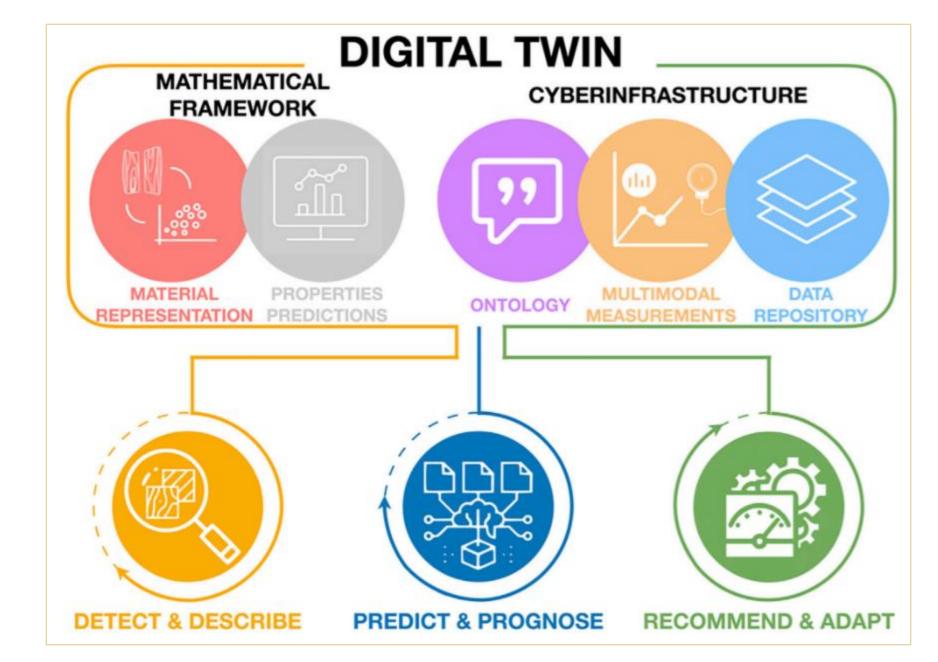
DGTAL TWINS FOR AEROSPACE MATERIALS

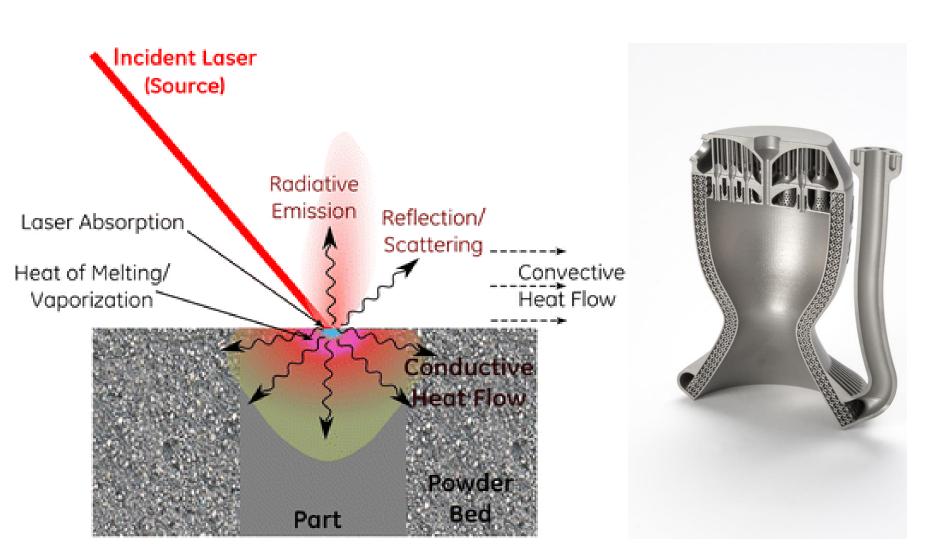
Digital Twin

- A digital twin is a replica in the digital space of a real product. They have begun to be developed in three different varieties:
- Descriptive models are live visual replicas of the product, like a CAD model.
- Predictive models can predict the behavior of the real product in response to an event.
- Prescriptive models are predictive models that also prescribes an optimal solution.

