Final Report

Lindsay Knupp

2024-05-14

Dataset

Our data was collected from Centers for Medicare & Medicaid Services on April 03, 2024. It features information about hospitals through annual cost reports in 2020. We were interested in understanding how certain characteristics of hospitals like location, number of full time equivalent employees, or number of beds, for example, affected the hospitals' total operating costs. To perform qualitative analyses, we categorized each hospital as above or below the median.

While the data is roughly annual, certain hospitals reported for different fiscal year lengths. To normalize, we divided some of our variables by the length of their cost reporting period to obtain daily estimates like average number of inpatients per day or average salary expense per day. Variables that are reported as "averages per day" are denoted with the word "average" in the predictor table below. Some hospitals were listed multiple times with distinct reporting periods. We learned that this could correspond to a change in control of the hospital. For example, the hospital could have been sold and transitioned from a voluntary to a governmental hospital. Duplicate hospitals were left in the dataset and a dummy variable, `duplicate` was added to indicate its status.

There were 13 different categories of control ranging from "Voluntary Non-Profit-Church" to "Governmental-Federal". To reduce our number of categories, we re-binned this variable to only include the broad categories: "Voluntary", "Proprietary", and "Governmental". We followed a similar procedure for the 12 different categories of provider type ranging from "Children" to "Cancer" to "General Long Term". In this case, we re-binned provider type to only distinguish between "General" and "Specialized" care. We classified "General Short Term", "General Long Term", and "Religious Non-Medical Health Care Institution" as "General" care and classified "Cancer", "Psychiatric", "Rehabilitation", "Children", "Reserved for Future Use", "Other", "Extended Neoplastic Disease Care", "Indian Health Services", and "Rural Emergency Hospital" as "Specialized" care.

To improve accuracy on methods like Lasso regression, we scaled our numerical variables using the `scale()` function which centered and scaled our data appropriately. The following table includes the ranges of the predictors and response before they were re-scaled.

Variables	Pre-scaled Range	Descriptions
Predictors		
Number of Beds	[1-2,791]	Total number of available beds including adult beds, pediatric beds, birthing room, and newborn ICU beds
FTE employees on payroll	[0.05-26,941.09]	Average number of full time-equivalent employees

Total hospital days	[1-772,819]	Total number of inpatient days (i.e. days all patients spent in the hospital)
Total discharges	[0.0027-462.63]	Average number of discharges including deaths
Total income	[-$6,129,919, $11,516,626]	Average income including net revenue from services given to patients
Total assets	[-$636,856,458, $29,465,487,958]	Total current assets
Salaries	[$128.51, $9,032,294.85]	Average salary expenses
Inpatients	[0.0033-2123.13]	Average number of inpatients
Rural versus Urban	[2487 rural, 3225 urban]	Location of hospital defined as rural or urban
Type of control	[2927 voluntary, 1728 proprietary, 1057 governmental]	Type of control under which hospital is conducted
Type of provider	[4779 general, 993 specialized]	Type of services provided
Duplicate hospital	[132 duplicates, 5580 non duplicates]	Whether or not hospital was listed multiple times
Response		
Total costs	[$2,718.28, $16,000,980.58]	Total hospital costs
Costs bin	[2856 above median, 2856 below median]	Whether or not total hospital costs was above/below median

Qualitative Outcome Analyses

For all of our qualitative outcomes, we were trying to predict whether a hospital's total costs were above or below the median. All of the methods' error rates were comparable except for LDA which had the highest misclassification rate at about 17%. KNN had no consistent choice of an optimal k across simulations and its variability inspired our simulation study.

