The Class Cover Problem and its Applications to Pattern Recognition

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Outline

- History of the Class Cover Problem (CCP)

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  - CCP-based Classifiers
  - Simulation Results

History of the Class Cover Problem

- Approximate Distance Clustering
  Cowen and Priebe
  Advances in Applied Mathematics, 19 (1997)
- Class Cover Problem
  Cannon and Cowen
  Annals of Math and A.I. to appear
- Closely Related Topics
  - Sphere Covers, Hochbaum and Maass (J. of the A.C.M. 1985)
  - Sphere Digraphs, Maehara (J.G.T. 1984)
  - Sphere of Attraction Graphs,
    McMorris and Wang (Con. Num. 2000)

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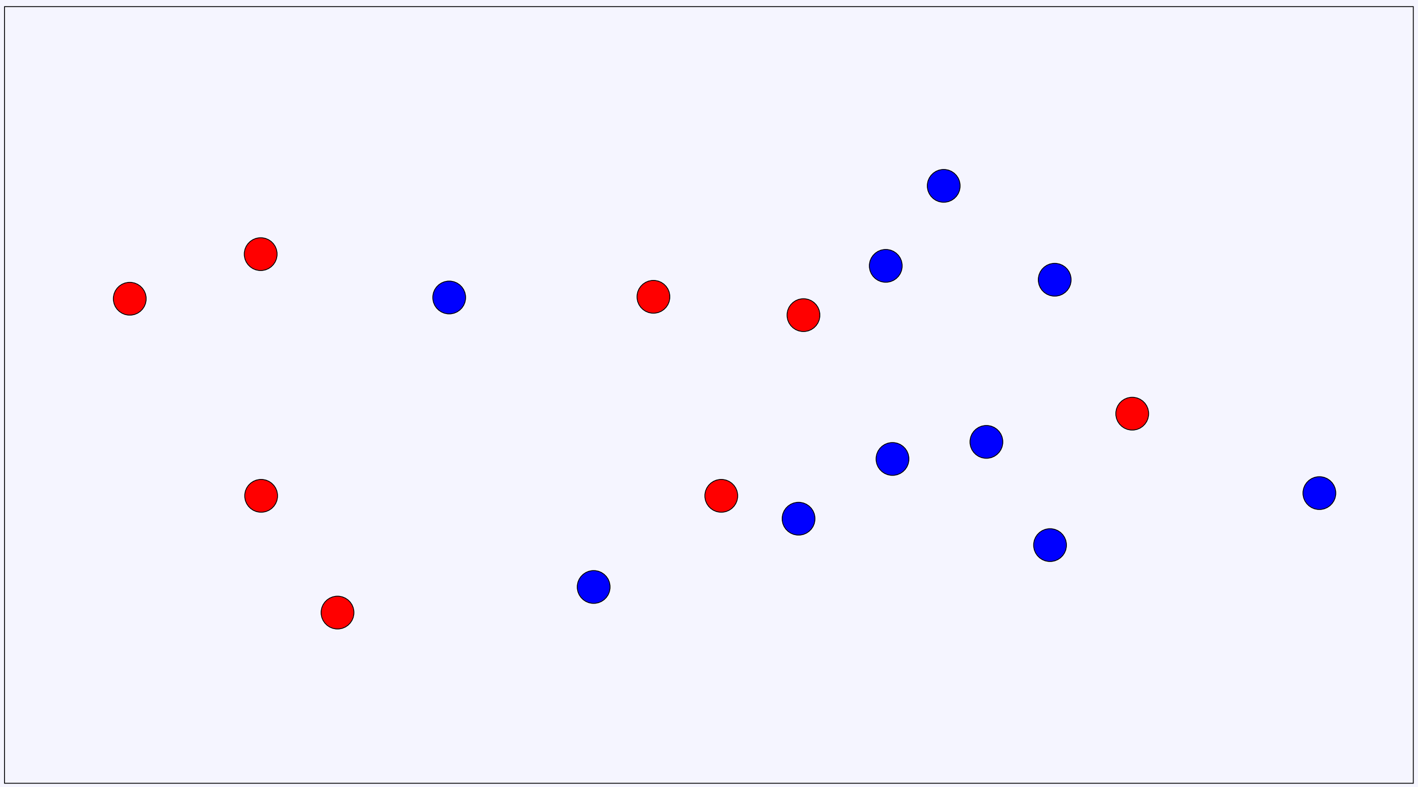
The Class Cover Problem (CCP)

Input: (Ω, d) (dissimilarity space) with $X, Y \subset \Omega$ and $X =$ target class.
Goal : Find the smallest set of “balls” (a cover), centered at points in X, such that every point in X is in at least one of the balls and no point in Y is in any ball.



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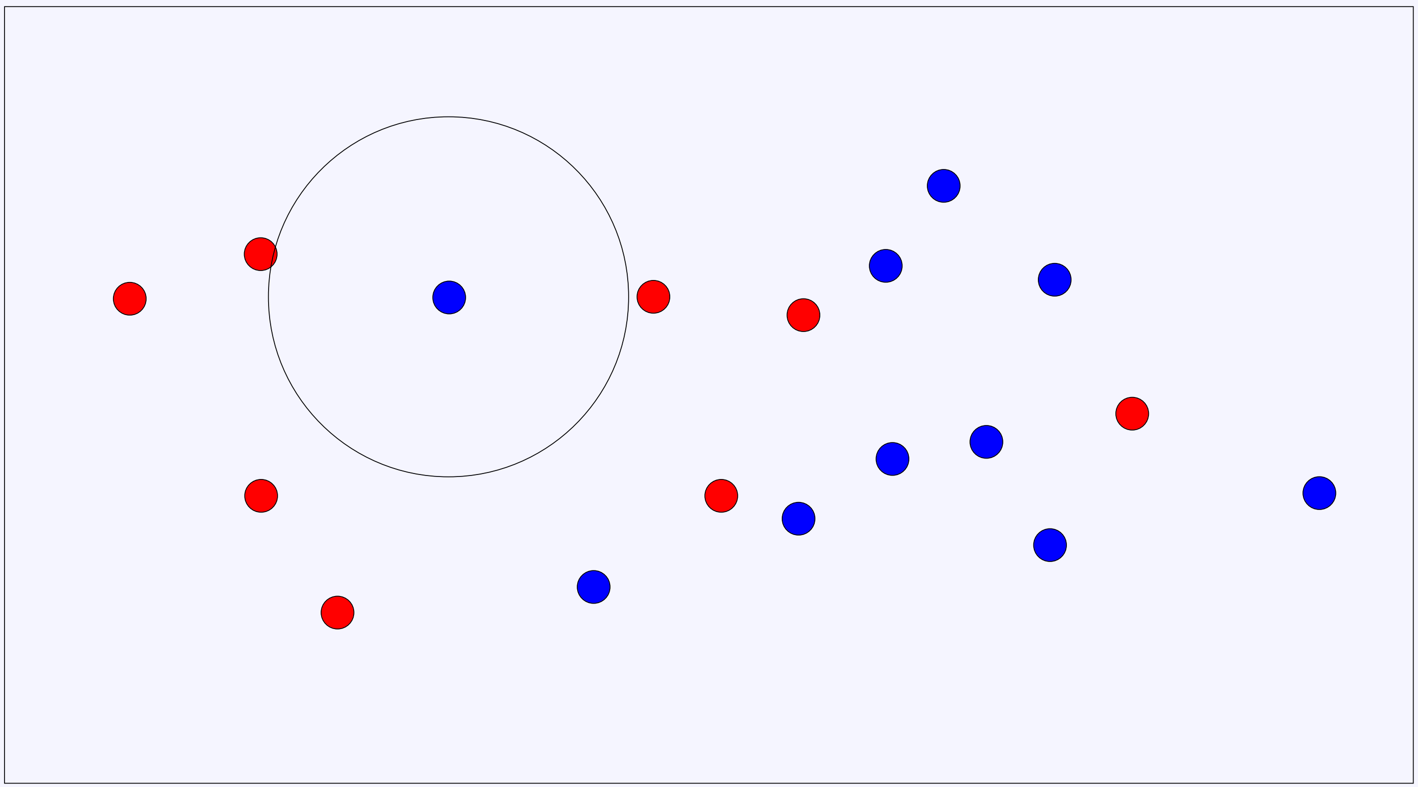

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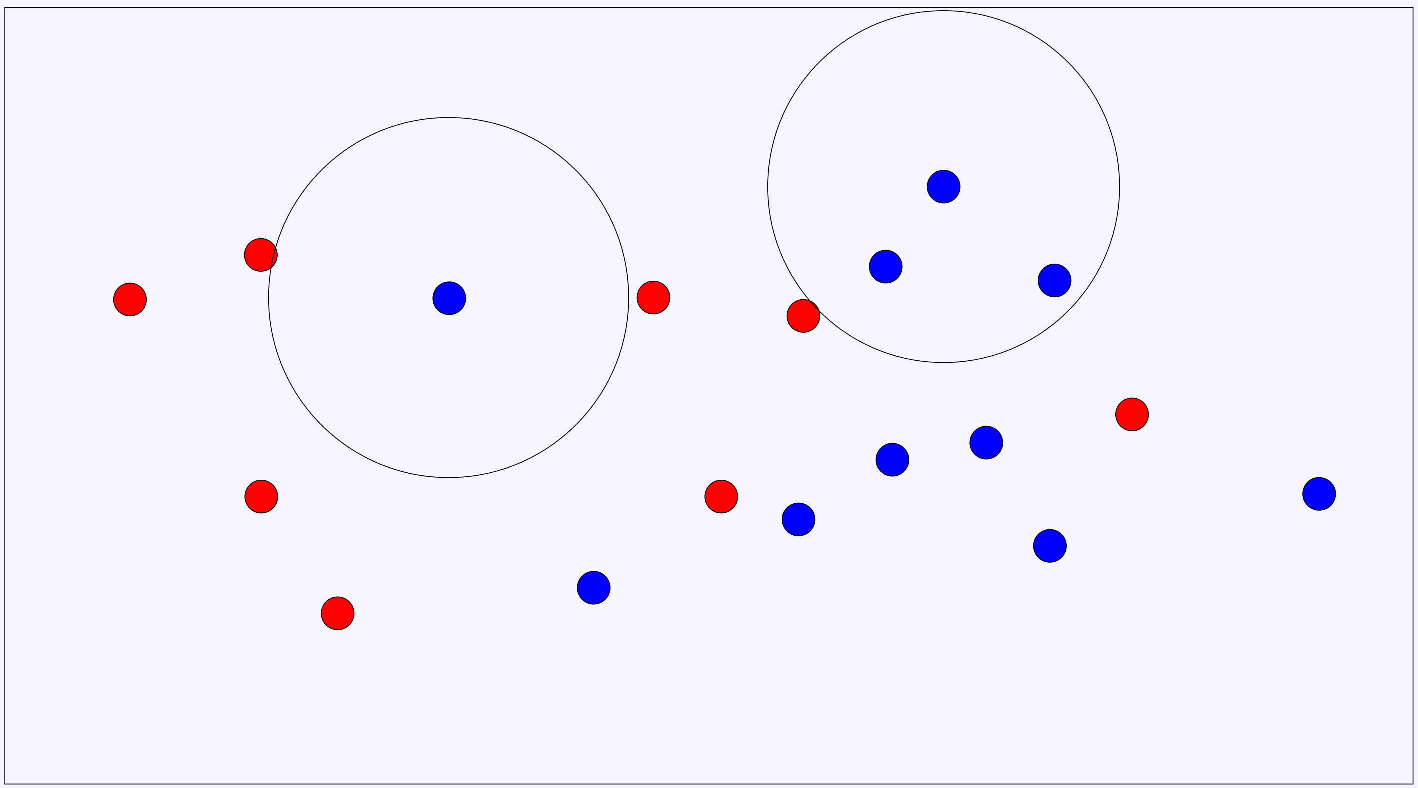

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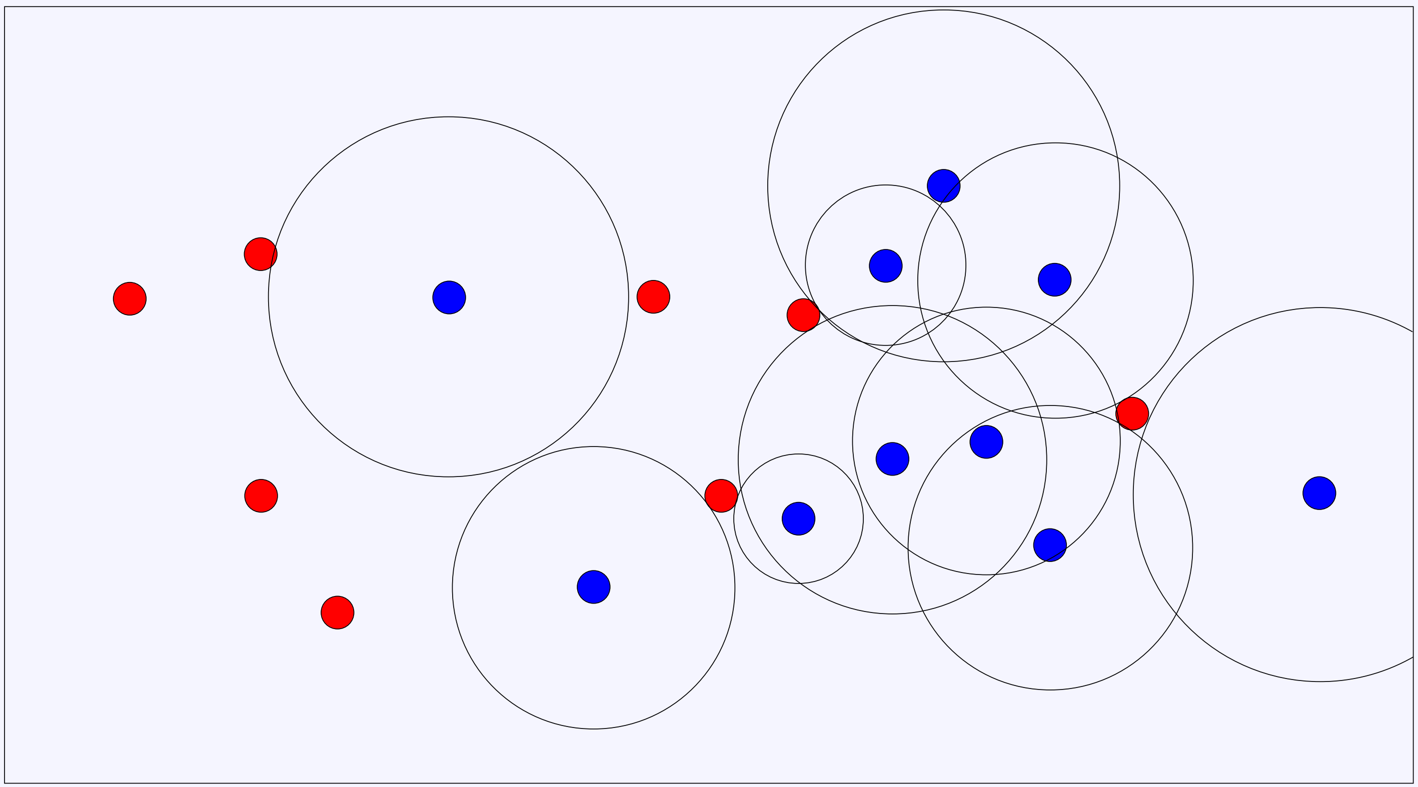

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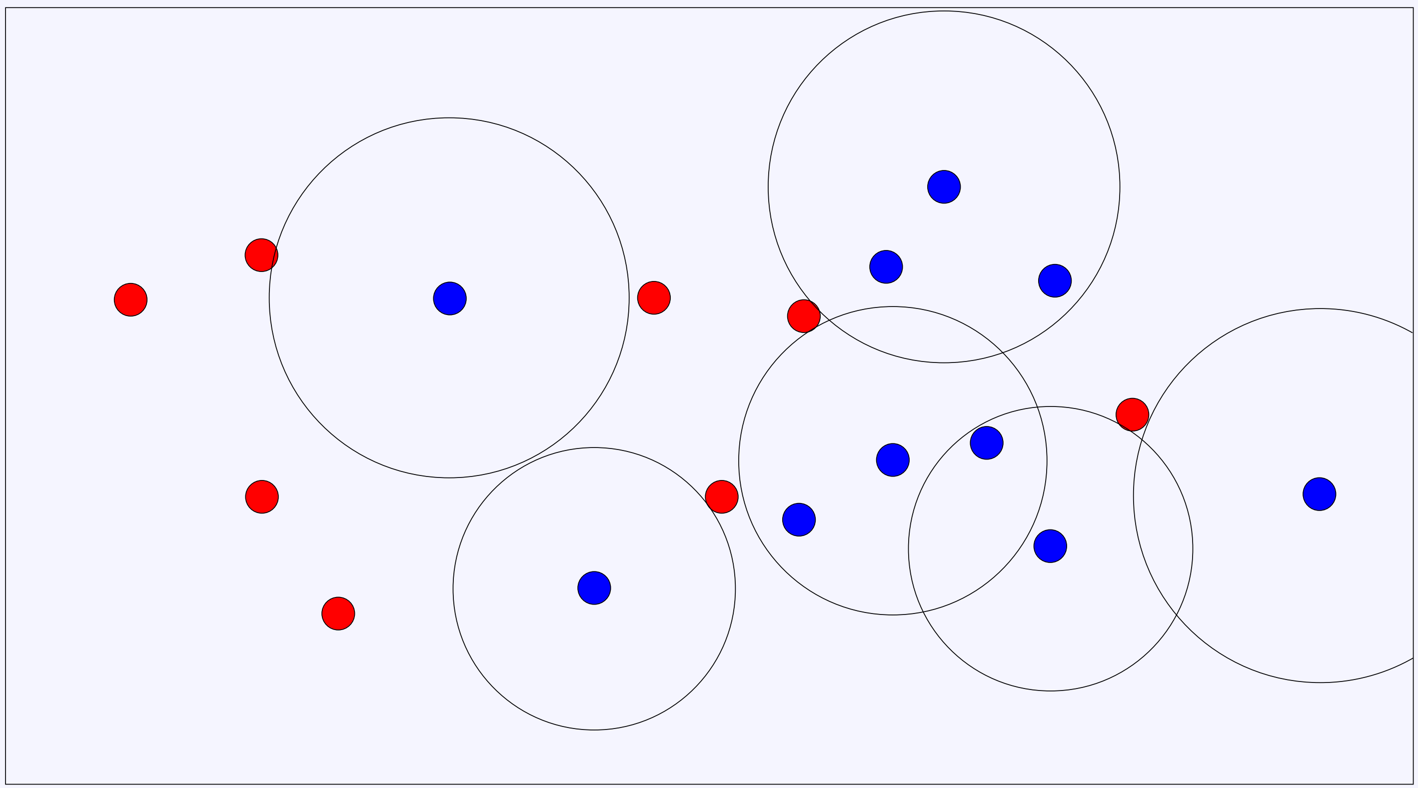

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Catch Digraphs

Given a collection of sets $\{S_1, S_2, \ldots, S_n\}$ with associated "base"points $\{t_1, t_2, \ldots, t_n\}$.

