Opportunities and challenges for probabilistic models of cascading line outages driven by historical utility data

Ian Dobson

Iowa State University

dobson@iastate.edu http://iandobson.ece.iastate.edu

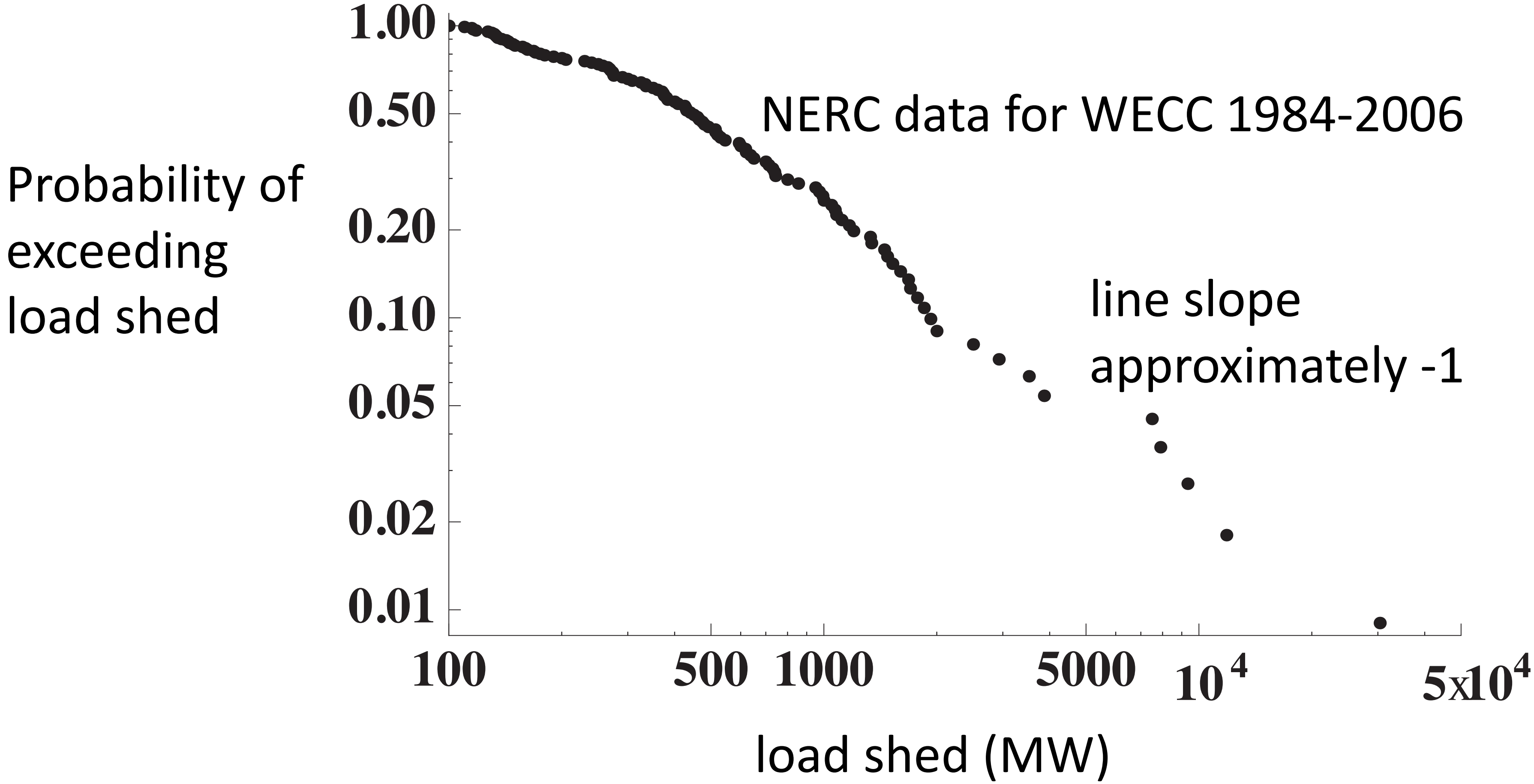
Collaborators: **Kai Zhou, Zhaoyu Wang, Paul Hines, Alex Roitershtein, Arka Ghosh, Ben Carreras, David Newman**

PSERC

PSERC Webinar, March 26 2019

Funding from NSF is gratefully acknowledged

Heavy tails in distribution of blackout size implies
Risk of large blackouts > risk of medium size blackouts



Overall challenges

- Large blackouts have the most risk, but are hardest: rare, dependent events, sparse data, complicated cascades with many mechanisms for initiation and propagation (mitigating only small blackouts can in some cases increase large blackouts)
- Need multiple approaches:
  - high level statistical models
  - simulation of detailed models
  - historical data

