Interpretable Representation Learning for High Resolution Satellite Image Time Series

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Sentinel-2 optical images

New opportunity for land monitoring

The Sentinel-2 Constellation has 2 satellites dedicated to land masses monitoring, launched in 2015 and 2017.

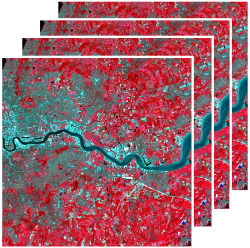


Figure 1 – Satellite Image Time Series

Figure 2 – Sentinel 2 image with clouds

Challenges of S2 data exploitation

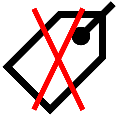
- High dimension data
- Irregular sampling (spatial & temporal)
- Labelled datasets are costly and rare
- Complex with high variability

Satellite data low dimensional representation learning

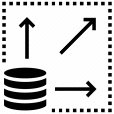
Data representation

Finding transformation $z = r(x)$ of data x that is useful for subsequent applications.

Desired representation requirements for satellite data

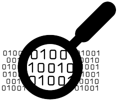


Unsupervised



Deployable at large scale

Probabilistic



Interpretable

Data representation

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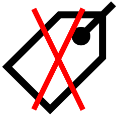
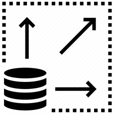
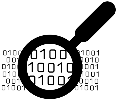
Desired representation requirements for satellite data


Unsupervised


Deployable at large scale


Probabilistic


Interpretable

Existing representation learning methodologies

Deep generative methodologies have been proposed for combining **deep learning** architectures and **Bayesian** inference framework with **unsupervised training** :
$\Rightarrow$ Variational Auto Encoders

$$\mathcal{L}(q_\lambda) = -\mathbb{E}[\log p(x|z)] + \mathbb{KL}(q_\lambda(z|x)||p(z))$$

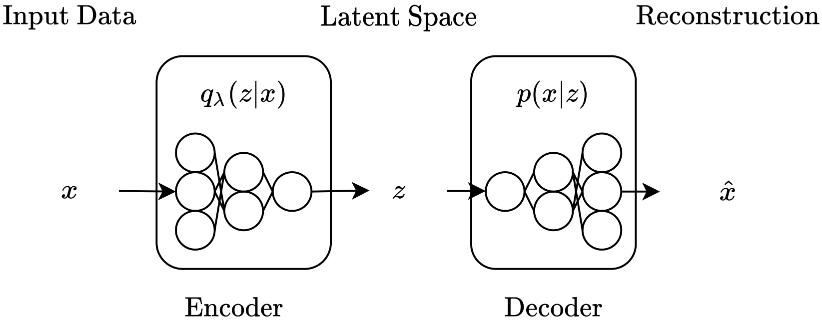


Figure 3 – Variational Auto Encoder [1]

Latent space

- Usual prior on latent space : $p(z) = \mathcal{N}(0, I)$
- Reparametrization trick :

$$z = \mu_z(x) + \varepsilon \cdot \sigma_z(x), \qquad \varepsilon \sim \mathcal{N}(0, I) \qquad \Rightarrow z \sim \mathcal{N}(\mu_z(x), \sigma_z^2(x)) \qquad (1)$$

1. Diederik P Kingma et Max Welling. *Auto-Encoding Variational Bayes*. 2014. arXiv : 1312.6114 [stat.ML].

Objectives

Limitation of using VAEs

- Not developped for SITS
- Uninterpretable latent space
- Usual $p(z) \sim \mathcal{N}(0, 1)$ is arbitrary

Objectives

- Adapt VAE for SITS
- Infer interpretable representation with VAE
- Integrate prior knowledge of data into VAE latent space

What is a good representation of physical data ?

