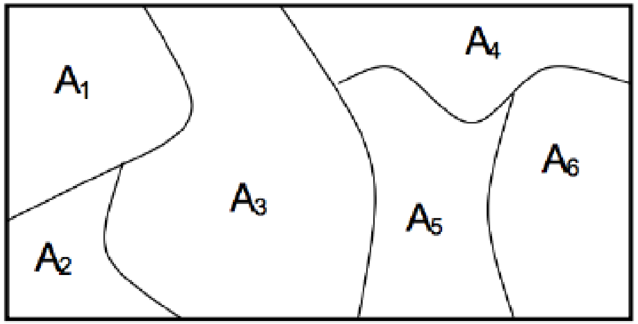


$\alpha_1 = 3.5\ \alpha_2 = 3.5\ \alpha_2 = 10$

Dirichlet Process Mixture Model

- Dirichlet process (DP) is an infinite-dimensional generalization of Dirichlet distribution
- DP also has two parameters
  - Strength σ likes an inverse-variance of DP
  - Base distribution H likes the mean of DP
- If for any partition $(A_1, \ldots, A_n)$ of $\mathbb{X}$:

$$\mathrm{G} \sim \mathrm{DP}(\alpha, \mathrm{H})$$



Dirichlet Mixture Model

- Dirichlet process mixture model generalizes finite mixture models
  - Total number of mixture components can be infinite
- Using the Dirichlet distribution to construct a finite mixture model

$$\theta_{c_i} \sim H \text{ for } c_i = \{1, \ldots, K\}$$
$$\{\pi_1, \ldots, \pi_K\} \sim Dirichlet\left(\frac{\alpha}{K}, \ldots, \frac{\alpha}{K}\right)$$
$$c_i \sim Multinomial(\pi_1, \ldots, \pi_K)$$
$$x_i \sim f(x|\theta_{c_i})$$

  - A data point is drawn from the mixture model $P(x)$

$$p(x) = \sum_{i=1}^{K} \pi_i f(x|\theta_i)$$

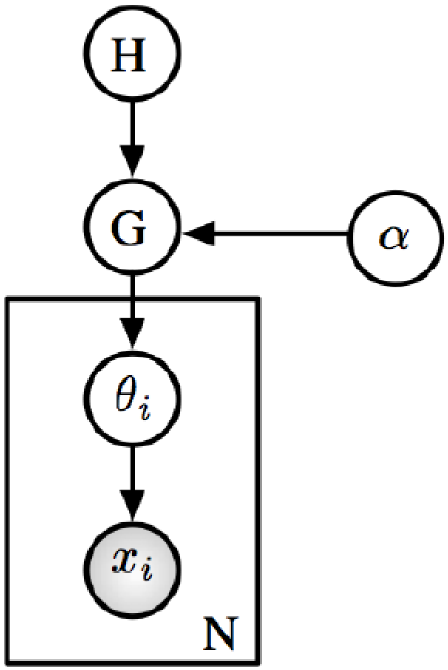
Dirichlet Process Mixture Model

- Using the Dirichlet process to construct an infinite mixture model
  - In other words, let $k \rightarrow \infty$

$$G \sim DP(\alpha, H)$$
$$\theta_i \sim G$$
$$x_i \sim f(x|\theta_i)$$

  - The mixture model becomes

$$p(x) = \sum_{i=1}^{\infty} \pi_i f(x|\theta_i)$$



Adaptive Learning on Online Mode

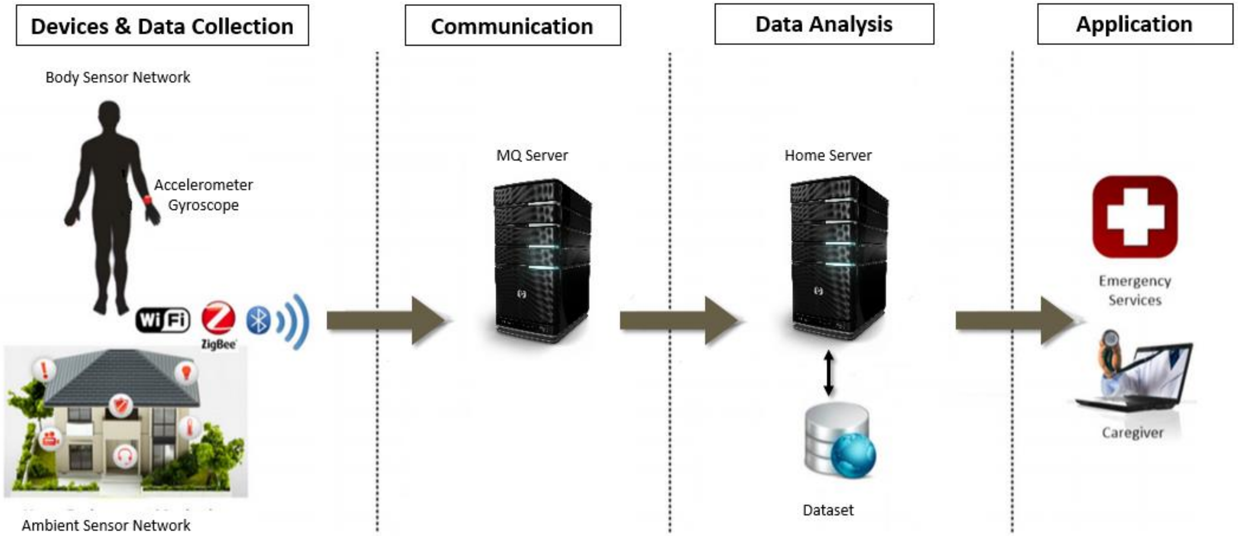
- A case-based reasoning measurement is denoted as CBR
  - CB is denoted as a set of input description C for which a service S
  - (C, S) is in the case base
- A similarity function is mapping to $C \times CBR \rightarrow [0,1] \in R$

