

Generative Models for Satellite Image Analysis

Learning with little or complex data

Valentine Bellet, Mathieu Fauvel, Jordi Inglada, Sivia Valero-Valbuena, Yoël Zerah

CESBIO, Université de Toulouse, CNES/CNRS/INRAe/IRD/UPS, Toulouse, FRANCE

Context

Land Cover Classification

Physic constraint auto-encoder

Conclusion and perspectives

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Chair *Learning with little or complex data* (Prof. Nicolas Dobigeon - IRIT-INPT)

▶ Themes

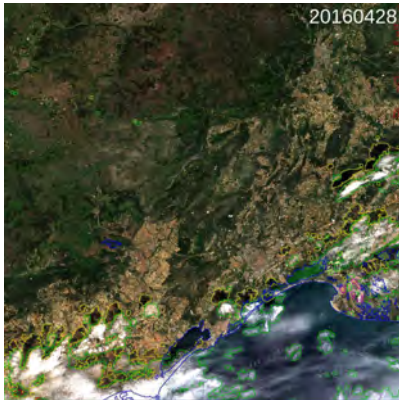
- ▶ AI and physical models
- ▶ Learning from noisy data
- ▶ Multi-source & -scale time series

▶ Members - CESBIO:

- ▶ Mathieu Fauvel, INRAe
- ▶ Jordi Inglada, CNES
- ▶ Julien Michel, CNES
- ▶ Silvia Valero, UT3

▶ ANITI Ressources

- ▶ 2 PhD (Region & CNES): Y. Zérah & V. Bellet
- ▶ 2 Ms
- ▶ 1 engineer (CS-Group)



Information extraction from EO imagery

- ▶ Land cover/use mapping
- ▶ Bio/geo-physical variable estimation
- ▶ Change detection and dynamic analysis

Hybrid IA

- ▶ Physical modeling
- ▶ Data Science / Machine Learning

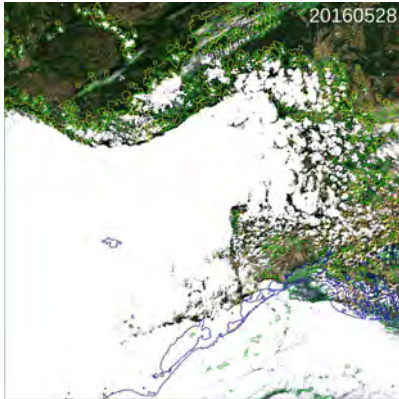


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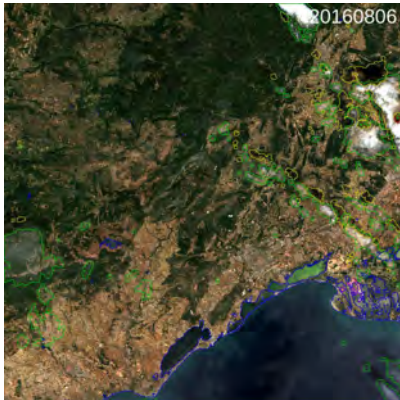


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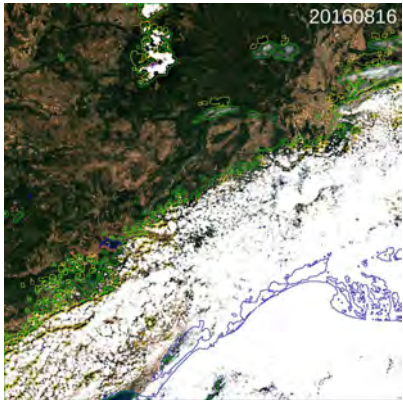


