A framework for revealing the human dynamics mechanism of ‘meet is fate’

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Abstract. Is it accidental or fate that people meet each other in space and time? If it is fate, what kind of scientific model does it contain? Mining the scientific model implied in ‘meet is fate’ is to analyse the correlation between ‘meet’ and ‘fate’, and to reveal its dynamics mechanism. ‘Meet’ is a kind of space-time interaction, and ‘fate’ is the prediction of future social relation, so the correlation analysis between ‘meet’ and ‘fate’ can be modelled as dynamic correlation analysis between space-time interaction and social relation of human group behaviour. How to achieve that from the original space-time behaviour data is a challenge. To address it, this article proposes a theoretical framework based on the theories and methods about geographic information science and complexity science. This article presents this framework for the first time to provide a feasible solution to verify and study this philosophical view of ‘meet is fate’ scientifically, and explores a meaningful research direction for the inter-cross application between geographic information science and human dynamics at the age of mobile big data.

1. INTRODUCTION
Buddha says ‘all things in the world have their own reasons of coming into being’, as people often say ‘meet is fate’, which is a philosophy of human life advocated in Buddhism. Nowadays, under the science-oriented materialistic world view, most people are more and more convinced of that all things in the world are nothing but accidental phenomena, random events. Especially in human society, the behaviour that people meet each other, most people believe it is a random occurrence. Nevertheless, in recent years, with the rapid development of complex science and human dynamics, many of the human behaviour have been confirmed not to occur randomly. Barabási, a pioneer in this field, in his book BURSTS[1] argues that ‘93% of human behaviour can be predicted, and there are some universal scientific models hidden behind the seemingly random, accidental human behaviour.’ So, actually, is it a random event or not that people meet each other in time and space? Even, does some scientific models are contained in it?

The purpose of human dynamics research is to discover the universal law implied in random human incident. In recent years, with the development of complex science, as well as advent of big data and Internet era, more and more experts and scholars from many different fields had begun to solve their problem from the human dynamics point of view. Counting from 2005, the number of human dynamics related articles is more than 50 that were published only in the Nature series, Science, PNAS, Physical Review Letters, PLoS series, BMC series, involving human space-time behaviour empirical analysis, theoretical modelling, specific application and other aspects [2]. Early studies of human behaviour patterns were confined to traditional statistical and survey studies because of a lack
of large-scale activity data and the tools to deal with them. Nowadays, thanks to the popularity of mobile internet, smart phone, as well as the rapid development of sensor, wireless communication and networking technology, more and more behaviour data of people's daily life are easily recorded as trajectories, which are sequences of geo-located and time-stamped points, often with associated social information, forming a space-time network with human footprint as clues. This network is called "Location-Based Social Networks" in article [3], and we call this network as ‘Internet of Human Footprints’ (IoHF) in article [4]. IoHF provides a wealth of behavioural data for the researchers, and promotes the deep and extensive development of human space-time dynamics. In 2013, San Diego State University set up the Center for Human Dynamics in the Mobile Age, which focuses on the researches of human dynamics from space-time data and social media data, and has achieved fruitful results in the part of spatiotemporal patterns and human dynamics[5,6]. In September 2016, IJGIS(the international journal of geographical information science) made a special issue on the topic of ‘Human Dynamics of Mobile Big Data Age ’, publishing 10 related articles[7]. It can be seen that the research of human dynamics based on human behaviour big data has become a hotspot in geographic information science.

Most current researches trying to make use of this data for behavioural analysis focus on the spatial or temporal dimensions in isolation[8]. Some scholars have pointed out the statistical law of their non-Poisson characteristics for some specific human behaviour, and proposed some relevant theoretical models, in which the most representatives are : 1) the model based on task queue theory[9], 2) the model based on memory, interest, orderliness, or other factors[10], 3) the model based on social interaction[11]. All of these models describe the dynamics mechanism of individual behaviour solely from the perspective of space or time, which have limited applicability. There are still a lot of human behaviour phenomena in the real world cannot be well explained by these current models, and there is little research on group behaviour especially from the perspective of space-time integration.

