Towards Argumentation-based Recommendations for Personalised Patient Empowerment

Juan Manuel Fernández
Felip Miralles
Alexander Steblin
Eloisa Vargiu
Eurecat Technology Center, eHealth Unit
Barcelona, Spain
name.surname@eurecat.org

Marco Mamei
Stefano Mariani
Franco Zambonelli
DISMI—Università di Modena e Reggio Emilia
Reggio Emilia, Italy
name.surname@unimore.it

ABSTRACT

Patient empowerment is a key issue in healthcare. Approaches to increase patient empowerment encompass patient self-management programs. In this paper we present $\mathcal{A}$rgo$\mathcal{R}$ec, a recommender system that exploits argumentation for leveraging explanatory power and natural language interactions so as to improve patients' user experience and quality of recommendations. $\mathcal{A}$rgo$\mathcal{R}$ec is part of a great effort concerned with supporting complex chronic patients in, for instance, their daily life activities after hospitalisation, pursued within the CONNECARE project by following a co-design approach to define a comprehensive Self-Management System.

CCS CONCEPTS

• **Applied computing** → **Consumer health**; **Health care information systems**; • **Information systems** → *Expert systems*; • **Human-centered computing** → *Ubiquitous and mobile computing systems and tools*; • **Computing methodologies** → *Discourse, dialogue and pragmatics*; *Multi-agent systems*;

ACM Reference format:
Juan Manuel Fernández, Felip Miralles, Alexander Steblin, Eloisa Vargiu, Marco Mamei, Stefano Mariani, and Franco Zambonelli. 2017. Towards Argumentation-based Recommendations for Personalised Patient Empowerment. In *Proceedings of International Workshop on Health Recommender Systems, Como, Italy, August 2017 (healthRecSys17),* 4 pages.
https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

Patient empowerment is a key issue in current healthcare that should be seen as both an individual and a community process. Four components are fundamental to the process: (i) understanding by the patient of her/his role; (ii) acquisition by patients of sufficient knowledge to be able to engage with their healthcare provider(s); (iii) patient skills; and (iv) a facilitating environment [1]. Although the idea of patient empowerment was introduced to healthcare in the 1970s [20], its popularity emerged in the mid 1990s [18], and became a feasible reality only in 2000s thanks to the advent of Web 2.0 [5]. In general, strategies to increase patient empowerment address two aspects of patients' experience [19]: (i) disease management and (ii) relationships with healthcare providers. Approaches to increase patient empowerment vary from patient *self-management* programs [16], to promoting patient involvement in treatment decision-making [13], to facilitating the physician-patient interaction [17].

In this paper, we present a *recommender system* named $\mathcal{A}$rgo$\mathcal{R}$ec, which is part of the great effort for providing support to *complex chronic patients* pursued by the CONNECARE project [23], by following a *co-design* approach. $\mathcal{A}$rgo$\mathcal{R}$ec distinctive feature is that it relies on *argumentation* to provide *justifiable* and *personalised* recommendations, increasing accuracy of recommendations based on continuously monitored data while improving patients' user experience. Current commercial solutions, in fact, aim to keep patients autonomous by providing them with wearable, non-intrusive devices (e.g., wristbands and medical devices), paired with proprietary smartphone apps. Nevertheless, recommendations are *predefined* by providers and usually cannot be personalised. On the contrary, clinicians interested in monitoring activities, health-status, and possibly habits, prefer to set the *goals* to be achieved by each patient (e.g., number of steps per day) and expect the system to generate tailored recommendations accordingly—as $\mathcal{A}$rgo$\mathcal{R}$ec does.

The rest of the paper is organised as follows. In Section 2 a minimal and necessary background on argumentation is given. Section 3 presents the proposed model and its architectural design. Section 4 discusses the benefits and challenges stemming from preliminary results. Section 5 ends the paper with final remarks and future directions.

