

SE4AI: Design of Digital Twins Architectures that Support AI and Machine Learning Formalisms working Side-by-Side as a Team

Sponsor: OUSD(R&E) | CCDC

By

UMD Team: Dr. Mark Austin and Maria Coelho

Stevens Team: Dr. Mark Blackburn (Presenter)

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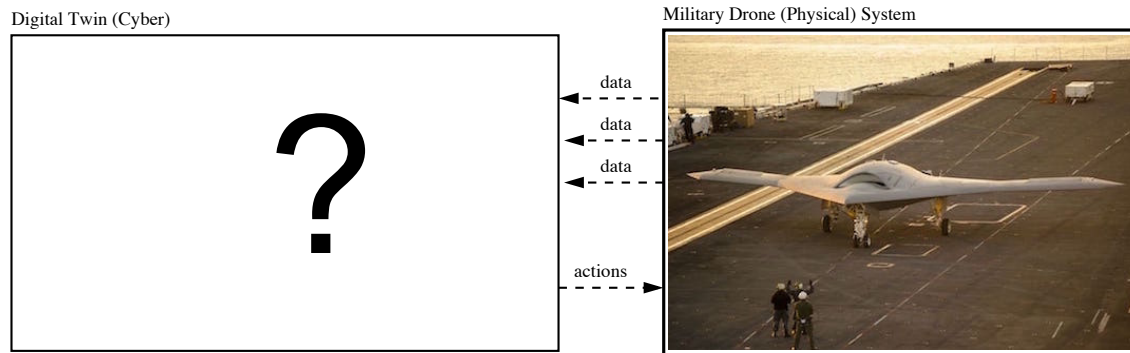
AI4SE/SE4AI Workshop

www.sercuarc.org

Cleared for Public Release

Definition (2000 – today)

- **Virtual representation** of a physical object or **system** that **operates across the system lifecycle** (not just front end).



Required Functionality

- **Mirror** implementation of **physical world** through **real-time-monitoring** and **synchronization of data** with **events**.
- Provide **algorithms and software** for **observation, reasoning** and **physical systems control**.

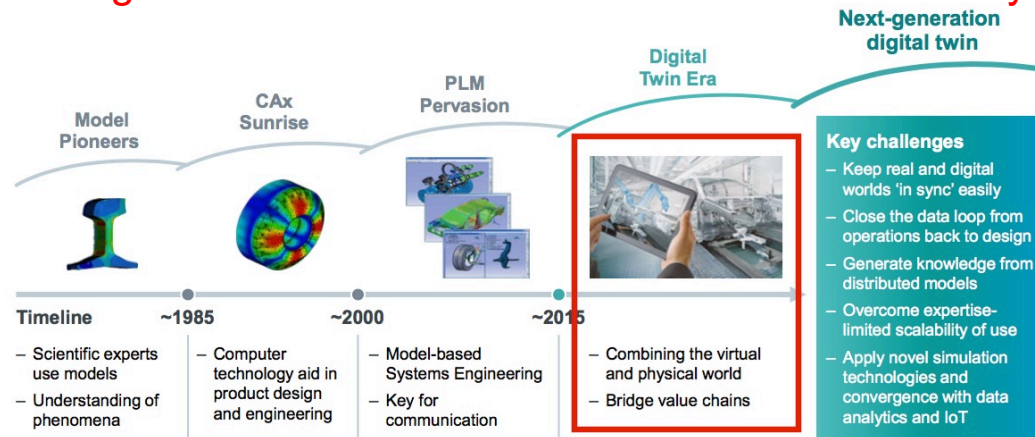
Many Application Domains

- NASA, manufacturing processes, building operations, personalized medicine, smart cities, among others.

Project Importance and Timeliness (Why?)

Business Drivers (Why this project is timely?)

Siemens, IBM, now see **Digital Twin Era** as the successor to **MBSE with SysML**



Digital Twin Era (Business Spin)

- New **methods and tools** for model-centric engineering.
- New **operating system environments** for observation, reasoning and physical systems control.
- Superior levels of system **performance**, agility, economy, etc.

Technical Implementation (2020, Google, Apple, Amazon, Siemens, IBM ...)

- **AI and ML** will be **deeply embedded** in new **software and algorithms**.

Definition of AI and ML

- **AI: Knowledge representation and reasoning** with ontologies and rules. Construction of semantic graphs, **executable event-based processing**, multi-domain reasoning.
- **ML: Modern neural networks (closely related to signal processing of data streams)**. Data Mining. Input-to-output prediction, Learn structure and sequence. Identify **objects, events, anomalies**. Remember stuff.

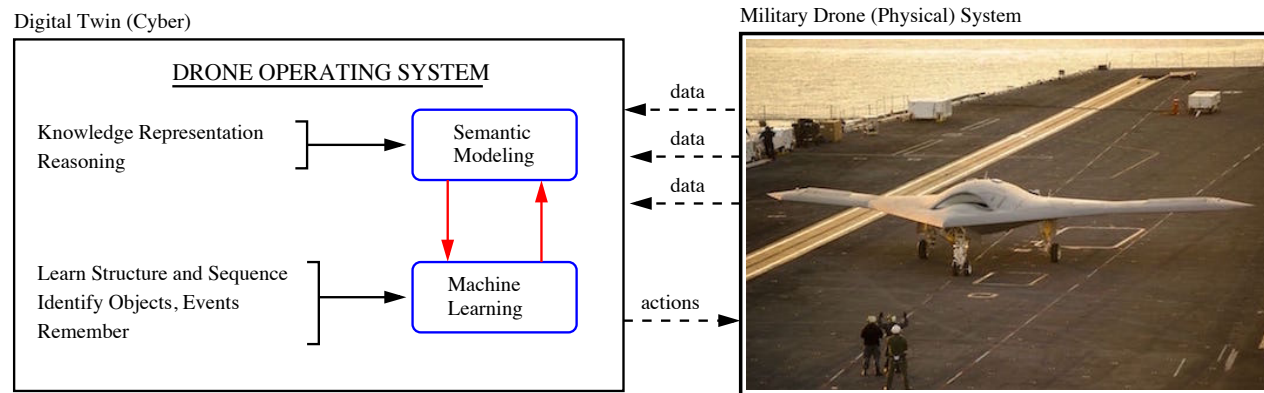
AI/ML Strengths and Weaknesses

State-of-the-art AI and ML technologies are **fragmented** in their capability:

- AI provides a **broad view of concepts** needed for reasoning. Decision making processes are **transparent**; semantic graphs are **flexible**.
- Semantic reasoning is **decision making in-the-moment** (no memory).
- Data mining algorithms can **organize information** from large data sources.
- ML procedures developed to solve very specific tasks.
- ML decision making procedures lack **transparency**.
- ML procedures can **identify anomalies** (events) in **streams of data**.

Digital Twins (What's New?)

- Explore design of **digital twin architectures** that support **AI** and **ML** formalisms **working side-by-side** as a **team**.



