

ML in Applications

***Dipartimento di Automatica e Informatica
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**Politecnico
di Torino**

Lab 3

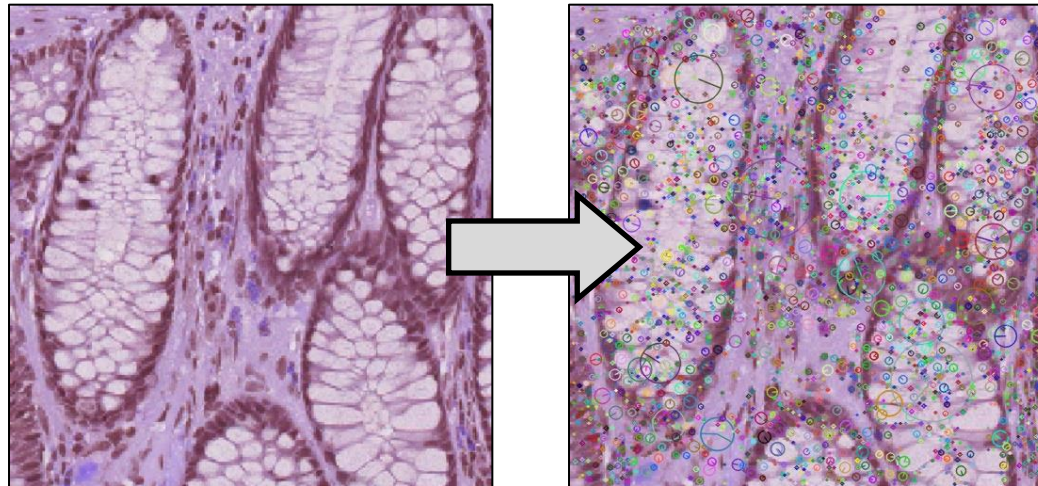
Image classification via bag of (visual)
features

Bag of Visual Words

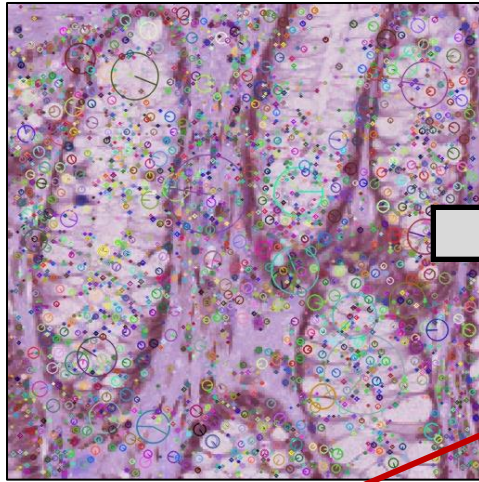
- Bag of Visual Words (or features) is an extension to the NLP algorithm Bag of Words
- Can be considered the state-of-the-art algorithm NOT deep learning based
- Essentially, it follows 3 steps
 - **Features** extraction
 - Construction of visual vocabulary by **clustering**, followed by frequency analysis
 - **Classification** of images, based on the generated vocabulary

Features extraction

- We will leverage the [SIFT](#) (Scale Invariant Feature Transform) algorithm developed by David Lowe, now available on OPENCV (patent expired)
 - First detects *key-points* in an images (the number changes among images)
 - Second calculates the descriptors (always 128 for SIFT)



Features extraction



```
[36] 1 helper = ImageHelpers()  
      2 kp, des = helper.features(image)
```

```
[37] 1 print(len(kp))  
      2 print(len(des))  
      3 print(des.shape)
```