2 ON ARGUMENTATION

Argumentation is amongst the most natural ways people interact through dialogue [22]: people argue by making claims, attack others' ones, and provide further premises for supporting own ones, with the goal of winning a debate. *Computational argumentation* is a research thread concerned with designing computational models and algorithms to analyse and construct arguments and their relationships with the aim of enabling *automatic reasoning* over acceptability of arguments [15].

In *abstract argumentation* arguments are considered as atomic units and the only considered relation is the *attack* one, meaning

healthRecSys17, August 2017, Como, Italy

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

arguments are in conflict [8], whereas in *structured argumentation* arguments may be constituted by *claims* ("what to be proven true") and *premises* ("what helps proving something true"), and relations amongst them also encompass the *support* one, linking premises to claims [4]. Moreover, attack relations are further divided into *rebuttal*, in case two claims clash, and *undercut*, when a claim contrasts the premise of the attacked claim.

Many different argumentation frameworks exist, extending the notion of argument or relation, or both. For instance, weighted [9] and value-based [3] frameworks attach quantitative labels to relations to express, respectively, *strength* of arguments over others. These kind of schemes are especially useful in those open and highly dynamic scenarios in which the relevance of arguments is likely to change over time, i.e., due to acquisition of new information.

In this paper, we exploit argumentation for (i) empowering recommendation systems with *explanatory* power regarding *why* and *how* recommendations are provided, and (ii) improve patients' user experience through *natural language* interactions—as discussed in Section 3. In particular, we adopt the simple structured argumentation framework depicted in Figure 1 as an argumentation graph, where darker nodes are claims whereas lighter ones are premises and shaded boxes are whole arguments, solid arrows are attack relations whereas dashed ones are support ones – darker ones are rebuttals and lighter ones are undercuts –, and the thickness of lines represents the strength of the relation. This serves well the purpose of discussing the benefits and challenges of argumentation based recommendations (Section 4), while keeping the paper accessible to readers unfamiliar with process algebraic descriptions of argumentation frameworks' semantics.

Although the idea of using argumentation to improve recommendations is not novel [2, 6], to the best of our knowledge this is the first attempt to exploit it in healthcare.

3 SYSTEM MODEL & ARCHITECTURE

This section presents our **Arg**umentation-based **Rec**ommender system, $\mathcal{A}$rgo$\mathcal{R}$ec, by first describing its model & inner functioning (Subsection 3.1), and then discussing the architecture of the overall *self-management ecosystem* it is part of (Subsection 3.2).

3.1 System Model

$\mathcal{A}$rgo$\mathcal{R}$ec revolves around the following main abstractions:

prescription any kind of prescription made by a clinician to a given patient to monitor, e.g., physical activities, health status through medical devices and/or suitable questionnaires, taking medications, and so on.

adherence the adherence of the patient to the clinician's prescriptions, both regarding individual prescriptions (*adherence level*) and their history based on a given time window (*adherence profile*).

fulfillment the fulfillment of a prescription achieved by the patient, necessary to measure the patient's adherence—either automatically (e.g., through an activity tracker) or manually (e.g., by the patient her/him-self tracking taken tablets).

recommendation the message to dispatch to the patient for *engagement*, *reward*, or *warning*, depending on her/his adherence, or the one to be sent to the clinician for continuous follow-up (in this case, it's called *feedback*). According to the corresponding adherence, recommendations may have a punctuation from 1 ("very bad") to 5 ("very good"), thus messages sent accordingly: an alert for low punctuation (e.g., "You've to be more active. Go out and take a walk!") and a reward for a high one (e.g., "Wonderful! Walk 100 steps more and you'll reach the goal!").

strategy the criteria guiding decision making about *how* to compute the adherence, and *which* recommendation/feedback to send, *when*.

recommendation engine the component responsible of generating and dispatching recommendations and feedbacks, based on the patients' adherence regarding their fulfillment of prescriptions, and on a dynamically configurable strategy.

