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Caractérisation de relations de proximité temporelle, spatiale et sémantique pour l'exploration d'un corpus d'images photographiques

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Une cathédrale de données numériques et connaissances pluridisciplinaires

Journées d'études du groupe de travail "données numériques" du chantier scientifique Notre-Dame de Paris
 19 – 21 juin 2024, Campus CNRS Joseph Aiguier, Marseille

Summary

Introduction Problem Statement	Introduction Distances	Data Images & Metadata
Structuring (I) Graph-oriented Database	Structuring (II) Embeddings	Exploring Image distances
Thank you for your attention! Acknowledgments <p>This work benefits from a French ANR with reference ANR-17-CYFR-0021 – Ecole Interdisciplinaire de Recherche Paris-Saclay/Université Catholique de Lille – 7 avenue des Sciences de Palaiseau.</p> <p>Credits of the images of the railway belong to SNCF, Florent Goussier and Roxane Riccardi. The map of the cathédrale is credited to the IGN.</p> <p>Caractérisation de relations de proximité temporelle, spatiale et sémantique pour l'exploration d'un corpus d'images photographiques Sylvain Millet, Sylvain LaSTIG, MAP, FSP</p>  <p>Une cathédrale de données numériques et connaissances pluridisciplinaires Bibliothèque d'histoire et d'archéologie de l'Université de Lille 20-22 rue de la République, 59645 Lille Cedex 03 20 33 53 54, lannee1880@univ-lille.fr</p>		

Introduction

Problem Statement

Introduction

Previously...

Illustration of tie-rod extraction protocol

Image uses:

- Documentation of protocols

Extraction des tirants

Paris, Notre-Dame, plan du rez-de-chaussée du chevet (Nomenclature des espaces, MOA, MOE, 2021)

Extraction du bouchon PE11W :

- 1-3 : avant extraction, inspection endoscopique
- 4-5 : retrait du bouchon, découverte d'un tirant en place
- 6-8 : sciage du goujon puis extraction du tirant

TIME

Dater le chevet de Notre-Dame de Paris : regards croisés
Yves Gallet, Jean-Yves Hunot, Mathilde Bernard, 2024

Introduction

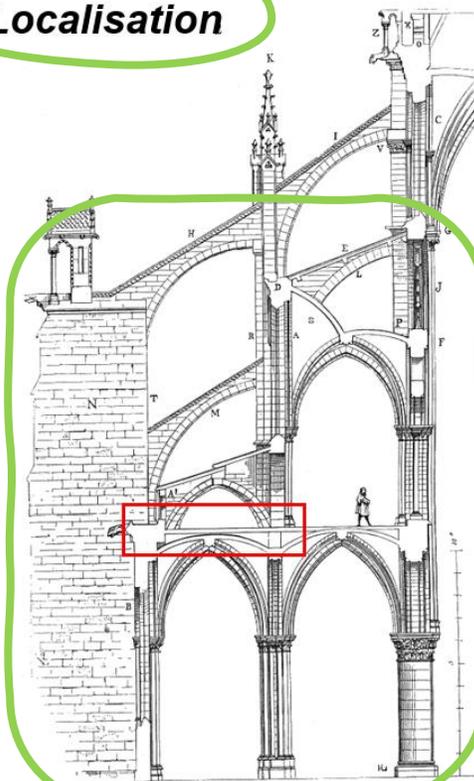
Previously...

Location of the cramps from the tribune

Image uses:

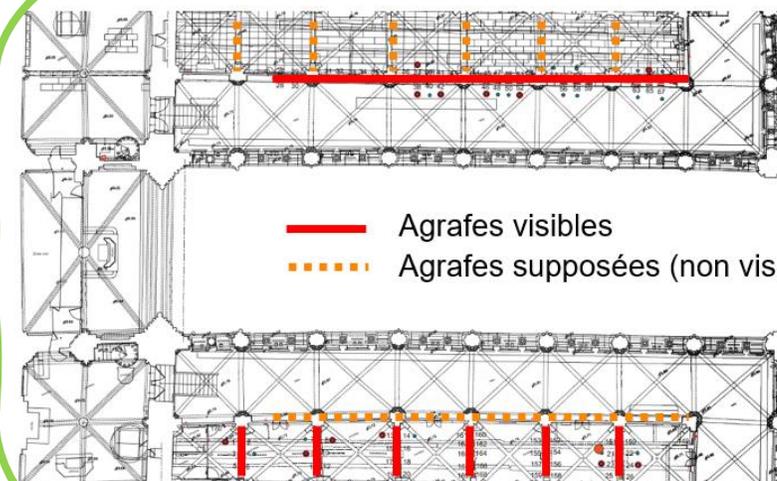
- Documentation of protocols
- Location of objects/artefacts

Localisation



Coupe de Notre-Dame de Paris, *Dict. raisonné de l'architecture française du XIe au XVIe siècle*, E. Viollet-le-Duc, 1854-1868

Éléments de datation : les agrafes des tribunes



SPACE

La construction de la nef : nouvelles données chronologiques,
Arnaud Ybert, Maxime L'Héritier, Olivier Girardclos, 2024

Introduction

Previously...

Illustration of post-fire observations

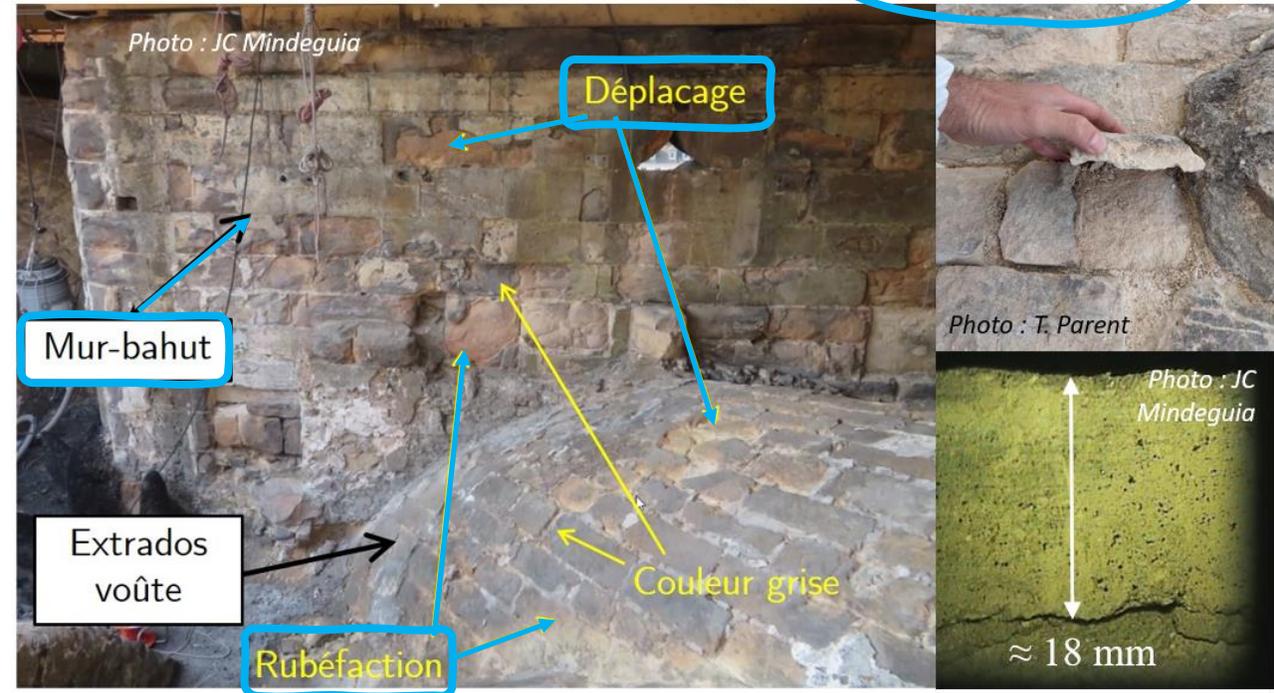
Image uses:

- Documentation of protocols
- Location of objects/artefacts
- Annotations of the observations

SEMANTICS

Données existantes et observations directes

➤ Analyse des données post-incendie : ce dont on dispose / ce que l'on observe



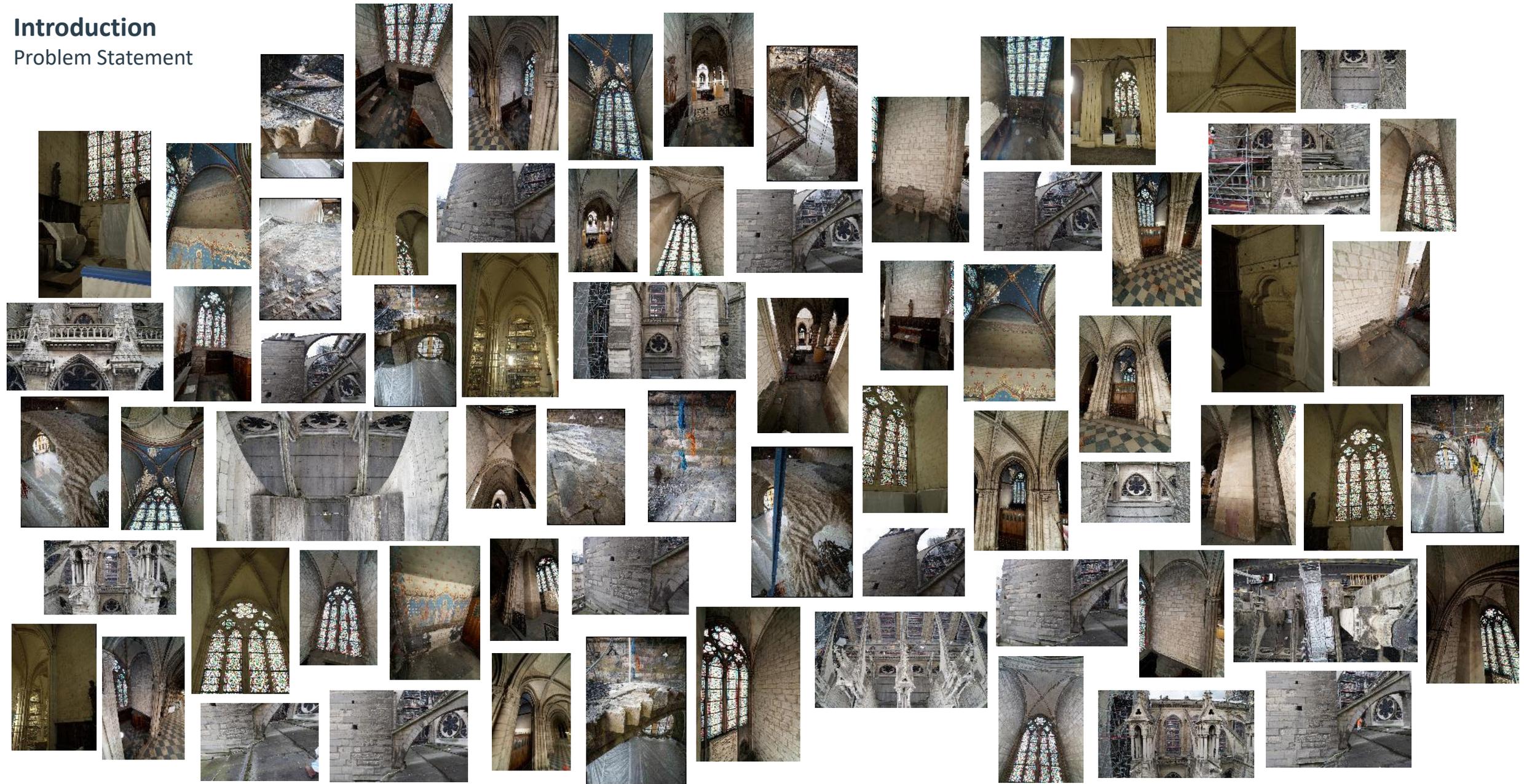
Effet de l'incendie sur un ensemble voûte-contrebutements du chœur de Notre-Dame / P. Morenon, J.C. Mindeguia & al.

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Effet de l'incendie sur un ensemble voûte-contrebutements du chœur de Notre-Dame, Pierre Morenon, Jean-Christophe Mindeguia, 2024

Introduction

Problem Statement



58,886

images in Aïoli

9,726

images in ArcheoGRID

Question: how to explore this corpus of images?

(not entirely) a solution: by defining similarity measures between images, based on some characteristic...

Introduction

Distances

Distance

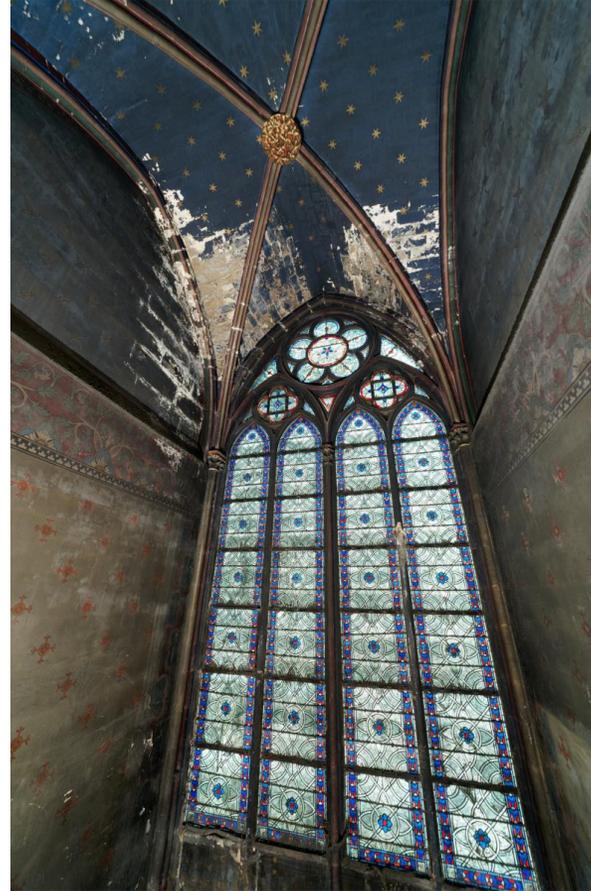
Example: Visual distance

Which images are closest to one another?

