PREDICTING AMBULANCE DIVERSION

Dr. Abey Kuruvilla

Dr Suraj Alexander

Dr. William E. Biles

Dept of Industrial Engineering

University of Louisville, KY

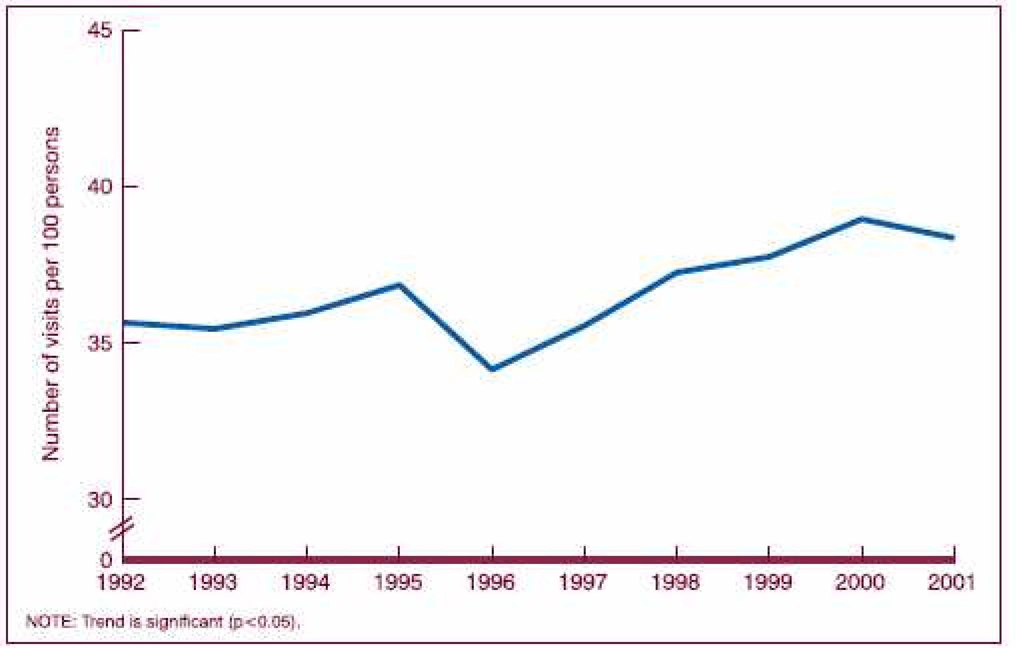
Objectives

- Understand Ambulance Diversion as it exists in the United States
- Develop a mathematical tool for hospitals/EMS systems to be able to predict when diversion can occur

Emergency Department Visits

ED visits rose from 90 m in 1992 to 107.5 m in 2001, about 20%
Number of EDs decreased about 15%.
In 2001 Ed visits went up by 5m.
No corresponding decrease in patient visits.

Source: GAO Report



Summary of a Growing Crisis

- EDs represent most critical access point to nation's health delivery system
  - * Available 24/7, 365 days a year * First response to epidemics and disasters
  - * Guaranteed access point for all who need care regardless of ability to pay
- 62% of all hospital EDs and 3 out of 4 urban EDs perceive they are "at" or "over" capacity
  - * A majority of urban hospitals experienced ED diversion--some more than 20 percent of the time
- ED overload is symptomatic of other capacity issues--lack of critical care beds and staff shortages
- ED volume is rising - capacity likely to worsen

