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# Self-Supervised Graph Representations of WSIs


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## Introduction

**Graph representations** of **histology images** have been proposed in order to leverage the patch positional information with patch graphs (PG) and to model the relationships between biological entities with cell graphs (CG). However, the PG approach relies on a CNN that ignores the entity space whereas the CG can only be applied to small images. We propose a framework based on **self-supervised learning** for the **representation of WSIs as graphs** whose nodes are seen as any-shape regions of the image, extending the PG approach, and their features encode **cell information**, as vector representations of CGs of the regions.

## Data

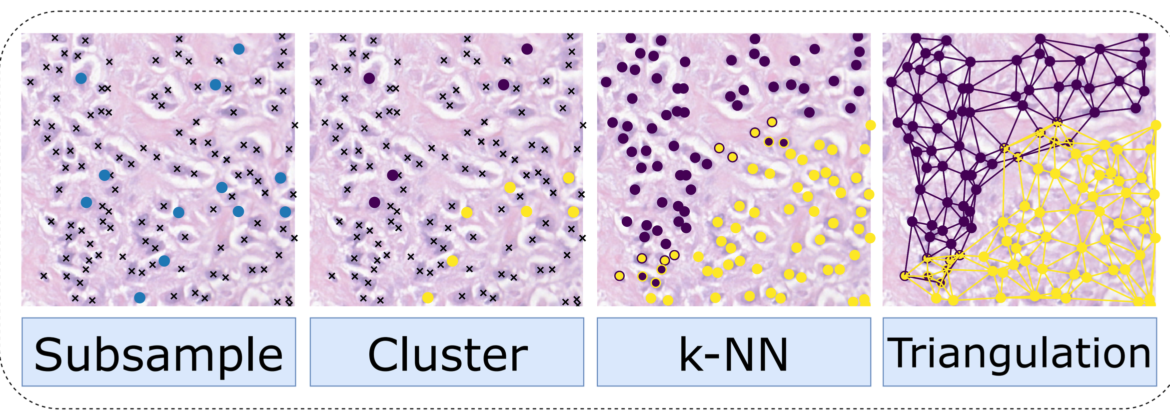
The data is provided by the *Institut Català de la Salut (ICS)*. We have two sets of breast and lung unannotated WSIs, which have been used independently to train two encoders.

| Data type | Tissue | Annotations | Quantity | Extracted cell graphs |
|---|---|---|---|---|
| WSI | Breast | - | 13 | 5948 |
| WSI | Breast | Region | 8 | 2780 |
| WSI | Lung | - | 7 | 4312 |
| Patch | Lung | Cell | 20 | 20 |

