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“Tensor Learning for Analysis of Multi-Temporal Observations”

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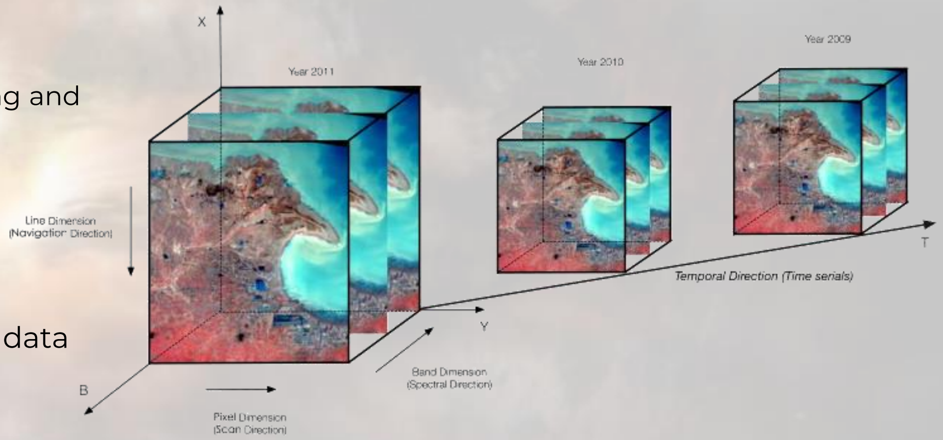
Multi-temporal Observations

- Developments in multi-sensor technology
- Massive timely and spatio-spectral observations
- Useful information on several applications
    - ❖ Time domain information is a key to the physical understanding of certain phenomena in astrophysics
    - ❖ Satellite data can contribute to environmental monitoring and other earth observation applications

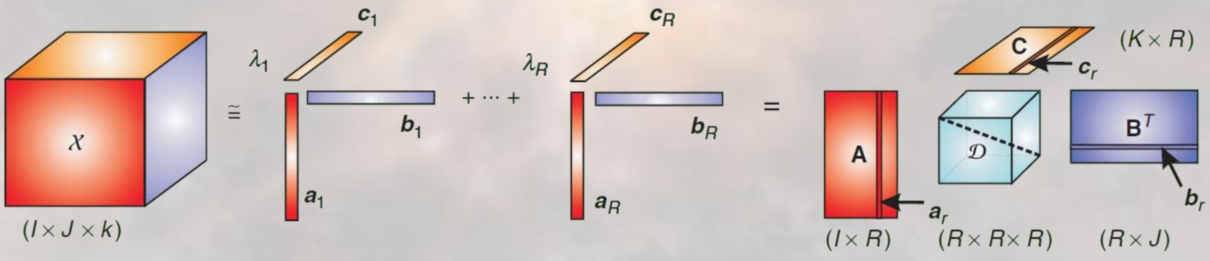


Challenges

- Leverage all time-series information in all dimensions
- Consider the structures of the multi-way relations of the data
- High demands on the signal analysis process
- Difficulty in handling and making operations
- Increased computational requirements

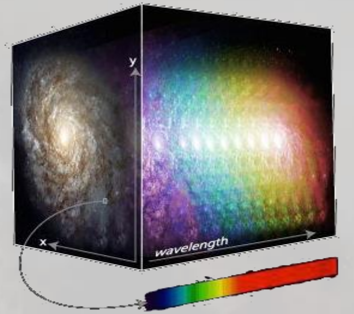
Tensors

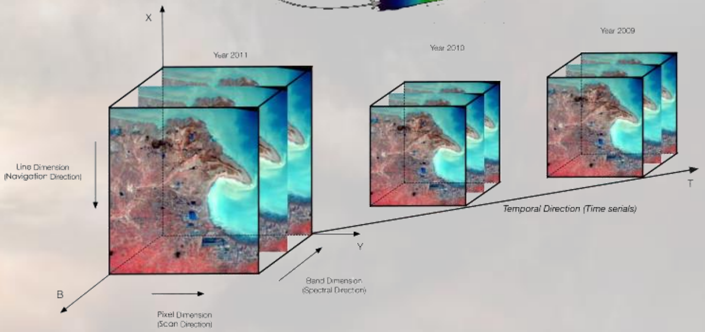
- Multidimensional arrays
- Processing using tensor analysis tools, e.g. tensor decomposition
- Reduce the complexity of the representation space
- Capture high-order relationships in the data
- Used in machine/deep learning
    - ❖ Feature extraction
    - ❖ Reduction of the number of parameters

