DIABETES 130-US HOSPITALS FOR YEARS 1999-2008 DATA SET

Analysis

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DESCRIPTION OF THE DATASET

The dataset represents 10 years (1999-2008) of clinical care at 140 US hospitals and integrated delivery networks.

It includes over 50 features representing patient and hospital outcomes. Information was extracted from the database for encounters that satisfied the following criteria :

INPATIENT

It is an inpatient encounter (a hospital admission).

DIABETIC

It is a diabetic encounter, that is, one during which any kind of diabetes was diagnosed.

1-14 DAYS

The length of the stay was at least 1 day and at most 14 days.

LABORATORY

Laboratory tests were performed during the encounter.

MEDICINE

Medication were administred during the encounter.

50 FEATURES (PART I)

- **Encounter ID:** Unique identifier of an encounter
- **Patient number:** Unique identifier of a patient
- **Race:** Values: Caucasian, Asian, African American, Hispanic, and other
- **Gender:** Values: male, female, and unknown/invalid
- **Age:** Grouped in 10-year intervals: [0, 10), [10, 20), . . ., [90, 100)
- **Weight:** Weight in pounds
- **Admission type:** Integer identifier corresponding to 9 distinct values, for example, emergency, urgent, elective, newborn, and not available
- **Discharge disposition:** Integer identifier corresponding to 29 distinct values, for example, discharged to home, expired, and not available
- **Admission source:** Integer identifier corresponding to 21 distinct values, for example, physician referral, emergency room, and transfer from a hospital

50 FEATURES (PART 2)

- **Time in hospital:** Integer number of days between admission and discharge
- **Payer code:** Integer identifier corresponding to 23 distinct values, for example, Blue Cross\Blue, Shield, Medicare, and self-pay
- **Medical specialty:** Integer identifier of a specialty of the admitting physician, corresponding to 84 distinct values, for example, cardiology, internal medicine, family\general practice, and surgeon
- **Number of lab procedures:** Number of lab tests performed during the encount
- **Number of procedures:** Number of procedures (other than lab tests) performed during the encounter
- **Number of medications:** Number of distinct generic names administered during the encounter
- **Number of outpatient visits:** Number of outpatient visits of the patient in the year preceding the encounter
- **Number of emergency visits:** Number of emergency visits of the patient in the year preceding the encounter
- **Number of inpatient visits:** Number of inpatient visits of the patient in the year preceding the encounter
- **Diagnosis 1:** "The primary diagnosis (coded as first three digits of ICD9): 848 distinct values"
- **Diagnosis 2:** "Secondary diagnosis (coded as first three digits of ICD9): 923 distinct values"
- **Diagnosis 3:** "Additional secondary diagnosis (coded as first three digits of ICD9): 954 distinct values“
- **Number of diagnoses:** Number of diagnoses entered to the system

50 FEATURES (PART 3)

- **Glucose serum test result:** Indicates the range of the result or if the test was not taken. (“>200,” “>300, “normal,” and “none” if not measured)
- **A1c test result:** Indicates the range of the result or if the test was not taken. Values: “>8” if the result was greater than 8%, “>7” if the result was greater than 7% but less than 8%, “normal” if the result was less than 7%, and “none” if not measured
- **Change of medications**: Indicates if there was a change in diabetic medications (either dosage or generic name). Values: “change” and “no change”
- **Diabetes medications:** Indicates if there was any diabetic medication prescribed. (YES or NO)
- **24 features for medications:** For the generic names: metformin, repaglinide, nateglinide, chlorpropamide,glimepiride, acetohexamide, glipizide, glyburide, tolbutamide, pioglitazone,rosiglitazone,acarbose, miglitol, troglitazone, tolazamide, examide, sitagliptin, insulin,glyburide-metformin, glipizide-metformin, glimepiride-pioglitazone,metformin-rosiglitazone, and metformin-pioglitazone, the feature indicates whetherthe drug was prescribed or there was a change in the dosage. Values:“up” if the dosage - was **increased during the encounter, “down” if the dosage was decreased, “steady” if the dosage did not change, and “no” if the drug was not prescri
- **Readmitted:** Days to inpatient readmission. Values: “<30” if the patient was readmitted in less than 30 days, “>30” if the patient was readmitted in more than 30 days, and “No” for no record of readmission.