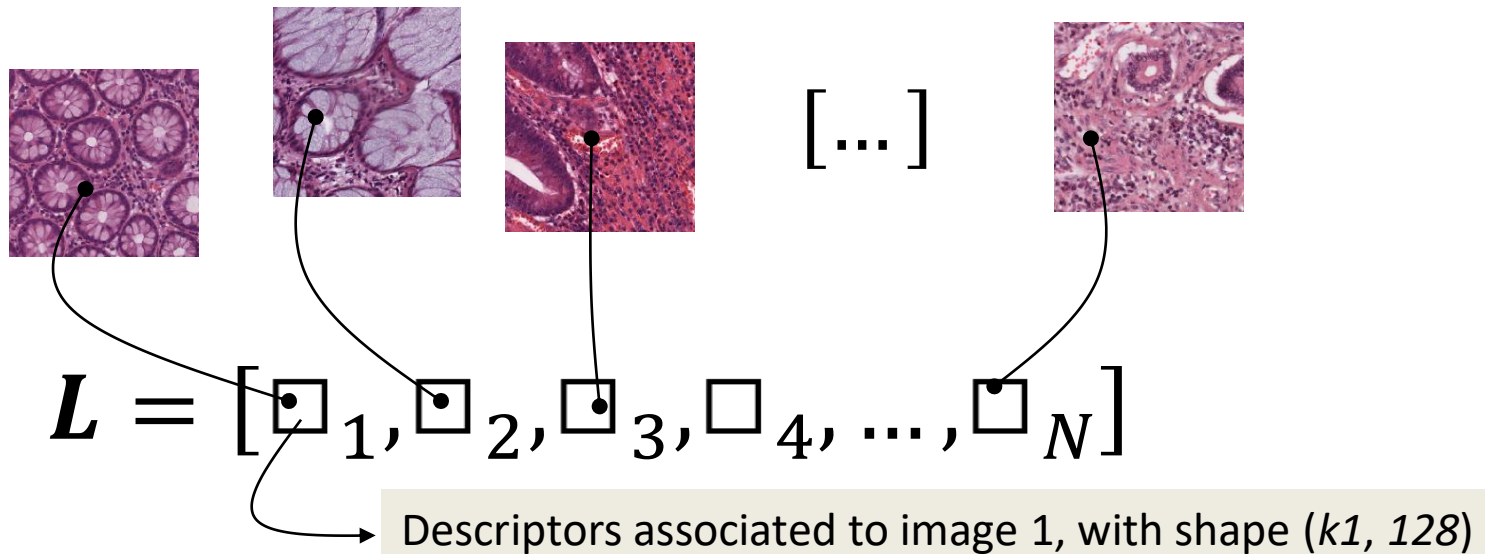
```
3629  
3629  
(3629, 128)
```

The number of key-points (and hence descriptors) varies among images

- Given a single image of our training set, we get several descriptors, each one of shape (128,)

From features extraction to clustering

- Over the whole dataset of N images, we get a list of N descriptors blocks, one for each image:



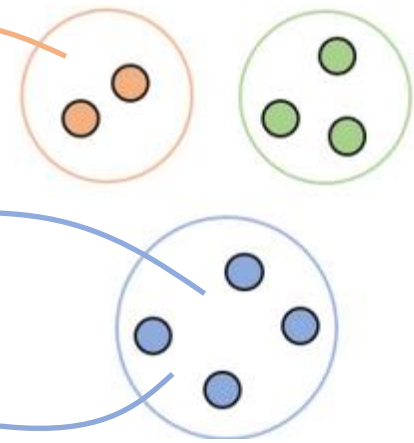
- We need to convert L to an array D of shape $(k1+k2+k3+k4+\dots+kN, 128)$ to be fed to clustering through *sklearn*