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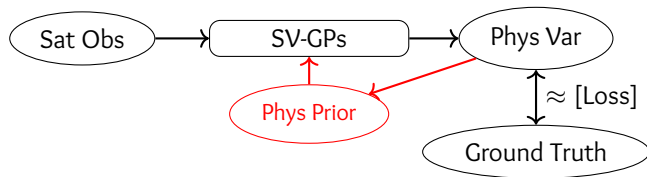
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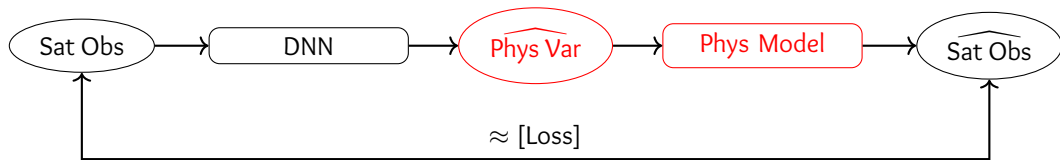
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- ▶ **Valentine Bellet**, *Artificial intelligence for ecosystem monitoring*



- ▶ **Yoël Zerah**, *Generative Models for Mapping Land Cover Changes with Time Series of Satellite Images*



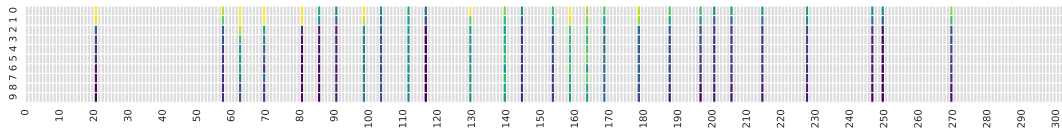
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Physic constraint auto-encoder

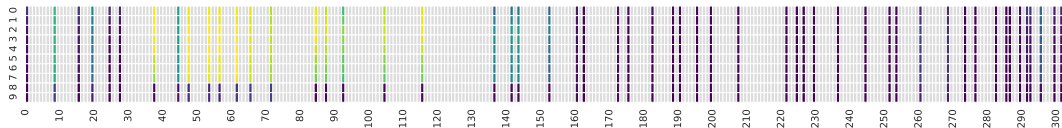
Conclusion and perspectives

Model 1/2 - Structured latent representation



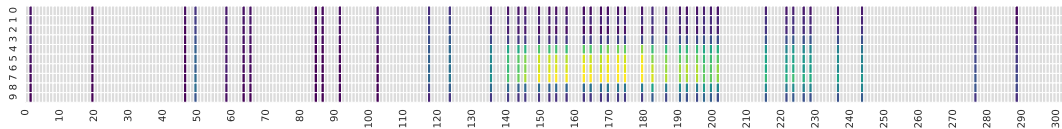
$$\mathbf{Z} = \mathbf{B} \left[\mathbf{X}^* + \mathbf{P} \right] \mathbf{\Gamma}$$

Model 1/2 - Structured latent representation



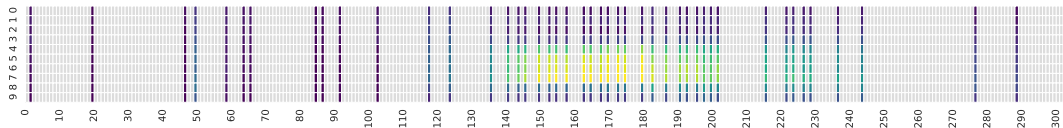
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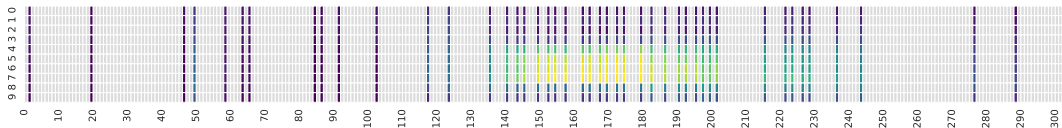


$$\mathbf{Z} = \mathbf{B} \left[\mathbf{X}^* + \mathbf{P} \right] \mathbf{\Gamma}$$

► Temporal embedding

$$\hat{x}_\ell(r) = \sum_{j=1}^T \frac{K(r, t_j) m_j}{\sum_{j'=1}^T K(r, t_{j'}) m_{j'}} x_\ell^*(t_j)$$

