# Activity 13: Expectation Maximization

# Goal

To be able to overlay a plot of the estimated pdf on your fruit feature space

## **Expectation Algorithm**

$$p(\mathbf{x}|\Theta) = \sum_{l=1}^{M} P_{l} p_{l}(\mathbf{x}|\mathbf{\theta}_{l})$$

This kind of algorithm shows the distribution parameters. The sum of weight pdfs is the equation above whe x is the pdf of an ensemble and  $\theta$  is the set of parameters. P\_l is the prior probability while p\_l is the probability of observing x given the parameter.

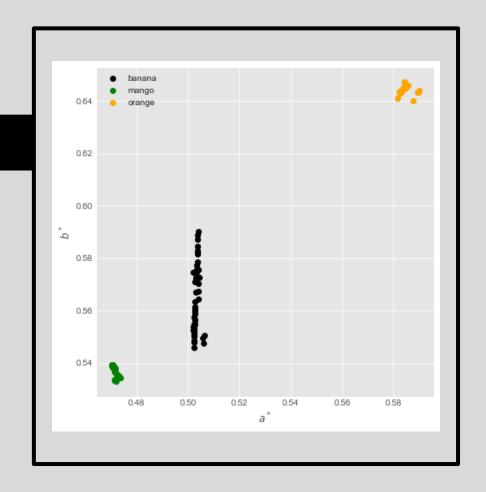
This algorithm is being used to define the probability of an observation belonging to the lth distribution:

$$P(l|x_i, \mathbf{\Theta}) = \frac{P_l p_l(x_i|\theta_l)}{p(x_i|\mathbf{\Theta})} = \frac{P_l p_l(x_i|\theta_l)}{\sum_{l=1}^{M} P_l p_l(x_i|\theta_l)}$$

For d-dimensional Gaussian distribution, component pdf is:

$$p_{l}(x|\mu_{l}, \Sigma_{l}) = \frac{1}{(2\pi)^{d/2} |\Sigma_{l}|^{1/2}} \exp\{-1/2(x-\mu_{l})^{T} \Sigma_{l}^{-1}(x-\mu_{l})\}$$

#### **Feature Space**



```
or j in range(3):
  filenames = os.listdir(dirs[j])
  for i,f in enumerate(filenames):
      if i == 50:
      img = cv.imread(dirs[j] + f)
      img_gray = cv.cvtColor(img, cv.COLOR_BGR2GRAY)
      thres, out = cv.threshold(img_gray, 127, 255, cv.THRESH_OTSU)
      out = (img_gray < thres).astype(float)</pre>
      img_label = meas.label(out)
      props = meas.regionprops(img_label)
      ecc = props[0]['eccentricity']
      img_Lab = cv.cvtColor(img, cv.COLOR_BGR2Lab).astype(float)
      img_Lab /= img_Lab[:,:,0].max()
      img_L, img_a, img_b = cv.split(img_Lab)
      ass[j].append(img_a.mean())
      bss[j].append(img_b.mean())
      ecs[j].append(ecc)
```

This snippet of code was already used several times in clustering three kinds of fruit: orange, banana, and mango.