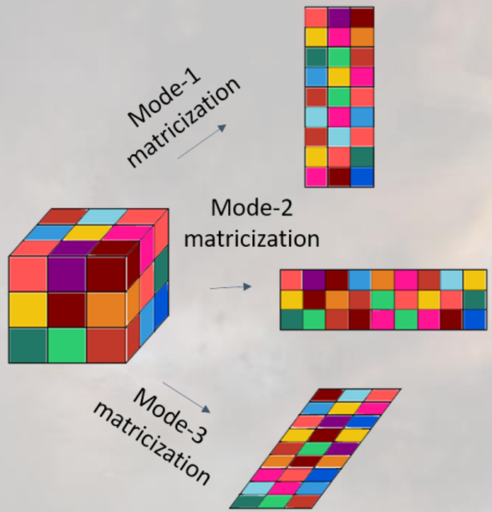


Tensor Based Observation Modeling

A tensor $\mathcal{X} \in \mathbb{R}^{I_1 \times \cdots \times I_N}$ is a N-way array, a higher-order generalization of vectors and matrices.





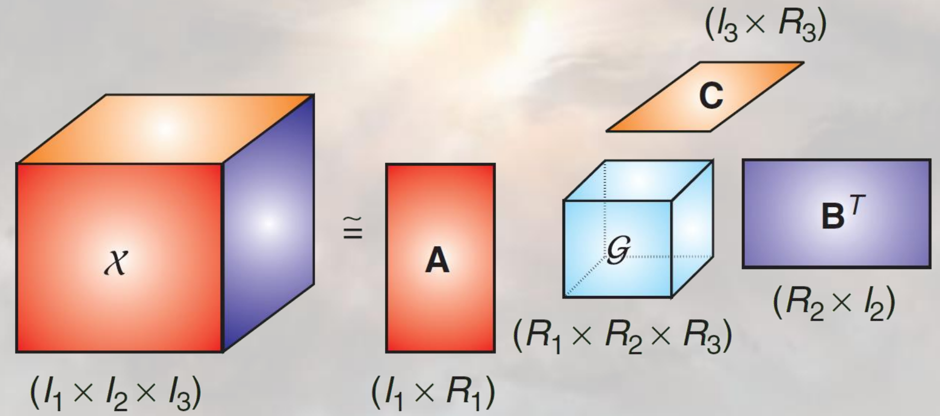


The mode-n unfolded matrix $\boldsymbol{X}_{(n)} \in \mathbb{R}^{I_n \times \prod_{i \neq n} I_i}$ corresponds to a matrix with columns being the vectors obtained by fixing all indices of $\mathcal{X}$ except the n-th index.

Tucker Decomposition

$\mathcal{X} \in \mathbb{R}^{I_1 \times \cdots \times I_N}$ is decomposed into a core tensor $\mathcal{G} \in \mathbb{R}^{R_1 \times \cdots \times R_N}$ and multiple matrices $\boldsymbol{A}^{(n)} \in \mathbb{R}^{I_n \times R_n}$ which correspond to different core scaling along each mode.

$$\mathcal{X} = \mathcal{G} \times_1 \boldsymbol{A}^{(1)} \times_2 \boldsymbol{A}^{(2)} \times_3 \cdots \times_N \boldsymbol{A}^{(N)}$$

