CS620: FM in ML

What, Why and How? A High-level Perspective

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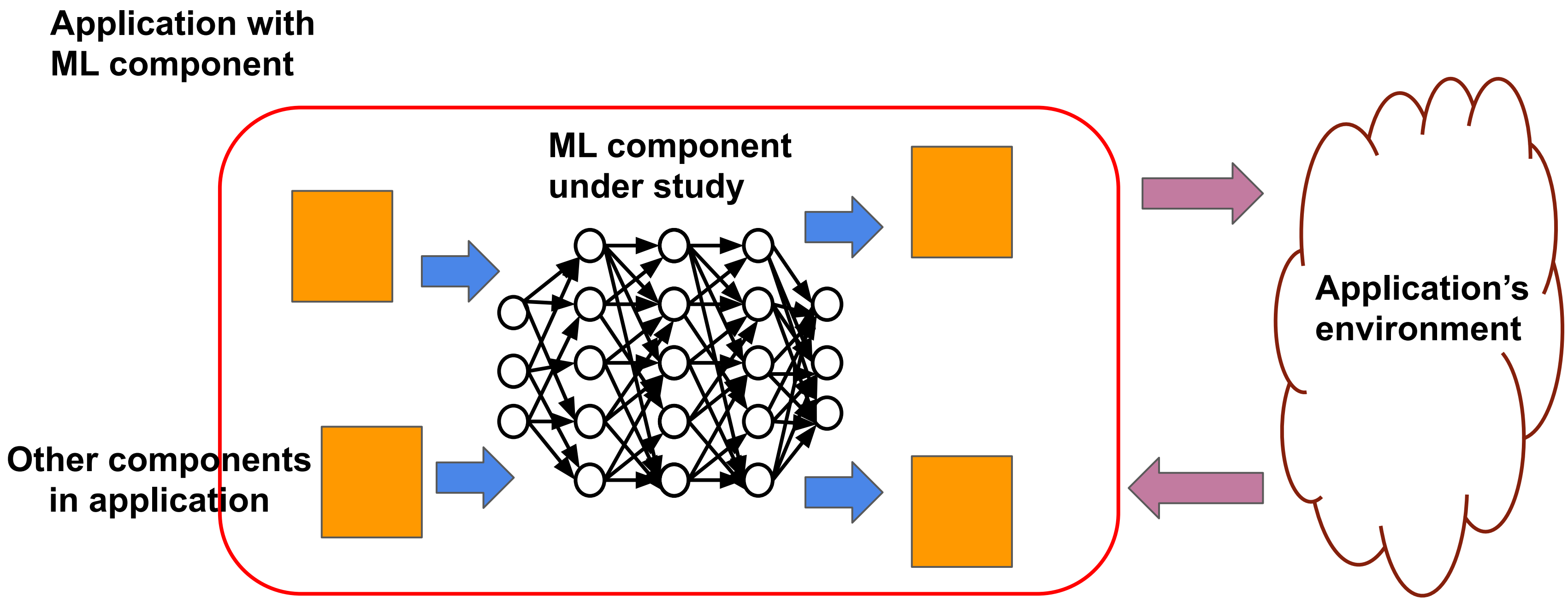
(Week 2 Lecture)

