Spatio-temporal Structure of US Critical Care Transfer Network

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Motivation: ICU

Why transfers exist:

- ICUs have limited capacity, so transfers are sometimes needed to distribute patient load
- Patients have different needs, so they must sometimes be transferred to a different ICU to ensure they get proper care
- Inefficiencies in current system
  - Patients recurrently transfer to secondary hospitals rather than most-preferred option
  - Inefficient cascades
- Time Sensitive transfers

The Data

- 1996-2005 Medicare Provider Analysis and Review (MedPAR)
  - Contains 96% of Americans aged 65+
  - Excluded group health organizations with premiums
  - Excluded “psychiatric critical care”
  - Excluded non-ICUs

- Transfers between hospitals are not directly from claims
  - Infer transfer from claims

Definition of a Transfer

- A transfer between two hospitals g and h occurs when:
  - Patient was observed to be at hospital g until a certain day
  - Patient was then observed to be at hospital h beginning on the same day (or next day)
- Critical Care Transfer
  - A transfer between two hospitals g and h where both hospitals g and h involved critical care use
- Structure of data S:

$$S = [(g1 \rightarrow h1, t1),(g2 \rightarrow h2, t2), \ldots ,(gn \rightarrow hn, tn)]$$

Primary Transfer

A primary transfer pair is two hospitals (i.e. A and B), such that there are more transfers from A to B than from A to any other hospital.

send(h) = {g: recv(g) = h, g $\in \mathcal{H}$} where:

send(h) denotes the set of hospitals for which h is the primary receiving partner

recv(g) = h denotes that hospital h is the primary recipient for hospital g.

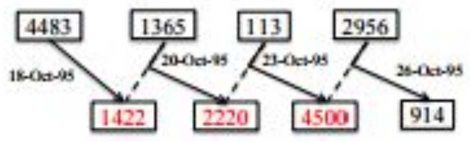
Secondary Transfer

- A secondary transfer from hospital A to B where B is not the primary recipient of transfers from A.

B != revc(A)

Cascade

- Cascade is defined in terms of an ordered list of hospitals
- Characterized by a sequence of transfers in the data:
  - $(x \rightarrow h1), t1 \rightarrow (g1 \rightarrow h2), t2 \rightarrow (g2 \rightarrow h3), t3 \ldots (gk-1 \rightarrow hk), tk \rightarrow (gk \rightarrow y), tk+1$
- Where the temporal proximity of the transfers:
  - $t2 - t1 \leq \delta; t3 - t2 \leq \delta; \ldots; tk+1 - tk \leq \delta$
  - For this experiment, δ was 1 day.



- Finding cascades in the transfers is combinatorially hard

Level-wise procedure for Cascade Mining

- Generate, reduce, repeat

1. Generate initial list of candidate cascades of size 2
2. Set k <- 2
3. Repeat until no candidate cascades remain
   a. Count non-overlapped occurrences of candidate cascades in data
   b. Retain only those cascades that occur more often than a threshold
   c. Generate k + 1- size candidate cascades, using the list of frequent n-size cascades
   d. Increment k
4. Output frequent cascades

Count cascade with primary transfer hospitals

- If the condition on Line 8 is met it implies that there exists a sequence of secondary transfers that together constitute an occurrence of the cascade α and also the consecutive pairs of transfers satisfy the gap constraint.

Algorithm 2 Count cascade with primary transfer hospitals $\alpha = \langle h_1, h_2, \ldots, h_k \rangle$ and a gap-constraint δ.

1: Initialize $count \leftarrow 0$
2: Initialize $T_\alpha[h_i] = \phi, \forall i = \{1, \ldots, k\}$
3: **for** $(g \rightarrow h, t) \in \mathcal{S}$ **do**
4:     **for** $i \in \{1, \ldots, k\}$ **do**
5:         **if** $h = h_i$ **then**
6:             **if** $(i = 1)$ or $(g \in send(h_{i-1})$ and $t - T_\alpha[h_{i-1}] \leq \delta)$ **then**
7:                 $T_\alpha[h_i] = t$
8:     **if** $(g \in send(h_k)$ and $h \notin \alpha)$ and $(t - T_\alpha[h_k] \leq \delta)$ **then**
9:         $count \leftarrow count + 1$
10:         $T_\alpha[h_i] = \phi\ \forall i = \{1, \ldots, k\}$
11: **return** $count$

Statistical Significance: Null Models

- Significant cascades have a temporal structure
  - Structure depends on the exact ordering and timing of the constituent transfers

- Goal: find a null model that removes such structure
  - Result: p-value of a cascade

Null Model 1: Temporal Shuffling

- Generates surrogate datasets by randomly shuffling the time of occurrence of transfers in consecutive chunks of 100 transfers
- First order statistics are preserved
  - No adding or removing to original data
- For each cascade discovered in level-wise mining, determine its count over n surrogate datasets.
  - Estimate distribution of number of occurrences of cascade under the null model
  - Determine p-value

