INFINITE VIRTUAL TESTING USING PHYSICS-INFORMED DEEP LEARNING

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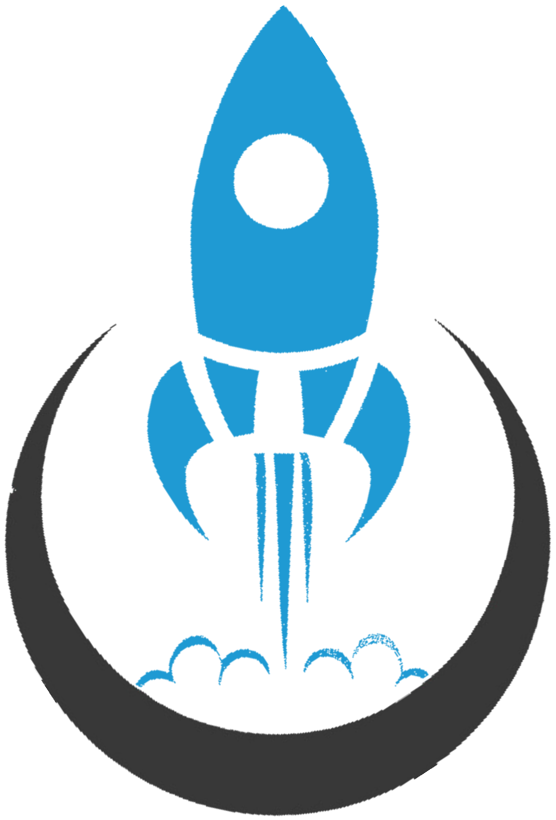
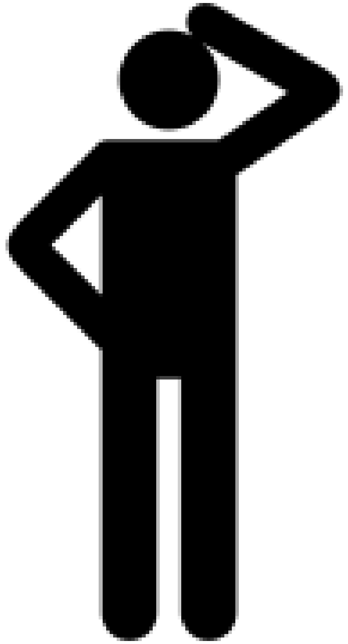
OVERVIEW & MOTIVATION

- Problem:
  - Traditional test-driven certification of novel materials and structures is expensive and time consuming.
- Mission:
  - To develop a novel approach that makes use of a new neural network architecture, called Physics-Informed Generative Adversarial Networks (PI-GANs), to generate an infinite amount of virtual tests for the certification of arbitrary materials.



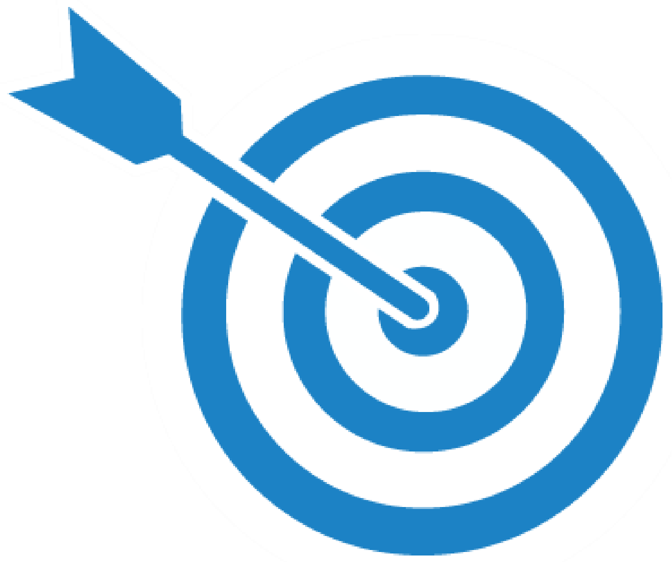
WHAT IS A PI-GAN?

- It's a neural network that uses adversarial training to learn to generate new samples based on the underlying distribution of some training data.
- The space of admissible solutions is constrained by some stochastic partial differential equation that encodes the governing physical laws of the system being studied into the training procedure.



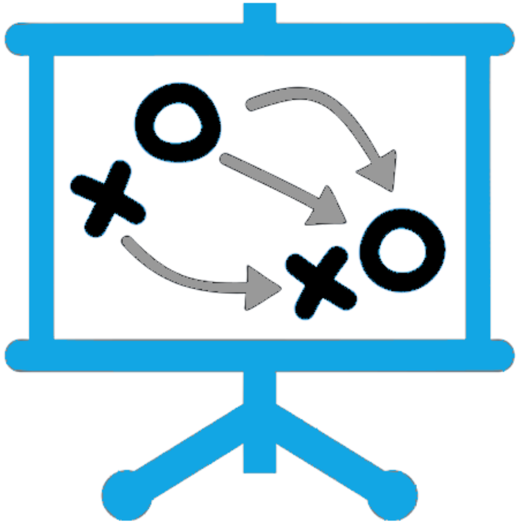
GOALS

- Efficiency
  - Able to learn from small data.
- Accuracy
  - Able to create new samples that belong to the material properties data's distribution.
- Reliability
  - Consistency in performance given a controlled set of hyperparameters.
- Robustness
  - Able to handle noise in the data.
  - Low sensitivity to changes in hyperparameters.
- Speed
  - As fast, if not faster than traditional test-driven methods.



APPROACH

- Study individual components
  - Generative Adversarial Networks (GANs)
  - Physics-Informed Neural Networks (PINNs)
- Apply components to toy problems similar to end goal
  - GAN – uncertainty in stress-strain curves
  - PINN – material identification
- Build PI-GAN
- Train PI-GAN to learn to generate samples based on DIC data that captures specimen's response.

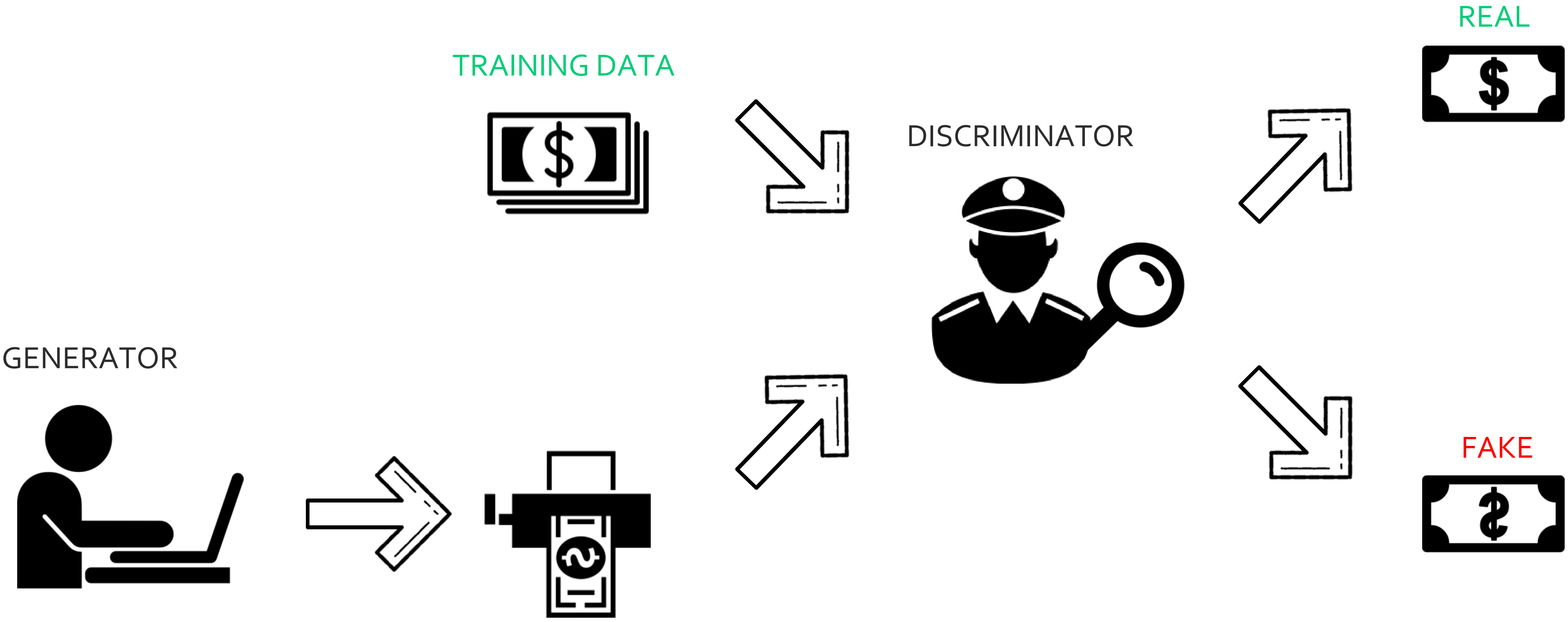


GENERATIVE ADVERSARIAL NETWORKS (GANS)

