CityDNA: Smart City Dimensions' Correlations for Identifying Urban Profile

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ABSTRACT

Smart cities evolve over multiple themes and areas with the development of cyber-physical systems and smart services that address several urban issues regarding economy, mobility, environment, people, living and governance. This evolution has obliged the definition of several conceptualization and evaluation models, which respect alternative smart city perspectives. This work proposes smart city profiling with the introduction of the "CityDNA" model, according which, smart city's dimensions' relevance can be captured and visualized. Based on this model, a smart city's profile can be defined and characterized, under a simple comprehensive view of local needs and challenges. A particular smart city scenario is highlighted as a proof of concept for CityDNA and future design and implementation ideas are identified and justified.

CCS Concepts

• Information systems~Information integration • Human-centered computing~Information visualization • Applied computing~IT governance

Keywords

smart cities; smart mobility; smart economy and mobility; city profiles; DNA structure; Greater London areas; city boroughs.

1. INTRODUCTION

Smart cities era has risen and progresses dynamically since cities can improve their status and increase their growth capacities by saving valuable resources, by providing high life quality and by attracting investments. Each city is a "system of systems" which dynamically evolves with respect to time and to multiple and often contradicting dimensions (economy, technology, governance) [1]. Therefore, smart cities have to deal with multiple challenges towards detecting and accurately measuring impact, potential and interoperability of existing smart policies and applications. Several earlier research efforts have been devoted to define and monitor smart cities concepts and measurements of their performance [2], [3], [4], [5], [6], [7], [8]. Anthopoulos et al. [2], in their systematic overview, have concluded that the term smart city describes all types of innovation in the urban ecosystem that address the six smart city dimensions, while Lee and Lee [4] have proposed a new typological framework for classifying smart city services focusing on citizens.

All these works summarize the competitive conceptualization and evaluation frameworks that are utilized in this study. More specifically, they adopt -as well as other scholars [2], [7], [10], [11], [12]- the six smart dimensions, which were initially defined by Giffinger and Gudrun [9]: i) smart economy, ii) smart mobility, iii) smart environment, iv) smart people, v) smart living and vi) smart governance. A city cannot develop a smart profile with only one dimension, but it utilizes interrelations among some or even all of them. For example, smart mobility is highly correlated with smart living, while it impacts smart economy etc. As smart cities evolve, such inter-dimensions' correlations and inter-dependencies can reveal important city's problems and detect unforeseen phenomena which require actions and decision making.

This work is motivated by the fact that based on such inter-dimensions' relevance, a smart city's profile can be better defined and understood, while the optimal management of these interdependencies influence the performance or in other words "health" of a city (i.e., if employment increases, public transportation must take care of corresponding mobility demands). In this context, it is important to introduce an appropriate methodology which will detect complementarities and correlations among these smart city's dimensions. Such a methodology should identify the smart city's profile by offering a comprehensive understanding of a city as an intelligent system and it will moreover be utilized as a driver for decision making and innovation. Furthermore, such an approach will contribute significantly to smart specialization and to constructive resource allocation in a smart city context. In this respect, this paper aims to answer the following questions:

RQ1: how can a smart city profile be conceptualized from the interrelation of its smart dimensions?

RQ2: how can some smart city dimensions be correlated?

Both these questions are important to be answered since the smart city as system has been prioritized and attempted to be examined in terms of energy efficiency and standardization [2]. The novelty of the proposed work is that it explores the interdependencies between the smart city dimensions, in order to structure the urban profile. Challenges are based on the complexities regarding

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correlating data and information originating from smart dimensions and services which deliver different data streams and data assets under varying rates and scales. In this work, a generic model is proposed to detect smart city dimensions' relevance. This model considers the city as a living organism at which its "CityDNA" can be detected and visualized, similarly to the human DNA model which captures complementarity and relevance among different entities. Each dimension has its own helix in the CityDNA model, which evolves over time, while pairwise city dimensions' attributes are related and visualized to characterize the city's liveability and "fitness".

