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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, Fondation des Sciences du Patrimoine



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

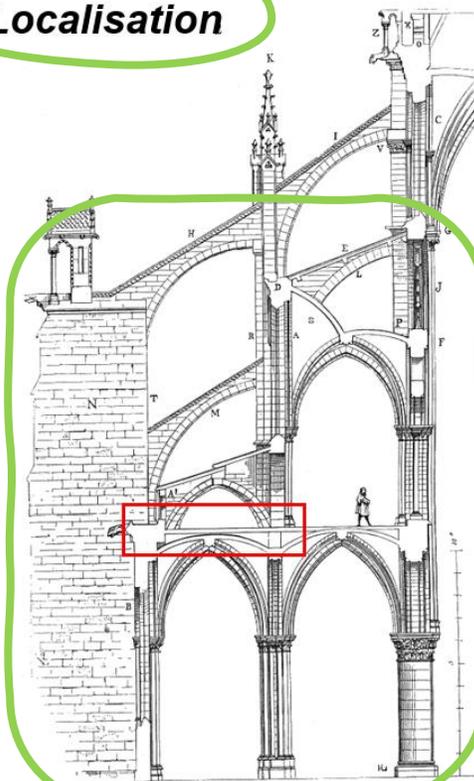
Previously...

Location of the cramps from the tribune

Image uses:

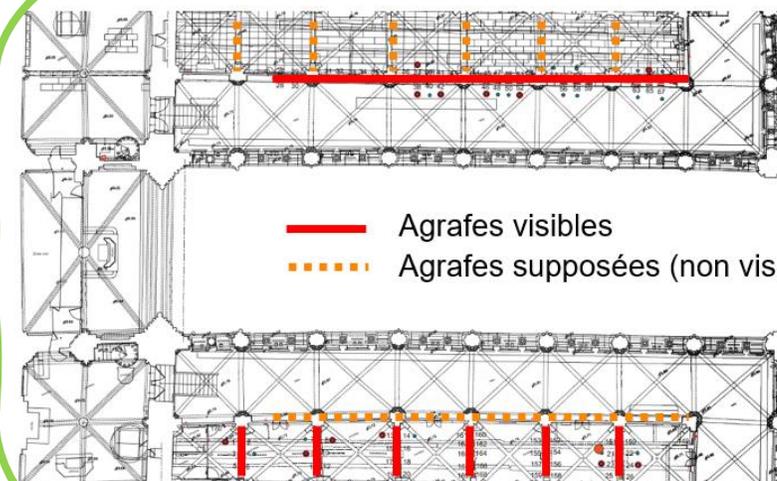
- Documentation of protocols
- Location of objects/artefacts

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

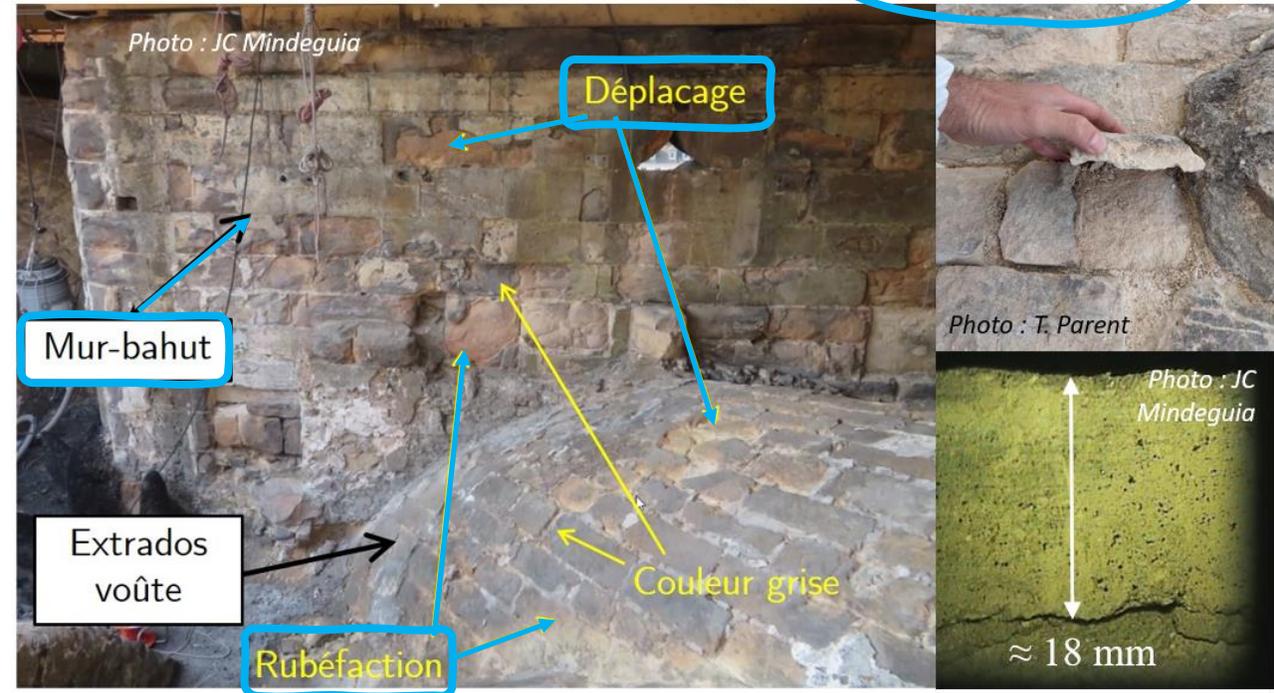
Image uses:

- 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



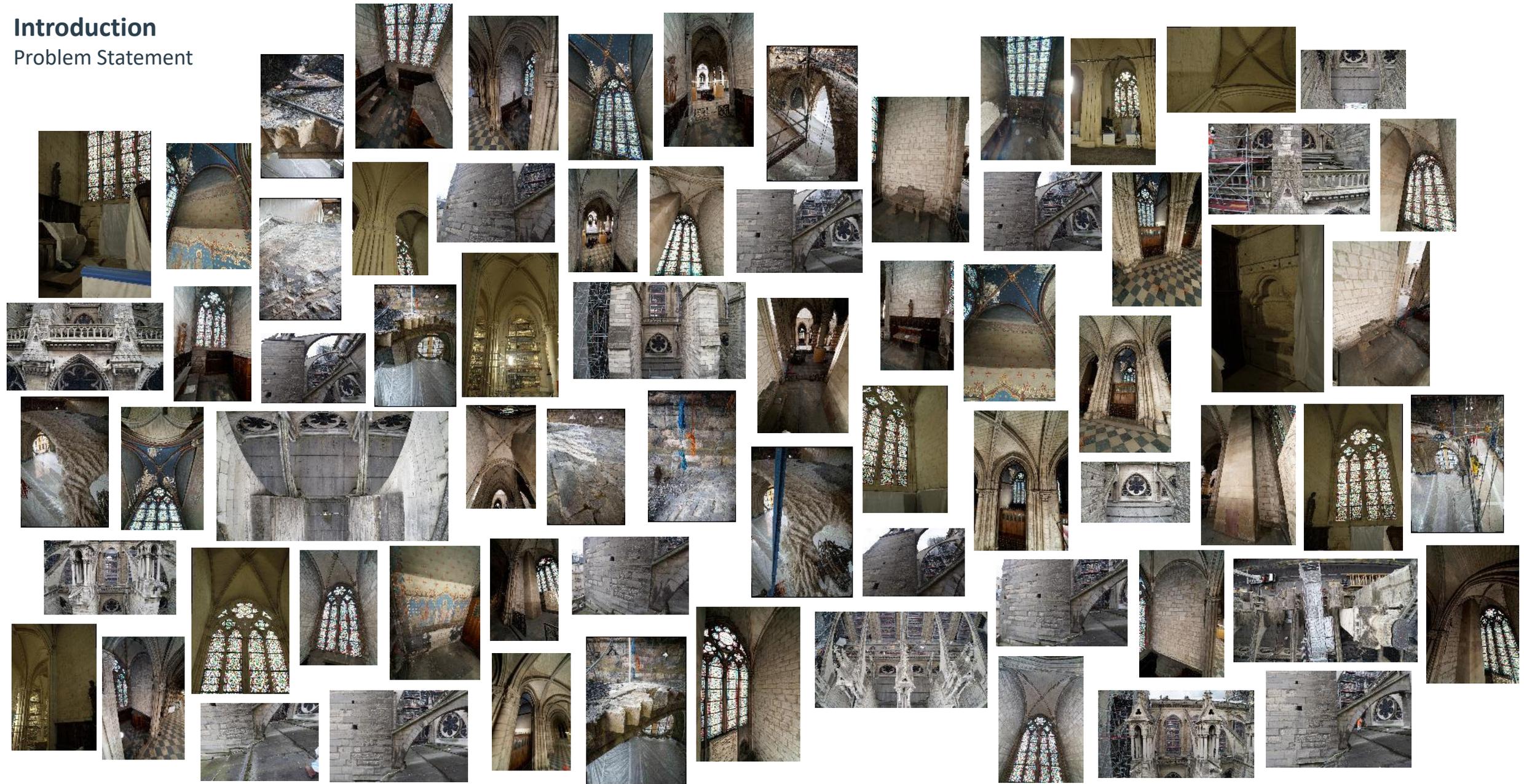
Effet de l'incendie sur un ensemble voûte-contrebutements du chœur de Notre-Dame / P. Morenon, J.C. Mindeguia & al.

5

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

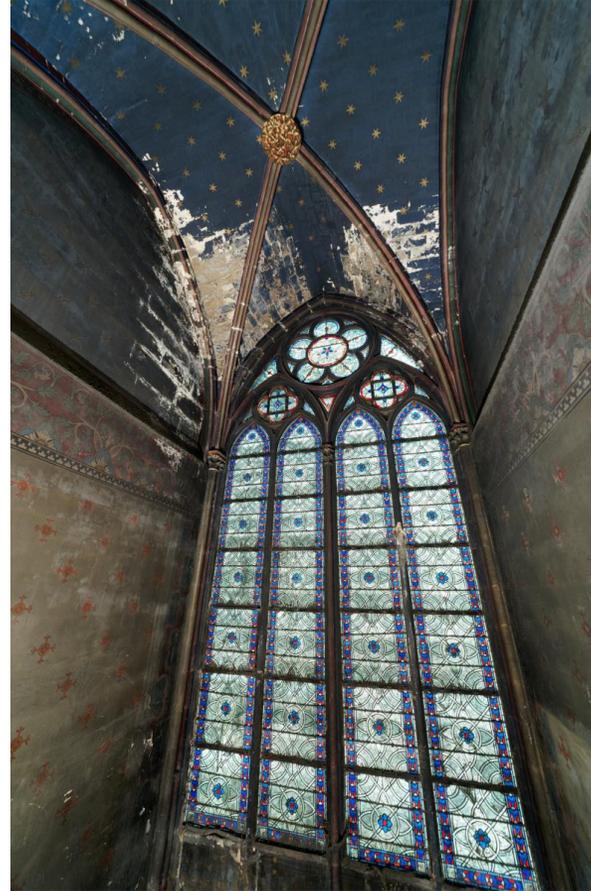
Example: Visual distance

Which images are closest to one another?

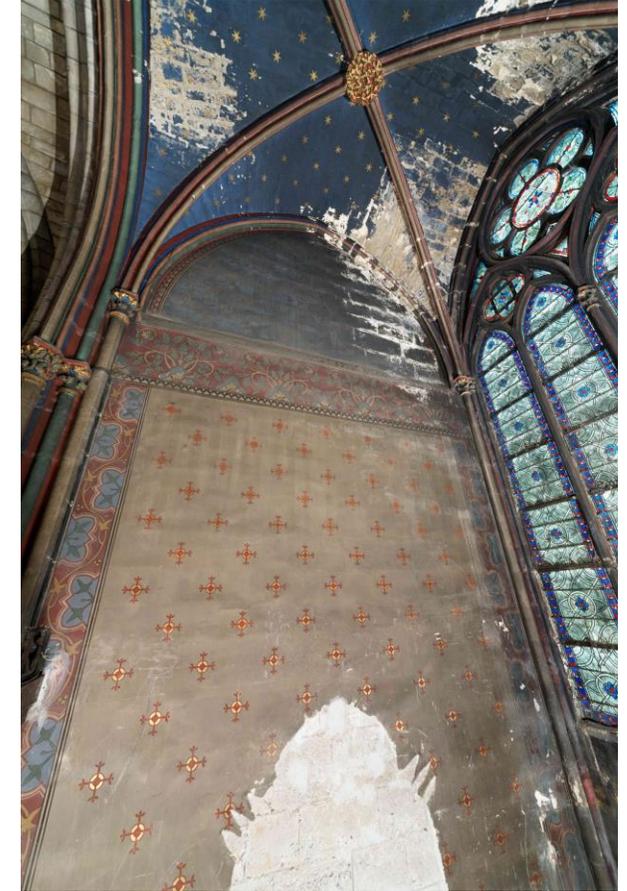
ITER_ca_19_04587



ITER_ca_19_04642



ITER_ca_19_04642

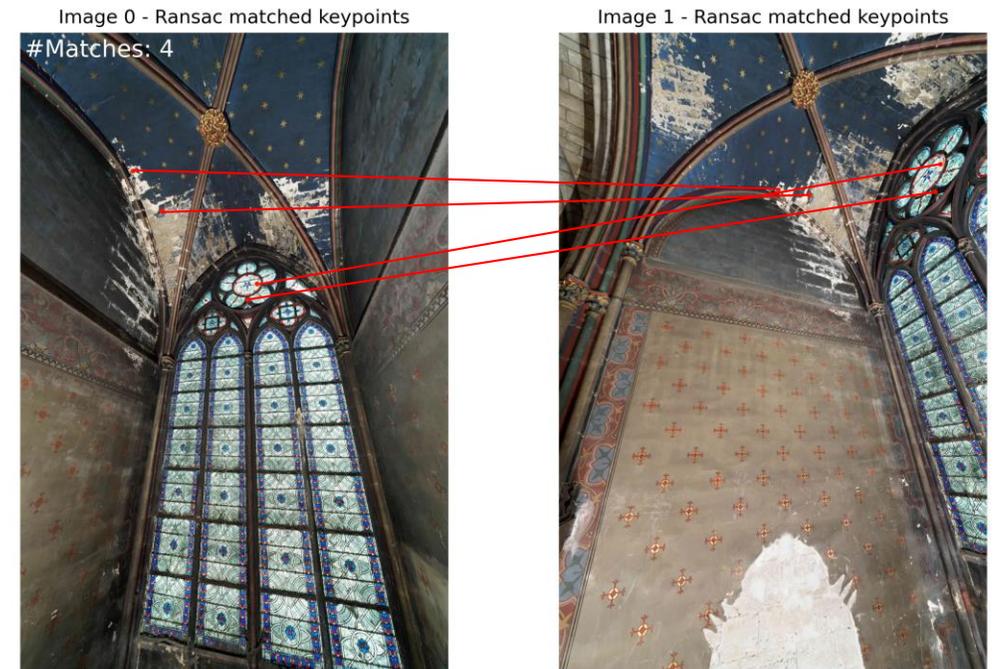
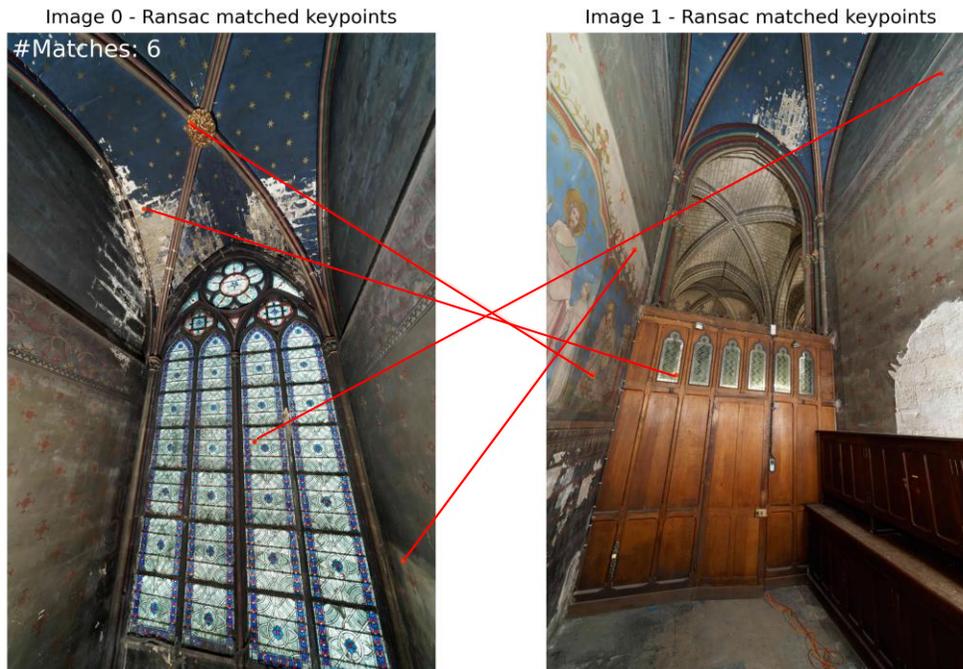


