



430.217

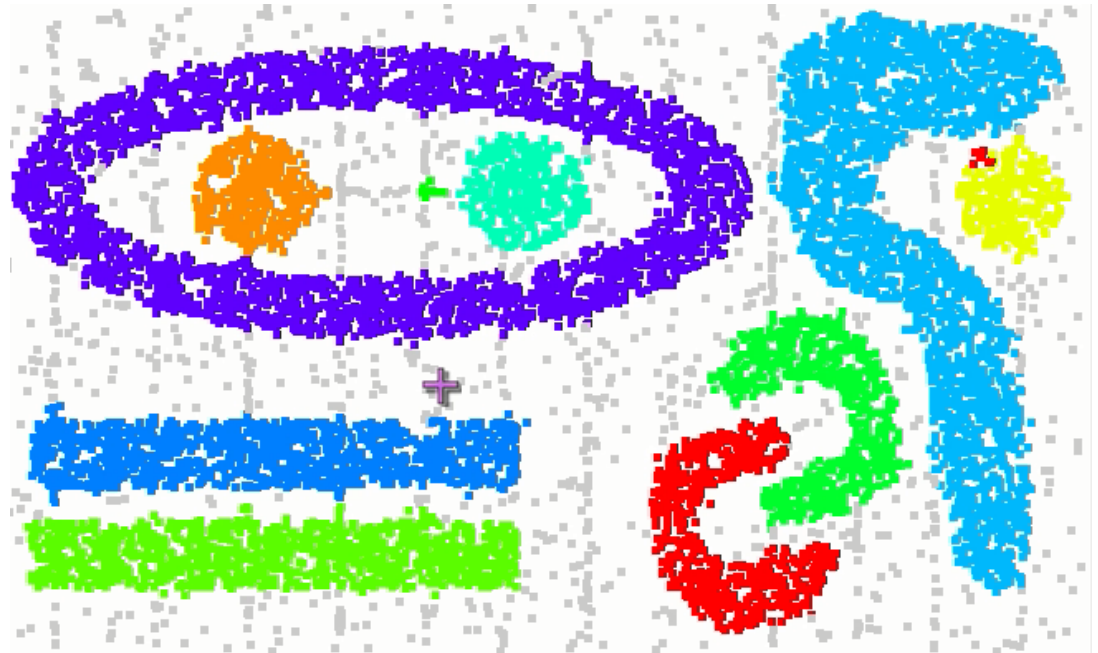
# Introduction to Data Structures

Project

Seoul National University  
Advanced Computing Laboratory

# DBSCAN

- Density based spatial clustering of applications with noise
  - 밀도가 높으면 하나의 cluster로 간주



- 구현에 필요한 자료구조
  - kd-tree
  - Disjoint set
  - Container (array / linked list / stack / queue / heap 등)

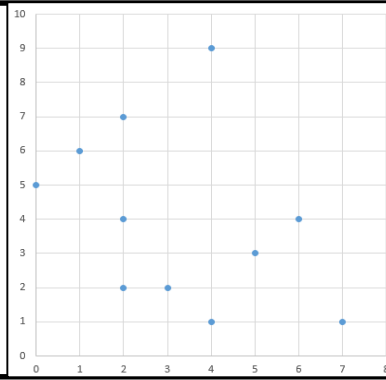
# Project Details

kd-tree

DBSCAN (union-find)

# DBSCAN Overview

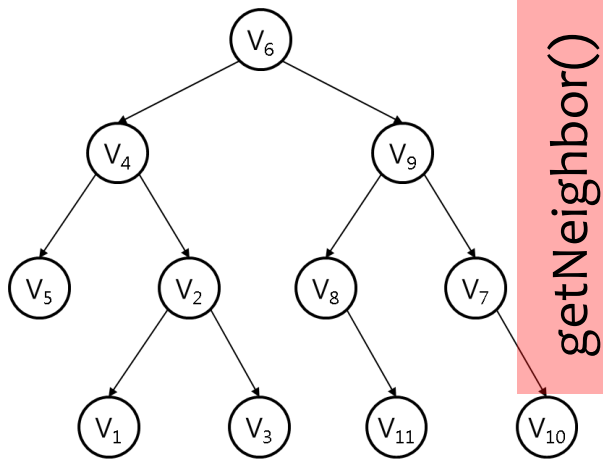
Coordinate data



Build a  
kd-tree

float\*\*

kd-tree



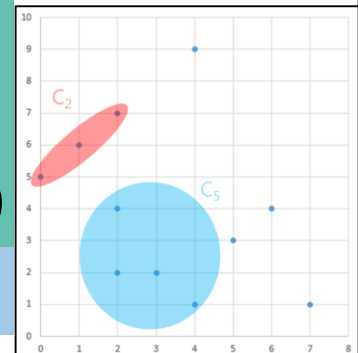
DBSCAN

Run()

Coordinate

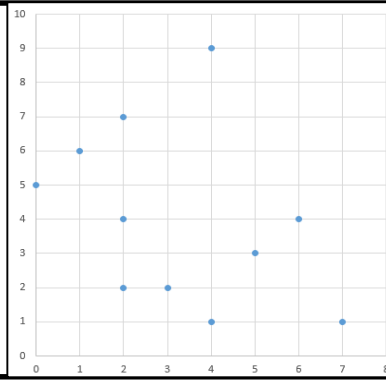
CoordinateSet

Check  
conditions  
&  
Clustering  
(Union & Find)



# DBSCAN Overview: kd-tree

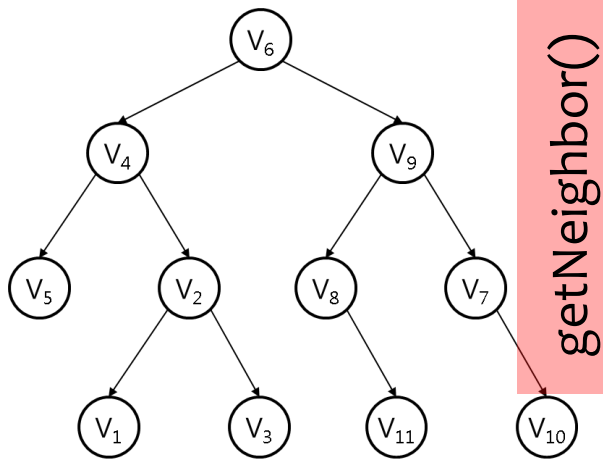
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getNeighbor()

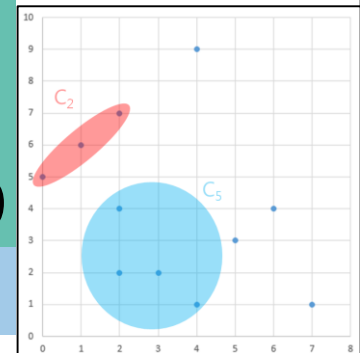
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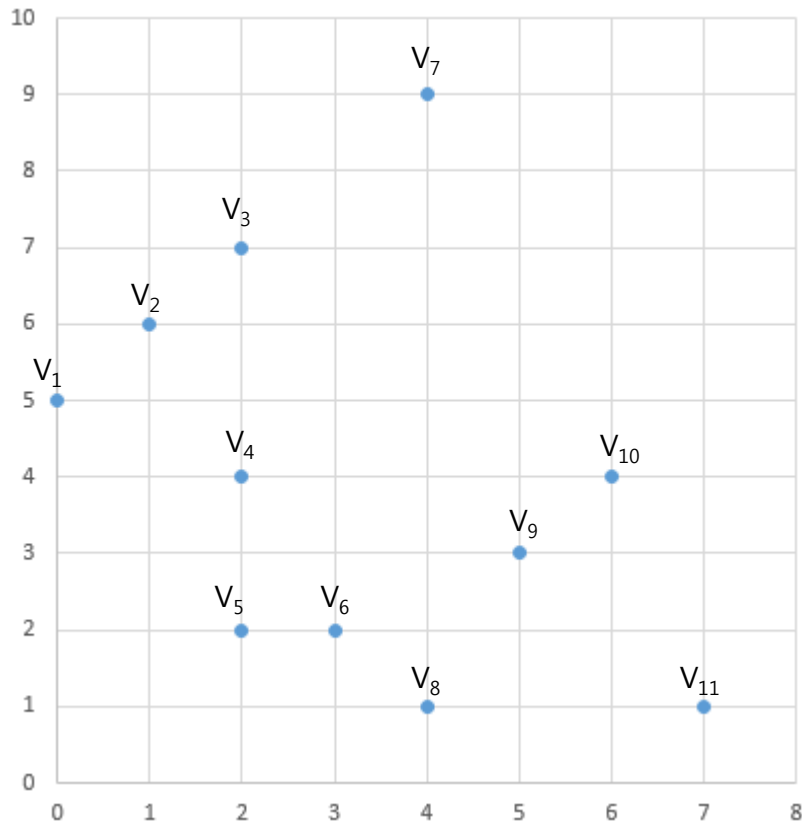
Coordinate

CoordinateSet



# kd-tree

- k-dimensional tree
  - A general version of a BST (BST = 1D tree)
  - Stores k-dimension coordinates data (same dimension in a kd-tree)
  - Fast region search

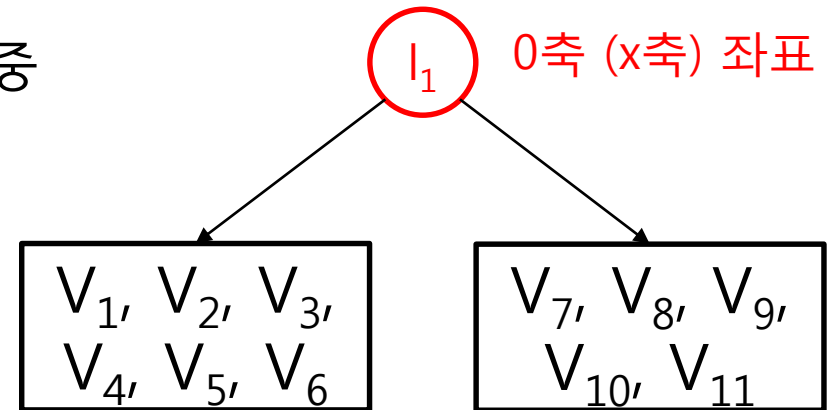
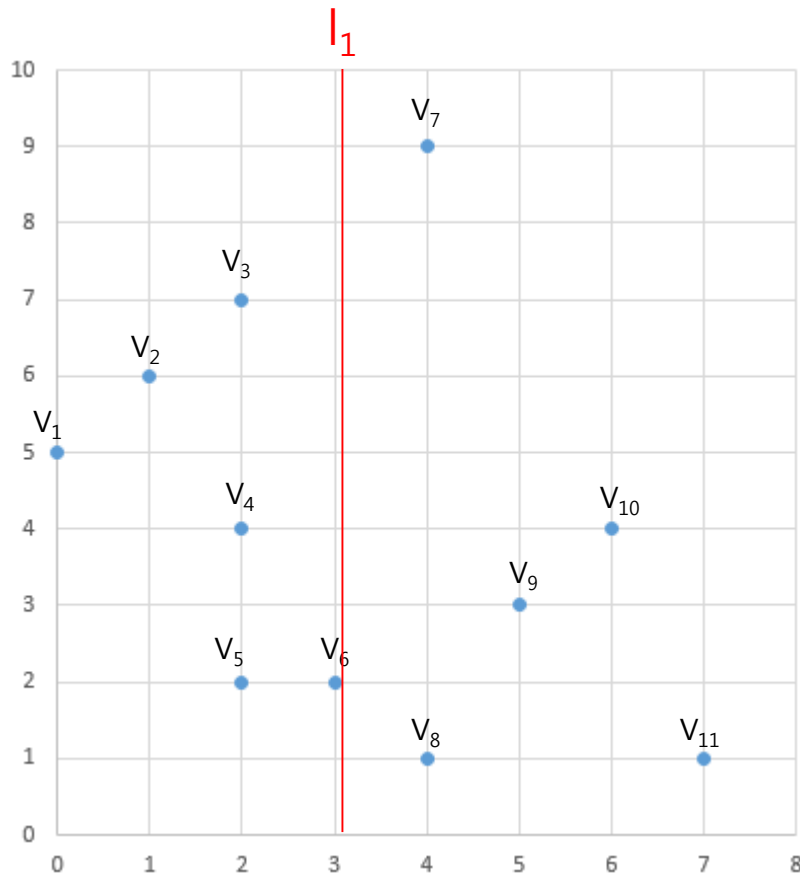


# Build a kd-tree

## ■ Example: 2D

- Parent node는 hyperplane 정보 저장  
(기준 point는 (depth % k) 축의 좌표 중  
median 값을 가지는 point이다.)

