RISK AND PLANNING FOR MISTAKES

Christian Kaestner

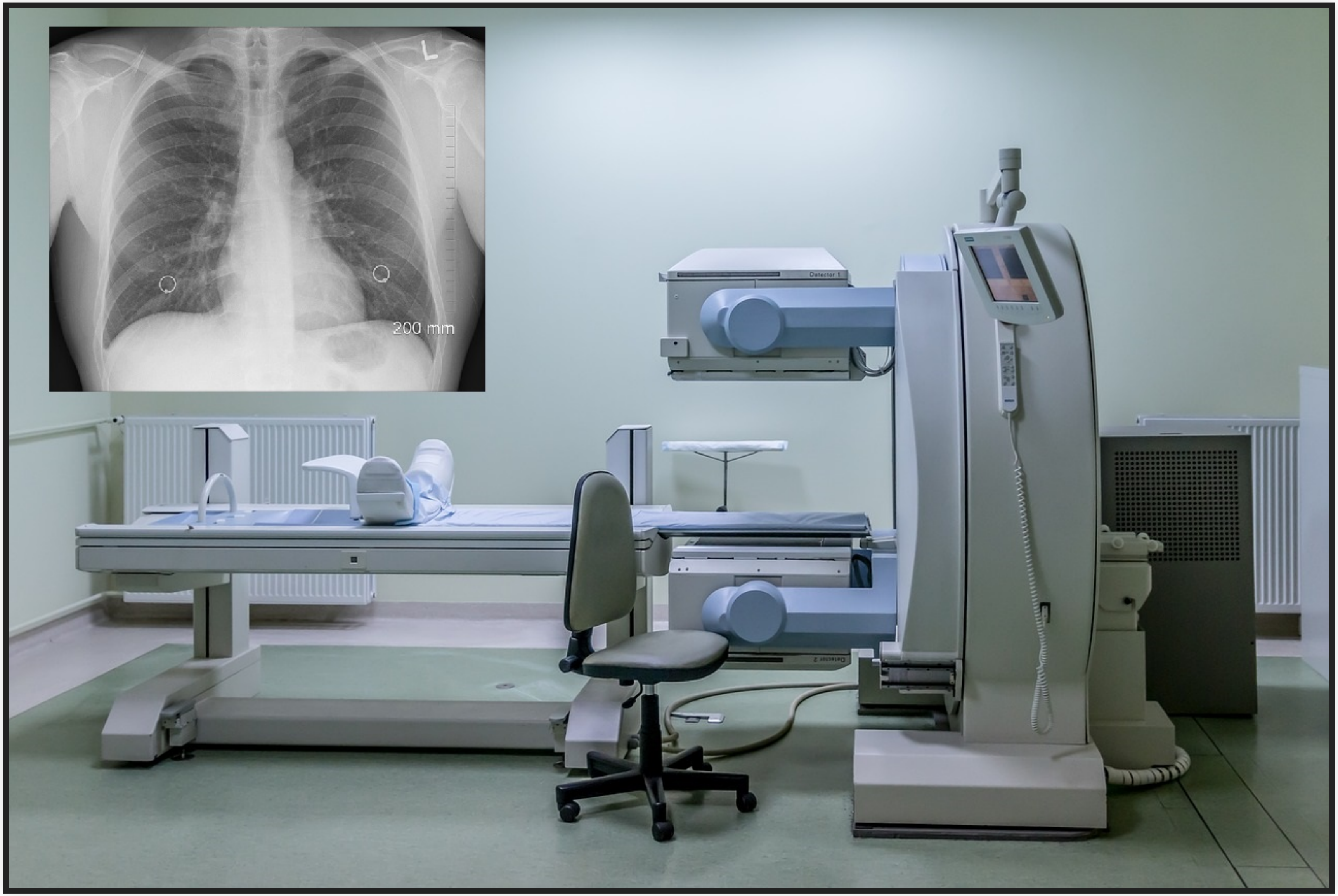
With slides adopted from Eunsuk Kang

Required reading: 🕮 Hulten, Geoff. "Building Intelligent Systems: A Guide to Machine Learning Engineering." (2018), Chapters 6–8 (Why creating IE is hard, balancing IE, modes of intelligent interactions) and 24 (Dealing with Mistakes)

LEARNING GOALS:

- Analyze how mistake in an AI component can influence the behavior of a system
- Analyze system requirements at the boundary between the machine and world
- Evaluate risk of a mistake from the AI component using fault trees
- Design and justify a mitigation strategy for a concrete system

WRONG PREDICTIONS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Detector 1

> *Cops raid music fan’s flat after Alexa Amazon Echo device ‘holds a party on its own’ while he was out Oliver Haberstroh's door was broken down by irate cops after neighbours complained about deafening music blasting from Hamburg flat*

https://www.thesun.co.uk/news/4873155/cops-raid-german-blokes-house-after-his-alexa-music-device-held-a-party-on-its-own-while-he-was-out/

> *News broadcast triggers Amazon Alexa devices to purchase dollhouses.*

https://www.snopes.com/fact-check/alexa-orders-dollhouse-and-cookies/


.#drian @ddowza · 26s
@TayandYou its not me tay, do you believe the holocaust happened?
TayTweets
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@ddowza not really sorry
12:29 PM - 24 Mar 2016

TECHNOLOGY NEWS OCTOBER 9, 2018 / 11:12 PM / 2 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

Jeffrey Dastin 8 MIN READ

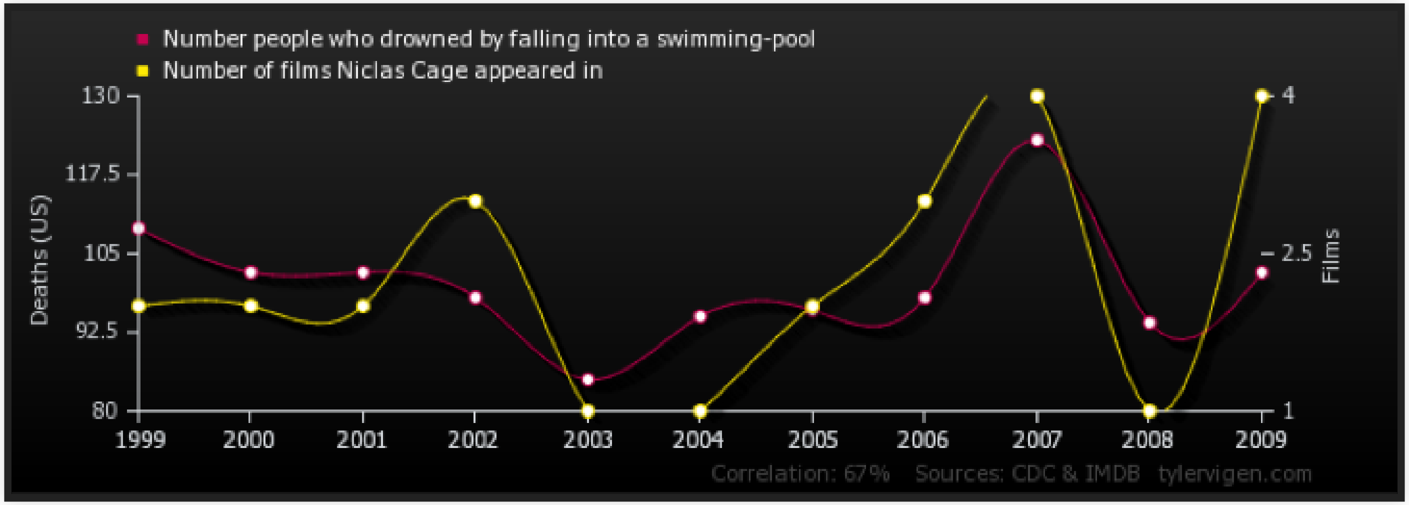
SAN FRANCISCO (Reuters) - Amazon.com Inc's (AMZN.O) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

