Contextualizing Space and Time for GeoAI JITAs (Just-in-Time Adaptive Interventions)

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ABSTRACT

The success of Just-in-Time Adaptive Interventions (JITAs) is contingent on the application's ability to understand, predict, and intervene upon the health behavior of interest. Advances in mobile technologies and wearable sensors are presenting further opportunities for "in the moment" intervention, however, integration of spatial and complex temporal concepts have been minimal in JITAs to date. Here we share thoughts on how health behaviors can be contextualized in space and time with the purpose of predicting health behaviors through the use of GeoAI JITA models, and highlight future challenges that need to be addressed.

CCS CONCEPTS

• **Information systems** → *Geographic information systems*; • **Applied computing** → *Health informatics*; • **Computing methodologies** → *Spatial and physical reasoning*.

KEYWORDS

machine learning, GIS, health behavior, GeoAI JITA

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1 INTRODUCTION

Precision medicine, loosely defined as prevention and treatment strategies that take individual variability into account, is a driving force behind mobile health (mHealth) and the development of mHealth biomarkers for specific health behaviors [2]. Such biomarkers are crucial components of Just-in-Time Adaptive Interventions (JITAs), an mHealth intervention approach often delivered on a smart device aimed at providing the right support at the right moment [4]. However, biomarker and behavioral prediction models largely exclude spatial and/or temporal data, or rely on static Euclidean distance metrics. GeoAI is the scientific discipline that bridges geographic information science and artificial intelligence

to advance knowledge discovery from spatial data. There is potential to improve mHealth biomarkers and predictive health behavior classification by integrating GeoAI into JITAs by expanding conceptualizations of space and time associated with the health behavior of interest.

When developing a GeoAI JITA, it is essential to keep in mind that the data points represent a series of action by the person. Thus, space and time should not only compose the movement trajectory but should provide contextual information about the behavior when systematically reviewed together - a role for GeoAI to fill in. Our recent project of predicting eating behavior in free-living individuals [5] shows that spatial and temporal features contribute to the prediction models. In this paper we expand on how the GeoAI JITA may further contextualize health behaviors, aid in developing better mHealth biomarkers, and result in better behavioral health interventions.

2 CONTEXTUALIZING SPACE AND TIME FOR HEALTH BEHAVIORS

Engineering features for a health behavior model must start with a thorough understanding of the spatial and temporal aspects of behavior. From the spatial perspective we should know if the behavior can only occur in specific contexts, is there an inherent spatial pattern of movement, and is there inherent spatial or contextual barriers for the behavior. From the temporal perspective, we should know how commonly the health behavior of interest occurs, if it is habitual vs. sporadic, and if there are certain time constraints associated with the behavior.

Representing space, context, and time for analysis of health behaviors can take on numerous formats ranging from simple to complex, and from incorporating only one element in a feature (e.g. time) to intermixing the three elements (e.g. time spent at a place in a specific context). The *properties* of spatial data define the frequency and structure of the human behavior in space such as a single GPS point, patterns or clustering, adjacency, fragmentation, or vector movement. Spatial representations of health behaviors can then be connected with contextual information. The *properties* of context defines the type of surrounding, such as physical, social, demographic, economic, or environmental. Finally the *properties* of time are tied to the 24-hour diurnal cycle, but can be stretched in include specific times of day, week, month or year, as well as more domain-specific temporal concepts such as "after work".

As free-living humans maneuver over space and through time, the dynamics of interaction between a person, the time, and the context can be translated into attributes for engineering model features. The health behavior of interest should ultimately drive

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Figure 1: JITAI using geo-fencing and time lapse for message triggering (a and b) compared to a GeoAI JITAI that includes spatio-temporal context for more targeted intervention.

selected representations, and decisions concerning *scale* (what resolution of data is needed) and *accuracy* (how accurate do the data need to be to effectively model the interactions of interest).