We form the *catch digraph* D with $V = \{v_1, v_2, \ldots, v_n\}$ and a directed edge from v_i to v_j iff $t_j \in S_i$.

A *sphere digraph* is a catch digraph where the sets are spheres and the base point for each sphere is its center.

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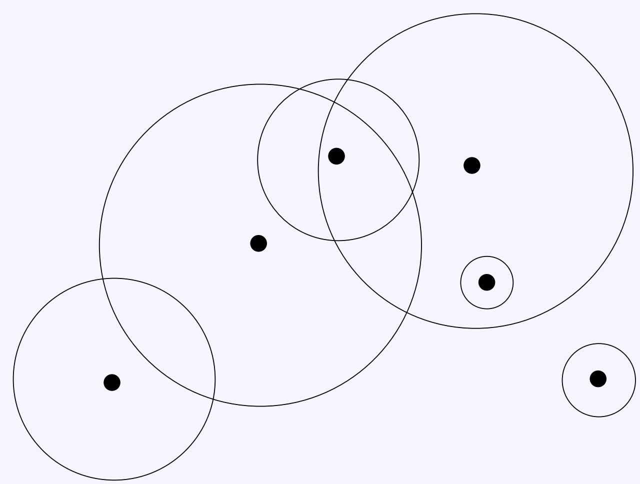

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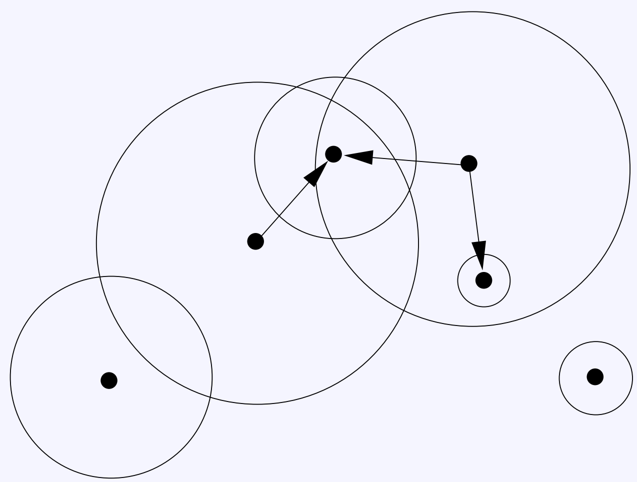

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Class Cover Catch Digraphs (CCCD)

For any sets $X, Y \subset \Omega$ we can define the *class cover catch digraph* to be the catch digraph formed from the sets $B_i = \{z \in \Omega : d(z, x_i) < r_i\}$ and associated base points $x_i \in X$.

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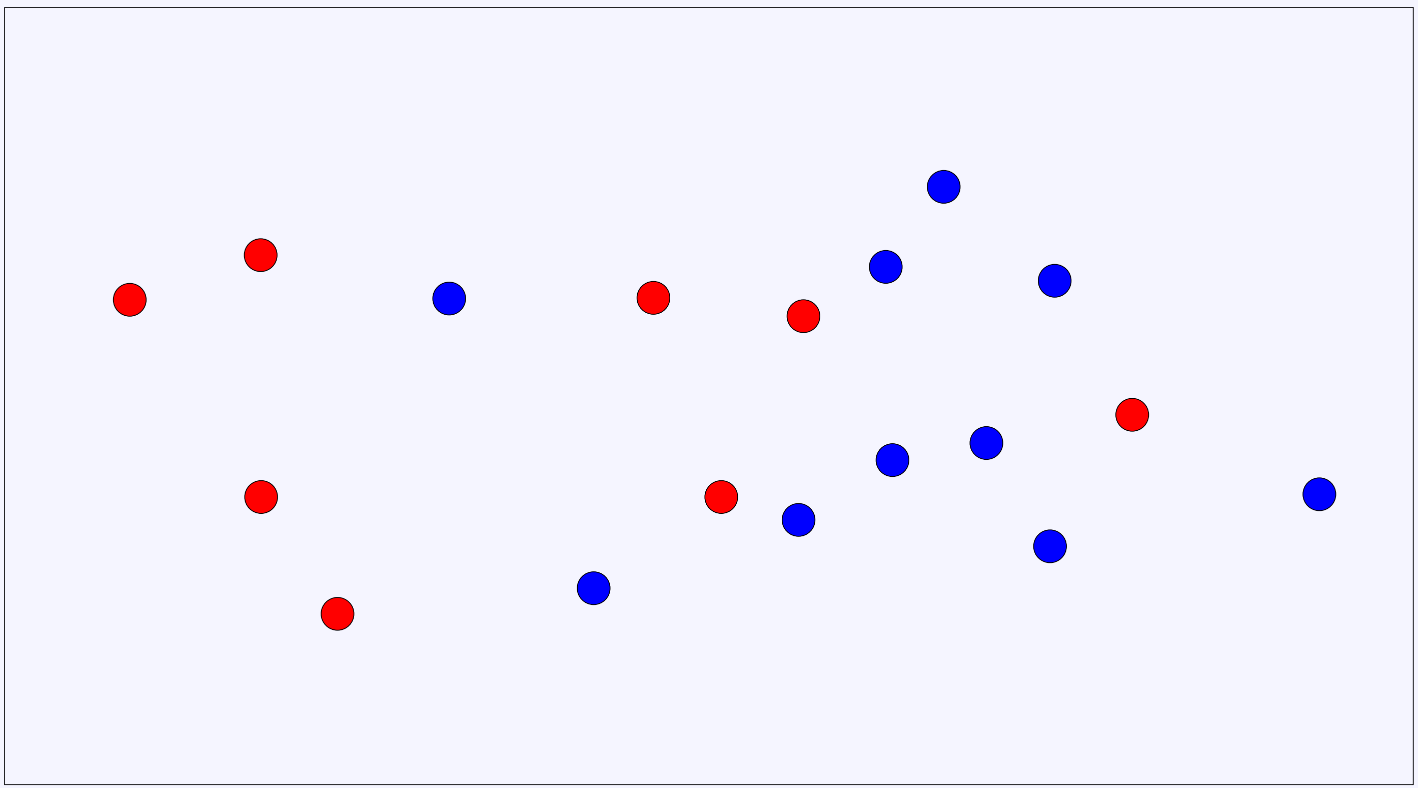

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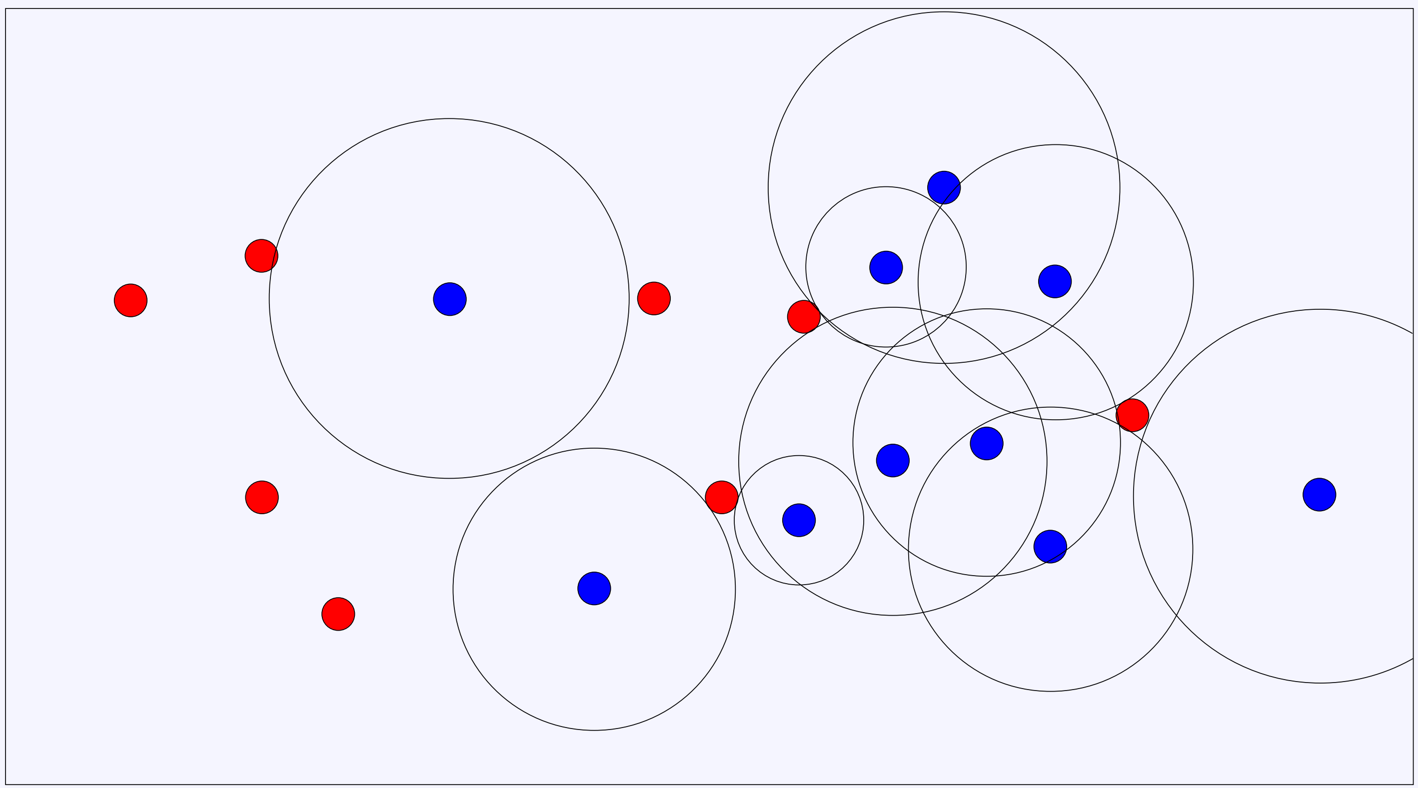

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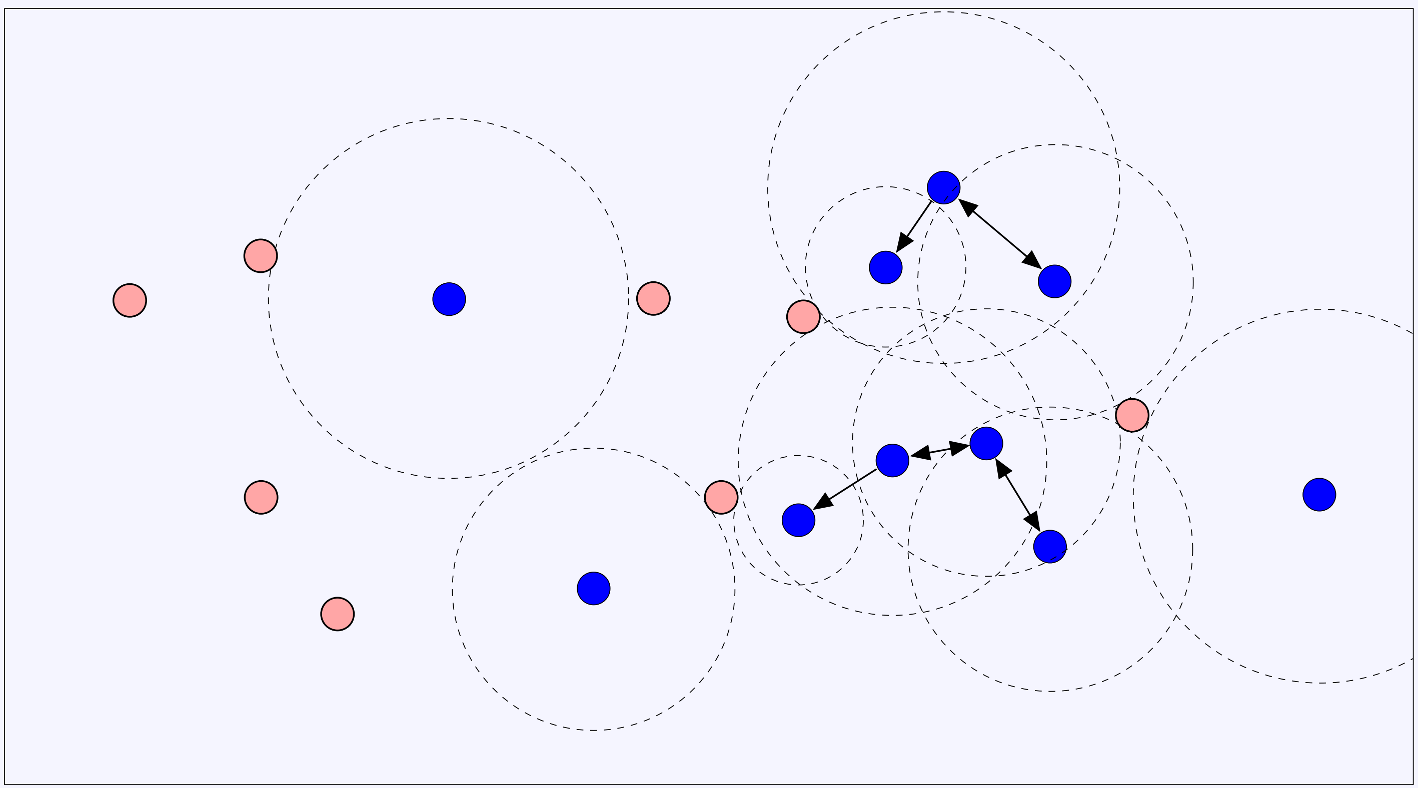

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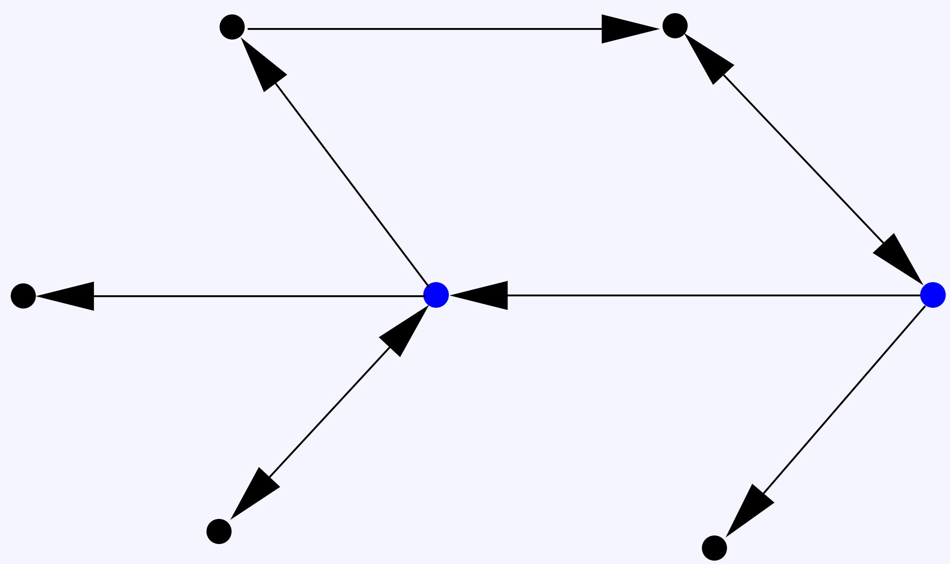
Dominating Sets

Define a *dominating set*, S, of a digraph $D = (V, A)$ as follows: $S \subset V$ such that $\forall v \in V,\ v \in S$ or $\exists w \in S$ such that $(w, v) \in A$.