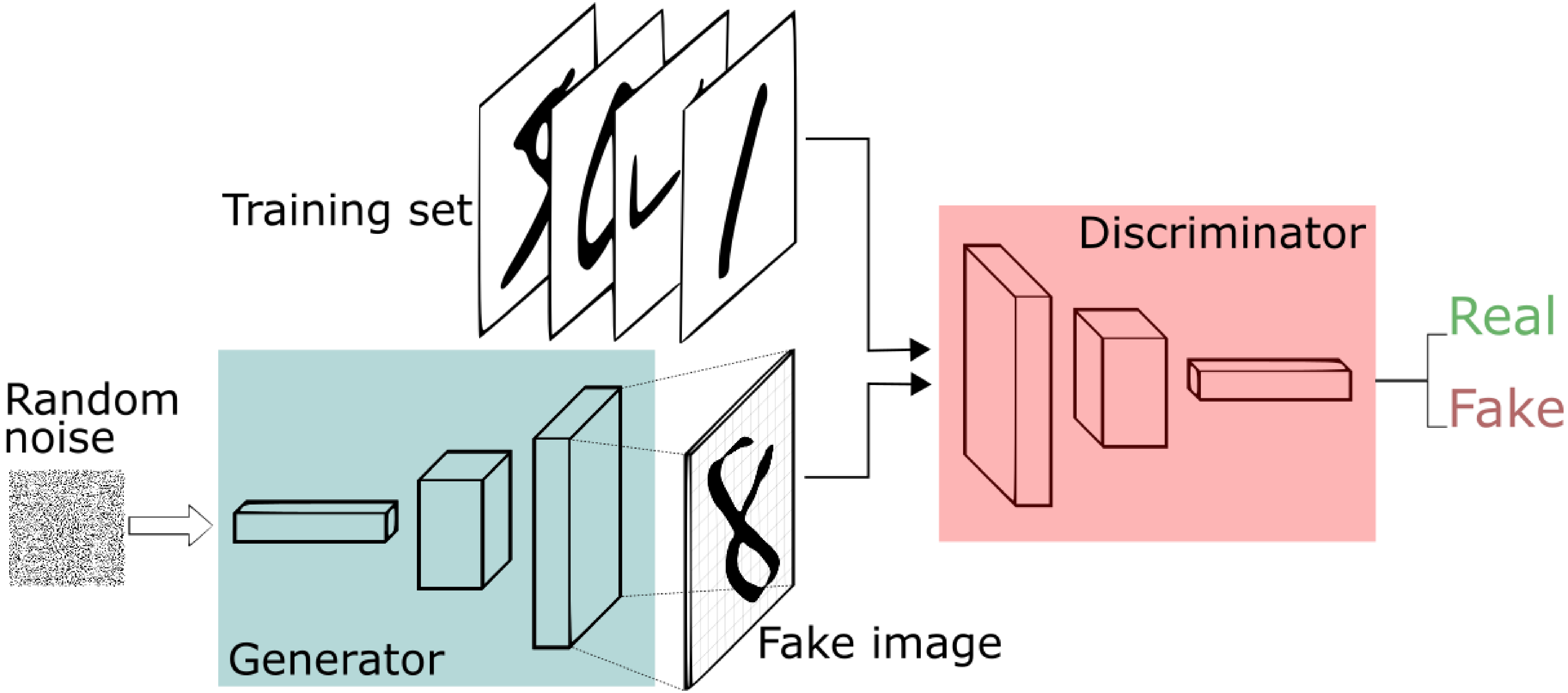
GANS ARCHITECTURE

- Generator
  - Learns to generate new samples based on the true distribution of the training data.
- Discriminator
  - Learns the true distribution from the training data and provides the generator with feedback by scoring the generated samples.

GANS INTUITION



GANS INTUITION (CONT.)



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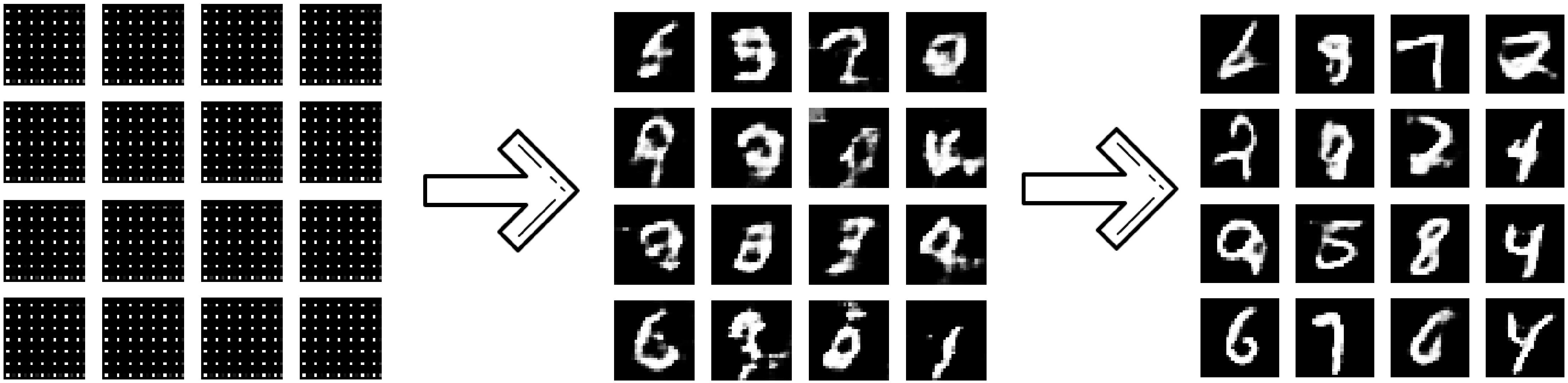


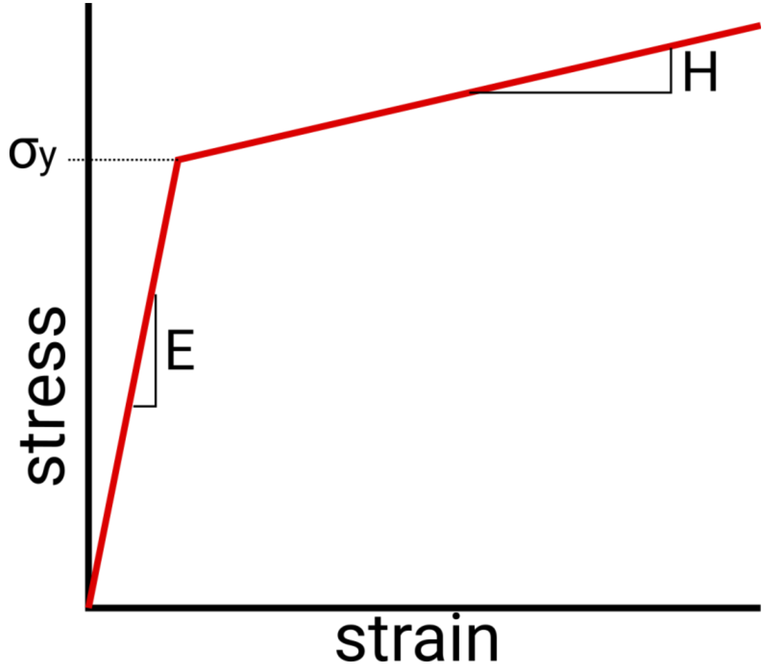
WASSERSTEIN GAN WITH GRADIENT PENALTY (WGAN-GP)

- Loss function
  - Wasserstein Distance – minimum cost of transporting mass in order to transform one distribution ***q*** into the distribution ***p*** (where the cost is mass times transport distance)
- Gradient Penalty
- Loss function is continuous everywhere, and differentiable almost everywhere.

