The National Academies of
SCIENCES · ENGINEERING · MEDICINE

TRANSPORTATION RESEARCH BOARD

Using Artificial Intelligence to Predict Deterioration of Highway Bridges

February 22, 2021

@NASEMTRB
#TRBwebinar

PDH Certification Information:

- 1.5 Professional Development Hour (PDH) – see follow-up email for instructions
- You must attend the entire webinar to be eligible to receive PDH credits
- Questions? Contact Reggie Gillum at RGillum@nas.edu

The Transportation Research Board has met the standards and requirements of the Registered Continuing Education Providers Program. Credit earned on completion of this program will be reported to RCEP. A certificate of completion will be issued to participants that have registered and attended the entire session. As such, it does not include content that may be deemed or construed to be an approval or endorsement by RCEP.

RCEP
REGISTERED CONTINUING EDUCATION PROGRAM

#TRBwebinar

Learning Objectives

1. Identify current applications of AI in highway asset management
2. Identify emerging sensing and analytical technologies
3. Discuss future applications of AI in highway asset management

#TRBwebinar

All images source: FHWA.

OFFICE OF RESEARCH, DEVELOPMENT, AND TECHNOLOGY

ARTIFICIAL INTELLIGENCE (AI) OPPORTUNITIES IN HIGHWAY INFRASTRUCTURE

TRB Webinar

Hoda Azari, Ph.D.
Non-Destructive Evaluation (NDE) Research Program Manager
Office of Infrastructure Research and Development (R&D)
Federal Highway Administration (FHWA)

February 22, 2021

U.S. Department of Transportation
Federal Highway Administration

TURNER-FAIRBANK
Highway Research Center

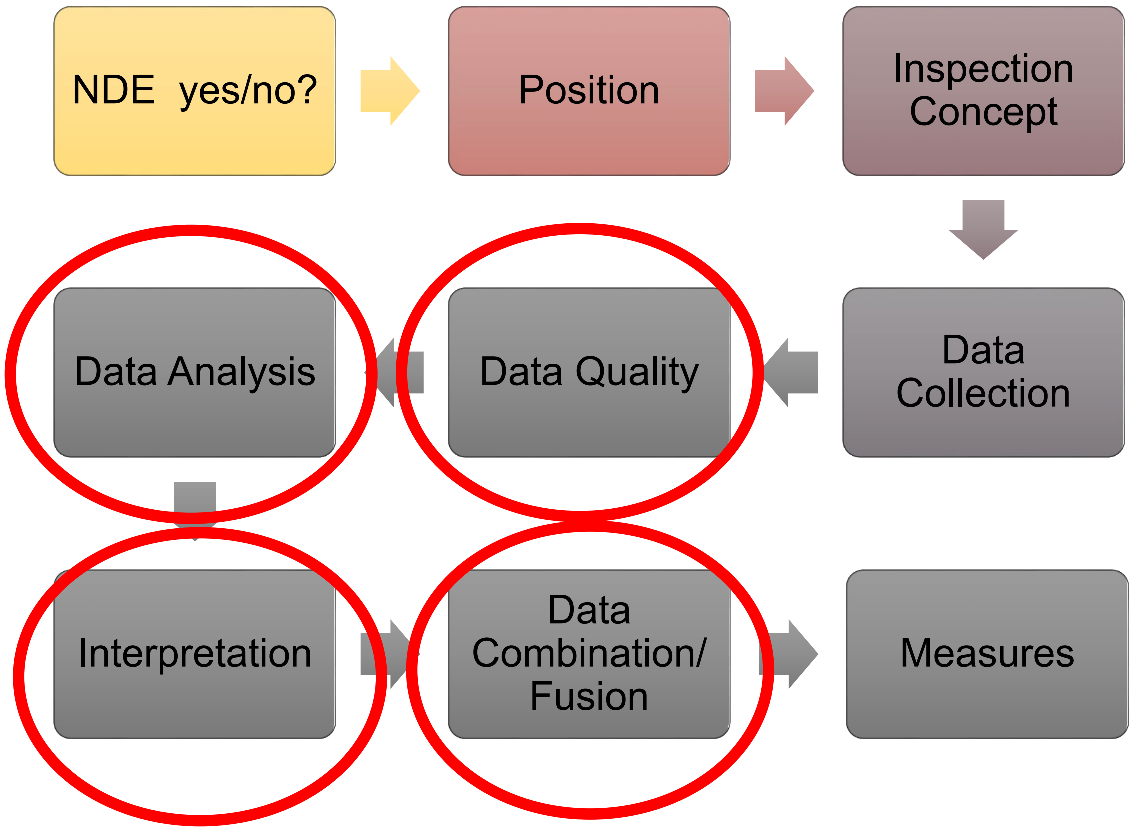
KEY STRENGTHS OF AI

- Allows ever-larger datasets to be processed
- Unveiling hidden correlations
- Automated way of extracting knowledge/information from data, differing from traditional scientific approaches
- Automated decision making

Source: iStock.com/monsitj.

AI POTENTIAL FOR NDE

- Automatically process massive NDE data
- Automate identification of hidden defects and damages
- Automate condition assessment
- What aspects can be assisted by AI?



CHALLENGES

- Along the entire process, expert decisions necessary
- Application of AI requires ground truth data
- Labor intensive to label data
- Identification of the most suitable learning models and optimization methods to process NDE data

CURRENT FOCUS

- Multimodal data fusion
- Forecast future NDE condition maps based on NDE map time series (tumor growth)
- Reproduce a NDE scan based on those from other modalities (reproduce MRI from X-ray)
- Develop Long Term Performance Prediction Models

CONTACTS

Hoda Azari

Hoda.Azari@dot.gov

Source: FHWA.

Artificial Intelligence (AI) in highway asset management

Transportation Research Board Webinar

Using Artificial Intelligence to Predict Deterioration of Highway Bridges

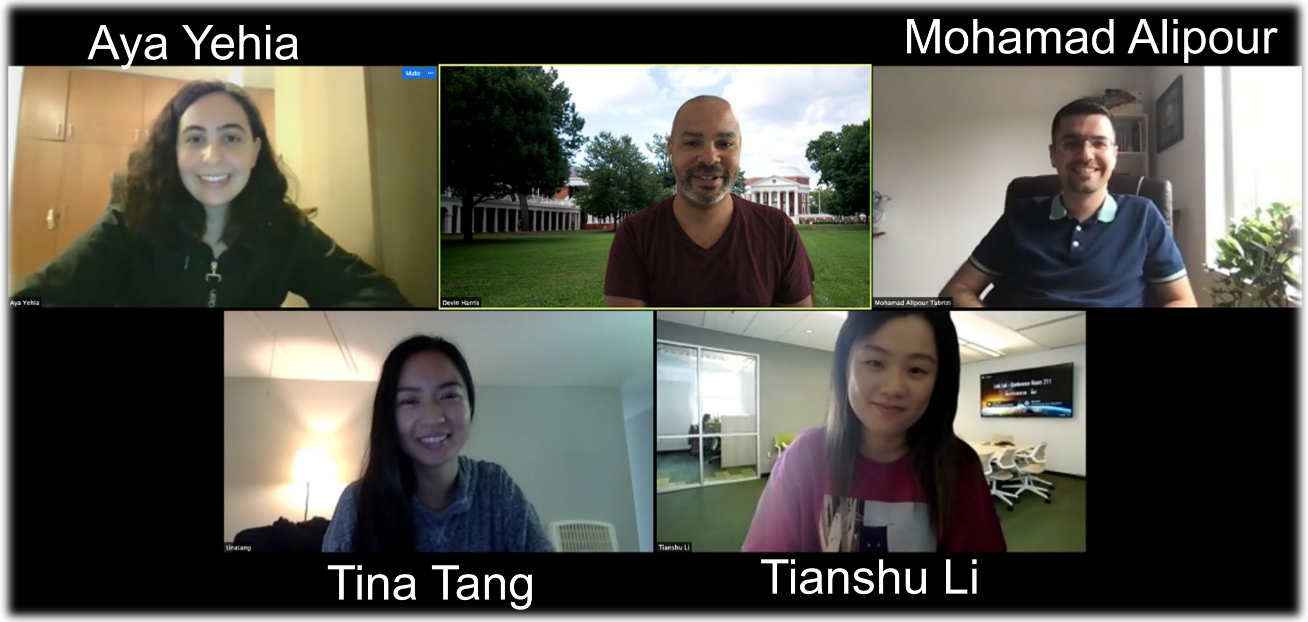
February 22, 2021

Devin K. Harris, Ph.D. – Associate Professor
Tianshu Li – Graduate Research Assistant
Mohamad Alipour Ph.D. – Former Graduate Research Assistant
Department of Engineering Systems and Environment
University of Virginia

MOB Lab @ the University of Virginia

Mobile Laboratory for Rapid Evaluation of Transportation Infrastructure (MOB Lab)

- Efficient methods to evaluate the performance of the built environment
- Understanding linkages between condition state and performance
- Minimal disruption of operations or service



Our Motivation

Transportation infrastructure systems represent the lifeblood of our economy, yet these systems are aging and are in a general state of disrepair.

- Tragic failures brought the challenges associated with the safety of national infrastructure to forefront of public scrutiny.

I-35, Minnesota (2007)

I-5, Washington (2013)

M bridge, Missouri (2013)

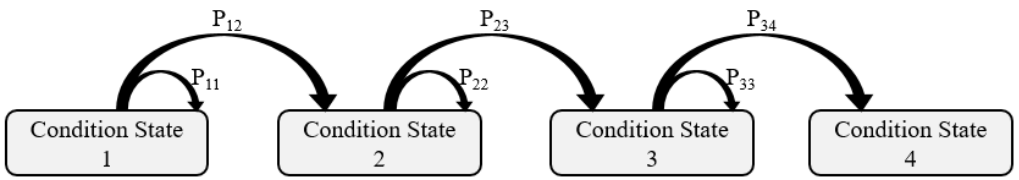
- ***Asset management*** represents a framework that describes systems to manage the infrastructure assets we already have in service (i.e. roads, bridges, ancillary structures, etc.) and plan for future assets.

State of Transportation Infrastructure…Bridges

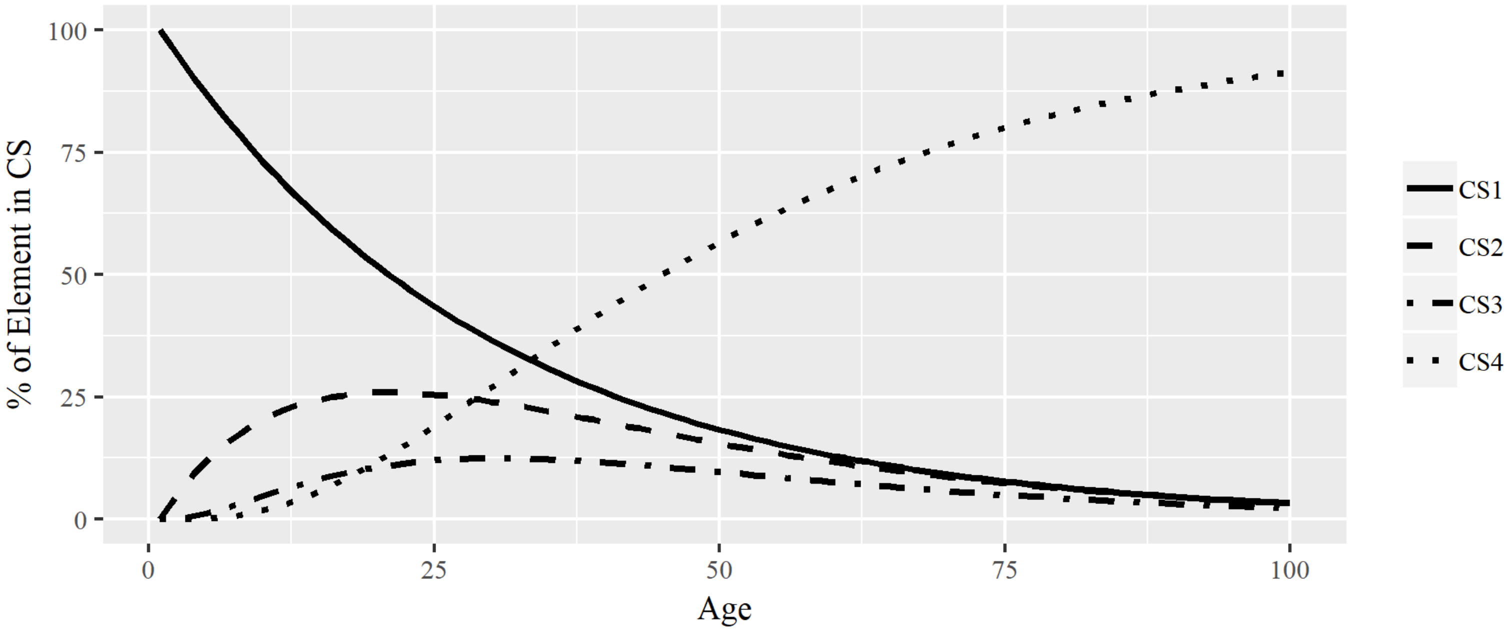
- Our infrastructure suffers from various sources of in-service degradations and these mechanisms remain as one of the greatest challenge for managing agencies (DOTs)
- To ensure safe, cost-effective, and reliable structures owners must understand the conditions that a structure experiences and the effects of condition on performance.
  - For many infrastructure systems, these decisions are often informed by inspections and the human-based observations derived from the inspection process.
  - **For Bridges**: Biennial inspections are required, which include documentation/verification of critical asset information and observation/measurement of condition state according to National Bridge Inspection Standards (NBIS)
    - General condition ratings
    - Element condition ratings
    - Load ratings*
- Much of the data is submitted to FHWA for inclusion in National Bridge Inventory (NBI) database
  - Principal use of the NBI is to determine the eligibility for and the amount of appropriation for funding the infrastructures in the National Bridge Program administered by FHWA

What do we currently do with this data?

- Condition data is used by state agencies (DOTs) to forecast future condition
  - Forecasting approaches rely on historical data to allocate **future expenditures**
  - While modeling is mathematical, much of this forecasting relies on heuristic knowledge



Predicted transition probabilities from one condition state to the next



How Might We Use the Data in New Ways?

