Measuring the likelihood of models for network evolution

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Abstract—Many researchers have hypothesised models which explain the evolution of the topology of a target network. The framework described in this paper gives the likelihood that the target network arose from the hypothesised model. This allows rival hypothesised models to be compared for their ability to explain the target network. A null model (of random evolution) is proposed as a baseline for comparison. The framework also considers models made from linear combinations of model components. A method is given for the automatic optimisation of component weights. The framework is tested on simulated networks with known parameters and also on real data.

I. INTRODUCTION

The field of modelling graph topologies (and in particular the topology of the Internet) has generated a huge degree of research interest in recent years (see [1] chapter 3] for a review of the subject and [2] for an Internet topology perspective). This paper introduces FETA (Framework for Evolving Topology Analysis) which can be used to assess potential underlying models for any network where information about the network evolution is available. Previously, many researchers have fitted probabilistic topology models by growing candidate models and assessing how well their model fitted against a selection of statistics made on a snapshot of the real network. The FETA approach, by contrast, uses a single statistic to get a rigorous estimate for the likelihood of a model for network evolution as consisting of two separate (but interconnected) models. The outer model chooses the entity for that operation. The operation and the entity together define the transition from \( G_{i-1} \) to \( G_i \). Both the outer and inner models may depend on the state of the graph \( G_i \) on the step of the evolution \( i \) and possibly on exogenous parameters. Outer model operations might be the following:

1) Add a new node and connect it to an existing node.
2) Connect the newest node to an existing node.
3) Connect two existing nodes.
4) Delete an existing connection.
5) Delete an existing node and its connections.

These outer models work with inner models which select either nodes or edges for the operation. The inner model assigns probabilities to each node (operations 1, 2 and 5) or edge
The theorem follows. is also the likelihood of choice be some hypothesised inner model which assigns a probability $1 \theta$ of one edge. For simplicity of explanation consider the outer and inner model. Each step involves the addition of one edge. For simplicity of explanation consider the outer model to consist only of the two operations:

1) add a new node and connect it to an existing node $N_i$; or
2) connect the newest node to an existing node $N_i$.

The inner model $\theta$ assigns probabilities to the existing nodes at a given step. Given the above outer model, from $G_{i-1}$ and $G_i$ the node $N_i$ chosen by the inner model can be inferred. Call the set of all observed choices $C = (N_1, \ldots, N_t)$.

**Definition 1:** An inner model $\theta$ is a map which at every choice stage $j$ maps a node $i$ to a probability $p_j(i|\theta)$. A model $\theta$ is a valid model if the sum over all nodes is one $\sum_i p_j(i|\theta) = 1$.

**Theorem 1:** Let $C = (N_1, \ldots, N_t)$ be the observed node choices at steps $1, \ldots, t$ of the evolution of the graph $G$. Let $\theta$ be some hypothesised inner model which assigns a probability $p_j(i|\theta)$ to node $i$ at step $j$. The likelihood of the observed $C$ given $\theta$ is

$$L(C|\theta) = \prod_{j=1}^{t} p_j(N_j|\theta).$$

**Proof:** If $L(C_j|\theta)$ is the likelihood of the $j$th choice given model $\theta$ then $L(C|\theta) = \prod_{j=1}^{t} L(C_j|\theta)$. Given $p_j(N_j|\theta)$ is the probability model $\theta$ assigns to node $N_j$ at step $j$, therefore it is also the likelihood of choice $N_j$ at step $j$ given model $\theta$. The theorem follows.

If two inner models $\theta$ and $\theta'$ are hypothesised to explain the node choices $C$ arising from observations of a graph $G_0, \ldots, G_t$ and a given outer model, then the one with the higher likelihood is to be preferred.\footnote{Note that the reason "add a new node" is not considered on its own is to confine the study here to connected graphs.} In practice, for even moderate sized graphs, this likelihood will be beyond the computational accuracy of most programming languages and the log likelihood $l(C|\theta) = \log(L(C|\theta))$ is more useful.

A common statistical measure is the deviance $D = -2l(C|\theta)$. (The deviance is usually defined with respect to a “saturated model” – in this case the saturated model $\theta_s$ is the model which has $p_j(C_j|\theta_s) = 1$ for all $j = 1, \ldots, t$ and hence $l(C|\theta_s) = 0$. The saturated model $\theta_s$ has likelihood one but is useless for anything except exactly reproducing $G_0, \ldots, G_t$.

**Definition 2:** Let $\theta_0$ be the null model. Here, an appropriate null model is the one which assigns equal probability to all nodes in the choice set (the random model). The choice set is either the set of all nodes or, if a simple graph is desired, the set of all nodes to which the new node does not already connect.

