Predictive Analytics and Quality Control in Healthcare

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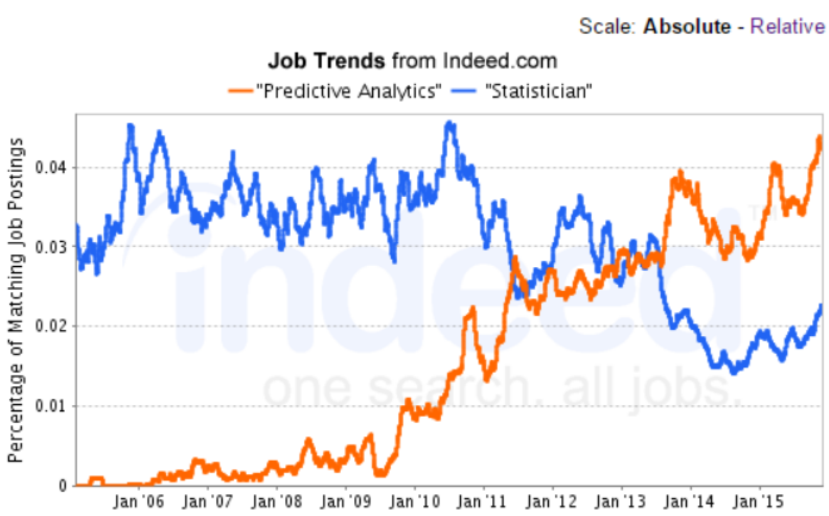
What is and Why Predictive Analytics

- Predictive Analytics is the use of information systems, statistics, and/or computer-based models to help decision makers analyze historical data to make predictions about the future.
- Dramatic growth of applications of analytics. Source: indeed.com



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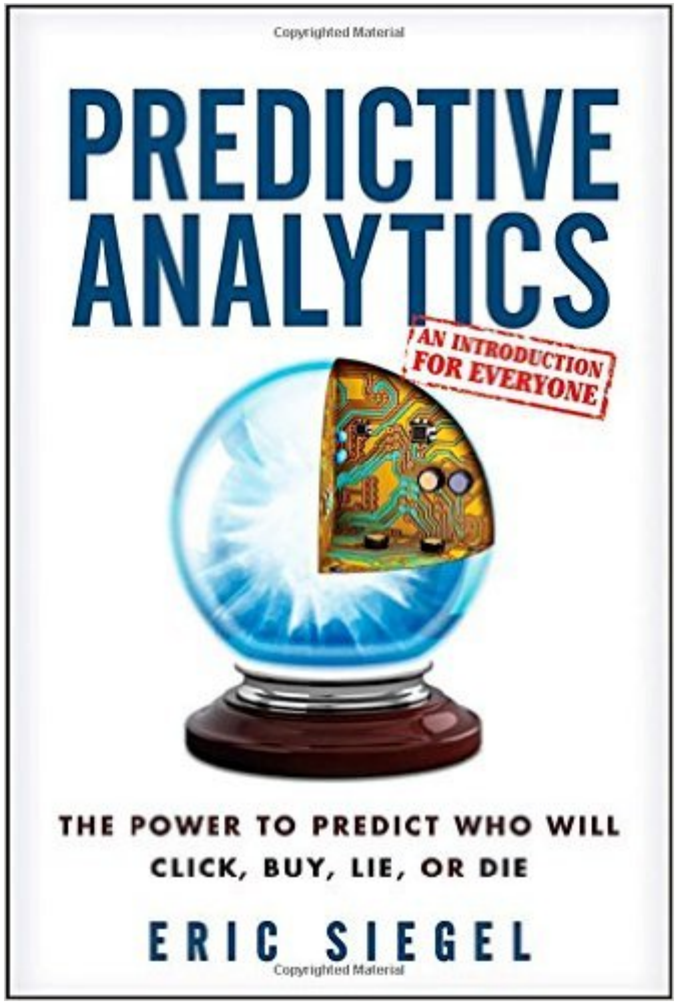
What is and Why Predictive Analytics

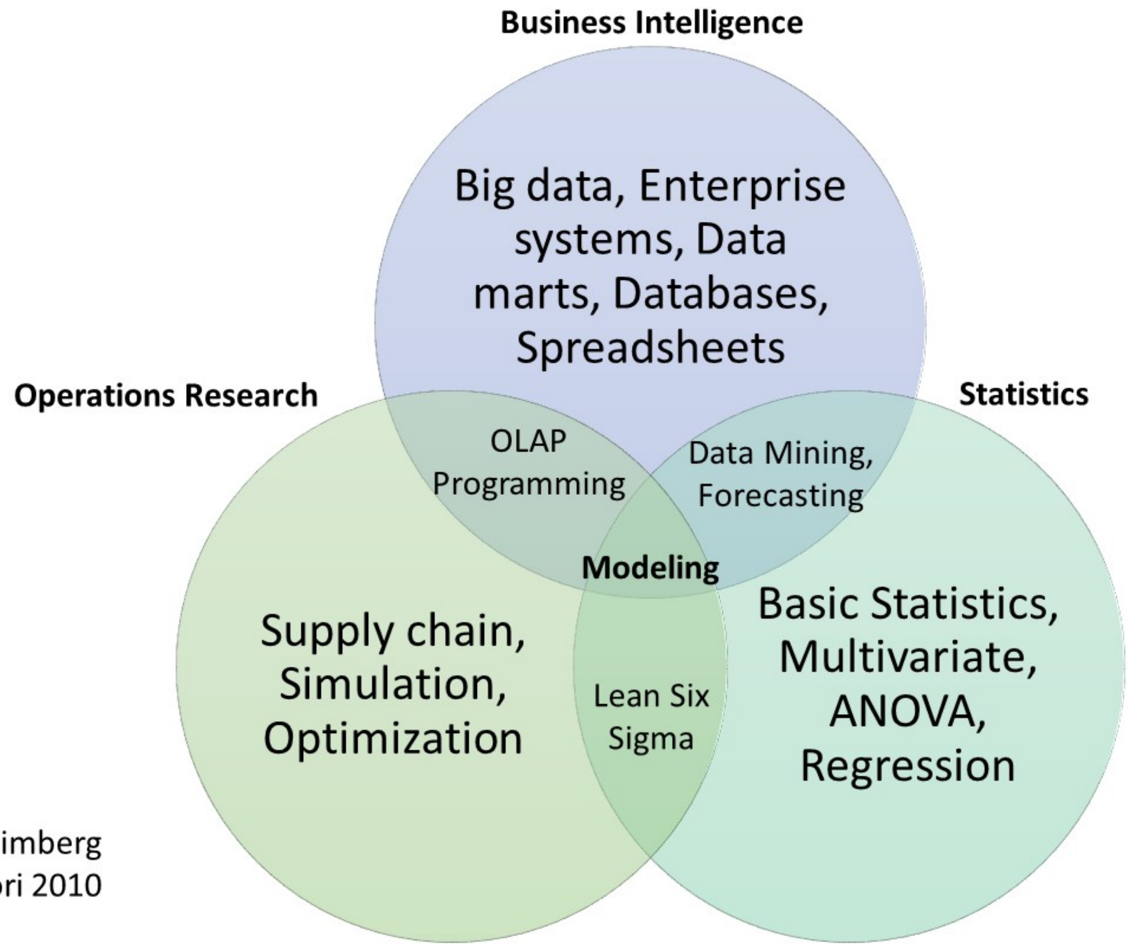
- As indicated by Eric Siegl's book the application of predictive analytics lies in the power to predict who will click, buy, lie or die.



