

Bigfoot, Sasquatch, and the Yeti: The Missing Links

What we don't know about the AS graph

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The Yeti

Apparently we have found the Yeti



http:

//www.canberratimes.com.au/news/local/news/
general/yeti-truth-a-hairs-breadth-away/
1227921.aspx

What about the other missing links?

Graph Theory and the Internet

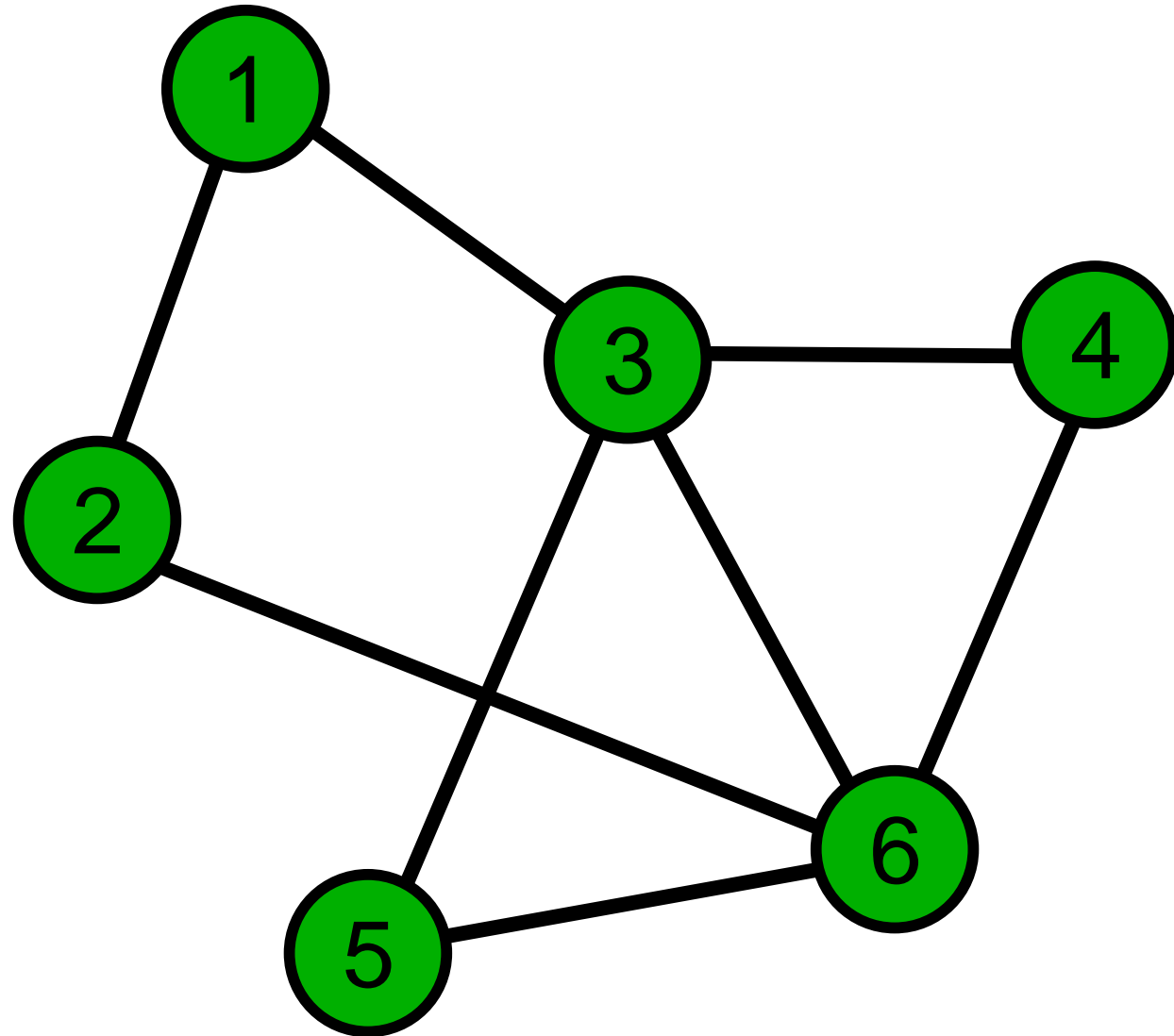


- The Internet is made up of a bunch of connected devices
 - devices = nodes or vertices
 - connections = links or edges
- Represent as a graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$
 - set of nodes \mathcal{N}
 - set of edges \mathcal{E}
- e.g. AS-graph
 - nodes are **Autonomous Systems** (ASs)
 - edges mean two ASs are connected by a "link"
 - a link can actually represent multiple connections

Example

$$\mathcal{N} = \{1, 2, 3, 4, 5, 6\}$$

$$\mathcal{E} = \{(1, 2), \\ (1, 3), \\ (2, 6), \\ (3, 4), \\ (3, 5), \\ (3, 6), \\ (4, 6), \\ (5, 6)\}$$



Measuring Graphs

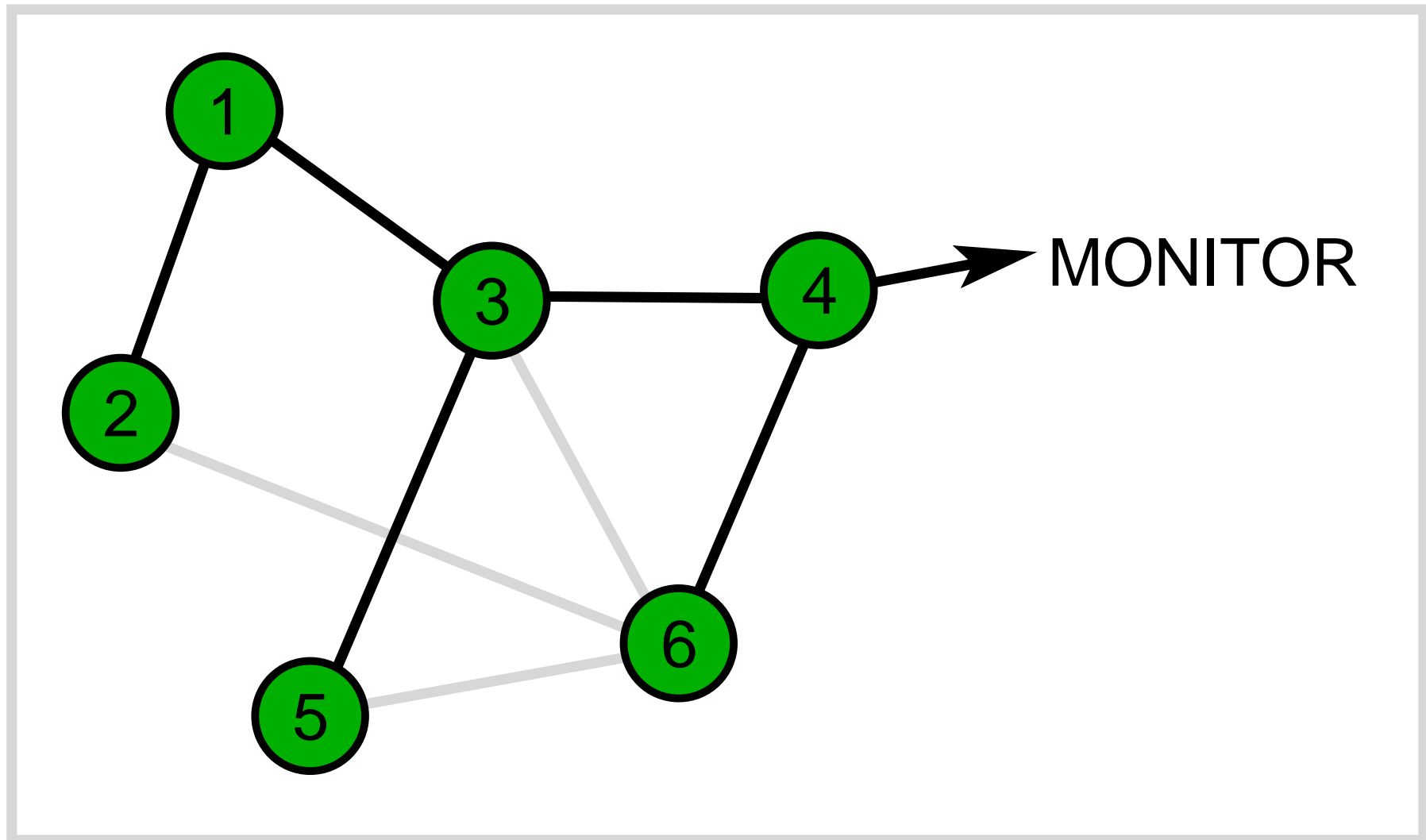
- We often want to measure a graph
 - structure of graph can tell us something
 - graph might be used later (e.g. to predict paths)
- Measurements in the Internet
 - tomography
 - traceroute
 - route monitors
- All measurements have problems
 - we'll focus on **route monitors** here
 - provide the most up to date information
 - can see dynamics

Route monitors

- Install our own "node"
 - listens for routing messages
 - can infer some of the routes in the network
 - each route tells us about some links
- Problem
 - missing links
 - a single viewpoint only sees a subset of links
 - multiple viewpoints increase coverage
 - how many are enough?
 - how do we know what we are missing?