The proposed model is at its design and prototyping phase and this work indicatively provides a proof of concept with a smart city scenario which considers the dimensions of smart economy and smart mobility and their correlation. This particular scenario is prioritized due to the large-scale impact of these two dimensions which are important drivers of the smart city's growth and capabilities [13], [14], and due to the particular interest that data developers pay in the development of corresponding data applications. Inter-relating economy and mobility in a smart city context is inspired by the fact that mobility attributes (e.g. driving to a location) highly impacts economy (e.g. cost of public transport) and vice versa (e.g. unemployment rate impacts ways of people's moves in the city). These two smart city dimensions are characterized by crucial attributes (such as unemployment rates, skills and competencies, transport means, mobility rates, traffic, etc), most of which concern the indexes that define and measure the corresponding dimensions [9]. Therefore, a novel scenario considers the CityDNA model as a driver of inter-relating these two dimensions over particular core attributes. These attributes are based on studies coming from the Human Resource Sciences [15], which demonstrate that people select moving to smart city for skills' and competencies' growth (e.g. to attend university lectures or seminars) and they utilize transportation services. The proposed scenario emphasizes social mining from several sources (LinkedIn, Twitter, Foursquare etc.) and data collection from open data websites (i.e., regarding unemployment and transportation). The outcome of the proposed correlation is to visualize the CityDNA.

The rest of this paper is organized as follows. Section 2 analyzes the CityDNA principles. Then, Section 3 presents the "CityDNA" framework and discusses its expected impact in modern cities, while Section 4 describes a case study related to Greater London. Finally, Section 5 contains some conclusions and future thoughts.

2. CityDNA: PRINCIPLES AND FEATURES

In this paper, the city is considered a living organism, at which multiple interactions and reciprocities shape its life and evolution. Inspired from DNA's role to an organization's well being, we propose to determine a city's "health" condition by the definition and visualization of its corresponding so called "cityDNA".

The Biology Science defines the human DNA as the basic unit of heredity and evolution, which stores information about human's state and captures chances of various disorder cases [16]. DNA information is encoded with four chemical bases: adenine (A), guanine (G), cytosine (C), and thymine (T). The order or sequence of these bases determines the information available for building and maintaining an organism. DNA bases pair up with each other and with specific pairwise relations (A with T and C with G), to form units called "base pairs". Each base is further attached to other substances which synthesize the well known entities which are visualized and arranged in two long strands that form a spiral called a double helix (as depicted in Figure 1a).

Inspired by the human DNA concepts, a simplified model for the city DNA visualization is proposed: data associated with smart city dimensions are utilized to explore potential correlations among them, targeting city's characterization and profiling. This conceptual model is different to existing modeling [2], which considers the smart city as a typical component-based system. In an attempt to synthesize and validate the potential of this concept at this early stage, two smart city dimensions are taken and analyzed.

Figure 1a. Human DNA helix

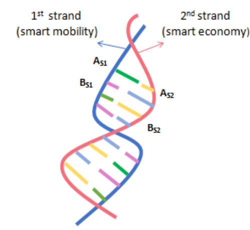

Figure 1b. CityDNA model

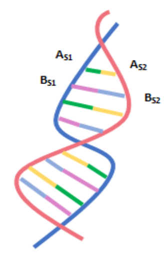

Figure 1c. CityDNA helix (r=±1)

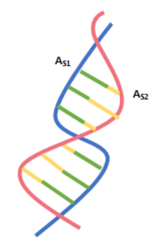

Figure 1d. Mutated CityDNA helix (r=0)

More specifically, economy and mobility dimensions and their correlation were prioritized. This selection was justified earlier and some insight regarding their usefulness and their modeling details remain. The aforementioned two dimensions are defined as the entities that form the smart city DNA's helix. Each city DNA's helix concerns a city neighborhood (or defined district) and it consists of two strands (S_1 and S_2) which correspond to the chosen city dimensions. As depicted in Figure 1b, the CityDNA model defines for each strand (i.e. city dimension), two attributes (A_{S1}, B_{S1}) which are pairwise complementary with the other strand's attributes (A_{S2}, B_{S2}), respectively. For example, in case that S_1 represents the "smart Mobility" and S_2 the "smart Economy" dimensions, the A_{S1} concerns *local accessibility*, which is paired with A_{S2} that concerns *entrepreneurship*; and similarly B_{S1} concerns *availability of ICT infrastructure* which is paired with B_{S2} which concerns *innovative spirit*. These attributes have been taken from the indexes that specify the smart city dimensions [9], and they are pairwise related since they interact and affect local mobility and economy.

