

Video summarization via kcenter clustering

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- You want to know the content without read it ?

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- You have a long text ?
- You want to know the content without read it ?
- Why do not do the same for video?



Our goal

- We attempt to produce abstracts for video

Motivations



Motivations for video summarization

- Discover quickly if the video content is of interest without watching it
- Allow comfortable browsing experience in video databases

Example

- Find a particular episode in a TV series

Motivations



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Video summary taxonomy

Static

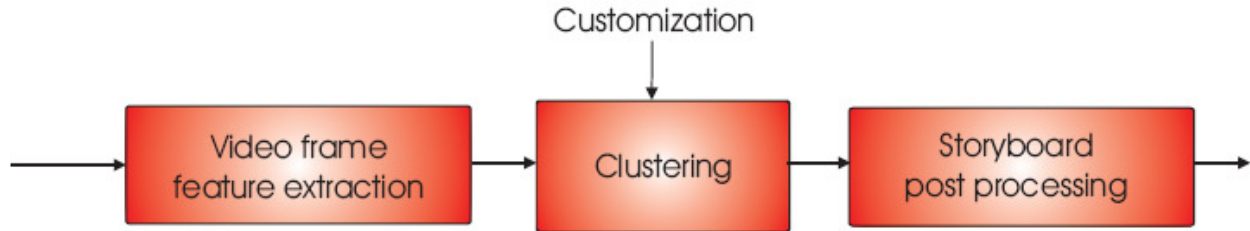


Dynamic



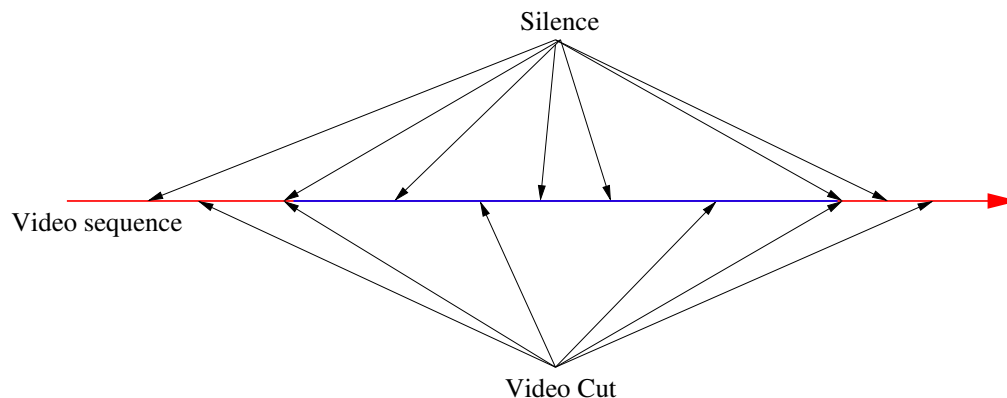
Summary computation time

- **.On-line:** for web applications, allow user to personalize it (i.e choose summary size)
- **.Off-line:** must to be computed in advance. (It is not acceptable to wait for a time comparable with the video length)



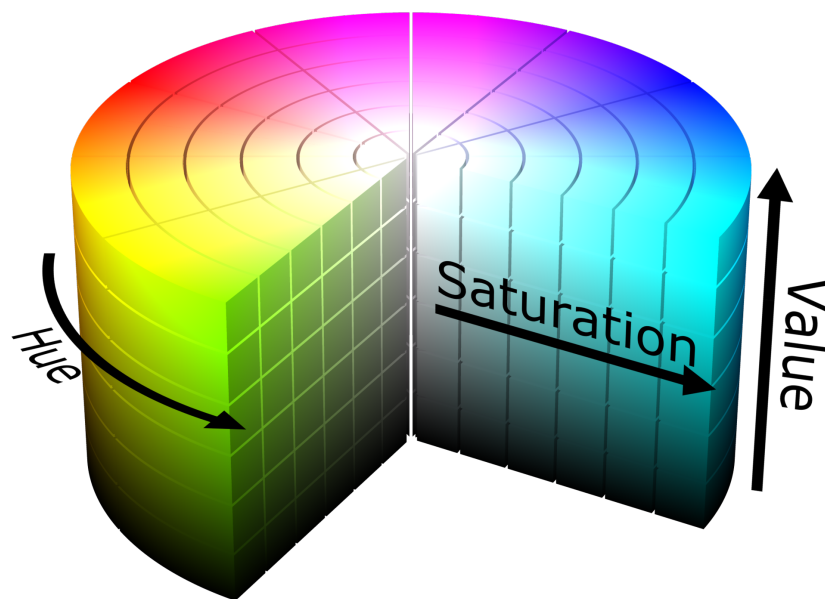
Video Summarization Pipeline

- **Input:** scenes/frames. 256-dimensional HSV vectors, extracted only once (on video submission)
- **Clustering:** determine the scenes to show. Customizations:
 - length of the storyboard,
 - clustering running time.
- **Post-processing:** filter out near-duplicates and extract the selected frames/scenes from the video.



- **Scene:** bounded set of consecutive frames,
 - represented by the mean of the HSV vectors of the frames
- a movie is a partition of scenes,
- a frame fall in just a single scene,
- audio and video must be combined to determine scene,
 - video cut alone can be only a camera change,
 - silence is frequent in dialogs among people.

A metric space for video (1)



- Convert each pixel in its HSV representation
- Build a histogram of the frequencies for each component

A metric space for video (2)

Generalized Jaccard distance (GJC)

- Given two vectors $H_1 = h_{1,1}, \dots, h_{1,256}$ and $H_2 = h_{1,1}, \dots, h_{1,256}$ representing two frames, the Generalized Jaccard distance is defined as:

$$d(H_1, H_2) = 1 - \frac{\sum_{i=1}^{256} \min(h_{1,i}, h_{2,i})}{\sum_{i=1}^{256} \max(h_{1,i}, h_{2,i})}$$

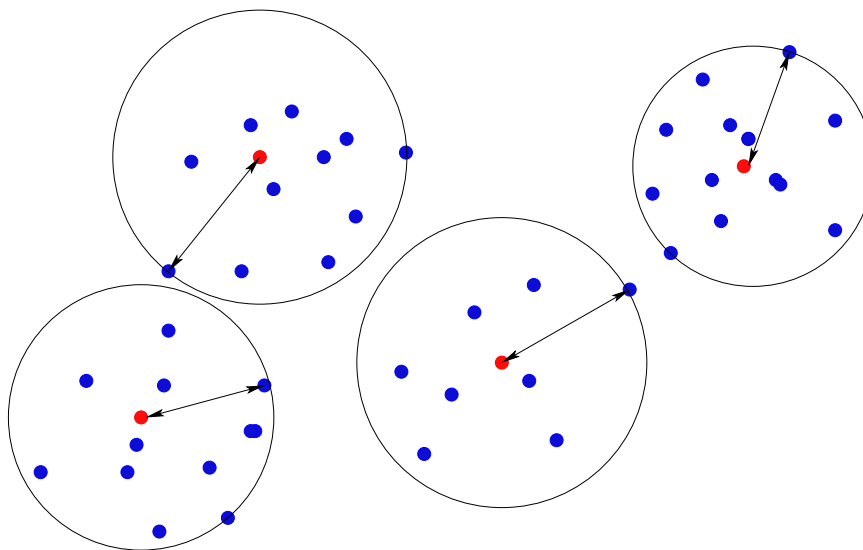
- The vectors H_i endowed with the Generalized Jaccard distance define a **metric space**,
- the GJC exploits better the distance between two frames with respect to other distance functions used in the literature,
- GJC is fast and simple to compute.

