

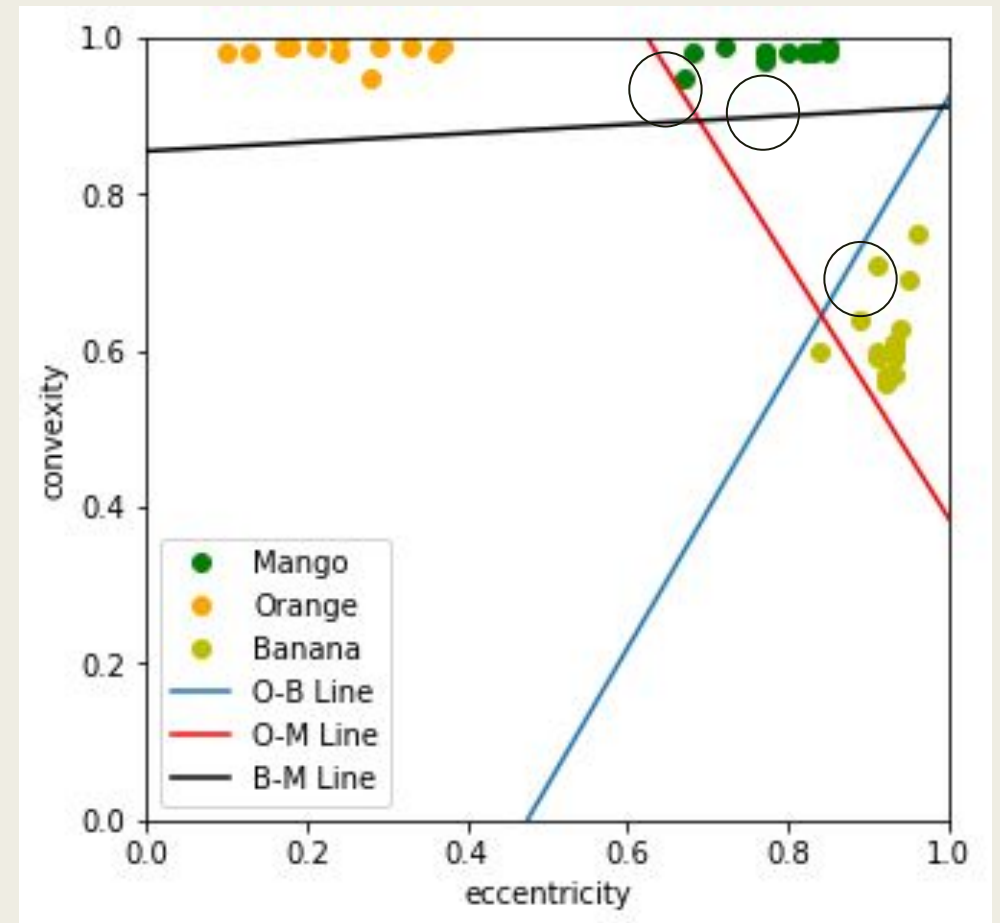


Support Vector Machines



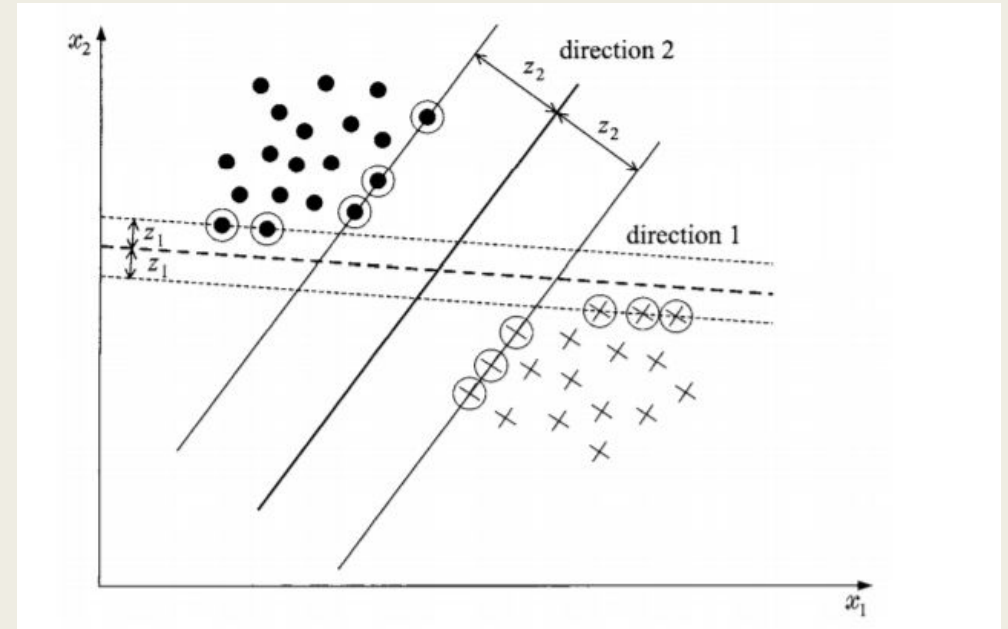
Objective

- In perceptron algorithm, the decision line is not optimal to split between 2 clusters thus we use support vector machines to find the optimal decision to split between 2 clusters.



Overview: Support Vector Machines

- In perceptron algorithm, the decision line is not optimal to split between 2 clusters.
- In support vector machines to find the optimal decision to split between 2 clusters using points the are close to the expected boundaries as shown in this image.
- We wish to maximize the margin z_1 or z_2 .



In this case there are two possible directions that the decision line can optimally split either horizontally looking at points close to the horizontal boundary or vertically with points close to the 'vertical' boundary.

Overview: Optimal Hyperplane

- Using the equation shown in the image we wish to maximize the margin using a vector α .
- Where α is the optimized solution, z_i are the values that identify what cluster a sample belongs and x_i are the sample values.
- The equations can be fitted in to this form [bottom image] for quadratic programming where for N samples H , A and B are $N \times N$ matrices while f , a and b are N length vectors.

$$\begin{aligned} \text{maximize} \quad & L_D(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n \alpha_i \alpha_j z_i z_j x_i^t x_j \\ \text{constrained to} \quad & \alpha_i \geq 0 \quad \forall i \quad \text{and} \quad \sum_{i=1}^n \alpha_i z_i = 0 \end{aligned}$$