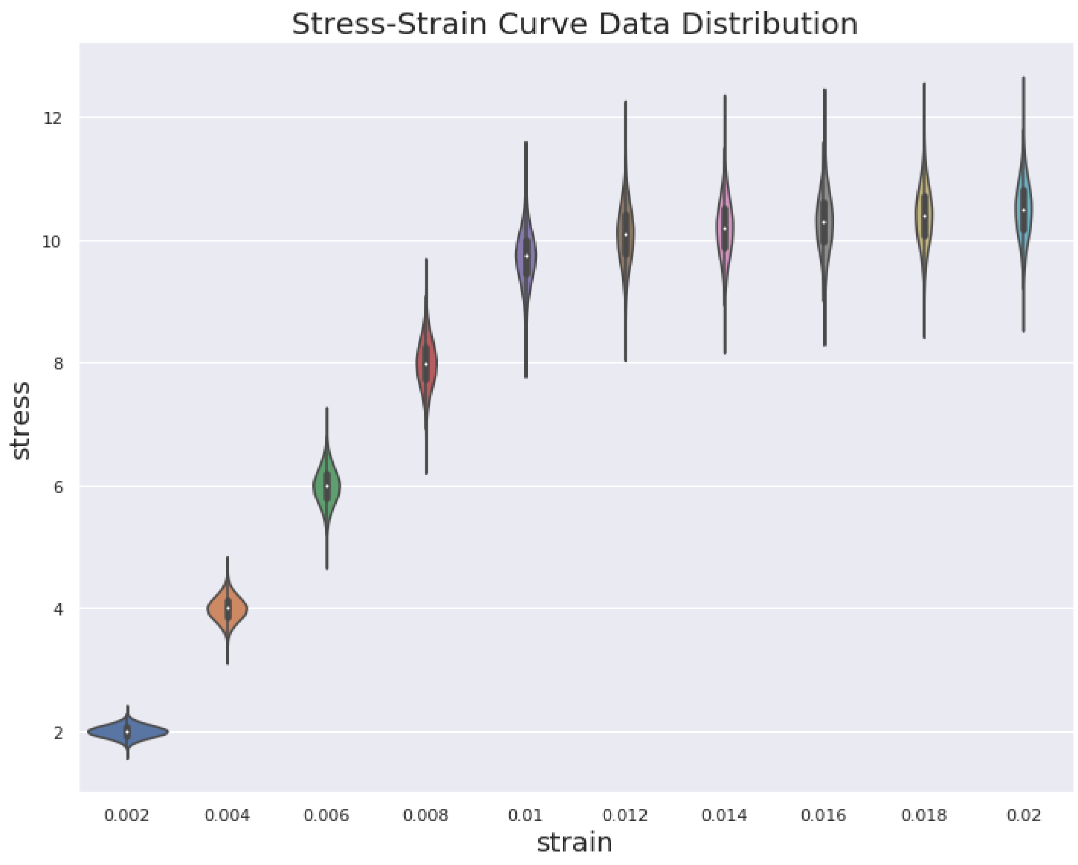
GANS TEST PROBLEM – UNCERTAINTY IN STRESS-STRAIN CURVES

- Assuming bi-linear stress strain behavior of a material (characterized by σ, E, and H), generate sample stress-strain curves based on some initial samples of a stress-strain curve distribution.

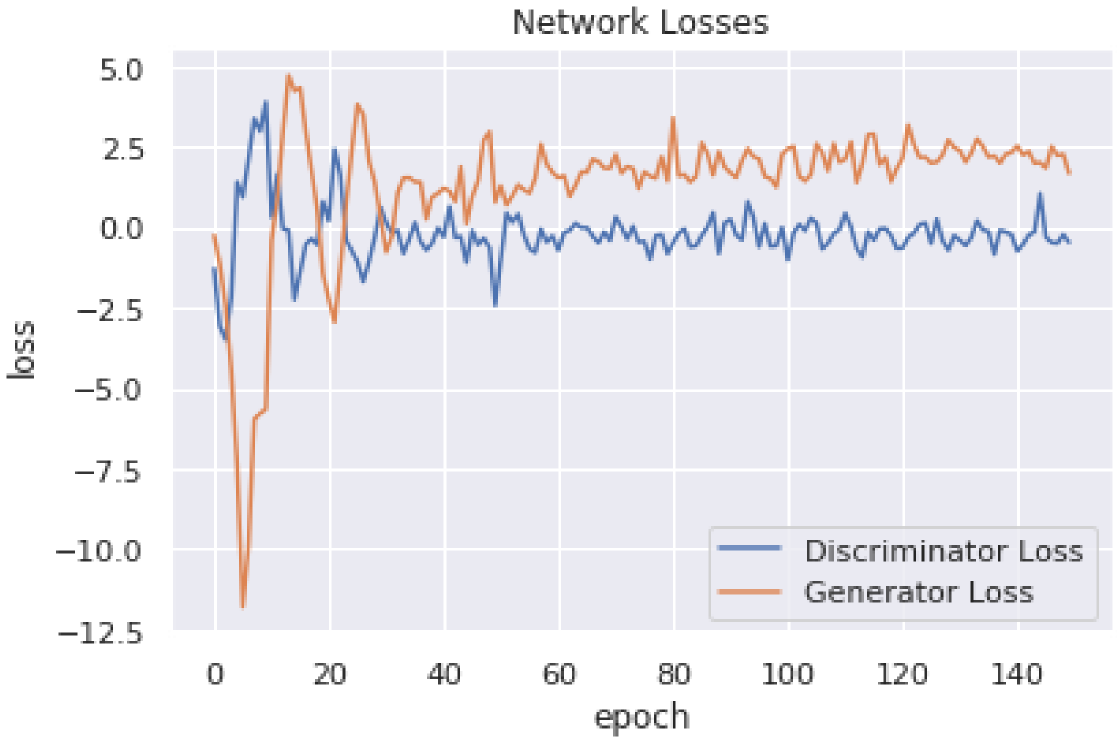
$$\sigma_y \sim \mathcal{N}(\mu = 10, \sigma = 0.5)$$
$$E \sim \mathcal{N}(\mu = 1000, \sigma = 50)$$
$$H \sim \mathcal{N}(\mu = 50, \sigma = 5)$$