I will discuss historical data and statistical models driven by the data

Detailed historical line outage data

Automatic (Unplanned) Transmission Line Outages: 2009 Complete

CHRONOLOGICAL ORDER

Outage#	Tred ID	Line Name	Gen Flag	kV	District	Own Code	Length (Mi)	Out Date/Time	In Date/Time	Out Mins	Disp Caus
157560	339	xxxx-xxxxxx (230 kV)		230	xxxx	2	0.5	6/18/07 23:48	2/23/09 14:38	886550	81
164651	140	xxxx-xxxxxx (230 kV)	G	230	xxxx	1	61.9	1/2/09 2:35	1/2/09 17:43	908	31
164652	497	xxxx-xxxxxx (115 kV)	G	115	xxxx	1	24.8	1/2/09 3:55	1/2/09 6:59	184	90

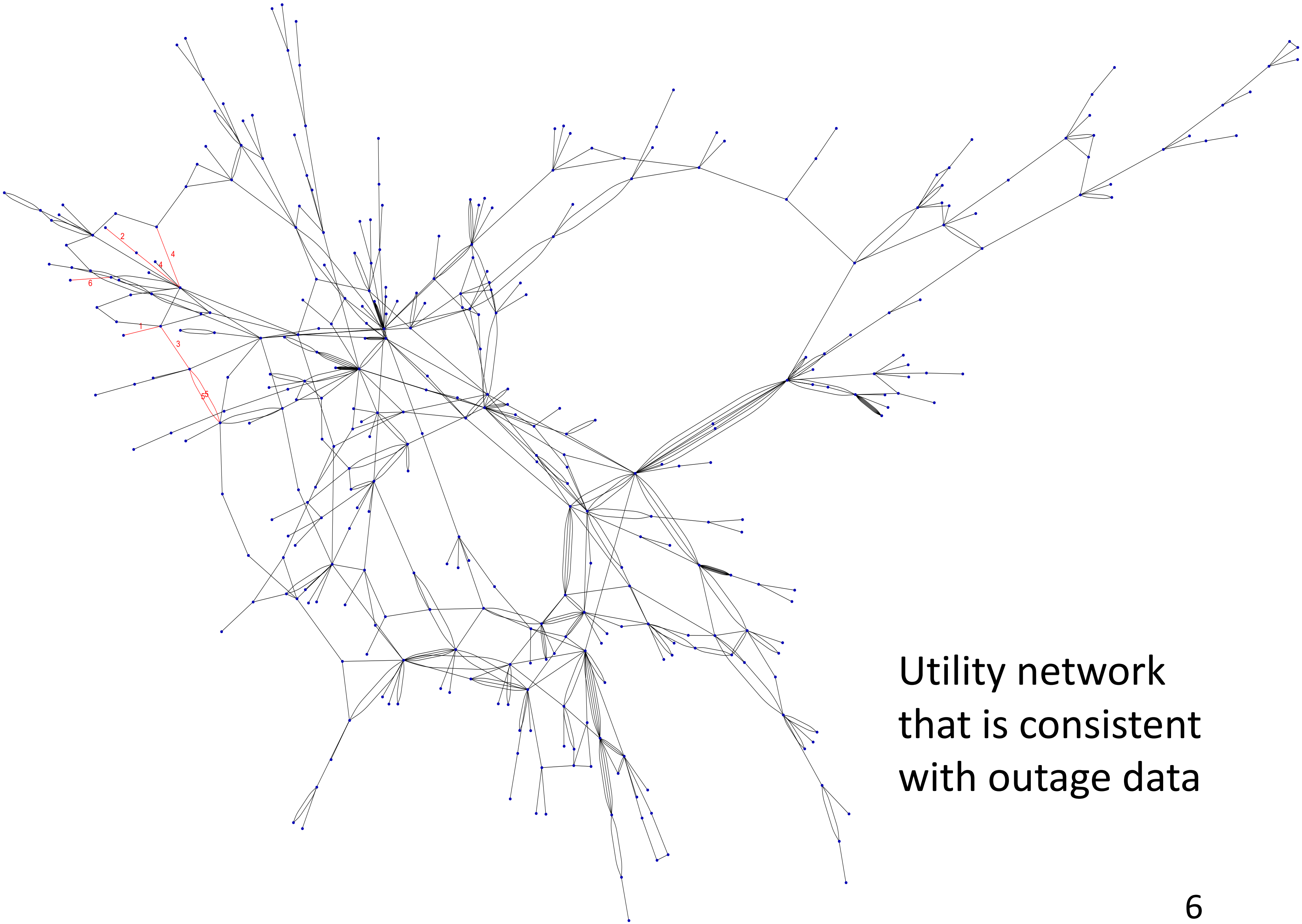
- Includes automatic line trip times to nearest minute
- All utilities in USA gather and report TADS data to NERC; similar data also gathered internationally
- We use BPA data that is published on the web
- 10942 automatic line outages over 14 years
- Simple approach: only look at time of outages
- Group outages into 6687 cascades and then into generations by their timing

