REQUIREMENTS AND RISKS II: PLANNING FOR MISTAKES

Eunsuk Kang

LEARNING GOALS:

- Evaluate the risks of mistakes from ML components using the fault tree analysis (FTA)
- Design strategies for mitigating the risks of failures due to AI mistakes

RISK ANALYSIS

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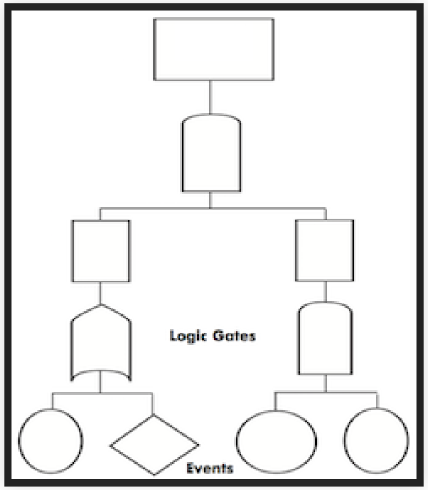
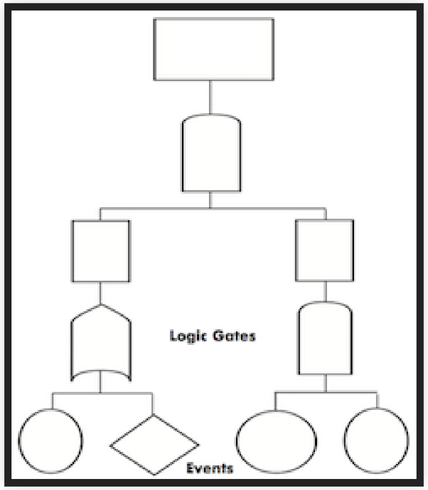
- Risk = Likelihood * Impact
- A number of methods:
    - Failure mode & effects analysis (FMEA)
    - Hazard analysis
    - Why-because analysis
    - Fault tree analysis (FTA) <= Today's focus!
    - ...

FAULT TREE ANALYSIS (FTA)



FAULT TREE ANALYSIS (FTA)

- Fault tree: A top-down diagram that displays the relationships between a system failure (i.e., requirement violation) and its potential causes.
  - Identify sequences of events that result in a failure
  - Prioritize the contributors leading to the failure
  - Inform decisions about how to (re-)design the system
  - Investigate an accident & identify the root cause



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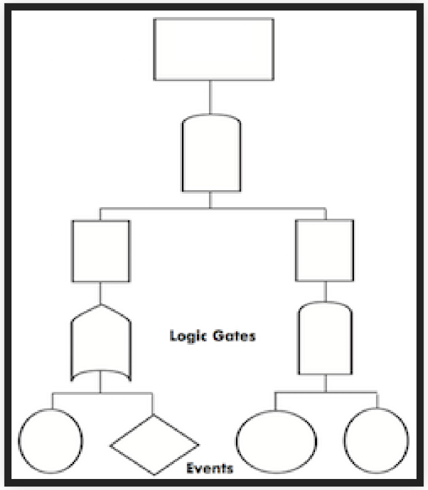
- Often used for safety & reliability, but can also be used for other types of requirement (e.g., poor performance, security attacks...)



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- ML models will EVENTUALLY make mistakes
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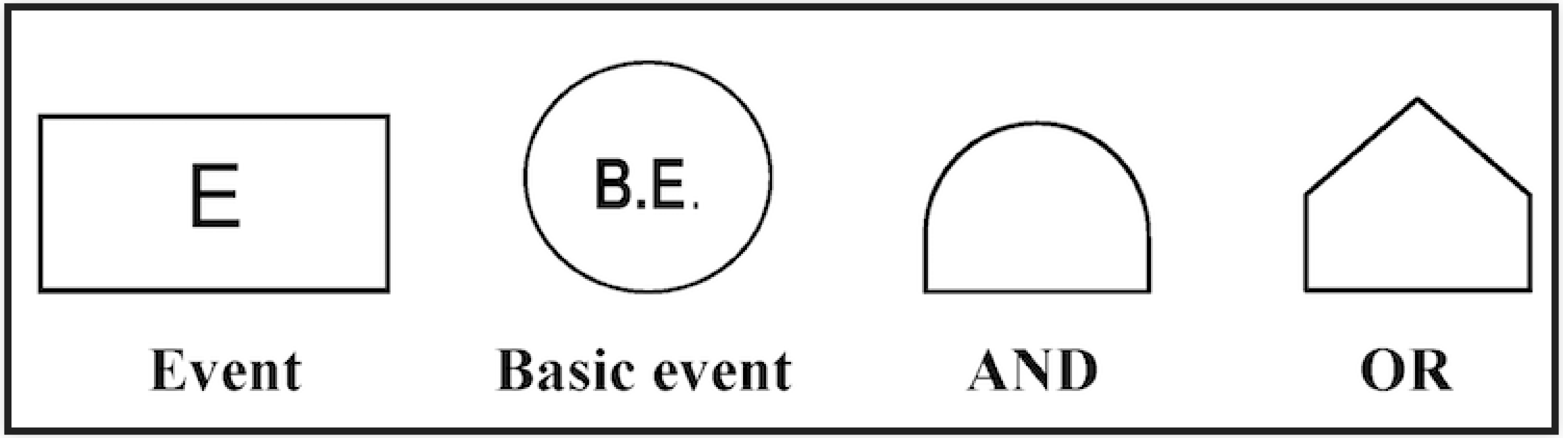
    - Confuse users, etc.,
- How do mistakes made by ML contribute to system failures? How do we ensure their mistakes do not result in a catastrophic outcome?

FAULT TREES:: BASIC BUILDING BLOCKS



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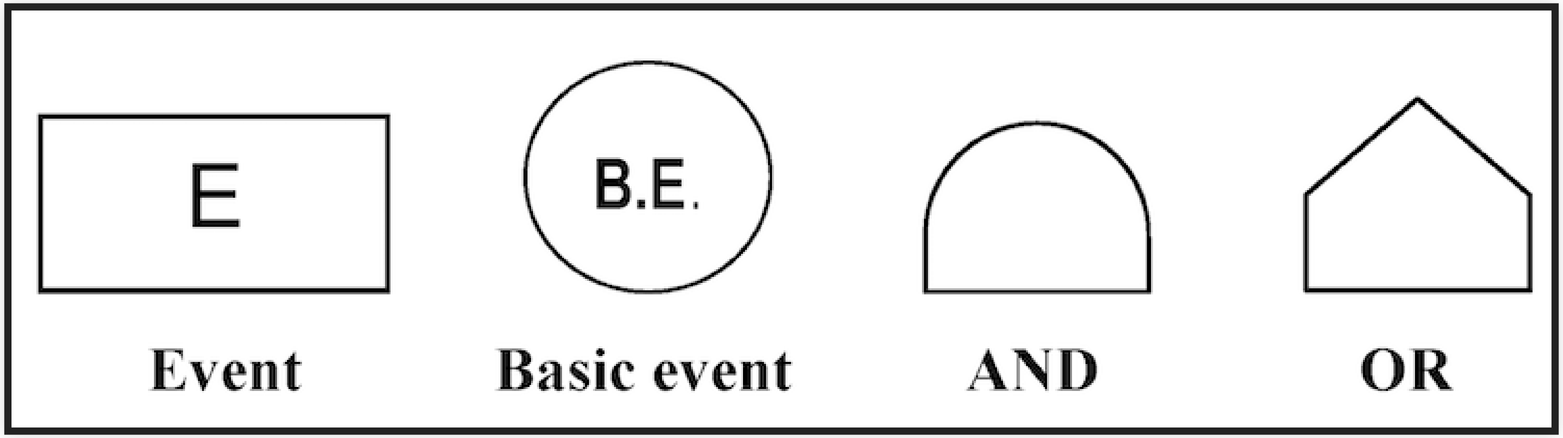

- Event: An occurrence of a fault or an undesirable action
  - (Intermediate) Event: Explained in terms of other events
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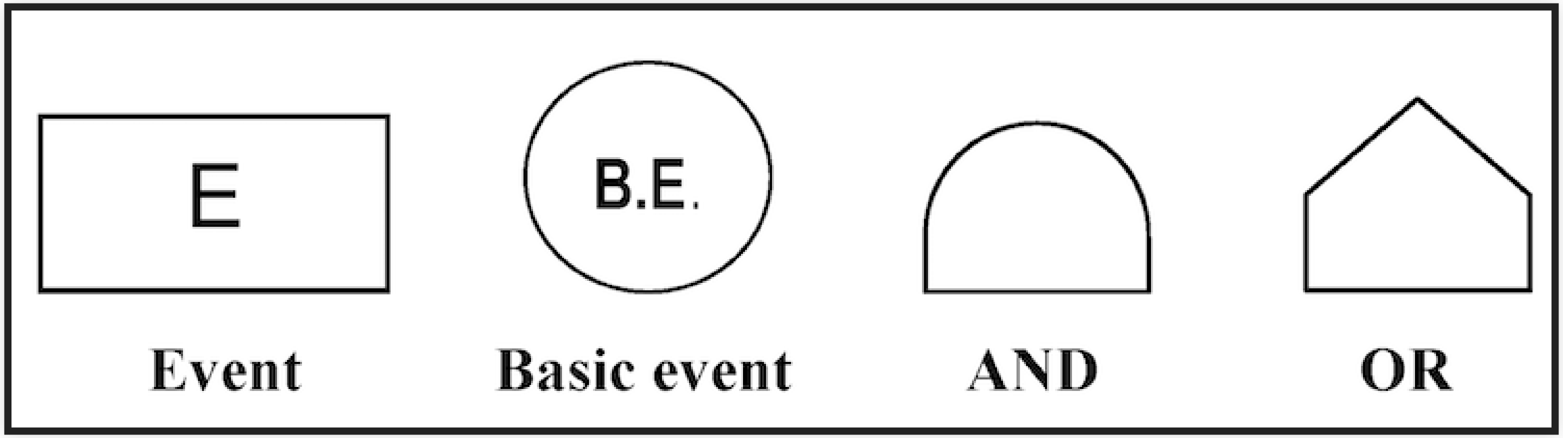