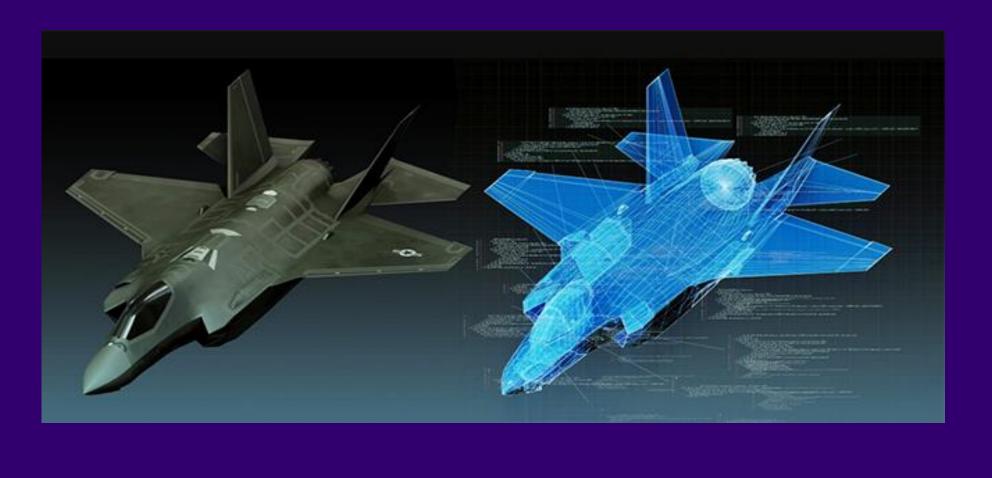


Additive Manufacturing

- Additive manufacturing (AM) processes in aerospace, compared to its conventional counterpart:
- (+) Reduces lead time for multi-layered electronics, which allows for more opportunities to redesign during product development
- (+) Reduces weight of aerospace systems, which reduces fuel consumption
- (+) Reduces waste compared to subtractive processes
- (+) Facilitates manufacturing of more complex components
- (-) Requires more expensive materials



• Selective laser melting (SLM), is an AM process that involves using a laser to melt powder in a bed to produce metal components.



Digital Material Twin

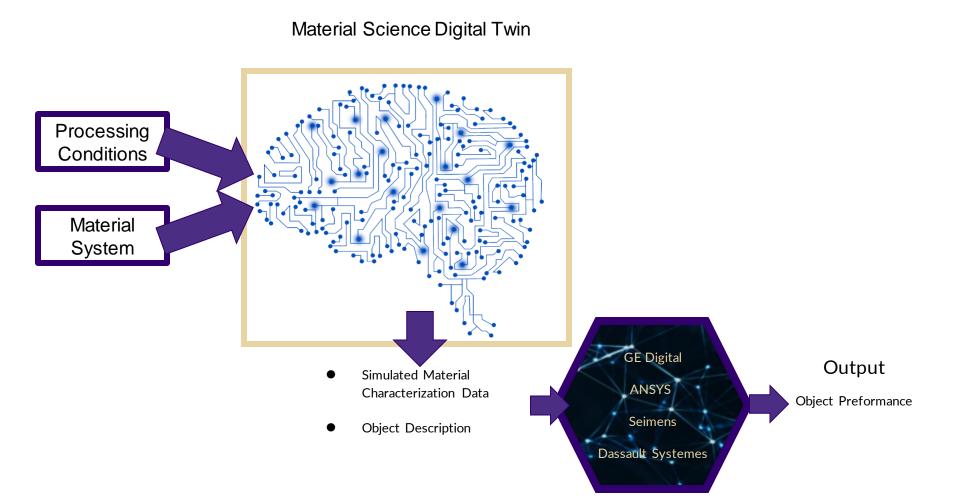
- A Digital Material Twin (DMT) is a model of a part, device, or process that encapsulates material behavior.
- A DMT exists at many length scales (atomic to component scale), requiring complex process-structure-property relationships to model a real counterpart.
- In application, linking the SLM process to the structure of the resulting metal component will allow a DMT to describe and predict a real component's properties.
- Current simulation software involves material data and object description inputs and object preformation.

