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Integrated visualisation of wearable sensor data and risk models for individualised health monitoring and risk assessment to promote patient empowerment

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Abstract Patient empowerment delivers health and social care services that enable people to gain more control of their healthcare needs. With the advancement of sensor technologies, it is increasingly possible to monitor people's health with dedicated wearable sensors. The consistent measurements from a variety of wearable sensors imply that a huge amount of data may be exploited to monitor and predict people's health using medically proven models. In the process of health data representation and analysis, visualisation can be employed to promote data analysis and knowledge discovery via mature visual paradigms and well-designed user interactions. In this paper, we introduce the role of visualisation for individualised health monitoring and risk management in the background of a European Commission funded project, which aims to provide self-management of cardiorenal diseases with the assistance of wearable sensors. The

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visualisation components of health monitoring, risk model exploration, and risk analysis are presented to achieve personalised health and risk monitoring and to promote people's wellbeing. It allows the patients not only to view existing risks, but also to gain awareness of the right pathway to change their lifestyles in order to reduce potential health risks.

Keywords Patient empowerment · Visualisation · Wearable sensor · Health monitoring · Risk assessment

1 Introduction

Chronic diseases are seen as a sustainability challenge for people's health. With the trend of “predictive, preemptive, personalised and participative” healthcare (Shneiderman et al. 2013), patient empowerment has become an important concern in healthcare, leading to the need to design and deliver health and social care services to enable people to gain more control of their healthcare needs. Patient empowerment is defined as “a process through which people increase their capacity to draw on their personal resources in order to live well with chronic conditions in their daily life” (EPF 2015). It requires a shift from disease-centered to patient-centered approaches, combining self-awareness and self-management with well-integrated professional support.

On the other hand, personal health information has been increasingly attainable and accessible in the information era, with the potential to serve more personalised health monitoring and predictive analysis systems in medical care (Pantelopoulos and Bourbakis 2010). The widespread use of wearable monitoring devices and mobile apps will enable ubiquitous capture of personal health data. Effective collection of long-term health-status data, together with the clinical information that has long played a major role in health and medical decision making, can introduce added value for health monitoring, risk management, and medical decision making in a more ubiquitous, personalised, and continuous manner.

The CARRE Project (CARRE) (<http://www.carre-project.eu/>)—Personalised Patient Empowerment and Shared Decision Support for Cardiorenal Disease and Comorbidities—funded by the 7th Framework Programme of the European Commission, aims to provide an innovative means for the management of cardiorenal diseases with the assistance of wearable sensors. The target of CARRE is to provide personalised empowerment and shared decision support for cardiorenal disease, which is a condition characterised by simultaneous kidney and heart disease, where the primarily failing organ may be either the heart or the kidney. In CARRE, sources of proven medical knowledge are semantically linked with sensor outputs to provide clinical information personalised to the individual patient, so as to be able to track the progression and interactions of comorbid conditions. The ultimate goal is to provide the means for patients with comorbidities in order to take an active role in care processes, including self-care and shared decision making, and also to support medical professionals in understanding and treating comorbidities via an integrative approach. In addition to medical data, CARRE can not only directly access personal health and lifestyle data from devices, such as Fitbit (Fitbit) (<http://www.fitbit.com/>), Withings (Withings) (<http://www.withings.com/>), and iHealth (iHealth) (<https://www.ihealthlabs.com/>), but also access data from multiple heterogeneous data sources via Microsoft HealthVault (HealthVault) (<https://www.healthvault.com/>) to collect personal health data, such as steps, walking distance, calories, heart rate, sleep quality, blood pressure, weight, etc.

The consistent measurements from a variety of data sources imply that a huge amount of data needs to be collected, represented, and analysed, which can hardly be achieved without proper data analysis and knowledge discovery via mature visual paradigms with well-designed user interactions. This paper presents the CARRE visualisation design and implementation: healthlines are employed for measurement data monitoring, risk model exploration is fulfilled by the Sankey diagram with a search box, and personalised risk evaluation is achieved with the risk node-link diagram and a measurement slider panel.

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The paper is organised as follows: Sect. 2 introduces related work in health data visualisation; Sect. 3 introduces the CARRE risk model followed by Sect. 4 which discusses the visualisation requirements and tasks. Section 5 describes the design and implementation of major visualisation components for health monitoring and risk assessment. The evaluation results are presented in Sect. 6 followed by Sect. 7 that concludes with the summary and future work.

