HAP 780: Final Project

LENGTH OF STAY IN HOSPITAL AFTER GETTING DISCHARGED FROM ICU WARD

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Project Description

In this project, I have used various machine learning models in weka for predicting the length of stay of patient's in the hospital who are in the ICU and after careful study, I have chosen the best model that has the best accuracy when compared to other models and then even checked their ROC, Precision and recall values and then came to a final conclusion. I have seen that the average stay after leaving ICU is 7 days and the median is around 4-5 days. So, I have decided to consider that if the length of stay after leaving ICU > 5 days then it would be that the patient is serious and if it is < 5 it shows that the patient had an issue but was cured easily.

Introduction

Forecasting Length of Stay hospitals to distinguish patients who might be in danger for a lengthy stay, and afterward change a patient's treatment plan from the purpose of admission to lessen the time in the clinic. The length of stay (LOS) in medical clinics is regularly utilized as a marker of productivity of care and clinic execution. Anticipating Length of Stay likewise engages clinics to improve patient treatment by meeting assumptions about the hospital stay that are set during confirmation. At last, it improves hospitals' ability in allocating resources and predicting the number of beds that are required in the ICU ward if the count of patients keeps increasing. Hospitals generally cannot predict that tomorrow they would have these many patients but once the patient is admitted in the hospital, we can check if the patient is going to be admitted in the ICU ward or the general ward. If the patient is admitted to the ICU ward, then it becomes critical in order to understand how many days he would stay in this ward and after he leaves the ICU ward. This can be affected due to several other reasons but in general, the length of stay would help allocate the beds accordingly and reduce the variance of the required beds and helps in efficient utilization of staff in the ICU. [1]

There are many factors that affect the length of stay of a patient. The patient might be wrongly diagnosed in the beginning and then later the way he responds to the medication might lead to the actual understanding of the problem the patient is going through. Even the lack of intensive care of the nurses, when required due to the wrong prediction of the length of stay in the hospital, might lead to such issues. All these factors play a major role in the prolonged length of stay in hospitals. But after keeping in mind all such factors as well I have considered proceeding with the dataset. In the United States of America alone the total amount that is spent on health services is 36% of the total budget. The average length of stay in the USA is around 4-5 days. The amount that is being spent on an average per stay is around $12,000 and the average ages were between 48-85 an older year. [2]
When a patient is admitted to the hospital, he/she might have multiple diseases with him or might have a single disease or even might be admitted due to an accident. So, in order to study the overall length of stay of any patient who is admitted in ICU and after leaving it to another ward, I have chosen this project.

Dataset

For the project I have used the MIMIC – III data set in order to predict the length of stay after data analysis and using machine learning models. Mimic – III data is one of the databases that comprise a relational database that contains data of patients who have stayed after leaving ICU. The tables are interlinked with each other and have two types of ID's that are HADM_ID and SUBJECT_ID that refer to unique patients. This is a free database containing insights on Laboratory measurements, Medications ordered, Hospital assigned diagnosis and Patient procedures. [3]

I have considered the following datasets from the mimic – III data for understanding the length of stay of the patients in ICU.

1. ADMISSIONS - this data set contains the data regarding the patient's admission to the hospital. Every unique hospitalization for each patient in the database (HADM_ID).
2. CPTEVENTS – procedures are recorded as CPT codes. This data can be helpful in determining which specific procedures have been performed. For every such procedure, there is a CPT code.
3. DIAGNOSES-ICD – this data set consists of data that helps in understanding the diagnosis that is undergone by each patient and the codes are present for the same.
4. ICU_STAYS – This data set helps us understand the information of each patient's stay in ICU hospital, this gives us the ICUSTAY_ID.
5. PATIENTS – This dataset contains data of all patients, but this is hospital – independent information and consists of attributes such as gender and DOB.
6. PROCEDURES_ID – In this data set we find all the procedures that each patient has gone through with ICD standards.
7. SERVICES – In this data set, we can understand what services the patient has taken like Ortho, GYN, etc.

In this data set, I have observed that every icustaysid is linked to a single hadm_id and subject_id. A single-subject can be subjected to many hamid and icustaysid. That means we can observe that the length of stay of each patient can be in one hospital or multiple hospitals or even both cases can be possible.

SW/HW

Software used: SQL Server Management Studio and Weka.
Hardware used: Windows 10 Good RAM and ROM.

Objective

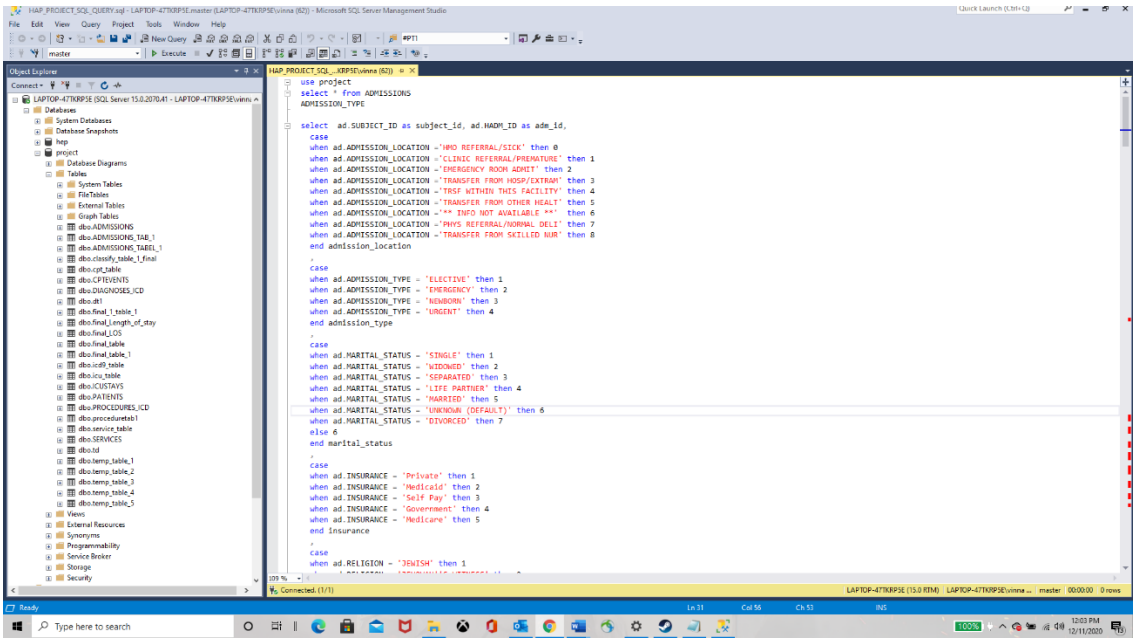
The main objective of this project is to understand the length of stay of patients in the hospital after leaving the ICU ward. The main motto is to understand that if the length of stay is >5 days after leaving the ICU then that means such patients have a high probability of getting back to the ICU ward. So, in order to avoid this, the results of this project would help the hospital administrators to understand the care with which such patients have to be treated. [4]

Data Pre-Processing

I have used the Microsoft SQL server management tool in order to understand the data and convert it into the format that supports data processing in Weka. Here I have taken the admissions table in the first place which has the following factors that have to be converted to meet the requirements of weka for data mining.

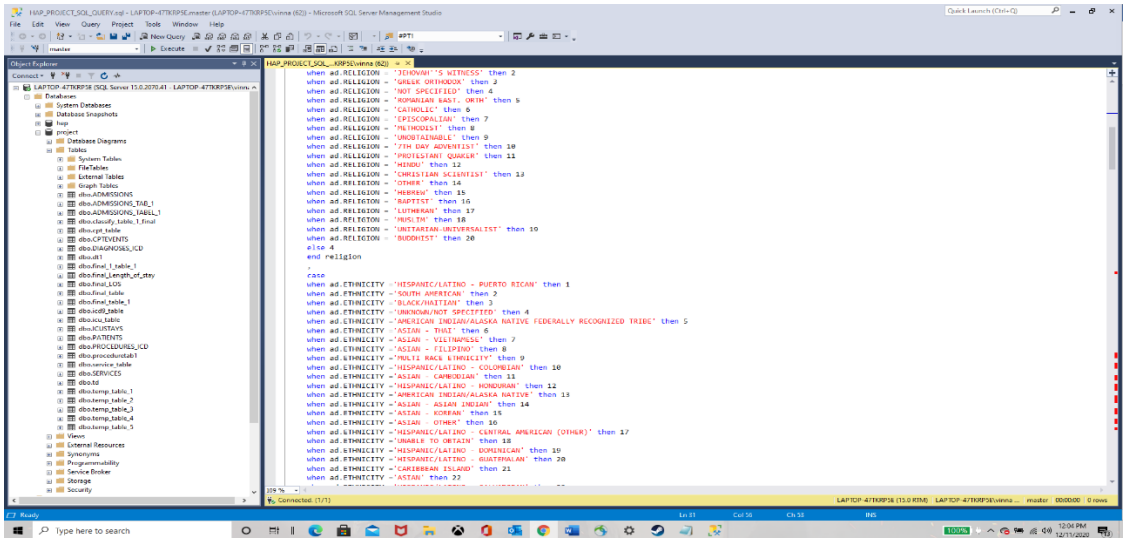
1. Admissions_Table

- Admission_Location
- Admission_Type
- Marital_Status
- Insurance
- Religion
- Ethnicity

