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Computational Intelligence and Citizen Communication in the Smart City

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Abstract Information and communication are at the core of the intelligent city of tomorrow, and the key components of a smart city cannot prescind from data exchanges and interconnectedness. Citizen communication is an integral part of the smart cities development plans: freedom of information and involvement in collective decisions, e-democracy and decision making feedback can be greatly enhanced in an intelligent city, and, among the other smart city components, foster a new era of partecipation and wise decisions. In this contribution we discuss a description of the methodologies that can be implemented in order to correctly develop automatic recognition systems for citizen communication, with special attention on Computational Intelligence approaches, and how such methodologies could be usefully employed in the essential task of understanding linguistic registers, and suggest how the use of argumentation techniques can be beneficial to citizen communication.

Keywords Smart Cities, Citizen Communication, Computational Intelligence

1 Introduction

Information and communication are at the core of the intelligent city of tomorrow, and the key components of a smart city cannot prescind from data

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exchanges and interconnectedness. When we discuss smart cities we tend to imagine a place based on a different concept of communication, encompassing both traditional infrastructures such as the telephone, mobile communication and web access and new means of data gathering, and especially means that are fast, cheap and ubiquitous, such as sensors and distributed intelligent components, integrating everything from personal objects to urban fixtures. Smart cities represent a step beyond usual one to one communication, and integrate the path of information across devices and users via an extended mesh of mobile and static sharing points. In this context the communication among citizens when finalised to policy discussion and decisions, and between citizens and public parties, which goes under the general term of citizen communication, is often imagined as a purely automated and transparent process that occupies a sort of background noise in the general flux of information. This is an unrealistic, unattainable idea: for one, smart cities will increase, not decrease, the need for communication and public discussion; and more, as long as a city, smart or not, will be built for humans by humans, as much may they be assisted by technology, the need for interaction with decision makers and public servants will not be exhausted by the pressing of a button or the measurement of a sensor. Citizen communication is an integral part of the smart cities development plans: as recognised by the Fraunhofer Institute, "newly accessible municipal information represents a significant development not only in the sense of public access but also in regards to general transparency. Smart cities make it easier for citizens, institutions and businesses to access information. Freedom of information and involvement in communal matters can be greatly enhanced in an intelligent city, of course in total compliance with data protection regulations and based on the reliability of data transmission. The development of new information sources and the constant exchange between users and public infrastructure combine to take communication to a new level. However, this not only applies to the communication infrastructure but also the content and the availability of information change. [...] Smart cities are meant to make data from municipal administrations available for everyone. Whether it is the current traffic report, environmental data like air and water quality, pollen count or the faster and more efficient exchange between public authorities – communication in the public sector has an immense potential for development and offers new opportunities for making everyday life easier." [29] Smart support of this kind of information exchange toward e-democracy and citizen communication requires a huge step forward in many research topics related to Artificial Intelligence (AI). The problems connected to an useful automatisation of citizen communication will constitute in our outlook a perfect workbench for the state of the art: this research field will require a massive use of innovative technologies, a deep comprehension of linguistic registers – including the intricacies of human communication – and possibly the use of formal structures in informal ways, such as argumentation. These are good reasons to watch with attention the development of this research sector, especially for its relationship and links with Computational Intelligence and the methods that are more suited to information retrieval and manipulation when dealing with typical natural language phenomena in citizen communication with the public sector especially considering written text, such as incomplete, imprecise and missing information, uncertainty, heavy dependence from the context.

In the present contribution we will briefly discuss a description of the methodologies that can be implemented in order to develop working automatic recognition systems for citizen communication, with a special attention on a Computational Intelligence approach. We will then discuss how such Soft Computing methodologies could be usefully employed in the essential task of understanding linguistic registers, and conclude by suggesting how the use of argumentation techniques can be beneficial to citizen communication. This paper is not a review of all the Computational Intelligence methods involved toward a solution of all human communication problems, neither a detailed technical exposition of some of them. The idea is to give an informed, but non-specialised reader the gist of how some of such methods are and can be employed to improve the automatic support to citizen communication, and why it is essential for the development of smart cities by and for humans.

