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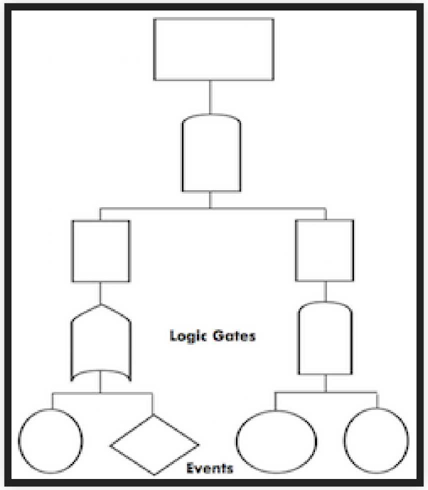
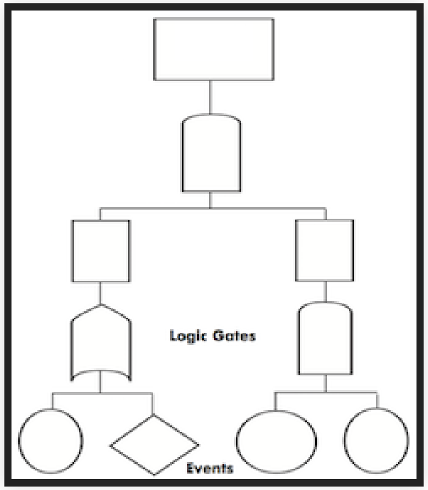
- Risk = Likelihood * Impact
- A number of methods:
    - Failure mode & effects analysis (FMEA)
    - Hazard analysis
    - Why-because analysis
    - Fault tree analysis (FTA) <= Today's focus!
    - ...

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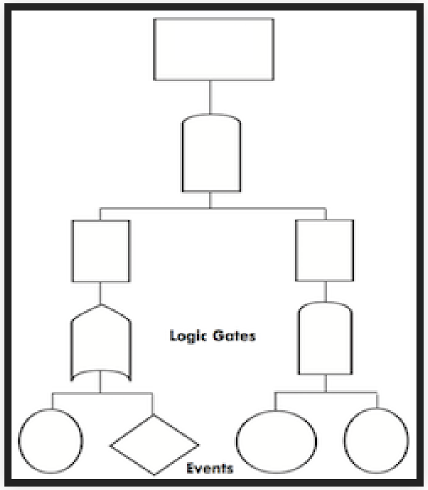
- Often used for safety & reliability, but can also be used for other types of requirements (e.g., poor performance, security attacks...)



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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

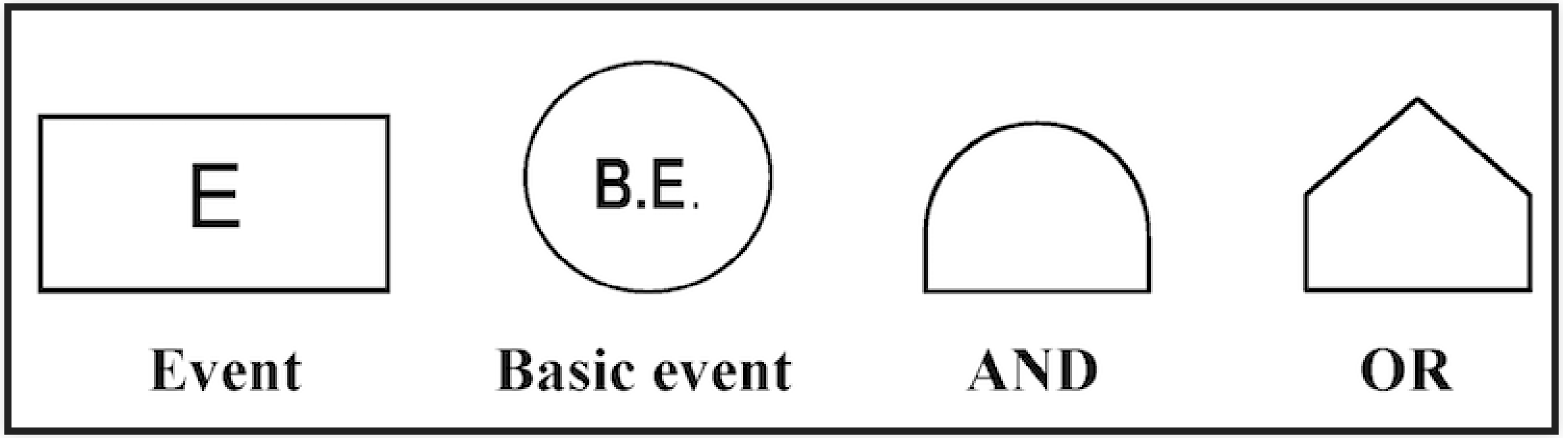

Figure from *Fault Tree Analysis and Reliability Block Diagram* (2016), Jaroslav Menčík.

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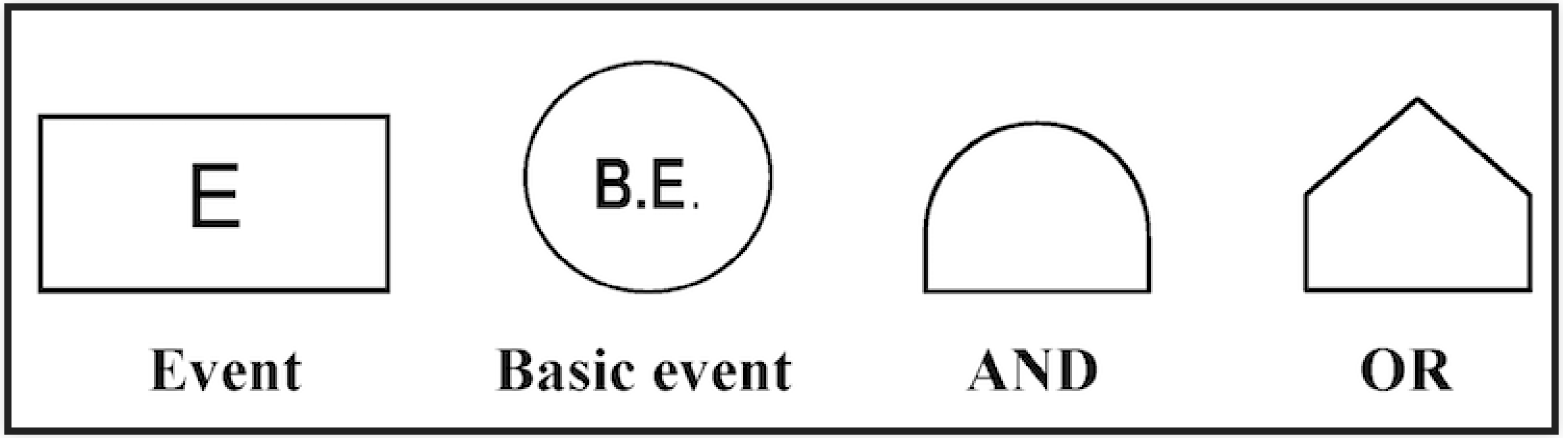

- Event: An occurrence of a fault or an undesirable action
  - (Intermediate) Event: Explained in terms of other events
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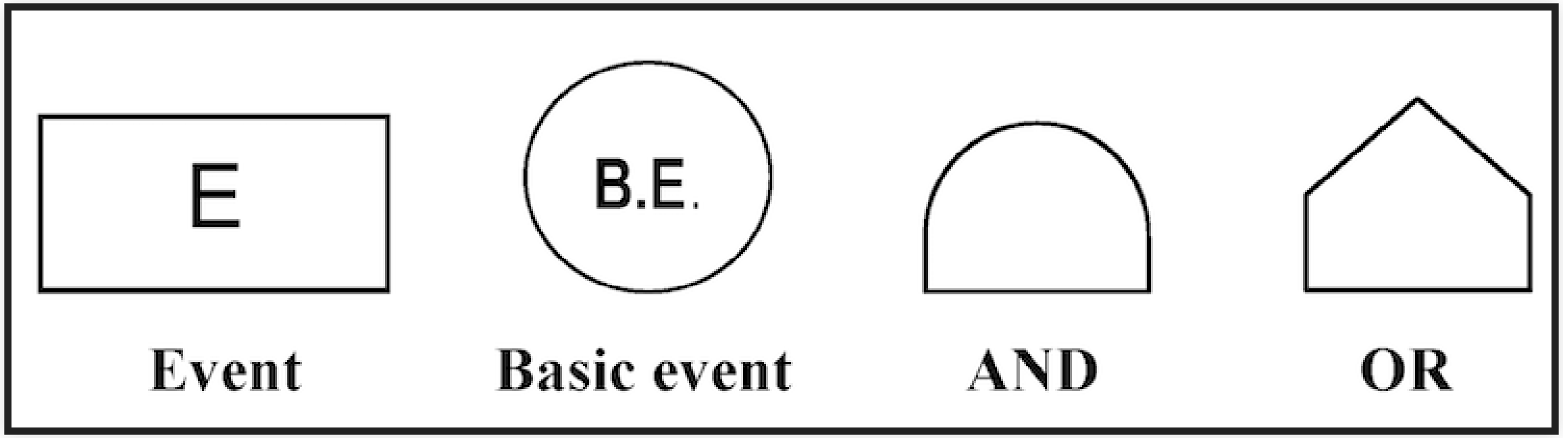

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  - Basic Event: No further development or breakdown; leafs of the tree
- Gate: Logical relationship between an event & its immedicate subevents
  - AND: All of the sub-events must take place
  - OR: Any one of the sub-events may result in the parent event