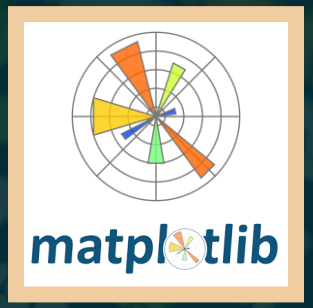
STEPS

1. LOAD AND CLEAN THE DATASET
2. ANALYSE , VISUALIAZE AND PREDICT
3. DISCUSS RESULTS

LIBRARIES

STRUCTURE

VISUALIZATION



MACHINE LEARNING

GOAL OF OUR ANALYSIS

- After observing all the differents variables of this dataset, it seemed logical to focus our attention on the 'readmitted' feature. This column presents 3 possibles responses types : 'No', to indicate that the patient was not readmitted to hospital; '<30', to indicate that the patient was readmitted within 30 days, or '>30', to indicate that he was readmitted after 30 days.

- We will therefore study the other variables to find out if there is a link between them that could provide information on a possible correlationbetween patient-specific data and/or medical data with being or not being readmitted to hospital.

FIRST VIEW OF THE DATA

0	encounter_id	101766 non-null	int64
1	patient_nbr	101766 non-null	int64
2	race	99493 non-null	object
3	gender	101766 non-null	object
4	age	101766 non-null	object
5	weight	3197 non-null	object
6	admission_type_id	101766 non-null	int64
7	discharge_disposition_id	101766 non-null	int64
8	admission_source_id	101766 non-null	int64
9	time_in_hospital	101766 non-null	int64
10	payer_code	61510 non-null	object
11	medical_specialty	51817 non-null	object
12	num_lab_procedures	101766 non-null	int64
13	num_procedures	101766 non-null	int64
14	num_medications	101766 non-null	int64
15	number_outpatient	101766 non-null	int64
16	number_emergency	101766 non-null	int64
17	number_inpatient	101766 non-null	int64
18	diag_1	101745 non-null	object
19	diag_2	101408 non-null	object
20	diag_3	100343 non-null	object
21	number_diagnoses	101766 non-null	int64
22	max_glu_serum	101766 non-null	object
23	A1Cresult	101766 non-null	object

Looking at the structure of our data, we have observed that the variables are of two different types. 'Int' and 'object'. The type 'object' is very existent (we can see some in this extract and the variables from 24 to 49 are too.)

We can also see that a lot of data is missing in some columns and may hinder our analysis.

So we're going to retrieve what's not going to help us.

We will also have to process these data to make them viewable and usable, so that we can deduce a meaning.

DATA REMOVING

- The first step was to remove the columns that had too many missing values. There are :
  - **'weight'**, for 97% of missing values
  - **'medical_specialty'**, for 49% of missing values
  - **'payer_code'**, for 40% of missing values

- The columns that would not be useful in the analysis and could even interfere with it were then removed :
  - '**encounter_id**', because not useful

  These columns because they provide a constant value for every rows and it is useless
  - '**examide**'
  - **'citoglipton'**
  - '**glimepiride-pioglitazone**'
  - **'metformin-rosiglitazone'**
  - **'metformin-pioglitazone'**

    - We observed too that some rows were redundant, they had the same patient value and can interfere with the analysis too. We decided to remove these rows.

MAPPING AND NEW COLUMNS

By observing with more attention the different values present in the columns, we realized that some needeed to be adapted in order to be able to treat them.

In first case, the '**diag_1**', '**diag_2**' and '**diag_3**' columns had too disparate values. Thanks this image that mapped in value intervals, we were able to transform the values of this column into 8 categories. And to later be able to analyze them with computational algorithms, we created 8 columns corresponding to these categories, with binary values.

Group name	icd9 codes
Circulatory	390–459, 785
Respiratory	460–519, 786
Digestive	520–579, 787
Diabetes	250.xx
Injury	800–999
Musculoskeletal	710–739
Genitourinary	580–629, 788
Neoplasms	140–239
	780, 781, 784, 790–799
	240–279, without 250

