Lies, Damn Lies, and Internet Measurements

Statistics and Network Measurements

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There are three kinds of lies: lies, damned lies, and statistics.
Mark Twain

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"There are lies, damn lies, and statistics. We're looking for someone who can make all three of these work for us."

Statistics and Network Measurements

- Everyone here understands the value of network measurements
- However, not wanting to be too controversial, the NM community is hopeless at statistics
  - it's not a unique problem (e.g., see health sciences)
  - but it can cause some misinterpretations and other problems
- War stories
  - e.g., X is better than Y, and related rankings
  - e.g., The red board

A little history of Network Measurements

1969- ARPANET and all that ...

- measurements are part of it, but not much is published (as far as I know)
- stochastic simulation is the norm
- lots of stochastic models proposed and used for data traffic – few measurements used

c1992-97 Beran, Erramilli, Leland, Taqqu, Sherman, Willinger, Wilson, and a few others publish a series of papers about self-similar traffic

c1992-97 Vern Paxson does his PhD at Berkeley on "Measurement and Analysis of End-to-End Internet Dynamics"

c1995-97 Cunha, Bestavros, and Crovella look at web traces

2000+ Network measurements exploded

- **2000** First PAM
- **2001** First IMW (becomes IMC in 2003)
- **2001** Endace founded

A little history of Network Measurements

- This is hardly a fair history
  - much is missing
  - focus on what I see as seminal (because it influenced me)
  - apologies to those I left out (CAIDA, Neville Brownlee, TMA, and many others)
- I'm trying to make a point though
  - around 92-97 the Internet was growing and changing very rapidly
  - and we went from being data poor to data rich very quickly
  - initial studies were motivated and supported by stochastic models
  - their impact derived from data
- We took the last bit on board
  - data is now seen as key
  - huge efforts to make this data "good"
  - we seem to have forgotten some of the original modelling and statistics that also made those early result so valuable

Some Little Examples

Let's look at a few illustrative examples

Case 1: the test

> Statistics means never having to say you're certain

- Common test: test for a problem
  - in medicine it might be a disease
  - in networks, often look for an "anomaly"
- Let me propose a test for disease X
  - there are two types of error

type I	false alarm or false positive
type II	failed to detect the problem (false negative)

Case 1: example

- Imagine a hypothetical test for cancer with the following properties
  - if you have the cancer, it will be detected 90% of the time
  - if you don't have the cancer, then 90% of the time, the test will tell you that you don't
  - 1/100 people have the disease
- You go to your doctor, and he tells you (in a serious voice) that your test has come back positive
- Should you be scared?
  - what is the chance that you actually have the disease?

Case 1: analysis

It's a conditional probability problem, but it's actually easier to just consider frequencies.

Consider 1000 people, on average

- 1 in 100 has cancer, so there are 10 with the disease
- The test will identify 9 in the 10
- 990 don't have cancer, but 1 in 10 of these will have a false alarm
- So the test tell us 108 people have the disease, but only 9 are correct: so the probability you have the disease, given the test is only

$$\frac{9}{108} \simeq 9\%$$

- Our "90% accurate" test has a less than 10% chance of being right

Case 1: network measurement case

- Anomaly detection:
  - 99% detection probability
  - 1% false alarm probability
- Applied to network
  - SNMP link traffic: bytes and packets
  - collected every 5 minutes, on each link
  - 1000 links
  - average 10 real problems per day

$$\text{false alarms per day} \simeq 1000 \times 24 \times 12 \times 2 \times 2 \times 0.01 = 11,520$$

$$Pr(\text{alarm is genuine}) = 9.9/11,520 \simeq 0.0009$$

- Result: ops switch off the alarm system

Case 1: the issues

- How many False Alarms are too many
  - often we report a "false-alarm probability"
  - but these test might be conducted many times
  - too many false alarms, and you are "crying wolf"
  - the number depends
    - ★ how critical are alerts?
    - ★ how easy is it to fix alarms?
- False Discovery Rate is often what we really need
  - average number of false alarms per discovery
- Tests often have tradeoffs
  - often through choice of a threshold or similar parameter
  - by tuning this, we can exchange false alarms for failed detections
  - testing one without the other is pointless
  - comparisons must be of (ROC) curves of the tradeoff

