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JBCA mlCon

K-Means and Support Vector Machines

Introduction and examples
13th of November 2018

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Part I

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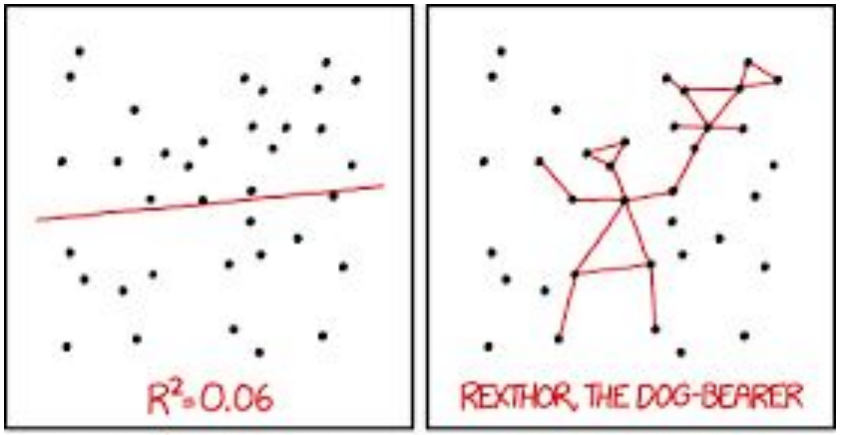
What kind of problem do I have?

OR



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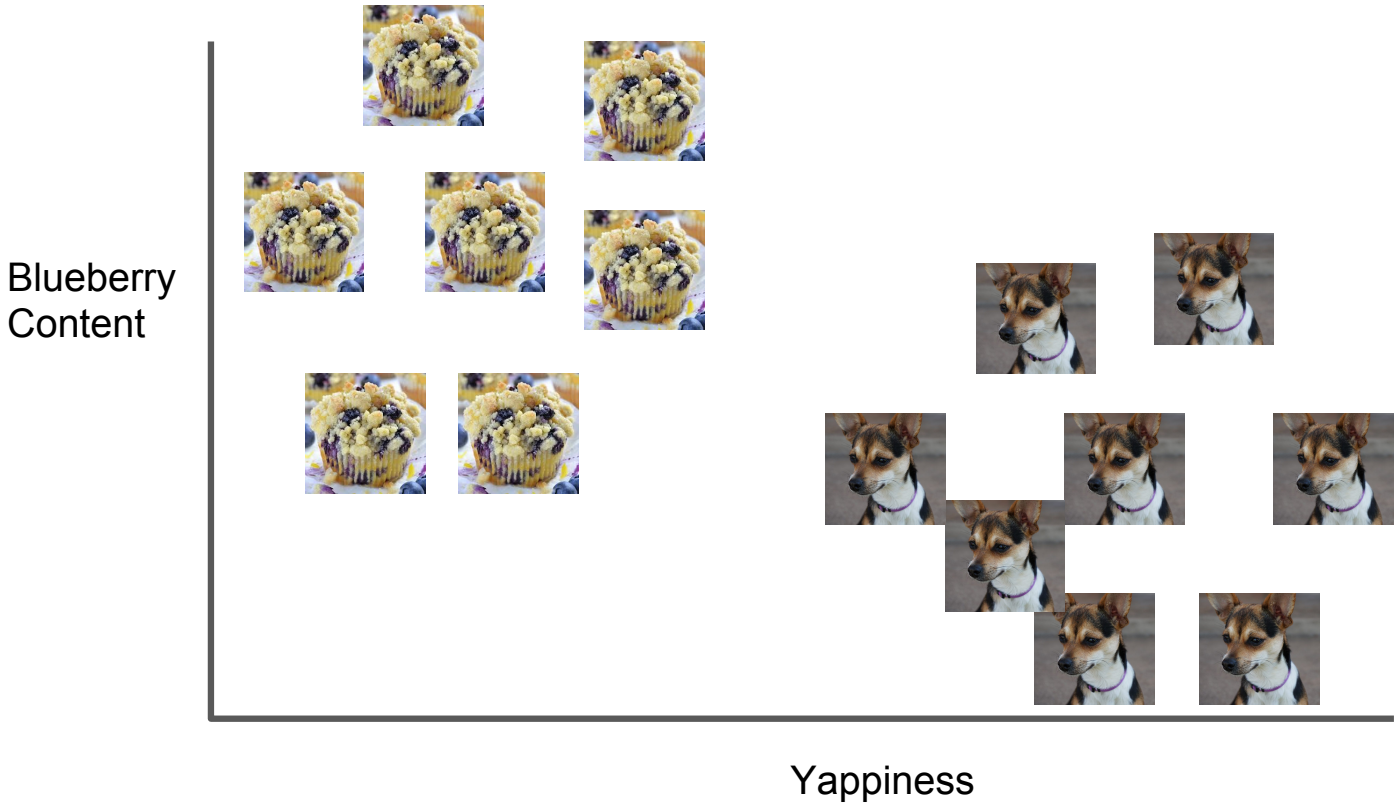
Classification Problems



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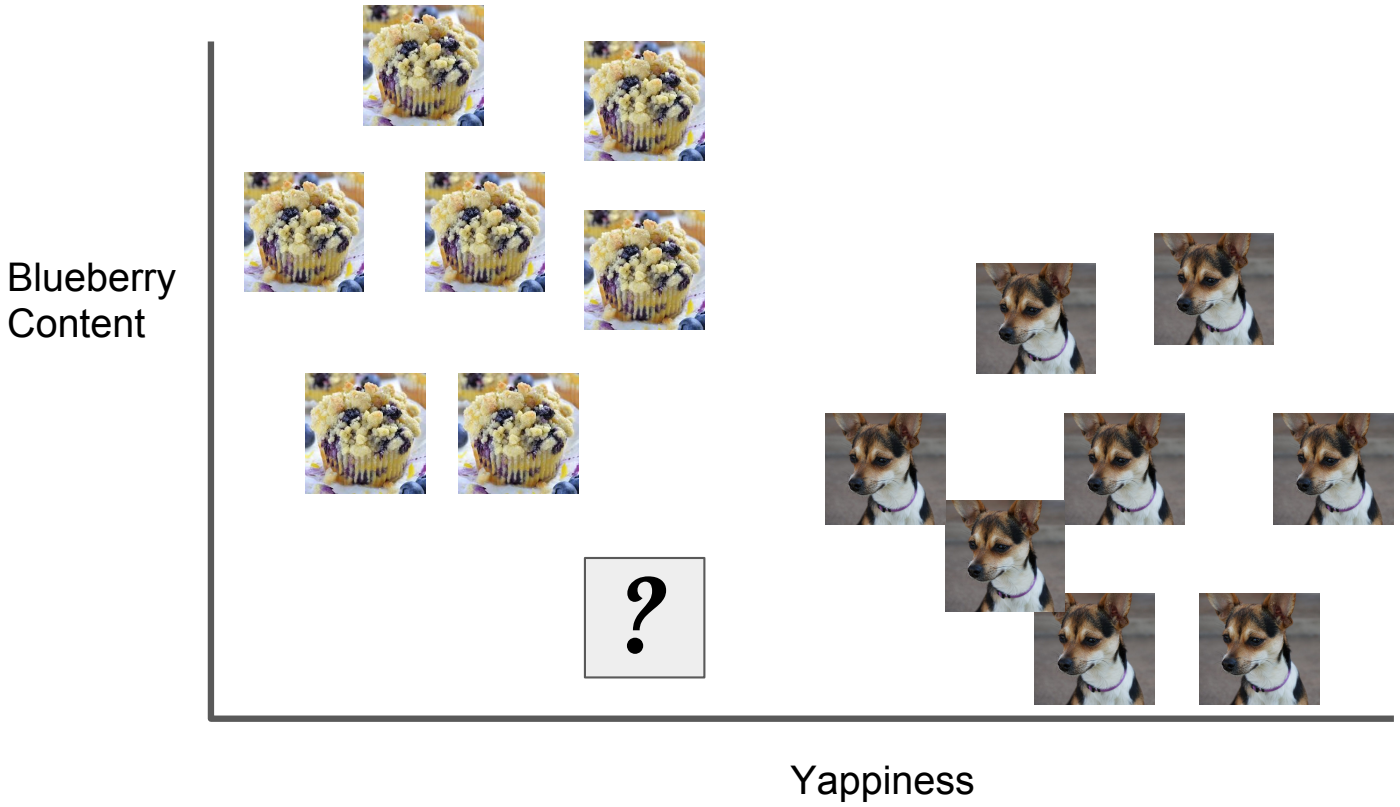
Classification Problems