2 Related work

Visualisation and visual analytics combine automated analysis techniques with interactive visualisations for effective understanding, reasoning, and decision making on the basis of very large and complex data sets (Keim et al. 2010). It is designed to promote knowledge discovery and utilisation of large data sets via effective visual paradigms and well-designed user interactions. Visualisation becomes the medium of an interactive analytical process, where humans and computers cooperate using their respective distinct capabilities for data processing and visual recognition for the most effective results and is an indispensable technology for healthcare information representation and analysis.

Healthcare has been a crucial research and application field of data analysis and visualisation for several decades (Reddy and Aggarwal 2015). Much of the focus is on the visualisation of electronic health records (EHRs). Rind et al. present a detailed review of the related work (Rind et al. 2011), categorising by individual patients or a group of patients. In each category, the work is further divided by visual analytics of time series data or status at a certain time point. West et al. also presents a systematic review of visual analytics approaches that have been proposed to illustrate EHR data (West et al. 2015).

Lifelines (Plaisant et al. 1998) is a pioneer work in visualisation of individual patient records, which provides a general visualisation environment for problems, diagnoses, test results, or medications using timelines. Lifeline 2 (Wang et al. 2009) provides visualisation of temporal categorical data across multiple records, which is better for a doctor to view to discover and explore patterns across these records to support hypothesis generation, and find causal relationships in a population.

VISITORS (Klimov et al. 2010), which is based on KNAVE (Shahar and Cheng 1999) and KNAVE II (Shahar et al. 2006), uses aggregation to extract meaningful interpretations from multiple patients' raw time-oriented data. PatternFinder (Fails et al. 2006) provides tools for the user to query patterns by specifying the attributes of events and time spans.

LifeFlow (Wongsuphasawat et al. 2011) and EventFlow (Monroe et al. 2013) are tools for event sequence analytics for a group of patients. They extract and highlight the common event sequences from patient records. Outflow (Wongsuphasawat and Gotz 2012) and DecisionFlow (Gotz and Stavropoulos 2014) use Sankey diagram (Riehmann et al. 2005) style visualisation to help visualise and analyse the causal relationships of events in complex event sequences.

The existing work has made detailed visualisation research mostly pertaining to EHRs and event analysis. While the work on predictive visual analysis of healthcare data is highly valuable (Groves et al. 2013), it is still rare due to its complexity and dependence on medical expertise. CARRE aims to provide personalised risk management and analysis with proven risk models (Kaldoudi et al. 2015) extracted from medical literature, which is a key difference from the existing healthcare visual analysis systems.

3 The risk model

In CARRE, the risk assessment is based on risk knowledge which is extracted from medical literature. It forms a large semantic graph structure of data consisting of interlinked entities, such as risk elements and risk evidence, that are either related to ground truth knowledge in cardiorenal disease and comorbidities (symptoms, diseases, risk factors, treatments, medical evidence source data, educational content, etc) or personalised to each patient (patient demographics, medical history, sensor data, lifestyle data, etc) (Kaldoudi et al. 2015). The data structure of the risk factor repository is shown in Fig. 1.

The key concepts in the CARRE risk model are defined as follows:

Risk element Risk elements include all the conditions/disorders/diseases involved in the comorbidity as well as any other risk causing agent, e.g., demographic (e.g., age, sex, and race), genetic (gene polymorphisms), behavioral (e.g., smoking, physical exercise), etc.