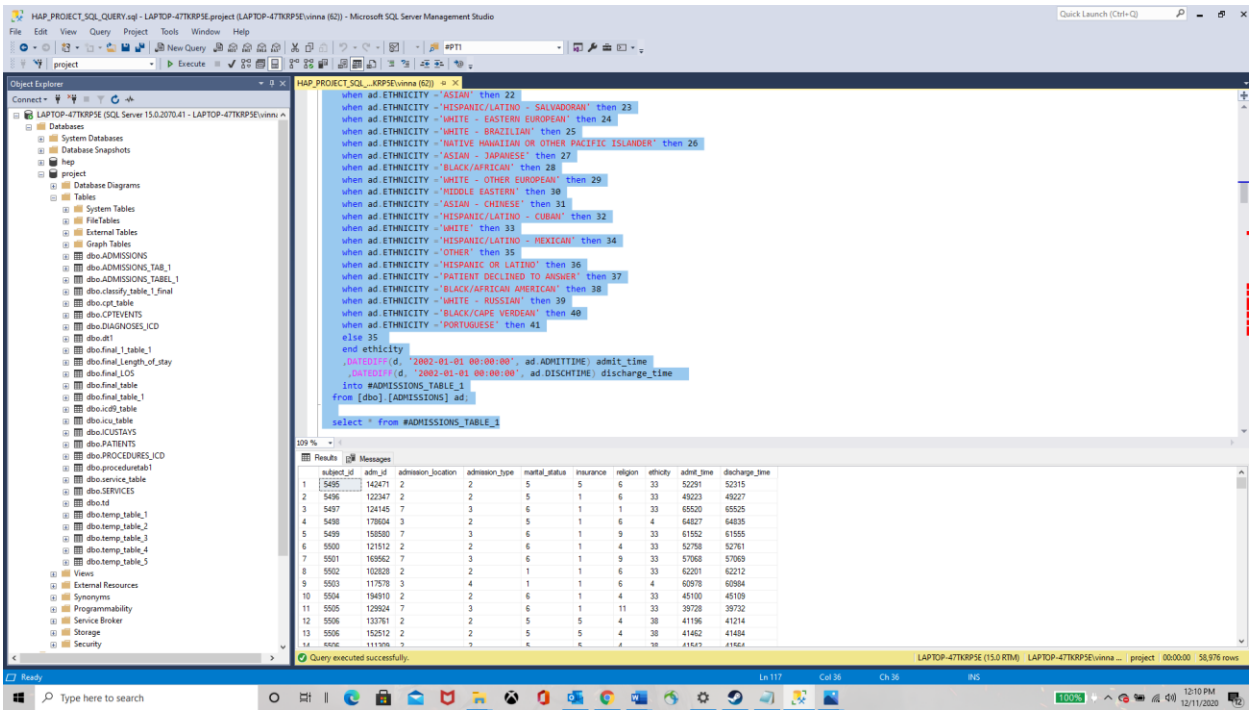


```
use project
select * from ADMISSIONS
ADMISSION_TYPE

select  ad.SUBJECT_ID as subject_id, ad.HADM_ID as adm_id,
 case
 when ad.ADMISSION_LOCATION ='HMO REFERRAL/SICK' then 0
 when ad.ADMISSION_LOCATION ='CLINIC REFERRAL/PREMATURE' then 1
 when ad.ADMISSION_LOCATION ='EMERGENCY ROOM ADMIT' then 2
 when ad.ADMISSION_LOCATION ='TRANSFER FROM HOSP/EXTRAM' then 3
 when ad.ADMISSION_LOCATION ='TRSF WITHIN THIS FACILITY' then 4
 when ad.ADMISSION_LOCATION ='TRANSFER FROM OTHER HEALT' then 5
 when ad.ADMISSION_LOCATION ='** INFO NOT AVAILABLE **'  then 6
 when ad.ADMISSION_LOCATION ='PHYS REFERRAL/NORMAL DELI' then 7
 when ad.ADMISSION_LOCATION ='TRANSFER FROM SKILLED NUR' then 8
 end admission_location
 ,
 case
 when ad.ADMISSION_TYPE = 'ELECTIVE' then 1
 when ad.ADMISSION_TYPE = 'EMERGENCY' then 2
 when ad.ADMISSION_TYPE = 'NEWBORN' then 3
 when ad.ADMISSION_TYPE = 'URGENT' then 4
 end admission_type
 ,
 case
 when ad.MARITAL_STATUS = 'SINGLE' then 1
 when ad.MARITAL_STATUS = 'WIDOWED' then 2
 when ad.MARITAL_STATUS = 'SEPARATED' then 3
 when ad.MARITAL_STATUS = 'LIFE PARTNER' then 4
 when ad.MARITAL_STATUS = 'MARRIED' then 5
 when ad.MARITAL_STATUS = 'UNKNOWN (DEFAULT)' then 6
 when ad.MARITAL_STATUS = 'DIVORCED' then 7
 else 6
 end marital_status
 ,
 case
 when ad.INSURANCE = 'Private' then 1
 when ad.INSURANCE = 'Medicaid' then 2
 when ad.INSURANCE = 'Self Pay' then 3
 when ad.INSURANCE = 'Government' then 4
 when ad.INSURANCE = 'Medicare' then 5
 end insurance
 ,
 case
 when ad.RELIGION = 'JEWISH' then 1
```



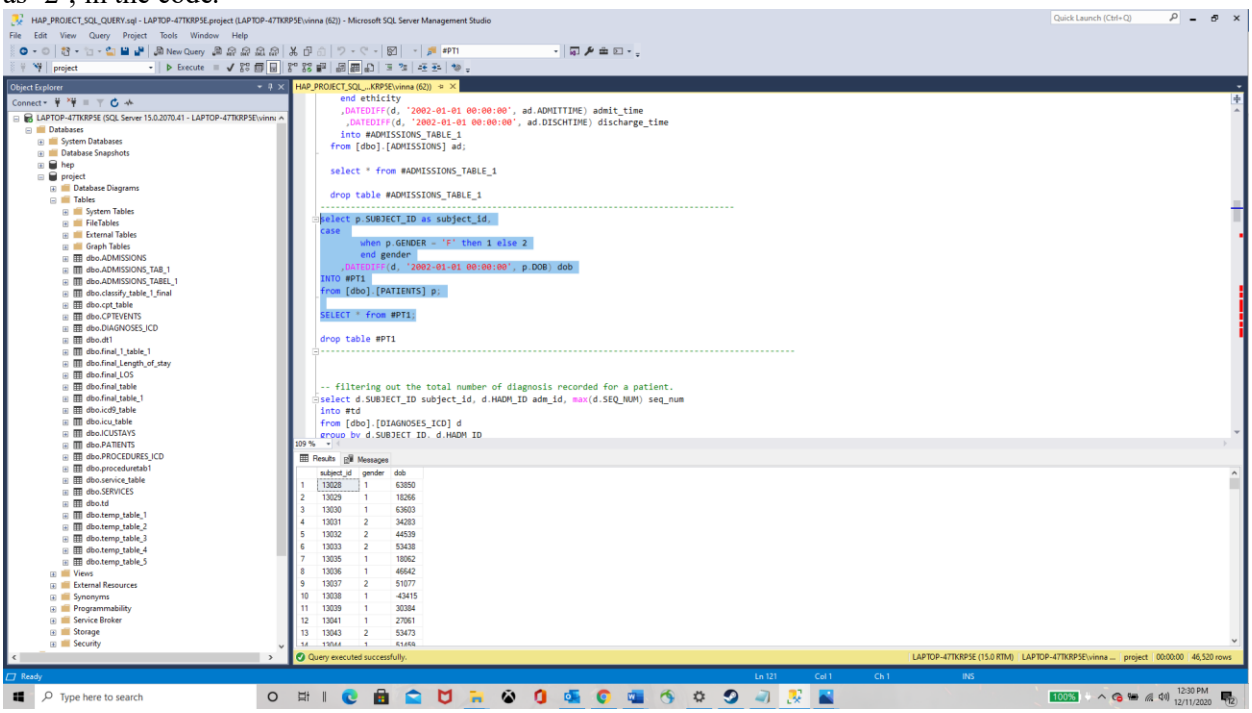
```
 when ad.RELIGION = 'JEHOVAH''S WITNESS' then 2
 when ad.RELIGION = 'GREEK ORTHODOX' then 3
 when ad.RELIGION = 'NOT SPECIFIED' then 4
 when ad.RELIGION = 'ROMANIAN EAST. ORTH' then 5
 when ad.RELIGION = 'CATHOLIC' then 6
 when ad.RELIGION = 'EPISCOPALIAN' then 7
 when ad.RELIGION = 'METHODIST' then 8
 when ad.RELIGION = 'UNOBTAINABLE' then 9
 when ad.RELIGION = '7TH DAY ADVENTIST' then 10
 when ad.RELIGION = 'PROTESTANT QUAKER' then 11
 when ad.RELIGION = 'HINDU' then 12
 when ad.RELIGION = 'CHRISTIAN SCIENTIST' then 13
 when ad.RELIGION = 'OTHER' then 14
 when ad.RELIGION = 'HEBREW' then 15
 when ad.RELIGION = 'BAPTIST' then 16
 when ad.RELIGION = 'LUTHERAN' then 17
 when ad.RELIGION = 'MUSLIM' then 18
 when ad.RELIGION = 'UNITARIAN-UNIVERSALIST' then 19
 when ad.RELIGION = 'BUDDHIST' then 20
 else 4
 end religion
 ,
 case
 when ad.ETHNICITY ='HISPANIC/LATINO - PUERTO RICAN' then 1
 when ad.ETHNICITY ='SOUTH AMERICAN' then 2
 when ad.ETHNICITY ='BLACK/HAITIAN' then 3
 when ad.ETHNICITY ='UNKNOWN/NOT SPECIFIED' then 4
 when ad.ETHNICITY ='AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGNIZED TRIBE' then 5
 when ad.ETHNICITY ='ASIAN - THAI' then 6
 when ad.ETHNICITY ='ASIAN - VIETNAMESE' then 7
 when ad.ETHNICITY ='ASIAN - FILIPINO' then 8
 when ad.ETHNICITY ='MULTI RACE ETHNICITY' then 9
 when ad.ETHNICITY ='HISPANIC/LATINO - COLOMBIAN' then 10
 when ad.ETHNICITY ='ASIAN - CAMBODIAN' then 11
 when ad.ETHNICITY ='HISPANIC/LATINO - HONDURAN' then 12
 when ad.ETHNICITY ='AMERICAN INDIAN/ALASKA NATIVE' then 13
 when ad.ETHNICITY ='ASIAN - ASIAN INDIAN' then 14
 when ad.ETHNICITY ='ASIAN - KOREAN' then 15
 when ad.ETHNICITY ='ASIAN - OTHER' then 16
 when ad.ETHNICITY ='HISPANIC/LATINO - CENTRAL AMERICAN (OTHER)' then 17
 when ad.ETHNICITY ='UNABLE TO OBTAIN' then 18
 when ad.ETHNICITY ='HISPANIC/LATINO - DOMINICAN' then 19
 when ad.ETHNICITY ='HISPANIC/LATINO - GUATEMALAN' then 20
 when ad.ETHNICITY ='CARIBBEAN ISLAND' then 21
 when ad.ETHNICITY ='ASIAN' then 22
```



In the above 3 steps (screenshots) we can see that I have converted all the data in the admissions table to numerical values that help in working in WEKA. The final output table is Admission_table_1. I have made this table a temporary table as it becomes easy to run the code even if the connection is lost.

