

# 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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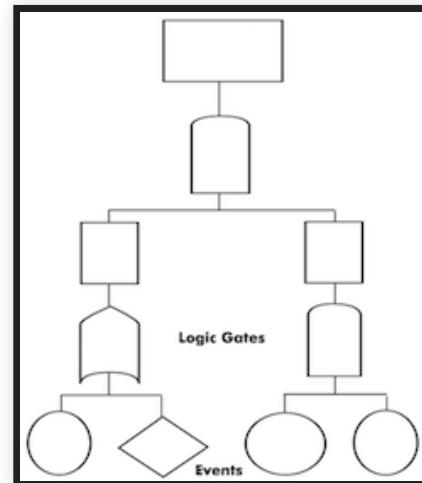
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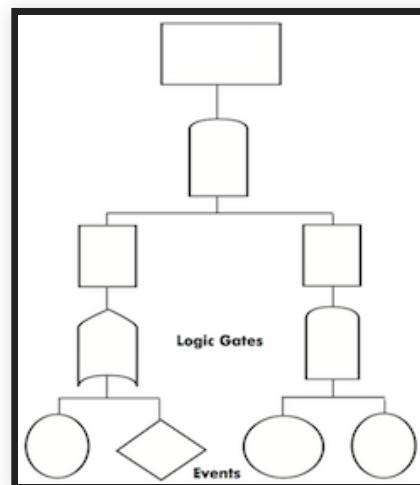
- What can possibly go wrong in my system, and what are potential impacts on system requirements?
- Risk = Likelihood \* Impact
- A number of methods:
  - Failure mode & effects analysis (FMEA)
  - Hazard analysis
  - Why-because analysis
  - Fault tree analysis (FTA) <= Today's focus!
  - ...

# FAULT TREE ANALYSIS (FTA)



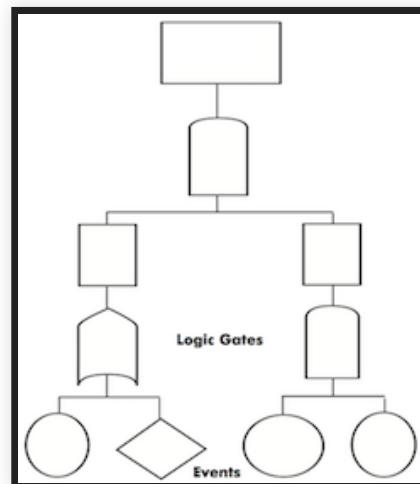
# FAULT TREE ANALYSIS (FTA)

- 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
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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

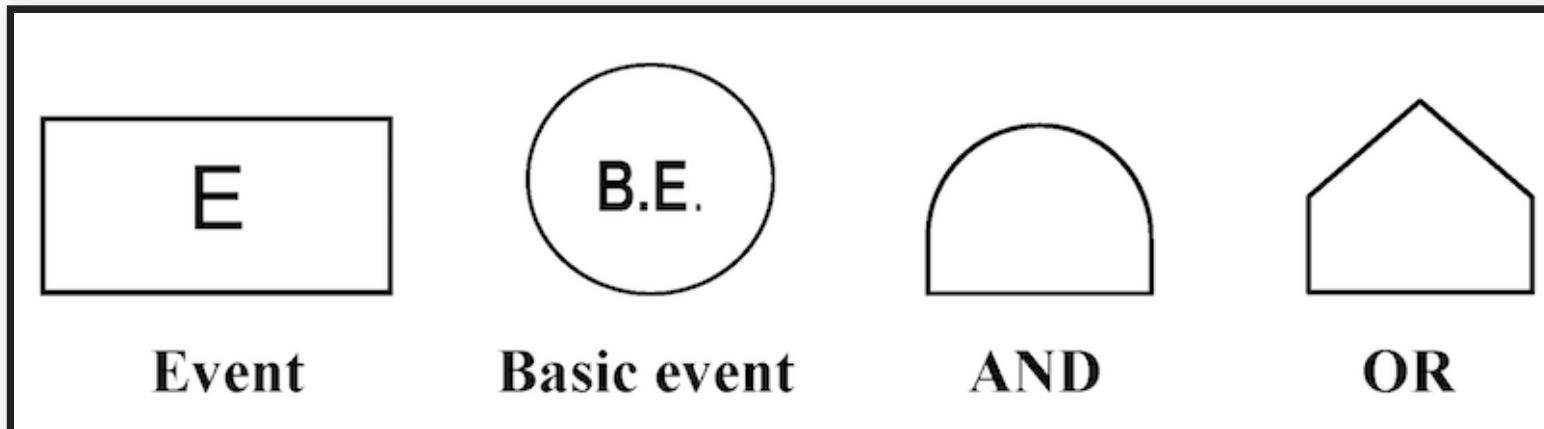
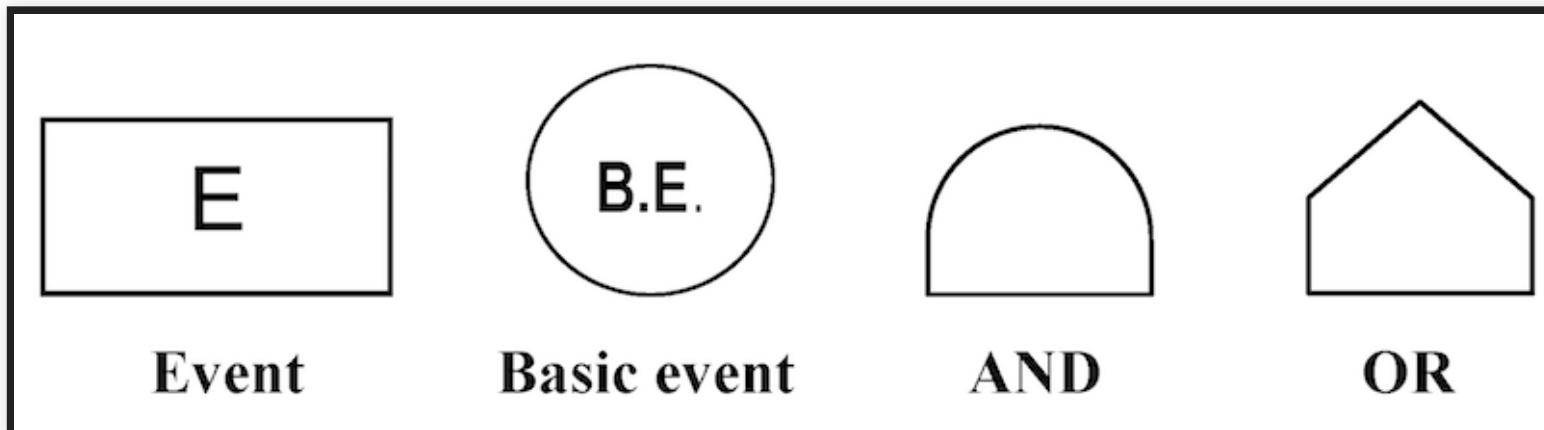


