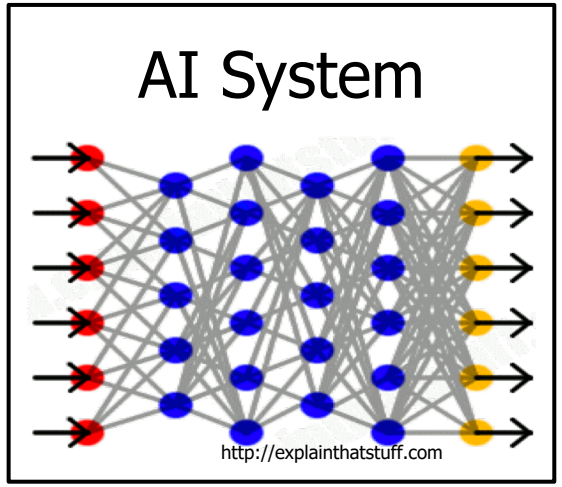
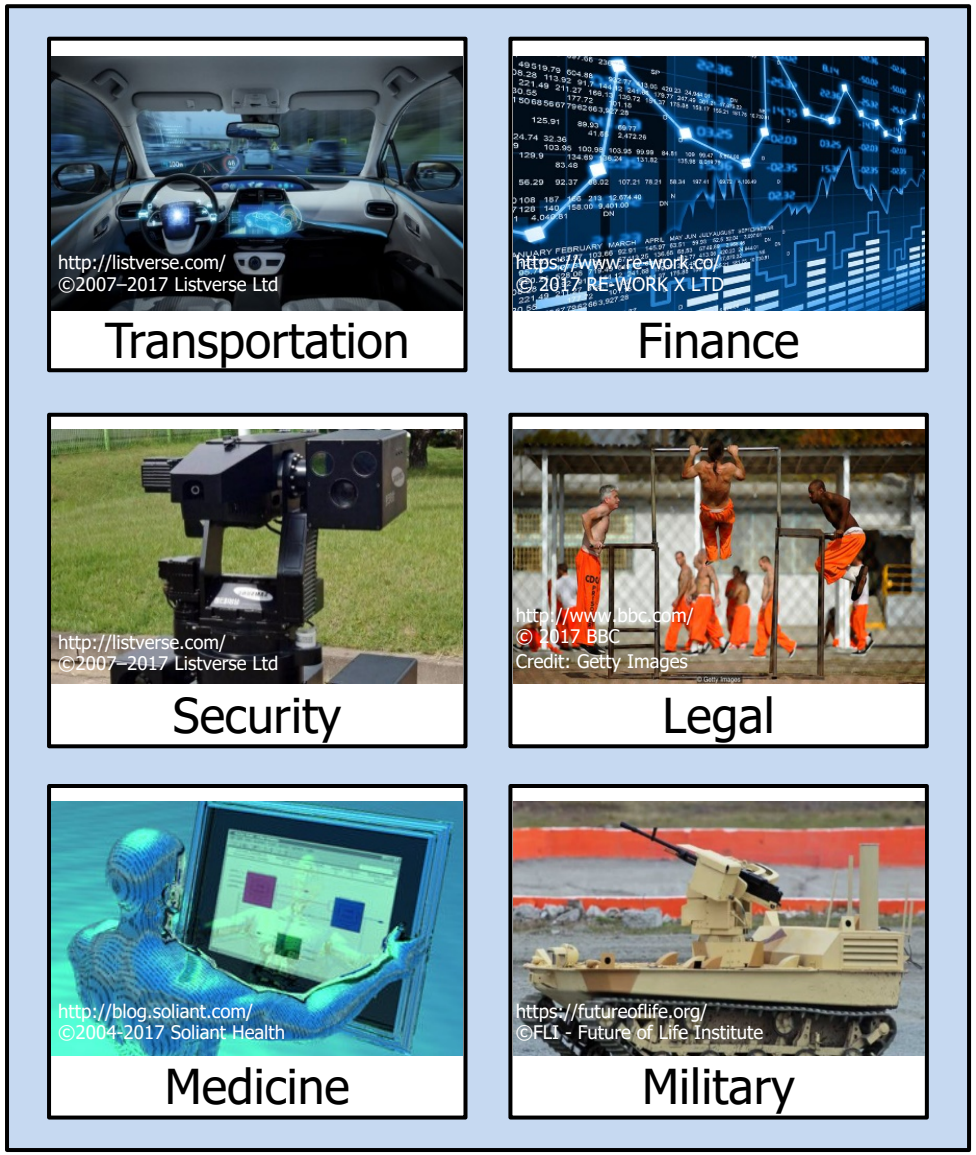
# Explainable Artificial Intelligence (XAI)