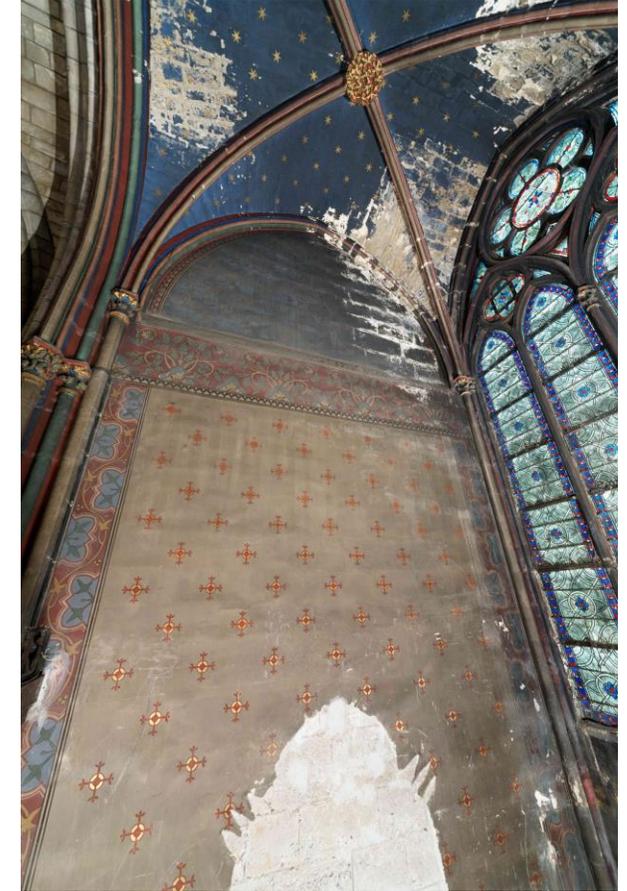
ITER_ca_19_04587



ITER_ca_19_04642



ITER_ca_19_04642

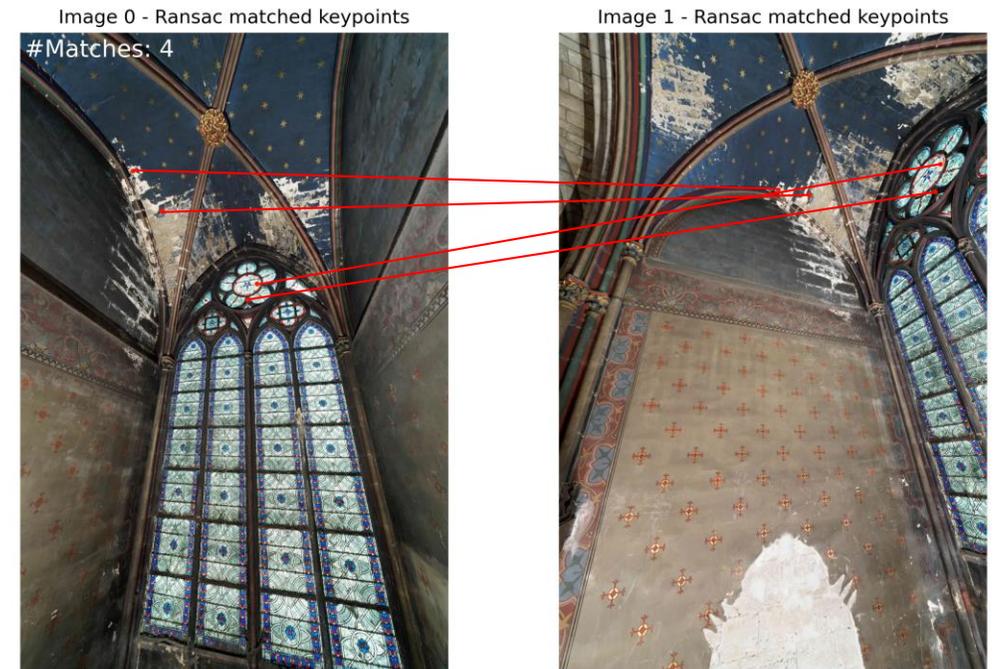
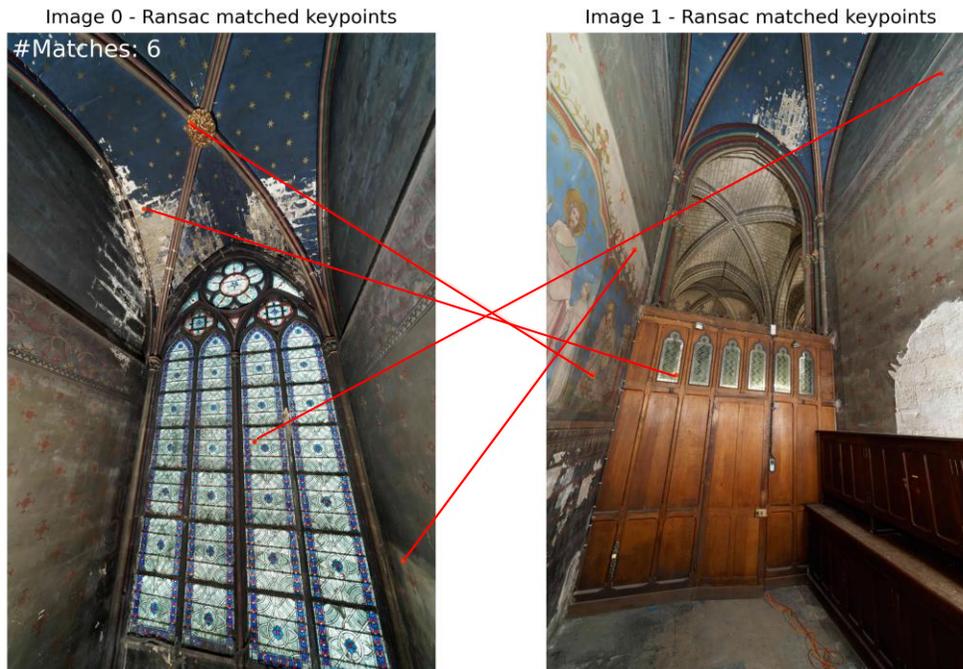


Distance

Example: Visual distance

Which images are closest to one another?

Image matching, [...], aims to identify then correspond the same or similar structure/content from two or more images. [Ma et al., 2021]



Examples using SIFT [Lowe, 1999] & RANSAC [Fischler & Bolles, 1981]

stay tuned...

Distance

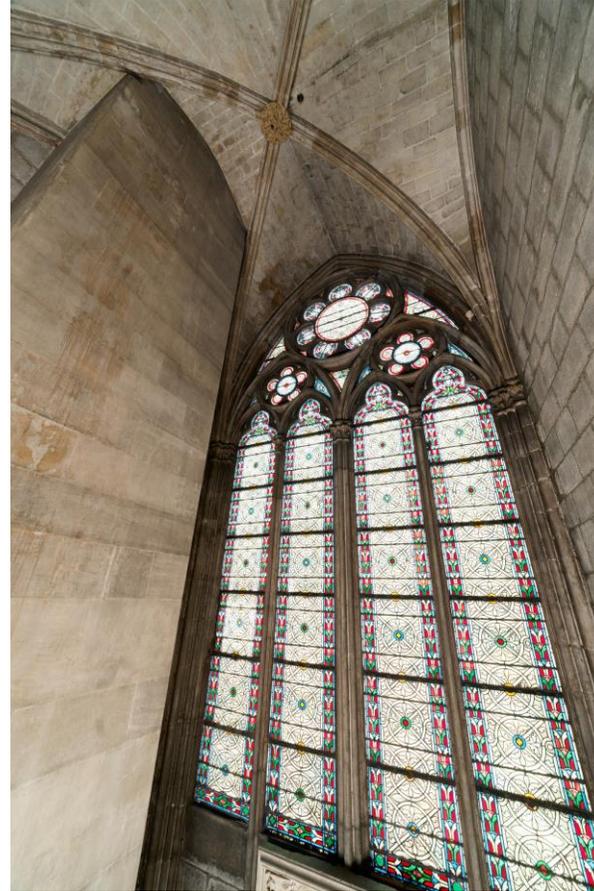
Example: Spatial distance

Which images are closest to one another?

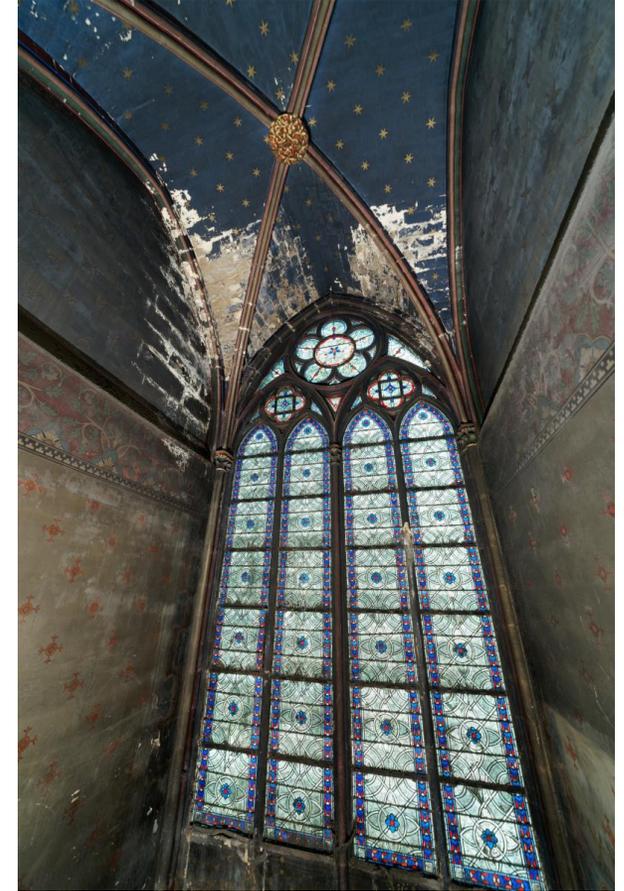
ITER_ca_25_03766



ITER_ca_25_03795



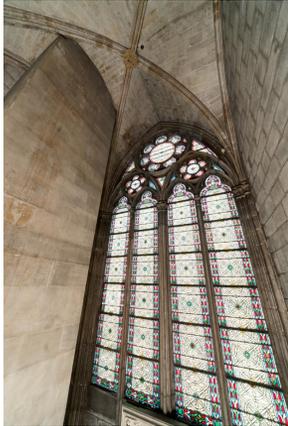
ITER_ca_19_04642



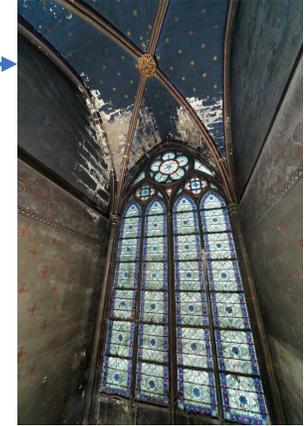
Distance

Example: Spatial distance

ITER_ca_25_03795



ITER_ca_19_04642



High euclidean distance
Short visual distance

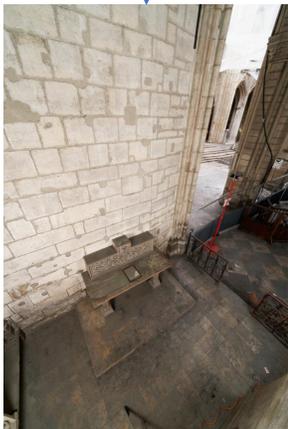


CA25

CA19



Short euclidean distance
High visual distance



ITER_ca_25_03766

Distance in the cathedral:
images from CA25 are closer to each other than they are to the image from CA19

Distance

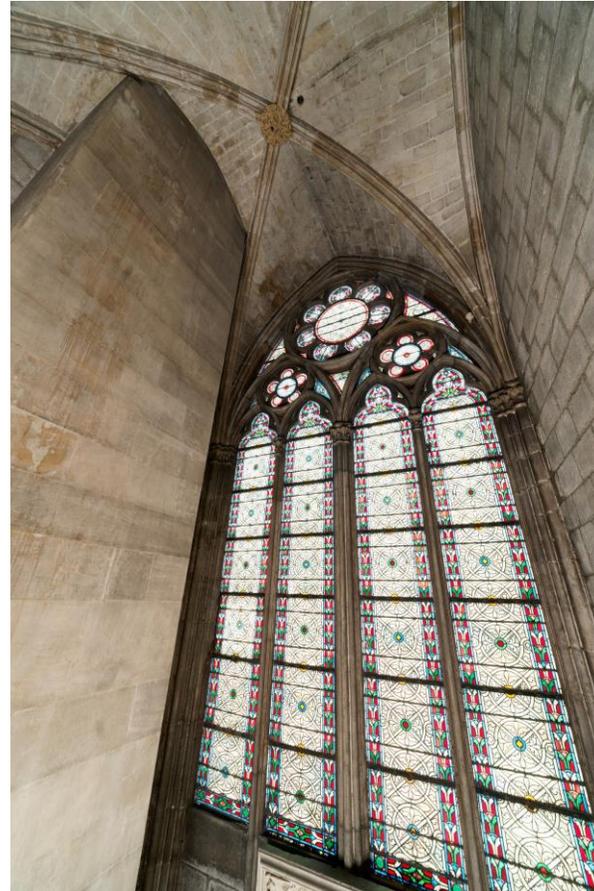
Example: Spatial distance

Which images are closest to one another?

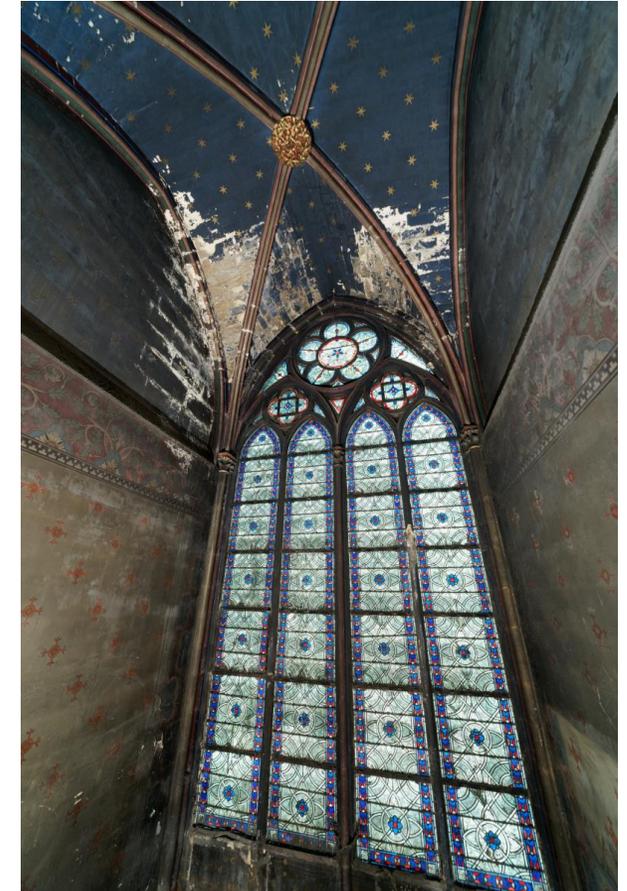
ITER_ca_38_07983



ITER_ca_25_03795



ITER_ca_19_04642



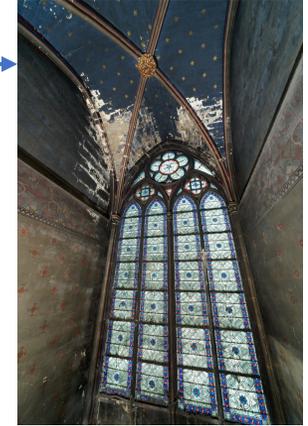
Distance

Example: Spatial distance

ITER_ca_25_03795



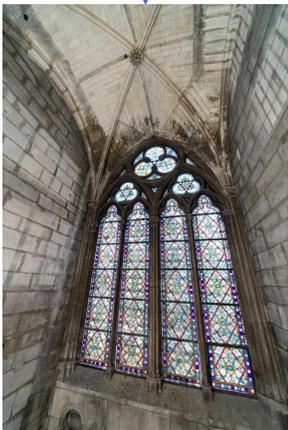
ITER_ca_19_04642



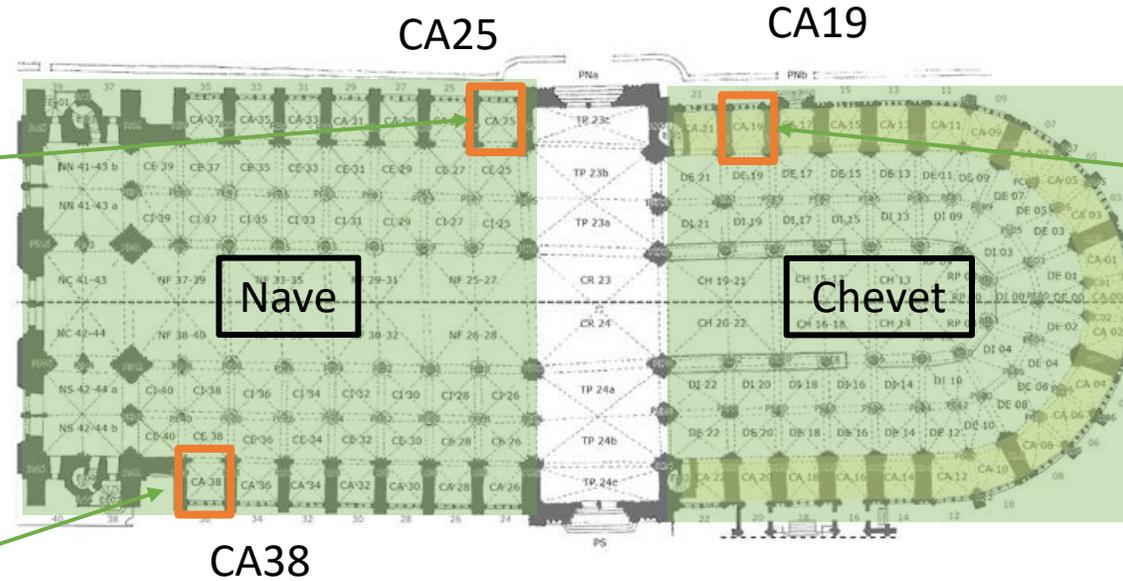
Smaller euclidean distance
Short visual distance