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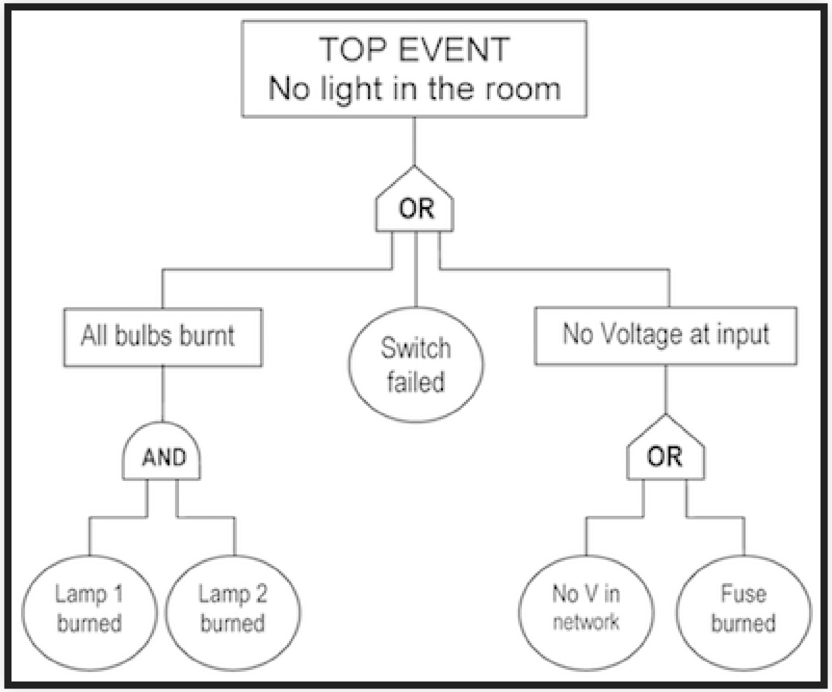
FAULT TREE EXAMPLE



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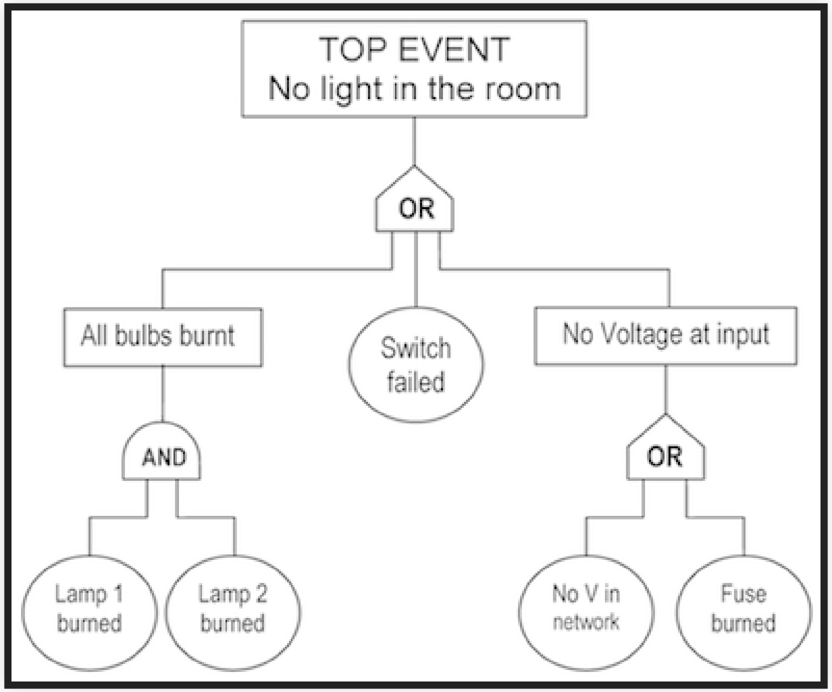

- Every tree begins with a TOP event (typically a violation of a requirement)

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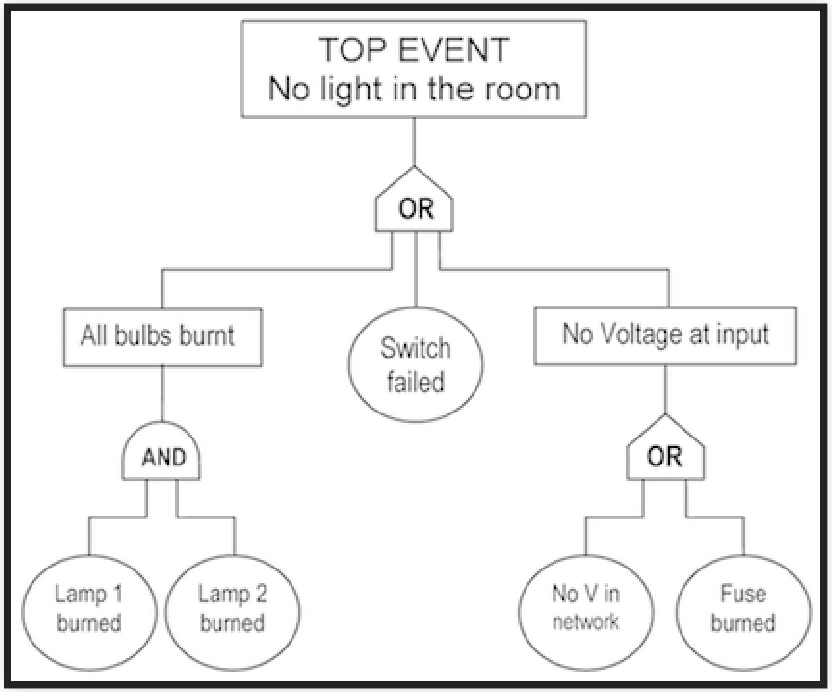

- Every tree begins with a TOP event (typically a violation of a requirement)
- Every branch of the tree must terminate with a basic event

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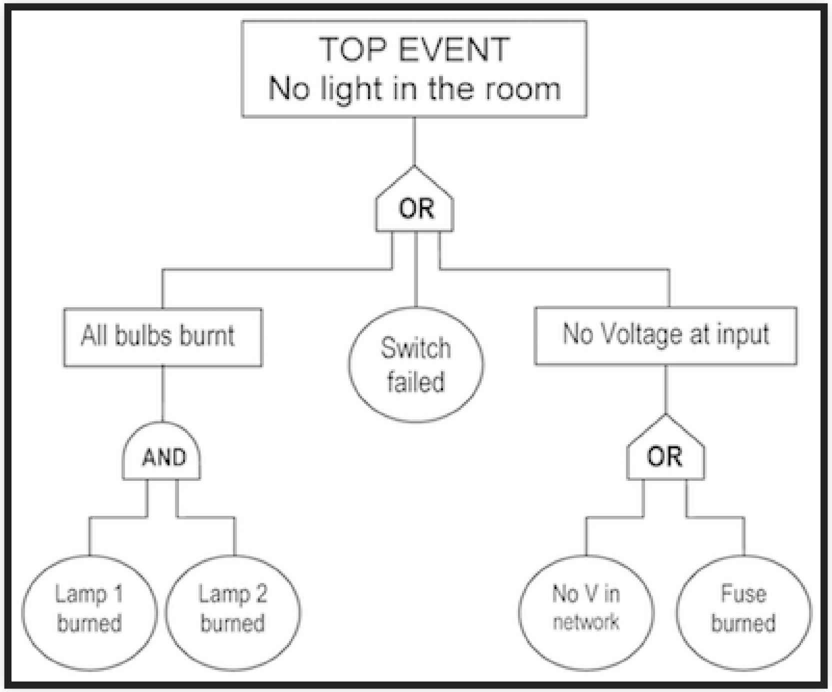
ANALYSIS

- 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't be obtained by removing a basic event.
- Q. What are minimal cut sets in the above tree?

FAILURE PROBABILITY ANALYSIS

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- To compute the probability of the top event:
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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”
- Draw on paper, scan & upload into Slack #lecture
- Or use the Google Slide template provided; make your own copy and paste the link into Slack

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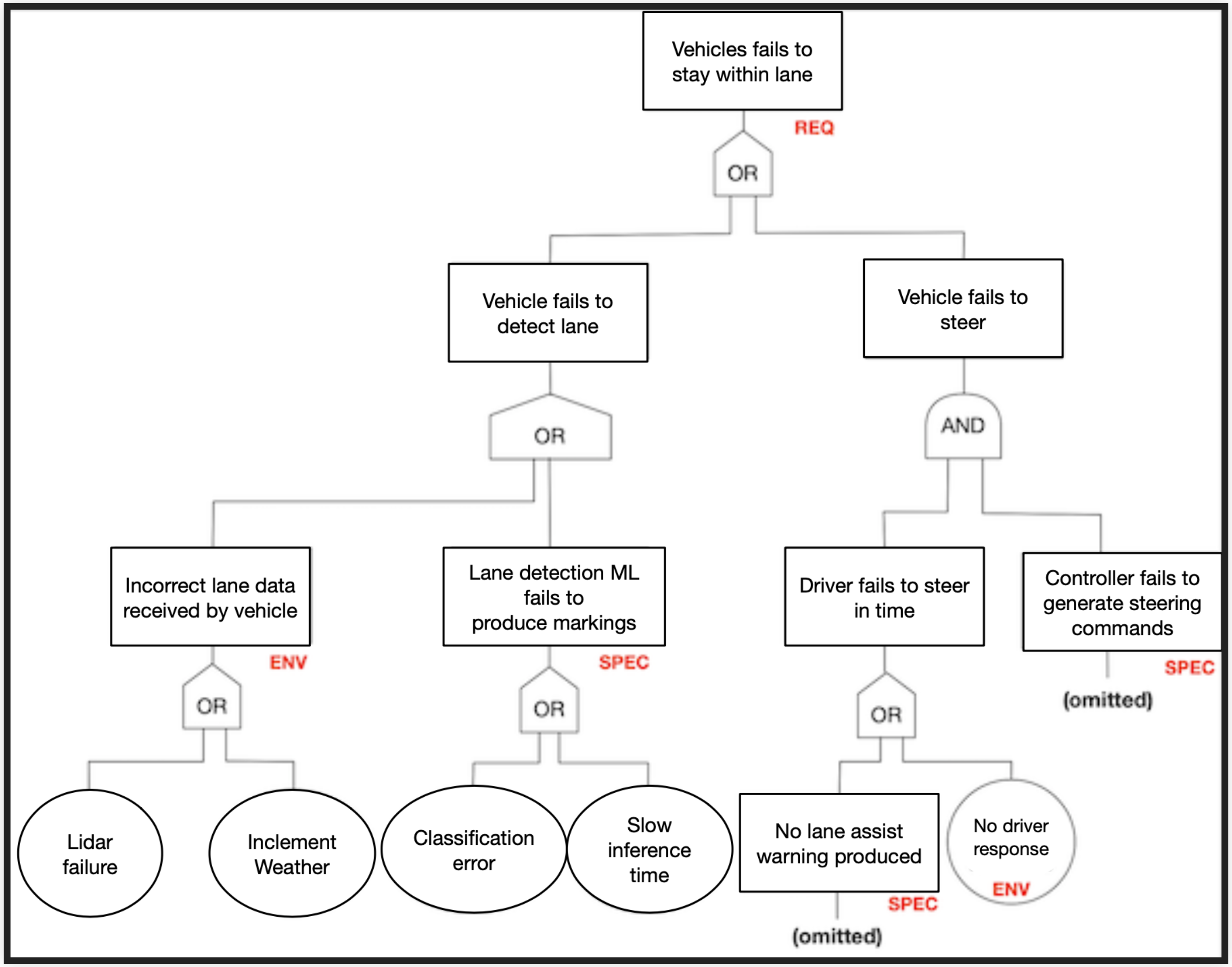