- Partition data in homogeneous groups;
- Data independent procedure;
 - Available also when no a-priori knowledge about the data domain;
 - No problem dependent optimizations allowed;
- Many fields of application: IR, bioinformatics.

Cluster hypothesis

If two objects are closely related and the former is also related to a third object, then more likely also the latter has a similar relation.

K -center problem



- **K -center** minimize the largest cluster diameter

$$\min_j \max_{x \in C_j} M_v(x, \mu_j)$$

The furthest-point-first (FPF) algorithm

Data: Let O be the input set, k the number of clusters

Result: \mathcal{C} , k -partition of O

$C = x$ such that x is an arbitrary element of O ;

for $i = 0; i < k; i++$ **do**

 | Pick the element x of $O \setminus C$ furthest from the closest element in C ;
 | $C_i = C_i = x$;

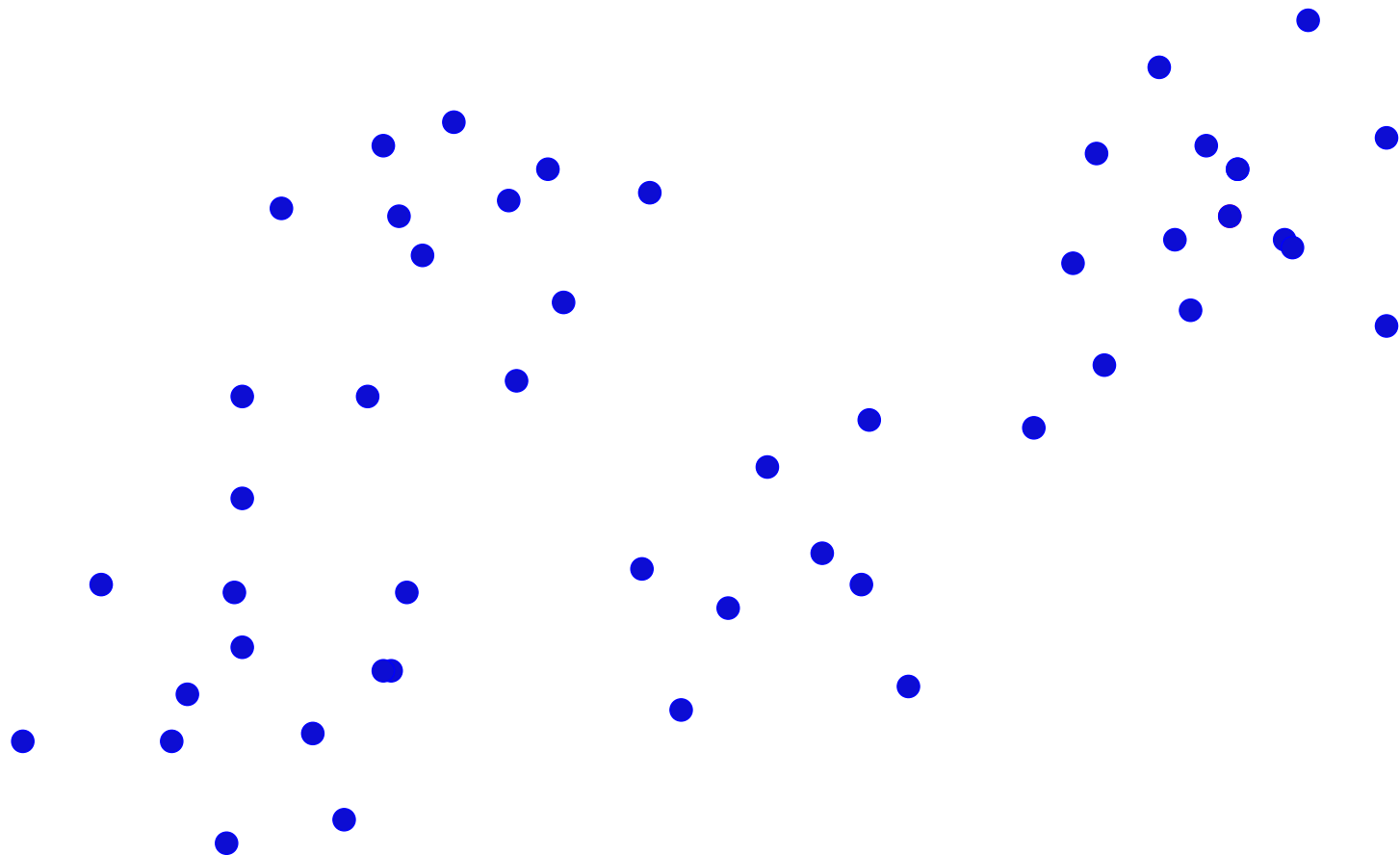
end

forall $x \in O \setminus C$ **do**

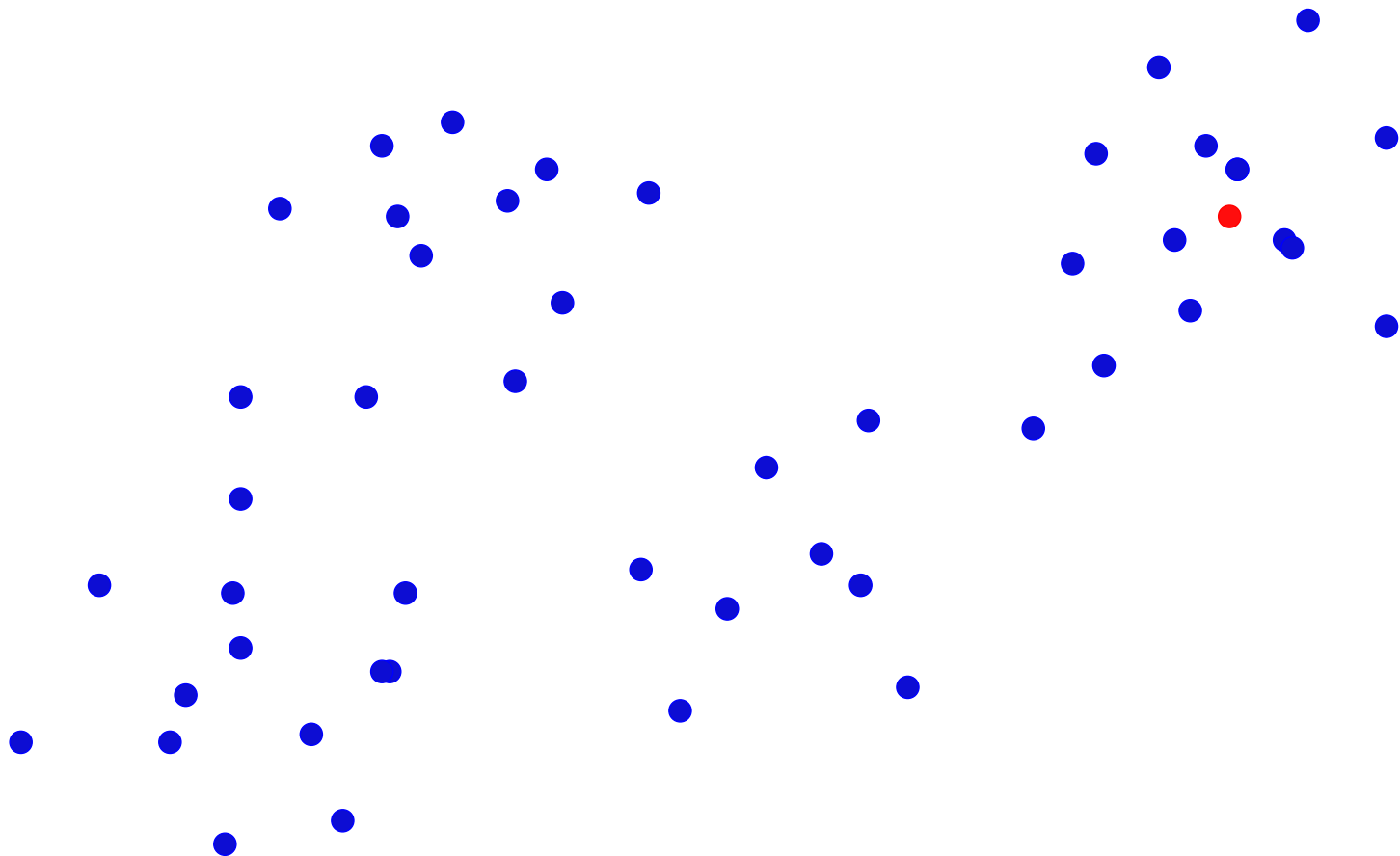
 | Let i such that $d(c_i, x) < d(c_j, x), \forall j \neq i$ $C_i.append(x)$;

