911 CALL AND OTHER REAL TIME DATA APPLICATIONS IN EMS DIVERSION

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Summary

- Brief Background
- Introduction to Ambulance Diversion
  - Overview
  - Predictor
  - Methodology
  - Discussion
- Current Focus
- Future Directions
- Conclusion

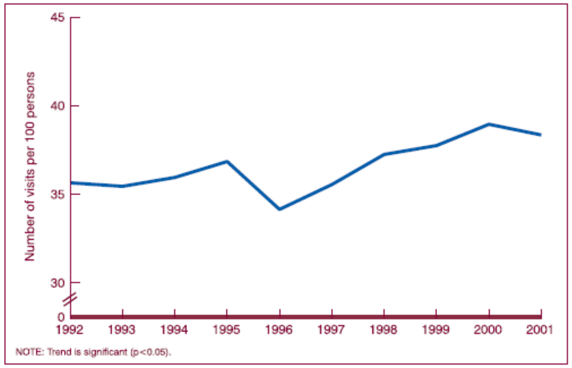
Definition of Ambulance Diversion

"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."

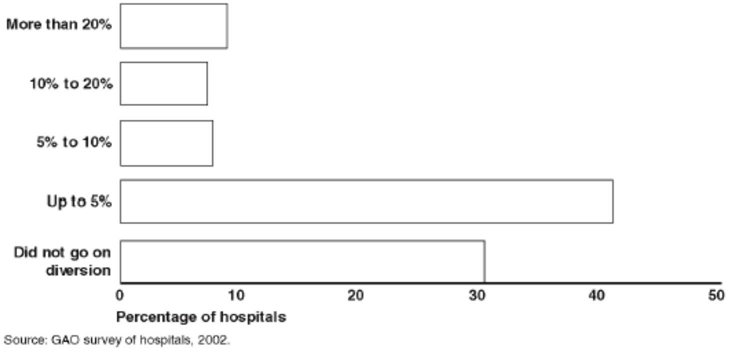
Objectives of Research

- 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

Background



ED visits rose from 90m in 92 to 107.5 m in 01, 20%
Number of EDs decreased about 15%.



GAO Survey of Hospitals 2002

2/3 of all hospitals on Diversion

1/10 more than 20% of time

Henry Waxman Report

Diversion lasts hours or days!

Source: GAO report

Summary of a Growing Crisis

- ED – Most Critical Access Point to Healthcare
- 62% of all EDs and 75% Urban EDs over capacity
- ED Volume rising – capacity likely to worsen

Threats to Patient Care

- Patients transported to other than closest ED
- Inconvenience/breaks in the continuity of care
- EMS Patients refusing transport
- Ambulances held up
- Delays in obtaining definitive care

Current Strategies

- Increases in day surgery
- Transfer protocols with other hospitals
- Early discharge planning, to lounge etc
- Adding physician, nursing, support staff to ED
- Enhancing testing services
- Admitting directly to inpatient units

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 that period
- Hospitals can free up more beds in ED
- Region can be better equipped to plan transports
- Transportation time can be reduced

Objective of Research

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

Methodology

- Developing and evaluating various causal models, using methods such as Logistic Regression, Markov property etc

Kansas City Profile

- 36 hospitals in the region, 26 in Missouri
- MAST - Ambulance service authority for Kansas City, MO
- MAST
  - operates a fleet of 64 ambulances
  - Services a population of over 586,000
  - Among the top ten ambulance services in the US.

911 Call Data

- 166,000 911 calls during 1 $^{1}/_{2}$ year period (303/day)
- 87,000 (52%) ended in a transport (159 per day)
- 1350(0.6) scheduled non-emergencies (2.5 per day)

