



Unsupervised Change Detection of Extreme Events Using ML On-Board

AI + HADR @ NeurIPS 2021



Vít Ružička, Anna Vaughan, Daniele De Martini, James Fulton, Valentina Salvatelli,
Christopher Bridges, Gonzalo Mateo-Garcia, Valentina Zantedeschi

- **The Problem:**

Current state of remote sensing:



This seems important



So does this



So does this

Limited bandwidth



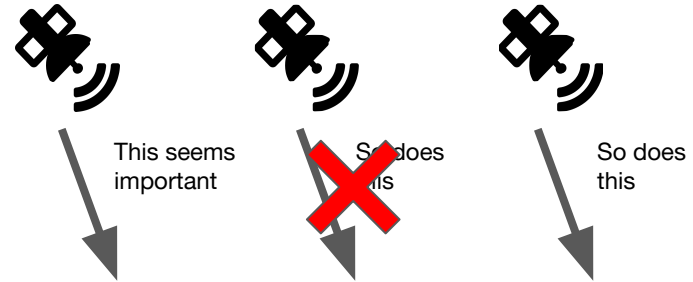
- **The Problem:**

Current state of remote sensing:

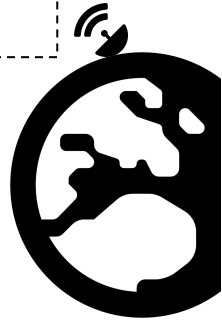


- **The Task:**

Detection of anomalies on-board



Limited bandwidth



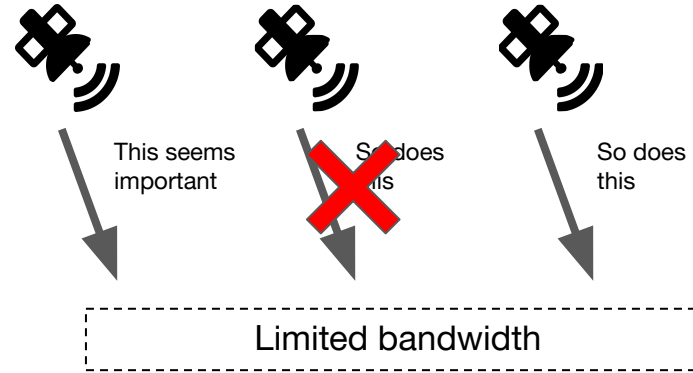
- **The Problem:**

Current state of remote sensing:



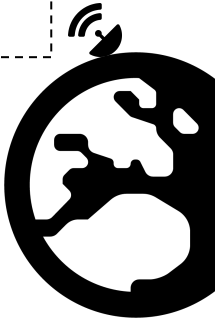
- **The Task:**

Detection of anomalies on-board



- **The Goal:**

Unsupervised Change Detection
of Extreme Events on-board of the satellite



Baseline: Detecting change in image space

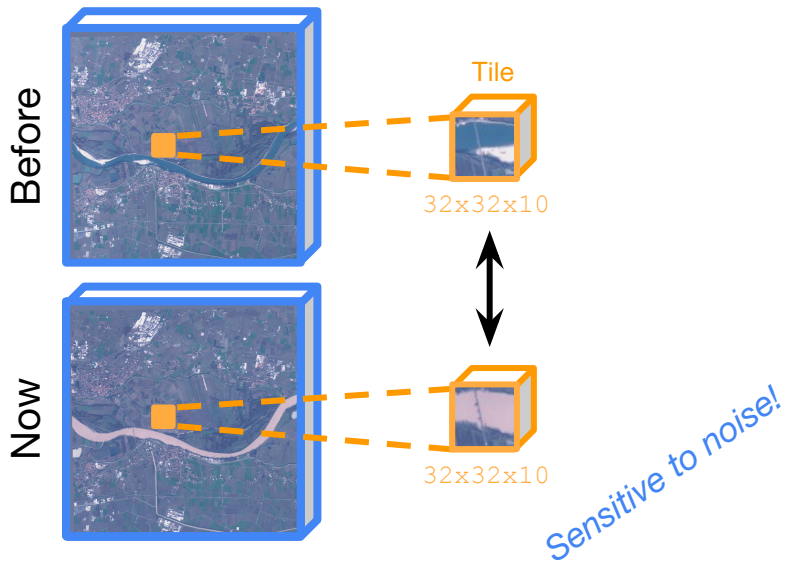


Image space
comparison

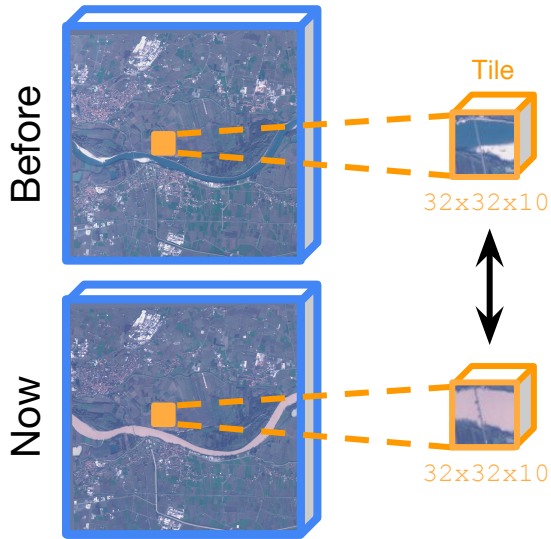
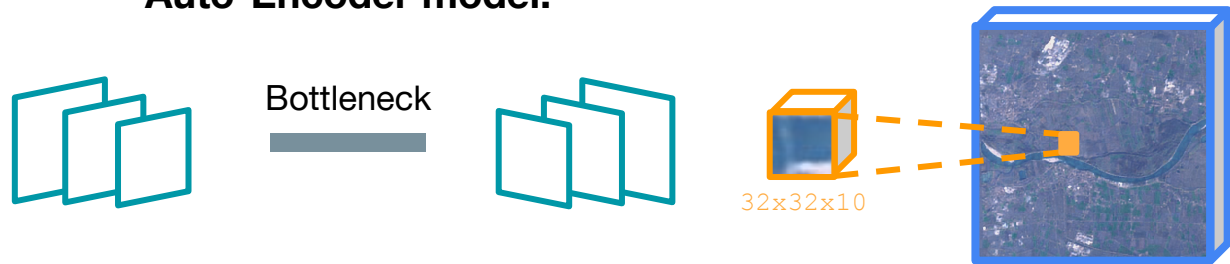


Image space comparison

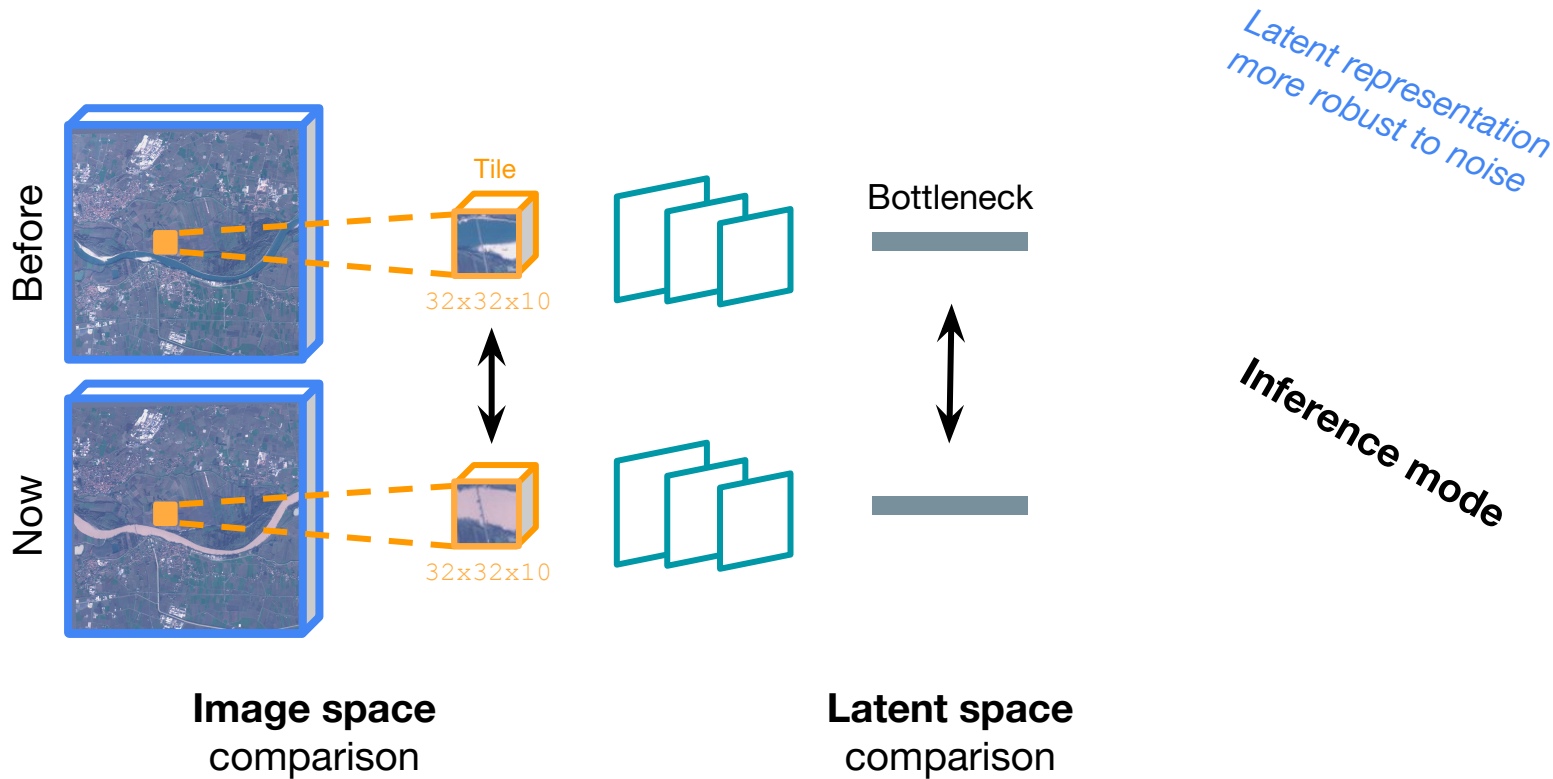
Auto-Encoder model:



Training mode

Reconstruction:
Unsupervised task
learn to encode (and
reconstruct) remote
sensing images.

Approach: Detecting change in latent space



Memory: Considers longer temporal changes

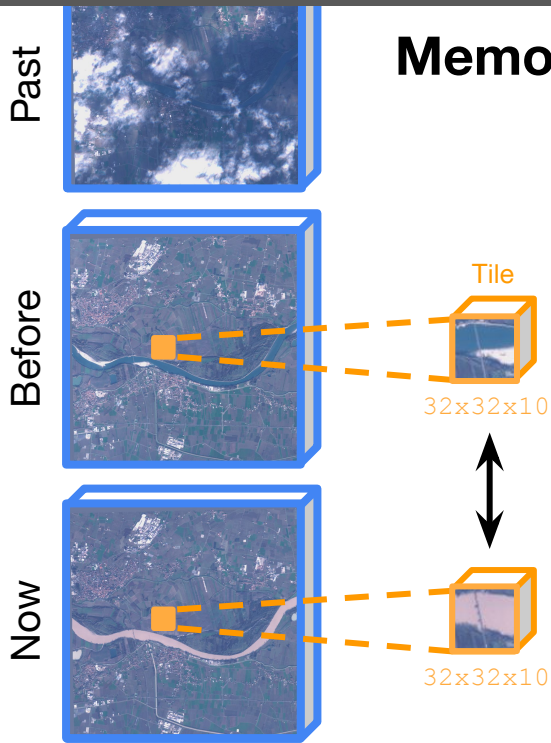
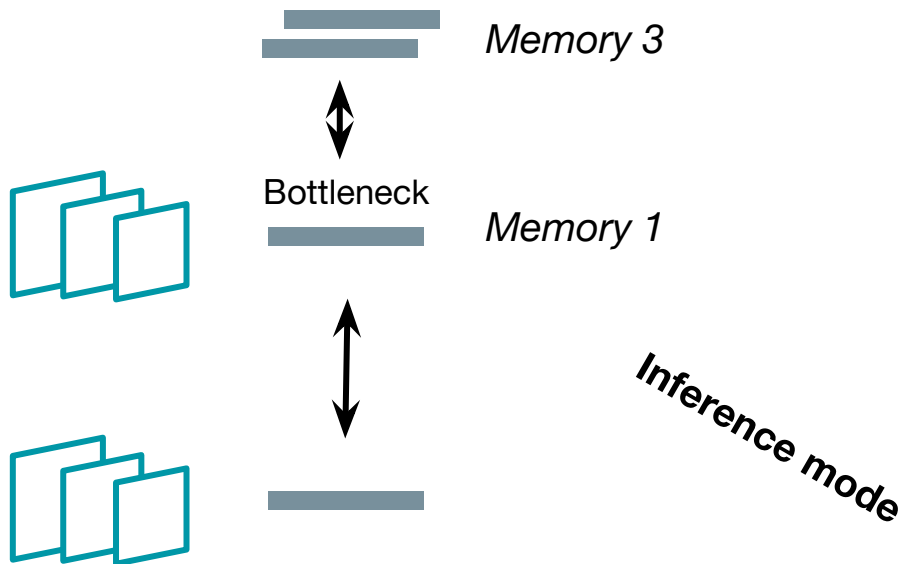


