

Predicting the unpredictable in violent political conflict

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large events in political conflict

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- large **international wars**
 - 7 wars with $x \geq 100,000$ battle deaths in 100 years
- large **terrorist attacks**
 - 37 attacks with $x \geq 100$ deaths in 40 years

such events have disproportionate impact



1939: WW2



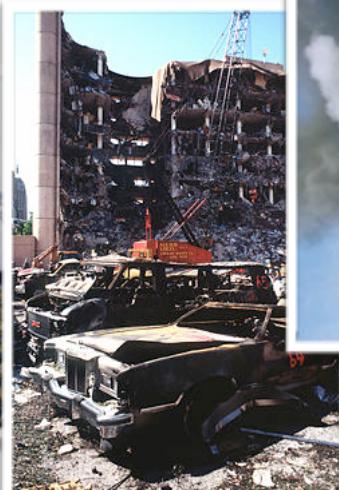
1980: Iran-Iraq War



1950: Korean War



1988: Pan Am Flight 103, Lockerbie



1995: Oklahoma City bombing



2001: World Trade Center

large events in political conflict

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can such events be predicted with algorithms?

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~~No.~~ **it depends...**

large events in political conflict



can such events be predicted with algorithms?

~~-no.~~ **it depends:**

X *in specific*

who, what, where, why, how, when

large events in political conflict



can such events be predicted with algorithms?

~~no.~~ it depends:

in specific

who, what, where, why, how, when

why? such events are *rare* (little data), too many relevant variables, too much historical *contingency*, human *agency*, *incomplete information*, etc.

→ **over-fit the past & under-fit the future**

→ **can't replace human expertise & evidence trails**

* Machine learning algorithms, being general models, require large amounts of data to learn which possible correlations in the observed data are relevant for accurate predictions, but rare events, by definition, lack the data required for that learning. Worse, for highly specific questions (who, what, when, where, etc.), machines are typically much worse than humans at *thinking like a human would*, and no machine learning algorithm exists that can account for human agency.

large events in political conflict



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in aggregate

statistical forecasts & risk estimates

why? robust statistical patterns exist, *in aggregate*, which allow probabilistic estimates, over populations (not individuals)

→ **average over contingencies & beyond individual agency**

→ **reflects fundamental constraints**

* An interesting middle ground exists in long-running conflicts with relatively stable conditions. There, it may be possible to use machine learning to make accurate out-of-sample predictions of future events, but such approaches are brittle, and fail spectacularly when the underlying conflict rules shift because of agency, contingency, or technology. Generally, it is not understood at what scale of aggregation, or what circumstances of conflict, such effects assert themselves.

large events in political conflict



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what are some of these patterns?

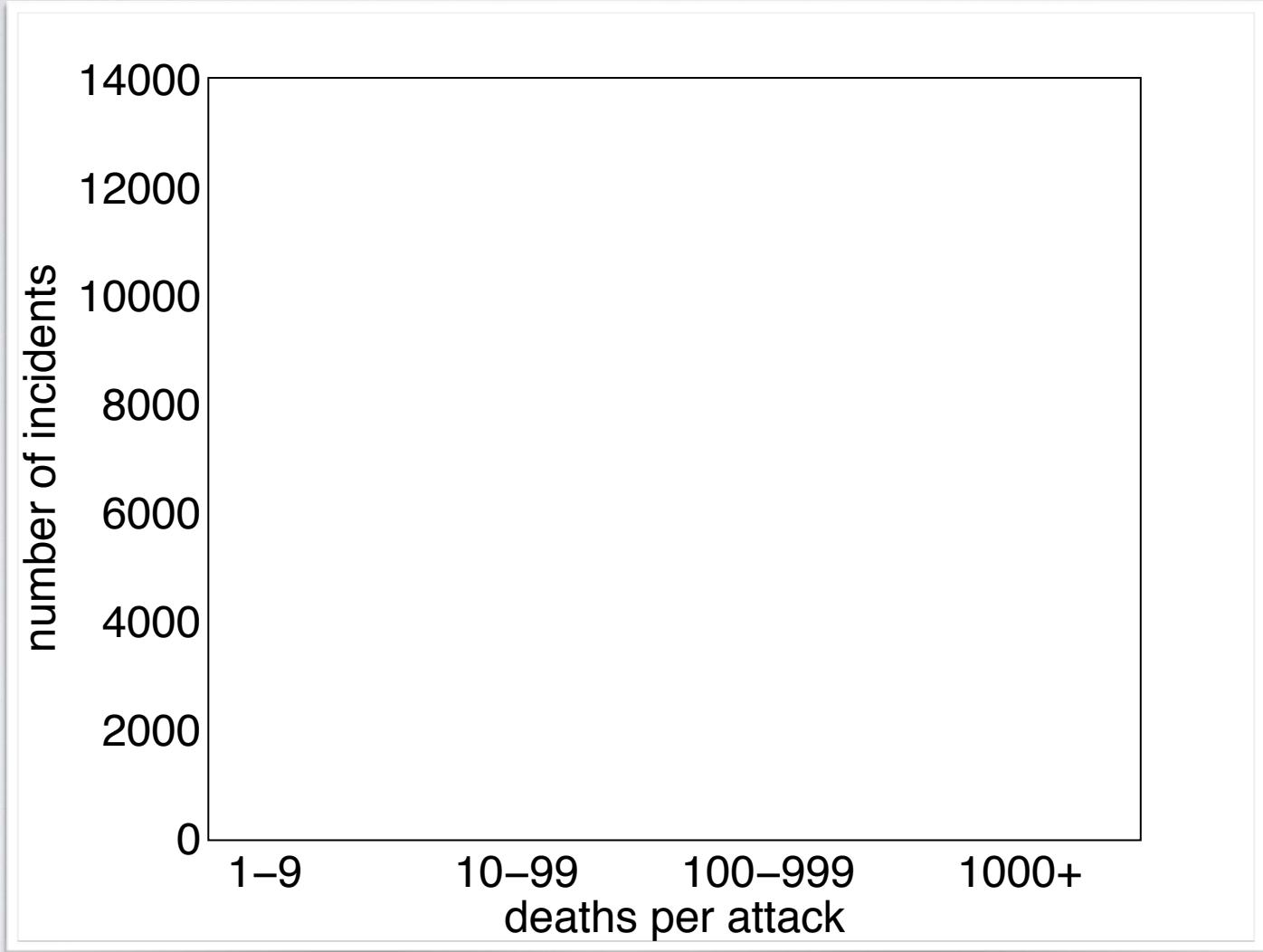
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a general pattern in terrorism

