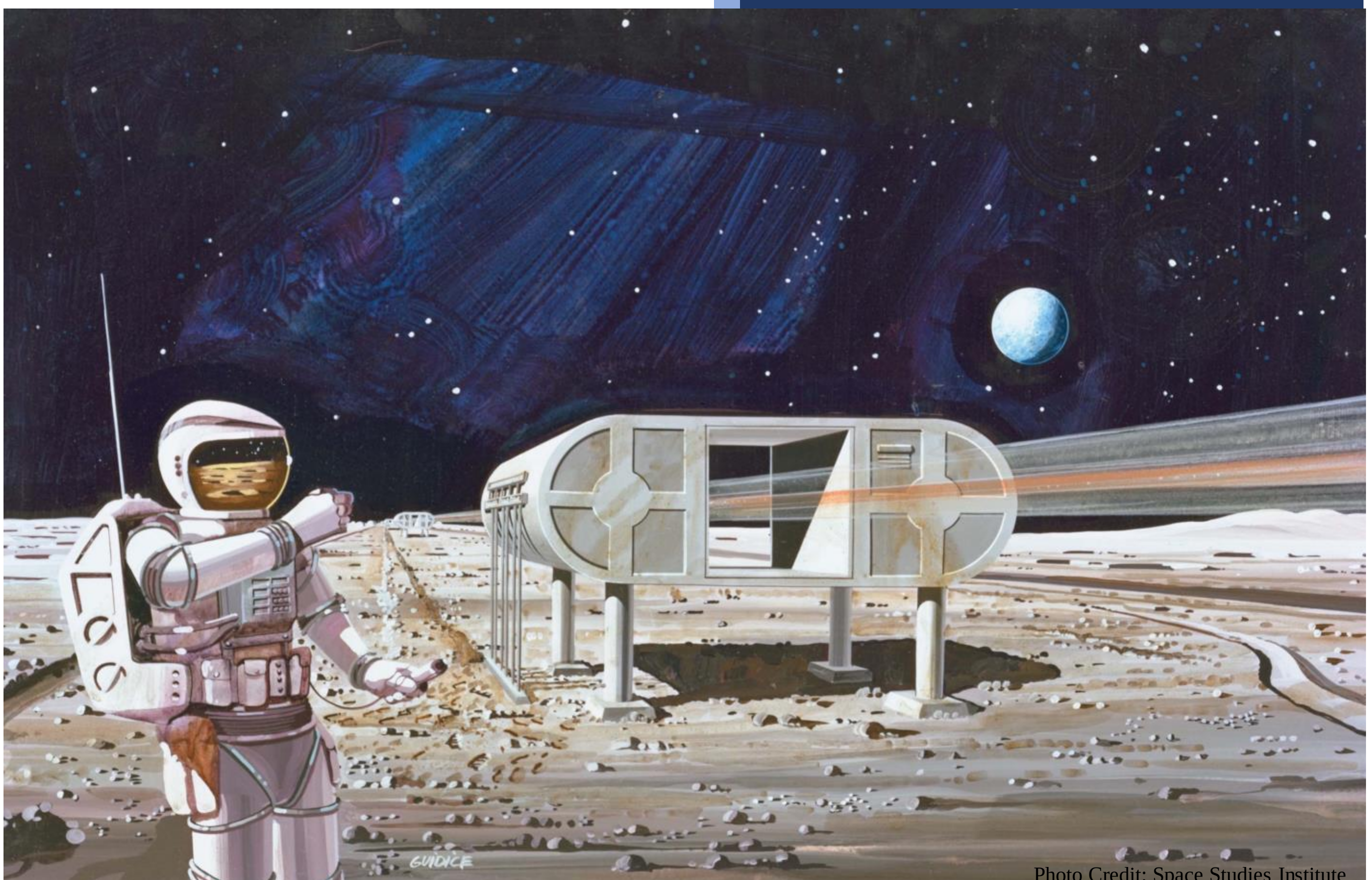
2020

# QI-Space: AI Revolution in Space



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**Dynamic Dimension Technologies**

