SQL-Mongo Project - Home Credit Data

BUAN 6320.001

Group Members

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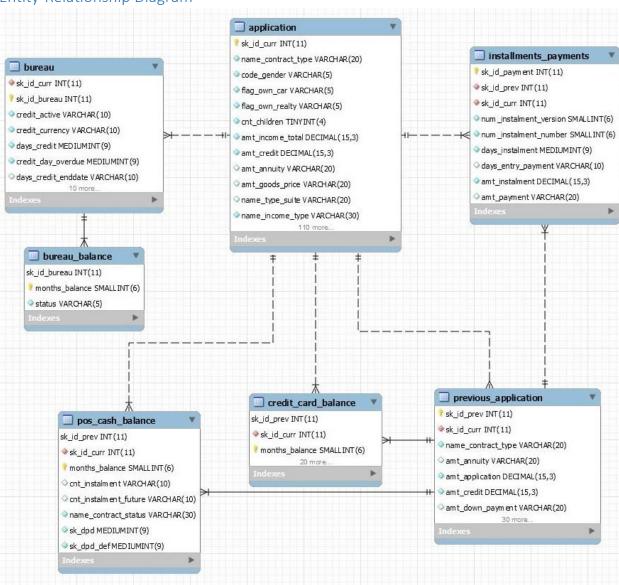
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Data Model

Assumptions/Notes About Data Entities and Relationships

application - each row represents one loan application and is identified by sk_id_curr as the primary key previous_application - each row is an old application, identified by sk_id_prev, associated to sk_id_curr bureau - each row is credit info with credit bureau, identified by sk_id_bureau, associated to sk_id_curr bureau_balance - each row is one month balance of previous credits in association with sk_id_bureau pos_cash_balance - each row is one month balance of point of sale loans in association with sk_id_prev credit_card_balance - each row is one month balance of credit card loans in association with sk_id_prev installments_payments - each row records every payment done or missed, identified by sk_id_payment

Entity-Relationship Diagram



Physical Database

Assumptions/Notes About Data Set

Merged application test and application train datasets with TARGET column as blank for test dataset Many columns in almost all the tables have missing values and are uploaded into database as blanks

Screen shot of Physical Database objects (tables on left side and indexes on right side)



Data in the Database

Table Name	Primary Key	Foreign Key	# of Rows in Table
application	sk_id_curr		356,255
previous_application	evious_application sk_id_prev sk_id_curr		1,670,214
bureau	sk_id_bureau	sk_id_curr	1,716,428
bureau_balance	sk_id_bureau, months_balance	sk_id_bureau	27,299,925
pos_cash_balance	sk_id_prev, months_balance	sk_id_curr, sk_id_prev	10,001,358
credit_card_balance	sk_id_prev, months_balance	sk_id_curr, sk_id_prev	3,840,312
installments_payments	sk_id_payment*	sk_id_curr, sk_id_prev	13,605,401



SQL Queries

Query 1

Question

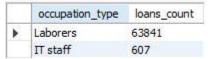
Which occupation types had the highest and lowest number of loans?

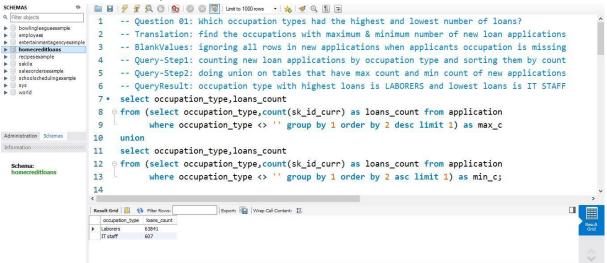
Translation

Find the occupations with maximum and minimum number of new loan applications

Notes/Comments About SQL Query and Results (Include # of Rows in Result)

Blank Values: ignoring all rows in new applications when an applicant's occupation is missing Query Step 1: counting new loan applications by occupation type and sorting them by count Query Step 2: doing union on tables that have max count and min count of new applications Query Result: occupation type with highest loans is LABORERS and lowest loans is IT STAFF





Question

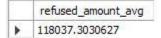
What was the average loan amount denied for Consumer Loans?