$l_i$  = hyperplane



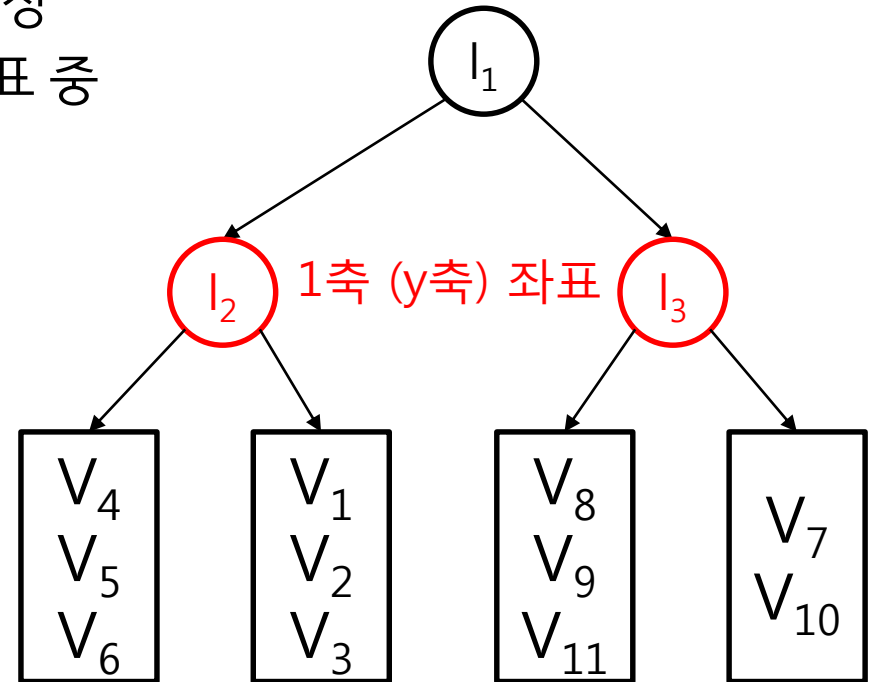
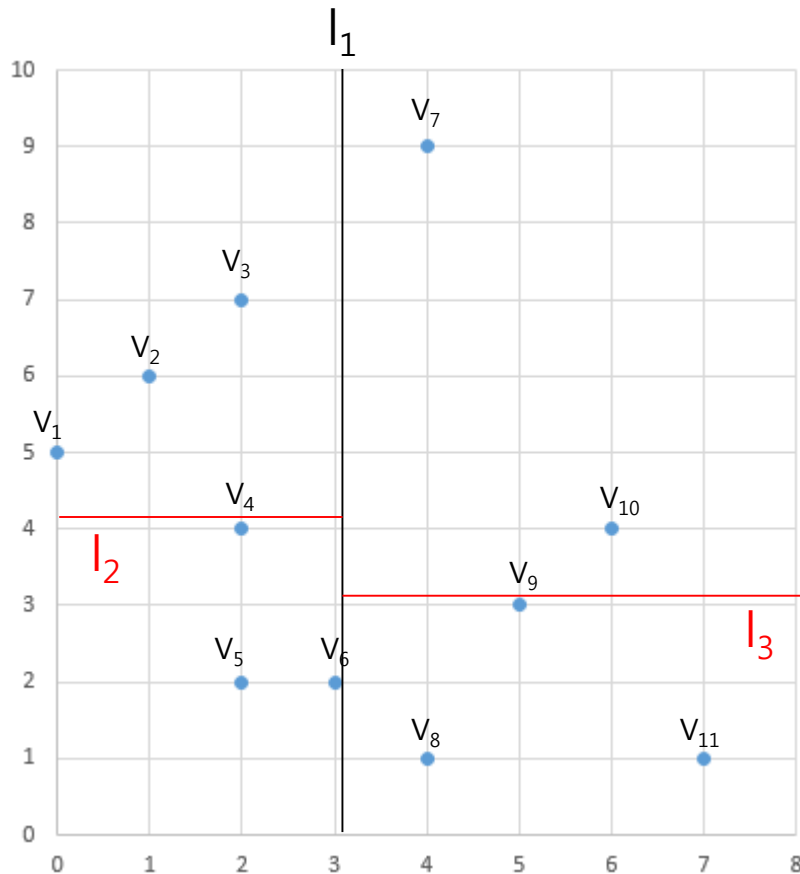
기준 point의 해당 축의 좌표보다  
작거나 같으면 left subtree  
크면 right subtree

# Build a kd-tree

- Build a kd-tree (ex: 2D)

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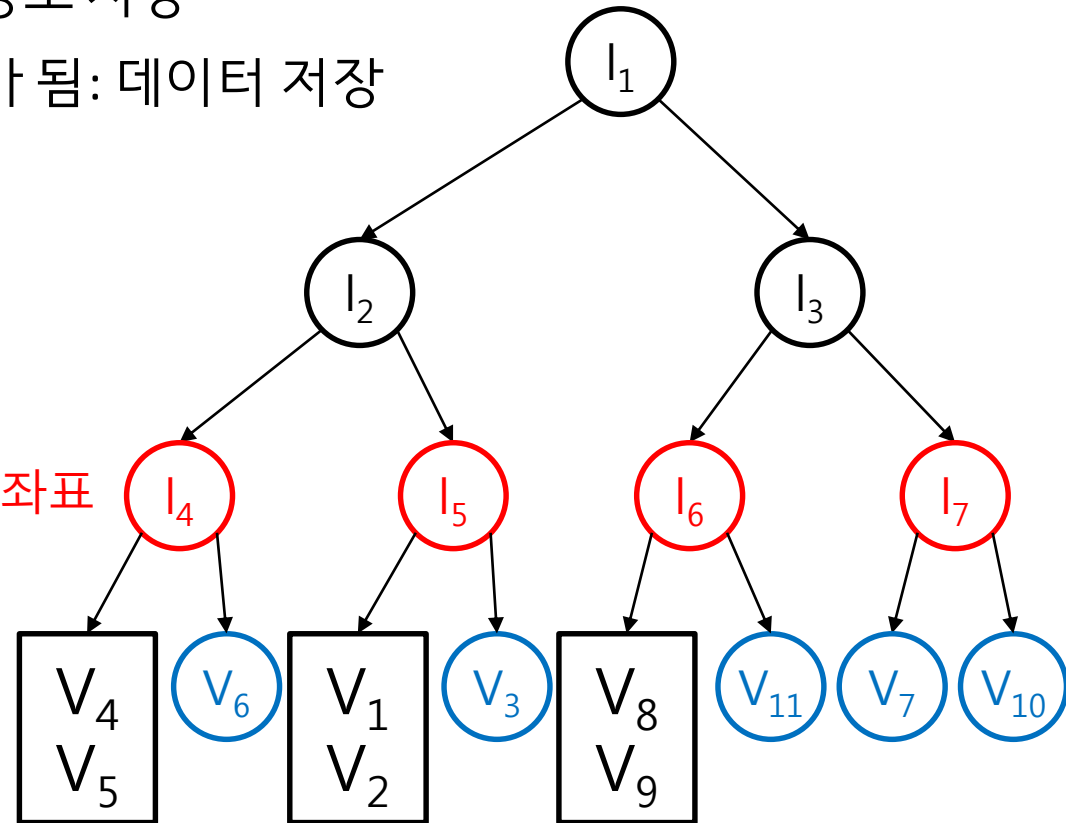
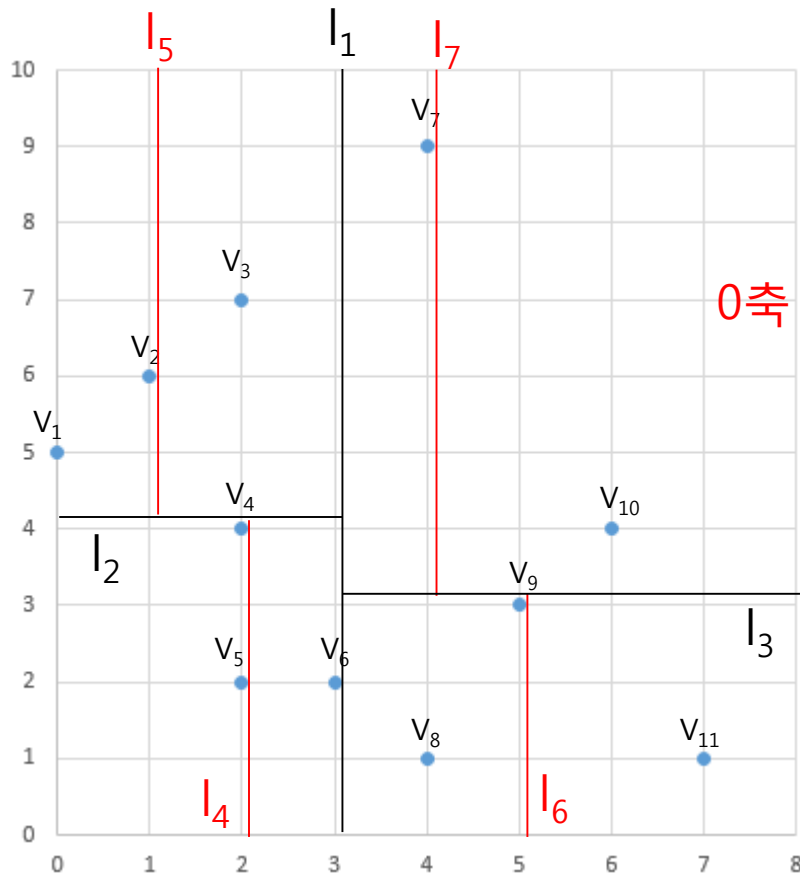


# Build a kd-tree

- Build a kd-tree (ex: 2D)

- Parent node는 hyperplane 정보 저장
- point가 1개 되면 leaf node가 됨: 데이터 저장

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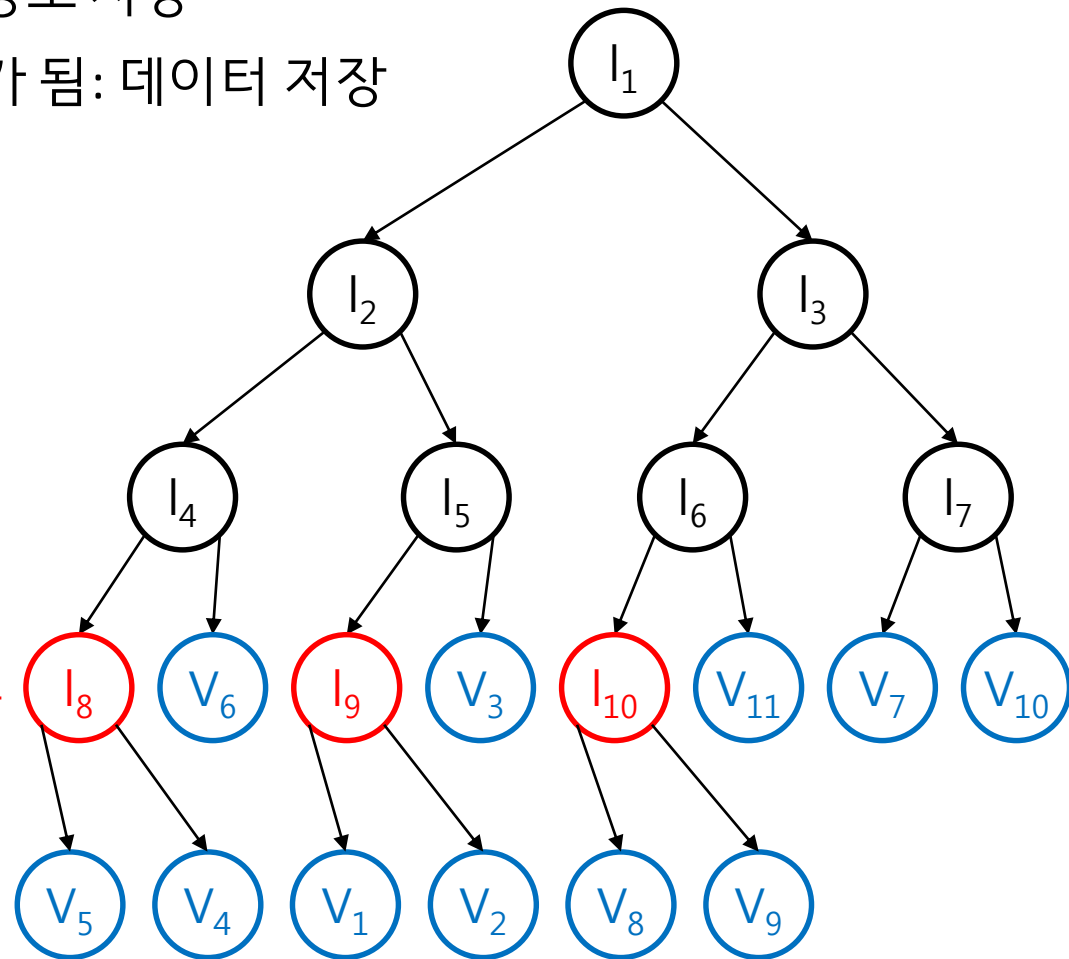
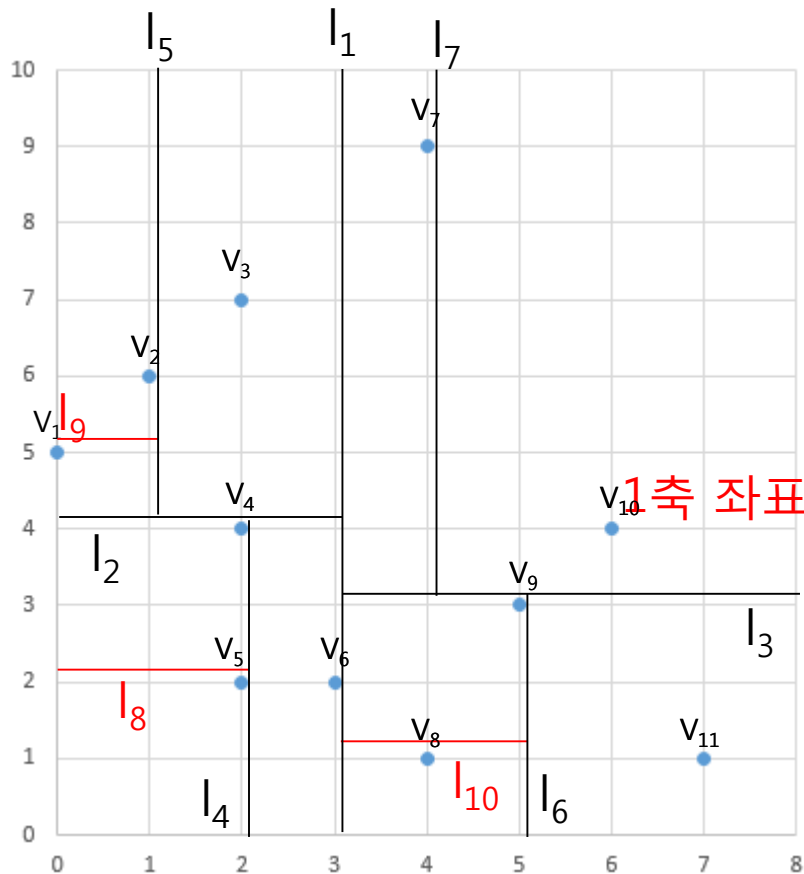