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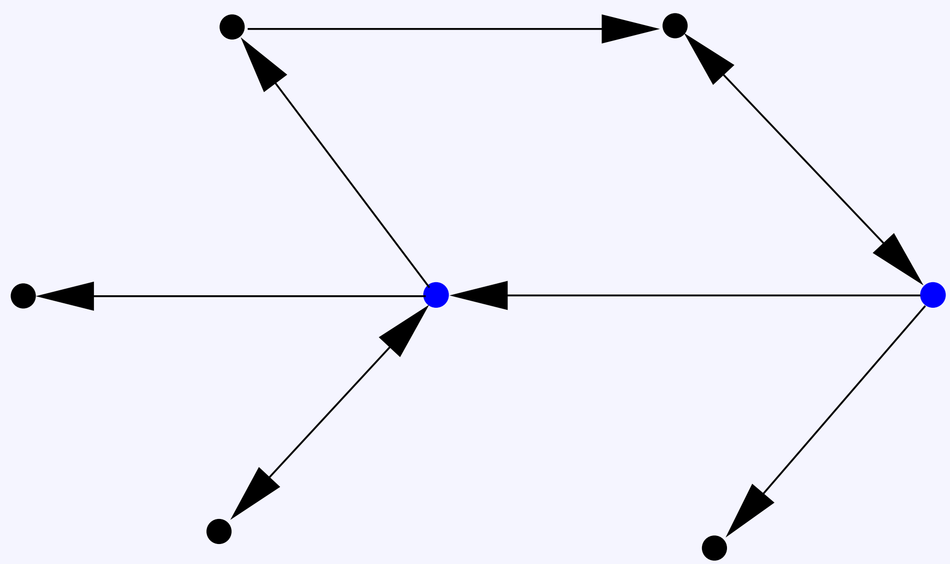
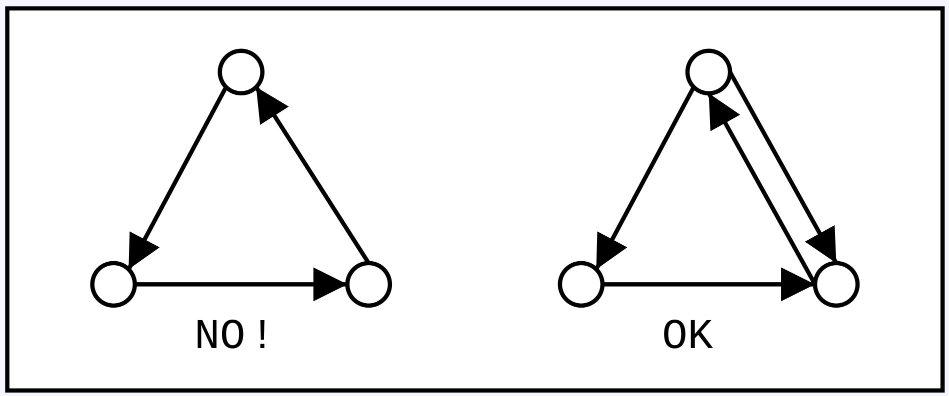


Solution to CCP $\Leftrightarrow$ Minimum Size Dominating Set in CCCD

Euclidean CCCD's

If $X, Y \subset \Re^q$ and d is the standard Euclidean metric, then we call the resulting digraph a Euclidean CCCD.
What digraphs are Euclidean CCCD's?



Definition: A simple cycle is a directed cycle with no bidirected edges.

Euclidean CCCD's

Theorem 1 *A digraph is a Euclidean CCCD if and only if it has no simple cycles.*

In other words...

Given $X, Y \in \Re^q$, they induce a digraph with no simple cycles.
Given a digraph D with no simple cycles, we can find $X, Y \in \Re^q$ which induce a digraph isomorphic to D (in fact we will need only one Y point, but we may need many dimensions).

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Proof of characterization theorem

$(\Leftarrow)$ Given D with a smallest simple cycle $v_1, v_2, \ldots, v_l$.

- $(v_i, v_{i+1}) \in A$ and $(v_i, v_{i-1}) \notin A$ implies $d(x_i, x_{i-1}) > d(x_i, x_{i+1})$ $\forall i$ modulo l

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$(\Rightarrow)$ Given D with no simple cycles.

- Create a poset on interpoint distances
- Extend poset to linear order
- Assign interpoint distances
- Show Euclidean interpoint distances exist which preserve the linear order using MDS.

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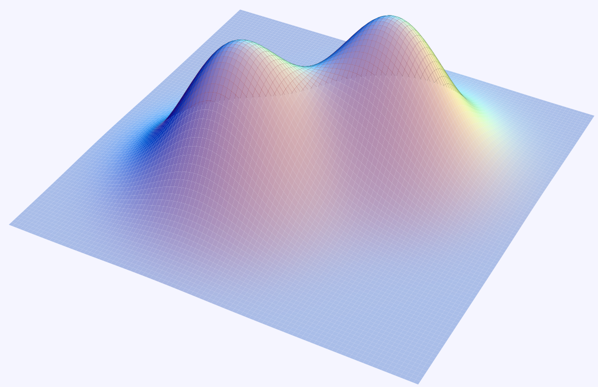
Random Model of CCP

n target class points are chosen from a distribution F_X

m non-target class points are chosen from a distribution F_Y

$\Gamma_{n,m}$:= the domination number of the CCCD induced by the sample.



Question: What is the distribution of the random variable $\Gamma_{n,m}$?

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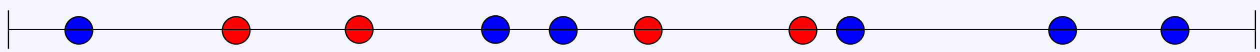
Random Model in $\Re$

Let F_X and F_Y be the uniform distribution on $[0, 1]$. In this case we use $\Gamma_{n,m}$ to represent the case with n target class points and m non-target class points.



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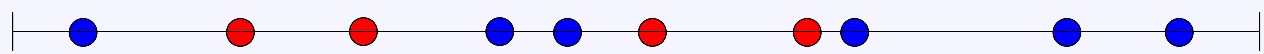
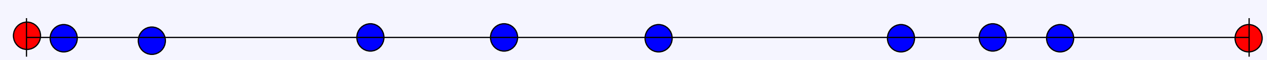


We need only consider the simplified case where $y_1 = 0, y_2 = 1$ and F_X is the uniform distribution on $[0, 1]$. We call such an induced CCCD C_n^*.



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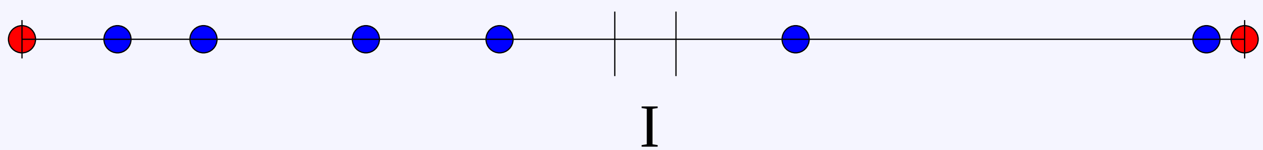
Random Model in $\Re$

$$\Gamma(C_n^*) = \begin{cases} 0 & \text{if } n = 0 \\ 1 & \text{if } I \cap X \neq \emptyset \\ 2 & \text{otherwise} \end{cases}$$



where $I = \left[\frac{x_n}{2}, \frac{1+x_1}{2}\right]$

$\kappa(n) = P[\Gamma(C_n^*) = 1] = \frac{5}{9} + \frac{4}{9} \cdot 4^{-(n-1)}$

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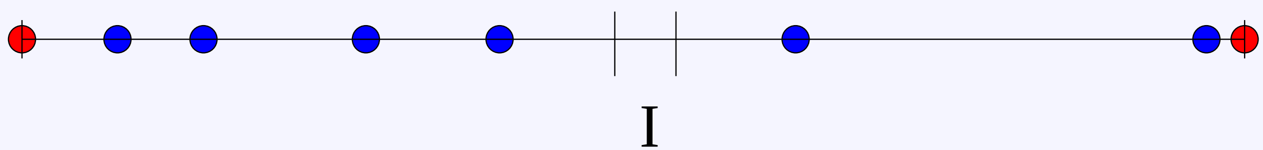

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This result allows the calculation of…

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Random Model in $\Re$

…probability mass function for $\Gamma_{n,m}$

$$P[\Gamma_{n,m} = d] =$$

$$\frac{n!m!}{(n+m)!} \sum_{\vec{n} \in \Delta^{Z_{n+1}}_{n,m+1}} \sum_{\vec{d} \in \Delta^{Z_3}_{d,m+1}} \alpha(d_1, n_1) \cdot \alpha(d_{m+1}, n_{m+1}) \prod_{j=2}^{m} \beta(d_j, n_j)$$

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and… expected value of $\Gamma_{n,m}$,

$$E[\Gamma_{n,m}] = \frac{2n}{n+m} + \frac{n!m(m-1)}{(n+m)!} \sum_{i=1}^{n} \frac{(n+m-i-1)!}{(n-i)!} \cdot (2 - \kappa(i))$$

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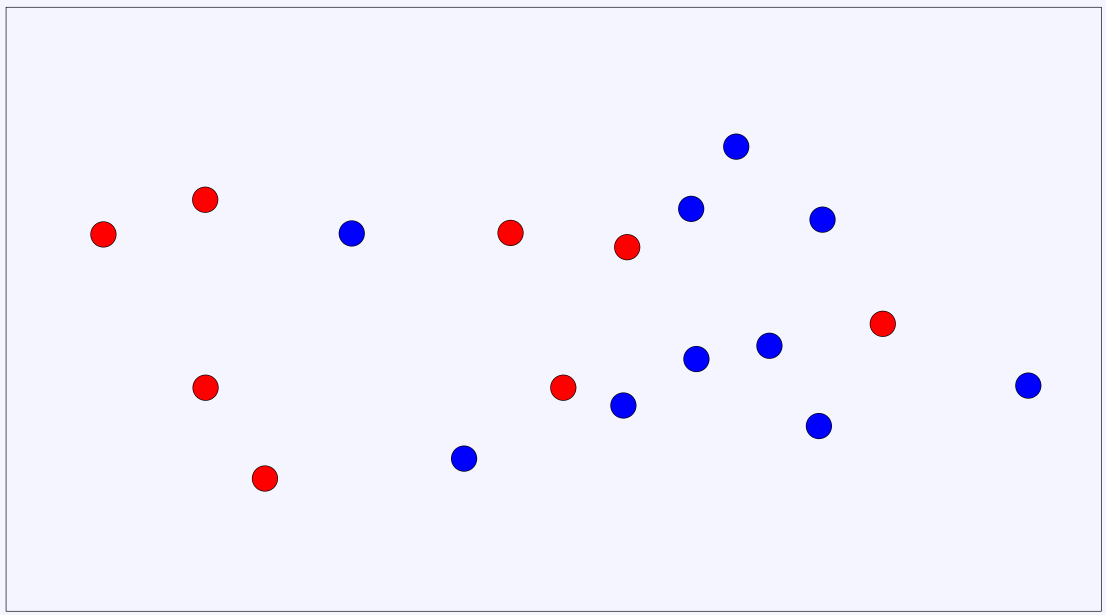
and… almost sure limit of $\Gamma_{n,m}$,

$$\lim_{n \to \infty} \frac{\Gamma_{\lfloor an \rfloor, n}}{n} = \frac{a(13a+12)}{3(a+1)(3a+4)} \text{ a.s.} \qquad a \in (0, \infty).$$

Application to Classification

Our framework for using the CCP in classification is a reduced nearest neighbor with a dissimilarity dependent on the balls in the classifier.



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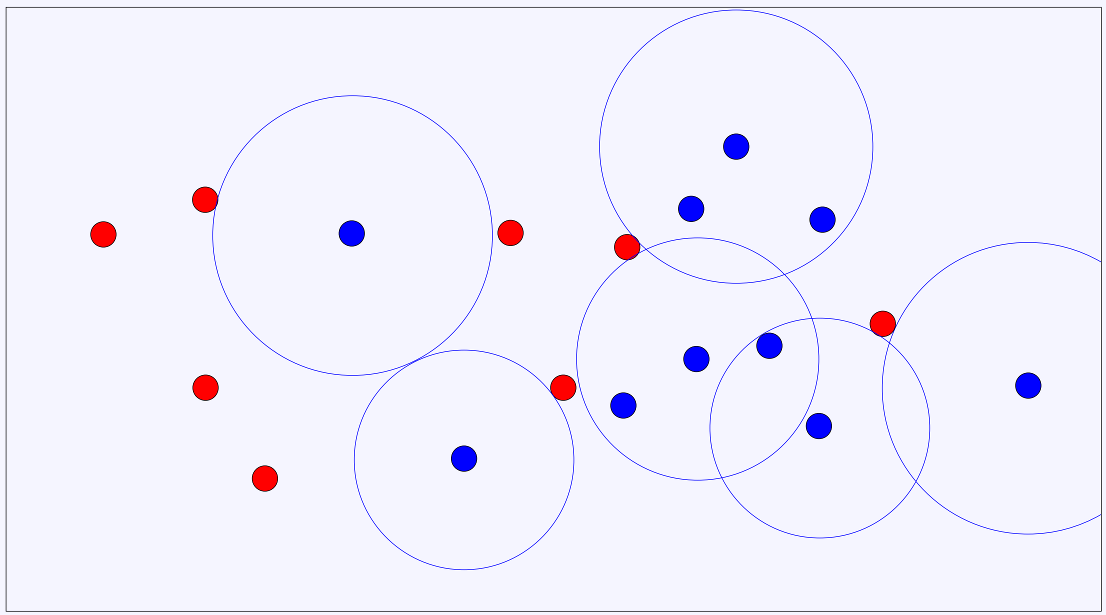
Find a cover C_X for X.



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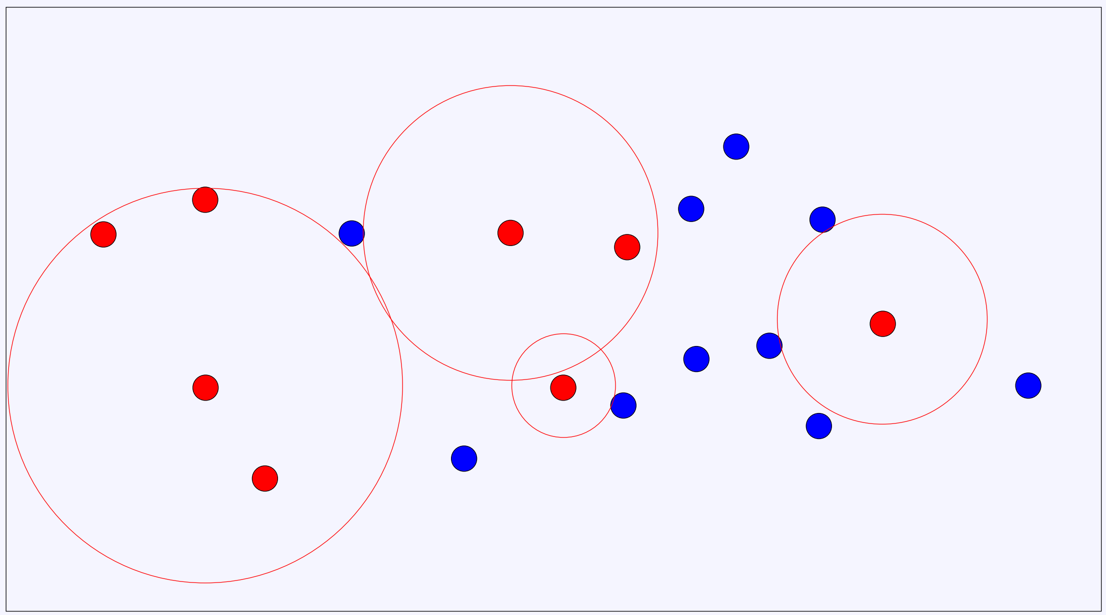
Find a cover C_Y for Y.



