

Architectural privacy

- Architectural layouts work as spatial filters
- Remote, filtered spaces are perceived as spaces for the self (private)
- More accessible, open spaces are perceived as spaces for the interaction (public)
- Spatial privacy is an architectural quality, quantifying it is challenging

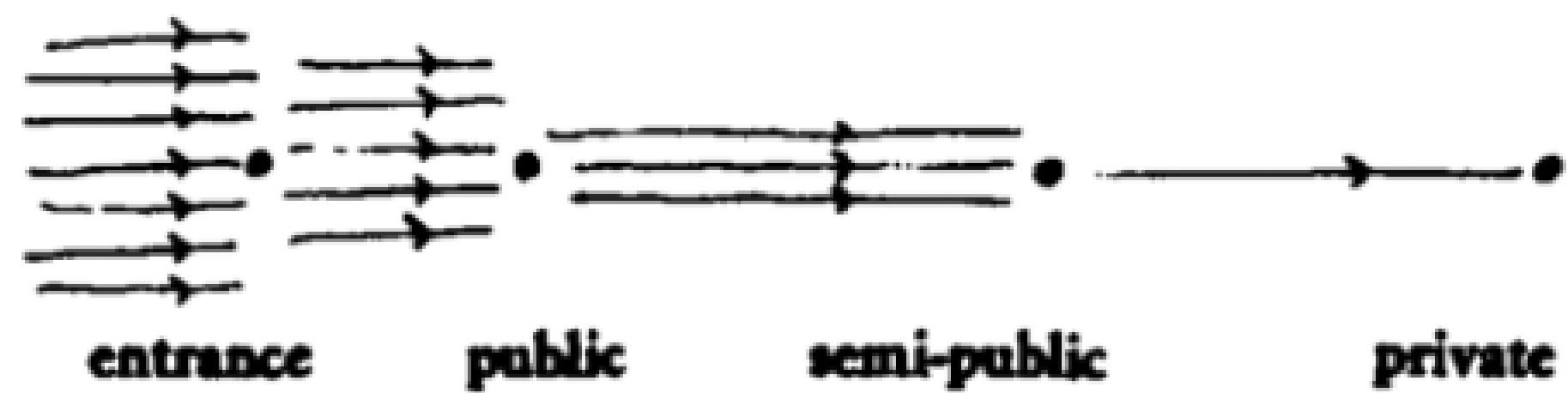


Figure 1: Intimacy as represented by Christopher Alexander

Space Syntax features

- Isovists → visualize and quantify **visual connectivity**
- Graph theory → study **accessibility** hierarchies