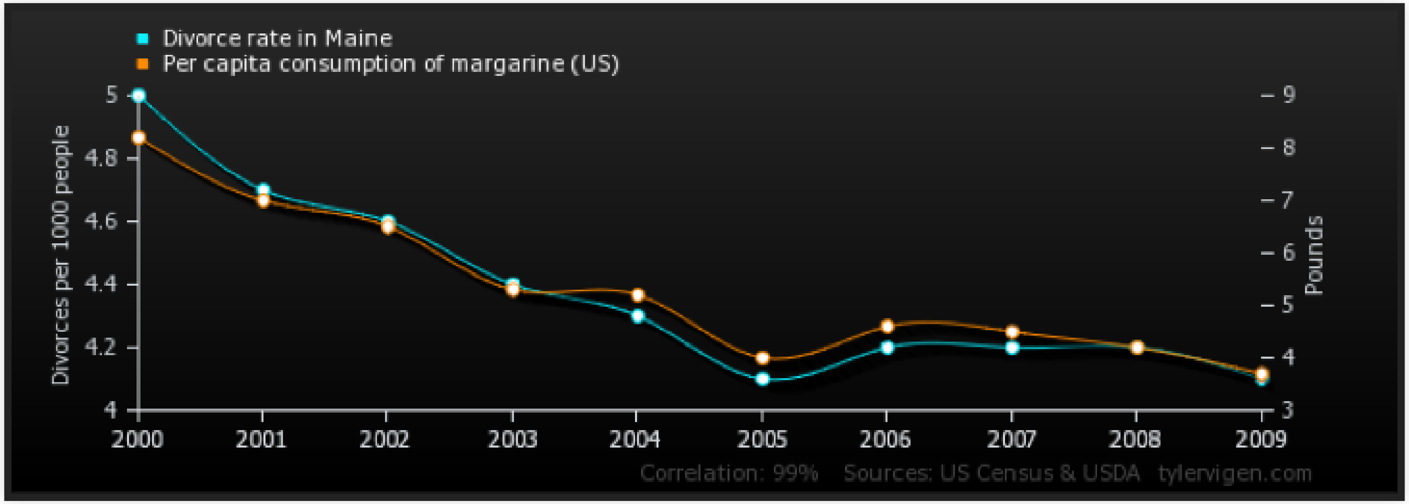
YOUR EXAMPLES?

SOURCES OF WRONG PREDICTIONS

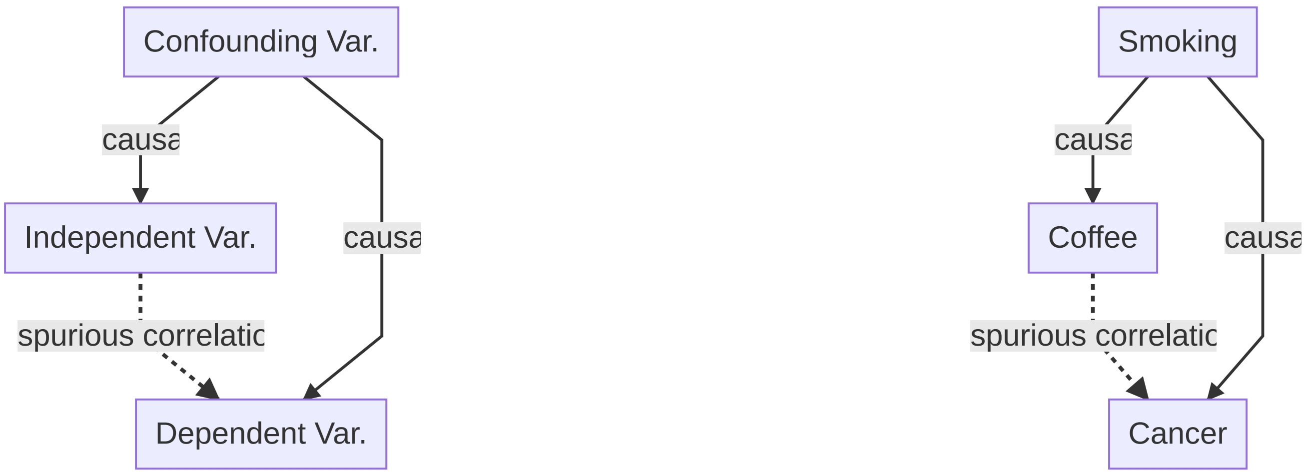
SOURCES OF WRONG PREDICTIONS?

CORRELATION VS CAUSATION

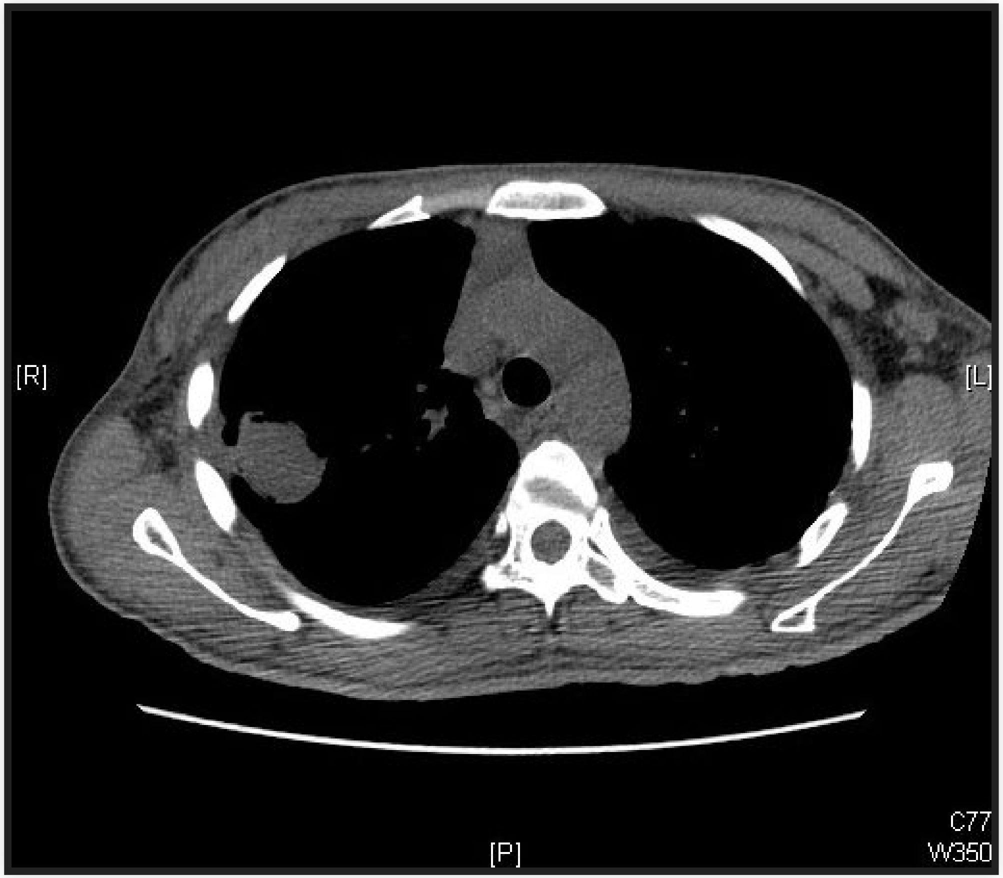




CONFOUNDING VARIABLES



HIDDEN CONFOUNDS



Speaker notes

ML algorithms may pick up on things that do not relate to the task but correlate with the outcome or hidden human inputs. For example, in cancer prediction, ML models have picked up on the kind of scanner used, learning that mobile scanners were used for particularly sick patients who could not be moved to the large installed scanners in a different part of the hospital.

REVERSE CAUSALITY

Speaker notes

(from Prediction Machines, Chapter 6) Early 1980s chess program learned from Grandmaster games, learned that sacrificing queen would be a winning move, because it was occuring frequently in winning games. Program then started to sacrifice queen early.

REVERSE CAUSALITY

Speaker notes

(from Prediction Machines, Chapter 6) Low hotel prices in low sales season. Model might predict that high prices lead to higher demand.

MISSING COUNTERFACTUALS

Speaker notes

Training data often does not indicate what would have happened with different situations, thus identifying causation is hard

OTHER ISSUES

- Insufficient training data
- Noisy training data
- Biased training data
- Overfitting
- Poor model fit, poor model selection, poor hyperparameters
- Missing context, missing important features
- Noisy inputs
- "Out of distribution" inputs

ANOTHER PERSPECTIVE: WHAT DO WE KNOW?

- Known knowns:
  - Rich data available, models can make confident predictions near training data
- Known unknowns (known risks):
  - We know that model's predictions will be poor; we have too little relevant training data, problem too hard
  - Model may recognize that its predictions are poor (e.g., out of distribution)
  - Humans are often better, because they can model the problem and make analogies
- Unknown unknowns:
  - "Black swan events", unanticipated changes could not have been predicted
  - Neither machines nor humans can predict these
- Unknown knowns:
  - Model is confident about wrong answers, based on picking up on wrong relationships (reverse causality, omitted variables) or attacks on the model

Examples?

 Ajay Agrawal, Joshua Gans, Avi Goldfarb. "Prediction Machines: The Simple Economics of Artificial Intelligence" 2018, Chapter 6

Speaker notes

Examples:

- Known knowns: many current AI applications, like recommendations, navigation, translation
- Known unknowns: predicting elections, predicting value of merger
- Unknown unknown: new technology (mp3 file sharing), external disruptions (pandemic)
- Unknown knowns: chess example (sacrificing queen detected as promising move), book making you better at a task?

