Towards Self-Tracking Personal Pollution Exposure using Wearables

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Outline

- Introduction
- Prototype
- Calibration
- Human Interference
- Contributions

Introduction

Urban Pollution

- Exposure to Urban Pollution is linked to many health risks particularly in older adults
- One of these risks is that Urban Pollution is positively associated with **Mild Cognitive Impairment (MCI)**
  - Air Pollution: **$PM_{2.5}$**
  - **Noise**

Mild Cognitive Impairment

- Precursor to **Dementia**
- It is estimated that 42.7 – 48.1 million people worldwide will have Dementia in 2020

Humans and Particulate Matter

- PM varies in size, shape, and chemical components
- Toxicity of PM differs with physical properties [Kelly and Fussell, 2012]
- Origin of suspended PM defines physical properties
- Outdoor-generated PM differs from Indoor-generated PM
  - Outdoor: Traffic and Industrial activities
  - Indoor: Activities, human emissions, and some outdoor PM

Personal Pollution Exposure

- Personal Cloud
  - Human emissions [Wallace et al.,2004]
  - Microenvironment emissions
- Personal Pollution Exposure is the amount of pollution inhaled
- Monitoring personal pollution exposure is key for health
  - Affected by humans-environment interactions
- Current solutions
  - Designed for quantified-selfers and scientists
  - Designed to be stationary

My thesis work

Personal pollution exposure **prototype**

Calibrating low-cost $PM_{2.5}$ Sensors

Study **human interference** with $PM_{2.5}$ Sensors

Where did the **noise** go?

- Noise is a commonplace: extensively studied
- Microphone and smartphone microphone **calibration** [Zhu el al.,2015]
- Microphones are used for **human activity recognition** [Stork et. Al, 2012]
- Incorporated in **smart home** applications [Brdiczka et al.,2009]
- Development of **3D acoustic localization** technology [Haddad and Hald,2008]
- Microphones in passive **Human-Robot interaction** [Sekmen et al.,2002]

We focus on **low-cost $PM_{2.5}$ sensors**

Prototype

Objectives

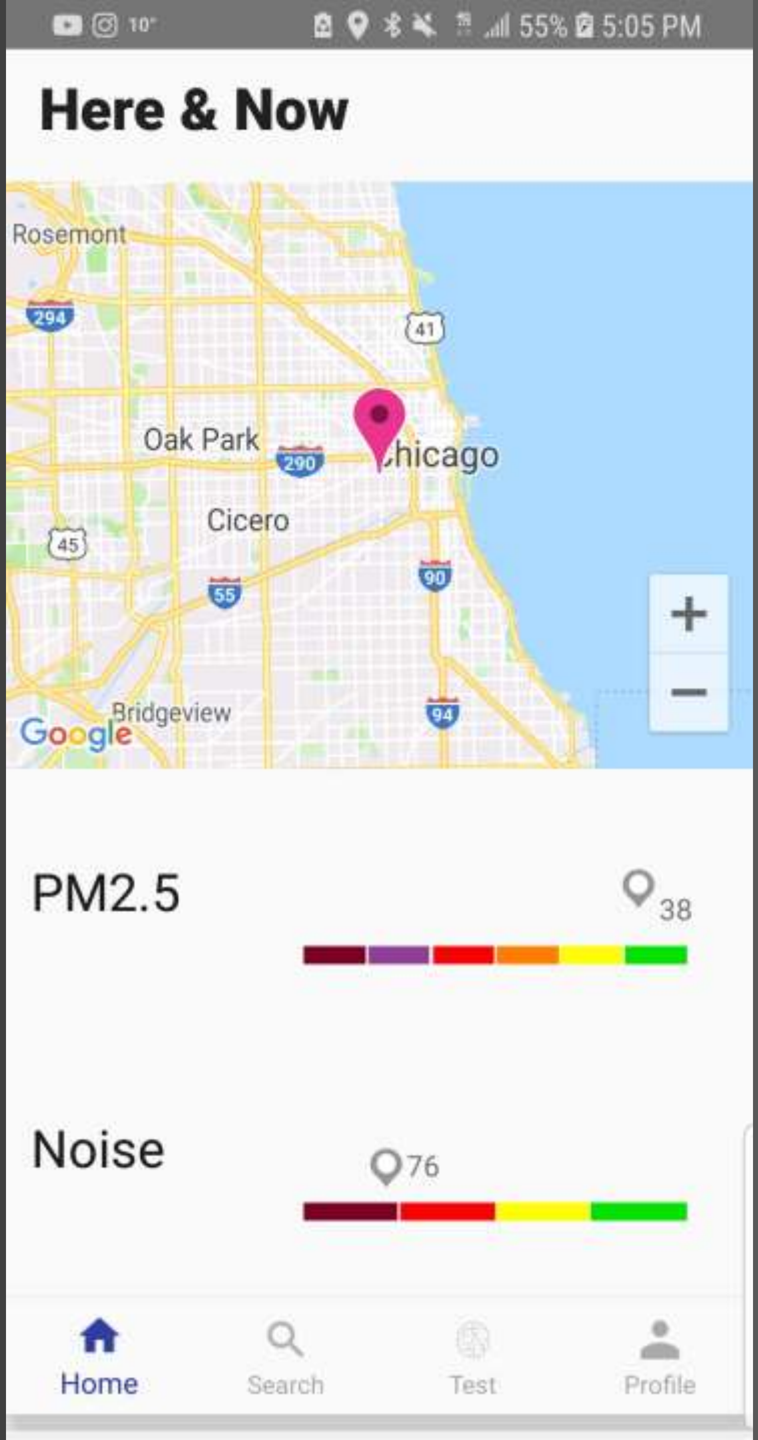
To create of a tool for older adults, and the general, to guide them to less polluted areas throughout their everyday activities

