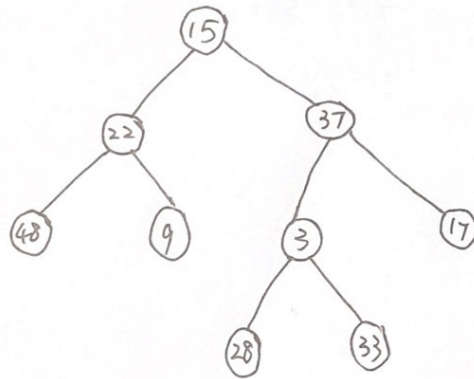


Q1. 1.



II. We can use binary ~~search~~ search to examine the midpoint recursively to see if it's larger or smaller than ^{or equal to} the element a_m in the same position in array $[1, 2, \dots, n]$. If the element is larger, meaning the missing element is in the left, otherwise it should be in the right half of the array. The pseudo-code is as follows.

```
int findmissing (int A[], int n) {
```

```
    int b = 0, e = n - 1;
```

```
    while (b < e) {
```

```
        int mid = int (b + e) / 2;
```

```
        if (A[mid] <= mid + 1) {
```

```
            s = mid + 1; }
```

```
        else {
```

```
            e = mid - 1; }
```

```
    }
```

```
    if (A[s] > s + 1) { return s + 1; }
```

```
    else if (A[s] == s + 1) { return
```

```
    else { return A[s] + 1; }
```

```
}
```

III. Apply the dynamic programming method, ~~For each node.~~

Q2. I. Note that 1 page can hold $\frac{2K}{4} = \frac{2^{11}}{2^2} = 2^9$ page entries.

The 32-bit address space has $\frac{2^{32}}{2^{11}} = 2^{21}$ pages in total.

Thus we need 3 levels of page tables, with one level of page table containing 2^3 entries, while the other 2 levels of page tables containing 2^9 page entries each.

II. 1, 2, 1, 2, 3, 2, 2, 4, 5, 4, 2, 5, 4, 2, 5, 4.

III. (1). abc should ^{be} set to 1.

(2). xyz can be set to 0.

(3). The disadvantages ~~is that~~ are that the spin-wait is a waste of CPU time, and some process may wait forever, which may cause starvation.

To avoid the starvation we can set a queue to hold the processes and ~~then~~ run them in order.

I. a $P \leftarrow \pi_{PID, Category} (\sigma_{Category = 'Toy'} (PRODUCT))$

$C \leftarrow \pi_{CID, Address} (\sigma_{Address = 'shatin'} (CUSTOMER))$

Result $\leftarrow \pi_{EID, Name} (TRANSACTION \bowtie EMPLOYEE \bowtie P \bowtie C)$.

b. ~~$((EID \text{ } \sum (Price * Quantity) (TRANSACTION)) \bowtie CUSTOMER)$~~

$R \leftarrow EID \text{ } \sum (Price * Quantity) \text{ as money } (TRANSACTION)$

Result $\leftarrow \pi_{EID, NAME, money} (R \bowtie EMPLOYEE)$.

II. a. select EID, EMPLOYEE.Name

from TRANSACTION, EMPLOYEE, CUSTOMER, PRODUCT

where TRANSACTION.EID = EMPLOYEE.EID

and TRANSACTION.PID = PRODUCT.PID

and TRANSACTION.CID = CUSTOMER.CID

and CUSTOMER.Address = "Shatin"

and PRODUCT.Category = "Toy".

b. select T.EID, E.Name, T.money

from (select EID, sum (Price * Quantity) as money

from TRANSACTION

group by EID) as T, EMPLOYEE as E

where T.EID = E.EID.

Q3. III. a. Note that $N_{\text{employee}} = 2000$, $B_{\text{employee}} = \frac{2000}{100} = 20$.

$$N_{\text{transaction}} = 100,000, \quad B_{\text{transaction}} = \frac{100,000}{50} = 20,000$$

For the nested-loop join, if use EMPLOYEE as the outer relation, we need ~~B_{employee}~~ $N_{\text{employee}} \times B_{\text{transaction}} + B_{\text{employee}} = 40,000,020$.

block accesses; while using TRANSACTION as the outer relation requires $N_{\text{transaction}} \times B_{\text{employee}} + B_{\text{transaction}} = 20,020,000$ block accesses.

Thus we should use TRANSACTION as the outer relation.

