Damage Detection for Structural Health Monitoring under Uncertainty using Deep Interval Neural Networks

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Presentation Outline

- Part I: Introduction
    - Interval Deep Neural Network algorithms
- Part II: Structural Health Monitoring under Uncertainty
    - Damage identification for structural health monitoring applications
- Part III: Conclusion

Part I

Motivations and Broader Impact

Goal:

(1) Predict damage in SHM using DINN with real-time capabilities.

(2) Make DINN more compatible with DNN architectures and training methods.

(3) Safer AI.

Application: Structural Health Monitoring (SHM)

Photo credit: Kai Friis
Animation credit: David Betancourt

Deep Neural Networks → Function Approximation

- A function approximation model, also known as curve estimation or regression model, is generally defined as

Predictions

Parameters

$$Y = f(X;\theta) + \varepsilon$$

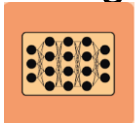
noise

Model

Inputs (observations)

- Deep neural networks act as the function approximation model, which is oftentimes needed to solve engineering problems.

$$f(X;\theta) =$$



DNN

Deep Interval Neural Network

Deep Interval Neural Network (DINN)

- DINN is a predictive model *F*. In regression setting:

  $$F : [\underline{X}, \overline{X}] \rightarrow [\underline{Y}, \overline{Y}] \in \mathbb{IR}$$

- Classification setting:

  $$F : [\underline{X}, \overline{X}] \rightarrow y \in \{1, \ldots, C\}$$

- To find the optimal parameter of the DINN (i.e. *training*):
  - Need a training dataset with *n* examples.
  - Each example has *d* dimensionality

- Learning of function **Y** by minimizing a loss (error) function $\mathcal{L}(\hat{F}(\mathbf{X}_i), \mathbf{Y}_i; \mathbf{W})$
  - Mean Square Error for regression, cross-entropy loss (monotonic and gradient is Lipschitz!)

DINN: training set (classification setting)

$$\mathcal{T} = \{(\mathbf{X}_1, y_1), \ldots, (\mathbf{X}_n, y_n)\}$$

Features

labels

	$\mathbf{X}_{i,1}$	$\mathbf{X}_{i,2}$	...	$\mathbf{X}_{i,d}$	$\mathbf{Y}_i$	**y_i**
example 1	[100.2, 110.3]	[250.1, 268.8]	...	[83.4, 85.7]	[31,33.1]	'green'
example 2	[93.7, 95.1]	[260.1, 271.1]	...	[72.1, 73.7]	[25.1, 26.7]	'blue'
...	...	...	...	...	...	...
example n	[85.3, 88.1]	[240.4, 255.7]		[78.8, 79.6]	[35.1, 36.1]	'blue'

$$\mathbf{X} \in \mathbb{R}^{n \times d} \qquad y_i \in \{1, \ldots, C\}$$

Mini-batch SGD

- Optimization is done via stochastic gradient descent
  - Update rule:

$$\mathbf{W}_{k+1}^{(l)} = \mathbf{W}_k^{(l)} - \alpha_k \nabla_{\mathbf{W}_k^{(l)}} \mathcal{L}(\hat{F}(\mathbf{X}_i), \mathbf{Y}_i)$$

- Also:
  - SGD + momentum: accounts for past gradients
  - Interval Adam: Adaptive

Interval Adam

- Adaptive learning rate

Algorithm 3: Adam Algorithm for Interval Input

Input: Step size α

Input: Decay rates $\beta_1, \beta_2 \in [0, 1)$

Input: Initial parameters $\mathbf{W} \in \mathbb{IR}$

Initialize $\mathbf{m}_0 \in \mathbb{IR} = 0$

Initialize $v_0 \in \mathbb{R} = 0$

Initialize $k = 0$

while *stopping criteria not met* **do**

$k \leftarrow k + 1$

$\mathbf{G}_k \leftarrow \nabla_{\mathbf{W}} \mathcal{L}_k$ compute interval gradients at step k

$\mathbf{m}_k \leftarrow \beta_1 \mathbf{m}_{k-1} + (1 - \beta_1)\mathbf{G}_k$ biased interval first moment estimate (interval)

$v_k \leftarrow \beta_2 v_{k-1} + (1 - \beta_2) \cdot \texttt{mid}(\mathbf{G}_k)^2$ biased real second moment estimate (real)