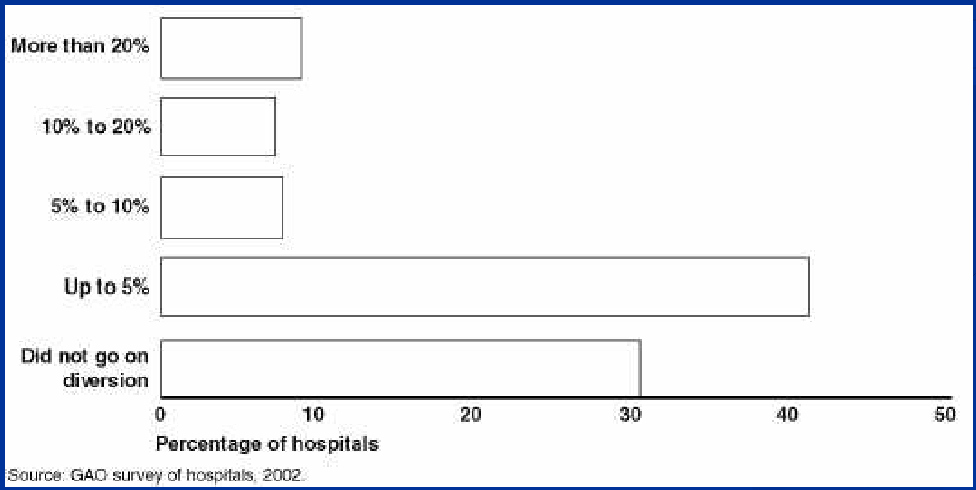
Source: The Lewin Group

Definition of Diversion

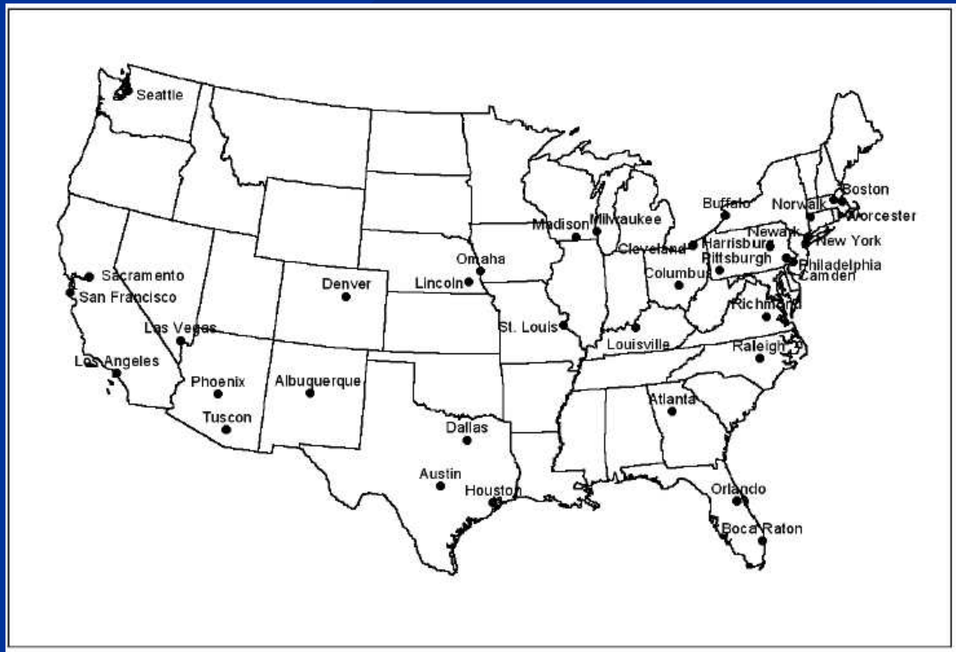
- "The decision to redirect incoming ambulance traffic when an emergency department has reached saturation, is anticipated to remain saturated, and there is capacity at surrounding facilities."

- 14% ED visits made by Ambulance patients
- 2/3 rd of all EDs were on diversion at some point in 2001,
- 1/10 hospitals—more than 20 % of time
- ED visits grew 20 % and # EDs dropped 9.2 %

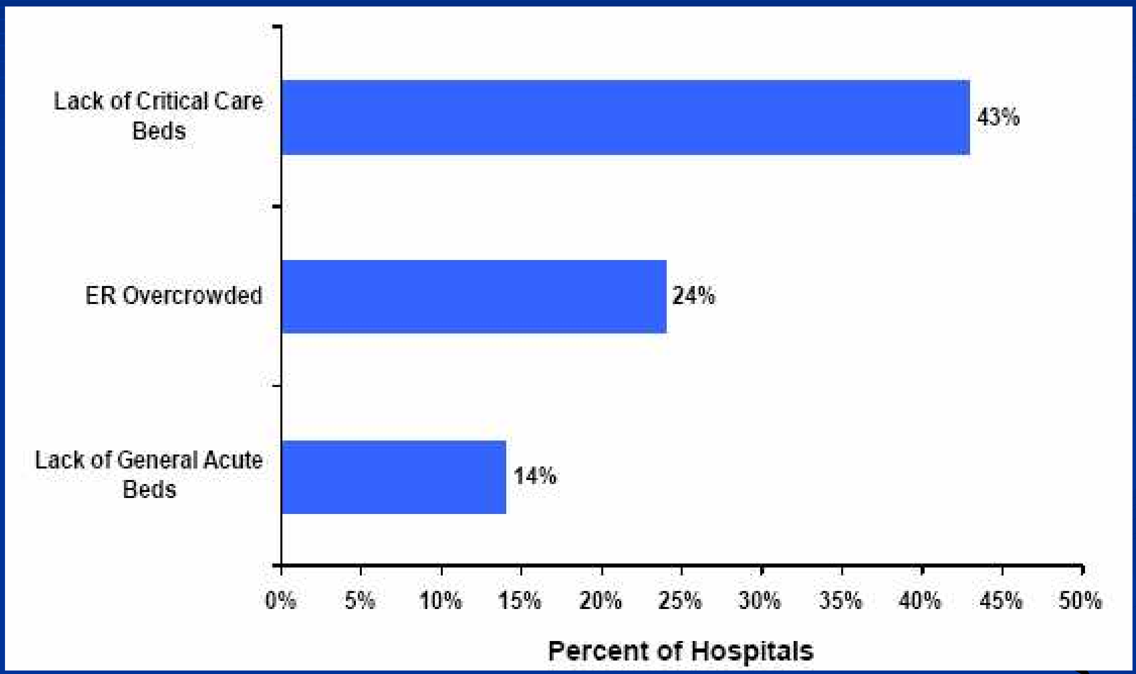
GAO Survey of hospitals 2002



- Diversion as early as 1960s
- Number of hours hospitals diverted patients, doubled in last couple of years
- Diversion can last hours or days



Percent of Hospitals Experiencing Diversion by Reason



- Source: The Lewin Group Analysis of AHA ED and Hospital Capacity Survey 2002.1501 hospitals with EDs (36% of all US hospitals with EDs)

Threats to Patient Care

- Patients transported to other than the closest ED
- Patients faced with long waits in the ED
- Cost to patients/payers increased, Continuity of care issues
- More ambulances needed
- Inconvenience and breaks in the continuity of care
- EMS patients refusing transport “against medical advise”
- Leading to delays for patients to obtain definitive medical care and can sometimes result in death.