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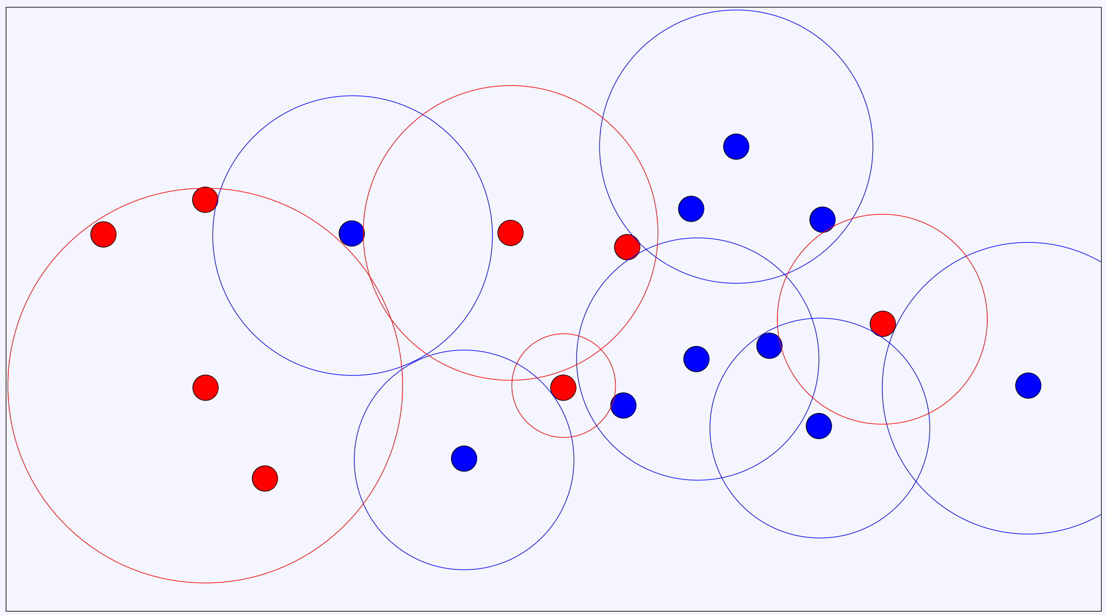

Create a dissimilarity function $\rho(z, C)$ to measure the dissimilarity between a point $z \in \Omega$ and a cover C.

Naive or Pre-classifier

Given training data $X, Y \subset \Omega$ and covers C_X, C_Y. Define

$$\rho(z, C) := 1 - I\{z \in C\}$$

Using the reduced nearest neighbor framework,

$$g(z) := \begin{cases} 1 & : \quad \rho(z, C_1) < \rho(z, C_2) \\ 2 & : \quad \rho(z, C_1) > \rho(z, C_2) \\ 0 & : \quad \text{otherwise} \end{cases}$$

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or more simply,

$$g(z) := \begin{cases} 1 & : \quad z \in C_1 \cap C_2^c \\ 2 & : \quad z \in C_2 \cap C_1^c \\ 0 & : \quad \text{otherwise} \end{cases}$$

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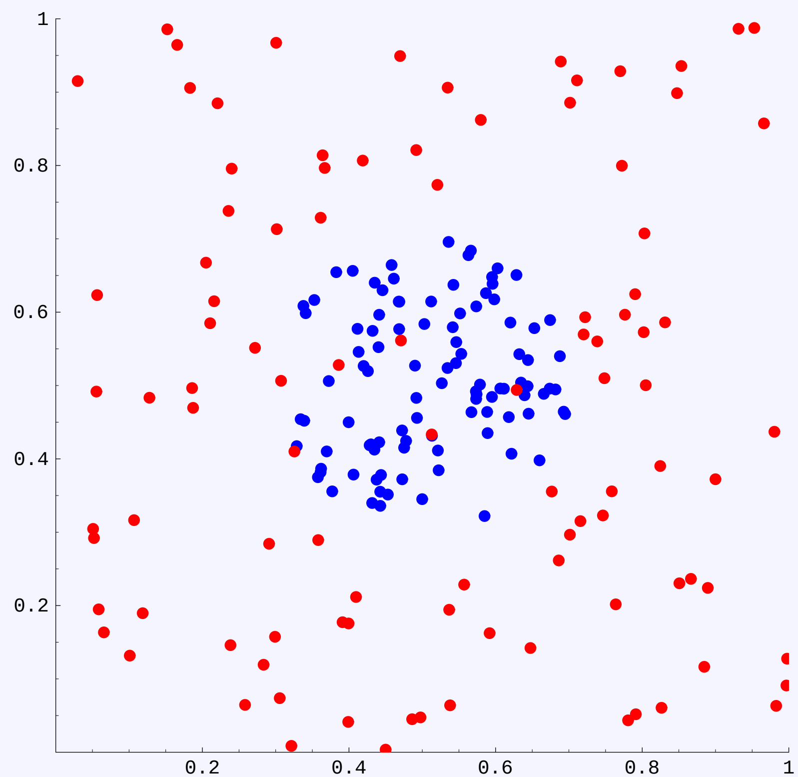
Simulation: Disk

100 Red Points $\sim U([0,1] \times [0,1])$.

100 Blue Points $\sim U(B((0.5, 0.5), 0.2))$



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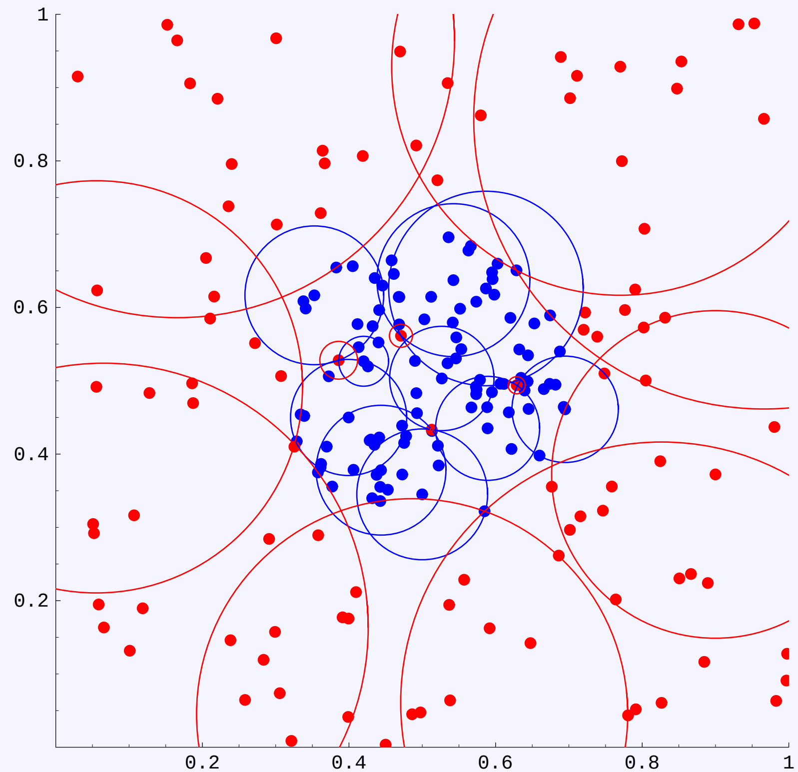

Drawbacks of Naive Classifier - overfitting

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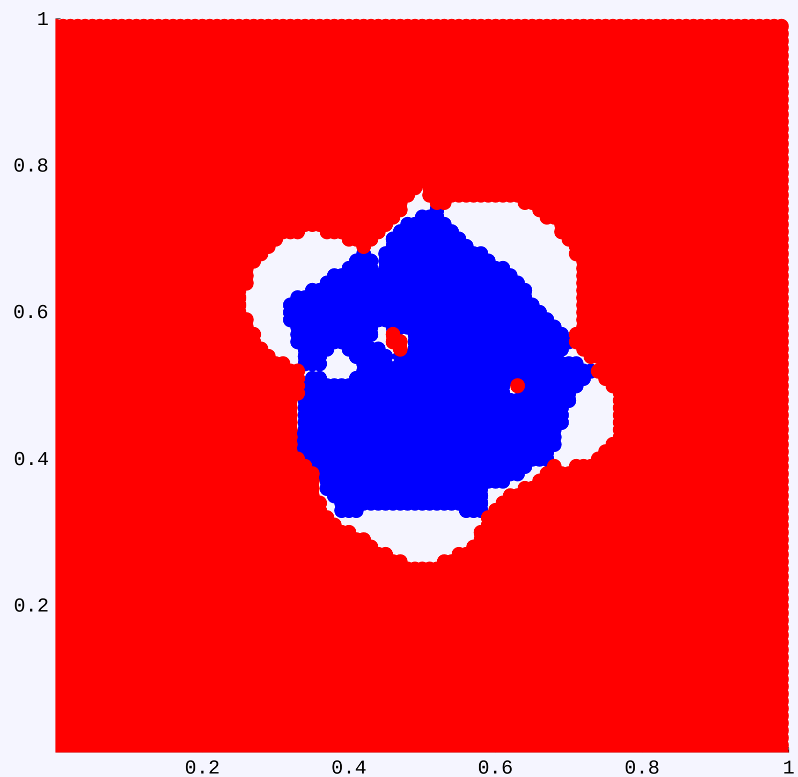
100 Red Points $\sim U([0,1] \times [0,1])$.

100 Blue Points $\sim U(B((0.5, 0.5), 0.2))$



Drawbacks of Naive Classifier - overfitting and “no decision” regions.

Scaled Dissimilarity Function

$\rho(z, C) := \min_{B_i \in C} \frac{d(c_i, z)}{r_i}$ where a ball B_i has center c_i and radius r_i.

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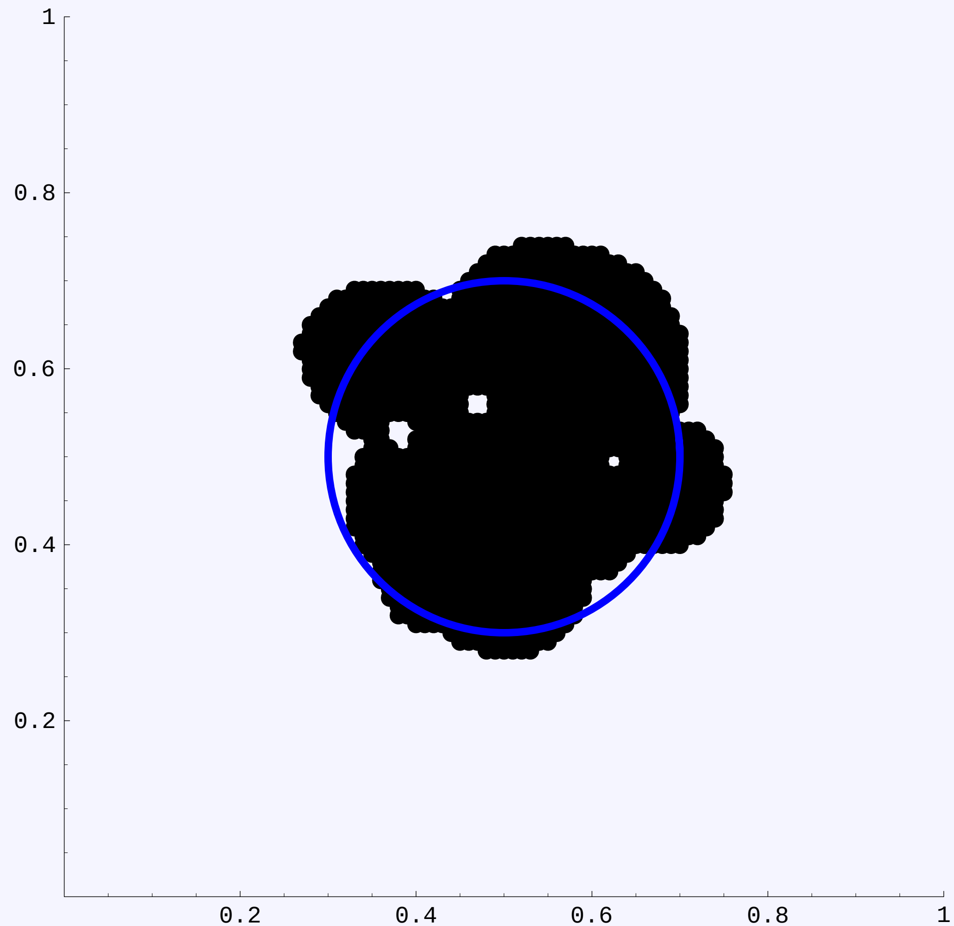

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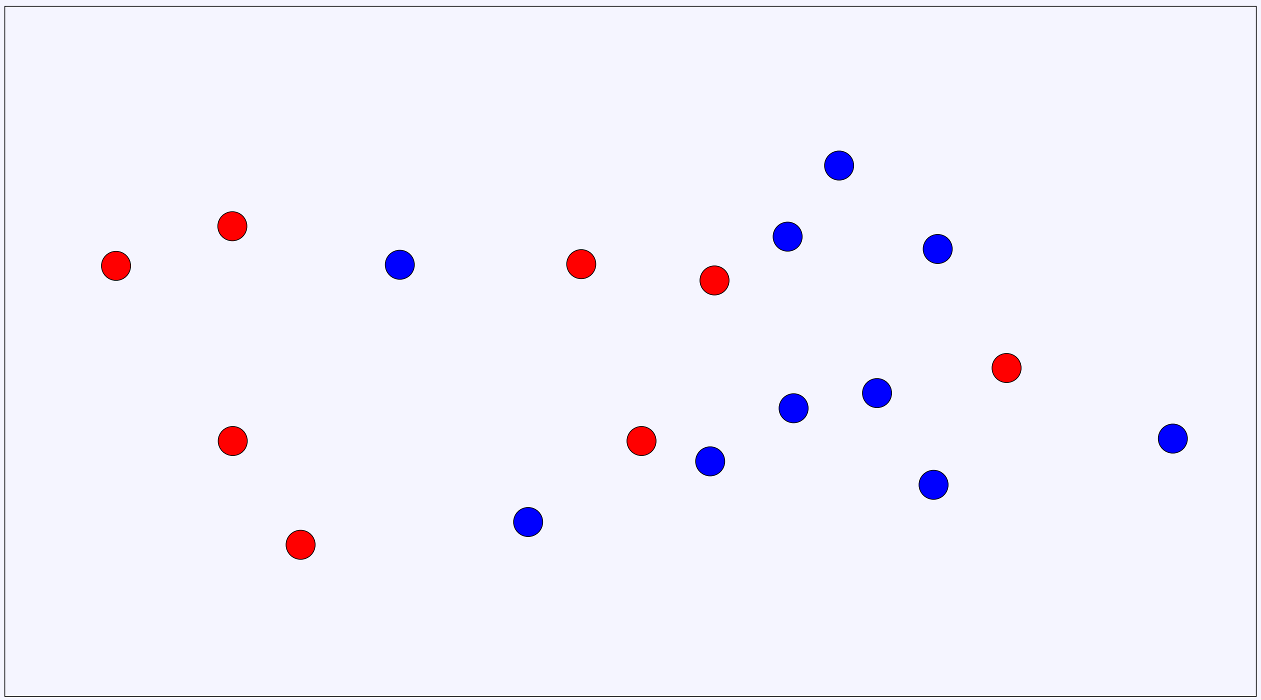
α,β CCP

$CCP(\alpha, \beta) :=$ the CCP where each ball may cover β of non-target class points and the cover may "miss" at most α of the target class points.