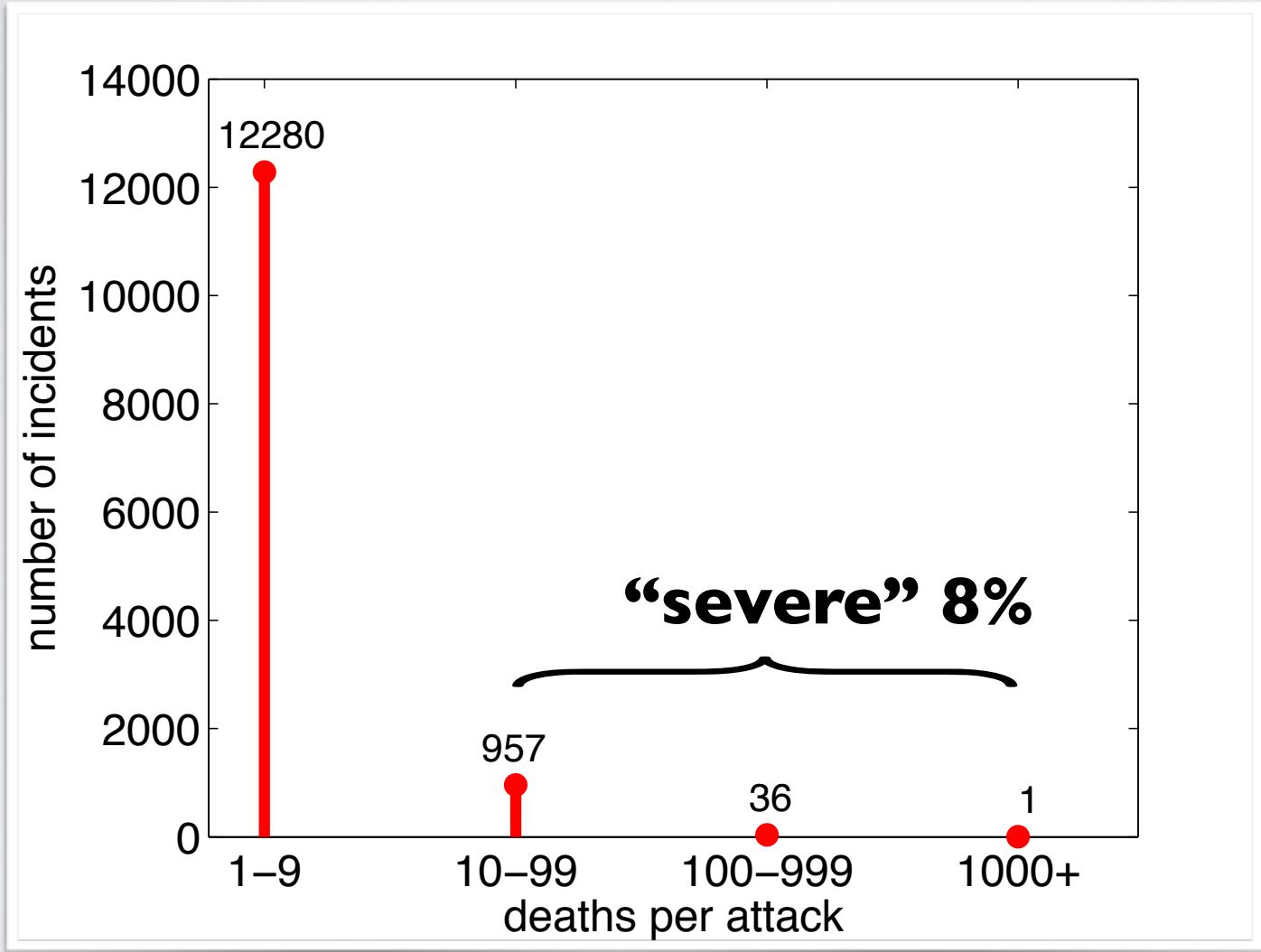


a general pattern in terrorism



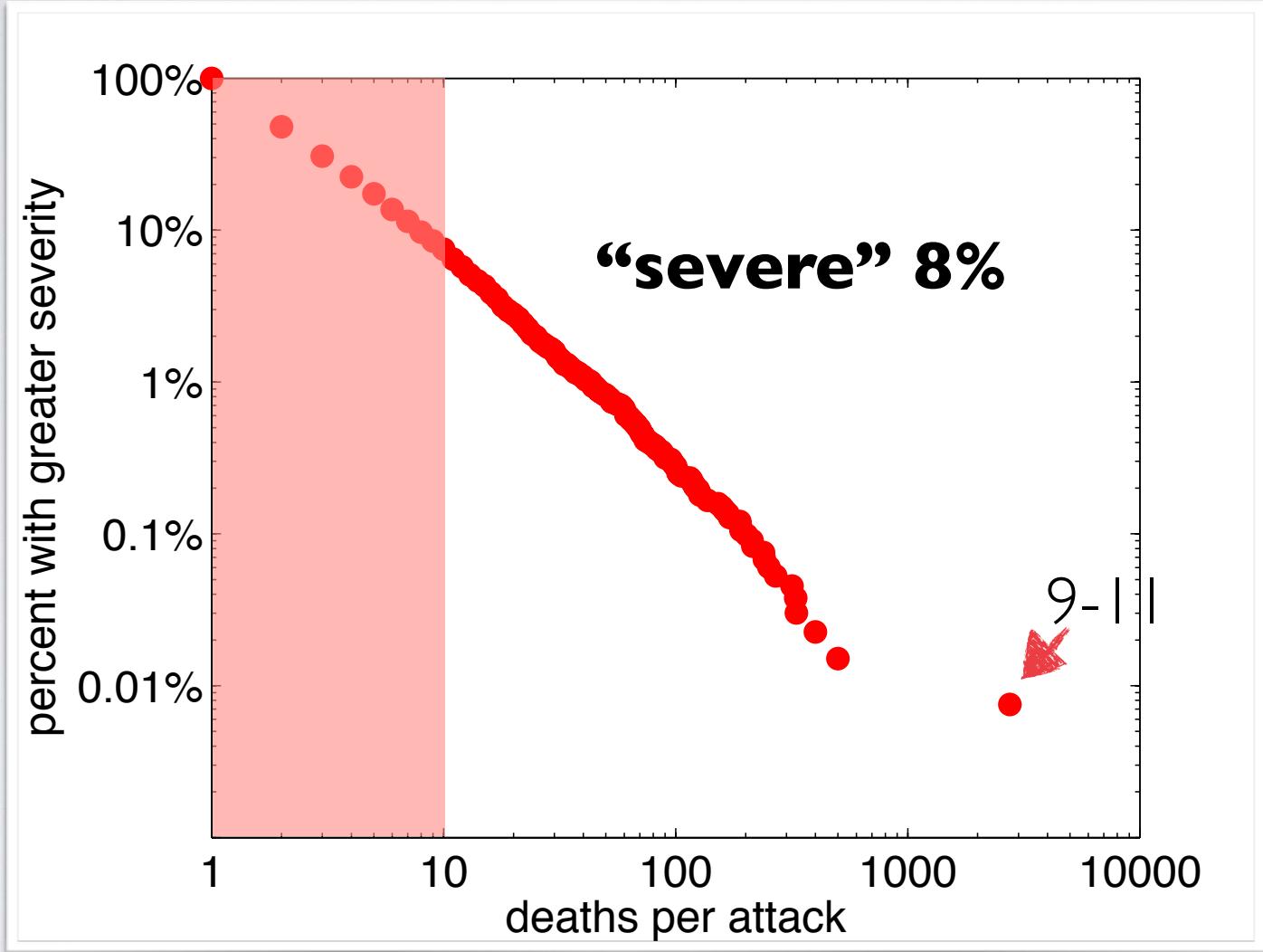


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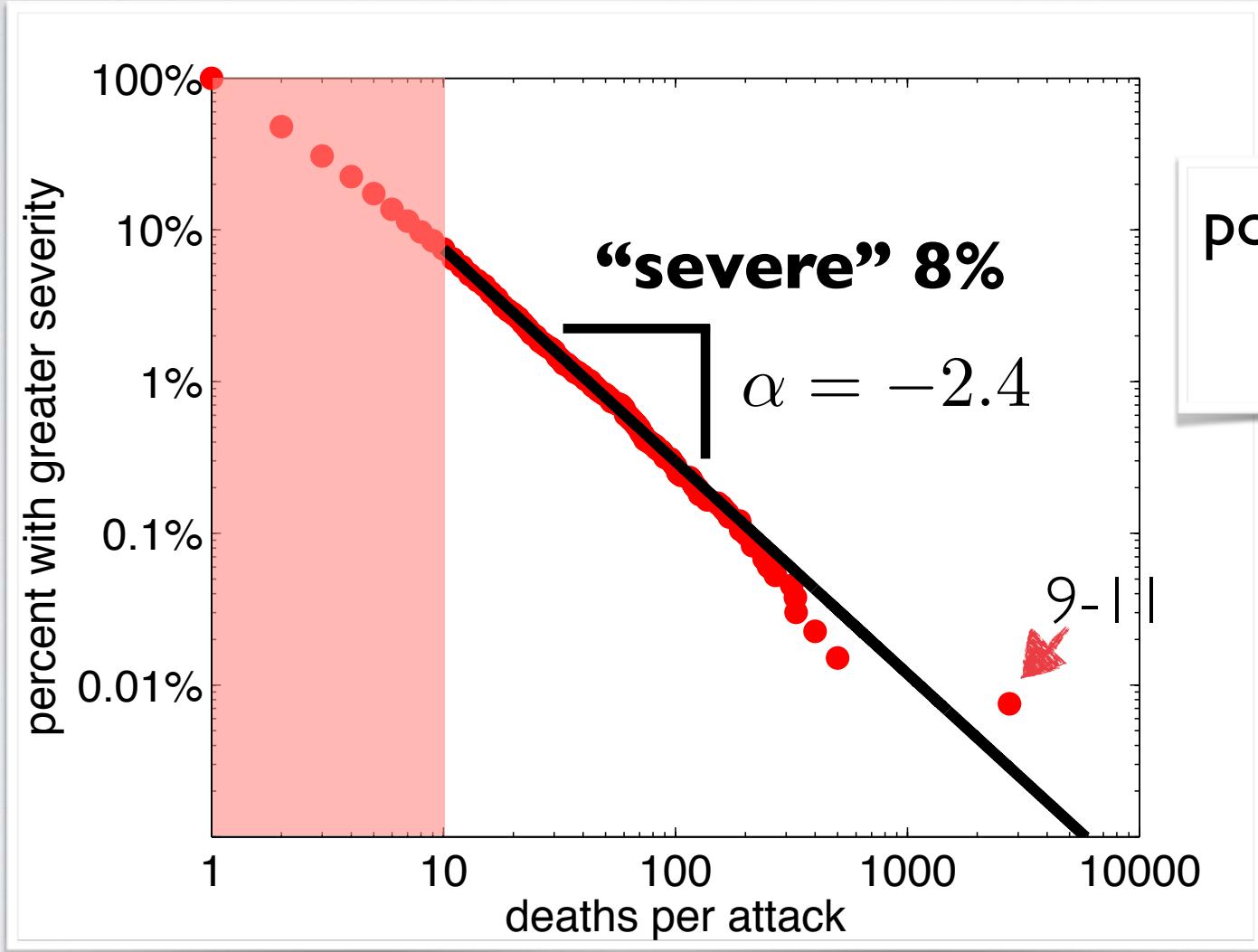


a general pattern in terrorism





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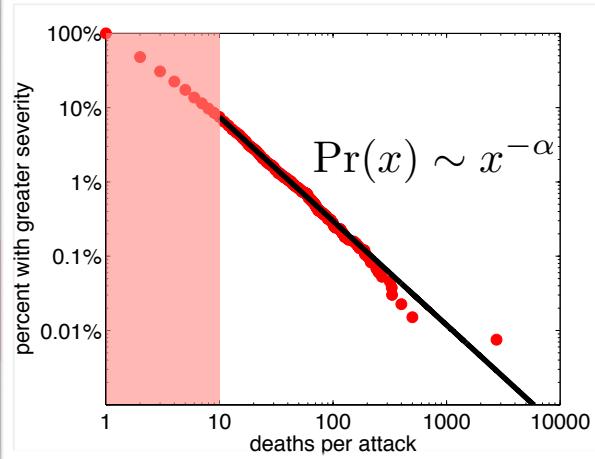


power-law model
 $\Pr(x) \sim x^{-\alpha}$

a general pattern in terrorism

power-law pattern holds across some covariates

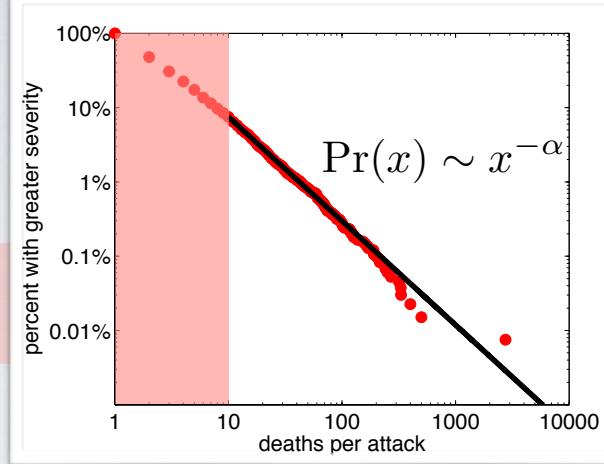
- different decades (70s, 80s, 90s, 00s, 10s)
- different types of weapon (guns, fire, bombs, etc.)
- different levels of economic development (OECD)
- but **not** with a universal exponent α
→ its shape varies, making predictions harder



a general pattern in terrorism

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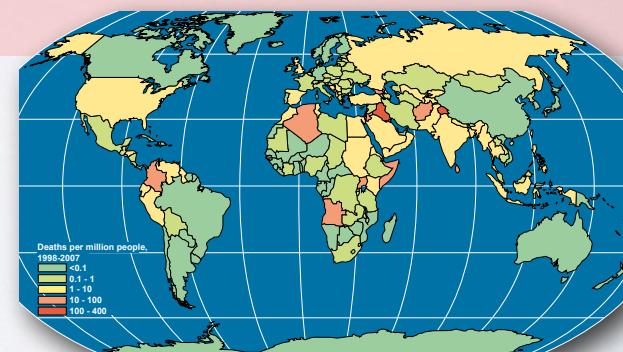
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the pattern **fails** for others

- suicide attacks alone
- arbitrary regions (North America, Asia, Europe, etc.)