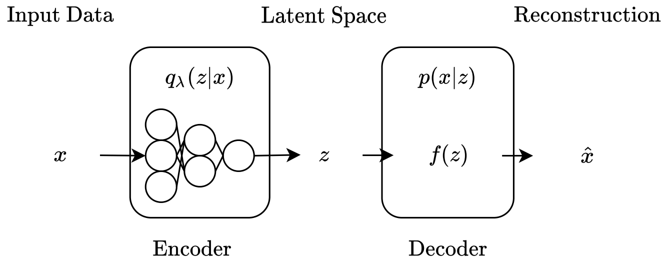
$\Rightarrow$ parameters of physical models

Summary

1. Integrating physics into VAE

2. NDVI time series model

3. Experimental results

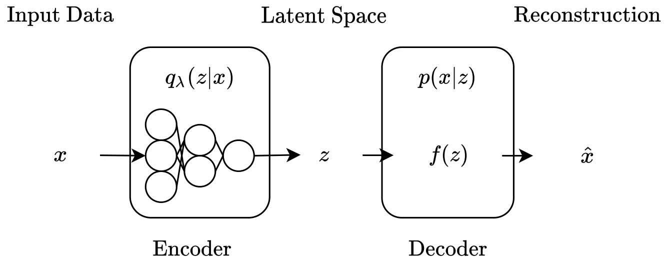


VAE with Decoder-Simulator (VAE-DS)

- Decoder's neural network is replaced by a user-defined model [2]
- Latent variables are **semantically bound to model's parameters**

2. Miguel A. Aragon-Calvo. "Self-supervised learning with physics-aware neural networks – I. Galaxy model fitting". In : *Monthly Notices of the Royal Astronomical Society* (2020).

Loss of VAE with decoder-simulator

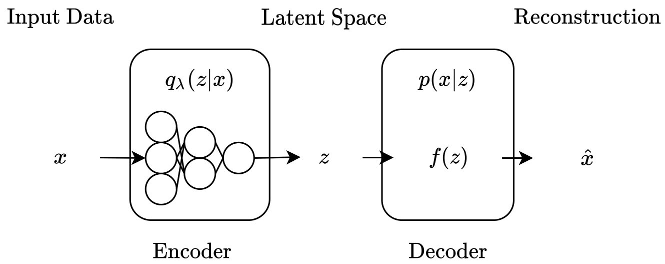


Loss of VAE-DS

Without specific prior $p(z)$:

$$\mathcal{L}(q_\lambda) = -\mathbb{E}[\log p(x|z)] + \cancel{\mathbb{KL}(q_\lambda(z|x) \| p(z))}$$

Loss of VAE with decoder-simulator



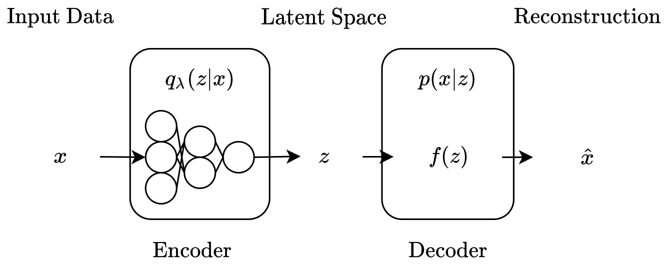
Loss of VAE-DS

Without specific prior $p(z)$:

$$\mathcal{L}(q_\lambda) = -\mathbb{E}\left[\log p(\mathrm{x}|\mathrm{z})\right] + \xcancel{\mathbb{KL}\left(q_\lambda(\mathrm{z}|\mathrm{x}) \| p(\mathrm{z})\right)}$$

$$\approx \frac{1}{L}\sum_{i=1}^{L} \log 2\pi\sigma_x(z_i) + \frac{(x - \mu_x(z_i))^2}{\sigma_x^2(z_i)}$$

Loss of VAE with decoder-simulator



Decoder's distribution's output parameters

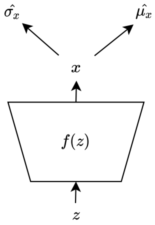


Figure 4 – **Simulator-decoder**

Monte Carlo sampling of latent space :

- $\mu_x(z) \approx \frac{1}{N}\sum_{i=1}^{N} \hat{x}_i$
- $\sigma_x(z) \approx \frac{1}{N}\sum_{i=1}^{N}(\hat{x}_i - \mu_x(z))^2$

with $\hat{x}_i = f(z_i)$.

