Generative Models for Satellite Image Analysis
Learning with little or complex data

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

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Outline

Context

Land Cover Classification

Physic constraint auto-encoder

Conclusion and perspectives
Plan

Context

Land Cover Classification

Physic constraint auto-encoder

Conclusion and perspectives
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)
CESBIO’s IA activities

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
CESBIO’s IA activities

Information extraction from EO imagery
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November 17, 2023
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Valentine Bellet, *Artificial intelligence for ecosystem monitoring*

- `Sat Obs` → `SV-GPs` → `Phys Var` → `Phys Prior` → `Ground Truth` 
  ≈ [Loss]

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

- `Sat Obs` → `DNN` → `Phys Var` → `Phys Model` → `Sat Obs` 
  ≈ [Loss]
Plan

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Conclusion and perspectives
Model 1/2 - Structured latent representation

\[
Z = BV \left[ X^* + P \right] \Gamma
\]
Model 1/2 - Structured latent representation

Z = B [X* + P] Γ
$Z = B \left[ X^* + P \right] \Gamma$
Model 1/2 - Structured latent representation

\[ Z = B \left[ X^* + P \right] \Gamma \]

Temporal embedding

\[ \hat{x}_\ell(r) = \sum_{j=1}^{T} \frac{K(r, t_j) m_j}{\sum_{j'=1}^{T} K(r, t_{j'}) m_{j'}} x^*_\ell(t_j) \]
Model 1/2 - Structured latent representation

\[ Z = B \left[ X^* + P \right] \Gamma \]

- Temporal embedding
- Spatial positional encoding:

\[ \hat{x}_\ell(r) = \sum_{j=1}^{T} \frac{K(r, t_j)m_j}{\sum_{j'=1}^{T} K(r, t_{j'})m_{j'}} x^*_\ell(t_j) \]
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- Temporal embedding
- Spatial positional encoding:
- Spectral embedding

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

\[ \| Z^i - Z^j \|_F^2 = \| B \left( X^{i*} \Gamma^i - X^{j*} \Gamma^j \right) \|_F^2 + \| B \left( P^{i*} \Gamma^i - P^{j*} \Gamma^j \right) \|_F^2 + 2 \left\langle B \left( X^{i*} \Gamma^i - X^{j*} \Gamma^j \right), B \left( P^{i*} \Gamma^i - P^{j*} \Gamma^j \right) \right\rangle_F \]
Model 2/2 - Variational Sparse Gaussian Process

\[ \mathbf{X^*} \rightarrow h_{\theta_1} \rightarrow \mathbf{Z} \rightarrow f_{\theta_2} \rightarrow \hat{y} \]

\[ \nabla_{\theta_1} \mathcal{L} \]

\[ \nabla_{\theta_2} \mathcal{L} \]

\[ \mathcal{L}(\hat{y}, y; \theta_1, \theta_2) \]

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

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

with

\[ q(g(Z_u)|\theta^v) \sim \mathcal{N}_M(m, S) \]

\[ q'(g(Z^i)|\theta^v, \theta) \sim \mathcal{N}_1 \left( g(Z^i) \mid k_{Mi}^T k_{MM}^{-1} m, k(Z^i, Z^i) - k_{Mi}^T k_{MM}^{-1} (K_{MM} - S) k_{MM}^{-1} k_{Mi} \right) \]

- Expectation approximate with MC sampling and reparametrisation trick
Data set

- 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

<table>
<thead>
<tr>
<th>Training</th>
<th>Validation</th>
<th>Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>92 000</td>
<td>23 000</td>
<td>230 000</td>
</tr>
</tbody>
</table>
Results

<table>
<thead>
<tr>
<th>mTAN-MLP</th>
<th>mTAN-SVGP</th>
<th>linInter-SVGP</th>
<th>linInter-RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>OA (%)</td>
<td>71.5</td>
<td>77.4 (0.2)</td>
<td>67.3 (0.4)</td>
</tr>
<tr>
<td>Time (s)</td>
<td>1207</td>
<td>1317.4</td>
<td>336.6</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>54.6</td>
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</tbody>
</table>

Publications:

- 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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Conclusion and perspectives
Physically aware ML

Sat Obs → DNN → Phys Var

≈ [Loss]

Ground Truth

Field survey and/or Phys. Model
Distribution of GT biased

*Use the physical model as the decoder in a AE framework*: no GT needed for training.
Variational AE with \textit{constrained Prior}
- Truncated Gaussian
- Auto-regressive

## Results

<table>
<thead>
<tr>
<th></th>
<th>RMSE BelSAR 2018</th>
<th>LAI Barrax 2018</th>
<th>LAI Barrax 2021</th>
<th>LAI Wytham 2018</th>
<th>LAI ALL</th>
<th>CCC Barrax 2018</th>
<th>CCC Barrax 2021</th>
<th>CCC Wytham 2018</th>
<th>CCC ALL</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLP-Reg</td>
<td>1.22</td>
<td>0.48</td>
<td>1.77</td>
<td>1.24</td>
<td>83.92</td>
<td>84.53</td>
<td>101.35</td>
<td>88.08</td>
<td></td>
</tr>
<tr>
<td>Prosail-VAE</td>
<td>1.30</td>
<td>1.42</td>
<td>1.21</td>
<td>1.16</td>
<td>27.60</td>
<td>20.51</td>
<td>80.78</td>
<td>42.33</td>
<td></td>
</tr>
</tbody>
</table>
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Take away

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


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