Topology-Guided Multi-Class Cell Context Generation for Digital Pathology

Stony Brook University

Shahira Abousamra, Rajarsi Gupta, Tahsin Kurc, Dimitris Samaras, Joel Saltz and Chao Chen

CVPR JUNE 18-22, 2023 VANCOUVER, CANADA

Introduction

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➔ *Solution:* **Augment** training **with generated labeled** data.

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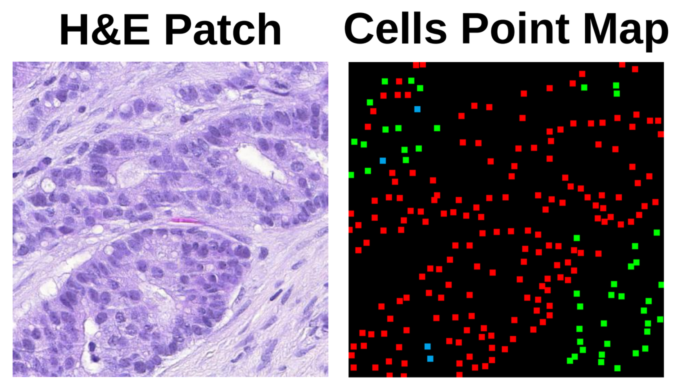
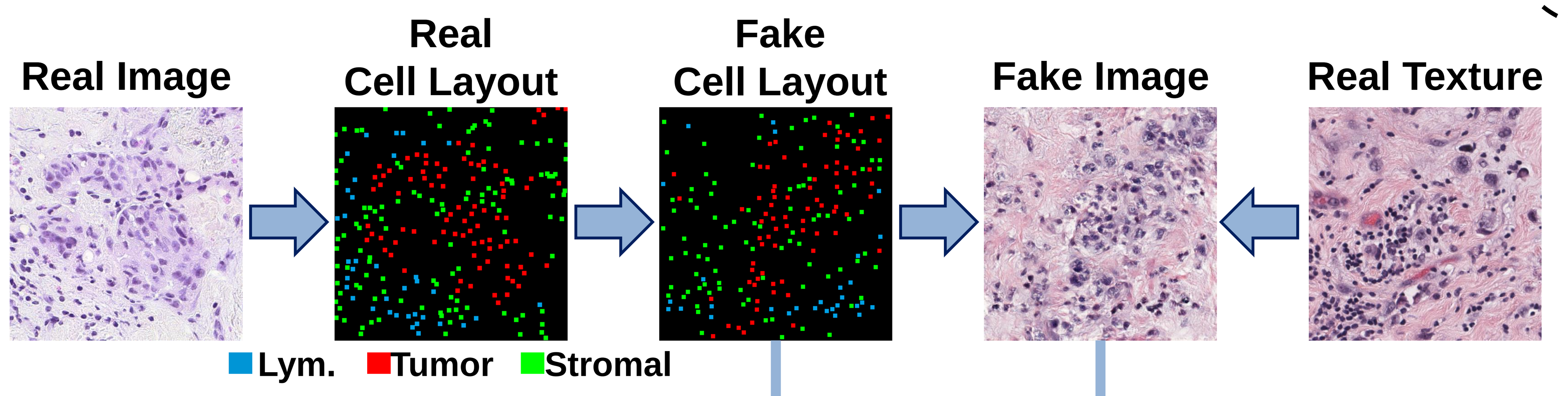
Cell Context

- The **arrangement** of cells.
- Their **spatial co-localization.**
- **Important** for pathology data analysis.





Challenges:

- **Complexity** of the cell layout.
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We introduce mathematical descriptors to model and learn the *spatial distribution* of multi-class cells and their *structural patterns*.

Cell Configuration Descriptors

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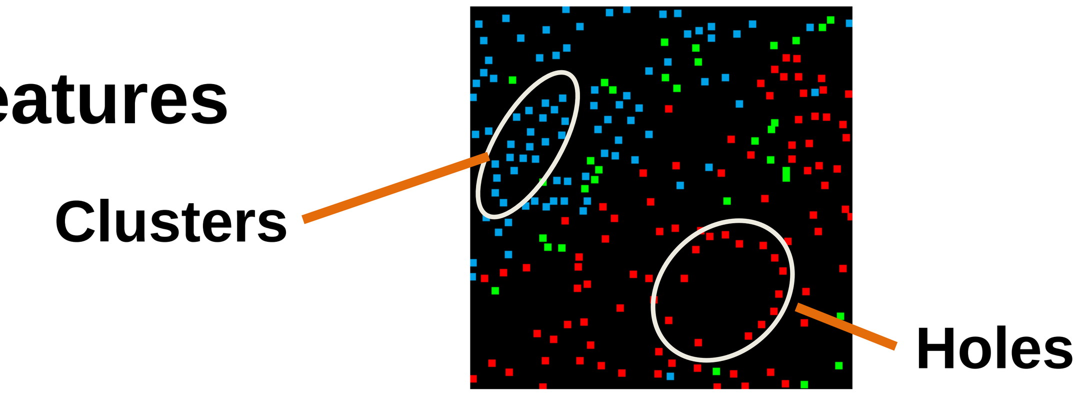

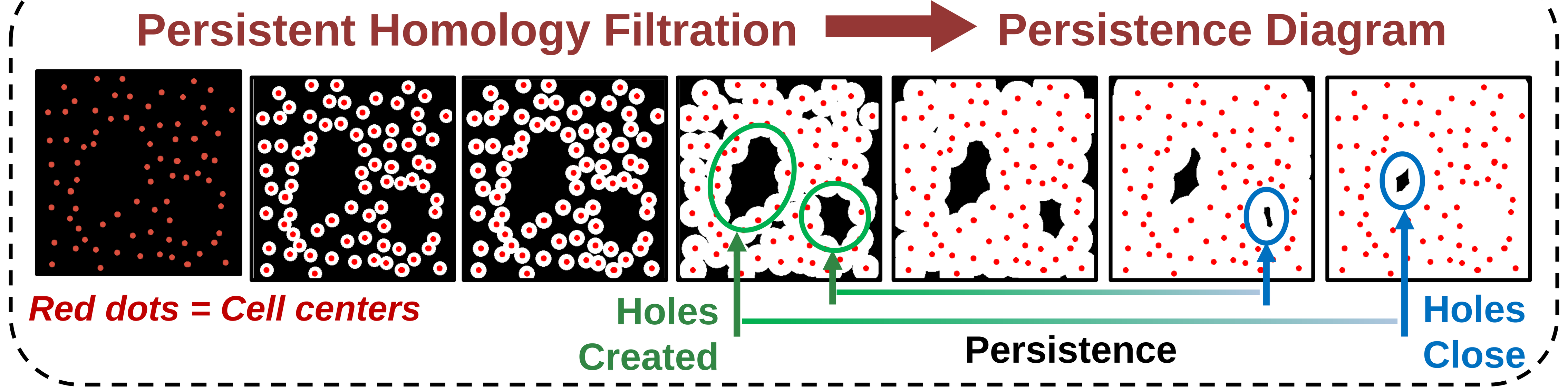

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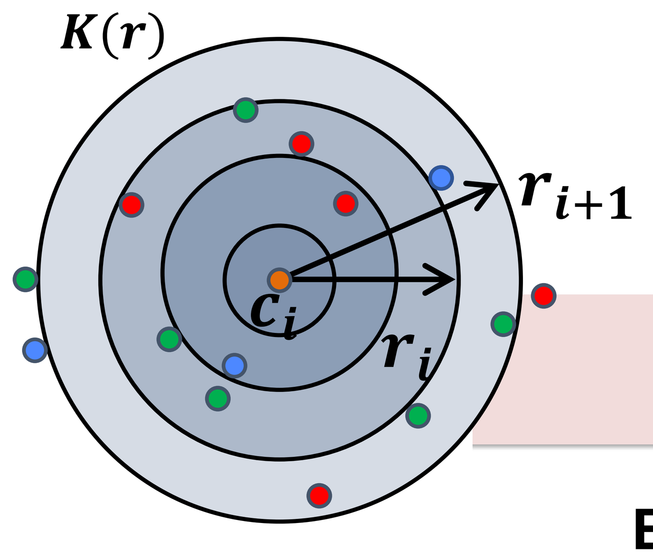
- **Cell types co-localization**
- **Characterize neighborhoods of holes**



