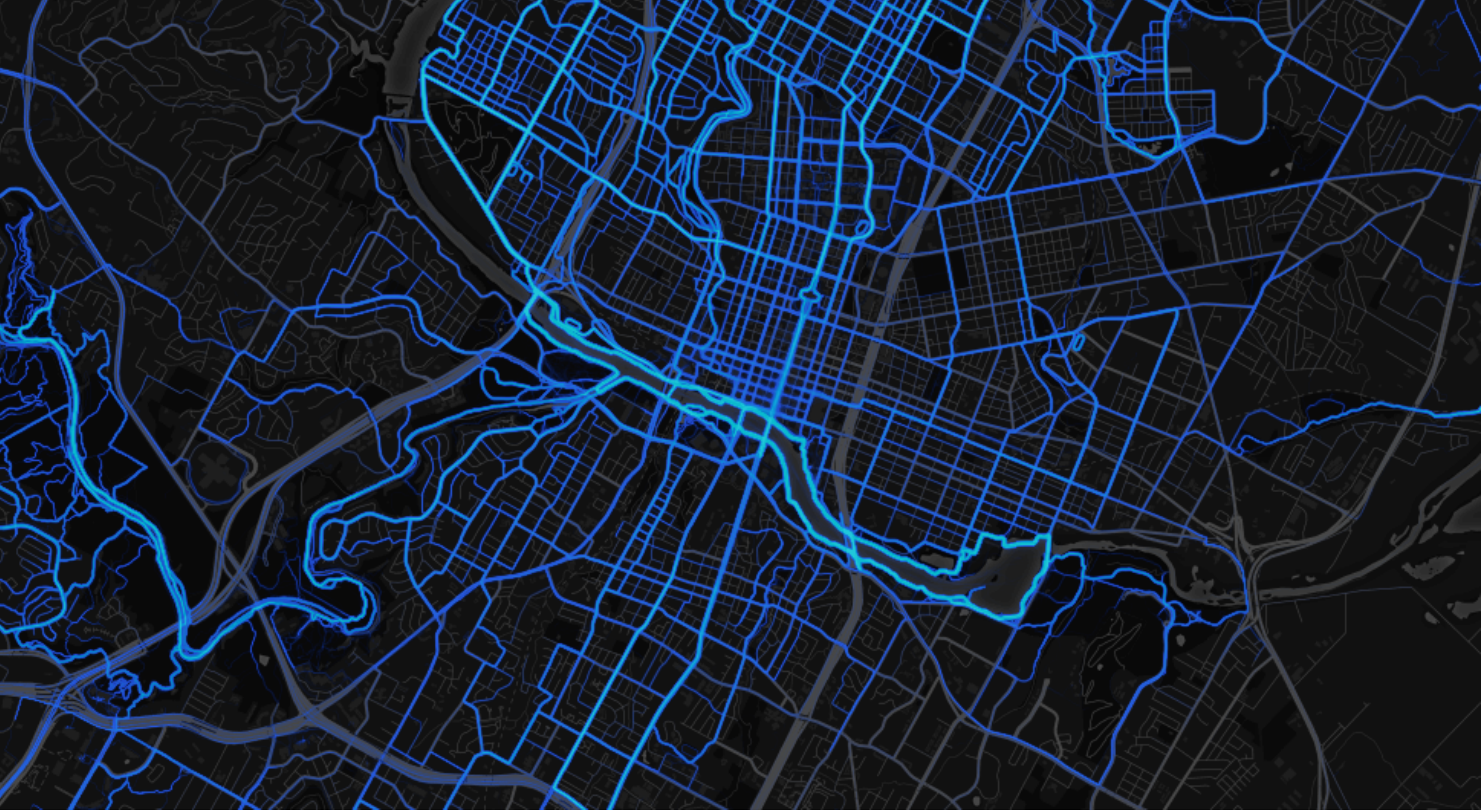


Inertial Sensing + Location

EE382V Activity Sensing and Recognition

UT Austin • Dept. Electrical and Computer Engineering • Fall 2016

Today

Continue Inertial Sensing Activity from Thursday

Location as a Sensing Modality

Panel of Experts

Continue Inertial Sensing Lab…

Now it’s your turn!

