Quantifying Predictive Information Flow Between Context and Behavior: A Transfer Entropy Analysis of the ExtraSensory Dataset

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1 Introduction and Motivation

Modern Human Activity Recognition (HAR) excels at classifying steady states such as ‘walking‘ or ‘sitting‘, supported by advances in multi-sensor fusion (Qiu et al., 2022). Yet, these systems often fail to anticipate the crucial moments of transition between activities (Reyes-Ortiz et al., 2016). In these predictive windows, a proactive system can decide when to intervene, for example, by scheduling a notification or adjusting a device’s power policy. Despite ongoing progress in recognition robustness (Khan et al., 2024), quantifying the predictive relationship that governs these transitions remains an open challenge.

To move from classification to prediction, this project will apply the tools of information dynamics. This project will use Transfer Entropy (TE), a powerful measure that quantifies the directed flow of predictive information from one time series to another (Schreiber, 2000). Unlike standard correlation metrics, TE is inherently directional and time-asymmetric, making it perfectly suited for the inquiry. All analyses will use the Java Information Dynamics Toolkit (JIDT), a standard software package for such analyses (Lizier, 2014).

It would apply the methodology to the in-the-wild *ExtraSensory* dataset (Vaizman et al., 2017) to answer a specific, actionable question: does a person’s physical activity level better predict an upcoming transition into a sitting state than the reverse? If so, the resulting asymmetry score (ΔTE) could serve as an efficient, on-device trigger for smarter mobile services (Bragança et al., 2020). To ensure the analysis is rigorous and that the measured information flow is not merely an artifact of daily routines, this project will also employ Conditional Transfer Entropy (CTE) to account for time-of-day as a confounding variable.

2 Research Question and Hypotheses

Research Question: Is there an asymmetric predictive relationship between a person’s physical activity level and their sitting state?

Formal Hypotheses: Let A be the time series for activity level and S be the time series for the sitting state. The study defines the net information transfer as $\Delta\text{TE} = \text{TE}(A \to S) - \text{TE}(S \to A)$. The hypotheses are:

- Null Hypothesis (H_0): There is no significant net directed predictability from activity level to sitting state. Formally: $E[\Delta\text{TE}] \leq 0$.
- Alternative Hypothesis (H_1): Activity level is more predictive of a future sitting state than the reverse. Formally: $E[\Delta\text{TE}] > 0$.

3 Methodology

3.1 Data and Preprocessing

This project will use the *ExtraSensory* dataset, chosen for its in-the-wild collection methodology and rich, minute-level annotations (Vaizman et al., 2017). The primary variables will be the phone's accelerometer data and the `SITTING` label. For each one-minute interval, this study will compute a composite activity index from the raw tri-axial accelerometer segment. This index will be a weighted average of the Signal Magnitude Area (SMA) and the variance of the vector magnitude. The resulting continuous time series will be z-scored within each subject to normalize scales. A critical methodological issue is the mixed data types of the variables (A is continuous, S is discrete). To resolve this, it will employ discretization, a standard approach for applying discrete estimators to continuous data. Specifically, this project will apply quantile discretization to partition each subject's continuous A series into five equal-frequency bins (quintiles). This transforms the activity data into a discrete time series with an alphabet of $\{0, 1, 2, 3, 4\}$, enabling the use of robust discrete estimators. The binary `SITTING` context label will be read on the same minute-level grid to form a binary time series.

3.2 Information-theoretic Analysis

The primary measure is TE, which quantifies directional predictive information in bits (Schreiber, 2000).

$$T_{A \to S} = \sum p(s_{t+1}, s_t^{(k)}, a_t^{(l)}) \log_2 \frac{p(s_{t+1}|s_t^{(k)}, a_t^{(l)})}{p(s_{t+1}|s_t^{(k)})} \tag{1}$$

Following important methodological discussions in the field, it will interpret TE strictly as *predictive information*, not as a direct measure of causation (James et al., 2016). To distinguish the influence of activity from shared daily rhythms, this project will also compute the CTE by conditioning on the hour-of-day. For a linear benchmark, it will compare the results to Granger causality (GC). Since TE and GC are equivalent for Gaussian systems, any divergence betweenthem will highlight nonlinear dynamics in the data (Barnett et al., 2009).

3.3 Implementation and Parameters

All calculations will be performed in JIDT using its purpose-built discrete TE and CTE calculators. For the crucial step of selecting embedding parameters (k, l, τ), in this project, it will leverage JIDT's automated routines, which are based on optimizing information-theoretic criteria such as Active Information Storage. This ensures a principled and reproducible methodology. Statistical significance will be confirmed via permutation testing (≥ 1000 surrogates) using JIDT's built-in resampling functions, with false discovery rate control applied for multiple comparisons.

3.4 Robustness and Sensitivity Analysis

To ensure the robustness of the findings, It will perform several checks. These include calculating the Symbolic Transfer Entropy (STE), which uses ordinal patterns to offer a different perspective on the information dynamics (Staniek & Lehnertz, 2008), and conducting sensitivity analyses using SMA-only or variance-only activity indices.

4 Expected Outcomes and Significance

It is expected to find a significant directional predictability where $\mathrm{TE}(A \to S) > \mathrm{TE}(S \to A)$, confirming the primary hypothesis. Critically, this project anticipates this asymmetry will persist even when conditioning on the hour-of-day, which would provide strong evidence for a direct predictive relationship. Scholarly, this study will offer a formal, information-theoretic quantification of the predictive dynamics within the widely-used *ExtraSensory* dataset. Practically, the findings can directly inform the design of more intelligent, less intrusive mobile applications. A primary challenge for smart devices is ill-timed notifications. The central hypothesis—that activity level changes predict imminent stable states—offers a novel "Just-in-time intervention" logic. For instance, a system could leverage the signal to delay non-urgent alerts until the user is about to enter a 'SITTING' state, significantly reducing interruptions and enhancing user experience (Bragança et al., 2020).

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