Urban-scale quantitative visual analysis

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What Makes Paris Look like Paris?

[Doersch, Singh, Gupta, Sivic, Efros SIGGRAPH'12]

On the left is a house in Paris

Raise your hand if...

...this is Paris

Raise your hand if …

Humans are good but
what about machine?

Can machine recognize visual elements characterizing an urban area?

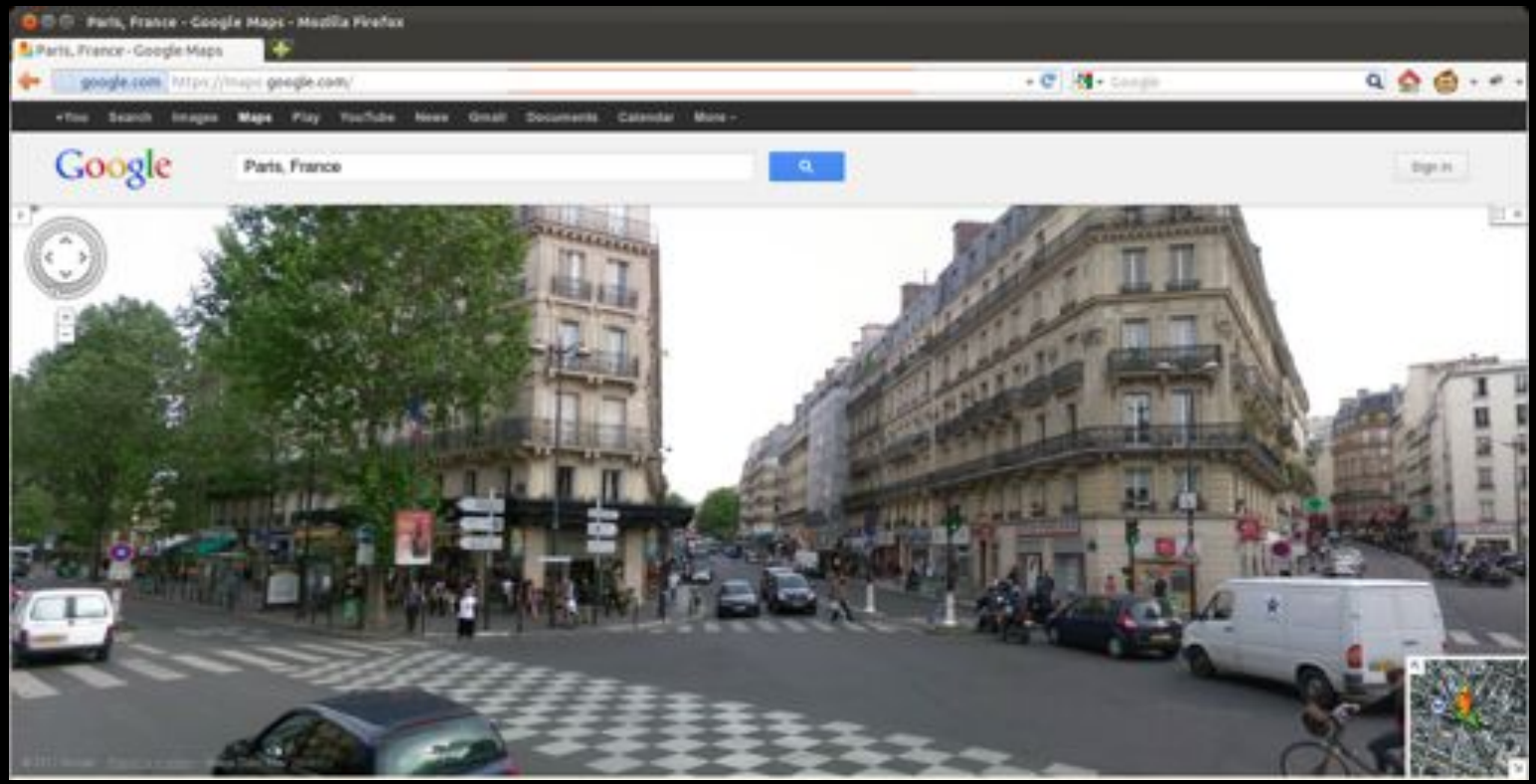
Our Goal:

Given a large geo-tagged image dataset, we automatically discover ***visual elements*** *that characterize a geographic location*

Our Hypothesis

- The visual elements that capture Paris:
  - Frequent: Occur often in Paris
  - Discriminative: Are not found outside Paris

Map based imagery provides a comprehensive visual record of a city




Paris


Bobigny
Courbevoie
Nanterre
Puteaux
Paris
Montreuil
Bois de Boulogne
Bois de Vincennes
Charenton-le-Pont
Meudon

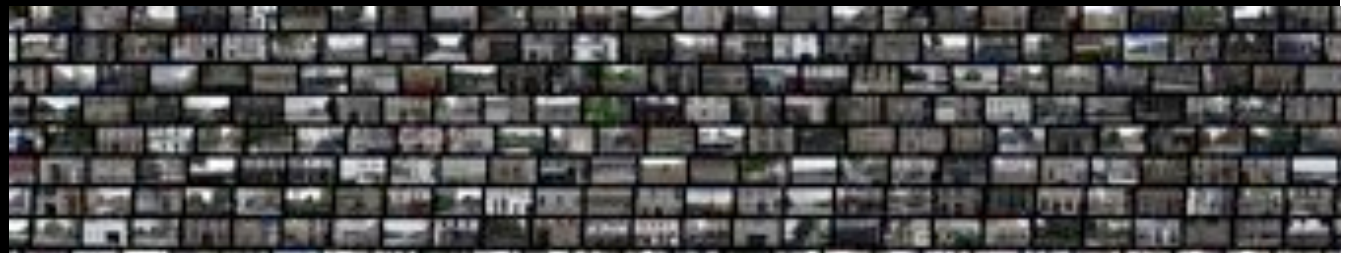

London
Prague
Paris
Milan
Barcelona
New York
Boston
San Francisco
Philadelphia
Tokyo
Mexico City
Sao Paulo
Positive Set
Negative Set

Hundreds of Millions of Patches

Scientific challenges

1. **Difficult learning problem**: How do you represent and automatically learn vocabulary of architectural elements characteristic for a city?