FTA: CAVEATS

- In general, building a **complete** tree is impossible
  - There are probably some faulty events that you missed
  - "Unknown unknowns"
- Domain knowledge is crucial for improving coverage
  - Talk to domain experts; augment your tree as you learn more
- FTA is still very valuable for risk reduction!
  - Forces you to think about & explictly document possible failure scenarios
  - A good starting basis for designing mitigations

STRATEGIES FOR HANDLING FAULTS IN ML-BASED SYSTEMS

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- Response
  - Graceful degradation (fail-safe)
  - Redundancy (fail over)
  - Human in the loop
  - Undoable actions

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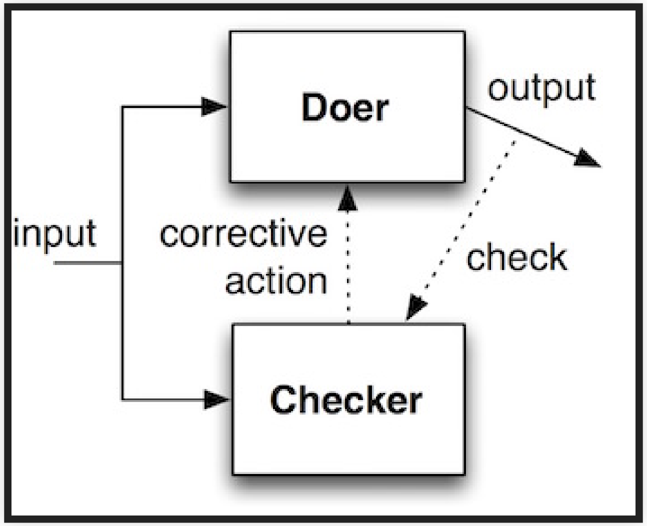
- Containment
  - Decoupling & isolation

DETECTION: MONITORING



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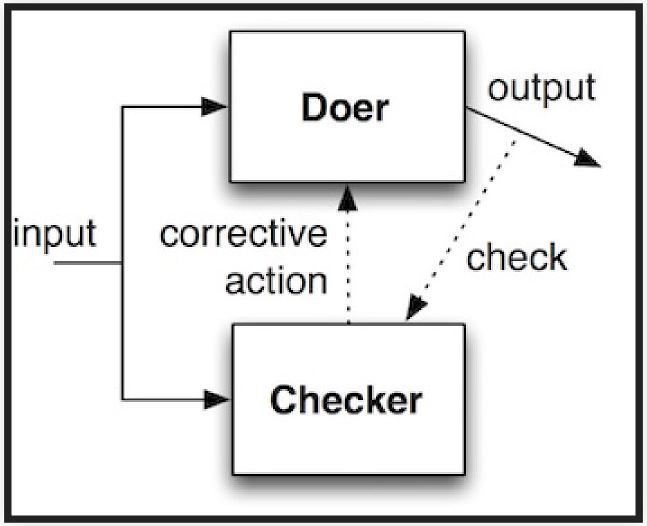

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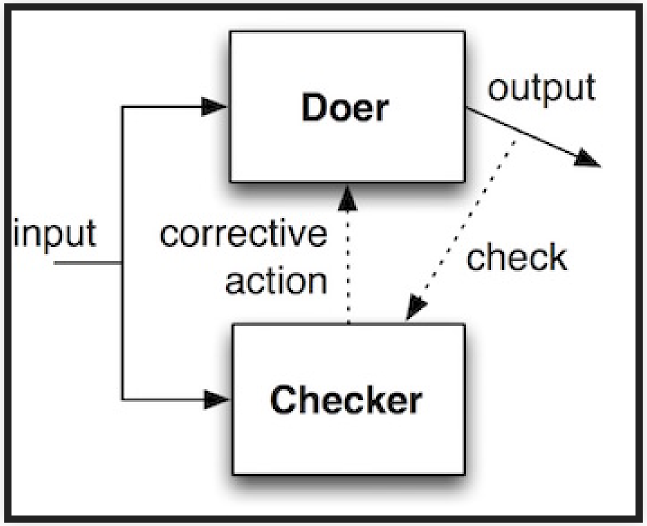

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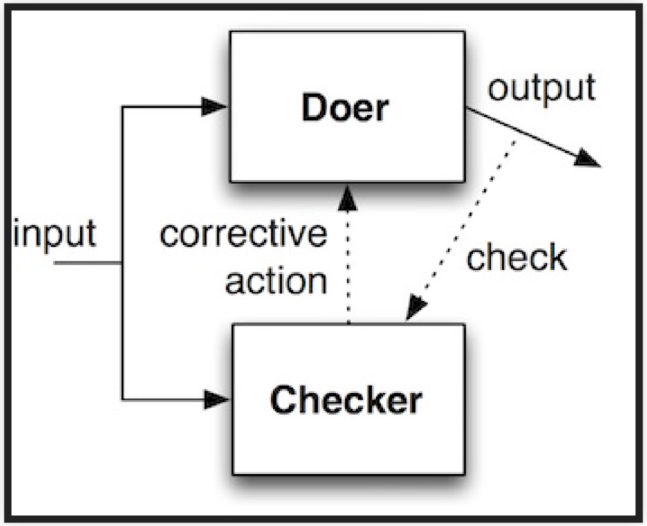

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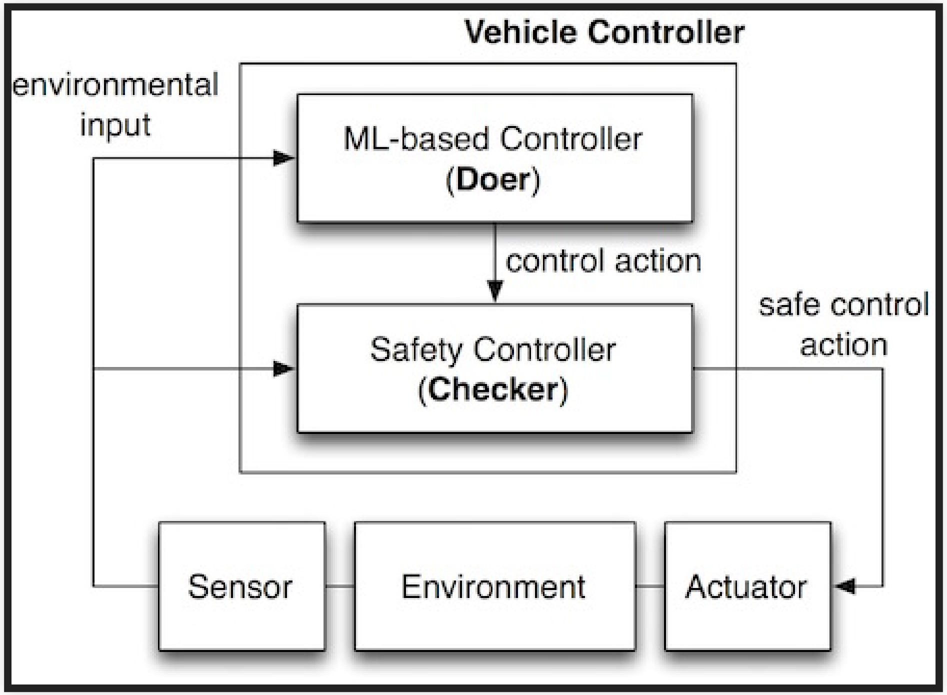
- Doer-Checker pattern
  - Doer: Perform primary function; untrusted and potentially faulty
  - Checker: If doer output is faulty, perform a corrective action (e.g., default safe output, shutdown); should be trustworthy

DOER-CHECKER EXAMPLE: AUTONOMOUS VEHICLE



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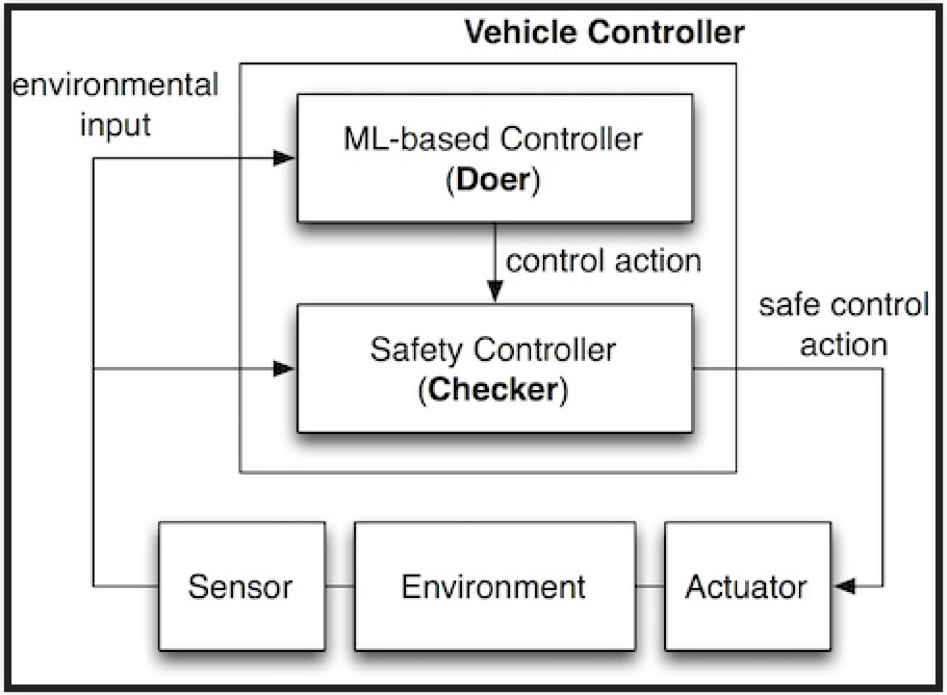

