(DEMO) Report for ICCS240: DBMS class project: SNPDB

Group Members: Kriangsak T., Hasdin,G. This report refers to this attached repository : SNPBD (https://github.com/Kriangsak1997/DatabaseClassProject)

Please treat this to be a small demo...

First of all, we used docker to run out protgresql database: used commands can be found in the file named "command_involvingDockerandPSQL.txt". In this file, you will find what is used to map data to the container.... since i have no time (more like brain) to build a proper image for it.... Please see the following

In [6]:
```
# filepath  = '/Users/kriangsak1997/Documents/MUIC/Term8/DBMS/Proje
ct/command_involvingDockerandPSQL.txt'
# with open(filepath) as fp:
#    line = fp.readline()
#    cnt = 1
#    while line:
#        print("Line {}: {}".format(cnt, line.strip()))
#        line = fp.readline()
#        cnt += 1
```

Connect to the Database

After having created the database and import the file into it, we will connect to the database using Java. Here with help of **Maven** dependencies, it allows to very easily connect to our database, we can dp so by creating a Maven project. Then access the file: *pom.xml*
and we add the dependencies:

```
</dependency/>
```

```
        </groupId/> org.postgresql</groupId/>
         </artifactId/>postgresql</artifactId/>
         </version/>42.2.10</version/>

    </dependency/>
```

What is SNP?

Here, please let me introtduce you with our schema. In case you have not heard of Single Nucleotide Polymorphisms (SNPs).
Single nucleotide polymorphisms, frequently called SNPs (pronounced “snips”), are the most common type of genetic variation among people. Each SNP represents a difference in a single DNA building block, called a nucleotide. For example, a SNP may replace the nucleotide cytosine (C) with the nucleotide thymine (T) in a certain stretch of DNA.

SNPs occur normally throughout a person’s DNA. They occur almost once in every 1,000 nucleotides on average, which means there are roughly 4 to 5 million SNPs in a person's genome. These variations may be unique or occur in many individuals; scientists have found more than 100 million SNPs in populations around the world. Most commonly, these variations are found in the DNA between genes. They can act as biological markers, helping scientists locate genes that are associated with disease. When SNPs occur within a gene or in a regulatory region near a gene, they may play a more direct role in disease by affecting the gene’s function.

Most SNPs have no effect on health or development. Some of these genetic differences, however, have proven to be very important in the study of human health. Researchers have found SNPs that may help predict an individual’s response to certain drugs, susceptibility to environmental factors such as toxins, and risk of developing particular diseases. SNPs can also be used to track the inheritance of disease genes within families. Future studies will work to identify SNPs associated with complex diseases such as heart disease, diabetes, and cancer. source (https://ghr.nlm.nih.gov/primer/genomicresearch/snp)

Schema Detail

We have created the following schema: Note that before inserting the data into our database, we needed to do a bit of porcessing to extract our data out from the origal input data, [please refer to (https://github.com/Kriangsak1997/DatabaseClassProject/blob/master/notebooks/processing.ipynb)]

SNP_DB(Main_Gene_name varchar, initialAA varchar,finalAA varchar,position_of_Change varchar,Type_of_Variant varchar,dbSNP varchar,Disease_name varchar)

That is,

> *Main_Gene_name* contains the name of the gene for each record, taking *strings* of gene names
>
> *initialAA* contains the amino acid (AA) abbreviation before a change occurs , taking *strings* of AA ,br>
>
> *finalAA* contains the amino acid (AA) abbreviation after a change occurs , taking *strings* of AA
>
> *position_of_Change* contains the position of AA (in the change of AA chains of a gene), taking **string** of position, which later will be altered to integer type
>
> *Type_of_Variant* contains the type of variants for which an SNP causes, taking *strings* of variant types
>
> *dbSNP* take takes in database code used to access more information regarding a change in NCBI SNP database, taking strings of DB-code
>
> *Disease_name* contains the name of diseases, if applicable, caused by SNPs, taking *strings* of disease names.

Abbreviations and Full names

The following dataframe displays to you the full AA names corresponding to abbreviations used in our database

In [7]:
```
AminoAcid_name =pd.read_csv('/Users/kriangsak1997/Documents/MUIC/Term8/DBMS/Project/aanames.csv')
AminoAcid_name
```

Out[7]:

	Abbreviation	Ful name
0	Ala	Alanine
1	Arg	Arginine
2	Asn	Asparagine
3	Asp	Aspartic acid (Aspartate)
4	Cys	Cysteine
5	Gln	Glutamine
6	Glu	Glutamic acid (Glutamate)
7	Gly	Glycine
8	His	Histidine
9	Ile	Isoleucine
10	Leu	Leucine
11	Lys	Lysine
12	Met	Methionine
13	Phe	Phenylalanine
14	Pro	Proline
15	Ser	Serine
16	Thr	Threonine
17	Trp	Tryptophan
18	Tyr	Tyrosine
19	Val	Valine

Now we can query from out database for all: CRUD queries

From this, we take a data-analytic approach to our database. That is, we will apply a small mining algorithm on the given dataset.