2 Computational Intelligence and Citizen Communication

Computational Intelligence methodologies try to emulate the human mind's ability to solve problems in contexts where information are incomplete, vague or ambiguous. In such scenarios, classical algorithms (i.e., those based on crisp inference rules and exhaustive search) are unable to provide a solution within a reasonable amount of time, especially when dynamic environments are involved. By taking inspiration from the characteristics of human reasoning, soft computing techniques try to find a sub-optimal, approximate solution that satisfies some requirements and assumptions apt at reducing the space of possible solutions. Many of such methodologies, especially those originating from the early days of soft computing, are a natural match for cognition, and are rooted in the basic idea that human cognition is not necessarily based on syntactical inference rules, but evolved to make some sense of a complex reality, too complex to be reduced by arithmetisation, but needing contextual selection, a nod to the uncertain nature of human exchange of information and subjective probability as a rule of behaviour. We have devoted a number of philosophical papers on the foundation of Fuzziness, which can be seen as a precursor of many Computational Intelligence techniques [43, 41, 36, 40, 39, 38, 32], some of which we briefly outline in the following:

Metaheuristics is a general term for a class of algorithms designed for finding approximate solutions to problems whose exact solution is hard to compute as they involve uncertainty, incomplete or imperfect information. Metaheuristic algorithms typically employ two kinds of tradeoffs: i) they look for a sub-optimal solution when exact solutions are difficult to find, and ii) they involve a careful planning and systematisation of the parameters reducing assumptions about the problem and relying instead on a wider exploration of the space of solutions. These two aspects make Metaheuristics a good fit for cognitive endeavours, as they both mimic those modalities of the human reasoning that were previously discussed: the idea of settling for a solution that may not be the best possible but that satisfies other, more stringent requirements (attainability, speed, practicality) as well as exploration, trial and error, collaboration and cooperation and further refinements.

Popular Metaheuristics that are used in the context of smart cities development and communication include but are not limited to simulated annealing, tabu search, local search, variable neighborhood search, ant colonies, particle swarms, evolutionary computation, and genetic algorithms, and have been applied to urban transportation [28], geographic information (Geospatial Analysis) [12], traffic and transportation systems [11], planning the adoption of strategies to promote sustainability [23].

Computing With Words (CWW), as its name suggests, is a computational methodology aimed at replicating human-style reasoning with words in natural language. As its father Lotfi Zadeh put it, "the role model for CWW is the human mind" [48]. In CWW, words are usually modelled in the form of fuzzy variables. It is sometimes claimed that CWW overcomes some limits of arithmetization by replacing numbers by words. Indeed, it has been argued that the failure of some theories of language has to do with those intrinsic properties of natural language [20] which cannot be captured by the mere application of syntactical rules. In the Smart Cities context CWW has been used e.g. in the analysis of linguistic phrases describing symptoms for diagnostic assessments of medical conditions [5].

Fuzzy Classifiers are a method of classification that works by stressing the significance of linguistic variables. Conventional classifier produce no further insights from a cognitive point of view. Fuzzy Classifiers output includes a linguistic model that is open to further analysis and interpretation by the users where information from different sources (the one from expert knowledge and from mathematical models or empirical measures) is joined and harmonised. Applications of Fuzzy Classifiers in smart cities development include e.g. economical planning [2], and collective resources management [1].

Fuzzy-based Ontologies incorporate implicit information in a complex ontologic system, and make the relationships between objects more adherent to reality and clearer to decode. Fuzzy Ontologies play a significant role in Theory of Concepts, supplying a compatibility layer in the framework of an intensional approach, another traditional problem with traditional ontologies. Applications in which Fuzzy Ontologies are employed in the domain of collective communication and development include weather forecast [44], crisis and emergency management scenarios [18], finding appropriate data in different corpora pertaining to patients' healthcare needs [30], and other social interactions [33]. In this context the idea of Fuzzy Cognitive Maps can also contribute to the handling of knowledge (see e.g. [24]).