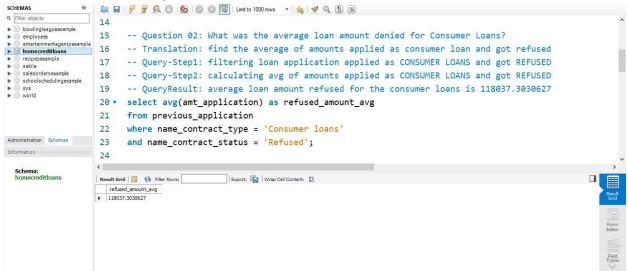
Translation

Find the average of amounts applied as consumer loan and got refused

Notes/Comments About SQL Query and Results (Include # of Rows in Result)

Query Step 1: filtering loan applications applied as CONSUMER LOANS and were REFUSED Query Step 2: calculating avg of amounts applied as CONSUMER LOANS and got REFUSED Query Result: average loan amount for all the refused consumer loans is 118037.3030627





Question

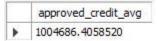
What was the average Cash loan amount approved for Married applicants with higher education?

Translation

Find the average total credit approved as cash loan for married applicants with higher education

Notes/Comments About SQL Query and Results (Include # of Rows in Result)

Query Step 1: calculating total credit amount that got APPROVED as CASH LOAN for each applicant Query Step 2: joining new applications to identify the applicant's family status and education type Query Step 3: calculating total credit amount avg for MARRIED applicant with HIGHER EDUCATION Query Result: average cash loan credit approved for married one with higher education is 1004686



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* 🗎 📓 | 🐓 🙊 🔘 | 🚳 | 🕲 🔞 | Limit to 1000 rows 🕝 🚕 | 🥩 🔍 🐧 🖃
              24 -- Question 03: What was the average Cash loan amount approved for Married with higher education?
 bowlingleagueexample employees
               25
                     -- Translation: find avg of total credit approved as cash loan for a higher educated married user
 28 -- Query-Step3: calculating total credit amount avg for a MARRIED applicant with HIGHER EDUCATION
  schoolschedulingexample
                29 -- QueryResult: avg cash loan credit approved for a married user with higher education is 1004686
 sys world
                30 • select avg(p.total_credit) as approved_credit_avg
                31 of from (select sk_id_curr,sum(amt_credit) as total_credit from previous_application
                32
                           where name_contract_type = 'Cash loans' and name_contract_status = 'Approved'
                33
Administration Schemas
                          group by 1) as p
Information as a on a.sk_id_curr = p.sk_id_curr
 Schema:
                35 where a.name_family_status = 'Married'
                36 and a.name_education_type = 'Higher education';
                Result Grid !!! 🛟 Filter Rows:
                                       Export: Wrap Cell Content: IA
                approved_credit_avg