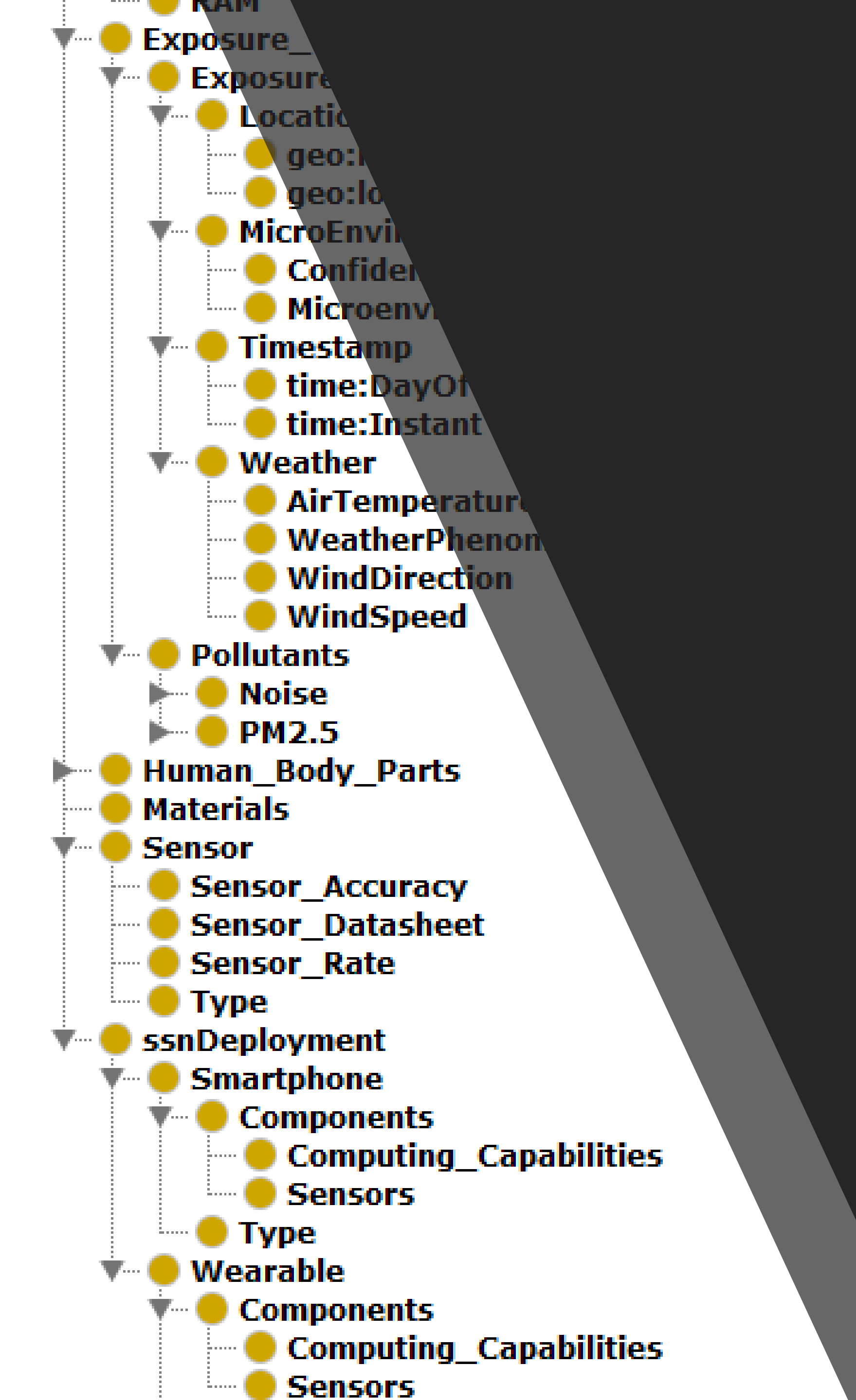
Results: Wearable

- Personal Pollution Exposure Monitoring Tool
- Components
  - Low-cost off-shelf SoC: Raspberry Pi 3b+
  - Low-cost $PM_{2.5}$ Sensor: Plantower PMS7003
  - Off-the-shelf power bank
- Size and Weight most comfortable as handheld
- Functions with a companion smartphone application and a cloud database hosted on Amazon AWS