2.1 Practical examples of Computational Intelligence applications to Citizen Communication

We now briefly present two examples of soft computing techniques employed in the setting of citizen communication, in order to provide the reader with some insight into the real implementation of the techniques described above.

2.1.1 Fuzzy linguistic textual sentiment analysis

Lack of clear or adequate communication among citizens, politicians and civil servants is a frequent source of problems in the management of the public good. An ineffective citizen communication constitutes sometimes a serious obstacle to democracy: the idea of democratic control through interaction and the a subsequent choice – usually implemented as the voting process – whose selective powers should be based essentially on the evaluation of political actions' consequences (something that in a smart city should be easier to quantify and whose relative information should be by definition open and accessible), and on the communication between decision makers and citizens (something which, as already stated in the introduction, has to be mediated by language, and by its very nature can be automated using Computational Intelligence techniques). In modern democracies a significant part of written correspondence (e.g. advices, complaints, applications) is directed from people to local governments. Governments can use these text to gather opinions without having to resort to polls, and evaluate levels of satisfaction to take action against collective problems. However, the manual extraction and analysis of every piece of information included in these text is a rather cumbersome process. The automated analysis of texts can help with this, by extracting the sentiments expressed by citizens in their communications.

Sentiment analysis methodologies can help not only to extract the category of messages (from social network posts to complex emails) but also to identify the feelings expressed by their authors, using Fuzzy Linguistic Concepts. It is possible, e.g. using available online tools and frameworks such as Google Prediction Framework [19], to develop a model that can help to classify new pieces of text by means of machine learning algorithms [8]. The construction of this model constitutes a preliminary phase during which the presence of feelings in the content is assessed. The emotions that we are looking for were originally described by [16]: happiness, sadness, surprise, fear, anger and disgust. In written communication the use of linguistic labels to express that we are "very angry" or "mildly happy" is very common. To improve the quality of analysis and to capture the different gradations of expressed feelings the use of an hybrid fuzzy systems based on Fuzzy Markov Chains can be employed to produce emotions annotated with fuzzy quantifiers that represent the weight of the sentiments extracted. We briefly discuss here a sentiment evaluation and analysis system we have devised, based on fuzzy linguistic textual analysis, which is able to help to identify the main feeling expressed by a short-to-medium-length text (e.g., a letter, a brief news piece, a social network interaction, a forum message), the presence of sub-feelings and their intensity [15,31]. In our view fuzzy concepts are a good match for emotions, as i) emotions come in different intensities, and this is usually rendered in the linguistic dimension using appropriate linguistic labels: "a little", "not much", "slightly", etc., ii) primary emotions are not mutually exclusive as it is sometimes erroneously assumed in classification, and texts may involve a mixture of them. Our algorithm is divided in two phases: a pre-analysis, in which the corpus as a whole is analysed using a classical approach aimed at quantifying the inclusion and the relative value of each feeling, snippet by snippet. In a second phase that utilises the Fuzzy inclusion of such expressions, interaction prediction correlating the possible range of emotions with the previous interaction between two users is studied. Data obtained from both phases helps computing appropriate feelings for each text, that in order to facilitate communication can also be portrayed by emojis, using an hybrid fuzzy system. This process (which is described in more detail in [31]) can be summarised as follows: an institution A produces a text which is read by citizen B who reacts by expressing some sentiment about it. An analysis of text for specific terms which are known to represent specific sentiments is accompanied by the search for quantifiers in the vicinity, to assign to each term a degree of membership to the set of a specific emotion. The same process used to discover the feelings linked to the presumed objective opinion expressed in a specific text are then employed to form a sentiment prediction and its gradation. A head start to the algorithm is given by the use of Google Prediction Framework [19], that trains a model using a training set of SN contents acquired randomly from public profiles, already manually labelled by users using Ekman's emotions. Once the training phase is completed, the obtained model is employed to predict the label of new data sharing some basic characteristics with the training set using a fuzzy membership degree of the term to the corresponding feeling. A constant updating of the model, which allows for predictions on the current text is implemented via Linguistic Fuzzy Markov Chains. Mixing Fuzzy Classifiers for sentiment prediction and Fuzzy Markov Chains as an update mechanism guarantees a significant improvement with respect to the standard use of Fuzzy Classifiers, especially in the instance of iterative and multi-party communication, as it often happens to be the case between citizens and authorities.

