Bio-Medical Visualization and Visual Analytics

Project Assignment 1

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Contents

Dataset Description

The dataset describes diabetes patient admissions/encounters in several US hospitals over a period of 10 years. It consists of over 100,000 rows and 50 variables. Each record is made up of patient information like gender, age group and weight group but also variables describing the encounter like the length of stay, the admission source and the readmittance duration.

The dataset can be accessed via https://archive.ics.uci.edu/dataset/296/diabetes+130-us+hospitals+for+years+1999-2008.

Raw Dataset Variables

The initial dataset consists of the following columns (variables):

> **Info**
>
> Some variables are not listed here, because their function is unknown or they are not relevant to our analysis.

Variable	Description	Possible Values
`encounter_id`	Every encounter with a patient has a unique identifying number.	Integers.
`patient_nbr`	Every patient has a unique identifying number.	Integers.
`race`	The race of the patient.	`'Caucasian', 'AfricanAmerican', '?', 'Other', 'Asian', 'Hispanic'`
`gender`	The gender of the patient.	`'Female', 'Male', 'Unknown/Invalid'`
`age`	The age group of the patient.	`'[0-10)', '[10-20)', '[20-30)', '[30-40)', '[40-50)', '[50-60)', '[60-70)', '[70-80)', '[80-90)', '[90-100)'`
`weight`	The weight group of the patient.	`'?', '[0-25)', '[25-50)', '[50-75)', '[75-100)', '[100-125)', '[125-150)', '[150-175)', '[175-200)', '>200'`
`admission_type_id`	An ID mapping to the type of admission.	`Emergency` (1), `Urgent` (2), `Elective` (3), `Newborn` (4), `Not Available` (5), `NULL` (6), `Trauma Center` (7), `Not Mapped` (8),
`discharge_disposition_id`	An ID mapping to the discharge disposition.	Integer from 1-29. Examples are `Discharged to home` (1), `Expired` (11), `Hospice / home` (13), `NULL` (18)

Variable	Description	Possible Values
admission_source_id	An ID mapping to the source of admission.	Integer from 1-26. Examples are Physician Referral (1), Clinic Referral (2), Transfer from a hospital (4), NULL (17)
time_in_hostpital	Number of days the patient stayed at the hospital.	Integers (number of days).
medical_specialty	What type of medical specialty was dealing with the patient.	'Pediatrics-Endocrinology', '?', 'InternalMedicine', 'Family/GeneralPractice', 'Cardiology', 'Surgery-General', 'Orthopedics', ...
num_lab_procedures, num_procedures, num_medications, number_outpatient, number_emergency, number_inpatient, number_diagnoses	Several metrics counting certain actions performed by the hospital staff or prior patient history.	Integers.
diag_1, diag_2, diag_3	Diagnosis as ICD-9 code. (See https://en.wikipedia.org/wiki/List_of_ICD-9_codes)	ICD-9 code.
max_glu_serum, A1Cresult	Result of laboratory tests, if performed	e.g.: 'Normal', '>200', '>300', 'None'
metformin, repaglinide, nateglinide, chlorpropamide, ..., insulin,	Several medication statuses.	'No', 'Steady', 'Down', 'Up'
change	If the medication changed in any way.	'Ch', 'No'
diabetesMed	If the patient takes diabetes medication.	'Yes', 'No'
readmitted	If and after how many days a patient has been readmitted.	'NO', '<30', '>30'

The variables have the following datatypes:

Variable Name	Data Type
encounter_id	int64
patient_nbr	int64
race	object
gender	object
age	object
weight	object
admission_type_id	int64
discharge_disposition_id	int64
admission_source_id	int64
time_in_hospital	int64
payer_code	object
medical_specialty	object
num_lab_procedures	int64
num_procedures	int64
num_medications	int64
number_outpatient	int64
number_emergency	int64
number_inpatient	int64
diag_1	object
diag_2	object
diag_3	object
number_diagnoses	int64
max_glu_serum	object
A1Cresult	object
metformin	object
repaglinide	object
nateglinide	object
chlorpropamide	object
glimepiride	object
acetohexamide	object
glipizide	object
glyburide	object
tolbutamide	object
pioglitazone	object
rosiglitazone	object
acarbose	object
miglitol	object
troglitazone	object
tolazamide	object
examide	object
citoglipton	object
insulin	object
glyburide-metformin	object
glipizide-metformin	object
glimepiride-pioglitazone	object
metformin-rosiglitazone	object
metformin-pioglitazone	object
change	object
diabetesMed	object
readmitted	object

Additionally, we checked, if encounter_id is a unique variable by checking if there are duplicates:

Are there duplicate entries for unique identifier: Encounter ID: [False]

Data Quality Issues

1. **Missing values:** Many records have missing values in certain fields, often, but not always, indicated by a question mark (?).
2. **Inconsistent naming of boolean categories:** Some variables have values that are binary but have named values, like 'Yes' or 'No'. The column 'change' has 'Ch' instead of 'Yes'.
3. **Categorical values that are represented by an ID**: Some values are represented by an ID and need to be corresponded to their string representation via an additional provided CSV-file.
4. **Categorical values with overlap**: Columns like '`admission_source_id`' have multiple values associated with incomplete or missing data like '`NULL`', '`Not Mapped`', '`Not Available`' and '`Unknown/Invalid`'.
5. **Limited number of detailed Diagnosis**: The dataset only includes up to three diagnosis per record even though there can be many more per encounter.
6. **Numerical values that have ben categorized into value ranges**: Values like age or weight were anonymized by replacing them with the respective range, making these columns harder to process.