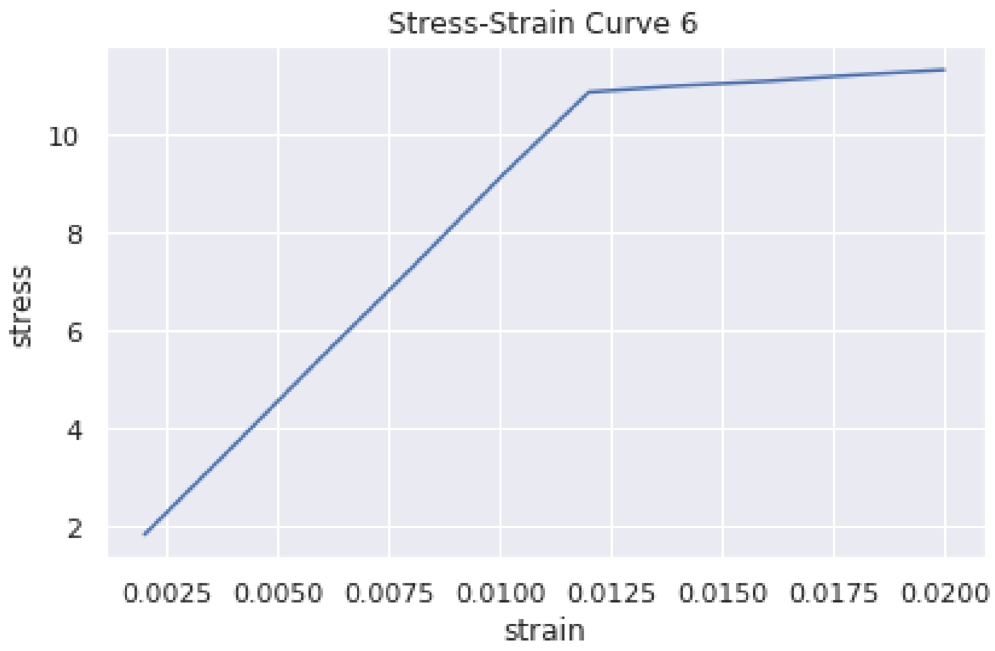
GANS TRAINING DATA

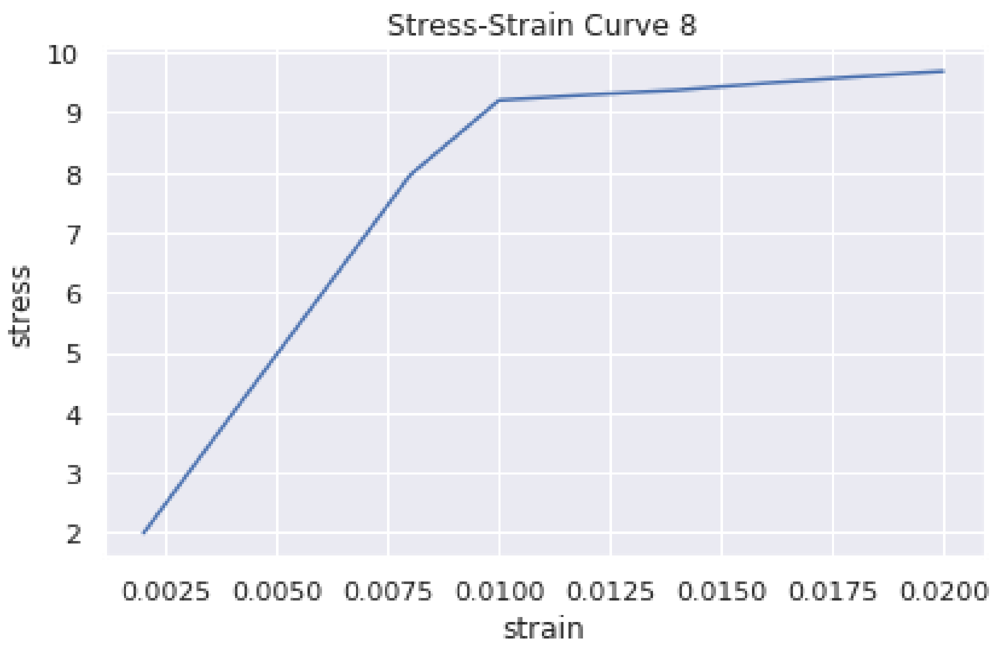


NETWORK LOSS



GANS RESULTS





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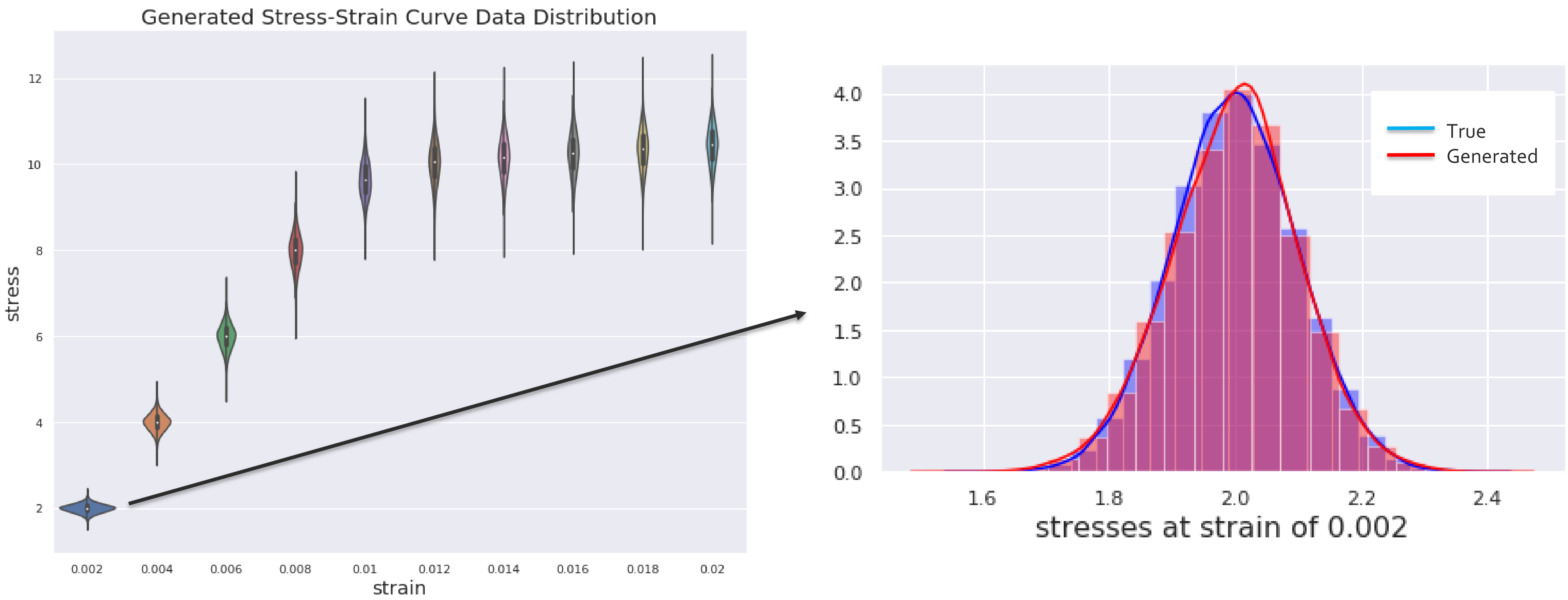

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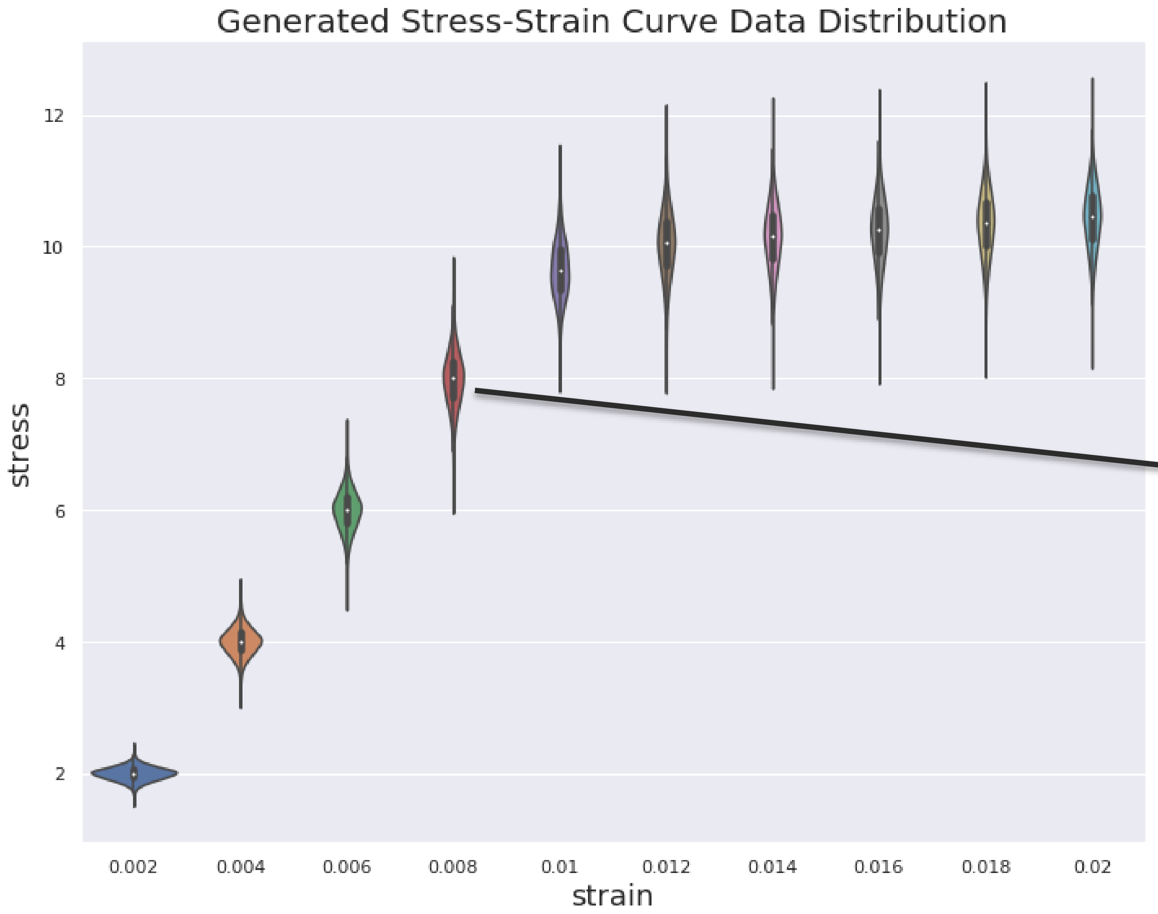

