

# Predicting readmission probability for diabetes inpatients

STAT 471/571/701, Fall 2017

*Due: April 2, 2017 at 11:59PM*

## Introduction

### Background

Diabetes is a chronic medical condition affecting millions of Americans, but if managed well, with good diet, exercise and medication, patients can lead relatively normal lives. However, if improperly managed, diabetes can lead to patients being continuously admitted and readmitted to hospitals. Readmissions are especially serious - they represent a failure of the health system to provide adequate support to the patient and are extremely costly to the system. As a result, the Centers for Medicare and Medicaid Services announced in 2012 that they would no longer reimburse hospitals for services rendered if a patient was readmitted with complications within 30 days of discharge.

Given these policy changes, being able to identify and predict those patients most at risk for costly readmissions has become a pressing priority for hospital administrators.

In this project, we shall explore how to use the techniques we have learned in order to help better manage diabetes patients who have been admitted to a hospital. Our goal is to avoid patients being readmitted within 30 days of discharge, which reduces costs for the hospital and improves outcomes for patients.

The original data is from the Center for Clinical and Translational Research at Virginia Commonwealth University. It covers data on diabetes patients across 130 U.S. hospitals from 1999 to 2008. There are over 100,000 unique hospital admissions in this dataset, from ~70,000 unique patients. The data includes demographic elements, such as age, gender, and race, as well as clinical attributes such as tests conducted, emergency/inpatient visits, etc. Refer to the original documentation for more details on the dataset. Three former students Spencer Luster, Matthew Lesser and Mridul Ganesh, brought this data set into the class and did a wonderful final project. We will use a subset processed by the group but with a somewhat different objective.

### Goals of the analysis

1. Identify the factors predicting whether or not the patient will be readmitted within 30 days.
2. Propose a classification rule to predict if a patient will be readmitted within 30 days.

### Characteristics of the Data Set

All observations have five things in common:

1. They are all hospital admissions
2. Each patient had some form of diabetes
3. The patient stayed for between 1 and 14 days.
4. The patient had laboratory tests performed on him/her.
5. The patient was given some form of medication during the visit.

The data was collected during a ten-year period from 1999 to 2008. There are over 100,000 unique hospital admissions in the data set, with ~70,000 unique patients.

## Description of variables

The dataset used covers ~50 different variables to describe every hospital diabetes admission. In this section we give an overview and brief description of the variables in this dataset.

### a) Patient identifiers:

- a. `encounter_id`: unique identifier for each admission
- b. `patient_nbr`: unique identifier for each patient

### b) Patient Demographics:

`race`, `age`, `gender`, `weight` cover the basic demographic information associated with each patient. `Payer_code` is an additional variable that identifies which health insurance (Medicare /Medicaid / Commercial) the patient holds.

### c) Admission and discharge details:

- a. `admission_source_id` and `admission_type_id` identify who referred the patient to the hospital (e.g. physician vs. emergency dept.) and what type of admission this was (Emergency vs. Elective vs. Urgent).
- b. `discharge_disposition_id` indicates where the patient was discharged to after treatment.

### d) Patient Medical History:

- a. `num_outpatient`: number of outpatient visits by the patient in the year prior to the current encounter
- b. `num_inpatient`: number of inpatient visits by the patient in the year prior to the current encounter
- c. `num_emergency`: number of emergency visits by the patient in the year prior to the current encounter

### e) Patient admission details:

- a. `medical_specialty`: the specialty of the physician admitting the patient
- b. `diag_1`, `diag_2`, `diag_3`: ICD9 codes for the primary, secondary and tertiary diagnoses of the patient. ICD9 are the universal codes that all physicians use to record diagnoses. There are various easy to use tools to lookup what individual codes mean (Wikipedia is pretty decent on its own)
- c. `time_in_hospital`: the patient's length of stay in the hospital (in days)
- d. `number_diagnoses`: Total no. of diagnosis entered for the patient
- e. `num_lab_procedures`: No. of lab procedures performed in the current encounter
- f. `num_procedures`: No. of non-lab procedures performed in the current encounter
- g. `num_medications`: No. of distinct medications prescribed in the current encounter

### f) Clinical Results:

- a. `max_glu_serum`: indicates results of the glucose serum test
- b. `A1Cresult`: indicates results of the A1c test

### g) Medication Details:

- a. `diabetesMed`: indicates if any diabetes medication was prescribed
- b. `change`: indicates if there was a change in diabetes medication
- c. `24 medication variables`: indicate whether the dosage of the medicines was changed in any manner during the encounter

### h) Readmission indicator:

Indicates whether a patient was readmitted after a particular admission. There are 3 levels for this variable: "NO" = no readmission, "< 30" = readmission within 30 days and "> 30" = readmission after more than 30 days. The 30 day distinction is of practical importance to hospitals because federal regulations penalize hospitals for an excessive proportion of such readmissions.

To save your time we are going to use some data sets cleaned by the group. Thus, we provide two datasets:

`diabetic.data.csv` is the original data. You may use it for the purpose of summary if you wish. You will see that the original data can't be used directly for your analysis, yet.

`readmission.csv` is a cleaned version and they are modified in the following ways:

- 1) Payer code, weight and Medical Specialty are not included since they have a large number of missing values.
- 2) Variables such as `acetoexamide` (col 30), `glimepiride.pioglitazone` (45), `metformin.rosiglitazone` (46), `metformin.pioglitazone` (47) have little variability, and are as such excluded. This also includes the following variables: `chlorpropamide` (28), `acetoexamide` (30), `tolbutamide` (33), `acarbose` (36), `miglitor` (37), `troglitazone` (38), `tolazamide` (39), `examide` (40), `citoglipton` (41), `glyburide.metformin` (43), `glipizide.metformin` (44), and `glimepiride.pioglitazone` (45).
- 3) Some categorical variables have been regrouped. For example, `Diag1_mod` keeps some original levels with large number of patients and aggregates other patients as `others`. This process is known as 'binning.'
- 4) The event of interest is **readmitted within < 30 days**. Note that you need to create this response first by regrouping **Readmission indicator**!

## Exploratory Data Analysis

```
## ===== STANDARD EDA TECHNIQUES
## =====

## <<<< READING IN DATA >>>> ===== FULL DATASET ===== bill.data.test <-
## read.csv('Bills.subset.test.csv', header=TRUE, sep=',', na.strings='') #
## accounts for header, CSV, and na strings
df.full <- read.csv("diabetic.data.csv", header = TRUE, sep = ",", na.strings = "") # accounts for header
dim(df.full) # 101,766 observations x 50 variables
```

```
## [1] 101766      50
```

```
head(df.full, 30)
```

	encounter_id	patient_nbr	race	gender	age	weight
## 1	2278392	8222157	Caucasian	Female	[0-10)	?
## 2	149190	55629189	Caucasian	Female	[10-20)	?
## 3	64410	86047875	AfricanAmerican	Female	[20-30)	?
## 4	500364	82442376	Caucasian	Male	[30-40)	?
## 5	16680	42519267	Caucasian	Male	[40-50)	?
## 6	35754	82637451	Caucasian	Male	[50-60)	?
## 7	55842	84259809	Caucasian	Male	[60-70)	?
## 8	63768	114882984	Caucasian	Male	[70-80)	?
## 9	12522	48330783	Caucasian	Female	[80-90)	?
## 10	15738	63555939	Caucasian	Female	[90-100)	?
## 11	28236	89869032	AfricanAmerican	Female	[40-50)	?
## 12	36900	77391171	AfricanAmerican	Male	[60-70)	?
## 13	40926	85504905	Caucasian	Female	[40-50)	?
## 14	42570	77586282	Caucasian	Male	[80-90)	?
## 15	62256	49726791	AfricanAmerican	Female	[60-70)	?
## 16	73578	86328819	AfricanAmerican	Male	[60-70)	?
## 17	77076	92519352	AfricanAmerican	Male	[50-60)	?
## 18	84222	108662661	Caucasian	Female	[50-60)	?
## 19	89682	107389323	AfricanAmerican	Male	[70-80)	?

