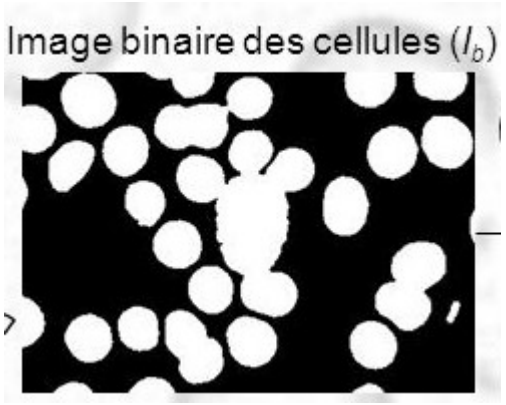
PARIS DESCARTES

Implement automatic thresholding isodata for images

Implement k-means algorithm or use one of them → link unsupervised learning with automatic thresholding and concept discovery

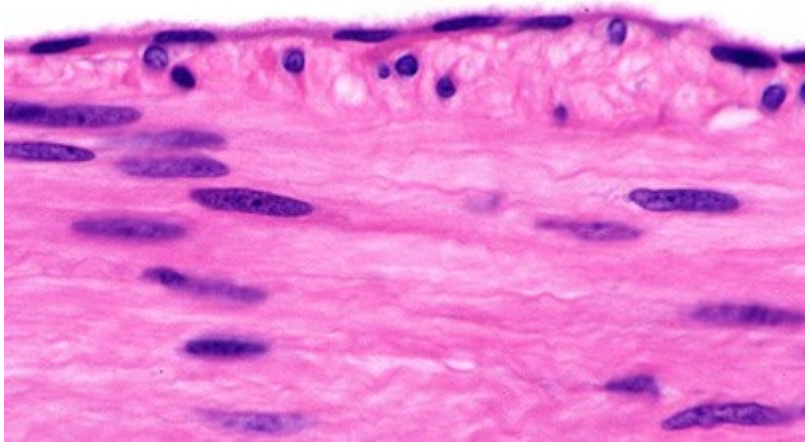


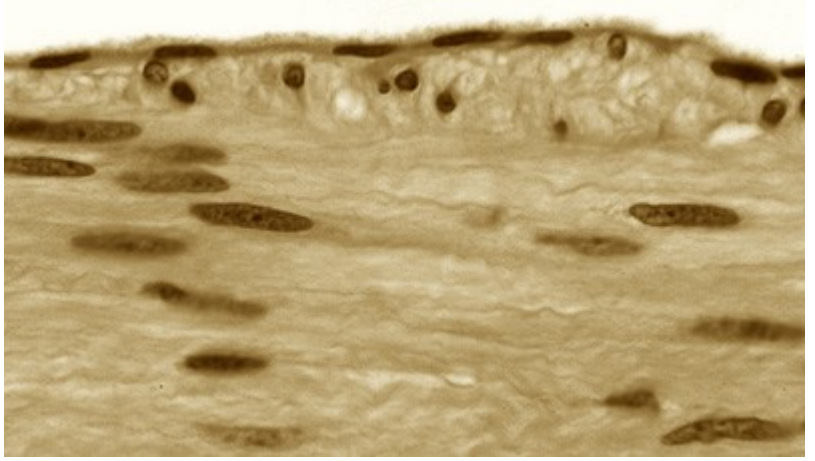

```
def redify(A):
    n,m =np.shape(A)

    B=[[[0,0,0] for j in range(m)] for i in range(n)]
    for i in range(n):
        for j in range(m):
            B[i][j][0]=A[i][j]
            B[i][j][1]=0
            B[i][j][2]=0
    return B
```

PARIS DESCARTES

Example : algorithme pour apprendre les deux types de cellules ?
http://medcell.med.yale.edu/histology/epithelia_lab.php

D’autres idées d’images ?





```
from copy import deepcopy
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
plt.rcParams['figure.figsize'] = (16, 9)
plt.style.use('ggplot')

# Importing the dataset
data = pd.read_csv('xclara.csv')
print("Input Data and Shape")
print(data.shape)
data.head()
```

```
# Getting the values and plotting it
f1 = data['V1'].values
f2 = data['V2'].values
X = np.array(list(zip(f1, f2)))
plt.scatter(f1, f2, c='black', s=7)
```

```
# Euclidean Distance Caculator
def dist(a, b, ax=1):
    return np.linalg.norm(a - b, axis=ax)
```

```
# Number of clusters
k = 3
# X coordinates of random centroids
C_x = np.random.randint(0, np.max(X)-20, size=k)
# Y coordinates of random centroids
C_y = np.random.randint(0, np.max(X)-20, size=k)
C = np.array(list(zip(C_x, C_y)), dtype=np.float32)
print("Initial Centroids")
print(C)
```

```
# Plotting along with the Centroids
plt.scatter(f1, f2, c='#050505', s=7)
plt.scatter(C_x, C_y, marker='*', s=200, c='g')

# To store the value of centroids when it updates
C_old = np.zeros(C.shape)
# Cluster Lables(0, 1, 2)
clusters = np.zeros(len(X))
# Error func. - Distance between new centroids and old centroids
error = dist(C, C_old, None)
```

```
# Loop will run till the error becomes zero
while error != 0:
    # Assigning each value to its closest cluster
    for i in range(len(X)):
        distances = dist(X[i], C)
        cluster = np.argmin(distances)
        clusters[i] = cluster
    # Storing the old centroid values
    C_old = deepcopy(C)
    # Finding the new centroids by taking the average value
    for i in range(k):
        points = [X[j] for j in range(len(X)) if clusters[j] == i]
        C[i] = np.mean(points, axis=0)
    error = dist(C, C_old, None)
```

```
colors = ['r', 'g', 'b', 'y', 'c', 'm']
fig, ax = plt.subplots()
for i in range(k):
        points = np.array([X[j] for j in range(len(X)) if clusters[j] == i])
        ax.scatter(points[:, 0], points[:, 1], s=7, c=colors[i])
ax.scatter(C[:, 0], C[:, 1], marker='*', s=200, c='#050505')
```

```
'''
============================================================
scikit-learn
============================================================
'''

from sklearn.cluster import KMeans

# Number of clusters
kmeans = KMeans(n_clusters=3)
# Fitting the input data
kmeans = kmeans.fit(X)
# Getting the cluster labels
labels = kmeans.predict(X)
# Centroid values
centroids = kmeans.cluster_centers_

# Comparing with scikit-learn centroids
print("Centroid values")
print("Scratch")
print(C) # From Scratch
print("sklearn")
print(centroids) # From sci-kit learn
```

Testez les ouvertures sklearn 2D et 3D, avec opencv choisir celui que vous préférez.