International Journal of New Technology and Research (IJNTR)
ISSN:2454-4116, Volume-3, Issue-11, November 2017 Pages 171-179

Interpretation of Health-Related Expressions and Dialogues: Enabling Personalized Care With Contextual Measuring and Machine Learning

Lauri Lahti

[1]

***Abstract*— We propose a new research framework that develops a method for interpretation of health-related expressions and dialogues to enable personalized care with contextual measuring and machine learning. The new research framework is implemented with a research project that gathers from various patient groups and other population groups a broad collection of essential perspectives towards health and well-being. In experimental setups persons (for example patients, their family members and representatives of care personnel) are asked to classify a given set of expressions (linguistic statements, image materials or other stimuli) into different categories, and these categorizations are then used as input vectors for computational models. To develop the method a central task is to classify with machine learning models health-related expressions and dialogues in respect to various events, processes and persons in healthcare. Our experimental results based on a sample of context-based linguistic health data indicated fruitful possibilities for gaining classifications of essential traits of language usage, appearance and activity for persons of diverse population groups based on various scales, perspectives, background assumptions and contexts.**

***Index Terms*— patient engagement, expression, dialogue, semantics, measurement, communication, artificial intelligence.**

I. Introduction

Among the most important themes for quality of human life are good health and possibility to get reliably and efficiently supporting health services. Besides the research of biomedical care the technological progress offers new possibilities to collect, communicate and analyze health-related information. Development of mobile devices, measuring sensors and imaging has enabled to track and analyze a person's health condition in a way that helps to prevent and address at an early stage problems and to support the success of personalized care. A central challenge for the development of health analytics is to enable interpretation of biomedical measurement data in natural language used in human thinking and communication [1],[2],[3],[4],[5].

We propose a new research framework implemented with a research project that gathers from various patient groups and other population groups a broad collection of essential perspectives towards health and well-being. The collected knowledge can be used in various ways to implement diverse personalized healthcare services and to promote addressing diverse needs belonging to everyday life and care. The current name of the new research project is ”Development of method for interpretation of health expressions based on machine learning to support various care events and persons (DIHEML)”. Data acquisition and the development of computational models based on that data in the research is carried out as a non-commercial academic research work that is aimed at serving especially the development of public healthcare. The original idea of gathering data about interpretations of the patient's essential health-related expression and dialogues measured on various perspective-oriented scales is developed by Lauri Lahti who is also the principal researcher of the new research project. The results of the research are planned to be archived by the National Institute of Health and Welfare in Finland. The research project is expected last from 2017 to 2020.

Promising results of our previous work concerning semantic modeling of care guidelines [6], dynamic patterns of medical knowledge [7], supporting diagnostics with computational linguistics [8] and semantic analysis of diary texts concerning care [9] motivates us for further development of models for health-related expressions and dialogues to enable personalized care with contextual measuring and machine learning.

II. Previous Research

Previous research has created promising methods and results in respect to identifying patterns of linguistic health data to support care processes [10], [11], [12], [13], [14], [15].

For analyzing associative patterns of data it has been suggested that besides the frequency of occurrences a useful test statistic is log-likelihood [16], [17], [18]. Likelihood ratio tests compare the fit of two nested models and a null hypothesis becomes rejected if the less simple (larger) model is a significant improvement over the simpler (smaller) model. Log-likelihood test statistic can be computed as the ratio between the log-likelihood of the simpler model and the log-likelihood of the less simple model. Log-likelihood values can be calculated based on a multinomial sampling distribution.

An important part of explored computational models are neural network architectures. Any function having mathematically reasonable properties can be approximated with a neural network having an arbitrary degree of accuracy [19], [20]. Based on the original function, dynamical systems can be represented with a class of continuous time recurrent neural networks [21]. Furthermore, an extended theory allows managing more general dynamical systems with time-variant properties and having inputs for control [22], [23]. A neural network architecture transforms an input vector of measurements to an internal representation (a hidden state) which is then further transformed to some observable manifestation of an output vector.

A recurrent neural network specifically supports a feedback mechanism so that past information can propagate

[1] **Lauri Lahti**, Department of Computer Science, Aalto University School of Science, Finland.

forward [21]. Based on a sequence of measurements a recurrent neural network architecture can generate temporally dynamic predictions of desired outcome variables at user-specified times.

Long short-term memory (LSTM) model [24] has been motivated by accumulated previous research results indicating that the operating principles of LSTM models can be justified on the basis of dopamine-based signaling processes emerging in the human neural systems [25]. For example the task of patient subtyping has been carried out successfully with time-aware LSTM networks [26].

Convolutional neural networks use layers based on convolving filters so that these filters can be applied to local features [27]. Besides computer vision convolutional neural networks have shown promising results in implementing semantic categorization tasks [28], [29], [30]. A practical implementation can be carried out so that the first layer creates embedding of words into low-dimensional vectors, then a layer with multiple filter sizes performs convolutions over the embedded word vectors (combining observations of several words at the same time) [28]. The result of the convolutional layer can be then max-pooled into a long feature vector, supplied with a regularization of dropouts and then categorized by using a softmax layer.