Difficulties arising from its application

- Evans [1] suggests that organizations are overwhelmed by data and have difficulty determining how to use it.
- Successful application of analytics requires the integration of data, statistics, and Operations Research. But most importantly it requires a high-level understanding of how analytics supports an organization's competitive strategy.

Analytics Framework



Adapted from Klimberg and Miori 2010

Predictive Analytic Tools

- ❑ **Principal Components Analysis**
- ❑ Partial Least Squares
- ❑ Cross Validation Techniques
- ❑ Binary Logistic Regression
- ❑ Risk-adjusted Monitoring Charts
- ❑ Rare Events Charts (and not so “rare”)

Principal Component Analysis

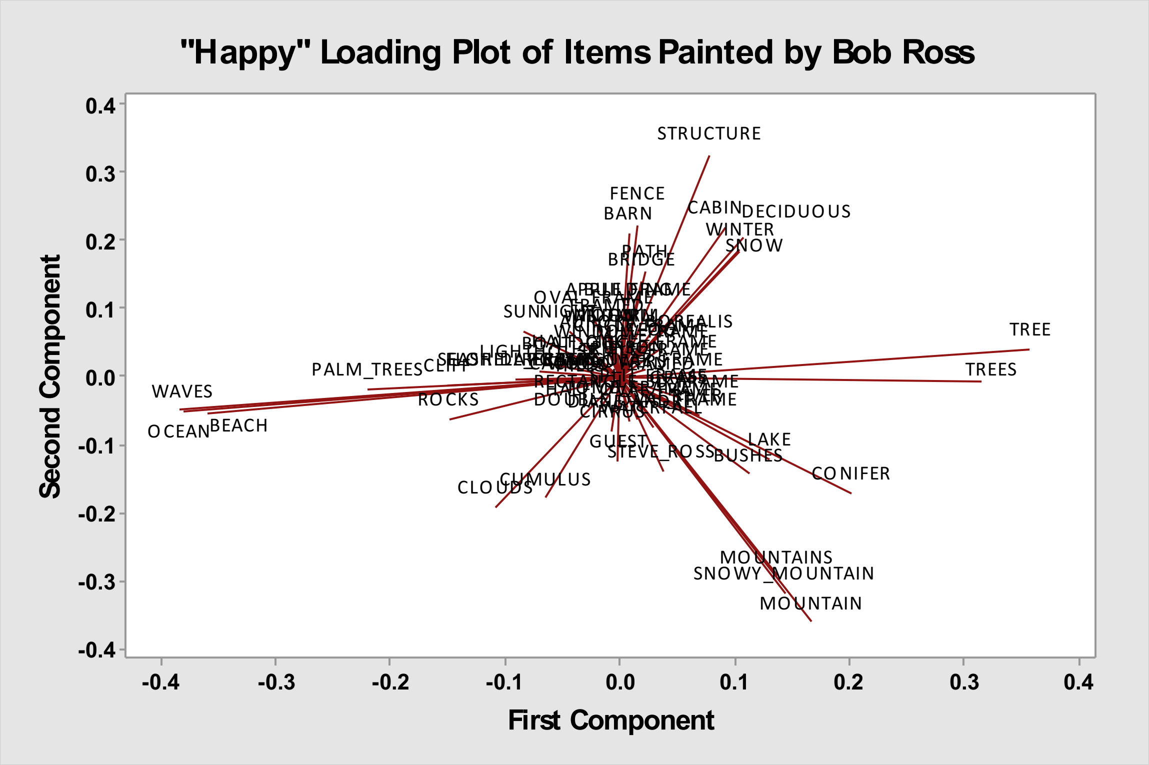
- How to analyze many variables that could be highly correlated with each other?
- How to identify the underlying relationships that could exist between these correlated variables?
- How to combine these variables to extract the essence of the data?

Principal Component Analysis

► Let's talk about the great Bob Ross.