Inspection reports are ripe with data (**untapped** and **passive**) that goes unused

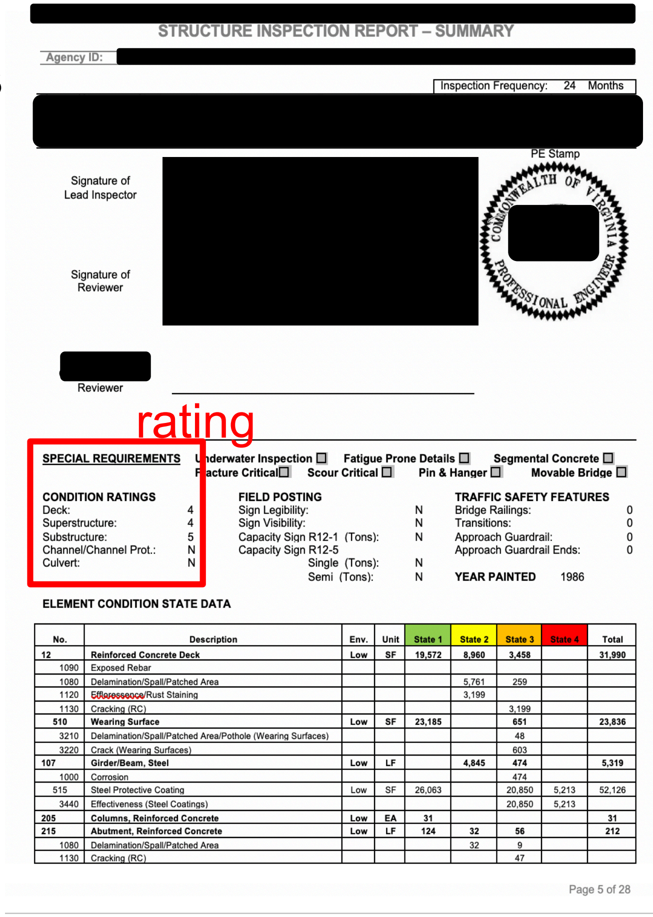
- Images of condition state
- Detailed narratives on condition states

What information can be extracted?

- Expert observations from ***trained*** and ***experienced*** inspectors
- Long history of detailed record collection

How can information it be extracted?

- Advances in Artificial Intelligence (AI)
  - Visual recognition (imagery)
  - Natural Language Processing (text)



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STRUCTURE INSPECTION REPORT – SUMMARY

Agency ID: [redacted]

Inspection Frequency: 24 Months

[redacted]

Signature of Lead Inspector [redacted]

PE Stamp

COMMONWEALTH OF VIRGINIA [redacted] PROFESSIONAL ENGINEER

Signature of Reviewer

[redacted]

Reviewer

rating

SPECIAL REQUIREMENTS Underwater Inspection ☐ Fatigue Prone Details ☐ Segmental Concrete ☐ Fracture Critical ☐ Scour Critical ☐ Pin & Hanger ☐ Movable Bridge ☐

CONDITION RATINGS
Deck: 4
Superstructure: 4
Substructure: 5
Channel/Channel Prot.: N
Culvert: N

FIELD POSTING
Sign Legibility: N
Sign Visibility: N
Capacity Sign R12-1 (Tons): N
Capacity Sign R12-5
Single (Tons): N
Semi (Tons): N

TRAFFIC SAFETY FEATURES
Bridge Railings: 0
Transitions: 0
Approach Guardrail: 0
Approach Guardrail Ends: 0

YEAR PAINTED 1986

ELEMENT CONDITION STATE DATA

No.	Description	Env.	Unit	State 1	State 2	State 3	State 4	Total
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1090	Exposed Rebar							
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3210	Delamination/Spall/Patched Area/Pothole (Wearing Surfaces)					48		
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1000	Corrosion					474		
515	Steel Protective Coating	Low	SF	26,063		20,850	5,213	52,126
3440	Effectiveness (Steel Coatings)					20,850	5,213	
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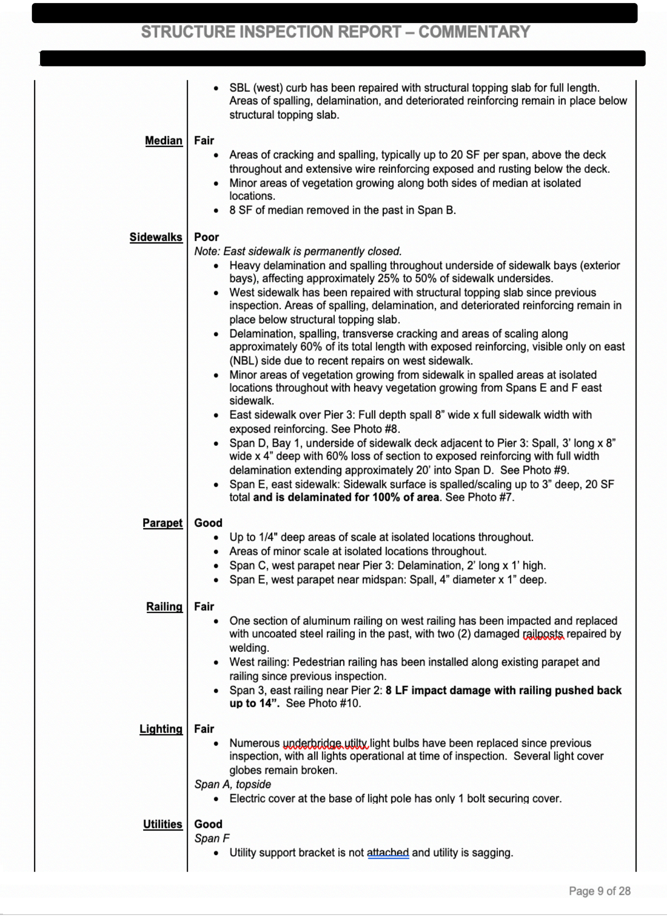
Page 5 of 28



[redacted]

STRUCTURE INSPECTION REPORT – COMMENTARY

[redacted]

- SBL (west) curb has been repaired with structural topping slab for full length. Areas of spalling, delamination, and deteriorated reinforcing remain in place below structural topping slab.

Median **Fair**
- Areas of cracking and spalling, typically up to 20 SF per span, above the deck throughout and extensive wire reinforcing exposed and rusting below the deck.
- Minor areas of vegetation growing along both sides of median at isolated locations.
- 8 SF of median removed in the past in Span B.

Sidewalks **Poor**
Note: East sidewalk is permanently closed.
- Heavy delamination and spalling throughout underside of sidewalk bays (exterior bays), affecting approximately 25% to 50% of sidewalk undersides.
- West sidewalk has been repaired with structural topping slab since previous inspection. Areas of spalling, delamination, and deteriorated reinforcing remain in place below structural topping slab.
- Delamination, spalling, transverse cracking and areas of scaling along approximately 60% of its total length with exposed reinforcing, visible only on east (NBL) side due to recent repairs on west sidewalk.
- Minor areas of vegetation growing from sidewalk in spalled areas at isolated locations throughout with heavy vegetation growing from Spans E and F east sidewalk.
- East sidewalk over Pier 3: Full depth spall 8" wide x full sidewalk width with exposed reinforcing. See Photo #8.
- Span D, Bay 1, underside of sidewalk deck adjacent to Pier 3: Spall, 3' long x 8" wide x 4" deep with 60% loss of section to exposed reinforcing with full width delamination extending approximately 20' into Span D. See Photo #9.
- Span E, east sidewalk: Sidewalk surface is spalled/scaling up to 3" deep, 20 SF total **and is delaminated for 100% of area**. See Photo #7.

Parapet **Good**
- Up to 1/4" deep areas of scale at isolated locations throughout.
- Areas of minor scale at isolated locations throughout.
- Span C, west parapet near Pier 3: Delamination, 2' long x 1' high.
- Span E, west parapet near midspan: Spall, 4" diameter x 1" deep.

Railing **Fair**
- One section of aluminum railing on west railing has been impacted and replaced with uncoated steel railing in the past, with two (2) damaged railposts repaired by welding.
- West railing: Pedestrian railing has been installed along existing parapet and railing since previous inspection.
- Span 3, east railing near Pier 2: **8 LF impact damage with railing pushed back up to 14".** See Photo #10.

Lighting **Fair**
- Numerous underbridge utilty light bulbs have been replaced since previous inspection, with all lights operational at time of inspection. Several light cover globes remain broken.

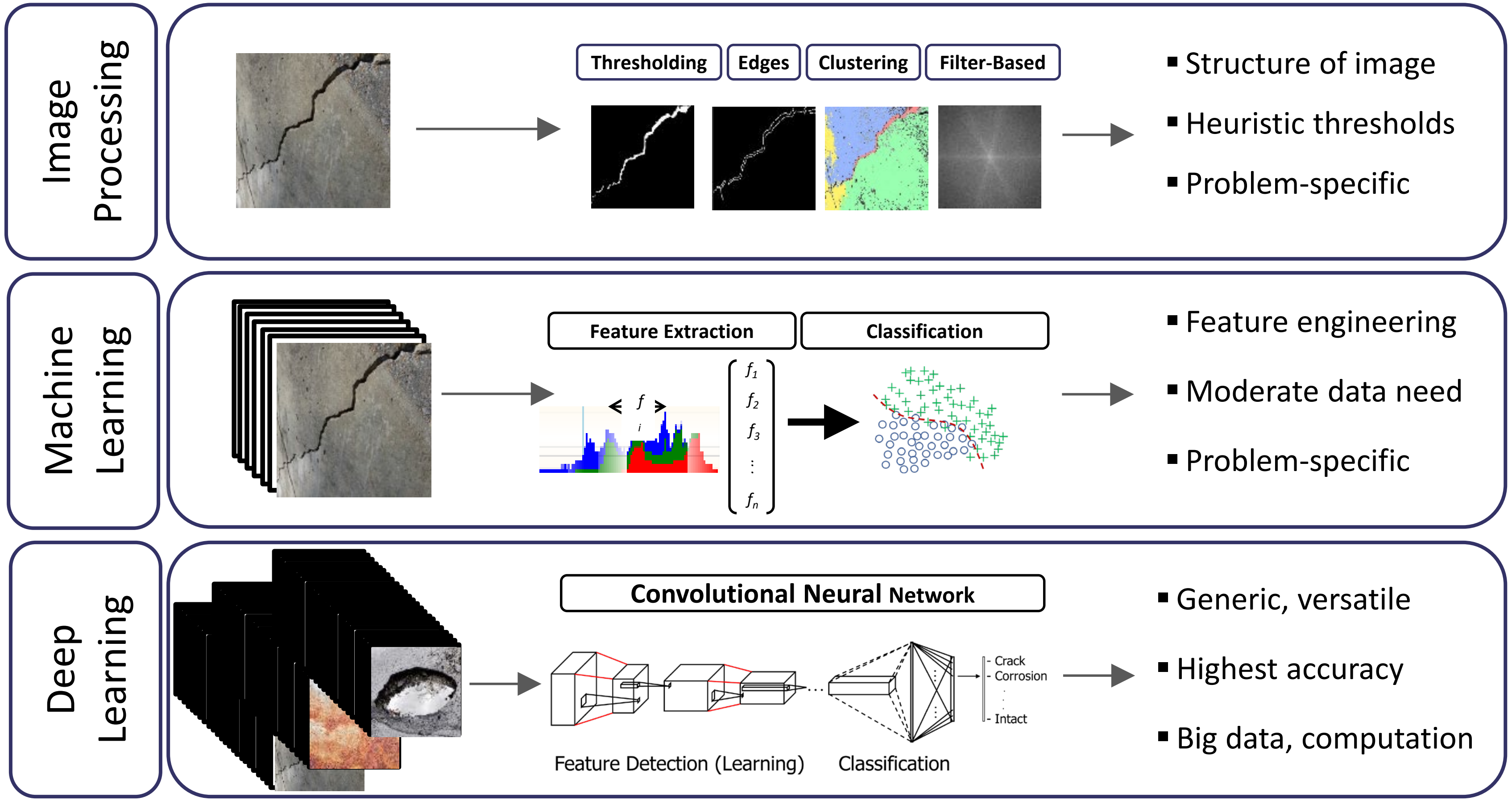
Span A, topside
- Electric cover at the base of light pole has only 1 bolt securing cover.

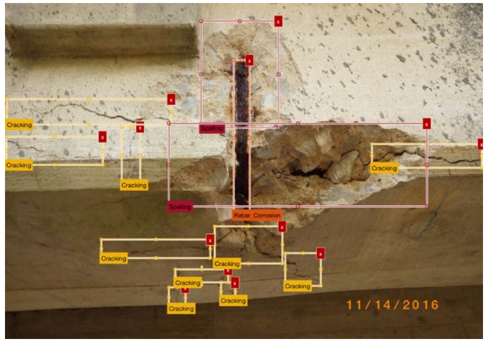
Utilities **Good**
Span F
- Utility support bracket is not attached and utility is sagging.

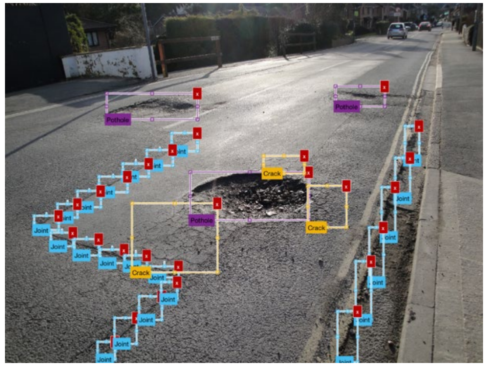
Page 9 of 28

Visual recognition for infrastructure assessment

- Visual recognition is a subset of artificial intelligence or computer vision aimed at the development of algorithms and representations to allow a machine to recognize objects, people, scenes, and activities (perception and interpretation)



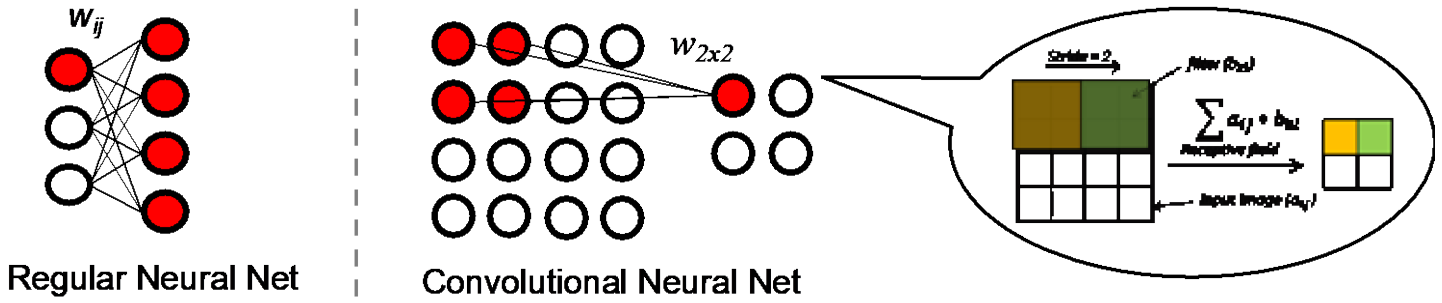




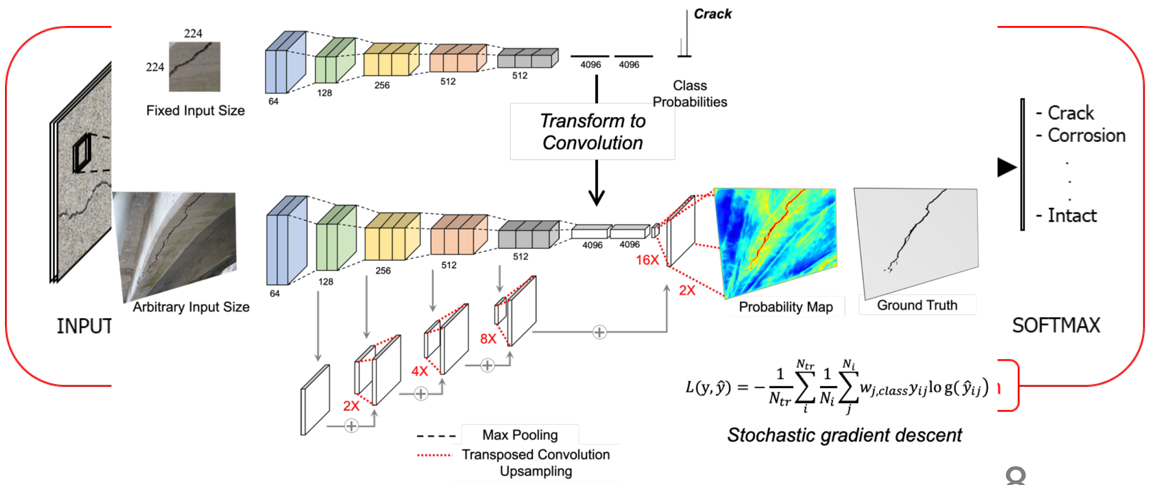
How might we interpret image data using CNNs?