The null model allows the assessment of the null deviance $D_0 = -2(l(C|\theta) - l(C|\theta_0))$. However, both $D$ and $D_0$ depend heavily on the size of $t$ (the number of choices made). A more useful measure created for this situation is now given.

**Definition 3:** Let $\theta$ be some inner model hypothesis for the set of node choices $C = (N_1, \ldots, N_t)$. Let $\theta_2$ be some rival model to compare with $\theta$. The per choice likelihood ratio with $\theta_A, c_A$, is the likelihood ratio normalised by $t$ the number of choices. It is given by

$$c_A = \left[ \frac{L(C|\theta)}{L(C|\theta_A)} \right]^{1/t} = \exp \left[ \frac{l(C|\theta) - l(C|\theta_A)}{t} \right].$$

A value $c_A > 1$ indicates that $\theta$ is a better explanatory model for the choice set $C$ than $\theta_A$ and $c_A < 1$ indicates it is worse. Particularly useful is $c_0$ the per choice likelihood ratio relative to the null model. Note that for a fixed $C$, given the $c_0$ statistic for two models $\theta$ and $\theta_A$ then $c_A$ can be shown to be the ratio of the former over the latter.

In summary, the likelihood $L(C|\theta)$ gives the absolute likelihood of a given model $\theta$ producing the choice set $C$ arising from a set of graphs $G_0, \ldots, G_t$. However, the per choice likelihood ratio produces a result on a more comprehensible scale.

**B. Fitting linear combinations of model components**

An inner model $\theta$ can be constructed from a linear combination of other inner models. Let $\theta_1, \theta_2, \ldots$ be probability models. A combined model can now be constructed from component models as follows, $\theta = \beta_1 \theta_1 + \beta_2 \theta_2 + \cdots + \beta_N \theta_N$. The $\beta_i$ are known as the component weights. The model $\theta$ is a valid model if all $\beta \in (0,1)$ and $\sum_i \beta_i = 1$. The weights $\beta$ that best explain $C$ can be obtained using a fitting procedure from statistics known as Generalised Linear Models (GLM).

Let $P_j(i) = 1$ if $i = N_j$, and $P_j(i) = 0$ otherwise. The problem of finding the best model weights becomes the problem of fitting the GLM, $P_j(i) = \beta_1 p_j(i|\theta_1) + \beta_2 p_j(i|\theta_2) + \cdots + \beta_N p_j(i|\theta_N)$.\footnote{A model with fewer parameters will sometimes be preferred if the gain in likelihood is small or the number of parameters added is large \cite{11} – the extreme case of this is the saturated model $\theta_s$.}
A GLM procedure can fit the $\beta$ parameters to find the combined model $\theta$ which best fits the $P_j(i)$. This fit is obtained by creating a data point for each choice $j$ and for each node $i$ giving information about that node at that choice time and also the value of $P_j(i)$.

GLM fitting in a statistical language such as R can be used to find the choice of $\beta$, which maximises the likelihood of this model. This is equivalent to finding the $\beta_i$ which gives the maximum likelihood for $\theta$ since for model $\theta$, the expectation $E[P_j(i)] = p_j(i|\theta)$. The fitting procedure estimates for each $\beta_i$, the value, the error and the statistical significance.

Because this procedure requires one line of data for each node at each choice then it produces a large amount of data and sampling is necessary. As will be seen in section III-B the method still recovers parameters accurately.

C. FETA in practice

For simplicity of discussion in previous sections, only operations which connected a new node to a single node were considered. Using the framework to connect edges between existing internal nodes requires a small extension. Since the number of potential edges is roughly the square of the number of nodes, it makes sense to decompose the choice of an edge into the choice of a start node and an end node. Once a start node is picked, the choice set for the end node can be constrained to ensure the graph remains simple. The likelihood of adding edge $(x, y)$ is calculated as the likelihood of choosing node $x$ then node $y$ plus the likelihood of choosing node $y$ then node $x$. For the purposes of definition III an edge counts as two choices (since definition III is in terms of node choices).

The outer model could be further generalised by, for example, adding the possibility of a "bare" node appearing (a node with no links) if this event could be observed. Another extension would be adding node or edge deletion operations. Separate inner models can be fitted to different outer model operations. For example, in the work on FETA reported in [3] separate models are fitted to the outer model operations which connect a single existing node to a new node and the outer model operations which connect an edge between existing internal nodes. Likelihoods from the two parts of the inner model can be directly combined by multiplication.