For the block nested-loop join:

EMPLOYEE outer: ~~B_{employee}~~ $B_{\text{employee}} + B_{\text{transaction}} = 20,020$.

Since ~~$B_{\text{transaction}}$~~ $B_{\text{transaction}} > M = 50$.

Thus EMPLOYEE should be chosen as the outer relation.

Q3 III. (b) Nested-loop join:

$$N_{\text{transaction}} \times B_{\text{employee}} + B_{\text{transaction}} = 20,020,000$$

~~Nested-loop~~

Block nested-loop join:

$$B_{\text{employee}} + B_{\text{transaction}} = 20,020.$$

Q4. I. (a). $\{a\} : \sup = 5$, $\{b\} : \sup = 4$, $\{c\} : \sup = 4$, $\{e\} : \sup = 3$

$\{a, b\} : \sup = 4$, $\{a, c\} : \sup = 4$, $\{a, e\} : \sup = 3$, $\{b, c\} : \sup = 3$

~~$\{a, b, c\} : \sup = 3$, $\{a, b, e\} : \sup = 3$,~~

$\{b, e\} : \sup = 3$, \emptyset

$\{a, b, c\} : \sup = 3$, $\{a, b, e\} : \sup = 3$.

(b). ~~$\{a\} \rightarrow \{b\}$~~ : $\text{conf}(\{a\} \rightarrow \{b\}) = \frac{\sup(\{a, b\})}{\sup(\{a\})} = 0.8$

$\{a\} \rightarrow \{c\}$: ~~conf~~ $\text{conf}(\{a\} \rightarrow \{c\}) = 0.8$

$\{b\} \rightarrow \{c\}$: $\text{conf}(\{b\} \rightarrow \{c\}) = 0.75$.

$\{b\} \rightarrow \{e\}$: $\text{conf}(\{b\} \rightarrow \{e\}) = 0.75$

$\{b\} \rightarrow \{a, c\}$: $\text{conf}(\{b\} \rightarrow \{a, c\}) = 0.75$

$\{b\} \rightarrow \{a, e\}$: $\text{conf}(\{b\} \rightarrow \{a, e\}) = 0.75$.

$\{c\} \rightarrow \{a\}$: $\text{conf}(\{c\} \rightarrow \{a\}) = 1.0$.

$\{c\} \rightarrow \{b\}$: $\text{conf}(\{c\} \rightarrow \{b\}) = 0.75$

$\{c\} \rightarrow \{a, b\}$: $\text{conf}(\{c\} \rightarrow \{a, b\}) = 0.75$

$\{e\} \rightarrow \{a\}$: $\text{conf}(\{e\} \rightarrow \{a\}) = 1.0$

$\{e\} \rightarrow \{b\}$: $\text{conf}(\{e\} \rightarrow \{b\}) = 1.0$.

$\{e\} \rightarrow \{a, b\}$: $\text{conf} = 1.0$.

$\{a, b\} \rightarrow \{c\}$: $\text{conf} = 0.75$, $\{a, b\} \rightarrow \{e\}$: $\text{conf} = 0.75$.

$\{a, c\} \rightarrow \{b\}$: $\text{conf} = 0.75$, $\{a, e\} \rightarrow \{b\}$: $\text{conf} = 1.0$.

$\{b, c\} \rightarrow \{a\}$: $\text{conf} = 1.0$, $\{b, e\} \rightarrow \{a\}$: $\text{conf} = 1.0$.

Q 4. (II). Model overfitting is ~~said~~ a case in which the model is ~~too~~ too complicated than the training data, thus the model can very accurately fit to the training data without the ability of generalization.

Method 1: Improve the size of the training data, or reduce the complexity of the model, (e.g. the number of ~~per~~ learnable parameters in the model).

Method 2: Introduce regularization term in the loss function to restrict the model to overfit to the training data.