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- Gate: Logical relationship between an event & its immedicate subevents
  - AND: All of the sub-events must take place
  - OR: Any one of the sub-events may result in the parent event

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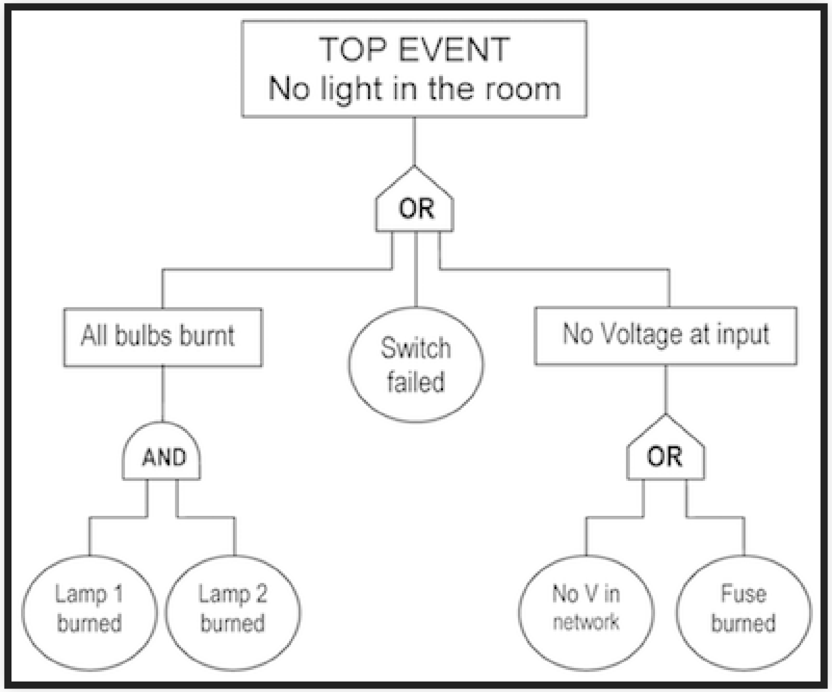

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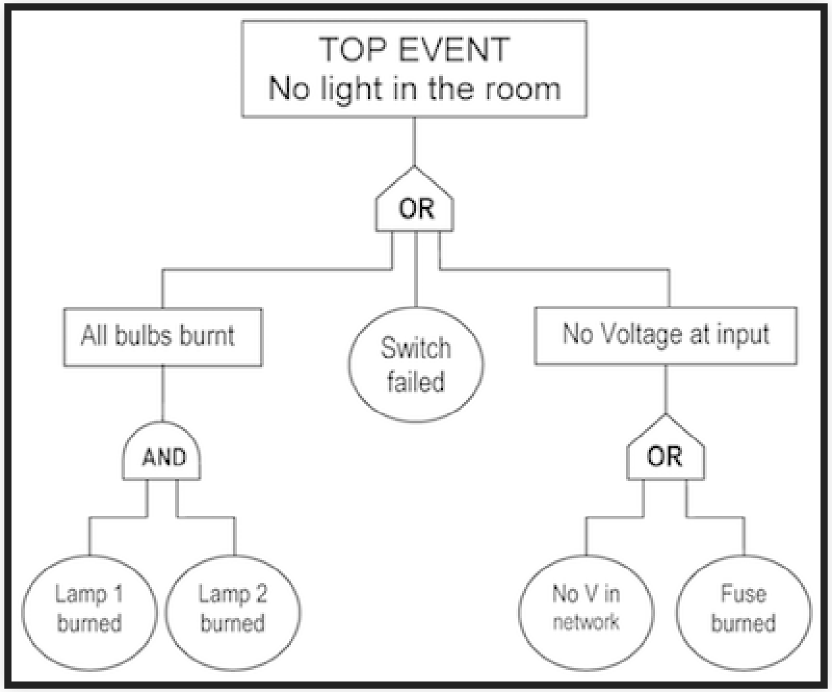

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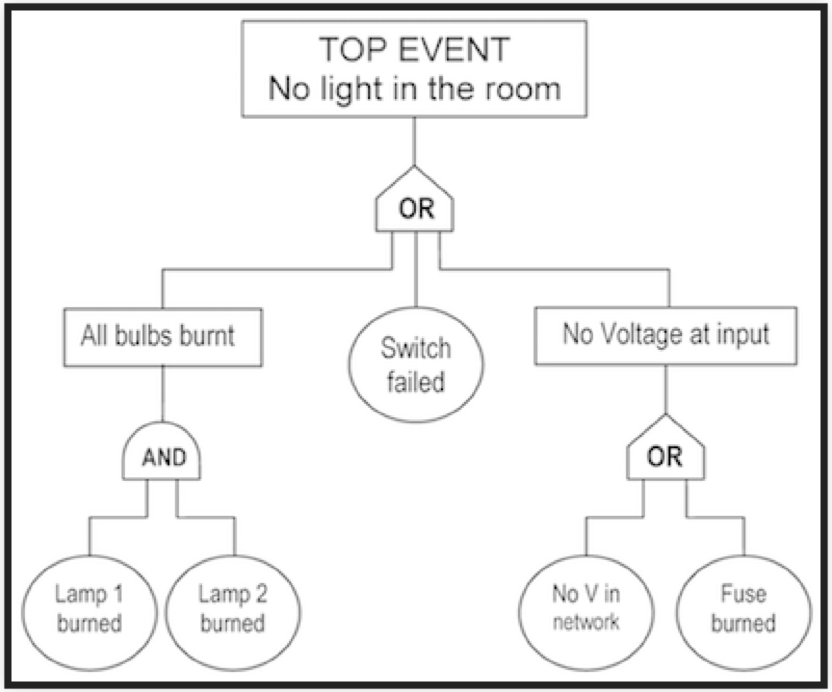

- Every tree begins with a TOP event (typically a violation of a requirement)
- Every branch of the tree must terminate with a basic event

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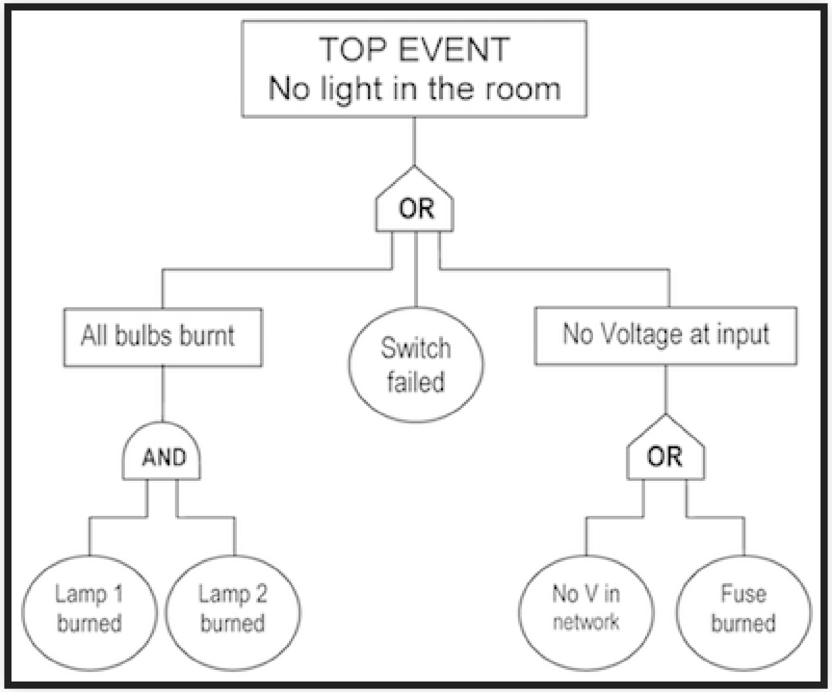
ANALYSIS

- What can we do with fault trees?
    - Qualitative analysis: Determine potential root causes of a failiure through *minimal cut set analysis*
    - Quantitative analysis: Compute the probablity of a failure

MINIMAL CUT SET ANALYSIS



- Cut set: A set of basic events whose simultaneous occurrence is sufficient to guarantee that the TOP event occurs.
- *Minimal* cut set: A cut set from which a smaller cut set can be obtained by removing a basic event.
- Q. What are minimal cut sets in the above tree?

FAILURE PROBABILITY ANALYSIS

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- In this class, we won't ask you to do this.
  - Why is this especially challenging for software?

