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# Using a signature-based machine learning model to analyse a psychiatric stream of data

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(JOINT WORK WITH T. LYONS AND K. SAUNDERS)

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Oxford  
Mathematics

# Signature of a path

Continuous paths with finite  $p$ -variation

- ▶ Given  $p \geq 1$  and  $X \in \mathcal{C}([s, t], \mathbb{R}^d)$  with  $s < t$  we define

$$\|X\|_{p,[s,t]} := \sup_{\{t_i\}_{i \in [s,t]}} \left( \sum_i \|X_{t_i} - X_{t_{i-1}}\|^p \right)^{1/p}.$$

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- ▶  $\mathcal{V}^p([s, t], \mathbb{R}^d) := \{X \in \mathcal{C}([s, t], \mathbb{R}^d) : \|X\|_{p,[s,t]} < \infty\}$ .

## Definition (Signature of a continuous path)

Let  $X \in \mathcal{V}^p([0, T], \mathbb{R}^d)$  so that the following integration makes sense. The signature of  $X$  is defined as

$$S(X) = (1, X^1, X^2, \dots) \in \bigoplus_{n=0}^{\infty} (\mathbb{R}^d)^{\otimes n}$$

where

$$X^n = \int_{0 < u_1 < u_2 < \dots < u_n < T} \dots \int dX_{u_1} \otimes \dots \otimes dX_{u_n} \quad \forall n \geq 1.$$

## Definition (Truncated signature of a continuous path)

Similarly, we define, for  $n \geq 0$ ,

$$S^n(X) := (1, X^1, X^2, \dots, X^n).$$

# Signatures and machine learning

Supervised learning

- ▶ We have two data sets: a known set of known input-output pairs (the *training set*),  $\{X_i, Y_i\}_i$ , which is used to train the model, and a set of inputs that is used for testing (the *out-of-sample set*).

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- ▶ Features play an important role in machine learning.

# Signatures and machine learning

Signatures as features: uniqueness

## Theorem (B. Hambly, T. Lyons)

*The signature of a path with bounded variation is unique up to tree-like equivalence.*



# Signatures and machine learning

Signatures as features: estimate

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## Theorem

Let  $X \in \mathcal{V}^1([0, T], \mathbb{R}^d)$  be a path with bounded variation. Then, given  $1 \leq i_1, i_2, \dots, i_n \leq d$  we have

$$\left\| \int \cdots \int_{0 < u_1 < u_2 < \dots < u_n < T} dX_{u_1}^{i_1} \cdots dX_{u_n}^{i_n} \right\| \leq \frac{\|X\|_{1, [0, T]}^n}{n!}.$$

# Signatures and machine learning

The model

- ▶ Given a training set  $\{R_i, Y_i\}_{i=0}^N$ , of input-output pairs, where  $R_i = \{t_{ij}, r_{ij}\}_j$  is a stream of data, construct a new set  $\{X_i, Y_i\}_{i=0}^N$  with  $X_i \in \mathcal{V}^1$ .

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- ▶ Compute  $\{S^n(X_i), Y_i\}_{i=0}^N$  for some  $n \in \mathbb{N}$ .

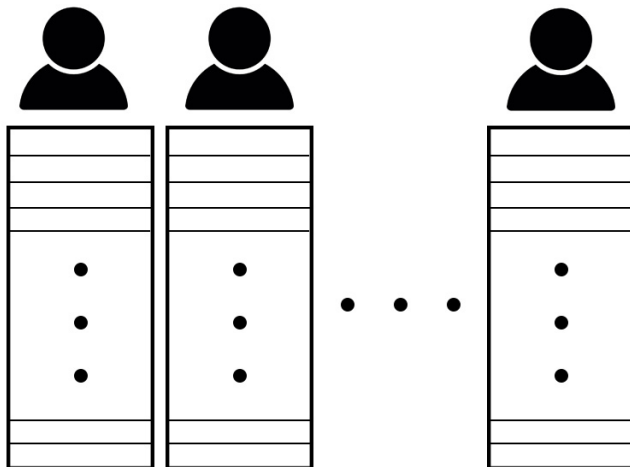
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- ▶ Compute  $\{S^n(X_i), Y_i\}_{i=0}^N$  for some  $n \in \mathbb{N}$ .
- ▶ Apply regression against the truncated signature.

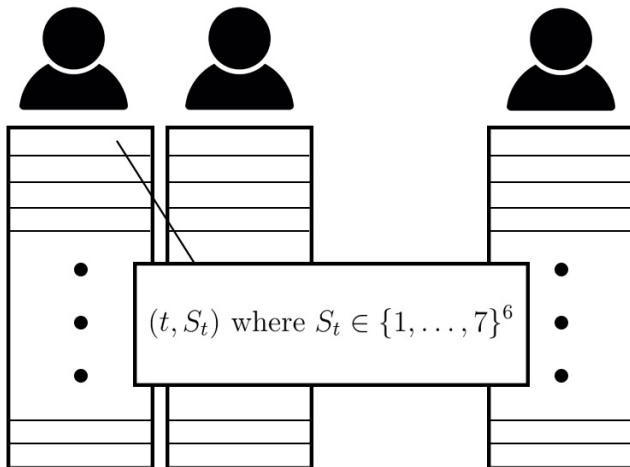
# Application to psychiatric data

The problem



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The problem

- ▶ Given some information about a participant, can we tell if he or she was diagnosed to have bipolar disorder, borderline personality disorder or to be healthy?