Figure from *Fault Tree Analysis and Reliability Block Diagram* (2016), Jaroslav Menčík.

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- Gate: Logical relationship between an event & its immediate 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

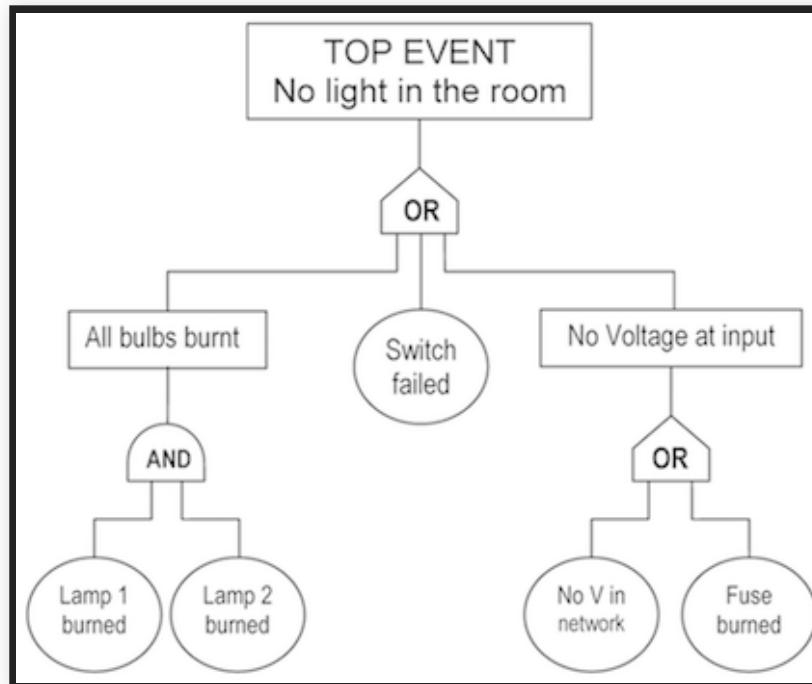


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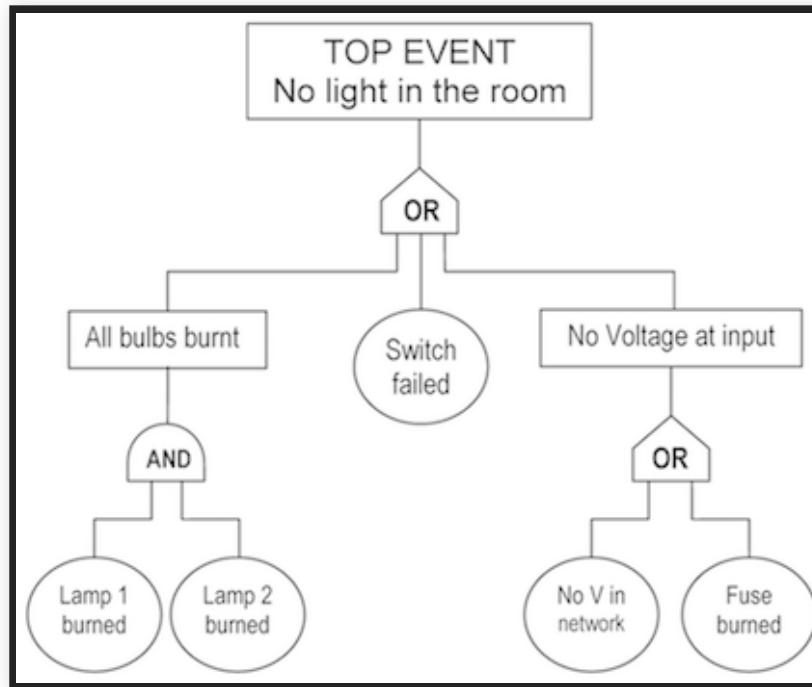
- Every tree begins with a TOP event (typically a violation of a requirement)
- Every branch of the tree must terminate with a basic event