Change frame and step sizes and see how that affects results

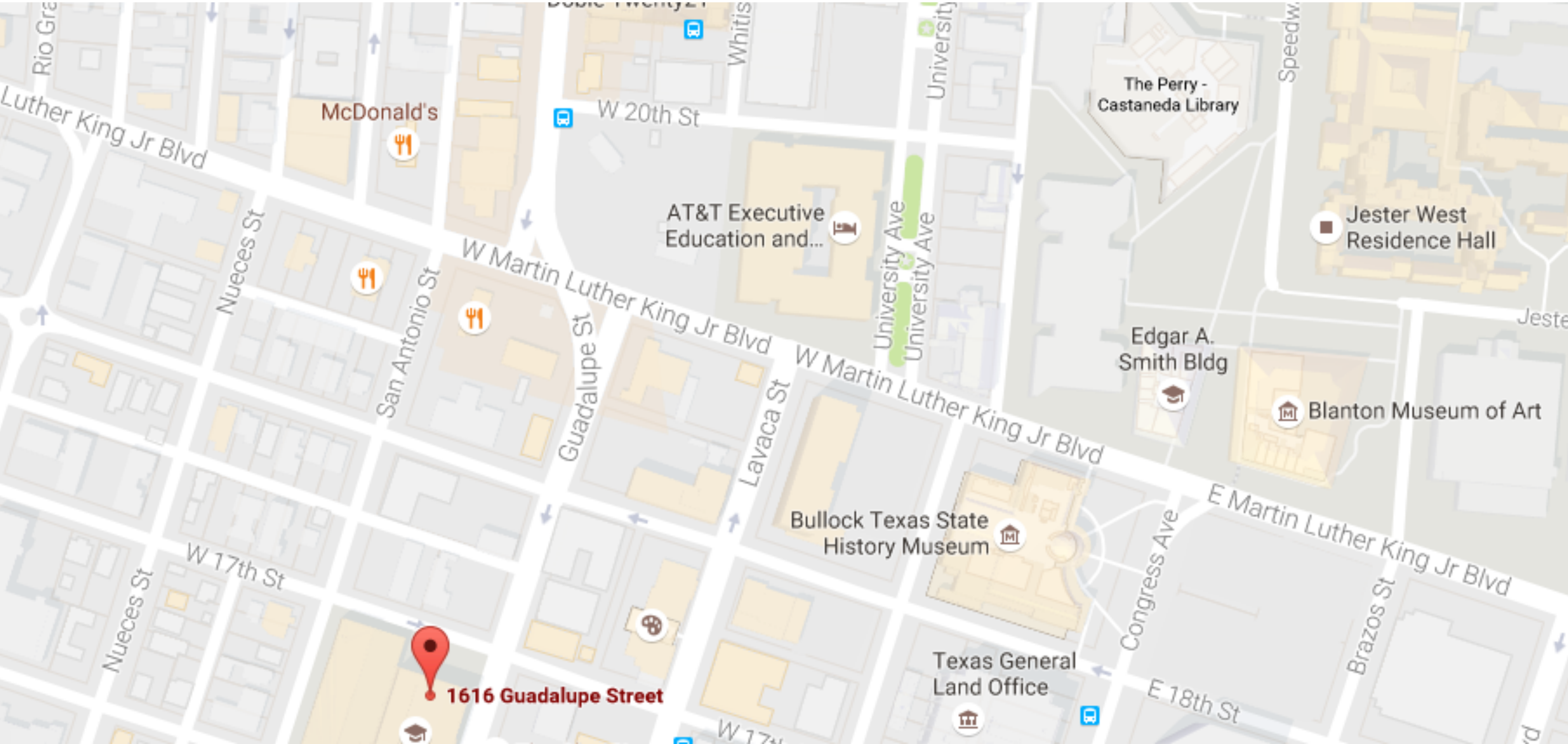
Calculate new features and add them to feature vector