Construction of visual vocabulary by clustering

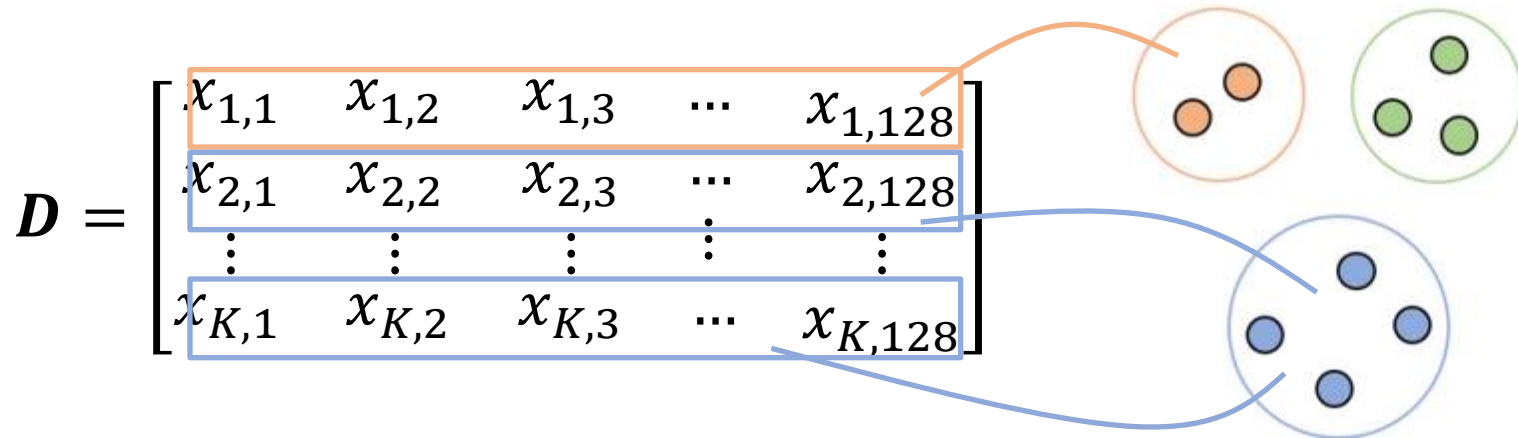
$D \rightarrow \text{ndarray with shape} = (k_1 + k_2 + \dots + k_N, 128) = (K, 128)$

$$D = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,128} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots & x_{2,128} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{K,1} & x_{K,2} & x_{K,3} & \dots & x_{K,128} \end{bmatrix} \xrightarrow{\text{clustering}} \begin{bmatrix} c_1 \\ \vdots \\ c_m \end{bmatrix}$$

$$D = \begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,128} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots & x_{2,128} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{K,1} & x_{K,2} & x_{K,3} & \dots & x_{K,128} \end{bmatrix}$$



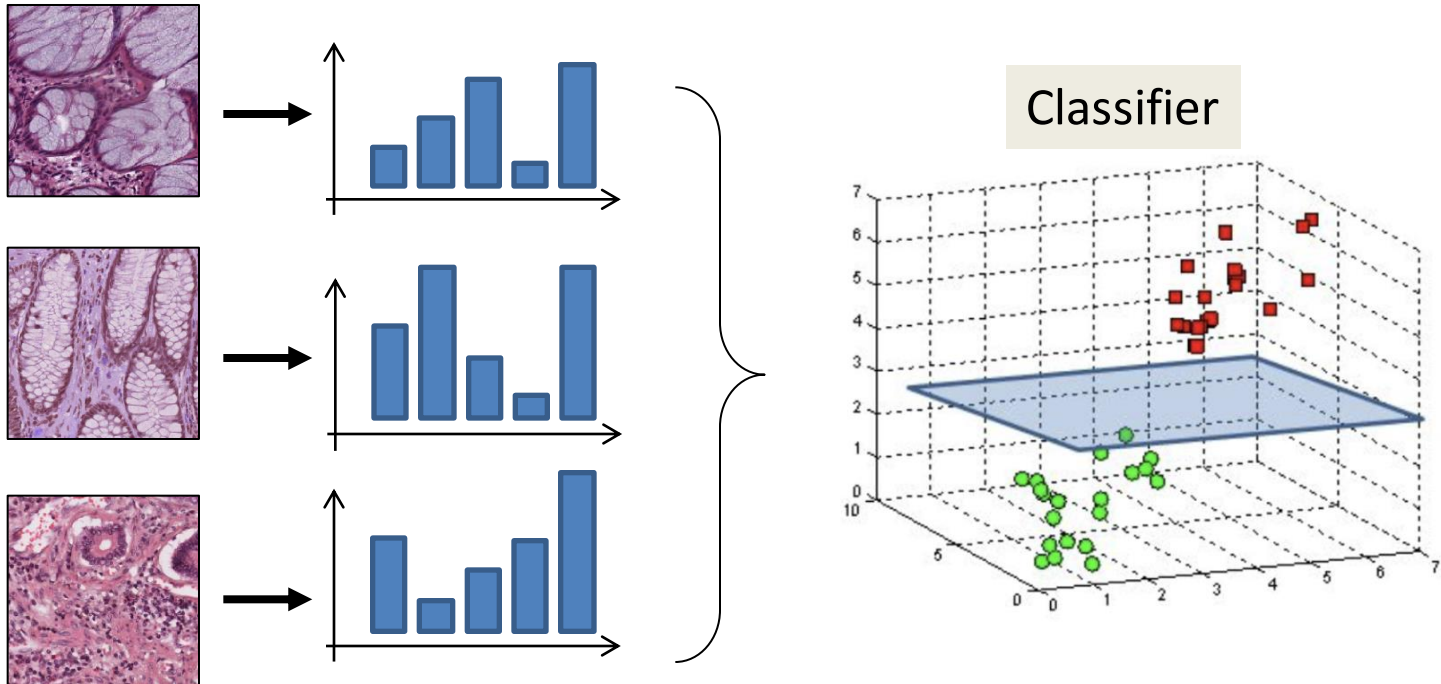
Construction of visual vocabulary by clustering



