

# Activity Recognition with Smartphone Sensors

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# Outline

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- ▶ Background
- ▶ Mobile Sensors
- ▶ Core Techniques
- ▶ Challenges
- ▶ Applications
- ▶ Conclusion



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- ▶ **Background**
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# Mobile Devices

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## ► Smartphones



## ► Sport Gadgets



## ► Medical Devices



- Powerful computers in the pocket!
- They are connected via networks (Cellular, WiFi, Bluetooth, etc.)

# Activity Recognition

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- ▶ “**Activity recognition** aims to recognize the actions and goals of one or more agents from a series of observations on the agents' actions and the environmental conditions.” [1]
- ▶ **Computer** takes **raw data** as input and recognizes the user's **motion activity**

# Activity Recognition

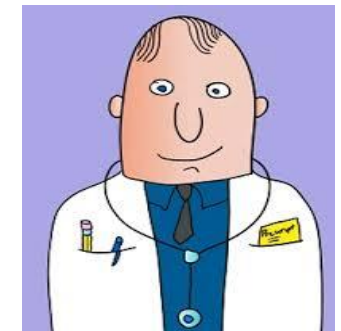
**Mobile App device is  
equipped to record  
the living activity**



**Real Time living  
activity is online!**



**Who is  
benefiting?**



# Activities

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Jogging



Vacuuuming



Cooking



Walking on stairs



Brushing Teeth



Blow Drying hair



Practicing yoga



Working on computer



Dinning at restaurant



Shopping



# Activities

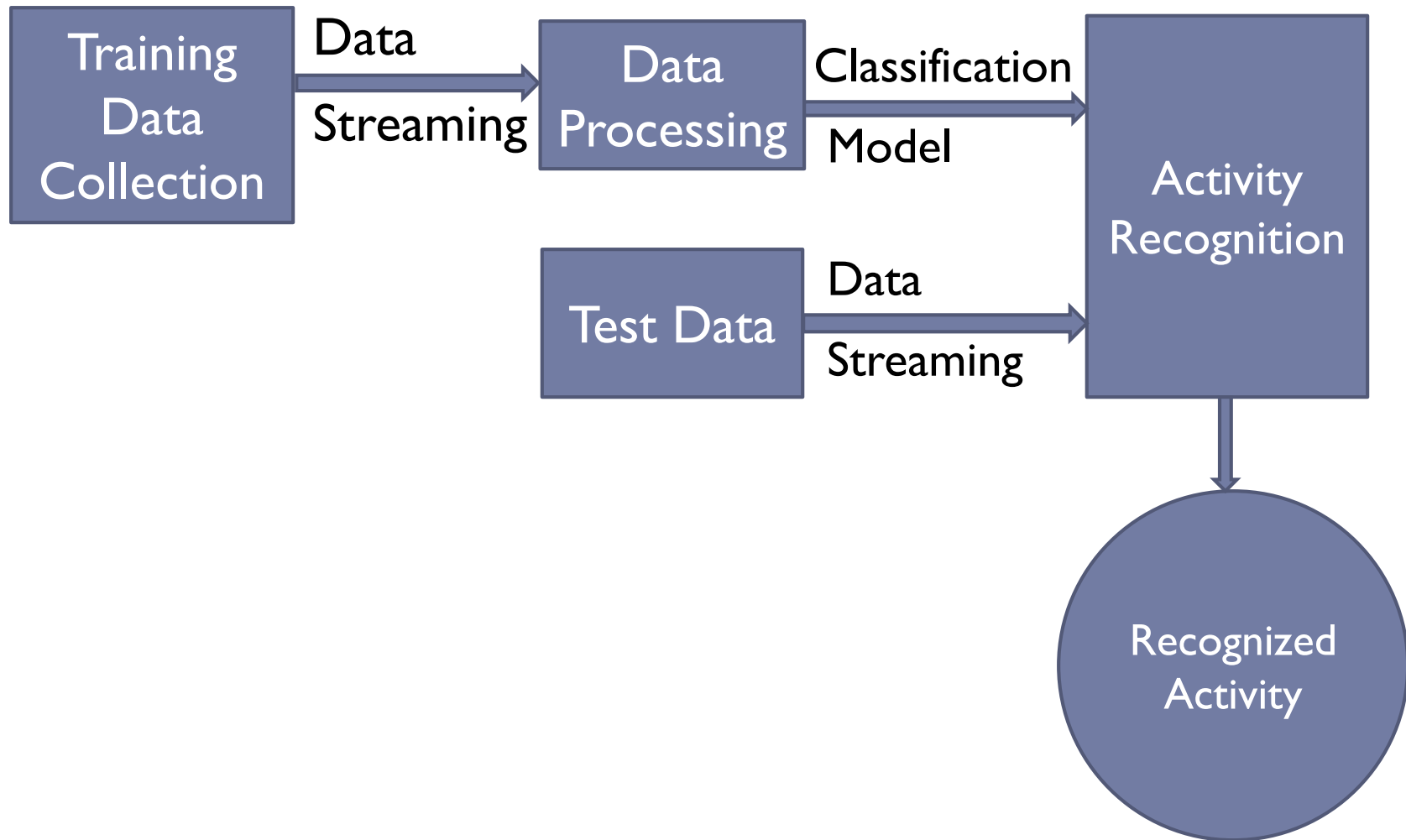
	Category	Activity Type
Complexity	Simple Activity	Walking, Jogging, Sitting, Standing, Lying, Walking Upstairs, Walking Downstairs, Jumping, Taking escalator up, Taking escalator down, Taking elevator up, Taking elevator down
	Complex Activity	Shopping, Taking buses, Driving a car
Scenario	Living Activity	Brushing Teeth, Vacuuming, Eating, Cooking, Washing hands, Meditation, Clapping hands, Watering plants, Sweeping, Shaving, Blow drying hair, Washing dishes, Ironing, Flushing the toilet, Cleaning
	Working Activity	Working on PC, Talking on the phone, On a break, Meeting, Typing, Writing, Doing a presentation
	Health Activity	Exercising, Fall, Rehabilitation activities, Following routines





