SAPTrees: Using Conditional Inference Trees to Characterize Heterogeneity in Human Activity Patterns

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Talk Outline

- Smartphone sensor data and Daynamica
- Smartphone data as a character sequence
- Sequential Activity Pattern Trees (SAPTrees)
 - Defining sequence distances
 - Multivariate distance matrix regression (MDMR)
 - Conditional inference trees (CTrees)
 - SAPTree Algorithm
- Application to smartphone data

Daynamica



Daynamica Data



Daynamica Data

Day	Start Time	End Time	Event
1	00:00:00	08:34:35	HOME
1	08:34:35	08:41:29	CAR
1	08:41:29	17:00:05	WORK
1	17:00:05	17:10:48	CAR
1	17:10:48	17:49:15	PERSONAL_BUSINESS
1	17:49:15	18:04:17	CAR
1	18:04:17	18:37:22	EAT_OUT
1	18:37:22	18:55:22	CAR
1	18:55:22	23:59:59	HOME
2	00:00:00	09:16:32	HOME
2	09:16:32	09:23:37	CAR
2	09:23:37	17:12:08	WORK

Goal: Formally characterize heterogeneity in user's activity patterns

Daynamica Data



Sequences from Daynamica Data



Sequences from Daynamica Data



Sequences from Daynamica Data



Sequence-Based Edit Distances

- Common in bioinformatics, computer science
- Minimum total cost of changing one sequence to another via series of operations:
 - Substitution
 - Insertion
 - Deletion
- Specified via a substitution cost matrix

Sequence-Based Edit Distances

$$\mathbf{\Gamma} = \begin{bmatrix} a & b & 1 & 2 & \phi \\ \gamma_{aa} & \gamma_{ab} & \gamma_{a1} & \gamma_{a2} & \gamma_{a\phi} \\ \gamma_{ba} & \gamma_{bb} & \gamma_{b1} & \gamma_{b2} & \gamma_{b\phi} \\ \gamma_{1a} & \gamma_{1b} & \gamma_{11} & \gamma_{12} & \gamma_{1\phi} \\ \gamma_{2a} & \gamma_{2b} & \gamma_{21} & \gamma_{22} & \gamma_{2\phi} \\ \phi & \gamma_{\phi a} & \gamma_{\phi b} & \gamma_{\phi 1} & \gamma_{\phi 2} & \gamma_{\phi\phi} \end{bmatrix}$$

- Cost matrix for sequences with states (a,b,1,2)
- ϕ is "null" state, responsible for indels

Sequence-Based Edit Distances

$$\mathbf{\Gamma} = \begin{bmatrix} a & b & 1 & 2 & \phi \\ \gamma_{aa} & \gamma_{ab} & \gamma_{a1} & \gamma_{a2} & \gamma_{a\phi} \\ \gamma_{ba} & \gamma_{bb} & \gamma_{b1} & \gamma_{b2} & \gamma_{b\phi} \\ \gamma_{1a} & \gamma_{1b} & \gamma_{11} & \gamma_{12} & \gamma_{1\phi} \\ \gamma_{2a} & \gamma_{2b} & \gamma_{21} & \gamma_{22} & \gamma_{2\phi} \\ \phi & \gamma_{\phi a} & \gamma_{\phi b} & \gamma_{\phi 1} & \gamma_{\phi 2} & \gamma_{\phi\phi} \end{bmatrix}$$

- Levenshtein edit distance: all diagonal entries 0, all other entries 1
- Distance between 'b12a' and 'a22' is 3:
 - 1. Delete 'a' \rightarrow 'b12'
 - 2. Substitute '1' with '2' \rightarrow 'b22'
 - 3. Substitute 'b' with 'a' \rightarrow 'a22'

Pairwise Sequence Distance Matrix

$$\boldsymbol{D} = \{d_{ij}\} = \begin{bmatrix} 0 & d_{12} & d_{13} & d_{14} & d_{15} & d_{16} \\ & 0 & d_{23} & d_{24} & d_{25} & d_{26} \\ & & 0 & d_{34} & d_{35} & d_{36} \\ & & & 0 & d_{45} & d_{46} \\ & & & & 0 & d_{56} \\ & & & & & 0 \end{bmatrix}$$

6x6 distance matrix summarizing dissimilarity between 6 sequences

Distance-Based Methods

- Heatmaps
- Dendrograms
- Hierarchical and other clustering methods
- Distance-based regression (distances as predictors)

Distance Matrix as Response

- Relate set of covariates were to sequence distance matrix outcome
- A regression method with a distance matrix as the "response variable"
- Multivariate Distance Matrix Regression (MDMR)

MDMR: Overview

- Regress an $n \times n$ distance matrix **D** (outcome) on covariates **X**
- Similar to OLS, partition sum of squared distances (SSD) instead
- MDMR p-values assess strength of evidence for "association" between covariate(s) and distance matrix
- No measure of effect size
- Interpretability of a "significant" association is lacking

Decision Tree



Conditional Inference Trees (CTrees)

Alternative to CART, primary differences:

- Variable selection and splitting distinct sequential processes
 - Variable selection: which variable to split on
 - Variable **splitting:** which **value** to split on
- Variable selection done in hypothesis testing framework
- Variable splitting determines optimal threshold for chosen variable

Sequence Activity Pattern Trees (SAPTrees)

SAPTrees use the CTree algorithm with:

- Sequences/resulting distance matrix as the outcomes
- MDMR used for the **selection** step and **splitting** step

Sequence Activity Pattern Trees (SAPTrees)

1. Compute distance matrix from sequences.

2. Variable selection step.

- Single covariate MDMR model for each candidate covariate
- Covariate w/ lowest p-value (also lower than threshold) chosen
- If none lower, terminate (controls Type I error)

3. Variable splitting step.

• MDMR at each split point used to determine optimal split value

4. Recursion.

• Repeat steps (2) and (3) recursively in each node until no more splits

SAPTree Application

- Minneapolis-area study. ~250 users with multiple days of data.
- SAPTree fit to 24-hour Wednesday sequence data for each individual
- 5-minute resolution: 288-character sequences
- **D** calculated using Levenshtein distance
- Covariates:
 - Gender (male vs. female)
 - Age (quantitative)
 - Education (HS, associate/some college, bachelor, graduate)
 - Race (white vs. other)
 - Income (<25k, 25-50k, 50-75k, 75-100k, >100k)
 - Parental Status (children vs. no children)
- Multiplicity adjustment: Bonferroni
- Nominal Type I error rate at each split point: α =0.05

SAPTree Visualization



Other

Shopping

States

Eat Out

Home

Functional Data Summaries



Node-specific probabilities of **Work** over time using function-on-scalar regression

Functional Data Summaries



Pointwise ANOVA to assess at what time points do terminal nodes significantly differ with respect to a particular state

Potential SAPTree Uses

"Personalized medicine": identifying activity-based subgroups for targeted interventions

 ID'ing patients in exercise rehab programs who differentially complete prescribed outpatient exercise regimens

Healthcare cost savings

• SAPTree analysis of sensor data collected from mobile care teams could be used to streamline their time use

Outside of healthcare

• Transportation planning: understanding how different population subgroups utilize public transit network

Conclusions

- A method for characterizing covariate-based heterogeneity in activity sequence patterns
- Interpretable results and visualizations
- Sensitive to variety of activity pattern differences undetectable using traditional outcomes
- Many potential application areas
- Future Work:
 - Effect of sampling resolution, distance metric choice
 - Multiple sequences (e.g., adding accelerometer data)

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Questions?