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Smart Cities, Big Data, and Communities: Reasoning From the Viewpoint of Attractors

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ABSTRACT In what sense is a city smart? There are established entities defining this rich area of cross-disciplinary studies, and they refer to social, technical, economic, and political factors that keep evolving, thus offering opportunities for constant refinement of the concept of smart city. The emerging properties are mostly contextual, and affect urban data types and their capacity to form complex information systems. A well-known problem in computational analysis is the integration of lot of generated data. The heterogeneity and diversity of smart city data sources suggest that a system's approach could be ideal to assemble drivers of multiple forces and dynamics, suggesting adaptive solutions too. However, the nature of such systems is quite unpredictable and chaotic, leading to the natural aim of stabilizing them. Studies have proposed methods based on various criteria, say parametric, entropic, anthropic etc. As many factors and variables underlie the system's drivers, attractors derived from dynamical systems are proposed to describe smart city contexts through the various interlinked big data and networks.

INDEX TERMS Smart cities, big data, networks, attractors.

I. INTRODUCTION: FROM SMART CITIES TO SMART CITY NETWORKS

The systemic analysis of urban areas has gained centrality with smart cities (SC), a concept presenting a diversity of working definitions centered on a core of dimensions, here summarized as society, institutions, and technology. SC are stimulating cross-disciplinary research, as their contextual analyses extend the several dimensions in many directions ending up with a classification according to *economy, mobility, environment, people, living, governance* [1]. Being this classification one among other subjective ones, a main question remains: in what sense is a city smart?

Simply speaking, only a non-universal answer exists. From such contingency, solutions to make a city smarter should be evaluated according to the associated complexity cost. In particular, elucidating the network of interrelationships between the six component entities is a key factor, as the complexity levels can be quite naturally summarized into network communities. The latter are the most important representational characteristic in networks, and indicate groups of nodes associated because of shared features. Once such features refer to the 6 SC entities, the term SC networks (SCN) seems to us the most effective one in establishing the reference methodological framework [2].

Owing to the fact that SC features are often measurable, their association with data implies high volumes of both analytical and computational work. First of all, a main contribution from such data to the definition of 'smartness' operates through a criterion of connectivity. Consequently, structural linkages are likely present in such data, involving observable patterns and also latent communication circuits that need to be uncovered. In network language, synergies detectable from modular configurations would play a key role, together with contextual information. Notably, this type of information partly explains the data relevance, and partly characterizes the relationships between SC entities, but also offers rationale for strategies and decisional processes designed to exploit the reduction of data complexities.

Networks naturally refer to many possible contexts, including social, media and communication ones, through the same topological features [3], [4], for instance sparsity, skewness, heavy-tailed distributions, short average path lengths. Then, at either node or module scales, degree, clustering coefficient, and centrality (among other network properties) allow for further topological assessment. Communities or modules present connectivity patterns between their participant elements that are significant (i.e. non-randomly), and also distinct, even if the informative

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contents of these aggregates depend on the so-called resolution limit, with reference to the chosen granularity [5]. Therefore, a second important question is: to what degree SC communities are relevant, and how can we measure significance from 6 given entities?

There exists a multitude of relationships and corresponding dynamics that can be targeted within a community map. SCN imply the attempt of identifying possible drivers influencing any observable characteristic. An advantage of networks is that any configuration can be monitored during its spatiotemporal evolution. A main goal is to infer the governing rules of communities, whose nature can be associative, interactive or regulative. An emerging inference strategy is aimed to exploit the synergistic dynamics in network communities, i.e. those not predictable from additive association of the individual components, and possibly revealing causality. In the context of SCN, it seems natural to parameterize the characterizing entities [6], for then deciphering them into measurable categories (communication, transport, etc.). Consideration would go to all urban activities regulating the interconnectivity maps, and determining effects which propagate system wide to multiple scales, affecting human interaction dynamics through communication and information diffusion.