Results: Smartphone Application

- Measures Noise in dBA using the built-in microphone
- Collects contextual data
  - Timestamps
  - Longitude and latitude
  - WiFi and GSM signal levels
  - Screen's brightness and illuminance values
  - Weather information
    - Outdoor temperature
    - Humidity
    - Dew point
    - Weather condition
    - Wind speed
  - Ambient temperature from battery temperature
  - Microenvironment and setting (manually input)





Results: Ontology

- Personal Pollution Exposure Ontology
  - In OWL using Protege 5.5.0 build beta-3
  - Ontology describes personal pollution exposure events extensively
- API transforms raw sensor data from database to OWL individuals and attaches them to the ontology

Mechanism

The wearable collects real-time PM2.5 data using the sensor and stores it locally

If WiFi is available, the wearable sends PM2.5 values to AWS cloud database

If WiFi is not available, the wearable connects with the smartphone via Bluetooth and sends the data to the smartphone. The smartphone sends the PM2.5 and the noise and contextual data to AWS database using GSM LTE

If Bluetooth is not available, wearable stores data locally until the next time it is connected

Ontology API pulls the data from the AWS database and attaches it to the ontology for further processing

Challenges

Choosing the best sensor for the prototype (size and performance)	• Started with PMS5003 then upgraded to PMS7003
Sensor port is not a standard port	• Designed and soldered our own connectors
Raspberry Pi is not 100% reliable and might break	• Gone through multiple iterations for designing our own circuit board at UIC Makerspace and mHUB • Still work in progress

myCityMeter

Helping Older Adults Manage the Environmental Risk Factors for Cognitive Impairment

UIC HCI LAB
University of Illinois, Chicago

Calibration

Objectives

Creating a model to rectify low-cost $PM_{2.5}$ sensors measurements

Understanding the effect of context on low-cost $PM_{2.5}$ sensors

Methods

- Used wearable with high-precision $PM_{2.5}$ monitoring tool: SidePak
- Collected data using the two meters at different contexts
- Classified the data and criteria-based subsets using three methods:
  - Naïve Bayes
  - Random Forest
  - Support Vector Machine

Tools

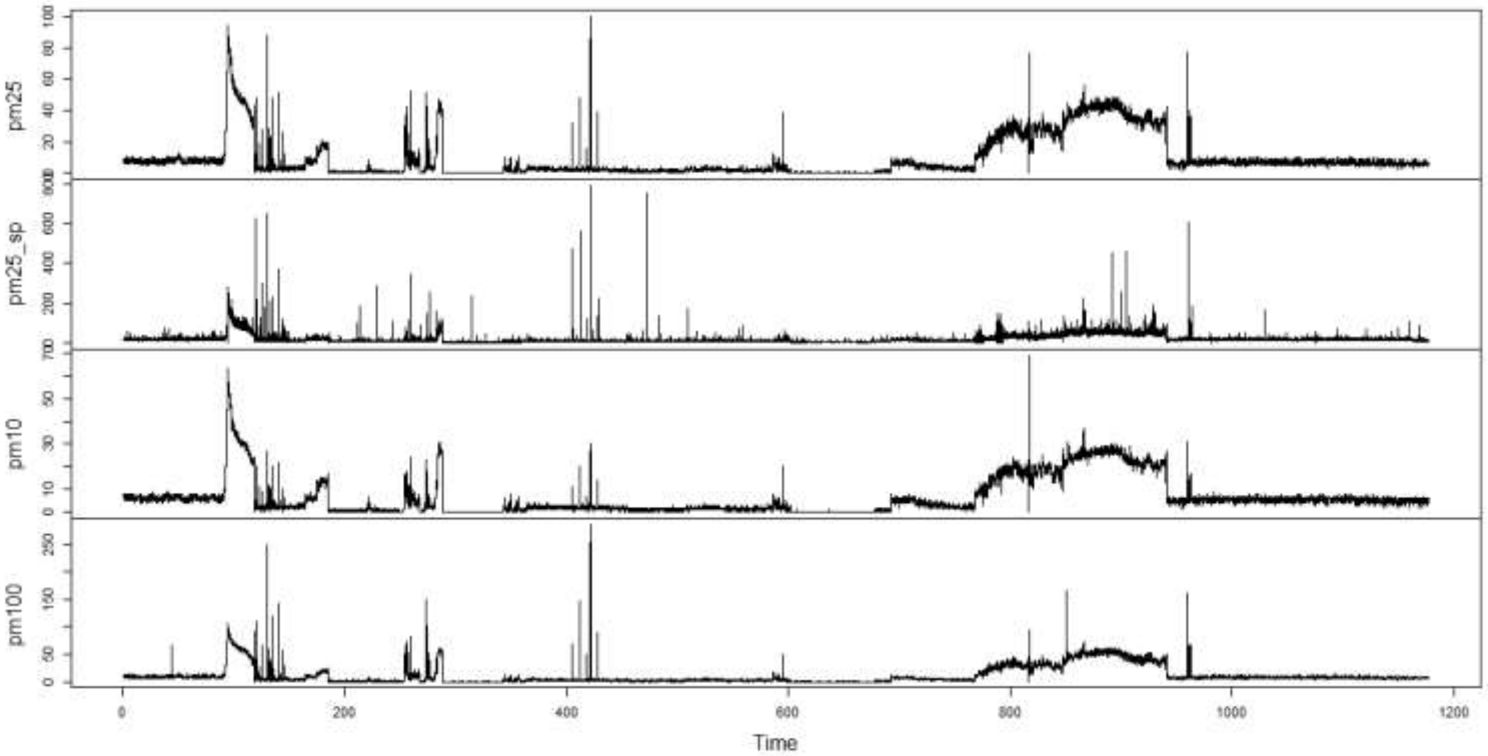
- SidePak
  - Laser photometer to measure personal pollution exposure in real-time
- The Wearable
  - Plantower PMS7003 $PM_{2.5}$ Sensor
  - Laser scattering principle

