Multimodal Signal Processing (MSP) lab
The University of Texas at Dallas
Erik Jonsson School of Engineering and Computer Science

Use of Triplet-Loss Function to Improve Driving Anomaly Detection Using Conditional Generative Adversarial Network

Yuning Qiu
Teruhisa Misu
Carlos Busso

Honda Research Institute US

THE UNIVERSITY OF TEXAS AT DALLAS

UT Dallas MSP Multimodal Signal Processing Laboratory

Examples of Dangerous Driving Condition

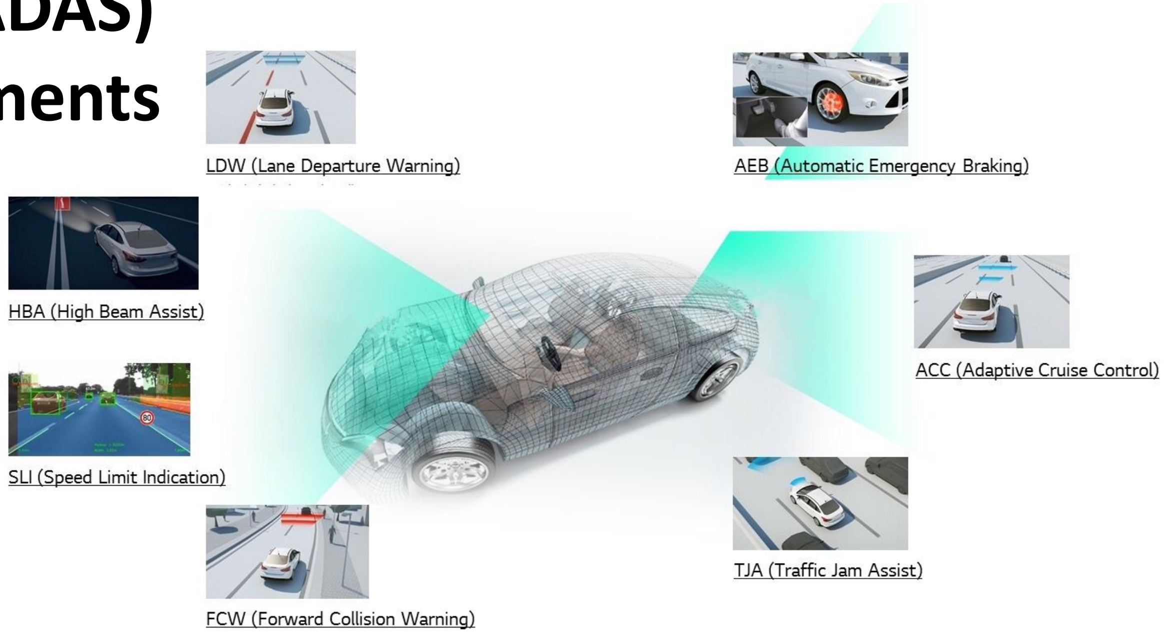
- **Driving is not always safe**

Avoid on-road pedestrian

Avoid on-road vehicle

Motivation

- **Advanced driver assistance systems (ADAS) have made important safety improvements**
  - Forward collision warning (FCW)
  - Intelligent speed advice (ISA)
  - Collision avoidance system
  - Blind spot monitor
- **To further improve ADAS functions**
  - Need to know what kinds of anomalies exist

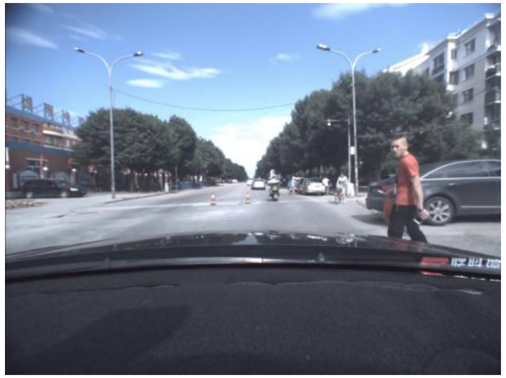


Motivation

Anomaly Detection on Driving Conditions

Driving anomalies are defined as events that deviate from expected driver behaviors that can lead to hazard situations

- **Examples include:**
  - Abrupt changes on driving maneuvers
  - Missing tasks required to complete a driving maneuver
    - Checking mirrors before turning
  - Lack of awareness of objects, pedestrians, or other vehicles
  - Hazard actions from other vehicles
  - Unexpected changes on the road that leads to hazard scenarios
    - Constructions on the road