SCN decision processes face the emerging role of collective sensing and swarm intelligence as key drivers in social media. These are determining an anthropic transformation towards neo-ecosystems whose unstable structure justifies conditions of non-equilibrium [7]. Data science [8] may facilitate the understanding of the impacts of the social entity. We cast in a network context particular inferential instruments known as 'attractors', which allow for the analysis of gravitational dynamics of flows across stable and unstable network states. Networks are endowed with regulation and control mechanisms that monitor a multitude of variables at various scales. One of such scales is established by technological developments (sensors, information routers, *etc*.), another scale is determined by the social context (media driving communication circuits), another scale is inherent to the environment and its physical constraints (geographic, logistic, *etc*.). Notably, such factors can be considered subjected to mediation by so-called 'anthropic sensors' [9], those enabled by people with actions and decisions which ultimately define all urban characteristics, and feed with information the available infrastructures (cloud systems, etc.).

II. METHODS: ATTRACTORS

We propose to exploit the potential of attractors in the design of SCN. After introducing them, we provide various representations aimed to emphasize their multidimensionality and utility in identifying multifunctional communities. The urban features we look at include both physical flows and virtual dynamics (social media), both to be considered generators of multi-type transmission mechanisms at SCN level, and capable of adapting to spatiotemporal changes.

Complex human interactions shape human systems dynamics that involve a wide range of ever-changing patterns of behavior at individual and group levels. Analytical models can be derived from the nonlinear dynamical concept of attractor patterns. Attractors are patterns characterizing a deterministic chaotic system. Here, the overall behavior seems random, but is instead complex and determined by a small number of nonlinearly associated variables.

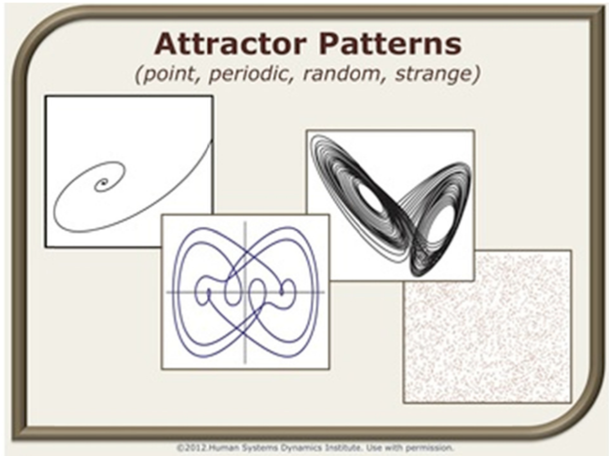

FIGURE 1. Attractor types. Image from http://wiki.hsdinstitute.org/attractor_patterns.

Among the various types of attractors in a dynamical system (see Figure 1), a strange attractor describes a pattern of behavior characterized by bounds preventing the system to move outside of the attractor, and allowing within the bounds unpredictable behavior. Therefore, while at a given time this behavior appears as random, observation of the system across time indicates the presence of patterns that are highly structured. The patterns of strange attractors appear at various levels of scale, but not in predictable way. Attractors are powerful inference tools of human systems considered as complex adaptive ones. Being bounded, such systems have limited variability, but with components appearing infinitely varied and of identifiable shape. Thus, while no component pair shows identical pattern, every component fits coherently with the whole systems pattern.

Since the state of a network at each instant is the union of all the states of the network nodes, observation for a certain period of time allows to monitor whether these states reach a stable configuration (equilibrium or stationarity). This may also be defined in terms of singleton attractors [10] allowing for the analysis of permanent changes in the network due to perturbing events. Conversely, the lack of stability implies the presence of non-singleton attractors, and only transient states would be present in the network.

The attractor state is generally operating under conditions which include proximity to a basin of attraction (BA). Equivalently, BA means the presence of unstable states as neighbors of attractors. Multiple attractors induce multistability in the system, and network states are thus stable ones with the capacity of attracting trajectories from surrounding non-stationary states (the region of BA). One problem is that enumerating the state space components is NP-hard, and a reduction of complexity is usually needed to determine the attractors. For example, a decomposition of the network into sub-networks or modules can help the analysis and allow singleton attractors to cluster according to some specialized functions, also establishing cross-linked modularity in lower-dimensional state space.