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## Significance and Unmet Needs

Artificial intelligence plays an important role and has great potential in the modern development of effective systems for autonomously operated spacecrafts and surface rovers. One of the significant challenges while operating in space is that large amounts of relevant data may not be readily available for algorithms to train models to enhance autonomy. Due to potentially high consumption of computing resources, artificial intelligence models will have to be trained on Earth using distributed computing resources with analogous source data and transformed to the various physical conditions and environments of the targeted extraterrestrial location.

Another feasible challenge in human space flight is disaster management and handling risks related to unknown conditions and events in space. Very little data may be available to identify and predict potential threats and disasters. Standard machine learning approach may not produce accurate results when large volume of relevant data is not readily available on-board of a spacecraft.

Consider following scenario, an autonomously operated rover moves on the surface with no atmosphere with initial speed of one foot per second. What would be the effect of natural forces, including atmosphere and gravity on operation of the rover? The solution may be found in instantiating and solving the relevant equations and applying **transfer learning** based upon physical insights.

## Innovation

DDT's innovative QI-Space AI system **Physics-Based Transfer Learning** combines our state-of-the-art physics-based modeling with Physics-Informed Deep Learning technologies functioning within the entire domain as well as specific and individual subdomains of the system, Figure 1.

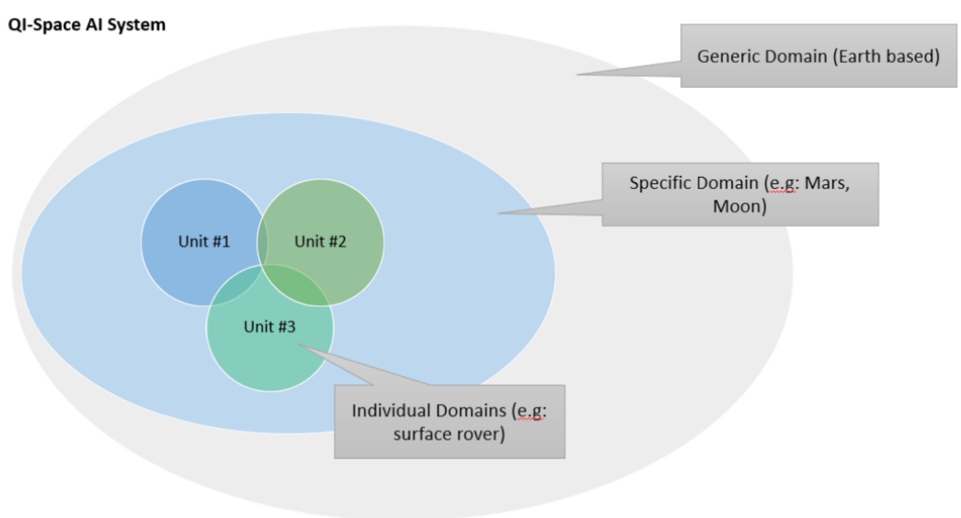


***Figure 1. Quantum Intelligence (QI-Space AI System) diagram***

QI-Space AI System is powered by individual case-based transfer learning AI models that transfer continuously obtained knowledge from individual units (e.g. surface rovers, autonomous exploration equipment) back to the specific domain system (e.g. Mars station) that feeds the generic model developed on Earth. On the other hand, the continuously updated generic domain model will transfer knowledge obtained from other specific and individual domains. QI-Space AI System aims to transfer knowledge obtained by various domains and subdomains of the system as well as solve lack of computing capabilities by individual units.