# Process of activity recognition

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# Outline

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- ▶ Background
- ▶ **Mobile Sensors**
  - ▶ Sensors Classification
  - ▶ Mobile Phone Sensors Overview
  - ▶ Important Mobile Sensors in Activity Recognition
- ▶ Core Techniques
- ▶ Challenges
- ▶ Applications
- ▶ Conclusion



# Sensors Classification

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- ▶ Video sensors
  - ▶ Installed at fixed location
  - ▶ Passive monitor
  - ▶ May have privacy problem
- ▶ Environment sensors
  - ▶ WiFi, Bluetooth, Infrared sensors
  - ▶ Fixed location, limited information
- ▶ Wearable sensors
  - ▶ Equipped on human body
  - ▶ Smartphones

# Mobile Phone Sensors

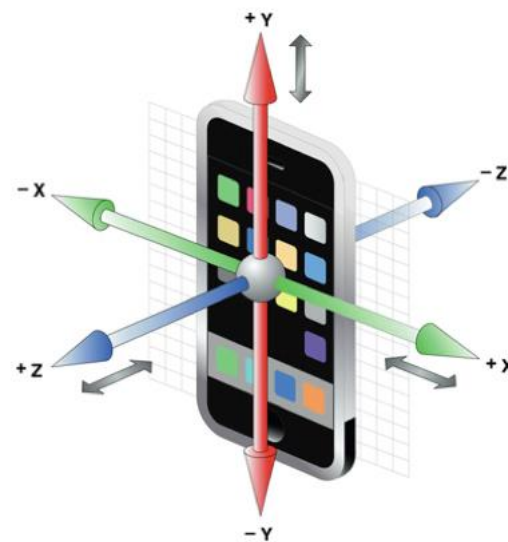
Sensor [2]	Description
Accelerometer	Measure the acceleration force that applied to the device, including force of gravity
Ambient temperature Sensor	Measure the ambient room temperature
Gravity Sensor	Measure the force of the gravity that applied to the device, in three axes (x,y,z)
Gyroscope	Measure the device's rotation in three axes (x,y,z)
Light Sensor	Measure the ambient light level (illumination)
Linear Acceleration	Measure the acceleration force that applied to the device, force of gravity is excluded
Magnetometer	Measure the ambient geomagnetic field in three axes(x,y,z)
Barometer	Measure the ambient air pressure
Proximity Sensor	Measure the proximity of an object relative to the view screen of a device.
Humidity Sensor	Measure the humidity of ambient environment

[2][http://developer.android.com/guide/topics/sensors/sensors\\_overview.html](http://developer.android.com/guide/topics/sensors/sensors_overview.html)

# Accelerometer

- ▶ Mobile Sensors
  - ▶ Sensors Classification
  - ▶ Mobile Phone Sensors Overview
  - ▶ Important Mobile Sensors in Activity Recognition

- ▶ Measuring acceleration along 3 spatial axes at a moment of time
- ▶  $Acc_i = \langle x_i, y_i, z_i \rangle, i = 1, 2, 3, \dots$   
 $-2.0 \leq x_i, y_i, z_i \leq 2.0$   
Unit: g-force [3]



[3] Apple, UIAcceleration Class Reference:

[https://developer.apple.com/library/ios/documentation/uikit/reference/UIAcceleration\\_Class/Reference/UIAcceleration.html](https://developer.apple.com/library/ios/documentation/uikit/reference/UIAcceleration_Class/Reference/UIAcceleration.html), 2014, Mar. 17.