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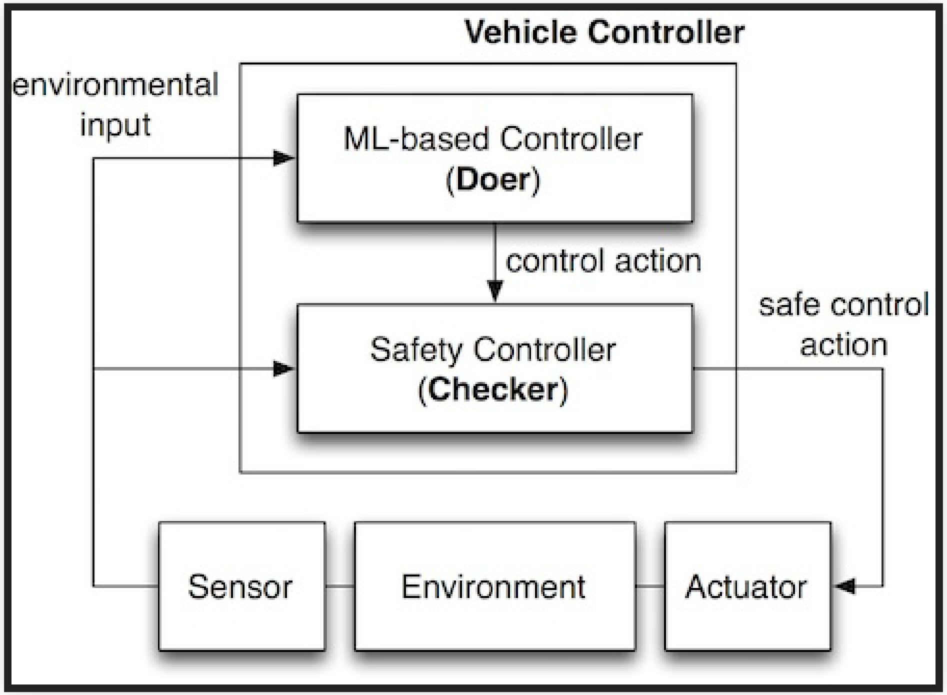

- ML-based controller (doer): Generate commands to steer the vehicle
  - Complex DNN; makes performance-optimal control decisions
- Safety controller (checker): Checks commands from ML controller; overrides it with a safe default command if the ML action is risky
  - Simpler, based on verifiable, transparent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

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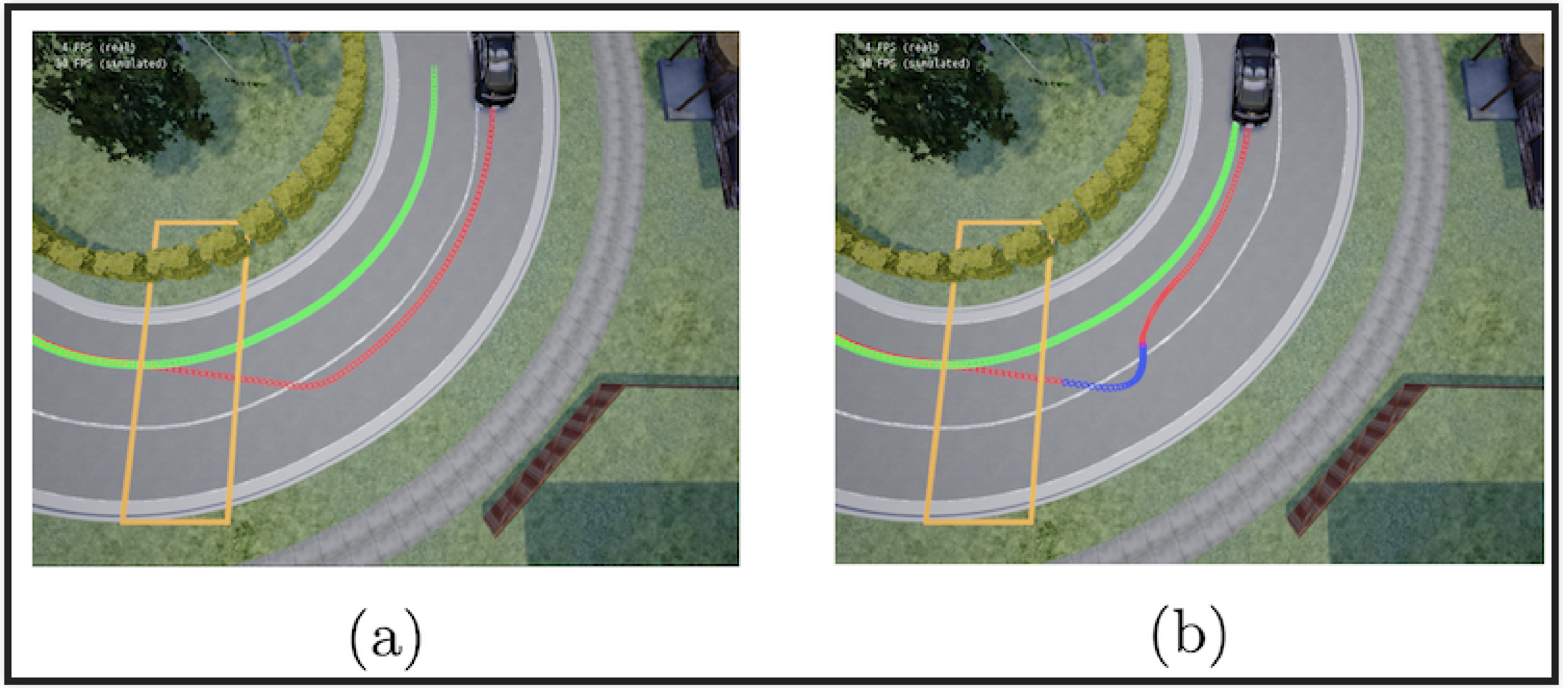

Runtime-Safety-Guided Policy Repair, Intl. Conference on Runtime Verification (2020)

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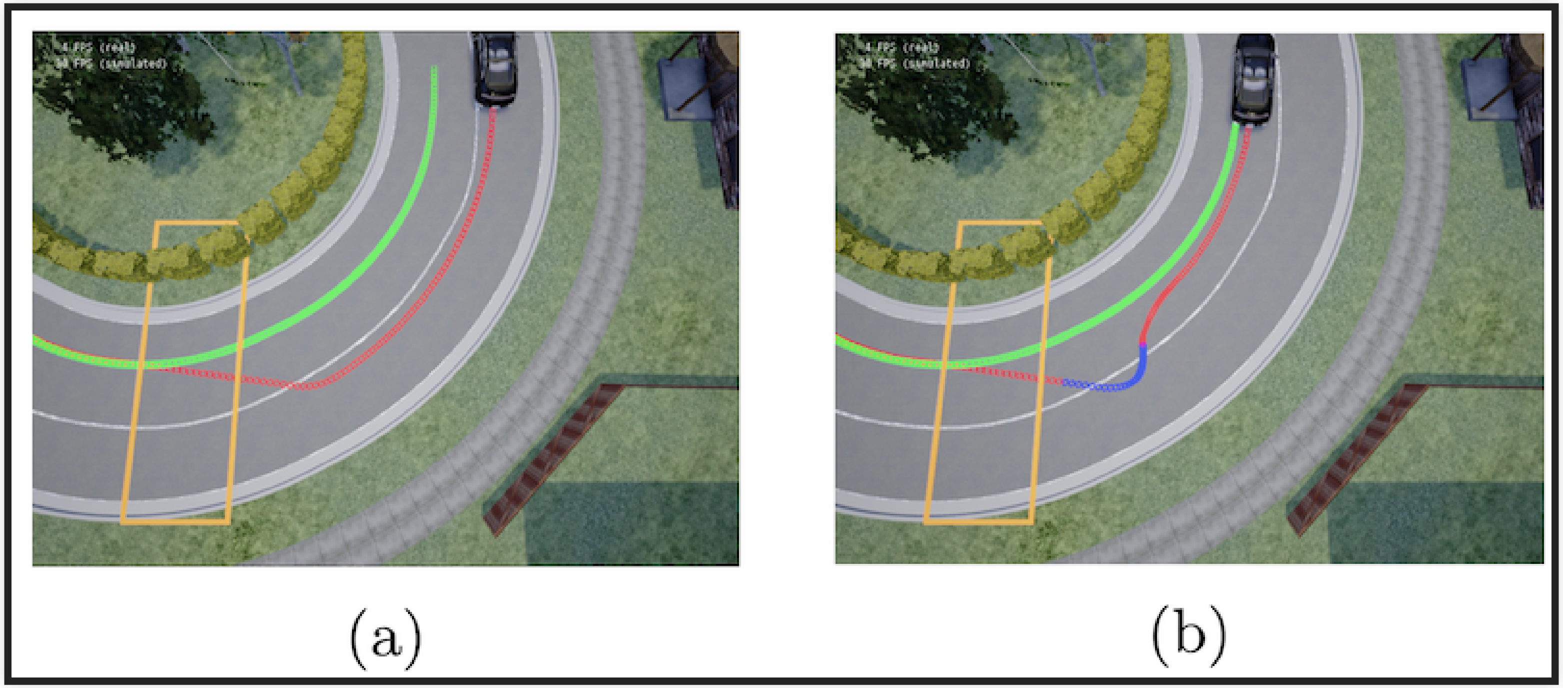