(III). (a) Iter 1: Allocation: cluster 1: $\{1\}$
cluster 2: $\{3, 4, 6, 8\}$
cluster 3: $\{13, 15, 17, 20, 25\}$.

centroids update: cluster 1: $\mu_1 = 1$
cluster 2: $\mu_2 = \frac{3+4+6+8}{4} = \frac{21}{4}$
cluster 3: $\mu_3 = \frac{13+15+17+20+25}{5} = 18$

Iter 2: Allocation: cluster 1: $\{1, 3\}$.
cluster 2: $\{4, 6, 8\}$
cluster 3: $\{13, 15, 17, 20, 25\}$.

centroids update: $\mu_1 = \frac{1+3}{2} = 2$.
 $\mu_2 = \frac{4+6+8}{3} = 6$
 $\mu_3 = 18$

Iter 3 : Allocation : cluster 1: { 1, 3, 4 }

cluster 2: { 6, 8 }

cluster 3: { 13, 15, 17, 20, 25 }

Centroids : $\mu_1 = \frac{1+3+4}{3} = \frac{8}{3}$

$$\mu_2 = \frac{6+8}{2} = 7.$$

$$\mu_3 = 18$$

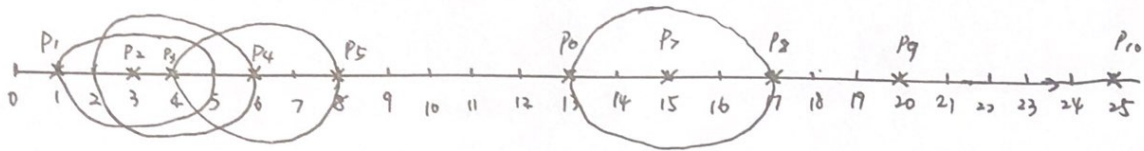
Iter 4 : Allocation : cluster 1: { 1, 3, 4 }

cluster 2: { 6, 8 }

cluster 3: { 13, 15, 17, 20, 25 }

terminates !

III.(b)



core points: P_2, P_3, P_4, P_7 .

border ~~points~~ points: P_1, P_5, P_6, P_8 .

noise points: P_9, P_{10} .

P_1 's ϵ -neighbor: P_2 .

P_2 's ϵ -neighbor: P_1, P_2, P_3 .

P_3 's ϵ -neighbor: P_2, P_3, P_4 .

P_4 's ϵ -neighbor: P_3, P_4, P_5 .

P_6 's ϵ -neighbor: P_6, P_7 .

P_7 's ϵ -neighbor: P_6, P_7, P_8 .

P_8 's ϵ -neighbor: P_7 .

P_9 's ϵ -neighbor: P_9 .

P_{10} 's ϵ -neighbor: P_{10} .

final clusters: cluster 1: $\{P_1, P_2, P_3, P_4, P_5\}$

cluster 2: $\{P_6, P_7, P_8\}$.

Q5. (I)(a) The minimum number of elements in total the method visit is

~~min(3, 4)~~

$$\min(M_1, M_2) + 1.$$

In this case ~~all~~ all ~~the~~ ~~larger~~ elements in the longer sequence are larger than those in the shorter one.

Sample: List 1: $1 \rightarrow 2 \rightarrow 3$

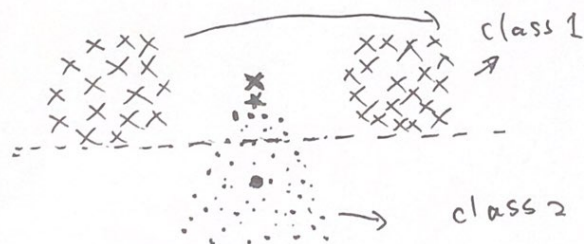
List 2: $4 \rightarrow 5 \rightarrow 6 \rightarrow 7 \rightarrow 8$.

(b). $M_1 + M_2$. In this case the last element in the shorter list is larger than the last element in the longer one.

sample: List 1: $1 \rightarrow 7 \rightarrow 11$

List 2: $2 \rightarrow 4 \rightarrow 6 \rightarrow 8 \rightarrow 10$.

(II.). There are two classes of data below, denoted by cross and dot, respectively. The **bold** cross and dot are their corresponding class prototypes. The dotted line is the Rocchio classification boundary. While the bold star "*" is closer to the ~~the~~ centroid of the class 1, the bold star "*" is closer to the centroid of the class 1,



It is ~~more~~ more reasonable to classify it as class 2. In this case the 3-NN method is more suitable.

III. $p(x|c)$ should equal to the fraction of times in which word x appears among all words in documents of class c .

$$p(x=w|c=c_j) = \frac{N(x_i=w) + 1}{N(\text{words in } c_j) + N_w}$$

where $N(x_i=w)$ is the number of times w appears in documents of class c_j , and $N(\text{words in } c_j)$ is the total number of words in documents of class c_j , N_w is the size of the dictionary.