Quadratic fcn the find a solution for α

$$\begin{aligned} \text{minimize} \quad & L_D(\alpha) = 0.5 \alpha^t H \alpha + f^t \alpha \\ \text{constrained to} \quad & A \alpha \leq a \quad \text{and} \quad B \alpha = b \end{aligned}$$

Equivalent eqns. for quadratic programming

Step 0: Initializing variables

- Data used: fruits data (bananas, mangoes oranges) using their eccentricity and convexity features.
- \mathbf{x} is a matrix the piles 2 fruits data with their respective features in a $N \times 2$ array.
- \mathbf{z} is a vector that collects all \mathbf{z}_i values (ex. 1 for bananas, -1 for mangoes)
- $\mathbf{H} = (\mathbf{x} * \mathbf{x}') . * (\mathbf{z} * \mathbf{z}')$
- \mathbf{f} is a N length vector with all values of -1
- \mathbf{a} and \mathbf{b} are N length vectors with all values of 0
- \mathbf{A} is a $N \times N$ identity matrix
- \mathbf{B} is a $N \times N$ matrix where the first row is the vector \mathbf{z} while the rest are 0.

Step 1: Using the α

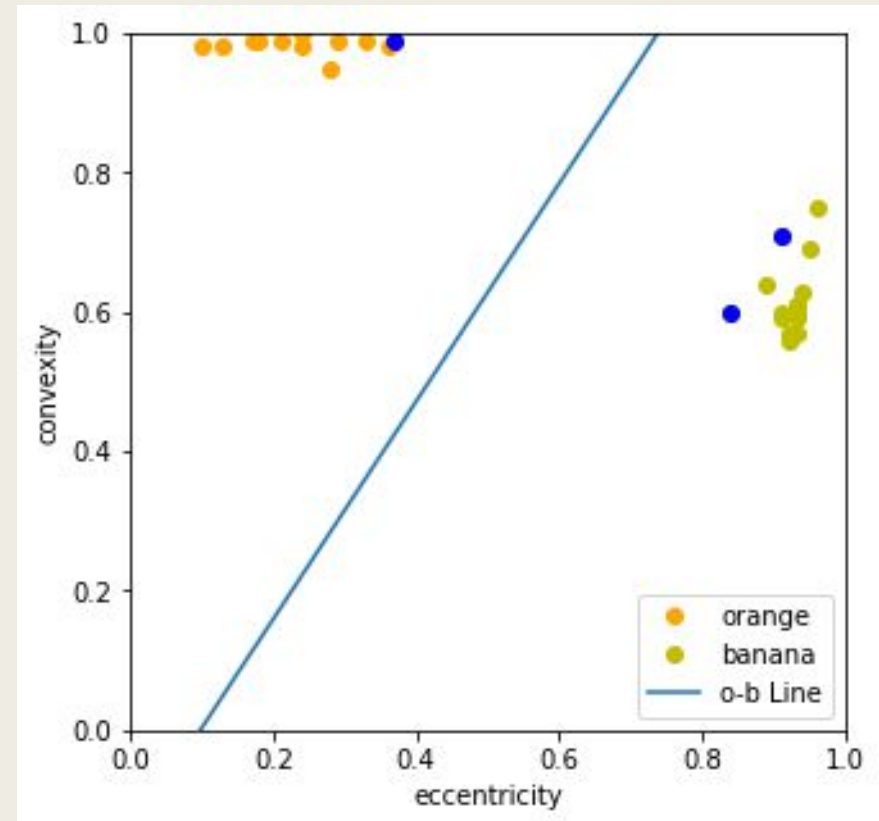
- I used qpsolvers' **solve_qp()** for the quadratic programming.
- When applying the quadratic programming a length N α vector was resulted. There are values that are not close to 0 thus those samples represent the **support vectors**.
- \mathbf{w} is a m length vector that represents the weights per feature used.
- \mathbf{w}_0 can be solved using \mathbf{x}_1 , a support vector.