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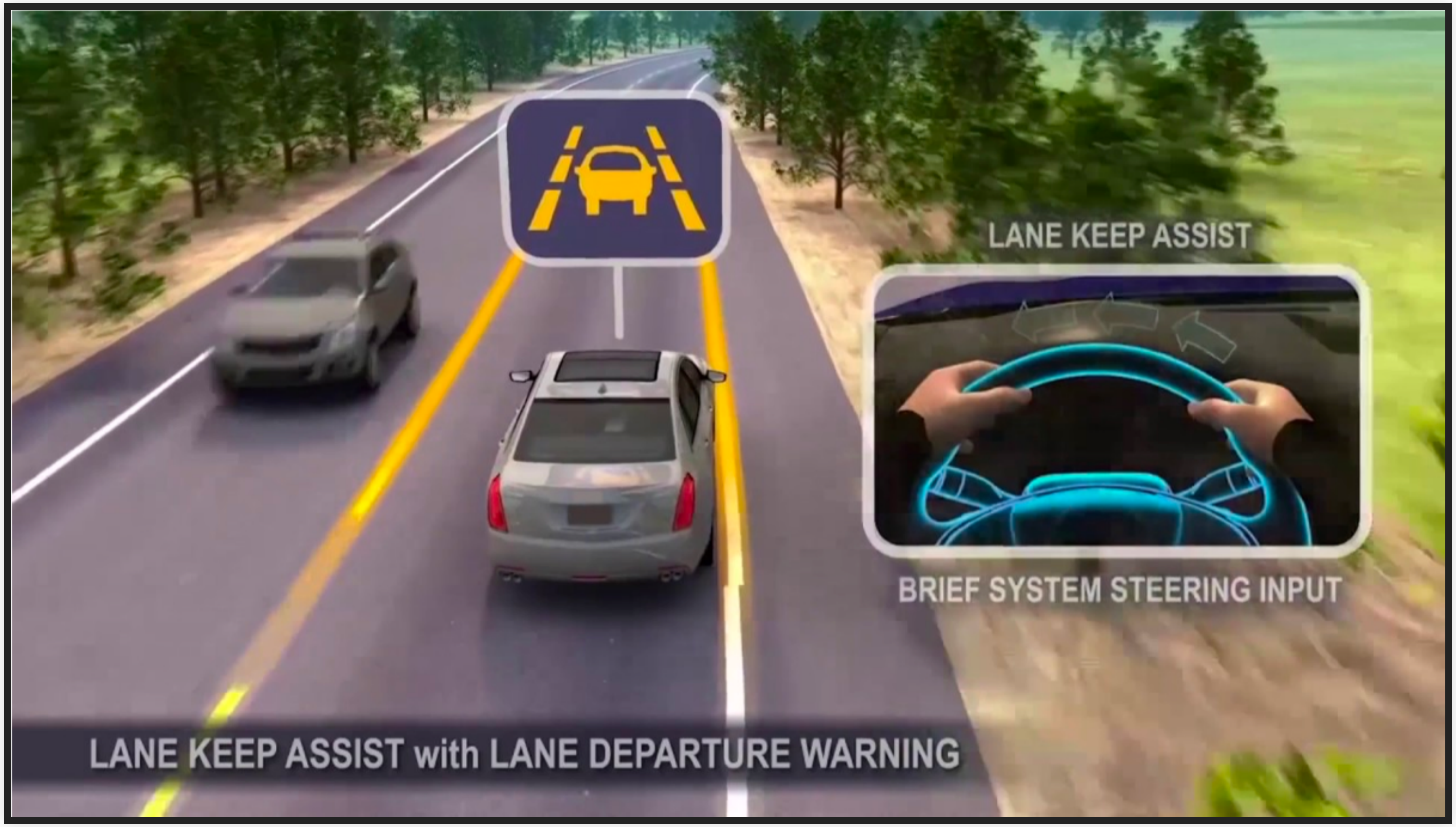
6. Repeat

EXAMPLE: BACK TO LANE ASSIST

- REQ: The vehicle must be prevented from veering off the lane.
- SPEC: Lane detector accurately identifies lane markings in the input image; the controller generates correct steering commands
- ENV: Sensors are providing accurate information about the lane; driver responses when given warning; steering wheel is functional

BREAKOUT: FTA FOR LANE ASSIST



Draw a fault tree for the lane assist system with the top event as “Vehicle fails to stay within the lane”

EXAMPLE: FTA FOR LANE ASSIST

STRATEGIES FOR HANDLING FAULTS IN ML-BASED SYSTEMS

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  - Redundancy (fail over)
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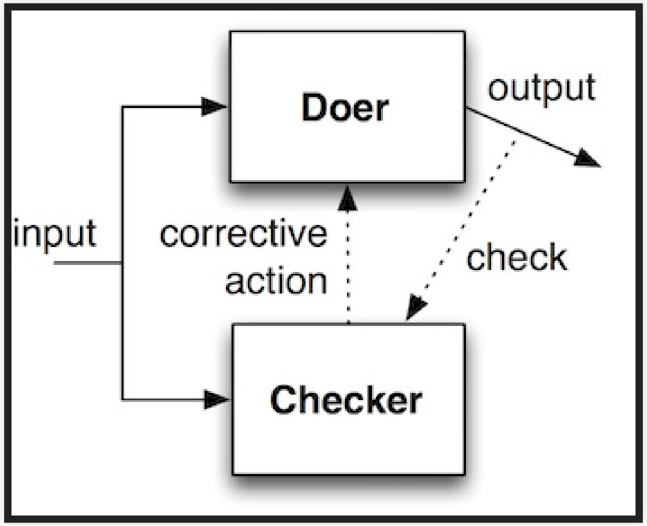
  - Undoable actions
- Containment
  - Decoupling & isolation

DETECTION: MONITORING



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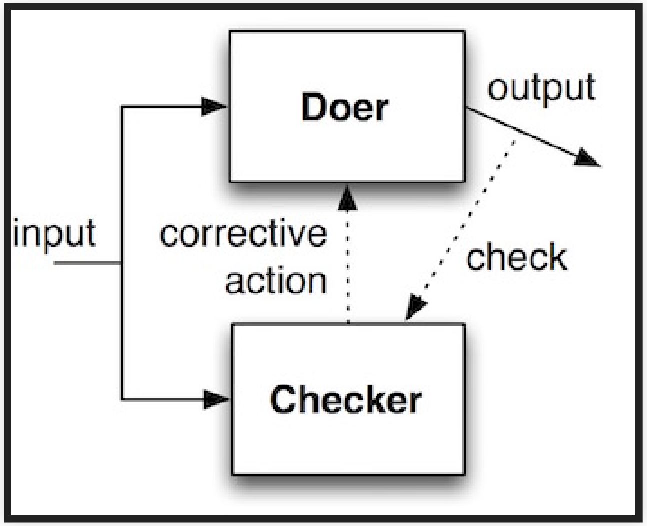

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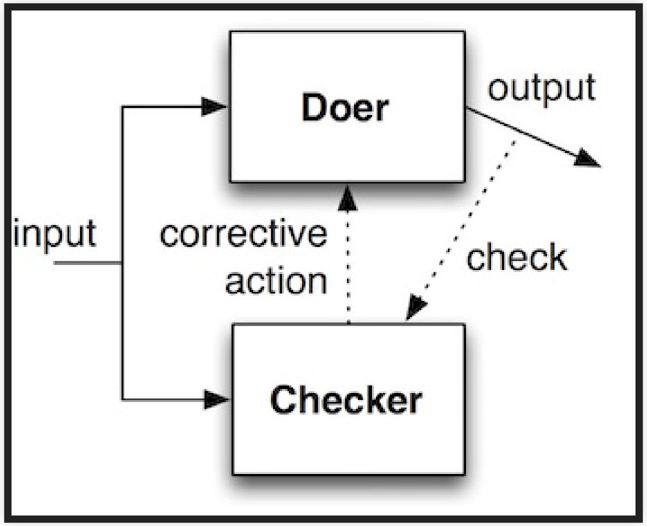

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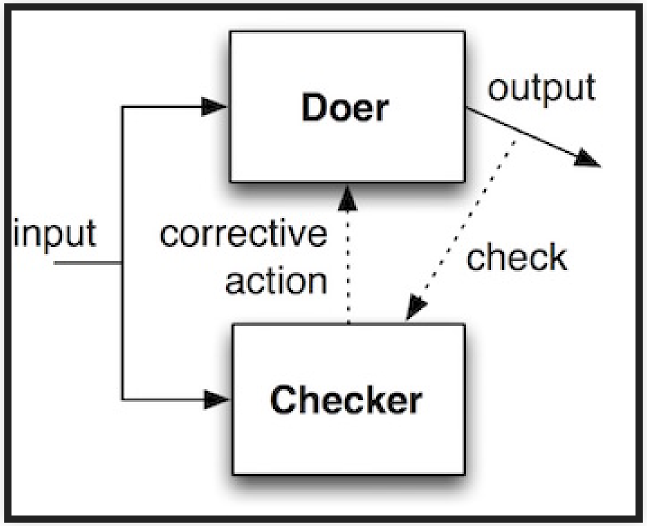