## 20	148530	69422211	? Male	[70-80)	?
## 21	150006	22864131	? Female	[50-60)	?
## 22	150048	21239181	? Male	[60-70)	?
## 23	182796	63000108	AfricanAmerican	Female [70-80)	?
## 24	183930	107400762	Caucasian	Female [80-90)	?
## 25	216156	62718876	AfricanAmerican	Female [70-80)	?
## 26	221634	21861756	Other	Female [50-60)	?
## 27	236316	40523301	Caucasian	Male [80-90)	?
## 28	248916	115196778	Caucasian	Female [50-60)	?
## 29	250872	41606064	Caucasian	Male [20-30)	?
## 30	252822	18196434	Caucasian	Female [80-90)	?
##	admission_type_id	discharge_disposition_id	admission_source_id		
## 1	6	25	1		
## 2	1	1	7		
## 3	1	1	7		
## 4	1	1	7		
## 5	1	1	7		
## 6	2	1	2		
## 7	3	1	2		
## 8	1	1	7		
## 9	2	1	4		
## 10	3	3	4		
## 11	1	1	7		
## 12	2	1	4		
## 13	1	3	7		
## 14	1	6	7		
## 15	3	1	2		
## 16	1	3	7		
## 17	1	1	7		
## 18	1	1	7		
## 19	1	1	7		
## 20	3	6	2		
## 21	2	1	4		
## 22	2	1	4		
## 23	2	1	4		
## 24	2	6	1		
## 25	3	1	2		
## 26	1	1	7		
## 27	1	3	7		
## 28	1	1	1		
## 29	2	1	2		
## 30	1	2	7		
##	time_in_hospital	payer_code	medical_specialty	num_lab_procedures	
## 1	1	? Pediatrics-Endocrinology		41	
## 2	3	?	?	59	
## 3	2	?	?	11	
## 4	2	?	?	44	
## 5	1	?	?	51	
## 6	3	?	?	31	
## 7	4	?	?	70	
## 8	5	?	?	73	
## 9	13	?	?	68	
## 10	12	?	InternalMedicine	33	
## 11	9	?	?	47	

## 12	7	?		?	62	
## 13	7	?	Family/GeneralPractice		60	
## 14	10	?	Family/GeneralPractice		55	
## 15	1	?		?	49	
## 16	12	?		?	75	
## 17	4	?		?	45	
## 18	3	?	Cardiology		29	
## 19	5	?		?	35	
## 20	6	?		?	42	
## 21	2	?		?	66	
## 22	2	?		?	36	
## 23	2	?		?	47	
## 24	11	?		?	42	
## 25	3	?		?	19	
## 26	1	?		?	33	
## 27	6	?	Cardiology		64	
## 28	2	?	Surgery-General		25	
## 29	10	?		?	53	
## 30	5	?	Cardiology		52	
##	num_procedures	num_medications	number_outpatient	number_emergency		
## 1	0	1	0	0		
## 2	0	18	0	0		
## 3	5	13	2	0		
## 4	1	16	0	0		
## 5	0	8	0	0		
## 6	6	16	0	0		
## 7	1	21	0	0		
## 8	0	12	0	0		
## 9	2	28	0	0		
## 10	3	18	0	0		
## 11	2	17	0	0		
## 12	0	11	0	0		
## 13	0	15	0	1		
## 14	1	31	0	0		
## 15	5	2	0	0		
## 16	5	13	0	0		
## 17	4	17	0	0		
## 18	0	11	0	0		
## 19	5	23	0	0		
## 20	2	23	0	0		
## 21	1	19	0	0		
## 22	2	11	0	0		
## 23	0	12	0	0		
## 24	2	19	0	0		
## 25	4	18	0	0		
## 26	0	7	0	0		
## 27	3	18	0	0		
## 28	2	11	0	0		
## 29	0	20	0	0		
## 30	0	14	0	0		
##	number_inpatient	diag_1	diag_2	diag_3	number_diagnoses	max_glu_serum
## 1	0	250.83	?	?	1	None
## 2	0	276	250.01	255	9	None
## 3	1	648	250	V27	6	None

## 4	0	8	250.43	403	7	None
## 5	0	197	157	250	5	None
## 6	0	414	411	250	9	None
## 7	0	414	411	V45	7	None
## 8	0	428	492	250	8	None
## 9	0	398	427	38	8	None
## 10	0	434	198	486	8	None
## 11	0	250.7	403	996	9	None
## 12	0	157	288	197	7	None
## 13	0	428	250.43	250.6	8	None
## 14	0	428	411	427	8	None
## 15	0	518	998	627	8	None
## 16	0	999	507	996	9	None
## 17	0	410	411	414	8	None
## 18	0	682	174	250	3	None
## 19	0	402	425	416	9	None
## 20	0	737	427	714	8	None
## 21	0	410	427	428	7	None
## 22	0	572	456	427	6	None
## 23	0	410	401	582	8	None
## 24	0	V57	715	V43	8	None
## 25	0	189	496	427	6	None
## 26	0	786	401	250	3	None
## 27	0	427	428	414	7	None
## 28	0	996	585	250.01	3	None
## 29	0	277	250.02	263	6	None
## 30	0	428	410	414	8	None
##	A1Cresult	metformin	repaglinide	nateglinide	chlorpropamide	glimepiride
## 1	None	No	No	No	No	No
## 2	None	No	No	No	No	No
## 3	None	No	No	No	No	No
## 4	None	No	No	No	No	No
## 5	None	No	No	No	No	No
## 6	None	No	No	No	No	No
## 7	None	Steady	No	No	No	Steady
## 8	None	No	No	No	No	No
## 9	None	No	No	No	No	No
## 10	None	No	No	No	No	No
## 11	None	No	No	No	No	No
## 12	None	No	No	No	No	No
## 13	None	Steady	Up	No	No	No
## 14	None	No	No	No	No	No
## 15	None	No	No	No	No	No
## 16	None	No	No	No	No	No
## 17	None	No	No	No	No	No
## 18	None	No	No	No	No	No
## 19	None	No	No	No	No	No
## 20	None	No	No	No	No	No
## 21	None	No	No	No	No	No
## 22	None	Steady	No	No	No	Steady
## 23	None	No	No	No	No	No
## 24	None	No	No	No	No	No
## 25	None	No	No	No	No	No
## 26	None	Steady	No	No	No	No

## 27	>7	Steady	No	No	No	No
## 28	None	No	No	No	No	No
## 29	None	No	No	No	No	No
## 30	None	Steady	No	No	No	No
##	acetohexamide	glipizide	glyburide	tolbutamide	pioglitazone	
## 1	No	No	No	No	No	
## 2	No	No	No	No	No	
## 3	No	Steady	No	No	No	
## 4	No	No	No	No	No	
## 5	No	Steady	No	No	No	
## 6	No	No	No	No	No	
## 7	No	No	No	No	No	
## 8	No	No	Steady	No	No	
## 9	No	Steady	No	No	No	
## 10	No	No	No	No	No	
## 11	No	No	No	No	No	
## 12	No	No	Up	No	No	
## 13	No	No	No	No	No	
## 14	No	No	No	No	No	
## 15	No	No	No	No	No	
## 16	No	No	No	No	No	
## 17	No	Steady	No	No	No	
## 18	No	No	Steady	No	No	
## 19	No	No	No	No	No	
## 20	No	No	Down	No	No	
## 21	No	No	No	No	No	
## 22	No	No	No	No	No	
## 23	No	No	No	No	No	
## 24	No	No	No	No	No	
## 25	No	Steady	No	No	No	
## 26	No	No	No	No	No	
## 27	No	No	Steady	No	No	
## 28	No	No	No	No	No	
## 29	No	No	No	No	No	
## 30	No	No	Steady	No	No	
##	rosiglitazone	acarbose	miglitol	troglitazone	tolazamide	examide
## 1	No	No	No	No	No	No
## 2	No	No	No	No	No	No
## 3	No	No	No	No	No	No
## 4	No	No	No	No	No	No
## 5	No	No	No	No	No	No
## 6	No	No	No	No	No	No
## 7	No	No	No	No	No	No
## 8	No	No	No	No	No	No
## 9	No	No	No	No	No	No
## 10	Steady	No	No	No	No	No
## 11	No	No	No	No	No	No
## 12	No	No	No	No	No	No
## 13	No	No	No	No	No	No
## 14	No	No	No	No	No	No
## 15	No	No	No	No	No	No
## 16	No	No	No	No	No	No
## 17	No	No	No	No	No	No
## 18	No	No	No	No	No	No

## 19	No	No	No	No	No	No
## 20	No	No	No	No	No	No
## 21	No	No	No	No	No	No
## 22	No	No	No	No	No	No
## 23	No	No	No	No	No	No
## 24	No	No	No	No	No	No
## 25	No	No	No	No	No	No
## 26	No	No	No	No	No	No
## 27	No	No	No	No	No	No
## 28	No	No	No	No	No	No
## 29	No	No	No	No	No	No
## 30	No	No	No	No	No	No
##	citoglipton	insulin	glyburide.metformin	glipizide.metformin		
## 1	No	No		No		No
## 2	No	Up		No		No
## 3	No	No		No		No
## 4	No	Up		No		No
## 5	No	Steady		No		No
## 6	No	Steady		No		No
## 7	No	Steady		No		No
## 8	No	No		No		No
## 9	No	Steady		No		No
## 10	No	Steady		No		No
## 11	No	Steady		No		No
## 12	No	Steady		No		No
## 13	No	Down		No		No
## 14	No	Steady		No		No
## 15	No	Steady		No		No
## 16	No	Up		No		No
## 17	No	Steady		No		No
## 18	No	No		No		No
## 19	No	Steady		No		No
## 20	No	Steady		No		No
## 21	No	Down		No		No
## 22	No	Steady		No		No
## 23	No	No		No		No
## 24	No	No		No		No
## 25	No	Steady		No		No
## 26	No	No		No		No
## 27	No	No		No		No
## 28	No	Steady		No		No
## 29	No	Down		No		No
## 30	No	No		No		No
##	glimepiride.pioglitazone	metformin.rosiglitazone	metformin.pioglitazone			
## 1		No		No		No
## 2		No		No		No
## 3		No		No		No
## 4		No		No		No
## 5		No		No		No
## 6		No		No		No
## 7		No		No		No
## 8		No		No		No
## 9		No		No		No
## 10		No		No		No