2. **Efficiency**: need to search through large amount of visual data (hundreds of millions of data points)



Problem formulation

Weakly supervised machine learning: [Bach and Harchaoui'08, Xu et al.'04]

Given a set of inputs x_i and supervisory meta-data y_i , $i = 1,\ldots,N$

learn vocabulary $\hat{z}_i = f(x_i)$ by solving

$$\min_{f,z} \overbrace{\sum_{i=1}^{N} \ell(z_i, f(x_i))}^{\text{Discriminative loss on data}} + \overbrace{\Omega(f)}^{\text{Regularization}}$$

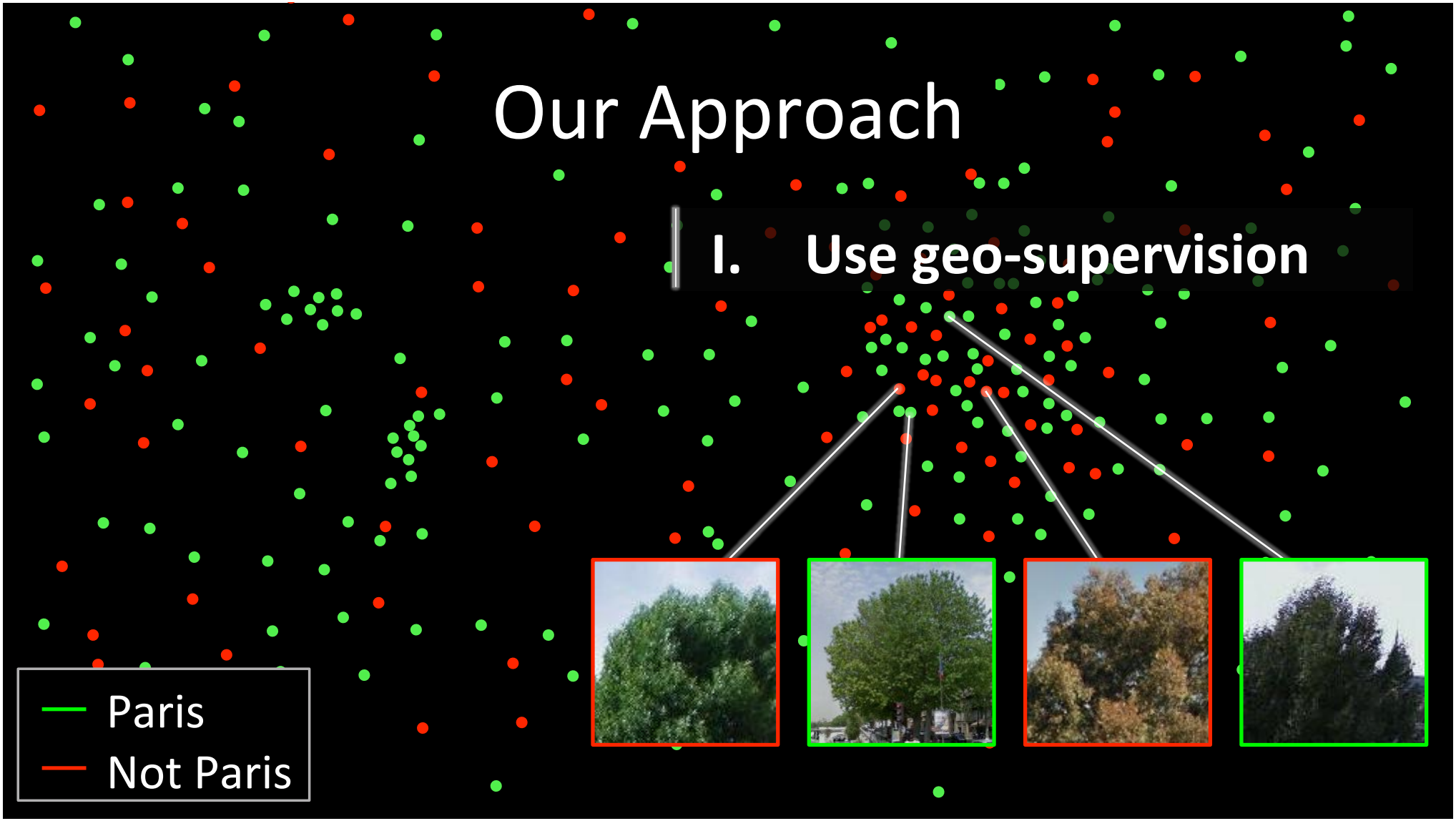
$$\boxed{\underbrace{s.t. \quad g(z) = y}_{\text{Supervision from available meta-data}}}$$