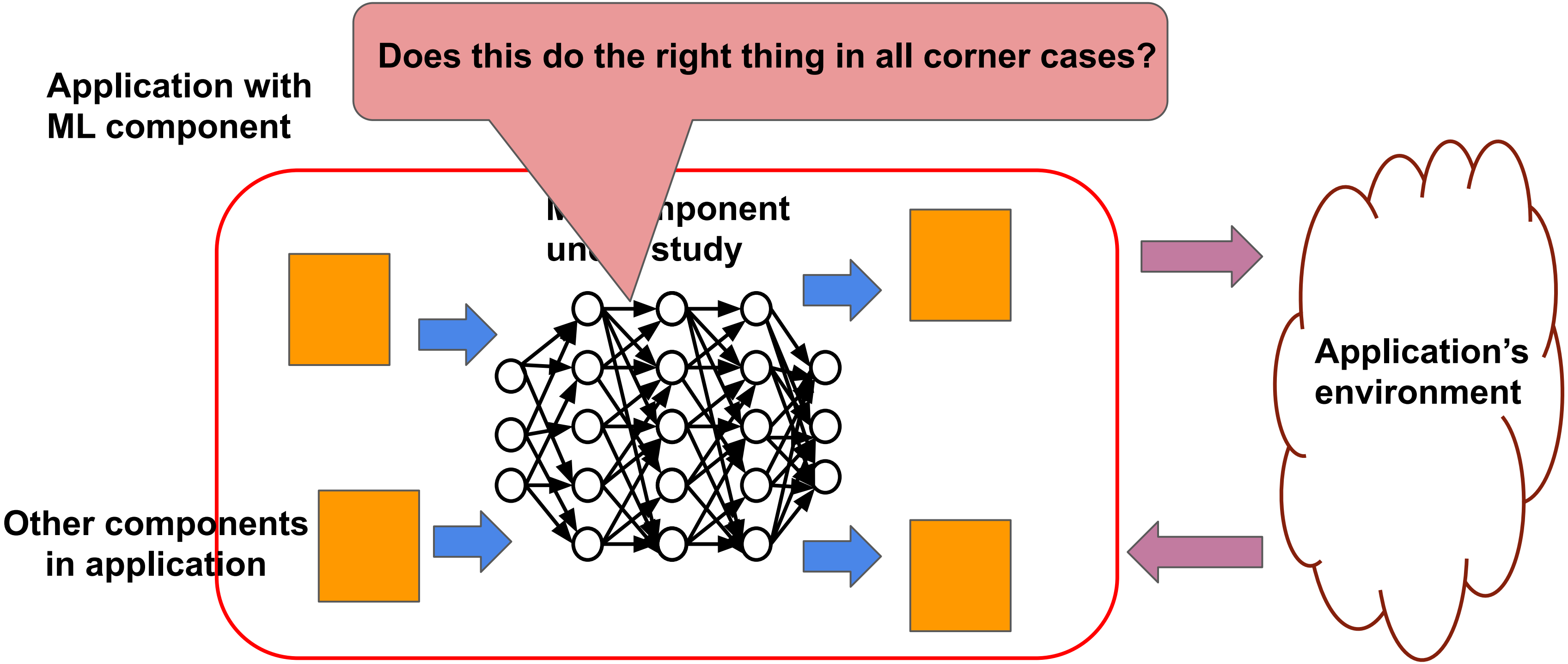
Safety in AI/ML

- AI/ML based systems
  - Computational systems that try to mimic (and improve upon?) human reasoning
  - Increasingly pervading our lives
- Applications span entire spectrum of consequences
  - Benign: Error causes nothing more than inconvenience
    - Auto completion in chat, game of chess, recommendation of restaurants, …
  - Potentally serious, but recoverable consequences:
    - Approval of bank loans, bail applications, ...
  - Serious irrecoverable consequences:
    - Collision avoidance in unmanned drones, self-driving cars, weapons systems, malware detection, …
- **Can we trust decisions by AI/ML based systems in applications where cost of errors is extraordinarily large?**
  - **Human lives, breach of privacy, security gaps, loss of critical infrastructure …**

A Typical Setup



A Typical Setup



Different perspectives

- **Machine learning perspective**
  - Reference reading: “Concrete Problems in AI Safety” by D. Amodei, C. Olah, J. Steinhardt, P. Christiano, J. Schulman and D. Mane
  - **“Accidents”**
    - Unintended, harmful behaviour stemming from “bad” design of ML components
    - Wrong objective function design?
      - Negative side effects, reward hacking
    - Too expensive to evaluate correct objective function frequently
      - Bad extrapolations
    - Training based on insufficient or poorly curated data`
    - Errors due to distributional shift of inputs
  - Core machine learning techniques can be used to reduce “accidents”
    - Scalable, works in a large spectrum of real-world settings
    - **Are all corner cases covered? Do we have proofs of correctness?**

Different perspectives

Large collection of promising approaches based on ML techniques

See Amodei et al’s paper for details, if interested

Can we **depend** on training/designing complex networks using to **always** work **as desired** in previously unseen corner cases, when **the cost of an error is huge**?

