The Hong Kong Polytechnic University
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Data-Driven Analytics of Human Dynamics

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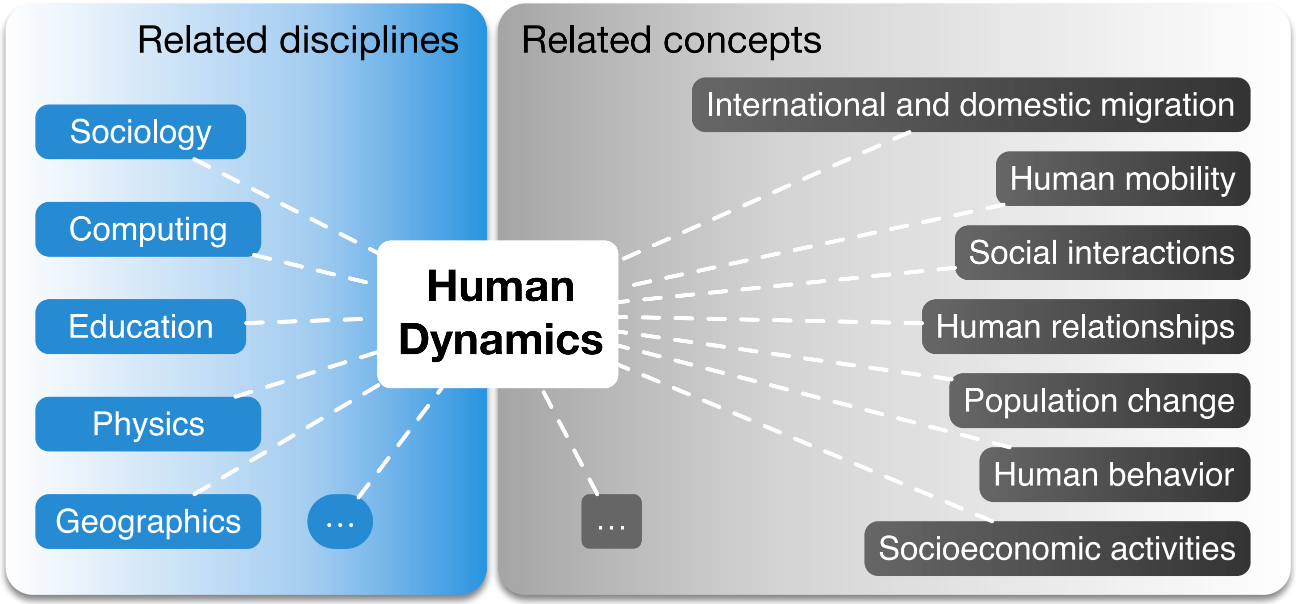
❖ Outline

- Introduction to Human Dynamics
- Research Taxonomy
- Opportunities and Challenges
- My Research Scope and Previous Works
  - Group Detection using WiFi Probes
  - User Profiling using Nonlinguistic audio data
- Conclusions

❖ What is Human Dynamics?

- Diverse definitions in different disciplines
- Defined as human activities and human interactions herein [1]
- Human dynamics research is a branch of complex systems research whose main goal is to understand human behaviors

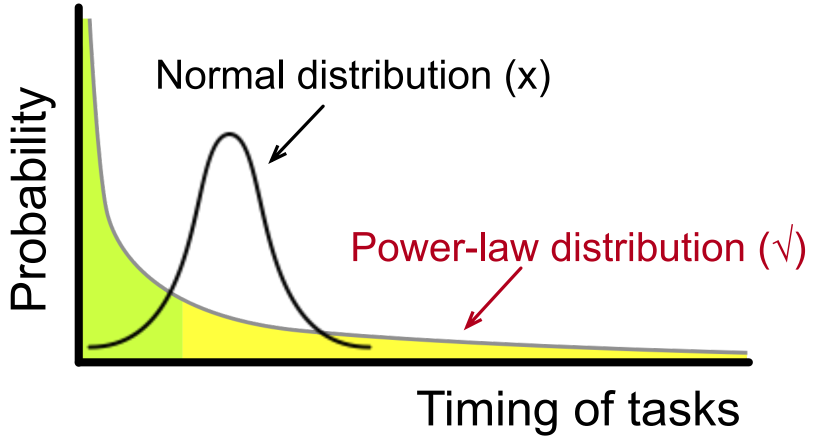


[1] M. Yuan, "Human dynamics in space and time: A brief history and a view forward," Transactions in GIS, 2018.

❖ Why Human Dynamics?

Questions

1) Are human actions randomly distributed in time?
2) Are human trajectories randomly distributed in space?



Never!

1) "when individuals execute tasks … most tasks being rapidly executed, whereas a few experience very long waiting times" [1]
2) "each individual being characterized by a time-independent travel distance and a significant probability to return to a few highly frequent locations" [2]

✓ **Gain comprehensive understandings and insights of human behaviors.**

[1] Barabasi, Albert-Laszlo. "The origin of bursts and heavy tails in human dynamics." Nature 435.7039 (2005): 207-211.
[2] Gonzalez, Marta C., Cesar A. Hidalgo, and Albert-Laszlo Barabasi. "Understanding individual human mobility patterns." Nature 453.7196 (2008): 779-782.

❖ Why Human Dynamics?

✓ **Benefit decision-makers/policy-makers in a wide range of applications**

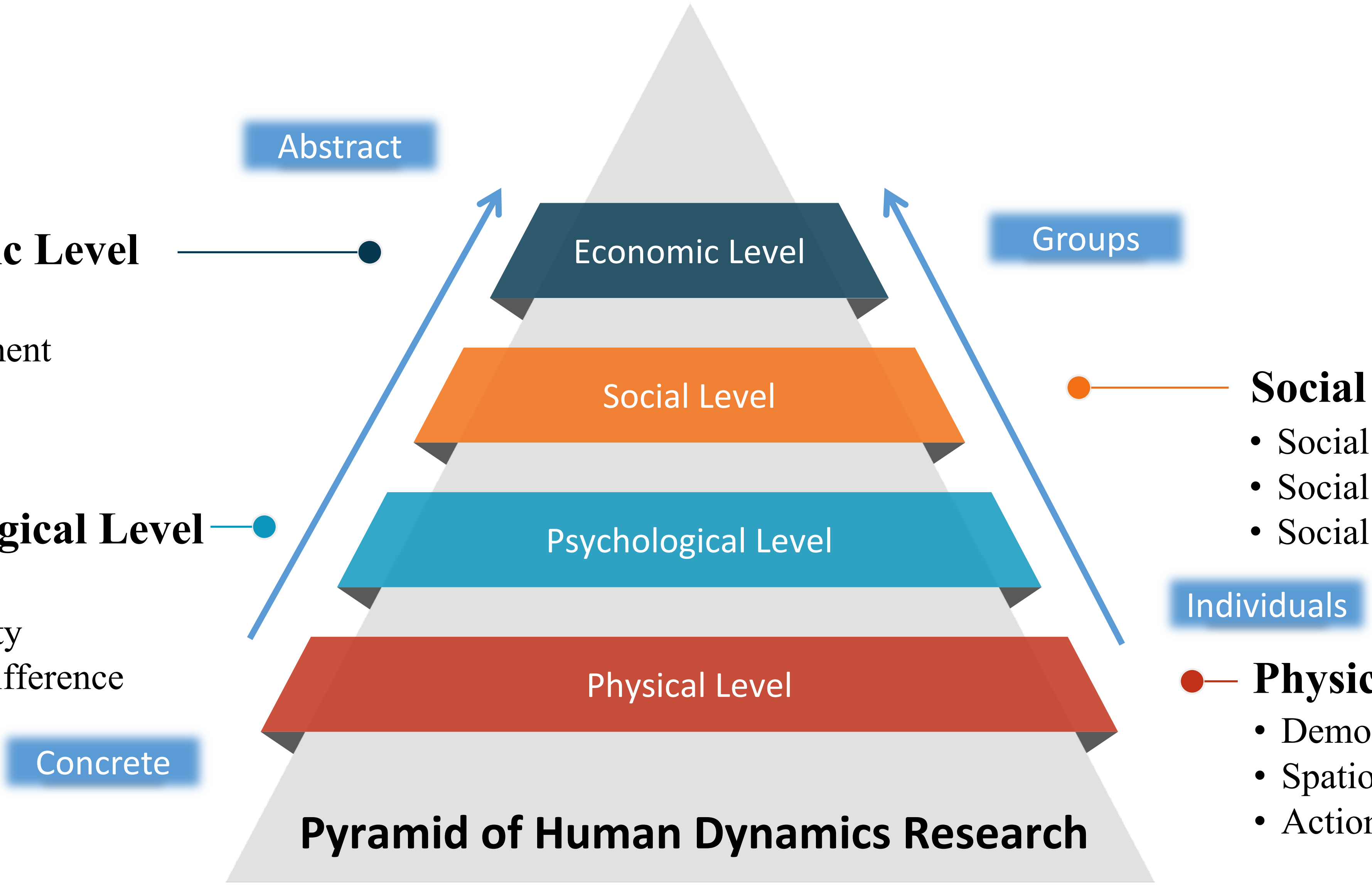
- Business Intelligence
  - Improve marketing strategy: mine social relationship and apply social homophily
  - Predict organization sustainability: inspect gender inequality
  - Improve service quality: examine facility utilization
- Public Health
  - Predict epidemics and viruses: analyse social networks
  - Cure mental disorders: detect early symptom
- Public Security
  - Identify suspects: detect groups

…

Taxonomy of Human Dynamics Research

Economic Level
- Business
- Employment

Psychological Level
- Emotion
- Personality
- Gender difference



Social Level
- Social ties
- Social interaction
- Social influence

Physical Level
- Demographics
- Spatiotemporal Status
- Actions

❖ Opportunities

Despite the great potential, conventional HD research progressed slowly

- Time-consuming, unrealistic settings, coarse-granularity, biased results, …

Big Data-Driven HD research bring great opportunities

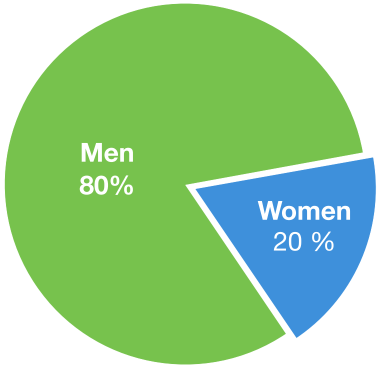
- Efficient in data collection, real-life env, fine-grained and comprehensive analysis, …

Characteristics	01 Early stage	02 Mobile and big data era
Data collection	Interview, survey, observe	ICT, IoT, Check-in
Scale	Small scale (several people)	Large scale
Setting	Mostly laboratory	Real-life scenario
Granularity	Coarse-grained	Fine-grained
Data volume	Small volume	"Big data"
User profiles	Complete	Incomplete