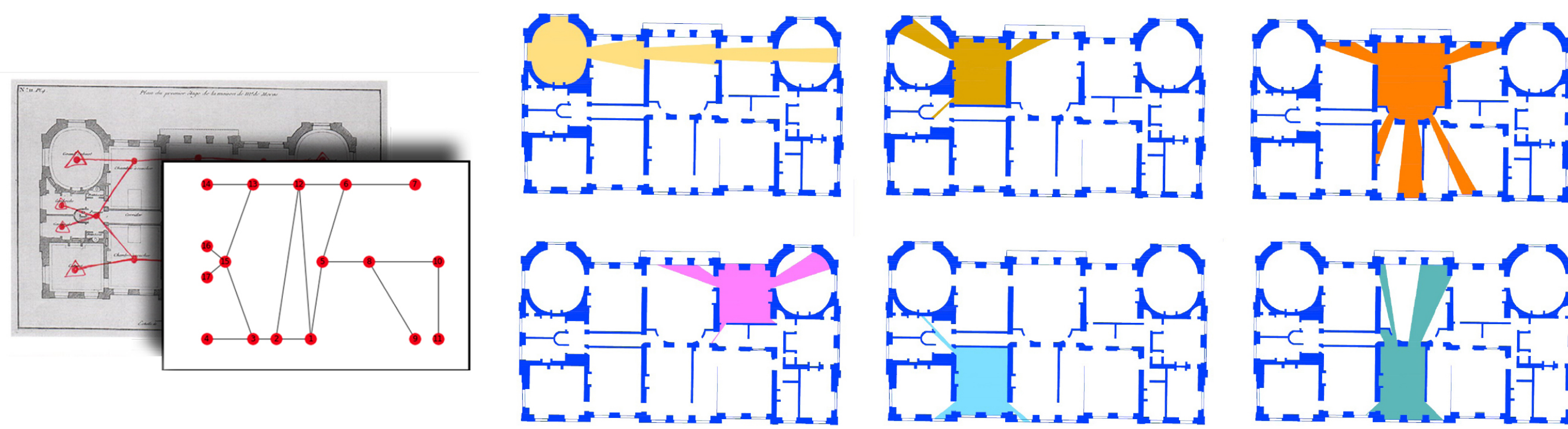


Figure 2: Graph representation and centered isovists. Hotel Biron, Paris

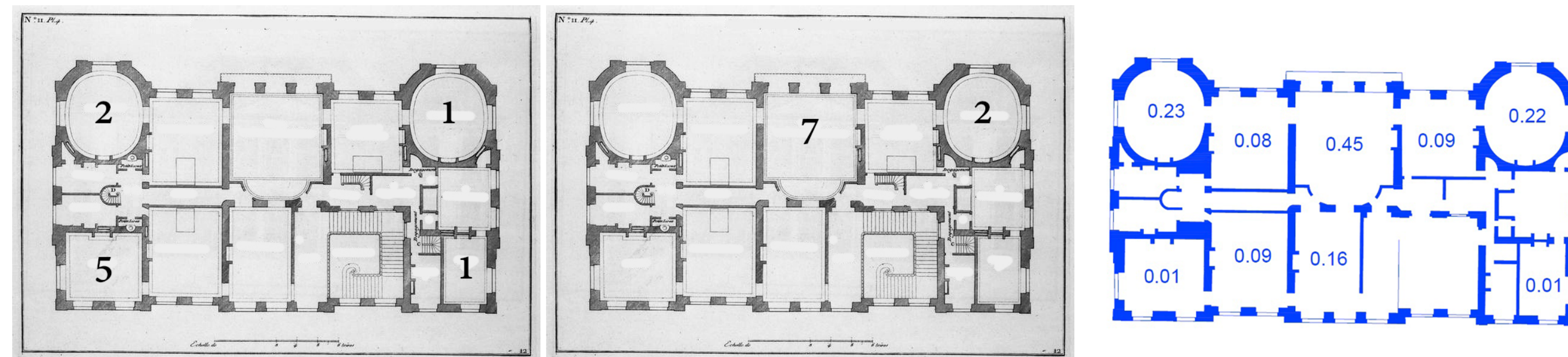


Figure 3: Choice experiment with expert group. Left: choices for private bedroom. Center: choices for reception space. Right: sum of degree centrality and isovist to floor ratio

From a plan, we can extract a series of **spatial features** that characterize visual connectivity and accessibility of the represented architectural space. For our further analysis, I worked with:

Feature	Unit	Type	Meaning
Room Area	m^2	General	-
Total Area	m^2	General	-
Room to Total Area	float	General	Weight of the room over floor area
Centered Isovist	m^2	Visibility	Area of visible space from the baricenter of the room
Centered Isovist to Room Area	m^2	Visibility	Visibility in relation to room floor area
Centered Isovist to Total Area	m^2	Visibility	Visibility in relation to total floor area
Number of Visual Neighbors	int	Visibility	Number of other rooms that fall in the centered isovist
Degree Centrality	float	Graphical property	How central the room is with respect to the graph
Betweenness Centrality	float	Graphical property	How many paths cross the room

Synopsis

Can Machine Learning algorithms become a useful tool in the analysis of architectural space? Motivated by this question, in this poster I introduce a Machine Learning framework for predicting the qualities of architectural spaces based on quantitative spatial features extracted out of plan images. In particular, I am interested in the quality of privacy. My goal is to train Machine Learning classifiers to distinguish intimate from non-intimate spaces on a plan based on a few quantitative features. I work with a sample dataset of house plans. For each room in each plan, a vector of spatial features is extracted that reflect either graphical or visibility properties. By running several Machine Learning classifiers on this dataset, patterns relating Space Syntax features and the level of intimacy of different rooms do emerge. At the same time, the limits in these results reinforce the need for a more complex function approximator (such as a Neural Network) to detect spatial patterns.