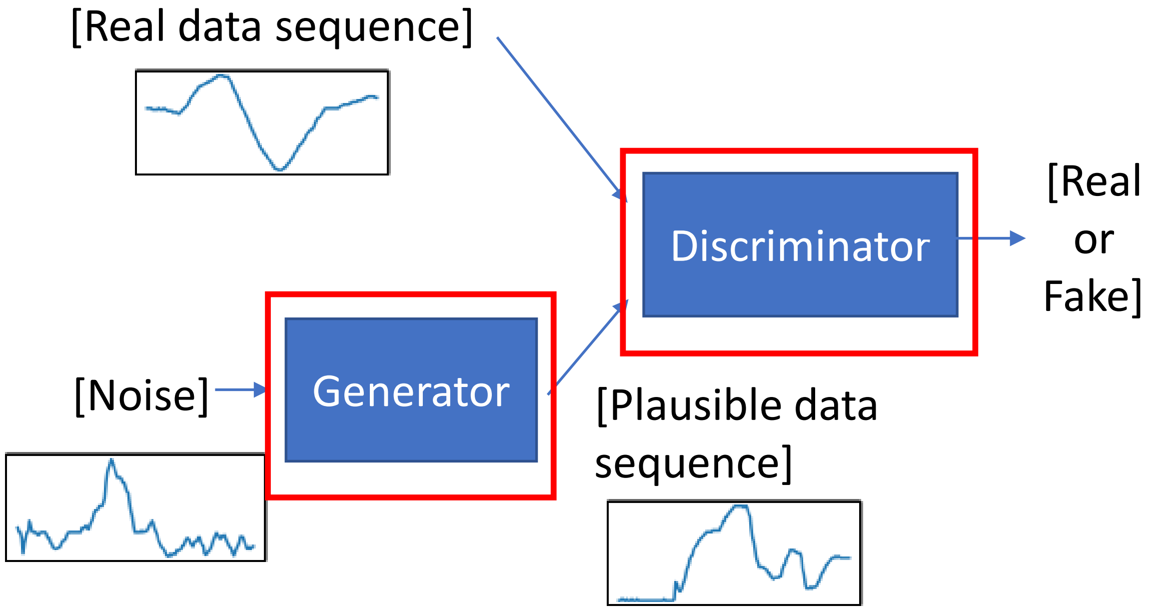


On-road pedestrian

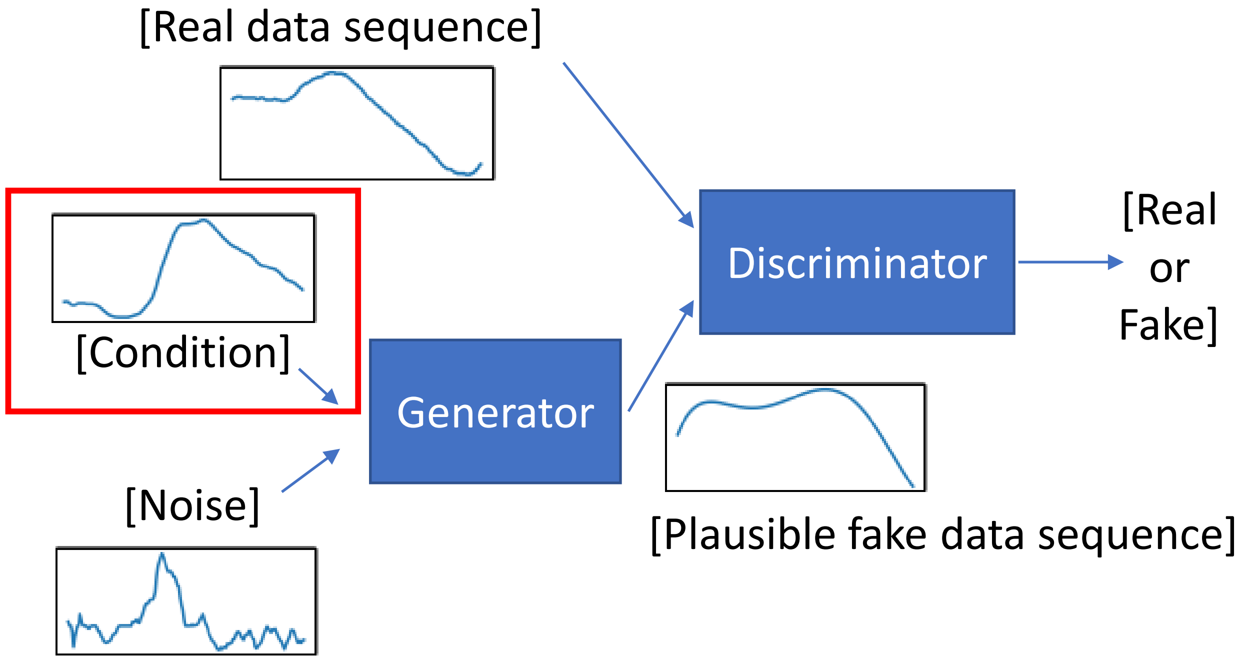
On-road bicyclists

Motivation – From our Previous Work

- **Generative Adversarial Network (GAN)**
  - Learn the distribution of data
  - Generate plausible data from random noise

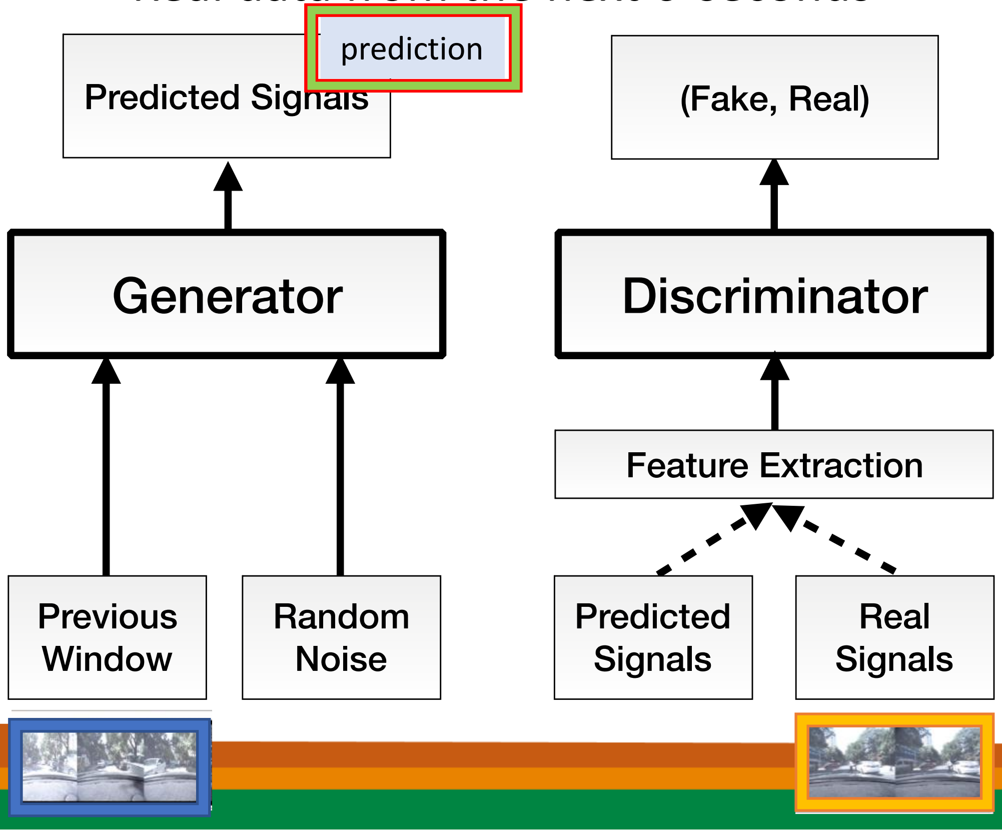


- **Conditional GAN**
  - Input: Condition & Random noise
  - Generate data constrained by *condition*



Motivation – From our Previous Work

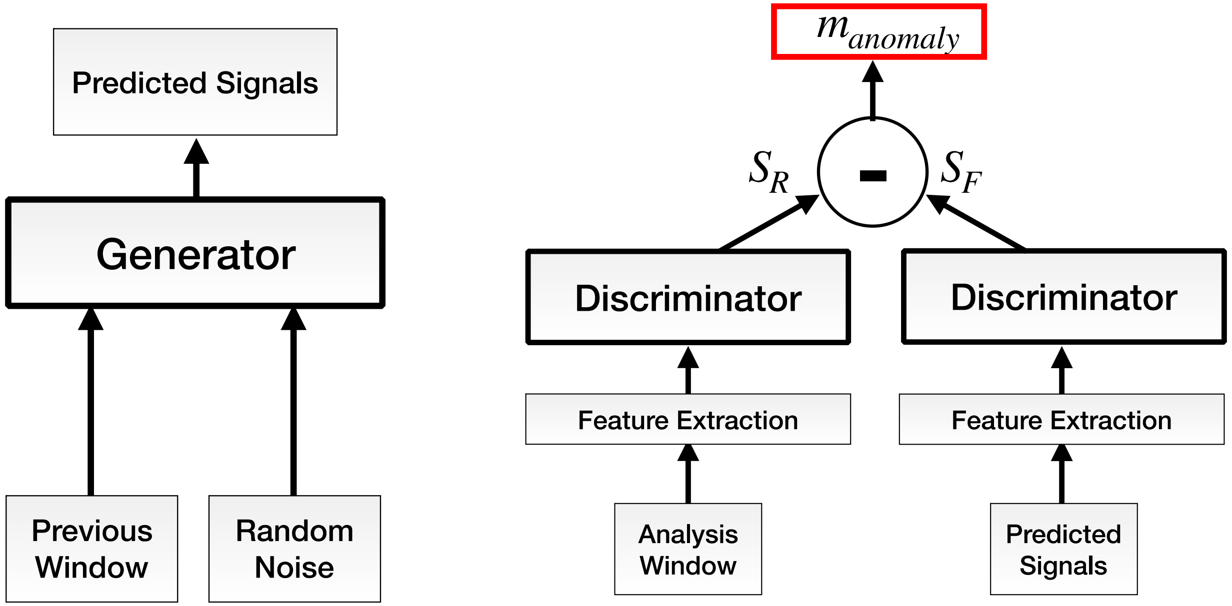
- **Condition (previous window)**
  - Real data from previous 6-seconds
- **Random noise:**
  - Random noise, totally unrelated to real data
- **Real signals:**
  - Real data from the next 6-seconds

