Readmittance Rate for Diabetes Treatment Objective: Identify certain factors that affect the rate at which diabetes patients are readmitted to impatient care with the goal of improving treatment and patient outcomes. The Data Set: This dataset represents 10 years worth of clinical care data spanning from 1998 - 2008 for patients being treated for diabetes and was taken from a national data warehouse that collects comprehensive clinical records across hospitals throughout the United States. The data contains info from 130 U.S. hospitals and contains over 50 features spanning from age, race, gender, time in hospital, the number of lab tests perfromed, the number of diagnoses, as well as over 20 different medications that may have been administered. In order to be included in this dataset, certain criteria had to be met: 1. It is an inpatient encounter (a hospital admission). 2. It is a diabetic encounter, that is, one during which any kind of diabetes was entered to the system as a diagnosi 3. The length of stay was at least 1 day and at most 14 days. 4. Laboratory tests were performed during the encounter. 5. Medications were administered during the encounter. The most important feature I will be examining however, is readmission. Patients are either readmitted in less than 30 days, greater than 30 days or not readmitted at all. The goal will be to identify specific factors pertaining to patient care that correlate to either higher or lower readmittance rates. By finding these factors, hospitals and caretakers will be able to focus on these specific areas in diabetes treatment, leading to improved patient outcomes. **Data Exploration** In [1]: import numpy as np import pandas as pd import matplotlib.pyplot as plt %matplotlib inline In [2]: diabetic_data = pd.read_csv(r'\Users\mike1\Documents\diabetic_data.csv') diabetes = diabetic data.sample(n = 10000) The first bit of information I wanted to gather was on the readmittance rates. I have drawn a sample of 10,000 patients and we see that in the sample, just over 53 percent of patients are not readmitted. Of the remaining patients, 35 percent are readmitted in over 30 days. The rest are readmitted in under 30 days. In [3]: | diabetes['readmitted'].value counts().plot.bar(title = "Patient Readmitted") print("Readmittance percentage \n", diabetes['readmitted'].value_counts()/10000) Readmittance percentage NO 0.5374 >30 0.3506 <30 0.1120 Name: readmitted, dtype: float64 Patient Readmitted 5000 4000 3000 2000 1000 **Patient Demographics** Next, I wanted to get a feel for the demographics of the patient population. From the charts below, we see that about 90 percent of the patient data is for individuals over 40. Also, the vast majority of patients are Caucasian (over 70%), with the remaining percentage being predominantly African American. Finally, females are slightly more represented than males (54% to 46%). In [4]: plt.figure(figsize = (15, 5)) print("Summary of Age, Race and Gender") print("Age percentage \n", diabetes['age'].value counts()/10000) print("Race percentage \n", diabetes['race'].value_counts()/10000) print("Gender percentage \n", diabetes['gender'].value counts()/10000) plt.subplot(1, 3, 1) diabetes['age'].value counts().plot.bar(title = "Patient Age") plt.subplot(1, 3, 2) diabetes['race'].value_counts().plot.bar(title = "Patient Race") plt.subplot(1, 3, 3) diabetes['gender'].value_counts().plot.bar(title = "Patient Gender") Summary of Age, Race and Gender Age percentage [70-80) 0.2523 [60-70)0.2262 [50-60) 0.1694 [80-90) 0.1666 [40-50)0.0943 [30-40)0.0372 [90-100)0.0280 [20-30)0.0165 [10-20)0.0080 [0-10)0.0015 Name: age, dtype: float64 Race percentage Caucasian 0.7506 0.1856 AfricanAmerican 0.0222 Hispanic 0.0202 Other 0.0158 Asian 0.0056 Name: race, dtype: float64 Gender percentage Female 0.5275 0.4724 Male Unknown/Invalid 0.0001 Name: gender, dtype: float64 Out[4]: <matplotlib.axes. subplots.AxesSubplot at 0x21ce66ccf98> Patient Age Patient Race Patient Gender 2500 5000 7000 6000 2000 4000 5000 1500 4000 1000 3000 2000 2000 500 1000 1000 (20-60) (90-100) **Patient Stay** To get an idea of the typical hospital stay, I have decided to examine the length of stay, the number of lab tests performed and the number of medications given. The average length of stay in the hospital is 4.4 days. The average number of lab tests performed is 43 and the average number of medication given during the stay is 16. In [6]: plt.figure(figsize = (10, 12)) plt.subplot(3, 2, 1) plt.hist(diabetes['time in hospital']) plt.title("Length of Stay") plt.subplot(3, 2, 2) diabetes.boxplot(column = 'time in hospital') print('Average time spent in hospital is', np.mean(diabetes.time in hospital), 'days') plt.subplot(3, 2, 3) plt.hist(diabetes['num lab procedures']) plt.title("Number of Lab Tests Performed") plt.subplot(3, 2, 4)diabetes.boxplot(column = 'num lab procedures') print("Average number of lab tests perfomed during stay", np.mean(diabetes.num_lab_procedures)) plt.subplot(3, 2, 5) plt.hist(diabetes['num_medications']) plt.title("Number of Medications Administered") plt.subplot(3, 2, 6) diabetes.boxplot(column = 'num medications') print("Average number of medications given during stay", np.mean(diabetes.num medications)) Average time spent in hospital is 4.3933 days Average number of lab tests perfomed during stay 43.063 Average number of medications given during stay 15.9997 Length of Stay 3000 12 2500 10 2000 1500 1000 500 time_in_hospital Number of Lab Tests Performed 2000 80 1500 60 1000 40 20 500 num_lab_procedures Number of Medications Administered 4000 70 3500 60 3000 50 2500 40 2000 30 1500 20 1000 10 500 num_medications **Patient Treatment** Finally, to get a sense of the patient's treatment, I will examine whether diabetes medication was prescribed and also if medication was changed (either the dosage or an actual change in medication). In 76 percent of the encounters diabetes medication was prescribed. Additionally, medication was changed 46 percent of the time. In [7]: plt.figure(figsize = (10, 5)) plt.subplot(1, 2, 1)diabetes['diabetesMed'].value counts().plot.bar(title = "Prescribing Diabetes Medication") print("The percentage of times diabetes medication was prescribed \n", diabetes['diabetesMed'].value counts()/10000) plt.subplot(1, 2, 2)diabetes['change'].value_counts().plot.bar(title = "Changing Medication") print("The percentage of times diabetic mediaction was changed \n", diabetes['change'].value counts()/10000) The percentage of times diabetes medication was prescribed 0.7652 Yes 0.2348 Name: diabetesMed, dtype: float64 The percentage of times diabetic mediaction was changed No 0.5399 0.4601 Name: change, dtype: float64 Prescribing Diabetes Medication **Changing Medication** 8000 5000 7000 6000 4000 5000 3000 4000 3000 2000 2000 1000 1000 **Analytic Questions** Having explored the data, we will now examine the patient demographics, stay and treatment in further detail. The goal is to find indications within these features that will provide insight into where diabetes treatment is having success, and also where there are shortcomings. The three main questions I will be looking to answer are: 1. Does race, gender, or age lead to higher or lower readmittance rates? 2. Does the length of stay, number of lab tests performed or medications given correlate to lower readmittance? 3. Does prescribing or changing medication have an affect on readmittance rates? The first step I have decided to take in answering these questions is splitting the data set into two separate sets; one containing the information for patients who were readmitted (for both less than 30 days and greater than 30 days) and the other containing patients who were not readmitted. In [8]: notreadmitted = diabetes.loc[diabetes['readmitted'] == 'NO'] readmitted = diabetes.loc[diabetes['readmitted'] != 'NO'] To answer the first question, I have decided to calculate probabilities of being readmitted given age, race or gender. For age, the probability of being readmitted stays above 42 percent after age 20, and peaks at just over 49 percent multiple times. In terms of race, readmittance is