$\widehat{\mathbf{m}}_k \leftarrow \mathbf{m}_k / (1 - \beta_1^k)$

$\widehat{v}_k \leftarrow v_k / (1 - \beta_2^k)$

$\mathbf{W}_k \leftarrow \mathbf{W}_{k-1} - \alpha \cdot \widehat{\mathbf{m}}_k / (\sqrt{\widehat{v}_k} + \epsilon)$

return $\mathbf{W}_k$

Regularization

- Prevents overfitting
- Stabilizes solution
  - Very important for intervals
- Currently using L1 and L2 regularization

Part III

Structural Health Monitoring (SHM) applications

SHM Tasks

- SHM tasks:
    - **Damage detection: detect whether damage exists.**
    - Damage localization
    - **Damage Type**
    - Damage Severity
    - Damage Prognosis: remaining useful lifeline

SHM methodologies

- Two general methodologies:
- 1) Solid mechanics-based using FEM and vibration analysis
  - Inverse problem: compare FEM with damage thresholds.
  - SHM analysis type: Inherently post-hoc or even forensic.
  - Costly!
- 2) Data-driven
  - Mainly machine learning.
  - Nowadays mainly deep learning.
  - SHM analysis type: real-time and predictive.
  - Less costly than solid-mechanics based.

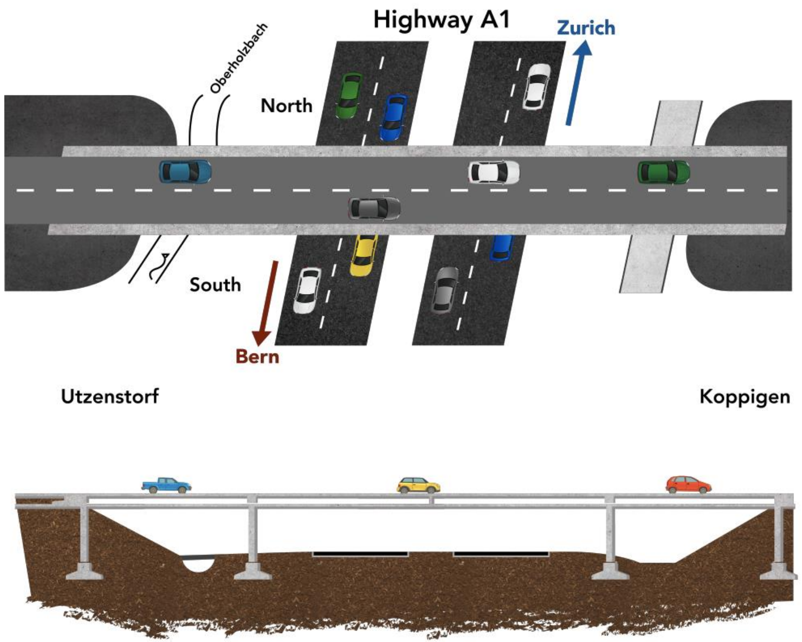
SHM methodologies

- Main paradigm in literature still solid-mechanics based.
- Why?
  - Researchers in SHM are more well-versed with structural mechanics techniques.
  - Lack of data.
  - Lack of labeled data.
  - Lack of “machine-learning ready” data.
- The impact of not using data-driven methods in SHM:
  - Not monitoring our public infrastructure in real-time
  - Higher costs of projects
  - Less quality of projects.
  - Less idea of useful prognosis.

SHM Experiments

- Z24 bridge dataset
- 3-span continuous post-tensioned concrete box girder bridge.
  - Main span: 30 m and two side spans of 14 m each.
- Demolished in 1998 under an SHM program.
  - Reason for demolition was that a wider bridge was required to support a railway.
- Two SHM sub-programs ran for nearly a year.
- First sub-program conducted continuous monitoring to quantify environmental effects on bridge dynamics.
- Second sub-program was conducted during the month prior to demolition. Consisted of 15 induced damage scenarios. Monitored with 33 sensors in different set-ups.

SHM Experiments: Z24 Bridge



SHM Experiments: Training Data

“normal”

#	Date	Scenario	#	Date	Scenario
1	04.08.98	1. Reference measurements	10	26.08.98	Chipping of concrete 24 m²
2	09.08.98	2. Reference measurements	11	27.08.98	Landslide
3	10.08.98	Settlement of pier, 20 mm	12	31.08.98	Concrete hinges
4	12.08.98	Settlement of pier, 40 mm	13	02.09.98	Failure of anchor heads
5	17.08.98	Settlement of pier, 80 mm	14	03.09.98	Anchor heads #2
6	18.08.98	Settlement of pier, 95 mm	15	07.09.98	Rupture of tendons #1
7	19.08.98	Tilt of foundation	16	08.09.98	Rupture of tendons #2
8	20.08.98	3. Reference measurements	17	09.09.98	Rupture of tendons #3
9	25.08.98	Chipping of concrete 12 m²			