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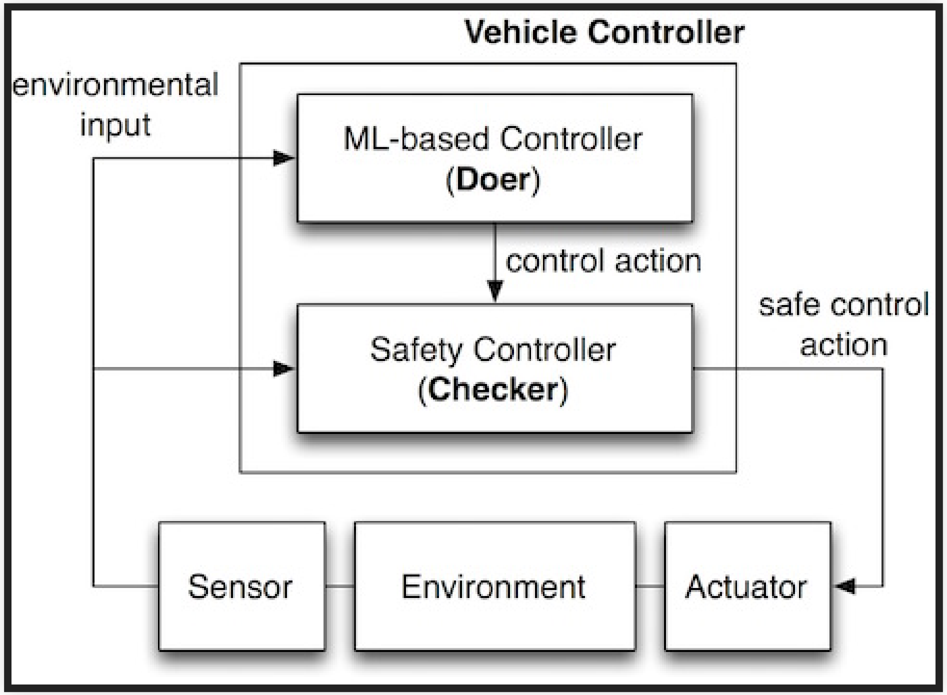
- Doer-Checker pattern
  - Doer: Perform primary function; untrusted and potentially faulty
  - Checker: If doer output is faulty, perform a corrective action (e.g., default safe output, shutdown); should be trustworthy

DOER-CHECKER EXAMPLE: AUTONOMOUS VEHICLE



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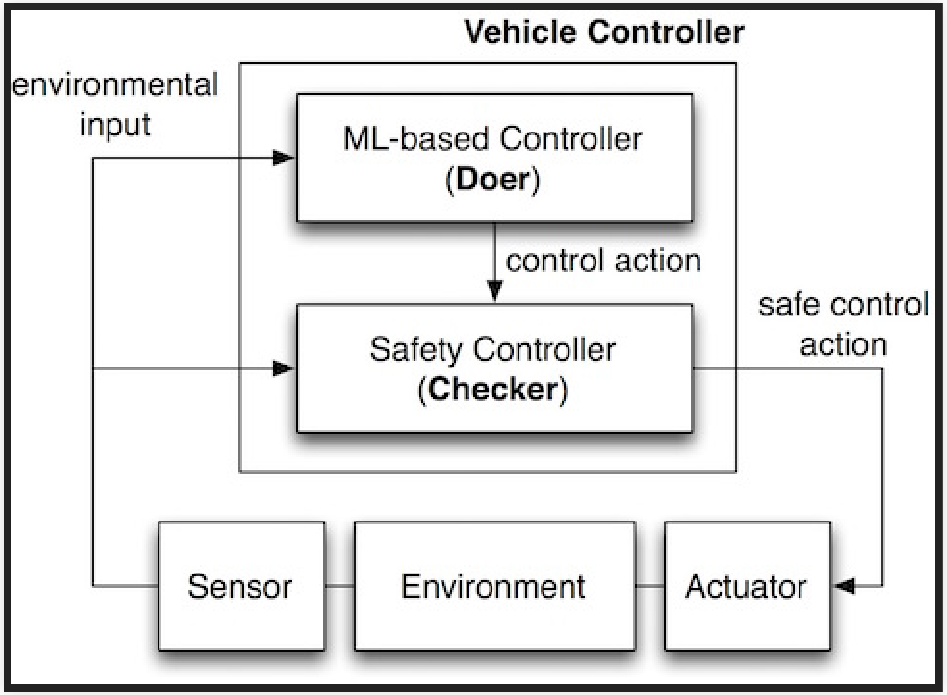

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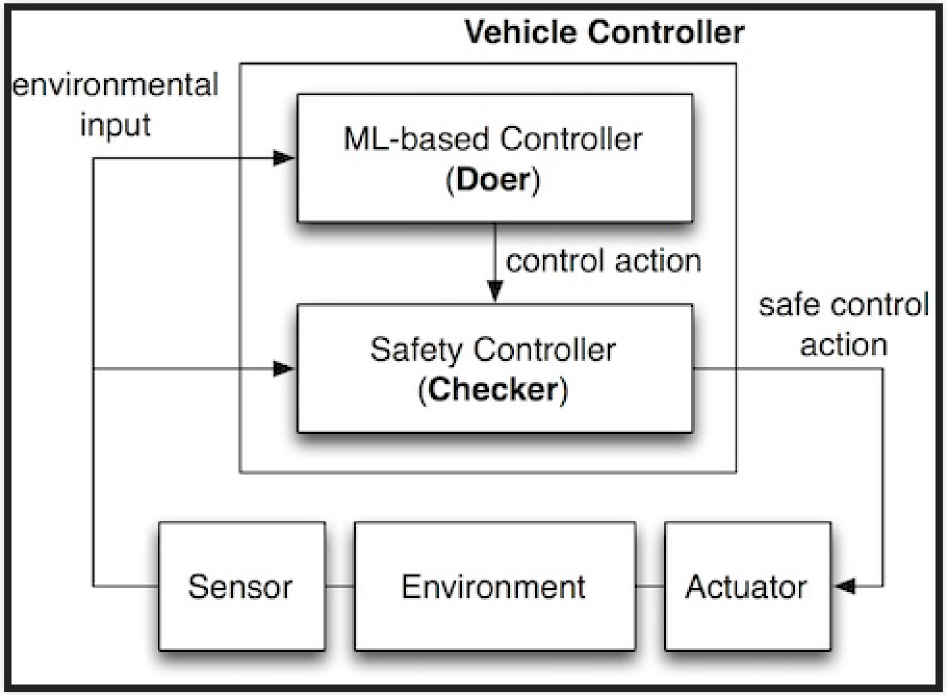

- ML-based controller (doer): Generate commands to steer the vehicle
    - Complex DNN; makes performance-optimal control decisions
- Safe controller (checker): Checks commands from ML controller; overrides it with a safe default command if the ML action is risky
    - Simpler, based on verifiable, transparent logic; conservative control

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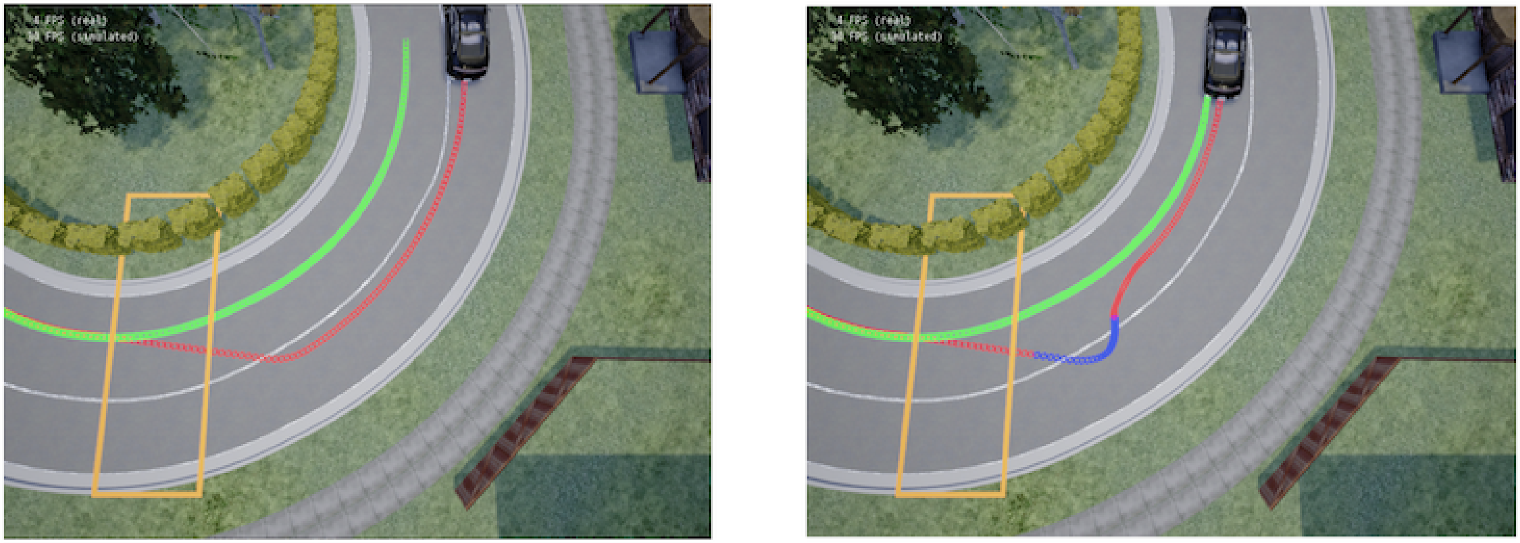

(a) (b)

Runtime-Safety-Guided Policy Repair, Intl. Conference on Runtime Verification (2020)