# Compass

- ▶ Mobile Sensors
  - ▶ Sensors Classification
  - ▶ Mobile Phone Sensors Overview
  - ▶ Important Mobile Sensors in Activity Recognition

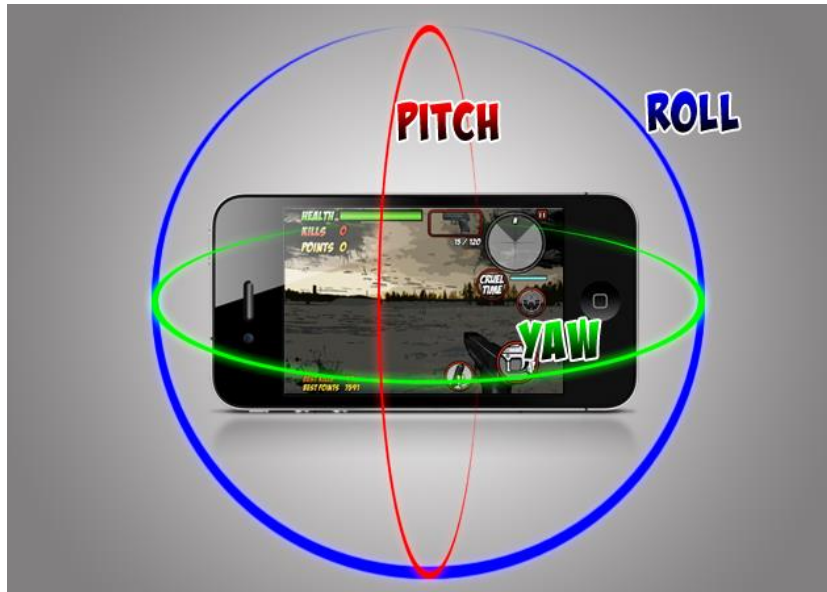
- ▶ Begins from 0 as the absolute north
- ▶ Actual reading: angle between the absolute north and current heading direction in clockwise
- ▶  $0 \leq Comp_i \leq 360, i = 1, 2, 3, \dots$



# Gyroscope

- ▶ Mobile Sensors
  - ▶ Sensors Classification
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- Measure the rotation: rad/s
- Along 3 axes: x, y and z



# Barometer

- ▶ Only equipped on some latest advanced phones (Samsung Galaxy S4, Google Nexus 4/10)
- ▶ Measure the air pressure in the environment

## Interesting Findings[4]:

- Air pressure varies with different altitude in same building
- Air pressure varies with different structures (narrow, wide, etc) of locations even at the same altitude of same building



Good for indoor  
location  
augmented activity  
recognition!



# Outline

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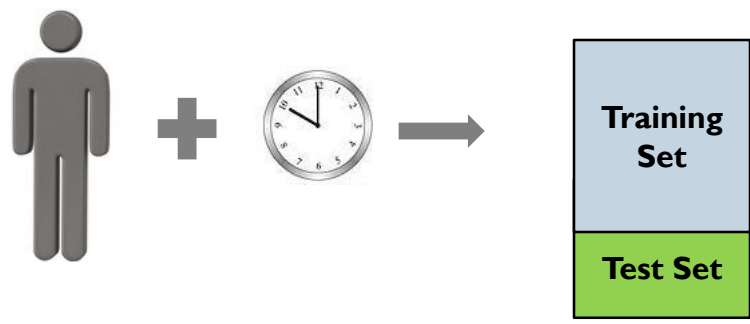
- ▶ Background
  - ▶ Mobile Sensors
  - ▶ **Core Techniques**
    - ▶ Data Collection
    - ▶ Data Preprocessing
    - ▶ Feature Computation
    - ▶ Classification
  - ▶ Challenges
  - ▶ Applications
  - ▶ Conclusion
- 



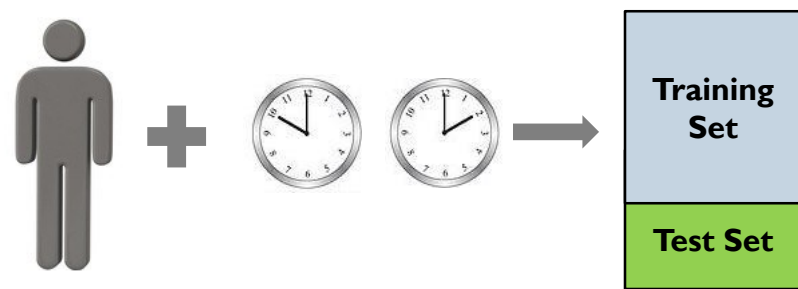
- Core Techniques
- ➔ Data Collection
- Data Preprocessing
- Feature Computation
- Classification