Strategies

- Flexible bed base (ability to open additional inpatient beds)
- Unisex wards
- Increases in day surgery
- Day of surgery admissions
- Transfer protocols with other hospitals
- Early discharge planning
- Discharge to transit lounge
- Centralized bed management system

Strategies

- Enhancing lab testing and imaging services
- Adding physician, nursing and support staff to the ED
- Developing a Rapid Diagnostic Unit in the ED
- Admitting certain patients directly to inpatient units, bypassing ED
- Referring patients to the Medical Walk-In Unit
- Opening new inpatient beds.

Literature Survey

- Literature studied over the last 30 years
- ACEP, JEMS, EMS Insider etc
- Literature does not address the issue of the importance of developing a predictor for diversion

Advantages of a Predictor

- Hospitals will be better prepared
- Hospitals can obtain more personnel for that period
- Hospitals can free up more beds in ED
- The region can be better equipped to plan EMS transports
- Transportation time can be reduced

Objective of Research

- Determine the probability of a hospital going on diversion by developing a model

- *Achieved by developing and evaluating various causal models, using methods such as logistic regression, Markov property etc*

Main Contribution

- Established a relationship between 911 calls and diversion
- Developed a methodology for predicting diversions in hospitals using causal factors

Data

- Received from Kansas City, MO

Records of all 911 calls received by MAST for a period of one and a half years

Diversion data entered by hospitals, into EMSystem

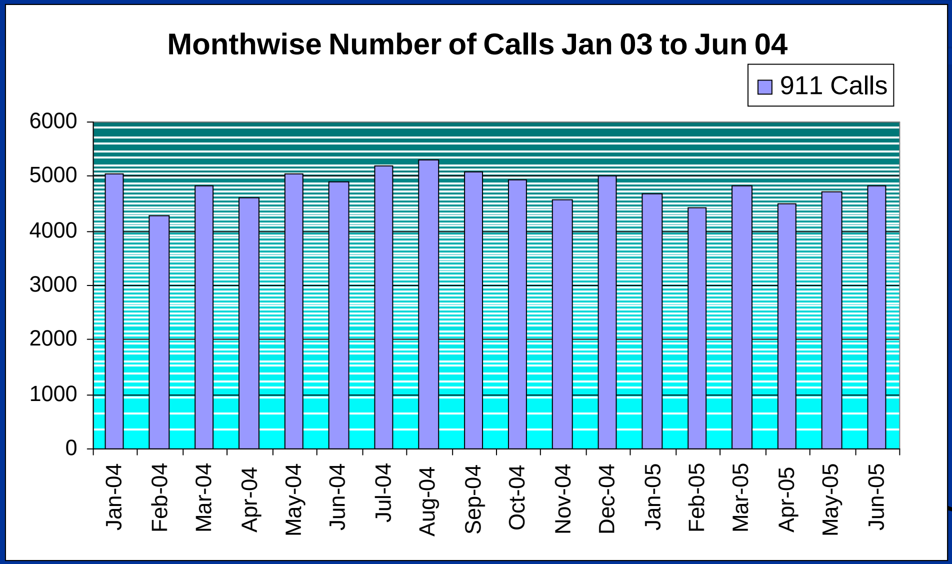
Site of Research

- 36 hospitals in the region with about 26 in Missouri alone
- MAST - Ambulance service authority for Kansas City, Missouri
- MAST operates a fleet of 64 ambulances
- Services a population of over 586,000
- Considered to be among the top ten ambulance services in the US.

911 Data details

- 166,000 911 calls during 11/2 year period (303 calls per day)
- 87,000 (52%) ended in a transport
  (159 per day)
- 1350 (about 0.6% of total transported patients) scheduled non-emergencies
  (2.5 per day)

