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Safety Performance Indicators and Continuous Improvement Feedback

SEAMS 2022 KEYNOTE

SEAMS 2022

17th International Symposium on Software Engineering for Adaptive and Self-Managing Systems

Virtual Events: 18, 19, 20 May. Physical Event: 23 May, Pittsburgh, USA, co-located with ICSE 2022

Overview

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- Lifecycle approach to Autonomous Vehicle safety
  - Historically we assume perfectly safe production release
  - Need move to lifecycle adaptation model
    - Operational metrics used as basis for continuous improvement


https://on.gei.co/2r2rjzg

- Safety Performance Indicators (SPIs)
  - Beyond "vehicle is acting unsafely"
  - Beyond dynamic risk management
  - Beyond run-time safety monitors

    …
  - ANSI/UL 4600 SPIs monitor safety case soundness

Big Changes In Safety Engineering for AVs

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- Conventional software safety engineering
  - Do hazard and risk analysis (e.g., ISO 26262)
  - Mitigate hazards; achieve acceptable risk
  - Assume "perfect" for safety when deployed
    - Human driver intervention to clean up loose ends
- Autonomous system safety is about change
  - Machine learning-based validation is immature
  - Open, imperfectly understood environment
    - Unknown unknowns, gaps in requirements, etc.
    - Keep up with a constantly evolving real world
  - System monitoring ➔ safety/security updates

Carnegie Mellon University Tartan Rescue's CHIMP in 2015

Safety Engineering: Hazards & Risks

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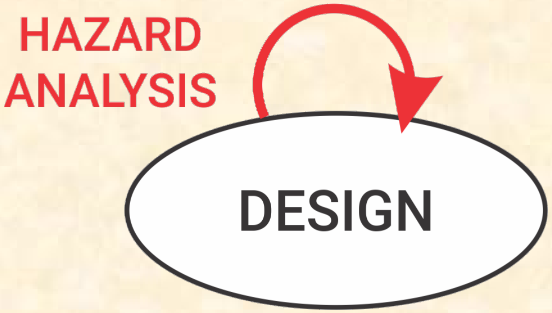
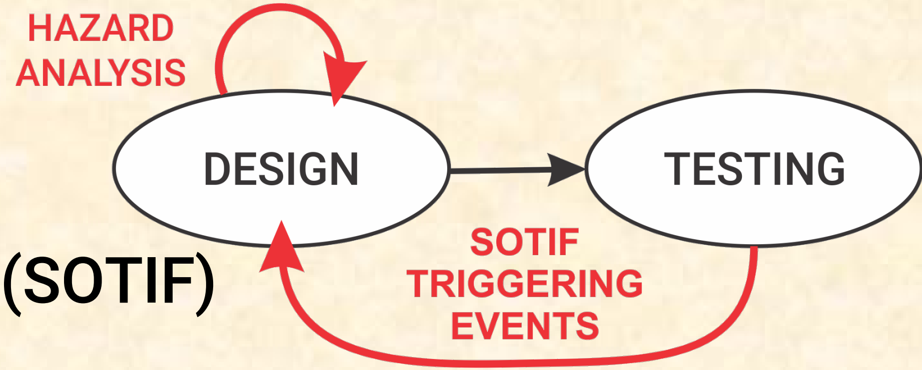
- Hazard and Risk Analysis for conventional systems
  - List all applicable hazards
  - Characterize the resultant risk
  - Mitigate risk as needed, e.g., update design
  - Iterate until all risks acceptably mitigated
- Use various techniques to create hazard list
  - Lessons learned from previous projects; industry standards
  - Brainstorming & analysis techniques
    - FMEA, Fault Trees, HAZOP, …. bring your own favorite approach …
- Presumption all hazards covered before deployment
  - Fully characterized operating environment



