

Part A. Σ a $\Pi_{\text{person_name}}(\sigma_{\text{company_name} = \text{"First Bank Corporation"}}(\text{works}))$

b. $\Pi_{\text{person_name}, \text{city}}(\sigma_{\text{company_name} = \text{"First Bank Corporation"}}(\text{works}) \bowtie \text{employee})$

c. $\Pi_{\text{person_name}, \text{street}, \text{city}}(\sigma_{\text{company_name} = \text{"First Bank Corporation"} \wedge \text{salary} > 10000}(\text{works} \bowtie \text{employee}))$

d. $\Pi_{\text{person_name}}(\text{employee} \bowtie \text{works} \bowtie \text{company})$

e. $\Pi_{\text{company_name}}(\text{Company} \rightarrow \Pi_{\text{city}}(\sigma_{\text{company_name} = \text{"Small Bank Corporation"}}, (\text{Company}))$

2.6 $\Pi_{\text{customer_name}, \text{customer_city}, \text{loan_number}, \text{amount}}((\text{borrower} \bowtie \text{loan}) \bowtie \text{customer})$

a. Jackson does not appear in the result because there is no tuple in the customer relation with Jackson's name and his city and street. The natural join operator uses the Cartesian product and select operations, where $\text{borrower} \times \text{customer}$ but only the tuples where $\text{borrower}. \text{customer_name} = \text{customer}. \text{customer_name}$ are selected. Since there is no tuple in customers with Jackson's name, there will be no tuple in $\text{borrower} \times \text{customer}$ where $\text{borrower}. \text{customer_name} = \text{Jackson}$ in customers . $\text{customer_name} = \text{Jackson}$. Thus, Jackson will not appear in the result.

b. We could modify the customers relation by inserting a tuple with $\text{customer_name} = \text{Jackson}$. If Jackson's city and street are unknown, we can use a null value for city and street, or another special value (e.g. N/A) that is not a name for an actual city/street.

C. $\Pi_{\text{customer_name}, \text{customer_city}, \text{loan_number}, \text{amount}}((\text{borrower} \bowtie \text{loan}) \bowtie \text{customer})$

2.7 a.

$\text{works} \leftarrow \Pi_{\text{person_name}, \text{company_name}, (\text{salary} * 1.1)}(\sigma_{\text{works}. \text{company_name} = \text{"First Bank Corporation"}(\text{works}))$

$\cup \sigma_{\text{company_name} \neq \text{"First Bank Corporation"}(\text{works})}$

b. $\text{temp} \leftarrow \Pi_{\text{works}. \text{person_name} \text{ as } \text{personname}, \text{company_name}, \text{salary}}(\sigma_{\text{personname} = \text{works}. \text{person_name}}(\text{works} \bowtie \text{manages}))$

$\text{updated} \leftarrow \Pi_{\text{person_name}, \text{company_name}, \text{salary} * 1.1}(\sigma_{\text{corp.salary} * 1.1 \leq 100000}(\text{temp})) \cup$

$\Pi_{\text{person_name}, \text{company_name}, \text{salary} * 1.03}(\sigma_{\text{corp.salary} * 1.1 > 100000}(\text{temp}))$

$\text{works} \leftarrow (\text{works} - \text{temp}) \cup \text{updated}$

C. $\text{works} \leftarrow \text{works} - \sigma_{\text{company_name} = \text{"Small Bank Corporation"}(\text{works})}$

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2.8 a. counts ← account-number G counts customer-name (depositor)

 $\prod_{\text{account-number}} (\sigma_{\text{customer-count} > 2} (P_{\text{counts}}(\text{account-number}, \text{customer-count}) \text{ (counts)}))$ b. product ← $P_{t_1}(\text{depositor}) \times P_{t_2}(\text{depositor}) \times P_{t_3}(\text{depositor})$ accounts ← $\delta_{t_1.\text{account-number} = t_2.\text{account-number} \wedge t_2.\text{account-number} = t_3.\text{account-number}}$ (product) $\prod_{t_1.\text{account-number}} (\sigma_{t_1.\text{customer-name} \neq t_2.\text{customer-name} \wedge t_2.\text{customer-name} \neq t_3.\text{customer-name}} (\text{accounts}))$
 $\wedge t_1.\text{customer-name} \neq t_3.\text{customer-name}$

2.9 a. counts ← company-name G count-distinct (person-name) as employee-count (works)

max-count ← $\sigma_{\text{max}(\text{employee-count}) \text{ as max}}$ (counts) $\prod_{\text{company-name}} (\sigma_{\text{employee-count} = \text{max}(\text{counts}) \times \text{max}})$

b. payrolls ← company-name G sum(salary) as payroll (works)

min-payroll ← min(payroll) as min (payrolls)

