Traffic Load Distribution Fairness in Mobile Social Networks

Mobile social networks suffer from an unbalanced traffic load distribution due to the heterogeneity in mobility of nodes (humans) in the network. A few nodes in these networks are highly mobile, and the proposed social-based routing algorithms are likely to choose these most "social" nodes as the best message relays.

1. Introduction

As a particular case of mobile ad-hoc networks (MANETs), opportunistic mobile networks [1] are unique dynamic wireless mobile networks. Unlike MANETs, in such networks persistent connectivity is not a necessity, and end-to-end paths from sources to destinations are not assumed to exist at all times. A link between a pair of nodes is established whenever they come into contact. In opportunistic mobile networks, pairwise node contacts occur randomly in time, and the duration of each contact is also random. Owing to the omnipresence of mobile devices nowadays, e.g., mobile phones and tablets, human can exploit contact opportunities to exchange information by means of short radio range connections. This leads to human-centric opportunistic mobile networks, also referred to *mobile social networks* (MSNs) in [2][3]. These networks have mainly been introduced by combining social networks and mobile communication networks. MSNs take a human-centric approach to networking, closing the gap between networks and human behaviour. Moreover, studies in [4][5][6] revealed that social interactions influence human mobility. As a result, MSNs are closely linked to social networks, and knowledge about social ties can be used to improve routing algorithms in such human-based networks.

Researchers currently focus on studying social relation patterns, e.g., node popularity and social similarity, as the choice parameters of relay nodes. Furthermore, the proposed social-based routing algorithms [7][8][9] typically favour nodes with many social ties as optimal carriers for message transfers. This might end up in heavy traffic load in the (socially) popular nodes, quickly draining the nodes' constraint resources, such as power and storage, and this unbalanced traffic load eventually deteriorates the network's delivery performance [10]. In addition, the poor traffic load balancing also results in unfair delivery success rate among individuals, where messages from popular individuals can reach the destinations with a high probability, but individuals with few social connections will experience in low delivery success [11]. This variance of the delivery rate becomes a deterrent for nodes to participate in the message forwarding. Ultimately, the unfairness of traffic load makes popular nodes easy target of attacks [12].

Unbalanced traffic distribution across network nodes leading to traffic congestion in social networks has been extensively studied in several areas [13][14][15]. In [13], (data) traffic congestion during crowd disaster was thoroughly discussed. In that crowd management scenario, mobile devices carried by individuals is used to detect and inform to the crowd managers about the crowd density. However, in crowded areas traffic can increase dramatically within a short period of time, and, in turn, traffic congestion starts to occur, making the crowd managers fail to handle the crowd. In [14], traffic in social networks was investigated in various applications, ranging from vehicular traffic in urban environments to data traffic in Internet of Things and human–machine networks. In these settings, local failures such as traffic congestion in some parts of networks might provoke a cascade of failures throughout systems. Machine learning approaches were therefore nominated to address such issues. In [15], pocket switched networks were proposed to transfer data between users' mobile devices. Such opportunistic networks exploit human mobility to enable a store-carry-forward mechanism to deliver messages from sources to destinations. In each contact, social-based routing algorithms [7][8][9] typically select popular nodes (individuals) as the best relays in the network, resulting in unbalanced traffic distribution across nodes and traffic congestion in the most central nodes.

2. Traffic Load Distribution Fairness in Mobile Social Networks

Fairness is important in many areas of human lives, e.g., sociology, economics and politics, and it is also true in technologies. In computer engineering, distinct computer resources should be shared equally amongst all processes and threads. In computer networking, all nodes require to attain the bandwidth and quality of service (QoS) equitably. In [16], fairness challenges and issues in wireless networks are thoroughly discussed, and some trade-offs between fairness and performance are reviewed. Mtibaa and Harras [10] studied the trade-offs between fairness and efficiency of social-based routing algorithms in mobile social networks. They found that excluding popular nodes on the message forwarding significantly degrades the delivery efficiency. Researchers [17] also showed that absolute traffic load fairness leads to the deterrent of delivery efficiency; yet, high delivery efficiency results in unfairness of traffic load.

To overcome the problem, fair routing algorithms have been proposed for mobile social networks [11][18][19][20]. Fan et al. [11] introduced a fair routing strategy based on packet priority to improve fairness in success rate among nodes. Ying et al. [18] proposed FSMF, a fair social aware message forwarding to solve the issues of imbalanced traffic load distribution as well as unfair delivery rate. Pujol et al. [19] proposed FairRoute that combines social strength and buffer queue length as the routing metrics to fairly distribute the traffic load among nodes. Milena and Grundy [20] presented CafRep, an adaptive congestion aware forwarding strategy that diverts the traffic from congested nodes (popular nodes) to less congested nodes (unpopular nodes).