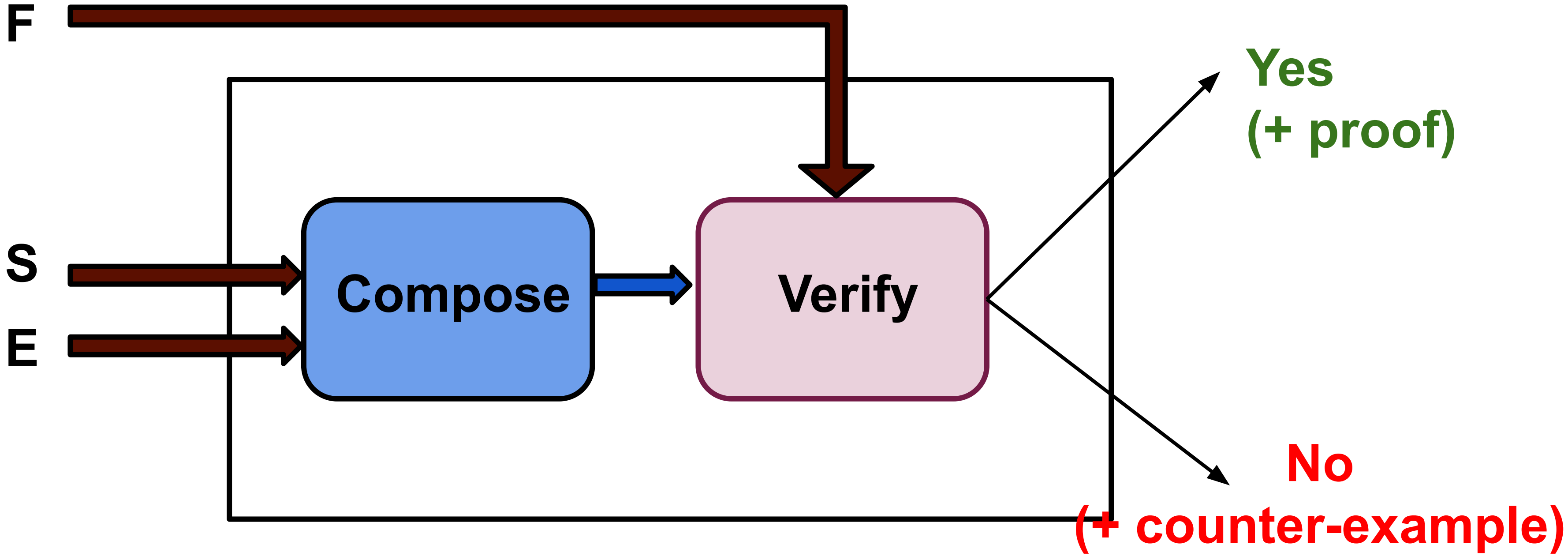
All ML based techniques to mitigate problem are **important** and **must be used**

But are these sufficient?

Different perspectives

- **Formal methods perspective**
  - **Required reading: "Towards Verified Artificial Intelligence" by Sanjit Seshia, Dorsa Sadigh, S. Shankar Sastry**
  - System: E.g., Neural net in self-driving car
    - Mathematical model of system's behaviour (**S**)
  - Environment: E.g., Road, weather, traffic, driver interventions, ...
    - Mathematical model of environment's behaviour (**E**)
  - Property: A precise mathematical formulation (**F**) of acceptable behaviour of **S** operating in **E**
  - Algorithmic search of proof space
    - Either obtain a proof that system satisfies property
      - $(S \mid\mid E) \models F$
    - Counterexample (network inputs) that demonstrate violation of property
      - Model of $(S \mid\mid E) \wedge \neg F$
  - **Several challenges along the way**

