Urban Human Mobility modelling and prediction: Impact of Comfort and Well-Being Indicators

Luís Rosa, Fábio Silva, and Cesar Analide *ALGORITMI Center, Dep. of Informatics*
University of Minho
Braga, Portugal
E-mail: id8123@alunos.uminho.pt

***Abstract*—There are increasingly more discussions on and guidelines about different levels of indicators surrounding smart cities. These indicators might help effectively provide quality services to citizens because smart cities involve not only technical elements but also complex elements (e.g., comfort, well-being and weather conditions). They are an important opportunity to illustrate how smart urban development strategies and digital tools can be stretched or reinvented to address localised social issues. Thus, multi-source heterogeneous data provide a new driving force for exploring urban human mobility patterns. In this survey, we forecast human mobility data using LinkNYC kiosks and MTA Wi-Fi Locations in New York City to provide a large-scale study on how people's habits influence comfort and well-being indicators. By comparing the forecasting performance of statistical and deep learning methods on the aggregated mobile data we show that each class of methods has its advantages and disadvantages depending on the forecasting scenario. However, for our time-series forecasting problem, deep learning methods are preferable when it comes to simplicity and immediacy of use, since they do not require a time-consuming model selection for each different cell. Deep learning approaches are also appropriate when aiming to reduce the maximum forecasting error. Statistical methods instead have shown their superiority in providing more precise forecasting results, but they require data domain knowledge and computationally expensive techniques in order to select the best parameters.**

***Index Terms*—Human Mobility Patterns, Device Network Dataset Collection, Deep Learning Methods, Statistical Methods.**

I. Introduction

Recent studies about human mobility, comfort and well-being and social interactions evaluated impacts on the perceptions of citizens [1]–[4]. The match between human activities in city and urban infrastructures may be the main contributor for these works. For example, human mobility trends by comparing day-by-day variations in public reactions to the virus are great help to fight COVID-19 in a strategic way. Additionally, human mobility is associated with a large personal and societal cost, with problems being attributed to a combination of individual factors (physical, cognitive and psychological) combined with environmental conditions [5]. As an example, the relationship between human mobility behavior and climate—namely, weather and environmental conditions when travel planning decisions are made. Meteorological effects could influence travel demand and route choices in various ways, including diversion to other trip modes or paths, or deferring and cancelling of trips [6].

On the other hand, smartphones and embedded sensor systems have given researchers unprecedented access to new and rich datasets, recording detailed information about how people live and move through urban areas. We can select a number of examples that highlight how generated datasets from these devices are lending insight into individuals lives and urban analysis. For example, in [7], embedded sensors were used to measure the spatio-temporal patterns of an entire city's usage of a shared-bicycle scheme. Other approaches used Bluetooth sensors to measure social interactions [8] or GPS sensors to show urban planning and design [9], [10]. Smartphones sensors were used to further to augment psychological research [11]. Lastly, [12] uses the dataset from public transport automated fare collection systems which was previously used to investigate travellers' perceptions and incentives.

In this survey, we apply deep learning and statistical models to data collected via mobile applications. This data includes dynamic observation windows, which provide the temporal variations of census over time. Other objectives were also defined, part of which contain sub-objectives, such as selecting the appropriate algorithms, including LSTM, CNN, hybrid CNN-LSTM, ARIMA, ARIMAX, SARIMA and SARIMAX. Each model must be studied and understood in a parameterized way so that the integration with any data set does not cause any problem. Then, we develop a platform for testing time series models with the studied algorithms and, finally, finding better models for the cases studied and the respective datasets - in order to achieve this objective, it is necessary to study some specific methods, namely grid search. All this is possible mainly thanks to the availability of data describing long-term human behaviour on mobile phones. The available data is based on a few years of network traffic generated by LinkNYC Kiosk devices, MTA Wi-Fi Locations, based on the city of New York, and context reactions of citizens via their smartphones. Basically, in a modern society where smartphones are widely used, understanding the impact of environmental factors, comfort and well-being indicators has both theoretical and practical implications in a variety of fields from the network design of digital services to human behaviour understanding and modelling.

The rest of the paper is planned as follows: Section 2 focuses on a survey about crowdsensed data from mobile devices and different human mobility forecasting methods such as deep learning and statistical models. In the next section, we execute an experimental study case that covers the benefits of neural network and statistical techniques in human mobility. In the same section, we also discuss the results. In Section 6, the conclusion summarizes the article's arguments before extending the debate further by offering trajectories for future investigation into human mobility prediction.

II. State of Art

For the realization of this project some concepts should be defined. In order to clarify their meaning and guarantee the quality of the project, the next sub-chapters introduce these and other concepts which are crucial to the understanding of the present work.

A. Crowdsensing Infrastructures

Contributing to this literature, this article investigates the human mobility that is captured with the development of the new public Wi-Fi infrastructure which is gradually making an appearance in cities across the world; such an infrastructure is growing steadily across New York City in recent times, called LinkNYC or Link. This infrastructure acts as a network device because it has been adapted and deployed to provide a free Wi-Fi service. It has transformed the way information is delivered on city streets, and supporting civic engagement has become a core part of our research. With thousands of screens encouraging New Yorkers to interact and offering helpful resources, it can provide strong participation of citizens in this survey. As we see in Fig. 1, there are more than 1,800 LinkNYC kiosks around the city, including hundreds in Brooklyn. A total of 7,500 of these kiosks is expected to be installed over the next decade where more 500,000 phone calls are made every month from the technology stations [13].

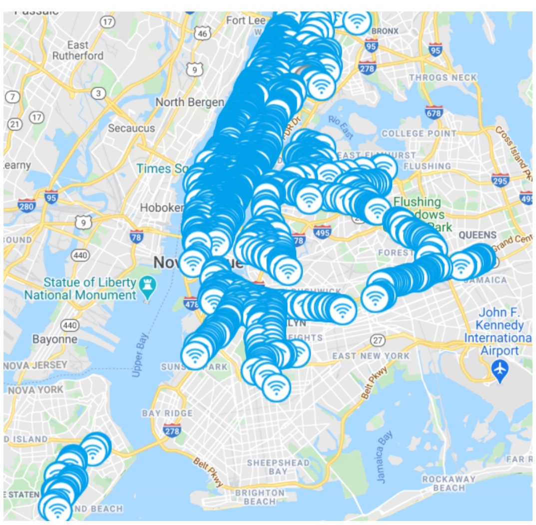


Fig. 1: Map of LinkNYC kiosk locations (based on [14]).