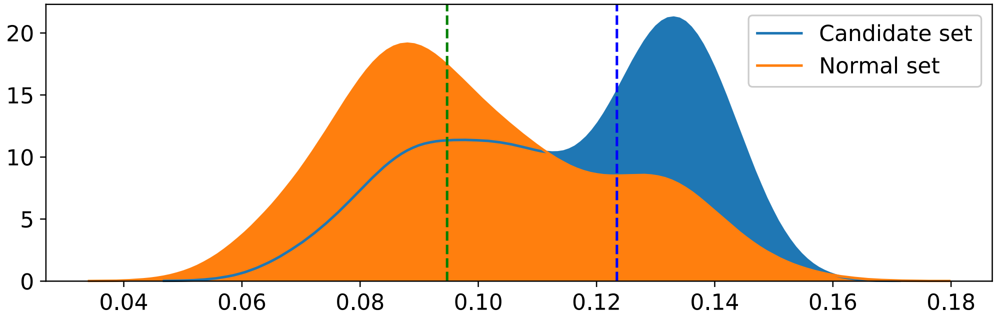


- **The generator made prediction**
  - Physiological and CAN-Bus data
  - Conditioned on the observed data from the previous six seconds
- **The discriminator made discrimination**
  - Real or Fake

Motivation – From our Previous Work

- **Inference**
  - Predict the future signals, based on previous data
  - Contrast their values with real observations