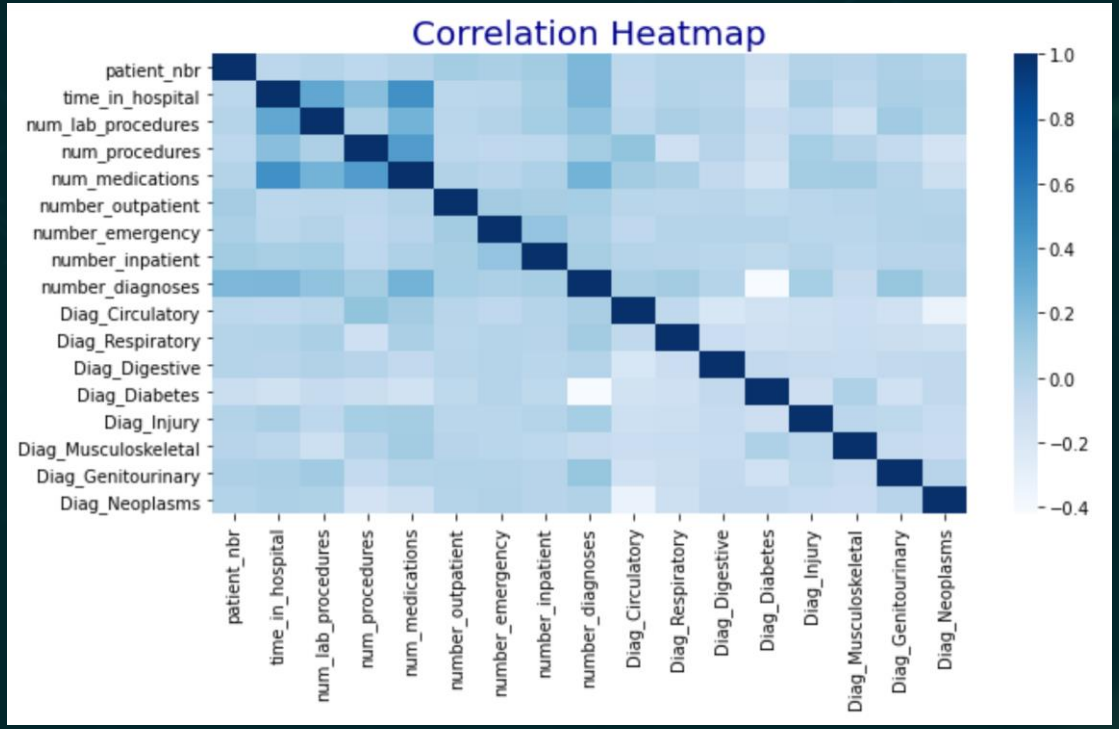
Other columns were mapped using a file provided with the data set. ('**admission_type_id**', '**discharge_disposition_id'** and '**admission_source_id**')

VISUALIZATION (I)

Secondly, visualization makes it possible to make the variations in the data visual and to establish certain opinions on behaviour between variables

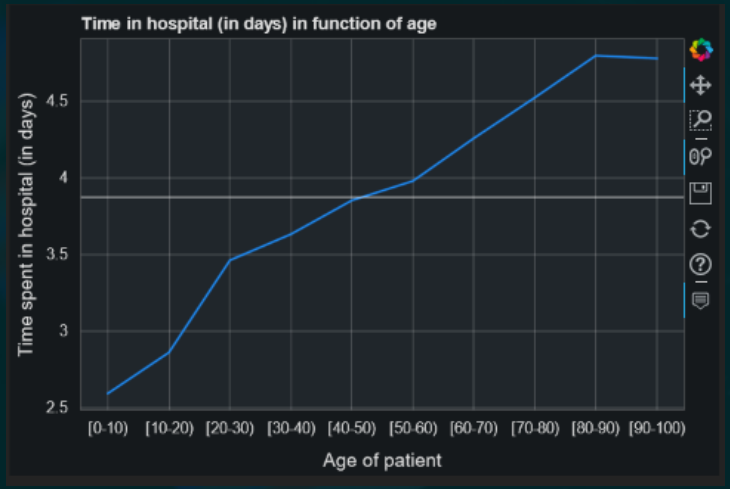
1. Correlation

This graph shows the existing correlations between the different variables in the dataset. A color scale represents the intensity of the correlation and makes it possible to visualize the hidden combinations of the data.



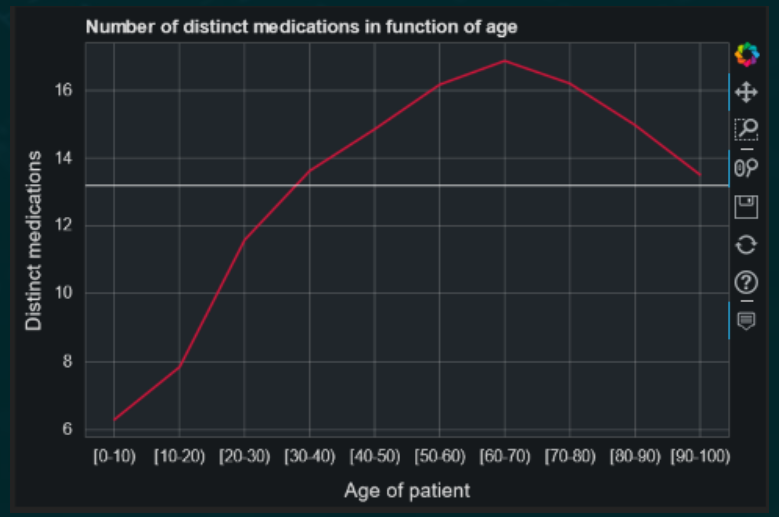
VISUALIZATION (II)