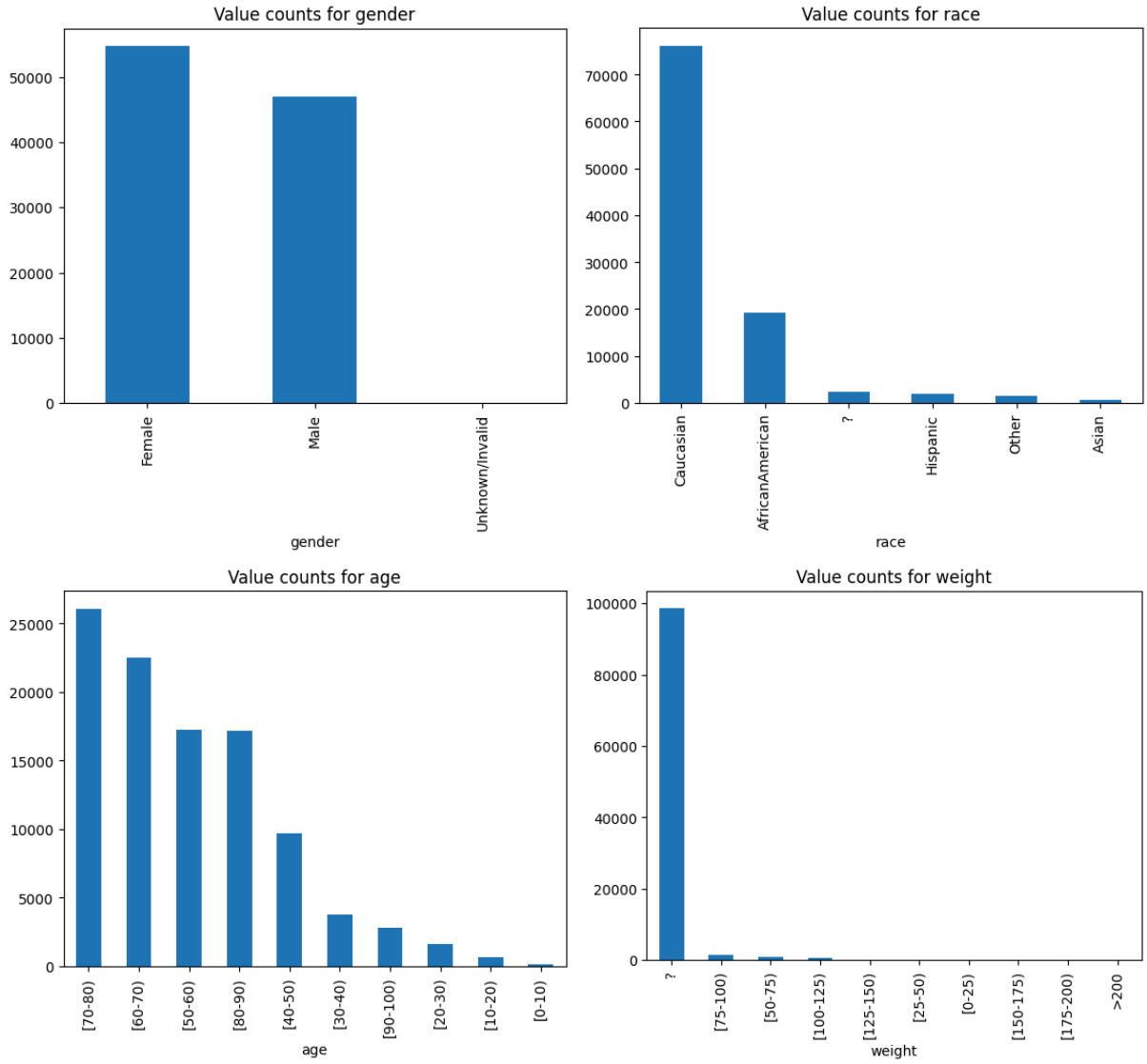
Initial Analysis Questions

These are the initial research questions we formulated:

1. What are the highest risk factors for patient readmission?
2. Which race, gender, or age-related differences are there?
3. What are the key differences between early and late readmission?
4. How does a change in medication strategy change the readmission risk?

Exploratory Analysis

First we want to get an overview of the dataset. We start by analyzing different patient attributes for each encounter.

