

Towards a Unified Theory of Time-Varying Data

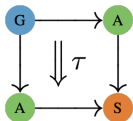
Wilmer Leal

Gatas Lab
Department of Computer Science
University of Florida, USA

Joint work with:

Benjamin Merlin Bumpus, James Fairbanks, Martti Karvonen & Frédéric Simard.

ACT 2024



Category theory for data analysis¹

- ▶ Object-based presentations in temporal data theories.
Categories of temporal data.
- ▶ A temporal data theory for each kind of mathematical structure?
Object-agnosticism.
- ▶ How are the cumulative and persistent Perspectives related?
Formally related via an adjunction.
- ▶ Can we systematically lift static properties to temporal ones?
Systematic “Temporalization”.
- ▶ Can we formally study connections between temporal data and dynamical systems?

¹Based on: *Towards a Unified Theory of Time-varying Data*. BM Bumpus, J Fairbanks, M Karvonen, W Leal, F Simard. arXiv:2402.00206

Question 1: What are the data structures for temporal data?

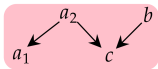
A huge, growing number of data sets generated by the underlying dynamics, e.g.:

- ▶ human and animal proximity networks,
- ▶ human communication networks,
- ▶ collaboration networks,
- ▶ economic networks,
- ▶ biological, chemical networks,
- ▶ and epidemiological networks

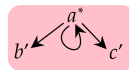
Question 1: What are the data structures for temporal data?

A huge, growing number of data sets generated by the underlying dynamics, e.g.:

- ▶ human and animal proximity networks,
- ▶ human communication networks,
- ▶ collaboration networks,
- ▶ economic networks,
- ▶ biological, chemical networks,
- ▶ and epidemiological networks



.....

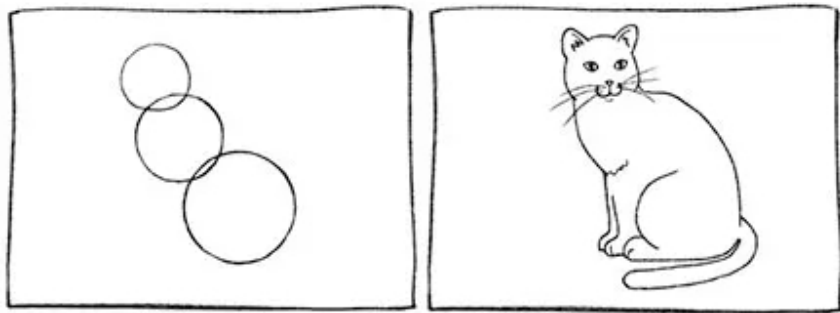


Question 1: What are the data structures for temporal data?

Let me teach you how to draw a cat!

Question 1: What are the data structures for temporal data?

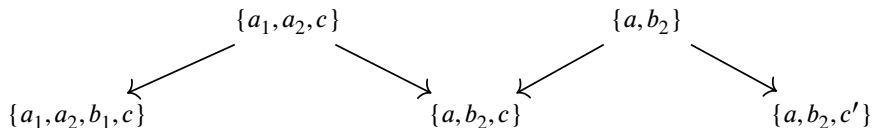
Let me teach you how to draw a cat!



Easy, right?

Question 1: What are the data structures for temporal data?

We can store many kinds of data transformation using morphisms between snapshots:



Narrative: Company a_1 and a_2 merged into a , which remained opened. Company b_1 disappeared in the second snapshot, while c remained open, etc.

Question 1: What are the data structures for temporal data?