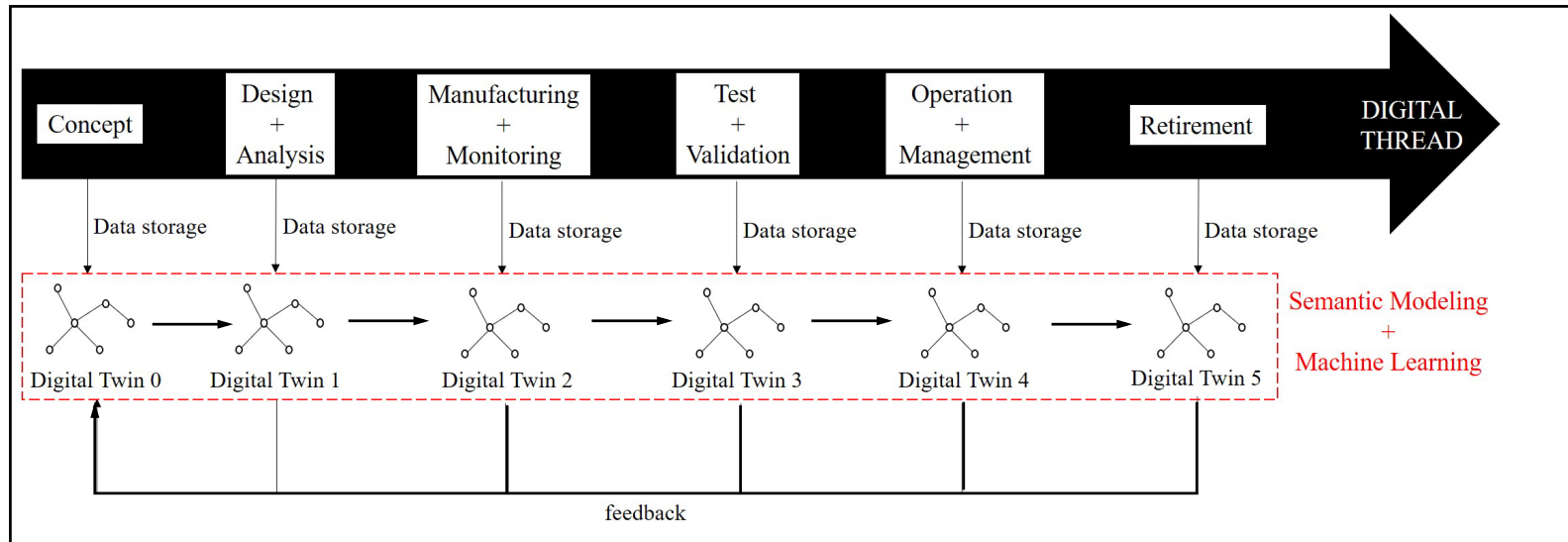
Key Research Challenge

- How to design **digital twin elements** and their **interactions** to support: (1) **methods** and **tools** for **model-centric engineering**, and (2) digital twin **operating system environments** for observation, reasoning, control.

Project Success (What does it look like?)

- Knowledge to **guide architectural development** of **future digital twins** enabled by **AI / ML technology**.

Cradle-to-Grave Lifecycle Support (Digital Threads)



Observation: A lot of model-centric engineering boils down to **representation of systems as graphs** and **sequences of graph transformations** punctuated by **decision making** and **work / actions**.

Reasonable Starting Point: Understand the **range of possibilities** for which **machine learning of graphs** and their attributes **support** and **enhance** activities in **model-centric engineering** and **systems operation**.

Example: Cross Domain Relationships Needed for System Trades, Analysis and Design

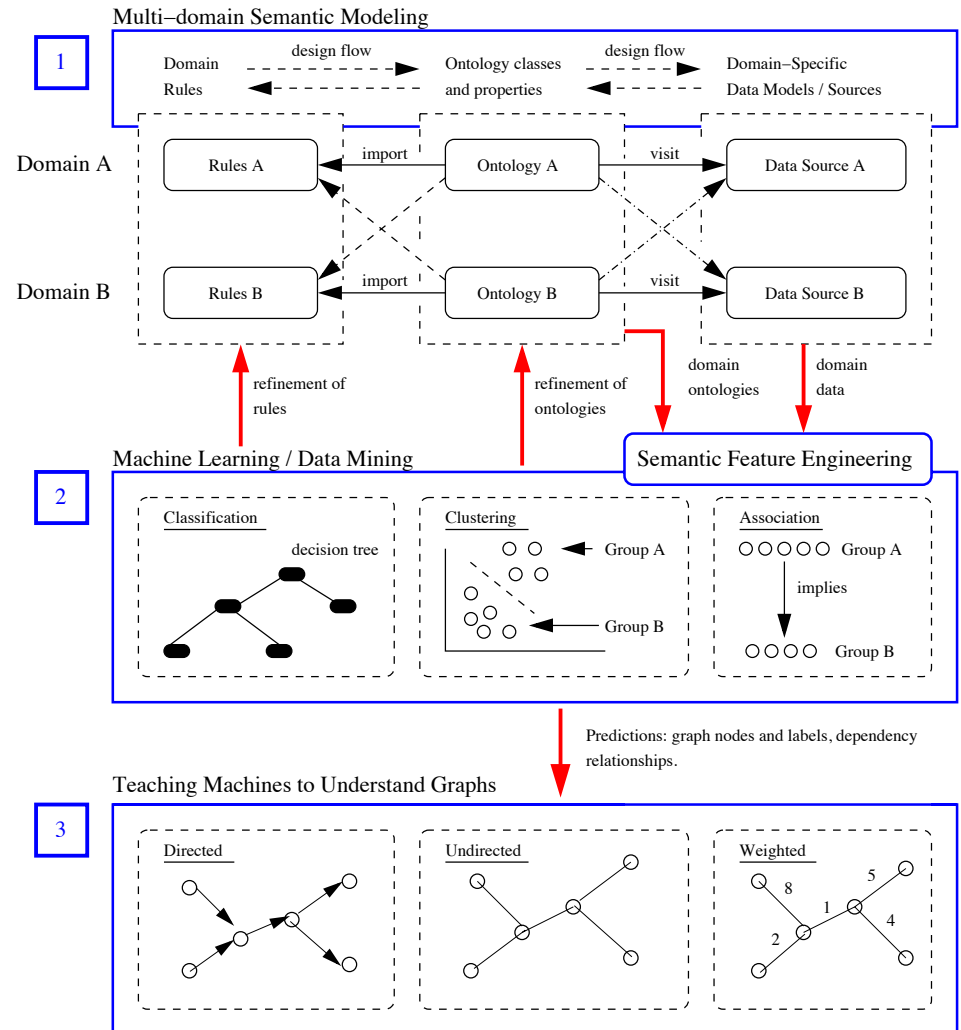
- Mission objective: continuous surveillance
- Capability Refueling UAV
- Systems: UAV and Refueler
- **Valve** – Cross-domain Object
- Mechanical Domain
 - Valve connects to Pipe
- Electrical Domain
 - Switch opens/closes Value
 - Maybe software
- Operator Domain
 - Pilot remotely sends message to control value
- Communication Domain
 - Message sent through network
- Fire control Domain
 - Independent detection to shut off valve
- Safety Domain



Post Incubator Project (What and How?)