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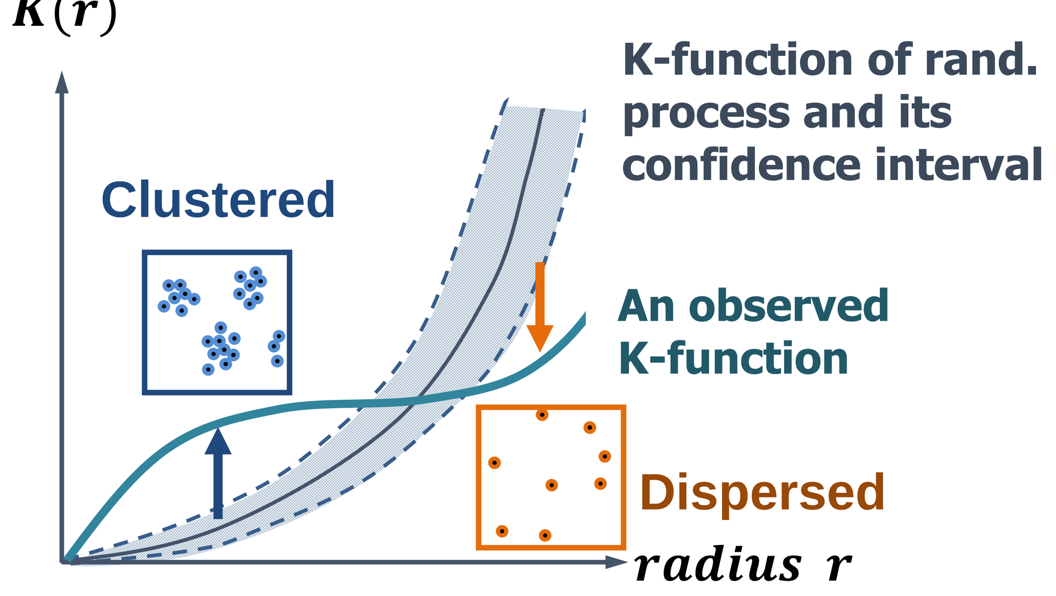

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Match holes based on::

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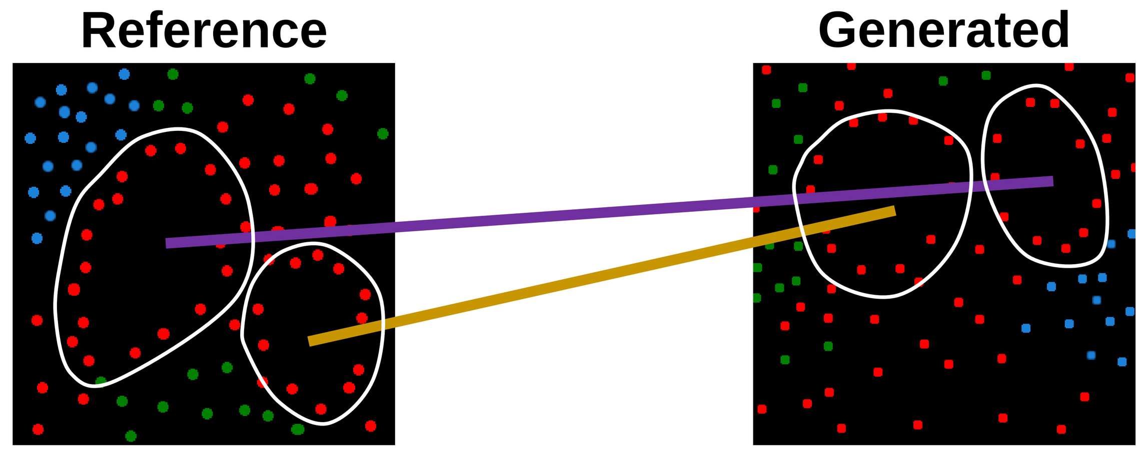

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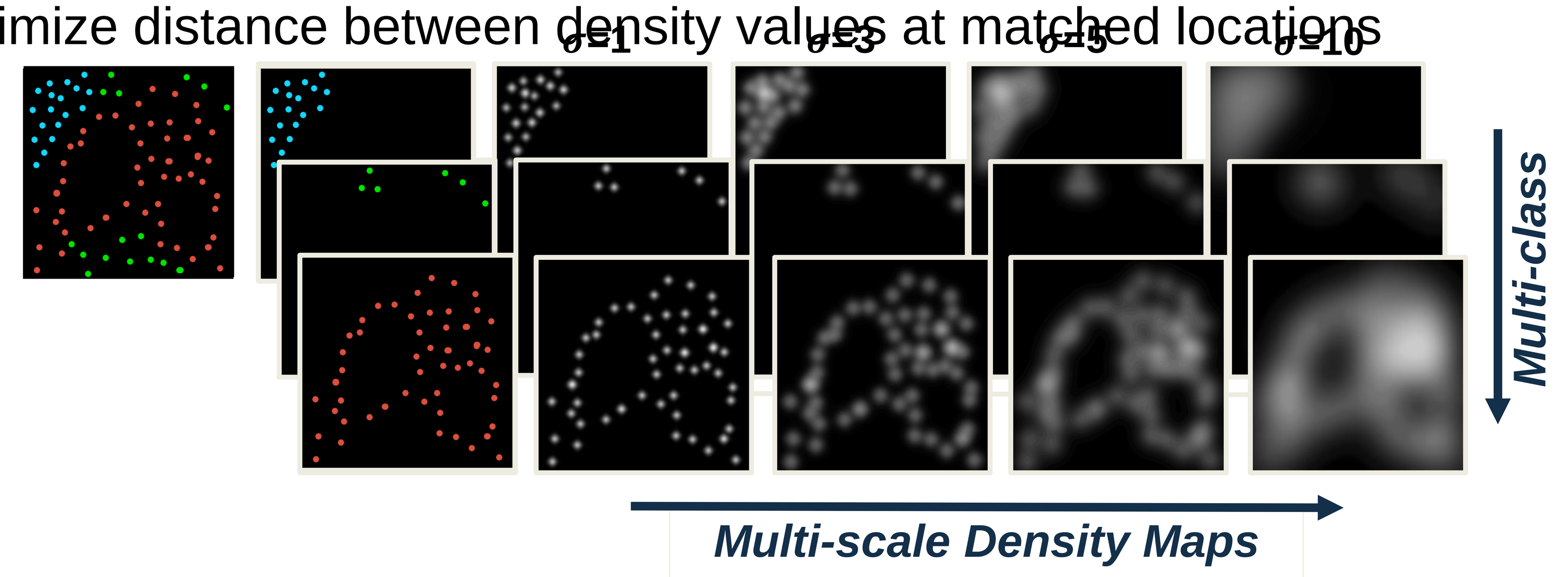

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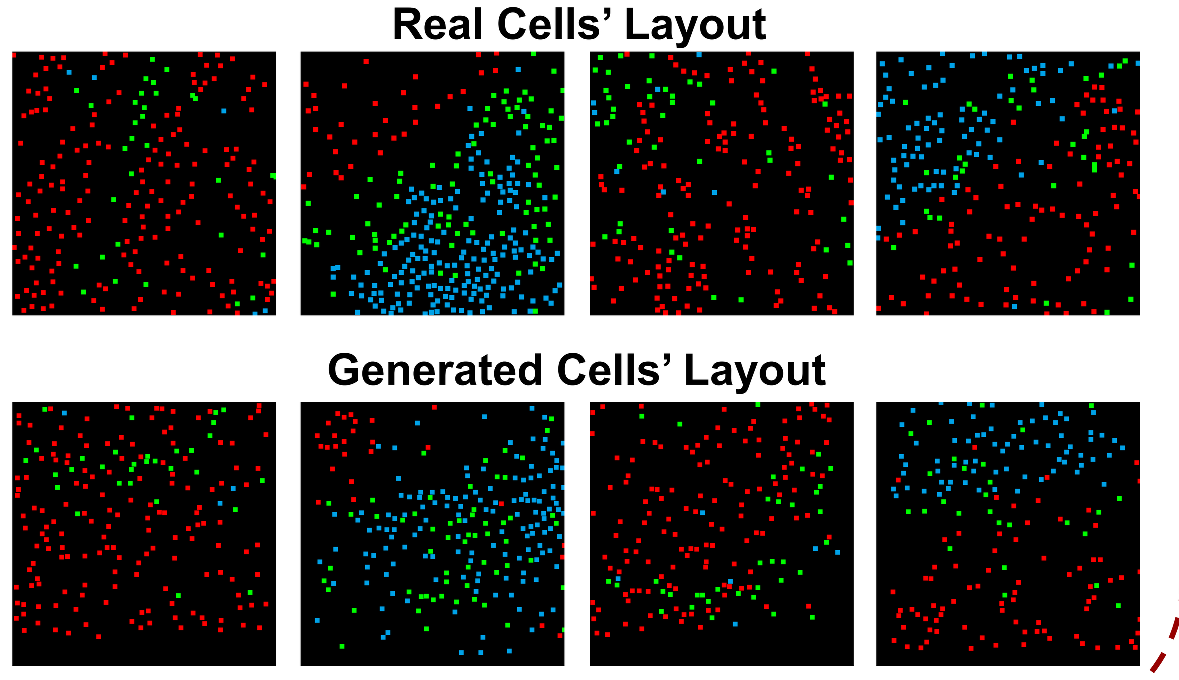
Sample Generated Cell Layouts