# Data Collection

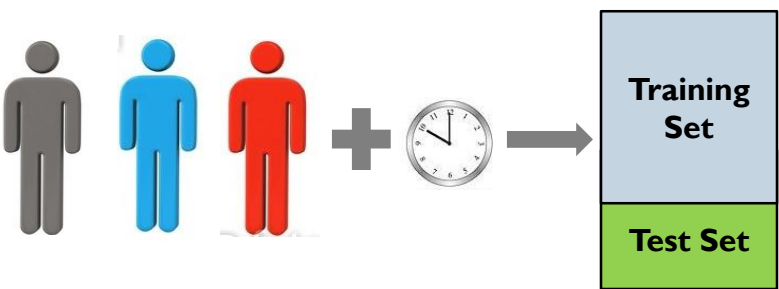
Single subject at one time



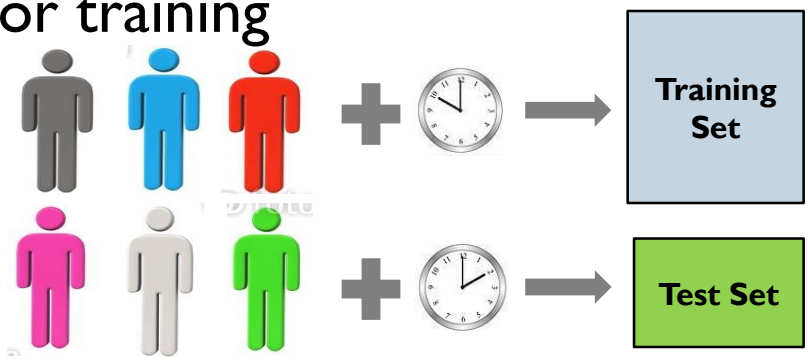
Single subject at different times



Multi subjects, same group for training and testing



Multi subjects, subjects used for testing are different from subjects for training



# Data Collection

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- ▶ **Sensors**
  - ▶ Single type of sensor
    - ▶ Single accelerometer
    - ▶ Multiple accelerometers
  - ▶ Multi modality:
    - ▶ different combinations



# Data Collection

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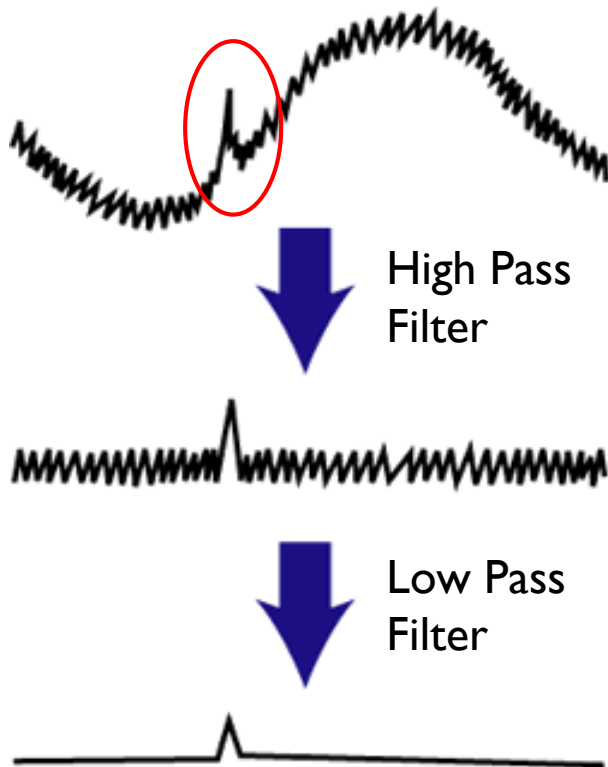
- Locations
  - Single location
  - Multiple location