Case 2: Simpson's Paradox

1. We commonly report results of experiments
   - often we group the data
   - often as percentages
   - and we think they are meaningful
     - e.g. we can see some causality in the data
   - we drawn conclusions from them
     - e.g., A is better than B
2. To do analysis properly
   - firstly we need to know whether our proportions are statistically significant
   - but even then beware Simpson's paradox

Case 2: Simpson's Paradox example

Berkeley gender bias case

- University was sued for bias against women
  - more men were accepted than women (of qualified applicants)

	applicants	admitted
Men	8442	44%
Women	4321	35%

- difference unlikely to be due to chance
  - looks like an obvious case of bias against women

Case 2: explanation

Examine individual departments

	Men		Women	
Department	Applicants	Admitted	Applicants	Admitted
A	825	62%	108	82%
B	560	63%	25	68%
C	325	37%	593	34%
D	417	33%	375	35%
E	191	28%	393	24%
F	373	6%	341	7%

- Larger proportion of female applicants to hard departments
- Not really any (provable) bias

Case 2: Simpson's Paradox

Other examples

The issue can often lead to reverses in conclusions

- Batting averages
  - player A has better average than B in 2012 and 2013
  - but player B's average over the two years is better
- Death penalty case
  - if you look uncritically, it looks like more white people than black are given the death penalty
  - if you control for the race of the victim, then the correlation goes the other way

Case 2: network measurement example

Cooked up example

We compare performance of two networks

- we conduct packet probe experiments
  - round-trip probes
  - assume we know how to do that correctly
  - assume we do enough to be statistically significant
- results

	loss rate
A	1%
B	5%

- Obviously A is better than B?

Case 2: network measurement example

Cooked up example

But really

- The networks carry 2 types of traffic
  - type X
    - is real-time, and unresponsive to congestion
    - both networks prioritise it and it has effectively 0% loss on both
  - type Y
    - is bulk data, and adapts to congestion
    - the two networks have the same "amount" of congestion, and a resulting loss rate of 10% for this type of traffic
- The two networks have different traffic mixes

	X	Y
A	90%	10%
B	50%	50%

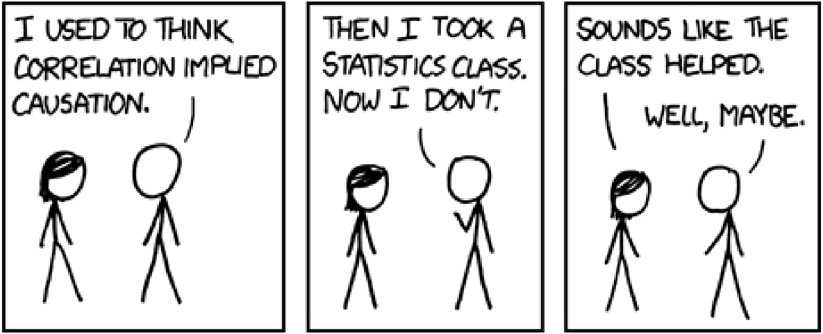
  - hence the loss measurements
  - but neither network is better than the other

Case 2: conclusion

- Obviously, the example is cooked
  - in reality, we might use two different types of probes to assess the different performance
  - but the problem is generic, not specific
- But the point remains
  - danger's of averages
  - correlation doesn't imply causality
  - beware hidden "confounding" variables

lurking variables

Obligatory xkcd cartoon



http://xkcd.com/552/

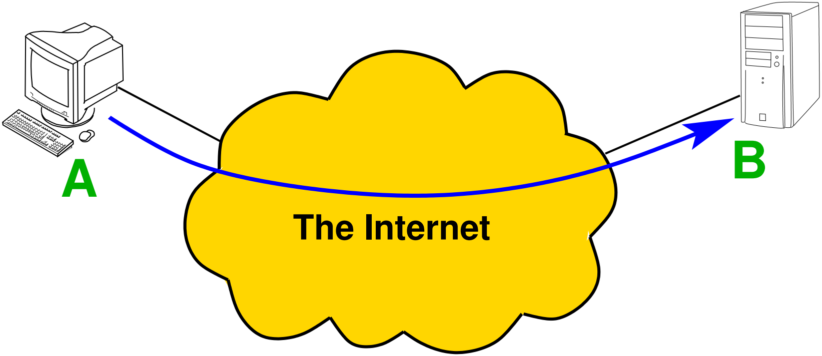
Case 3: estimating loss

- Estimating loss probability
  - packets are dropped in queues
  - want to measure end-to-end loss probability
  - it's a useful measure of how well the network is working
  - high loss rate indicates congestion, or other problems
  - SLAs (Service Level Agreements)
- Strategies
  - active: send probe packets
  - passive: measure traffic at two points
- Metric