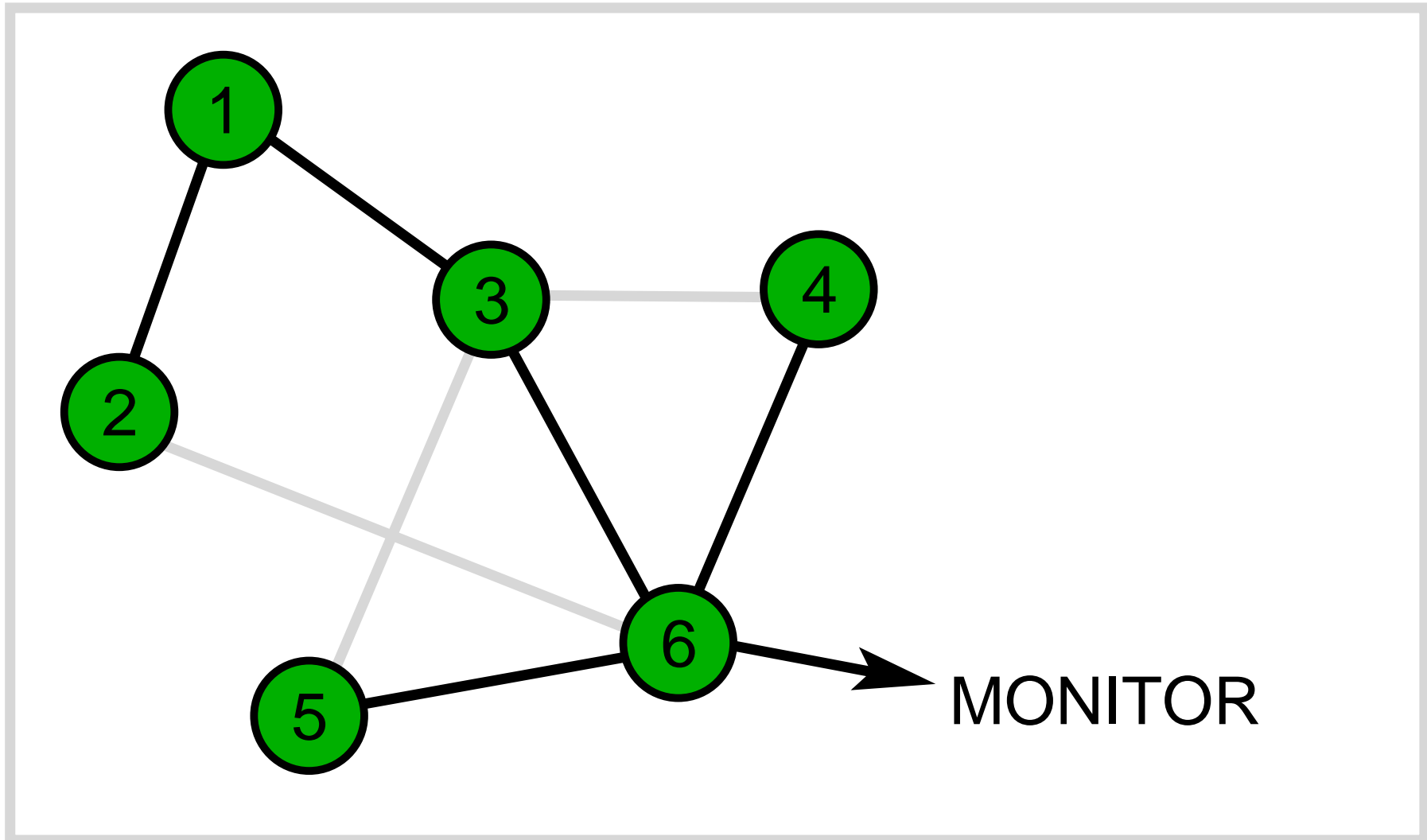
Example

Monitor 1



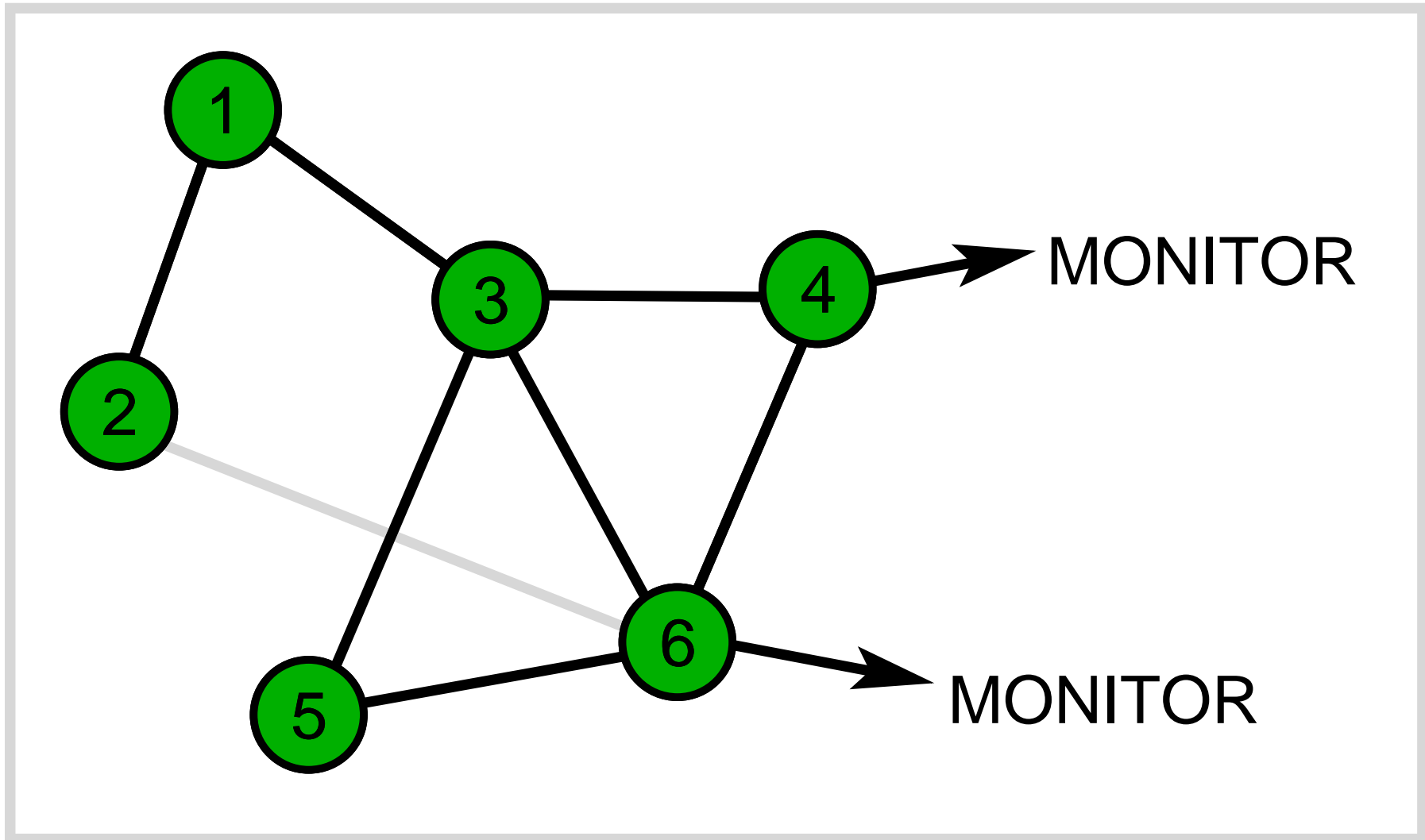
Example

Monitor 2



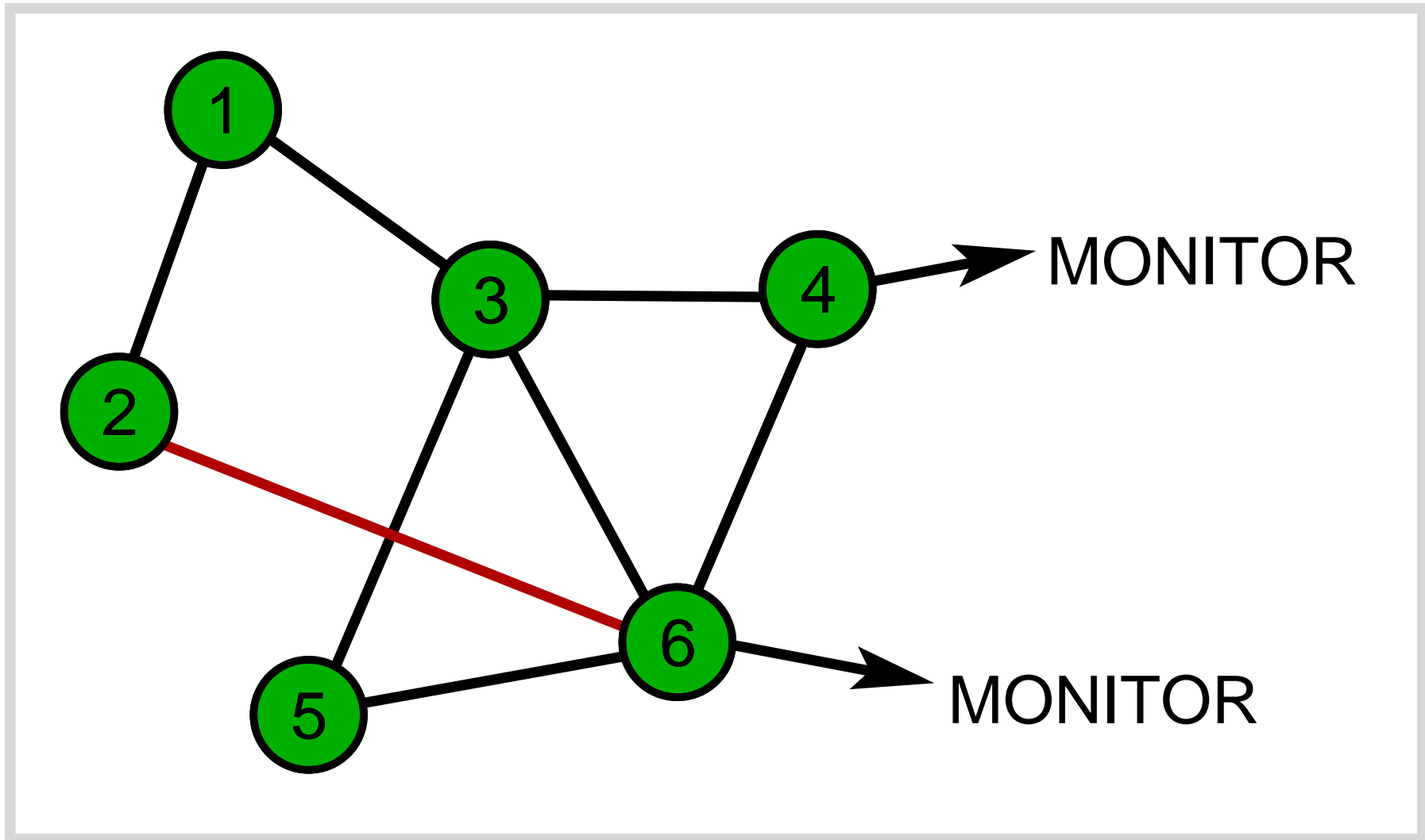
Example

Both monitors

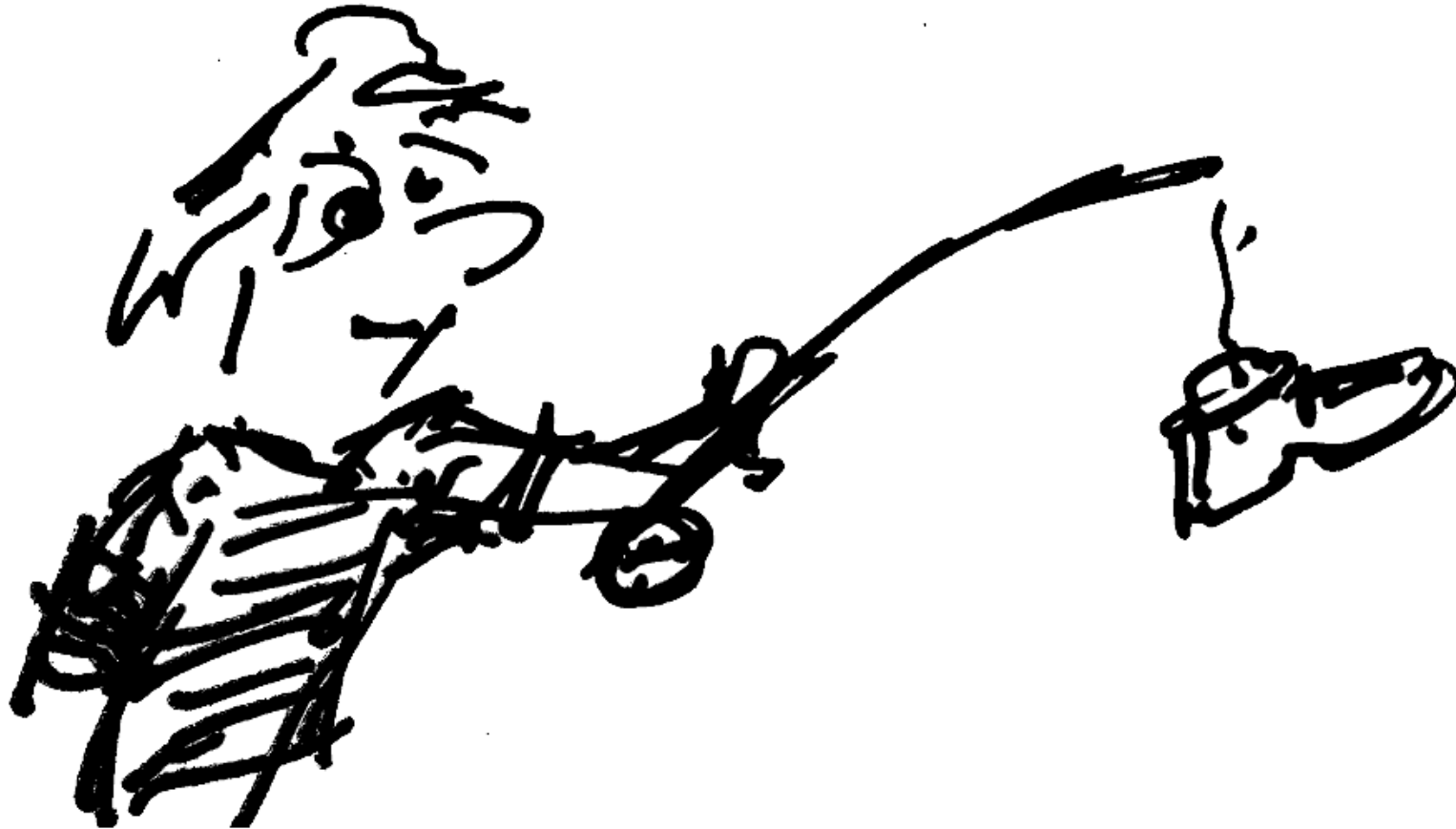


Example

Missing links



Capture-recapture



How many fish are there in the lake?

Standard biological approach



- capture a group of fish, tag them, and release
- some time later
 - capture another group of fish
 - note how many are tagged

Petersen's formula

$$\hat{E} = \frac{E_1 E_2}{E_{12}}$$

where

- E_1 = the number of "fish" seen in capture 1
- E_2 = the number of "fish" seen in capture 2
- E_{12} = the number of tagged "fish" seen in capture 2
- \hat{E} = the estimated number of "fish" in the pond

Links = fish

- Capture-recapture Assumptions
 - No change in population over time
 - Tags don't fall off
 - Homogeneity: all fish are the same
 - Independence between experiments
- In our case we want to estimate links
 - number of links = number of fish
 - don't perform successive experiments