III. Method

A. Broad collaborative research framework

We propose a new research framework implemented with a research project that has gained important supporters and the broad collaboration network has become significant. There is active planning for further expansion and coordination of the collaboration network. Since the research project emphasizes developing public healthcare in Finland and in Finnish language certain organizations appear as natural collaborators to enable the most influential impact on national-level public health: National Institute of Health and Welfare in Finland (a national-level authority for health data acquisition and archival processes), Finnish patient organizations (acquisition of personal-level and community-level patient experience data), Finnish organizations of healthcare personnel (acquisition of personal-level and community-level care expertise data), Finnish educational institutions (acquisition of national-level data of future patients in various demographic groups (including gender, age, language ability and ethnicity) and persons currently in study programs of various healthcare professions), Finnish official care guidelines (a knowledge frame for practical implementation of care and its web portal Terveyskirjasto.fi [31] enables analysis of national-level needs in solving health problems and formulation of health queries) and Emergency Response Centre Administration in Finland (records of emergency calls and primary care enables analysis of dialogues for urgent diagnosis, prioritization and decision making concerning care events).

To illustrate clearly in the current article the research project its implementation is described so that patient groups are used as a main example of population groups. Anyway, the aim of the research is to develop new solutions to support health and well-being for many diverse population groups besides patient groups. Thus when reading the current research description the expression ”patient” can be interpreted to represent neutrally each population group in question.

B. Research questions and aims

For the new research project the main research question is: How can machine learning models be used to classify semantically health-related expressions and dialogues in respect to various events, processes and persons in healthcare? This main research question is supplemented with two supplementary research questions: What is the dependency between health-related expressions and various events, processes and persons in healthcare? What is the dependency between health-related dialogues and various events, processes and persons in healthcare?

The aims of the research can be expressed in respect to five consecutive steps of development architecture: *1. Classification of expressions and dialogues*: A central aim of the research is to develop a method for interpretation of health expressions based on machine learning, IHEML method. The method enables to semantically classify health-related expressions and dialogues in respect to various events, processes and persons in healthcare. *2. Creation of predictive models*: A supplementing aim is that based on this classification it is possible to develop and implement predictive models (health expression relation model, HER, and health dialogue relation model, HDR). *3. Clinical applicability*: From the perspective of practical application the research aims at examining if the predictive HER and HDR models can be applied in clinical care contexts. *4. Validation of a measurement tool*: When implementing the research an important aim is to examine if a measurement tool created based on HER and HDR models (health expression and dialogue relation instrument, HEDRI) is valid when applied in various clinical contexts (such as care for children, elderly and disabled). *5. A routine registry archival*: In addition, a long-reaching aim of the research is to examine what kind of requirements and needs can be identified so that data related to the HEDRI measurement tool could be routinely collected and exploited in respect to national patient records and health registries.

C. Machine learning based on linguistic health data

In the research project the aim is to examine with various persons the interpretation of health-related expressions and dialogues. To develop the IHEML method a central task is to classify with machine learning models health-related expressions and dialogues in respect to various events, processes and persons in healthcare. In practice this requires acquisition of suitable context-based linguistic health data and development and implementation of appropriate machine learning models. In the research acquired *context-based linguistic health data* consists of various complementing resources, including personal-level patient data and population-level health-related data.

The *personal-level patient data* is gathered concerning the patient's clinical visits (before, during and after). This data

contains patient records data and transcripts of the patient's communication with health personnel at clinical visits and when seeking for admission to the care. The personal-level patient data is also collected outside clinical visits in the patient's everyday life containing notes from the patient's health diary, data gained from the patient's mobile health-tracking devices and recordings of the patient's online health information retrieval sequences as well as other person-related data gathered for example with questionnaires.

The *population-level health-related data* is gathered from various registries and text corpuses, including the corpuses of care guidelines, health recommendations, medical ontologies and online patient peer-support discussion forums.

In the *development of machine learning models* it is central to create computational models that can identify and represent patterns manifested in the data. In respect to health-related expressions and dialogues, the research focuses on patterns that describe distinctive dependencies between the patient's language usage and the patient's care process and various characteristics of everyday life. Thus the research creates computational models which enable to identify and represent expressions and dialogues that are characteristic and significant for the persons of the target population (for example for a heart patient related to expressions "chest pain" and "difficulty to breathe"). In the development of machine learning models a computer program is supplied with context-based linguistic health data as an input. Then based on the gained results the functional principles of the model are iteratively adjusted gradually (for example by adjusting the calculations performed by the program and the classification of the input data) to produce the results that appear to be the most appropriate.

The development of machine learning models relies on using unsupervised and supervised learning algorithms (such as clustering methods and bayesian classification) and deep learning algorithms (such as recurrent, long short-term memory and convolutional neural networks). The machine learning models can exploit semantic analysis methods using algorithms based on finite automata, collocation, n-grams and paraphrases to interpret meanings of natural language texts.