Associative Rule Mining with Apriori Algorithm

for those wishing to understand more about this concept, consult (https://blog.usejournal.com/association-rule-mining-apriori-algorithm-c517f8d7c54c) There are a few things to introduce for those new to Associative Rule Mining or, perhaps also, Apriori Algorithm.
the results of out experiments is in the file: notebooks/Association Rule Mining with Apriori algorithm.ipynb with a few tials of different hyperparemeters (supports, Confidence). It turns out that the with conditional probabiity of 25%, this gives out 3 frequent item set(of 2 elements):

('Asp', 'Asn'), ('Tyr', 'Cys'), ('Glu', 'Lys')

This will be examined later in this demo.

In addition to the first submission, there is a need for a moer thorough anaysis of the data. To do so, the problem that was not fixed, purposely actually ^^, is that we need to convert the type of attibute **position_of_change** into an **integer** type. It is very simple to do so, we can simply run the following command to our datbase.

```
ALTER TABLE snp_db ALTER COLUMN position_of_change TYPE INT USING
position_of_change::integer;
```

From here on, we can do analysis associated with position of chnages and our obtained frequent itemsets obtained from associative rule mining. For simplicity, let's bring in a few functions which will later be used in this demo.

In [6]:
```
import psycopg2
import pandas as pd
import numpy as np
from apyori import apriori
import matplotlib.pyplot as plt
from sqlalchemy import create_engine
"""
This connection function will acts as a connection factory as it is
in our ConnectionFactory.java
in this repository.
"""
def connection(user,pwd,host,port,db):
    try:
       connection = psycopg2.connect(user=user,
                                     password=pwd,
                                     host=host,
                                     port=port,
                                     database=db)
       cursor = connection.cursor()
       return cursor
    except (Exception, psycopg2.Error) as error :
        print ("Error while fetching data from PostgreSQL", error)

"""
this select class will return the output from input queries and ret
urn, for the moment, as a numpy array object.
"""
user ="postgres"
pwd = "1997"
host ="localhost"
port = "5432"
db= "postgres"
def select(q):
    c = connection(user,pwd,host,port,db)
    c.execute(q)
    arr = np.array(c.fetchall())
    return arr
```

In [51]:
```
snp =pd.DataFrame(select("select initialAA,finalAA from snp_db"))
snp.columns=[ 'initialAA', 'finalAA']
snps = []
for row in range(0,len(snp)):
    snps.append([str(snp.values[row,j]) for j in range(0,2)])
association_rules = apriori(snps,min_support=0.0093,min_confidence=
0.250,min_lift =3,min_length=2)
association_results =list(association_rules)
finals = []
rows = []
for item in association_results:
#     to display the rule, the support, the confidence, and lift fo
r each rule in a more clear way:

    # first index of the inner list
    # Contains base item and add item
    eachrow=[]
    pair = item[0]
    items = [x for x in pair]
#     print("Rule: " + items[0] + " -> " + items[1])
    eachrow.append(items[0] + " -> " + items[1])

    #second index of the inner list
#     print("Support: " + str(item[1]))
    eachrow.append(item[1])

    #third index of the list located at 0th
    #of the third index of the inner list

#     print("Confidence: " + str(item[2][0][2]))
    eachrow.append(item[2][0][2])
#     print("Lift: " + str(item[2][0][3]))
    eachrow.append(item[2][0][3])
    rows.append(eachrow)
#     print("=====================================")
miningresults = pd.DataFrame(rows)
cols = ["rule", "Support", "Confidence", "Lift"]
miningresults.columns = cols
```

In [55]:
```
miningresults
# miningresults.to_csv(r'/Users/kriangsak1997/Documents/MUIC/Term8/
DBMS/Project/miningResults.csv', index = False)
```

Out[55]:

	rule	Support	Confidence	Lift
0	Asn -> Asp	0.020755	0.283619	3.397908
1	Tyr -> Cys	0.021931	0.254751	4.943691
2	Lys -> Glu	0.031555	0.369445	5.063446

Note that we have added the result into the 8th case of our switch case class so that the user can see this obtained result

What can see learn from the following rules

we shall try to zoom in into each of an associative frequent itemsets and see what can be drawn from it. For example, we can ask the following questions.

> (1) What type of variants are caused by the obtained rules.
> (2) What are are the positions of change when we specify with obtained initial and final AAs. we can bin this, say, into 3 subintervals. From this quetion, we can deepen the quetion into: once binneed into 3 subintervals, which subinterval containes the largest number of changes recorded

(1) What type of variants are caused by the obtained rules

In [8]:
```
#Prepare the queries for the 3 rules
final_Queries = ["select count(main_gene_name) from snp_db where in
itialaa='Asp' and finalaa = 'Asn' group by type_of_variant;",
                 "select count(main_gene_name) from snp_db where ini
tialaa='Tyr' and finalaa = 'Cys' group by type_of_variant; ",
                  "select count(main_gene_name) from snp_db where in
itialaa='Glu' and finalaa = 'Lys' group by type_of_variant;"]
records= [select(final_Queries[i]).T.flatten().tolist() for i in ra
nge(3)]
framessss = pd.DataFrame(records)
framessss.insert(0,"Rule",["Asp -> Asn", "Tyr -> Cys", "Glu -> Lys"
],True)
framessss.columns = ["Rule\Type of Variant","Disease","Polymorphism
","Unclassified"]
#note that pgsl return the count in alphabetical order.
framessss.set_index(['Rule\Type of Variant'])
```