## Method

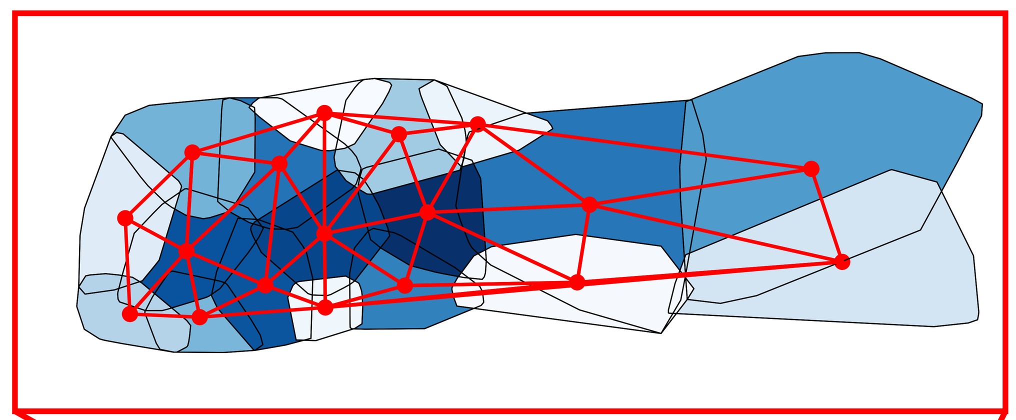
### 1 Cell Clustering

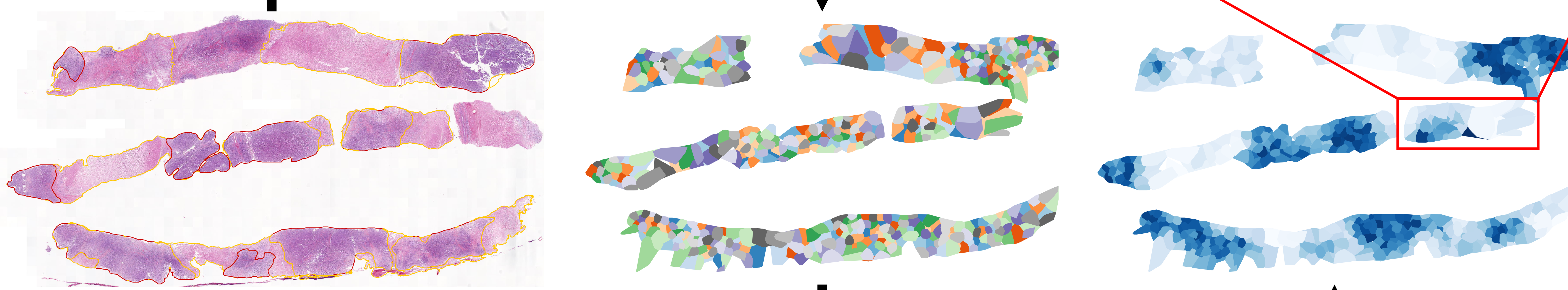
Split the cells into overlapped clusters, create a cell graph for every cluster




### 3 WSI Graph

Represent the WSI as a graph whose nodes are the encoded cell graphs



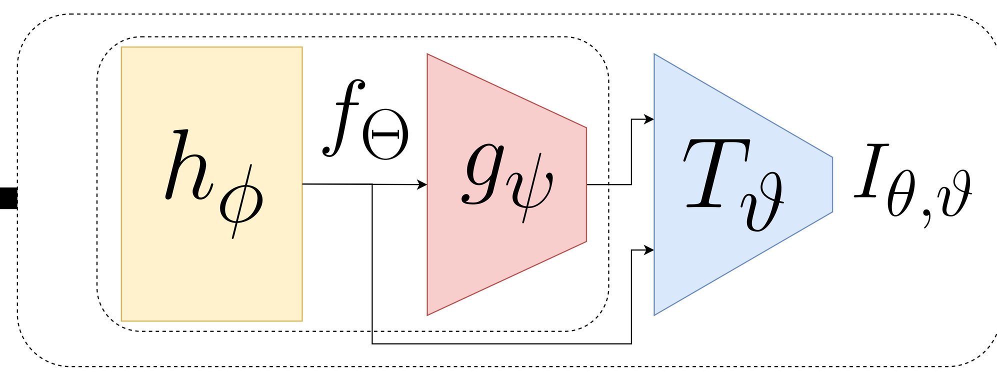


### Intuition

The clusters can be seen as any-shape image regions

### 2 Cell Graph Encoding

Encode the cell graphs to vector representations with a GNN encoder trained with the self-supervised InfoGraph algorithm