Principal Component Analysis

- ► FiveThirtyEight published an article in 2014 on "A Statistical Analysis of the Work of Bob Ross"



Predictive Analytic Tools

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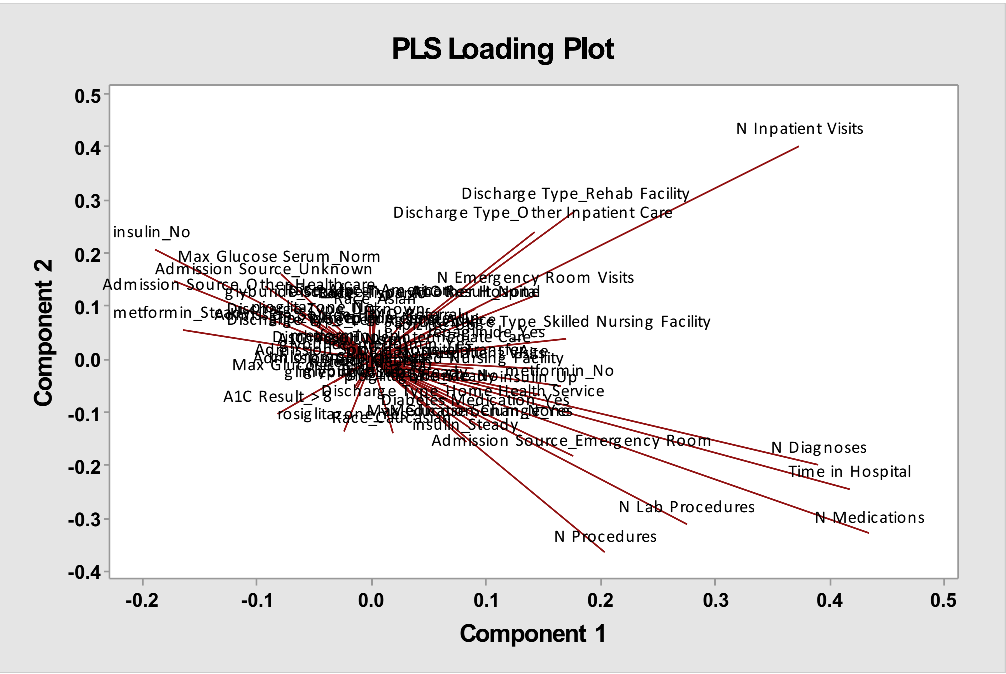
Partial Least Squares – Readmission Diabetes

- 130 hospitals in the US from 1999-2008, patients with diabetes.
- 55 attributes from over 100,000 patients.
- The data contains such attributes as patient number, race, gender, age, admission type, time in hospital, medical specialty of admitting physician, number of lab tests performed, HbA1c test result, diagnosis, number of medications, diabetic medications, number of outpatient, inpatient, and emergency visits in the year before the hospitalization, etc.

Partial Least Squares – Readmission Diabetes

- ► Binary logistic regression could be used but…



PLS Regression: Readmitted < versus Time in Hosp, N Lab Proced,

Method

Cross-validation	None
Components to calculate	User specified
Number of components calculated	5
Categorical predictor coding	1, 0

Analysis of Variance for Readmitted <30?

Source	DF	SS	MS	F	P
Regression	5	54.84	10.9685	109.59	0.000
Residual Error	11849	1185.93	0.1001		
Total	11854	1240.77			

Model Selection and Validation for Readmitted <30?

Components	X Variance	Error	R-Sq
1	0.039156	1199.41	0.0333395
2	0.064883	1188.22	0.0423590
3	0.109367	1187.16	0.0432131
4	0.134803	1186.36	0.0438588
5	0.158539	1185.93	0.0442002

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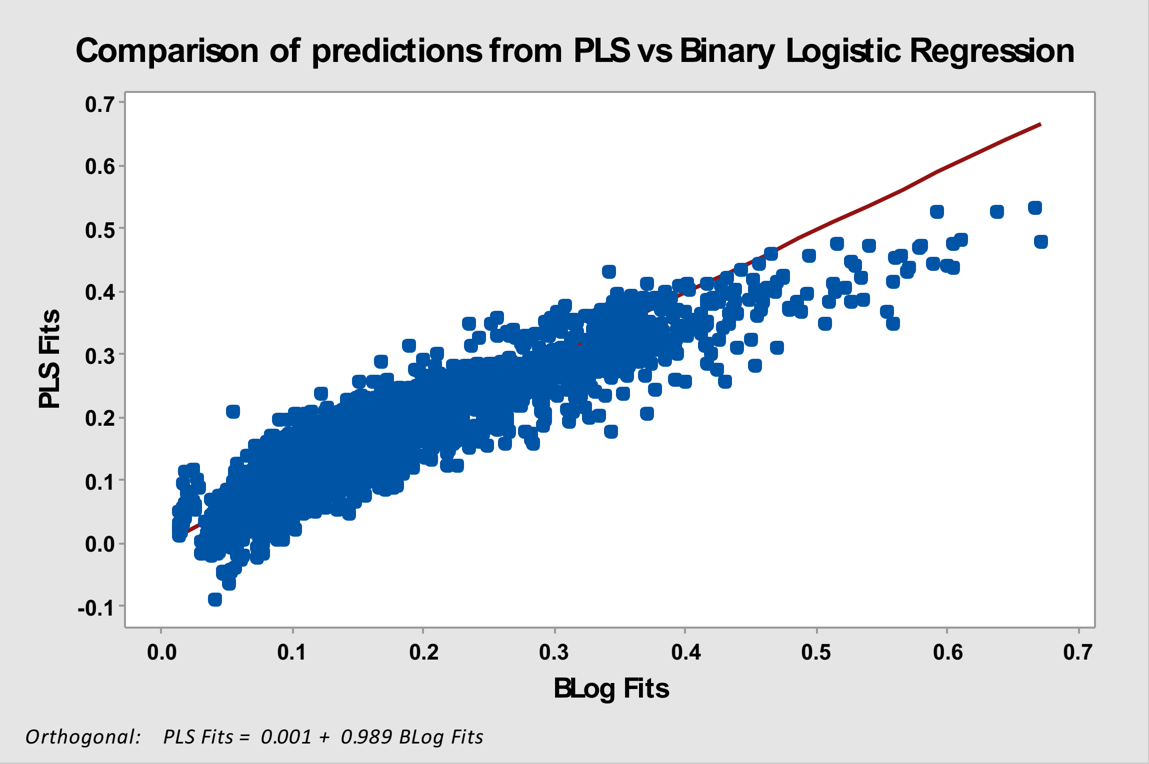
Partial Least Squares – Readmission Diabetes

- Comparable results are obtained in terms of prediction but in a less painful way.



