Physics Informed Generative Adversarial Networks for Virtual Mechanical Testing

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Abstract

This work leverages physics-informed generative adversarial networks (PI-GANs)[1] to learn the underlying probability distributions of spatially-varying material properties (e.g., microstructure variability in a polycrystalline material). While standard GANs rely solely on data for training, PI-GANs encode governing physical laws in the form of stochastic differential equations using automatic differentiation. The goal of the project is to demonstrate that experimental data from a limited number of laboratory mechanical tests can be used in conjunction with PI-GANs to enable an unlimited virtual testing capability of materials for aerospace applications.

Preliminary results using synthetically generated data were used to demonstrate the utility of the proposed PI-GANs virtual testing framework. The approach was developed using deep learning and automatic differentiation capabilities in Tensorflow 2 and implemented on Nvidia Tesla V100 GPUs. Results suggest the proposed framework is capable of generating realistic samples of material properties (Young's Modulus) provided noisy mechanical response data (surface displacements) with 16.9x speedup provided by running the code on V100 GPUs over a CPU implementation.

Application

Challenge: reduce costs and accelerate certification for:

- new materials (e.g., additive-manufactured components, functionally graded materials)
- new structures (e.g., next-generation aircraft)

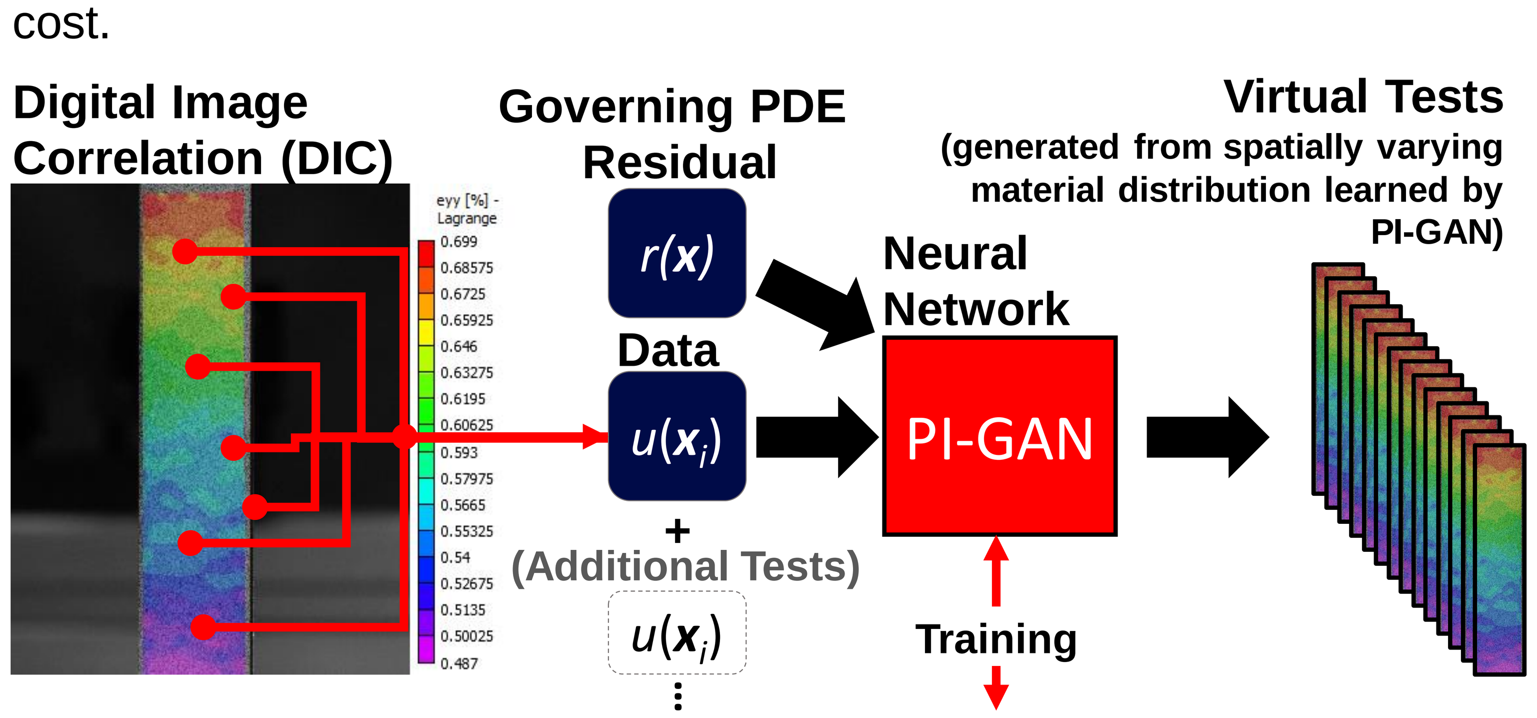
Current practice: extensive mechanical tests, (time consuming and expensive).