In real smart city scenarios, the attributes A_{S1} and A_{S2} are captured in the CityDNA model by datasets which typically are represented as streams of data which evolve over time:

$$A_{S1} \rightarrow a_{S1,1}, a_{S1,2}, \dots a_{S1,n} \; and \; A_{S2} \rightarrow a_{S2,1}, a_{S2,2}, \dots a_{S21,n} \; ,$$

For example, such data streams can be the transportation data from open data platforms and the tourism sector (restaurants, cafes, hotels) incomes.

Correlating the attributes of the two city strands can then be employed by the use of appropriate data correlation metrics, such as the popular Pearson's Correlation Coefficient (PCC) [17] which is defined as next :

$$r = \frac{Cov(A_{S1}, A_{S2})}{\sqrt{Var(A_{S1}) \cdot Var(A_{S2})}},$$

$$\text{where } Cov(X,Y) = \frac{\sum_{i=1}^{n} a_{S1,i} \cdot a_{S2,i}}{n} - \overline{a_{S1}} \cdot \overline{a_{S2}}$$

The PCC ranges from −1 to 1, while when it tends to 1 it is implied that A_{S1} and A_{S2} are under linear correlation; when it tends to 0 it is implied that there is no linear correlation among these variables; and the value -1 represents a completely negative linear correlation. PCC should be calculated for all of pairwise attributes i.e. A_{S1} and A_{S2} as well as for B_{S1} and B_{S2}. If a correlation between these attributes is extracted, then they will be connected and the double helix schema will be formed as shown in Figure 1c. In case no correlation is resulted, the helix will demonstrate its mutated attributes, similarly to new attributes' consideration (see Figure 1d).

Taking into account that the values of these attributes change over time progressively (daily, weekly etc.), the length of the attributes' lines in the CityDNA's plot, will also vary accordingly. Each helix turn will occur according to a pre-defined criterion (i.e., a helix strands curve can turn direction once attributes' correlations change or when certain patterns are reached). For the purposes of this paper, it is assumed that a turn will take place at specified intervals, which can either be pre-defined or can be adapted to new data streams arrival.

With the above conceptualization, the CityDNA can indicate city's "healthy" or "mutated" attributes per neighborhood and at the same time multiple helix figures can offer neighborhood comparative views. This model will easily indicate points of success (strong correlations), points of failure (mutations), as well as hidden knowledge especially in cases when unforeseen attributes relevance is revealed by the CityDNA helix.

3. CityDNA: PROPOSED FRAMEWORK DESIGN

The CityDNA principles require a novel framework which will support the above conceptualization and it will enable the development and testing of use cases. Such a framework is at its design phase and it is based on a smart city scenario at which the CityDNA will be employed for the two dimensions of the smart economy and the smart mobility.

This framework will enable results' generation that will synthesize each CityDNA double helix with data changes over time and per neighborhood (i.e., the CityDNA generator will result in many helixes (as many as the defined neighborhoods)). The initial DNA formulation will be based on data collection and analysis from neighborhoods' data sources, while real time social mining results will be combined with updated data from neighbourhoods' datasets.

The proposed framework considers the next components (see Figure 2):

Data Collector: This component will collect and store the appropriate data streams from social media (i.e., location, occupation, gender etc.), historical and census data retrieved from municipality's websites, as well as online data from city service platforms (i.e., datasets of unemployment rates, people without skills, public transportation and cycle use, etc.).

CityDNA generator per neighborhood: The CityDNA generator concerns the DNA visualization and monitoring tool that will carry out the correlation analysis and synthesize the city's profile. This component will operate according to the methodology described in Section 2 and the datasets retrieved from the Data Collector. According to the presented scenario, the results concern the interrelation of smart mobility (with chosen attributes A_{S1} and B_{S1} concern the transportation means in a city) and smart economy (with chosen attributes A_{S2} and B_{S2} concern the labour market).