Hazard Analysis for Novel, Open World Systems

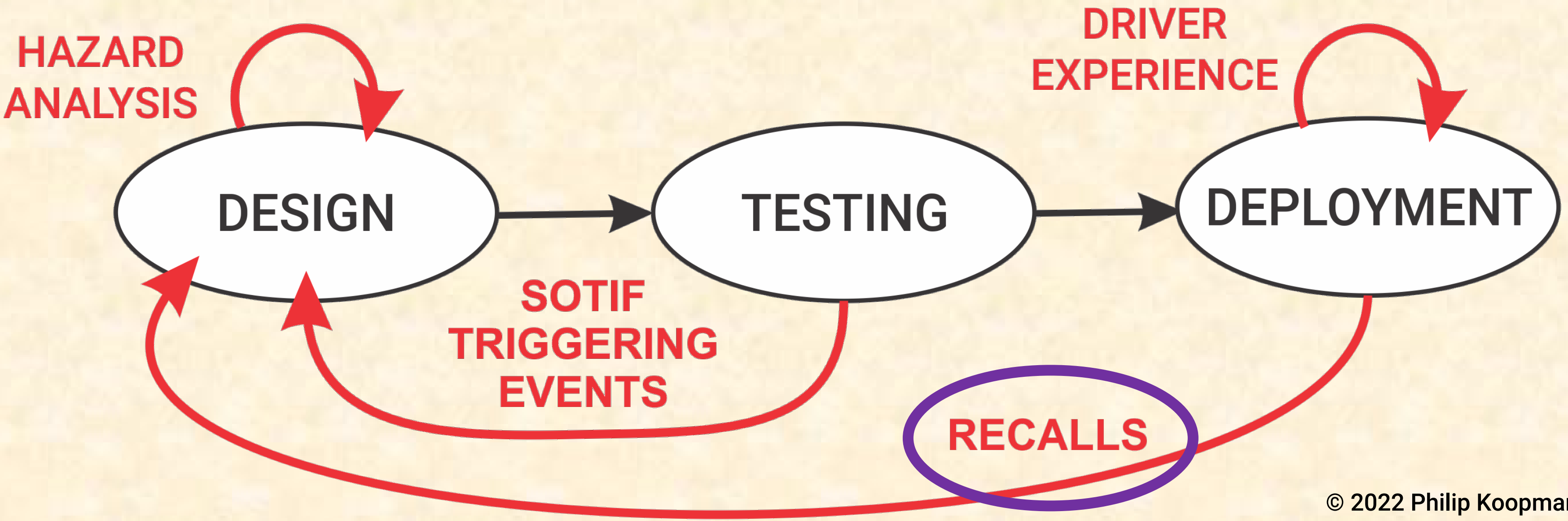
- Operating in the open world
  - All hazards aren't known at first
  - Test, test, test until you have uncovered enough hazards



- Safety Of The Intended Function (SOTIF)
  - Operate in the real world
  - Unknowns manifest "triggering events" (ISO 21448 terminology)
  - Mitigate newly discovered hazards caused by triggering events
  - Repeat until you stop seeing triggering events
- Limitation: residual unknown unknowns (requirements gaps)
  - Hypothesize you can find enough of the unknowns

Driver Assistance Feedback Model

- Driver does dynamic risk mitigation
- Useful fiction: systems safe forever when released
  - Driver expected to help mitigate risks & surprises
  - Recalls for defects drivers can't handle – not supposed to happen



Reaction To Incidents and Loss Events

- Conventional systems (in practice) too often:
  - Ignore if not reproducible
  - Blame it on the operator
  - Educate operators on workarounds
  - Try again to blame it on the operator
  - VERY reluctantly do a software update

- This persists across domains:
  - Power imbalance between victims and system designers
  - Normalization of #MoralCrumpleZone strategies [https://bit.ly/3qX2D92]
  - Poor adoption of software engineering practices
  - The fact that the feedback loop is called a "recall"

How Is The Recall Approach Working Out?