Higher euclidean distance
Short visual distance



ITER_ca_38_07983

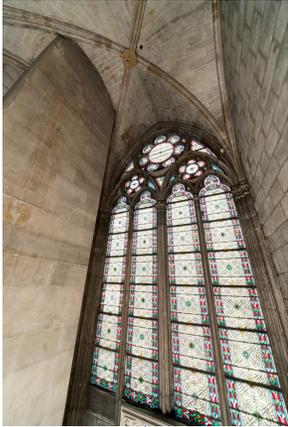


Distance in the cathedral:
images from CA19 & CA25 are closer to
each other than any of them is to image
from CA38

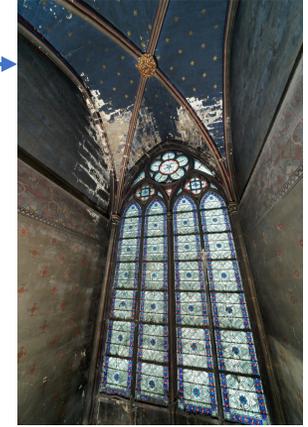
Distance

Example: Spatial distance

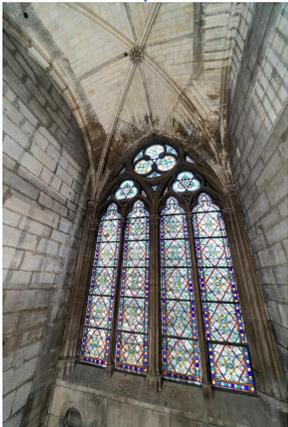
ITER_ca_25_03795



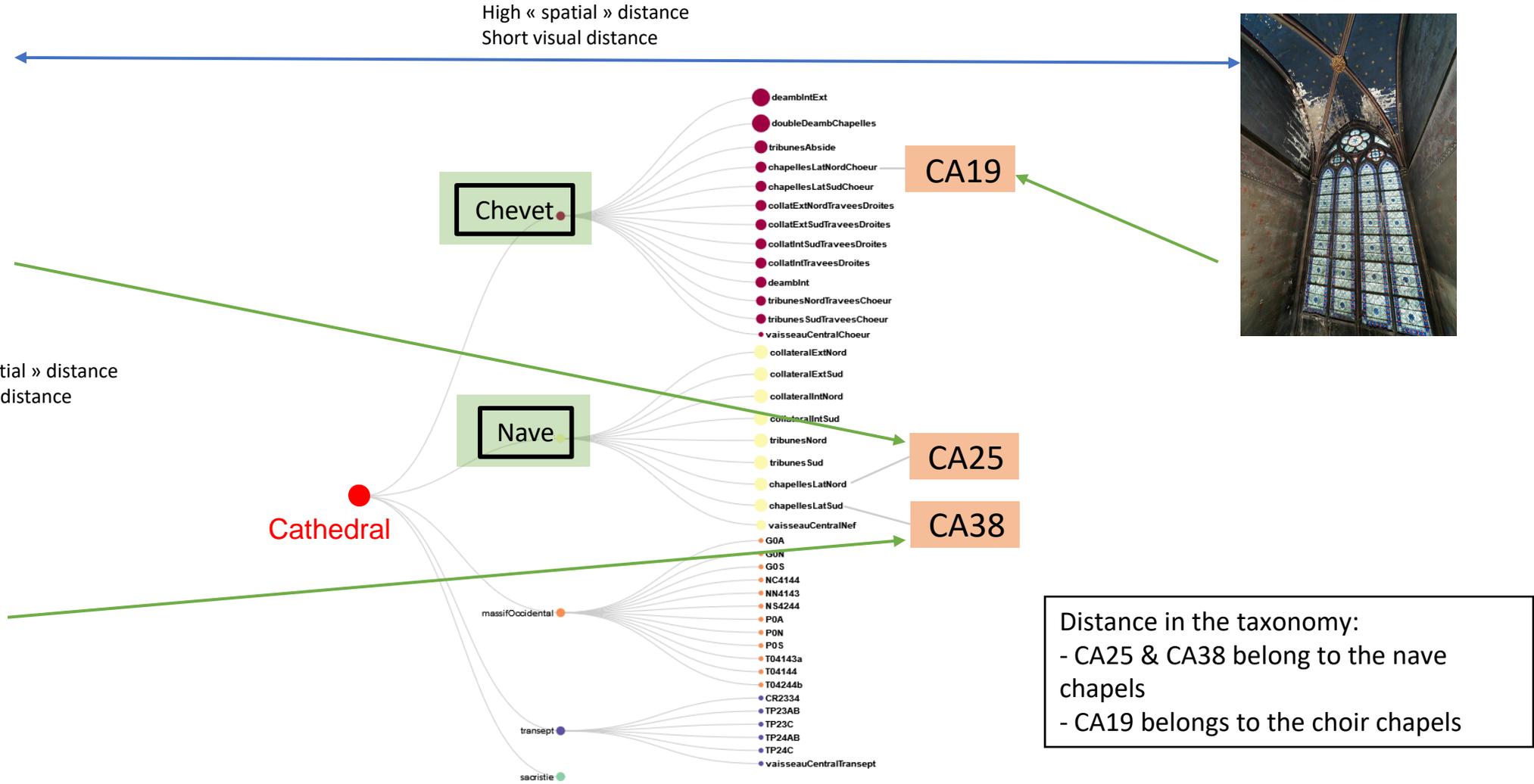
ITER_ca_19_04642



Short « spatial » distance
High visual distance



ITER_ca_38_07983



Distance in the taxonomy:
- CA25 & CA38 belong to the nave chapels
- CA19 belongs to the choir chapels

Question: How to *compute* a distance/proximity between images?

1. Data

Data

Images & Metadata

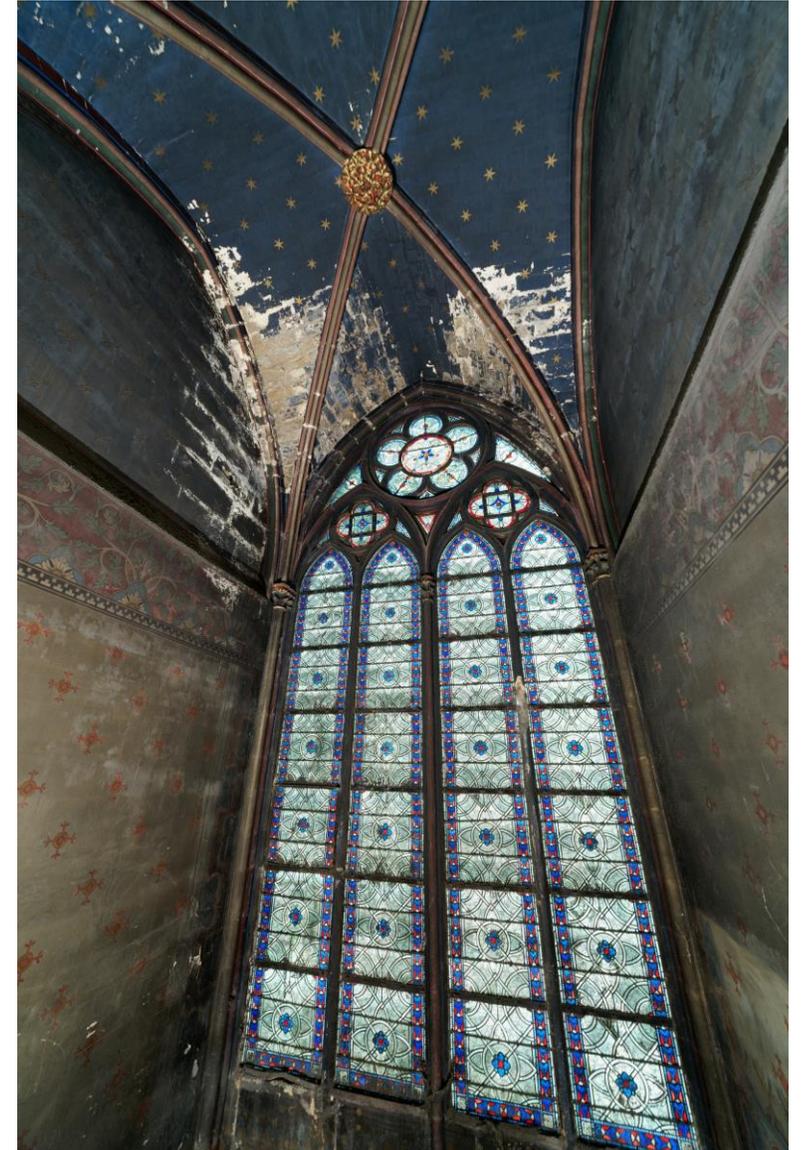
Data

Description

Data:

- Visual Content

ITER_ca_19_04642

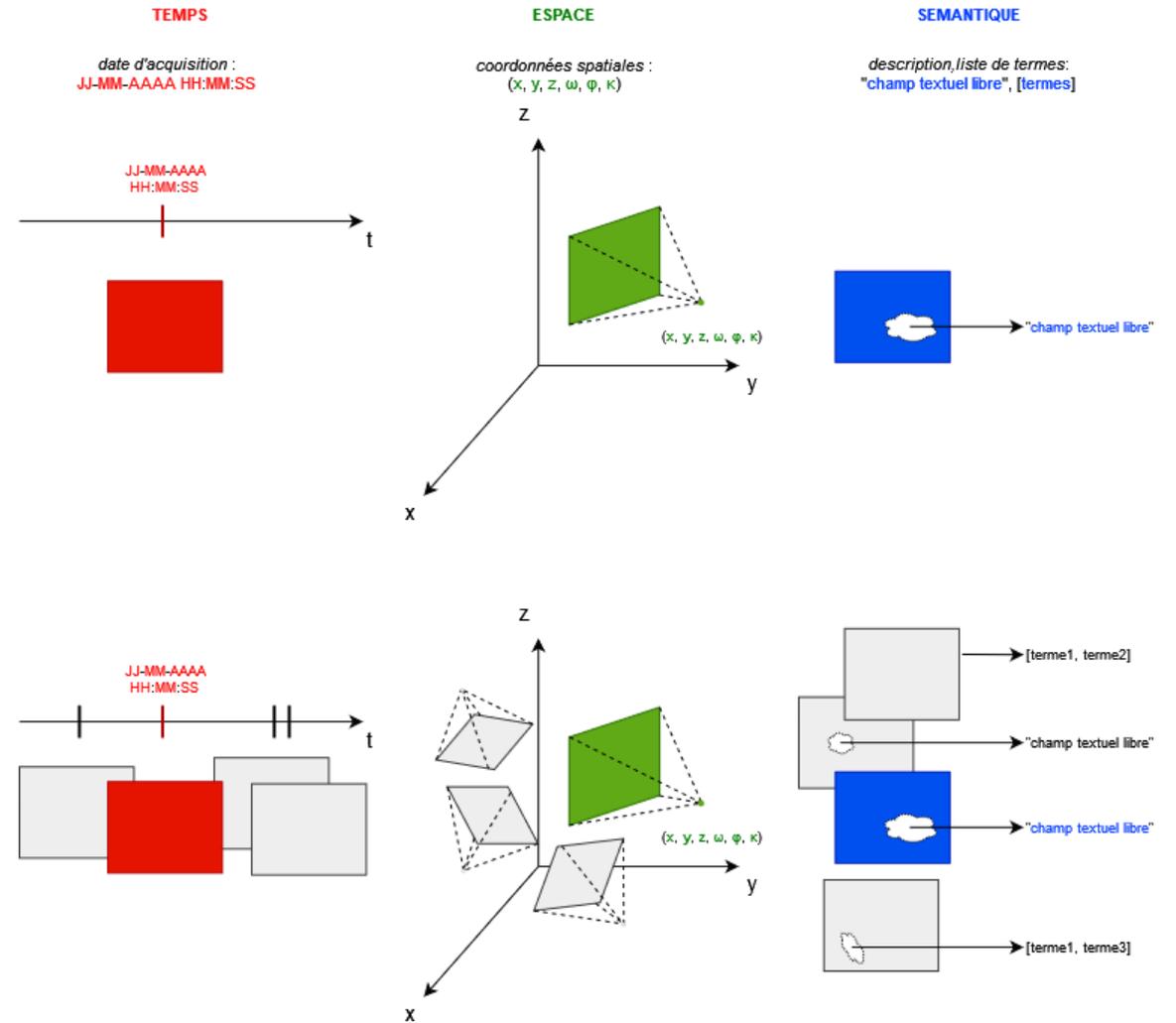


Data

Description

Data:

- Visual Content
- Image-related metadata

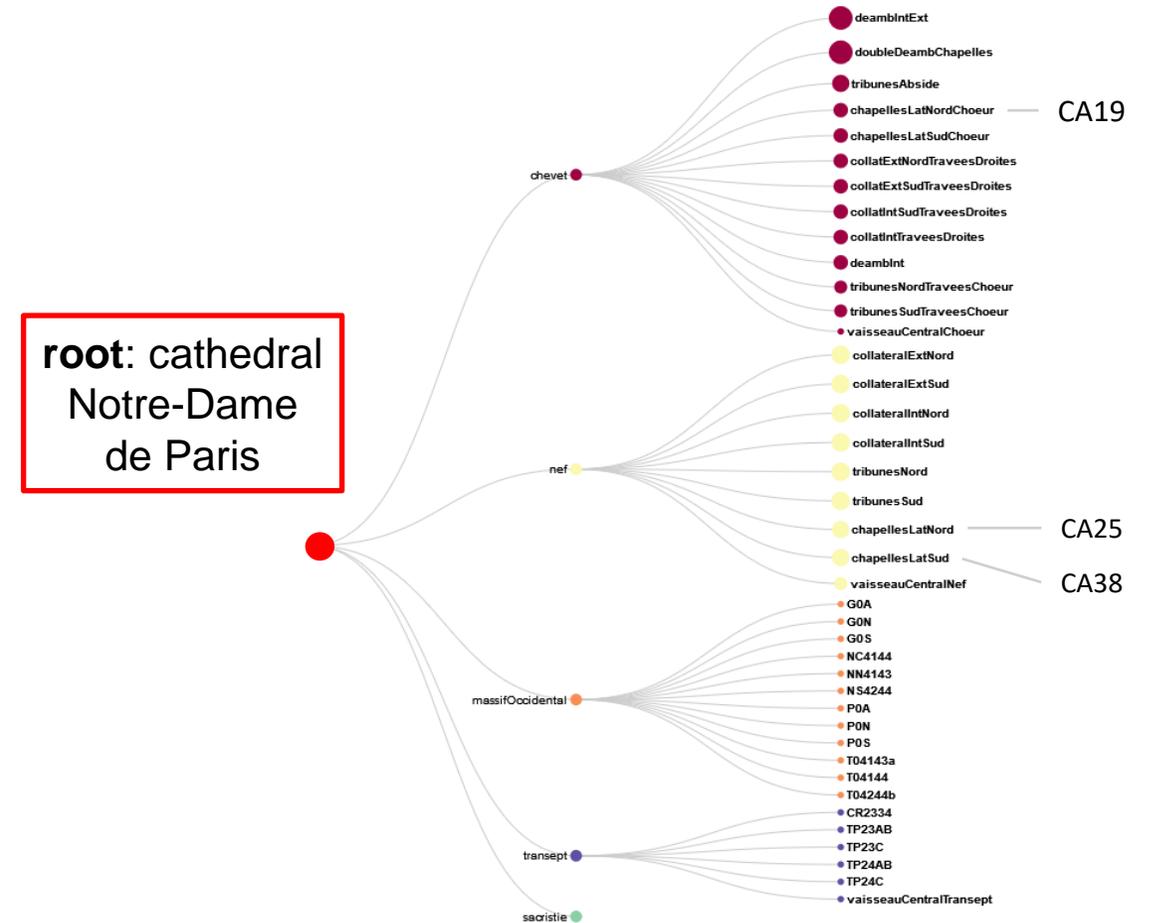


Data

Description

Data:

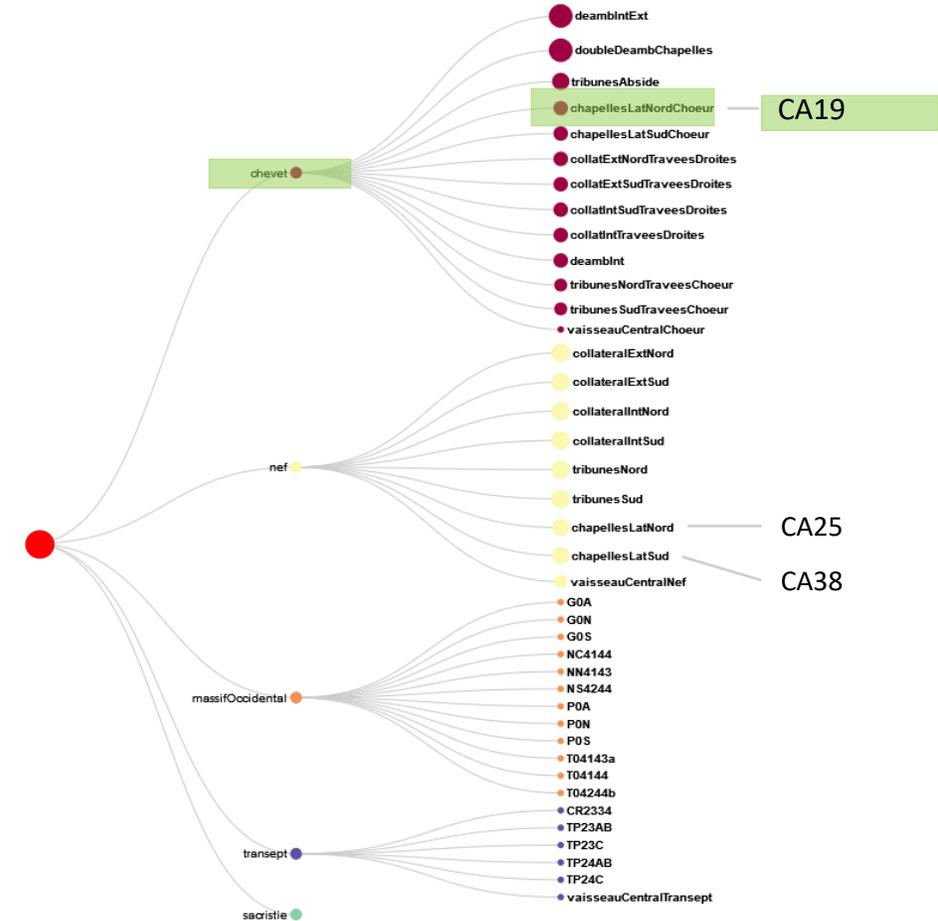
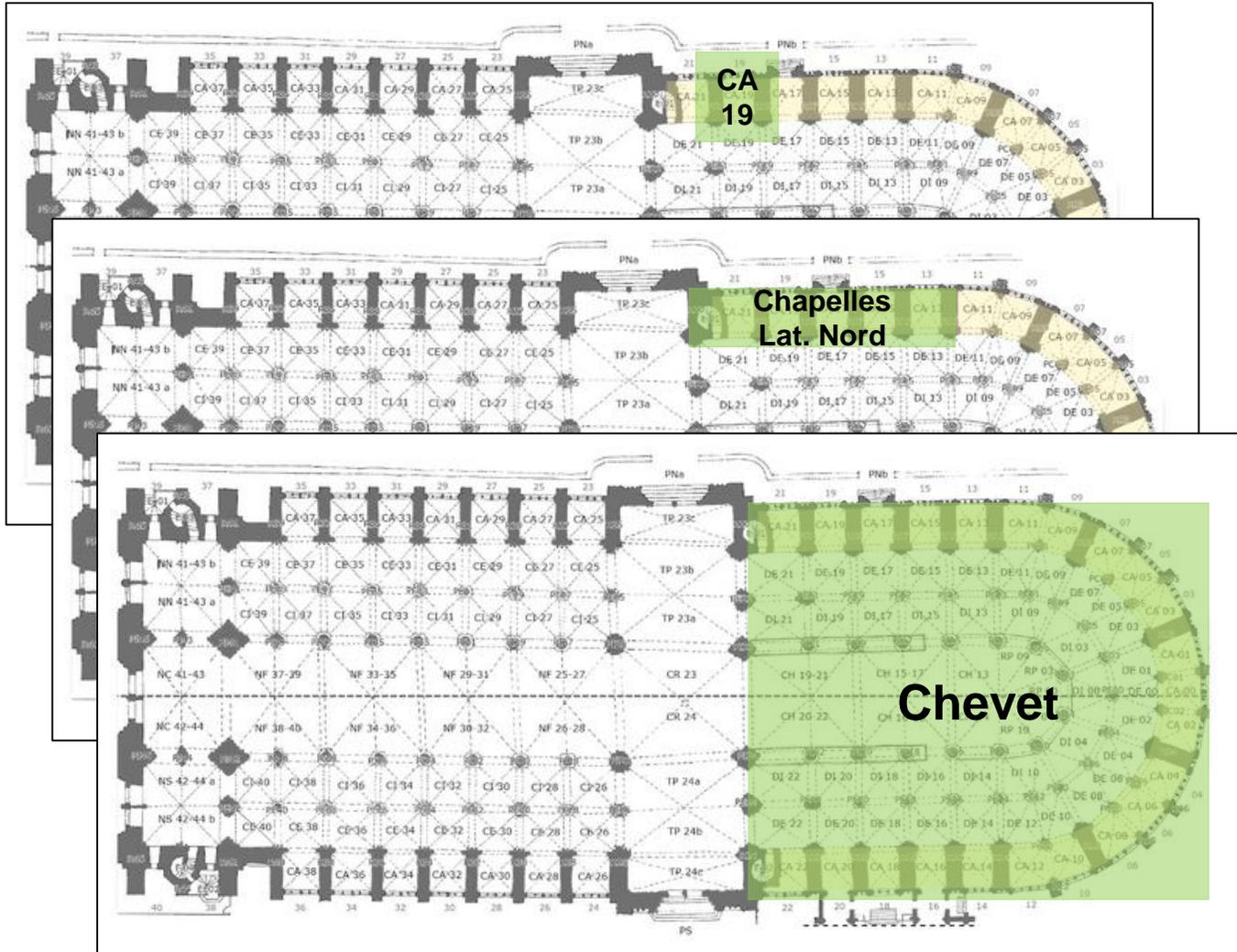
- Visual Content
- Image-related metadata
- Corpus-related metadata



Taxonomy of the spatial envelopes describing the spaces of Notre-Dame de Paris

Data

Example: Spatial Data

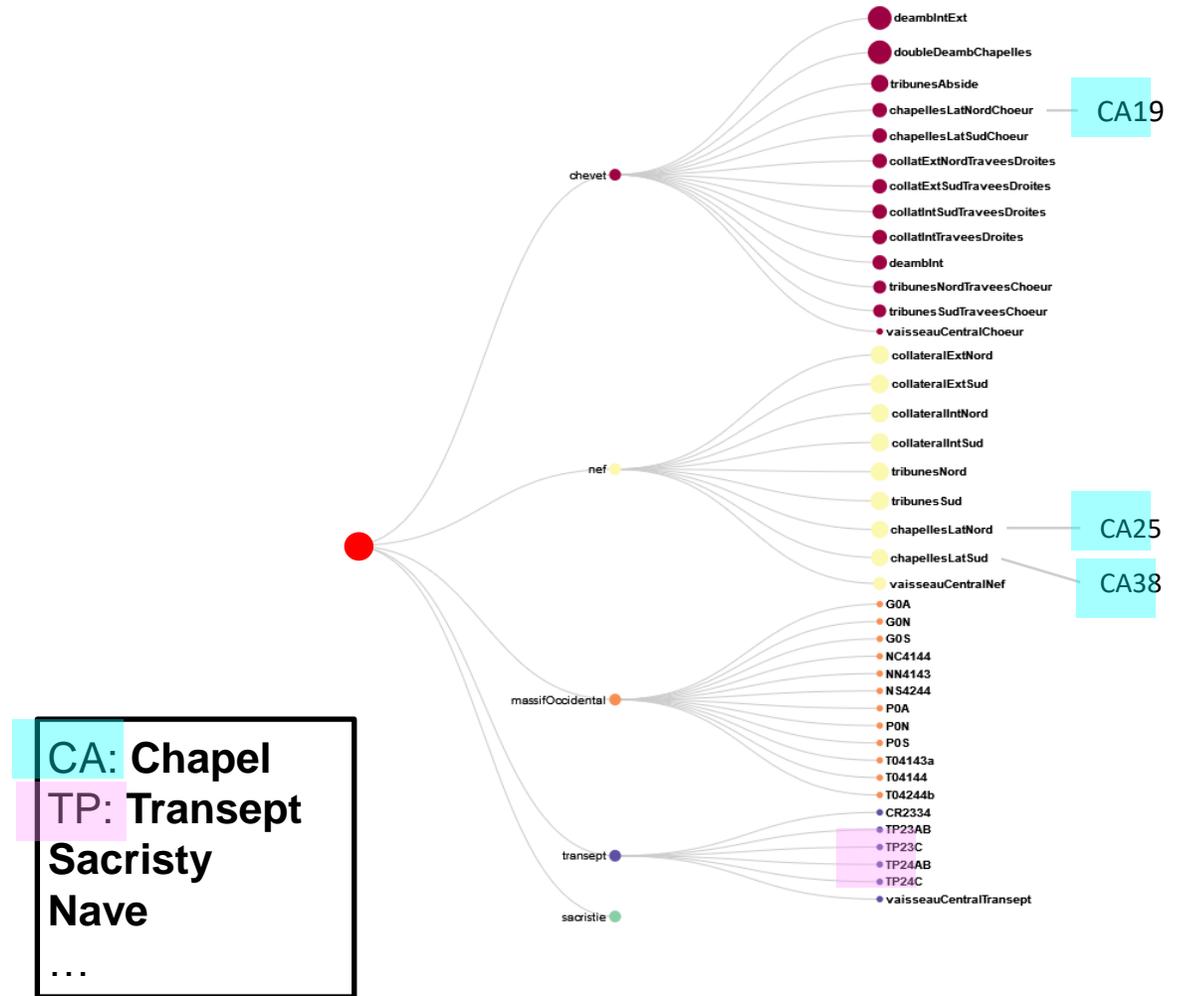


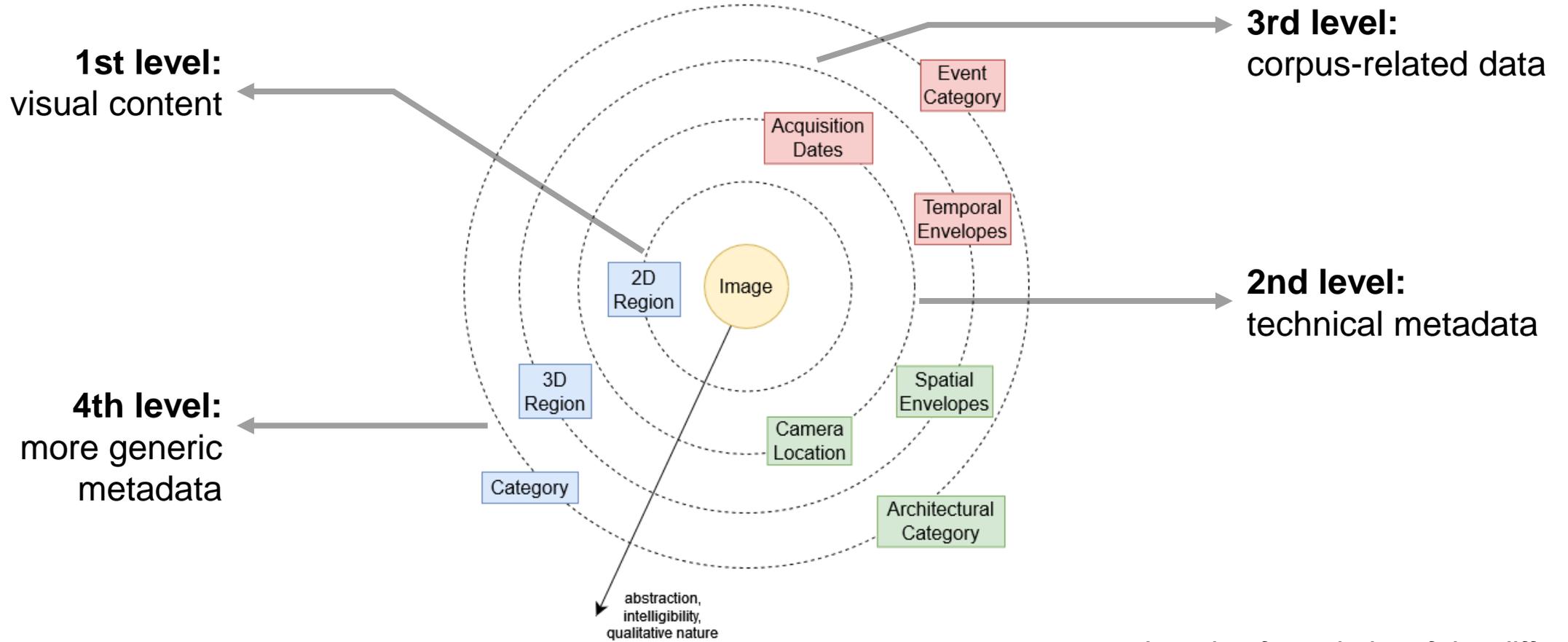
Data

Description

Data:

- Visual Content
- Image-related metadata
- Corpus-related metadata
- Generic metadata





Levels of proximity of the different metadata characterising the images

Question: How to *compute* a distance/proximity between images?

1. Data

2. Structuring

a. Graph-oriented Database

Structuring (I)