Similarly to how a nation-wide communication network obtained from telephone data gives access to new and rich datasets, recording detailed information about how people live and move through urban areas and embedded sensors is used to measure the spatio-temporal patterns of an entire city. Smartphones impact their immediate surroundings by providing an additional interactivity option which promotes greater human activity around LinkNYC kiosks, from which local businesses may also benefit. Due to a local navigation option and advertising displays, LinkNYC kiosks enhance awareness of the local area and may turn pedestrians into potential customers for local businesses. Existing literature points to the evidence that pedestrian-friendly environments increase retail sales performance and local business activity [15]. The generated dataset by LinkNYC Kiosks provides a historical listing of devices, their location, and the status of the Link's wifi, comfort and well-being indicators. In this study, we describe a select number of examples that highlight how new datasets are lending insight into individuals' lives and urban analysis.

In a smart city we expect continuous connectivity. Transit Wireless' mission keeps millions of New York City subway riders connected, safe and informed via Wi-Fi network connectivy. Fig. 2 shows the 282 stations more than 100 feet below ground, and 109 stations above ground where they transit seemingly endless miles of tunnels and bustle [16]. It only contains stations that are considered WIFI-ready. A station is considered WIFI-ready once the work from Transit Wireless and at least one provider have completed their installations. Some stations, such as 42^{nd} Avenue and Grand Central, are the size of a major airport in terms of passenger volume.

Throughout their journeys, riders can access free Wi-Fi, and can make and receive mobile calls in the underground stations, as well as in the mile-and-a-half long Canarsie Line Tunnel that runs under the East River. These connections let riders check schedules and route journeys on their smartphones. They can also summon emergency services at over 1,200 Help Points with the touch of a button. Continuous connectivity delivers helpful information where it matters. On the platforms, riders get up-to-the-minute train arrival information through countdown clock displays connected to the network.

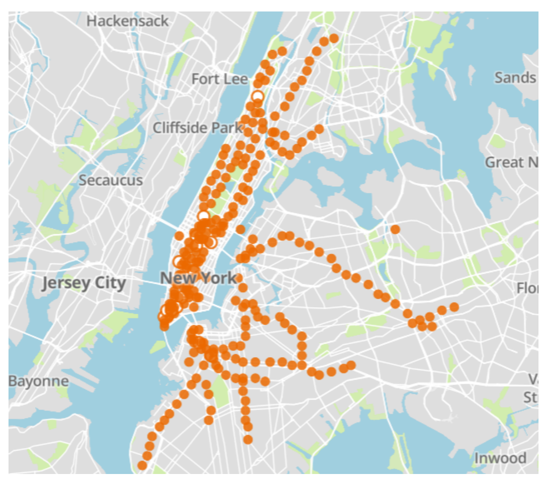


Fig. 2: Map of MTA Wi-Fi Locations (based on [17]).

Connecting riders to cellphone providers, data, applications and timely information on a massive scale takes a strong partnership with the Metropolitan Transportation Authority (MTA), tier-one carriers, and takes an equally massive and reliable data network. "We manage a state-of-the-art network with a 160-mile fiber-optic backbone, five data centers, 5,000 Wi-Fi access points, and a Distributed Antenna System (DAS) with over 7,000 antennas," said Saeid Malaki [18], Transit Wireless director of Network and Special Projects. That network must work flawlessly in the harshest conditions to connect millions of phones while tying together tens-of-thousands of devices every day, around the clock.

B. Well-Being and Comfort

These new data sources allow researchers to quantitatively test past assertions made by urban planners, local authorities, and social scientists. According to Kevin Lynch, in the book titled "The Image of the City", one of the most important conditions for a liveable and enjoyable city is visibility or imaginability" [19]. Considerable research is done into quantifying visibility and imaginability or, more specifically, the recognizability of a city adding cognitive factors namely well-being and comfort.

In well-being indicator, Elena Alatarsteva and Galina Barysheva [20] argue that the modern man can be defined with regard to two levels of well-being: internal (subjective) and external (objective). In the external strand, well-being could be characterizing by wage levels, residence conditions, educational opportunities, social quality, the environment, security and civil rights. In its turn, the internal strand is conceptualized only as an internal state of an individual. However, other authors from different branches specify the definition of this concept. Their articles categorized it into different classes: Community Well-being [21], Economic Well-being [22], Emotional Well-being [23], Physical Well-being [24], Social Well-being [25], Development and activity [26], Psychological well-being [27] and Work Well-being [28]. Although these classes categorize well-being in multiple ways, they have common points.

On the other hand, regarding comfort, it is difficult to reach a consensus from literature on its definition. According to Oxford dictionary, this indicator can be defined from a physical and a psychological perspective. In the physical case, it is seen as a "state of physical ease and freedom from pain or constraint". From a psychological perspective, it is defined as: "The easing or alleviation of a person's feelings of grief or distress". But some papers show factors that influence comfort. One them shows that different activities can influence comfort, concluding that characteristics of the environment and the context, can change how people feel [29]. Although it is often associated with a synonym for well-being, it classifies the atmosphere that surrounds the human being. However, mental health organization in the UK have argued that "it is important to realize that well-being is a much broader concept than moment-to-moment happiness" [30]. In other words, the comfort indicator arises characterized by an exhaustive variety of factors, which makes it associated with a long-term context, e.g a person may find himself comfortable but unhappy (and vice versa).

As we see, comfort and well-being are distinct terms, but this does not imply that they exist separately. Many authors describe well-being as improving progressively, while comfort can be improved with time. Indeed, comfort at a certain level contributes to well-being.