KNN

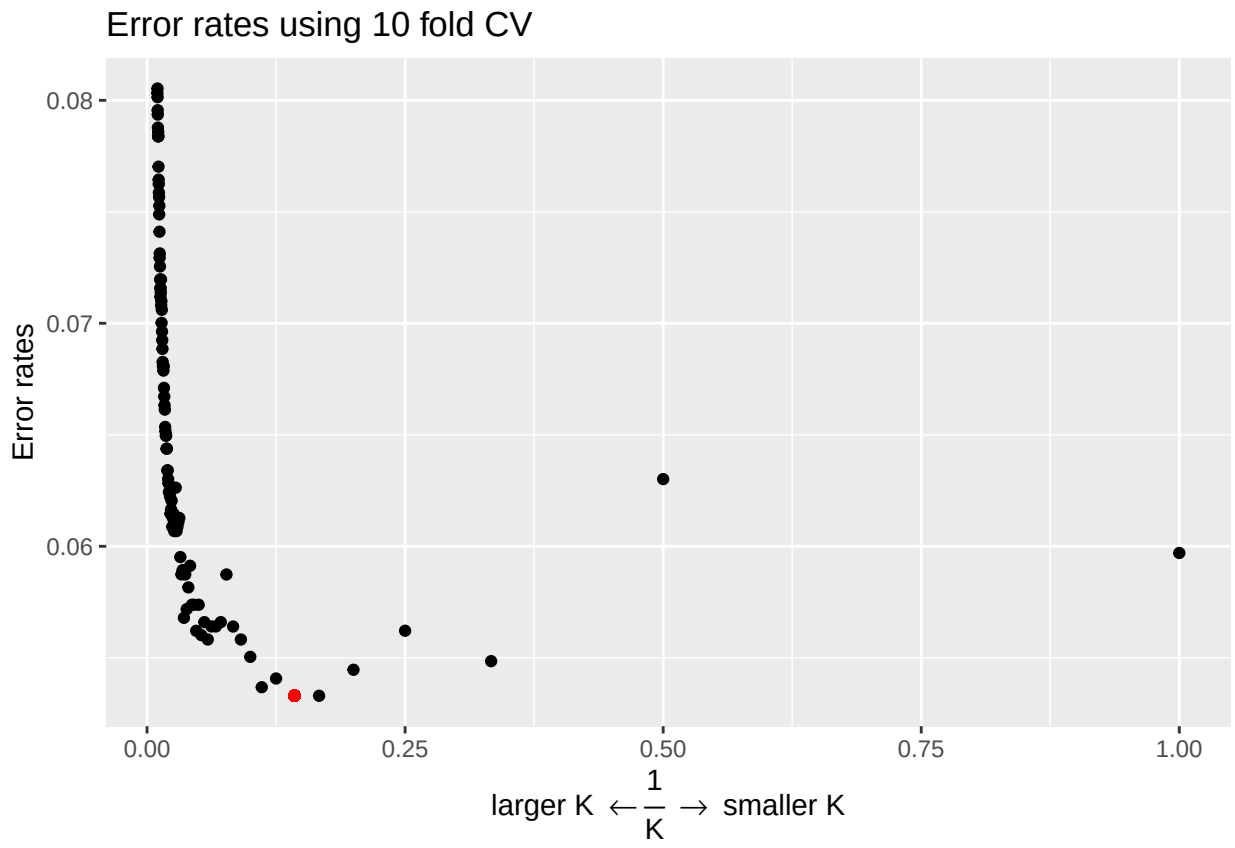
Assumptions

We assumed that hospitals with similar predictor values have similar total costs.

Results

We used 10 fold cross validation to first choose an optimal number of neighbors, k and found $k = 7$ to be optimal with an error rate of 0.0533 using Euclidean distance. The true error rate with $k = 7$ was 0.0490 and the true/false positive and negative rates are summarized in the table below. When plotting the cross validation error rates against the chosen k, we see a condensed U shape. This may suggest that large k suffers from high inaccuracy but too small k can lead to overfitting.

Classification Rates	Values
True positive	0.91200
True negative	0.99300
False positive	0.00722
False negative	0.08840



Multiple Logistic Regression

Assumptions

We assume that our predictors are not correlated with one another.

Results

The coefficients and standard errors associated with our model can be found below. We found that `total_discharges`, `total_assets`, `salaries`, `rural`, and `provider_bin_Specialized` were the most sta-

tistically significant. Further, most predictors increased the probability of a hospital's total costs being above the median; unsurprisingly, `salaries` stood out the most. A one unit increase in `salaries` increased the log odds of an above median classification by 50.27. It also produced a z statistic of 21.001 providing strong evidence of an association between salaries and total costs.