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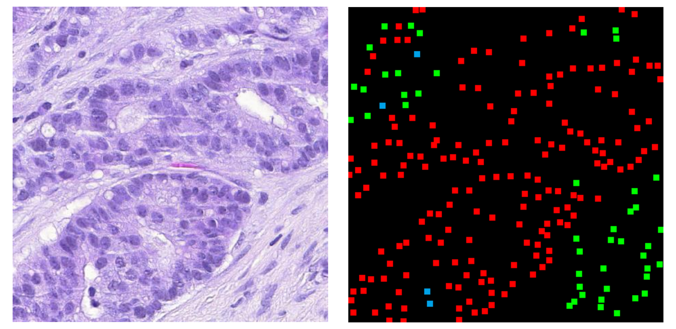

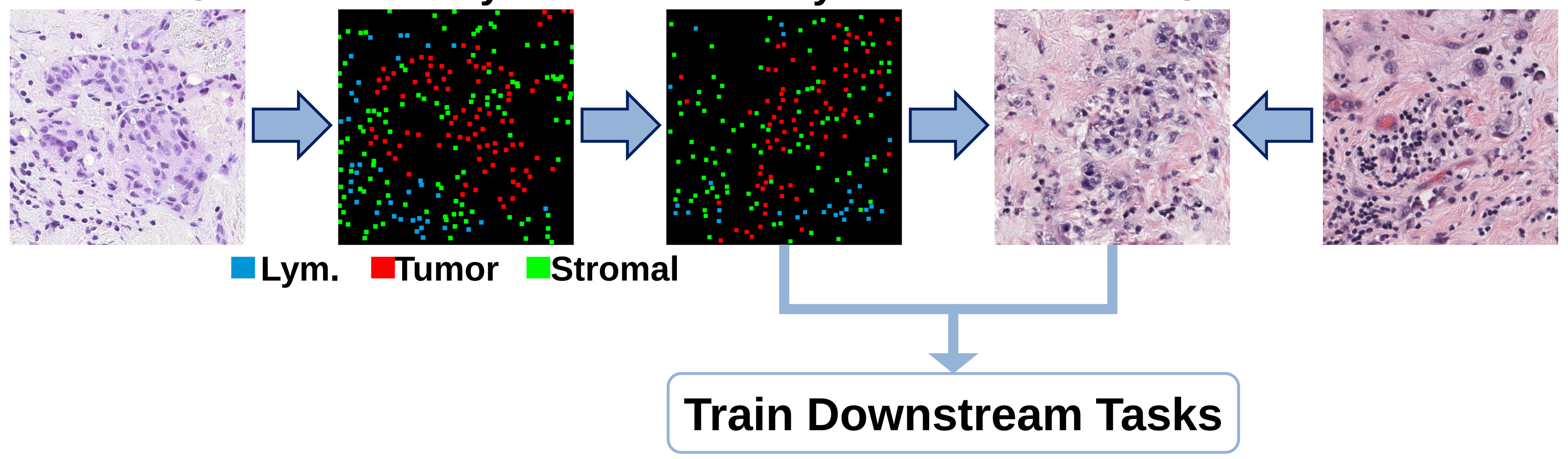

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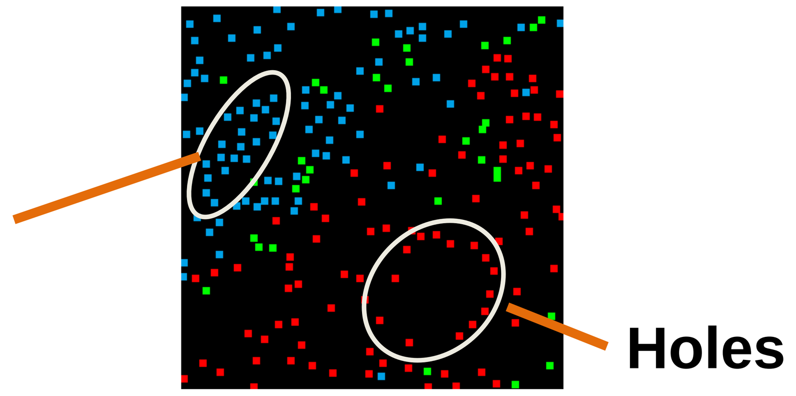

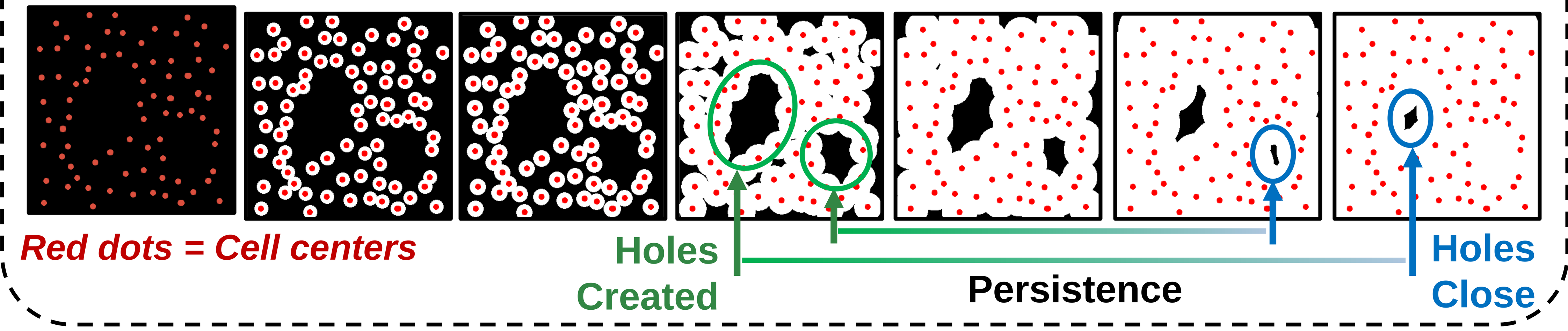

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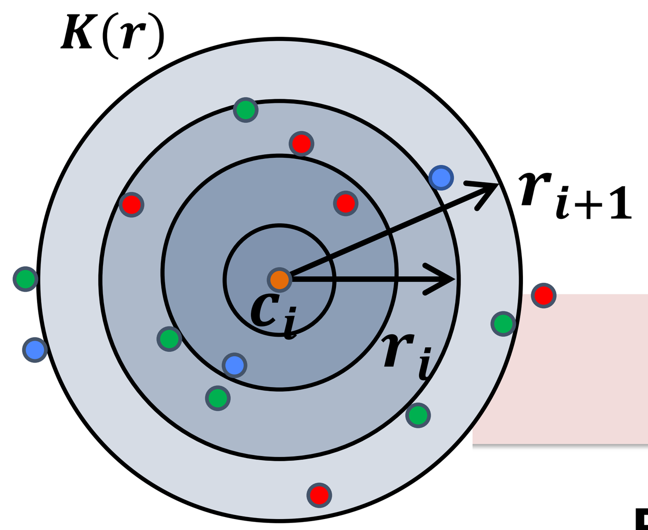