Different perspectives



Ref: Towards Verified Artificial Intelligence, Seshia, Sadigh and Sastry

Different perspectives

Formal methods perspective

- Hugely successful in hardware industry
- Moderately successful in software industry
- Formal methods based verification/analysis routine in several industrial hardware/software design flows
    - Every processor chip from Intel/AMD has parts of the design formally verified
    - Every time you fly an Airbus aircraft, large parts of the auto-pilot software formally verified
    - Every time you insert a USB device into a Windows machine, formal verification of downloaded drivers happens
- **Can we make the technology work for AI/ML based systems?**

Different perspectives

FM in ML goes beyond proofs/counterexamples of safety properties

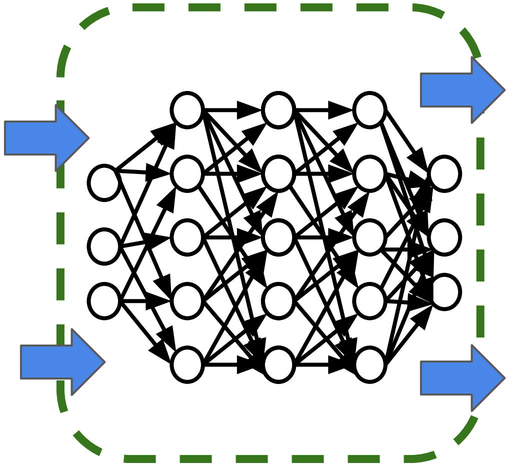
Can we use formal methods based reasoning to

- Verify correctness of algorithms used to train complex ML components?
- Do correct-by-construction design of ML components that satisfy formally specified properties?
- Provide explanations based on formal models like decision diagrams, probabilistic programs, Markov Decision Processes?
- Fish out adversarial inputs for well-trained ML components?
- Analyze robustness, fairness, privacy, security, transparency etc.?

