



PROJECT:
Segmenting Immune Cells
in Breast Cancer Tissue

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BACKGROUND

Context: Breast cancer – the most prevalent cancer in the world.

Currently: Breast examination, mammography, breast ultrasound, MRI, and other imaging modalities.

Overall problem: Early diagnosis is key for successful cancer treatment. However, interpretations of screenings can vary from doctor to doctor → misdiagnosis

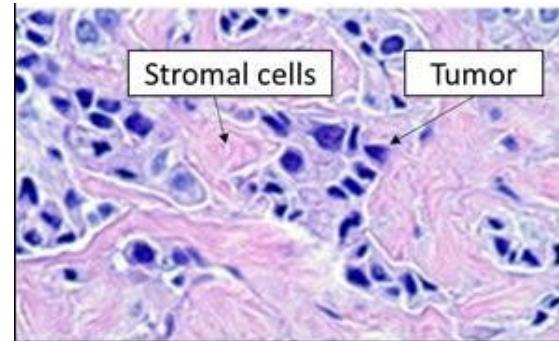
PROJECT SCOPE

Data: Utilize H&E stained images (.svs) of cancerous breast tissue to segment tumor infiltrating lymphocytes (**TILs**) in the stroma → have clinical significance

Outcome: Better visualize the spatial organization of immune cells in the tumor microenvironment.