Data Collection

- SidePak and Wearable
- Pollutants: $PM_{2.5}$, PM_1, PM_{10}, and, noise
- We collected data in different settings
  - Concentrations
  - Weather Conditions
  - Stationary and movement
  - Microenvironments
- Contextual data collected by smartphone app

The Data

- 70558 observations of 22 variables
- Approximately 20 hours
- 1 read/second

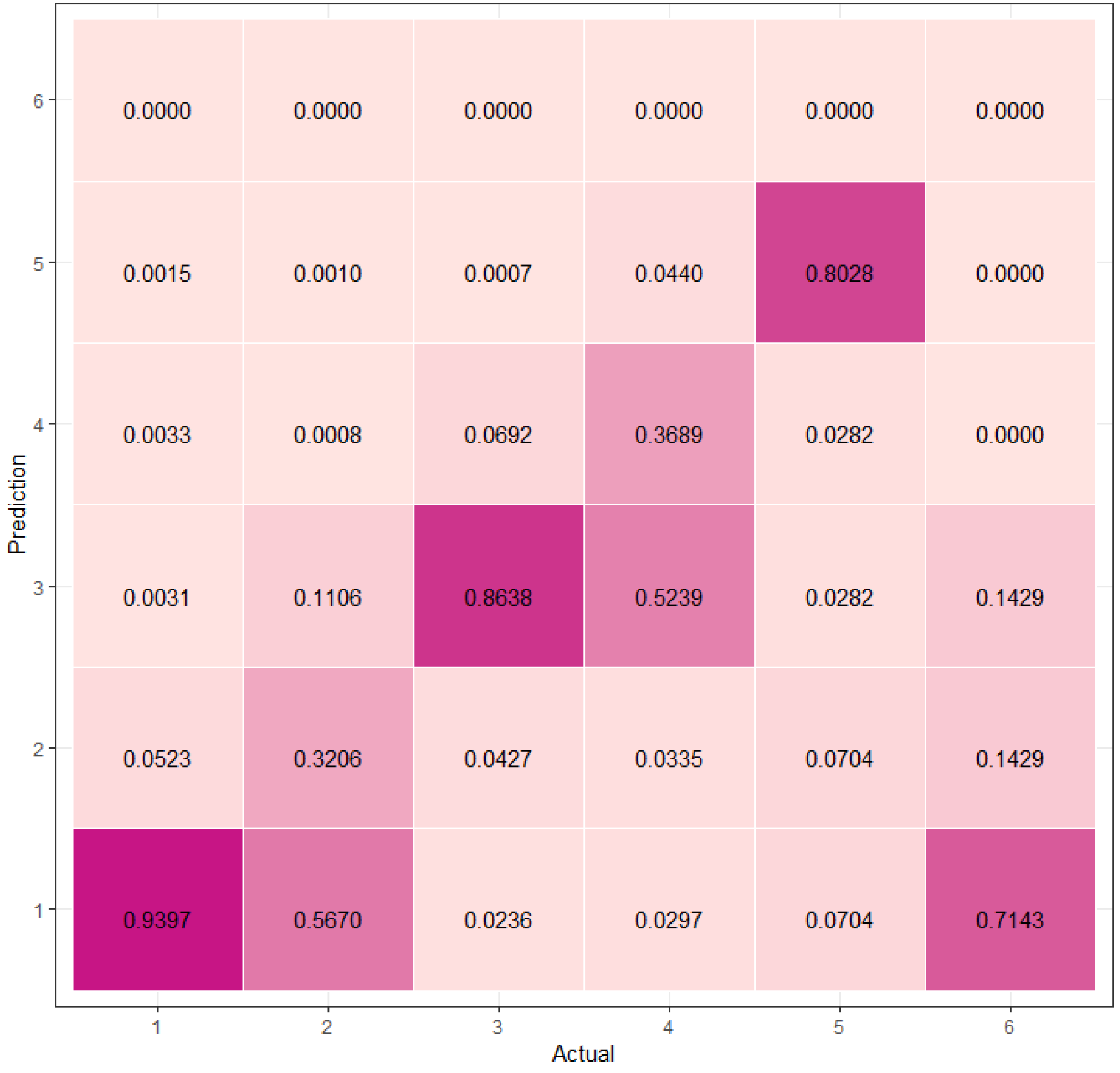


Results

