AI4EO

Special Topics in Applications (AIL861)
Artificial Intelligence for Earth Observation
Lecture 8

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Multi-Temporal Image Analysis

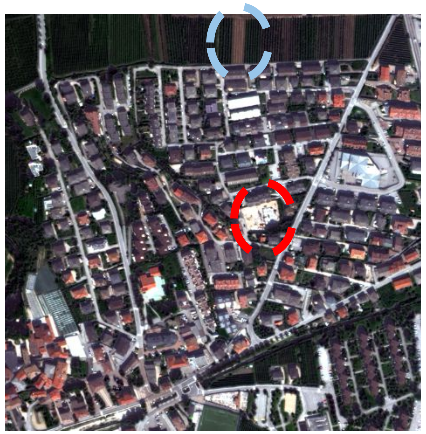
- ✔ Multi-temporal image analysis: Analysis of images of same object / place acquired at different times.

- ✔ Increased interest of multi-temporal image analysis over last decade due to:
  - ❑ Increased space mission -> better temporal resolution.
  - ❑ Free data access policy.

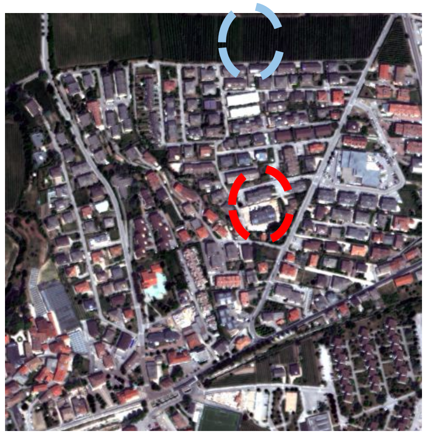
Change Detection

✔ Most important aspect of multi-temporal image analysis: change detection (CD).

Pre-change



Post-change



Applications

- ✔ Environmental monitoring
- ✔ Infrastructure monitoring
- ✔ Mining operations
- ✔ Disaster management
- ✔ Climate change
- ✔ Precision Agriculture
- ✔ Planetary operations

Environmental monitoring

- ✔ Change in forest cover
- ✔ Urban area monitoring
- ✔ Vegetation change
- ✔ Sea and rivers related changes
- ✔ CD of glacier surface

Modalities

✔ Many modalities:

❑ Multi-spectral

❑ Hyperspectral

❑ Synthetic Aperture Radar (single band, polarimetric)

✔ Additionally, different resolutions.

Supervision?

- ✔ There are supervised methods, e.g., based on Siamese networks.
- ✔ Difficult to collect large-scale multi-temporal labeled datasets.
- ✔ Several issues with labeled datasets, including generalization to new tasks/areas.
- ✔ Sometimes impractical, e.g., in disaster management.

- ✔ So, unsupervised methods are preferred.

Traditional Unsupervised Methods

✔ Differencing (Change Vector Analysis – CVA and variants) or clustering:

❑ Pixel values

❑ Shallow features computed from pixels

✔ Object based notions: super-pixels

✔ Higher resolution – higher spatial complexity

✔ Limited capability to capture spatial context and temporal complexity.

A superpixel is a concept in image processing and computer vision that refers to a group of adjacent pixels in an image that are merged into a single, more compact region. The goal of superpixel segmentation is to divide an image into a set of smaller, uniform regions, while preserving the overall structure and content of the image.
Superpixels are created by clustering adjacent pixels based on their color, texture, or other attributes. This grouping process can help simplify the image representation and reduce the number of pixels to be processed, making subsequent image analysis tasks, such as object recognition and segmentation, more efficient.
Superpixels can be created using various algorithms, including graph-based methods, watershed segmentation, and K-means clustering. The choice of algorithm and the parameters used can significantly affect the quality and accuracy of the superpixel segmentation results.