 - each monitor is a separate measurement
 - don't need tags because links have unique ID
 - we have $K \simeq 40$ monitors

But it doesn't work!

- Produces inaccurate estimates
 - below a lower bound
- Assumptions of Petersen aren't valid:
 - links in AS-graph aren't homogeneous
 - P2P and C-P links have different visibility
- propose a stratified model
 - C different classes of links
 - probability of class j is w_j
 - observation probability of class j is p_j

New model

- New model is called a **Binomial Mixture Model**
- We actually observe a truncated version of this model.
- We have a new EM algorithm for estimating the parameters w_j and p_j for a given number of classes.

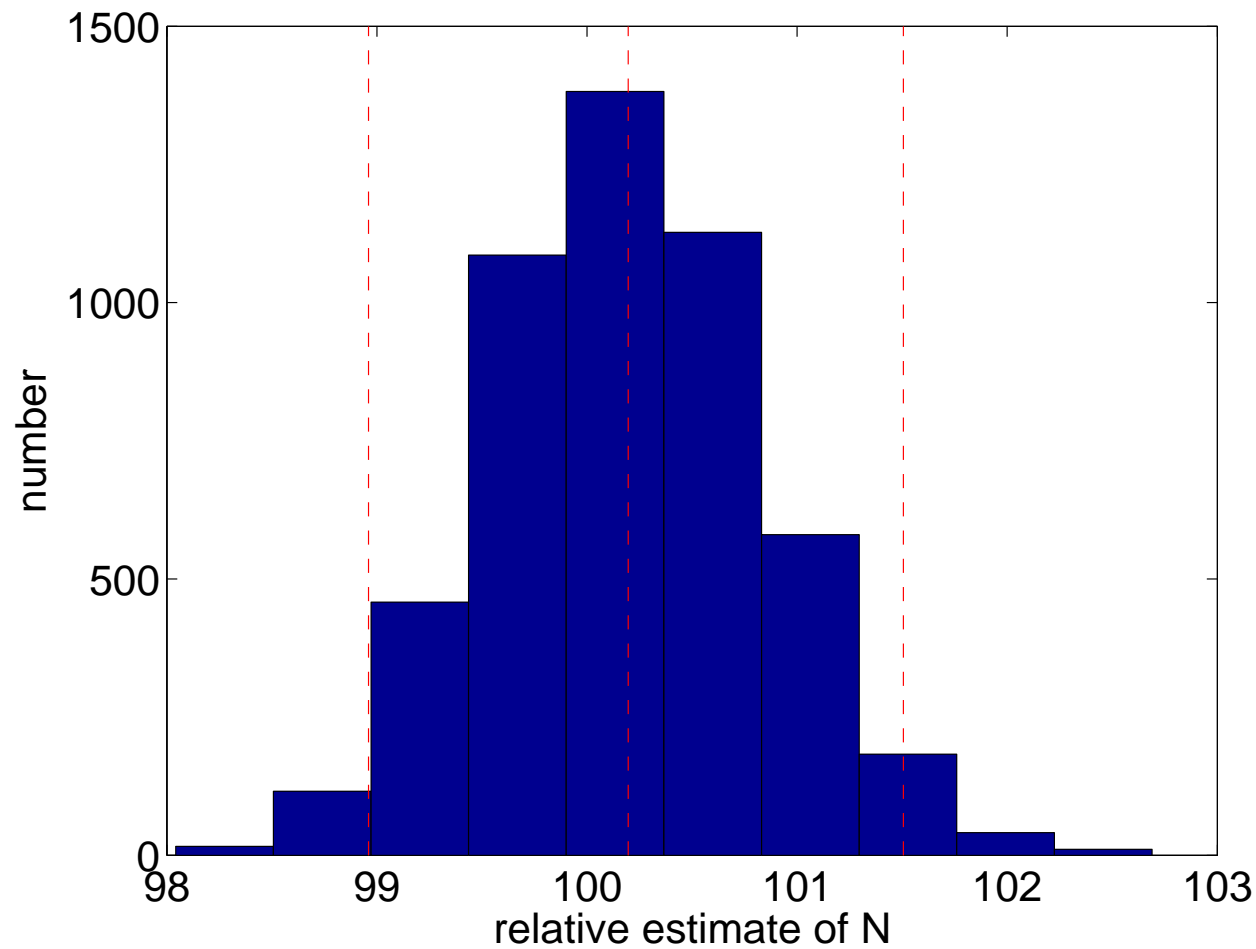
Simulations

Parameters, $C = 7$

Class	Parameter	
	p_j	w_j
1	0.010906	0.248714
2	0.140579	0.052389
3	0.345960	0.036864
4	0.557597	0.049963
5	0.758552	0.060776
6	0.917098	0.068741
7	0.998352	0.482553

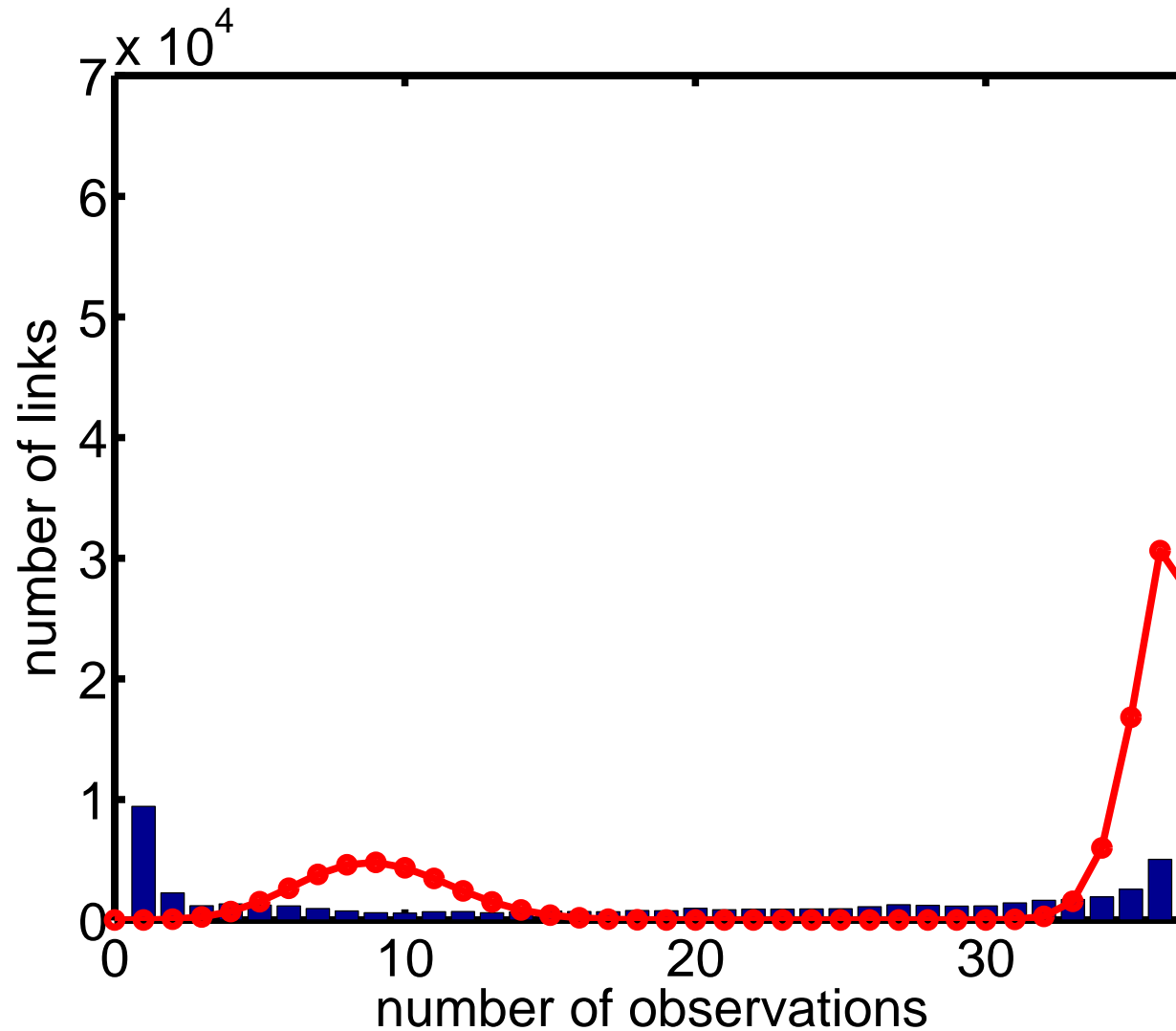
Performance of EM Algorithm

Simulated performance:



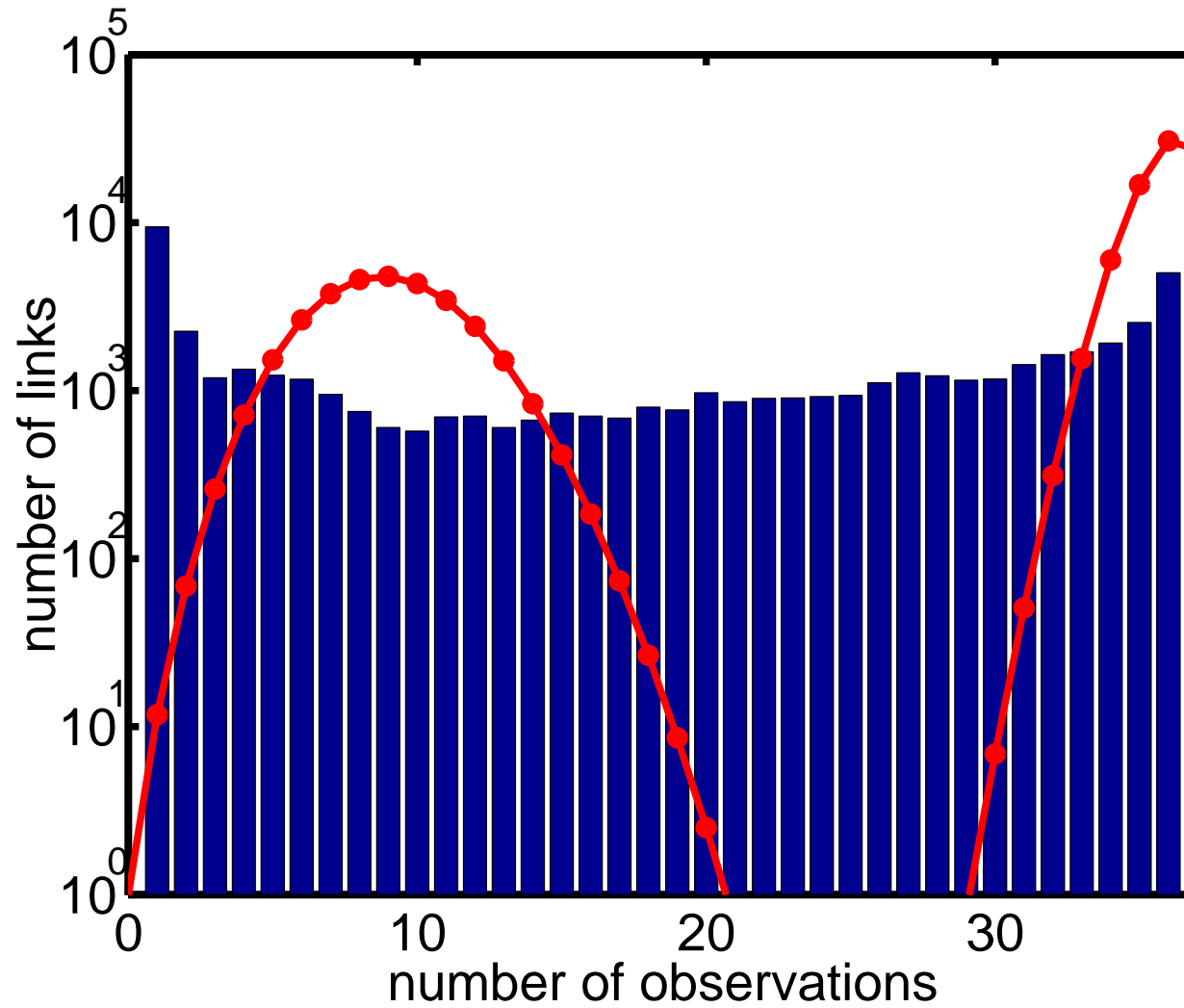
Choice of C

Need to choose C for real data



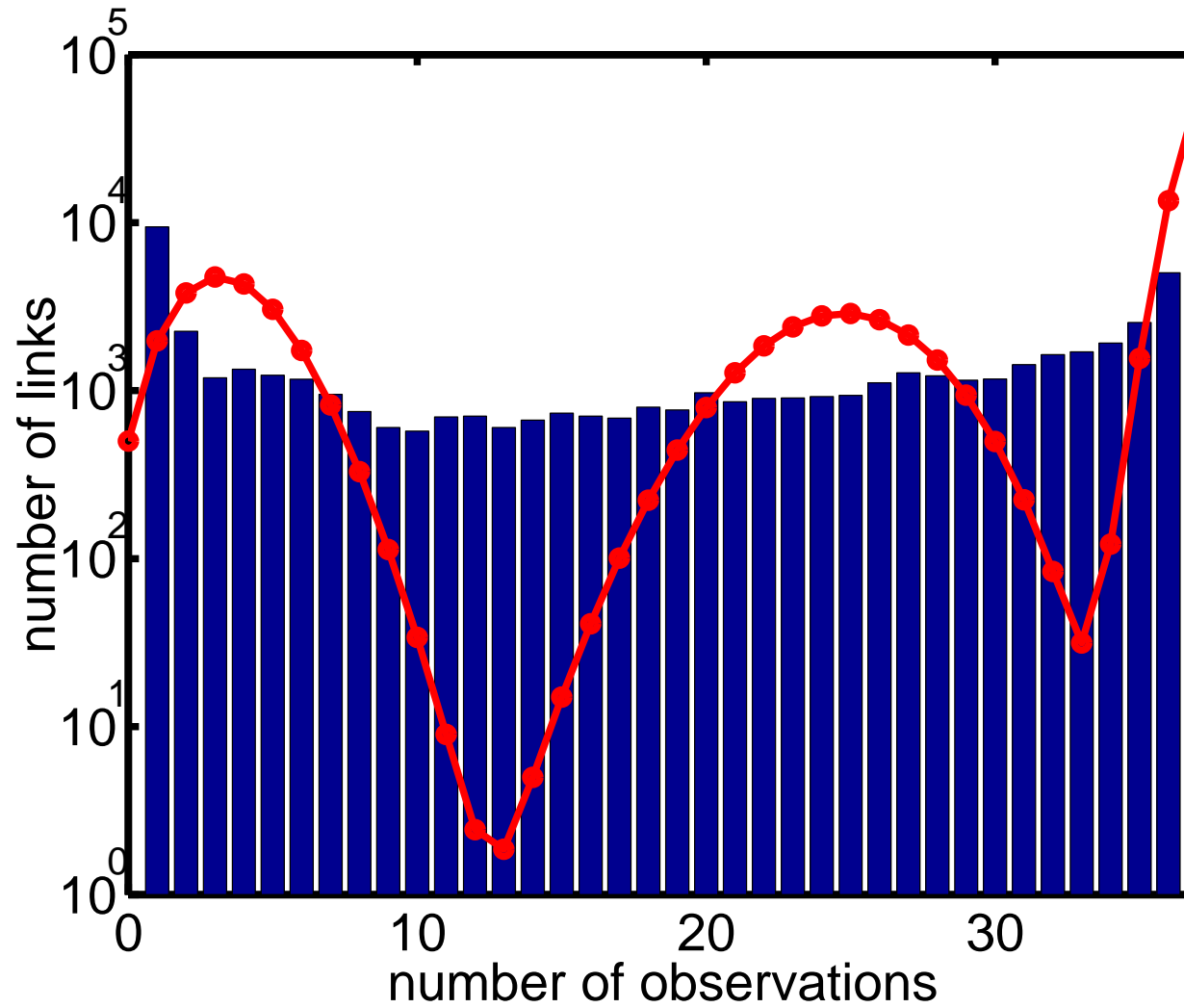
Choice of C

$$C = 2$$



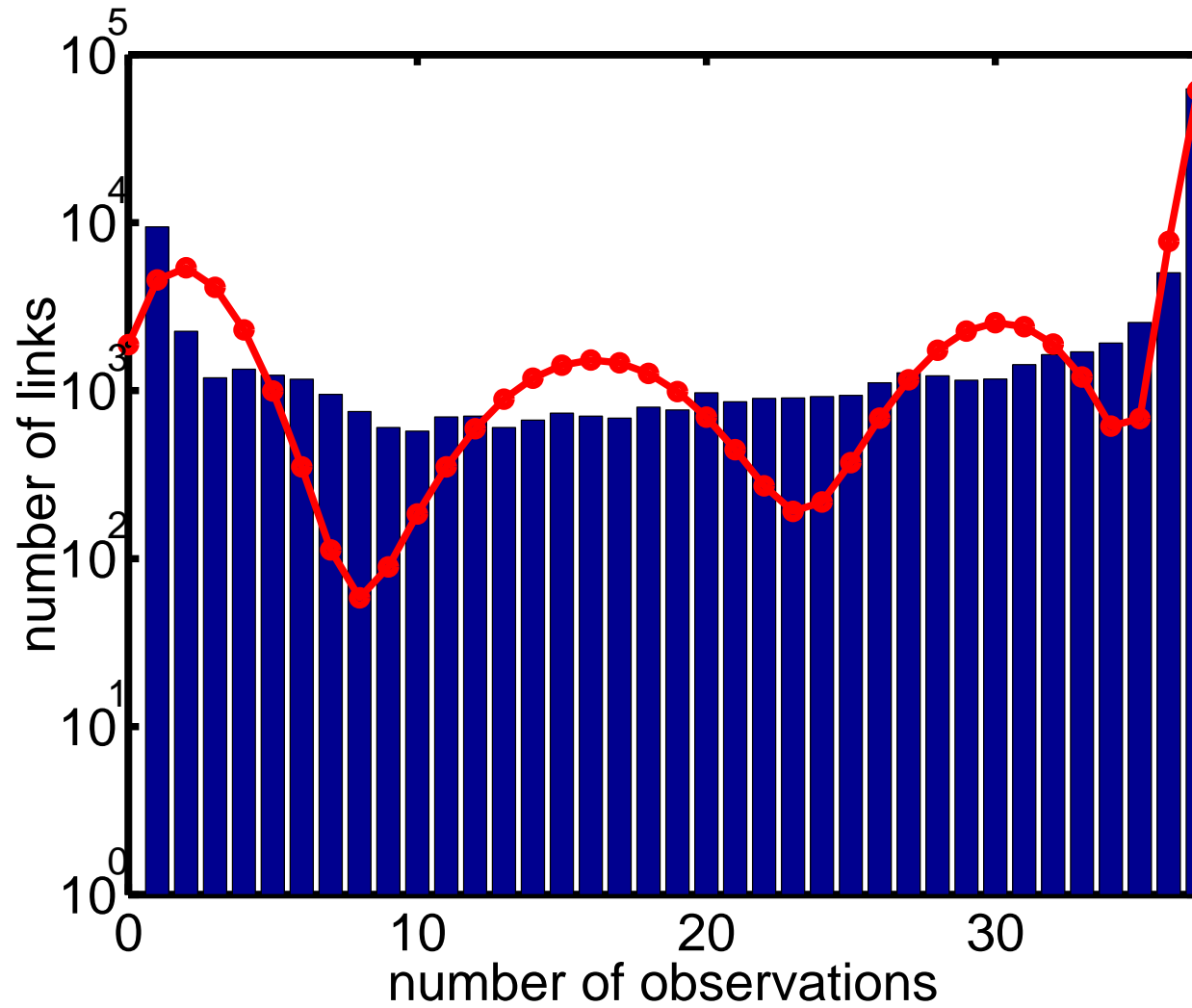
Choice of C

$$C = 3$$



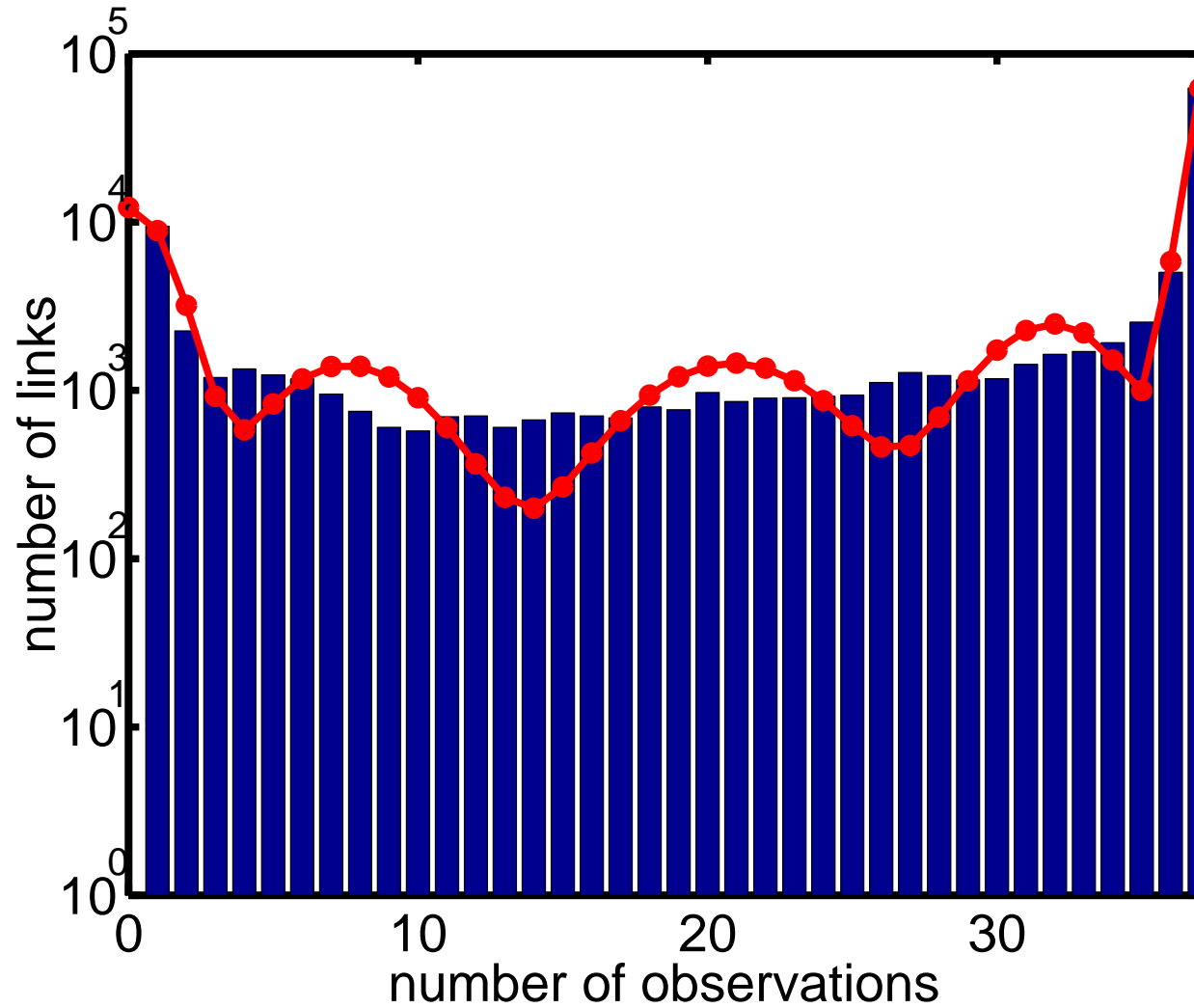
Choice of C

$$C = 4$$



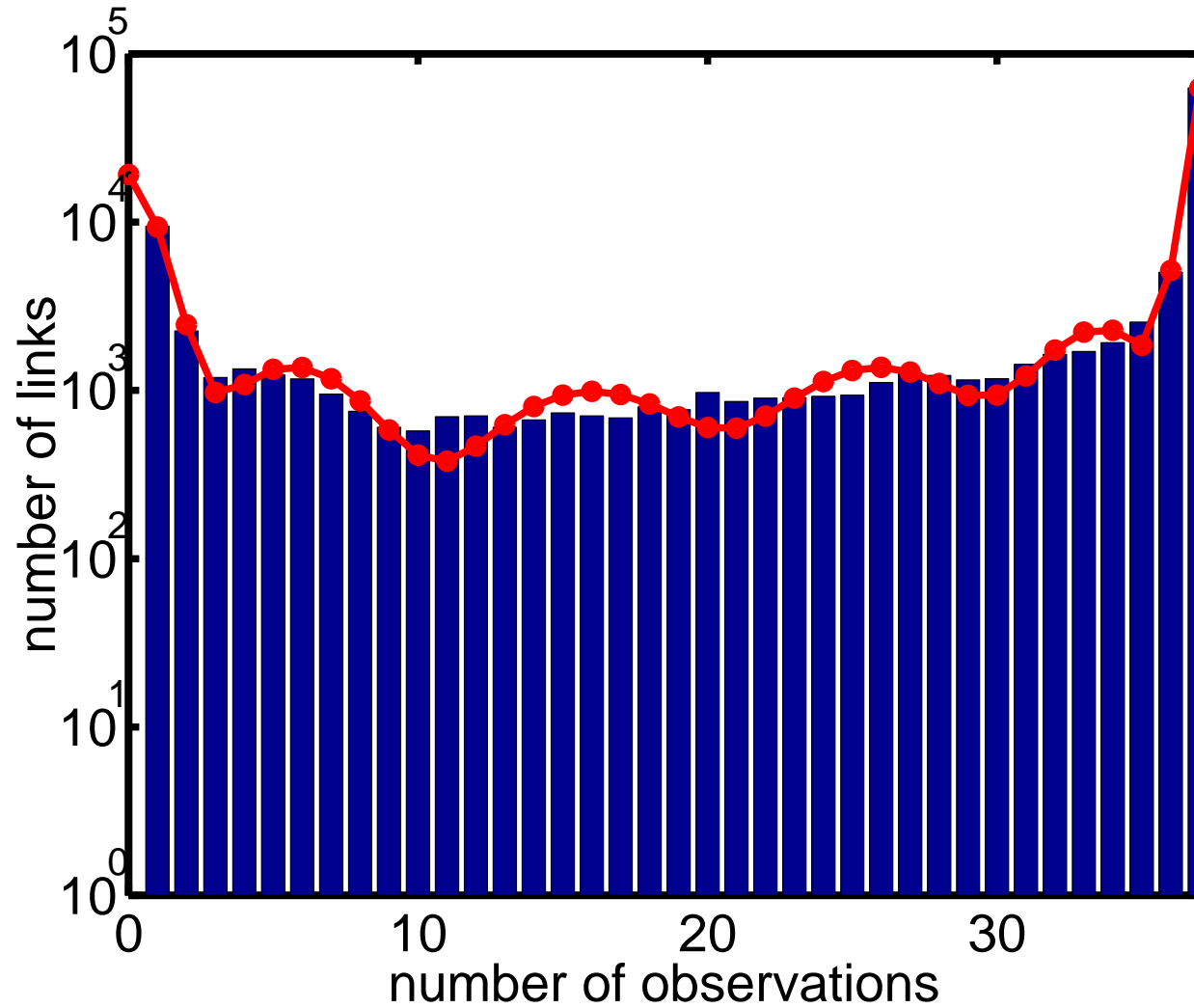
Choice of C

$$C = 5$$



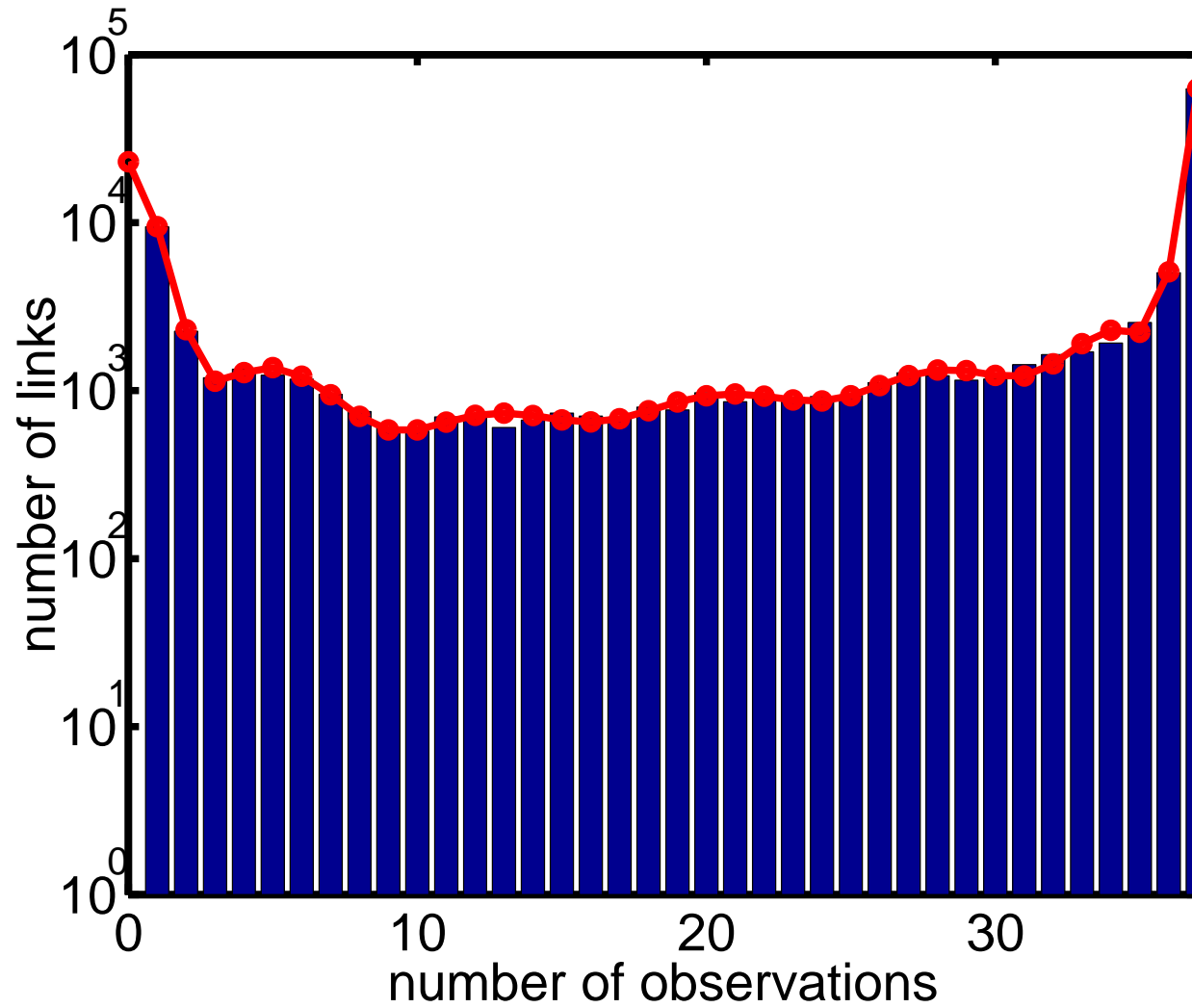
Choice of C

$$C = 6$$



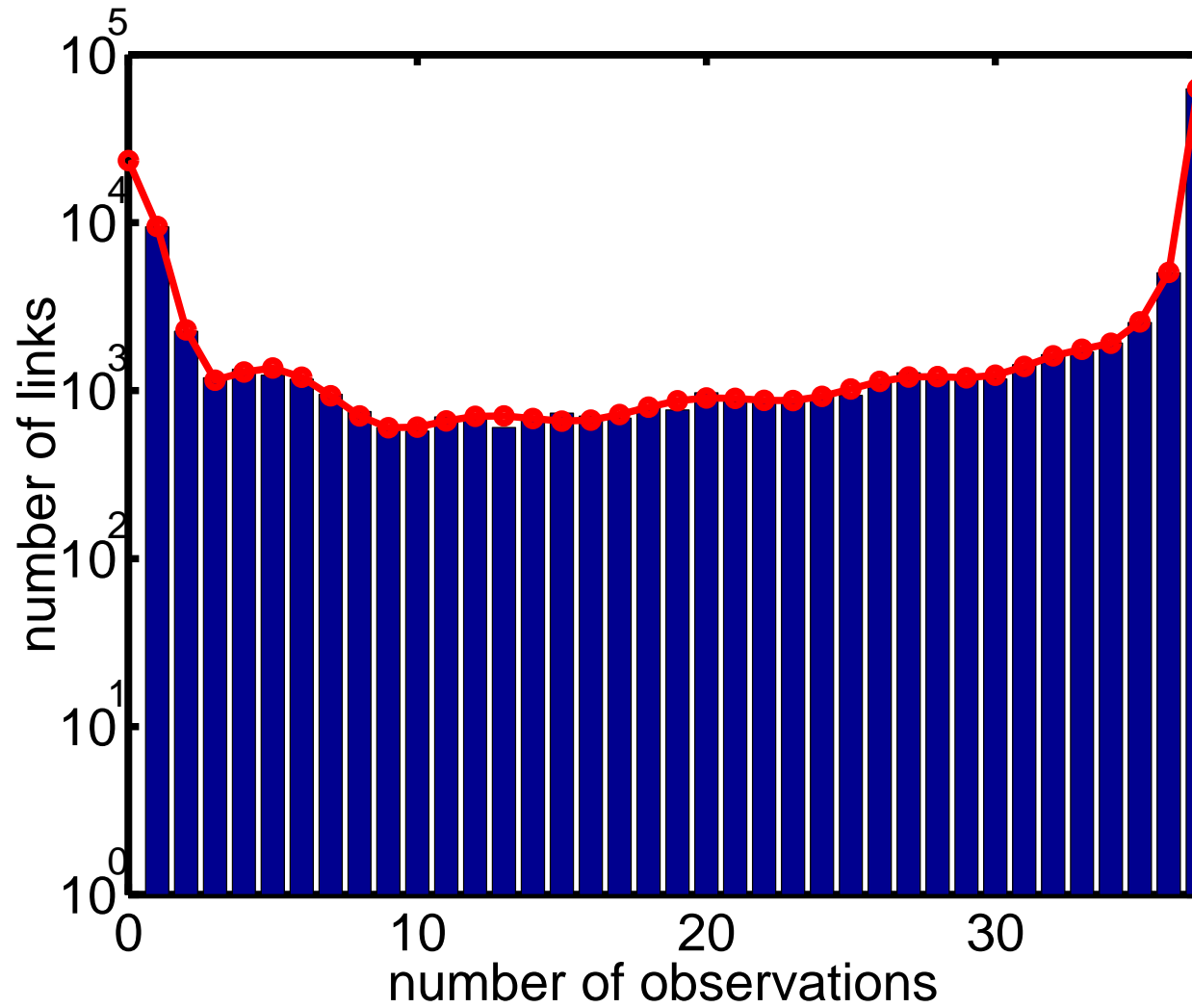
Choice of C

$$C = 7$$



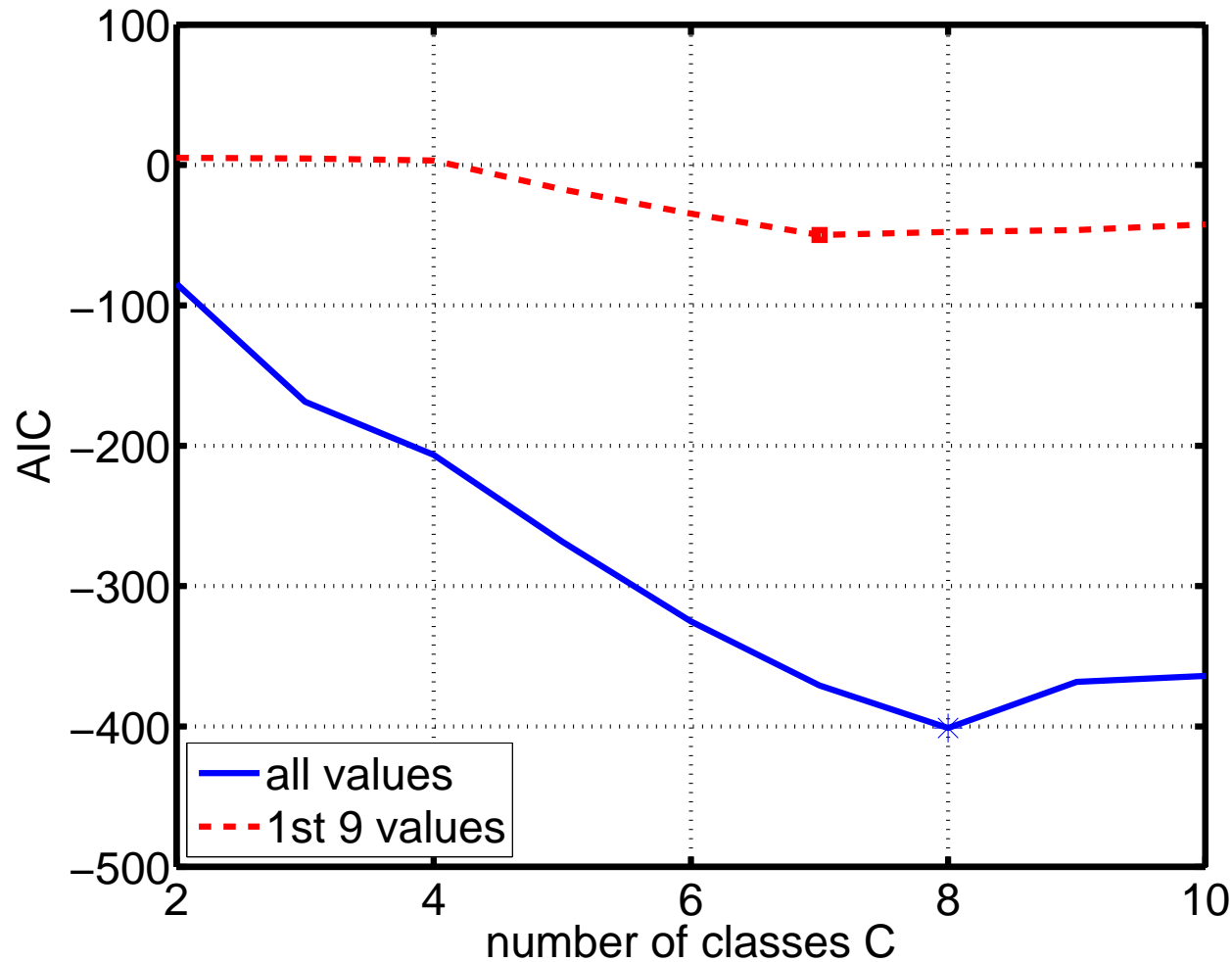
Choice of C

$$C = 8$$

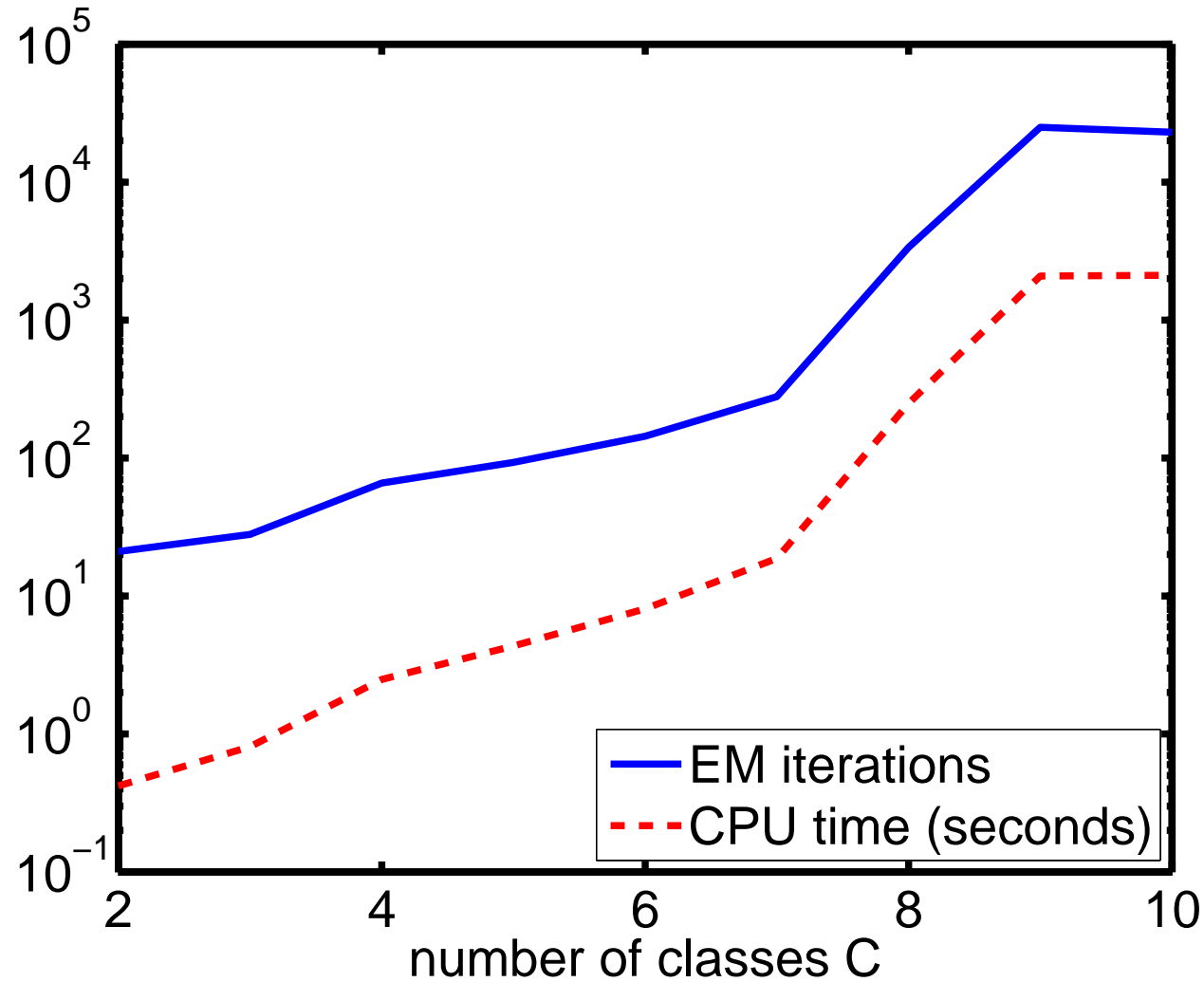


Systematic choice of C

Akaike's Information Criteria = $n[\ln(2\pi RSS/n) + 1] + 2C$,