Dataset

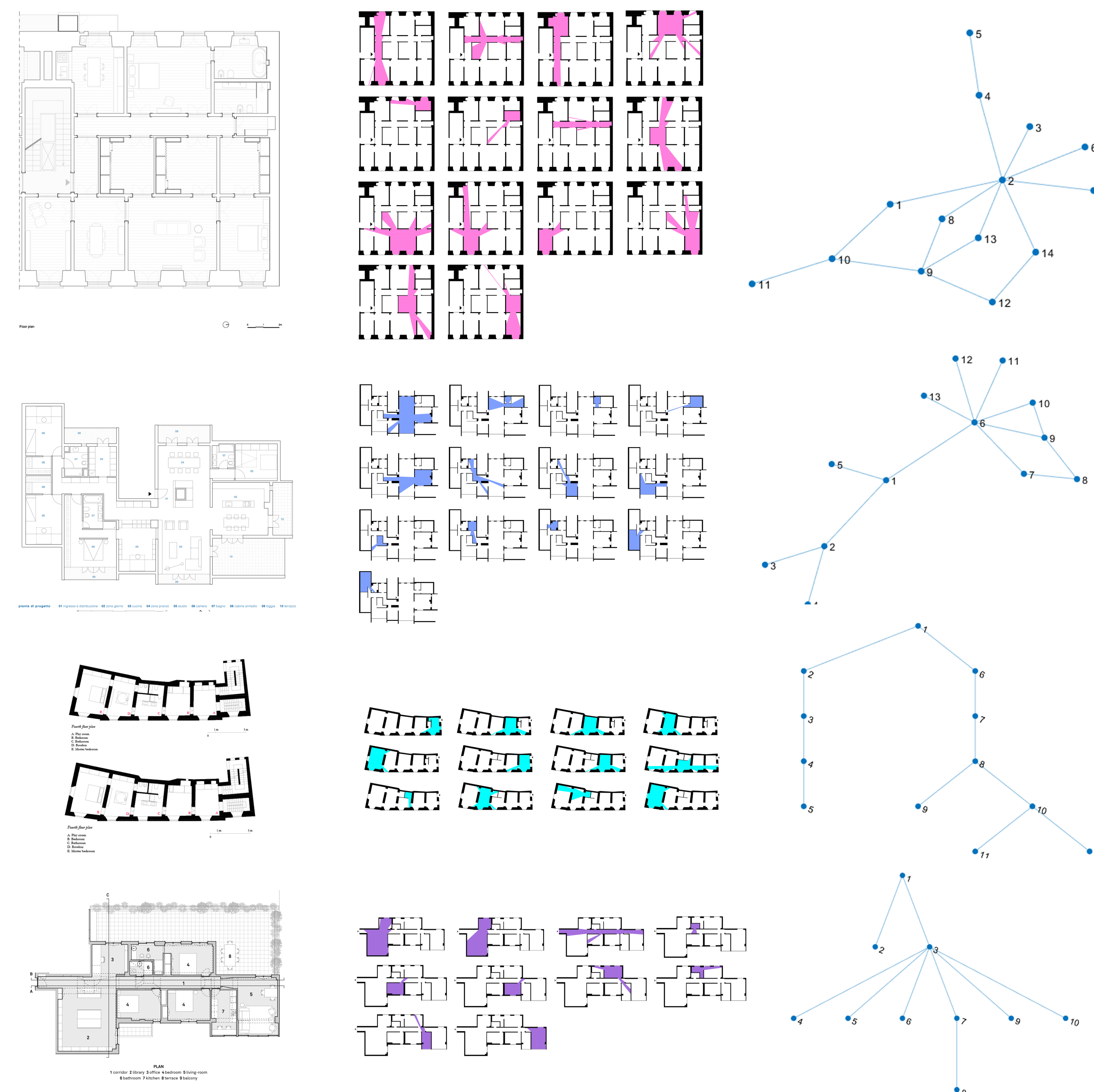
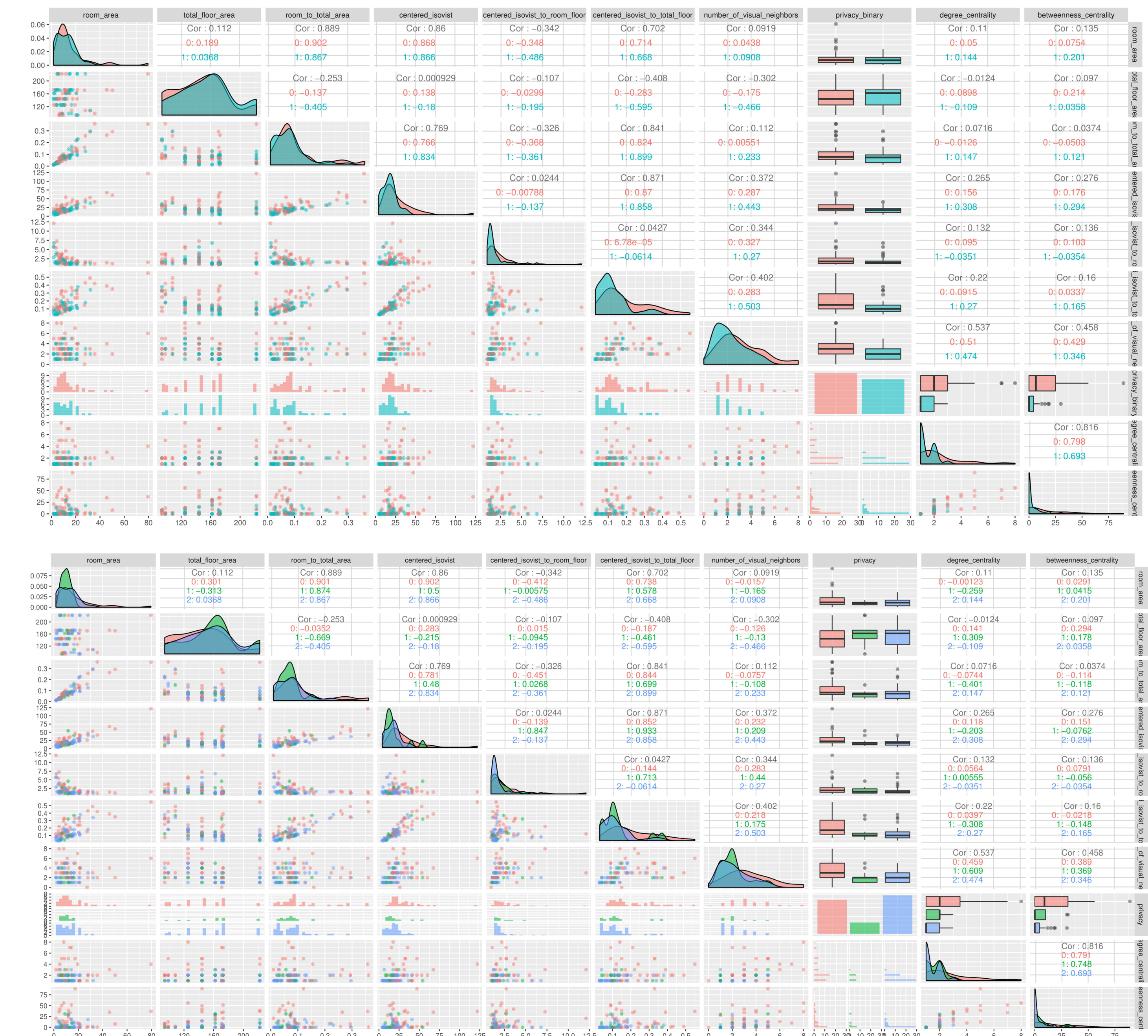