Input

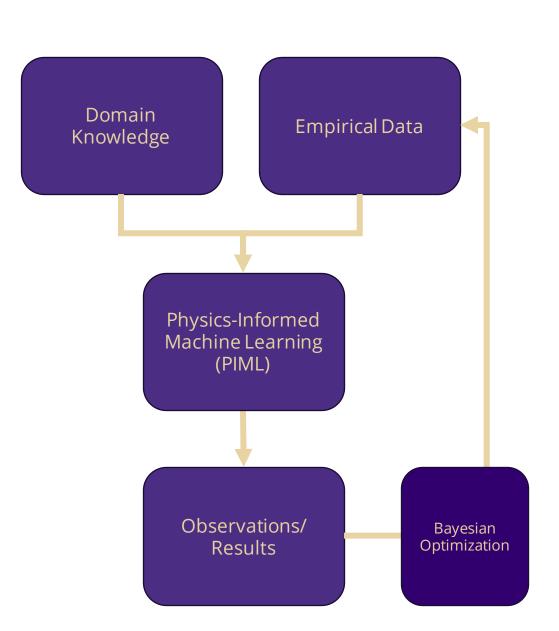
- Measured Material Characterization Data
- Object Description
- Machine learning (ML) expedites simulations.
- Using processing conditions as input, the characteristic data of a certain material system can be obtained using a DMT.

Seimens

Dassault Syst



- Ultimately a DMT seeks to understand how stimuli affect a device, its constituents, and material physics
- Physics-Informed Machine Learning (PIML) combines domain knowledge and machine learning to draw powerful conclusions from otherwise noisy data.
- By using PIML, models can encapsulate material physics while abiding by constraints.
- Machine learning ensembles determine the accuracy of models and poll which data points the model needs to improve via Bayesian optimization.