Add labels to the file and build classifier for gestures

Evaluate three classification algorithms with cross-validation

Location as Sensing Modality

Methods and techniques for determining a physical location of an object or a person in the real world

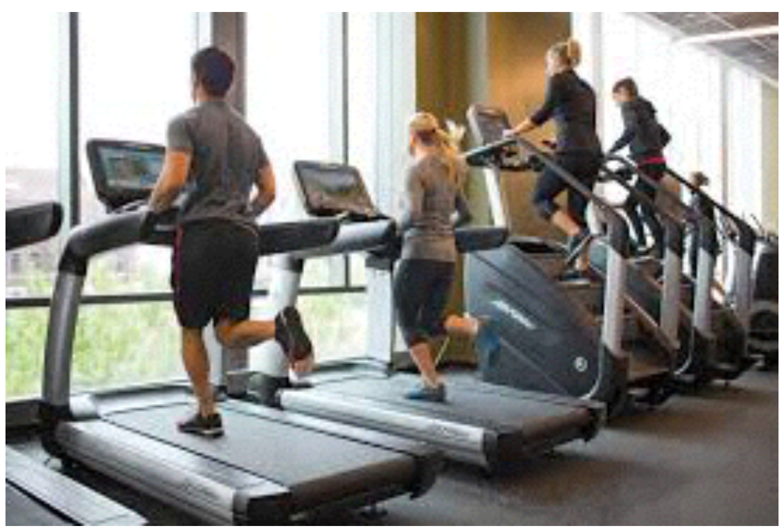


Location as Sensing Modality

Location is key element of context (and activity recognition)

At the center of many pioneering mobile phone apps

Why is it so valuable?



Time

Change

Repetition

Location as Sensing Modality

My Smartphone Knows I am Hungry

Fanglin Chen, Rui Wang, Xia Zhou , Andrew T. Campbell
Dartmouth College
{chentc,ruiwang,xia,campbell}@cs.dartmouth.edu

ABSTRACT

Can a smartphone learn our eating habits without the user being in the loop? Clearly, the phone could use checkins based on location to infer that if you are in a cafe, for example, there is a good possibility you might eat or drink something. In this paper, we use inferred behavioral data and location history to predict if you are going to eat or not in the near future. These predictors could serve as a basis for future eating trackers that work unobtrusively in the background of your phone rather than relying on burdensome user input. We report on a simple model that predicts the food purchases of a group of undergraduate college students (N=25) using inferred behavioral and location data from smartphones. The 10-week study uses the dining related purchase records from student college cards as ground-truth to validate our prediction model. Initial results show that we can predict food and drink purchases with an accuracy of 74% using three weeks of training data.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

Keywords

Food; human behavior dynamics; smartphone sensing.

1. INTRODUCTION

College students typically do not have healthy eating habits and as a result are at higher-risk of weight gain [5]. The basis of our work is to develop a predictive model capable of inferring the food buying habits of a student population. If we can build such a predictive model based on smartphone sensing data then we can provide just-in-time feedback to students about healthy food and drink choices.

Location (e.g., at cafe) is typically an excellent predictor of eating or drinking. However, many locations on a campus are multi-purpose and include restaurants, classrooms and arts facilities such as the Hopkins Center at Dartmouth College. We show that simply by using location you cannot easily infer eating from other activities without false positives or negatives. In addition, simply using the near instantaneous location label (e.g., Ramunto's Pizza) is too little too late in terms of potentially guiding a user to a better choice (e.g., Gym, followed by the Salad Hut). If we have predictive power to gain knowledge of what people might do in the near future based on the behavioral data and past location history we might be able to intervene before the user hits the bad food choice (e.g., fast food) in the first place.

In this paper, we propose a simple predictive model based on automatically inferred behavioral and location data from smartphones. The idea is that the phone is smart enough to determine if a user might eat or not in the near future without any burdensome input from the user. Such a predictive model could serve as a basis for novel interventions in the future or as a basis for implementing eating trackers.