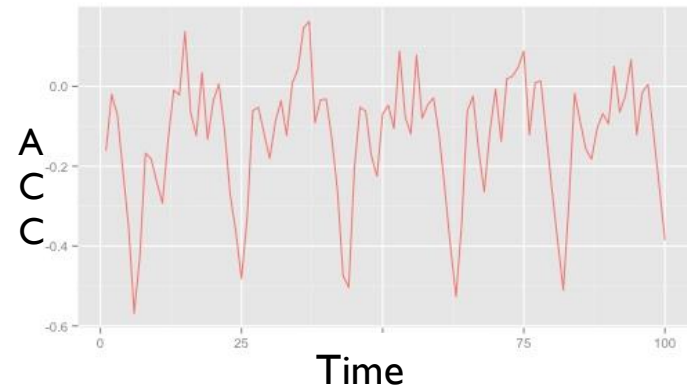
# Preprocessing

## ▶ De-noising

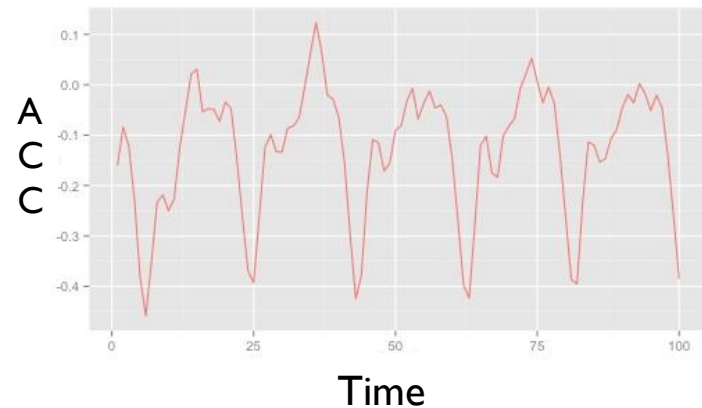
- Signal Filter



- Average



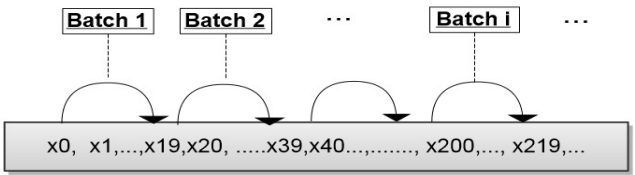
Acceleration  
Before  
Smoothing



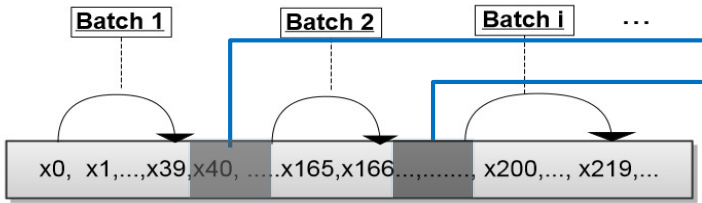
Acceleration  
after  
Smoothing

# Segmentation

## ▶ Windows without data overlapping

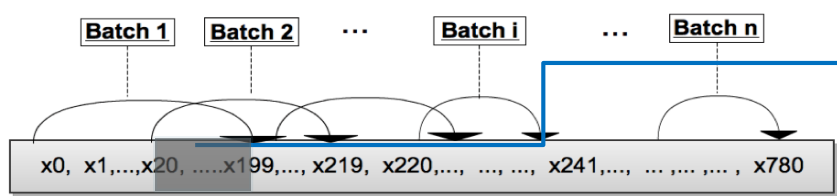


## ▶ Windows with dynamic size (no overlapping)[6]



Some sensors are deactivated, data are excluded in segmentation

## ▶ Windows with data overlapping (Sliding Window)[7]



Overlapped data

[6] L. Wang, T. Gu, X. Tao, and J. Lu. A hierarchical approach to real-time activity recognition in body sensor networks. Pervasive and Mobile Computing, 2012

[7] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman. Activity recognition from accelerometer data: AAAI, 2005

# Feature Computation

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## ▶ Time-Domain Features

- ▶ Mean
- ▶ Max, Min
- ▶ Standard Deviation, Variance
- ▶ Signal-Magnitude Area [8]

- ▶  $\sum_{i=1}^n \sqrt{x_i^2 + y_i^2 + z_i^2}$

- ▶ Correlation:

- ▶  $\frac{cov(x,y)}{\sigma_x \sigma_y}$

# Feature Computation

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## ▶ Frequency Domain Features


- ▶ Energy:  $\sum_{i=0}^n \sqrt{A_{real}_i^2 + A_{image}_i^2}$ , n is the window's size. [9]
- ▶ Entropy: Normalized information entropy of the discrete FFT component [10]
- ▶ Time Between Peaks [11]
- ▶ Binned Distribution: histogram of FFTs [11]

[9] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman. Activity recognition from accelerometer data: AAAI, 2005

[10] L. Bao and S. S. Intille. Activity recognition from user-annotated acceleration data. In Pervasive computing, Springer, 2004

[11] J. R. Kwapisz, G. M. Weiss, and S. A. Moore. Activity recognition using cell phone accelerometers. ACM SigKDD Explorations Newsletter, 2011.



- ▶ Core Techniques
  - ▶ Data Collection
  - ▶ Data Preprocessing
  - ▶ Feature Computation
  -  Classification

# Classification

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- ▶ Base-level Classification
- ▶ Meta-level Classification




# Base-level Classification

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- ▶ Decision Tree
- ▶ Decision Table
- ▶ K-Nearest Neighbor(KNN)
- ▶ Hidden Markov Model(HMM)
- ▶ Support Vector Machine(SVM)
- ▶ Naïve Bayes, Artificial Neural Networks, Gaussian Mixture Model, etc



- ▶ Core Techniques
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# Base-level Classification

Classifier	Decision Tree	Decision Table	KNN	HMM	SVM
Noise Sensitivity				!	✓
Cross-Person Adaption			!		
Model Update	!				
Computation Cost	✓	✓			!
Transition Model				✓	
Hierarchical Structure	✓	!			



# Other Classifiers

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- ▶ Gaussian Mixed Model
- ▶ Artificial Neural Network
- ▶ Naïve Bayes
- ▶ Rule-based Classifier
- ▶ Fuzzy Inference

# Meta-Level Classification[12]

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## ▶ Voting

- ▶ Each base level classifier gives a vote, the class label receiving the most votes is the final decision.

## ▶ Stacking

- ▶ Learning algorithm to learn how to combine the predictions of the base-level classifiers.

## ▶ Cascading

- ▶ Iterative process to combine base-level classifiers.
- ▶ Sub-optimal compare to others.