- <u>Small</u> sampling of NHTSA recalls (confirmed defects)
  - 22V-169 and many others: Backup camera & display failures
  - 21V-972: Parking lock system error leads to vans rolling away when parked
  - <u>**21V-873 *and MANY others*: Airbags disabled**</u>
  - 21V-846: Phantom braking due to inconsistent software state after power up
  - 21V-109: Battery controller reset disconnects electric drive motor power
  - 20V-748: Improper fail-safe logic degrades brake performance
  - 20V-771: Malfunctions of wipers, windows, lights, etc. due to comms failure
  - <u>**20V-557 *and others*: Airbags deploy too forcefully or when they should not**</u>
  - 17V-713: Engine does not reduce power due to ESP software defect
  - 15V-569: Unexpected steering motion causes loss of control
  - 15V-145: Unattended vehicle starts engine → carbon monoxide poisoning

See: https://betterembsw.blogspot.com/p/potentially-deadly-automotive-software.html

Autonomous Vehicles Are Even Worse

- Machine Learning (ML) only learns things it has seen
  - Learns by example
  - Can be brittle; generalization is limited
  - Spectacular failures for the unexpected

[Mitchells vs. Machines]

- ML complicates safety engineering
  - Safety engineering assumes “V” model
  - Prone to brittleness to unexpected data variations
  - Were there biases or gaps in training data?
  - Assurance for rare objects and events in the real world?
    - Safety tends to be limited by rare, high-consequence events

Incomplete Open World Requirements

- Unusual road obstacles & conditions
- Strange behaviors
- Subtle clues

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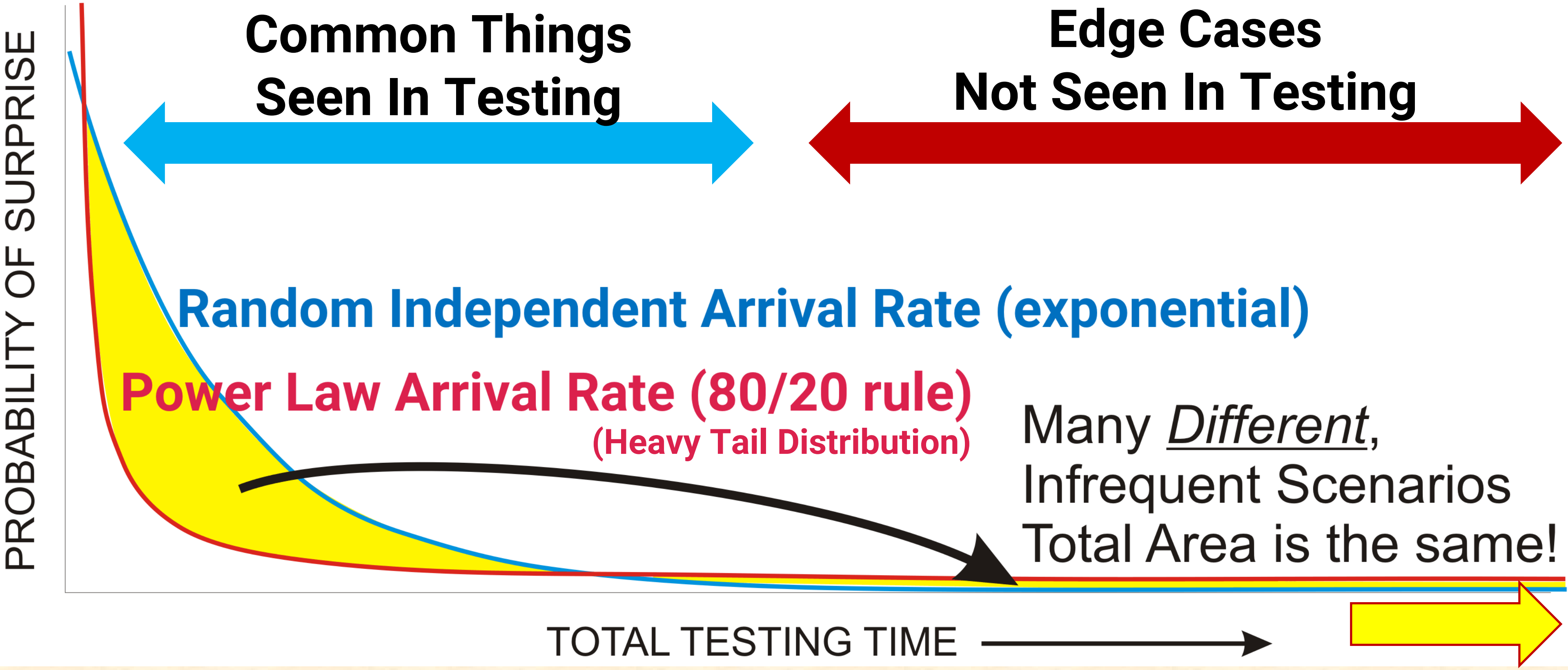
https://goo.gl/J3SSyu