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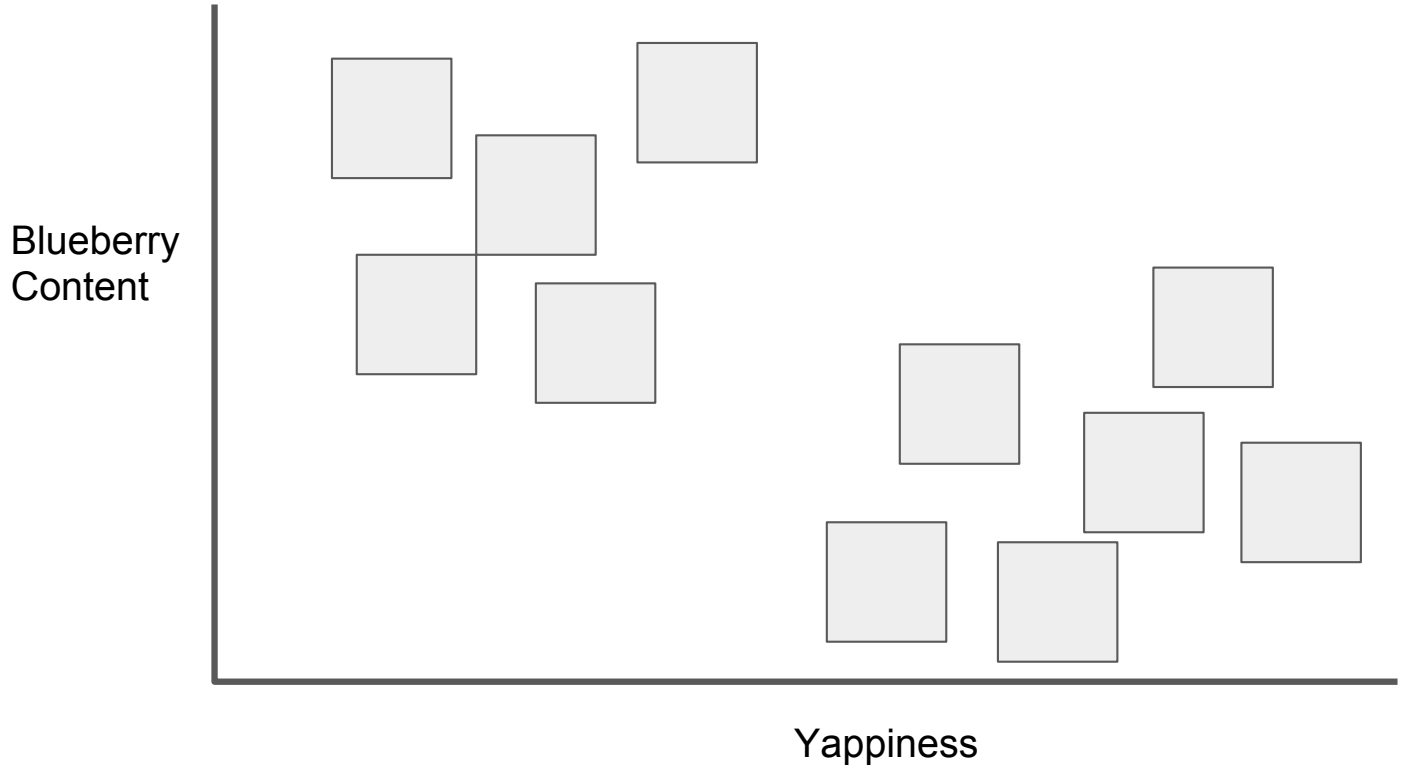
What if we have no training data?



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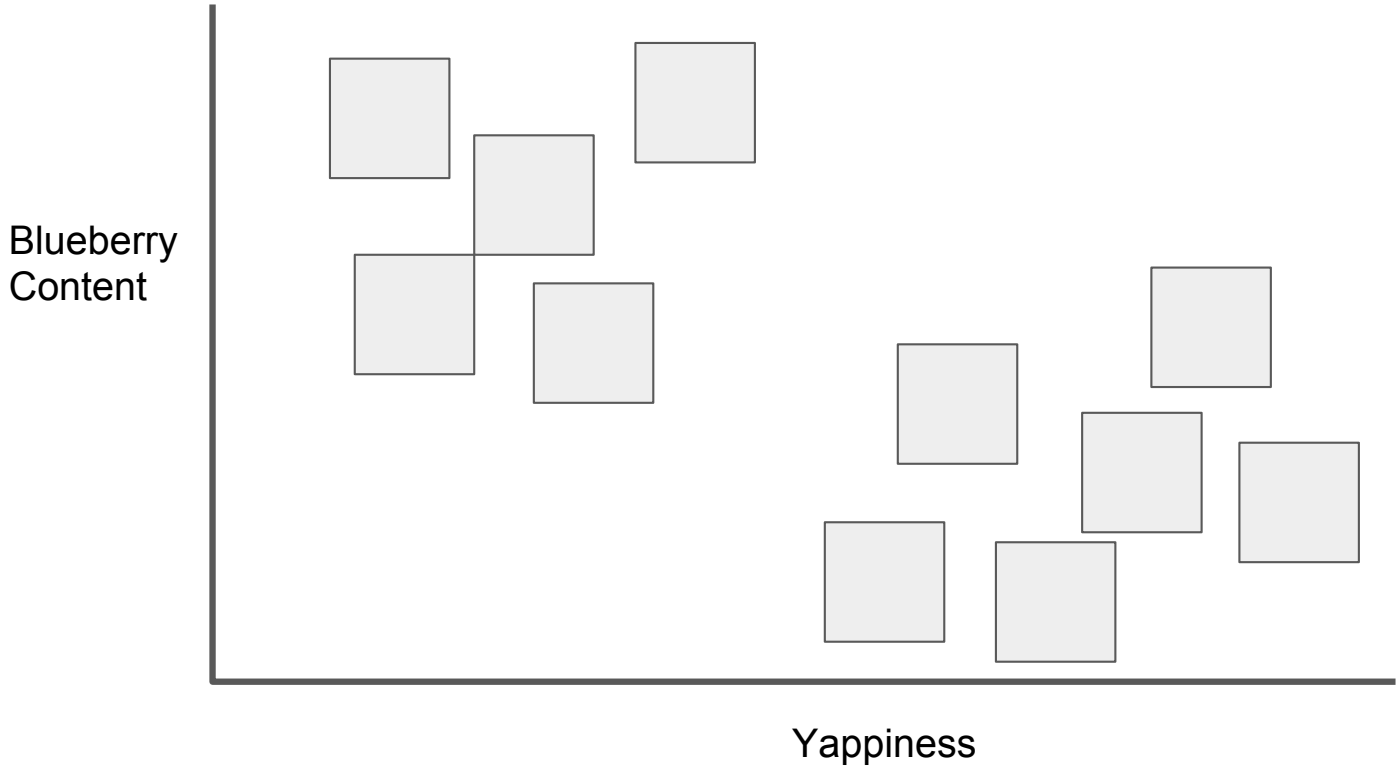
What if we have no model?

Intuitions: We know that there are two types of thing represented in the data



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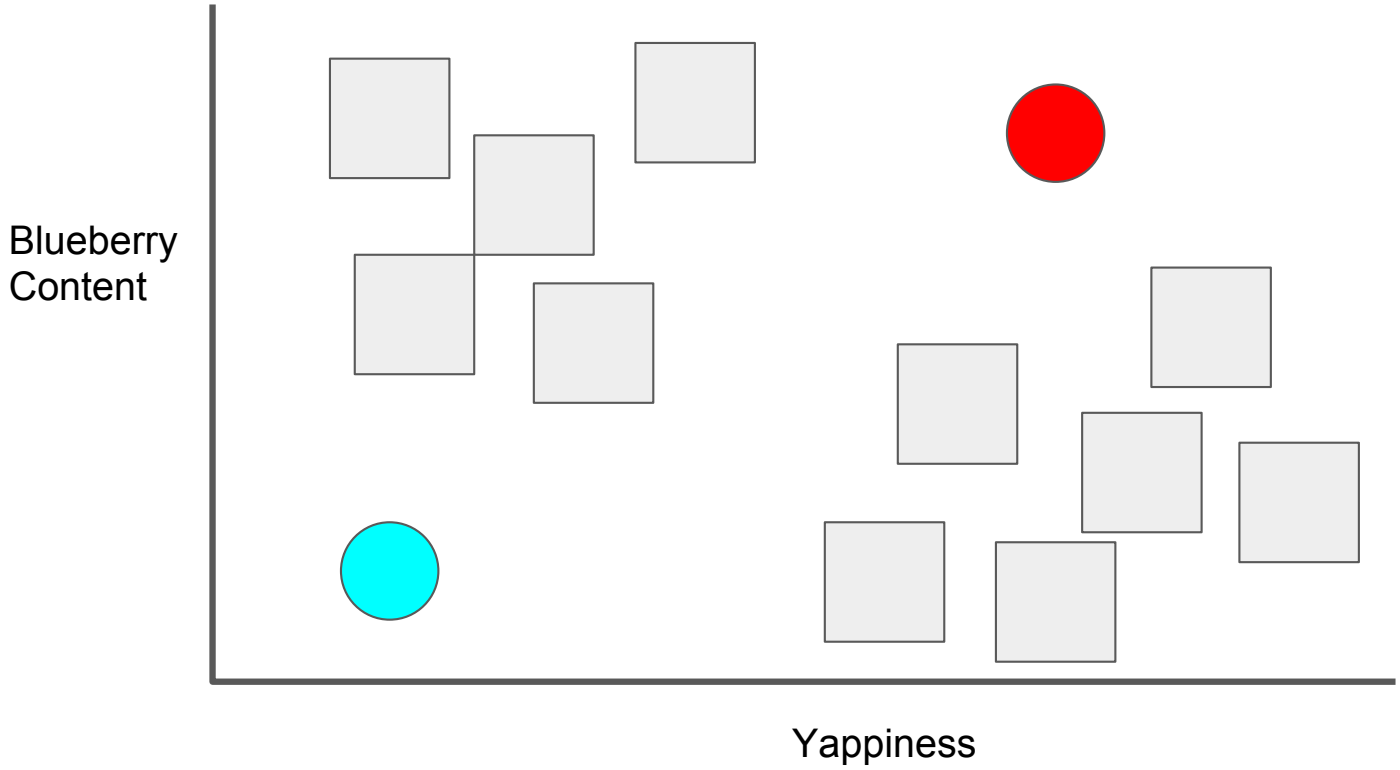

Algorithm:

1. Pick some random centre points in our parameter space

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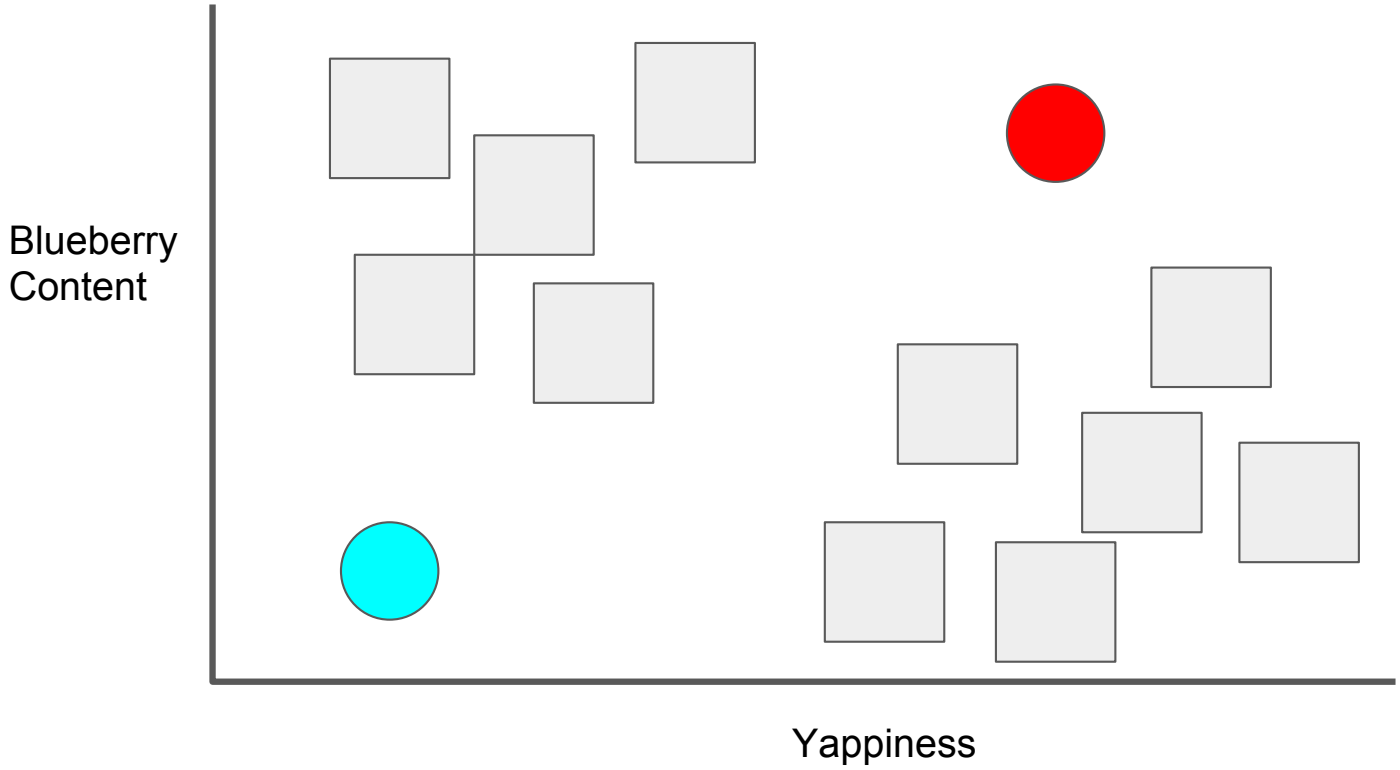

Algorithm:

1. Pick some random centre points in our parameter space
2. Calculate distance between all data and all centre points

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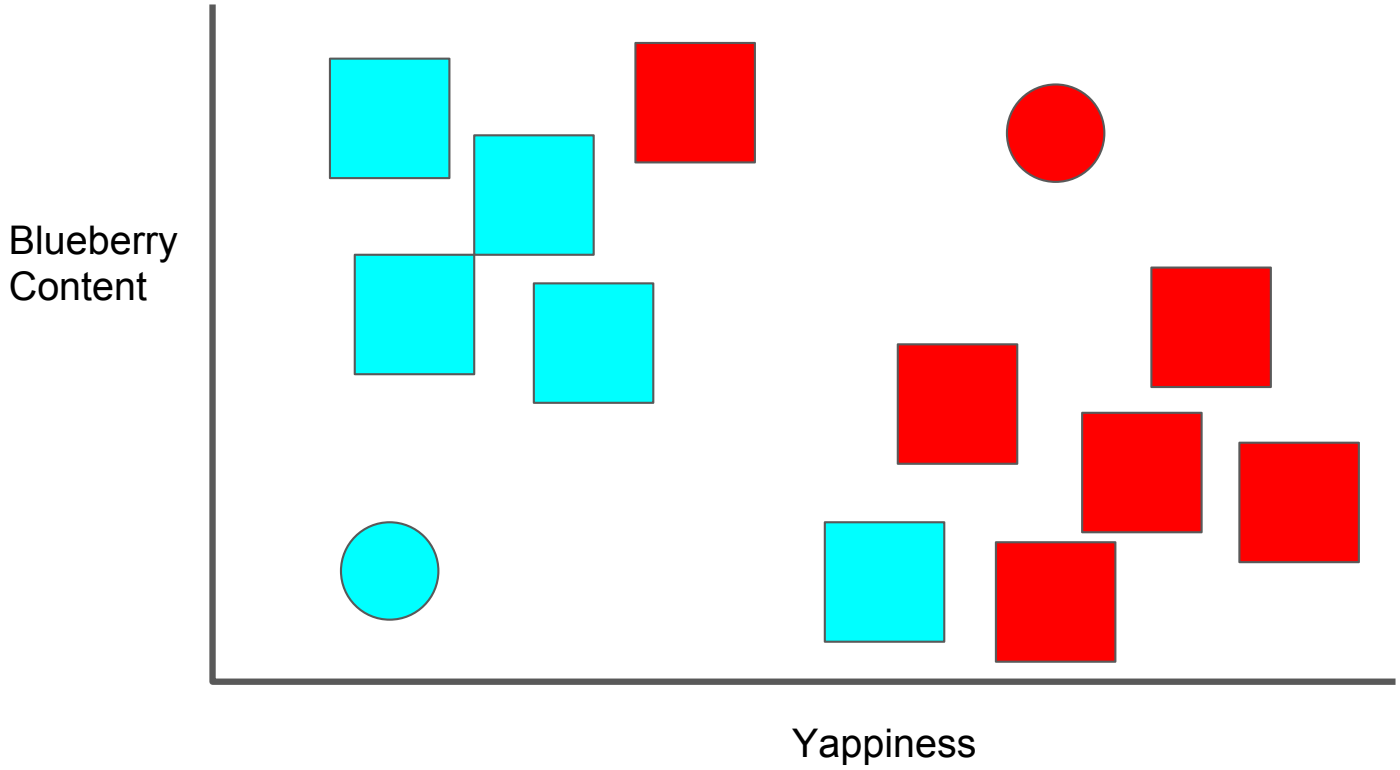

Algorithm:

1. Pick some random centre points in our parameter space
2. Calculate distance between all data and all centre points
3. Assign every datum to a centre point

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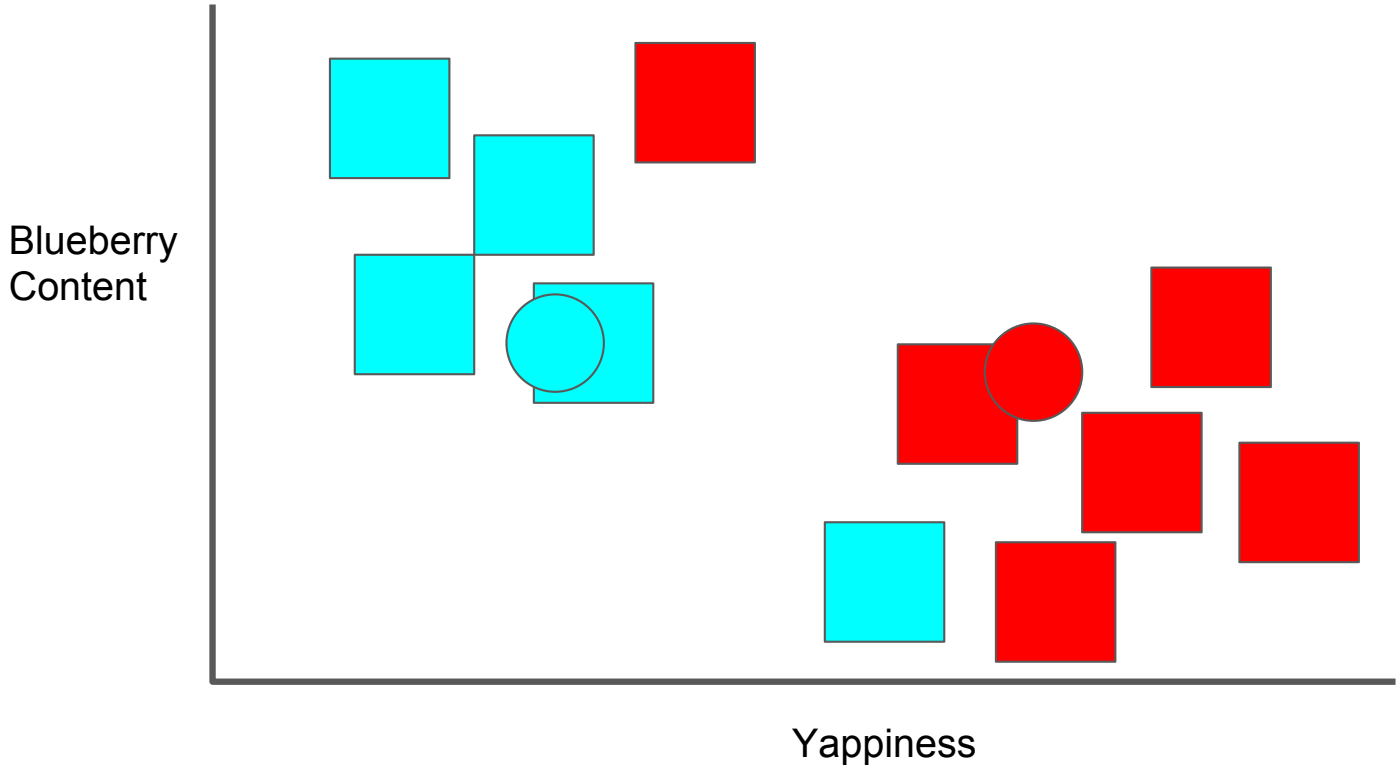

Algorithm:

1. Pick some random centre points in our parameter space
2. Calculate distance between all data and all centre points
3. Assign every datum to a centre point
4. Set centre points to means of each cluster