Distance

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

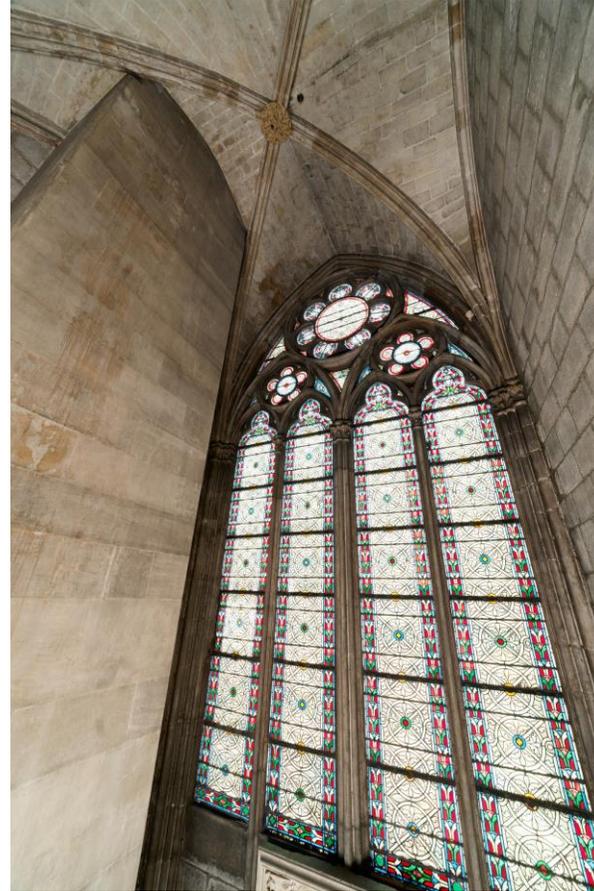
Example: Spatial distance

Which images are closest to one another?

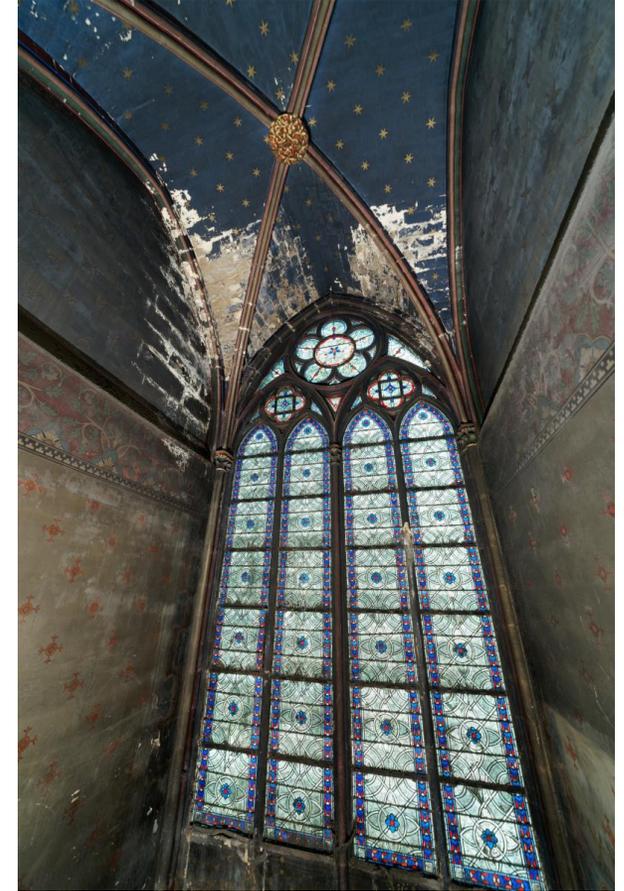
ITER_ca_25_03766



ITER_ca_25_03795



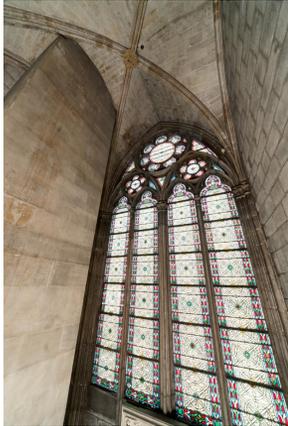
ITER_ca_19_04642



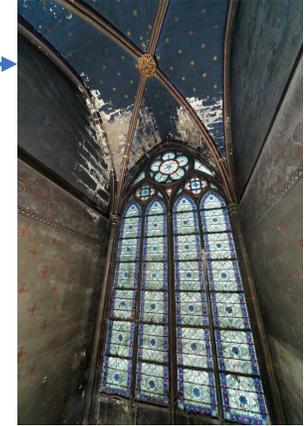
Distance

Example: Spatial distance

ITER_ca_25_03795



ITER_ca_19_04642



High euclidean distance
Short visual distance

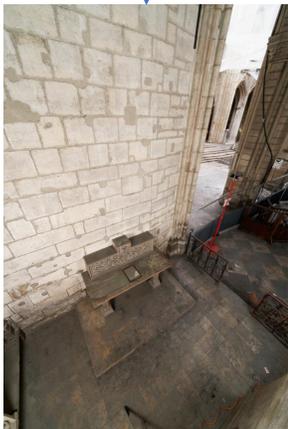


CA25

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

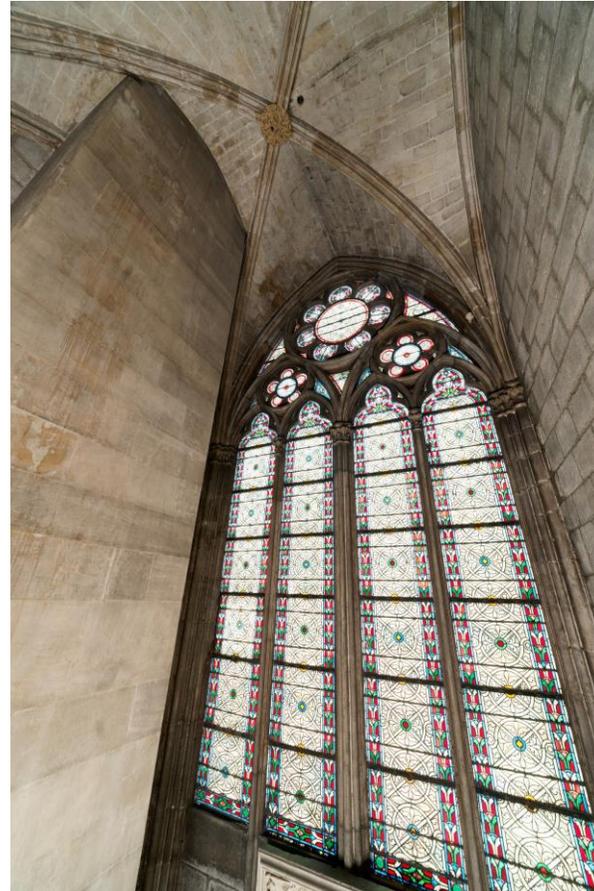
Example: Spatial distance

Which images are closest to one another?

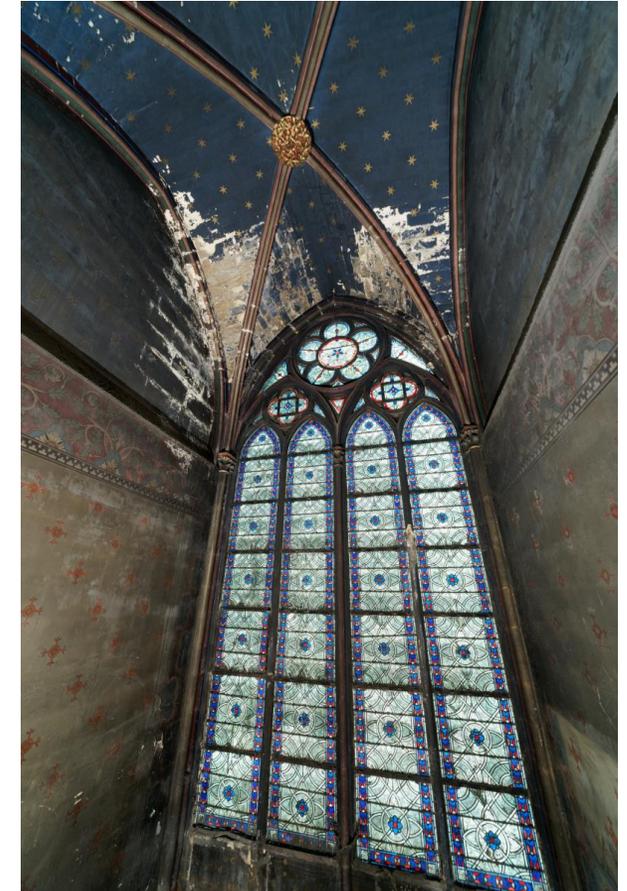
ITER_ca_38_07983



ITER_ca_25_03795



ITER_ca_19_04642



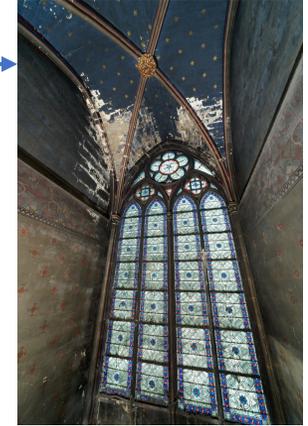
Distance

Example: Spatial distance

ITER_ca_25_03795



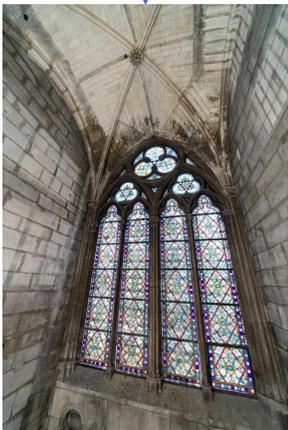
ITER_ca_19_04642



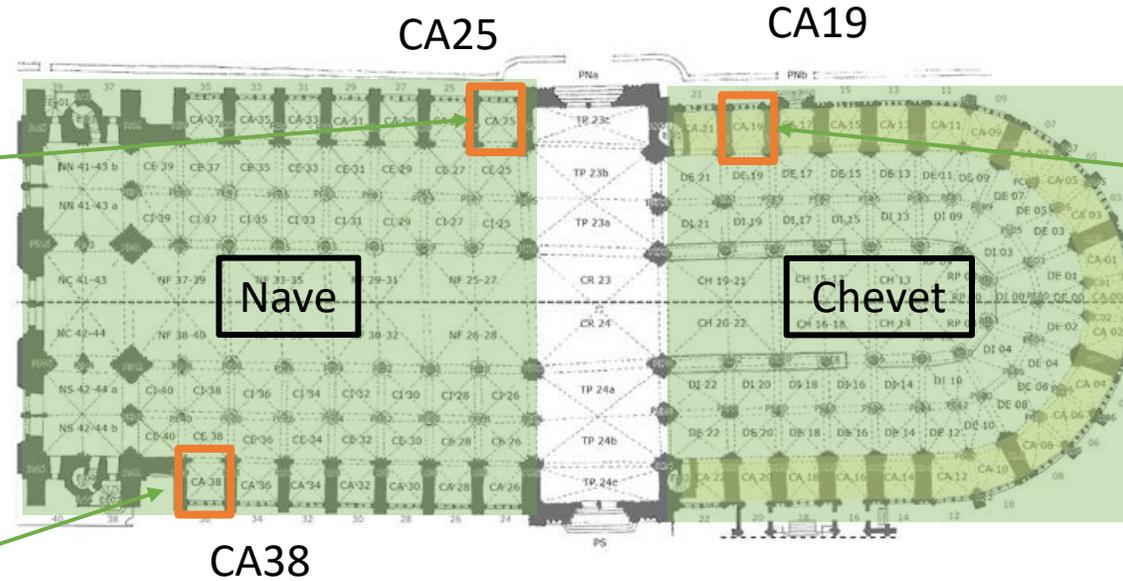
Smaller euclidean distance
Short visual distance