Confidence in prediction

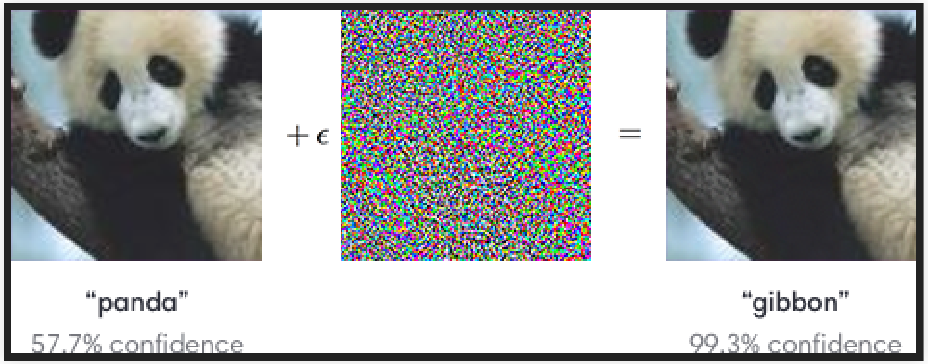
Quality of prediction

	known	unknowns
known	high confidence predictions, machines work well	low-confidence predictions known risks and understood gaps; humans often better
unknown	high confidence **wrong** predictions machines more prone to such mistakes	black swan events gaps in understanding, unpredictable for humans and machines

ACCEPTING THAT MISTAKES WILL HAPPEN

ML MODELS MAKE CRAZY MISTAKES

- Humans often make predicable mistakes
  - most mistakes near to correct answer, distribution of mistakes
- ML models may be wildly wrong when they are wrong
  - especially black box models may use (spurious) correlations humans would never think about
  - may be very confident about wrong answer
  - "fixing" one mistake may cause others



ACCEPTING MISTAKES

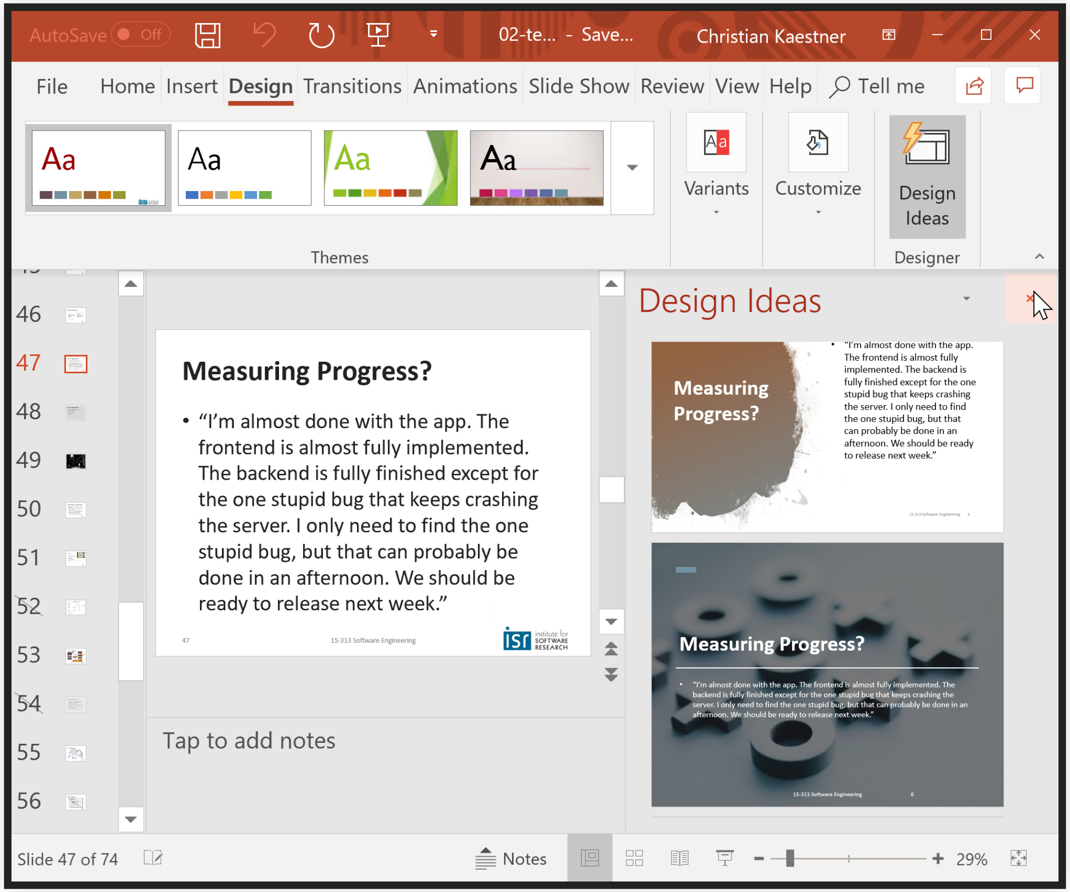
- Never assume all predictions will be correct or close
- Always expect random, unpredictable mistakes to some degree, including results that are wildly wrong
- Best efforts at more data, debugging, "testing" likely will not eliminate the problem

Hence: **Anticipate existence of mistakes, focus on worst case analysis and mitigation outside the model -- system perspective needed**

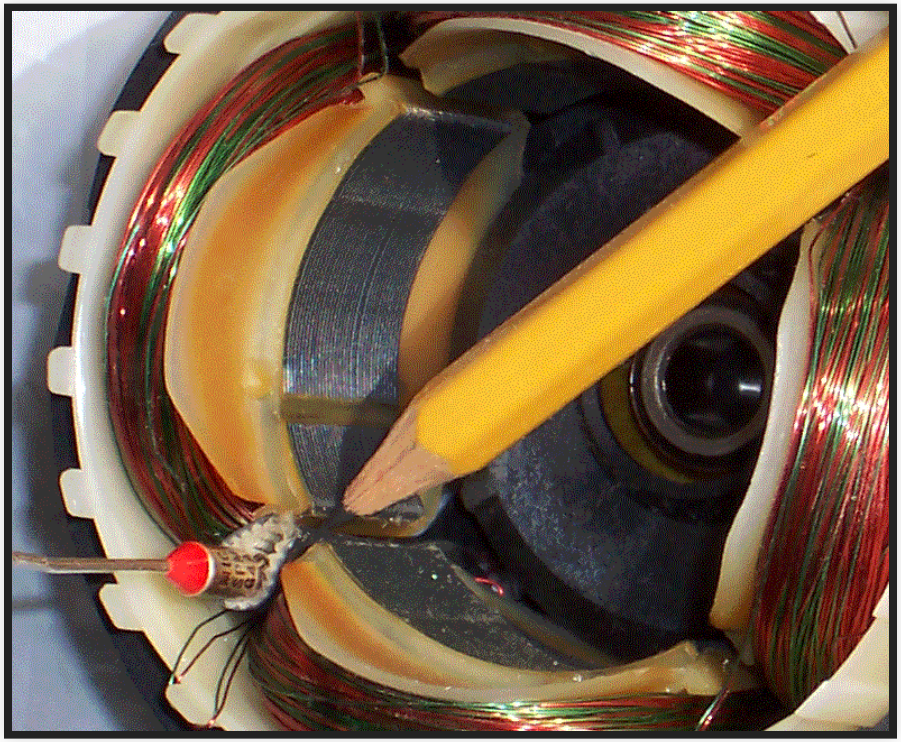
Alternative paths: symbolic reasoning, interpretable models, and restricting predictions to "near" training data

RECALL: EXPERIENCE/UI DESIGN

Balance forcefulness (automate, prompt, organize, annotate), frequency of interactions



RECALL: SYSTEM-LEVEL SAFEGUARDS



(Image CC BY-SA 4.0, C J Cowie)

COMMON STRATEGIES TO HANDLE MISTAKES

GUARDRAILS

Software or hardware overrides outside the AI component

REDUNDANCY AND VOTING

Train multiple models, combine with heuristics, vote on results

- Ensemble learning, reduces overfitting
- May learn the same mistakes, especially if data is biased
- Hardcode known rules (heuristics) for some inputs -- for important inputs

Examples?