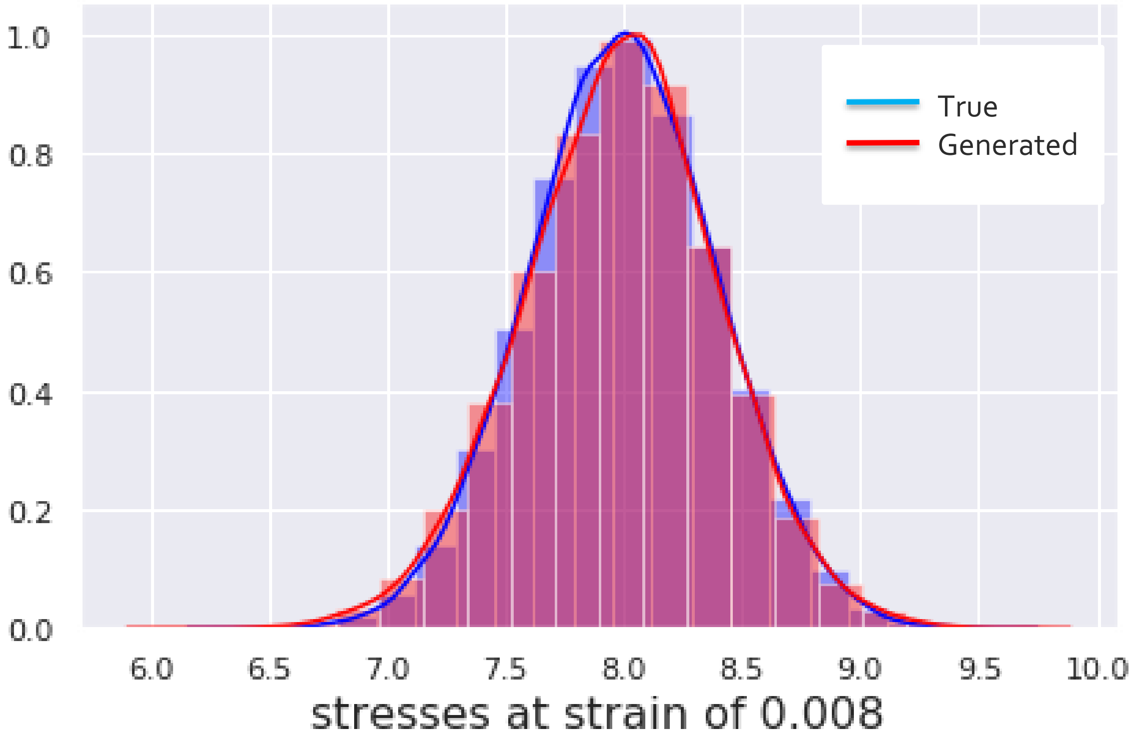

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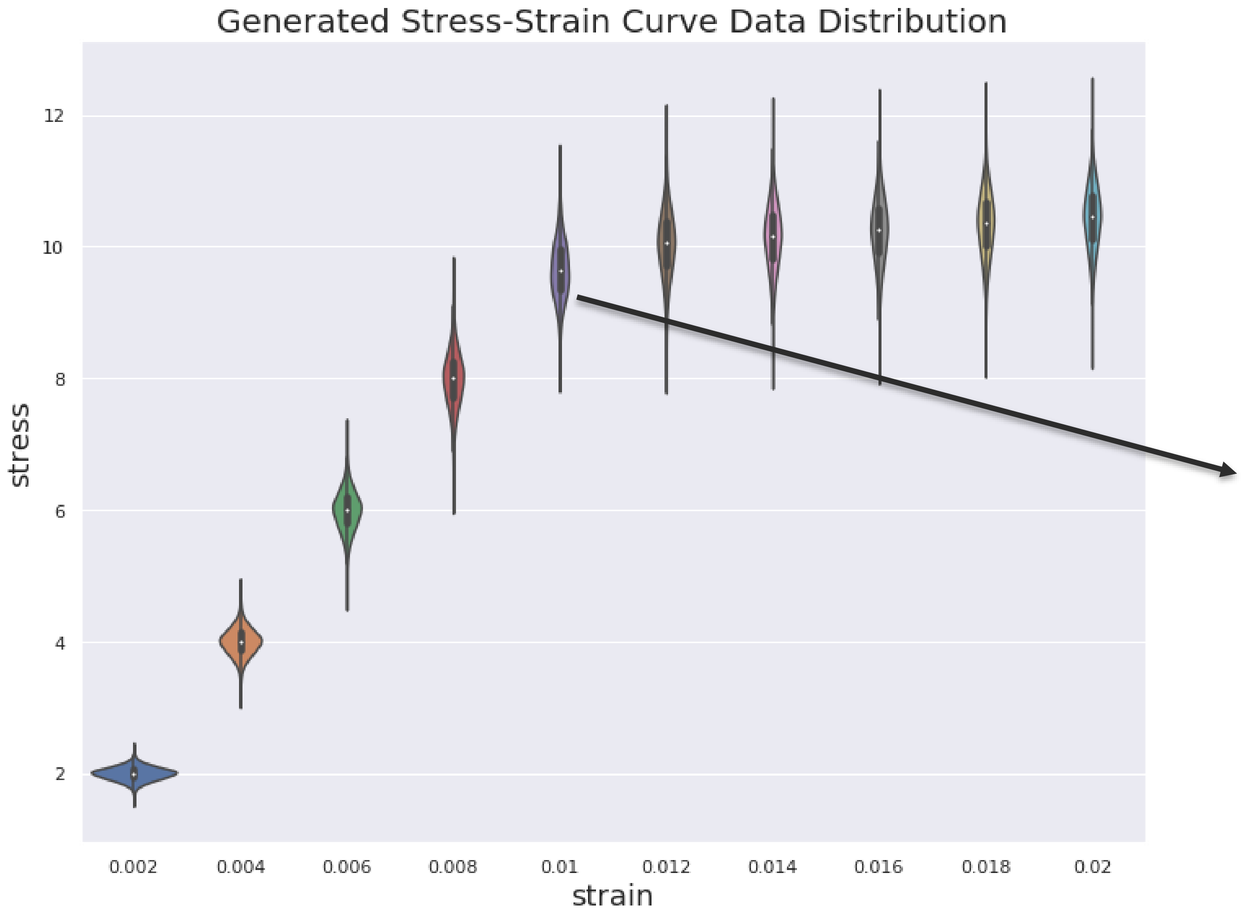
