The Thirty-Second AAAI Conference
on Artificial Intelligence (AAAI-18)

Water Advisor — A Data-Driven, Multi-Modal, Contextual Assistant to Help With Water Usage Decisions

Jason Ellis, Biplav Srivastava, Rachel K. E. Bellamy, Andy Aaron
IBM T J Watson Research Center
Yorktown Heights, New York 10598

Abstract

We demonstrate *Water Advisor*, a multi-modal assistant to help non-experts make sense of complex water quality data and apply it to their specific needs. A user can chat with the tool about water quality and activities of interest, and the system tries to advise using available water data for a location, applicable water regulations and relevant parameters using AI methods.

Introduction

Water, due to its role as a critical resource for health, is relevant to many aspects of a person's daily decisions about living (e.g., drinking, bathing), profession (e.g., fishing, irrigation) or recreation (e.g, boating). A decision in this space needs to consider the activity (purpose) of the water use, relevant water quality parameters and their applicable regulatory standards for safety, and actual data. A further complication is that there may be missing data for a given location, time or parameters of interest; there may be overlapping regulations and there may be alternative ways to measure a particular water quality parameter. Finally, end users need to understand the suggested advice and not take it out of context.

Given the importance of water decisions, it is surprising that there are not many assistant tools available. There are a few public tools that make water quality data available such as WaterLive mobile app for Australia [1], Bath app for UK[2], and GangaWatch for India (Sandha, Srivastava, and Randhawa 2017), but their user interfaces are oriented towards expert users.

As a consequence, public health challenges such as the Flint water crisis (Pieper, Tang, and Edwards 2017) are hard to manage. Figure 1 shows examples of advisories that the US Environment Protection Agency (EPA) provides on its website in response to a crisis or civic agencies give proactively. Water Advisor (WA) is intended to be a data-driven assistant that can guide people who do not have any special water expertise. Figure 2 shows the Water Advisor user interface.

[1]http://www.water.nsw.gov.au/realtime-data

[2]2https://environment.data.gov.uk/bwq/profiles/

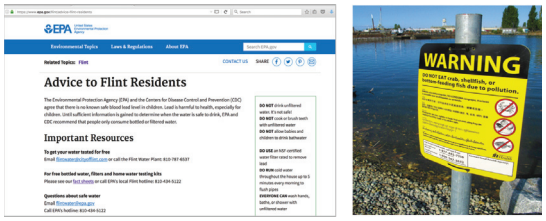

Figure 1: Sample advisories - by EPA for Flint residents (left) and by state for visitors (right; Washington State).

Data, Analysis and (AI) Challenges

WA relies on the following data: a mapping of activities (e.g., bathing, drinking, fishing) to water quality parameters, regulations applicable to activity plus water quality parameters, and actual water quality data. For mapping, we rely on previous work by (Sandha, Randhawa, and Srivastava 2015).

For regulations, we rely on information provided by the EPA for drinking and aquatic activities[3], state regulatory bodies (Michigan[4] and New York[5]) and regulations collected by (Sandha, Randhawa, and Srivastava 2015) for India. Some key decision-related challenges regarding regulations are: what regulation to use and what limits to apply depending on the region of interest, the purpose of water usage, the parameters for which data is available and their safe limits depending on parameters characteristics. We currently support four types of parameters, which is easily extendible. (a) lowAccept: where a lower quantity is preferred, like Faecal Coliform (FC); (b) highAccept: where higher quantity is preferred, like Dissolved Oxygen (DO); (c) accept_range: where non-trivial acceptable limit is directly specified, like pH; and (f) generic: where acceptable limit is generally unknown and contextual, like temperature. We provide this data publicly in JSON format for others

[3]https://www.epa.gov/wqc/national-recommended-water-quality-criteria-human-health-criteria-table; https://www.epa.gov/wqc/national-recommended-water-quality-criteria-aquatic-life-criteria-table