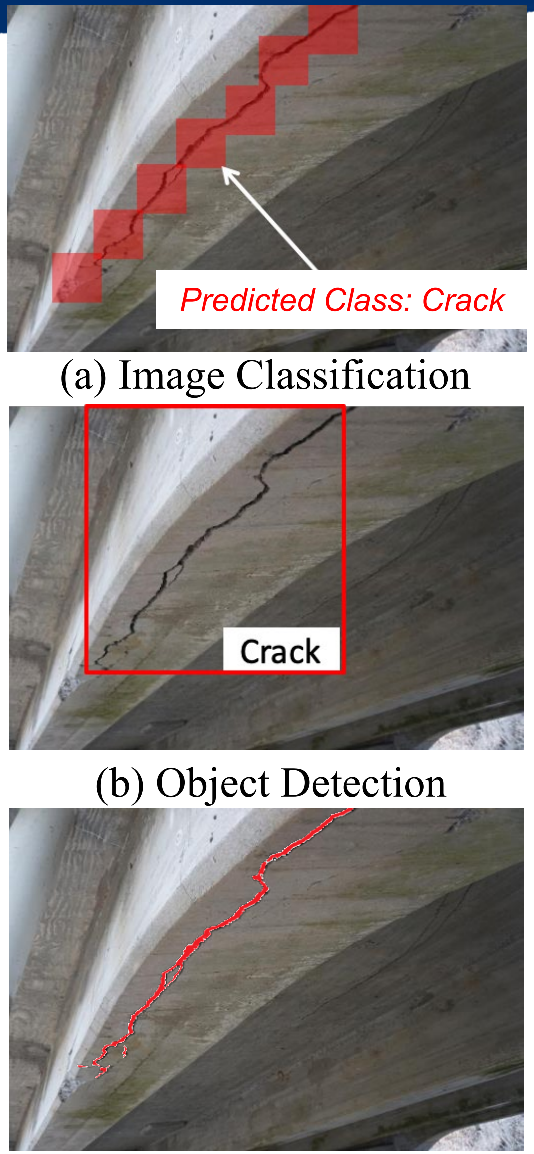
Convolutional Neural Networks (CNN)

- CNN: Receptive fields connected to hidden neurons by shared weights.



- CNNs transform input image into layers of increasingly meaningful representations
  - Deep neural networks: multistage information-distillation operation, where information goes through successive filters and comes out increasingly purified





(a) Image Classification

(b) Object Detection

(c) Semantic Segmentation

Leveraging Bridge Inspection Report Imagery

[redacted] [redacted]

STRUCTURE INSPECTION REPORT – COVER PHOTOS

Agency ID: [redacted] [redacted]

WEST ELEVATION

EAST ELEVATION

Page 3 of 28

Overview

[redacted] [redacted]

STRUCTURE INSPECTION REPORT – PHOTOS

Agency ID: [redacted] [redacted]

Photo #13

Looking at Span F, Pier 5, Bay 12 side of Beam 12.

Up to ½" loss of section (previously ¼" loss of section) on Bay 12 side of bottom flange x 2' long. **Web has up to 1/4" loss of section x 6" high**, with up to 1/8" loss of section x full height behind bearing stiffener.

Photo #14

Looking at Span G, Pier 6, Bay 13 side of Beam 13.

Up to 3/8" loss of section x 3' long x 8" wide on bottom flange due to water/debris channeling and localized severe corrosion with up to 100% section loss 12" long x 6" wide (3/4" original flange). Bottom flange has a 4" long x 3" wide perforation near bearing. Adjacent beam web has up to 7/16" loss of section x 6" high x 2' long.

Page 21 of 28

Local Defects

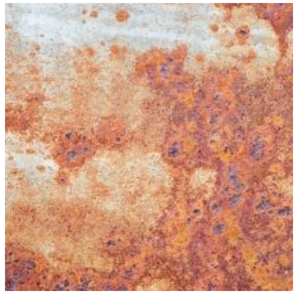
How can we apply AI to this inspection data?

Crack Detection Problem

- Detection across Different Materials
- Pixel-level detection
- Quantification

Corrosion Detection Problem

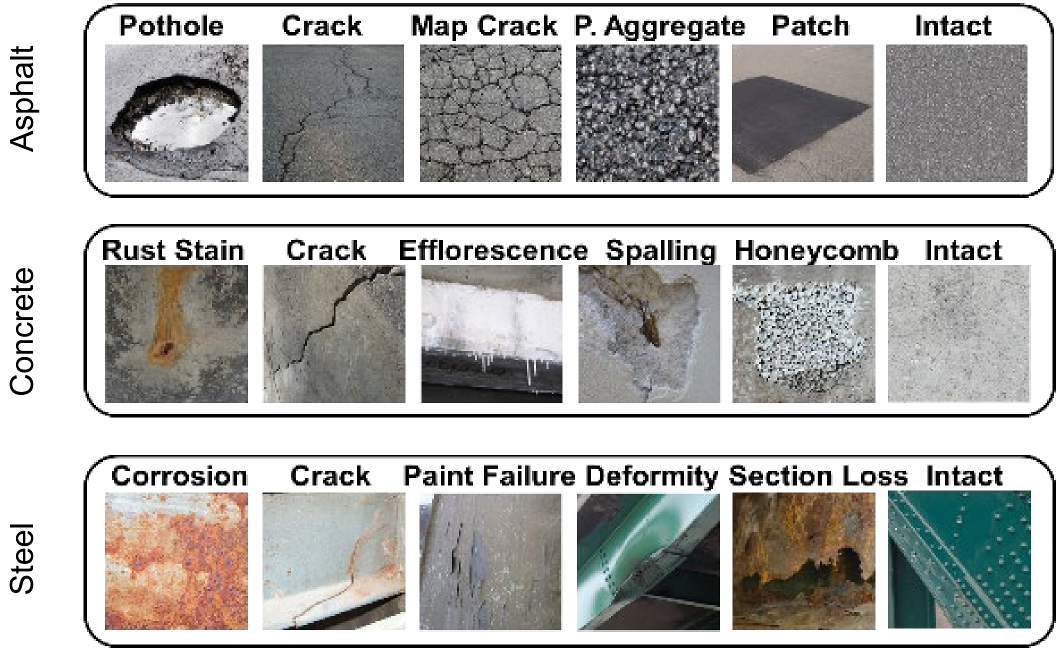
- Pixel-level detection



Multi-Defect Detection Problem

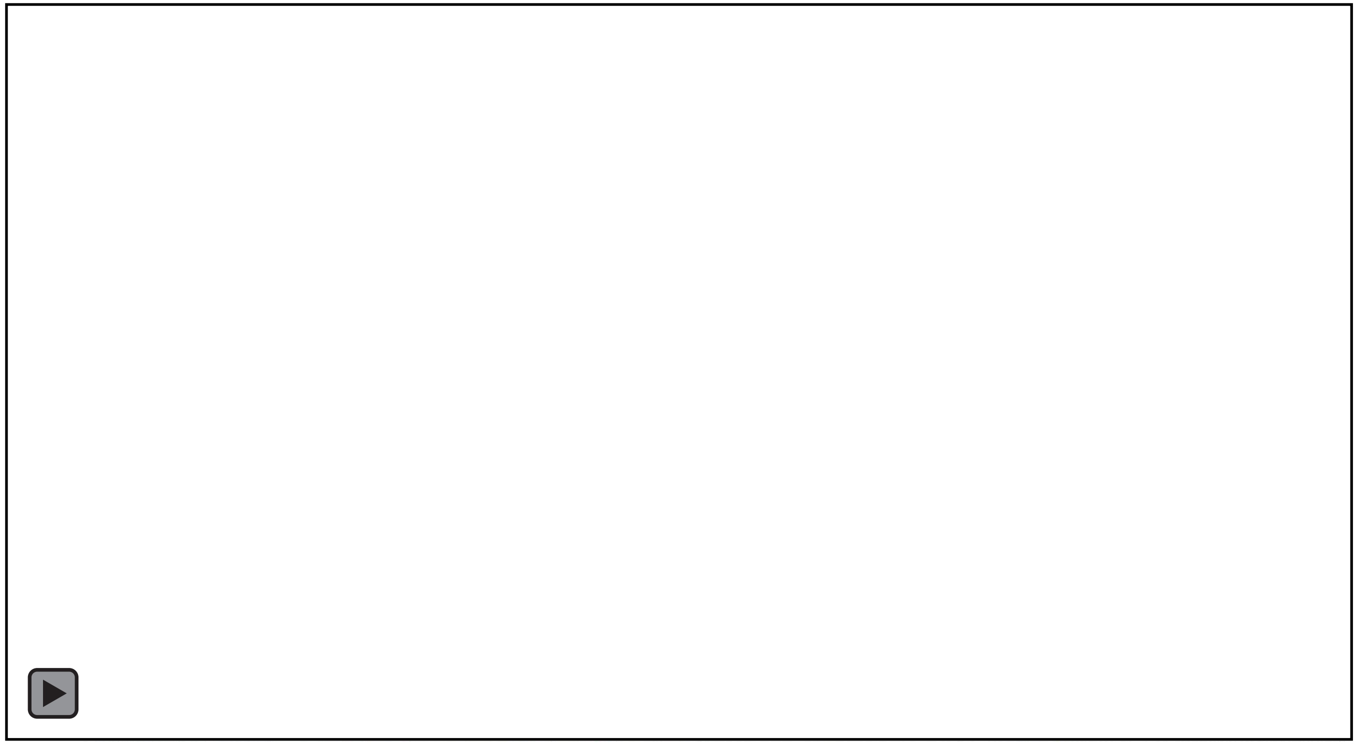
-Crowd-sourced urban monitoring

-Inspection image dataset



How we have used these models so far…

- Our current models can:
  - Detect and measure defects (qualitative and quantitative)
  - Provide a map of the changes (geo-location)
  - Determine damage pattern change since the last inspection (temporal)



Other Potential Applications:

- Automated inspection
- robotic inspection
- crowd-sourced monitoring

NLP for infrastructure assessment

- Natural Language Processing (NLP) is a subset of artificial intelligence or linguistics aimed at the development of algorithms and representations to allow a machine to analyze natural language, extract information and insights, as well as categorize the documents.

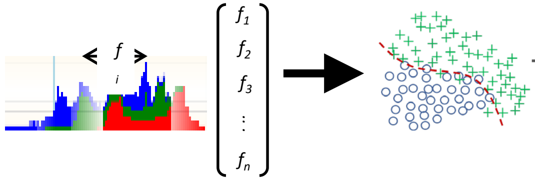
Machine Learning

Syntactic Features
- Part-of-speech tags
- Casing
- Prefix

Semantic Features
- Ontology

Bag-of-Word Features

Feature Engineering | **Model Selection**

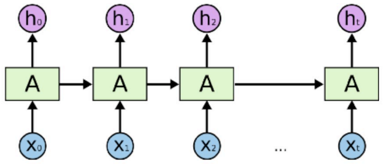


- Problem-specific
- Feature engineering
- Ontology building

Deep Learning

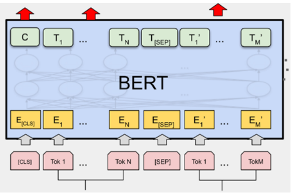
Dense Embedding
- Word2Vec
- GloVe
- FastText

Recurrent Neural Network

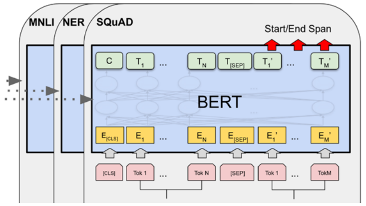


- Problem-specific
- Semantic features
- Directional training

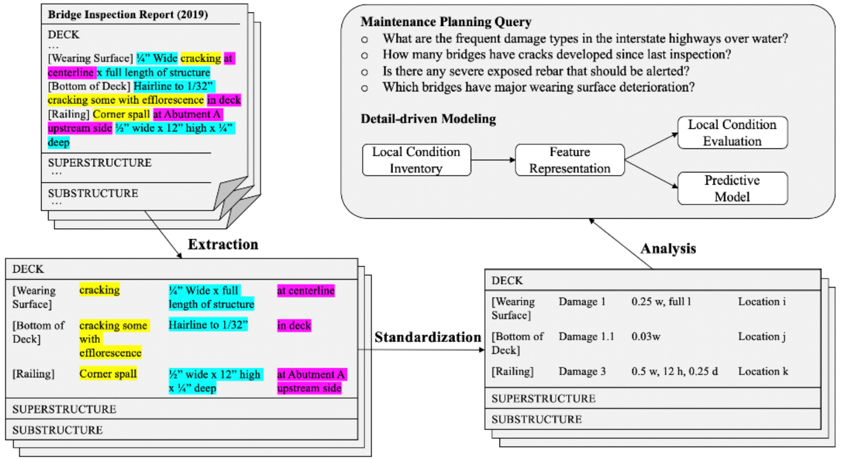
Bi-directional multi-task pre-training



Fine-Tuning



- Generic, versatile
- Highest accuracy
- Big data, multi-task
- Parallelizable



Can we effectively extract context derived from expert observations?