Generations (tiers) of outages

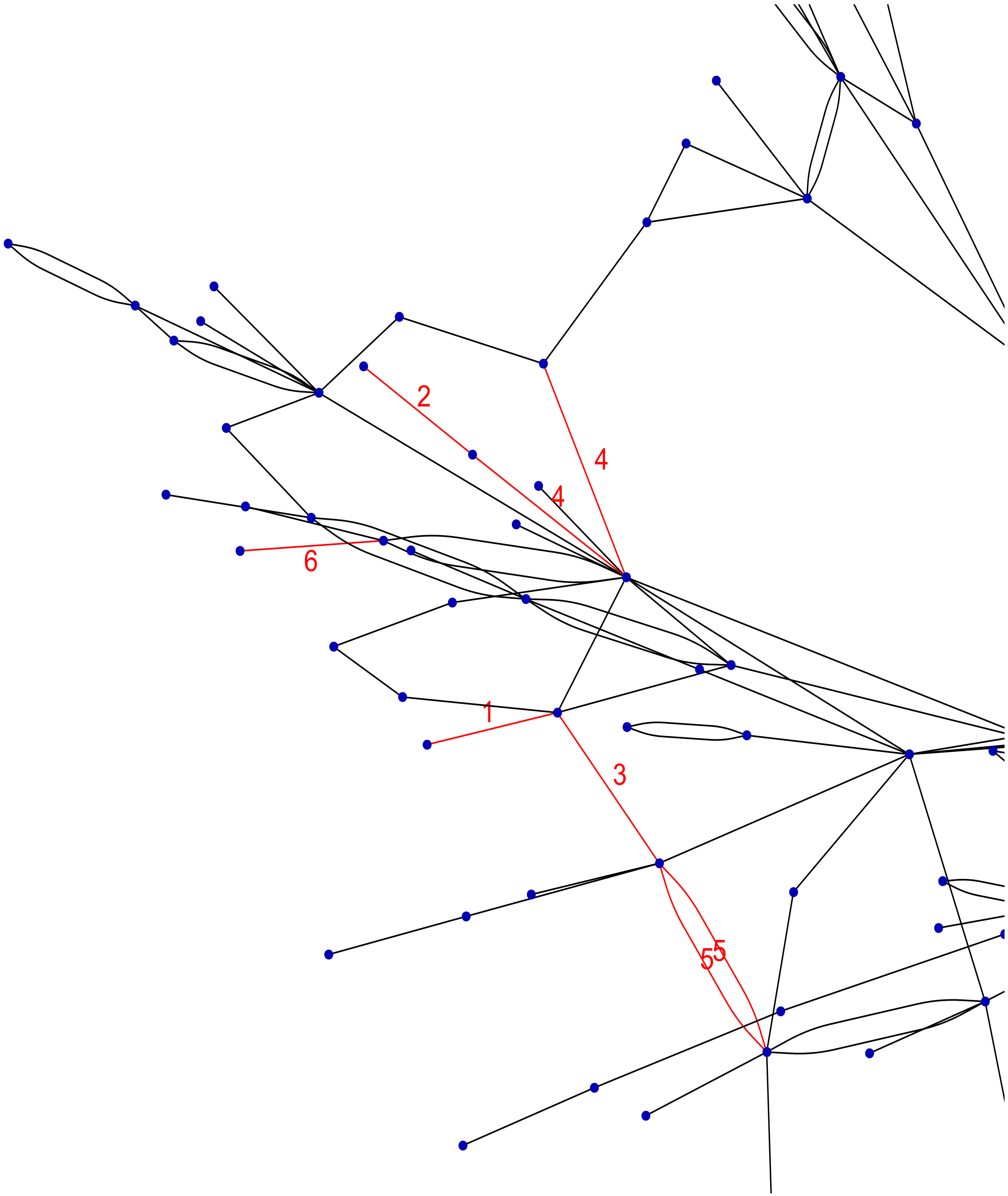
Cascading outages can be divided into generations;
each generation of outages is the outages very close in time
e.g. line outages within one minute

top-down analysis;
no causal relations are identified

can show generations of the cascade
evolving on the network



Utility network that is consistent with outage data



For this cascade, red lines outage in generations 1,2,3,4,5,6 as shown

HISTORICAL DATA BASIC CHARACTERISTICS

- Reality! (no modeling assumptions)
- Utilities have detailed outage data such as TADS;

  If you start with available data, then methods can be applied.