end

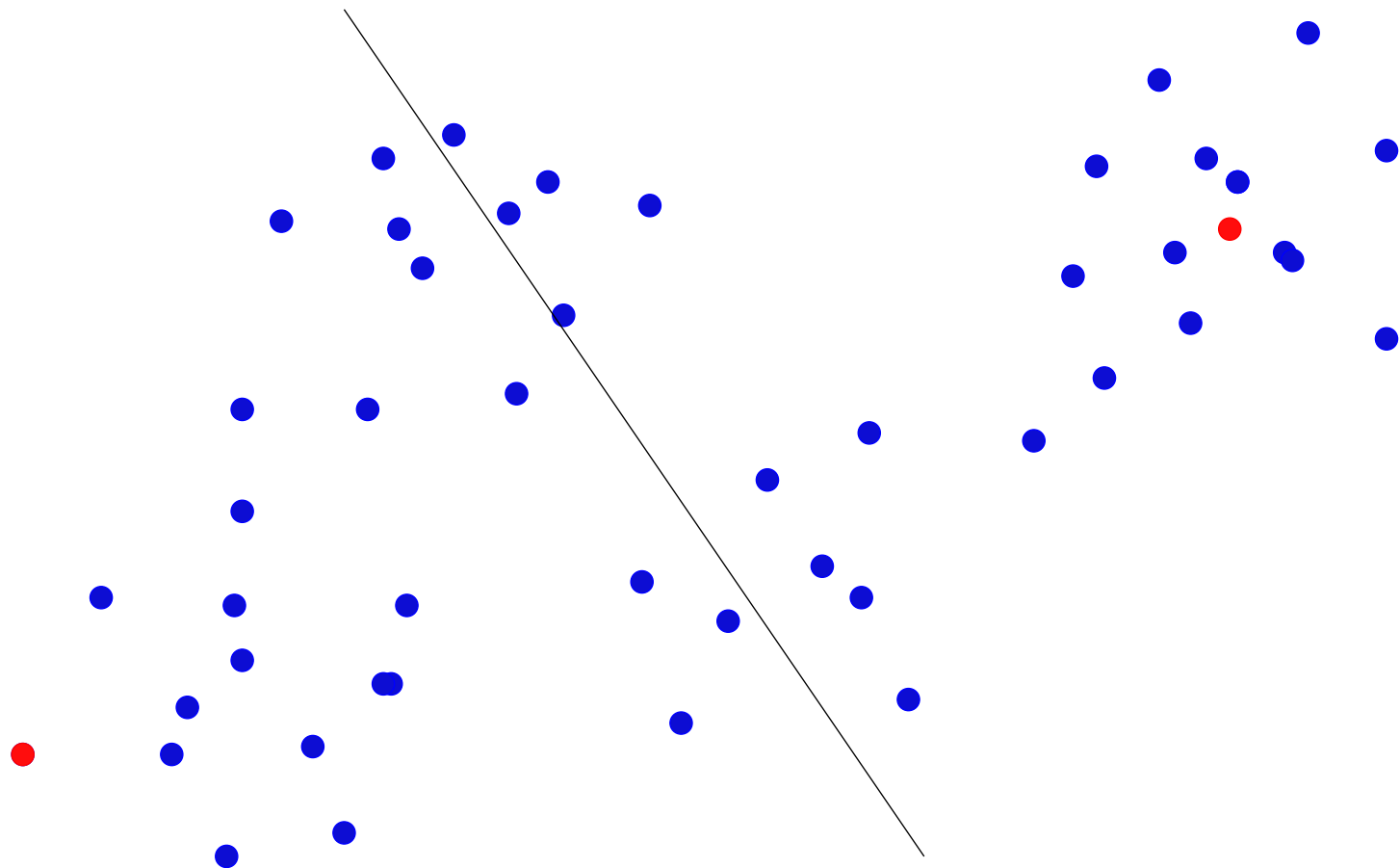
FPF algorithm example



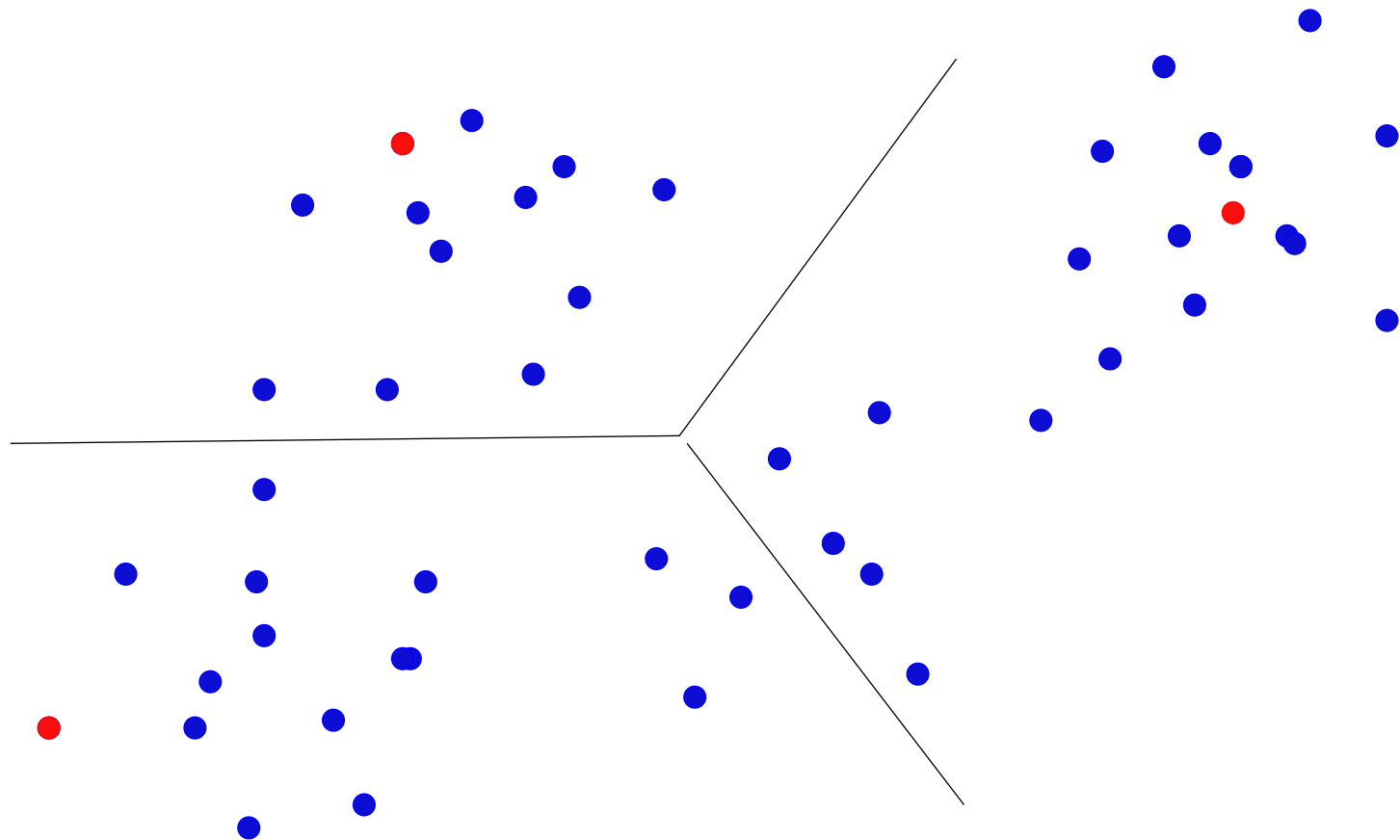
FPF algorithm example



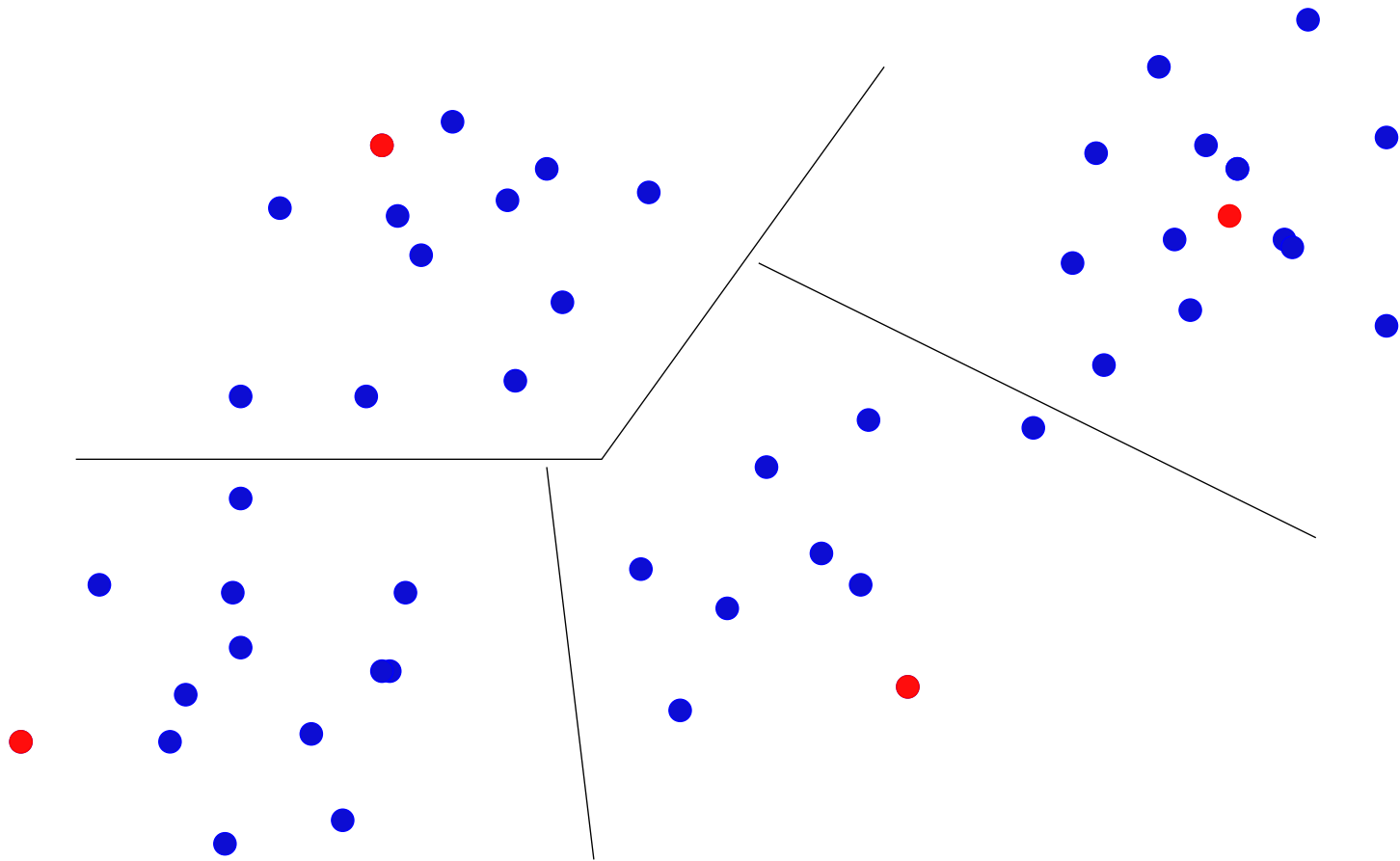