Predictive Analytic Tools

- ❑ Principal Components Analysis
- ❑ Partial Least Squares
- ❑ **Cross Validation Techniques**
- ❑ Binary Logistic Regression
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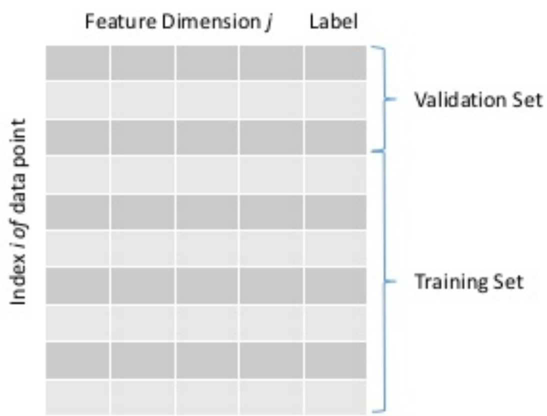
Partial Least Squares – Readmission Diabetes

- Using all data to fit a predictive model can result in overfitting.
- Cross Validation is a technique commonly used to ensure the predictive model can do its job.

Model selection: Use Cross Validation



Held Out Cross Validation

1. Randomly split all data into 2 subsets:
   - Training set (70%)
   - Validation set (30%)
2. Train machine learning model on training set.
3. Pick model with lowest error on validation set.

K Fold Cross Validation

1. Divide data into K pieces
2. Train on K – 1 pieces
3. Validate on remaining piece
4. Average over K results to get generalization error of model

Partial Least Squares – Readmission Diabetes

- ► Cross Validation results are displayed:

Predicted Response for New Observations Using Model for Readmitted <30?

Row	Fit	SE Fit	95% CI	95% PI
1	0.122134	0.0042283	(0.113846, 0.130422)	(-0.498049, 0.74232)
2	0.087821	0.0041636	(0.079659, 0.095982)	(-0.532361, 0.70800)
3	0.111752	0.0057949	(0.100393, 0.123111)	(-0.508480, 0.73198)
4	0.058298	0.0050403	(0.048419, 0.068178)	(-0.561908, 0.67851)
5	0.137080	0.0055988	(0.126105, 0.148054)	(-0.483146, 0.75730)
6	0.067705	0.0057181	(0.056497, 0.078914)	(-0.552524, 0.68793)
7	0.078760	0.0055305	(0.067919, 0.089600)	(-0.541463, 0.69898)
8	0.053087	0.0046128	(0.044045, 0.062129)	(-0.567107, 0.67328)
9	0.113272	0.0081526	(0.097292, 0.129253)	(-0.507062, 0.73361)
10	0.190371	0.0065148	(0.177601, 0.203141)	(-0.429889, 0.81063)
11	0.143275	0.0053386	(0.132810, 0.153739)	(-0.476942, 0.76349)
12	0.152966	0.0055641	(0.142060, 0.163873)	(-0.467258, 0.77319)
13	0.155946	0.0078333	(0.140591, 0.171301)	(-0.464372, 0.77626)
14	0.133558	0.0085276	(0.116843, 0.150274)	(-0.486795, 0.75391)
15	0.145832	0.0051384	(0.135760, 0.155904)	(-0.474378, 0.76604)
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
5093	0.086446	0.0036699	(0.079253, 0.093640)	(-0.533724, 0.70662)
5094	0.048609	0.0072496	(0.034398, 0.062819)	(-0.571682, 0.66890)
5095	0.118740	0.0042138	(0.110480, 0.127000)	(-0.501443, 0.73892)
5096	0.165044	0.0059720	(0.153337, 0.176750)	(-0.455195, 0.78528)

Test R-sq: 0.0383581

Partial Least Squares – Readmission Diabetes

► Another way to assess the model is to look at the correct classification of patients in a confusion matrix.

	Prediction according to model	
Observed Outcome	Not likely to be readmitted	Likely to be readmitted
No readmission	4076	427
Readmission	455	138

Model classification = 83%

A natural follow-up would be to investigate what factors can be used to more accurately predict this group.

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Predictive Analytic Tools

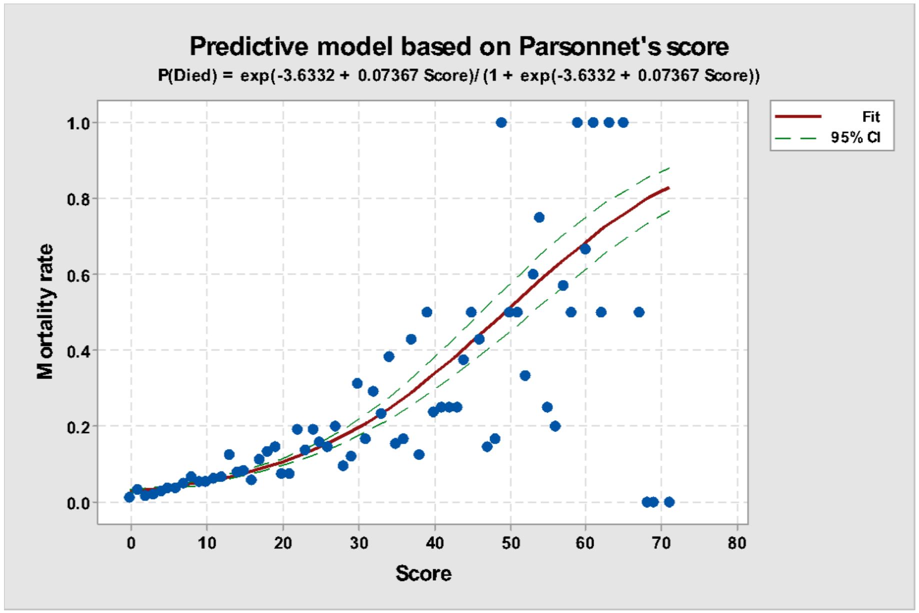
- Principal Components Analysis
- Partial Least Squares
- Cross Validation Techniques
- **Binary Logistic Regression**
- Risk-adjusted Monitoring Charts
- Rare Events Charts (and not so “rare”)

Assessing the level of pre-operative risk for cardiac surgery patients

- There is considerable variation in the level of risk
- There are multiple variables that can be used to evaluate this risk: age, gender, hypertension, diabetic status, renal function, and left ventricular mass
- The Parsonnet score summarizes this in a single number
- To illustrate we use the data from Steiner et al. [3] that includes 6,994 patients and whether or not they died within 30 days of surgery.