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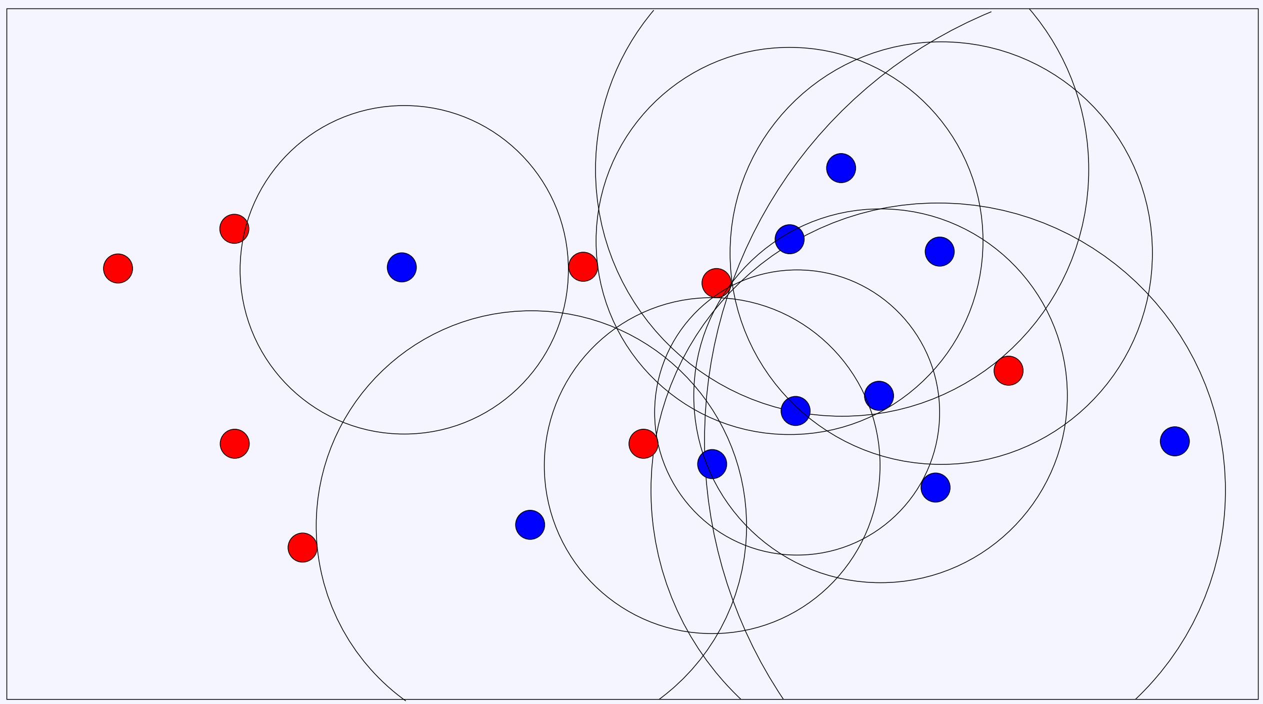

$\beta = 1$

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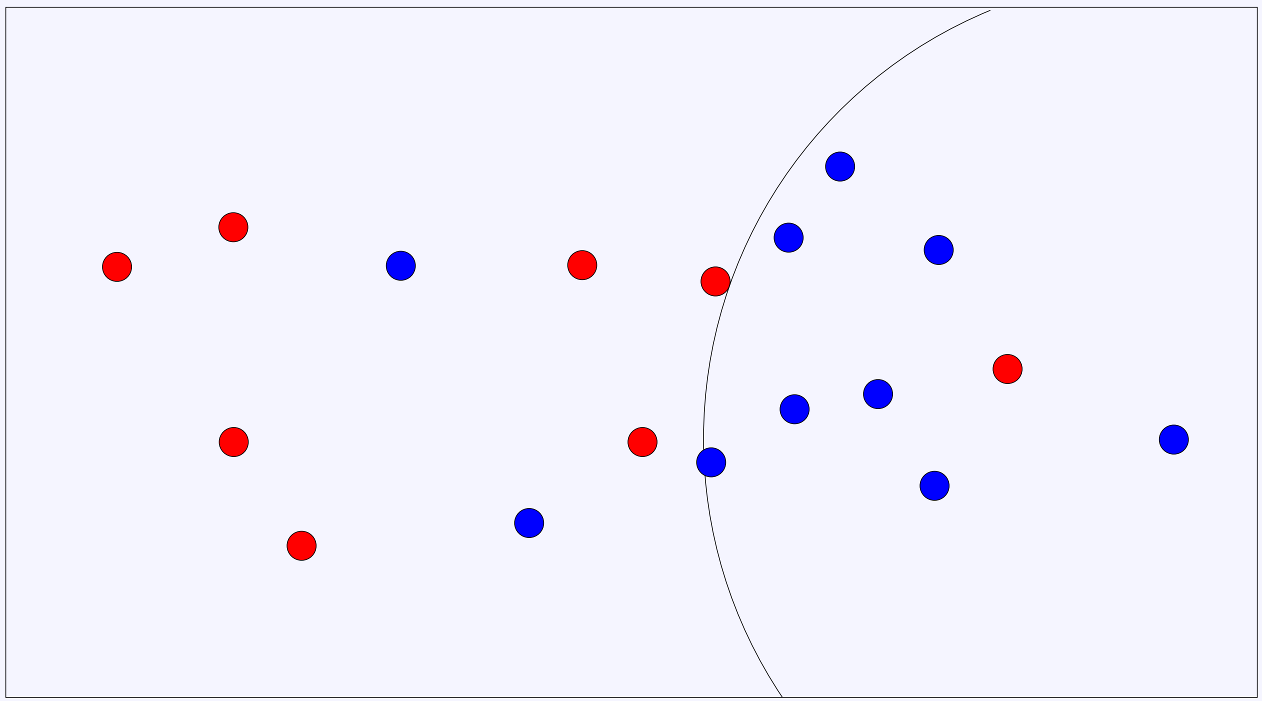
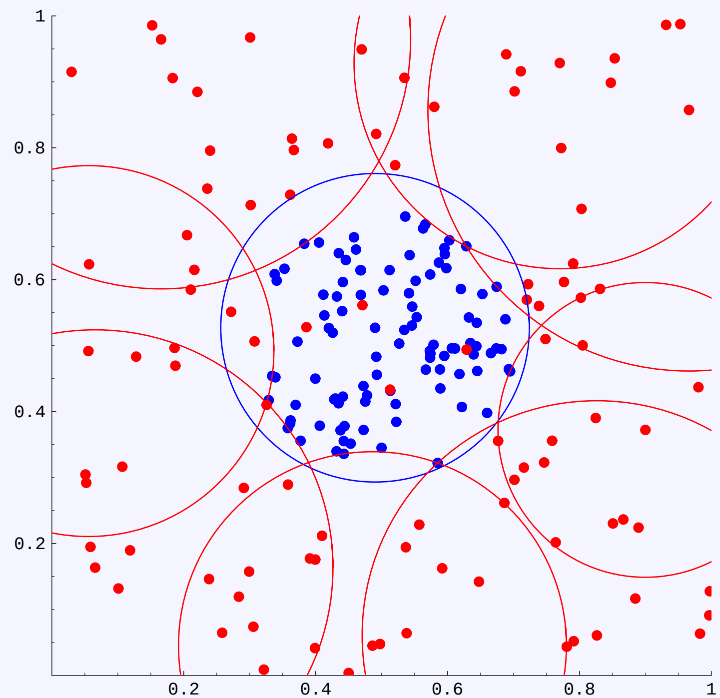


$\beta = 1 \qquad \alpha = 2$

α,β CCP

Benefits of α,β CCP.

- α parameter allows us to “ignore” outlying target class points. Moving toward modeling the discriminant region.
- β parameter allows us to “ignore” outlying non-target class points.



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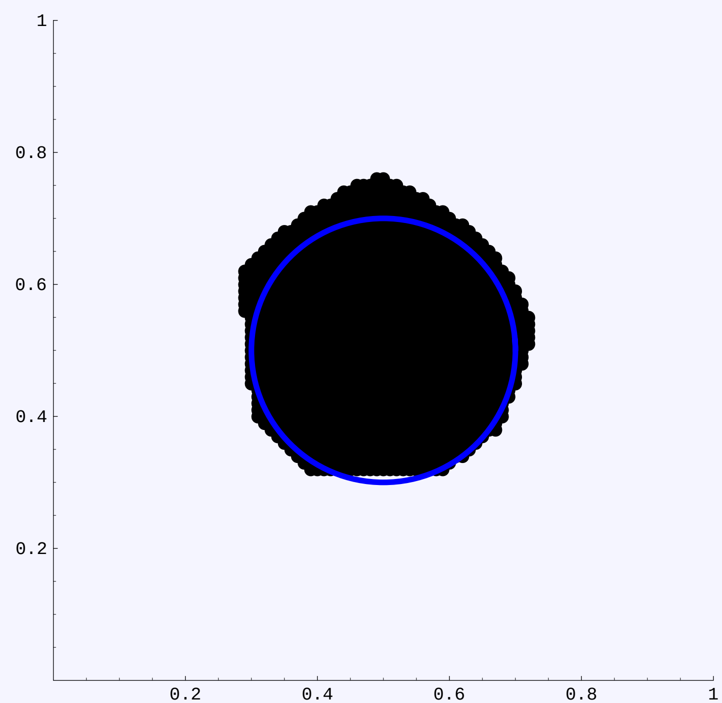

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α,β CCP

Disadvantages of α,β CCP.

- User must choose parameters α, β for each class.
- β parameters are global. We would only like balls to cover non-target class points in the discriminant region of the target class.

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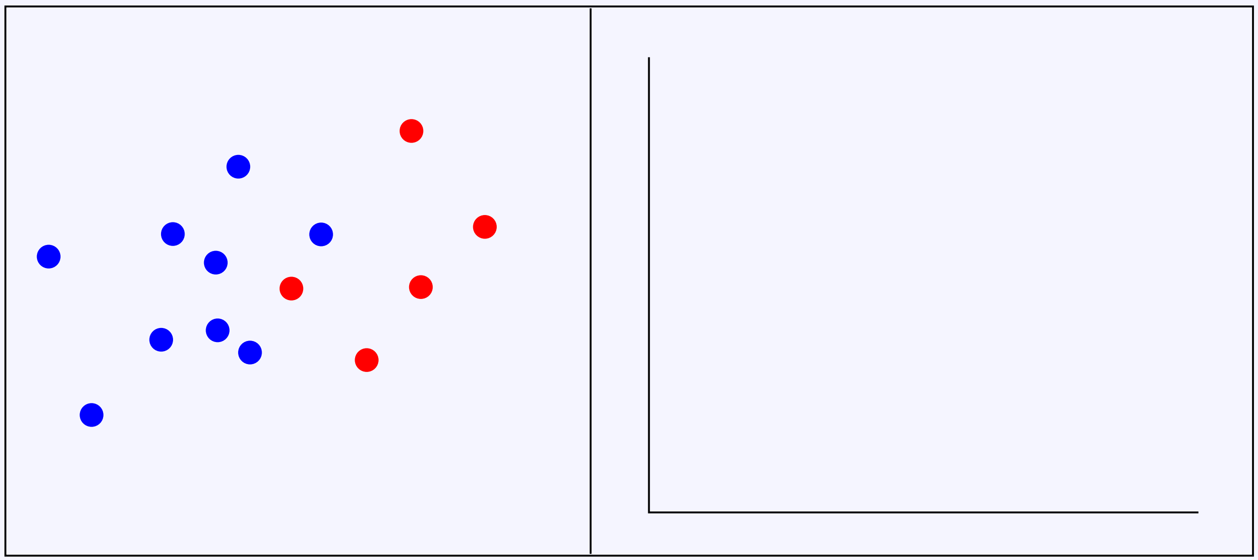
Random Walk CCP

Idea: Let each point choose the radius of its covering ball.



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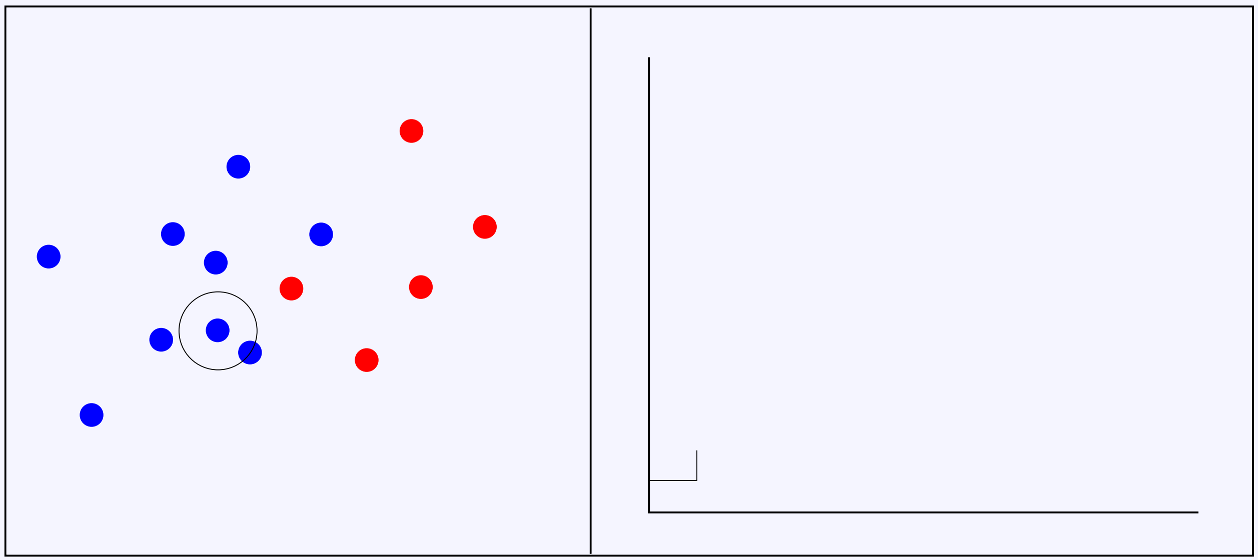

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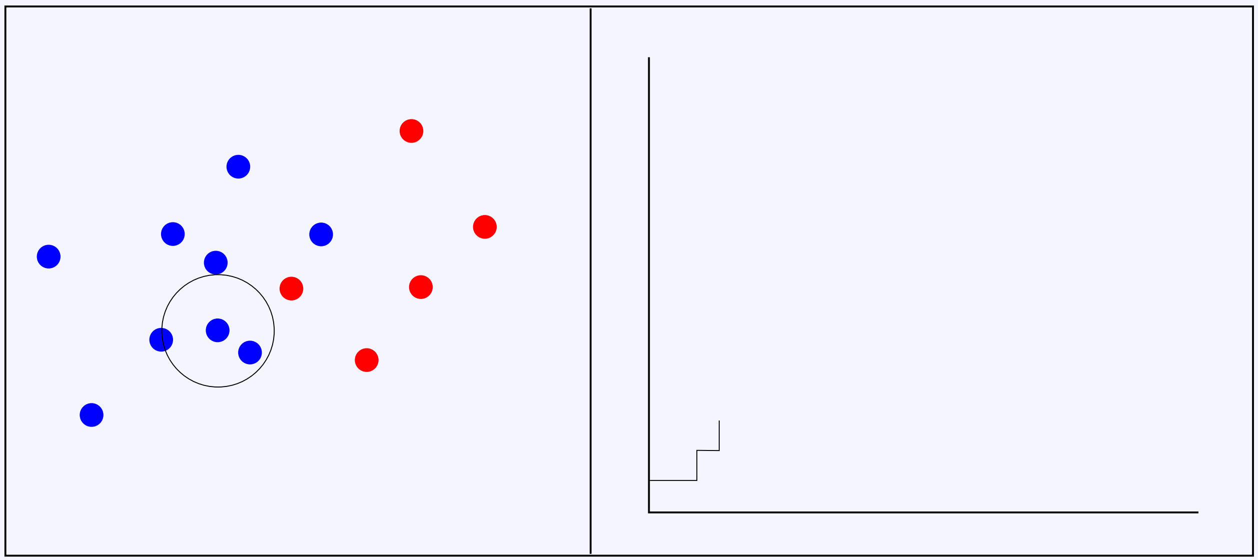

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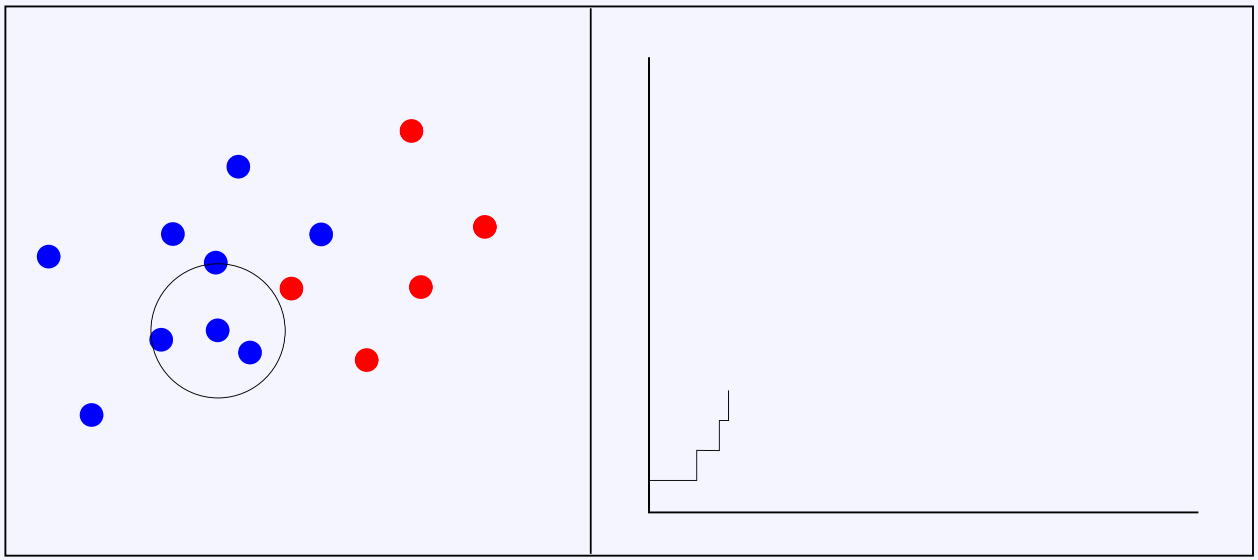