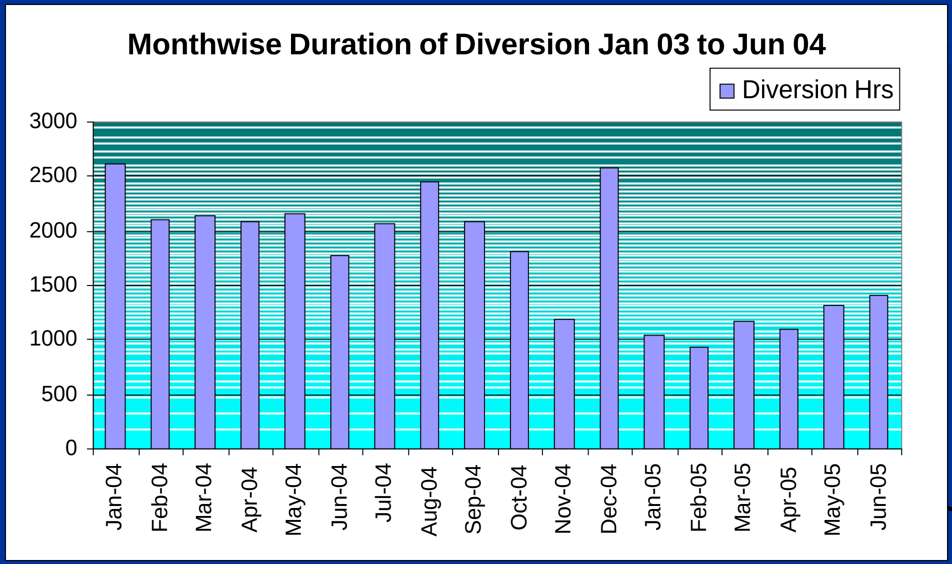
911 Calls Jan 03 to Jun 04



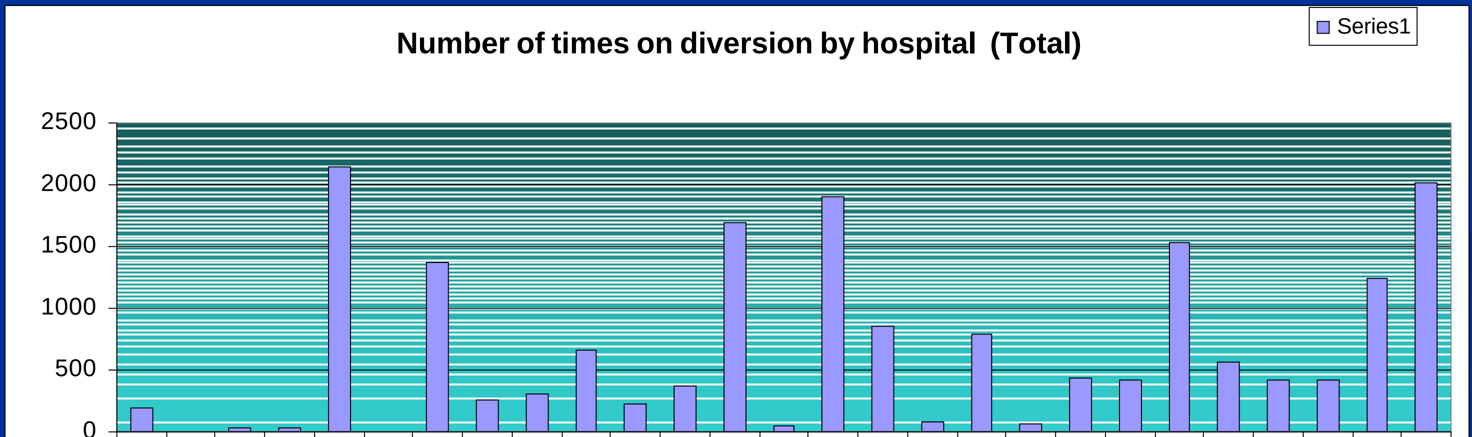
Diversion data

- EMSystem website
- 25 out of 29 hospitals on diversion at some point of time
- Total of 32,000 diversion hours

Duration of Diversion Jan 03 to Jun 04

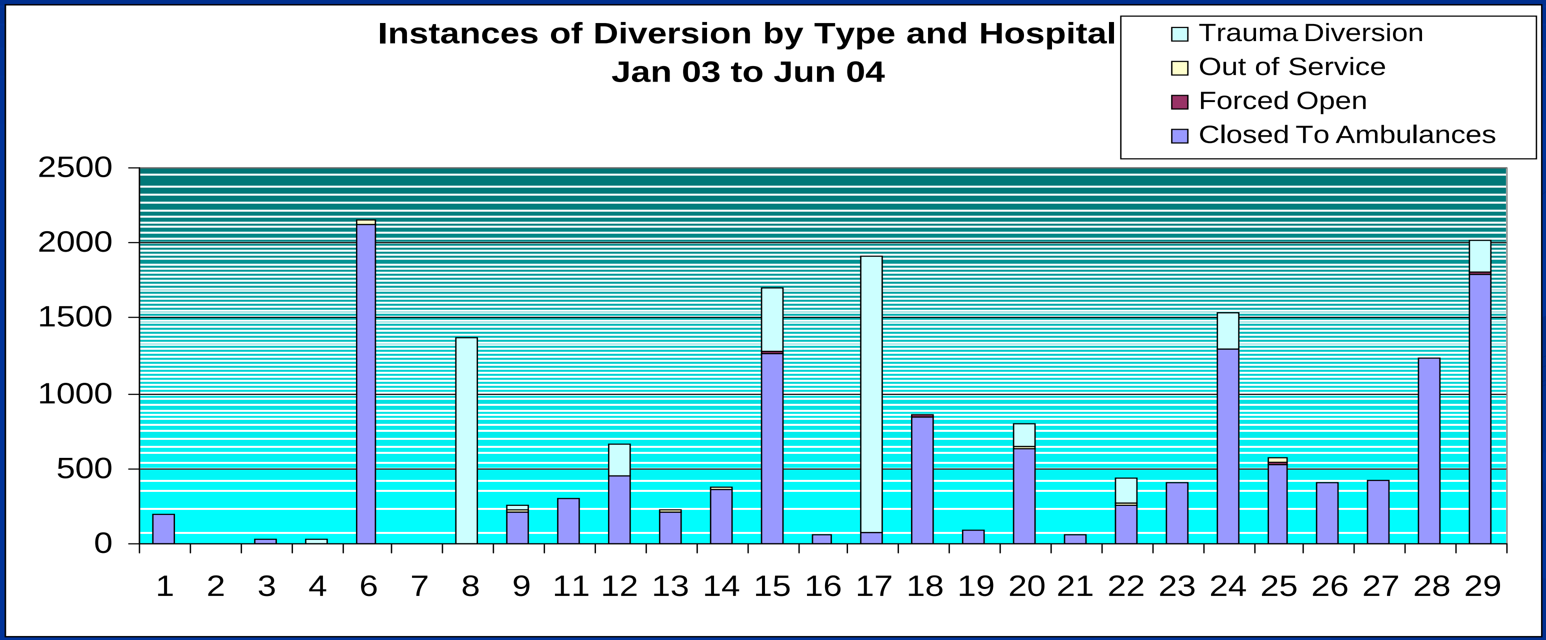


Instances of Diversion



	1	2	3	4	6	7	8	9	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29
Series1	194	2	28	25	2152	6	1364	262	307	669	229	369	1700	53	1910	858	85	794	60	436	414	1529	569	414	418	1238	2012