1004686.4058520
```

Question

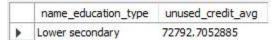
Applicants of which education type had the lowest average unused credit?

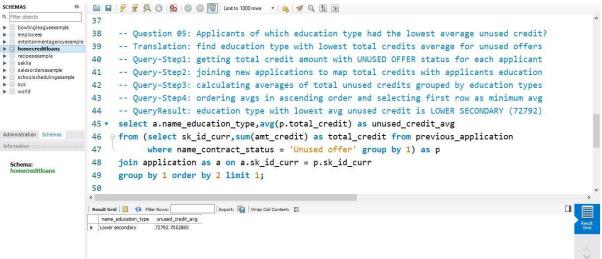
Translation

Find the education type with lowest average of total amount credits with unused offers

Notes/Comments About SQL Query and Results (Include # of Rows in Result)

Query Step 1: getting total credit amount of each applicant with UNUSED OFFER status Query Step 2: joining new applications to map total credits with education of applicant Query Step 3: calculating averages of total unused credits grouped by education types Query Step 4: ordering averages in ascending order and selecting first row as minimum Query Result: education type with lowest average unused credit is LOWER SECONDARY





Question

What was the max, min and avg number of loan applications made by an applicant in each family status?

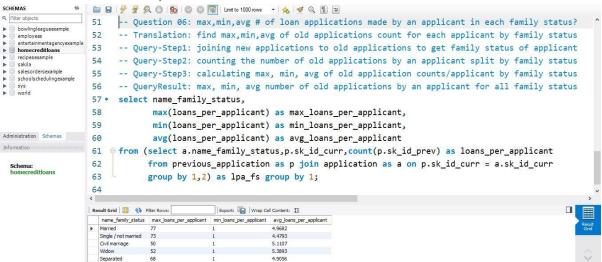
Translation

Find the maximum, minimum and average of old applications counts for each applicant by family status

Notes/Comments About SQL Query and Results (Include # of Rows in Result)

Query Step 1: joining new applications to old applications to get family status of applicants Query Step 2: counting the number of old applications by an applicant split by family status Query Step 3: calculating max, min, avg of old application counts/applicant by family status Query Result: max, min, avg number of old applications by an applicant for all family status

	name_family_status	max_loans_per_applicant	min_loans_per_applicant	avg_loans_per_applicant
•	Married	77	1	4.9682
	Single / not married	73	1	4.4793
	Civil marriage	50	1	5.1107
	Widow	52	1	5.3893
	Separated	68	1	4.9056



Data Review for MongoDB

Assumptions/Notes About Collections, Attributes and Relationships between Collections

- application {train | test}.csv
 - o This is the main table, broken into two files for Train (with TARGET) and Test (without TARGET).
 - Static data for all applications. One row represents one loan in our data sample.
 - Every loan has its own row and is identified by the feature SK_ID_CURR. The training application data comes with the TARGET indicating 0: the loan was repaid or 1: the loan was not repaid.

bureau.csv

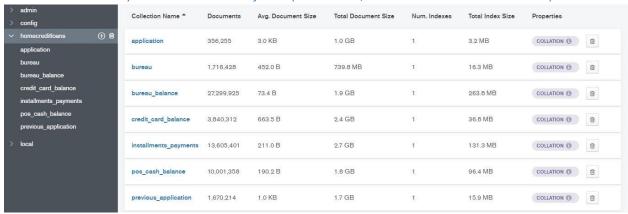
- o All client's previous credits provided by other financial institutions that were reported to Credit Bureau (for clients who have a loan in our sample).
- For every loan in our sample, there are as many rows as number of credits the client had in Credit Bureau before the application date.
- o Each previous credit has its own row in bureau, but one loan in the application data can have multiple previous credits
- bureau balance.csv
 - Monthly balances of previous credits in Credit Bureau.
 - This table has one row for each month of history of every previous credit reported to Credit Bureau i.e. the table has (number of loans in sample * number of relative previous credits * number of months where we have some history observable for the previous credits) rows.
 - Each row is one month of a previous credit, and a single previous credit can have multiple rows, one for each month of the credit length.
- POS CASH balance.csv
 - Monthly balance snapshots of previous POS (point of sales) and cash loans that the applicant had with Home Credit.
 - This table has one row for each month of history of every previous credit in Home Credit (consumer credit and
 cash loans) related to loans in our sample i.e. the table has (number of loans in sample * number of relative
 previous credits * number of months in which we have some history observable for the previous credits) rows.