Approach: Certification by analysis using artificial intelligence; reduce time and cost of certification by reducing reliance on testing.

Training Data: Digital image correlation (DIC) is used to measure full-field displacements over the surface of a small number of test specimens.

Details: The data is used to train the PI-GAN, which incorporates the governing physical laws relating displacement and material properties. This process involves inference of the underlying probability distributions of spatially-varying material properties.

Goal: Generate an infinite number of virtual tests that can replace or supplement traditional testing, accelerating certification and reducing cost.

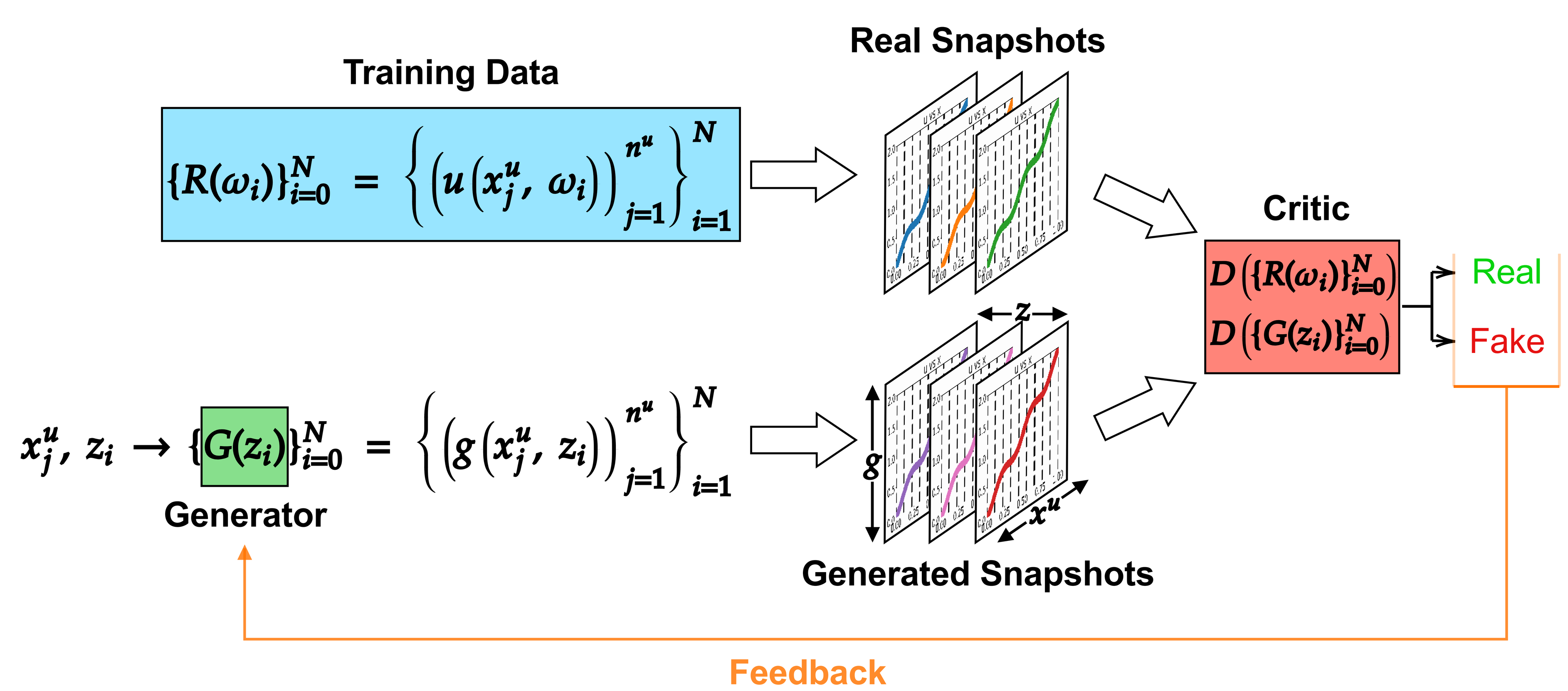


PI-GAN Formulation

The proposed neural network is a **Physics-Informed Generative Adversarial Network (PI-GAN)**[1]. This network results from the combination of:

- ***Physics-Informed Neural Networks*** **(PINNs)**[2] - allows for the incorporation of known physics to reduce the data required for training and ensure the resulting predictions obey known constraints (e.g., conservation of energy)