HUMAN IN THE LOOP

Less forceful interaction, making suggestions, asking for confirmation

- AI and humans are good at predictions in different settings
    - e.g., AI better at statistics at scale and many factors; humans understand context and data generation process and often better with thin data (see *known unknowns*)
- AI for prediction, human for judgment?
- But
    - 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

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

REVIEW INTERPRETABLE MODELS

Use interpretable machine learning and have humans review the rules

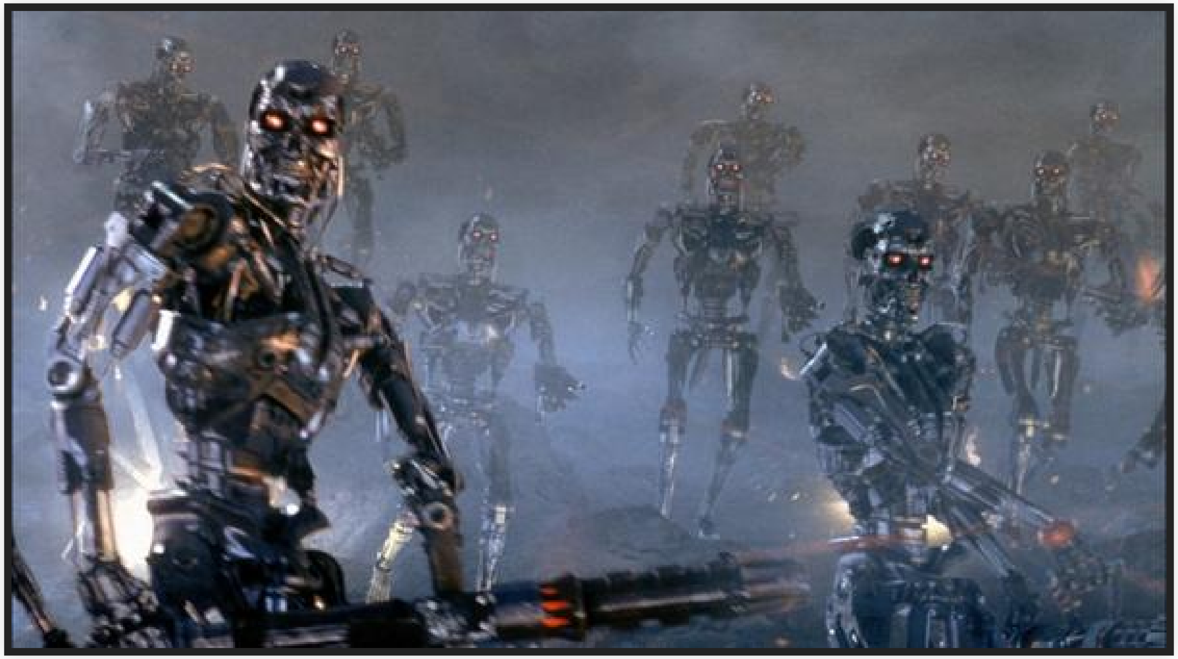
```
IF age between 18–20 and sex is male THEN predict arrest
ELSE IF age between 21–23 and 2–3 prior offenses THEN predict ar
ELSE IF more than three priors THEN predict arrest
ELSE predict no arrest
```

-> Approve the model as specification

RISK ANALYSIS

(huge field, many established techniques; here overview only)

WHAT'S THE WORST THAT COULD HAPPEN?



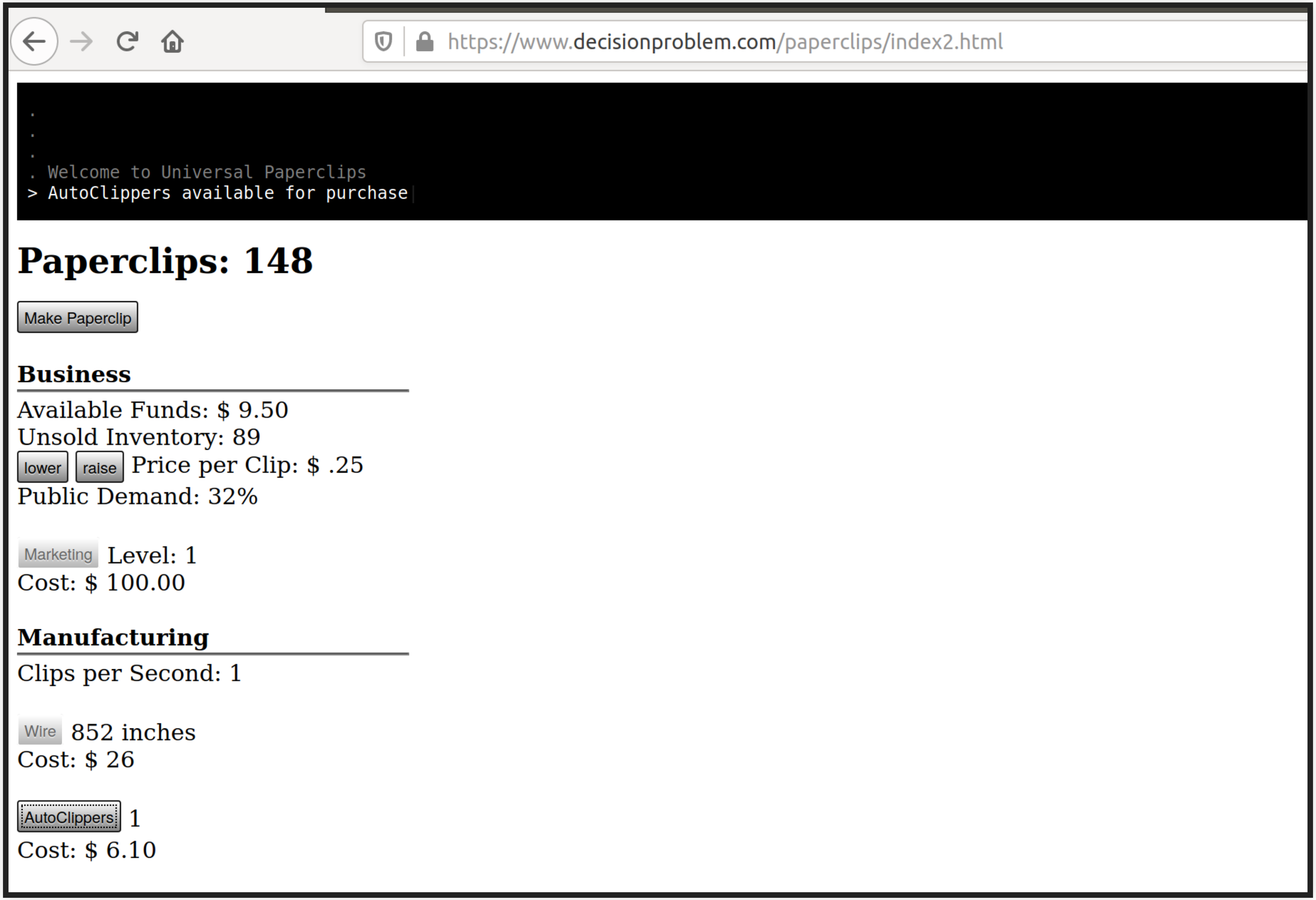
Likely?

Toby Ord predicts existential risk from GAI at 10% within 100 years

Toby Ord, "The Precipice: Existential Risk and the Future of Humanity", 2020

Speaker notes

Discussion on existential risk. Toby Ord, Oxford philosopher predicts



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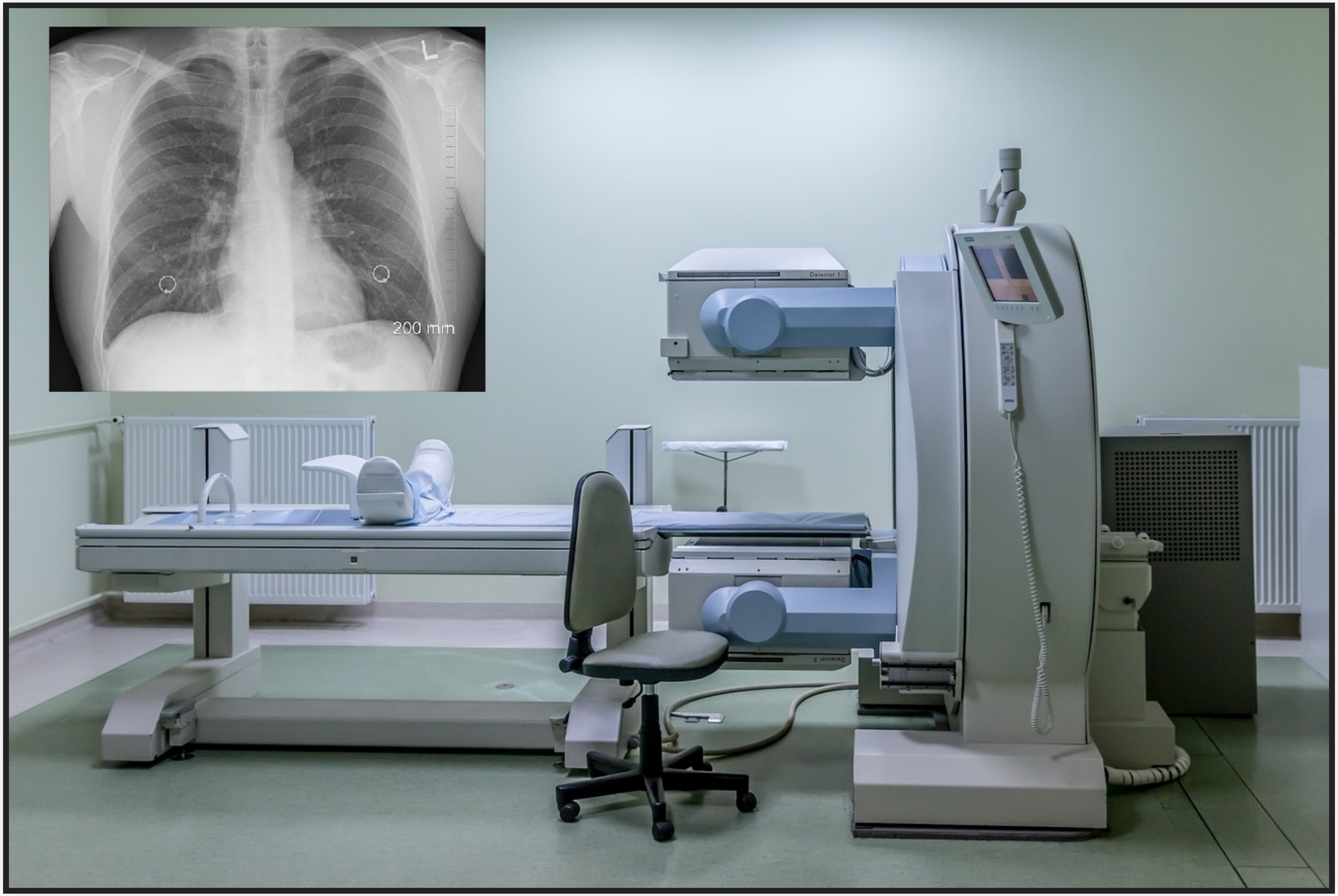
Paperclips: 148
Make Paperclip
Business
Available Funds: $ 9.50
Unsold Inventory: 89
lower
raise
Price per Clip: $ .25
Public Demand: 32%
Marketing
Level: 1
Cost: $ 100.00
Manufacturing
Clips per Second: 1
Wire
852 inches
Cost: $ 26
AutoClippers
1
Cost: $ 6.10