## 11	No	No	No
## 12	No	No	No
## 13	No	No	No
## 14	No	No	No
## 15	No	No	No
## 16	No	No	No
## 17	No	No	No
## 18	No	No	No
## 19	No	No	No
## 20	No	No	No
## 21	No	No	No
## 22	No	No	No
## 23	No	No	No
## 24	No	No	No
## 25	No	No	No
## 26	No	No	No
## 27	No	No	No
## 28	No	No	No
## 29	No	No	No
## 30	No	No	No

##	change	diabetesMed	readmitted
## 1	No	No	NO
## 2	Ch	Yes	>30
## 3	No	Yes	NO
## 4	Ch	Yes	NO
## 5	Ch	Yes	NO
## 6	No	Yes	>30
## 7	Ch	Yes	NO
## 8	No	Yes	>30
## 9	Ch	Yes	NO
## 10	Ch	Yes	NO
## 11	No	Yes	>30
## 12	Ch	Yes	<30
## 13	Ch	Yes	<30
## 14	No	Yes	NO
## 15	No	Yes	>30
## 16	Ch	Yes	NO
## 17	Ch	Yes	<30
## 18	No	Yes	NO
## 19	No	Yes	>30
## 20	Ch	Yes	NO
## 21	Ch	Yes	NO
## 22	Ch	Yes	NO
## 23	No	No	NO
## 24	No	No	>30
## 25	Ch	Yes	NO
## 26	No	Yes	NO
## 27	Ch	Yes	NO
## 28	No	Yes	>30
## 29	Ch	Yes	>30
## 30	Ch	Yes	>30

```
# View(df.full) summary(df.full)
summary(df.full$readmitted)
```

```
##    <30    >30    NO
## 11357 35545 54864
```

```
# ===== CLEANED DATASET =====
```

```
data1 <- read.csv("diabetic.data.csv", header = TRUE, sep = ",", na.strings = "") # accounts for header
dim(data1) #101766 observations x 50 variables
```

```
## [1] 101766      50
```

```
tail(data1, 20)
```

##	encounter_id	patient_nbr	race	gender	age	weight
## 101747	443797298	89955270	Caucasian	Male	[70-80)	?
## 101748	443804570	33230016	Caucasian	Female	[70-80)	?
## 101749	443811536	189481478	Caucasian	Female	[40-50)	?
## 101750	443816024	106392411	Caucasian	Female	[70-80)	?
## 101751	443824292	138784172	Caucasian	Female	[80-90)	?
## 101752	443835140	175326800	Caucasian	Male	[70-80)	?
## 101753	443835512	139605341	Other	Female	[40-50)	?
## 101754	443841992	184875899	Other	Male	[40-50)	?
## 101755	443842016	183087545	Caucasian	Female	[70-80)	?
## 101756	443842022	188574944	Other	Female	[40-50)	?
## 101757	443842070	140199494	Other	Female	[60-70)	?
## 101758	443842136	181593374	Caucasian	Female	[70-80)	?
## 101759	443842340	120975314	Caucasian	Female	[80-90)	?
## 101760	443842778	86472243	Caucasian	Male	[80-90)	?
## 101761	443847176	50375628	AfricanAmerican	Female	[60-70)	?
## 101762	443847548	100162476	AfricanAmerican	Male	[70-80)	?
## 101763	443847782	74694222	AfricanAmerican	Female	[80-90)	?
## 101764	443854148	41088789	Caucasian	Male	[70-80)	?
## 101765	443857166	31693671	Caucasian	Female	[80-90)	?
## 101766	443867222	175429310	Caucasian	Male	[70-80)	?
##	admission_type_id	discharge_disposition_id	admission_source_id			
## 101747	1		1			7
## 101748	1		22			7
## 101749	1		4			7
## 101750	3		6			1
## 101751	3		1			1
## 101752	3		6			1
## 101753	3		1			1
## 101754	1		1			7
## 101755	1		1			7
## 101756	1		1			7
## 101757	1		1			7
## 101758	1		1			7
## 101759	1		1			7
## 101760	1		1			7
## 101761	1		1			7
## 101762	1		3			7
## 101763	1		4			5
## 101764	1		1			7
## 101765	2		3			7
## 101766	1		1			7
##	time_in_hospital	payer_code	medical_specialty	num_lab_procedures		
## 101747	4	MC	?			2
## 101748	8	MC	InternalMedicine			51

## 101749	14	MD	?	69	
## 101750	3	MC	Orthopedics	27	
## 101751	3	MD	?	31	
## 101752	13	MC	?	77	
## 101753	3	HM	?	13	
## 101754	13	?	?	51	
## 101755	9	?	?	50	
## 101756	14	MD	?	73	
## 101757	2	MD	?	46	
## 101758	5	?	?	21	
## 101759	5	MC	?	76	
## 101760	1	MC	?	1	
## 101761	6	DM	?	45	
## 101762	3	MC	?	51	
## 101763	5	MC	?	33	
## 101764	1	MC	?	53	
## 101765	10	MC	Surgery-General	45	
## 101766	6	?	?	13	
##	num_procedures	num_medications	number_outpatient	number_emergency	
## 101747	0	7	1	0	
## 101748	6	19	0	0	
## 101749	0	16	0	0	
## 101750	1	29	0	1	
## 101751	2	24	0	0	
## 101752	6	65	0	0	
## 101753	1	5	0	0	
## 101754	2	13	0	0	
## 101755	2	33	0	0	
## 101756	6	26	0	1	
## 101757	6	17	1	1	
## 101758	1	16	0	0	
## 101759	1	22	0	1	
## 101760	0	15	3	0	
## 101761	1	25	3	1	
## 101762	0	16	0	0	
## 101763	3	18	0	0	
## 101764	0	9	1	0	
## 101765	2	21	0	0	
## 101766	3	3	0	0	
##	number_inpatient	diag_1	diag_2	diag_3	number_diagnoses
## 101747	0	427	427	250	5
## 101748	0	410	311	250	9
## 101749	0	295	305	250	5
## 101750	0	715	401	250	9
## 101751	0	574	574	250	9
## 101752	0	424	429	486	16
## 101753	0	348	784	782	8
## 101754	0	250.8	730	731	9
## 101755	0	574	574	250.02	9
## 101756	0	592	599	518	9
## 101757	1	996	585	403	9
## 101758	1	491	518	511	9
## 101759	0	292	8	304	9
## 101760	0	435	784	250	7

##	101761	2	345	438	412	9
##	101762	0	250.13	291	458	9
##	101763	1	560	276	787	9
##	101764	0	38	590	296	13
##	101765	1	996	285	998	9
##	101766	0	530	530	787	9
##		max_glu_serum	A1Cresult	metformin	repaglinide	nateglinide
##	101747	None	None	No	No	No
##	101748	None	>7	No	No	No
##	101749	None	>7	Up	No	No
##	101750	None	Norm	Steady	No	No
##	101751	None	None	No	No	No
##	101752	None	Norm	No	No	No
##	101753	None	None	Steady	No	No
##	101754	None	None	Steady	No	No
##	101755	None	>7	No	No	No
##	101756	None	>8	No	No	No
##	101757	None	None	No	No	No
##	101758	None	None	No	No	No
##	101759	None	None	No	No	No
##	101760	None	None	No	No	No
##	101761	None	None	No	No	No
##	101762	None	>8	Steady	No	No
##	101763	None	None	No	No	No
##	101764	None	None	Steady	No	No
##	101765	None	None	No	No	No
##	101766	None	None	No	No	No
##		chlorpropamide	glimepiride	acetohehexamide	glipizide	glyburide
##	101747	No	No	No	Steady	No
##	101748	No	No	No	No	No
##	101749	No	No	No	No	Steady
##	101750	No	No	No	Steady	No
##	101751	No	No	No	No	No
##	101752	No	No	No	No	No
##	101753	No	No	No	No	Steady
##	101754	No	No	No	No	No
##	101755	No	No	No	No	Up
##	101756	No	No	No	Steady	No
##	101757	No	No	No	No	No
##	101758	No	No	No	No	No
##	101759	No	No	No	No	No
##	101760	No	No	No	No	No
##	101761	No	No	No	No	No
##	101762	No	No	No	No	No
##	101763	No	No	No	No	No
##	101764	No	No	No	No	No
##	101765	No	No	No	Steady	No
##	101766	No	No	No	No	No
##		tolbutamide	pioglitazone	rosiglitazone	acarbose	miglitol
##	101747	No	No	No	No	No
##	101748	No	No	No	No	No
##	101749	No	No	No	No	No
##	101750	No	No	No	No	No
##	101751	No	No	No	No	No