Leveraging Bridge Inspection Report Text

- Condition ratings (score)
- Condition details of local defects, and their evolution history, in narratives

[redacted]

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YEAR PAINTED 1986

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Span A, topside
- Electric cover at the base of light pole has only 1 bolt securing cover.

Utilities Good
Span F
- Utility support bracket is not attached and utility is sagging.

Page 9 of 28

How can we apply AI to this inspection data?

Condition Extraction

- Dissect sentence into chunks
- Sequence labeling task

Bridge Inspection Report (2019)

DECK
…
[Wearing Surface] ¼” Wide cracking at centerline x full length of deck
[Bottom of Deck] Hairline to 1/32” cracking some with efflorescence in deck
[Railing] Corner spall at Abutment A upstream side ½” wide x 12” high x ¼” deep

SUPERSTRUCTURE
…

SUBSTRUCTURE
…

Bi-Directional LSTM-CRF

DECK			
[Wearing Surface]	cracking	¼” Wide x full length of deck	at centerline
[Bottom of Deck]	cracking some with efflorescence	Hairline to 1/32”	in deck
[Railing]	Corner spall	½” wide x 12” high x ¼” deep	at Abutment A upstream side
SUPERSTRUCTURE			
SUBSTRUCTURE			

Condition Rating

- Map sentences to general condition rating (GCR)
- Text classification task

Bridge Inspection Report

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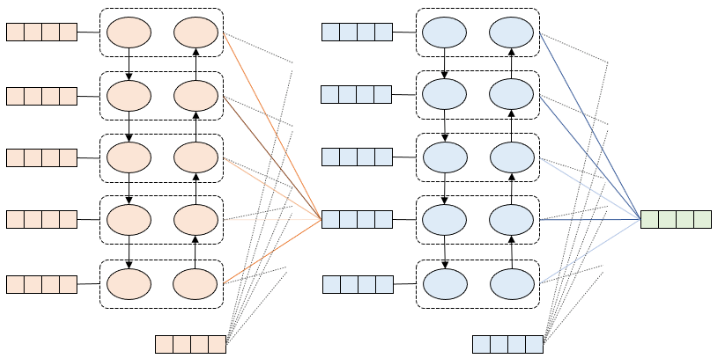
…

Hierarchical Attention Network



GCR: 6

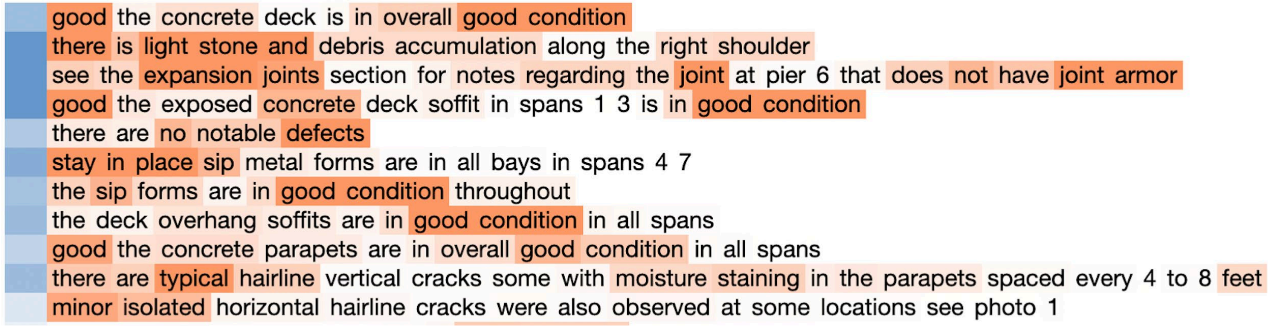
How models can be used for asset management…

- Extract local condition information
- Construct a condition inventory to assist analysis

Track local defect changes since last inspection

Year	Damage	Location	Severity	Deterioration?
2014	spalling and delamination	bottom of deck downstream side	a 47" long x 29" wide x 2 3/4" deep area	NO
2017				
2014	exposed longitudinal bars	bottom of deck downstream side	4 (rebars)	YES
2017			5 (rebars)	
2014	exposed transverse bar	bottom of deck downstream side	75% (section loss)	YES
2017			75% to 100% (section loss)	

- Generate condition rating given textual description
- Reveal key word/sentence in the mapping from texts to ratings (what drives decision)



Also provides a mechanism for quality control of selected ratings (training)

Summary of AI Applications for Asset Management

Bridge Inspection reports are ripe with data (**untapped** and **passive**) that goes unused

- Long history of detailed record collection that are independent of reporting requirement changes
- Images are routinely collected as part of a typical inspection and provide observations of condition state
- Inspector also provide detailed narratives of their observations during an inspection which contains expert observations

Inspection report data are largely **untapped** and **underutilized**, but have the potential to reframe how we manage assets

Advances in artificial intelligence create opportunities to effectively leverage these **passive** datasets

- Visual recognition (imagery)
- Natural Language Processing (text)

Fusion

Potential for creating consistent, reliable, and scalable asset management strategies

Thanks for your attention

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Emerging Data Analytics & Artificial Intelligence Technologies for Bridge Deterioration Prediction


Image sources: Pinterest & Stephen Chadwick

Nora El-Gohary, Ph.D.
Associate Professor
Department of Civil and Environmental Engineering
University of Illinois at Urbana-Champaign

Civil Infrastructure Systems Open Knowledge Network (CIS-OKN)

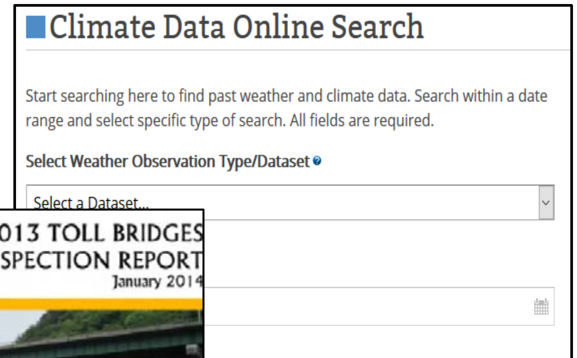
BIG Data Analytics & Artificial Intelligence (AI) open unprecedented opportunities

- Better predict bridge deterioration
- Enhance maintenance decision making

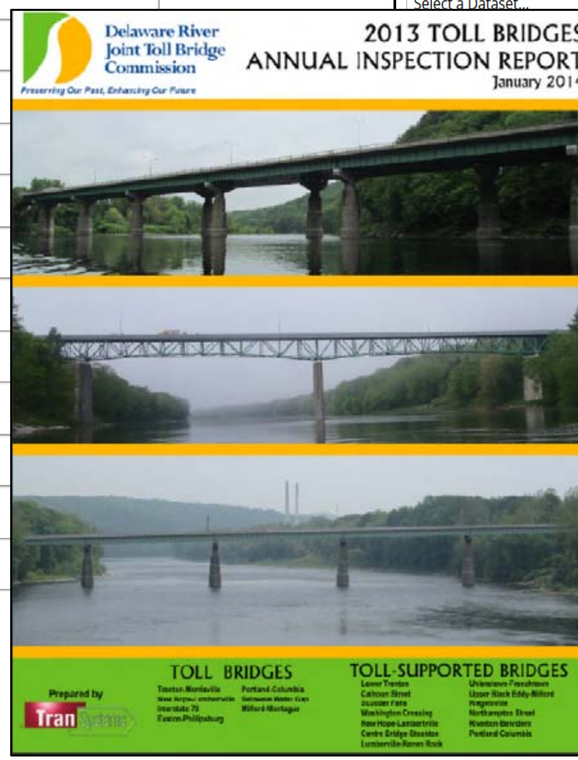
- 6 universities (Lead: UIUC; partners: USC, Purdue, CMU, ASU, Stevens)
- State DOTs: CA, IL, FL, CT, IA, SC, UT, IN, AZ
- Transportation centers: ICT, METRANS, TOPS, other
- Data/AI centers and hubs: Midwest Big Data Hub, NCSA, NJ Innovation Inst., Stevens Inst. for AI, other
- Contactors, consultants, and technology providers in the transportation domain: Oracle, WSP, Jobsite Tech, RoadBotics, Hexagon, Alta Vista, FCC
- Industry bodies: buildingSMART, NIBS
- Technology industry: Google, Microsoft, Facebook, Amazon, Esri, Cambridge Semantics

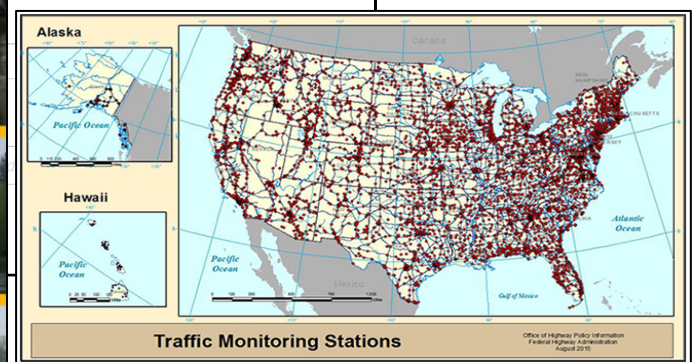
Big Data for Bridge Deterioration Prediction

Volume, Variety, Velocity



ITEM NO	ITEM NAME
1	State Code
8	Structure Number
5	Inventory Route
5A	Record Type
5B	Route Signing Prefix
5C	Designated Level of Service
5D	Route Number
5E	Directional Suffix
2	Highway Agency District
3	County (Parish) Code
4	Place Code
6	Features Intersected





Image/map sources: Federal Highway Administration

Long-Term Bridge Performance Program

Structure No. 24 0287L

Defect Number	Component	Defect Status	Defect Type	Defect Date	Comments	Characteristics
1	Bridge > Span 2 > Span 2 - Deck Underside	New	1110 - Crack CRAC	12/13/2011	Transverse cracks with efflorescence	
1	Bridge > Span 2 > Span 2 - Inside of Deck > Face B	New	1110 - Crack CRAC	12/13/2011	Fine longitudinal crack on underside of deck.	
1	Bridge > Span 2 > Span 2 - Inside of Deck > Face B	New	1110 - Crack CRAC	12/13/2011	Very fine longitudinal crack on underside of deck.	
1	Bridge > Span 2 > Span 2	New	1110 - Crack CRAC	12/13/2011	Very fine longitudinal crack on underside of	

Long-Term Bridge Performance Program

Structure No. 24 0287L

Photo Description	Photos
Photo #: DSCN2755 Comments: North end of span 1, right lane, right wheel path, longitudinal cracking. Location: Bridge > Span 2 > Span 2 - Top of Deck Observations: CRAC #: 1110 - Crack_1	

Image sources: Long-Term Bridge Performance Program

Challenge #1: Dealing with unstructured data

Information Extraction from Inspection Reports and Images

- Semantic, semi-supervised machine learning for information extraction

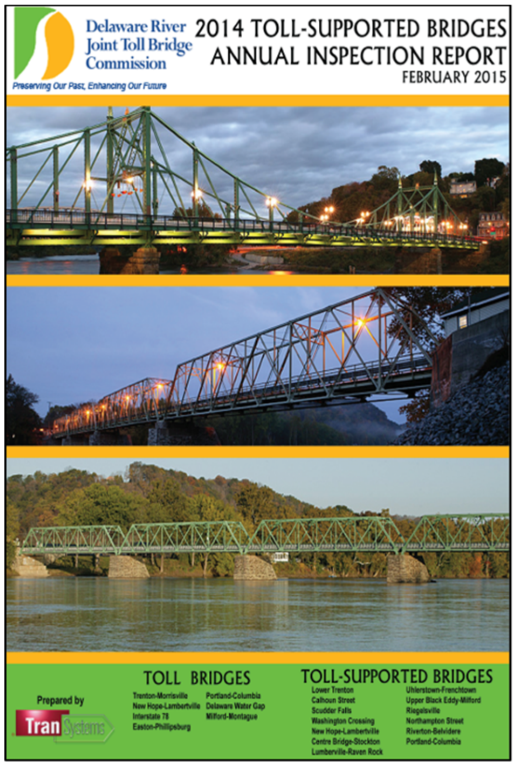


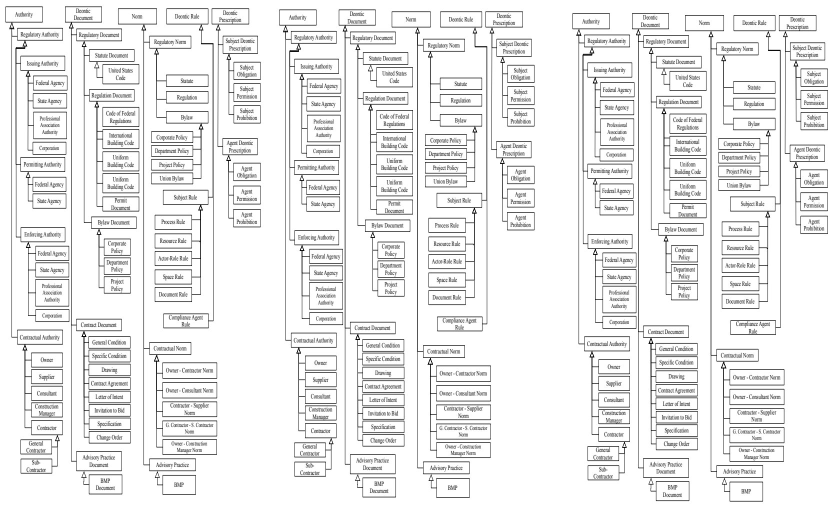
Image sources: Long-Term Bridge Performance Program & Maeda et al. 2018

Opportunities:
- Natural language processing
- Computer Vision
- Machine learning

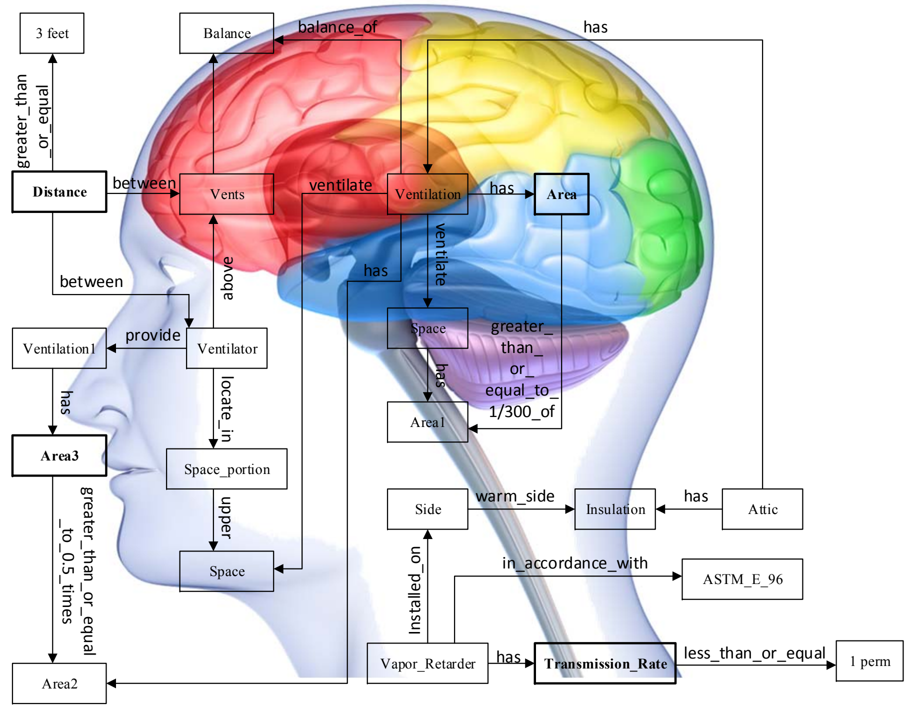
NLP is a theoretically-based computerized approach to analyzing, representing, and manipulating natural language text

Challenge #2: We cannot use off-shelf models

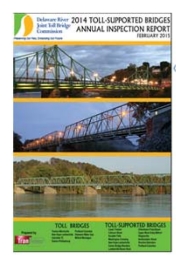
Challenge #3: Lack of training data

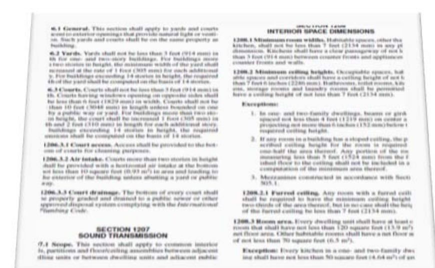


Semantic Modeling & Ontology



http://greenbeings.com.au/greenroom/index.php/2010/11/19/update-on-solar-rebates/





LL #1: Adaptive and advanced ML models are the way to go!