http://bit.ly/2tvCCPK

https://dailym.ai/2K7kNS8

https://en.wikipedia.org/wiki/Magic_Roundabout_(Swindon)

The Real World: Heavy Tail Distribution



Why The Heavy Tail Matters

- Where will you be after 1 Billion miles of testing?
  - At 100M miles per fatality, need perhaps 1 billion miles
- Assume 1 Million miles between unsafe “surprises”
  - Example #1:
    100 “surprises” @ 100M miles / surprise
  - Example #2:
    100,000 “surprises” @ 100B miles / surprise
    - Only 1% of surprises seen during 1B mile testing
    - SOTIF fixes of triggering events don’t really help

https://goo.gl/3dzguf

- “Perfect when deployed” no longer a useful fiction
  - We’re going to need feedback measurements from deployment

Which Metrics Should We Use?

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- Key Performance Indicator (KPI) approach is typical:
  - Deviation from intended vehicle path
  - Ride smoothness
  - Hard braking incidents
  - Disengagements during testing
  - Coverage of defined scenario catalog
  - Risk metrics such as Time to Collision
- But how do we predict operational safety?
  - Are KPIs good leading metrics for loss events?
  - Does a particular KPI set cover all aspects of safety?
  - How can we select KPIs for traceability to safety?

Safety Performance Indicator (SPI)

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- SPI (per ANSI/UL 4600):
  - Measurement used to measure or predict safety
- Lagging SPI metrics (how it turned out):
  - Arrival rate of adverse events compared to a risk budget
    - Example: Loss events (crashes) per hour
  - Incidents (could have been a loss event)
    - Example: running a red light, wrong lane direction
- Also need leading metrics to predict safety
  - We can do that by linking to a safety case


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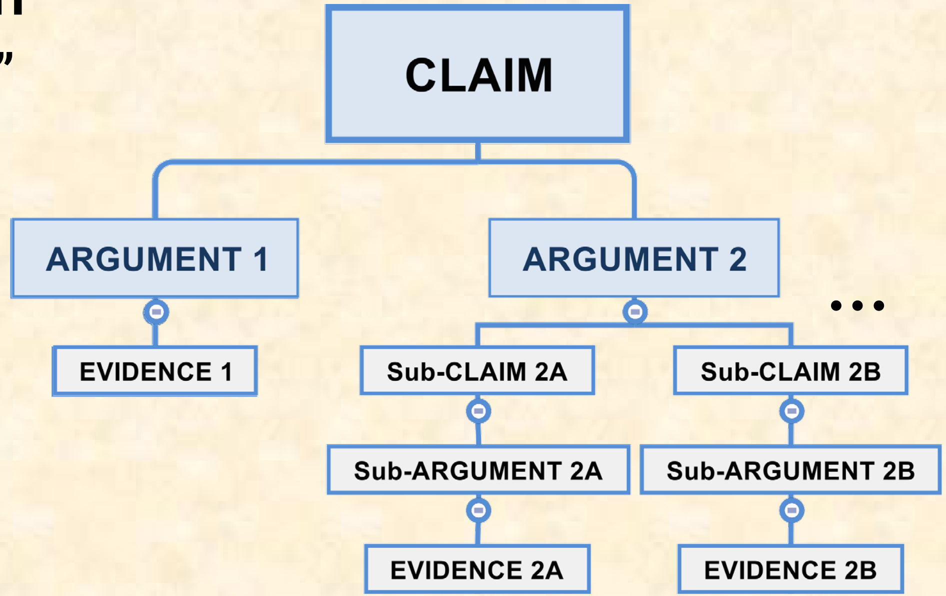
Safety Cases for Autonomous Vehicles