Classifier	Train	Test	Features	Accuracy
Naïve Bayes	28386	42172	$PM_{2.5}$, PM_1, PM_{10}	71.10%
Random Forest	28431	42127	$PM_{2.5}$	61.80%
Support Vector Machine	28431	28431	$PM_{2.5}$, PM_1, PM_{10} luminosity, noise level, microenvironment, and, GSM signal strength	42%

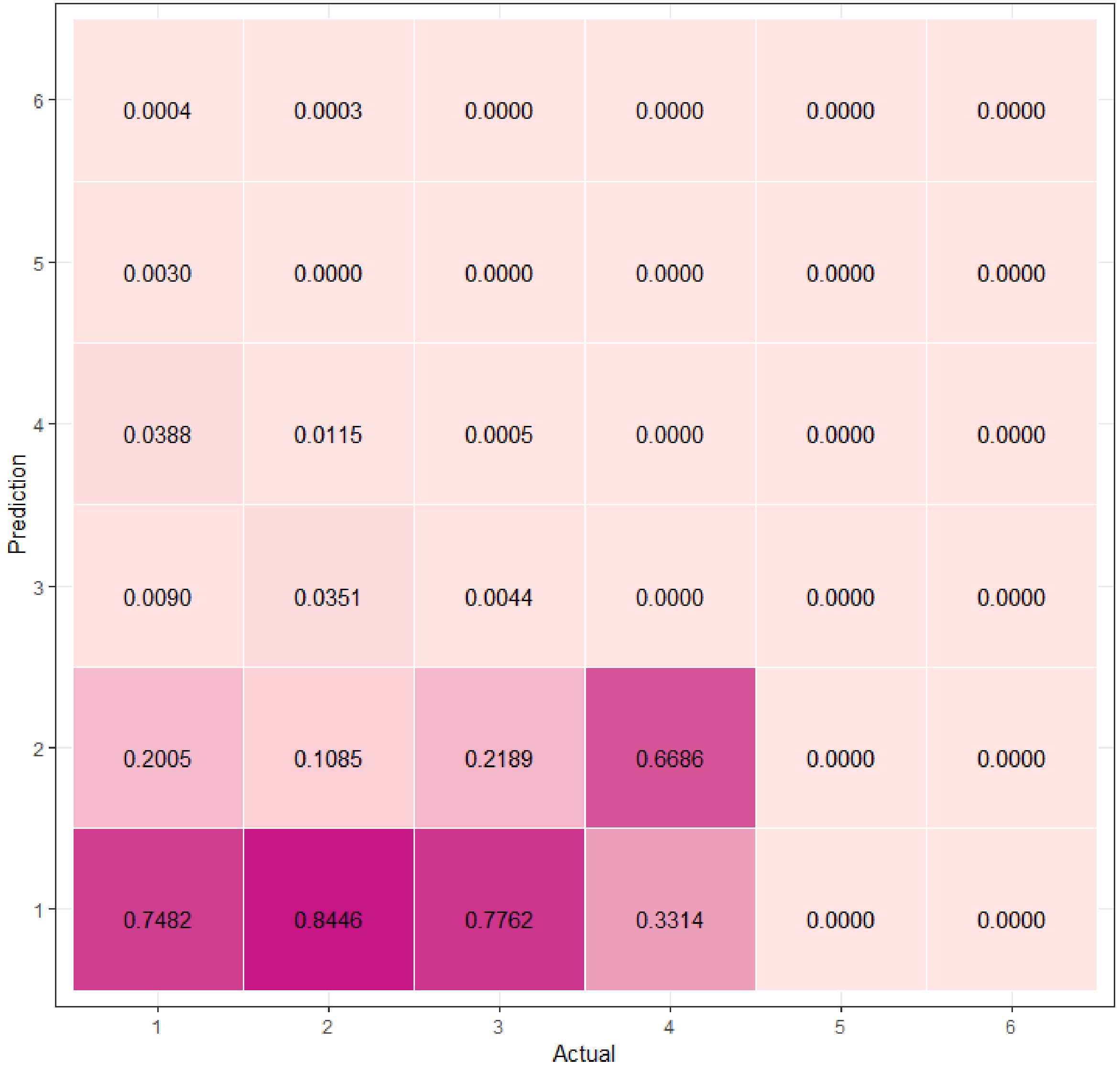
Naïve Bayes

- Fairly Good Accuracy 71.1%
- Performed best with $PM_{2.5}$, PM_1, and, PM_{10} as features