Workload



Previous studies

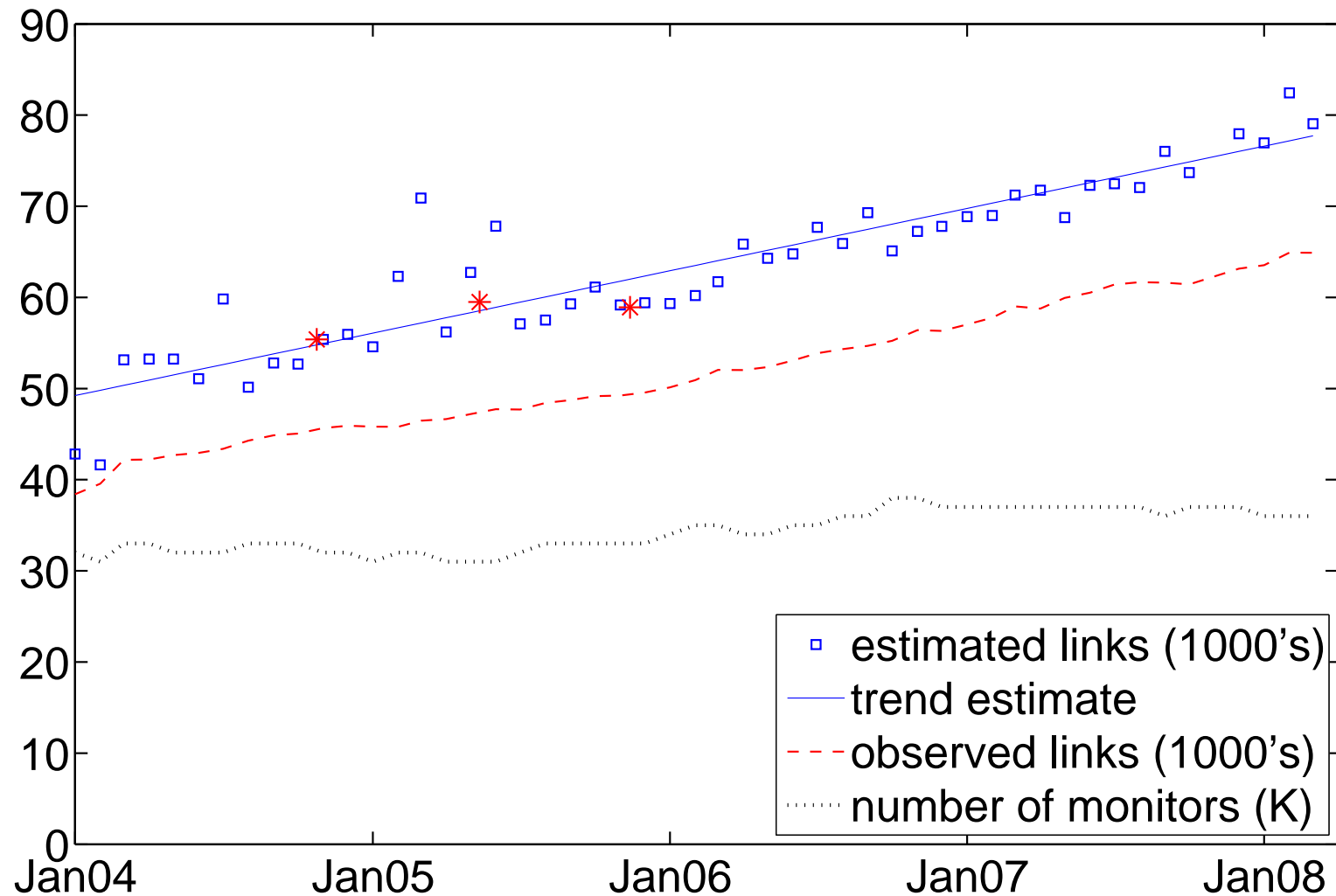
Paper	label	date	\hat{E}
Zhang et al. [1]	Updates(1M)	2004-10-24	55,388
He et al. [2]	All	2005-05-12	59,500
Mühlbauer et al. [3]	N/A	2005-11-13	58,903

References

- [1] B. Zhang, R. Liu, D. Massey, and L. Zhang, “Collecting the Internet AS-level topology,” *ACM SIGCOMM Computer Communication Review (CCR) special issue on Internet Vital Statistics*, January 2005.
- [2] Y. He, G. Siganos, M. Faloutsos, and S. V. Krishnamurthy, “A systematic framework for unearthing the missing links: Measurements and impact,” in *USENIX/SIGCOMM NSDI*, (Cambridge, MA, USA), April 2007.