- Claim – a property of the system
  - "System avoids hitting pedestrians"
- Argument – why this is true
  - "Detect & maneuver to avoid"
- Evidence – supports argument
  - Tests, analysis, simulations, …
- Sub-claims/arguments address complexity
  - "Detects pedestrians" // evidence
  - "Maneuvers around detected pedestrians" // evidence
  - "Stops if can't maneuver" // evidence



SPIs Instrument a Safety Case

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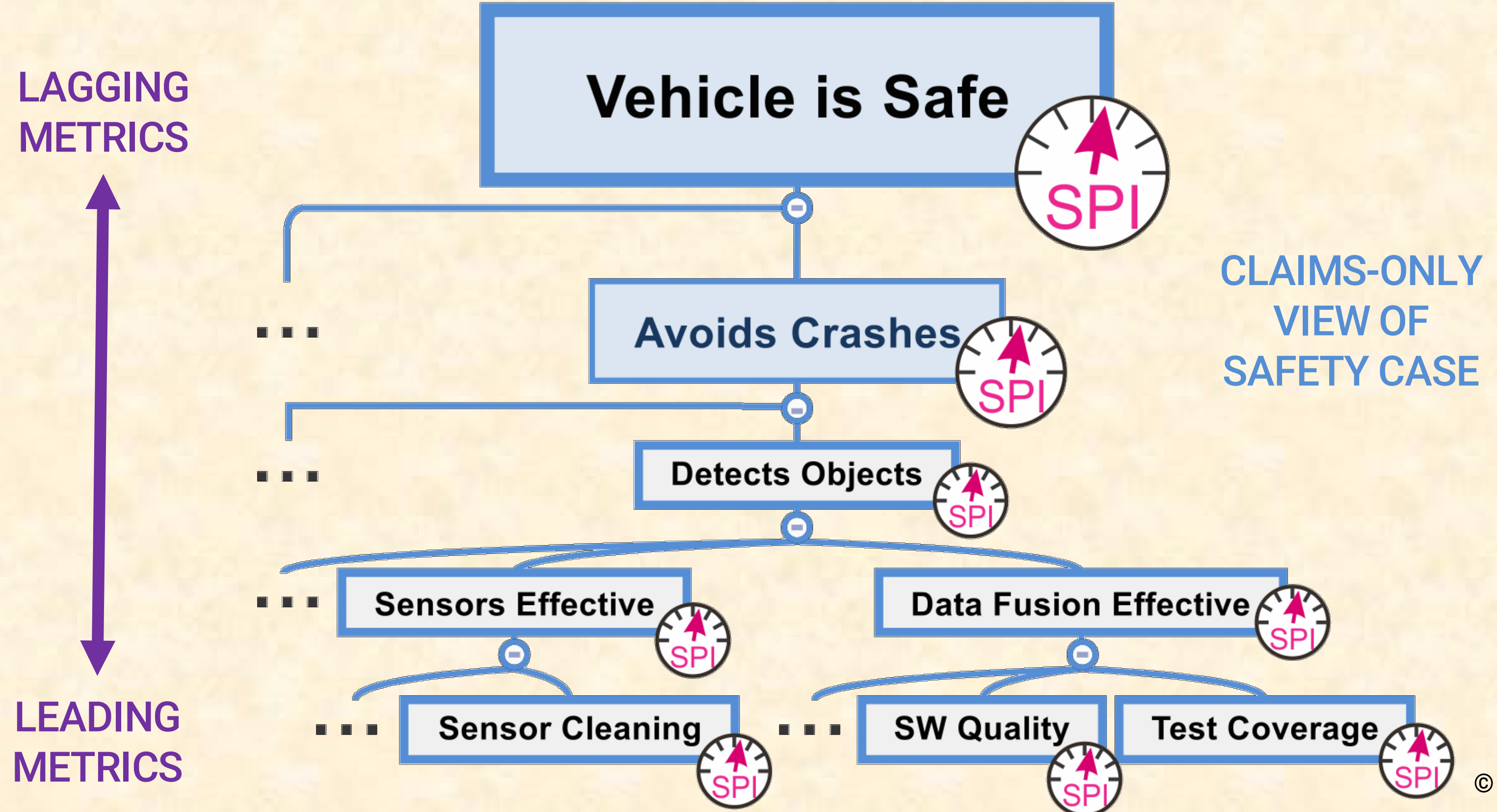
- SPIs monitor the validity of safety case claims



