Graph-based Virtual Sensing from Sparse and Partial Multivariate Observations

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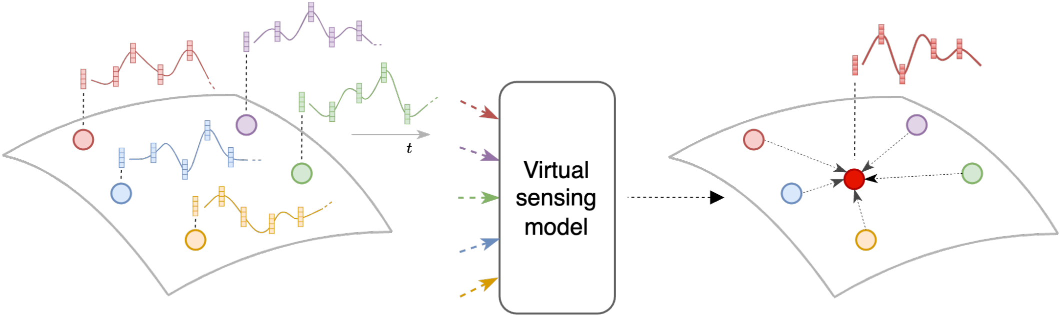
Virtual sensing



- Spatio-temporal data are a collection of time series coming from distinct spatial locations.
- Virtual sensing models allow for inferring signals at unmonitored locations by exploiting neighbouring spatio-temporal measurements.
- Applications: reduce physical sensors or recover faults.

Sparse setting

Our focus: settings with sparse sensor coverage.

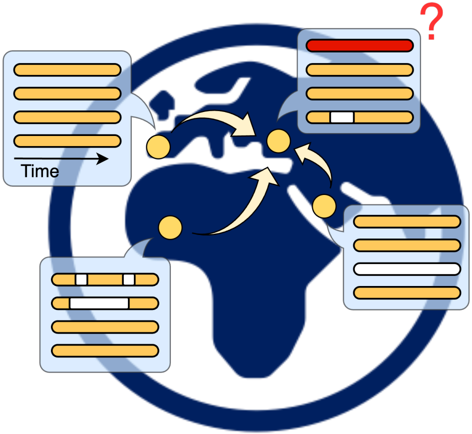
- Common due to cost or other (e.g. ecological) concerns.

But challenging:

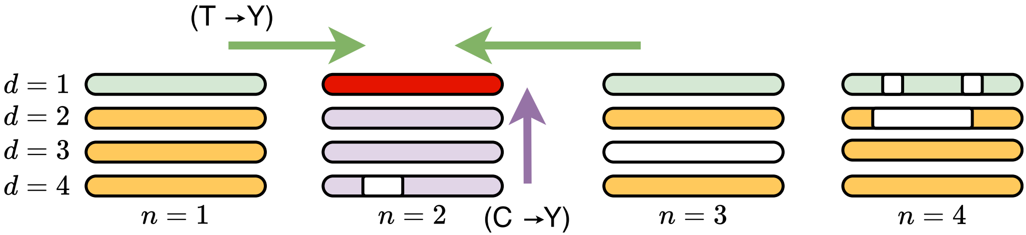
- Limited information from neighbours.
- Intractable if no additional information is available at the target location.

Multivariate virtual sensing

We study multivariate settings where other variables (covariates) provide partial observability at the target location.



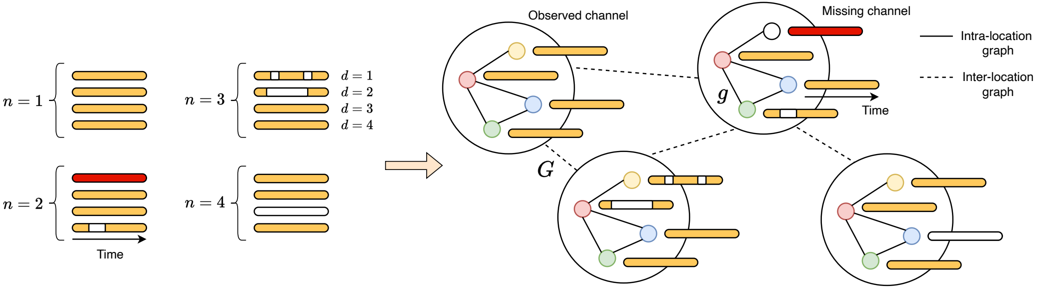
Methodology



- **T ! Y**: Relations between observed target channels at other locations and the target.
- **C ! Y**: Relations between observed covariate channels at the target location and the target.

