A Framework for Comparing Early Warning Systems across Domains: A Step Toward a Data-Integrated Public Health EWS*

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***Abstract*— Early Warning Systems (EWS) are a crucial tool for public health, providing time for agencies to devise and enact control and mitigation measures in the face of emerging health threats. EWS offer similar benefits to agencies that manage other domains such as natural disasters or financial markets. After surveying various EWS, we developed a novel framework for characterizing EWS across domains. Key to this framework is the characterization of EWS's domain and focal event; whether its aim is prediction, detection, or warning, whether its focus is model, systems, or infrastructure; the extent of human intervention required; and its input data. We believe this framework is quite novel, but more importantly, it serves as a reference to chart future projects. We use it to verify that an opportunity exists in developing a public health EWS that integrates a spectrum of inputs from Web 2.0 and social media data, data from sensors, data from, say, electronic health records, as well as human opinions and behaviors.**

I. Introduction

Google Flu Trends is an example of how advances in how we use the Web are leading to novel means of addressing public health issues. It is a Big Data application in which the premise that noticeable increases in searches for flu-related terms in a given geographical location is correlated with an increase in flu occurrences in that area can be used as a proxy for flu activity to inform individuals and public health policy-makers [1, 2]. In a similar vein, there are applications that leverage social media and Web 2.0: Increases in Twitter feeds and use of flu-related hashtags [3], and even prediction markets are used as proxies for flu activity [4]. There are myriad of different works that address use of Big Data, social media, and Web 2.0 applications for public health surveillance such as flu monitoring in South China [5], monitoring interest in preventable causes of death (e.g. smoking and obesity) in the US [6], and tracking kidney stone incidences [7]. Beyond their roots in Web and social computing, another commonality amongst these efforts is their reliance upon the Web as a convenient, large-volume, proxy representation of the collective public health concerns—as expressed as search queries or tweets—of a population in a certain area during a certain time period. The purpose is for monitoring and surveillance of phenomena relevant for public health.

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A more general application in which variety of data analysis methods are applied to varied forms of data for public health, and which pre-dates Web 2.0, represents a topic of research and practical interest under the labels of syndromic surveillance [8] and digital disease detection [9]. Much more generally, a domain-independent term for such systems that encompass other modes of surveillance such as human observations and control sensor inputs is *Early Warning Systems (EWS)* [10, 11].

The purpose of this paper is bridge that gap between the very specific—aggregating Web 2.0 and social media data as a proxy for incidences of public health phenomena—to the very general—Early Warning Systems. By outlining a framework that characterizes how an application like Google Flu Trends is an instance of an Early Warning System, this paper represents a first step in our efforts to incorporate and integrate social media and Web 2.0 data analytics to other public health syndromic surveillance/disease detection system capabilities.

II. Early Warning Systems in Different Domains

A. Public Health and Medical Applications

Incorporating both data about patients such as time and place of their hospital visits along with specific DNA tests on them, Mellman et al. [12] propose early warning algorithms for the MSRA bacteria, which causes treat staph infections that are often difficult to treat. Hethcote surveys such mathematical models of infectious diseases [13]. Izydorczyk et al. [14] present work that is typical of studies that focus on drawing causal relationships that can be used to provide early warnings. In their work, they show that increases in water fluorescence can be a marker for heightened levels of bacteria that cause bad odor and taste in water. In another work, factors like ventilatory frequency, heart rate, body temperature, and blood pressure of incoming patients are used to provide early warnings of increased mortality risk [15]. Sometimes when causal factors are well-understood and dominant factors can be measured, early warnings with significant lead time may be possible. Thompson et al. [16] show that ocean-atmosphere climate models can predict malaria incidences in African up to four months in advance.

Rather than focus on algorithms and causal modelling, some EWS works focus on systems aspects, i.e. how warnings are triggered and how alerts are given. *ProMED-mail* collates information about plant and animal diseases useful to agriculturalists, as well as about zoonosis possibilities, and posts them on Websites and alerts subscribers [17]. Or in another, Britain planned for a national infrastructure for an early warning system for public health [18].