fairly similar for each race. Caucasian's have the highest rate at just under 47 percent while Asians have the lowest readmittance rate at 42 percent. One important note is that the sample contains predominantly Caucasian and African American patients, so probabilities for other races are likely less reliable. Finally, in terms of gender females have a slightly probability for being readmitted at around 47 percent versus 45 percent for males. After examining the demographics, there doesn't appear to be any statistically significant features that affect readmittance rates as all probabilities are fairly close to one another and close to the total readmittance percentage of 53 percent. In $[9]: | \mathbf{x} = ['0-10', '10-20', '20-30', '30-40', '40-50', '50-60', '60-70', '70-80', '80-90', '90-100']$ y_no = (notreadmitted.groupby(['age']).size()/diabetes.groupby(['age']).size()).tolist() y yes = (readmitted.groupby(['age']).size()/diabetes.groupby(['age']).size()).tolist() plt.figure(figsize = (15, 4)) plt.subplot(1, 2, 1) plt.plot(x, y_yes, color = 'red') plt.title("Probability of Being Readmitted") plt.xlabel('Age') plt.ylabel('Probability') plt.subplot(1, 2, 2) plt.plot(x, y no) plt.title("Probability of Being Not Readmitted") plt.xlabel('Age') plt.ylabel('Probability') print("Probability of being readmitted\n", readmitted.groupby(['age']).size()/diabetes.groupby(['age']).size()) print("Probability of NOT being readmitted\n", notreadmitted.groupby(['age']).size()/diabetes.groupby(['age']).size()) Probability of being readmitted age [0-10)0.066667 [10-20)0.325000 [20-30) 0.496970 [30-40)0.424731 [40-50)0.448568 [50-60) 0.426800 [60-70) 0.456233 0.493460 [70-80) [80 - 90)0.493397 0.407143 [90-100) dtype: float64 Probability of NOT being readmitted age [0-10)0.933333 [10-20)0.675000 [20-30)0.503030 [30-40)0.575269 [40-50)0.551432 [50-60)0.573200 [60-70)0.543767 [70-80)0.506540 [80-90)0.506603 0.592857 [90-100) dtype: float64 Probability of Being Readmitted Probability of Being Not Readmitted 0.5 0.9 0.4 0.8 0.3 Probabi 0.7 0.2 0.6 0.1 0.5 0-10 10-20 20-30 30-40 40-50 50-60 60-70 70-80 80-90 90-100 0-10 10-20 20-30 30-40 40-50 50-60 60-70 70-80 80-90 90-100 In [10]: x = ['?', 'AfricanAmerican', 'Asian', 'Caucasian', 'Hispanic', 'Other'] y_no = (notreadmitted.groupby(['race']).size()/diabetes.groupby(['race']).size()).tolist() y_yes = (readmitted.groupby(['race']).size()/diabetes.groupby(['race']).size()).tolist() plt.figure(figsize = (15, 4)) plt.subplot(1, 2, 1) plt.plot(x, y_yes, color = 'red') plt.title("Probability of Being Readmitted") plt.xlabel('Race') plt.ylabel('Probability') plt.subplot(1, 2, 2) plt.plot(x, y_no) plt.title("Probability of Being Not Readmitted") plt.xlabel('Race') plt.ylabel('Probability') print("Probability of being readmitted\n", readmitted.groupby(['race']).size()/diabetes.groupby(['race']).size()) print("Probability of NOT being readmitted\n", notreadmitted.groupby(['race']).size()/diabetes.groupby(['race']).size()) Probability of being readmitted race 0.373874 0.455819 AfricanAmerican 0.428571 Asian Caucasian 0.467359 0.440594 Hispanic 0.481013 dtype: float64 Probability of NOT being readmitted 0.626126 AfricanAmerican 0.544181 0.571429 0.532641 Caucasian 0.559406 Hispanic Other 0.518987 dtype: float64 Probability of Being Readmitted Probability of Being Not Readmitted 0.48 0.62 0.46 0.60 ≥ 0.44 **≦** 0.58 0.56 මී 0.42 0.40 0.54 0.38 0.52 Other AfricanAmerican Other AfricanAmerican Asian Caucasian Hispanic Hispanic Asian Caucasian Race In [11]: print("Probability of being readmitted\n", readmitted.groupby(['gender']).size()/diabetes.groupby(['gender']).size()) print("Probability of NOT being readmitted\n", notreadmitted.groupby(['gender']).size()/diabetes.groupby(['gender']).size()) Probability of being readmitted gender Female 0.472417 0.451736 Male Unknown/Invalid NaN dtype: float64 Probability of NOT being readmitted gender Female 0.527583 0.548264 Male Unknown/Invalid 1.000000 dtype: float64 I will now look to see how the patient's hospital stay affects readmission by first