- Adaptation of out-of-domain training data to our domain
- Semi-supervised learning
- Unsupervised learning
- Transfer learning

Challenge #4: Multisource, heterogeneous data

LL #2: Semantic data linking & fusion is the way to fully-integrated, multi-source analytics

- Unsupervised linking of data extracted from the reports
- Data fusion to fuse the measures

Challenge #5: Unbalanced data

Machine Learning

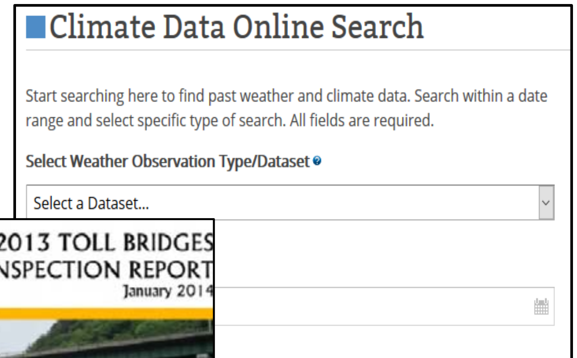
- Predicting deterioration
  - corrosion, cracking, decay, delamination, efflorescence, scaling and spalling, scour, settlement
  - type of deterioration, quantity, severity, onset timing, condition rating, propagation in quantity and severity with time
- Learning how to better maintain our bridges
- Prediction results linked to fused and original data to ascribe quality and provenance to the results

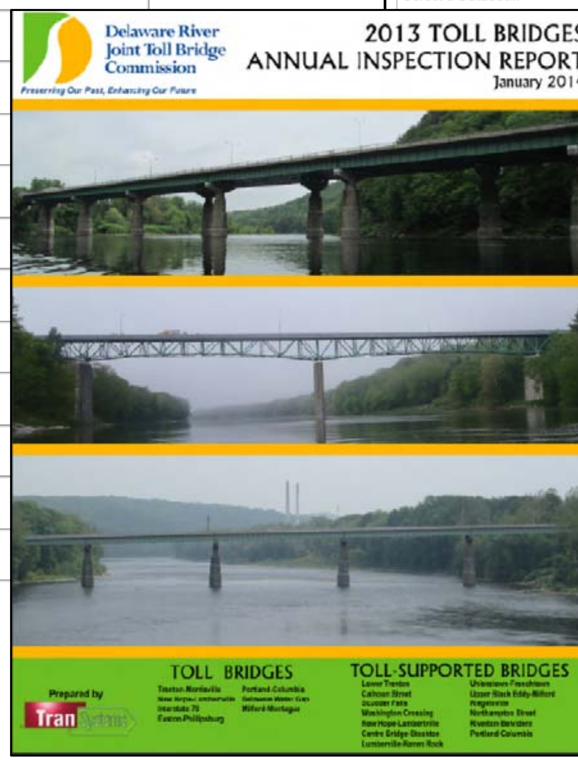
Data Unbalance Problems!

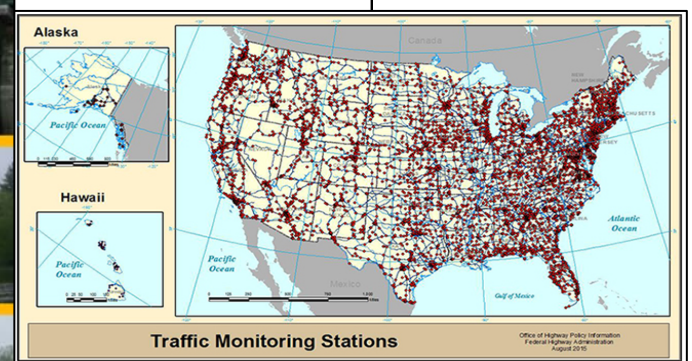
Challenge #6: Data sharing & knowledge convergence

Volume, Variety, Velocity

ITEM NO	ITEM NAME
1	State Code
8	Structure Number
5	Inventory Route
5A	Record Type
5B	Route Signing Prefix
5C	Designated Level of Service
5D	Route Number
5E	Directional Suffix
2	Highway Agency District
3	County (Parish) Code
4	Place Code
6	Features Intersected







Image/map sources: Federal Highway Administration

LL #3: Convergence is a must!

- 6 universities (Lead: UIUC; partners: USC, Purdue, CMU, ASU, Stevens)
- State DOTs: CA, IL, FL, CT, IA, SC, UT, IN, AZ
- Transportation centers: ICT, METRANS, TOPS, other
- Data/AI centers and hubs: Midwest Big Data Hub, NCSA, NJ Innovation Inst., Stevens Inst. for AI, other
- Contactors, consultants, and technology providers in the transportation domain: Oracle, WSP, Jobsite Tech, RoadBotics, Hexagon, Alta Vista, FCC
- Industry bodies: buildingSMART, NIBS
- Technology industry: Google, Microsoft, Facebook, Amazon, Esri, Cambridge Semantics

Acknowledgement of Support

- National Science Foundation
  - Grant No. #1937115
  - Title: Convergence Accelerator Phase I (RAISE): Civil Infrastructure Systems Open Knowledge Network (CIS-OKN)
  - 10/10/2019-05/31/2021

- National Center for Supercomputing Application (NCSA)

- Strategic Research Initiative, University of Illinois at Urbana-Champaign

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Application of Artificial Intelligence in highway bridge infrastructure condition assessment and management

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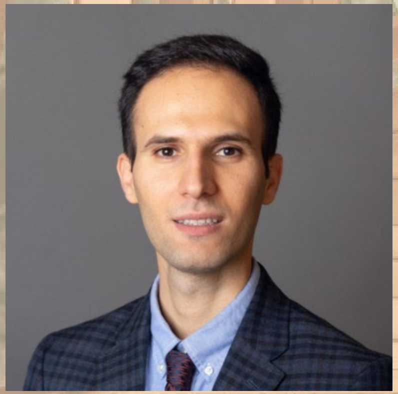
Collaborators

Sila Gulgec



Soheil Sadeghi Eshkevari

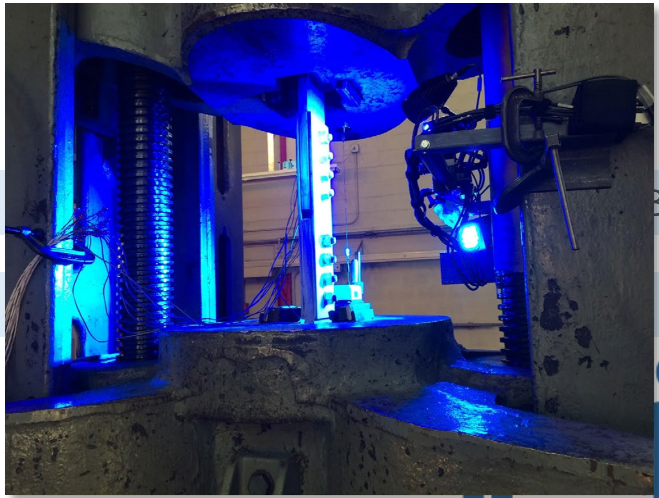
Soheila Sadeghi Eshkevari

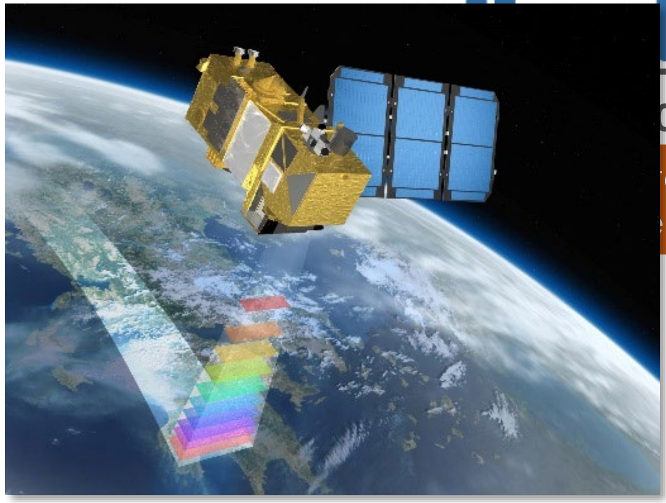
Thomas Matarazzo

Majid Jahani

Motivation

- **High resolution** of **long-term monitoring** data with today's sensing technology
- **Integration of data** collected by traditional means with emerging sensing systems
- **Smartphones** as data sources? What if the general public had access to portable, high-quality sensors and contributed to SHM every day?
- Soon SHM will meet the **Big Data standards** and need to deal with storing and processing such large datasets





Measuring Strain vs Acceleration

- Directly related to stress, fatigue and failure
- Strain gauges:
  - High installation cost
  - Power issues
  - Hard to capture strain field

- DIC, fiber optic sensors:
  - Installation and calibration
  - Expensive

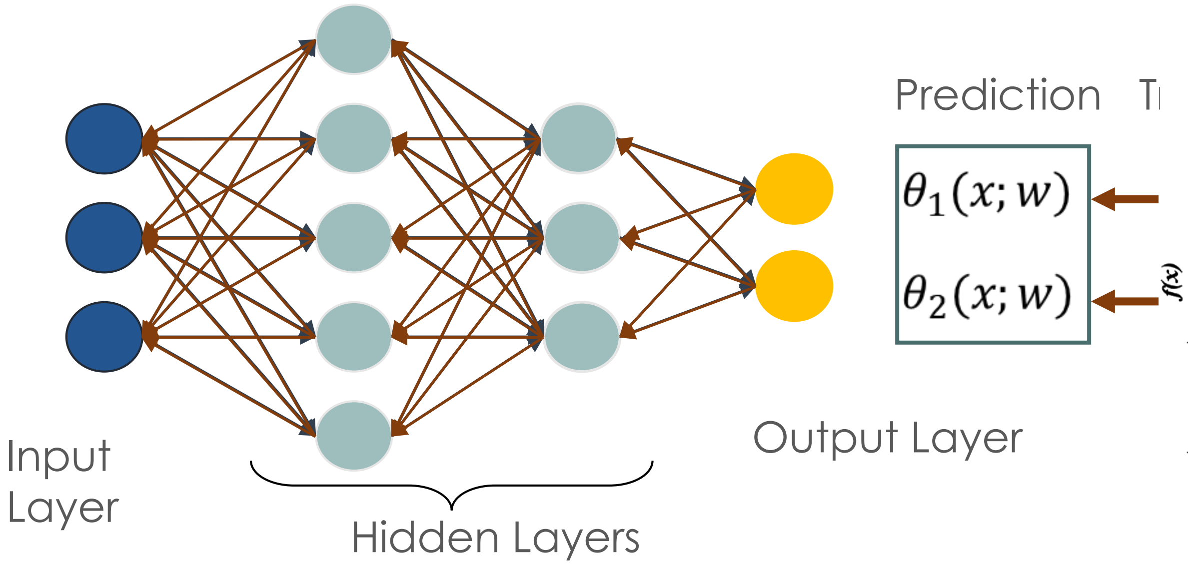
- Modal analysis, system identification
- Wireless sensor networks:
  - Cheap
  - Works with battery
  - Easy installation

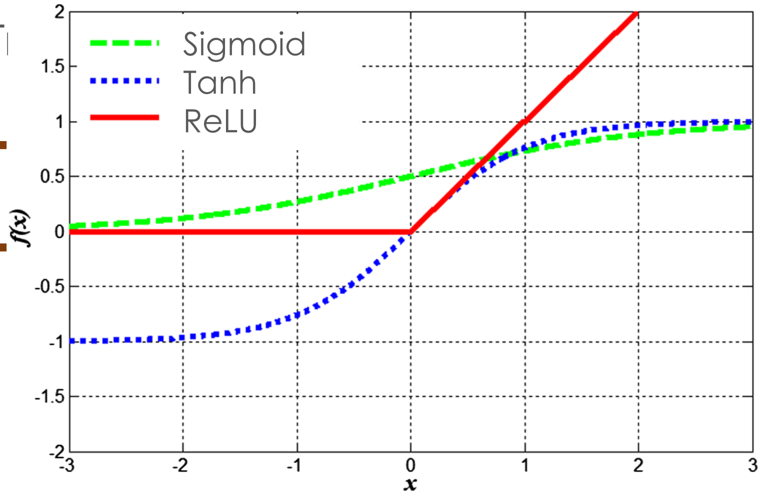
- Mobile sensors:
  - No installation cost
  - Crowd-sourcing potential
  - Dense geographic coverage

Can we collect **acceleration** data from WSN or mobile sensing to obtain **strain** information?