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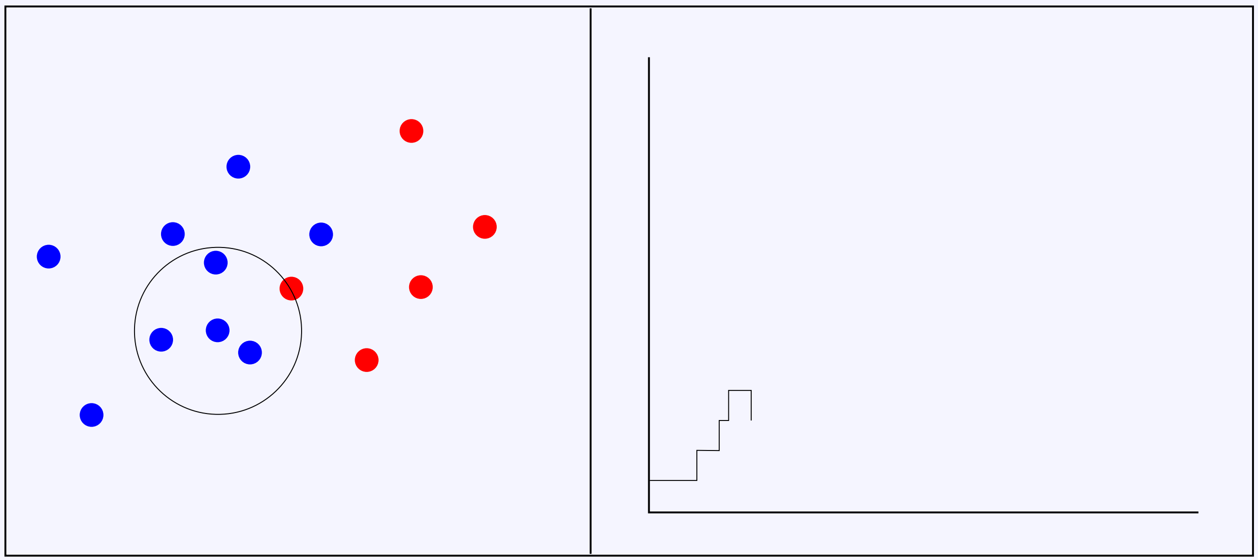

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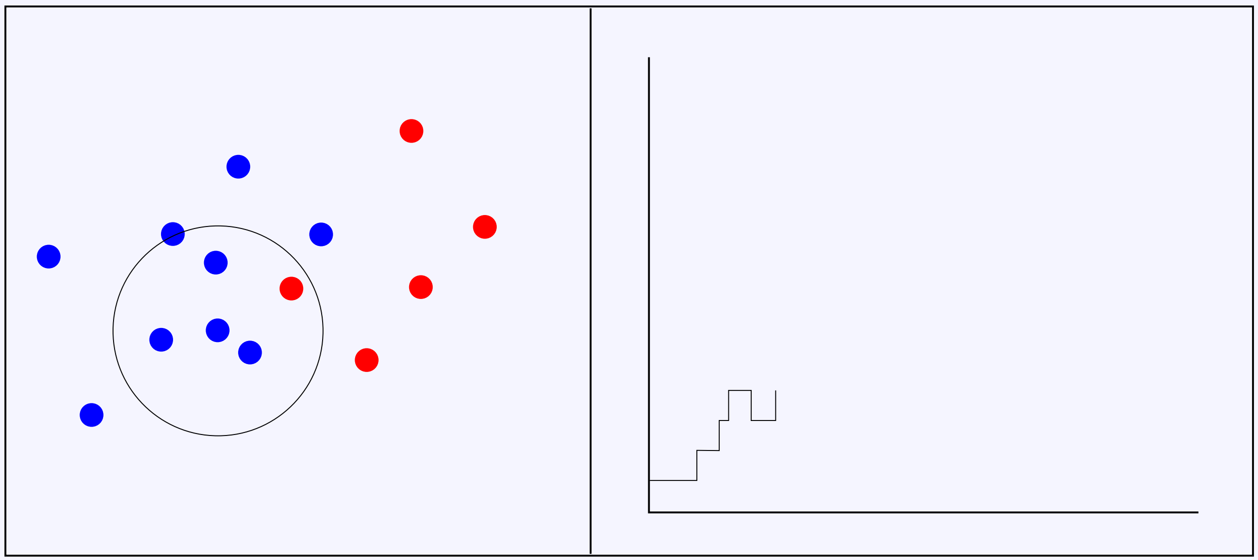

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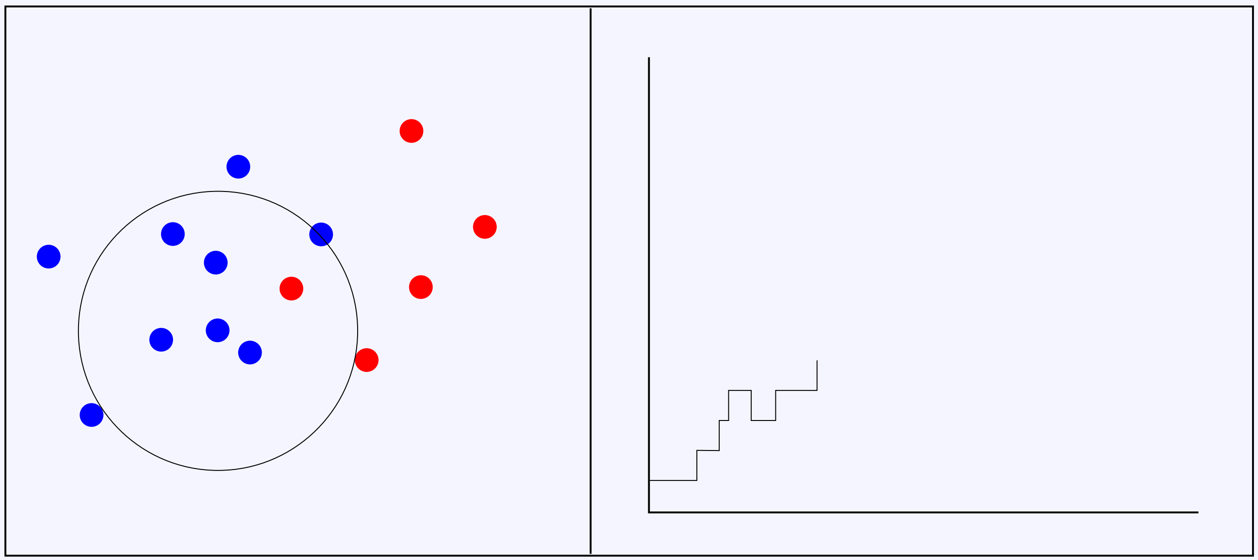

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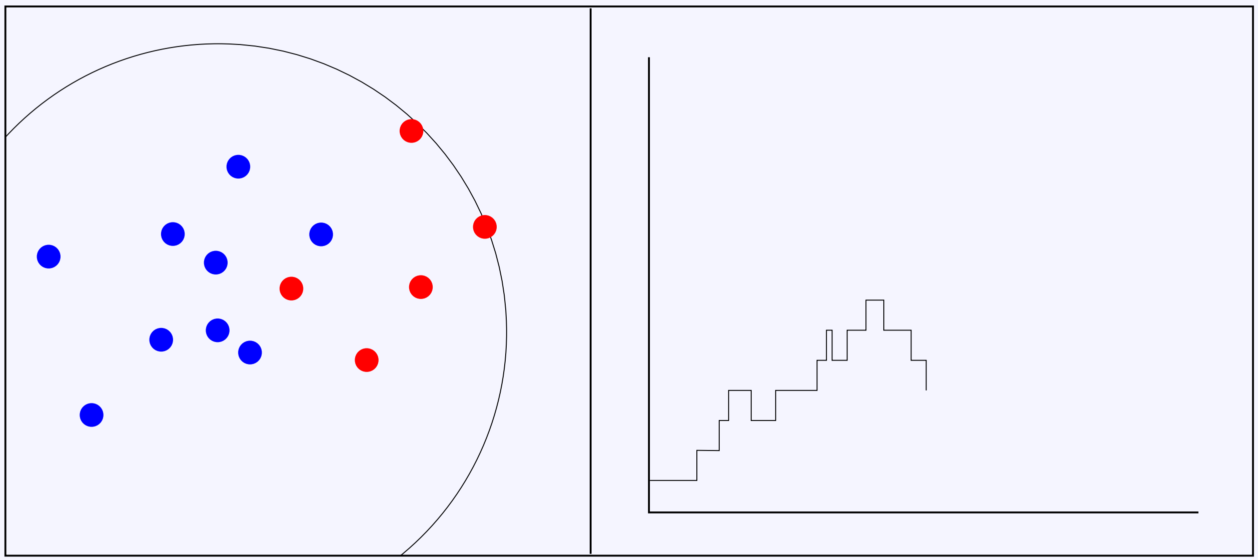

We choose the radius according to:

$$r^* = argmax_{r \geq 0}\{RW(r) - f(r)\}$$

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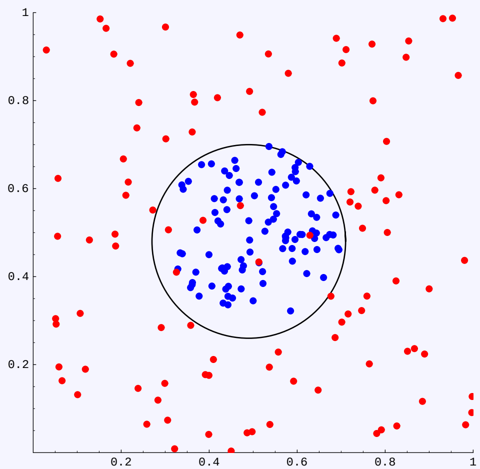
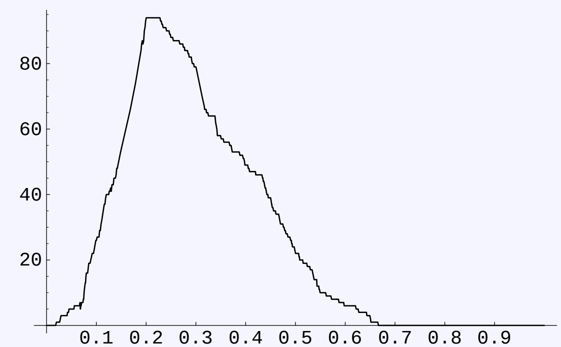
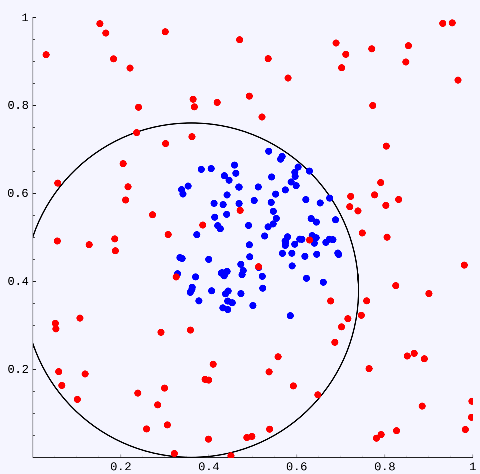
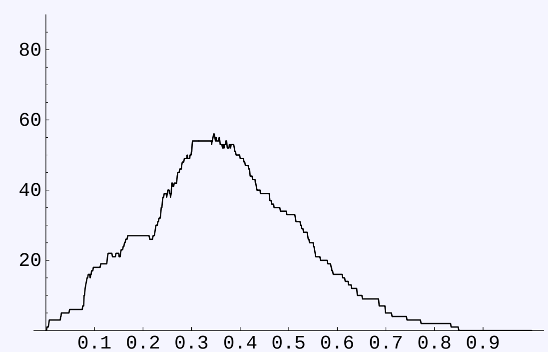
Random Walk CCP









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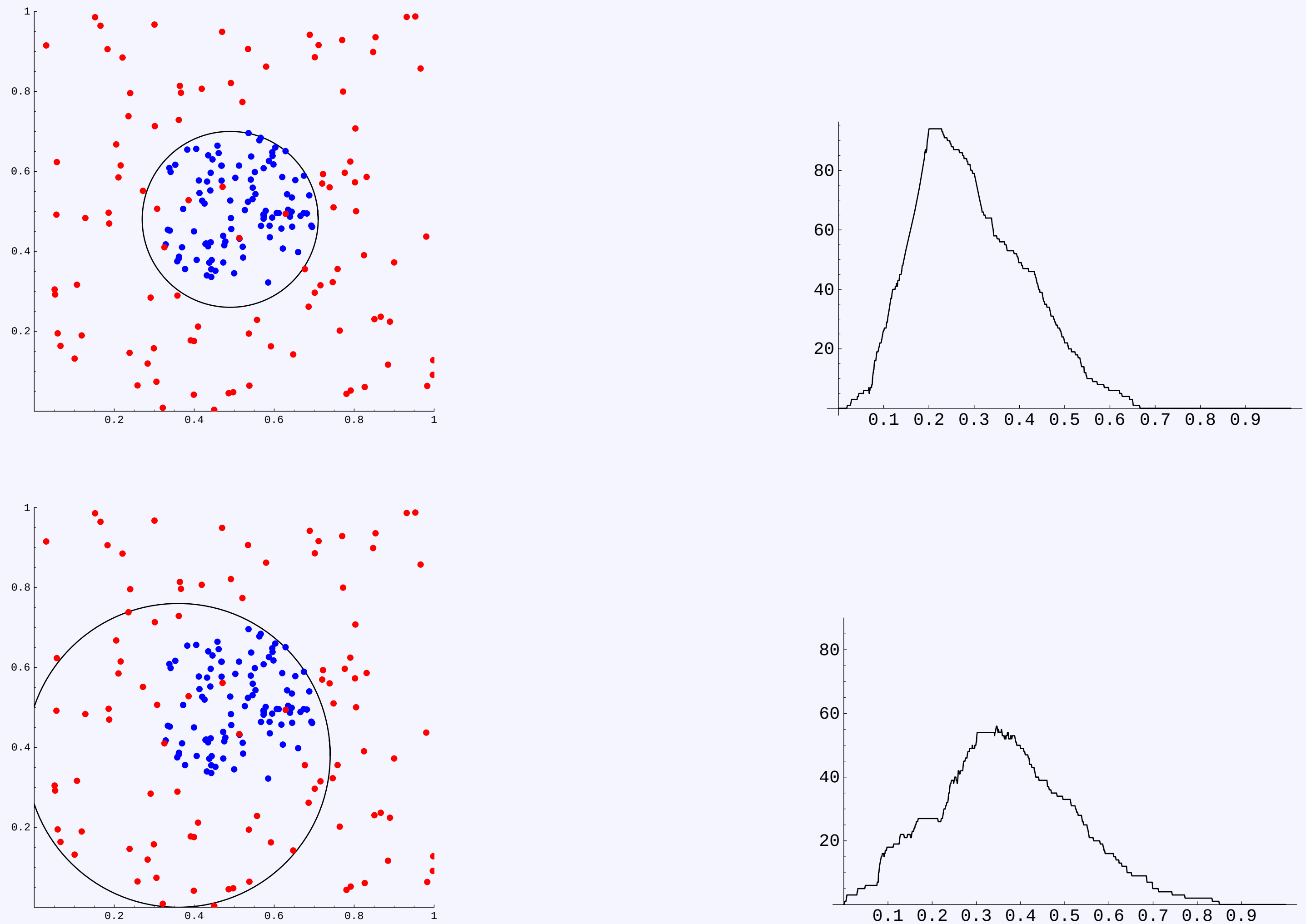
Random Walk CCP



We will need the concept of a score for a covering ball.

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Random Walk CCP

We want to chose the cover that is made up of the “best” or highest scoring covering balls instead of the fewest number of balls.