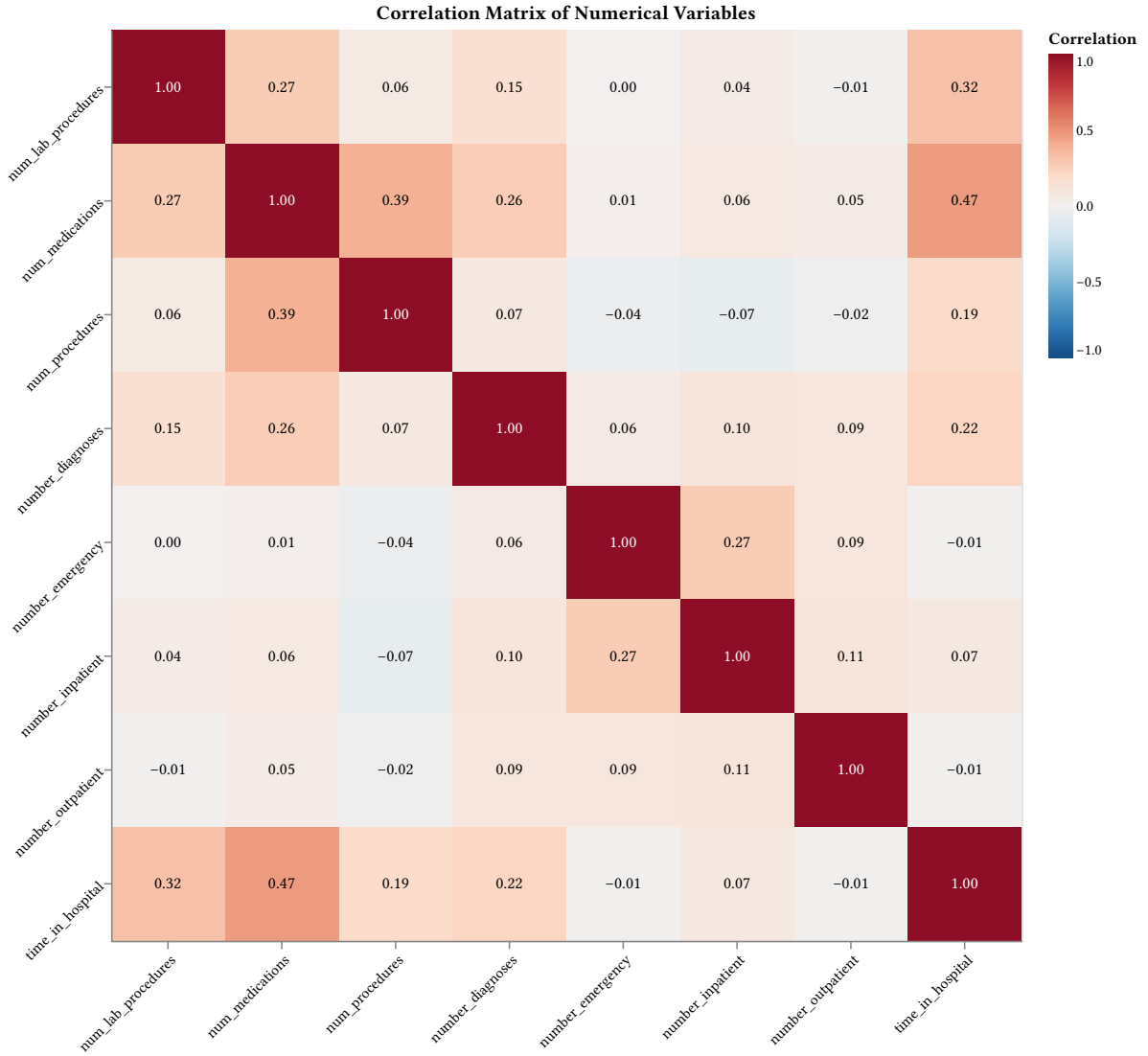


Let us analyze each attribute:

- **Gender**: The majority of encounters feature patients classified as female in the dataset.
- **Race**: Most encounters feature patients classified as Caucasian, followed by African American. This makes sense given the origin of the data. A significant portion of the dataset has missing values for this attribute.
- **Age**: The age distribution shows that most encounters feature patients between 50 and 80 years old.
- **Weight**: The weight attribute has a large number of missing values, which is probably because patients were not weighed consistently during their visits. Among the available data, most encounters feature patients in the weight categories between 75 and 125.

To test the reliability of the dataset we want to test some hypotheses regarding the variables. If we analyse the values of the variable `time_in_hospital`, `num_procedures` and `num_medications` we should see some correlation between them. The more procedures and medications a patient has, the longer they should stay in the hospital.

We check for this by exploring the numerical correlations in the dataset. The following correlation matrix shows the correlations between the values in the dataset (id values excluded).

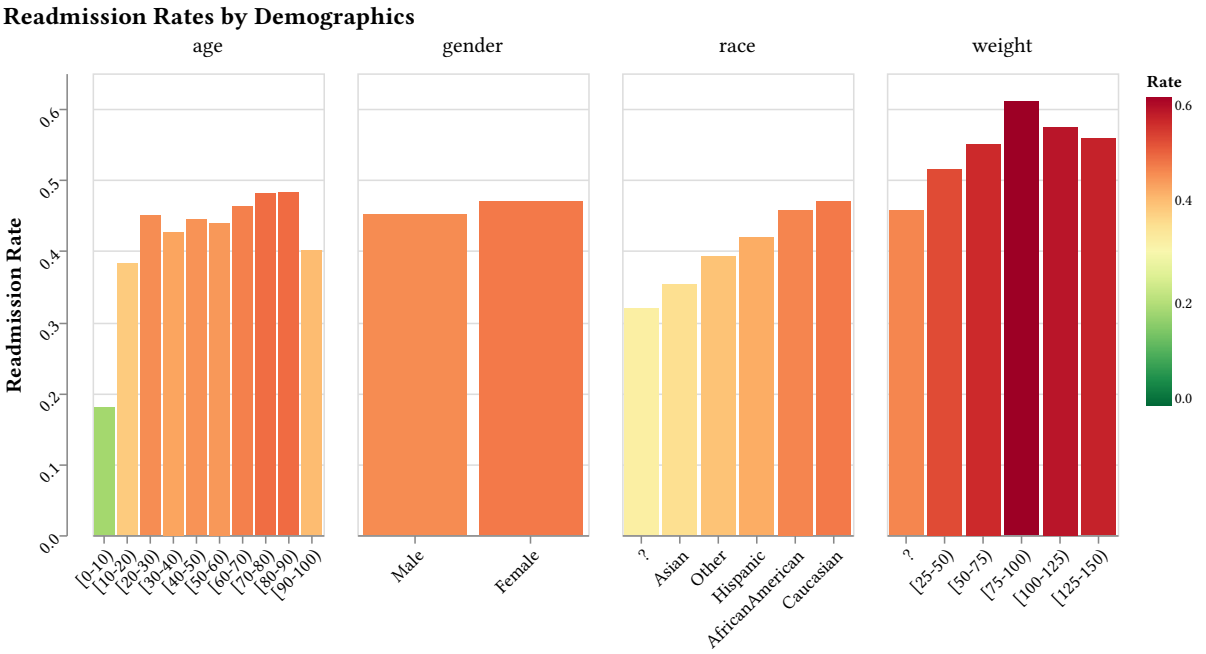


This visualization shows that there are indeed correlations between the number of procedures/ medications and the time spent in the hospital. Other correlations that can be seen are for example between the number of emergency and inpatient visits.

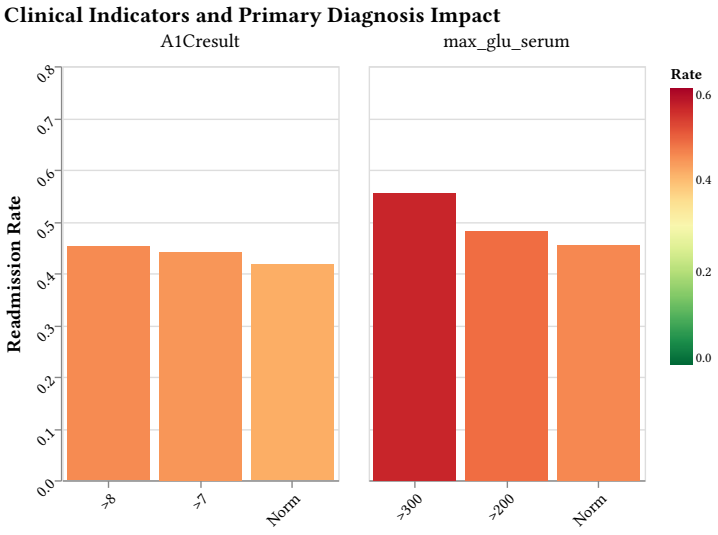
What are the highest risk factors for patient readmission?