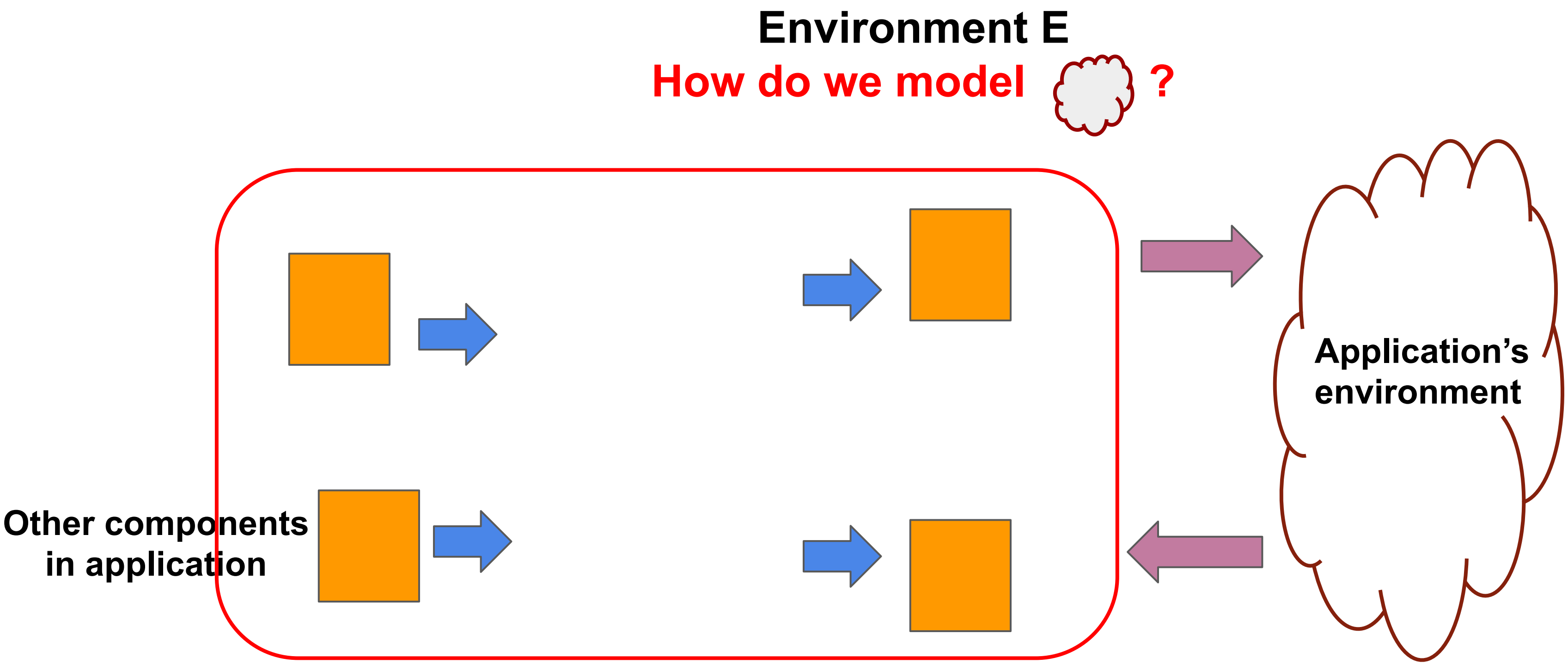
Some common problems

System S

High dimn input space, parameter space: scalability of analysis?

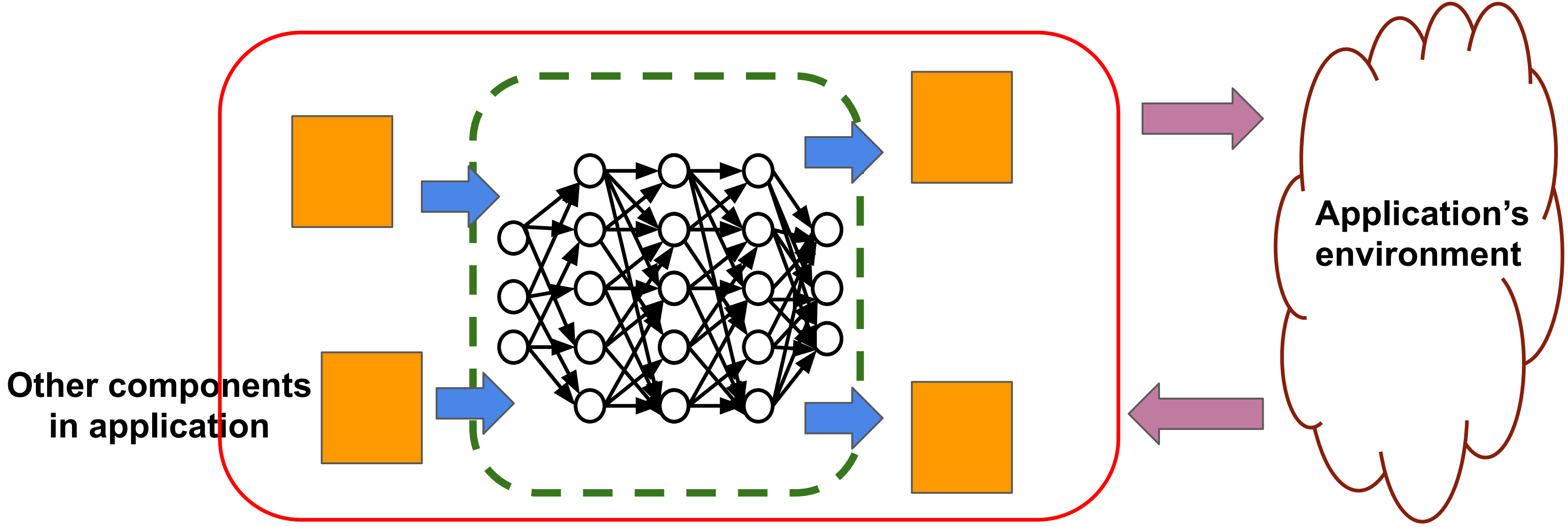


Some common problems



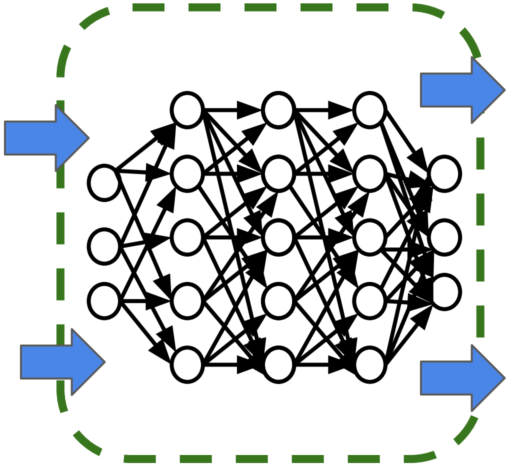
Some common problems

Property F: (Vehicle within 5m on left) $\Rightarrow \neg$ (Steer left)



Some common problems

What is the corresponding property for S?