- Basically, **each descriptor** of the training set is **associated** with a **cluster**
- Each **cluster** is a **visual word**
- Descriptors belonging to the same cluster are **«synonyms»**

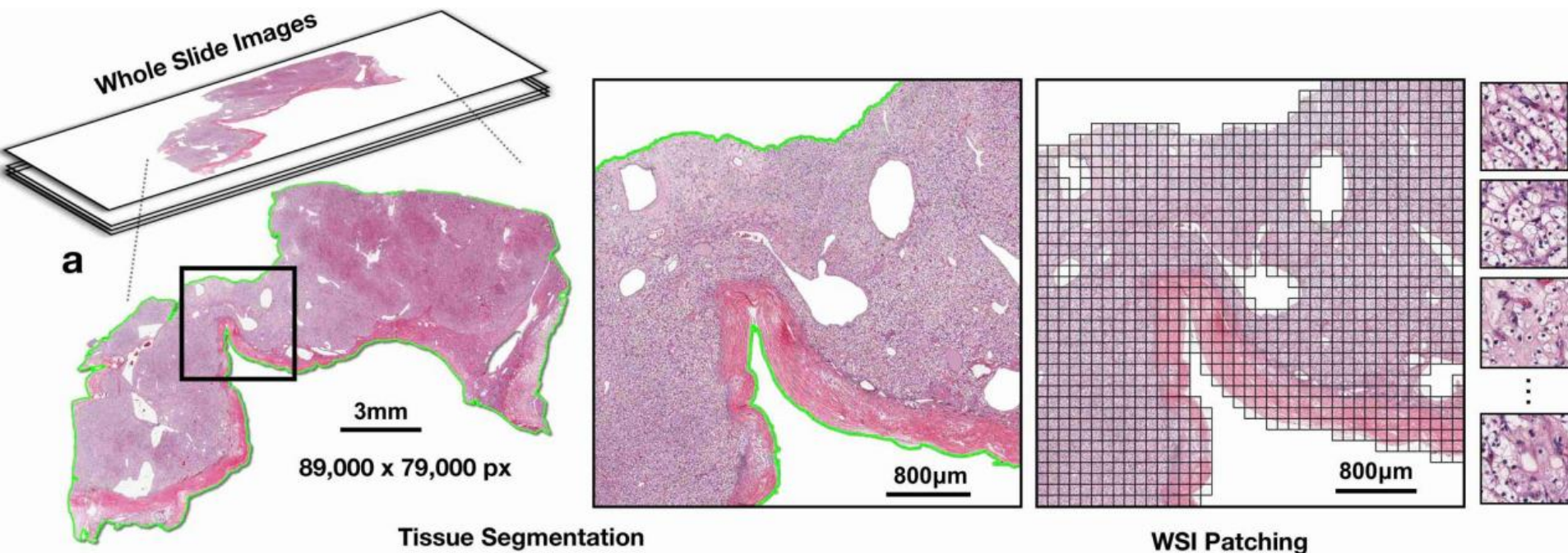
Classification

- Finally, the **image** is represented by a **histogram of the visual words** by counting the number of features that belong to each visual word (i.e., cluster)