C. Other Indicators

On March 11^{th} 2020 when WHO announced the COVID-19 outbreak as a global pandemic, many countries were the top infected nations in the early stage of the pandemic (e.g Central Asia, European and North American regions). As a solution, they have implemented a series of "lockdown" policies to limit the transmission of COVID-19 infection by restricting human mobility, keeping social distance, shutting down local communities, and encouraging residents to stay at home with exceptions of limited outdoor activities in local neighbourhoods [31], [32]. These policies can significantly reduce certain input variables like the number of individuals connecting their the devices to the Kiosk or WiFi point access. In fact, researchers compile data from multiple sources containing international travel restriction and internal movement control policies (such as curfew and other forms of domestic travel restrictions) [33]. In addition, reducing the spread of the epidemic does not solely depend on international travel restrictions and would also rely on the effective internal movement control within each country. Once a touristic city, a clear decreasing trend has been observed in New York since early March in terms of the capacity and number of individuals walking in the streets and public transportation and, consequently, decreasing connections to the crowdsensing infrastructures [34].

Another indicator to be considered is the obligation to wear a facial mask. Local authorities decreed that from April 17, 2020 any individual who is over 2 years old and able to medically tolerate a face-covering shall be required to cover their nose and mouth with a mask or cloth face-covering when in a public place and when unable to maintain, or when not maintaining, social distance [35]. [36] shows that wearing a mask significantly reduces the person's thermal comfort level and air quality perception, which in turn leads to a decline in comfort level. This is mainly because the space behind the mask is blocked, and nasal airflow will become hot on the sides of the cheek, which makes people feel more hot and humid. Consequently, the vote on the well-being and comfort can be influenced by wearing such a mask during our survey.

D. Learning Frameworks

Though great contributions have been made for improving the prediction accuracy of various machine learning techniques, there is still a main bottleneck for datadriven human mobility modelling. The learning techniques are applied to many real-world applications involving Deep Neural Network (DNN) and Autoregressive (AR) frameworks. Similarly, the general purpose of these models is to provide powerful solutions to classifications, clusters and predictions problems. In this study, we use several learning models including:

- Convolution Neural Network (CNN): The CNN is the applied method for high-dimensional image analysis. It consists of convolutional filters, which transform 2D into 3D.

- Long Short-Term Memory (LSTM): This technique is well-suited to learn from experience to classify, process and predict time series with time lags of unknown size. It is a neural net architecture with recurrent connections between hidden states and has the capability of learning sequences and model time dependencies also.
- Bi-Directional Long Short-Term Memory (BI LSTM): This model has a bidirectional connection and learns the representation of current frame from both historical frames and subsequent frames, the proposed tracker can simultaneously incorporate forward plays and backward plays.
- Hybrid CNN-LSTM Model: This model combines Convolutional Neural Network (CNN), which can efficiently extract the inherent features of comfort, well-being and meteorological data, and LSTM, which can sufficiently reflect the long-term historic process of the input time series data.
- Autoregressive Integrated Moving Average (ARIMA): This model uses the relationship between an observation and a number of delayed observations; uses differentiation of observations (for example, removing an observation from an observation, in the previous step) in order to keep the time series stationary; and uses the dependency between an observation and the residual error of a moving average model applied to delayed observations.
- Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX): This model is the same as the ARIMA model with the addition of Exogenous Variables. These variable values are determined outside the model and are imposed on the model (in this case they will be used to help make the predictions).
- Seasonal Autoregressive Integrated Moving Average (SARIMA): This model is very similar to the ARIMA model. There are more differences than in the ARIMAX model. This model is the same as ARIMA model with the addition of an extra set of parameters characteristic of this type of models.
- Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX): This model is a combination of the SARIMA and ARIMAX models, since it contains the characteristic parameters of the SARIMA models and also contains Exogenous Variables.

This subsection shows that these models can aid in human mobility based on regression and classification techniques, pedestrian's historical data to predict their mobility and associate map of LinkNYC Kiosks interactions. In the case of deep learning techniques, time series is a sequence of numerical data ordered sequentially over time. The order of the data is fundamental, unlike in linear regression models. Depending on whether the interest is to understand a data set or make predictions, the objectives are different. However, they help to build a comprehensive tutorial about the state of the art in mobility research, which introduces and discusses popular crowdsensed data types, different human mobility subjects, and analysis methods.

III. Experimental Case Study

This experimental case is particularly useful in investigating "how" and "why" questions concerning human mobility behaviours. As a qualitative research methodology, this case study focuses on understanding these phenomenons in broader circumstances in which is located. Our study aims to investigate the comfort, well-being and motivation through questionary-based online surveys, and further understand a complex social phenomenon in human mobility: how citizens react in indoor and outdoor environments, and why.

A. Research environments

Two datasets were used to test the developed algorithms, in order to obtain different results and contexts. The first dataset addresses the comfort and well-being in indoor environment via LinkNYC Kiosks, while the second studies the same indicators in outdoor environment via MTA Wi-Fi Locations. Generally speaking, the LinkNYC Kiosks and Wi-Fi access points are found in different locations. In the case of outdoor environment, based on 3, a high proportion of interaction from citizens originated from the Manhattan, Brooklyn and Bronx. On the other hand, the indoor environment, the places where more interaction was recorded are Manhattan, Brooklyn and Queens. The human density data in this study aggregated human tracking totals by day (such as census); the remaining steps (e.g, data processing and analysis) are explained in the next subtopic.

B. Data collection

We designed and conducted this survey involving LinkNYC kiosk data contributed by one hundred thousand of users , while MTA Wi-Fi Locations captured fifty thousand interactions with smartphones in subway locations. Then, we analyse citizens perceptions about comfort and well-being in indoor and outdoor environments. We also incorporated the meteorological conditions to research to understand the impact of these factors in the human mobility survey.