- Limited to past observations
- Statistics averaged over past time; grid slowly changes
- Data processing matters:

  e.g. what counts as a line outage?
- Data of most interest (large cascades) is sparse
- Cannot experiment or ask "what if"

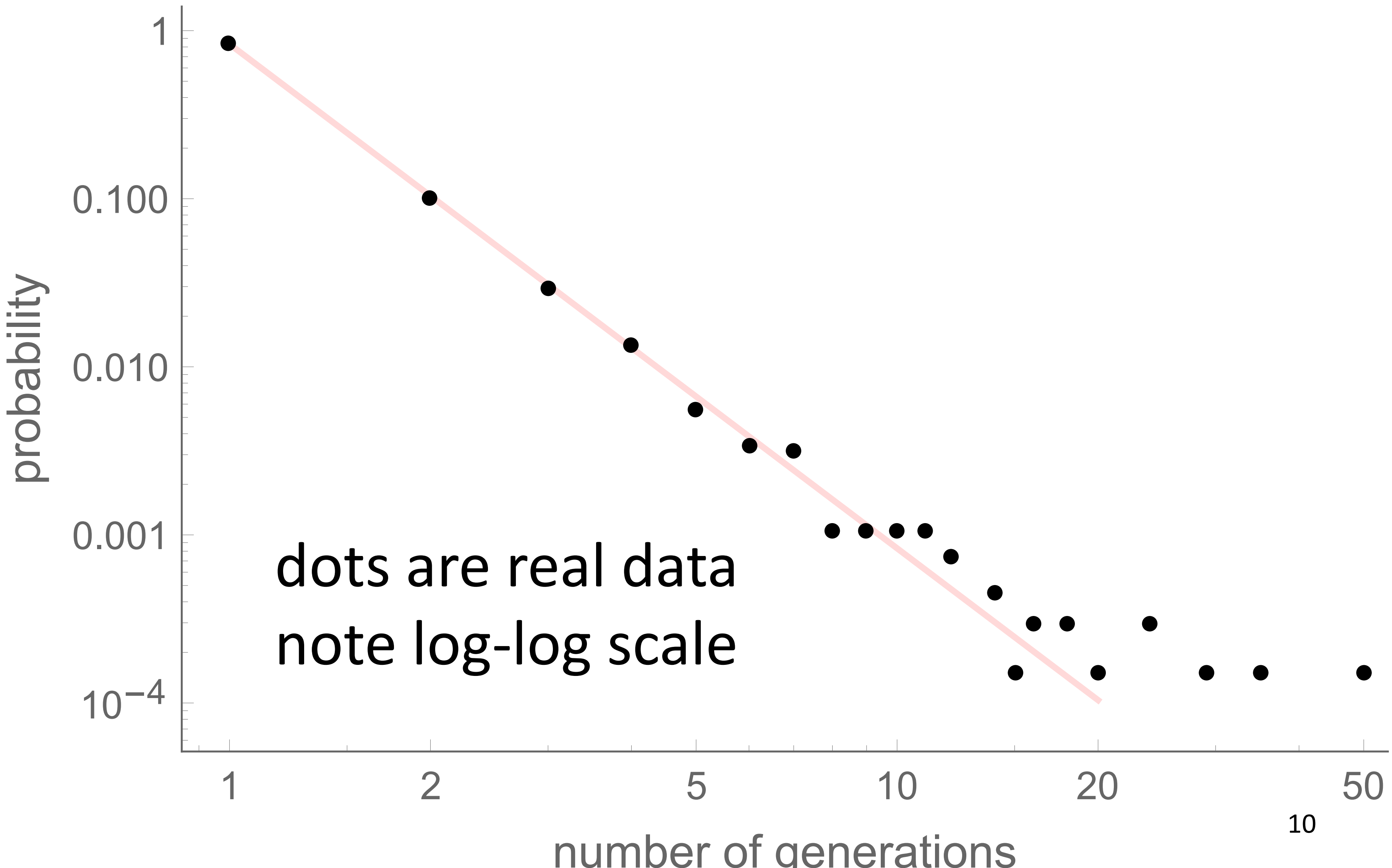
  ... but influence graphs can work!