❖ Open Challenges

Emerging challenges of HD research in the mobile and big data era

- Incomplete user profiles
  - What: datasets collected by IoT lack detailed demographics
  - Why: would hinder or lead to opposite understandings



- Noisy data
  - What: deviation of sensors and unexpected situation of real-life scenarios
  - Why: data quality is vital to the performance
- The complex and dynamic nature of human behaviors
  - What: human behaviors are affected by various factors
  - Why: degrade the effectiveness and robustness of the system

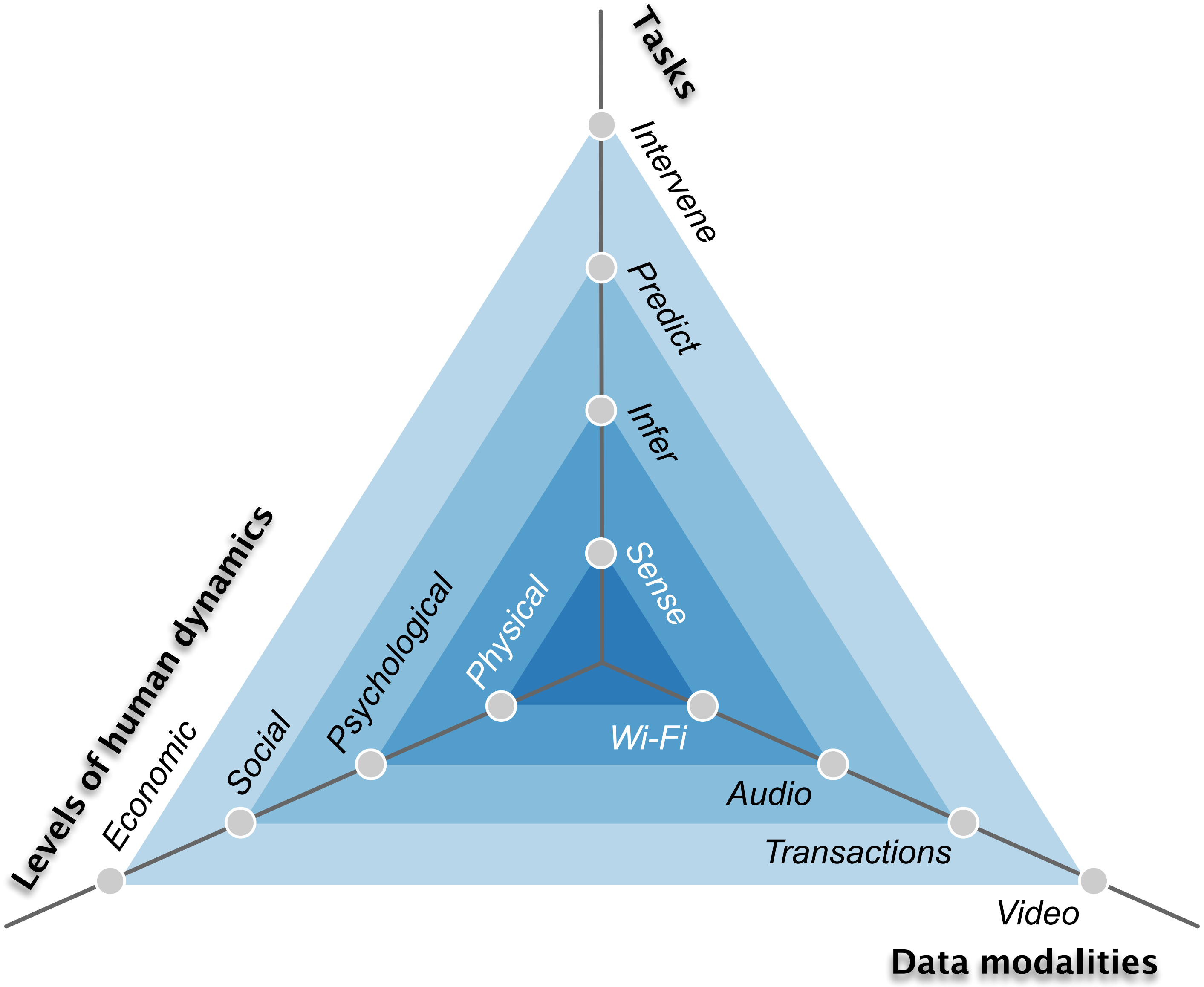
❖ Potential Solution

Inferring contextual information is usually the key to address the dynamics of human behaviors [1].

- Relative context
  - Spatiotemporal information of an event
- Relational context
  - Various social relationships among different entities
- Mental context
  - Subjective feelings include emotion, perception, and motivation

[1] Shih-Lung Shaw and Daniel Sui. “Introduction: Human Dynamics in Perspective”. In: Human Dynamics Research in Smart and Connected Communities. 2018.

Research Scope: 3D Research Space



Three Dimensions

1) Levels of human dynamics
2) Tasks
   - Sense observable behavior
   - Infer hidden behavior
   - Predict future behavior
   - Intervene human behavior
3) Data modalities
   - Wi-Fi
   - Audio
   - …

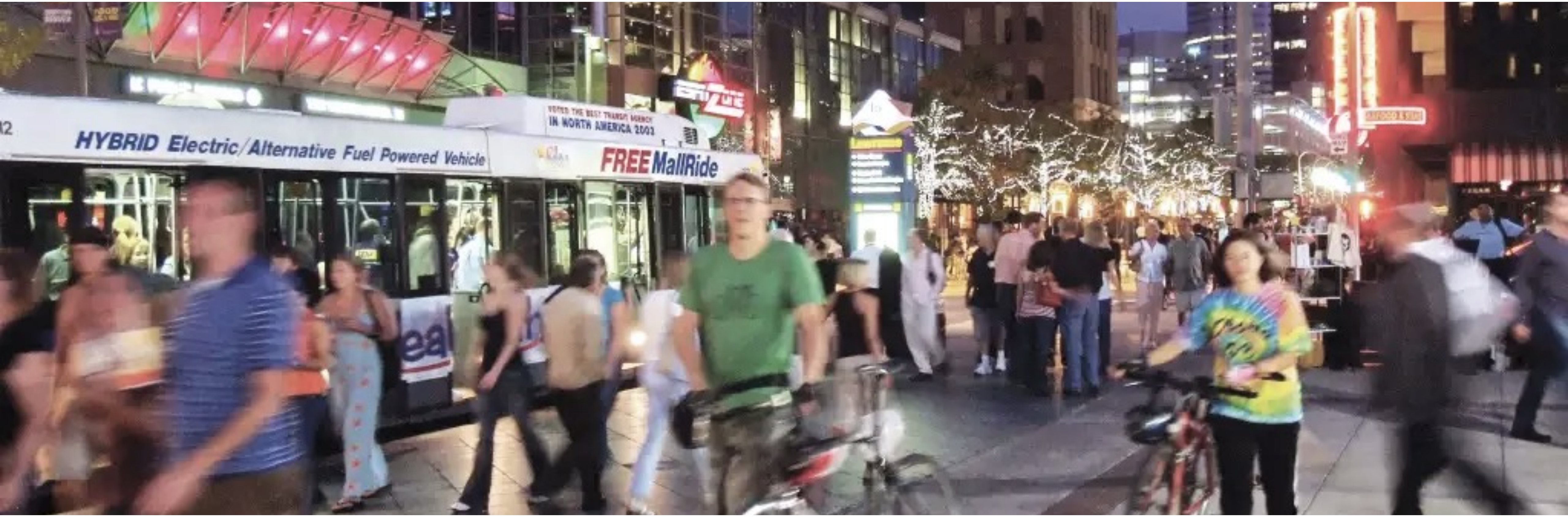
Examples

- Sense gesture with acoustic signal
- Infer gender with audio data
- Infer social ties from Wi-Fi logs
- Predict learning performance with transactions and online learning traces

Our Works on Data-Driven Analytics of Human Dynamics

- BaG: Behavior-aware Group Detection in Crowded Urban Spaces using WiFi Probes
  - Level: social level; Data: WiFi probes; Task: group detection
- SNOW: Detecting Shopping Groups Using WiFi
  - Level: social level; Data: WiFi data; Task: group detection
- User Profiling based on Nonlinguistic Audio Data
  - Level: psychological and physical levels; Data: nonlinguistic audio; Task: gender detection and personality recognition
- Feature-Based Room-Level Localization of Unmodified Smartphones
  - Level: physical levels; Data: WiFi probes; Task: sense location
- Inferring Real-life Social Ties based on Smart Card Transaction Data
  - Level: social levels; Data: smart card transaction; Task: infer social ties

…



BaG: Behavior-aware Group Detection in Crowded Urban Spaces using WiFi Probes

Jiaxing Shen, Jiannong Cao, and Xuefeng Liu
The Hong Kong Polytechnic University
Published in WWW 2019 and IEEE TMC

❖ Group Detection – Background and Motivation

Definitions

- Group: individuals with similar locations or behaviors [1-2]
- Group detection: detect whether two individuals belong to a group or not

Motivations of group detection

- Marketing: group-aware promotions in buy x and get 1 free
- Healthcare: accurate disease transmission model considering grouping information
- Urban planning: group-aware taxi dispatching in railway stations and airports

[1] Rijurekha Sen, Youngki Lee, Kasthuri Jayarajah, Archan Misra, and Rajesh Krishna Balan. [n. d.]. Grumon: Fast and accurate group monitoring for heterogeneous urban spaces. In Proceedings of ACM SenSys, 2014.
[2] Francesco Solera, Simone Calderara, and Rita Cucchiara. 2016. Socially constrained structural learning for groups detection in crowd. IEEE TPAMI (2016).

