Data-driven approximate Bayesian computation

Application to fusion-based inference from heterogeneous remote sensing data

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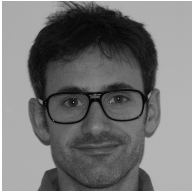

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Remote sensing for Earth science

- Numerous tasks to be conducted automatically, without resorting to thorough and fastidious on-ground surveys.
- To provide crucial information, e.g., relative to macroscopic and phenological indices.
- Opportunity: multi-modality and/or multi-sensor acquisition.

State-of-the-art

- Data exploitation/analysis generally relies on specific models/methods dedicated to each modality.

Objective

- Joint processing of multi-* data.
- Setting up a framework overcoming a crude and marginal description of a single measurement.
- Learning a (joint) latent space where to infer the parameters of interest.

► Bottleneck: no straightforward physical model able to offer a joint description of heterogeneous measurements.

Archetypal example: change detection (CD)

Input

- Two or more multitemporal images.
- Same geographical spot (scene).

Output

- Change map.

Archetypal example: change detection (CD)

Favorable scenario

Figure: Landsat 8 04/15/2015 (PAN - 15m)

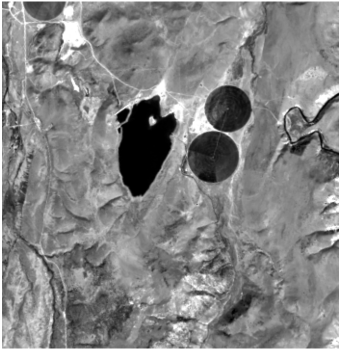
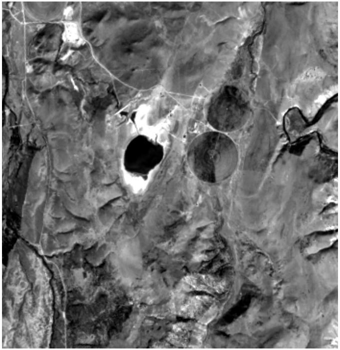


Figure: Landsat 8 09/22/2015 (PAN - 15m)

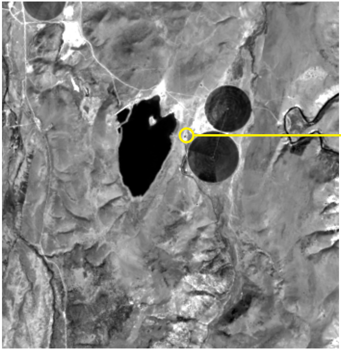


- Same modality.
- Identical resolutions.

Archetypal example: change detection (CD)

Favorable scenario

Figure: Landsat 8 04/15/2015 (PAN - 15m)



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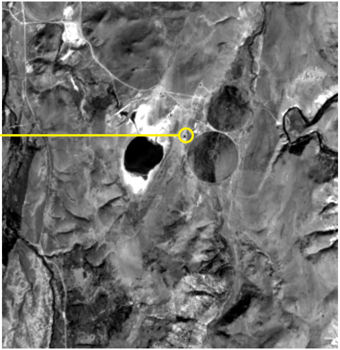


- Same modality.
- Identical resolutions.

→ Comparison of homologous pixels!

Same modality CD!

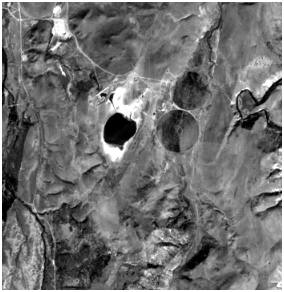
Archetypal example: change detection (CD)

Unfavorable situation for CD

Emergency situations:

- natural disasters, on-demand missions, defense & security

Landsat 8 04/15/2015 (MS - 30m)



Landsat 8 09/22/2015 (PAN - 15m)

Archetypal example: change detection (CD)
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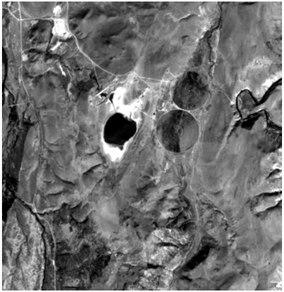
Landsat 8 09/22/2015 (PAN - 15m)

Need:

- Multimodal CD.

Archetypal example: change detection (CD)

Multimodal CD

Same modality and different resolutions

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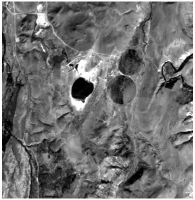

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Archetypal example: change detection (CD)

Multimodal CD

Same modality and different resolutions

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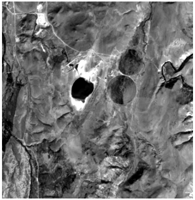


Landsat 8 09/22/2015 (PAN - 15m)

Not so unfavorable

Assume there is no change. Then it exists a *fused* image $\mathbf{X}$ related to the observed images $\mathbf{Y}_{\mathrm{LR}}$ and $\mathbf{Y}_{\mathrm{YR}}$ through explicit physical models

$$\mathbf{Y}_{\mathrm{LR}} = \mathcal{M}_1(\mathbf{X}) \quad \text{(i.e., spatial degradation)}$$
$$\mathbf{Y}_{\mathrm{HR}} = \mathcal{M}_2(\mathbf{X}) \quad \text{(i.e., spectral degradation)}$$

where $\mathbf{X}$ lies on the latent space of high spatial & spectral resolution images.

$\rightarrow$ suggests a 3-step CD framework.