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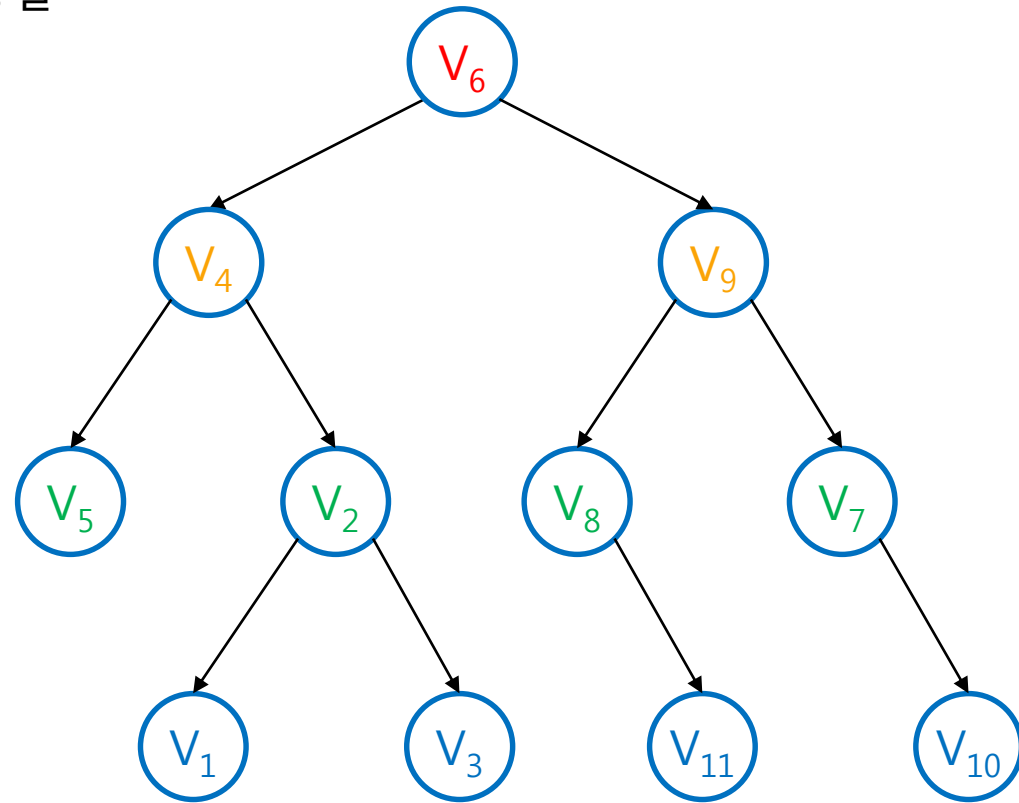
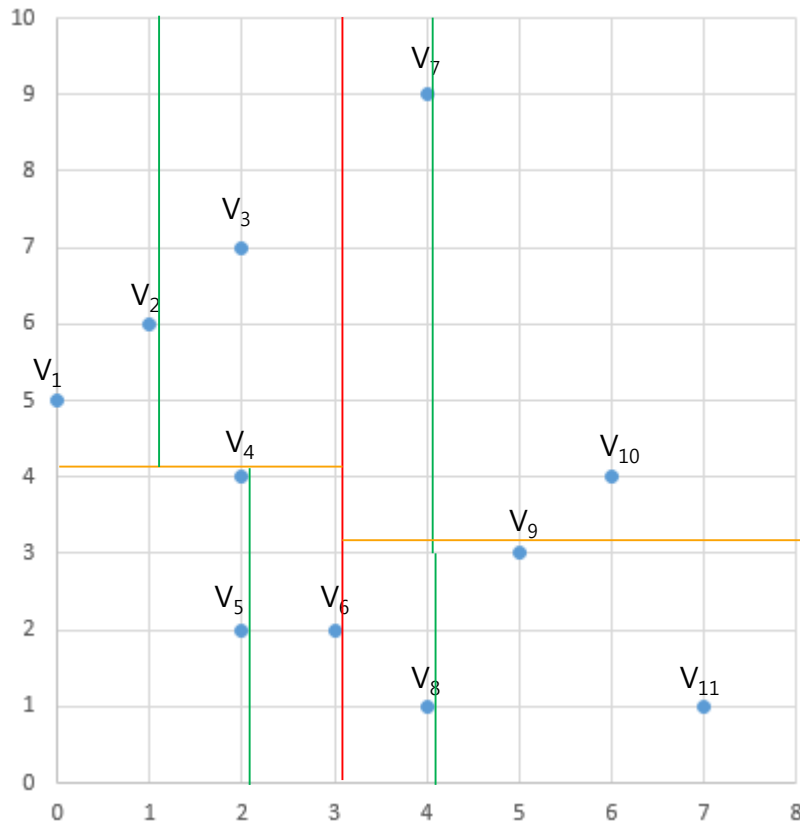
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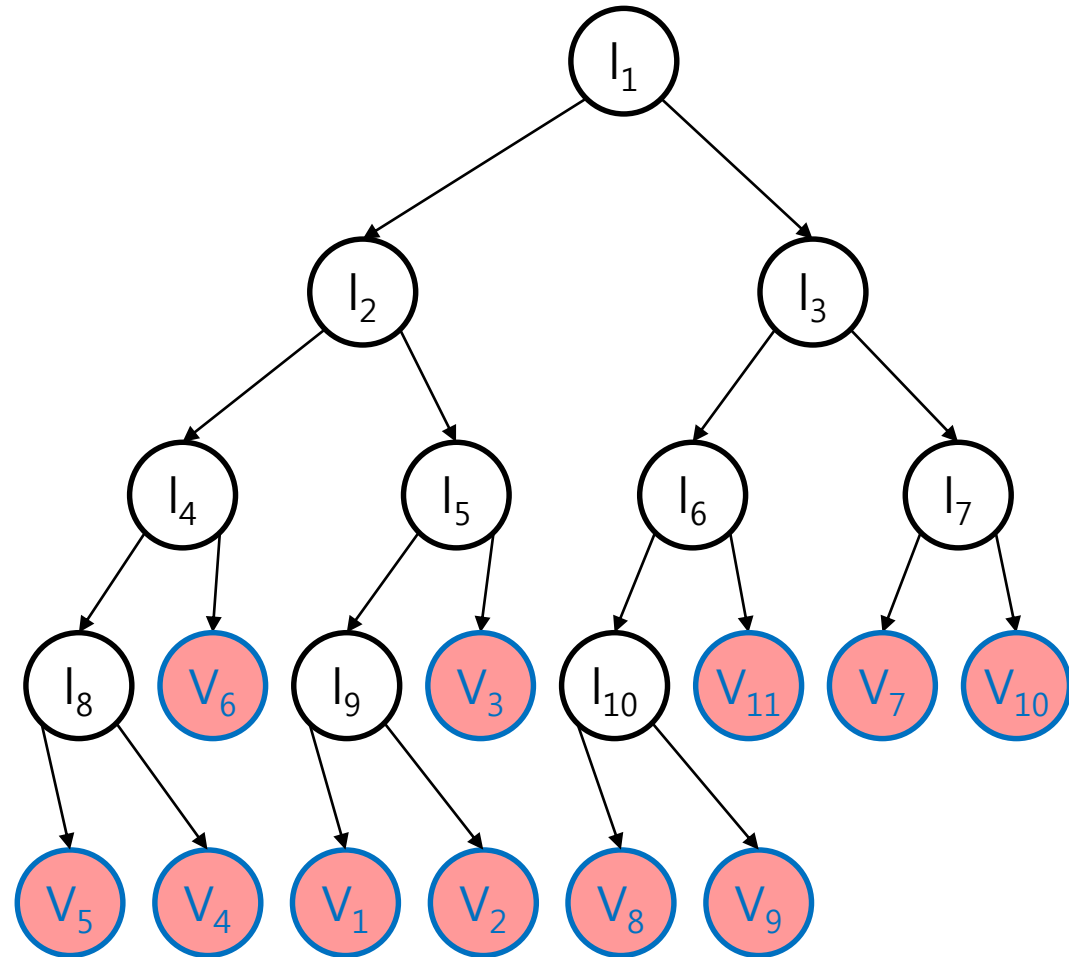
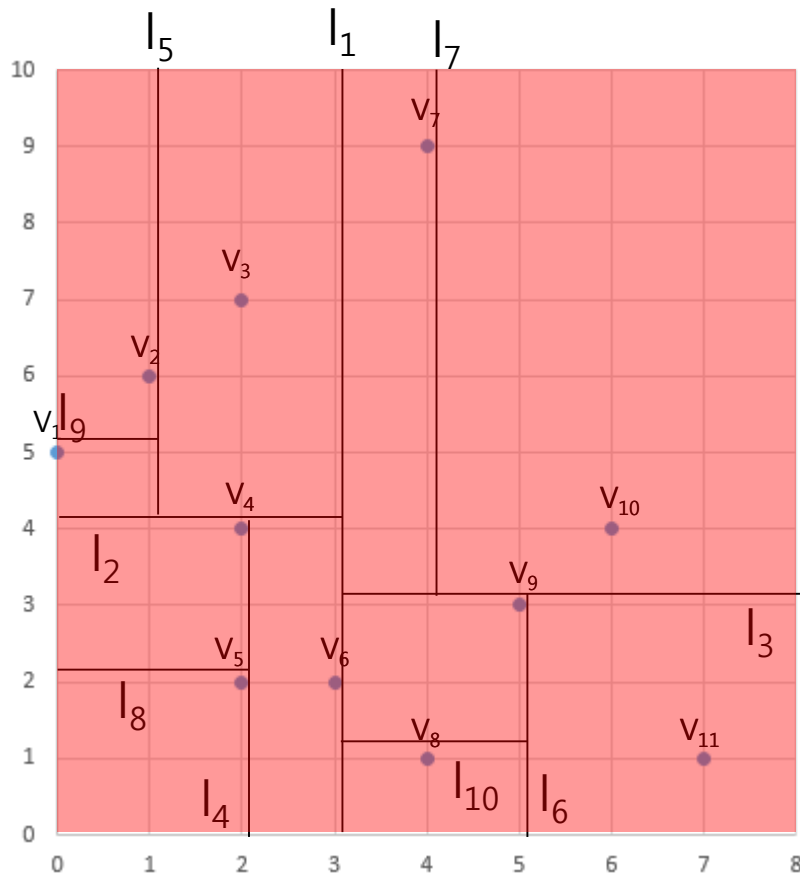
# Another Way to Build a kd-tree

- Build a kd-tree 다른 방법 (기존의 BST에서 배운 방법대로)
  - 모든 노드가 좌표 데이터 저장
    - Subtree 설정은 앞 방법과 동일



