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Model-Centered Assurance For Autonomous Systems

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Topic: Assurance for Autonomous Systems

- Quintessential example: self-driving cars
- Autonomy architecture invariably has two components

  Perception: use sensors to build a model of the local world

  Action: use the model to calculate safe and effective behavior
- Both components may use Artificial Intelligence (AI) software, including Machine Learning (ML)
  - Difficult to predict/guarantee behavior in all circumstances
- Yet we want assurance:
  - i.e., confidence in claims about the system within some context
    - ⋆ e.g., safety of self-driving on freeways
  - To very high levels (100 times better than human; 10^{-9} and beyond)

Assurance and Predictability

- Assurance requires predictable system-level behavior
  - While using unpredictable components
  - Within an unpredictable environment
  - Predictable behavior need not be deterministic
  - But requires some predicates to hold, given assumptions
- Components may be unpredictable, provided larger architecture ensures predictability
  - e.g., unpredictable action component is guarded by a predictable monitor
    - ⋆ Calculating effective behavior may require AI
    - ⋆ But can check its safety with conventional software (e.g., run a simulation)
    - ⋆ Given a model of the world
    - ⋆ So the model becomes the focus of our attention
- Action and monitor components might use different models
- Monitor model needs to be accurate, or at least safely approximate
- For simplicity, we mostly speak of just the model

Safely Approximate Models

- Safety is defined in human-focused (i.e., naturalistic) terms
- Therefore model needs to be naturalistic
  - i.e., defined on the variables of some human-defined framework
  - Not on the latent variables of a learned classifier
- Model need not be perfectly accurate
- Requirement:
  if behavior looks safe in the model, then it must be safe in the real world
- Reverse need not be true
- So model can be conservative: safely approximate

(Un)Predictable (In)Accuracy of Models

- Models are built by machine learning
  - Typical self-driving model has detected objects list (what it is, size, velocity, intent)
  - Plus occupancy grid (bird's eye view of road and object layout)
- Despite astonishing performance, accuracy of these ML methods is not predictable

  Evidence: observed failures
    - Real-world testing (reveals large fat tails)
    - Adversarial examples (minor input changes produce big & bad effects)

  ML explanation: there's no understanding of the world
    - Debate on memorization vs generalization in deep learning
    - It's just curve fitting (Pearl)
    - Will always be anomalies adjacent to correct behavior (Shamir et al)

  Deeper explanation: perception is anti-causal (i.e., backwards)
    - The world causes impressions that our sensors observe
    - Sensors try to infer world from sense impressions: anti-causal
    - Unpredictable because different worlds can generate same sense impressions

Example of Unpredictability and Unsafe Model

- Uber Tempe crash of 2018 (killed pedestrian crossing with bike)
  - Fused inputs using a "prioritization schema that promotes certain tracking methods over others, and is also dependent on the recency of the observation" (NTSB)
- This resulted in a "flickering" classification of the victim
  - 5.6 seconds before impact, victim classified as vehicle, by radar
  - 5.2 seconds before impact, victim classified as other, by lidar
  - 4.2 seconds before impact, victim classified as vehicle, by lidar
  - Between 3.8 and 2.7 seconds before impact,
    classification alternated between vehicle and other, by lidar
  - 2.6 seconds before impact, victim classified as bicycle, by lidar
  - 1.5 seconds before impact, victim classified as unknown, by lidar
  - 1.2 seconds before impact, victim classified as bicycle, by lidar
- Did not establish safely approx model, even though victim detected for several seconds
- Cannot expect to understand world from single snapshot, good model develops over time
- Updates/fusion should prioritize model over individual sensors, but model must be current

Dealing with (Un)Predictable (In)Accuracy of Models

- Massive training to reduce unpredictability ("collecting miles") requires infeasible effort
  - Billions of training and test miles (RAND and others)
- Runtime checking for unfavorable cases can help
  - E.g., detect when input is far from training data
  - Or influential parts of input do not coincide with decision
    - ⋆ e.g., pixels that affect cat vs. dog do not coincide with face