2. Patients_Table

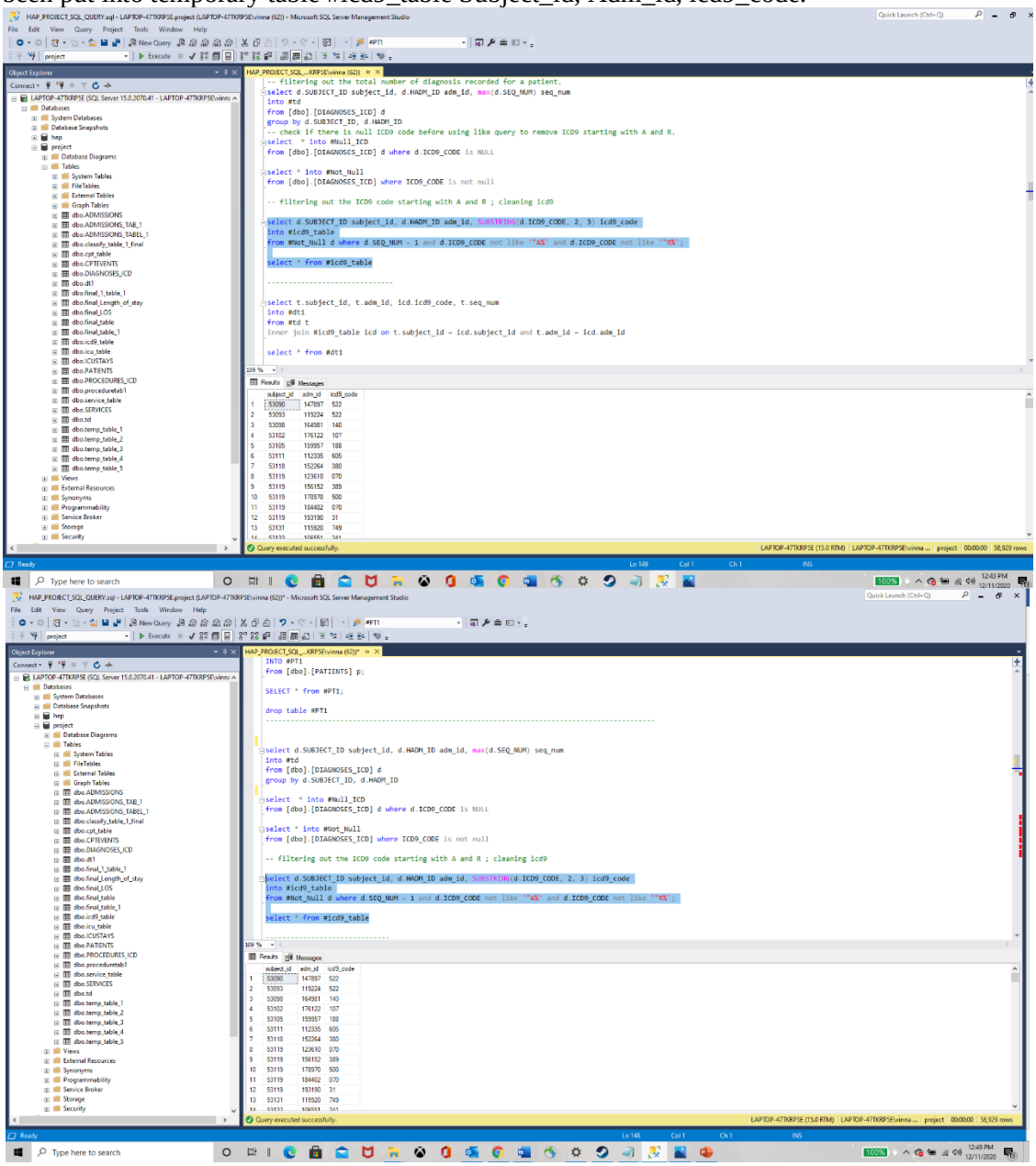
Now I have taken into consideration the patient's table where we can find the gender column. Gender is one of the important factors that contribute to the length of stay. I have converted Female 'F' as 1 and Male as '2', in the code.



3. Diagnosis_Table

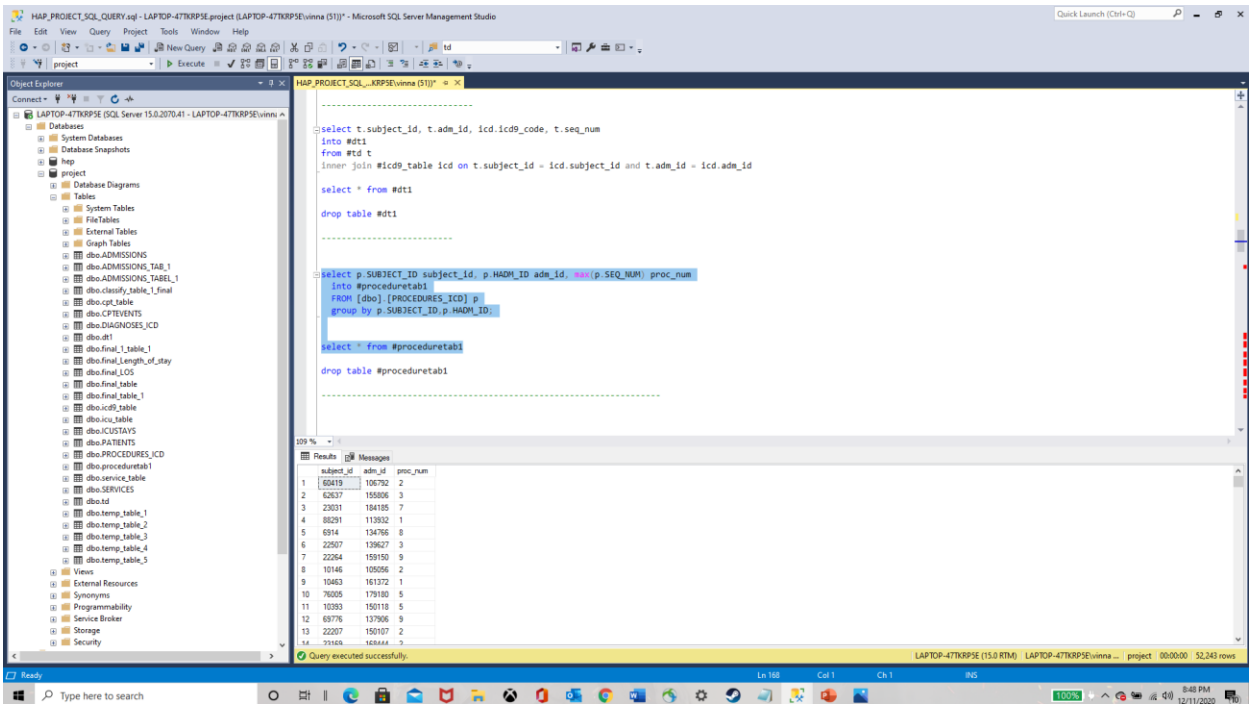
Here I have taken into consideration the diagnosis table with ICD codes here I have removed the codes that start with A and R because ICD9 codes that start with ‘A’ or ‘R’ do not help in my criteria as they do not consist of data that deals with diseases or external injuries.

In the below figure we can see the table that consists of codes that do not include the codes that are starting from A and R. This table is put into a temporary table named #icd9_table. We can see three columns that have been put into temporary table #icd9_table Subject_id, Adm_id, icd9_code.



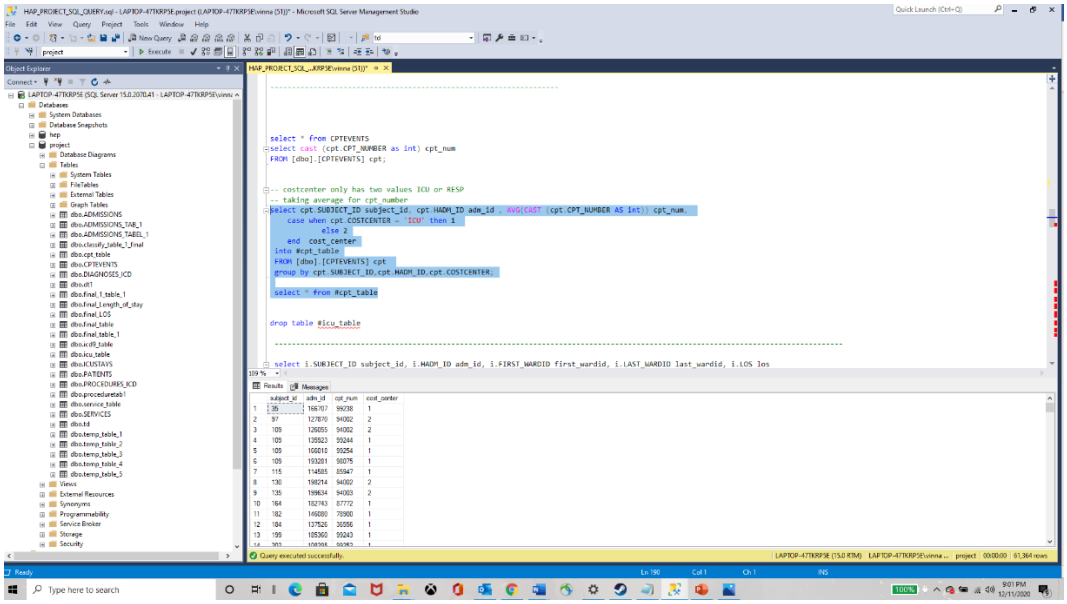
In the above figure I have joined the table based on subject_id and admin_id with seq_num hence, this additional column has been added into #dt1 from the #td table. The following are the columns in the table: Subject_id, Adm_id,icd9_codes and Seq_num.

4. Procedures_Table



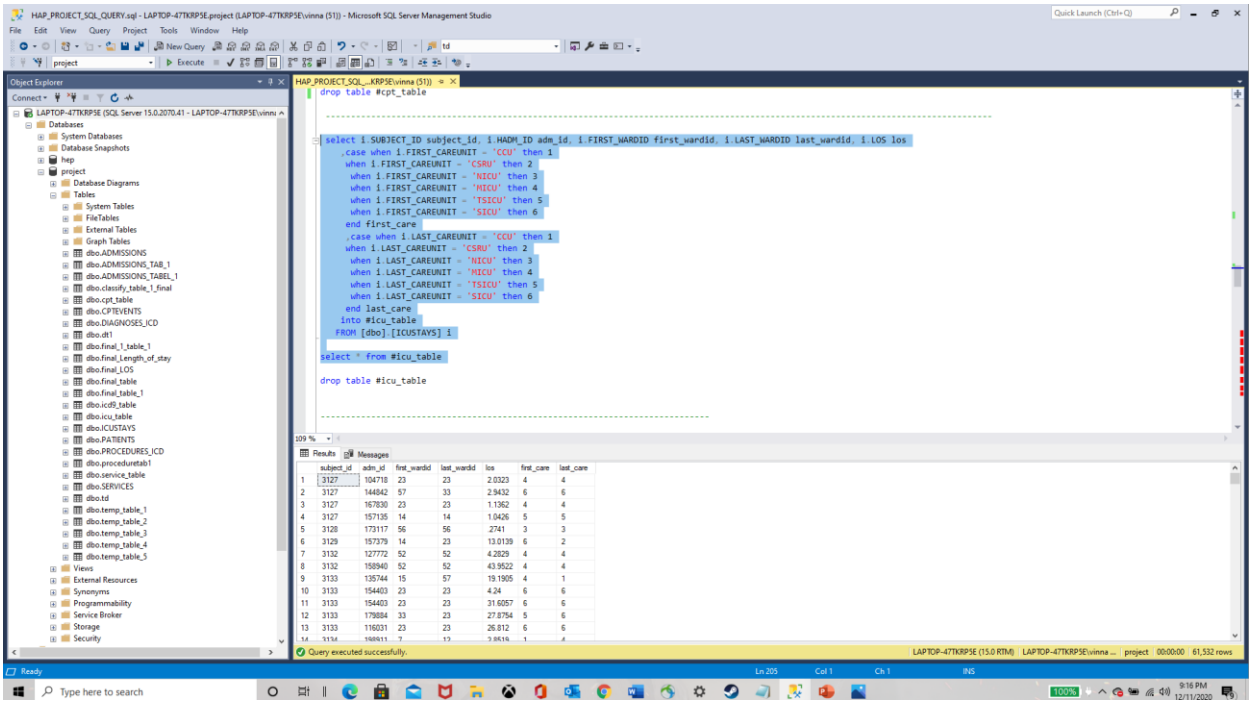
In the above figure, we can see that I have calculated the total number of procedures that every patient has gone through. This even lets us guess that the total number of procedures would be one of the leading factors that lead to the length of stay in the hospital after they are discharged from ICU.