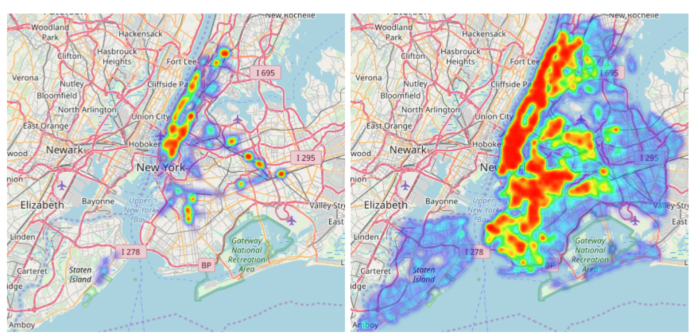


Fig. 3: Population density distribution in indoor and outdoor environment.

As we mentioned, these data sets are the measurements of the population quantity in indoor or outdoor environments in New York. Advantages can be pointed out such as: forecasting the number of people in a given location, which can be an excellent way of preventing COVID-19. Fig. 3 shows the population density for the year 2018.

In these datasets, other indicators were captured from a questionnaire-based mobile application. In this individual form, users were asked about their comfort and well-being voluntarily based on the environment they were in. In order to collect respondents' attitudes and opinions, we adapted a response scheme like Likert scale, commonly used in opinion polls. The questionnaire for well-being is more complex to be possible to associate the different type of data collected to different types of well-beings (defined in state of art). These surveys were designed with the aim of being short answer so that users could answer quickly and without effort. The following answers were implemented:

1) Comfort form
   a) Are you in an Indoor or Outdoor Environment?
   b) How comfortable are you?
2) Well-being form
   a) Are you in an Indoor or Outdoor Environment?
   b) What is your social interaction level?
   c) How are you physically?
   d) How is your financial situation?
   e) How is your work going?
   f) How are you psychologically?
   g) How is your participation in the community?
   h) Overall, how is your life going?

Other information can be considered, like the weather. We intend to use a API so that the information gathered was even wider. This includes, for example, the Meteostat API that allows collecting a vast amount of data associated with weather conditions such as date, temp, heating degree, cooling degree, precipitation, snowfall and snow/ice depth [https://meteostat.net/en]. The archived data is provided for many legacy weather stations.

C. Data Pre-processing

This study involved the daily participation of citizens that connected to LinkNYC Kiosks and Wifi Metro Stations and used the application with the questions stated above during the period from 1 January 2017 to 31 December 2020. The collected dataset contains 1054 lines and a total of 23 features. But because data is taken from multiple sources which are in different formats, it is simply unrealistic to expect that the data will be perfect. Therefore, first of all, the following steps of data processing were done:

- Elimination of irrelevant variables: Some variables like the wifi status, tablet status, phone status, which is not relevant to the prediction, were deleted;
- Duplicate values: Some rows were duplicate data. We removed them to not give to data object an advantage or bias, when running machine learning algorithms.
- Handling of missing values: In the treatment of missing values, we replaced these values by the preceding value, due to the fact the data is captured sequentially. This method results in less introduction of variability in the dataset. We also applied other techniques, for example, the mean in the case of meteorology, or median for features of well-being or comfort such as physical and psychological state of health, social interaction, financial situation, work, and satisfaction;
- Feature aggregation: This process reduces memory consumption and processing time. Aggregations provide a high-level view of the data and an idea of the daily behaviour of citizens;
- Handling non-numerical data: Since deep learning models only accept numbers, we apply One Hot Encoder method to perform with some type of pre-processing in several features represented by strings. For this purpose, it was used;
- Feature scaling: Techniques for framing the values were applied such as Standardization and Normalization methods. They aim to reduce the discrepancy between values;
- Target encoding: Since the target presents values in a certain way sorted from 1 to 5, a label encoding technique was used to normalize these values (thus transforming these values into classes 0 to 4);
- Splitting the dataset: We split the dataset into a 70:30 ratio. This means that you take 70% of the data (2 years) for training the model while leaving out the rest 30% (1 year).
- Model selection: Data should be organized so that it serves as input to predict the target of the next line when we use deep learning and auto-regression models.

The data preprocessing transforms the data to bring it to such a state that the machine can easily parse it. In other words, the features of the data can be easily interpreted by Machine Learning algorithms. In this case, we want to study if the treated data is relevant to the prediction of physical well-being. Therefore, we used neural network and dynamic regression models where the order of the treated data is quite relevant, although no shuffle has been done. In addition to preprocessing, other special precautions regarding the way data had to be processed were taken, which we will detail in the next subsection.

D. Building the models

This step is the most important and most meticulous requirement of the entire research. It is essential that the study of the models (CNN, LSTM, Hybrid CNN-LSTM, BI Directional LSTM, ARIMA, ARIMAX, SARIMA and SARIMAX) is well done and that there is a good understanding of them also, otherwise not only is the design theory misunderstood, but the project itself is hampered by the poor development of the platform. To perform the execution of the models, we must indicate the algorithms to be tested and the common and unusual parameters of each algorithm.

Univariate and multivariate analyzes are routinely used to understand citizens' behavioral patterns, in particular, well-being and comfort, playing an important role in solving urban problems. It can help urban agencies to understand the underlying driving forces of people in cities and to develop a better city and allocating resources to improve public space efficiency, although an analysis of the relationship between them is not always carried out. With this, the aim of this work was to relate univariate and multivariate analysis in daily census in different environments (indoor and outdoor). In univariate time series dataset is generally provided as a single column of data, in this study, it's "census" column. On the other hand, a multivariate time series covers several variables that are recorded simultaneously over time. The variables contributing to the model's forecast are census, temperature, heating degree, cooling degree, precipitation , snowfall, snow/ice depth, comfort, social interaction, physical, financial life, work, psychology, participation, satisfaction. Other elements such as wifi status, tablet status, phone status can be discarded. A sample of collected data of indoor environment can be seen in Table I.

TABLE I: MTA Wi-Fi Locations dataset.

Date	Comfort	Physical	Psychology	Satisfaction	Census	Temp (°C)	Humidity (%)
2016-02-12	4	2	4	1	4	7829	12
2017-01-01	4	3	5	5	5	3888	12
...	...	...	...	...	...	...	...