Figure 4: Examples of sample plans from the dataset, and corresponding extracted features for each room. The dataset included a total of 97 rooms labeled according to their privacy level

ML algorithms: **Nearest Neighbors, Support Vector Machines, Logistic Regression, Gradient Boosted Trees, Random Forests.**

- binary classification, room privacy in the set $\{0, 1\}$
- ternary classification, room privacy in the set $\{0, 1, 2\}$

Data analysis



- The **statistical distributions** of features for rooms of different privacy level do tend to **decouple** in both scenarios
- This suggests that spaces with different privacy levels are characterized by different **combination of feature values**
- The **degree centrality** and **betweenness centrality** of a room tend to have higher values for the non-private spaces then for the private spaces
- Degree centrality is **positively correlated** with the number of visual neighbors (correlation 0.459 for the spaces with privacy=0, 0.609 for privacy=1 and 0.474 for privacy=2)

The overall best performing model for classification in the binary case was found to be the **Gradient Boosted Trees with scaled features**, which correctly classifies 12/14 cases of privacy=0 rooms and 9/15 cases of privacy=1 in the held-out set. Interestingly enough, no model was able to correctly predict the class of privacy=1 rooms in the **ternary case**, which are the hybrid-privacy spaces. This reinforces the idea of the complexity in studying the relationship between spatial features and qualities, and justifies the need for larger datasets and a more complex function approximator, such as **Deep Neural Networks**.

Applications and Extensions

- automatic extraction** of spatial features from the plans images (image processing, computer vision)
- AI-assisted** analytic and generative work in architecture research
- Real time spatial privacy analysis from plan images (applications in real estate)