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# ANALYSIS

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

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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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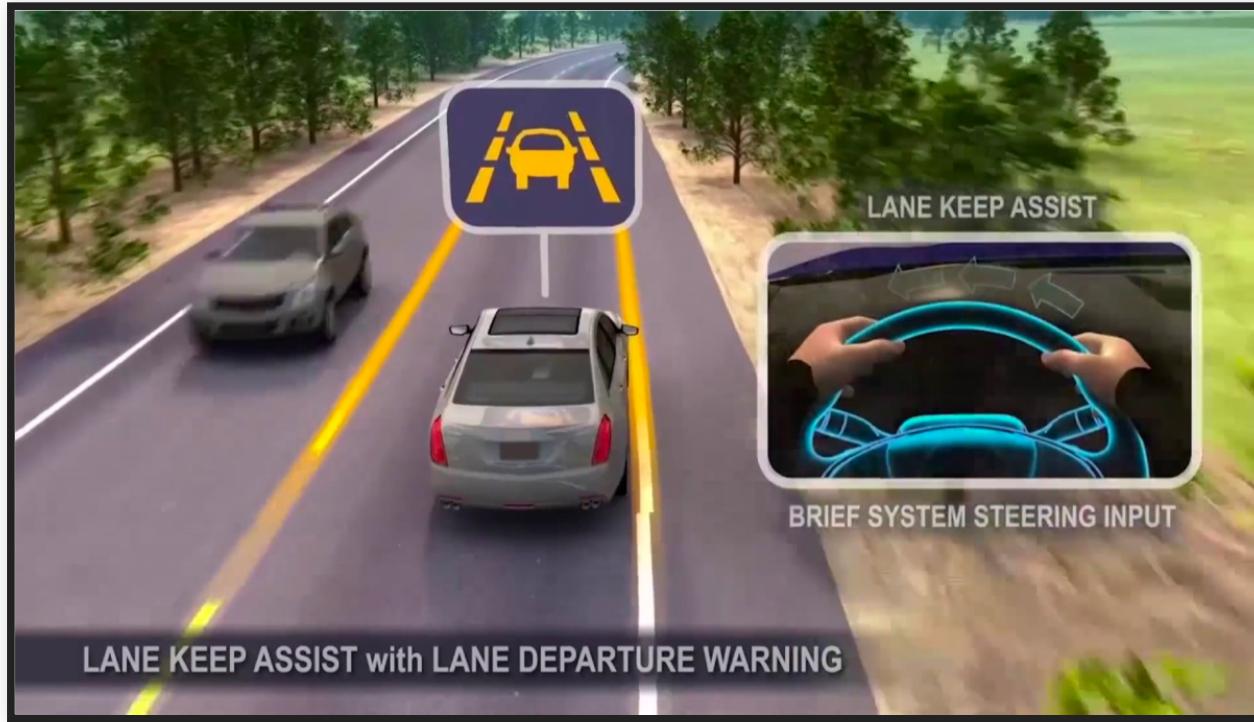
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## 6. Repeat

# 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

# EXAMPLE: FTA FOR LANE ASSIST



# 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 & explicitly 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

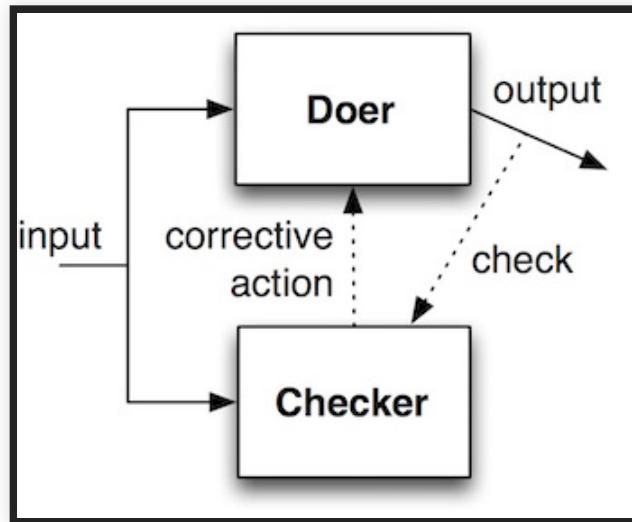
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- Containment
  - Decoupling & isolation

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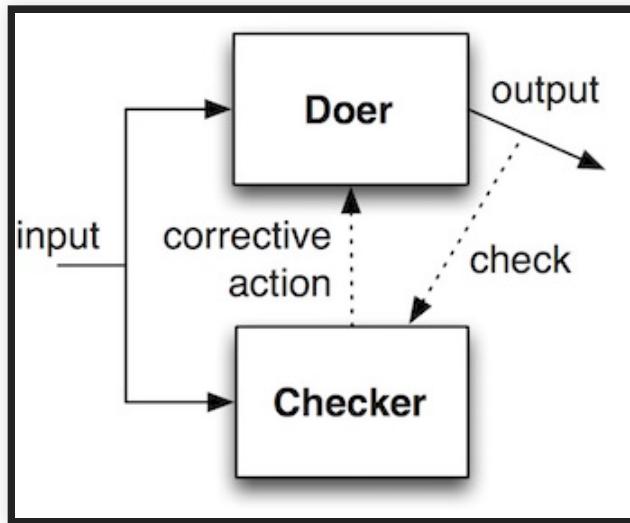


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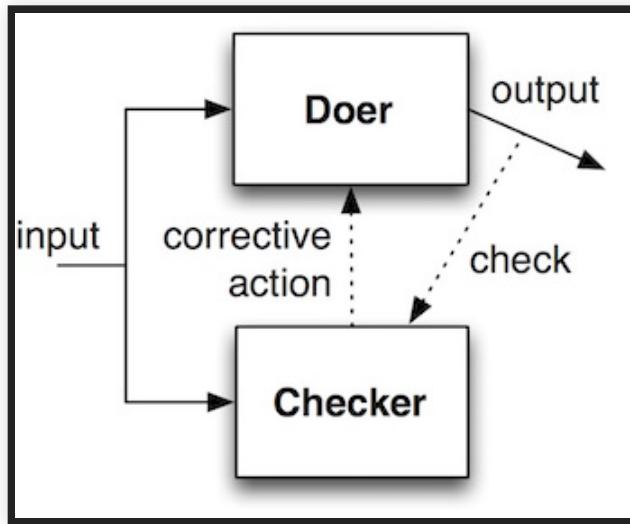
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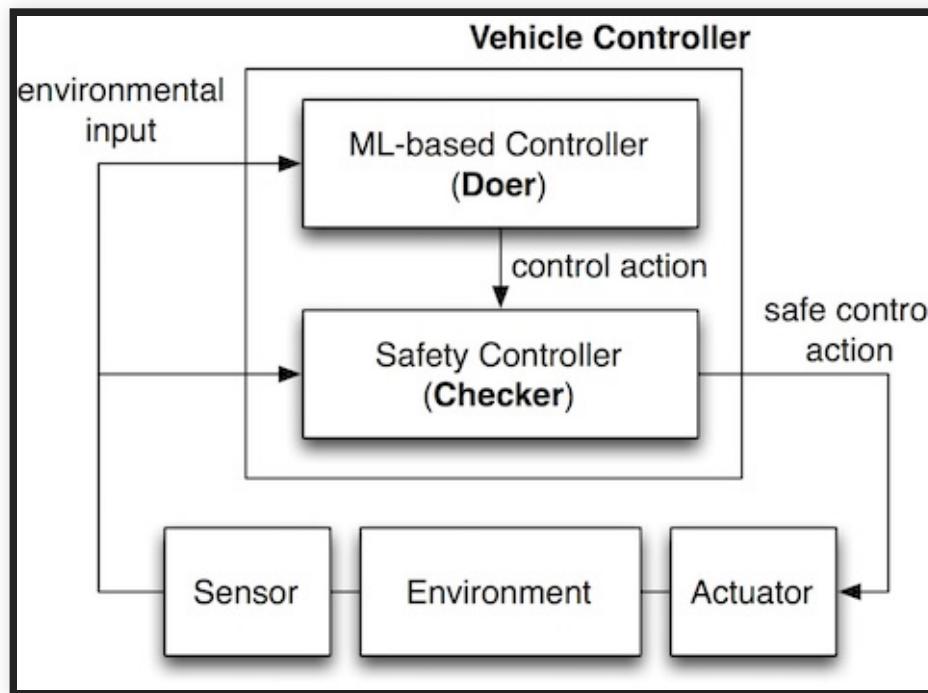