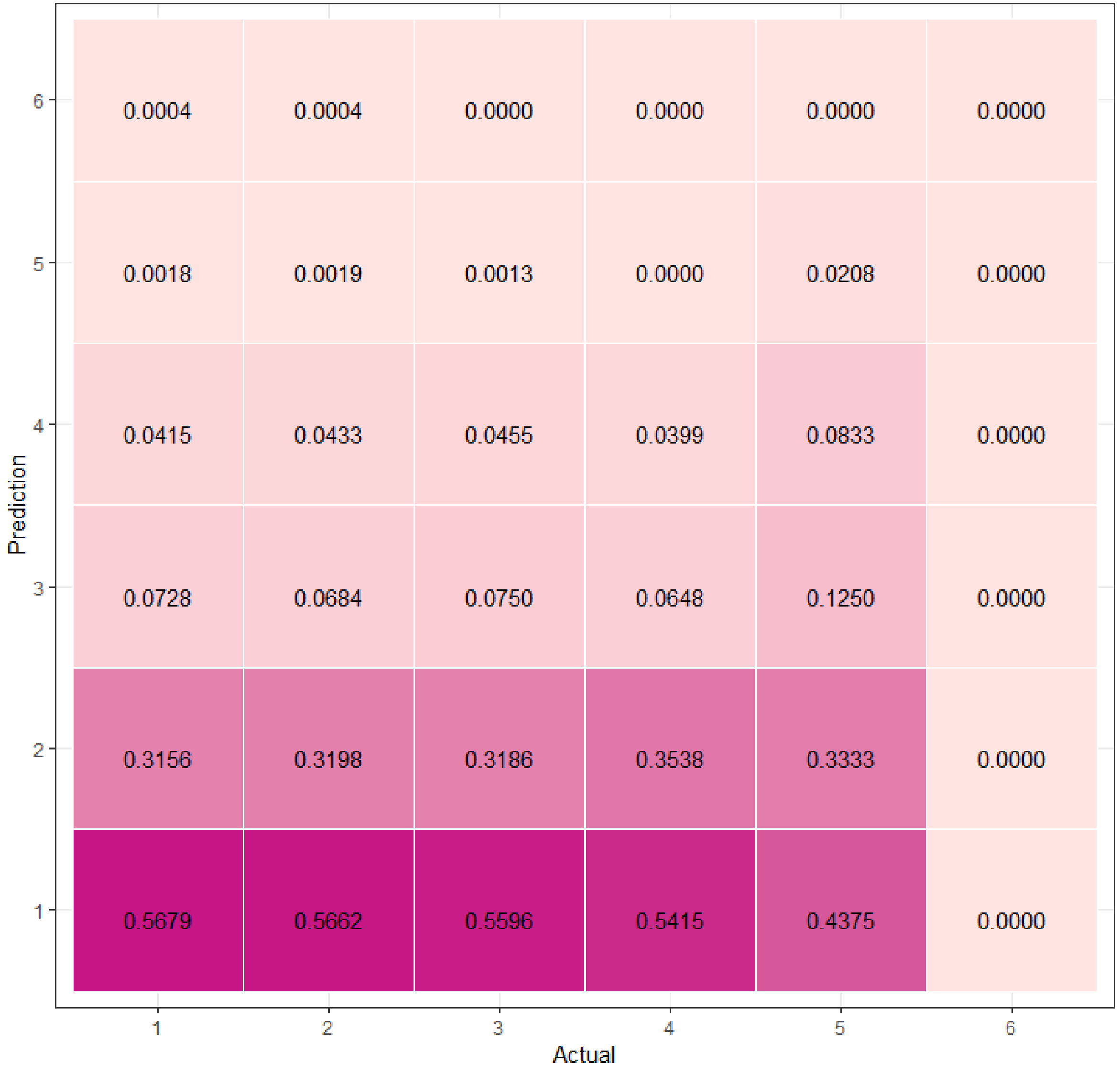
Random Forest

- Accuracy 61.8%
- Performed better without any features: $PM_{2.5}$ only
- Data is biased toward groups with higher number of observations



Support Vector Machine

- Accuracy 42%
- Performed better with a large set of features: $PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal strength
- Data is biased toward groups with higher number of observations



Dividing per $PM_{2.5}$ concentrations

	$PM_{2.5}$ <= 55.4 μg/m^3		**$PM_{2.5}$ > 55.4 μg/m^3**	
	Features	Accuracy	Features	Accuracy
Naïve Bayes	$PM_{2.5}$, PM_1, PM_{10}	58.7%	$PM_{2.5}$, PM_1, PM_{10}	91.7%
Random Forest	$PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal Strength	55.8%	$PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal strength	92.6%
SVM	$PM_{2.5}$, PM_1, PM_{10} , luminosity, noise level, microenvironment, and, GSM signal Strength	45.0%	$PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal strength	91.6%