David Gunning
Information Innovation Office (I2O)
Defense Advanced Research Projects Agency (DARPA)

# The Need for Explainable AI



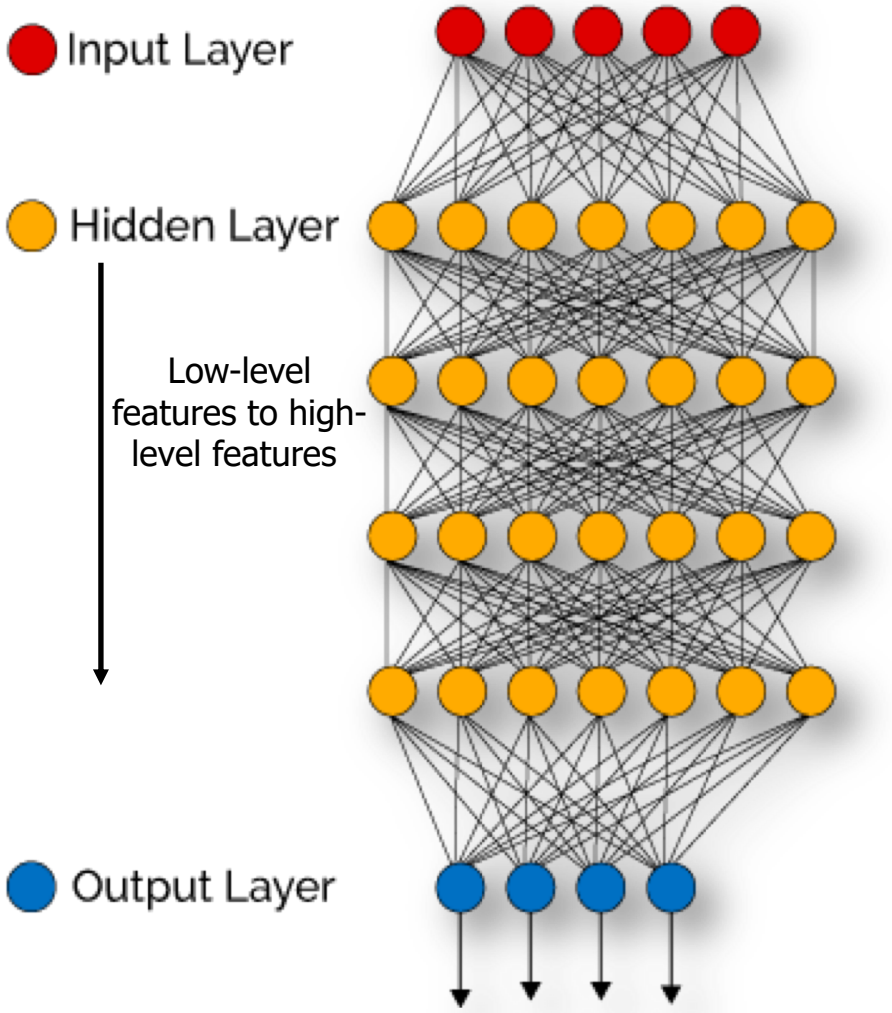

- We are entering a new age of AI applications
- Machine learning is the core technology
- Machine learning models are opaque, non-intuitive, and difficult for people to understand