looking at the length of the stay. In [12]: x = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]y_no = (notreadmitted.groupby(['time_in_hospital']).size()/diabetes.groupby(['time_in_hospital']).size()).tolist() y_yes = (readmitted.groupby(['time_in_hospital']).size()/diabetes.groupby(['time_in_hospital']).size()).tolist() plt.figure(figsize = (15, 4)) plt.subplot(1, 2, 1) plt.plot(x, y_yes, color = 'red') plt.title("Probability of Being Readmitted") plt.xlabel('Length of Stay') plt.ylabel('Probability') plt.subplot(1, 2, 2) plt.plot(x, y no) plt.title("Probability of Being Not Readmitted") plt.xlabel('Length of Stay') plt.ylabel('Probability') print("Probability of being readmitted\n", readmitted.groupby(['time_in_hospital']).size()/diabetes.groupby(['time_in_hospital']) print("Probability of NOT being readmitted\n", notreadmitted.groupby(['time_in_hospital']).size()/diabetes.groupby(['time_in_ hospital']).size()) Probability of being readmitted time_in_hospital 0.388125 0.438534 0.459026 0.503715 5 0.486071 0.523438 0.465116 0.481297 9 0.508897 10 0.467249 11 0.492611 12 0.405594 13 0.429907 14 0.519231 dtype: float64 Probability of NOT being readmitted time_in_hospital 0.611875 0.561466 0.540974 0.496285 0.513929 0.476562 0.534884 0.518703 0.491103 9 0.532751 11 0.507389 12 0.594406 13 0.570093 14 0.480769 dtype: float64 Probability of Being Readmitted Probability of Being Not Readmitted 0.52 0.60 0.50 0.58 0.48 ≥ 0.56 0.46 면 0.54 g 0.44 0.52 0.42 0.50 0.40 0.48 14 12 12 2 10 Length of Stay Length of Stay In [13]: plt.figure(figsize = (10, 8)) plt.subplot(2, 2, 1) plt.hist(readmitted['time_in_hospital'], color = 'red') plt.title("Readmitted") plt.subplot(2, 2, 2) readmitted.boxplot(column = 'time in hospital') print('Average time spent in hospital and readmitted is', np.mean(readmitted.time_in_hospital), 'days') print("Standard deviation is", np.std(readmitted.time in hospital)) plt.subplot(2, 2, 3) plt.hist(notreadmitted['time_in_hospital']) plt.title("Not Readmitted") plt.subplot(2, 2, 4) notreadmitted.boxplot(column = 'time_in_hospital') print('Average time spent in hospital and not readmitted is', np.mean(notreadmitted.time in hospital), 'days') print("Standard deviation is", np.std(notreadmitted.time in hospital)) Average time spent in hospital and readmitted is 4.528318201469952 days Standard deviation is 2.9408636950258304 Average time spent in hospital and not readmitted is 4.277074804614812 days Standard deviation is 2.995606372547925 Readmitted 1200 12 1000 10 800 600 400 200 10 2 time_in_hospital Not Readmitted 1750 12 1500 10 1250 1000 750 500 250 time_in_hospital Examining the data for patients who are readmitted and those who are not in terms of the length of stay, we see that in general after day 4, the probability that a patient will be readmitted remains above 46 percent (except for stays of 12 or 13 days where the probability decreases to 40 and 43 percent respectively). This peaks at about a 52 percent probability for patients who stay six days. This does seem to be an area of concern because the longer a patient stays in the hospital, the goal should be to decrease the likelihood of being readmitted and after days 12 and 13 the probability increases back to 52 percent. In fact, the average length of stay for patients who are readmitted is longer than for patients who are not readmitted. In [14]: plt.figure(figsize = (10, 10)) plt.subplot(2, 2, 1) plt.hist(readmitted['num_lab_procedures'], color = 'red') plt.title("Readmitted") plt.subplot(2, 2, 2) readmitted.boxplot(column = 'num lab procedures') print('Average number of lab tests performed and readmitted', np.mean(readmitted.num lab procedures)) print("Standard deviation is", np.std(readmitted.num_lab_procedures)) plt.subplot(2, 2, 3) plt.hist(notreadmitted['num lab procedures']) plt.title("Not Readmitted") plt.subplot(2, 2, 4) notreadmitted.boxplot(column = 'num_lab_procedures') print('Average number of lab tests performed and not readmitted', np.mean(notreadmitted.num lab procedures)) print("Standard deviation is", np.std(notreadmitted.num