How to understanding ‘meet is fate’ is a typical human dynamics problem of research on group behaviour. ‘Meet’ is a kind of spatiotemporal behaviour, which describes the interaction between person and person in time and space; ‘Fate’ is a predication of future social relations between people, so if there is ‘fate’ between two persons, it can be understood as that there is a high probability to establish close social relationship between these two persons. Therefore, the question of whether meet is fate or not can be modelled as correlation analysis between space-time interaction and social relation. At the age of mobile big data, based on space-time trajectory data and social relation data, we integrate geographic information system, complex network and other related theories and methods, use space-time data mining, complex network measurement, visualization and other technologies, propose a theoretical framework for analysing the correlation between space-time interaction and social relation, and revealing its dynamics mechanism.

2. METHODOLOGICAL FRAMEWORK

2.1 Ideas
In order to reveal the human dynamics mechanism hidden in "meet is fate", we proposed a framework in this article based on the following ideas:

(1) To research the dynamics mechanism of ‘meet is fate’ must firstly verify its correctness, that is to verify whether people meet each other in space and time is accidental or fate. If it is accidental, there is not necessary to explore its mechanism, else if it is fate, then we go to explore its dynamics mechanism.

(2) ‘Meet’ is a kind of space-time behaviour, ‘fate’ is the predication of future social relations between people. Therefore, the question of ‘meet is accidental or fate’ can be verified through correlation analysis between space-time interaction and social relation of human group behaviour, which includes: whether high-frequency space-time interaction today is related to today's close social relation, or whether high-frequency space-time interaction today will cause close social relation in the
future, and whether the close social relation today will cause future high-frequency space-time interaction.

(3) If it is confirmed that people meet in space and time is not accidental, that is to say meet is fate, then we can construct a complex network of human group behaviour, and through analysing its structural topology, evolution and other complexity characteristics, to reveal the dynamics mechanism, and sum up the scientific model.

Based on the above ideas, the theoretical framework needs to solve the following problems:

- How to obtain the space-time trajectories and social interaction data of people’s behaviour in a group scene, and the data must should have high space-time resolution and high sampling rate.
- How to construct a theoretical model to describe the process of human space-time behaviour comprehensively and accurately, based on this model, individual space-time profiles can be built.
- How to model and analyse the dynamic correlation between space-time interaction and social relation.
- Based on what model to build a complex network for human group space-time behaviour.

2.2 Solution process

These four points are realized by four steps as follows:

(1) **IoHF application platform i4People implementation:** A typical group behaviour scene in the urban environment is chosen as the research target. Based on the application framework of the IoHF, i4People platform is used to establish the behaviour data acquisition system for the scene to realize collection and storage of the group behaviour data, including space-time trajectories and social relations (IoHF and i4People platform are the concepts that we defined in article [4]).

(2) **Space-time behaviour profiling:** Considering the significance of both time and space in the travel process, the behaviour process model is established from the perspective of integrated time and space. Based on this model, the space-time behaviour profile of each person is extracted and built from the collected original spatiotemporal trajectory data.

(3) **Evolutionary similarity measure of hierarchical community structure:** From the perspective of complex network, space-time interaction and social relations are two different types of edges connecting nodes (different people) in the human group behaviour network. Based on these two different types of edges, two subnets are formed in the group behaviour network, which are the space-time network and the social network respectively. In a complex network, the hierarchical community structure is the best way to describe the interactions among nodes, which can fully express the density and hierarchical relationship of the interactions. Therefore, the dynamic correlation problem between space-time interaction and social relation can be solved by the evolutionary similarity measure of hierarchical community structure of complex network.

(4) **Modelling and analysis of multi-subnet composite complex network:** Human group space-time behaviour network is a typical composite complex network which contains two different types of edges of space-time interaction and social relation, forming two subnets. So, based on multi-subnet composite complex network model, to build a group space-time behaviour network is an ideal choice. Taking person as the node, and space-time interaction and social relation as the edge, the human group behaviour network is create.

These four steps are demonstrated by the flow chart in Figure 1. The next section is organized according to the procedure illustrated in the flow chart, explaining the method developed in each step of the framework.
3.**DETAILED STEPS**

3.1 **i4People application for data acquisition**

The data for this research is a multidimensional data integrating space-time trajectory and social relation. Moreover, the data needs to have two characteristics: high space-time resolution and high sampling rate. High space-time resolution can ensure the accuracy and integrity of the behaviour process, and only the high sampling rate can support the research on human group behaviour.