Superpixels have found applications in a wide range of fields, including computer vision, remote sensing, and medical imaging, as they can provide a fast and efficient way to represent and analyze complex images.
There are several advantages of creating superpixels in image processing and computer vision:
Computational Efficiency: By reducing the number of pixels to be processed, superpixels can significantly reduce the computational load of subsequent image analysis tasks, such as object recognition and segmentation. This can lead to faster processing times and more efficient use of computational resources.
Simplified Image Representation: Superpixels can provide a simplified representation of an image by grouping similar pixels together into larger, more uniform regions. This can make it easier to identify and analyze the underlying structure and content of the image.
Improved Accuracy: By preserving the overall structure and content of the image, superpixels can help improve the accuracy of subsequent image analysis tasks. For example, superpixels can provide more meaningful and representative features for object recognition and classification compared to individual pixels.
Reduced Over-segmentation: Superpixels can help reduce the over-segmentation problem, which occurs when an image is divided into too many small regions, leading to a loss of important image information. Superpixels provide a balance between detailed and coarse image representation, preserving the important structures and content of the image while simplifying the analysis process.

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Deep learning, how?

Transfer learning

✔ Do Deep Features Generalize from Everyday Objects to Remote Sensing and Aerial Scenes Domains?

2015 paper introducing transfer learning to Earth observation.

Unsupervised DL

✔ Over years we observe an evolution of unsupervised/semi-supervised/self-supervised DL:

❑ Transfer learning

❑ Generative adversarial network

❑ Graph Convolutional Network

❑ Unsupervised methods, e.g., deep clustering

✔ Unsupervised multi-temporal analysis methods co-evolved with the above evolution.

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Deep CVA (2018/2019)

✔ Goal: Propose a CD method employing CNN for VHR optical bi-temporal images for single-sensor scenario

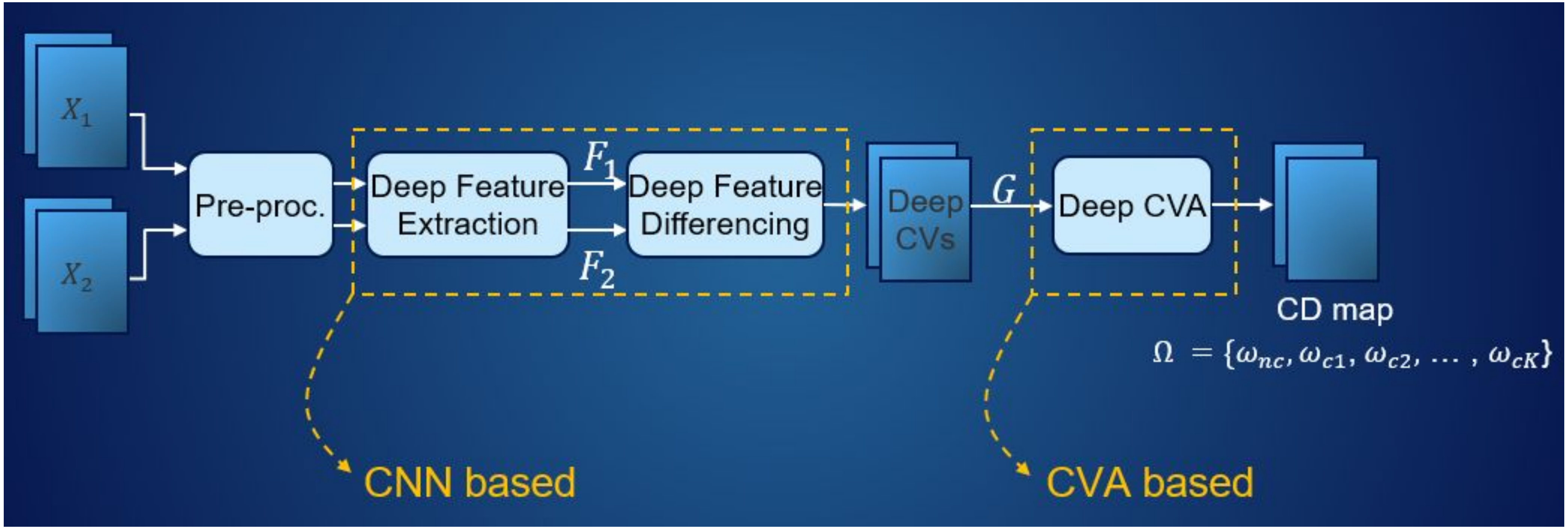
✔ Given input bi-temporal VHR images acquired using the same sensor, to devise CD techniques to:

❑ Distinguish changed pixels from the unchanged ones (binary CD)

❑ Further segregate changed pixels into different kinds of changes (multiple CD)

✔ Assumption: We have a network trained on VHR optical images, for classification or segmentation

DCVA



X_1
X_2
Pre-proc.
Deep Feature Extraction
F_1
F_2
Deep Feature Differencing
Deep CVs
G
Deep CVA
CD map
$\Omega = \{\omega_{nc}, \omega_{c1}, \omega_{c2}, \ldots, \omega_{cK}\}$
CNN based
CVA based

Feature Extraction

✔ Selected network:

❑ Pre-trained for semantic segmentation.

❑ On Potsdam dataset.

✔ Feature selection:

❑ From selected convolution, deconvolution layers.

❑ Hypercolumn/hypervector: multiscale representation of the multi-temporal information.

❑ A variance based strategy is used to select features that emphasize change information.

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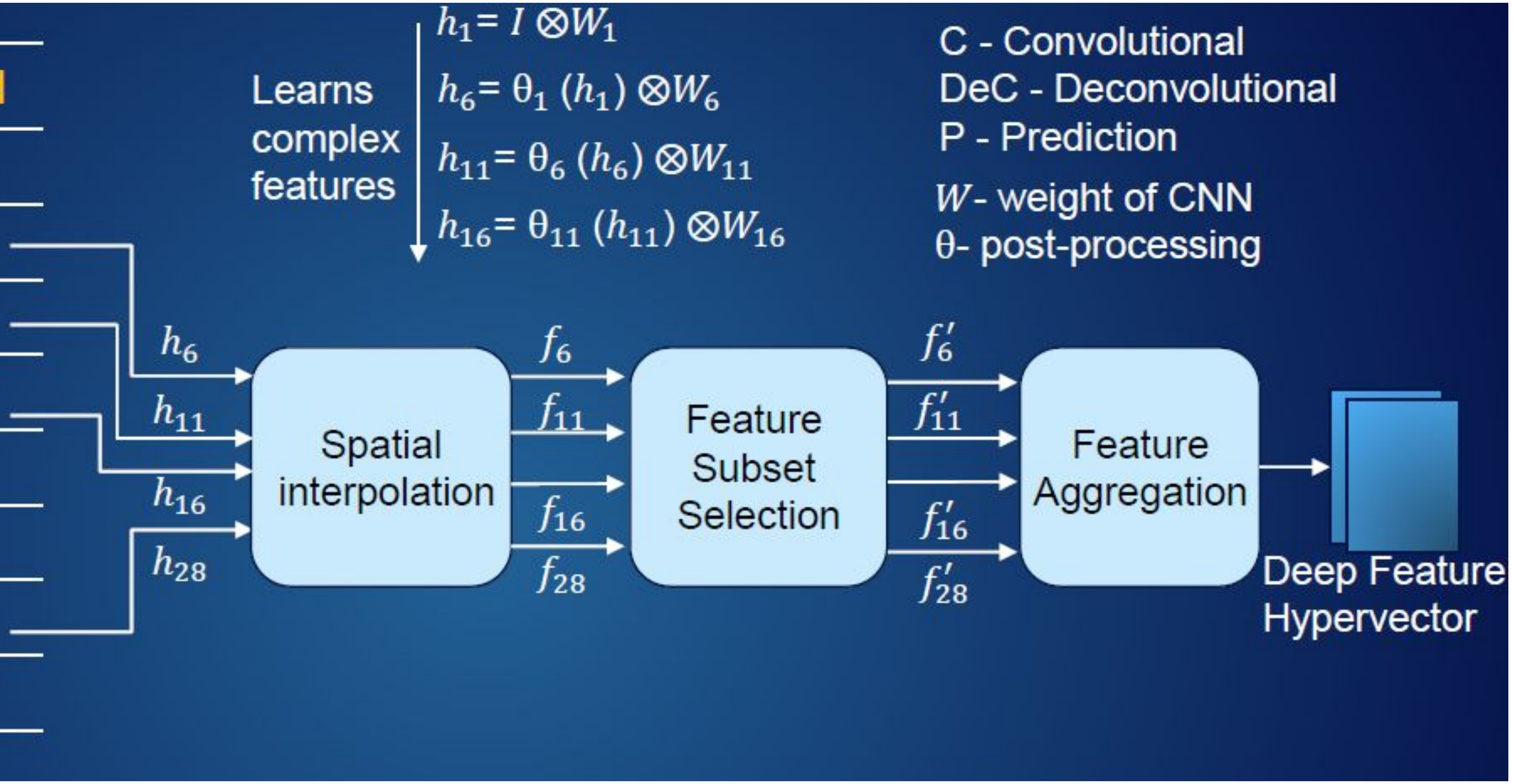
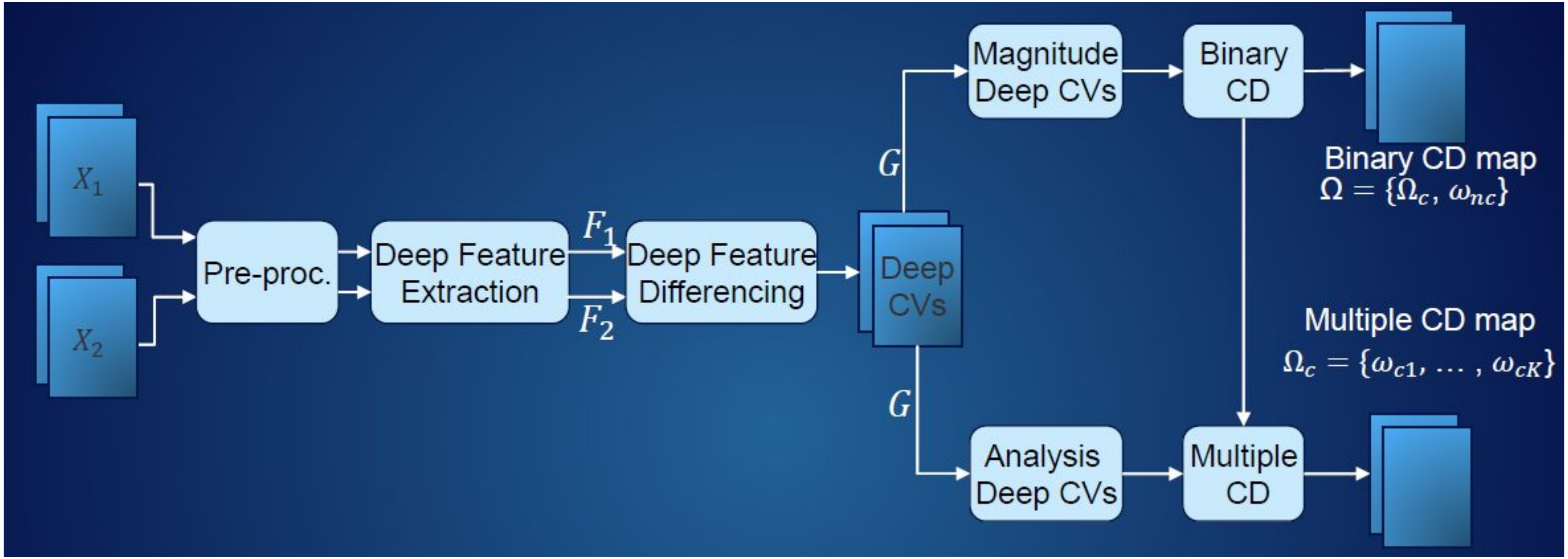
Feature Extraction