DDT's solution leverages the governing partial differential equations (PDE) for the physics-based models to produce an informed deep learning neural network with realistic and relevant data. DDT's **V**irtual e**x**perimental **Sim**ulation environment (**VxSIM**) is capable to accurately represent the multi-domain environmental states which influences amphibious vehicle motions and developed to address Navy's needs for autonomous system development and verification, Figure 2.VxSIM utilizes various sensor models (i.e. EO, IR, RF, Lidar, MMWR, etc.), and permits easy integration with new sensor models. The simulation environment provides a rich source of data for training the AI and autonomous systems. Our innovative framework is fully parameterized such that gravity, material properties, atmospherics, environment, terrain, ephemeris, etc., can be configured to represent any intended deployable environment.

***Figure 2: DDT's Virtual experimental Simulation (VxSIM), a physics-based modeling, simulation and analysis environment designed for advancing, training and testing AI and Autonomy systems. Supports sensor modeling, deformalble terrain soil/regolith, parameter driven, multi-physics and ROS interface.***

To realize the benefits of *QI-Space AI System*, DDT would collaborate with our NASA partners to define a use case such as an autonomously operated rover operating on Mars. Then based on NASA supplied data, we would:

1. Build the physics models for the systems and the intended environment.
2. Develop a methodology for PDE transition and representation in the Physics-Informed Deep Learning framework.
3. Conduct a study with NASA provided data driving the simulation, to demonstrate the prototype QI-Space AI System and feasibility of successfully transferring the model across domains and environments.

## Approach

As we know humans frequently learn by leveraging different experiences and knowledge gained in the past to improve upon new, novel tasks. Transfer learning is similar in nature as it allows to apply knowledge learned from one source to solve novel problems in another source. Methods for transfer learning hold the promise of being exceedingly useful, because it could dramatically decrease the amount of training required by successfully employing knowledge obtained from different, but related, problems. A transfer learning evaluation compares performance measures such as learning rate, initial advantage and asymptotic advantage. Initial advantage (or jump start) is the initial increase in an agent's performance resulting from transfer. Learning rate is a decrease in the time required to reach a particular performance level, particularly asymptotic performance. (Klenk, M., Aha, D. W., & Molineaux, M., 2011). Due to its ability to extract insights from existing experimental and simulation data, transfer learning is a promising tool for scientists who face unknown factors and other challenges.

Case-based reasoning (CBR) is a problem-solving process in which inferences about a situation are drawn from individual cases. While the roots of CBR lie in observations of human reasoning (Schank 1982; Kolodner 1993), this discipline is now aligned closely with computer science. This can be applied to a transfer learning methodology when previously learned knowledge from individual cases transfers to new scenarios. For example, the learned and transferred knowledge could be the case base after training on source problems. During learning on target problems, the same CBR cycle can be used to solve problems in the target, updating the same case base. Thus, the CBR system is unaware that it is being evaluated for transfer learning and makes no distinction between source and target cases. For these systems, transfer distance and initial advantage provide a useful metric for evaluating the retrieval and reuse mechanisms of the CBR system. (Klenk, M., Aha, D. W., & Molineaux, M., 2011).