We conduct a study of 25 undergraduate students at Dartmouth College over a single 10 week academic term. All the students live, eat and drink on campus. The students in the study ran the StudentLife app on their Android phones which inferred everyday activity (e.g., walking, stationary), sociability based on conversational data, and sleep, location, co-location, etc. To capture the participants food buying behavior, we collected the purchase history from their Dartmouth food cards at the end of the term. We use the sensing data on the phone to build a model that predicts the food buying habits captured by the Dartmouth food card. Our Initial results show that we can predict food and drink purchases with an accuracy of 74% using three weeks of training data. Note, our study only considers undergraduate purchasing behavior in a campus environment. We make no claims that our results present generalized behavior for a general population. We consider this future work.

2. RELATED WORK

There is little work on the prediction of eating habits using smartphone sensing data. In the participatory sensing community, researchers track users' eating behavior auto-

densome user input. We report on a simple model that predicts the food purchases of a group of undergraduate college students (N=25) using inferred behavioral and location data from smartphones. The 10-week study uses

Location as Sensing Modality

Days of Our Lives: Assessing Day Similarity from Location Traces

James Biagioni — Department of Computer Science, University of Illinois at Chicago, Chicago, IL USA, jbiagi1@uic.edu

John Krumm — Microsoft Research, Microsoft Corporation, Redmond, WA USA, jckrumm@microsoft.com

Abstract. We develop and test algorithms for assessing the similarity of a person's days based on location traces recorded from GPS. An accurate similarity measure could be used to find anomalous behavior, to cluster similar days, and to predict future travel. We gathered an average of 46 days of GPS traces from 30 volunteer subjects. Each subject was shown random pairs of days and asked to assess their similarity. We tested eight different similarity algorithms in an effort to accurately reproduce our subjects' assessments, and our statistical tests found two algorithms that performed better than the rest. We also successfully applied one of our similarity algorithms to clustering days using location traces.

Keywords: location traces, similarity, anomaly detection, clustering

1 Introduction

Both consumers and corporations recognize the value of location traces for understanding daily habits and anticipating occasional needs, and the proliferation of GPS-equipped smart phones is making them ever easier to collect. These traces can help in understanding our daily activities; in particular, we can use location traces to find anomalous days and to cluster similar days, leading to a better understanding of our daily routines. Both of these tasks require a way to compare days to one another.

This paper develops and tests algorithms to measure the similarity of days represented by location traces, tested against similarity assessments from real users. With a reliable way to measure similarity we can find days that stand out from the rest as anomalies, which may indicate confusion (an important phenomenon to detect among populations of users with cognitive impairments [3]) or a change of habits. We can also make sensible clusters of days that belong together to assess variety and make predictions about how a day will evolve, providing useful basic knowledge for future adaptive systems to leverage. We believe this is the first effort aimed at measuring the similarity of days using location traces in a way that reflects human assessments.

A variety of sensors could be used to characterize a day, such as activity measured on a person's mobile phone, desktop computer, vehicle, social networking sites, biometric sensors, *etc.* Our work is aimed at location traces, usually measured with GPS. One advantage of this is that location is a constantly existent state (if not always measurable) as opposed to event-based activities, such as texting events, that only happen occasionally. Location is also dynamic for most people and easy to measure

adfa, p. 1, 2013.

Abstract. We develop and test algorithms for assessing the similarity of a person's days based on location traces recorded from GPS. An accurate similarity measure could be used to find anomalous behavior, to cluster similar days, and to predict future travel. We gathered an aver-

Location Information

Absolute	180 Park Avenue, Florhan Park, NJ
Relative	10mi north of downtown Austin, TX
Symbolic	Home, Work, Bedroom

Determing Location

Client-Based	Client computes location No need for infrastructure e.g., GPS
Network-Based	Infrastructure computes location Client can be lightweight e.g., Active Badge
Network-Assisted	Device + infrastructure compute location e.g., Assisted GPS (A-GPS)

Determing Location

Proximity

Simplest

Closeness of device to detection point

e.g., stepping on pressure sensor

e.g., communicating with Wifi access point

e.g., can “hear” a particular signal

Time of Flight

Distance between device and reference point

Time for signal to travel a distance

Speed of sound and light

Determing Location

Triangulation

- Measures angle of arrival of signals
- Two reference points for device location in 2D
- AOA measure at reference point

