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

Analysis

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DESCRIPTION OF THE DATASET

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.

STEPS

1 LOAD AND CLEAN THE DATASET

2 ANALYSE , VISUALIAZE AND PREDICT

3 DISCUSS RESULTS

LIBRARIES

STRUCTURE

NumPy

pandas

VISUALIZATION

matplotlib

seaborn

bokeh

MACHINE LEARNING

scikit learn

GOAL OF OUR ANALYSIS

- Attention focus on the 'readmitted' feature
  --> 3 possibles types : 'No', '<30' and '>30'

- Goal : Study the variables and correlations and try to predict the 'readmitted' feature

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
```

```
24   metformin                  101766 non-null   object
25   repaglinide                101766 non-null   object
26   nateglinide                101766 non-null   object
27   chlorpropamide             101766 non-null   object
28   glimepiride                101766 non-null   object
29   acetohexamide              101766 non-null   object
30   glipizide                  101766 non-null   object
31   glyburide                  101766 non-null   object
32   tolbutamide                101766 non-null   object
33   pioglitazone               101766 non-null   object
34   rosiglitazone              101766 non-null   object
35   acarbose                   101766 non-null   object
36   miglitol                   101766 non-null   object
37   troglitazone               101766 non-null   object
38   tolazamide                 101766 non-null   object
39   examide                    101766 non-null   object
40   citoglipton                101766 non-null   object
41   insulin                    101766 non-null   object
42   glyburide-metformin        101766 non-null   object
43   glipizide-metformin        101766 non-null   object
44   glimepiride-pioglitazone   101766 non-null   object
45   metformin-rosiglitazone    101766 non-null   object
46   metformin-pioglitazone     101766 non-null   object
47   change                     101766 non-null   object
```

```
48   diabetesMed                101766 non-null   object
49   readmitted                 101766 non-null   object
dtypes: int64(13), object(37)
memory usage: 38.8+ MB
```

DATA REMOVING

Number of null values

	0
diag_1	0.020636
diag_2	0.351787
diag_3	1.398306
race	2.233555
payer_code	39.557416
medical_specialty	49.082208
weight	96.858479

Dropping columns with too much missing values

With the precedent results, we eliminate the columns that have too many missing values

```
diabetes_df.drop(columns = ['weight', 'medical_specialty', 'payer_code', 'encounter_id'], inplac
```

Some columns provide a constant value for every row, it is useless so we can eliminate them too.

```
diabetes_df.drop(columns = ['examide', 'citoglipton', 'glimepiride-pioglitazone', 'metformin-ros
```

Dropping redundant rows

When we analysed some data in this dataset, we observed that there was some redundant rows, some rows had the same number of patient value, and sometimes the linked variables were not coherent

We also drop these rows

```
diabetes_df.drop_duplicates(subset = "patient_nbr", keep = 'first', inplace = True)
```

MAPPING AND NEW COLUMNS

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

```
map_admission_type_id = {1: 'Emergency',
                         2:'Urgent',
                         3:'Elective',
                         4:'Newborn',
                         5:'Not Available',
                         6:'NULL',
                         7:'Trauma Center',
                         8 :'Not Mapped'}

diabetes_df.admission_type_id = diabetes_df.admission_type_id.map(map_admission_type_id)
```

```
map_admission_source_id = {1:"Physician Referral",
                           2:"Clinic Referral",
                           3:"HMO Referral",
                           4:"Transfer from a hospital",
                           5:"Transfer from a Skilled Nursing Facility (SNF)",
                           6:"Transfer from another health care facility",
                           7:"Emergency Room",
                           8:"Court/Law Enforcement",
                           9:"Not Available",
                           10:"Transfer from critial access hospital",
                           11:"Normal Delivery",
                           12:"Premature Delivery",
                           13:"Sick Baby",
                           14:"Extramural Birth",
                           15:"Not Available",
                           17:"NULL",
                           18:"Transfer From Another Home Health Agency",
                           19:"Readmission to Same Home Health Agency",
                           20:"Not Mapped",
                           21:"Unknown/Invalid",
                           22:"Transfer from hospital inpt/same fac reslt in a sep claim",
                           23:"Born inside this hospital",
                           24:"Born outside this hospital",
                           25:"Transfer from Ambulatory Surgery Center",
                           26:"Transfer from Hospice"}