why? → contingency matters



patterns across terrorist groups





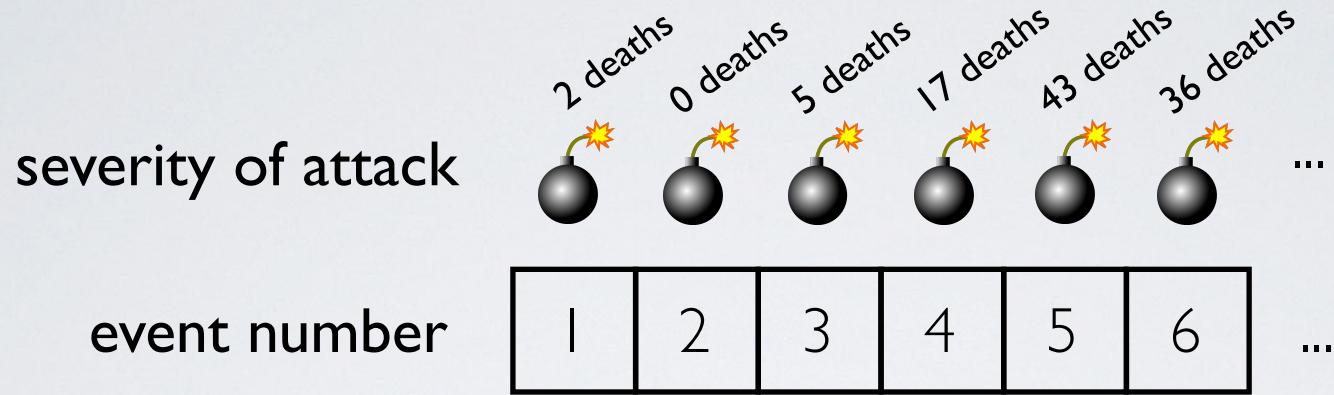
patterns across terrorist groups

800+ known terrorist groups, worldwide, over 40 years

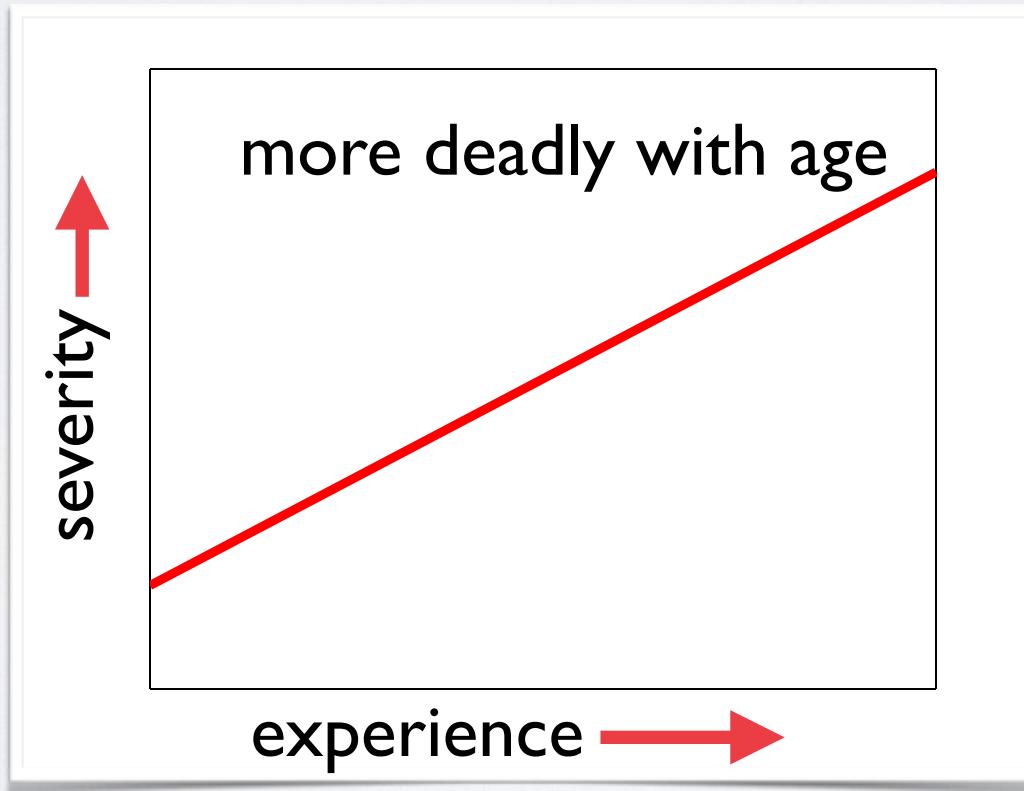
- do older / more experienced groups create *larger* events?
- how often do they launch attacks?



patterns across terrorist groups : severity

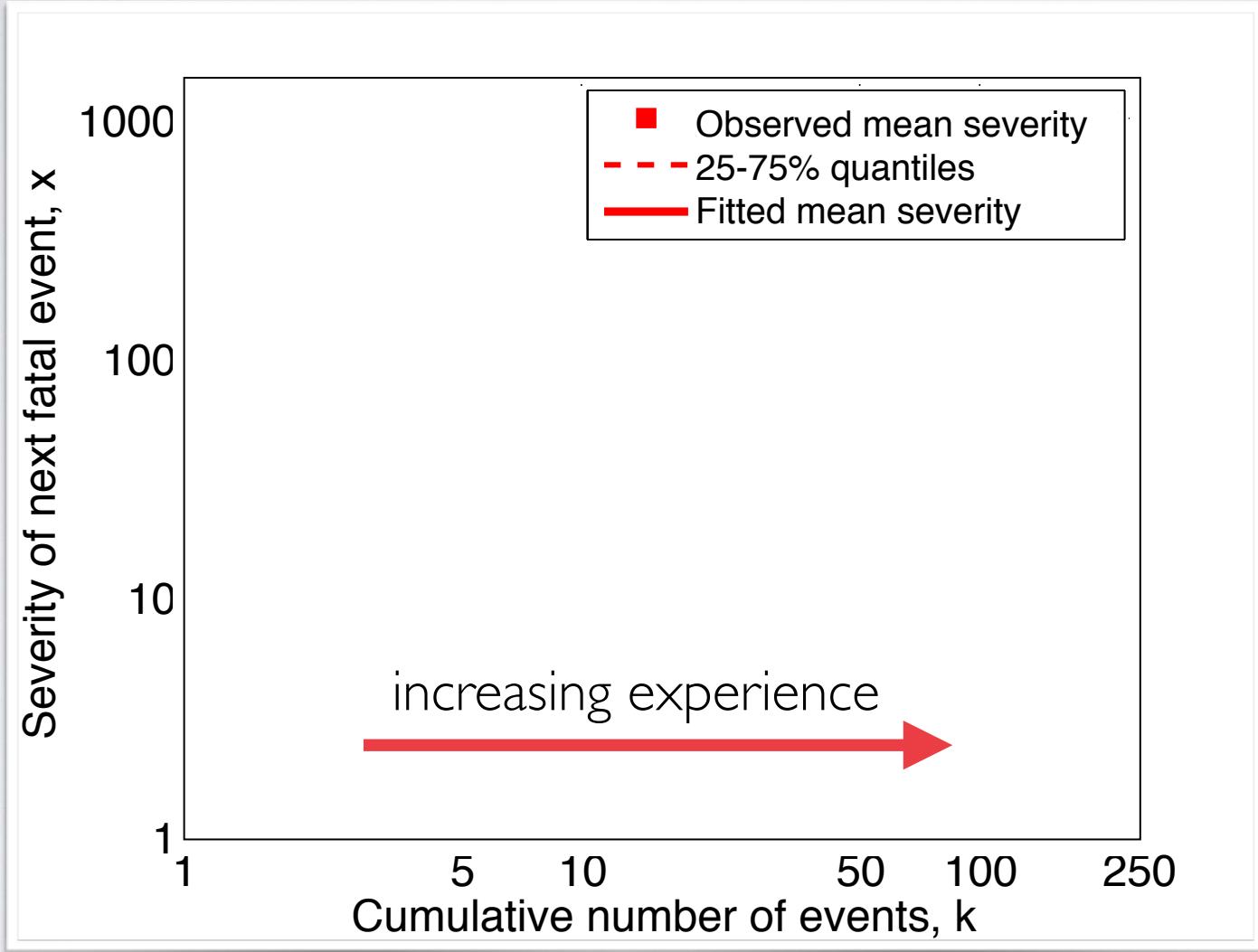


example:



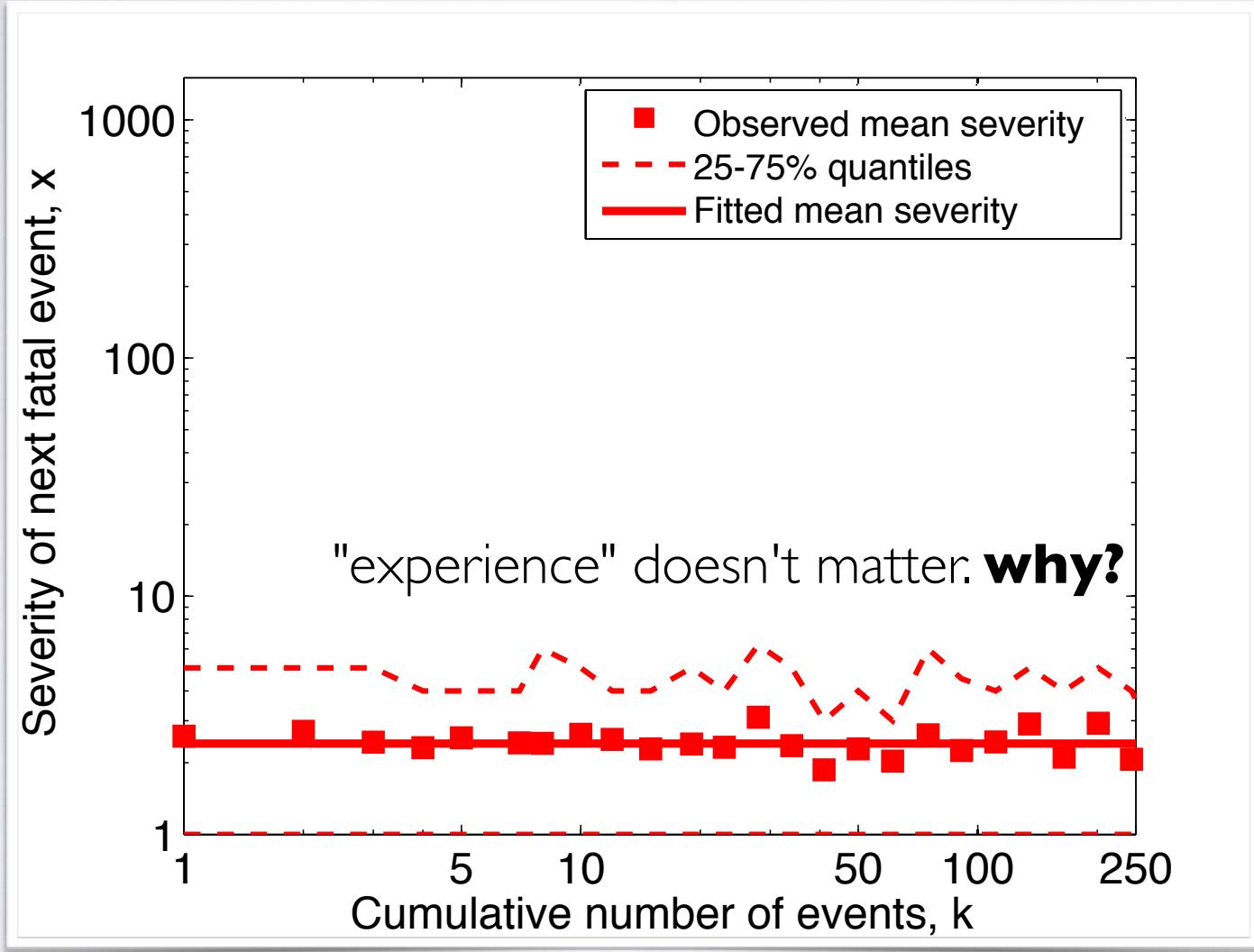


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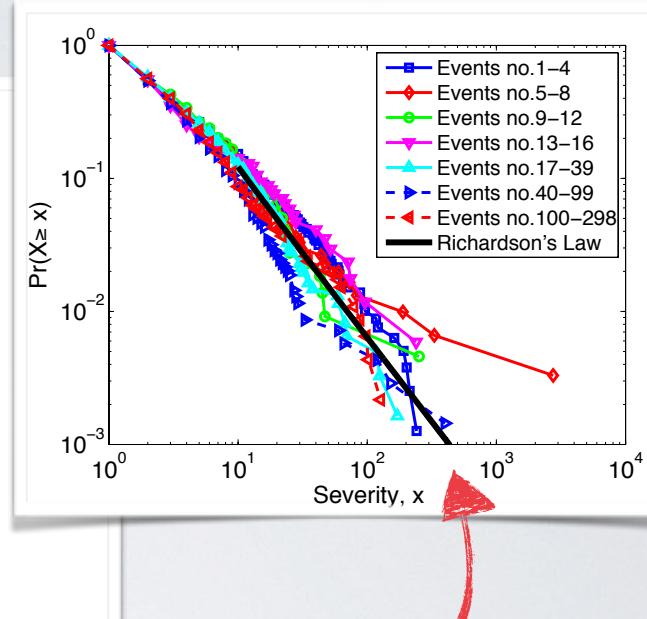
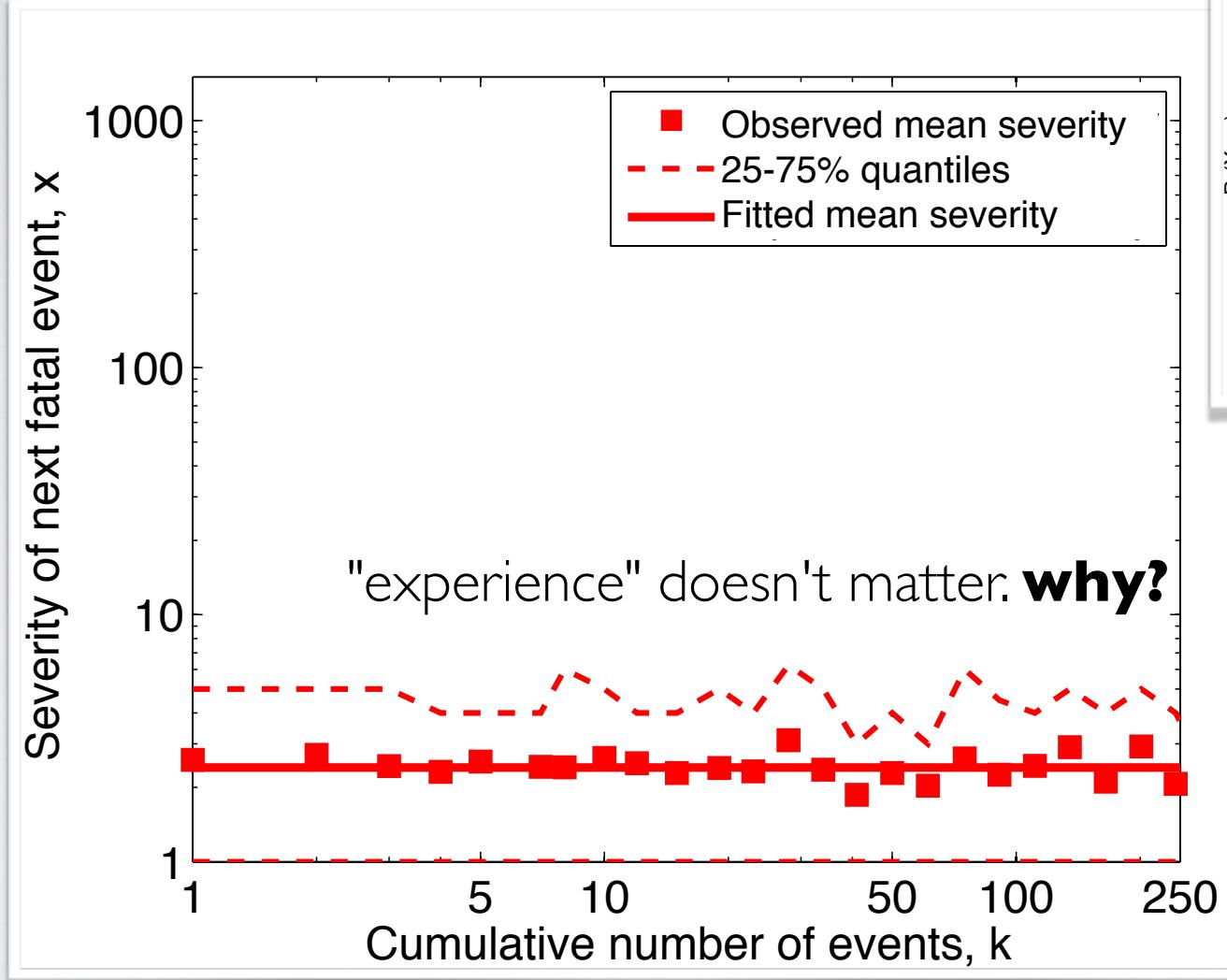