## 101752	No	No	No	No	No
## 101753	No	No	No	No	No
## 101754	No	No	No	No	No
## 101755	No	No	No	No	No
## 101756	No	No	No	No	No
## 101757	No	No	No	No	No
## 101758	No	No	No	No	No
## 101759	No	No	No	No	No
## 101760	No	No	No	No	No
## 101761	No	No	Steady	No	No
## 101762	No	No	No	No	No
## 101763	No	No	No	No	No
## 101764	No	No	No	No	No
## 101765	No	Steady	No	No	No
## 101766	No	No	No	No	No
##	troglitazone	tolazamide	examide	citoglipton	insulin
## 101747	No	No	No	No	No
## 101748	No	No	No	No	Steady
## 101749	No	No	No	No	Down
## 101750	No	No	No	No	Steady
## 101751	No	No	No	No	Down
## 101752	No	No	No	No	Up
## 101753	No	No	No	No	Steady
## 101754	No	No	No	No	Down
## 101755	No	No	No	No	Steady
## 101756	No	No	No	No	Up
## 101757	No	No	No	No	Steady
## 101758	No	No	No	No	Steady
## 101759	No	No	No	No	Up
## 101760	No	No	No	No	Up
## 101761	No	No	No	No	Down
## 101762	No	No	No	No	Down
## 101763	No	No	No	No	Steady
## 101764	No	No	No	No	Down
## 101765	No	No	No	No	Up
## 101766	No	No	No	No	No
##	glyburide.metformin	glipizide.metformin	glimepiride	pioglitazone	
## 101747	No	No	No	No	No
## 101748	No	No	No	No	No
## 101749	No	No	No	No	No
## 101750	No	No	No	No	No
## 101751	No	No	No	No	No
## 101752	No	No	No	No	No
## 101753	No	No	No	No	No
## 101754	No	No	No	No	No
## 101755	No	No	No	No	No
## 101756	No	No	No	No	No
## 101757	No	No	No	No	No
## 101758	No	No	No	No	No
## 101759	No	No	No	No	No
## 101760	No	No	No	No	No
## 101761	No	No	No	No	No
## 101762	No	No	No	No	No
## 101763	No	No	No	No	No

```

## 101764          No          No          No
## 101765          No          No          No
## 101766          No          No          No
##      metformin.rosiglitazone metformin.pioglitazone change diabetesMed
## 101747          No          No          No          Yes
## 101748          No          No          No          Yes
## 101749          No          No          Ch          Yes
## 101750          No          No          Ch          Yes
## 101751          No          No          Ch          Yes
## 101752          No          No          Ch          Yes
## 101753          No          No          Ch          Yes
## 101754          No          No          Ch          Yes
## 101755          No          No          Ch          Yes
## 101756          No          No          Ch          Yes
## 101757          No          No          No          Yes
## 101758          No          No          No          Yes
## 101759          No          No          Ch          Yes
## 101760          No          No          Ch          Yes
## 101761          No          No          Ch          Yes
## 101762          No          No          Ch          Yes
## 101763          No          No          No          Yes
## 101764          No          No          Ch          Yes
## 101765          No          No          Ch          Yes
## 101766          No          No          No          No
##      readmitted
## 101747      <30
## 101748      >30
## 101749      >30
## 101750      NO
## 101751      <30
## 101752      NO
## 101753      NO
## 101754      NO
## 101755      >30
## 101756      >30
## 101757      >30
## 101758      NO
## 101759      NO
## 101760      NO
## 101761      >30
## 101762      >30
## 101763      NO
## 101764      NO
## 101765      NO
## 101766      NO

```

```
# head(data1, 20) View(data1)
```

```
data1 <- data1[-c(6, 11:12, 28, 30, 33, 36:41, 43:47)] # getting rid of unhelpful vars
names(data1)
```

```

## [1] "encounter_id"      "patient_nbr"
## [3] "race"              "gender"
## [5] "age"               "admission_type_id"
## [7] "discharge_disposition_id" "admission_source_id"

```

```
## [9] "time_in_hospital"      "num_lab_procedures"
## [11] "num_procedures"        "num_medications"
## [13] "number_outpatient"     "number_emergency"
## [15] "number_inpatient"      "diag_1"
## [17] "diag_2"                "diag_3"
## [19] "number_diagnoses"      "max_glu_serum"
## [21] "A1Cresult"             "metformin"
## [23] "repaglinide"           "nateglinide"
## [25] "glimepiride"           "glipizide"
## [27] "glyburide"             "pioglitazone"
## [29] "rosiglitazone"         "insulin"
## [31] "change"                "diabetesMed"
## [33] "readmitted"
```

```
dim(data1) # 101766 x 33
```

```
## [1] 101766      33
```

```
summary(data1)
```

```
## encounter_id      patient_nbr      race
## Min.   : 12522     Min.   : 135   ?      : 2273
## 1st Qu.: 84961194  1st Qu.: 23413221 AfricanAmerican:19210
## Median :152388987  Median : 45505143 Asian      : 641
## Mean   :165201646  Mean   : 54330401 Caucasian  :76099
## 3rd Qu.:230270888  3rd Qu.: 87545950 Hispanic   : 2037
## Max.   :443867222  Max.   :189502619 Other      : 1506
##
## gender            age            admission_type_id
## Female           :54708      [70-80):26068  Min.   :1.000
## Male             :47055      [60-70):22483  1st Qu.:1.000
## Unknown/Invalid: 3      [50-60):17256  Median :1.000
##                  [80-90):17197  Mean   :2.024
##                  [40-50): 9685  3rd Qu.:3.000
##                  [30-40): 3775  Max.   :8.000
##                  (Other): 5302
## discharge_disposition_id admission_source_id time_in_hospital
## Min.   : 1.000      Min.   : 1.000      Min.   : 1.000
## 1st Qu.: 1.000      1st Qu.: 1.000      1st Qu.: 2.000
## Median : 1.000      Median : 7.000      Median : 4.000
## Mean   : 3.716      Mean   : 5.754      Mean   : 4.396
## 3rd Qu.: 4.000      3rd Qu.: 7.000      3rd Qu.: 6.000
## Max.   :28.000      Max.   :25.000      Max.   :14.000
##
## num_lab_procedures num_procedures num_medications number_outpatient
## Min.   : 1.0      Min.   :0.00      Min.   : 1.00      Min.   : 0.0000
## 1st Qu.: 31.0     1st Qu.:0.00     1st Qu.:10.00     1st Qu.: 0.0000
## Median : 44.0     Median :1.00     Median :15.00     Median : 0.0000
## Mean   : 43.1     Mean   :1.34     Mean   :16.02     Mean   : 0.3694
## 3rd Qu.: 57.0     3rd Qu.:2.00     3rd Qu.:20.00     3rd Qu.: 0.0000
## Max.   :132.0     Max.   :6.00     Max.   :81.00     Max.   :42.0000
##
## number_emergency number_inpatient      diag_1      diag_2
## Min.   : 0.0000      Min.   : 0.0000      428      : 6862      276      : 6752
## 1st Qu.: 0.0000      1st Qu.: 0.0000      414      : 6581      428      : 6662
```

```

## Median : 0.0000 Median : 0.0000 786 : 4016 250 : 6071
## Mean : 0.1978 Mean : 0.6356 410 : 3614 427 : 5036
## 3rd Qu.: 0.0000 3rd Qu.: 1.0000 486 : 3508 401 : 3736
## Max. :76.0000 Max. :21.0000 427 : 2766 496 : 3305
## (Other):74419 (Other):70204
## diag_3 number_diagnoses max_glu_serum A1Cresult
## 250 :11555 Min. : 1.000 >200: 1485 >7 : 3812
## 401 : 8289 1st Qu.: 6.000 >300: 1264 >8 : 8216
## 276 : 5175 Median : 8.000 None:96420 None:84748
## 428 : 4577 Mean : 7.423 Norm: 2597 Norm: 4990
## 427 : 3955 3rd Qu.: 9.000
## 414 : 3664 Max. :16.000
## (Other):64551
## metformin repaglinide nateglinide glimepiride
## Down : 575 Down : 45 Down : 11 Down : 194
## No :81778 No :100227 No :101063 No :96575
## Steady:18346 Steady: 1384 Steady: 668 Steady: 4670
## Up : 1067 Up : 110 Up : 24 Up : 327
##
##
##
## glipizide glyburide pioglitazone rosiglitazone
## Down : 560 Down : 564 Down : 118 Down : 87
## No :89080 No :91116 No :94438 No :95401
## Steady:11356 Steady: 9274 Steady: 6976 Steady: 6100
## Up : 770 Up : 812 Up : 234 Up : 178
##
##
##
## insulin change diabetesMed readmitted
## Down :12218 Ch:47011 No :23403 <30:11357
## No :47383 No:54755 Yes:78363 >30:35545
## Steady:30849 NO :54864
## Up :11316
##
##
##

