Scale Free: Twitter's Retweet Network Structure

Ramine Tinati, Leslie Carr, Wendy Hall
{rt506, lac, wh}@ecs.soton.ac.uk

Jonny Bentwood
Jonny.Bentwood@edelman.com

1. ABSTRACT

Studies have identified scale free networks – a real-world and man-made phenomena – in networks such as the human brain [7], protein networks [9], market investments networks [8], journal co-citation networks [2] and the World Wide Web [3]. Common properties such as preferential attachment and growth enable these networks to be classified as scale-free, which belong to a family of networks known as "small-world" networks, characterized by a short network distance and high clustering coefficient [14].

These properties can clearly be identified in networks such as the World Wide Web; a complex man-man network of documents and links that grows in uncontrollable manner [4], they produce the 'rich-get-richer' effect [3], where nodes increase their connectivity at the expense of younger less well connected ones. By mapping the complex real-world and man-made networks, these studies are helping improve our knowledge on the "weblike" world we live in [2]. However, as many of these scale-free networks still yet to be discovered, generalizing a scale-free model requires is still problematic [3][5].

In this paper we study a network which is both a product of man-made networks, and real-life phenomena. Twitter, a micro-blogging social networking service provides a simple service to enable users to broadcast messages and form networks of 'friends' and 'followers'.

Studies have examine the structure of Twitter's static networks that form as a result of the friends and follower links between users [6,13]. There has also been a growing interest in exploring how it can be used to solve real-world problems [10][15], and findings ways to classifying [11] and identifying influential users [16] [1].

As an alternative approach, we have examined the dynamic network structures of Twitter conversations – which form through the passing of messages between users – and found that they exhibit scale-free properties such as preferential attachment and growth.

In this study, a number of Twitter datasets were collected varying in size, region and topic, and their dynamic 'retweet' (shared messages) structures were examined. The findings of the analysis have shown that there exhibit a power law with similar exponents across all datasets, in regards to the decay of 'retweeted' (or shared) messages between users. The exponents found – d which ranged from 1.2 to 1.5 – are lower than similar scale-free networks such as the Web; typically such a low exponent would indicate a skewed and uncorrelated network as a result of the number of edges growing faster than the number of nodes [12]. However the Twitter networks examined exhibit the same scale-free properties including preferential attachment and growth as networks of a higher exponent. The findings of this study not only expands the current knowledge on documented scale-free networks, but also raises questions about the nature of communication in social networking sites.

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