 $\prod_{\text{company-name}} (\sigma_{\text{payroll} = \text{min-payroll} (\text{payrolls} \times \text{min-payroll})})$

c. avg-pays ← company-name G avg(salary) as pay (works)

first-bank ← $\sigma_{\text{company-name} = \text{"First Bank Corporation"}} (\text{avg-pays})$

product ← avg-pays × first-bank

 $\prod_{\text{avg-pays, company-name}} (\sigma_{\text{avg-pays.pay} > \text{first-bank.pay}} (\text{product}))$

Part B

 $R = \text{customer_likes}$, $S = \text{customer_drinks}$ $R - S = \text{names}$, $S = \text{drink}$

$\Pi_{R-S}(r) = \text{all 4 names}$, $\Pi_{R-S}(r) \times S = \text{Cartesian product of all names and drinks, excluding tea since tea is not in customer_drinks}$

In customer_drinks

 $\Pi_{R-S,S}(r) = \text{all tuples in customer_likes}$

$\Pi_{R-S}(r) \times S - \Pi_{R-S,S}(r) = \text{difference of Cartesian product and actual tuples},$
 thus all tuples of the original customer_likes relation would not be
 in this result. This result will be the names of the customers and the
 drinks that they do not like. Arlette and Pascal do not like coffee or espresso,
 coffee and mocha so the result will still contain (Arlette, coffee) and
 (Pascal, espresso). Eli and Oppa will have tuples corresponding to all drinks in customer_drinks
 in both $\Pi_{R-S}(r) \times S$ and $\Pi_{R-S,S}(r)$. This will also be $\{\text{Oppa, tea}\} \cap \Pi_{R-S,S}(r)$,
 but the - operation will exclude $\{\text{Oppa, tea}\}$. Thus, Eli and Oppa are not in the result.

$$\rightarrow \Pi_{R-S}((\Pi_{R-S}(r) \times S) - \Pi_{R-S,S}(r)) = \boxed{\begin{array}{c} \text{Arlette} \\ \text{Pascal} \end{array}}$$

$$\begin{aligned} \Pi_{R-S}(r) &= \boxed{\begin{array}{c} \text{Arlette} \\ \text{Pascal} \\ \text{Eli} \\ \text{Oppa} \end{array}} & \text{so } \Pi_{R-S}(r) - \Pi_{R-S}((\Pi_{R-S}(r) \times S) - \Pi_{R-S,S}(r)) \\ &= \boxed{\begin{array}{c} \text{Eli} \\ \text{Oppa} \end{array}} \end{aligned}$$

b) $r|_S = r|_S - \Pi_{R-S}(\Pi_{R-S,S}(r) - (\Pi_{R-S}(r) \times S))$

We know that $\Pi_{R-S,S}(r)$ is all the tuples in r with their attributes reordered.

$\Pi_{R-S}(r) \times S$ is the Cartesian product of $\Pi_{R-S}(r)$ and S , which is

the Cartesian product of rows in r with attributes only in R and row S with

all the rows in S . Thus, $\Pi_{R-S,S}(r) - (\Pi_{R-S}(r) \times S)$ will only have the

tuples that are not in $\Pi_{R-S}(r) \times S$. In our case, (Oppa, tea) is not

in $\Pi_{R-S}(r) \times S$. Then, we subtract these tuples which appears at $R-S$

from our original relation, which means that $r|_S$ will exactly match the

content of S . In our case, $r|_S$ gives $\{\text{Eli}\}, \{\text{Oppa}\} \setminus \{\text{Oppa, tea}\}$ but $\Pi_{R-S}(\Pi_{R-S,S}(r) - (\Pi_{R-S}(r) \times S))$

will give $\{\text{Oppa}\} \setminus \{\text{Oppa, tea}\}$. Since $\{\text{Oppa, tea}\}$ does not match

customer_drinks. Thus, we will end up with $\{\text{Eli}\}$.

Part B C.