lab procedures)) Average number of lab tests performed and readmitted 44.06139213143104 Standard deviation is 19.56629050957145 Average number of lab tests performed and not readmitted 42.20357275772237 Standard deviation is 20.302903901864706 Readmitted 1000 100 80 800 60 600 40 400 20 200 60 80 20 40 num_lab_procedures Not Readmitted 1200 100 1000 80 800 60 600 40 400 20 200 num_lab_procedures In terms of the number of lab tests that are performed per stay, the averages are pretty similar. Readmitted patients undergo just over 44 lab tests on average while patients who are not readmitted average just over 42. To me this seems to indicate two things. First, there is likely a standard procedure in place and each patient undergoes the same tests, but also that the results from these tests don't seem to be correlating to better patient outcomes. In [15]: plt.figure(figsize = (10, 8)) plt.subplot(2, 2, 1) plt.hist(readmitted['num_medications'], color = 'red') plt.title("Readmitted") plt.subplot(2, 2, 2) readmitted.boxplot(column = 'num medications') print('Average number of medications administered during admission and readmitted', np.mean(readmitted.num medications)) print("Standard deviation is", np.std(readmitted.num medications)) plt.subplot(2, 2, 3) plt.hist(notreadmitted['num medications']) plt.title("Not Readmitted") plt.subplot(2, 2, 4) notreadmitted.boxplot(column = 'num_medications') print('Average number of medications administered during admission and not readmitted', np.mean(notreadmitted.num medications print("Standard deviation is", np.std(notreadmitted.num medications)) Average number of medications administered during admission and readmitted 16.248378728923477 Standard deviation is 7.490065662135347 Average number of medications administered during admission and not readmitted 15.785634536657982 Standard deviation is 8.659491770724618 Readmitted 1600 60 1400 50 1200 800 30 600 20 400 10 200 10 20 30 40 num_medications Not Readmitted 2000 70 1750 60 1500 50 1250 1000 30 750 20 500 10 250 20 num medications Similar to the number of lab tests performed, the average number of medications given does not seem to vary much between patients who are readmitted and those who are not. This leads me to a similar conclusion that most of the treatments are standardized (although there are more outliers), but not necessarily correlated with better patient outcomes. The last question I would like to answer pertains to the patient's treatment. I want to examine if changing a patient's medication or prescribing medication leads to lower readmittance rates. I will again calculate probabilities to assess the effectiveness of treatment. In [16]: # Indicates if there was any diabetic medication prescribed. Values: "yes" and "no" plt.figure(figsize = (10, 5)) plt.subplot(1, 2, 1) readmitted['diabetesMed'].value counts().plot.bar(title = "Medication Prescribed: Readmitted") plt.subplot(1, 2, 2) notreadmitted['diabetesMed'].value counts().plot.bar(title = "Medication Prescribed: Not Readmitted") print("Probability of NOT being readmitted\n", notreadmitted.groupby(['diabetesMed']).size()/diabetes.groupby(['diabetesMed']) print("Probability of being readmitted\n", readmitted.groupby(['diabetesMed']).size()/diabetes.groupby(['diabetesMed']).size ()) Probability of NOT being readmitted diabetesMed 0.595826 Yes 0.519472 dtype: float64 Probability of being readmitted diabetesMed 0.404174 Yes 0.480528 dtype: float64 Medication Prescribed: Readmitted Medication Prescribed: Not Readmitted 4000 3500 3500 3000 3000 2500 2500 2000 2000 1500 1500 500 500 ŝ First is a look at whether or not medication was prescribed during the stay. The bar charts show us that more often than not, medication is prescribed. When this occurs, patients have a probability of being readmitted just over 48 percent of the time. This seems to be a very high and calls into question the effectiveness of the medication being prescribed. When medication is not prescribed, patients have a probability of being readmitted just over 40 percent of