The definition of attractors in SCN involves all their characterizing features, a variety that can in turn be associated with the communities, creating conditions of either stability or instability. The latter may or may not be properly governed, but it contributes to the degree of attraction of each component entity in the system. Therefore, attractor states identify conditions under which a city is smart, while the surrounding instability represents residual entropy induced by endogenous and exogenous forces. The system representation is displayed in Figure 2.

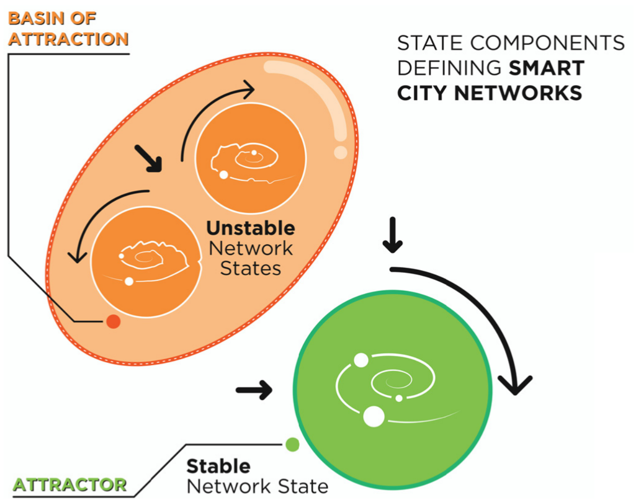

FIGURE 2. SCN context, with attractors dynamics. An attractor is a set of states (points in the phase space), invariant under the dynamics, towards which neighboring states in a given BA asymptotically approach in the course of dynamic evolution. An attractor can be briefly defined as *the smallest unit which cannot be itself decomposed into two or more attractors with distinct BA*. Source: *http://mathworld.wolfram.com/Attractor.html*. The dynamics can be characterized by gradient descent in an energy landscape thus yielding a space partition into basins of attraction [24].

In discrete-time dynamical systems consisting of a locally compact metric space X called the phase space, an attracting set represents a closed subset A of its phase space. The phase space X can be a smooth manifold, for instance an open subset of Euclidean space in which sets of measure zero and sets of positive measure are distinct. Note that it is reasonable to ignore any behavior which occurs only on a set of measure zero, because not observable in any real world application.

The system will evolve towards A from multiple possible initial points, and attractors are minimal entities that cannot be further partitioned. Therefore, what will be described is the asymptotic behavior of typical dense orbits whose union converging towards A is called the basin of attraction $B(A)$.

The concept of attracting set can be defined in different but equivalent ways. Ruelle and Takens [11] and Ruelle [12] have defined strange attractors in the presence of chaotic dynamics and dependence on initial conditions. Strange attractors are also examples of fractals, whose structure appears complicated at any point and scale of magnification.

III. RESULTS

Figure 2 illustrates an abstract configuration of attractors in a space that we assign to SC. We can think about examples of application, therefore. Notably, these maps might recall in stylized form the geography of an urban context. In particular, one might be interested in studying traffic congestion to identify locations affected by this phenomenon and evaluate the effects exerted by the spatial structure. Recently, an interesting study was proposed in [13] on multiplex networks in the context of metropolitan areas.

A common topological property, betweenness centrality, is a good proxy informing about traffic, thus usable to identify congested spots. Interestingly, the introduction of an underground system revealed quite disruptive in spatial distribution effects, determining a shift from internal to peripheral spots of the underground networks. However, a mismatch between the urban areas and the underground networks implies that congestion can be created in sub-optimal locations. In our view, attractors could be the hotspots which parallel the identified congested locations, as these latter are points in which dynamics aggregate together eventually, leaving to other spots more transient and unstable behaviors.

