This Wheel's on Fibre: using fibre-optic sensing for traffic monitoring

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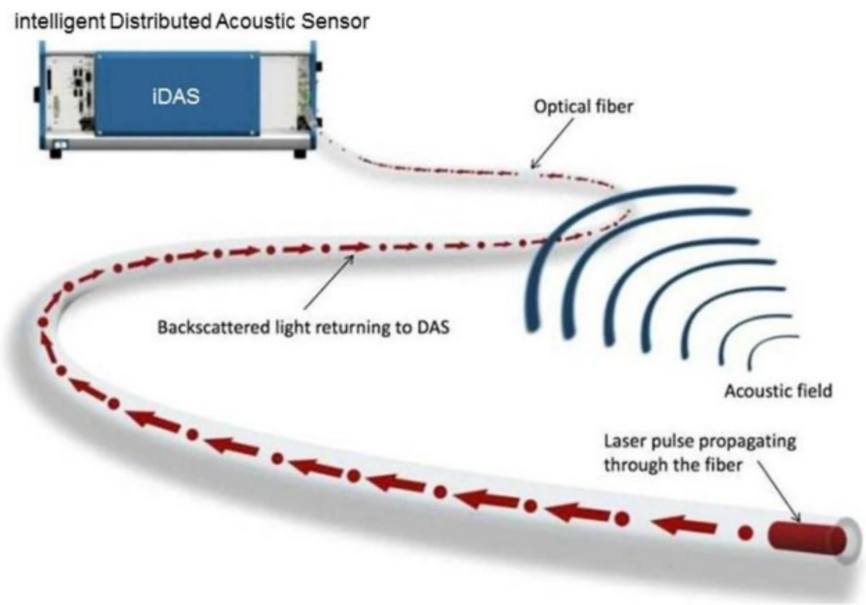
Distributed Acoustic Sensing (DAS)

As a subcategory of fibre-optic sensing, Distributed Acoustic Sensing measures stretching of the fibre over distances of tens of km.

Independent measurements every few metres!



Many applications

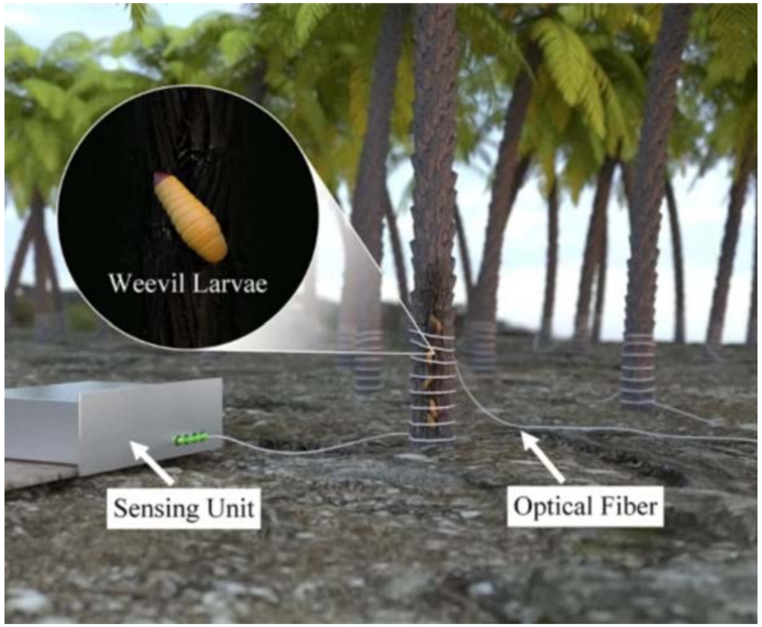
- Fluid flows (water, air)
- Swaying and resonance of high-rise structures
- Earthquakes, landslides, rock falls, avalanches
- Cars, trains, pedestrians, boats
- Whales, weevils



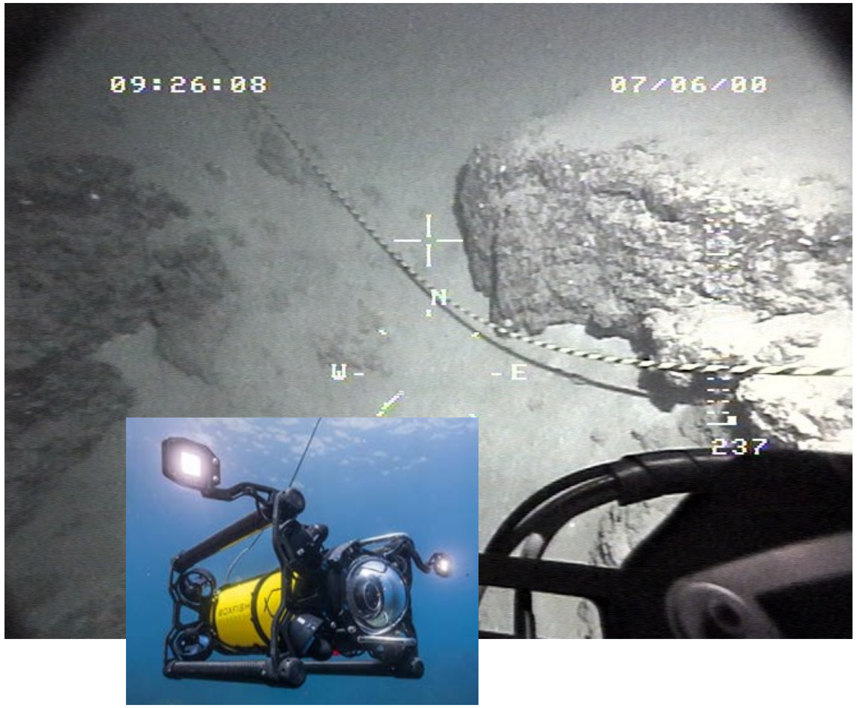

Diverse deployment scenarios

Glaciers
Walter et al. (2020)

Trees
Ashry et al. (2020)