patterns across terrorist groups : severity





patterns across terrorist groups : severity



power-law model

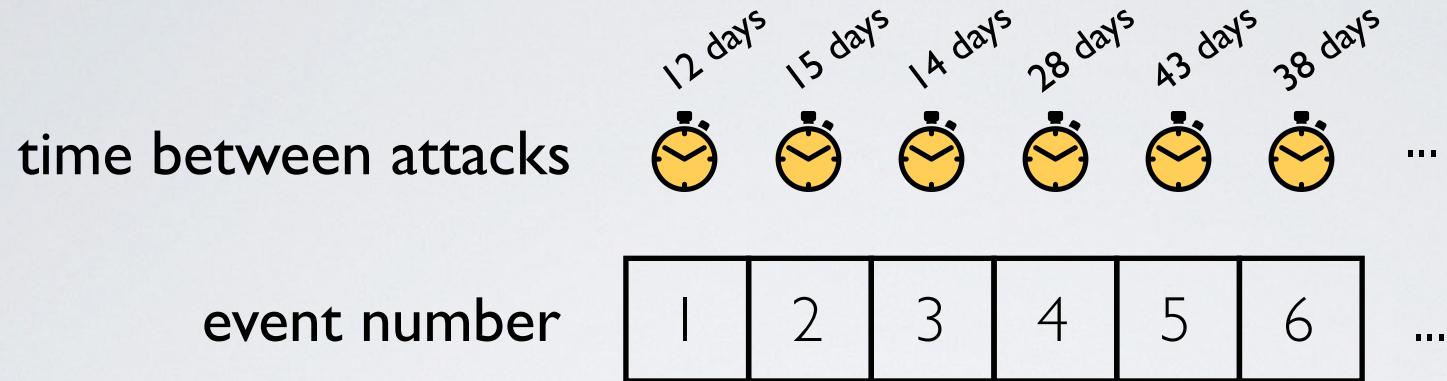
$$\Pr(x) \sim x^{-\alpha}$$

patterns across terrorist groups : frequency

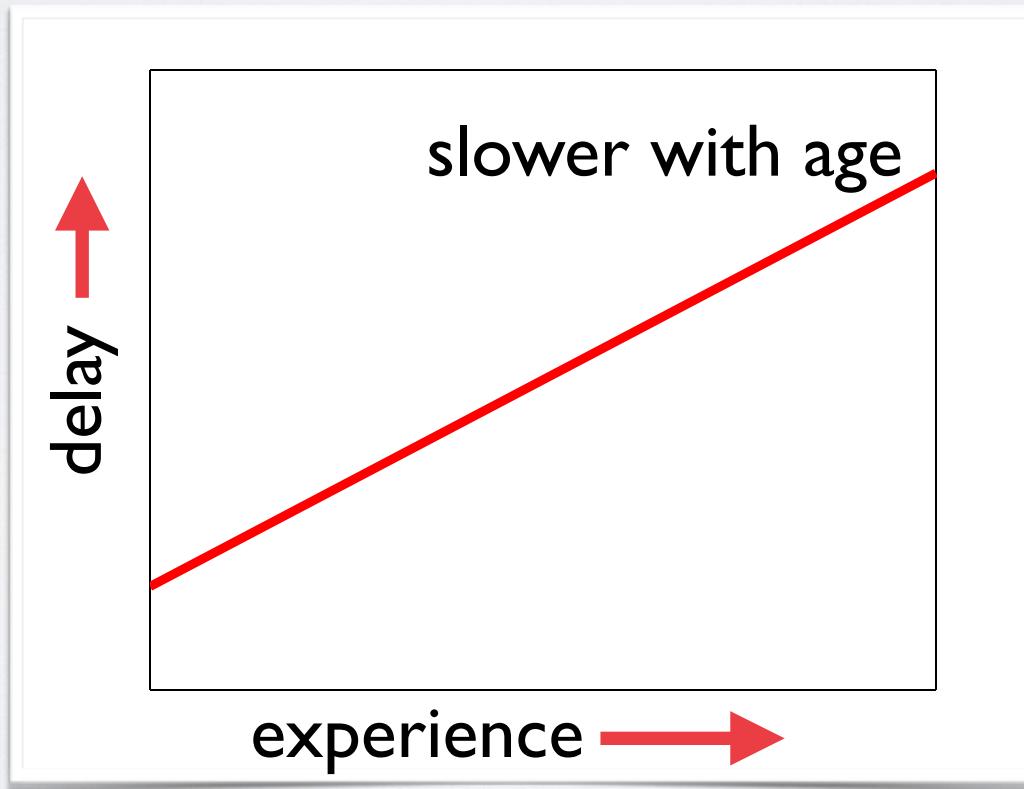




patterns across terrorist groups : frequency

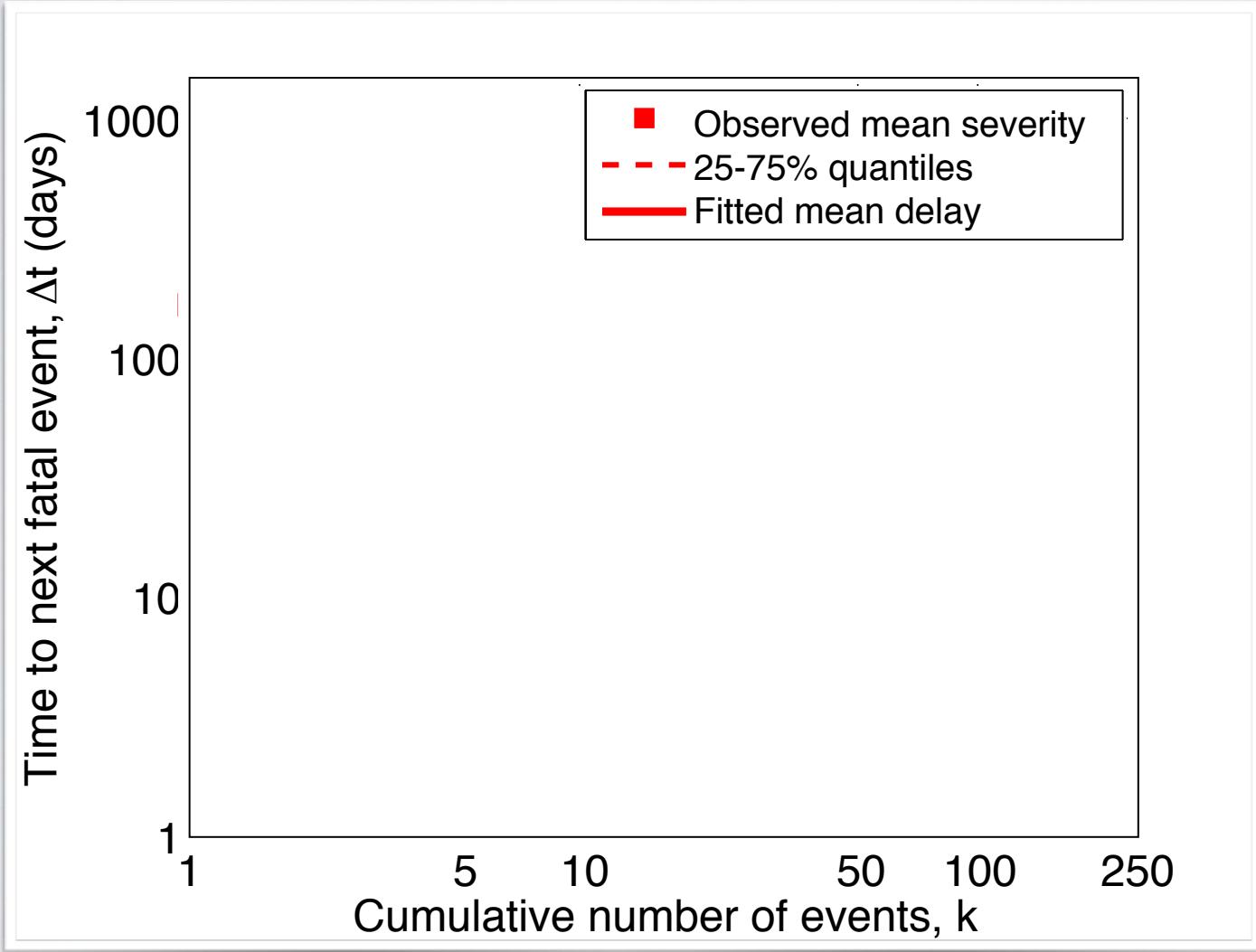


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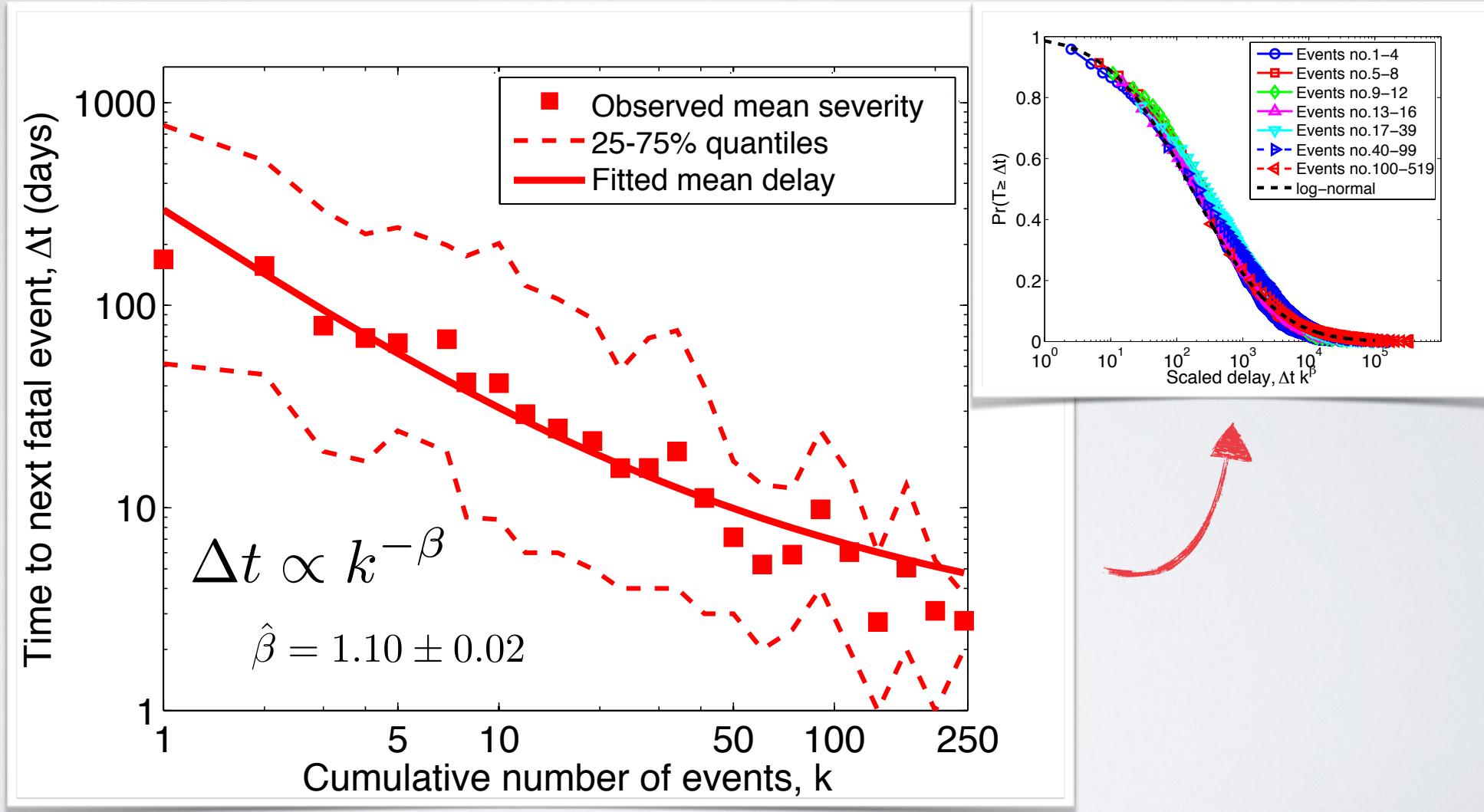


patterns across terrorist groups : frequency





patterns across terrorist groups : frequency

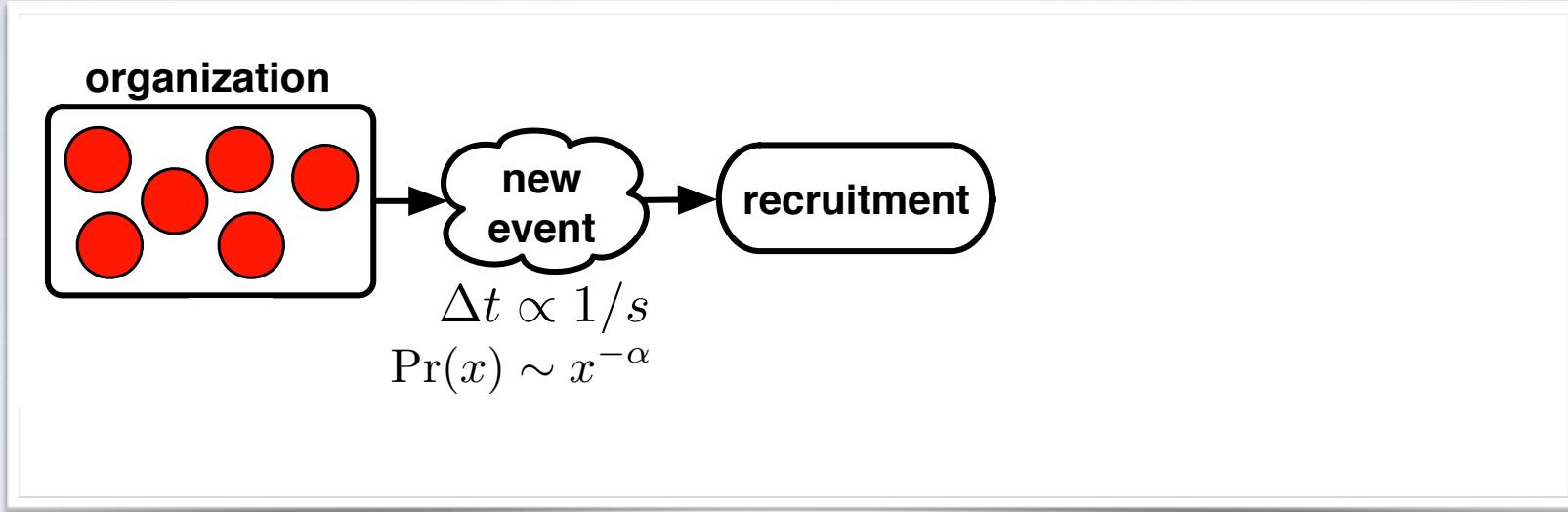


The inset shows a "data collapse" of the marginals, indicating that each follows a lognormal distribution, whose location is determined by k
Clauset & Gleditsch, PLoS ONE (2012)



patterns across terrorist groups : frequency

a simple explanation : organizational growth



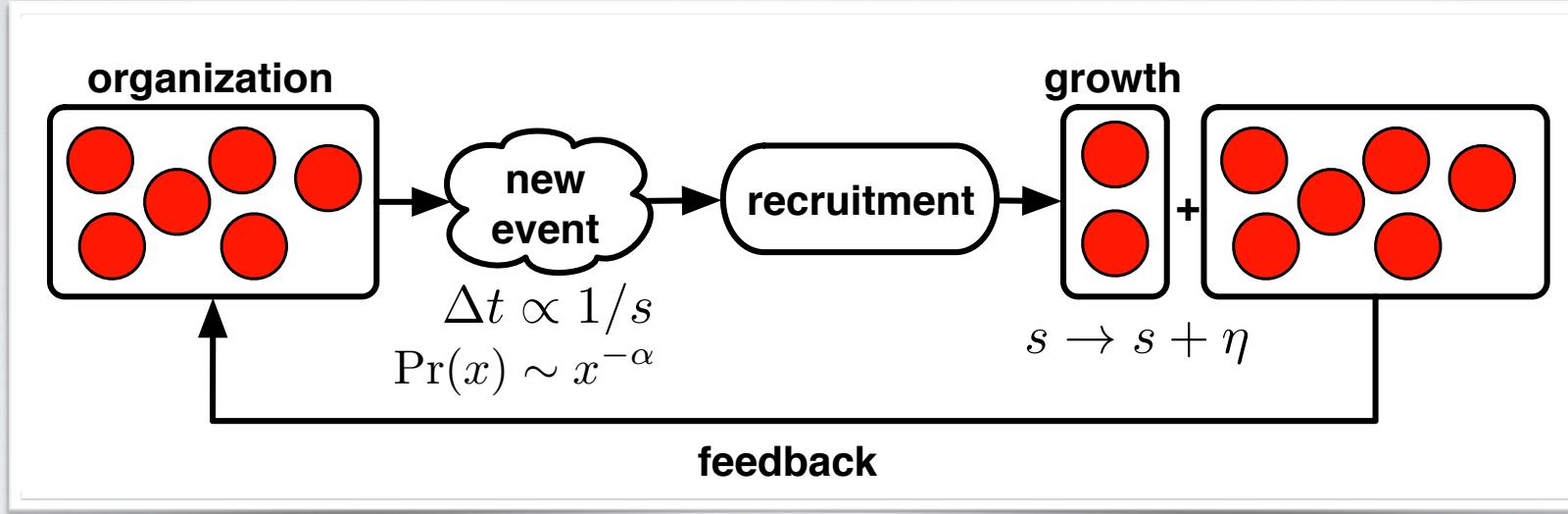
Δt delay between consecutive events

x severity of events (deaths)