❖ Group Detection – Existing Methods

- Vison-based approaches
  - Use camera to track users
  - Cluster users' trajectories into disjoint subsets
- Sensor-based approaches
  - Use wearable devices or install apps on smartphones to collect users' multimodal behavioral data
  - Groups are detected through correlation analysis of multiple sensor data
- WiFi-based approaches
  - Signal strength indicates co-location
  - Individuals with frequent co-locations are groups

Vision-based

Pros
- Accurate

Cons
- High deployment cost
- Privacy erosion

Sensor-based

Pros
- Accurate

Cons
- User intervention
- Energy consumption

WiFi-based

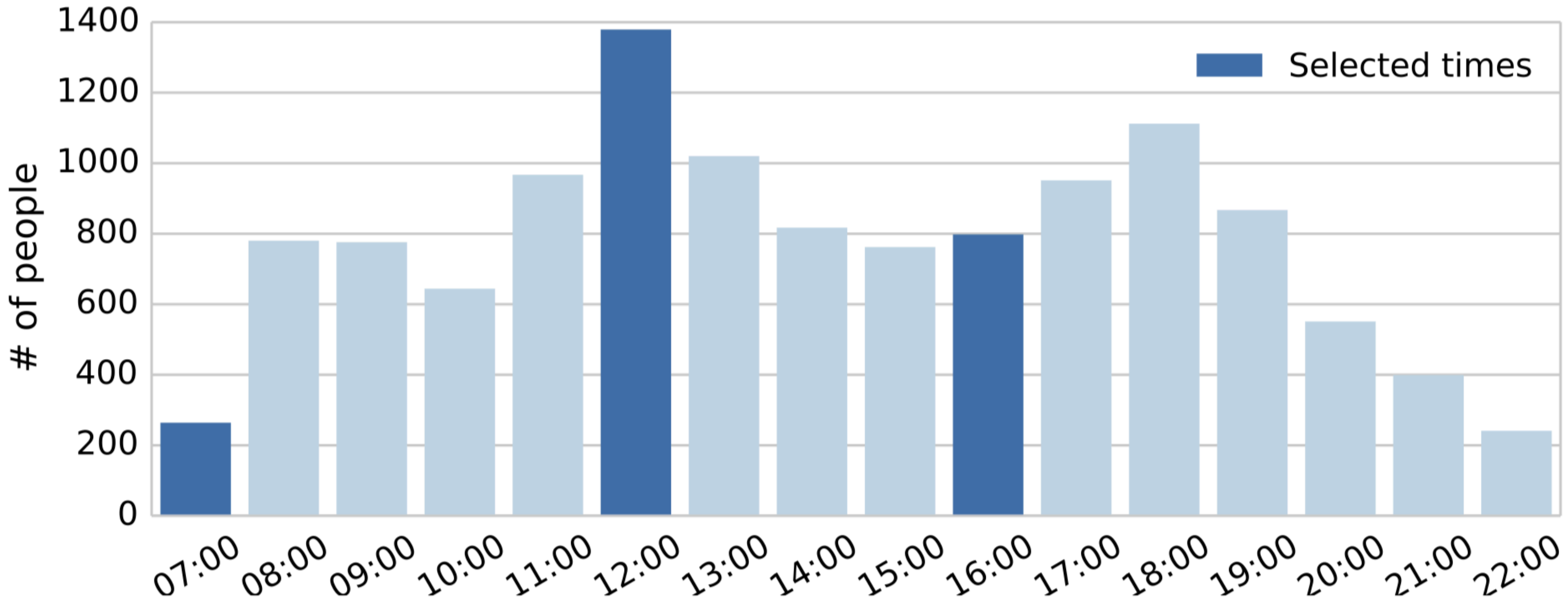
Pros
- Pervasive

Cons
- Inaccurate
- Unstable

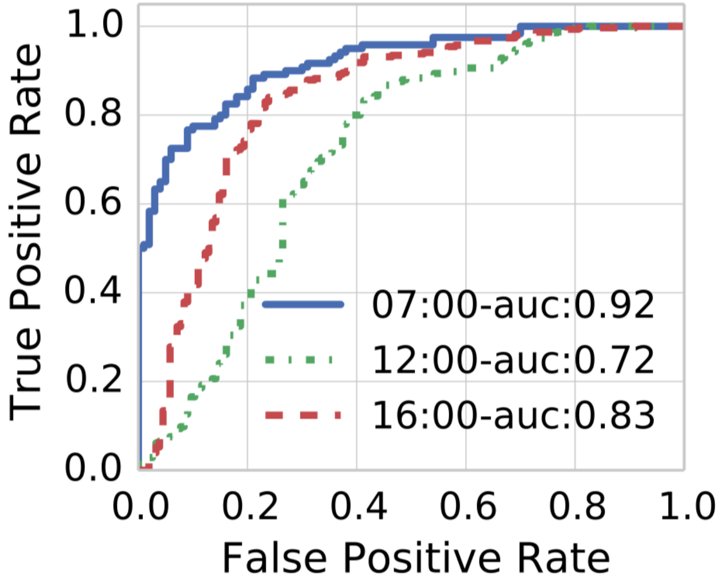
❖ Group Detection – Existing Methods

- The Main drawback of WiFi-based approaches
  - WiFi signal is vulnerable to many factors like the human body attenuation
  - It is thus unreliable in crowded scenarios

Question: Can we reliably detect groups using WiFi data in crowded urban spaces?

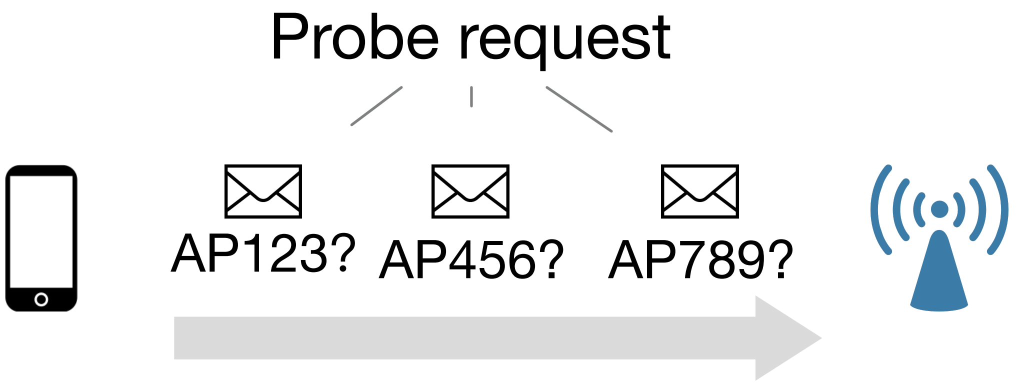


Average number of people in a day in a mall



ROC curves of existing WiFi-based Method

Group Detection – Observation of Heuristics

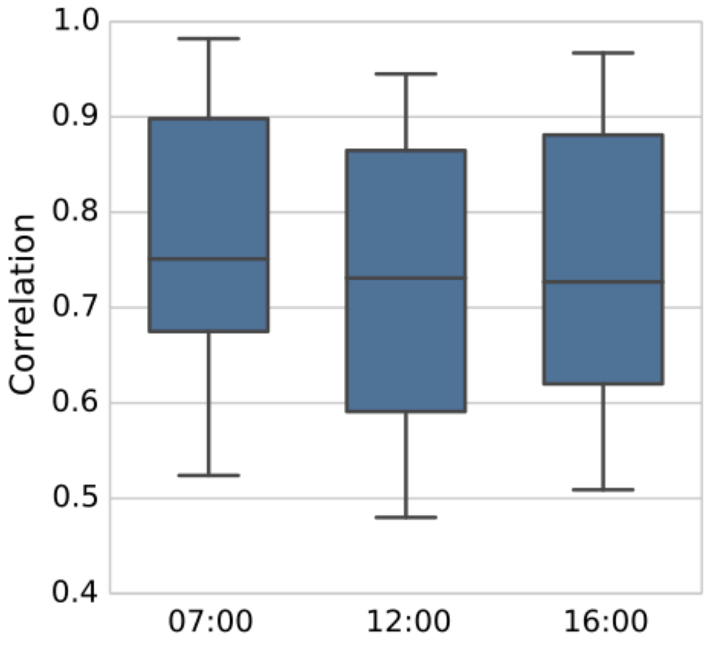


- Timestamp
- Source MAC
- SSID
- RSSI
- ……

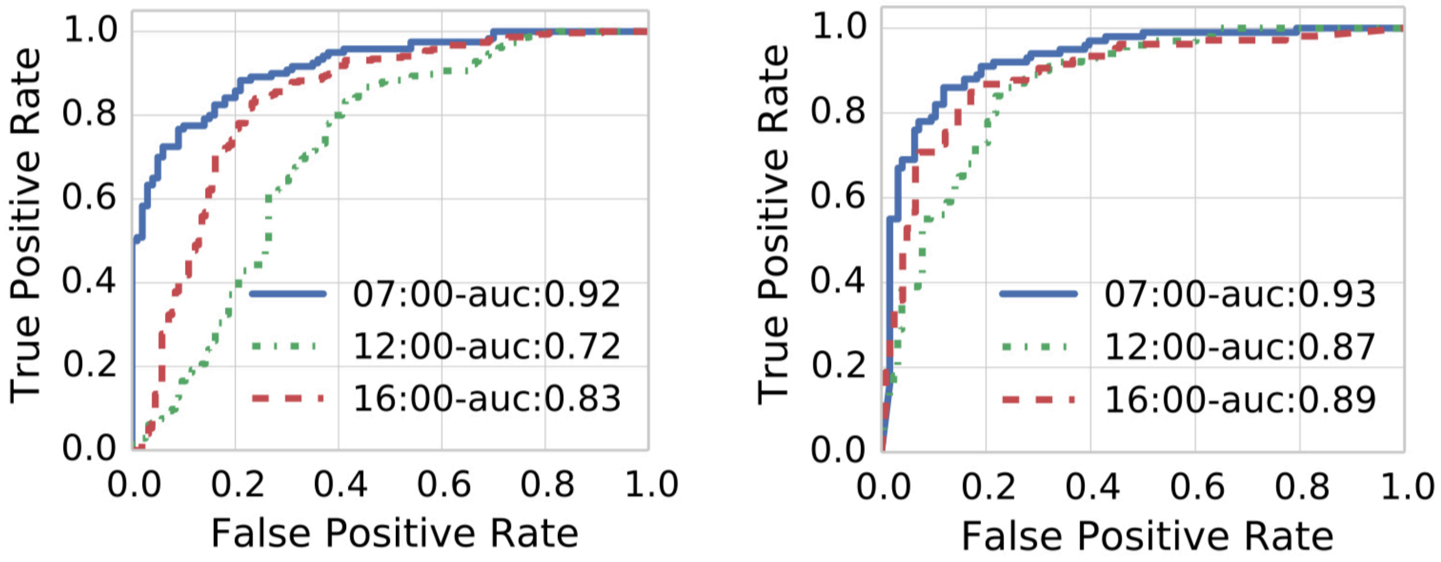
Mobility

- Send in bursts
- Number of bursts (NoB)