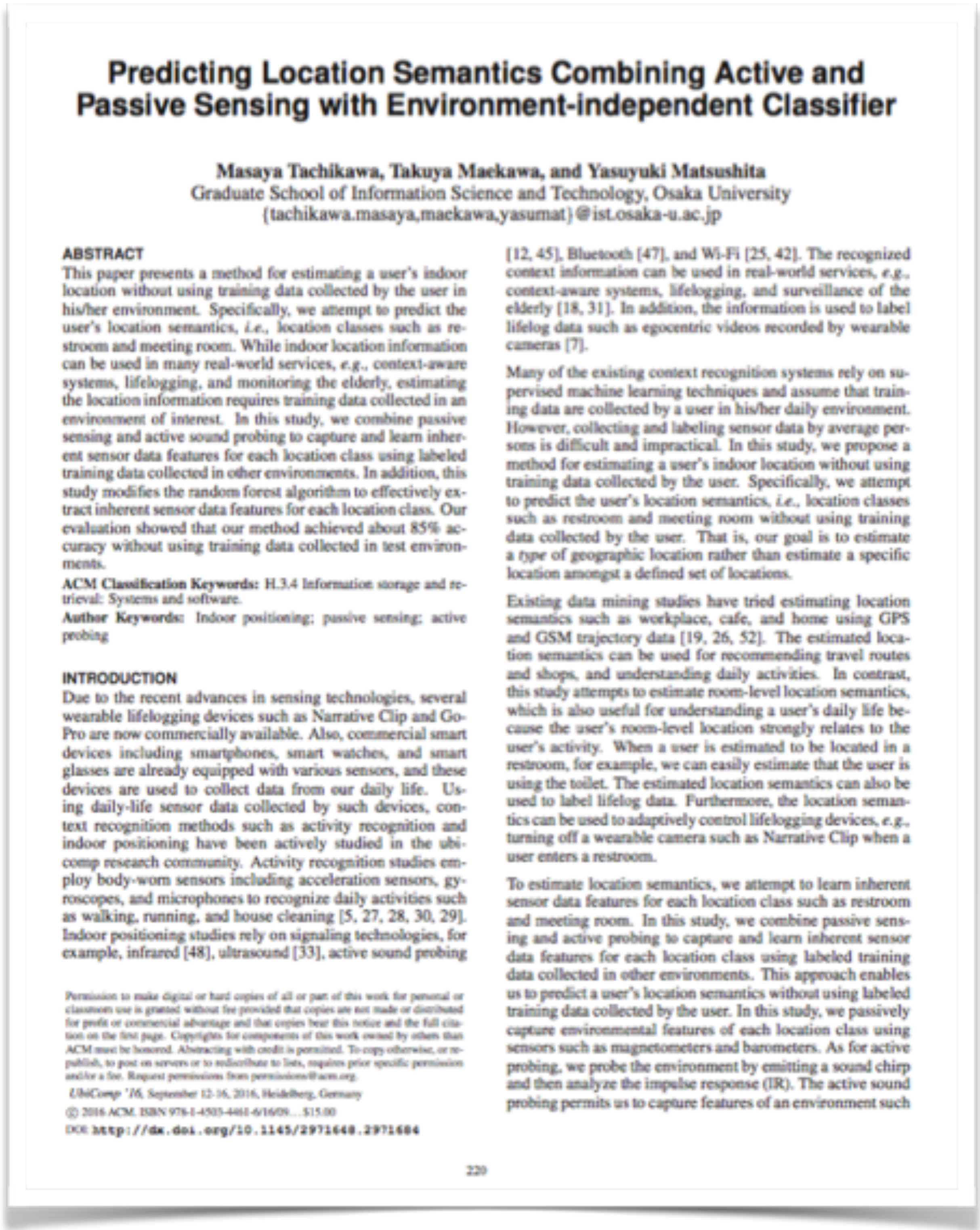
Fingerprinting

- Based on pattern matching
- Relies on 2 properties of radio signals
  - Temporal stability
  - Spatial variability
- Training phase to map radio environment

