# Intelligence Augmentation for Aviation-based NDE Data

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# Acknowledgments – Critical Contributors


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- Dr. John Aldrin – Computational Tools
- Mr. David Forsyth – TRI Austin

# Outline

- Motivation / Impact
- Challenges
- Technical Approach
  - Data
  - Algorithms
  - Examples
  - Considerations
- Way Forward / Summary




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# Motivation / Impact

## The potential of Artificial Intelligence / Machine Learning (AI/ML)


**“The Air Force aims to harness and wield the most optimal forms of artificial intelligence to accomplish all mission-sets of the service with greater speed and accuracy”**

**USAF News release, “https://www.af.mil/News/Photos/igphoto/2002319445/”**

# Distilling AI /ML

**AI / ML is, in its simplest form:**

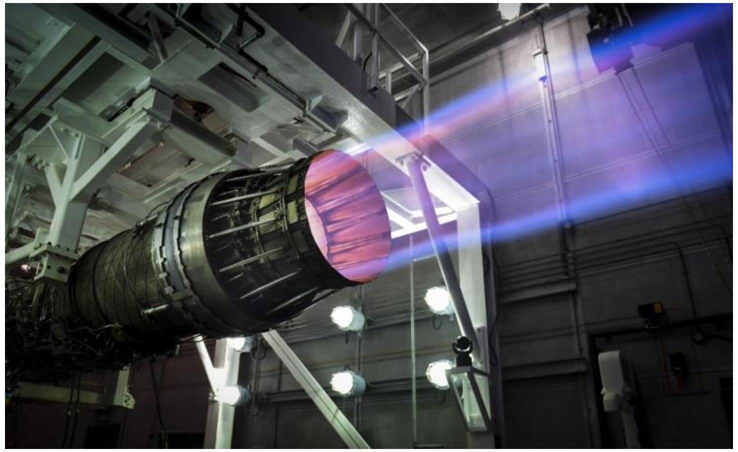
- **Statistical regression**
- **Statistical classification**

**Can be trained:**

- **Supervised**
- **Unsupervised**

**Dependent on:**

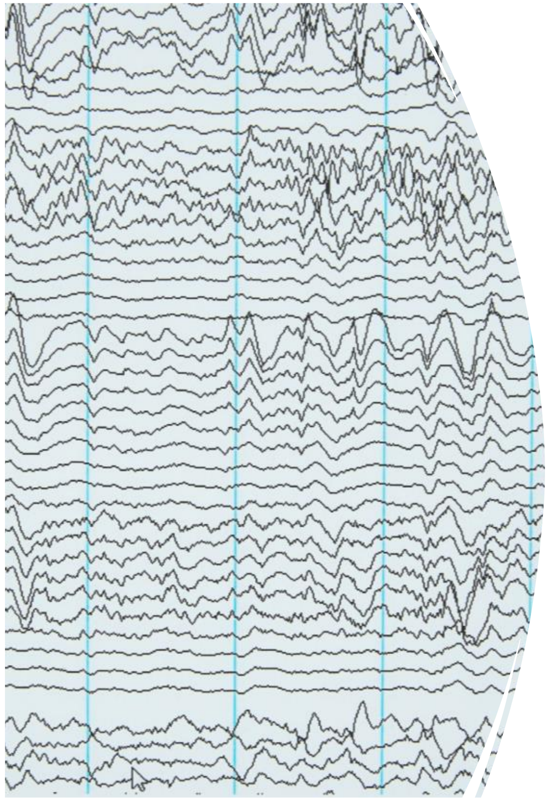
- **Amount of data**
- **Accuracy of data**
- **Noise in data**

# Data Quantity and Noise

## Objective: how does sample size and noise affect accuracy

- **Illustrated with synthetic data for stress intensity factors**
- **Add synthetic Gaussian noise**
  - **Use signal-to-noise ratio to set standard deviation of the noise**
- **Determine mean square error as a function of data quantity**