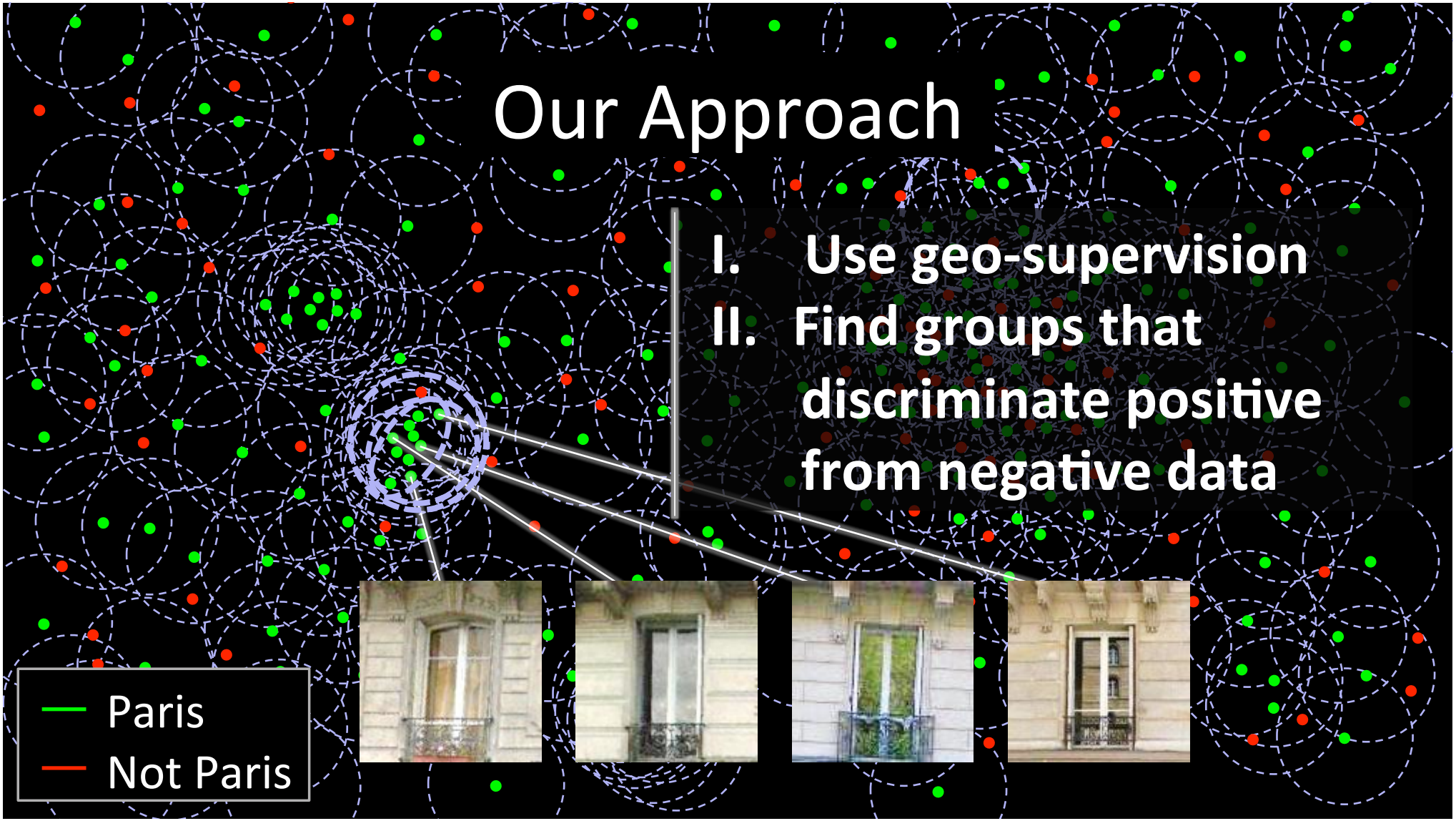
Input $\{x_i\}$: Millions of image patches extracted from street-view images from different cities
Supervisory meta-data $\{y_i\}$: geo-tags for each image