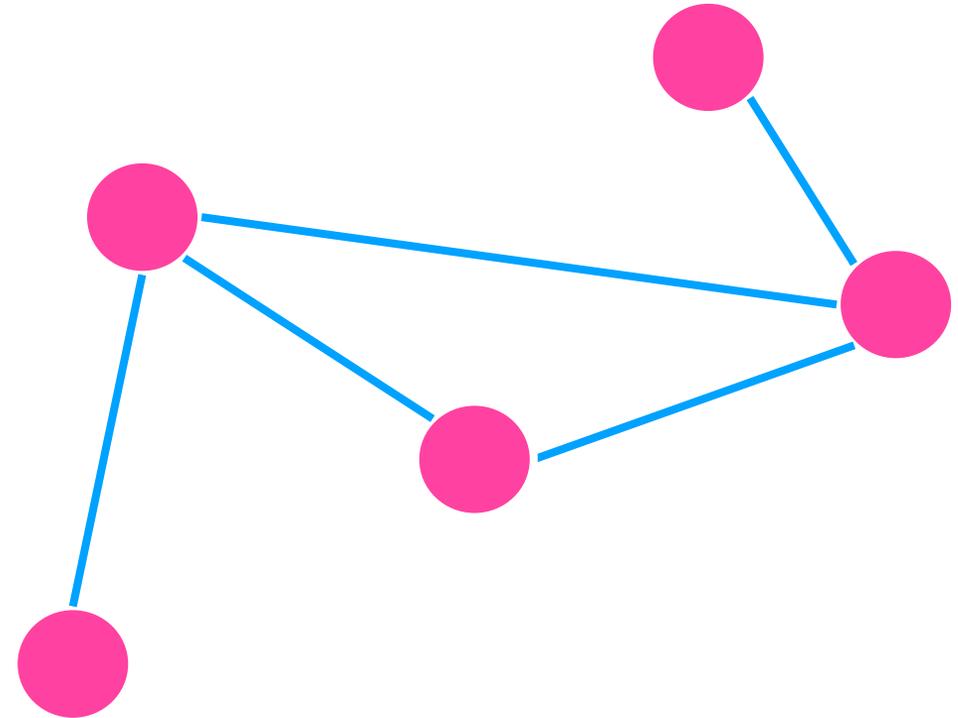
Graph-oriented Database

Structuring

Description

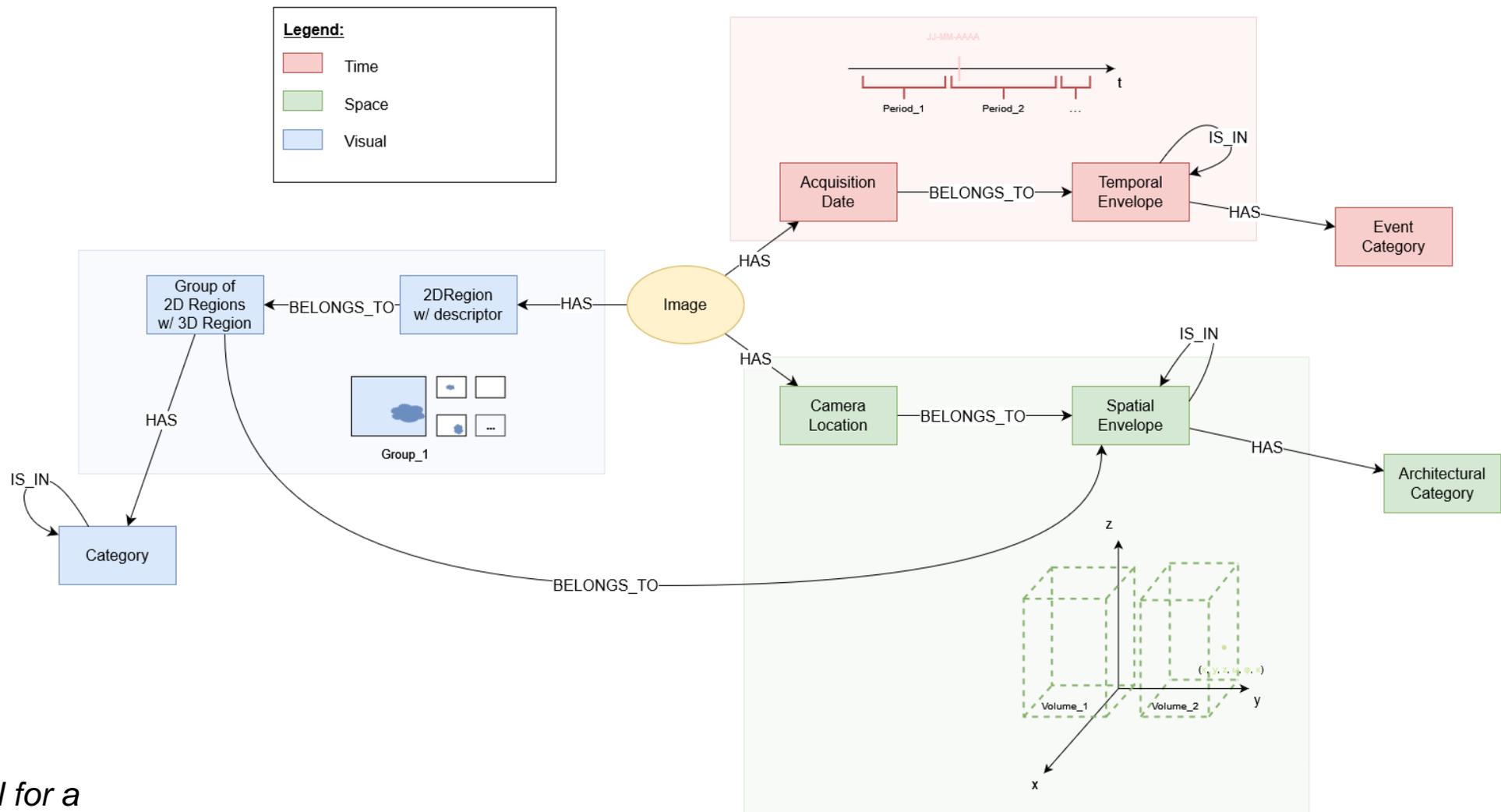
Data:

- Heterogeneous
- (Un-)directly related to the images
- Characterizing the images



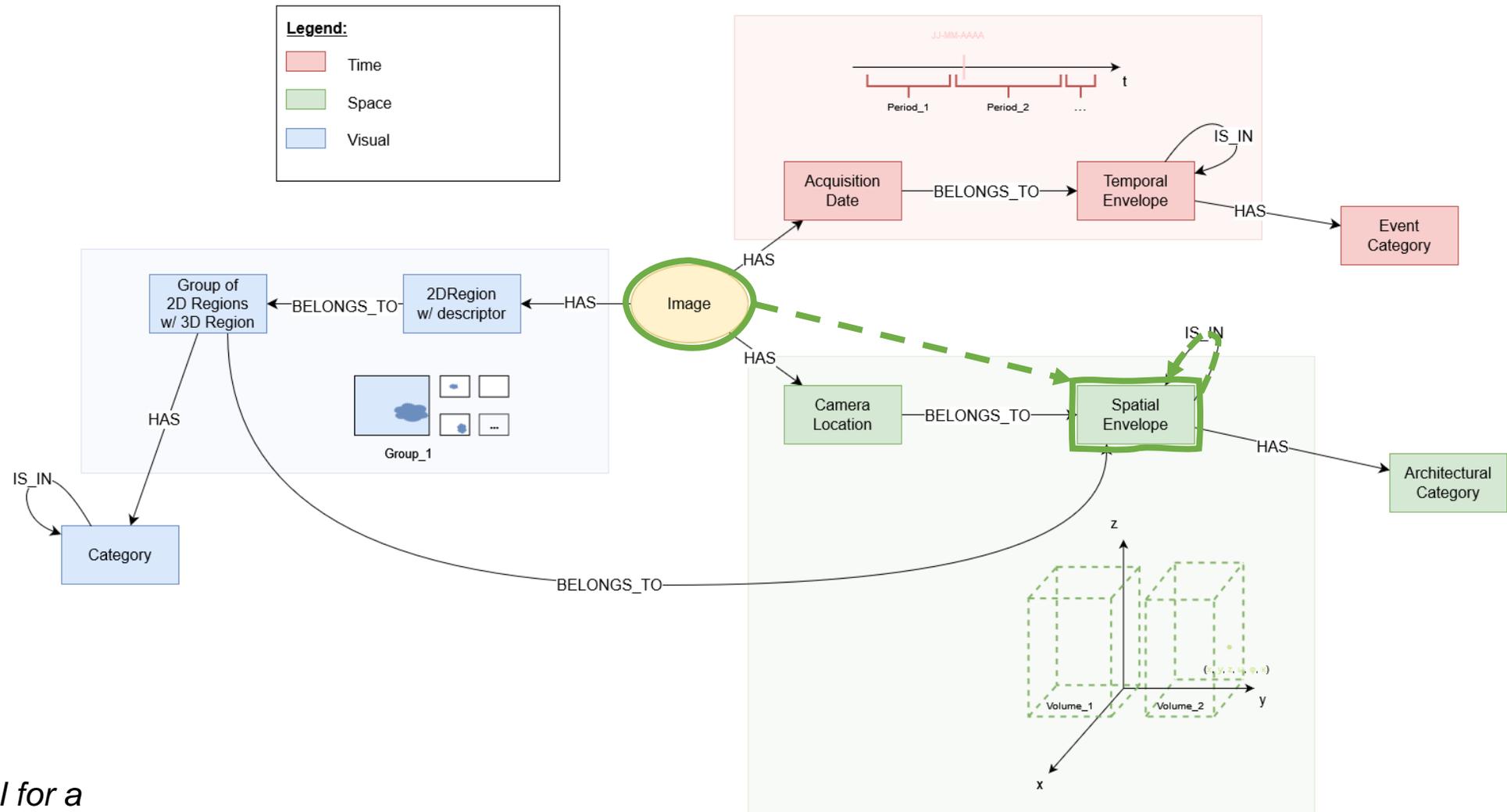
*Graphs are a ubiquitous data structure [...] a collection of objects (i.e., **nodes**), along with a set of interactions (i.e., **edges**) between pairs of these objects. [Hamilton, 2020]*

Structuring Graph Data Model



*Data Model for a
graph-oriented database*

Structuring Graph Data Model

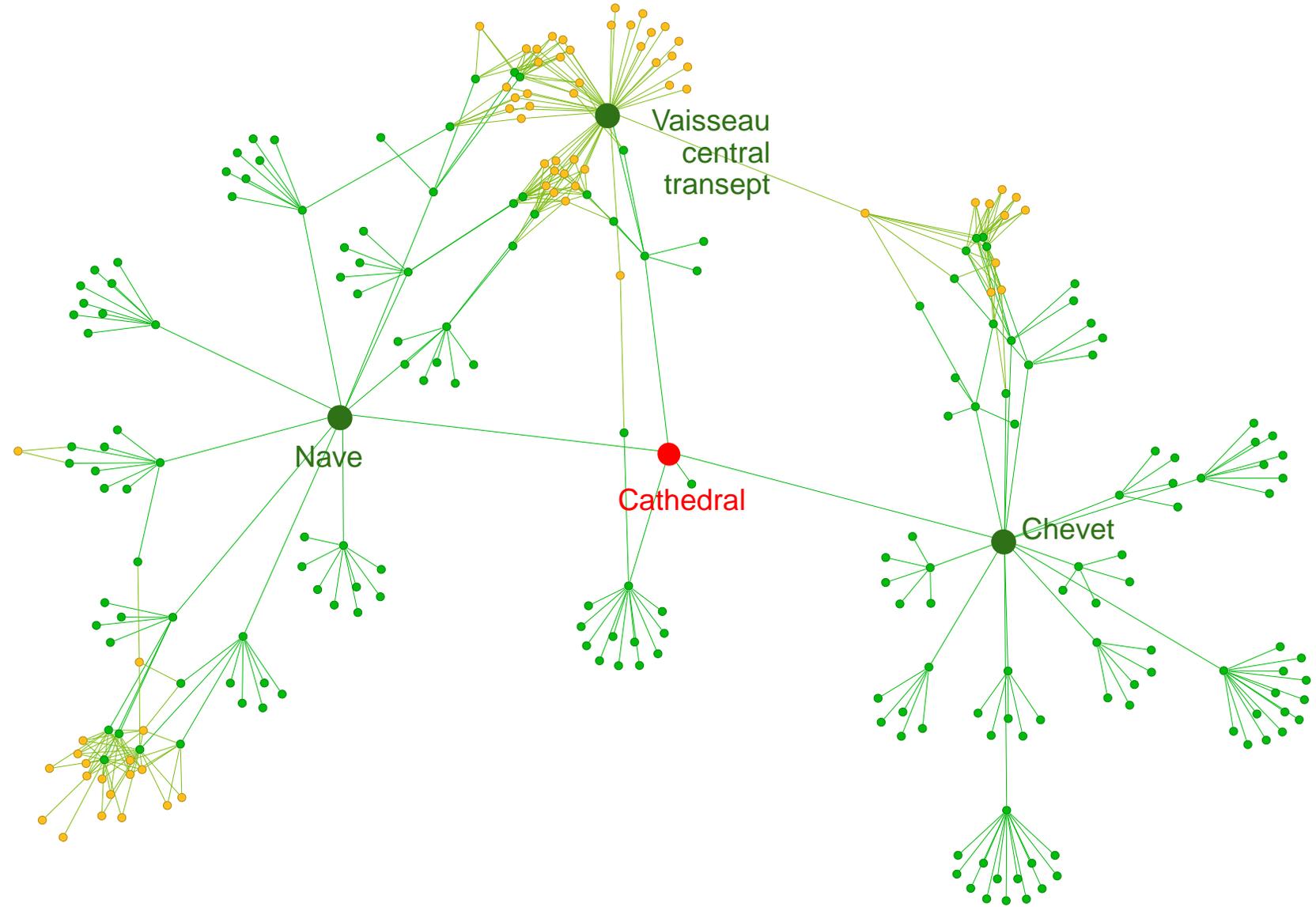


*Data Model for a
graph-oriented database*

Structuring

Example: Spatial Data

Each **Image** node is related to $\{0..n\}$ **SpatialEnvelope** nodes

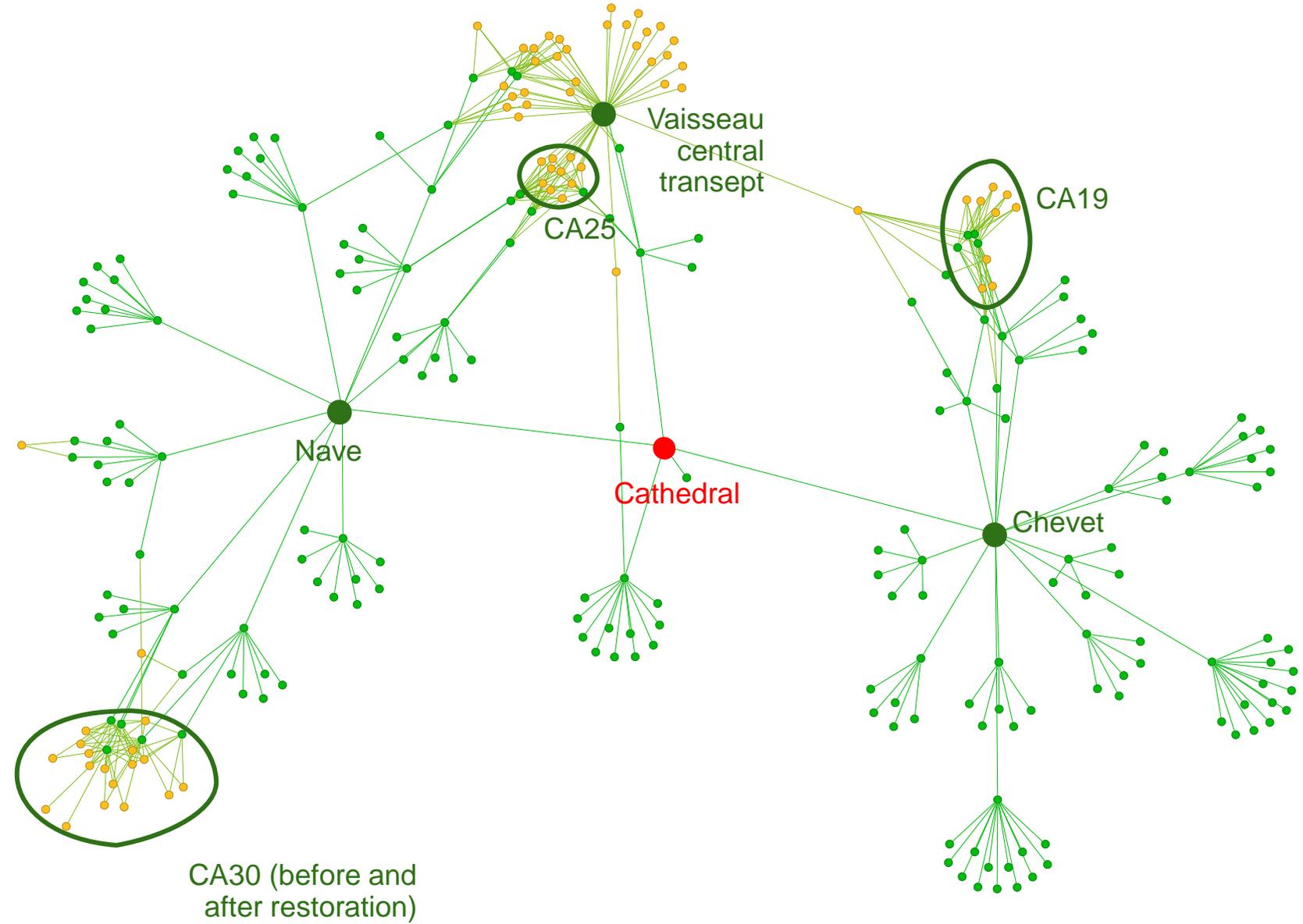


Example graph of *Images* and *SpatialEnvelopes*

Structuring

Example: Spatial Data

Each **Image** node is related to $\{0..n\}$ **SpatialEnvelope** nodes



Example graph of **Images** and **SpatialEnvelopes**

Question: How to *compute* a distance/proximity between images?