TIL

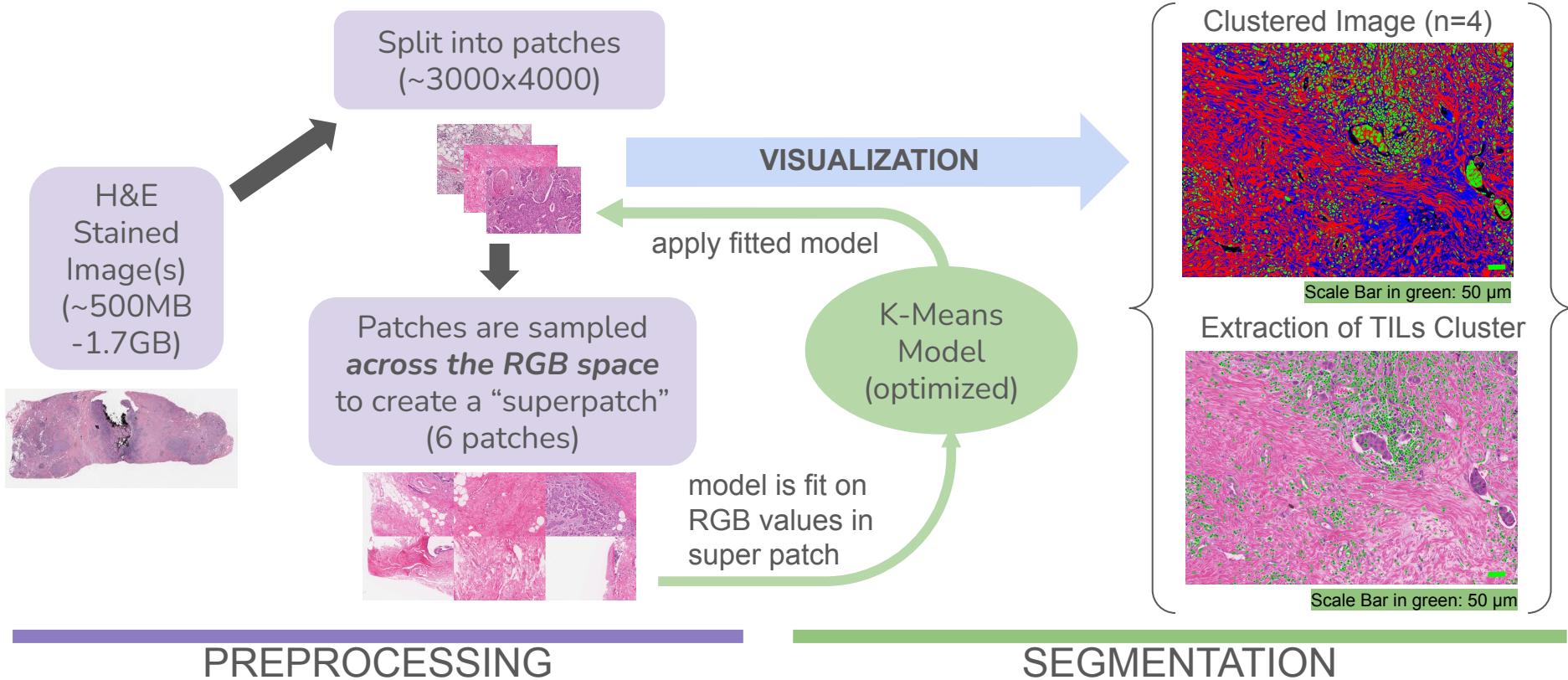


Note: no scale bars available for images

Sakiyama, Nobuyuki & Nagayama, Katsuya (2018)

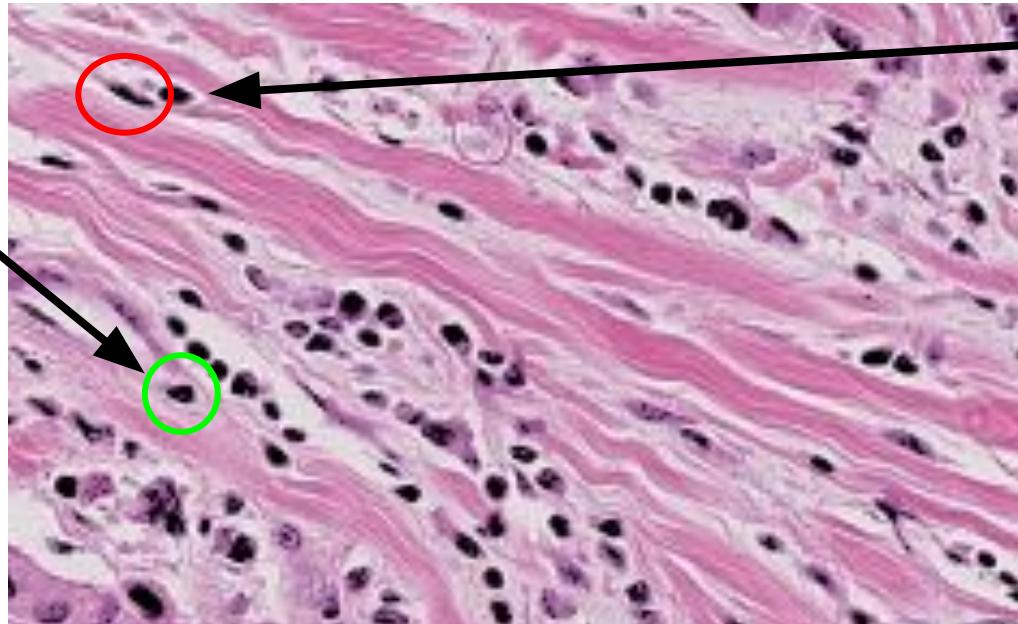


PREVIOUS CODE (SEMDS WINTER 2023): WHAT WE WERE GIVEN



PROJECT SCOPE

TIL



Note: no scale bars available for images

NOT a TIL

K-Means will cluster all purple/black cells together →
How to filter out just TILs?

PREPROCESSING

1

Creating Patches from .svs Image

1	2	3	4	5
6	7	8	9	10
11	12	13	14	15
16	17	18	19	20
21	22	23	24	25

2

Remove White
Background Patches

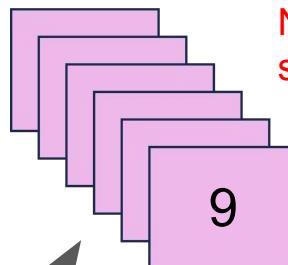
Poorly
documented
method - hard
to make
changes to

1	2	3	4	5
6	8	9	12	13
14	15	16	18	20
21	22	23	24	25

3

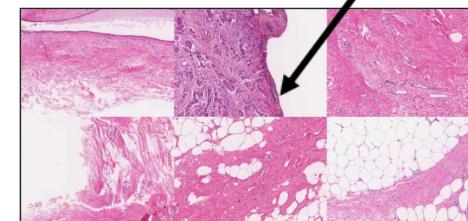
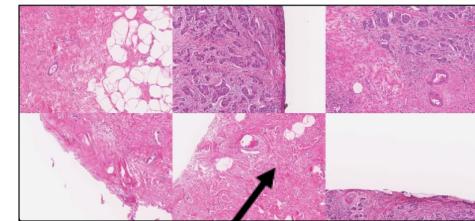
Determine patches to
use in superpatch