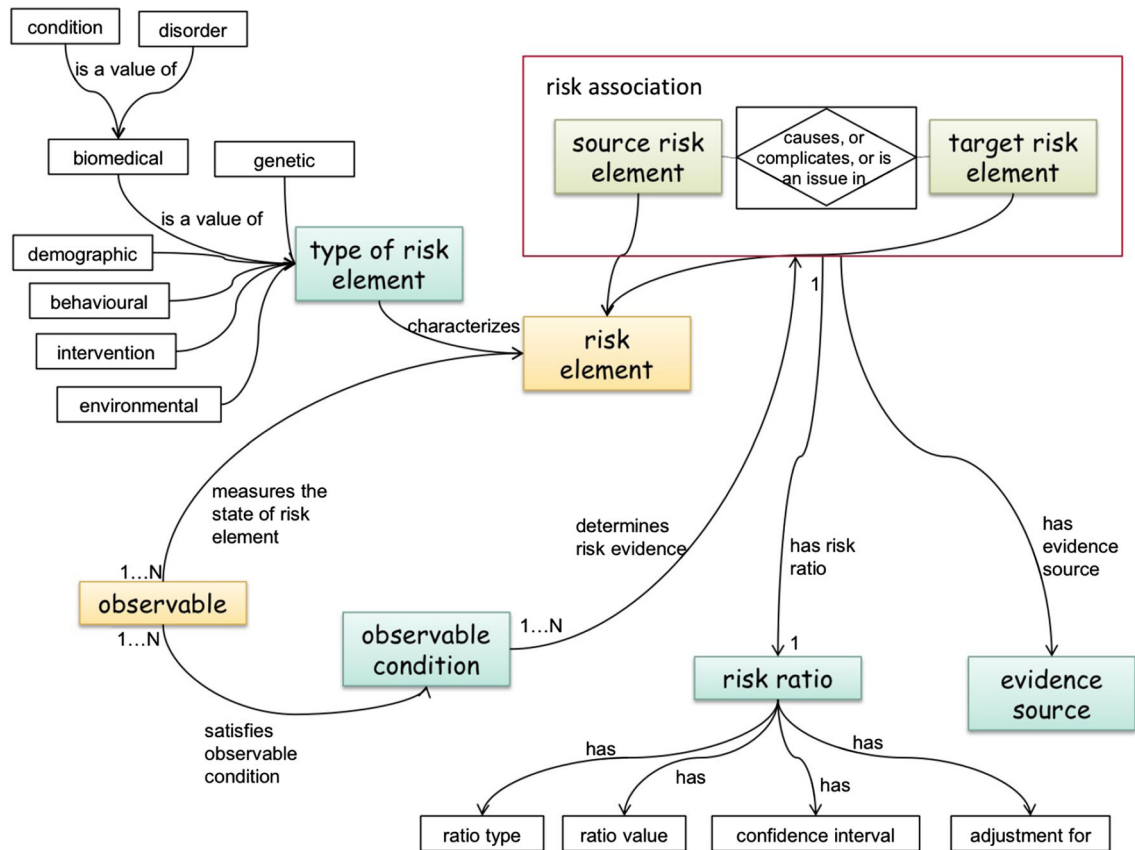


Fig. 1 Risk model structure in CARRE risk repository

Risk factor The association of one risk element as the risk source with another risk element as the outcome under certain conditions. A source risk element can be associated with a target risk element with more than one condition.

Risk observable Risk observables are physical variables that can be measured or otherwise ascertained (e.g., biomarkers, biometric variables, biological, etc).

Risk evidence Risk evidence is a criteria controlled by one or more observables to invoke a risk association. For example, diabetes will cause heart failure with a risk ratio of 1.39 when diabetes diagnosis is true and glycated hemoglobin is between 9.0 and 10.0. A risk factor can be activated by multiple risk evidences with different risk ratios.

The risks are acquired from medical literature manually and then input and stored in the CARRE repository (Third et al. 2015) by medical professionals via the web-based risk entry system. Currently, there are 98 risk factors (associations), 53 risk elements, 253 risk evidences, and 63 observables in the CARRE risk data repository.

4 Design requirements

In CARRE, the data can be generally categorised as fitness measurement data collected from sensors, medical biomarker measurements from personal electronic health records (PHR), and risk model data extracted from medical literature. The role of visualisation is to visualise health data and risk factor data and provide integrated visual analysis of health data and risk data.

To gain intuitive knowledge of the health-status data and the risk data, visualisation is employed in CARRE to provide patients and clinicians with the ability to view, understand and interact with this linked knowledge, and also take advantage of personalised empowerment services. The aim is to help patients to

understand their own health status and risks, which in turn empower them to take more active control of their health self-management and disease treatment.