patterns across terrorist groups : frequency

a simple explanation : organizational growth



Δt delay between consecutive events

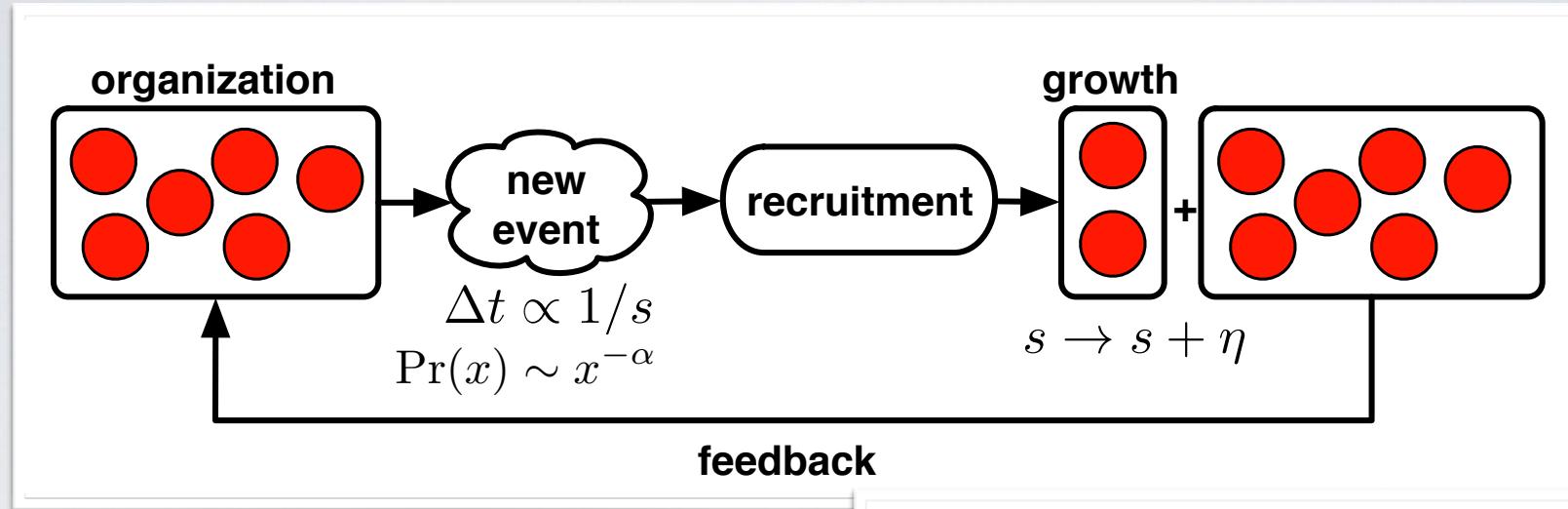
x severity of events (deaths)

simulate this process, plot Δt vs. k →



patterns across terrorist groups : frequency

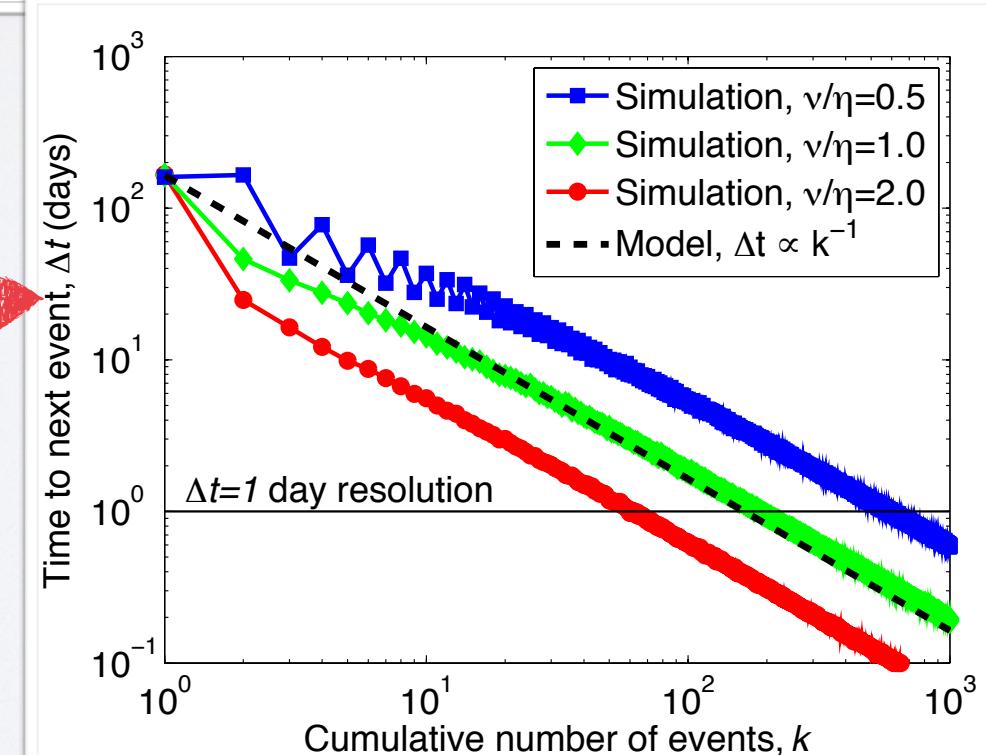
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Δt delay between consecutive events

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simulate this process, plot Δt vs. k

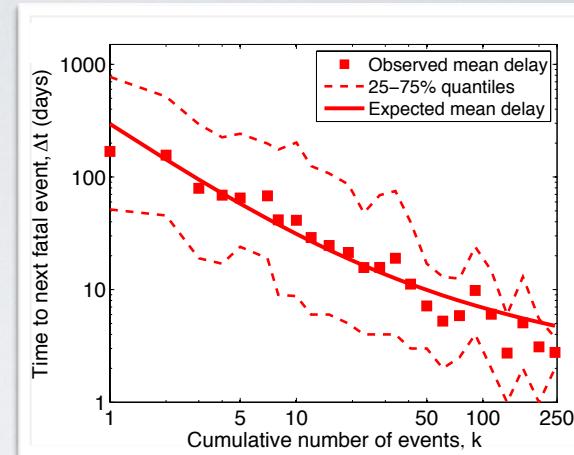




patterns across terrorist groups

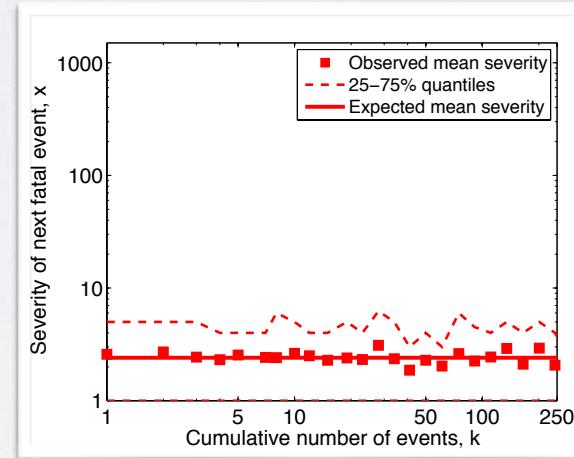
attack production is labor constrained

- bigger groups → more / faster attacks
- attack-recruitment cycle
- acceleration rate varies by group ideology
[religious groups progress more quickly than secular]



attack severity is independent of labor, experience

- older groups more deadly because faster attacks
- large events just as likely from small groups



prediction: "starve the beast" of recruits → less growth → fewer attacks → lower risk of large events



predicting the unpredictable



~~forecasting~~ **predicting the unpredictable**

how probable was a 9/11-sized event?



~~forecasting~~ **predicting the unpredictable**

how probable was a 9/11-sized event?
requires a probability model $\Pr(x)$

key observations

- care only about large events
disproportionate consequences
- unknown upper tail structure
several models fit well
- little data in upper tail
large statistical uncertainty



~~forecasting~~ **predicting the unpredictable**

how probable was a 9/11-sized event?
requires a probability model $\Pr(x)$

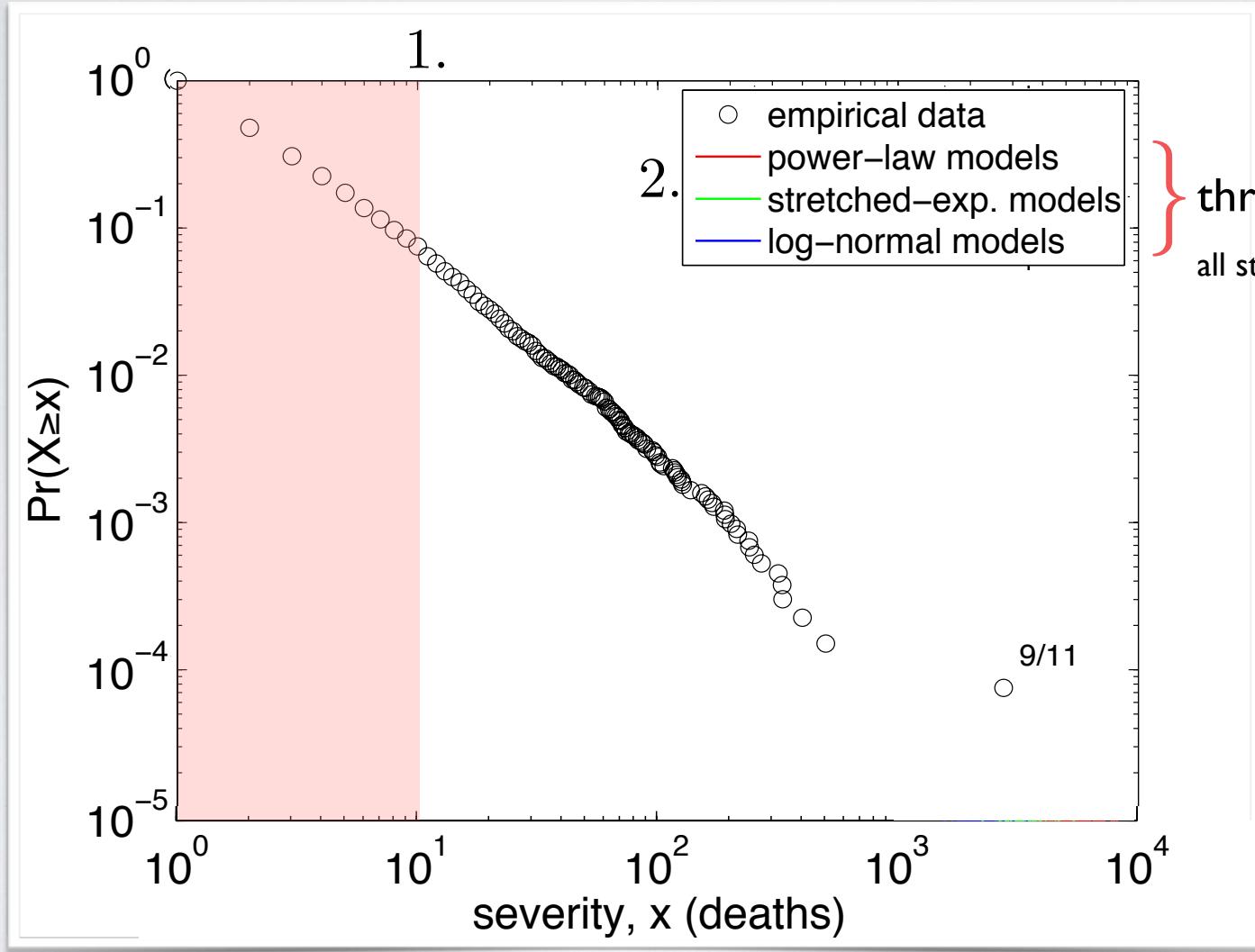
key observations

- | | |
|--|---------------------------------|
| 1. → care only about large events
disproportionate consequences | → separate tail from body |
| 2. → unknown upper tail structure
several models fit well | → multiple tail models |
| 3. → little data in upper tail
large statistical uncertainty | → distribution over conclusions |