5. CPT Events Table



In the above figure, we can see that I have used cpt events table in order to calculate the Mean value and then for the cost center we can see that there are only 2 values, so for ICU I have assigned 1 and for the other value I have assigned 2 (RESP), and then I have put them into a temporary table #cpt_table. The column names in the table are: subject_id,adm_id,cpt_num and cost_center.

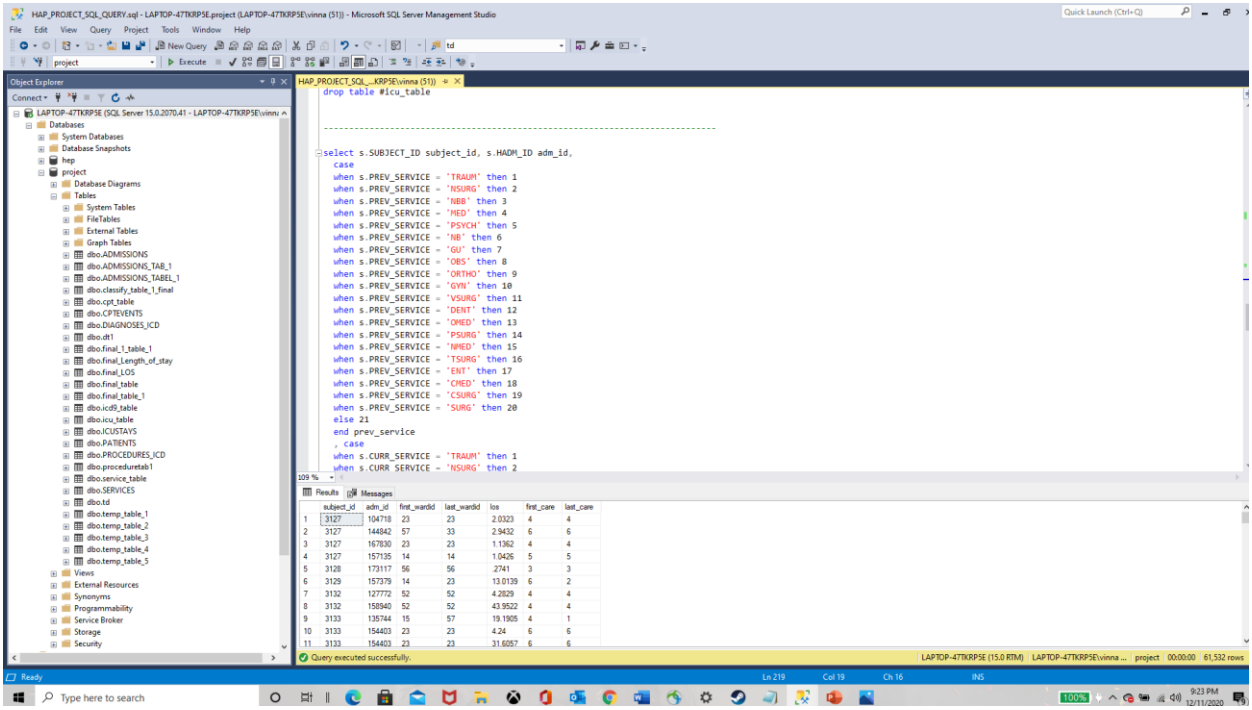
6. ICUSTAYS Table

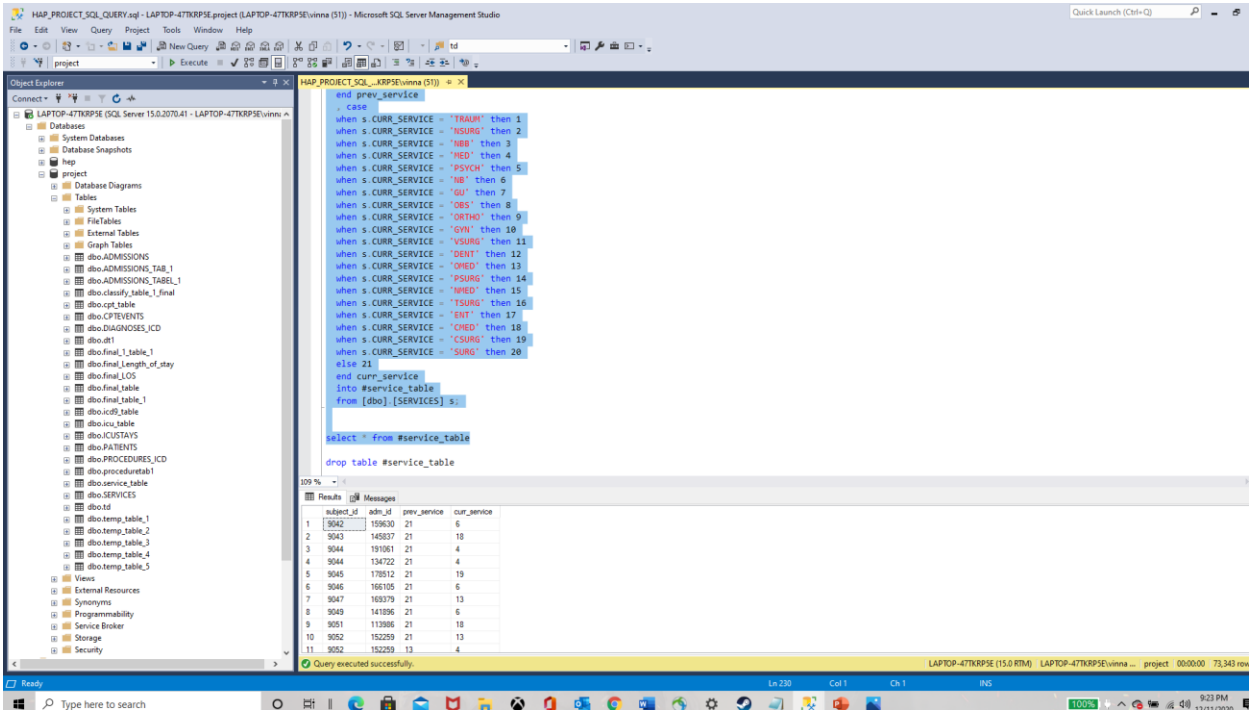


Here in the above figure, I have taken into consideration about firstcareunit, lastcareunit, length of stay into consideration and have converted the nominal data into numerical data and then transferred them into a temporary table #icu_table.

7. Service Table

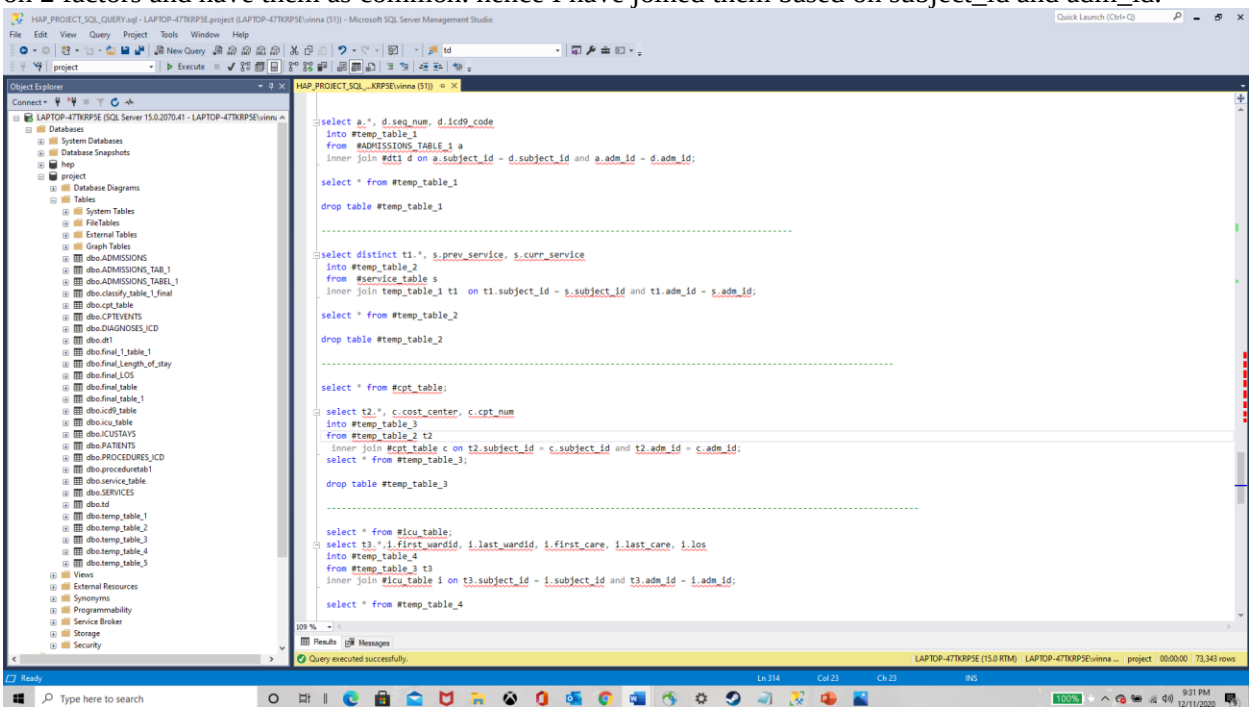
In the two figures below I have converted all the services that a patient goes through in his length of stay. If a person has multiple issues, then he has to go through different services and if the patient has only one service then there would be only one associated with the patient. For example, the services are as follows: GYN, ORTHO, NB, SURG, etc. I have converted them into numbers as seen in the figure and then transferred them into a temporary table #service_table.