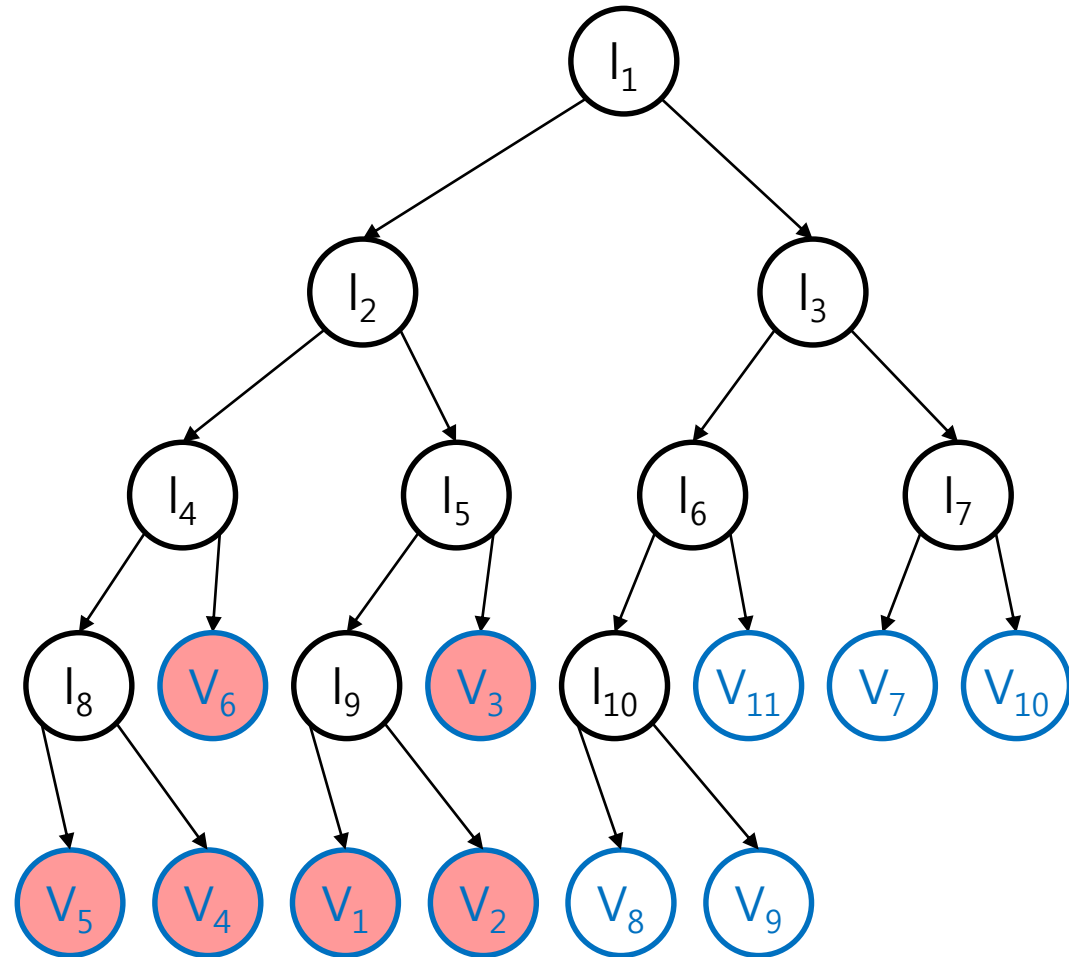
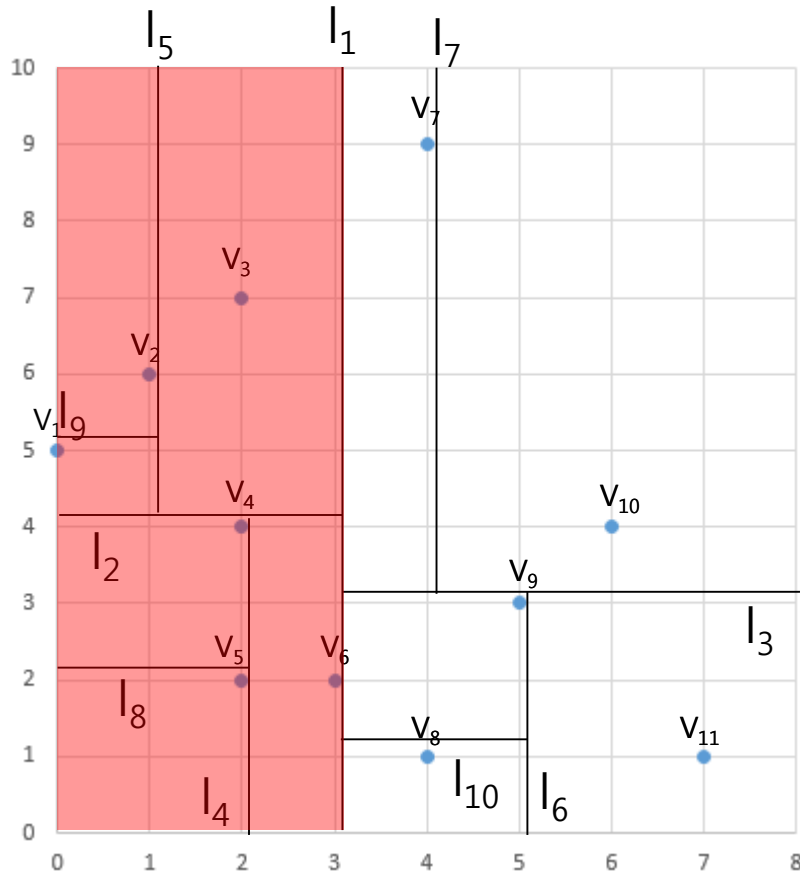
# Geometric Meaning

- $l_1$  노드의 후손들은 모든 data



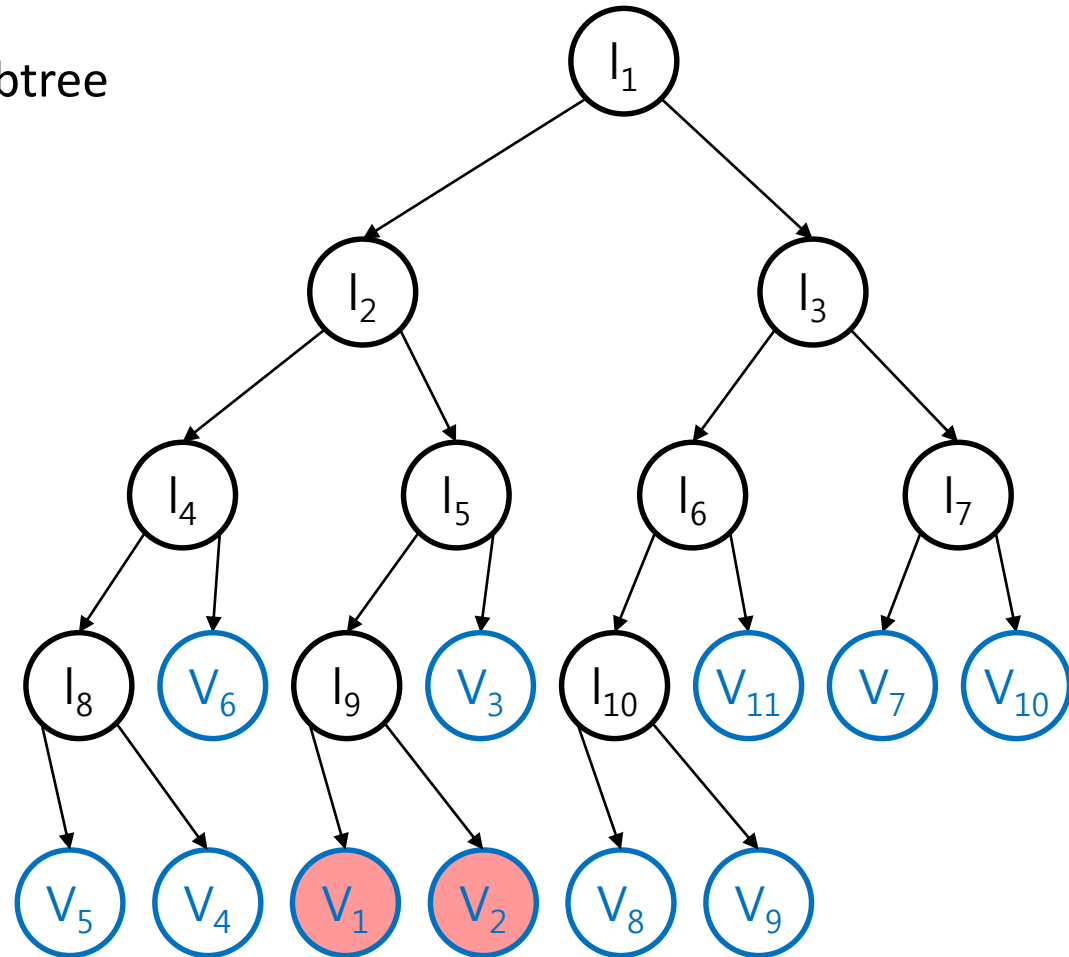
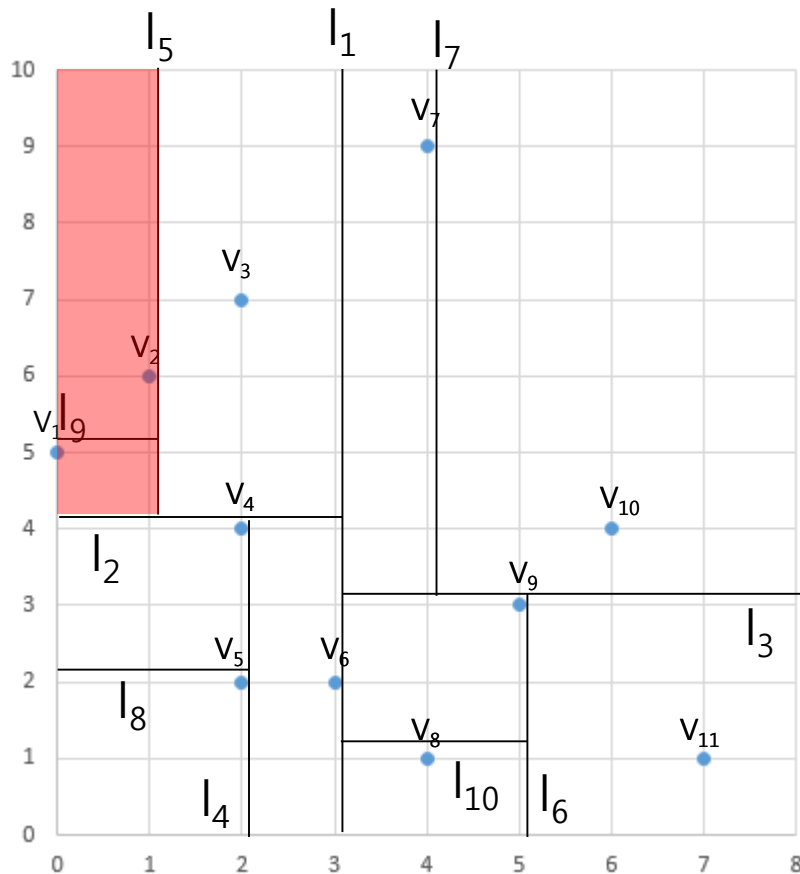
# Geometric Meaning

- $l_2$  노드의 후손들은 0축의 값이 3보다 작거나 같은 data



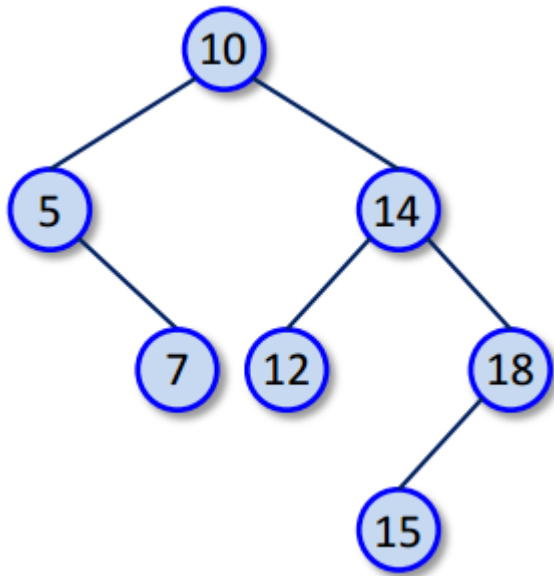
# Geometric Meaning

- $l_9$  노드의 후손들은 ...
  - $l_5$ 의 left subtree
  - ( $l_2$ 의 right subtree)의 left subtree



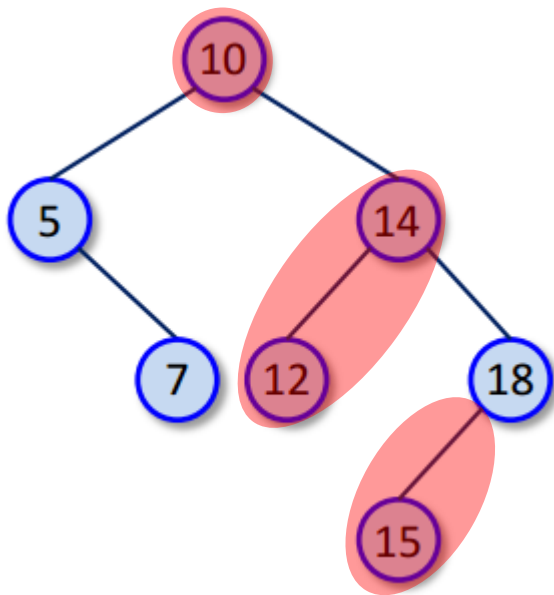
# How to Search Region

- 수업시간에 BST는 find만 배웠음 → kd-tree의 find도 쉽고 빠르다!
- 구간 검색은 어떻게 할까.
  - Get data in [9, 15]