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- Doer-Checker pattern
  - Doer: Perform primary function; untrusted and potentially faulty
  - Checker: If doer output is faulty, perform a corrective action (e.g., default safe output, shutdown); should be trustworthy

# DOER-CHECKER EXAMPLE: AUTONOMOUS VEHICLE

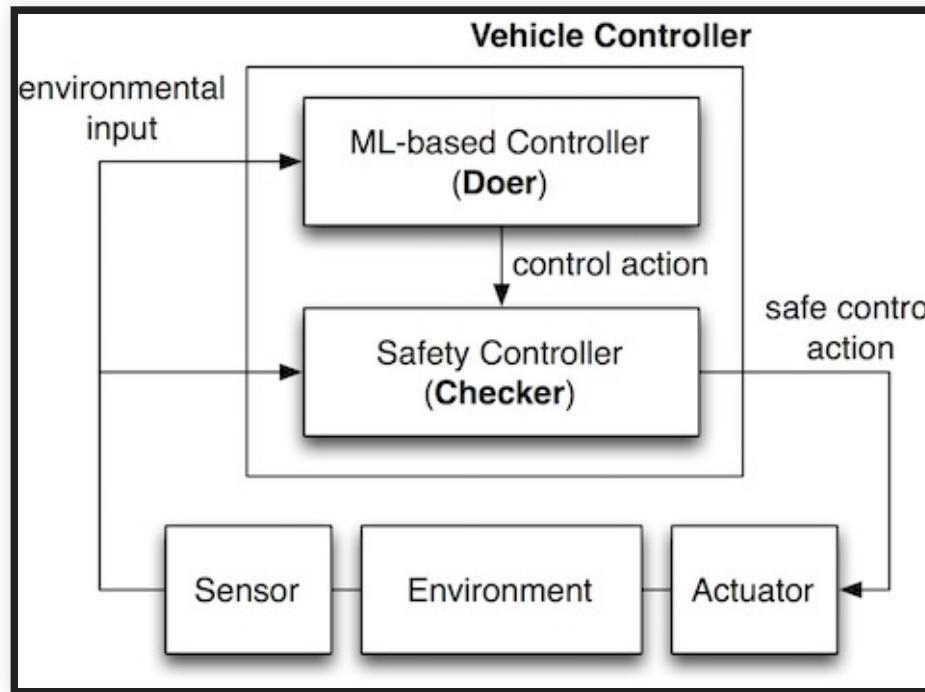


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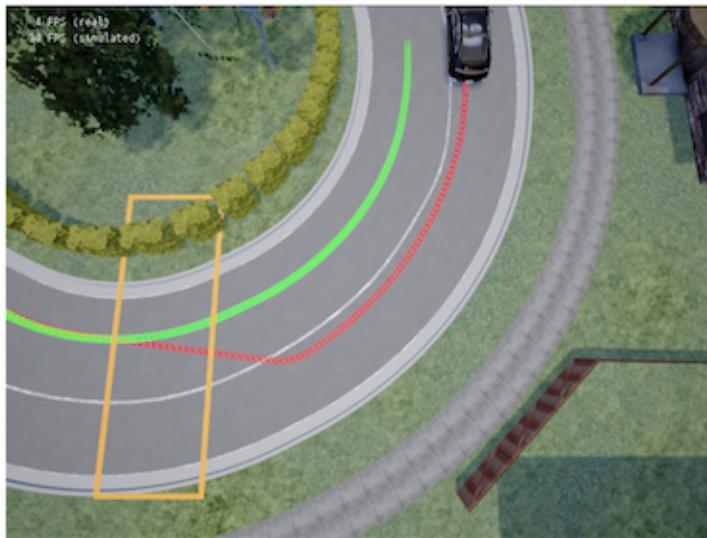
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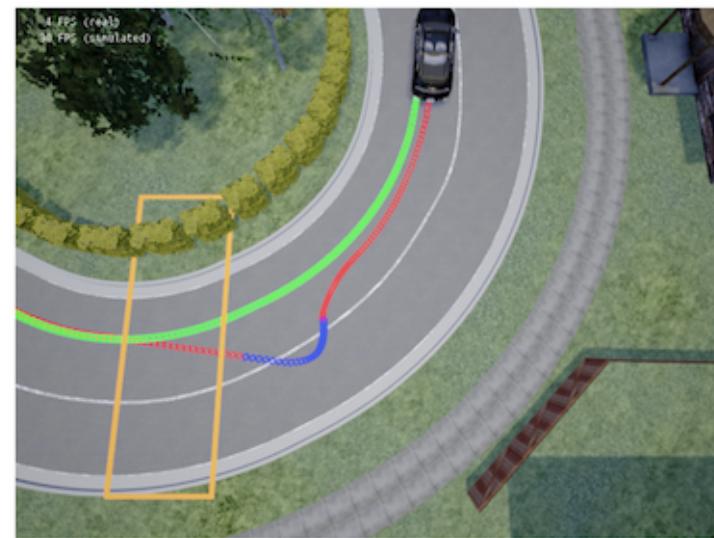