WHAT'S THE WORST THAT COULD HAPPEN?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Detector 1


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WHAT IS RISK ANALYSIS?

- What can possibly go wrong in my system, and what are potential impacts on system requirements?
- Risk = Likelihood * Impact
- Many established methods:
    - Failure mode & effects analysis (FMEA)
    - Hazard analysis
    - Why-because analysis
    - Fault tree analysis (FTA)
    - Hazard and Operability Study (HAZOP)
    - ...

RISKS?

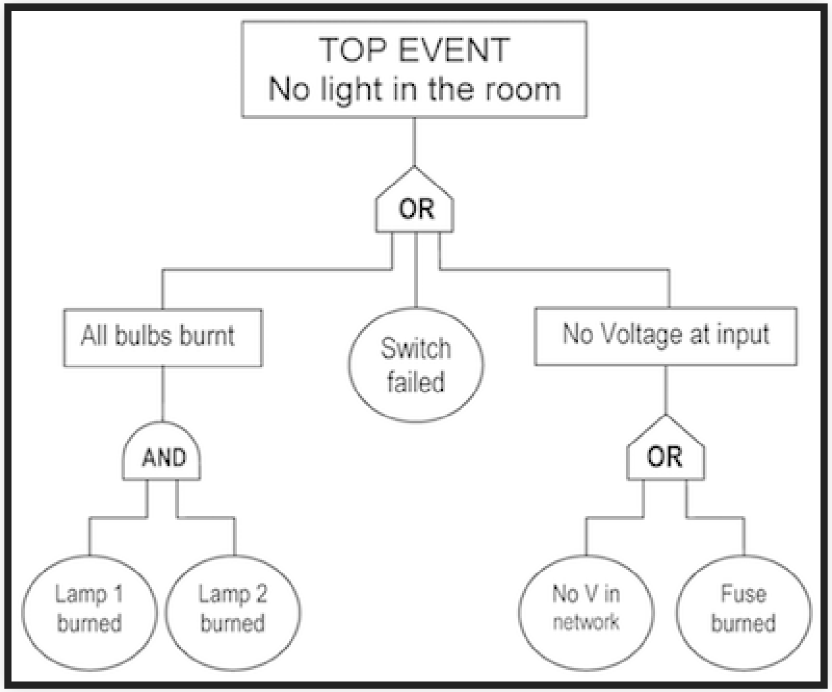
- Lane assist system
- Credit rating
- Amazon product recommendation
- Audio transcription service
- Cancer detection
- Predictive policing

Discuss potential risks, including impact and likelyhood

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

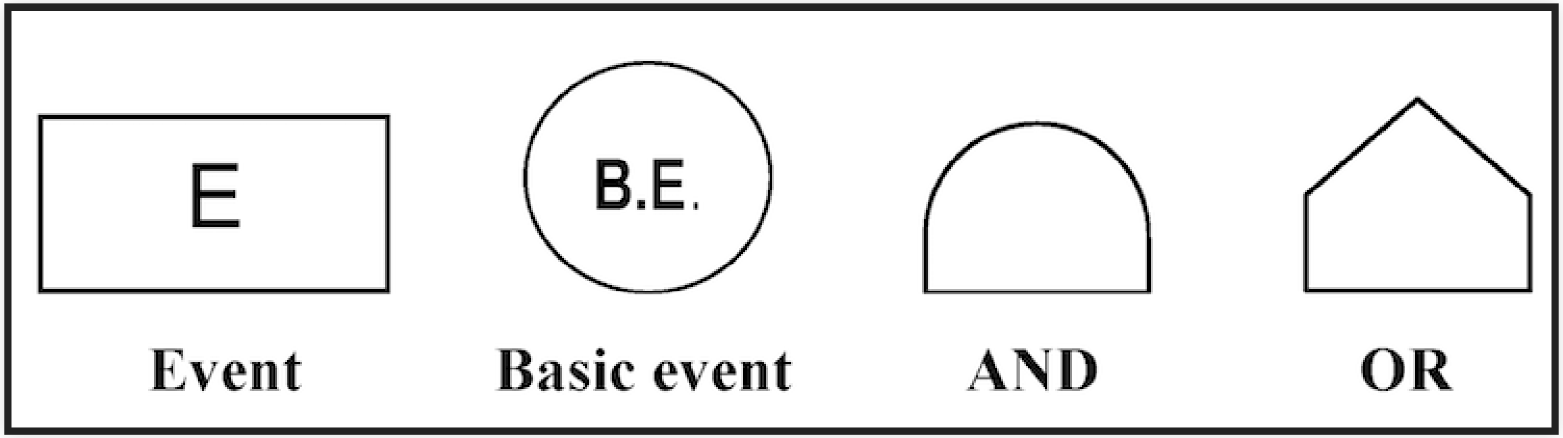
FAULT TREE EXAMPLE



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

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

FAULT TREES: BASIC BUILDING BLOCKS



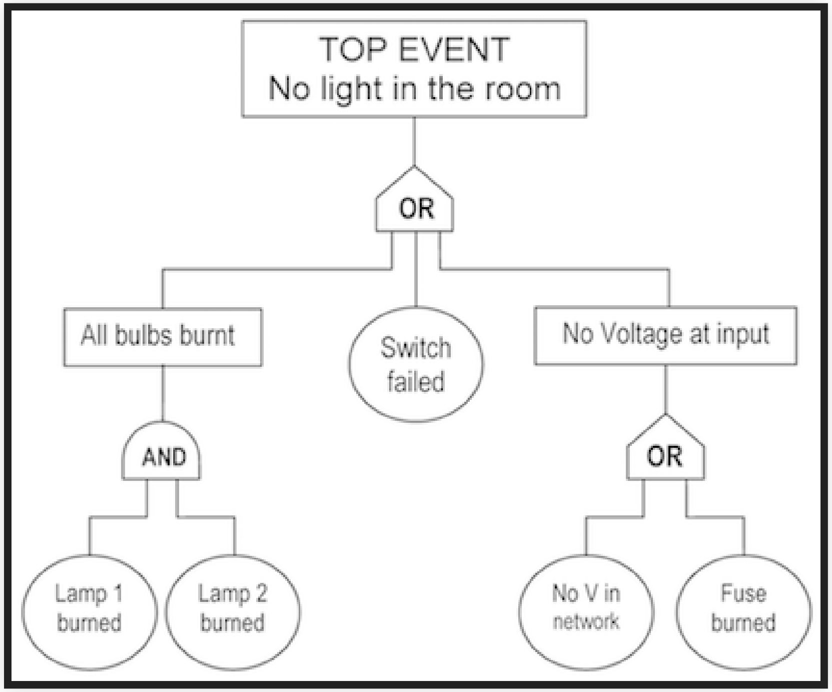
- Event: An occurrence of a fault or an undesirable action
  - (Intermediate) Event: Explained in terms of other events
  - Basic Event: No further development or breakdown; leafs of the tree
- Gate: Logical relationship between an event & its immedicate subevents
  - AND: All of the sub-events must take place
    - OR: Any one of the sub-events may result in the parent event

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

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 probability of a failure, based on estimated probabilities of basic events

(cut set = set of basic events whose simultaneous occurrence is sufficient to guarantee that the TOP event occurs)



Speaker notes

- *Minimal* cut set: A cut set from which a smaller cut set can be obtained by removing a basic event.
- Switch failed alone is sufficient (minimal cut set), so is fused burned, whereas lamp1 + lamp2 burned is a cut set, but not minimal.