Dividing per Microenvironment

	Indoor and Deep Indoor		Outdoor and Semi-outdoor	
	Features	Accuracy	Features	Accuracy
Naïve Bayes	$PM_{2.5}$, PM_1, PM_{10}	82.9%	$PM_{2.5}$, PM_1, PM_{10}	65.5%
Random Forest	PM2.5, PM1, PM10 luminosity, noise level, microenvironment, and, GSM signal strength	53.2%	$PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal strength	36.9%
SVM	$PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal strength	50.4%	$PM_{2.5}$, PM_1, PM_{10}, luminosity, noise level, microenvironment, and, GSM signal Strength	35.6%

Takeaways

- Low-cost $PM_{2.5}$ sensors is suboptimal when compared to SidePak
- Collected data across contexts
- Classified data using three classification methods:
  - Naïve Bayes
    - The best classifier
    - Shows sensitivity towards contexts
  - Random Forest
    - Affected by the number of observation for each class
    - Not a very good classifier although it was used in recent works for calibration of other sensor [Zimmerman et al., 2018]
  - Support Vector Machine with Radial-Based Function kernel
    - Based on the number of observation for each class
    - The weakest classifier
- Next: improve the model by collecting data in more contextual conditions

Human Interference

Human Interference

- Everyday activities affect the concentrations of $PM_{2.5}$ in the personal cloud
- Skin and Textile emissions affect the concentration of $PM_{2.5}$ around the human body
- Interactions such as holding the sensor in hands affect the quality of sensor readings
- Physical characteristics of the $PM_{2.5}$ in personal cloud vary per source
- $PM_{2.5}$ varies in toxicity of PM based on its source

Objectives

Identifying types of Human Interference that affect $PM_{2.5}$ sensors

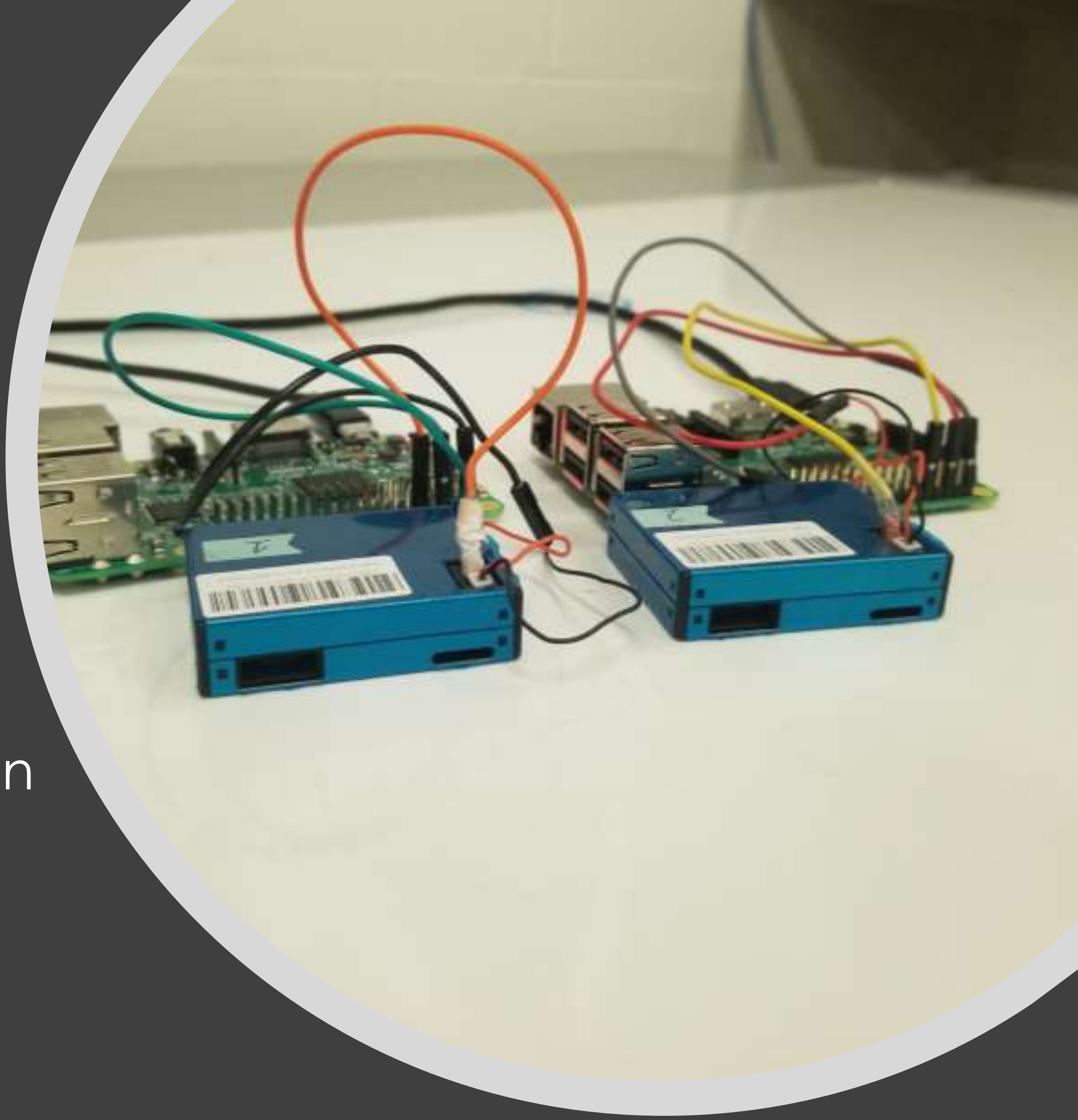
Creating design guidelines for pollution-assessing wearables