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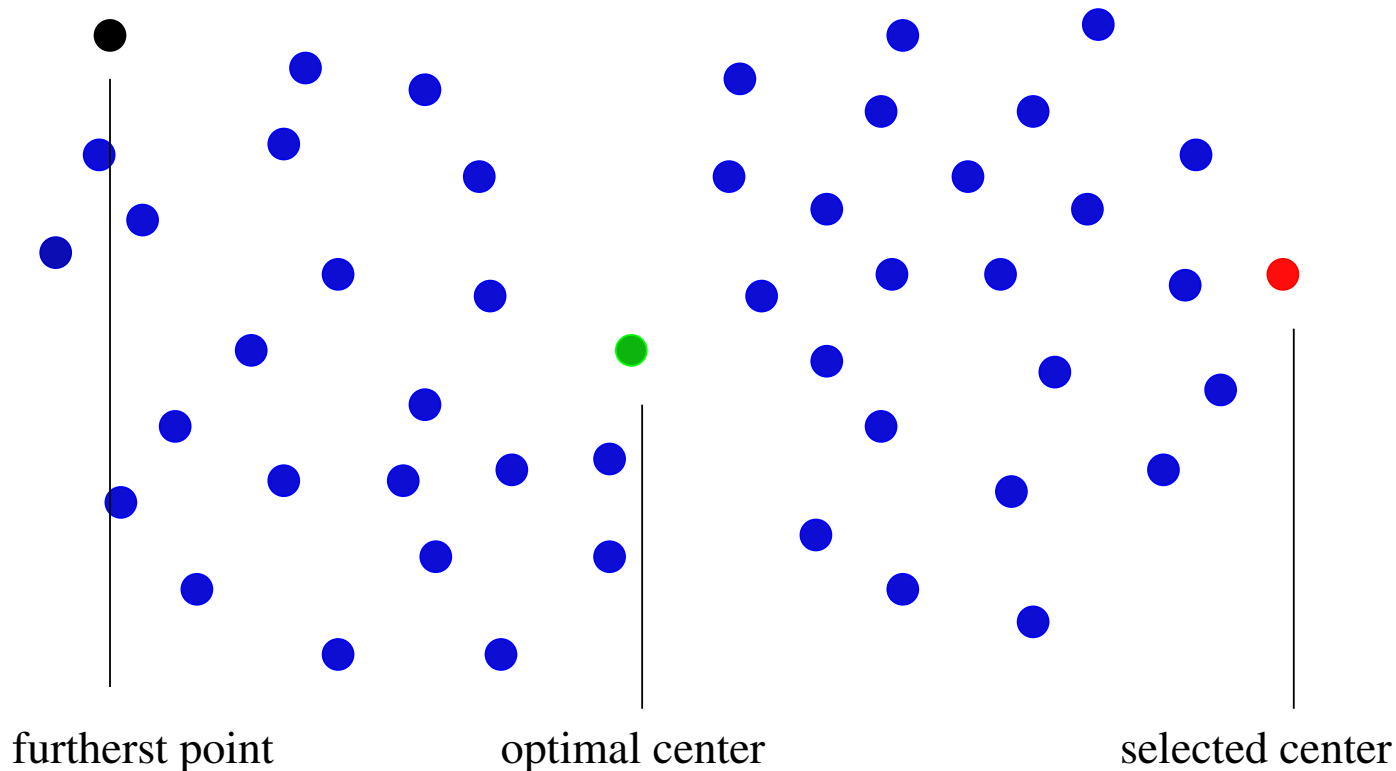
An incomplete prove of the 2-approximation

