

# Brief | CMS Artificial Intelligence Health Outcomes Challenge



Healthcare in 3D

# The Team

**Robert Ripley, MD**, the CEO and founder of Ripley and Associates, brings his interest and medical expertise in data management to promoting cost effective health care. This interest is founded on a multi-decade practice in Cardiology where it has become clear that wise decisions on patient's behalf must be disseminated among provider networks to achieve desired outcomes.

**Donna Abercrombie**, is the Project Manager at Ripley and Associates and a team member since 2001. Donna works to coordinate Accountable Care Organization programs and Alternative Payment Models. She is a seasoned medical practice executive with 20 years of experience in the health care industry.

**Allen Hall MCDBA, MCSD, MCSE, MCT Alumni**, has been a team member since 2013, providing Information Technology support and creative assistance in multiple areas of specialty including systems infrastructure, website, documentation, illustration, and proof-of-concepts. He has extensive experience as a consultant and trainer in both the private and public sectors over the last quarter century.

**David Langer, MS Computer Science & Software Engineering**, is a recent addition to the team, providing expertise in analytics, data science, and artificial intelligence. Dave has over 2 decades of experience in technology and analytics, including hands-on work applying Artificial Intelligence for companies like Microsoft, Data Science Dojo, and Schedulicity.

More Information... <http://hcn3d.com/Introduction/OurTeam>

# The Solution

The ranking of Future Value Outcomes determined via counterfactual analysis. Future Value Outcomes are simply the result of possible decision or actions the provider and/or patient may execute that have the greatest potential to result in the desired outcome.

Counterfactual analysis allows one to distinguish single entities such as individual patients in the context of a variety of defined populations. A counterfactual is the result of a single action given specific context; the same event or need for action can elicit different effects on the individual given different extrinsic (or intrinsic) conditions.

This is a basis for realizing preferences of primary care physicians. They wish to be holistic, accounting for all factors relevant for the patient. And when they do so they avoid certain unwanted outcomes (e.g. unplanned hospital admissions), or move through the patient's path more efficiently. And they want to do this for a single patient, not to conform to population averages as a purely statistical approach would require.

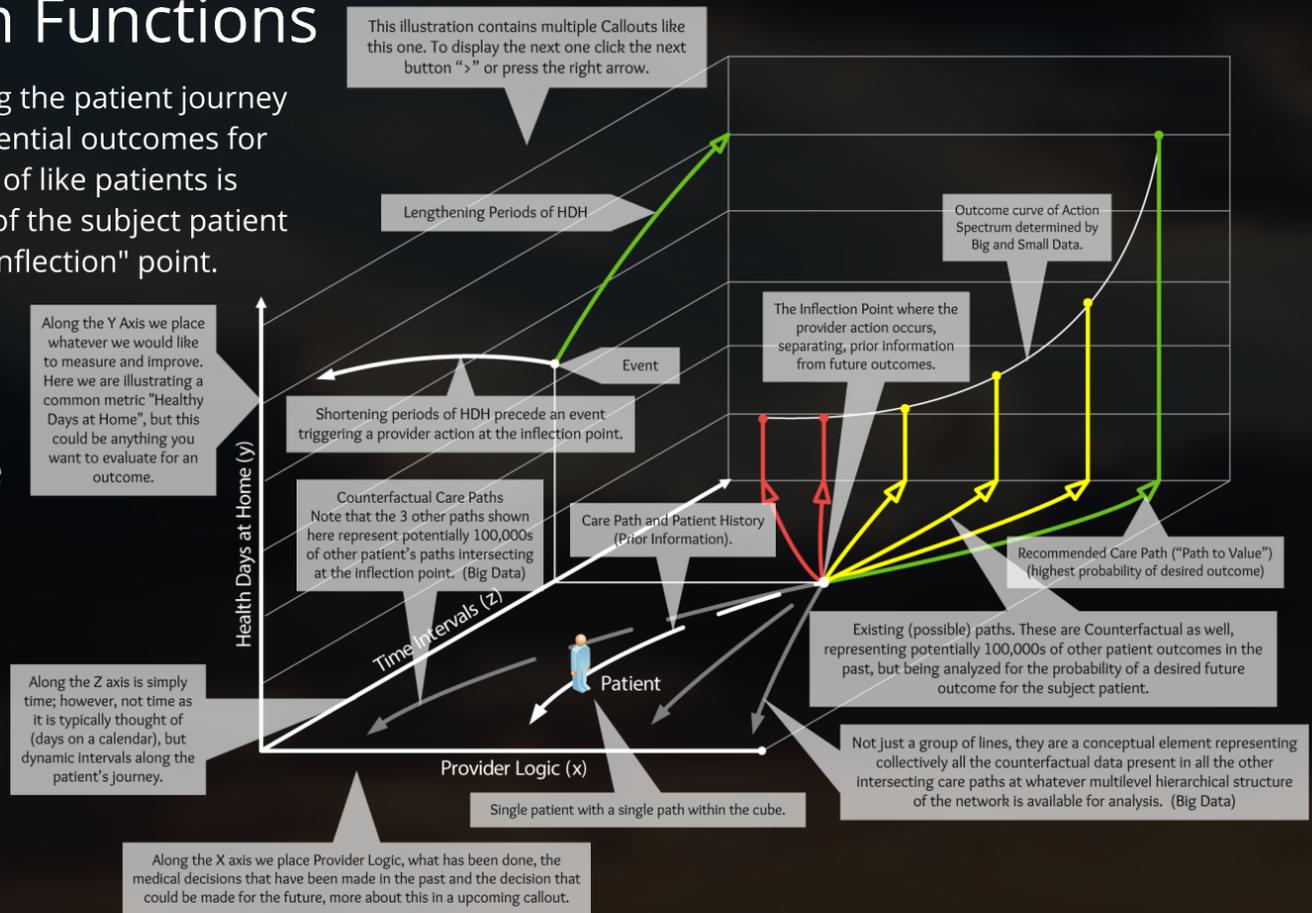
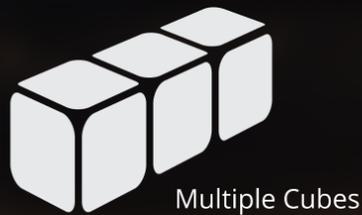
The following video conceptualizes how HCn3D can not only predict unplanned hospital stays along a patient journey, but any scenario/question it's configured and trained for.



# How the Solution Functions

The solution functions by analyzing the patient journey of "like patients" to determine potential outcomes for the subject. In essence the history of like patients is analyzed to determine the future of the subject patient at the point of action we call the "inflection" point.

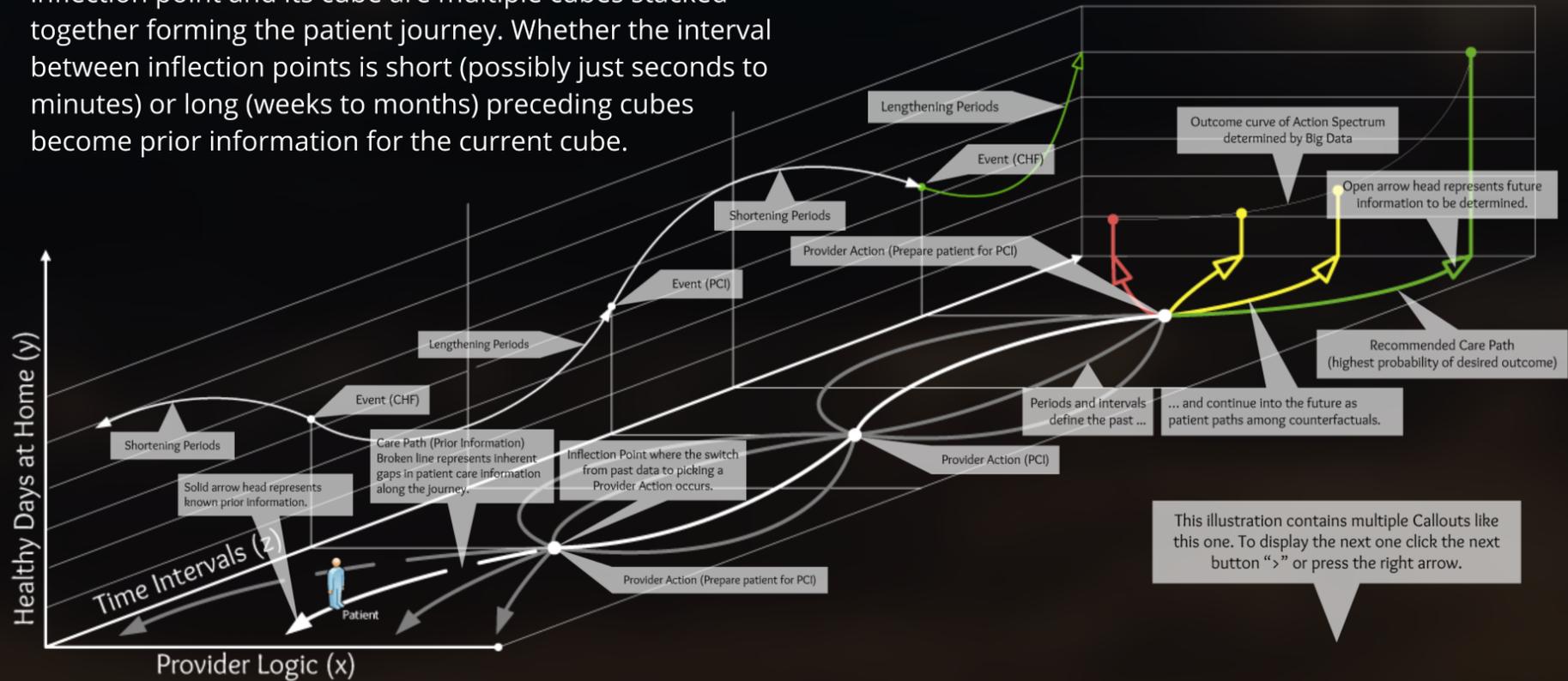
Conceptually multiple cubes and their associated inflection points are stacked together to analyze the past retrospectively for both the "like patients" and subject. The result is a stack of cubes looking forward, prospectively ranking the actions that could be taken to realize the desired future outcomes.



Note: Due to the new requirement to provide this Brief in a PDF, instead of the Power Point format, the call-outs are necessarily part of the graphic and maybe appear less the 11 points depending on the viewers level of magnification. For an interactive version of this presentation please review this link: <https://prezi.com/view/W47fEAarBtQKQTmY74zh/>

# Multiple Cubes

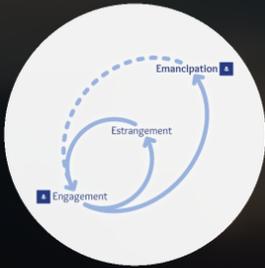
As you would expect the natural extension of a single inflection point and its cube are multiple cubes stacked together forming the patient journey. Whether the interval between inflection points is short (possibly just seconds to minutes) or long (weeks to months) preceding cubes become prior information for the current cube.



# Methods to Build Explainable AI

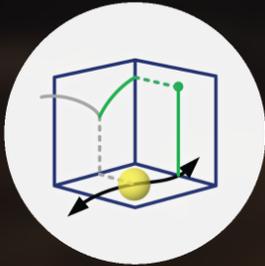
For the last few years the HCn3D team has approached this conceptually in two distinct ways, with plans to implement user interface and business intelligence tools, some of which will deliver AI driven solutions directly to the clinician (and patient) at the point of service.

## Via Provider Engagement



Any and all discussions of improving outcomes via technology, require an alert and attentive provider community. Physician burnout is clearly an impediment to this attention. It is estimated that 50% of physicians either have, or are at risk for burnout. Adding complexity in the form of new systems and/or programs will only exacerbate the problem unless they deliver tangible value that serves to emancipate. Perhaps no one understands this cycle of engagement, estrangement, and emancipation better than the HCn3D team led by Robert Ripley, MD a 42 year veteran of cardiology practice.

## Via "The Cube"



Understanding the challenges faced by providers combating burnout is not enough. Understandable explanations of the technology are still required if the physician (and patient) is going to believe that the technology can in fact emancipate, making their jobs easier not more difficult. For this facet the HCn3D team has turned to the analogy of "The Cube". It has been extremely effective because it can be sited figuratively, literally, and most importantly visually in the context of the patient journey, incorporating as little or as much complexity as desired to explain and model how HCn3D works.

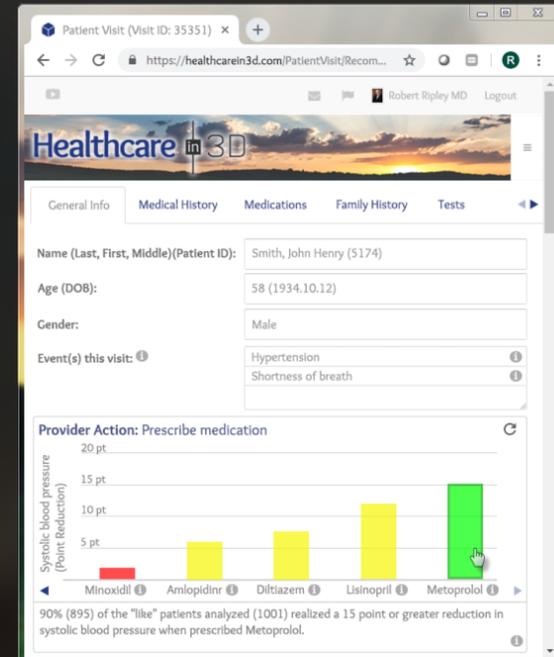


UI & BI

# User Interface and Business Intelligence Tools

Mobile (and desktop) applications where the clinician and/or patient is presented with possible actions/decisions. These potential decisions are supported with the most relevant variables or dimensions analyzed.

For instance, a clinician would be presented with the top 5 (option to see more) desired outcomes and the decision(s) that would have to be made to result in those outcomes. Supporting information would include readily understood natural language explanations. (e.g. *90% (895) of the "like" patients analyzed (1001) realized a 15 point or greater reduction in systolic blood pressure when prescribed Metoprolol*). The clinician would have the option to review more detail, like the total number of patients analyzed for "likeness" and ranking of what made them most like their subject patient. So AI is not only used to identify the potential outcomes, but also describe them to the clinician or patient.



Please note: The patient and recommend actions shown here are contrived simply to illustrate the user interface, they represent no actual patient or computations.

# How the AI Model will be Trained

The Team's use of counterfactual analysis as the main AI engine differentiates our solution. Specifically, our solution will not have a "model" as one would expect from a trained random forest or deep neural network. In machine learning terms, the counterfactual analysis AI engine (CAE) is akin to the k-nearest neighbors (kNN) algorithm. As with kNN, the CAE provides predictions/guidance to the provider via application of the algorithm(s) to the data at the time of prediction/guidance request. As such, the CAE (as with kNN) learns and improves over time as additional high-quality data is added to the algorithm's search space.

The challenge and promise of this methodology lies in the curation of the data to determine the like patients in the context of the question or scenario being posed (e.g. Unplanned admissions within the next 30 days).

# Team's Cross Disciplinary-design Process

The Team's process will be iterative, mirroring the scientific method. First, our health care domain experts will formulate questions and hypotheses that directly align to the goals of the CMS AI Outcomes Challenge. Second, our data scientists will be guided by these questions/hypotheses to select datasets, features, and tools/techniques for analysis. As needed, our data scientists will consult with our health care domain experts for clarification and feedback on analytical findings. These first two steps will iterate a number of cycles as preparation for the third step of the process – model exploration. Our data scientists will then leverage the analyzed and curated datasets to begin the process of training and testing models. Model exploration is conducted with both our health care (to validate model findings) and IT (to provide need technical infrastructure) experts. The final phase of the process is construction of a production solution where the data scientists and IT experts collaborate to deliver the final solution.

# Development Timeline

For the HCn3D team certain facets of the AI Outcome Challenge are currently considered complete because they are already being used. This is particularly true as they relate to Goal #2, explaining how AI-derived predictions have value. As a result the HCn3D Team will focus on implementation and testing to address the specifics of the Challenge, delivering a functional solution well in advance of November 18th. The additional LDS data made available in Stage 2 will be used to verify the solution as prescribed by the Challenge.

- July, wk. 4: Solution design and review, facet assignment.
- July, wk. 4: *LDS request submitted.*
- Aug, wk. 1: Begin loading LDS records into repository.
- Aug, wk. 2: Start draft of White Paper for Stage 1 submittal.
- Aug, wk. 2: Begin mapping LDS schemas to HCn3D system schemas.
- Aug, wk. 3: Curation of data begins.
- Aug, wk. 4: Identify other metadata. Schemas linked to CMS data.
- Sept, wk. 1: HCn3D System configured and trained to predict unplanned hospital and SNF stays within the next 30 days.
- Sept, wk. 4: Prototype Web application and business intelligence tools setup to deliver requirements of Challenge.
- Oct, wk. 4: Final prototype testing performed with validation sets if available from CMS.
- Nov, wk. 1: White Paper finalized for Stage 1 submittal.
- Nov, wk. 2: Stage 1 package submitted.
- Dec, wk. 3: LDS request Submitted for additional data.
- Jan, wk. 2: Begin loading additional LDS records into repository.
- Jan, wk. 3: Solution tested and refined. A portion of the additional 5 years of LDS records will be treated as a validation data set unless CMS makes available a set specifically for validation testing.
- Feb, wk. 1: Prototype Web application and business intelligence tools refined as needed to support additional data and validation.
- Mar, wk. 1: White Paper finalized for Stage 2 submittal.
- Mar, wk. 3: Stage 2 package submitted.

Appendix

## Appendix

The Team | <http://hcn3d.com/Introduction/OurTeam>

The Patient Journey Through HCn3D | <https://youtu.be/cMIbTdbNRZg>

A Pathway for Burnout... | <https://bit.ly/2H7bNlf>

HCn3D Website | <http://hcn3d.com>

Brief: CMS AI HOC | <https://prezi.com/view/W47fEAarBtQKQTmY74zh/>