In $\mathcal{A}$rgo$\mathcal{R}$ec, recommendations and feedback are interpreted as *arguments*, whose *claims* (i.e. the fact that the patient is doing well or not) are supported by *premises* constituted by the patient's adherence. The strength of *support* relations is *dynamically* computed (and adjusted), and depends on the time window that the adherence of the patient refers to: recent activity events (that is, fulfillment to more recent prescriptions) are stronger premises with respect to more ancient events. Accordingly, *attack* relations between arguments are possible because the recommendation engine may be tempted to generate conflicting recommendations based on different *time windows*, i.e., focusing on the adherence level (memoryless) versus the adherence profile (historical). In this case, argumentation helps $\mathcal{A}$rgo$\mathcal{R}$ec to generate the most correct recommendation (or feedback), by exploiting argumentation-based reasoning to select the stronger claim—that is, the one supported by the strongest premises. Figure 1 depicts an example argumentation graph in which recommendation "keep going" is the strongest argument, thus gets generated and dispatched. Essentially, despite comparison of latest fulfillment event ($fulfillment_{i,t}$) with previous one ($fulfillment_{i,t-1}$) suggests to warn the patient about the need for improvement (recommendation "must improve") – since her/his adherence is worsening –, the fact that there is still time left to complete prescription ($prescription_i$) steers arguments' strength in favour of recommendation "keep going", to further motivate the patient.

Besides correctness, this way $\mathcal{A}$rgo$\mathcal{R}$ec can, on the one hand, provide to patients more convincing recommendation messages, by motivating and *explaining* the reasons behind them (the *why*) and, on the other hand, provide to clinicians *insights* on the decision making process leading to that precise feedback (the *how*). Both can

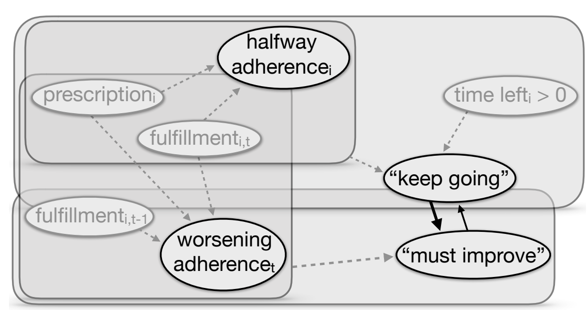

Figure 1: Example of argumentation graph exploited by $\mathcal{A}$rgo$\mathcal{R}$ec.

be achieved by navigating the argumentation (sub)graph whose claim is the recommendation or feedback itself to, for instance, generate explanation sentences through *Natural Language Processing* (NLP) techniques and *argumentation mining*—as better discussed in Subsection 4.1.

To deliver its functionalities, ArgoRec works as follows (see also Figure 2). Whenever an activity fullfillment event is received: (i) it is checked against the corresponding prescription to compute adherence level of the patient and update her/his adherence profile, depending on the configured strategy (i.e. defining how to weight older vs. newer events); (ii) new arguments are generated accordingly and added to ArgoRec argumentation graph (i.e., an "halfway" fullfillment may support a "keep going" recommendation); and (iii) weights of relations are updated depending on the newly-added arguments (i.e. new premises for a claim increasing support strength) and ArgoRec's own strategy (i.e. decreasing strength of arguments as time flows). Finally, periodically and depending on the configured policies, ArgoRec generates recommendations and feedback based on the strongest argument(s) in the graph—i.e. navigating the graph to generate sentences through NLP.

3.2 System Architecture

ArgoRec is part of a *Self-Management System* (SMS) developed within the CONNECARE project and aimed at monitoring patients habits in terms of physical activities, health status, taking medications, as well as nutrition. It consists of, among others, an app for the patient to receive messages (i.e., tasks and appointment requests), set which activities to monitor depending on clinician's prescription, accept or decline a request sharing certain parts of her/his data with a specific clinician, and keep a calendar for tasks and appointments.