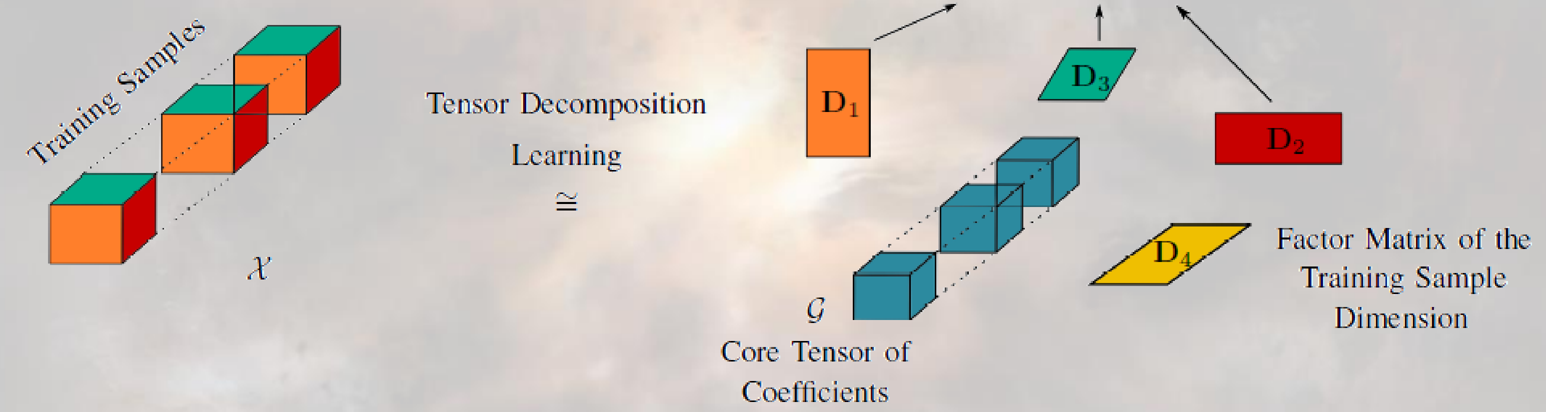


Tensor Decomposition Learning

Learn a basis for each mode, $\boldsymbol{D}_n \in \mathbb{R}^{I_n \times R_n}$ for $n = 1, .., N$ from S training samples $\mathcal{X} = (\mathcal{X}^1, .., \mathcal{X}^S) \in \mathbb{R}^{I_1 \times \cdots \times I_N \times S}$ such that

$$\min_{\mathcal{G}, \boldsymbol{D}_1, .., \boldsymbol{D}_{N+1}} \frac{1}{2} \|\mathcal{X} - \mathcal{G} \times_1 \boldsymbol{D}_1 \times_2 \cdots \times_N \boldsymbol{D}_N \times_{N+1} \boldsymbol{D}_{N+1}\|_F^2 + \lambda \|\boldsymbol{A}\|_*$$
$$\text{subject to } \boldsymbol{A} = \boldsymbol{D}_{N+1} \text{ and } \boldsymbol{D}_n^T \cdot \boldsymbol{D}_n = I_{R_n}, n = 1, .., N$$

where $\mathcal{G} \in \mathbb{R}^{R_1 \times \cdots \times R_N \times S}$, $\boldsymbol{D}_{N+1} \in \mathbb{R}^{S \times S}$ and $\boldsymbol{A} \in \mathbb{R}^{S \times S}$.



!!! Tensor decomposition techniques in the machine learning framework

A. Aidini, G. Tsagkatakis, and P. Tsakalides. "Tensor decomposition learning for compression of multidimensional signals." IEEE Journal of Selected Topics in Signal Processing 15.3 (2021): 476-490.

Application: Change detection of extreme events in multi-temporal images

- Monitor and assess the impacts of extreme events
- Identify changes in image time series
- The location of actual changes is not available in real-world scenarios
- Related works focus on detecting changes in bi-temporal images, underutilizing the wealth of available observations