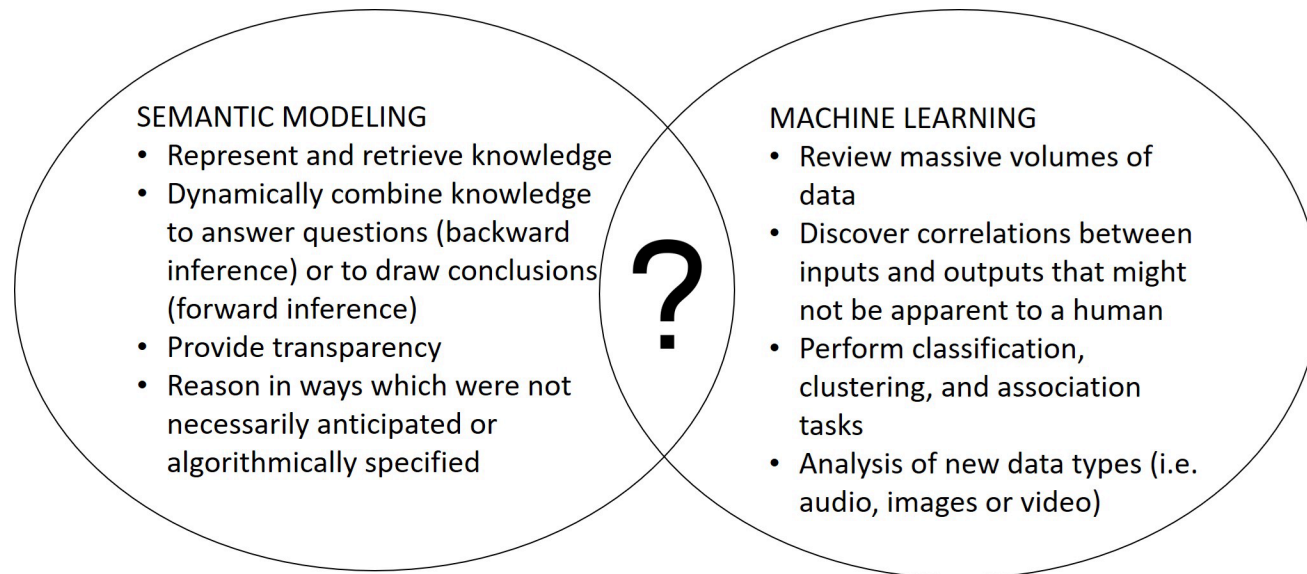
- Business Drivers
- Post Incubator Project
- Real-World Considerations
- **Step 1: Multi-Domain Semantic Modeling**
- **Step 2: Semantic Modeling + Data Mining**
- **Step 3: Teaching Machines to Understand Graphs**
- Opportunities and Extensions
- Plan of Work

So what will the machine learning do?



Initial Research Questions (low hanging fruit)

- What **types of graphs** (e.g., undirected, directed, weighted, multi-graph) are **easy** for the **ML to learn**?
- What can the ML do that is outside the capability of semantic modeling? And vice-versa?



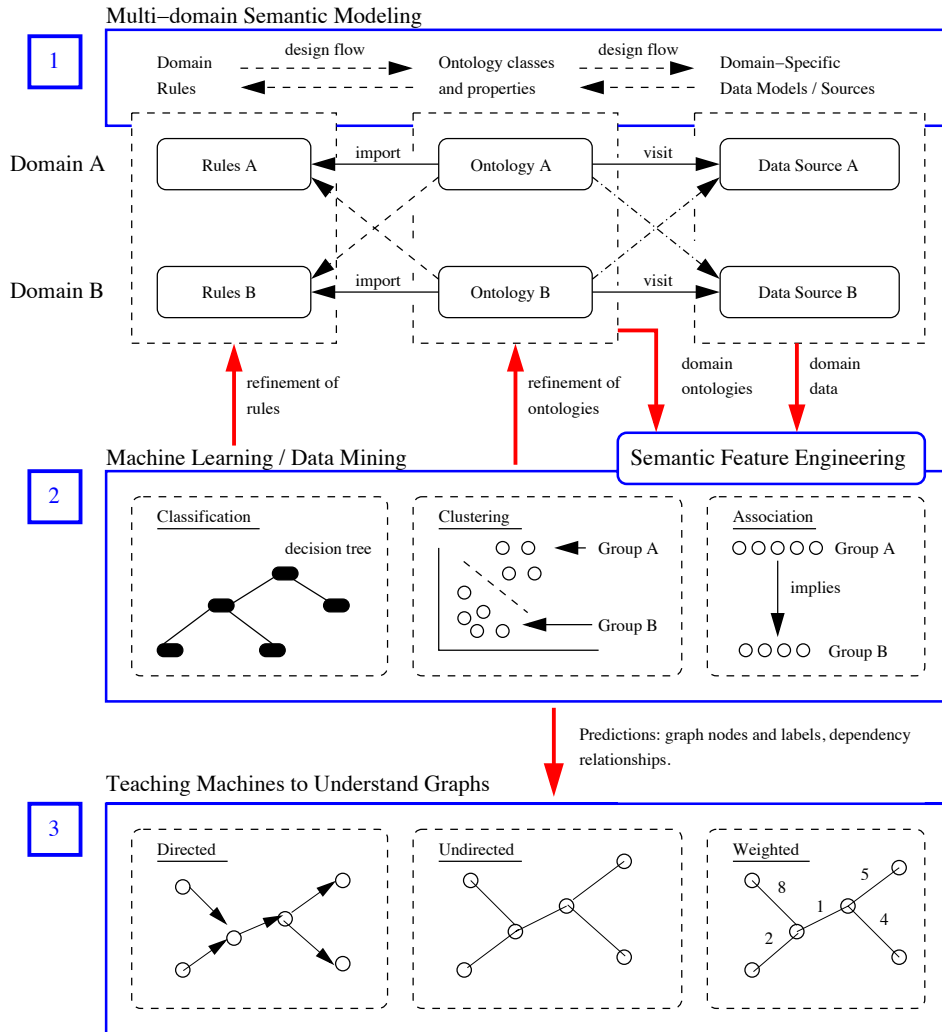
- How can the **ML improve** the **semantic modeling**? And vice-versa?
- How to **design** the **interactions** connecting layers 1, 2 and 3
- How well do these techniques work with **graph topology** and **attributes** that are **dynamic**?

Semantic Modeling + Machines Trained to Understand Graphs

Is this even possible?