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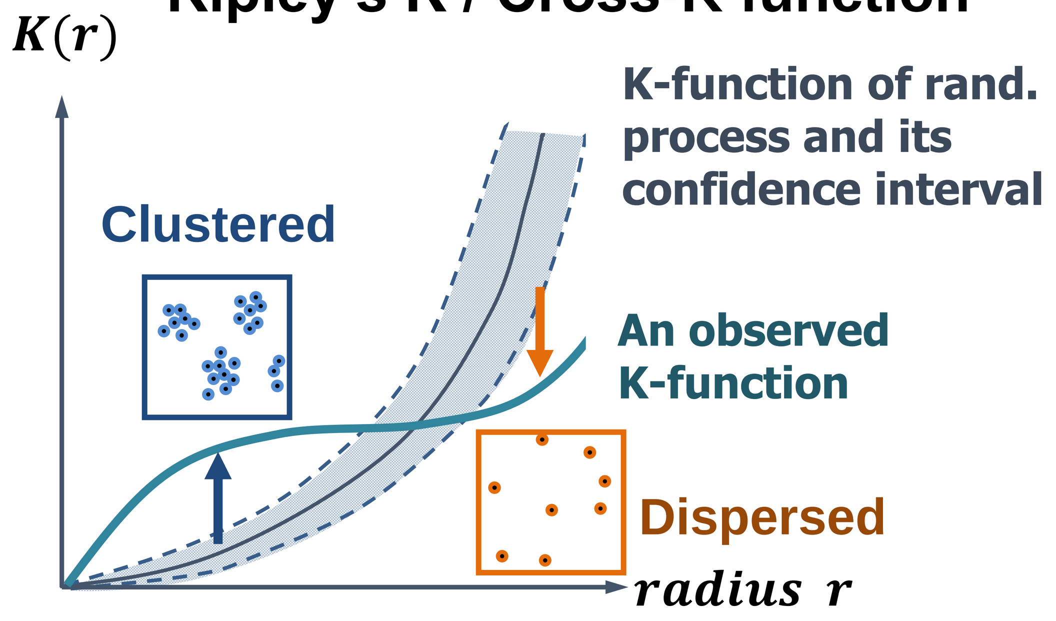

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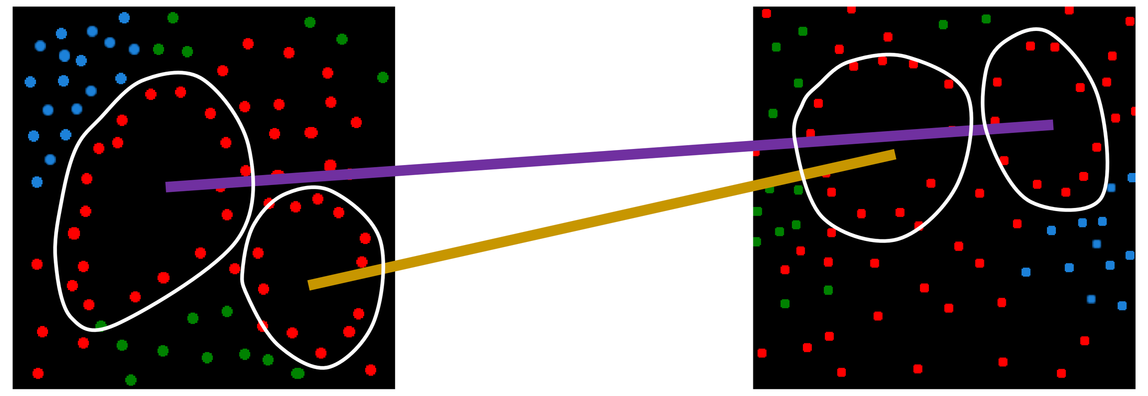

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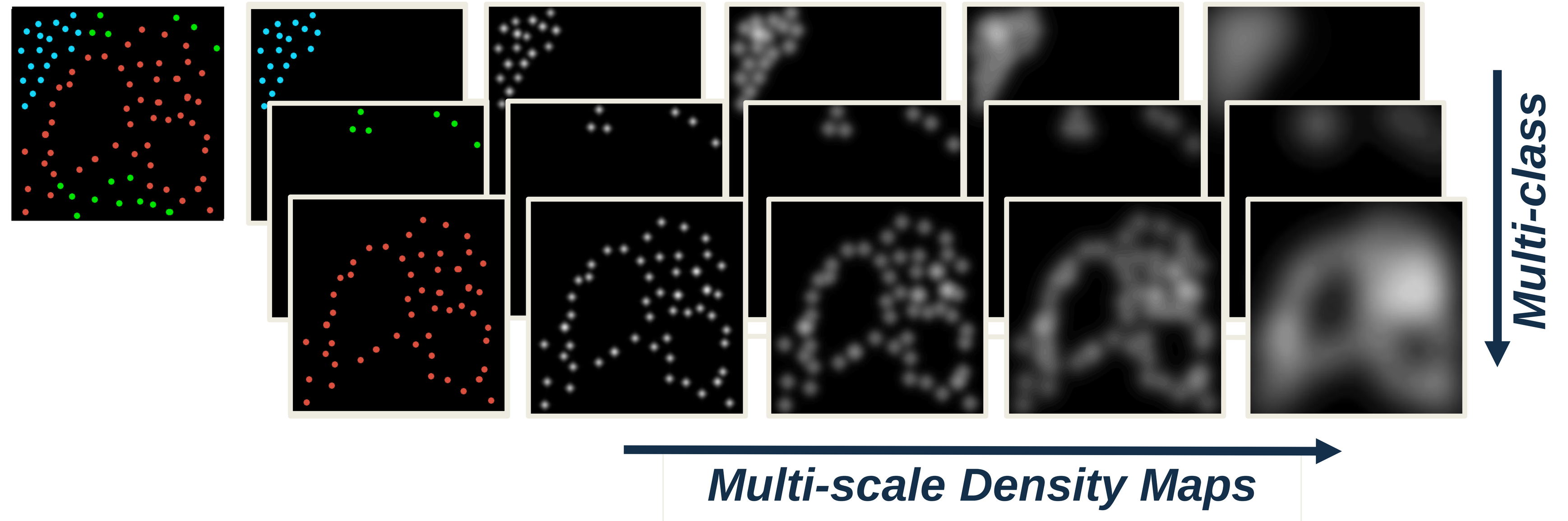

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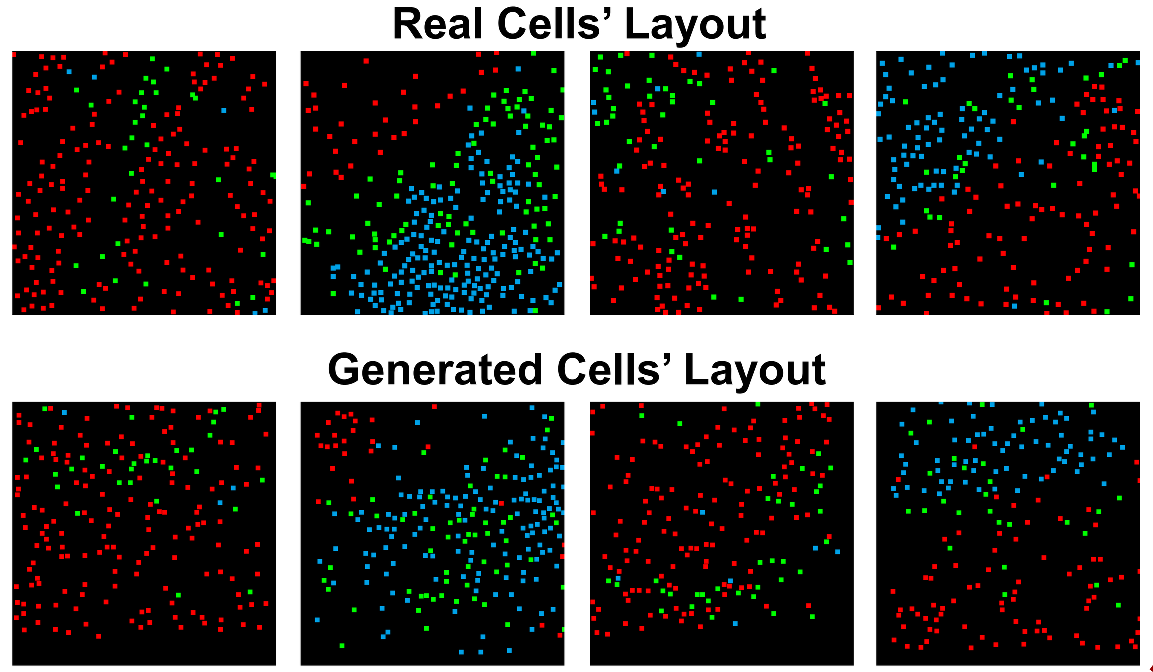