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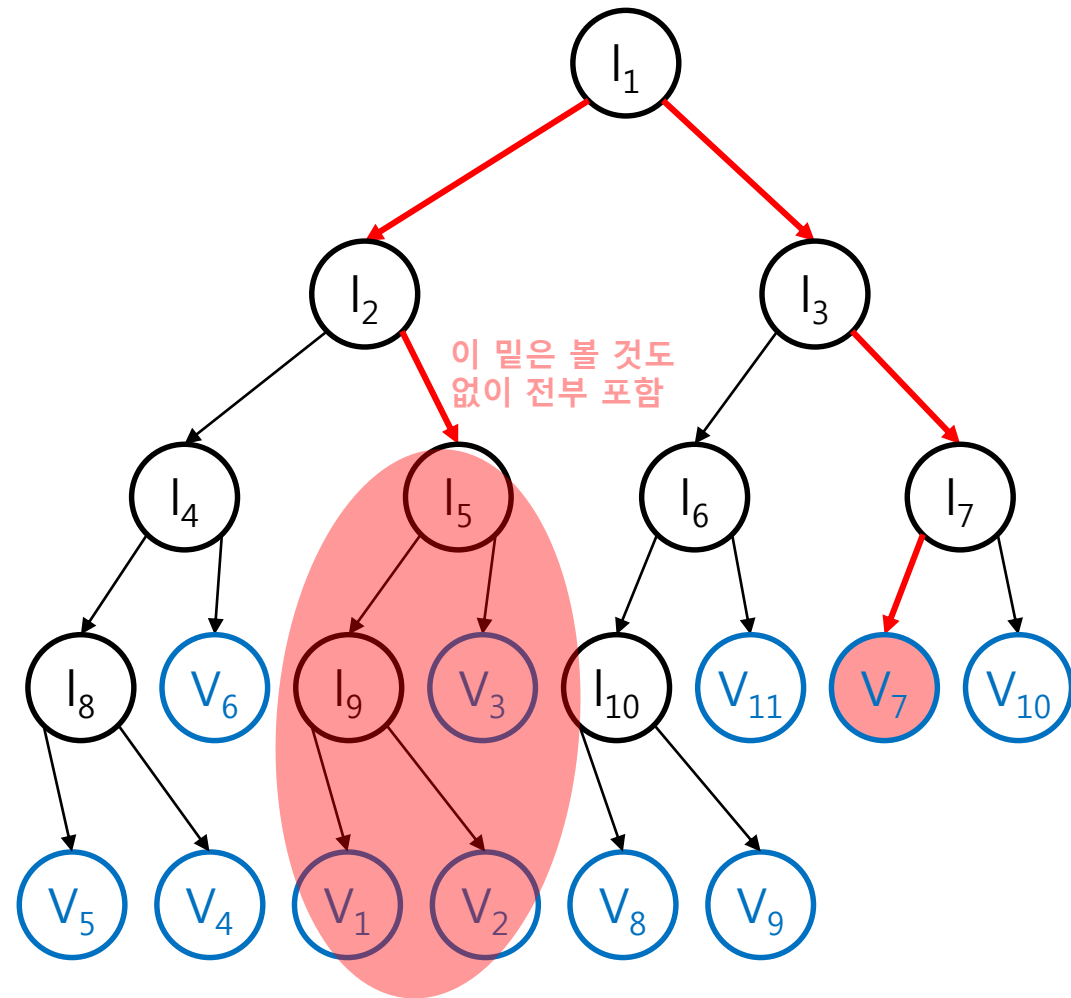
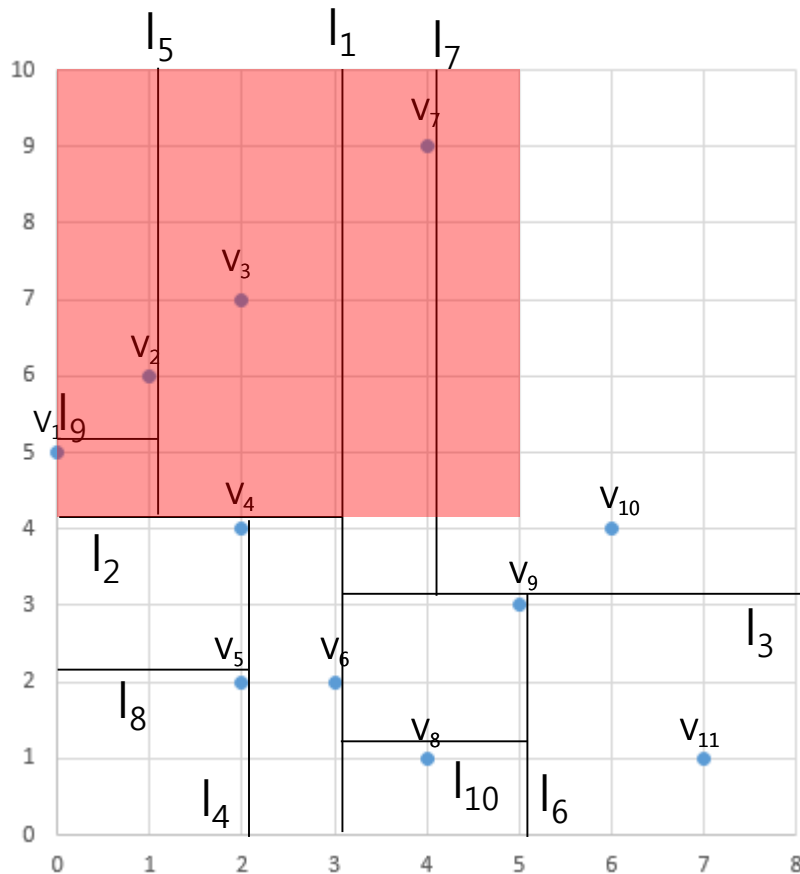
정렬할 필요 없음

10	12	14	15
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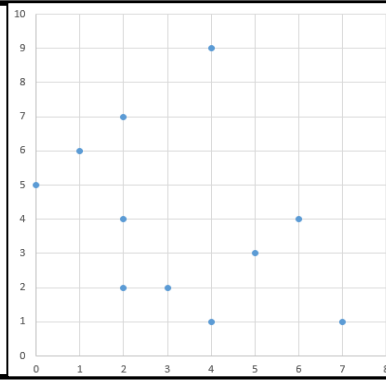
# How to Search Region

- Get data in ( $0\text{축} = [-\infty, 5]$ ,  $1\text{축} = (4, \infty]$ )



# DBSCAN Overview: DBSCAN

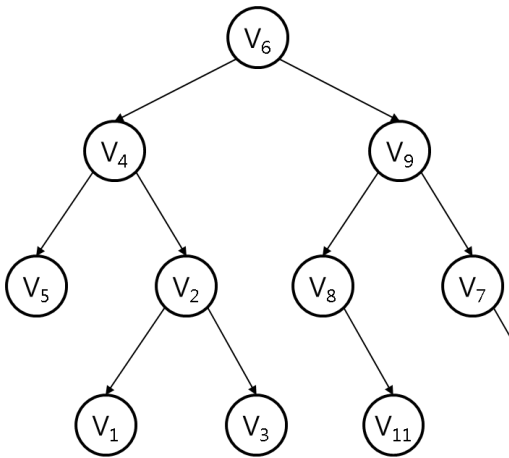
Coordinate data



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kd-tree



getNeighbor()

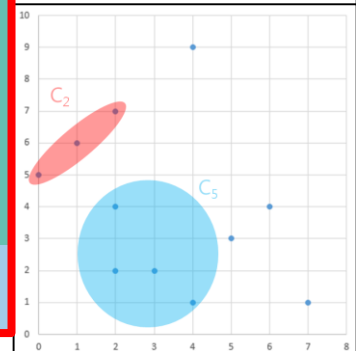
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Check  
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Clustering  
(Union & Find)



# DBSCAN: Project Algorithm

- Disjoint set 사용
  - Union & Find operation을 사용해 DBSCAN 알고리즘 진행

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**Algorithm 2** The disjoint-set data structure based DBSCAN Algorithm (DSDBSCAN). Input: A set of points  $X$ , distance  $eps$ , and the minimum number of points required to form a cluster,  $minpts$ . Output: A set of clusters.