- ML-based controller (doer): Generate commands to steer the vehicle
  - Complex DNN; makes performance-optimal control decisions
- Safety controller (checker): Checks commands from ML controller; overrides it with a safe default command if the ML action is risky
  - Simpler, based on verifiable, transparent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

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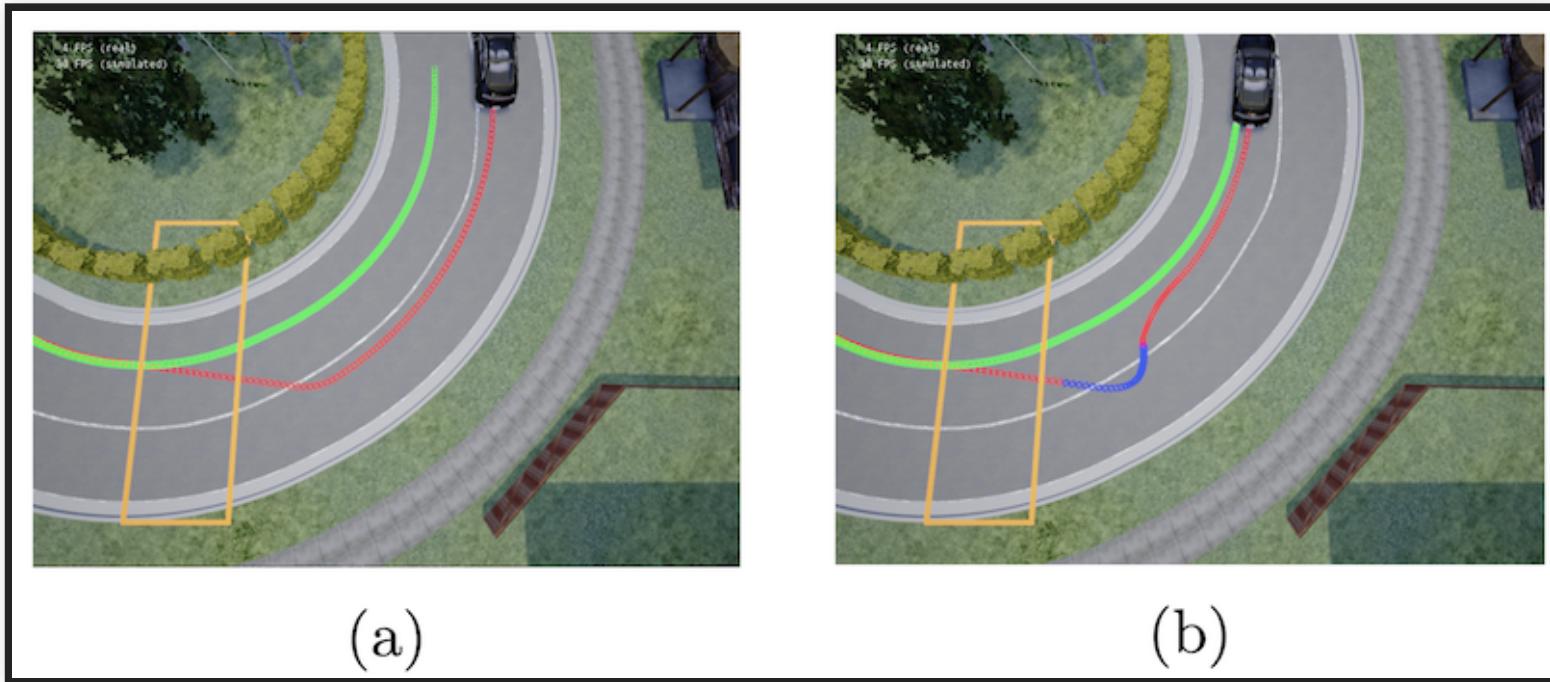
(a)



(b)



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- Yellow region: Slippery road, causes loss of traction; unexpected by ML