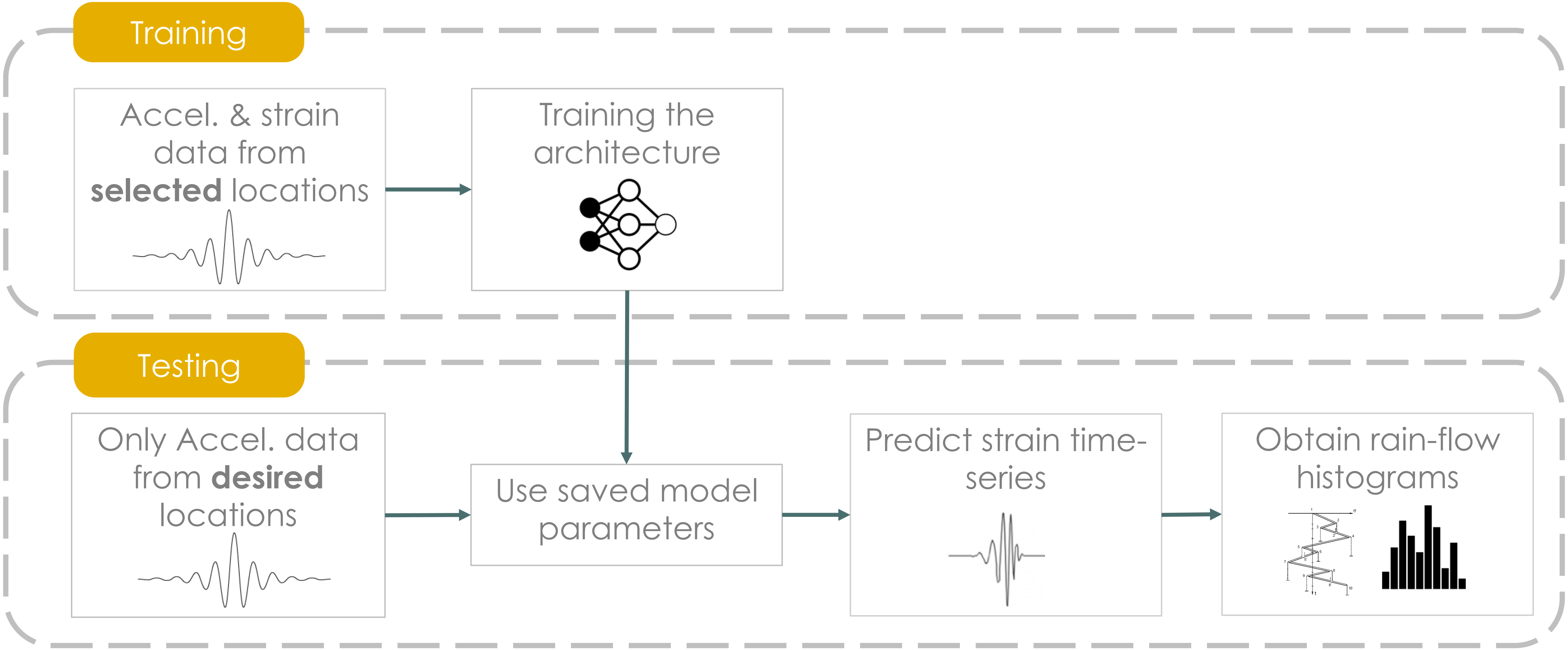
Deep Neural Networks (DNN)

- DNNs form a model using deep graph organized in multiple linear layers and non-linear transformations
- The output of the neuron is found by a weighted sum of inputs composed with a non-linear mapping, e.g., tanh, relu etc.



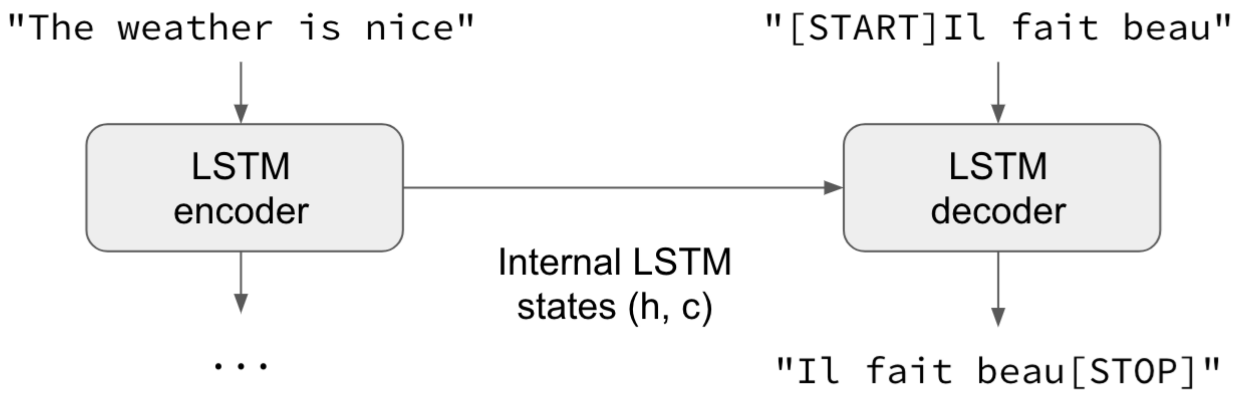


Proposed Framework



Long Short-Term Memory (LSTM)

- State-of-the-art performance in time series prediction, language translation and speech recognition
- LSTMs (Gers et al., 2000) can capture dynamics of the sequence
- Current decisions are affected by the previous states



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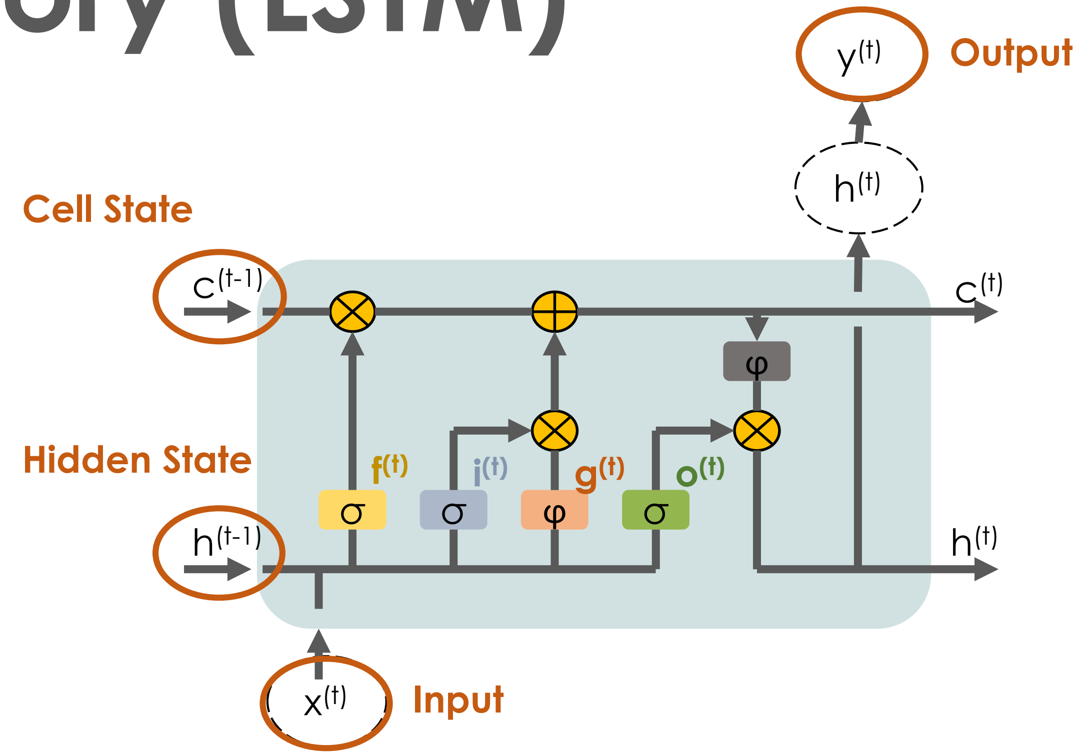
Long Short-Term Memory (LSTM)

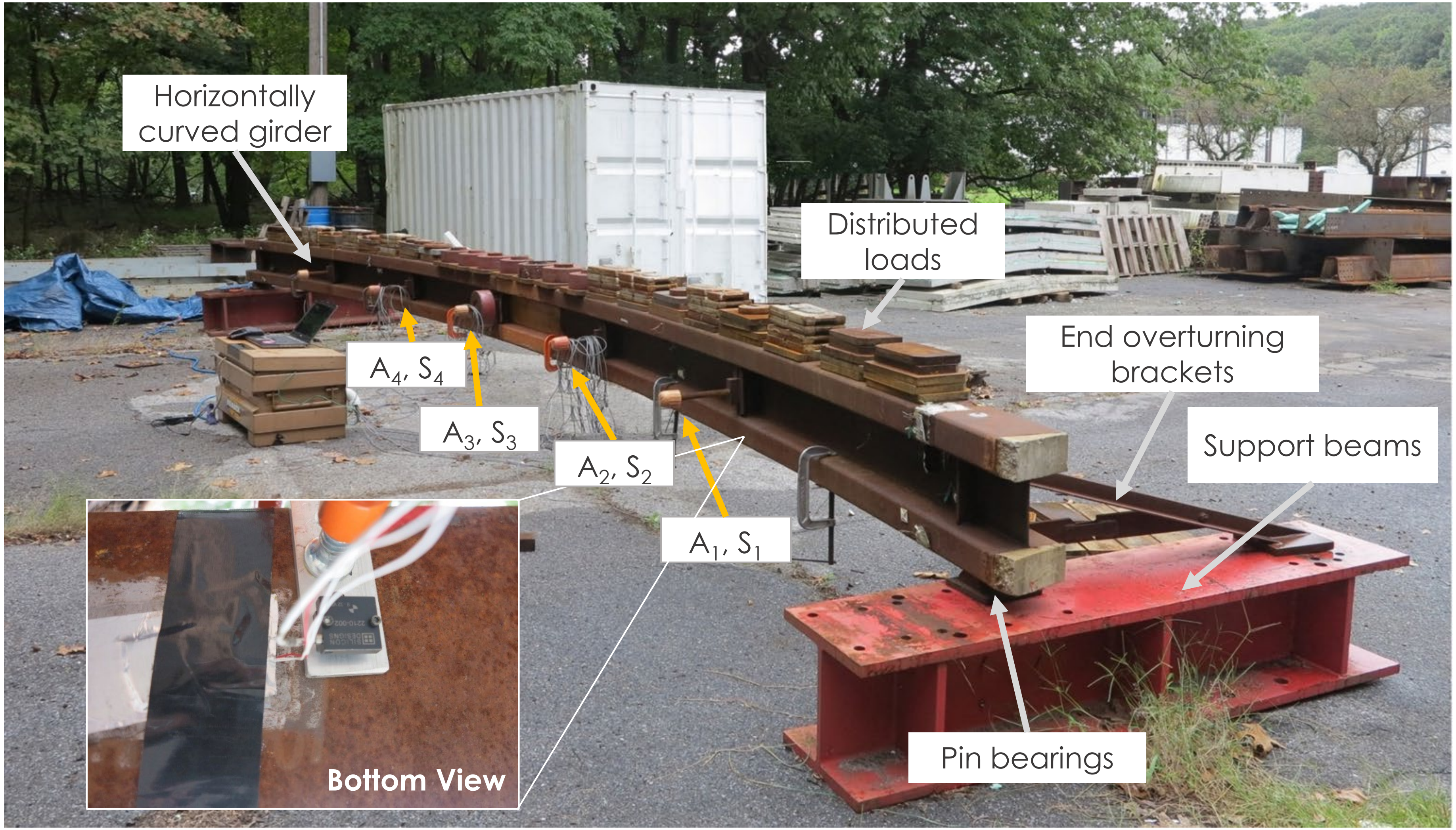
- SHM-specific challenges:
  - The difficulty of training **long sequences**
  - **The initialization** of network parameters
- Language model - initial state = 0
- in SHM - continuous stream of data



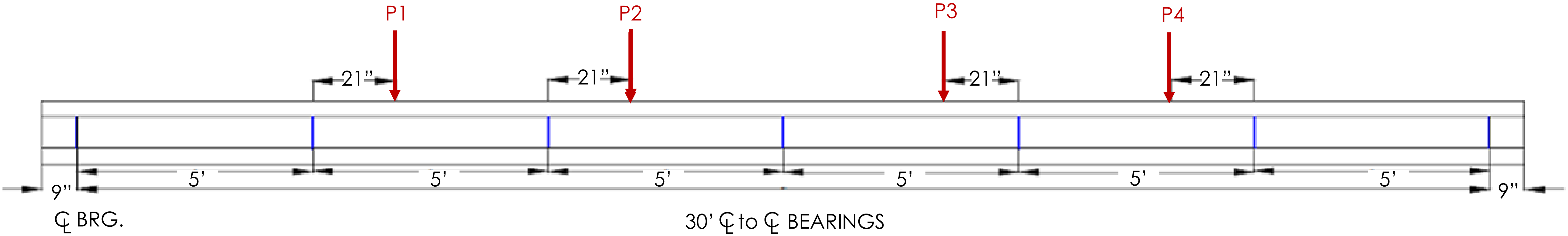
New way of training LSTMs!
- ➢ Randomized mini-batches
- ➢ Step-wise learning

Felix A Gers, Jürgen Schmidhuber, and Fred Cummins. Learning to forget: Continual prediction with lstm. Neural computation, 12(10):2451–2471, 2000.

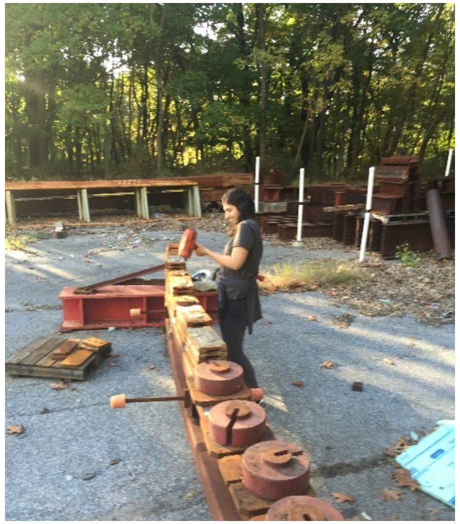
Setup and Instrumentation



Procedure

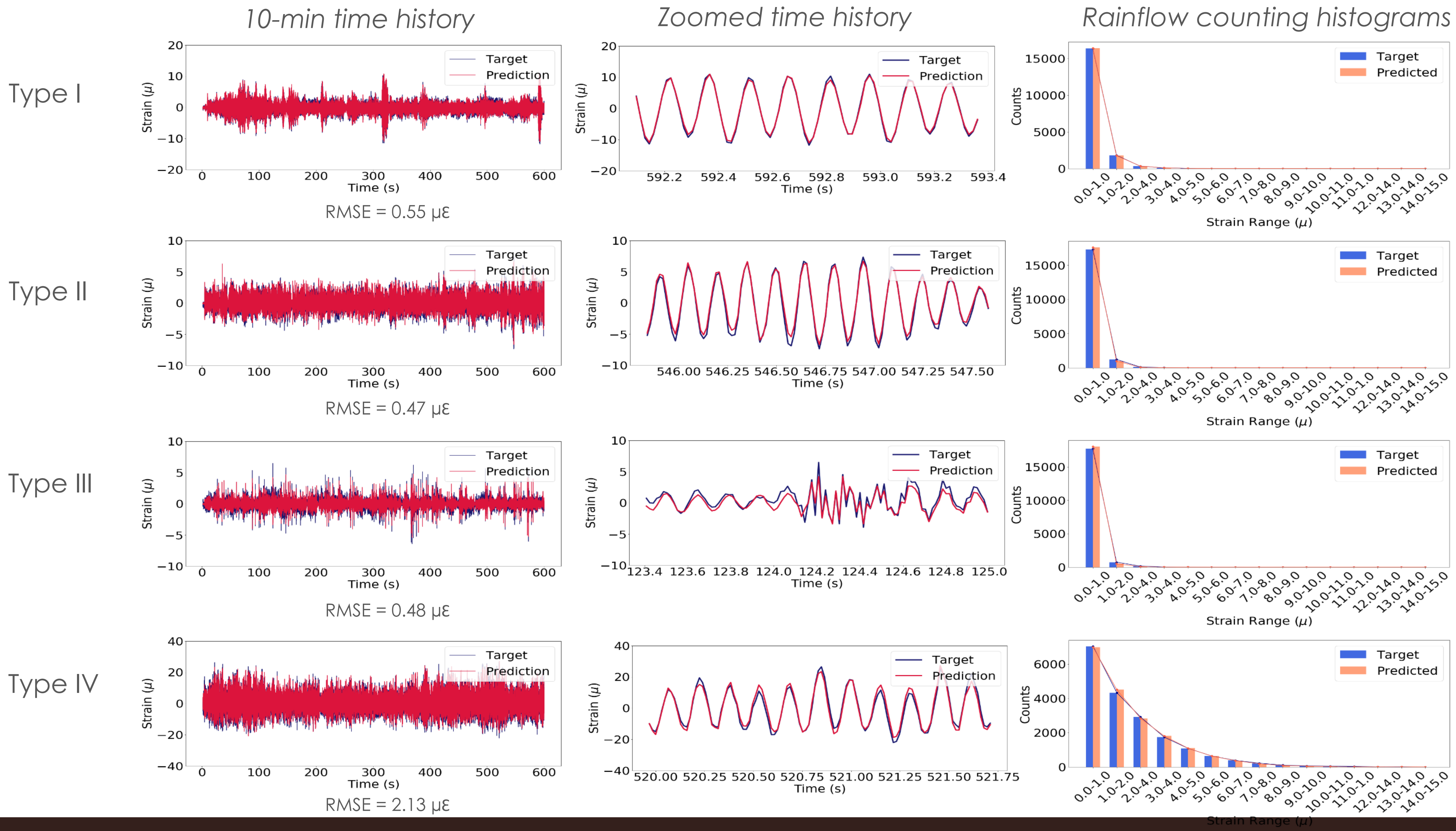


Type	Loading Scheme	No of Loading Case
Type I	Stepping at P1/ P2/ P4	54
Type II	Stepping at P1 and P4	20
Type III	Hammer + Stepping at P1/ P4	16
Type IV	P1, P2, P3 and P4	12

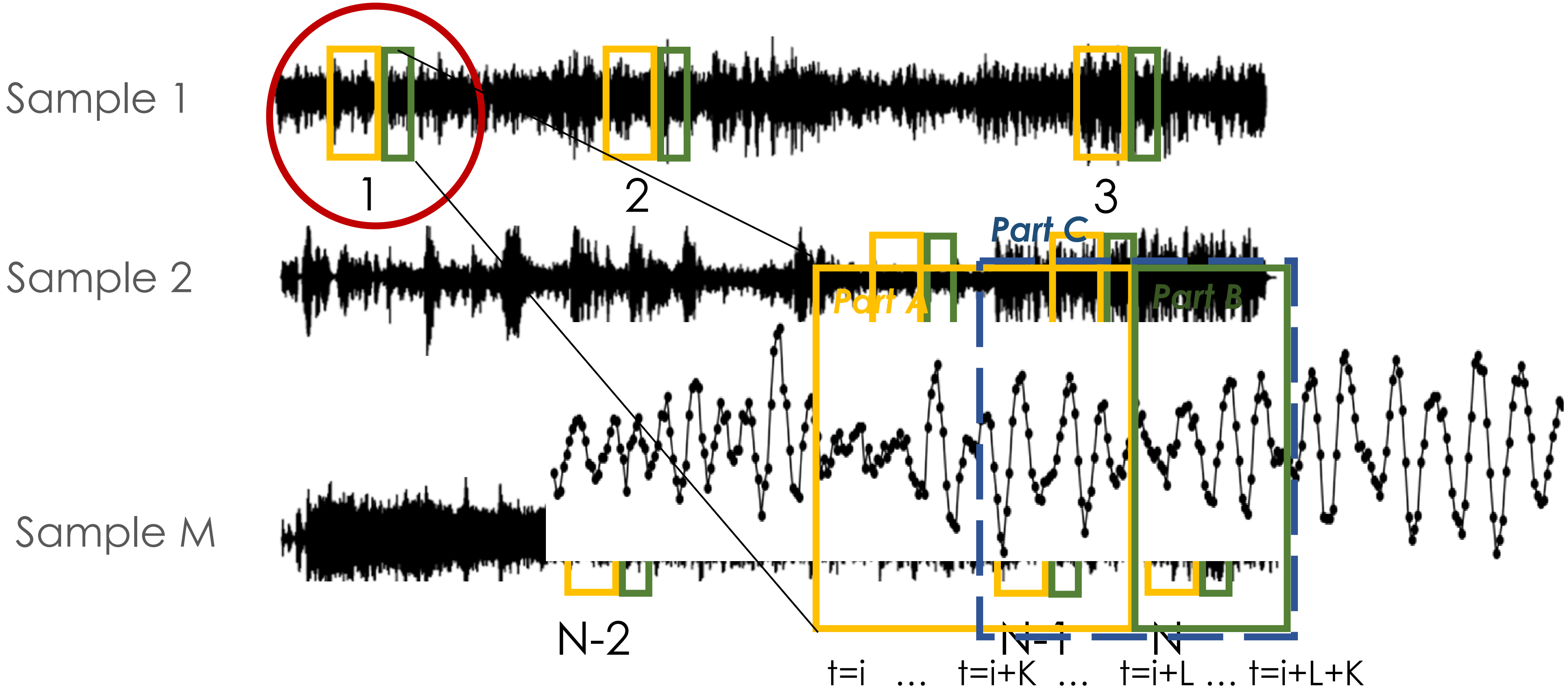


Excitement by using hammer

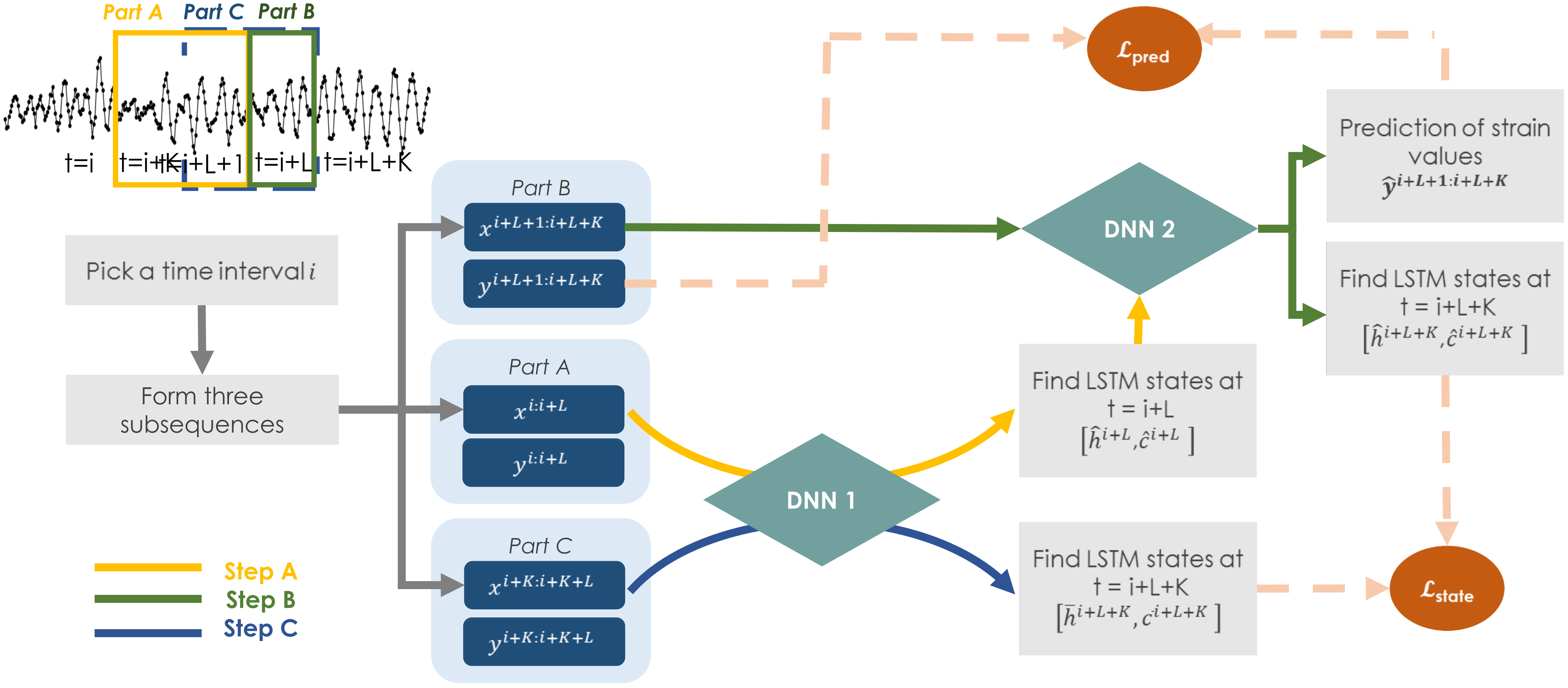
Excitement by stepping


10-min time history
Zoomed time history
Rainflow counting histograms
Type I
Type II
Type III
Type IV
Target
Prediction
Predicted
Strain (μ)
Time (s)
Counts
Strain Range (μ)
0.0-1.0
1.0-2.0
2.0-4.0
3.0-4.0
4.0-5.0
5.0-6.0
6.0-7.0
7.0-8.0
8.0-9.0
9.0-10.0
10.0-11.0
11.0-1.0
12.0-14.0
13.0-14.0
14.0-15.0
RMSE = 0.55 με
RMSE = 0.47 με
RMSE = 0.48 με
RMSE = 2.13 με