No random seed
specified in sampling



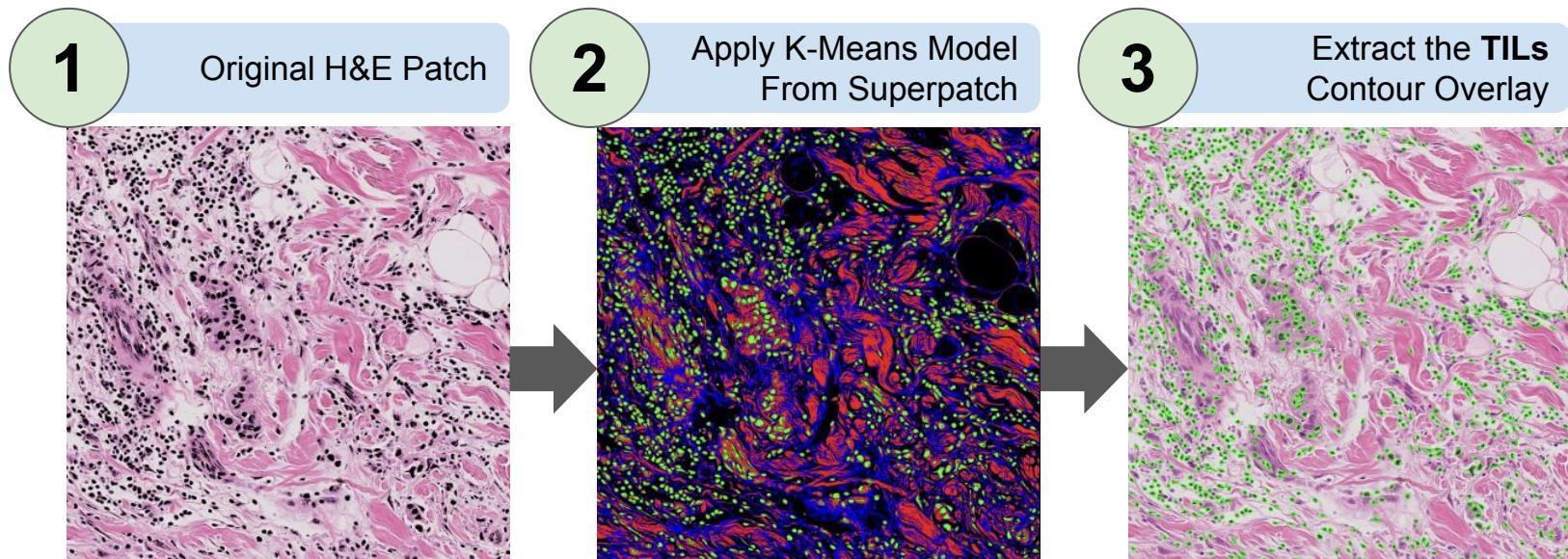
4

Stitch patches
into superpatch



Different superpatch output
each run and patches still
contain a lot of white

SEGMENTATION: K-MEANS



Currently the clustering cannot be performed easily on a single image with no superpatch.
The TILs are also not all of the green, how can we further segment them out?



GOALS

Previously: Optimized a K-Means model that can segment TILs from an H&E stained image.

Our Initial Goals:

- Fix issues in the inherited code
- Quantify/qualify how “good” (i.e. representative) a superpatch is
 - Explore sampling methods with more images
- Incorporate spatial algorithms to further cluster TILs
- Focus segmentation on just the stroma (the pink parts!)



