RISK AND PLANNING FOR MISTAKES II

Eunsuk Kang

LEARNING GOALS:

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

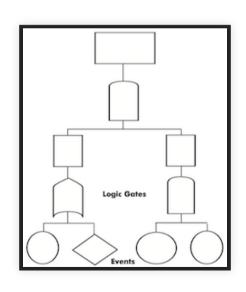
RISK ANALYSIS

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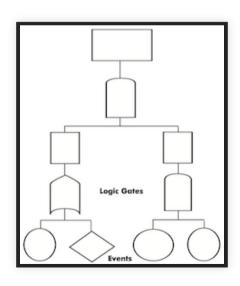
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- A number of methods:
 - Failure mode & effects analysis (FMEA)
 - Hazard analysis
 - Why-because analysis
 - Fault tree analysis (FTA) <= Today's focus!
 - **...**

FAULT TREE ANALYSIS (FTA)



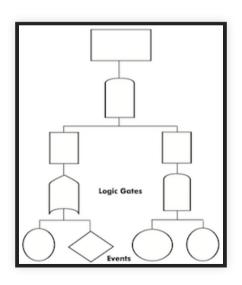
FAULT TREE ANALYSIS (FTA)

- 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...)



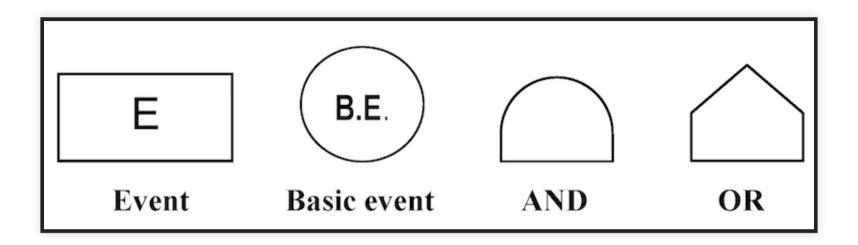
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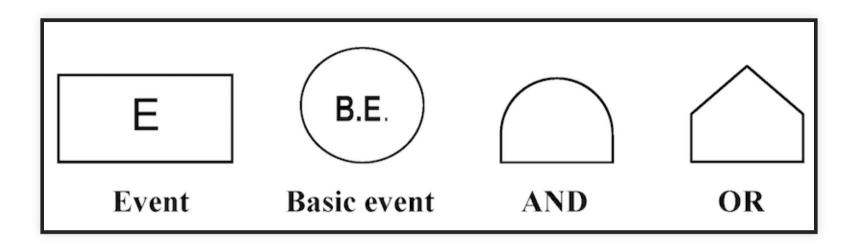
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 - Ouput wrong predictions/values
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- How do mistakes made by AI contribute to system failures? How do we ensure their mistakes do not result in a catastrophe?