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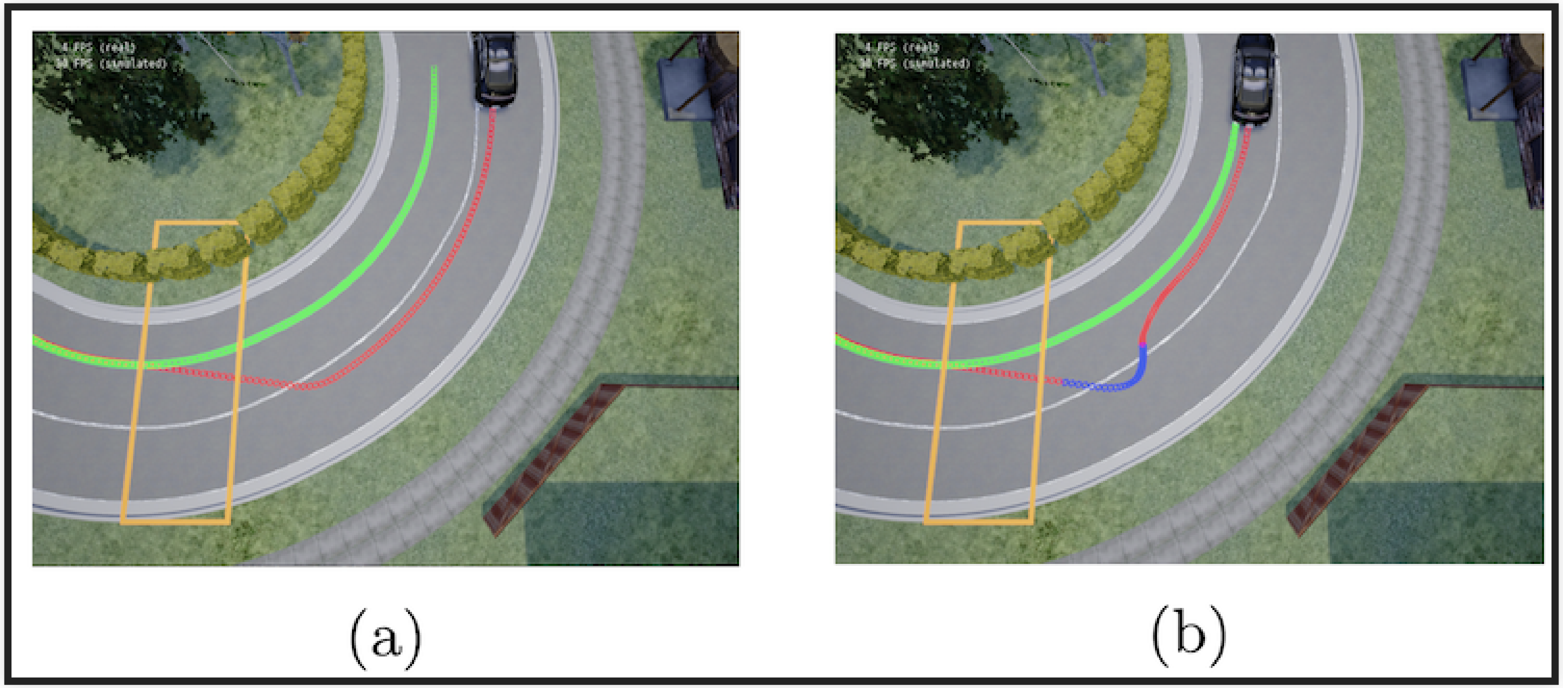

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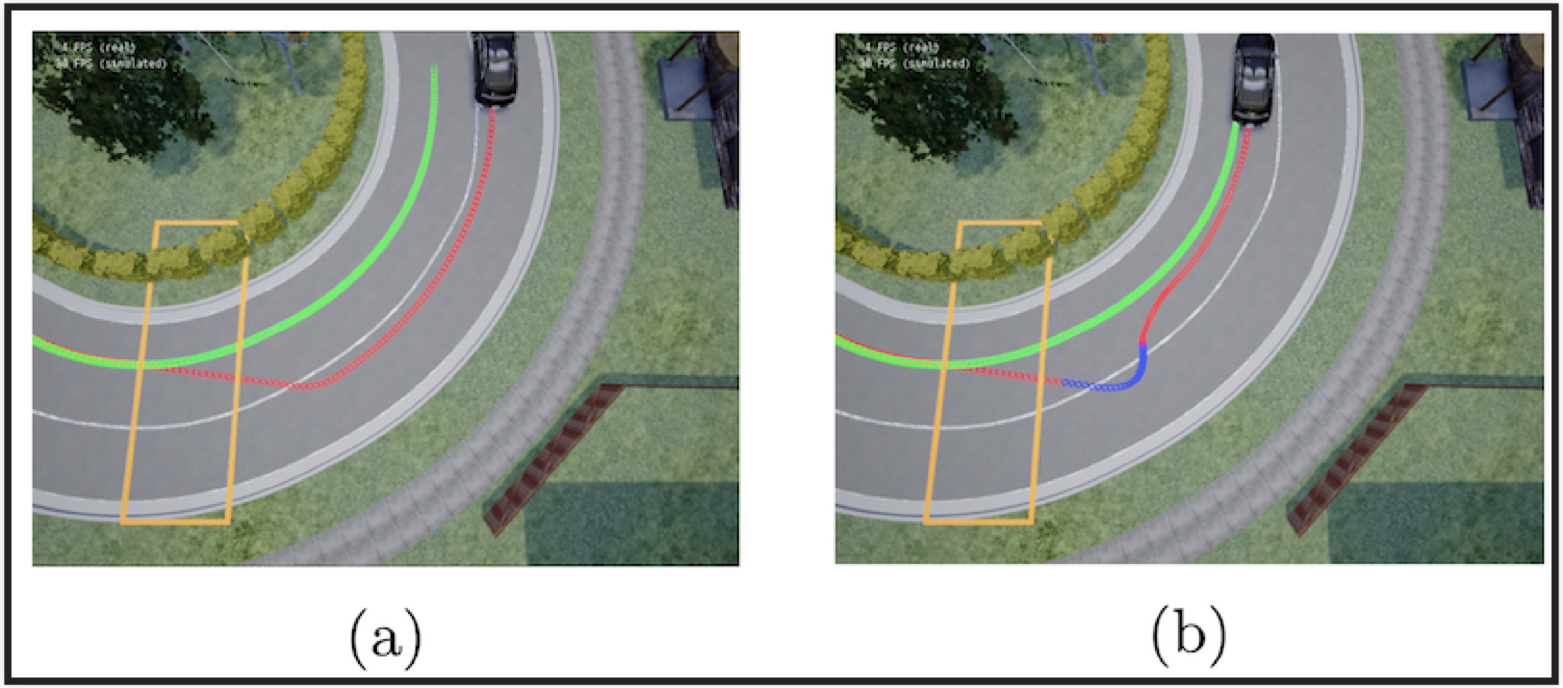

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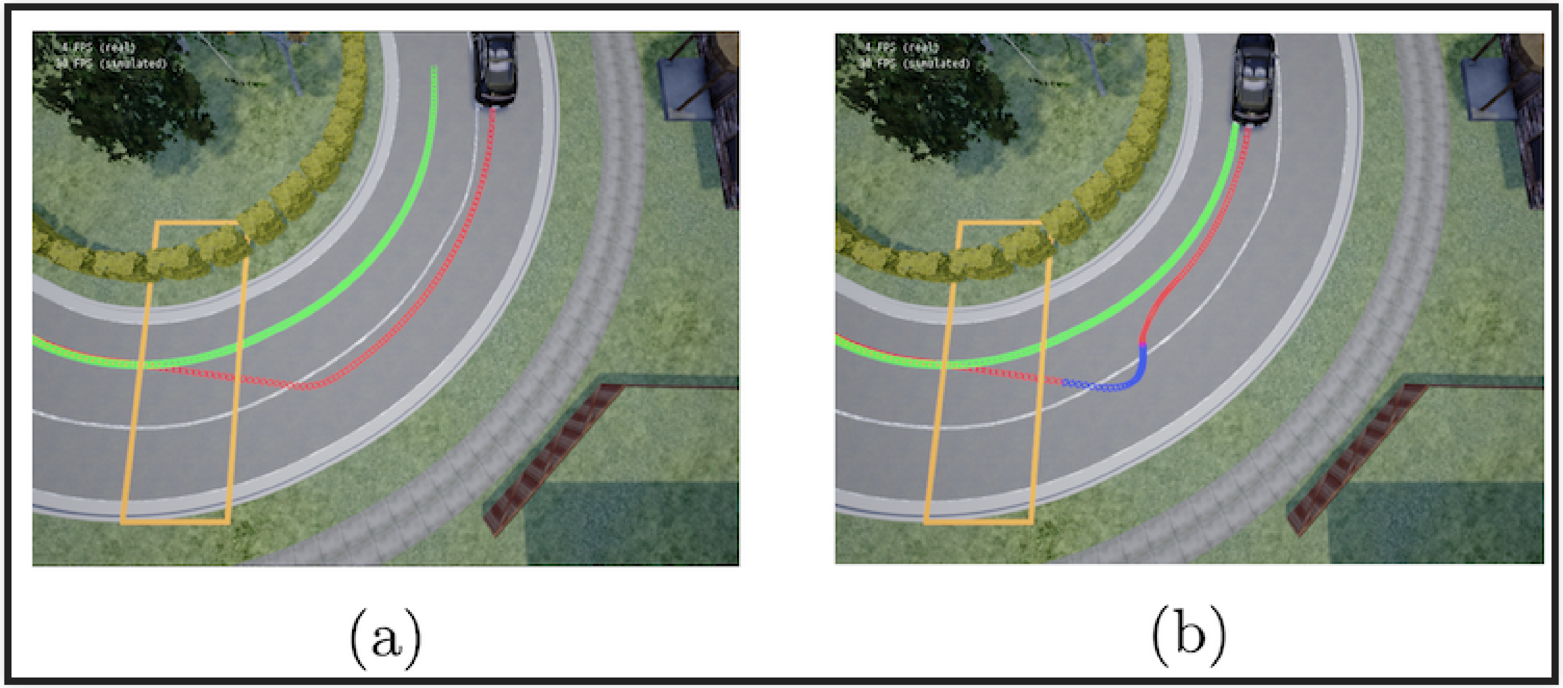