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

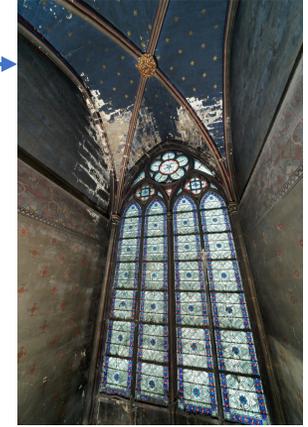
Distance

Example: Spatial distance

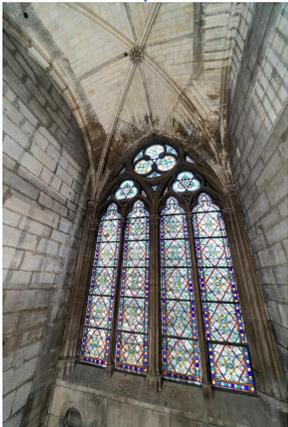
ITER_ca_25_03795



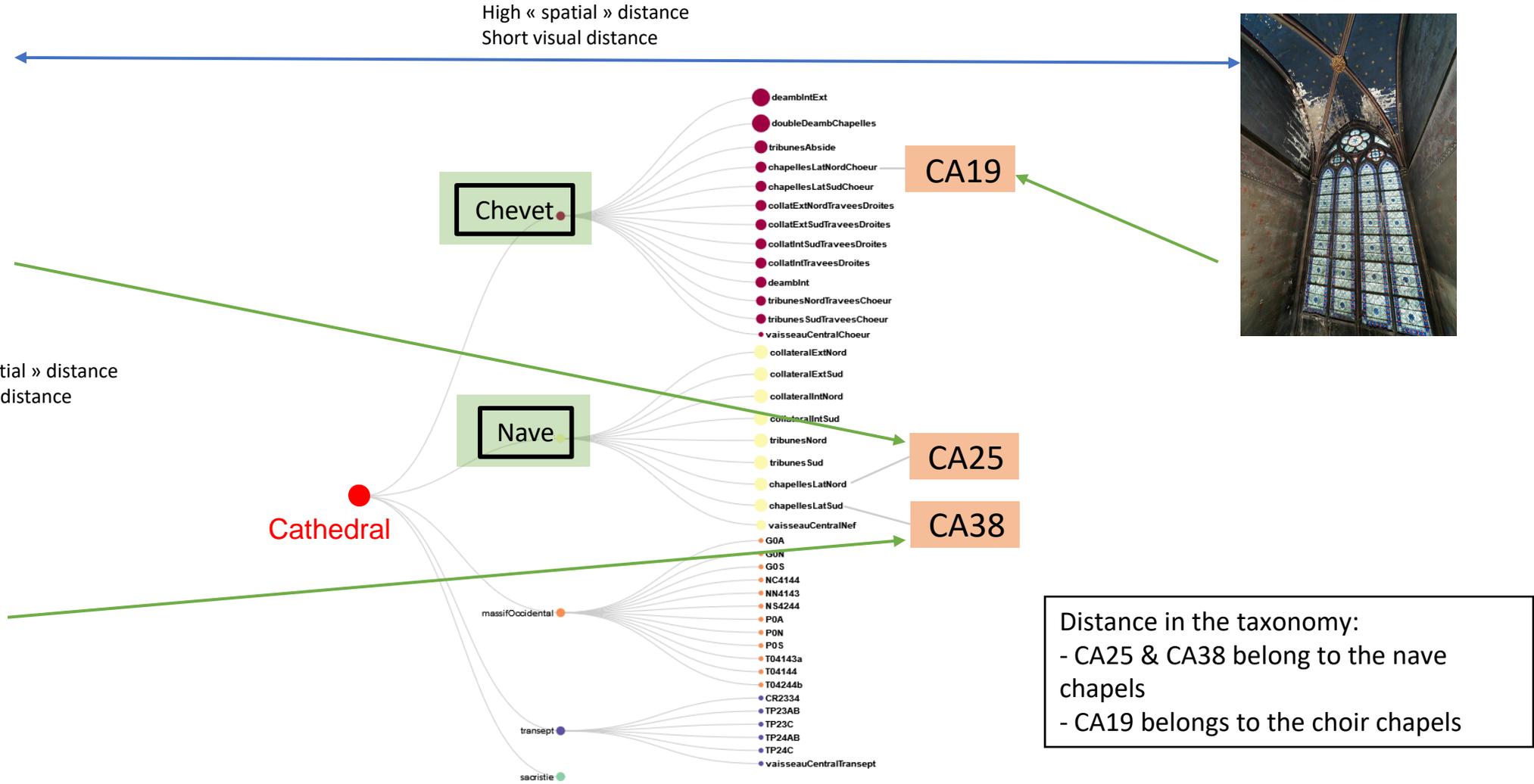
ITER_ca_19_04642



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

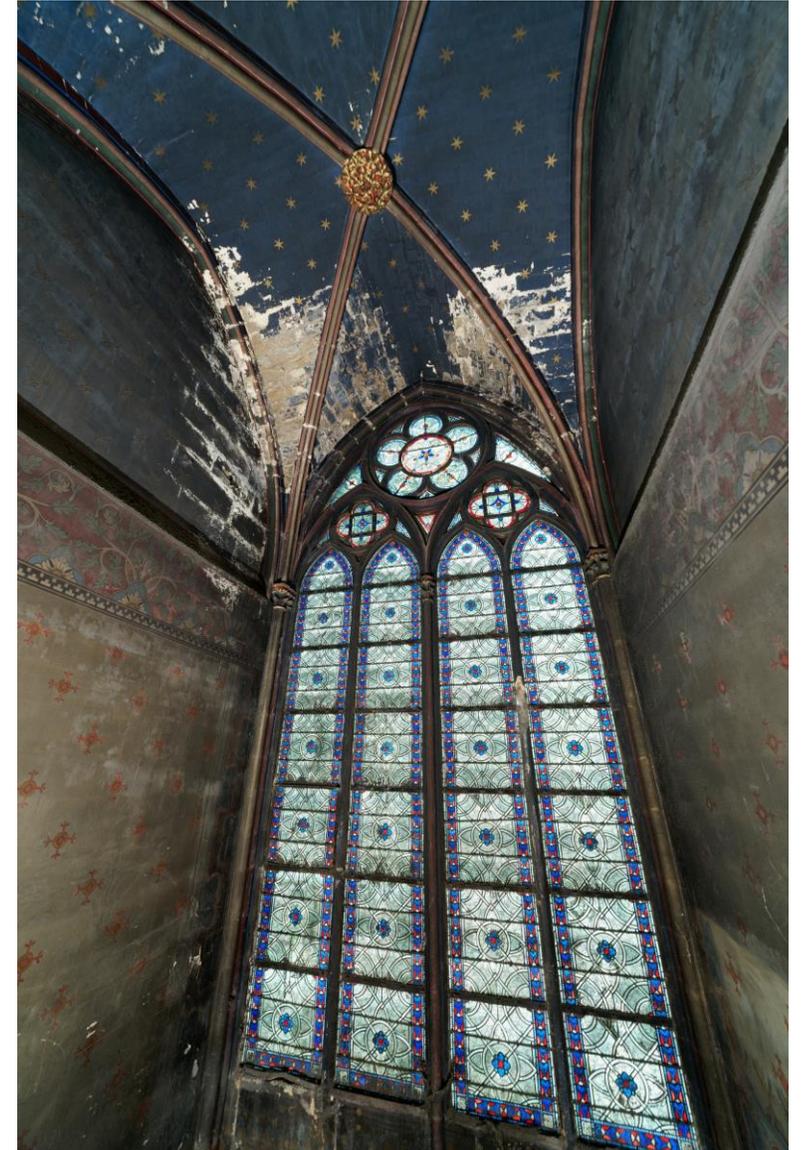
Data

Description

Data:

- Visual Content

ITER_ca_19_04642

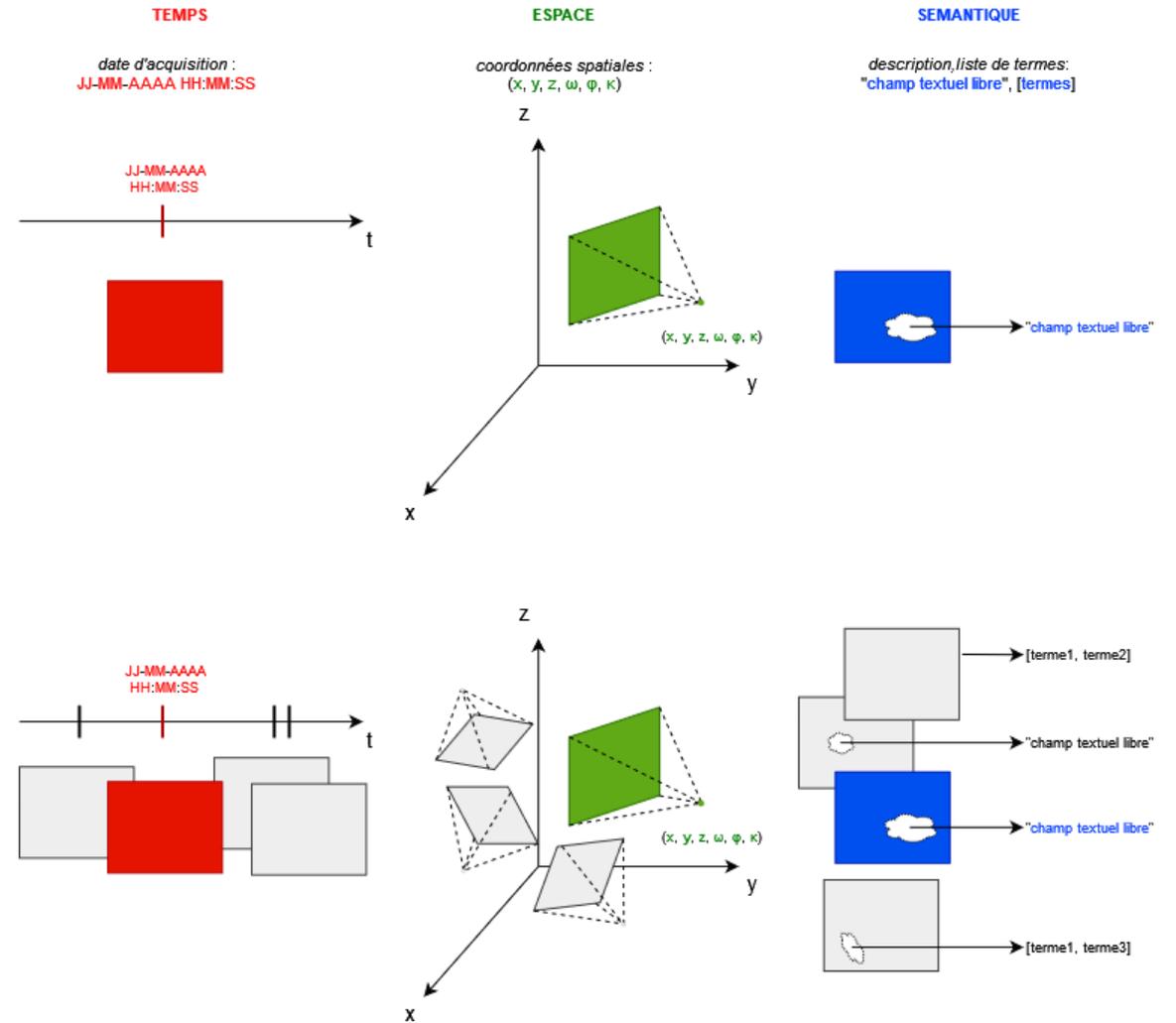


Data

Description

Data:

- Visual Content
- Image-related metadata

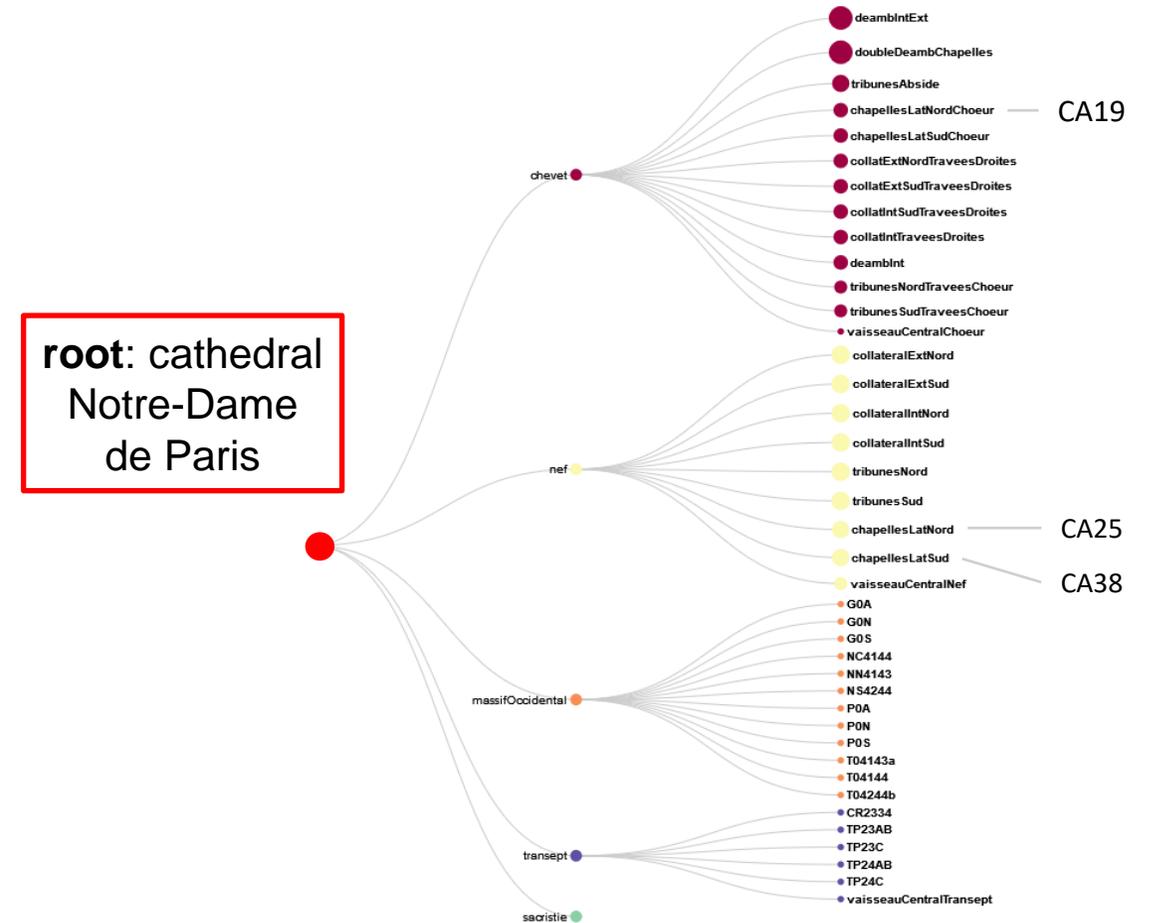


Data

Description

Data:

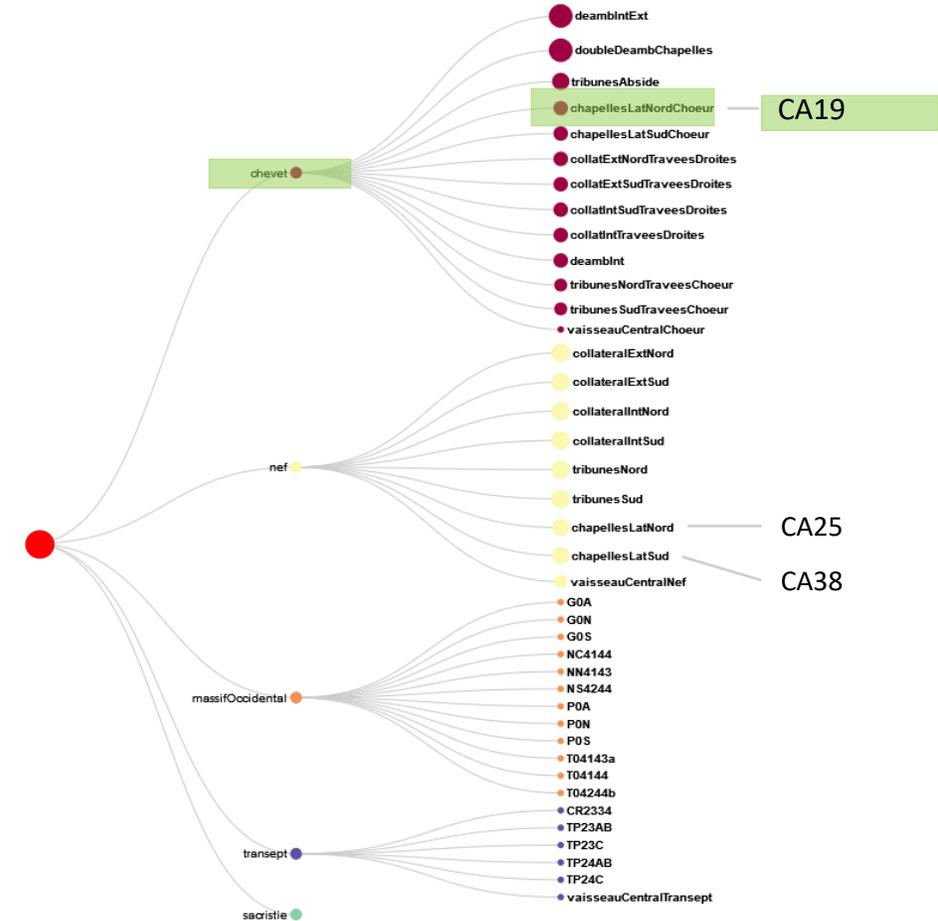
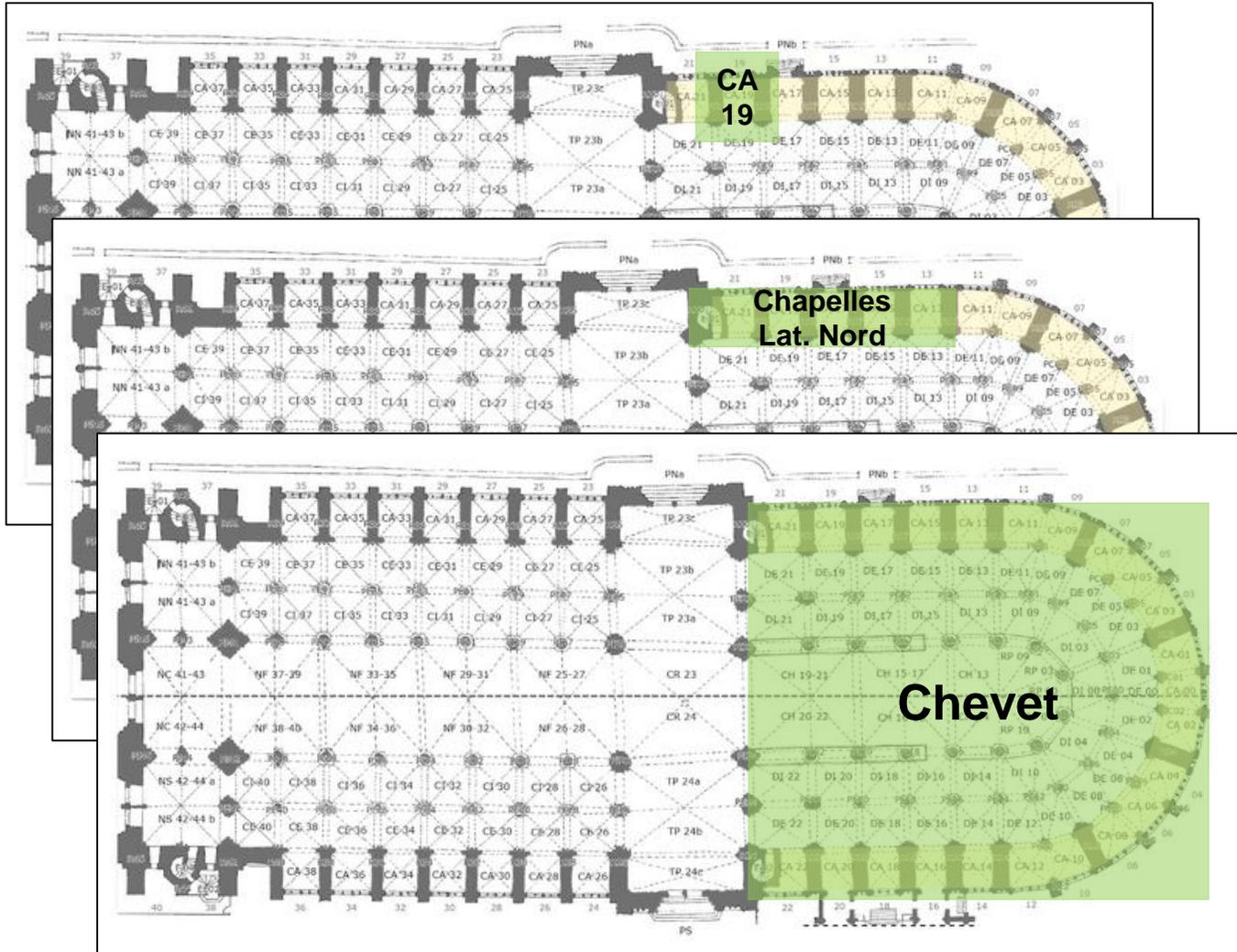
- Visual Content
- Image-related metadata
- Corpus-related metadata



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

Data

Example: Spatial Data

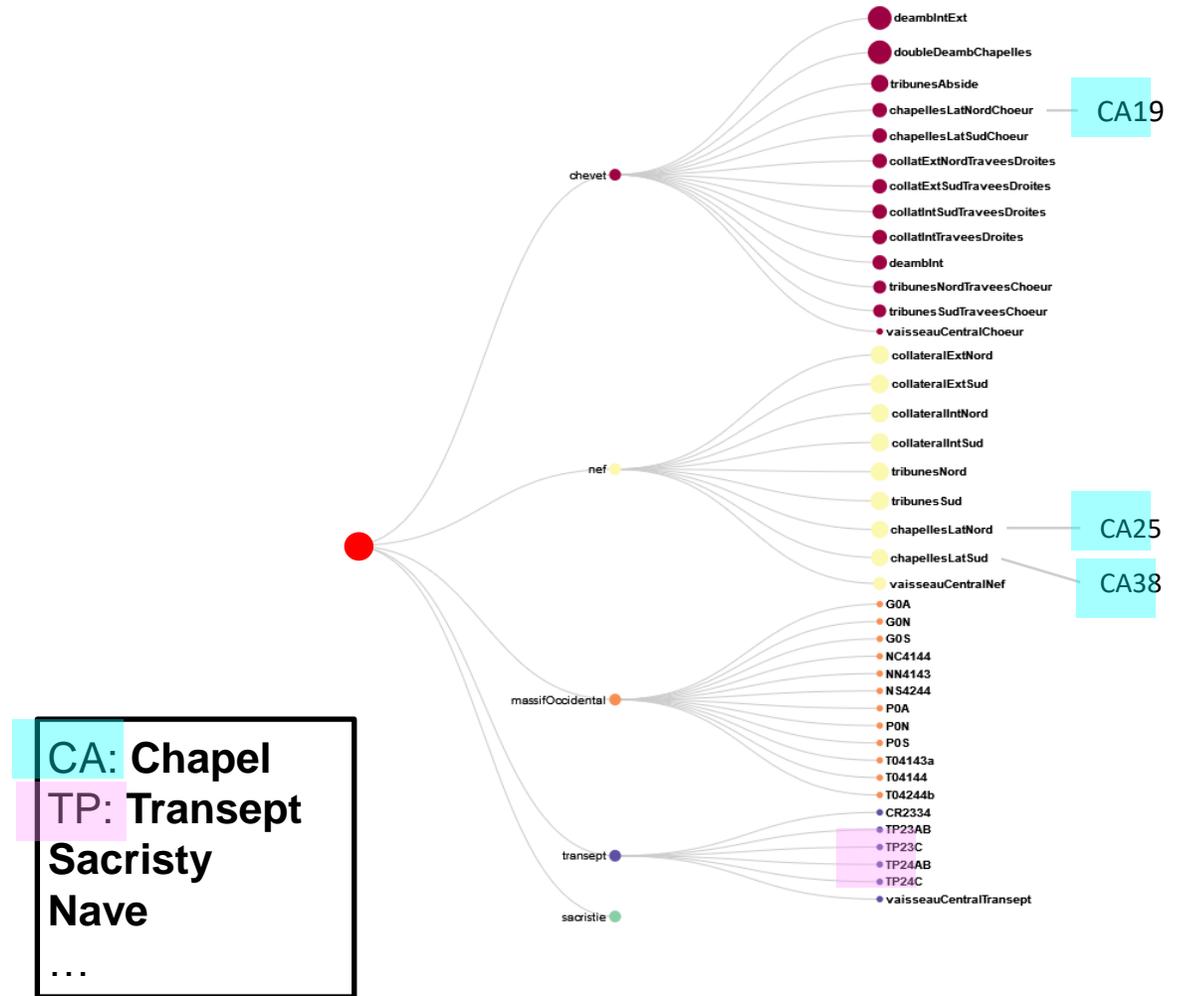


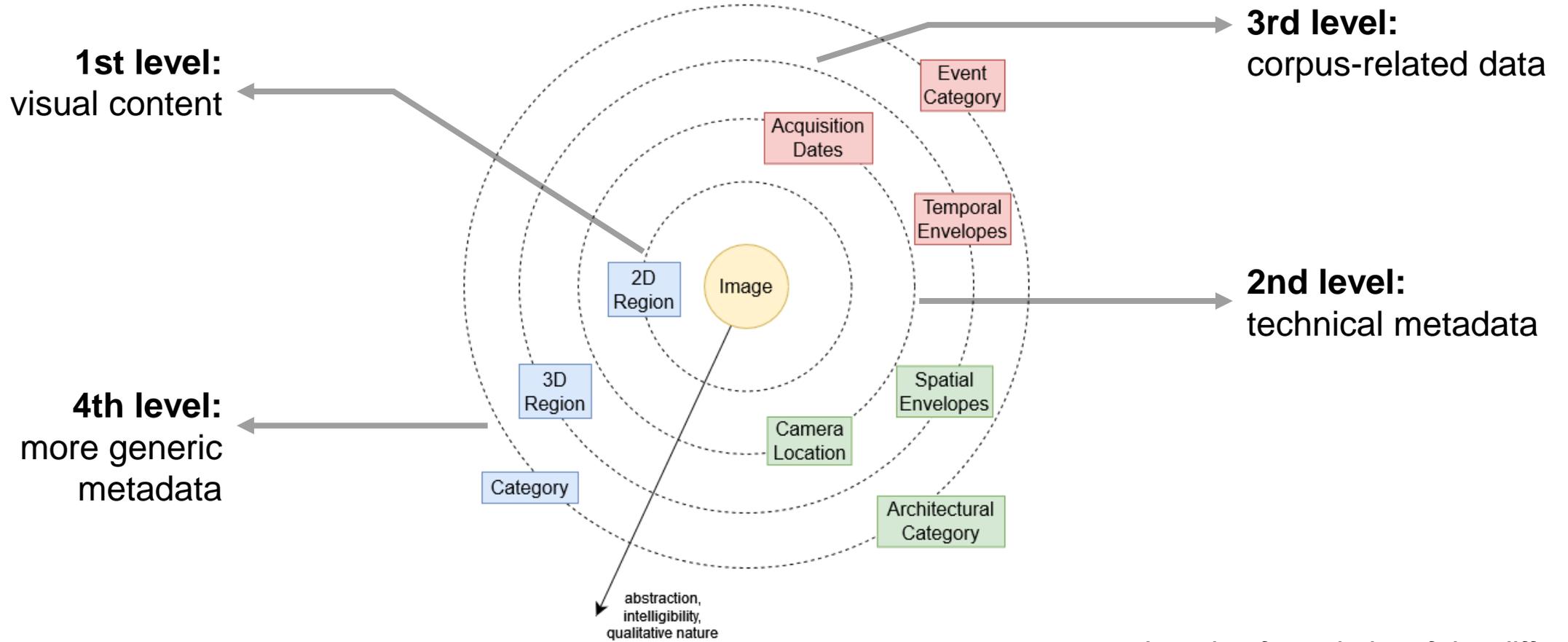
Data

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)