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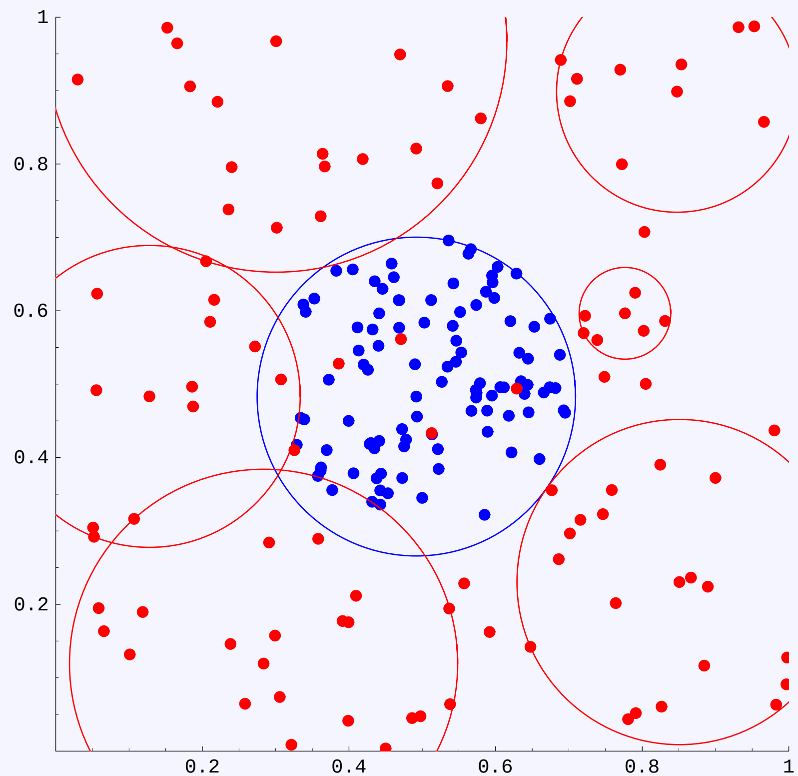

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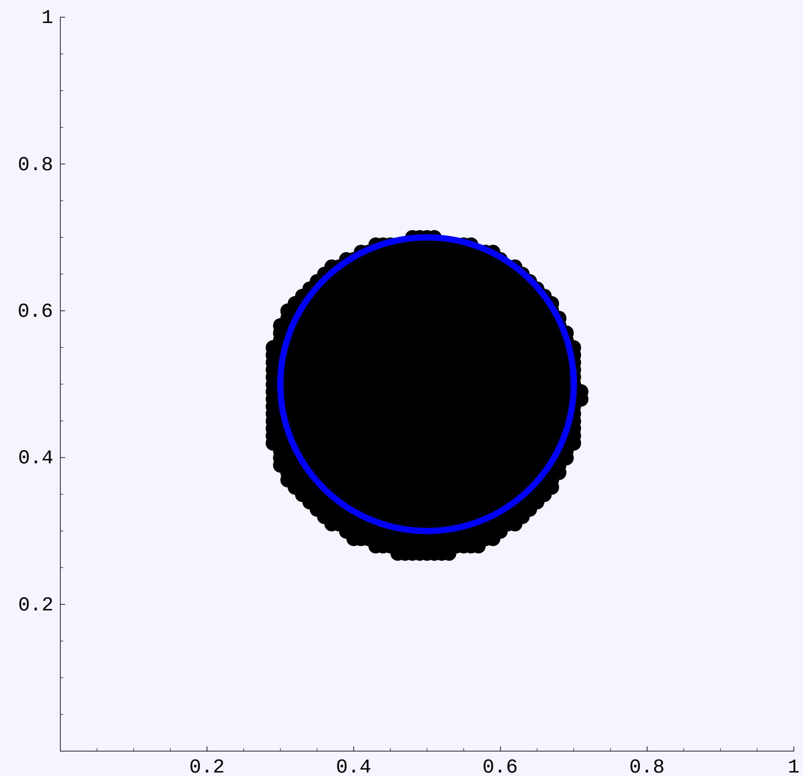

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Random Walk CCP

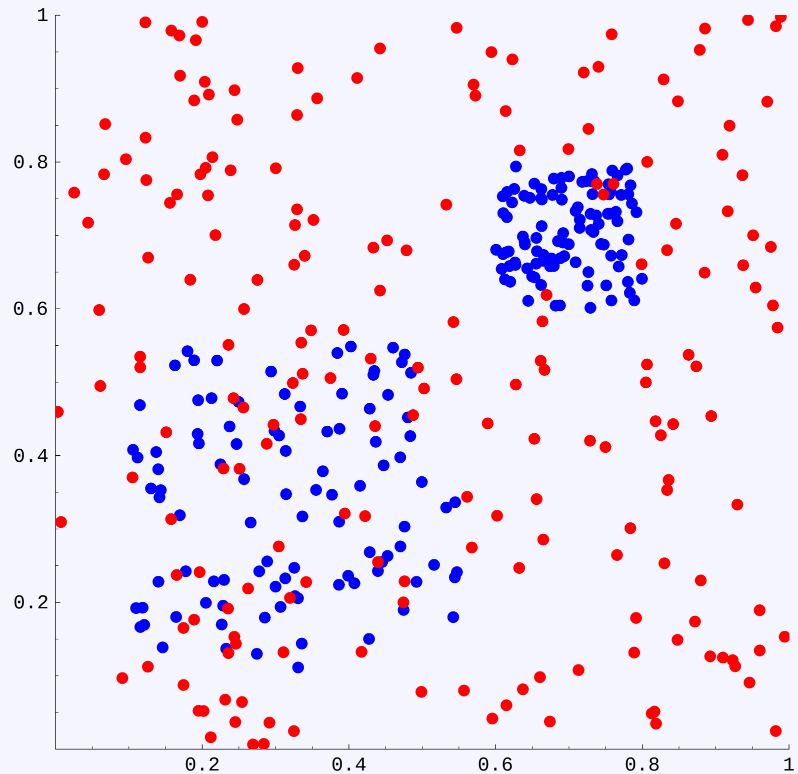
Benefits of Random Walk.

- Same motivation as α, β version, but adaptively chooses the α, β parameters for each ball.
- Each covering ball for a class lies approximately in the discriminant region of that class.
- Covers are less complex than pre-classifier and α, β classifiers. For Disk data,
    - Pre-classifier - $\Gamma_X = 10, \Gamma_Y = 12$
    - α, β classifier - $\Gamma_X = 1, \Gamma_Y = 8$
    - Random Walk Classifier - $\Gamma_X = 1, \Gamma_Y = 6$

Simulation: Data

Red Points $\sim U([0,1] \times [0,1])$.

Blue Points $\sim \frac{1}{2}U([0.1, 0.55] \times [0.1, 0.55]) + \frac{1}{2}U([0.6, 0.8] \times [0.6, 0.8])$



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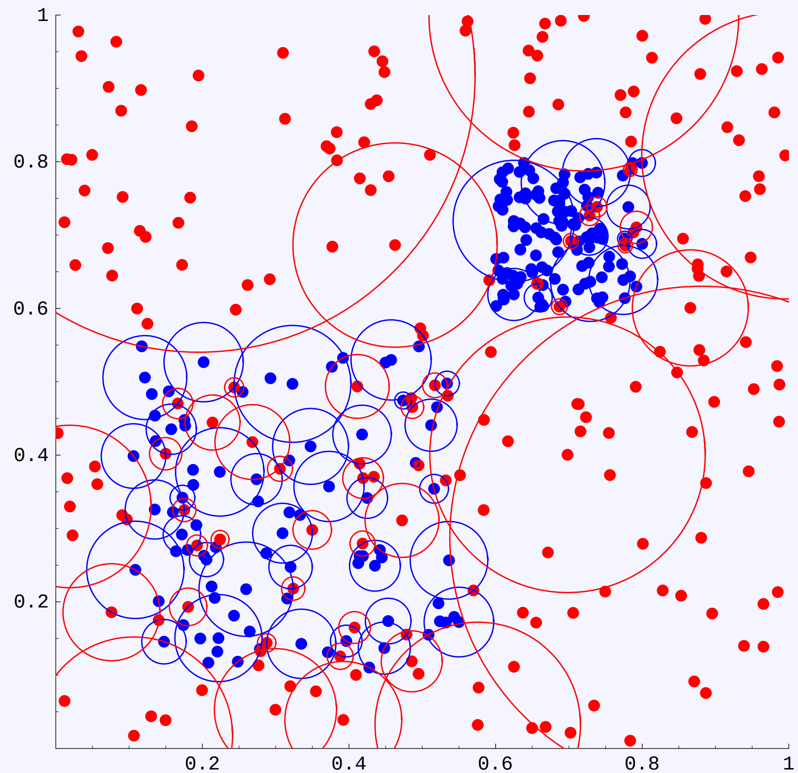
Simulation: Covers



Pure Proper Cover

$$\Gamma_X = 46 \ \ \Gamma_Y = 44$$

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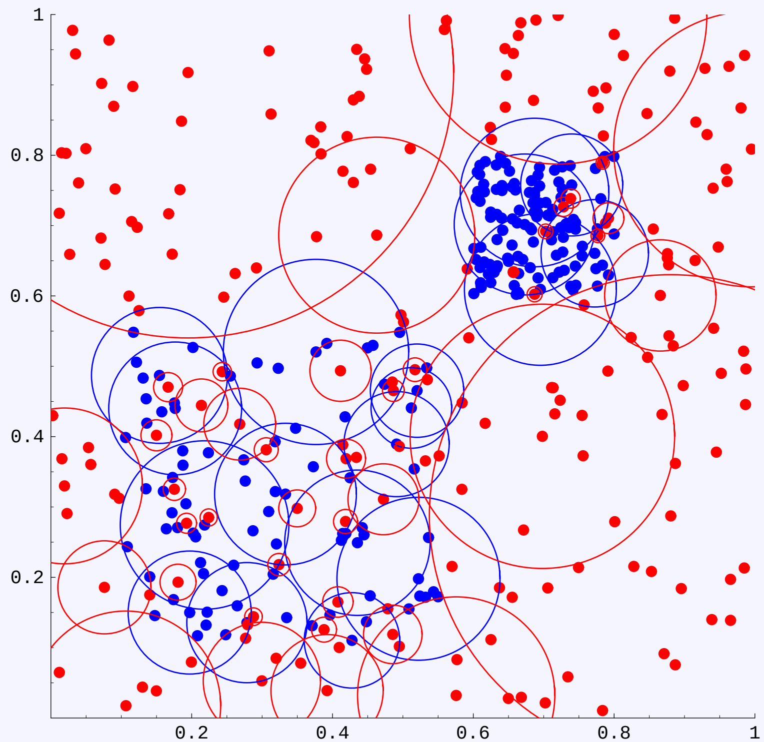
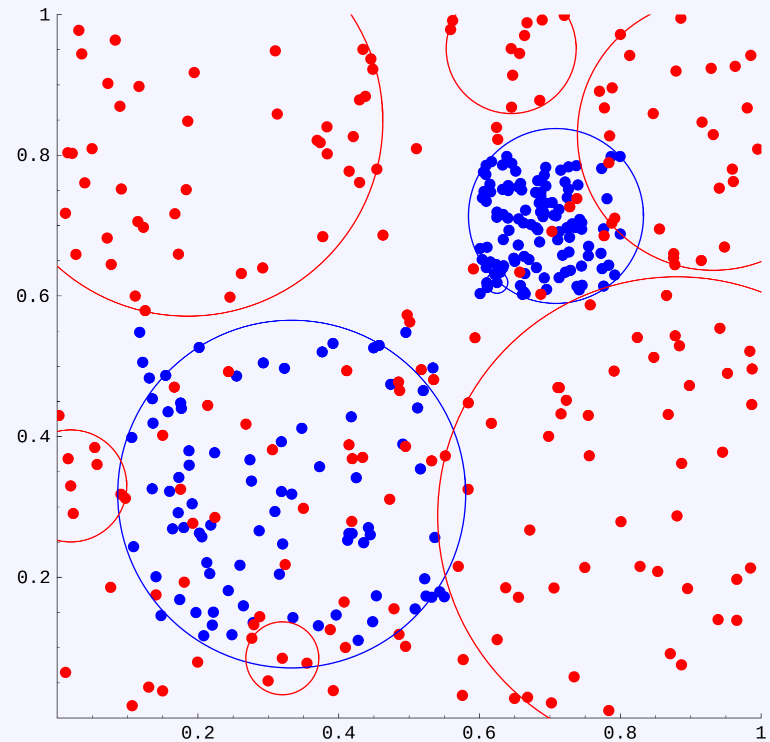
Simulation: Covers



α, β Cover



RW Cover

$\Gamma_X = 14 \;\; \Gamma_Y = 44$

$\Gamma_X = 3 \;\; \Gamma_Y = 6$

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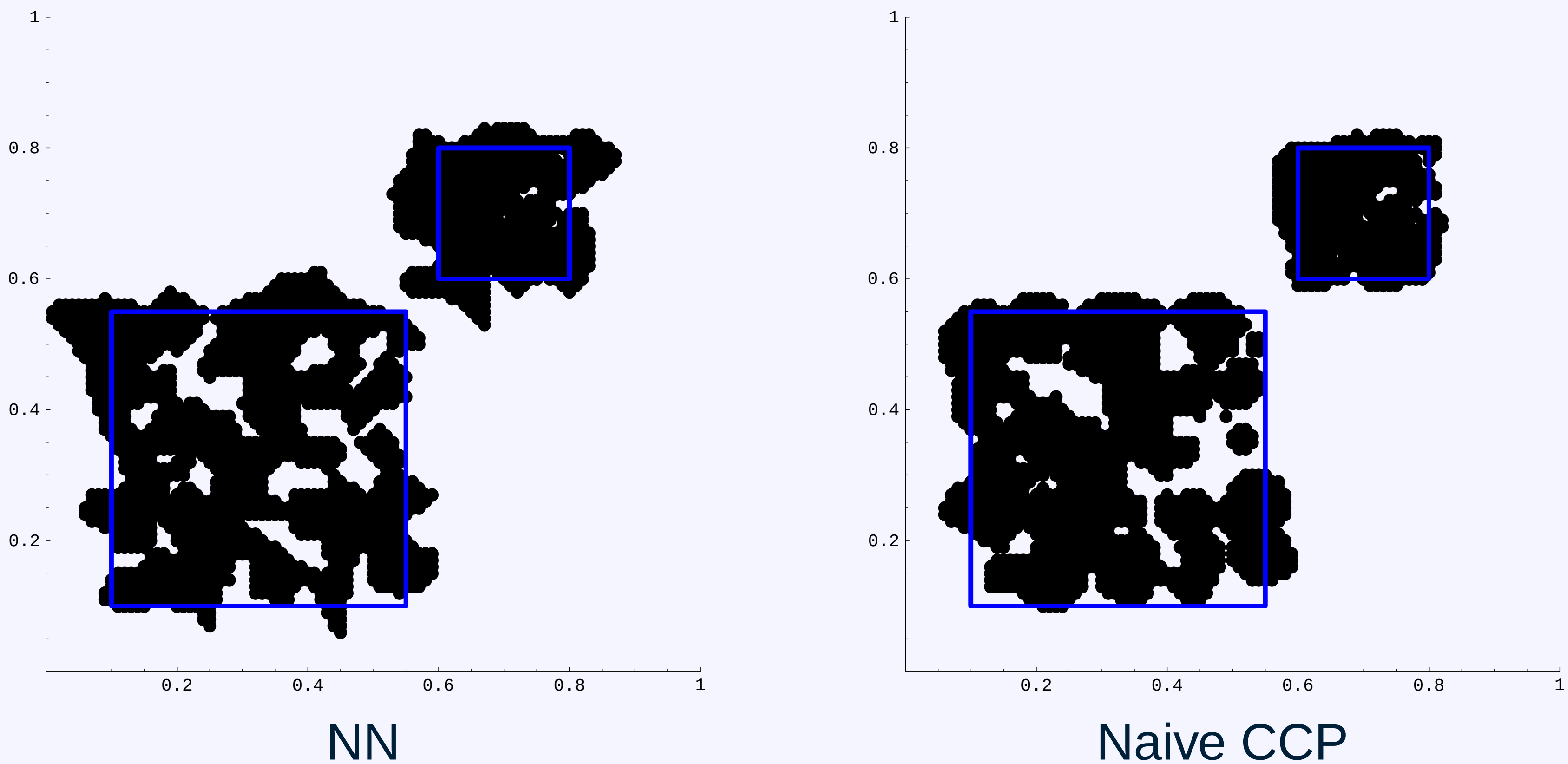
Simulation: Classifier Results