The current data are divided into the following categories: (1) Social life data, including social media (micro-blog, WeChat, QQ, etc.), online forums, blog, etc. [12]. (2) Business activity data, including credit card transactions, electronic business platform (Amazon, Taobao, etc.), supermarket membership records, shopping malls trading records, business management data, marketing analysis data, etc. [13]. (3) Traffic travel data, including GPS, Beidou and other positioning data, road monitoring data, call detail records (CDR), etc. [14]. These data have their own advantages, but also their limitations. For example, CDR data include a large number of users, however CDR data do not
include the actual contents of phone or text communications. Social media data can express a good semantic, but its space-time expression is not complete. GPS, Beidou and other positioning data has the high space-time resolution, but its user coverage is small, so it cannot support the human behaviour research of a large scale group scene. Thus, among the current available data, the data with high sampling rate is low in space-time resolution; the data with high space-time resolution doesn’t have a high sampling rate. Therefore, the use of a single data source cannot meet the needs of our research, meanwhile these data are from diverse platforms, scenes and groups, so it is difficult to use these multi-source data integrated in one research.

To address this, targeting a specific experimental scene, based on the application framework of IoHF, through constructing i4People platform, the human footprint data are collected and stored, which have a high space-time resolution and high sampling rate. Human footprint data is a kind of daily behaviour data combined with space-time trajectory and social relation, including not only the trajectory data of high space-time resolution, but also the social relation data formed by social interaction among people in the experimental scene.

i4People is a mobile space information service platform, which integrates MobileGIS and ARGIS[15] to realize the application framework of IoHF, as shown in Figure 2. Based on the spatial information construction of the scene, i4People integrates the spatial information into the daily behaviour, and provides the spatial services to users for the daily behaviour guidance in the scene through mobile APP, meanwhile collects the HF data during daily use of APP. Various typical scenes of human group behaviour in an urban environment, the large-scales like a city, the small-scales as parks, factories, schools, etc., are actively building the mobile application service platform, which provides data guarantee for our researches.

3.2 Space-time behaviour profiling
Data acquisition is the first step, the second step is to profile individual space-time behaviour from original space-time trajectories. In order to completely and accurately describe individual space-time behaviour process, the space-time behaviour profiling must consider both time and space simultaneously from the point of view of space-time integration. In reality, people carry out different activities at different places at different times of the day. The activity they are doing is not only indicated by where they are, but also how long they spend in the place and when they do it [8]. In 2016, paper [8] proposed a model that can express the time, place, and span of the behavioral process. Referring to this model, it need 3 steps to create individual space-time behaviour profile from original trajectory data, as shown in Figure 3.

Space-time stay point (ST-SP) detection. From the original trajectory data, to detect individual stay points during travels in a day is the first step. A stay point stands for a geographic region with a practical functional requirement in the process of personal travel, which carries a particular semantic meaning. It is a set of trajectories that satisfy the specific time threshold $T_r$ and spatial threshold $D_r$. 
Figure 4 is a typical example proposed by paper [16] of stay points in a trajectory. In this article, the stay point is defined as a spatial coordinate point with the start time and the end time, that is \( ST-SP = (x, y, t_s, t_e) \), where \((x, y)\) is the average coordinate of the set of trajectories in the stay point; \(t_s\) represents the arrival time, and is the minimum timestamp in the trajectory collection of the stay point; \(t_e\) represents the departure time, and is the minimum and timestamp.

**Space-time region of function (ST-ROF) detection.** It is fact that there are some do not have travel significance existed in the set of individual stay points, which represent only some of the specific functional requirements of a person, such as a car accident, a refuelling, a temporary toilet, and so on, and these stay points do not work in space-time behaviour profiling, and they are invalid data for the computation of space-time interaction between two persons, which reduces the computational efficiency. Therefore, furtherly we need to detect the functional regions having actual travel significance in the scene from individuals’ stay points. We consider the spatial region with a high density of access in a short time as a spatial and temporal functional region having real travel significance. In other words, an ST-ROF is a region of high density clustering of stay points with spatial boundaries, as well as start and end times [8]. ST-ROF integrates the two dimensions of time and space, \( ST-ROF = (x, y, r, t_s, t_e) \), where \((x, y)\) is the central coordinate of the region, \(r\) is the radius, \(t_s\) and \(t_e\) represent the arrival time and departure time. Among the many variations of density-based approach to cater to different research purposes, ST-DBSCAN [17] is an extension particularly developed to deal with space and time intervals comprehensively. ST-DBSCAN is capable of clustering objects with a combination of both spatial and temporal measurements and detecting noise when different densities exist. These characteristics make ST-DBSCAN the best option to detect the location as well as the life span of ST-ROFs, revealing where ST-ROFs are, when they emerge and when they disappear [8].