What priors can be brought to latent space ?

- Model parameters can be bounded
- Model parameters can be ordered

Bounding latent distributions

Bounded distributions can be directly sampled with **Inverse Transform Method** :

$$z = F_{\mathcal{A}}^{-1}(u), \quad u \sim \mathcal{U}(0,1) \quad \Rightarrow \quad z \sim \mathcal{A} \tag{2}$$

with $F_{\mathcal{A}}^{-1}$ a tractable inverse CDF of distribution $\mathcal{A}$.

Ordering Latent Distributions

ordered samples $z_0 < z_1$ are rectified :

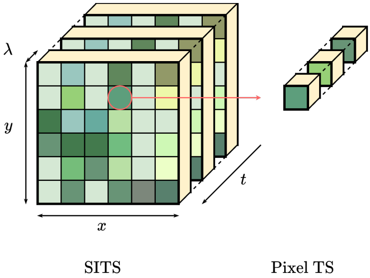
$$\begin{aligned} z_0 &\leftarrow z_0 \\ z_1 &\leftarrow \max(z_0, z_1) \end{aligned} \tag{3}$$

Summary

Normalized Difference Vegetation Index (NDVI)

$$\text{NDVI} = \frac{\rho_{\text{NIR}} - \rho_{\text{R}}}{\rho_{\text{NIR}} + \rho_{\text{R}}} \in [-1, 1]$$

NDVI characterizes photsynthetic vegetation vigor and activity.



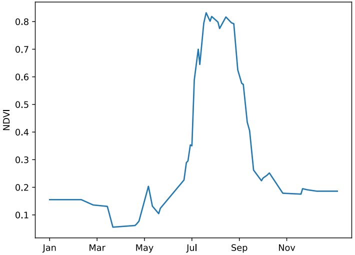
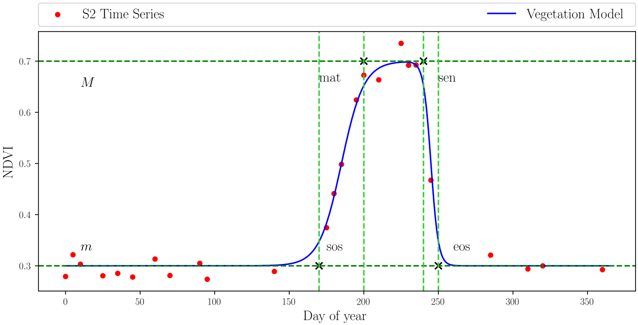


Figure 5 – **Sunflower NDVI time series**

Phenological model

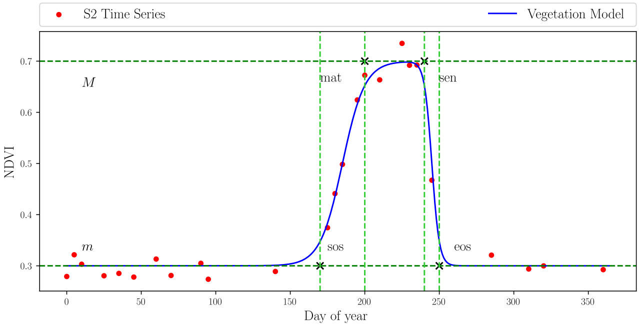


Variable	Description
M	Maximum of double logistic
m	minimum of double logistic
sos	date of *Start Of Season*, the start of NDVI growth
mat	date of *Maturity*, the end of the NDVI growth
sen	date of *Senescence*, the start of NDVI decay
eos	date of *End Of Season*, end of NDVI decay

Figure 6 – **Phenological model** [3]

3. Xiaoyang Zhang et al. "Monitoring vegetation phenology using MODIS". In : *Remote Sensing of Environment* 84.3 (2003), p. 471-475.