Another possible example involves the spatial analysis of communities within cities [14]. In particular, it is interesting to investigate how connected components emerge with reference to the distance in urban social networks. In this case, the network property we need to look at is called searchability, which establishes relationships between geographic proximity and social distance. The structure that allows this property to take place has not been tested yet in large social networks, and it is quite natural to identify the main bottleneck in the lack of a suitable metric for the assessment of social distance.

Since network communities are associated to dense sub-networks, and many algorithms exist to detect them, once again attractors offer a dynamic view of the same problem, as they represent density regions in the space characterized elsewhere by sparsity, or in any case by structures that do not reach sufficient mass to create dense regions, thus remaining subject to fluctuations and instability.

Lastly, a third example is inspired by studies on interconnections in complex networks [15], and the crucial role of a few gateway nodes, or influencers, that regulate the spread of information to the rest of the network. Clearly enough, once this core of nodes is identified and immunized, the consequences would be relevant for the control of phenomena such as diffusion of large scale epidemic or mitigation of other cascade dynamics that might occur (power networks, for instance). Interestingly, this problem can be mapped onto an optimal percolation problem providing the mathematical framework in which the goal is finding the minimal number of nodes which, once removed, would break the connectivity structure of the network. Attractors visibly respond to such logic, even if probably represent a local representation of the phenomenon that the influencers aim to regulate at a global scale.

As a final observation regarding Figure 2, a traditional aspect debated with networks is the probing of dynamics through perturbation experiments affecting the steady-state activity at the overall network scale. The problem remains how to measure the effects, linearly or nonlinearly, for then establishing measures such as impact, stability, propagation and cascades as in [16]. These same measures, as it is immediate to notice, fit within the domain of attractors.

Links between community detection, controllability and stability-propagation studies can be easily seen as part of a *continuum*. Limitations occur too, naturally enough. One is that communities can only provide a coarse view of the network configuration and organization. Depending on the methods we choose to compute these properties, the correlative dynamics that discriminate between the retained internal nodes and the retained external nodes with respect to a community, a dense region, an influencing set, or an attractor, can be different, and thus not allow direct comparative evaluations [17]. However, with attractors we expect to face systems that are highly non-linear, which implies to study them with control parameters that need to vary in order interpret the occurrence of non-equilibrium, critical transitions between unstable and stable points, and the early-warning signals for such transitions or tipping points [18].

Figure 3 is the synthesis of our methodological proposal, implementing the principles displayed in Figure 2 in a distributed way across identified data source classes. The six canonical entities of smartness are centered on data-driven analysis of economic activity, resource consumption, mobility patterns, etc. Other entities such as technology bursting innovation, organization to manage technology, and policy making to create the context enabling the organization to work, are collapsed into the selected entities.

At the top of Figure 3 we have reported an additional entity, the social one, indeed a meta-entity. Its influence is exerted i) Directly on the system, i.e. at the SC level, and therefore can be regarded as measurable; ii) Indirectly on the system, through the influences exerted on the other canonical entities, which remains difficult to measure. Instrumental to such direct and indirect influence are populations and their inherent relationships, then environmental changes and their human interaction dynamics, socioeconomic vulnerabilities and the adaptation and resilience present at the social dimension. Notably, the social pervasive impact works across all the previous entities. Recent contributions have intensified the reasoning on the concept of virtual dimension, which relates to the anthropic system component [19], [20] a driver influenced by collective sensing [21], [22]. A synthesis could be derived by merging technological sensitivity, aimed at systemic innovations (intelligent sensing), with social sensitivity, aimed at system's functional changes in interaction and communication dynamics (smart sensing).