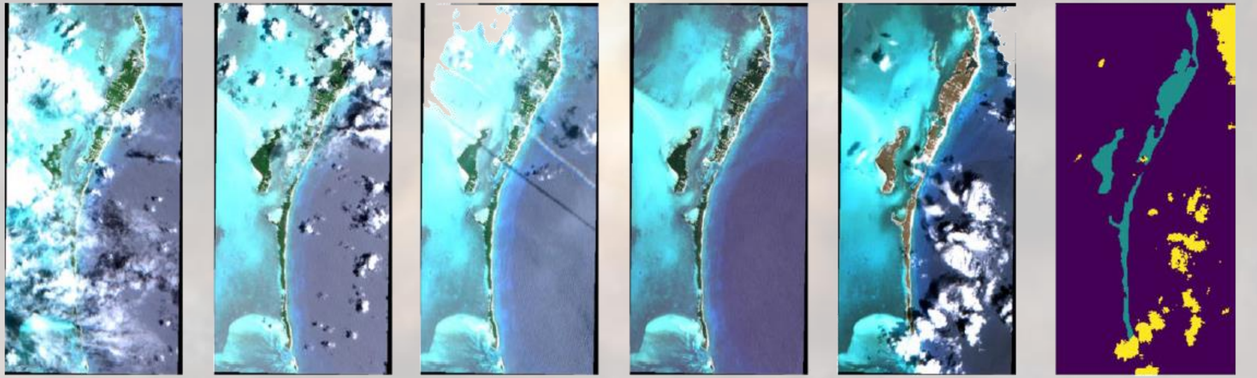


Image 1 Image 2 Image 3 Image 4 After event Change mask

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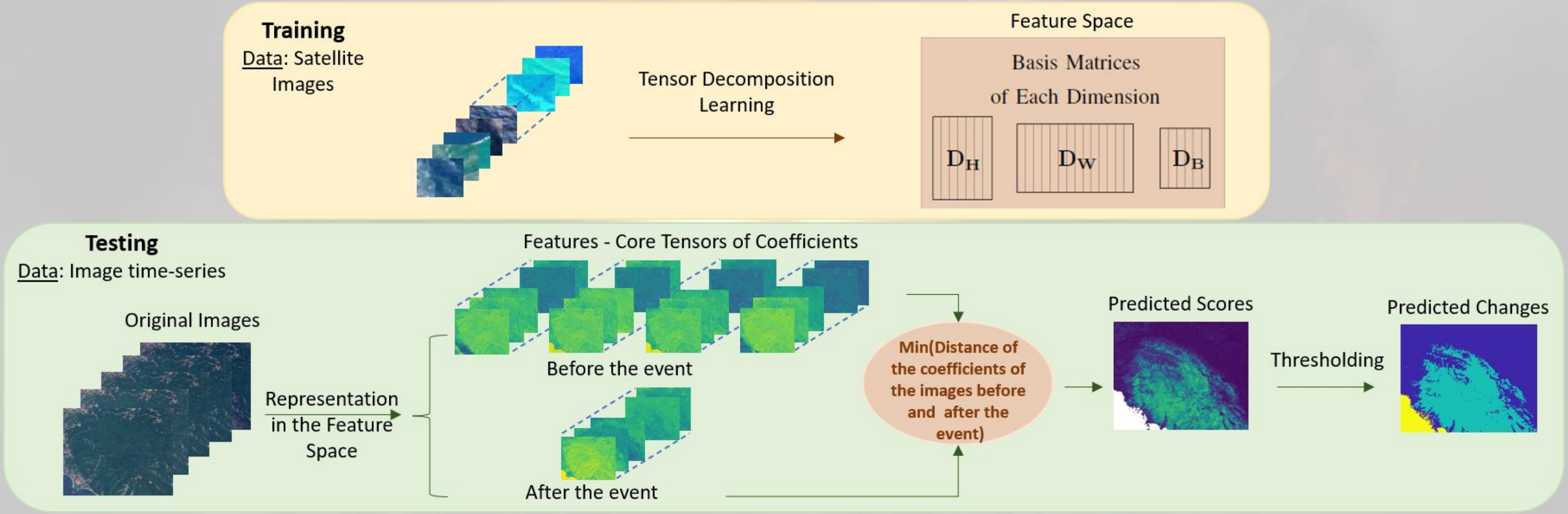
Proposed Change Detection Method

- Unsupervised approach based on tensor decomposition learning
- Exploit simultaneously the spatial and spectral features in the images with low complexity
- Applied to multi-temporal multispectral images



A. Aidini, G. Tsagkatakis, and P. Tsakalides, "Unsupervised Change Detection on Multi-Temporal Satellite Images Using Tensor Decomposition Learning," in Proc. 2024 IEEE International Geoscience and Remote Sensing Symposium (IGARSS '24), Athens, Greece, July 7-12, 2024.

Experimental Results

- Events: 5 locations of fires, 4 locations of floods
- Time series: 4 images before the event, 1 image after the event
- 5 Monte-Carlo Simulations, 3 × 3 patches
- Multilinear Rank: 1 for the spatial dimensions, full rank for the spectral dimension

***Table:** Comparison of the proposed method with RaVÆn on each extreme event, using 1 and 3 history frames.*

AUPRC	History	Fires	Floods
Proposed Method	1	**0.939** (1.71 · 10-10)	**0.764** (8.78 · 10-9)
	3	**0.937** (1.91 · 10-10)	**0.741** (5.18 · 10-9)
RaVÆn	1	0.833 (0.008)	0.448 (0.011)
	3	0.913 (0.008)	0.443 (0.009)

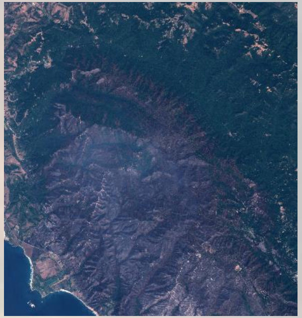
Complexity:

Proposed Method: The number of parameters is the number of elements in the 3 basis matrices learned for the representation of the feature space.