diabetes_df.admission_source_id = diabetes_df.admission_source_id.map(map_admission_source_id)
```

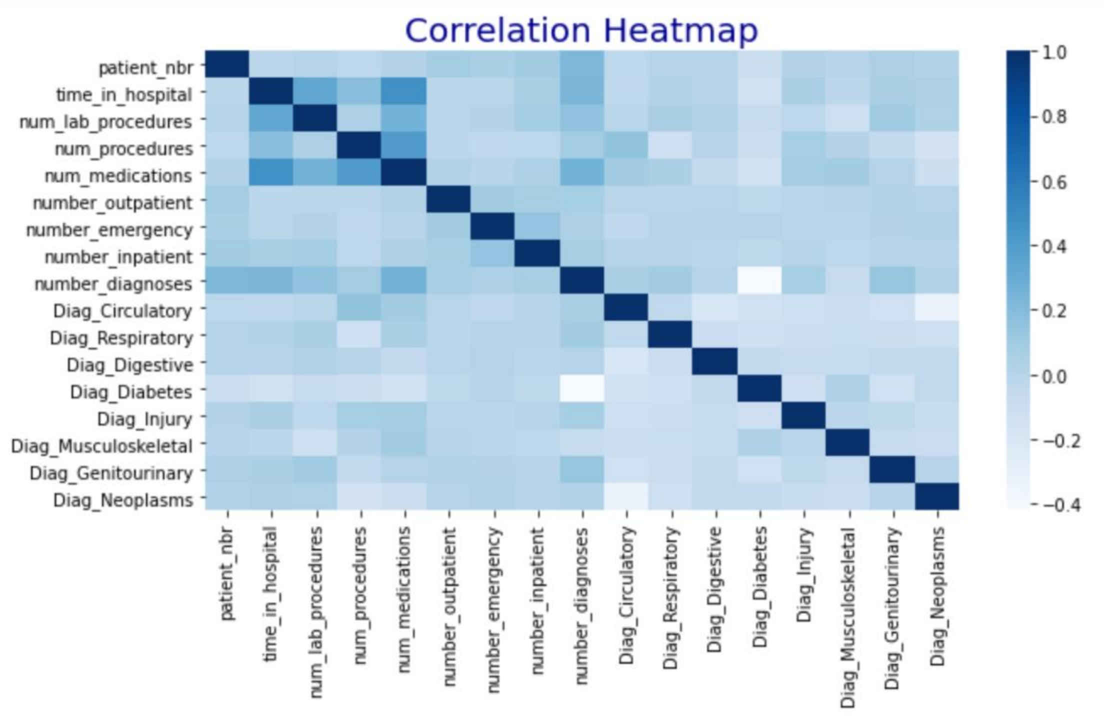
```
map_discharge_disposition_id = {1:"Discharged to home",
                                2:"Discharged/transferred to another short term hospital",
                                3:"Discharged/transferred to SNF",
                                4:"Discharged/transferred to ICF",
                                5:"Discharged/transferred to another type of inpatient care inst
                                6:"Discharged/transferred to home with home health service",
                                7:"Left AMA",
                                8:"Discharged/transferred to home under care of Home IV provider
                                9:"Admitted as an inpatient to this hospital",
                                10:"Neonate discharged to another hospital for neonatal aftercar
                                11:"Expired",
                                12:"Still patient or expected to return for outpatient services"
                                13:"Hospice / home",
                                14:"Hospice / medical facility",
                                15:"Discharged/transferred within this institution to Medicare a
                                16:"Discharged/transferred/referred another institution for outp
                                17:"Discharged/transferred/referred to this institution for outp
                                18:"NULL",
                                19:"Expired at home. Medicaid only, hospice.",
                                20:"Expired in a medical facility. Medicaid only, hospice.",
                                21:"Expired, place unknown. Medicaid only, hospice.",
                                22:"Discharged/transferred to another rehab fac including rehab
                                23:"Discharged/transferred to a long term care hospital.",
                                24:"Discharged/transferred to a nursing facility certified under
                                25:"Not Mapped",
                                26:"Unknown/Invalid",
                                30:"Discharged/transferred to another Type of Health Care Instit
                                27:"Discharged/transferred to a federal health care facility.",
                                28:"Discharged/transferred/referred to a psychiatric hospital of
                                29:"Discharged/transferred to a Critical Access Hospital (CAH)."