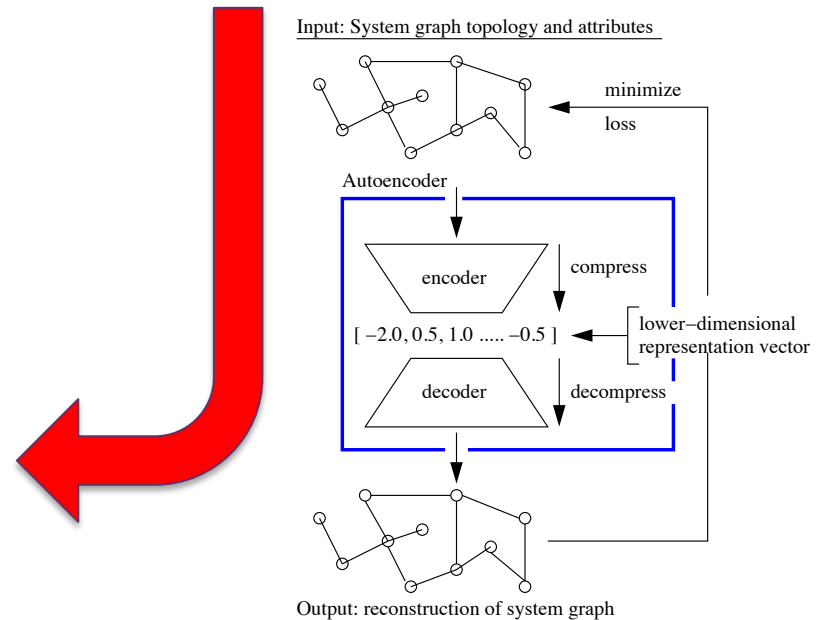
What will the machine learning do?

Focus on Machine Learning of Graphs and Model-Centric Engineering.



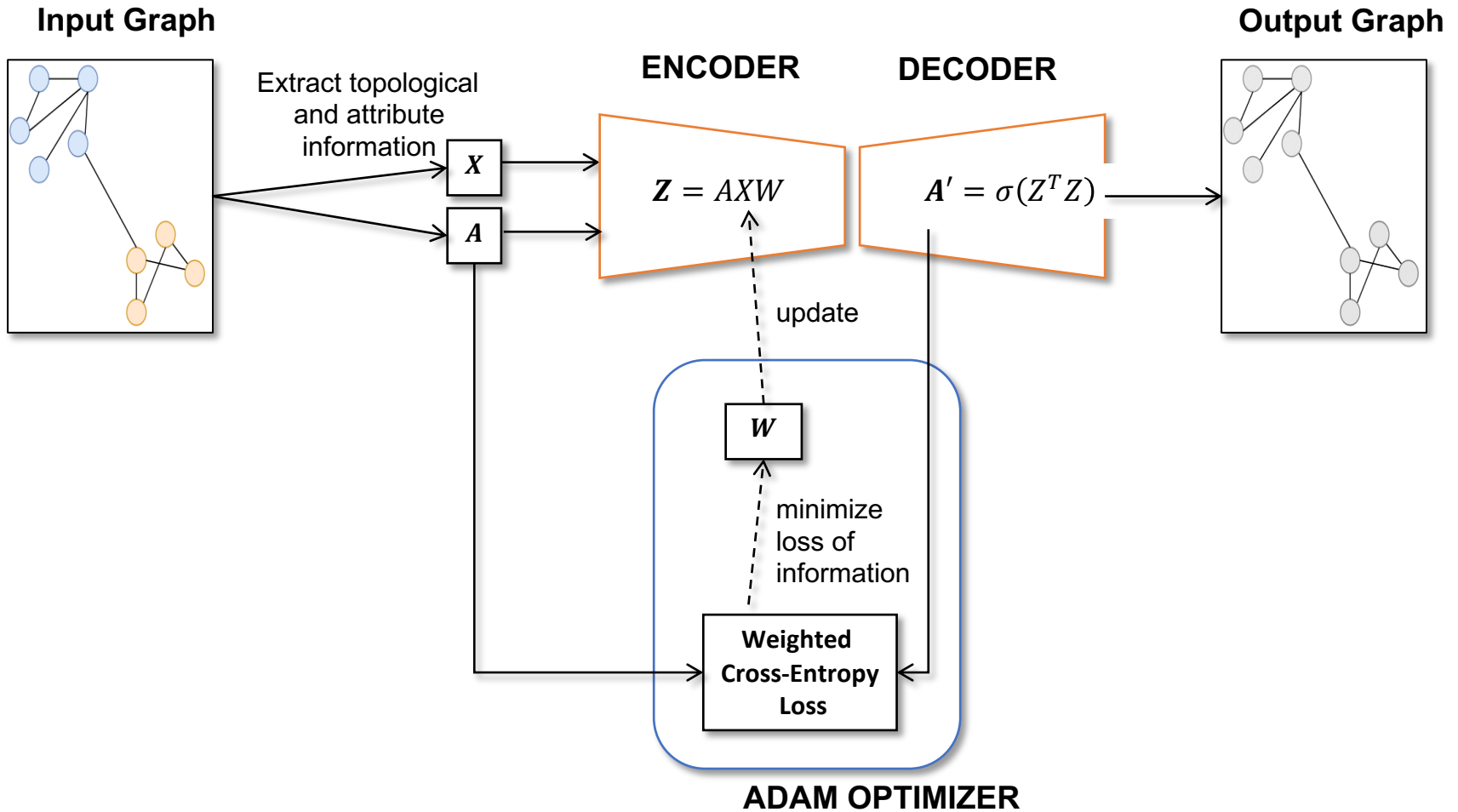
Observation: A lot of model-centric engineering boils down to **representation of systems as graphs and sequences of graph transformations** punctuated by **decision making and work / actions**.

Hence: Explore opportunities for **training machines to understand graphs**.



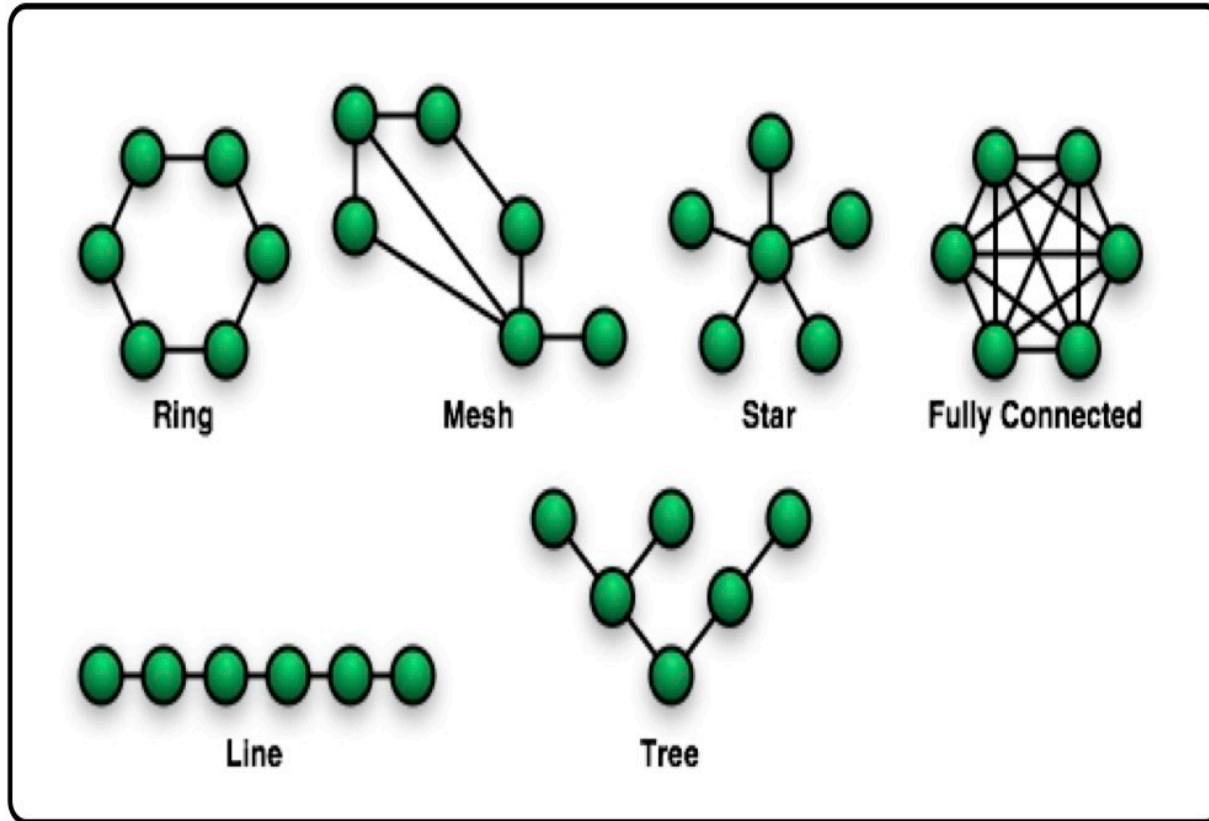
Teaching Machines to Learn the Topology of Graphs