$$Prob\{packet\ loss\} = \frac{N_{\text{lost packets}}}{N_{\text{measured packets}}}$$

Examples: Performance

- Active performance measurements
- Send probe packets from $A \rightarrow B$ across the network
- Measure the performance experienced by packets



Case 3: estimating loss

Questions?

- How many probe packets should I send?
- How accurate is a particular measurement?
- My measurement of network A $>$ network B, what does that mean?

These questions are all really asking the same question!

Case 3: estimating loss

Real question

- If we repeated a set of measurements under the same exact circumstances how much could the result vary?

  or the other way around

- Given a desired maximum variability in the estimates, how many measurements do I need?

We often wrap these ideas up in **confidence intervals**, though this isn't the only way to approach the problem.

Case 3: estimating confidence intervals for loss

Naive approach using Gaussian Confidence Intervals (CIs)

- For N measurements, with n losses

  $$\hat{p} = \frac{n}{N}$$

  and this estimate $\hat{p}$ is unbiased (its mean is correct) and its variance is

  $$\sigma_p^2 = p(1-p)/N$$

  and so we choose confidence intervals

  $$\hat{p} \pm z_\alpha \sigma_{\hat{p}}/\sqrt{N}$$

  where for 95% CIs (the typical case) $z_\alpha = 1.96$.
- Stats intuition: you need enough measurements for the Gaussian approximation to be correct, so make sure N is big enough that

  $$N\hat{p}(1-\hat{p}) > 10$$

Case 3: estimating confidence intervals for loss

What's wrong with this?

- The result is widely cited, but WRONG!
- Why?
  - The estimate $\hat{p}$ is used also to estimate CIs
  - The CIs are symmetric, which means you can have negative values!
  - The measure is continuous, but the experimental results are discrete
  - **The measure assumes that loss measurements are not correlated!**

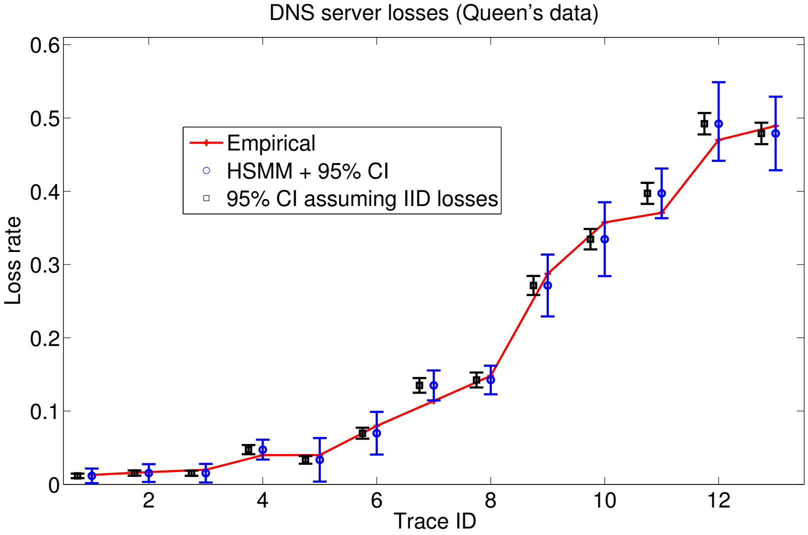
Case 3: what do we do about it?