Our Approach

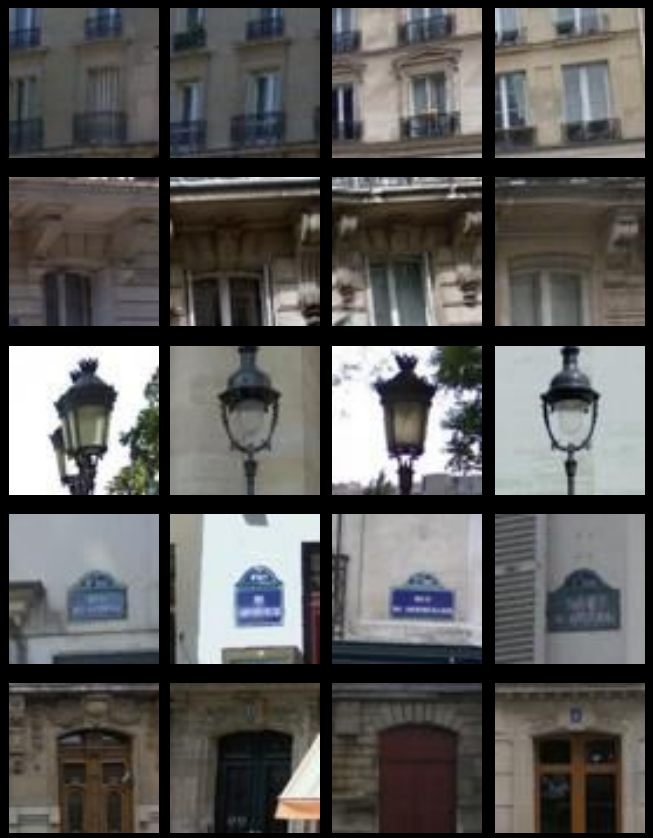
Our Approach

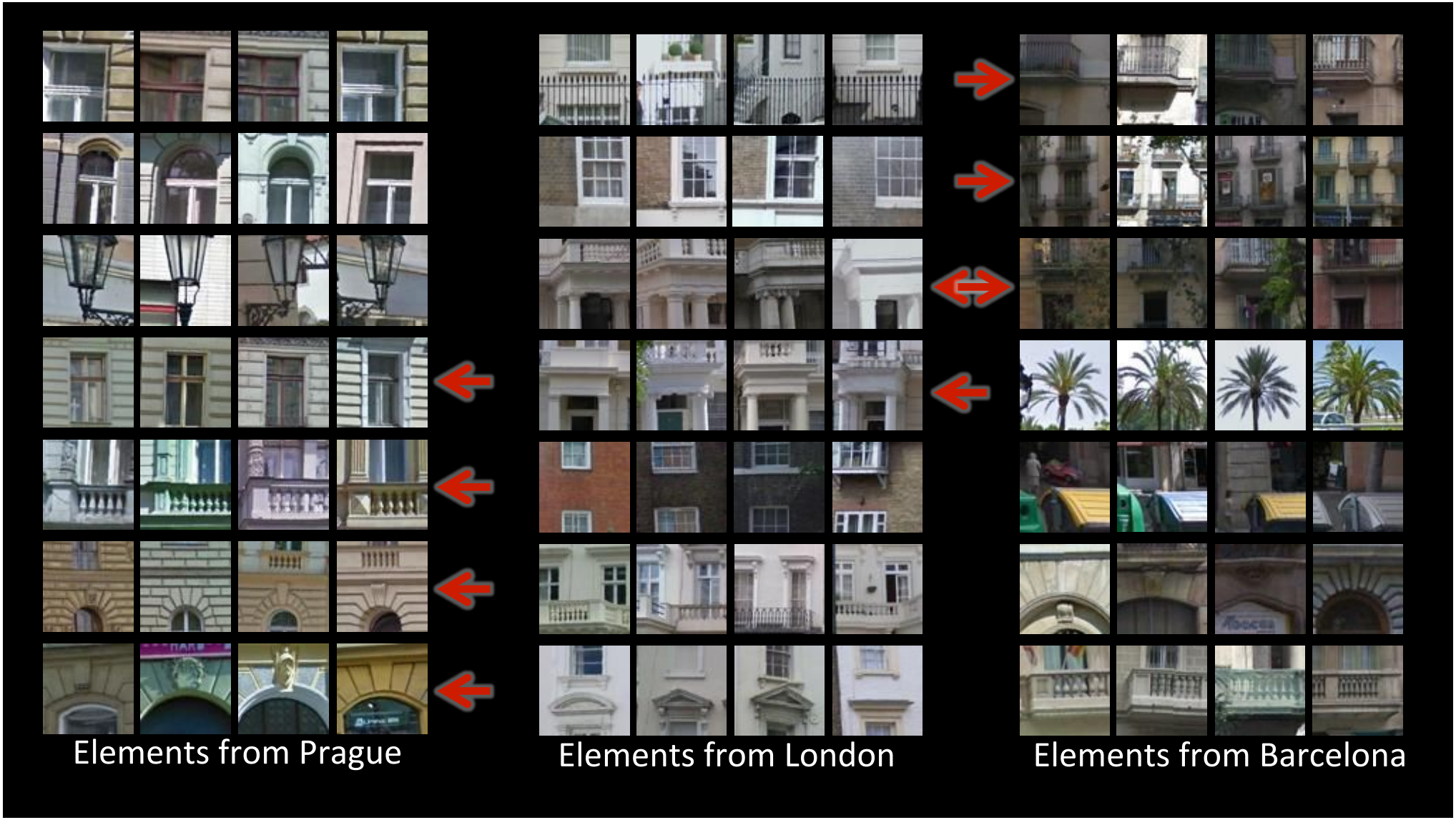
I. **Use geo-supervision**