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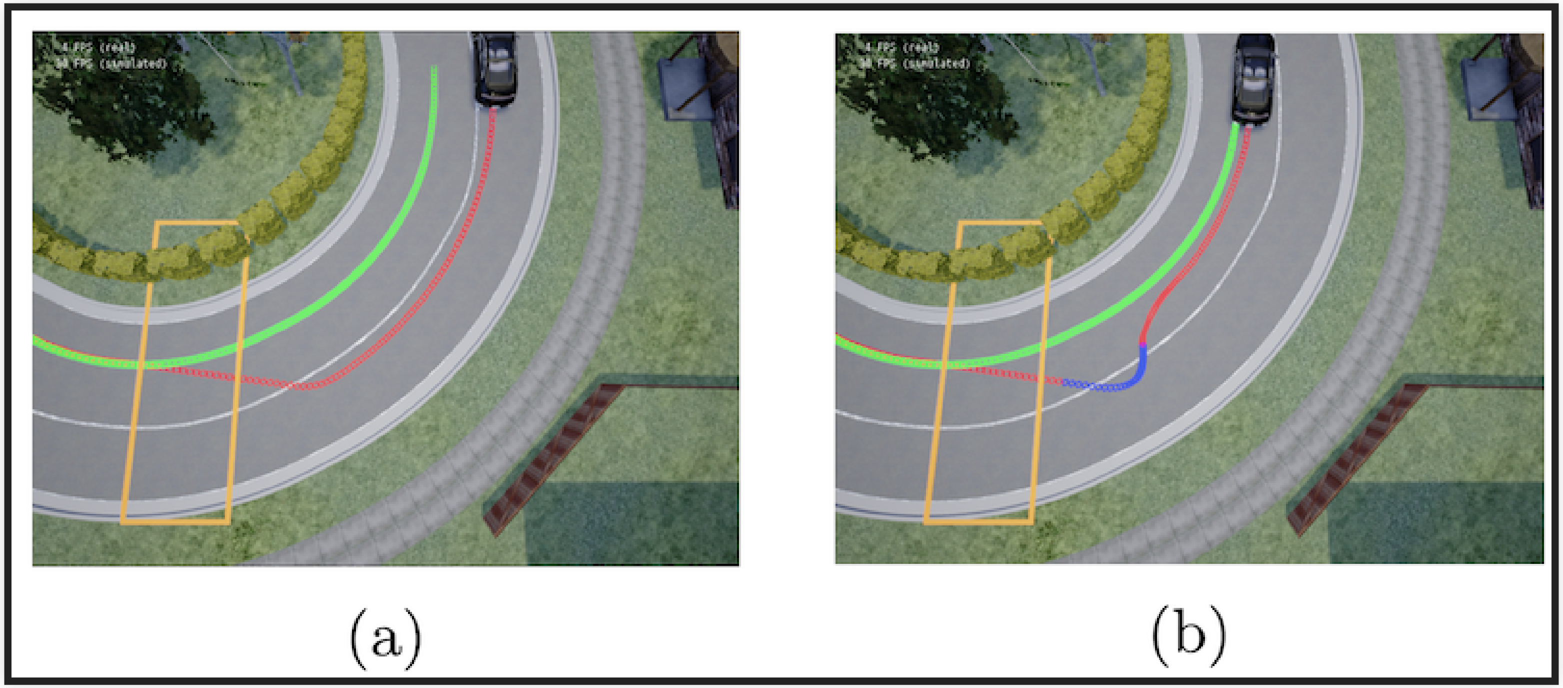

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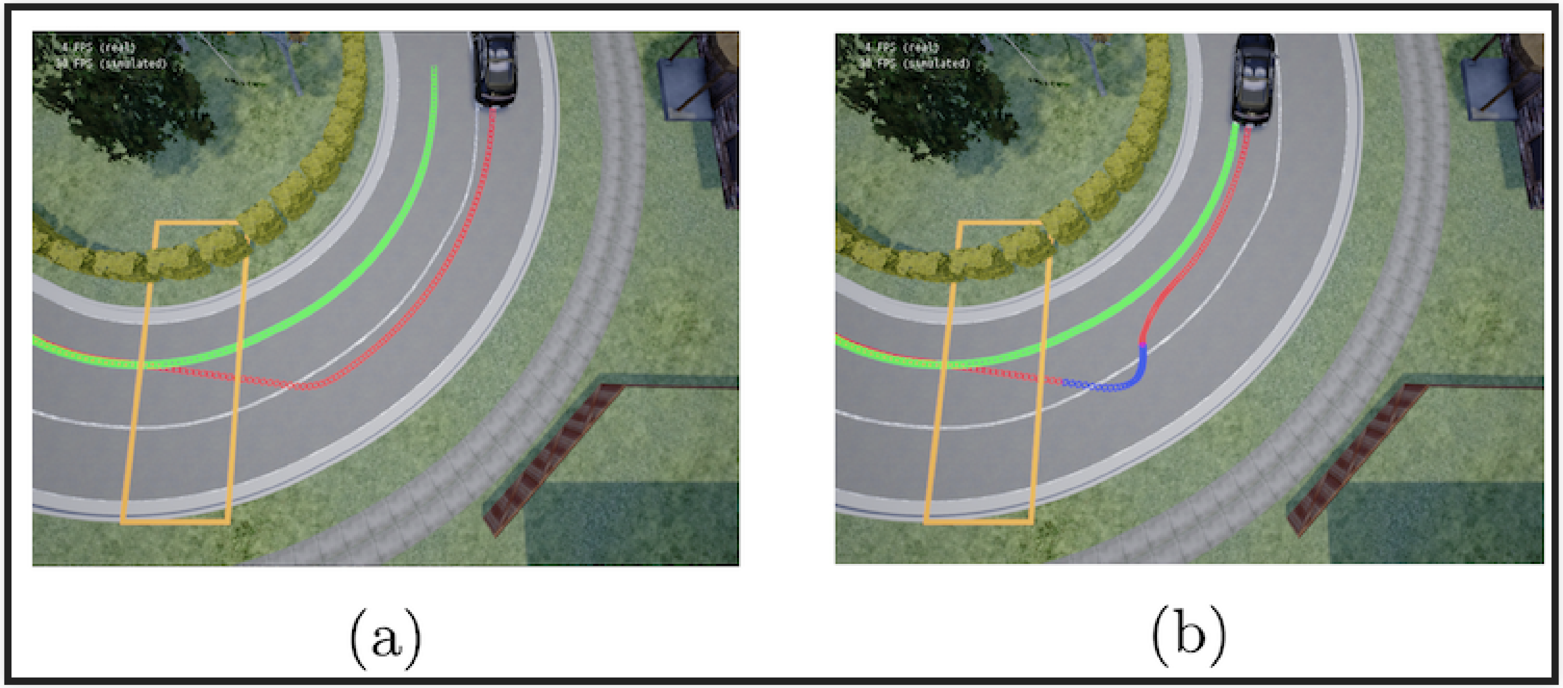

- Yellow region: Slippery road, causes loss of traction; unexpected by ML
- ML-based controller (doer): Model ignores traction loss; generates unsafe steering commands (a)
- Safety controller (checker): Overrides with safe steering commands (b)

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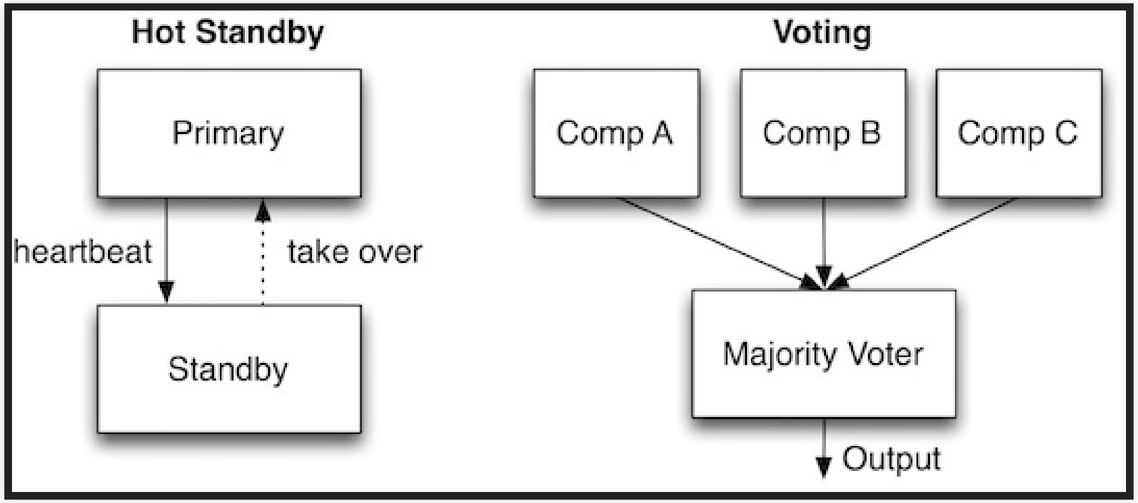
- Goal: When a component failure occurs, achieve system safety by reducing functionality and performance
- Relies on a monitor to detect component failures
- Example: Perception in autonomous vehicles
    - If Lidar fails, switch to a lower-quality detector & be more conservative about maintaining distance

DETECTION & RESPONSE: REDUNDANCY



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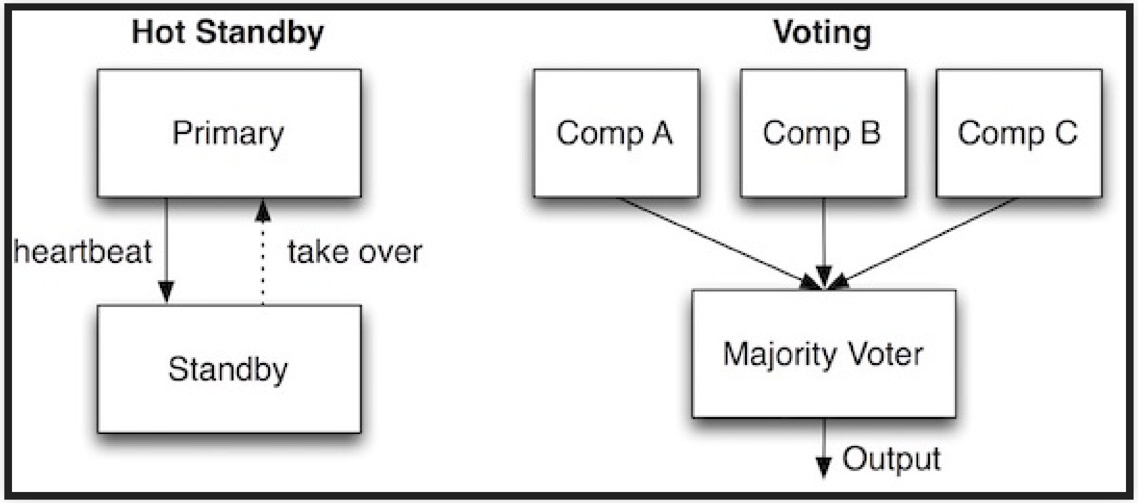