Coefficients	Estimate	Std. Error	z value	p-value
(Intercept)	18.98	0.86	21.96	0.00
number_of_beds	-0.84	0.68	-1.23	0.22
fte_employees_on_payroll	0.68	0.33	2.02	0.04
total_days	-4.44	5.80	-0.77	0.44
total_discharges	4.94	0.75	6.55	0.00
total_income	0.94	0.36	2.58	0.01
total_assets	1.76	0.52	3.35	0.00
salaries	50.27	2.39	21.00	0.00
inpatients	3.62	5.91	0.61	0.54
rural	-1.22	0.20	-6.16	0.00
control_bin_Governmental	-0.46	0.24	-1.94	0.05
control_bin_Proprietary	0.44	0.23	1.93	0.05
provider_bin_Specialized	-4.02	0.40	-9.92	0.00
duplicate	0.56	0.53	1.06	0.29

Our estimated and true error rates were pretty close to one another with our cross validation error of 0.073 and true test error of 0.0333.

Classification Rates	Values
True positive	0.9460
True negative	0.9890
False positive	0.0108
False negative	0.0544

Multiple Logistic Regression with Transformations

Assumptions

We again assume that our predictors are not correlated with one another.

Results

We decided to transform `total_income`,`fte_employees_on_payroll`, `salaries`, and `total_days` to experiment with how less significant predictors in conjunction with `salaries` affected the response. We computed polynomial models up to degree 2 for `total_days` and interaction terms between `total_income` & `fte_employees_on_payroll` and between `fte_employees_on_payroll` & `salaries`.

With our smaller model, all of our new predictors were statistically significant with extreme z statistics. However, it is important to note that the standard errors associated with each coefficient were extremely high suggesting a poor fit.

Coefficients	Estimate	Std. Error	z value	p-value
(Intercept)	6.583056e+14	971394.8	677691118	0

total_income	1.743355e+14	1667476.0	104550530	0
fte_employees_on_payroll	7.442677e+14	3289614.4	226247710	0
salaries	2.737959e+15	3725566.4	734910894	0
total_days	2.542708e+14	2645218.8	96124663	0
total_days_sq	-8.915542e+13	360959.8	-246995412	0
income_emp	-2.830918e+13	259889.2	-108927893	0
sal_emp	-2.512173e+14	333727.6	-752761545	0

Compared to our original multiple logistic regression, our true error rate shot up from 0.033 to 0.158 and our cross validation error rate shot up from 0.073 to 0.130. Interestingly enough though, the model perfectly predicted hospitals whose total costs were below the median with a true negative rate of %100.

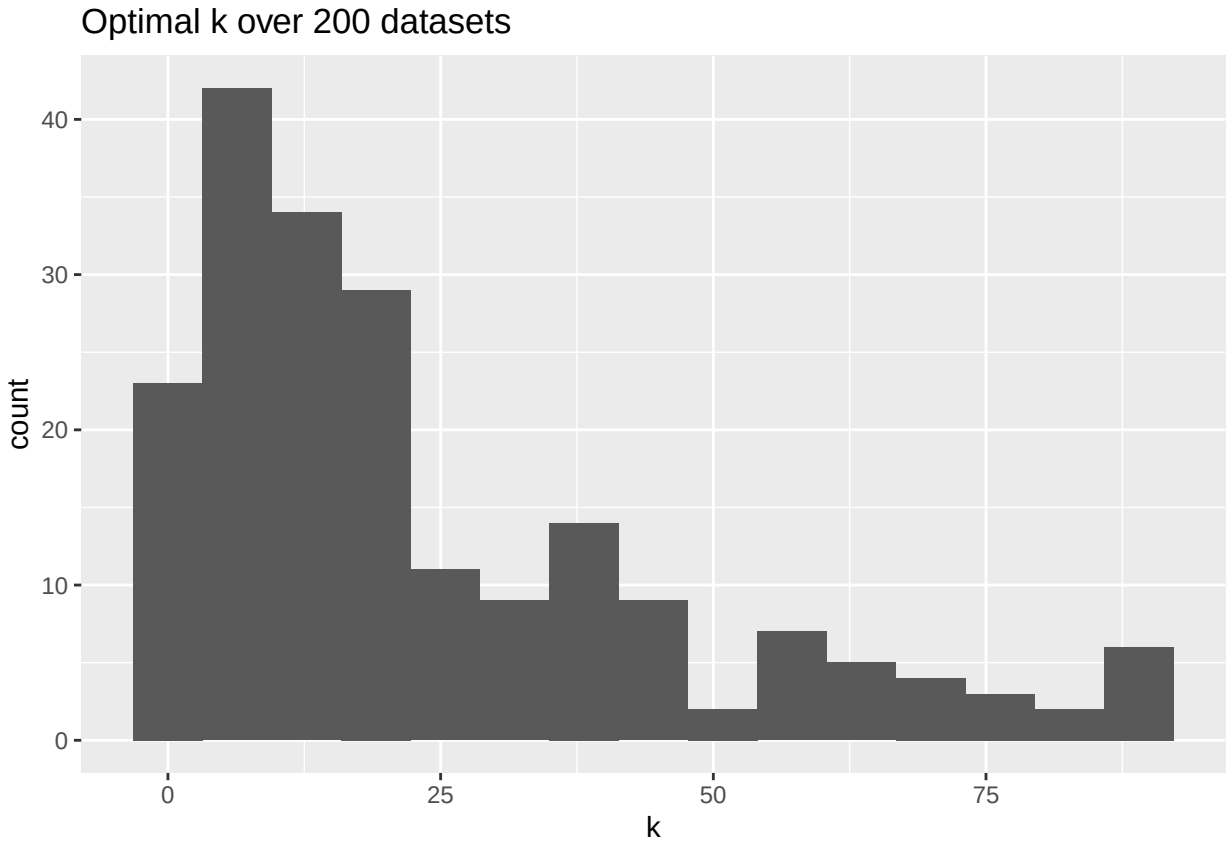
Classification Rates	Values
True positive	0.694
True negative	1.000
False positive	0.000
False negative	0.306