D. Target populations and experimental setups

In the research one essential method for forming input vectors and their subcomponents for computational models is based on experimental setups. In *experimental setups* persons (for example patients, their family members and representatives of care personnel) are asked to classify a given set of expressions (linguistic statements, image materials or other stimuli) into different categories, and these categorizations are then used as input vectors for computational models. These classification tasks can be based on various scales, perspectives, background assumptions and contexts. In the research the persons are asked to do the categorization in respect to separately defined measuring dimensions concerning expressions.

Thus the classification given by the person can be used as an input of the computational models which are developed.

A central part of designing and implementation of experimental setups is carried out with representatives and experts of each target population. The designing of experimental setups – which is based on essential traits of language usage, appearance and activity for persons of the target population – aims at identification and selection of measuring dimensions and measuring material concerning expressions. Respectively the research aims at identification and selection of measuring dimensions and measuring material concerning dialogues for persons of the target population.

Essential *target populations* for the research are formed based on various population special groups, including patient groups (for example patients having a specific diagnosis and patients currently being in a certain phase of the care path), care personnel representing different care-giving roles (general medical doctors, specialized medical doctors, nurses, emergency medical responders, midwives and practical nurses), children, elderly and so called basic-level healthy adults. In observation of patient groups the subgroups include patients reached via patient organizations, impaired people reached via impaired organizations, patients reached via the national health registries and patients of the local hospital district of public healthcare. An aim is to form target populations also based on for example gender, age groups, profession groups, native language and cultural background (ethnicity).

To fulfill the aims of the research project it is important that questionnaire responses are collected especially from such a broad complementing combination of target population groups (contrasting and comparison of responses generated by different populations is important).

Testing of various models and user interface prototypes in experimental setups enable comparative analysis concerning classification done by the persons as well as background variables of the person and the event and the implementation of data acquisition and user interface.

With a broad and diverse set of populations and experimental setups it is possible to evaluate the effect of various events on the person's language usage and thinking processes (for example intuitiveness in conveying the person's expression).

E. Finding out the important expressions and interpretations for different patient groups

The new research project aims at identifying for population groups (target populations) the differences for the interpretation of essential expressions that are used in respect to health. Especially the aim is to find out how the representatives of different population groups interpret essential expressions concerning care. Different patients can interpret differently for example the expression ”My health condition feels to be ordinary.”. Besides the patient groups an aim is to identify also how the representatives of different disability groups interpret essential expressions that are used in their everyday life and to promote and support their well-being.

When the research has enabled to experimentally define a so called reference level for the interpretation of an expression, then it is possible to relate to it proportionally other interpretations. By analyzing the dependencies

between expressions it is possible to compare the usefulness of different dialogues for activities such as the success of care and managing in everyday life. The computational methods developed in the research project aim at enabling for care-related analytics new advanced computer-assisted support services (artificial intelligence) that can supplement decision making done by human resources.

Data acquisition in the research aims at creating for each different patient group a new kind of *knowledge entity* about the community's special needs for everyday life and care. The patient group (and the corresponding patient organization) can use this knowledge entity in its initial formulation in various ways to promote the well-being of the community. In addition, an aim is that the gained knowledge entity can form a new kind of computer-assisted resource for both the patient group and its supporting health personnel. This computer-assisted resource aims at helping to promote public healthcare thus addressing well the needs of special population groups with support for decision making.

To ensure the success of the research project it is very important that questionnaire responses are collected especially broadly from various complementing patient groups (it is important to compare responses generated by different populations). Data acquisition and the experimental setups related to it are designed and implemented with representatives and experts of each patient group in a fruitful collaboration. An aim is to carry out a great part of the designing and implementing of experimental setups with mobile web-based services so that participation in the research is the most easy and efficient for all interested persons (for example it is possible to participate also from home at a freely chosen time point).

In the research a central task is to choose together with the patient group a set of the most essential health-related expressions (so called measuring material, for example ”In an appropriate position the pain relieves.” or ”By changing the diet my symptoms decreased.”). In addition a central task is together with the patient group to define for these expressions suitable measuring scales (so called measuring dimensions, for example what degree of worry or encouragement can be interpreted in the expression). After performing these two central tasks (see chapter III.F) the research aims at gathering interpretations for the most essential health-related expressions in respect to the various measuring scales with an online questionnaire from an extensive set of representatives of the patient group (see chapter V.A).

F. Measuring material and measuring dimensions

The *measuring material* concerning expressions consists of an appropriate collection of expressions which are characteristic and meaningful for the persons of the target population in respect to e.g. language usage, appearance and activity. In the research a reasonable measuring material concerning expressions can be naturally defined together with representatives and experts of each target population. When defining the measuring material, attention is given to address the special population group in question; thus for a certain patient group the measuring material is supplied with expressions that are characteristic and meaningful specifically for this patient group's symptoms, diagnoses, care guidelines and care path events. Respectively for example for a children's group the measuring material concerning expressions can be naturally selected according to the language ability levels of children. The measuring material concerning expressions can be formed based on different contents, such as a set of linguistic statements, image materials or other stimuli.