Out[8]:

Rule\Type of Variant	Disease	Polymorphism	Unclassified
Asp -> Asn	457	592	147
Tyr -> Cys	574	285	80
Glu -> Lys	785	813	214

In [9]:
```
# framessss.to_csv(r'/Users/kriangsak1997/Documents/MUIC/Term8/DBMS
/Project/frequent_thingy.csv', index = False)
```

In [10]:
```
# check = "select * from frequent_things"
# select(check)
```

Here we go, the above dataframe displays different types of variants based on the given associative rules. It is obvious to see that 2 out of 3 rules (Asp -> Asn,Glu -> Lys), when these changes occur, they give rise to polymorphism more than the other two types of genetic variations

(2) Binning of positions of changes

like we said earilier, we would like to know What are are the positions of change when we specify with obtained initial and final AAs. we can bin this, say, into 3 subintervals. From this quetion, we can deepen the quetion into: once binneed into 3 subintervals, which subinterval containes the largest number of changes recorded. Here is the plans of what we are going to do in the next few cells

> First, we want to bin the entire dataset
> Second, we will do the same for each of the 3 obtained assiciative frequent itemset.
> finally, we will compare the result accordingly.

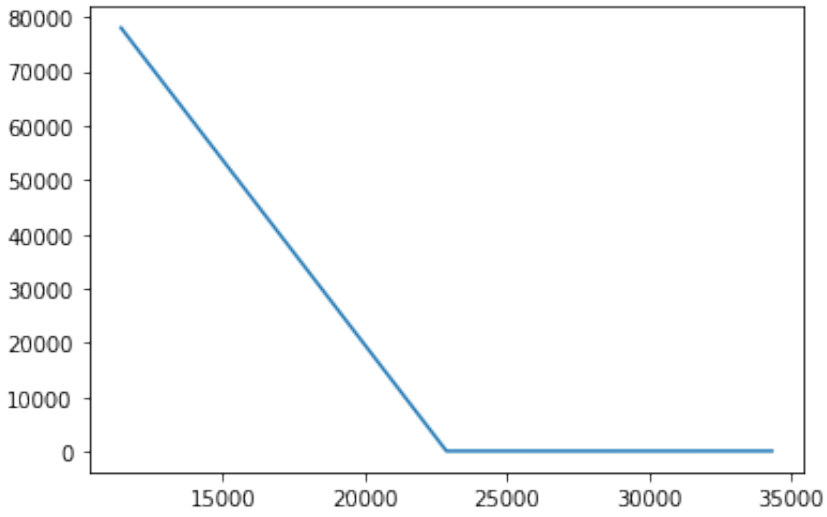
Binning the whole dataset

In [11]:
```
count_main, bin_main = np.histogram(select("select position_of_chan
ge from snp_db"),3)
# plt.hist(bins[:-1], bins, weights=counts)
```

In [12]:
```
intv= [11439.6, 22877.3,34315.0]
vals = count_main.flatten().tolist()
vals
```

Out[12]:
```
[78023, 108, 114]
```

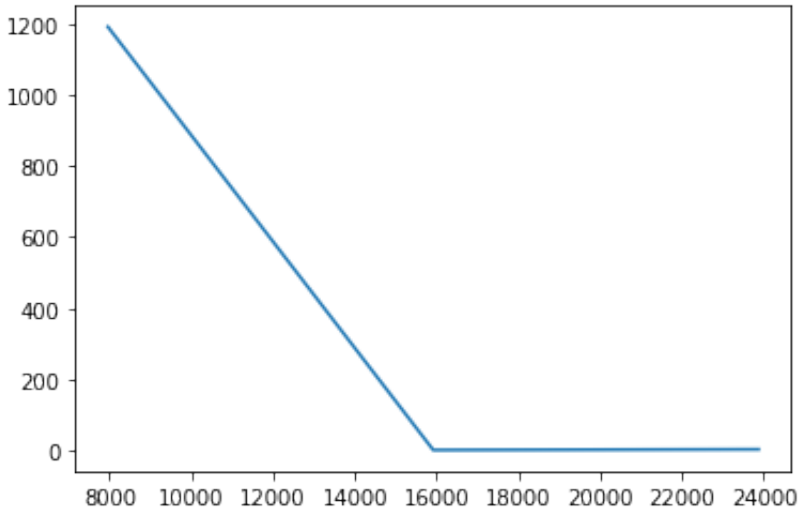
In [13]:
```
plot_main = plt.plot(intv,vals)
```