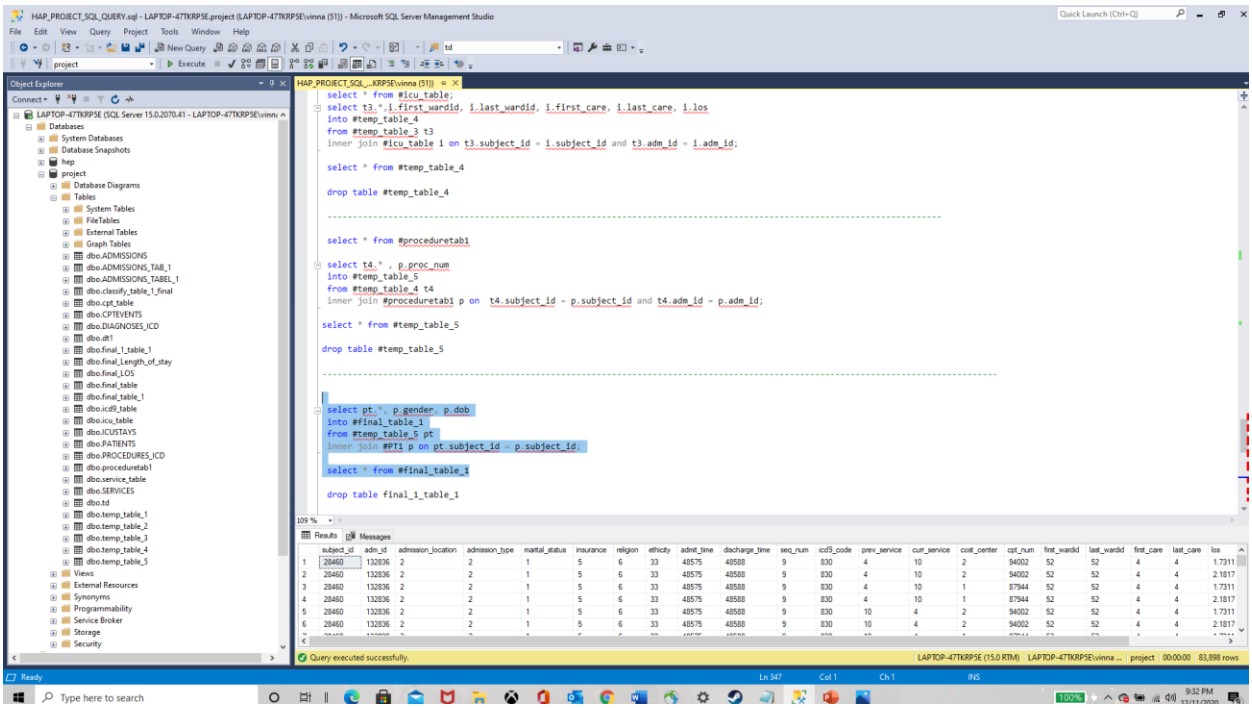

HAP_PROJECT_SQL_QUERY.sql - LAPTOP-47TKRP5E.project (LAPTOP-47TKRP5E\vinna (51)) - Microsoft SQL Server Management Studio
drop table #icu_table
select s.SUBJECT_ID subject_id, s.HADM_ID adm_id,
case
when s.PREV_SERVICE = 'TRAUM' then 1
when s.PREV_SERVICE = 'NSURG' then 2
when s.PREV_SERVICE = 'NBB' then 3
when s.PREV_SERVICE = 'MED' then 4
when s.PREV_SERVICE = 'PSYCH' then 5
when s.PREV_SERVICE = 'NB' then 6
when s.PREV_SERVICE = 'GU' then 7
when s.PREV_SERVICE = 'OBS' then 8
when s.PREV_SERVICE = 'ORTHO' then 9
when s.PREV_SERVICE = 'GYN' then 10
when s.PREV_SERVICE = 'VSURG' then 11
when s.PREV_SERVICE = 'DENT' then 12
when s.PREV_SERVICE = 'OMED' then 13
when s.PREV_SERVICE = 'PSURG' then 14
when s.PREV_SERVICE = 'NMED' then 15
when s.PREV_SERVICE = 'TSURG' then 16
when s.PREV_SERVICE = 'ENT' then 17
when s.PREV_SERVICE = 'CMED' then 18
when s.PREV_SERVICE = 'CSURG' then 19
when s.PREV_SERVICE = 'SURG' then 20
else 21
end prev_service
, case
when s.CURR_SERVICE = 'TRAUM' then 1
when s.CURR_SERVICE = 'NSURG' then 2
Results
Messages
Query executed successfully.
Ready


HAP_PROJECT_SQL_QUERY.sql - LAPTOP-47TKRP5E.project (LAPTOP-47TKRP5E\vinna (51)) - Microsoft SQL Server Management Studio
end prev_service
, case
when s.CURR_SERVICE = 'TRAUM' then 1
when s.CURR_SERVICE = 'NSURG' then 2
when s.CURR_SERVICE = 'NBB' then 3
when s.CURR_SERVICE = 'MED' then 4
when s.CURR_SERVICE = 'PSYCH' then 5
when s.CURR_SERVICE = 'NB' then 6
when s.CURR_SERVICE = 'GU' then 7
when s.CURR_SERVICE = 'OBS' then 8
when s.CURR_SERVICE = 'ORTHO' then 9
when s.CURR_SERVICE = 'GYN' then 10
when s.CURR_SERVICE = 'VSURG' then 11
when s.CURR_SERVICE = 'DENT' then 12
when s.CURR_SERVICE = 'OMED' then 13
when s.CURR_SERVICE = 'PSURG' then 14
when s.CURR_SERVICE = 'NMED' then 15
when s.CURR_SERVICE = 'TSURG' then 16
when s.CURR_SERVICE = 'ENT' then 17
when s.CURR_SERVICE = 'CMED' then 18
when s.CURR_SERVICE = 'CSURG' then 19
when s.CURR_SERVICE = 'SURG' then 20
else 21
end curr_service
into #service_table
from [dbo].[SERVICES] s;
select * from #service_table
drop table #service_table
Results
Messages
Query executed successfully.
Ready

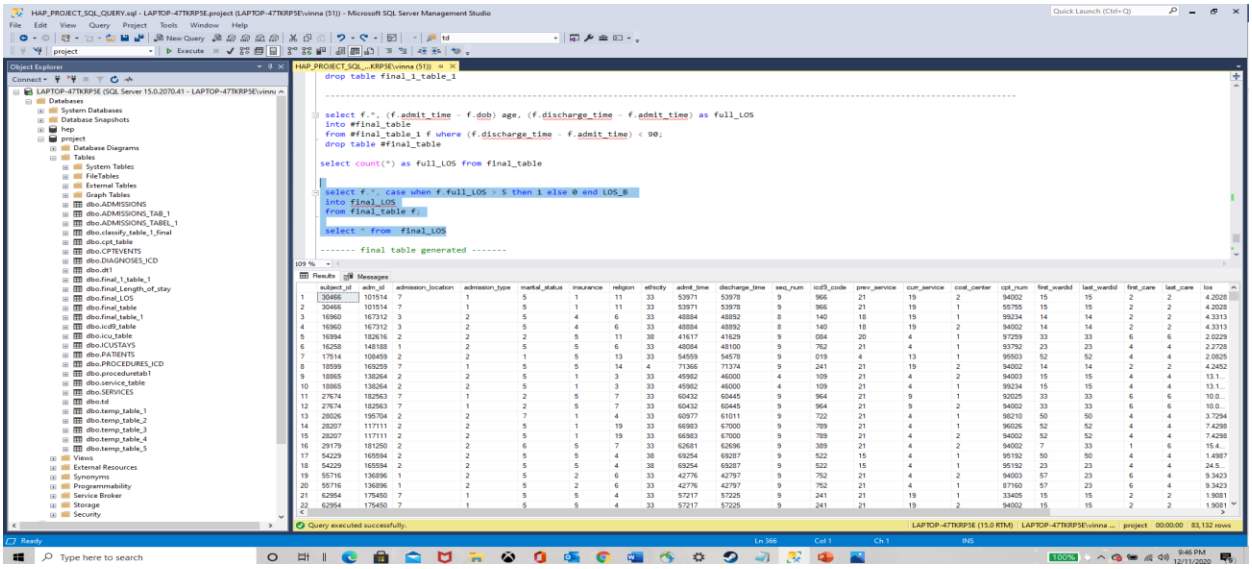
8. Joining all temporary tables

In the below 2 figures we can clearly see that all the temporary tables that I have created have been based on 2 factors and have them as common. hence I have joined them based on subject_id and adm_id.