1. Data

2. Structuring

a. Graph-oriented Database

b. Embeddings

Structuring (II)

Embeddings

Graph embedding:

- *Graph embedding converts a graph into a low dimensional space in which the graph information is preserved. [Cai et al, 2018]*

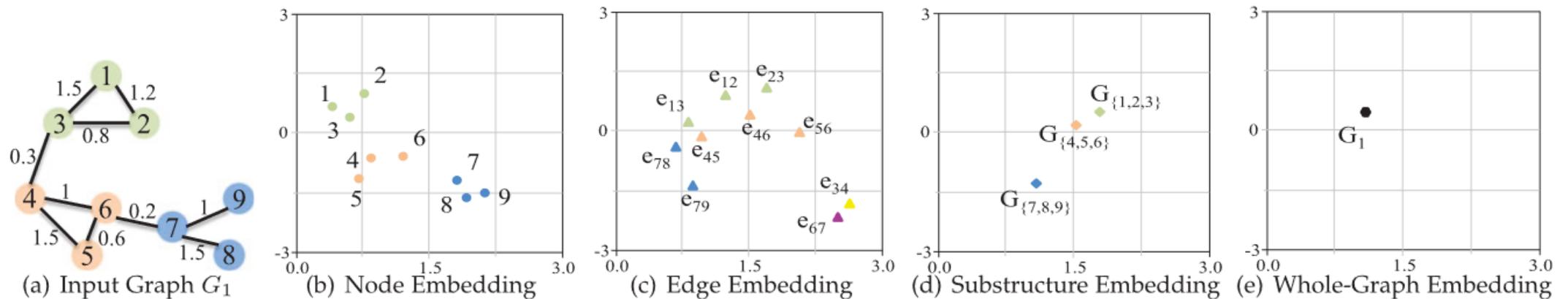


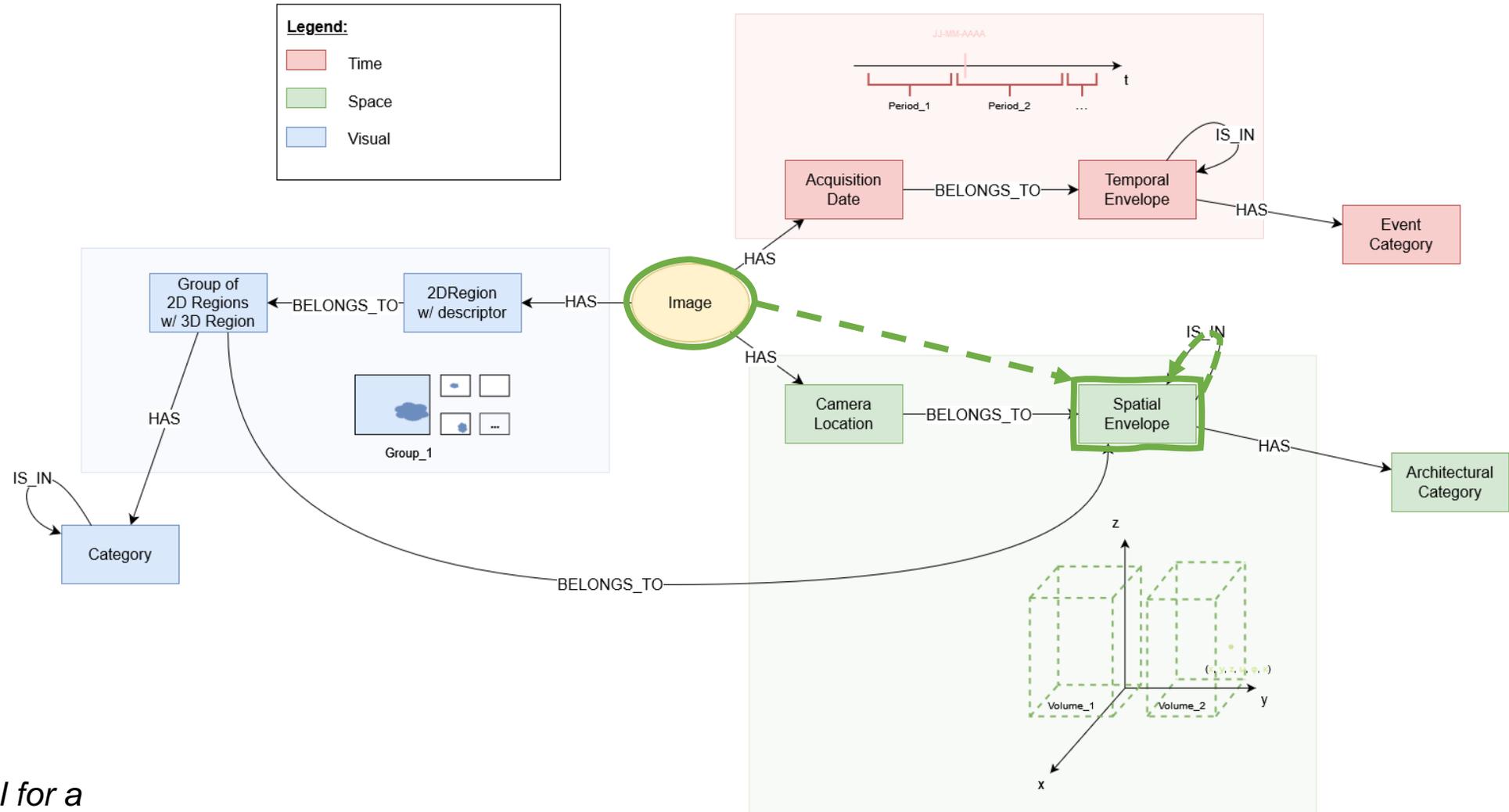
Fig. 1. A toy example of embedding a graph into 2D space with different granularities. $G_{\{1,2,3\}}$ denotes the substructure containing node v_1, v_2, v_3 .

From [Cai et al., 2018]

Graph embedding:

- *Graph embedding converts a graph into a low dimensional space in which the graph information is preserved. [Cai et al, 2018]*
- *The challenge [...] is that there is **no straightforward way** to encode this high-dimensional, non-Euclidean information about graph structure into a feature vector. [Hamilton et al, 2018a]*

Structuring Graph Data Model

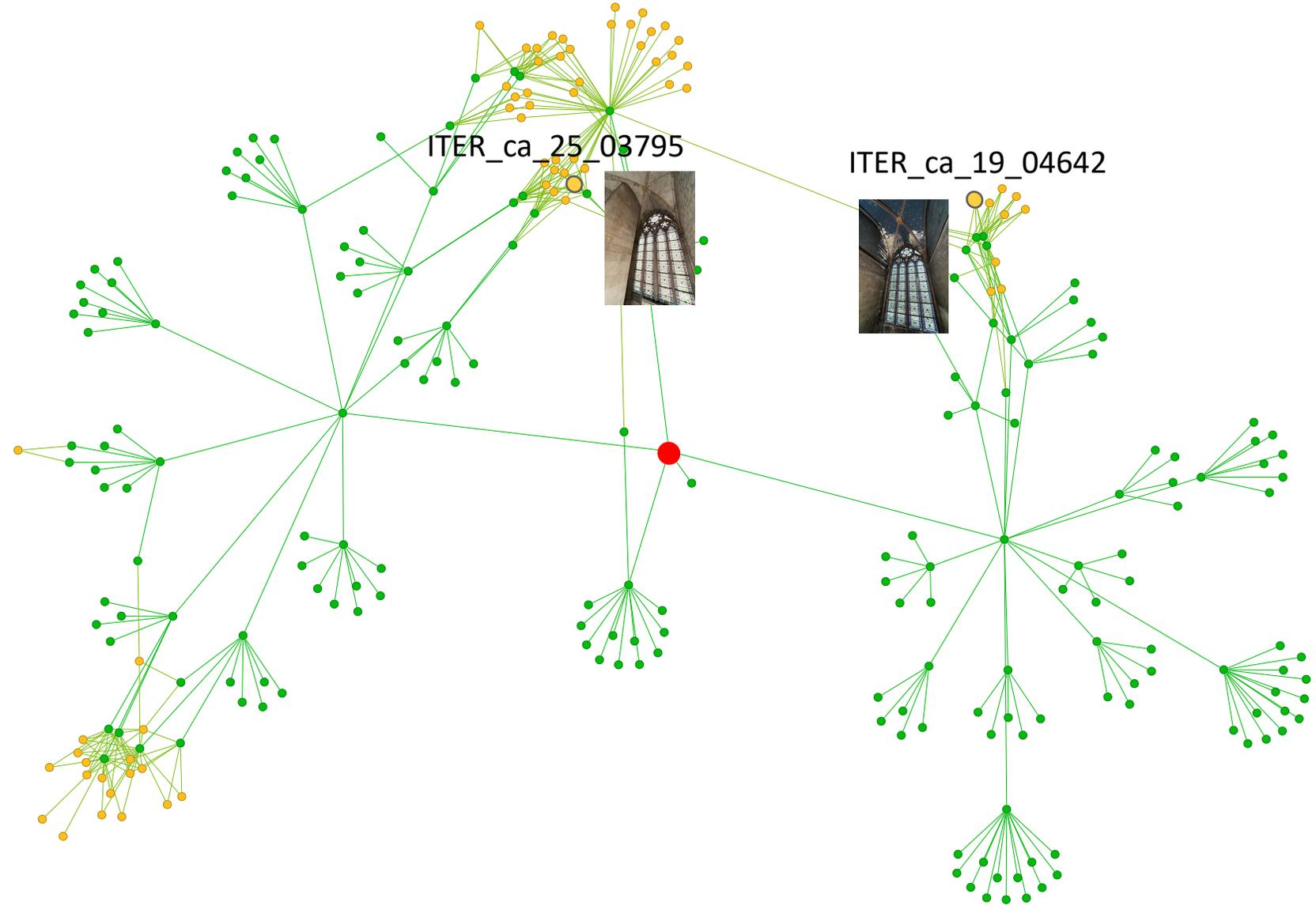


*Data Model for a
graph-oriented database*

Structuring

Example: Spatial Data

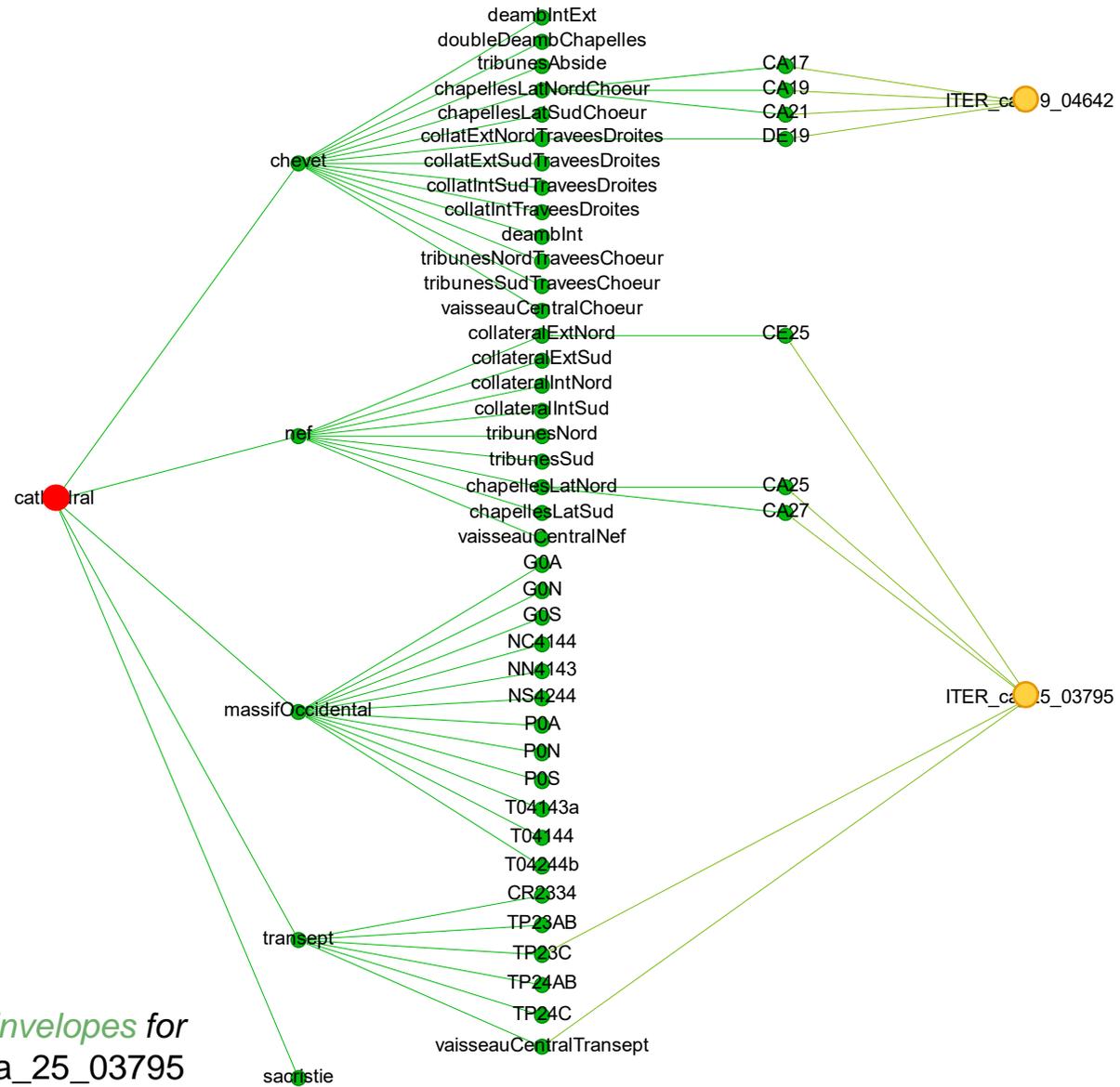
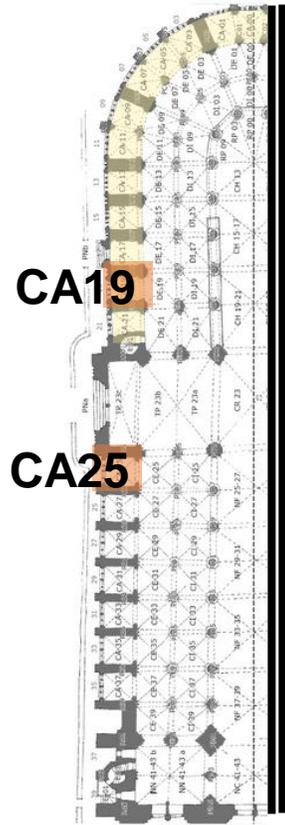
Each **Image** node is related to {0..n} **SpatialEnvelope** nodes



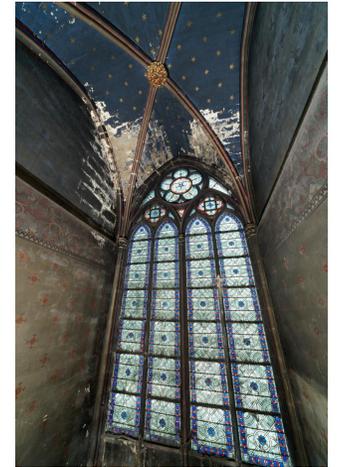
Example graph of *Images* and *SpatialEnvelopes*