Null Model 2: Spatial Shuffling

- Redistribute the receivers of secondary transfers
- For every secondary transfer, g -> h replace h with h*, where:
    - h* is randomly chosen from the set of hospitals known to receive transfers from g
    - h* is not primary recipient
- Model ensures spatial structure of secondary transfers is removed

Results

- Discovered 163 cascades of size 3
  - P <= 0.001 with respect to both null models
- 3204 cascades discovered
  - Cascades accounted for 10208 transfers
  - 1.33% of total transfers

Max distance = 250 miles
Max delay = 3 days
Min count for mining = 15

Cascade	Count	p-value-1	p-value-2
1422-2220-4500	57	0.001	0.001
2419-1099-552	55	0.001	0.001
4661-1204-225	48	0.001	0.001
552-1099-839	47	0.001	0.001
4661-1204-4531	45	0.001	0.001

Top 5 Cascades

Geographical Distribution

- Figure shows the potential transfers that were diverted
- High number or cascades on east coast.
- High density of hospitals shows the true alternatives in bigger cities.

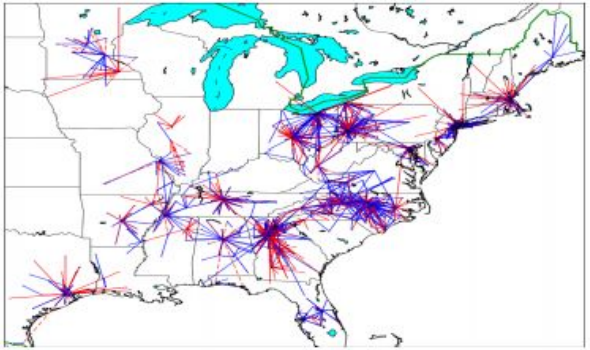
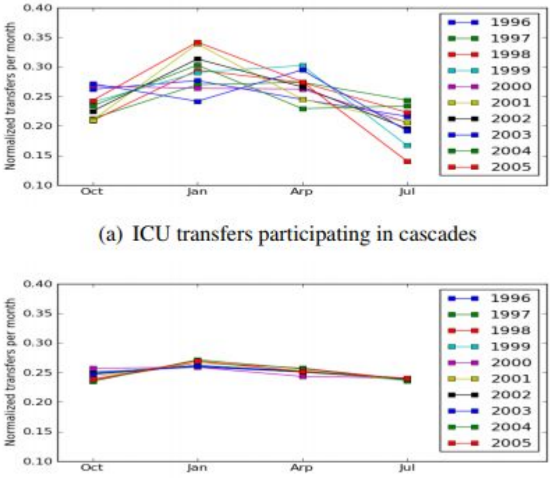


Figure 3: Plot of the cascade occurrence on the US map. In the figure, red arrows indicate primary transfer pairs and blue arrows show the actual secondary transfers.

Seasonal Variations

- Data is normalized with respect to number of transfers in occurrences of cascades.
- Winter quarter has significant increase in transfers involving cascades.
  - Increase is not as significant when viewing all ICU transfers
- Cascades can be used as early predictors of seasonal effects
  - Potentially help with capacity planning for ICU



(a) ICU transfers participating in cascades

(b) All ICU transfers

Figure 4: Seasonal variation in the occurrence of cascades. The transfers are presented in buckets of three months. The data is normalized with respect to the total number of transfers in occurrences of cascades in (a) and all transfers in (b).

Network Hot-spots

- Network Hotspot: a hospital involved in many cascades
- Hospital 39 is present in 717 distinct cascade occurrences

- Potential indication of bottlenecks

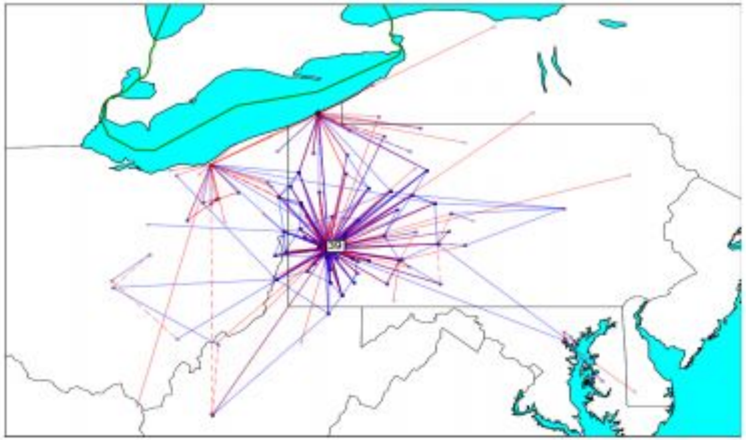


Figure 5: Plot of cascades involving Hospital 39.

Application of Potential Bottlenecks

- Use cascades to identify bottlenecks
- Concentration of cascades in hot-spots suggests these areas have a binding capacity constraint in critical care transfers.
    - Potential implication: data suggests that transfers from hotspot hospitals may have been delayed by the time it took to identify a secondary transfer location
        - Delays could have consequences on patients
- Patterns may provide an important screening tool
    - Target quality improvement initiatives
        - Optimize the availability of high quality ICU referral capacity