Archetypal example: change detection (CD)

Same modality and different resolutions: 3-step procedure

1. (Bayesian) fusion: estimating $\hat{\mathbf{X}}$ from $\mathbf{Y}_{\mathrm{LR}}$ and $\mathbf{Y}_{\mathrm{HR}}$

$$\hat{\mathbf{X}} = \operatorname{argmin}_{\mathbf{X}} \mathcal{D}_1\left(\mathbf{Y}_{\mathrm{LR}} | \mathcal{M}_1(\mathbf{X})\right) + \mathcal{D}_2\left(\mathbf{Y}_{\mathrm{HR}} | \mathcal{M}_2(\mathbf{X})\right) + \lambda \mathcal{P}(\mathbf{X})$$

$\rightarrow$ exploits the physical models (likelihood/data-fitting terms)

2. Prediction: reconstructing $\hat{\mathbf{Y}}_{\mathrm{LR}}$ and $\hat{\mathbf{Y}}_{\mathrm{HR}}$ from $\hat{\mathbf{X}}$

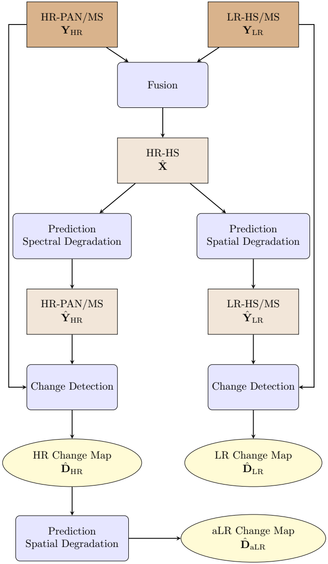
$$\begin{aligned} \hat{\mathbf{Y}}_{\mathrm{LR}} &= \mathcal{M}_1(\hat{\mathbf{X}}) \\ \hat{\mathbf{Y}}_{\mathrm{HR}} &= \mathcal{M}_2(\hat{\mathbf{X}}) \end{aligned}$$

$\rightarrow$ again, exploits the physical models (direct models)

3. Decision: deriving 2 change maps $\hat{\mathbf{D}}_{\mathrm{LR}}$ and $\hat{\mathbf{D}}_{\mathrm{HR}}$

$$\hat{\mathbf{D}}_{\mathrm{LR}} \leftarrow \texttt{compare}\left\{\mathbf{Y}_{\mathrm{LR}}, \hat{\mathbf{Y}}_{\mathrm{LR}}\right\}$$

$$\hat{\mathbf{D}}_{\mathrm{LR}} \leftarrow \texttt{compare}\left\{\mathbf{Y}_{\mathrm{HR}}, \hat{\mathbf{Y}}_{\mathrm{HR}}\right\}$$

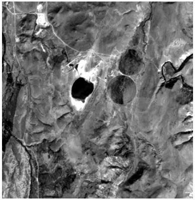


Archetypal example: change detection (CD)

Multimodal CD

Same modality and different resolutions

Landsat 8 04/15/2015 (MS - 30m)



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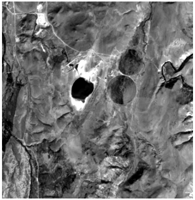
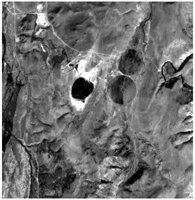


Landsat 8 09/22/2015 (PAN - 15m)

Different modalities and different resolutions

Sentinel 1 04/12/2016 (SAR - 10m)



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Archetypal example: change detection (CD)

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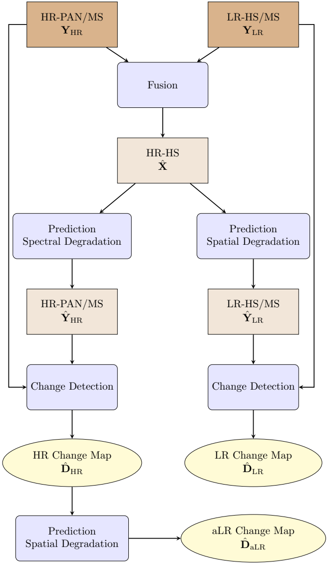

Archetypal example: change detection (CD)

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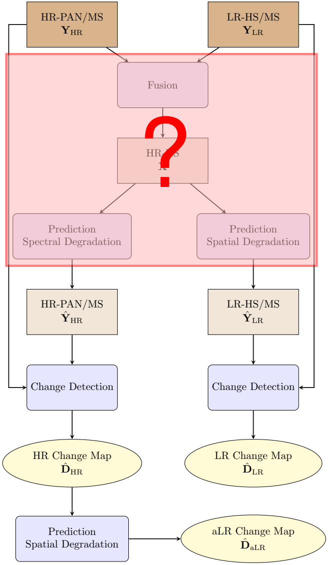

Summary

Challenges

- data heterogeneity (multi-sensor/modality/scale/temporal)
- incomplete physical models
- large-scale inference problems

Tools and methods

- Bayesian framework
  - $\rightarrow$ prior knowledge
- Monte Carlo sampling
  - $\rightarrow$ point estimation (Bayesian estimators)
  - $\rightarrow$ full description of the posterior (credibility intervals)

Opportunities

- approximate Bayesian computation (e.g., likelihood-free methods)
  - $\rightarrow$ control of the approximation
- deep generative models
  - $\rightarrow$ data-based description of the latent space

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