- ***Generative Adversarial Networks*** **(GANs)**[3] - enables uncertainty to be quantified by the network.

Training Process



Where:

- $\{R(\omega_i)\}_{i=0}^N$ - set of training data snapshots (simultaneous read of all sensors)
- $\{G(z_i)\}_{i=0}^N$ - set of generated snapshots
- $\{x_j^u\}_{j=1}^{n^u}$ - position setup of n^u sensors for u
- ω_i - random event that denotes the random instance of the
- z_i - input noise vector (normally distributed, mean of zero and variance of 1)

Loss Function

PINN Loss

$$r(\mathbf{x}) = \mathcal{N}_x[\mathbf{u}; k] - f(\mathbf{x}) = 0, \mathbf{x} \in \Omega$$

$$\mathcal{L}_{PDE}(\theta, \phi) = \frac{1}{N_r} \sum_{i=1}^{N_r} \|\hat{r}_\theta(\mathbf{x}_r^i)\|^2$$

$$\mathcal{L}_{PI}(\theta, \phi) = \mathcal{L}_{data}(\theta) + \mathcal{L}_{PDE}(\theta, \phi)$$

The PINN loss is a function of u and k, which are individual neural networks; i.e.,

$$\hat{k}_\phi \approx k(x)$$

The PDE loss is derived through automatic differentiation of these networks. In this application, k represents the material properties.

Standard Neural Network Loss

$$\mathcal{L}_{data}(\theta) = \frac{1}{N_u} \sum_{i=1}^{N_u} \|\hat{u}_\theta(\mathbf{x}_u^i) - \mathbf{u}^i\|^2$$