Graph Auto-Encoding Process

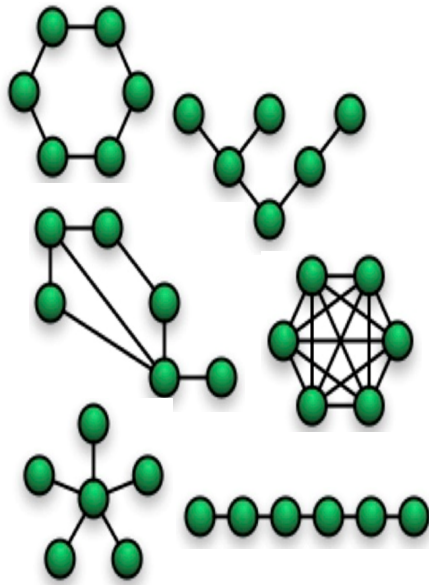


Common Graph Topologies

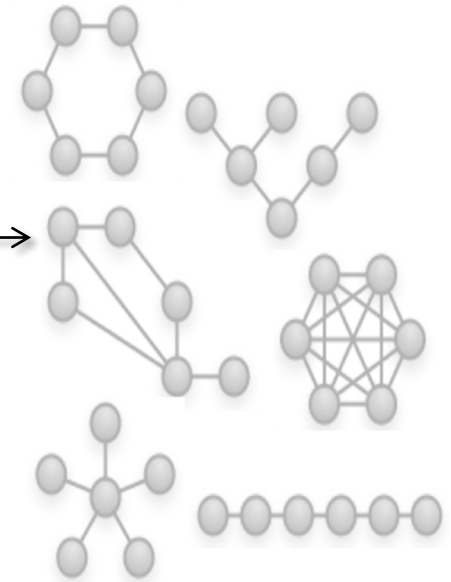
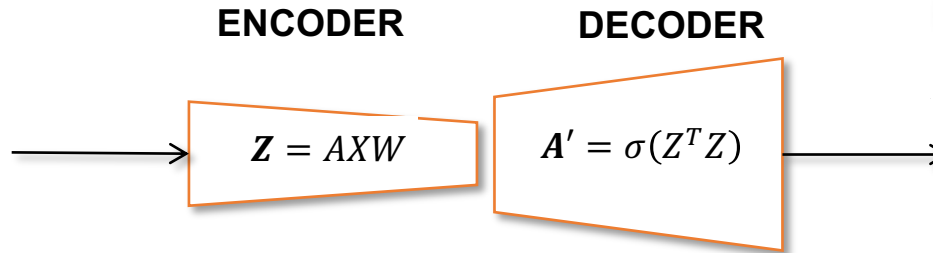
What types of graphs can we auto-encode?



Auto-Encoding Case Studies



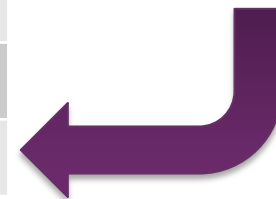
Input Graphs



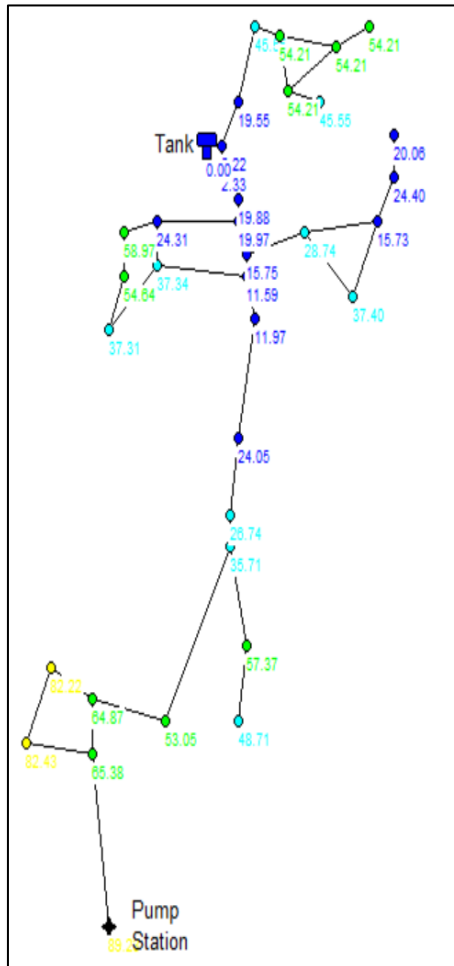
Output Graphs

Graph	No. of Embedding-Layer Neurons Required for Learning
Line	2
Ring	2
Mesh	3
Star	5
Tree	3
FC	1