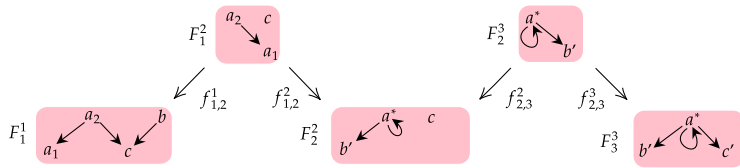


Figure: Relational data for companies as graphs

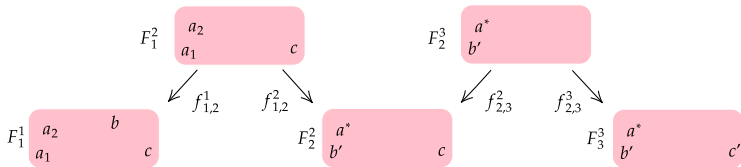
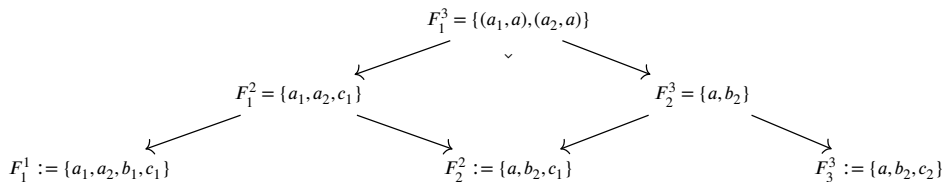


Figure: Distances between companies as metric spaces

Question 1: What are the data structures for temporal data?

We should be able to compute long-term relationships: Which companies $\{a_1, a_2, b_1, c_1\}$ **persisted** over the course of three years?

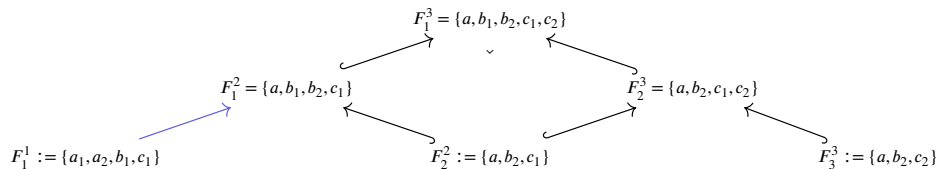


Just compute the pullback of the sets F_1^2 and F_2^3 :

$$F_1^3 := \{(x, y) \in F_1^2 \times F_2^3 \mid f_{1,2}^2(x) = f_{2,3}^2(y)\}$$

Question 1: What are the data structures for temporal data?

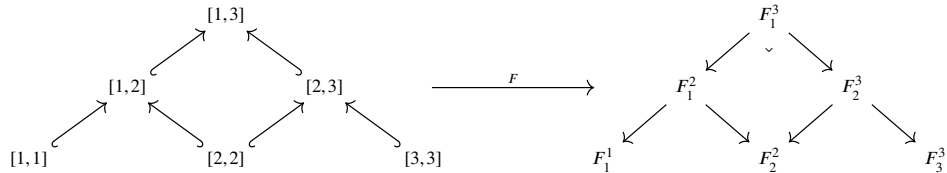
We should be able to compute long-term relationships: Data (companies) and relationships **accumulated** (seen) over a period of time.



Compute the pushout of the diagram involving sets F_1^2 , F_2^2 and F_2^3 .

Question 1: What are the data structures for temporal data?

This temporal data structure can be seen as a functor defined on certain time category:



With the additional condition that $F([a, b])$ is the pullback $F([a, p]) \times_{F([p, p])} F([p, b])$ for any $p \in [a, b]$.

Question 1: What are the data structures for temporal data?

We borrow interval categories from Schultz, Spivak and Vasilakopoulou:

Definition (Interval categories²)

The **category of intervals**, denoted Int , is the category having closed intervals $[a, b]$ in \mathbb{R}_+ (the non-negative reals) as objects and orientation-preserving isometries as morphisms. Analogously, one can define the category $\text{Int}_{\mathbb{N}}$ of **discrete intervals** by restricting only to \mathbb{N} -valued intervals.

These categories can be turned into sites by equipping them with the Johnstone coverage which stipulates that a **cover** of any interval $[a, b]$ is a partition into two closed intervals $([a, p], [p, b])$.

²Schultz, P., Spivak, D. I., and Vasilakopoulou, C. Dynamical systems and sheaves. Applied Categorical Structures 28, 1 (2020), 1–57.

Question 1: What are the data structures for temporal data?