Based on two cases

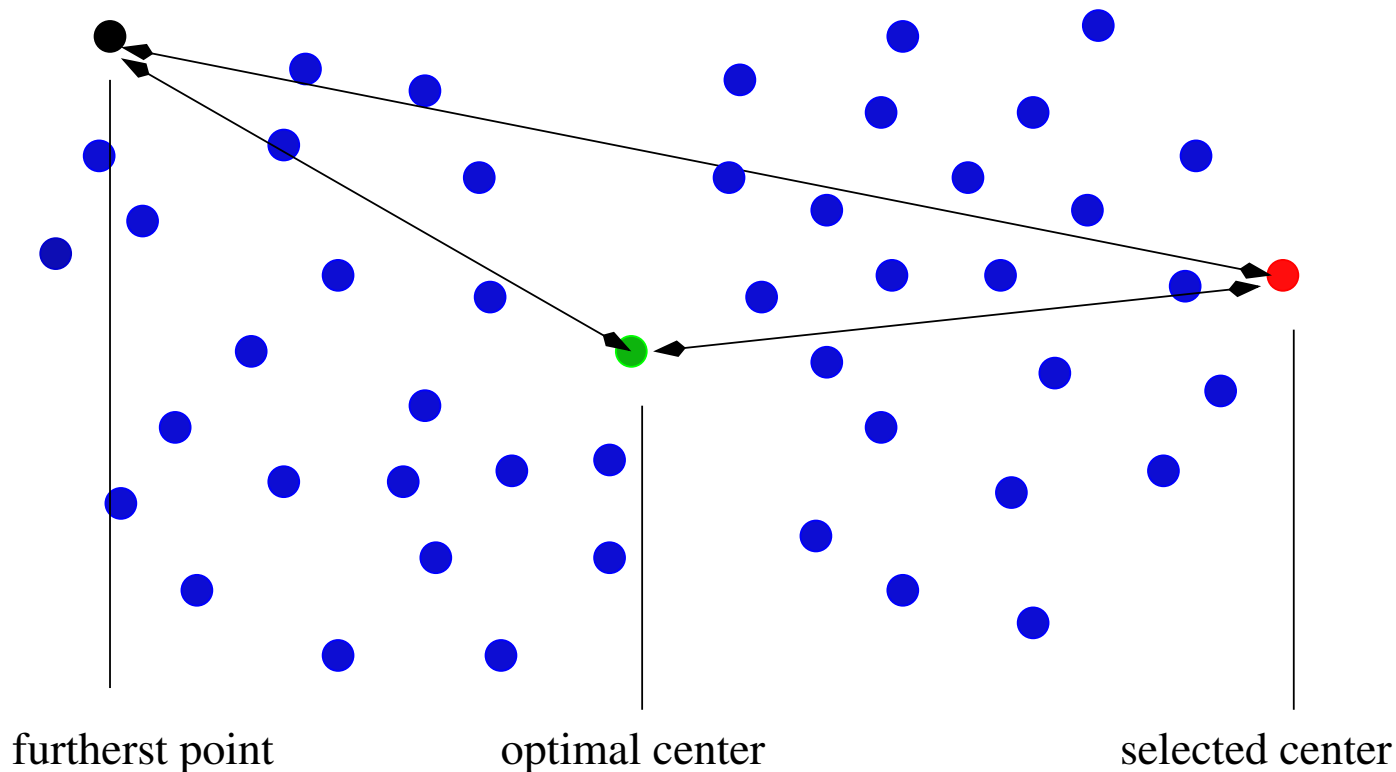
- 1 There is one center of FPF for each center of the optimal clustering
- 2 There are two centers of FPF for each center of the optimal clustering

Unproved here: there are no other possible cases

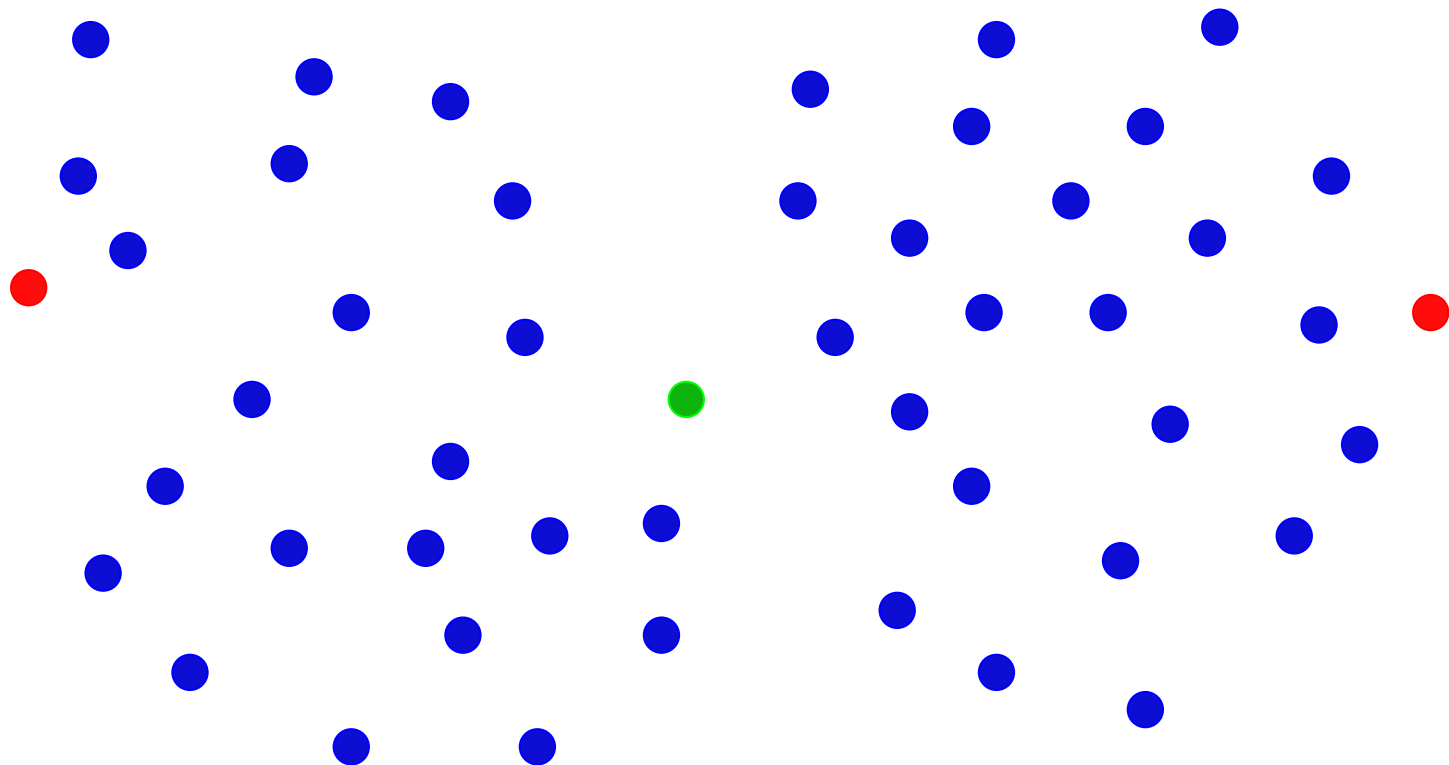
An incomplete prove of the 2-approximation - Example