Simulation Study

We were interested in understanding how our data affected the optimal choice of k in the k -nearest neighbors algorithm. We already experienced some variability when running our model through on different computers. Therefore, we wanted to see if more simulated datasets would produce the same variablility.

To replicate our 13 predictors and 2 response variables, we used a package called `faux` to simulate our numerical predictors from a multivariate normal distribution.

We used a standard normal distribution to replicate our 13 predictors.


Optimal k over 200 datasets
count
k
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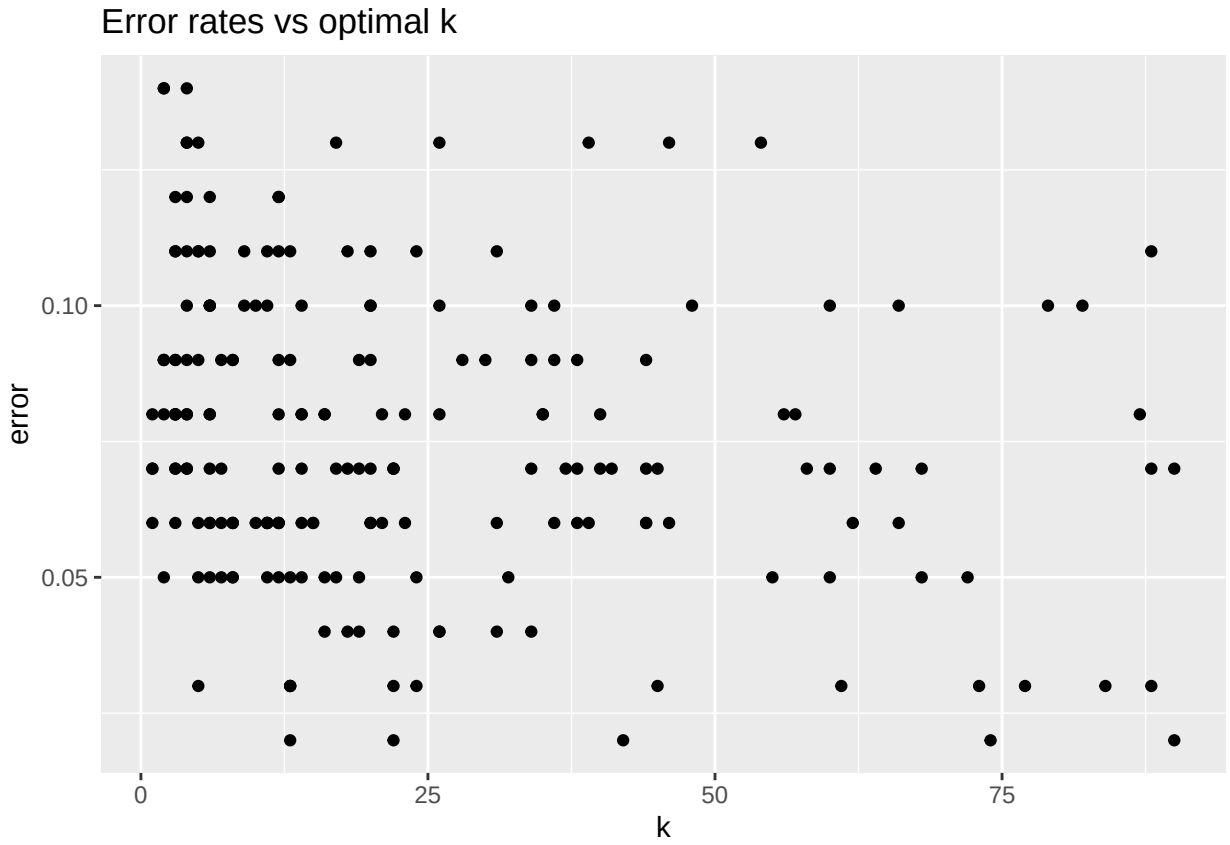
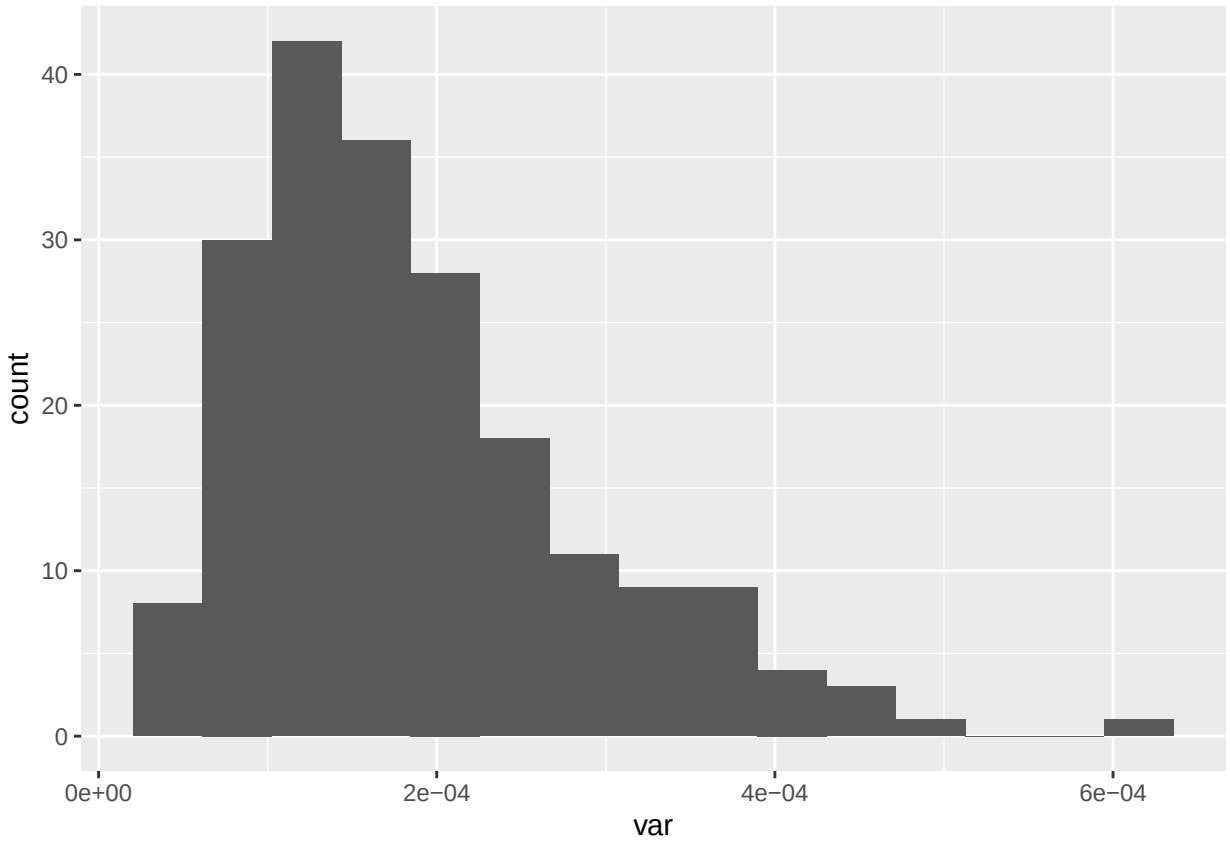
10
20
30
40
0
25
50
75