$$\mathbf{w} = \sum_{i=1}^n \alpha_i \mathbf{z}_i \mathbf{x}_i = (\alpha . * \mathbf{z})^t \mathbf{x}$$

$$w_0 = \frac{1}{z_1} - \mathbf{w}^t \mathbf{x}_1$$

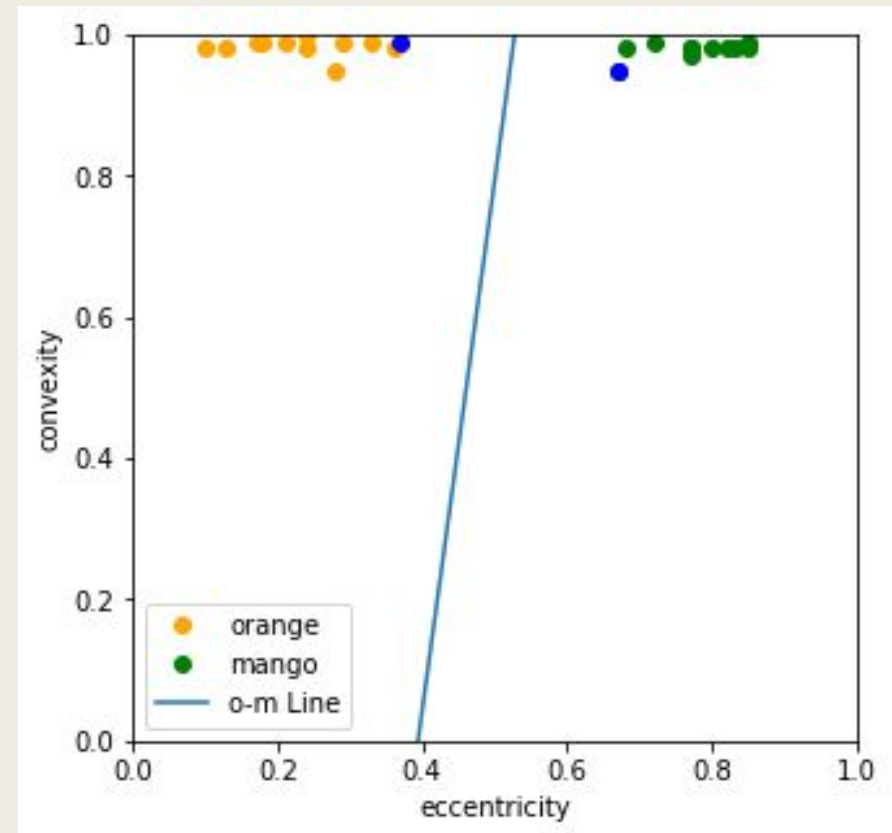
Results: Orange vs Banana

- Using the data of orange and banana, the algorithm found an optimized decision line using 3 support vectors (in blue).



Results: Orange vs Mango

- Using the data of orange and banana, the algorithm found an optimized decision line using 2 support vectors (in blue).



Results: Banana vs Mango

- Using the data of orange and banana, the algorithm found an optimized decision line using 2 support vectors (in blue).