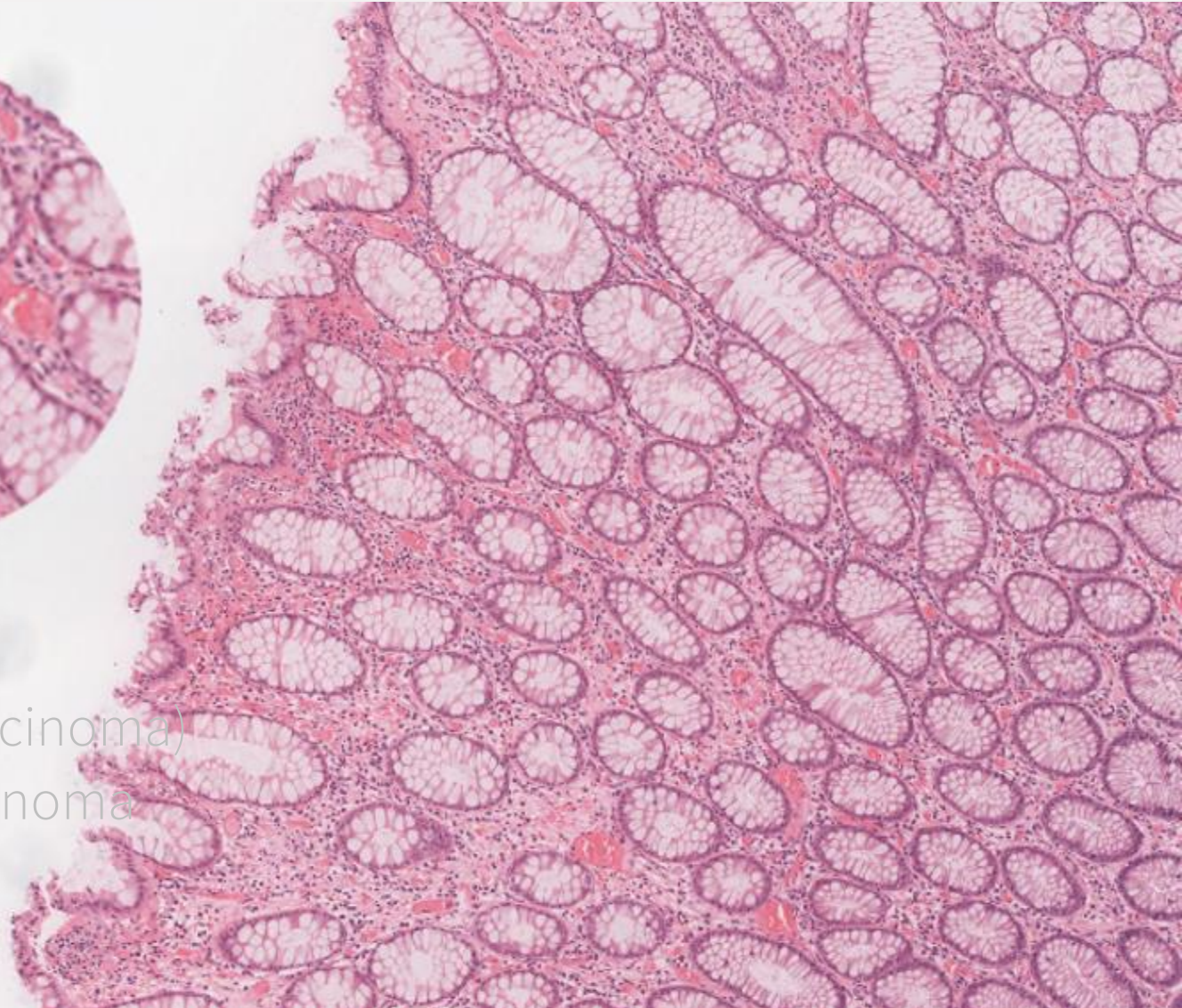
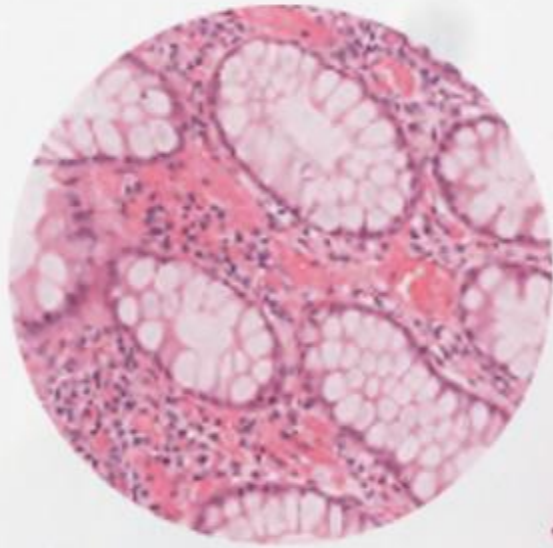
Case study