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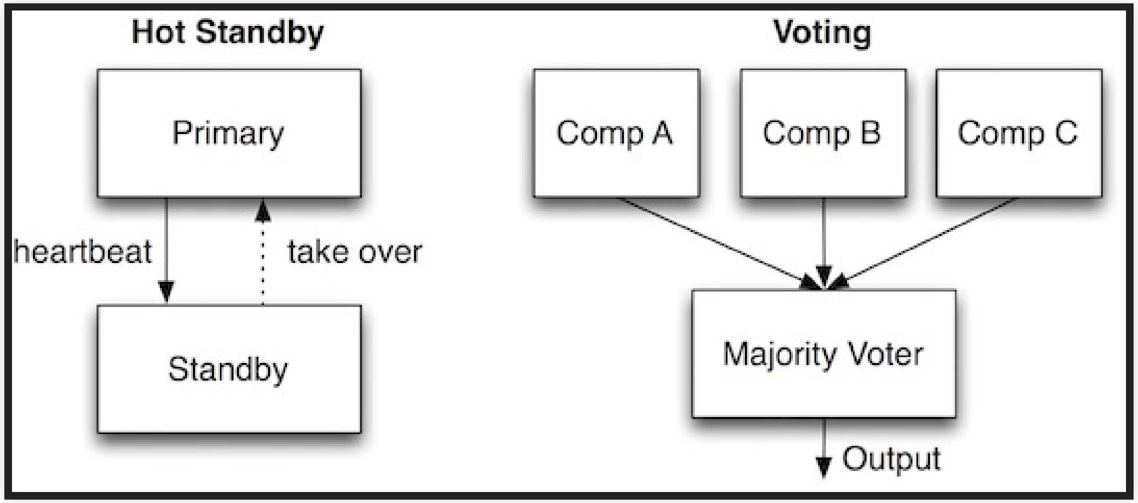

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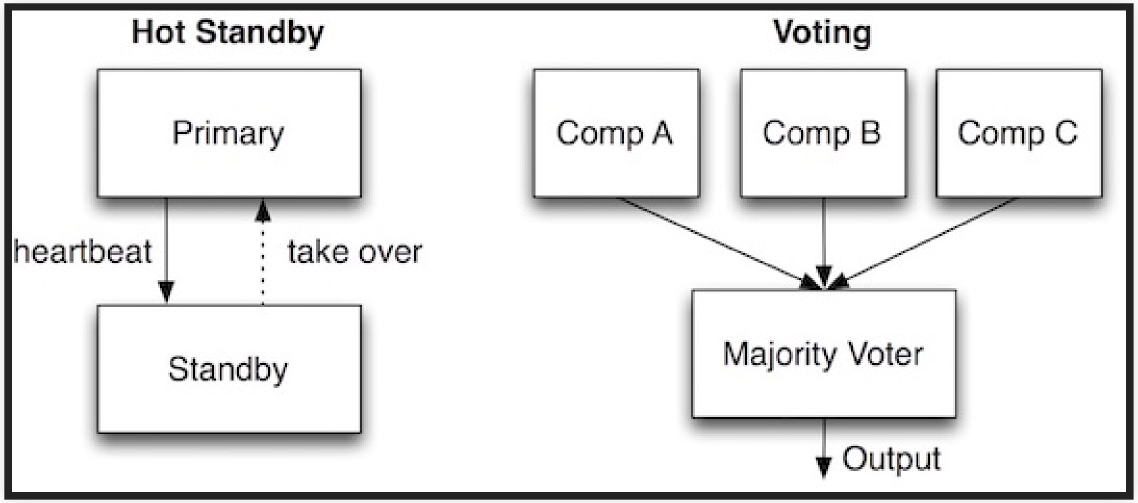

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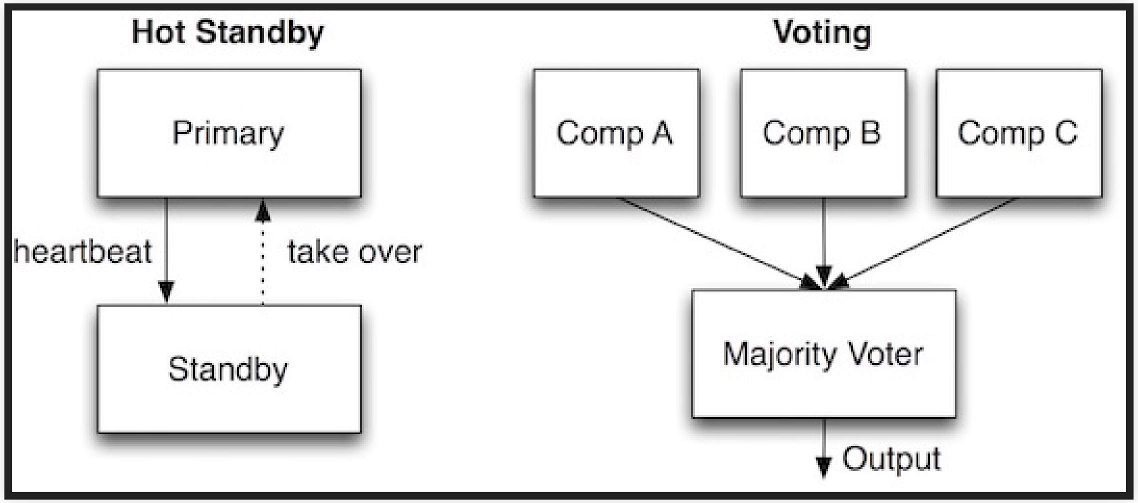

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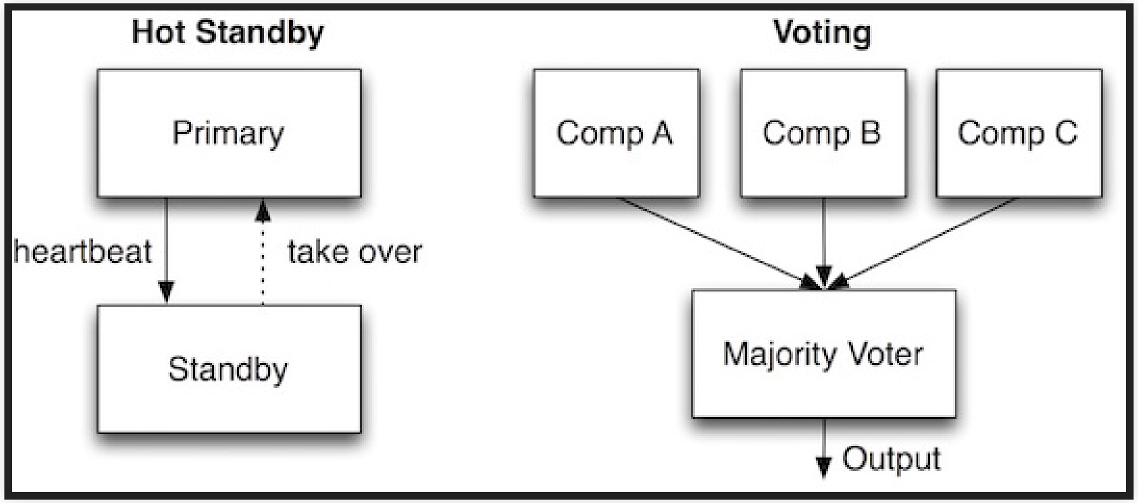