Example SPIs

- System Level SPIs:
  - Road test incidents caught by safety driver in testing
  - Simulator (SIL/HIL) incidents
- Subsystem SPIs:
  - Vehicle Controls: compromised vehicle stability
  - Path Planning: insufficient clearance to object
  - Perception: false negative (non-detection)
  - Prediction: unexpected object behavior
- Lifecycle SPIs:
  - Maintenance errors
  - Invalid configuration installed

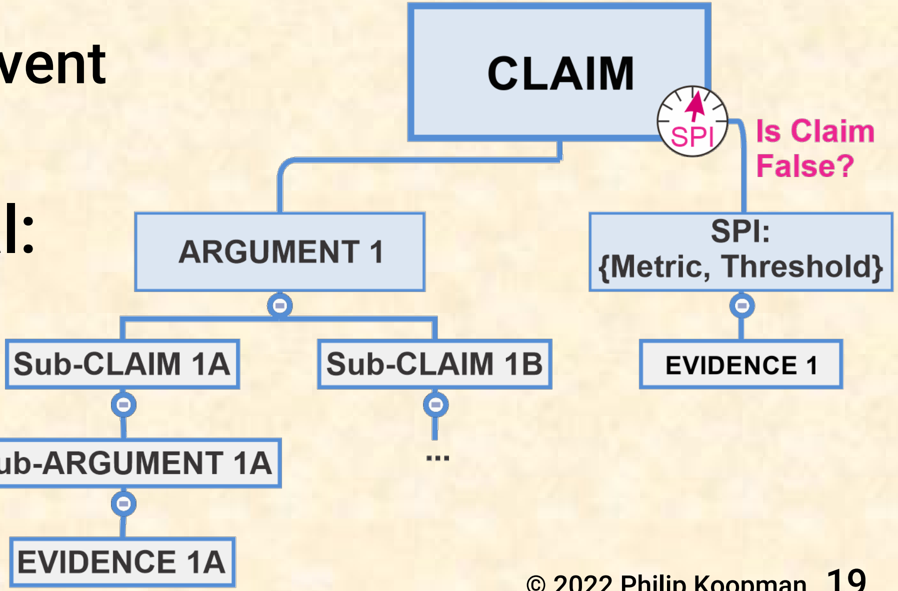
Detailed SPI Definition

- An SPI is a metric supported by evidence that uses a threshold comparison to condition a safety case claim.
  - Metric: measurement of performance, design quality, process quality, operational procedure conformance, etc.
  - Threshold: acceptance test on metric value
    - Often statistical (e.g., fewer than X events per billion miles)
  - Evidence: data used to compute the metric
  - Condition a claim: threshold violation falsifies a specific claim
    - Argument for claim is (potentially) proven false by SPI
  - Anything that does not meet all criteria is a KPI, not an SPI