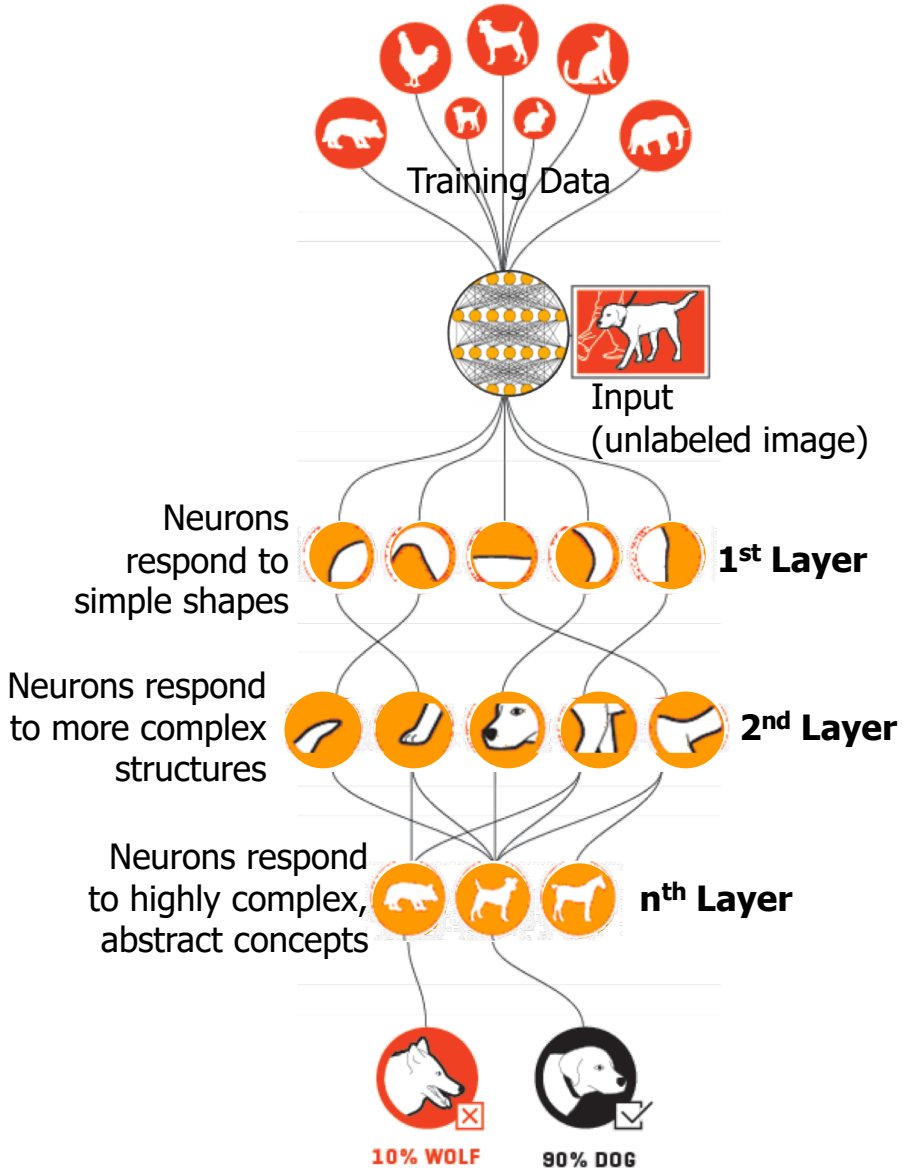




- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?