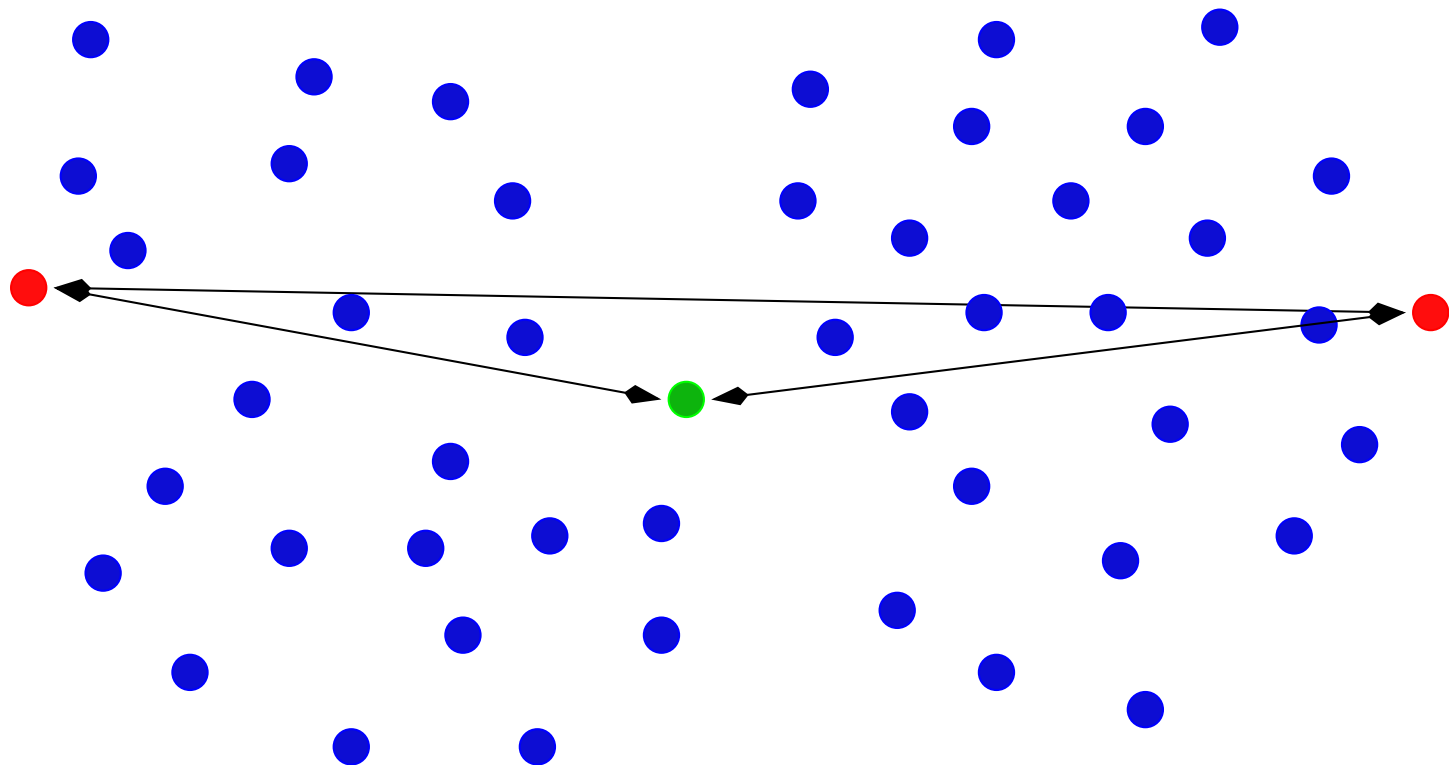
An incomplete prove of the 2-approximation - Example



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The furthest-point-first (FPF) algorithm

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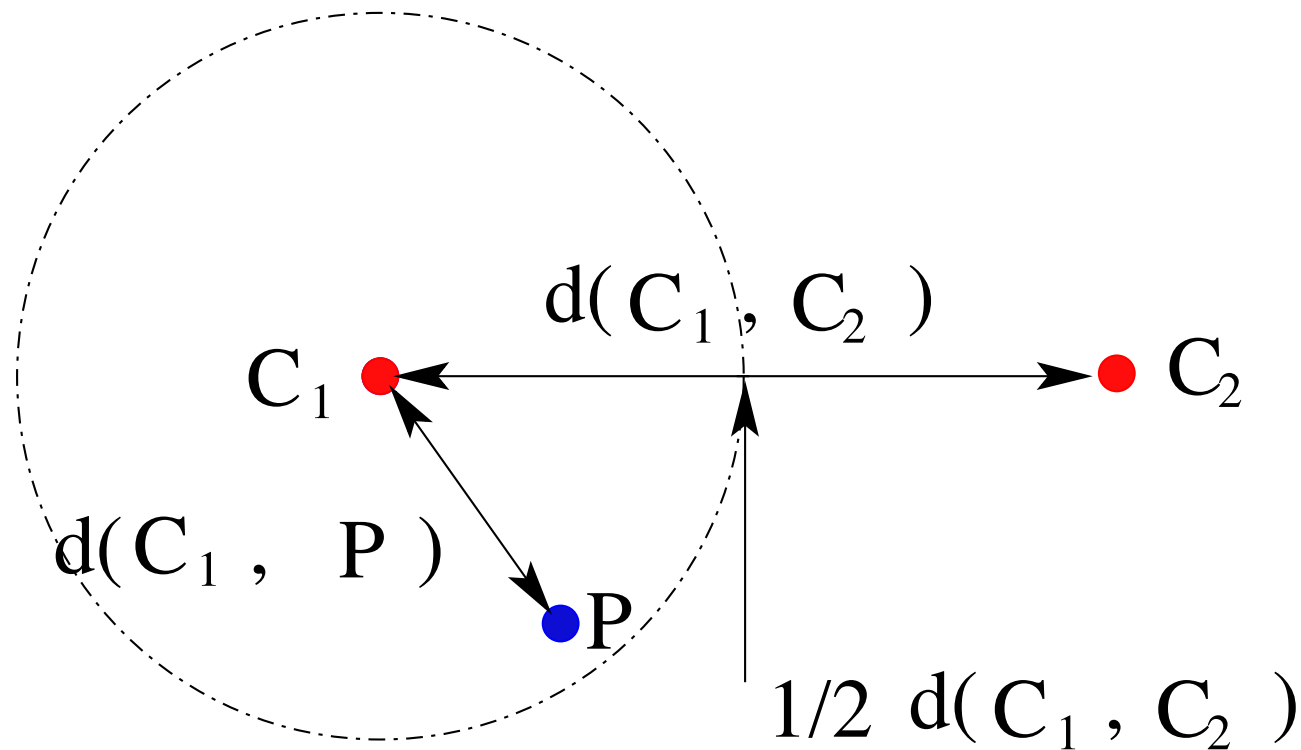
end