First we want to analyze which patient attributes have the highest impact on readmission rates. The following chart shows the readmission rates for different patient demographics. Since readmission is a categorical variable in the original dataset, we convert it to a binary variable indicating whether a patient was readmitted or not, for the following charts.

> **Info**
>
> Only categories with a significant number of samples (>50) are shown.

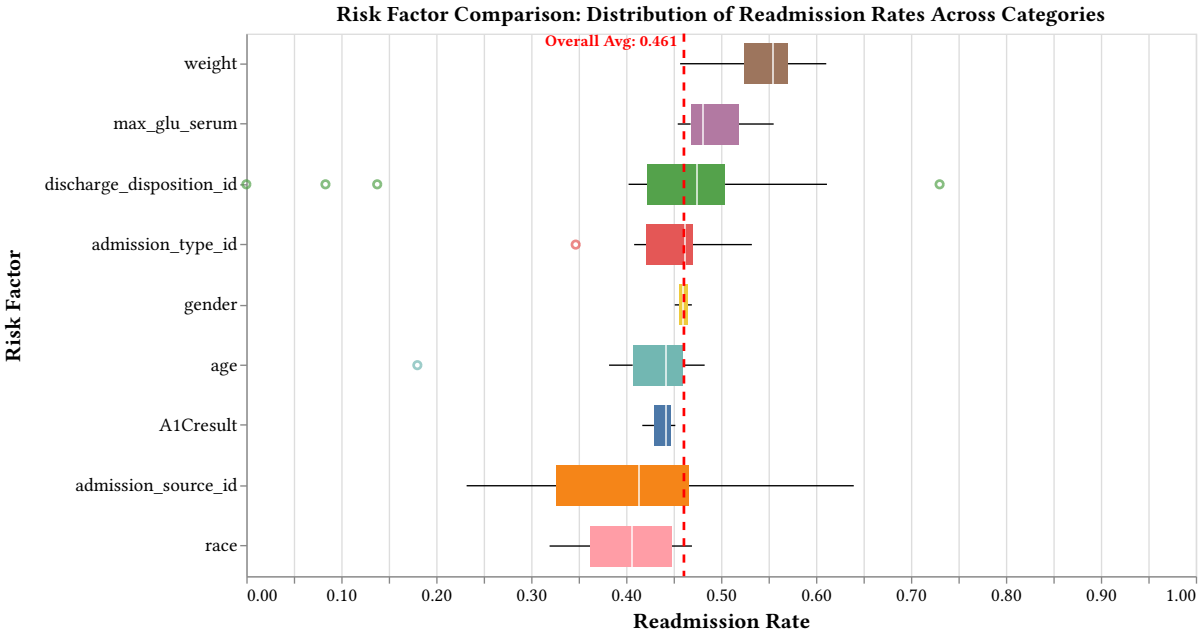


Next, we are able to analyze different lab test results and their impact on readmission rates.



We can see that that a high glucose serum level (>300) is associated with a higher readmission rate in this dataset. The same applies to the A1C result to a lesser extent.

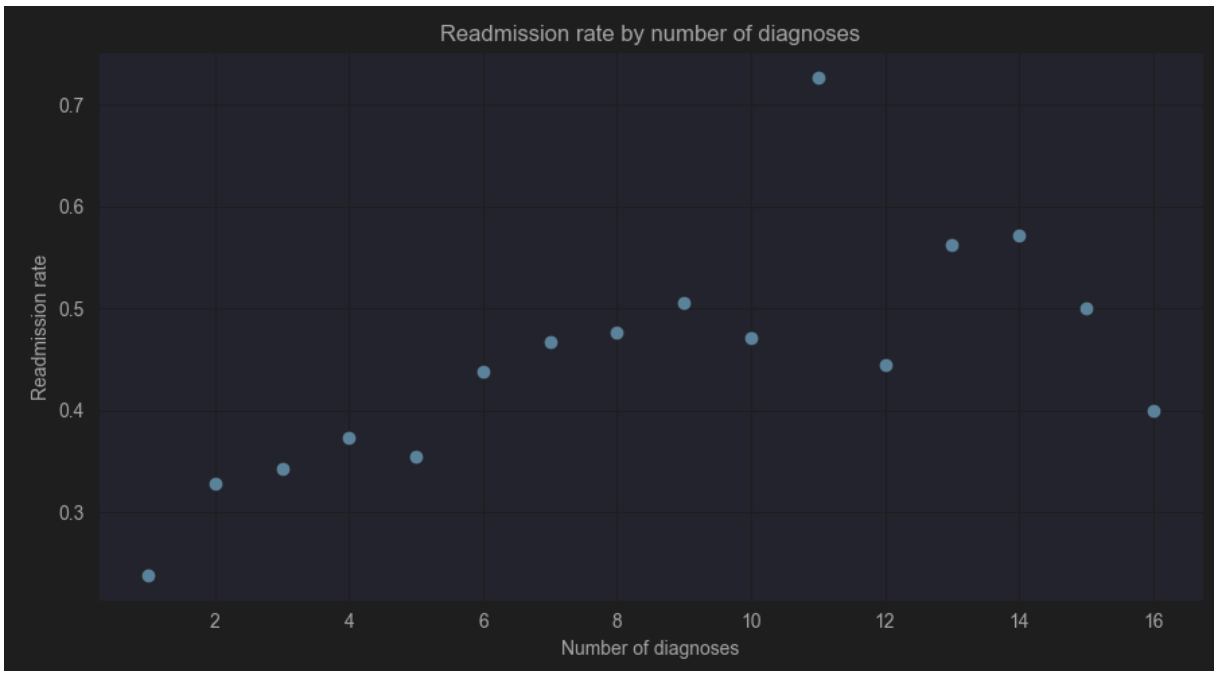
Here we analyzed the distribution of readmission risks across different categories. Category groups with a low sample size (<50) were excluded from this analysis to ensure statistical significance.



We can see that certain factors like the admission source have a wide distribution of readmission rates across their categories, indicating that some categories within these factors are associated with significantly higher or lower readmission risks. Other factors like gender or A1C result have a very narrow distribution, indicating that they are not significant predictors of readmission risk.