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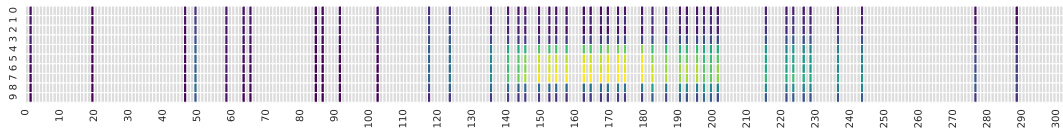


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- ▶ Temporal embedding
- ▶ Spatial positional encoding:

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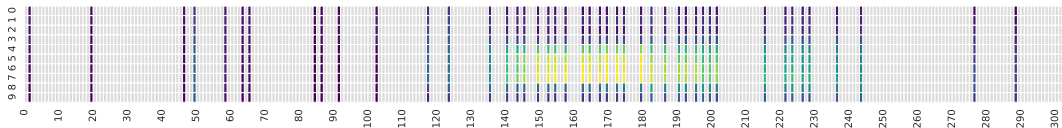


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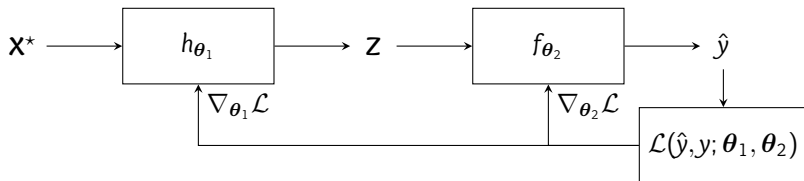


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$$\|\mathbf{Z}^i - \mathbf{Z}^j\|_F^2 = \|\mathbf{B}(\mathbf{X}^{i*} \mathbf{\Gamma}^i - \mathbf{X}^{j*} \mathbf{\Gamma}^j)\|_F^2 + \|\mathbf{B}(\mathbf{P}^i \mathbf{\Gamma}^i - \mathbf{P}^j \mathbf{\Gamma}^j)\|_F^2 + 2 \left\langle \mathbf{B}(\mathbf{X}^{i*} \mathbf{\Gamma}^i - \mathbf{X}^{j*} \mathbf{\Gamma}^j), \mathbf{B}(\mathbf{P}^i \mathbf{\Gamma}^i - \mathbf{P}^j \mathbf{\Gamma}^j) \right\rangle_F$$



- Optimize a lower bound of the log-likelihood (ELBO) [HMG15]

$$\mathcal{E}(q) = \sum_{i=1}^N \mathbb{E}_{q'(g(\mathbf{Z}^i) | \theta^v, \theta)} \left[\log p(y^i | g(\mathbf{Z}^i)) \right] - \text{KL} \left[q(g(\mathbf{Z}_u) | \theta^v) \parallel p(g(\mathbf{Z}_u) | \theta) \right],$$

with

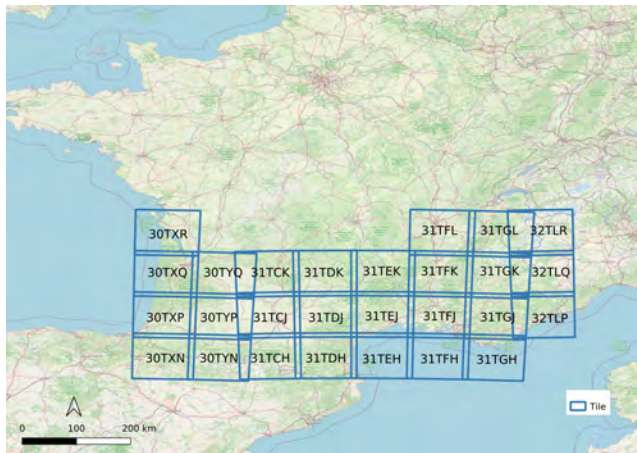
$$q(g(\mathbf{Z}_u) | \theta^v) \sim \mathcal{N}_M(\mathbf{m}, \mathbf{S})$$

$$q'(g(\mathbf{Z}^i) | \theta^v, \theta) \sim \mathcal{N}_1 \left(g(\mathbf{Z}^i) \mid \mathbf{k}_{Mi}^\top \mathbf{K}_{MM}^{-1} \mathbf{m}, k(\mathbf{Z}^i, \mathbf{Z}^i) - \mathbf{k}_{Mi}^\top \mathbf{K}_{MM}^{-1} (\mathbf{K}_{MM} - \mathbf{S}) \mathbf{K}_{MM}^{-1} \mathbf{k}_{Mi} \right)$$

