"Predicting the Unpredictable" Make Crucial Decisions in Real Time

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ABSTRACT

Existing solutions to support decision makers in their preparedness and execution of operations during catastrophes are currently insufficient. 4Cast solutions help first responders and organizations improve disaster intelligence, readiness, competence and real-time decision-making. Achieved by the incorporation of a robust suite of on-demand services, integrating big data, historical trends, AI and academic research to deliver a total solution that supports decision-making before and during events.

Our Methodology is based on integrating big data predictive analytics and AI. We started by bringing a new approach to Natural Language Generation (NLG). Our platform analyzes data, extracts insights, and displays it all in plain language. This produces a layer integrating models for competency & readiness to ensure effective decision-making. The next layer is a constructive simulation engine based on doctrine, physical behavior and M.O.R. data running Agent-Based Model Simulation (ABMS). Complex scenarios are generated in a quick, intuitive manner. The calculation algorithms are based on the principles of Event Driven Architecture (EDA). Combining this principle with the mathematical method of Markov chains enables the simulation of command and control and operational processes. The last layer is a tailor-made AI algorithm based on doctrine combined with self-play.

- Altogether, the platform is a game changer for decision makers.
- Automated approach generating scenarios based on competence assessment creates simulations that reflect real-life situations.
- NLG increases plain language usage in incident response and Real-time assessment provides insights into organizational, team, and individual performance.

ABOUT THE AUTHORS

Nissim Titan - Nissim understands that everything we do in our personal and professional lives is based on our ability to make decisions, and that making good decisions when it counts requires knowledge, experience and insight. He joined the company in 2004, bringing with him extensive expertise in the development of qualification methodologies and CRPM, which he pioneered in the IDF. His career has included the initiation and leadership of complex projects for the implementation of organizational measurements and qualification approaches used today in the IDF, from which he retired with rank of Lieutenant Colonel. Nissim has an MSc in Industrial Engineering and Management from Tel Aviv University.

Morgan Brooke - Morgan has over two decades of experience in government sales, managing contracts and international business development. Morgan is a leader in the 4Cast United States office where he brings a wealth of knowledge in working with a wide range of industries including defense, homeland security, disaster relief and healthcare. He is focused on developing the U.S. market as he understands the requirements of clients as they implement 4Cast services. Morgan received a Bachelor of Science degree in Business Administration from Colorado State University.

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The need to deal with day-to-day emergency scenarios and extreme situations requires peacetime preparations and "capability-building" activities. This is essential to ensure readiness for emergencies caused by natural disasters, epidemics, operational failures, terrorist incidents and conflicts between countries.

All these events require preparation, training and practice by a range of different groups and service providers, such as military, government, municipal councils, national rescue and lifesaving forces, police agencies, firefighters and medical centers, to ensure that they are ready and coordinated to play their respective roles. To be adequately prepared for all eventualities, a wide spectrum of possible scenarios need to be tested at various levels of intensity and in different geographic locations and possible engagements by stakeholder groups.

True decision-support preparation requires close examination and ongoing verification of force building plans, emergency procedures and operation doctrines alongside existing capabilities, modeled outcomes, and an evaluation of the alternatives.

Today, there are many "decision-support systems", including solutions that incorporate training, exercise and simulation. However, these systems tend to be too artificial and disconnected from reality. Furthermore, they fail to quickly adapt to lessons learned and incorporate operational doctrines, evaluate capabilities and recommend solutions.

Military and Emergency responders complain that these decision support systems often fail to prepare them for real-world situations, particularly because they:

- Do not provide the level of precision.
- Do not have the cognitive computing.
- Often focus on new methods to aggregate data and present consolidated information products and reports.
- Presume a level of user competence that is often not supported, measured or actualized in reality.

The ability to make decisions is one of the most important skills that managers, leaders and commanders have to develop. Decision making within an organization involves a systematic process of identifying and solving problems; of asking questions and searching for answers. In emergency situations, the decision-making process is usually performed under conditions of uncertainty and is affected by changes and circumstances that are often uncontrollable.

The barrier to progress in the training for readiness in emergency situations can be overcome by integrating environmental and physical models such as competency readiness models, artificial intelligence and predictive analytics with world-class training, simulation and decision-support systems. This will result in solutions that are designed to measurably improve competencies and capabilities of defense and public safety officials.

LIMITATIONS OF CURRENT TECHNOLOGIES

The limitations of current technologies focus on three main areas:

Lack behavior-based research: The majority of current technologies are typically developed in silos. While they offer wide-ranging functionality, they require significant software development to ensure interoperability with the existing systems of a host organization. Furthermore, many technologies in the defense, public safety and first responder community often lack the behavior-based research which is essential for design, development and implementation. Consequently, technologies are frequently developed to support automation or efficiencies through enhanced business process workflows, without taking into account the development, enrichment or measurement of competencies, capabilities and results of use.

Address tactical, rather than strategic, problems: Existing technologies in the marketplace are typically developed to solve tactical problems introduced by a specific set of use cases. They are not designed to solve strategic problems of an organization and do not incorporate cognitive computing. For example, an organization may have the ability to monitor situational awareness, conduct predictive analysis and coordinate tactical resource deployments. However, it may not be able to strategically understand or communicate its competencies, readiness and likelihood of success on a mission, or be able to navigate new risks and exposure related to previously made decisions. While many current technologies can mathematically predict some probabilities, they are not designed to account for the human dimension, including the competencies, readiness and experiential needs of "tired, dirty and hungry" responders.

Lack the interoperability offered by well-documented APIs and a services-based approach: Most current technologies in the market are built as an "all-or-nothing" capability. They lack a well-documented API and a services-based approach that would enable users to leverage and integrate components of a system into their existing architecture. Such all-or-nothing systems have no concern for interoperability, whereas services-based systems with well-documented APIs are strategically positioned to be fully interoperable and leveraged in legacy systems and application environments.

4CAST APPROACH AND CONCEPT

Our solution is a dynamic, cognitive computing and decision-support system for military and homeland security service providers. It is designed to help military forces and HLS support organizations improve disaster intelligence, readiness, competence and decision-making through the integration of a robust suite of on-demand services, artificial intelligence and simulation of human thought processes in a computerized model.

Our platform, integrates the following:

- Data on the readiness of the forces and authorities
- A geographic engine that includes data on the location of the incident and an interface to weather conditions, in order to simulate real-life conditions, such as the spread of fire and the dispersion of hazardous materials
- An interface to systems such as Google Maps / Waze in order to present a picture of the situation on roads, etc.
- Simulation of possible military, first responder and crowd behaviors

The combination of all this data turns the platform into a big data infrastructure which includes Natural Language Generation (NLG), advanced analytics to turn all relevant data into recommendations to decision makers. However, success of the system requires that three main issues have to be addressed:

- How is it possible to verify that the recommendations produced by the simulation engine are as close as possible to reality i.e., real-life situations?
- How is it possible to filter the data according to the different roles of people involved in military and homeland security and responsible for providing emergency services e.g., police commanders, medical support teams, firefighters and city mayors?
- How is it possible to provide users optimal accessibility to the data as simply as possible, in real time?

It is these key issues that we address and resolve with our solution.

System Components Overview

Our concept includes the following components:

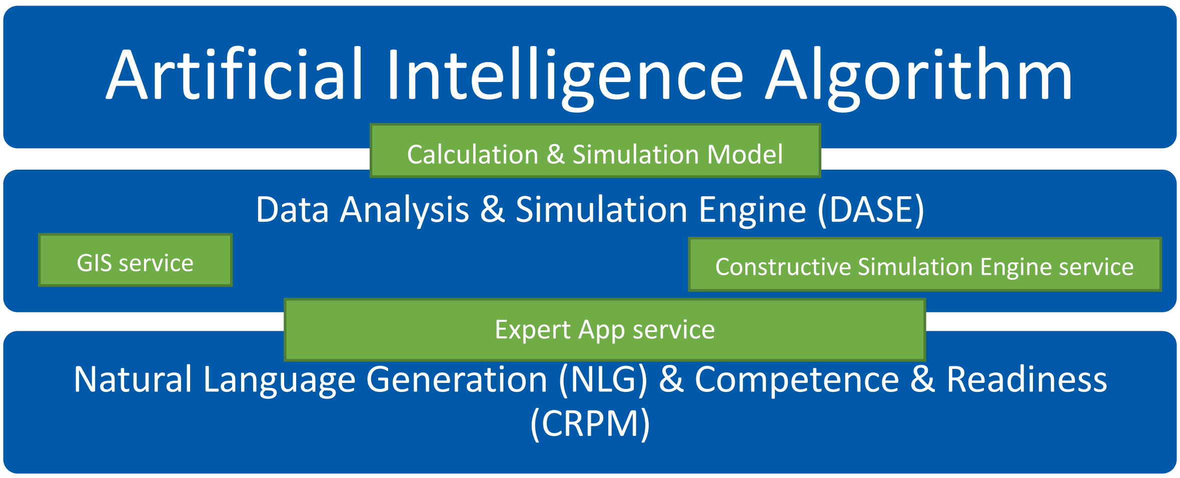

Figure 1: Artificial Intelligence Algorithm

System Components

The result received will be displayed in three parts:

A list of interpretations based on the overall situation picture and of each entity in the system, and the ability to cope with a task in accordance with varying scenarios and a crowd behavior model.
A list of recommendations for execution / non-execution, according to the summary of recommendations received from all of the systems.
A visual display of a detailed, full situation picture for each entity, based on a physical map and relative to location, progress of other entities and changes in physical conditions.

LAYER 1 – NATURAL LANGUAGE GENERATION (NLG) & COMPETENCE AND READINESS PERFORMANCE CALCULATION ENGINE (CRPM)

The CRPM calculation engine is a data processing layer that weights the marks for existing entities in the system according to a measurement methodology. It includes a system expert module, which constitutes a platform that builds a methodology for the measurement of entities from a universe of content, procedures and doctrines. Consequently, the calculation engine is directly dependent on the CRPM system expert module. Methodologies are translated into models, parameters and input forms, and the calculation engine creates a current situation picture of the abilities of the entity and the subunits composing it. **Consequently, the function of the calculation engine is processing and application of the methodology, and transferring the results reflecting the abilities of the entity.**

LAYER 2 – DATA ANALYSIS & SIMULATION ENGINE (DASE)

The DASE is a tool that aggregates the results of information from the sensors and calculations engines and conducts high-fidelity analysis and simulation of results. Consequently, it will allow users to test their actual situation in various scenarios by utilizing predictive analytics and constructive simulation tools. Furthermore, the DASE will allow validation of preferred means of action and presentation of the consequences, while considering various aspects such as the competence levels and geographical aspects.

DASE has three main services:

- **Expert app service** – receives all data integrated in the platform from Layer 1 and structures all the data in predictive models.
- **GIS service** - a suite of analytical algorithms that calculate a range of predictive analytics, such as location-based risk analyses and economic loss estimations.
- **Constructive Simulation engine service** - runs predictive analytics and trend for different scenarios.

Expert App Service
Expert app service receives all data integrated in the platform from Layer 1 and structures all the data in predictive models, parameters and input forms, and the calculation engine creates a current situation picture of the abilities of the entity and the subunits composing it. Consequently, the function of the calculation engine is processing and application of the methodology, and transferring the results reflecting the abilities of the entity before running the agent-based model simulation calculation.

GIS Service
The GIS calculation engine focuses on the use, analysis, service and delivery of data on a range of subjects such as GIS, weather and natural models (see Figure 2). The GIS service calculates the physical behavior of an object or entity in space, according to the scenario, calculation processes and algorithmic processes received from the simulation engine.

The use of uniform geographic infrastructures from geographic information data is of primary importance and is essential for the uniform calculation of results. These infrastructures are mapped according to the layers described. Additionally, the GIS service will include a suite of analytical algorithms that calculate a range of predictive analytics, such as location-based risk analyses and economic loss estimations.

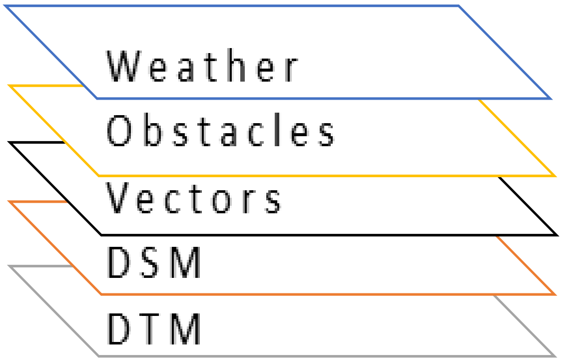

Figure 2: Geographic Information Data Model

The GIS service calculation engine offers a single, centralized and unified standard for all data. By reducing the infrastructure to different layers, it enables the development of knowledge systems that will serve all existing and future simulations. This careful mapping of services for simulation calculations is based on two systems – the calculation of the line of sight and the electromagnetic spectrum – both of which have a critical impact on the simulation results.

Constructive Simulation Engine Service

The constructive simulation engine based on doctrine, physical behavior and M.O.R. data running Agent-Based Model Simulation (ABMS) (see Figure 3). Calculations derived from simulations serve as a data layer that is taken and incorporated into other elements of the platform.

The data layer contains the base data, physical equations, calculation processes, algorithmic processes, data dissemination and user management processes, as well as the session service, i.e., user-specific simulation sessions, allowing the loading of data relevant for each scenario in the system. Complex operational scenarios are generated in a quick, intuitive manner, and the loaded relevant scenario data includes the definitions of the entities participating in the scenario.

The calculation algorithms are based on the principles of Event Driven Architecture (EDA). Combining this principle with the mathematical method of Markov chains enables the simulation of command and control processes, and other operational processes. **The simulation calculation engine provides a "real world" simulation based on a range of algorithms and produces the results of the scenario for the entities in the system.**

This will help to support the force-building processes for military, emergency and rescue service providers. Simulations will include the examination of activities and decisions made by commanders/managers in the various scenarios, with an emphasis on the behavior of crowds in different events.

This is particularly important since around the world, government ministries, local authorities, essential establishments and emergency and rescue agencies are required by law to prepare for emergencies and practice the readiness of all emergency units in providing services to citizens and functional continuity of emergency situations. The authorities involved in emergency situations routinely gather relevant data and enable them to examine existing gaps and processes in different scenarios.

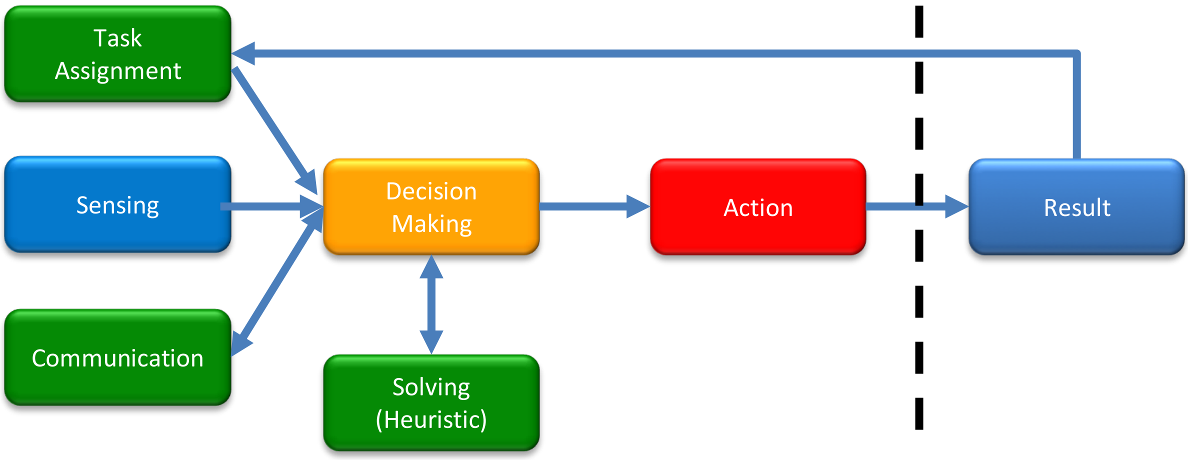

Figure 3: Agent-based Simulation Model

In general, the technology and infrastructure leverage the following three recognized mathematical models, which are used in the DASE calculation model:

- Systemic relationship model
- Model for calculation of the state (level of preparedness)
- Problem-solving model (heuristic).

The integration of these models provides the possibility of modeling very complex processes that cannot be modeled in a single process.

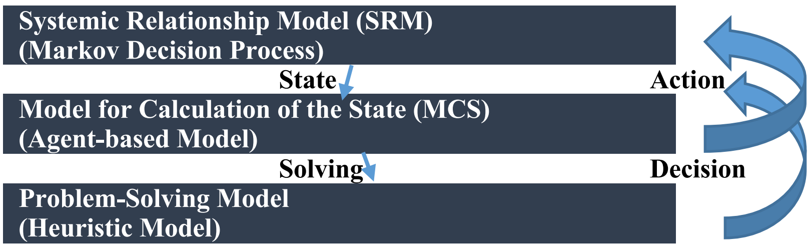

Figure 4: Calculation & Simulation Model

The Systemic Relationship Model (SRM)

The SRM allows for connecting and linking of different processes to form a complete sequence of events, with the ability to link and connect different events into the overall process. This model is based on the Markov Decision Process (MDP) (see Figure 5), which enables calculation of the probability of the action in the next state according to the result of the previous state.

This multistate process is also implemented in some of the models by a Hidden Markov Model (HMM), which enables the combination of models that are "hidden" from the viewer in the calculation process and the combination of links to unexpected models in the process. The use of these models forms complexity that leads to a number of causes yielding the same effect. Therefore, the integration in a Bayesian network that allows for combining of guiding values received from analysis systems and various expert systems (such as competency systems) will enable receipt of a full process that allows for simulation of the various processes that integrate decisions from different types alongside action options and rule sets.

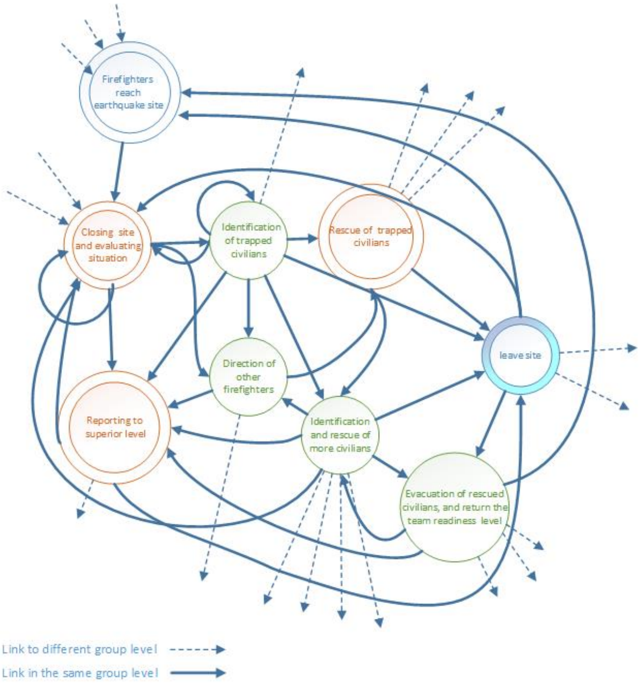

Figure 5: Sample Markov Firefighter Unit Model

Model for Calculation of the State (MCS)

Each state in this complex chain contains a calculation process that can be both simple and complex. Consequently, the agent-based model must allow for combining different types of calculations, from simple observation of events to complex decision-making on the manner of operations.

Problem Solving Model (Heuristic Model)

The problem-solving stage can be complex and includes parameters that cannot be interpreted in simple mathematical terms. Therefore, it will sometimes use a heuristic calculation that will allow for a result that simulates the human decision-making process so that cognitive understanding can be reached. This calculation will often use a number of parameters such as social norms, genetic heredity, cumulative experience, new/previous knowledge and the ability to analyze and understand the situation being faced (see Figure 6). **In some situations, this calculation ability is the most important and critical for making the decision.**

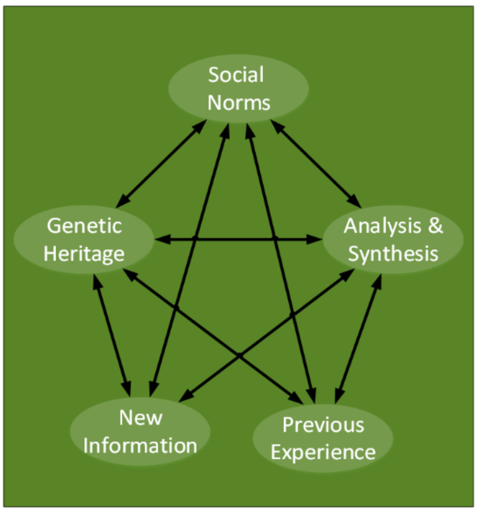

Figure 6: Problem Solving Model (Heuristic Model)

LAYER 3 – ARTIFICIAL INTELLIGENCE ALGORITHMS

One of the key focuses in the development is how to deliver to the end user (the decision maker) the best recommendation as fast as possible, according to the situation and the actual role of the decision maker. The main challenge is how to utilize the analyzed data and translate it to the range of recommendations, based on an AI algorithm.

We now seek to provide a decision support system that could provide good, appropriate advice and recommendations to commanders facing adversaries and new situations in unknown environments. This is a challenge, particularly since:

- Only partial information exists of the world arena
- There is uncertainty about the effects of actions
- An adversary is involved.

This challenge is similar to poker, backgammon and Go games in two aspects: huge spaces and the presence of adversaries. In backgammon, complete information exists on how to play the game, but uncertainty exists because of random actions. In poker, only partial information exists.

This involves one of our biggest innovations, the integration of academic research on how decision makers react in real time. At present, our platforms and real-life decision makers act according to doctrines. We seek to provide added value by including human behavior patterns in real situations.

The Research Plan: Relevant Work

The TD-Gammon algorithm is an algorithm relating to backgammon game strategies. It uses a neural network without prior knowledge of the game to teach itself to play backgammon by playing against itself. The agent learns from the results using a TD reinforcement learning algorithm, thereby improving its decision-making iteratively. This very successful approach was presented in 1992.

The game Go would appear to be an easier challenge, because no random action of rolling dice is involved. However, a good agent was only proposed in 2016. The main reason is that the search space is huge in comparison to backgammon, so the reinforcement algorithms failed to give good results.

A Monte Carlo tree search (MCTS) was used for the Go game. It involved first reducing the depth of the search by truncating the search tree and replacing the state value with a predicted value of the state's outcome. The breadth of the search was then reduced by sampling actions from a policy with a high probability over possible actions in the state. The result was a weak, amateur-level player in Go.

The AlphaGo player developed by Silver et al also used MCTS, but their novel approach used neural networks to reduce the effective depth and breadth of the search tree. AlphaGo evaluates the Go game state using a value network, and samples the actions using a policy network. The neural network first learned examples from experts, then improved itself through self-play. AlphaGo player was the first computer Go player to beat a 9-dan professional.

A similar approach was used for poker, utilizing an algorithm also based on a deep neural network. However, here there was insufficient training data, forcing the researchers to adopt a novel approach of using a simulator at every step, in order to gain more data. Heinrich and Silver also introduced an approach using a neural network called Neural Fictitious Self-Play (NFSP). The network first trained users through reinforcement learning, by playing against other agents from previous competitions. The network then trained users through supervised learning from the agent’s own behavior (the agent behaves according to a mixture of its average strategy and its best response strategy).

This research showed good results against the known approach of Bowling et al., known as Counterfactual Regret minimization (CFR). CFR explores all possible states in poker, in order to decide the next best action. Its success is limited to a specific version of poker (heads-up limit Texas Holdem), where the search space is lower than other versions of poker.

Our AI layer is based on behavior-based modeling research program. We drill-down through the research findings and run a "self-play" entity in order to gain better insights for HLS and military decision makers.

We have many examples of situations where middle-range commanders need to make decisions while fighting an adversary. We can also produce more data from a simulator. Consequently, our approach will tend to use a neural network. We will start by building a neural network from the training data and then improve the network using self-play. Using the results of the network, we will be able to simulate possible actions and utilize the action that returns the best result.

We add typical behavior patterns as machine learning into the platform, thereby creating an AI layer that will support decision makers in emergencies. This will enable the pushing of recommendations through the AI layer which will support both the training and real-time operations of decision makers based on their actual roles, their geographic location, the location of the event and the actual scenario, from earthquake and flood to fire and terrorist attack.

Conclusion

Consequently, there is a military and civilian need for a system that will analyze abilities, provide insights, and deliver recommendations to decision makers as part of their preparation of manpower, forces, deployment and operations in various scenarios and during emergencies. Such a system must allow for simulation of events using a reality simulating algorithm of crowd behavior to a significant scale. In particular, the ability to simulate the reaction of a crowd to an emergency event in a public area (such as fleeing, panic and crowding) is required. Furthermore, the simulation must be authentic, i.e., as close as possible to real life behavior. This means that the simulation has to be based on actual research of social behavior. NLG increases plain language usage in incident response and Real-time assessment provides insights into organizational, team, and individual performance. An automated approach generating scenarios based on competence assessment creates simulations that reflect real-life situations. 4Cast combines all of the items into one platform creating a game changing solution for decision makers.

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