

# A Statistician Worries About Random Network Modeling

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And as a statistician, many aspects of the current state of random network models worry me.

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Let's look at some issues with these points in mind.

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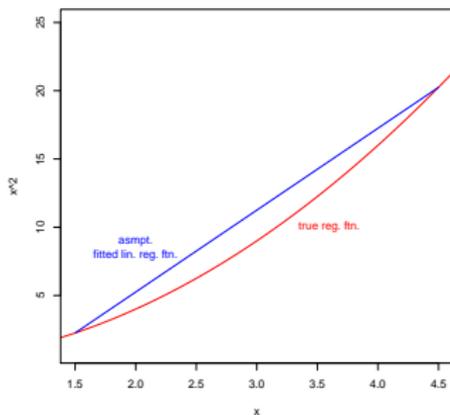
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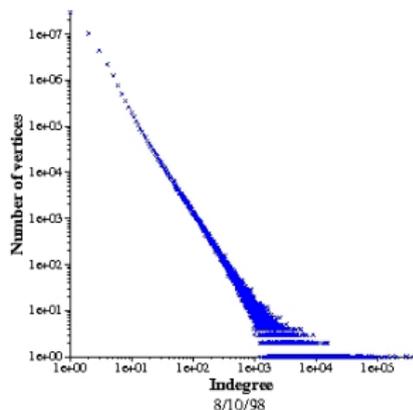


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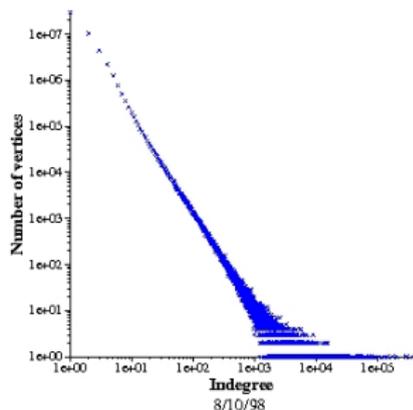


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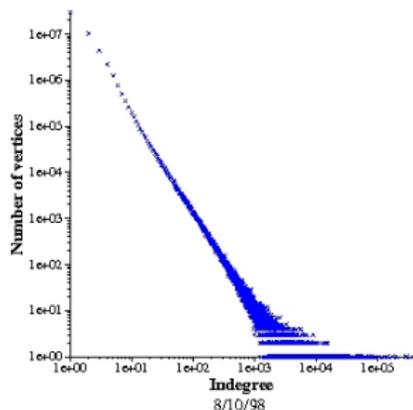


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- ▶ Model problems in tail raises concern about both Prediction and Understanding.
- ▶ Seemingly small change in assumptions can greatly change qualitative behavior [D'Souza *et al*, 2009].

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## **Regression:**

- ▶ If desire formal testing, have a natural hierarchy of models (multivariate polynomial) for assessing GOF.
- ▶ Informal graphical assessment (residuals, nonparametric estimation) is simple and easily interpretable.
- ▶ Cross-validation (splitting data into training, assessment sets) is easy.

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- ▶ N often huge, so tests are meaningless anyway.
- ▶ Graph subsets often behave differently from the full set [Stumpf *et al*, 2005], so cross-validation doesn't work.

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  - ▶ The bootstrap, “the statistician’s Swiss army knife,” inoperable (subgraph, nonindependence problems).
- ▶ Bias issues [Achlioptas, 2005] more common here than in classical statistics.

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- ▶ Model fragility, GOF assessment issues are troubling.
- ▶ Potential for misunderstanding, and thus misuse, is significant.