Diversion by Type



Data Analysis

- Unique form of data
- Developed a program using “R”
- Breakdown of 911 calls into any interval of time
- Breakdown of instances of diversion into any interval of time

Data Analysis

- A variety of Preliminary Statistical Analyses was performed. This provided
  - 1. A better understanding of nature of data
  - 2. Indicated that Logistic Regression Analysis would be appropriate
- In preparing the data for analysis data was put into bins of length 24/h.

Methodology

- In developing an appropriate model, the following notation is useful

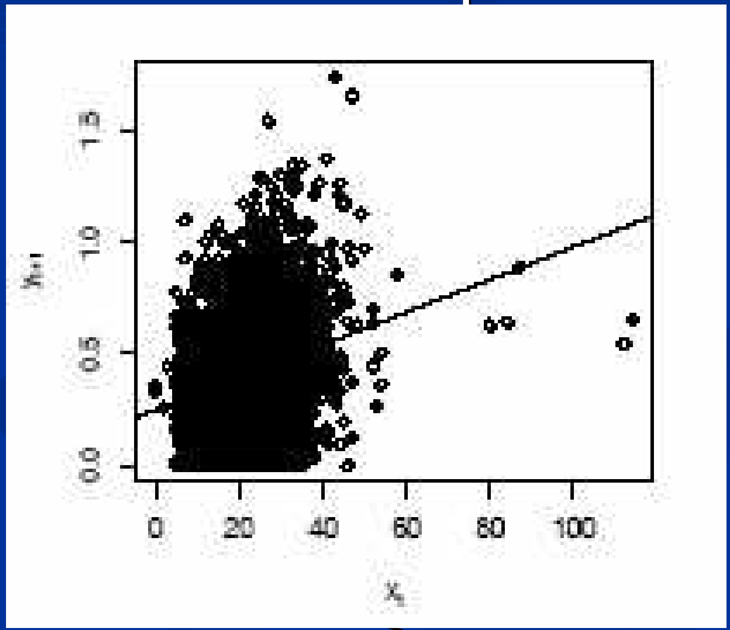
$$
\begin{aligned}
y_t &= \text{duration of hospital diversion during period } t \\
g_t &= \begin{cases} 1 & \text{if } y_t > 0 \\ 0 & \text{if } y_t = 0 \end{cases} = \text{indicator for an occurrence of diversion in period } t \\
x_t &= \text{911 calls during period } t \\
N &= \text{number of days considered by model} \\
h &= \text{number of periods per day} \\
d &= \text{number of lag periods.}
\end{aligned}
$$

- Tried Preliminary regression models to predict the duration of diversion y_{t+1} in period $t+1$ based on the number of 911 calls x_t in period t

Results

- Highly significant regression coefficients
- V. Low R^2 statistic
- Highest R^2 13.21% when @ 4 hour periods

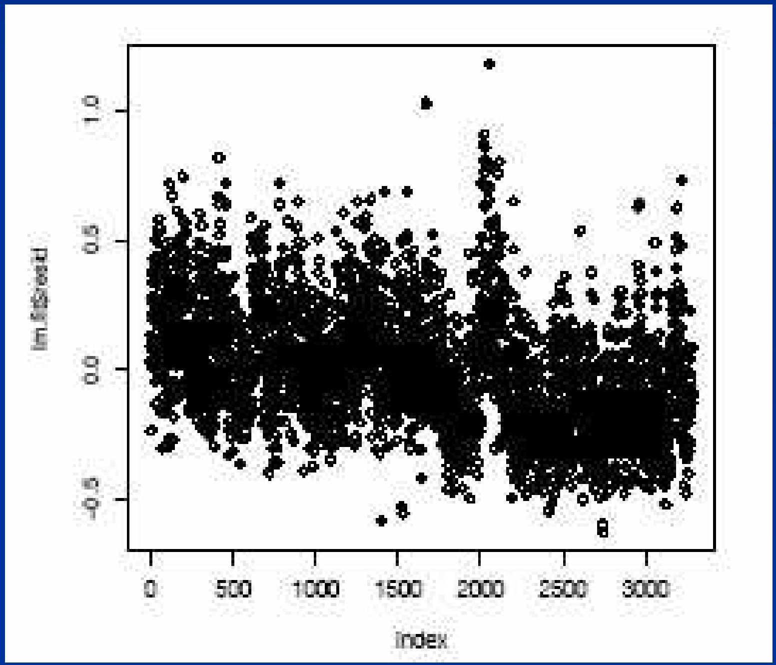
- Plot of data and regression line for four hour periods



- Large amount of variation about reg line
- By adding additional lag periods of 911 calls, adj R sq rose slightly.

