I will follow the following structure to write the paper. And I will fill each part one by one.

Some parts like literature review have been filled, but it is the first version so that still need to be edited.

**Title**

Brief and topic-specific summary of the whole research

**Abstract**

A concise summary of the content and direction of the paper. I will write this part last.

**Introduction**

The introduction will be split to two parts: motivation and background.

In the past year, with the unstoppable global outbreak of COVID-19, many countries have adopted travel bans to prevent the further spread of infectious diseases. Undoubtedly, the movement of people will accelerate the transmission of infectious diseases. However, mobility data describes the mobility behaviour of people in a particular area, such as the journey-to-work data in a country. Otherwise, not only efffectively reflects human behavior and activities, movement data also contains a wealth of information on user behavior patterns and important location attributes. Due to the development of mobile application technology and spatial data acquisition technology, it is not difficult to obtain user’s trajectory data. Zheng (2015) proposed the entire process of trajectory data mining as well as techniques applied in each step [2]. In addition, social interactions are another concerned factor that promotes the spread of diseases. Past research has investigated the attributes of social encounters by conducting a telephone survey [3].

Moreover, great understanding of the relationship between infectious disease transmission and the trajectory of human movement is critical for predicting and preventing future outbreaks of infectious diseases. And, effective public interventions can be designed in a timely manner to control the further spread of infectious disease in this case [1]. Much research has been done to explore the association between the transmission of infectious diseases and geographical or demographic indicators (such as per-head income) at different scale (city, urban, country etc.) [1,4]. Furthermore, the research incorporating trajectory data with social encounters have been conducted to reveal the spatial distribution of infection depending on specific locations [6].

Here, we will combine the trajectory data with social encounters to explore the spatial distribution of infectious disease. In this process, cluster algorithms, which are a group of efficient algorithms to do unsupervised machine learning, will be applied to find general patterns in movement dataset. Then, the social interaction of participants and basic information (such as age etc.) will be combined with movement patterns to reveal the law of disease distribution.

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In parallel

1. **Motivation**

This part will mainly introduce why I am undertaking this research. I will explain it from two aspects: 1. The reason why I am interested in this topic (the outbreak of COVID-19 in my country China); 2: The reason why this topic worth investigating (a lot of benefit for finding out the relationship between movement data and the outbreak of infections).

1. **Background**
2. The context of the research (the rationale for the present study)
3. What the research is about (an outline of the research questions and hypotheses)
4. The plan of doing the research
5. A brief introduction of methods used in latter research
6. Key terms and definitions (terminology)

In recent years, due to the population explosion and the convenient of transportation, the incidence of infectious diseases shows a sharp increasing trend. And it becomes a major public health problem globally, killing more than 13 million people each year (Sorell, 1985). Several studies, particularly from rural areas, have shown a link between mobility and HIV infection (Lydié et al., 2004). As the mobility of people who with the infectious virus, infectious diseases can be spread to a wider area. In this case, it is possible that mobility data of population in a certain area contains information about the spatial distribution or outbreak trend of infection. Mobility data describes the mobility behaviour of people in a particular area, such as the journey-to-work data in a country which basically describes the trajectory of people going to work at a country scale. If we can find the relationship between the outbreak trend of infectious diseases and mobility data through the establishment of models, then we can take certain measures to prevent the outbreak or spread up to a point. Moreover, Modeling is the process of simulating the causal relationship between two things. In order to reveal the relationship between mobility data and the distribution of infectious diseases, the study is divided into two stages: mining mobility data; modeling and analyzing.

**Literature review**

The review will be a selection of carefully organized, focused and relevant literature that develops a narrative ‘story’ about the topic. The review will answer questions about the literature:

1. What is the current state of knowledge on the topic?
2. What differences in approaches / methodologies are there?
3. Where are the strengths and weaknesses of the research?
4. What further research is needed?
5. Identify a gap in the literature which provides a rationale for my study and supports the research questions and methodology.

1. mobility data mining

With the maturity of location acquisition technology, the popularization of wireless network and the convenience of transportation, a large number of trajectory data created by human, animal, transportation tools and even climate change have been excavated for making applications or doing research (Zheng, 2015). In “Trajectory Data Mining”, Zheng proposes the whole process of mining and processing trajectory data created by moving objects (Colyer, 2019), which is mainly composed of the derivation of trajectory data, trajectory data preprocessing, trajectory data management, and various data mining tasks. Zheng also introduces the similarities and differences between the existing technologies of mining data. In addition, this paper also identifies methods of transforming trajectory data into other data structures, such as graphics, matrices and tensors. Data in these formats can be applied to more apps and researches, which facilitates this research topic. At the end of the article, the author presents some trajectory data sets for use by researchers or developers. Also, it points out the future direction of research based on this data set (Zheng, 2015). The trajectory data mining technology proposed by Zheng encourages researchers and developers to research or develop applications based on the analysis of trajectory data. In addition, the data set provided in this paper facilitates the subsequent study of the spatial distribution of infectious diseases.