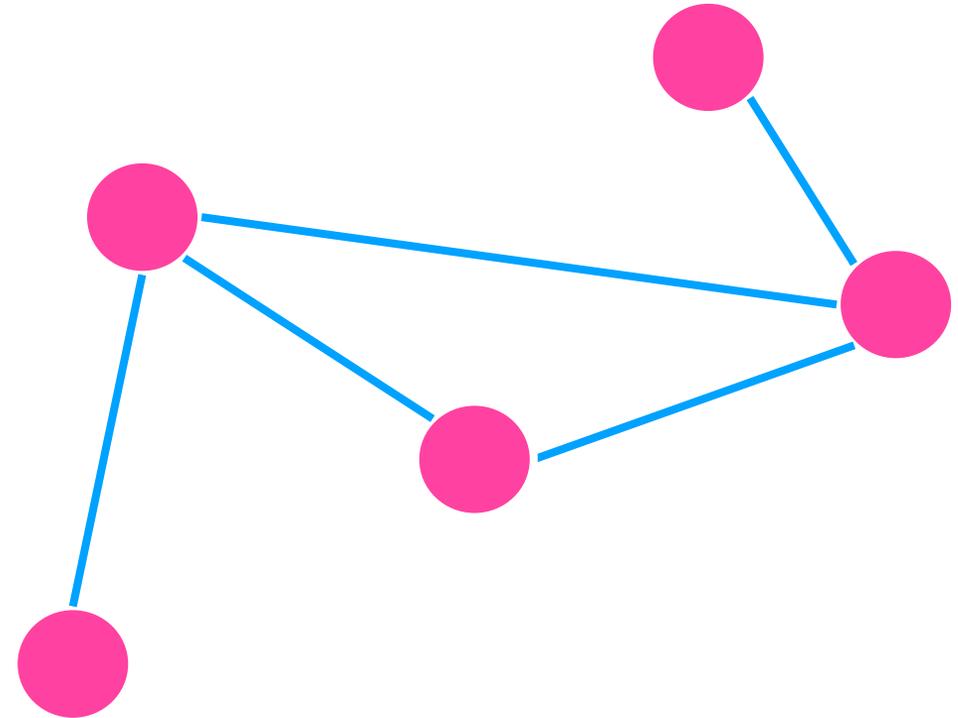
Graph-oriented Database

Structuring

Description

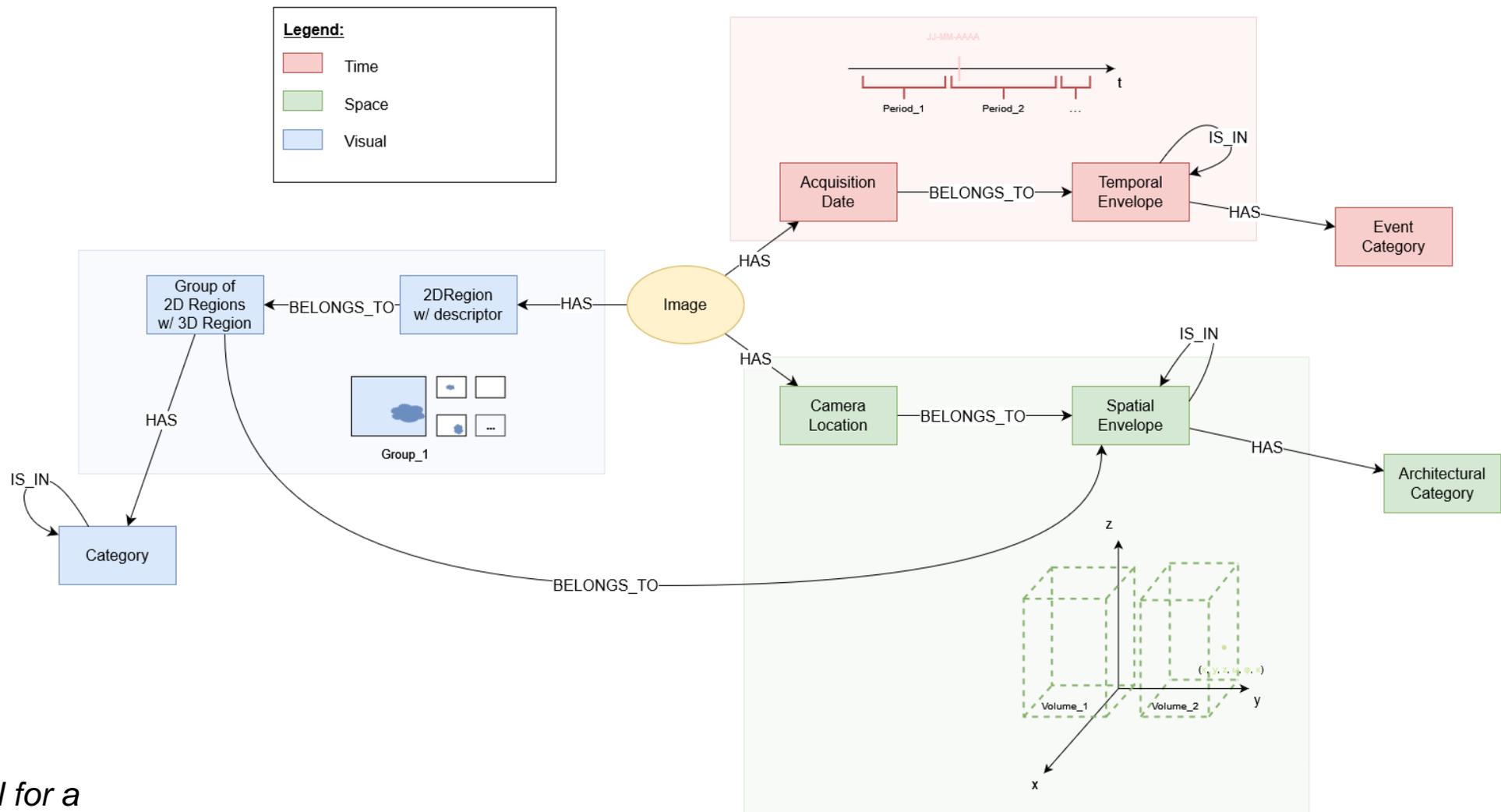
Data:

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



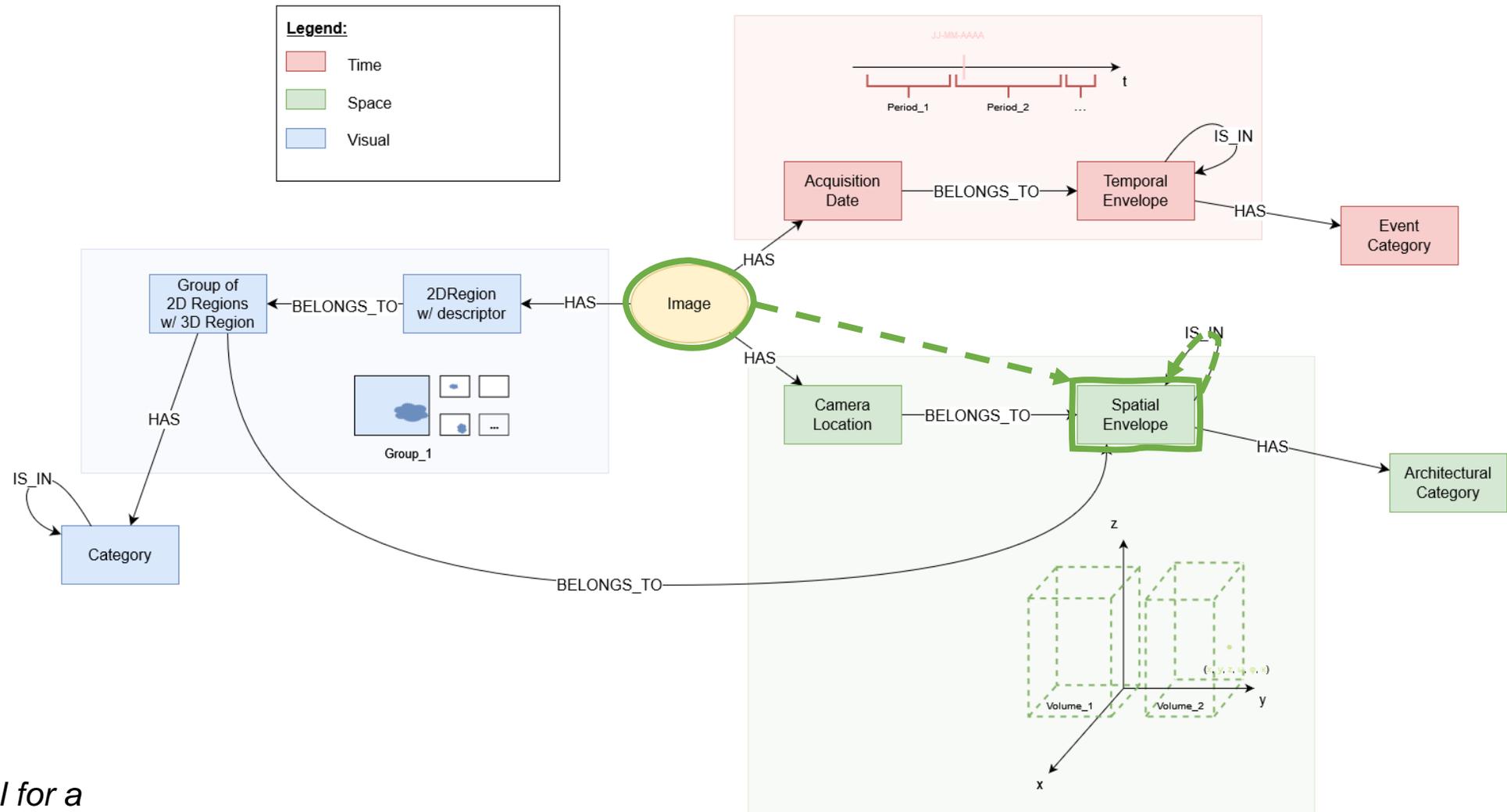
*Graphs are a ubiquitous data structure [...] a collection of objects (i.e., **nodes**), along with a set of interactions (i.e., **edges**) between pairs of these objects. [Hamilton, 2020]*