Build Predictive Model: Binary Logistic

► A very simple model can be built based on a patient's Parsonnet's score.



Binary Fitted Line Plot

Method

Link function Logit
Rows used 69

Response Information

Variable	Value	Count	Event Name
Died	Event	460	Died
	Non-event	6534	
Total	Total	6994	

Deviance Table

Source	DF	Adj Dev	Adj Mean	Chi-Square	P-Value
Regression	1	431.5	431.540	431.54	0.000
Parsonnet Score	1	431.5	431.540	431.54	0.000
Error	67	103.4	1.544		
Total	68	535.0			

Model Summary

Deviance R-Sq	Deviance R-Sq(adj)	AIC
80.67%	80.48%	2965.37

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Build Predictive Model: Binary Logistic

- Using Parsonnet's Score we can assign the Predicted Mortality to each patient.

↓	C1-D	C2	C3-T	C4
	Operation Date	Parsonnet Score	Died within 30 days	Predicted Mortality
1	1-Jan-92	19	No	0.096785
2	2-Jan-92	0	No	0.025751
3	2-Jan-92	0	No	0.025751
4	2-Jan-92	3	No	0.031917
5	2-Jan-92	17	No	0.084648
6	2-Jan-92	40	No	0.334834
7	2-Jan-92	3	No	0.031917
8	3-Jan-92	0	No	0.025751
9	3-Jan-92	2	No	0.029717
10	3-Jan-92	5	No	0.036797
11	3-Jan-92	9	No	0.048792
12	3-Jan-92	35	Yes	0.258314
13	5-Jan-92	30	No	0.194176
14	6-Jan-92	20	No	0.103419
15	6-Jan-92	12	No	0.060134
16	6-Jan-92	5	No	0.036797
17	6-Jan-92	25	No	0.142895
18	7-Jan-92	3	No	0.031917
19	7-Jan-92	0	No	0.025751
20	7-Jan-92	2	No	0.029717
21	7-Jan-92	3	No	0.031917

Predictive Analytic Tools

- ❑ Principal Components Analysis
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- ❑ **Risk-adjusted Monitoring Charts**
- ❑ Rare Events Charts (and not so “rare”)

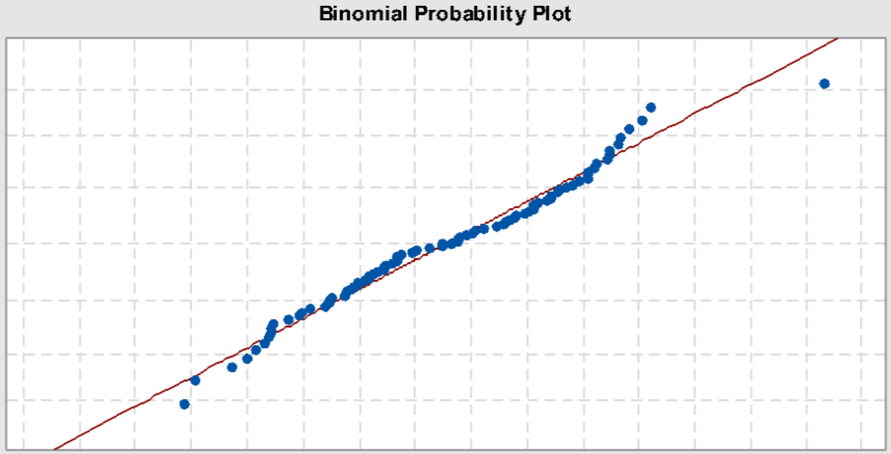
How should we Monitor Mortality Rate?

- We have a Binary Outcome
- We have the Operation Date Recorded
- We have the risk of Mortality associated with each Patient

Monitoring the Mortality Rate

Time	Death Events	Patients
Apr 1992	3	101
Apr 1993	8	85
Apr 1994	7	81
Apr 1995	7	78
Apr 1996	6	52
Apr 1997	4	100
Apr 1998	2	57
Aug 1992	6	74
Aug 1993	4	92
Aug 1994	6	90
Aug 1995	7	90
Aug 1996	3	74
Aug 1997	7	76
Aug 1998	2	67
Dec 1992	7	70
Dec 1993	9	52
Dec 1994	3	66