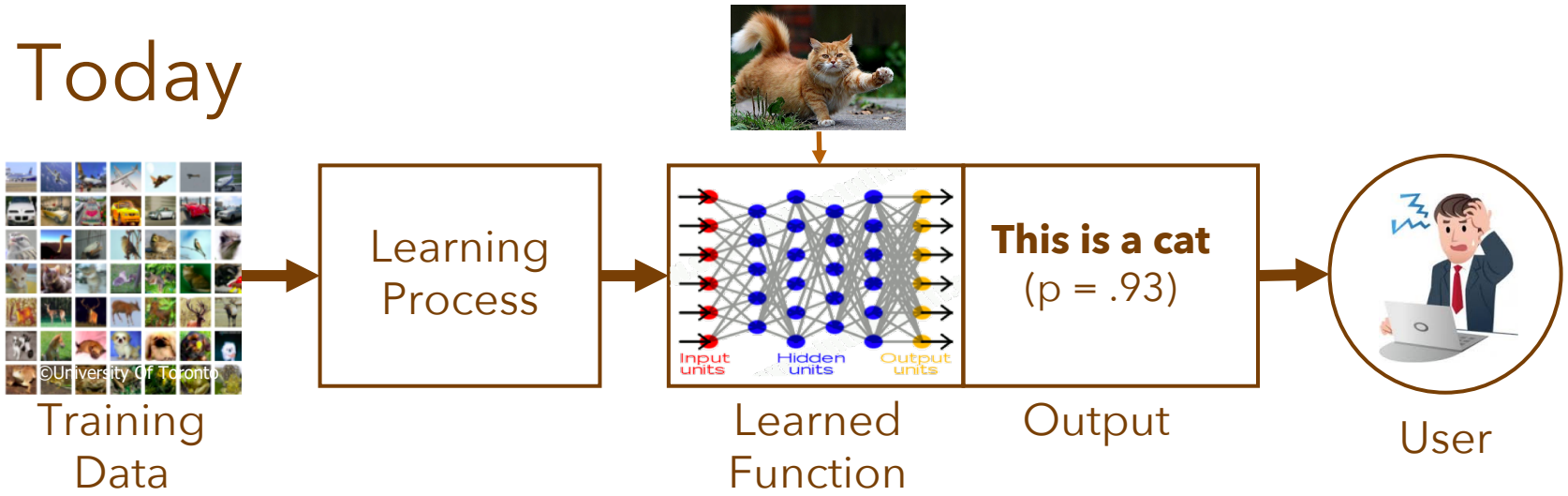
# Deep Learning Neural Networks



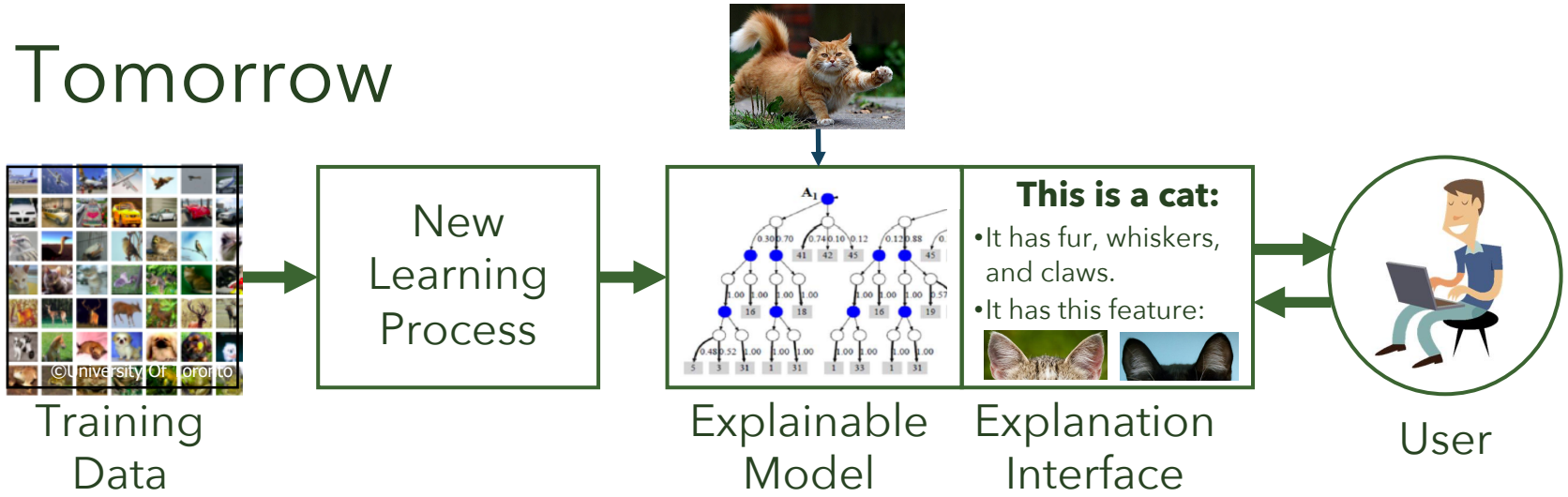
# What are we trying to do?