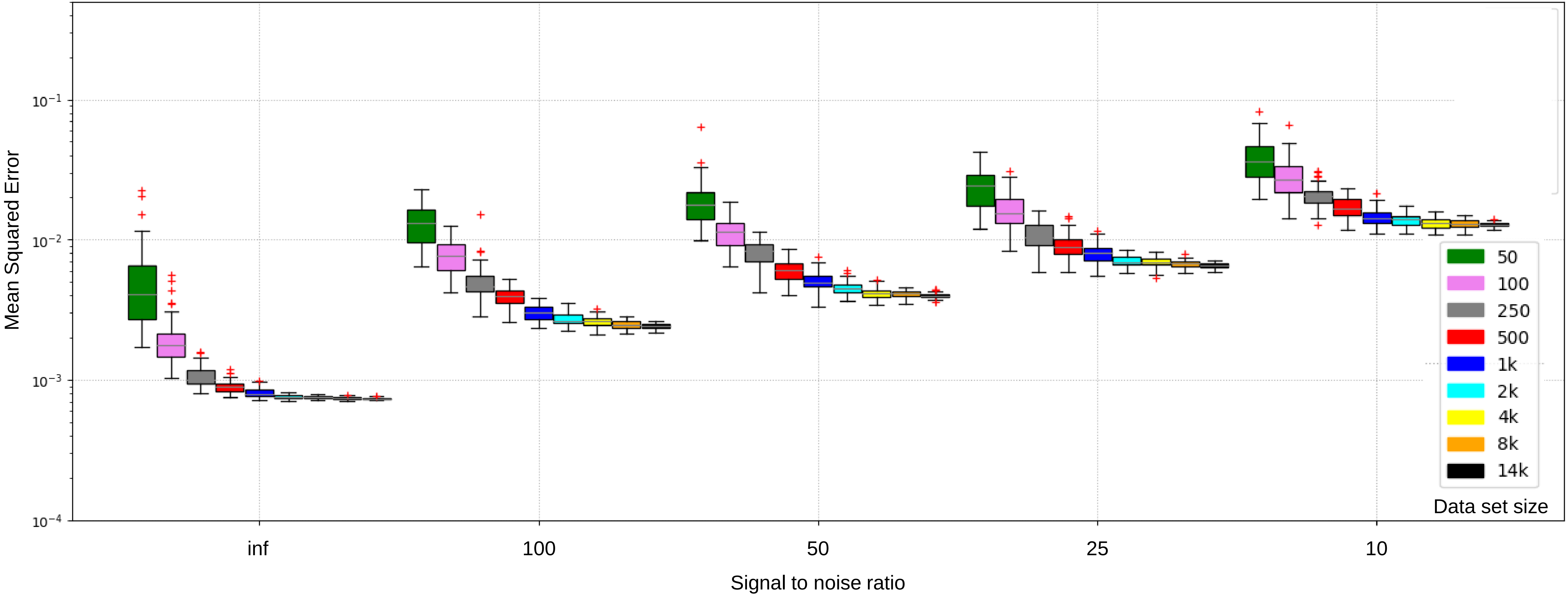


Incorporating noise

# Neural Net Parameters

- Initialization is fixed
  - Minimize learning variations in neural net
- SNR and number of training examples fixed
  - Run 50 times with differing data samples from pool of 15,000 data points
- Multi-layered perceptron
  - Four-layer neural network with 50 layers in each hidden layer
  - Tanh activation in hidden layers, followed by exponential activation in output layer
- Neural Network is trained for 20,000 epochs
  - Early stopping when change in error from one epoch to next drops below 1.0e-8

# Multi-layer Perceptron Results



# Lessons Learned…

- Need the right data
  - Not just more data
  - Independent data from flaws
- Ensure data quality
  - Noise and other factors can confound statistics
- Understand data quantity
  - How much required to obtain desired outcomes
  - Model-based data must be representative
- Define desired precision / accuracy
  - Can you get there from here?