### 4 Target

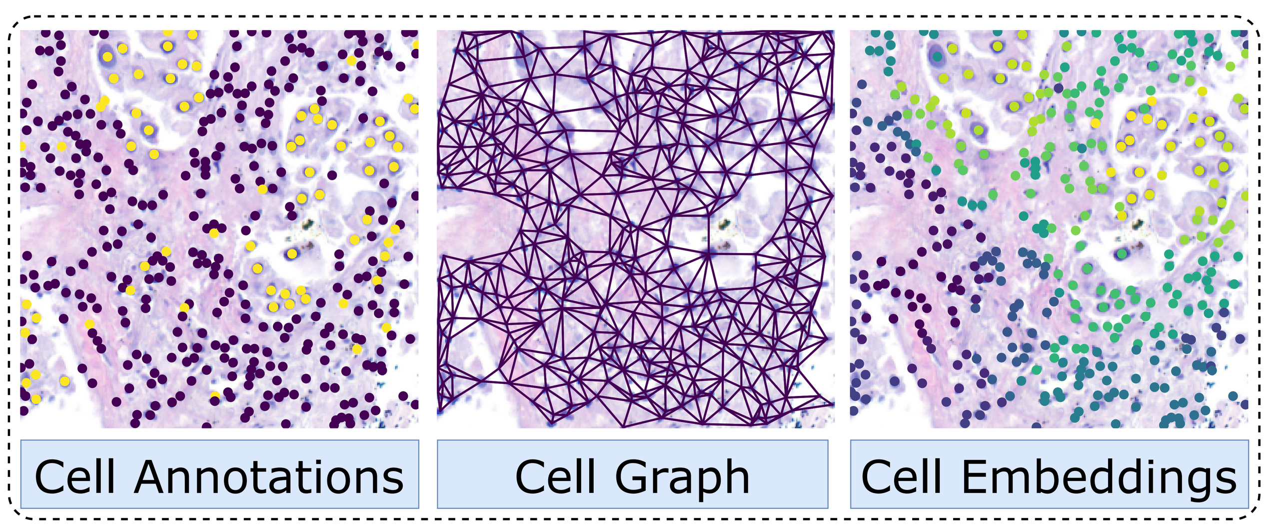
Employ the representations for downstream tasks

## Linear Evaluation Protocol

**Linear evaluation protocol** at cell and region level

### A Cell Level

Encoder trained with unnanotated **lung WSIs**. The cell level evaluation is done on patches with labelled cells




### B Region Level

Another encoder is trained with unannotated **breast WSIs**. For region level evaluation the annotated WSIs the cell graphs are labelled

**A**

| Input | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Random | $50.0 \pm 1.0$ | $34.3 \pm 1.4$ | $49.5 \pm 1.6$ | $40.5 \pm 1.4$ |
| $x_i$ | $78.6 \pm 0.6$ | $76.2 \pm 3.1$ | $54.7 \pm 1.9$ | $63.7 \pm 1.2$ |
| $z_i$ | $\mathbf{87.5 \pm 0.7}$ | $\mathbf{83.3 \pm 1.2}$ | $\mathbf{79.5 \pm 1.5}$ | $\mathbf{81.3 \pm 0.9}$ |