**Space-time behaviour description.** Based on ST-SPs and ST-ROFs, we can construct space-time behaviour profiles for individuals by noting when the person visits a particular ST-ROF and how long she/he stays before leaving for another ST-ROF. In this way, the space-time behaviour process description of a person can be represented by the time she/he arrives at an ST-ROF and then leaves for another, thus the whole travel process of a person in a day is simplified as a series of ST-ROFs she/he visits. Figure 5 is an example proposed by paper [8].
Figure 5. The simplified representation of two example persons’ travels, (a) with the trajectory of two persons in space-time; (b) simplified movements with sequence of time-stamped ST-ROFs.

3.3 Evolutionary similarity measure of hierarchical community structure

In this article, the space-time network is an undirected weighted network, in which the node represents the person in the scene, the edge represents the space-time interaction between people (meet), and the edge weight is the number of people meeting; the social network is also an undirected weighted network, where the node represents the person, the edge represents the social relationship between people, and the edge weight is the number of social interaction.

For these two networks, we first need to select the appropriate algorithm to extract the hierarchical community structure of the network. Current recognition algorithms of hierarchical community structure can be divided into two types: top-down splitting method and bottom-up agglomerative method. GN algorithm [18] is a classical splitting method. The representative agglomerative methods are as follows: the algorithm based on modularity [19], the EA-GLE algorithm based on the maximal clique similarity [20], and the algorithm of detecting both overlapping and hierarchical community based on the edge [21] and so on. Most of the current hierarchical structure mining algorithms do not pay attention to the hierarchical relationship among the members of the community. Paper [22] introduced the granular computing [23] idea into the hierarchical community structure mining of complex networks, and proposed the fuzzy tolerance relation based hierarchical structure detection algorithm (FHSD). For an undirected and unweighted network, the algorithm can realize the detection of hierarchical community structure of the network and the hierarchical structure of the membership in the community.
Currently, there is no specific method available to measure the similarity of hierarchical community structure. In this article, the hierarchical community structure is modelled as an unordered multi-tree, and the tree structure similarity measure method is used to achieve the similarity measure of community structure. As shown in Figure 6-(a), it is a network $G = (V, E)$ with a typical hierarchical structure, where $V = \{1, 2... 34\}$ is the set of nodes and $E$ is the set of edges. Mapping the hierarchical community structure of $G$ to the structure of the unordered multi-tree $T$ is shown in Figure 6-(b), the node of $T$ represents a part or all of the elements in $V$, such as $A = V = \{1, 2, ..., 34\}$, $E = \{25, 26, 32\}$.

Due to the wide range of tree applications, researchers have proposed a variety of similarity measure methods for different application requirements. Currently, there are six kinds of similarity measure methods of tree structure summarized in the article [24]. Among them, there are four kinds of methods available for ordered tree, including the method based on the operation strategy, the method based on decomposition strategy, the method based on path comparison and the method based on node comparison; for the unordered tree, the methods mainly include the bilateral matching method and the largest common subtree method. As can be seen from the article [24], a variety of similarity measurement methods have their targeted applications, resulting their universality are deficiencies. The two types of unordered tree similarity measure methods do not consider the strict hierarchy of tree

Figure 6. (a) is a typical hierarchical community structure of a network; (b) is the corresponding unordered multi-tree.
structure and the difference of node content. For the similarity measure of hierarchical community structure, it is necessary to consider both the hierarchy and the content of the node, at the same time the accuracy of the algorithm is also necessary.

3.4 Modelling and analysis of multi-subnet composite complex network

Human group behaviour network is a composite complex network, in which nodes are the persons and edges are the space-time interactions and social relations. Based on the related theories of composite complex network, through the co-evolution analysis of multiple subnets, the dynamics characteristics of the group space-time behaviour of the experimental scene are studied. For the construction of this composite network with single-type node and multi-type edge, the multi-subnet composite complex network model [25] is an ideal choice. Multi-subnet composite complex network is defined as follows:

The multi-subnet composite complex network is a quaternion $G = (V, E, R, F)$, where,

1. $V = \{V_1, V_2, ..., V_m\}$ represents the set of nodes, $m = |V|$ is the order of the set $V$;
2. $E = \{<v_i, v_j>| v_i, v_j \in V, 1 \ll h, 1 \ll m\} \subseteq V \times V$, which represents the set of edges between nodes;
3. $R = R_1 \times R_2 \times ... \times R_n = \{(r_1, ..., r_i, ..., r_n)| r_i \in R_i, 1 \ll i \ll n\}$, $R_i$ is the set of ith relations between nodes, $n$ is the total number of relationships between nodes;
4. Mapping $F: E \rightarrow R$.