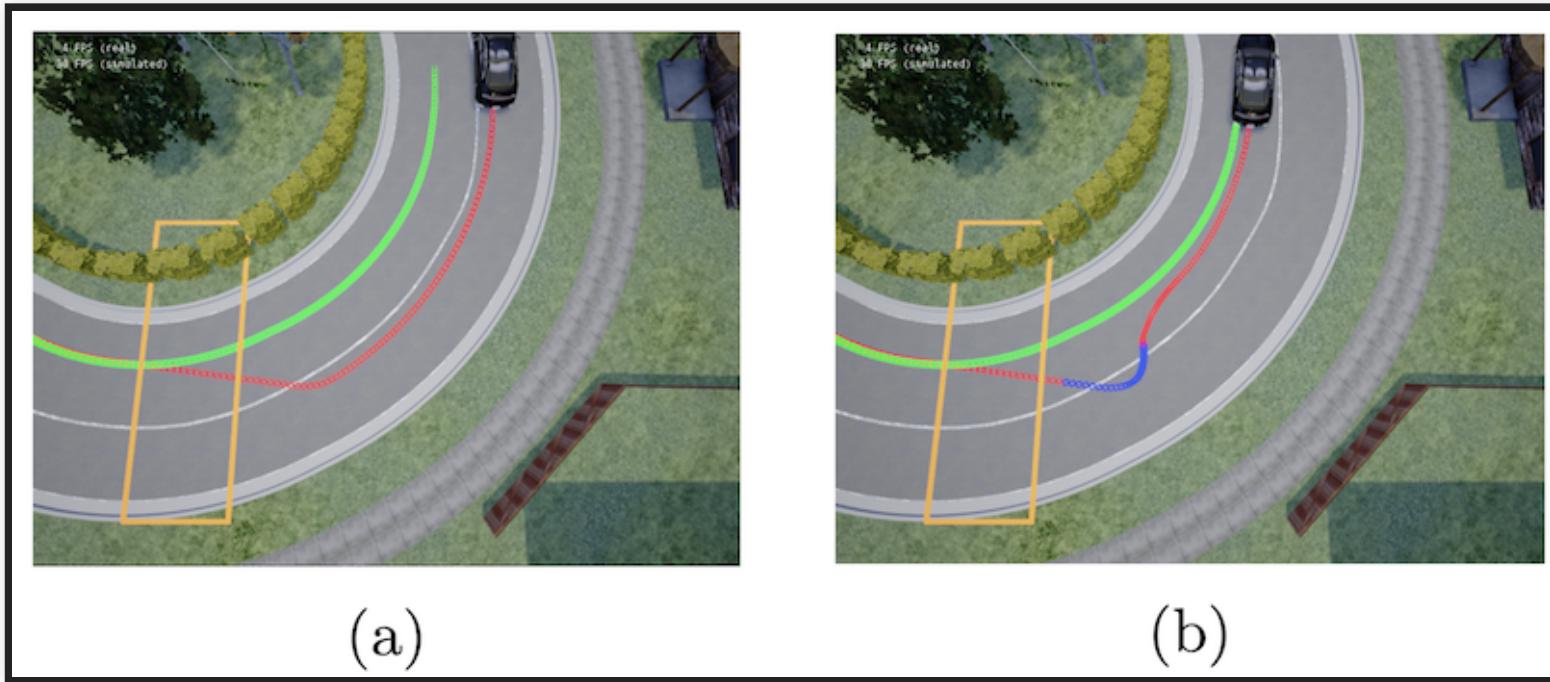
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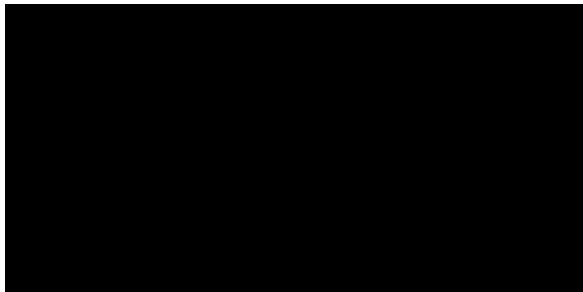
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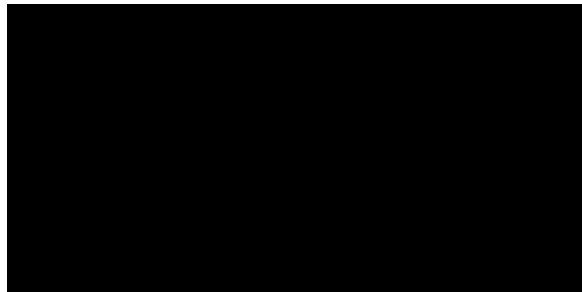
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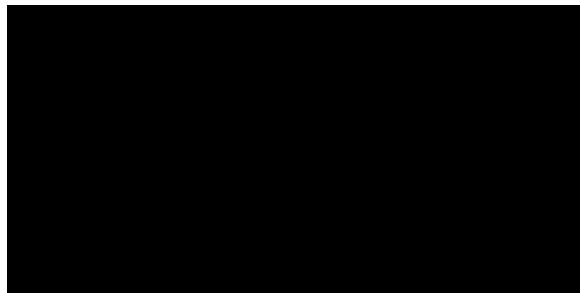
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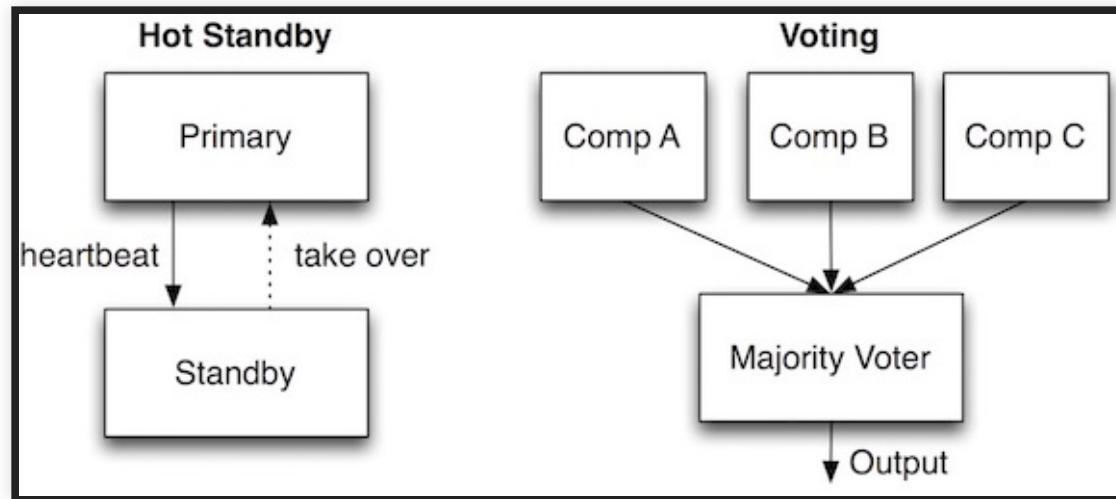
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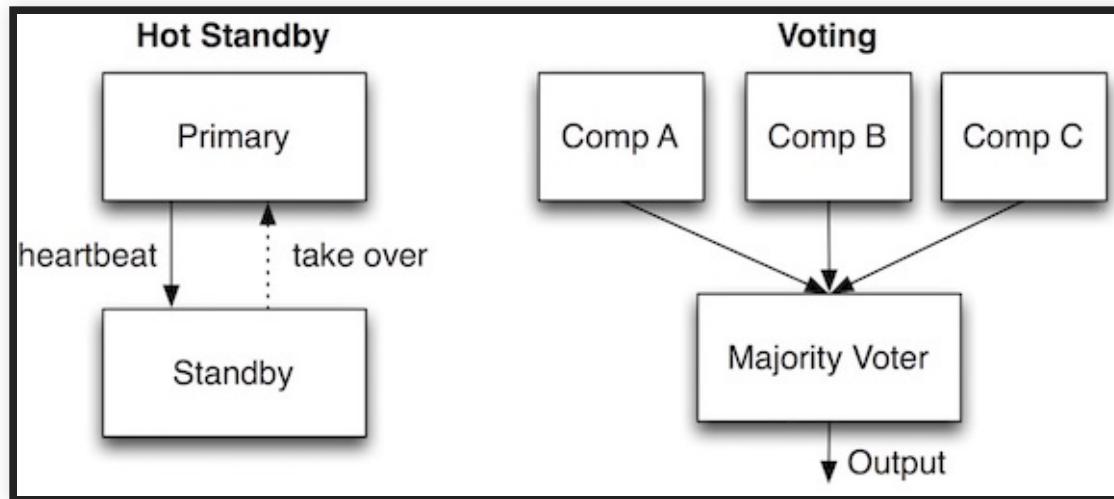