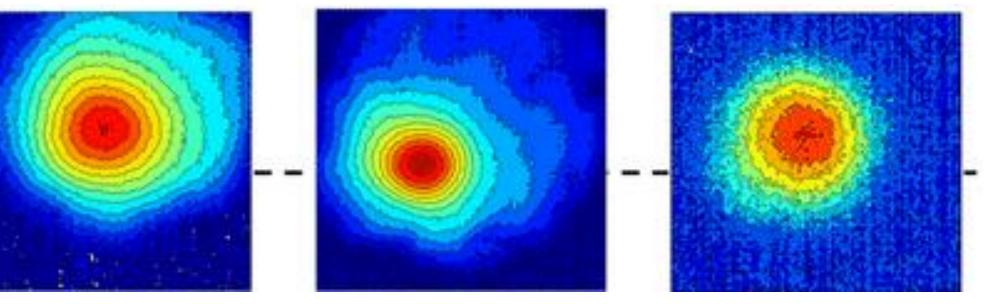
Output

Object Performance

LOCKHEED MARTIN

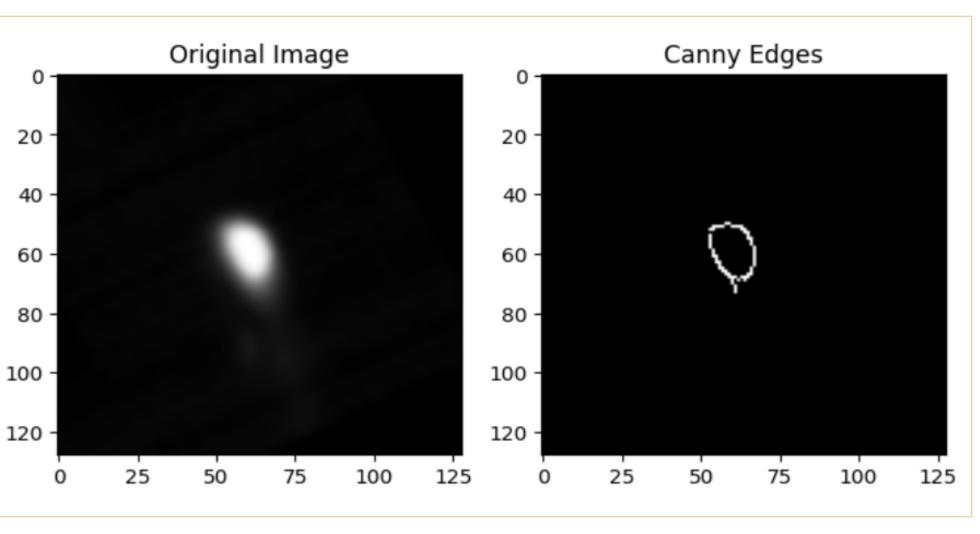
Melt Pool Data

• Our data examines the nickel alloy, IN625. • A melt pool is the area of laser melt in the SLM process. • Melt pool data is easy and cheap to collect compared to methods that require higher quality cameras to observe the component's microstructure.



• Linking SLM melt pool data to microstructure data establishes a process-structure relationship that can become part of a more comprehensive digital material twin. • Image preprocessing steps before training the model: • Centering melt pool spot

- Classifying images by laser activity by filtering • **Denoising spatter**
- Determining laser direction with canny edge detection



• We successfully classified and denoised melt pool images like the one above.

• The white spot shows the melt pool at a certain instant. • Due to the lack of unique features present in a melt pool image, canny edge detection did not return significant results.

Data Registration

- Data registration involves recording metadata associated with a certain dataset.
- Useful metadata to have for the melt pool
- image dataset would be the temperature and direction of the laser scan path, the latter of which would eliminate the need for a canny edge detection preprocessing step.
- We worked with secondary data from the National Institute of Standards and Technology (NIST) which we didn't have control over what metadata was included in the

images.



- processing.

meet-vp-dale-tutt/ <u>is-metadata</u>

Faculty Advisor: Luna Huang Industry Advisor: Amit Pandey, Kelsey Cannon



Conclusion

• We consistently encountered obstacles that taught us about the challenges a prospective digital material twin team would face. • Our foremost conclusion is that data collection and registration must be an involved step in DMT data analysis. Data scientists and material specialists need to work together to ensure that the model's dataset has necessary detail and documentation.



• While there are existing tools and methods, such as canny edge detection, to extract metadata from an image dataset, it is difficult to avoid inaccuracies due to data loss after

• Furthermore, additional resources need to be allocated for data collection and registration. A large amount of data is necessary to connect different material length scales.

• The linkage between SLM processing conditions and the IN625 microstructure is only one process-structure relationship. A digital material twin of an aircraft would

necessitate various materials, processing and

connection methods, and their subsequent linkages. • The future of digital material twins for aerospace applications requires extensive and rigorous data documentation through

collaboration between data collectors and material analysts.

References & Acknowledgements

"The Lockheed Martin Aeronautics Win – Integration and Digital Twins the Secret to Siemens' A&D Success | PLM & ERP News," Feb. 02, 2022. http://plm-erpnews.se/aktuellt-pa-engineering-com-the-lockheedmartin-win-integration-is-the-secret-to-siemens-success-in-aerospace-defense-

S. R. Kalidindi, M. Buzzy, B. L. Boyce, and R. Dingreville, "Digital Twins for Materials," *Frontiers in Materials*, vol. 9, Mar. 2022, doi: https://doi.org/10.3389/fmats.2022.818535.

T. G. Spears and S. A. Gold, "In-process sensing in selective laser melting (SLM) additive manufacturing," Integrating Materials and Manufacturing *Innovation*, vol. 5, no. 1, pp. 16–40, Feb. 2016, doi:

https://doi.org/10.1186/s40192-016-0045-4.

"Additive Manufacturing - Aviation and Aeronautics," SLM Solutions. https://www.slm-solutions.com/industries/aerospace-and-defense/

Khanzadeh M, Chowdhury S, Tschopp MA, Doude HR, Marufuzzaman M, Bian L. In-situ monitoring of melt pool images for porosity prediction in directed energy deposition processes. IISE Transactions 2019;51:437-55. https://doi.org/10.1080/24725854.2017.1417656.

P. Kononow, "What is Metadata (with examples) - Dataedo Data terminology," Dataedo.com, 2018. https://dataedo.com/kb/data-glossary/what-

[7] D. Pickell, "What is the data analysis process? 5 key steps to follow," G2, https://www.g2.com/articles/data-analysis-process(accessed May 24, 2024).