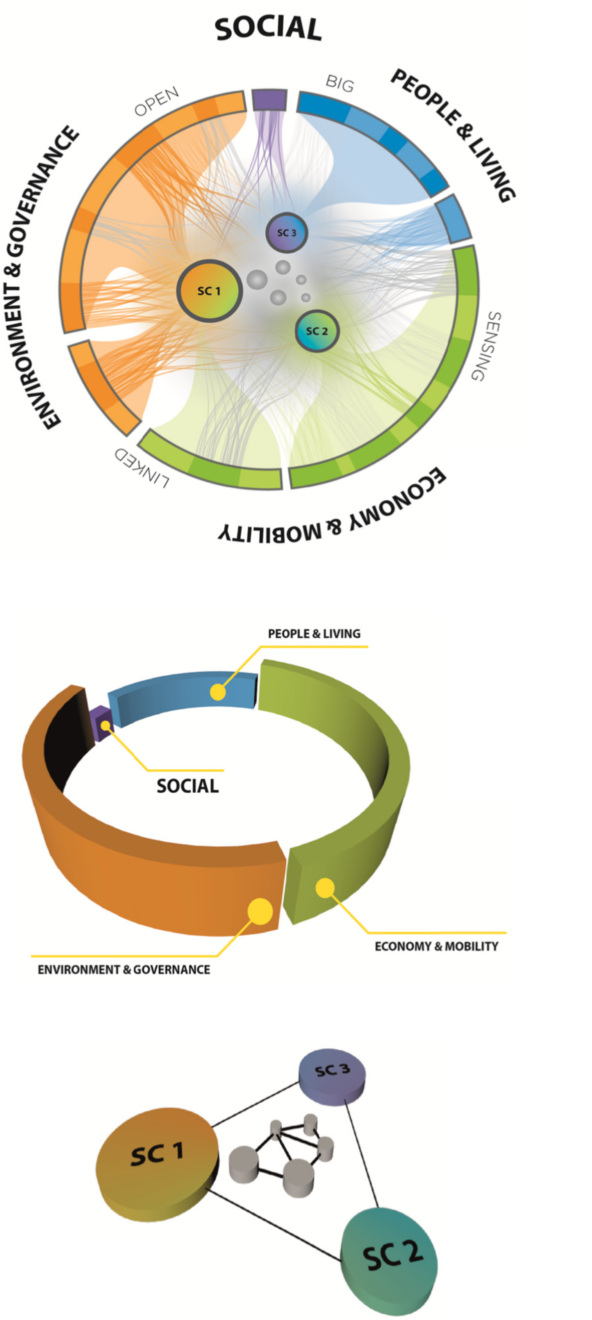

FIGURE 3. Multidimensionality of attractor-driven SCN context. Top Panel. SCN in attractor's view. Outer circle includes the smart entities; Inner circle lists the data types. SC are represented by the main bubbles, while the unlabeled smaller bubbles represent system's instabilities. Central Panel. Lateral view of top panel to appreciate the height of the smart entities addressing relevance and volumes, this in terms of each data type. Bottom Panel. The three SC are set in relation with the instabilities, again in a magnified view compared to the nexus of the top panel. Therefore, three attractors are in communication with each other, and appear as separated from residual instability.

Table 1 summarizes a taxonomy-based knowledge representation referred to such entities and indicators.

TABLE 1. Smart cities taxonomy.

Smart City	Indicator	Variable	Data Source	Data Type
People	Residents, tourists, workers, students	Presences, Arrivals	Exhaustive	Big, Open
Economy	Shopping Malls, Trade Centers, Fairs, Exhibitions, Sport Centers	Consumption, Public	Exhaustive	Big
Economy (cont.)	Banks, Financial Services, Insurance Firms. Law Offices	Transactions, Accidents	Exhaustive	Big
Mobility	Ports, Airports, Railways, Cabs, Uber, Bikers	Transits, Passengers	Sensor	Big, Sensing
Living	University, Research Cent., Schools, Technical Institutes	Classes, Seminars	Exhaustive	Big, Open, Linked
Living (cont.)	Museums, Foundations, Conventions, Art Galleries	Visits, Participations Contributions	Exhaustive	Big
Environ ment	Hospitals, Clinics, Med Centers	Health state, Hospitalizations	Sensor	Big, Sensing
Governa nce	Institutions, Agencies, Lobbies, Associations	Applications, Demands	Behavior	Big, Open, Linked
Social	Members, Community Partecipants	Tweets, fb posts, blogs	Behavior	Big, Open, Linked, Sensing

Entities, indicators, variables, data sources/types. Entities refer to Fig. 3. As indicators, we report a non-exhaustive classification (overlaps might be possibly included). Variables are reported not comprehensively, only as examples. Data sources can be exhaustive, generic, well characterized, and specific. The data types are assigned.