Authorities and Markets: This component concerns the end users of the CityDNA generator (i.e., local government, local markets, etc.) that will have access to the city's liveability and "health" with respect to the selected scenario. The proposed design facilitates city's profile perception and it can largely affect local government's views, decisions and policies. Specifically, the CityDNA generator will provide the local government with the ability to monitor the city's profile and to proceed to the appropriate policy interventions or public transportation changes. Furthermore, the local markets will be enabled to monitor the labour capacity, as well as the skills and the availability of local human resources.

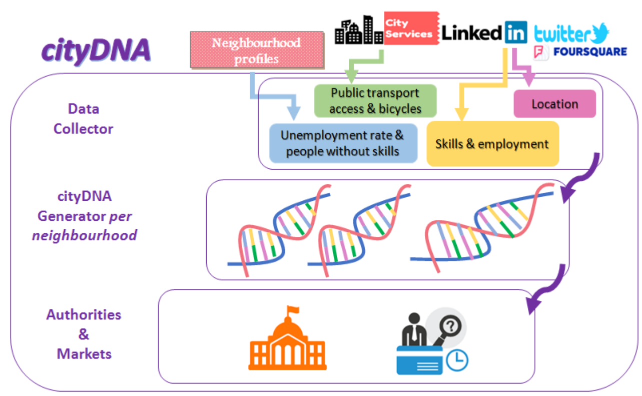

Figure 2. The CityDNA framework

The CityDNA framework can be implemented with on existing and well advanced technology solutions, which will support data collection, data summarization and data visualization. Such technologies will vary depending of the data types and the data processing task. For example, in case of static (relational) data, typical databases schemas and organization will be followed, whether in case of evolving data streams, NoSQL technologies will be utilized to appropriately store and manage the data and their evolving threads.

4. PROOF OF CONCEPT PLAN

Since CityDNA framework is at its design phase, a proof of concept is proposed to test its feasibility potential. To safeguard data availability and large scale of correlations and interactions among data a metropolitan city is an ideal choice for initiating such a proof of concept plan.

4.1 Use Case: exploring London's DNA

The proof of concept plan is proposed for the Greater London region at which multiple connecting communities interact for various economy parameters, while transport challenges are part of city's everyday reality. The specific division of the London city into 33-available boroughs [18] offers the setting for generating 33 different helixes as a result of the different data sources delivered per borough.

More specifically, data regarding the indexes of labor market (1st strand) -such as the unemployed proportion- will be collected, analyzed and correlated with the indexes of transportation (2nd strand) -such as public transportation use and cycling use-. These attributes are chosen due to their high impact on the city's economy and the flexibility to collect data from them out of the city's official sources. Similarly, for the dimension of smart transport, the considered attributes are chosen due to their high impact on the city's transportation and the flexibility to collect data from them out of the city's data streams or from social mining.

However, employment data do not change in time so frequently compared to transportation data and in this respect, this interrelation could be complex. Thus, this potential weakness will be surpassed with an extra scenario of executing and monitoring vocational training to these citizen segments (unemployed and people with no skills). More specifically, this work will utilize the fact that enhancing the labor potential requires training and skills development. In order to generate and visualize data with similar change frequency rates, the CityDNA framework considers training within the smart city environment, which can be undertaken (e.g., by volunteers) and can train specific groups of citizens (i.e., unemployed and working age people with no qualification) on several types of skills. These training activities can represent employment increase, while it requires mobility either from the trainee or from the trainer side that can influence transportation indexes too.

This extra scenario, which is called "social training" service, requires an external app service for its implementation. The social training service enhances the co-creation with citizens and addresses connecting community challenge in cities, since trainers from the borough *x* can be encouraged to be engaged to enhance skills of trainees in the borough *y*.