 - o Each row is one month of a previous point of sale or cash loan, and a single previous loan can have many rows.
- credit card balance.csv
 - o Monthly balance snapshots of previous credit cards that the applicant has with Home Credit.
 - This table has one row for each month of history of every previous credit in Home Credit (consumer credit and cash loans) related to loans in our sample i.e. the table has (number of loans in sample * number of relative previous credit cards * number of months where we have some history observable for the previous credit card) rows.
 - o Each row is one month of a credit card balance, and a single credit card can have many rows.
- previous application.csv
 - All previous applications for Home Credit loans of clients who have loans in our sample.
 - o There is one row for each previous application related to loans in our data sample.
 - Each current loan in the application data can have multiple previous loans. Each previous application has one row and is identified by the feature SK_ID_PREV.
- installments payments.csv
 - o Repayment history for the previously disbursed credits in Home Credit related to the loans in our sample.
 - o There is a) one row for every payment that was made plus b) one row each for missed payment.
 - One row is equivalent to one payment of one installment OR one installment corresponding to one payment of one previous Home Credits credit related to loans in our sample.

Physical Mongo Database

Assumptions/Notes About Data Set

Merged application test & application train datasets with the target column as blank for test dataset Many columns in almost all the tables have missing values and are uploaded into database as blanks

Screen shot of Physical Database objects (Database, Collections and Attributes)



Data in the Database

Collection Name	Relationships with Other Collections (if any)	# of Rows in Table
application	indexed on sk_id_curr	356,255
previous_application	indexed on sk_id_prev sk_id_curr references sk_id_curr from application	1,670,214
bureau	indexed on sk_id_bureau sk_id_curr references sk_id_curr from application	1,716,428
bureau_balance	indexed on sk_id_bureau, months_balance sk_id_bureau references sk_id_bureau from bureau	27,299,925
pos_cash_balance	indexed on sk_id_prev, months_balance sk_id_curr references sk_id_curr from application sk_id_prev references sk_id_prev from previous_application	10,001,358
indexed on sk_id_prev, months_balance sk_id_curr references sk_id_curr from application sk_id_prev references sk_id_prev from previous_application		3,840,312
indexed on sk_id_payment sk_id_curr references sk_id_curr from application sk_id_prev references sk_id_prev from previous_application		13,605,401

MongoDB Queries/Code

Query 1

Question

Which occupation types had the highest and lowest number of loans?

Translation

Find the occupations with maximum and minimum number of new loan applications

Notes/Comments About MongoDB Query/Code and Results (Include # of Rows in Result)

Blank Values: ignoring all rows in new applications when an applicant's occupation is missing Query Step 1: counting loan applications by occupation type and sorting in descending order Query Step 2: limiting result to top row that has occupation with maximum number of loans Query Step 3: counting loan applications by occupation type and sorting in ascending order Query Step 4: limiting result to top row that has occupation with minimum number of loans Query Result: occupation type with highest loans is LABORERS and lowest loans is IT STAFF

Screen Shot of MongoDB Query/Code and Results

C:\WINDOWS\system32\cmd.exe - mongo