2.1.2 Medical Dictionaries

One of the main topics in smart cities research is the administration of health care services, especially when the elderly and extremely severe medical conditions are involved. A sometimes overlooked aspect in this context is the written interaction between patients and healthcare professionals: it is often the case that texts produced by experts make use of complex lexicon that might prevent the correct transmission of information about symptoms, diseases and remedies, as the medical field is very broad and an advanced knowledge of the medical vocabulary is required for a correct understanding of the meaning of a report [47,25]. The problem is amplified e.g. when the choice of a therapy depends on the patient's exact understanding of a report. However, the problem of reducing the complexity of a medical report requires a targeted effort from the experts. An automated system that supplements medical texts in traditional form through the translation of specific terms to more uniform and comprehensible terms, and adds further information in plain text in order to support the uninformed reader in comprehending the exact meaning of the text and formulating eventual questions and request for clarifications would fit perfectly in the citizen communication paradigm. Fuzzy Ontologies and CWW are good match for the intrinsically imprecise nature of the problem. Such a system could take advantage of the existence of online dictionaries, vocabularies and thesauruses such as the 'Unified Medical Language System' (UMLS) or the 'Open Access Collaboration Consumer Health Vocabulary' (OAC-CHV). Using techniques based on CWW, we have built an automated fuzzy system that, starting from an arbitrary medical text, enriches the input with annotations obtained from Fuzzy Ontologies, by translating technical terms into simpler words. The system takes as input an arbitrary text and, using the vocabulary, extracts all the technical terms in the area of the chosen subject and connects each term to an equivalent consumer terms using the ontology built using the thesaurus. The research of related terms is not restricted to technical words that have a consumer translation but also extended to synonyms retrieved by a consumer dictionary. This definition will also be processed by the whole system and transformed in an annotated hypertext that highlights the technical terms so to allow the user a deeper analysis and friendlier navigation through the text. Mapping between terms is taken care of considering the fuzzy degree of significance for each term, calculated by building a Fuzzy Ontology built by weighting the contribution of the term in each snippet of related text, and recreating OAC-CHV links in a fuzzy fashion using FuzzyOWL2. Using this system, the precise meaning of technical documents can be easily grasped by patients without any previous knowledge of medical terms, and can improve the ability of subjects without a specific background to understand and make informed choices. This in turn may be used to enrich automatic interaction and care options with the patient.

3 Linguistic Registers and Citizen Communication

An effective communication between institutions and citizens should consider feedbacks from the citizens side, and while it is desirable that there exists someone who actually reads them, it is often an unrealistic scenario. In order to get a summary of the comments from the public it may be useful to employ Sentiment Analysis, a tool adopted e.g. by politics and companies in order to understand the effectiveness of their marketing campaigns. Social media are the favourite sites where to allow such a kind of communication because of both the huge number of people subscribed and the kind of communication that is allowed in them which is naturally divided in topics, for example with comments to posts or direct answers. Sentiment Analysis makes it possible to extract sentiment from texts with different granularities, where simplest is the ternary one, that is positive, negative and neutral, but finer grained granularities are possible too. A finer granularity makes it possible to distinguish between different levels of enthusiasm, but usually the performances of SA software deteriorate with the number of possible outcomes. Hence, a trade-off must be taken between the level of detail and software quality. One well known open problem relates to the inability of existing sentiment analysis algorithms to detect particular linguistic registers in texts, thus obtaining a wrong classification about the real meaning of a sentence [27]. Some of the registers often included in human communications are sarcasm, irony, nastiness and attack. Each of them represents a particular way of expressing ideas: irony and sarcasm (usually treated interchangeably) express a sentiment that is different with respect to the one directly assigned to the text; nastiness and attack usually are an expression of pre-existent hatred due to several factors that can also be personal or political. So, while these kind of registers are expression of a negative sentiment, a correct analysis may want to treat them differently.