Another practical concern is scalability – how the likelihood computation time increases as graphs become large. Tests were run on a 2.66GHz quad core Xeon CPU using the same codebase for two tasks, one to measure the likelihood of a target network arising from a given model and the second to actually create a network. The number of links created was varied from 1,000 to 100,000. While both processes increased approximately as $O(n^2)$ where $n$ is the number of links, the likelihood calculation is much quicker than the network creation process. For 100,000 links the likelihood calculation took 53 seconds, the network creation took 2,600 seconds. Compared with producing a test network and measuring it, the FETA approach is extremely efficient. If the runtime were to become onerous, sampling could be used as it is in the GLM procedure. This was not necessary for the results in this paper.

It is worth briefly noting two points about data requirements. Firstly, FETA does not require data from the entire history of a network, the graph $G_0$ can be any stage of graph construction. Secondly, for a sufficiently large graph, knowing the exact order of link arrival should not be necessary (this may occur if the graph state is measured periodically rather than recorded as every node or edge arrives). A graph with a large number of nodes will not change its topology greatly for a small number of arrivals and therefore a small reordering of link arrival order should make little difference to the model likelihood. Future work will seek to quantify the inaccuracies introduced by this reordering.

III. Testing the framework

The obvious way to test the framework is on simulated data sets where the underlying inner model is known. Testing models using the likelihood procedure from II-A is demonstrated in section II-B. Optimising models using the GLM procedure in section II-C is done in section III-B. A demonstration on real data is described in section III-C.

Let $d_i$ be the degree of node $i$ and $t_i$ be the triangle count (the number of triangles, or 3–cycles, the node is in). The model components used in the testing are the following: $\theta_0$ – the null model (random model) assumes all nodes have equal probability $p_i = k_n$; $\theta_d$ – the degree model (preferential attachment) assumes node probability $p_i = k_d d_i$; $\theta_t$ – the triangle model assumes node probability $p_i = k_t t_i$; $\theta_S$ – the singleton model assumes node probability $p_i = k_S$ if $d_i = 1$ and $p_i = 0$ otherwise; $\theta_D$ – the doubleton model assumes node probability $p_i = k_D$ if $d_i = 2$ and $p_i = 0$ otherwise; $\theta_R(n)$ – the "recent" model where $p_i = k_R$ if a node was one selected in the last $n$ selections and $p_i = 0$ otherwise and $\theta_P^{(\delta)}$ – the PFP model assumes node probability $p_i = k_P d_i^{\delta} + 5 \log_{10}(d_i)$. The $k_s$ are all normalising constants to ensure $\sum_i p_i = 1$.

A. Testing the likelihood framework

The best way to test the likelihood framework is on simulated networks with a known underlying inner model. Test model one has a simple outer model which creates a new node and then connects it to exactly three distinct nodes with a high number of triangles also have a high degree otherwise; $\theta_D$ – the doubleton model assumes node probability $p_i = k_D$ if $d_i = 2$ and $p_i = 0$ otherwise; $\theta_R(n)$ – the "recent" model where $p_i = k_R$ if a node was one selected in the last $n$ selections and $p_i = 0$ otherwise and $\theta_P^{(\delta)}$ – the PFP model assumes node probability $p_i = k_P d_i^{\delta} + 5 \log_{10}(d_i)$. The $k_s$ are all normalising constants to ensure $\sum_i p_i = 1$.
The likelihood surface produced is shown in Figure 1 with contour lines projected below. As can be seen, the maximum likelihood is in the correct part of the region ($\beta = 0.5$, $\delta = 0.05$). In fact the highest $c_0$ was with $\delta = 0.0525$ and $\beta = 0.5$, an almost exact recovery of the correct parameters.

First tests were performed on $\theta_1 = 0.5\theta_p(0.05) + 0.5\theta_t$ as described in the previous section. The test network again had 10,000 edges. Sampling was used to generate just over 4,000,000 items of data for the GLM fit. Fitting $\theta = \beta_p\theta_p(0.05) + \beta_t\theta_t$ gave the following results.

| Parameter | Estimate | Significance |
|-----------|----------|--------------|
| $\theta_p(0.05)$ | $0.53 \pm 0.031$ | 0.1% |
| $\theta_t$ | $0.47 \pm 0.031$ | 0.1% |

The parameters were recovered almost exactly. However, this assumed that $\delta$ was known precisely. If $\delta$ is not known then the GLM procedure behaves reasonably with incorrect $\delta$. The table below shows fits of the model with $\delta = 0.2$ and $\delta = 0.01$ – considerably above and below the correct values.

| Parameter | Estimate | Significance |
|-----------|----------|--------------|
| $\theta_p(0.2)$ | $0.12 \pm 0.022$ | 0.1% |
| $\theta_t$ | $0.84 \pm 0.021$ | 0.1% |
| $\theta_p(0.01)$ | $0.43 \pm 0.025$ | 0.1% |
| $\theta_t$ | $0.57 \pm 0.025$ | 0.1% |

In both cases the model correctly gave statistical significance to the $\theta_p$ component of the model. The actual estimates were not 0.5, nor were they expected to be. The true $\delta$ parameter could be found by trying a range of values within the GLM procedure just as it was with the likelihood estimator in Figure 1.