- The actual variance of the estimate is

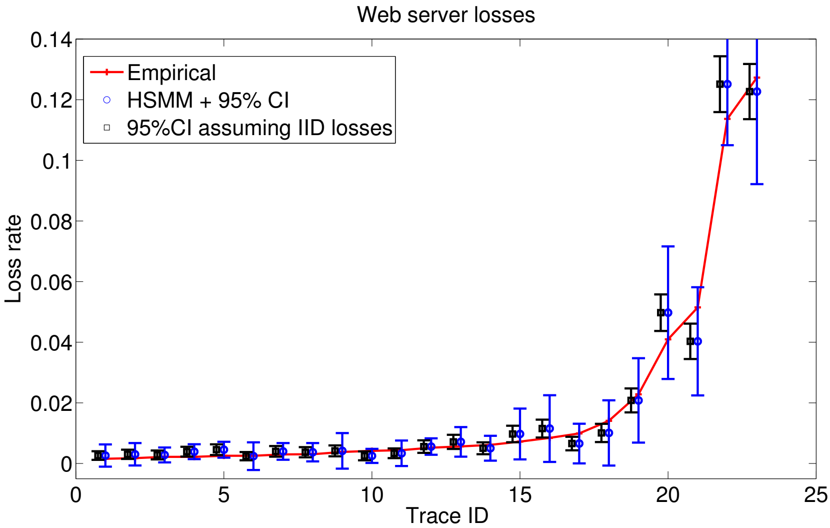
$$\mathrm{Var}(\hat{p}) \quad = \quad \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} R(\tau_{ij}),$$

  where $R(\cdot)$ is the autocovariance function and the τ_{ij} are the times between measurements
- Process
  - Estimate $R(\cdot)$
    - ★ have to be careful how to do this with limited measurements [NR13]
  - Use CIs, but with a better variance estimate

Case 3: cross-validation



Case 3: cross-validation



Case 3: conclusion

- CIs for loss-probabilities estimates need more care
  http://bandicoot.maths.adelaide.edu.au/SAIL/
  - reasonable CIs are usually MUCH wider than IID Gaussian CIs
  - more measurements are needed than you think
- Most Internet loss measurements studies and tools have ignored the problem
  - many research conclusions are WRONG!!!!
  - there may have been SLA violations reported that weren't supportable
  - network op.s decisions made on the basis of bad information, or network op.s stop listening to measurements
- And that doesn't even take into account the other problems which occur when probabilities are small [SBE+11, BCD01, Wil27]

Some other statistical problems

- Sampling
  - do I need to test everyone?
  - remember many experiments are just samples of some underlying phenomena
    - ★ e.g., packet probes sample a network's performance
- Comparisons
  - is A better than B?
  - this is a statistical question, whether you know it or not
  - there are aspects to the question not discussed above
  - ranked orderings are particularly dangerous
- Models
  - curve fitting is potentially misleading
  - but lots of people do even that part really badly
- Gnarly "little" issues
  - long-range correlations
  - infinite variance
  - PASTA

What to do

- There's lots of research going on
  - some is on how to do this stuff better
- Be careful with statistics (obviously)
  - learn enough (to be dangerous)
  - consult with a statistician
    - this seems to be becoming the norm for medical studies
- Consult your statistician early

> To consult the statistician after an experiment is finished is often merely to ask him to conduct a post mortem examination. He can perhaps say what the experiment died of.
> *Ronald Fisher*

- Sorry about the Stats 101 for those already initiated
- Any questions?

Further reading I

- Lawrence D. Brown, T. Tony Cai, and Anirban DasGupta, **Interval estimation for a binomial proportion**, Statistical Science **16** (2001), no. 2, 101–133.
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- Will E. Leland, Murad S. Taqqu, Walter Willinger, and Daniel V. Wilson, **On the self-similar nature of Ethernet traffic (extended version)**, IEEE/ACM Transactions on Networking **2** (1994), no. 1, 1–15.
- H.X. Nguyen and M. Roughan, **Rigorous statistical analysis of internet loss measurements**, IEEE/ACM Transactions on Networking **21** (2013), no. 3, 734–745.
- V. Paxson, **Measurements and analysis of end-to-end internet dynamics**, Ph.D. thesis, U.C. Berkeley, 1997, ftp://ftp.ee.lbl.gov/papers/vp-thesis/dis.ps.gz.

Further reading II

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Edwin B. Wilson, **Probable inference, the law of succession, and statistical inference**, Journal of the American Statistical Association **22** (1927), no. 158, 209–212.