P Chart Diagnostic for Estimated Probability of Death

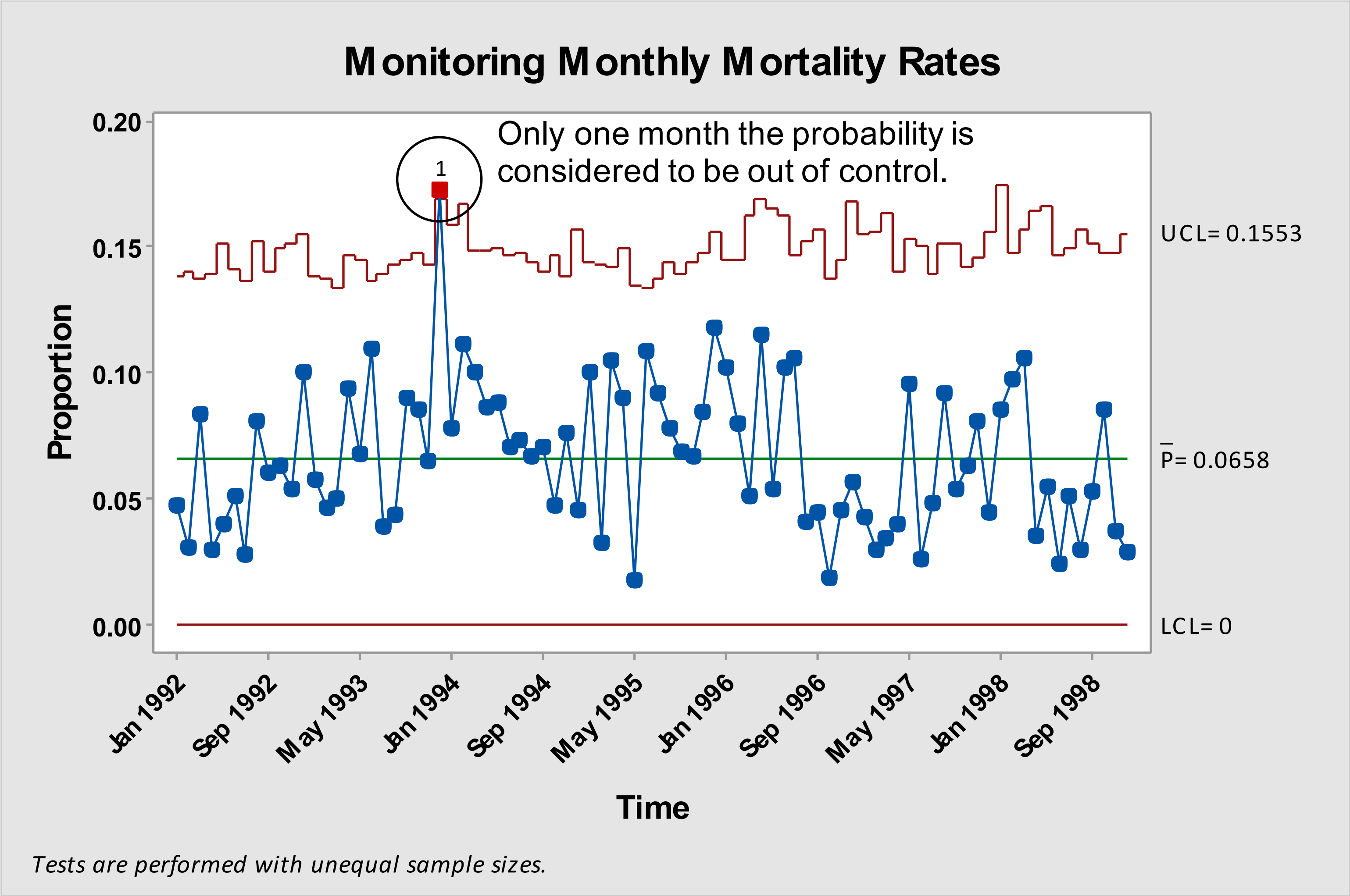


Ratio of observed variation to expected variation = 134.8%
95% Upper Limit for ratio if process P is constant = 135.2%

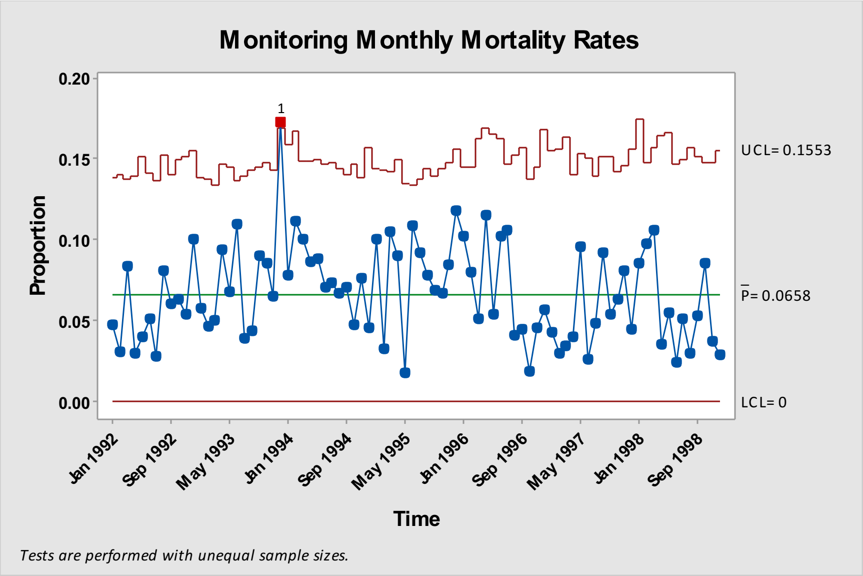
Using a P chart should not result in an elevated false alarm rate.

The upper limit depends on the number of subgroups, the average subgroup size, and the overall process P.

Monitoring the Mortality Rate



Monitoring the Mortality Rate



What is wrong with the P-Chart approach?

Parsonnet Score	Died within 30 days	Predicted Mortality
19	No	0.096785
0	No	0.025751
0	No	0.025751
3	No	0.031917
17	No	0.084648
40	No	0.334834
3	No	0.031917
0	No	0.025751
2	No	0.029717

- We are assuming each patient has the same risk of Mortality going into his/her surgery.

Monitoring the Mortality Rate

- So what type of chart do we need?