Smartphone usage behavior



Pearson correlation of Screen-on ratio and NoB



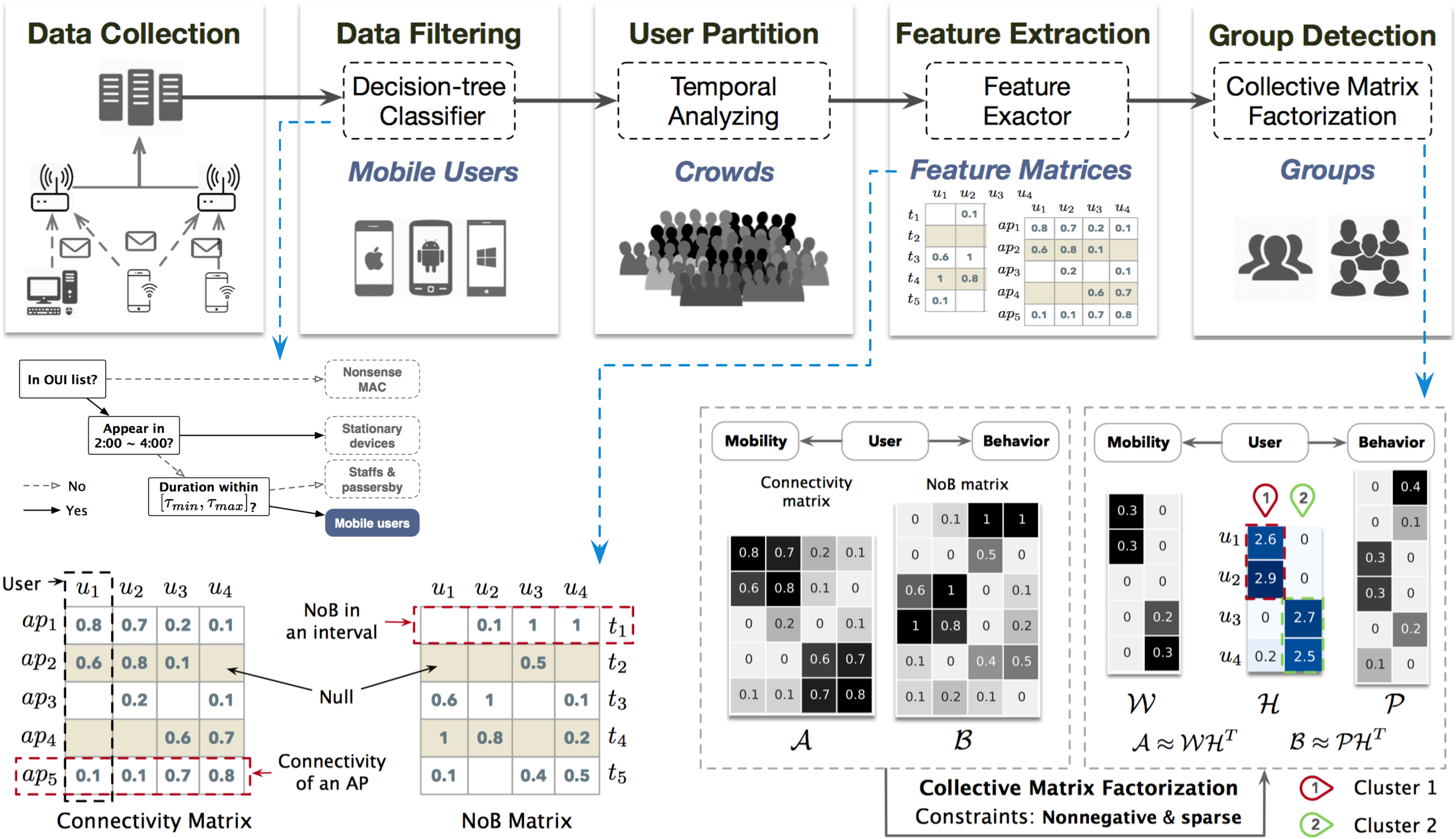
(a) RSS difference (b) Behavior difference

ROC Curves of using mobility features and behavior features

❖ Group Detection – Research Challenges and Solutions

- How to handle spatiotemporal sparsity of WiFi data?
  - Spatial sparsity and temporal sparsity
  - ✓ Represent mobility and behavior information as two matrices
  - ✓ Apply matrix factorization (MF) to handle data sparsity by decomposing an input matrix into the product of several factor matrices.

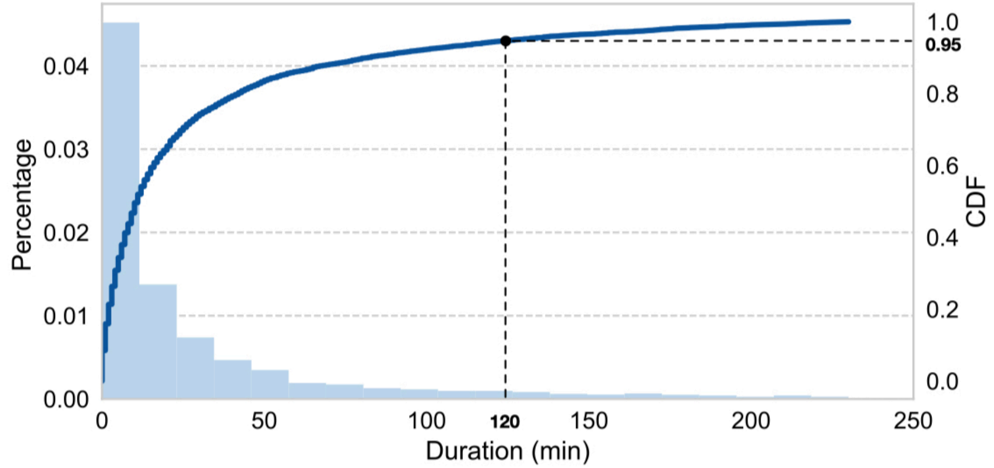
- How to cluster users considering both mobility and behaviors?
  - Mobility and behaviors have latent associations since both are different perspectives of the real grouping information.
  - ✓ Consider sparsity-constrained collective nonnegative MF.


Data Collection
Data Filtering
Decision-tree Classifier
Mobile Users
User Partition
Temporal Analyzing
Crowds
Feature Extraction
Feature Exactor
Feature Matrices
Group Detection
Collective Matrix Factorization
Groups
In OUI list?
Nonsense MAC
Appear in 2:00 ~ 4:00?
Stationary devices
Staffs & passersby
Duration within $[\tau_{min}, \tau_{max}]$?
Mobile users
No
Yes
User
NoB in an interval
Null
Connectivity of an AP
Connectivity Matrix
NoB Matrix
Mobility
User
Behavior
Connectivity matrix
NoB matrix
$\mathcal{A}$
$\mathcal{B}$
$\mathcal{W}$
$\mathcal{H}$
$\mathcal{P}$
$\mathcal{A} \approx \mathcal{W}\mathcal{H}^T$
$\mathcal{B} \approx \mathcal{P}\mathcal{H}^T$
Collective Matrix Factorization
Constraints: Nonnegative & sparse
Cluster 1
Cluster 2

Group Detection – Experimental Evaluation

Collected data

- 4,184,778 probes from 59,282 devices are collected daily on average in one week
- Only 3,951 mobile devices; 95% duration within 120 minutes



Evaluation metrics

$$\begin{cases} \text{Precision(P)} = \frac{tp}{tp+fp} \\ \text{Recall(R)} = \frac{tp}{tp+fn} \\ \text{F-score} = 2 \cdot \frac{\text{P}\cdot\text{R}}{\text{P}+\text{R}} \end{cases}$$

Detection \ Truth	g	$\tilde{g}$
g	tp	fp
$\tilde{g}$	fn	tn

g : Group
$\tilde{g}$: Non-group

Baseline approaches

Code	Features	Method
R-M (G)	RSSI	MCL
RN-M (G)	RSSI + NoB	MCL
MN-M (G)	Mobility + NoB	MCL
BaG (M)	Mobility + NoB	SCNMF