3.1 Irony and Sarcasm detection

In recent years there has been a flourishing of studies regarding irony and sarcasm detection on texts captured from several social media such as Amazon (reviews), Twitter, Reddit or other online forums. The main approach models the task as a binary classification problem that uses statistical machine learning techniques. The two classes to detect are ironic (sarcastic) and not ironic (not sarcastic). The main challenge is to find a viable way of representing texts in order to allow a classifier to work.

3.2 Document level vs. Sentence level classification

The first issue to face when solving opinion mining tasks on textual documents is the one of selecting whether to tackle the problem at the document level or sentence level of detail. Document level classification aim is to detect whether a whole document uses sarcastic tones regarding its subject, or if the document contains sarcasm. Sentence level classification provides a binary label for each sentence. An example of document level classification is found in [17] which collected a corpus of Amazon reviews by asking to the labelers whether each text contains sarcasm or irony, and asking to provide at least one utterance as a proof of the actual presence. Eventually the binary label is given to the whole document. The main drawback of such kind of approach is the total absence of cues about the position of the sarcasm in the text, but in return the sarcastic utterances are provided with a lot of contextual information. A diametrically opposed approach is the one proposed by [13] who segment texts in sentences and provide a binary label for each sentence. While they obtain good results in finding structural patterns of sarcastic sentences, those are not contextualized, thus making difficult to understand if some sarcastic sentences are misclassified due to lack of information. Most of the studies in this field don't face this ambiguity because they make use of data collected from Twitter, where the 140 characters limit makes very hard to distinguish between the two levels of detail.

3.3 The problem of labelling

Sarcasm detection, being treated as a supervised learning problem, needs an accurate labelling of samples in order to be tackled effectively. Due to the need of labelling a huge number of texts, the only viable way to collect a corpus is to hire people to do the job. Moreover, sarcasm detection is a hard task for humans too, so each text is usually presented to multiple persons before assigning a label to it. This fact makes hard to collect huge datasets, which allow better generalization properties. In fact, training a classifier over a small training set could make it good at recognizing sarcasm for the topics which are treated in the data set, but totally unable to perform when new topics arise. This is crucial as public administrations make decisions over several sectors of public life, that do not necessarily connect linguistically: garbage collection has a totally different dictionary than building policies. Some strategies have been used to automatize the labelling process to take advantage of the high availability of hinted examples over the internet, such as Twitter texts containing hashtags such as #irony, #sarcastic, #sarcasm and so on. The drawback in this approach is the belief that no hashtags would be needed if the sarcastic intent was clear by the text only. This would mean that the sarcastic tweets does not contain enough information to let even a human to understand the sarcasm contained within. Another approach uses bootstrap to obtain new labelled samples by starting from a relatively small set of labelled data. This method has been used with some variants. [45] extract patterns using a search engine to search the web for sentences similar to the sarcastic ones, and exploited the fact that usually sarcastic sentences does not occur alone in texts, in order to retrieve also "accompanying" sarcastic sentences. The increasing in performance they got show that this kind of bootstrap actually works. A second bootstrap method has been used by [26] on Internet Argument Corpus [46] Two high-precision classifiers (where precision is given by the number of true positive divided by the sum of true positives and false positives) have been built, one for the sarcastic class and one for the non sarcastic, by extracting patterns from the sentences to use as training data. These two classifiers (implemented as Support Vector Machines) are then used to label with high confidence unlabelled texts from the corpus. The bootstrap process is a cyclic one, and new labelled data are used as part of the training data in order to improve the original classifiers.