Finally, most early warning systems are driven by manual intervention; that is, organizations such as World Health Organization (WHO) and the Centers for Disease Control (CDC), for example, have standard operating procedures and protocols that are followed by doctors, nurses, hospital administrators, and public health and other governmental officials to determine how early warnings for outbreaks and other concerns are initiated and escalated [19]. For example, in the SARS outbreak of 2003, Dr. Carlo Urbani of the WHO was instrumental in attending to a SARS patient, recognizing the patient's illness as something new, and then escalating that finding to the WHO: "Working in a hospital in Hanoi, Vietnam, as a mysterious pneumonia felled one nurse after another, he sang out the first warning of the danger, saw the world awaken to his call — and then died" [20]. In the case of SARS, tools like ProMED-mail and Global Public Health Intelligence Network (GPHIN) were then used to ensure that warnings were accurate and disseminated and heeded appropriately worldwide. GPHIN is a multi-lingual early warning system that gathers publicly available reports on a real-time basis, and organizes and filters this information using automated processes complemented by human analyses [21]. Whether it's Dr. Urbani's efforts leading to disseminating information using ProMED-mail, or it's GPHIN's use entailing automated processes complemented by human analyses, the SARS case illustrates that early warning systems practically entail complementary automated and manual processes.

In 2004, an EWS was set up in war-torn Darfur, Sudan to warn and manage outbreaks of disease amongst refugees living in close quarters across 54 camps, encompassing an effective population of refugees and city inhabitants nearly totaling one million [22]. The EWS provided value as a common information system where health care workers working in different camps could input and share patient data and their insights, and where they could escalate an early warning to the WHO and their peers. As in the SARS case, proper EWS use required effective execution of complementary automated and manual processes.

These highlighted works are but a few of the many efforts that fall under the area of early warning systems for public health and medical applications. In fact, there are many survey papers, which fall under mainly two categories: general syndromic surveillance, digital disease detection, or biosurveillance [23-27]; and systems using Web 2.0, Big Data search queries, and social media [28-30].

B. *Natural Disaster Applications*

There are many early warning systems that aim to warn of impending natural disasters. Gasparini et al. classify those for earthquakes [31]. Most systems for earthquakes interpret readings from ground sensors and can give fairly accurate warnings 6-10 seconds before an event [32]. The aim of the PRobabilistic and Evolutionary early warning SysTem (PRESTo) project in southern Italy is more expansive insofar as it encapsulates real-time earthquake location and magnitude estimation algorithms as a software tool [33]. Therefore there is focus on both early warning algorithms and the IT or systems aspect of an EWS. By far, the most expansive is Japan's earthquake early warning system, especially in its use of infrastructures like television and cellular networks as well as the Internet for warning dissemination. However, the warnings are alerted after an earthquake event, not before [34]. Interestingly, there are efforts that exploit the phenomenon that animals as varied as dogs, horses, and toads sometimes exhibit anomalous behavior prior to an earthquake [35]. They aim to use animal behavior as indirect, proxy predictive sensors for an earthquake, which provides the benefit of greater lead-time for warning but with accuracy much lower than ground sensor-based predictions. There is even an interesting effort to integrate tweets, along with their geo-tags and other tweet meta-data, with earthquake data shortly following an earthquake event to give an accurate estimate of ground shaking intensity [36].

Closely related are tsunamis, which are usually triggered by earthquakes or volcano eruptions in the ocean. A key difference is that because of the lag between the earthquake event and its impact on distant coastal populations, there can be time to react and prepare for the tsunami. After the devastating Indian Ocean tsunami of 2004, the German Indonesian Tsunami Early Warning System (GITEWS) established an extensive system and infrastructure, employing components like communication satellites, simulation models, GPS buoys, pressure sensors in the seabed, and a warning center. There are other systems that focus on warning the population for events such as hurricanes [37], heat waves [38], tornadoes [39], and famines and droughts [40]. For all these, a time dimension is an important way to characterize the different types of early warning systems: "early warning systems provide tens of seconds of warning for earthquakes, days to hours for volcanic eruptions, and hours for tsunamis. Tornado warnings provide minutes of lead-time for response. Hurricane warning time varies from weeks to hours. Warning time, provided by warning systems, increases to years or even decades of lead-time available or slow-onset threats (as El Nino, global warming etc.)" [41][1].

C. *Other Applications*

Some examples of early warning systems efforts that focus on algorithms and analytics include those for predicting future financial crises [42], early detection in strategic planning [43], and even suspicious betting on soccer matches [44].