  Update the model conservatively when these trigger
  - These yield some improvement, but not to the levels required (beyond 10^{-9})
- Need to address the basic problem: anti-causal inference
- So turn things around and reason causally from model to sensors
- We use the model to generate/predict sensor input: Predictive Processing (PP)
- Difference between predicted and sensed input is prediction error
- Use prediction error for model update and fault detection

Predictive Processing Architecture

- Use anti-causal methods (and prior knowledge) to construct initial model
- Thereafter use predictive processing to refine and update it
- Prediction error provides constant feedback on quality of model and sensor interpretations
- In addition, predictions can guide/improve perception (e.g., where to look for lane markers)
- At what level are the predictions?
  - Pixel/point cloud level is too low
    - ⋆ e.g., color is irrelevant, so need some abstraction
  - Detected object list is attractive
    - ⋆ May require some anti-causal interpretation to get there
- PP itself may have multiple layers (objects at bottom, then situation/scenario/domain)
  - e.g., sub-ODD (situation) detects open freeway, vs. roadworks, crash, diversion
  - Lower-level models are like sensors to upper levels
  - But they all use machine learning for anti-causal interpretation

The model is a central repository of all information about the world

Predictive Processing and Model Update

- Predictive processing is the application of generative modeling to model-based control
- Prediction error is a single organizing principle for model update and fault detection
- Large prediction errors trigger/guide fault detection (later)
- Small prediction errors adjust the model
- Latter is like a Kalman Filter, generalized to complex data representations
- May have several candidate models and use prediction error to discriminate
  - E.g., detected object might be a bicycle or a pedestrian
  - The alternative models generate different predictions
    - ⋆ Bicycles tend to go with traffic, pedestrians across it
  - Over time, better model will have smaller prediction errors
- Models can be probabilistic
  - Bayesian framework: predictions are priors, errors give posteriors
  - Whole loop can be mechanized as Variational Bayes
  - Provides iterative model refinement to minimize prediction error

Predictive Processing and Fault Detection

- Large prediction errors suggest something is wrong: surprise
  - Single method detects all sources of failure: untrained space, adversarial, inaccurate model, unexpected evolution of world
- There are exactly three ways to respond to surprise
  1. Adjust the sensors (or their interpretation or lower level model)
     - e.g., change interpretation algorithm/ML parameters
     - Or ignore troublesome sensors for a while
  2. Adjust the model
     - e.g., increase uncertainty
     - Or make more surgical adjustments
  3. Adjust the world
     - e.g., get in shadow of adjacent truck to avoid blinding sun

  Or could use a combination
- How to choose?

Managing Surprise in Practice

Want to try to determine cause, then choose one/some of the three responses

Possible causes

- Localized (e.g., single) sensor fault (e.g., ML blip, hardware hiccup)
  - Ride it out for a while, using other sensors
- Major fault in (an entire) class of sensors
  - We assume different classes of sensor fail independently
    - ⋆ e.g., cameras dazzled by sun, radar unfazed
    - ⋆ Ride it out, using other sensors, increase uncertainty
  - Systematic misinterpretation: must not happen, see later
  - Hardware or other fault: not our problem,