HISTORICAL DATA OPPORTUNITIES

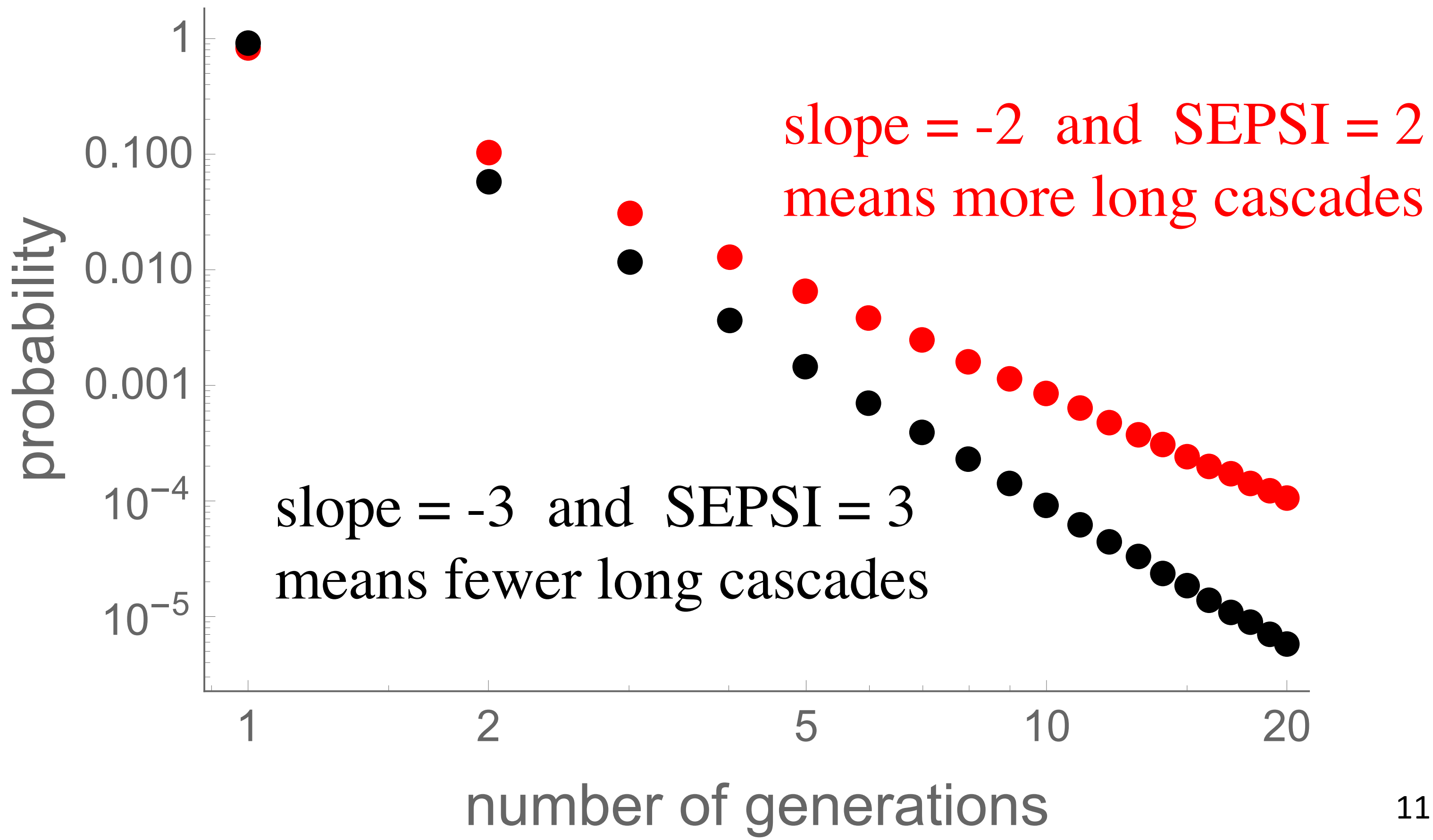
- Direct observation of initiating and propagating outages from processed data; lines most involved in initiating or continuing large cascades: “top-down statistics”
- Validating, calibrating and improving simulations; distributions of quantities can be matched
- Insights into cascading; Enables discovery
- Cascading metrics
- Mitigation of large cascades with influence graphs

Now we will look at a potential cascading metric based on the number of generations in a cascade

Distribution of number of generations fits a Zipf distribution with slope -3.0



System Event Propagation Slope Index
SEPSI = - slope



CASCADING METRIC
System Event Propagation Slope Index (SEPSI)

1. get sample of enough cascades
2. empirical distribution of number of generations on log-log plot
3. SEPSI = - slope of fitted line
4. SEPSI smaller means worse cascading

condition	SEPSI
all	3.0
storms	2.2
no storms	3.1
summer	2.9
not summer	3.2
peak hours	2.7
non-peak hours	3.1

SEPSI needs testing on other data sets

CHALLENGES

- historical data has good reality but we cannot experiment with mitigations
- sparse cascading data

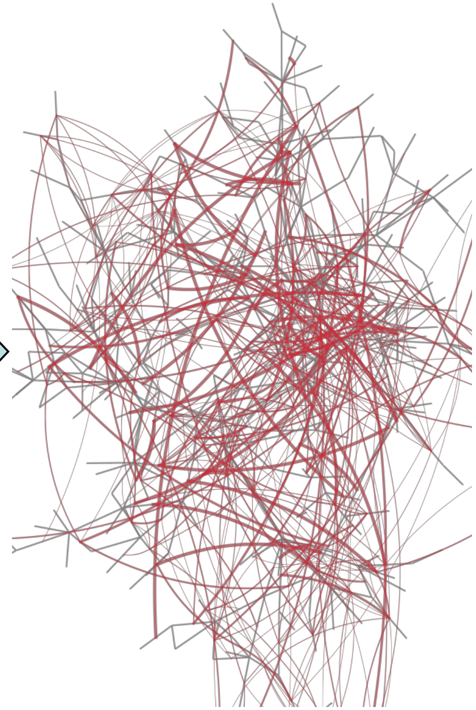
OPPORTUNITY: Use data to build Markov chain **influence graph** that describes pair-wise interactions between cascading line outages
Get:

- probabilities of small, medium, large cascades
- critical lines to upgrade
- try out mitigation of large cascades

Mitigation of cascading with Markov chain influence graphs

DATA ➡ INFLUENCE GRAPH ➡ BLACKOUT MITIGATION

historical line outage data ➡



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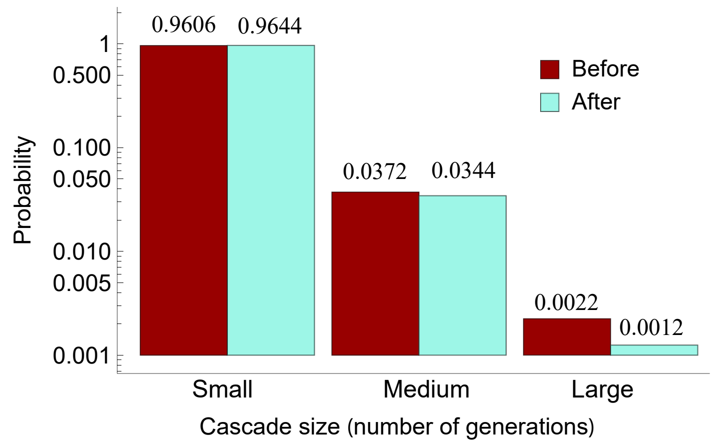
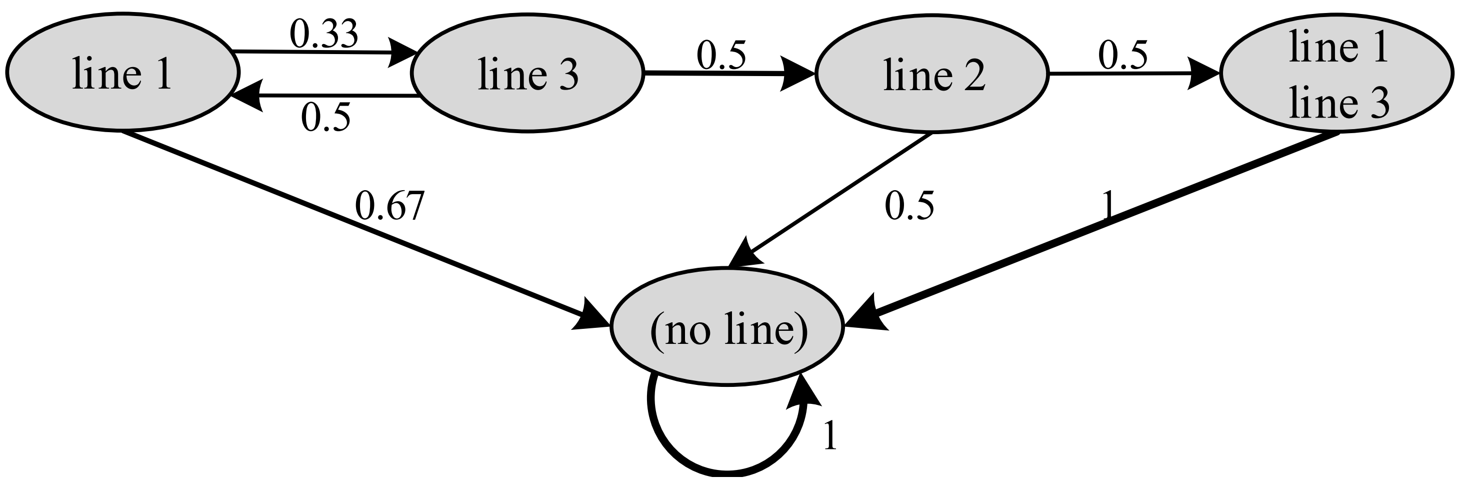
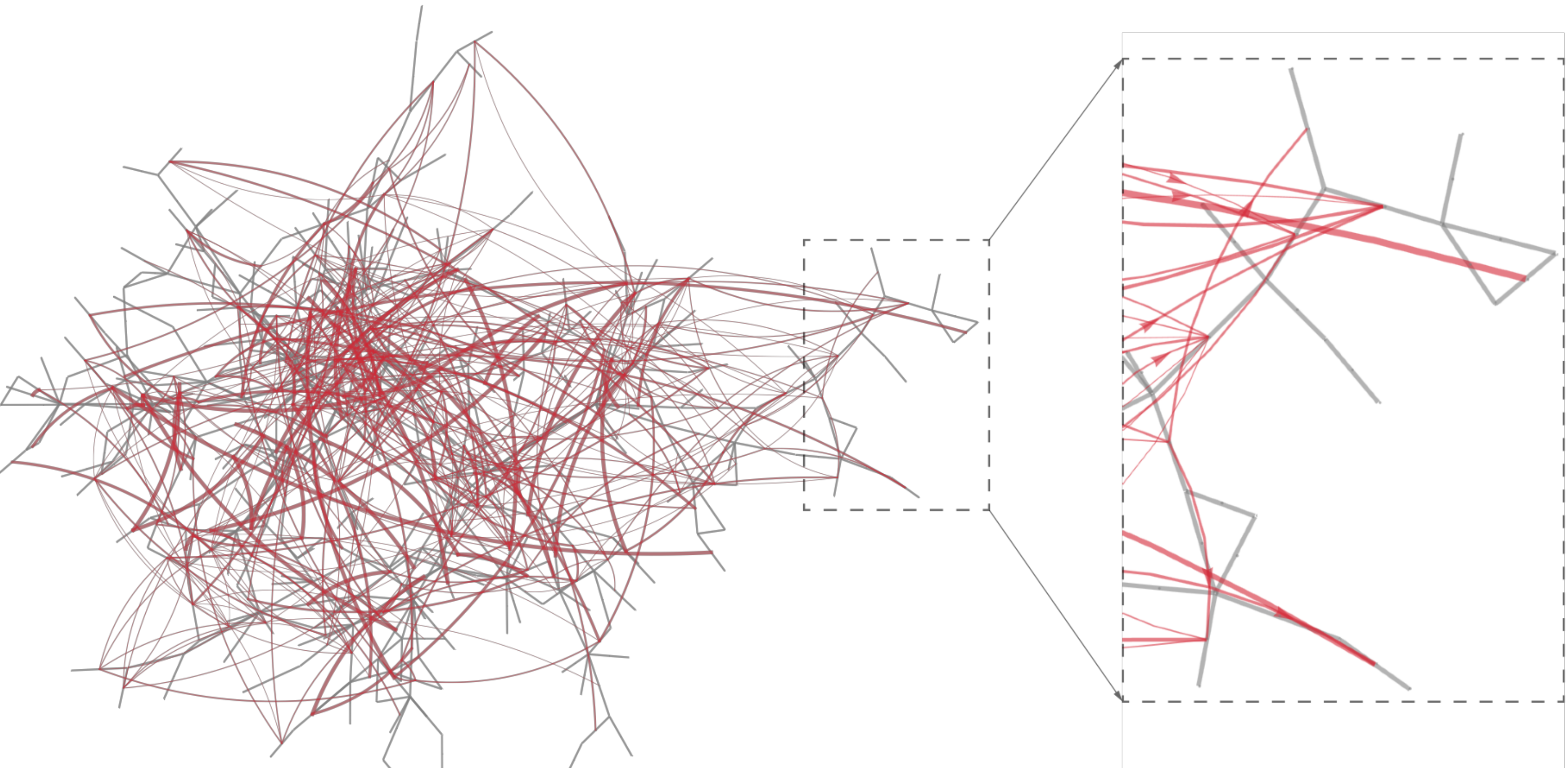