## Today




- Why did you do that?
- Why not something else?
- When do you succeed?
- When do you fail?
- When can I trust you?
- How do I correct an error?

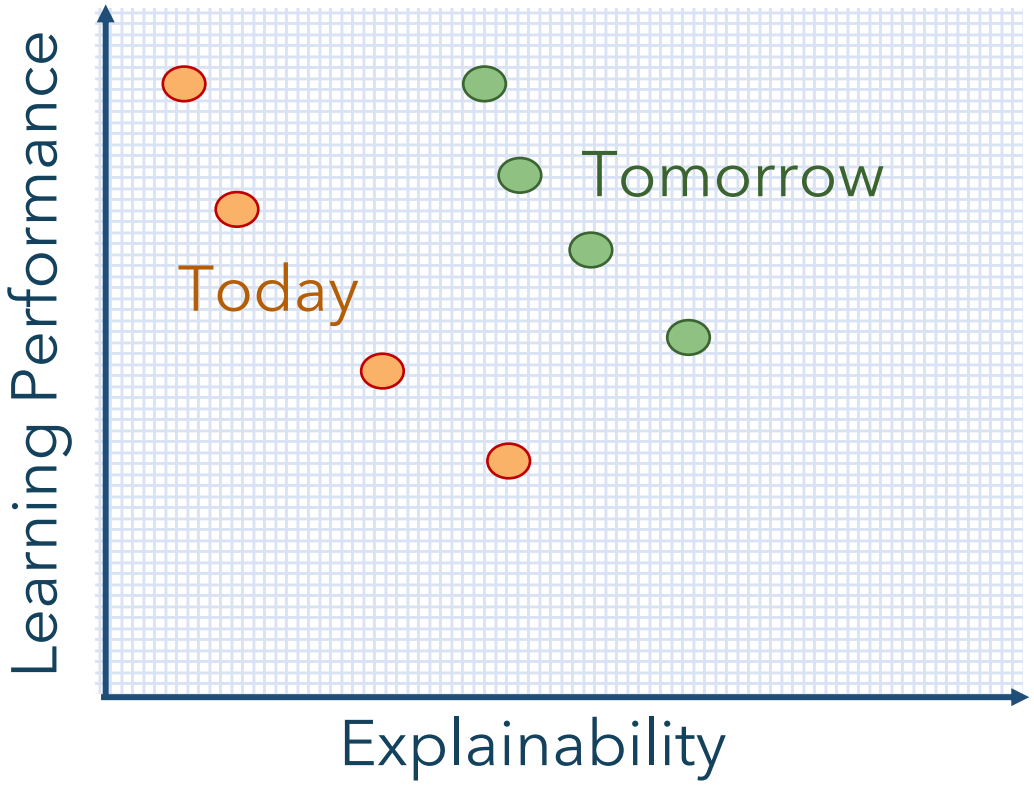
## Tomorrow



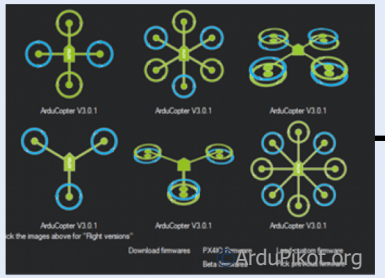

- I understand why
- I understand why not
- I know when you'll succeed
- I know when you'll fail
- I know when to trust you
- I know why you erred