2.1 Engineering spatial features

Generating spatial features for a GeoAI must go beyond simply inputting latitude/longitude location, in particular due to the spatial dependencies inherent in human movement and health behaviors that can cause over-fitting and misinterpretations [3]. In the simplest case crossing location data with contextual data layers can offer meaningful information to clarify what an individual is doing, or help predict a behavior that is about to happen. Trajectories toward or away contextual objects or places of interest can offer clues to health behaviors. Continuously decreasing in distance between a person and a restaurant could mean an increasing propensity of interaction with the restaurant (e.g. food purchasing behavior). These types of features can achieve higher precision if background information is available and the data *accuracy* is high, such as the spatial query of within the building footprint to decide if the person is at a location. If confidence in data accuracy is lower, other spatial configurations such as clustering thresholds or buffered areas could be utilized in conjunction with smoothed contextual representations (such as kernel densities or spatial interpolations) to account for inherent error in spatial measurement. Further complexity can be introduced into spatial features with elements such as speed, trip mode, and activity patterns from other sensors.

2.2 Engineering temporal features

Certain behaviors must occur regularly and can be modeled with time elapsed features. For example, eating will often occur every 2-4 hours or an addicted smoker can only let so much time go by before lighting up, etc. Another approach to generate temporal features is through time-binning by breaking up a day (or week or month) into potentially meaningful time windows related to the behavior. Eating is more likely to happen around early morning, noon, and evening, while sleep is most likely to happen during the night hours. The time windows for common health-related behaviors can be generated from analyzing larger time-use survey samples to get average patterns.

2.3 Engineering space-time features

The definition of exposure varies from the behavior of interest and can be quite different across cases. When quantifying exposures that affect a health behavior that happens at a certain type of places, time could be contextualized by the authority constraints [1] that limits place access, or by learning the propensity of being at a location. Opening hours of restaurants (fixed), some parks close after sunset (slightly more dynamic), and popularity patterns of a place (very dynamic, i.e. Google's popular times for business) are some examples to be considered before tying a person's location to their context. Features can also consider the length of time spent in a context to assign weighting of the feature. In some instances more time spent in a context may follow a linear curve for predicting a health behavior or see a decaying function.

3 EXAMPLE CASE: A GEOAI JITAI TO SUPPORT HEALTHIER EATING BEHAVIOR

To develop a JITAI that supports reducing adverse eating behavior, it is essential to capture the moments when potentially unhealthy eating episodes are about to take place. With real-time data streaming from wearable devices, the location and physical activity of a participant can be represented in a GeoAI model.

A JITAI for this example goal without GeoAI would likely utilize a logic-based geo-fencing model that sends out a notification to its user when the person enters a specific range of an unfavorable eating outlet (Figure 1 a). A modified model that considers time might only trigger a notification when the person stays in the fence over a defined time threshold (Figure 1 b). The GeoAI JITAI would learn the context of the activity to support the decision making in the system. After identifying the person is in a vehicle, the moving speed (e.g. not slowing down) and moving direction (e.g. moving away from the restaurant) supports the decision of not sending a notification although the person is in the range of a food establishment (Figure 1 c). The GeoAI JITAI could also identify the longer duration of stoppage time is a result of waiting for the traffic light at the intersection and thus no message gets pushed to the user (Figure 1 d). These are just some of the examples of what GeoAI JITAI could achieve when space and time are contextualized in conjunction with health behaviors.

4 CONCLUDING NOTES

The development of GeoAI JITAI can be considered as an improved view on how health behaviors can be better predicted using spatial and temporal features. However, which human behaviors may be best suited for the GeoAI JITAI approach will need to be assessed. Applying GeoAI to on-the-ground JITAI will face many challenges. On the fly feature generation and prediction deployment with spatial data is a significant computing task. Utilizing spatial autocorrelation may be able to help reduce data and increase computing speeds. Additionally, a hierarchy of complexity may be built into the model where spatial or temporal engineered features are only deployed when confidence in the behavioral prediction with other sensor measures is low. Another challenge will be finding a good balance between engineering representative spatial and temporal features and the possible increase of uncertainty of the model that may come with smoothed data. Lastly, personalized GeoAI JITAI needs to learn and acknowledge its user's habitual patterns that connect exposures, surrounding environments, and

health behavior. We envision more research efforts in this domain to advance the development of GeoAI JITAI in the future.

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