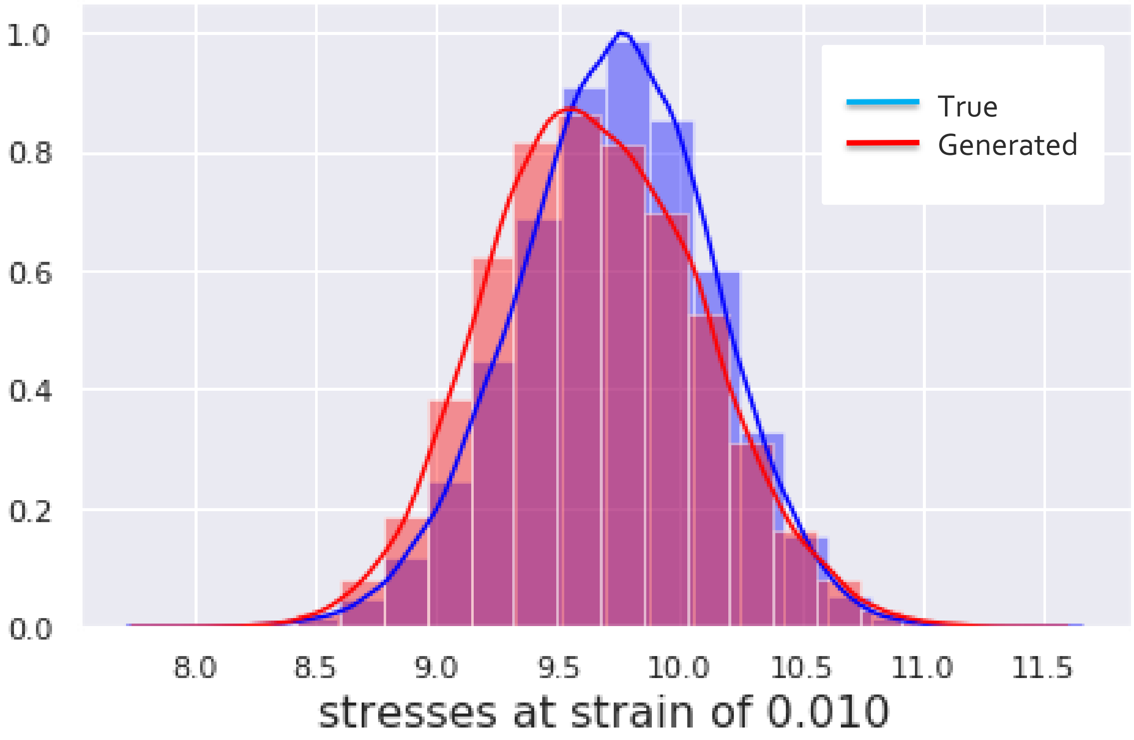
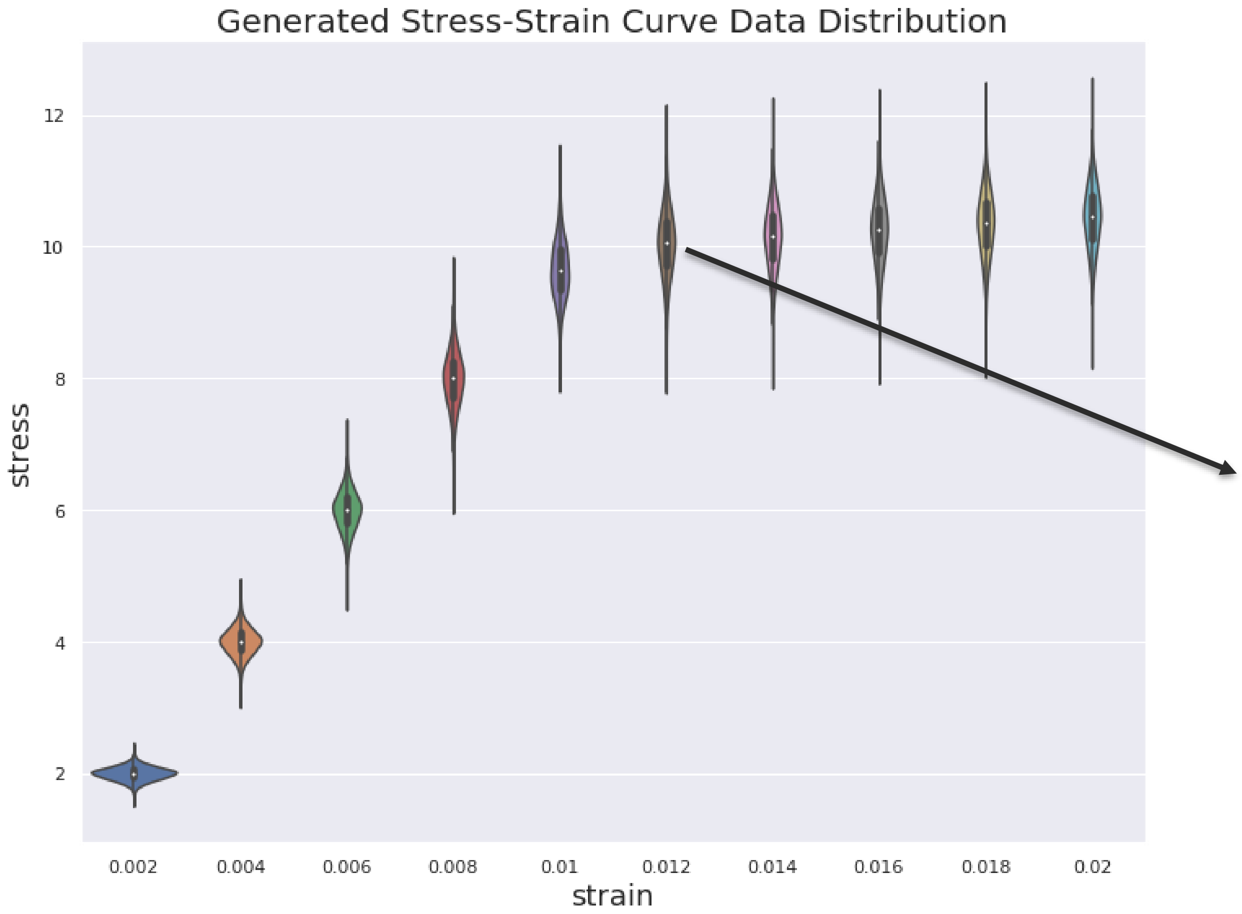
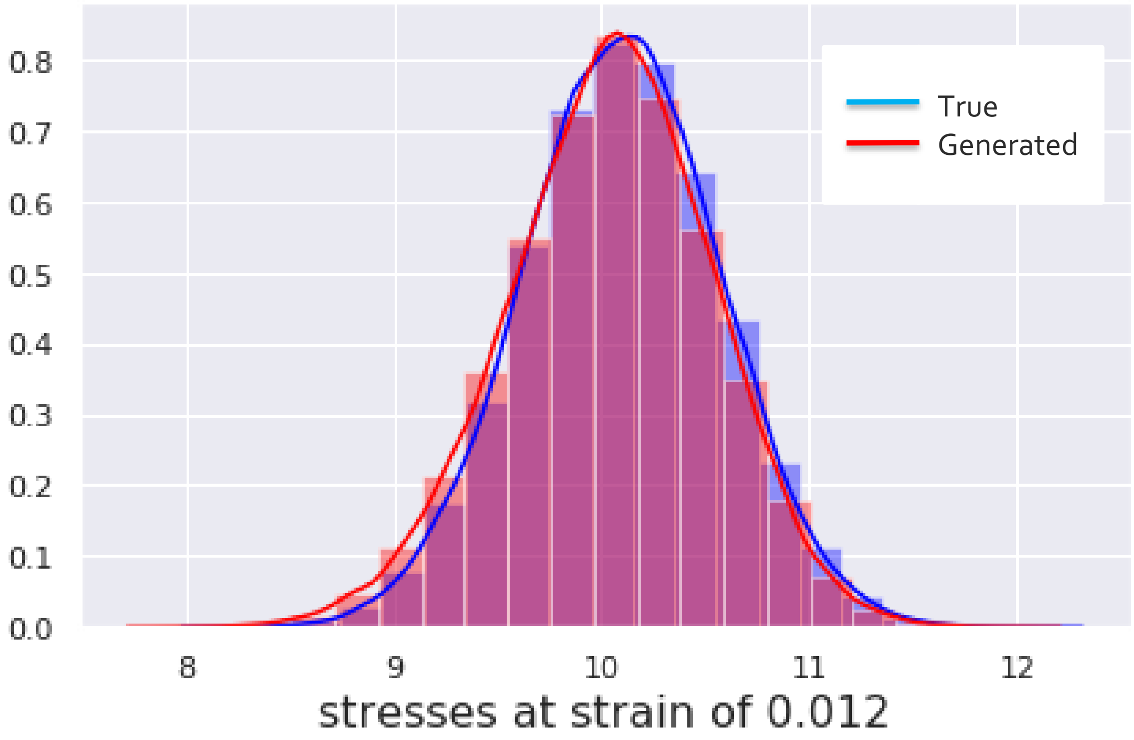




GANS RESULTS (CONT.)