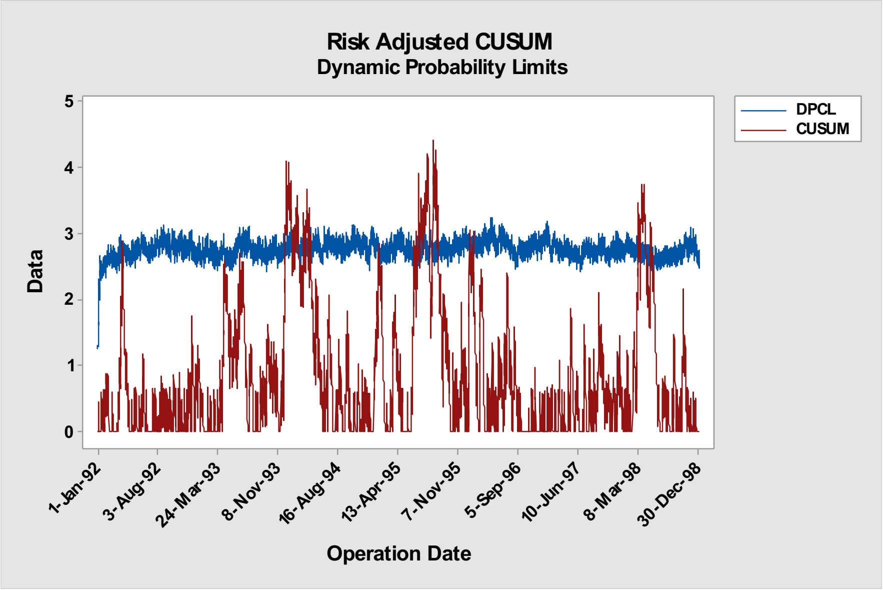
  1. We need to account for the different patient risk level for the plotted points
  2. We need to have proper detection when the mortality rate is increasing while ensuring we adjust for the proper risk level.
  3. Therefore, we need control limits based on the varying risk levels of the patients.

- We need to monitor mortality with:

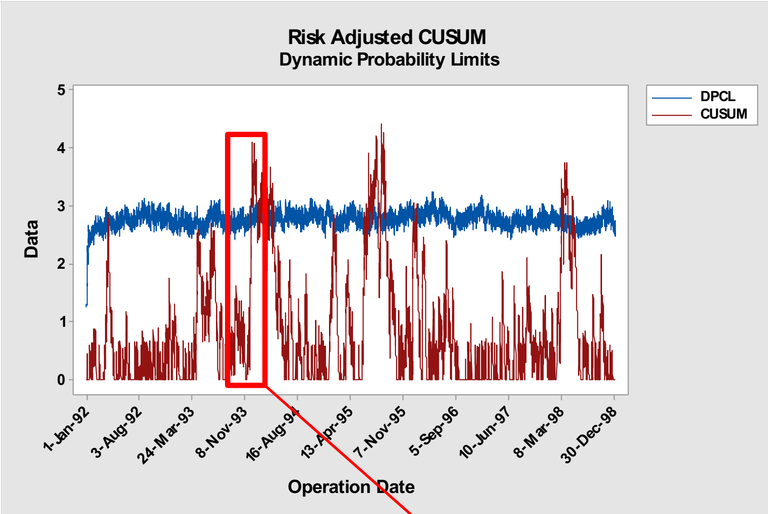
Risk Adjusted Bernoulli CUSUM with Dynamic Probability Control Limits

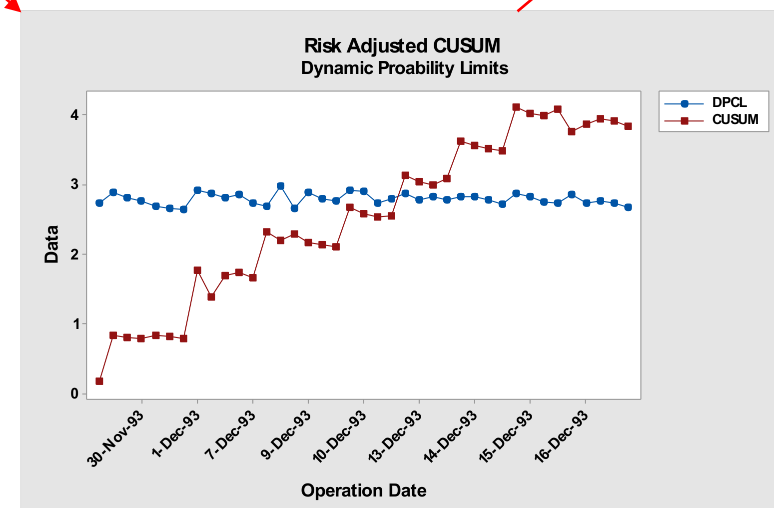
Risk-adjusted Charts

↓	C1-D	C2	C3-T	C4
	Operation Date	Parsonnet Score	Died within 30 days	Predicted Mortality
1	1-Jan-92	19	No	0.096785
2	2-Jan-92	0	No	0.025751
3	2-Jan-92	0	No	0.025751
4	2-Jan-92	3	No	0.031917
5	2-Jan-92	17	No	0.084648
6	2-Jan-92	40	No	0.334834
7	2-Jan-92	3	No	0.031917
8	3-Jan-92	0	No	0.025751
9	3-Jan-92	2	No	0.029717
10	3-Jan-92	5	No	0.036797
11	3-Jan-92	9	No	0.048792
12	3-Jan-92	35	Yes	0.258314
13	5-Jan-92	30	No	0.194176
14	6-Jan-92	20	No	0.103419
15	6-Jan-92	12	No	0.060134
16	6-Jan-92	5	No	0.036797
17	6-Jan-92	25	No	0.142895
18	7-Jan-92	3	No	0.031917
19	7-Jan-92	0	No	0.025751
20	7-Jan-92	2	No	0.029717
21	7-Jan-92	3	No	0.031917