$$sim(c_1, c_2) = \sum_{i=1}^{n+m} distance_i\ (c_1, c_2)$$

  - Where $distnace_i$ is the Manhattan distance of feature i

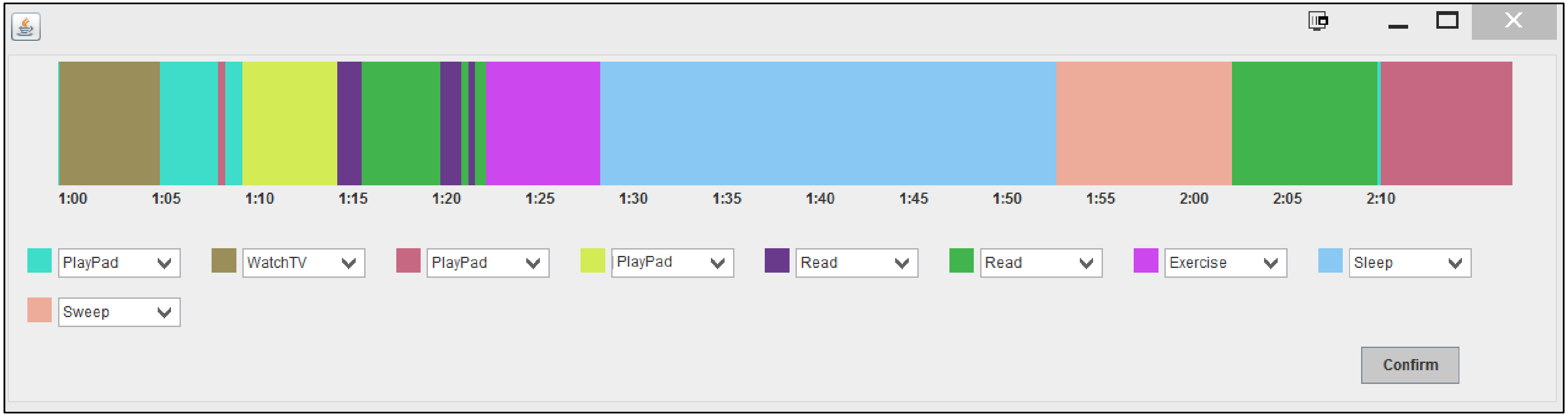
Activity of Daily Living-aware System

- The healthcare system can real-time aware residents' activity based on proposed activity recognition models
- Three main components of activity-aware system
  - The function of activity recognition
  - The interface of labeling data
  - The function of discovering unknown activity



The Interface of Labeling Data

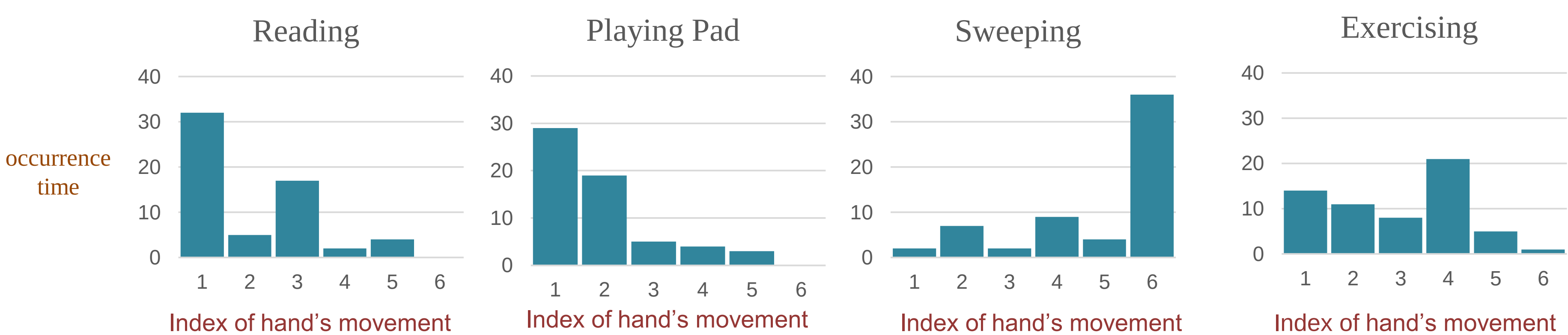
- According to the timeline presented information
  - Each color represents a cluster
  - A set of living activities integrated into a list, so user can choose cluster's activity by the list
- After labeling them, generating the new dataset



Activity Clustering: Only Vital Sign

- Finding the histogram of 60 successive hand's movements
- Each histogram represents a specific activity

The histogram of different hand's movements for four activities



Performance of Online Activity Recognition

- Testing 10 folds cross-validation of online AR model
  - Using labeling data from NHARM
  - The equation of Precision and Recall

$$\text{Precision} = \frac{TruePositive}{(TruePositive + FalsePositive)}$$

$$\text{Recall} = \frac{TruePositive}{(TruePositive + FalseNegative)}$$