Binning the case when Asp changes into Asn

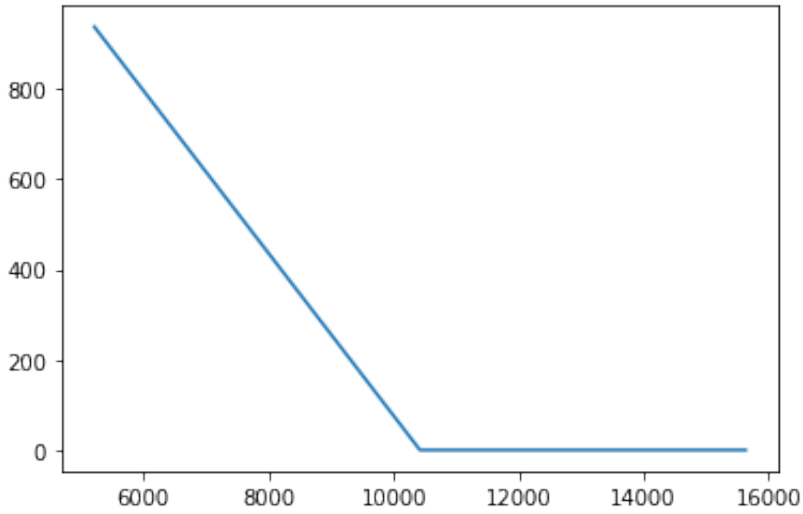
In [14]:
```
count_1, bins_1 = np.histogram(select("select position_of_change fr
om snp_db where initialaa='Asp' and finalaa = 'Asn'"),3)
plt.plot(bins_1.flatten().tolist()[1:],count_1.flatten().tolist())
count_1,bins_1
```

Out[14]:
```
(array([1192,    1,    3]),
 array([2.00000000e+00, 7.95866667e+03, 1.59153333e+04, 2.38720000
e+04]))
```



Binning the case when Tyr changes into Cys

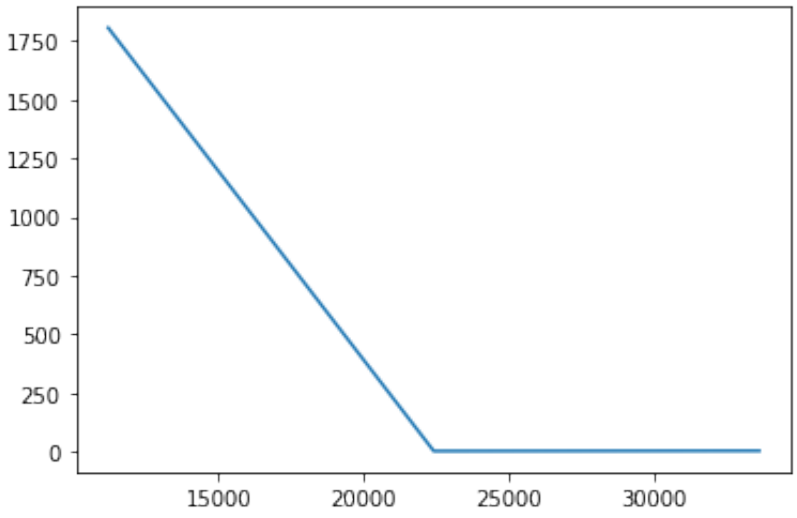
In [59]:
```
count_2, bins_2 = np.histogram(select("select position_of_change fr
om snp_db where initialaa='Tyr' and finalaa = 'Cys'"),3)
plt.plot(bins_2.flatten().tolist()[1:],count_2.flatten().tolist())
count_2,bins_2
from IPython.display import Image
```



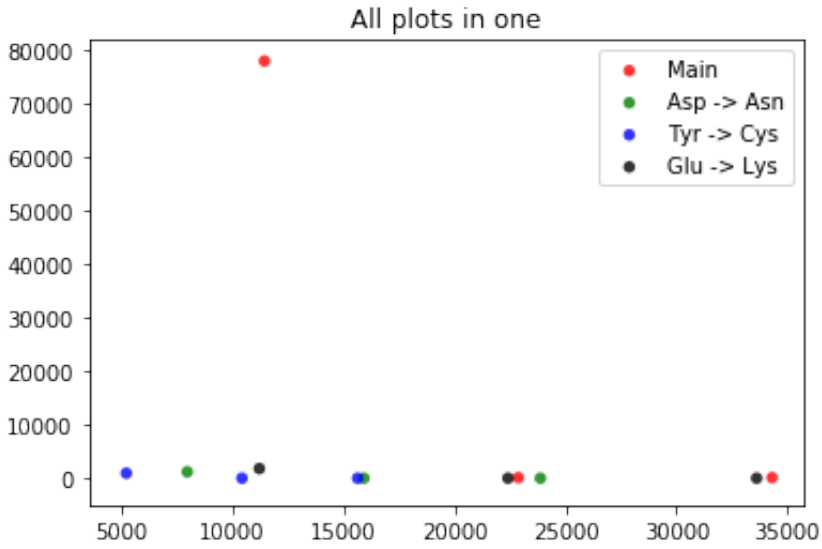
Binning the case when Glu changes into Lys

In [16]:
```
count_3, bins_3 = np.histogram(select("select position_of_change fr
om snp_db where initialaa='Glu' and finalaa = 'Lys'"),3)
plt3 =plt.plot(bins_3.flatten().tolist()[1:],count_3.flatten().toli
st())
count_3,bins_3
```

Out[16]:
```
(array([1805,    3,    4]),
 array([2.00000000e+00, 1.12066667e+04, 2.24113333e+04, 3.36160000
e+04]))
```