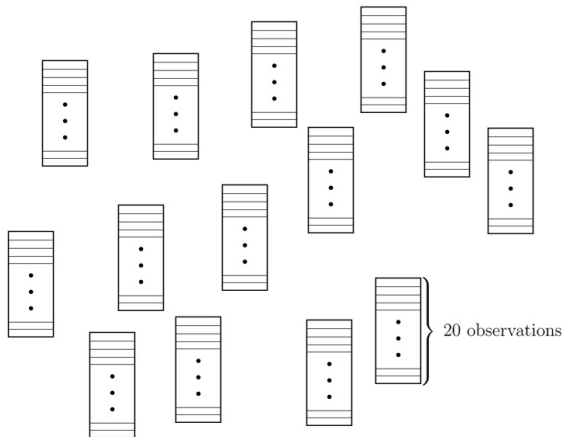
# Application to psychiatric data

The problem

- ▶ Given some information about a participant, can we tell if he or she was diagnosed to have bipolar disorder, borderline personality disorder or to be healthy?
- ▶ Given a participant and information about the last few days, can we predict the mood the following day?

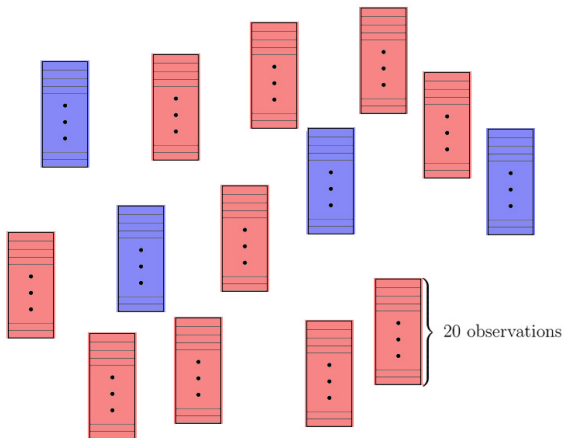
# Application to psychiatric data

Methodology



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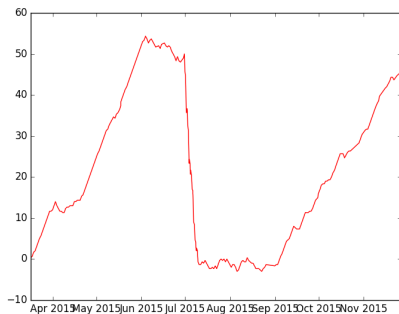


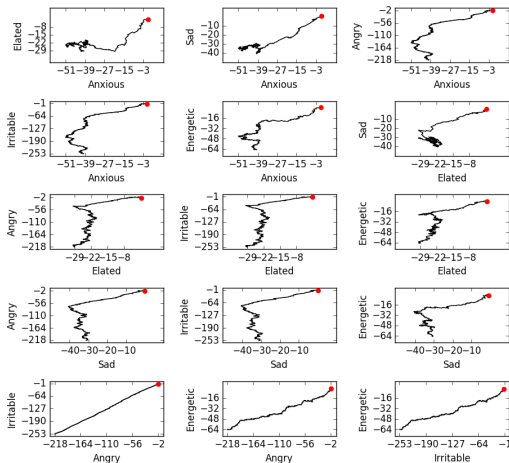
Figure: Normalised path for anxiety scores.

# Application to psychiatric data

Methodology



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# Application to psychiatric data

Predicting if a person is healthy, has bipolar disorder or has borderline disorder

$$\{t_i, S_{t_i}\}_{i=0}^{19} \rightarrow \begin{cases} (-1, 1), & \text{if the participant is healthy} \\ (-1, -1), & \text{if the participant is bipolar.} \\ (1, 0), & \text{if the participant is borderline.} \end{cases}$$

# Application to psychiatric data

Predicting if a person is healthy, has bipolar disorder or has borderline disorder

| Order | Correct guesses |
|-------|-----------------|
| 2nd   | 75%             |
| 3rd   | 70%             |
| 4th   | 69%             |

**Table:** Percentage of people correctly classified in the three clinical groups.

# Application to psychiatric data

Predicting the future mood

$$\{t_i, S_{t_i}\}_{i=0}^{19} \rightarrow S \in \{1, \dots, 7\}^6$$

where  $S$  is the scores of the participant the following observation.



# Application to psychiatric data

Predicting the future mood

| Category  | Healthy | Bipolar | Borderline |
|-----------|---------|---------|------------|
| Anxious   | 98%     | 82%     | 73%        |
| Elated    | 89%     | 86%     | 78%        |
| Sad       | 93%     | 84%     | 70%        |
| Angry     | 98%     | 90%     | 70%        |
| Irritable | 97%     | 84%     | 70%        |
| Energetic | 89%     | 82%     | 75%        |

**Table:** Percentage of correct guesses for mood predictions

Thank you!

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