The selection of the *measuring dimensions* can be naturally based on evaluating characteristic patterns in a linguistic material collection that is central for the target population (the measuring material) done together with representatives and experts of each target population. With collaborators of the research (including patient organizations) it has been initially planned that some of the possible measuring dimensions are for example the significance of the expressions in respect to the following things: addressing own everyday life (even despite the disease, for example hobbies, interests); addressing own disease; managing everyday life so that addressing the disease; description of properties of the disease or the symptoms; addressing the actual care event; patient-driven activity; development of the care for long-term patients; fainting of functionality or management (for example dementia); an incurable chronic disease, a disease leading to the death without a cure (for example cancer); emphatic listening; making sure the patient becomes heard; implementing peer-support (from the patient to peers and from peers to the patient); making contact to healthcare personnel (doctors, nurses etc.); pain; the need of help; emergency; worriedness, anxiety and fearfulness; hopefulness, optimism; sensitiveness, shamefulness; stressfulness, nervousness; incomprehensibleness, rudeness, impoliteness; empowering, cheering, boosting, encouraging, inspiring; consoling, calming; empathy and responsiveness (especially from peers and healthcare personnel).

Based on initial planning with collaborators of the research (including patient organizations) it has been identified that in the beginning of the research project the interpretation of expressions can be measured on scales which represent properties such as the need of help and the pain.

IV. Experiments

Motivated by the previous results (e.g. [10], [11], [12]) we carried out a *sentence extraction experiment* for evaluating possible ways to extract from online text resources some candidates of the most essential health-related expressions and their measuring dimensions. In our sentence extraction experiment we have examined various approaches concerning how a set of the most essential health-related expressions can emerge from a set of collective online discussions in respect to certain health-related themes and population groups. Thus we have extracted with computational methods distinctive sentence collections and collocative word pairs in a text-based data set of Finnish online discussions [32]. We extracted three collections of unique sentences from online discussions so

that the first collection was from the discussion topic group "Children's health" ("Lasten terveys" in Finnish), the second collection from the discussion topic group "Health" ("Terveys" in Finnish) and the third collection was extracted with a randomization from any type of discussion topic group of the online discussion forum (we refer to this third collection as "General discussion"). Each of the three collections equally consisted of 98 229 unique sentences. In the following analysis all conjugated Finnish words are observed in the non-conjugated base form relying on the part-of-speech tagging of Turku Dependency Treebank statistical dependency parser.

For each of the three sentence collections we computed a list of words in a decreasing order of the frequency and a list of collocation word pairs in a decreasing order of the log-likelihood value supplied with the frequency (these test statistics were motivated by the analysis of [16]). Table 1 shows ten highest-ranking words and collocation word pairs for each of the three sentence collections when focusing on words that are nouns (n), adjectives (a) or verbs (v).

In the data set [32] some examples of the original sentences containing the collocation word pairs having the highest log-likelihood values are: "The greatest part of influence on the decision was given by the price." (in the sentence collection General discussion, for the word pair "great part (a n)"), "The greatest part of romantic asexuals anyway like such things as kissing with their partners." (Health, "great part (a n)") and "Is it ok that the child is pale now during the winter?" (Children's health, "child be (n v)").

To identify those collocation word pairs that emerge typically for a certain sentence collection in contrast with an other sentence collection we computed the proportion of collocation word pair log-likelihood values between the three sentence collections (see Table 2). Thus we gained three lists of protruding collocation word pairs contrasting the sentence collections (Health vs. General discussion, Children's health vs. Health and Children's health vs. General discussion). The proportion of log-likelihoods is gained for example for "Children's health vs. Health" by dividing the log-likelihood of "high fever" in the sentence collection Children's health by the log-likelihood of "high fever" in the sentence collection Health). These computations were carried out among the 7000 highest-ranking collocation word pairs. Table 2 shows ten highest-ranking and ten lowest-ranking protruding collocation word pairs for all three compared pairs of sentence collections when focusing on words that are nouns (n), adjectives (a) or verbs (v).

Motivated by the model described by [28] we carried out a *sentence classification experiment* with a convolutional neural network architecture for evaluating possible ways to classify with machine learning some candidates of the most essential health-related expressions and their measuring dimensions. In our sentence classification experiment we trained a convolutional neural network model (adapted from the model of [28]) with a sample of 1000 unique sentences taken from the sentence collection of Children's health and a sample of 1000 unique sentences taken from the sentence collection of Health (based on Finnish online discussions [32] as explained earlier). We then tested the ability of the trained convolutional neural network model to classify correctly new input sentences of Chidren's health and Health that had not been used in the training phase of the model. With a diverse sampling of test sentences the results showed that the trained convolutional neural network model managed to classify correctly 88,6 percent of the new Chidren's health sentences and 91,4 percent of the new Health sentences.

An extended listing of our experimental results illustrated here only partially is available in a supplement to this research article [33].