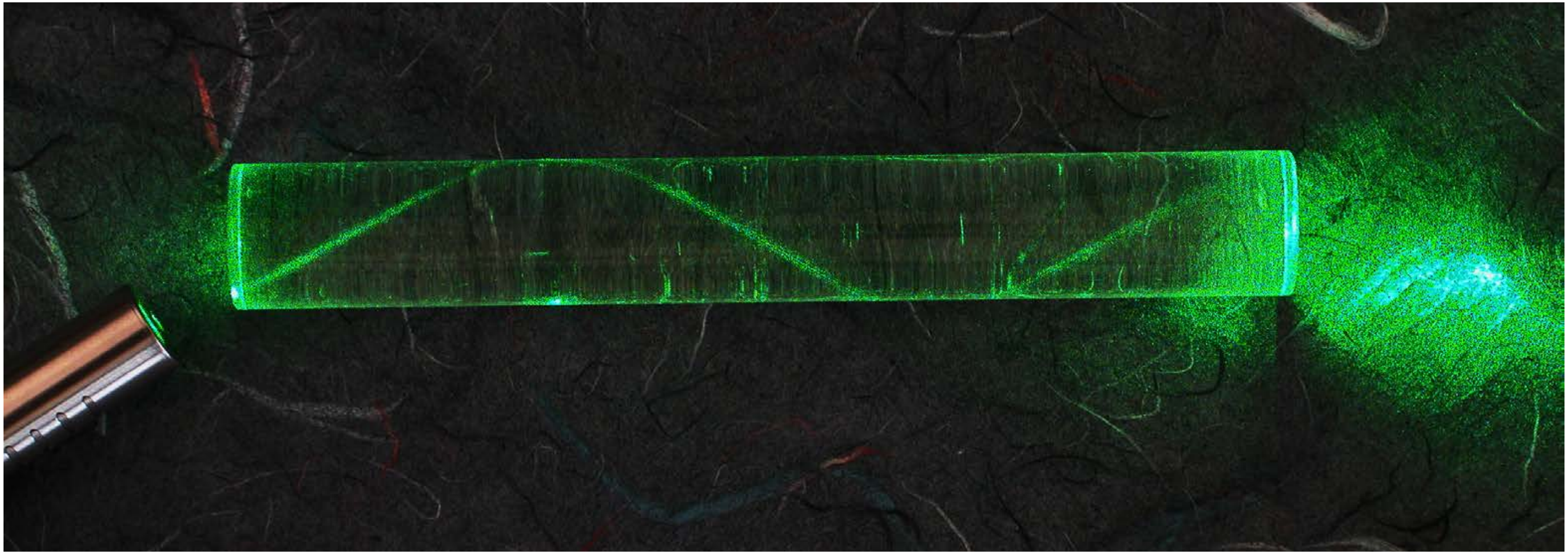


Offshore
Géoazur team

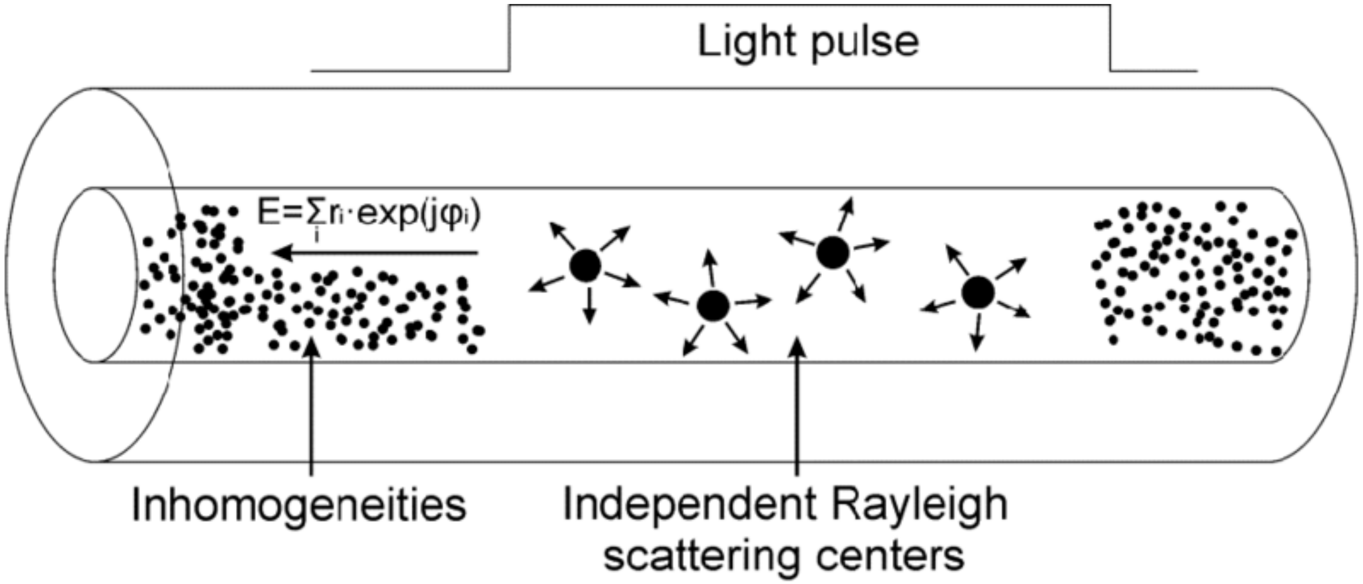


Diverse deployment scenarios

How it works

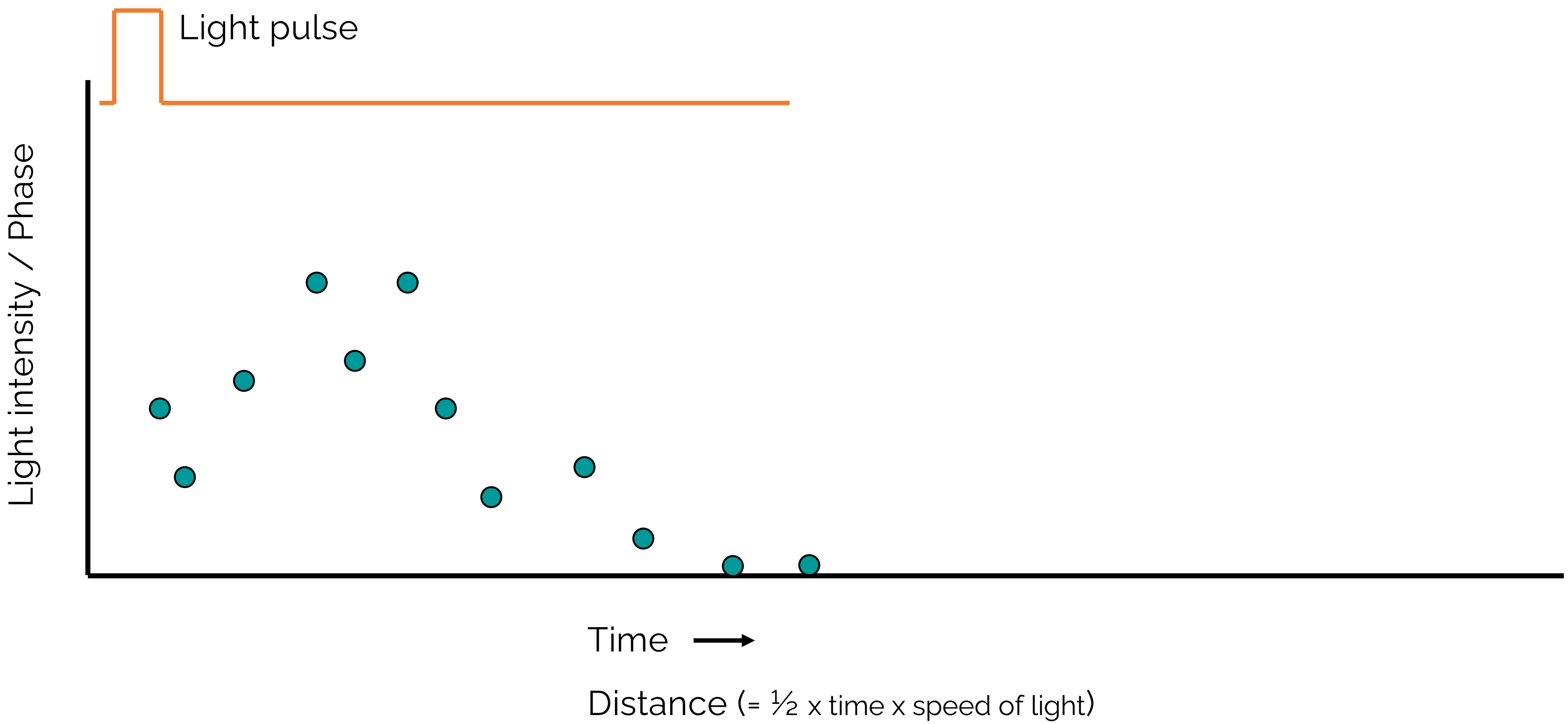


How it works



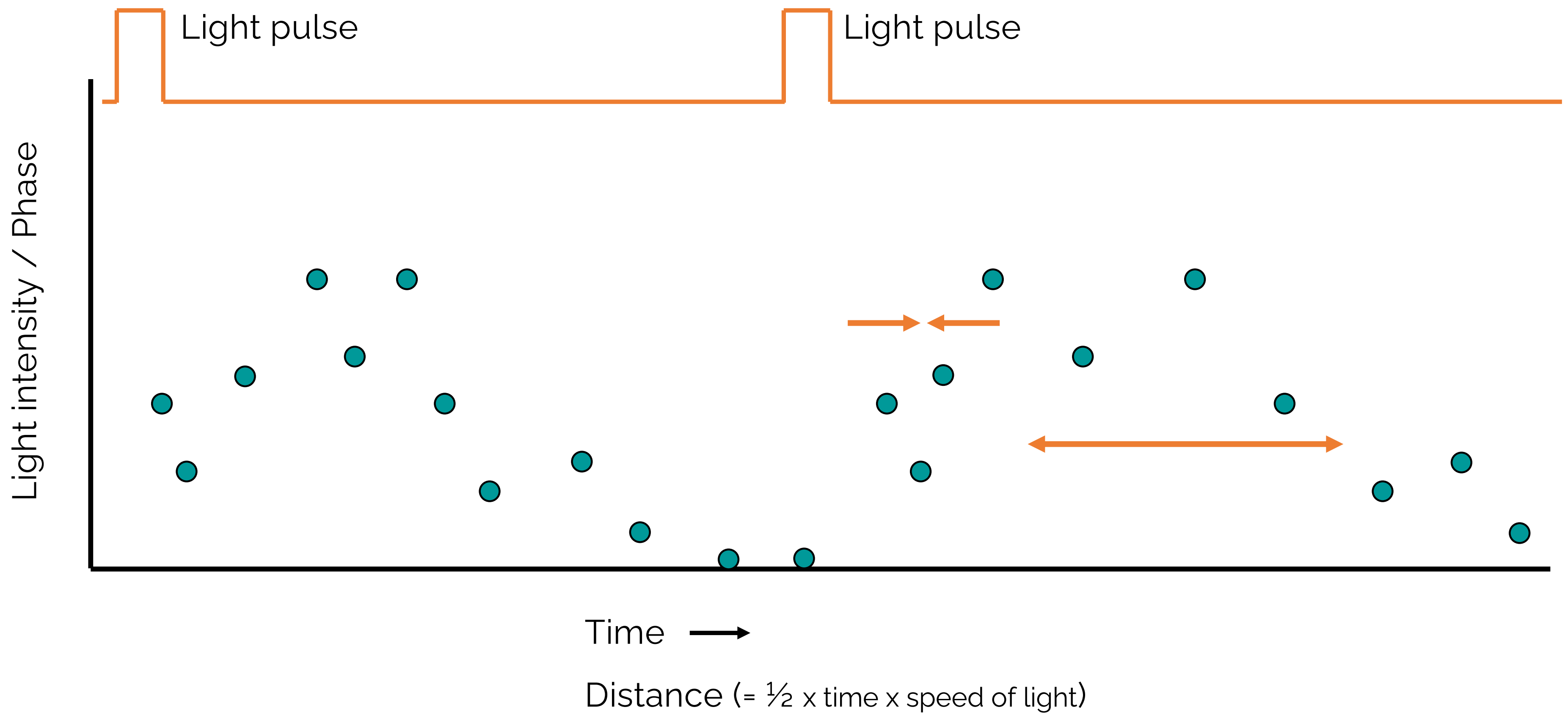
Pniov et al. (2015)

How it works



Light pulse
Light intensity / Phase
Time
Distance (= ½ x time x speed of light)

How it works


Light pulse
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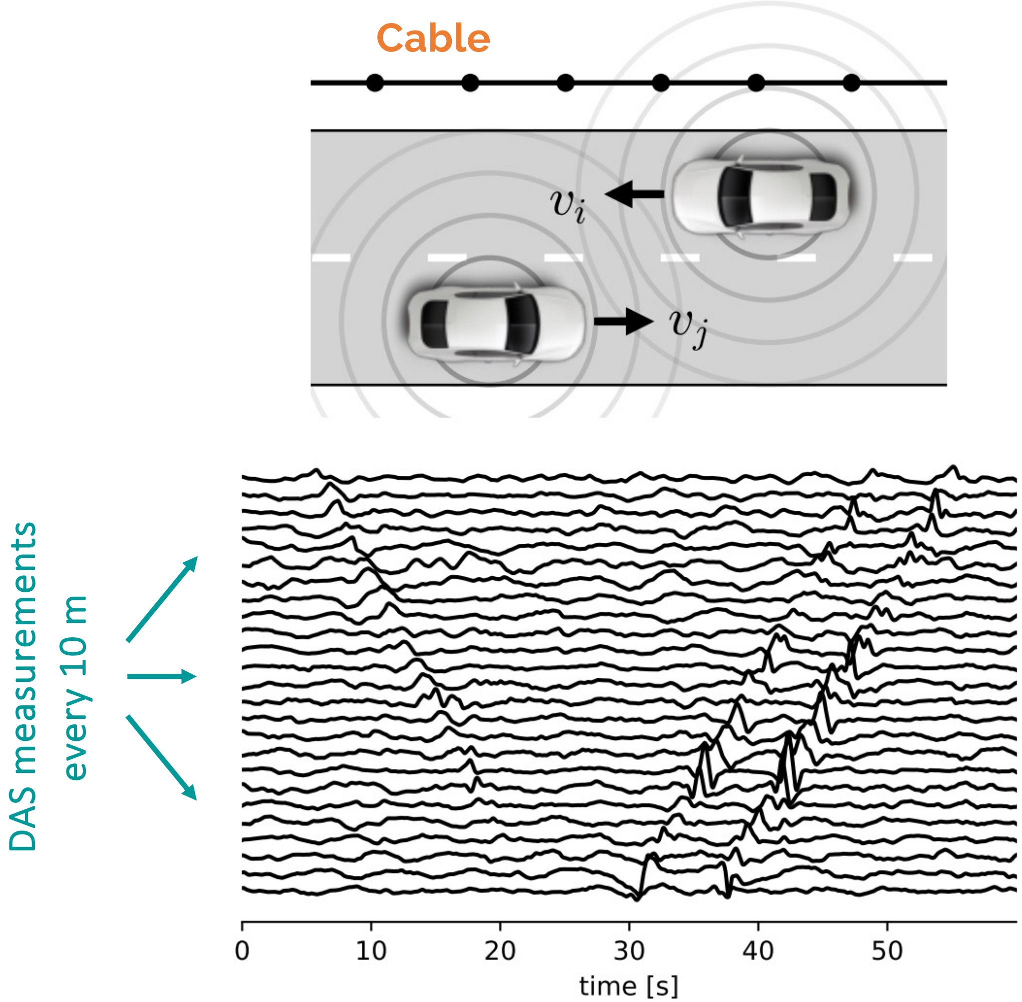
How it works

Roadside DAS

- Commercial telecom fibre deployed alongside streets in Nice, France
- Independent measurements every 10m
- DAS system records deformation induced by cars



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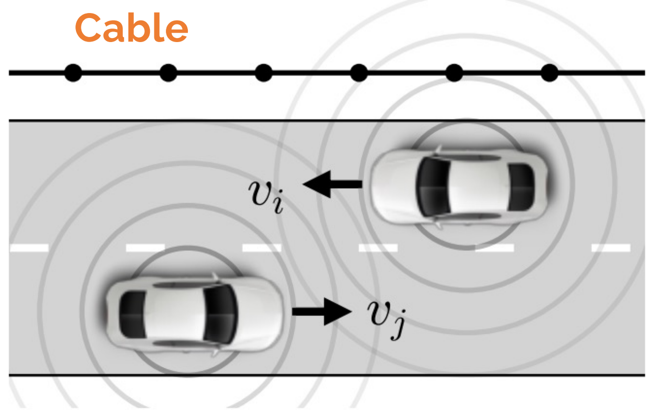
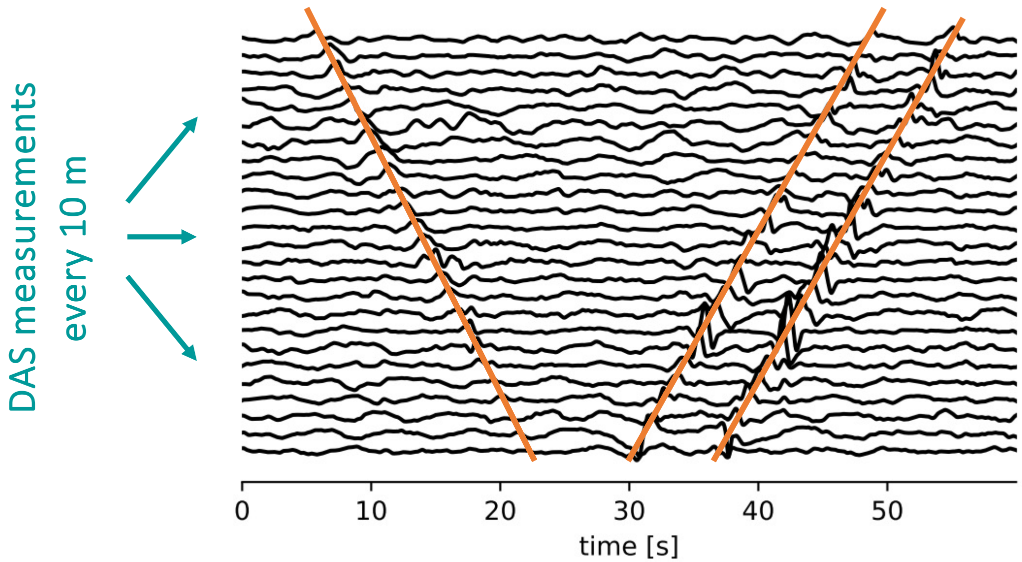