verify NoB
verify Mobility
verify CMF

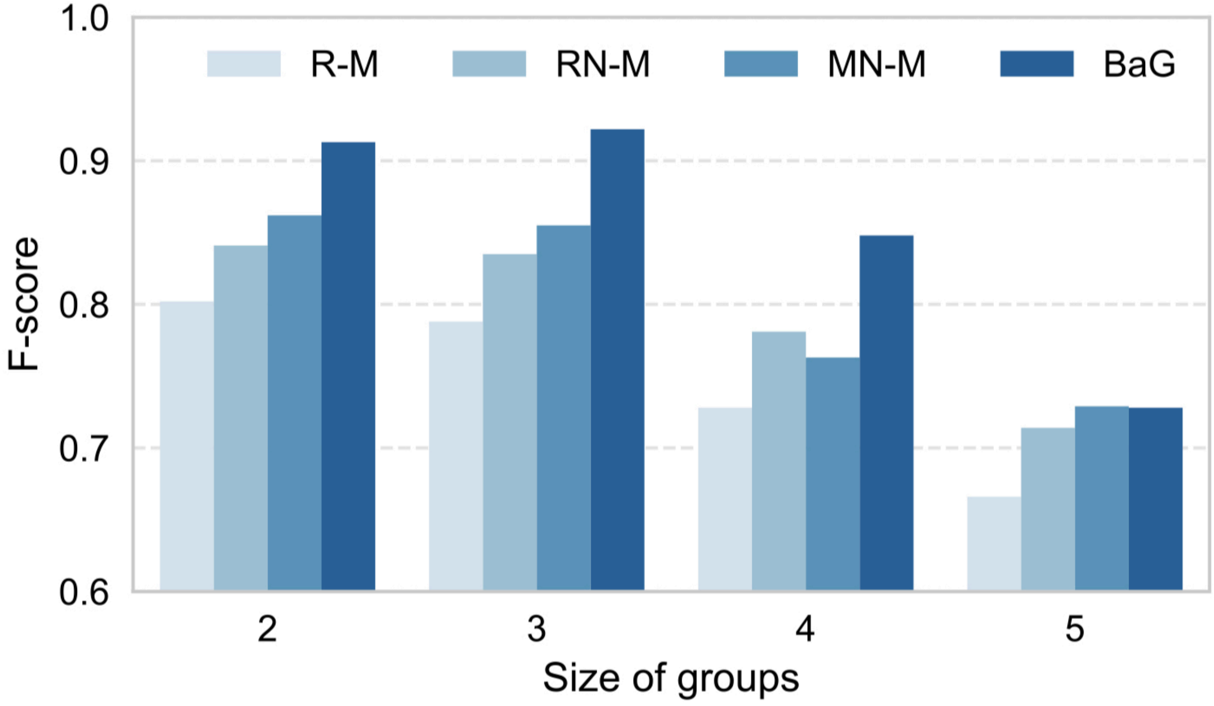
G Graph Approach   M Matrix Approach

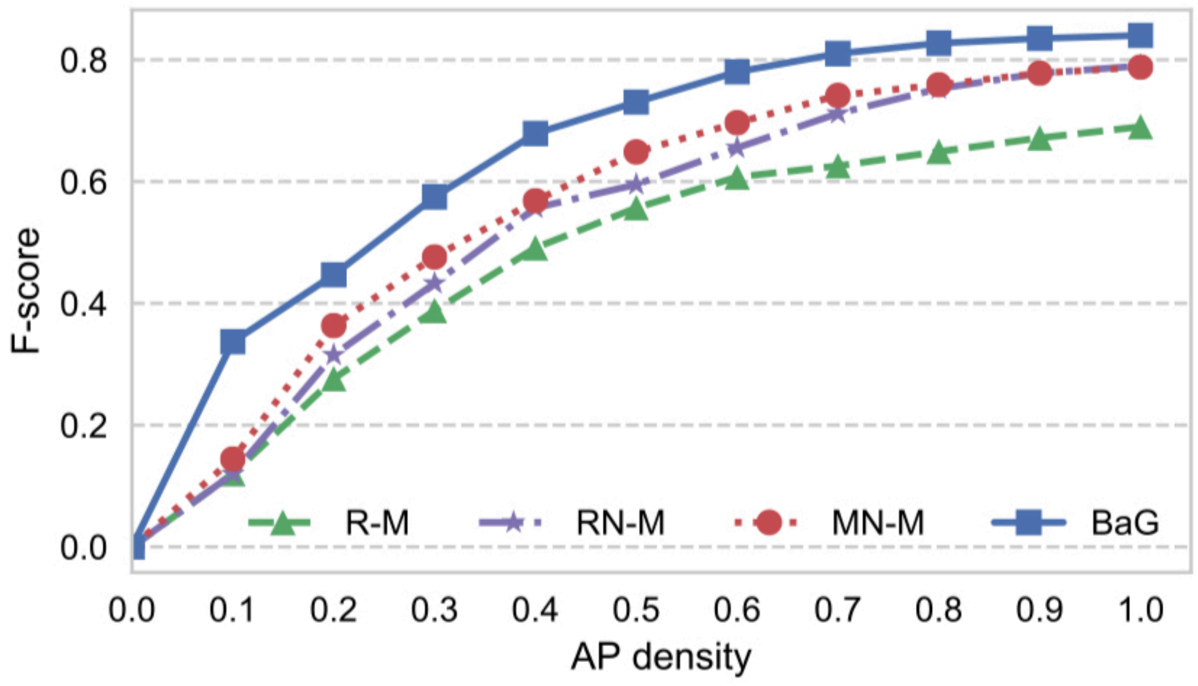
Group Detection – Experimental Evaluation

Codes	7:00 P[1]	7:00 R[2]	7:00 F[3]	16:00 P	16:00 R	16:00 F	12:00 P	12:00 R	12:00 F
R-M	.874	.886	.880	.755	.788	.771	.700	.720	.710
RN-M	.920	.935	.927	.848	.876	.862	.815	.799	.807
MN-M	.905	.922	.914	.856	.886	.871	.817	.849	.832
BaG	.934	.954	.944	.887	.915	.901	.859	.892	.875

[1] Precision [2] Recall [3] F-score

	7:00	16:00	12:00
R-M	7.3%	16.9%	23.2%
RN-M	1.8%	4.5%	8.4%
MN-M	3.3%	3.4%	5.2%





User Profiling based on Nonlinguistic Audio Data

Jiaxing Shen[1], Jiannong Cao[1], Oren Lederman[2], Shaojie Tang[3] and Alex ‘Sandy’ Pentland[2]

[1] The Hong Kong Polytechnic University

[2] Massachusetts Institute of Technology

[3] The University of Texas at Dallas

Published in IEEE ICDM 2018 and Submitted to ACM TOIS

❖ User Profiling – Background and Motivation

Definitions

- User profiling refers to the process of inferring users' attributes of interest (AoIs) including gender and personality.
- Nonlinguistic audio
  - What: coarse-grained audio without linguistic content
  - Why: privacy concerns and ethical issues in truly spontaneous conversations

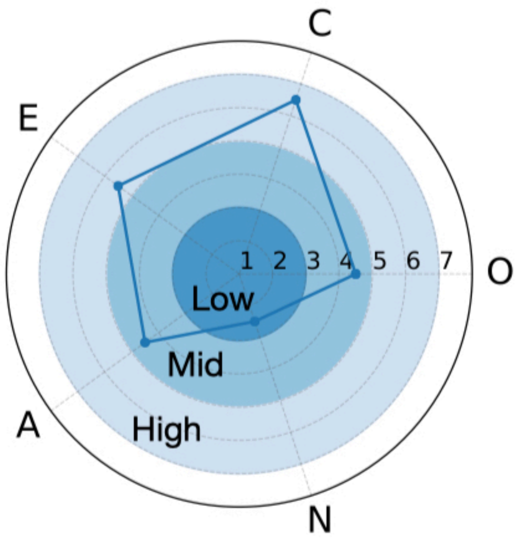
Motivation

- User profiles are foundation of human dynamics research
- Benefit stakeholders in many application areas
  - Healthcare: personalized treatments
  - Organization administration: optimize group productivity

❖ User Profiling – Background and Motivation

- Gender: a binary variable
- Personality: five-factor model (aka big five) [1]

***O**penness*	Artistic, Curious, Imaginative, Insightful, Original, Wide interests, etc.
***C**onscientiousness*	Efficient, Organized, Planful, Reliable, Responsible, Thorough, etc.
***E**xtraversion*	Active, Assertive, Energetic, Outgoing, Talkative, etc.
***A**greeableness*	Appreciative, Kind, Generous, Forgiving, Sympathetic, Trusting, etc.
***N**euroticism*	Anxious, Self-pitying, Tense, Touchy, Unstable, Worrying, etc.



[1] Alessandro Vinciarelli and Gelareh Mohammadi. 2014. A survey of personality computing. IEEE Transactions on Affective Computing (2014).

❖ User Profiling – Related Works

Gender identification and personality recognition have been studied with raw audio [1,2].

- Gender identification
  - o Acoustic features caused by physiological differences and phonetic differences
  - o For example, females have higher pitch
- Personality recognition
  - o Linguistic features and acoustic features reflect personality
  - o For example, extroverts tend to speak more frequently

However, hard to extract acoustic or linguistic features from nonlinguistic audio

[1] Musaed Alhussein, Zulfiqar Ali, Muhammad Imran, and Wadood Abdul. 2016. Automatic gender detection based on characteristics of vocal folds for mobile healthcare system. Mobile Information Systems (2016).
[2] Guozhen An, Sarah Ita Levitan, Rivka Levitan, Andrew Rosenberg, Michelle Levine, and Julia Hirschberg. 2016. Automatically Classifying Self-Rated Personality Scores from Speech.. In Interspeech.

User Profiling – Main Idea

Extract conversational features (turn-taking and interruption patterns)

Qualitative findings from Sociology and psychology studies

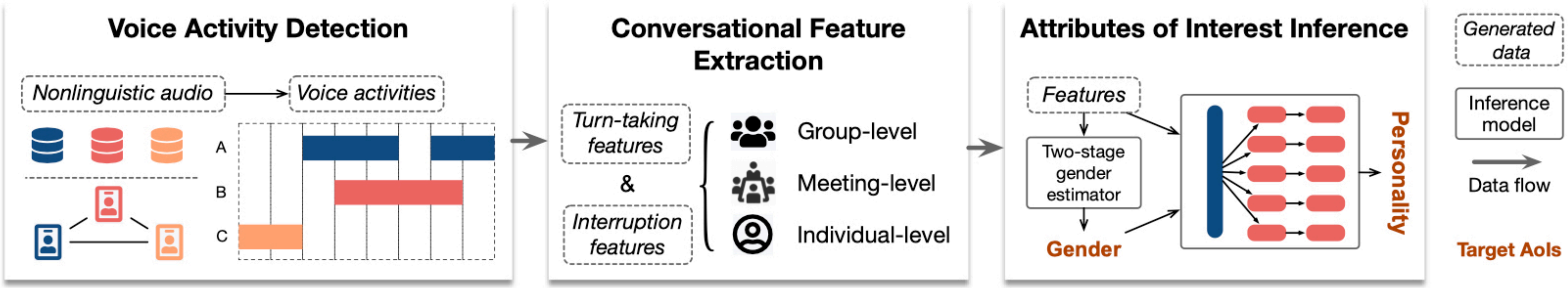
- Men have longer speaking turns [1] and are more likely to interrupt women than been interrupted by women [2]
- Extroverts, for example, tend to talk more, louder, faster, and have fewer hesitations[3]

[1] Cecilia L Ridgeway. 1992. Gender, interaction, and inequality. Springer.
Xiaoquan Zhao and Walter Gantz. 2003. Disruptive and cooperative interruptions in prime-time television fiction:
[2] The role of gender, status, and topic. Journal of Communication (2003).
[3] Ligia Maria Batrinca, Nadia Mana, Bruno Lepri, Fabio Pianesi, and Nicu Sebe. 2011. Please, tell me about yourself: automatic personality assessment using short self-presentations. In ICMI. ACM.

❖ User Profiling – Challenge and Solution

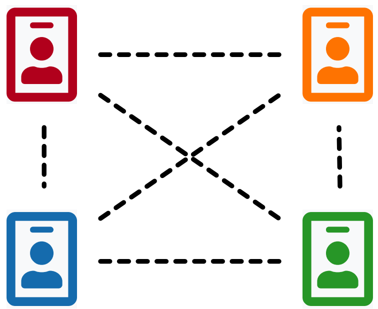
- How to accurately detect individual voice activities from nonlinguistic audio?
  - First, variations in people's vocal features and ways of collecting the audio data pose serious challenges to accurate voice activity detection (VAD).
  - Second, due to physical proximity, the nonlinguistic audio may come from other participants, which leads to false-positive detections.
  - ✓ Adaptive Bayesian VAD algorithm
- How to fill in the gap between dynamic conversational behaviors and stable AoIs?
  - Both gender and personalities are consistent over time.
  - Conversational behaviors are dynamic and could be affected by many factors like emotions and environments.
  - ✓ Extract and fuse multi-level features

User Profiling – System Overview

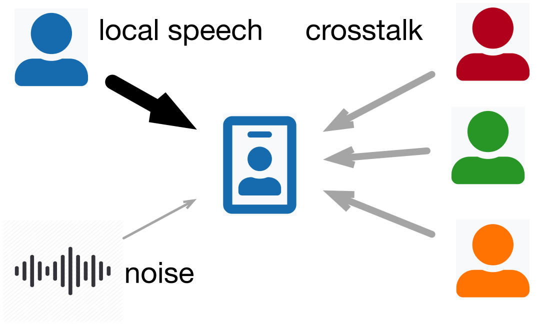


- Voice activity detection (VAD): to detect whether a participant speaks or not given the nonlinguistic audio of all participants of a meeting
- Conversational feature extraction: based on the detected voice activities, conversational features are then extracted including turn-taking behaviors and interruption patterns.
- Inferring AoI: to identify gender with a two-stage classification model and recognize personality traits using a gender-assited multitask learning model