V. Implementation of Measurement and Support

A. The measurement of interpretation

The measurement of interpretation of the properties of an expression shown in text format can be illustrated with the following example in respect to a measuring scale based on the pain dimension.

In the experimental setup a person can be asked to classify a given set of expressions in text format with such a task that consists of showing to the person a sentence "There is a wound in my hand." and he/she is asked to express how strong impression of pain this sentence evokes in him/her, on a scale 1-5 (value 1 meaning the smallest possible pain and value 5 meaning the greatest possible pain). Alternatively the task consists of showing to the person two different sentences which are "There is a wound in my hand." and "My hand is covered with red pimples." and he/she is asked to express which one of these two expressions evokes in him/her a stronger impression of pain.

Respectively like in the case of expressions shown in text format it is also possible to ask the person to classify a given set of expressions in for example image format or video format.

In the classification task the person can be asked to interpret the given expression concerning his/her *own experience* (as if the shown sentence would describe his/her current situation, i.e. for example there would be a wound in his/her hand) or to interpret the given expression concerning an *other person's experience* that he/she happens to be witnessing (as if he/she would have just met another person who tells that there is a wound in this other person's hand).

Designing and implementation of experimental setups for dialogues follows similar principles as just described for expressions, thus the research aims to identify and select with the representatives and experts of each population group the measuring material and the measuring dimensions concerning dialogues taken into the focus of the research.

B. Data acquisition enables development of artificial intelligence to support everyday life and care events

The aim of the research is fundamentally relatively simple although the theoretical description can give an impression of complexity. In brief, the research aims at finding out what things are important for the patient group in question and how the interpretation and communication of these things can be clarified. Responses gathered with online questionnaires from different patient groups offer a valuable

opportunity to develop artificial intelligence that helps to interpret the patient's needs. By identifying the needs the artificial intelligence can offer support to implement personalized healthcare services.

identified and interpreted with artificial intelligence and based on that it is possible to offer support for the person's communication, information retrieval and decision making. Based on the models created in the research it is possible to

Table 1 Ten highest-ranking words and collocation word pairs for all three sentence collections when focusing on words that are nouns (n), adjectives (a) or verbs (v). Note: f=frequency; logl.=log-likelihood.

General discussion					Health					Children's health				
word	f.	word pair	f.	logl.	word	f.	word pair	f.	logl.	word	f.	word pair	f.	logl.
be (v)	59140	great part (a n)	227	2072	be (v)	67518	great part (a n)	203	2004	be (v)	72999	child be (n v)	2505	2277
can (v)	5829	holy spirit (a n)	103	1374	can (v)	7803	long time (a n)	144	953	child (n)	15912	boy be (n v)	1343	1960
get (v)	5552	question is (n v)	238	731	get (v)	6415	take connection (v n)	114	886	get (v)	8092	great part (a n)	178	1777
come (v)	4653	be good (v a)	543	654	come (v)	5618	thyroid gland hypofunction (n n)	57	846	can (v)	7719	take connection (v n)	186	1563
do (v)	3738	seem be (v v)	242	623	do (v)	4232	next day (a n)	106	827	boy (n)	5983	can be (v v)	1413	1371
like (v)	3497	apartment price (n n)	64	614	human (n)	4188	year time (n n)	163	761	come (v)	5695	doctor say (n v)	228	1153
other (a)	3424	long time (a n)	88	608	other (a)	3959	bad feeling (a n)	97	757	thing (n)	4577	atopic skin (a n)	102	1127
thing (n)	3065	take account (v n)	64	565	go (v)	3723	can be (v v)	1100	710	other (a)	4278	question is (n v)	376	1035
human (n)	2915	year time (n n)	111	522	thing (n)	3653	question is (n v)	241	702	doctor (n)	3975	atopic rash (a n)	84	994
good (a)	2872	god word (n n)	71	520	like (v)	3608	be good (v a)	626	699	do (v)	3910	attract attention (v n)	73	977

Table 2. Ten highest-ranking and ten lowest-ranking protruding collocation word pairs for all three compared pairs of sentence collections when focusing on words that are nouns (n), adjectives (a) or verbs (v). Note: p.l.=proportion of log-likelihoods.