Indeed, fair routing algorithms in distributed, intermittently connected wireless networks such as mobile social networks are more complex than those in conventional networks, such as the Internet, since: (i) negotiation and compromise amongst autonomous nodes is more complicated, for example non-cooperative nodes may be reluctant to help other nodes in forwarding; and (ii) due to the lack of knowledge about the global states, routing decisions are made solely based on nodes' local information. For the first issue, the impact of selfish nodes on delivery performance and resource consumption fairness has been investigated in [21]. In addition, to increase fairness in forwarding an incentive or a credit was applied on the routing decisions in [18]. Finally, in [22] a game theoretic approach is used to support fair cooperation among nodes in opportunistic networks. For the second issue, current works of fair routing schemes searched for proper nodes' locally available information to ensure a better fairness and efficiency trade-off. Furthermore, there are two sorts of node local knowledge which are commonly used to improve traffic fairness and reduce congestion: (i) buffer statistics and (ii) social measures. For the former case, some algorithms consider node burden, inferred from the node's buffer queue length, as the forwarding metric to achieve a balanced traffic distribution. For example, FOG [10] and GreBurD [23] prioritise nodes with higher residual buffer space as suitable relays to distribute load away from the congested nodes; CafRep [20] defines node retentiveness, calculated as an expected weighted moving average of the node's remaining storage, as the congestion heuristic to detect storage congestion in popular nodes. For the latter case, on the other hand, researchers search for better social network measures for improving fairness in forwarding of social-based routing schemes. For example, FairRoute [19] improves the calculation of pairwise tie strength based on the short-term and long-term relationships; SimBet [24] adds connection strength information to the routing metrics to offload traffic from popular nodes; Socially-Aware Prediction (SAP) [25] estimates future contacts based on the node (social) similarity, and forwards messages to nodes with a higher similarity with the destinations, thus reducing messages forwarded to globally popular nodes.

As opposed to [19][24][25], which focus on improving the calculation of destination-dependent (DD) utility metrics, researchers' proposed scheme TraLDA chooses to improve the computation of node popularity in the network, since as noted in [26], this destination-independent (DI) utility metric primarily contribute to the traffic imbalance among nodes in mobile social networks. In social network analysis, Freeman [27] proposed three distinct centrality measures to identify the importance of nodes (individuals) in social networks, namely degree centrality, betweeness centrality and closeness centrality. Degree centrality is the number of direct neighbours or friends a node has; betweeness centrality is the number of shortest paths connecting any two nodes that pass through a given node; and closeness centrality is the average distance (proximity) between a node and all other nodes in the network. Freeman's centrality metrics have been widely used to detect nodes which are capable of disseminating information in mobile social networks; for example, BubbleRap [28] and SimBet [24] consider degree centrality and betweeness centrality, respectively, computed in a distributed, ad-hoc fashion to determine node popularity. In BubbleRap, node degree is calculated as the cumulative average of total number of distinct peers encountered by the node in all previous time windows. In SimBet, node betweeness centrality is computed based on a binary model of a social relation, i.e., a value of "1" means two nodes know each other and "0" otherwise. However, researchers argue that the node popularity or centrality calculations in BubbleRap and SimBet do not cope with the dynamics of a social network. Furthermore, as confirmed in [29][30] human activity typically exhibits a regularity (periodicity) pattern. Considering this matter, as the first contribution in this research, researchers propose a

novel method to calculate node inherent popularity at a given time interval based on the Kalman prediction [31] which takes into account the node's periodicity behaviour.

Nevertheless, Freeman's centrality measures typically disregard the influence of the neighbours. The researchers of [32] argued that a node's importance in the social network should also be determined by the importance of its neighbours. In [33], the researchers studied a strategy to find persons that are able to spread advertisements as far as possible in a social network. They showed that a person that receives high respects from her friends, her advertisements will be highly probable to spread over the social network quickly. In addition, Ursino and Virgili [34] integrated the concept of social networks and IoT to determine the reputation of IoT objects. They proposed a formula to calculate reputation of an object in a social Internet of Things based on the well-known Google PageRank. In that technique, the reputation of an object is determined by the level of trust it obtains from other IoT objects. Almost similar, Cauteruccio et al. [35] attempted to introduce concepts and behaviours of social networks into the IoT settings. In that work, to measure the reputation of an IoT object, the researchers defined Impact Degree, calculated as the average trust degree that the object receives from the other objects in its scope (neighbourhood). Meanwhile, from the social network theory, there exist centrality measures that consider a richer range of direct and indirect influence of neighbours, such as the Katz's prestige measure [36]. This centrality metric is developed based on the premise that a node's importance in the network is influenced by its neighbours' importance. Thus, this prestige measure considers a node's connectedness to other nodes as well as its proximity to other important nodes. In this regard, node popularity calculation in TraLDA should take into account the influence of more popular neighbours when determining the popularity of a node. Therefore, as the second contribution in this research, researchers propose a method to calculate node social-relations popularity based on the Katz's prestige measure [36]. Researchers perform some modifications on the calculation of this centrality metric to make it appropriate for distributed, ad hoc environments, such as mobile social networks.

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