❖ User Profiling – Voice Activity Detection



A meeting with four people

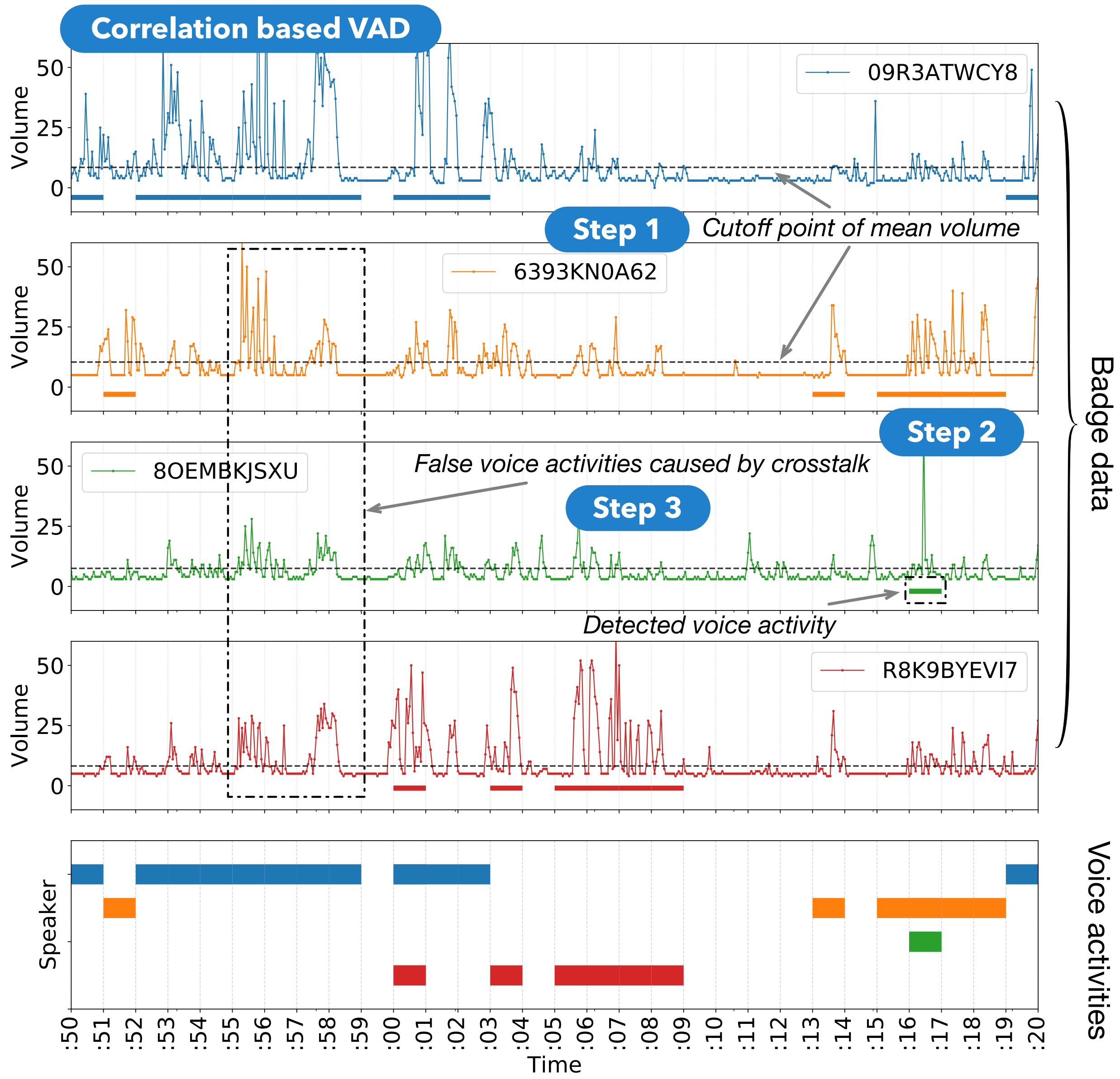


Composition of the badge data

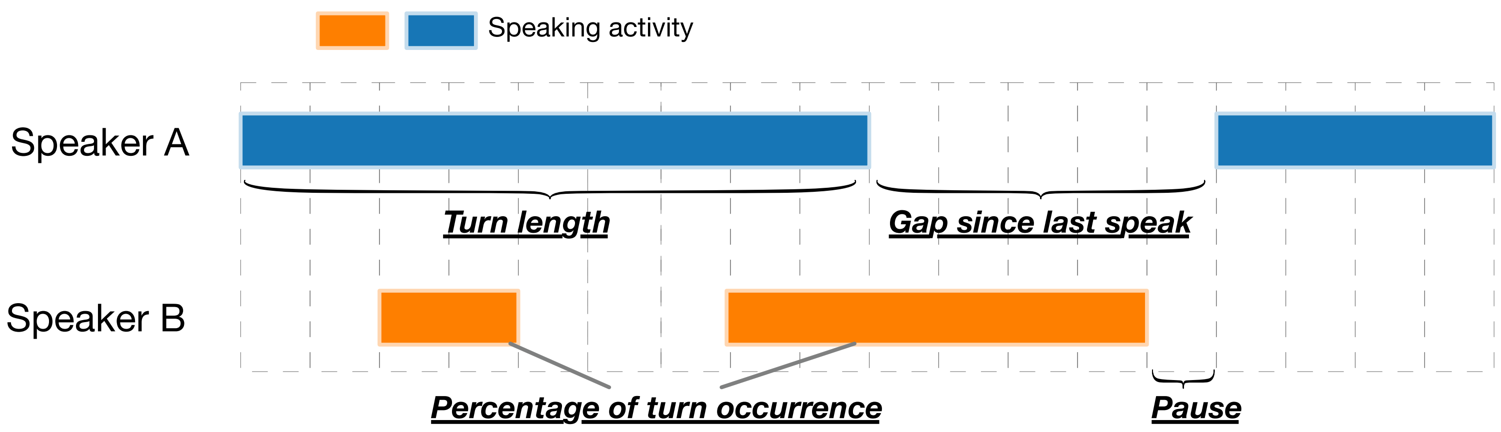
$$\mathbf{S}_i = \underbrace{\boxed{\mathbf{V}_i}}_{\text{Local speech}} + \underbrace{\boxed{\sum_{j \in \mathbf{P}} \phi_{ij} \cdot \mathbf{V}_j}}_{\text{Crosstalk}} + \underbrace{\boxed{\rho_d + \rho_e}}_{\text{Noise}}, j \neq i$$

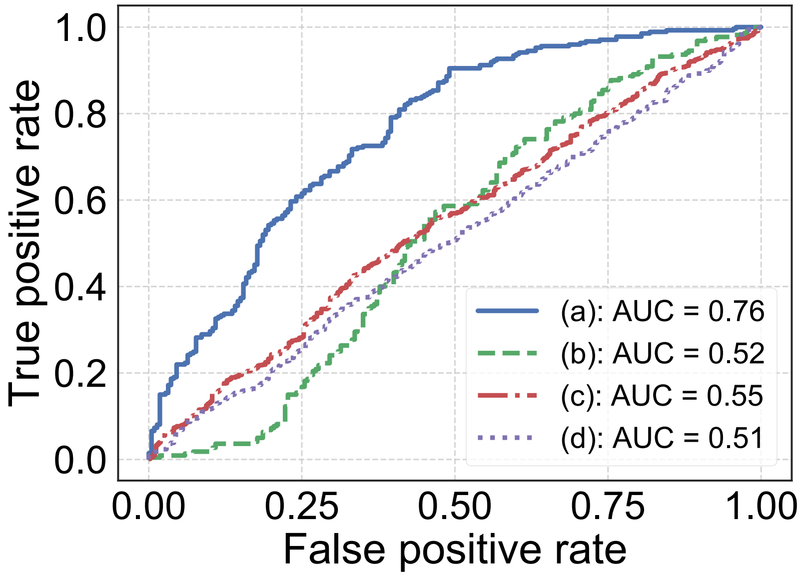
$$\begin{cases} \mathbf{S}_i(k) = \mathbf{V}_i(k) + \rho \approx \mathbf{V}_i(k) \\ \mathbf{S}_j(k) = \phi_{ij} \cdot \mathbf{V}_i(k) + \rho \approx \phi_{ij} \cdot \mathbf{V}_i(k) \end{cases}$$

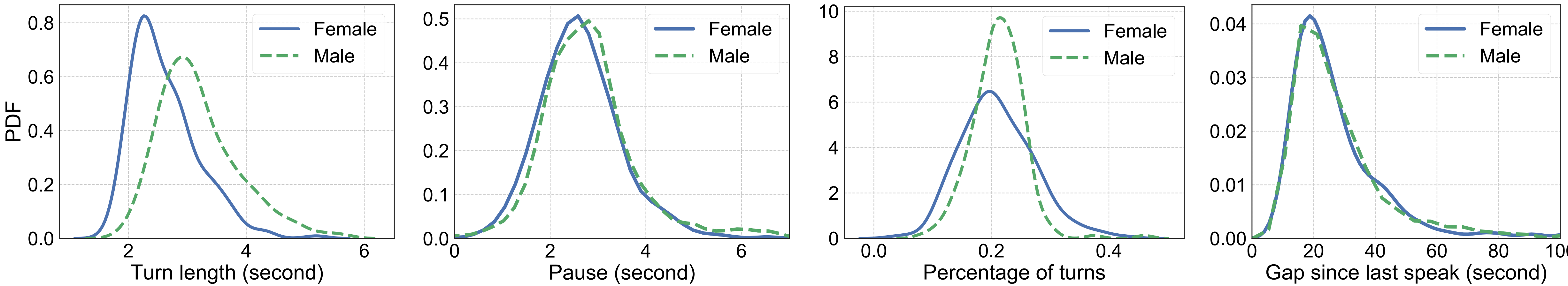
- Observation: when only one person speaks, his badge signal is linearly correlated with other badge signals.