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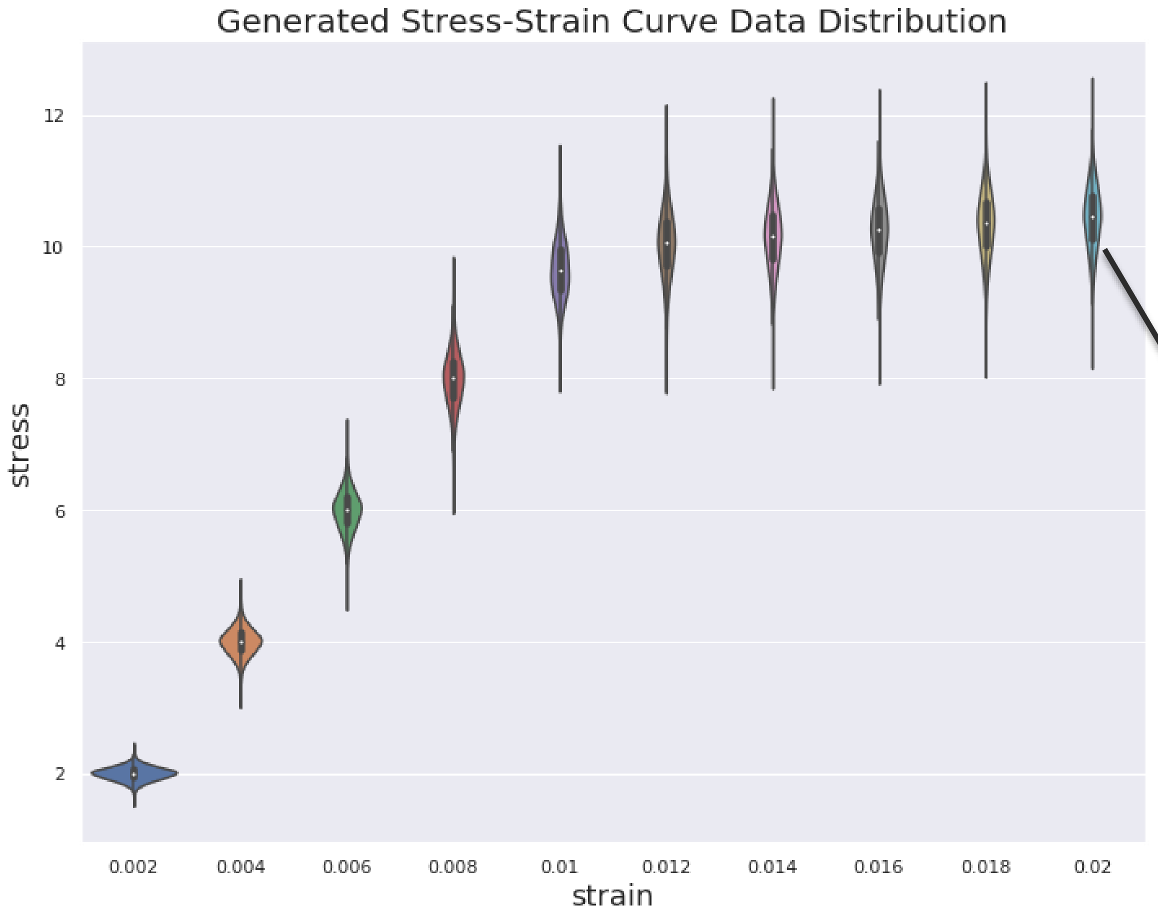
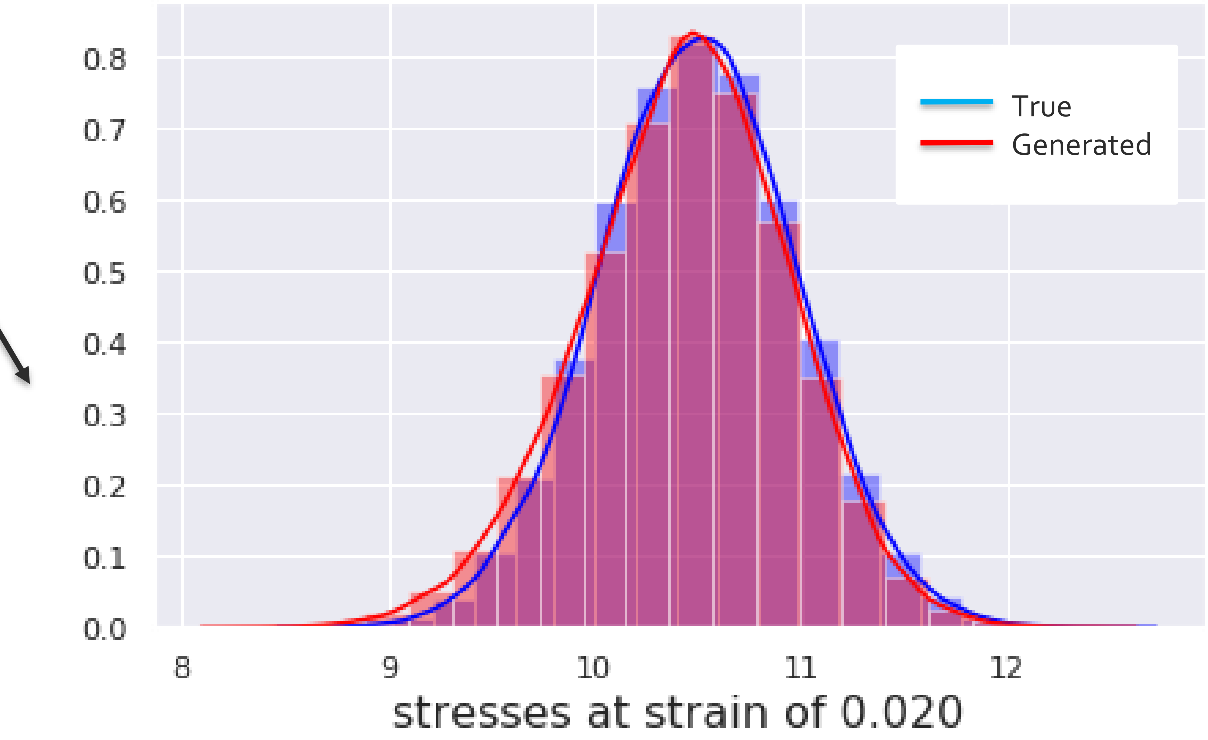




GANS TAKEAWAYS

- Noise dimensions
  - Small number of noise dimensions didn't provide enough degrees of freedom.
- Model dimensions
  - Depends on your problem, but a balance between depth and width is important
- Penalty Coefficient
  - If it's too small, network training is unstable.
- Discriminator Iterations
  - Too many leads to the discriminator overpowering the generator.

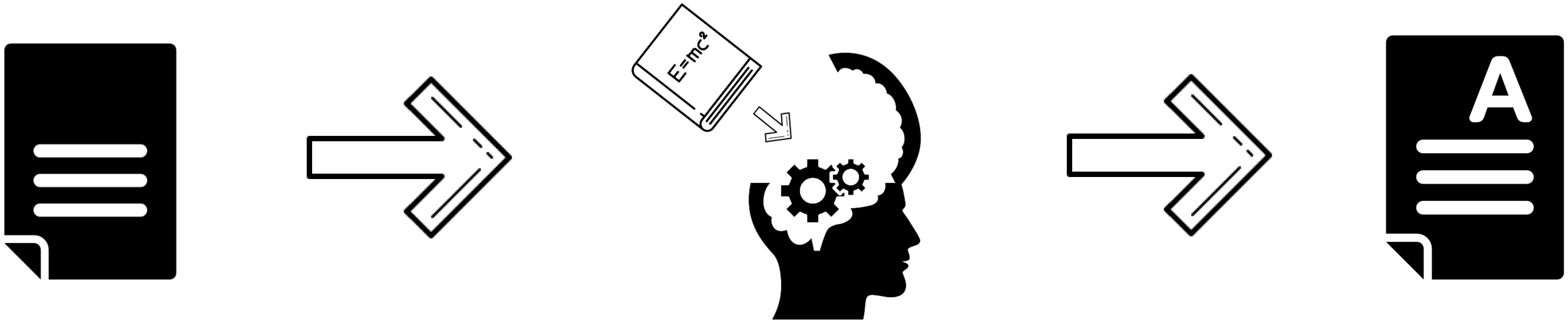
PHYSICS-INFORMED NEURAL NETWORKS

PINNS ARCHITECTURE

- DenseNet
- Custom loss function
  - PINNs encode the physics constraint through the network's loss function:

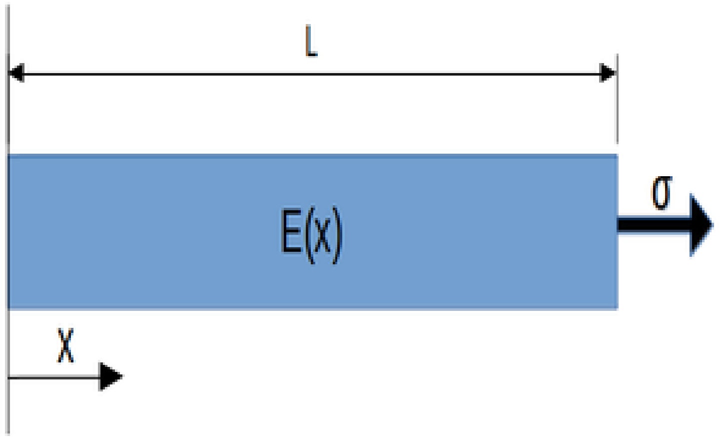
$$Loss = MSE_t + MSE_{t_b} + PDE$$

INTUITION



TEST PROBLEM – MATERIAL IDENTIFICATION

- Estimating material stiffness based on noisy displacement measurement data.
  - L - material length
  - E(x) - stiffness at x
  - σ - stress
  - u(x) - displacement