# Goal: Performance and Explainability

- XAI will create a suite of machine learning techniques that
  - Produce more explainable models, while maintaining a high level of learning performance
  - Enable human users to understand, appropriately trust, and effectively manage the emerging generation of AI systems

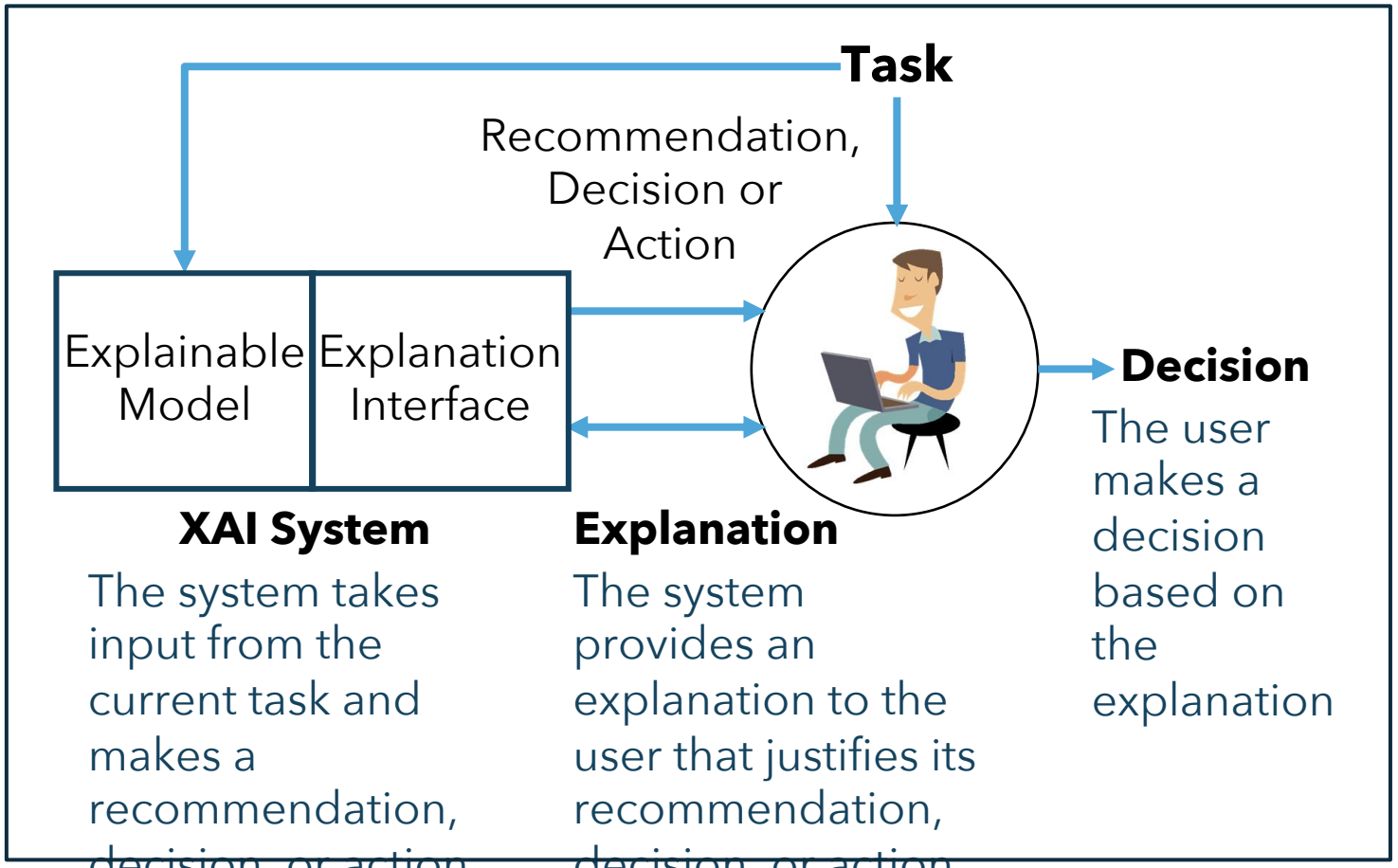


# Challenge Problems

| | Learn a model | Explain decisions | Perform a task | |
|---|---|---|---|---|
| **Data Analytics**<br>Classification Learning Task |  <br>Multimedia Data | Explainable Model \| Explanation Interface | Recommend<br>Explanation |  | An analyst is looking for items of interest in massive multimedia data sets |
| | Classifies items of interest in large data set | Explains why/why not for recommended items | Analyst decides which items to report, pursue | |
| **Autonomy**<br>Reinforcement Learning Task |  <br>ArduPilot & SITL Simulation | Explainable Model \| Explanation Interface | Actions<br>Explanation |  | An operator is directing autonomous systems to accomplish a series of missions |
| | Learns decision policies for missions | Explains behavior in an after-action review | Operator decides which future tasks to delegate | |