forall $x \in O \setminus C$ **do**

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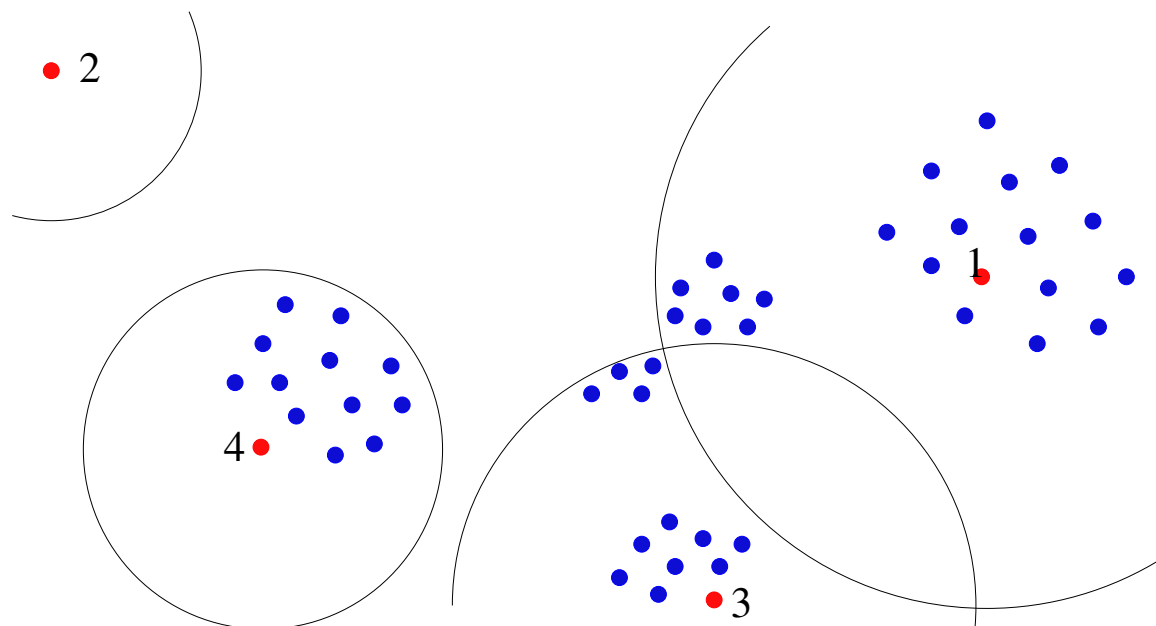
end

Exploit triangular inequality



- Most of the time spent to find the closest center
- In some cases can avoid to check all points of a cluster

Drawbacks in FPF



- Outlayers became centers with high probability
- Poor clusters and affect the choice of k
- Centers are not so representative

Data: Let O be the input set, k the number of desired clusters

Result: \mathcal{C} : a k -partition of O

Initialize R with a random sample of size $\sqrt{|O|k}$ elements of O ;

$\mathcal{C} = \mathbf{FPF}(R, k)$;

forall $C_i \in \mathcal{C}$ **do**

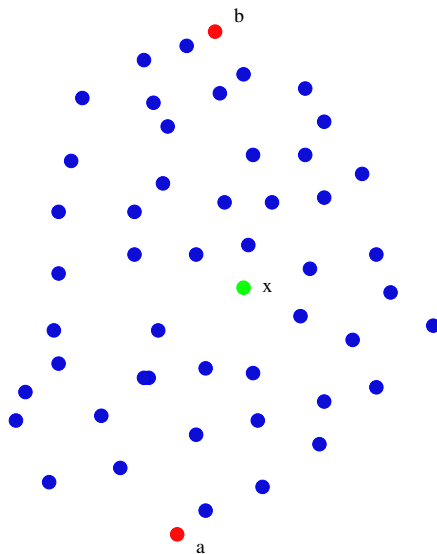
 | $\mu_i = \text{getCenter}(C_i)$;

end

forall p in $O \setminus R$ **do**

 | assign p to cluster C_i such that $d(p, \mu_i) < d(p, \mu_j), \forall j \neq i$;

end



- Given a set of points C , let $a, b \in C$ be two diametral points of C . The **medoid** of C is the point $x \in C$ that minimize:
- $M(x) = |D(a, x) - D(b, x)| + |D(a, x) + D(b, x)|$,

Diametral points heuristic

- Select a random point R
- find the farthest point A from R
- find the farthest point B from A
- Return (A, B) as the diametral pair

Partition around medoids

Data: Let O be the input set, k the number of desired clusters

Result: \mathcal{C} : a k -partition of O

Initialize R with a random sample of size $\sqrt{|O|k}$ elements of O ;

$\mathcal{C} = \mathbf{FPF}(R, k)$;

forall $C_i \in \mathcal{C}$ **do**

$t_i = \text{getRandomPoint}(C_i)$;

$a_i = c_i$ such that $\max d(c_i, t_i)$ for each $c_i \in C_i$;

$b_i = c_i$ such that $\max d(c_i, a_i)$ for each $c_i \in C_i$;

$m_i = c_i$ such that $\min |d(c_i, a_i) - d(c_i, b_i)| + |d(c_i, a_i) + d(c_i, b_i) - d(a_i, b_i)|$;

end

forall p in $O \setminus R$ **do**

 assign p to cluster C_i such that $d(p, m_i) < d(p, m_j), \forall j \neq i$;

if $d(p, b_i) > d(a_i, b_i)$ **then** $a_i = p$;

if $d(p, a_i) > d(a_i, b_i)$ **then** $b_i = p$;

if $d(p, b_i) > d(a_i, b_i)$ **or** $d(p, a_i) > d(a_i, b_i)$ **then**

$m_i = c_i$ such that $\min |d(c_i, a_i) - d(c_i, b_i)| + |d(c_i, a_i) + d(c_i, b_i) - d(a_i, b_i)|$;

end

end

How many clusters?