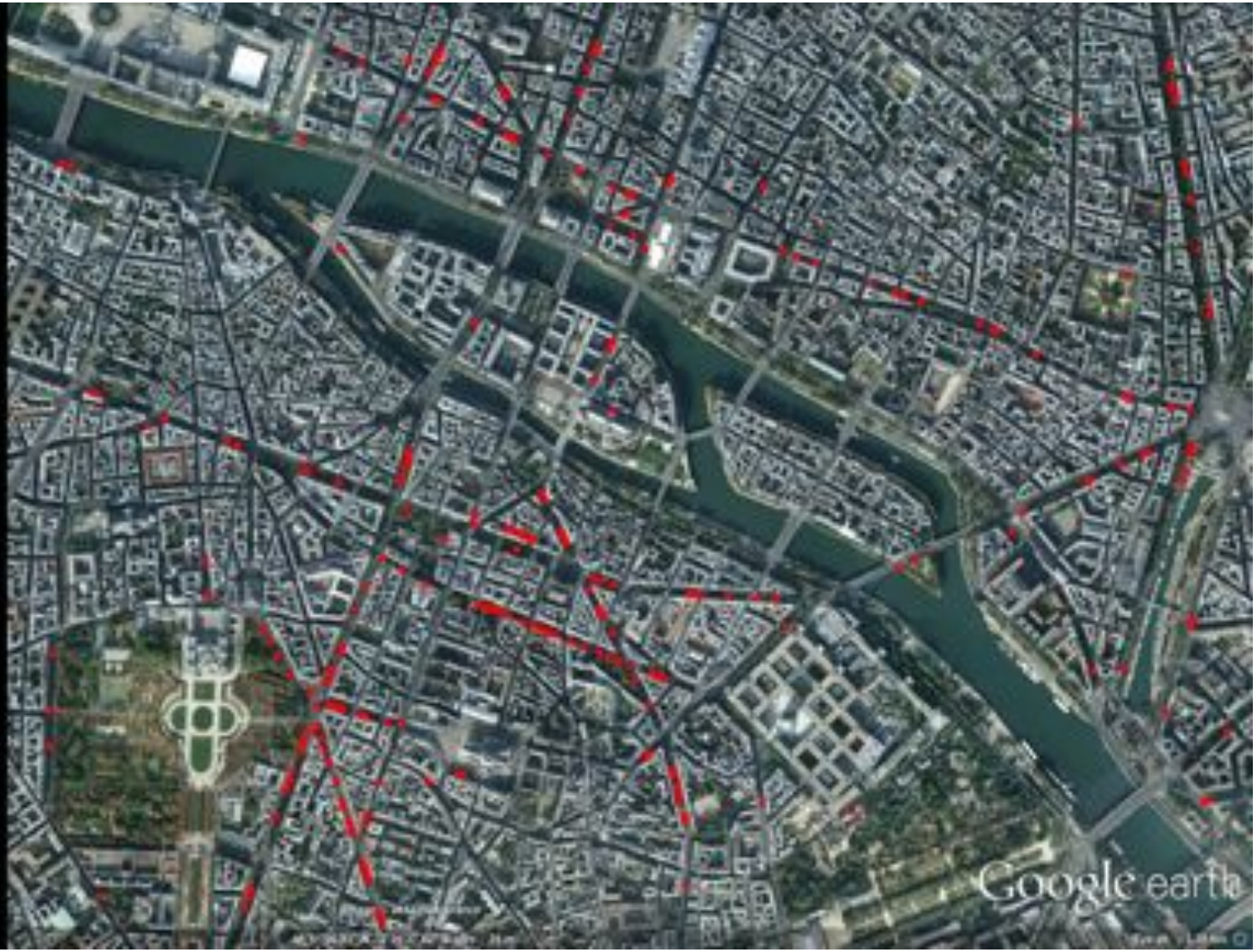

Our Approach
I. Use geo-supervision
II. Find groups that discriminate positive from negative data
Paris
Not Paris