**Algorithms to assist in decisions and diagnostics much more practical**

# Pros and Cons of AI / ML

## Pros:

- Handle Laborious and Repetitive Tasks
- Error Reduction (Complex Tasks)
- Faster Decisions/Actions
- Reduction in Overall Risk
- Act as ‘Digital Assistant’
- Repository for Human ‘Expertise’

## Cons:

- Cannot make decisions well for scenarios not trained
- Lack of Inherent Flexibility / Poor at Judgement Calls
  - e.g. SAS flight 751
- Degradation of Human Skills
- High Cost: Development, Validation
- Lack Moral Values
- Change in Employment

# Back to NDE….

## Data diagnostics outcome depends on function and location:

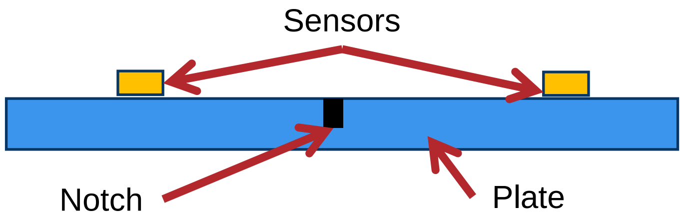
- **Research, manufacturing, and sustainment: differing requirements on accuracy and precision**

AFRL Testing

Representative Manufacturing

Representative Depot Maintenance

# Challenges: Flaw Detection / Characterization

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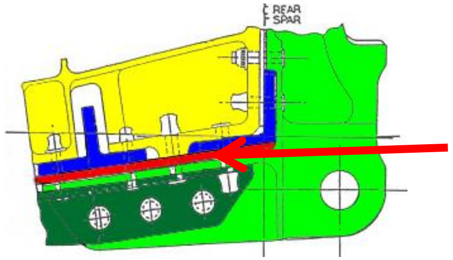



- **Equipment Variability**
- **Structural Complexity / Variability**
  - **From design, manufacturing, repair, modification, maintenance, and usage**
- **Flaw Complexity / Variability**
  - **Stochastic variability (e.g. cracks)**
  - **Microstructural variability**
  - **Scale of flaw to detect**
  - **Boundary Conditions**

- **Validation of Capability**
  - **Required for ASIP / PSIP driven applications**
  - **POD or equivalent**
- **Qualification**
- **Time variance in performance**
  - **Includes durability**
- **Environment**
  - **Temperature, loads, etc.**

**Data variability affects reproducible detection/characterization of flaws**

# Addressing Challenges: Intelligence Augmentation

**Also known as Collaborative Intelligence**

**Integrates three general classes of algorithms:**

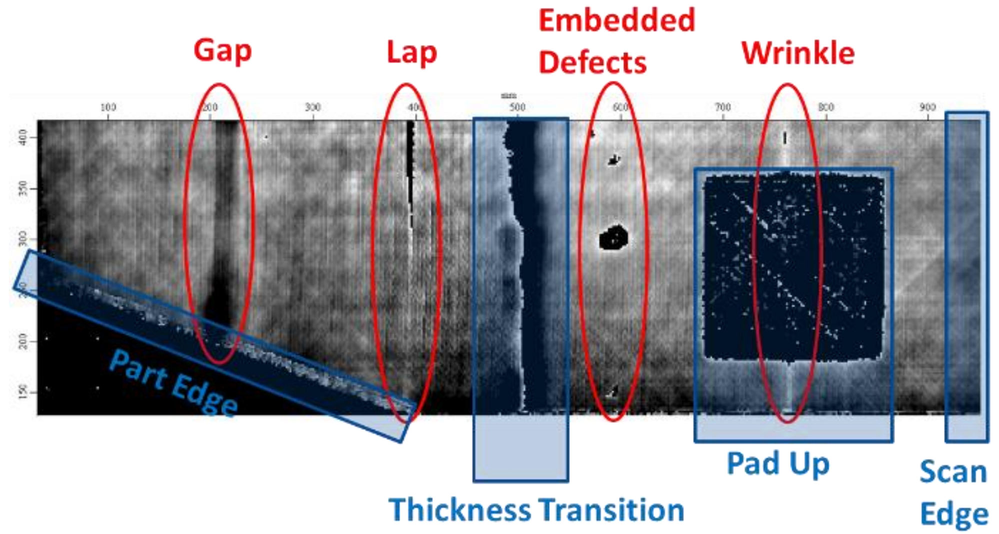
- **Expert / heuristic-based algorithms**
  - **“Rules of the road” to help make decisions**
- **Model-based algorithms**
  - **Mental “what-if” scenarios**
- **AI / ML**
  - **Data-driven experience, aka “lessons learned”**
  - **Data quality is quantified**