Health vs. General discussion				Children's health vs. Health				Children's health vs. General discussion			
highest word pairs	p.l.	lowest word pairs	p.l.	highest word pairs	p.l.	lowest word pairs	p.l.	highest word pairs	p.l.	lowest word pairs	p.l.
public side (a n)	11	thing familiarize (n v)	0,32	transport child (v n)	15	human air (n n)	0,22	boy be (n v)	50	other doing (a n)	0,39
can cause (v v)	8,0	public sector (a n)	0,32	high fever (a n)	15	healthy food (a n)	0,21	child be (n v)	44	have wealth (v n)	0,38
drink water (v n)	7,5	great trait (a n)	0,31	own child (a n)	14	go sleep (v v)	0,21	ill child (a n)	29	man be (n v)	0,35
good feeling (a n)	7,4	year old (n a)	0,29	be allergic (v a)	12	healthy human (a n)	0,20	doctor say (n v)	24	referred person (a n)	0,34
have courage go (v v)	7,3	sexual abuse (a n)	0,29	x years old boy (n n)	11	drink water (v n)	0,18	transport child (v n)	22	year behind (n a)	0,31
other corresponding (a a)	7,1	god will (n n)	0,28	positive feedback (a n)	8,2	x years old woman (a n)	0,16	can cause (v v)	17	question is (n v)	0,27
doctor say (n v)	6,8	woman be (n v)	0,26	child father (n n)	8,0	other human (a n)	0,15	child get (n v)	15	alcohol usage (n n)	0,26
bad feeling (a n)	6,5	god create (n v)	0,22	allergic reaction (a n)	7,3	alcohol usage (n n)	0,13	other experience (a n)	14	finland law (n n)	0,25
get help (v n)	6,5	other country (a n)	0,22	ask referral (v n)	7,3	social event (a n)	0,12	can be based on (v v)	13	young girl (a n)	0,21
go sleep (v v)	6,2	finland law (n n)	0,17	get diagnosis (v n)	7,2	good feeling (a n)	0,12	visit doctor (v n)	13	only right (a a)	0,16

Many commercial corporations are rapidly gaining a strong position in the acquisition and analysis of data concerning patients with closed and paid architectures. Thus with encouragement from the patient communities the new research project aims at developing an open free (non-commercial) solution for public healthcare.

Artificial intelligence providing support can be currently flexibly incorporated into online services accessed with mobile phones, for example to support communication, information retrieval and decision making. Thus in practice the expression written or spoken by the person can be

implement into a mobile phone a programmed extra feature that when a person using a wheel chair is requesting information about traffic routes he/she can get specifically routes accessible with a wheel chair. Correspondingly based on the models created in the research it is possible to implement into a mobile phone a programmed extra feature that a diabetic visiting a shop can get automatic suggestions for communication that enables to ensure buying products according to his/her diet.

The research creates new methods to interpret and address the meanings of language usage of different patient groups

exactly and differentially in everyday life and care events. The research enables that the meanings of language usage of patient groups can be contrasted with context, background and personal profile. The research offers new methods for interpreting the language usage of patient groups to prevent misinterpretations and to promote mutual understanding. The research offers also methods for highlighting in language usage of patient groups themes which are important to address in implementation and development of healthcare services. Thus the research aims at promoting that the personal needs and rights of the patient are taken better into account in decision making. The research aims at promoting the creation of support services needed by special groups in everyday life and care. Thus the research enables promoting the equality of different population groups and special groups.

VI. Discussion

A. Some findings based on the experiments

In our experiments we evaluated possible ways to extract from a sample of context-based linguistic health data some candidates of the most essential health-related expressions and their measuring dimensions and furthermore we evaluated possible ways to classify these expressions and dimensions with machine learning. In our experiments the sample of context-based linguistic health data was retrieved from online text resources [32]. These experiments provided promising results to support the development of the IHEML method so that health-related expressions and dialogues could be classified with machine learning models in respect to various events, processes and persons in healthcare.

Our results relying on the sample of context-based linguistic health data indicated fruitful possibilities for gaining classifications of essential traits of language usage, appearance and activity for persons of diverse population groups based on various scales, perspectives, background assumptions and contexts. Relying on our results in the context of children's health the most essential health-related expressions and the measuring dimensions might be formed for example based on such original sentences of [32] that contain some of the highest-ranking protruding word pair collocations "transport child (v n)" or "high fever (a n)" (as shown in Table 2). Thus one possible part of the development of the IHEML method can then be to gather input data for machine learning models by asking each person of the population group to classify a sentence "My child got a *high fever* a week ago, a mild period of flu before that." in respect to the measuring dimension “transport child” (or the measuring dimension can be even another sentence "Presumably it would be the most important to *transport the child* quickly to a pediatric."). Thus the person is asked to express how strong impression of transporting the child (to a pediatric) is evoked in him/her by reading the sentence about (a child having) a high fever.

B. Special needs of the population groups are taken into account in the research

Our proposed new research framework implemented with a research project aims at addressing the special needs and wishes gained from the patients of patient groups, experts and organizations in the research domain. In the following are some essential questions formulated to facilitate the design of questionnaire implementation of the research specifically adapted to the traits of the patient group:

What seem to be the most important well-being-related themes in everyday life for the patient group in question? Which are the themes that are specifically discussed among the representatives of the patient group in question in respect to reasons for happiness, worries, encouragement, risks and survival? Which are the most important healthcare-related themes that the representatives of the patient group in question need to take into account in everyday life to ensure well-being (for example living habits, medication, diet, assistive devices, rehabilitation etc.)? What are the things that the representatives of the patient group in question wish to be taken better into account by the care personnel of the public healthcare when interacting with the representative of the group in question?