```

```
# <<<<<<<<< NA VALUES >>>>>>>>
```

```
sum(is.na(data1))
```

```
## [1] 0
```

```
# show how many NA values in each column
```

```
sapply(data1, function(x) sum(is.na(x))) # no 0 values
```

```

## encounter_id patient_nbr race
## 0 0 0
## gender age admission_type_id
## 0 0 0
## discharge_disposition_id admission_source_id time_in_hospital
## 0 0 0
## num_lab_procedures num_procedures num_medications
## 0 0 0
## number_outpatient number_emergency number_inpatient
## 0 0 0

```



```
##           diag_1           diag_2           diag_3
##           0           0           0
##      number_diagnoses      max_glu_serum      A1Cresult
##           0           0           0
##           metformin      repaglinide      nateglinide
##           0           0           0
##           glimepiride      glipizide      glyburide
##           0           0           0
##           pioglitazone      rosiglitazone      insulin
##           0           0           0
##           change      diabetesMed      readmitted
##           0           0           0
```

## Variables of interest

### Readmitted

```
summary(data1$readmitted)
```

```
##    <30    >30    NO
## 11357 35545 54864
```

```
# <30 >30 NO 11357 35545 54864
```

### Race

```
# variables of interest
```

```
summary(data1$race) # boxplot readmit by race
```

```
##           ? AfricanAmerican           Asian           Caucasian
##           2273           19210           641           76099
##           Hispanic           Other
##           2037           1506
```

```
# filter by race (AfricanAmerican, Asian, Caucasian, Hispanic, Other) &&&
```

```
# ----- AfricanAmerican -----
```

```
readmit_less30.afamer <- filter(data1, race == "AfricanAmerican", readmitted ==
  "<30")
```

```
dim(readmit_less30.afamer) # 2155
```

```
## [1] 2155    33
```

```
readmit_more30.afamer <- filter(data1, race == "AfricanAmerican", readmitted ==
  ">30")
```

```
dim(readmit_more30.afamer) # 6634
```

```
## [1] 6634    33
```

```
readmit_none.afamer <- filter(data1, race == "AfricanAmerican", readmitted ==
  "NO")
```

```
dim(readmit_none.afamer) # 10421
```

```
## [1] 10421    33
```

```
slices.afamer <- c(2155, 6634, 10421)
```

```
lbls.afamer <- c("<30", ">30", "none")
```

```

pct.afamer <- round(slices.afamer/sum(slices.afamer) * 100)
lbls.afamer <- paste(lbls.afamer, "-(", pct.afamer, ")") # add percents to labels
lbls.afamer <- paste(lbls.afamer, "%", sep = "") # ad % to labels

# ---- ASIAN ----
readmit_less30.asian <- filter(data1, race == "Asian", readmitted == "<30")
dim(readmit_less30.asian) # 65

## [1] 65 33

readmit_more30.asian <- filter(data1, race == "Asian", readmitted == ">30")
dim(readmit_more30.asian) # 161

## [1] 161 33

readmit_none.asian <- filter(data1, race == "Asian", readmitted == "NO")
dim(readmit_none.asian) # 415

## [1] 415 33

slices.asian <- c(65, 161, 415)
lbls.asian <- c("<30", ">30", "none")
pct.asian <- round(slices.asian/sum(slices.asian) * 100)
lbls.asian <- paste(lbls.asian, "-(", pct.asian, ")") # add percents to labels
lbls.asian <- paste(lbls.asian, "%", sep = "") # ad % to labels

# ---- CAUCASIAN ----
readmit_less30.cau <- filter(data1, race == "Caucasian", readmitted == "<30")
dim(readmit_less30.cau) # 8592

## [1] 8592 33

readmit_more30.cau <- filter(data1, race == "Caucasian", readmitted == ">30")
dim(readmit_more30.cau) # 27124

## [1] 27124 33

readmit_none.cau <- filter(data1, race == "Caucasian", readmitted == "NO")
dim(readmit_none.cau) # 40383

## [1] 40383 33

slices.cau <- c(8592, 27124, 40383) #76099 total
lbls.cau <- c("<30", ">30", "none")
pct.cau <- round(slices.cau/sum(slices.cau) * 100)
lbls.cau <- paste(lbls.cau, "-(", pct.cau, ")") # add percents to labels
lbls.cau <- paste(lbls.cau, "%", sep = "") # ad % to labels

# ---- HISPANIC ----
readmit_less30.hisp <- filter(data1, race == "Hispanic", readmitted == "<30")
dim(readmit_less30.hisp) # 212

## [1] 212 33

readmit_more30.hisp <- filter(data1, race == "Hispanic", readmitted == ">30")
dim(readmit_more30.hisp) # 27124

## [1] 642 33

```

```
readmit_none.hisp <- filter(data1, race == "Hispanic", readmitted == "NO")
dim(readmit_none.hisp) # 40383
```

```
## [1] 1183 33
```

```
slices.hisp <- c(212, 642, 1183) #76099 total
lbls.hisp <- c("<30", ">30", "none")
pct.hisp <- round(slices.hisp/sum(slices.hisp) * 100)
lbls.hisp <- paste(lbls.hisp, "-(", pct.hisp, ")") # add percents to labels
lbls.hisp <- paste(lbls.hisp, "%", sep = "") # ad % to labels
```

```
# ---- OTHER ----
```

```
readmit_less30.oth <- filter(data1, race == "Other", readmitted == "<30")
dim(readmit_less30.oth) # 145
```

```
## [1] 145 33
```

```
readmit_more30.oth <- filter(data1, race == "Other", readmitted == ">30")
dim(readmit_more30.oth) # 446
```

```
## [1] 446 33
```

```
readmit_none.oth <- filter(data1, race == "Other", readmitted == "NO")
dim(readmit_none.oth) # 915
```

```
## [1] 915 33
```

```
slices.oth <- c(145, 446, 915)
lbls.oth <- c("<30", ">30", "none")
pct.oth <- round(slices.oth/sum(slices.oth) * 100)
lbls.oth <- paste(lbls.oth, "-(", pct.oth, ")") # add percents to labels
lbls.oth <- paste(lbls.oth, "%", sep = "") # ad % to labels
```

```
par(mfrow = c(3, 2))
```

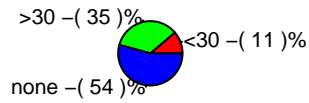
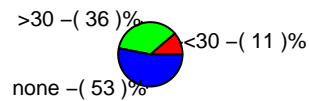
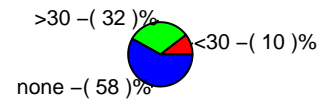
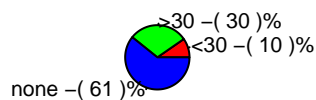
```
pie(slices.afamer, labels = lbls.afamer, col = rainbow(length(lbls.afamer)),
    main = "Pie Chart of African American Readmits")
```

```
pie(slices.asian, labels = lbls.asian, col = rainbow(length(lbls.asian)), main = "Pie Chart of Asian Readmits")
```

```
pie(slices.cau, labels = lbls.cau, col = rainbow(length(lbls.cau)), main = "Pie Chart of Caucasian Readmits")
```

```
pie(slices.hisp, labels = lbls.hisp, col = rainbow(length(lbls.hisp)), main = "Pie Chart of Hispanic Readmits")
```

```
pie(slices.oth, labels = lbls.oth, col = rainbow(length(lbls.hisp)), main = "Pie Chart of Other Races Readmits")
```

**Pie Chart of African American Readmits****Pie Chart of Asian Readmits****Pie Chart of Caucasian Readmits****Pie Chart of Hispanic Readmits****Pie Chart of Other Races Readmits**