Residual Plots

- Should be random when reg model is valid
- Here we see a pattern around Nov. Can be attributed to Influenza season
- Seasonal effect must be considered
- Typical residual plots for all models I considered



1.0
0.5
0.0
-0.5
lm.fit$resid
0
500
1000
1500
2000
2500
3000
Index

Logistic Regression

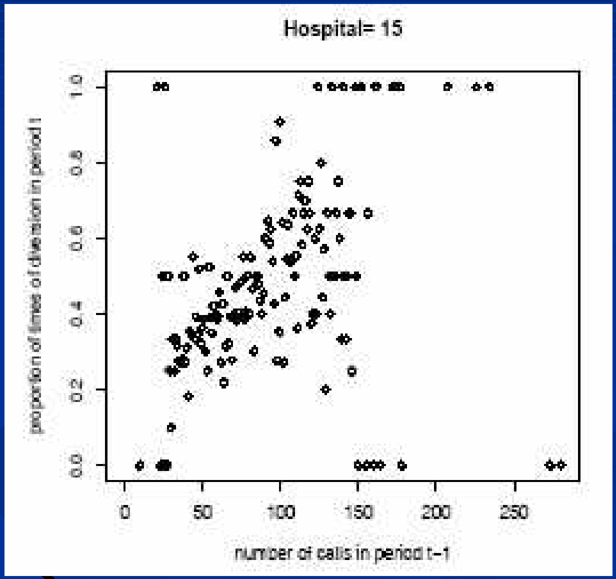
- More likelihood of 911 calls being related to occurrence rather than duration of diversion
- Hospitals have internal factors when deciding to go on diversion

  (*Average waiting time, # pts in waiting room, # waiting ambulances*)
- An appropriate model–Logistic Regression where we look at whether a hospital goes on diversion or not.

Evidence for Logistic Regression

- Plotting

Proportion of time
Hospital went on diversion
In period t based on calls in
Period t



- *Clear Increasing pattern that Logistic regression can effectively model*
- *Some hospitals did not have this pattern*
- *Very few instances of diversion*

- The above model was for individual hospitals
- We need to look at lag periods as we want to see what time intervals 911 calls effect diversion
- Therefore, increased the number of lag periods.

Increased number of lag periods, so model becomes……..

$$\mathbf{P}(g_{t+1} = 1 | g_t = 0) = \frac{e^{\beta_0 + \beta_1 x_t + \ldots + \beta_d x_{t-d+1}}}{1 + e^{\beta_0 + \beta_1 x_t + \ldots + \beta_d x_{t-d+1}}}, \quad t = d, \ldots, Nh - 1$$

- Diversion at time t+1 given not on diversion at time t
- New condition and adding extra lag periods, d.

Results

- p-values for the coefficients of x_t became closer to 0, as more lags were added
- Significant coefficients exhibited the correct sign up to a certain point
- Later some signs were negative, which are typical of time series and also warn us to choose correct number of lags.

- Logistic Regression has proved to be an effective tool to model probability for diversion based on 911 calls
- Specially suited for hospitals with more diversion (for whom we need a model)
- Modify model to consider correlation between 911 calls and locations of hospitals

(*state of one hospital effects state of another*)

- Therefore multinomial model

- The model we looked at works only for one hospital. We need to know the joint probability for a collection of hospitals
- $g_{l,t}$ = indicator for an occurrence of diversion at hospital *l*, in period *t*
- *Then Response Vector is coded by:*

$$b_t = \sum_{\ell=1}^{H} 2^{\ell-1} g_{\ell,t}$$

- Example: If two hospitals are on diversion, then

There are four combinations

Hospital	A	B
$b_t = 0.$	0	0
$b_t = 1$	1	0
$b_t = 2$	0	1
$b_t = 3$	1	1

Multinomial model

- Its important to look at all hospitals together. How does one on diversion affect another?
- Here we model the joint probability to a multinomial model

$$\mathbf{P}(b_{t+1} = k \mid b_t, x_t) = \frac{e^{m_k(x_t;b_t)}}{\sum_{\ell=1}^{2^H} e^{m_\ell(x_t;b_t)}}, \quad k = 0, 1, \ldots, 2^H - 1$$

$$\mathbf{P}(b_{t+1} = k \mid b_t, x_t) = \frac{e^{m_k(x_t;b_t)}}{\sum_{\ell=1}^{2^H} e^{m_\ell(x_t;b_t)}}, \quad k = 0, 1, \ldots, 2^H - 1$$

- X_ts = vector of all explanatory variables eg duration
- bs are a way of coding gs
- x_t = number of calls
- K = index for the code that says what combination os hospitals we are looking at.