- Colorectal classification via Whole Slide Images (WSIs)



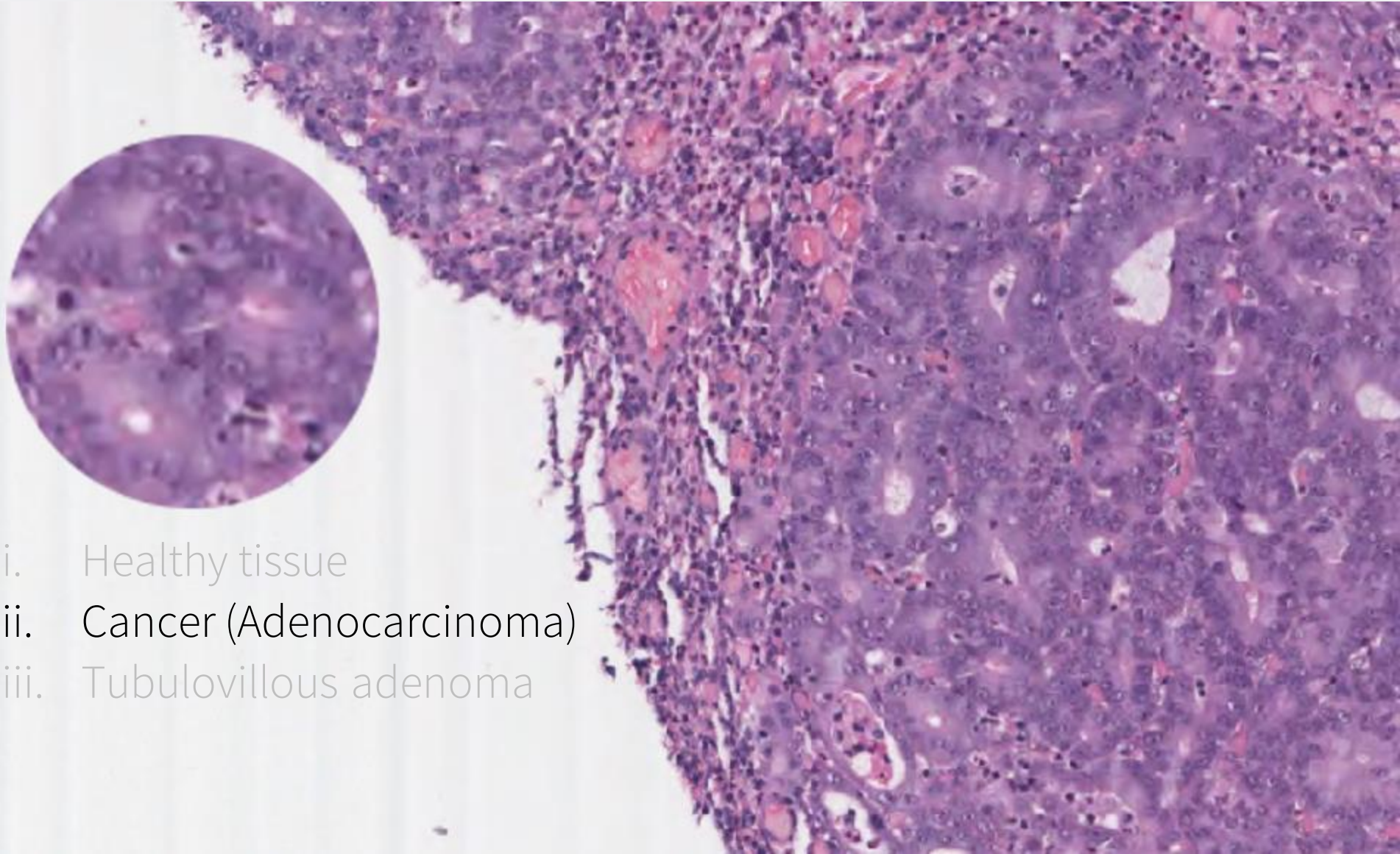
Source: Lu, M. Y., Williamson, D. F., Chen, T. Y., Chen, R. J., Barbieri, M., & Mahmood, F. (2021). Data-efficient and weakly supervised computational pathology on whole-slide images. *Nature biomedical engineering*, 5(6), 555-570.