The clinician makes the prescription of each habit to be monitored (i.e., how many steps per day, which and how many pills to take, and which health variable to measure and with which frequency) through a dedicated web-based application, in which a case may be defined according to the corresponding clinical pathway, the set of prescriptions to be sent to the SMS, and the clinicians involved in follow-up of the case. Figure 2 sketches the overall flow of data. The clinician prescribes an activity, the patient receives it through the SMS smartphone app, then performs the activity; the patient's wristband monitors the activity, sends data to the smartphone, which are then sent to "the cloud" in which ArgoRec lives together with the SMS back-end, analysing data and sending recommendations and feedback. Let us note that how the SMS and the web application interact is out of the scope of this paper.

4 KEY BENEFITS & CHALLENGES

Experiments with ArgoRec just started with healthy-volunteers in Catalonia. Volunteers were asked to wear a Fitbt charge HR and to perform their normal activity. In a first period they will be using ArgoRec with the argumentation capability turned off, then it will be turned on. Patients' improvement rate in the two periods will be measured, as well as efficacy of recommendations—i.e. in terms of short-term changes in patients behaviour. This will serve as a first indication of whether argumentation helps motivating patients.

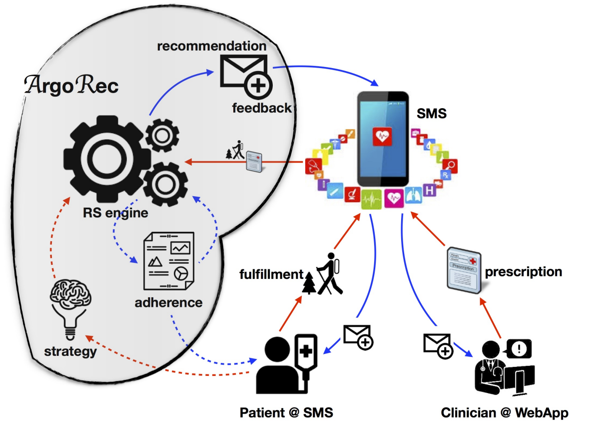

Figure 2: Flow of data regarding the prescription of a physical activity.

In this Section we briefly summarise the key benefits that we envisage in using the proposed recommender system (Subsection 4.1) as well as the challenges to be faced by the SMS and ArgoRec for deployment in production (Subsection 4.2)[1].

4.1 Key Benefits

Argumentation may play a crucial role in dealing with the fear of *algocracy* [7], that is, of having our everyday life influenced by some form of *opaque* algorithmic decision making, we have no control on nor clue about its inner functioning. This is very relevant in case of recommendations for patients that suffer of chronic illness and that are, usually, elderly. In fact, clinicians need to have control on the feedback given to patients to avoid self-defeating messages that may affect patients and/or do not fit with the real needs of a given patient. This motivates the need for moving from *black-box* to *grey-box* algorithms, lending themselves to (at least, partial) *inspection* and *interpretability* by human users. In this respect, argumentation straightforwardly enables algorithms to *explain* and *justify* decision making—both to patients and clinicians.

This may happen, for instance, by integrating argumentation with NLP techniques to generate explanatory sentences [10]. Accordingly, NLP may prove to be invaluable especially in healthcare-related scenarios involving chronic patients and/or elderly people, who may be much more accustomed to interact with other people (thus, through oral communication) than with technology (that is, through GUI or gestures) [14].

Argumentation also brings along an interesting opportunity regarding *autonomous learning* of recommendation rules, that is, the criteria upon which recommendations are provided to the patient. In fact, pattern mining techniques are already proficiently employed in many applications of the IoT, where they enable *associated rule discovery* [21] and *user profiling* through preferences learning [11]. In this respect, *statistical relational learning* [12] is a promising source of solutions, since it merges logic with probabilistic models to detect correlations between data despite uncertainty of perceptions,

[1] Clinical studies will start at the end of 2017 in 4 sites: Barcelona, Lleida, Groningen, and Israel.

while exploiting background knowledge to provide *explanations* about the learning process itself—i.e. *why* and *how* a given rule has been inferred.