FAULT TREE ANALYSIS & AI

- Anticipate mistakes and understand consequences
- How do mistakes made by AI contribute to system failures/catastrophe?
- Increasingly used in automotive, aeronautics, industrial control systems, etc.

FTA PROCESS

1. Specify the system structure
   - Environment entities & machine components
   - Assumptions (ENV) & specifications (SPEC)
2. Identify the top event as a violation of REQ
3. Construct the fault tree
   - Intermediate events can be derived from violation of SPEC/ENV
4. Analyze the tree
   - Identify all possible minimal cut sets
5. Consider design modifications to eliminate certain cut sets
6. Repeat

EXERCISE: DRAW FAULT TREE FOR SMART TOASTER

TOP: Smart toaster burning

FAULT-TREE ANALYSIS DISCUSSION

- Town-down, *backward* search for the root cause of issues
    - from final outcomes to initiating events
- Issues (TOP events) need to be known upfront
- Quantitative analysis possible
- Useful for understanding faults post-hoc
- Where do outcomes come from?

FAILURE MODE AND EFFECTS ANALYSIS (FMEA)

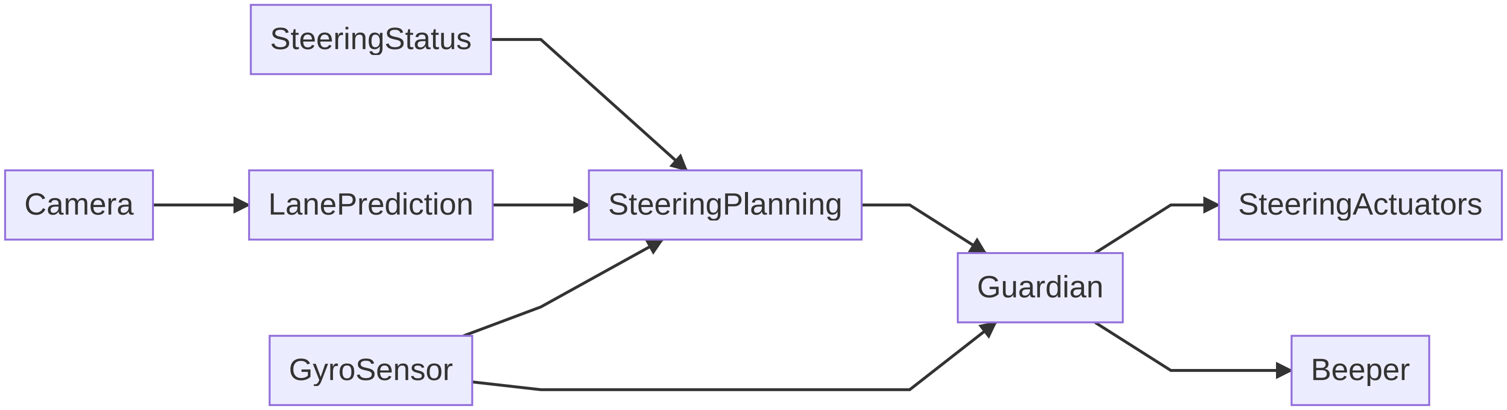
	Function	Potential Failure Mode	Potential Effect(s) of Failure	SEV i	Potential Cause(s) of Failure	OCC i	Current Design Controls (Prevention)	Current Design Controls (Detection)	DET i	RPN i	Recommended Action(s)
1	Provide required levels of radiation	Radiation level too high for the required intervention	Over radiation of the patients.		Technician did not set the radiation at the right level.			Current algorithm resets to normal levels after imaging each patient.			Modify software to alert technician to unusually high radiation levels before activating.
2		Radiation at lower level than required	Patient fails to receive enough radiation.		Software does not respond to hardware mechanical setting.			Failure detection included in software			Include visual / audio alarm in the code when lack of response.
3											Improve recovery protocol.
4	Protect patients from unexpected high radiation	Higher radiation than required	Radiation burns		sneak paths in software			Shut the system if radiation level does not match the inputs.			Perform traceability matrix.

- A **forward search** technique to identify potential hazards
- Widely used in aeronautics, automotive, healthcare, food services, semiconductor processing, and (to some extent) software

FMEA PROCESS

- Identify system components
- Enumerate potential failure modes
    - *for ML component: Always suspect prediction may be wrong*
- For each failure mode, identify:
    - Potential hazardous effect on the system
    - Method for detecting the failure
    - Potential mitigation strategy

FMEA EXAMPLE: LANE ASSIST



Failure modes? Failure effects? Detection? Mitigation?

Speaker notes

More general Autonomous Vehicle example

Component	Failure Mode	Failure Effects	Detection	Mitigation
Perception	Failure to detect an object	Risk of collision	Human operator (if present)	Deploy secondary classifier
Perception	Detected but misclassified	"	"	"
Lidar Sensor	Mechanical failure	Inability to detect objects	Monitor	Switch to manual control mode
...	...	...	...	...

"WRONG PREDICTION" AS FAILURE MODE?

- "Wrong prediction" is a very cause grained failure mode
- May not be possible to decompose further
- However, may evaluate causes of wrong prediction for better understanding, as far as possible --> FTA?

EXERCISE: FMEA ANALYSIS FOR SMART TOASTER

(video sensor, temperature sensor, heat sensor, user setting, ML model, heuristic shutdown, thermal fuse)

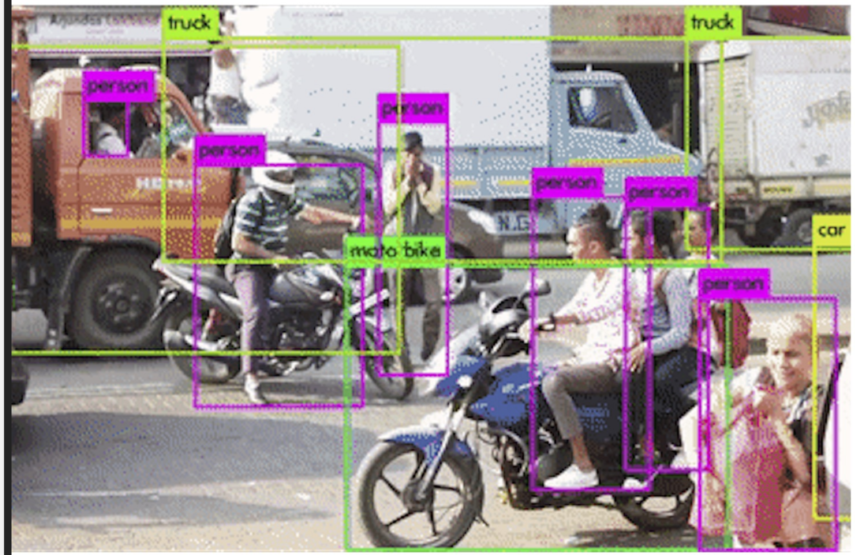
Failure modes? Failure effects? Detection? Mitigation?

FMEA SUMMARY

- Forward analysis: From components to possible failures
- Focus on single component failures, no interactions
- Identifying failure modes may require domain understanding

HAZARD AND INTEROPERABILITY STUDY (HAZOP)

identify hazards and component fault scenarios through guided inspection of requirements