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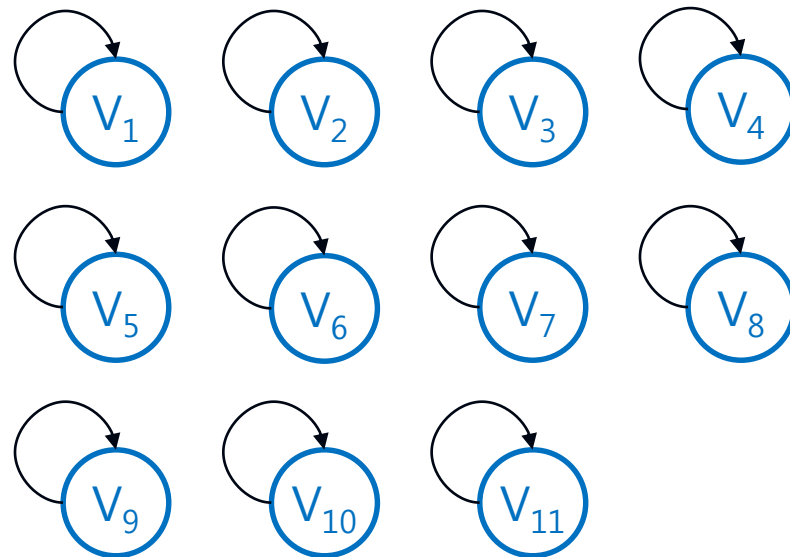
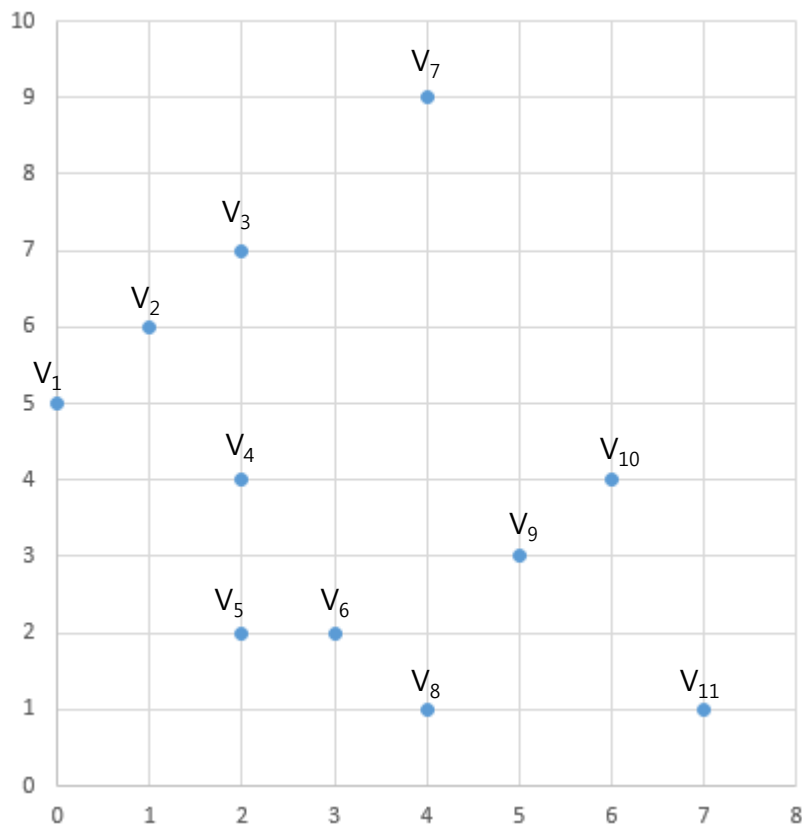
```
1: procedure DSDBSCAN( $X, eps, minpts$ )
2:   for each point  $x \in X$  do
3:      $p(x) \leftarrow x$ 
4:     for each point  $x \in X$  do
5:        $N \leftarrow \text{GETNEIGHBORS}(x, eps)$ 
6:       if  $|N| \geq minpts$  then
7:         mark  $x$  as core point
8:         for each point  $x' \in N$  do
9:           if  $x'$  is a core point then
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11:           else if  $x'$  is not yet member of any cluster then
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```

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※ input point 순서대로  
for문이 진행되도록 하면,  
구현에 따라 결과 달라지지 않음.

# DBSCAN: Project Algorithm

- 먼저 모든 point의 parent를 자기 자신으로
  - 수업시간의 Make-Set(x)와 동일한 역할

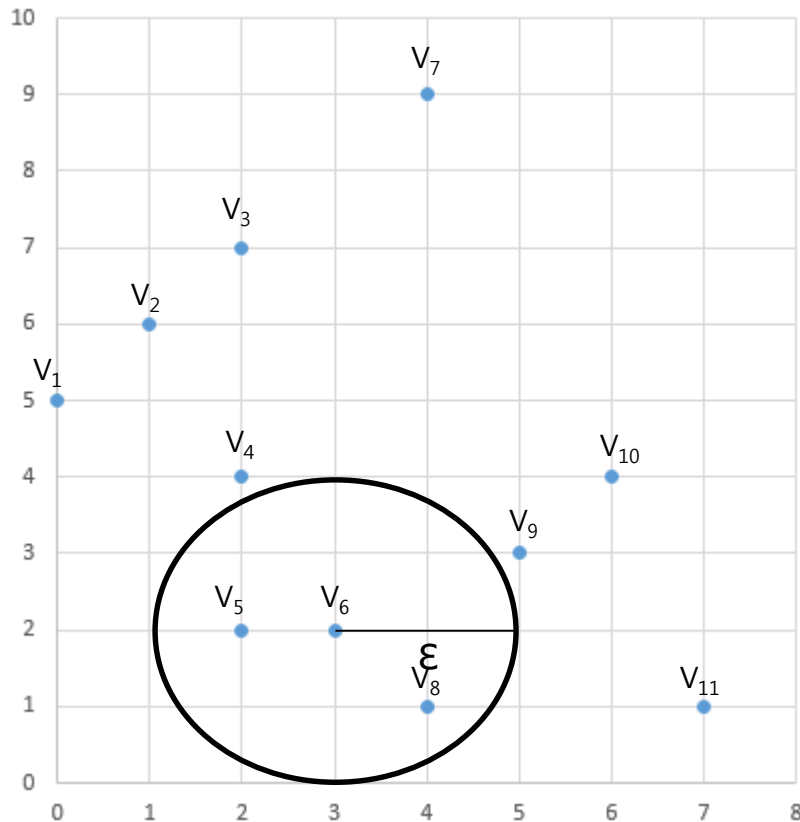


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# DBSCAN: Project Algorithm

- 각 point들의  $\epsilon$ -neighbor를 검색
  - kd-tree로부터 얻을 수 있음



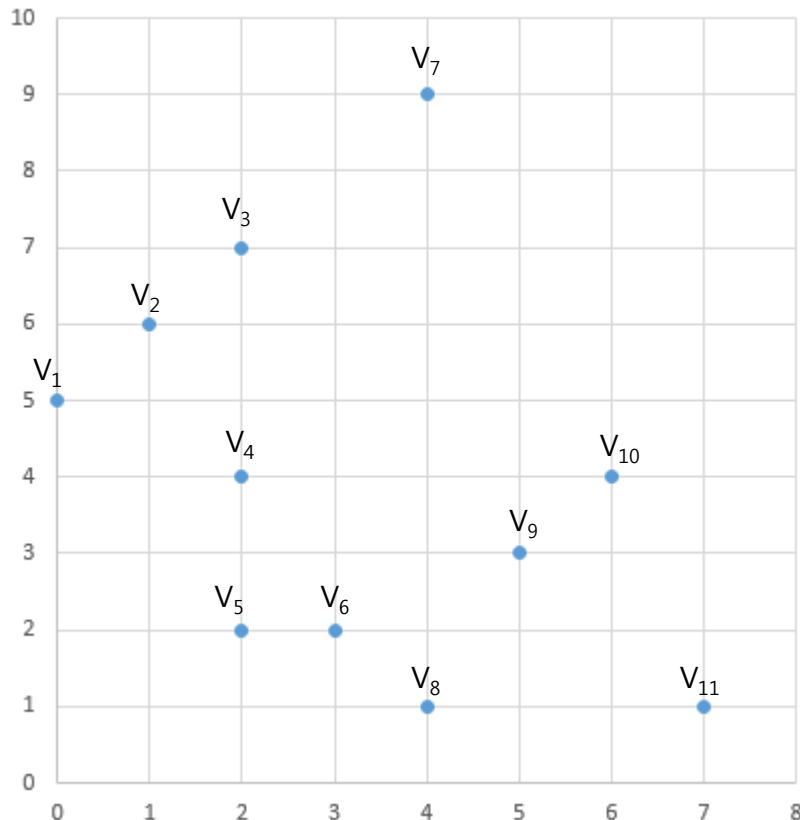
$V_1$ :  $V_2$   
 $V_2$ :  $V_1, V_3$   
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 $V_4$ :  $V_5$   
 $V_5$ :  $V_4, V_6$   
 $V_6$ :  $V_5, V_8$   
 $V_7$ :  
 $V_8$ :  $V_6$   
 $V_9$ :  $V_{10}$   
 $V_{10}$ :  $V_9$   
 $V_{11}$ :

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# DBSCAN: Project Algorithm

- Core point 조건 (if문) 을 만족하는 point들에 대해서 알고리즘 진행
  - Core point 만족조건 예시: neighbor가 2개 이상



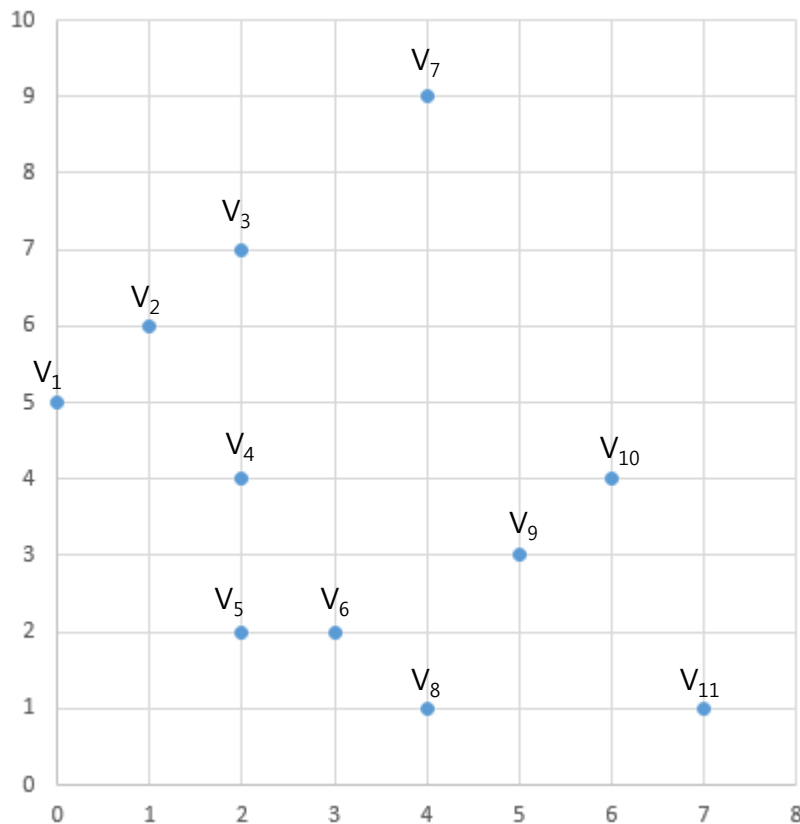
V<sub>1</sub>: V<sub>2</sub>  
V<sub>2</sub>: V<sub>1</sub>, V<sub>3</sub>  
V<sub>3</sub>: V<sub>2</sub>  
V<sub>4</sub>: V<sub>5</sub>  
V<sub>5</sub>: V<sub>4</sub>, V<sub>6</sub>  
V<sub>6</sub>: V<sub>5</sub>, V<sub>8</sub>  
V<sub>7</sub>:  
V<sub>8</sub>: V<sub>6</sub>  
V<sub>9</sub>: V<sub>10</sub>  
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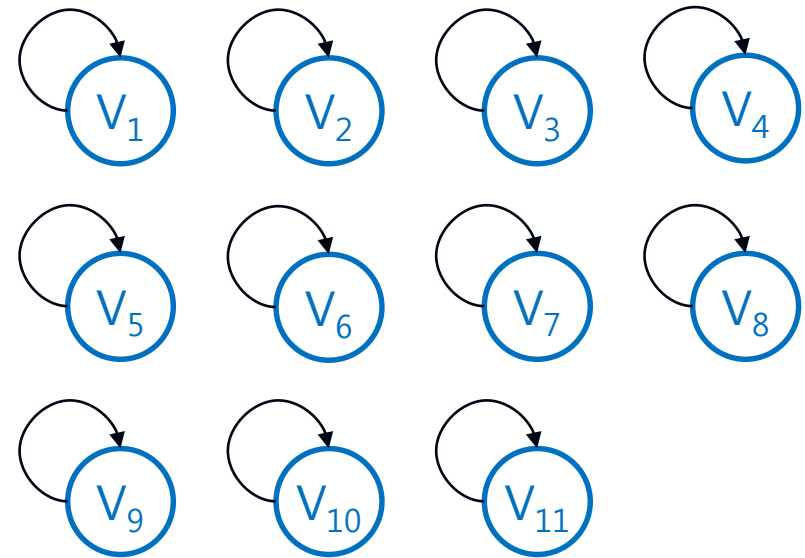
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- Neighbor들을 union (pseudo code에 따라)
  - Union by rank
  - Path compression



$V_2: V_1, V_3$   
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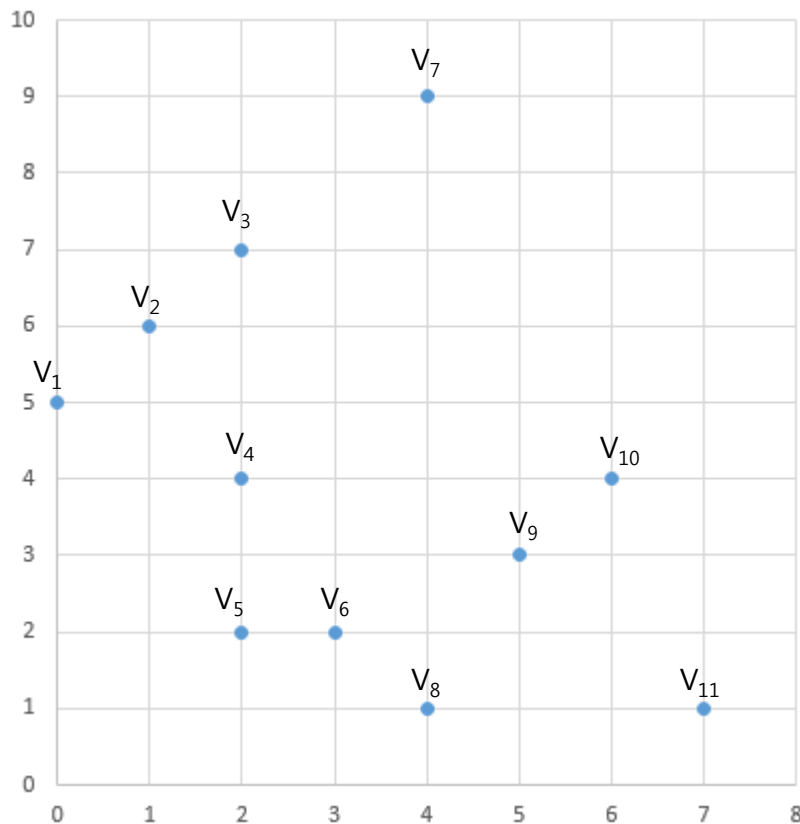


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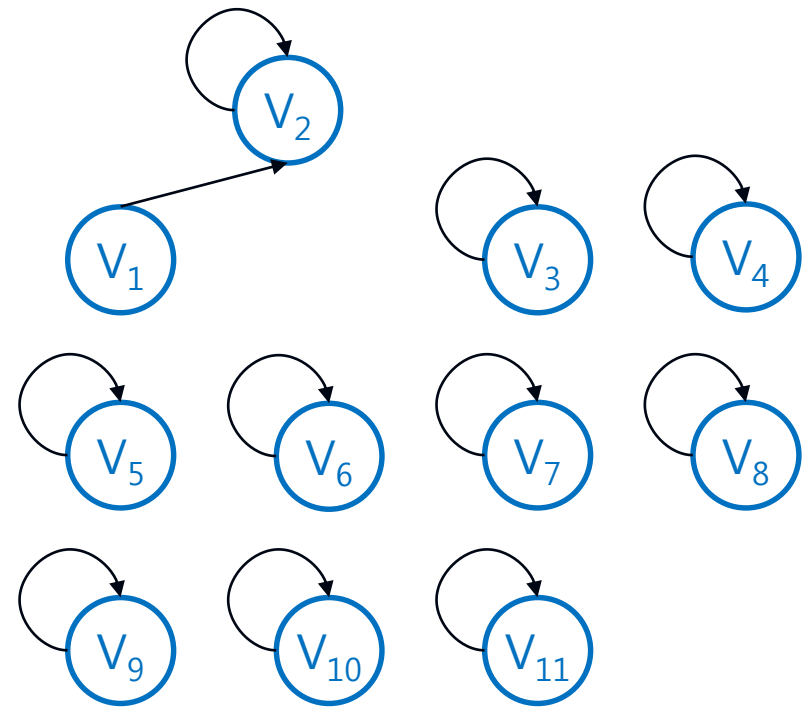
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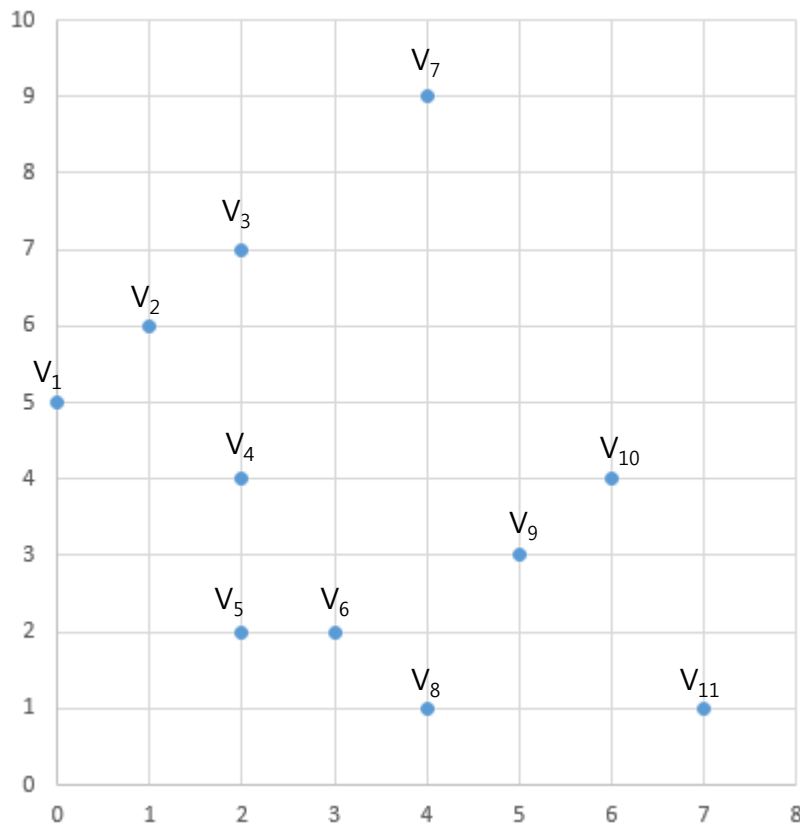
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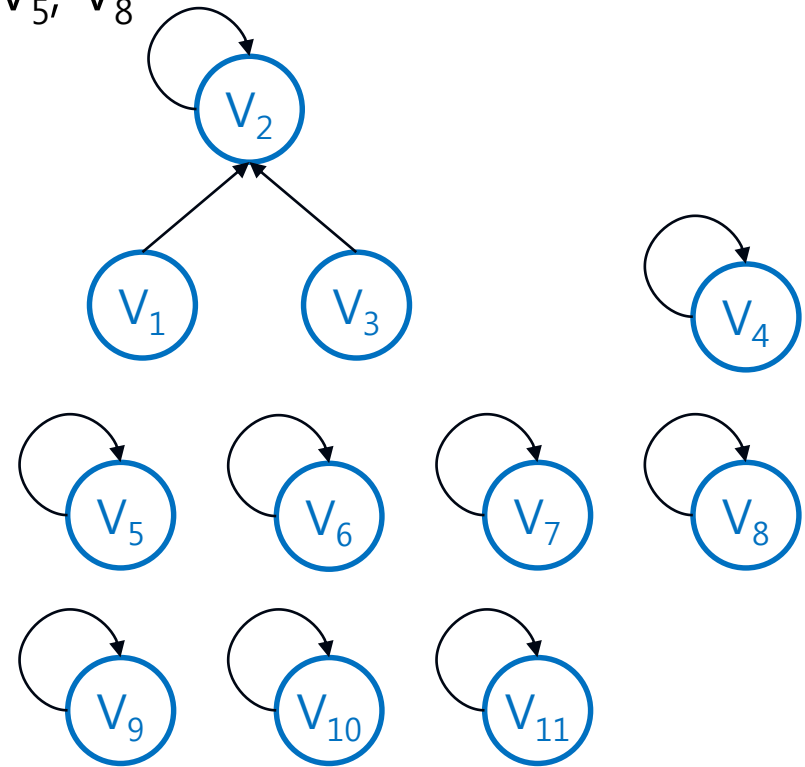


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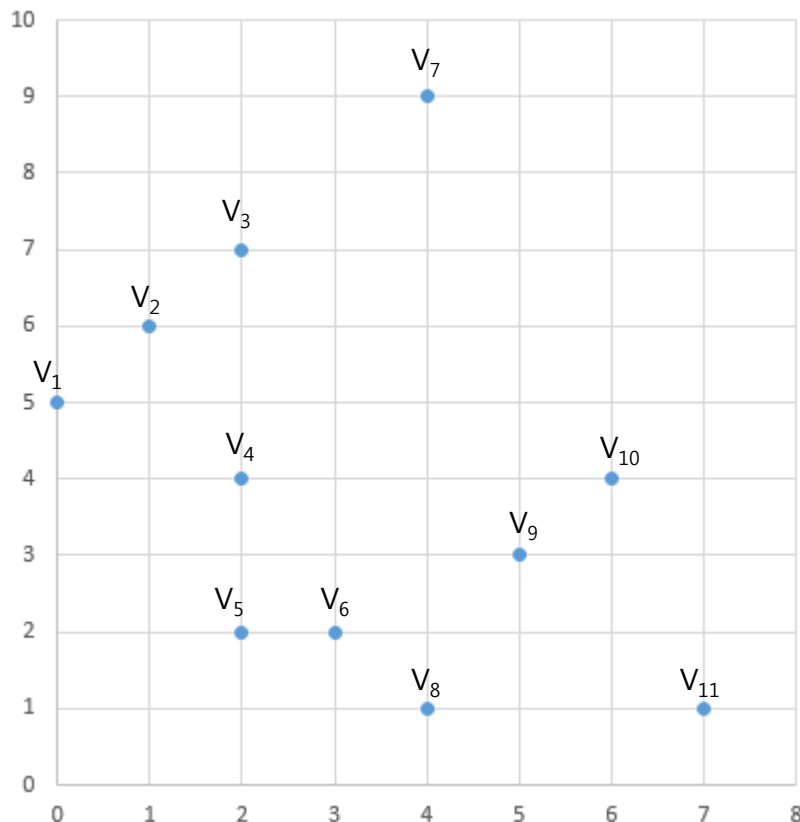


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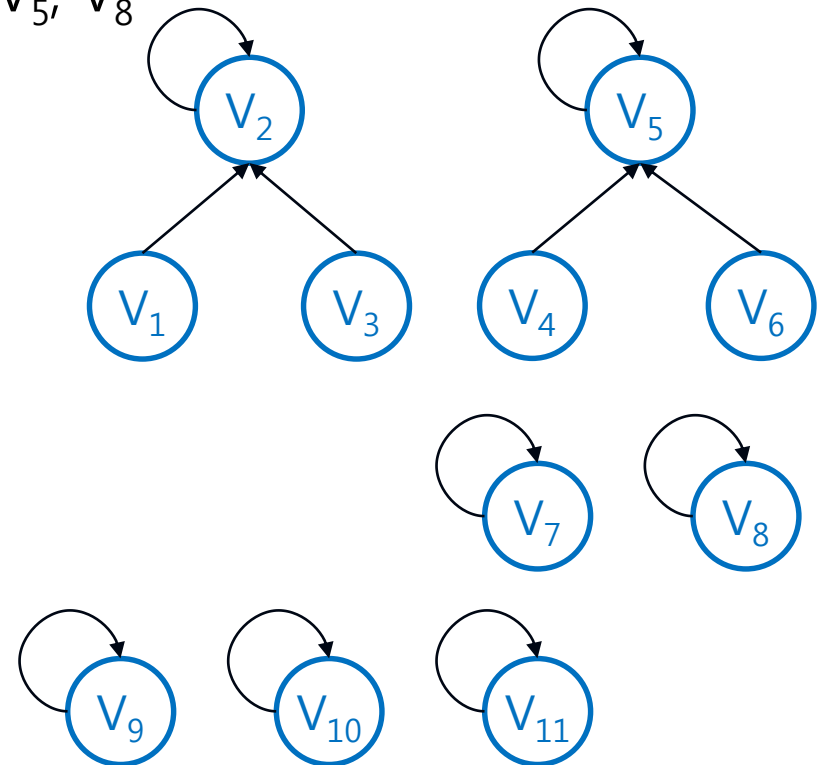
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 $V_6: V_5, V_8$

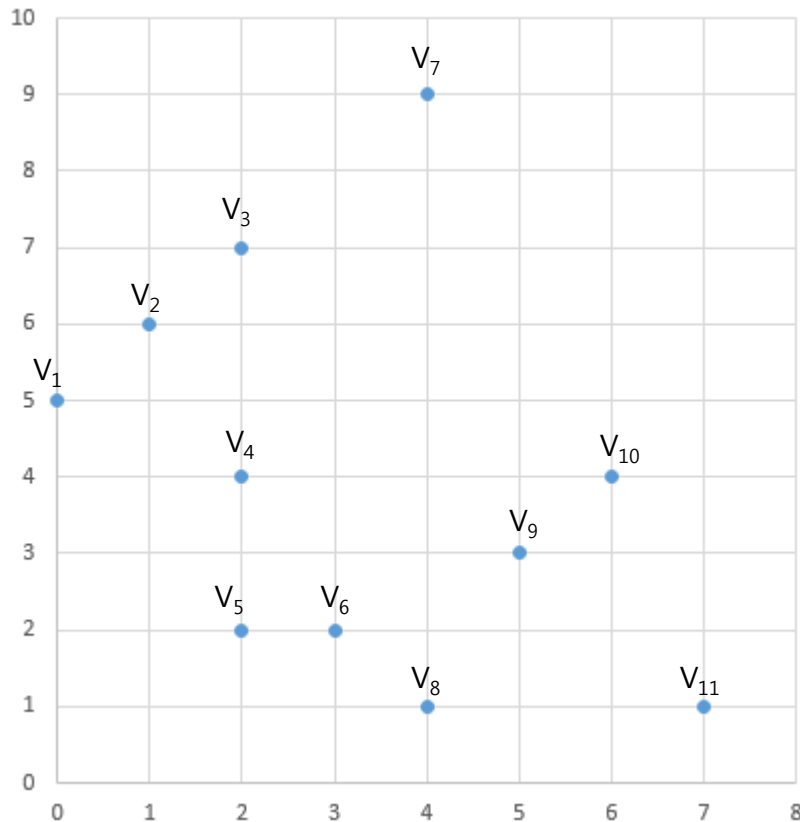


**Algorithm 2** The disjoint-set data structure based DBSCAN Algorithm (DSDBSCAN). Input: A set of points  $X$ , distance  $eps$ , and the minimum number of points required to form a cluster,  $minpts$ . Output: A set of clusters.

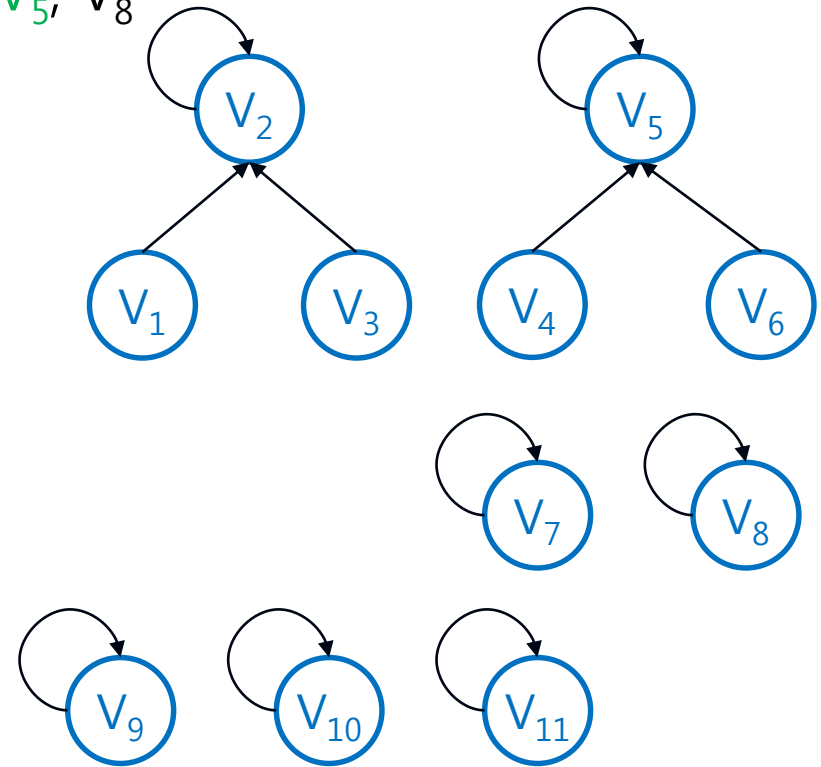
```
1: procedure DSDBSCAN( $X, eps, minpts$ )
2:   for each point  $x \in X$  do
3:      $p(x) \leftarrow x$ 
4:   for each point  $x \in X$  do
5:      $N \leftarrow \text{GETNEIGHBORS}(x, eps)$ 
6:     if  $|N| \geq minpts$  then
7:       mark  $x$  as core point
8:       for each point  $x' \in N$  do
9:         if  $x'$  is a core point then
10:          UNION( $x, x'$ )
11:        else if  $x'$  is not yet member of any cluster then
12:          mark  $x'$  as member of a cluster
13:          UNION( $x, x'$ )
```

# DBSCAN: Project Algorithm

- Neighbor들을 union (pseudo code에 따라)
  - Union by rank
  - Path compression



$V_2: V_1, V_3$   
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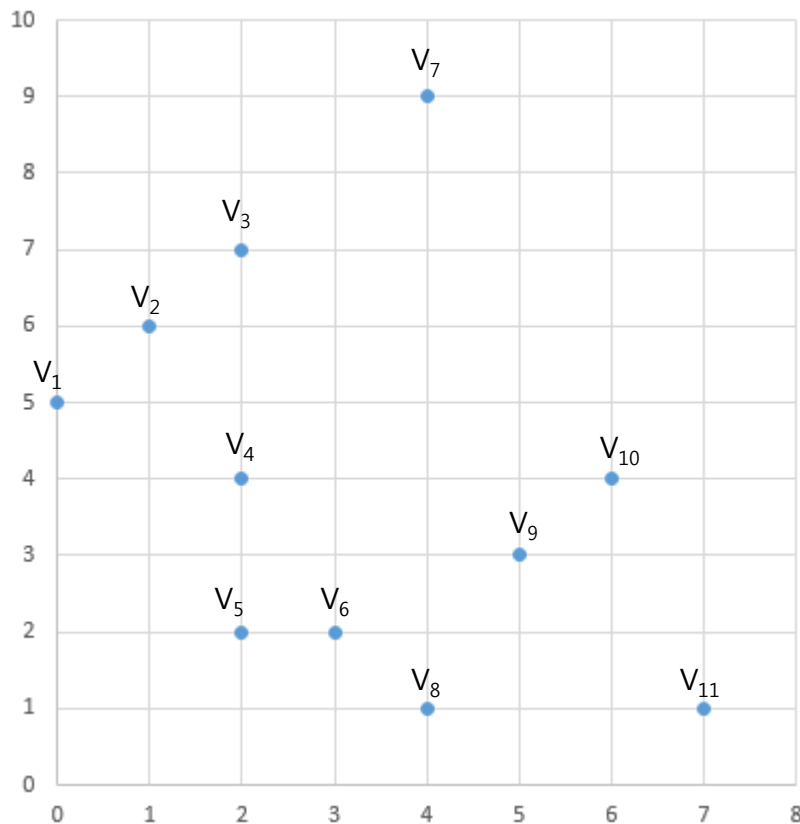


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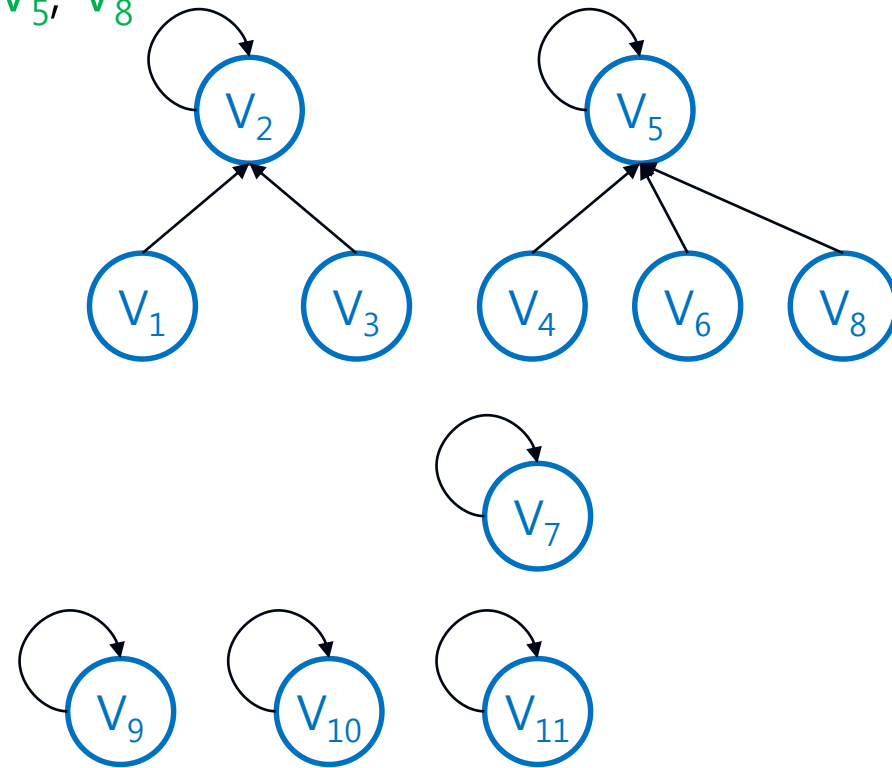
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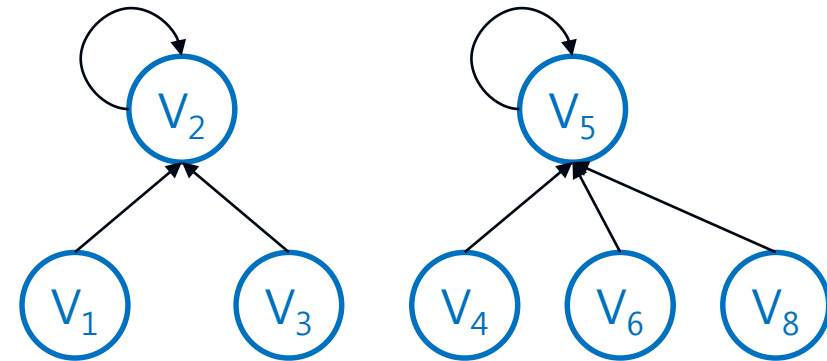
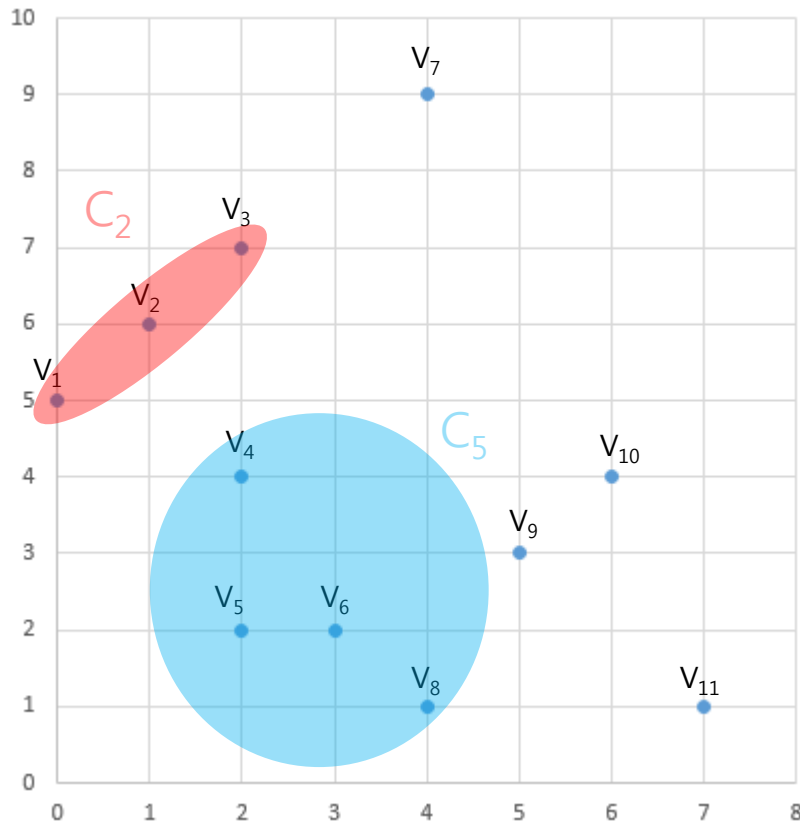
# DBSCAN: Project Algorithm

- Output은 각 point가 어떤 cluster에 속하는지 출력 (cout 이용)
  - Cluster id는 root point id로 출력
  - Noise는 -1로 출력

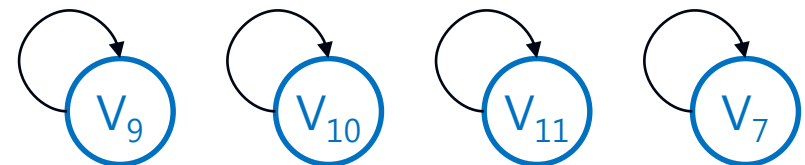
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```

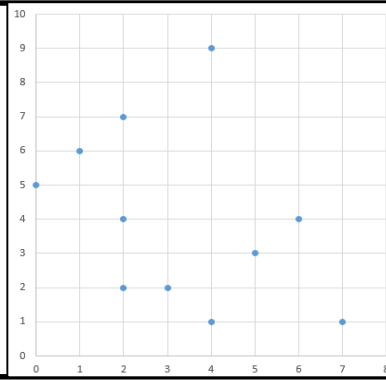


나머지는 noise



# DBSCAN Overview

Coordinate data

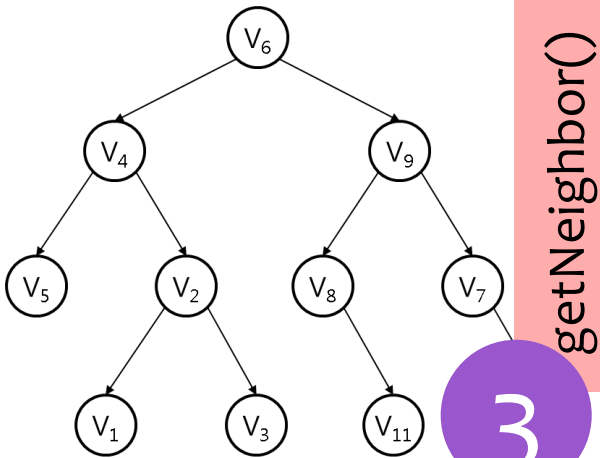


1

Build a  
kd-tree

float\*\*

kd-tree



getNeighbor()

3

2

DBSCAN

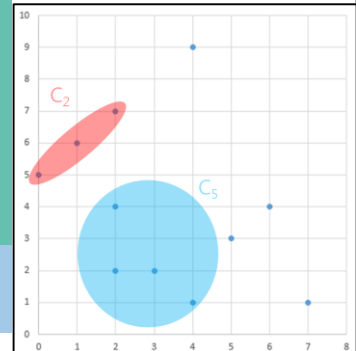
Run()

4

Check  
conditions  
&  
Clustering  
(Union & Find)

Coordinate

CoordinateSet



# Project Information

# Project

- 최소 필요 class
  - Coordinate
  - CoordinateSet      각 class들의 제시된 함수들 반드시 구현
  - KDtree
  - DBSCAN
  - Class들의 디자인 (member variables, functions) 은 직접 생각할 것.
  - 이 외 class 추가해도 된다. (disjoint set class, container class)

## ■ Member function들 input/output 예시

예: foo()

Input: int a, float b

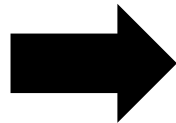
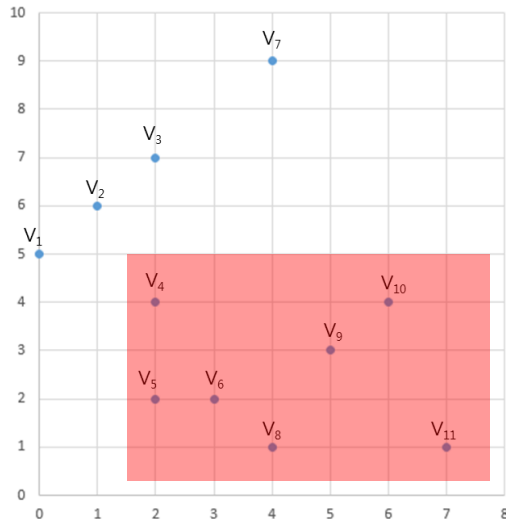
Output: CoordinateSet cset

1. CoordinateSet foo(int a, float b)
2. CoordinateSet\* foo(int a, float b)
3. CoordinateSet& foo(int& a, float\* b)
4. void foo(int a, float b, CoordinateSet\* cset)
5. void foo(int a, float b, CoordinateSet& cset)
6. ...



# Project

- **Coordinate** class
  - 좌표 데이터를 저장하는 저장 class
- **CoordinateSet** class
  - 여러 Coordinate object (좌표데이터) 들을 저장하는 저장 class
  - print()
    - Input과 Output은 없으나, cout을 이용하여 다음과 같이 출력할 것