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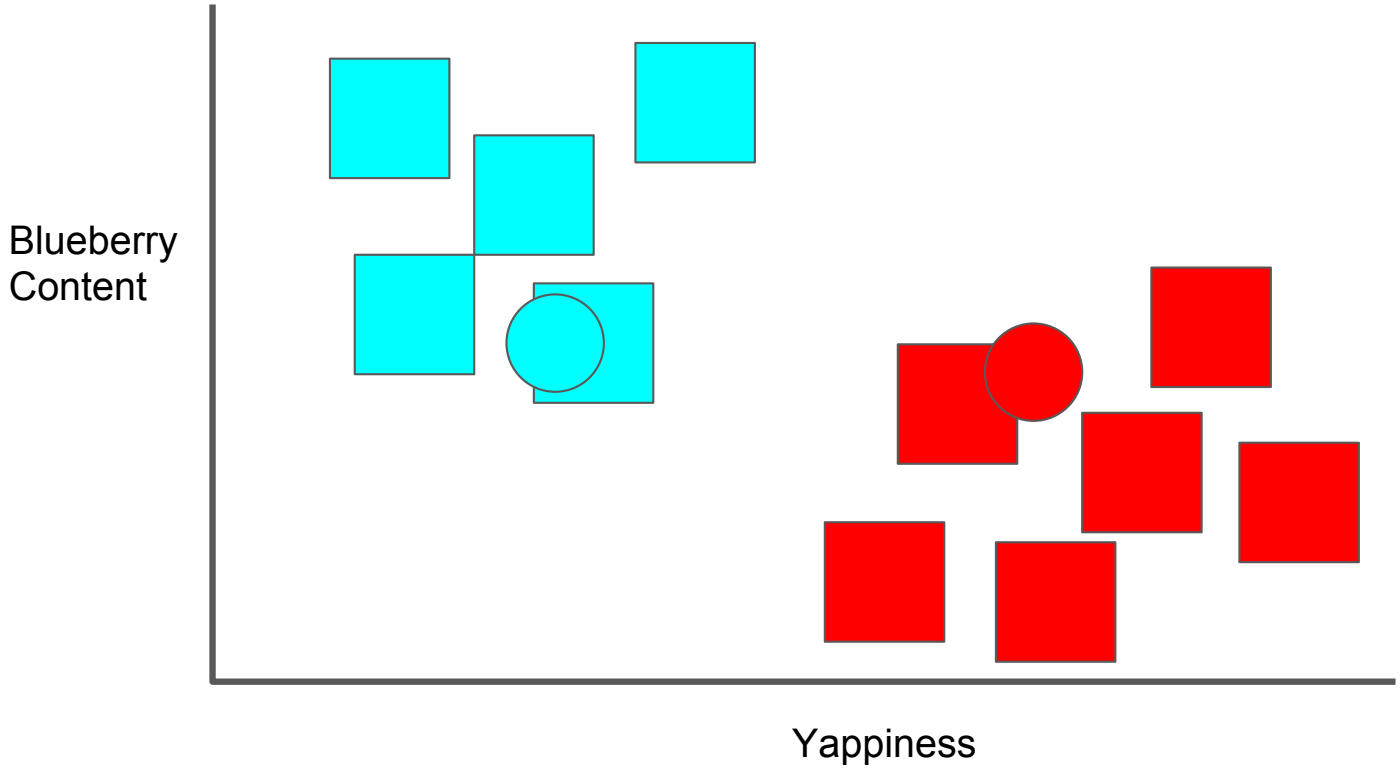
Intuitions: We know that there are two types of thing represented in the data



Algorithm:

1. Pick some random centre points in our parameter space
2. Calculate distance between all data and all centre points
3. Assign every datum to a centre point
4. Set centre points to means of each cluster
5. Repeat

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What if we have no model?

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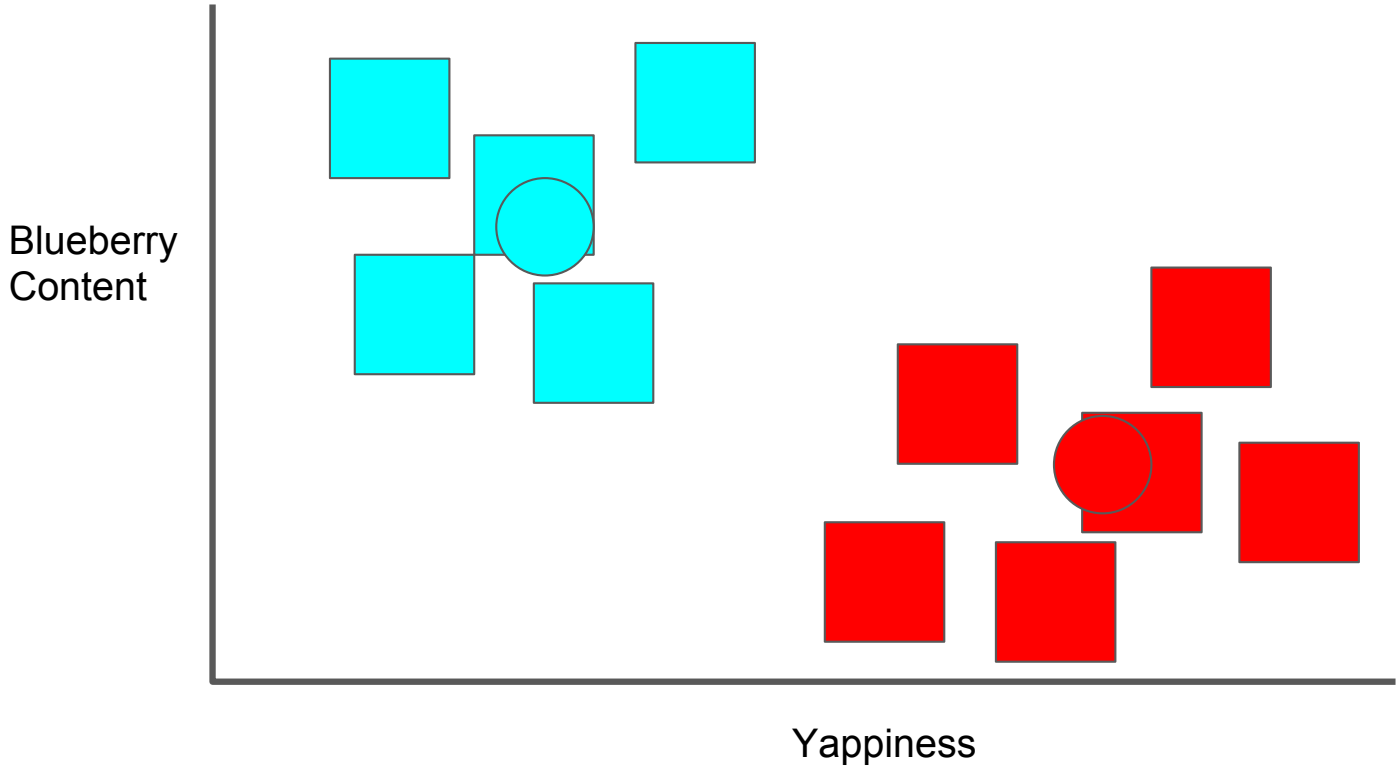

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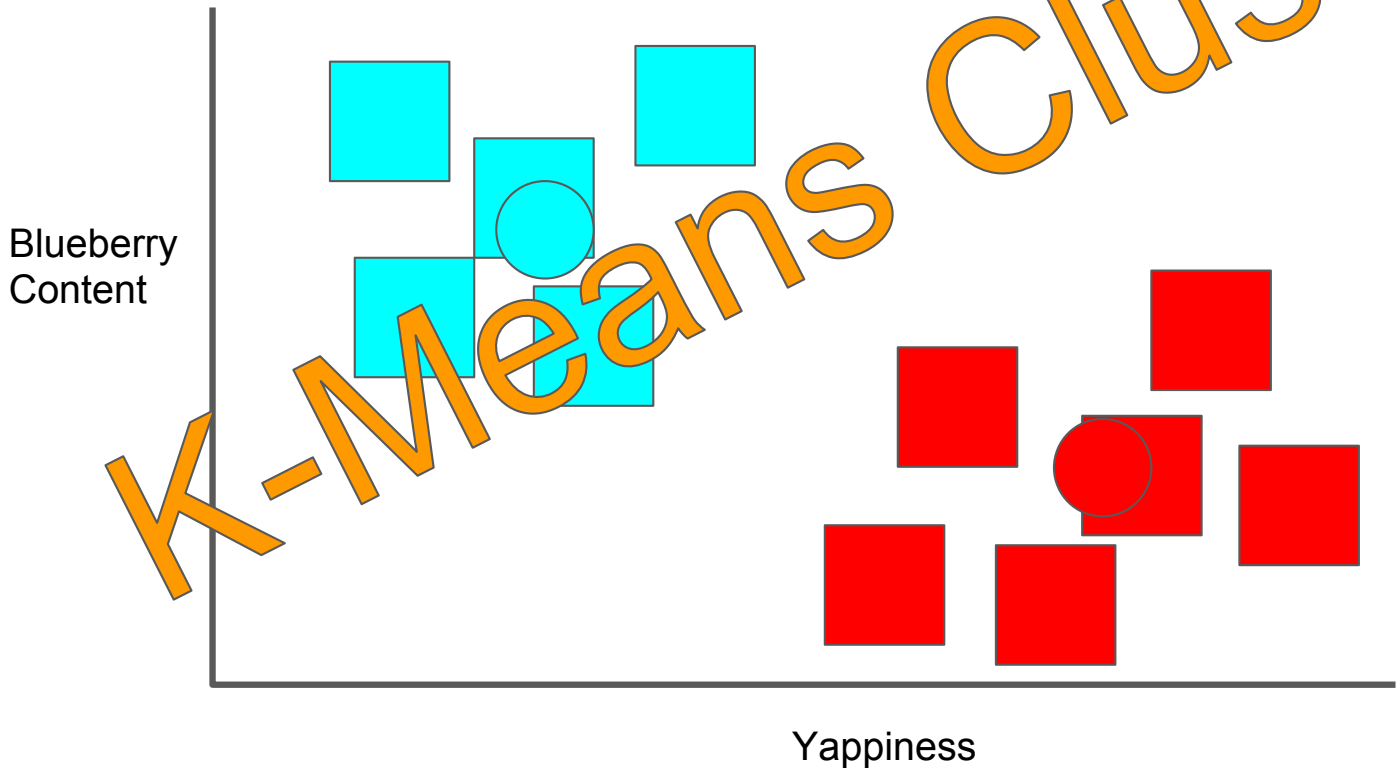

