

## Setting

We are interested in predicting from a data stream, for example:

- Time series prediction,
- Online recognition of characters or handwriting,
- Sound recognition,
- Automated medical diagnosis from sensor data...

In all of these cases, the predictor can be seen as a path  $X : [a, b] \rightarrow \mathbb{R}^d$ .

**Goal:** find a good representation of these processes as vectors of finite dimension.

## History

- 1960s Chen notices in [1] that a path can be represented by its iterated integrals.
- 1990s The signature is at the center of Lyons' rough paths theory.
- 2010s Combined with a deep learning algorithms, it achieves state of the art results for several applications, see e.g. [2] or [3].

## Dataset

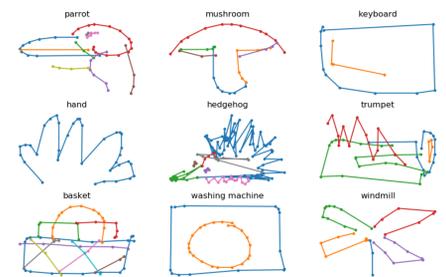


Figure: Quick, Draw! dataset [4]. The task is to classify 340 different objects from 50 million samples.

## Definition

Let  $X : [0, 1] \rightarrow \mathbb{R}^d$  be a continuous path of bounded variation. We denote by  $(X^1, \dots, X^d)$  its coordinates. Let  $I = (i_1, \dots, i_k) \subset \{1, \dots, d\}^k$  be a multi index. The signature coefficient corresponding to  $I$  is

$$S^{(i_1, \dots, i_k)}(X) = \int_{0 \leq u_1 < \dots < u_k \leq 1} dX_{u_1}^{i_1} \dots dX_{u_k}^{i_k}.$$

The signature of  $X$  is the vector containing all signature coefficients:

$$S(X) = \left( 1, S^{(1)}(X), \dots, S^{(d)}(X), S^{(1,1)}(X), S^{(1,2)}(X), \dots, S^{(d,d)}(X), \dots, S^{(i_1, \dots, i_k)}(X), \dots \right).$$

The signature of  $X$  truncated at order  $m$  is:

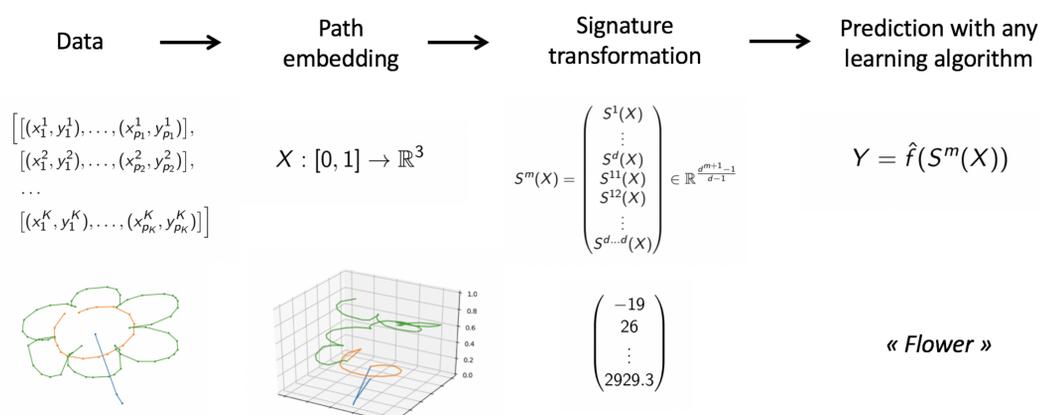
$$S^m(X) = \left( 1, S^{(1)}(X), S^{(2)}(X), \dots, \overbrace{S^{(d, \dots, d)}(X)}^m \right).$$

## Properties

- **Invariance under time reparametrization:** Let  $\psi : [0, 1] \rightarrow [0, 1]$  be a reparametrization. Then, if  $\tilde{X}_t = X_{\psi(t)}$ ,  $S(\tilde{X}) = S(X)$ .
- **Uniqueness:** If  $X$  has at least one monotonous coordinate, then  $S(X)$  determines  $X$  uniquely.
- **Signature approximation:** Let  $D$  be a compact subset of the space of paths from  $[0, 1]$  to  $\mathbb{R}^d$  of bounded variation. Let  $f : D \rightarrow \mathbb{R}$  continuous. Then, for every  $\epsilon > 0$ , there exists  $N \in \mathbb{N}$ ,  $w \in \mathbb{R}^N$  such that, for any  $X \in D$ ,

$$|f(X) - \langle w, S(X) \rangle| \leq \epsilon.$$

## Learning process



## Conclusion

- The signature is a generic method that can be used for multidimensional sequential data.
- It encodes, in a fixed number of coefficients, geometric properties of the input path.
- Data embedding has a huge influence on prediction performance.

## Mathematical challenges

- Truncation order selection in a regression model: estimator, rate of convergence and simulation study.
- Theoretical understanding of embedding properties.
- Extension to paths of finite  $p$ -variation with  $p \geq 2$ .
- Sparsity in the signature vector.

## Embedding results

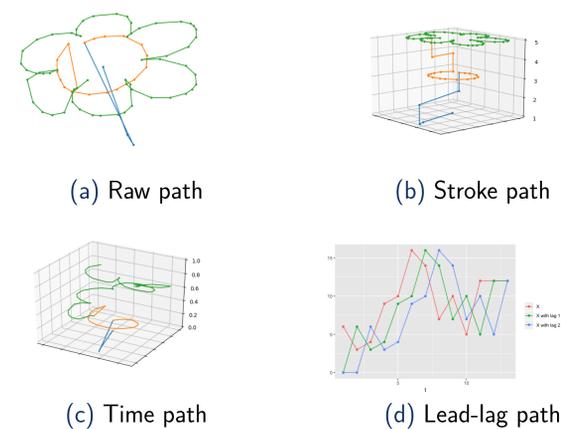


Figure: Different possible data embeddings.

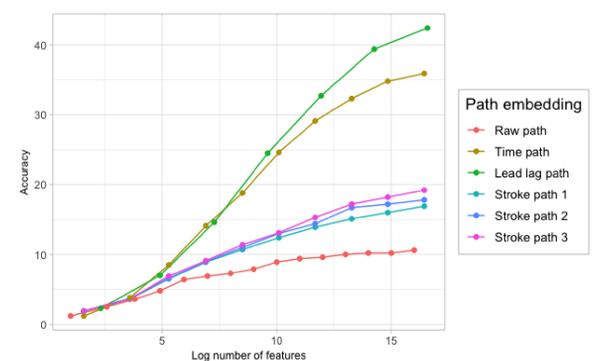


Figure: Prediction accuracy on the "Quick, Draw!" dataset with a small linear neural network with one hidden layer and different path embeddings.

## References

- [1] Kuo-sai Chen. Integration of paths—a faithful representation of paths by non-commutative formal power series. *Transactions of the American Mathematical Society*, 89(2):395–407, 1958.
- [2] Weixin Yang, Terry Lyons, Hao Ni, Cordelia Schmid, Lianwen Jin, and Jiawei Chang. Leveraging the path signature for skeleton-based human action recognition. *arXiv preprint arXiv:1707.03993*, 2017.
- [3] Weixin Yang, Lianwen Jin, and Manfei Liu. Deepwriterid: An end-to-end online text-independent writer identification system. *IEEE Intelligent Systems*, 31(2):45–53, 2016.
- [4] Quick, draw! dataset. <https://quickdraw.withgoogle.com/data>. Data made available by Google, Inc. under the Creative Commons Attribution 4.0 International license.