PROGRESS: DEBUGGING

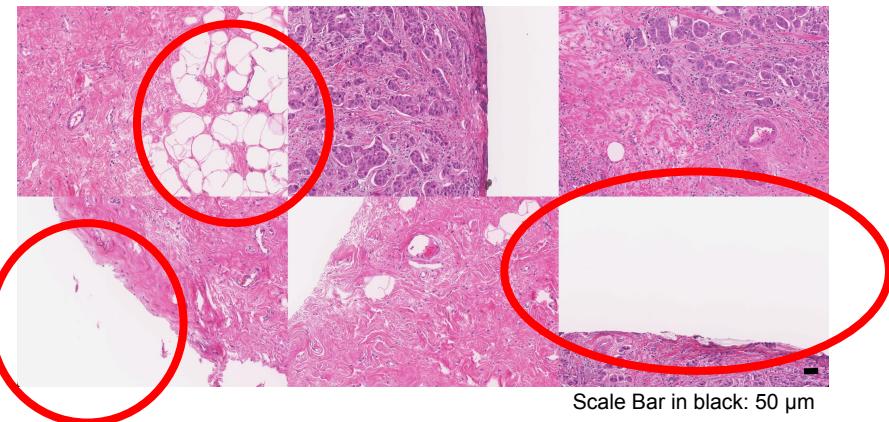
Problem: How do we effectively integrate code from another team within our own project?

- **Random state arguments:**
 - Produces the same superpatch for individual .svs image
- **Background Filtering:**
 - Accurately removes white background within patches
- **Miscellaneous:**
 - Correct os file handling
 - Running previously written unit tests were failing

PROGRESS: BACKGROUND FILTERING

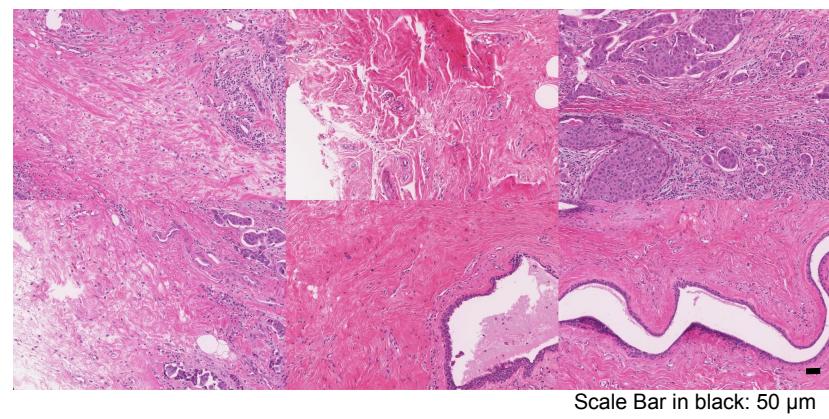
Problem: the previous code did not properly filter out the background in the preprocessing step

Super Patch: Previous Code



Background

Super Patch: Gaussian Mixture Model
(2 Peaks)



Goals

Progress

Conclusions

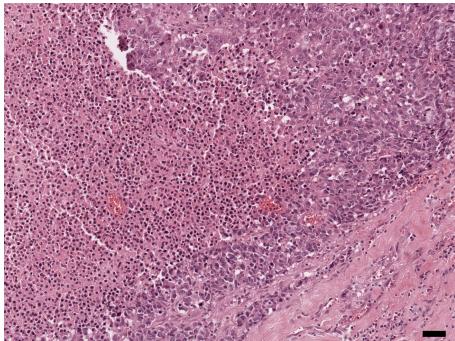
PROGRESS: SUPERPATCH

Problem: How “good” is the superpatch?

- **Creating a score + visualizing to determine how ‘good’ a superpatch is:**

(Quantified with mean squared error)

Reference Patch

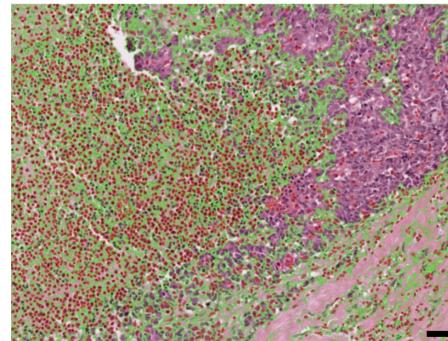


Scale Bar in black: 50 μm

1. Fit and apply K-Means on reference patch
2. Apply pre-fitted superpatch model on reference patch



Segmented Reference Patch



Scale Bar in black: 50 μm

Green = ‘ground truth’