```
4 (2, 4)
5 (2, 2)
6 (3, 2)
8 (4, 1)
9 (5, 3)
10 (6, 4)
11 (7, 1)
```

Point\_id (k dimesion 좌표들)

·  
·  
·

**CoordinateSet 안에 있는  
point id 순서대로 출력**

예시에서는 2D이기 때문에 (x, y) 출력  
만약 4D라면 (a, b, c, d) 로 출력

# Project

- **KDtree** class

- Constructor

- Input: k-dimensional point들의 좌표 (**float\*\*** points) → n x k 행렬
    - Input: dimension (int dimension)
    - Input: point 개수 (int numOfPoints)

- getNeighbors()

- Input: query point 좌표 (**Coordinate** queryPoint)
    - Input: query radius 길이 (float radius)
    - Output: query 결과 검색된 k-dim point들의 좌표  
(**CoordinateSet** neighborPoints)

# Project

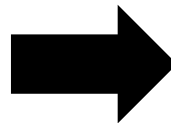
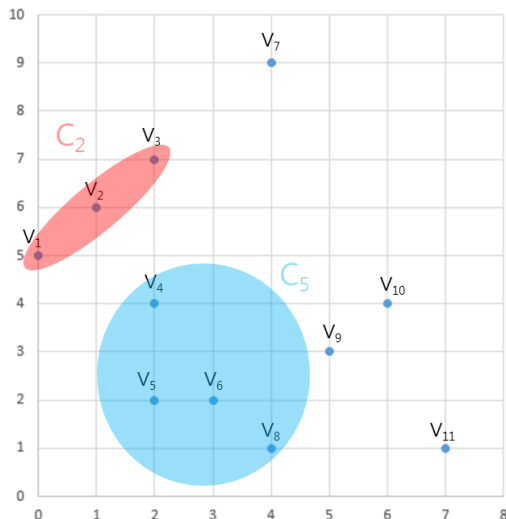
## ■ DBSCAN class (project algorithm 구현)

### — Constructor

- Input: 만들어진 KDtree (**KDtree&** kdtree)
- Input: DBSCAN parameter  $\epsilon$  (float epsilon)
- Input: core point가 되기 위한 neighbor의 최소 개수 (int minPoints)  
(= cluster를 이루기 위한 최소 개수)

### — run()

- Input과 Output은 없으나, cout을 이용하여 다음과 같이 출력할 것