C. Research develops services of the public healthcare respecting the privacy

Acquisition and handling of the research data is performed confidentially respecting the privacy of all persons involved, addressing carefully appropriate ethical principles. Data acquisition and the development of computational models based on that data (artificial intelligence) in the research is carried out as a non-commercial academic research work and the results are planned to be archived by the National Institute of Health and Welfare in Finland. While addressing privacy concerns the research aims at publishing the developed models and results as open data to be freely used by anyone. The research aims at serving especially the development of public healthcare with computer-assisted support services which are available for all citizens for free without any costs. The development of computational models in the research (artificial intelligence for health data analysis) is aimed at being connected to other development projects of public healthcare so that the biggest benefits could be gained for the development of the patients' care.

D. The results offer various benefits for the population groups

The knowledge entity gathered in the research about the interpretation of expressions and dialogues can support the representatives of patient groups and other population groups in various ways. The research project especially offers a possibility to support patient groups according to their own characteristics. Thus it is possible to support activities such as communication between different patient groups and between the patient groups and the surrounding society (e.g. from the patient to a friend, an assistant, care personnel and the persons encountered in everyday life, such as a school teacher, a shop keeper, a taxi driver or a cafeteria worker). In practice this support available for the patient group can be implemented by building new computer-assisted support services based on the knowledge entity generated by the research.

In all communication between humans the successful

interpretation of the meanings of natural language has a central role. This successful interpretation of communication is especially important for representatives of special groups having a vulnerable position. For them already relatively small misinterpretations can make significantly more difficult to manage in independent everyday life and possibly endanger their health and well-being.

For all population groups the classifications and models created based on the research enable implementing new kind of artificial intelligence (computer programs). This artificial intelligence supports for example to automatically identify and interpret the needs and wishes of the persons based on their expressions and dialogues in everyday life and in care events.

In addition the person's own ability to express needs and wishes can be contextually supplemented by suggesting automatically expressions related to the event in question. These support methods concerning expressions can be correspondingly extended to greater entities which can be dialogues in respect to various events and persons.

REFERENCES

[1] Hoffman, A., Volk, R., Saarimaki, A., Stirling, C., Li, L., Härter, M., Kamath, G., & Llewellyn-Thomas, H. (2013). Delivering patient decision aids on the Internet: definitions, theories, current evidence, and emerging research areas. BMC Medical Informatics and Decision Making, 13(2):S13. doi: 10.1186/1472-6947-13-S2-S13

[2] Dutta-Bergman, M. (2005). Developing a profile of consumer intention to seek out additional information beyond a doctor: the role of communicative and motivation variables. Health Communication, 17(1), 1-16.

[3] Parascandola, M., Hawkins, J., & Danis, M. (2002). Patient autonomy and the challenge of clinical uncertainty. Kennedy Institute of Ethics Journal, 12(3), 245-64.

[4] Payne, P. (2012). Chapter 1: Biomedical knowledge integration. PLoS Computational Biology, 8(12), e1002826.

[5] Politi, M., Wolin, K., & Légaré, F. (2013). Implementing clinical practice guidelines about health promotion and disease prevention through shared decision making. Journal of General Internal Medicine, 28(6), 838–844. doi: 10.1007/s11606-012-2321-0.

[6] Lahti, Lauri (2016a). Semantic modeling of healthcare guidelines to support health literacy and patient engagement. Proc. Global Learn 2016: Global Conference on Learning and Technology, 28–29 April 2016, Limerick, Ireland (eds. Kirby, P., & Marks, G.), 298–304. Association for the Advancement of Computing in Education (AACE), Chesapeake, VA, USA. ISBN 978-1-939797-23-0. https://www.learntechlib.org/p/172737 http://urn.fi/URN:NBN:fi:aalto-201603291477

[7] Lahti, Lauri (2016b). Supporting online health queries by modeling patterns of creation, modification and retrieval of medical knowledge. Proc. EdMedia 2016 - World Conference on Educational Media and Technology, 28–30 June 2016, Vancouver, B.C., Canada (ed. Veletsianos, G.), 705–712. Association for the Advancement of Computing in Education (AACE), Chesapeake, VA, USA. ISBN 978-1-939797-24-7. http://www.learntechlib.org/p/173023 http://urn.fi/URN:NBN:fi:aalto-201606202682

[8] Lahti, Lauri (2016c). Supporting diagnostics and decision making in healthcare by modular methods of computational linguistics. Proc. E-Learn 2016 - World Conference on E-Learning. ISBN 978-1-939797-25-4. https://www.learntechlib.org/p/174196 http://urn.fi/URN:ISBN:978-1-939797-25-4

[9] Lahti, Lauri, Tenhunen, Henni, Heinonen, Seppo, Helkavaara, Minna, Pöyhönen-Alho, Maritta, & Torkki, Paulus (submitted 2017). Manuscript "Development of computational models for emotional diary text analysis to support maternal care" submitted for peer-review. https://arxiv.org/abs/1710.04158

[10] Brown, P., Halász, S., Goodall, C., Cochrane, D., Milano, P., & Allegra, J. (2010). The ngram chief complaint classifier: A novel method of automatically creating chief complaint classifiers based on international classification of diseases groupings. Journal of Biomedical Informatics, 43(2), 268–272.