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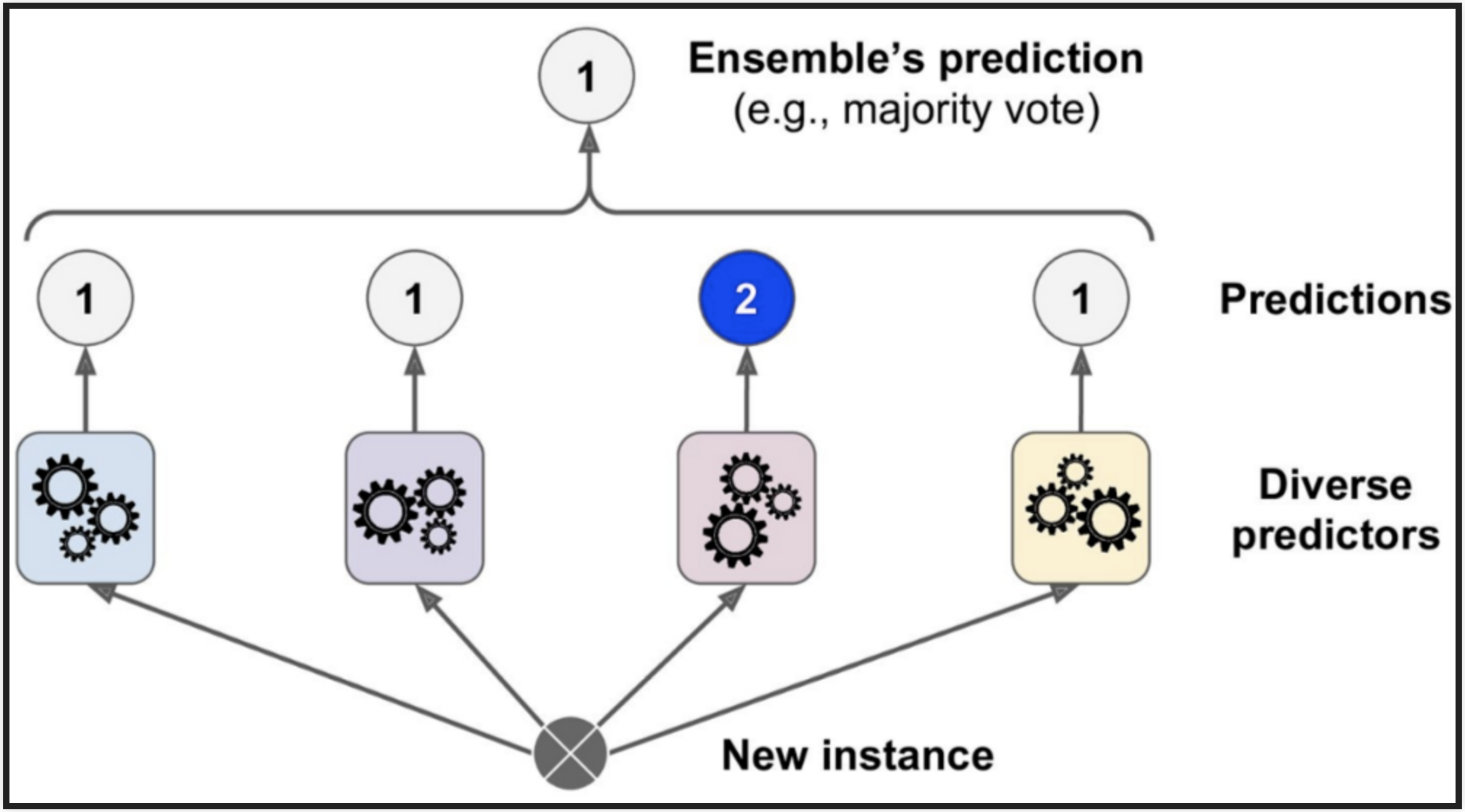
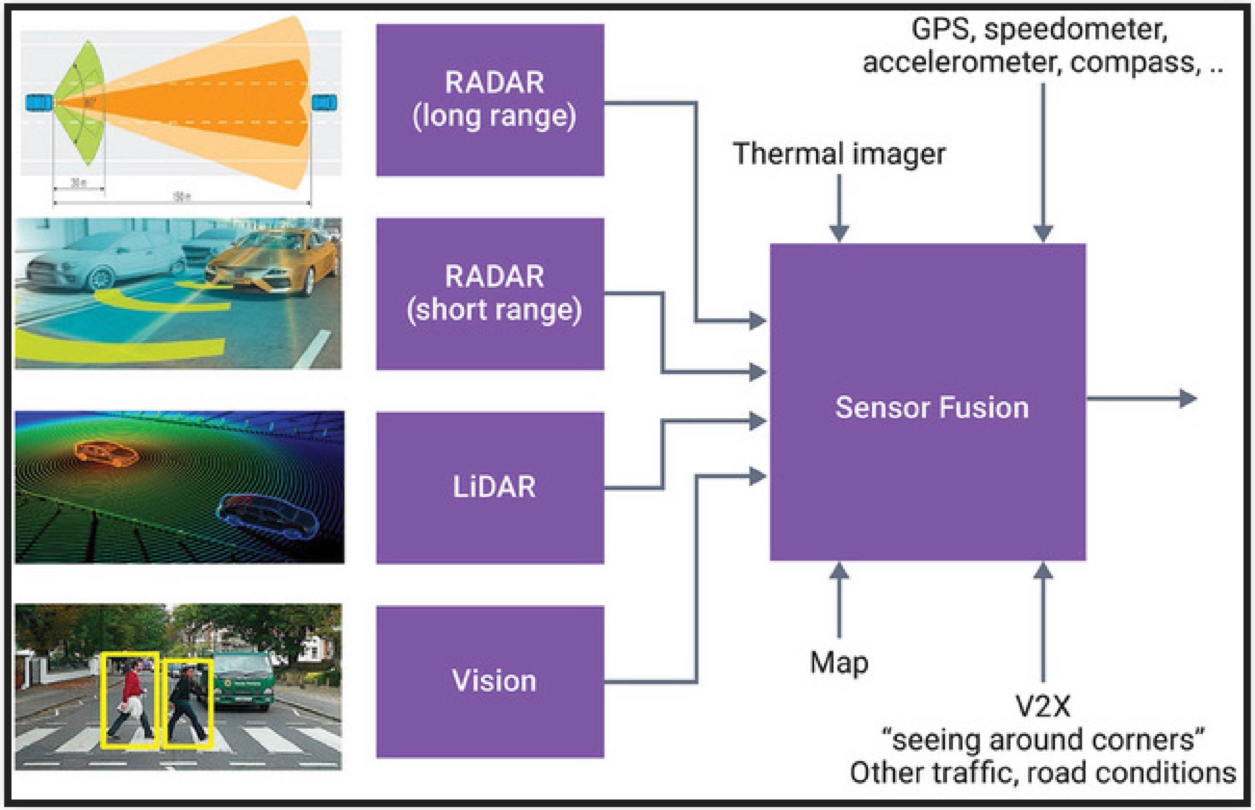
- Voting: Select the majority decision
- Caution: Do components fail independently?
  - Reasonable assumption for hardware/mechanical failures
  - Q. What about ML components?

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

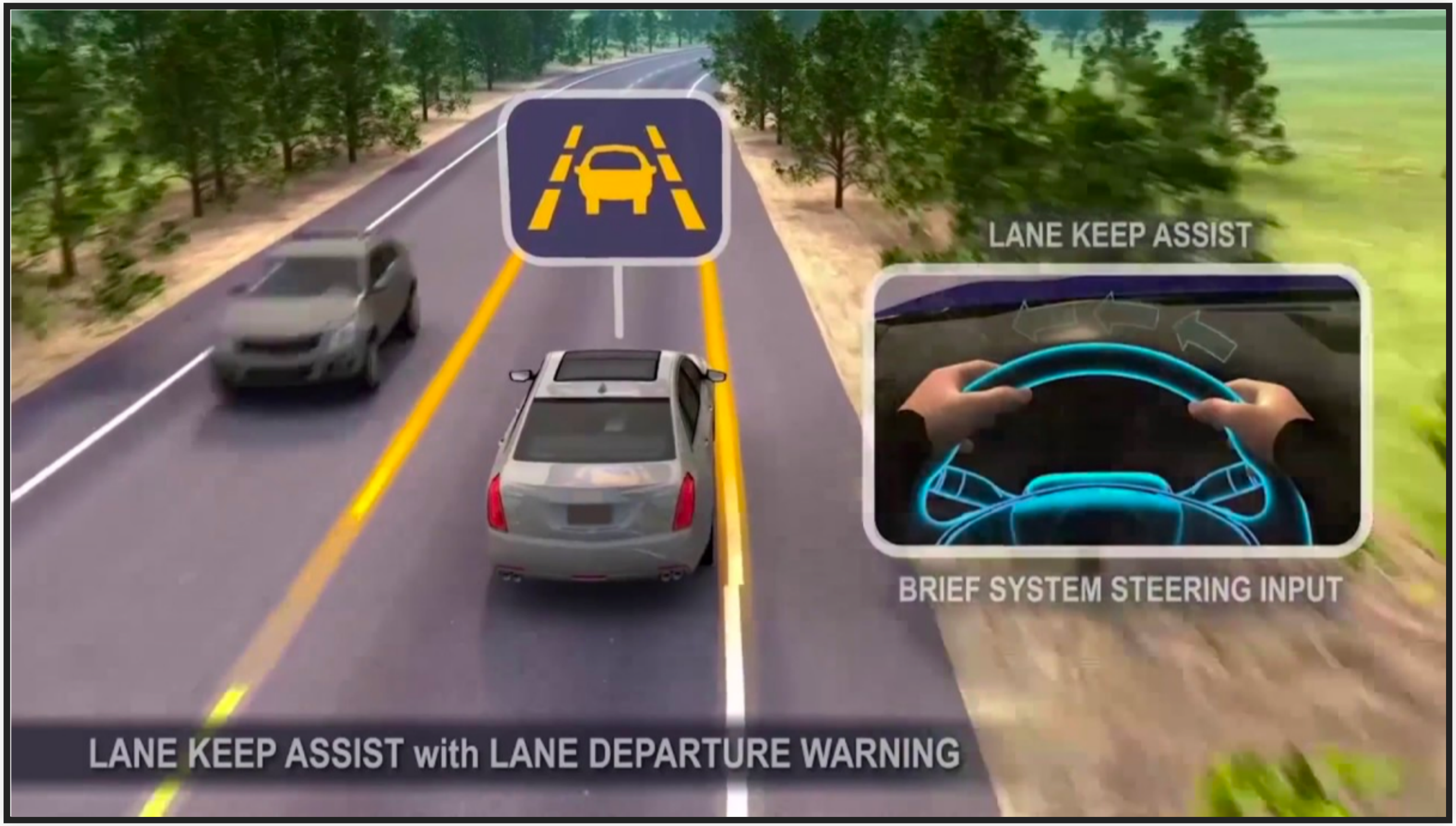
Design the system to reduce the consequences of wrong predictions, allowing humans to override or undo

Examples?