- [3] W. Mühlbauer, A. Feldmann, M. R. O. Maennel, and S. Uhlig, “Building an AS-topology model that captures route diversity,” in *ACM SIGCOMM*, (Pisa, Italy), 2006.

Results: $C = 7$

Monthly data since January 2004.



Conclusion

- Method for estimating how much we don't know
- Used it to study the AS graph
 - Potential improvements
 - account for monitor dependencies
 - account for heterogeneity amongst monitors
- There still might be something missing - what about a class of links that we **never** observe?
- Much wider applicability
 - Social networks?
 - Network Dynamics

Truncated binomial

Using same assumptions as Petersen's the number of observations k of a link will follow a Binomial distribution

$$\text{prob}\{k\} = \binom{K}{k} p^k (1-p)^{(K-k)}$$

However, we only observe a link if $k > 0$, so we observe the conditional distribution

$$\text{prob}\{k|k > 0\} = \binom{K}{k} \frac{p^k (1-p)^{(K-k)}}{1 - (1-p)^K}$$

which is a truncated Binomial distribution.

Estimator

MLE (Maximum Likelihood Estimator) \hat{p} has to satisfy

$$E_{\text{obs}} K \hat{p} = [1 - (1 - \hat{p})^K] \sum_{i=1}^{E_{\text{obs}}} k_i$$

where

- K = the number of monitors
- E_{obs} = the number of observed links (via all monitors)
- k_i = the number of observations of the i th link
- \hat{p} = the MLE estimator of the observation probability p