FAULT TREES:: BASIC BUILDING BLOCKS

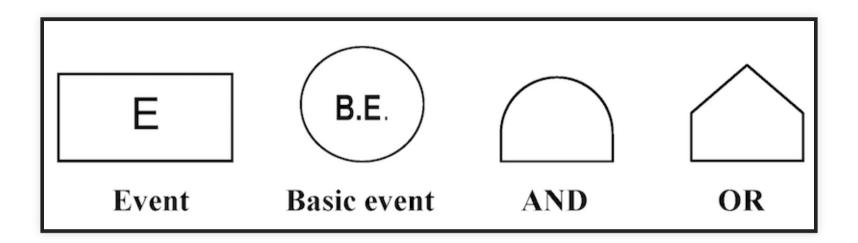


FAULT TREES:: BASIC BUILDING BLOCKS



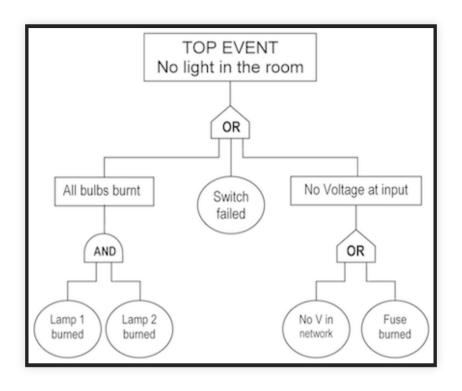
- Event: An occurrence of a fault or an undesirable action
 - (Intermediate) Event: Explained in terms of other events
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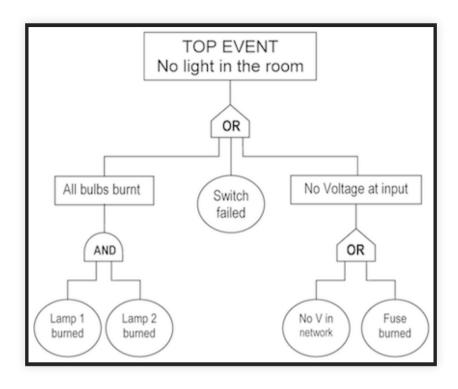


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 - OR: Any one of the sub-events may result in the parent event

FAULT TREE EXAMPLE

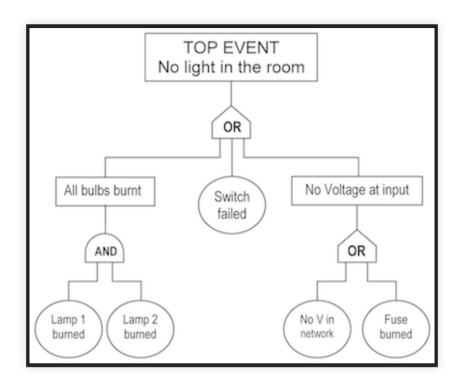


FAULT TREE EXAMPLE



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

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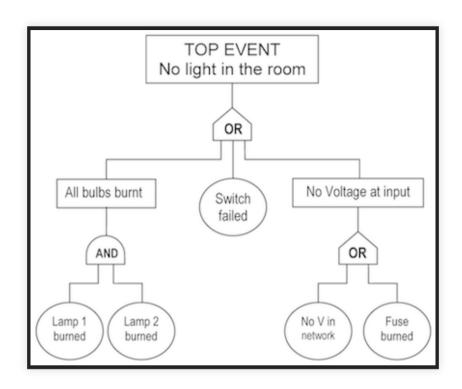


- Every tree begins with a TOP event (typically a violation of a requirement)
- Every branch of the tree must terminate with a basic event

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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 - Assign probabilities to basic events (based on domain knowledge)
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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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 - Identify all possible minimal cut sets

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- 6. Repeat

EXAMPLE: FTA FOR LANE ASSIST



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

BREAKOUT: FTA FOR LANE ASSIST



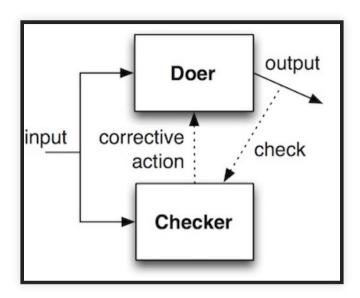
Draw a fault tree for the lane assist system with the top event as "Vehicle fails to stay within lane"

MITIGATION STRATEGIES

ELEMENTS OF FAULT-TOLERANT DESIGN

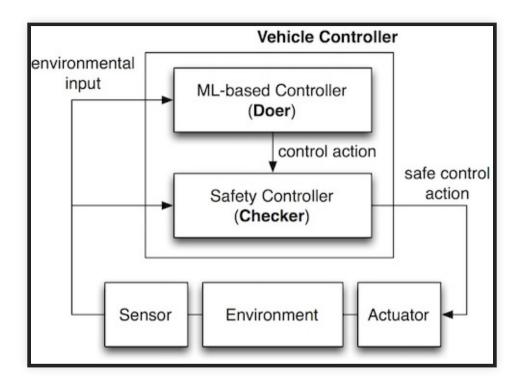
- Assume: Components will fail at some point
- Goal: Minimize the impact of failures
- Detection
 - Monitoring
 - Redundancy
- Response
 - Graceful degradation (fail-safe)
 - Redundancy (fail over)
- Containment
 - Decoupling & isolation