2. Observation of the variables with each others, some significant examples



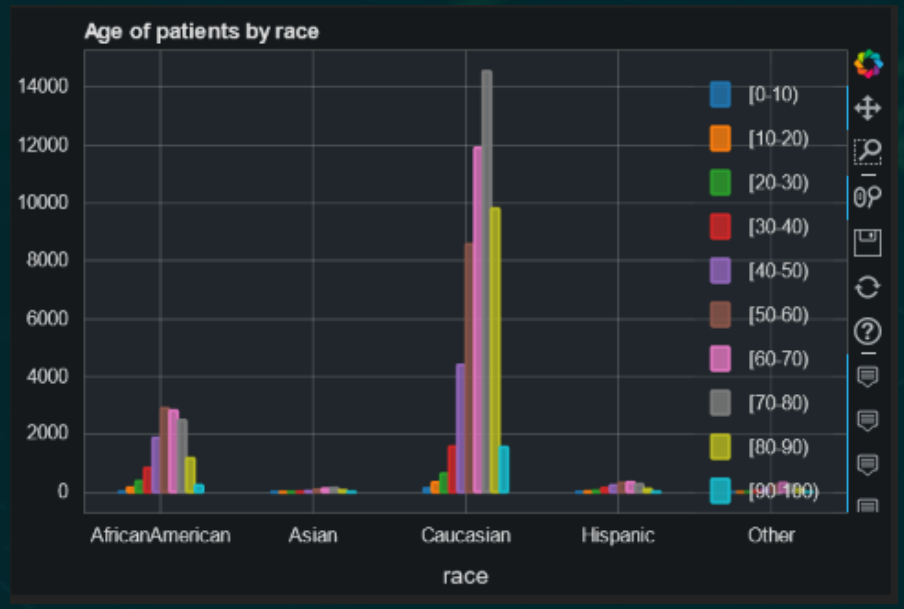
We can see here that there is a relationship between the age of the patient and the time he spent in hospital. On average, the older patients spend more time in hospital than the youngers.

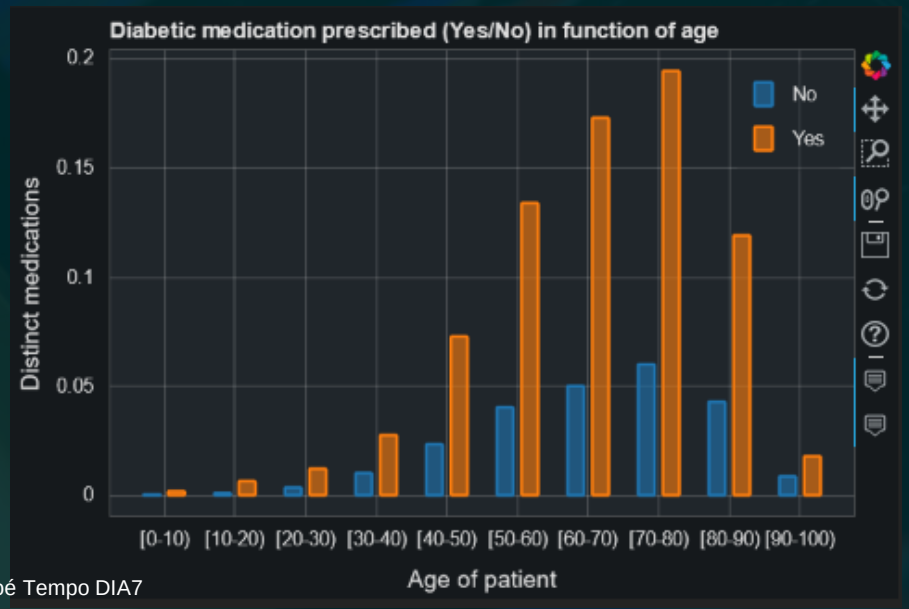
Here, the number of distinct medication seems to depend a lot on the patient's age with a peak for patients around 60-70 years old.
Once again, older patients seems to be more affected.