```
> db.application.aggregate(
... {$match:{'OCCUPATION_TYPE':{$ne:''}}},
... {$group:{_id:'$OCCUPATION_TYPE',loans_count:{$sum:1}}},
... {$sort:{loans_count:-1}},{$limit:1});
{ "_id" : "Laborers", "loans_count" : 63841 }
> db.application.aggregate(
... {$match:{'OCCUPATION_TYPE':{$ne:''}}},
... {$group:{_id:'$OCCUPATION_TYPE',loans_count:{$sum:1}}},
... {$sort:{loans_count:1}},{$limit:1});
{ "_id" : "IT staff", "loans_count" : 607 }
```

Question

What was the average loan amount denied for Consumer Loans?

Translation

Find the average of amounts applied as consumer loan and got refused

Notes/Comments About MongoDB Query/Code and Results (Include # of Rows in Result)

Query Step 1: filtering loan applications applied as CONSUMER LOANS and were REFUSED

Query Step 2: calculating avg of amounts applied as CONSUMER LOANS and got REFUSED

Query Result: average loan amount for all the refused consumer loans is 118037.3030627

Screen Shot of MongoDB Query/Code and Results

C:\WINDOWS\system32\cmd.exe - mongo

```
> db.previous_application.aggregate(
... {$match:{'NAME_CONTRACT_TYPE':{$eq:'Consumer loans'}}},
... {$match:{'NAME_CONTRACT_STATUS':{$eq:'Refused'}}},
... {$group:{_id:null,applied_amount_avg:{$avg:'$AMT_APPLICATION'}}});
{ "_id" : null, "applied_amount_avg" : 118037.30306271199 }
```

Question

What was the average Cash loan amount approved for Married applicants with higher education?

Translation

Find the average total credit approved as cash loan for married applicants with higher education

Notes/Comments About MongoDB Query/Code and Results (Include # of Rows in Result)

Query Step 1: joining new applications to identify the applicant's family status and education type Query Step 2: filtering all the old loan applications applied as CASH LOANS which were APPROVED Query Step 3: filtering all loan application applied by MARRIED applicant with HIGHER EDUCATION Query Step 4: calculating the total credit amount applied by an applicant with the above attributes Query Step 5: calculating avg credit APPROVED as CASH LOANS for MARRIED, HIGHER EDUCATION Query Result: average cash loan credit approved for married one with higher education is 1004686

Screen Shot of MongoDB Query/Code and Results

```
c \text{C\WINDOWS\system32\cmd.exe-mongo}
> db.previous_application.aggregate(
... {\$lookup:{from:'application',localField:'SK_ID_CURR',foreignField:'SK_ID_CURR',as:'a'}},
... {\$unwind:'\$a'},
... {\$project:{SK_ID_CURR:1,AMT_CREDIT:1,NAME_CONTRACT_TYPE:1,NAME_CONTRACT_STATUS:1,
... 'a.NAME_FAMILY_STATUS':1,'a.NAME_EDUCATION_TYPE':1}},
... {\$match:{'NAME_CONTRACT_TYPE':{\$eq:'Cash loans'}}},
... {\$match:{'NAME_CONTRACT_STATUS':{\$eq:'Approved'}}},
... {\$match:{\'a.NAME_FAMILY_STATUS':{\$eq:'Married'}}},
... {\$match:{\'a.NAME_EDUCATION_TYPE':{\$eq:'Higher education'}}},
... {\$group:{\_id:'\$SK_ID_CURR',total_credit:{\$sum:'\$AMT_CREDIT'}}},
... {\$group:{\_id:'\$SK_ID_CURR',total_credit:{\$sum:'\$AMT_CREDIT'}}},
... {\$group:{\_id:null,approved_credit_avg:{\$avg:'\$total_credit'}}});
{ "__id": null, "approved_credit_avg": 1004686.40585200999 }
```

Question

Applicants of which education type had the lowest average unused credit?

Translation

Find the education type with lowest average of total amount credits with unused offers

Notes/Comments About MongoDB Query/Code and Results (Include # of Rows in Result)

Query Step 1: filtering the old loan applications with contract status as UNUSED OFFER Query Step 2: getting total credit amount of each applicant with UNUSED OFFER status Query Step 3: joining new applications to identify the education types of the applicant Query Step 4: calculating averages of total unused credits grouped by education types

Query Step 5: ordering average in ascending order and selecting the top row as lowest Query Result: education type with lowest average unused credit is LOWER SECONDARY

Screen Shot of MongoDB Query/Code and Results

```
c\text{cvmNDOWS\system2\cmdexe-mongo}
> db.previous_application.aggregate(
... {\smatch: \nAME_CONTRACT_STATUS': \seq: \unused offer'\}},
... {\sgroup: \square id: \ssk_ID_CURR', \total_credit: \ssum: \saMT_CREDIT'\}},
... {\slookup: \sqrain \text{from: \underset application', localField: \underset id. SK_ID_CURR', \underset foreignField: \underset SK_ID_CURR', \underset as: \underset \un
```

Question

What was the max, min and avg number of loan applications made by an applicant in each family status?

Translation

Find the maximum, minimum and average of old applications counts for each applicant by family status

Notes/Comments About MongoDB Query/Code and Results (Include # of Rows in Result)

Query Step 1: joining new applications to old applications to get family status of applicants Query Step 2: counting the number of old applications by an applicant split by family status Query Step 3: calculating max, min, avg of old application counts/applicant by family status Query Result: max, min, avg number of old applications by an applicant for all family status

Screen Shot of MongoDB Query/Code and Results