# Meta-level Classification

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- ▶ **Activity classification:**
  - ▶ Beneficial from more than one base-level classifiers
- ▶ **Feature selection:**
  - ▶ Choose the most discriminative features subset



# A Comparative Study

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- ▶ *Ravi et. al in Activity Recognition from Accelerometer Data*
  - ▶ *Tool: Weka*
  - ▶ *Test: Offline*
  - ▶ *Single Accelerometer*
  - ▶ *Eight activities:*
    - Standing, Walking, Running, Climbing Upstairs, Climbing Downstairs, Sit-ups, Vacuuming, Brushing teeth.*
  - ▶ *4 Settings:*
    - ▶ *Setting 1: Single subject at different times, mixed together and cross-validated*
    - ▶ *Setting 2: Multi subjects at different times, mixed together and cross-validated*
    - ▶ *Setting 3: Same subject, data collected at two different time are used as training data and test data, respectively.*
    - ▶ *Setting 4: Training on the data collected on one subject at one time, Test on the data collected on another subject at another time.*

# A comparative Study

## ► Results and conclusion

Classifier	Accuracy(%)			
	Setting1	Setting2	Setting3	Setting4
Naive Bayes(NB)	98.86	96.69	89.96	64.00
Boosted NB	98.86	98.71	89.96	64.00
Bagged NB	98.58	96.88	90.39	59.33
SVM	98.15	98.16	68.78	63.00
Boosted SVM	99.43	98.16	67.90	<b>73.33</b>
Bagged SVM	98.15	98.53	68.78	60.00
kNN	98.15	99.26	72.93	49.67
Boosted kNN	99.15	99.26	72.93	49.67
Bagged kNN	99.15	99.26	70.52	46.67
Decision Table(DT)	92.45	91.91	55.68	46.33
Boosted DT	97.86	98.53	55.68	46.33
Bagged DT	93.30	94.85	55.90	46.67
Decision Tree(DTr)	97.29	98.53	77.95	57.00
Boosted DTr	98.15	98.35	77.95	57.00
Bagged DTr	97.29	95.22	78.82	63.33
<b>Plurality Voting</b>	<b>99.57</b>	<b>99.82</b>	<b>90.61</b>	65.33
Stacking (MDTs)	99.00	99.26	89.96	64.00
Stacking (ODTs)	98.86	98.35	84.50	64.00

- Plurality Voting is the best
- Subjects used in training and setting matter





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- ▶ **Challenges**
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# Challenges

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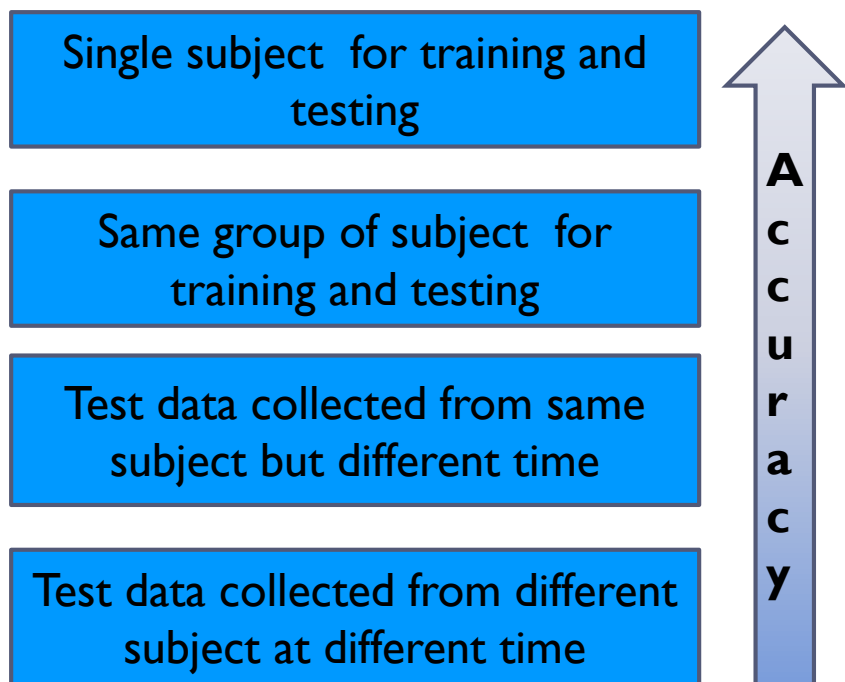
- ▶ **Challenges**
  - ▶ Subject Sensitivity
  - ▶ Location Sensitivity
  - ▶ Activity Complexity
  - ▶ Energy and Resource Constrains
  - ▶ Data Sparsity



- ▶ Challenges
  - ▶ Subject Sensitivity
  - ▶ Location Sensitivity
  - ▶ Activity Complexity
  - ▶ Energy and Resource Constrains
  - ▶ Data Sparsity

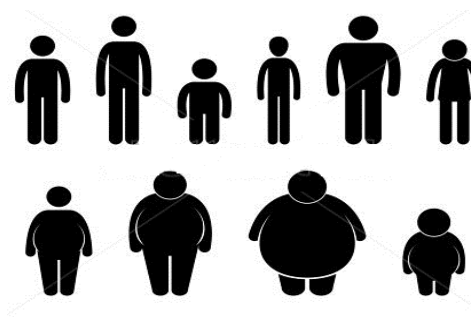
# Subject Sensitivity

- ▶ A comparative result in Ravi et. al's comparative study shows :



## Proposed solutions:

- Diversify subjects for training[13]



- Cross-person model [14]:  
Model is trained offline, in the online phase, use the most confident result to generate the new training set, so as to update the model.