We borrow interval categories from Schultz, Spivak and Vasilakopoulou:

Definition (Strict Embedding Intervals)

*We denote by I (resp. $I_{\mathbb{N}}$) the full subcategory (specifically a join-semilattice) of the subobject poset of \mathbb{R} (resp. \mathbb{N}) whose objects are intervals. We will refer to I , $I_{\mathbb{N}}$ and any sub-join-semilattices thereof as **time categories**.*

The following lemma states that time categories can be given Grothendieck topologies in much the same way as the interval categories:

Lemma

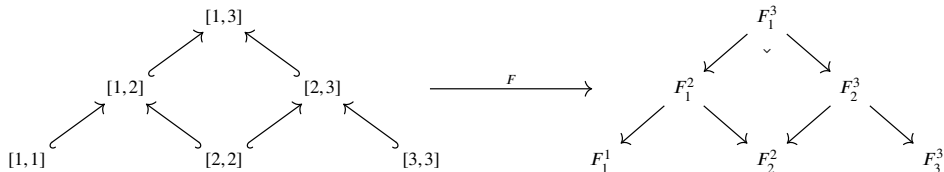
Any time category forms a site when equipped with the Johnstone coverage.

Question 1: What are the data structures for temporal data?

Now we are ready to give the definition of a sheaf with respect to any of the sites described in the previous Lemma.

Proposition (T-sheaves)

Let \mathcal{T} be any time category equipped with the Johnstone coverage. Suppose \mathcal{D} is a category with pullbacks, then a **\mathcal{D} -valued sheaf on \mathcal{T}** is a presheaf $F: \mathcal{T}^{op} \rightarrow \mathcal{D}$ satisfying the following additional condition: for any interval $[a, b]$ and any cover $([a, p], [p, b])$ of this interval, $F([a, b]) = F([a, p]) \times_{F([p, p])} F([p, b])$.

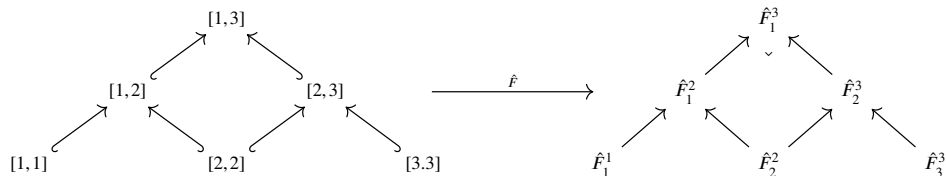


Question 1: What are the data structures for temporal data?

Similarly, we can define the temporal data structure that can encode accumulated data and relationships using cosheaves:

Proposition (T-cosheaves)

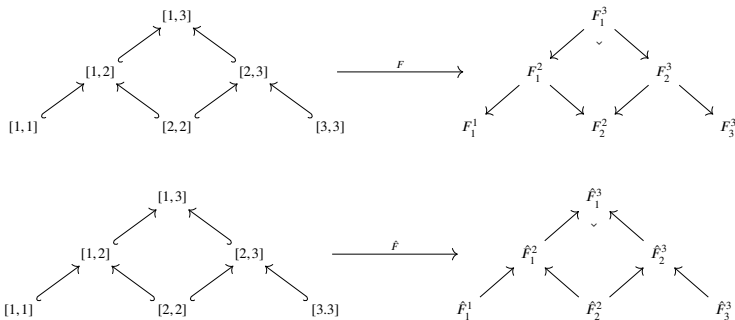
Let \mathcal{T} be any time category equipped with the Johnstone coverage. Suppose \mathcal{D} is a category with pushouts, then a **\mathcal{D} -valued cosheaf on \mathcal{T}** is a copresheaf $\hat{F}: \mathcal{T} \rightarrow \mathcal{D}$ satisfying the following additional condition: for any interval $[a, b]$ and any cover $([a, p], [p, b])$ of this interval, $\hat{F}([a, b])$ is the pushout $\hat{F}([a, p]) +_{\hat{F}([p, p])} \hat{F}([p, b])$.



Question 1: What are the data structures for temporal data?

Definition (Persistent and cumulative)

We denote by $\text{Pe}(T, D)$ (resp. $\text{Cu}(T, D)$) the category of D -valued sheaves (resp. cosheaves) on T and we call it the category of **persistent D-narratives** (resp. **cumulative D-narratives**) with T -time.



Question 2: How are the persistent and cumulative perspectives related?

Theorem

Let D be category with limits and colimits.

There exist functors $\mathcal{P}: \text{Cu}(T, D) \rightarrow \text{Pe}(T, D)$ and $\mathcal{K}: \text{Pe}(T, D) \rightarrow \text{Cu}(T, D)$.