More elaborate early warning systems that integrate such analytics with information systems and infrastructures exist for terrorism surveillance [45], surveillance of financial crimes such as money laundering [46], for automatic monitoring of vehicle collisions [47].

Numerous other health, disaster, and miscellaneous early warning systems exist that we did not catalogue. Nevertheless, we have surveyed enough of the literature to characterize the space of early warning systems.

III. Analysis of Early Warning Systems

One characterization is *what is the event* for which an early warning system is developed? Is it clearly understood

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and identifiable, as is the case with occurrences of earthquakes, hurricanes, and common forms of influenza? For those types of events, sensors and input filters can be instrumented to warn of the event. Or is the event more difficult to clearly identify, as was the case with SARS, where it was known that there was a spread of an infectious disease but the disease itself was not well understood. Similarly, in 2008-9, the world knew that it was in the throes of a financial crisis but it was not a particularly well understood. In the parlance of the Black Swan theory [48], it is worthwhile to ask if the event to warn for is a "known known" (where means to identify and manage a well-understood event are well-established as in outbreaks of the common flu); a "known unknown" (where means of identification and management are well-established, but the event itself is not well-understood as with SARS [a disease previously unknown] or a natural disaster like earthquake or flash tornado that occurs and devastates with little warning). If the event is an "unknown unknown," (where before the event, such an event was not foreseen as with 9/11 or the collapse of Lehman Brothers), only a domain-independent EWS would be of use.

Related to the Black Swan theory is the *extent to which we can control the event*. Climatology and meteorological models may allow us to effectively predict famines and droughts, hurricanes, and heat waves with reasonable lead times to prepare for the event. So prediction is possible. With tools like Google Flu Trends and effective communications amongst healthcare institutions, policy makers in developed countries can expect reasonably early detection of the common flu. Because SARS was a "known unknown" that started in a developing country with a government that was initially not transparent about the outbreak, early detection did not occur, at least not to the extent necessary to avoid the virus being carried to other countries and continents. However, with the co-operation of the Chinese government and the work of dedicated professional like Dr. Urbani, early warning of SARS arguably did occur, aided by systems such as ProMED-mail and GPHIN. The key aspect of Japan's earthquake early warning system or Indonesia's tsunami warning system, and the reason why the systems use critical infrastructures and are so large in scale, is that the focus is on alerting the population, i.e. widespread warning.

Further characterization evaluates the early warning system itself. *Where is the focus placed on the effort?* Is the focus on the mathematical models and algorithms for disease detection? Is it on the Big Data processing and social media text mining algorithms necessary to draw inferences about flu activity? Or does it have an IT and systems focus, as does ProMED-mail, GPHIN, and the system used in Darfur to warn of infectious outbreaks? Some systems aim to integrate the analytics and algorithms with IT and systems necessary to provide early warning to those who may benefit from them. Google Flu Trends and PRESTo system for earthquake detection in Italy are integrative that way. Finally, some like Japan and Indonesia's systems have as their main aim to provide warnings to as many as possible so they use IT and systems in a much larger scale, using critical infrastructures and sensor networks to prepare the population.

Related to the focus is the *extent to which the processes performed by the Early Warning System are manual or automated*. How important is human intervention in the operation of the system? The researcher who writes a paper on an epidemiological model of disease outbreak, the Google engineer who tweaks parameters for Flu Trends, Dr. Urbani for SARS, the doctors using the system in Darfur, the operators who runs Japan's earthquake system, and even the driver who uses the early warning system to avoid a collision all play different roles.

Finally, *what type of data is used as inputs to the early warning system?* Is it digitized; that is, is it in electronic form or is observational or conversational, as in Dr. Urbani's actions that escalated SARS as of interest to the WHO. What is the source of the data? Is it from the publicly accessible Web? Is it from electronic health records or other privileged databases? Is it from a sensor network? How formal is the electronic data represented? Is it free form text that requires natural language processing? Is it semi-structured data like search terms, keywords, or hashtags? Is it structured data from a domain-independent data model like, say, Twitter time and location metadata? Or is it structured data from a domain model like, say, patient's electronic health records? Or is it structured data coming from a sensor, say, a medical device?