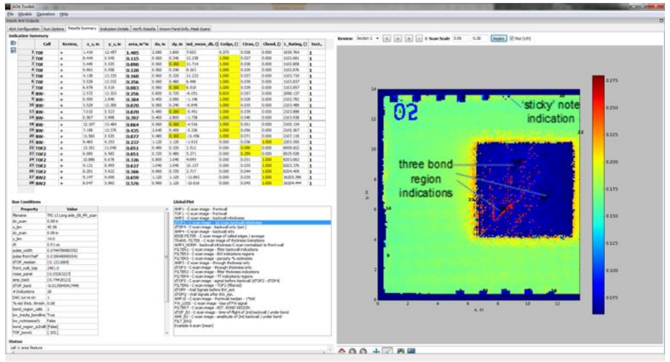
**All three in use today as part of daily life:**

- **Optimal decision making can include two or more**
  - **Depends on circumstances**

Retaining human-in-the-loop

# AFRL Success: Heuristics

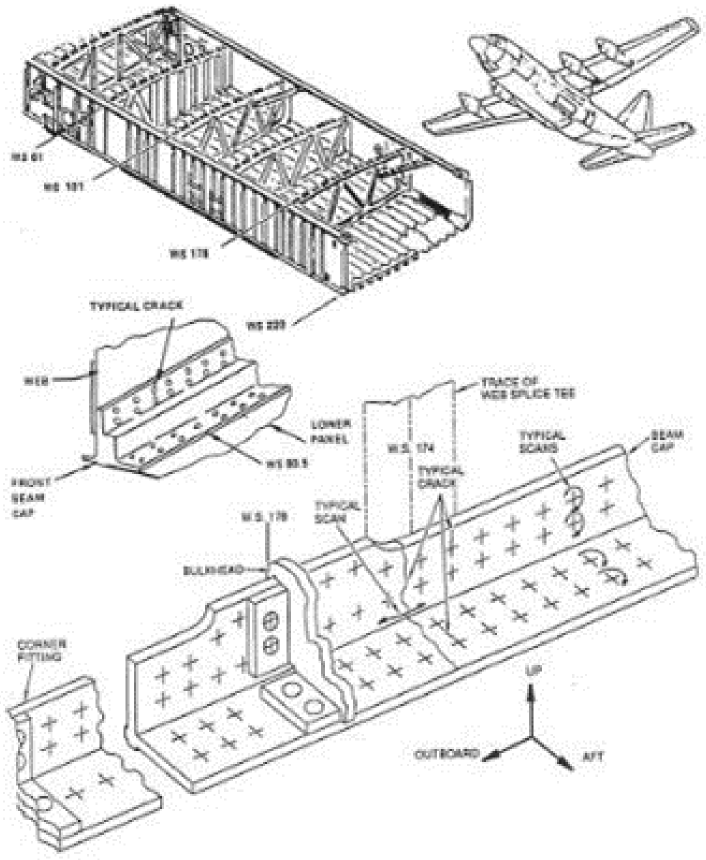



- Assisted Data Analysis (ADA) for ultrasonics of composite panels
  - 100% Ultrasonic inspection for manufacturing QA
- Implement human data review procedures in algorithms
  - Not required for fielded systems: localized inspections only

# AFRL Success: Heuristics and Classification

- **C-130 Lower Forward Spar Cap****
  - **Leveraged C-141 successes**
- **Leaky Rayleigh waves for holes with fasteners installed**
- **Automated analysis of data**
- **Verified by human review**
- **Validated by full POD study**