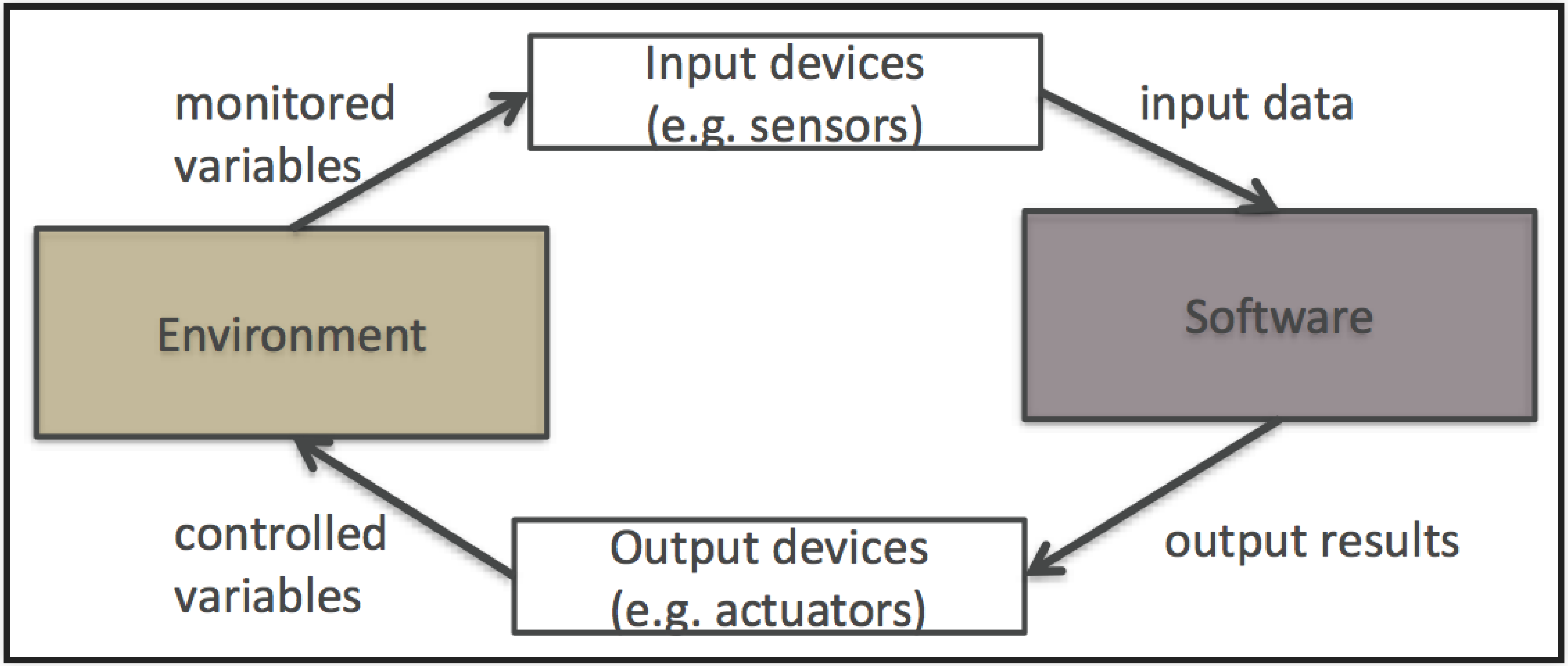
Guide Word	Meaning
NO OR NOT	Complete negation of the design intent
MORE	Quantitative increase
LESS	Quantitative decrease
AS WELL AS	Qualitative modification/increase
PART OF	Qualitative modification/decrease
REVERSE	Logical opposite of the design intent
OTHER THAN / INSTEAD	Complete substitution
EARLY	Relative to the clock time
LATE	Relative to the clock time
BEFORE	Relating to order or sequence
AFTER	Relating to order or sequence

DECOMPOSING REQUIREMENTS TO UNDERSTAND PROBLEMS

THE ROLE OF REQUIREMENTS ENGINEERING

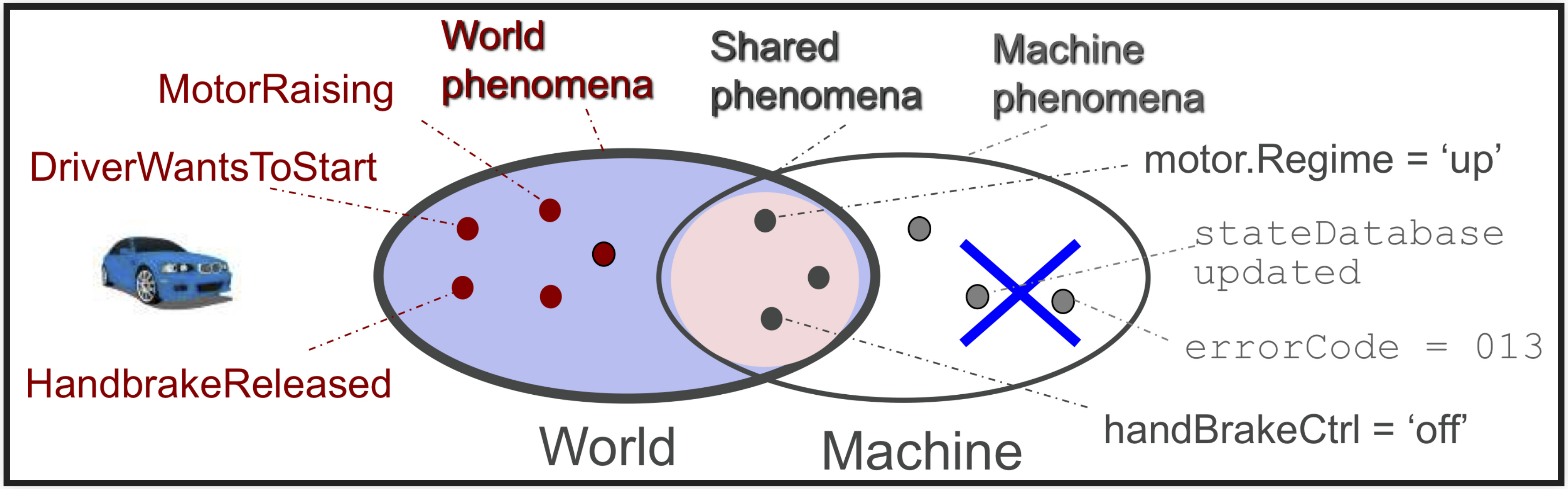
- Requirements engineering essential to understand risks and mistake mitigation
- Understand
    - user interactions
    - safety requirements
    - security and privacy requirements
    - fairness requirements
    - possible feedback loops

MACHINE VS WORLD



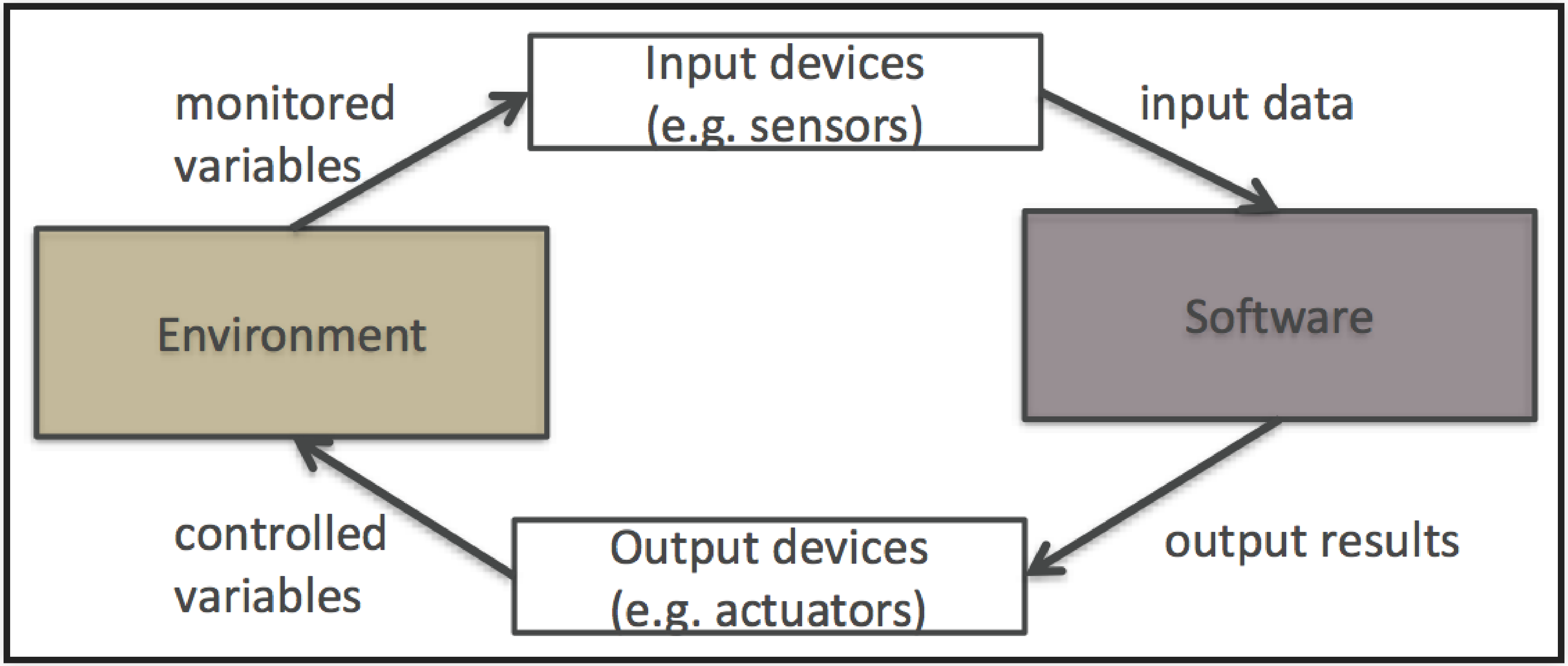
- No software lives in vacuum; every system is deployed as part of the world
- A requirement describes a desired state of the world (i.e., environment)
- Machine (software) is *created* to manipulate the environment into this state

SHARED PHENOMENA



- Shared phenomena: Interface between the world & machine (actions, events, dataflow, etc.,)
- Requirements (REQ) are expressed only in terms of world phenomena
- Assumptions (ENV) are expressed in terms of world & shared phenomena
- Specifications (SPEC) are expressed in terms of machine & shared phenomena

DISCUSSION: MACHINE VS WORLD



Discuss examples for self-driving car, Amazon product recommendation, smart toaster

EXAMPLE: LANE ASSIST

- Requirement: Car should beep when exiting lane / adjust steering to stay in lane
- Environment assumptions: ??
- Specifications: ??