4.2 Challenges

Despite argumentation being an active field of research for so long, most of the fundamental results achieved are theoretical. Being interested in applying argumentation in a recommender system to empower complex chronic patients, we move from a theoretical perspective to the real-world. It is worth noting that the main challenge is moving from a technical perspective (such as finding the best logic frameworks) to an organisational and social change in case management for both patients and clinicians. In fact, on the one hand, patients have to learn how to interact with suitable devices (i.e., wristband and smartphone or wireless medical devices) and they have to be confident about the recommendations they receive. On the other hand, clinicians have to receive the right information (*grey-box* approach) to trust the recommendations automatically generated. What may happen is that, if not correctly motivated, patients stop to use the self-management system and clinicians interrupt prescription of activities through the SMS or checking of the received feedback due to the lack of trust and transparency of decision making.

5 CONCLUSIONS & FUTURE WORK

In this paper, we presented the model and architecture of $\mathcal{A}$rgo$\mathcal{R}$ec, a novel kind of recommender system that relies on argumentation to provide suitable information (rewards, alerts, feedback) to patients and clinicians in natural language. $\mathcal{A}$rgo$\mathcal{R}$ec has the potential to sensibly improve patients' engagement as well as clinicians insights into decision making of recommender systems.

To substantiate our claim, we just started the evaluation of a first proof-of-concept prototype of $\mathcal{A}$rgo$\mathcal{R}$ec. The prototype will be used by healthy volunteers in Catalonia during the summer to monitor physical activity (i.e., performed number of steps). According to the underlying co-design approach, recommendations will be analyzed by the users as well as by clinicians from Hospital Santa Maria in Lleida (Catalonia, Spain). The corresponding feedback will be used to improve the system and get it ready to be used in the CONNECARE project with patients from Barcelona, Lleida, Groningen and Israel. In particular, two case studies will be considered: (1) Community-based management of complex chronic patients, and (2) Preventive patient-centered intevention in complex chronic patients undergoing elective major surgical procedures.

ACKNOWLEDGMENTS

The work is supported by the CONNECARE (Personalised Connected Care for Complex Chronic Patients) project (EU H2020-RIA, Contract No. 689802). The authors would like to thank the anonymous referees for their valuable comments and helpful suggestions.

REFERENCES

[1] Reinhard Angelmar and Philip C Berman. 2007. Patient empowerment and efficient health outcomes. *Financing sustainable healthcare in Europe: new approaches for new outcomes* 1, 2 (2007), 3.

[2] Punam Bedi and Pooja Vashisth. 2014. Empowering recommender systems using trust and argumentation. *Information sciences* 279 (2014), 569–586.

[3] Trevor JM Bench-Capon. 2003. Persuasion in practical argument using value-based argumentation frameworks. *Journal of Logic and Computation* 13, 3 (2003), 429–448.

[4] Philippe Besnard, Alejandro Javier García, Anthony Hunter, Sanjay Modgil, Henry Prakken, Guillermo Ricardo Simari, and Francesca Toni. 2014. Introduction to structured argumentation. *Argument & Computation* 5, 1 (2014), 1–4. https://doi.org/10.1080/19462166.2013.869764

[5] Lodewijk Bos, Andrew Marsh, Denis Carroll, Sanjeev Gupta, and Mike Rees. 2008. Patient 2.0 Empowerment. In *Proceedings of the 2008 International Conference on Semantic Web & Web Services, SWWS 2008, July 14-17, 2008, Las Vegas, Nevada, USA*, Hamid R. Arabnia and Andy Marsh (Eds.). CSREA Press, 164–168.

[6] Carlos Iván Chesnevar and Ana G Maguitman. 2004. Arguenet: An argument-based recommender system for solving web search queries. In *Intelligent Systems, 2004. Proceedings. 2004 2nd International IEEE Conference*, Vol. 1. IEEE, IEEE, 282–287.

[7] John Danaher. 2016. The threat of algocracy: Reality, resistance and accommodation. *Philosophy & Technology* 29, 3 (2016), 245–268.