In its turn, the Table II shows a sample of collected data of outdoor environment.

TABLE II: LinkNYC Kiosks dataset.

Date	Comfort	Physical	Psychology	Satisfaction	Census	Temp (°C)	Humidity (%)
2016-01-11	2	2	3	2	3	4129	12
2018-12-17	1	1	3	3	2	2590	12
...	...	...	...	...	...	...	...

Loading the dataset is a high priority requirement. Using a Python language library (pandas), we have the ability to open a .csv file and load it to a "DataFrame" object. From this object, we enter the number of times the dataset should be divided, performing 10-fold cross-validation in the model tests. Subsequently, the data is separated into training data and test data. The amount of test data defined is 745 days and to be forecasted 350 days.

In deep learning predictions and being a multiclass classification problem, the loss function is therefore categorical_crossentropy. Furthermore, in the final layer, a softmax activation function was used. Here we have to take into account the type of this activation function and the loss function, as incorrect use of these can lead to false results. With the use of values in MinMaxScaler technique, the final step was validating and tuning the models. In these approaches, the objective was to experiment some combinations in order to find a good fit. The number of layers, the number of neurons, the windows size, epochs, batch size, among other, in deep learning models, were tested together.

In the case of auto-regression, components are specified in the model as a parameter. The notations used by ARIMA and ARIMAX models are number of delayed observations, number of times that gross observations are differentiated, size of the moving media window and, besides these, the SARIMA and SARIMAX models add the number of iterations for each seasonal period parameter.

An important point to underline is that this research can be extremely computationally expensive and can take a long time to obtain results. The grid search will build a model on each possible combination of parameters. It iterates through each combination of parameters and stores a model for each combination, improving the results.

E. Results

Since we want to classify the well-being some precautions have to be taken when we use deep learning (or neural network models) and auto-regression models (or statistical models). Given that we are studying two datasets, they compute the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) errors for each them. Essentially eight approaches are presented in Table III and Table IV.

TABLE III: RMSE and MAE for deep learning models with univariate and multivariate time series.

	MTA Wi-Fi Locations				LinkNYC Kiosks			
	Univariate		Multivariate		Univariate		Multivariate	
Model	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
CNN	519.4	411.2	1145.7	970.4	659.3	532.1	1716.7	1407.4
LSTM	969.5	742.3	1014.6	798.4	1375.4	752.9	1348.7	1143.3
CNN-LSTM	1054.0	859.5	825.5	639.5	1173.0	968.4	1145.7	970.4
Bi-Dir LSTM	32.3	24.6	131.4	101.9	1287.3	1104.8	256.9	203.7

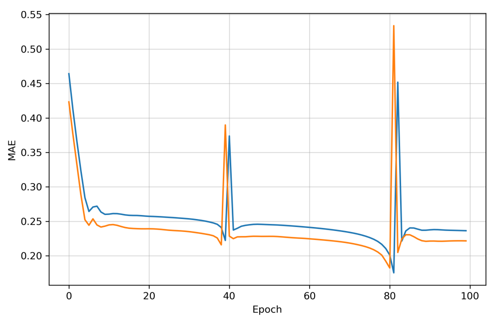
Using the four neural network models, besides building a predictive model that returns a minimization in error, we also adopt another data mining strategy based on the loss functions [37]. Basically, these two-fold approaches enable (i) presenting performance bounds of MAE, and (ii) demonstrating new properties of MAE that make it more appropriate than mean squared error (MSE) as a loss function for Deep Neural Network.

TABLE IV: RMSE and MAE for statistical models with univariate and multivariate time series.

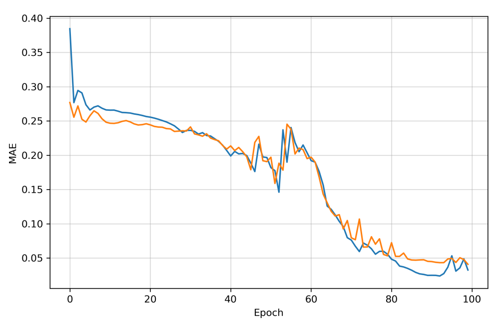
	MTA Wi-Fi Locations				LinkNYC Kiosks			
	Univariate		Multivariate		Univariate		Multivariate	
Model	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
ARIMA	1111.6	899.4	-		1559.2	1201.6	-	
ARIMAX	-		1333.6	905.4	-		1617.0	1290.7
SARIMA	1496.9	1186.1	-		1659.7	1388.9	-	
SARIMAX	-		1696.2	1211.0	-		1796.9	1441.0

In proposed statistical models case, we exploit the performance of prediction model using error metrics and plot observed versus predicted values. Performance metrics were calculated per dataset, which means they were calculated separately for the training, test and validation dataset per iteration.

Based on the above tables, we can draw two different perceptions concerning the experimental results. In this study, the whole experiment is carried out in two phases. The first phase of the experiment includes the eight models in the indoor environment dataset and then studying the outdoor environment dataset. Then, the models' performance is analyzed the performance the models with metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Globally, these metrics show different performances between proposed types of models in study. In two datasets, the RMSE and MAE values are more higher in autoregressive models than deep learning models. However, we can find approximate values, for example, between the hybrid CNN-LSTM model and ARIMA models applied on MTA Wi-Fi Locations dataset, using univariate time series. Or comparing accuracy between the LSTM and SARIMAX models applied on LinkNYC Kiosks dataset with all variables. But then we can find extreme values, in the case of MTA Wi-Fi Locations dataset, between the Bi-Directional LSTM and SARIMA models using unique variable and, in LinkNYC Kiosks dataset, the Bi-Directional LSTM and ARIMAX models when applied in multivariate time series. Although each metric has its own pros and cons, they enabled to address the problems such as underfitting and overfitting which can lead to a poor performance on the final model despite the accuracy value. The quality assurance of results was only possible based on the loss functions.