However, it involves many problems and challenges that must be met during the data mining process. Firstly, in many countries and regions, obtaining location and mobility information on mobile phones remains difficult and even restricted by legislation (Wesolowski, Buckee, Engø-Monsen & Metcalf, 2016). Moreover, despite the high prevalence of mobile phones, the data can be biased. For instance, without possession of mobile electronic devices, the trajectory data of children generally is not recorded. Therefore, the main source of data is adults. But for infectious diseases, children are also a major source of infection. Another point is the collection of data can be affected by making or receiving calls. Although the impact is small, it involves the privacy concerns of device owners. Furthermore, it is difficult to detect position of device owners due to the weakness of signal in some particular area. In this case, the trajectory is not continuous which lead to the inaccuracy of the analysis of spatial distribution of infections.

According to Hung, Peng and Lee (2011), there are specific solutions to solve the last challenge. Generally, there are many trajectories in a particular area created by different people,

Generally, some clues can be found from these trajectories. So, from we can cluster the trajectories based on these clues. Hung et al. call this approach the clue-aware clustering algorithm (CACT). In a hot spot, there must be some trajectories share the same clues. For example, following a prescribed touring route in a scenic spot, all the visitors create the same trajectory. In this case, this scenic spot is a clue that can help cluster trajectories. Based on this trajectory group and CACT, we can find the common track of people in a hot spot even if the mobile device only captures some motion fragments (Hung, Peng & Lee, 2011). CACT solves the potential problems caused by incomplete trajectories mentioned in ‘Trajectory Data Mining’ and further improve the process of data mining. However, a lot of information other than track is needed, and simple stay point detection is not sufficient for clustering trajectories.

2. modeling and analyzing

Much Research has been done to identify the model of the spread of infections based on mobility data at either national and international or individual buildings such as school or hospitals. However, in fact, the mobility pattern at city scale is quite different from country scale (Moss, Naghizade, Tomko & Geard, 2019). According to Moss, Naghizade, Tomko and Geard (2019), the most appropriate size of mobility data is that collected at metropolitan scale. In this article, the author conducts the research form determining the data set of the study (journey-to-work and GPS data set) based on the city size, to analyze the influence of hub and spoke commuting patterns, to apply mathematical method to represent the mixing pattern, to establish model, finally analyze the relationship between the spatial distribution of infectious diseases and the mobility data. Also, the article identifies some problems to be solved. Privacy issues are inevitably when doing such research, which makes it difficult to obtain report of infectious cases. Secondly, it is also a major challenge to combine case information with mobility information. In all, Moss et al. innovatively propose to explore the spatial distribution of infectious diseases from the perspective of cities. Although the mobility and contact of people in urban areas are more complex and difficult to identify, it provides some ideas and methods for studying the distribution of infectious diseases in urban areas. For example, consider the impact of the characteristics of highly connected areas, or focus on the information contained at transportation hubs.

Due to the lack of consideration of contact information between people and the focusing on the mobility information, there may be some bias for the conclusion. In other words, some uncertainties may affect the results of the analysis, such as the duration that an object spends at a certain location, or the influence of the heterogeneity of people's social encounters. Rolls et al. (2015) conduct a telephone survey on the social encounter attributes of people in two areas of Melbourne. It turns out that regardless of gender, age, location and area of residence, people's contact behavior patterns are completely different. For example, the frequency and length of contact between adult women and young children is higher than that of adult men of the same age, which may explain the fact that young children are more likely to be cared for by their mothers from a sociological perspective. In this case, if one of the members in this family carry infectious virus, other members in the family can be infected. In addition, this paper identifies several kinds of human-to-human interactions that may affect the distribution of infectious diseases. Including duration of social encounters, encounter with known or unknown individuals, the impact of local government area of residence. And it also gives conclusions like “The highest reported number of median contacts was among individuals aged between 30 and 49 years”. Assumptions about the number, duration, and aggregation of contacts in the model framework all have important implications for the simulated transmission of infection, without building model based on this data set and analyzing the concrete relationship between social encounters and the reported disease cases, this article cannot adequately explain the point that social encounter can affect the distribution of infection.

Other technologies have been proposed to extract information from dataset, by combining trajectory sample points with geographic data, behavioral knowledge which is more useful and meaningful to application users can be extracted from semantic trajectory (Chakri, Raghay & El Hadaj, 2017). And Mossong et al conduct a survey to record and analyze different contact patterns of different individuals during one day. And give conclusion that 5- to 19-year-olds are expected to suffer the highest incidence during the initial epidemic phase of an emerging infection transmitted through social contacts measured here when the population is completely susceptible (Mossong et al., 2008). It is the first paper that provides quantitative approaches to study the contact patterns of infectious disease.

3. Challenge

Although much research has been done for revealing the laws of the distribution of infection, there are still some challenges. From collecting data to processing data to analyzing data, there are unsolved problems.