diabetes_df.discharge_disposition_id = diabetes_df.discharge_disposition_id.map(map_discharge_di
```

VISUALIZATION (I)

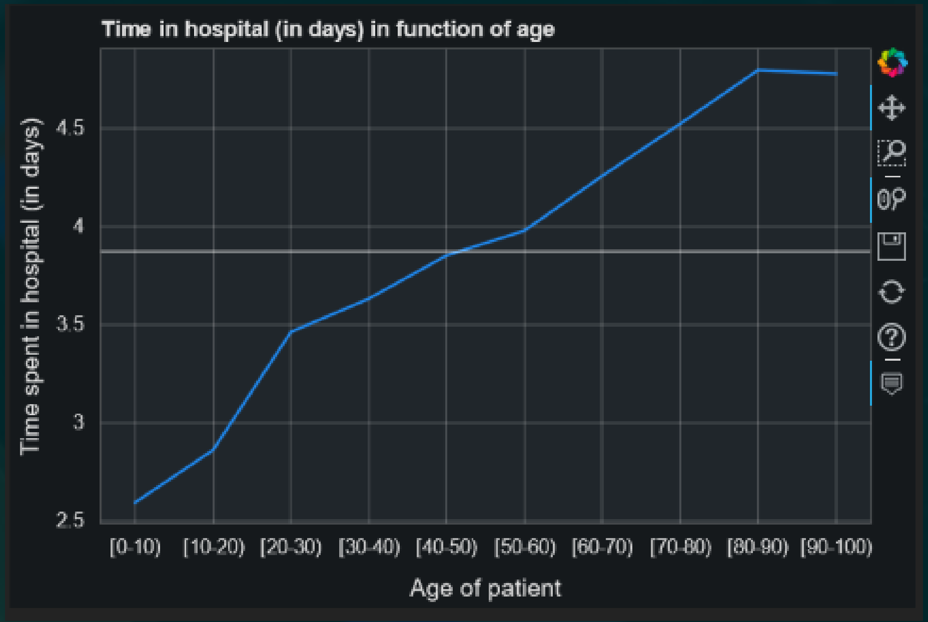
Secondly, visualization makes it possible to make the variations in the data visual and to establish certain opinions on behaviour between variables

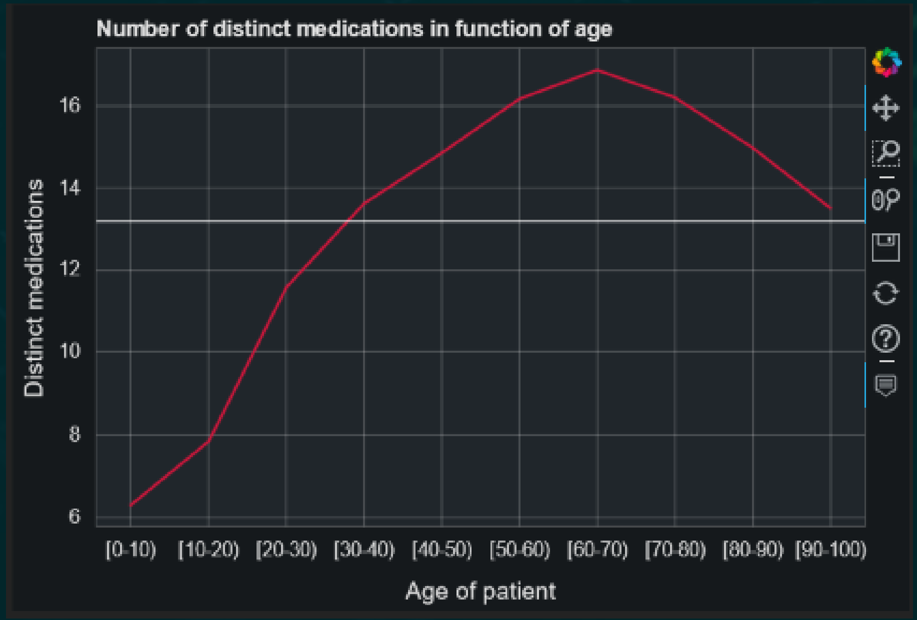
1. Correlation



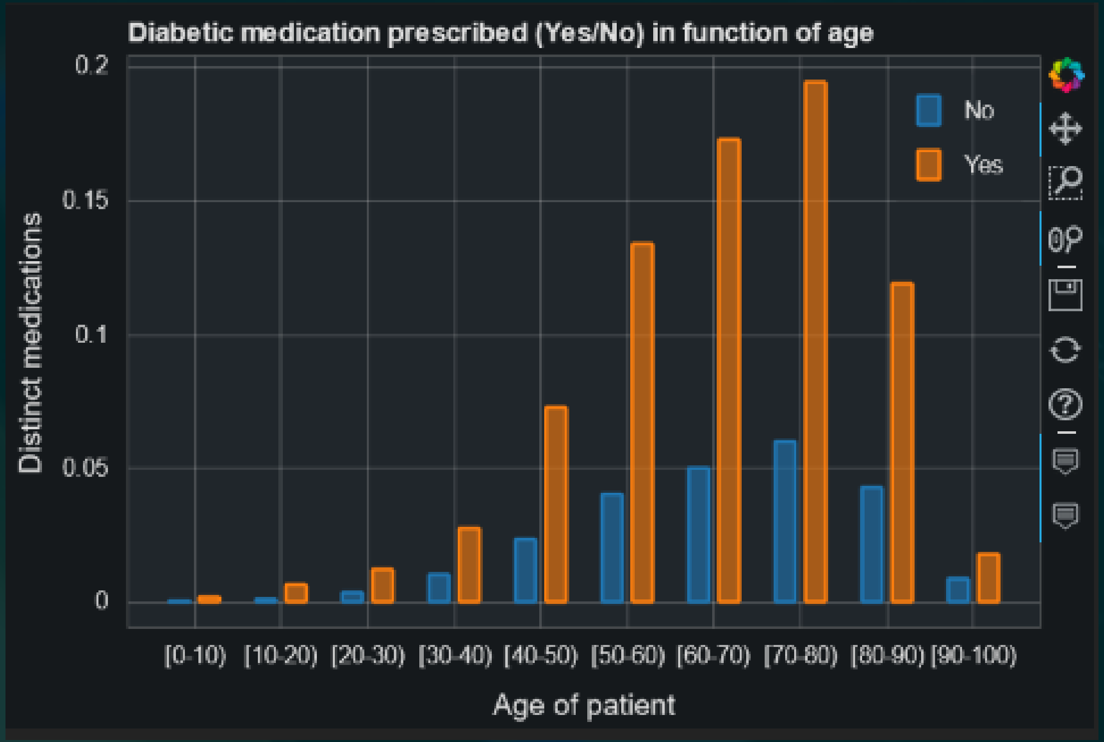
