**CRAIG:** Hi, I’m Craig Smith and this is Eye on AI.

Symbolic AI vs Deep Learning, Glass box vs Black box; Stephen DeAngelis reminds us that so-called Old-Fashioned AI continues to be a powerful tool. Stephen, head of Enterra Solutions, talked about leveraging knowledge bases, inference engines and symbolic logic to make decisions about large dynamic systems.

I hope you find the conversation as informative as I did.

Why don't we begin Stephen by having you introduce yourself, and then we'll start talking about what Enterra does?

**STEPHEN:** I'm Stephen DeAngelis. I'm the president of Enterra Solutions. We are a cognitive computing company that focuses on work in the consumer manufacturing industries and in life sciences industries. We're located in Princeton, New Jersey and Cambridge, Massachusetts.

**CRAIG:** And we were just talking before I started recording about what Enterra does. And you were describing the under the hood mechanics of what you call autonomous decision science, I think is what you call it.

**CRAIG:** And you were saying that it's symbolic AI. Is that rule-based AI that we're talking about?

**STEPHEN:** We have a platform that has three pieces to it. The first piece of it is based on the area of computer science called semantic reasoning against symbolic logic.

**STEPHEN:** So, we use a large, common sense knowledge base with industry and domain-specific knowledge bases that are expansions of that commonsense repository. And we use technologies like inference reasoners or rules engines to allow the machine to make decisions about business objectives, data science capabilities, or play the role of a subject matter expert in a domain that we've educated the AI about.

**STEPHEN:** And we combine that AI with computational intelligence or understanding of data through the use of machine learning and other mathematical techniques where we use a glass box machine learning engine that we built called a representation learning machine to interrogate data and find the driver, or the function, a combination of variables, that explain the observable behavior of the dataset.

**STEPHEN:** And the third piece we call nonlinear optimization. And we were able to then optimize core functions of a company.

**STEPHEN:** So, from a technological perspective. We've tried to bridge the gap between semantic reasoning and computational intelligence in one platform that allows us to process data, perform analysis automatically, generated an insight, and then execute that insight and then learn from the outcome that we had in a platform.

**CRAIG:** I'm very familiar and certainly my listeners are very familiar with knowledge bases and rule-based systems that sit on top of those knowledge bases. Is that what you're talking about? And who writes the rules?

**STEPHEN:** Think of it as a commonsensical understanding of the way the world works. Banana's a fruit, lettuce is a vegetable. Tomato is sometimes considered a fruit, sometimes considered a vegetable. We know that red could mean the Pantone color red. But red could also mean fury or stop or danger, depending on the context.

**STEPHEN:** So, we have a large commonsense corpus about twenty-five million ground axioms, rules that searches in the commonsense repository. On expanding that, we build domain specific knowledge bases. Think about them as knowledge base of how the consumer products industry works or the life sciences industry works. And functional knowledge bases.

**STEPHEN:** Like knowledge about sales and marketing or supply chain or things that are very practical functions within a commercial enterprise, or a governmental agency. And then those knowledge bases are accessed by an inference reasoner, which uses forward chaining and backward chaining of logics.

**STEPHEN:** This is mathematical logic encoded into calculus that lives as software and allows you to forward chain. I want to beat you in chess, what steps do I need to go through to beat you in chess, given the moves that you're making, right. Backward chaining, which we use a lot. Think of it as like Sherlock Holmes puffing on a pipe. Backward chaining says, I beat you in chess.

**STEPHEN:** What predicates did I have to have in place in order to beat you in chess? Or I eat a piece of cake. What did I have to do to be able to eat a piece of cake? I would have had to have had a piece of cake. To have it, I would have had to have baked it, bought it at a store, have a gifted to me. In each one of those, there are predicates.

**STEPHEN:** So, the AI allows you to, to reason using forward chaining and backward chaining of logic, accessing the common sense and domain specific knowledge bases. And then combine that with rules that allow the reasoner to reason, according to a set of rules. That allows us to create a human like reasoning-based AI component of our platform and we've found that to be very powerful

**CRAIG:** just so that we can boil it down to a common vocabulary that the listeners will understand.

**CRAIG:** Are you talking about decision trees?

**STEPHEN:** Semantic reasoning in symbolic logic using an inference reasoner to reason against a knowledge base. That is the basic formulation of how this works. A decision tree is more of a concept in mathematics where you will use other neural net or random forest algorithm or support machine to go through the various tree structures to mathematically interrogate data and to understand relationships.

**STEPHEN:** This is a little bit different, but we feel that in order to solve some of the problems that you're facing in the world today, we need to bring those two areas together, the ability to reason with the more computational ability to understand what are the drivers in a dataset, how do we optimize things and how do we learn from investigating data that has a lot of variables in it.

**CRAIG:** And the knowledge base, the commonsense knowledge base you talked about, where did you get that? Is that public?

**STEPHEN:** It's not, the company that we partner with provide a knowledge base, we license exclusively from them in our application. it's embedded in our company. It's been curated over 35 years, had its origins in the government sector, then was tech transferred out a number of years ago. And it's been used in government applications and in research applications.

**CRAIG:** The criticism of symbolic systems is that there has to be so much hand tuning and hand building of the knowledge base and the rules. Was all of this constructed by hand. Or do you use deep learning in any way to build the rules or the knowledge.

**STEPHEN:** The knowledge base was started originally by handcrafting it, and then you crowdsource knowledge. Think about if you were to ingest all the Wikipedia, you would learn all of the information. You would represent that in an ontology. The notion is that the ontology has ways of handcrafting and also scaled ingestion of knowledge.

**STEPHEN:** And then when you scale and ingest obviously you have to curate that to make sure you're not getting, garbage in garbage out type of function. So, you have to have very strict mechanism of ingesting that information in order to scale it, but it happens both ways.

**CRAIG:** And then on the other side, the cognitive computational engine, I think you called it, what technology is behind that

**STEPHEN:** we have a proprietary engine that we built.

**STEPHEN:** We have a bunch of very bright mathematicians out of leading universities who created a glass box machine learning capability. So, it's in an area of mathematics called high dimensional model representation or HDMR. And what we do there is we have built an engine that allows us to investigate data and then generate a function that describes the observable effect in that dataset. So let me give you an example. One large pharma firm had invented a drug, but they needed to formulate it. So, they gave us a dataset that had about 2,700 variables in this dataset. And we wanted to investigate that dataset to find how to formulate that drug, according to FDA guidelines. So, we ingested the data, and we ran it through the math engine. We found that there was a seven manifold or a seventh order combination of variables. Only when those variables came together, they described about 84% of the variation in the data. And then when those 11 came together, three of them had a secondary effect that described in another 9% of the variation in the data.

**STEPHEN:** So, we could describe about 93% of the variation in the data from the interactions of seven out of that 2700 variables. then we isolate the effect of each of those variables, variable one's responsible for this variable two is responsible for that and so forth. And the output was a function, that described how these variables interacted in that dataset. And they then became control knobs in the optimization function that we did to optimize that drug, to be shelf stable. When you use typical machine learning algorithms, you don't get a function. It's a pattern recognition technology.

**STEPHEN:** Here we use our engine to find the combination of variables that are in high dimensions. It's resistant to multicollinearity, confounding variables. It's resistant to interweaving Weaving of variables so you can't explain it. And we were able to then have explanatory value and transparency in the engine because now we could fully lay out to the client.

**STEPHEN:** Hey, these seven variables are the ones you need to work on. Forget about the other 2,690-odd. You just focus on those seven and we could optimize that drug according to the objective function, or the goal state that we needed to have.

**CRAIG:** Is there a reason why you haven't gone the deep learning route? You mentioned glass box and that's obviously a counter point to Blackbox and that's the criticism of deep learning is that you can't explain what's happening because you can't look into all of the layers of the deep network. And in this case, it’s not depending on weights within a hidden layers of a network it's depending on the functions in an equation, is that right?

**STEPHEN:** It's depending on the interactions of those variables in showing the contribution value, those variables in the overall effect that you find. So, we seek to perform enterprise class optimization and decision making for very big companies or governmental agencies.

**STEPHEN:** So, the type of problems that we go after need scale, they're very big organizations. So, we need to be able to adjust tons of data. We need to be able to analyze the data very quickly, the market changes very quickly. We need to be able to ingest data, analyze it, generate an insight, take an action, and then learn from that action.

**STEPHEN:** We call that sense, think, act, and learn. So, we found that the human based reasoning AI gave us scalability because the AI can't play the role of the data scientists or the subject matter experts. Now, not in everything but in constrained areas of domain focus, we could have an AI reason as a human expert would, right? Against a set of applications.

**STEPHEN:** And then the math engines allowed us to investigate big field data, find the combination of variables that describe what's going on, and then reveal essentially the underlying dynamic of the system, and then be able to make a decision based upon that and then learn from it. And so that interplay between semantic reasoning, where we understand why things happened and we're able to make a decision and take an action, are the type of problems that we solve for very large fortune 500 companies when they optimize the value chain of their business.

**CRAIG:** I was looking at the list of clients that you had. Some of them fascinated me McCormick for one.

**CRAIG:** Can you talk about what you did with McCormick

**STEPHEN:** sure. What we did with McCormick is we built a system called flavor prints, which was a multidimensional representation of the flavor experience. we use ontologies and inference reasoners to create a multidimensional representation of the way that every product ingredient and recipe tasted.

**STEPHEN:** McCormick has a very large knowledge of how flavor and flavor science works. We created a proprietary overlay for them, the knowledge base on top of our commonsense knowledge base that encoded, that flavor science knowledge, and we were able to create a unique fingerprint.

**STEPHEN:** Fingerprint for the way that every product through reading recipe tasted based upon the flavor it's aroma and its texture wrapped with lifestyle. So, you have 3000 dimensions of taste, aroma and texture wrapped with lifestyle. Are you vegan? Are you anti GMO? Are you this? Are you that? And what type of meal is it?

**STEPHEN:** A breakfast, lunch dinner. And you create this fingerprint for the way that every product and reading recipe, taste and then you marry that with an individual or a household preference for flavor. So, you create bomb on target marketing or representation of, or recommendation rather of a product or a recipe to an individual that is satisfying to their taste palette.

**STEPHEN:** And then you can try to expand people's pallets by looking at expanded areas of flavor around. What they had liked in the past. And the notion is to create an extremely satisfying experience with food for that individual.

**CRAIG:** Is this a software as a service, or you building on premise systems for customers?

**STEPHEN:** We are a solution as a services company. So, we provide a technology solution in a multi-year license to clients. And so, we're a technology firm.

**STEPHEN:** We're not a consulting firm that builds stuff for people by hand, but we provide a solution as a service. Which is software wrapped with a light service to customers in a multi-year solution as a service agreement,

**CRAIG:** and they access that solution remotely,

**STEPHEN:** we deploy in cloud-based environments, behind the firewalls of our clients.

**CRAIG:** And you were saying that this the original knowledge base or the original engine came out of a government project. What was the government using it for?

**STEPHEN:** It had its origins in in 1980s where it was set up combat what they perceived as a Japanese software competitive advantage threat to the United States. So, they allowed these firms to, to collaborate. And one of the things that came out of that was the creation of a common sense, ontology and inference, reasoner. It had original funding from DARPA and then tech transferred out from those organizations to a private enterprise. And then we've engaged in that for the last 14 years.

**CRAIG:** How did you get involved? What were you doing before Enterra?

**STEPHEN:** I've been running Enterra for 18 years, so it's been half of my career. But before that I ran a supply chain optimization company and before that I was the CEO of a specialty chemicals, manufacturing company.

**CRAIG:** When this was sold by the government or licensed out by the government, or however the transaction happened, were you involved in acquiring it or

**STEPHEN:** no, I was involved in subsequently exclusively licensing that technology for the work that we do.

**CRAIG:** Why would a company come to you as opposed to one of the new, deep learning solution providers? One of the things I'm interested in is ML as a service, and there are now a lot of no code or low code platforms that people can leverage deep learning through without having, to have a team of data scientists, building something from scratch.

**CRAIG:** And it's powerful, but you have a very different approach. Obviously, there's a legacy reason, but are you looking at deep learning as well?

**STEPHEN:** Those companies are creating data science platforms for people inside the company, to be able to perform data science services without having to create the low-code or no-code platform. We are taking that up a level of abstraction instead of a do it for myself capability.

**STEPHEN:** We are a do-it-for-you capability. A system of insight that goes along the value chain to these companies and allows them to have an enterprise class optimization and decision-making framework that sends instructions to the requisite systems of record that those companies have. So, you're probably familiar with SAP or other very big systems.

**STEPHEN:** Those systems were engineered to not make a mistake. And record all the transactions that a company has. But they weren't engineered to dynamically think. We designed a capability that allows us to reason, in a human- like fashion, investigate data with a glass box engine and then perform enterprise class optimization at the speed of the market.

**STEPHEN:** So, we take data from various business applications, consumer insights, like we talked about with flavor print or sales and marketing analytics, like we do integrated revenue, growth, optimization, trade promotion, pricing, others, or supply chain optimization. So, we create that system of insight that takes the data and very quickly analyzes it generates an insight that then sends instructions to the transactional systems of record to take an action.

**STEPHEN:** So, instead of humans trying to calculate stuff by hand really quickly. We have a system that ingests the data, generates an insight, and then tells the system of record to do this, and do that. Respond to this, respond to that, take an action like this. So, think of it as a self-driving company, a company that has a degree of autonomy about how it operates.

**STEPHEN:** And that's a very different application than the low-code or no-code data science platform that firms will use to build analytic capabilities within their company.

**CRAIG:** And what you just described is a little different than the McCormick example.

**CRAIG:** Can you give an example? You have P&G on there. I don't know if they're one that's using it in this way, but when you say that it sends, an action or decision signal, is that then taken by an individual or are you embedded in systems where you're, I don’t know, adjusting or schedules that sort of.

**STEPHEN:** So, let me give you an example of what we did during COVID last year for a large global company in the area of revenue growth optimization, which is the use of trade promotions as a temporary price incentive to incentivize a consumer to buy a product. We deployed our revenue growth optimization capabilities to the client and in doing so, we analyzed the marketplace that our clients operated in.

**STEPHEN:** Were able to predict analyzing syndicated data and internal data from the company what was happening in the regions of the country that the client operated in. We were able to then make informed recommendations about trade promotions and inventory levels that allowed the client to effectively create a multi-dimensional grid of possible scenarios to navigate a very tumultuous landscape in the last 24 months.

**STEPHEN:** We're able to use that to plot strategies in order to maximize the corporate goals, which was to maximize revenue, maximize profit. We're able to use the engine to both substantively understand what was happening in the regions around the world, given the pandemic, and also understand how consumers buying patterns were changing. I'm sure you've heard of pantry loading and pantry maintenance. People

**STEPHEN:** once they heard about COVID, they're buying stuff from the stores as fast as I can cause draw supply chain challenges. So, we help navigate then reallocate trade promotion and incentives to throttle up or throttle down demand for those products in the markets that they operated in and allowed them to navigate that landscape.

**CRAIG:** So, what's the future for Enterra? I keep on asking whether you're looking at incorporating deep learning.

**STEPHEN:** we are. Technologically, we believe there is an ensemble of technologies that are necessary to solve complex problems that my company's business model seeks to solve, which is making corporations and governmental agencies, systemically resilient to challenges that they face in the marketplace.

**STEPHEN:** Whether they be challenges from global competitors or economic challenges or environmental challenges, companies need to be nimble and agile to respond. So, the applications that we build and the platform that we built is aimed at solving that class of analysis and control of complex system problems.

**STEPHEN:** The large corporation, like a Nestle to us, looks like a large complex dynamical. And our job is to analyze and control that as best we can, given the external stimuli that happens. So, in that case, deep learning techniques or reinforcement learning capabilities are all tools in the toolbox that can be integrated.

**STEPHEN:** Now we've decided that there are very big players, companies much bigger than us, involved in the deep learning area. Google and others investing billions of dollars into that space, that piece of the puzzle, we felt we would integrate those capabilities as we need to because they're investing there.

**STEPHEN:** We're investing in the glass box, machine learning capability, the nonlinear optimization and the semantic reasoning and symbolic logic work. But I think that deep learning capabilities, Craig can fuel ontologies. The knowledge that is extracted from a deep learning exercise can be put on steroids if it's connected to an ontology that allows you to then reason about it with subtlety and judgement. I don't think these are exclusive worlds.

**STEPHEN:** I think each one of these capabilities and tools can be integrated into a platform that is evergreen, right? You want to be able to keep refreshing your platform with the newest and most evolved capabilities to help solve the problems that you're seeking to solve. I do think structurally that there will be a fusion of deep learning and reinforcement learning with semantic reasoning where the knowledge can go into an ontology much like we export out of our high dimensional math engine today

**STEPHEN:** while we're 18 years old, the first 12 years of our existence, we were a government contract.

**STEPHEN:** Came into the commercial sector about six years ago. So, we've been focusing on commercial applications for that amount of time.

**CRAIG:** And who is the competition? Because there are a lot of people in the optimization space and a lot of these companies are developing services based on deep learning. how do you see the competitive landscape forming?

**STEPHEN:** So, we compete with Palantir, and a firm called C3 AI in the advanced analytics space. Right? Drawing a distinction between the different types of AI is usually something that is outside the experience of most people that we interact with in business. So, we compete with those two and then there's a universe of smaller companies that compete in specific areas of the value chain.

**STEPHEN:** So, you may have supply chain optimization and another firm that focuses on pricing optimization. Then another firm that focuses on consumer insights. We uniquely span the value chain with a platform that is generalized so it could go across the entire breadth of a governmental agency or a commercial entity. And then we build applications on top of that platform that address key components, but uniquely share the knowledge across the value chain. So, we have a lot of competition in areas, but we have very little competition in end-to-end optimization and decision-making.

**STEPHEN:** So, to answer your question, not a lot of competition in directly what we do, but a lot of competition for different players in different piece parts of what we do.

**CRAIG:** You're still working as a government contractor.

**STEPHEN:** No.

**CRAIG:** So, you're purely in the private sector now.

**STEPHEN:** We are purely in private sector.

**CRAIG:** Is that a business decision or just the way the market has shifted

**STEPHEN:** I had spent three and a half years going back and forth to Iraq and we had decided after the surge to take the learnings that we had about AI and mathematics and bring it to the commercial sector. We want to work there because we thought that we would have easier to explain contracts and be able to raise capital and go public.

**STEPHEN:** We're raising large institutional round of capital now.

**STEPHEN:** Our goal is to always stay a step or two ahead of the market where we are. And that's why we have not delved into deep learning where some of the bigger players are investing tons of money because we felt we could adopt those capabilities.

**STEPHEN:** We looks at a large corporation as a complex dynamical system.

**STEPHEN:** You think about Nestle or Unilever or Procter and gamble in their ecosystem. Those are enormous complex dynamical systems. And analyzing and controlling that is a unique problem set that we address. So that's our niche is to focus on how do we analyze and control those complex dynamical systems and allow their systems of record to take actions, to make decisions at the speed of the marketplace to get competitive advantage. So, we use techniques like game theory and various simulation techniques to diagnose competition in the market, understand strategies and tactics of competitors, and use that knowledge of how those complex ecosystems work to make sets of decisions to allow our clients, to weaponize their data, to create asymmetric advantage in the marketplace

**STEPHEN:** Being able to see the entire company understand how consumer behavior changes during COVID or changing economic landscapes, then understand how to use the levers of revenue growth pricing, trade promotion, market media mix assortment, how to put stuff on the shelf to drive consumption behavior, and then be able to make the global supply chain dance, that requires a degree of coordination and interplay that usually it was the best senior humans along the company, making decisions as fast as they can make a decision as a human here, we're taking vast amounts of data we're bringing into the system, and this system is performing analysis, generating insights, telling the system of record what to do while at the same time sending information to a dashboard or to a user interface that humans can see also. And then some decisions get made automatically some decisions are human augmented. Some decisions are machine augmenting the human, but there's some combination that is happening, where we're helping analyze to control that complex dynamical system using this platform.

**STEPHEN:** We have COVID challenges, global warming challenges. We have inflation challenges. We have wage inflation for the first time in a long time. Companies are having to be nimble at a way that they've never had to been before, to compete in flourish in the market.

**CRAIG:** When you approach a company or when a company approaches you, when you start working with a company, how do you pull together all of the data, all of the feeds across an enterprise so that you can build the system that's making these decisions or recommending these decisions. Do you work exclusively with the IT department? Do you work across departments?

**CRAIG:** Is it through surveys? It’s pretty difficult to get your arms around a large corporation.

**STEPHEN:** That's a great question. So, most of the perspiration on implementations is in organizing the data luckily over the last five or six years, most of our clients have gone through large data lake investments where they've invested a tremendous amount of money in integrating critical data into what they call data lakes.

**STEPHEN:** We access those data lakes, or we help them construct a data lake based upon input from us as to what we would need to fuel our capabilities. But most of our clients are rather sophisticated. Luckily with having most of their transactional data, their SAP data, their syndicated data, their other data brought to a lake where we can analyze that data.

**STEPHEN:** Where they don't have that, we partner with Accenture, for example, where they have both very cool automated techniques to go out and grab data within a company, bring it to one location, or we work with them to help the client integrate that data, put it into a data lake. But most of the data that we get are from systems of records from Syndicated sources and from retail or another key ecosystem partners that are fairly well understood by now. And the integration to those is really not that much of a hassle. Oftentimes it's time consuming a little bit at the beginning, but most of the time, these companies are at a level of sophistication that they've already organized that.

**STEPHEN:** And then where it's not, we have partners that bring that data together to then fuel the data models and analytics tables. We deploy behind the firewalls of our clients in their cloud computing environments, whether most of the time in our industries and consumer products or retail, it's Microsoft Azure. But it could be AWS. It could be snowflake.

**STEPHEN:** The engine, the math engine is transparent. It is a glass box. It gives explainable answers, which is a big deal because people don't like to trust black boxes. They really need to know what's going on.

**STEPHEN:** You can't just tell me it's a black box and whatever comes out. So having that degree of explainability is a huge attribute.

**CRAIG:** That’s it for this episode. If you’d like a transcript of what we talked about today, you can find one on our website, eye-on.ai. You can learn more about Enterra Solutions at enterrasolutions.com.

Remember, the Singularity may not be near, but AI is changing your world. So, pay attention.