Paris: A Few Top Elements



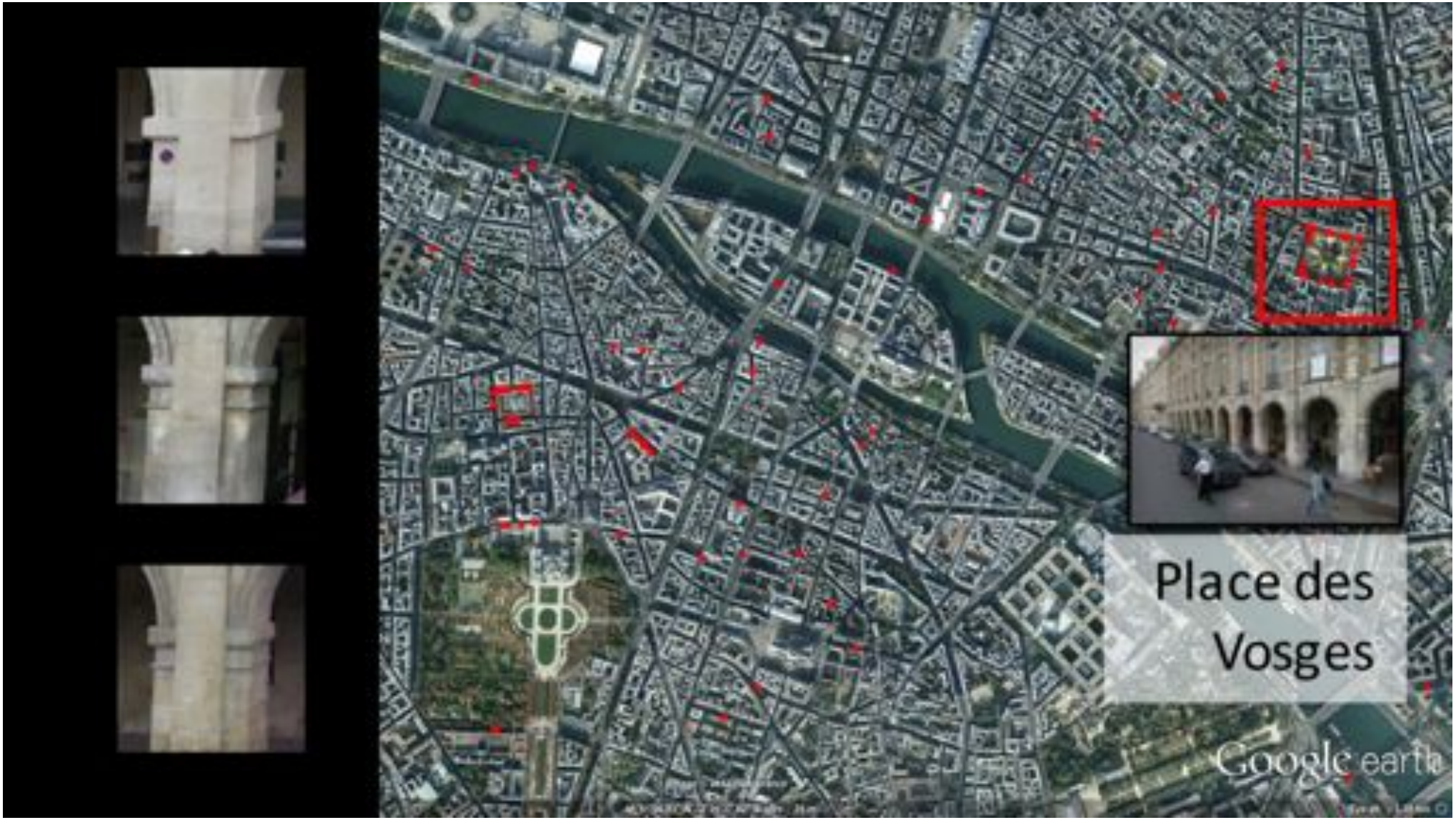

Elements from Prague
Elements from London
Elements from Barcelona


Google earth


Google earth

Google earth

Google earth


Place des
Vosges
Google earth


Marché
St. Germain
Place des
Vosges
Google earth


London
Prague
Paris
Milan
Barcelona
Google earth


London
Prague
Paris
Milan
Barcelona
Google earth


London
Prague
Paris
Milan
Barcelona
Google earth


Louvre
/Opera
Marais
Latin Quarter

Analyze architecture style over time

Geo-located Google street-view images

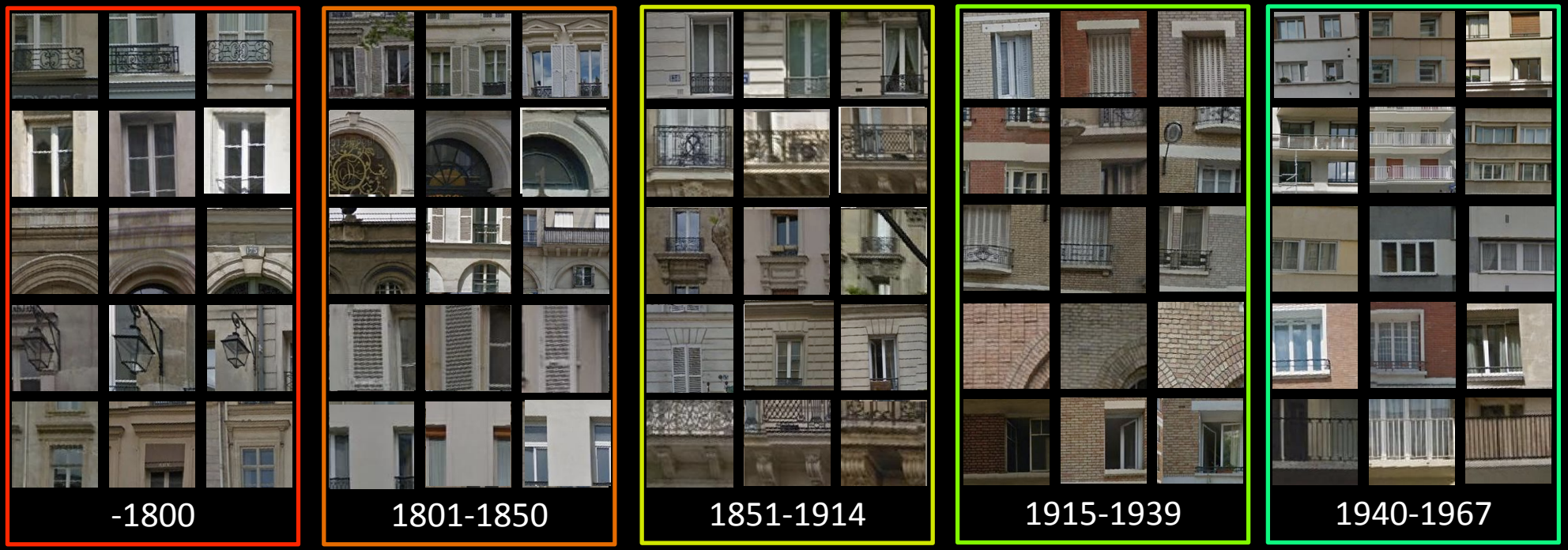
+

Cadastre maps

[Lee, Maissonneuve, Efros, Sivic, 2014]