Based on the risk model and the personal health data, the visualisation design requirements of CARRE include:

- visualisation of individual's measurement data, including fitness data and PHR data, to help users to understand the data;
- visualisation of the risk models to help medical professionals to explore the general disease progression model and to help patients to understand individual disease progression;
- visualisation of individual risks and allowing for analysis of the impact of behaviour changes to the risks to help the patient to understand the relations between the outcomes and their behaviours.

CARRE provides web-based components for interactive health data visualisation and risk analysis, including healthlines for fitness and biomarker data, Sankey diagram and search box-based risk exploration, and interactive risk evaluation diagram for risk monitoring and analysis.

5 Visualisation

5.1 Visualisation of measurements

Fitness and medical measurement data are inherently time dependent. To visualise time-varying data, a linear form timeline is a natural choice and has been used by many of the previous works. To visualise multiple variables, the CARRE Healthlines, a special form of timeline group, is used to visualise multiple variables of fitness sensors and biomedical markers. Data trends can be observed and data correlations may be discovered by comparison of the data curves. As the data records may cover a long period, interactive techniques, such as zooming and overview + details (Cockburn et al. 2009), are employed. The users can also select the interested variables from the variable list by drag-and-drop. Figure 2 shows multiple measurements visualised in the interactive healthline in CARRE.



Fig. 2 Healthline visualises personal fitness and biomarker measurements

5.2 Visual exploration of the risk factor repository

As introduced in Sect. 3, the risk factor repository stores a number of risk factors. Instead of viewing all the risk factors in a single view, medical professionals and patients are often interested in risk factors related to some particular or individualised diseases, such as diabetes, cardiovascular disease, etc. Therefore, it is often desired to provide interactive visual exploration of risk factors of interest. CARRE provides search box-based filtering of the risk elements within the visualisation to achieve selective visual exploration of the risk factor repository, as shown in Fig. 3. The user inputs and edits interested risk elements in the search box, and the visualisation only shows those risk factors which contains the selected risk elements. The advantage of the Sankey diagram is that it shows the multi-layer causal relationships of the elements in a much clearer and understandable way than the node-link diagram, though it is not suitable for visualisation of general graph data. From the visualisation, it is fairly easy to identify the risks relating to a disease (risk element) and to recognise the routes of risk propagation.

5.3 Interactive visual risk assessment of an individual patient

The ultimate goal of CARRE is to integrate the measurement data and the risk factor repository to promote patient empowerment and individualised risk assessment. To achieve that goal, an interactive risk evaluation diagram is designed and implemented based on the risk model and measurements, both real and simulated, of the user. The visual interface is composed of a risk node-link diagram and a measurement slider panel. The risk assessment is performed by the risk condition parser which takes the risk evidence condition equations and the measurement values as input and evaluates them if the conditions hold true. For example, if the blood pressure drops to the normal range, the hypertension risk element may disappear. In another example if the user walks more, the obesity risk element and all risk factors related to obesity may disappear.