- ODE:

$$E(x)u'' + E'(x)u' = 0$$

  - Or if σ is known:

$$E(x)u' - \sigma = 0$$

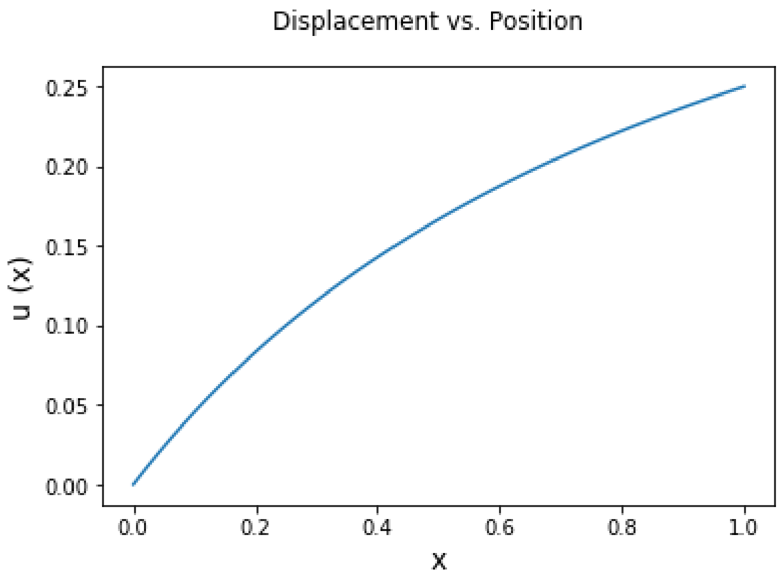
TRAINING DATA

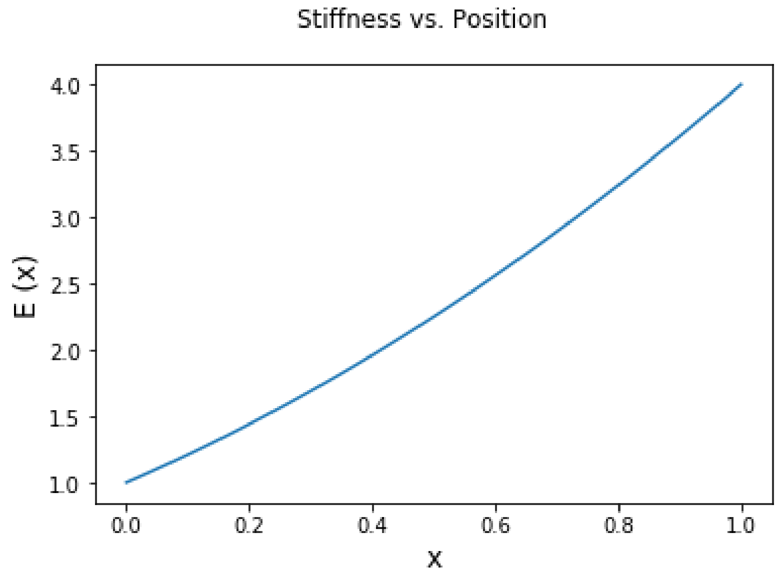
- Boundary Conditions:

$$u(0) = 0$$
$$L = 1$$
$$\sigma = 0.5$$

- Start with known solution of $E(x) = (1+x)^2$

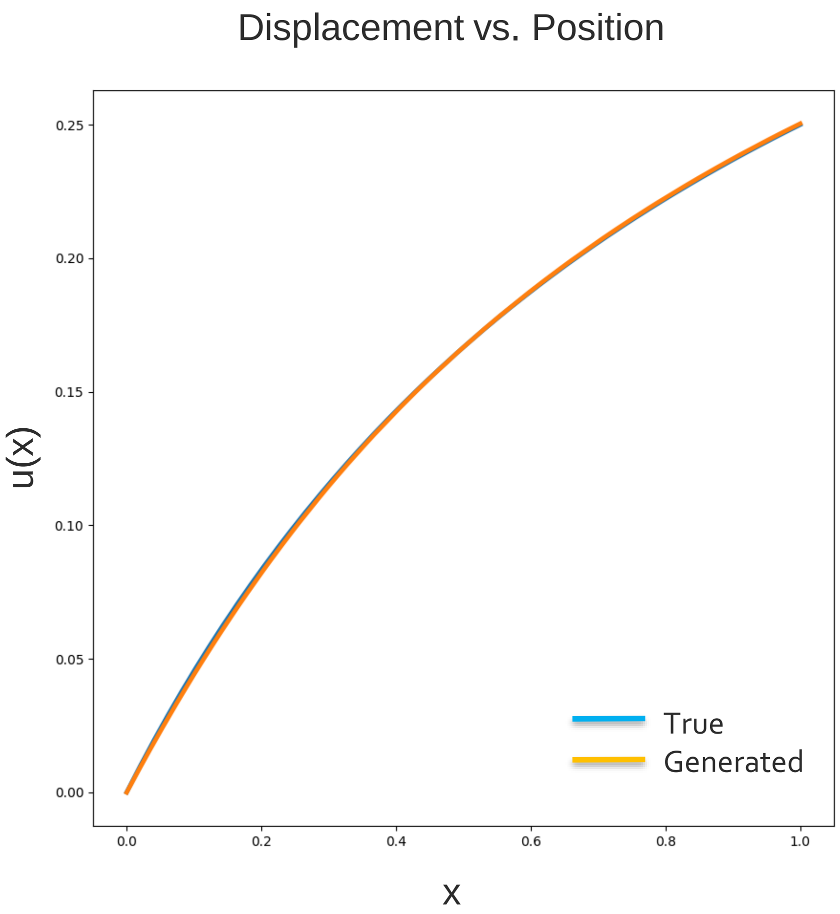
$$E(x)u' - \sigma = 0$$
$$u = \sigma \int \frac{1}{(1+x)^2} = -\frac{\sigma}{(1+x)} + c$$
$$u(0) = 0 \rightarrow c = \sigma$$
$$u_{true} = \sigma(1 - \frac{1}{1+x})$$

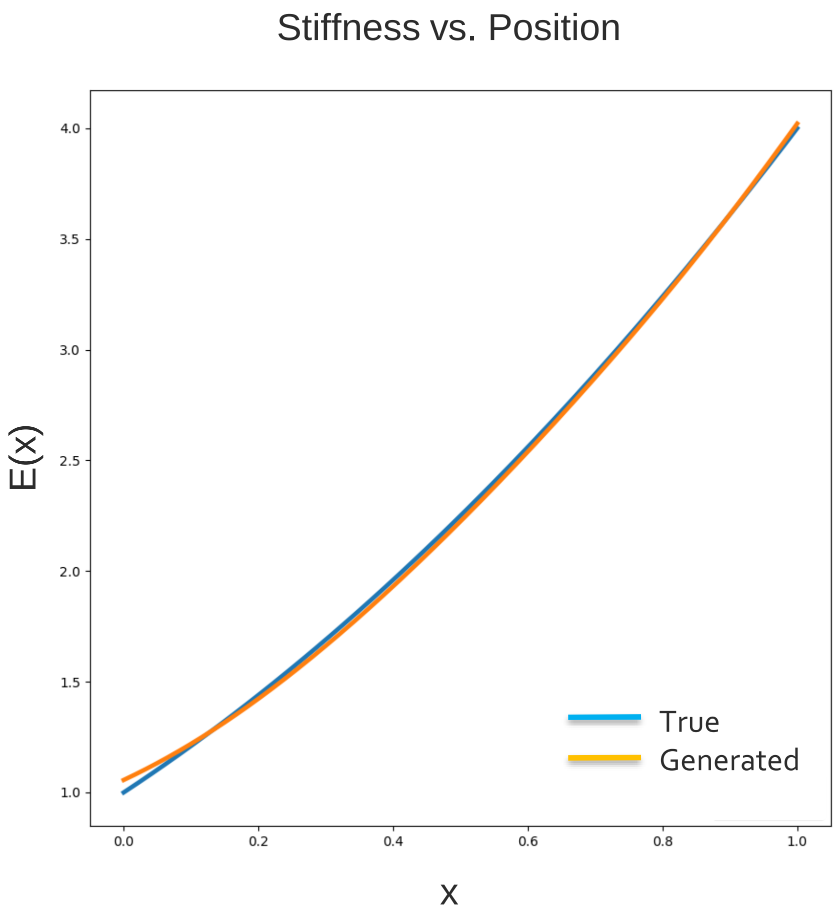




PINNS RESULTS

- 256 measurements at 5% Noise





PINNS TAKEAWAYS

- Can be trained on small datasets.
- Weight initialization might be a problem.
- Vanishing gradients appear often.
- Requires a large number of collocation points to enforce physics constraints.
- ADAM (standard optimizer) might not be optimal.

FUTURE WORK

- PINNs
  - Work on network weight initialization.
  - Look at different optimizers.
  - Look into accuracy metrics.
- Build PI-GAN
- Apply PI-GAN to Digital Image Correlation data.

ACKNOWLEDGEMENTS

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