Error rates vs optimal k
error
0.10
0.05
0
25
50
75
k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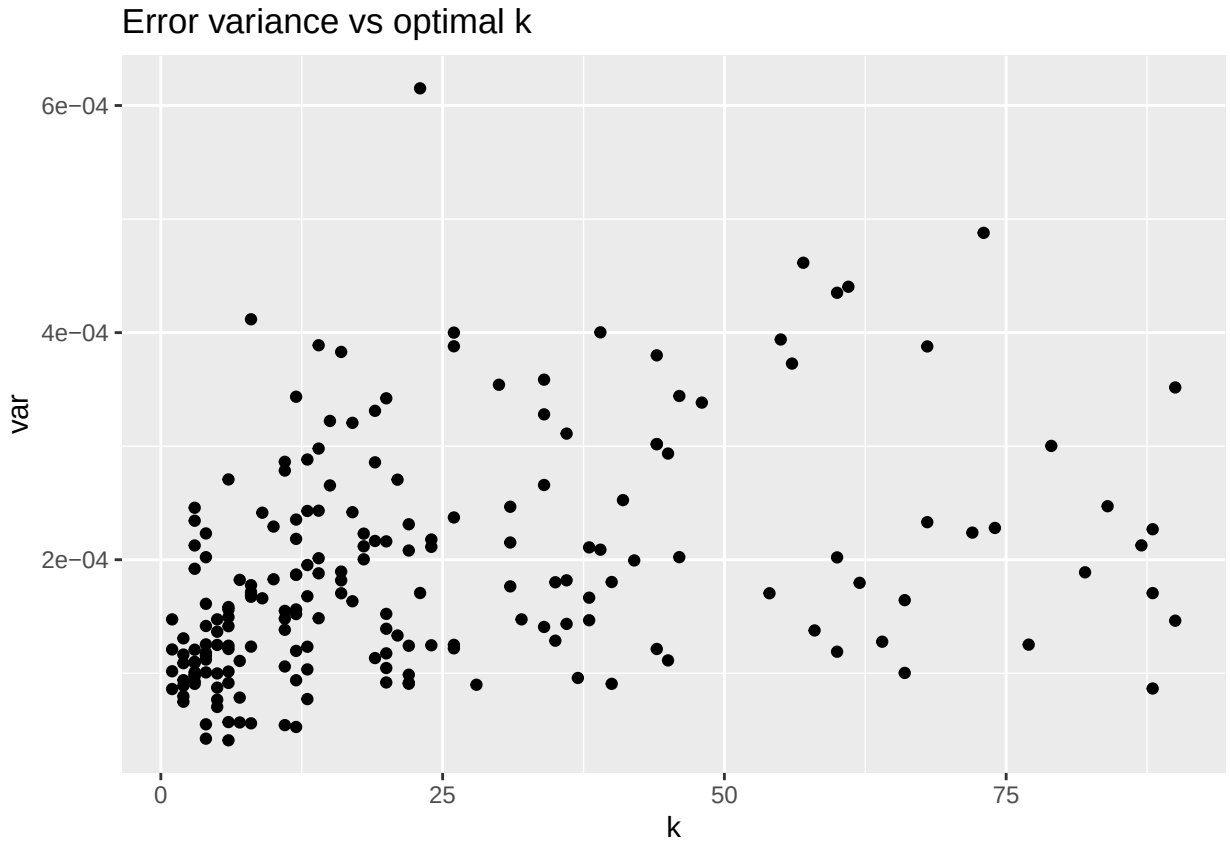
Error variance vs optimal k
6e−04
4e−04
2e−04
var
0
25
50
75
k