## Gender

```
summary(data1$gender) #boxplot
```

```
##           Female           Male Unknown/Invalid
##           54708           47055                 3
```

```
# Female Male Unknown/Invalid 54708 47055 3
```

```
readmit_less30.gender <- filter(data1, readmitted == "<30")
```

```
dim(readmit_less30.gender) # 11357 total observations
```

```
## [1] 11357    33
```

```
dim(filter(readmit_less30.gender, gender == "Female")) #6152 female ~54% of <30 dataset, 11.2% of fema
```

```
## [1] 6152    33
```

```
dim(filter(readmit_less30.gender, gender == "Male")) #5205 male, 45% of <30 dataset, 11.1% of males of
```

```
## [1] 5205    33
```

```
readmit_more30.gender <- filter(data1, readmitted == ">30")
```

```
nrow(readmit_more30.gender) #35545 total observations
```

```
## [1] 35545
```

```

nrow(filter(readmit_more30.gender, gender == "Female")) #19518 female ~54% of >30 dataset, 35.7% of fe

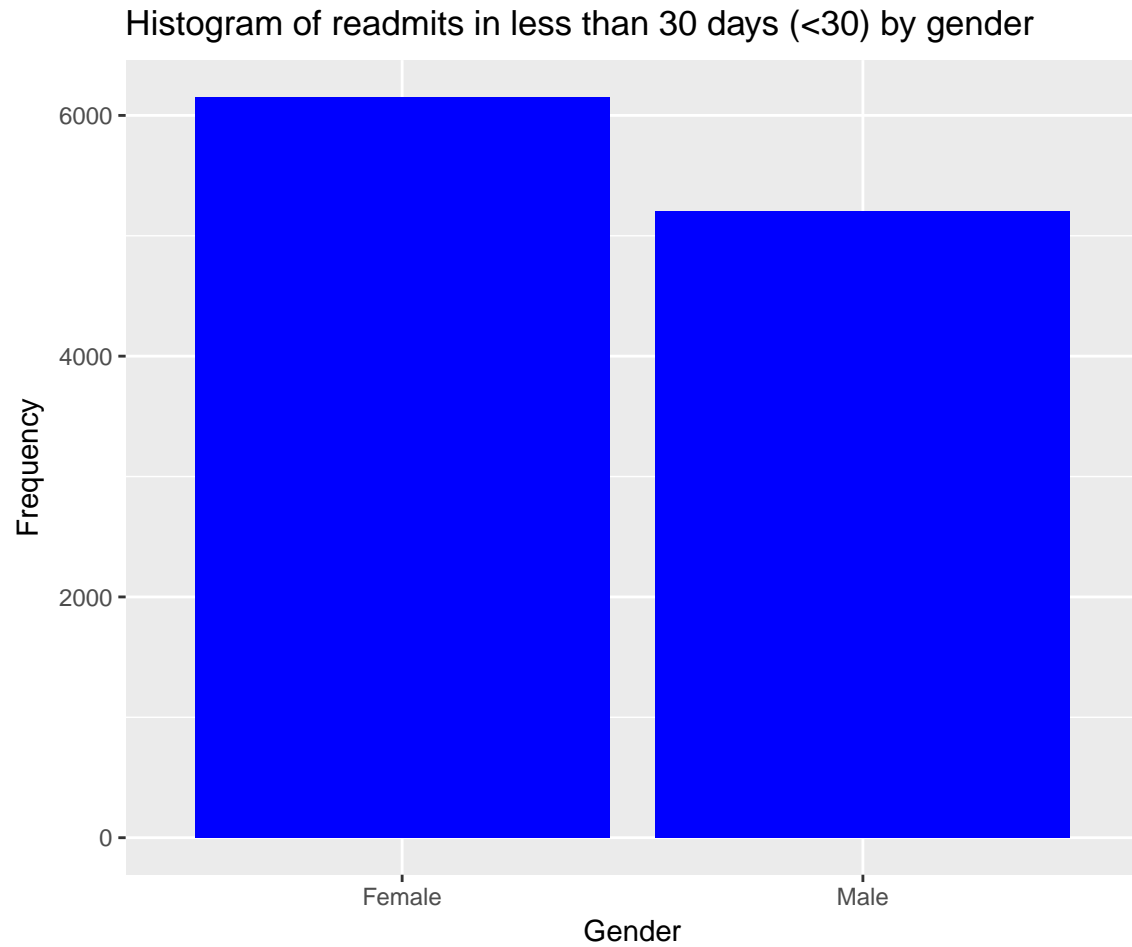
## [1] 19518
nrow(filter(readmit_more30.gender, gender == "Male")) #16027 male, 45%, 34.1% of males of total datase

## [1] 16027
perc.female <- (19518/35545)
perc.female #0.5491068

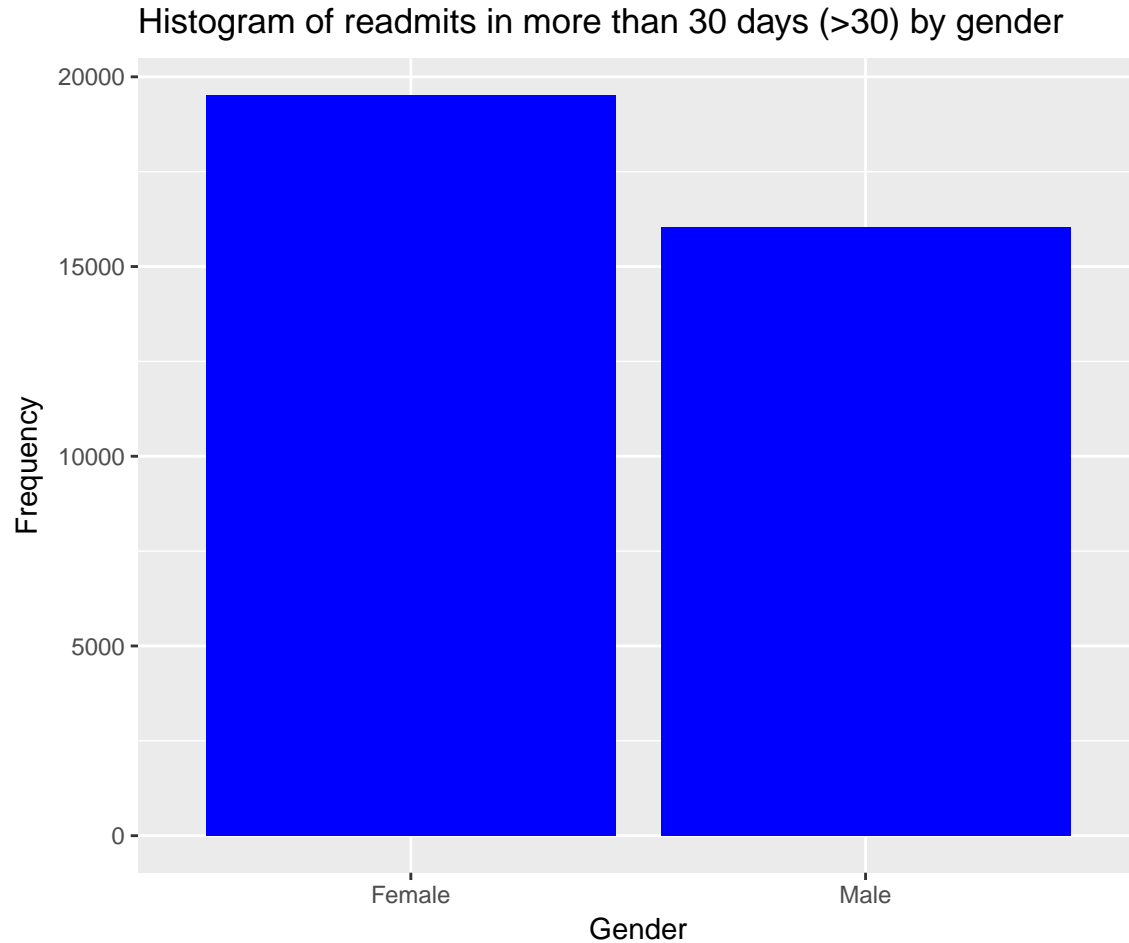
## [1] 0.5491068
perc.male <- (16027/35545)
perc.male # 0.4508932

## [1] 0.4508932
par(mfrow = c(2, 2))
# nrow(which(readmit_less30.gender == 'Female'))
# nrow(filter(readmit_less30.gender, gender == 'Female'))
# nrow(readmit_less30.gender) x.perc.gender <-
# c(nrow(filter(readmit_less30.gender, gender ==
# 'Female'))/nrow(readmit_less30.gender), nrow(filter(readmit_less30.gender,
# gender == 'Male'))/nrow(readmit_less30.gender)) x.perc.gender
ggplot(readmit_less30.gender) + geom_bar(aes(x = gender, fill = "blue") + labs(title = "Histogram of r
  x = "Gender", y = "Frequency")

```



```
ggplot(readmit_more30.gender) + geom_bar(aes(x = gender), fill = "blue") + labs(title = "Histogram of r  
x = "Gender", y = "Frequency")
```



In the cleaned dataset we have 54708 female observations and 47055 male observations, which means roughly 54% of the patients under consideration were female (for all readmission categories), while ~46% were male. When comparing hospital readmits striated by gender, of the patients that were readmitted in *under* 30 days approximately 54% (6152/11357) were female, matching the overall female representation. Similarly, of patients that were readmitted *over* 30 days again 54% (19518/35545) were female. It's worth noting that the total number of patients (male & female) readmitted over 30 days is about 3 times that of those readmitted in *less* than 30 days.