- Yellow region: Slippery road, causes loss of traction; unexpected by ML
- ML-based controller (doer): Model ignores traction loss; generates unsafe maneuvering commands (a)
- Safe controller (checker): Overrides with safe steering commands (b)

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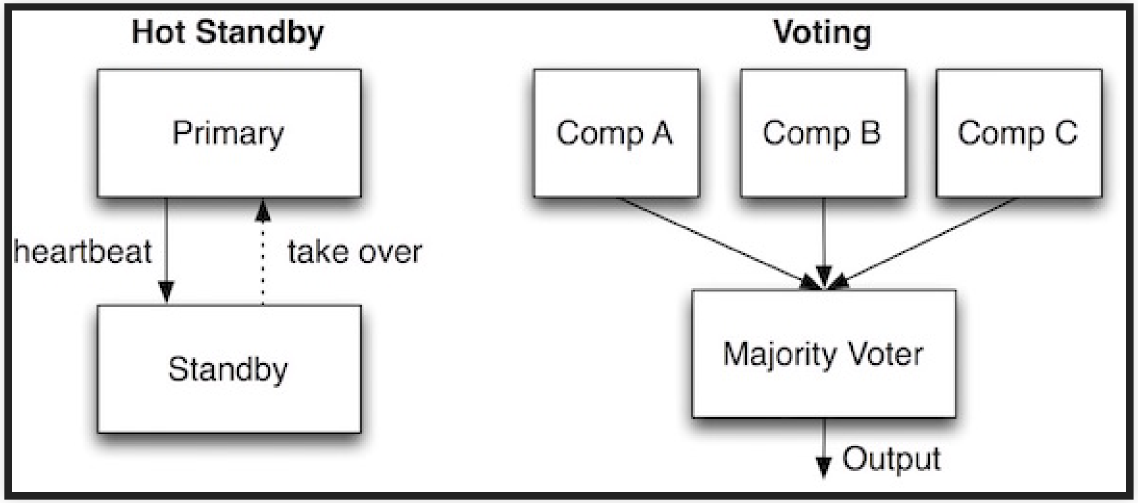
- Goal: When a component failure occurs, continue to provide safety (possibly at reduced functionality and performance)
- Relies on a monitor to detect component failures
- Example: Perception in autonomous vehicles
  - If Lidar fails, switch to a lower-quality detector & be more conservative about maintaining distance

DETECTION & RESPONSE: REDUNDANCY



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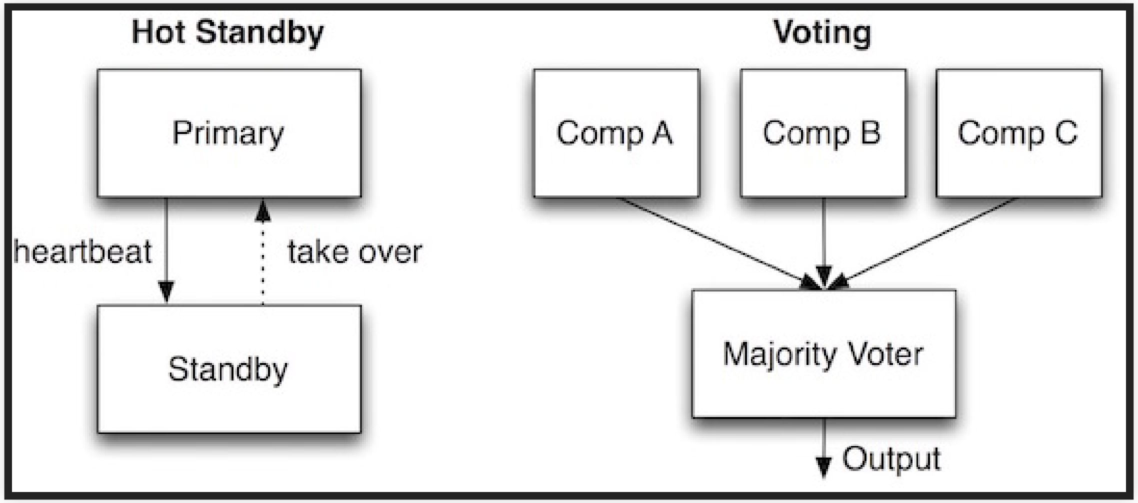

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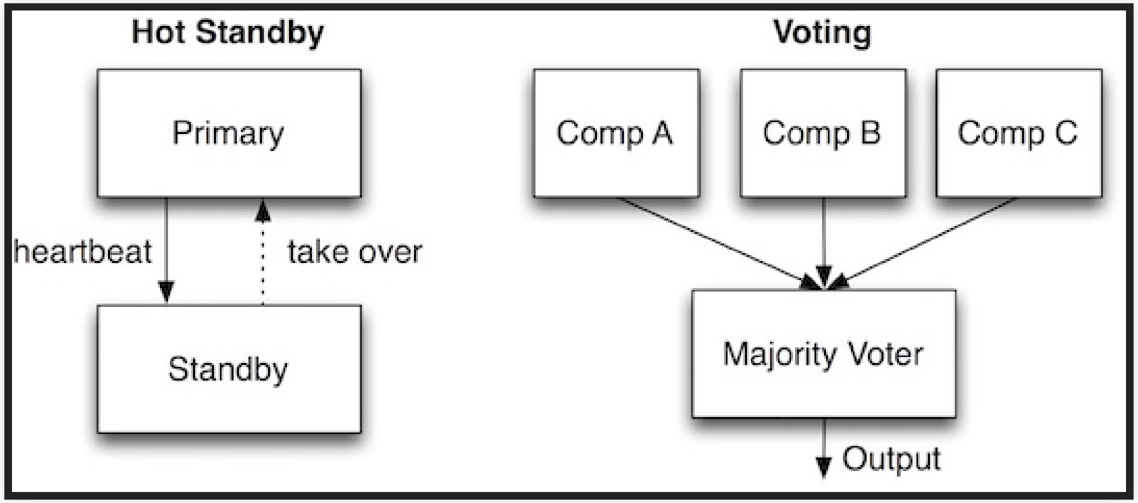

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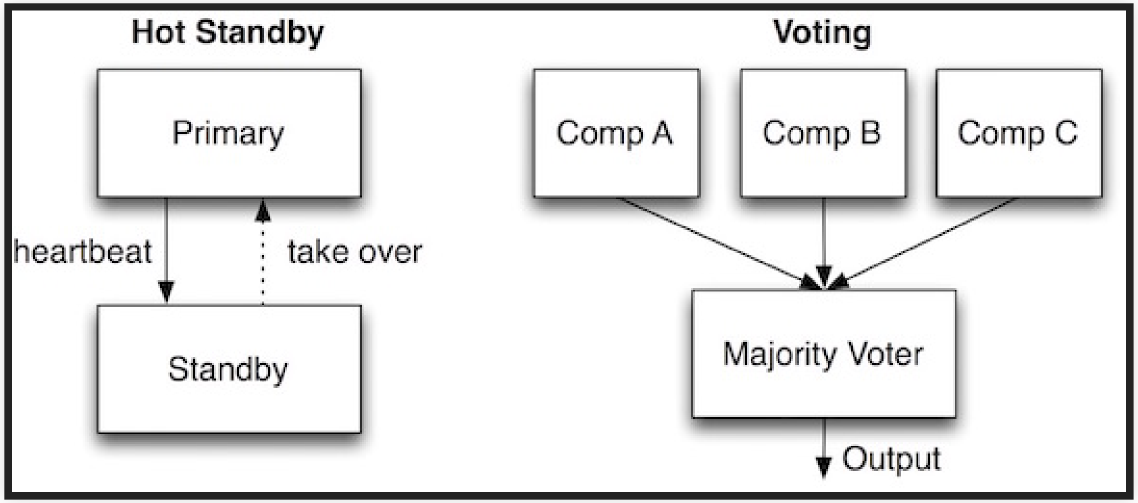

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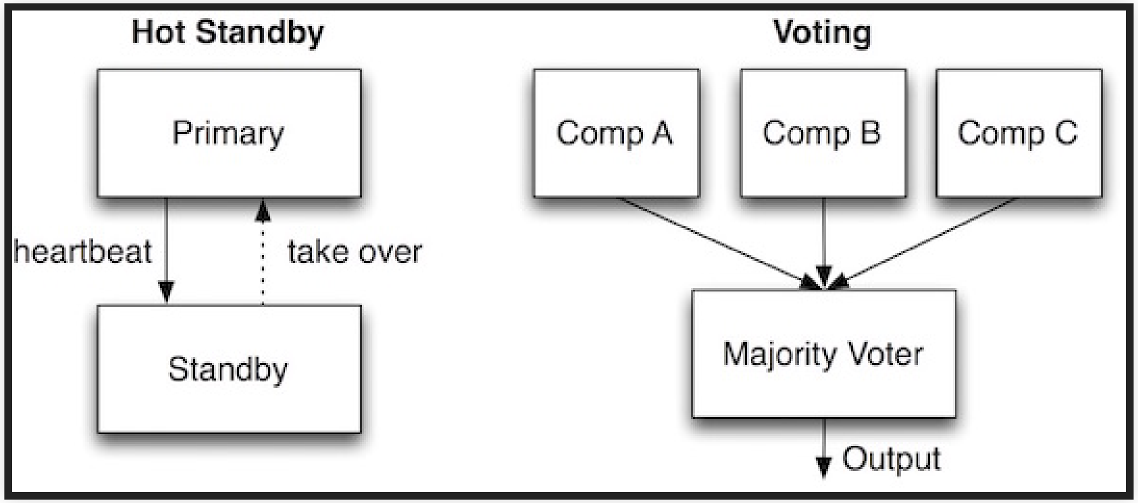