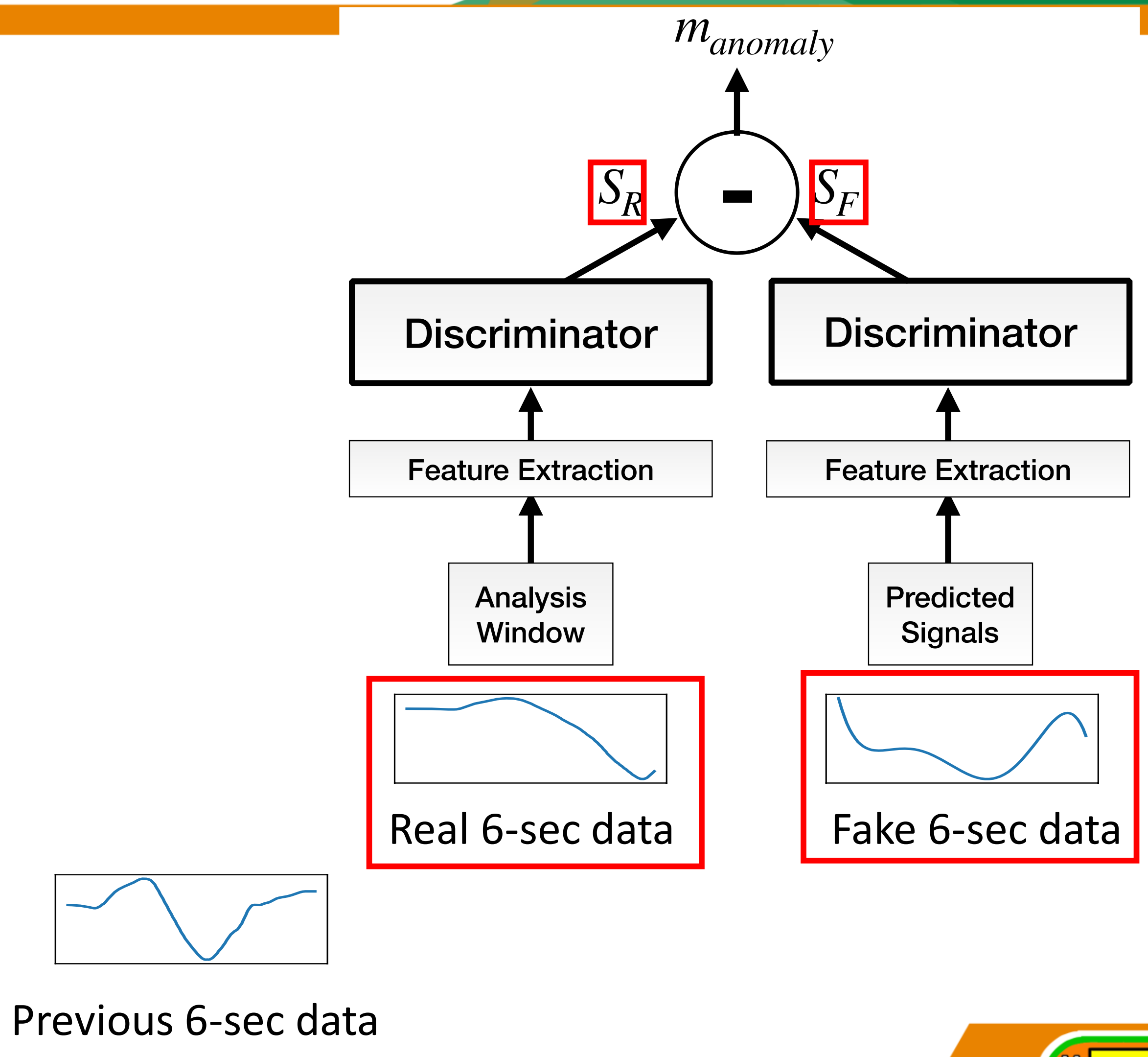




Histogram of $m_{anomaly}$

Motivation – From our Previous Work

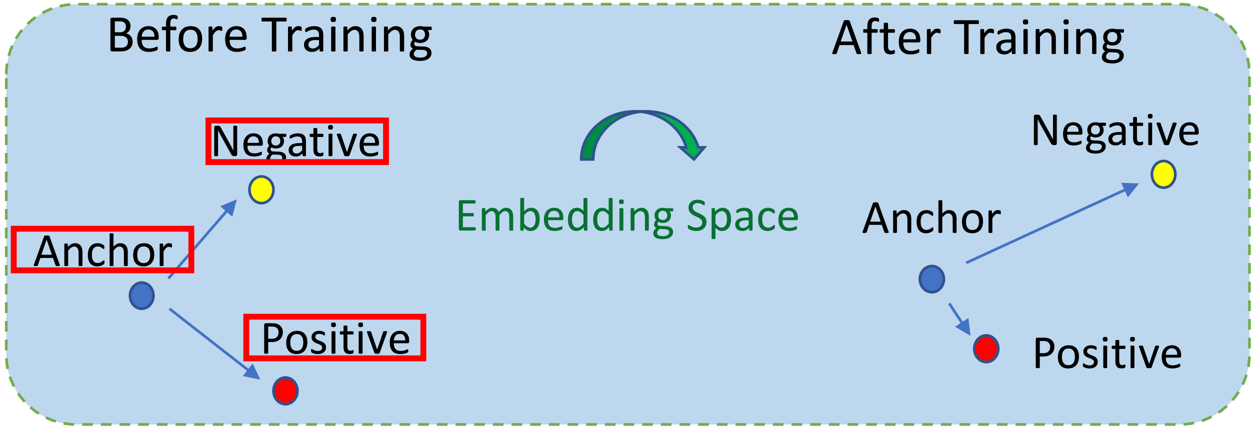
- **Limitation in the quantifying the anomaly score**
  - The discriminator was trained to identify whether the input was real or fake
  - Two very different samples that are classified as real can have similar scores, leading to small anomaly values
  - This approach cannot fully contrast the differences between the predicted and real samples



1. Motivation
2. Proposed Model
3. Experimental Evaluation
4. Conclusions

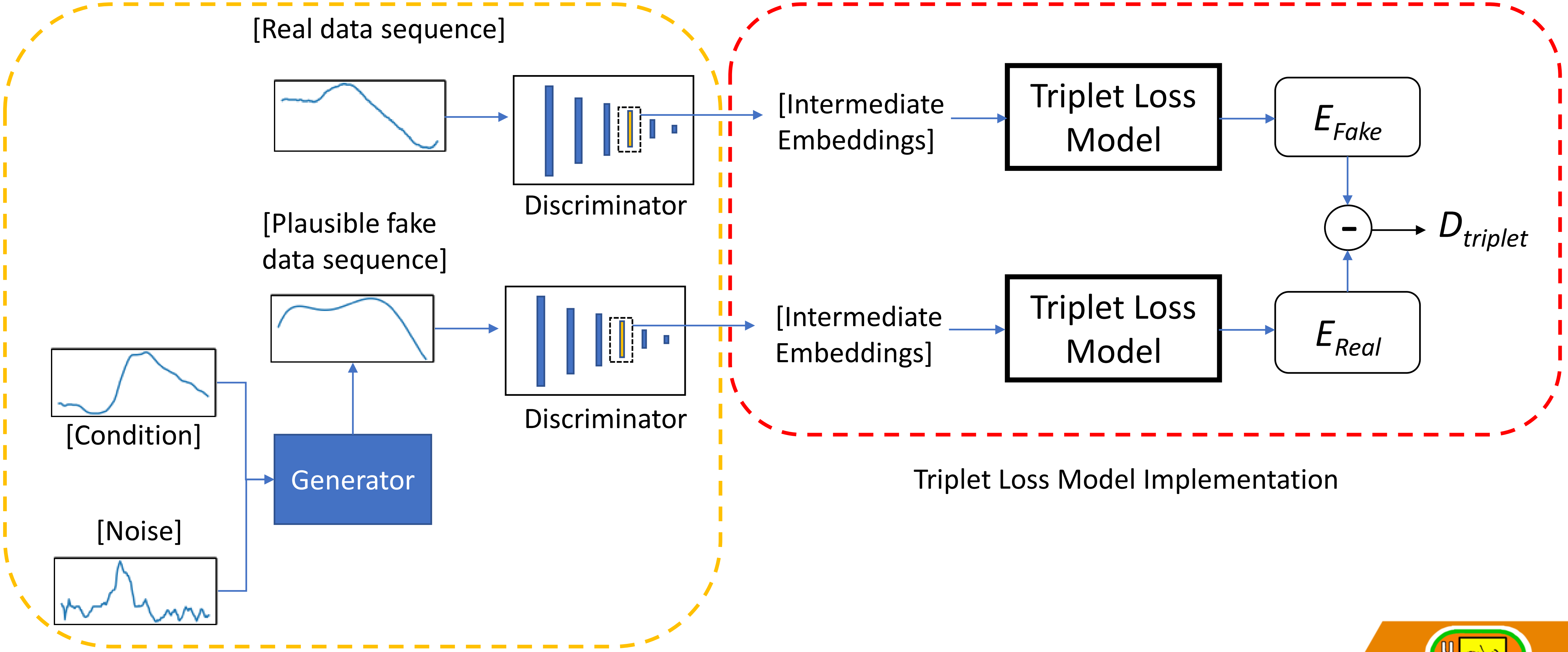
New Metric

- **New metric to better quantify the difference between predicted and real signals**
- **<u>Triplet Loss Function</u>**
  - Decrease the distance between the embeddings of the predicted and real signals
  - Increase the distance between the embeddings of unpaired predictions and real signals