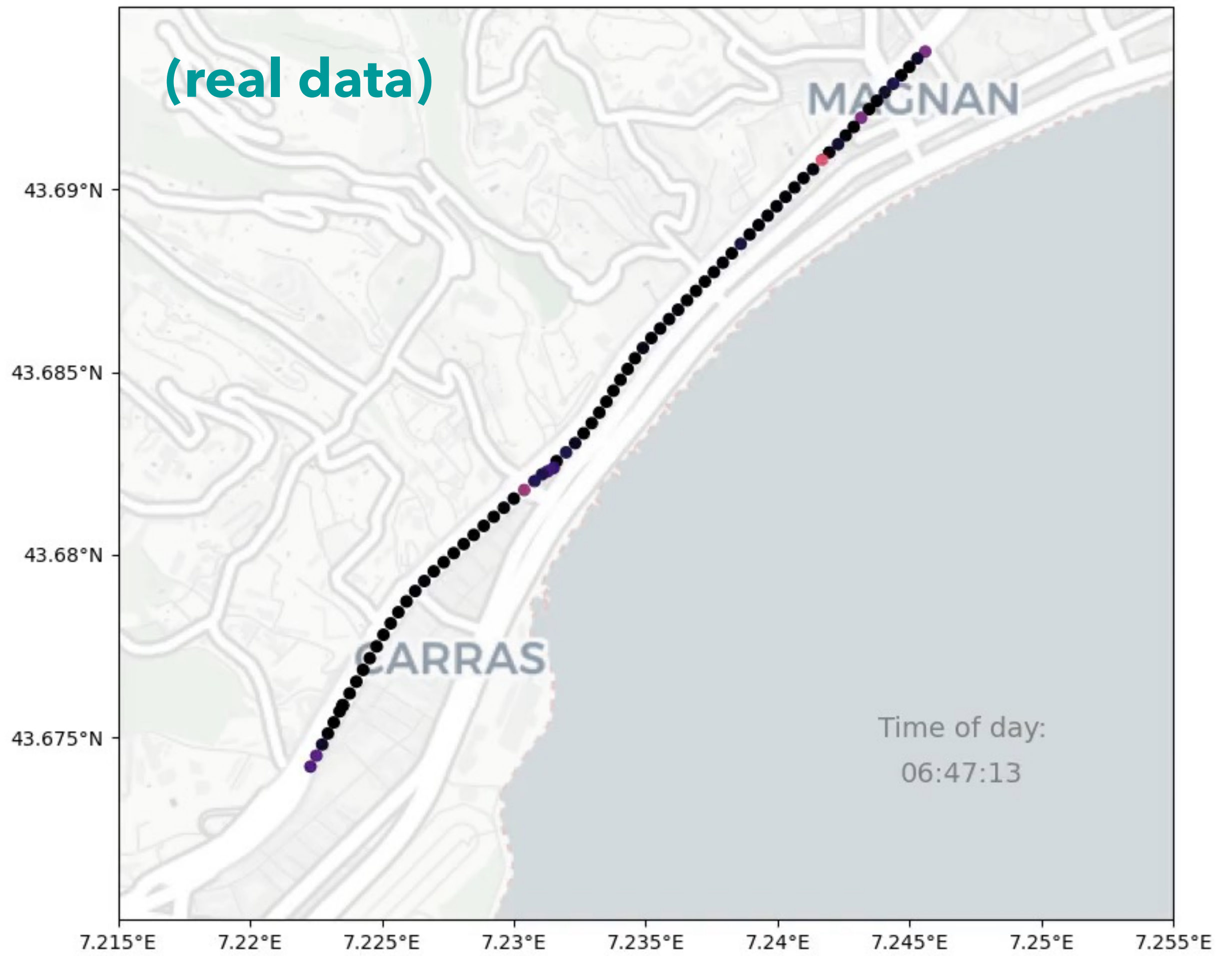
Pilot experiment

Metropole Nice Côte d'Azur

Individual vehicle tracking

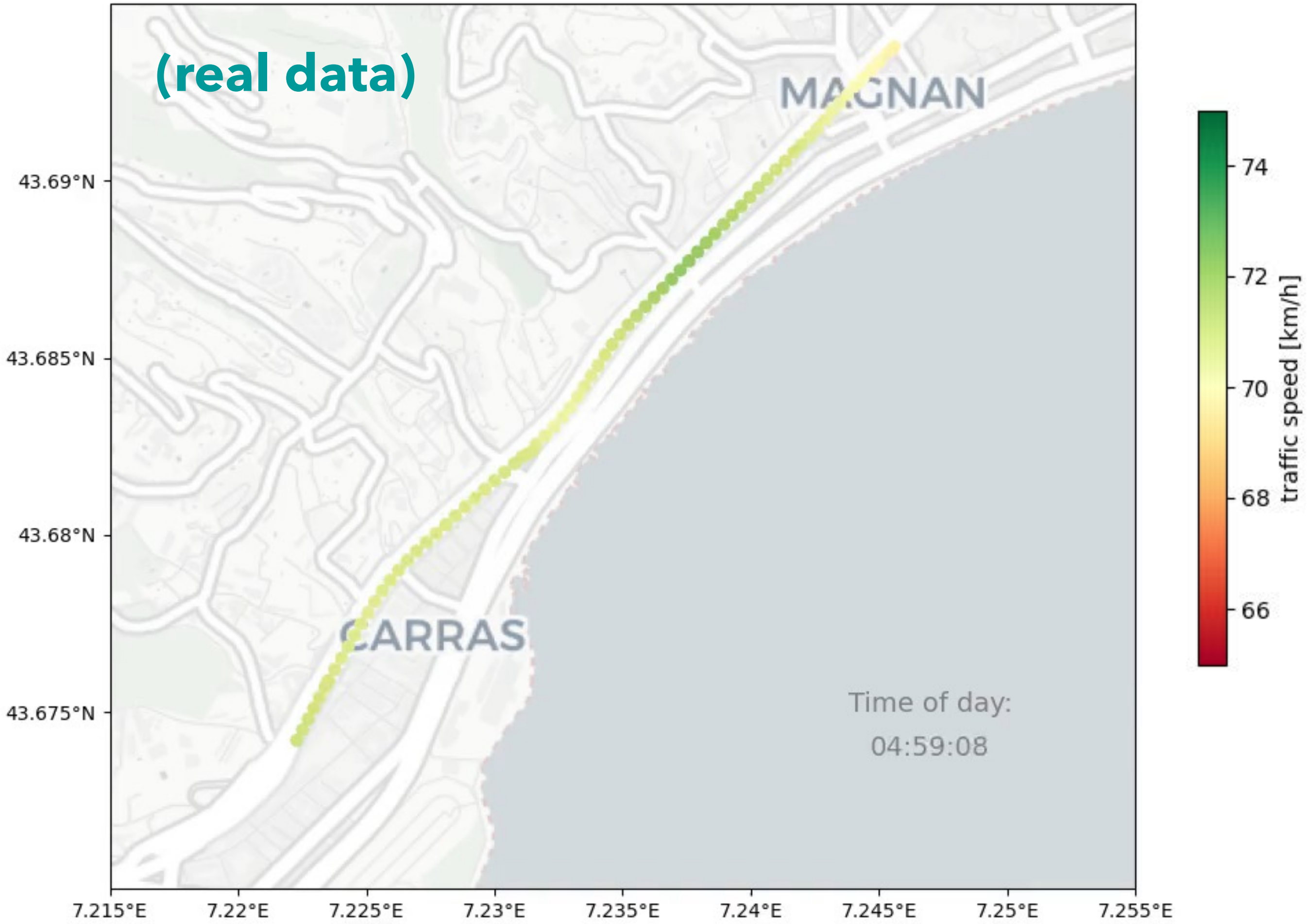
With self-supervised Machine Learning methods, we can track individual vehicles over long distances

(100% anonymous)

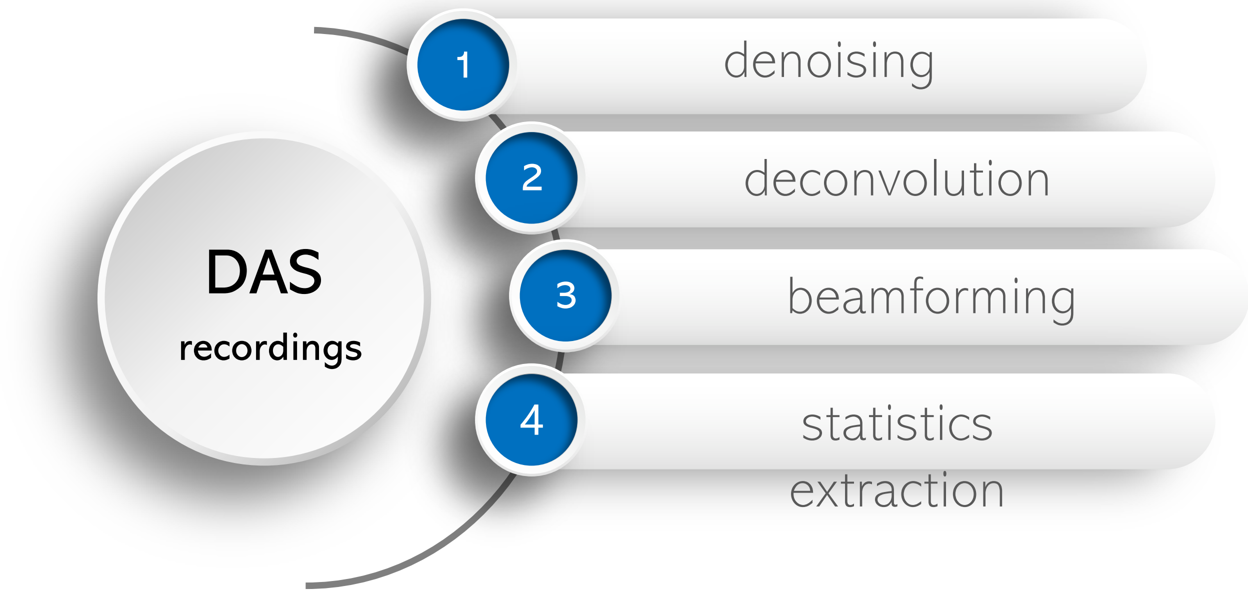


Macroscopic traffic statistics

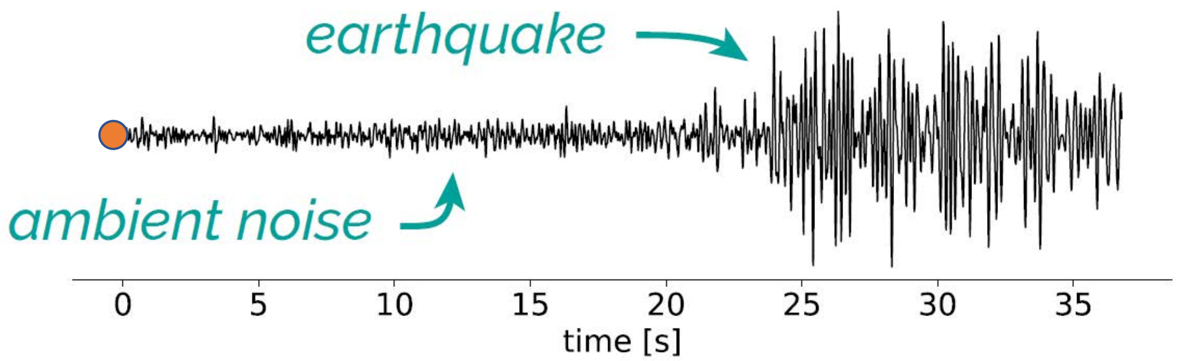
Using advanced array processing techniques, we obtain macroscopic traffic statistics, like the average traffic speed and number of vehicles