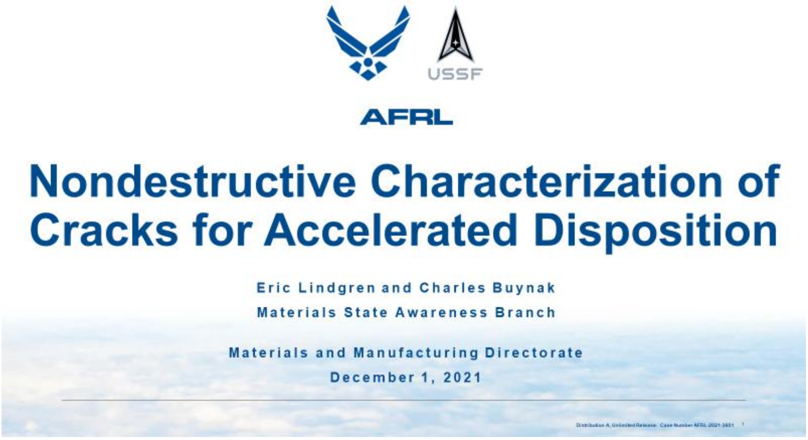


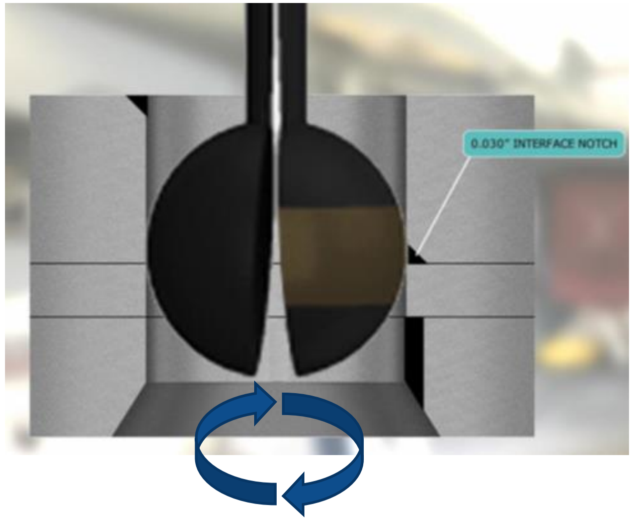
**Lindgren, E., Judd, D., Concordia, M., Mandeville, J., Aldrin, J. C., Spencer, F., Fritz, D., Pratt, E., Waldbusser, R., Mullis, R. T., "Validation and Deployment of Automated Ultrasonic Inspections for the C-130 Center Wing," ASIP Conference, Savannah, Georgia, (December 2 - 4 2004).

# AFRL Progress: Combining All Three

**Presented at 2021 ASIP Conference:**

- Bolt Hole Eddy Current Crack Sizing
    - Depth and length
- Addresses ill-posed inversion – translating impedance plane to crack dimensions
- Accuracy: within 8.5% of actual depth
    - Mitigated all equipment / sensor variability
    - Within bounds of first oversize
    - Enables one-step disposition
- Next step: address structural variability
- Enhances risk management, including unexpected cracks



# Way Forward – IA for USAF NDE Data

- **Enhance understanding of impact of data variability**
  - **Synthetic and real (when available) data to quantify impact**
  - **Consider quantity, quality, accuracy, precision**
- **Integrate variability into diagnostic algorithms**
  - **Sensitivity analysis to provide answer with statistical metrics of accuracy**
  - **Develop mitigation for factors with greatest impact**
- **Integrate at least two of three approaches**
  - **Heuristics, model-based, and data AI/ML-driven**
- **Develop capability to address multiple material systems**
- **Validate on representative challenge problems**
- **Integrate into architecture of next gen NDE analytics**

# Summary

- **AI / ML requires large data sets**
  - **Consider data quantity, quality, variability, and noise**
- **Sparseness and variability in engineering data challenge current analytical methods**
  - **NDE data diagnostics must detect outliers and nuances**
- **Optimal assisted diagnostic algorithms for NDE include at least two: heuristics, model-based, and data-driven**
- **AFRL has history of developing and transitioning NDE data diagnostic algorithms**
- **Lessons learned from NDE diagnostics relevant for all engineering data – must have all attributes of data to enable optimal decisions**

# Discussion

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*Caelum Domenari*



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