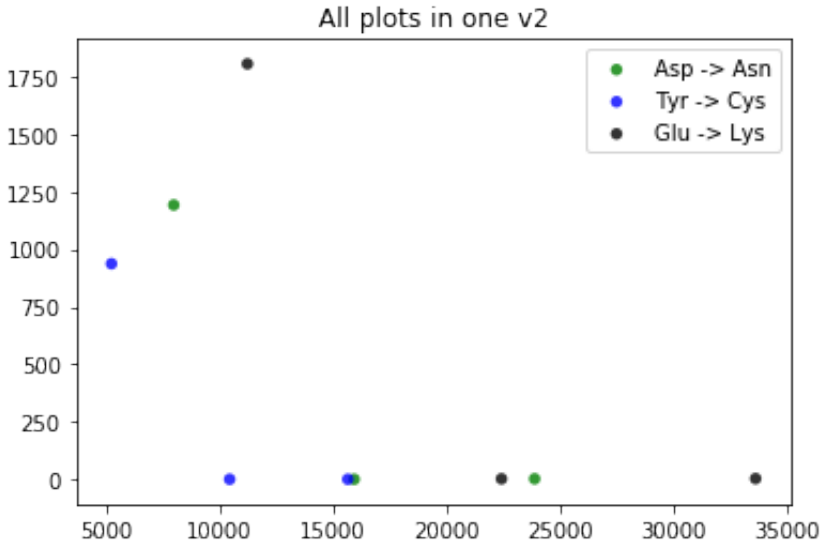
In [17]:
```
colors = (0,0,0)
area = np.pi*3

# Plot

g1 = (bin_main.flatten().tolist()[1:], count_main.flatten().tolist(
))
g2 = (bins_1.flatten().tolist()[1:], count_1.flatten().tolist())
g3 = (bins_2.flatten().tolist()[1:], count_2.flatten().tolist())
g4 = (bins_3.flatten().tolist()[1:], count_3.flatten().tolist())
data = (g1, g2, g3,g4)
colors = ("red", "green", "blue","black")
groups = (["Main","Asp -> Asn", "Tyr -> Cys", "Glu -> Lys"])

# Create plot
fig = plt.figure()
ax = fig.add_subplot(1, 1, 1)

for data, color, group in zip(data, colors, groups):
    x, y = data
    ax.scatter(x, y, alpha=0.8, c=color, edgecolors='none', s=30, l
abel=group)

plt.title('All plots in one')
plt.legend(loc=0)
plt.show()
```



Plotting with the main dataset makes it hard to see the actual trend for the subplots: all the frequent iremsets.

We will try to construct a new plot excluding the main dataset

In [18]:
```
colors = (0,0,0)
area = np.pi*3

# g1 = (bin_main.flatten().tolist()[1:], count_main.flatten().tolis
t())
g2 = (bins_1.flatten().tolist()[1:], count_1.flatten().tolist())
g3 = (bins_2.flatten().tolist()[1:], count_2.flatten().tolist())
g4 = (bins_3.flatten().tolist()[1:], count_3.flatten().tolist())
data = ( g2, g3,g4)
colors = ( "green", "blue","black")
groups = (["Asp -> Asn", "Tyr -> Cys", "Glu -> Lys"])

# Create plot
fig = plt.figure()
ax = fig.add_subplot(1, 1, 1)

for data, color, group in zip(data, colors, groups):
    x, y = data
    ax.scatter(x, y, alpha=0.8, c=color, edgecolors='none', s=30, l
abel=group)

plt.title('All plots in one v2')
plt.legend(loc=0)
plt.show()
```



from here we can see that the the most significant intervals are the first interval of every subplot.

In addition to that, we can also try to check for which of the frequent itemset, which one has the most number of changes cross all subitervals

In [57]:
```
countsss = [count_1, count_2, count_3]
sumcol = [np.sum(count_1),np.sum(count_2),np.sum(count_3)]
countframes = pd.DataFrame(countsss)
countframes.columns= ["1st-inv'l","2nd-inv'l","3rd-inv'l"]
countframes
countframes.insert(0,"Rule",["Asp -> Asn", "Tyr -> Cys", "Glu -> Ly
s"],True)
countframes.insert(4,"total",sumcol,True)
countframes.columns = ["Rule\intvl","1st-inv'l","2nd-inv'l","3rd-in
v'l","total"]
#note that pqsl return the count in alphabetical order.
countframes.set_index(['Rule\intvl'])
new = countframes
new
```

Out[57]:

	Rule\intvl	1st-inv'l	2nd-inv'l	3rd-inv'l	total
0	Asp -> Asn	1192	1	3	1196
1	Tyr -> Cys	937	1	1	939
2	Glu -> Lys	1805	3	4	1812

As we can see from the summary table, when Asp changes into Asn, it has the largest number of changes. In fact, we also know this from the outout from our associative mining. That is, we can pinpoint this fact by looking at the conditional probabilities, confidence values.