Mathematical Anomaly



Auto-Encoding an Urban Graph



Input Graph

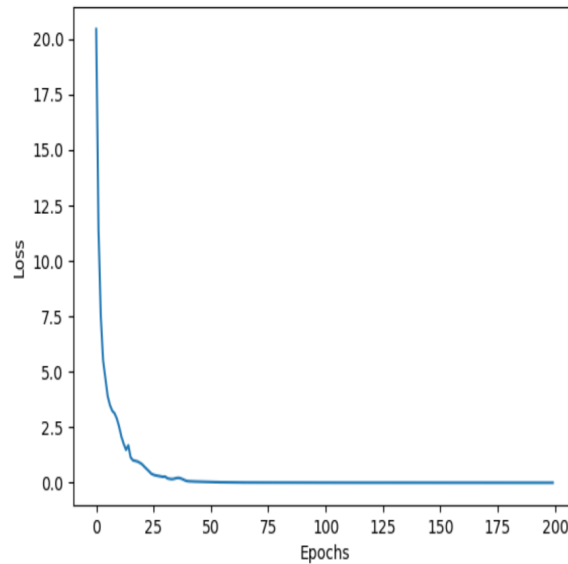
ENCODER

DECODER

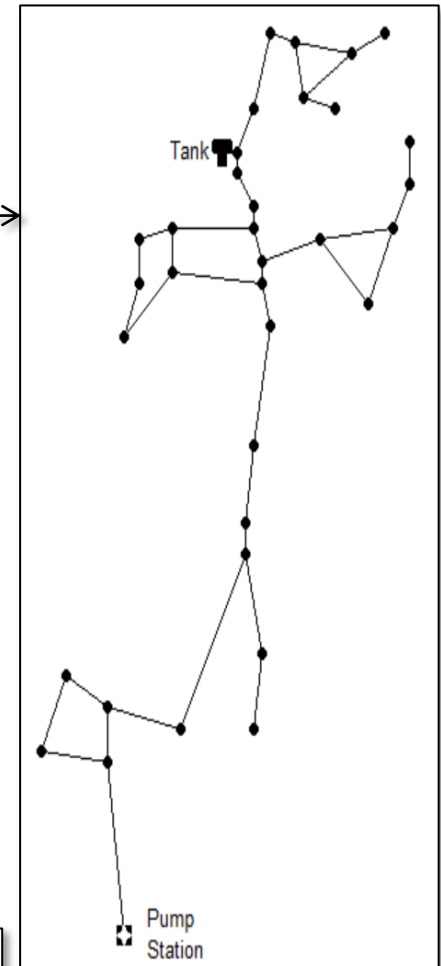
$$Z = AXW$$

$$A' = \sigma(Z^T Z)$$

Learning Curve

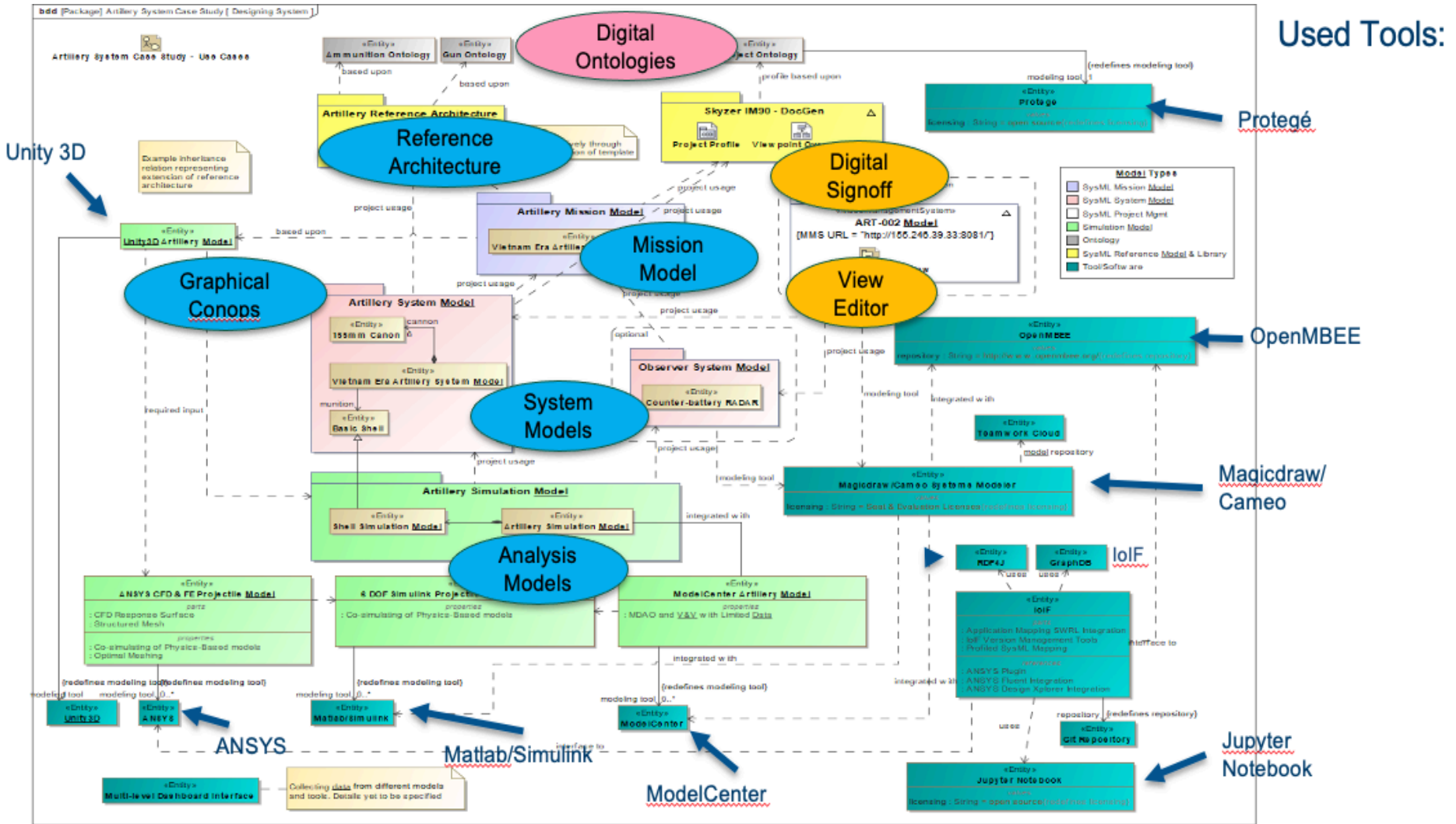


Number of embedding layer neurons = 74
Minimum Loss = 0.00196
Input/Output isomorphism = True



Output Graph

Kind of Data? Semantics with Domain Ontology for “Full Stack” of Models Aligned with Reference Architecture



Distribution Statement A: Approved for public release. Distribution is unlimited.

Year 1: Teaching Machines to Understand Graphs

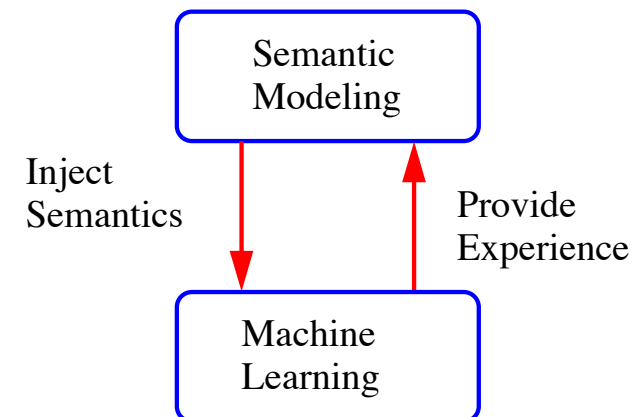
- Teaching machines to understand small graphs having static graph topologies.
- Auto-encoder design (guarantees on system graph representation).
- Formulae for design of neural network architectures for specific types of graph.
- Explore opportunities for composition of neural network architectures.
- Identification of events via time-series anomaly detection.
- Basic mechanisms for semantic / machine learning interaction.
- Integration of simulation and machine learning.

Year 2: Go Deep, Dynamic, Broad, Hybrid

- Deep graph neural networks / dynamic graph topologies.
- Reasoning with events, space and time.
- Inject semantics into machine learning models.
- Applications.

Year 3: Create Digital Twin Experience

- AI/ML architectures for digital twin experience.
- Applications.



Questions?