[13] J. Lester, T. Choudhury, and G. Borriello. A practical approach to recognizing physical activities.

[14] W.-Y. Deng, Q.-H. Zheng, and Z.-M. Wang. Crossperson activity recognition using reduced kernel extreme learning machine.

# Location Sensitivity

## ▶ Sensor's location on human body:

- ▶ Different part of the body's movement is different in magnitude for a same activity
- ▶ It may contain different signal information

→ Train a device position classifier first! [15]

## ▶ Sensor's placed orientation:

- ▶ The feature vector for each axis is different when sensor's orientation is different

→ Use Gyroscope sensor reading to convert the reading from body coordination to earth coordination [16]

[15] Y. E. Ustev, O. Durmaz Incel, and C. Ersoy. User, device and orientation independent human activity recognition on mobile phones: challenges and a proposal.

[16] J.-g. Park, A. Patel, D. Curtis, S. Teller, and J. Ledlie. Online pose classification and walking speed estimation using handheld devices.

# Activity Complexity

- ▶ Multi tasks at the same time



Only predict the activity which is dominating the sensor?

- ▶ Activities' transition state



- Use HMM to smooth the transition states [17]
- Make the transition states as activities: e.g. Sit-Stand [18]

- ▶ Culture Difference



Globalization VS Localization

- ▶ Activities that only involves part of the body



iWatch

[17] J. Lester, T. Choudhury, and G. Borriello. A practical approach to recognizing physical activities.


[18] M. Khan, S. I. Ahamed, M. Rahman, and R. O. Smith. A feature extraction method for realtime human activity recognition on cell phones.

# Energy and Resource Constrains

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## ▶ Continuous sensing, Online updating

- ▶ Memory limit
- ▶ Battery limit

- 
- Adaptive sensing model: make adaption to different activities [19]
  - Algorithm that requires less computing resource: Lower sampling rate + no frequency domain features [20]

[19] Z. Yan, V. Subbaraju, D. Chakraborty, A. Misra, and K. Aberer. Energy-efficient continuous activity recognition on mobile phones: An activity-adaptive approach.

[20] Y. Liang, X. Zhou, Z. Yu, and B. Guo. Energy efficient motion related activity recognition on mobile devices for pervasive healthcare.

# Data Sparsity

- ▶ Not easy to get as many variety of training set as possible
- ▶ Difficult to coordinate people to same experiment setting

- Semi-supervised Learning: [21] [22]
  - Use unlabeled data as part of the training set. And can produce considerable improvement in accuracy!
- • SIC-R: [23]
  - Introduced feature descriptor to allow feature get from one training set to describe events of the same semantic class which may taken place over varying time scale.

- [21] D. Guan, W. Yuan, Y.-K. Lee, A. Gavrilo, and S. Lee. Activity recognition based on semisupervised learning.
- [22] M. Mahdavian and T. Choudhury. Fast and scalable training of semi-supervised crfs with application to activity recognition. In NIPS, volume 20, 2007.
- [23] J. Xie and M. S. Beigi. A scale-invariant local descriptor for event recognition in Id sensor signals. In Proc. Int. Multimedia and Expo Conf., 2009.

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- ▶ Challenges
- ▶ **Applications**
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# Applications

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- ▶ Daily Life Monitor
- ▶ Personal Biometric Signature
- ▶ Elder and Youth Care
- ▶ Localization
- ▶ Industry Manufacturing Assisting

- ➔ Daily Life Monitor
  - Personal Biometric Signature
  - Elder and Youth Care
  - Localization
  - Industry Manufacturing Assisting

# Daily Life Monitoring

## ► Fitness status tracking gadget

- Expensive!



## ► Mobile apps:

- Free or cheap enough
- No extra devices to wear
- Convenient



Fig. 1: Nike Fuel Band: <http://www.nike.com/FuelBand/>

Fig. 2: Nike Run App: [http://nikeplus.nike.com/plus/products/gps\\_app/](http://nikeplus.nike.com/plus/products/gps_app/)

- ▶ Applications
  - ▶ Daily Life Monitor
  - ▶ Personal Biometric Signature
  - ▶ Elder and Youth Care
  - ▶ Localization
  - ▶ Industry Manufacturing Assisting

# Personal Biometric Signature

- ▶ Exclusive and unique motion pattern:
  - ▶ Biometric signature: e.g. shake phone in a special way[25]
  - ▶ Role recognition: in games
- ▶ Can be used in malicious ways:
  - ▶ Use the learned signature to infer the keyboard typing [26]