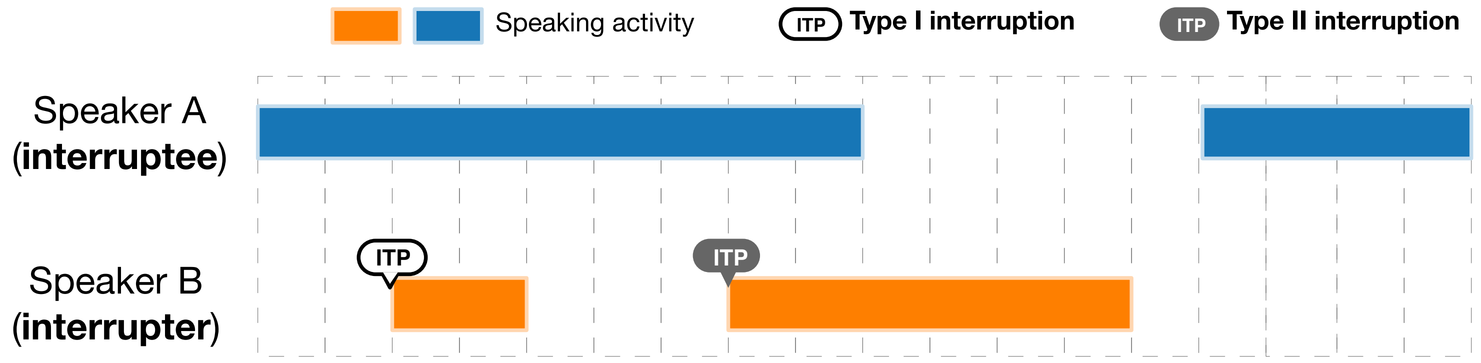
❖ User Profiling – Extract Turn-Taking Features







User Profiling – Extract Interruption Feature



Interruption ratios

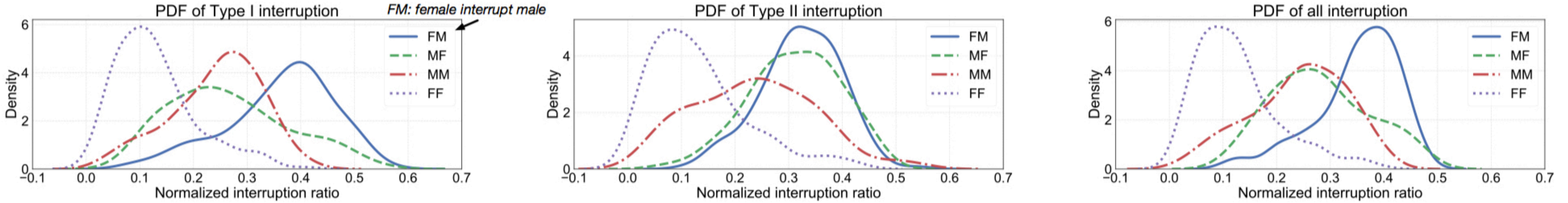
$$\begin{array}{c|c} \mathbf{FF} & \mathbf{FM} \\ \hline \mathbf{MF} & \mathbf{MM} \end{array} = \begin{array}{c|c} \dfrac{\mathbf{I}_{FF}}{\mathbf{I}_F \cdot \mathbf{N}_F} & \dfrac{\mathbf{I}_{FM}}{\mathbf{I}_F \cdot \mathbf{N}_M} \\ \hline \dfrac{\mathbf{I}_{MF}}{\mathbf{I}_M \cdot \mathbf{N}_F} & \dfrac{\mathbf{I}_{MM}}{\mathbf{I}_M \cdot \mathbf{N}_M} \end{array}$$

$\mathbf{I}_{FF}$: Number of FF interruption

$\mathbf{I}_F$: Number interruption started by females

$\mathbf{N}_F$: Number of females in group

FM>MF>MM>FF



	FM	MF	MM	FF
FM		2.7e-16	4.1e-28	8e-53
MF	2.7e-16			1.8e-33
MM	4.1e-28			4.1e-30
FF	8e-53	1.8e-33	4.1e-30	

***FM** is greater than **MF** with a p-value 2.7e-16*

(a)

	FM	MF	MM	FF
FM			1.5e-15	1.6e-44
MF			6.5e-12	4.6e-41
MM	1.5e-15	6.5e-12		2.6e-18
FF	1.6e-44	4.6e-41	2.6e-18	

(b)

	FM	MF	MM	FF
FM		5.3e-14	6.9e-30	4.5e-55
MF	5.3e-14		0.0003	8e-43
MM	6.9e-30	0.0003		7.9e-29
FF	4.5e-55	8e-43	7.9e-29	

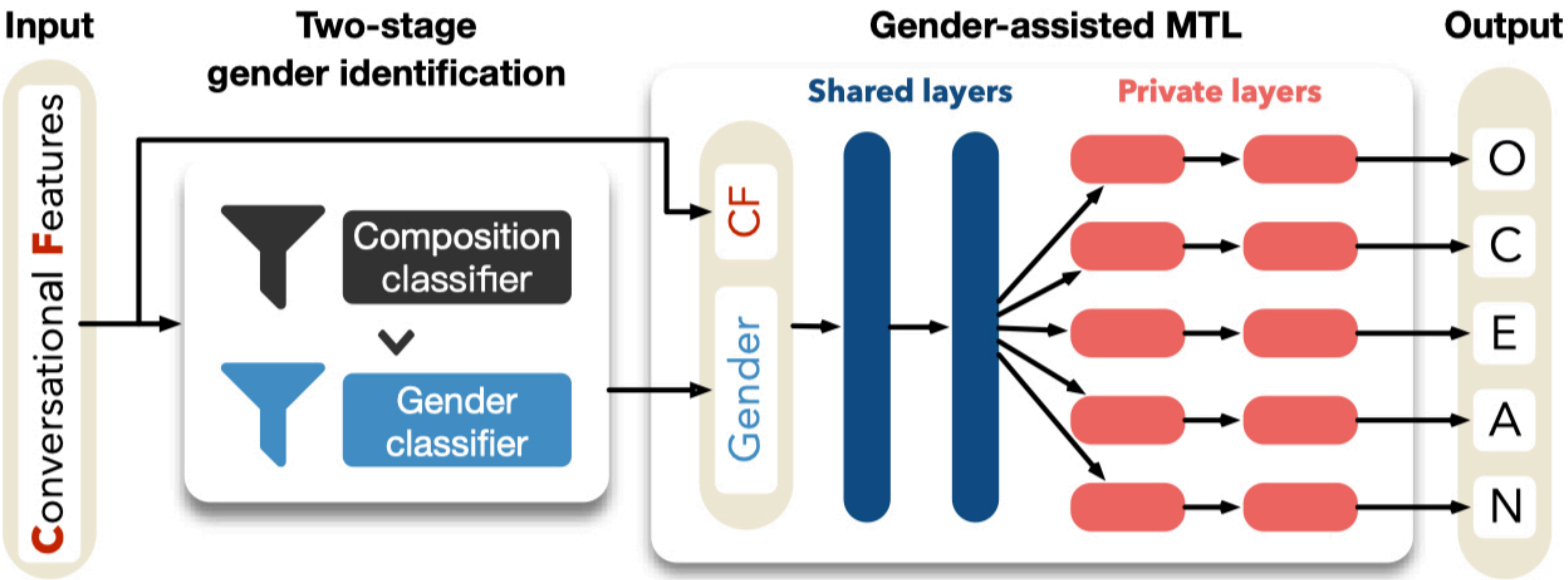
greater

less

(c)

❖ User Profiling – Gender Identification & Personality Recognition

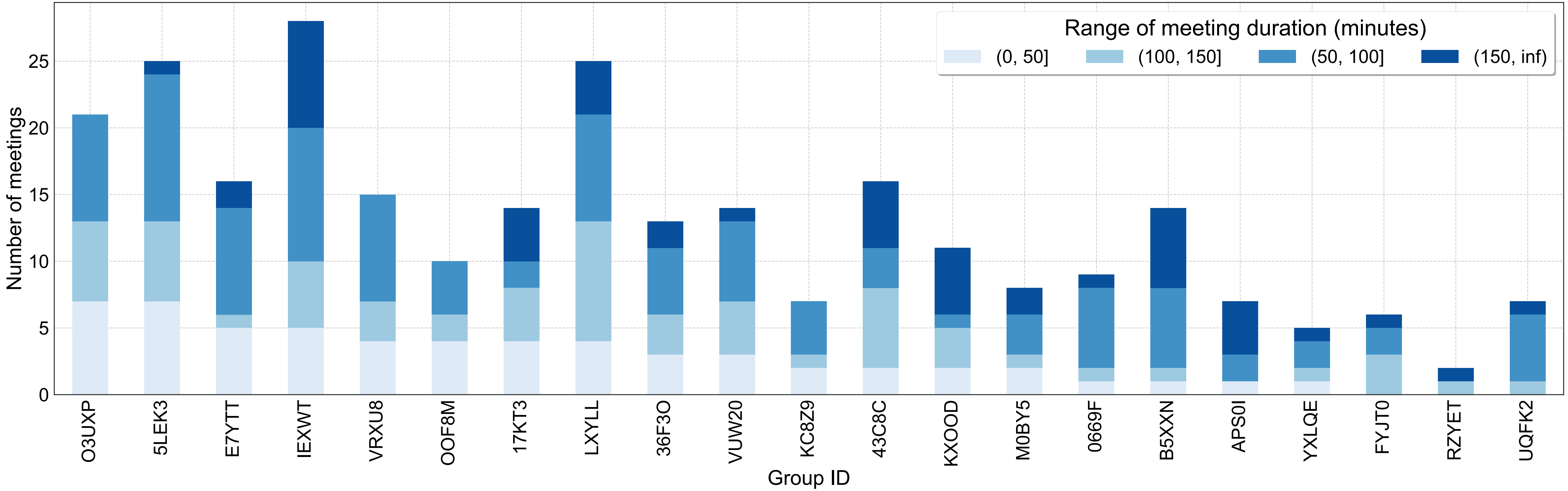
- Two-stage gender identification
  - Gender composition first, then gender of each individual
- Gender-assisted multitask learning for personality recognition
  - Gender is important; personality traits are correlated.