Methods

- Used 2 prototypes of the wearable with high-precision $PM_{2.5}$ monitoring tool: SidePak
- Collected data for different human interference situations
- Analyzed data to identify human interference with $PM_{2.5}$ sensors

Data Collection

- Two sensors
  - **Reference sensor** set at a fixed distance from the experiment
    - Distances: 30 cm and 100 cm
    - Some human interference situation has a larger radius of effect
  - **Experiment Sensor**
- Pollutants: PM_1, $PM_{2.5}$, PM_{10}, and noise measured in dBA
- Contextual data collected by smartphone app



Experiments

Group	**Experiments**					
Control	Baseline Control					
Breath Group	Normal Breathing		Laugh	Yawn	Cough	
Textile	Cotton	Fur	Leather	Wool	Synthetic	Silk
Skin Group	Skin no interference		Skin sweating	Skin touching	Bracelets	Skin scratch
Hair Group	Hair touching			Hair heat style		
Toiletries	Face spray	Hair spray	Powder makeup		Spray perfume	

Analysis

Between Experiment **Groups** and Baseline

Between **Experiments** and Baseline

Within experiment: between **experimental sensor** and **reference sensor**

Control

Measuring pollutants without interference

SidePak and Wearable

Sensors are on a clean flat surface

Breath Group

- The effect of breath on $PM_{2.5}$ values in the personal cloud
- 4 breath situations
  - Normal breathing
  - Yawning
  - Coughing
  - Laughing
- SidePak and Wearable
- Sensor clipped on a collar doing lightweight activities

Tool \ Type	Control
SidePak	X
Wearable Sensor	✓

Hair Group

- Measuring hair emissions
- Two situations
  - Touching and playing with hair
  - Heat styling
- Sensor clipped on collar

Type / Tool	Control
Wearable Sensor	✓

Skin Group

- Measured skin emissions
  - Near bare skin with no interference
  - Touching skin
  - Scratching skin
  - Wearing bracelets
  - Sweaty skin with no interference
- SidePak and Wearable
- Sensor was worn like a wristwatch with no interference with the outfit doing lightweight activity

Type / Tool	Control
SidePak	✓
Wearable Sensor	✓

Toiletries

- Measuring use of toiletries as a day-to-day activity
  - Spraying perfume
  - Facial spray
  - Hair spray
  - Loose-powder makeup
- SidePak and Wearable
- Sensor clipped to the collar

Type / Tool	Control
SidePak	X
Wearable Sensor	✓

Textiles

- Measuring textile emissions
- 6 types of textile:
  - Cotton
  - Leather
  - Silk
  - Synthetic fabrics
  - Wool
  - Fur
- Sensor clipped on shirt pocket (or approximate location) doing lightweight activity

Type / Tool	Control
Wearable Sensor	✓

Human Interference and Baseline Comparison

Experiment	**SidePak**	**Wearable**
Cough	✓	✓
Hair touching	NA	✓
Skin touching	✓	✓
Leather	NA	✓
Face spray	X	X

Human Interference and Distance

Experiment	**@ 30 cm**	**@ 100 cm**
Cough	X	X
Hair touching	✓	✓
Skin touching	✓	✓
Wool	X	✓
Powder makeup	X	✓

Takeaway

- $PM_{2.5}$ concentrations are affected by human interference
- Human PM differ to industrial PM in physical characteristics
- SidePak and two replicas of our wearable: experiment and reference at two distances 30 cm and 100 cm
- Experiments: control, breath, hair, skin, toiletries, and textile

More emissions

Human Interference	Design practice
Skin emissions	Minimize contact with skin
Hair emissions then	Care for head area
Breath emissions	Care for head area
Textile (effect up to 30 cm distance)	Make account for textile emissions

Less emissions

Contributions to HCI

Identified a set of **human interference situations** that affect pollution monitoring wearables

Inferred a set of basic **design guidelines** for personal pollution monitoring wearables

A **framework** for studying human interference with low-cost sensors

- Study different types of $PM_{2.5}$ sensors
- Study sensors that measure other types of pollutants

Questions?

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