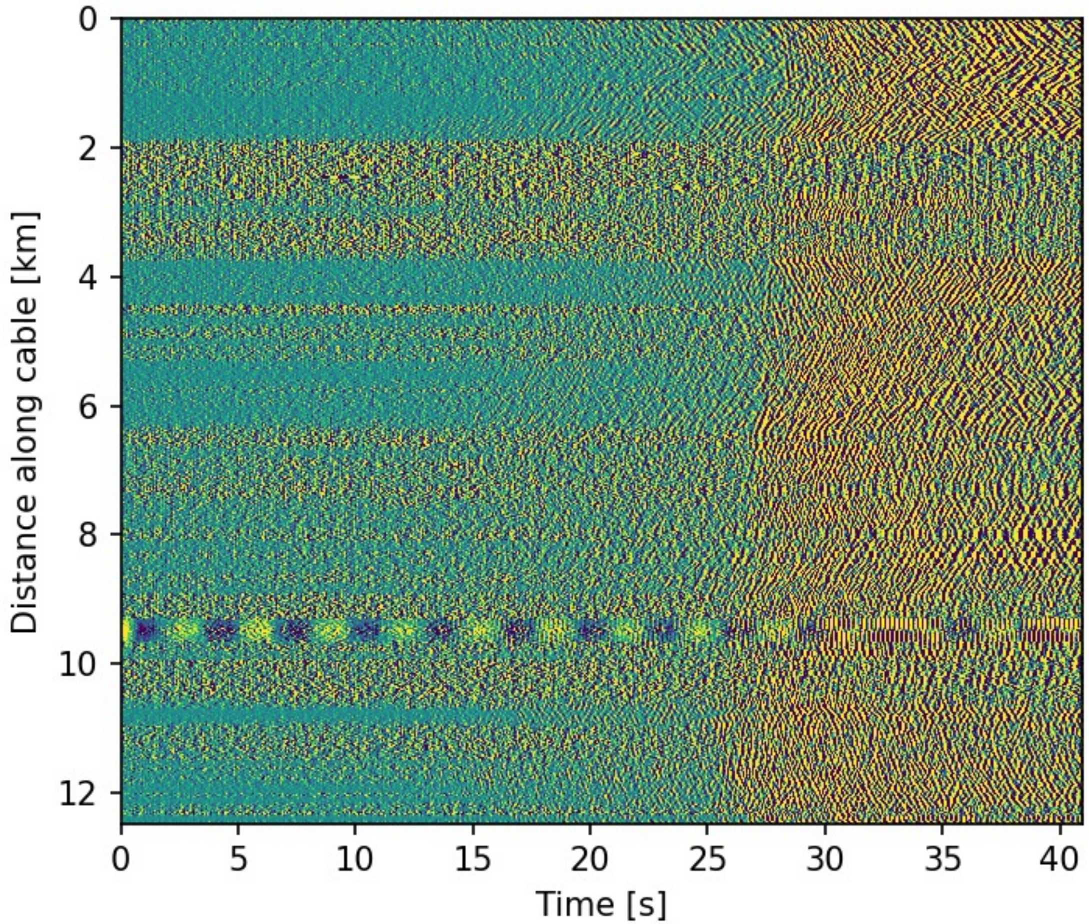
Key actions


DAS
recordings
1
denoising
2
deconvolution
3
beamforming
4
statistics
extraction

DAS earthquake monitoring

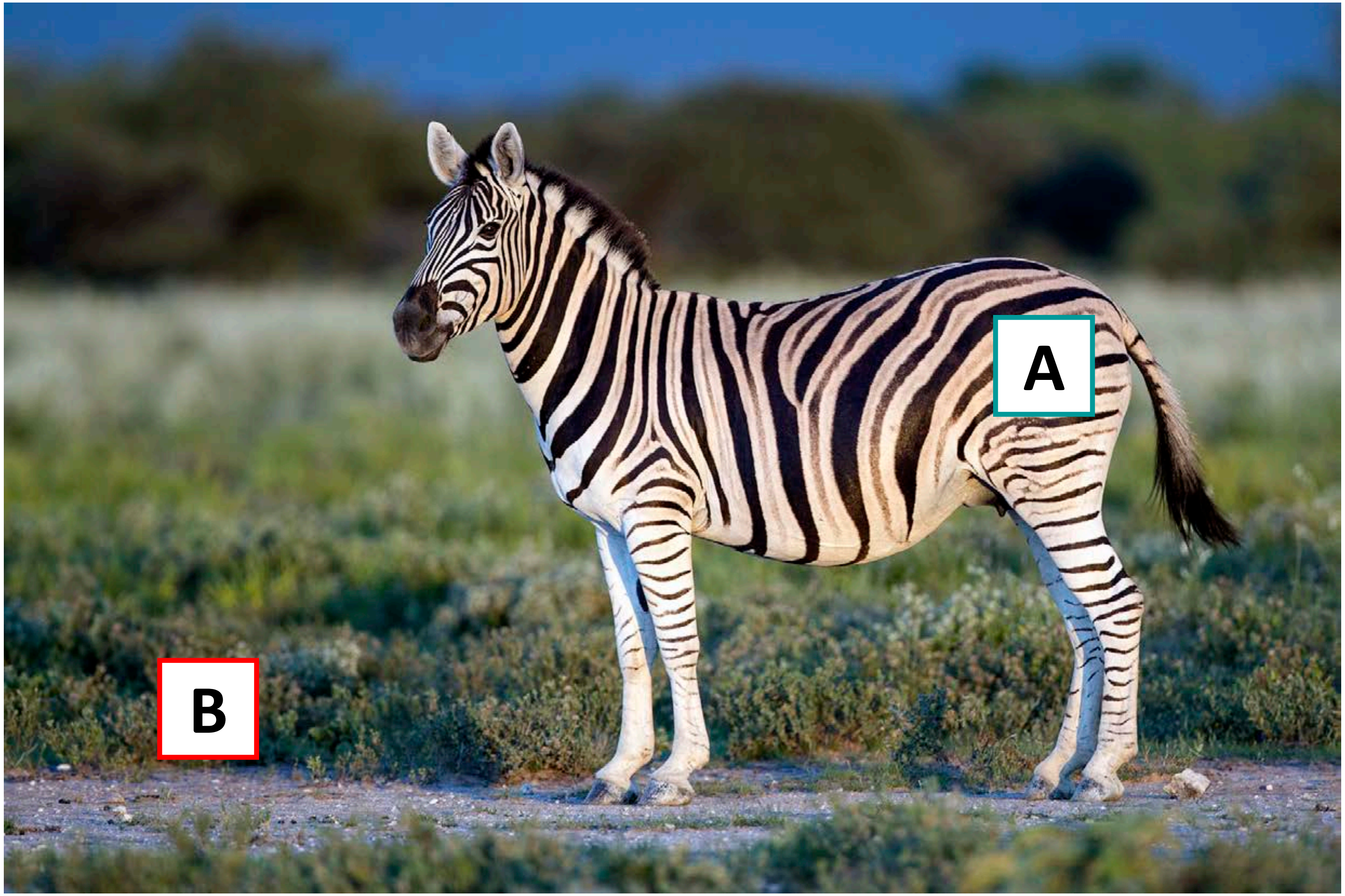


DAS earthquake recordings



Leveraging spatiotemporal coherence

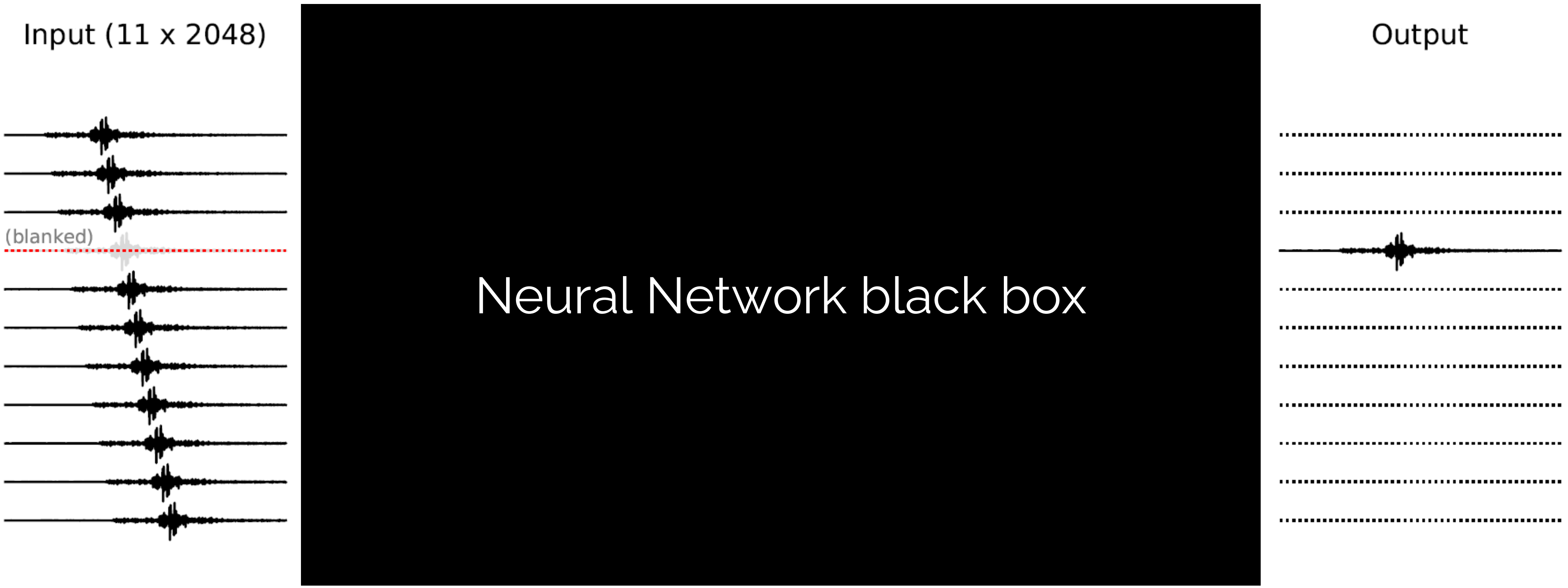
- Traditional seismic data: frequency-based filtering
- Does not work when noise freq. band = signal freq. band
- DAS data has 2D structure: time & space
- Leverage spatiotemporal patterns in denoising efforts with J-invariance
- J-invariant filtering: separate J-invariant signals (earthquakes, ocean waves, …) from J-variant noise (local vibrations, thermal noise, …)


A
B

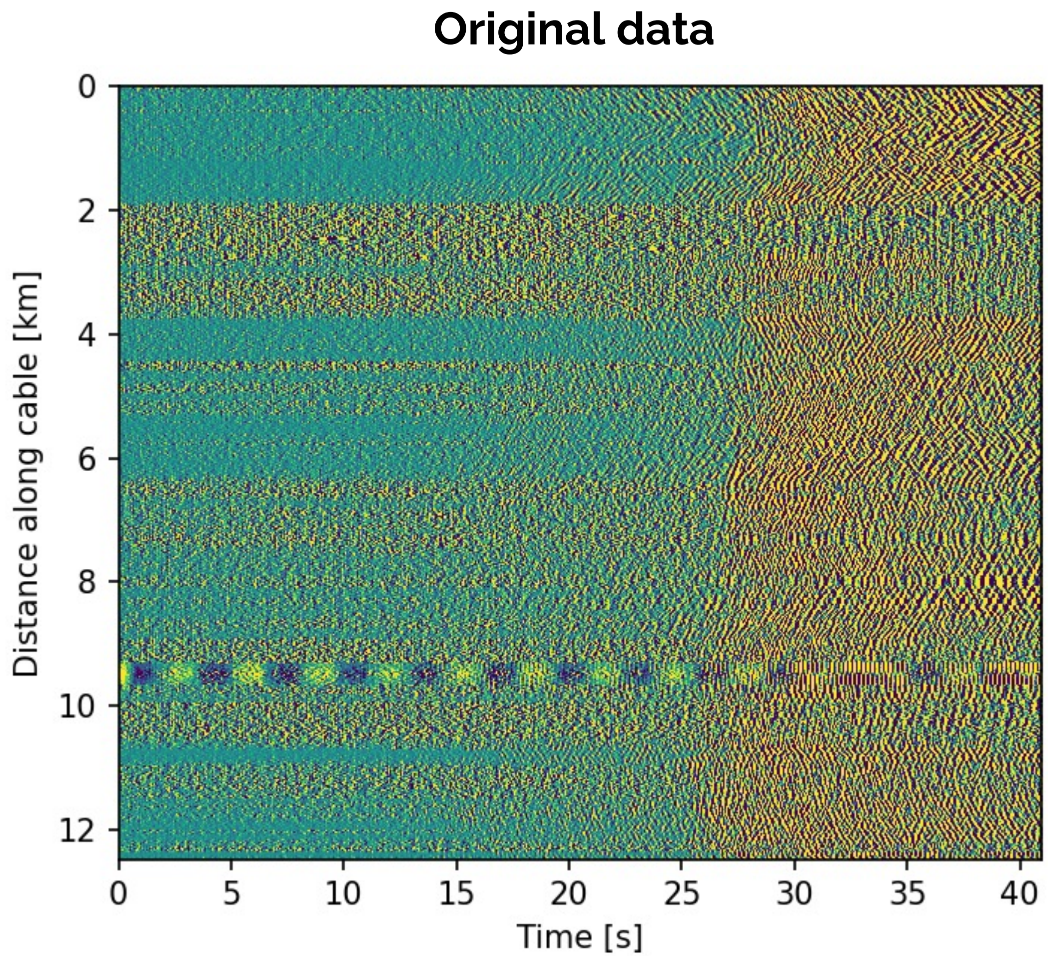
J-invariance (Batson & Royer, ICML 2019)

- Suppose we have an input z, for which we can define a partition J
- A J-invariant function $g(z)_J$ is one for which the output does not depend on z_J for all z and partitions J
- Zebra example: input z is the picture of the zebra, J is a patch of pixels, and $g(z)_J$ is the prediction of the contents of J
- J-invariant filtering: separate J-invariant signals (earthquakes, ocean waves, …) from J-variant noise (local vibrations, thermal noise, …)