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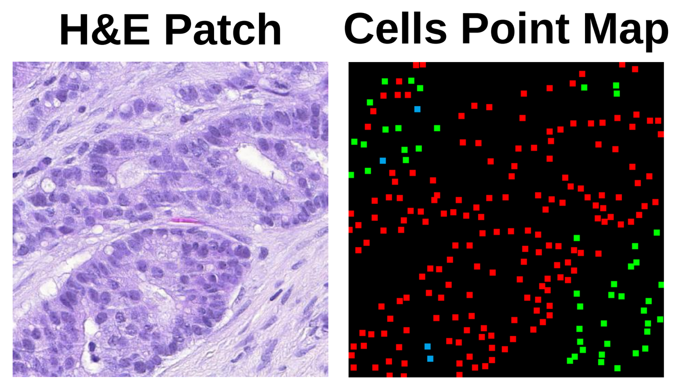

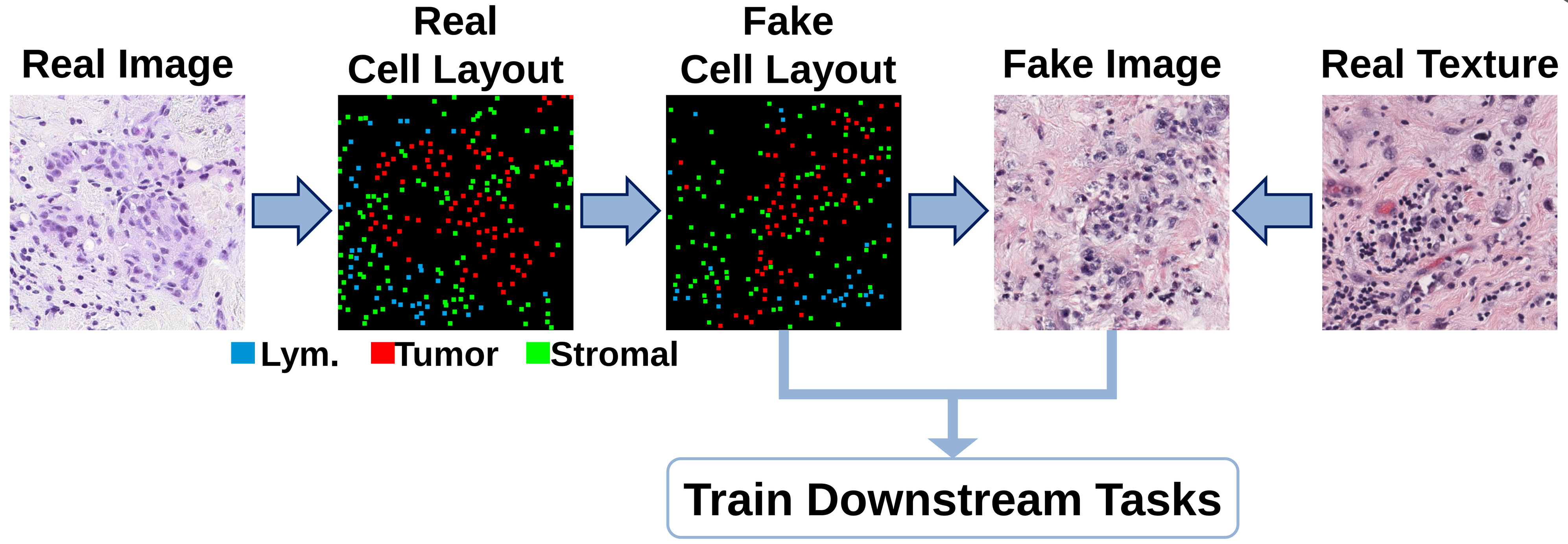

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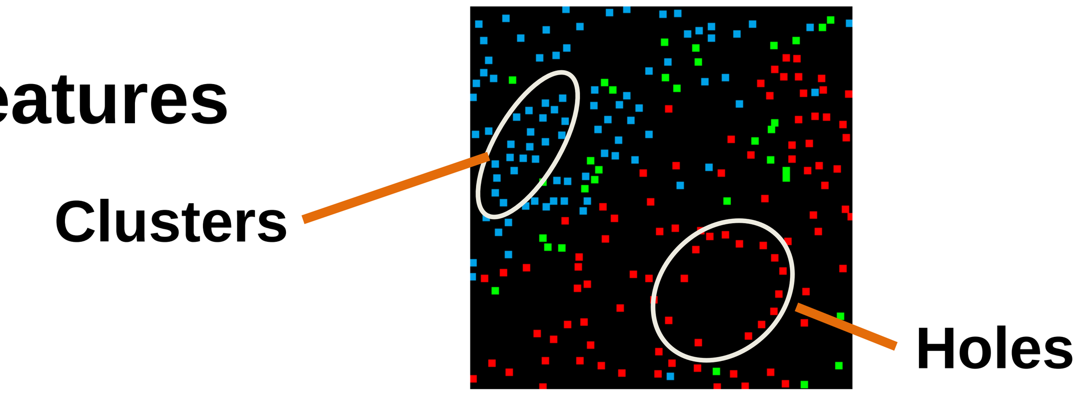

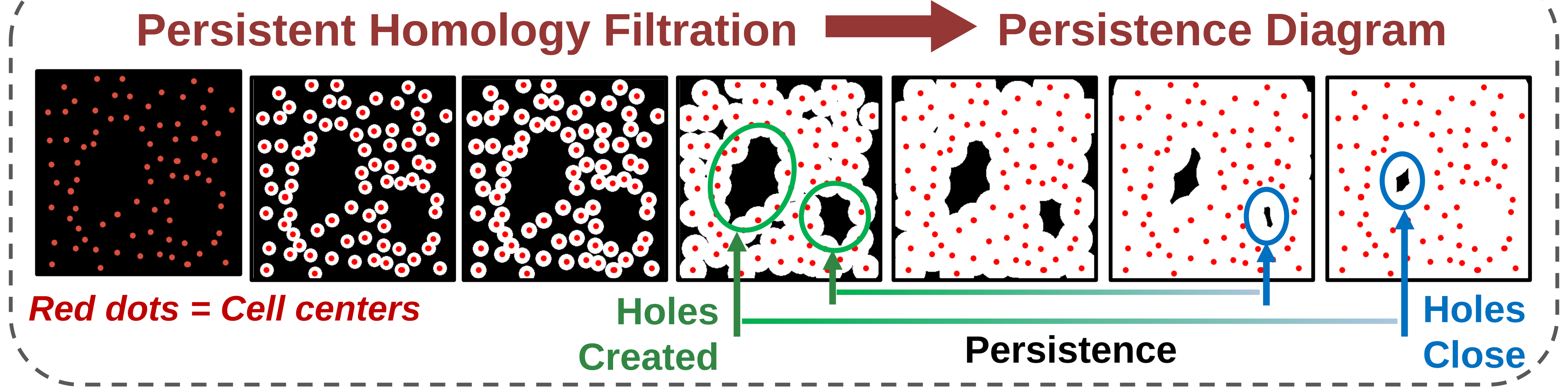

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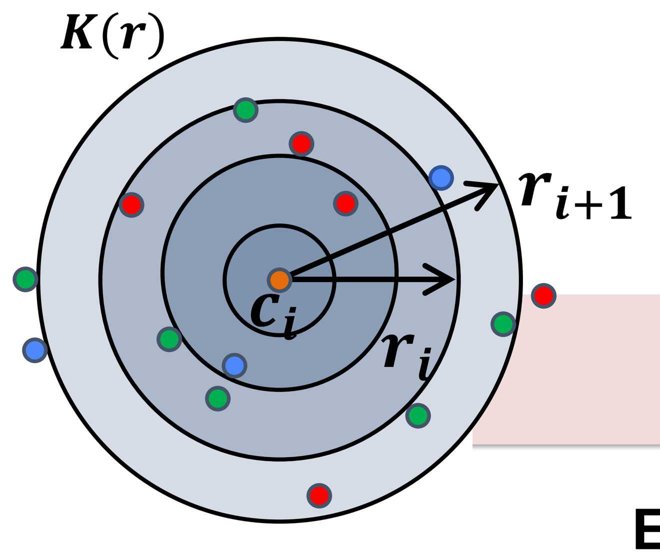