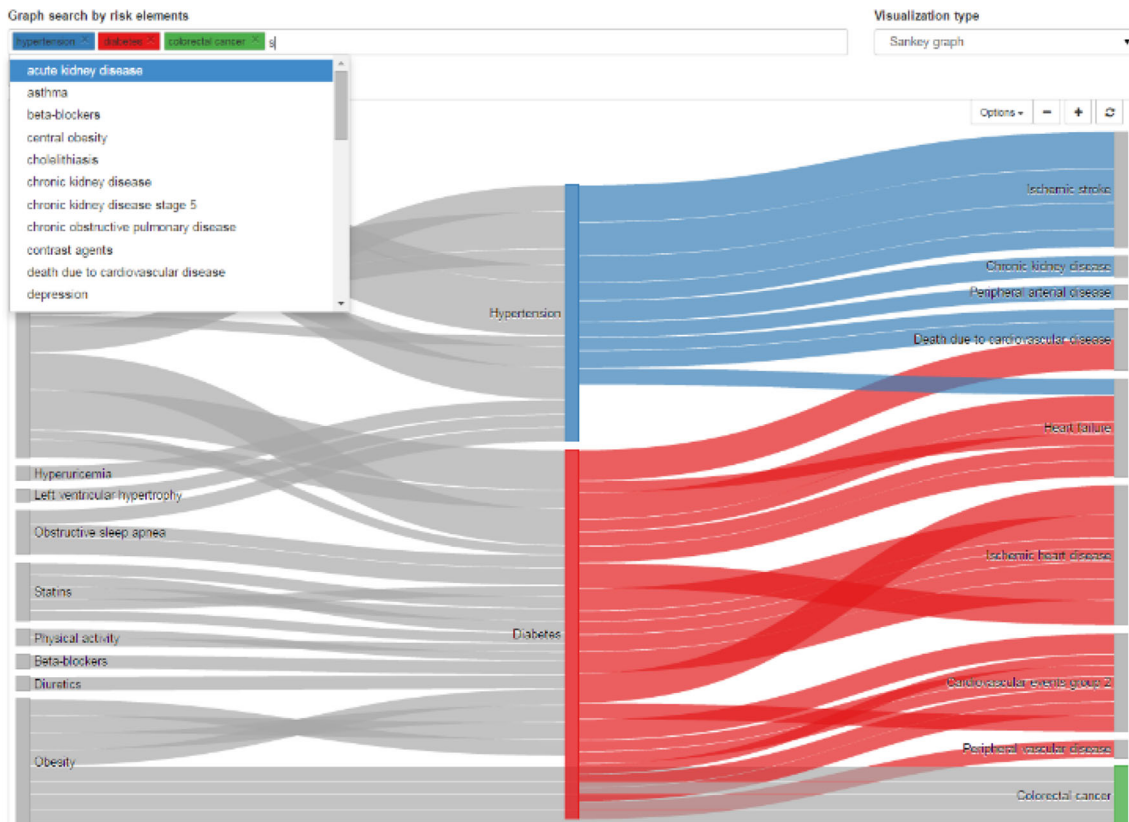


Fig. 3 Sankey diagram exploration of risk factors based on risk element filtering

5.3.1 Interface design

To empower the patients to perform interactive risk analysis, a node-link risk diagram and an interactive measurement slider panel are introduced as the user interface to enable the user to understand potential risks and the ways to reduce existing risks. By interactively adjusting the measurement values in the slider panel, the risks highlighted in the node-link diagram may emerge, grow, shrink, or disappear to reflect the risk changes with the patient's predicted conditions.

5.3.2 The risk diagram

The risk diagram is an interactive force-directed node-link diagram visualisation (Liu et al. 2014), where the nodes represent the risk entities and the links represent proven risk progressions (associations) extracted from medical literature. Though all the risk associations in the CARRE system are included in the diagram, only those risks that are considered highly possible by the risk condition parser based on the risk model and the patient's measurements are highlighted in the diagram, as shown in Fig. 4, thus reducing the visual complexity.

The node fill color represents the general disease type based on disease ontology, while the border color and the shape of a node represent the risk element types: risk source, risk target, or both.

The size of a node indicates the estimated scale of risks: the higher the risks, or the number of the incoming risk sources, the larger is the node size. However, this size is only used in an indicative sense for patients and does not reflect the real risk probability.

The direction of the link represents the direction of the risk association, and the thickness of the links represents the relative risk ratio of the risk association.

The risk elements and associations that do not apply to the user are visualised with a transparency as the background in the diagram. The opacity can be adjusted by the opacity slider in the right panel.

5.3.3 The measurement slider list panel

The measurement slider panel is introduced to enable the user to understand potential risks and the potential ways to reduce existing risks. Risk predictions can be made by interactively adjusting the measurement values in the slider panel to reflect the risk changes with the patient's predicted conditions dynamically. The slider list shows and allows adjustment of all the numeric, enumerate, and Boolean measurements of the user.

The background color of the sliders represents if the measurement relates to the risk model and user risks. A grey slider background implies that the measurement is not directly associated with any risks in the risk model, while light blue and pink indicate the potential risk measurements and the acting risk measurements, respectively.