9. Final Dataset

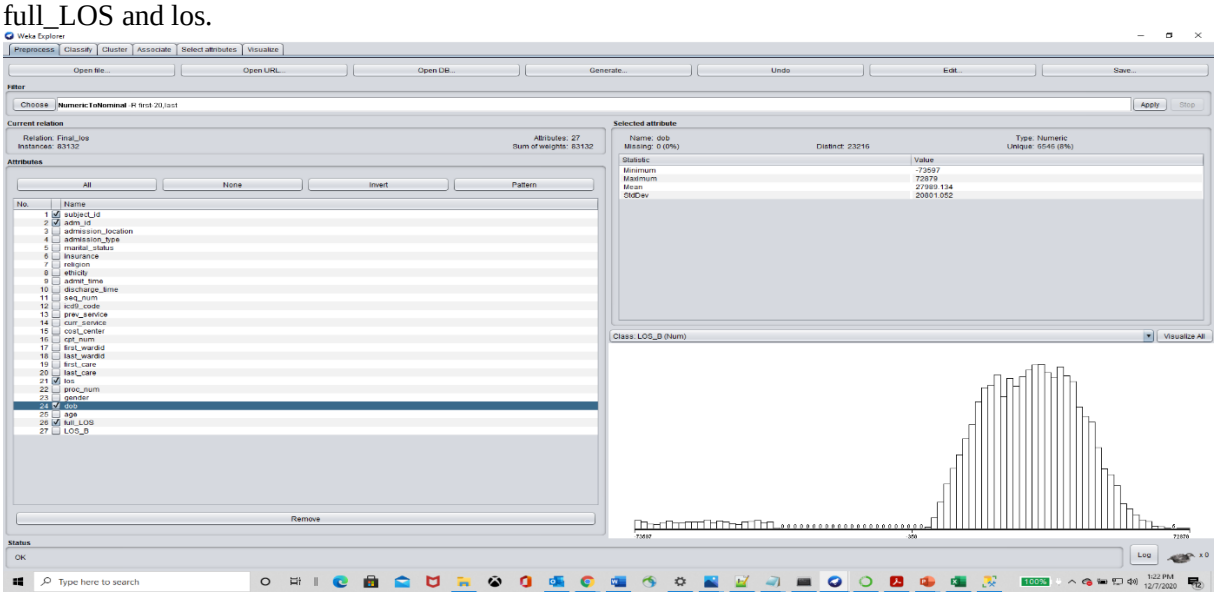


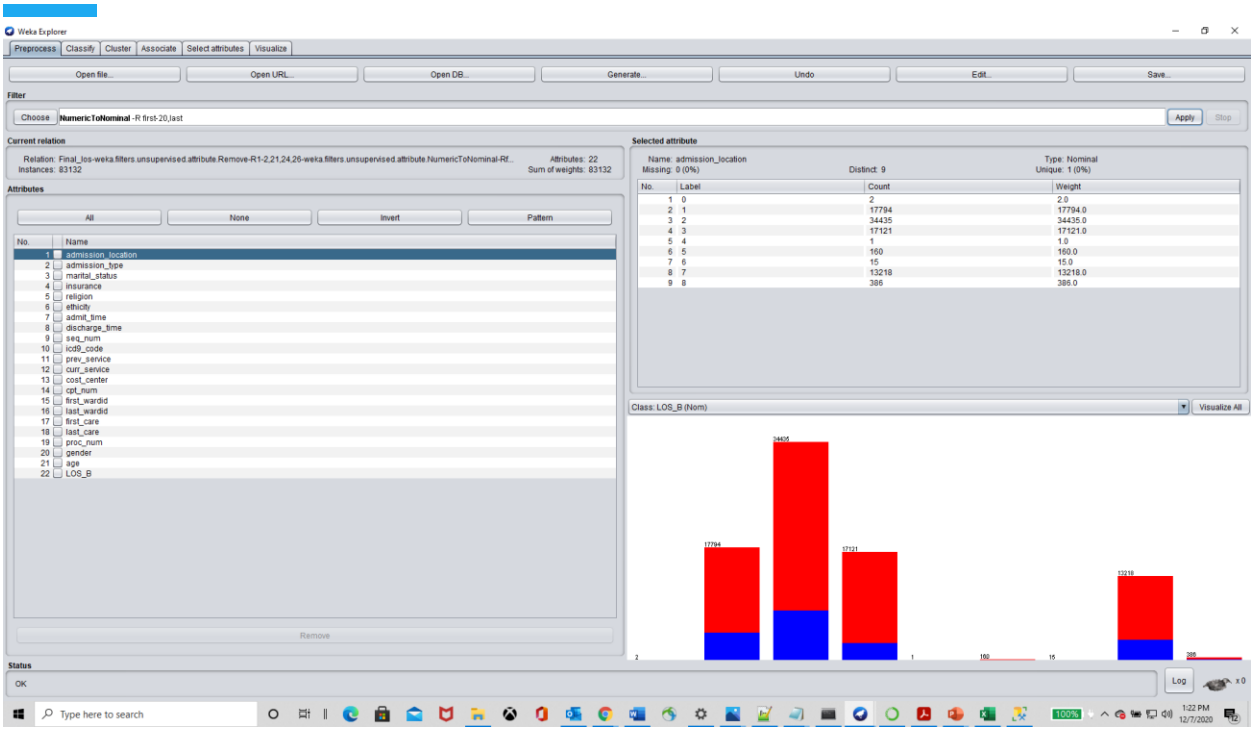
In the final data set, I have considered the length of stay of patients > 5 as 1 and <= 5 as 0. For getting to this conclusion, I have subtracted the total length of stay of a patient in the hospital and the length of stay in ICU which gave me the length of stay of patients after they have left the ICU ward.

WEKA

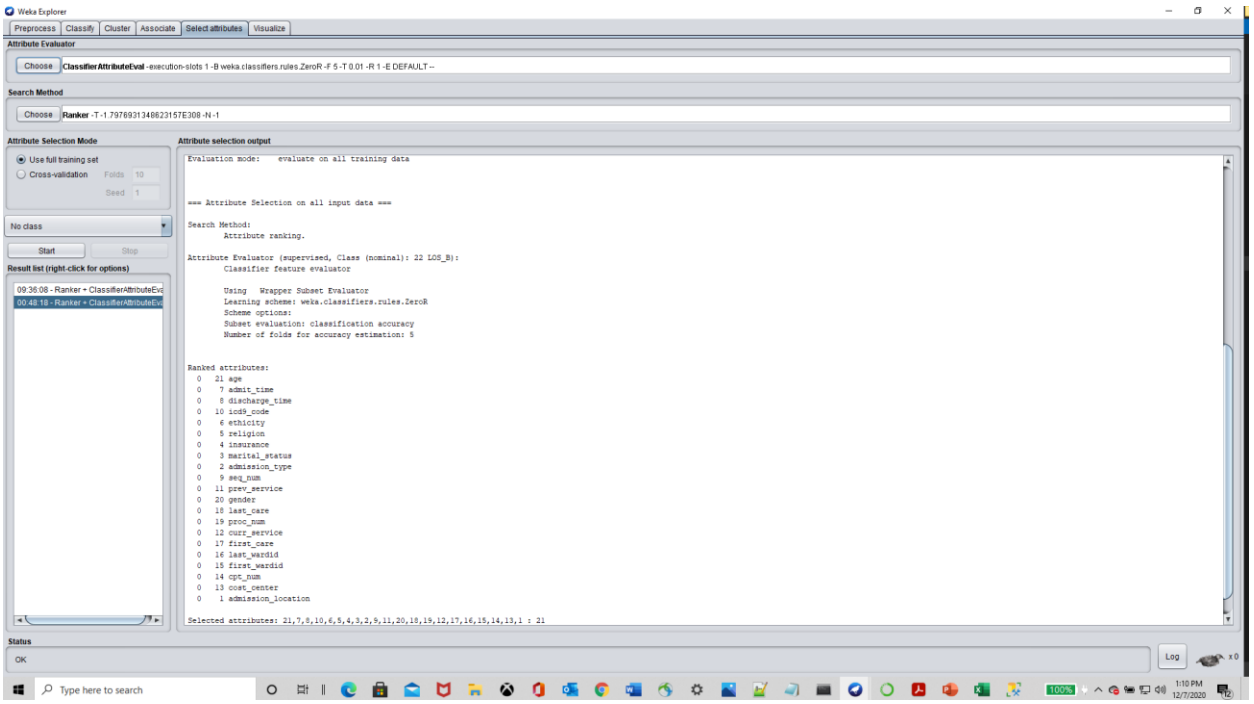
After getting the final dataset from SQL I have exported that data into CSV from SQL and saved in CSV format. Then I have imported that CSV file into weka.

In the above figure, you can see that I have selected a few variables that I feel do not contribute to the prediction of the target variable (LOS). I have removed the following variables: Subject_Id, adm_id, dob, full_LOS and los.





In the above figure, we can see that I have converted the required variables to nominal data that is from the 1st variable to 20 and the last variable. LOS_B is my final target variable that consists of 1 and 0.



In the above figure, we can see that I have used the ranked function in order to rank the attributes according to their contribution towards LOS_B. I thought of considering the top 10 variables and run the models but then that would lead to overfitting the model and hence I have considered all the data that I have selected to predict the LOS_B. There are a total of 21 variables that contribute to the prediction of length of stay.

Machine Learning Models

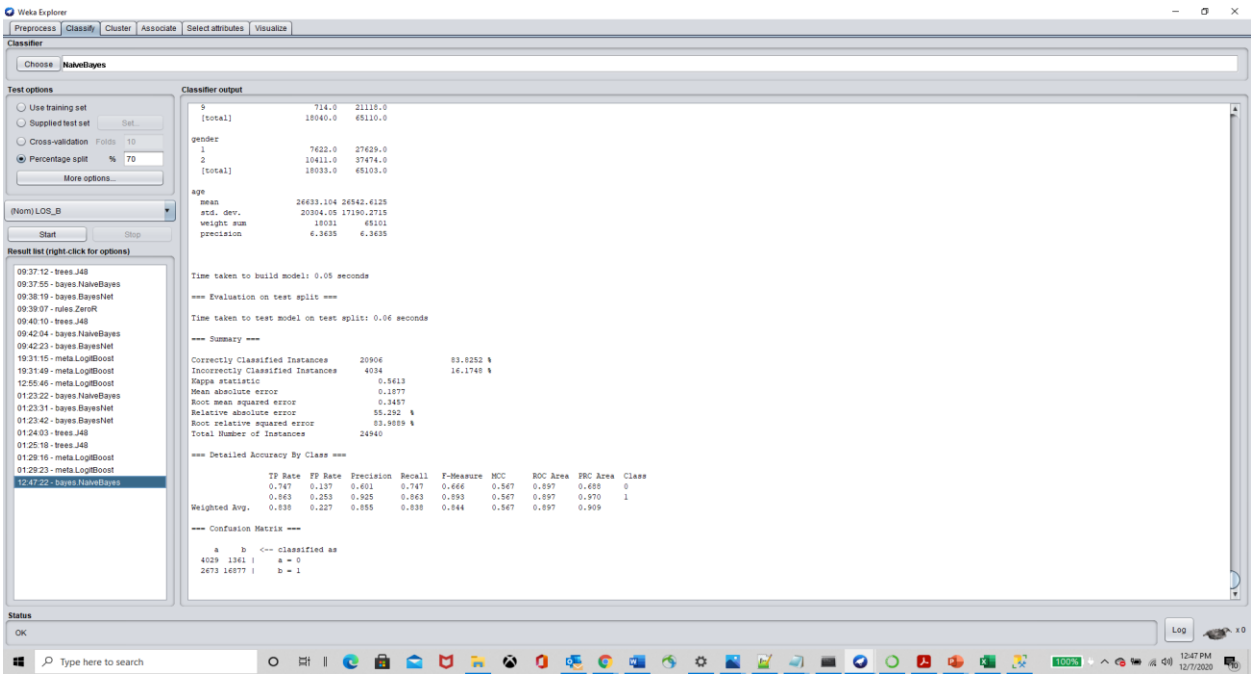
I have used 4 machine learning models for the prediction of LOS.

- Decision Tree Classifier
- Naïve Bayes Classifier
- Bayes Network Classifier
- Additive Logistic Regression

I have used 2 methods to check which method performs better.