Contact Information

Mark Austin: austin@umd.edu

Maria Coelho: mecoelho@terpmail.umd.edu

Mark Blackburn: mblackbu@stevens.edu

- **Austin M.A., Delgoshaei P., Coelho M. and Heidarinejad M.** , Architecting Smart City Digital Twins: Combined Semantic Model and Machine Learning Approach (Special Collection on Engineering Smarter Cities with Smart City Digital Twins), Journal of Management in Engineering, ASCE, Volume 36, Issue 4, July, 2020.
- **Coelho M., Austin M.A. and Blackburn M.R.** , Semantic Behavior Modeling and Event-Driven Reasoning for Urban System of Systems, International Journal on Advances in Intelligent Systems, Vol. 10, No 3 and 4, December 2017, pp. 365-382.
- **Coelho M., and Austin M.A.** , Teaching Machines to Understand Urban Networks, The Fifteenth International Conference on Systems (ICONS 2020), Lisbon, Portugal, February 23-27, 2020, pp. 37-42.
- **Coelho M., Austin M.A. and Blackburn M.** , Distributed System Behavior Modeling of Urban Systems with Ontologies, Rules and Many-to-Many Association Relationships, The 12th International Conference on Systems (ICONS 2017), Venice, Italy, April 23-27, 2017, pp. 10-15.
- **Coelho M., Austin M.A., and Blackburn M.R.**, The Data-Ontology-Rule Footing: A Building Block for Knowledge-Based Development and Event-Driven Execution of Multi-Domain Systems, 2018 Conference on Systems Engineering Research, Charlottesville, VA, May 8-9, 2018. Also see: [Chapter 21, Systems Engineering in Context](#), Springer, 2019.
- **Coelho M., Austin M.A. and Blackburn M.R.**, "Semantic Behavior Modeling and Event-Driven Reasoning for Urban System of Systems," International Journal on Advances in Intelligent Systems, Vol. 10, No 3 and 4, December 2017, pp. 365-382.

Extra Slides

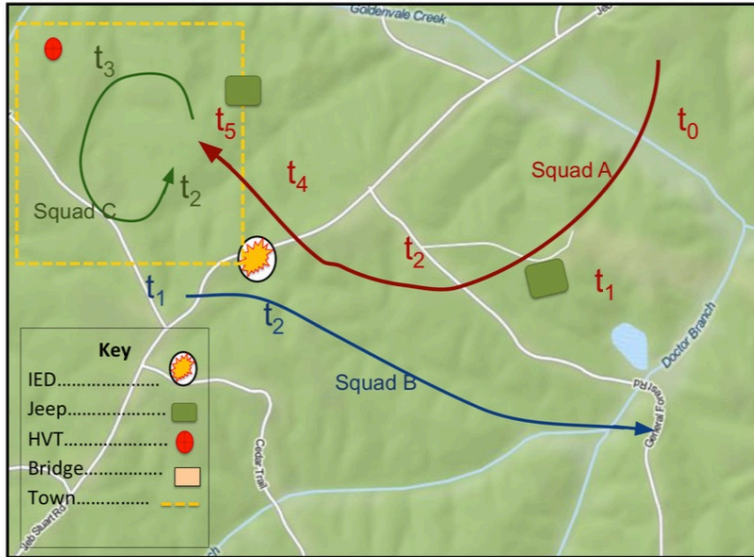
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Mark Blackburn: mblackbu@stevens.edu