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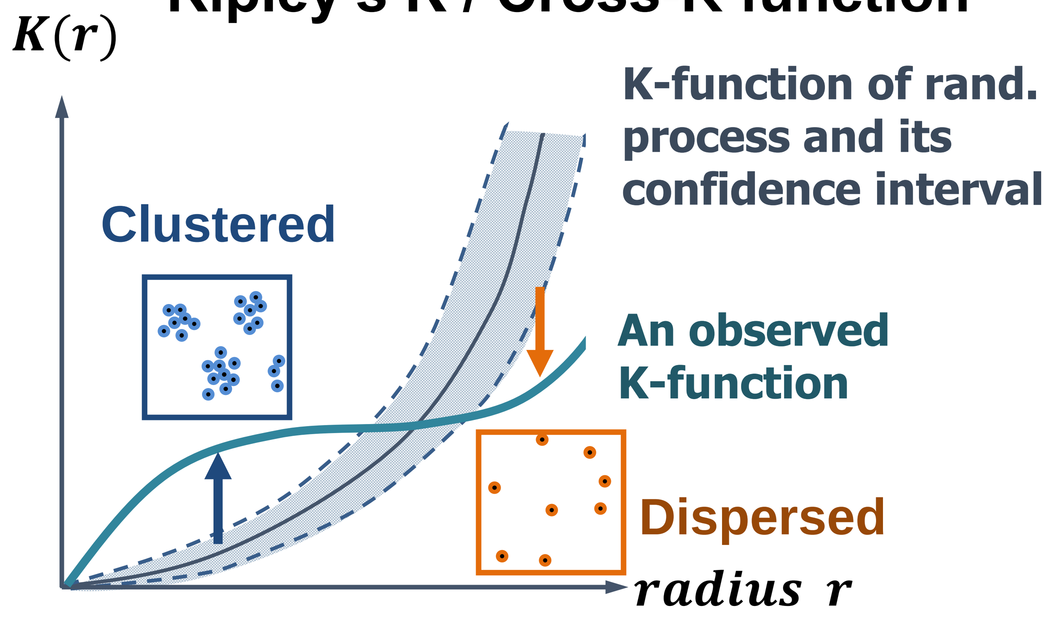

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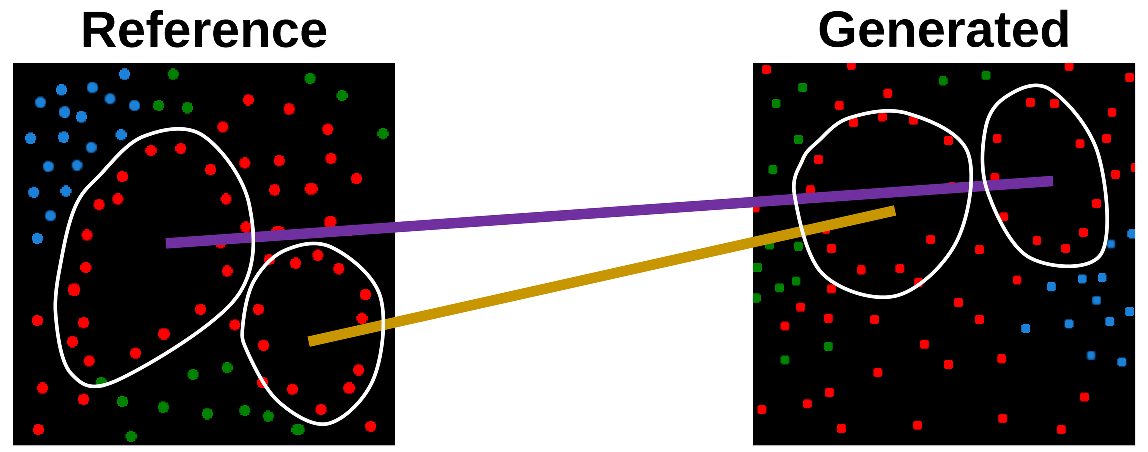

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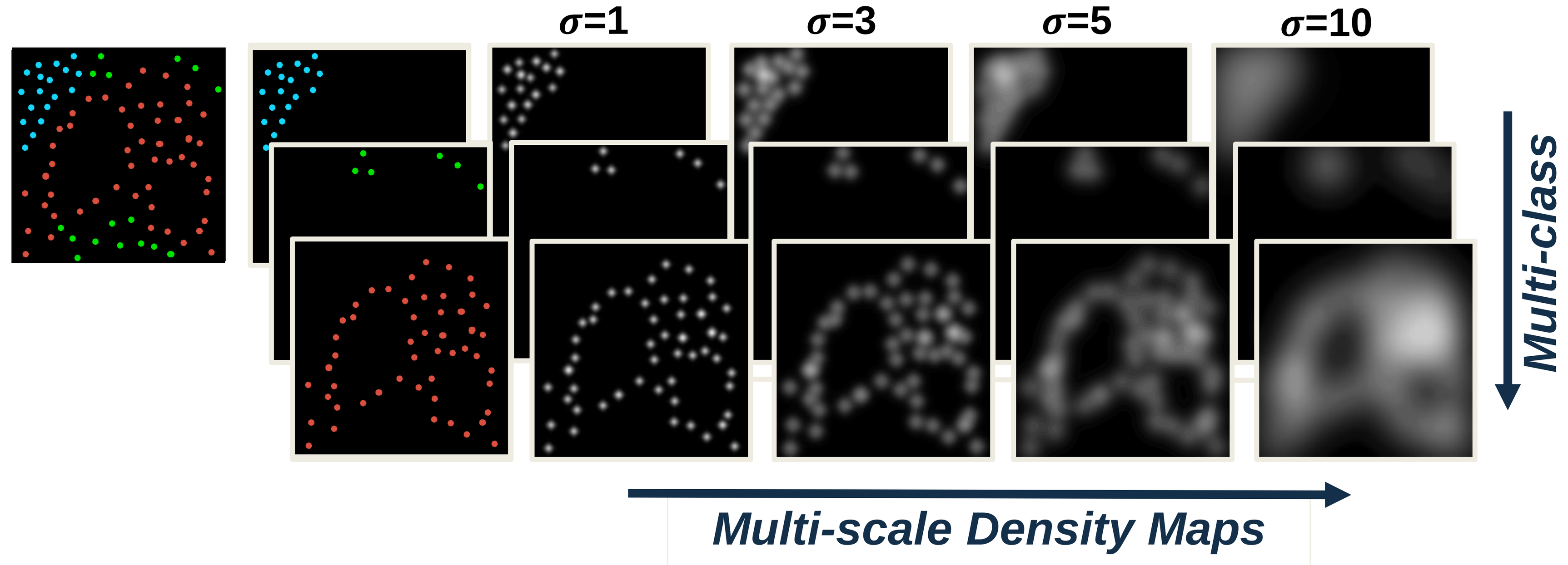

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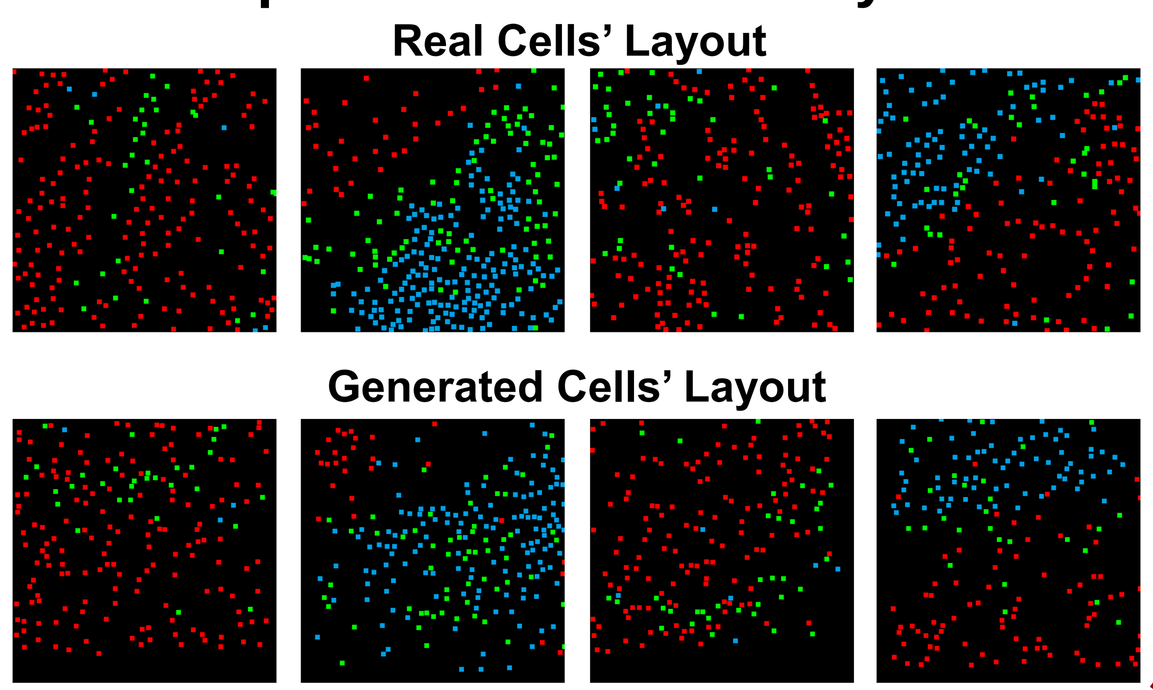