[8] Phan Minh Dung. 1995. On the Acceptability of Arguments and its Fundamental Role in Nonmonotonic Reasoning, Logic Programming and n-Person Games. *Artif. Intell.* 77, 2 (1995), 321–358. https://doi.org/10.1016/0004-3702(94)00041-X

[9] Paul E Dunne, Anthony Hunter, Peter McBurney, Simon Parsons, and Michael Wooldridge. 2011. Weighted argument systems: Basic definitions, algorithms, and complexity results. *Artificial Intelligence* 175, 2 (2011), 457–486.

[10] Michael Elhadad. 1995. Using argumentation in text generation. *Journal of Pragmatics* 24, 1–2 (1995), 189 – 220. https://doi.org/10.1016/0378-2166(94)00096-W Argumentation Within Language.

[11] Tom Fawcett. 2015. Mining the quantified self: personal knowledge discovery as a challenge for data science. *Big Data* 3, 4 (2015), 249–266.

[12] Lise Getoor and Ben Taskar. 2007. *Introduction to Statistical Relational Learning (Adaptive Computation and Machine Learning).* The MIT Press.

[13] Guro Huby, Jenny Holt Brook, Andrew Thompson, and Alison Tierney. 2007. Capturing the concealed: Interprofessional practice and older patients' participation in decision-making about discharge after acute hospitalization. *Journal of interprofessional care* 21, 1 (2007), 55–67.

[14] Matthias Kranz, Paul Holleis, and Albrecht Schmidt. 2010. Embedded interaction: Interacting with the internet of things. *IEEE internet computing* 14, 2 (2010), 46–53.

[15] Marco Lippi and Paolo Torroni. 2016. Argumentation Mining: State of the Art and Emerging Trends. *ACM Trans. Internet Technol.* 16, 2, Article 10 (March 2016), 25 pages. https://doi.org/10.1145/2850417

[16] Kate R Lorig, David S Sobel, Philip L Ritter, Diana Laurent, and Mary Hobbs. 2000. Effect of a self-management program on patients with chronic disease. *Effective clinical practice: ECP* 4, 6 (2000), 256–262.

[17] S McCann and J Weinman. 1996. Empowering the patient in the consultation: a pilot study. *Patient education and counseling* 27, 3 (1996), 227–234.

[18] Richard B Saltman. 1994. Patient choice and patient empowerment in northern European health systems: a conceptual framework. *International journal of health services* 24, 2 (1994), 201–229.

[19] David Samoocha, David J Bruinvels, Nieke A Elbers, Johannes R Anema, and Allard J van der Beek. 2010. Effectiveness of web-based interventions on patient empowerment: a systematic review and meta-analysis. *Journal of medical Internet research* 12, 2 (2010), e23.

[20] Nancy Tomes. 2007. Patient empowerment and the dilemmas of late-modern medicalisation. *The Lancet* 369, 9562 (2007), 698–700.

[21] Chun-Wei Tsai, Chin-Feng Lai, Ming-Chao Chiang, Laurence T Yang, et al. 2014. Data mining for Internet of Things: A survey. *IEEE Communications Surveys and Tutorials* 16, 1 (2014), 77–97.

[22] Frans H Van Eemeren, Rob Grootendorst, Ralph H Johnson, Christian Plantin, and Charles A Willard. 2013. *Fundamentals of argumentation theory: A handbook of historical backgrounds and contemporary developments.* Routledge.

[23] Eloisa Vargiu, Juan Manuel Fernández, Felip Miralles, Isaac Cano, Elena Gimeno-Santos, Carme Hernandez, Gerard Torres, Jordi Colomina, Jordi de Batlle, Rachelle Kaye, Bella Azaria, Shauli Nakar, Maarten M.H. Lahr, Esther Metting, Maarten Jager, Hille Meetsma, Stefano Mariani, Marco Mamei, Franco Zambonelli, Felix Michel, Florian Matthes, Joanna Goulden, John Eaglesham, and Charles Lowe. 2017. Integrated Care for Complex Chronic Patients. In *ICIC 17 - 17th International Conference on Integrated Care "Building a platform for integrated care: delivering change that matters to people". May 8-10, 2017, Dublin (Ireland).* Internation Foundation for Integrated Care, Dublin, Ireland.