- Expectation approximate with MC sampling and reparametrisation trick

- ▶ All S2 acquisitions between [01-2018, 12-2018]
- ▶ 10 bands + 3 spectral indices
- ▶ $T = 303$ & $D = 13$
- ▶ 23 land cover classes
 - ▶ Training: 4000 pixels/class
 - ▶ Validation: 1000 pixels/class
 - ▶ Test: 10,000 pixels/class
 - ▶ 9 random (train, val, test) sets

<i>Training</i>	<i>Validation</i>	<i>Test</i>
92 000	23 000	230 000



	mTAN-MLP	mTAN-SVGP	linInter-SVGP	linInter-RF
OA (%)	71.5	77.4 (0.2)	67.3 (0.4)	65.4 (0.4)
Time (s)	1207	1317.4	336.6	54.6

► Publications:

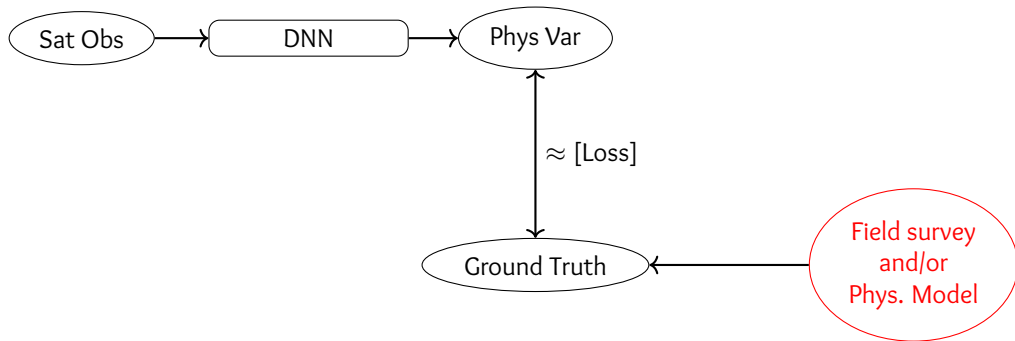
- [Valentine Bellet, Mathieu Fauvel, and Jordi Inglada](#). “Land Cover Classification with Gaussian Processes using spatio-spectro-temporal features.” In: *IEEE Transactions on Geoscience and Remote Sensing* (Jan. 2023). DOI: 10.1109/TGRS.2023.3234527. URL: <https://hal.science/hal-03781332>
- [Valentine Bellet et al.](#) “End-to-end Learning for Land Cover Classification using Irregular and Unaligned SITS by Combining Attention-Based Interpolation with Sparse Variational Gaussian Processes.” [working paper or preprint](#). July 2023. URL: <https://hal.science/hal-04112115>