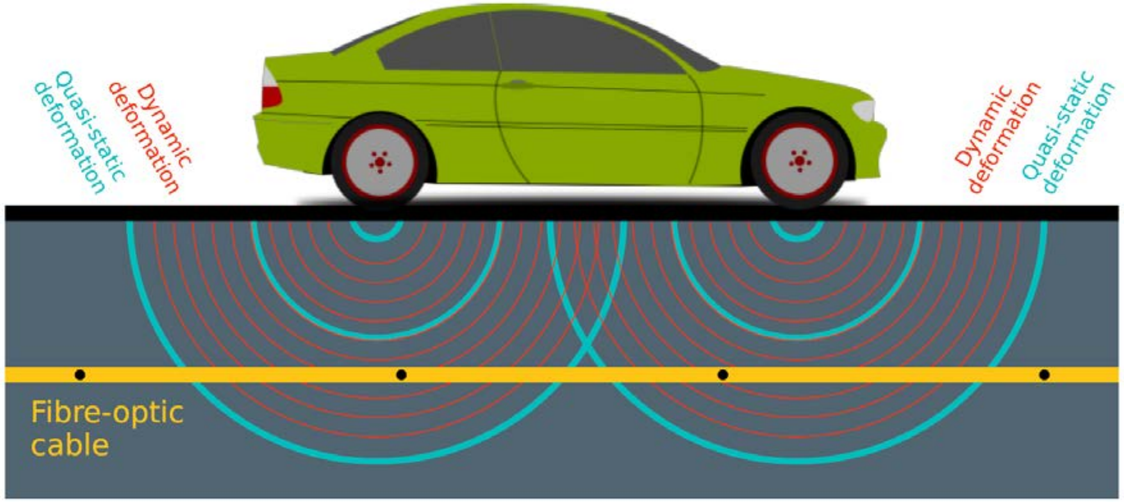
J-invariant denoising



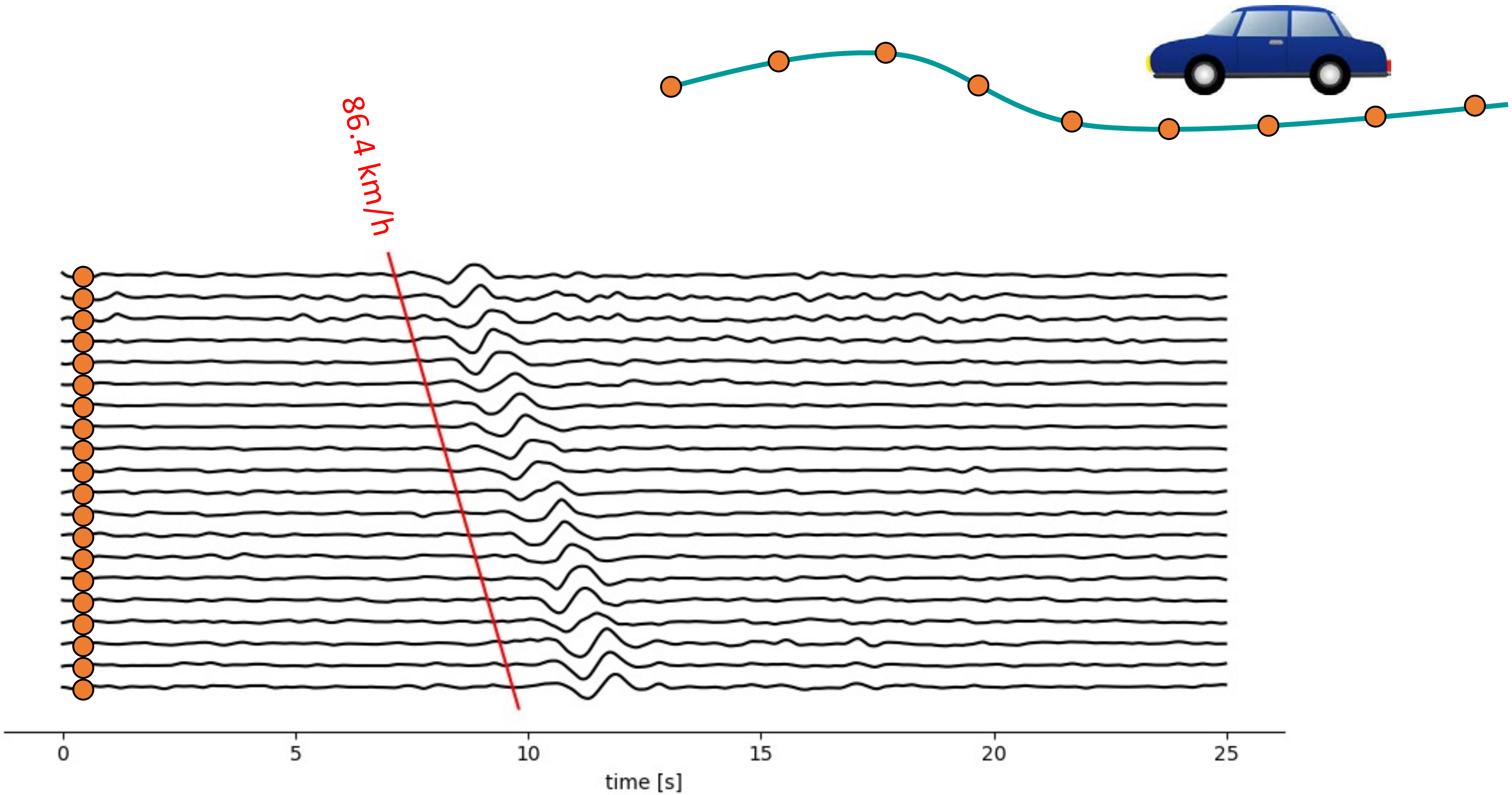
J-invariant denoising (results)



Switching gears…

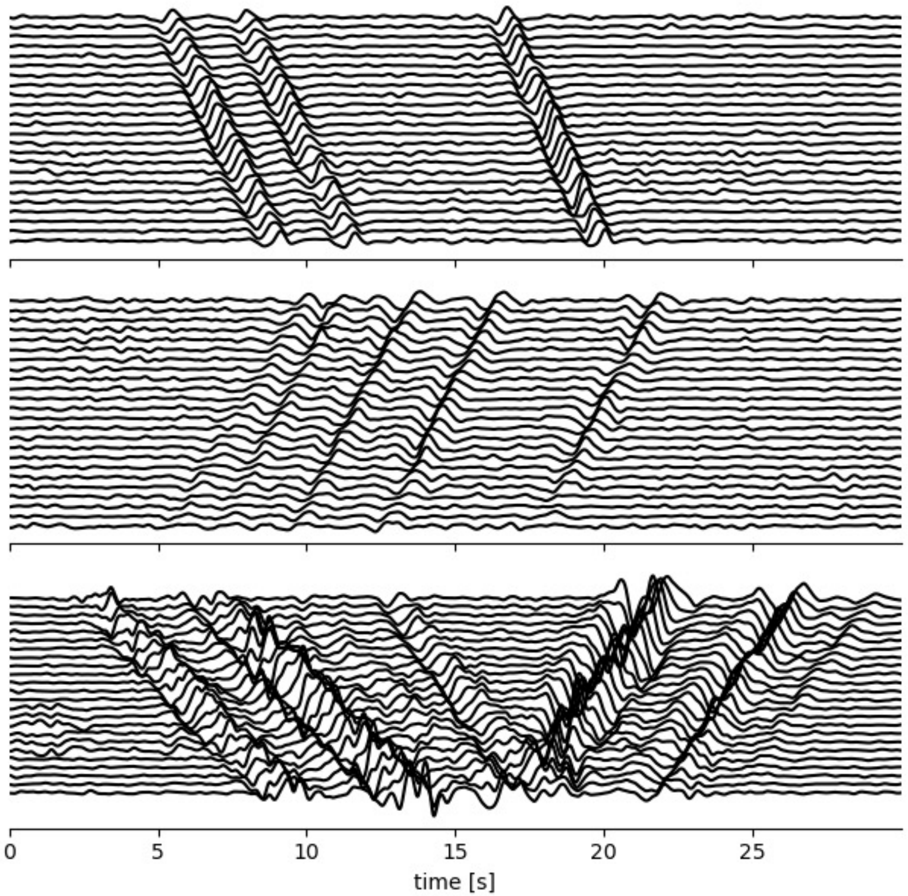


Signatures of cars



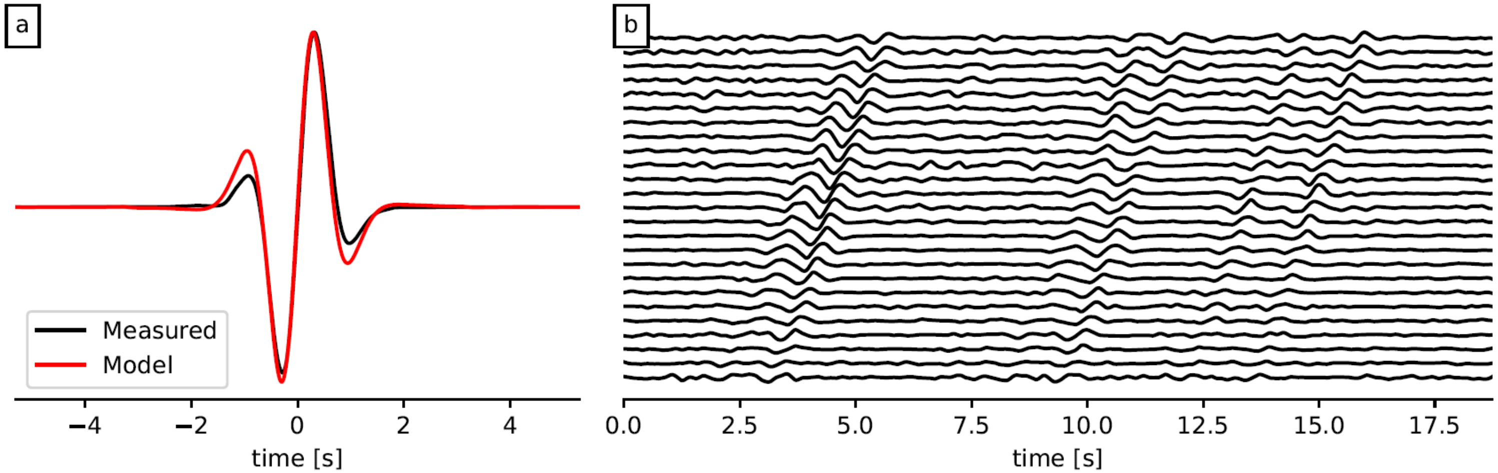
Challenge of detection

- Spatial footprint of a car is ~75 m
- Overlap in signals when cars are trailing within 2-3 seconds
- Challenge for vehicle counting and velocity estimation