Cadastre map of Paris:
128k buildings with meta-data

Visual elements specific for a time-period



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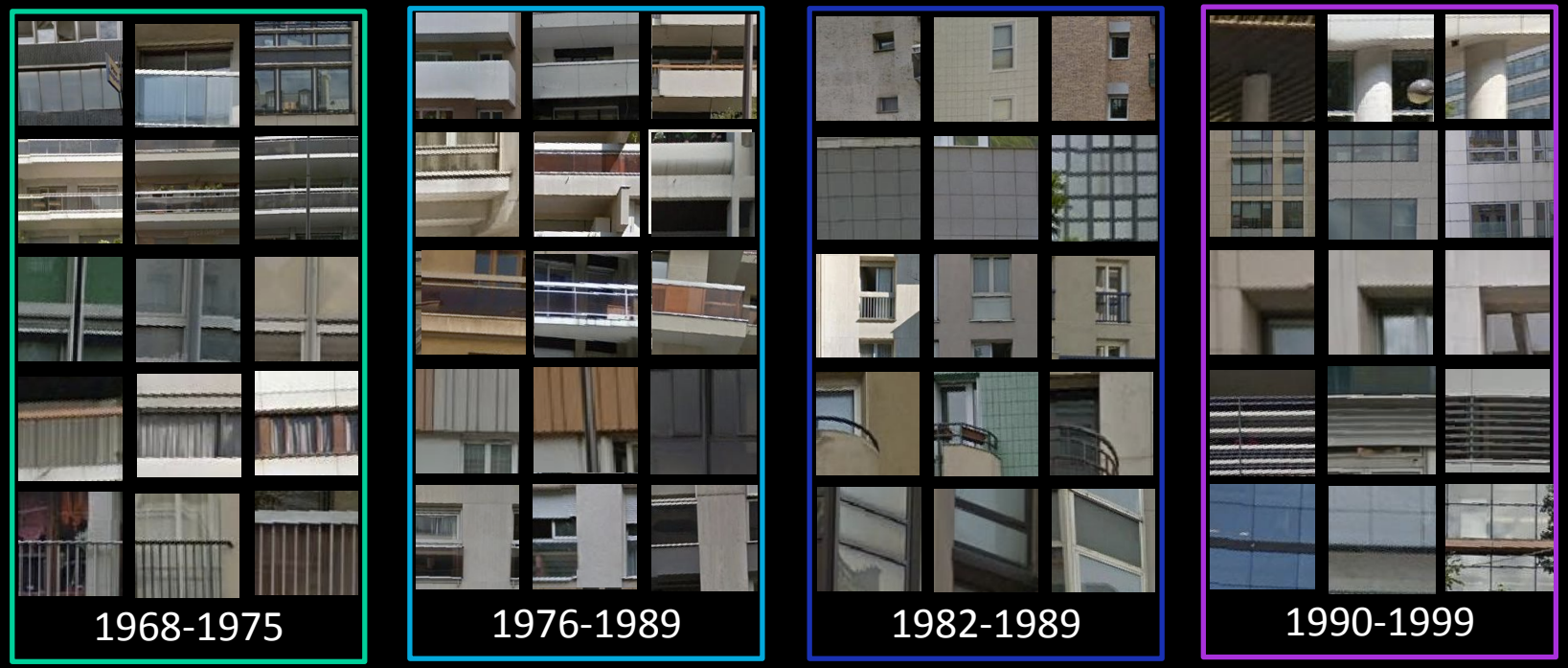

On Relating Visual Elements to City Statistics

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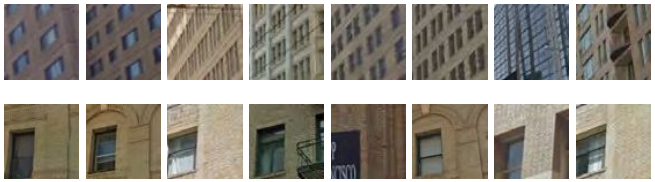
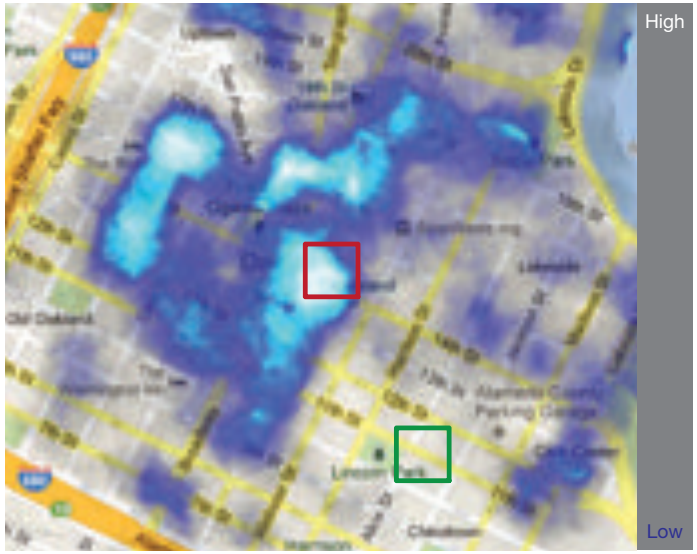
(a) Predicted High Theft Location in Oakland

(b) Predicted Low Theft Location in Oakland



(c) Visual Elements for Thefts in San Francisco



(d) Predicted Theft Rate in Oakland

So far: analysis of Street-view imagery

- Static 2D record of the city at present time

What next?