Structuring Graph Data Model



*Data Model for a
graph-oriented database*

Structuring Graph Data Model

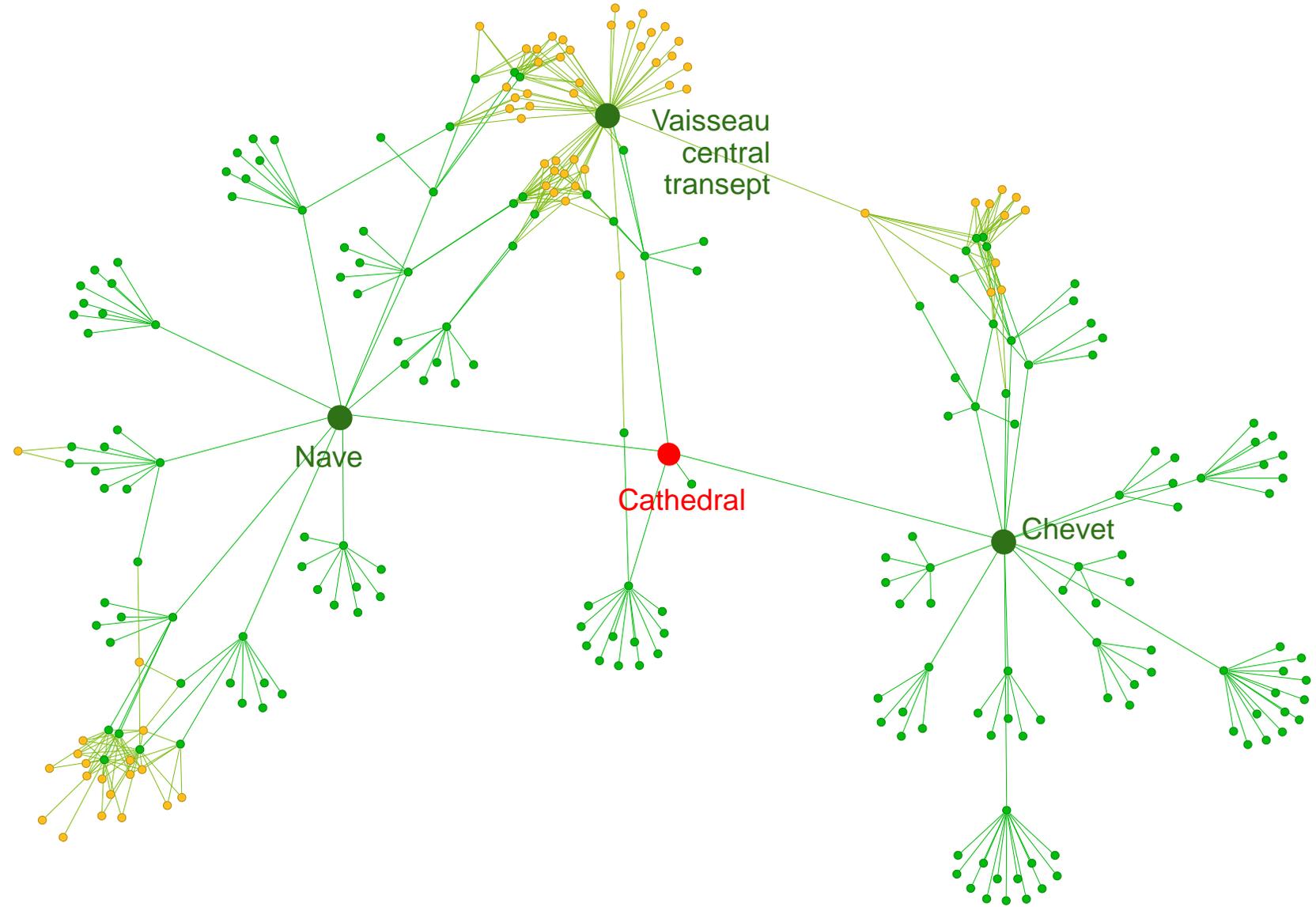


*Data Model for a
graph-oriented database*

Structuring

Example: Spatial Data

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

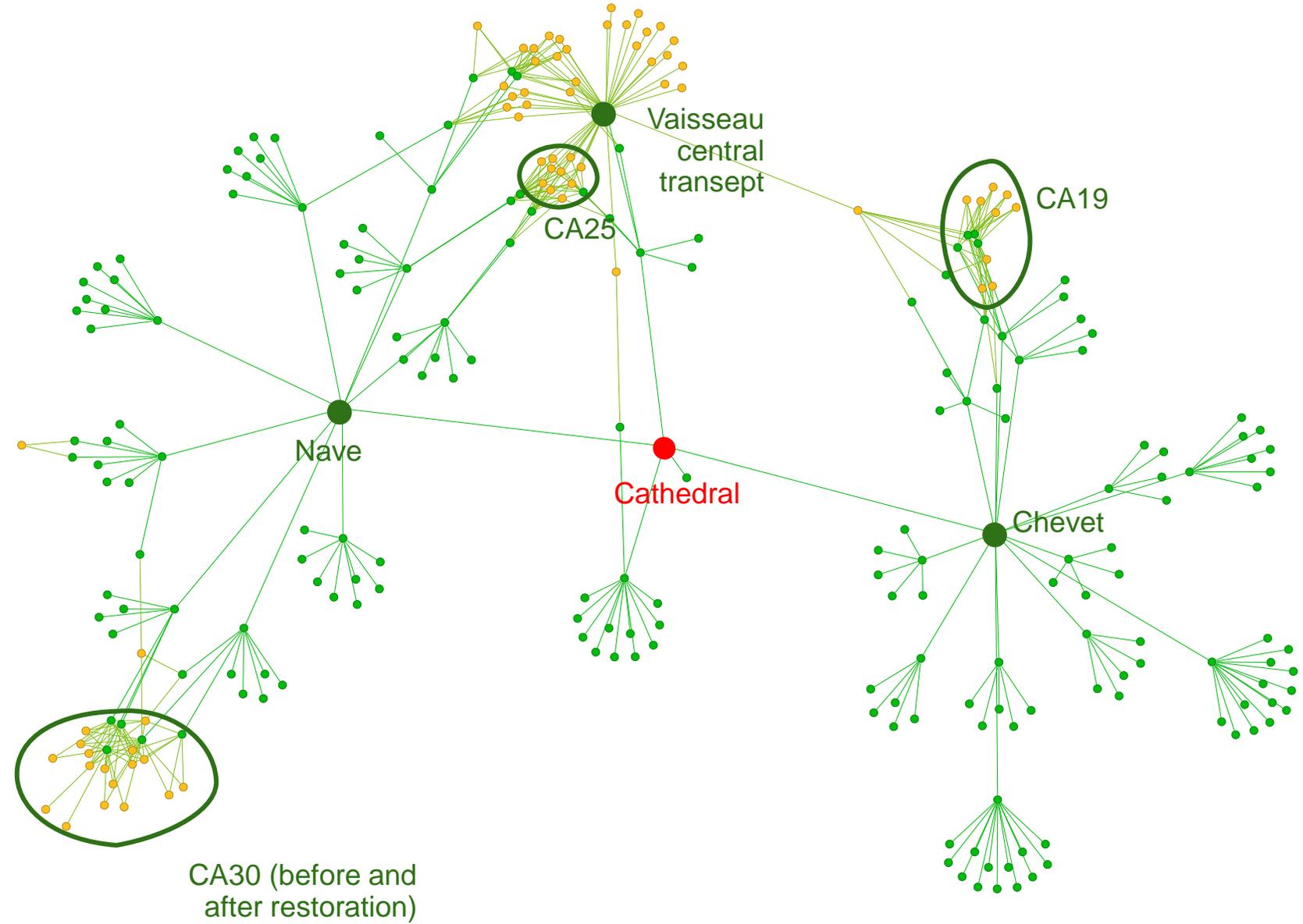


Example graph of *Images* and *SpatialEnvelopes*

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]*

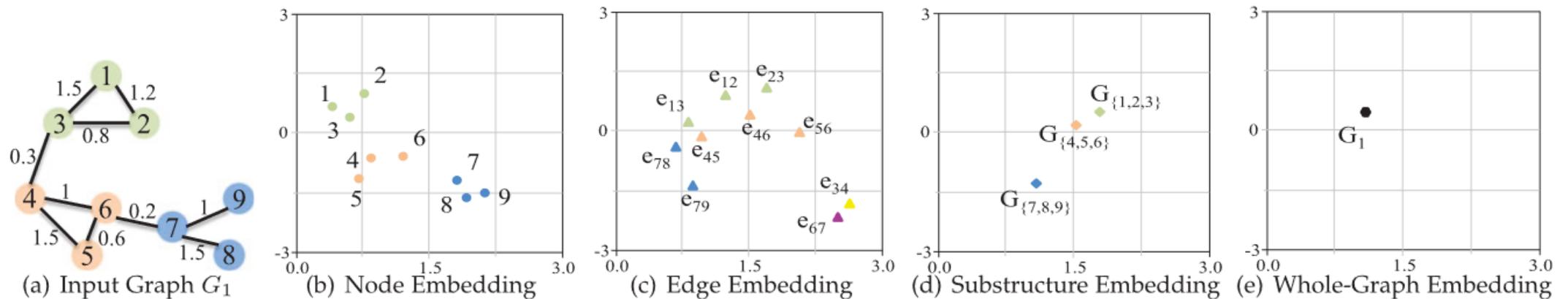


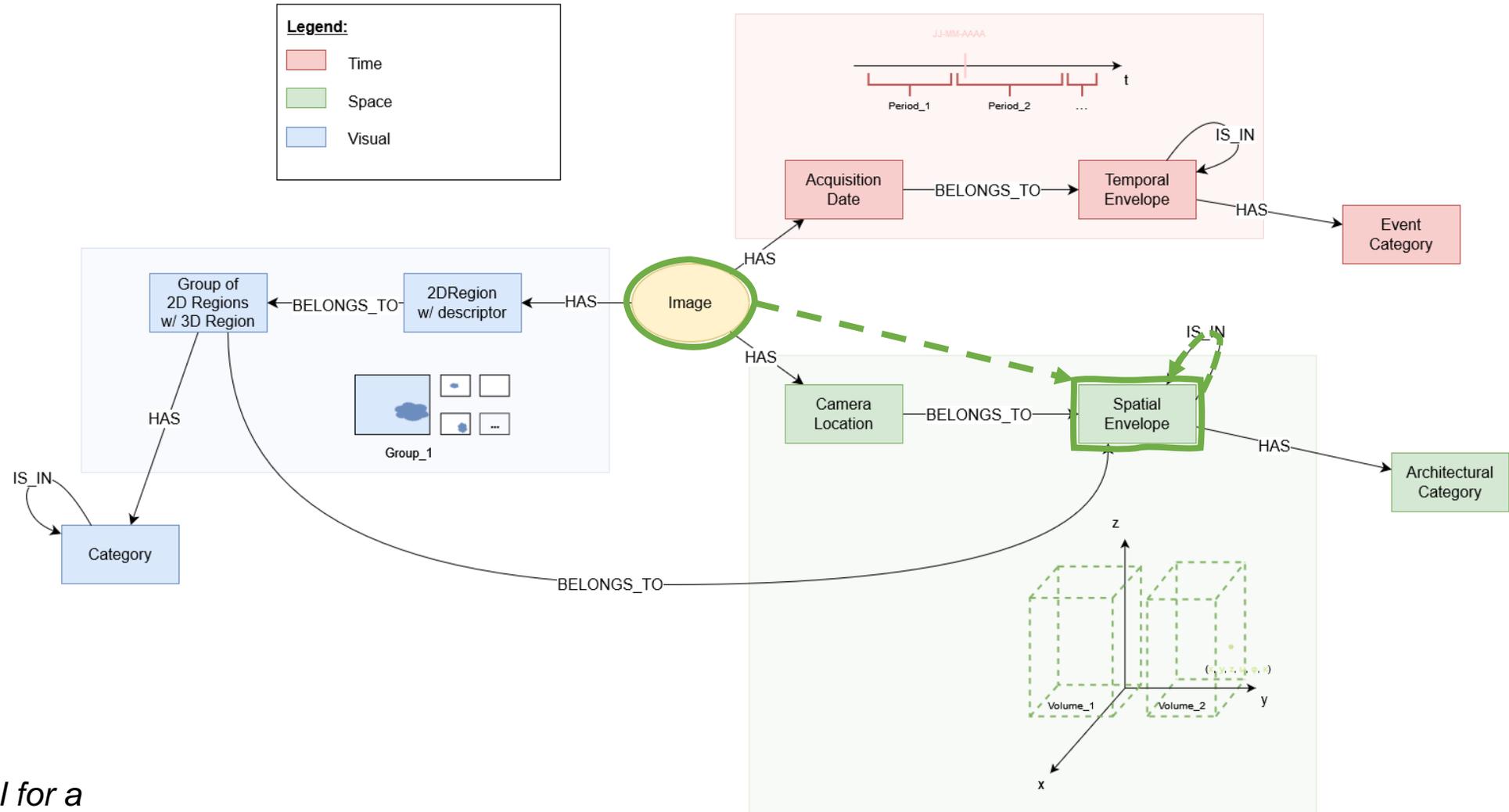
Fig. 1. A toy example of embedding a graph into 2D space with different granularities. $G_{\{1,2,3\}}$ denotes the substructure containing node v_1, v_2, v_3 .

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

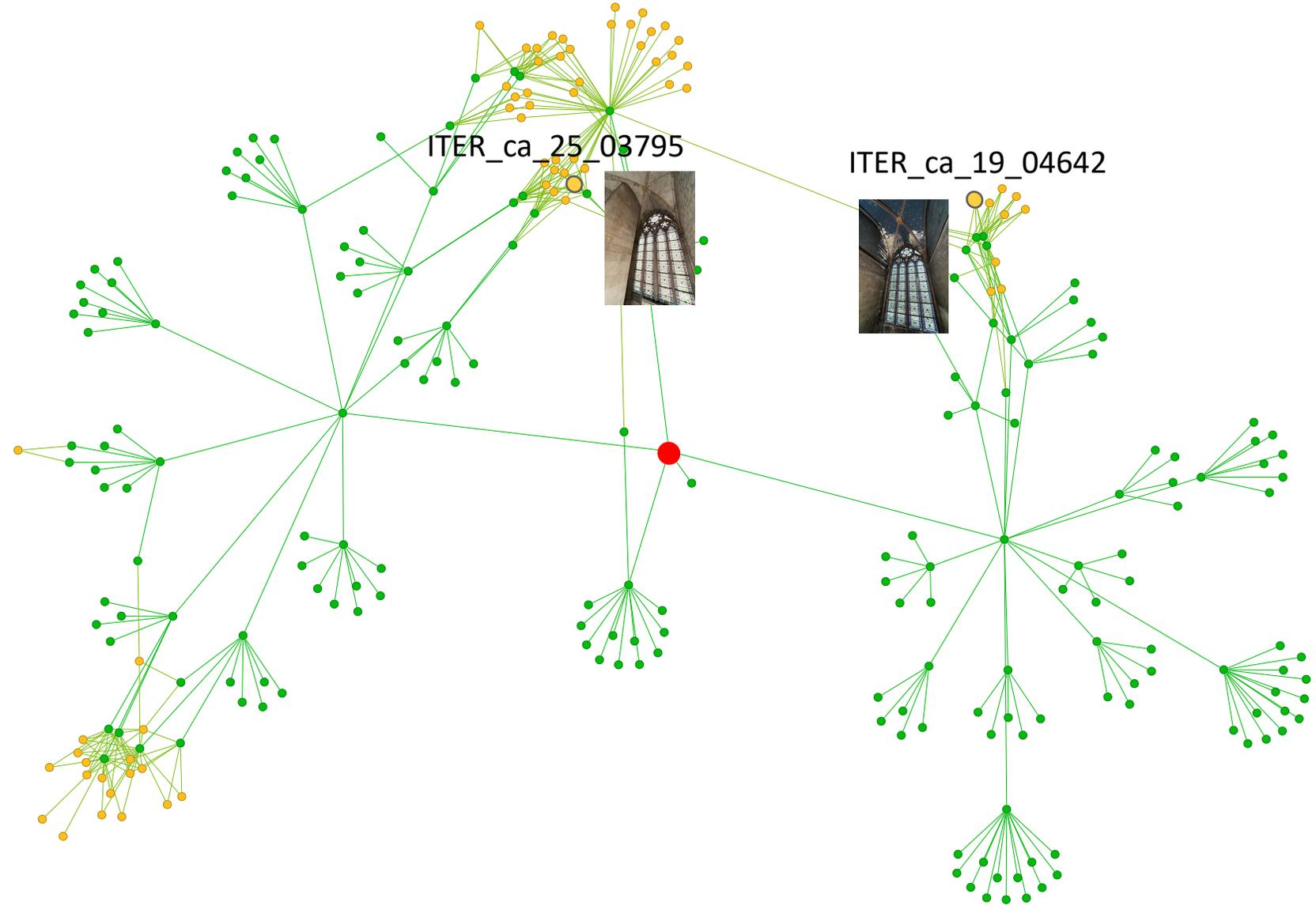


*Data Model for a
graph-oriented database*

Structuring

Example: Spatial Data

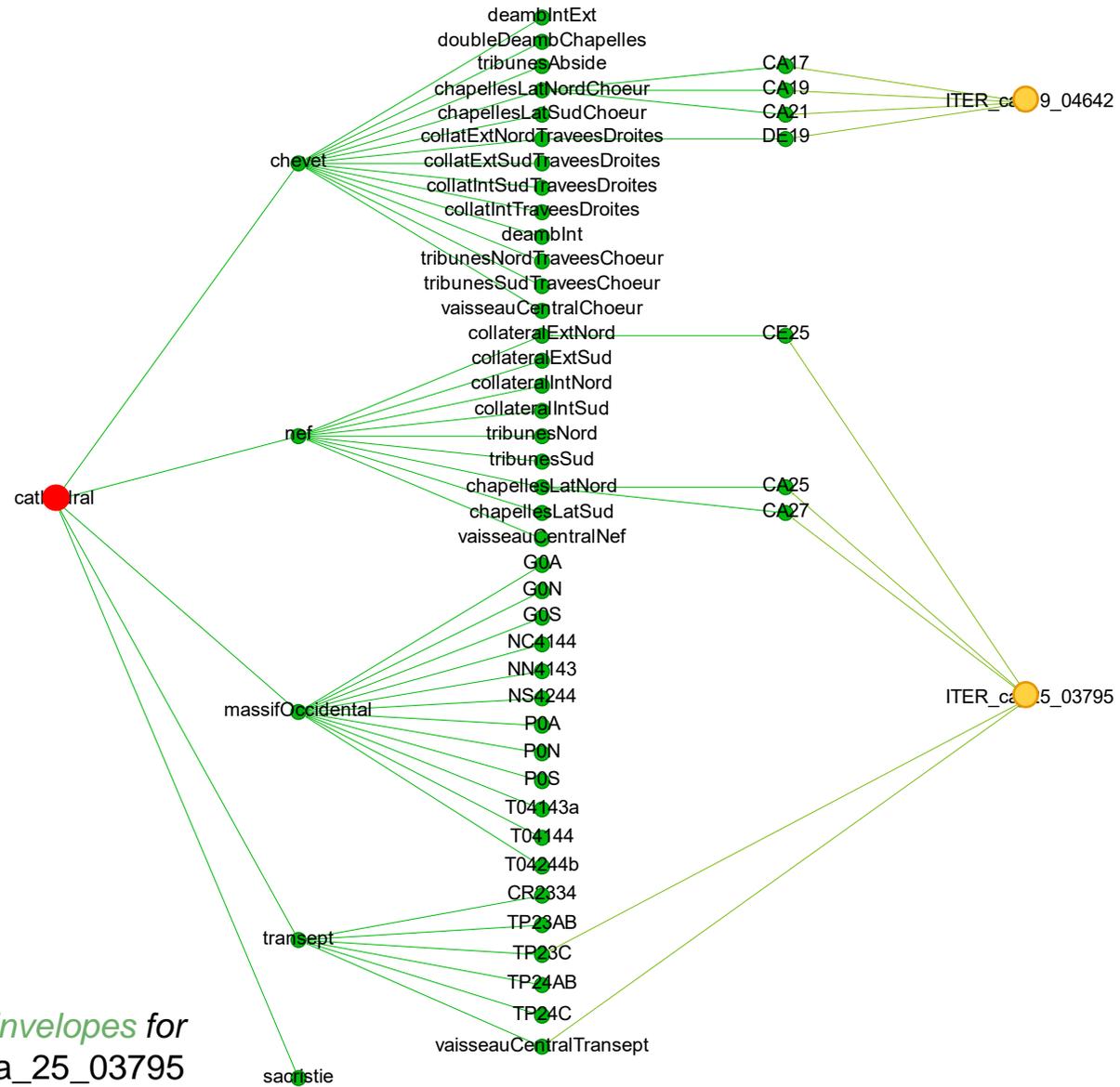
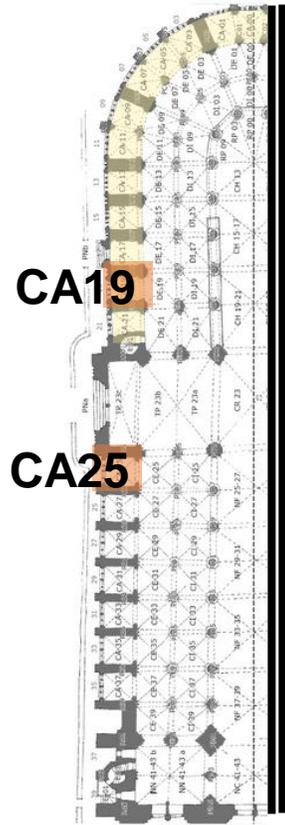
Each **Image** node is related to {0..n} **SpatialEnvelope** nodes



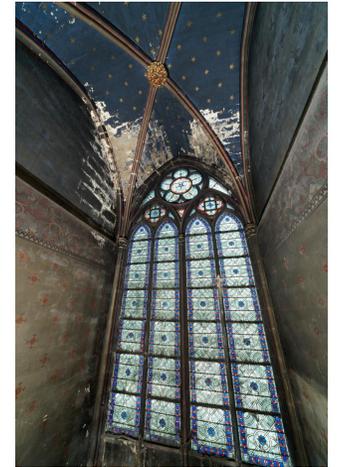
Example graph of *Images* and *SpatialEnvelopes*

Structuring

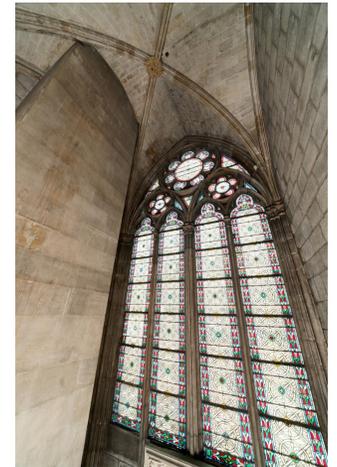
Example: Spatial Data



ITER_ca_19_04642



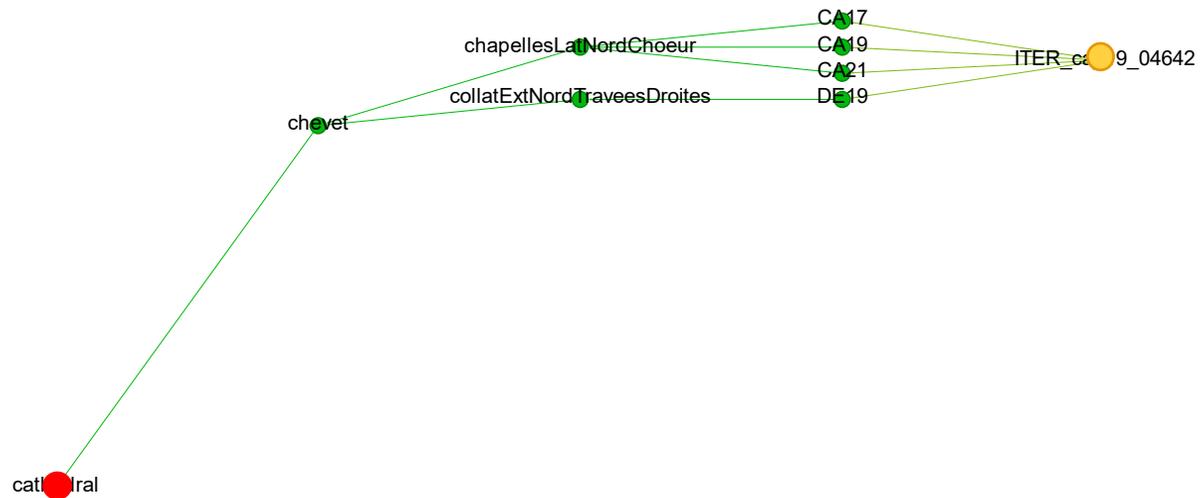
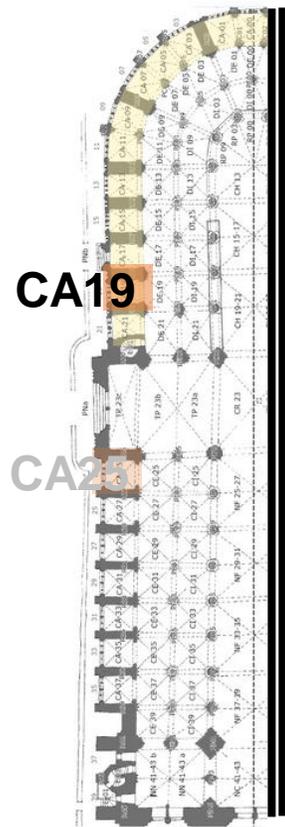
ITER_ca_25_03795