$$L_{Triplet} = \max(d(a,p) + margin - d(a,n), 0)$$

Big Picture of the Proposed Model



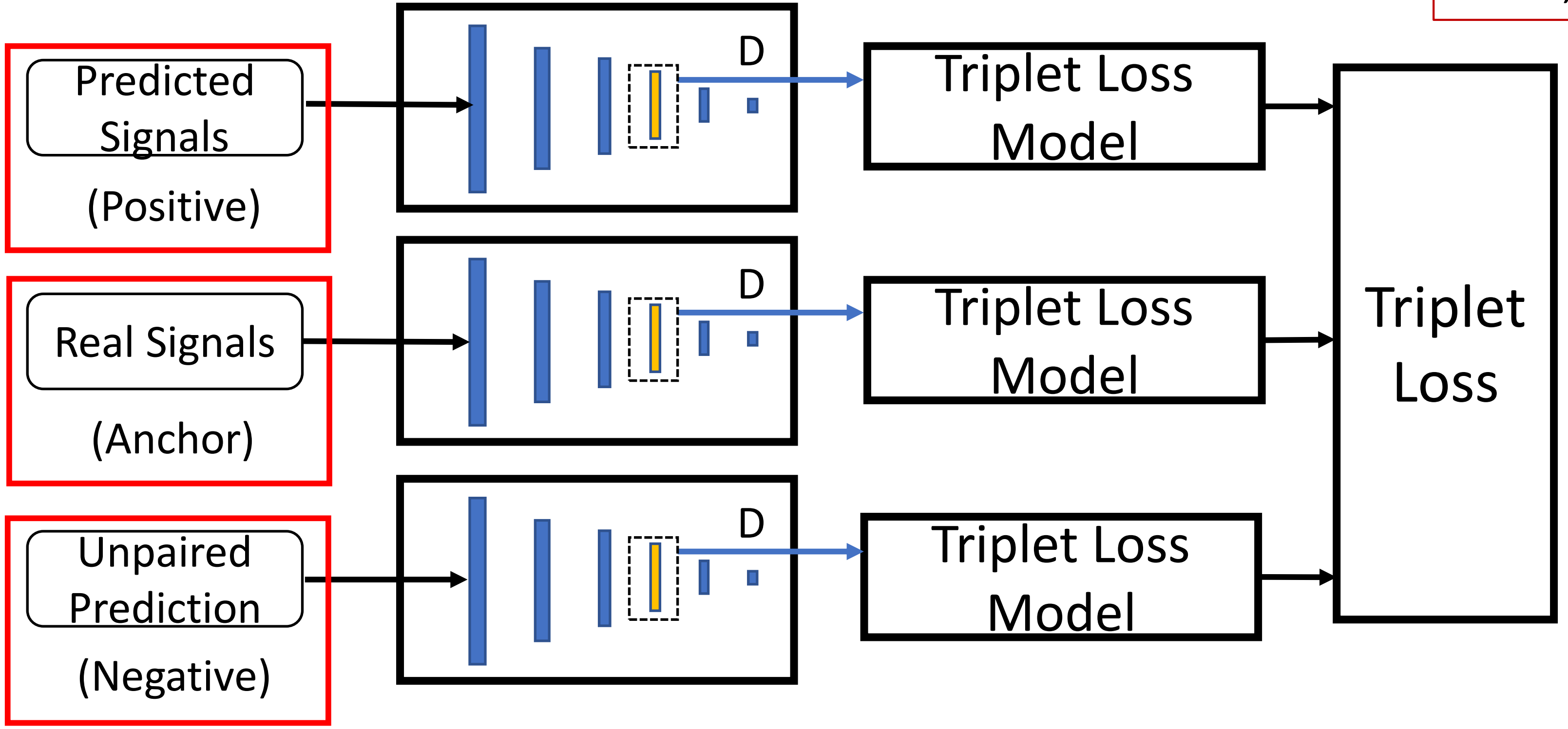
Triplet Loss Model Implementation

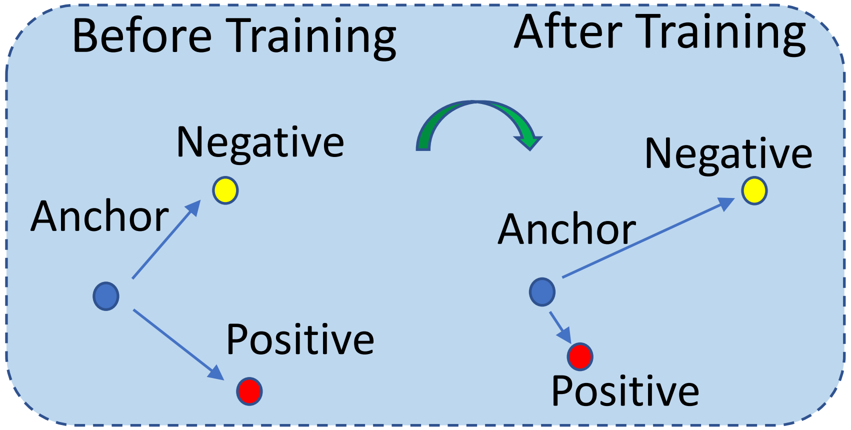
Conditional GAN Implementation

Proposed Triplet Model for Better Discrimination

- **Training Process (Triplet Loss Model)**

After training the Conditional GAN models, we freeze the parameters of the G and D, and train the Triplet loss model.

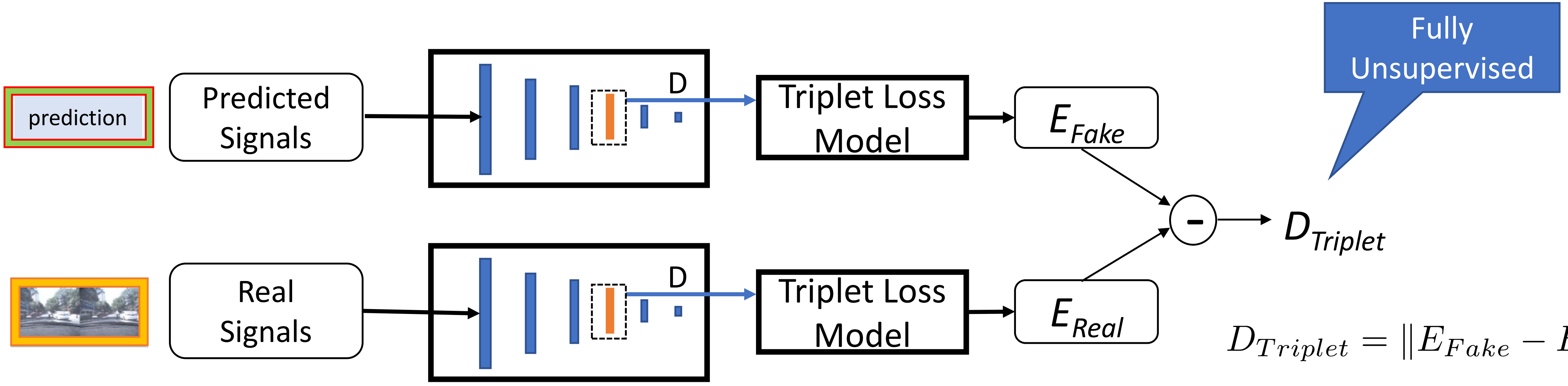




$$L_{Triplet} = max(\|E_a - E_p\| + margin - \|E_a - E_n\|, 0)$$

Proposed Model Structure

- **Testing Process**
  - Identify the difference between the Real and the Predicted triplet loss score