(a) Bi-Dir. LSTM - Univariate

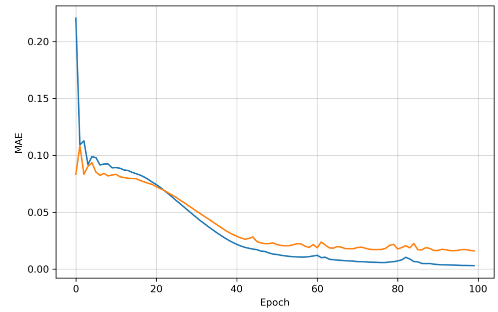


(b) Bi-Dir. LSTM - Multivariate

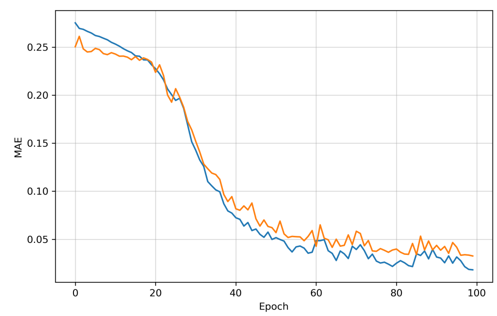
Fig. 4: Loss functions with lowest score based on MTA Wi-Fi Locations dataset.

First of all, we choose the functions based on the number of variable (i.e, univariate and multivariate), and lowest score. In MTA Wi-Fi Locations dataset, either with one or several variables, the Bi-Directional LSTM model presented the loss functions with lowest score. Fig. 4 show that, initially, the model has good performance, after 30 epochs it tends to converge, then it degrades. Taking Table III into account, CNN model for univariate model or hybrid CNN-LSTM model for multivariate also presents reasonable values and acceptable to be used for prediction and forecasting human mobility. They can be a good alternative for predictive modelling to human mobility.

In Fig. 5, the loss functions were chosen based on the same conditions than the previous dataset, but they differ at the level of the models that present the best results with one or more variables.



(a) CNN - Univariate



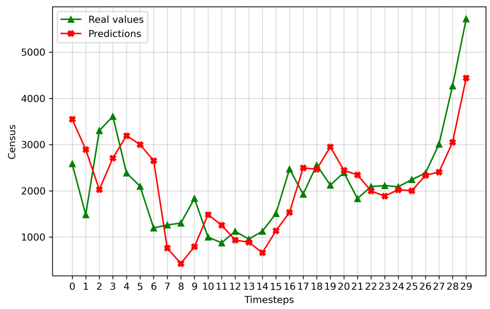
(b) Bi-Dir. LSTM - Multivariate

Fig. 5: Loss functions with lowest score based on LinkNYC Kiosks dataset.

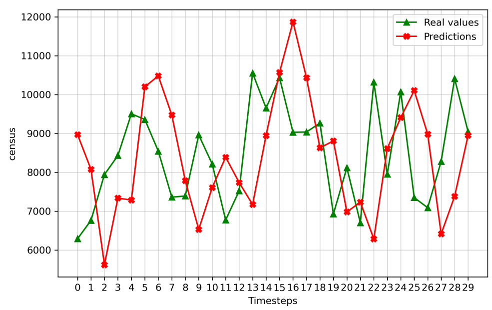
When LinkNYC Kiosks dataset only has a variable the lines of function in CNN model until 20 epoch seems to be converging, then it tends to degrade. While Bi-Directional LSTM model with multivariate (or multi variables) the lines of test and train data never converge, although, the distance between them is decreasing over time. Additionally, we can see in Table III that the RMSE and MAE values in remaining models are worse than these models, being hard to choose an alternative model.

On the other hand, we describe the forecasting performance of the statistical methods for a multi-step prediction task. The validation and consequently the final accuracy was obtained using the indoor and outdoor datasets. In particular, we consider 30-step-ahead forecasting, with a step equal to one day. We test the forecasting methods illustrated in Fig. 6 and Fig. 7 with each time series in our datasets.

As ours is a multi-step forecasting process, we also compute the forecasting error represented in Table IV. Based on them, when we applied Autoregression models on outdoor dataset with a univariate, the lowest RMSE and MAE values obtained were 1111.6 and 899.4, but in multivariate were 1333.6 and 905.4. This means that ARIMA and ARIMAX models presented the best results. In Fig. 6a, we can observe that predicted values closely match the actual values of Census. When the actual value changes direction, predicted value follows, which seems great at first sight. But in Fig. 6b, predicted values were worse. We can observe that predicted values didn't mimic the actual values.

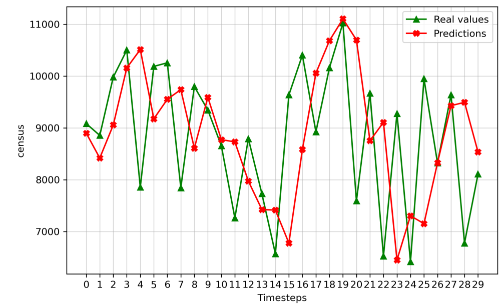


(a) ARIMA model - Univariate

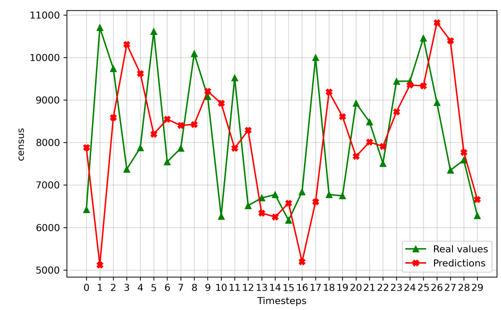


(b) ARIMAX model - Multivariate

Fig. 6: Autoregression models for time series forecasting based on LinkNYC Kiosks dataset.



(a) ARIMA model - Univariate



(b) ARIMAX model - Multivariate

Fig. 7: Autoregression models for time series forecasting based on LinkNYC Kiosks dataset.