K-Means Clustering

Algorithm:

1. Pick some random centre points in our parameter space
2. Calculate distance between all data and all centre points
3. Assign every datum to a centre point
4. Set centre points to means of each cluster
5. Repeat

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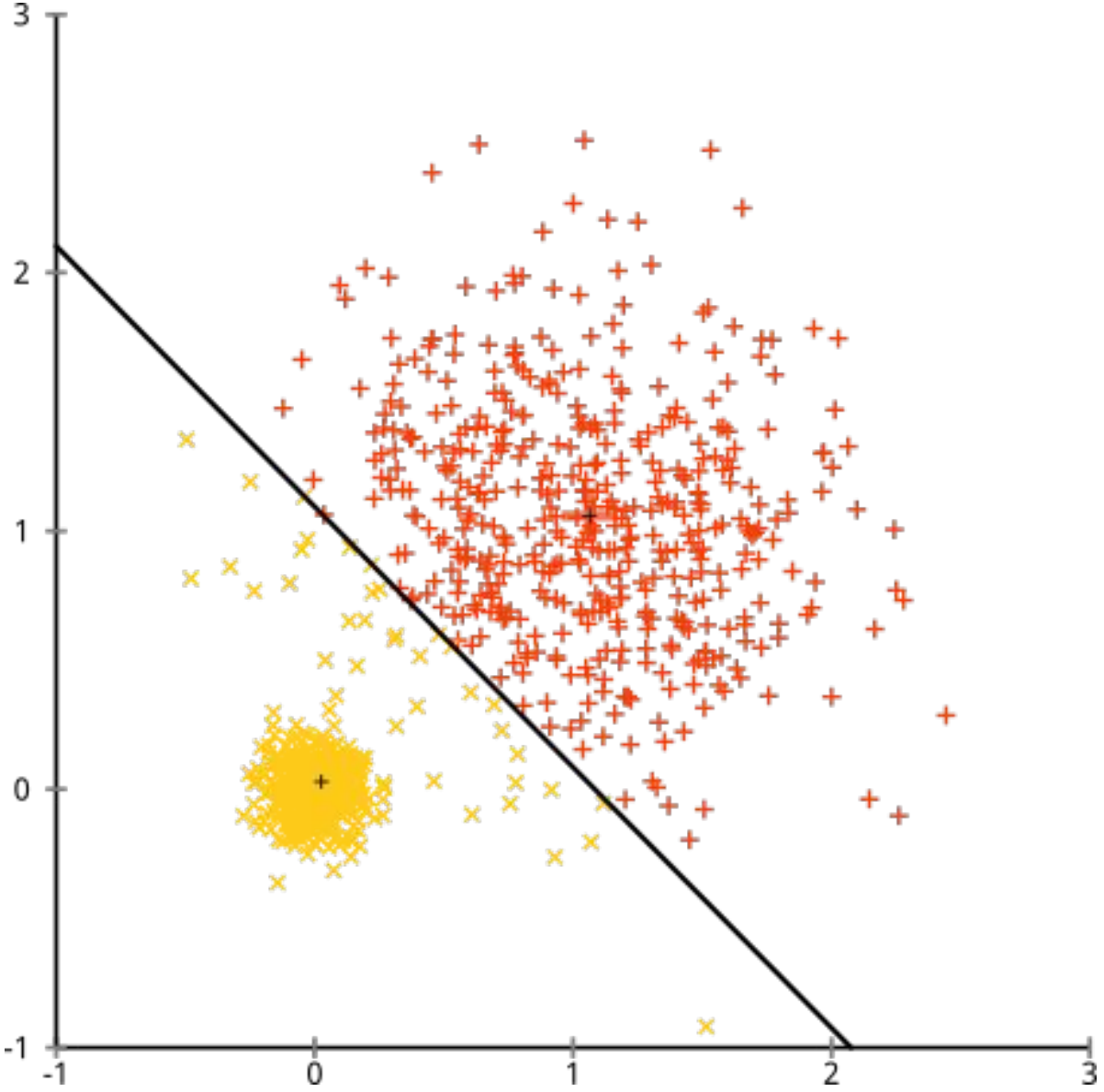
https://stats.stackexchange.com/questions/133656/how-to-understand-the-drawbacks-of-k-means?answertab=oldest#tab-top

K-Means issue #1

Sensitive to scale

Performs badly where parameters have differing variance



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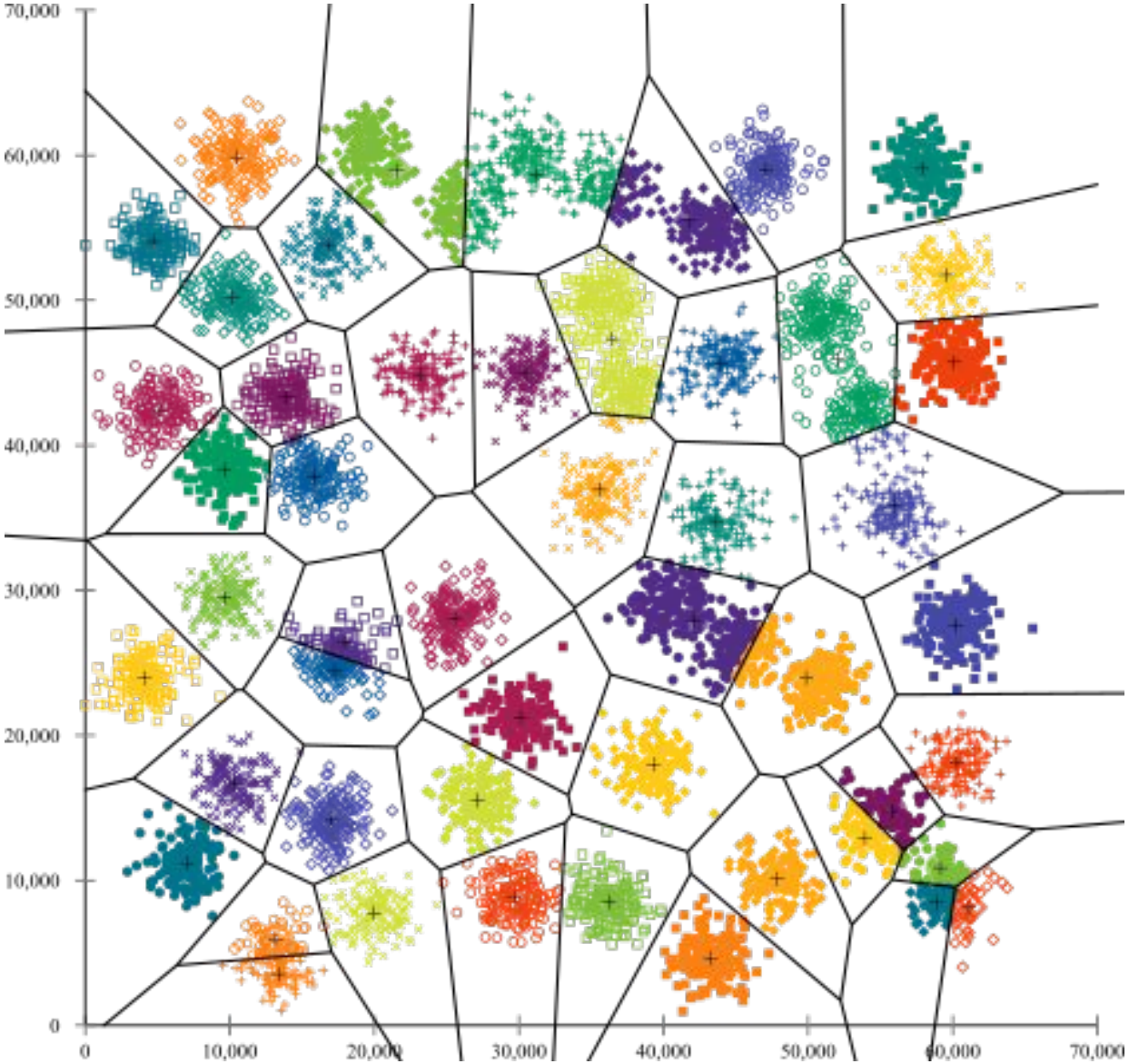
K-Means issue #2