- Goal: When a component failure occurs, achieve system safety by reducing functionality and performance
- Relies on a monitor to detect component failures
- Example: Perception in autonomous vehicles
  - If Lidar fails, switch to a lower-quality detector & be more conservative about maintaining distance

# DETECTION & RESPONSE: REDUNDANCY

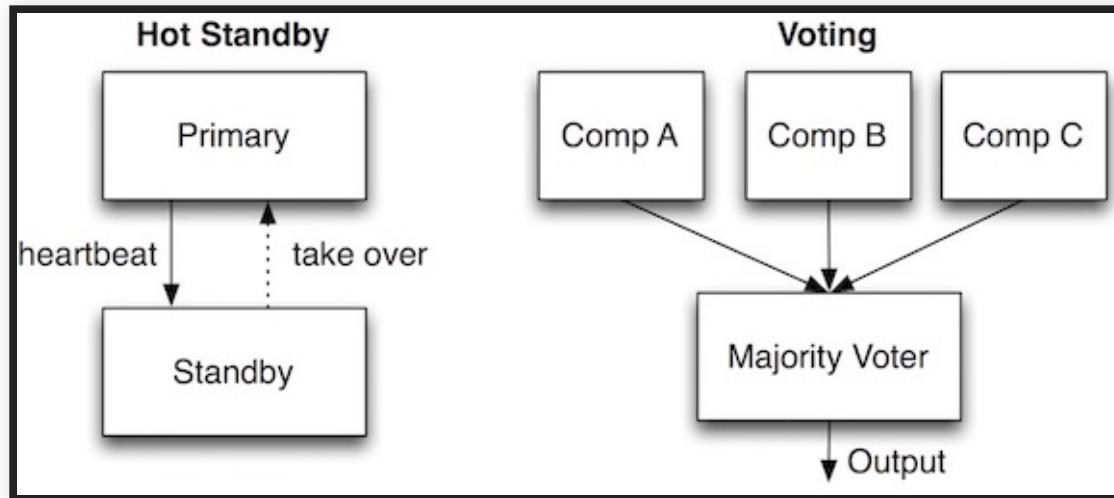


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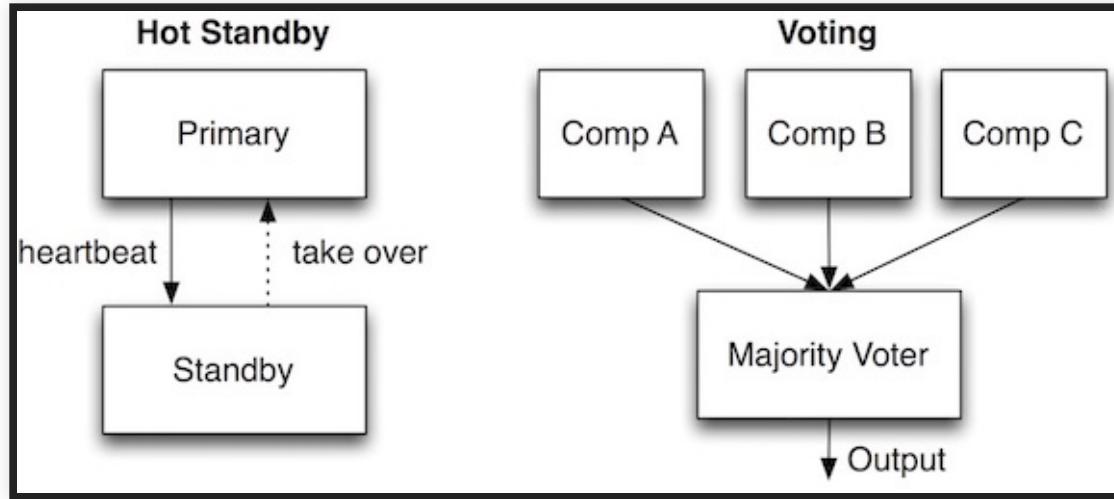
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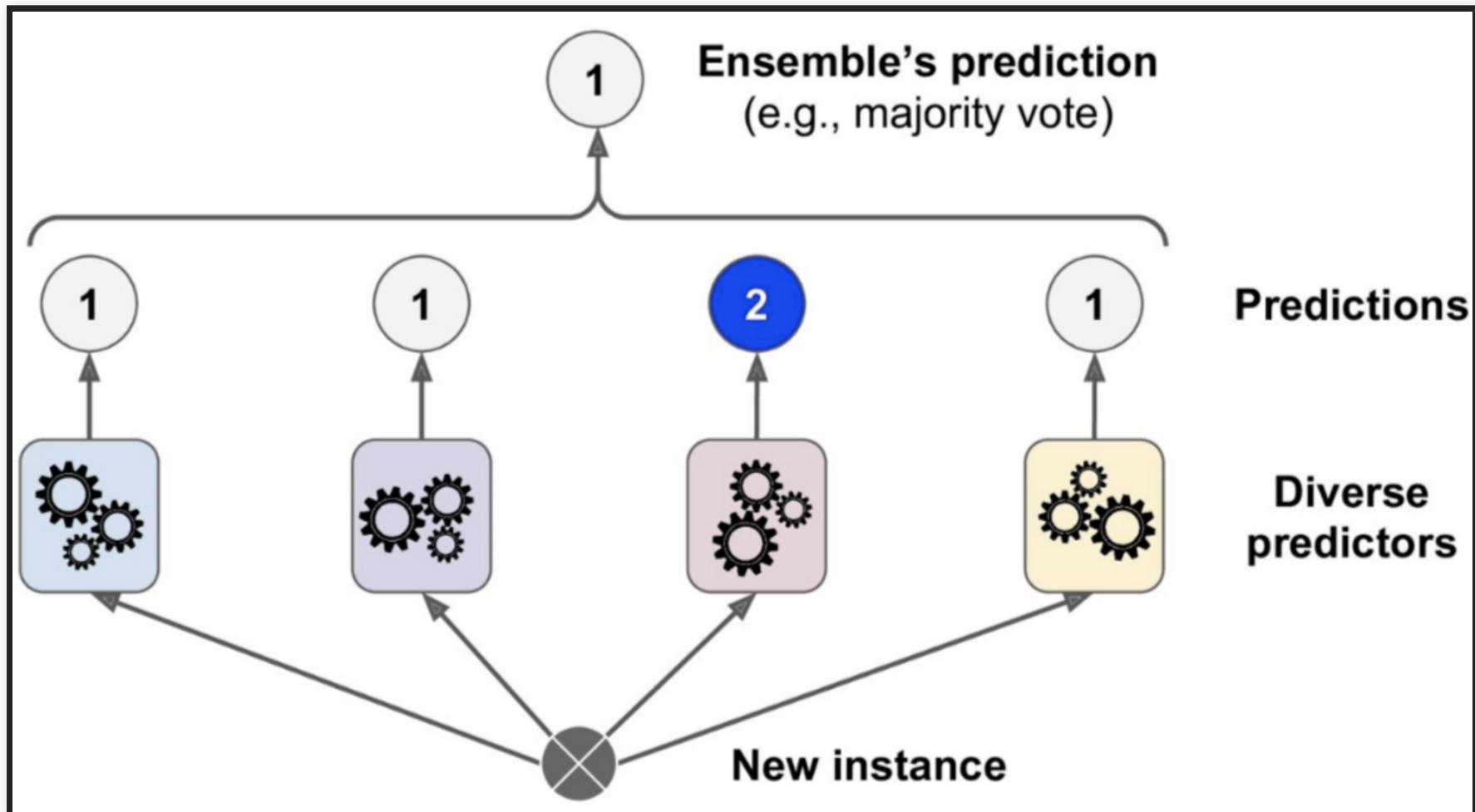