VISUALIZATION (II)

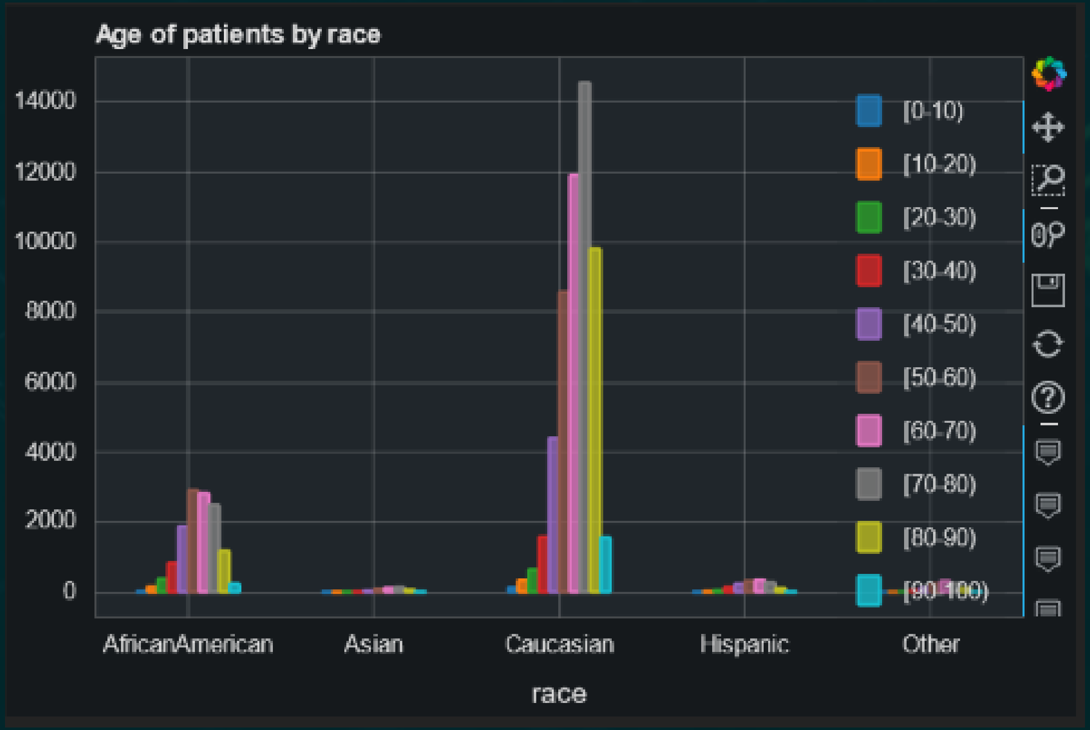
2. Observation of the variables with each others, some significant examples





VISUALIZATION (II)





MACHINE LEARNING

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

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

API

python™

Streamlit

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