There seems to be a gap between genders here implying that women are more prone to readmission, but this is quickly rebuked when we compare the genders in terms of their total observations. For patients who were readmitted in *less* than 30 days, female patients represent 11.2% (6152/54708) of the total female population, while those who are male represent a similar 11.1% (5205/47055) of the overall male population. The same is true for patients readmitted *over* 30 days: female patients account for 35.7% (19518/54708) of the total female population, while male patients comprise 34.1% (16027/47055) of the total male population.

This lends credence to the notion that gender does not contribute to likelihood of readmission.

## Age

```
summary(data1$age) #scatterplot
```

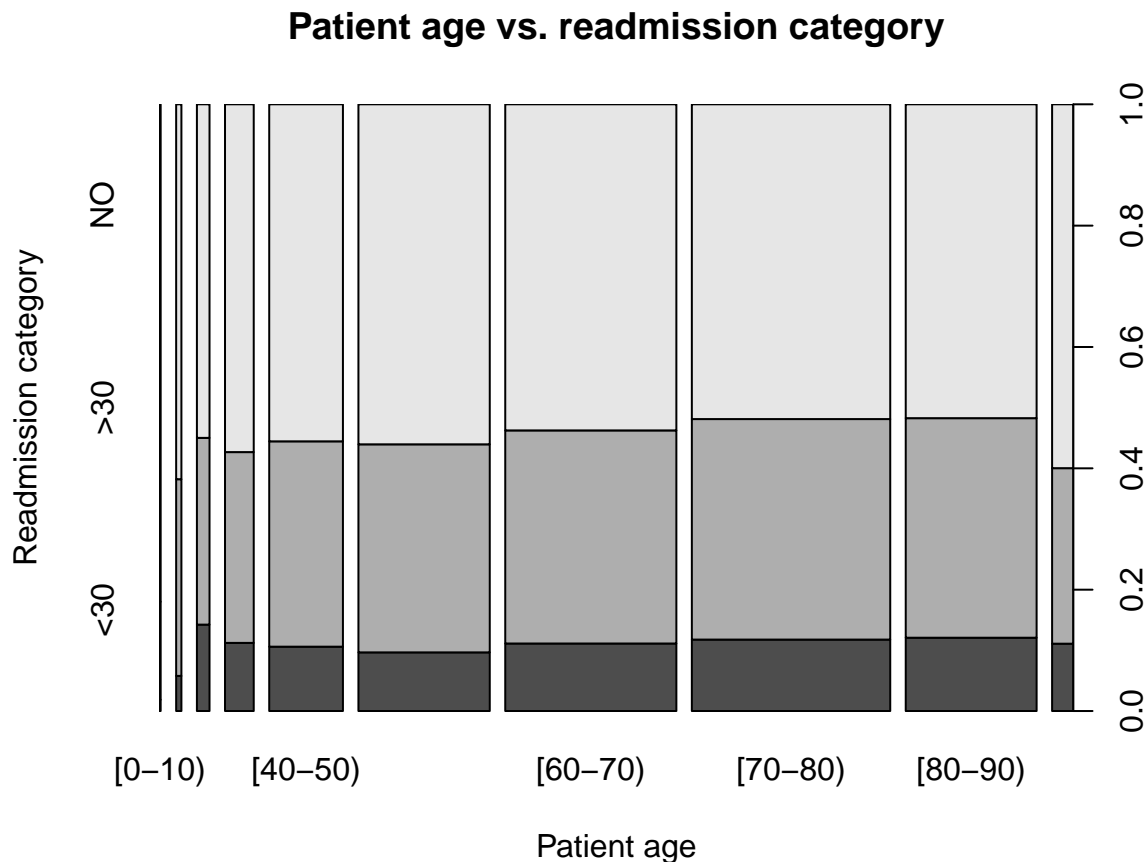
```
##    [0-10)  [10-20)  [20-30)  [30-40)  [40-50)  [50-60)  [60-70)  [70-80)
##         161        691       1657       3775       9685      17256      22483      26068
##    [80-90) [90-100)
```

```
##      17197      2793
# <<< SCATTERPLOT WITH LS LINE ADDED >>>>
lm.age <- lm(readmitted ~ age, data = data1)

## Warning in model.response(mf, "numeric"): using type = "numeric" with a
## factor response will be ignored

## Warning in Ops.factor(y, z$residuals): '-' not meaningful for factors
plot(data1$age, data1$readmitted, pch = 16, xlab = "Patient age", ylab = "Readmission category",
     main = "Patient age vs. readmission category")
abline(lm.age, col = "red", lwd = 4)

## Warning in abline(lm.age, col = "red", lwd = 4): only using the first two
## of 10 regression coefficients
```



```
# abline(h=mean(county_data$dem12_frac), lwd=5, col='blue')
```

It appears that the categories with the largest number of readmits is 70-80 and 80-90, which are almost identical. An interesting trend that we see is that the 20-30 age group has the overall highest readmit frequency under 30 days, which is surprising.

Change (in diabetes medication)



```

summary(data1$change)  #boxplot - change in diabetes medication

##      Ch      No
## 47011 54755
# Ch No 47011 54755

# <30 readmit patients
readmit_less30.change <- filter(data1, readmitted == "<30")
dim(readmit_less30.change)  # 11357 total observations

## [1] 11357      33
dim(filter(readmit_less30.change, change == "Ch"))  #5558 patients with a change of med readmitted <30

## [1] 5558      33
dim(filter(readmit_less30.change, change == "No"))  #5799 patients with NO change in meds readmitted <30

## [1] 5799      33
# >30 readmit patients
readmit_more30.change <- filter(data1, readmitted == ">30")
dim(readmit_more30.change)  #35545 observations

## [1] 35545      33
dim(filter(readmit_more30.change, change == "Ch"))  #17272

## [1] 17272      33
perc.readmit_more30.ch <- 17272/35545
perc.readmit_more30.ch  #0.4859193

## [1] 0.4859193
perc.all.ch <- 17272/47011
perc.all.ch  #0.3674034

## [1] 0.3674034
dim(filter(readmit_more30.change, change == "No"))  #18273

## [1] 18273      33
perc.readmit_more30.no <- 18273/35545
perc.readmit_more30.no  #0.5140807

## [1] 0.5140807
perc.all.no <- 18273/54755
perc.all.no  #0.3337229

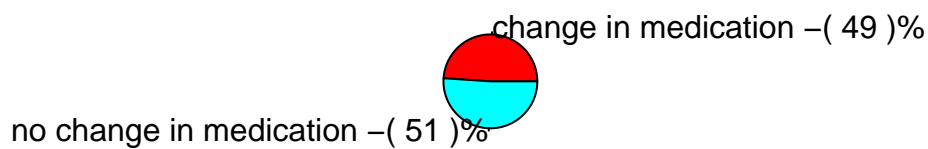
## [1] 0.3337229

# pie charts
par(mfrow = c(2, 1))
slices.change <- c(5558, 5799)
lbls.change <- c("change in medication", "no change in medication")
pct.change <- round(slices.change/sum(slices.change) * 100)
lbls.change <- paste(lbls.change, "-(", pct.change, ")")  # add percents to labels
lbls.change <- paste(lbls.change, "%", sep = "")  # ad % to labels

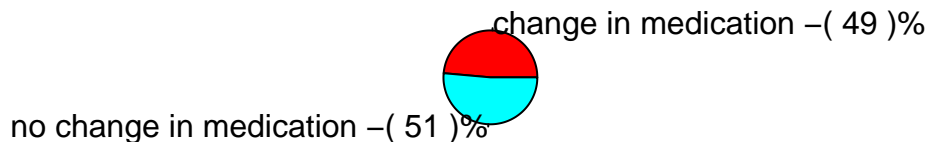
```

```
pie(slices.change, labels = lbls.change, col = rainbow(length(lbls.change)),
    main = "Pie Chart of change in diabetes medication status for patients readmitted <30 days")
slices.nochange <- c(17272, 18273)
lbls.nochange <- c("change in medication", "no change in medication")
pct.nochange <- round(slices.nochange/sum(slices.nochange) * 100)
lbls.nochange <- paste(lbls.nochange, "-(", pct.nochange, "%)" # add percents to labels
lbls.nochange <- paste(lbls.nochange, "%", sep = "") # ad % to labels
pie(slices.nochange, labels = lbls.nochange, col = rainbow(length(lbls.nochange)),
    main = "Pie Chart of change in diabetes medication status for patients readmitted >30 days")
```