Simple Military Exercise

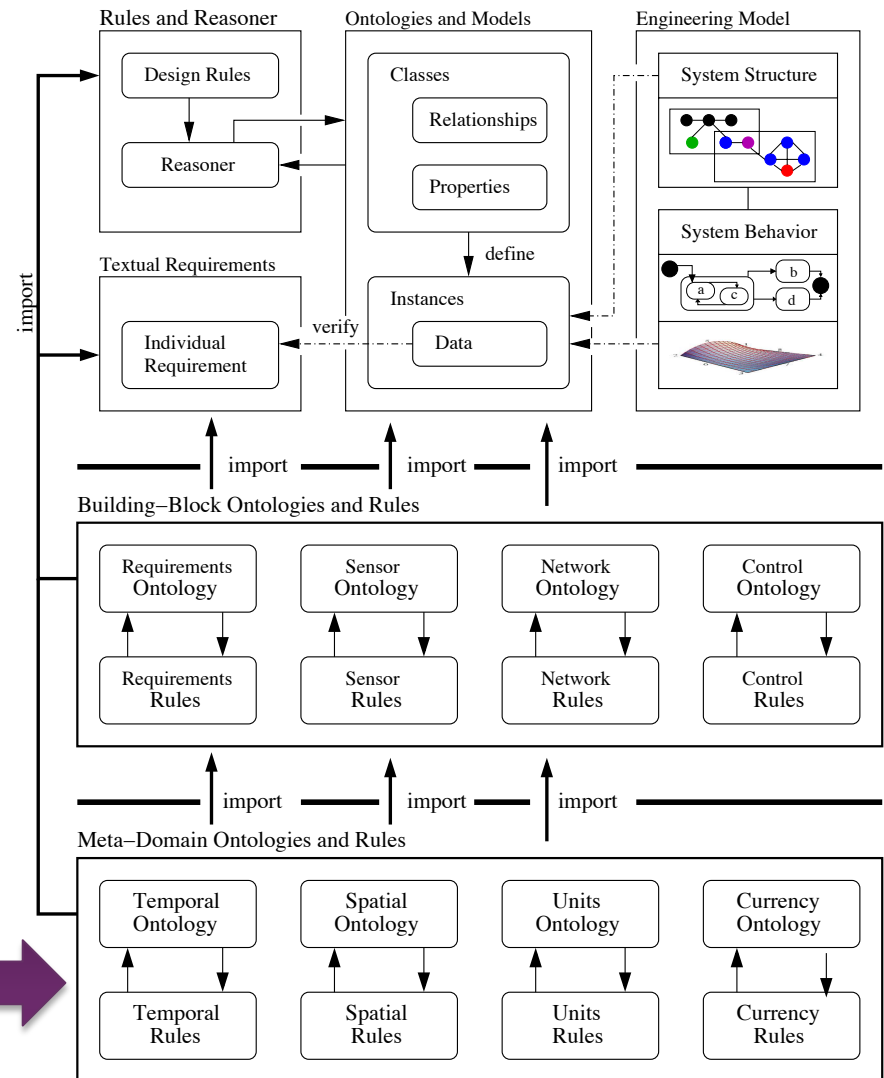


Decision Making / Exercise Actions

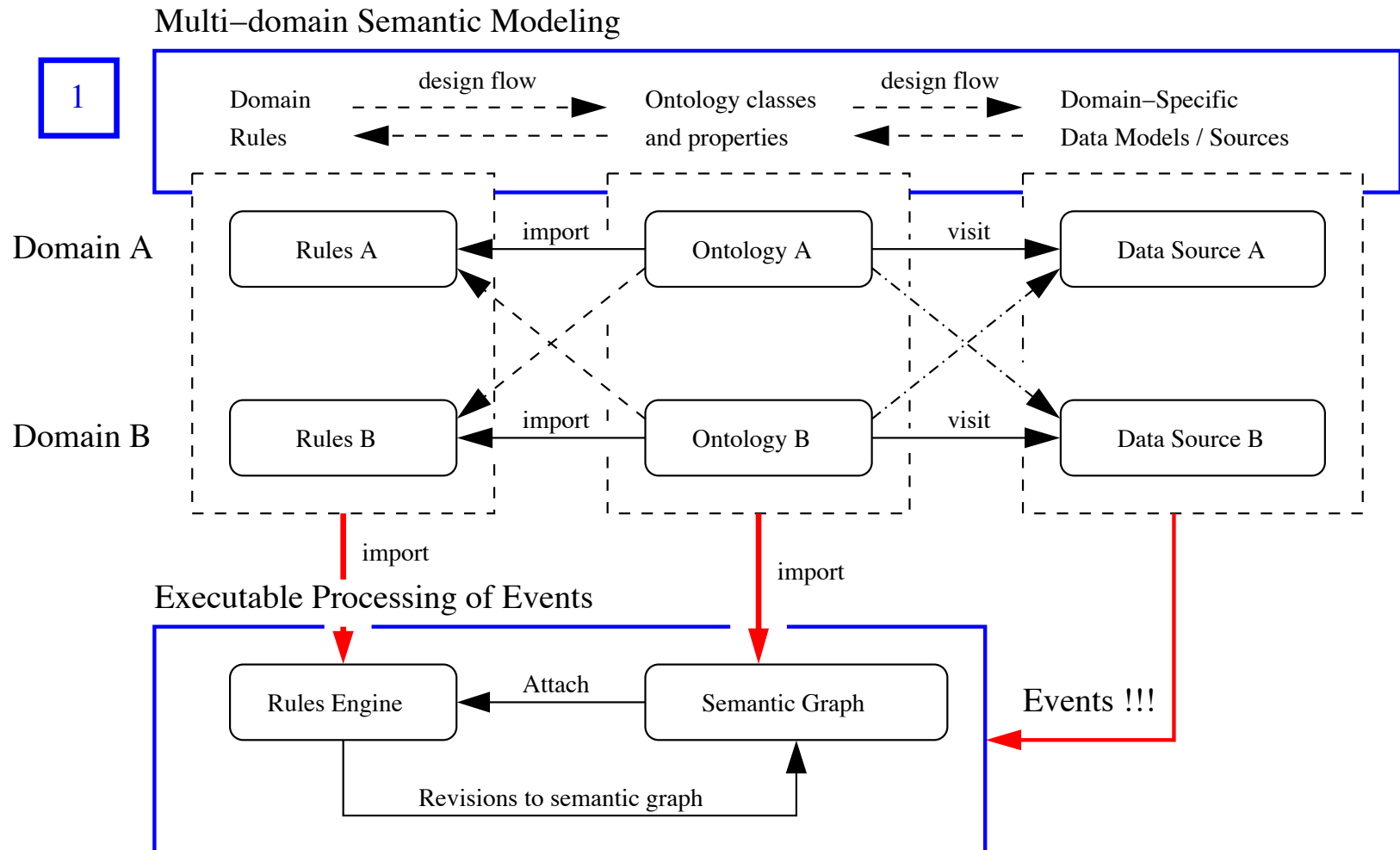
Military exercise **actions need to occur at the right time and in the right place.**

Source: Regli W., et al.

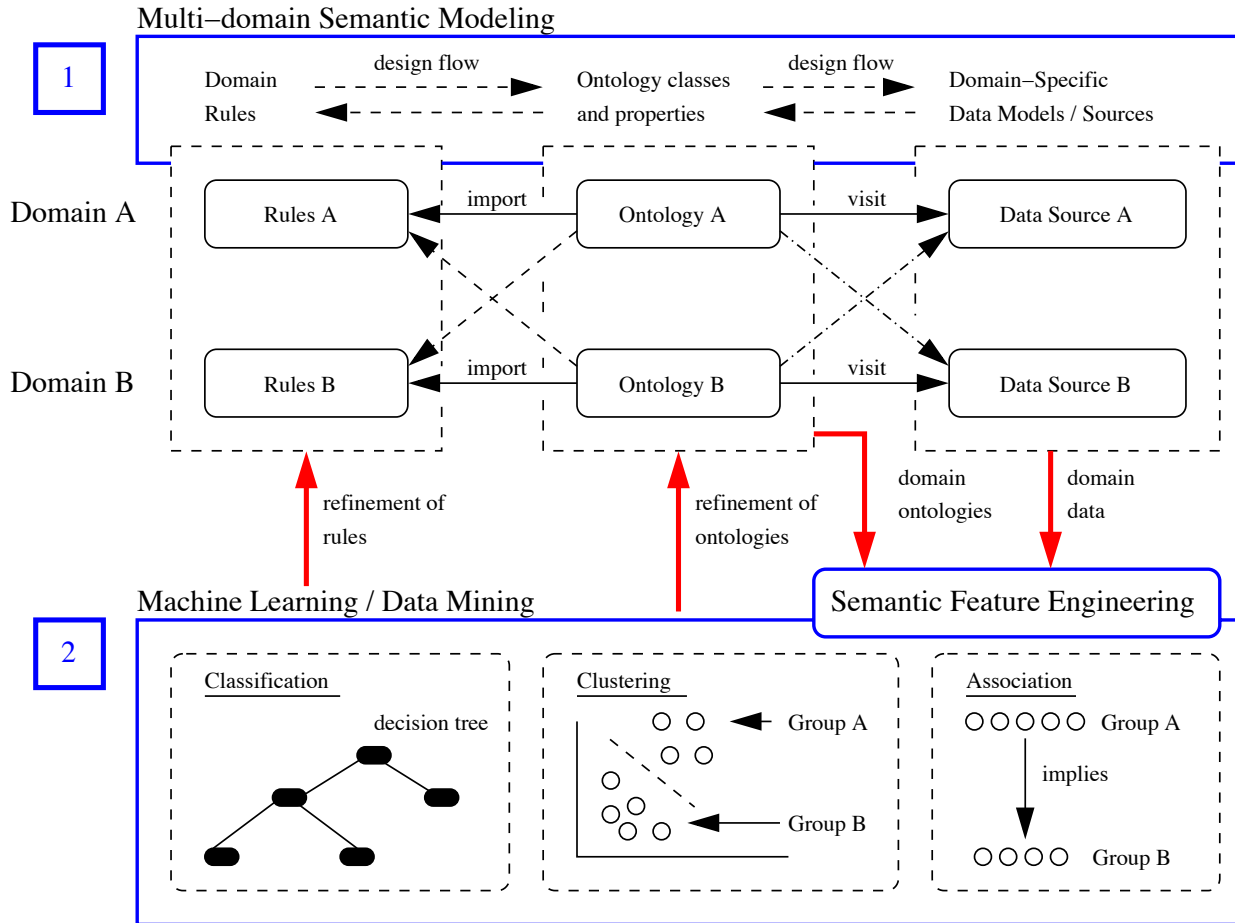
Semantic Modeling and Reasoning for Model-Centric Engineering



Data-Ontology-Rule Footing (Work at UMD / NIST / SERC in 2017).



Work at UMD / Building Energy Group at NIST / NCI, 2018-2019



Research Question: How can semantic modeling + machine learning / data mining work together as a team?