PI-GAN Loss

GAN Loss

$$\max_{\psi} \mathcal{L}_{\mathcal{D}}(\psi)$$

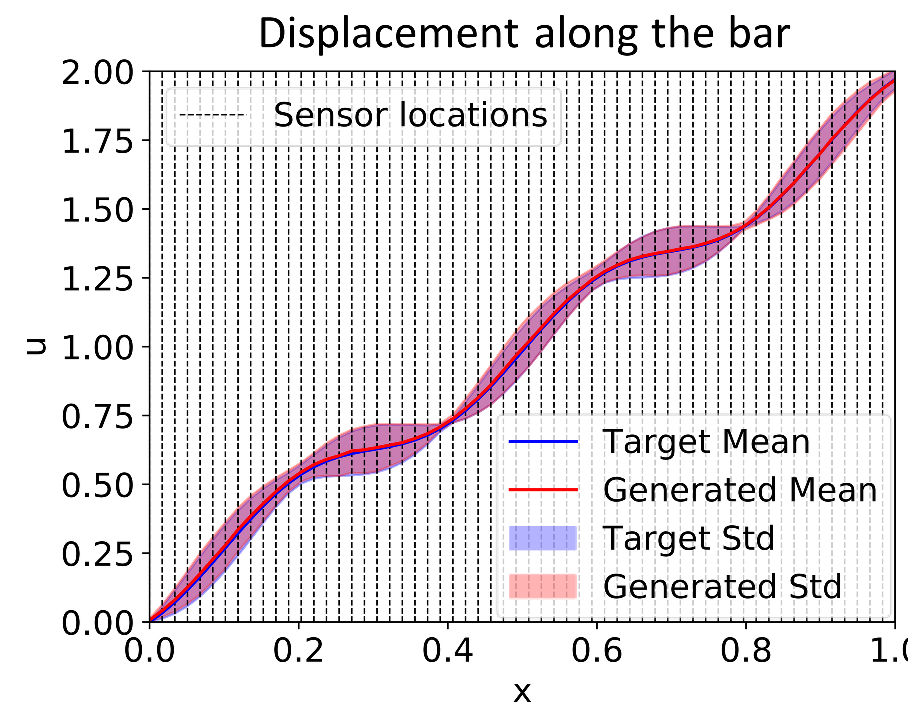
$$\min_{\theta,\phi} \mathcal{L}_{\mathcal{G}}(\theta) + \beta \mathcal{L}_{PDE}(\theta, \phi)$$

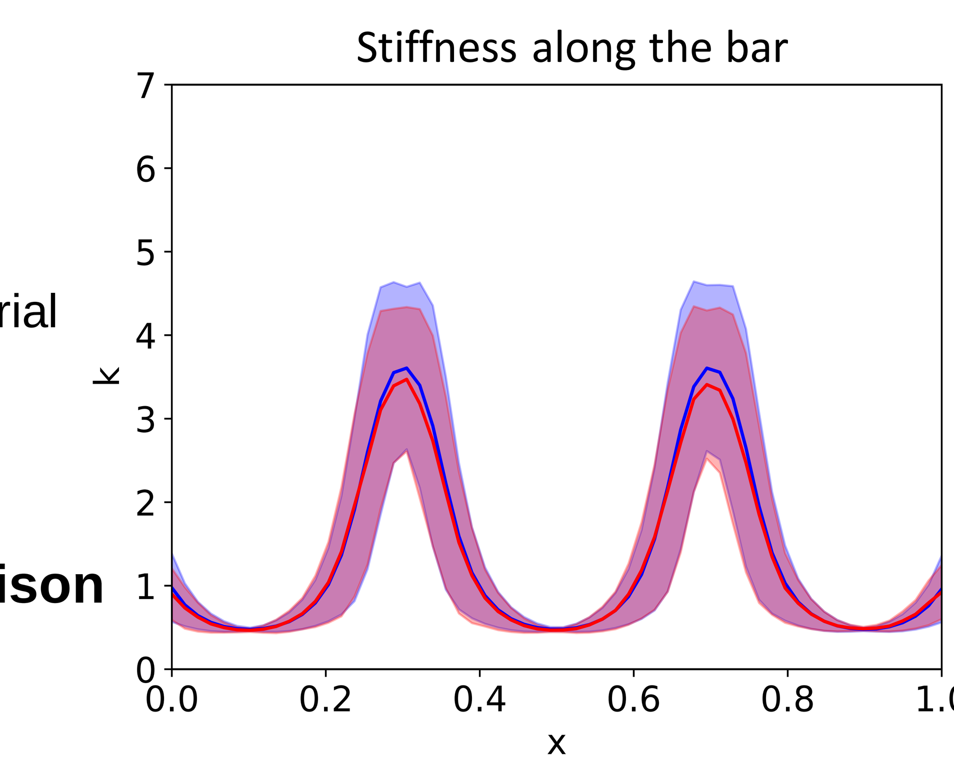
Results (preliminary)