 σ customer-likes & customer-drinkes

$$\text{name} \cap_{\text{customer-likes}} (\text{likes} \bowtie \text{drinks}) = \begin{array}{l} \text{Archie 2} \\ \text{Eli 3} \\ \text{Pascal 2} \\ \text{Oppen 3} \end{array}$$

$$\text{customer-drinkes} = \begin{array}{l} \text{Archie 2} \\ \text{Eli 3} \\ \text{Oppen 3} \end{array}$$

$$\overline{\overline{\text{name} \cap_{\text{customer-likes}} (\text{likes} \bowtie \text{drinks})}} \Delta \text{A} \cap_{\text{customer-drinkes}}$$

$$\boxed{\overline{\overline{\text{R-S}(\text{R} \cap_{\text{customer-likes}} (\text{R-S G}_{\text{customer}}(\text{S})) \times \text{G}_{\text{customer}}(\text{S}) \text{as count}_2)}}}$$

Part C

- a) Yes, $\sigma_{\theta}(A G_F(r))$: we select tuples from $A G_F(r)$ where θ only uses attributes from A . Since we have $A G_F(r)$, the aggregate functions will not act on attributes from B because we group on A . Thus, the tuples will have the same values for the attributes in A . This is same as $A G_F(\sigma_{\theta}(r))$ because when we select tuples with θ , those attributes are the grouping attributes. Thus will not modify the grouping attributes, so the grouping will still be the same as $\sigma_{\theta}(A G_F(r))$.

- b) No. Consider the example:

$$r = \begin{array}{|c|c|} \hline \text{name} & \text{drink} \\ \hline \text{Eli} & \text{coffee} \\ \hline \text{Eli} & \text{mocha} \\ \hline \text{Oppen} & \text{coffee} \\ \hline \end{array} \quad s = \begin{array}{|c|c|} \hline \text{name} & \text{drink} \\ \hline \text{Eli} & \text{coffee} \\ \hline \text{Pascal} & \text{coffee} \\ \hline \text{Pascal} & \text{espresso} \\ \hline \end{array}, \quad A = \text{name}$$

$$\overline{\overline{\text{A}}(r-s)} = \overline{\overline{\text{name}} \left(\begin{array}{|c|c|} \hline \text{name} & \text{drink} \\ \hline \text{Eli} & \text{mocha} \\ \hline \text{Oppen} & \text{coffee} \\ \hline \end{array} \right)} = \begin{array}{|c|} \hline \text{name} \\ \hline \text{Eli} \\ \hline \text{Pascal} \\ \hline \end{array}$$

$$\overline{\overline{\text{A}}(r)} - \overline{\overline{\text{A}}(s)} = \begin{array}{|c|} \hline \text{Eli} \\ \hline \text{Oppen} \\ \hline \end{array} - \begin{array}{|c|} \hline \text{Eli} \\ \hline \text{Pascal} \\ \hline \end{array} = \begin{array}{|c|} \hline \text{name} \\ \hline \text{Oppen} \\ \hline \end{array}$$

Part C c) No. Consider

r	name	drink
Eli	coffee	

s	name	state
Oppm	CA	

t	name	city
Eli	LA	

$$(r \bowtie s) \bowtie t = \begin{array}{|c|c|c|} \hline & name & drink & state \\ \hline Eli & coffee & null & null \\ \hline \end{array} \bowtie \begin{array}{|c|c|} \hline & name & city \\ \hline Eli & LA & \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline & name & drink & state & city \\ \hline Eli & coffee & null & null & LA \\ \hline \end{array}$$

$$r \bowtie (s \bowtie t) = \begin{array}{|c|c|} \hline & name & drink \\ \hline Eli & coffee & \\ \hline \end{array} \bowtie \begin{array}{|c|c|c|} \hline & name & state & city \\ \hline Oppm & CA & null & null \\ \hline \end{array} = \begin{array}{|c|c|c|c|} \hline & name & drink & state & city \\ \hline Eli & coffee & null & null & null \\ \hline \end{array}$$

d) Yes. We only select tuples based on attributes from r. The left outer join will not exclude any tuples from r in $r \bowtie s$, thus the tuples we select from this will have the same values for attributes from r as $\sigma_b(r)$. If we select then left join, the same tuples from s will be excluded as in $\sigma_b(r \bowtie s)$ since s is only based on attributes from r.

e) No.

r	name	b ₁
Eli		1
Oppm		2

s	name	b ₂
Eli		3
Oppm		4

$$\theta : b_2 = 3$$

$$\sigma_b(r \bowtie s) = \begin{array}{|c|c|c|} \hline & name & b_1 & b_2 \\ \hline Eli & 1 & & 3 \\ \hline \end{array}$$

$$r \bowtie \sigma_b(s) = \begin{array}{|c|c|} \hline & b_1 \\ \hline Eli & 1 \\ \hline Oppm & 2 \\ \hline \end{array} \bowtie \begin{array}{|c|c|} \hline & b_2 \\ \hline Eli & 3 \\ \hline \end{array} = \begin{array}{|c|c|c|} \hline & b_1 & b_2 \\ \hline Eli & 1 & 3 \\ \hline Oppm & 2 & null \\ \hline \end{array}$$

Feedback Survey Submitted :)