For realistic scenarios, the true underlying model is not known. Thus some “misspecified” models (models known to be incorrect) were tried to see whether incorrect components could be identified. Thus, the model $\theta = \beta_d\theta_d + \beta_t\theta_t + \beta_0\theta_0$ which includes extraneous $\theta_d$ (preferential attachment) and $\theta_0$ (null or random) models.

| Parameter | Estimate | Significance |
|-----------|----------|--------------|
| $\beta_d$ | $0.46 \pm 0.057$ | 0.1% |
| $\beta_t$ | $0.57 \pm 0.031$ | 0.1% |
| $\beta_0$ | $-0.031 \pm 0.032$ | none |

The $\theta_0$ component has been rejected having both a low value and a low statistical significance. The $\theta_d$ model has stayed in, almost certainly because it has such a strong correspondence with the $\theta_p(\delta)$ model – indeed, for $\delta = 0$ it is the same model.

The GLM fitting procedure does not always produce the correct answer, in particular, when $\theta_d$ and $\theta_p$ are included in the same fitting procedure problems can occur. Fitting $\theta = \theta_d + \theta_p(0.05) + \theta_t$ gives the following.

| Parameter | Estimate | Significance |
|-----------|----------|--------------|
| $\beta_d$ | $0.28 \pm 0.085$ | 0.1% |
| $\beta_p(0.05)$ | $0.18 \pm 0.11$ | none |
| $\beta_t$ | $0.54 \pm 0.038$ | 0.1% |

Here the GLM procedure gave an incorrect answer. The $\theta_p(\delta)$ model was incorrectly rejected and given no statistical significance. This kind of error is common when $\theta_d$ and $\theta_p(\delta)$ are combined in the same model. This model gives $c_0 = 5.17$ compared with $c_0 = 5.18$ for the correct model.
the likelihood still identifies the correct model even when
the GLM procedure fits an incorrect model.

The GLM procedure was next used to recover parameters
from \( \theta_d = 0.25\theta_0 + 0.25\theta_t + 0.25\theta_s + 0.25\theta_D \). The test network
had 10,000 edges as previously. Sampling was used to obtain
just over 3.5 million data points for model fitting.

| Parameter | Estimate | Significance |
|-----------|----------|--------------|
| \( \beta_0 \) | \( 0.23 \pm 0.021 \) | 0.1% |
| \( \beta_t \) | \( 0.28 \pm 0.017 \) | 0.1% |
| \( \beta_s \) | \( 0.24 \pm 0.016 \) | 0.1% |
| \( \beta_D \) | \( 0.25 \pm 0.020 \) | 0.1% |

As can be seen, this recovery of parameters was quite
successful, although \( \beta_t \) is actually 0.25 and therefore slightly
outside the error range \( 0.28 \pm 0.017 \). The next test was to add
a spurious model component \( \theta_d \).

| Parameter | Estimate | Significance |
|-----------|----------|--------------|
| \( \beta_0 \) | \( 0.33 \pm 0.059 \) | 0.1% |
| \( \beta_t \) | \( 0.29 \pm 0.017 \) | 0.1% |
| \( \beta_s \) | \( 0.24 \pm 0.016 \) | 0.1% |
| \( \beta_D \) | \( 0.23 \pm 0.022 \) | 0.1% |
| \( \beta_d \) | \( -0.089 \pm 0.059 \) | 5% |

The \( \beta_d \) parameter was given a negative value (which is
likely to produce an invalid model for the likelihood estimate)
and the relatively low statistical significance also suggests
\( \theta_d \) should be removed from the model. An important caveat
exemplified here is that the GLM model is not constrained to
produce the \( \beta \) parameters in the range \( 0 \), \( 1 \). This needs to be
considered when analysing model fitting.

In most circumstances tested, the GLM model performed
extremely well. When the correct model was tested, the
correct results were obtained and spurious model components
were only accepted if they correlated strongly with genuine
model components. The GLM model is a very useful tool for
exploratory data analysis but the likelihood framework remains
the true test of model fit to data.