Moreover, these functors are adjoint to each other:

$$\begin{array}{ccc} \text{Cu}(T, D) & \xrightarrow{\mathcal{P}} & \text{Pe}(T, D) \\ & \perp & \\ & \xleftarrow{\mathcal{K}} & \end{array}$$

Proof.

Define \mathcal{P} to be the map that assigns to any cosheaf $\hat{F}: T \rightarrow D$ the sheaf

$\mathcal{P}(\hat{F}): T^{op} \rightarrow D$ defined on objects by:

$$\mathcal{P}(\hat{F}): [a, b] \mapsto \lim(T(-, [a, b]) \hookrightarrow T \xrightarrow{\hat{F}} D).$$



Question 2: How are the persistent and cumulative perspectives related?

Theorem

Let D be category with limits and colimits.

There exist functors $\mathcal{P} : \text{Cu}(T, D) \rightarrow \text{Pe}(T, D)$ and $\mathcal{K} : \text{Pe}(T, D) \rightarrow \text{Cu}(T, D)$.

Moreover, these functors are adjoint to each other:

$$\begin{array}{ccc} & \xrightarrow{\mathcal{P}} & \\ \text{Cu}(T, D) & \perp & \text{Pe}(T, D) \\ & \xleftarrow{\mathcal{K}} & \end{array}$$

Proof.

Define $\mathcal{K} : \text{Pe}(T, D) \rightarrow \text{Cu}(T, D)$ as the map that takes any sheaf $F : T^{op} \rightarrow D$ to the cosheaf $\mathcal{K}(F) : T \rightarrow D^{op}$ defined on objects by:

$$\mathcal{K}(F) : [a, b] \mapsto \text{colim}(T(-, [a, b]) \hookrightarrow T \xrightarrow{F} D).$$



Temporal networks can be written as narratives

Definition (Temporal networks³)

Take \mathbb{T} to be either \mathbb{N} or \mathbb{R} . A \mathbb{T} -temporal (directed) network is a quintuple $(G, \rho_e, \eta_e, \rho_v, \eta_v)$ where G is a (directed) graph and ρ_e, η_e, ρ_v and η_v are functions of the following types:

$$\rho_e : E(G) \times \mathbb{T} \rightarrow \{\perp, \top\},$$

$$\eta_e : E(G) \times \mathbb{T} \rightarrow \mathbb{T},$$

$$\rho_v : V(G) \times \mathbb{T} \rightarrow \{\perp, \top\},$$

$$\eta_v : V(G) \times \mathbb{T} \rightarrow \mathbb{T}$$

where ρ_e and ρ_v are functions indicating whether an edge or vertex is active at a given time and where η_e and η_v are latency functions indicating the amount of time required to traverse an edge or vertex.

³Casteigts, Flocchini, Quattrociocchi and Santoro. Time-varying graphs and dynamic networks. International Journal of Parallel, Emergent and Distributed Systems 27, 5 (2012), 387–408.

Temporal networks can be written as narratives

- ▶ Consider the monoid of natural numbers viewed as a single-vertex graph with a loop edge for each natural number $G_{\mathbb{N}} : \text{SGr} \rightarrow \text{Set}$ having $G_{\mathbb{N}}(V) = 1$ and $G_{\mathbb{N}}(E) = \mathbb{N}$
- ▶ The slice category $\text{Set}^{\text{SGr}}/G_{\mathbb{N}}$ will have pairs $(G, \lambda: G \rightarrow G_{\mathbb{N}})$ as objects where G is a graph and λ is a graph homomorphism that assigns a natural number label to each edge of G .
- ▶ Thus narratives valued in $\text{Set}^{\text{SGr}}/G_{\mathbb{N}}$ can be interpreted as time-varying graphs whose edges come equipped with **latencies** (which can change with time).

Temporal networks can be written as narratives

- ▶ Consider the monoid of natural numbers viewed as a single-vertex graph with a loop edge for each natural number $G_{\mathbb{N}} : \text{SGr} \rightarrow \text{Set}$ having $G_{\mathbb{N}}(V) = 1$ and $G_{\mathbb{N}}(E) = \mathbb{N}$
- ▶ The slice category $\text{Set}^{\text{SGr}}/G_{\mathbb{N}}$ will have pairs $(G, \lambda: G \rightarrow G_{\mathbb{N}})$ as objects where G is a graph and λ is a graph homomorphism that assigns a natural number label to each edge of G .
- ▶ Thus narratives valued in $\text{Set}^{\text{SGr}}/G_{\mathbb{N}}$ can be interpreted as time-varying graphs whose edges come equipped with **latencies** (which can change with time).