- SPI violation: part of a safety case has been falsified

SPIs and Lifecycle Feedback

- SPI: direct measurement of claim failure
  - Independent of reasoning (“claim is X … yet here is ~X)
  - Partial measurement(s) OK; multiple SPIs for a claim OK
- A falsified safety case claim:
  - Not (necessarily) imminent loss event
  - Safety case has some defect
- Root cause analysis might reveal:
  - Product or process defect
  - Invalid safety argument
  - Issue with supporting evidence
  - Assumption error, …



SPI-Based Feedback Approach

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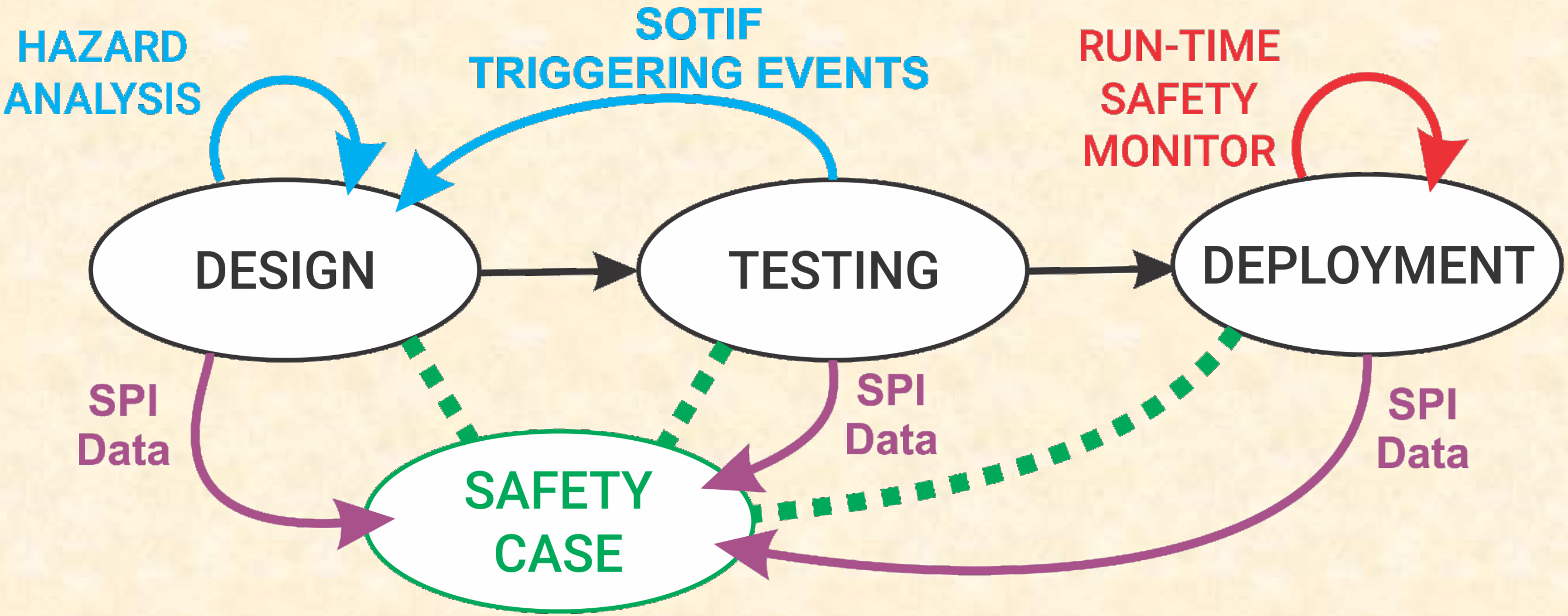
- Safety Case argues acceptable risk
  - SPIs monitor validity of safety case