IV. A Framework for Characterizing Early Warning Systems

Though there are a myriad of different EWS, surveys of such works nearly always appear to be done with respect to a given domain. When EWS across domains are compared, the emphasis is on domain-independent modelling techniques [10], does not entail systematic characterization [49], or is not truly domain-dependent but rather is applicable for a class of domains, e.g. for disaster and environmental applications [41].

So based on our analysis, here is a novel framework for characterizing an Early Warning System.

- What is its domain?
- What is the event for which a warning is needed?
  - Is it a "known known," "known unknown," or "unknown unknown" event?
- To what extent can the event or its outcome be controlled?
  - Is the aim prediction, early detection, early warning, or widespread warning?
- Where is its focus?
  - On early warning models, algorithms, and analytics?
  - On IT and systems
  - IT and systems at the scale of critical infrastructure use
  - Integrative—i.e. on more than one foci
- What is the extent and importance of human intervention in its operations?

- What kind of data input is required?
  - Is it digital or not (i.e. conversations or observations that trigger the system)?
  - What is the source of the data? Is it from the publicly accessible Web, privileged databases like electronic health records, or sensors?
  - How formal is the representation? Is it freeform text, semi-structured data, structured data with a limited accompanying domain model (e.g. simple metadata), or structured data with an accompanying data model (or ontology).

V. CONCLUSION

We surveyed works in Early Warning Systems in public health and medical domains, as well as in natural disaster and miscellaneous domains. After reviewing these works, we developed a novel framework for characterizing EWS across domains. Key to this framework is the characterization of EWS's domain and focal event; whether its aim is prediction, detection, or warning, whether its focus is model, systems, or infrastructure; the extent of human intervention required; and its input data.

Beyond the novelty of this framework, we use it to plan a roadmap for our future works in using Web and social media for public health applications. Can we for instance, use data from these sources to make a model that is more predictive, not one that is useful mainly for early detection as is the case with Google Flu Trends? Or can we integrate data from these sources with data from other sources such as privileged databases and sensor networks? So as to be economical, can we integrate the data as a fully- or semi-automated process? Can we ensure that human opinions and behaviors can also be sufficiently integrated? We are able to more objectively raise and answer these kinds of questions as a result of developing our framework.

Finally, the framework also allows us to more objectively classify and understand merits of others' recent works. For instance, what makes the effort to combine tweets following an earthquake with their locational, time, and relational metadata, as well as other earthquake data [36] so interesting? Based on the framework, we believe it is because the effort endeavors to integrate a wide spectrum of input data types from free form and semi-structured tweets to structured tweet metadata to structured data from earthquake databases to structured data from ground sensors.

VI. REFERENCES

[1] S. Cook, C. Conrad, A.L. Fowlkes and M.H. Mohebbi, "Assessing Google flu trends performance in the United States during the 2009 influenza virus A (H1N1) pandemic," PloS One, vol. 6, pp. e23610, 2011.

[2] J. Ginsberg, M.H. Mohebbi, R.S. Patel, L. Brammer, M.S. Smolinski and L. Brilliant, "Detecting influenza epidemics using search engine query data," Nature, vol. 457, pp. 1012-1014, 2009.

[3] H. Achrekar, A. Gandhe, R. Lazarus, S. Yu and B. Liu, "Predicting flu trends using twitter data," in Computer Communications Workshops (INFOCOM WKSHPS), 2011 IEEE Conference on, pp. 702-707, 2011.

[4] J. Ritterman, M. Osborne and E. Klein, "Using prediction markets and Twitter to predict a swine flu pandemic," in 1st international workshop on mining social media, 2009.

[5] M. Kang, H. Zhong, J. He, S. Rutherford and F. Yang, "Using google trends for influenza surveillance in South China," PloS One, vol. 8, pp. e55205, 2013.

[6] L.J. Carr and S.I. Dunsiger, "Search query data to monitor interest in behavior change: application for public health," PloS One, vol. 7, pp. e48158, 2012.

[7] R. Zeiger and M.H. Mohebbi, "Re: Breyer et al.: Use of Google Insights for Search to Track Seasonal and Geographic Kidney Stone Incidence in the United States (Urology 2011; 78: 267-271)," Urology, vol. 79, pp. 486-486, 2012.

[8] K.J. Henning, "Overview of syndromic surveillance. What is syndromic surveillance," MMWR Morb.Mortal.Wkly.Rep., vol. 53, pp. 5-11, 2004.