3.4 Feature Engineering for sarcasm detection

CWW is an appealing framework to work with on natural language texts. One possible application that is been worked on is its application to classic NLP techniques, which involve the vectorization of texts by means of feature engineering. [34] analyse a Twitter-extracted corpus by using four different features: signatures (textual elements that throw focus onto certain aspects, such as punctuation marks, emoticons, quotes and capitalized words), unexpectedness (a numerical value that represents the surprise that a sentence should elicit in the reader), style (frequent repeated sequences of texts that allow to distinguish two different writers) and emotional scenarios (activation, imagery and pleasantness). The features provide us with a representation of a text which spans several level of abstractions, spanning from the mere counting of signs in the text to psychological effects of words, and the implementation of word definitions through CWW will represent a marked improvement over the simple binary classification offered by traditional methods. [4] introduce a broader set of features for tweets, divided in six categories that are Frequency, Written-spoken, Intensity, Structure, Sentiments, Synonyms, Ambiguity. The ownership of parts of the text to these categories can be represented by the accurate use of Fuzzy Sets, this way rendering the inferential process of computing the feature classification a straight-on application of fuzzy operators to the class membership. None of the above approaches use words as features, neither in bag-of-words nor in word embeddings form. Bag of words methods have been widely used in classical text mining tasks, especially information retrieval. [9] report an increase in performance by adding a bag of words representation, albeit using a small data set in which there are lots of words that occur in just one of the two classes. Once again, the use of fuzzy operators to better discriminate between the classes would improve significantly the end result, and would also allow an uncertain classification of text, which would enable a better control over automated delivery of texts toward specific decision makers in citizen communication.

4 Putting it all together: argumentation and Computational Intelligence

In previous sections we have presented a simple scenario in which an institution writes a post and a citizen reacts to it, eventually producing a text with emotional content, and some possible Computational Intelligence techniques to attempt at recognising and handling such emotional content. We now wish to conclude by introducing a formal framework which is suitable for dealing with even more general scenarios in which citizens support or attack their peers' point of views by producing recursively nested contents. If the institution wants to make sense of it all, typically to make a decision based on citizens' feedback and gain consensus, other techniques must be employed, which combine all the contributions together in order to provide an overall view on the structure of the argument and its ramifications. Recent developments in European internal politics, especially when dealing with hot issues such as economy and immigration, have shown how the lack of a more formal treatment of the relationship between facts and consequences can lead to unexpected and damaging decisions, both from the decision makers and the general public. Smart cities, with their ample availability of open data should act as a facilitator for more informed decisions, but as the data at citizens' disposal becomes bigger and deeper, the need for a reasoning system that helps navigating toward a compute implementation of e-democracy will require a development of argumentation techniques, whose implementation using Computational Intelligence methodologies has recently been at the upfront [22, 37, 35, 42]. In [14] a general framework for argumentation was introduced, based on the commonsensical principle that "The one who has the last word laughs best" which Dung illustrates with the following toy example: suppose that two people A and B, whose countries are at war, argue about which country is responsible for stopping negotiations by providing the following arguments:

A: "My government cannot negotiate with your government because your government doesn't even recognize my government."

B: "Your government doesn't recognize my government either."

According to our common sense, such mutual responsibility attribution would result in nobody winning the argument over their opponent. However, if an another argument attacking B was added, e.g.