SPIs Go Beyond Overt Dangerous Behavior

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- "Acts dangerously" is only one dimension of SPIs
  - Violation rate of pedestrian buffer zones
  - Time spent closer than safe following distance
- Components meet safety related requirements
  - False negative/positive detection rates
  - Correlated multi-sensor failure rates
- Design & Lifecycle considerations
  - Design process quality defect rates
  - Maintenance & inspection defect rates
- Is it relevant to safety? ➔ Safety Case ➔ SPIs

Quality vs. Runtime Monitor vs. SPI

- Functionality (KPIs):
  - Are all the features implemented?
  - Does each feature work as intended?
  - Is testing progress on track per schedule?
- Runtime safety monitors:
  - Triggers risk reduction during run time
- Safety Feedback (SPIs):
  - Did runtime safety monitor miss something?
  - Are there dangerous gaps in the Operational Design Domain?
  - Are there problems with requirements, design, upkeep, etc.?
  - Are there dangerous gaps in fault responses?

https://bit.ly/2MaLkfY

Following Distance Example

- Responsibility-Sensitive Safety (RSS) Scenario:

- KPI: is average following distance appropriate for driving conditions
- Runtime monitor: force an increase of following distance if too close
- SPIs: situation more dangerous than expected (e.g., ODD issues)
  - Spent more time in too-dense traffic than expected
  - Lead/own vehicle brake violate expectations (too often; too aggressive)
  - Spent too long to recover from lead vehicle cut-in

Sketch of an AV Safety Argument

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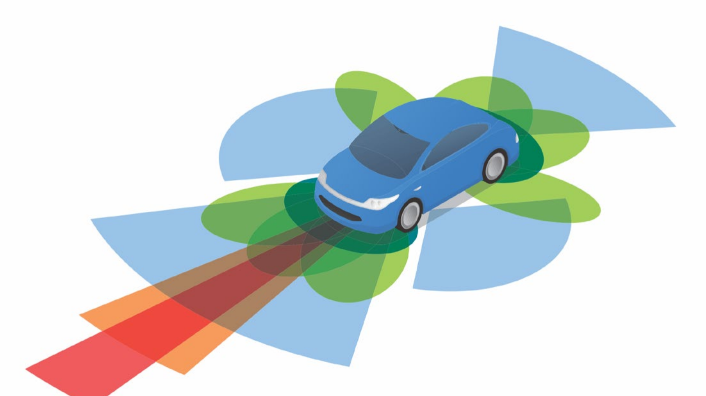
AV is safe enough to deploy because:

- We've followed industry safety standards
  - ISO 26262, ISO 21448, ANSI/UL 4600, …
  - Safety culture is robust
- Known hazards have been mitigated
  - Residual risk is acceptable at system level
- Arrival rate of unknowns is low
  - Incidents which do not trigger runtime safing
- Safety case has good SPI coverage
  - SPIs usually detect unknowns without an actual crash
  - System is fixed to mitigate unknowns before likely reoccurrence



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Conclusions

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- Removing human drivers makes safety much harder
  - Tactical: run-time safety monitoring in vehicle
  - Strategic: SPI monitoring across fleet
  - Field feedback as lifecycle adaptation
- SPIs predict and monitor system safety
  - KPIs: "how well do we drive?"
  - SPIs: "how often are safety claims falsified?"
  - SPIs can detect safety problems with no crash
- SPIs: are you as safe as you think you are?
  - See ANSI/UL 4600 Chapter 16 for SPI guidance
  - Field feedback via SPIs provides lifecycle safety adaptation


https://shutr.bz/38cKv4u