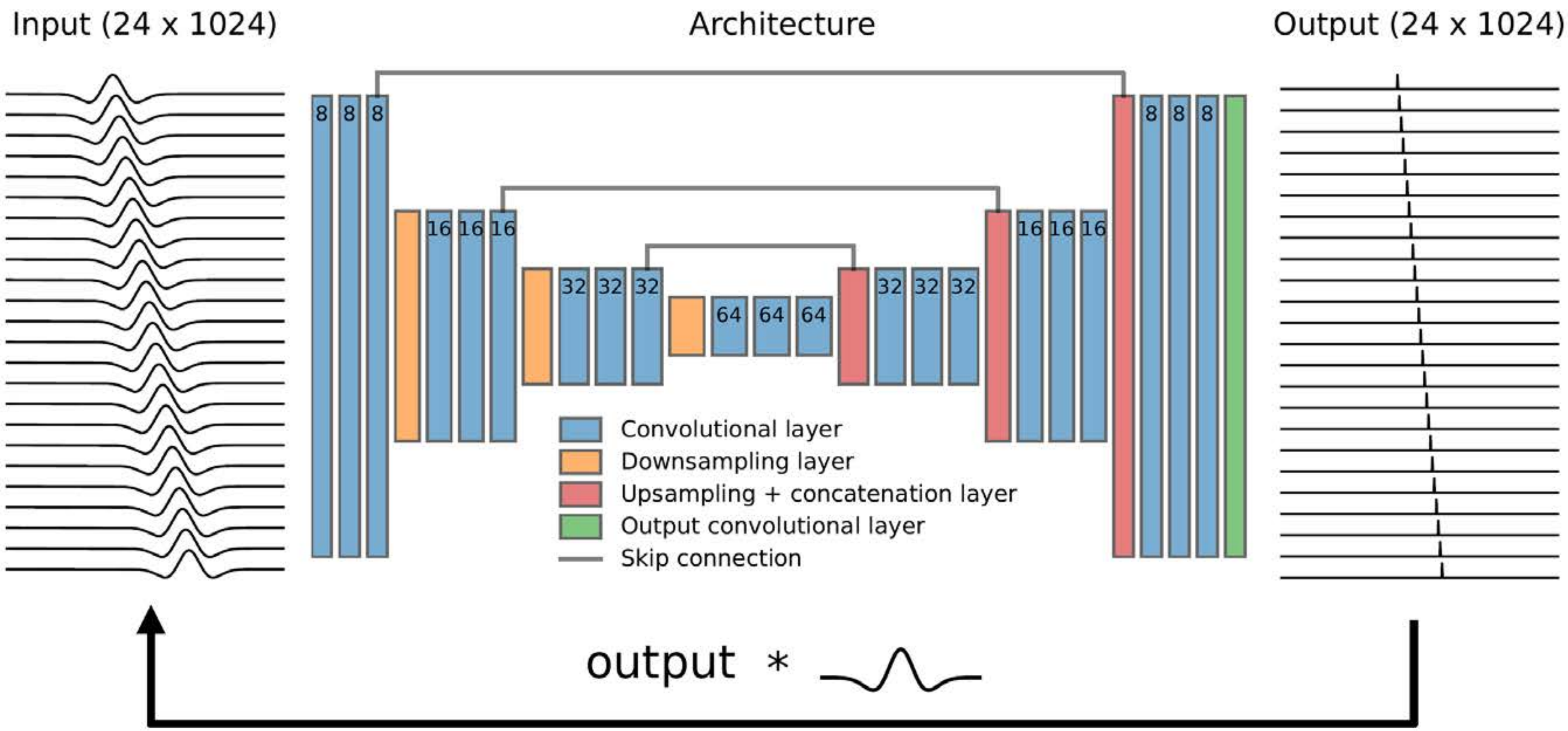


Exploiting similarity

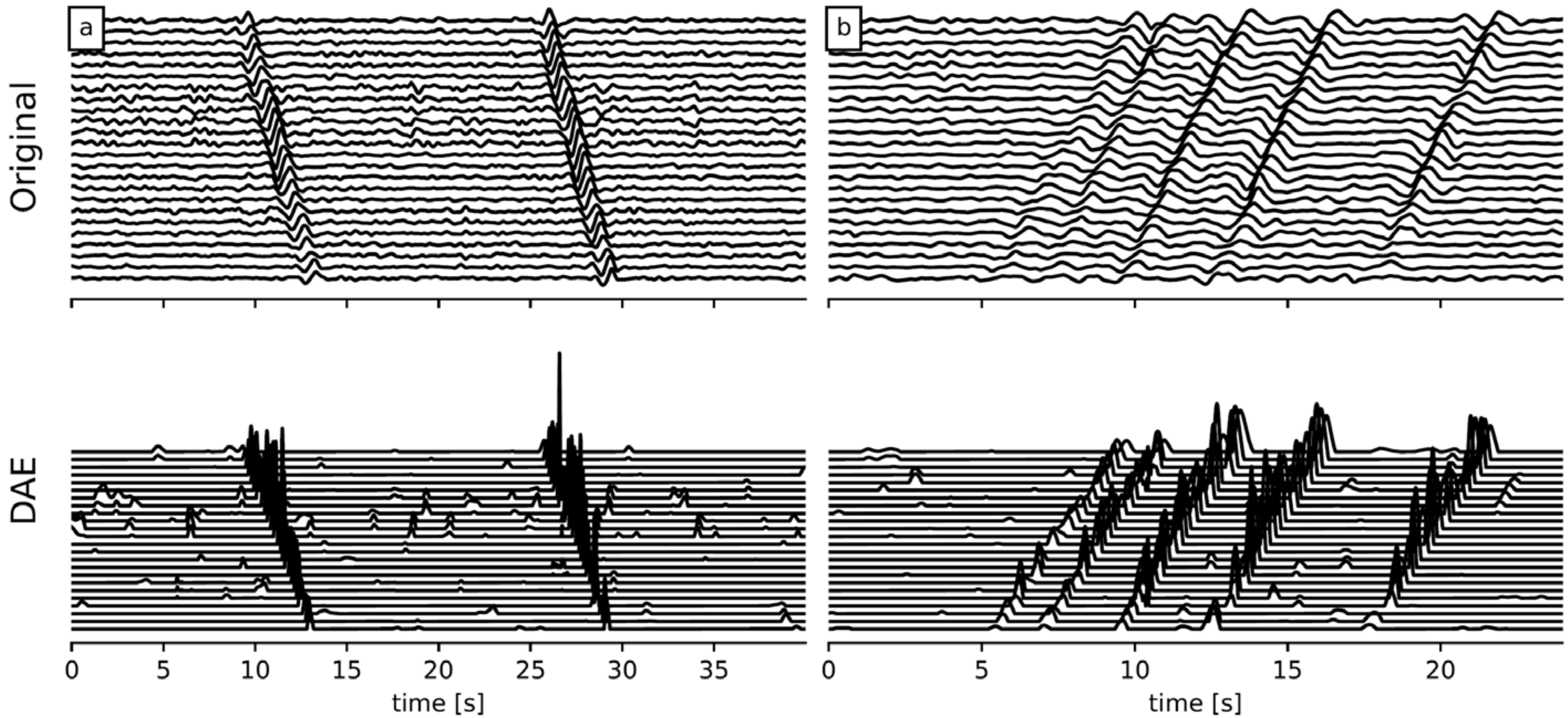
- Characteristic signature of a car recorded at a given location is the same for each car (up to a proportionality constant)
- Make measurements of cars more "compact" by deconvolving this characteristic signature from the DAS data



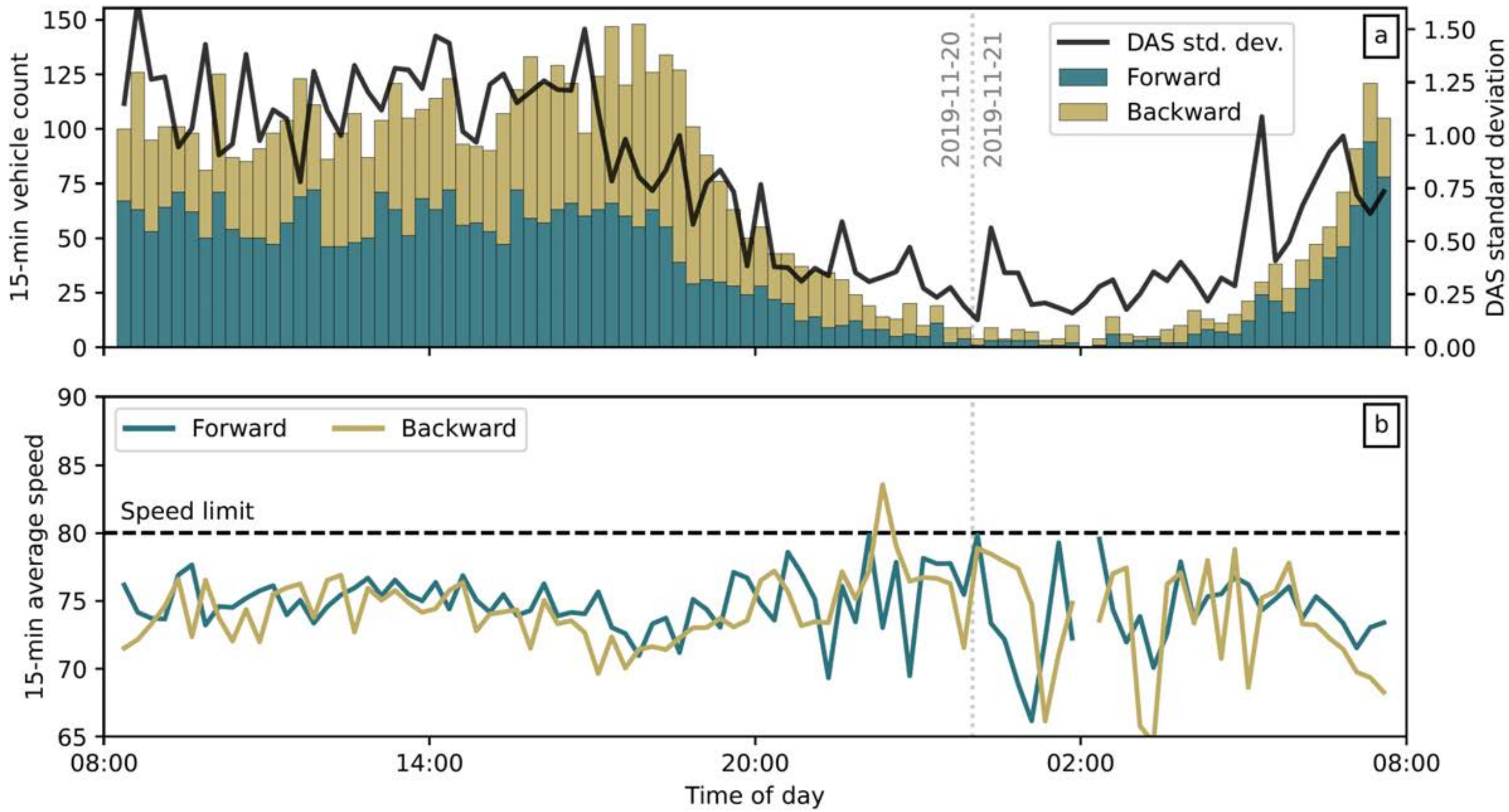
Deconvolution Auto-Encoder (DAE)



Deconvolution results



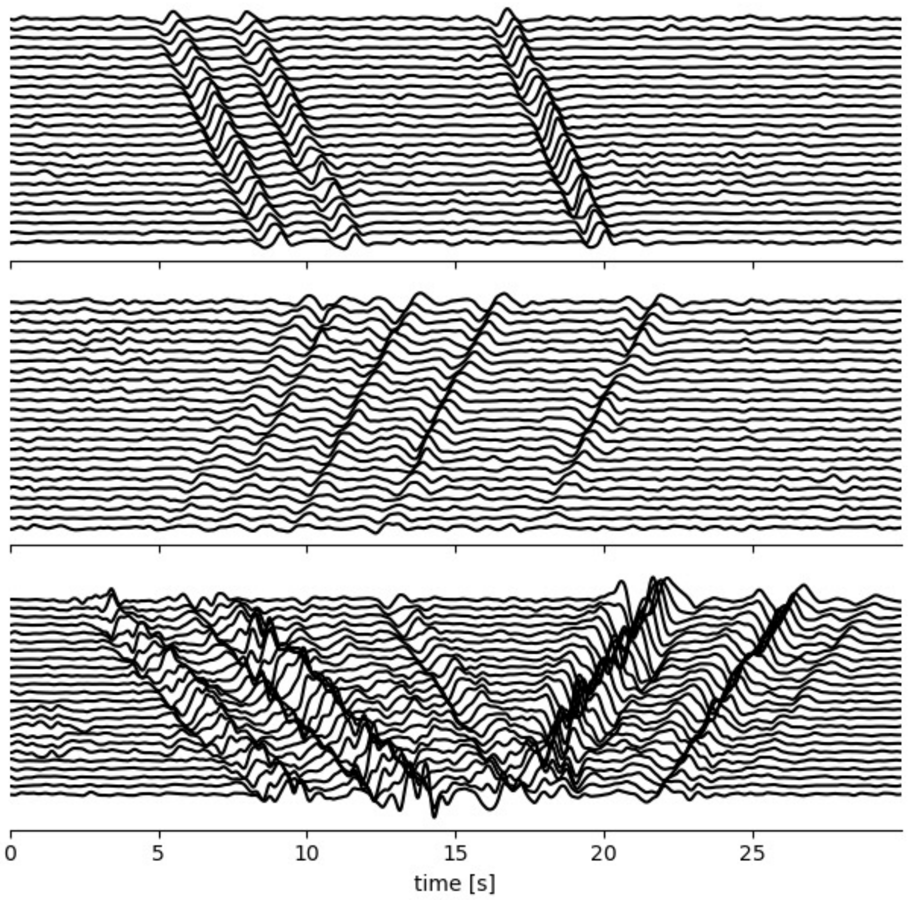
Traffic analysis



Traffic analysis

DAS beamforming (Model #1)

- Cars are identified as coherent waveforms propagating at a constant speed
- DAS is an array of sensors: ideally suited for beamforming analysis



DAS beamforming (Model #1)

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Model #1

Define a DAS measurement of a car with **velocity v** at **sensor q** (separated by **distance d**) and time instant n as:

$$y_q(n) = s\left(n - q\frac{d}{v}\right) + n_q(n)$$

The Discrete Fourier Transform of this measurement is:

$$Y_q(k) = S(k)\exp\left(\frac{-j2\pi k}{N}\frac{qd}{v}\right) + V_q(k)$$

DAS beamforming (Model #1)

- Cars are identified as coherent waveforms propagating at a constant speed
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Model #1

Define steering vector:

$$\boldsymbol{e}_k(v) = \left[1, \exp\left(\frac{-j2\pi k}{N}\frac{d}{v}\right), \exp\left(\frac{-j2\pi k}{N}\frac{2d}{v}\right), \dots\right]^{\mathrm{T}}$$

Define signal vector:

$$\boldsymbol{y}_q(k) = \left[Y_q(k), Y_{q+1}(k), \dots\right]^{\mathrm{T}} = S(k)\boldsymbol{e}_k(v) + \boldsymbol{n}(k)$$

Covariance matrix:

$$\boldsymbol{C}(k) = \mathrm{E}_q\left[\boldsymbol{y}_q(k)\boldsymbol{y}_q^{\dagger}(k)\right]$$

DAS beamforming (Model #2)

- DAS is uniformly sampled in time and in space
- Instead of performing the DFT and beamforming in time, we take the DFT in space

Model #2

Define a DAS measurement of a car with **velocity v** at sensor q (separated by **distance d**) and **time instant n** as:

$$y_n(q) = r\left(q - n\frac{v}{d}\right) + n_n(q)$$

The Discrete Fourier Transform of this measurement is:

$$Y_n(k) = R(k)\exp\left(\frac{-j2\pi k}{M}\frac{nv}{d}\right) + V_n(k)$$

Given a wavenumber k and time window L, define a temporal sliding vector:

$$\boldsymbol{y}_n(k) = [Y_n(k), \dots, Y_{n+L-1}(k)]^{\mathrm{T}}$$

DAS beamforming (Model #2)

- DAS is uniformly sampled in time and in space
- Instead of performing the DFT and beamforming in time, we take the DFT in space