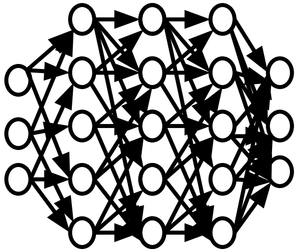
Modeling environment

- Uncertainty omnipresent: First class entity in reasoning
- Some things are inherently hard to model
  - Human behaviour, traffic conditions
- Probabilistic models with uncertainty of parameters built in
- Non-determinism used liberally may result in too many false negatives
- Need to combine probabilistic and non-deterministic modeling intelligently
- Markov Decision Processes (MDPs), probabilistic programs, …
- Abstractions in environment modeling
  - Different environment components may need to be abstracted differently

Specification of what is desired behaviour

- Often hard to formalize
  - Significant chunk of time spent on this even in software/hardware verification
  - Even harder in general for AI/ML based systems
- "Data as specification" vs "formal specification"
  - Can this gap be bridged?
  - Specification mining from behaviours, traces?
  - Evolving specification, as system used in different contexts?
- Quantitative vs Boolean specifications
  - Quantitative specs often have an optimization flavour
  - Does a system satisfy/fail a property or get a formal score for property satisfaction?
- End-to-end spec as opposed to compositional spec is often more feasible
  - Can we infer compositional spec from end-to-end spect (needn't be human readable)

Modeling the system



- Very high dimensional input space
  - Semantic feature spaces can lower dimension
- Very high dimensional parameter space
  - Reasoning over parameter space can quickly turn hopelessly intractable
- Need abstraction mechanisms suitable for scale of ML component complexity
  - Walking a tight rope -- computational efficiency vs precision of analysis
- Use logical formalisms to “explain” ML components
  - Some of these can be used as models
- Model systems in context
    - Perhaps not necessary to model arbitrary behaviours

Efficient computational engines

- Hardware & software verification settings
  - Symbolic model checking, SAT/SMT solvers, numerical simulation techinques ..
  - These may not suffice out-of-box for AI/ML contexts.
- AI/ML context
  - Data generation, satisfying soft, hard, distributional constraints (realism)
  - Efficient constraint solving techniques with ReLUs, sigmoids, etc.
  - New abstraction/refinement techniques for ReLUs, sigmoids for sound analysis
  - Compositional reasoning
    - Assume-guarantee reasoning for Boolean models/specifications relatively mature
    - Similar reasoning for probablistic/quantitative models/specifications?

Holy grail: Correct by construction

- Significant success in hardware, restricted software context
- Can we design ML components that provably satisfy given specs?
  - Inductive synthesis
  - Safe learning-based control
  - Safe reinforcement learning
- Theorem proving for correctness of algorithms used for training ML models
- Resilience and fault tolerance at run time essential given the complexities of AI/ML components
  - Wrap within run-time assurance framework to ensure nothing unsafe happens

Realistic expectations

- Given scale and complexity of today's AI/ML based systems
  - Challenging, if not impossible, to design correct-by-construction ML system, or formally verify overall correct operation without restrictive/unrealistic assumptions
  - Nascent area, lots of promising ideas in literature
- Therefore,
  - **Core ML techniques, Formal Analysis/Verification AND Run-Time Assurance needed**

Focus of this course: Formal Analysis/Verification

Topics to be covered

- Specifying properties for ML components
- Modeling environments and neural networks
- Abstract interpretation for analyzing deep neural networks
- Customized constraint solvers
- Automata theoretic analysis of recurrent neural networks
- Verified Reinforcement Learning
- Robustness analysis through formal methods lens
- Explainability of ML components: logic based approach