❖ User Profiling – Experimental Evaluation

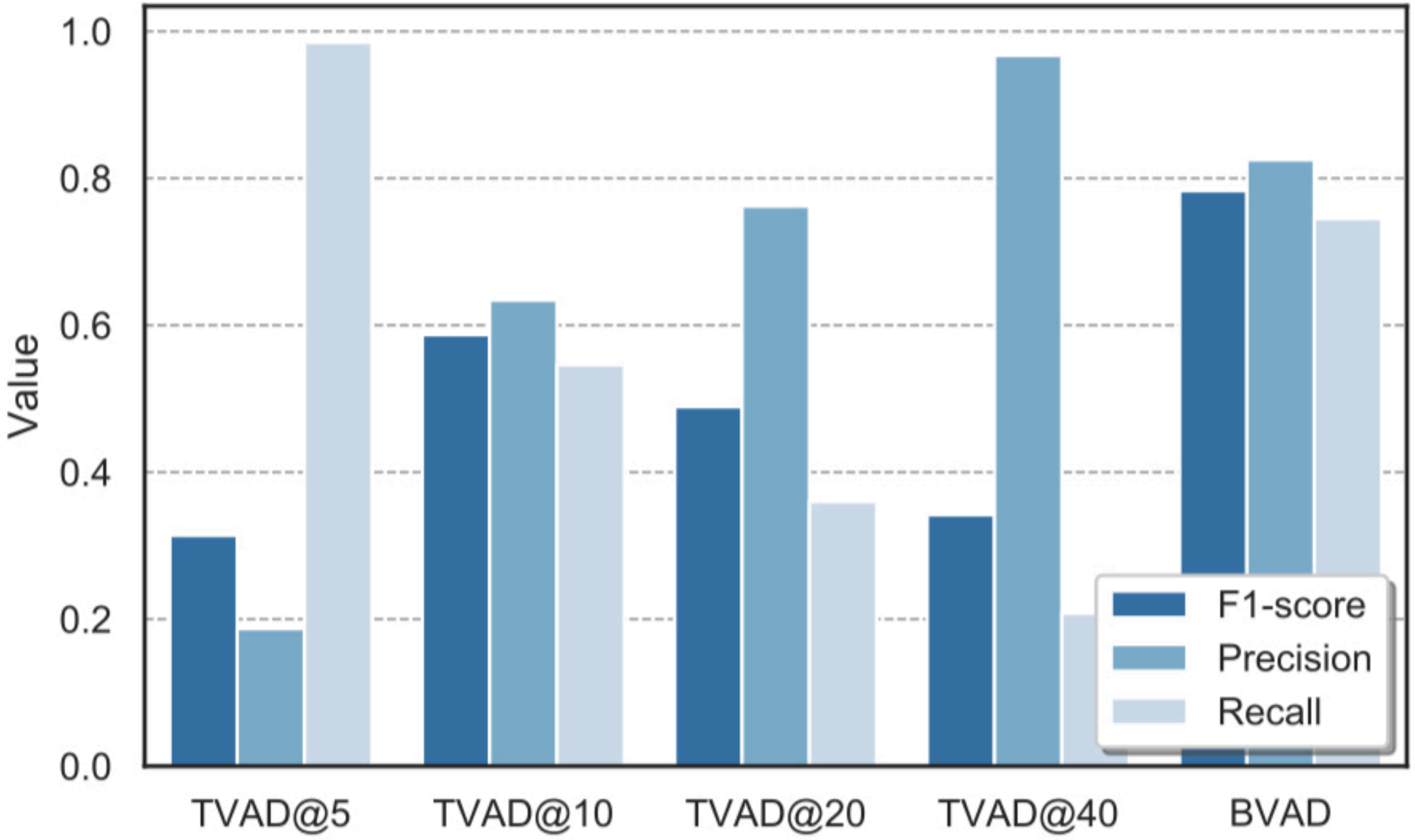
Dataset

- 21 study groups, each with 4~5 students (100 in total)
- 273 effective meetings with a total length of 438.25 hours in 4 weeks



❖ User Profiling – Experimental Evaluation

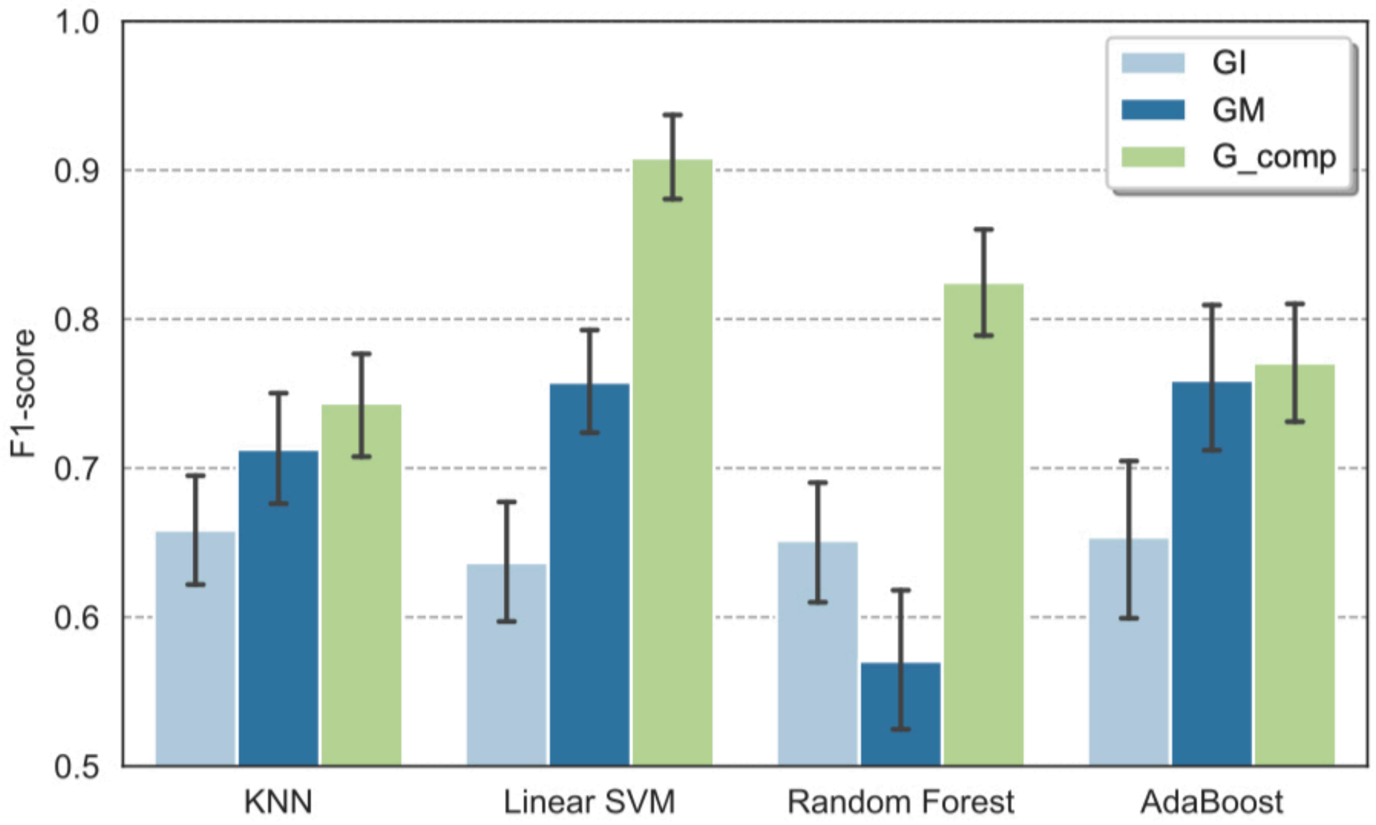
Performance of voice activity detection



Performance of Bayesian VAD (BVAD) and threshold VAD (TVAD).
“TVAD@5” means the threshold is set to 5.

❖ User Profiling – Experimental Evaluation

Performance of gender identification



Performance of gender composition detection (G_comp) and gender identification with different features.

❖ User Profiling – Experimental Evaluation

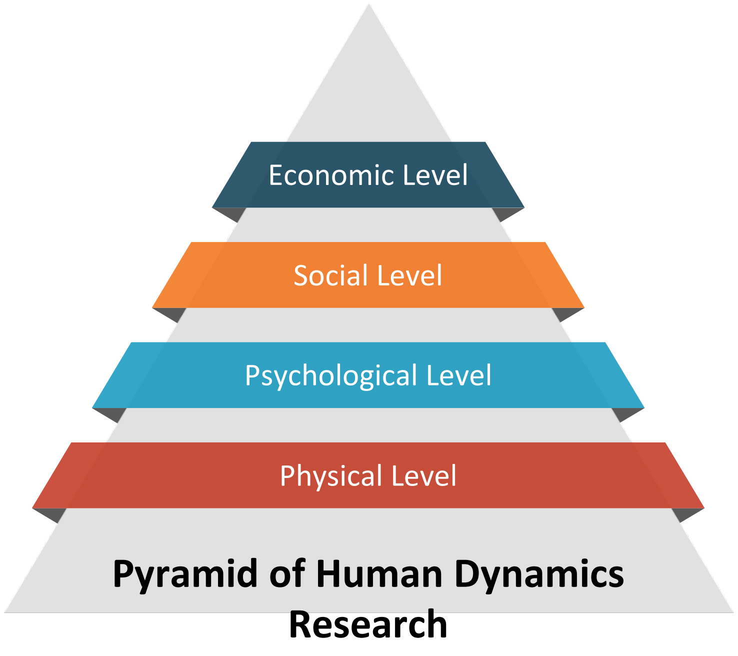
Performance of personality recognition

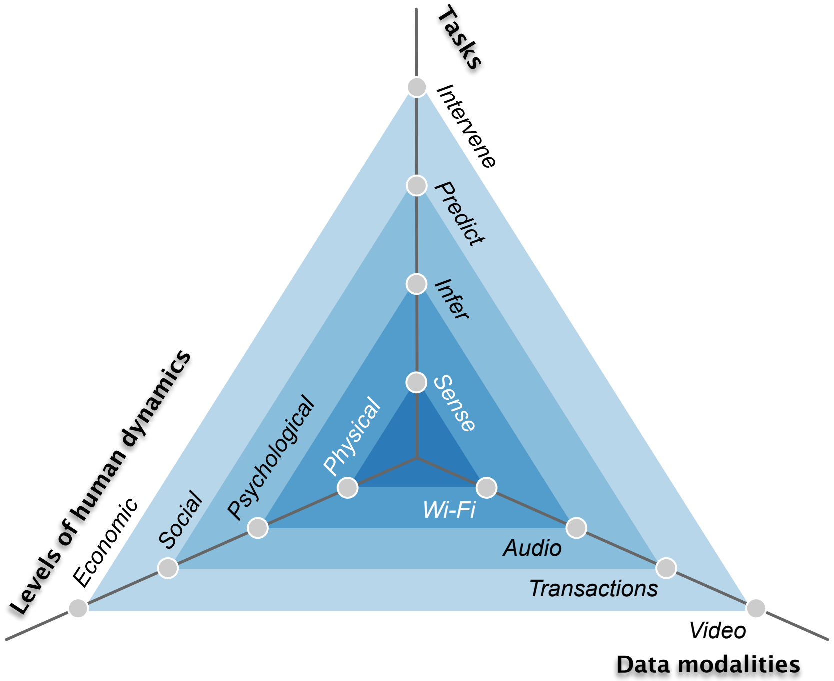
GAMTL_idl	Personality	Individual-level	Gender-assisted MTL
GAMTL	Personality	Multi-level	Gender-assisted MTL
MTL	Personality	Multi-level	MTL
NN	Personality	Multi-level	Neural networks for each trait

Method\Trait	Openness (O)			Conscientiousness (C)			Extraversion (E)			Agreeableness (A)			Neuroticism (N)		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1	P	R	F1
NN	0.793	0.573	0.665	0.600	0.639	0.619	0.634	0.492	0.554	0.533	0.487	0.509	0.537	0.486	0.510
MTL	0.854	0.622	0.720	0.655	0.661	0.658	0.660	0.558	0.605	0.585	0.579	0.582	0.577	0.502	0.537
GAMTL_idl	0.724	0.695	0.709	0.595	0.701	0.644	0.574	0.588	0.581	0.577	0.500	0.536	0.680	0.426	0.524
GAMTL	0.828	0.706	**0.762**	0.682	0.659	**0.670**	0.608	0.604	**0.606**	0.663	0.639	**0.651**	0.709	0.475	**0.569**

❖ Conclusions

- Human dynamics research are multilayered and have both great scientific and commercial potentials
  - Focus on human behaviors and human interactions
- Inferring contextual features are effective ways of addressing the dynamics of human behaviors
  - Three common contexts: relative, relational, and mental
- Find research problems by exploring the 3D space
  - Cross-modality research
  - To to answer the “what if ” questions





Thanks for listening!
Any questions?