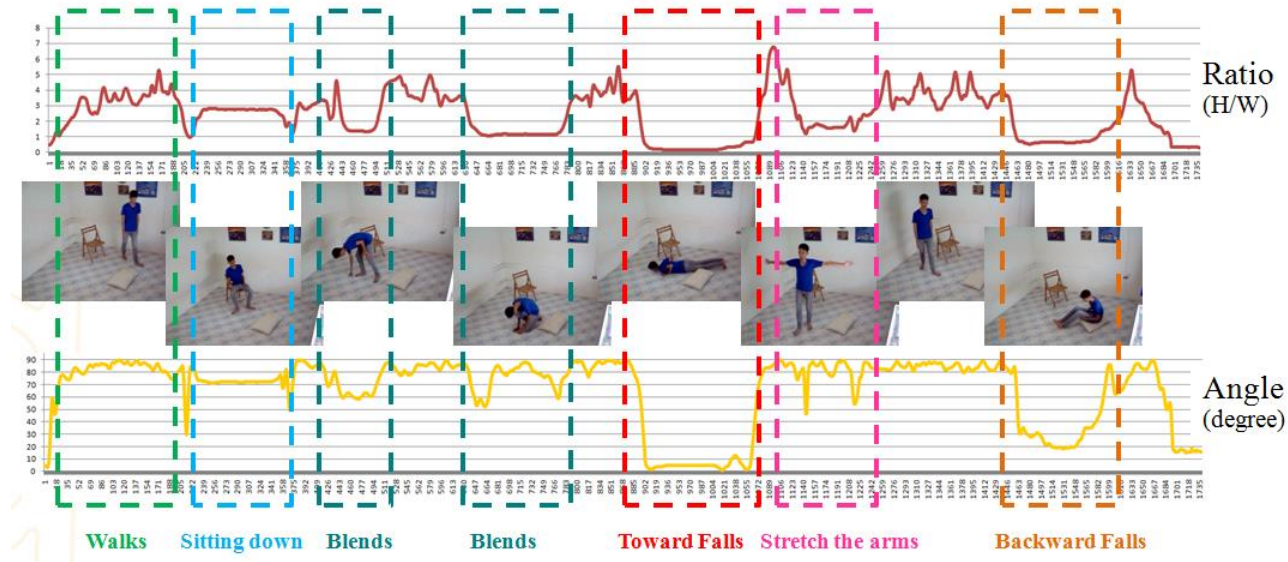
[25] J. G. Casanova, C. S. A'vila, A. de Santos Sierra, G. B. del Pozo, and V. J. Vera. A real-time in-air signature biometric technique using a mobile device embedding an accelerometer. In *Networked Digital Technologies*, Springer, 2010.

[26] M. Goel, L. Findlater, and J. Wobbrock. Walktype: using accelerometer data to accomodate situational impairments in mobile touch screen text entry. In *Proc. Human Factors in Computing Systems*, 2012.

- Applications
  - Daily Life Monitor
  - Personal Biometric Signature
  - ➔ Elder and Youth Care
  - Localization
  - Industry Manufacturing Assisting

# Elder and Youth Care

## ▸ Fall detection [27]



## ▸ Youth Care

- Infant sleeping monitor and demand prediction
- In class children's ASD stereotypical movement detection [28]

[27] Fall Detection in realtime: <http://fivedots.coe.psu.ac.th/~kom/?p=1347>  
[28] F.Albinali, M. S. Goodwin, and S. Intille. Detecting stereotypical motor movements in the classroom using accelerometry and pattern recognition algorithms. Pervasive and Mobile Computing, vol 8 no. 1, 2012.

# Localization

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## ▶ Assist GPS:

- ▶ Indoor vertical information: 9-1-1 caller location inferring, daily routine logger [29]
- ▶ Signal in city: weak!
  - ▶ Augmented localization based on context detected using activity information [30]
  - ▶ E.g. Theater and Restaurant, which maybe too close for GPS to tell the different, but activities in each place have their own signature

[29] W. Song, J. Lee, H. G. Schulzrinne, and B. Lee. Finding 9-1-1 callers in tall buildings. <http://academiccommons.columbia.edu/item/ac:156057>, 2014, Mar. 1st.

[30] A. Ofstad, E. Nicholas, R. Szcodronski, and R. R. Choudhury. Aampl: Accelerometer augmented mobile phone localization. In Proc. 1st Int. Mobile entity localization and tracking in GPS-less environments Workshop, 2008.

- ▶ Applications
  - ▶ Daily Life Monitor
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  - ▶ Elder and Youth Care
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# Industry Manufacturing Assisting

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- ▶ To assist workers in their daily job [31]:



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- ▶ **Conclusion**

# Conclusion

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- ▶ Activity Recognition Background
- ▶ Core Techniques
- ▶ Challenges and Proposed Solutions
- ▶ Applications
- ▶ Possible research directions:
  - ▶ Data Capturing - e.g., de-noising, energy efficient
  - ▶ Algorithms - Complex Activity Recognition
    - ▶ Multi-modal, Multi-position, Multi-person & Dynamics
  - ▶ Applications
    - ▶ Traffic Mode Recognition, Navigation, Remote Control





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Thank you!

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