A correlation analysis regarding the indexes of labour and transport is challenging due to the following rational that will be also addressed under the proposed framework and testing scenario:

1. The indexes of "unemployment rate" and "proportion of working age people with no qualification" (labour market group) are proposed to be correlated with transportation performance ("% of adults who cycle at least once per month" and "average public transport accessibility score" or "daily bus coach count" and "daily pedal cycle count") respectively.
2. "Proportion of working age people with no qualification" could be supported by specific volunteers (trainers) in developing their professional skills (i.e., in simple ICT skills). Volunteers represent people coming from the index "% adults that volunteered in past 12 months" (labour market group).
3. Volunteers could be available in all the boroughs but, they will be tested in the selected ones, which means that the corresponding communities could be connected via trainers' or trainees' mobility.
4. Such mobility would influence transportation demand values ("% of adults who cycle at least once per month" or "average public transport accessibility score" or "daily bus coach count" and "daily pedal cycle count"). Moreover, when unemployed find a job after their skills' enhancement, corresponding transportation demand would increase too.

The external app service (see Figure 3) will offer data to CityDNA framework with the execution of the following process:

1. Collect skill development offers by volunteers in social media (social trainers);
2. Present the above trainer offers to people with no skills or to unemployed and collect expressions of interest (social trainees);
3. Organize classes between social trainers and social students;
4. Monitor with social mining how social trainers move across the city to offer lectures;

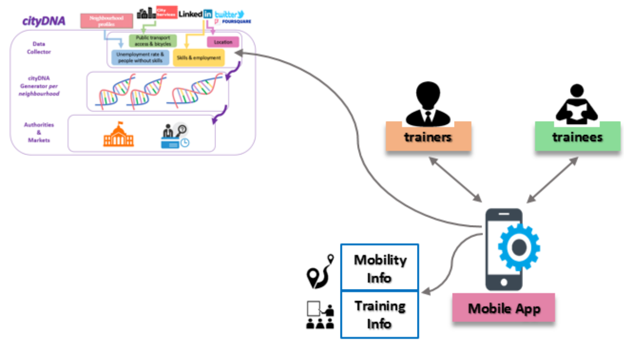

Figure 3. The External Service App

4.2 Data Sources and Scenario Execution

The CityDNA Collector will collect and analyze information from various multiple and appropriate data sources, such as open data sources and social media. The next indicative data sources can immediately be utilized as follows (Fig. 4):

1. A number of boroughs *N* will be identified, out of which, data will be collected for smart economy and mobility indexes and in this regard, N helixes will be structured based on the CityDNA model and framework.
2. The pairwise attributes that will be correlated are the A_{S1}-stands for *"average public transport accessibility score" or "daily bus coach count (London Traffic Counts)"* and B_{S1} for *"proportion of adults who cycle at least once per month" or "daily pedal cycle count (London Traffic Counts)"* indexes; and A_{S2} represents *Proportion of working age people with no qualification* and B_{S2} concerns *"proportion of adults that volunteered in past 12 months" (labor market group)* indexes accordingly.
3. Data for these indexes will be collected from the appropriate data sources. Some indicative such data sources are listed later in this subsection.
4. The CityDNA generator will employ the proper attributes correlations based on metrics such as Pearson's PCC and helixes will be formed to reflect linear correlations or non-correlations (i.e., mutations).
5. The CityDNA interfaces will visualize helixes in a user-friendly pane which will be accessed by the city stakeholders.

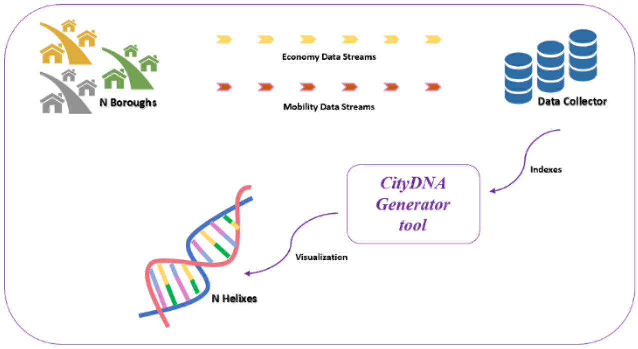

Figure 4. The Scenario Execution

In this paper's use case scenario, the following datasets will be utilized as data sources:

1. ***London Borough and Neighborhood Profiles:*** data regarding labour market and transport indexes will be analyzed for correlation discovery and visualization. Moreover, this retrieved data will synthesize the economy DNA strand on the CityDNA Generator, where the labour market indexes' values will be demonstrated real-time (at least at a day basis) in order for being monitored and recognize a potential effect of the offered social training service. This data comes from the London Datastore[1].
2. ***London Traffic Counts (bicycles, motorcycles, cars, vans, trucks, etc.):*** similarly, this dataset will be analyzed initially with regard to correlation between labour market indexes and transport indexes presented in TfL[2] (Transport for London) and in London Datastore.
Moreover, this retrieved data will synthesize the transport DNA strand on the CityDNA Generator, where the traffic indexes' values will be demonstrated real-time in order for being monitored and recognize a potential effect of the offered social training service.
3. ***Social media:*** the generated app will invite people from several social media (i.e., Twitter, Facebook, Foursquare, LinkedIn). Indicatively, an initial social mining will be performed to LinkedIn profiles, located in the involved boroughs and who express volunteer activity. They will be invited to participate in social training, while profiles of people seeking for work will be also queried.

Economy and transport concern two primary dimensions, which affect local city "health" and in this regard, they structure the double helix in city DNA, across the engaged neighbourhoods (cells). The CityDNA tool will use data from the corresponding sources and from social mining in order to visualize the DNA performance in real-time terms. This tool will enable the local government to monitor the performance of city DNA and proceed to the appropriate policy interventions (i.e., plan cycle lanes) or public transportation changes and in this regard it will co-create the transport service together with the social training citizen activity.

City's health will be based on the values of the 4 selected and observed attributes, which will be measured on a specific time scale (i.e., daily basis). Such a DNA set of helixes will be produced for each borough (organization cell) and in this regard, city's health will be normally based on health performance of each cell.

[1] https://data.london.gov.uk/dataset
[2] https://tfl.gov.uk/

5. CONCLUSIONS AND FUTURE WORK

This paper addressed the problem of smart city conceptualization with means that enable the identification of interrelations between the smart city dimensions. This interrelation is crucial for city monitoring and policy making, since it respects the city-as-a-system approach and the effects that policy measures has to the overall urban system.

In this regard, this paper grounded 2 research questions. *RQ1* questioned how this interrelation can be identified with a conceptual model and the CityDNA model with the helixes and attributes correlation concerns a potential answer. The second research question *RQ2* addressed the feasibility of such an interrelation. Finding correlations between the smart city dimensions is not a simple process and can be based on hypotheses foundation and corresponding testing and correlation analysis. In this regard, this paper hypothesized something rational: the economy and mobility dimensions are normally interrelated and more specifically, when employment increases, then transportation demand increases too (in all mobility types). However, after performing several tests, data collection and analysis with the use of PCC can validate these interrelations. In this respect, the CityDNA framework is proposed, which is at a design phase, it will be tested with data sources from London and it is accompanied by a particular scenario that involves training with the contribution of volunteers (volunteer engagement is something usual for smart cities and it is addressed in multiple service co-design processes). This framework provides with answer RQ2.

Some future direction for this work concerns the execution of tests and the validation of these correlation hypotheses. Certainly, the complexity that will be caused by the inter-related dimensions of an operating city and the various temporal rates applied to these dimensions may restrict and hamper the development of a comprehensive and adequate model, such as the proposed idealized CityDNA model. Nevertheless, the anticipated difficulties will be addressed through the systematic research in the smart cities' field and the establishment of the appropriate assumptions and rules.

Moreover, the engagement of volunteers in training services has to be supported with technology and in this respect, an additional feature will accompany the CityDNA platform, in the form of a so called *Social Training Mobile App*. This will be a mobile application that will support training (trainees will declare their interests; trainees will be invited from volunteers; classes will be structured; mobility options will be identified etc.). Except from supporting this testing, the Social Training App is expected to benefit citizens and communities in general, since connections will be established during social training service execution. Moreover, local businesses will be also benefit from this service, since unemployed and workers without skills will enhance their knowledge capacity in various fields (i.e., project management and ICT skills).

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