In their construction [9], [23], SC are complex systems consisting of connected components, say physical, functional and anthropic. The smartness refers to the states of such components, and their capacity of self-regulation under the constant influence of technological innovation. Urban activities and functions belong to both physical and virtual dimensions, and this dichotomy is not just perceived, but also measurable owing to the emerging role of crowdsourced and sentiment analysis data.

We identified 4 data types: Big, Open, Linked and Sensing. Common characteristics are identified in the degrees of scale, complexity and completeness. The derived systems may be oriented to one type, but often present a mix of them. In particular, incremental knowledge can be extracted by linked data, i.e. using the Web to connect related data and information which currently appear separately, or also linked but without exploiting the Semantic Web.

Sensing reported as a data type naturally interfaces with the others when information is organized according to common standards such as RDF (Resource Description Framework), allowing the interconnectivity between data clouds in distributed fashion. Challenges, apart from reliability, security and privacy aspects, include fusion of multi-type sensors within decision support systems and interoperability of their user-friendly communication interfaces.

A few examples are now provided in the form of use cases in order to appreciate how the logic of attractors can naturally adapt to SCN contexts.

Use Case 1 (Community Affiliation): We might ask what makes a network community a sort of immune body with respect to various kinds of influences, rather than an integrable unit, i.e. something destined to become part of something else. In general, nodes that cluster together may do so non-exclusively, thus belonging to multiple communities at the same time. In turn, they share multiple dynamics. The effect of this so-called community affiliation [25] is something which characterizes many real-world phenomena. It is believed that higher densities are more likely observed in well separated communities, while their overlapping regions remain sparse. However, changes in the overall community structure may occur such that it becomes difficult to distinguish densities of separate communities and of their shared space. Interestingly, dynamics may induce dense single communities to become sparser, or vice versa overlapping regions to gradually densify.

In terms of attractors, both types of network dynamics – sparsification and densification – influence the network states with regard to their capacity of attracting nodes and forming communities. The overlapping community regions may include marginally relevant or transient dynamics, i.e. those destined to prevent attractors to form, and remaining instead subject to instability. However, novel community-driven dynamics or external factors may often act as effectors, transforming the network states. When a switch occurs in terms of relative densities, such that community overlaps get higher densities than single communities, this dynamic can eventually lead to an attractor state.

Use Case 2 (Information Diffusion): Information diffuses in networks due to exchange between nodes through links. Internal drivers or external influences can induce the diffusion of information at network scale [26]. Typically, it is important to study systems subject to viral attacks. The information flow which is expected to change due to the presence of external entities, may diffuse at rates that depend on the mutual interaction between external and internal entities with regard to the reference system. A dangerous scenario is one in which the equilibrium present in the system is disrupted and, due to the dominance of external perturbing agents, a new attractor state appears. Conversely, internal entities can also re-establish an attractor state, when the perturbation is neutralized. These two possible attractors determine opposite effects in terms of system's equilibrium, but similarly and inherently embody dynamics leading to stable (low-entropy) states or unstable ones (high entropy). Moreover, the perturbation (external force) and propagation (internal force) dynamics may interact differently in time and in space. Viral dynamics ate mostly self-sustained, and propagate by escaping any possible control until a stationary condition is reached, and a stable network configuration is achieved. Before such endpoint, the system remains unstable, likewise an attractor remains a latent state.