Risk-adjusted Charts





Operation Date	Parsonnet Score	Died within 30 days	Predicted Mortality
30-Nov-93	5	Yes	0.036797
1-Dec-93	0	No	0.025751
1-Dec-93	0	No	0.025751
1-Dec-93	41	Yes	0.351437
1-Dec-93	19	Yes	0.096785
6-Dec-93	9	No	0.048792
6-Dec-93	0	No	0.025751
7-Dec-93	6	No	0.039499
7-Dec-93	1	Yes	0.027665
8-Dec-93	20	No	0.103419
8-Dec-93	0	No	0.025751
9-Dec-93	4	No	0.034273
9-Dec-93	3	No	0.031917
9-Dec-93	0	No	0.025751
9-Dec-93	24	Yes	0.134107
10-Dec-93	19	No	0.096785
10-Dec-93	1	No	0.027665
10-Dec-93	0	No	0.025751
11-Dec-93	19	Yes	0.096785
13-Dec-93	10	No	0.052327
13-Dec-93	9	No	0.048792
13-Dec-93	7	No	0.042391
13-Dec-93	12	Yes	0.060134
14-Dec-93	14	No	0.069021
14-Dec-93	6	No	0.039499
14-Dec-93	2	No	0.029717
14-Dec-93	16	Yes	0.079112
15-Dec-93	12	No	0.060134

Predictive Analytic Tools

- Principal Components Analysis
- Partial Least Squares
- Cross-validation Techniques
- Binary Logistic Regression
- Risk-adjusted Monitoring Charts
- **Rare Events Charts (and not so “rare”)**

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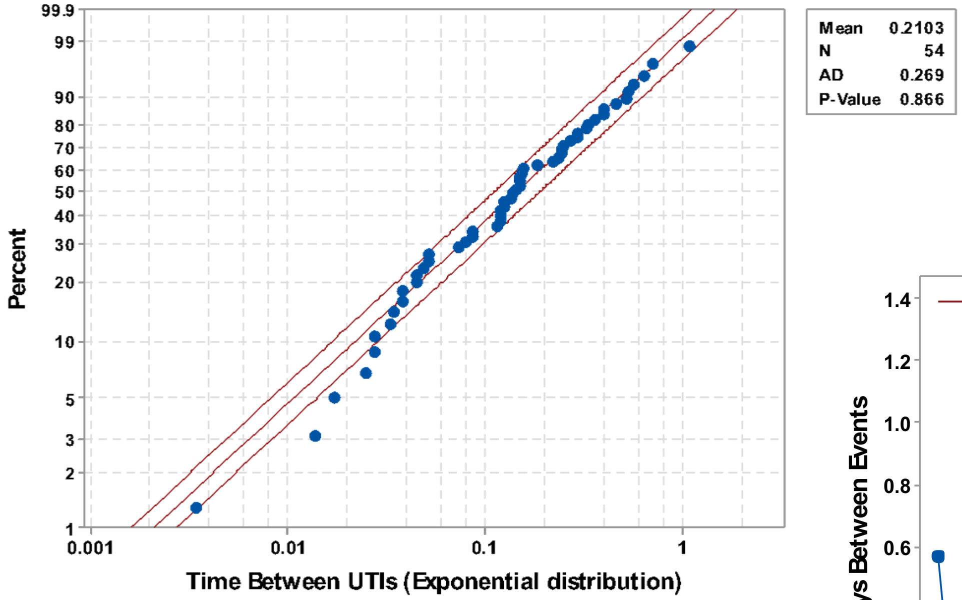
Monitoring Rare Events – UTI's

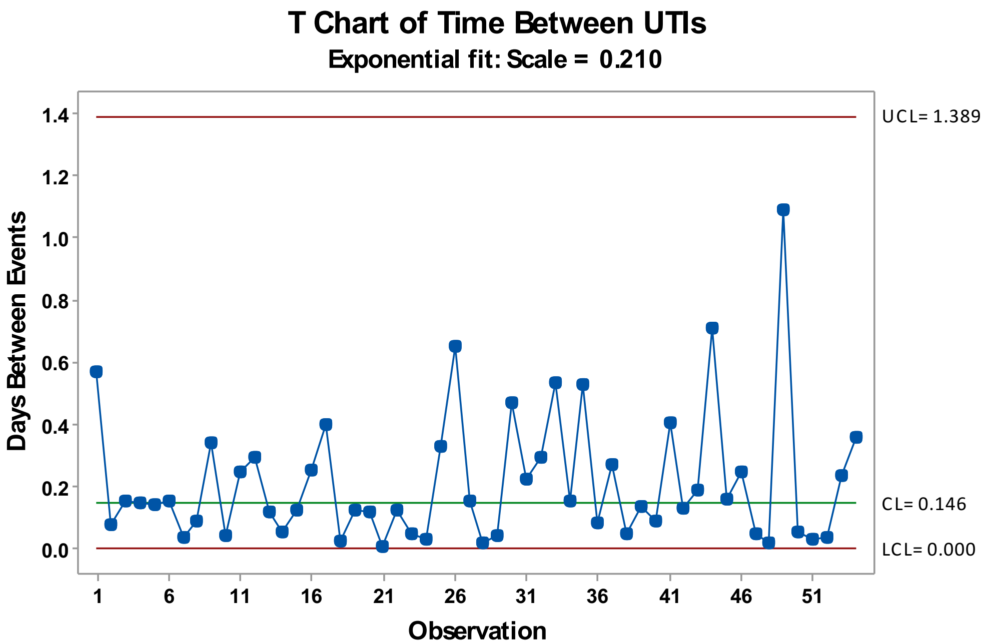
- Description: A large hospital system concerned with a very high rate of hospital-acquired urinary tract infections (UTIs) is trying to evaluate if their processes are in statistical control.

- Because the root cause often differs based on gender, male and female patients are charted separately.

- The financial cost to the hospital is significant, with Medicare no longer covering the cost to treat hospital-acquired infections (historically 80% coverage).

Monitoring Rare Events – UTI's





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Conclusions

- With the increasing size of datasets, predictive analytics should be part of LSS professionals toolset
- Classification problems in Healthcare include modeling readmissions, or mortality but can be generalized to handle problems from various disciplines
- Binary logistic regression, Partial Least Squares are two popular modeling techniques that can incorporate cross validation to ensure robust models
- Process monitoring is a difficult task to achieve when the "samples" are not homogeneous

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