In [56]:
```
# new.to_csv(r'/Users/kriangsak1997/Documents/MUIC/Term8/DBMS/Proje
ct/count_per_interval.csv', index = False)
```

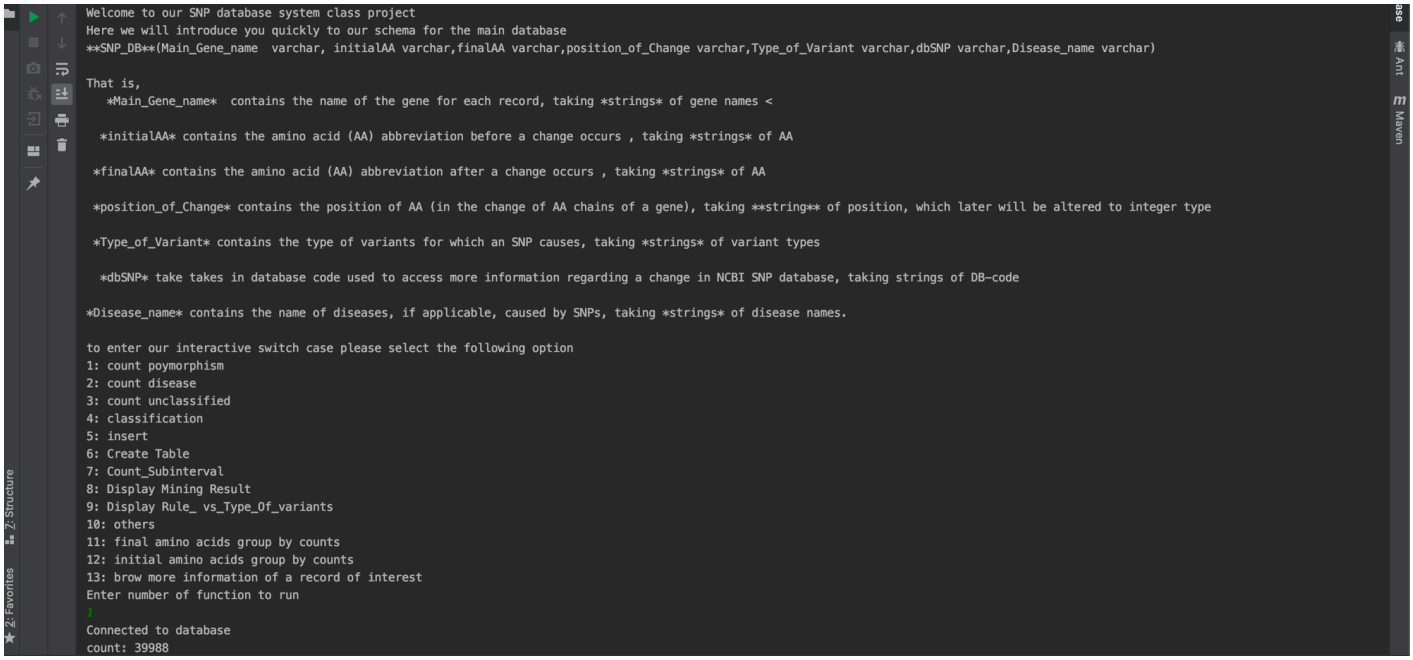
Put the rules aside

Apart from the ontained results, we can also pose a few quetions directly to our databse. Let's assume that there exists a curious user wanting to know the followig:

- what is the count the each amino acid in the database: initial and final counts: to see this please select case 11 ans 13.
- what if the user wants to know more about a specific record, then go ahead with case 13: where the input parameter is taken from attribute "dbSNP". The user shall have a brower opening the NBCI page linked to the specified record. Let's see how each of the switch cases works!!

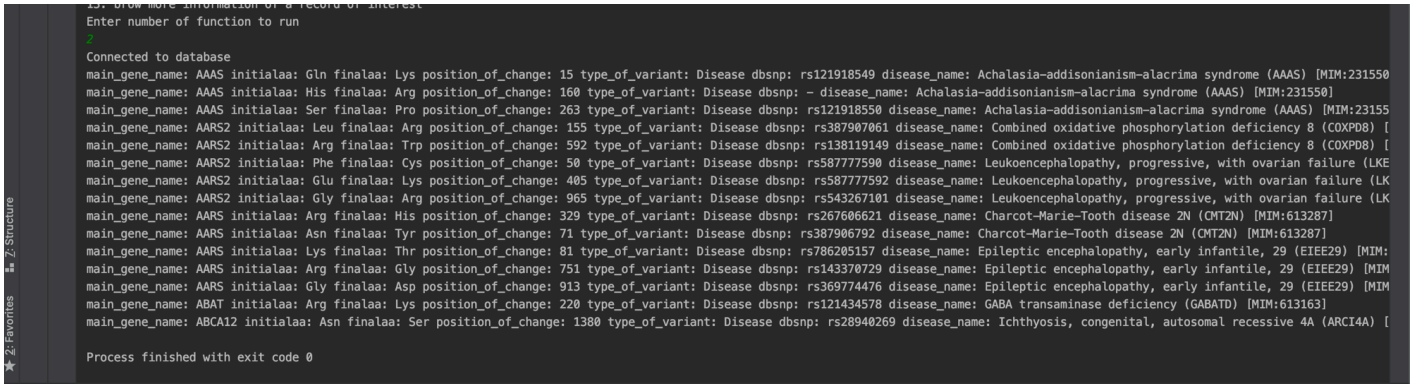
Case 1: Count polymorphism

this query return to the user: the total number of polymorphism cases in the database