In a search for finding a good model the same steps followed before were applied in the second approach presented in Fig. 7. Although, the ARIMA and ARIMAX models also present better results than SARIMA and SARIMAX models, if we compare with indoor environment dataset, globally, the RMSE and MAE values are worse. In other words, while ARIMA and ARIMAX have value pairs 1559.2 & 1201.6 and 1617.0 & 1290.7, respectively, the SARIMA is 1659.7 & 1388.9 and SARIMAX is 1796.9 & 1441.0, that means first pair of statistical models presents a better performance.

Fig. 7a also compares predicted and actual census. We can observe that while the model outputs predicted values, they are not so close to actual values than occur in another dataset. But when it starts to generate values, the output almost resembles the sine wave. Later, in the final period, values tend to converge.

Something we can infer after results, the proposed Deep Learning techniques (especially Bi-Directional LSTM) may work better than statistical methods. First of all, thanks to universal approximation theorem, a neural network can approximate any given algorithm, given sufficient computational power and a correct architecture. Then, a neural network is fully modular and integrates any other information (i.e, change univariate to multivariate or vice-versa). With Autoregressive Models, we forecast ”only” on prior events, but are computationally intensive, more than NN models.

IV. Conclusions

In this article the study modelling and prediction were extended to several human mobility phenomena. It combines mobility restrictions and wearing masks indicators to evaluate human health and comfort in an indoor or outdoor environment. Some surveys estimate the impact of mobility-related policies by crowdsensing infrastructures that reflects the expected effects of each policy. Others conclude that wearing a mask for a long time significantly increases discomfort which will eventually lead to a decline in the level of health and comfort. Although this might seem a subjective evaluation, decreasing census of human mobility and wearing a mask surely influenced the Psychological and Work Well-being indicators of our work.

We also described how LinkNYC kiosks and MTA Wi-Fi Locations could have been used to identify the context in which a given user is inserted. The experiments carried out have shown good results. Based on them, selected deep learning algorithms (CNN, LSTM, CNN-LSTM and Bi-directional LSTM) are more suitable, when compared to Autoregressive models. They were trained with the proposed data sets to predict the next Census (Census of the next 30 days) based on historical data. The neural network models are evaluated using the test data and loss functions, where the performance is defined by the difference between the actual or real and the predicted or forecast value of a time series. In addition, evaluating the RMSE and MAE results, enabled us to choose the best parameters. Consequently, they showed the neural networks models provide better prediction accuracy than the statical models.

In fact, according to the results obtained, it is possible to answer the question ”Is it possible to predict human mobility in a pandemic?” affirmatively. Thus, it enabled us to build a model capable of mainly predicting census at the moment in which we are. Indeed, it has been shown that human mobility can be conditioned based on several indicators. From weather conditions to well-being and comfort, they have shown that the process is comprehensive and extensive, where all types of well-being and comfort influence prediction human mobility in this study.

In the future, we hope to add human mobility indicators such as Movement-based, Link-based, Network-based, Spatial, Temporal and Social in collections of the proposed dataset. Thus, taking their effects into consideration in predicting human mobility will not only be able to improve the prediction accuracy but also many actions can be supported by the use of these indicators that may provide improvements to the planning in several urban areas. Measuring walking or pedestrian crossing (primarily British English) gives a much better understanding of how people really travel and what they need and allows for mobility to be more inclusive. The increase of inclusive mobility could be reached providing a safe and suitable mobility and accessibility features to the largest number of users (especially vulnerable ones), to the greatest number of places, building and maintaining high quality socially inclusive services and facilities. The planning and managing of pedestrian spaces should take into consideration the correct design of paths (also cycle paths), recognizing that the roads are both a social space and a space for mobility.

References

[1] D. Sousa, F. Silva, and C. Analide, "Learning User Comfort and Well-Being Through Smart Devices," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12489 LNCS. Springer Science and Business Media Deutschland GmbH, nov 2020, pp. 350–361. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-030-62362-3_31

[2] F. Thornton, K. E. McNamara, C. Farbotko, O. Dun, H. Ransan-Cooper, E. Chevalier, and P. Lkhagvasuren, "Human mobility and environmental change: a survey of perceptions and policy direction," *Population and Environment*, 2019.

[3] M. Lee, J. Zhao, Q. Sun, Y. Pan, W. Zhou, C. Xiong, and L. Zhang, "Human mobility trends during the early stage of the COVID-19 pandemic in the United States," *PLoS ONE*, 2020.

[4] O. Lawal and C. Nwegbu, "Movement and risk perception: evidence from spatial analysis of mobile phone-based mobility during the COVID-19 lockdown, Nigeria," *GeoJournal*, 2020.

[5] M. De Nadai, A. Cardoso, A. Lima, B. Lepri, and N. Oliver, "Strategies and limitations in app usage and human mobility," *Scientific Reports*, 2019.

[6] A. P. Vanky, S. K. Verma, T. K. Courtney, P. Santi, and C. Ratti, "Effect of weather on pedestrian trip count and duration: City-scale evaluations using mobile phone application data," *Preventive Medicine Reports*, 2017.

[7] D. Loaiza-Monsalve and A. P. Riascos, "Human mobility in bike-sharing systems: Structure of local and non-local dynamics," *PLoS ONE*, 2019.

[8] K. Katevas, K. Hänsel, R. Clegg, I. Leontiadis, H. Haddadi, and L. Tokarchuk, "Finding dory in the crowd: Detecting social interactions using multi-modal mobile sensing," in *SenSys-ML 2019 - Proceedings of the 1st Workshop on Machine Learning on Edge in Sensor Systems, Part of SenSys 2019*, 2019.

[9] I. Blečić, T. Congiu, G. Fancello, and G. A. Trunfio, "Planning and design support tools for walkability: A guide for Urban analysts," 2020.

[10] X. Zhou and D. Li, "Quantifying multi-dimensional attributes of human activities at various geographic scales based on smartphone tracking," *International Journal of Health Geographics*, 2018.

[11] R. J. Dwyer, K. Kushlev, and E. W. Dunn, "Smartphone use undermines enjoyment of face-to-face social interactions," *Journal of Experimental Social Psychology*, 2018.