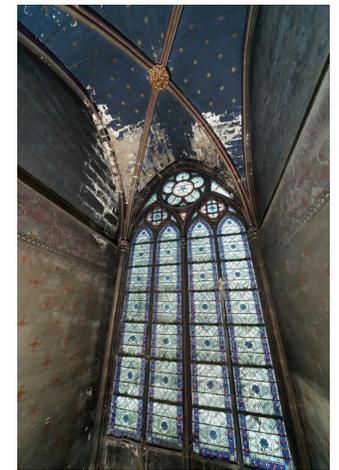
Selected subgraph of *Images* and *SpatialEnvelopes* for the images ITER_ca_19_04642 and ITER_ca_25_03795

Structuring

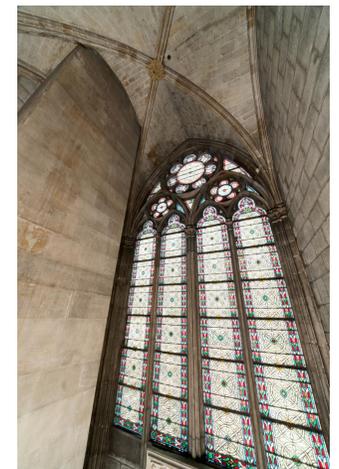
Example: Spatial Data



ITER_ca_19_04642



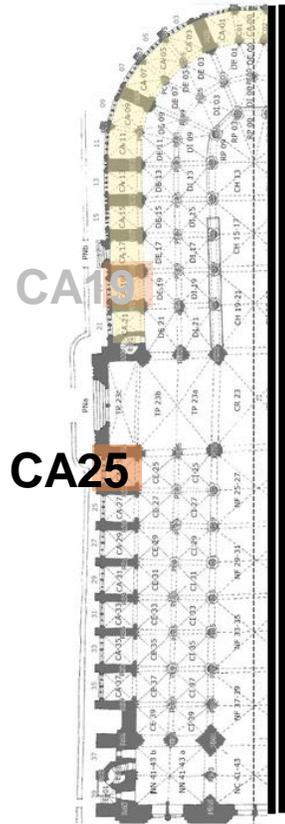
ITER_ca_25_03795



Subtree of *Spatial Envelopes* characterising the image ITER_ca_19_04642

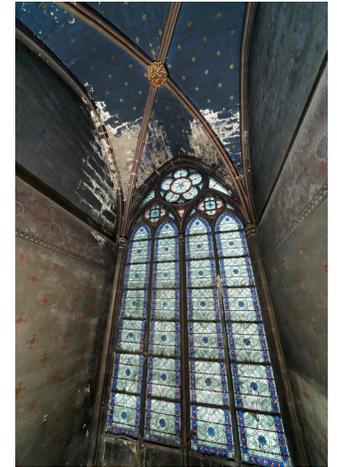
Structuring

Example: Spatial Data

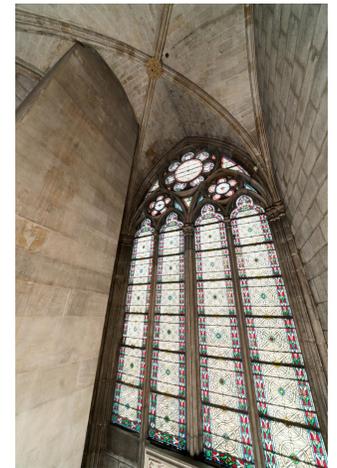


Subtree of *SpatialEnvelopes* characterising the image ITER_ca_25_03795

ITER_ca_19_04642



ITER_ca_25_03795



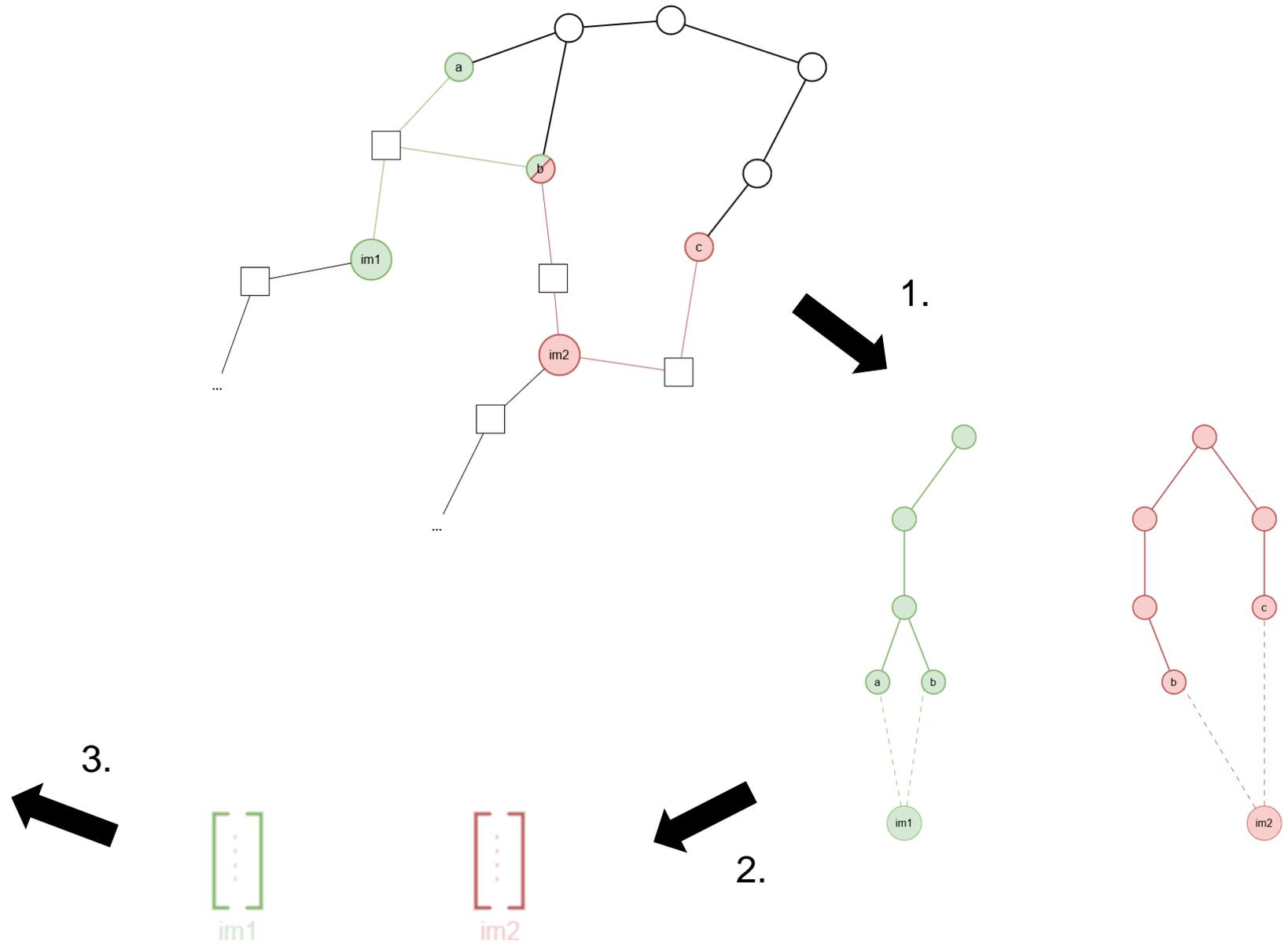
Structuring

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

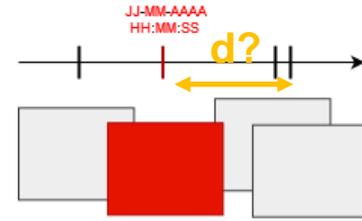
Exploring

Distances

Exploring based on:

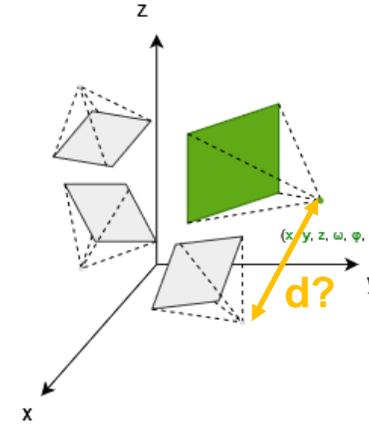
- Data values

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



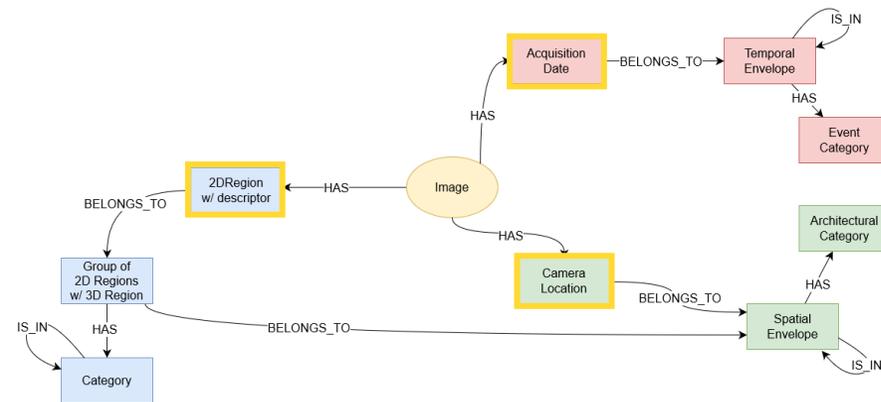
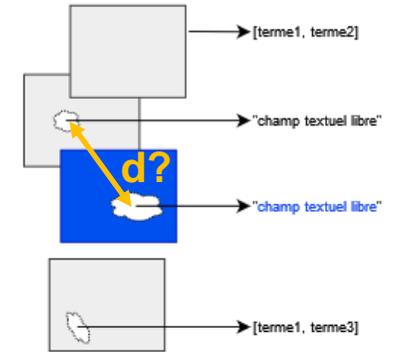
ESPACE

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



SEMANTIQUE

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



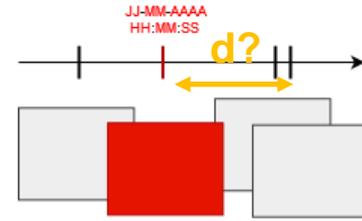
Exploring

Distances

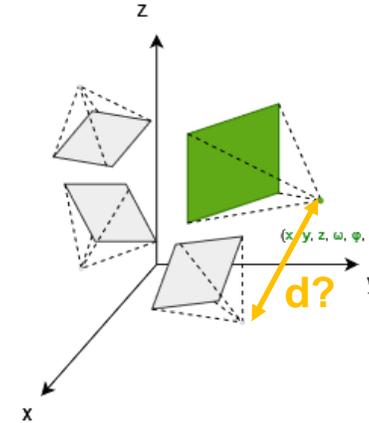
Exploring based on:

- Data values
- Data structures (embeddings)

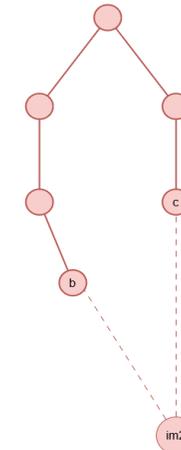
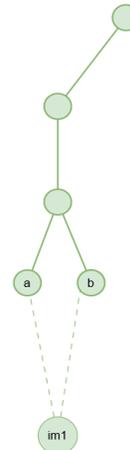
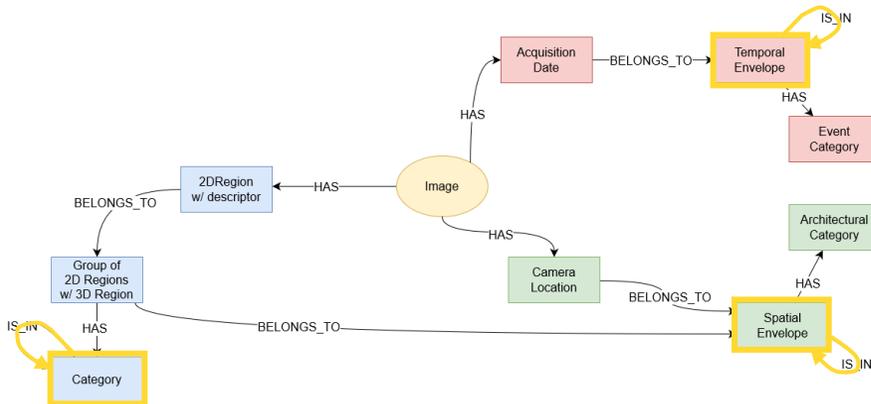
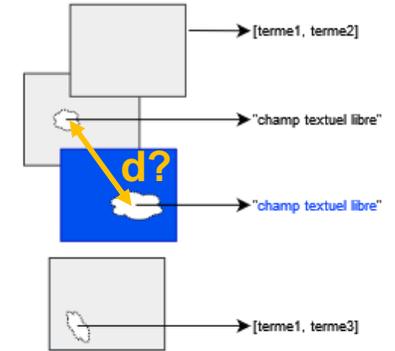
TEMPS
date d'acquisition :
JJ-MM-AAAA HH:MM:SS