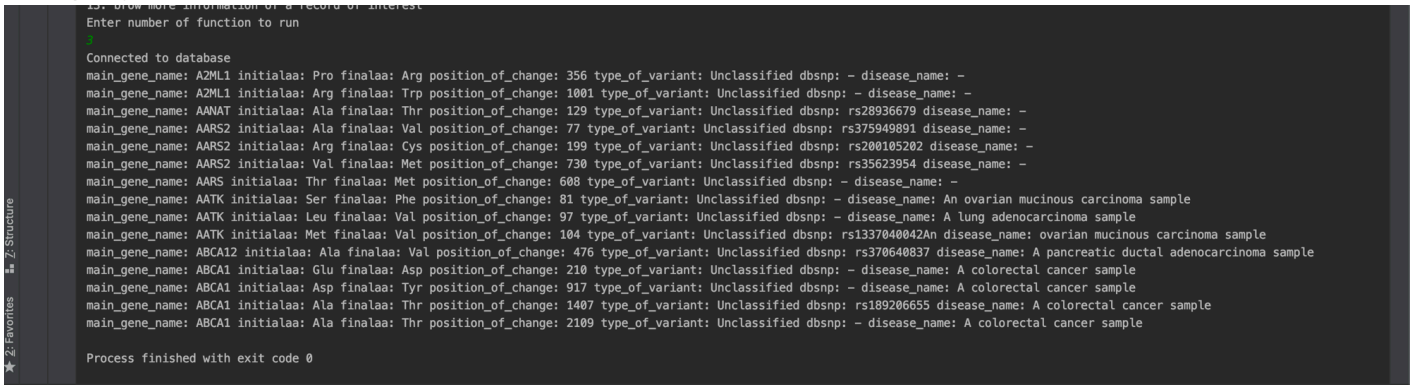
Case 2: Count disease

this query return to the user: the total number of disease cases in the database



Case 3: Count unclassified

this query return to the user: the total number of unclassified cases in the database



Case 4: Classification,

I know this is just the aggregation of case 1,2 and 3, but why not, let's just see it!

```
13: brow more information of a record of interest
Enter number of function to run
4
Connected to database
type_of_variant: mutation total_counts: 1
type_of_variant: Unclassified total_counts: 7934
type_of_variant: Disease total_counts: 30322
type_of_variant: Polymorphism total_counts: 39988

Process finished with exit code 0
```

Case 5: Insert record

This case takes care of record insertion

```
13: brow more information of a record of interest
Enter number of function to run
5
Enter Main_Gene_name
cattofatto
Enter initialAA
GRA
Enter finalAA
TEM
Enter position
8
EnterType_of_Variant
unclassified
Enter dbSNP
-
EnterDisease_name
CatLoversDisease
Connected to database
Insertion Completed

Process finished with exit code 0
```

Case 6: Create Table

This case takes care of creating a new table...it shows some sort of error, but it works.... I dont know how to fix this bug...admitedly.

```
Enter number of function to run
6
Enter create queries
create table catto(ncanname varchar);
Connected to database
org.postgresql.util.PSQLException: No results were returned by the query.
    at org.postgresql.jdbc.PgStatement.executeQuery(PgStatement.java:226)
    at WorkingWithDB.Create.createdb(Create.java:19)
    at WorkingWithDB.switchc.run(switchc.java:84)
    at WorkingWithDB.switchc.main(switchc.java:200)

Process finished with exit code 0
```

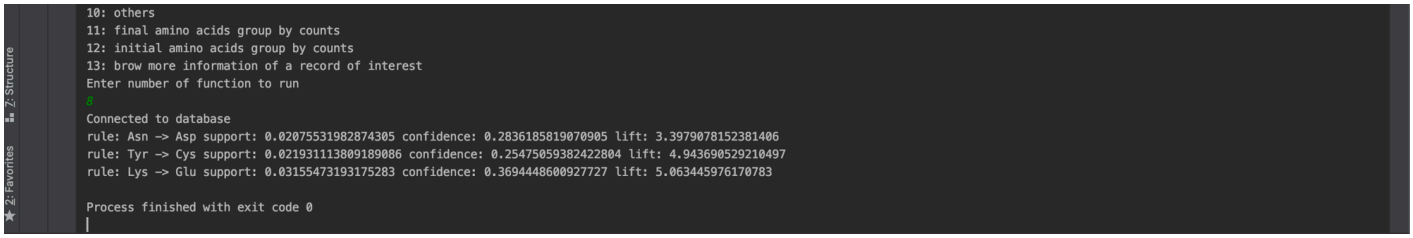
Case 7: Count_Subinterval

This case returns to the user the counts for each subintervals resulted from our Associative rule mining

```
10: others
11: final amino acids group by counts
12: initial amino acids group by counts
13: brow more information of a record of interest
Enter number of function to run
7
Connected to database
rule: Asp -> Asn count_firstsub: 1192 count_secondsub: 1 count_thirdsub: 3 total: 1196
rule: Tyr -> Cys count_firstsub: 937 count_secondsub: 1 count_thirdsub: 1 total: 939
rule: Glu -> Lys count_firstsub: 1805 count_secondsub: 3 count_thirdsub: 4 total: 1812

Process finished with exit code 0
```