VISUALIZATION (II)

Race repartition by age category





We can see that the Yes and No values follow the same pattern with many values for patients between 50 and 90 years old but this can simply be explained by the fact that the pattern follows the distribution of patient of this dataset.
But here we can deduce that for a class of age, almost 2 patient over 3 were given diabetic medication

MACHINE LEARNING

The aim of this section is to use the diabetes dataset to train some Machine Learning models using the diabete dataset in order to **predict the readmission of a patient**

After preparing a machine learning oriented dataset from the original dataset, we decided to distinguish two cases according to the data:

Case 1: Predict patient's readmission under 30 days
Case 2: Predict patient's readmission under and above 30 days

MODEL SELECTION

In this study, we try to predict a qualitative binary variable. We also have a fairly large set of data, which leads us to use some models more than others.

We therefore tested and implemented the following models to compare their prediction performance :

- K-Nearest Neighbors (KNN)
- Logistic Regression
- Linear SVC
- Random Forest
- Adaptive Boosting
- Decision Tree
- Extra Trees
- Naïve Bayes Classifier

MACHINE LEARNING

We obtained the following results :

- **Case 1: Predict patient's readmission under 30 days**

Model	Score	Accuracy
K-Nearest Neighbors	0.9067	0.9067
Logistic Regression	0.9128	0.9128
Linear SVC	0.9130	0.9130
Random Forest	0.9109	0.9121
Adaptive boosting	0.9128	0.9128
Decision Tree	0.8342	0.8327
Extra Trees	0.9112	0.9117
Naive Bayes	0.8783	0.8783

- **Case 2: Predict patient's readmission under or above 30 days**

Model	Score	Accuracy
K-Nearest Neighbors	0.5805	0.5805
Logistic Regression	0.6238	0.6238
Linear SVC	0.6231	0.6231
Random Forest	0.6093	0.6065
Adaptive boosting	0.6323	0.6323
Decision Tree	0.5600	0.5575
Extra Trees	0.6032	0.6032
Naive Bayes	0.6077	0.6077

MACHINE TUNING

Models can be configured with different settings. We can then conduct research to see which parameters best adapt to our dataset to obtain the best prediction results.

We obtained the following results :

- **Case 1: Predict patient's readmission under 30 days**

Model	Score	Accuracy
Linear SVC	0.9130	0.9067
Logistic Regression	0.9128	0.9128
Random Forest	0.9117	0.9130
Adaptive Boosting	0.9116	0.9121
Extra Trees	0.9115	0.9128
K-Nearest Neighbors	0.9067	0.8327
Naive Bayes	0.8865	0.9117
Decision Tree	0.8342	0.8783

- **Case 2: Predict patient's readmission under or above 30 days**

Model	Score	Accuracy
Adaptive Boosting	0.6366	0.6351
Random Forest	0.6359	0.6360
Naive Bayes	0.6359	0.6260
Logistic Regression	0.6238	0.6238
Linear SVC	0.6231	0.6231
Extra Trees	0.6230	0.6201
K-Nearest Neighbors	0.5805	0.5805
Decision Tree	0.5600	0.5575

DISCUSSION

After observing the results, the following conclusions can be drawn.

For case number 1, we can see that the predictions are made with a rather high score but we must qualify this result because the problem is unbalanced. You can't really rely on those results.

For case number 2, the prediction performance is lower, less accurate, but this result is closer to reality.

We can conclude from this that this dataset is rather little correlated, that the variables seems to have relations between them but without having very large and significant ones.

It is therefore difficult to predict whether or not a patient will be readmitted to hospital with the features available in this dataset. We can put out an idea but it will not be very reliable on the subject.

API

API

To make the project a little more visual and accessible, we created a streamlit project that we linked to our python code to create an API. It presents different tabs with the description of the dataset, the notebook, our results in machine learning and an interactive parts.

TEAM

CHLOÉ TEMPO

MATTHIEU THIBAUT

GitHub

https://github.com/chlotmpo/python_data_analysis

WEBSITE

https://share.streamlit.io/chlotmpo/python_data_analysis/master/API_diabetes(Streamlit)/API_diabetes.py

ET BIEN NON TAMPIS C'EST LA VIE BEN OUAI GENIAL … C'EST ENCORE LA CA ?? BAH OUI HEIN CA A PAS DE

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