Model #2

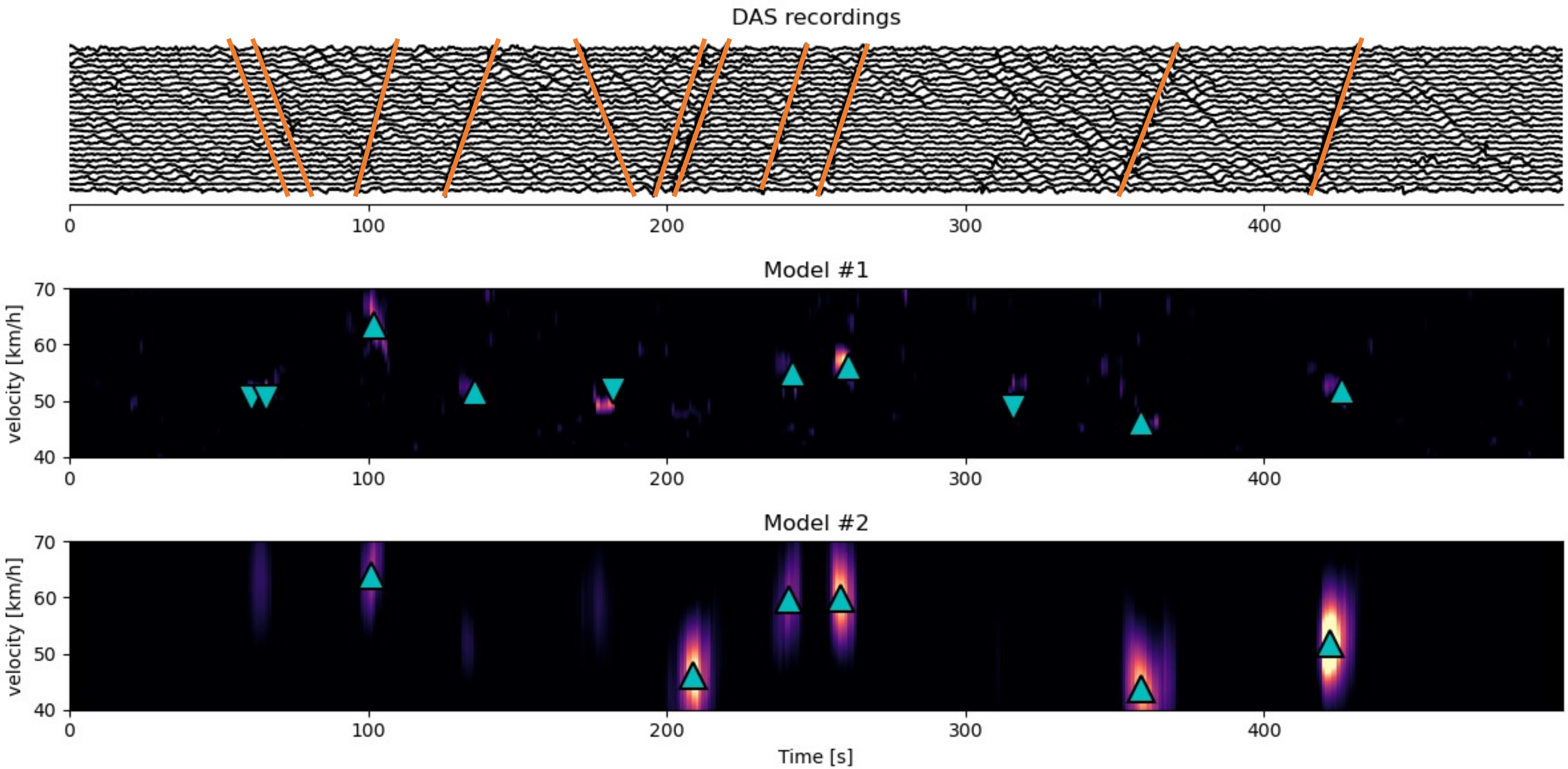
Define steering vector:

$$\boldsymbol{e}_k(v) = \left[1, \exp\left(\frac{-j2\pi k}{M}\frac{v}{d}\right), \exp\left(\frac{-j2\pi k}{M}\frac{2v}{d}\right), \dots\right]^{\mathrm{T}}$$

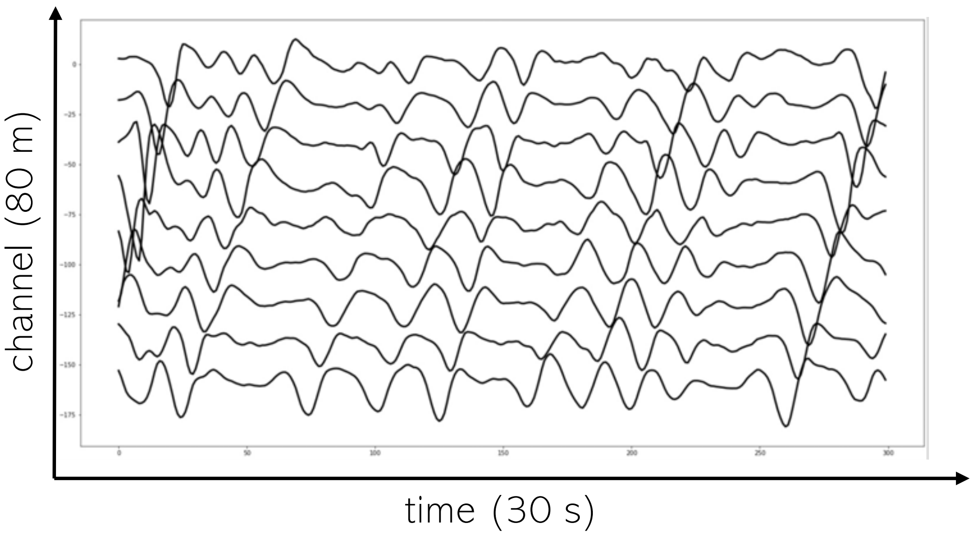
Covariance matrix:

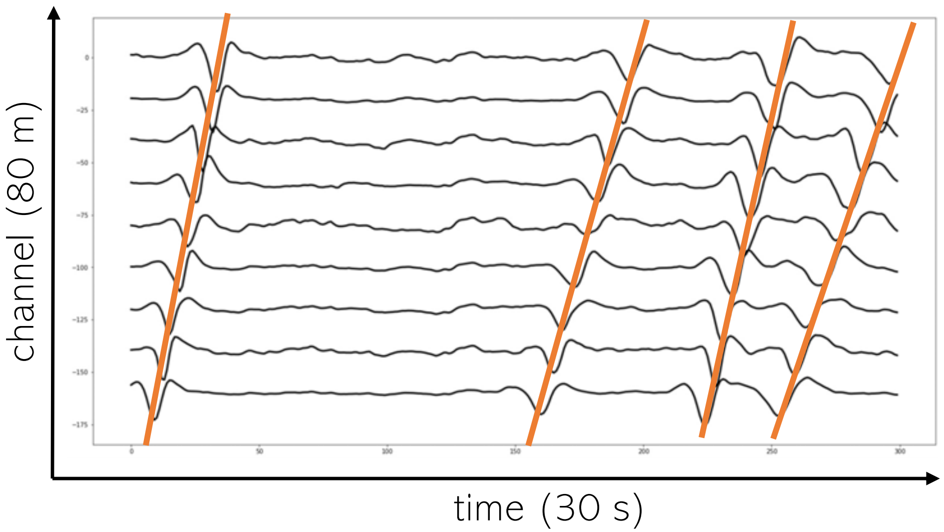
$$\boldsymbol{C}(k) = E_n\left[\boldsymbol{y}_n(k)\boldsymbol{y}_n^{\dagger}(k)\right]$$

Beamforming detection

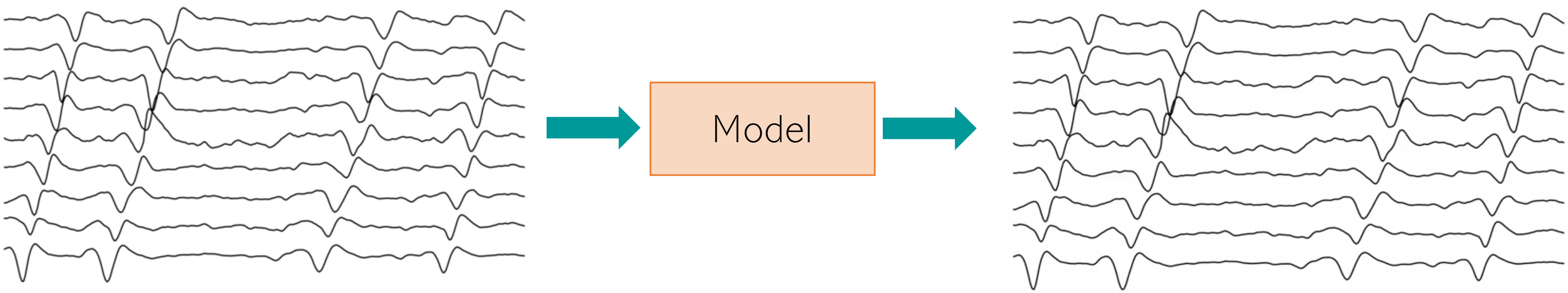


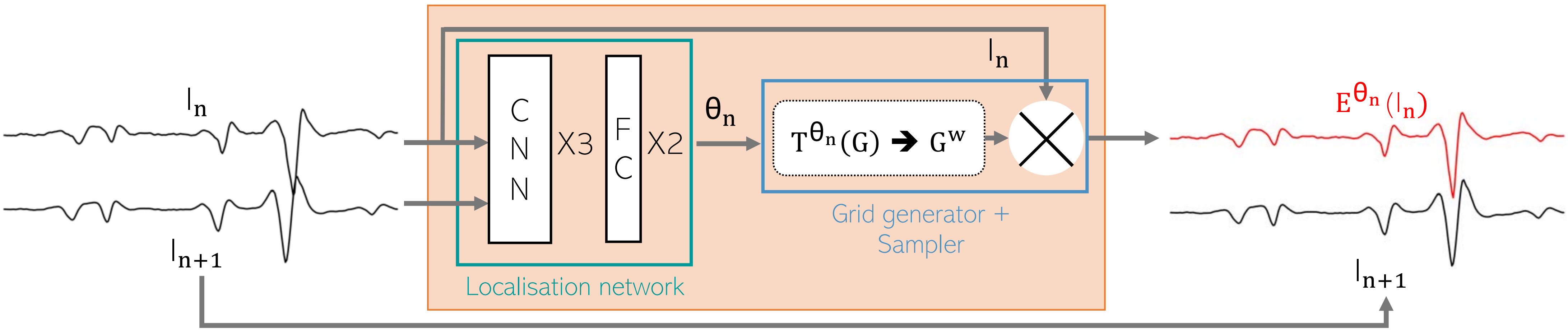
DAS traffic monitoring





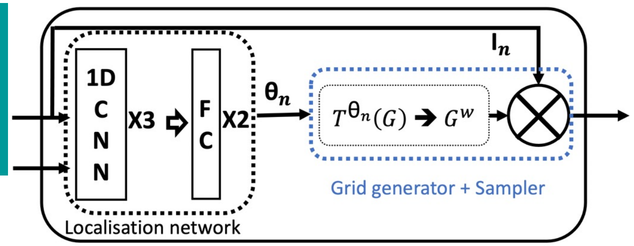
Model architecture



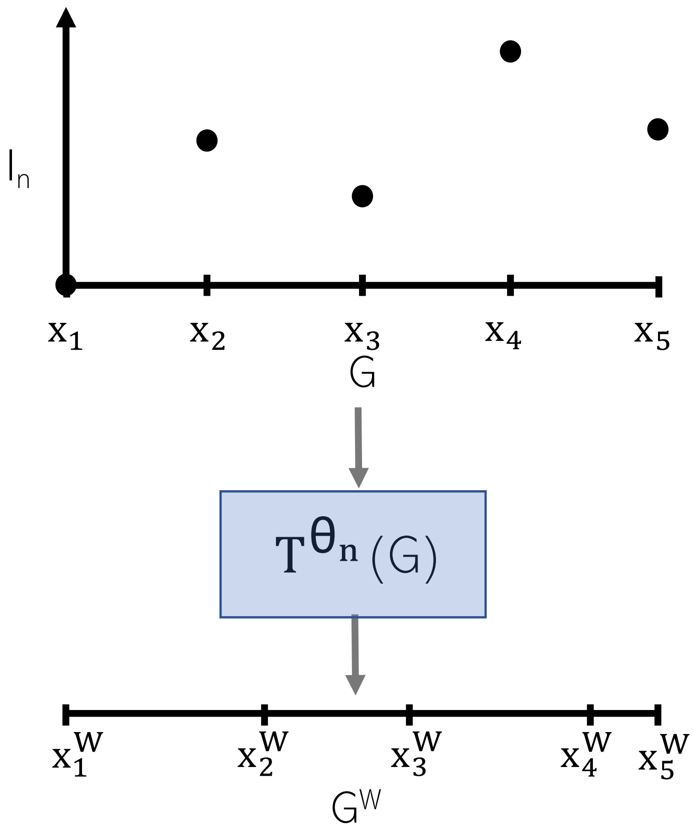


[1] Shapira Weber, Ron A., et al. "Diffeomorphic temporal alignment nets." Advances in Neural Information Processing Systems 32 (2019).