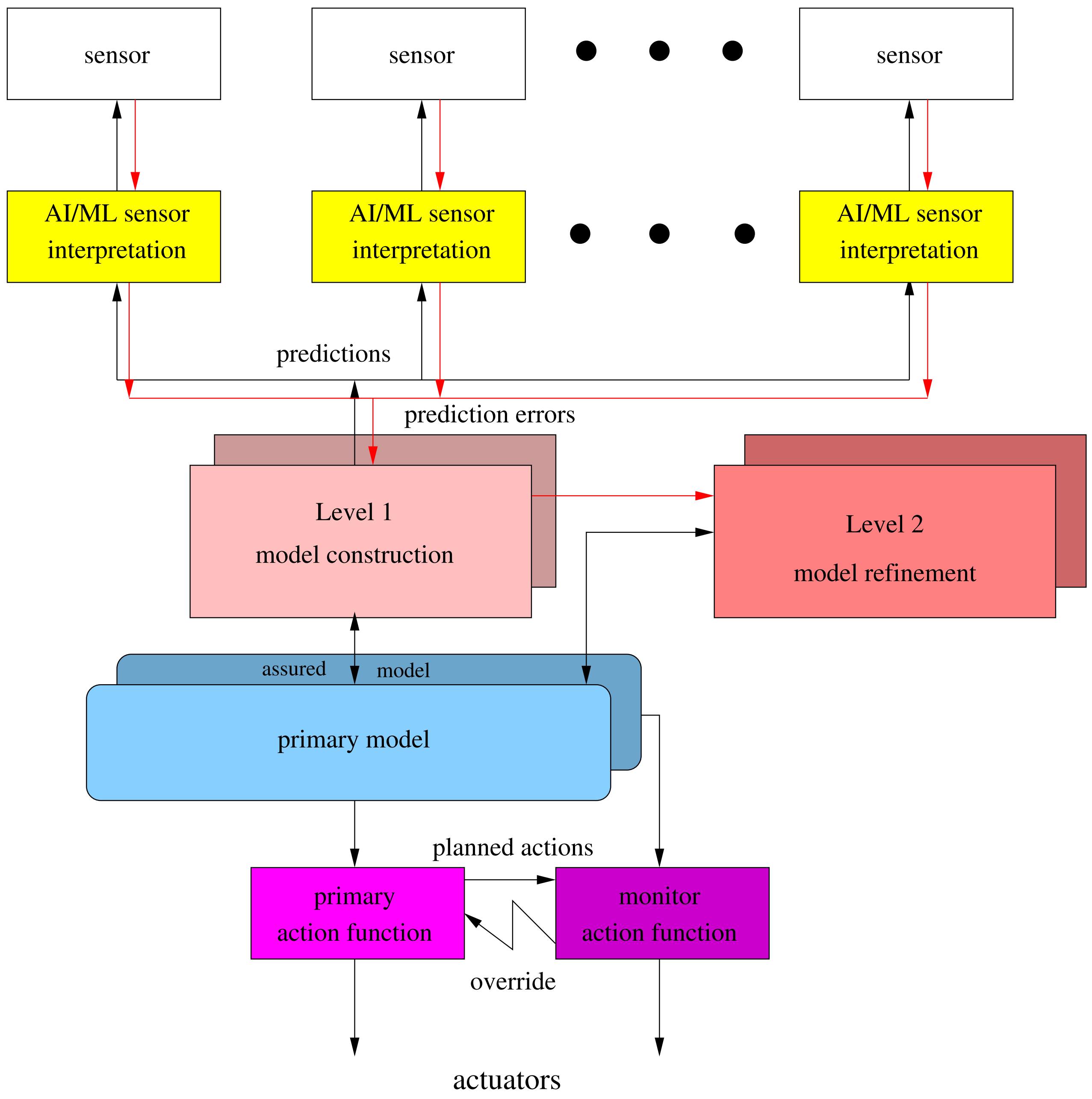
    Must be resolved by FT platform that supports whole thing
- Surprise from several sensors
  - Real world did not evolve as model expected
  - Need to adjust either the model or the world, but what information to trust?
  - Employ dual-process architecture for just this reason

Dual-Process Architecture

- Suppose we're on a freeway, camera detects a truck ahead
  - Truck has bicycle painted on its rear
- As we get closer, camera changes detected object to bicycle
  - Or flickers between truck and bike
  - Or says probability x for truck, y for bicycle
- Prior was truck, so large prediction errors: a surprise
- But we are on a freeway, bicycles not allowed
- So object must be a truck
- System needs to apply AI knowledge and reasoning to model
  - Here, it is "laws and rules of the road"
  - The more you know, the less you need to sense

  Locate this in a separate "higher level" process
  - Hence, dual-process architecture

Dual-Process Architecture (ctd. 1)



Dual-Process Architecture (ctd. 2)

- System 1 (lower) does automated model construction
  - Based on predictive processing
  - May itself have multiple layers (e.g., objects, situations/scenarios/domains)
  - But they all use machine learning for anti-causal interpretation
- System 2 (upper) does model refinement
  - Based on symbolic methods, rules, reasoning, general AI
  - May operate asynchronously to PP layers
  - Intervenes on surprise (persistent, large prediction errors)
  - But its goal is to minimize surprise (later)
- Model is like a blackboard: repository for all relevant knowledge
- Again: prediction errors provide single organizing principle