Local Minima

Can be improved using KMeans++



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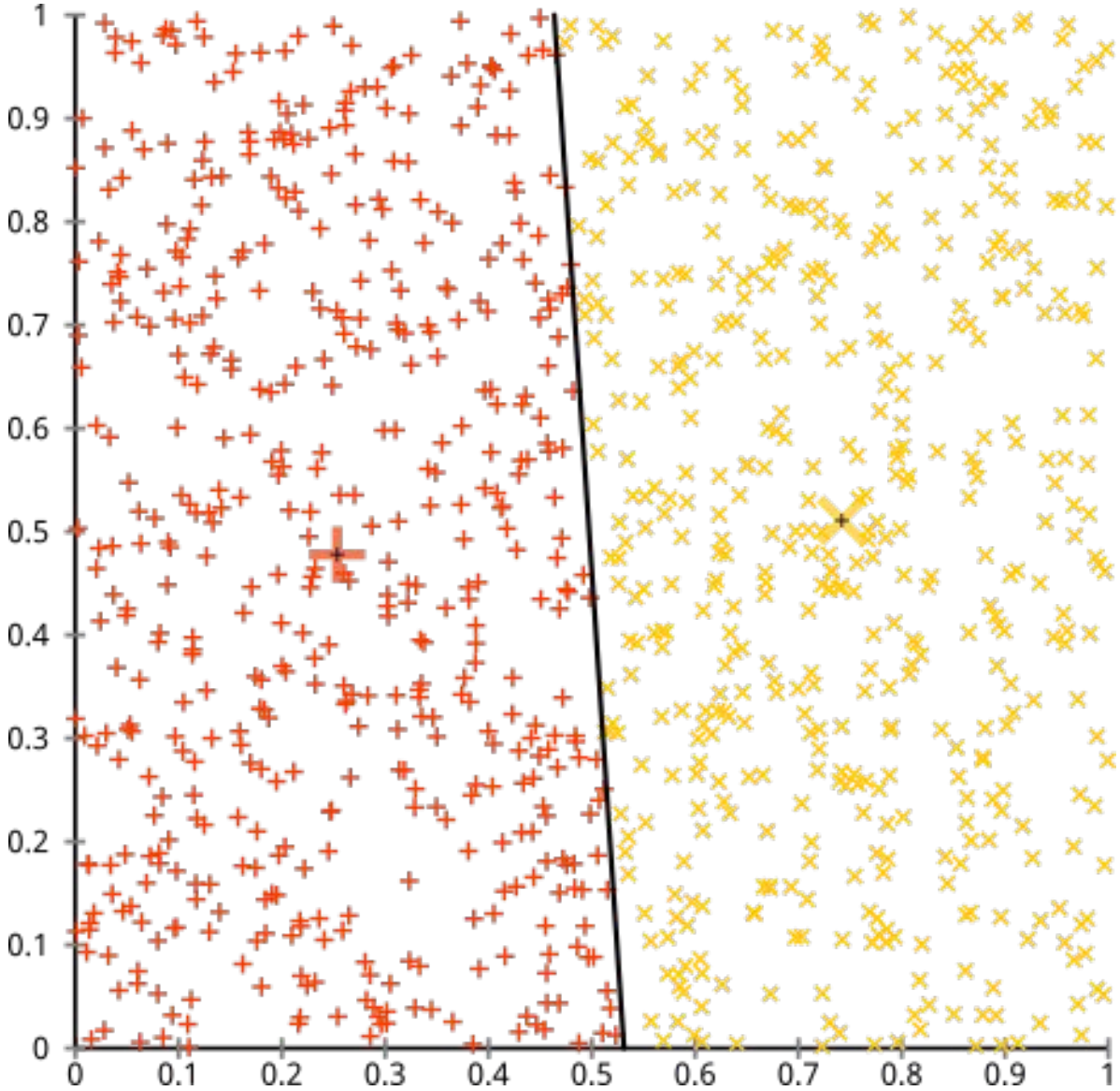
K-Means issue #3

It will cluster non-clustered data



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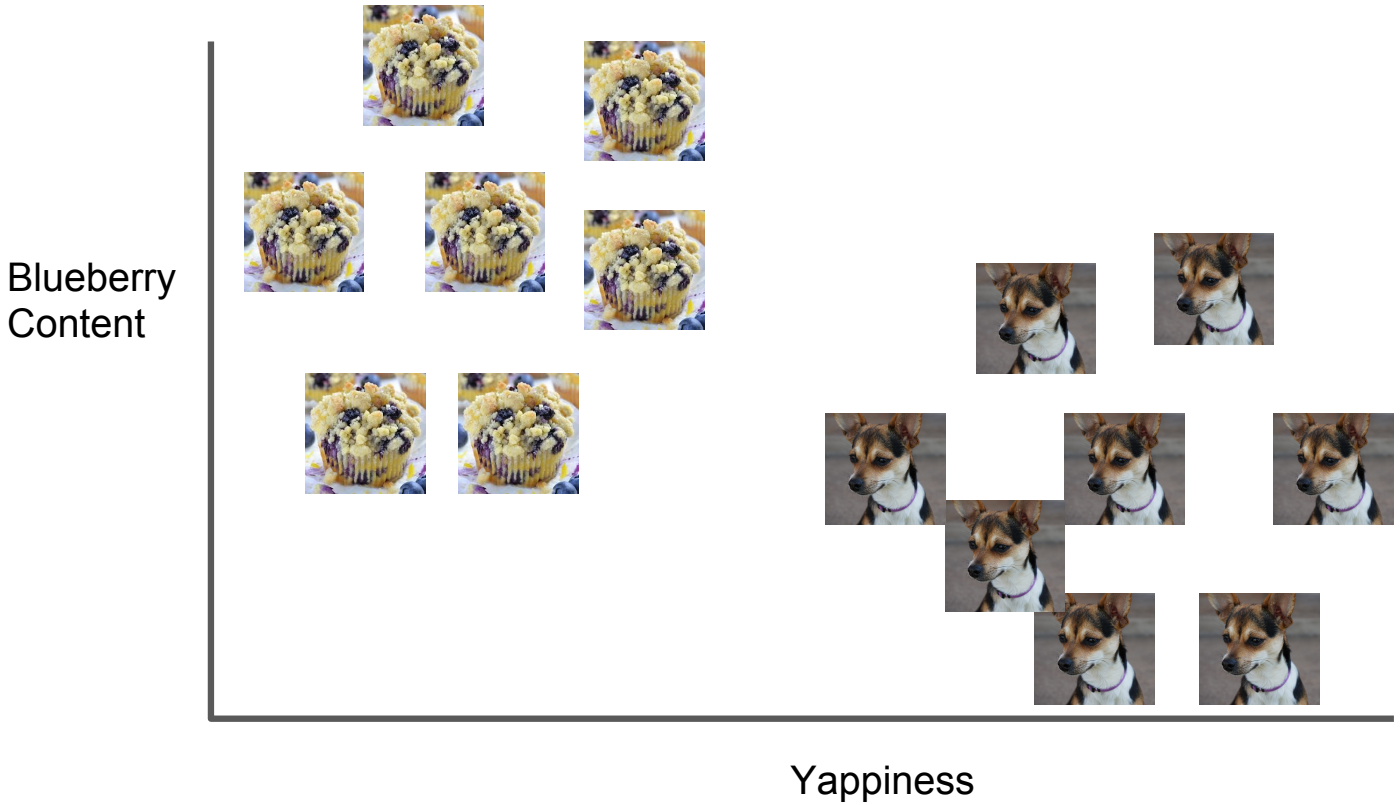
But what if we have a training set?



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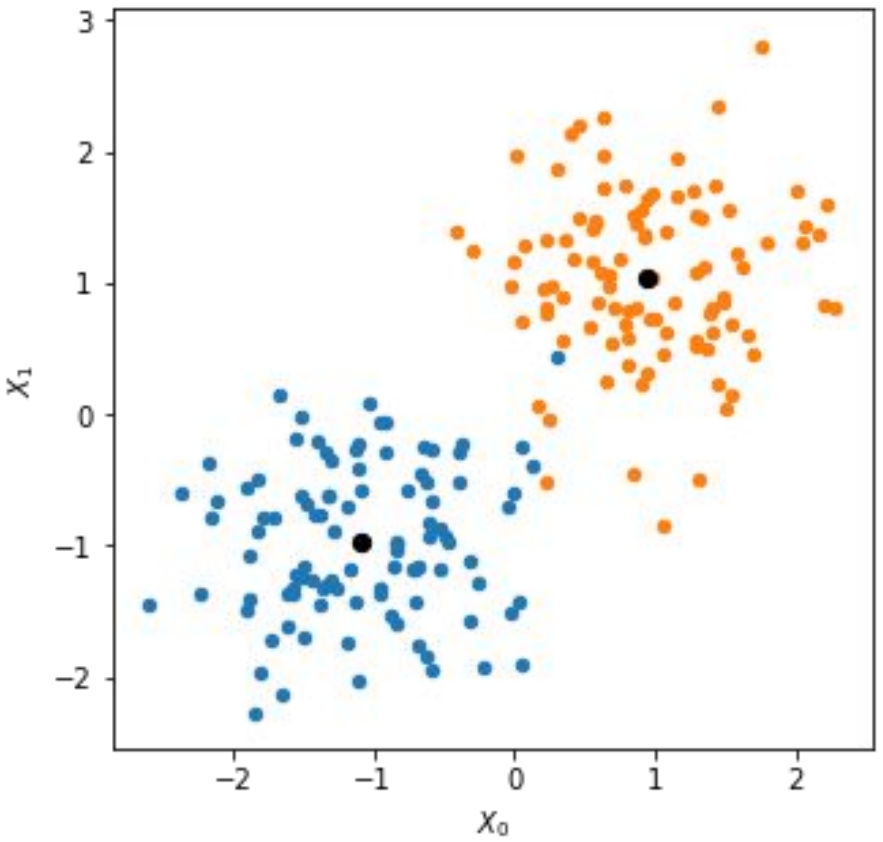
Simple approach?