Model architecture

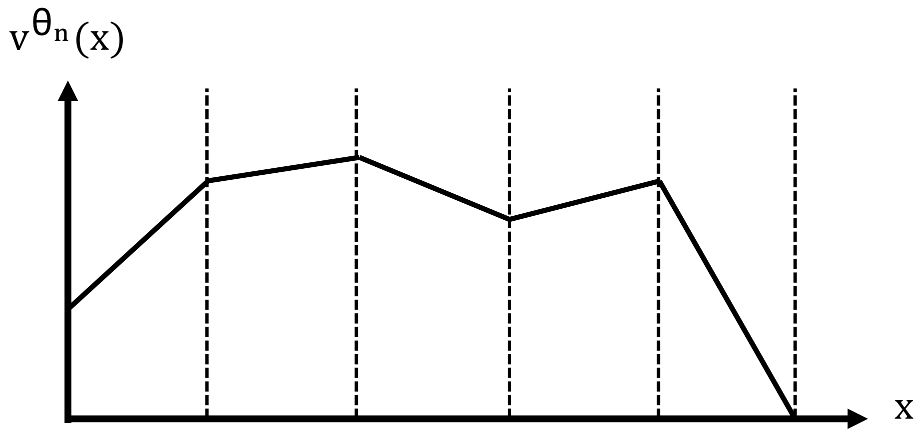


Grid generator (toy example)



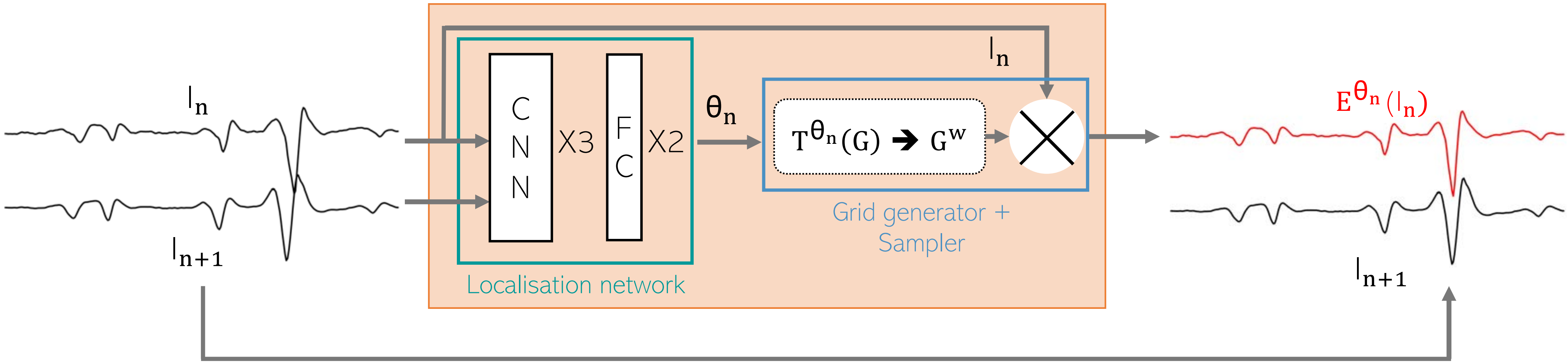
T^{θ_n} is a Continuous Piecewise-Affine Based (CPAB) transformation

$$T^{\theta_n}(x) = x + \int_0^1 v^{\theta_n}\left(\phi^{\theta_n}(x, \tau)\right) d\tau$$



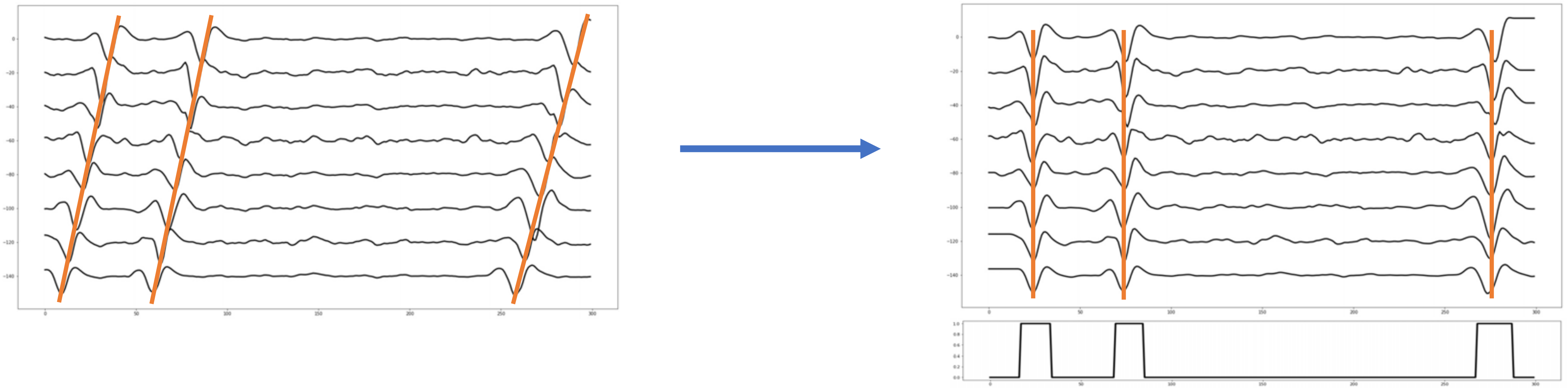
Freifeld, Oren, et al. "Transformations based on continuous piecewise-affine velocity fields."

Self-supervised training



$$\text{Loss} = \sum_{n=0}^{Nch-1} \left\| E^{\theta_n}(I_n) - I_{n+1} \right\|_{l2}^{2} + \alpha \sum_{n=0}^{Nch-1} \left\| \theta_n \right\|_{\Sigma_{CPA}^{-1}}$$

Velocity estimation



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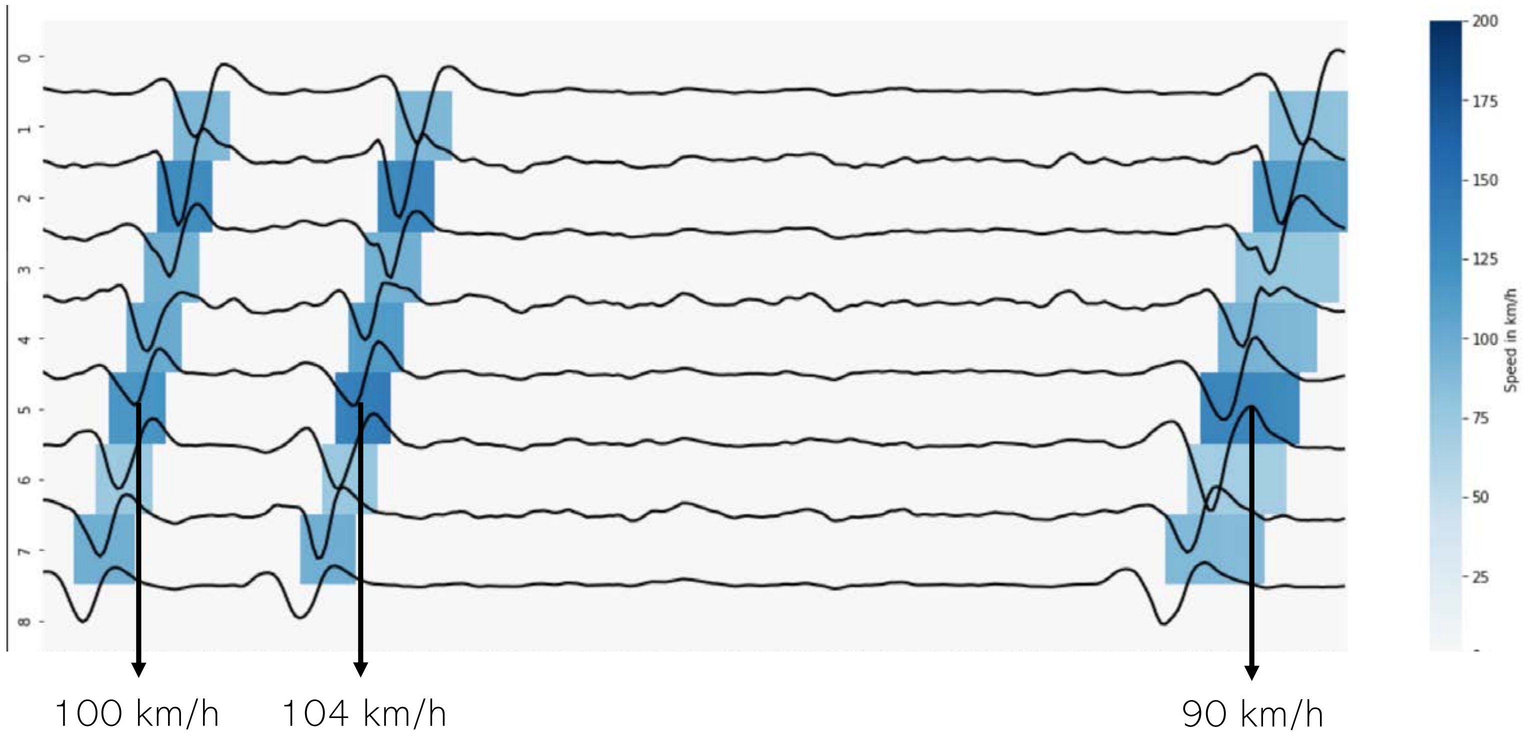
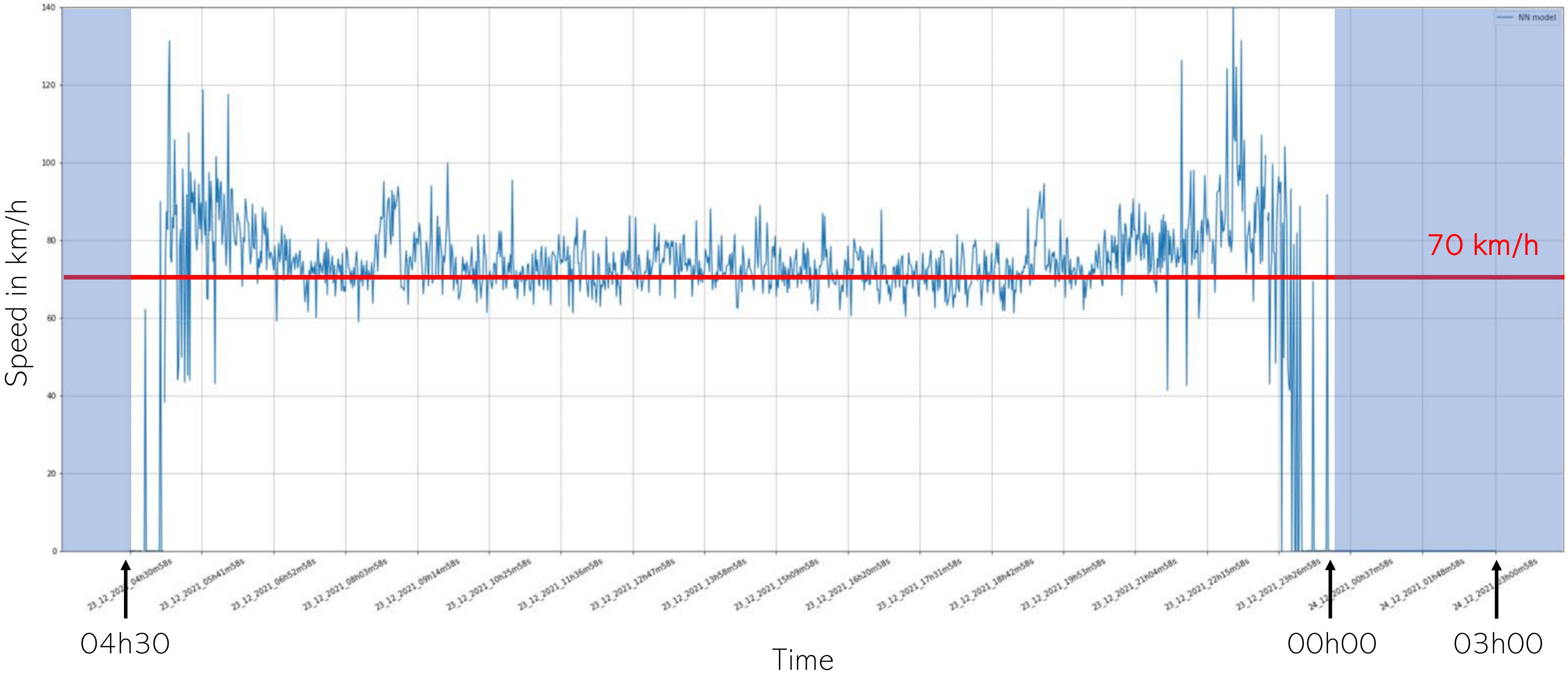


Window average speed:
97 km/h

Velocity estimation



Take-home messages

1. DAS provides the tools to make very dense measurements in previously inaccessible environments

2. The 2nd dimension of DAS data facilitates new analyses and processing techniques based on spatiotemporal coherence

3. Lots of unexplored potential and applications by combining DAS with Machine Learning

Thanks!

Contact

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Papers and codes available online.

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