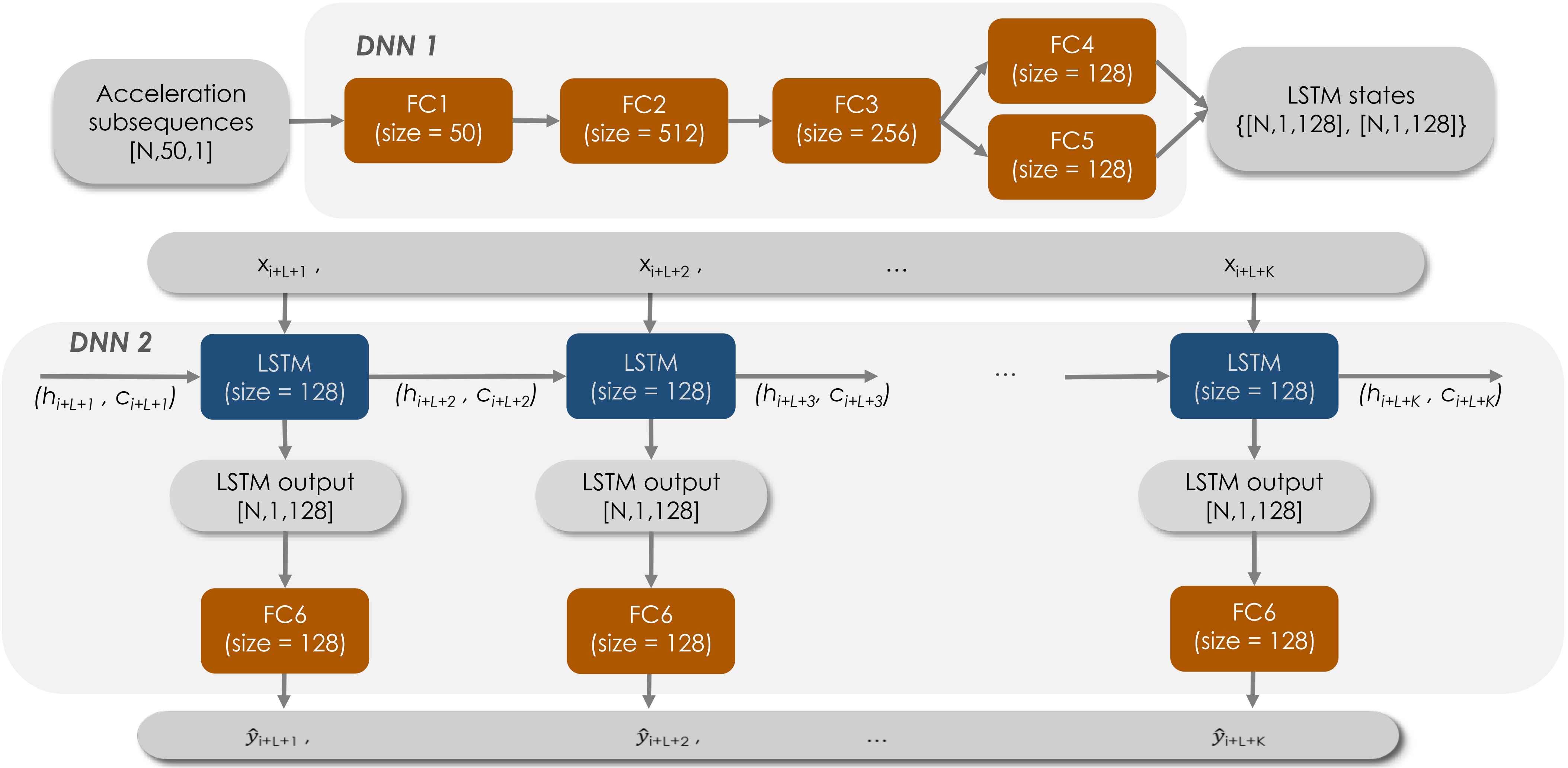
Training: Randomized Mini-Batches



Training: Step-wise Learning



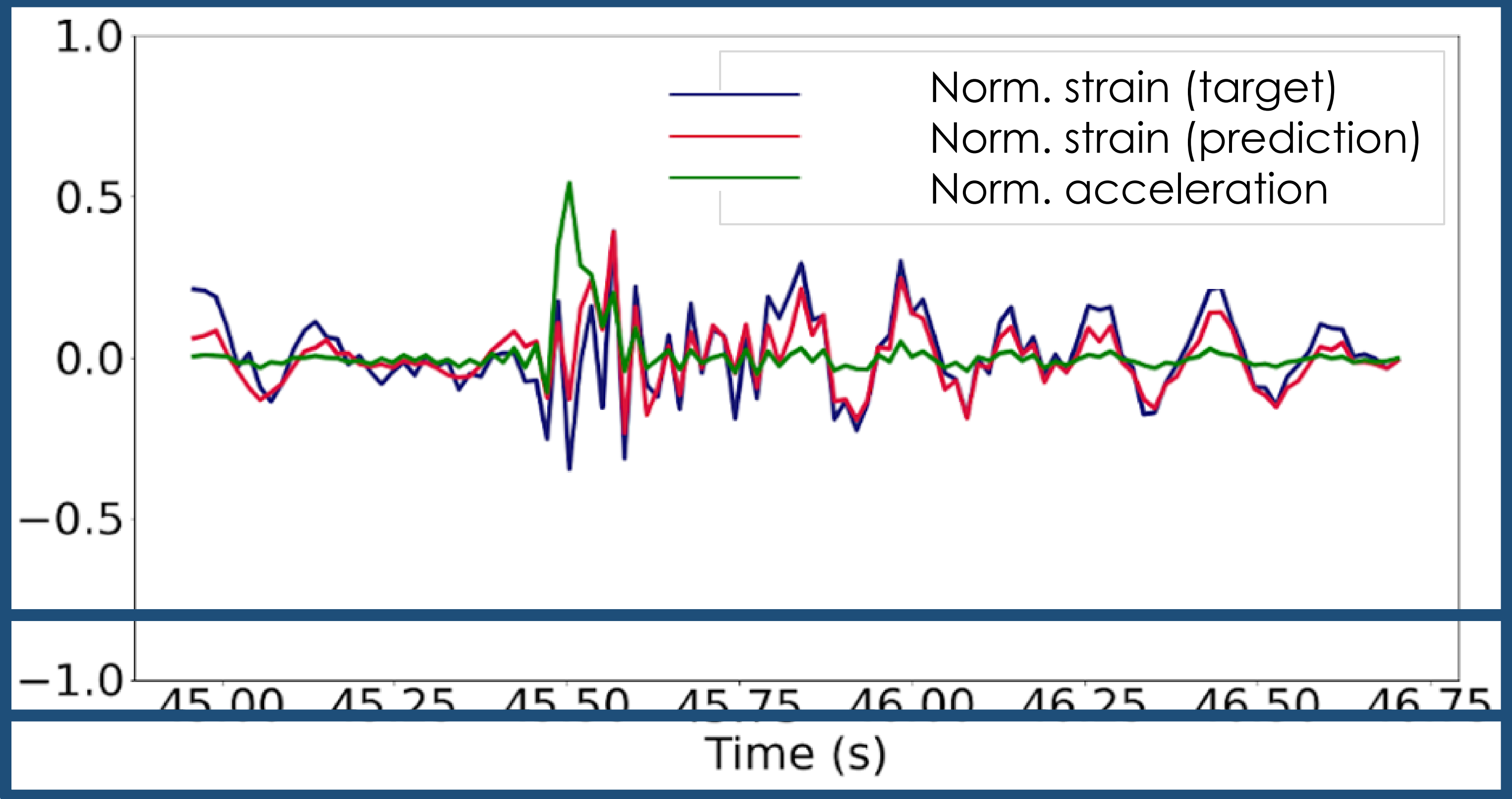
Proposed Architecture



TRAC Results

$$\text{TRAC} = \frac{\left(\sum_{t=0}^{t=T} \hat{y}(t) y(t)\right)^2}{\left(\sum_{t=0}^{t=T} \hat{y}(t)\hat{y}(t)\right)^2 \left(\sum_{t=0}^{t=T} y(t)y(t)\right)^2}$$

			Type I							Type II						Ty. III	Ty. IV
Case	Trained Sensor Pair	Est. Strain	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
C_1	A_1-S_1		0.83	0.92	0.90	0.90	0.89	0.95	0.90	0.90	0.88	0.87	0.91	0.89	0.90	0.68	0.90
															[illegible]	0.68	0.91
															[illegible]	0.64	0.89
C_2	A_2-														[illegible]	0.62	0.86
															[illegible]	0.68	0.89
															[illegible]	0.56	0.73
C_3	A_3-														[illegible]	0.58	0.90
															[illegible]	0.66	0.91
															[illegible]	0.61	0.91
C_4	A_4-														[illegible]	0.67	0.89
															[illegible]	0.68	0.89
			0.85	0.92	0.93	0.91	0.90	0.96	0.85	0.89	0.91	0.87	0.88	0.86	0.93	0.69	0.91



1.0-0.9	
0.9-0.8	
0.8-0.7	
0.7-0.6	
0.6-0.5	
<0.5	

Key Outcomes

- Accurate estimation of strain time series is possible with acceleration acquired from **inexpensive sensing system**
- The proposed network exploits the **temporal modeling of LSTM** and **nonlinear mapping of FC layers** to be able discover temporal dependencies and complex relationships between input and output sequences
- This study also introduces a **novel step-wise training methodology** to deal with the computational cost of sequential learning and long time histories obtained as a nature of fatigue life assessment

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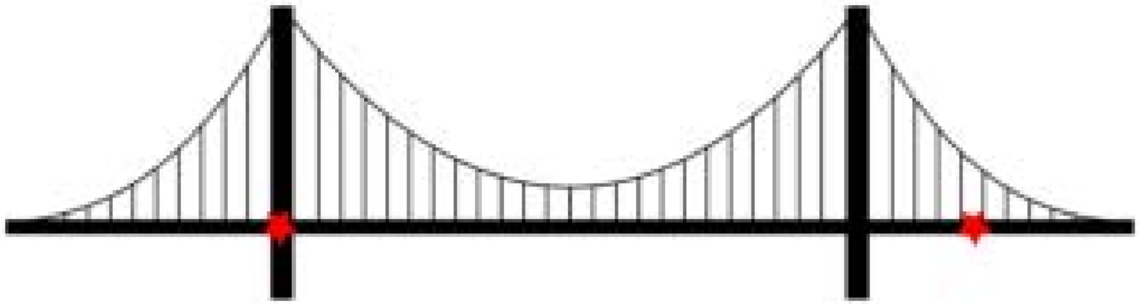
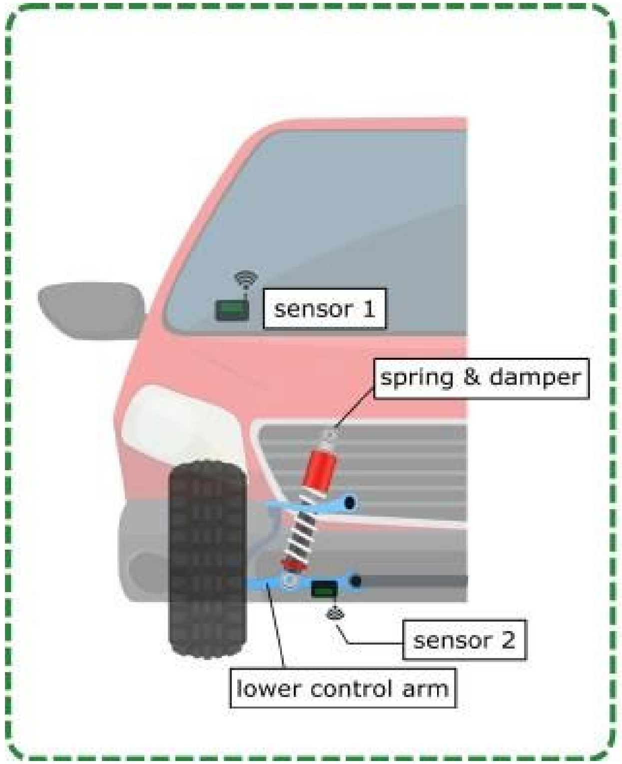
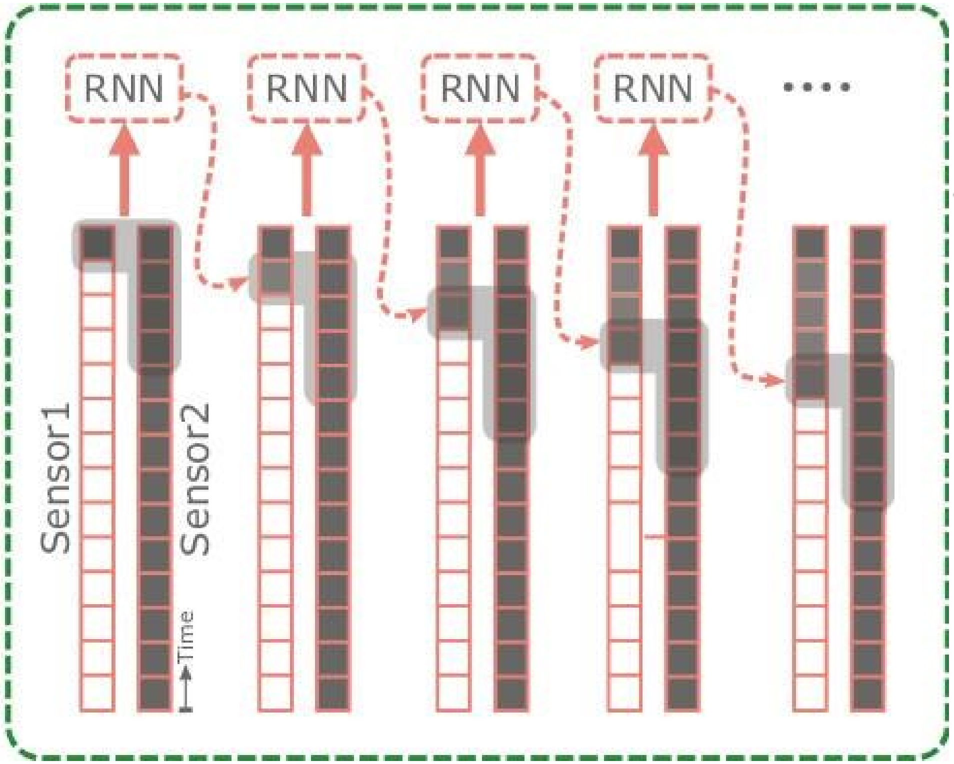
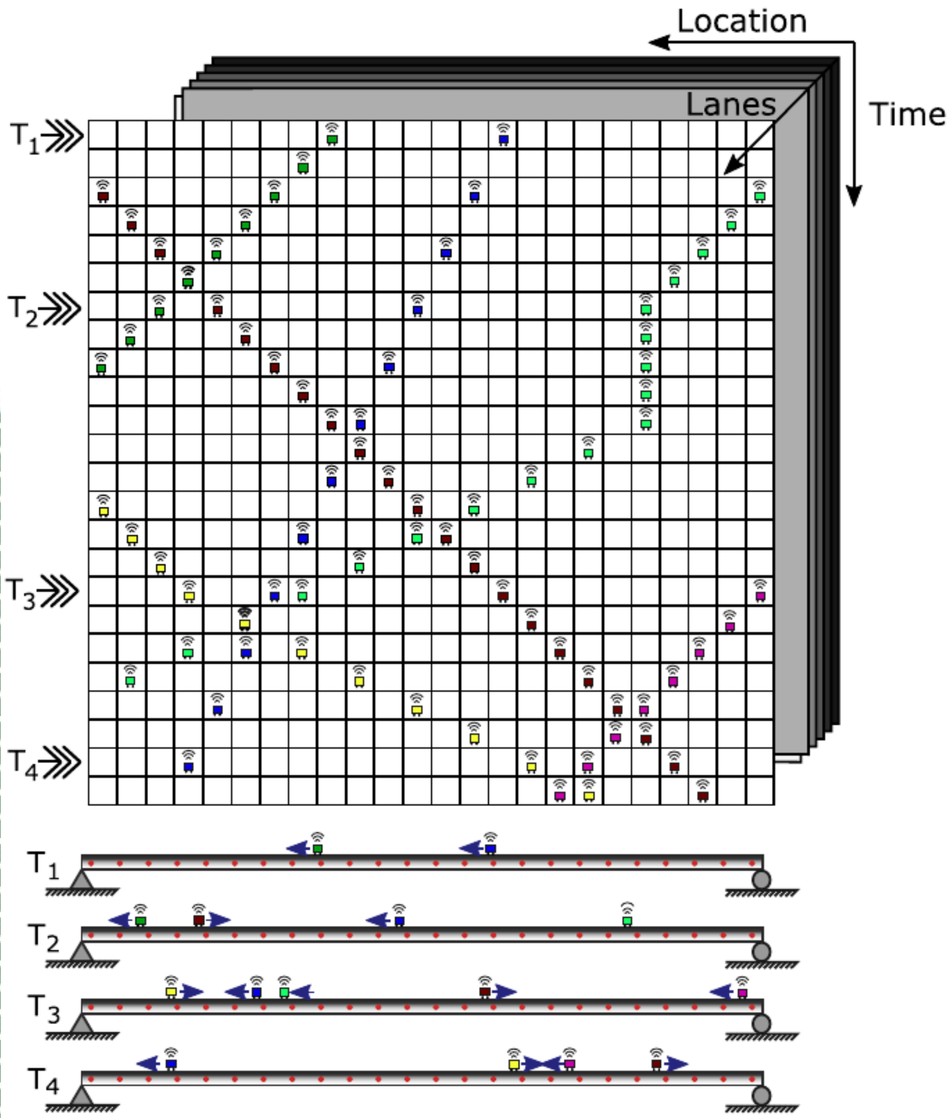
Using Crowdsourced Data









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- *Pennsylvania Infrastructure Technology Alliance (PITA)*
- *Computational Optimization Research at Lehigh (COR@L) laboratory*

Thank you
Any questions?

Today's Panelists

#TRBWebinar

- Hoda Azari, *Federal Highway Administration*
- Devin Harris, *University of Virginia*
- Nora El-Gohary, *University of Illinois, Urbana-Champaign*
- Shamim Pakzad & Martin Takac, *Lehigh University*
- Moderated by: Sreenivas Alampalli, *New York State DOT (ret.)*

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