

# A Predictive Analytics Toolbox for Medical Applications

Michael L. Valenzuela and Jerzy W. Rozenblit  
Electrical and Computer Engineering Department  
University of Arizona  
mvalenz@ece.arizona.edu, jr@ece.arizona.edu

Allan J. Hamilton  
College of Medicine  
University of Arizona  
allan@surgery.arizona.edu

**Keywords:** Management, Decision Support, Healthcare, Visualization

## Abstract

Ever more frequently business enterprises are benefiting from the collection and analysis of large data. This paper reports on a work in progress of adapting intelligence, predictive analytics tools for analysis of medical data. While large data has been used in medical research, only recently has this become a trend for hospital management. A suite of tools originally developed for military intelligence analysts are repurposed for hospital management. The original design concepts is reviewed, its medical applications and challenges are described along with an illustrative example.

## 1. INTRODUCTION

Over the last two decades, information technology (IT) systems are being increasingly adopted by hospitals. Even seemingly mundane IT systems such as computerized patient records were already installed in 1997 at Cabarrus Family Medicine in Concord, NC [1]. In 1996, the Johnson Medical Center in Johnson City, TN, decided it needed a data warehouse to spot trends and anomalies [1]. The next natural progression of this pattern is to use a computer system driven by the data warehouse to provide medical decision support.

Hospital management is in need of decision-support systems (DSS). DSS have been used in many domains, ranging from stability and support operations [2, 3], to intelligence analysis [4–6], to the medical domain [7–11]. Such a system would help hospitals in many ways: cut costs; discover and prevent causes of medical mistakes; decide whether a patient should recover from home or have a longer hospital stay; identify risk factors; optimize bed assignments; analyze work flow; and in general uncover actionable information. Yet, most prior DSS in the medical domain have focused on recommending drug prescriptions, diagnosing the source of chest pain, treating infertility, and promptly administering immunizations [8, 11]. Yes, hospital management systems have lagged behind that of medical science.

A multitude of work applies advanced data analysis techniques to biomedical problems. [12] use hidden Markov models (HMM) to shed light on the folding pathways of a complex protein. [13] built a metamorphic virus detector based on HMM. [14] uses reinforcement learning and an artificial neu-

ral network to improve the outcome of fractionated radiotherapy. Back in 2002, support vector machines improved cancer classification using gene selection from 86% accurate to 98% accurate [15]. However, the use of advanced tools for hospital administration has lagged behind advances in biomedical research, possibly due to the different nature of hospital administration.

The demands on biomedical research are similar, but not the same as that of hospital administration. Both share ethical concerns, but biomedical ethics concerns itself with “playing God” and the dangers of the substances/organisms. Hospitals have to worry more about privacy concerns and patient safety. The top ranking concerns for hospitals have been financial concerns for the last 10 years [16]. As such hospitals are concerned with avoiding bad debt, reducing operating costs, and preventing lawsuits. Whereas in the world of research the primary demand is get valid, significant results, before anyone else.

In this paper, we present a single comprehensive tool, Med-Think<sup>TM</sup>. Med-Think, previously developed as an intelligence analyst’s toolbox [4–6], reduces the gap between hospital management tools and those tools used for biomedical research. It offers a plethora of data visualization, exploration, querying, analysis, and management capabilities. Even though Med-Think is still under development, it offers hospital management a data driven management and decision support system.

The rest of this article proceeds as follows. Section 2 reviews alternative systems and briefly discusses the history of Med-Think. This is followed by a description of how Med-Think’s models data in Section 3. Section 4 describes Med-Think’s capabilities and applications. We discuss immediate challenges to the adoption of the system in Section 5. Last, we conclude and discuss future directions for Med-Think in Section 6.

## 2. BACKGROUND

Due to the rapidly emerging interest in advanced data driven hospital management, the breadth, variety, and number of these tools are likely to explode in the coming years. However, the recent demand for advanced data driven hospital management tools has been left unmet. This is partially due to the lack of available tools. As such, we only review a

few of these systems.

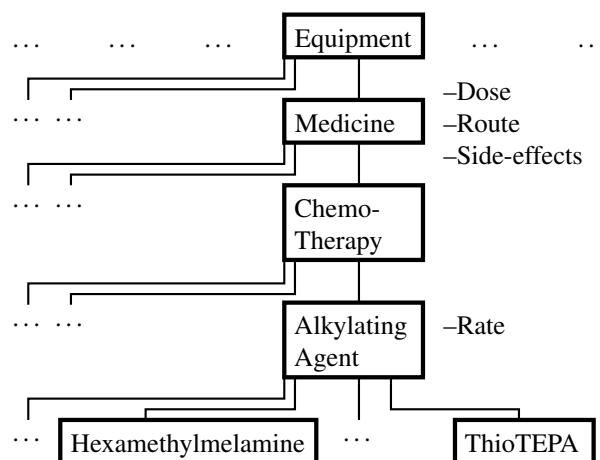
Recent progress in health informatics has focused primarily on data visualization and basic regression analysis. [17] apply temporal data mining and exploratory data analysis methods to hospital management data. They visualize pairs of trends as trajectories, plot data, and use a generalized linear model to predict hospital revenue in terms of stay duration, gender, age, treatment outcomes, and admission time. However, their analysis is adhoc, being built upon an amalgam of tools. They performed the generalized linear model analysis using the “R Project” and a custom C++ program for the trajectory analysis [18]. Furthermore, the applied techniques are far from as sophisticated as the techniques applied in biomedical research.

While there is little known about Raytheon’s INTERSECT CONNECT®, the available public information suggests that it can easily be adapted to be a contender as an advanced data driven management tool. Officially INTERSECT CONNECT® is “[s]oftware that enables users to monitor and analyze multi-source streams of data and to produce reports based thereon” [19]. Much is still unknown about this project. Furthermore, at the time this article was written, it was non-trivial to purchase a license to use the software.

Another available tool is the Hospital Management System.<sup>1</sup> It is a free and open source management system, meaning that a programmer can make changes to the software to better suit the needs of the hospital. However, this tool handles only hospital logistics. It supports managing “patient information, staff information, stores and medicines, billing and report generation. This complex application communicates with a backend database server and manages all information related to hospital logistics.” It lacks the data analysis capabilities needed to offer data driven decision support.

Med-Think, at its roots, is derived from an intelligence analyst’s toolbox known as the Asymmetric Threat Response and Analysis Program (ATRAP) [4, 5]. As such, it was originally developed to assist in the processing and dissemination of massive data in an unstable, rapidly changing environment. Its capabilities are the abilities to: a) ingest large data sets in multiple formats, b) derive links and pattern over data sets and carry out extensive social network analysis, c) visualize data patterns in geo-temporal spaces, and d) carry out “what if scenarios” through sophisticated game-theory based algorithms. ATRAP’s capabilities were appropriate to port over to Med-Think. Our system focuses on both geo-temporal data (*e.g.*, the spread of a pathogen through a hospital) and relational data (*e.g.*, how doctor X, nurse Y, patient Z, and a medical error are connected). We discuss these capabilities in more detail in the following section.

<sup>1</sup>It is an open source project hosted at <http://hospitalmanagesourceforge.net/>



**Figure 1.** Example Entity Hierarchy

### 3. MODELING DATA

Med-Think possesses a database backend to handle large, varied data. Having such, Med-Think’s modeling is not limited by computer memory. The database mostly comprises:

- raw imported data including reports, comma separated value (CSV) files, and multimedia,
- “entities” (organizations, persons, places, events, equipments, etc.),
- a hierarchy of entity types and their corresponding data fields,
- five-tuples composed of an entity, latitude, longitude, date, and time,
- directed, typed relationships between two entities, and
- queries and their results.

We use the generic term “entity” to refer to any object we wish to model. Fundamentally, an entity has a type from a user-customizable type hierarchy. Each type in the hierarchy may have its own data fields and inherited data fields from its ancestor types. For example, an entity might be specified as a medicine (parametrized by a dose, route, etc.), an alkylating agent (furthermore parametrized by a rate), or specific substances such as hexamethylmelamine and ThioTEPA (*cf.* Figure 1). Entities may be an instantiation a type or a singleton for that type. Additionally, an entity may have zero or more geo-temporal data points. Each five-tuple assigns an absolute time and location to an entity. This is particularly useful for modeling the spread of a disease through a hospital, city, or country. Lastly, entities may have any number of directed, typed relationships to other entities. For example, a doctor may specialize in treating a disease, but a patient may have a disease. The types of relationships are also user customizable.

Queries are modeled as the following 10-tuple:

- an input (specifically a collection of entities), if none is provided the whole database is used,
- an input entity type,
- an option to match more general entity types,
- a search string,
- a collection of data fields and their values,
- a collection of relationships the entity must share,
- an optional start date-time,
- an optional end date-time,
- a geographic area, and
- an output entity type.

The query allows for any data associated with entities to be searched. This means the entity type, its specific data fields, relationships with other entities, times, or locations may be searched. Moreover, since each query has an input type and output type, the results from one query can be fed into another query. The input into a query must be the same as-, a decedent of-, or an ancestor of the query's input entity type. The option to match more general entity types allows an ancestor type to match at a reduced matching "score." We will talk more about the matching score in the next paragraph. The search string is used to search all the entity's data field. When more precision is required, individual fields may be searched. Furthermore, entities may be searched by time and location.

Fuzzy matching makes a search resilient by returning results which fit a looser query. To avoid flooding the user with too much information, we sort the results by the matching score. The matching score for an entity is reduced based on how "far off," from the query it is. Entities may be "off" by type, location, or time. The score decays exponentially, at a user-adjustable rate  $\delta$ , for each level of entity type abstraction. Assuming the hierarchy in Figure 1, a search for alkylating agents returns entities of the type ThioTEPA without penalty and entities of the type medicine with a penalty of  $\delta^2$ . Similarly, queries for time (specified as an interval) and location (specified by a polygon drawn on a map) may be made fuzzy. The penalties follow user-adjustable functions. The matching score comes from the product of these penalties and is in  $(0.0, 1.0]$ .

#### 4. SELECTED SYSTEM FEATURES AND CAPABILITIES

The system is compelling as an advanced investigatory tool for hospital administration. It is built upon mature software that already handles most data-oriented tasks. It can serve as a "cognitive amplifier" for data analyst in that it offers facilities

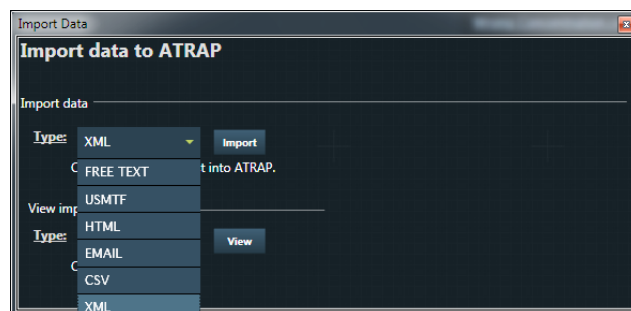


Figure 2. Med-Think supports importing data from many and varied sources

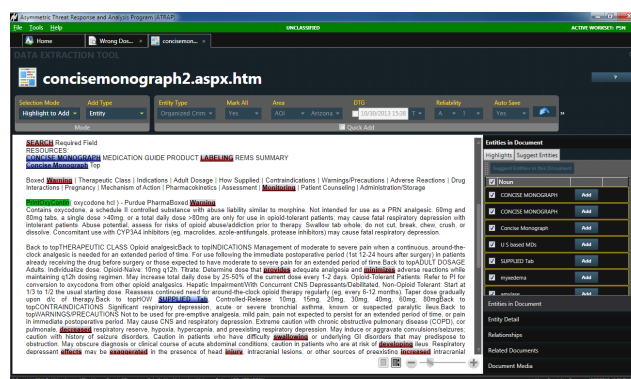


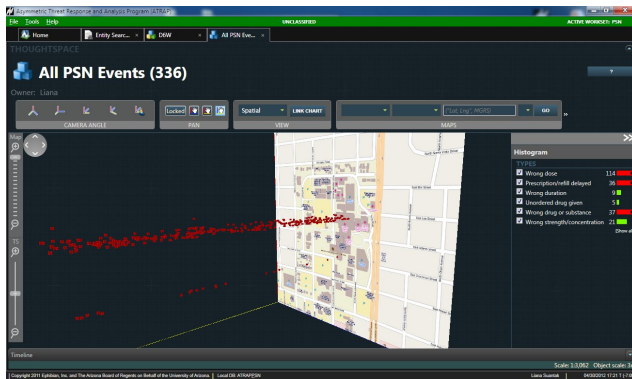
Figure 3. Med-Think's natural language processing converting free text document into structured data

to that lead to discover of facts from large sets of information. We show its capabilities through a revealing example.

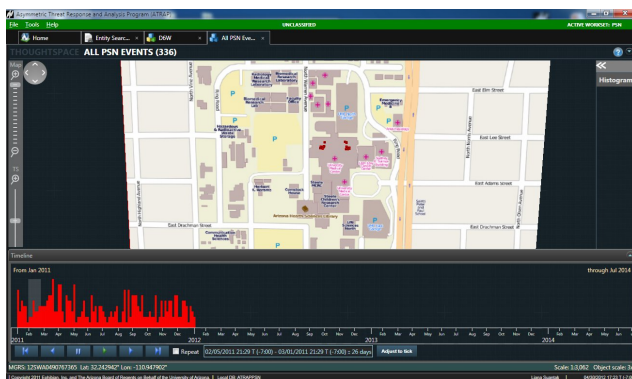
A local hospital donated sanitized data. The data came in the form of .XML, charts, and reports. Med-Think imports data from a manifold of sources (*cf.* Figure 2). We supplemented this with data based on real stories in the news, particularly that of pharmacists stealing drugs.

Structured data can be searched more efficiently and precisely than unstructured text. Unfortunately most of the reports are written in free text, leaving the task of structuring the data to a human. To aid in this task we used Med-Think's natural language processing (NLP), which is built upon a regular-expression corpus [20]. Figure 3 illustrates how the NLP tool can automatically highlight suspected entities and suggest their entity types as indicated by the color of the highlighting. Nevertheless, Med-Think keeps a human in-the-loop to improve confidence in the structured data.

To analyze the hospital data, we began by visualizing all the medical incidents. Using a unique module called Thoughtspace™, we overlaid the medical incidents with a map of the hospital. Thoughtspace has two types of views. One where entities are plotted against a map and their relative time is illustrated as their height on the map (*cf.* Figure 4). A histogram shows the most common type of medical incident



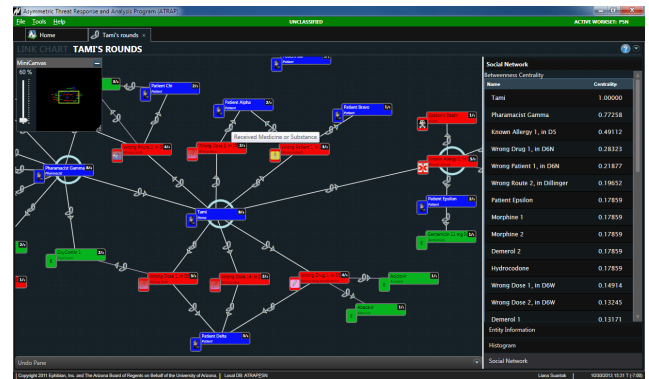
**Figure 4.** Med-Think's Thoughtspace™ illustrating medical incidents plotted across the hospital



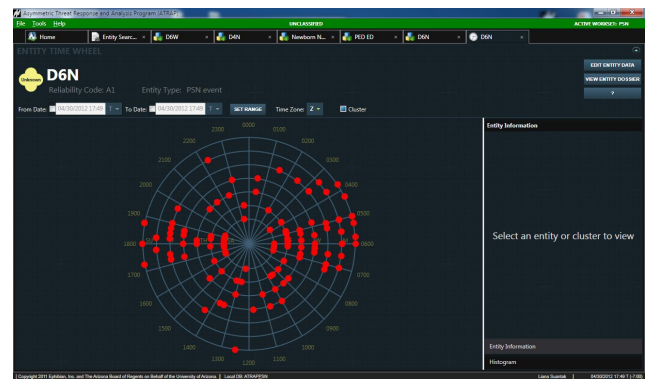
**Figure 5.** Med-Think's Thoughtspace™ depicting a time slice and histogram of medical incidents

is a wrong dose while rarely are unordered drugs given. This figure also shows how few medical errors occur on the south side of the hospital. Thoughtspaces's other view plots all the entities within a sliding-time-window flat against the map (cf. Figure 5). In this view, the histogram along the bottom shows two to four spikes in the number of medical incidents: one in March, one in August, maybe one in June, and maybe one spanning November and December. The spikes in March and August correlate with the hiring of new nurses. New doctors are hired in the summer, and the spike in November and December is likely due to the holidays.

Figure 6 visualizes the relationships between entities in the data. This figure shows a number of medical mistakes surrounding a nurse; the majority of which were wrong dose related. The data shows that most of the wrong dose substances were narcotics and that most of the doses were too low. Further analysis shows that these wrong doses were dispensed by the same pharmacist, who happened to be associated with more wrong doses. As it turned out, in the pharmacist was eventually fired for drug abuse. A tool such as Med-Think could catch this kind of trend early-on, preventing some of the wrong dose medical incidents.



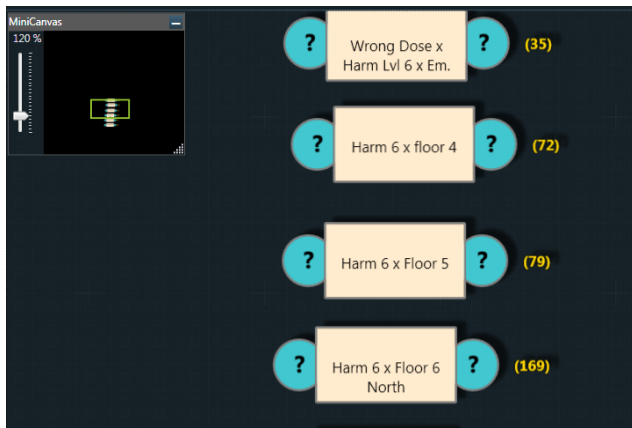
**Figure 6.** Med-Think's visualization of relationships between entities



**Figure 7.** Med-Think can also plot occurrences on a time wheel

Lastly, we turn our attention to a different time span. Rather than looking at yearly trends, we look at mistakes made on a weekly basis. Figure 7 illustrates events plotted by time of day and day of the week on a time wheel. The angle around the wheel represents time of day of the incidents and the distance from the center represents the day of the week. The two clusters of mistakes which occur around 6:00am and 6:00pm coincide with the change of staff. This makes sense as just before the shift change, the staff is tired from working 12-hour shifts, and just after the shift change, the new staff has to quickly catchup on their new patients. The hospital administration may try to reduce the number of mistakes caused by the shift change by using either short shifts or by staggering the shift changes throughout the day.

Next, we wish to investigate not all medical incidents, but only those with a high level of harm. Specifically, we ask "which hospital ward has the most incidents with the highest level of harm?" Med-Think allows us to quickly query this because the medical incidents have a field called "harm level." The process is as simple as selecting the type of medical incidents, selecting a hospital ward from a drop down list, and selecting the highest harm level field. This makes it possi-



**Figure 8.** Comparing the number of high harm incidents by floor

ble to query which hospital ward has the most incidents with the highest level of harm. Figure 8 shows the results of such a query. Sixth floor north has the most significant-mistakes. Further investigation shows that ward is an intensive care unit (ICU); maybe the higher stress environment or the patients needing more care contribute to more mistakes. Further querying should be considered to determine what the mistakes were, when they occurred, and which personnel were working when the medical incidents occurred.

## 5. CHALLENGES AND SOLUTIONS

The challenges in repurposing a defense intelligence analyst's "cognitive amplifier" tool for the medical community are complex. They arise from adjusting the tool for a different audience. Doctors and hospital administrators have different thought processes than military intelligence analysts. One possible solution to this problem is to trace how medical professionals intend to use the system, re-optimizing the process flow to match their intended use.

The medical community uses a different jargon. For instance, when showing ATRAP, the term "query model" confused the medical professionals. Confusion leads to wasted time which leads to increased operating costs. Perhaps more common terms such as "chains of reasoning" or "sequential queries" are more intuitive.

Adoption of the tool has also been slowed by an overly complicated graphical user interface (GUI). By default Med-Think shows advanced features with which few doctors and hospital administrators have experience. As such, the advanced features only serve to confuse novices. Yet, we must be careful to avoid over simplifying the tool and "insulting" the user's intelligence. The solution would be to employ Human-Computer-Interaction (HCI) experts and to hold studies evaluating the user-friendliness and perceived benefit of design and visuals. One idea is to allow a user to select

Novice	Advanced	Expert
Search: _____	Search: _____	Search: _____
	Cross with Data Type ▾	Field ▾ Value ▾
		Has a connection to Other Entity ▾
		Cross with Data Type ▾

**Figure 9.** A possible method to balance power and user-friendliness

his/her competency as illustrated in Figure 9. This solution may solve yet another problem: that of evolving software.

New versions of software introduce bug-fixes, new features, and changes to the interface; but new versions also present challenges. The new features make the software's learning curve steeper and hence less likely to be adopted by novices. Changes to the interface may alienate experienced users. This is what has happened to ATRAP, leading to both its complex search capabilities and challenges in repurposing it for a medical audience. Again, these problems can be mitigated with an appropriate user interface. Perhaps each new version's features and interface changes could be as a level of competency (see Figure 9).

In some respects, Med-Think is over-engineered. The database structure is unnecessarily complex providing much unnecessary functionality (for the medical domain) at the cost of performance and ease of use. The individual capabilities are more powerful and complex than standard users need. This leads back to the problem of a crowded, less user-friendly GUI. We have several ways in which we can resolve these issues. We can effectively remove unnecessary degrees of freedom from the system by removing unused database fields/tables and merging database tables. Again, allowing the user to select their level of experience will allow him or her to hide the advanced options, reduce screen clutter, and make the default tools more user-friendly.

The last set of challenges originate from missing capabilities needed by the new audience. While Med-Think is a powerful tool, there are several missing features, some of which we are still unaware. Med-Think needs to offer some form of spell checker when a user is building a query. Another commonly requested feature is to allow the user to specify free variables in their queries. In the previous example where we answered, "which ward has the most incidents with the highest harm level," it required one query per ward. It would be more efficient to specify one query where the ward is a free variable. While there is some trend and correlation extraction capabilities, they need to be improved. Overall, these chal-

lenges are surmountable and will ultimately lead to a better tool.

## 6. CONCLUSION

The growing gap between data analysis techniques used in biomedical sciences and hospital administration has left hospitals lacking good data-driven decision support systems. The growing interest in data-driven hospital administration tools has lead us to investigate some of the available software systems. One tool was an amalgam of disparate tools, offering basic statistical analysis, visualization, and analysis of trajectories (paired temporal trends). Raytheon's INTERSECT CONNECT®, seems powerful but few details are publicly released. We also reviewed one open source program which managed hospital data, but did not perform any advanced analysis on it. Ultimately, we felt that none of these systems effectively closed the gap between biomedical research and that of hospital administration. We repurpose a "cognitive amplifier" for intelligence analysts, the Asymmetric Threat Response and Analysis Program (ATRAP), for the medical community as Med-Think.

We presented Med-Think, its capabilities and applications through an enlightening example based on sanitized hospital data. Med-Think can import diverse data sets, both structured (Excel files) and unstructured (text files). Thanks to the use of natural language processing, Med-Think augments the process of structuring the unstructured data. Med-Think's visualization capabilities allows one to plot patients, events, staff, etc. across time and space in a myriad of ways. This includes plotting the data directly on a map, through histograms, through timewheels, or through relationship charts. Med-Think also supports general purpose querying to quickly and easily answer questions such as "which hospital ward is responsible for most of the serious medical incidents."

Challenges presented by repurposing ATRAP for the medical domain are discussed and potential solutions are posited. The change in audience requires Med-Think (the repurposed ATRAP) to become more user friendly and less overwrought. A good way to balance its full capabilities with user-friendliness would be to have each user select a level of experience with the tool. Novices would have the advanced features hidden by default but still accessible, while experts are shown the advanced features from the start.

Future directions for Med-Think will predominately be determined by the medical community, but some directions are more certain. For instance, Med-Think needs better statistical analysis capabilities and times-series analysis. Eventually, we would like to integrate the more advanced features from artificial intelligence and machine learning to detect novel health risks, predict future trends, and model hospital costs and revenue. This should help hospital administration improve hospital efficiency and cut costs. Ultimately, we hope to make

Med-Think better suited to helping hospital administration and doctors alike.

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## Biography

Michael L. Valenzuela is a Graduate Research Associate and Ph.D. student in the Electrical and Computer Engineering Department. His research interests include modeling, simulation, decision theory, and machine learning. He is developing a novel meta-learning prospect exploiting theoretical equalities in the No Free Lunch theorems for search, optimization, and supervised learning. His goal is to design new strategies to help computers reason and learn more like humans. He has also previously worked on the Asymmetric Threat Response and Analysis Program (ATRAP). On this project he worked with a subject matter expert to help design the Query Model (QM), which mimics how intelligence analysts work.

Dr. Jerzy W. Rozenblit is University Distinguished Professor, Raymond J. Oglethorpe Endowed Chair in the Electrical and Computer Engineering (ECE) Department, and Professor of Surgery in the College of Medicine at The University of Arizona. From 2003 to 2011 he served as the ECE Department Head. During his tenure at the University of Arizona, he established the Model-Based Design Laboratory with major projects in design and analysis of complex, computer-based systems, hardware/software codesign, and simulation modeling. The projects have been funded by the National Science Foundation, US Army, Siemens, Infineon Technologies, Rockwell, McDonnell Douglas, NASA, Raytheon, and Semiconductor Research Corporation. Dr. Rozenblit has been active in professional service in capacities ranging from editorship of ACM, IEEE, and Society for Computer Simulation Transactions, program and general chairmanship of major conferences, to participation in various university and departmental committees. He had served as a research scientist and visiting professor at Siemens AG and Infineon AG Central Research and Development Laboratories in Munich, where over he was instrumental in the development of design frameworks for complex, computer-based systems. Currently, jointly with the Arizona Surgical Technology and Education

Center, he is developing computer guided training methods and systems for minimally invasive surgery. Co-author of several edited monographs and over two hundred publications, Jerzy holds the PhD and MSc degrees in Computer Science from Wayne State University, Michigan, and an MSc degree from the Wrocław University of Technology. He presently serves as Director of the Life-Critical Computing Systems Initiative, a research enterprise intended to improve the reliability and safety of technology in healthcare and life-critical applications.

Dr. Allan Hamilton holds four Professorships at the University of Arizona in Neurosurgery, Radiation Oncology, Psychology, and Electrical and Computer Engineering. He graduated from Harvard Medical School and completed his neurosurgical residency training at the Massachusetts General Hospital in Boston. He has been chosen by his neurosurgical peers as “One of America’s Best Doctors” for the last twelve consecutive years. Dr. Hamilton has held the positions of Chief of Neurosurgery and Chairman of the Department of Surgery at the University of Arizona. Dr. Hamilton serves as Executive Director of the Arizona Simulation Technology and Education Center, a multi-disciplinary think-tank at the Arizona Health Sciences Center devoted to developing new technologies and training procedures to reduced preventable medical adverse events. He has authored more than twenty medical textbook chapters, fifty peer-review research articles, and has served on the editorial board of several medical journals. He is also a decorated veteran Army officer who served in Operation Desert Storm. Dr. Hamilton’s first book, “The Scalpel and the Soul” <http://www.allanhamilton.com/scalpelsoul.html>. “Encounters with Surgery, the Supernatural,” and “the Healing Power of Hope” (2008, Tarcher/Penguin USA) was awarded the 2009 Nautilus Silver Award <http://www.nautilusbookawards.com/>, which was conceived to recognize world-changing books. Previous Nautilus Award winners include Deepak Chopra, Eckhart Tolle, and His Holiness the Dalai Lama. “The Scalpel and The Soul” has been translated into several languages and is now in a paperback edition. For the last several years Dr. Hamilton has served as medical script consultant to the TV series “Grey’s Anatomy.”