Use Case 3 (Pulsatility or Intermittency): Network communication is possibly subject to intermittency, or pulsatile behavior. This generate bursts in the signal dynamics, which in networks are visible through the presence of many decentralized hubs (i.e. highly connected nodes) inducing clustered sub-networks. More importantly, intermittency is hypothesized as the consequence of intertwining between stationary and non-stationary states. This may translate into multiple attractors, due to switching regimes and frequent network reconfiguration. For such reasons, these dynamics may characterize bi-stability (say, with two attractors). Notably, the identification of inflection points related to particular events is a key factor, something which refers also to so-called 'tipping points'. Social phenomena behind such critical patterns can be analyzed in structural or contextual terms. Event pulse dynamics can typically characterize social media and broadcast news, and the focus naturally goes to how words may provide causal reasoning.

Consider Twitter: the text structure is constrained in length, thus communication by this media aims at clear sentences with unequivocal meaning. However, it is likely that pulsatile dynamics under some particular conditions (contexts) occur. For instance, tweet-retweet dynamics can be transient or persistent, depending on the particular topic which is the object of the communication.

*Use Case 4 (MEME Patterns): MEME*s are short phrases (or other content types) that travel through the internet and can mutate. Memes clusters are possible patterns indicating repetitive changes, and identifying for example a specific type of mutation prevailing over the other possible ones during the meme's path. A mutation which is more typical than another one, can thus determine an attractor state, owing to the tendency of the system to return to it (i.e. return to stationarity) from different non-stationary conditions. These patterns can be sorted in time according to their appearance and importance, which can be assessed by the length of exposure time of a certain topic and/or the achieved popularity levels. Mutations can occur because of re-definitions and re-interpretations, false perceptions, errors, error-correction mechanisms, etc. Patterns may change unpredictably (amplifying or flattening out). Finally, these dynamics can substantially differ, depending on the context. When mutations are cumulative along the transmission, several dynamics can be observed, some smoothly deviating (say, gravitating around a main concept) others diversified along the process, and changing dramatically the initial meaning, and therefore inducing convolutions. Only the former dynamics would lead to an attractor state, quite evidently.

IV. CONCLUSION

We introduced the principle of attractors in SCN contexts as a novel paradigm of dynamic adaptation operating in such complex system, in light of the centrality of central aspects such as stability and evolution. When translated into the context of SCN, we have indicated possible sources of information, including those deciphering virtualization, by virtue of the principal role played by the social dimension, and emphasized the perspective of its implementation in cloud systems.

The initial state of attractors is typically determined by input dynamics that change over time towards a different configuration of states. Here, we represented the attractors' potential of naturally modulating stability and instability aspects typical of many SC contexts, involving especially networks. Therefore, the attractor dynamics arise from the interaction among the network nodes. In particular, instability may refer to endogenous system's adjustments affecting the various entities (say, hidden economy, unofficial statistics, inaccurate records of various kind), and may also refer to exogenous factors, perturbations or shocks with the power of determining structural changes (environmental or social emergencies, financial crises, exceptional political events).

Data multitudes populate SCN and are modulated by the attractor dynamics that take place in such systems, originating from a a mix of passive data types (marketing, retail, financial services, electronic medical records, telecom, media etc.) and active data types of social origin (crowdsourcing from blog, tweet interactions and aimed to propel sales, products development and customer services). The role of sensor-driven data is likely becoming pervasive, and integrate the other two data types in many urban contexts (traffic, pollution, climate, etc.).

Finally, other relevant impacts are expected once predictive models of connectivity between the data become available, and can be measured in relation with urban services (from planning to emergency control) in terms of the optimization achieved in the usage of resources. In particular, the discovery of significant patterns and signatures from collective traffic data in many contexts will allow a separation between good and bad types of data, and thus a better approximation of the value and impact of collective sensing.

Especially social influences, those referred to decisions and actions that starting from individuals can be replicated at a larger community scale, represent a new human interaction dimension. Both macro-influences (diffusion phenomena such as epidemic) and micro-influences (in relation to smaller assemblies) need to be investigated in depth to assess transient and persistent effects, the relevance of novel interaction dynamics between individuals, and early warning signals enabling timely correction mechanisms.

***Nihil est magnum somnianti**: Cicero*

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