Preliminary example: predicting response of a bar in uniaxial tension

- ***Training Data****:* 1,000 snapshots of displacement measurements at 60 uniformly distributed sensors (with inherent randomness)
- ***PDE constraint****:* enforced at 10,000 uniformly distributed collocation points
- ***Training Steps:*** 50,000
- ***Training Time:*** 2h15m

Results show that the PI-GAN models both displacement, u, and material properties, k, under uncertainty and using observations of u only.

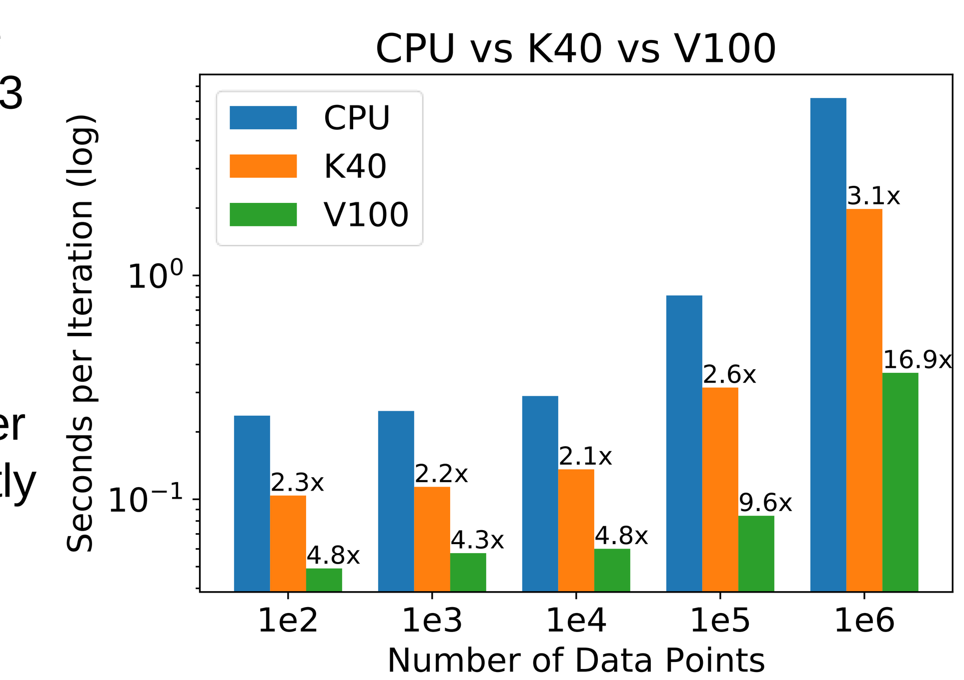




GPU Speed-Up Comparison

- ***Number of Data Points:*** #Snapshots x #Sensors
- ***CPU:*** Dual socket 8 core 2.60 GHz Intel E5-2640v3 Haswell Node
- ***GPUs:***
  - NVIDIA Tesla K40
  - NVIDIA Tesla V100

Future work involves higher dimensions and significantly more data. The scalability and efficiency provided by GPUs will be critical.



Conclusions

- Phase one of the project has been completed with successful demonstration of the PI-GAN proof-of-concept exercises.
- **Future work**:
  - Scale the approach to the final application of a real uniaxial test specimen (or set of specimens)
  - Validating the results using high-throughput testing.

References

[1] Y. Yang et al. 2019. Adversarial uncertainty quantification in physics-informed neural networks. J. Comput. Phys. 394(2019), 136–152.
[2] M. Raissi et al. 2019. Physics- informed neural networks: a deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. J. Comput. Phys. 378 (2019), 686–707.
[3] Ian Goodfellow et al. 2014. Generative adversarial nets. In Advances in neural information processing systems. 2672–2680.