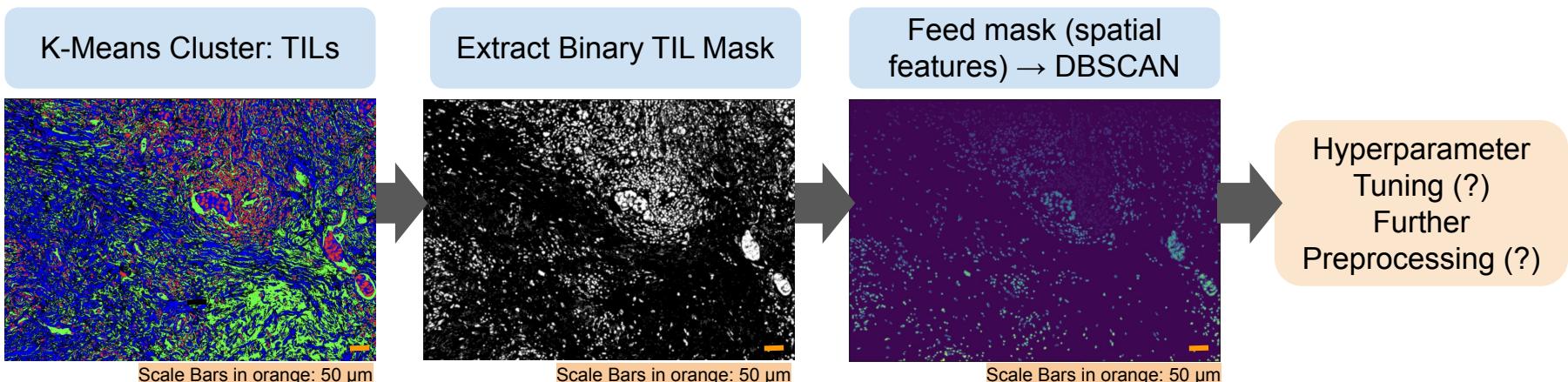
Red = disagreement with superpatch model fit

MSE → difference

PROGRESS: DBSCAN

Problem: Is K-Means enough?

- **Implementing DBSCAN:** Integrating a pipeline from K-Means → Spatial algorithms (e.g. DBSCAN)



DOCUMENTATION



- Previous jupyter notebooks outlining process flow used local file paths
 - Added new notebooks for future users for both similarity scoring and DBSCAN/-Means models
 - Updating documentation → make code more modifiable and understandable for future users/researchers
 - Including bug fixes
 - Updates + future progress sections

Kmeans-Dbscan Segmentation

How to Run Notebook

1. Set up virtual conda environment if you have not already done so.

Similarity Use

This part utilizes KMeans_.superpatch_fit and segment_TILs from seg.py reference patch and a superpatch, and then used to predict clusters on t gives a dictionary containing a masks of the TILs, which is then converted computes the mean squared error between the masks trained on two different mask (red) on the top of the reference image.

```
# use the github cloned folder path
import os
directory_path = os.getcwd()
repository_path = os.path.dirname(directory_path)
```

Last Updated: March 13th, 2024

SINCE PREVIOUS UPDATE (March 15th, 2023)

DEVELOPMENTS

- **K-Means to DBSCAN:** Previously, K-Means was found to be the best for Birch, and Optics. We have built a pipeline in `refine_kmeans.py` to apply K-Means to patches of a whole slide image and then uses them for further clustering.



CHALLENGES

Technical/Logistical Difficulties:

- Lag time in acquiring data
- Long run times (massive amount of data + complex modeling)
- Creating a working environment
- Understanding 1000s+ lines of code in 2 weeks...

However, good documentation!

- Detailed README File
- Docstrings for each function
- Line by line explanation of code



CONCLUSIONS

Progress:

- Creating pipelines to...
 - Quantify/qualify how “good”/representative) a superpatch is
 - Incorporate DBSCAN to further cluster TILs from K-Means
- Debug previous code
- Improved documentation

Future Directions:

- Test methods on a larger dataset → robustness
- Explore hyperparameter tuning + preprocessing
- Integrate with the pipeline currently used in the Mittal lab

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Thank you!