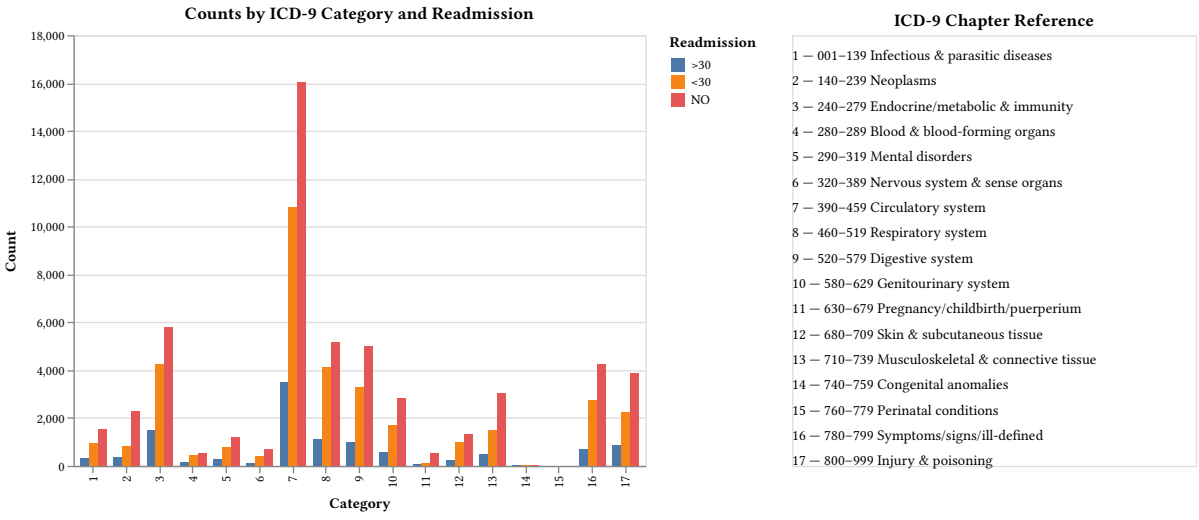
Within each primary diagnosis group, what are the top independent predictors of a readmission?

This scatterplot shows the readmission rate grouped by the number of diagnosis of a patient.



This plot shows a clear trend in readmissions as the odds of readmission increase directly proportional with the number of diagnosis. Now it would be interesting if there are some diagnosis types which increase the readmission odds more then others.

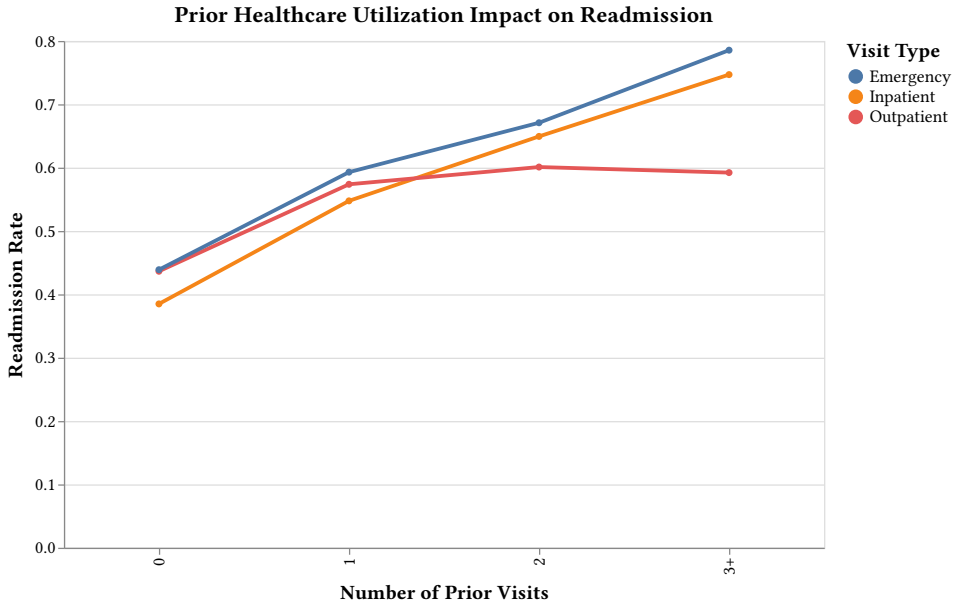
The following graph shows exactly this.



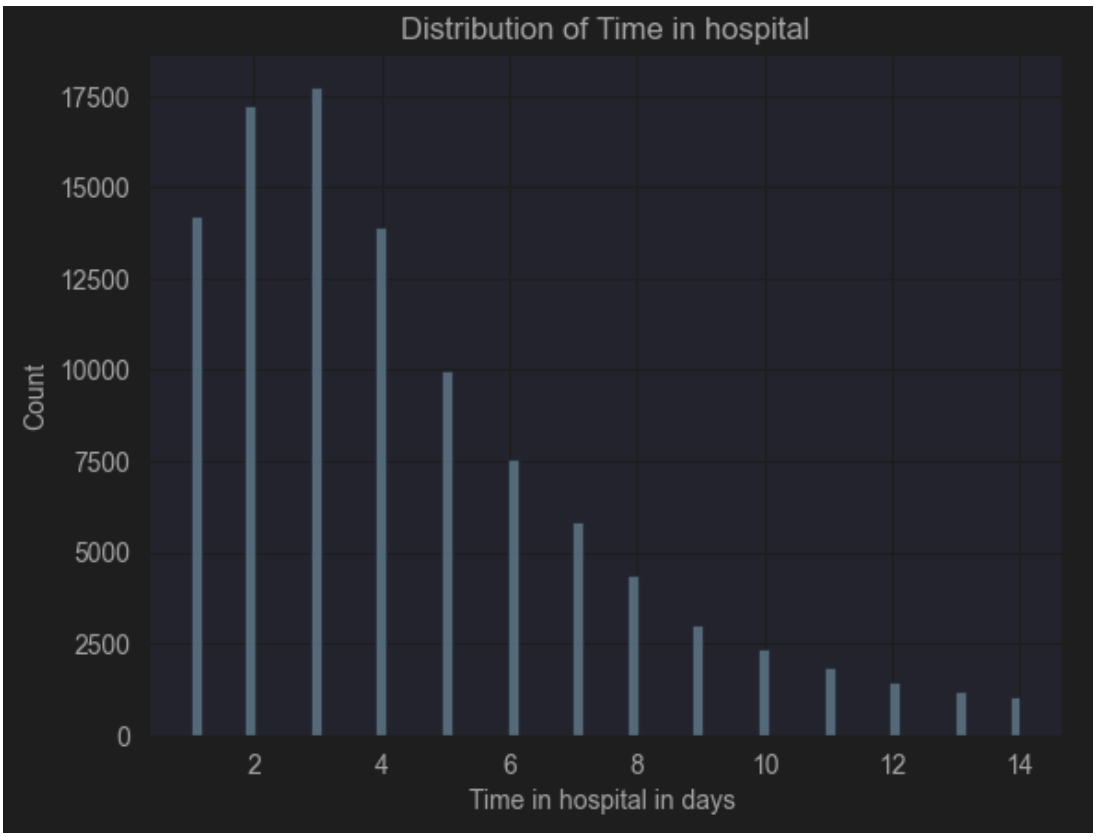
The main insight we gain here is that in all ICD-9 chapters the amount of people who are not readmitted is the highest. We can also see that the distribution is similar in all areas. Therefore this does not show us a clear trend