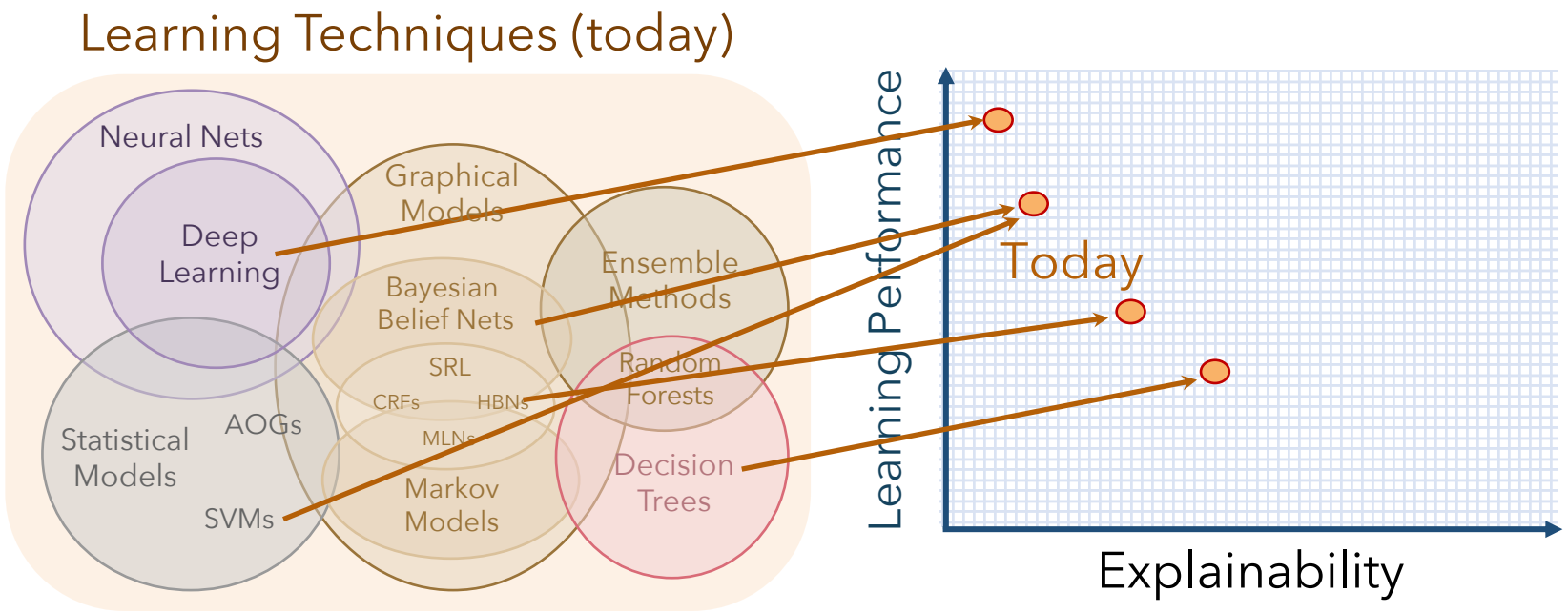
# Measuring Explanation Effectiveness

## Explanation Framework




| |
|---|
| **User Satisfaction** |
| • Clarity of the explanation (user rating)<br>• Utility of the explanation (user rating) |
| **Mental Model** |
| • Understanding individual decisions<br>• Understanding the overall model<br>• Strength/weakness assessment<br>• 'What will it do' prediction<br>• 'How do I intervene' prediction |