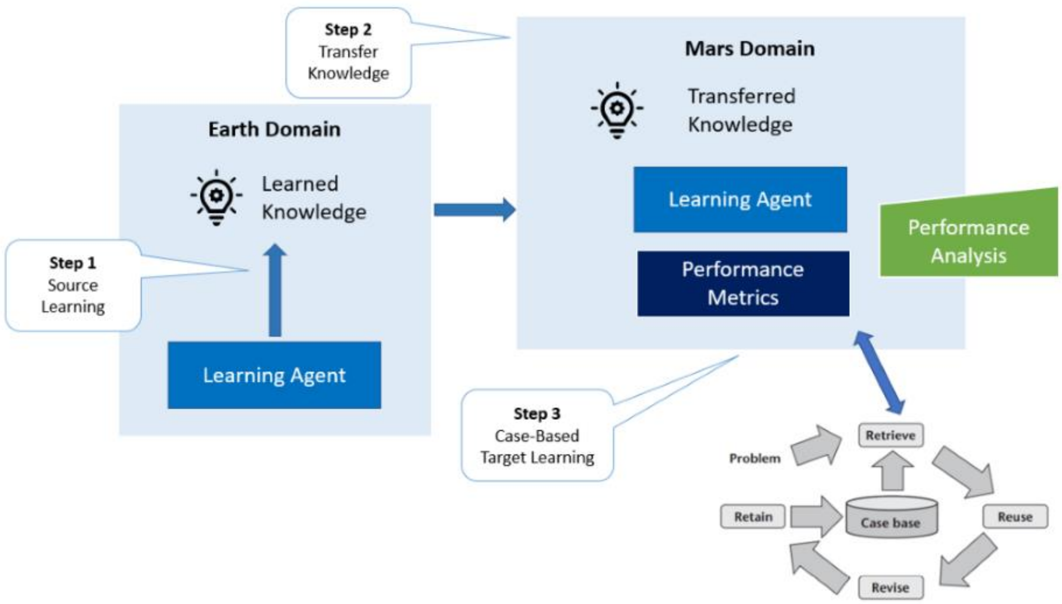


***Figure 3. Case-based Transfer Learning diagram***

Physics based problem solving requires reasoning over a wide range of entities and scenarios. Traditional Machine learning, case-based reasoning and AI approaches may not work well on limited data with generic descriptors, but it may produce better results by using insights from physical equations. This is a novel approach for solving the problem by transferring physical insights into more generic descriptors, such as invariant risk minimization where we learn causal factors from data. The causal factors have the properties that stay invariant even when the environment changes and they transfer well. In this approach, we learn invariances across environments by finding a data representation such that the model on top of that representation performs equally well for all environments, in this case in the target environment. ***Unlike traditional applications, this approach allows to screen conditions which have not necessarily been tested before with minimum amounts of available data combined with high details of physical understanding.***

## Commercialization

DDT's commercialization team has developed a lean transition process that works quickly and more affordably for our clients. We focus on nine key business drivers to ensure success and use a Build-Measure-Learn loop that minimizes funding needed to get a prototype to the next gate.

The nine key business drivers are: Customer Segments, Value Propositions, Channels, Revenue Streams, Key Activities, Key Resources, Key Partnerships, Customer Relationships and Cost Structures. It is a phased process where each step must be completed and gated to move on to the next step. The phased technology transition process includes: 1) a review and prioritization of the pipeline of opportunities; 2) a developed project description, documentation, and a communication plan to ensure all interested parties know their responsibilities; 3) initial documentation of the intellectual property (both government owned and Team DDT owned), initial business model development plan, staffing plan, development of initial hypotheses; 4) review/approve hypotheses and plans; 5) iteratively validating hypotheses through lean startup principles; 6) document validated business model, value proposition, projections, recommended path forward, and business proposal; 7) establish and review business proposal; 8) develop business plan to scale product, obtain financing, execute plan.

We start with a minimum viable product (MVP), providing users/clients with real but imperfect utility early in the product evolution to stimulate feedback. Cycling through changes, where coherent bundles of features advance the product toward the ideal, our process advanced to converge with the customer's needs. Throughout, the focus is on interaction with current and potential customers, to gain first hand insight into their needs, operating context, and business to prove or challenge our assumptions and hypotheses about our product and refine to meet reality in the marketplace.

We anticipate our initial customers to include NASA's Artemis Program, Gateway and mission to Mars, along with commercial offshore oil and gas industry, deep ocean and artic exploration, and the DoD. All of these organizations have applications for AI's deployed to environments that can best be replicated with digital simulation. Therefore, our innovative physics-based transfer learning technology not only would significantly reduce the risks associated with the AI employment but also provide opportunities to deploy AI in environments that was never possible before or very costly.