Phenological model



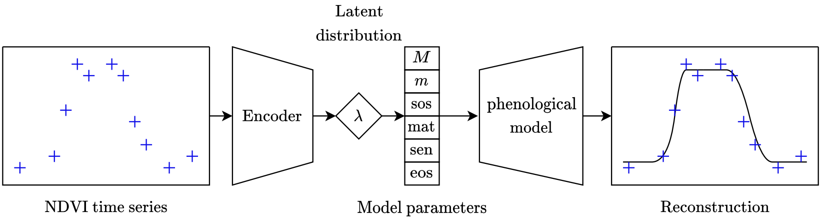
Double-logistic model

$$f_\phi(t) = \left(\max_{\text{NDVI}} - \min_{\text{NDVI}}\right)\left(S_1(t) - S_2(t)\right) + \min_{\text{NDVI}}$$

$$S_1(t) = \left(1 + \exp\left(2\frac{\text{sos} + \text{mat} - 2t}{\text{mat} - \text{sos}}\right)\right)^{-1} \qquad S_2(t) = \left(1 + \exp\left(2\frac{\text{sen} + \text{eos} - 2t}{\text{eos} - \text{sen}}\right)\right)^{-1}$$

Proposed approach : integrating phenological model into VAE

Latent variables are semantically bound to phenological parameters.



Summary

Datasets

S2 dataset

- 10^6 S2 time series
- 2018 time series from 31TCJ tile
- 20 land cover classes
- Time series interpolated to 5-day sampling.

Simulated dataset

Using the phenological model, we simulate NDVI Time series for validation purposes.

Experimental setup

Training Setup

- Number of Monte Carlo samples of latent space per time series : 10
- Learning rate : 10^{-4}
- Latent distribution : Truncated gaussians

Validation experiences

- Evaluation of the quality of reconstruction
- Evaluation of the quality of inferred phenological parameters.

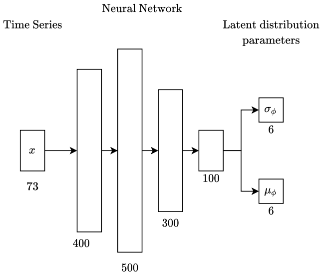


Figure 6 – **Simple encoder architecture with 4 hidden layers and ReLU activation**

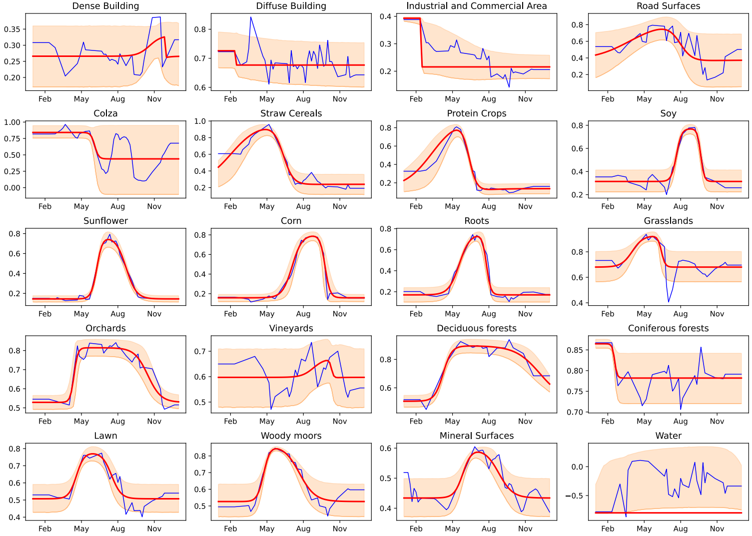


Figure 7 – Time series reconstructions for 20 class samples. Blue : Original time serie - Red : Reconstruction of phenological mode - Orange 90% confidence interval