Image space comparison

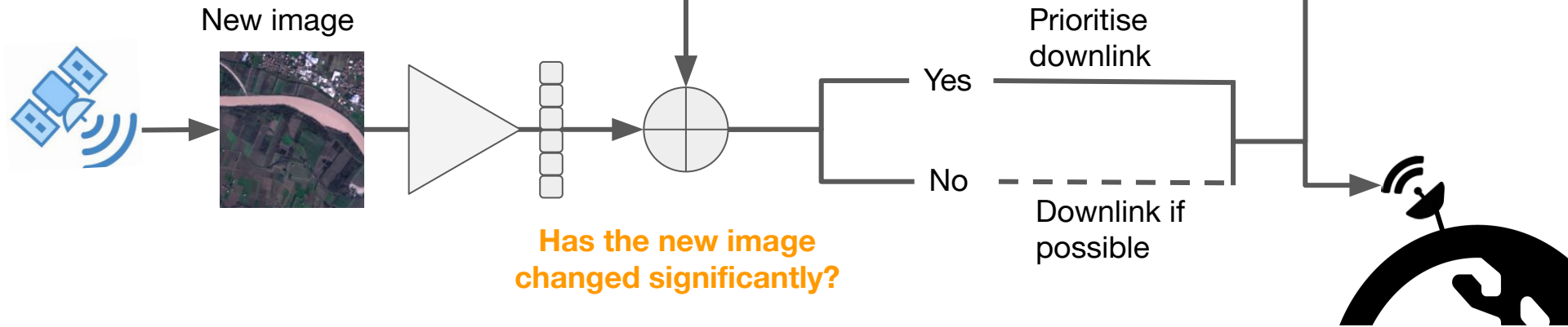


Latent space comparison



RaVAEn:

Intelligent decision making on board:



Dataset of Extreme Events

Diverse unlabeled **training** dataset
(233 scenes x 5 timesteps)



And non-overlapping
labeled **evaluation**
dataset (4 classes, 5
timesteps)



Extreme Event examples



BEFORE

AFTER

- We want to detect **all kinds of change, not just one**

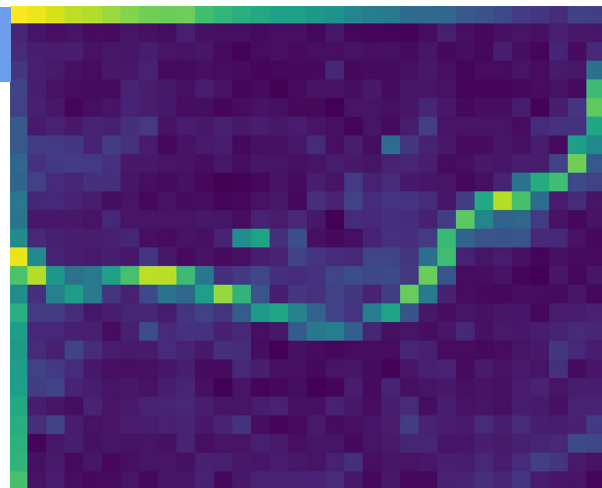
Prediction example:

BASELINE:

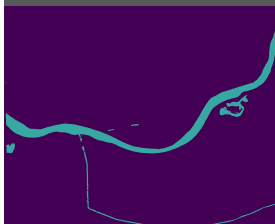
BEFORE



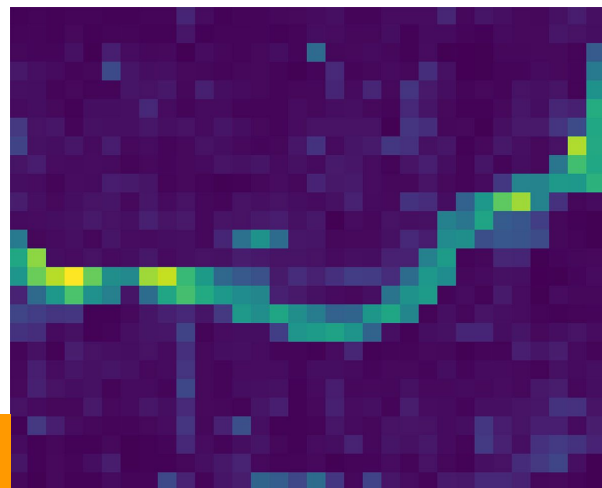
AFTER



GT



OURS:







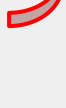


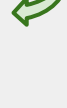








Results

Area under the precision-recall curve shown in percentage. (averaged over 5 runs)

| | Landslides | Floods | Hurricanes | Fires |
|---------------------------------|-------------------|---------------|-------------------|--------------|
| Cos baseline (memory 1) | 62.9 | 37.8 | 51.3 | 81.8 |
| Cos embedding (memory 1) | 59.9 | 44.8 | 67.6 | 83.3 |
| KL-divergence (memory 1) | 25.8 | 24.7 | 30.1 | 73.1 |
| Cos baseline (memory 3) | 62.2 | 37.8 | 57.0 | 86.5 |
| Cos embedding (memory 3) | 75.9 | 44.3 | 72.6 | 91.3 |

Results

Area under the precision-recall curve shown in percentage. (averaged over 5 runs)

| | Landslides | Floods | Hurricanes | Fires |
|---------------------------------|---|---|---|--|
| Cos baseline (memory 1) | 62.9  -5% | 37.8  +19% | 51.3  +32% | 81.8  +2% |
| Cos embedding (memory 1) | 59.9  | 44.8  | 67.6  | 83.3  |
| KL-divergence (memory 1) | 25.8 | 24.7 | 30.1 | 73.1 |
| Cos baseline (memory 3) | 62.2  +22% | 37.8  +17% | 57.0  +27% | 86.5  +6% |
| Cos embedding (memory 3) | 75.9  | 44.3  | 72.6  | 91.3  |

- *Our **proposed method** outperforms the **baseline solution** in most scenarios when using **memory = 1** and **in all scenarios with memory = 3**.*

Results on dedicated hardware*

**) Xilinx Pynq, 650MHz ARM
Cortex-A9 CPU, 512MB RAM
Used on ESA PhiSat-1, OPSSAT, ...*

Showing cos embedding with memory 3

Encoding area of 25km²

| | Landslides | Floods | Hurricanes | Fires | # params | runtime |
|---------------|-------------------|---------------|-------------------|--------------|-----------------|----------------|
| small | 74.8 | 44.5 | 74.8 | 90.7 | 0.4M | 2.1s |
| medium | 75.8 | 42.8 | 73.8 | 91.2 | 0.9M | 4.8s |
| large | 75.9 | 44.3 | 72.6 | 91.3 | 1.5M | 13.9s |

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Showing cos embedding with memory 3

Encoding area of 25km²

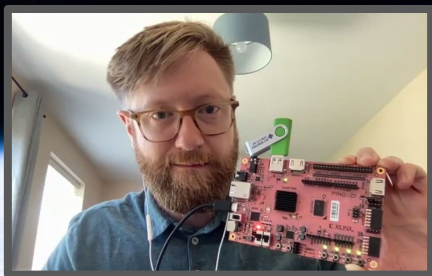
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- While maintaining the model's performance ($\pm 3\%$) we show that the model size and it's runtime can be greatly reduced (by 85%).



Conclusions:

- **RaVÆn**: variational autoencoder for **unsupervised change detection**
- Demonstrated that this can be used to detect **new types of disaster hot-spots**
- Developed the RaVÆn library & dataset ready for **public release**
- Achieve **competitive results on constrained hardware** (Xilinx-Pynq)



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Thank you for your attention!

Any questions?