DETECTION: MONITORING



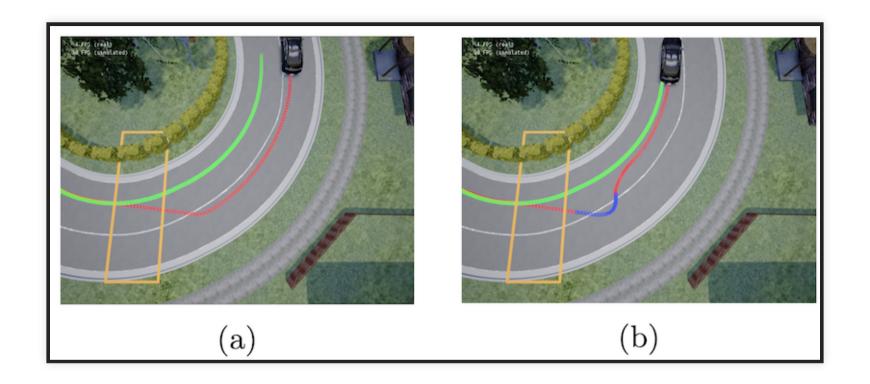
- Goal: Detect when a component failure occurs
- Monitor: Periodically checks the output of a component for errors
 - Challenge: Need a way to recognize errors
 - e.g., corrupt sensor data, slow or missing response
- Doer-Checker pattern
 - Doer: Perform primary function; untrusted and potentially faulty
 - Checker: If doer output faulty, perform corrective action (e.g., default safe output, shutdown); trusted and verifiable

DOER-CHECKER EXAMPLE: AUTONOMOUS VEHICLE



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

DOER-CHECKER EXAMPLE: AUTONOMOUS VEHICLE



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

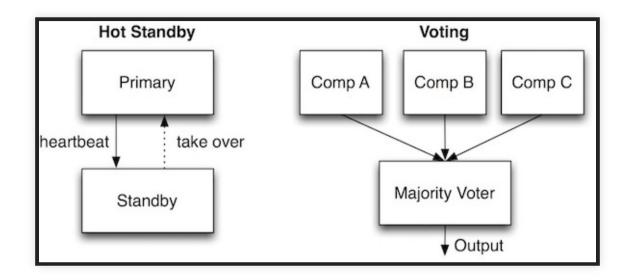
Runtime-Safety-Guided Policy Repair, Intl. Conference on Runtime Verification (2020)

RESPONSE: GRACEFUL DEGRADATION (FAIL-SAFE)



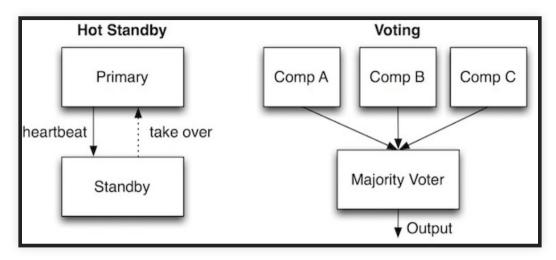
- **Goal**: When a component failure occurs, continue to provide safety (possibly at reduced functionality and performance)
- Relies on a monitor to detect component failures
- Example: Perception in autonomous vehicles
 - If Lidar fails, switch to a lower-quality detector; be more conservative
 - But what about other types of ML failures? (e.g., misclassification)

DETECTION & RESPONSE: REDUNDANCY



- **Detection**: Compare output from redundant components
- Reseponse: When a component fails, continue to provide the same functionality
- Hot Standby: Standby watches & takes over when primary fails
- Voting: Select the majority decision
- Caution: Do components fail independently?
 - Reasonable assumption for hardware/mechanical failures
 - Q. What about software?

