Towards Trustworthy Autonomous Systems

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Motivation

- Autonomous systems are responsible for decisions previously entrusted to humans. • The failure of these systems can have catastrophic consequences with significant loss
- of life and property.
- It is essential that these systems perform reliably and that their decisions are *trustworthy* even in the presence of anomalies and cyber attacks.
- **Explanations** can help ensure that these systems are working in our best interest and to help identify attacks and anomalies.
- Applications: self driving cars, adversarial ML (with Dr. Bhargava's group), IoT, disaster management, etc.













Vision: Articulate Systems that can Coherently Communicate to Resolve Issues

With Other Systems



Common language to complete tasks.

- Redundancy: systems solve problems in multiple ways.
- Hybrid processes: systems that learn from each other.

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Explanations are a debugging language.

- Debugging: humans can improve complex systems
- Education: complex systems can "improve" or teach humans.

How can we leverage Explanations for **Anomaly Detection**

Black-box

Decisions supported with commonsense.

Imprecise

Localize errors with reasons.

Common language for debugging.

Domain: Self driving cars

Caused By Software Set to Ignore Objects

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Failure of Complex Systems

AI Mistakes Bus-Side Ad for Famous CEO, Charges Her With Jaywalking

By Tang Ziyi / Nov 22, 2018 04:17 PM / Society & Culture

Complex Systems Fail in Two Ways

1. Failure *local* to a specific subsystem.

2. A failed cooperation amongst subsystems.

Local Problem: Neural Networks are Brittle and Biased

For self-driving, and other mission-critical, safety-critical applications, these mistakes have CONSEQUENCES.

K. Eykholt et al. "Robust Physical-World Attacks on Deep Learning Visual Classification."

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Predictive Inequity in Object Detection

Benjamin Wilson¹ Judy Hoffman¹ Jamie Morgenstern¹

Monitor Opaque Subsystems for Reasonableness

+

Commonsense Knowledge Base

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Flexible Representation

- 2.

Opaque Mechanism

+

+

Identify (Un)reasonability

(Un)reasonability

Judgement of reasonableness Justification of reasonableness

System Architecture for Self-Driving Cars

L.H. Gilpin. Explaining possible futures for robust autonomous decision-making. Proceedings of the AAAI Fall Symposium on Anticipatory Thinking, 2019.

Anomaly Detection Through Explanations in Three Steps Synthesizer 1. **VISION** Lidar TACTICS '**. 2.** .! 3. Steering Brakes Power

L.H. Gilpin, V. Penubarthi, L. Kagal. "Anomaly Detection through Explanations." To be submitted.

Generate Symbolic Qualitative Descriptions for each committee.

Input qualitative descriptions into local "reasonableness" monitors.

Use a synthesizer to reconcile inconsistencies between monitors.

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Local Monitoring

approximate dimensions of [0.621, 0.669, 1.642] is approximately the correct size in meters.

This perception is reasonable. An adult is typically a large person. They are usually located walking on the street. Its

Start with Baseline Rules

:safe_car_policy a air:Policy; air:rule :light-rule; air:rule :pedestrian-rule; air:rile :speed-rule; rdfs:comment "Safe driving tactics"; rdfs:label "Safe driving tactics by the state of MA." :pedestrian-rule a air:Belif-rule; rdfs:comment "Ensure that pedestrians are safe."; air:if { :EVENT a :V; car_ont:InPathOf :V. }; air:then [air:description ("There is a pedestrian"); air:assert [air:statement{:Event air:compliant-with :safe_car_policy .}]]. air:else [air:description ("There is not a pedestrian"); air:assert [air:statement{:Event

L.H. Gilpin and L. Kagal. "An Adaptable Self-Monitoring Framework for Opaque Machines." AAMAS 2019.

L.H. Gilpin

Identify (Un)reasonability

```
air:non-compliant-with :safe car policy .}]].
```

http://dig.csail.mit.edu/2009/AIR/

MIT Explanation-based Anomaly Detection

+ reasoner

Semantic Knowledge Bases Provide Commonsense

Opaque Mechanism

Supplement with Commonsense Knowledge Base

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Input qualitative descriptions into local

This vision perception is unreasonable. There is no commonsense data supporting the similarity between a vehicle, bike and unknown object except that they can be located at the same location. This component should be ignored.

This lidar perception is reasonable. An object moving of this size is a large moving object that should be avoided.

This system state is reasonable given that the vehicle has been moving quickly and proceeding straight for the last 10 second history.

Flexible Representation with Implicit Reasonableness Rules

Data from Nuscenes

L.H. Gilpin and L. Kagal. "An Adaptable Self-Monitoring Framework for Opaque Machines." AAMAS 2019.

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	<pre>@prefix foo: <http: foo#="">. @prefix car_ont: <http: car_ont#="">.</http:></http:></pre>
actor	<pre>foo:my_car a car_ont:Vehicle ; car_ont:LastState "stop" ; car_ont:CurrentState "stop" ; car_ont:direction foo:some_traffic_light .</pre>
woman	<pre>foo:some_pedestrians a car_ont:Pedestrian ; car_ont:label woman ; car_ont:CurrentState "move" ; car_ont:propel foo:woman-object ; car_ont:InPathOf foo:my_car .</pre>
man	a car_ont:Pedestrian ; car_ont:label man ; car_ont:CurrentState "move" ; car_ont:NextTo foo:woman-object ; car_ont:InPathOf foo:my_car .
object	foo:woman-object a car_ont:Object ; car_ont:CurrentState "propel" ; car_ont:InPathOf foo:my_car .
direction	foo:some_traffic_light a car_ont:TrafficLight ; car_ont:LightColor "red" .