[4]http://www.michigan.gov/deq/0,4561,7-135-3313_3675_3691-9677–,00.html

[5]https://www.health.ny.gov/regulations/nycrr/title_10/part_6/subpart_6-2.htm

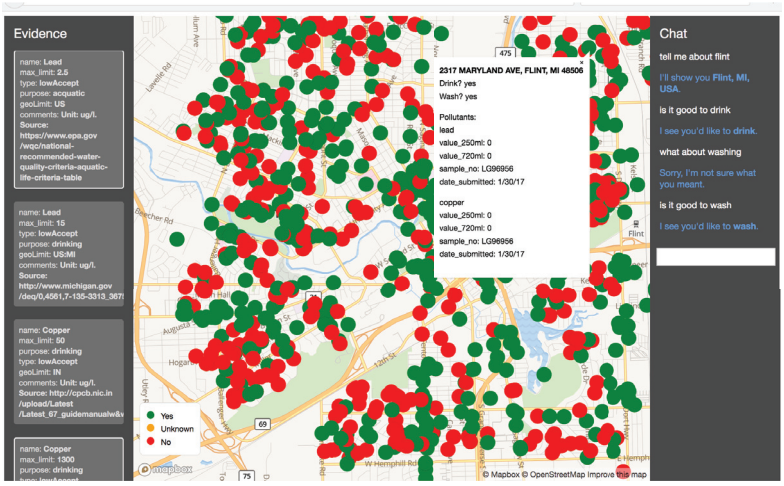

Figure 2: A screenshot of *Water Advisor*. See video of it in action at https://youtu.be/z4x44sxC3zA.

to use and make contributions[6]. Another research question is to decide whether regulations for another region should be used if local regulations are under-specified (e.g., regulation governing copper levels for drinking not specified by Michigan but provided by EPA at US level), and if so, what explanation and disclaimer to generate. WA uses the closest, spatially-relevant regulation for all parameters relevant to user's water purpose and describes them in its output.

WA uses water quality data available from Flint, MI[7]. Our approach is general and in the future, we plan to incorporate open water data from US Geological Survey[8] (USGS), research organizations (Sandha, Srivastava, and Randhawa 2017) and non-profits. Another research question for WA is what advice to generate when available data does not cover all parameters for a specified purpose. For example, for Flint, although data for Lead and Copper are available, there is no data for pH or DO in the samples that are used to determine fitness for drinking. One could assume or estimate missing data and also use alternative source to complement, but they rarely overlap for the exact location and time, which introduces errors. Currently, we provide a broad disclaimer about the system's output but recognize that user would benefit from specific caution based on importance of missing data to their activity. WA's advice for Flint is similar to the EPA's guidance but uses more precise data, regulations and activities.

User Interface - Design and Implementation

The display is broken into three sections: the Chat (right) is where users express queries to the system using natural language. The Map (center) shows locations where water data is available, indicated by dots. Once the user tells us what activity they are interested in, these dots are colored green (safe) or red (unsafe) based on the analysis of water data. The Evidence (left) shows all the regulations the system knows about. Once the activity and location are known, the regulations applicable to that activity/location combination are highlighted.

WA uses a visual information seeking approach to exploring water data: overview first, filter and zoom, then details on demand (Shneiderman 1996). The map starts with an overview of the US. The user can then begin filtering by entering text in the chat. For example, a user might type "I want to drink water in Flint" (many forms of such utterances are understood). The map would then zoom in on Flint and highlight the dots red/green based on the activity (drink). The user may then click on individual dots to get more detail on the location, pollutant levels, and analysis. WA uses the following services to enable this experience: Watson Services[9] - Conversation and Natural Language Understanding (NLU) for conversation management and NLP, respectively, and Mapbox[10] for visualization.

[6]https://github.com/biplav-s/water-info

[7]http://www.michigan.gov/flintwater/0,6092,7-345-76292_76294_76297—,00.html

[8]https://waterdata.usgs.gov/nwis/current/?type=quality

[9]https://www.ibm.com/watson/products-services/

[10]https://www.mapbox.com/

References

Pieper, K. J.; Tang, M.; and Edwards, M. A. 2017. Flint water crisis caused by interrupted corrosion control: Investigating "ground zero" home. *Environmental Science & Technology* 51(4):2007–2014.

Sandha, S. S.; Randhawa, S.; and Srivastava, B. 2015. Blue water: A common platform to put water quality data in india to productive use by integrating historical and real-time sensing data. In *IBM Res. Rep. RI15002*.

Sandha, S. S.; Srivastava, B.; and Randhawa, S. 2017. The gangawatch mobile app to enable usage of water data in every day decisions integrating historical and real-time sensing data. *CoRR* abs/1701.08212.

Shneiderman, B. 1996. The eyes have it: A task by data type taxonomy for information visualizations. In *IEEE Symposium On Visual Languages*, 336–343.