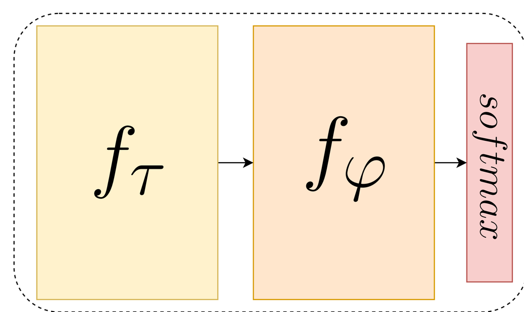
**B**

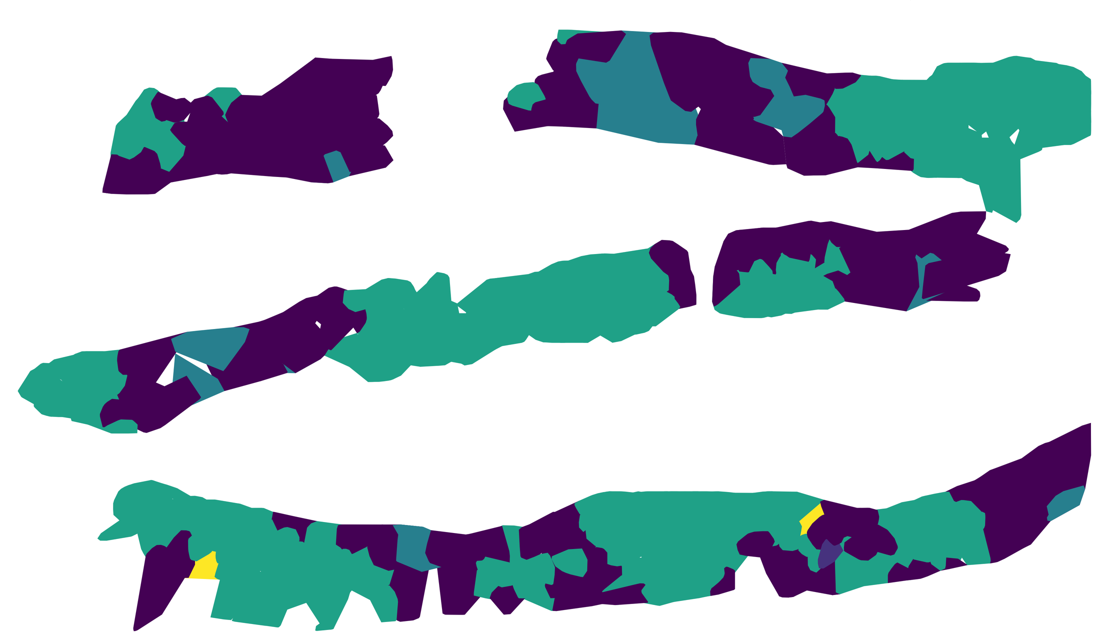
| Method | Accuracy | Precision | Recall | F1 |
|---|---|---|---|---|
| Random | $50.4 \pm 0.6$ | $79.8 \pm 0.5$ | $50.5 \pm 0.9$ | $61.9 \pm 0.7$ |
| $\lvert\mathbf{V_k}\rvert$ | $72.0 \pm 0.6$ | $72.2 \pm 0.6$ | $\mathbf{100.0 \pm 0.0}$ | $83.7 \pm 0.4$ |
| $\overline{\mathbf{x_k}}$ | $78.6 \pm 0.6$ | $79.8 \pm 1.3$ | $94.6 \pm 2.0$ | $86.4 \pm 0.2$ |
| $\mathbf{z_k}$ | $\mathbf{86.5 \pm 0.6}$ | $\mathbf{88.7 \pm 0.9}$ | $92.7 \pm 1.2$ | $\mathbf{90.6 \pm 0.4}$ |

## Clustering for ROI detection

### 5 Graph Clustering

Perform graph clustering with Deep Modularity Networks algorithm for ROI detection



### Intuition

Clustering with GNNs includes both graph topology and node embeddings

### C Evaluation

Quantitative evaluation

| Clustering | ARI | NMI | F |
|---|---|---|---|
| Random | $0.0 \pm 0.0$ | $0.0 \pm 0.0$ | $11.6 \pm 0.4$ |
| k-Means | $18.3 \pm 6.3$ | $19.5 \pm 6.5$ | $30.3 \pm 3.6$ |
| DMoN | $\mathbf{19.8 \pm 20.2}$ | $\mathbf{21.2 \pm 15.7}$ | $\mathbf{60.9 \pm 10.3}$ |

## Conclusions

We present a framework for the analysis of WSIs that learns representations for overlapped regions of a slide based on the their cells and creates a graph of regions to represent the WSI. The scarce annotations available for unseen images during training are employed to evaluate the representations at both cell and region level, outperforming the raw input features. We also employ this graph representation for ROI detection addressed as a graph clustering task with GNNs that efficiently includes both graph topology and node embeddings.


**References**

[1] Sun, F.-Y., Hoffman, J., Verma, V., & Tang, J. (2019). InfoGraph: Unsupervised and Semi-supervised Graph-Level Representation Learning via Mutual Information Maximization. *International Conference on Learning Representations*.

[2] Tsitsulin, A., Palowitch, J., Perozzi, B., & Müller, E. (2020). *Graph Clustering with Graph Neural Networks*.



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