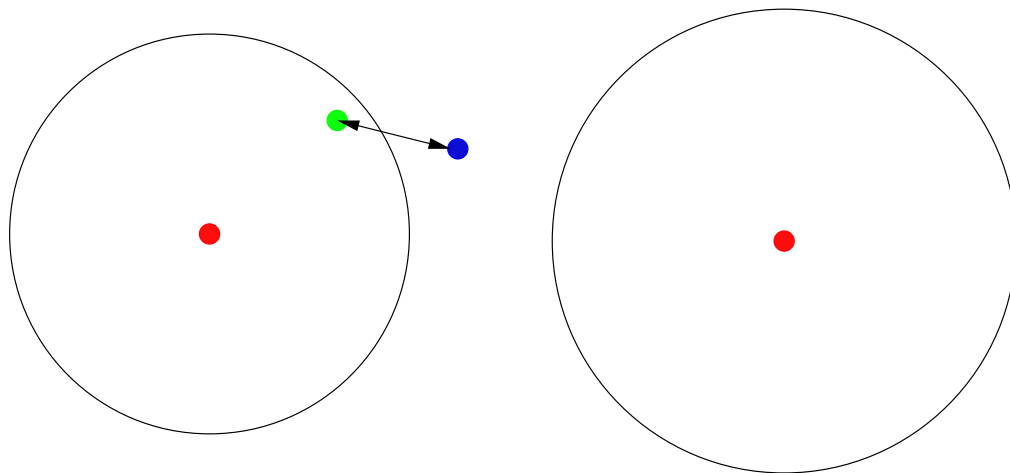
- Problem dependent question
- Few clusters are often not homogeneous
- Too many break homogeneous clusters

... and so?

- ad-hoc solutions
 - may be not feasible
- theoretical approaches (i.e stability):
 - always available
 - not related to the problem

Approximations for video summaries

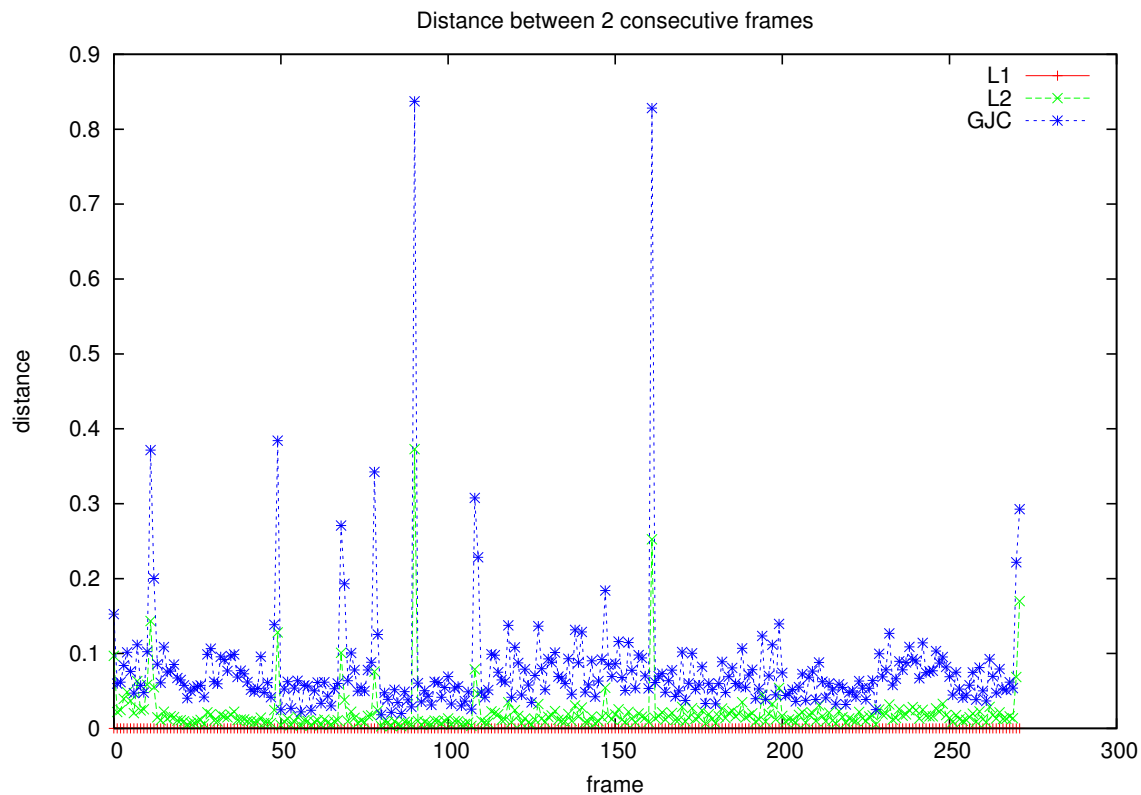
Approximations

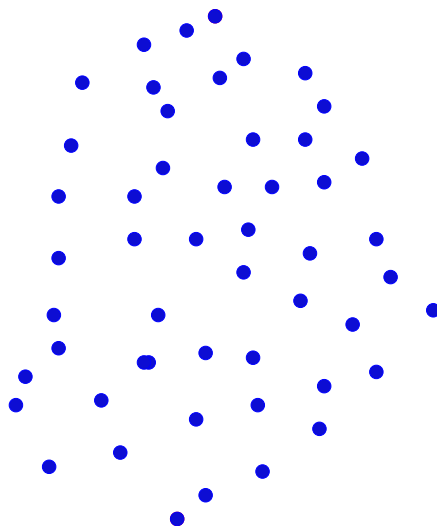


Adding a new point to cluster

- Most of the time is spent to decide for each point to which cluster it should be assigned.
- If the new point is “close” to the previous one, it is inserted in the same cluster.

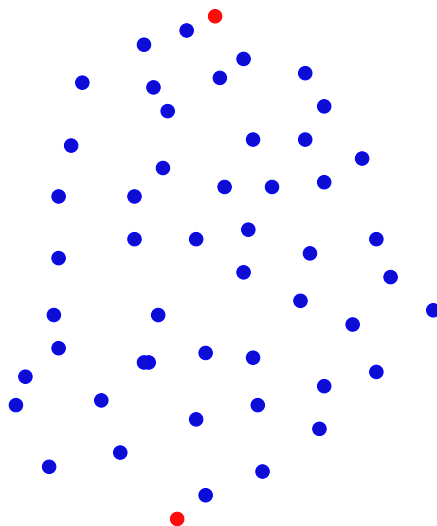
Distance between two consecutive frames





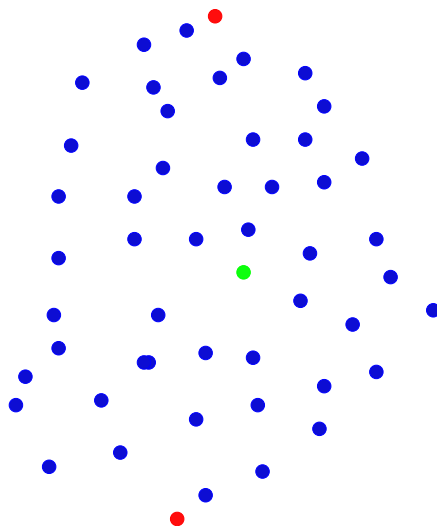
Medoid

- Given a set of points C , let $a, b \in C$ be two diametral points of C . The **medoid** of C is the point $x \in C$ that minimize:
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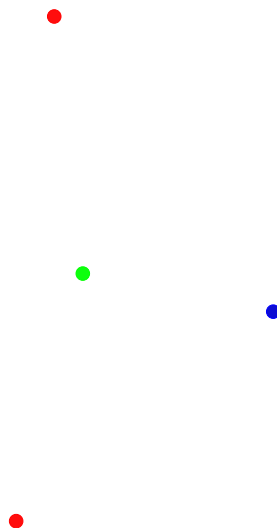
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Video summary using the approximated FPF algorithm



- **Python module for clustering and other machine learning tasks:** <http://scikit-learn.org/stable/modules/clustering.html#clustering>