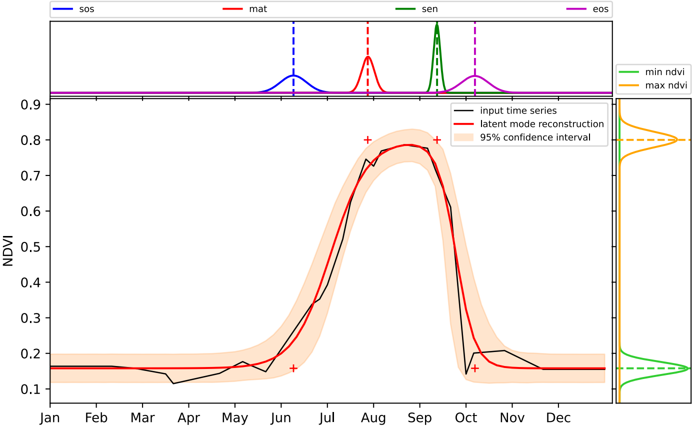


Figure 7 – **Reconstruction and latent distributions of corn ndvi time series**

Compartive evaluation of phenological parameters inference

We use our method to solve the phenological model inverse problem. We compare it to 2 other classical methods.

Characteristics	MCMC [3]	NN Regression	VAE-DS
Unsupervised	✓		✓
Probabilistic	✓	✓	✓
Large Scale		✓	✓
Training Dataset	None	Simulated	S2
Inferred distribution	Full approximate distribution	Truncated Gaussian parameters	Truncated Gaussian parameters

Table 1 – **List of experiences for inverting the phenological model**

Note :

- NN regression has the same NN structure than encoder of VAE-DS

3. Markov Chain Monte Carlo

Evaluation of the quality of phenological parameters estimation

Inference error of the three methods :

- NN regression has the best MAE
- MCMC & VAE-DS are comparable.

Method	MCMC	NN Regression	VAE-DS
Point estimate	Median	Mode	Mode
M	0.04	0.04	0.06
m	0.02	0.01	0.02
sos	8.58	6.83	10.34
mat	11.78	7.84	10.44
sen	11.54	7.22	11.96
eos	12.04	6.83	14.36

Table 2 – **Mean Absolute Error**

Evaluation of the quality of inferred latent distributions

Quality of 5-95th centile confidence intervals :

- MCMC & NN regression very close confidence interval belonging rate
- VAE-DS underestimates uncertainty
- MCMC has smaller (more precise) confidence intervals

	Confidence Interval Belonging Rate			Mean Confidence Interval Width		
	MCMC	NN Regression	VAE-DS	MCMC	NN Regression	VAE-DS
M	88.90	91.62	62.63	0.08	0.16	0.13
m	85.20	89.47	96.80	0.03	0.06	0.13
sos	85.40	91,19	36.88	10.12	29.90	14.53
mat	84.40	90,58	22.18	10.46	33.29	7.54
sen	84.00	90,54	34.37	6.41	30.14	16.03
eos	83.30	90,24	52.09	7.12	28.89	27.54

Table 3 – **5-95th centiles confidence interval metrics**

Inference performance : inference time

Deep learning methods have much faster inferrence.

Characteristics	MCMC	NN Regression	VAE-DS
Unsupervised	✓		✓
Probabilistic	✓	✓	✓
Large Scale		✓	✓
Training Dataset	None	Simulated	S2
Inferred distribution	Full approximate distribution	Truncated Gaussian parameters	Truncated Gaussian parameters
Inference Time per time series	≈ 10 s	$\approx 10^{-5}$ s	$\approx 10^{-5}$ s

Table 4 – **Inference time of phenological distributions (Laptop i5 CPU)**

Conclusion

Contributions

- New physics-guided unsupervised representation learning methodology.
- Methodology can be used to solve inverse problems.

Envisonned developments

- Encoder complexification
- Apply methodology to more complex physics models, for different data
- Use auxillary neural network to model residuals [4]

4. Naoya Takeishi et Alexandros Kalousis. "Physics-Integrated Variational Autoencoders for Robust and Interpretable Generative Modeling". In : *CoRR* (2021).

Thank you for your attention !

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