C: "B's government is a terrorist government"

this would allow A to claim victory over B as B's argument is somewhat lessened by C's objection. In this case, C has the "last word" and since no other argument is attacking C, we can reasonably conclude that A has won the argument. Argumentation, at least in its original formulation, laid the basis for a scientific account of this simple mechanism by representing the structure of arguments using a directed graph AF=$\langle$AR, Attacks$\rangle$ in which the set of vertices AR contains the arguments, and the set of edges Attacks is used to specify which argument attacks which; in the previous example, AR=A, B, C and Attacks= (A,B), (B,A), (C,B) (where with an abuse of notation we have identified A, B and C with A, B and C's arguments respectively). The argumentation semantics then defines which arguments are "acceptable" in a given setting (in the original Dung's framework, it is the case that A and C are acceptable in the previous example). Due to its simplistic nature, it is not difficult to imagine that difficulties and counterintuitive results can be obtained from this framework. This motivated its extension to more sophisticated cases for instance by taking into account the internal logical structure of arguments [7], by adding the possibility of arguments that support other arguments [10], or by considering the strength of attacks, expressed in the form of probabilities [21]. This arsenal of techniques, in our view, can be appropriately used and extended to enhance citizen communication in several ways; in fact it has been used e.g. for supporting decision support, persuasion and planning in e-Democracies, Medicine and Law [3]. On a superficial level, it provides a ground onto which conflicting arguments can be analysed to work out which arguments are rationally acceptable on the basis of the available data. This can be exploited, for example, by institutions to produce justifications for their decisions that are sound with a large basin of citizen-provided arguments, while enabling citizen themselves to participate to discussions (through the use of e-Participation tools, see e.g. [6] [3]), with a guarantee for their arguments to have an impact on the institution's decisions provided they are rationally sound with respect to the given argumentation semantics. In our view, an integration with the soft computing tools for Sentiment Analysis introduced in the two previous sections would provide institutions with a double edged weapon and would have a strong impact towards the realisation of platforms which can be used for practical reasoning about human emotions on a large scale due to its proven ability of dealing with complex object such as emotions; indeed, it is often the case that arguments are won not only on the sole basis of rational scrutiny – in fact, emotions, sarcasm, confidence of the speaker and many other factors contribute to make an argument successful or unpopular in an open debate. By analysing such features and combining them into an appropriate argumentation framework, an institution would then be able e.g. to spot emotionally-driven reactions to its decisions and to tune its strategy accordingly. For example, a "populist" institution could respond by trying to please those citizens who are strongly biased by emotional contents, or, on the contrary, by firmly objecting to inconsistencies in popular arguments.

5 Conclusions

Citizen Communication is an integral part of the strategy for the development of the smart cities of the future, and as long as a channel of communication between citizens and decision makers will be needed, Computational Intelligence techniques and methodologies will help further development and refinement. Recent advancement in AI using Big Data and statistical methods, such as IBM Watson ability to beat humans at their own reasoning games comes, on top of the finesse brought by cognitive algorithms, from the contextualisation of a wealth of well connected, curated and expanded information about the state of the world. Other similar results applied to autonomous vehicles have still a strong root in Big Data and require the ability to discriminate useful information in real time amongst floods of semi-unstructured data and the ample availability of cheap and powerful sensors and all the data that comes with it, that is typical of the smart cities environment. Results from such research project are evident and indisputable, and are leading to products that are real and marketable, but tend to hide under the rug of commercial success (and not necessarily on purpose) the overlooking of one of the head missions in the original research project of AI: the emulation of human cognitive behaviour, and with it the hope of being capable of building intelligent machines that are not only able to effortlessly achieve their task in a dependable and effective way, but also show the way natural selection and evolution gifted our specie and us as individuals the power to reason, understand, decide, imagine and shape our future. In other world, the Big Data and the statistical approaches lack introspection. Due to the arbitrary, complex, ambiguous nature of the human language, we still are not able to flawlessly perform a semantic analysis of text, and to use the information extracted to properly assess the meaning (implied and explicit) hereby contained and act upon it. The problem is intrinsically multidomain-specific, and as the brief examples given in this paper should have made clear, each facet of the problem should be afforded with different techniques, and the results integrated with a thoughtful bottom-up approach. The effort of the scientific community, of which this paper has given not even a glimpse, is currently more geared toward statistical methods, but we feel confident that the contribution of Computational Intelligence towards a development of Citizen Communication will bring a significative contribution to the development of the more 'human' aspect of smart cities.

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