Speaker notes

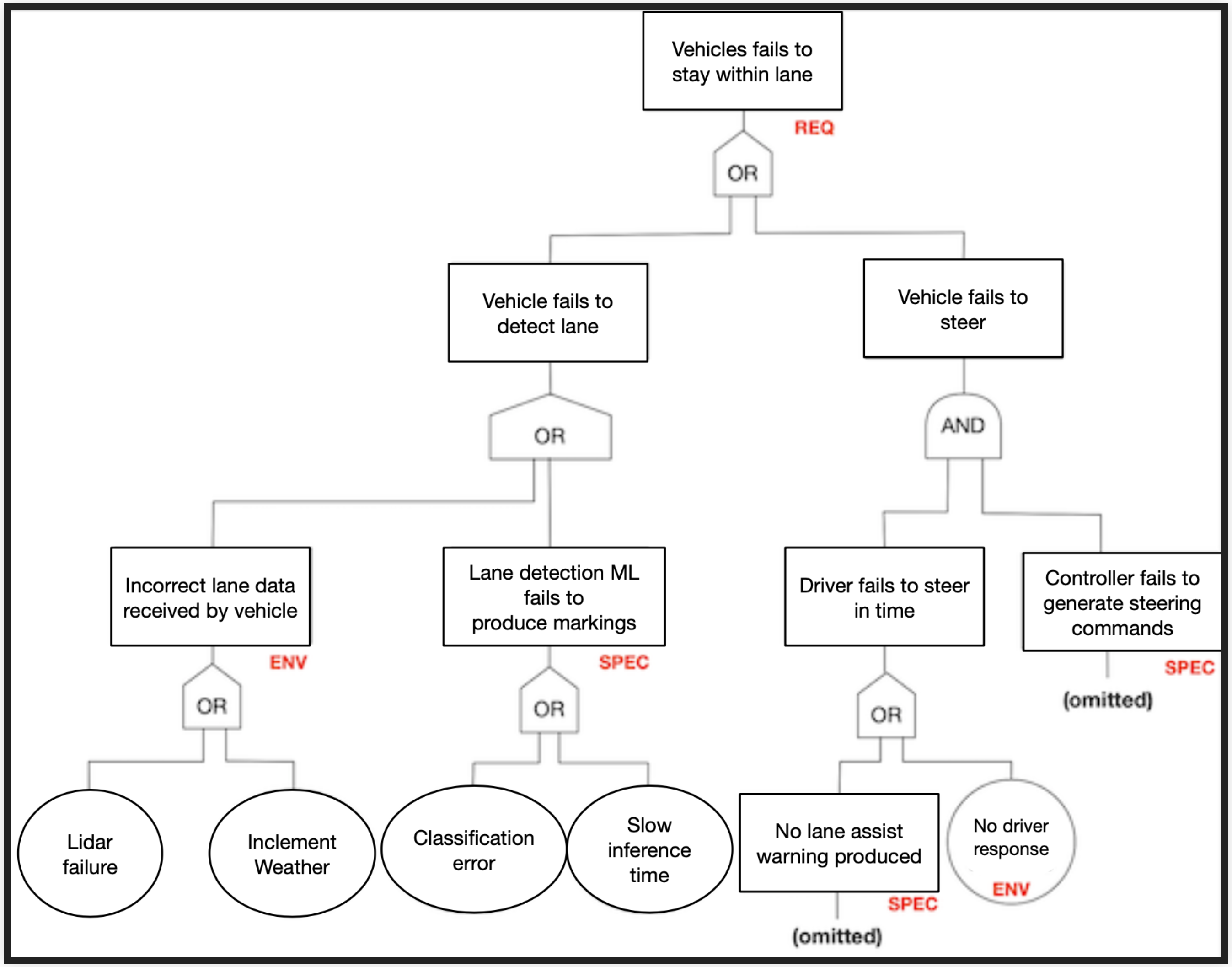
Smart home devices, credit card applications, Powerpoint design suggestions

EXAMPLE: LANE ASSIST

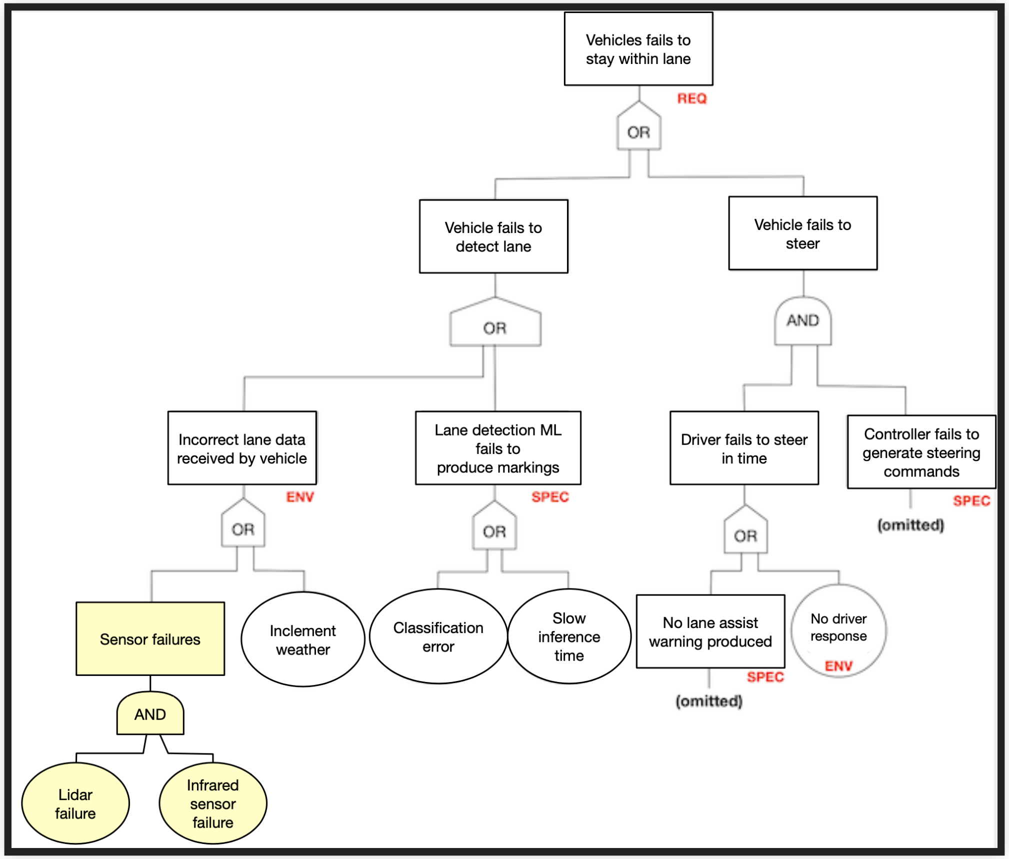


Possible mitigation strategies? Discuss with your neighbors

EXAMPLE: FTA FOR LANE ASSIST



MODIFIED FTA FOR LANE ASSIST



- Fault mitigation strategy: An additional sensor (infrared) for redundancy
  - Both sensors need to fail instead of just one
  - Reflected in the FTA as an additional basic event in the minimal cutset

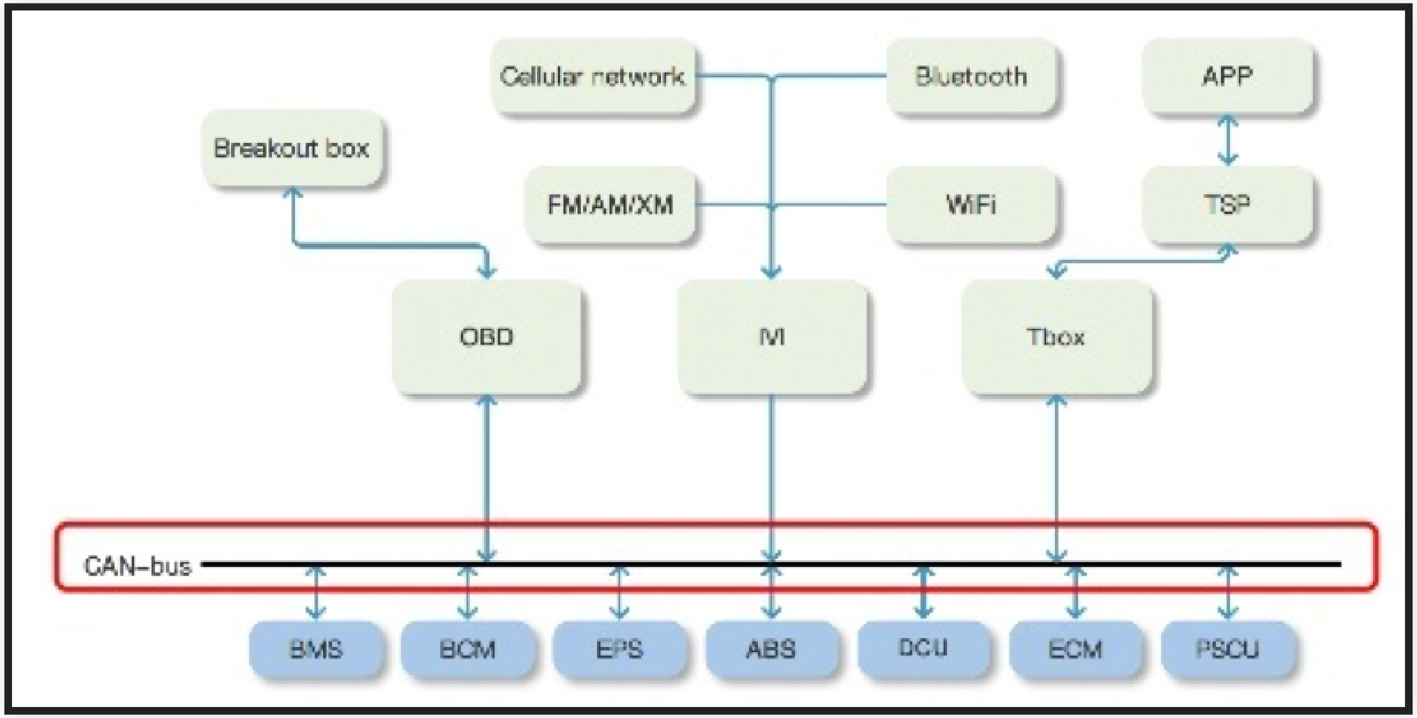
CONTAINMENT: DECOUPLING & ISOLATION

- **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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    - LC components should be allowed to access min. necessary functions

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- Limit interactions across criticality boundaries
    - Deploy LC & HC components on different networks
    - Add monitors/checks at interfaces

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- **Design principle**: Faults in a low-critical (LC) components should not impact high-critical (HC) components
- Apply the principle of least privilege
    - LC components should be allowed to access min. necessary functions
- Limit interactions across criticality boundaries
    - Deploy LC & HC components on different networks
    - Add monitors/checks at interfaces
- Is an ML component in my system performing an LC or HC task?
    - If HC, can we "demote" it into LC?
    - Alternatively, if possible, replace/augment 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