Simple example of forming influence graph = Markov chain

cascade number	generation 0 X_0	generation 1 X_1	generation 2 X_2	generation 3 X_3
1	{line 1}	{line 3}	{line 2}	{}
2	{line 2}	{line 1, line 3}	{}	{}
3	{line 3}	{line 1}	{}	{}
4	{line 1}	{}	{}	{}



Data-driven influence graph: gray is real grid; red indicates cascading connections



Can analyze influence graph to suggest mitigations; can test mitigations

Estimating influence graph from sparse data

- Objective is to estimate Markov chain probability transition matrices (red line thicknesses)
- Combine all data after the first transition
- Use Bayesian methods to improve estimates of stopping probabilities
- Account for outages during cascade that are independently generated
- Adjust each transition so that it matches observed propagation at that generation

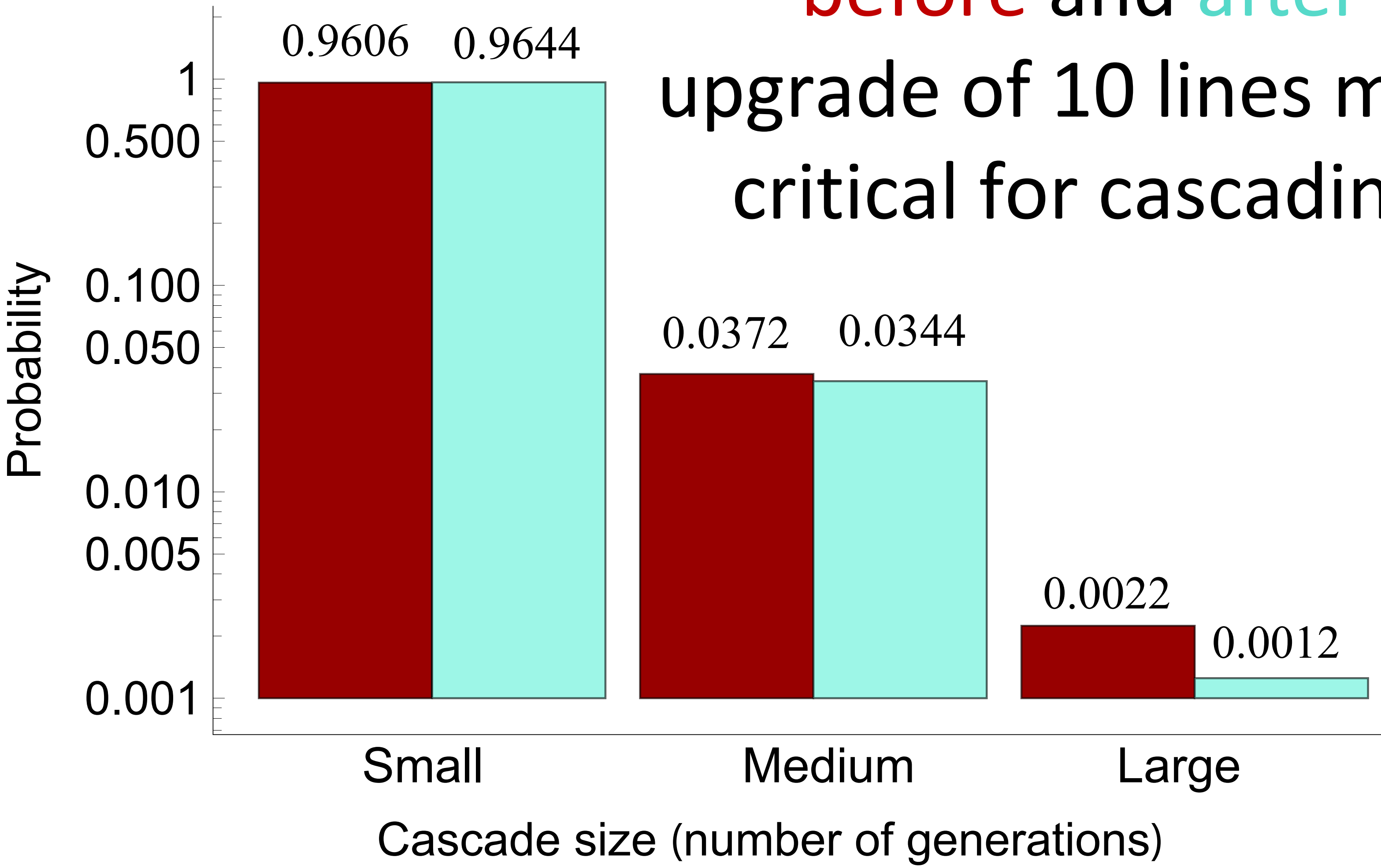
Estimating probabilities of cascade size

- Given Markov chain transition matrices and the probability distribution of initial outages, can calculate probability of stopped cascade at generation k and hence the probability of cascade length k or more.
- Hence the probabilities of
  - small cascades (1-2 generations)
  - medium cascades (3-9 generations)
  - large cascades (10 or more generations)
- Then we use bootstrap to estimate the uncertainties of these probabilities
  e.g. probability of large cascades is estimated to within a factor of 1.5 with 95% probability

Markov chain theory gives the lines eventually most involved in long cascades

- Every cascade has a series of transient states and then stops (goes to the state with no lines out)
- But before they stop, cascades tend towards a stationary distribution over the transient states, that is an eigenvector of a submatrix of the transition matrix. We calculate this eigenvector.
- The most likely states in the stationary distribution are the states eventually most involved in long cascades
- “Projecting” the states down to the lines gives the critical lines eventually most involved in long cascades
- Mitigation is modeled by reducing the probability of transitions to the critical lines

Distribution of cascade size before and after upgrade of 10 lines most critical for cascading



large cascades (⩾10 generations) reduced by 45%

Conclusions

- Data has rich opportunities. Also if you start with available data, then methods can be applied. We use standard utility data (TADS).
- Can see cascade spread on network in generations
- Number of generations has a Zipf distribution for our data set. Slope of line suggests a cascading metric.
- Influence graph
  - Markov chain that describes pairwise outage interactions; cascades move along influence graph
  - Transition matrices can be estimated and analyzed to give lines critical for propagation
  - Mitigating large cascades by upgrading those lines can be tested on influence graph

- I offer to process your historical TADS data to try out the methods

REFERENCES

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Questions?

Ian Dobson

email dobson@iastate.edu

webpage iandobson.ece.iastate.edu