```
db.previous_application.aggregate(
.. {$lookup:{from:'application',localField:'SK_ID_CURR',foreignField:'SK_ID_CURR',as:'a'}},
.. {$unwind:'$a'},{$project:{SK_ID_CURR:1,SK_ID_PREV:1,'a.NAME_FAMILY_STATUS':1}},
.. {$group:{_id:{family:'$a.NAME_FAMILY_STATUS',curr:'$a.SK_ID_CURR'},loans_per_applicant:{$sum:1}}},
.. {$group:{_id:'$_id.family',max_loans_per_applicant:{$max:'$loans_per_applicant'}}});
 "_id" : "Married", "max_loans_per_applicant" : 77 }
 "_id" : "Single / not married", "max_loans_per_applicant" : 73 }

"_id" : "Civil marriage", "max_loans_per_applicant" : 50 }

"_id" : "Widow", "max_loans_per_applicant" : 52 }

"_id" : "Separated", "max_loans_per_applicant" : 68 }
 db.previous_application.aggregate(
.. {$lookup:{from:'application',localField:'SK_ID_CURR',foreignField:'SK_ID_CURR',as:'a'}},
.. {$unwind:'$a'},{$project:{SK_ID_CURR:1,SK_ID_PREV:1,'a.NAME_FAMILY_STATUS':1}},
    {\sqroup:{_id:{family:'\$a.NAME_FAMILY_STATUS',curr:'\$a.SK_ID_CURR'},loans_per_applicant:{\$sum:1}}},
 . {\sqroup:{\id:\$_id.\family',min_loans_per_applicant:{\$min:\$\loans_per_applicant'}}});
"_id" : "Married", "min_loans_per_applicant" : 1 }

"_id" : "Single / not married", "min_loans_per_applicant" : 1 }

"_id" : "Civil marriage", "min_loans_per_applicant" : 1 }

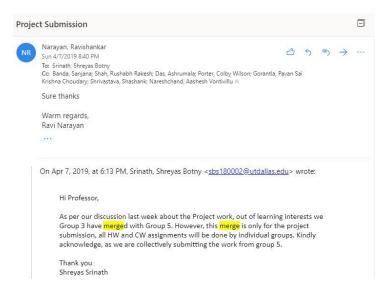
"_id" : "Widow", "min_loans_per_applicant" : 1 }

"_id" : "Separated", "min_loans_per_applicant" : 1 }
 db.previous_application.aggregate(
   {\$lookup:\{from: 'application', localField: 'SK_ID_CURR', foreignField: 'SK_ID_CURR', as: 'a'\}, \{\$unwind: '\$a'\}, \{\$project:\{SK_ID_CURR:1, SK_ID_PREV:1, 'a.NAME_FAMILY_STATUS':1\}\},
    {$group:{_id:{family:'$a.NAME_FAMILY_STATUS',curr:'$a.SK_ID_CURR'},loans_per_applicant:{$sum:1}}},
   {\sqroup:{\_id:\$_id.\family',avg_loans_per_applicant:{\$avg:\$\loans_per_applicant'}}});
             "Married", "avg_loans_per_applicant" : 4.968177001 }
    id" : "Single / not married", "avg_loans_per_applicant" : 4.479289820 }
    id" : "Civil marriage", "avg_loans_per_applicant" : 5.110745377 }
id" : "Widow", "avg_loans_per_applicant" : 5.389349381 }
             "Separated", "avg_loans_per_applicant" : 4.905629062 }
```

Project Contributors

Activity	Pavan Sai Krishna Gorantla	Aashesh Nareshchand	Shashank Srivastava	Colby Porter
Prepared Data Model			X	X
Created Physical Database			X	X
Loaded Data into Database	X	X		
Wrote SQL Queries	X	X		
Prepared Mongo Database			X	X
Loaded Data into Mongo DB	X	X		
Wrote Mongo Queries	X	X		
Prepared Report	X	X		
Reviewed Report			X	X

With professor's permission, Group #3 members requested us to be included into our Group #5



Activity	Shreyas Botny Srinath	Rushabh Rakesh Shah	Ashrumala Das
Prepared Data Model	X	X	X
Created Physical Database	X	X	X
Prepared Mongo Database	X	X	X