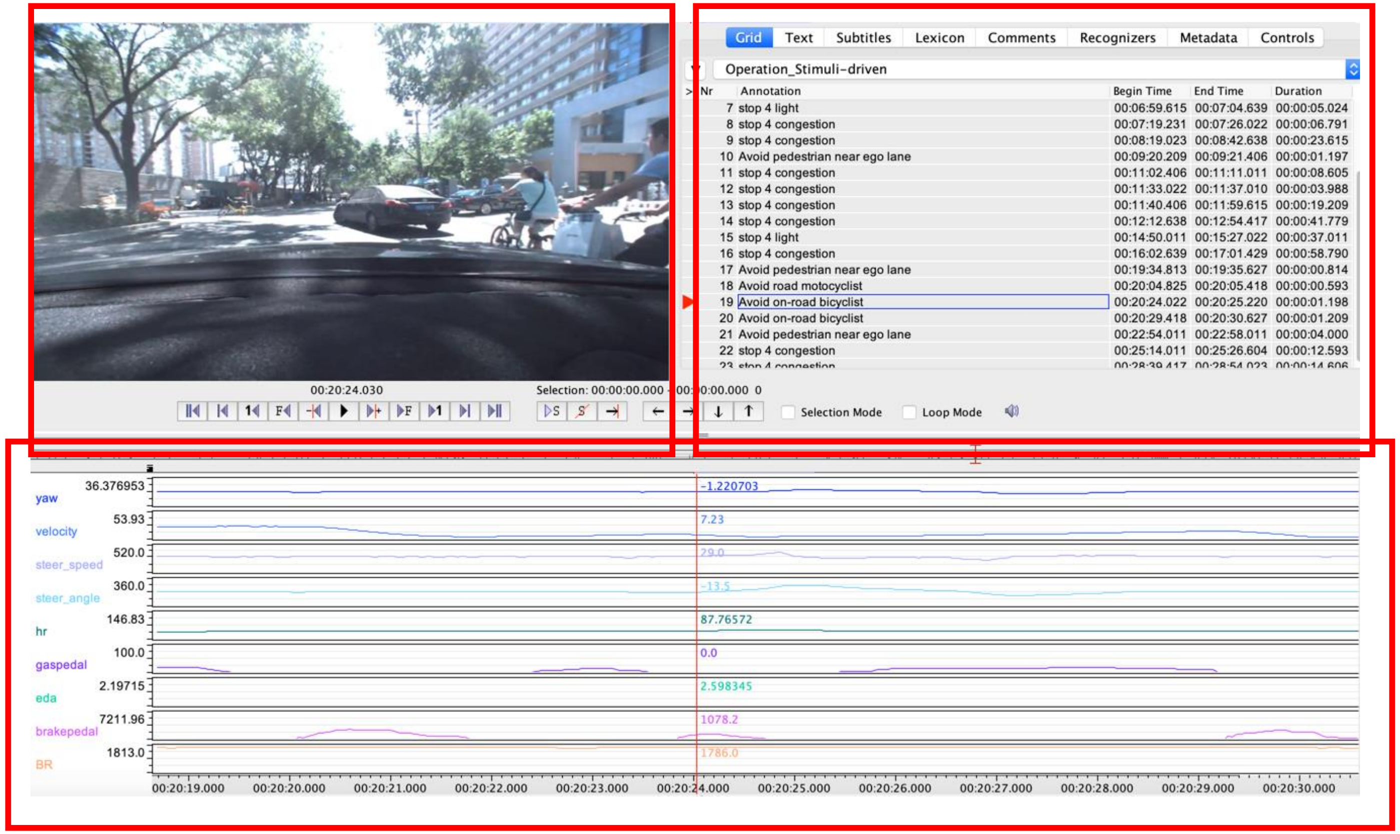
$$D_{Triplet} = \|E_{Fake} - E_{Real}\|$$

  - A bigger value for $D_{Triplet}$ ⟶ A more abnormal driving segment

1. Motivation
2. Proposed Model
3. Experimental Evaluation
4. Conclusions

Experimental Evaluation – Driving Anomaly Dataset (DAD)

- **250 hours of naturalistic driving recordings**
  - 48 hours used in this study
- **Collected by Honda Research Institute in an Asian city**
- **Road scenarios**
- **Manually added annotations**
- **Driver's physiological signals**
- **Vehicle's CAN-Bus signals**



Experimental Evaluation – Driving Anomaly Dataset (DAD)

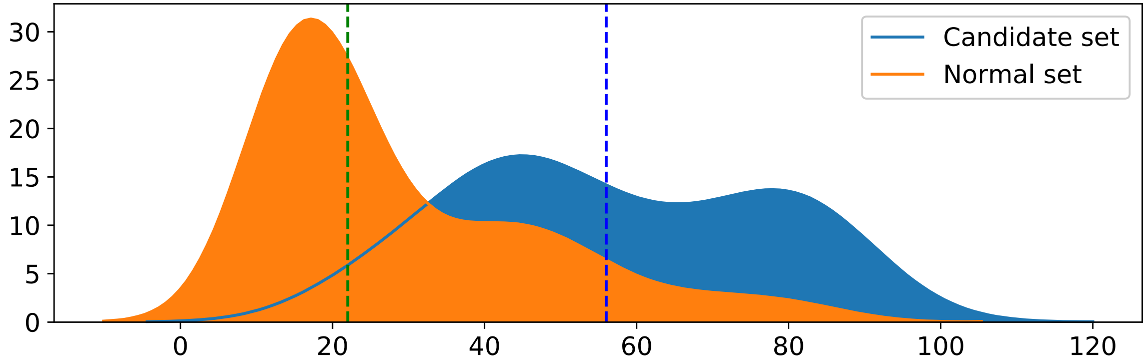
- **Annotations**
  - A four-layer representation
    - Goal-driven Operation
    - Stimulus-driven Operation
    - Traffic Rule/Manner Violation
    - Attention

	Annotations
Goal-oriented Operation	Left turn; Right turn; Intersection passing; Cross-walk passing; Left lance change; Right lance change; U-turn
Stimulus-driven Operation	Stop for congestion; Avoid pedestrian near ego lane; Avoid road motorcyclist; Avoid on-road bicyclist
Traffic rule/manner violation	Traffic rule violation
Attention	Crossing vehicle; Crossing pedestrian; Red light; Cut-in; Sign; On-road bicyclist; Parked vehicle; Merging vehicle; Yellow light; Road work; Pedestrian near ego lane

- **Data collected**
  - Drivers' physiological data
    - Heart Rate
    - Breath Rate
    - Skin conductance (EDA)
  - Vehicle controller area network (CAN)-bus data
    - Speed
    - Yaw
    - Steer speed
    - Steer angle
    - Pedal pressure
    - Pedal angle

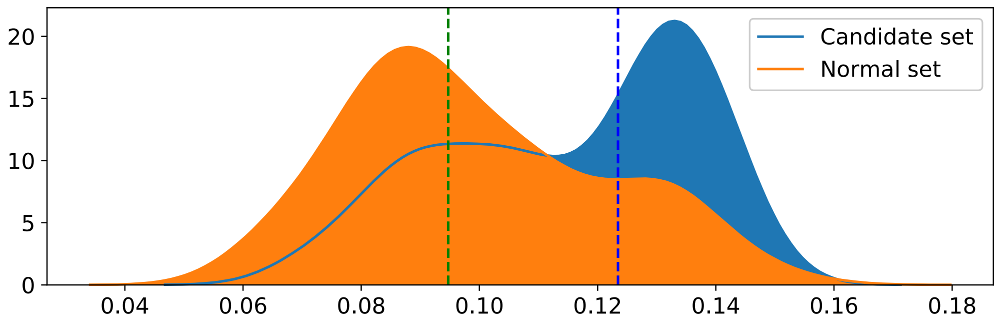
Experimental Evaluation – Anomaly Score Distribution