Analysis of patient encounter variables

We can also analyze certain variables that describe the patient encounters. First we want to look at the prior healthcare utilization of patients and its effect on readmission risk.

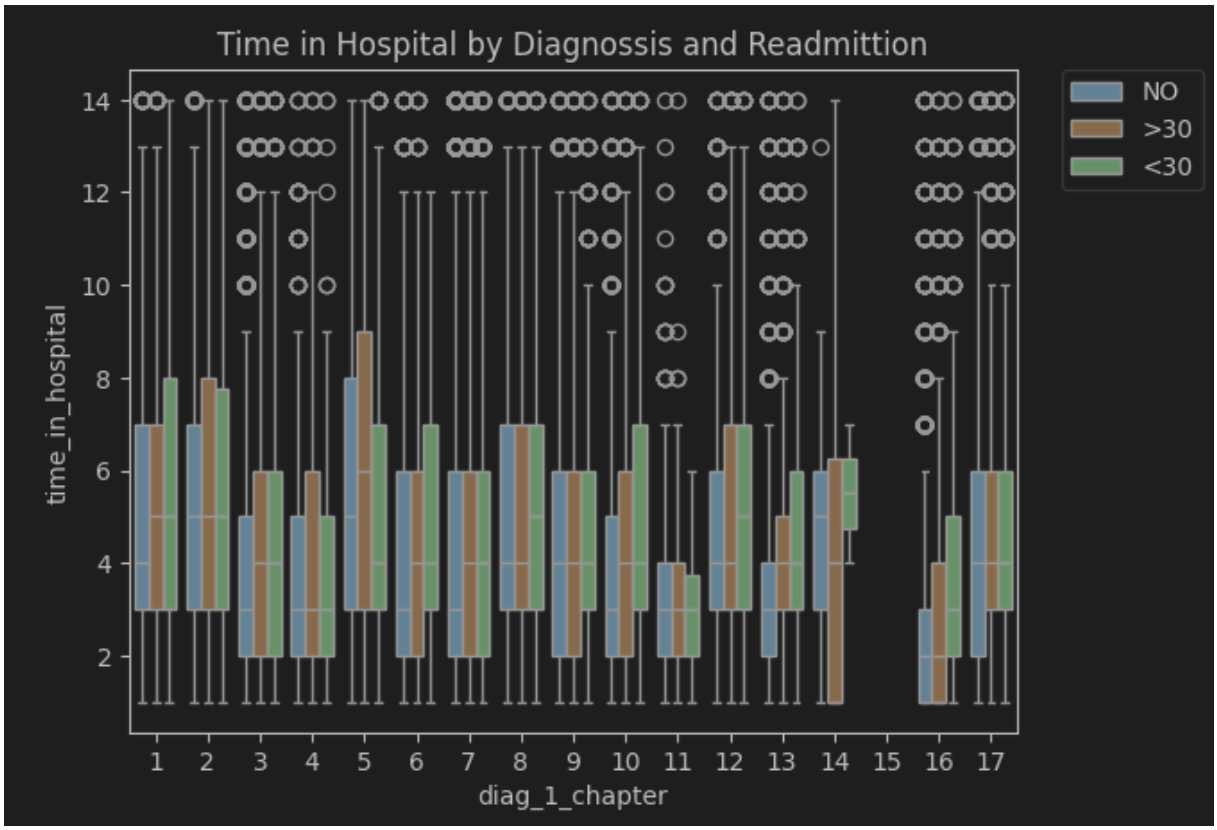


Now let us take a look at the time spent per encounter. The following Graph shows how many people spent how much time in the hospital.



A broad overview over how long patients are in the hospital is displayed here. The goal of this is to understand the more detailed stay duration visualization in the next graph better.

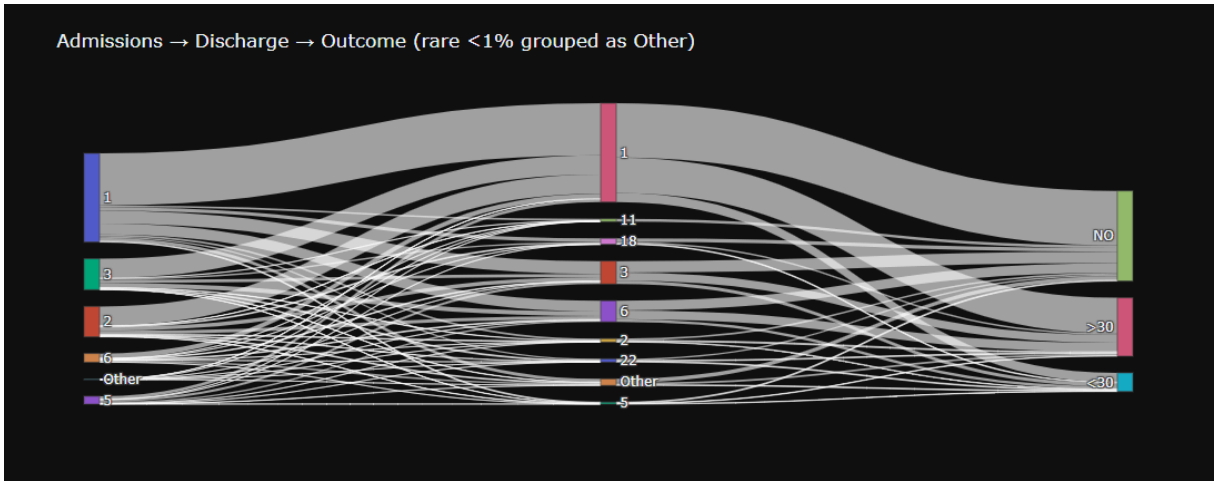
The next graph has the aim to show the correllation of diagnosis and the time spent in the hospital to readmissions



One can see that the time stayed in the hospital generally has a high variance with some outliers. In the chapter 16, Symptoms/signs/ill-defined, the time in hospital is very low for patients who are not readmitted but get visibly higher the sooner the readmission is. This can be investigated.