Next, I found the probability of being readmitted or not when medication is changed, either dosage or an actual change in medication. Unlike with prescribing medication, changing medication happens less often than not. When medication is changed the probability of being readmitted is close to 50 percent. When medication is not changed, the probability of being readmitted is 44 percent. These probabilities, along with the probabilities above indicate that patient treatment, in terms of prescribing or changing medication, does not have a strong correlation with lowering readmittance.

Conclusions and Further Research

Overall, the data has provided numerous insights into diabetes treatment. The data shows that patients are readmitted greater than 45 percent of the time indicating there is a need for better treatment to improve patient outcomes. There appears to be little evidence that age, race or gender significantly affect readmittance rates. There also does not appear to be a strong correlation between the features of a patient's stay or their treatment that significantly

the time. Even though this is a lower probability, it could be that these patients are in better shape to begin with since no medication is being prescribed.

 $print("Probability of NOT being readmitted \verb|\n"|, notreadmitted .groupby(['change']).size()/diabetes.groupby(['change']).size()/diabete$

print("Probability of being readmitted\n", readmitted.groupby(['change']).size()/diabetes.groupby(['change']).size())

Medication Changed: Not Readmitted

5

decreases the likelihood of being readmitted. Although this does not provide us with any specific factors of treatments for hospitals and caretakers to focus on as hoped, it does show that there is room for improvement and further research. One aspect of this data set that I did not examine as of yet was the 20+ medications that were listed. It could be worth while to dig into each one of these medications and find which drugs, that when administered lead to a lower probability of readmittance. Additionally, it would be beneficial to build out classification models such as a logistic regression or a random forest that can predict

notreadmitted['change'].value_counts().plot.bar(title = "Medication Changed: Not Readmitted")

readmitted['change'].value counts().plot.bar(title = "Medication Changed: Readmitted")

3000

2500

2000

1500

1000

500

5

readmittance and identify combinations of factors that lead to the best patient outcomes.

In [17]: plt.figure(figsize = (10, 5))

plt.subplot(1, 2, 2)

plt.subplot(1, 2, 1)

change

change

2000

1500

1000

500

Ch 0.508585 No 0.561956 dtype: float64

dtype: float64

0.491415 0.438044

Probability of NOT being readmitted

Probability of being readmitted

Medication Changed: Readmitted