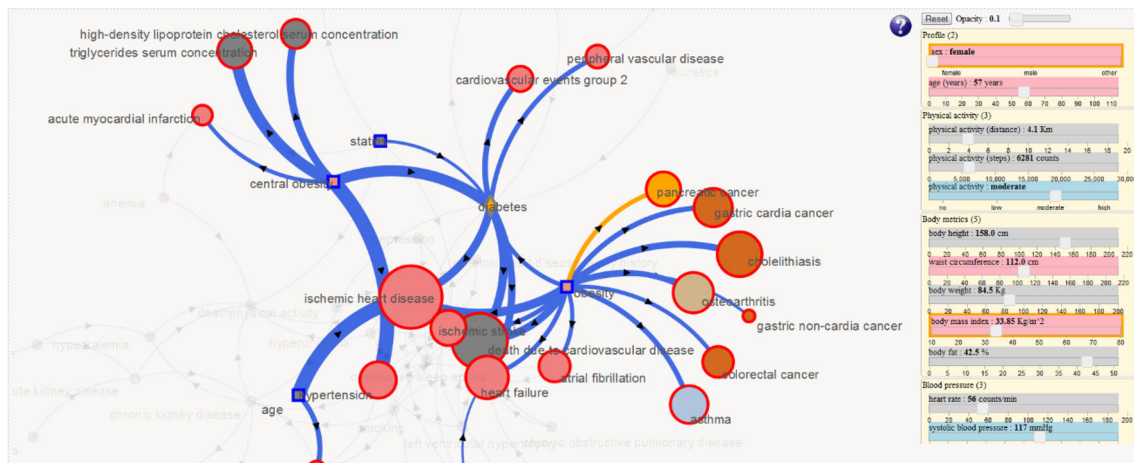


Fig. 4 Interactive risk analysis: risks highlighted and changed according to individualised measurements

When the user clicks on a risk link, the link is highlighted. Meanwhile, the borders of related acting measurement sliders will also be highlighted to remind the user the related measurements of the selected risk association (disease development), as shown in Fig. 4.

5.4 Implementation

CARRE system has been implemented as a web-based tool for integrated visualisation and analysis of personalised measurements and risks. The risk model and measurement data are stored as RDFs (RDF 2014) on the server and accessed by the client sides via SPARQL (SPARQL 2013) queries (Third et al. 2015). The data analysis and visualisation are implemented in JavaScript with the use of HTML5, CSS, jQuery, and the visualisation library D3.js.

6 Evaluation

An evaluation of the web-based visualisation modules has been undertaken by eight users through a survey. The questions focus on the functionality and usability of the visualisation components, and the answers are collected in the Likert scale (Likert 1932).

For healthlines, all eight participants agree (62.5%) or strongly agree (37.5%) with that it effectively represents the measurements collected over a time period. A majority of 62.5 and 12.5% agree or strongly agree with that it displays sufficient information. On the smooth operations of the healthlines, 50% respond with “agree” and 12.5% respond with “strongly agree”.

For the risk evaluation diagram, all eight participants agree with that it shows clear information of risks. A majority of 87.5% agree with that it displays sufficient information. All eight participants agree (75%) or strongly agree (25%) with the conclusion that the risk diagrams are easy to understand.

The evaluation results show that the visualisation tools of the healthlines and risk graph are generally easy to understand and interact with. The healthlines effectively visualise the time-varying measurement data, and the risk evaluation diagram can clearly visualise risk associations and promotes understanding of existing and potential risks. However, there is still room for improvements with the healthlines to meet the user’s expectations to display more information.

7 Conclusions and future work

The increasing availability of personal health data in the internet era has promoted patient empowerment in the healthcare sector. Data collected from wearable sensors can be used with medical data to contribute to health monitoring, risk assessment, and decision support with the support of professional clinicians. While there is a large amount of data collected from a variety of data sources, without effective visualisation, it is almost impossible to present the data and perform interactive data analysis. This paper introduces in particular the role of visualisation for health monitoring and risk assessment based on patient measurements and proven risk models in CARRE.

Multiple time-dependent measurements visualised in linear healthlines help to study and analyse fitness and biomarker data. The network of risk elements and risk factors can be visualised and explored with Sankey diagrams and a search box, which is especially useful for patients or medical professionals interested in particular disease paths. To empower the patients to view and assess their own risks, an interactive risk evaluation diagram based on adjustable measurements is presented to support risk monitoring and assessment.

In conclusion, the CARRE system provides effective interactive visualisation in health risk management and analysis to promote patient empowerment. The future work will focus on integrating the risk evaluation diagram and the healthlines to achieve time-varying risk assessment. It is also highly desirable to assist the manual risk extraction with automatic text mining, such as the techniques proposed in Dr Inventor (Wei et al. 2016).

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