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



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

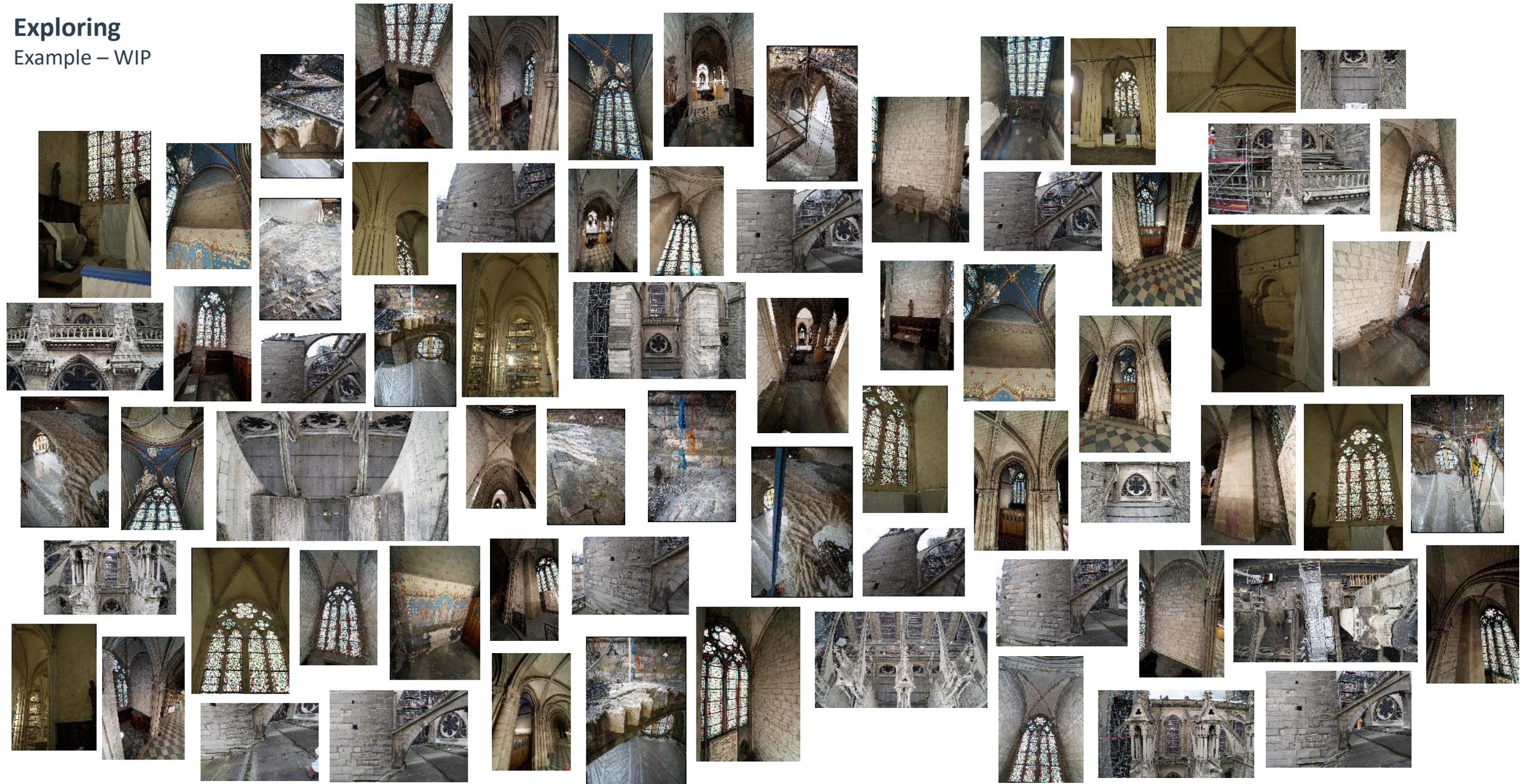


Graph embedding method



Exploring

Example – WIP



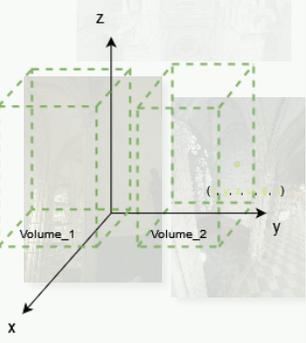
Exploring

Example – WIP

Spatial Envelope



CA30



Exploring

Example – WIP

Acquisition Date



CA30

Before restoration

Exploring

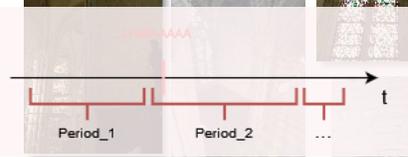
Example – WIP

Acquisition Date



CA30

After restoration



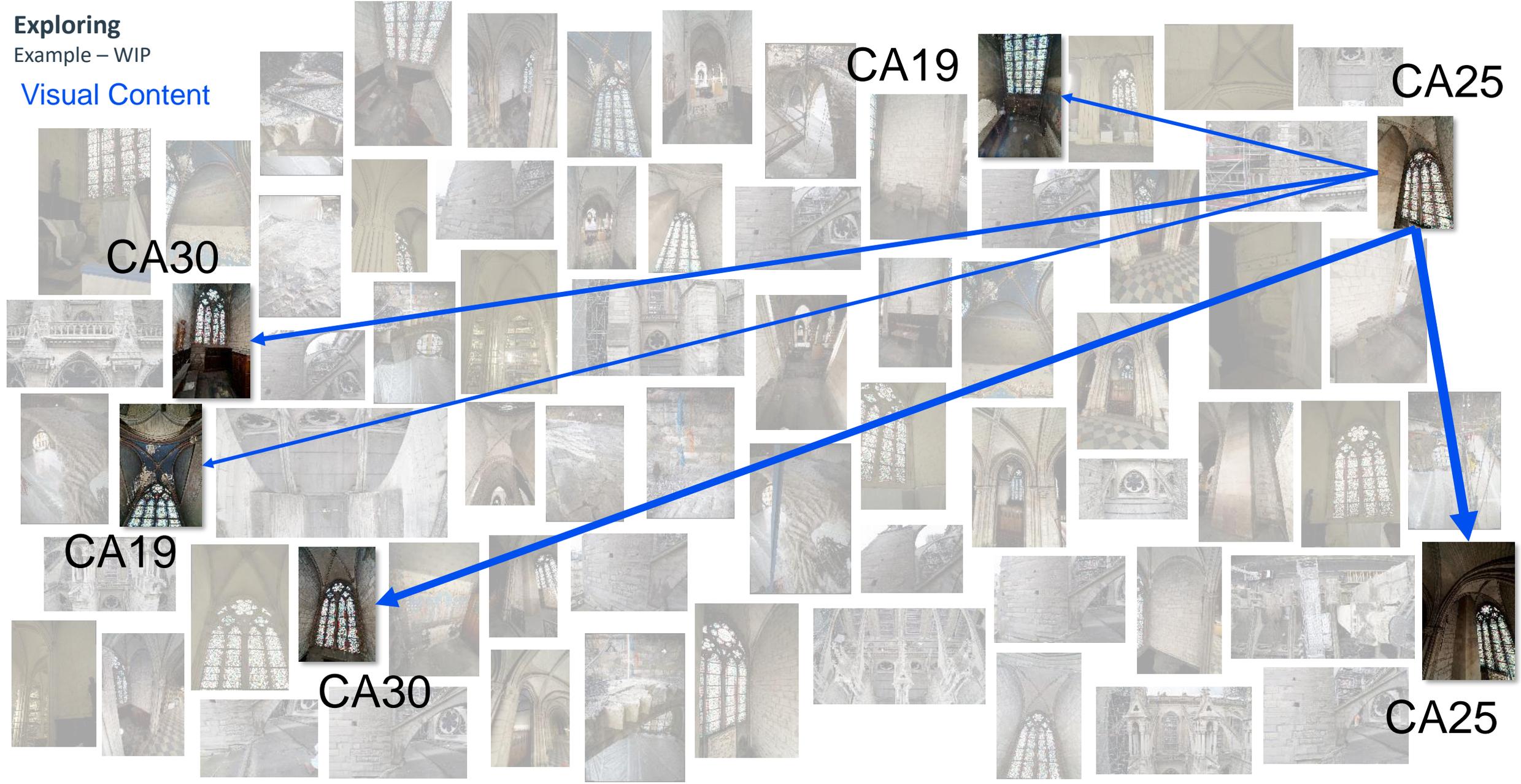
Exploring

Example – WIP

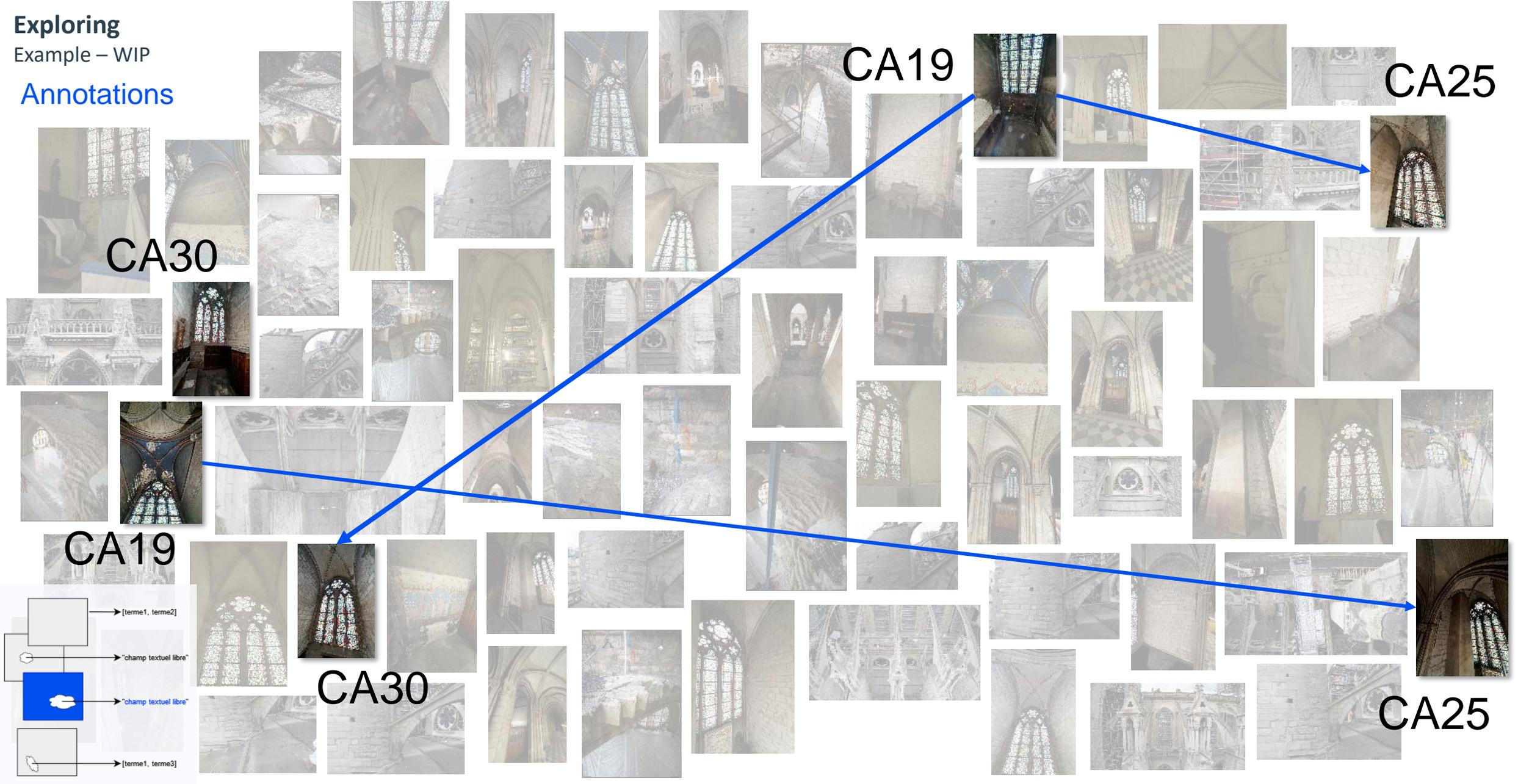
Camera Position



Exploring
Example – WIP
Visual Content

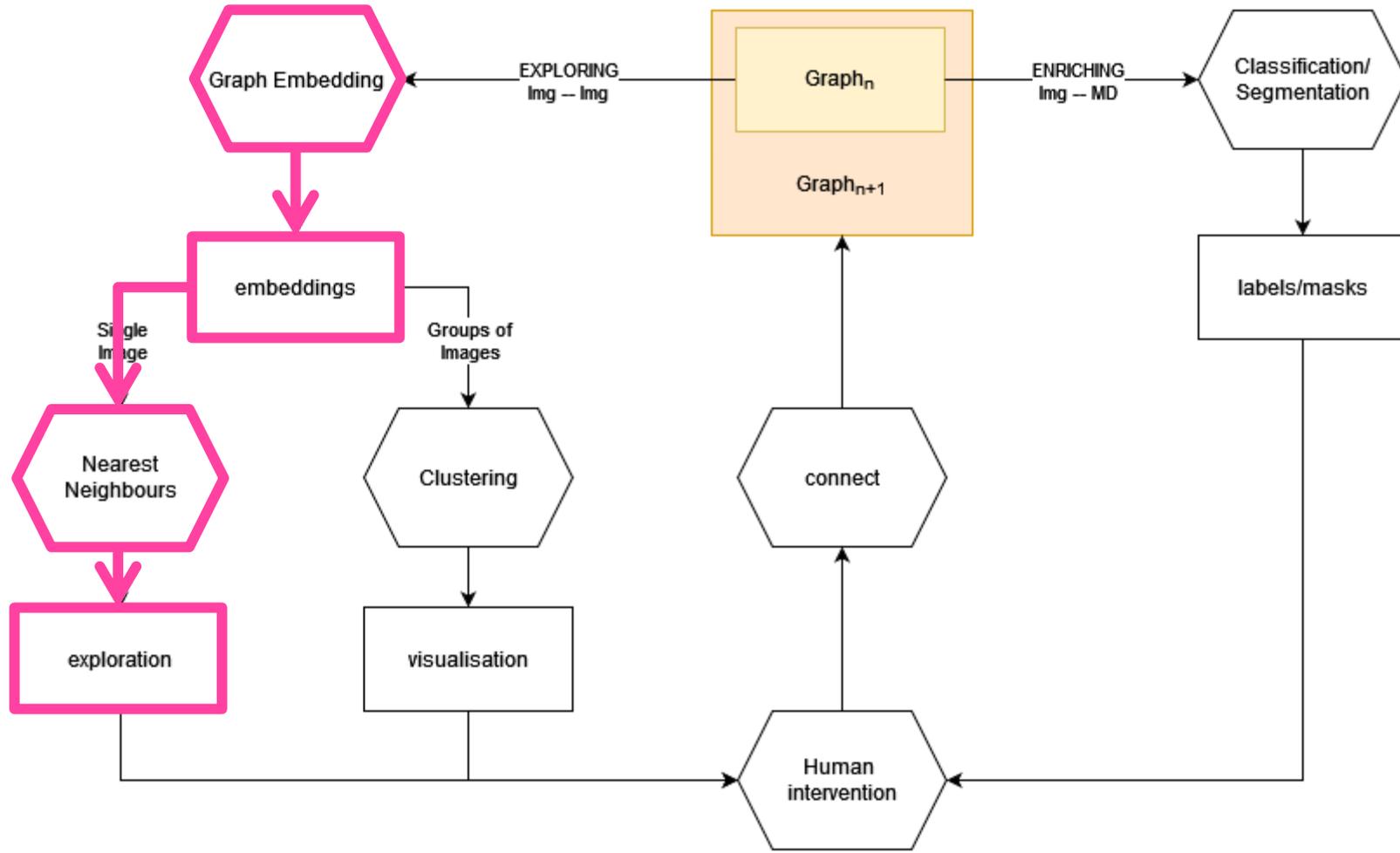


Exploring
Example – WIP
Annotations



Exploring

... and beyond



Exploring and Enriching the Graph-oriented Database

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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

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