Structuring

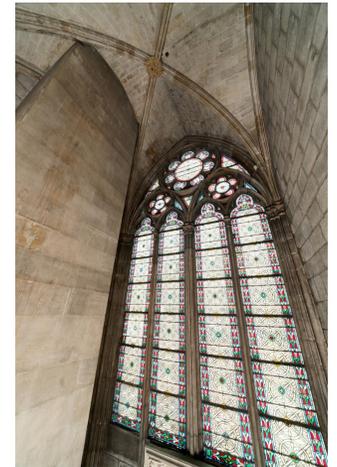
Example: Spatial Data



ITER_ca_19_04642



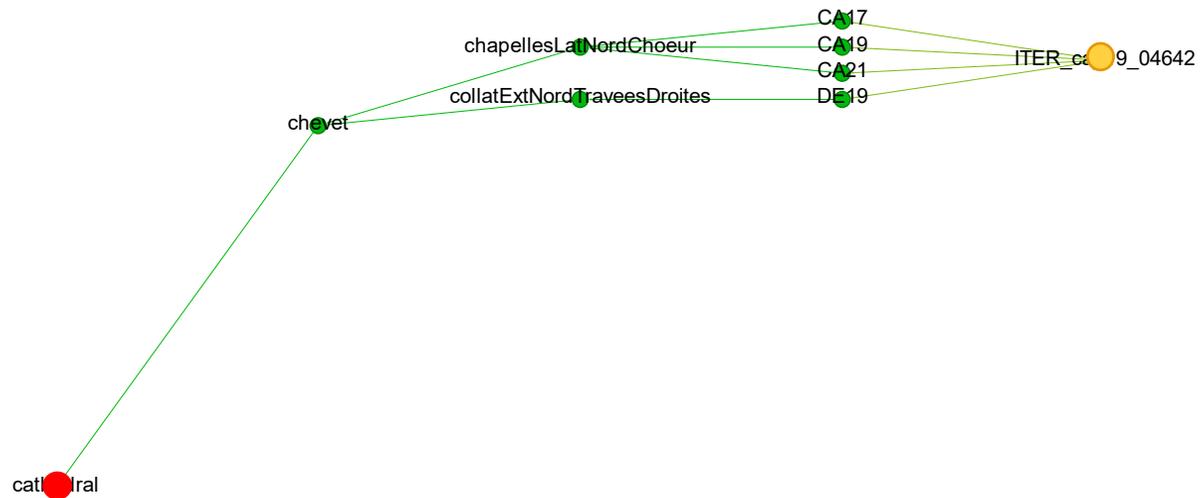
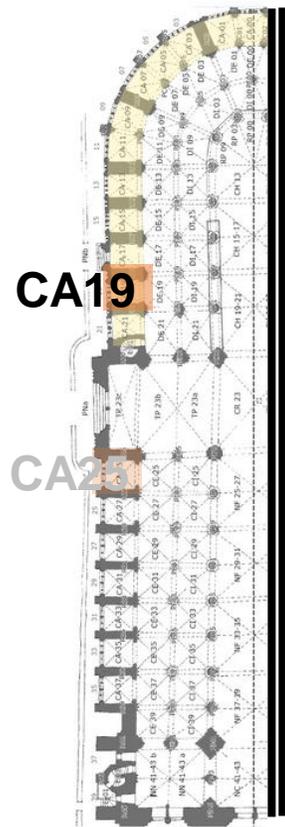
ITER_ca_25_03795



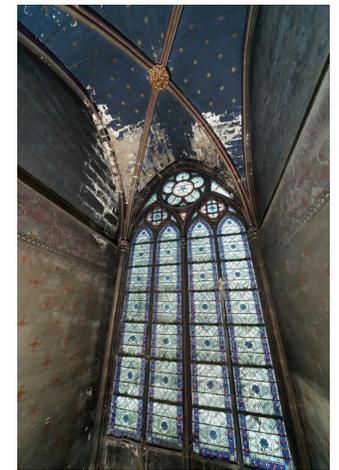
Selected subgraph of *Images* and *SpatialEnvelopes* for the images ITER_ca_19_04642 and ITER_ca_25_03795

Structuring

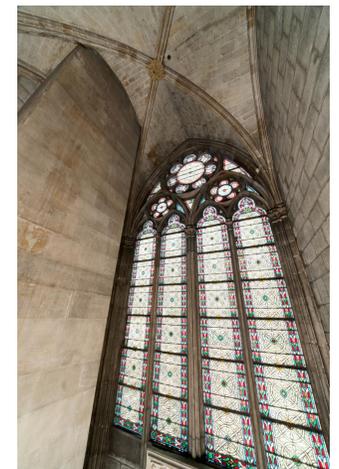
Example: Spatial Data



ITER_ca_19_04642



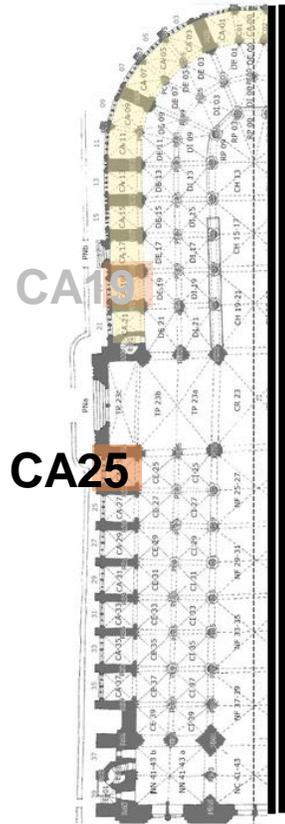
ITER_ca_25_03795



Subtree of *Spatial Envelopes* characterising the image ITER_ca_19_04642

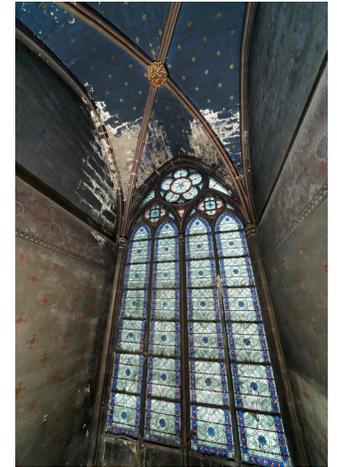
Structuring

Example: Spatial Data

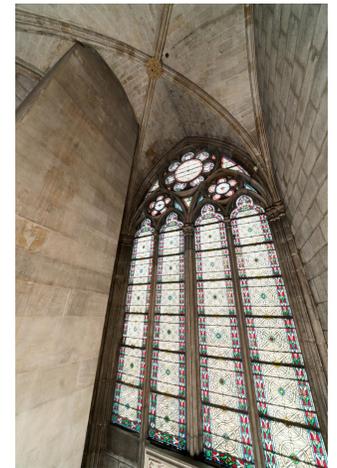


Subtree of *SpatialEnvelopes* characterising the image ITER_ca_25_03795

ITER_ca_19_04642



ITER_ca_25_03795



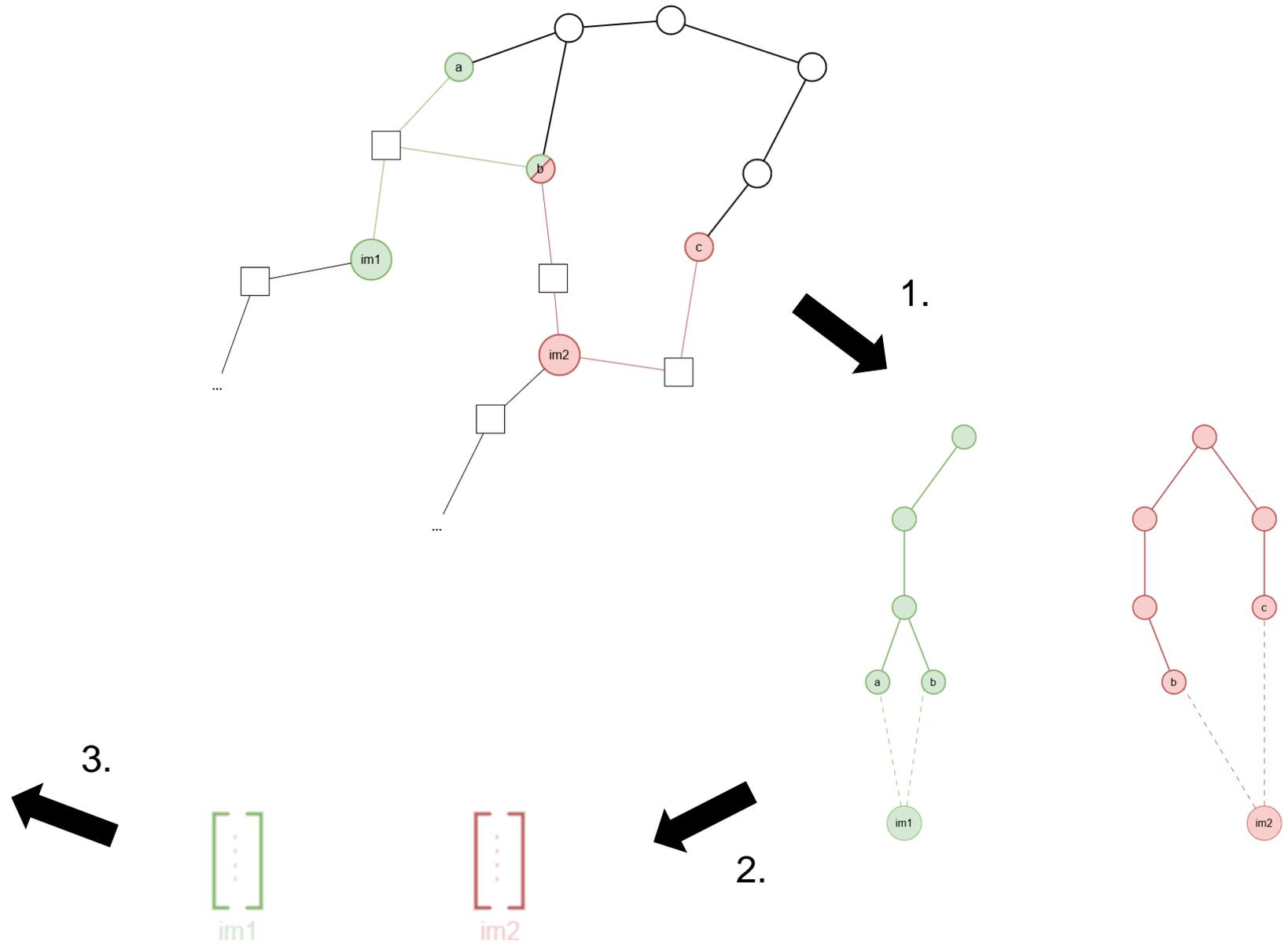
Structuring

Embedding: Method

For each image:

1. Extract subtree
2. Compute embedding
3. Store embedding

Image
name: str
embedding: vector



Distance

How to?

Question: How to *compute* a distance/proximity between images?

1. Data
2. Structuring
 - a. Graph-oriented Database
 - b. Embeddings
3. Exploring

Exploring Image distances

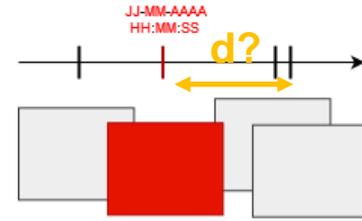
Exploring

Distances

Exploring based on:

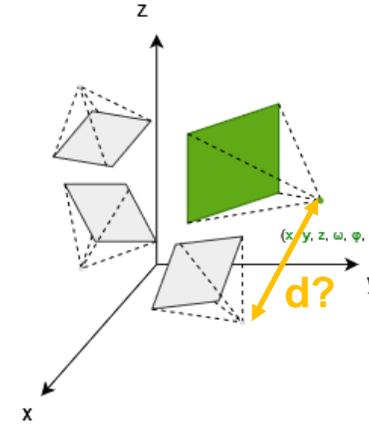
- Data values

TEMPS
date d'acquisition :
JJ-MM-AAAA HH:MM:SS



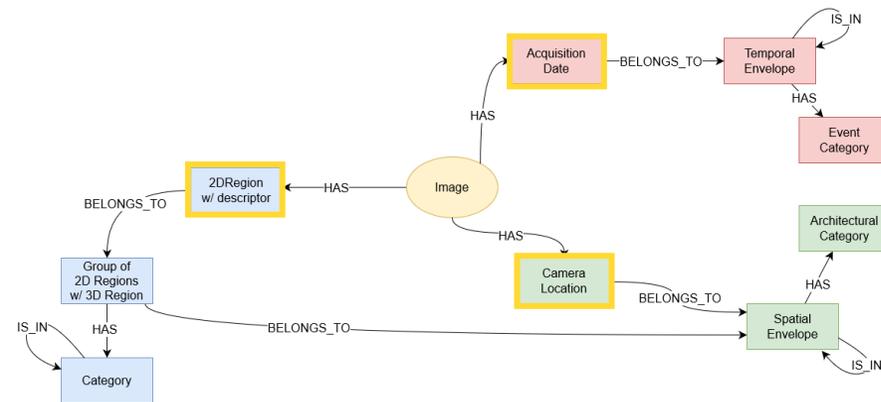
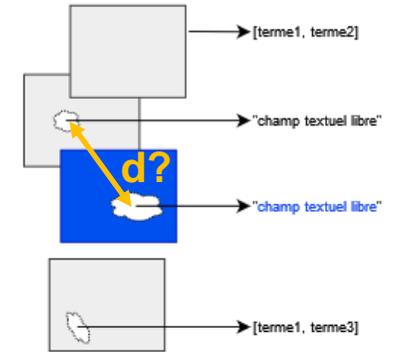
ESPACE

coordonnées spatiales :
(x, y, z, ω, φ, κ)



SEMANTIQUE

description, liste de termes:
"champ textuel libre", [termes]



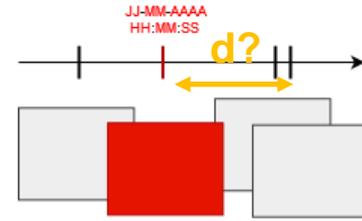
Exploring

Distances

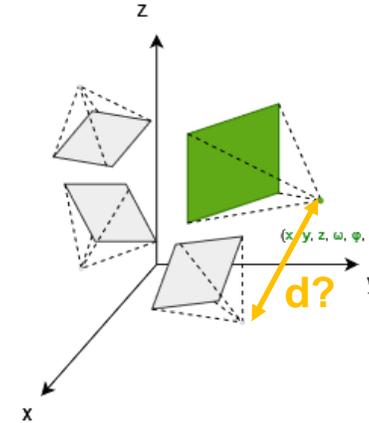
Exploring based on:

- Data values
- Data structures (embeddings)

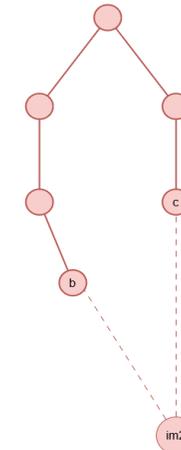
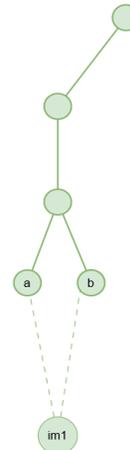
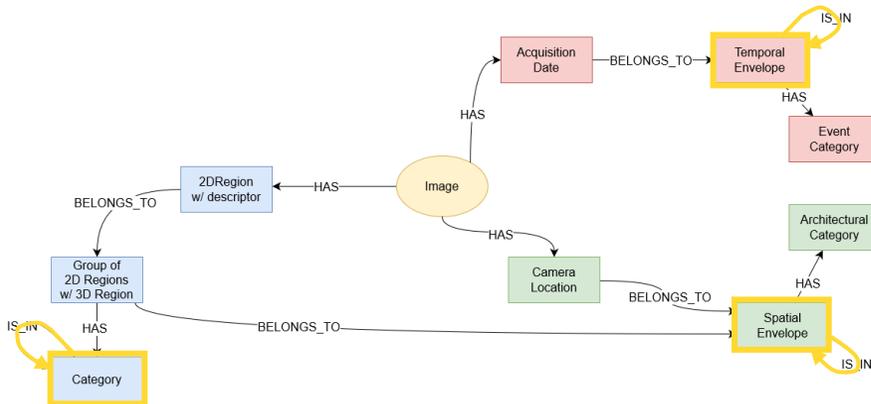
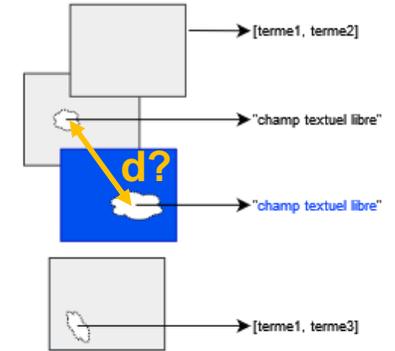
TEMPS
date d'acquisition :
JJ-MM-AAAA HH:MM:SS



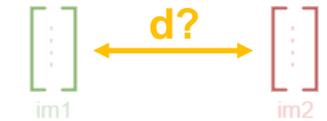
ESPACE
coordonnées spatiales :
(x, y, z, ω, φ, κ)



SEMANTIQUE
description, liste de termes:
"champ textuel libre", [termes]