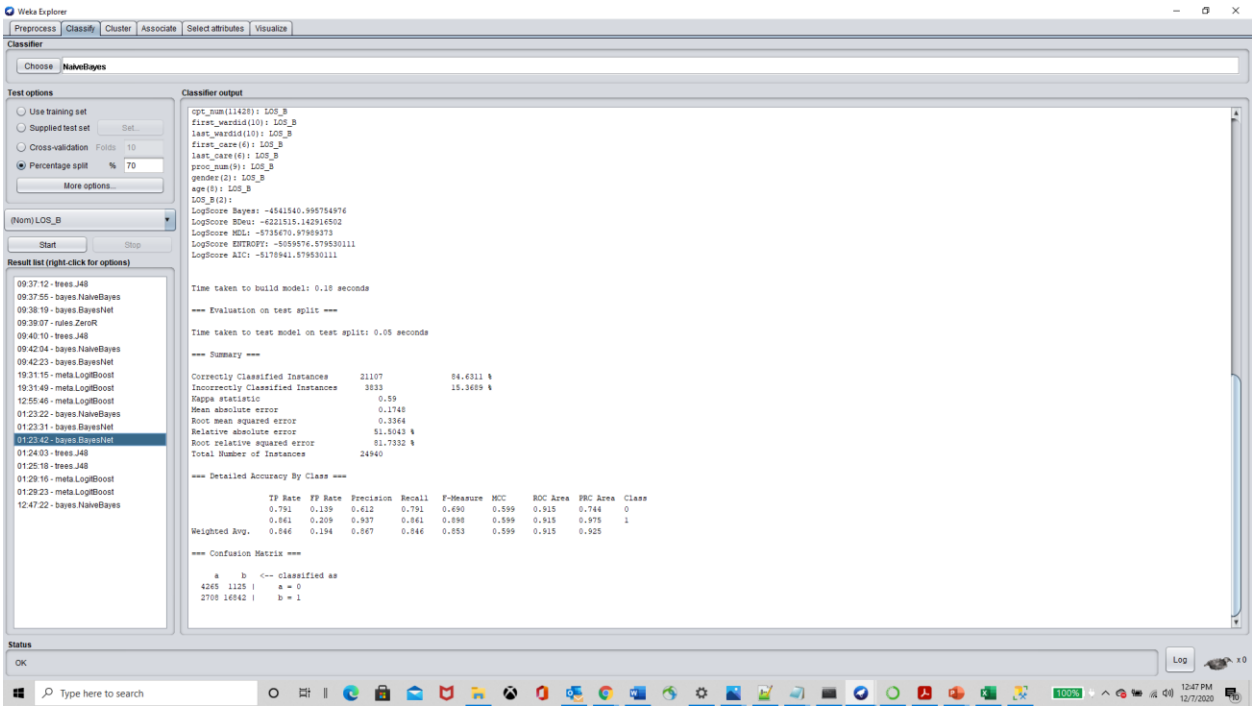
- 70 – 30 Split
- 10 – Fold Cross-Validation

Naïve Bayes Classifier 70 – 30 Split



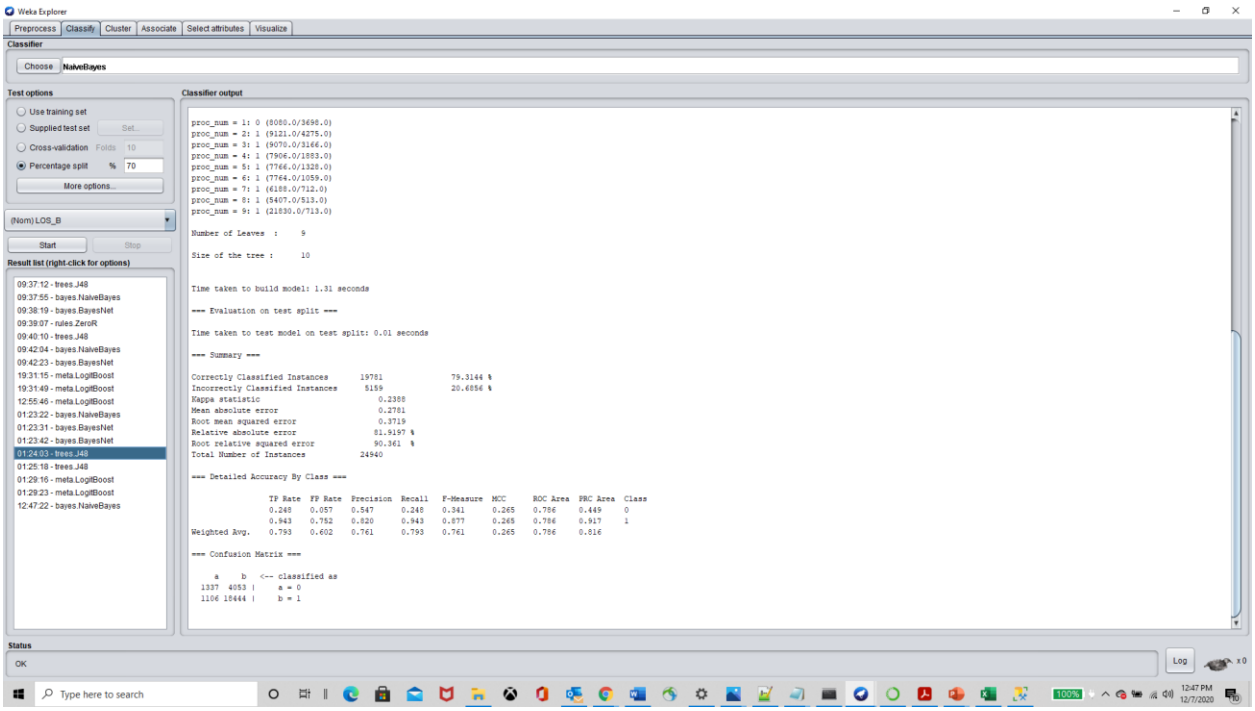
The above figure shows the results of Naïve Bayes using a 70-30 split.

Bayes Net Classifier 70 – 30 Split



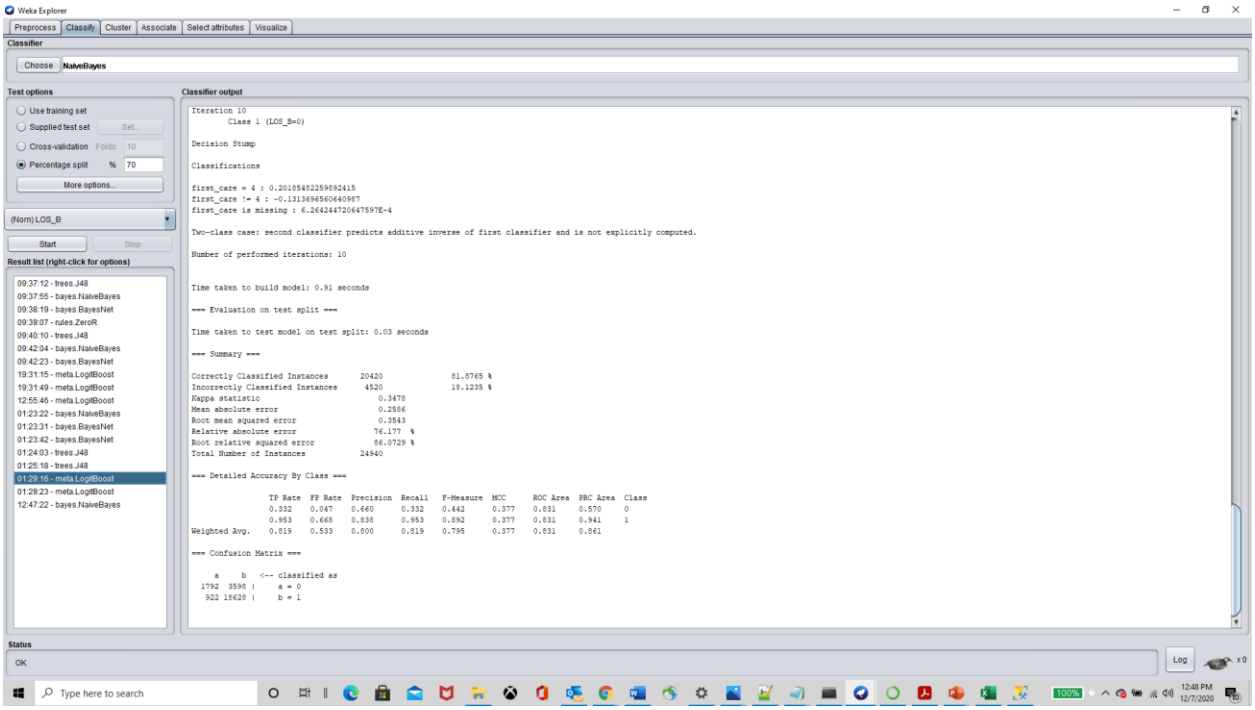
The above figure shows the results of Bayes Net Classifier using 70-30 split.

Decision Tree 70 – 30 Split



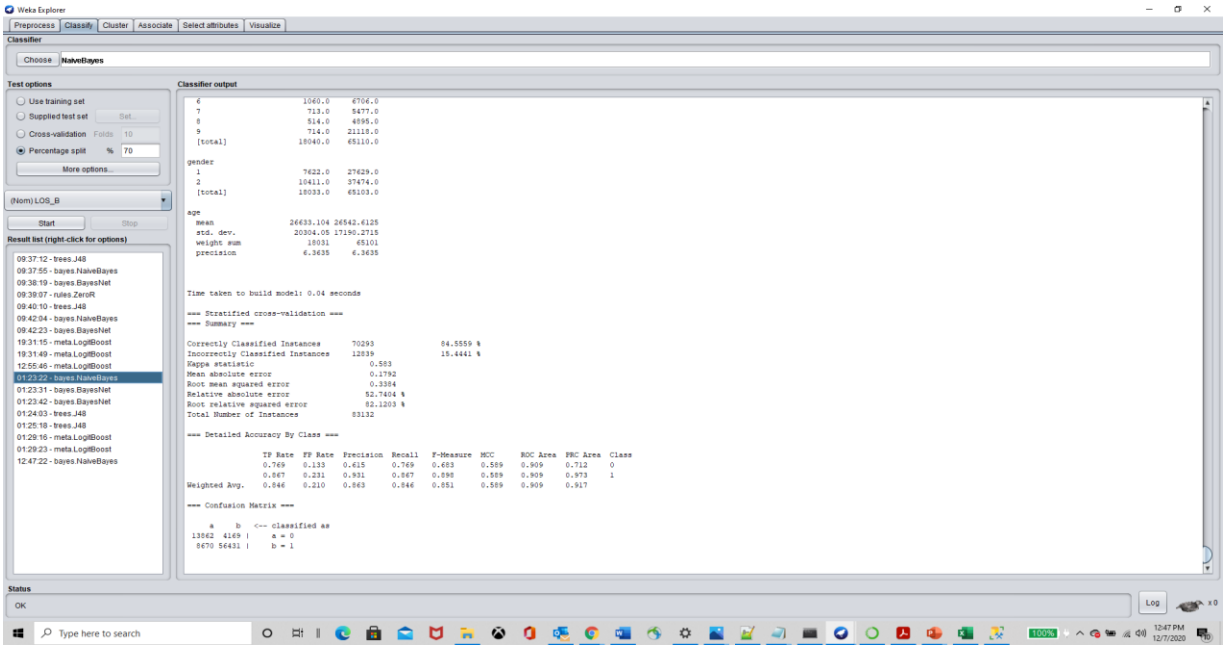
The above figure shows the results of the Decision Tree using a 70-30 split.

Additive Logistic Regression (Logit Boost) 70 – 30 Split.