“damaged”

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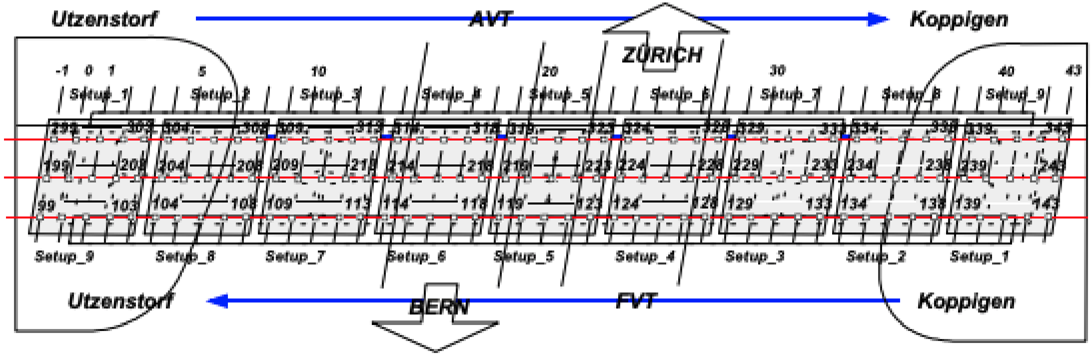
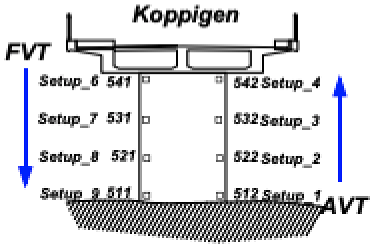
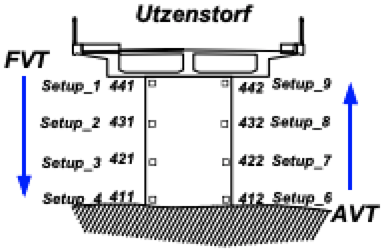
SHM Experiments



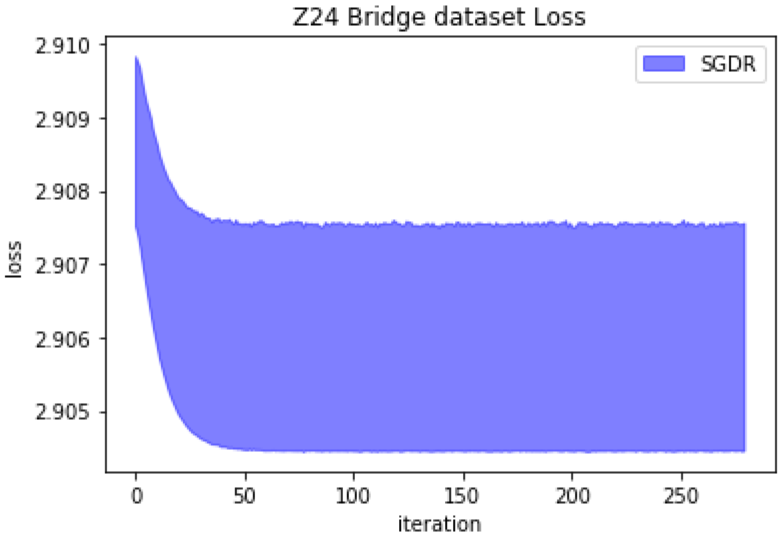




SHM Damage Detection

- Using labeled dataset. 50% normal, 50% damaged.
- 21 sensor readings = 21 features.
- Binary classification task.
- Uncertainty quantification. 2 settings:
    - 10% uncertainty level for 1 feature and 1% for all other features.
    - 10% uncertainty level for 1 feature and 5% for all other features
- DINN model:
    - 2 hidden layers (500,500), batch size = 2048, split 60/10/30, 300 epochs
    - Used Interval Adam (initial *lr* = 5e-5) and SGD with cosine decay with warm restarts (SGDR) with initial *lr* = 1e-3.
    - Learning rate annealing is key!

SHM Experiments: Damage Detection



Submitted to REC 2021

SHM Experiments: Damage Detection

Table 5.1: Z24 test set results

Accuracy			
{ 1%, 10%}		{5%, 10%}	
SGDR	I-Adam	SGDR	I-Adam
95.8%	85.3%	90.6%	72.2%

High accuracy even under a somewhat wide interval.

Adam is too ambitious for this task! Overfits to training set.

Conclusion

- Deep Interval Neural Network was developed in the classification setting for damage detection.

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Thank you!

Questions?