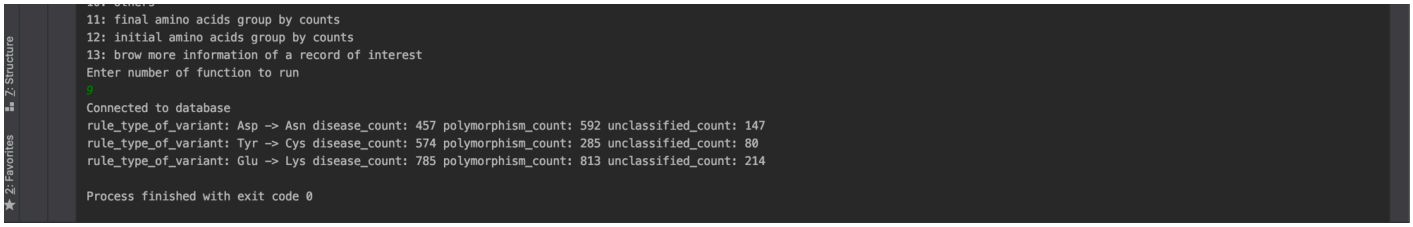
Case 8: Display Mining Result

This case returns to you the result of our mining on the database: and yes I know it shuold have come before case 7....but whatever.



Case 9: Display Rule_ vs_Type_Of_variants

This case presents to the user, with three obtained associative frequent itemsets, the catagorizations of variants associated to each rule.



Case 10: others

This case allows users to query from the database

Case 11: final amino acids group by counts

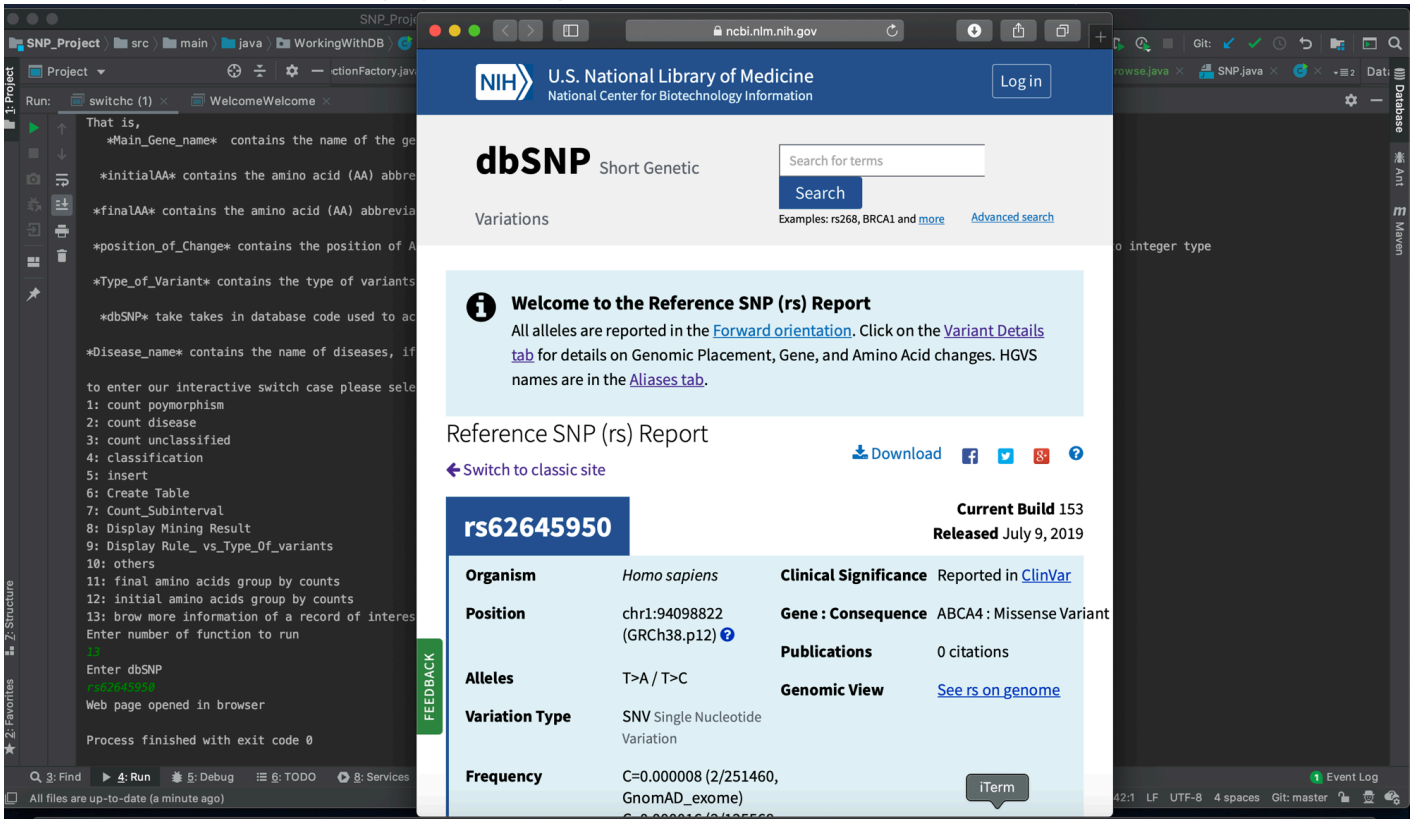
This case counts the final amino acids

Case 12: initial amino acids group by count

This case counts the initla amino acids: and again, this case should have been the 11th case, i guess....

Case 13: brow more information of a record of interest

This case allows rthe user to browse more information regarding the record of interest opening the brower with NCBI database page of the specified record.



End of Demonstration

Thank you for you attention, please stay safe!

In [ ]: