

June 2017, San Francisco
Autodesk *Ideas Driving Change* Summit

Learning with Machines

*Co-creating with machine intelligence
through the lens of generative design*

Participants

Autodesk

Education Experiences

Randy Swearer, VP, Education Experiences
Mickey McManus, Fellow, Future of Learning
Sunand Bhattacharya, Global Education Strategist
Jeremy Carter, Design Education Evangelist

Office of the Chief Technology Officer

Francesco Iorio, Director of Computational Science Research
Erin Bradner, Distinguished Research Scientist
Mike Haley, Head of Machine Intelligence
Mark Davis, Head of Design Research

Others

Peggy Salz, Journalist and Writer
Mike Vergalla, Artist in Residence, Pier 9

Invited Participants

Francis Bitonti

Founder and President
Studio Bitonti

Kate Compton

Computational Creativity Researcher and Educator
University of California, Santa Cruz
Independent Game Developer

Lysandre Follet

Director of Generative Design
Nike Innovation Kitchen

Fawwaz Habbal

Executive Dean
Engineering and Applied Science
Harvard University

Danil Nagy

Senior Research Scientist
The Living
Faculty, Columbia University

Kat Park

Senior Digital Design Manager
Skidmore, Owings & Merrill

Thanassis Rikakis

Executive VP and Provost
Virginia Tech University

Vadim Shapiro

Weideman Professor of Mechanical Engineering &
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University of Wisconsin at Madison
Distinguished Research Fellow, ICSI
Editor in Chief, Computer-Aided Design

Oliver Walter

Senior Strategy Program Manager for R&D
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Overview of This Document

What are Ideas Driving Change summits?

The summits are designed to create dialogs between academia and business that generate insights on matters critical to the future of the company and the sectors it serves. The gatherings result in co-created points of view developed with attendees during and after each summit.

The summit POV has three sections:

1. A synopsis of the POV (pages 2–8)
2. The POV itself (pages 9–33)
3. The afterword: How you can prepare for co-creating with machine intelligence (pages 34–36)

Synopsis of Summit: *Co-Creating with Machine Intelligence*

Preface

Summit delegates discuss the historical shift from tools as instruments to co-creative agents. A central theme emerges: the importance of understanding learning reciprocities between humans and tools defined by machine intelligence. These discussions fall into subthemes that surface during the summit:

1. Tools that teach—and learn
2. Attacks on the learning process: algorithmic banality and bias
3. Learning and higher education in a world of machine intelligence
4. Co-creating with machines: What academic inquiry methods will define this era?
5. Three central questions for learning and co-creating with machines: What is computable? What is reasonable? What is acceptable?

The point of view ends with an afterword about what business and academic institutions can do now to prepare for a world of co-creating with machine intelligence.

1. Is this real?

Summit delegates debate changes brought on by machine intelligence¹ and their implications for industry and education—and the workforce in general. The group feels an urgency to more deeply understand and respond to emerging dynamics linking machines and humans.

1A. Conveying the complexity and urgency of the moment through storytelling: The delegates discuss storytelling as a means of conveying the urgency and complexity of this historical moment and influencing others to take action. Oliver Walter, Senior Strategy program manager for R&D at BMW Group, observes that “a few strong stories that show how AI dramatically increases productivity, creativity or effectiveness” are needed to trigger more investment. That will mark a milestone when “money and resources will follow that will speed up [AI] innovation exponentially.” Right now, without real-life examples to prove the real value of AI, he believes we are witnessing “the quiet before the storm.” It’s a period best used to prepare for a wave of change caused by the

¹ The term *machine intelligence* is used throughout this document as a broad descriptor for artificial intelligence (AI) and machine learning. Delegates often use the term *AI* to generally refer to intelligent computational systems.

combination of AI, generative design, and manufacturing that he freely compares to a “tsunami.”

2. Tools that teach—and learn

What characterizes this historical moment from the standpoint of tool makers and users? Delegates discuss the historical shift from tools as instruments to tools as co-creative agents. Instead of conceiving of something and then using a tool-instrument to make that conception real, the user *frames a problem* to work on with an intelligent tool. *In a sense, the tool becomes a framework for learning—a learning machine.*

2A. Learning as a form of problem framing: Delegates discuss problem framing as the process of shaping human intent. Kat Park makes the point that CAD tools today are good at capturing explicit intent, but machine intelligence could help us better capture ambiguous intent. She discusses utilizing emerging tools as platforms for two-way learning.

2B. Shaping intent by creating a “possibility space”: Machine intelligence allows us to create a solution space with many design options driven by algorithmic optimizations across multiple variables. Kate Compton, an expert in game design and procedural content generation, prefers to talk about creating and “exploring the possibility space” with machine intelligence. Francis Bitonti sees machine intelligence as a means of exploring and making sense of the possibility space relative to data inputs linked to customer needs. Lysandre Follet sees the possibility that machine intelligence could help organize the possibility space for the specializations of diverse team members that are typical of his company. Danil Nagy sees the goals and constraints embodied in the possibility space as a productive means of structuring conversations with and to better receive feedback from clients.

3. Learning reciprocity

Building on the idea of intelligent tools as platforms for two-way learning between machines and humans, delegates discuss the fact that humans will need to become experts at learning from machines—and likewise about teaching machines the right things to learn. In this world, a continuum of learning emerges, with new learning sensibilities and an imperative to invent learning modalities that creatively align humans and machines.

3A. User interfaces are a medium for learning and need to be more expressive: Delegates are concerned that, in the age of co-creating with machine intelligence, creativity will hit a wall if tool makers do not invent more expressive interfaces.

3B. *A new kind of “friendship”*: Delegates discuss designing relationships between tools and humans that increase the probability of “friendship,” or predictable patterns or expectations, a desirable field of surprises, mutual respect, an intuitive sense of what makes the other tick, and trust. Kate Compton talks about broadening our repertoire of dance moves with machine intelligence, including knowing when to “let the algorithm lead.”

4. Bias and algorithmically generated banality

The summit group was also concerned about *algorithmically generated banality*, where machine intelligence perfectly discerns human intent and delivers well-tuned solutions but offers nothing more, effectively ending the learning process between human and machine and reinforcing the user’s original biases. Mickey talks of “a denial of creativity attack” he experienced.

4A. Algorithmic bias amplified by platforms—a virulent form of banality:

It is common sense that the data we feed to learning algorithms can encode biases. In addition, digital platforms have the power to amplify these biases, cascading them across the Web and feeding them into a multitude of algorithms, decision-making processes, and policies that compound their effects.

4B. *The imperative for transparency*: The following question arose during the summit: If the final responsibility for a decision made with AI ultimately rests on the individual human user and not the computational system, should AI have the obligation to explain itself? In a word, yes. Delegates agree that transparency—lifting the lid on the reasoning, processes, and, most importantly, background biases at work—is essential to co-creating with machine intelligence.

4C. *It’s not just about learner algorithms and data—it’s also about human brains*. Thanassis Rikakis believes that the inherent biases in AI can be mitigated with the help of an education that is as broad as it is deep. “Bias starts in the head,” he says. “But, if people are broadly educated, they are less likely to develop narrow biases.”

5. Co-creating with machine intelligence: the role of bias and how to mitigate it

During an interview at the summit with Randy Swearer (VP of Autodesk Education Experiences), Mike Haley (head of Autodesk Machine Intelligence), asserts, “Human biases are the way in which we deal with complexity. I mean we live in a very, very complex world with a brain that actually isn’t that powerful.” Most buildings today look alike *because humans alone are making them*. Mike Haley pauses for a moment and says, “It is really hard to make different things. In fact, it is often much

cheaper just to make the same thing over and over” because it is too complex to consider all the new variables novel designs would introduce. Mike Haley explains that the inherent biases that dilute creativity could be mitigated with machine intelligence.

5A. *Hay moving*: Mike Haley’s comments generate a number of responses from delegates. Vadim Shapiro asserts, “The question is not whether I can find my bias in the spaces already constructed but whether I can bring new information to that design space, which is not [encoded] in your systems.” Mike Haley and Thanassis Rikakis reflect on the ways artists work and look for ways to “knock aside bias.” Thanassis Rikakis builds on the idea of circumventing bias with the example of the impressionist composer Claude Debussy: “When he started the whole impressionist movement in France, he used to tell his students, ‘Don’t go to the Conservatoire . . . Go out into the fields and look at the hay moving.’ So, in the context of buildings and machine intelligence, this means the data that you’re putting in can’t just be buildings. *You should also be putting in the moving hay.*”

6. A new horizon for education and learning in a world of machine intelligence

Just as industry representatives are identifying challenges and opportunities presented by our new world, which is rapidly incorporating machine intelligence, so too are leaders from universities recognizing that their sector has moved into a phase of disruption that challenges many fundamental assumptions about the purpose, meaning, and function of higher education.

6A. *Misalignment between industry and academia*: The industry representatives speak of the challenges of hiring employees who have the backgrounds and sensibilities to thrive in an environment of constant change and the need to continually learn (and unlearn) and co-create with machines. The academics fully recognize that it will be challenging for universities to adapt to a world infused with machine intelligence and prepare students for the professions of tomorrow.

6B. *Learning as an “n-of-1”*: Thanassis Rikakis speaks of a new learning environment that needs to emerge at universities: “n-of-1” meaning that the typical lockstep industrial-age pathways through fixed curricular avenues (like majors) need to give way to learning customized to the needs of each student. “AI and computation allow educators to offload some of the complexity of n-of-1 to machines, allowing us to move up a level and create higher-level augmentation as teachers,” he says. According to Thanassis Rikakis, preparing students to work with machines may no longer hinge on answering the question of what to teach. Instead, it becomes a question of how—or how much—to teach,

as universities strive to “open up the aperture of what is learning” to empower students to make the choices that will enable them to co-create with machine intelligence on their own terms.

6C. *Learning pathways with machine intelligence:* As a thought experiment, Randy Swearer asks how we could work with machine intelligence *to co-create customized learning pathways that individuals could never conceive of on their own*. For example, the potential of what we call “generative learning” is to move beyond industrial era framing of fixed “professions” fed by a static handful of university “majors” by helping learners identify fluctuating “flows” of professional activities that we might not even have words for yet.

6D. *Spreading wings by opening up the aperture of learning:* At one level, $n = 1$ education, powered by machine intelligence, allows academia to address what Thanassis Rikakis calls “the unevenness and missed opportunities in the current KT12 system.” At the other end of the spectrum, machine intelligence also allows academia to be more connected and committed to addressing broader societal challenges, “spreading one wing toward secondary education and the other to the professional world of graduates and continuous adult learning.”

6E. *Breadth versus depth? The question of our era:* The ideal early 21st-century student is often referred to as T-shaped, with both breadth (horizontal stroke) and depth (vertical stroke). Randy Swearer questions whether a T-shaped individual is simply a transitional concept that accommodates how knowledge is structured at some universities today, with their specialized majors and general education courses. This raises the question of whether we need to organize knowledge in new, more sophisticated ways, where expertise is intentionally braided into more integrative knowledge frameworks such as those discussed below.

7. A constellation of inquiry methods for a world of machine intelligence (and beyond)

The summit delegates spend several sessions discussing core competencies for an age of co-creating with machine intelligence and considering the kinds of academic inquiry methods that would support them. The most significant discussions concern the liberal arts, problem framing, and systems thinking—and the question of “*what is computable*.”

7A. *Beyond and between disciplines—the centrality of “soft” skills:* Again and again, summit delegates from both academia and industry emphasize the importance of intentionally teaching and repeatedly exercising soft skills in diverse contexts throughout the university experience. The delegates discuss the idea of soft skills in a world of

machine intelligence, emphasizing that a core member of a team will increasingly be an AI. As humans and machines work together with more frequency, new types of collaborative methods, protocols, learning reciprocities, and mind-sets will have to be developed.

7B. Liberal learning: A top-quality liberal learning experience builds students' abilities to reason broadly about problems and issues, incorporating data from diverse disciplines, interrogating assumptions, respecting diverse viewpoints, and balancing reasoning methods that are deductive, inductive, and abductive. Francis Bitonti observes, "We are going to see a massive cultural change driven by AI in the next 20 to 30 years. We are at a unique point where this technology is potentially as much a cultural enabler as it is a productivity tool, and education must equip us to have a deeper understanding of both."

7C. Problem framing: Working with AI and machine learning in the multidisciplinary teams that will lead these efforts will require students to become more adept at framing problems, not just solving them. "Problem definition and problem formulation are not going away," says Thanassis Rikakis. "In fact, education will probably need to focus more on [this] than ever before."

7D. Systems thinking: The problem framing issue incorporates other essential 21st-century inquiry methods discussed by the group. First among these is *systems thinking*, or the ability to productively manage complexity by understanding the interdependent components of dynamic systems. To properly teach systems thinking, universities will also need to ensure that students can view problems from *all* angles. For this reason, universities must equip graduates with a firm grasp of deductive, inductive, and abductive reasoning skills, all required to co-create with machine intelligence and work in teams that collaborate with machines, Fawwaz Habbal says.

7E. What is computable? During a discussion about problem framing as the first co-creative handshake between humans and machines, one delegate makes the simple statement, "Humans need to know what is computable." The summit returns to this simple framing several times to discuss, for example, the idea that just as humans need to know what is computable, so too do computational systems need to be designed in such a way that they understand what for humans is "reasonable." Understanding "what is computable" raises the issue of meta-disciplines that seek to incorporate aspects of problem framing and systems thinking in a computational framework.

7F. You can define what is computable, but what is acceptable? Some delegates question whether there should be boundaries to what we

should seek to make computable. Fawwaz Habbal makes the point that, as machine intelligence evolves with us as a learning partner, it will open our eyes to ideas and answers that we might not otherwise have considered. In this scenario, he says, machine intelligence becomes “a partner and a mentor that possesses a different wisdom—not a better one, but an extremely powerful one.” It’s a force he compares to the value of human diversity, as AI would bring in different viewpoints and perceptions, thus augmenting and enhancing our intelligence in ways we cannot yet imagine.

8. Being human

It is not possible to fully engage the idea of co-creating with machine intelligence without asking the following questions: What is human? What are the unique attributes we bring to the table when we collaborate with machines? The satisfactory answer is far beyond the scope of the summit—and yet, the summit emphasizes the importance of addressing it during a number of conversations.

8A. Being human means embracing our full capabilities as a species. It means building new equations between our soft skills and the crucial mind-sets they generate—and hard skills and the measurable expertise they make possible. It requires us to honestly confront our innate weaknesses and singular strengths relative to machine intelligence. Finally, it should focus us on understanding the unique learning dynamics that define our species—and the singular learning modalities needed by machines. However, the most important question is how can we optimally learn *together* to make the world a better place.

Afterword

Preparing for a world of co-creating with machine intelligence:

1. Share stories from others and generate your own.
2. If you’re a business, establish a machine learning intern program for humans, but raise a few algorithmic machine learners along the way.
3. Let your interns play with your data to drive discovery and insights.
4. Practice building and mining possibility spaces and invest in pilots.
5. Learn systems thinking: It’s helpful for co-creating with MI.

Machine learning is making human learning more urgent and important than ever. Put together policies and invest in systems that encourage co-creation and co-learning.

6. Whenever possible, build in learning reciprocity between machines and humans and invent new dance moves with machines.
7. Beware of biases and find ways to build trust between human and machine teammates.

Learning with Machines

Preface

During two remarkable days in June 2017, thought leaders from industry and academia convened at Autodesk to debate how our lives will transform as we increasingly co-create the world with machine intelligence. This point of view was created collaboratively with summit participants during and after the summit concluded.

Delegates agree that the new relationships between humans and machines are already having far-reaching effects on our societies and economies—and that these effects will accelerate in the coming years. They stress the urgency of more deeply understanding the emerging co-creative dynamics between humans and machine intelligence.

A central theme emerges during the summit: the historical shift from tools as instruments to tools as co-creative agents. Instead of conceiving of something and then using a tool-instrument to make that conception real, the user *frames a problem* to work on with an intelligent tool. In this new type of working relationship, the tool becomes a framework for learning—a learning platform.

Delegates explore the co-creative learning reciprocities between humans and tools defined by machine intelligence. These discussions fall into subthemes that emerge during the summit:

1. Tools that teach—and learn
2. Attacks on the learning process: algorithmic banality and human bias
3. Learning and higher education in a world of machine intelligence
4. Co-creating with machines: What academic inquiry methods will define this era?
5. Three central questions for learning and co-creating with machines: What is computable? What is reasonable? What is acceptable?

I. Is this real?

Throughout the summit, the delegates agree that the societies and economies represented in the room (North America and Europe) are at an important inflection point in how humans work with intelligent machines. It's a threshold moment—where to move forward we need to step back and look at our deeply held beliefs about work and education. The summit occurs at a historical moment when an interwoven group of

changes—driven in part by the combined effects of new digital cloud platforms, computational design, advanced manufacturing, and machine intelligence—are altering the landscape of imagining, designing, and making things. These changes have begun to affect the nature and organization of work in many sectors.

Fawwaz Habbal, executive dean of Engineering and Applied Sciences at Harvard, believes that we are at a crossroads “unlike any other moment in our history” driven by “extreme connectivity” and technologies that have moved beyond simple mechanical challenges to “intellectual problem solving” in augmented relationships to humans. He makes the point that the speed of these developments has defied expectations and says, “A machine that is able to write you a story is something you would have never guessed would take place.” AI technologies have allowed machines to “learn and create with a ‘mental power’ that we didn’t expect.”

Given these developments, it is no wonder many today feel some disequilibrium in the face of AI-driven change and breakthroughs. “The genie is out of the bottle and *it* is going to happen,” predicts Vadim Shapiro, professor of engineering and computer science at the University of Wisconsin. In his view, *it* is a variety of scenarios: an increase in productivity, an unleashing of “inconceivable creativity,” and an “unstoppable (r)evolution driven by AI, machine learning, big data, and the raw power of computing.”

This combination is what Oliver Walter believes is going to ensure AI innovation will be much faster and more far-reaching than we can imagine. “AI is much more powerful when you have connectivity that allows several computers to simultaneously ask different questions to address the same challenge,” he says. “We are entering a phase where the computer starts, working by itself, and then comes up with solutions the engineer is either not capable of thinking of or never has thought of in the first place.”

However, the tipping point will come with scale, enabled by three key components. One is computing power and cloud connectivity that gives one AI the reach and power of millions of computers. He likens it to the ability to tap the wisdom of crowds—only this time the wisdom is individual computers, not people. The second is speed. “This won’t take days; it will take milliseconds.” And that speed will add up, increasing the competitive advantage of the companies and industries that can harness it. Imagine all the AI and algorithms working in one direction to solve problems in parallel. “That is going to be the big wake-up call,” he says. “Whoever can prepare to tap the power [of AI in the cloud] is going to take a huge step forward.”

“It is going to propagate everywhere.”

— Vadim Shapiro

Vadim Shapiro believes that key industry developments, such as the decision by Ford to establish a Global Data Insights and Analytics division, speak volumes. This action established an enterprise-wide vision for analytics and integrating all research, processes, standards, and tools, including AI. “[The Ford example] answers the question [of whether] AI is going to affect engineering from design conceptualization and manufacturing to business operations and analysis,” Vadim Shapiro explains. “It is going to propagate *everywhere*,” and these effects have major implications for industry, which must cultivate new skill sets and mind-sets to co-create with machine intelligence and academia, which must foster new attitudes and aptitudes.

But the academics in the room clearly understand that the existing, industrial-age paradigm for university education no longer optimally aligns with the emerging world of work, where machine intelligence plays a central role. This phase-change moment presents unprecedented challenges to higher education, from the organizational logic of our current universities to the ways students learn and are assessed, the traditional student populations they serve, and their professional preparation functions. Even fundamental pillars of the educational system, such as accreditation, require updating. Sharon Wood, dean of Engineering at the University of Texas, says the current accreditation system can sometimes “not allow us to be as creative as we want to be.”

The industry representatives also see the world changing. Significantly, the catalyst is not the advance of AI alone but rather the combination of AI with additive manufacturing and generative design. Against this backdrop, AI represents what Oliver Walter, senior strategy program manager for R&D at BMW Group, calls the “Third Wave” of innovation, one that will create a “tsunami” of change.

Oliver Walter expects that industry will see the full impact and potential of AI in “four to five years.” For now, he says, AI innovation mirrors the advance of the iPhone, an innovation that first affected communications and has since disrupted many industries and redefined many aspects of human behavior. Like the iPhone, he says, AI is destined to have a much more profound impact than we can imagine at this moment in time. It’s a given that AI will play a role in everything BMW does—from design and production to testing and verification. But, he explains, the real revolution will take place as companies like BMW grasp how AI will affect the customer side of the equation. Through sensor networks and data, BMW will gather insights about how consumers interact with materials—and give feedback about how the materials themselves react. “This will be the biggest step,” he says, and it will reveal “the real power of AI.”

Storytelling: framing, teaching, and learning

Storytelling is a uniquely human way of framing the complexity of the world, particularly at moments of dramatic change, and aligning it with our individual lives and collective goals. It helps us frame problems, see and feel them, convey (teach) to others their most salient features, and learn from the responses of those who listen. Shaping a story and telling it are powerful forms of learning.

Stories and storytelling initiate the process of shaping our intent and directing it toward solutions. They are a precursor to constructive action. If done well, stories weave disparate phenomena into richly illustrated human-scale narratives that focus on the issues that are most salient for describing present and future states. They can break down unhelpful binaries identified during summit discussions, such as *machine versus human*, and help us identify new ways of understanding educational and business value.

The summit defines two simple yet fundamental questions that stories can help us imagine answers to: How will my organization and I have to change? And in what time frame will this change take place? Indeed, during a conversation about which academic and professional skills and mind-sets should move to the center in the emerging age of machine intelligence (and what should move to the periphery), storytelling is identified as a central component of leadership.

The process of storytelling can help us frame broad new futures, but it can be equally pragmatic. Oliver Walter and his colleagues used storytelling to help persuade the company that they needed to invest in the i3, a radically new kind of electric car. Storytelling helped shape the collective intent to act and commit to a new path forward. He recalls that the result was a “moment of truth when I realized there is no way back. . . Suddenly you [the company] start focusing on one goal and one direction. You’ve got everyone behind you, so you’ve got to have the story and tell it.” Simply put, he says, “The biggest hurdle is a psychological one”—and one that can be cleared with the help of increased transparency and trust and communicated through real-life stories and examples that express the benefits and allay our fears.

“You’ve got to have the story and tell it.”

— Oliver Walter

II. Tools that teach—and learn

The summit is about co-creating with machine intelligence, but a lens on one topic repeatedly emerges during the discussions: *problem framing as a form of learning*. This perspective begins to surface during the first hour of the summit as the group defines the historical phase we live in. To understand the threshold moment, many of our preconceptions need to be set aside. In a sense, we need to *unlearn* what we know while

learning about and framing the future in front of us. For many in the room, there is a sense of urgency regarding influencing our organizations to help them adapt and prepare for the future.

And one of the things that people have said when they've been exposed to these new tools is that they get smarter as the tool gets smarter. So the tool can't be a black box; it needs to allow you to watch the learning happen.

—Erin Bradner

This phase change is in part about our tools, which have evolved from instruments to co-creative agents. During the industrial era, our tools were instruments. We used them most often to make our preconceived intentions real—to give form to ideas in a manner that was linear and sequential. I conceived of a door, designed it, and then used my tools to bring it into the world. The tools gave form to my fixed intentions. I learned how to use the tool and then applied this expertise to accurately realize form.

The summit group contrasts this type of *instrumental thinking* with tools shaped by machine intelligence. This emerging class of algorithmic tools is characterized by their more nonlinear, co-creative relationships with users—where users enter into deeply collaborative relationships with the tools. Instead of conceiving of something and then using an instrument to make that conception real, the user *frames a problem* to work on with the tool. *In a sense, the tool becomes the framework for learning—a learning machine.* We begin by clearly articulating our intention, but this initiates loops of learning between the user and machine intelligence.

To use the example of generative design, the problem framing then generates a set of solutions co-created with the tool. The user “curates” the solution set, learning from the tool what the problem framing produced and modifying the solutions accordingly to iterate better results. Of course, the machine intelligence also learns about what the user is shooting for and hones in on his or her intent.

In fact, the user *and the tool* could both be characterized as *learners* in this new paradigm.

Learning as a form of problem-framing

Problem framing is a crucial way of shaping intent; it generates a path forward for learning. Shaping intent through problem framing requires that the learner deal with stages of ambiguity, often in iterative cycles. Here is where the group sees a role for machine intelligence. Kat Park, senior digital design manager at Skidmore, Owings & Merrill, makes the point that the common tools we have now are good at capturing *explicit* intent once a problem has been framed. Most common CAD tools would fall into this category; however, machine intelligence could help us explore ambiguous intent, the type of exploration that is so critical to design development, and could greatly enrich the learning process.

“The designer and engineer need to think more abstractly about how to frame problems. And they need to focus that energy on specifying and iterating goals and constraints—not just the geometry.”

—Erin Bradner

Tools as rich, two-way learning platforms: a game-changer

If the software were transparent about its assumptions, “It could actually teach you as it’s running.”

— Kat Park

Kat Park then says something about learning reciprocity that emerges as a critical strand of thought during the summit. If the software were transparent about its assumptions, “It could actually teach you as it’s running.” In other words, the machine learning system would communicate to users what it is learning about the solution space and why it is iterating with certain patterns and not others to help users learn and grow as they use the system. “I think that if that’s articulated and shown to the user as a kind of two-way process, it would be pretty amazing. I think that would be a game-changer.”

Several summit delegates describe the process of defining learning through problem framing and shaping intent with machine intelligence as *exploring a possibility space*. Kate Compton’s work in procedural content generation consists of “building a really big possibility space,” and she distinguishes between “things that generate and build out the possibility space” and ways “to navigate the possibility space.” Both are crucial for co-creating with machine intelligence.

“AI adds value by helping us leverage a customer’s sensor data or knowledge about their preferences and habits, which is about designing for experience.”

— Francis Bitonti

Kate Compton’s comment resonates with other summit members. Francis Bitonti believes that machine intelligence can help us generate a massive possibility space with multiple axes and parameters, which can result in an enormous data set. He sees machine intelligence as a powerful way of navigating this space and explains, “Before this, that might have been the job of a room of interns, but now the computer can sort through designs.” For example, in a market of sub-niches and increasing expectation of personalization, “AI adds value by helping us leverage a customer’s sensor data or knowledge about their preferences and habits, which is about designing for experience.”

With the same enthusiasm reflected in Oliver Walter’s comments, Lysandre Follet is excited about a future where AI moves from being one person or one team looking for solutions to a “more distributed system.” Then, he says, industry will benefit from “leveraging a cluster of different people working with different AI on a distributed system toward one goal.” Another advantage for consumer-facing companies such as Nike will be the increased ability of AI to understand consumers and deliver design and experience “much more tailored to the individual as opposed to a sort of common denominator.” Another advantage of AI is that it can be another set of smart eyes to pinpoint “micro-trends.” It’s all about understanding what the consumer wants—based on data and sensors—and how to feed that back into the products and experiences Nike produces. “Today we have to design for the common denominator because we cannot keep up [with micro-trends] and fully understand what each individual consumer needs and wants. AI can constantly learn from the consumer and then extrapolate to say, ‘Here is the micro-trend you, the designer, need to know.’”

“The tools not only help us design things we couldn’t before, such as complex geometries and performance-driven things, but they also let us get feedback from the client in more structured ways.”

— Danil Nagy

Helping clients learn about possibilities

Creating and curating the solution set also creates a learning space that can help make interactions with clients more productive. Danil Nagy, senior research scientist at The Living, makes the point that the design process today is in many ways still very traditional. “You produce something, you get feedback, and then you kind of readjust your assumptions and methods again,” he says. “But . . . computation kind of interjects in that process in productive ways. . . . The general framework of goals and constraints gives us a really productive way of talking to our clients and getting feedback from them. . . . The tools not only help us design things we couldn’t before, such as complex geometries and performance-driven things, but they also let us get feedback from the client in more structured ways.”

Team learning in the solution space

Interacting and learning in the solution space is not just between a single human and machine. Lysandre Follet, director of generative design at the Nike Innovation Kitchen, sees this space as a place for radical collaboration with diverse team members. This is crucial at a place such as the Nike Innovation Kitchen, where the key to success is having teams with disparate mind-sets, tool sets, and skill sets. He makes the point that the solution spaces created by “computation in design offers a very collaborative way of working where each person can become a curator of his part. The machine learning system then finds the subset of the solution space that is almost placed at everybody’s feet. . . . So, what’s really intriguing for me is that collaborative tool that brings everything together. The machine . . . becomes the means of finding the subsets of that space” and aligning them with team members.

Beyond “curation”

A term often used to describe the learner’s interaction with the possibility space is *curation*, and, yet, as the summit progresses, it seems increasingly inadequate. Curation connotes more of a binary and linear relationship between humans and machines: The human frames the problem, the machine creates a solution set, the human curates the solutions, and the process continues to the end solution. The delegates imagined a much richer set of interactions with the solution set—perhaps captured better with Kate Compton’s use of the term “possibility space.”

Rich and meaningful curation in the world of co-creating with machine intelligence is a powerful, reciprocal learning relationship between machines and humans. Kat Park comments that, for humans alone to optimally engage with the solution set, they would need to be “a lot more informed about the different disciplines, the multi-variable

For humans alone to optimally engage with the solution set, they would need to be “a lot more informed about the different disciplines, the multi-variable optimizations, or multi-discipline optimizations.”

— Kat Park

optimizations, or multi-discipline optimizations” that the solutions represent. “I think we [would have to be] a little more educated” to independently curate that space as humans.

“Let the algorithms do what they’re good at: chewing on these multi-objectives. And let the designer and engineer do what they’re good at, which is creating new problem definitions to exploring a space that’s not yet explored.”

—Erin Bradner

III. Learning reciprocity

The summit group extensively discusses the *reciprocity of learning* between humans and machine intelligence. Humans will need to become experts at learning from machines—and likewise about teaching machines the right things to learn. In this world, the industrial-age binary of machine versus human melts into air, and in its place emerges a continuum of learning, new learning sensibilities, and an imperative to invent learning modalities that creatively align human and machine.

One member of the summit illustrates this point using the example of the Socratic method, an ancient pedagogy in which learning is driven by a dialog between learners that progressively seeks to probe the underlying presumptions of a position. What would the learning reciprocity of the Socratic method look like if applied to the relationship between humans and machines?

But learning reciprocity between humans and machine intelligence is a two-way street. The design of intelligent computational tools needs to take into account the human need to understand and intuit how best to collaborate with (to use a delegate’s phrase) “the algorithmic black box.”

The user interface is a medium for learning

Another obstacle on the path to close collaboration with AI is the interface. Encouraging designers to think like programmers might be necessary to ensure machine intelligence is fed with data that makes problems computable, but the rigid structure of this process and the programming skills necessary to input such data can stifle creativity, not unleash it, Kat Park notes. Typically, designers have a mind-set that allows them to be “comfortable with ambiguity and not knowing all the constraints,” she explains. Unfortunately, this is not the way AI works; however, it is why highly visual tools and interfaces such as Grasshopper and Dynamo help ignite the creativity of AI *and* the user. In practice, it provides designers the flexibility of a blank sheet of paper while making it easier for them to “think like programmers” to co-create with machines.

Indeed, delegates worry that creativity may hit a wall if the makers of tools don’t evolve more expressive interfaces. If we accept that the next generation of AI will be partners in the process and not mere tools, we will need to communicate with them, not command them. As Danil Nagy says, “We need a language that can express every possibility, not just ten buttons.” Lysandre Follet takes this idea a step further, suggesting that

the answer lies in the user interface (UI) that will equip both parties (AIs and users) to “understand and express larger concepts in ways that go far beyond code.”

In his view, interfaces must also enhance, not limit, his ability to co-create with AI. In his view, the idea interface is “very visual” (as designers are the same way) and allows users to “explore all the creative possibilities while maintaining some sort of constant curation—because otherwise you’re going to get lost.” Finally, there must be “some sort of override function” to ensure the human is the “final curator.”

Will the interface be the language of computer code or something else? We can’t know for sure.

A new kind of “friendship”

Another member of the summit speaks of designing relationships between tools and humans that increase the probability of *friendship*. The idea of a machine *friend* is discordant to some ears, but it is a useful metaphor here because the term describes a relationship based (in part) on predictable patterns or expectations, a desirable field of surprises, mutual respect, and an intuitive sense of what makes the other tick. Of course, in any friendship, there is a sense of trust: an understanding of when to listen, talk, follow, lead, and collaborate.

Engaging with machine intelligence across these dimensions of *friendship* is not intuitive for humans, but as Kate Compton emphasizes, we need to broaden our repertoire of dance moves with AI, including knowing when to “let the algorithm lead.” Elaborating on this idea, Kate Compton says, “I don’t want to push my AIs in directions that they have troubles going. . . . You have to have a very playful attitude. A Zen butcher never sharpens his knives, which means the knife goes where it has to go and you are not forcing it.” This is similar to AI.

Know when to “let the algorithm lead.”

— Kate Compton

IV. Bias and algorithmically generated banality

But the summit group is also concerned about *algorithmically generated banality*, where machine intelligence perfectly discerns human intent and delivers well-tuned solutions, but offers nothing more, effectively ending the human–machine learning process and reinforcing the user’s original preconceptions.

Traditional instrumental uses of tools require the user to conceive of a solution and use the tool to create it accurately. The solution becomes the focused goal of tool use—a necessary fixation to guide the making process; however, in a world of machine intelligence, the solution itself and the path to making it real *are co-created with the tool*. The role of

the intelligent tool is certainly to help realize the user's intent, but to do so in ways that keep the learning process open to new possibilities.

Kate Compton, with her deep experience in game design and procedural content generation, speaks of embarking on journeys of discovery with machine intelligence. Mickey McManus brings up the concept of *desirable difficulties* (prevalent in the gaming world), where players are constantly nudged to learn more about the possibilities in a game to expand their understanding of opportunities and enhance their experience through growth.

Lysandre Follet talks about how machine intelligence can take brainstorming to new levels of magnitude and creativity. "It's about involving multiple participants with multiple talents." And the outcome should be "creativity that pushes you to the next level." This state of hypercreativity doesn't exist yet, but it's only a temporary "limitation in how the system has been designed." It's the same everywhere, he says. "I don't think there is a system that is capable of reaching out to a new sort of creative space."

However, he shares Mike Haley's enthusiasm for the arrival of hypercreativity in the longer term that will "unleash amazing creativity from co-creation with AI." Right now, with generative design, "there are a lot of designs that are quite similar because a lot of people are looking at the same algorithms in the same systems." This will change as AI develops the "capacity to look at things that are unrelated and inspire designers to see things differently."

A denial of creativity attack

Related to the issue of banality are applications of machine intelligence that accurately discern a user's intention but deny its creative richness and full implications by grinding down intent into accurate but banal solutions that effectively end the process of learning. To create an image for this phenomenon, Mickey McManus gives the example of a simple drawing tool, where the machine intelligence discerns his sketch (house, person, door, etc.) but denudes its complexity into a homogenized icon. "I felt like I had been the victim of a *denial of creativity attack*," he says. Mickey continues explaining that, in the process of co-creating with machine intelligence, "there is an opportunity for organizations to use machines to amplify creativity by providing dynamic 'noise cancellation' for biases that feed into design fixation."

"I felt like I had been the victim of a 'denial of creativity' attack."

— Mickey McManus

Platforms and virulent bias

AI-generated bias is a virulent form of algorithmic banality. It is common sense that the data we feed to learning algorithms can encode bias. The power of digital platforms means that this bias can be powerfully

amplified, cascading across the Web and feeding into a multitude of algorithms, decision-making processes, and policies that compound its effects.

Transparency and trust

The following question arises: If the final responsibility for an AI-made decision ultimately rests on the individual human user—not the computational system—does the AI have an obligation to explain itself?

“If I get a report from an employee and it doesn’t make sense to me, I’m going to question where they got their information and how they came to their conclusion. And it’s the same with AI.”

— Francis Bitonti

In a word, yes. Delegates agree that transparency—lifting the lid on the “reasoning,” processes, and, most importantly, biases at work in machine intelligence—is essential to the co-creation process. Delegates point out that it’s not very different from what they already demand of their human colleagues. “If I get a report from an employee, and it doesn’t make sense to me,” observes Francis Bitonti, “I’m going to question where they got their information and how they came to their conclusion. And it’s the same with AI.”

The power of machine intelligence to augment and enhance human intelligence increases the importance of developing inquiry methods and strategies that give users deep insights into how the system “thinks” and the inherent biases that influence outcomes. Bias is embedded into machine intelligence by its creators and programmers and is often reinforced by the data it is fed, making it difficult to have complete transparency into “what’s behind the curtain,” observes Sharon Wood, dean of the Cockrell School of Engineering at the University of Texas. Nonetheless, this embedded bias is what “really scares” her when she looks at the future of machine learning.

Society demands safeguards to control or at least expose inherent bias in AI. For now, delegates suggest, the situation is like the quiet before the storm. “Currently, you can train a computer to recognize [that] an image of a cat is a cat, but you have no explanation about how this is done,” Vadim Shapiro explains. That may be sufficient for dealing with the low-level tasks we currently relegate to AI, but lack of transparency has the potential to become a “much bigger problem” as AI evolves to become an equal partner in the co-creative exchange.

This view is shared by Oliver Walter, who points out that people, including his peers, don’t always trust AI because “we don’t know what is going on in the black box or behind the screen.” But lack of transparency is just one side of the problem. We also lack the imagination to envision how AI will affect and benefit our lives. Oliver Walter compares it to the arrival of steam power. At first, people were used to riding in carriages, and then steam power came along. “Not understanding it and what it could do, people were frightened.” People embraced the technology as

the power and potential of steam power became clearer. Simply put, “the biggest hurdle is a psychological one”—and one that can be cleared with the help of increased transparency and trust and communicated through real-life stories and examples that express the benefits and allay our fears.

Algorithms, data, and human brains

Thanassis Rikakis, executive vice president and provost of Virginia Tech University, believes that the inherent biases in machine intelligence can be mitigated with the help of an education that is as broad as it is deep. “Bias starts in the head,” he says. “But if people are broadly educated, they are less likely to develop narrow biases.” In practice, he believes programmers with a liberal arts background would be less likely to transfer biases to software. Even if programmers do influence the computational system with their personal biases, the beneficiaries of a broad education would be more likely to see them for what they are.

“Bias starts in the head. But if people are broadly educated, they are less likely to develop narrow biases.”

— Thanassis Rikakis

V. Co-creating with machine intelligence:

The role of bias and how to mitigate it

Human bias powerfully undermines learning with machines. So the summit discussion focuses on the promise of machine intelligence as a means of mitigating biases such as design fixation. During an interview with Mike Haley, who leads the Autodesk Machine Intelligence group, Randy Swearer, vice president of education experiences at Autodesk, asks about how machine intelligence could help humans creatively define and explore the solution space—in a sense, circumventing bias or leveraging it.

“Human biases are how we deal with complexity.”

— Mike Haley

“Most buildings look alike because humans alone are making them.” Mike pauses for a moment and says, “It is really hard to make different things.”

— Mike Haley

Mike Haley says, “Human biases are the way in which we deal with complexity. I mean we live in a very, very complex world with a brain that actually isn’t that powerful. . .” He explains that if architects had to design a building without bias, they might think, “Oh my God, there’s a hundred million possible designs. I don’t even know where to start. You’d never get anywhere, right?” Mike Haley recounts the story of an architect who attended one of his presentations on AI and architecture. During the question and answer session, the man said, “This is ridiculous. Every building in the world is going to look the same.” Mike Haley replies, “I am saying precisely the opposite of that.” He explains that today, most buildings look alike *because humans alone are making them*. Mike pauses for a moment and says, “*It is really hard to make different things*. In fact, it is often much cheaper just to make the same thing over and over” because it is too complex to consider all the new variables novel designs would introduce.

Mike Haley finishes the thought by returning to machine intelligence and adds, “What if you had a system that was kind of tapping you on the shoulder all the time and saying, ‘Hey Randy, I know you’re over there, but there’s this other solution over here that you might never have thought about, and we’ve done all of the assessment for it [with machine intelligence].’ So, I think there’s the possibility of [using] AI as the counter to bias, which I think is very interesting.”

Mike Haley’s comments unleash a flood of responses from delegates. Vadim Shapiro replies, “The question is not whether I can find my bias in the spaces already constructed but whether I can bring new information to that design space, which is not [encoded] in your systems.” Mike Haley reflects that he enjoys watching artists work because “they come up with mechanisms to break out of their biases. In fact, they’re often sort of energized by almost challenging themselves and generating [creative] discomfort in themselves and others. . . . When you look at Gaudi or other famous architects and artists, [they] are actually trying to come up with human ways of knocking [aside bias]. But my point is that there are ways machines can do this too.”

“When he [Debussy] started the whole impressionist movement in France, he used to tell his students, ‘Don’t go to the Conservatoire . . . go out into the fields and look at the hay moving.’ [So, in the context of buildings and AI] this means the data you’re putting in can’t just be buildings. You should also be putting in the moving hay.”

—Thanassis Rikakis

Look at the hay moving

Thanassis Rikakis builds on the idea of circumventing bias with the following example of the impressionist composer, Claude Debussy: “When he started the whole impressionist movement in France, he used to tell his students, ‘Don’t go to the Conservatoire . . . go out into the fields and look at the hay moving.’ [So, in the context of buildings and AI,] this means the data that you’re putting in can’t just be buildings. *You should also be putting in the moving hay.*” Later he says that, in the case of buildings, the data and the programming are always going to be very biased if they are only associated with the building industry. “You’ve got to consider the [broader] artistic dimensions.”

VI. A new horizon for education *and learning* in a world of machine intelligence

Many of the most powerful discussions at the summit occur in dialog between members of academia and industry. In some respects, the perspectives of these groups are distinct, but in other ways, there is broad agreement.

Just as industry representatives identify challenges and opportunities presented in a world rapidly incorporating machine intelligence, so too do university leaders recognize that their sector has moved into a phase of disruption that challenges many fundamental assumptions about the purpose, meaning, and functions of higher education.

The industry representatives speak of the challenges of hiring employees who have the background and sensibilities to thrive in an environment of constant change, the need to continually learn (and unlearn), and the desire to co-create with machines. The academics fully recognize that there is sometimes misalignment between the needs of leading-edge industries incorporating machine intelligence and the sensibilities and capabilities of university graduates. Similar to large industrial companies with fixed costs and legacy processes, universities are slow to change. Contrary to worn clichés about the inability of universities to respond to change, however, it is striking to see the breadth of experimentation occurring at the universities represented at the summit, as well as their willingness to discuss new organizational frameworks, missions, and visions of the future.

Learning as an “n-of-1”

The same academic leader speaks of a new learning environment that needs to emerge at universities with an “n-of-1,” or learning pathways personalized for individual learners. This means that the typical lockstep industrial-age pathways through fixed curricular avenues (such as majors) need to give way to learning customized to the needs of each student.

To achieve this ideal, machine intelligence could be pivotal. The summit uses the framework of *generative design* described earlier to concretely think about new kinds of relationships between humans and machines, but in a sense, the same framework could be used to think about learning.

From generative design to generative learning?

As described earlier, with generative design, the design process starts through collaboration with intelligent computer systems. You work with the system to frame not so much a blind instrumental action advancing the creation of your project but rather how you want it to collaborate with you to achieve a design outcome. By co-creatively working with the system to frame design problems, you give it the fuel to explore a massive possibility space no individual could ever conceive of alone. The designer becomes both a problem framer and a curator of the solution set.

As a thought experiment, Randy Swearer asks whether we could work with machine intelligence *to co-create learning pathways we could never conceive of on our own* by using this framework. For example, the potential of what we might call “generative learning” is to move beyond industrial era framing of fixed “professions” fed by a static handful of

university “majors” by helping learners identify fluctuating “flows” of professional activities that we might not even have words for yet.

Generative learning embraces the reality that learners are no longer bound by time, place, and graduation dates. We now need to learn and grow forever as our professional world morphs. Could generative learning frameworks help align the unending process of learning with constantly shifting flows of professional activities? In an age of accelerating workforce disruptions caused by automation, the broader social impact of generative learning could be substantial—even pivotal—to finding a dynamic equilibrium in the emerging world of work.

Opening the aperture of learning with machine intelligence

According to Thanassis Rikakis, preparing students to work with machines might no longer hinge on answering the question of what to teach. Instead, it becomes a question of how—or how much—to teach as universities strive to “open up the aperture of what is learning” to empower students to make the choices that will enable them to co-create with machine intelligence on their own terms.

In his view, the next 20 years will see universities move away from the idea that “there’s only one way of excelling.” He sees one potential outcome: a new level of disruption in academia as universities position themselves to address a market that’s going to be highly diversified. “So, we will have to be highly diversified as well.” Significantly, this is where machine learning takes on a new role and importance as a way to customize learning and “assist in predictive advising to help students find the right courses and focus to suit them.” In this scenario, machine learning lays the groundwork for “ $n = 1$ ” education that is individual and inclusive. “AI and computation allow educators to offload some of the complexity of $n = 1$ to machines, allowing us to move a level up and create a higher-level augmentation as teachers,” he says.

At one level, $n = 1$ education powered by machine intelligence allows academia to address what Thanassis Rikakis calls “the unevenness and missed opportunities in the current KT12 system.” At the other end of the spectrum, machine intelligence also allows academia to be more connected and committed to addressing broader societal challenges, “spreading one wing toward secondary education and the other to the professional world of graduates and continuous adult learning.”

The advances in machine learning require universities to “produce people who can reinvent themselves 20 times from the time they come out of the school until the time they retire because that’s what the world needs,” Thanassis Rikakis says. “Customization in a rich environment, where every component is available and there are also parts that can be

customized and optimized with students' participation, allows an outcome where I know I am graduating a highly diverse workforce." It's the skill set that co-creating with machine intelligence demands—and it's the outcome it makes possible.

Thanassis Rikakis might be the champion of the $n = 1$ education based on his personal resolve to make decisions on "how they affect the human condition first," but his ideas also resonate with other delegates. Sharon Wood, for example, would like to explore ways machine intelligence might assist in designing and delivering supplemental courses to benefit students and further lifelong learning. For now, she is fascinated by experiments at universities where machine intelligence is behind the scenes, crunching the big data in real time to help faculty figure out what students don't understand. "It's a useful tool and worthwhile investment to make sure you are teaching the students what they need to know, when they need to know it," she says. She is trying to motivate faculty to embrace her vision but needs more concrete examples of how machine intelligence can lay the groundwork for an $n = 1$ education for all.

Vadim Shapiro believes it is conceivable that machine intelligence will play a larger role in the design and customization of education but warns there may be much less room for flexibility than we anticipate. "It's going to [be] much more structured in the sciences and engineering because the amount of material students need to know is massive," he says. Regardless of what students may want from their $n = 1$ education, there's no getting around the basics. "You can't say, 'I'm going to be an engineer, but I'm going to be a special kind of engineer who does not need to know mathematics because design appeals to me more than math.' It's fine to focus more on aesthetics, but you are not going to be called an engineer." For this reason, he suggests, the real value of the $n = 1$ education may be the support it provides students who pursue more interdisciplinary studies.

Breadth versus depth: the question of our era

The conversations about university education raise a concept widely discussed in academic circles during the past decade: depth versus breadth of learning, or the relationship between specialized expertise and knowledge that is general and foundational to all learning. The ideal early 21st-century student is often referred to as T-shaped, with both breadth (horizontal stroke) and depth (vertical stroke). In this summit, a delegate questions whether a T-shaped individual is simply a transitional concept that accommodates how knowledge is structured at some universities today with specialized majors and general education courses. This raises the question of whether we need to organize knowledge in new, more sophisticated ways, where expertise is intentionally braided

into more integrative knowledge frameworks such as those discussed below.

Universities have conducted a number of experiments with new ways of organizing learning knowledge, such as the Carnegie Mellon IDEATe program, which was created under the leadership of Thanassis Rikakis when he was vice provost at Carnegie Mellon University. There are many interesting experiments with breaking down learning into more complex and integrative pathways organized with micro-credentials, but these experiments are nascent and need to be intensified, and our summit delegates believe that innovation would be spurred by considering the use of machine intelligence for organizing learning.

“Why couldn’t academic credentials be machine learning agents co-creating learning pathways?”

— Randy Swearer

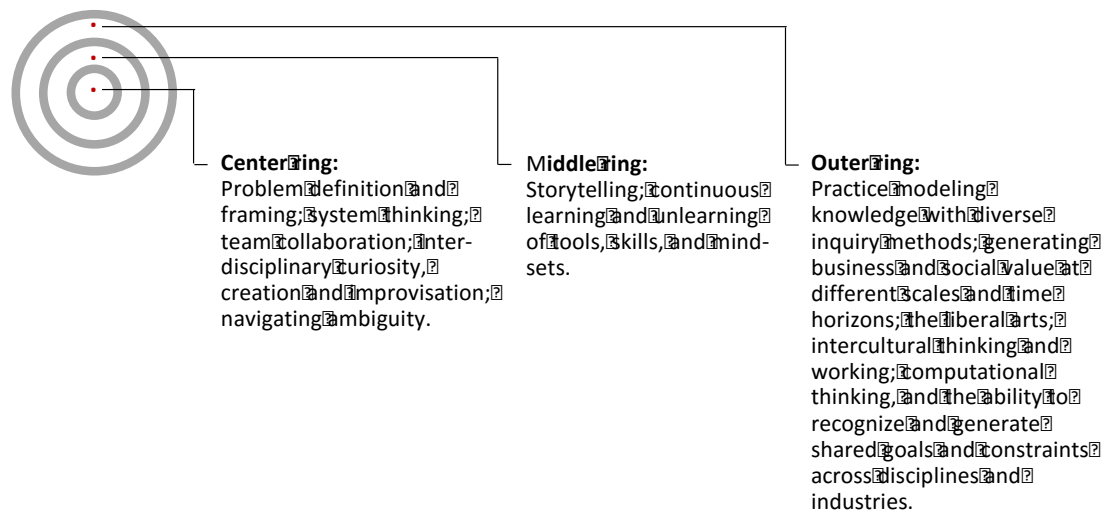
Beyond degrees: credentials as intelligent agents

In this context, Randy refers back to the idea of *generative learning* by asking delegates to envision a future where micro-credentials become more than simply certifications of learning outcomes. He imagines them as machine-learning agents that define learning pathways based on the emergent behaviors of thousands of learners, inquiries from graduate schools for students, hiring manager requests, or the needs of colleagues and teammates.

What if these intelligent micro-credentials incessantly communicated with one another in a system that identified, even helped define, emergent practices and trends that aligned with but also expanded a student’s view of professional flows? And beyond students, what if such a system could help identify emerging areas of professional knowledge and stimulate the creation of learning materials and modalities to extend them further? Such a learning system would not only incorporate existing educational institutions but also integrate them into a much broader framework of learning experiences that shift as professional flows morph and mutate into new kinds of jobs.

VII. A constellation of inquiry methods critical for a world of co-creating machine intelligence

Several summit sessions involve discussing core competencies for an age of co-creating with machine intelligence and considering the types of academic inquiry methods that would support them. The most significant discussions concern “soft skills,” the liberal arts, problem framing, systems thinking, and the question of *what is computable*.



Bull's-eye diagram resulting from an exercise delegates completed during the summit. All three rings are crucial and interconnected.

Beyond and between disciplines: the centrality of “soft” skills

Again and again, summit members from both academia and industry emphasize the importance of intentionally teaching and repeatedly exercising soft skills in diverse contexts throughout the university experience. These discussions come from several angles. First, the complexity of many problems today requires a “collective brain” consisting of diverse groups of people and functions, often geographically distributed. The ability of team members to efficiently and creatively collaborate in such an environment is fundamental to successfully generating value. Second, crucially, the range of behaviors and attitudes represented by the term “soft skills” coalesces into a *mind-set* that aligns one’s internal sense of self, background, and expertise with the capabilities of others to solve problems. *Mind-set* in fact becomes an essential integrator of knowledge and collaborative behaviors fundamental to innovating and generating value.

The delegates discuss the idea of soft skills in a world of machine intelligence—emphasizing that increasingly a core member of a team will in fact be machine intelligence. As humans and machines work together

with more frequency, new types of collaborative methods, protocols, learning reciprocities, and mind-sets will have to be developed.

Universities could play a key role in this emerging world of work by developing and prototyping new inquiry methods that facilitate the ways humans and machines creatively engage with one another; however, the bias against incorporating soft skills must be overcome first on our campuses. It feels dated—a reflection of an earlier industrial era when universities focused exclusively on producing and teaching “hard” knowledge that was scientific and clearly measurable.

Liberal learning

The liberal arts issue surfaces a number of times during the summit. There is broad agreement that the type of critical, contextual thinking that an effective liberal arts education encourages is important in the emerging age of machine intelligence. A top-quality liberal arts learning experience builds students’ abilities to reason broadly about problems and issues; incorporating data from diverse disciplines; interrogating assumptions; respecting diverse viewpoints; and balancing reasoning methods that are deductive, inductive, and abductive. All these abilities are important for a world of co-creating with machine intelligence—and beyond.

“We are at a unique point where this technology is potentially as much a cultural enabler as it is a productivity tool, and education must equip us to have a deeper understanding of both.”

— Francis Bitonti

Liberal learning at its core is about teaching students to learn, continually and passionately. Francis Bitonti observes that liberal learning establishes the knowledge base and learning aptitudes that allow students to grow and evolve throughout their lives. Although he is not convinced university training is what definitively distinguishes leading engineers and designers, he is concerned that an engineering education doesn’t put proper emphasis on the humanities. “We are going to see more cultural change through AI in the next 20 to 30 years than ever in our history,” he says. “We are at a unique point where this technology is potentially as much a cultural enabler as it is a productivity tool, and education must equip us to have a deeper understanding of both.”

The problem is finding ways to incorporate more elements of a liberal arts education into what is already an “overly constrained curriculum.” Thanassis Rikakis suggests universities could accomplish more (and faster) by identifying the “meta-concepts” needed by students in engineering *and* the liberal arts. He says that starts with making an honest assessment of the number of tool sets a human being can master. Realistically, humans can master two or three. “But there are basic fundamental concepts across the tool sets,” he adds. Whether you are playing the violin or designing a building, there are “high-level concepts,” such as the ideas of conditional iteration, variation, or repetition that hold as constant. Identifying and focusing on the meta-concepts lays the

groundwork for a “layered approach,” where the first layer delivers the basics and the second layer—and all layers after that—go deeper and allow students to specialize.

Applying this to machine intelligence will allow universities to identify the basic principles that must be part of both an engineering and a liberal arts education, Thanassis Rikakis says. In practice, it means asking questions such as the following: What are the basic principles of machine intelligence? How do various machine intelligence algorithms approach problems?

Gaining clarity on these concepts and questions will allow education to adapt to students and provide them with the skills they need to co-create with machine intelligence now and 30 years from now. “We need to keep in mind that there are meta-concepts that really cut across many areas, and they provide very opportune spaces for different types of knowledge to fuse,” Thanassis Rikakis says. In this scenario, it is the purpose of education to equip every single one of us with a “common vocabulary” that will allow us to co-create with machine intelligence. “After that comes specialization, and people can deliberately follow the career path they choose,” concludes Thanassis Rikakis.

But there is also concern among the delegates that liberal learning has too often become fractured into fragmented distribution requirements: a group of disconnected buckets of courses from which students make arbitrary choices. The group feels that, if designed intentionally, the liberal arts could serve, in part, as an important integrator of critical thinking competencies (several described below) that are fundamental for graduates moving into a world where machines and humans regularly form creative partnerships.

Problem framing

Working with machine intelligence requires students to be more adept at framing problems, not just solving them. “Problem definition and problem formulation are not going away,” says Thanassis Rikakis. “In fact, education will probably need to focus more on [this] than ever before.” Sharon Wood, for example, is exploring ways to introduce multidisciplinary design activities into the curriculum, in some cases teaming engineers with students from the fine arts. These efforts underline the importance of problem framing. “It’s about reassessing the framework because students have got to learn to communicate and collaborate with others who don’t use the same terminology,” says Sharon Wood. She is not sure whether teaching problem framing can be achieved at scale, but she is excited to try.

“I think we are going to get to the point where it’s going to be more and more about how we pose the problem rather than worrying about what you have to do to get the answer.”

—Vadim Shapiro

Fortunately, tools have advanced to allow academia to pursue this goal. “Today we can focus on formulating a stress analysis problem and worry a lot less about how the solution is actually computed because the tools have gotten so much better,” Vadim Shapiro explains. As a result, teaching can focus less on how a problem is computed or solved. “That transition is happening,” he continues. “It’s an evolutionary process, and I think we are going to get to the point where it’s going to be more and more about how we pose the problem rather than worrying about what you have to do to get the answer.”

The summit returns many times to the fundamental importance of problem framing as an essential method of inquiry in a world where we will increasingly collaborate with machine intelligence to do our work and live our lives. The group also recognizes that this same inquiry method has broad relevance for helping graduates navigate the 21st-century world of increasing complexity and interdependent problems.

Understood specifically in terms of machine intelligence, problem framing is an essential means of defining the dimensions of a problem and interrogating the assumptions beneath to catalyze the co-creative relationship between humans and machines. It is important to understand that problem framing is not a one-way street. Machine intelligence also participates in the process by interpreting the users’ initial framing—and feeding back results accordingly to help them more deeply and productively understand the nature of the problem they are trying to solve.

Systems thinking

Problem framing can incorporate other essential 21st-century inquiry methods, as the group discusses. First among these is *systems thinking* or the ability to productively manage complexity by understanding the interdependent components of dynamic systems—including stocks and flows, limits, delays—and emergent, longitudinal behavioral patterns. Problem framing relies on systems thinking to manage complexity and understand the dynamic, interdependent nature of problems. To properly teach systems thinking, universities will also need to ensure students can view problems from *all* angles.

“System design and awareness are not impossible for a machine to learn, but understanding how things relate to each other and the real cost to society is related to basic beliefs, ethics, and culture.”

— Fawwaz Habbal

Reinforcing comments from the conversation on liberal learning, Fawwaz Habbal says this is why universities must equip graduates with a firm grasp of deductive, inductive, and abductive reasoning skills, all required to co-create with machine intelligence and work in teams that collaborate with machines. However, the mastery of systems thinking, which he believes is the basis of problem framing, rests on understanding two types of knowledge. These are the building blocks of the discipline (math, physics, chemistry, etc.) and the broad understanding of culture,

ethics, and areas of the liberal arts “that cannot be grasped through computation.”

It’s about delivering the undergraduate “something that is very rooted,” he explains. At one level, this encompasses the basics and the principles so that a newton is understood by both engineers and designers. At the other end of the spectrum, it’s the values and ethics that allow students to evaluate and judge the solutions and answers that the machines suggest. “System design and awareness are not impossible for a machine to learn, but understanding how things relate to each other and the real cost to society is related to basic beliefs, ethics and culture,” Fawwaz Habbal explains.

What is computable?

During a discussion about problem framing as the first co-creative handshake between humans and machines, one delegate makes the following simple statement: “Humans need to know what is computable.” The summit returns to this framing several times to discuss, for example, the idea that just as humans need to know what is computable, so too do computational systems need to be designed in such a way that they understand what, for humans, is “reasonable.”

Understanding “what is computable” raises the issue of meta-disciplines that seek to incorporate aspects of problem framing and systems thinking in a computational framework. One such inquiry method is *computational thinking*, which requires the ability to understand complex systems and their dynamics, decompose them into interdependent pieces, abstract away complexity by focusing on the most important components of the system, and use algorithmic thinking to create precise instructions to address those components.

Computability is where machine intelligence can be of genuine assistance to us, Vadim Shapiro says. The ideal scenario is one in which the AI makes valuable suggestions during the process of co-creation, “and I am driving the computer, and sometimes the computer is driving me. But all these scenarios rely on the assumption that machines are able to compute because we have made it computable,” he says. Many engineering concepts are currently physical, geometric, and difficult to compute, which is why machine intelligence and what we co-create with it is limited by what is computable.

But this is rapidly changing, and so will our view of what is computable. According to Vadim Shapiro, there is the glass-is-half-empty view that says most of the computations that are currently used in machine intelligence are trivial because we have difficulties with making complex computations and systems computable. However, if you want to take the

“Humans need to know what is computable.”

— Vadim Shapiro

glass-is-half-full view, you would say machine intelligence is not about those computations—which are currently difficult to perform—it’s about anticipating what will someday soon be computable.

“Tools are getting better and better, and it is conceivable that something that is very difficult to compute today is going to be very easy to compute in just a few years,” he explains. “Once these tasks are easy to compute, and hence computable, artificial intelligence can really make a huge difference. It will provide a massive way to search and explore huge spaces and collect statistical data and organize them in a new way because all of this data and sample points and computations will be there for AI to utilize. When that day arrives, “you will have extremely powerful artificial intelligence tools that can compete with people and probably do better.”

There’s what is computable, but what is *acceptable*?

As more of the world becomes computable or learnable for machines, machine intelligence will become more mainstream; however, some delegates question whether there are boundaries to what we should seek to make computable in the first place. “There are very few parts of the human experience that AI will not touch,” says Thanassis Rikakis; however, some parts are not supposed to be computable—and it should stay that way. An example is the uniqueness of interpersonal human experience. “The richness of that experience is fully embodied in that moment,” continues Thanassis Rikakis. “It’s a space that doesn’t need to be enhanced by machines. In fact, in these deep experiential spaces, enhancement actually gets in the way.” Against this backdrop, the question moves from “What is computable?” to “Where is enhancement through AI needed?”

“The richness of that [interpersonal human] experience is fully embodied in that moment. It’s a space that doesn’t need to be enhanced by machines.”

— Thanassis Rikakis

There are instances when AI enhances the human experience with collective wisdom, and this is richness we should embrace, Thanassis Rikakis says. In these scenarios, the individual enters into an interaction with a large social body of knowledge and benefits from those insights. “It can enrich the human experience—whether you are learning calculus or trying to build a better bridge—if you have social knowledge accessible at your fingertips,” he explains. In the background, the machine looks at other people who had similar problems and draws from their experience to help the user navigate similar concepts and arrive at a solution.

Indeed, there is a tremendous opportunity for machine intelligence to enhance the human experience—and education—at scale. However, humans are responsible for making the final decisions. For this reason, Fawwaz Habbal suggests our focus should not be on what is computable

because that will expand and evolve to encompass *everything* in time. Instead, we should set boundaries according to “what is acceptable.”

In his view, machines will be able to do a lot. It’s our responsibility to view the answers we are provided through the lens of what is plausible and what is acceptable. “A solution exists but is it acceptable in our cultural norms?” he asks. We need to ask ourselves the following: What does the solution replace? Put another way, it’s not a question of what machines can or cannot do; it’s a question of what we are willing to accept while we uphold the principles of philosophy, ethics, and diverse thought.

“Co-creation is a must.”

— Fawwaz Habbal

It’s why the emphasis on co-creation with machines is of utmost importance. “Co-creation is a must,” Fawwaz Habbal says. The alternative is to leave the machines to do what they will, and leave humans to do what they will—and both are dangerous extremes. To avoid a negative outcome, tools and people must enter co-creative learning relationships, ones governed by “rules and policies that bind us as humanity” and are enhanced by capabilities that allow AI to make genuinely worthwhile contributions.

As AIs evolve with us as learning partners, Fawwaz Habbal says, they will open our eyes to ideas and answers that we might not otherwise have considered. In this scenario, AI becomes “a partner and a mentor that possesses a different wisdom—not a better one, but an extremely powerful one.” It’s a force he compares to diversity. AIs bring different views and perceptions, thus augmenting and enhancing our intelligence in ways we cannot yet imagine.

VII. Being human

It is not possible to fully engage the idea of co-creating with machine intelligence without asking the following question: *What is human?* What are the unique attributes that we bring to the table when we collaborate with machines? The satisfactory answer is far beyond the scope of this piece—and the summit itself. Yet, the importance of addressing it comes up multiple times, during a number of conversations, in the summit.

Being human means embracing our full capabilities as a species. It means building new equations between our soft skills—and the crucial mind-sets they generate—and our hard skills and the measurable expertise they make possible. It requires us to honestly confront our innate weaknesses and particular strengths relative to machine intelligence. Finally, as Randy Swearer says at the end of the summit, “[We should] focus on understanding the unique learning dynamics that define our species—and those singular learning modalities needed by machines. But

the most important question is how machines and humans can optimally *learn together*. This is what we should strive for—and it will define a remarkable new era of co-creation.”

VIII. Afterword

Now what: next week, next month, next year?

Our primary advice? Get started now. The challenges and immense opportunities for co-creating with machine intelligence mean that you need to find talent, launch pilot projects, and—most importantly—*learn*.

1. Share stories from others and generate your own that highlight the opportunities for co-creating with machines. This watershed moment demands that organizations invest in storytelling to bridge the current way things are done and the new emergent paths ahead. This is the era to look for stories from other fields or organizations that can help you reframe the ways you think and work. Avoid the knee-jerk dismissal of stories as irrelevant because “they don’t understand what our business or discipline is like.” As you pilot co-creative projects with machine intelligence, share the failures as well as the successes to create new origin stories for your organization. Remember: you could be making history!

2. If you’re a business, establish a machine learning intern program for humans, but raise a few algorithmic machine learners along the way. Pick some small subset of a problem that is data rich and challenge the interns to build a machine learner, an M-intern, to explore the problem space. Give them the mission of finding an “aha” moment in the data—something that will capture the imagination of company executives.

Einstein once noted, “If I had an hour to solve a problem I’d spend 55 minutes thinking about the problem and 5 minutes thinking about solutions.” To frame compelling problems, ask the interns to think in terms of goals and constraints: defining the boundaries of the problem space and determining what kinds of data could help them explore its dimensions.

3. Let your interns play with your data to drive discovery and insights. Given the pace of discovery in the field in most cases, you won’t be able to find seasoned engineering, business, or design professionals with more than a decade of experience co-creating with machine intelligence. What you *can do*, however, is hire interns from the burgeoning machine learning academic programs—and offer them opportunities to work with your company’s data. *Remember that, for machine learning students and professionals, the quality, quantity, and nature of your data is a primary attractor.*

4. Practice building and mining possibility spaces and invest in pilots that cut across two or more interlocking challenges. Generative design is a powerful way of learning about co-creating with machine intelligence.

Find a set of pilot projects that encourage problem framing in the generative design paradigm to build “muscle memory” for defining the dimensions and variability of problems. Team members should focus not on solving problems but on framing the system constraints, variables, goals, and intersection points. This will help them articulate what they believe is “computable.” Such an effort or series of efforts will sensitize your team to the language gap between human and machine learners—as well as provoke discussion across disciplines.

5. Systems thinking is crucial for co-creating with machine intelligence, but we don’t teach it consistently or with enough breadth and depth beyond perhaps narrow paradigms of systems engineering. Unless we do, it is very challenging for those co-creating with machine intelligence to collaborate across goals and constraints or determine what problem dimensions are sensitive to initial conditions or become non-deterministic across their range.

6. Machine learning is making human learning more urgent and important than ever. Put together policies and invest in systems that encourage co-creation and co-learning. If you build tools, products, or spaces that have machine intelligence embedded in them, look for ways to build virtuous reciprocity between your customers, your employees, and the things you produce. *Consider reframing your customers as learners* who can both unlearn what they’ve known—and learn entirely new ways of thinking more suited for a world saturated with machine intelligence. *Whenever possible, build in learning reciprocity between machines and humans and invent new dance moves with machines.*

7. Beware of biases and find ways to build trust between human and machine teammates. Our increasing understanding of bias in machine learning has made it crucial to be more aware of human biases and blind spots. The difference in this emerging age is that software can encode and amplify biases at a scale that has never been seen before. Consider putting together a policy group and joining with other organizations to work to identify algorithmic and data biases. Intentionally build richer and more balanced data sets and systems. Insist on maximum transparency for results generated by machine intelligence—or decisions made by human-machine teams.

8. Adapt and expand education through AI-powered learning customization. Problem framing relies on systems thinking to manage complexity and understand the dynamic, interdependent nature of problems. Ideate and introduce courses (supplemental, interdisciplinary, experiential) to define and teach this core competence and overcome the typical university bias against incorporating “soft skills.” If possible, partner with industry for summer workshops or seminars to provide

students understanding of systems thinking “on the job.” Identify pilots and efforts where you can harness AI systems to work toward the goal of customizing education for your students. Use these insights to help faculty teach students what they need to know, when they need to know it, and—most importantly—how students optimally learn.

Support industry and academia through good stewardship. Respond to the need for “tools that teach users” and ideate methods that will support a two-way Socratic dialog. Rethink interfaces and interactions to go beyond code and programming to help designers (in collaboration with AI) to be more expressive and effective. Lift the lid on how tools are helping to document or capture important aspects of design such as ambiguous intent. Curate a broad range of stories, equipping all stakeholders to show what is possible and what has already been achieved in co-creation with AI. Support education in teaching tools and articulating what students must know to teach their tools. In the words of one delegate, “I think this is a really important unresolved issue with a great opportunity for a company like Autodesk to take a lead. If you are serious about education, you should not just think about supporting education; you should take the lead in the curriculum.”