## art of change in diabetes medication status for patients readmitte



## art of change in diabetes medication status for patients readmitte



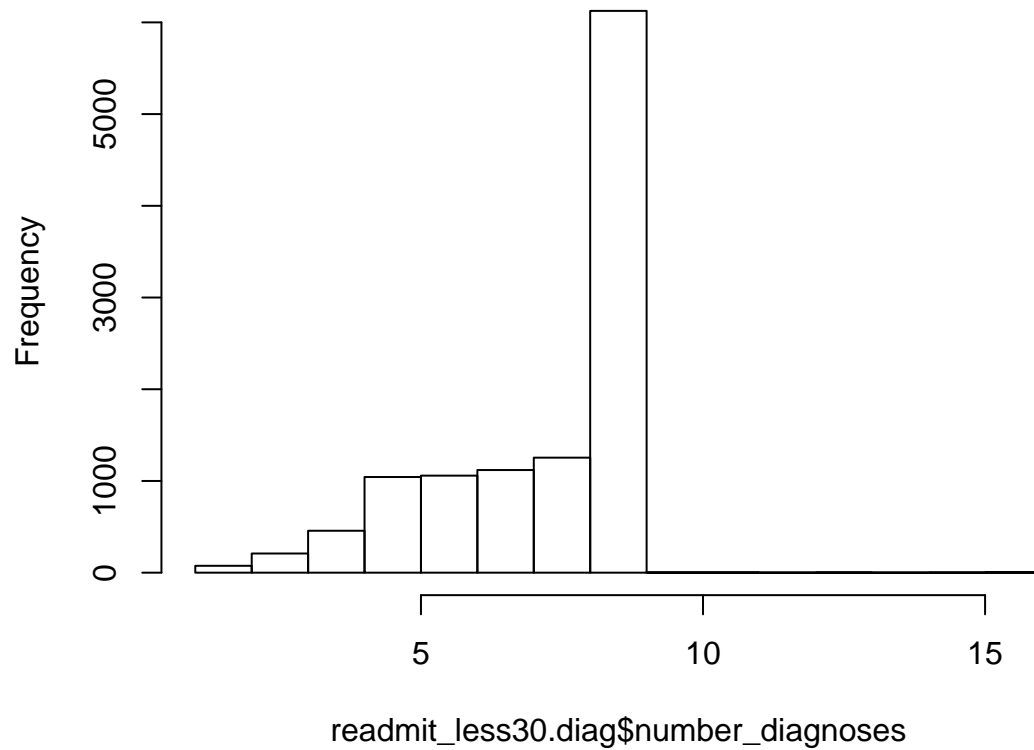
### Number of diagnosis

```
summary(data1$number_diagnoses) #bar plot
```

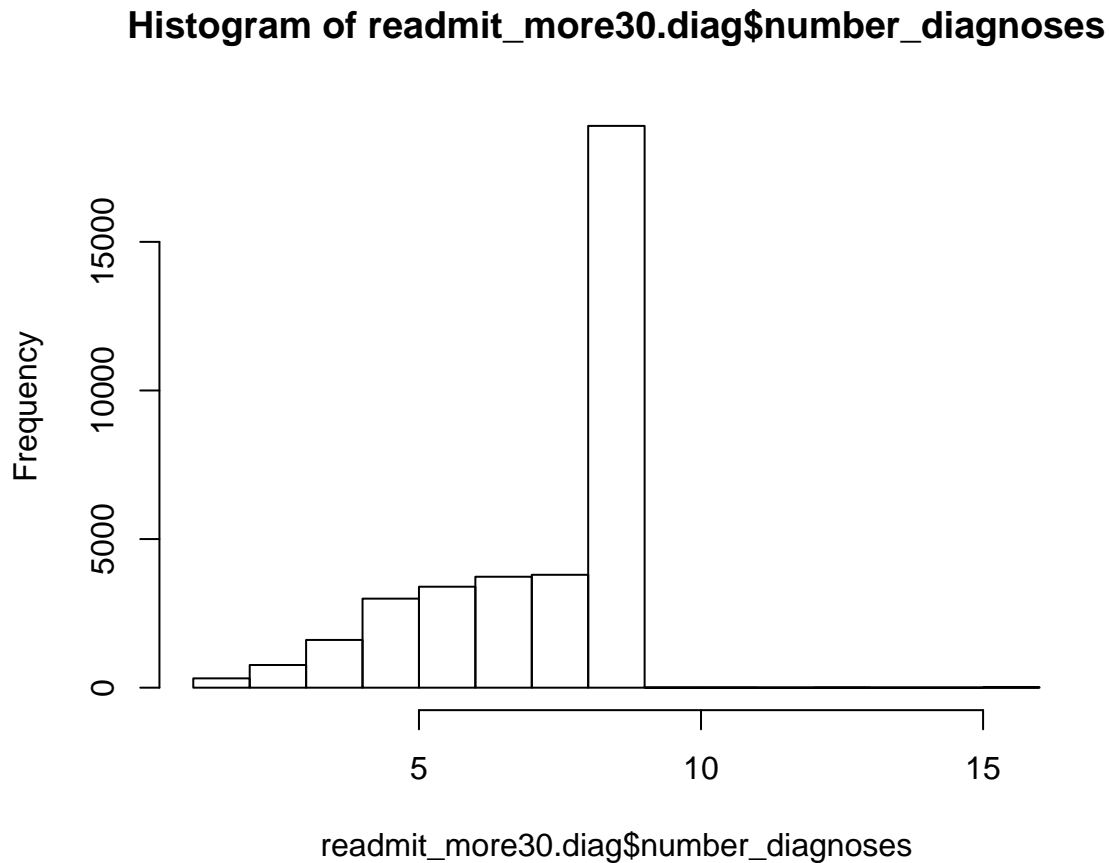
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1.000   6.000   8.000   7.423   9.000  16.000
```

```
readmit_less30.diag <- filter(data1, readmitted == "<30")
hist(readmit_less30.diag$number_diagnoses)
```

### Histogram of readmit\_less30.diag\$number\_diagnoses



```
readmit_more30.diag <- filter(data1, readmitted == ">30")  
hist(readmit_more30.diag$number_diagnoses)
```



There consistently seems to be a large spike in frequency around 9 diagnoses.

## Research approach

From the *Goals* section above, your study should respond to the following:

- 1) Identify important factors that capture the chance of a readmission within 30 days.

The set of available predictors is not limited to the raw variables in the data set. You may engineer any factors using the data, that you think will improve your model's quality.

- 2) For the purpose of classification, propose a model that can be used to predict whether a patient will be a readmit within 30 days. Justify your choice. Hint: use a decision criterion, such as AUC, to choose among a few candidate models.

Based on a quick and somewhat arbitrary guess, we estimate it costs twice as much to mislabel a readmission than it does to mislabel a non-readmission. Based on this risk ratio, propose a specific classification rule to minimize the cost. If you find any information that could provide a better cost estimate, please justify it in your write-up and use the better estimate in your answer.

Suggestion: You may use any of the methods covered so far in parts 1) and 2), and they need not be the same. Also keep in mind that a training/testing data split may be necessary.

## Suggested outline

As you all know, it is very important to present your findings well. To achieve the best possible results you need to understand your audience.

Your target audience is a manager within the hospital organization. They hold an MBA, are familiar with medical terminology (though you do not need any previous medical knowledge), and have gone through a similar course to our Modern Data Mining with someone like your professor. You can assume thus some level of technical familiarity, but should not let the paper be bogged down with code or other difficult to understand output.

Note then that the most important elements of your report are the clarity of your analysis and the quality of your proposals.

A suggested outline of the report would include the following components:

1) Executive Summary

- This section should be accessible by people with very little statistical background (avoid using technical words and no direct R output is allowed)
- Give a background of the study. You may check the original website or other sources to fill in some details, such as to why the questions we address here are important.
- A quick summary about the data.
- Methods used and the main findings.
- You may use clearly labelled and explained visualizations.
- Issues, concerns, limitations of the conclusions. This is an especially important section to be honest in - we might be Penn students, but we are statisticians today.

2) Detailed process of the analysis

i) Data Summary

- Nature of the data, origin
- Necessary quantitative and graphical summaries
- Are there any problems with the data?
- Which variables are considered as input

ii) Analyses

- Various appropriate statistical methods: e.g. glmnet
- Comparisons various models
- Final model(s)

iii) Conclusion

- Summarize results and the final model
- Final recommendations

Maintain a good descriptive flow in the text of your report. Use Appendices to display lengthy output.

iii) Appendix

- All your R code (code without comments is no good!) if you are not using `rmd` format.
- Any thing necessary to keep but for which you don't want them to be in the main report.

## Collaboration

This is an **individual** assignment. We will only allow private Piazza posts for questions. If there are questions that are generally useful, we will release that information.