- Implicitly requires construction of Markov Chains

Will Consider:

- Variations to g's
- Variations to x's
- Seasonal Effects daily, weekly, yearly
- Other confounding factors (ER beds, locations, available beds)
- Best lag d for x's in terms of model fit

Once the model is complete we can:

- Estimate the probability that a particular hospital will be on diversion based on the number of 911 calls and other explanatory variables
- Estimate the correlation between two hospitals being on diversion at the same time one after another
- Determine a threshold region to assess the probability that a particular hospital will go on diversion within a specified amount of time

Hospitals in KC, MO

Top Five hospitals in KS, MO

Summary of Results

- Top five hospitals were studied
- Calls upto 3 hours were significant
- Most other factors like flu, day of week, quarter of day and b_t were significant

Significance of 911 Calls

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	156410.705	163753.150	154674.705(a)	.000	0	.
calls0t30	156401.703	163481.918	154727.703	52.998	31	.008
calls30t60	156409.715	163489.930	154735.715	61.010	31	.001
calls60t90	156429.293	163509.508	154755.293	80.588	31	.000
calls90t120	156420.894	163501.109	154746.894	72.189	31	.000
calls120t150	156407.892	163488.107	154733.892	59.187	31	.002
calls150t180	156411.100	163491.314	154737.100	62.394	31	.001
calls180t210	156395.106	163475.320	154721.106	46.400	31	.037
calls210t240	156405.862	163486.077	154731.862	57.157	31	.003
calls240t270	156402.602	163482.817	154728.602	53.897	31	.007
calls270t300	156395.423	163475.638	154721.423	46.718	31	.035
calls300t330	156388.227	163468.442	154714.227	39.522	31	.140
calls330t360	156383.581	163463.796	154709.581	34.876	31	.289
calls360t390	156380.898	163461.113	154706.898	32.193	31	.407
calls390t420	156386.864	163467.079	154712.864	38.159	31	.176
calls420t450	156372.793	163453.007	154698.793	24.087	31	.807
calls450t480	156379.835	163460.050	154705.835	31.130	31	.460

Significance of Other Factors

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
bt	157904.166	163935.460	156478.166	1803.461	155	.000
flu	166826.465	173906.679	165152.465	10477.759	31	.000
weekend	157070.226	164150.440	155396.226	721.520	31	.000
quarter	157043.627	163599.381	155493.627	818.921	93	.000
year	184649.379	191729.594	182975.379	28300.674	31	.000

Case Summary 911 Calls

		N	Marginal Percentage
g_t	00001	5026	14.40%
	00010	2537	7.30%
	00011	1499	4.30%
	00100	1984	5.70%
	00101	1033	3.00%
	00110	1126	3.20%
	00111	448	1.30%
	01000	1595	4.60%
	01001	2443	7.00%
	01010	518	1.50%
	01011	391	1.10%
	01100	531	1.50%
	01101	555	1.60%
	01110	206	0.60%
	01111	155	0.40%
	10000	1139	3.30%

		N	Marginal Percentage
	10001	1344	3.90%
	10010	540	1.50%
	10011	501	1.40%
	10100	693	2.00%
	10101	445	1.30%
	10110	493	1.40%
	10111	277	0.80%
	11000	292	0.80%
	11001	587	1.70%
	11010	121	0.30%
	11011	163	0.50%
	11100	209	0.60%
	11101	270	0.80%
	11110	118	0.30%
	11111	148	0.40%
	99999	7471	21.40%

Case Summary - Other Factors

		N	Marginal Percentage
flu	0	29034	83.30%
	1	5824	16.70%
weekend	0	24814	71.20%
	1	10044	28.80%
quarter	12am-6am	8727	25.00%
	12pm-6pm	8703	25.00%
	6am-12pm	8738	25.10%
	6pm-12am	8690	24.90%
year	0	17467	50.10%
	1	17391	49.90%
Valid		34858	100.00%
Missing		0	
Total		34858	
Subpopulation		34857(a)	

Marginal Classification Tables

911 Calls 30-60 min

	A	B	C	D
1	Marginal classification table for 30-60 minutes into future			
2				
3	Hospital 17			
4	**Observed**	Diversion	Not Diversion	**Percent Correct**
5	Diversion	15249	153	99.00662
6	Not Divers	155	19520	99.2122
7	**Frequenc**	43.91482	56.08518	99.12193
8				
9	Hospital 8			
10	**Observed**	Diversion	Not Diversion	**Percent Correct**
11	Diversion	8870	443	95.24321
12	Not Divers	443	25321	98.28055
13	**Frequenc**	26.55016	73.44984	97.47413
14				
15	Hospital 6			
16	**Observed**	Diversion	Not Diversion	**Percent Correct**
17	Diversion	7338	1441	83.58583
18	Not Divers	1441	24857	94.5205
19	**Frequenc**	25.0278	74.9722	91.78379
20				
21	Hospital 29			
22	**Observed**	Diversion	Not Diversion	**Percent Correct**
23	Diversion	7421	955	88.59838
24	Not Divers	957	25744	96.41586
25	**Frequenc**	23.8846	76.1154	94.54913
26				
27	Hospital 17			
28	**Observed**	Diversion	Not Diversion	**Percent Correct**
29	Diversion	5800	1641	77.94651
30	Not Divers	1641	25995	94.06209
31	**Frequenc**	21.21333	78.78667	90.64344

Classification Tables

Classification Table for 911 calls from 30 to 60 minutes									
bt	**Predicted**								
Observed	**1**	**10**	**11**	**100**	**101**	**110**	**111**	**1000**	**% Correct**
1	4259	0	62	0	134	0	1	2	84.4
10	0	2056	14	4	0	148	0	5	80.66
11	61	11	1214	0	1	0	55	0	80.56
100	1	11	0	1389	16	40	0	5	69.87
10000	1	3	0	21	0	0	0	5	64.2
10001	204	0	2	0	16	0	0	0	71.69
11010	0	4	0	0	0	1	0	0	53.28
11011	0	0	5	0	0	0	1	0	65.06
11100	0	0	0	10	0	1	0	5	54.55
11101	1	0	0	0	7	0	0	0	55.64
11110	0	0	0	0	0	5	0	0	58.82
11111	0	0	0	0	0	0	9	0	55.48
99999	35	80	1	367	5	5	0	140	87.11
Overall %	14.39	7.27	4.3	5.67	2.96	3.23	1.3	4.55	76.39