Estimator

MLE (Maximum Likelihood Estimator) \hat{p} has to satisfy

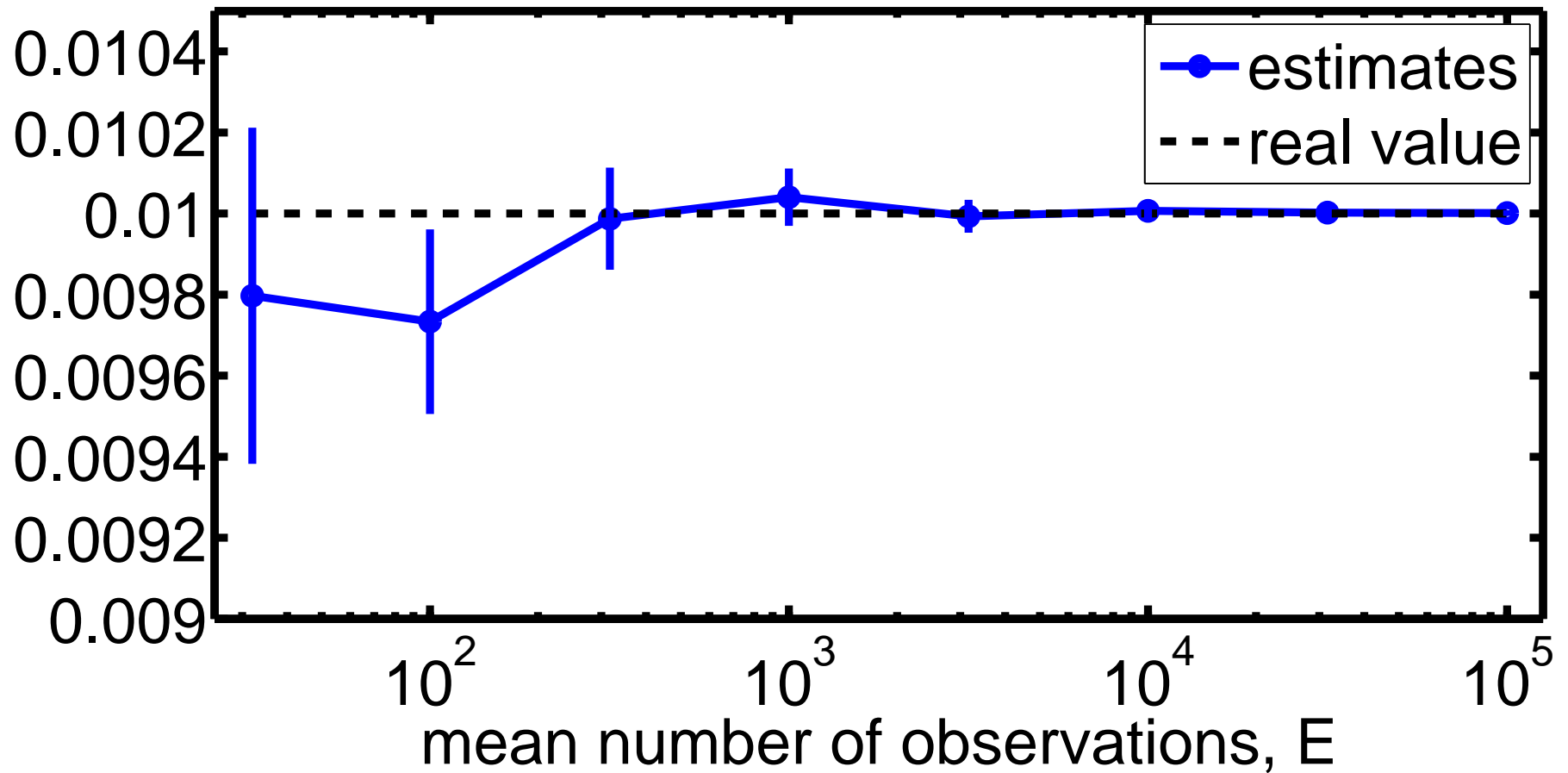
$$E_{\text{obs}} K p = [1 - (1 - p)^K] \sum_{i=1}^{E_{\text{obs}}} k_i$$

Solution by repeated substitution

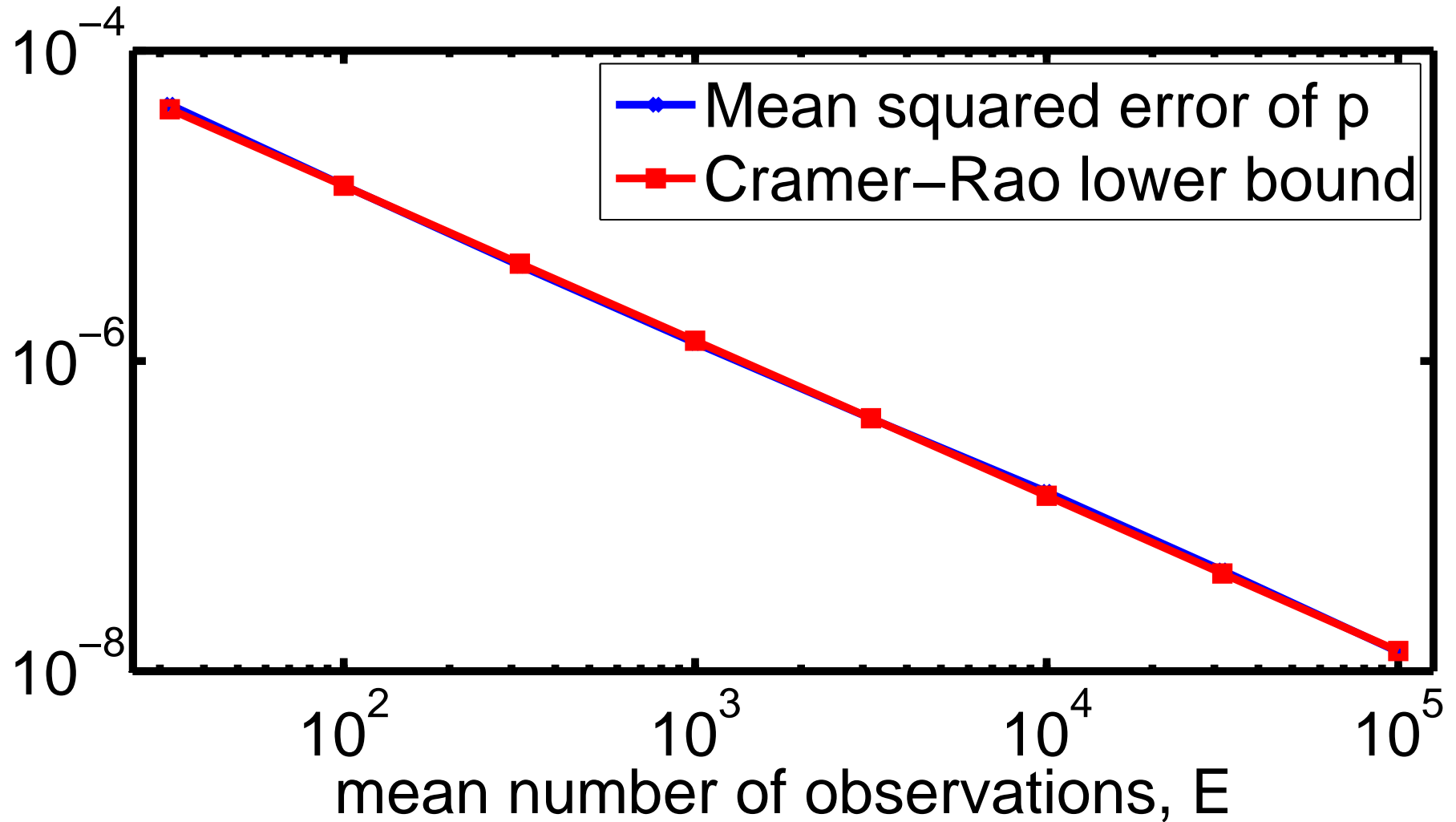
$$\hat{p}_0 = \frac{\sum_{i=1}^{E_{\text{obs}}} k_i}{E_{\text{obs}} K}$$
$$\hat{p}_{i+1} = \frac{\sum_{i=1}^{E_{\text{obs}}} k_i}{E_{\text{obs}} K} [1 - (1 - \hat{p}_i)^K]$$

Can prove that this converges to a fixed point of the above equation.

Simulated estimates \hat{p}



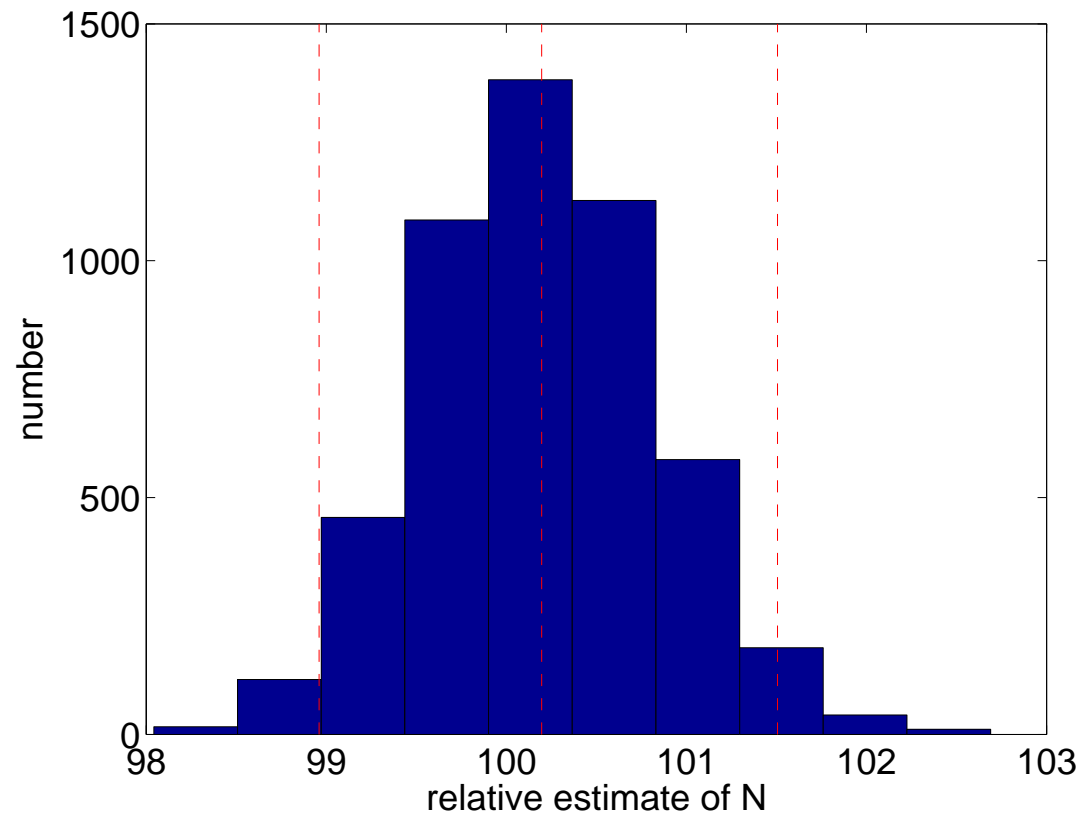
Variance of \hat{p}



Estimator \hat{E}

Once we know p , then MLE for E is

$$\hat{E} = \frac{E_{\text{obs}}}{1 - (1 - \hat{p})^K}$$



New model

Binomial mixture model

- probability of class j is w_j
- Binomial distribution $B(K, p_j)$ for each class

Distribution function

$$\text{prob}\{k\} = \sum_{j=1}^C w_j \binom{K}{k} p_j^k (1 - p_j)^{(K-k)}$$

Of course, we observe a truncated version of this.

EM Algorithm

While (not converged 1) do

E step:

estimate $c_j^{(i)}$

$$c_j^{(i)} \leftarrow \hat{w}_j P\{k_i | K, \hat{p}_j\}$$

M step:

for j=1 to C

While (not converged 2) do

$$\hat{p}_j \leftarrow \frac{\sum_i k_i c_j^{(i)}}{K \sum_i c_j^{(i)}} [1 - (1 - \hat{p}_j)^K]$$

end while 2

$$\hat{w}_j \leftarrow \sum_i c_j^{(i)} / (E(1 - (1 - \hat{p}_j)^K))$$

end for

end while 1

Systematic choice of C