[12] A. Fadeev, S. Alhusseini, and E. Belova, "Monitoring Public Transport Demand Using Data From Automated Fare Collection System," 2018.

[13] I. C. c. Q. C. S. LLC, "LinkNYC Kiosks: Free super fast Wi-Fi and that's just the beginning." p. 1, 2021. [Online]. Available: https://www.link.nyc/

[14] NYC Department of Information Technology & and Telecommunications, "Find a Link," p. 1, 2021. [Online]. Available: https://www.link.nyc/find-a-link.html

[15] S. Sobolevsky, E. Levitskaya, H. Chan, S. Enaker, J. Bailey, M. Postle, Y. Loukachev, M. Rolfs, and C. Kontokosta, "Impact of urban technology deployments on local commercial activity," 2017.

[16] M. T. Authority, "Transit Wireless Wifi: Product Reviews, Howtos & Buying Advice," p. 1, 2021. [Online]. Available: https://transitwirelesswifi.com/

[17] M. R. E. Department, "MTA Wi-Fi Locations," p. 1, 2021. [Online]. Available: https://data.ny.gov/Transportation/MTA-Wi-Fi-Locations/pwa9-tmie

[18] N. SUBWAY, "NYC Subway Active Stations." [Online]. Available: https://web.archive.org/web/20161005024140/http://transitwirelesswifi.com/active-stations/

[19] E. H. Chapman and K. Lynch, "The Image of the City," *The Journal of Aesthetics and Art Criticism*, vol. 21, no. 1, p. 91, 1962. [Online]. Available: https://mitpress.mit.edu/books/image-city

[20] E. Alatartseva and G. Barysheva, "Well-being: Subjective and Objective Aspects," *Procedia - Social and Behavioral Sciences*, vol. 166, pp. 36–42, 2015. [Online]. Available: www.sciencedirect.com

[21] S. Atkinson, A.-M. Bagnall, R. Corcoran, J. South, S. Curtis, S. Di Martino, and G. Pilkington, "Review team: What is Community Wellbeing?" Tech. Rep., 2017.

[22] OECD Publishing, *OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth*. OECD, jun 2013.

[23] C. Trudel-Fitzgerald, R. A. Millstein, C. Von Hippel, C. J. Howe, L. P. Tomasso, G. R. Wagner, and T. J. Vanderweele, "Psychological well-being as part of the public health debate? Insight into dimensions, interventions, and policy," *BMC Public Health*, 2019.

[24] T. Rath and J. Harter, "The economics of wellbeing," *Gallup Press*, 2010.

[25] U. S. I. of Peace, "Social Well-Being," Tech. Rep., 2007. [Online]. Available: https://www.usip.org/guiding-principles-stabilization-and-reconstruction-the-web-version/end-notes/social-well-being-0

[26] PBS: Public Broadcasting Service, "Physical Well-Being and Motor Development," p. 1, 2019. [Online]. Available: https://www.pbs.org/pre-school-u/pre-school-u-domains/physical-well-being-and-motor-development/

[27] K. Ruggeri, E. Garcia-Garzon, Á. Maguire, S. Matz, and F. A. Huppert, "Well-being is more than happiness and life satisfaction: A multidimensional analysis of 21 countries," *Health and Quality of Life Outcomes*, 2020.

[28] A. L. Bartels, S. J. Peterson, and C. S. Reina, "Understanding well-being at work: Development and validation of the eudaimonic workplace well-being scale," *PLoS ONE*, 2019.

[29] P. Vink and S. Hallbeck, "Editorial: Comfort and discomfort studies demonstrate the need for a new model," pp. 271–276, 2012. [Online]. Available: https://www.researchgate.net/publication/51462478_Editorial_Comfort_and_discomfort

[30] W. Across, W. W. Centre, and T. Centre, "What works well to improve wellbeing," Tech. Rep., 2020.

[31] World Health Organization, "COVID-19 weekly epidemiological," p. 31, 2021. [Online]. Available: https://apps.who.int/iris/bitstream/handle/10665/339963/nCoV-weekly-sitrep2Mar21-eng.pdf.pdf?sequence=1&isAllowed=y

[32] L. Abenavoli, P. Cinaglia, F. Luzza, I. Gentile, and L. Boccuto, "Epidemiology of Coronavirus Disease Outbreak: The Italian Trends," *Reviews on Recent Clinical Trials*, vol. 15, no. 2, pp. 87–92, apr 2020.

[33] C. Zhang, L. X. Qian, and J. Q. Hu, "COVID-19 Pandemic with Human Mobility Across Countries," *Journal of the Operations Research Society of China*, pp. 1–16, aug 2020. [Online]. Available: https://doi.org/10.1007/s40305-020-00317-6

[34] Y. Pan, A. Darzi, A. Kabiri, G. Zhao, W. Luo, C. Xiong, and L. Zhang, "Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States," *Scientific Reports*, vol. 10, no. 1, pp. 1–9, dec 2020. [Online]. Available: https://doi.org/10.1038/s41598-020-77751-2

[35] G. A. Cuomo, "No. 202.10: Continuing Temporary Suspension and Modification of Laws Relating to the Disaster Emergency — Governor Andrew M. Cuomo," pp. 1–4, 2020. [Online]. Available: https://www.governor.ny.gov/news/no-20217-continuing-temporary-suspension-and-modification-laws-relating-disaster-emergency

https://www.governor.ny.gov/news/no-20210-continuing-temporary-suspension-and-modification-laws-relating-disaster-emergency

[36] C. Liu, G. Li, Y. He, Z. Zhang, and Y. Ding, "Effects of wearing masks on human health and comfort during the COVID-19 pandemic," in *IOP Conference Series: Earth and Environmental Science*, vol. 531, no. 1. Institute of Physics Publishing, jul 2020.

[37] R. Parmar, "Common Loss functions in machine learning," 2018. [Online]. Available: https://towardsdatascience.com/common-loss-functions-in-machine-learning-46af0ffc4d23