[9] J.S. Brownstein, C.C. Freifeld and L.C. Madoff, "Digital disease detection—harnessing the Web for public health surveillance," N.Engl.J.Med., vol. 360, pp. 2153-2157, 2009.

[10] M. Scheffer, J. Bascompte, W.A. Brock, V. Brovkin, S.R. Carpenter, V. Dakos, H. Held, E.H. Van Nes, M. Rietkerk and G. Sugihara, "Early-warning signals for critical transitions," Nature, vol. 461, pp. 53-59, 2009.

[11] L. Fuld, "Be prepared," Harv.Bus.Rev., vol. 81, pp. 20-21, 2003.

[12] A. Mellmann, A.W. Friedrich, N. Rosenkötter, J. Rothgänger, H. Karch, R. Reintjes and D. Harmsen, "Automated DNA sequence-based early warning system for the detection of methicillin-resistant Staphylococcus aureus outbreaks," PLoS Medicine, vol. 3, pp. e33, 2006.

[13] H.W. Hethcote, "The mathematics of infectious diseases," SIAM Rev, vol. 42, pp. 599-653, 2000.

[14] K. Izydorczyk, M. Tarczynska, T. Jurczak, J. Mrowczynski and M. Zalewski, "Measurement of phycocyanin fluorescenceas an online early warning system for cyanobacteria in reservoir intake water," Environ.Toxicol., vol. 20, pp. 425-430, 2005.

[15] R.W. Duckitt, R. Buxton-Thomas, J. Walker, E. Cheek, V. Bewick, R. Venn and L.G. Forni, "Worthing physiological scoring system: derivation and validation of a physiological early-warning system for medical admissions. An observational, population-based single-centre study," Br.J.Anaesth., vol. 98, pp. 769-774, Jun. 2007.

[16] M. Thomson, F. Doblas-Reyes, S. Mason, R. Hagedorn, S. Connor, T. Phindela, A. Morse and T. Palmer, "Malaria early warnings based on seasonal climate forecasts from multi-model ensembles," Nature, vol. 439, pp. 576-579, 2006.

[17] L.C. Madoff, "ProMED-mail: an early warning system for emerging diseases," Clin.Infect.Dis., vol. 39, pp. 227-232, Jul 15. 2004.

[18] G. Smith, J. Hippisley-Cox, S. Harcourt, M. Heaps, M. Painter, A. Porter and M. Pringle, "Developing a national primary care-based early warning system for health protection--a surveillance tool for the future? Analysis of routinely collected data," J.Public.Health.(Oxf), vol. 29, pp. 75-82, Mar. 2007.

[19] A.R. McLean, R.M. May, J. Pattison and R.A. Weiss, SARS: A case study in emerging infections. Oxford University Press, 2005, .

[20] D. McNeil Jr, "Disease's pioneer is mourned as a victim," New York Times, April 8, 2003. 2003.

[21] E. Mykhalovskiy and L. Weir, "The Global Public Health Intelligence Network and Early Warning Outbreak Detection." Canadian Journal of Public Health, vol. 97, 2006.

[22] A. Pinto, M. Saeed, H.E. Sakka, A. Rashford, A. Colombo, M. Valenciano and G. Sabatinelli, "Setting up an early warning system for epidemic-prone diseases in Darfur: a participative approach," Disasters, vol. 29, pp. 310-322, 2005.

[23] C. Castillo-Salgado, "Trends and directions of global public health surveillance," Epidemiol.Rev., vol. 32, pp. 93-109, Apr. 2010.

[24] N.E. Kman and D.J. Bachmann, "Biosurveillance: a review and update," Adv.Prev.Med., vol. 2012, pp. 301408, 2012.

[25] E.O. Nsoesie, J.S. Brownstein, N. Ramakrishnan and M.V. Marathe, "A systematic review of studies on forecasting the dynamics of influenza outbreaks," Influenza and Other Respiratory Viruses, 2013.

[26] B. Cakici, "The Informed Gaze: On the Implications of ICT-Based Surveillance," 2013.

[27] S. Funk, M. Salathe and V.A. Jansen, "Modelling the influence of human behaviour on the spread of infectious diseases: a review," J.R.Soc.Interface, vol. 7, pp. 1247-1256, Sep 6. 2010.

[28] D. Capurro, K. Cole, M.I. Echavarria, J. Joe, T. Neogi and A.M. Turner, "The use of social networking sites for public health practice

and research: a systematic review," J.Med.Internet Res., vol. 16, pp. e79, Mar 14. 2014.
[29] N. Collier, "Uncovering text mining: A survey of current work on web-based epidemic intelligence," Global Public Health, vol. 7, pp. 731-749, 2012.
[30] T.M. Bernardo, A. Rajic, I. Young, K. Robiadek, M.T. Pham and J.A. Funk, "Scoping review on search queries and social media for disease surveillance: a chronology of innovation," J.Med.Internet Res., vol. 15, pp. e147, Jul 18. 2013.
[31] P. Gasparini, G. Manfredi and J. Zschau, Earthquake early warning systems, Springer, 2007, .
[32] R.M. Allen and H. Kanamori, "The potential for earthquake early warning in southern California," Science, vol. 300, pp. 786-789, May 2. 2003.
[33] C. Satriano, L. Elia, C. Martino, M. Lancieri, A. Zollo and G. Iannaccone, "PRESTo, the earthquake early warning system for Southern Italy: concepts, capabilities and future perspectives," Soil Dyn.Earthquake Eng., vol. 31, pp. 137-153, 2011.
[34] O. Kamigaichi, M. Saito, K. Doi, T. Matsumori, S. Tsukada, K. Takeda, T. Shimoyama, K. Nakamura, M. Kiyomoto and Y. Watanabe, "Earthquake early warning in Japan: warning the general public and future prospects," Seismol.Res.Lett., vol. 80, pp. 717-726, 2009.
[35] J.L. Kirschvink, "Earthquake prediction by animals: evolution and sensory perception," Bulletin of the Seismological Society of America, vol. 90, pp. 312-323, 2000.
[36] L. Burks, M. Miller and R. Zadeh, "RAPID ESTIMATE OF GROUND SHAKING INTENSITY BY COMBINING SIMPLE EARTHQUAKE CHARACTERISTICS WITH TWEETS," 2014.
[37] J. Lauterjung, U. Münch and A. Rudloff, "The challenge of installing a tsunami early warning system in the vicinity of the Sunda Are, Indonesia." Natural Hazards & Earth System Sciences, vol. 10, 2010.
[38] K. Ebi, "Towards an early warning system for heat events," Journal of Risk Research, vol. 10, pp. 729-744, 2007.
[39] P. Bieringer and P.S. Ray, "A comparison of tornado warning lead times with and without NEXRAD Doppler radar," Weather and Forecasting, vol. 11, pp. 47-52, 1996.
[40] A. Herman, V.B. Kumar, P.A. Arkin and J.V. Kousky, "Objectively determined 10-day African rainfall estimates created for famine early warning systems," Int.J.Remote Sens., vol. 18, pp. 2147-2159, 1997.
[41] V.F. Grasso and A. Singh, "Early warning systems: State-of-art analysis and future directions," United Nations Environment Programme (UNEP)., 2011.
[42] M. Bussière and M. Fratzscher, "Towards a new early warning system of financial crises," J.Int.Money Finance, vol. 25, pp. 953-973, 2006.
[43] P. Rossel, "Beyond the obvious: Examining ways of consolidating early detection schemes," Technological Forecasting and Social Change, vol. 78, pp. 375-385, 2011.
[44] D. Aquilina and A. Chetcuti, "Match-fixing: the case of Malta," International Journal of Sport Policy and Politics, pp. 1-22, 2013.
[45] CDC, "Biological and chemical terrorism: strategic plan for preparedness and response," MMWR, vol. 49, pp. 1-14, 2000.
[46] M. Levi and P. Reuter, "Money laundering," Crime and Justice, vol. 34, pp. 289-375, 2006.
[47] D. Greene, J. Liu, J. Reich, Y. Hirokawa, A. Shinagawa, H. Ito and T. Mikami, "An efficient computational architecture for a collision early-warning system for vehicles, pedestrians, and bicyclists," Intelligent Transportation Systems, IEEE Transactions On, vol. 12, pp. 942-953, 2011.
[48] N.N. Taleb, The Black Swan:: The Impact of the Highly Improbable Fragility, Random House LLC, 2010, .
[49] G.F. Treverton, "Comparing Early Warning Across Domains," by: The Swedish National Defence College., 2011.