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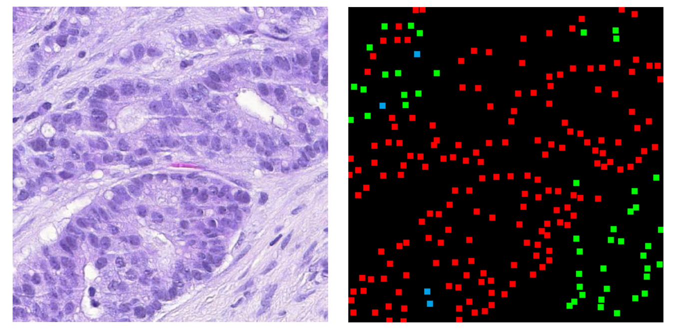

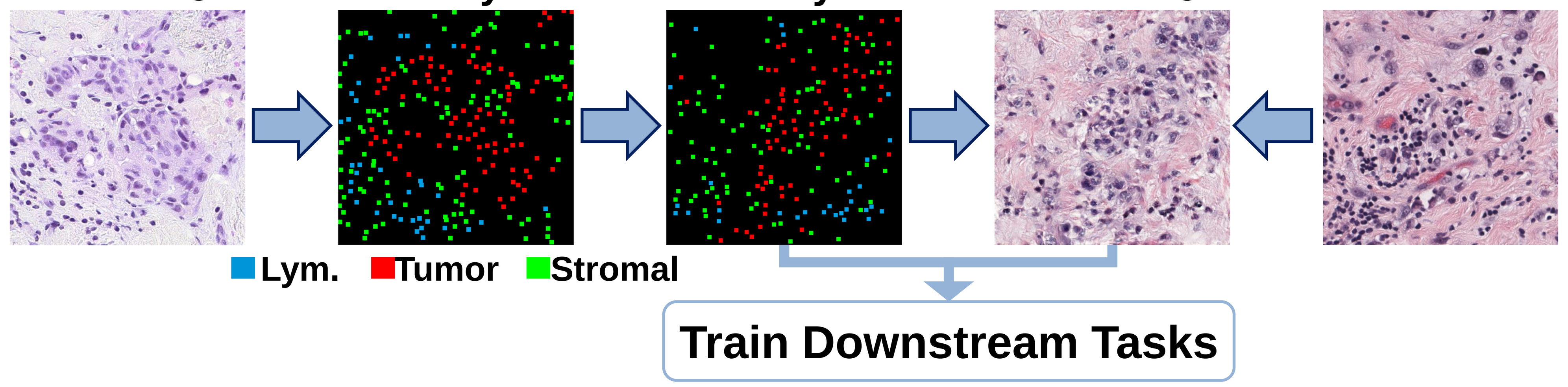

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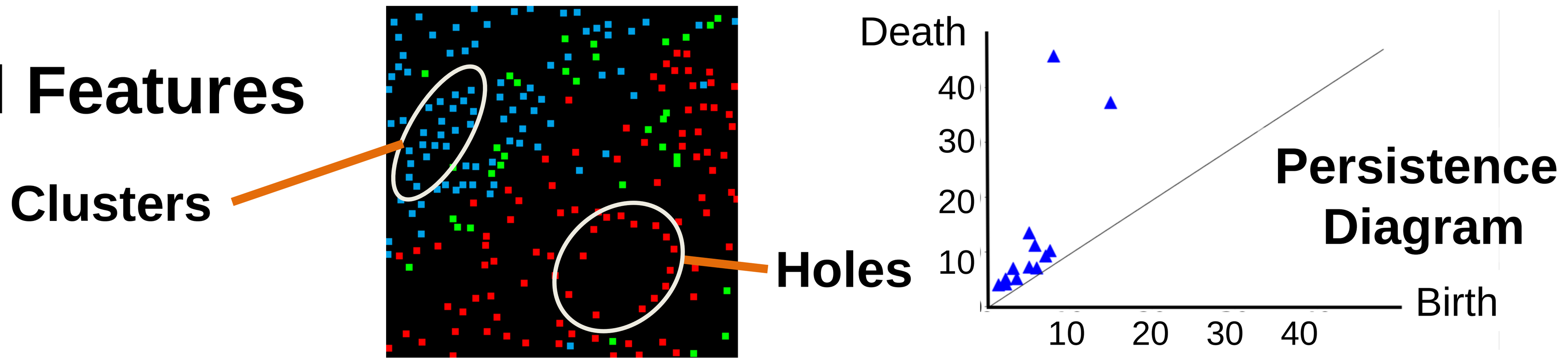
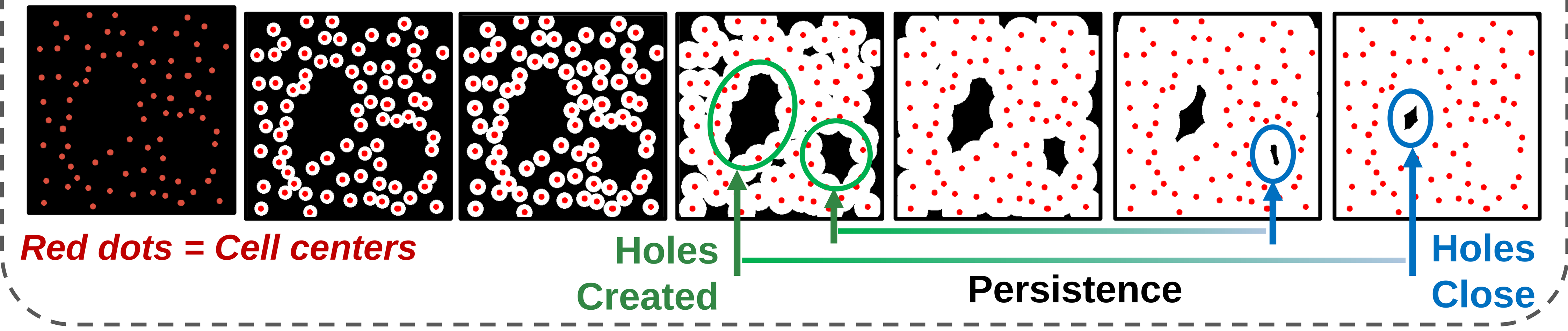


Persistent Homology Filtration ➔ Persistence Diagram (PD)



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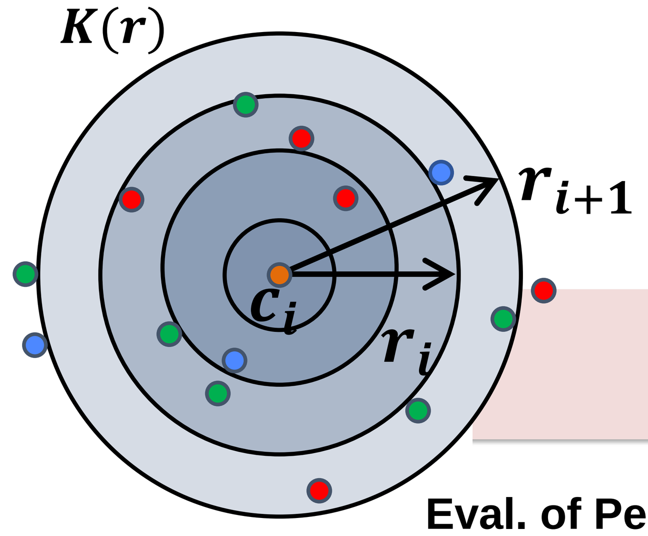