Many other kinds of temporal graphs and networks, including reflexive graphs, symmetric-and-reflexive graphs, half-edge graphs and Petri nets, can be constructed using this approach.

Question 3: How to change the base category?

Proposition (Covariant Change of base)

Let C and D be categories with limits (resp. colimits) and let T be any time category. If $K: C \rightarrow D$ is a continuous functor, then composition with K determines a functor $(K \circ -)$ from persistent (resp. cumulative) C -narratives to persistent (resp. cumulative) D -narratives. Spelling this out explicitly for the case of persistent narratives, we have:

$$(K \circ -): \text{Pe}(T, C) \rightarrow \text{Pe}(T, D)$$

$$(K \circ -): (F: T^{op} \rightarrow C) \mapsto (K \circ F: T^{op} \rightarrow D).$$

Application: Defining temporal counterparts of static properties

- ▶ Any class P of objects in C can be identified with a subcategory

$$P: P \rightarrow C$$

this functor picks out those objects of C that satisfy a given property P .

- ▶ If this functor P is cocontinuous, then we can apply our previous proposition to identify a class

$$(P \circ -): \text{Cu}(T, P) \rightarrow \text{Cu}(T, C)$$

of C -narratives which satisfy the property P at all times.

- ▶ For example, consider the full subcategory $\mathfrak{P}: \text{Paths} \hookrightarrow \text{Grph}$ which defines the category of all paths and the morphisms between them. \mathfrak{P} determines a subcategory $(\mathfrak{P} \circ -): \text{Cu}(T, \text{Paths}) \hookrightarrow \text{Cu}(T, \text{Grph})$ whose objects are temporal path-graphs.

Application: the cumulative temporal tree is equivalent to the persistent temporal path problem

$$\begin{array}{ccc} \text{Cu}(\mathcal{T}, \text{Grph}_{\text{mono}}) & \begin{array}{c} \xrightarrow{\mathcal{P}} \\ \perp \\ \xleftarrow{\mathcal{K}} \end{array} & \text{Pe}(\mathcal{T}, \text{Grph}_{\text{mono}}) \end{array}$$

The change of base proposition applied to the full subcategory

$$\mathfrak{T}: \text{Trees}_{\text{mono}} \rightarrow \text{Grph}_{\text{mono}}$$

yields:

$$\begin{array}{ccc} \text{Cu}(\mathcal{T}, \text{Trees}_{\text{mono}}) & \xrightarrow{(\mathfrak{T} \circ -)} & \text{Cu}(\mathcal{T}, \text{Grph}_{\text{mono}}) \\ & & \uparrow \mathcal{K} \\ \text{Pe}(\mathcal{T}, \text{Paths}_{\text{mono}}) & \xrightarrow{(\mathfrak{P} \circ -)} & \text{Pe}(\mathcal{T}, \text{Grph}_{\text{mono}}) \end{array}$$

Taking the pullback yields a category with pairs (T, P) as objects: a cumulative tree narrative T and a persistent path narrative P such that, when both are viewed as cumulative $\text{Grph}_{\text{mono}}$ -narratives, they give rise to the *same* narrative.

Conclusions⁴

- ▶ **Categories of temporal data:** We have introduced a data structure for temporal data, *categories of narratives*.
- ▶ **Object-agnosticism:** All kind of mathematical structures representing data can be encoded as narratives, provided they have limits or colimits.
- ▶ **Cumulative and Persistent Perspectives:** Formally related via an adjunction.
- ▶ **Systematic “Temporalization”:** Can lift static properties to temporal ones.
- ▶ **Sampling:** our framework of temporal opens the possibility of formally studying connections between temporal data and dynamical systems.

⁴Based on: *Towards a Unified Theory of Time-varying Data*. BM Bumpus, J Fairbanks, M Karvonen, W Leal, F Simard. arXiv:2402.00206