Firstly, for collecting data, new approaches in recent years have given us the opportunity to collect data on individuals and population sizes to empirically describe patterns of exposure within host populations (Eames, Bansal, Frost & Riley, 2015). But there are still some challenges. It is divided into two parts: mobility data collecting, social encounter profile identifying. In terms of mobility data collecting, it is hard to decide which scope is most appropriate. Sometimes, it also involves privacy problems. When it comes to social encounter data collecting, six challenges presented by Eames, Bansal, Frost & Riley, (2015). It involves the difficulty of defining a contact and avoiding privacy issues such as personal information and ethical concerns (Eames, Bansal, Frost & Riley, 2015). In particular, some data collection processes may involve illegal content even though it is for research purpose.

The next part is about processing data. Quantifying data can be a big challenge. As the data obtained from such surveys are generally descriptive, it is difficult to use some numerical methods to represent it. Since no matter how you represent this kind of data, not all the information is going to be contained. Other challenges of processing data are proposed by Eames et al., including bounding networks in space, time, and scope, dealing with missing data, measuring weighted and dynamic networks, exploiting in direct information about networks (Eames, Bansal, Frost & Riley, 2015).

Moreover, in order to comprehensively analyze the distribution of infectious diseases and predict the incidence trend of infectious diseases, many factors need to be considered. Firstly, incorporating geographical space into representations of social networks in the field of infectious disease modelling is one of the biggest challenges (Rolls et al., 2015). Moreover, infections are always seasonal, so time is also an important factor that can affect the distribution of infections, similar factors are climate, temperature and so on. In addition to these environmental factors, proper techniques for extracting information from data sets should be figured out. What's more complicated is that conclusions based on a particular region are not universal. In other words, every country, region or city is of different situation. The law cannot be applied to predict infection trend of other cities or regions.

After obtaining proper dataset, some technologies should be applied to build model. Traditionally, the distribution of infectious diseases in human populations has been modelled with static parameters (Funk et al., 2015). But with individuals changing their behaviour, these parameters can change. In other word, how to incorporate these behavioural changes in models of infectious disease is the challenge.

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**Methodology**

The purpose of this section is to detail how I conducted my research so that others can understand and replicate my approach. I will briefly describe the equipment or materials used and the approach taken. There will be two parts in this section.

1. Methods used in dataset analysis

Mobility data describes the mobility behaviour of objects in a particular area, such as the journey-to-work data in a country. Movement patterns can be explored from mobility data. Having known patterns of movement, we can discuss the relationship between the outbreak of specific infectious disease and movement patterns. Then, prevent the outbreak by predicting the trend of outbreak.

Much Research has been done to identify the model of the spread of infections based on mobility data at either national and international or individual buildings such as school or hospitals. Moss et al focus on the infection at metropolitan scale. However, how to gain appropriate mobility data increasingly becomes a difficult and important topic. Many technologies have been used to mining this kind of data. Zheng et al. developed a complete process to mining and process trajectory data of human or animals.

**Data set**

We explores movement patterns based on the data set “day\_in\_the\_life”.

Basic information

In the data set given, we can get information of age, gender, locations (type) have been and its duration etc.

There are totally 1307 objects in this data set, 514 males and 793 females.

Age distribution

A screenshot of a cell phone

Description automatically generated

Age distribution based on gender

A screenshot of a cell phone

Description automatically generated

Distribution of number of locations

A screenshot of a cell phone

Description automatically generated

Distribution of number of location types

A close up of a logo

Description automatically generated

Relationship between age range and num of locations

A picture containing building, drawing

Description automatically generated

A picture containing drawing

Description automatically generated

Relationship between age range and location types

A close up of a logo

Description automatically generated

A picture containing drawing

Description automatically generated

Relationship between gender and number of locations

A close up of a logo

Description automatically generated

A screenshot of a cell phone

Description automatically generated

Relationship between gender and number of location types

A picture containing drawing

Description automatically generated

A screenshot of a cell phone

Description automatically generated

The distribution of how many unique locations on has gone

A screenshot of a cell phone

Description automatically generated

The distribution of how many unique locations on has gone bases on age

A close up of a piece of paper

Description automatically generated

Relationship between age range and the number of unique locations

A close up of a logo

Description automatically generated

A picture containing drawing

Description automatically generated

1. Methods(techniques) used in Trajectory patterns exploration

Need more research

**Results**

In this section, I will show patterns found by each technique in methodology part. It will be the tabular or graphic summary of the findings.

No analysis of these results will be given in this part.

**Discussion**

The Discussion focuses on the research question. This section is where I will interpret the results in last section, account for the findings and explain their significance within the context of other research.

Consider the adequacy of the sampling techniques, the scope and longevity of the study, any problems with data collection or analysis and any assumptions on which the study was based.

**Conclusion**

This part will follow on naturally from key points raised in the discussion. The significance of the findings should be discussed in this section.

**Reference list**