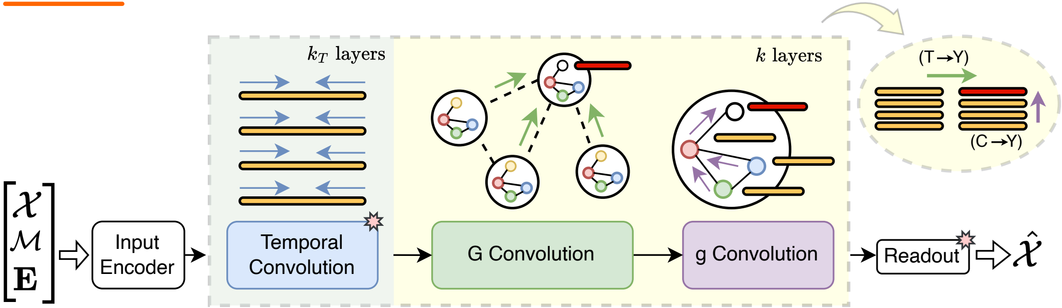
We model both types of relations as edges in a nested graph.

Nested graph representation



- Associate each location to a node of a graph G, (inter-location) modelling T ! Y relations.
- Associate each channel to a node of a graph g, (intra-location) modelling C ! Y relations.
- Both adjacency matrices can be learned from data!

Graph-graph Network



Encode inputs at all time stamps, use node embeddings for missing channels.

Propagate information across time, locations and channels utilizing convolutions over time, inter-location and intra-location graph

Decode representations to predictions at all time steps with D different MLPs.

Some empirical results

We perform extensive empirical evaluation:

- Explore different use cases.
- Demonstrate superior performance w.r.t. graph-based and time series imputation methods.

Climatic variables (MRE)

Ch.	Temp. mean	Temp. range	Wind speed	Rel. hum.	Clouds	Irr. short	Avg (D)	Avg (H)
BRITS	$4.0_{\pm 0.6}$	$17.5_{\pm 2.3}$	$32.1_{\pm 1.5}$	$5.5_{\pm 0.8}$	$29.9_{\pm 0.9}$	$20.9_{\pm 1.0}$	$20.5_{\pm 0.5}$	$26.3_{\pm 0.8}$
GRIN$_m$	$2.9_{\pm 0.9}$	$12.9_{\pm 1.3}$	$30.7_{\pm 3.9}$	$3.6_{\pm 0.9}$	$\underline{20.5}_{\pm 0.9}$	$\underline{11.7}_{\pm 0.6}$	$16.5_{\pm 0.6}$	$22.7_{\pm 0.4}$
SAITS	$\underline{2.4}_{\pm 0.4}$	$\underline{11.2}_{\pm 1.3}$	$\underline{26.9}_{\pm 1.0}$	$\underline{3.3}_{\pm 1.0}$	$20.6_{\pm 0.7}$	$14.2_{\pm 0.9}$	$\underline{15.5}_{\pm 0.5}$	$\underline{22.2}_{\pm 0.5}$
GgNet	$\mathbf{2.1}_{\pm 0.4}$	$\mathbf{9.6}_{\pm 0.7}$	$\mathbf{23.9}_{\pm 2.2}$	$\mathbf{2.7}_{\pm 0.7}$	$\mathbf{16.5}_{\pm 0.5}$	$\mathbf{9.2}_{\pm 0.8}$	$\mathbf{13.4}_{\pm 0.2}$	$\mathbf{20.4}_{\pm 0.6}$
% Imp.	12.5%	14.3%	11.1%	18.1%	19.9%	21.4%	13.5%	8.1%

- and much more... !

Summary of contributions

- Tackle a new problem: virtual sensing in sparse settings.
- Introduce a general methodology for performing multivariate virtual sensing.
- Propose a graph representation and an architecture allowing for modeling dependencies within multivariate spatio-temporal data with general level of sparsity.
- Carry out an extensive empirical evaluation.