- **Split the driving segments into 3 sets of segments according to the annotations**
  - Candidate (Expected to be more anomalous)
    - Avoid on-road pedestrian
    - Avoid pedestrian near ego-lane
    - Avoid on-road bicyclist
    - Avoid bicyclist near ego-lane
    - Avoid parked vehicle
    - Traffic rule violation
  - Normal
    - No annotations during the segment
- **Histogram of anomaly scores $m_{anomaly}$ for segments from the normal set and the candidate set**

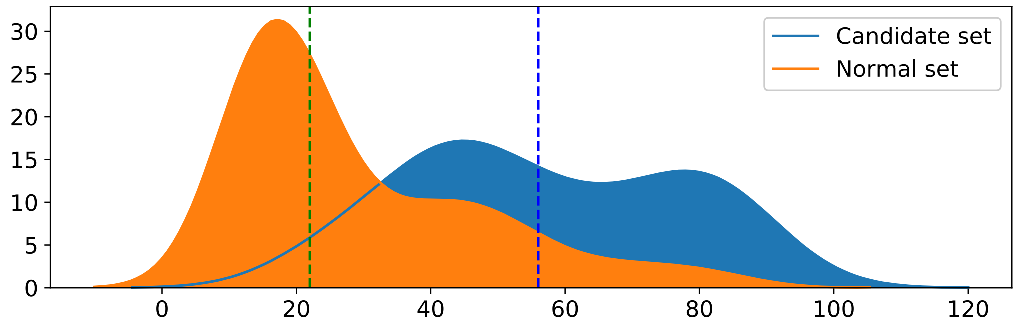


Experimental Evaluation – Compared with Conditional GAN

- **Histogram of anomaly scores $m_{anomaly}$ for segments from the <u>normal</u> and the <u>candidate</u> set**
  - The dash lines are the medians of anomaly scores for each group



Conditional GANs Activation Metric

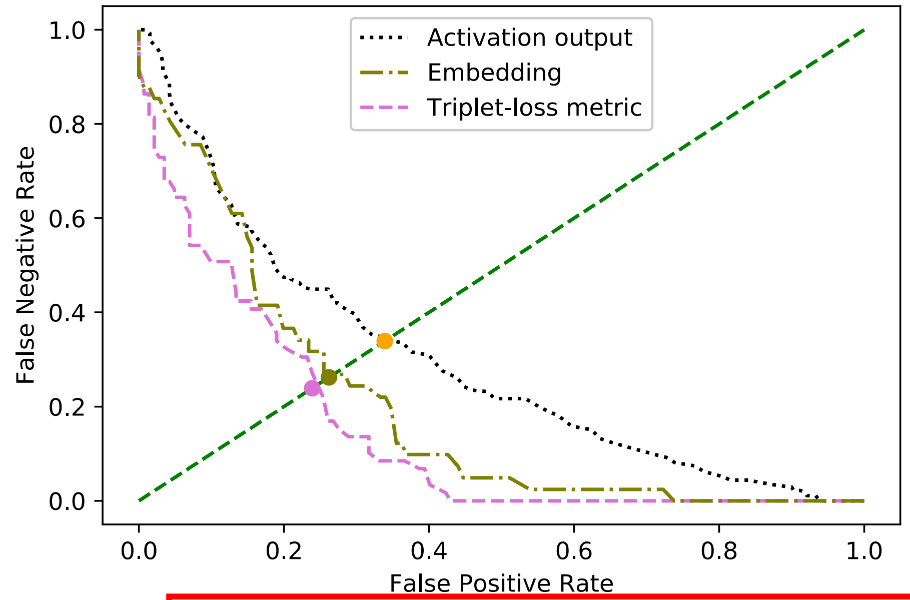


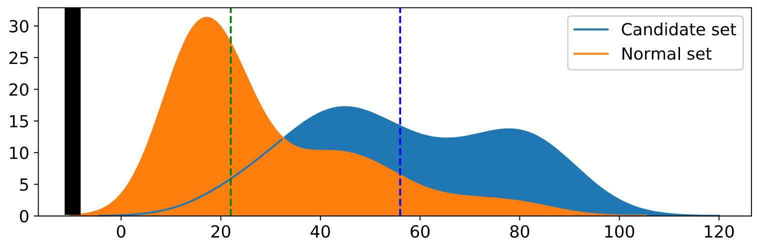
Proposed Triplet Loss Metric

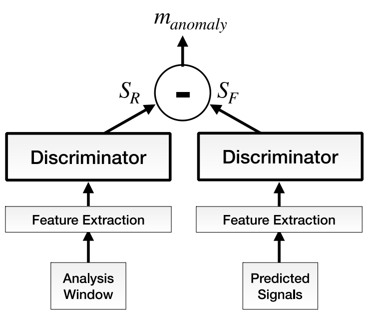
- **Observation:**
  - Proposed model increases separation between normal and candidate sets

Experimental Evaluation – Compared with Conditional GAN

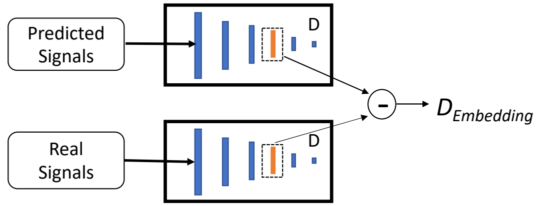
- ***Detection error tradeoff* (DET)**
  - It better visualizes the performance differences
  - A binary classification problem,
    reporting the results by moving the hyperplane
  - Show *false negative rate* (FNR) versus
    false positive rate (FPR)