RaVÆn: Million parameters

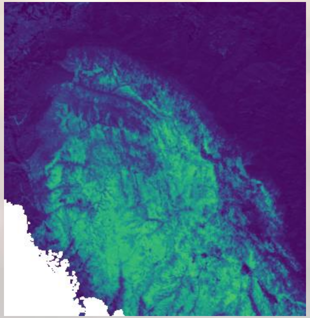
Predicted Maps

Before Fire

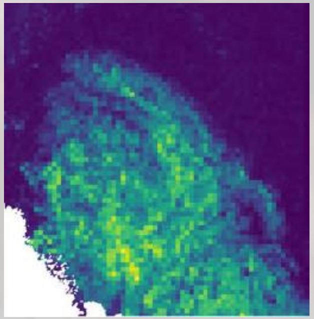


After Fire

Change Mask



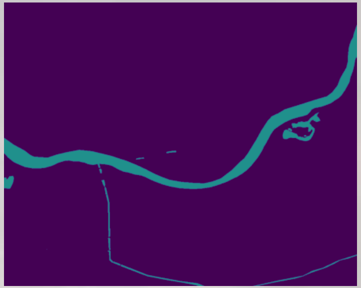
Prediction-
Proposed Method



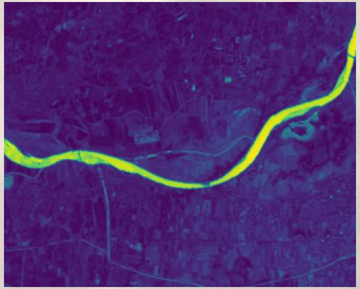
Prediction-
RaVÆn

Before Flood

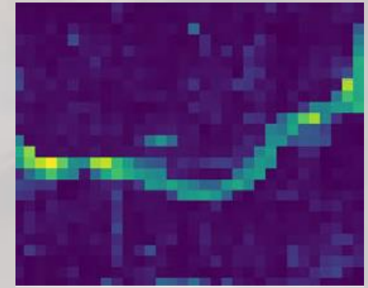
After Flood



Change Mask



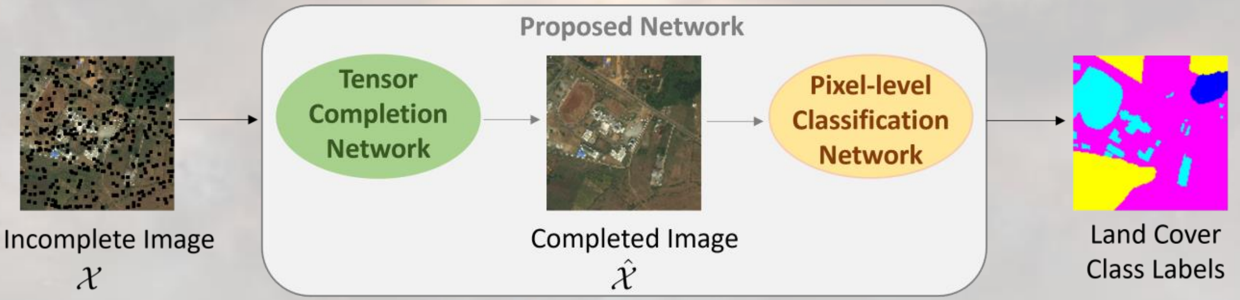
Prediction-
Proposed Method



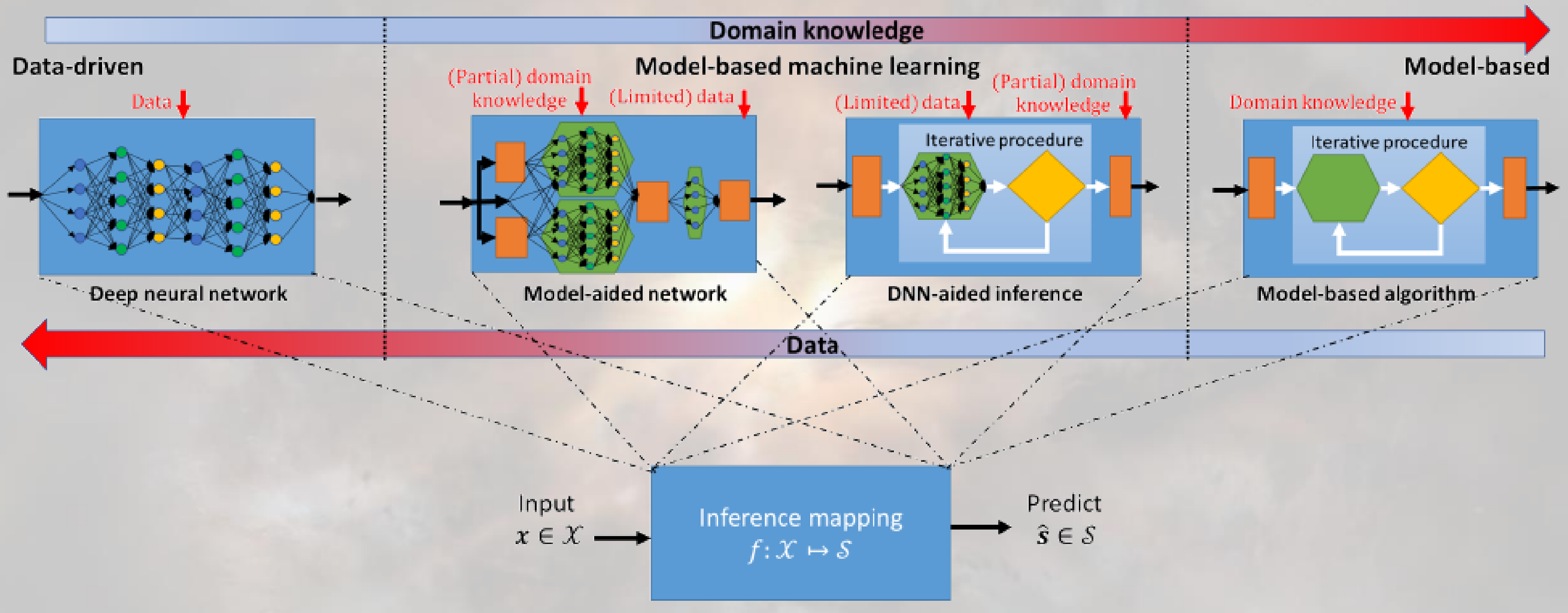
Prediction-
RaVÆn

Tensor-based Models in the Deep Learning Framework

- Leverage the benefits of both tensor analysis and deep learning techniques
- Analyze high-dimensional data in all dimensions
- Improve the performance of standard models
- Use prior domain knowledge
- Interpretable networks
- Combination of tensor-based networks with other popular networks to perform two tasks simultaneously
    - ❖ Recovery of missing or corrupted measurements in combination with classification problems in multitemporal data