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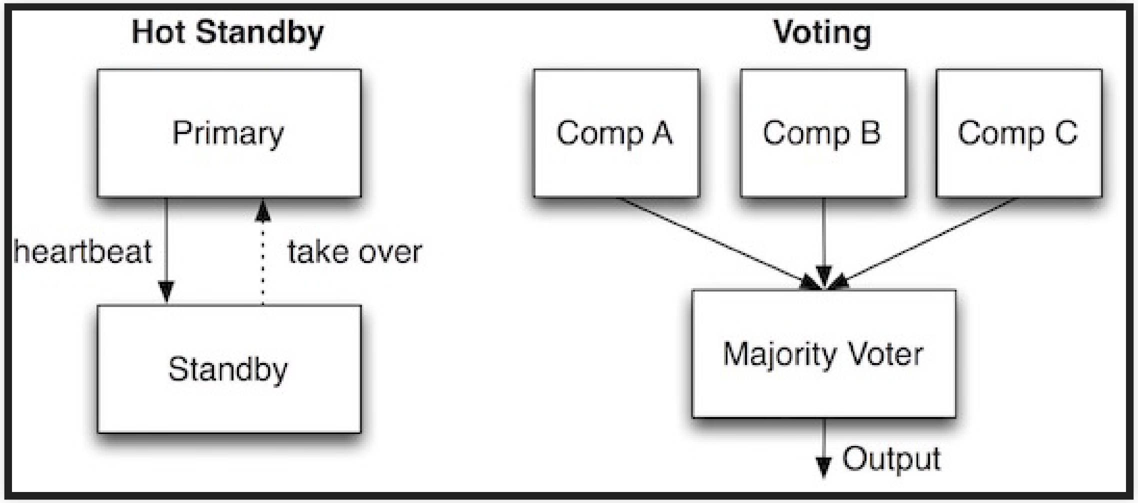

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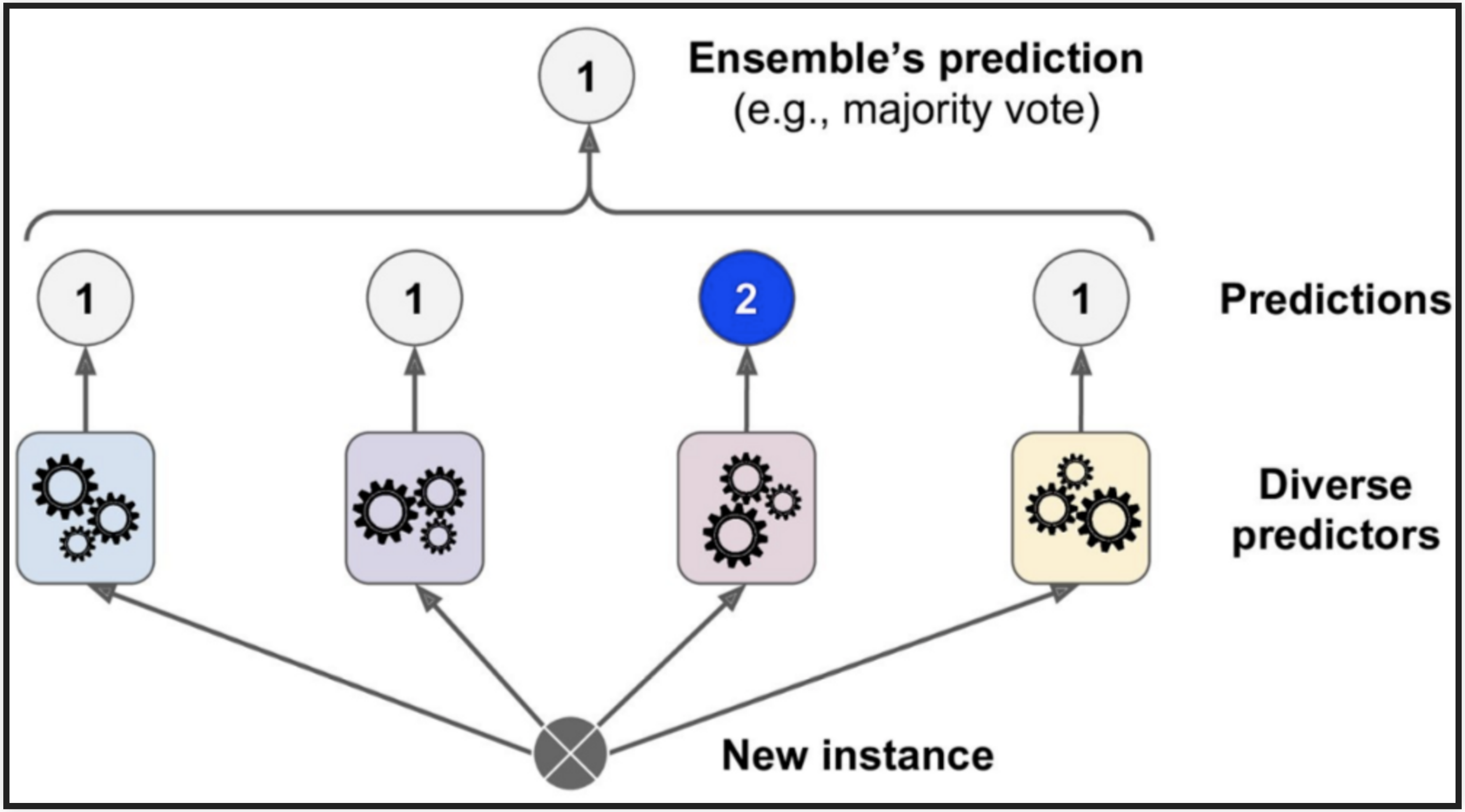
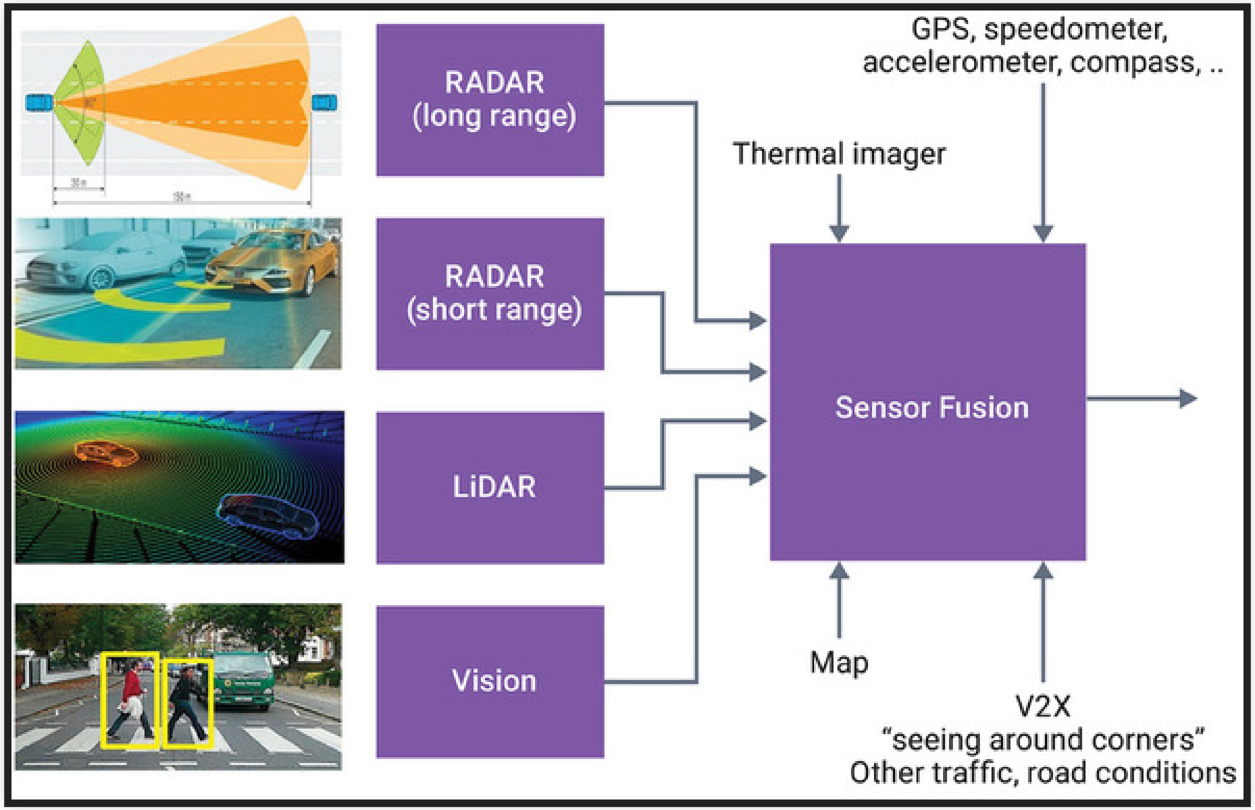
- Caution: Do components fail independently?
    - Reasonable assumption for hardware/mechanical failures
    - Q. What about ML components?