Diversion data

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

Data Analysis

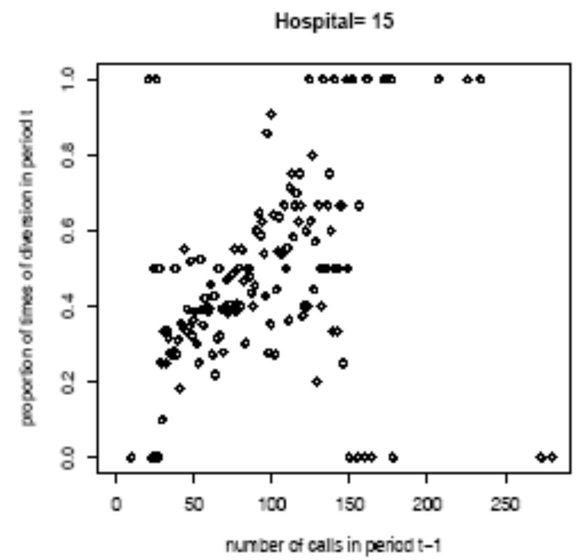
- Unique form of data
- Developed a program using “R”
  - Breakdown of 911 calls into any interval of time
  - Breakdown of diversion into any time interval
  - **Initially looked at duration of diversion at yt based on calls**
- Variety of preliminary stat analysis
  - Indicated Logistic Regression Analysis would be appropriate

Case for Logistic Regression

- More likelihood of 911 calls being related to occurrence rather than duration of diversion
- An appropriate model–Logistic Regression
  - whether a hospital goes on diversion or not.

Evidence for Logistic Regression

Plot of proportion of time hospital went on diversion in period *t* based on calls in period *t-1*



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

Further Modeling

- Logistic Regression 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)
- Further modified 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 just looked at works only for one hospital. We need to know the joint probability for a collection of hospitals. How does one affect another?

- $g_{l,t}$ = indicator for an occurrence of diversion at hospital *l*, in period *t*
- *Response Vector 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

Modeling the joint probability to a Multinomial model....

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

- $\mathbf{x}_t$s = vector of all explanatory variables e.g duration
- b's are a way of coding g's
- x_t = number of calls
- K = index for the code that says what combination of hospitals we are looking at.

- Implicitly requires implementation of the Markov property

Considered:

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

Summary of Results
(Top five hospitals)

- Calls up to 3 hours were significant
- Most other factors like flu, day of week, quarter of day and b_t were significant

Significance of 911 Calls

	Model Fitting Criteria			Likelihood Ratio Tests		
Effect	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

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

Conditional Tables

- Based on the Statistic

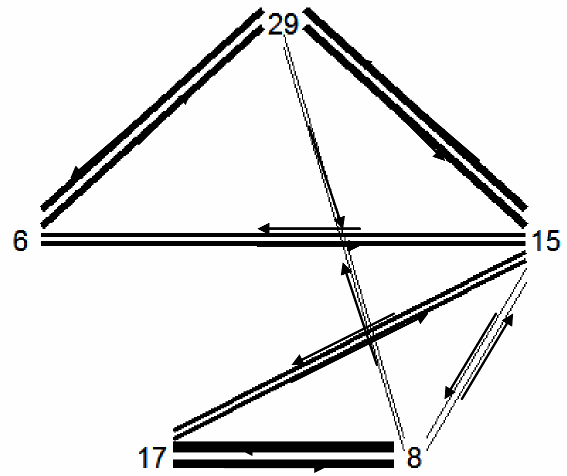
$$\frac{p_0 - p_1}{\sqrt{\dfrac{p_0(1-p_0)}{n_0} + \dfrac{p_1(1-p_1)}{n_1}}}$$

- 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

Major Contributions

- Established a relationship between 911 calls (and other factors) and diversion
- Developed a methodology for predicting diversions in hospitals using causal factors
- First attempt to apply statistical analysis via logistic regression to predict and therefore avert diversion decision

What could Hospitals/EMS do?

- *Benefits for EMS with this model*
- *Benefits for hospitals with the model*
- *Financial Benefits to both*

- The model helps EMS/hospitals to better manage the health of the community!

- Current Focus

Publishing and Research Presentations

- Papers for International Journal of Information Sytems in the Service Sector
- Conference Presentations – INFORMS, SHS, Canadian Operations Research Society
- Presentation at Univ of Calabria, Italy
- Poster presentations

Collaboration and Additional Streams

- University of Calabria, Italy
  - Prof Guiseppe Paletta – Dynamic Scheduling of Ambulances
- University of Louisville, KY
  - Prof Ryan Gill, Prof Suraj Alexander
- University of Wisconsin Parkside
  - Graduate Students 911 calls to predict the Flu – Acceptance and Presentation at CORS

Future Research

- Test the model at other locations - Seattle
- Scale the model for larger areas
- Look at origin and types of 911 calls to analyze causes and origin areas
- Optimization of EMS Resources
- Department of Homeland Security

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Questions!

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- Email me at abeykuruvilla@gmail.com

Thank You!