Determing Location

Dead Reckoning	Location from previously known location
	Speed/direction of movement can be estimated
	Often used to refine position of other systems
	Kalman Filter often used for this

Panel of Experts



Predicting Location Semantics Combining Active and Passive Sensing with Environment-independent Classifier

Masaya Tachikawa, Takuya Maekawa, and Yasuyuki Matsushita
Graduate School of Information Science and Technology, Osaka University
{tachikawa.masaya,maekawa,yasumat}@ist.osaka-u.ac.jp

ABSTRACT

This paper presents a method for estimating a user's indoor location without using training data collected by the user in his/her environment. Specifically, we attempt to predict the user's location semantics, *i.e.*, location classes such as restroom and meeting room. While indoor location information can be used in many real-world services, *e.g.*, context-aware systems, lifelogging, and monitoring the elderly, estimating the location information requires training data collected in an environment of interest. In this study, we combine passive sensing and active sound probing to capture and learn inherent sensor data features for each location class using labeled training data collected in other environments. In addition, this study modifies the random forest algorithm to effectively extract inherent sensor data features for each location class. Our evaluation showed that our method achieved about 85% accuracy without using training data collected in test environments.

ACM Classification Keywords: H.3.4 Information storage and retrieval: Systems and software.

Author Keywords: Indoor positioning; passive sensing; active probing

INTRODUCTION

Due to the recent advances in sensing technologies, several wearable lifelogging devices such as Narrative Clip and GoPro are now commercially available. Also, commercial smart devices including smartphones, smart watches, and smart glasses are already equipped with various sensors, and these devices are used to collect data from our daily life. Using daily-life sensor data collected by such devices, context recognition methods such as activity recognition and indoor positioning have been actively studied in the ubicomp research community. Activity recognition studies employ body-worn sensors including acceleration sensors, gyroscopes, and microphones to recognize daily activities such as walking, running, and house cleaning [5, 27, 28, 30, 29]. Indoor positioning studies rely on signaling technologies, for example, infrared [48], ultrasound [33], active sound probing [12, 45], Bluetooth [47], and Wi-Fi [25, 42]. The recognized context information can be used in real-world services, *e.g.*, context-aware systems, lifelogging, and surveillance of the elderly [18, 31]. In addition, the information is used to label lifelog data such as egocentric videos recorded by wearable cameras [7].

Many of the existing context recognition systems rely on supervised machine learning techniques and assume that training data are collected by a user in his/her daily environment. However, collecting and labeling sensor data by average persons is difficult and impractical. In this study, we propose a method for estimating a user's indoor location without using training data collected by the user. Specifically, we attempt to predict the user's location semantics, *i.e.*, location classes such as restroom and meeting room without using training data collected by the user. That is, our goal is to estimate a *type* of geographic location rather than estimate a specific location amongst a defined set of locations.

Existing data mining studies have tried estimating location semantics such as workplace, cafe, and home using GPS and GSM trajectory data [19, 26, 52]. The estimated location semantics can be used for recommending travel routes and shops, and understanding daily activities. In contrast, this study attempts to estimate room-level location semantics, which is also useful for understanding a user's daily life because the user's room-level location strongly relates to the user's activity. When a user is estimated to be located in a restroom, for example, we can easily estimate that the user is using the toilet. The estimated location semantics can also be used to label lifelog data. Furthermore, the location semantics can be used to adaptively control lifelogging devices, *e.g.*, turning off a wearable camera such as Narrative Clip when a user enters a restroom.

To estimate location semantics, we attempt to learn inherent sensor data features for each location class such as restroom and meeting room. In this study, we combine passive sensing and active probing to capture and learn inherent sensor data features for each location class using labeled training data collected in other environments. This approach enables us to predict a user's location semantics without using labeled training data collected by the user. In this study, we passively capture environmental features of each location class using sensors such as magnetometers and barometers. As for active probing, we probe the environment by emitting a sound chirp and then analyze the impulse response (IR). The active sound probing permits us to capture features of an environment such

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