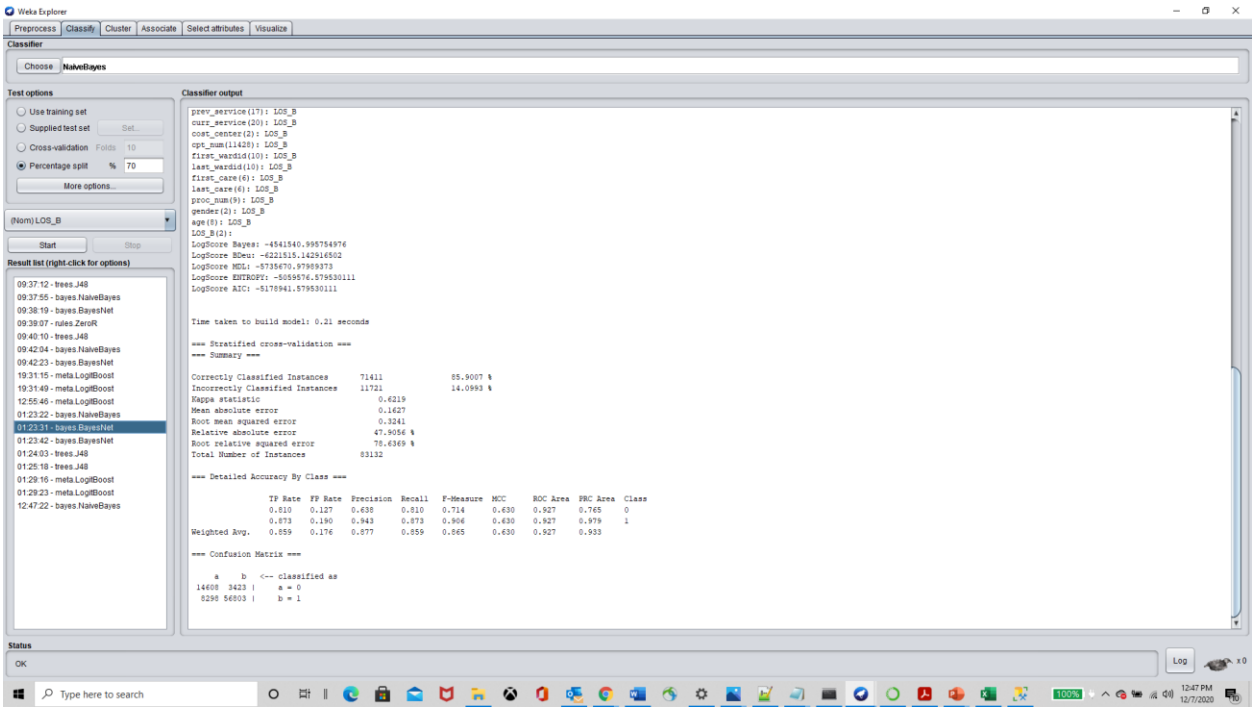
The above figure shows the results of the Logit Boost using a 70-30 split.

Naïve Bayes Classifier 10 - Fold Cross-Validation



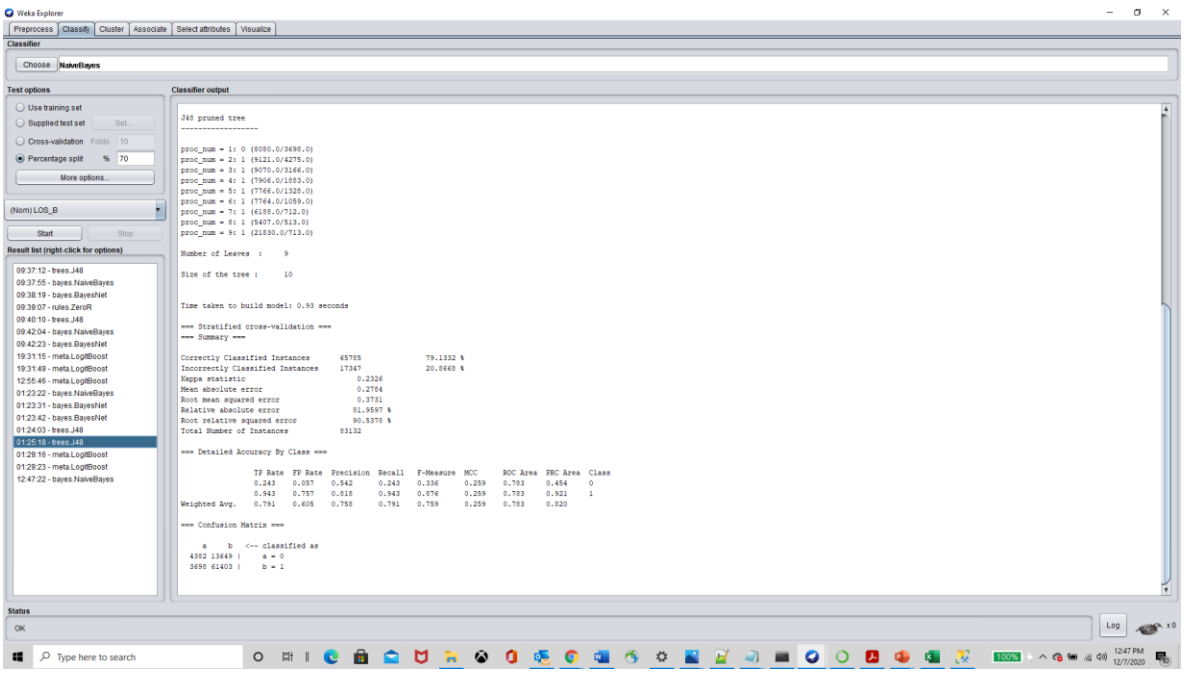
The above figure shows the results of Naïve Bayes using 10 – Fold cross-validation.

Bayes Net Classifier 10 - Fold Cross-Validation



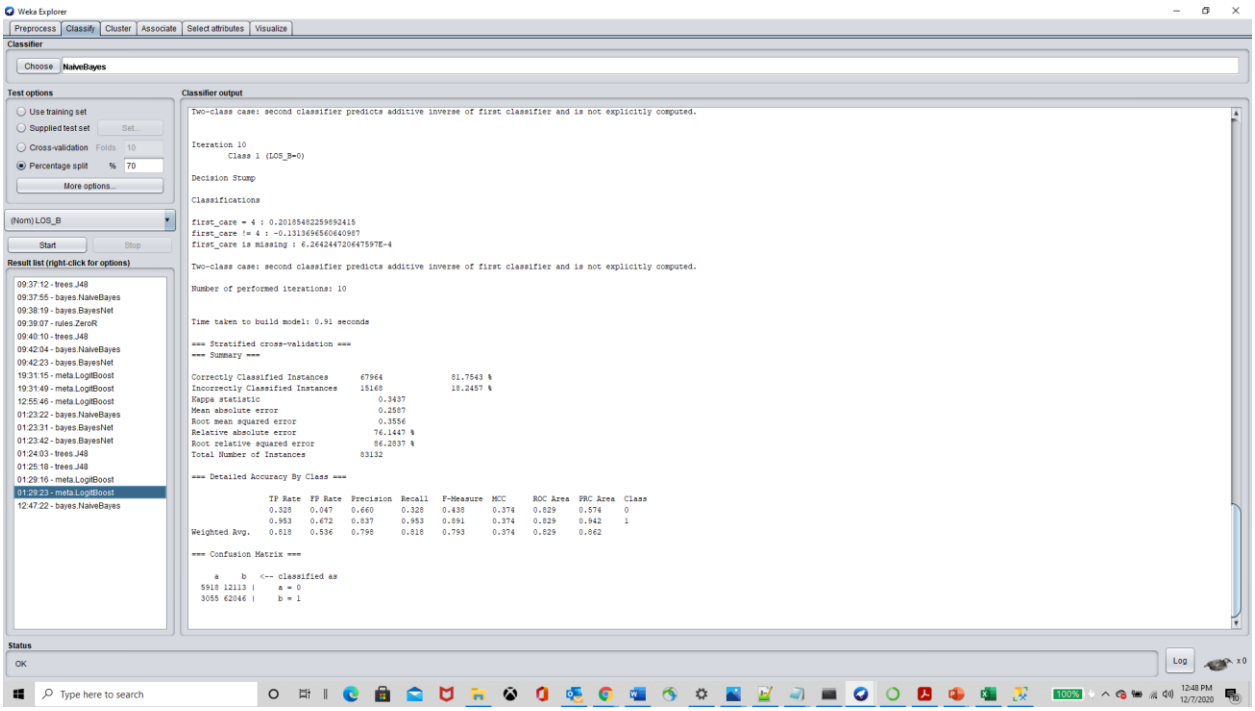
The above figure shows the results of Bayes Net using 10 – Fold cross-validation.

Decision Tree Classifier 10 - Fold Cross-Validation



The above figure shows the results of the Decision Tree using 10 – Fold cross-validation.

Additive Logistic Regression Classifier 10 - Fold Cross-Validation



The above figure shows the results of the Additive Logistic Regression (Logit Boost) using 10 – Fold cross-validation.

RESULTS

70 - 30 Split

MODEL	ACCURACY	RECALL
J48	79%	94.3%
NaiveBayes	83%	86.3%
BayesNet	84%	86.1%
LogitBoost	81%	95.3%

Model	ROC	Precision	Recall
J48	0.786	82.0 %	94.3%
NaiveBayes	0.897	92.5%	86.3%
BayesNet	0.915	93.7%	86.1%
LogitBoost	0.831	83.5%	95.3%

10 – FOLD CROSS VALIDATION

MODEL	ACCURACY	RECALL
J48	79%	94.3%
NaiveBayes	84%	86.7%
BayesNet	85%	87.3%
LogitBoost	81%	95.3%

Model	ROC	Precision	Recall
J48	0.783	81.8%	94.3%
NaiveBayes	0.909	93.1%	86.7%
BayesNet	0.927	94.3%	87.3%
LogitBoost	0.829	83.7	95.3%

Conclusion

From the above, we can see that the accuracy is highest in the Bayes Net classifier using 10 – Fold Cross-validation. But I am more interested in understanding the recall of the model as when we check the model, we can understand that recall tells us that there is a chance of predicting that the patient is in the hospital after getting discharged from the ICU for less than or equal to 5 days but, the patient is actually in the hospital for more than 5 days. I would like to get a recall of 100% as it matches my problem statement that if the patient is in the hospital for more than 5 days after getting discharged from ICU then there is a great probability that the patient might get back to the ICU due to any of the multiple issues. Hence my model should not misclassify this part. When we check the precision, it says in the prediction that there are chances that the patient is in the hospital after ICU for > 5 days but actually, the patient is < or = 5 days. This case could be considered to have some error as it could not lead to/implicate serious complications to the patient's health.

In my opinion, the best model that gives me the best recall value and it is Logit Boost using 10 – Fold Cross-Validation and it also has an accuracy of 81% which is not far away from the model that has the highest accuracy (85%). Hence, I would choose this model to give it to the administration department of the hospital as it would help them in keeping the length of stay of a patient after getting discharged from the ICU ward as quickly as possible with proper treatment else if it is more than 5 days then proper attention should be given to the patient, which actually requires an experienced staff of doctors and nurse.

Future Work

In future I would like to understand the length of stay of patients with multiple diseases and single disease. Further, I would also like to explore more on accident-related cases and disease-ridden cases, which of these categories lead to greater length of stay in hospitals, that is calculated after they are discharged from the ICU or their complete hospital stay.

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