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 - Reasonable assumption for hardware/mechanical failures
 - Software: Difficult to achieve independence even when built by different teams (e.g., N-version programming)
 - Q. ML components?

RESPONSE: HUMAN IN THE LOOP

Less forceful interaction, making suggestions, asking for confirmation

- Al and humans are good at predictions in different settings
 - AI better at statistics at scale and many factors
 - Humans understand context and data generation process and often better with thin data
- Al for prediction, human for judgment?
- But be aware of:
 - Notification fatigue, complacency, just following predictions; see
 Tesla autopilot
 - Compliance/liability protection only?
- Deciding when and how to interact
- Lots of UI design and HCI problems

Examples?

Speaker notes

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

RESPONSE: UNDOABLE ACTIONS

Design system to reduce consequence of wrong predictions, allowing humans to override/undo

Examples?

Speaker notes

Smart home devices, credit card applications, Powerpoint design suggestions

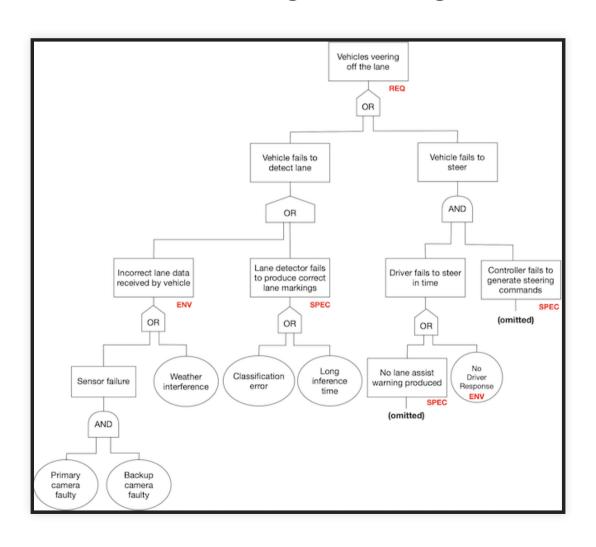
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CONTAINMENT: DECOUPLING & ISOLATION

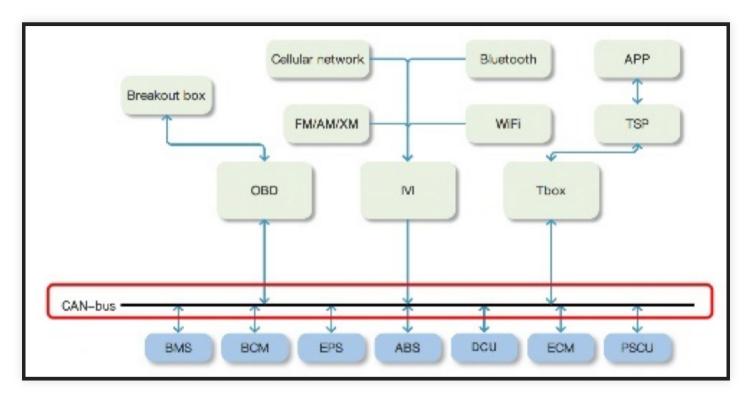
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POOR DECOUPLING: USS YORKTOWN (1997)



- 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)

CONTAINMENT: DECOUPLING & ISOLATION

- Goal: 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 AI in my system performing an LC or HC task?
 - If HC, can we "demote" it into LC?
 - Alternatively, replace HC AI components with non-AI ones with stronger guarantees
 - Q. Examples?

SUMMARY

- Accept that ML components will make mistakes
- Use risk analysis to identify and mitigate potential problems
- Design strategies for detecting and mitigating the risks from mistakes by Al



