Hierarchical Model Transfer Between Bridges for Multi-Task Damage Diagnosis Using Drive-by Vehicles

Jingxiao Liu, Susu Xu,
Mario Bergés, Hae Young Noh

Stanford University
Stony Brook University
Carnegie Mellon University

Scalable bridge health monitoring (BHM) is needed

Early deterioration detection can reduce

- bridge collapse risk
- rehabilitation cost (~$123 billion, backlog)
- traffic-interruption cost

22% of over half a million nation's bridges are in poor condition.

Need a **scalable** BHM solution

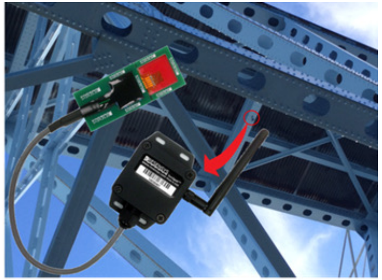
I-35W Mississippi River bridge collapse, 2007 (13 killed, 145 injured)

Current bridge health monitoring is hard to scale

Manual inspection
(pic credit: RocTest)

Pros:
- Detailed assessment with expertise

Cons:
- High labor Cost (~**$2.7 billion**, bi-annual)
- Delayed detection of damages (due to infrequent monitoring)



Direct sensing method
(pic credit: RESENSYS)

Pros:
- Continuous and autonomous monitoring

Cons:
- Vulnerable electrical system
- Traffic interruption
- On-site installation and maintenance

Dedicated Mobile sensing methods (pic credit: BDI)

Pros:
- One system monitors multiple bridges
- No need for on-site installation and maintenance

Cons:
- Operate at low speed
- Disrupt regular traffic

Drive-by Bridge Health Monitoring (BHM) is a Scalable Solution

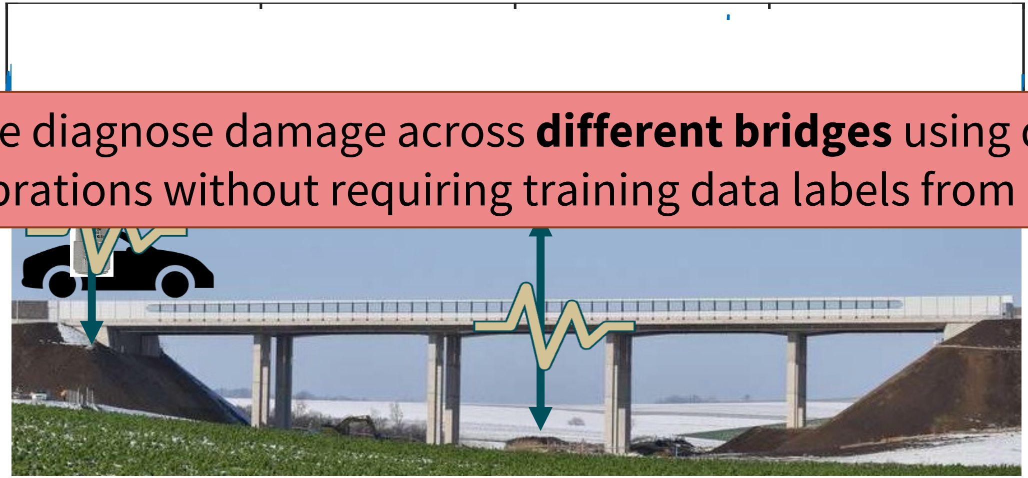
Pros:

- Scalable
- No need for on-site instrumentation;
- Operate at regular traffic speed;
- Protective from outside environment.

Cons (analysis challenges):

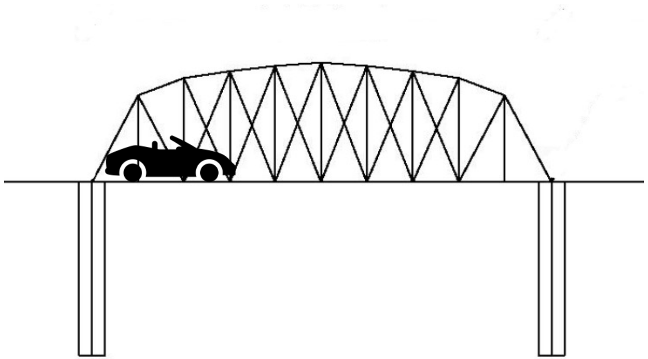
- Expensive to obtain ground truth
- Distinct bridge characteristics

Vertical acceleration of vehicle



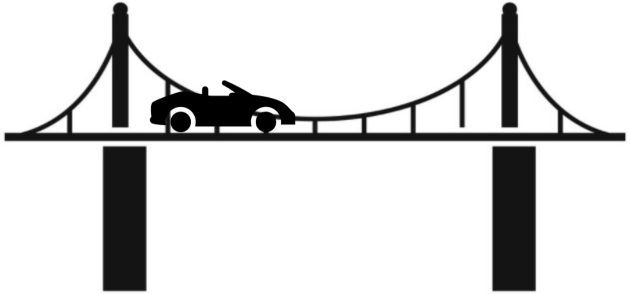
How do we diagnose damage across **different bridges** using drive-by vehicle vibrations without requiring training data labels from every bridge?

Challenge 1: data distribution mismatch



Learn model $f: X_s \rightarrow y_s$

$\neq$



Apply Model $f: \hat{y}_d = f(X_d)$

- Different bridges have **distinct characteristics**

  → Data distributions are mismatched between **different** bridges;

  → Model may have limited **generalizability**

  → Significantly worse performance for bridges without labeled data

Challenge 2: multiple learning tasks

Stiffness reduction

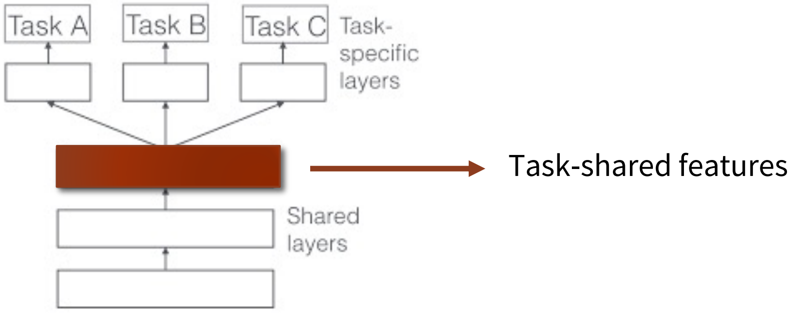
Damage location: ¼ span

Damage severity: mild damage

- Multiple diagnostic tasks are generally coupled.
  → Learn correlated tasks **separately** may lose shared information;
    → Require **more data** to learn multiple tasks.
  → Learn **sequentially** may have large error propagation;
    → Worse performance for learning multiple tasks.

Unsupervised domain adaptation (UDA) and Multi-task learning (MTL)

- Feature-based UDA: extracts features that are **informative** to labels and **invariant** across different systems



- Feature-based MTL: simultaneously learns multiple tasks and extracts **shared information** when the tasks are correlated to improve accuracy in multiple tasks.

Simply combining UDA + MTL has problems

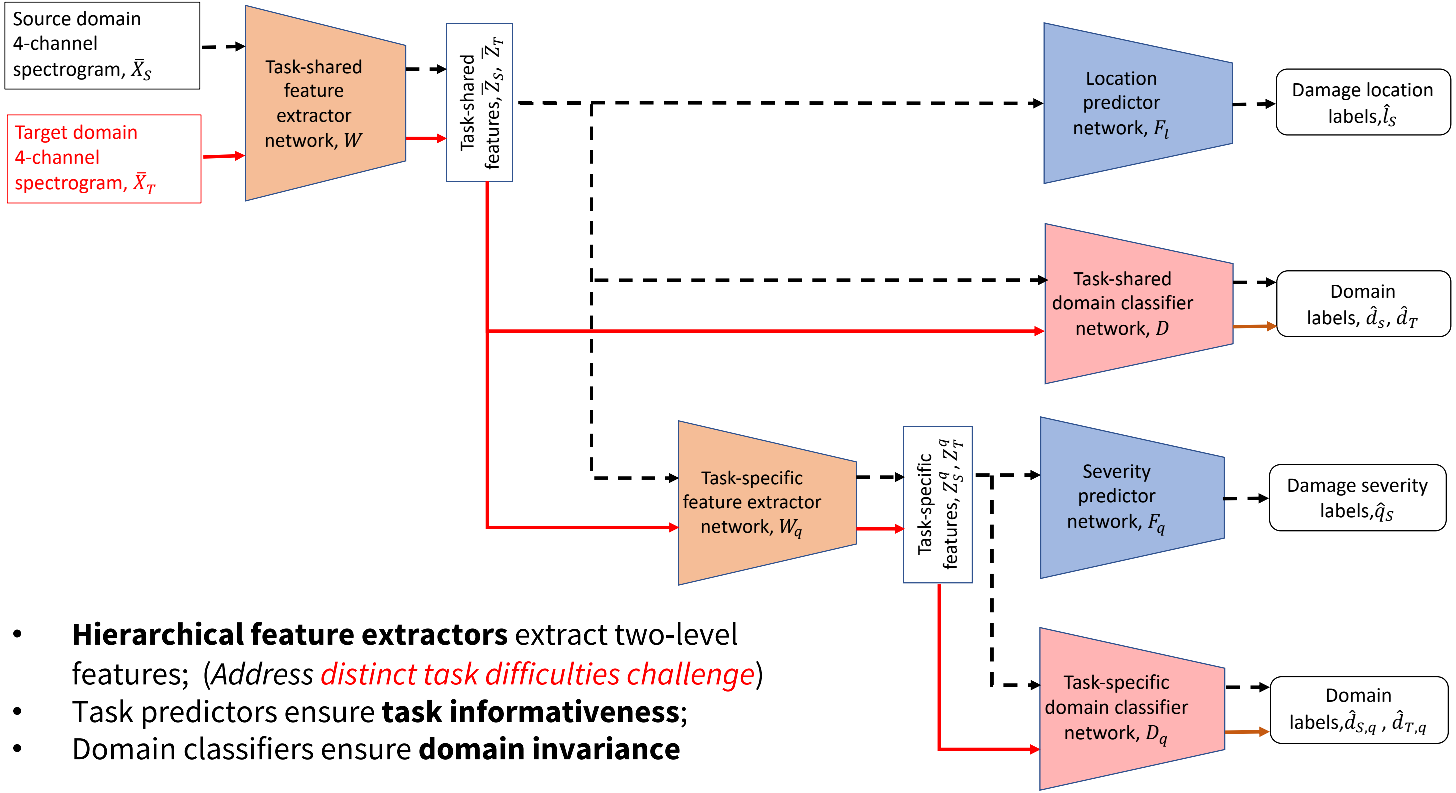
- Learning multiple tasks that have **distinct task difficulties**.
  → Equally learning multiple tasks would result in **biased training dominated by easy task**

We formulate the **task hierarchy** to reallocate learning resources for multiple tasks

- Having a **complex model** that is hard to optimize.
  → Different tasks have **different data distributions to match**
    → **Hard to optimize** if we equally align data distributions for every task

We introduce a new optimization strategy that prioritizes task has more mismatched data distributions

Hierarchical multi-task unsupervised domain adaptation



- **Hierarchical feature extractors** extract two-level features; (*Address distinct task difficulties challenge*)
- Task predictors ensure **task informativeness**;
- Domain classifiers ensure **domain invariance**

Hierarchical multi-task unsupervised domain adaptation

The corresponding loss function:

$$\min_{\substack{\theta_W, \theta_{W_1} \cdots, \theta_{W_{M_2}}, \\ \theta_{F_1}, \cdots, \theta_{F_M},}} \Big[$$

Task-averaged source domain cross-entropy loss in damage localization task

Task-averaged source domain cross-entropy loss in damage quantification task

MTL related losses

Soft-max of task-shared domain classifier losses

Combines **gradients from all tasks** and **adaptively prioritize** tasks with larger data distribution difference

(Address the optimization challenge)

Task-specific domain classifier loss

UDA related losses

Experimental evaluation

lab-scale experiment setup

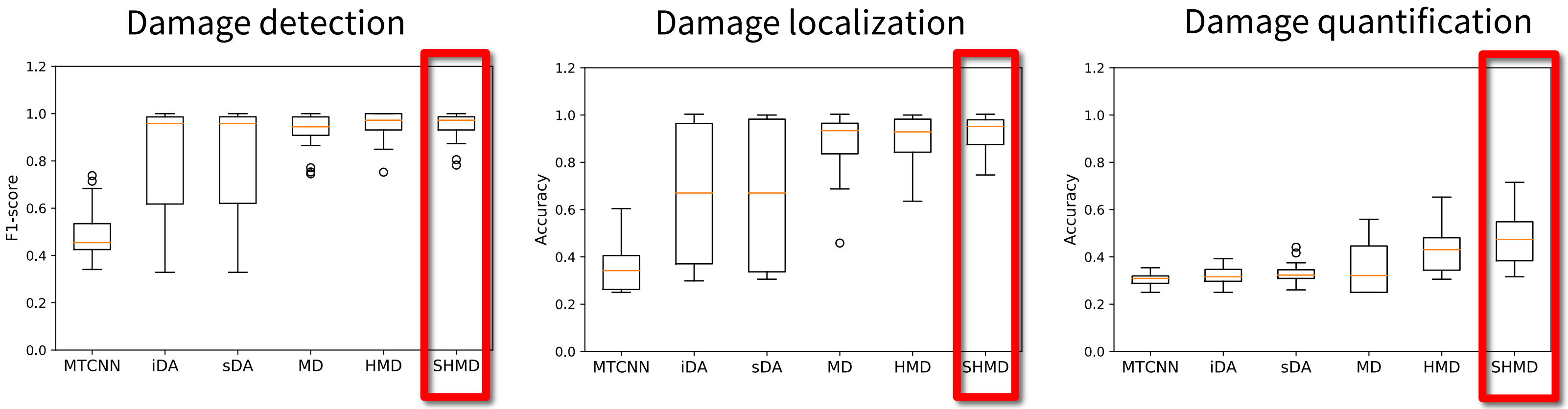
- Evaluated through lab-scale experiments
  - 2 structurally different bridges and 3 different loaded vehicles
  - 4 damage severity levels and 3 damage locations.
  - (2 bridges) X (3 vehicles) = (6 evaluations)

Experimental evaluation

Our methods and baselines:

- MTCNN: MTL without UDA;
- iDA: UDA with independent task learning;
- sDA: UDA with sequential task learning;
- MD: MTL + UDA;
- **HMD** (Ours): Hierarchical structure + MTL + UDA;
- **SHMD** (Ours): Soft-max loss + Hierarchical structure + MTL + UDA.

Experimental evaluation



Our methods has

- 2X accuracy improvement in all tasks, when compared to method without UDA (MTCNN);
- about 1.5X accuracy improvement in damage quantification, when compared to methods without MTL or hierarchical structure (iDA, sDA, and MD).

Conclusions

- We introduce an **end-to-end framework** that transfers the model learned from one bridge to achieve multiple damage diagnostic tasks in another bridge without any labels from the target bridge in all tasks.

- We design a **hierarchical architecture** and a **new loss function** to efficiently optimize our multi-task unsupervised domain adaptation algorithm.

- We **evaluate** the effectiveness of our approach on comprehensive lab-scale experiments. Our approach outperforms baseline methods.

Thank you!

Jingxiao Liu
liujx@stanford.edu

Stanford University

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Drive-by bridge health monitoring
with Port Authority of Allegheny County