C. Tests on real data

Tests on five different data sets are reported in [3]. Here, for
space reasons, only one network is reported, the RouteViews
AS network, a view of the AS topology collected by the
University of Oregon RouteViews project. The data set gives
the growth of the AS topology from 42,000 edges to over
90,000. Throughout this section, it is important to keep in
mind the aim of this paper, to test the FETA framework. The
models described here are not claimed to be the best known
models for the network in question. The PFP model [8] with
its special outer model gets a closer match to the final network
statistics. The ORBIS model [9] does not model evolution but
is very good at matching statistics on a target network. The
model presented here as “best” is the best model found using
the FETA framework with a simple outer model. The claim
being verified in this section is not that this is the best possible
model of the real network but that models can be assessed and
optimised using the FETA framework without looking at any
target statistics other than likelihood.

Three inner models were compared to the RouteViews AS
network. The outer model was simple – the choice of operation
(add new node, add link to new node or add inner edge) was
exactly that sequence observed in the real data. The inner
model \( \theta_0 \) was used as a base for comparison. The other two
models were a “pure” PFP model (but without the PFP special
outer model) \( \theta_p(0.005) \) and the “best” model found which
was \( 0.81\theta_p(0.014) + 0.17\theta_R(1) \) (PFP “recent”) to connect
new nodes and \( 0.71\theta_d + 0.22\theta_R(1) + 0.07\theta_S \) (preferential
attachment “recent” + singleton) to connect edges between
existing nodes. The PFP model \( \theta_p(0.005) \) had \( c_0 = 4.81 \) and
the “best” model had \( c_0 = 8.06 \). From these results PFP and
“best” should be a significant improvement on random and
“best” should be better than PFP. These modelling results
should not be taken as a criticism of PFP as described in
[3] since the special “interactive growth” outer model of that
paper was not used (the focus here is on the inner model).

Each model grew a test network from the seed network of
42,000 edges. The first point in each plot is after edge 40,000
and hence shows all models to perform the same (since the
network is still the seed network at this point). Figures 2 and
3 show the evolution of various graph statistics for the real
network compared with the three models. The leftmost point
for each is within the seed graph and hence should always be
the same. The statistics are \( d_1 \) and \( d_2 \) the proportion of nodes
degree one and two, \( \max d \) the degree of the highest node,
\( \bar{d} \) (the mean square node degree), the assortativity coefficient
\( r \) and the clustering coefficient \( \gamma \). See [2] for full descriptions
of these statistics. (Note that \( \bar{d} \) is fixed by the outer model and
is an exact match to the real topology).

As mentioned at the start of this section, the claim is not
that these models are a perfect fit to the evolution of the
target network but, instead, that the order in which they fit
the target network is that given by the likelihood estimator: the
“best” model being better than pure PFP, and both being much
better than random. The models and the \( c_0 \) measures which
predicted this were produced before any artificial topologies
were generated and without reference to the graph statistics
plotted in the figures. This is a convincing demonstration that
the likelihood measure translates directly into fit to real data
over a number of statistical measures.

For most statistics, the ordering seems correct with “best”
being closest to real, followed by PFP and then random.
An exception is in the graphs for \( \gamma \) and \( r \) where PFP is
slightly better than “best”. However, in \( d_1 \) and \( \max d \) the
PFP model is approximately the same as random, when we
would expect it to be better. In the case of \( \max d \), random
predicts unrealistically slow growth. For some statistics, no
models given are close (for reproducing the statistics of a graph
snapshot it seems likely that ORBIS, for example, might be
better). However, the framework has clearly shown its ability
to assess which model best fits a target graph and this is clearly
reflected in these statistics.

http://www.routeviews.org
A useful toolset for investigating growth models of networks constructed multiplicatively from components (\(\theta_1, \theta_2, \cdots\)) would seem natural than but normalisation problems exist. Network models could be considered which remove nodes or edges as well as add them and which do not necessarily remain connected. Finding new data sets to apply the method to is also a priority. Other researchers are encouraged to download and try the software and data.

### IV. Conclusions

The Framework for Evolving Topology Analysis (FETA) is a useful toolset for investigating growth models of networks where evolution information is available. Network growth models were described in terms of an outer model (which selected the operation to perform on the graph) and an inner model (which selected the entity for the operation). A likelihood statistic was given for an inner model giving rise to a target network. The likelihood statistic given is a rigorous and quick to calculate. It has been shown to recover the statistics of a known model from a network grown using that model. A method was given for exploring and optimising linear combinations of model components and this was tested successfully. The fitting procedure can give insight into what model components are required to best fit the data. Models output by the fitting procedure can then be assessed and try the software and data.

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[http://www.richardclegg.org/software/FETA](http://www.richardclegg.org/software/FETA)