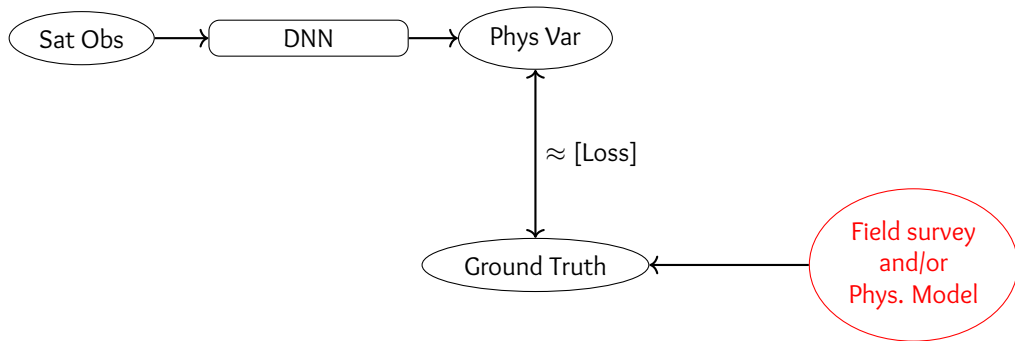
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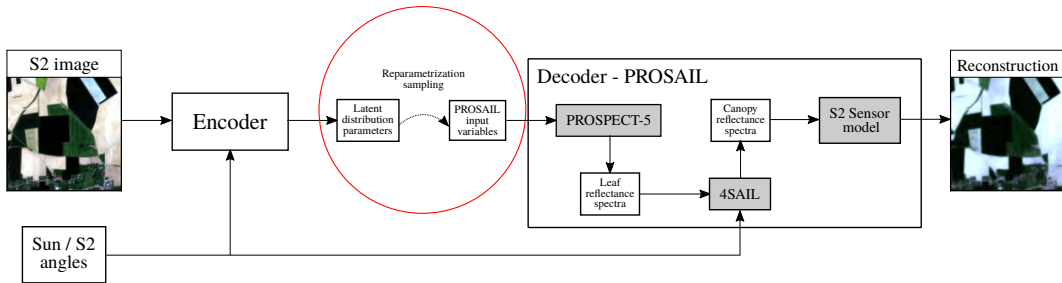
Physic constraint auto-encoder

Conclusion and perspectives





- ▶ Distribution of GT biased
- ▶ *Use the physical model as the decoder in a AE framework: no GT needed for training.*



- ▶ Variational AE with *constrained Prior*
 - ▶ Truncated Gaussian
 - ▶ Auto-regressive
- ▶ Yoël Zérah, Silvia Valero, and Jordi Inglada. “Physics-Driven Probabilistic Deep Learning for the Inversion of Physical Models With Application to Phenological Parameter Retrieval From Satellite Times Series.” In: *IEEE Transactions on Geoscience and Remote Sensing* 61 (June 2023). DOI: 10.1109/TGRS.2023.3284992. URL: <https://hal.science/hal-03837736>

RMSE	BelSAR 2018	Barrax 2018	LAI			CCC			
			Barrax 2021	Wytham 2018	ALL	Barrax 2018	Barrax 2021	Wytham 2018	ALL
MLP-Reg	1.22	1.43	0.48	1.77	1.24	83.92	84.53	101.35	88.08
Prosail-VAE	1.30	1.42	0.72	1.21	1.16	27.60	20.51	80.78	42.33



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Conclusions

Generative Models for Satellite Image Analysis

- ▶ More robust to noisy data
- ▶ More robust to limited (no) training data
- ▶ More accurate

Perspectives

ANITI 2.0 - RELEO

- ▶ More data source
- ▶ Richer prior distribution
- ▶ Meteo & Agro model
- ▶ Essential Biodiversity/Climate variables
- ▶ Industrial Chair

- [1] Valentine Bellet, Mathieu Fauvel, and Jordi Inglada. “Land Cover Classification with Gaussian Processes using spatio-spectro-temporal features.” In: *IEEE Transactions on Geoscience and Remote Sensing* (Jan. 2023). DOI: 10.1109/TGRS.2023.3234527. URL: <https://hal.science/hal-03781332>.
- [2] Valentine Bellet et al. “End-to-end Learning for Land Cover Classification using Irregular and Unaligned SITS by Combining Attention-Based Interpolation with Sparse Variational Gaussian Processes.” working paper or preprint. July 2023. URL: <https://hal.science/hal-04112115>.
- [3] James Hensman, Alex Matthews, and Zoubin Ghahramani. “Scalable Variational Gaussian Process Classification.” In: *In Proceedings of the 18th International Conference on Artificial Intelligence and Statistics*. 2015, pp. 351–360.
- [4] Yoël Zérah, Silvia Valero, and Jordi Inglada. “Physics-Driven Probabilistic Deep Learning for the Inversion of Physical Models With Application to Phenological Parameter Retrieval From Satellite Times Series.” In: *IEEE Transactions on Geoscience and Remote Sensing* 61 (June 2023). DOI: 10.1109/TGRS.2023.3284992. URL: <https://hal.science/hal-03837736>.

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