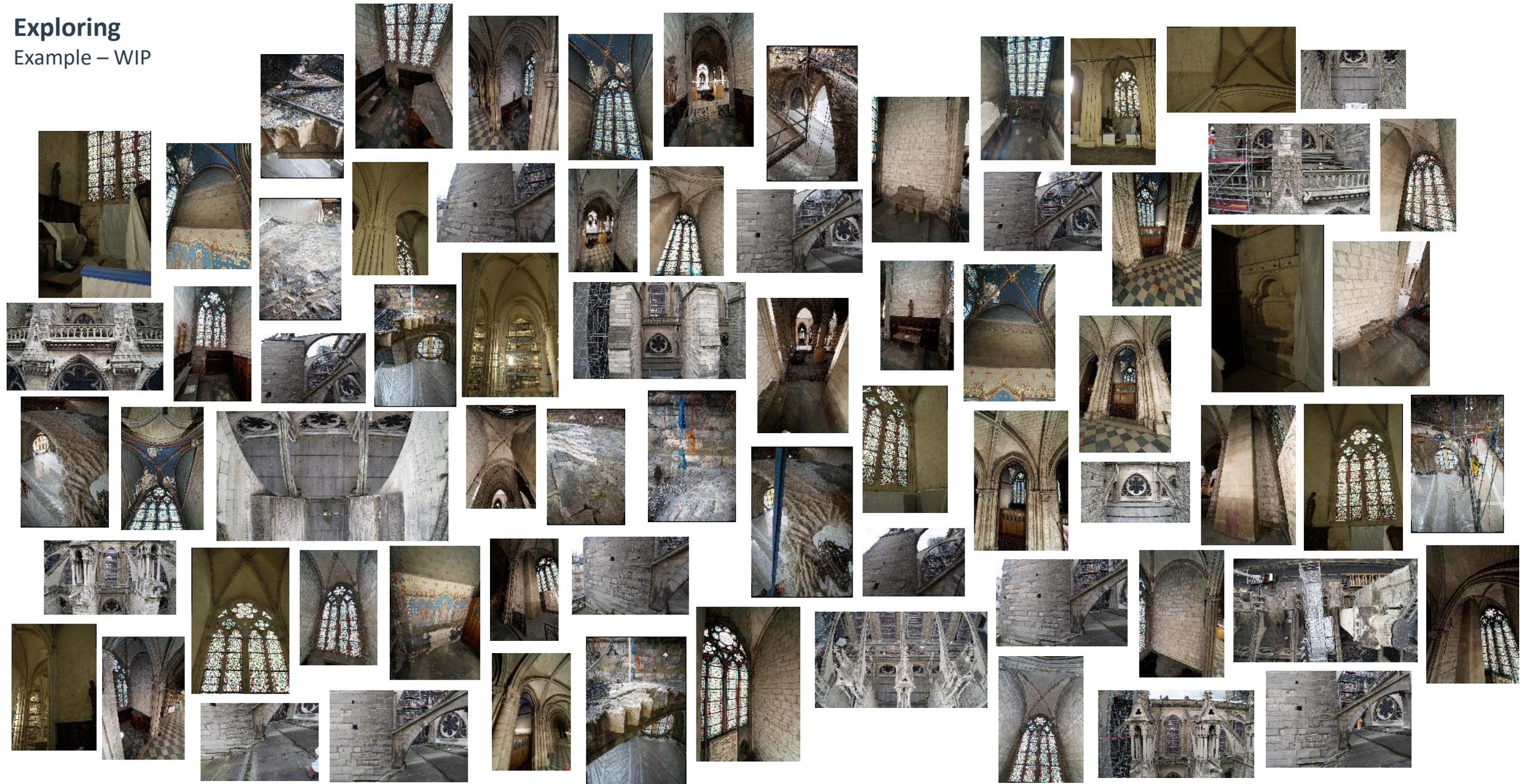


Graph embedding method



Exploring

Example – WIP



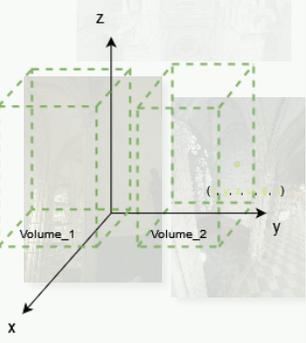
Exploring

Example – WIP

Spatial Envelope



CA30



Exploring

Example – WIP

Acquisition Date



CA30

Before restoration

Exploring

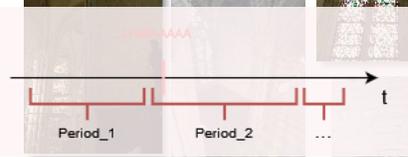
Example – WIP

Acquisition Date



CA30

After restoration



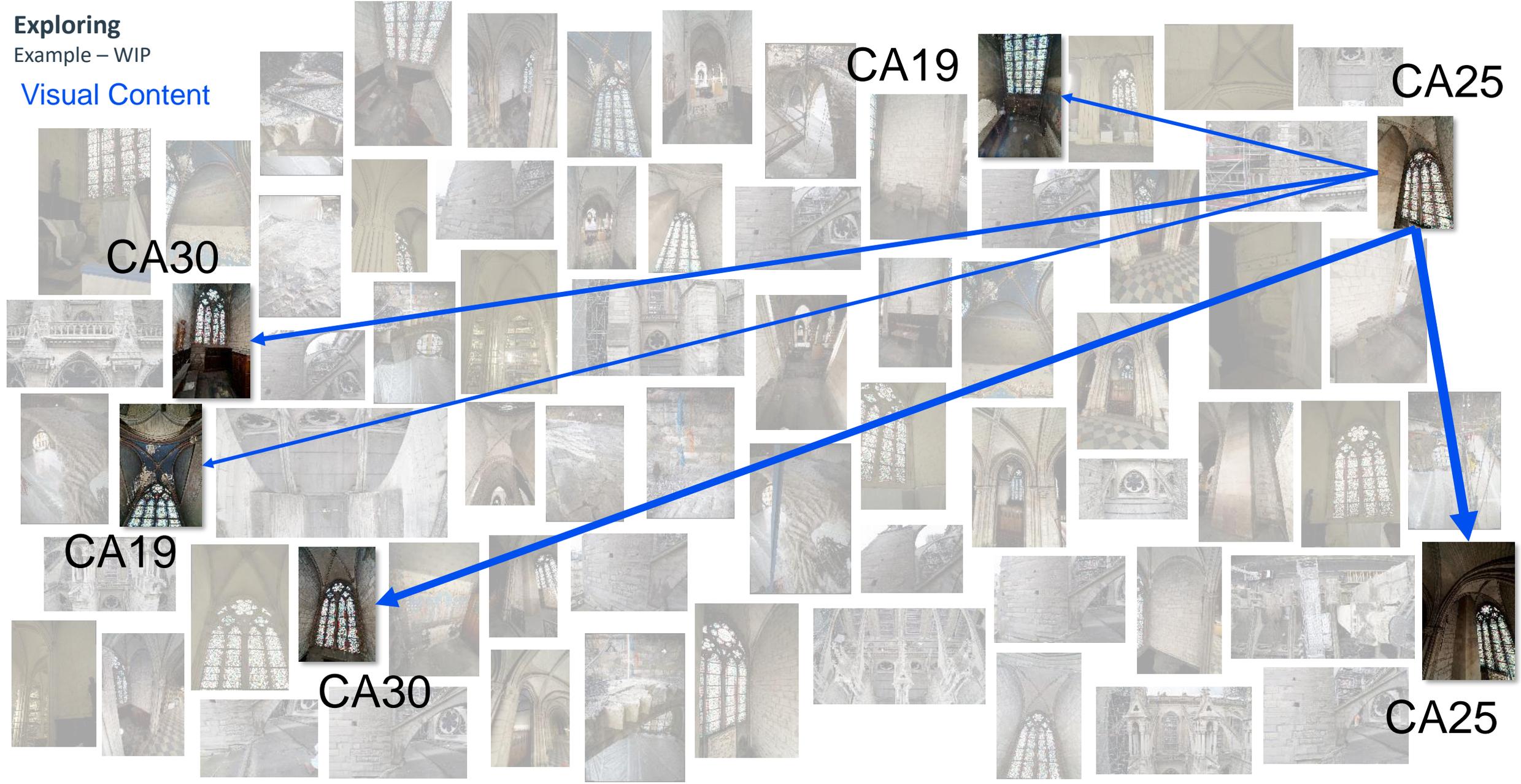
Exploring

Example – WIP

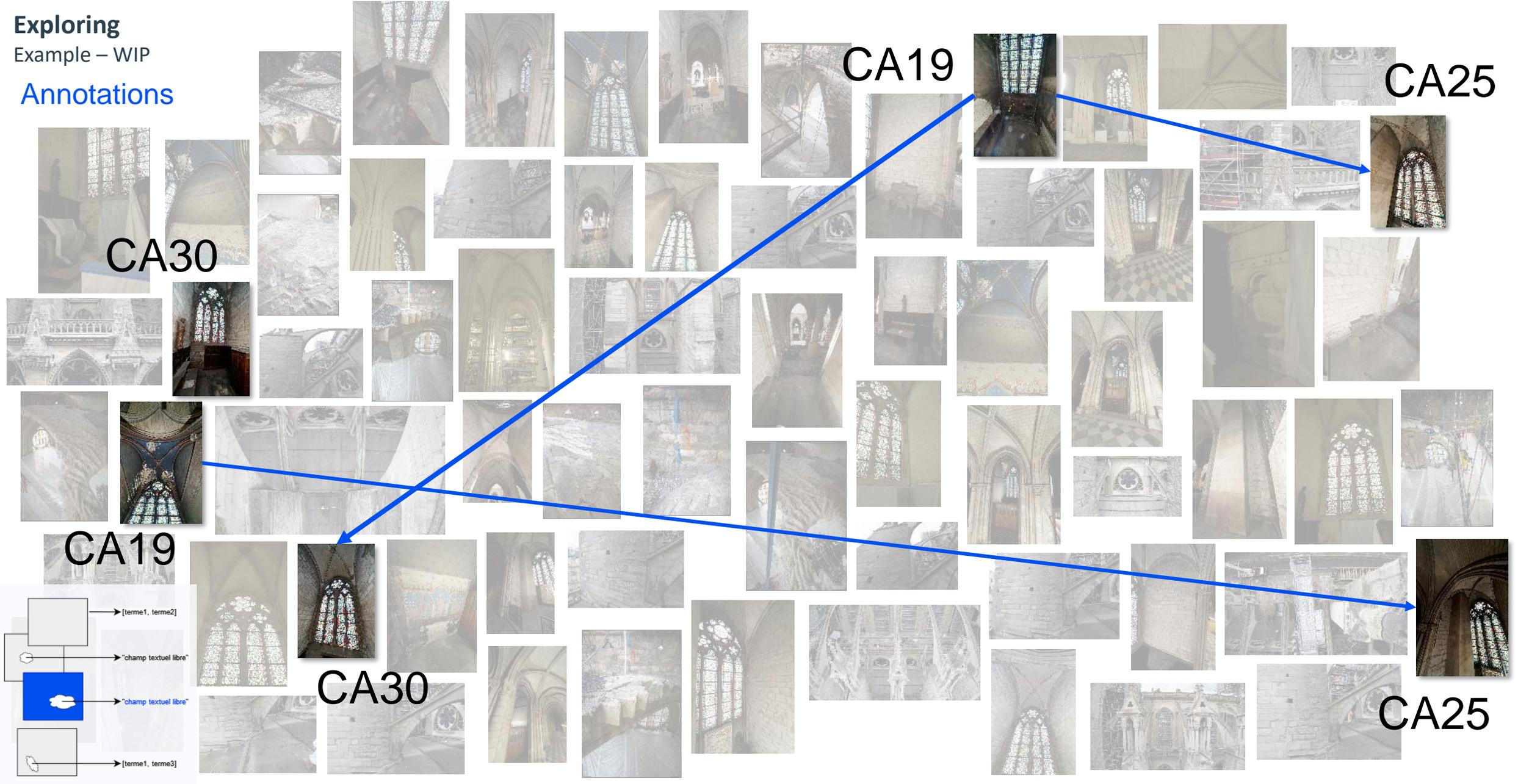
Camera Position



Exploring
Example – WIP
Visual Content

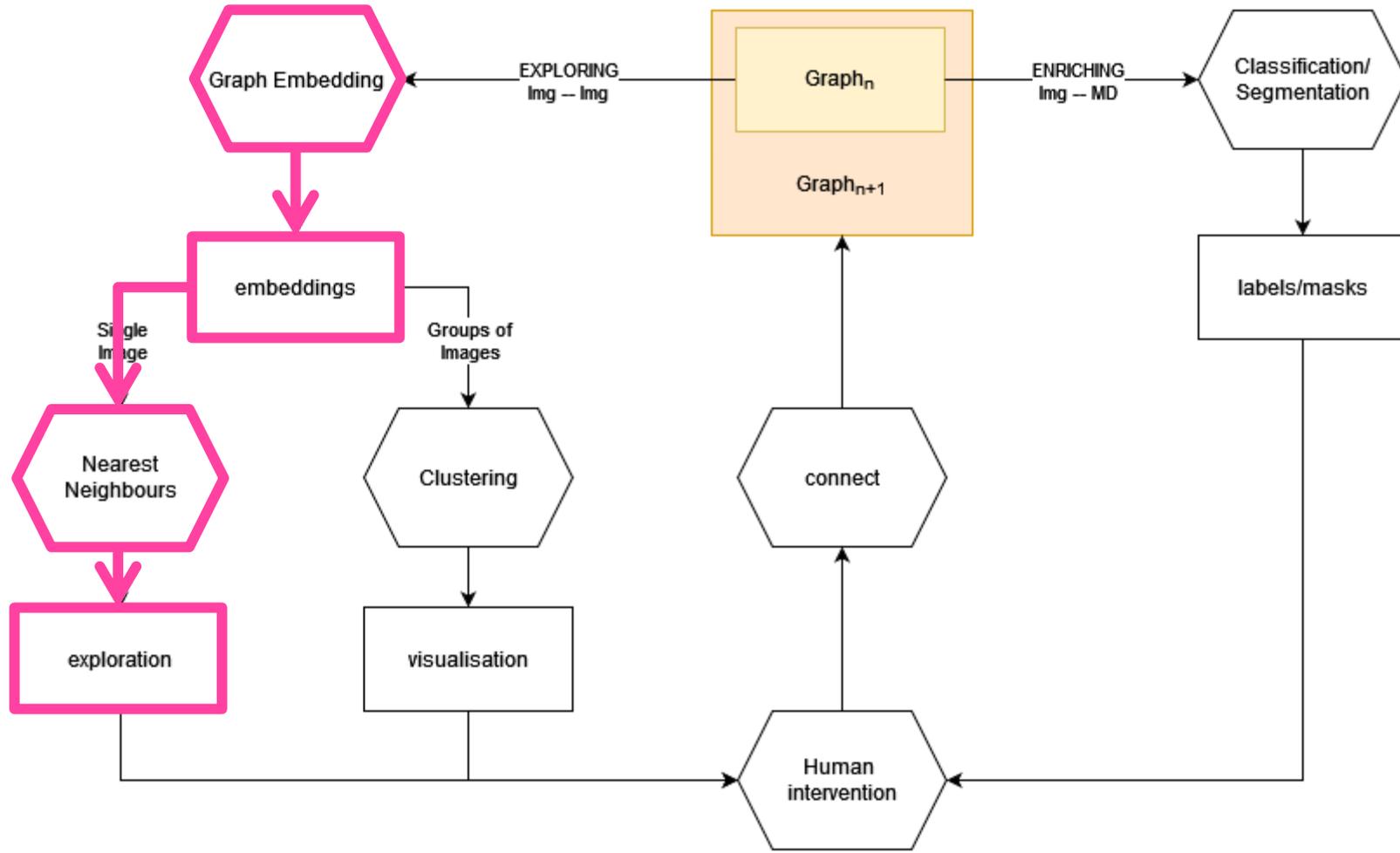


Exploring
Example – WIP
Annotations



Exploring

... and beyond



Exploring and Enriching the Graph-oriented Database

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Thank you for your attention!

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Caractérisation de relations de proximité temporelle, spatiale et sémantique pour l'exploration d'un corpus d'images photographiques

Laura Willot, ETIS, LaSTIG, MAP, FSP



Une cathédrale de données numériques et connaissances pluridisciplinaires

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