```
1 2
2 2
3 2
4 5
5 5
6 5
7 -1
8 5
9 -1
10 -1
11 -1
```

Point\_id cluster\_id

·  
·  
·

Point id 순서대로 출력

# Project 주의사항

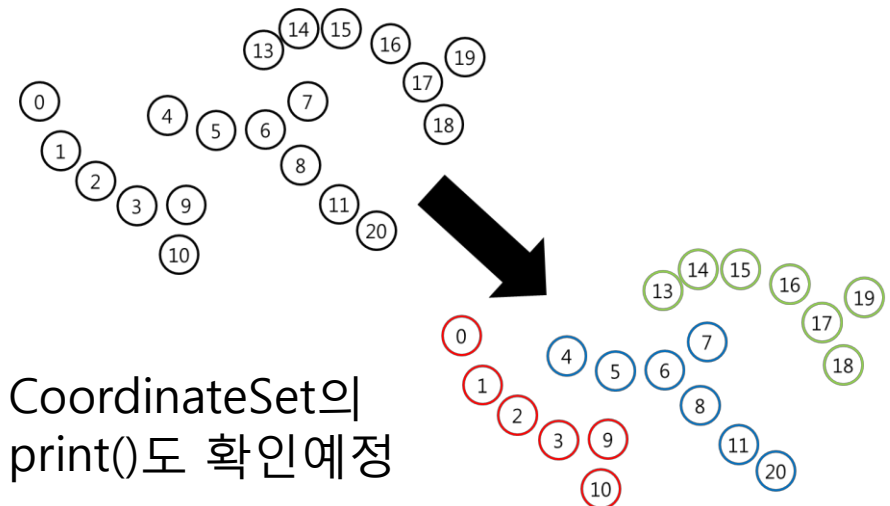
## ■ Input 관련

- Input은 k-dimensional point들의 좌표들이 float\*\* 타입으로 main에서 주어질 것이고, 이는 KDtree를 생성할 때 parameter로 들어갈 것.
- Point의 index는 input 순서대로 할당하고 **0부터 시작한다.**
  - 예시에서는 이해를 돕기 위해 1부터 시작.

## ■ Test 관련

- 자신이 구현한 알고리즘을 확인하기 위해 여러 test를 해볼 것.
- Test 코드는 다음과 같다.

```
void test()
{
    float** data = ...;
    KDtree myTree(data, 2, 20);
    DBSCAN myDBSCAN(myTree, 0.5, 3);
    myDBSCAN.run();
}
```



# Project 주의사항

- 제출 관련
  - 제출 압축파일명: 2015-12345.zip
    - visual studio project 폴더 (“빌드 → 솔루션 정리” 후)
    - Project 보고서
- Project 보고서
  - 개발자의 입장에서, 사용자들에게 배포할 문서라 생각
    - 간결하고 명확한 설명
    - Class들의 디자인 및 관계 (overview)
    - 함수들의 설명: 동작원리·역할 / 사용방법 / input과 output
  - 분량은 평가 요인 아님 (되도록 짧게)
  - 예시
    - <https://cran.r-project.org/web/packages/gputools/gputools.pdf>
    - <http://kr.mathworks.com/help/matlab/ref/plot.html>

# Project 주의사항

- 채점 관련

- 채점 방식: On/Off

- 코드 정확도

- 주어진 테스트셋에서 동작하면 On, 안 하면 Off

- 코드 효율성

- 비 효율적 (Time, Memory) → Off

- 가이드 무시 → Off

- 코드 도용 및 공유

- 학칙에 의거 처리

- 기한

- 제출: 12월 21일 (월) 23:59 까지

- 질문: 12월 21일 (월) 18:00 까지