### Algorithm

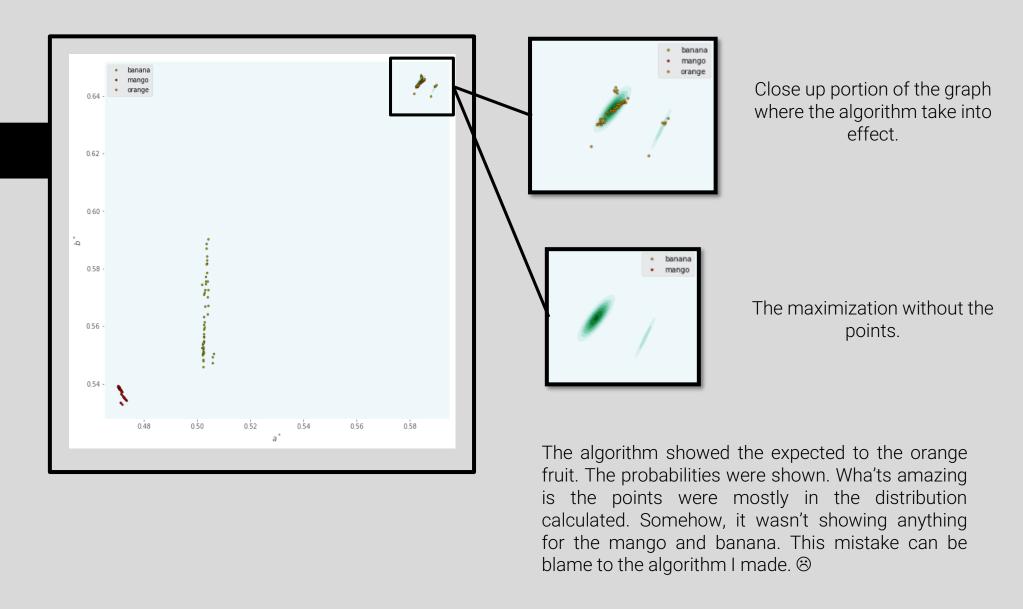
```
train(self, X, cluster_means, epochs=int(1e6)):
    self.graph_loss = []
    self.epochs = epochs
    N = len(X)
    11 \text{ old} = 0.
    self.theta = dict({'mu': cluster means,
                       'cov': np.array([np.identity(self.dimensions) \
                                        for _ in range(self.n_classes)])
                      })
    self.P = np.ones(self.n_classes) * 1/self.n_classes
    for count in thrange(epochs, desc='Epoch'):
        exp_A = []
        exp_B = []
        11 \text{ new} = 0.
        ws = np.zeros((self.n_classes, N))
        for 1 in range(self.n_classes):
           for i, x in enumerate(X):
                ws[l,i] = self.P[l] * \
                          stats.multivariate_normal(self.theta['mu'][1],
                                                     self.theta['cov'][1],
                                                    ).pdf(x)
        ws /= ws.sum(0)
Epoch
```

```
xs = np.linspace(astars.min()-5e-3, astars.max()+5e-3, 5000)
ys = np.linspace(bstars.min()-5e-3, bstars.max()+5e-3, 5000)
```

Under class ExpectationMaximization is the def train that will try our machine. It will become easier right after this. We 'concatenate' three strings to append one string to the end of another. For this, we concatenate the three fruits for a and b. We stack them together through np.column\_stacks.

We apply np.meshgrid xs and xy then np.vstack the values from it. We can then plot the first column of features of the fruit versus the second column of it. We can superimposed the maximization and the points which will be show in the next slide.

#### **Expectation Maximization**

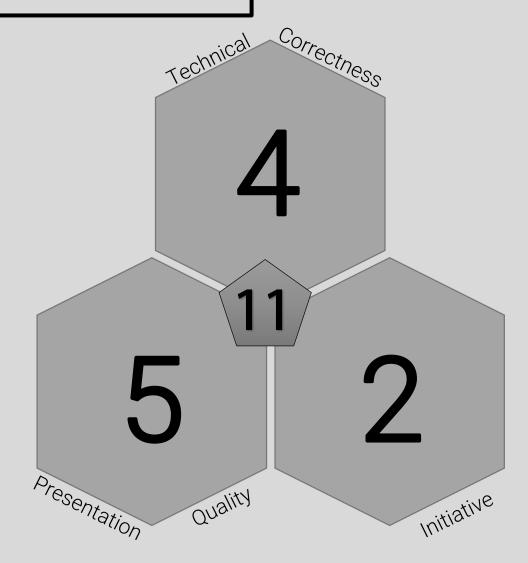


## Summary

I was able to pull it off but only for one fruit. It is still a mystery to me as to why it's not showing for the other fruits. This problem is something to look in the future to learn more about the topic also. Thank you to some of my classmates who helped me along the way.

All in all, it was frustrating to do it. But since there are two deadlines to beat for 186 this week, I can't give full time attention to this. Though it was a good learning.

# Self-Evaluation



# References

• Soriano, M., "Expectation Maximization". 2019