- Calculate the arithmetic mean of each class
- Classify a new point by calculating the distance to each mean point and finding the minimum geometric distance



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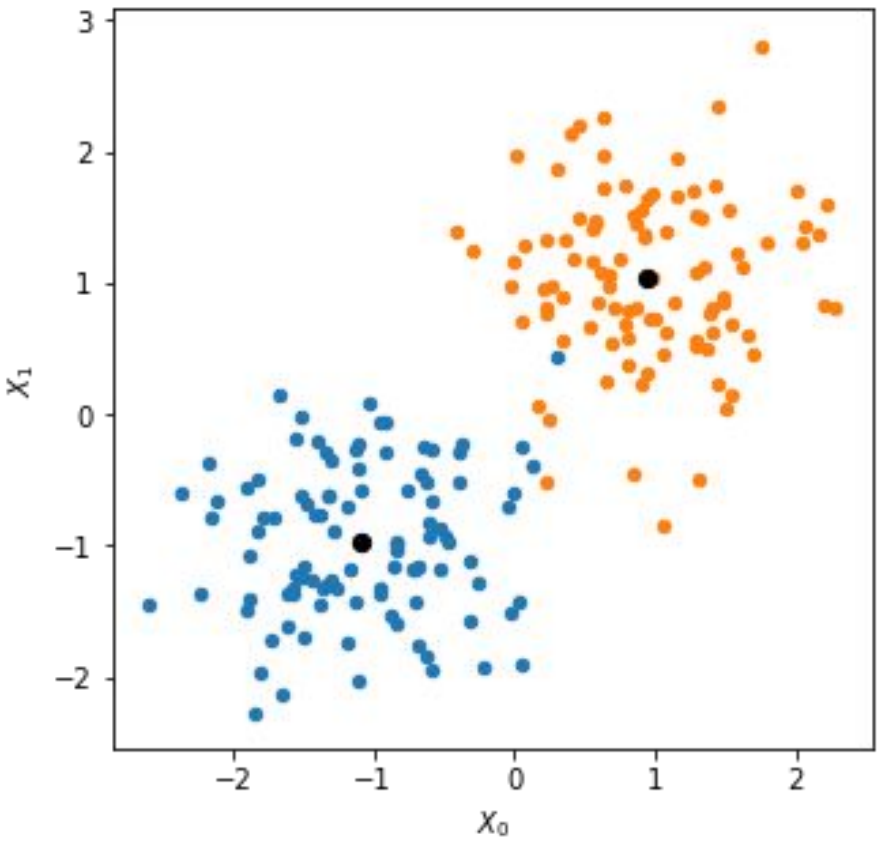
Simple approach?

- Calculate the arithmetic mean of each class
- Classify a new point by calculating the distance to each mean point and finding the minimum geometric distance
- **But this only holds if our parameters are normally distributed**



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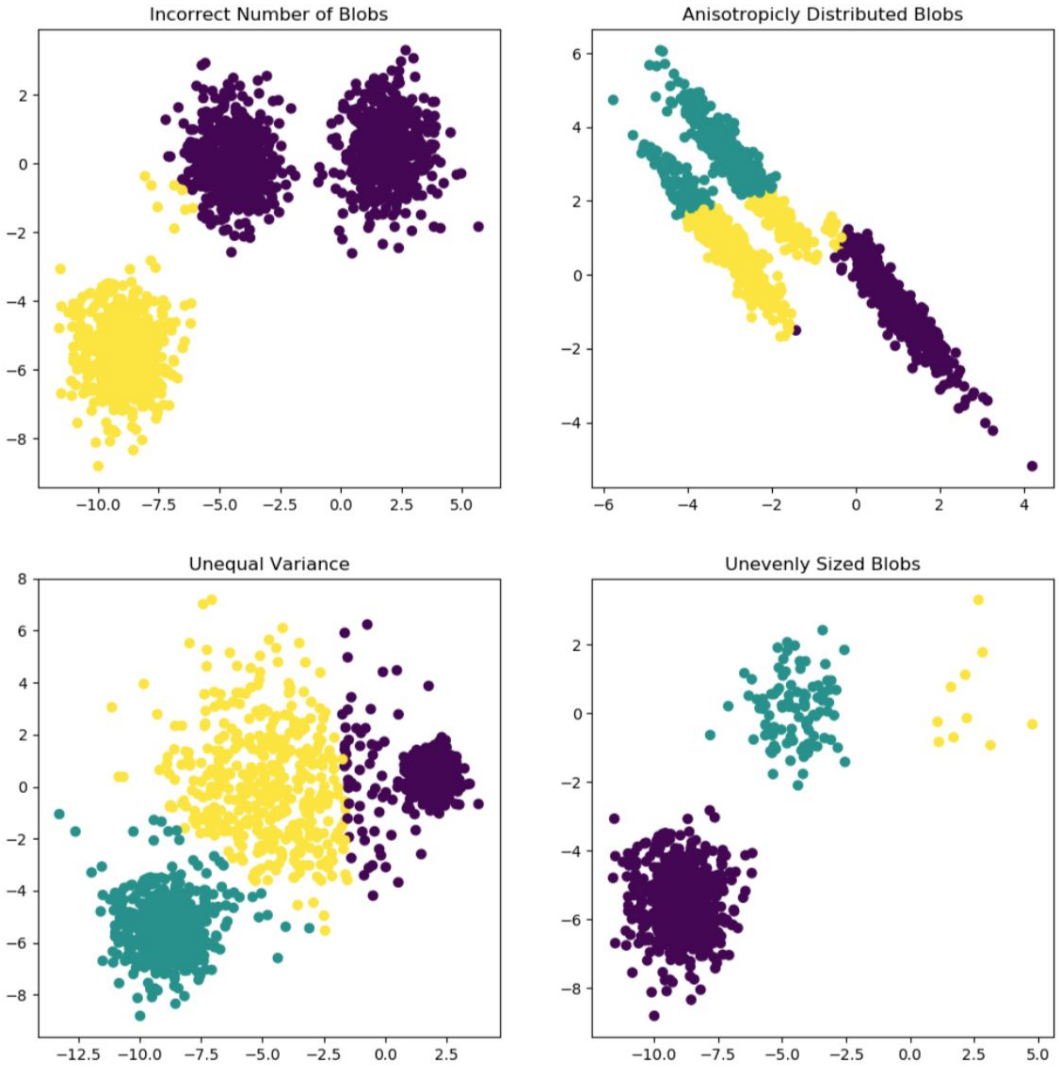
Simple approach?



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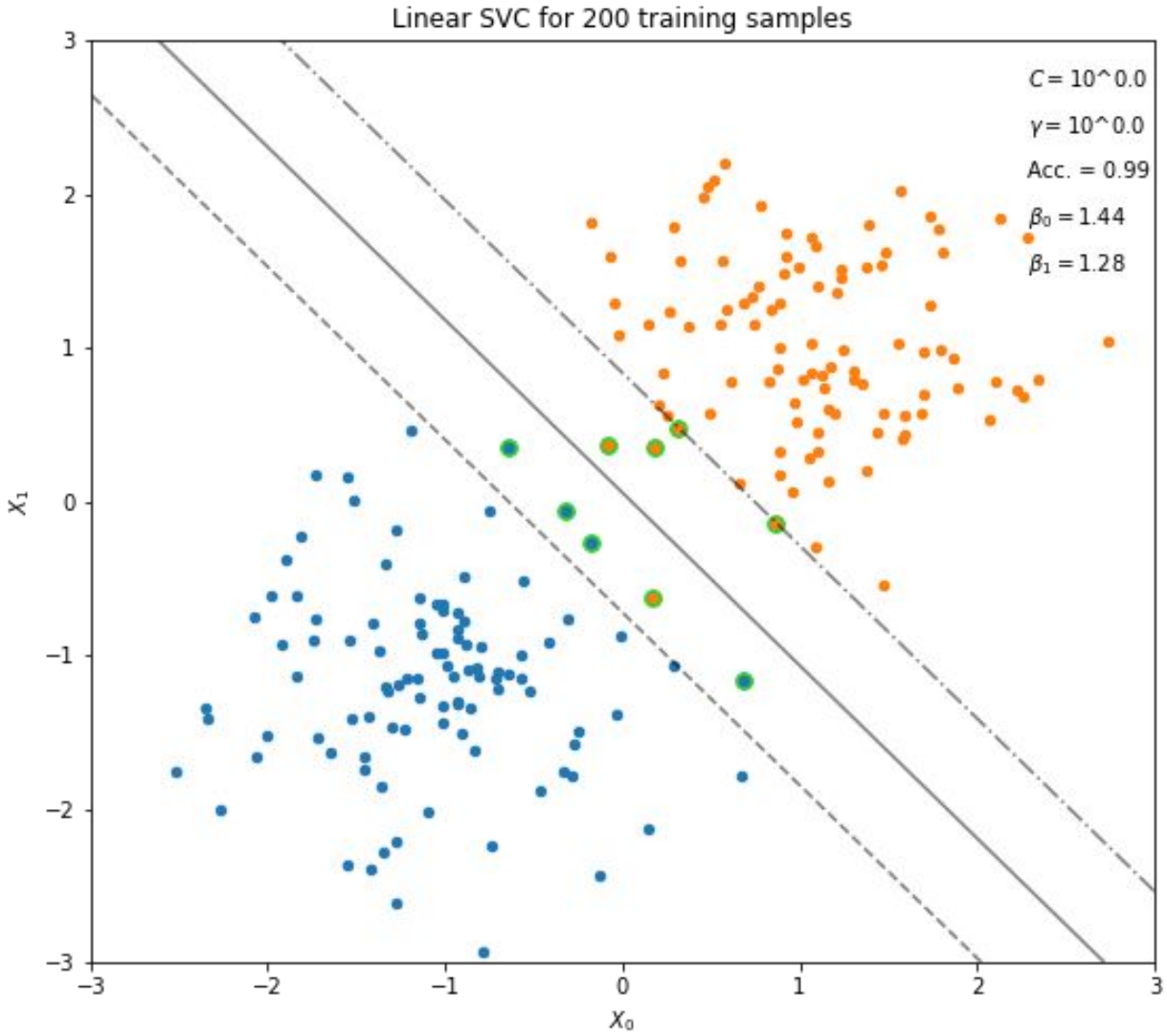
A solution?