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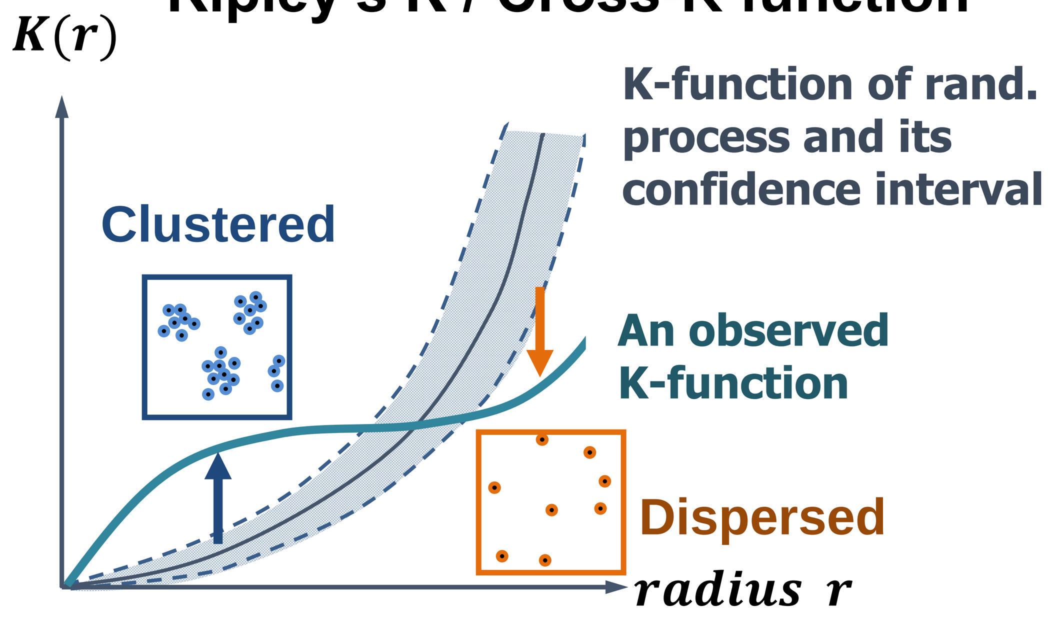

Model Backbone: A modified version of SPGAN*

* Li et al. SP-GAN: sphere-guided 3d shape generation and manipulation. SIGGRAPH, 40(4), 2021.

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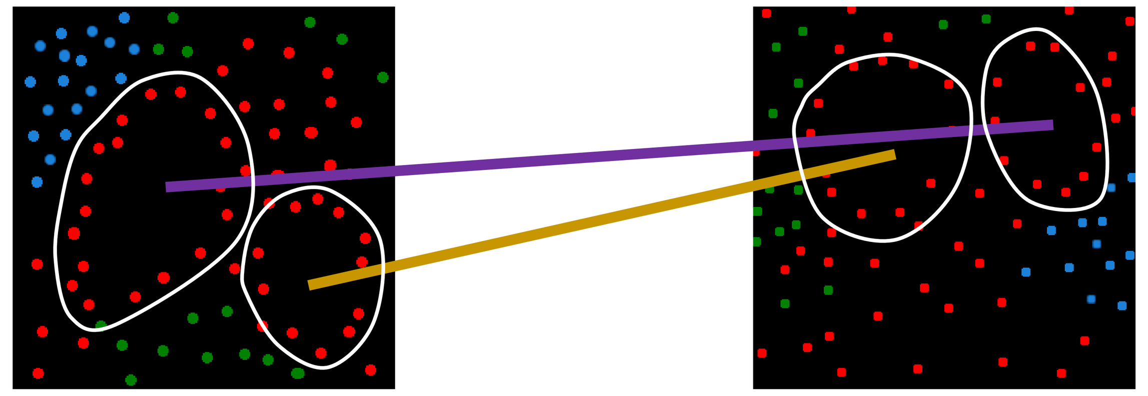

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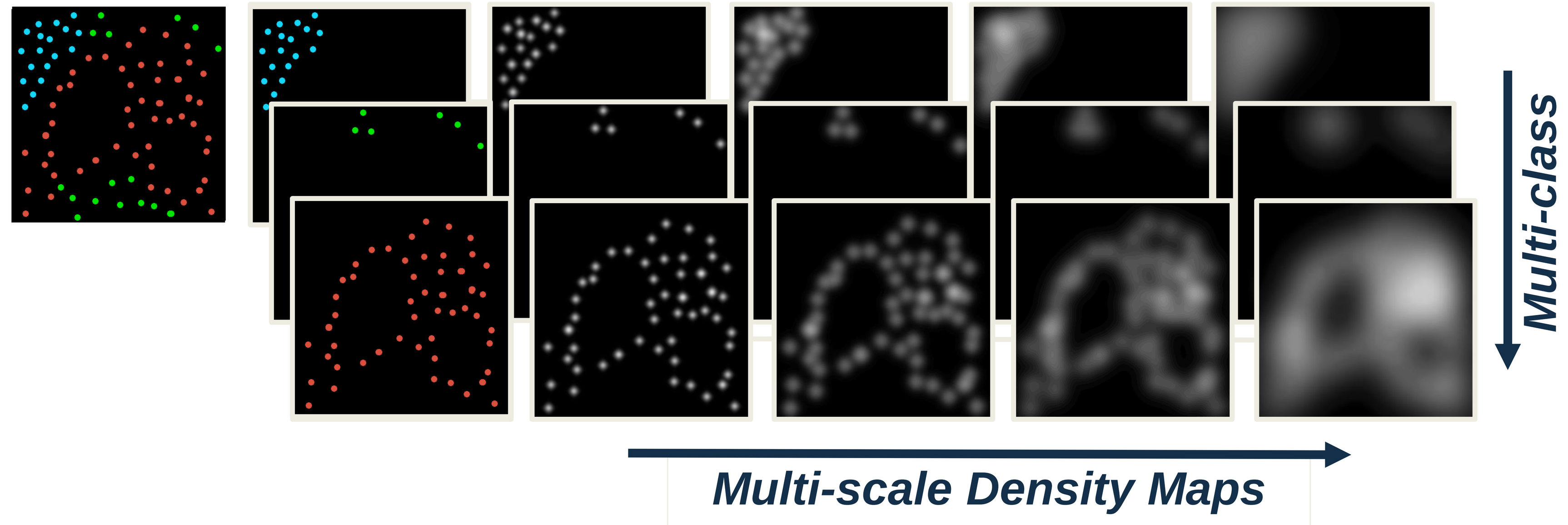

Results

Eval. of Persistence Diagrams (Cell Config. Matching)↓

Method	Lym.	Tumor	Stro.	Mean
w/o Spatial Descriptors + w/o $\mathcal{L}_{cc}$	0.8	1.74	1.66	1.4
w/o $\mathcal{L}_{cc}$	0.9	1.69	1.79	1.46
w/o Cross K-function Descriptor	0.75	1.74	1.77	1.42
Ours	0.74	1.64	1.71	**1.36**

Eval. on Cell Classification (F-Score) ↑

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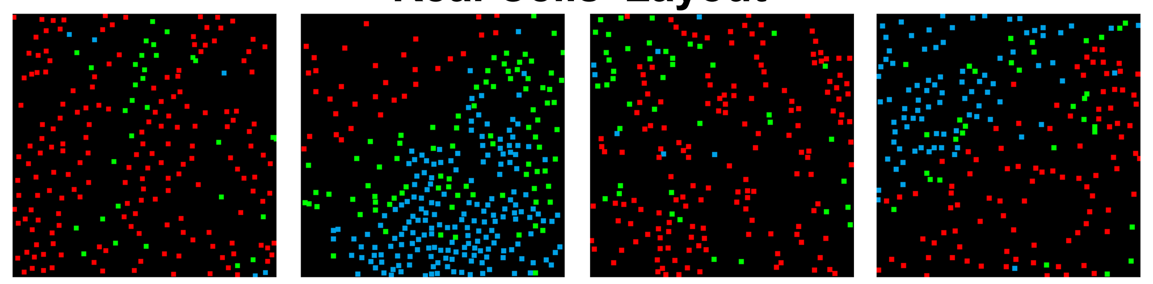
Real Cells' Layout



Generated Cells' Layout