model-based, data-driven forecasts

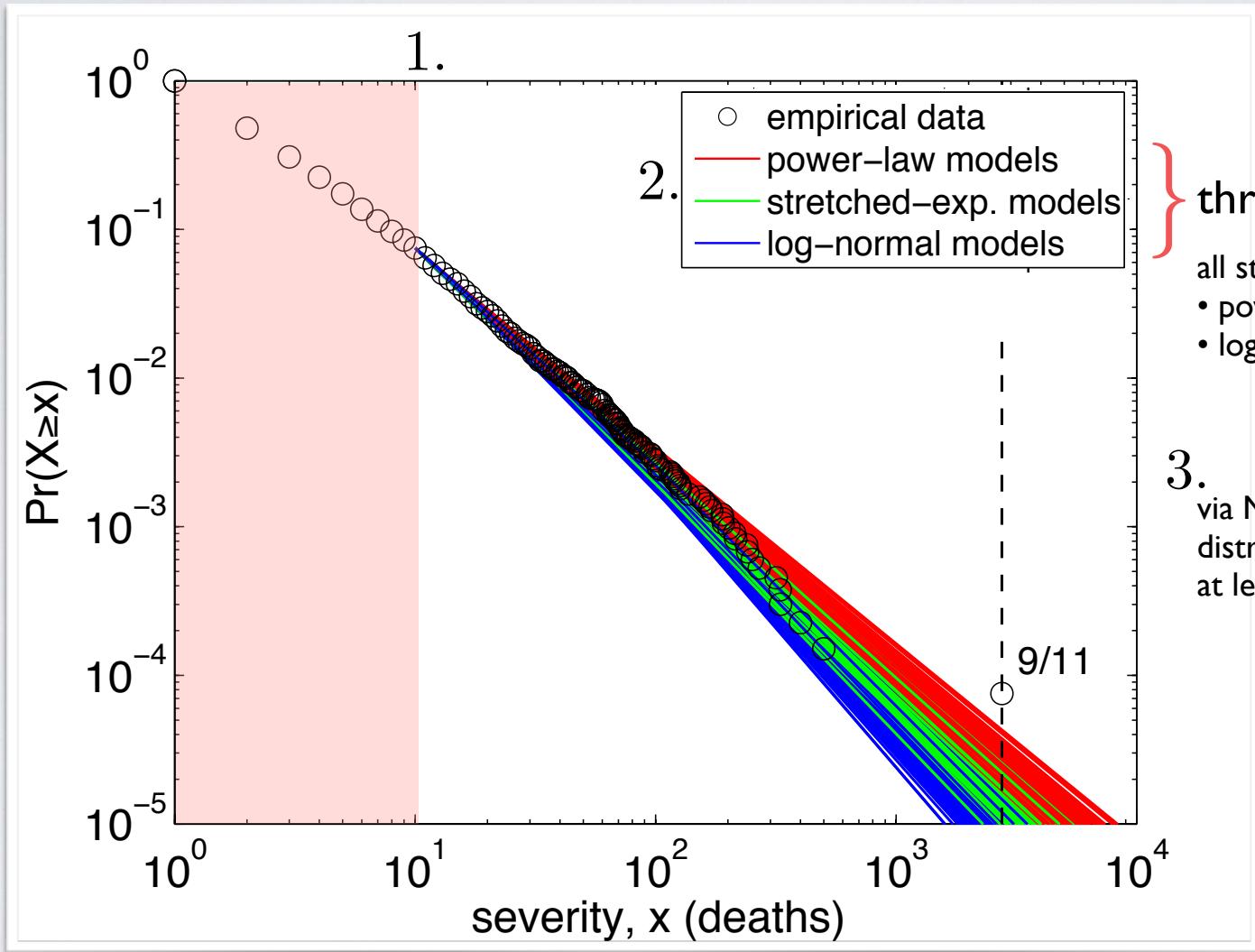


forecasting ~~predicting~~ the unpredictable





~~forecasting~~ predicting the unpredictable



} three high-variance models

all statistically *consistent* with upper tail

- power law is most "pessimistic"
- log-normal is most "optimistic"

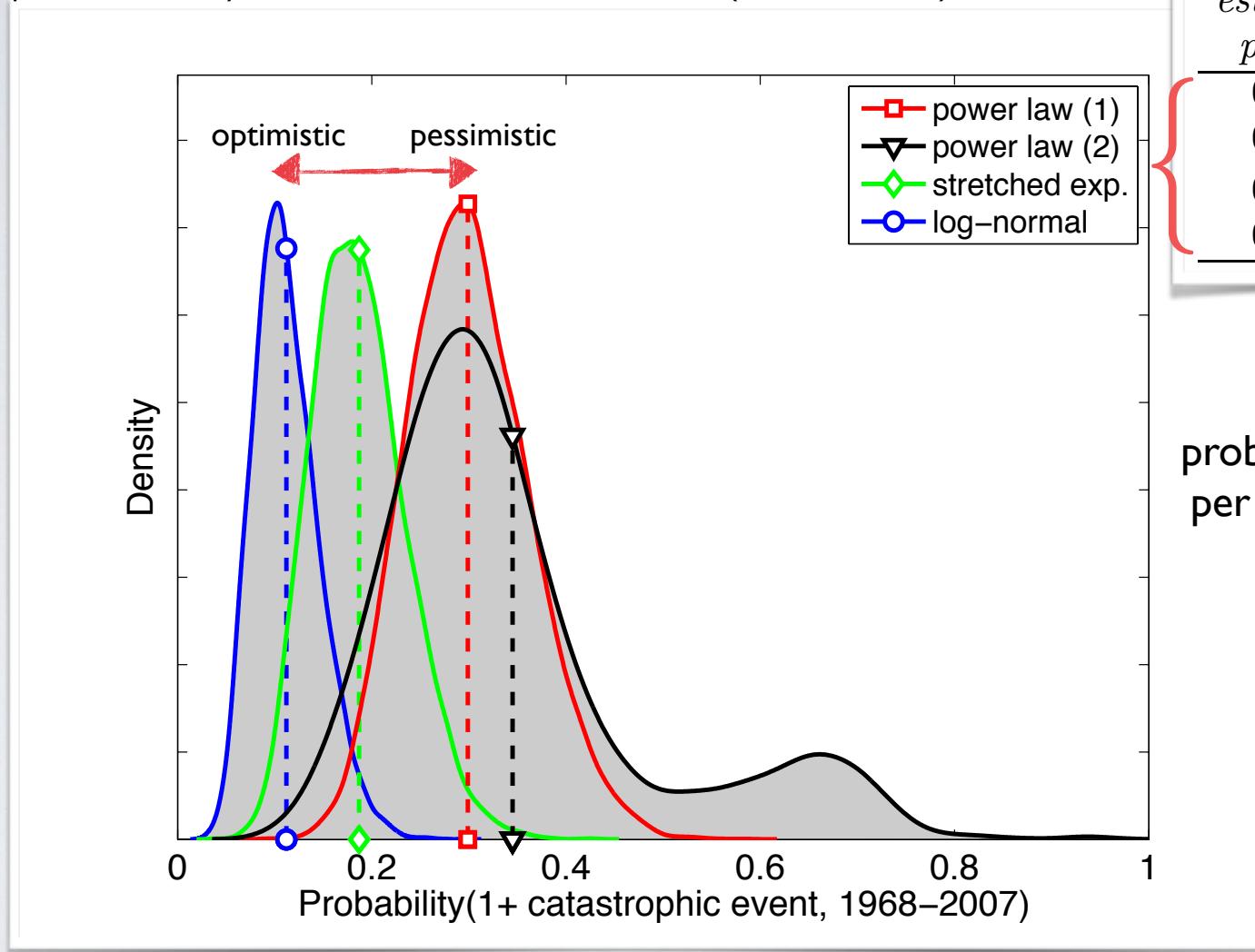
via Monte Carlo, estimate posterior
distribution of fraction of histories with
at least one 9/11-sized event

$$\rho = 1 - F(x | \theta(Y, x_{\min}))^{n_{\text{tail}}}$$

~~forecasting~~ predicting the unpredictable



3. probability of 9/11-sized event (historical)



est. $\Pr(x \geq 2749)$ per event, $q(x)$	est. prob. p , 1968–2007
0.0000270200	0.299
0.0000346345	0.347
0.0000156780	0.187
0.0000090127	0.112

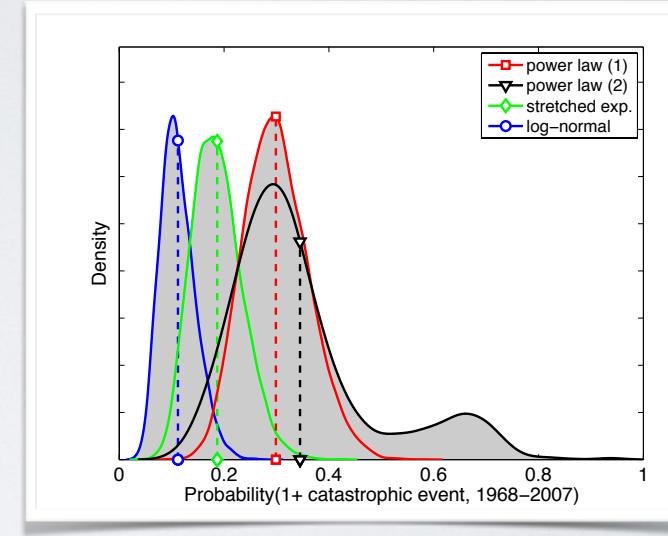
probability per event 40 year probability



forecasting ~~predicting~~ the unpredictable

recipe for large event forecasts

1. focus on *large events only*
separate "body" from "tail", then use tail models
2. use *multiple models*
true tail structure unknown → large model uncertainty
3. compute *distribution over outcomes*
little data in tail → large statistical uncertainty
4. combine with time series model $n(t)$
more events per unit time → more risk of a large event



- start with population (all terrorism, all wars), in aggregate
- add covariates to model, but avoid over-fitting*
- greater uncertainty better than false certainty