When $n=1$, the complex network is a traditional single complex network model, which describes the relationships between nodes. When $n>1$, it shows that there are many relations among nodes, and the relation set $R$ in the network is the Descartes product of a set of relations, which indicates that the relation between nodes is a n-tuple. $F$ is a mapping between any edge in the network and the only one n-tuple in the set $R$.

According to the above definition, the group space-time behaviour network will be constructed as a non-directed multi-subnet composite complex network, where $n = 2$; $V$ is the set of all the persons in the scene; $E$ is the set of all relationships between people; $R = R_1 \times R_2$ where $R_1$ denotes the space-time interaction, and $R_2$ denotes the social relation. Considering the large difference in the frequency of space-time interaction between people, and the difference in the density of social relations, the network will be constructed as a weighted network, i.e. $E = \{<v_h, v_l, w_{hl}>\}$, $w_{hl}$ denotes the weight of the edge connecting two nodes $v_h$ and $v_l$, where the weight of the spatiotemporal edge is the number two persons visit a ST-ROF at the same time; the weight of the social edge is the number of social interactions between this two persons.

4. CONCLUSIONS AND FUTURE WORK

In order to reveal the human dynamics mechanism implied in the group space-time behaviour of "meet is fate", this article proposes a theoretical framework based on the combination of geographic information science and complex network science.

In this framework, a representative scene of human group space-time behaviour is selected as the experiment target; the IoHF application platform i4People is implemented for the scene to get the human footprint data with high space-time resolution and high sampling rate, integrating space-time trajectory and social interaction; based on the human behaviour process model of space-time integration, the space-time behaviour profiles are constructed; based on the profiles the space-time network and the social network are built; through the evolutionary similarity measure of the hierarchical community structure of this two networks, the dynamic correlation analysis between the space-time interaction and social relation is carried out, so as to verify whether the meet is accidental or fate, and in which the hierarchical community structure is furtherly modelled as unordered multi-tree. After verifying 'meet is fate', based on multi-subnet composite complex network model, the human group behaviour network with two kinds of edges of space-time interaction and social relation is established. By analysing the dynamics characteristics of the network, such as the topological characteristics, structural evolution and others, the scientific model implied in "meet is fate" can be revealed.
"Meet is fate" this statement has been saying in China since ancient times, which expresses a kind of philosophy of life. This article presents a framework for the first time to provide a feasible solution to verify and study this statement scientifically, and explores a meaningful research direction for the inter-cross application between geographic information science and human dynamics at the age of mobile big data.

This article proposed only a theoretical framework, the specific experimental research work has not yet started, and then we will be based on the framework to start the specific experimental work, in which the following issues need to be solved:

(1) The experimental scene is selected to get the experiment data. To select the experimental scene, we should consider current situation of mobile information platform construction in China's urban environment, choose the scene to be built or is building a mobile information platform as an experimental target.

(2) The generalization of ST-ROFs is based on density-based clustering method and it is very time-consuming. A new searching tree and the parallel computation techniques will be used to optimize the retrieval strategy of STDBSCAN and speed up the calculation when even larger movement datasets are given.

(3) FHSD has realized the detection of hierarchical community structure of the network and the hierarchical structure among the members of the community for the unweighted and undirected networks, but has not been applied to the weighted and directed networks. In this article, the space-time network, social network and composite network are all weighted networks. Therefore, we need to study the hierarchical community structure detection algorithm for the weighted networks and even for the multi-subnet composite complex networks.

The current two kinds of structural similarity measurement algorithms, bilateral matching method and maximum common subtree method for the unordered tree, do not consider the strict hierarchy of tree structure and the difference of node content. Hierarchical community structure similarity measurement algorithm, not only need to consider the hierarchical structure and node content, but also need a higher accuracy. Our next work will continue to study the more practical and more accurate measurement algorithms for hierarchical community structure based on the existing algorithms.

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