[11] Workman, T., Rosemblat, G., Fiszman, M., & Rindflesch, T. (2013). A Literature-Based Assessment of Concept Pairs as a Measure of Semantic Relatedness. Proc. American Medical Informatics Association (AMIA) 2013, 1512–1521.

[12] Henriksson, A. (2013). Semantic spaces of clinical text. Leveraging Distributional Semantics for Natural Language Processing of Electronic Health Records. Licentiate Thesis, Department of Computer and Systems Sciences, Stockholm University. https://www.diva-portal.org/smash/get/diva2:653288/FULLTEXT01.pdf

[13] White, R., & Horvitz, E. (2009). Cyberchondria: studies of the escalation of medical concerns in web search. Proc. ACM Transactions on Information Systems (TOIS), 27(4), article 23. http://research.microsoft.com/en-us/um/people/ryenw/papers/whitetr-2008-178.pdf

[14] Ashutosh, J., Andrews, D., Fiksdal, A., Kumbamu, A., McCormick, J., Misitano, A., Nelsen, L., Ryu, E., Sheth, A., Wu, S., & Pathak, J.(2014). Comparative analysis of online health queries originating from personal computers and smart devices on a consumer health information portal. Journal of Medical Internet Research, 16(7).

[15] Fiksdal, A., Kumbamu, A., Jadhav, A., Cocos, C., Nelsen, L., Pathak, J., & McCormick, J. (2014). Evaluating the process of online health information searching: a qualitative approach to exploring consumer perspectives. Journal of Medical Internet Research, 16(10): e224. doi: 10.2196/jmir.3341

[16] Evert, S. (2005). The statistics of word cooccurrences. Word pairs and collocations. Doctoral dissertation. University of Stuttgart. http://www.stefan-evert.de/PUB/Evert2004phd.pdf

[17] Dunning, Ted E. (1993). Accurate methods for the statistics of surprise and coincidence. Computational Linguistics, 19(1), 61–74.

[18] Agresti, Alan (1990). Categorical Data Analysis. John Wiley & Sons, New York.

[19] Funahashi, K. (1989). On the approximate realization of continuous mappings by neural networks. Neural networks, 2(3):183–192.

[20] Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. Neural networks, 2(5):359–366.

[21] Funhashi, K. & Nakamura, Y. (1993). Approximation of dynamical systems by continuous time recurrent neural networks. Neural networks, 6(6):801–806.

[22] Chow, T. & Li, X. (2000). Modeling of continuous time dynamical systems with input by recurrent neural networks. IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications, 47(4):575–578, 20

[23] Li, X., & Ho, J., & Chow, T. (2005). Approximation of dynamical time-variant systems by continuous-time recurrent neural networks. IEEE Transactions on Circuits and Systems II: Express Briefs, 52(10):656–660, 2005.

[24] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation, 9(8):1735–1780.

[25] Wang, J., Kurth-Nelson, Z., Tirumala, D., Leibo, J, Soyer, H., Kumaran, D., & Botvinick, M. (2017). Meta-reinforcement learning: a bridge between prefrontal and dopaminergic function. In Cosyne Abstracts, 2017. http://cosyne.org/cosyne17/Cosyne2017_program_book.pdf

[26] Baytas, I., Xiao, C., Zhang, X., Wang, F., Jain, A., & Zhou, J. (2017). Patient subtyping via time-aware LSTM networks. Proc. 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '17), 65-74. http://www.kdd.org/kdd2017/papers/view/patient-subtyping-via-time-aware-lstm-networks

[27] LeCun, Y., Bottou, L., Bengio, Y. Haffner, P. (1998). Gradient-based learning applied to document recognition. Proc. IEEE, 86(11), 2278–2324, November 1998.

[28] Kim, Y. (2014). Convolutional neural networks for sentence classification. Proc. Conference on Empirical Methods in Natural Language Processing (EMNLP), 1746–1751. Association for Computational Linguistics. http://www.aclweb.org/anthology/D14-1181

[29] Kalchbrenner, N., Grefenstette, E., Blunsom, P. (2014). A convolutional neural network for modelling sentences. Proc. 52nd Annual Meeting of the Association for Computational Linguistics.

[30] Yih, W., He, X., Meek, C. (2014). Semantic parsing for single-relation question answering. Proc. 52nd Annual Meeting of the Association for Computational Linguistics.

[31] Terveyskirjasto (2017). Finnish healthcare guidelines for ordinary people provided by The Finnish Medical Society Duodecim. http://www.terveyskirjasto.fi/terveyskirjasto/tk.koti

[32] The Suomi 24 Corpus (2016). The corpus of discussion forums of the Suomi24 online social networking website. A linguistic resource provided by the Language Bank of Finland and CSC - IT Center for Science. http://urn.fi/urn:nbn:fi:lb-2017021630

[33] Lauri, Lahti (2017b). Supplement to Lauri Lahti's research article ”Interpretation of health-related expressions and dialogues: enabling personalized care with contextual measuring and machine learning”, to appear online at http://aaltodoc.aalto.fi.