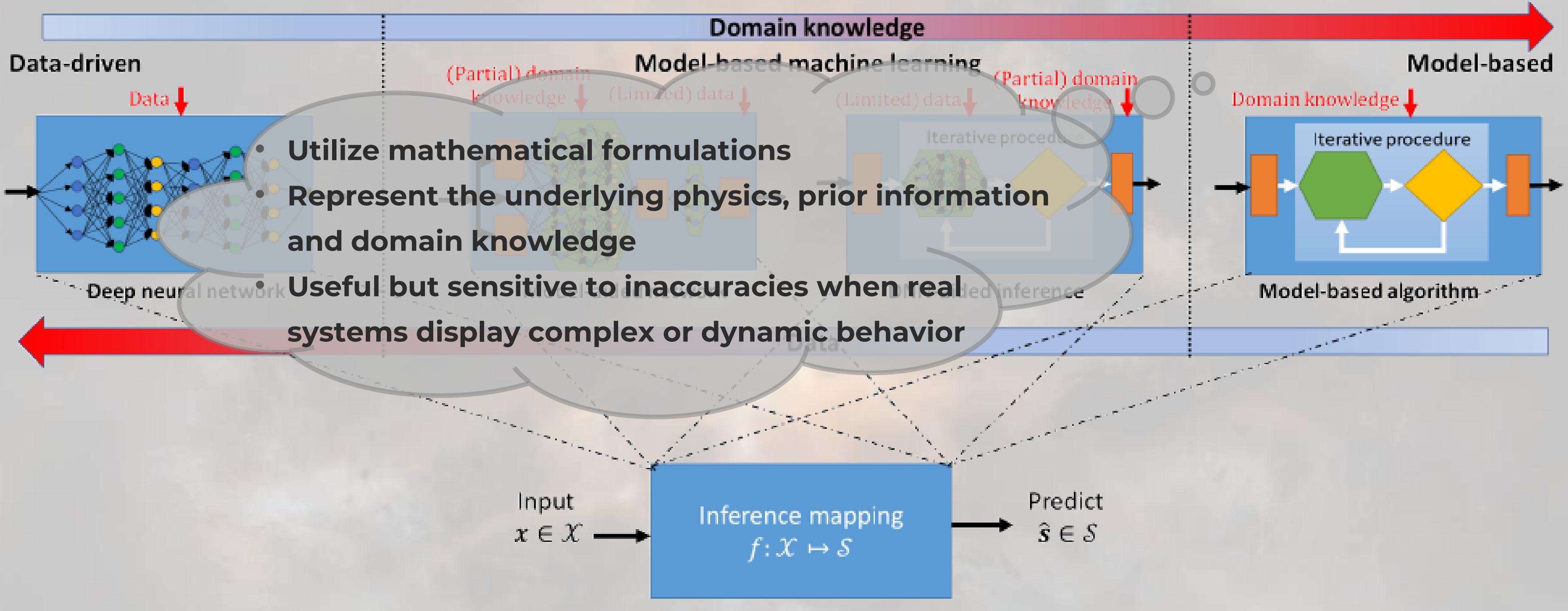
Model-based Deep Learning



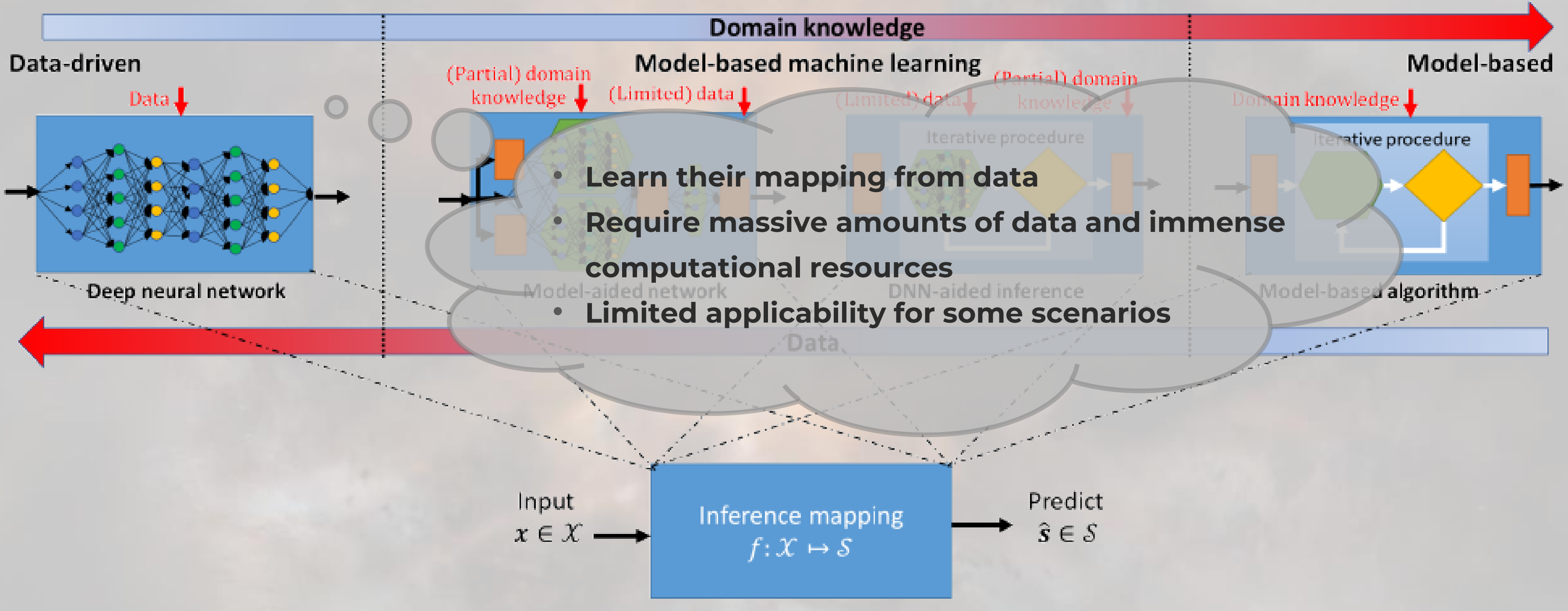
Shlezinger, N., Whang, J., Eldar, Y. C., & Dimakis, A. G. (2023). Model-based deep learning. Proceedings of the IEEE.