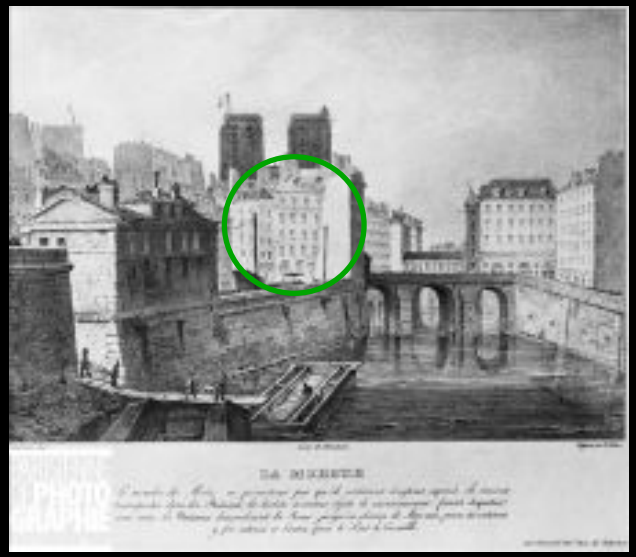
I. Historical urban visual record

II. 3D urban visual record

III. Dynamic urban visual record

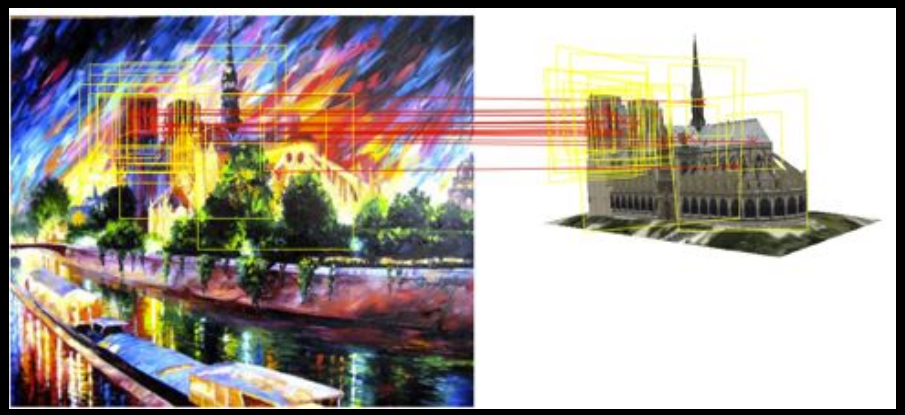
I. Historical urban visual record

Quantify evolution of a particular place over time

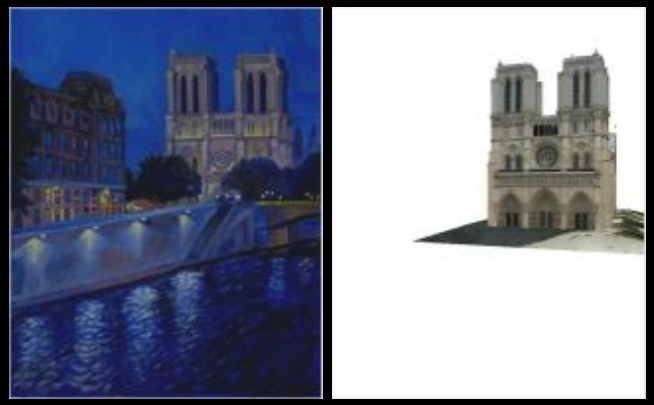


Applications: new ways to access archives for archeology, history, or architecture…

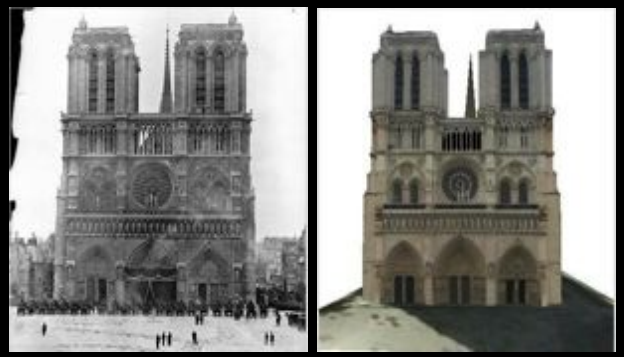
Example: painting to 3D model alignment



Painting



Painting



Historical photograph

Sketch

[Aubry, Russell, Sivic, *Painting-to-3D model alignment via discriminative visual elements*, Transactions on Graphics, 2013]

II. 3D urban visual record

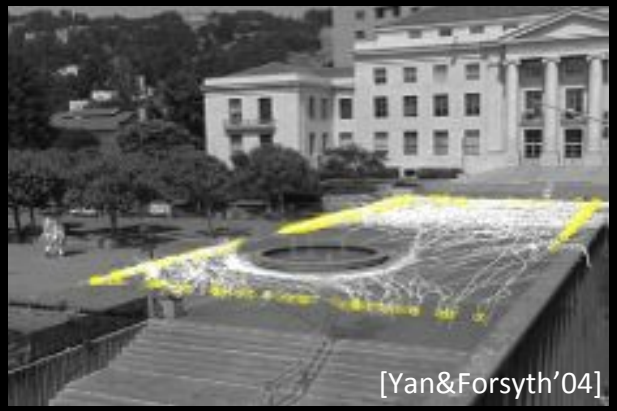
Goal: detailed semantic 3D reconstruction for simulation of urban environments (e.g. noise, pollution, energy consumption).
[ANR project SEMAPOLIS, 2013-2016]

Towards semantic 3D reconstruction

Goal: detailed semantic 3D reconstruction for simulation of urban environments (e.g. noise, pollution, energy consumption).
[ANR project SEMAPOLIS, 2013-2016]

III. Dynamic urban visual record

Cameras around us



Public space cameras

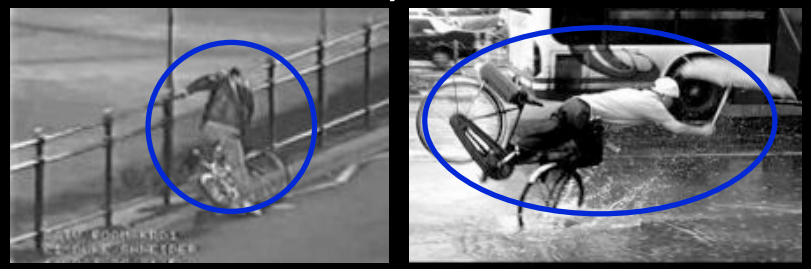
Car cameras

Citizen cameras

Towards large-scale temporal analysis

Extract statistics of human behaviors across a city over time

crossing street



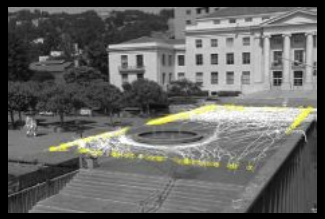
"bicycle accident"

riding bicycle

Applications: new ways to optimize road safety, urban planning or commerce in cities

Summary

- Multiple data sources and archives provide a comprehensive visual record of cities.



- Goal: develop visual quantitative analysis tools to:
  - understand, simulate and optimize urban environments