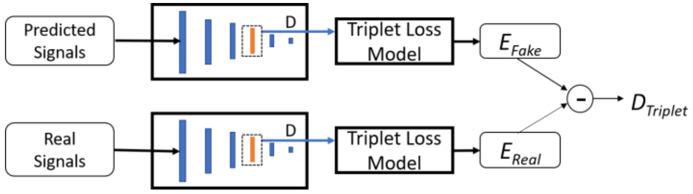




Activation output



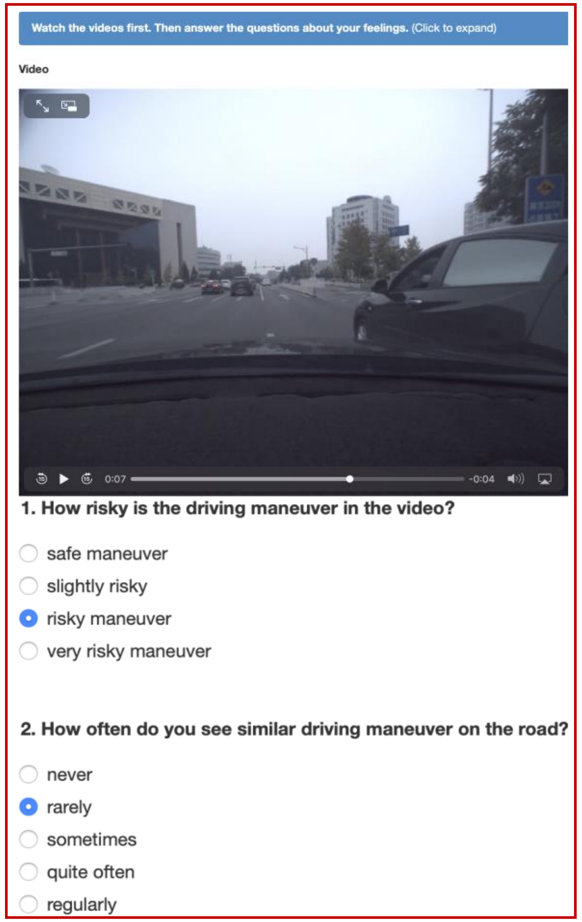
Embedding



Triplet-loss metric

Experimental Evaluation – Compared with Conditional GAN

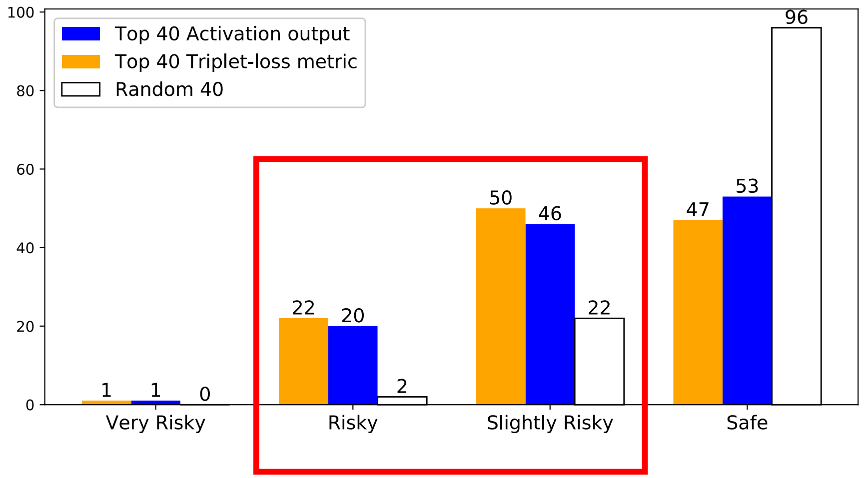
Subjective Measure: Perceptual Evaluation



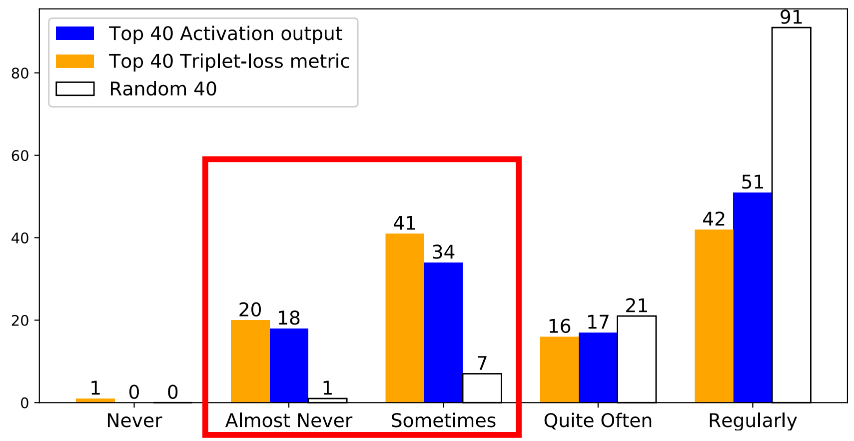
Evaluation GUI

- The selected Top-40 segments and Random-40 segments
- 40 videos × 3 evaluators per condition

- How risky is the driving maneuver in the video?



- How often do you see similar driving maneuver on the road?



Examples of Events Identified as Anomalous

- **Some segments (Candidate) with high anomaly score**

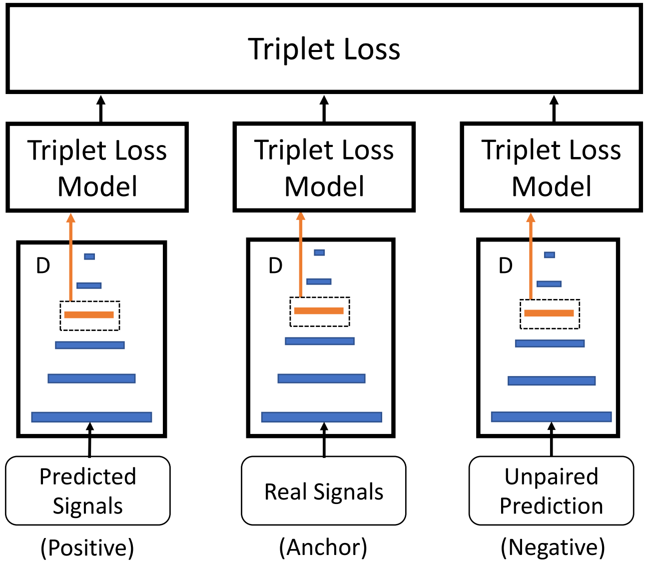
Avoid on-road motorcyclist

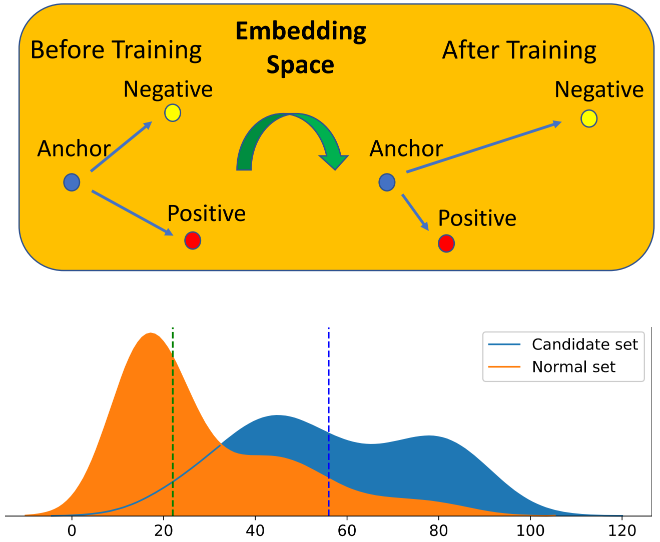
Avoid on-road bicyclist

1. Motivation
2. Proposed Model
3. Experimental Evaluation
4. Conclusions

Conclusions

- **Improved metric using the triplet-loss function for driving anomaly detection**
  - Predict physiological signals and CAN-Bus data
  - Condition by previous frames
  - Quantify the deviations from expected values
  - Intermediate embeddings of the discriminator are the input of a triplet-loss network
  - Triplet-loss metric is more effective to distinguish anomaly





Many thanks!

Yuning Qiu

yxq180000@utdallas.edu