REDUNDANCY EXAMPLE: ENSEMBLE LEARNING



- An example of redundancy by voting

REDUNDANCY EXAMPLE: SENSOR FUSION



- Combine data from a wide range of sensors
- Provides partial information even when some sensor is faulty
- A critical part of modern self-driving vehicles

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- Lots of UI design and HCI problems
- Q. Examples?

Speaker notes

Cancer prediction, sentencing + recidivism, Tesla autopilot, military "kill" decisions, powerpoint design suggestions

RESPONSE: UNDOABLE ACTIONS

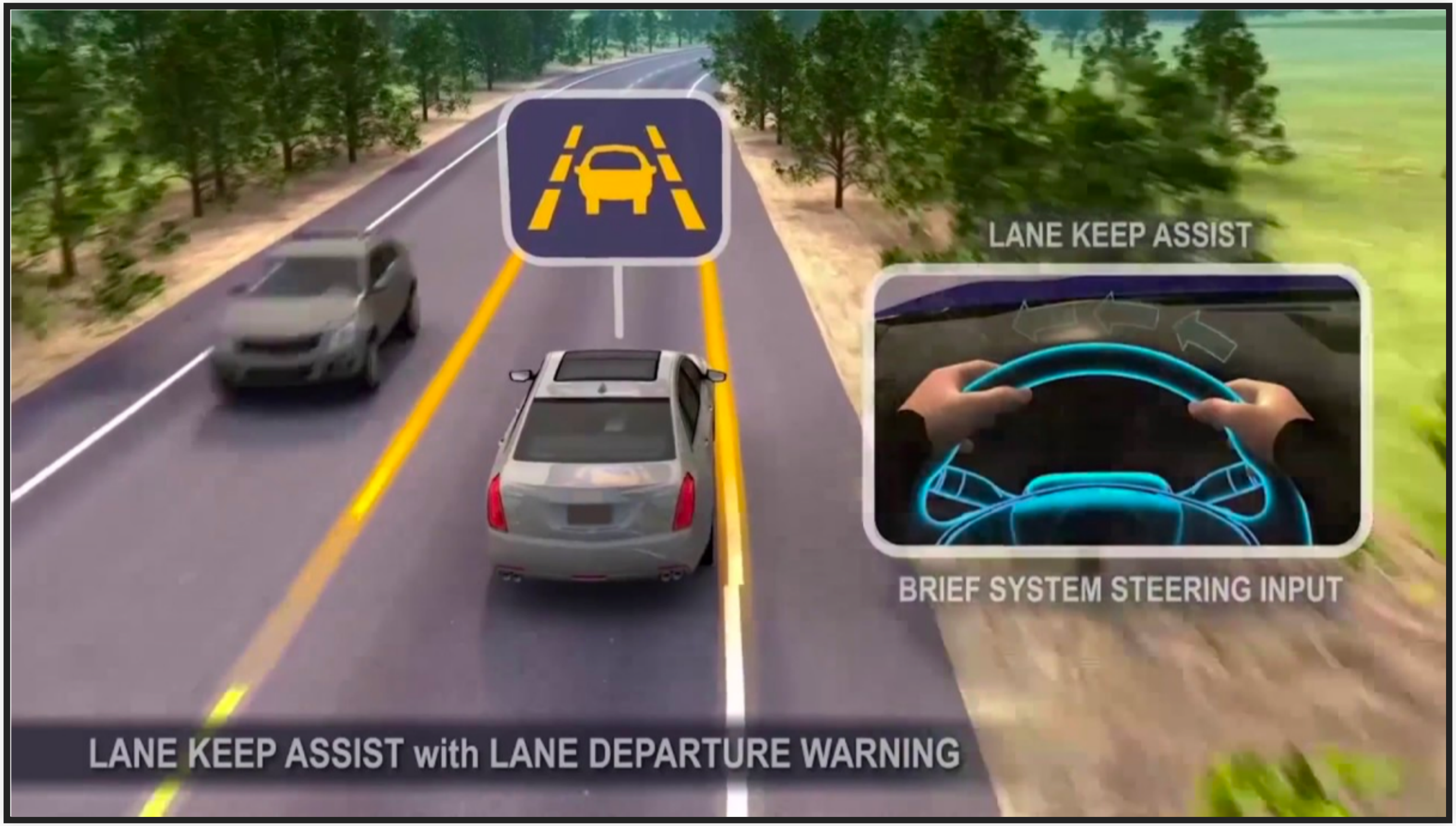
Design the system to reduce the consequences of wrong predictions, allowing humans to override or undo

Examples?

Speaker notes

Smart home devices, credit card applications, Powerpoint design suggestions

EXAMPLE: LANE ASSIST



Possible mitigation strategies? Discuss with your neighbors

EXAMPLE: LANE ASSIST

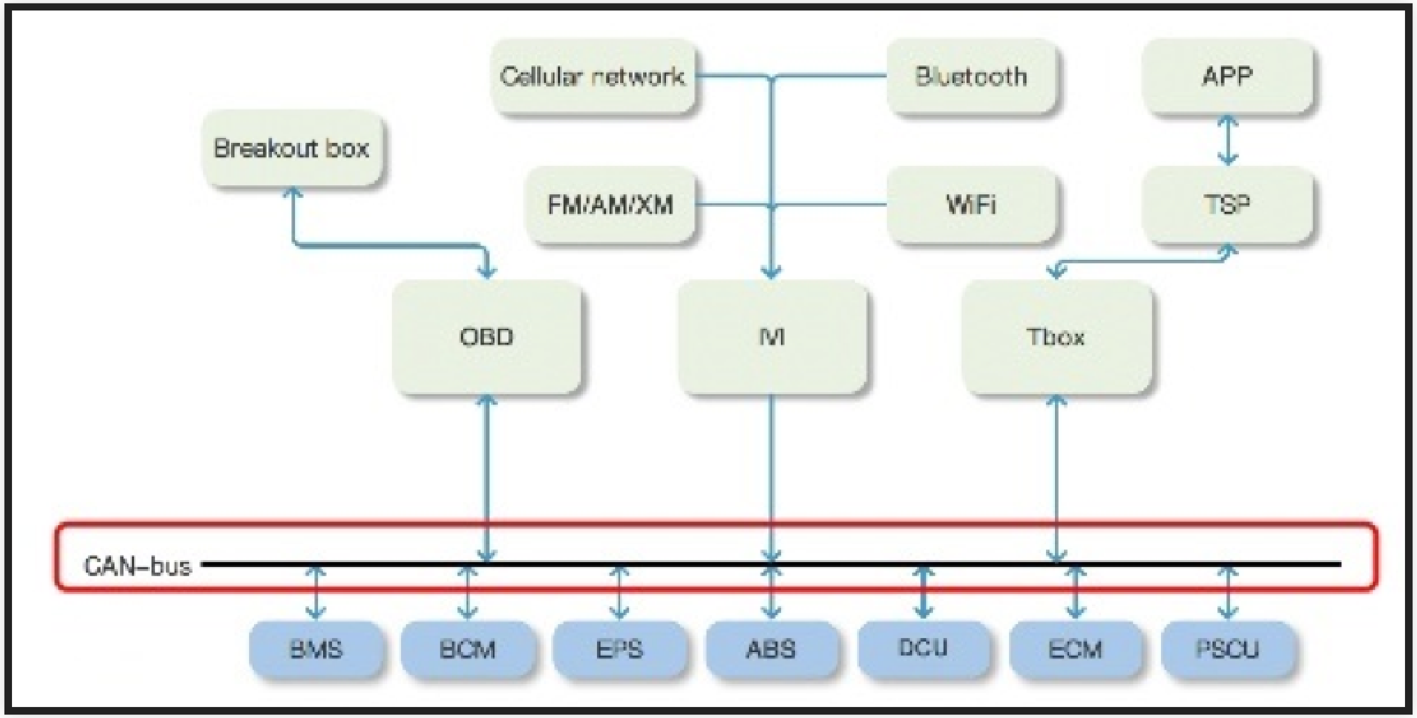
CONTAINMENT: DECOUPLING & ISOLATION

- **Design principle**: Faults in a low-critical (LC) components should not impact high-critical (HC) components

POOR DECOUPLING: USS YORKTOWN (1997)

- Invalid data entered into DB; divide-by-zero crashes entire network
- Required rebooting the whole system; ship dead in water for 3 hours
- Lesson: Handle expected component faults; prevent propagation

POOR DECOUPLING: AUTOMOTIVE SECURITY



- Main components connected through a common CAN bus
    - Broadcast; no access control (anyone can read/write)
- Can control brake/engine by playing a malicious MP3

Experimental Security Analysis of a Modern Automobile, Koscher et al., (2010)

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    - Deploy LC & HC components on different networks
    - Add monitors/checks at interfaces

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- Limit interactions across criticality boundaries
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- Is an ML component in my system performing an LC or HC task?
    - If HC, can we "demote" it into LC?
    - Alternatively, replace HC ML components with non-ML ones
    - Q. Examples?

SUMMARY

- Accept that a failure is inevitable
  - ML components will eventually make mistakes
  - Environment may evolve over time, violating its assumptions
- Use risk analysis to identify and mitigate potential problems
- Design strategies for detecting and mitigating the risks from mistakes by ML