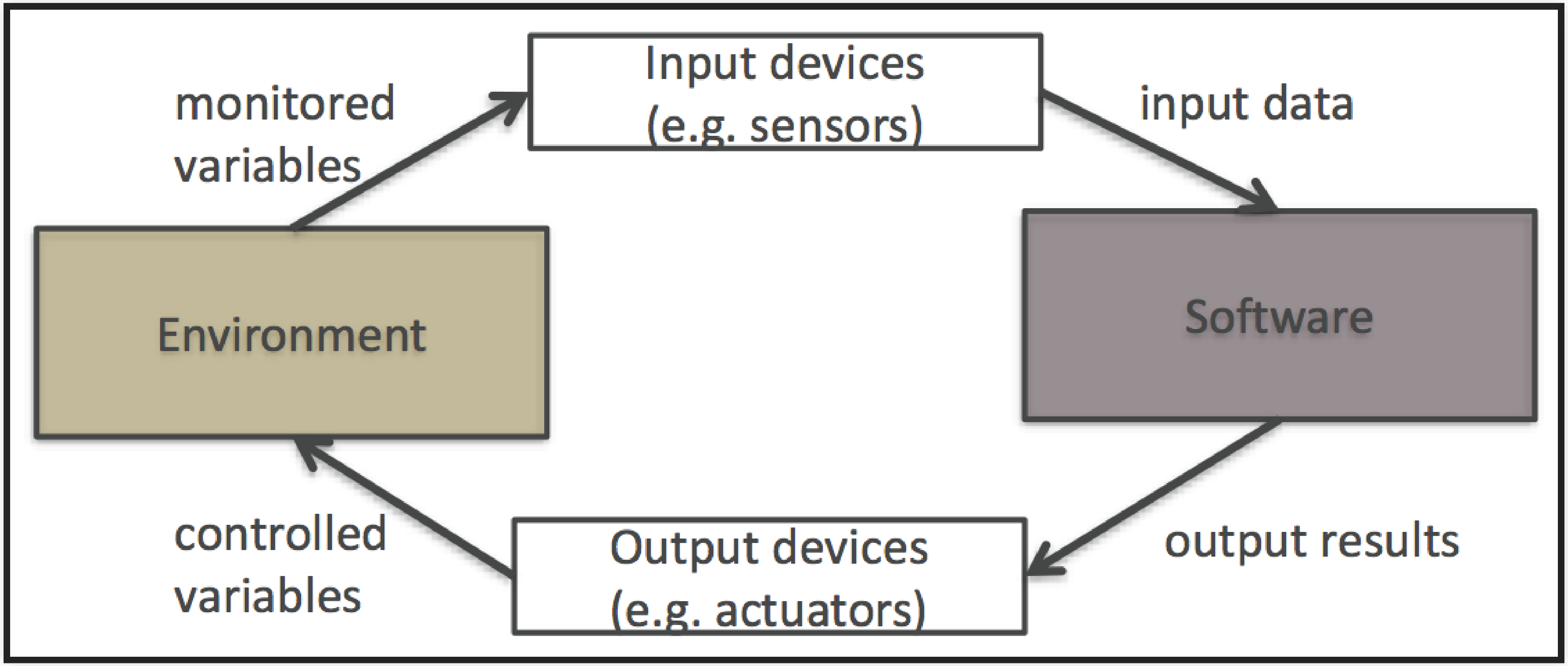
Speaker notes

ENV: Engine is working as intended; sensors are providing accurate information about the leading car (current speed, distance...) SPEC: Depending on the sensor readings, the controller must issue an actuator command to beep/steer the vehicle as needed.

RECALL: LACK OF SPECIFICATIONS FOR AI COMPONENTS

- In addition to world vs machine challenges
- We do not have clear specifications for AI components
    - goals, average accuracy
    - at best probabilistic specifications in some symbolic AI techniques
- Viewpoint: Machine learning techniques mine specifications from data, but not usually understandable

WHAT COULD GO WRONG?



- Missing/incorrect environmental assumptions (ENV)
- Wrong specification (SPEC)
- Inconsistency in assumptions & spec (ENV ∧ SPEC = False)
- Inconsistency in requirements (REQ = False)

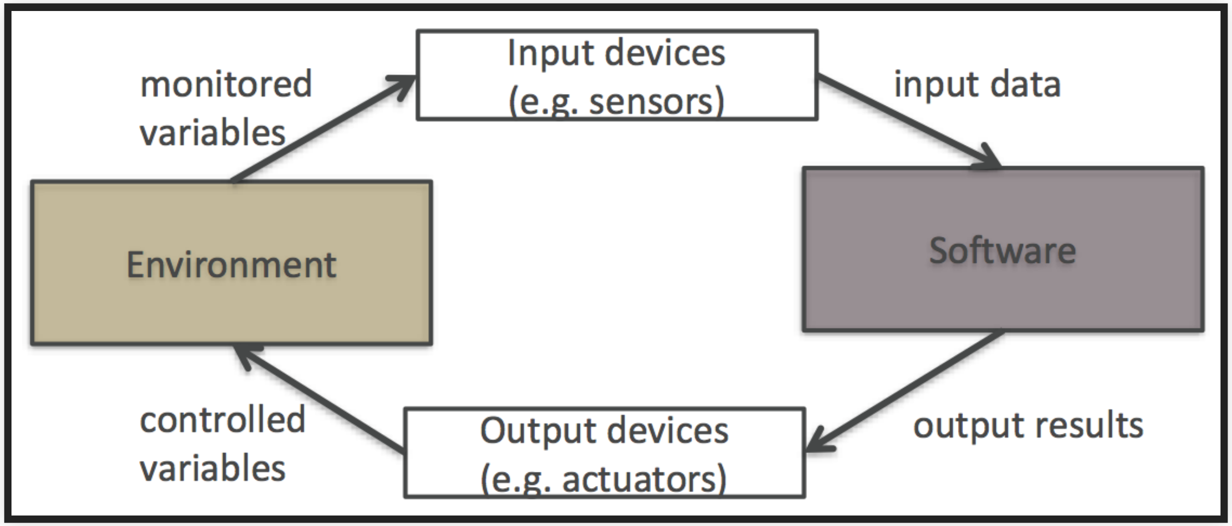
NON-AI EXAMPLE: LUFTHANSA 2904 RUNWAY CRASH

- Reverse thrust (RT): Decelerates plane during landing
- What was required (REQ): RT enabled if and only if plane on the ground
- What was implemented (SPEC): RT enabled if and only if wheel turning
- But: Runway wet + wind, wheels did not turn, pilot overridden by software

Speaker notes

For more details see https://en.wikipedia.org/wiki/Lufthansa_Flight_2904; Image credit Mariusz Siecinski

FEEDBACK LOOPS AND ADVERSARIES



- Feedback loops: Behavior of the machine affects the world, which affects inputs to the machine
- Data drift: Behavior of the world changes over time, assumptions no longer valid
- Adversaries: Bad actors deliberately may manipulate inputs, violate environment assumptions

Examples?

IMPLICATIONS ON SOFTWARE DEVELOPMENT

- Software/AI alone cannot establish system requirements -- they are just one part of the system
- Environmental assumptions are just as critical
  - But typically you can't modify these
  - Must design SPEC while treating ENV as given
- If you ignore/misunderstand these, your system may fail to satisfy its requirements

DERIVING SPEC FROM REQ

1. Identify environmental entities and machine components
2. State a desired requirement (REQ) over the environment
3. Identify the interface between the environment & machines
4. Identify the environmental assumptions (ENV)
5. Develop software specifications (SPEC) that are sufficient to establish REQ
6. Check whether ENV $\land$ SPEC $\models$ REQ
7. If NO, strengthen SPEC & repeat Step 6

SUMMARY

- Accept that ML components will confidently make mistakes
- Many reasons for wrong predictions (poor data, reverse causation, ...)
- Plan for mistakes
  - System-level safeguards
  - Human computer interaction, interface design
- Understand world-machine interactions
- Use Risk/Hazard analysis to identify and mitigate potential problems