Managing Surprise at Level 2

- Use AI knowledge and reasoning to resolve difficulty
- Recall, three possible adjustments: sensor, model, world
- In fog, cannot see lane markings: adjust sensor
  - Synthesize fallback sensors
  - e.g., use proximity and radar to detect neighboring cars and derive lanes
- Startup, and recovery when all else fails: adjust model
  - i.e., rebuild model starting with some anti-causal frames
- Very few safe actions, or repeated sensor errors: adjust world
  - Try to get to a better state
  - e.g., change lanes

Minimizing Surprise: Situation Awareness

- System 2 intervenes on surprise
- But it should also anticipate and reduce future surprises
- So it should explore counterfactuals, hypotheticals, theory of mind
- This is situation awareness
- Plausible contingencies added to model with suitable probabilities
- E.g., hypotheticals due to occluded vision
  - "If there were a car the other side of that truck, we would not be able to see it"
    - ⋆ Add car to model with low probability (ghost)
  - "A car just dissapeared from my list; must be some occluding object I have not detected"
    - ⋆ Add likely occluding object to model, adjust System 1 to better perceive it
  - "The driver of that car may not be able to see us"
    - ⋆ Increase probability car will pull out (adjust intent)

  These make the model more conservative: fewer safe actions
- Actual world will then cause adjustments in probabilities, not surprise

Assurance Argument

- Assurance for monitor is conventional, but relies on model
- So need assurance that model is safely approximate
- Level 1 Predictive processing provides constant run-time verification of model, assuming sensor interpretation faults are independent, rare, and localized
- Level 2 AI provides situation awareness, responds to surprise
  - Typically, increases uncertainty in model
  - Makes it more approximate, therefore safer
- Must be no systematic (i.e., nonlocalized) interpretation faults
  - e.g., blind to red cars:
    predict no red cars, see no red cars
    so no prediction error. . . and then collide with red car
  - Provide evidence by model comparison during development
- Whole argument provides prior for assurance by Conservative Bayesian Inference (CBI)
- Testing and real-world experience then provide Bootstrap (see Strigini et al for both)

Model Comparison for Evidence of No Systemic Faults

- Construct modeled world in simulation environment
- Calculate sensor interpretation of that world
- And derive and maintain a model of the world by predictive processing
- Compare that to the model you started with
- Repeat millions of times
- Ensure failures are few, do not persist over many frames
- This is not the same as collecting miles
  - We are verifying general behavior
  - Not seeking edge cases

Prior Art: The Human Brain

- Although our architecture is derived and justified on engineering grounds
- It happens to be the way the brain works
- Predictive Processing (Rao and Ballard)
  - Also known as Predictive Coding, Predictive Error Minimization
    - ⋆ Helmholtz (1867), Metzinger, Clark, Hohwy
  - "Perceptions As Hypotheses," explicit comparison to testing scientific theories (Gregory)
  - Generalization: Free Energy (Friston)
- Dual Process model
  - Frankish, Evans & Stanovich
  - Thinking, Fast and Slow (Kahneman)

Conclusions

- Can guard autonomous actions with conventional, assured, software
- But it depends on a safely approximate model of the world
- ML used in construction of that model; anti-causal, so infeasible to assure it directly
- Do it indirectly by run-time checking of the model
- Best framework for this is a two-level architecture
  - Level/System 1: Predictive processing (casual ML framework)
    - ⋆ Small prediction errors indicate all is well
    - ⋆ Assumes sensors fail independently, and no systematic ML flaws
  - Level/System 2: Model Refinement
    - ⋆ Invoked on surprise: large prediction errors
    - ⋆ Goal is to avoid these, and recover when they occur
    - ⋆ Uses AI, reasoning for fault detection/recovery, and situation awareness
- Prediction errors provide a single organizing principle:, so assurance is itself autonomous!
- Needs experimental validation; Susmit Jha et al now have some (see his github)
- On my website: SafeComp 2020 paper, and arXiv paper on Confidence in Assurance