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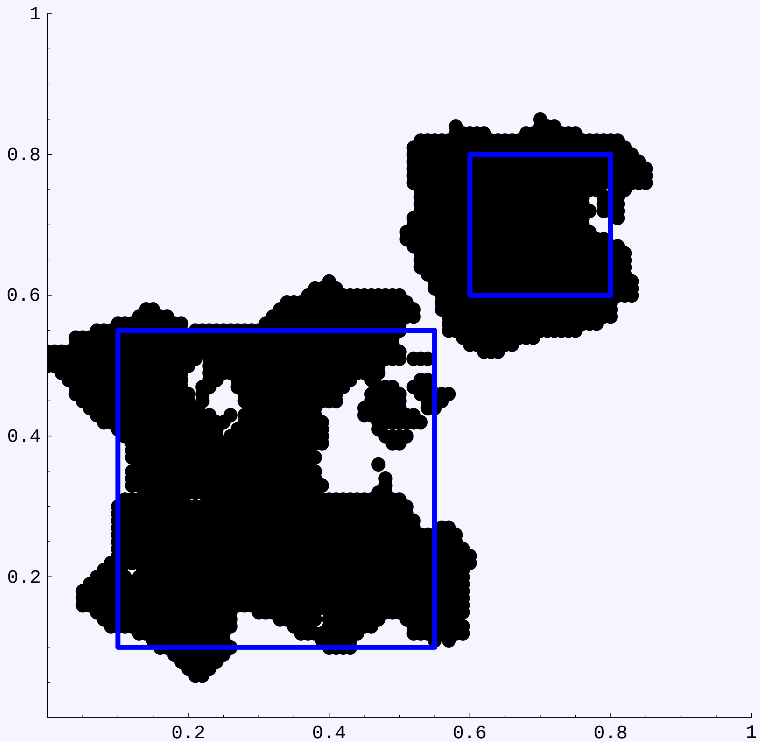
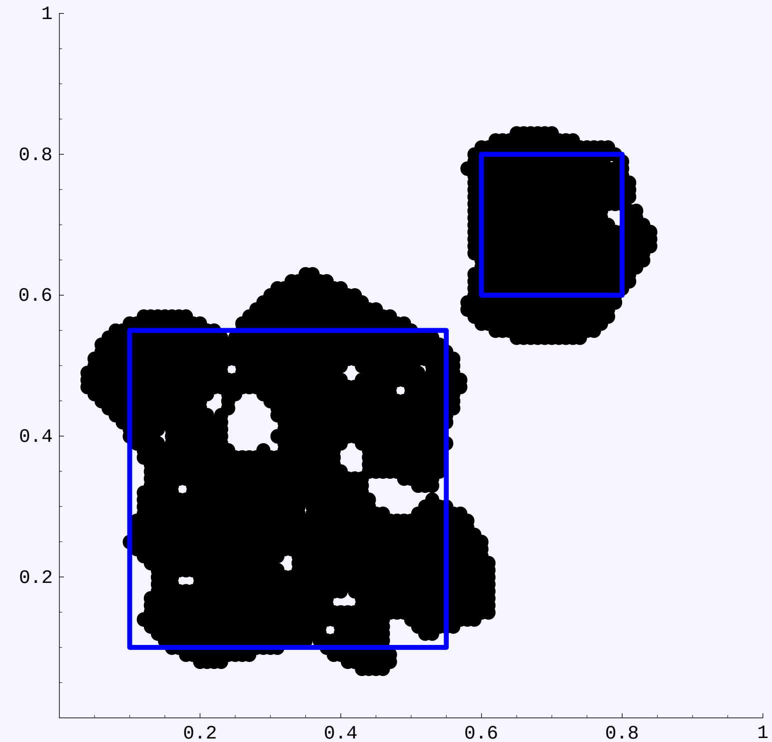


k-NN



α, β CCP

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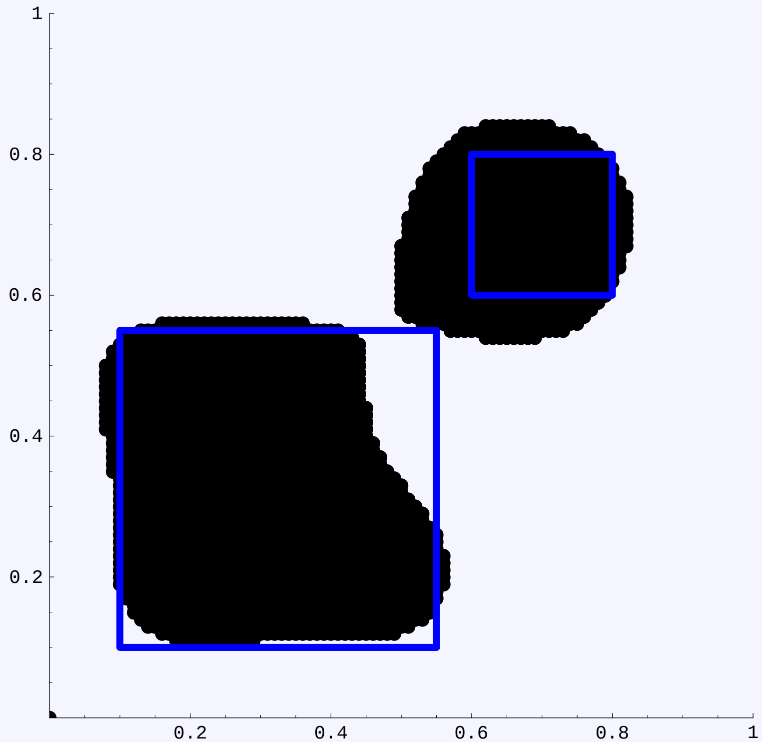
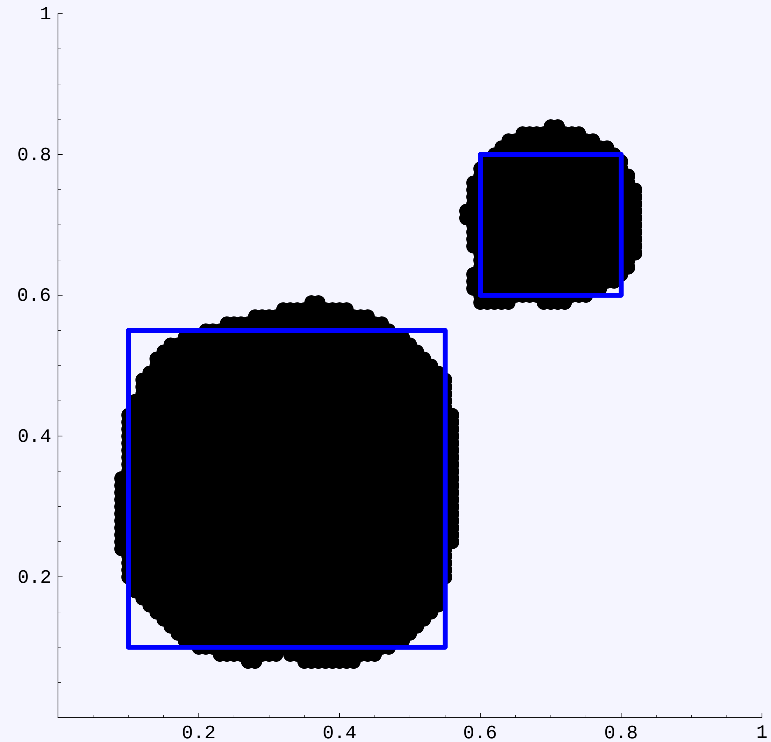
Simulation: Classifier Results



SVM



RW-CCP

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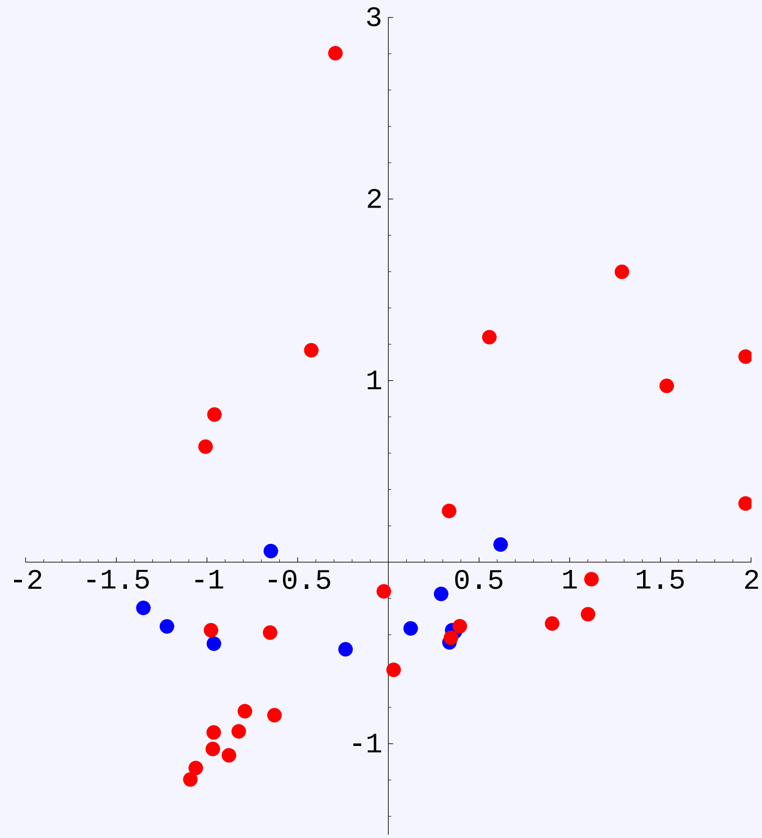
Simulation: Classifier Results

Here are the estimates for the misclassification rate $\hat{L}$ as observed after 1000 trials.

Tr. Size	NN	k-NN	SVM	Nv. CCP	α, β CCP	RW-CCP
50	0.242	.0.240	0.201	0.228	0.212	0.212
100	0.224	0.212	0.184	0.213	0.190	0.183
200	0.210	0.188	0.168	0.201	0.171	0.165
500	0.199	0.166	0.152	0.194	0.154	0.153

Experiment: Minefield Data

39 observations of multispectral images in a minefield.



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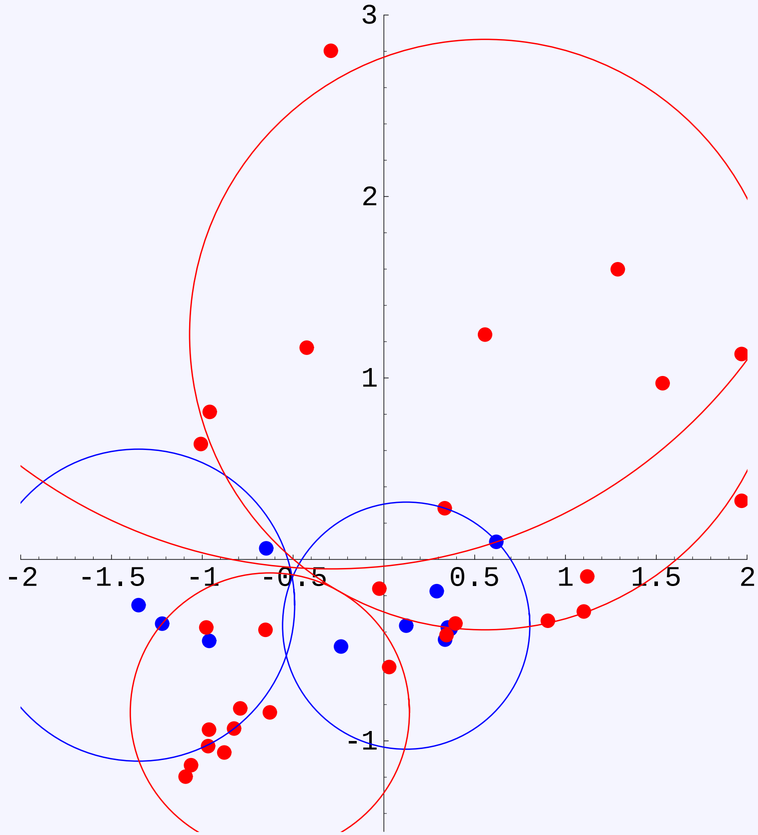
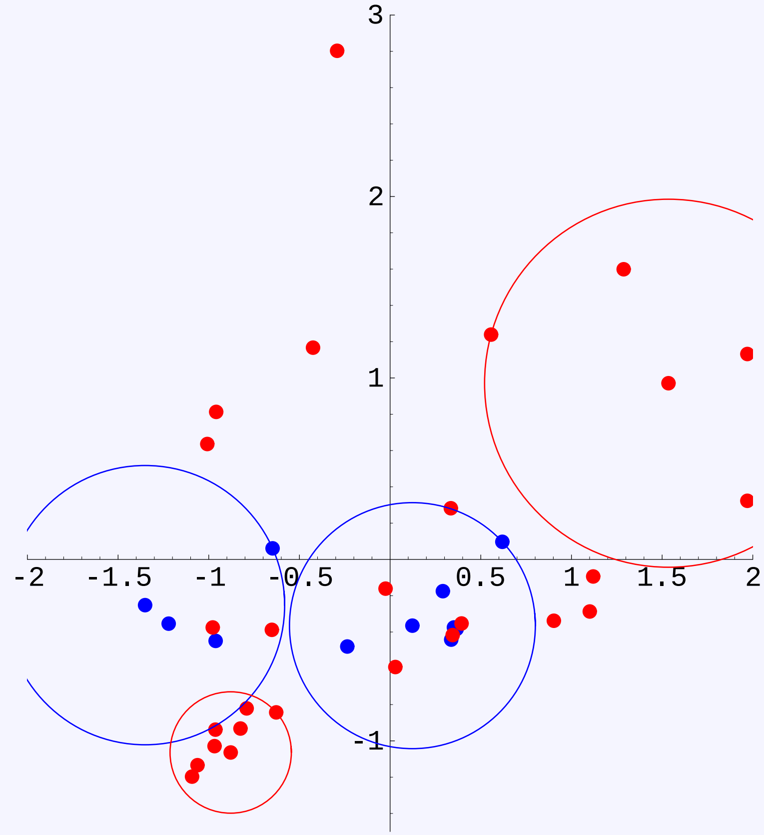
Experiment: Covers



α, β- CCCD



RW-CCCD

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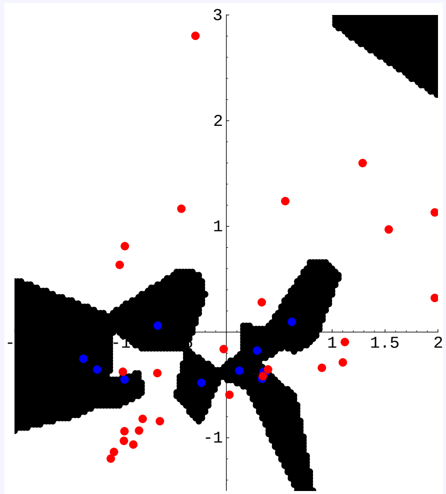
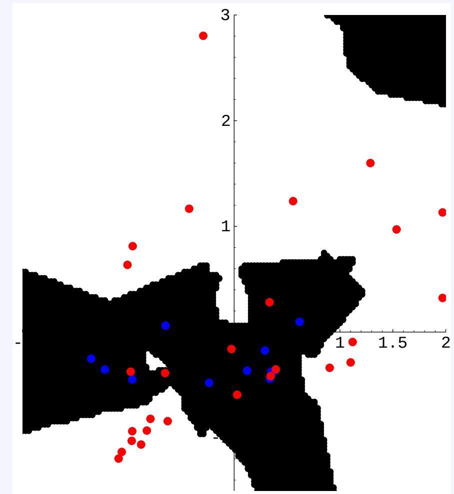
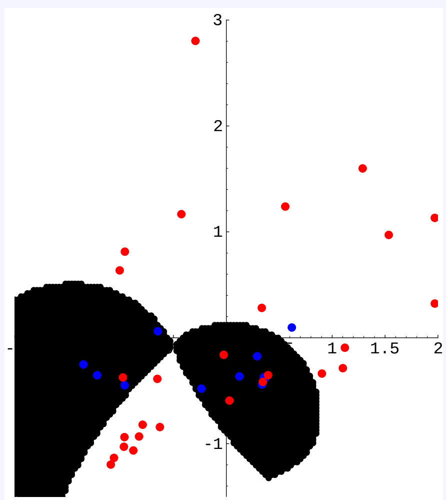
Experiment: Classifiers



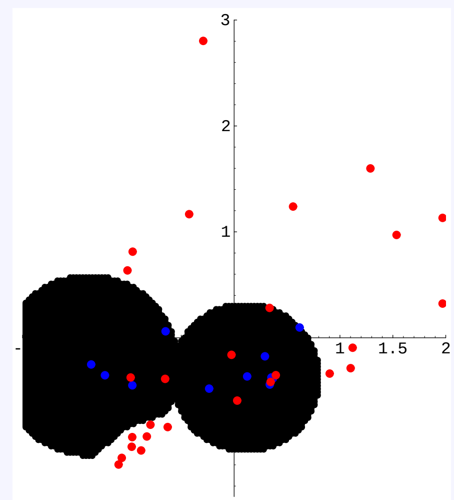
NN



k-NN



α, β CCCD



RW-CCCD

The End

CCCD home page : http://www.mts.jhu.edu/∼devinney/cccd

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- Ed Scheinerman - Math/Sci Dept. Johns Hopkins U.

SVM results courtesy of SVM_light by T. Joachims (http://www-ai.cs.uni-dortmund.de/svm_light)

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