Model-based Methods

- Utilize mathematical formulations
- Represent the underlying physics, prior information and domain knowledge
- Useful but sensitive to inaccuracies when real systems display complex or dynamic behavior

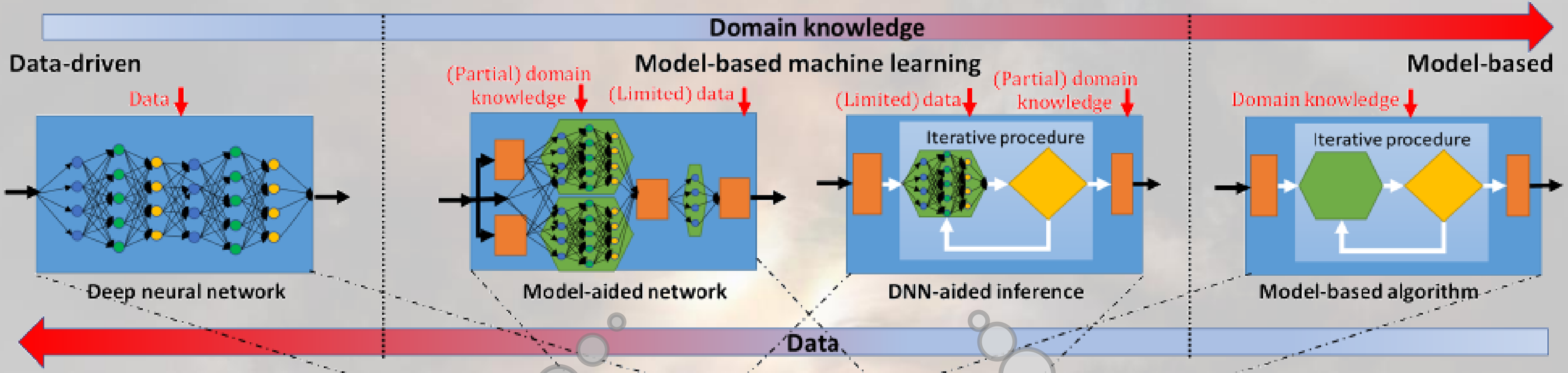


Data-driven Methods



- **Learn their mapping from data**
- **Require massive amounts of data and immense computational resources**
- **Limited applicability for some scenarios**

Model-aided Networks – DNN-aided Inference

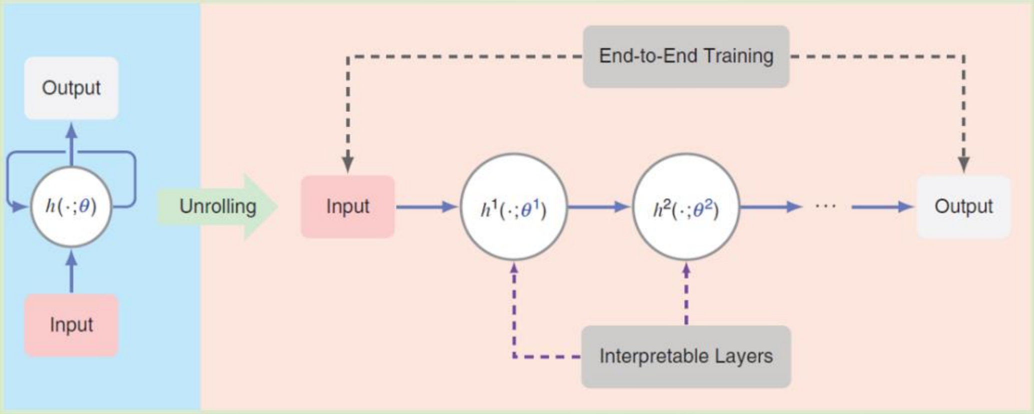


- Utilize DNNs for inference
- A specific DNN tailored for the problem at hand is designed by following the operation of suitable model-based methods

- Use model-based methods for inference
- Specific parts are augmented with deep learning tools
- Learning to overcome partial or mismatched domain knowledge from data

Algorithm unrolling technique

- A connection of the iterative algorithms with neural networks
- Higher representation power than the iterative algorithms
- Better generalization than generic networks
- Fewer parameters and require less training data, so they can be computationally faster



Conclusion

- Tensor analysis tools for multi-temporal observations processing
- Tensor decomposition techniques in the machine learning framework
  - Tensor decomposition learning method
  - Applicable to several problems e.g. Unsupervised change detection of extreme events
- Deep learning formulation of tensor models
  - Model-based deep learning approaches

Thank you