Layer	Type	Used
1	C	N
6	C	Y
11	C	Y
16	C	Y
20	DeC	N
24	DeC	N
28	DeC	Y
33	P	N



Deep CVA



X_1
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Deep Feature Extraction
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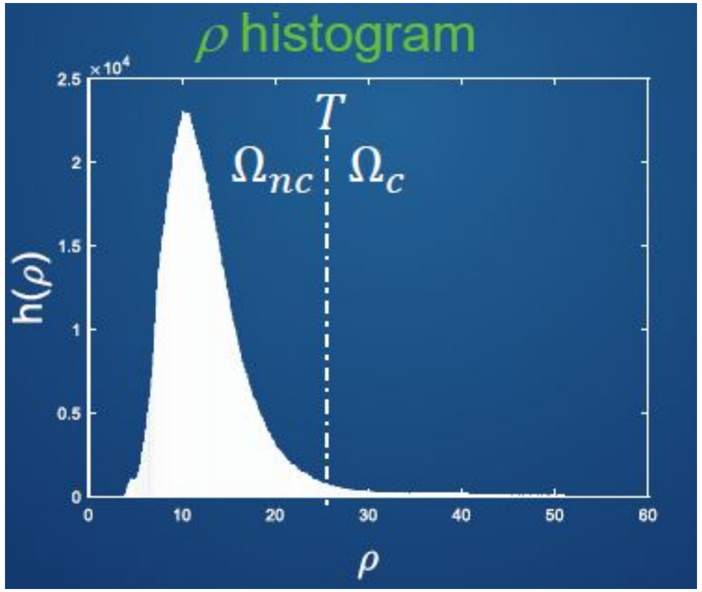
Deep Feature Differencing
Deep CVs
G
G
Magnitude Deep CVs
Binary CD
Binary CD map
$\Omega = \{\Omega_c, \omega_{nc}\}$
Analysis Deep CVs
Multiple CD
Multiple CD map
$\Omega_c = \{\omega_{c1}, \ldots, \omega_{cK}\}$

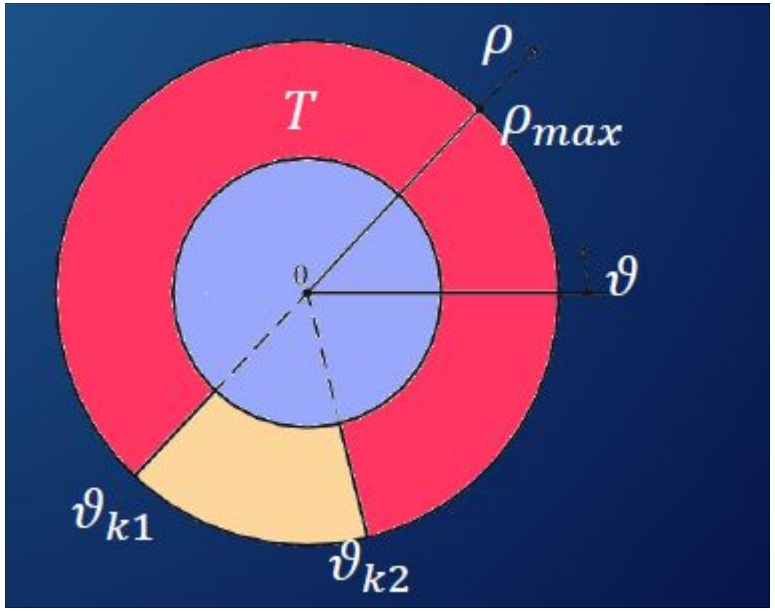
Deep CVA

✔ Binary CD:

- ❑ Magnitude based analysis
- ❑ Magnitude ρ is calculated as L2 norm of deep change hypervector *G*.
- ❑ Changed pixels: higher ρ
- ❑ Threshold determination using any suitable algorithm, e.g., Otsu or adaptive.



Deep CVA



✔ Multiple/multi-class CD:

- ❑ Deep change hypervector – high dimensional vector, not trivial to cluster
- ❑ Considering changed pixels' property, we are likely to have components of *G*, which are either positive or negative.
- ❑ Binarize deep change vector
- ❑ Iterative hierarchical clustering

	Change 1				Change 2			
G	0.7	0.4	…	0.8	-0.7	-0.4	…	-0.8
Binarized G	1	1	…	1	0	0	…	0