Instead of finding the centres of the cluster, let's focus our efforts on finding margins



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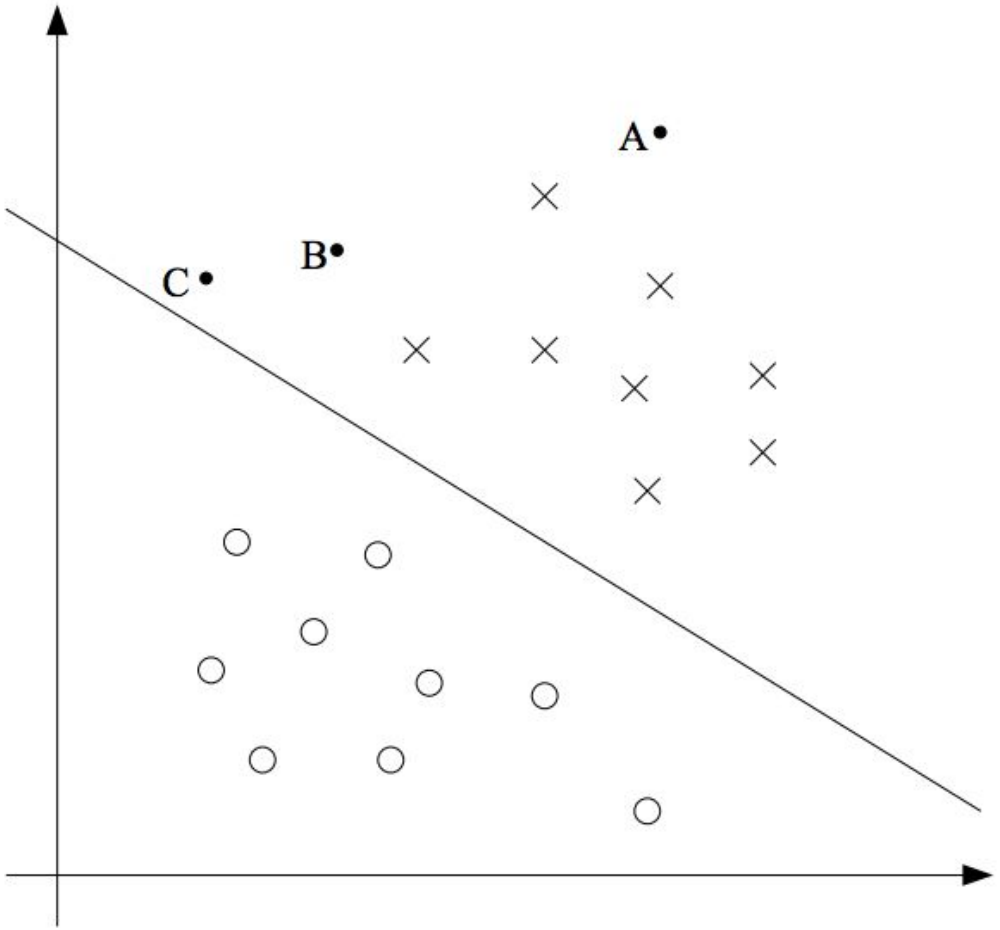
A new intuition



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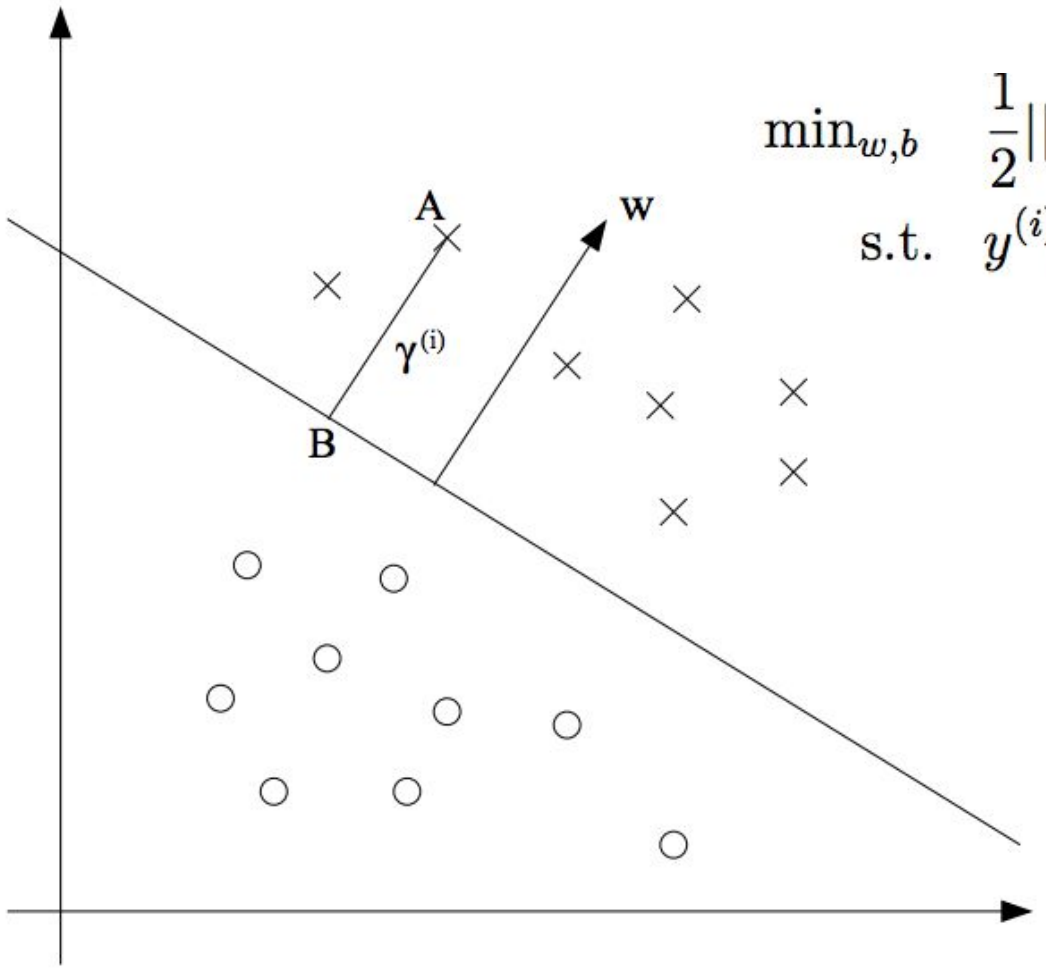
SVM

$$\max_{\gamma,w,b} \quad \gamma$$
$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq \gamma, \quad i = 1, \ldots, m$$
$$||w|| = 1.$$



$$\min_{w,b} \quad \frac{1}{2}||w||^2$$
$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq 1, \quad i = 1, \ldots, m$$

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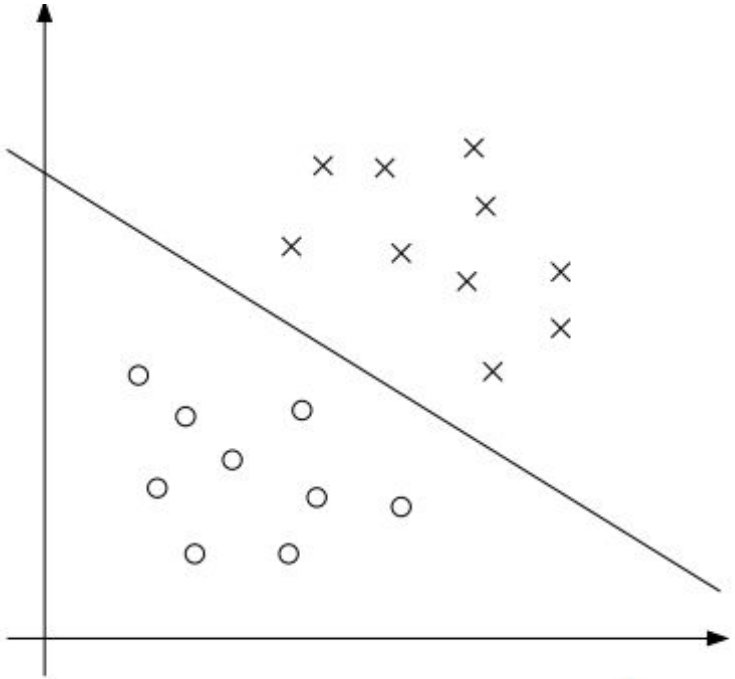
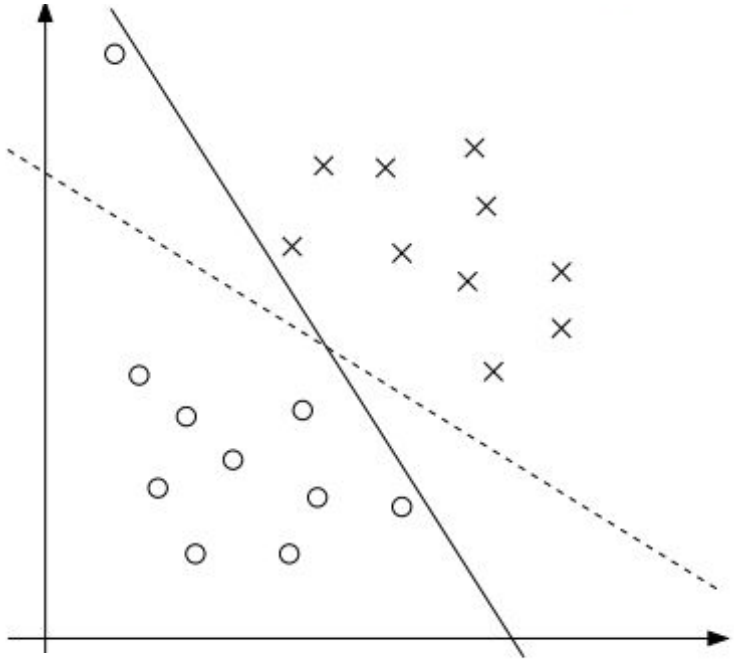
Pretty Simple?

http://cs229.stanford.edu/notes/cs229-notes3.pdf

(Full notes on SVM)

Non-separable cases





$$\min_{\gamma,w,b} \quad \frac{1}{2}||w||^2 + C\sum_{i=1}^{m}\xi_i$$

The cost term

$$\text{s.t.} \quad y^{(i)}(w^T x^{(i)} + b) \geq 1 - \xi_i, \quad i = 1, \ldots, m$$

$$\xi_i \geq 0, \quad i = 1, \ldots, m.$$

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Summary points

- K-means is great for ‘well-behaved’ data in low dimensional feature space but performs badly in high dimensional feature space
- Classifying in terms of the mean is somewhat difficult with less well behaved data - other clustering techniques
- For supervised learning, SVM can be really successful but is costly to train with very large data