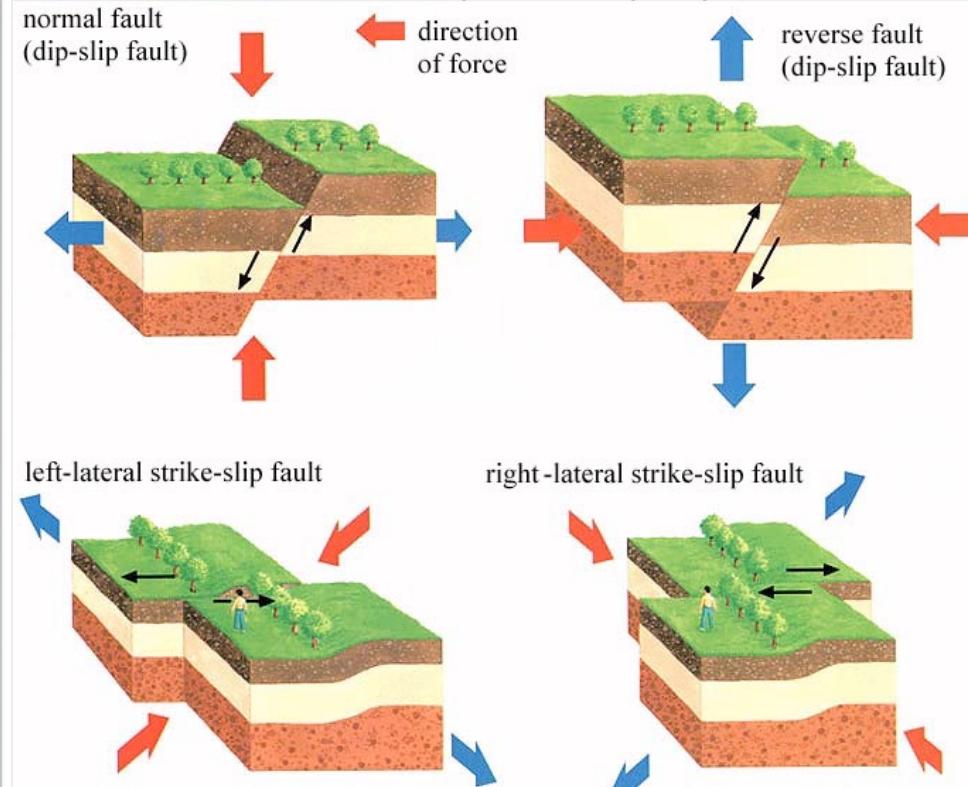
* easier said, than done

Clauset & Woodard, Annals of Applied Statistics (2013)

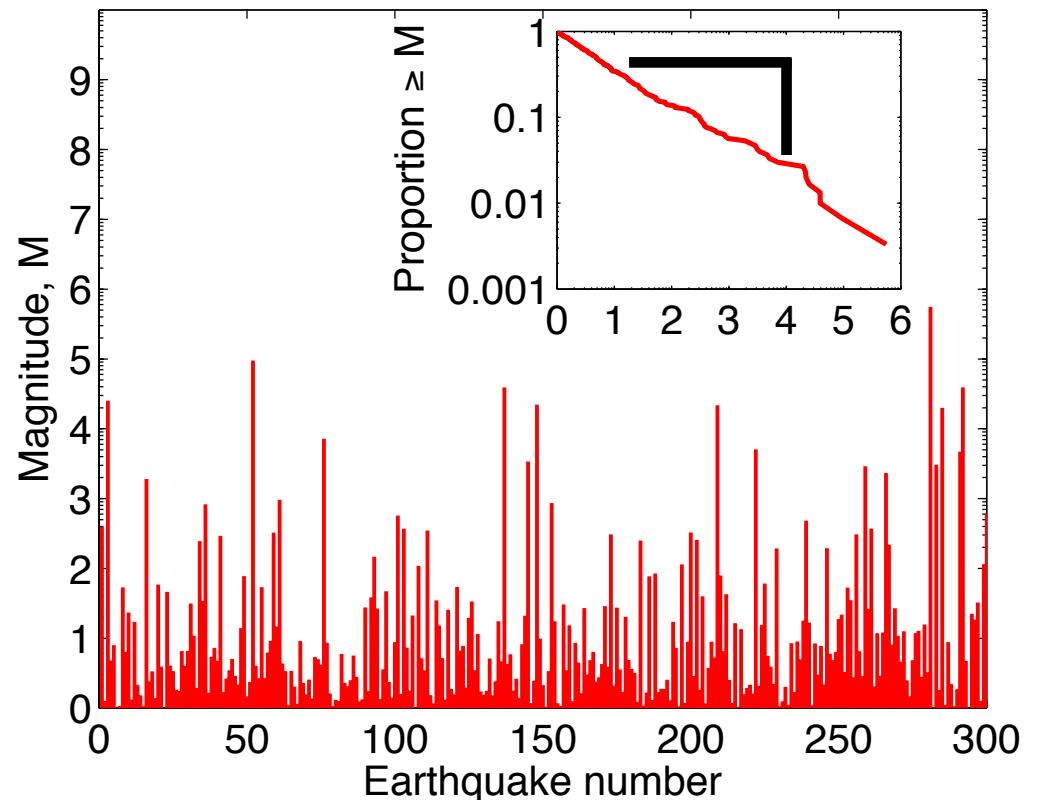
prediction in violent political conflict

seismology prediction in ~~violent political conflict~~

earthquake physics



Gutenberg-Richter law



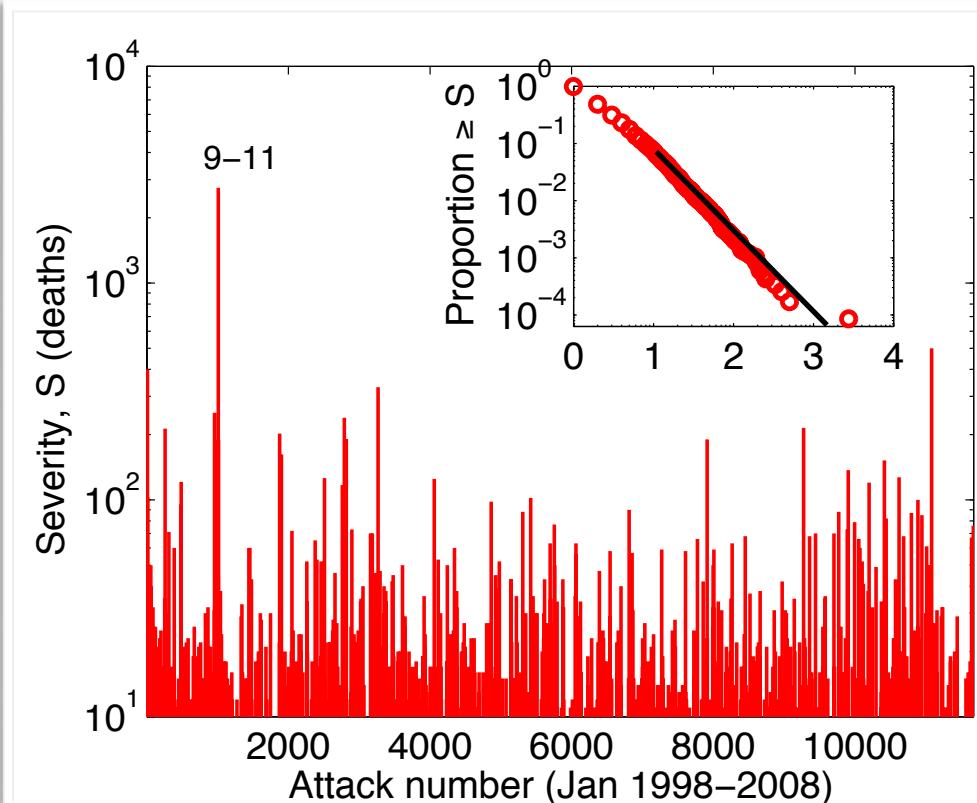
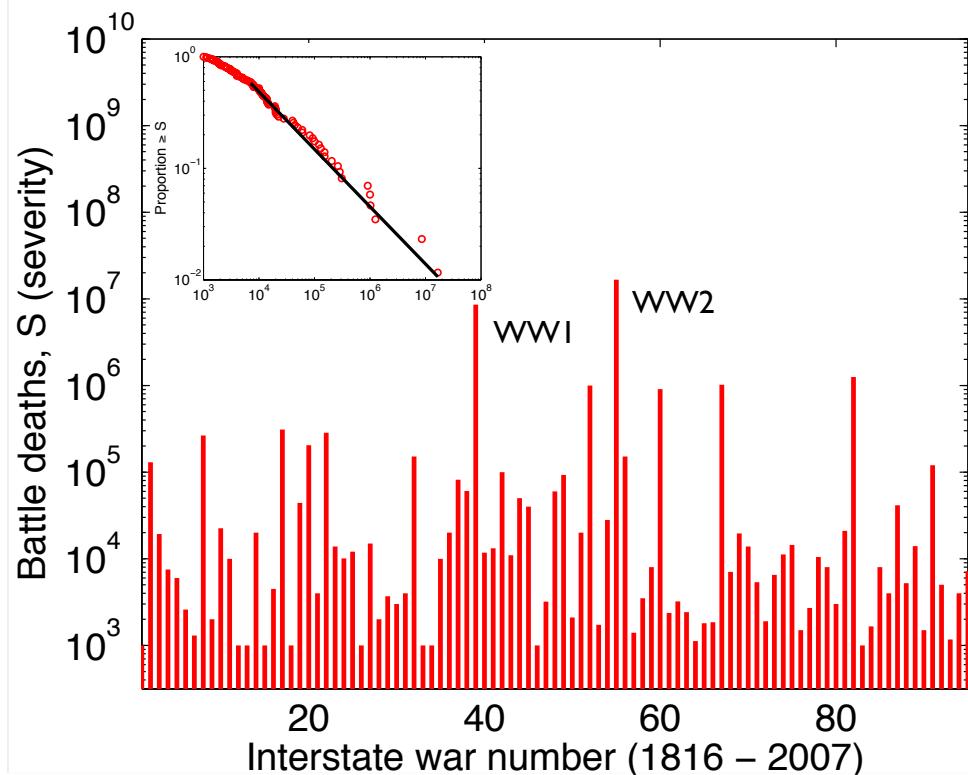
$$(\text{frequency}) \propto (\text{magnitude})^{-\alpha}$$

power-law relation

international wars & global terrorism



international wars also follow power-law statistics



$$(\text{frequency}) \propto (\text{magnitude})^{-\alpha}$$

power-law relation

earthquakes

Gutenberg-Richter law

$$F \propto M^{-\alpha}$$

physics largely known

processes fixed

forecasting possible
(years of successes)

prediction very hard
(years of failures)

terrorism & war

Richardson's law

$$F \propto S^{-\alpha}$$

processes largely *unknown*

processes *dynamic, adaptive*

forecasting is possible
(over long term)

prediction very hard
(agency & contingency)

large events in political conflict



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~~no.~~ **it depends:**

X *in specific* : who, what, where, why, how, when

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→ over-fit the past & under-fit the future

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in aggregate : statistical forecasts & risk estimates

why? robust statistical patterns exist, *in aggregate*, which allow probabilistic estimates, over populations (not individuals)

- **average over contingencies & beyond individual agency**
- **capture fundamental constraints**
- **best predictions made using *multiple* means for controlling *model uncertainty* and *statistical uncertainty***

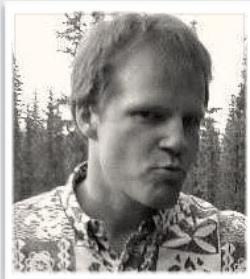
acknowledgements



Kristian Gleditsch
Government, Essex



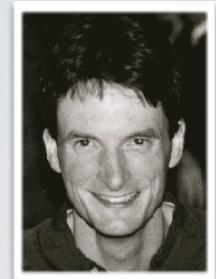
Maxwell Young
Computer Science, MSU



Ryan Woodard
ETH Zürich



Cosma Shalizi
Statistics, CMU



Mark Newman
Physics, Michigan

and

Lars-Erik Cederman

Barbara Walter

James McNerney

Brian Tivnan

Valerie Wilson

references

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PLoS ONE (2012)

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SOCIAL SCIENCES

Trends and fluctuations in the severity of interstate wars

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