What are the key differences between early (<30 days) and late (>30 days) readmission?

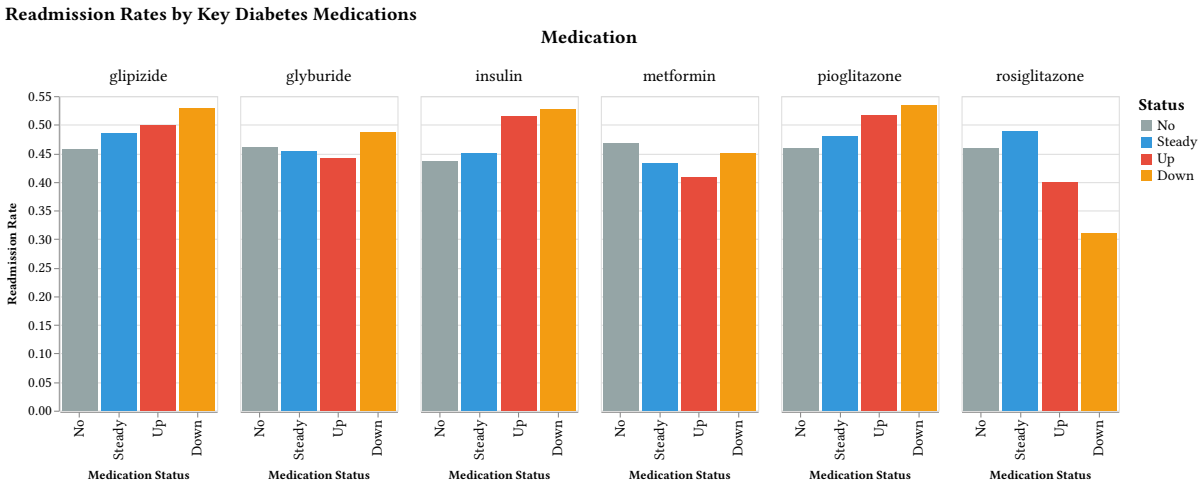
This Visualization shows a Sankey diagram where the patient flow from the first admission to the discharge type to the readmission is shown. Only patient flows over 1% are shown. The oders are grouped in others



We learn from this where patients most likely are admitted from and we can get an overview. Most patients are admitted through the emergency room or are admitted by another physician. But there is no clear trend visible that shows which kind of discharge type is most likely to result in readmission, as all look quite similar.

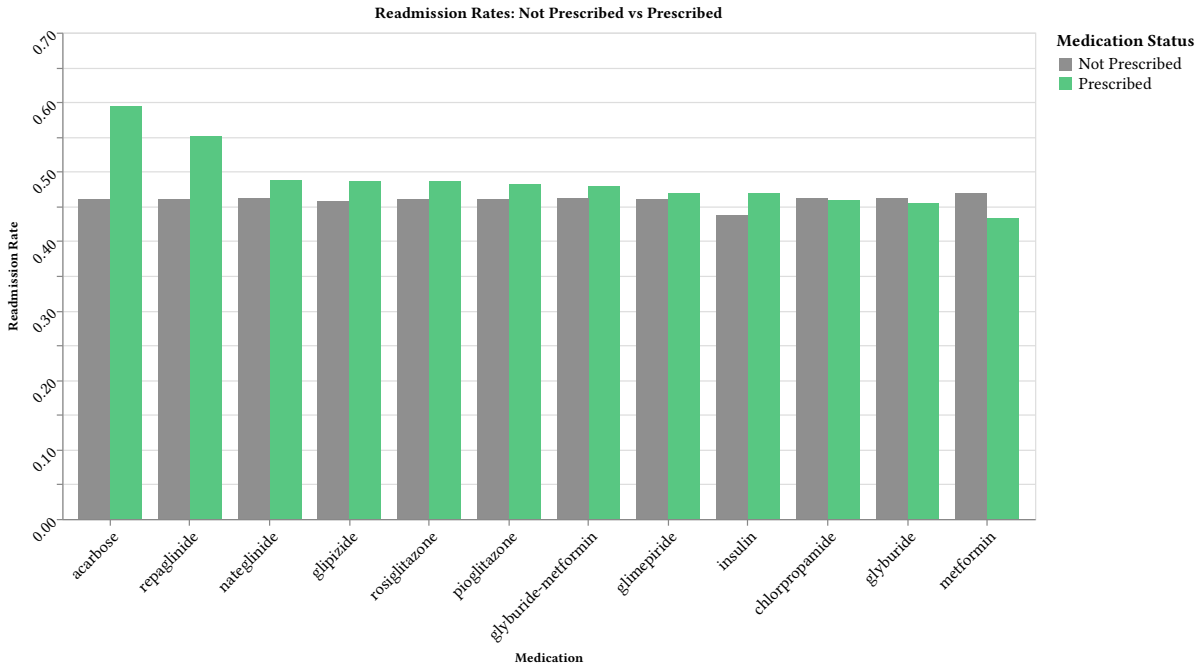
How does a change in medication strategy change the readmission risk?

Next we want to look at the effect of medication changes on readmission risk. In the following chart we can see the readmission rates by medication and change status.