Conditional Tables

- Based on the Statistic

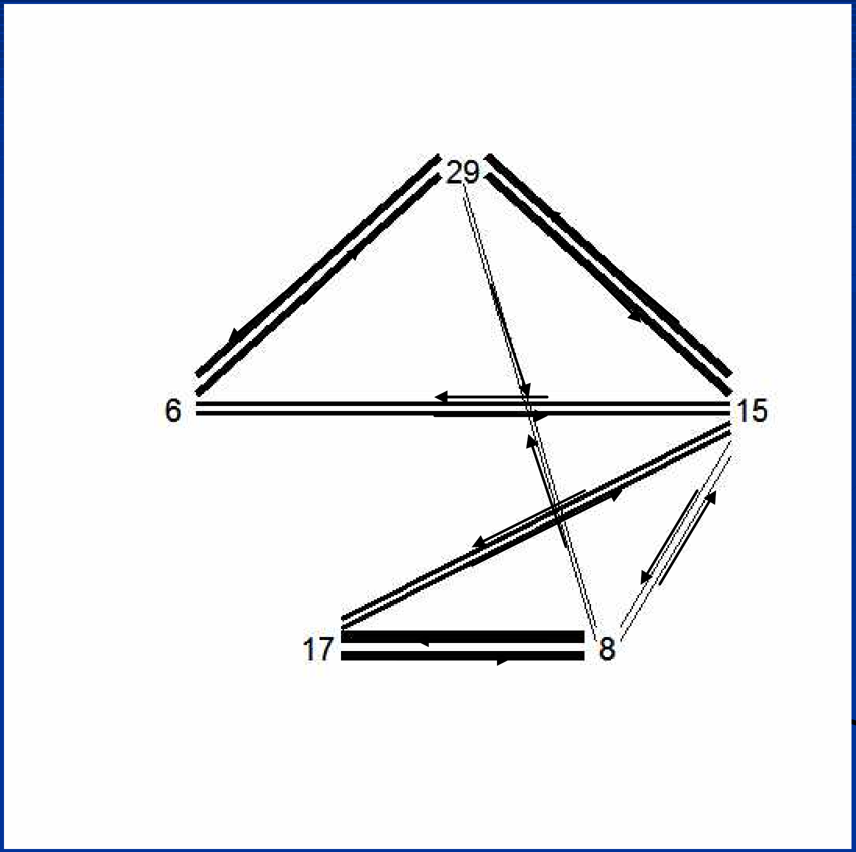
$$\frac{p_0 - p_1}{\sqrt{\frac{p_0(1-p_0)}{n_0} + \frac{p_1(1-p_1)}{n_1}}}$$

- where *p0* and *p1* are the sample proportions and *n0* and *n1* are the sample sizes for each current state which is asymptotically standard normal

Conditional Probabilities

P(hospital k on diversion during period t+1 | hospital j on/not on diversion during period t)						
j/k	17	6	29	8	15	n
17	0.994805	0.235225	0.219249	0.308936	0.245941	15398
not 17	0.004016	0.289265	0.274423	0.183796	0.185473	19674
p-value	0	1	1	8.54E-161	1.62E-42	
6	0.388597	0.975733	0.325352	0.197573	0.257919	9313
not 6	0.457238	0.008774	0.223029	0.25362	0.195427	25759
p-value	1	0	1.94E-77	1	5.03E-34	
29	0.384344	0.339449	0.915679	0.254102	0.309253	8776
not 29	0.457256	0.240873	0.028103	0.23361	0.179571	26296
p-value	1	2.78E-67	0	6.03E-05	1.85E-124	
8	0.567897	0.219635	0.264421	0.941837	0.230861	8373
not 8	0.398592	0.279936	0.24574	0.01824	0.206113	26699
p-value	3.86E-165	1	0.000336	0	1.10E-06	
15	0.508404	0.32029	0.357806	0.261127	0.887186	7437
not 15	0.420337	0.250805	0.221241	0.232712	0.030324	27635
p-value	5.87E-42	2.95E-31	1.53E-111	2.99E-07	0	

Conditional Connections



- Conditional Connections between diversion at one hospital at time t and diversion at other hospitals at time t + 1

Expected Solutions

- *EMS predicting when hospitals go on diversion thus providing early warning signs*
- *decreasing the average length of stay in the ED and throughout the hospital*
- *enhancing lab testing and imaging services to decrease wait times for patients*
- *adding physician, nursing and support staff to the ED*
- *opening new inpatient beds.*

Conclusion

- The comprehensive model addresses several other factors to predict diversion besides 911 calls
- The model can be modified to be used at other locations

Contribution

- Solutions have mostly been of a stop-gap nature
- Simulation have been attempted at University of Virginia
- First attempt to apply statistical analysis via logistic regression to predict and therefore help avert a diversion
- Help communities to predict the likelihood of when a specific hospital will be on diversion

Acknowledgements

- Jonathan Washko, Managing Partner, Firstwatch
- Todd Stout, President, Firstwatch
- Staff at MAST, KS

- Thank you !!