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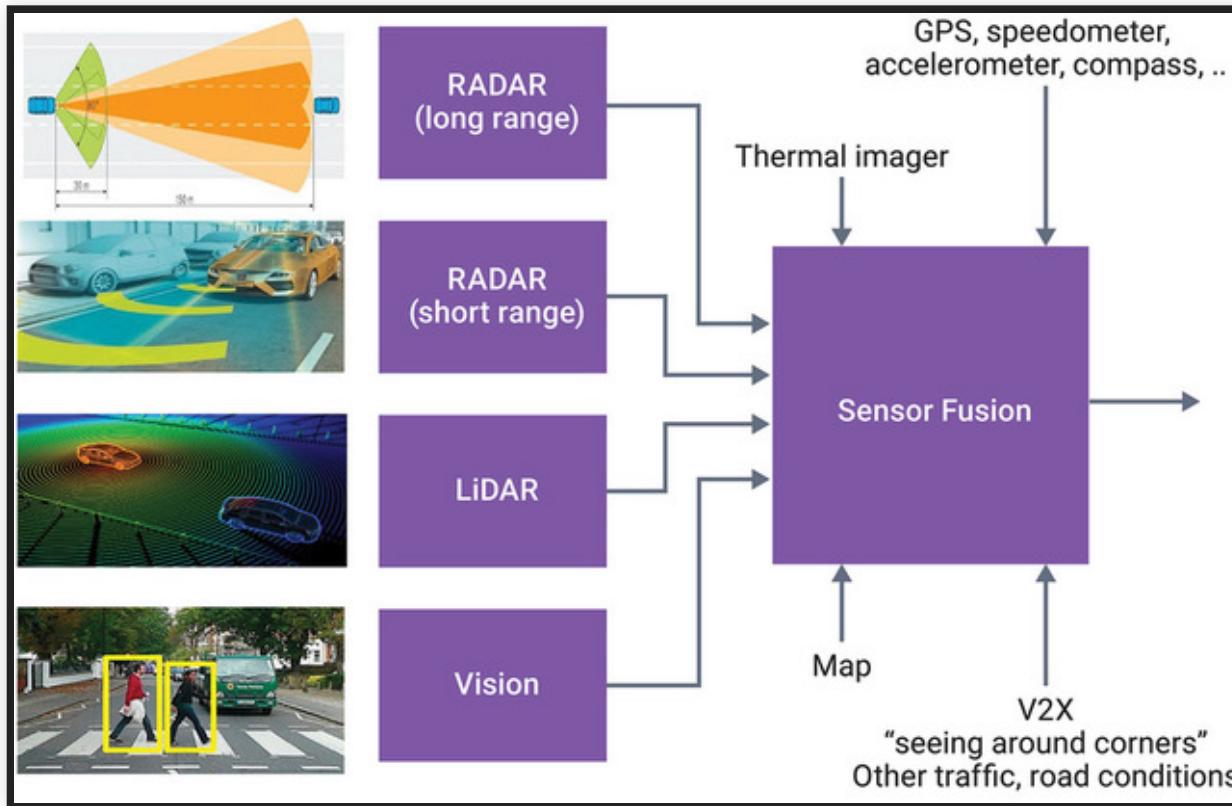
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- Caution: Do components fail independently?
  - Reasonable assumption for hardware/mechanical failures
  - Q. What about ML components?

# 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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- 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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  - 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