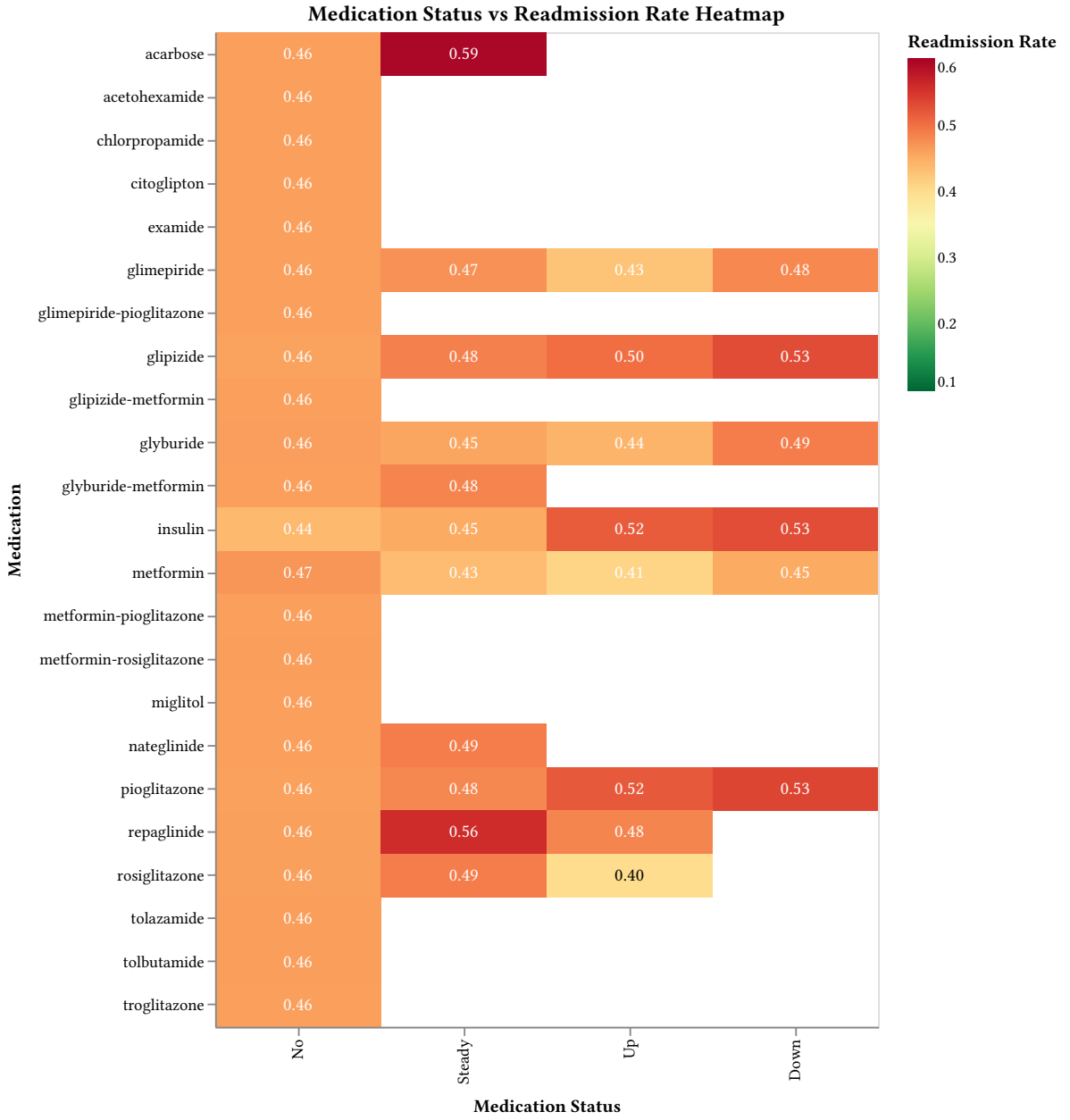
What is immediately apparent is that different medications have very different readmission rates depending on whether the medication was increased, decreased or stayed the same. For example, for Metformin, patients whose medication was increased ('Up') have a significantly lower readmission rate compared to those whose medication stayed the same ('Steady') or decreased ('Down'). This suggests that increasing Metformin dosage may be beneficial in reducing readmission rates.

For the next analysis we grouped the medication statuses into two categories: 'Prescribed' (which includes both 'Steady' and 'Up') and 'Not Prescribed'. This allows us to compare the overall effect of being on a medication versus not being on it at all.



From this chart, we can see that for most medications, being prescribed the medication is associated with a higher readmission rate compared to not being prescribed it. However, not being prescribed metformin, for example, is associated with a notably higher readmission rate compared to being prescribed it.

This heatmap shows the readmission rates for each medication based on whether it was never prescribed, decreased, increased, or stayed the same. It excludes status changes with fewer than 100 samples to ensure statistical significance.



Interestingly, increasing the dosage of rosiglitazone ('Up') is associated with a lower readmission rate compared to other medications. This would suggest that increasing rosiglitazone dosage may be particularly effective in reducing readmission rates. Notably, rosiglitazone is known to have cardiovascular side effects[1], which led to it being withdrawn from the market in several countries (e.g. the EU[2]).

> ⚠ **Warning**
>
> These findings should be interpreted with caution. Other factors my influence readmission rates and medication changes beyond the scope of this analysis.

[1] https://www.pharmawiki.ch/wiki/index.php?wiki=Rosiglitazon
[2] https://www.ema.europa.eu/en/medicines/human/EPAR/avandia

Summary

In this document, we visually explored a large diabetes patient admissions dataset from multiple US hospital over a ten-year period, containing over 100,000 rows and 50 variables.

The analysis begins with an overview of the structure of the dataset as well as the challenges it contains, such as missing values, inconsistent namings, overlapping categorical entries. Then, four Research Questions were proposed, which were investigated in the following analysis. These focus on the identification of major risk factors for readmissions, the role of demographics, differences of early and late readmission as well as the influence of medication strategies.

Our visualizations show a clear correlation between number of procedures and medications and the length of the hospital stay. They also show slight differences when grouping patients based on different demographics. Despite this, high glucose serum levels seems to have an effect on the readmission rate. The analysis also shows that weight is the biggest risk factor for readmission, while race and the admission source have the smallest risk factor of readmission. It also reveals a clear trend between the number of diagnosis and the readmission rate. Investiagtions into effects due to the medications reveal that with some medications, an increase in dosage decreases the risk for readmission, while for others this is true for an decrease of dosage.

Summing up, there seem to be some correlations between certain influence factors and readmission, however, no definitive actions can be derived without the need for further analysis.