*Market Size:* Since the market for physics-based transfer learning is nascent, we extrapolate from the deep learning market. According to Markets and Markets research, deep learning was worth USD 2.28 Billion in 2017 and is expected to reach USD 18.16 Billion by 2023, at a CAGR of 41.7% from 2018 to 2023. We conservatively estimate capturing approximately 0.058% market share of the year 2023 market size, which brings our pro forma revenue forecast for product and services to approximately $10.5M in 2030.

*Go-to-Market Strategy*. DDT implements a multi-pronged approach which includes direct marketing and displays at selected technology conferences and organizational memberships. We intend to work with NASA to determine SBIR path for prototype funding and technology demonstrations. Then leverage our extensive connections within DoD, industry partners, affiliates, and the Maryland Tech Council ecosystem to discover opportunities for new applications.

## Team DDT

### *Mr. Karl Leodler, Founder and CEO of DDT*

A seasoned professional with over 30 years of experience developing physics-based software simulations and over 14 years applying simulation technologies to advance, train and test AI and autonomy systems. As Principal Investigator on over 14 SBIR/STTR awards, Mr. Leodler demonstrates a passion for research and a refined skill for transforming R&D to commercial applications. Prior to founding DDT in 2015, Mr. Leodler served as President of JRM Technologies for 2 years and Modeling and Simulation Department Manager for General Dynamics Robotic Systems for 6 years.

***Dr. Pooyan Jamshidi, University of South Carolina***

Dr. Jamshidi is an Assistant Professor at the University of South Carolina and Director of the AISys Lab, where he investigates the development of novel algorithmic and theoretically principled methods for machine learning systems. Prior to his current position, he was a research associate at Carnegie Mellon University and Imperial College London, where he primarily worked on transfer learning for performance understanding of highly-configurable systems including robotics and big data systems. Dr. Jamshidi's general research interests are at the intersection of systems/software and machine learning. He received his Ph.D. in Computer Science at Dublin City University in 2014, and M.S. and B.S. degrees in Computer Science and Math from the Amirkabir University of Technology in 2003 and 2006 respectively. Current research projects include "A Generic Data-Driven Framework via Physics-Informed DeepLearning" and "Robust Software Testing of Autonomous Aerospace Robotic Systems Using Transfer Learning" with NASA, and "Online Transfer Learning and Self-Adaptation of Robots" with DARPA.

***Dr. Saman Nezami, Sr. Research Scientist, DDT***

Dr. Nezami has over 14 years of engineering model development and analysis experience. His technical skills include physics-based structural, multibody dynamics and vibration analysis, design optimization and energy harvesting. Prior to joining DDT, as a PhD candidate, he worked for the UMBC ME Department as a Graduate Research Assistant where he conducted research on energy harvesting for conditional sensors from vibration available in their surrounding environment, investigated durability of the vibrational energy harvesters' structure under dynamic and random impulses to improve their structure and extend operational life, conducted geometrical optimization of structural elements of vibrational energy harvesters using Shape Optimization and Topology Optimization techniques and lead the experimental test team in multiple researches topics. Dr. Nezami earned his PhD in Mechanical Engineering, from UMBC.

***Ms. Olga Perera, Sr. Data Scientist, DDT***

Ms. Olga Perera is a Senior Data Scientist with background in natural language processing, data engineering, and cloud computing. Ms. Perera is currently pursuing her PhD in Information Systems from Dakota State University. She completed her MS in Applied Data Science from Syracuse University and received the iSchool Applied Data Science Award that recognizes one student in each graduate program who exemplifies excellence in graduate study, through class projects, research, and other forms of scholarship. Ms. Perera has worked on NASA data integration project. Presented at AIAA (American Institute of Aeronautics and Astronautics) 2019 Technical Symposium on Natural Language Processing Techniques and its Application in Space Exploration. She has working knowledge of AWS platform and serverless architecture, Data Lake architecture, AWS managed services, Search applications.

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