Symbolic reasons

Use a synthesizer to reconcile inconsistencies between monitors.

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The best option is to veer and slow down. The vehicle is traveling too fast to suddenly stop. The vision system is inconsistent, but the lidar system has provided a reasonable and strong claim to avoid the object moving across the street.

Use a synthesizer to reconcile inconsistencies between monitors.

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Priority Hierarchy

- Passenger Perceived Safety
- Efficiency (e.g. Route efficiency)

Abstract Goals

A passenger is safe if:

- The vehicle proceeds at the same speed and direction.
- The vehicle avoids threatening objects.

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Framework for Real World Error Detection

- End-to-end prototype
 - Machine perception
 - Represented with frame-based primitives (Schank conceptual dependency primitives).

L.H. Gilpin, J.C. Macbeth and E. Florentine. "Monitoring scene understanders with conceptual primitive decomposition and commonsense knowledge." ACS 2018.

- Generalized framework
 - Reusable web standards
 - Extended primitive representations to apply to multiple applications.

L.H. Gilpin and L. Kagal. "An Adaptable Self-Monitoring Framework for Opaque Machines." AAMAS 2019.

Carla Simulations - real-world inspired scenarios

ollisio

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umber of vehicles

NHTSA-inspired pre-crash scenarios

0 traffic scenarios from the NHTSA pre-crash typology to inject challenging driving situations into traffic patterns encountered by us driving agents during the challeng

Traffic Scenario 01: Control loss without previous action · Definition: Ego-vehicle loses control due to bad conditions on the road and it must recover, coming back to its original lane Traffic Scenario 02: Longitudinal control after leading vehicle's brake Definition: Leading vehicle decelerates suddenly due to an obstacle and ego-vehicl must react, performing an emergency brake or an avoidance maneuve

Traffic Scenario 03: Obstacle avoidance without prior action

• Definition: The ego-vehicle encounters an obstacle / unexpected entity on the road and must perform an emergency brake or an avoidance maneuver.

System Evaluation

NuScenes dataset

• <u>Detection</u>: Generate logs from scenarios to detect failures.

- Invoke errors: Scrambling *multiple* labels on existing datasets.
- Real errors: Examining errors on the validation dataset of NuScenes leaderboard.

Invoking and Validating Errors

This perception is unreasonable. The movable_object.trafficcone located in the center region is not a reasonable size: it is too tall. There is no commonsense supporting this judgement. Discounting objects detected in the same region.

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Evaluating the UBER accident

(monitor, judgement, unreasonable) (input, isType, labels) (all labels, inconsistent, negRel)

```
(all labels, notProperty, nearMiss)
(all labels, locatedAt, consistent)
(monitor, recommend, ignore)
```

```
(monitor, judgement, reasonable)
(input, isType, sensor)
(input data[4], hasSize, large)
(input data[4], IsA, large object)
(input data[4], moving, True)
(input data[4], hasProperty, avoid)
(monitor, recommend, avoid)
(monitor, judgement, reasonable)
(input, isType, history)
(input data, moving, True)
(input_data, direction, forward)
(input data, speed, fast)
(input data, consistent, True)
(monitor, recommend, proceed)
```


'passenger is safe', AND ('safe transitions', NOT('threatening objects')

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Abstract Goal Tree

The best option is to veer and slow down. The vehicle is traveling too fast to suddenly stop. The vision system is inconsistent, but the lidar system has provided a reasonable and strong claim to avoid the object moving across the street.

Evaluation of Reasonableness on NuScenes

```
{ 'token': '70aecbe9b64f4722ab3c230391a3beb8',
'sample token': 'cd21dbfc3bd749c7b10a5c42562e0c42',
'instance token': '6dd2cbf4c24b4caeb625035869bca7b5',
'visibility_token': '4',
'attribute tokens': ['4d8821270b4a47e3a8a300cbec48188e'],
'translation': [373.214, 1130.48, 1.25],
'size': [0.621, 0.669, 1.642],
'rotation': [0.9831098797903927, 0.0, 0.0, -0.18301629506281616],
'prev': 'a1721876c0944cdd92ebc3c75d55d693',
'next': '1e8e35d365a441a18dd5503a0ee1c208',
'num_lidar_pts': 5,
'num_radar_pts': 0,
'category_name': 'human.pedestrian.adult'}
```


Data from NuScenes

L.H. Gilpin, V. Penubarthi, L. Kagal. "Anomaly Detection through Explanations." To be submitted.

Summary

Generate Symbolic Qualitative Descriptions for each committee.

Input qualitative descriptions into local "reasonableness" monitors.

Use a synthesizer to reconcile inconsistencies between monitors.

Society

Systems that articulately communicate with humans on shared tasks.

Applications

Liability

Systems that can testify, answer questions, and provide insights.

Robustness

Dynamic detection of failure and intrusion with precise mitigation.