Dataset



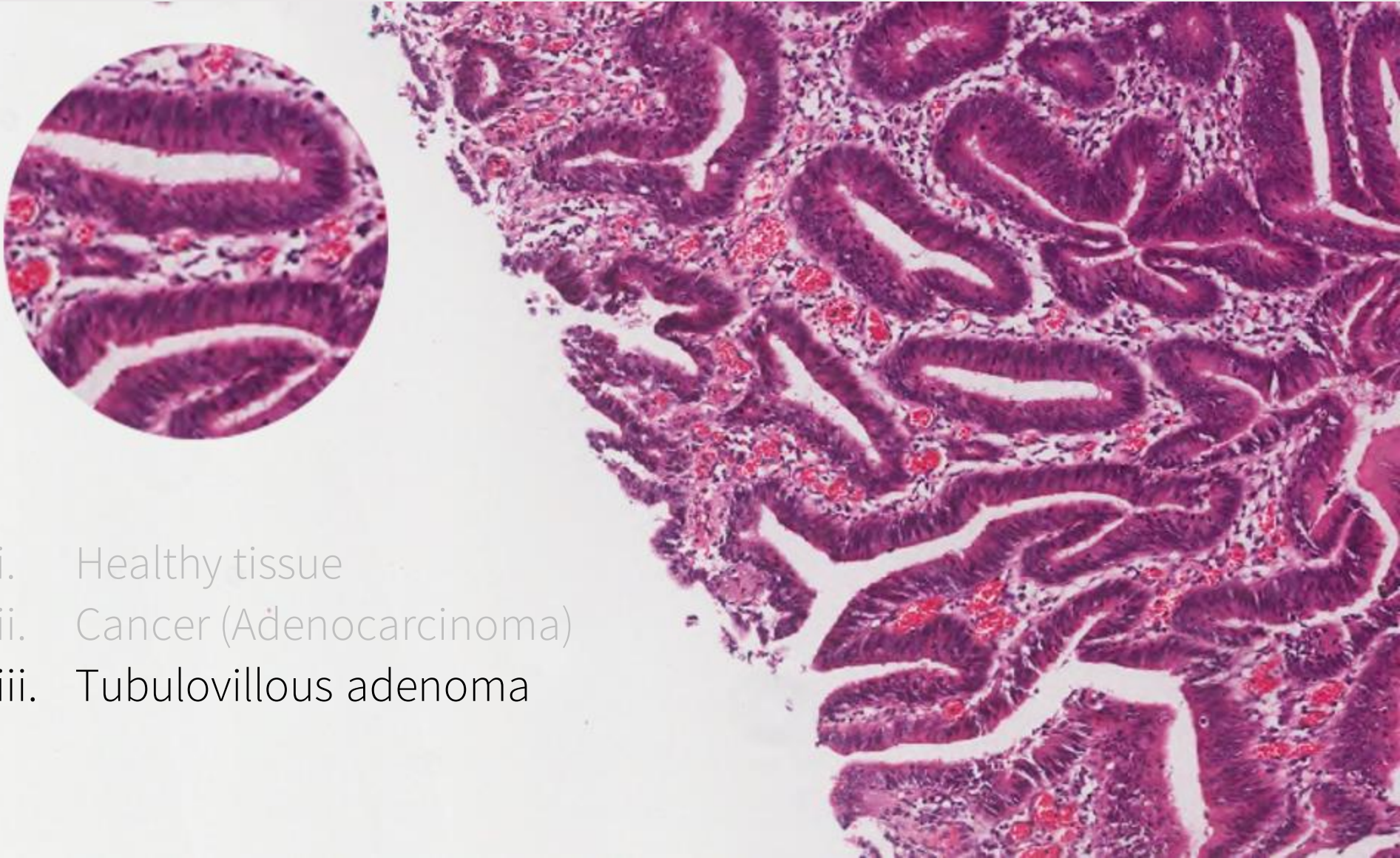
- i. Healthy tissue
- ii. Cancer (Adenocarcinoma)
- iii. Tubulovillous adenoma

Dataset



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Dataset



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