| **Task Performance** |
| • Does the explanation improve the user's decision, task performance? |
| **Trust Assessment** |
| • Appropriate future use and trust |
| **Correctability (Extra Credit)** |
| • Identifying errors<br>• Correcting errors |

# Developing an Explainable Model

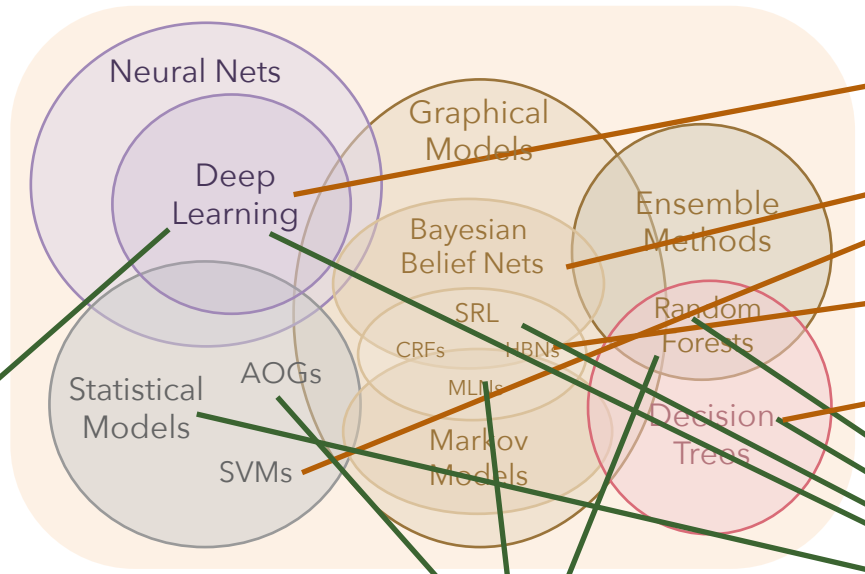


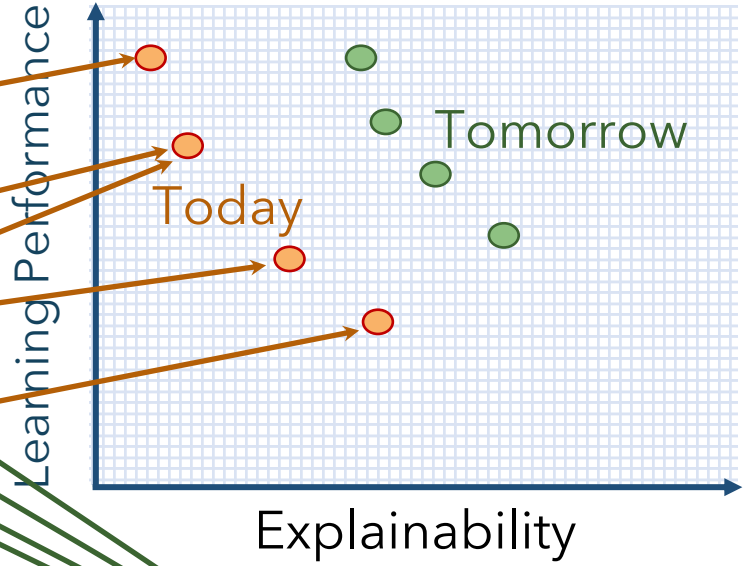
# Developing an Explainable Model

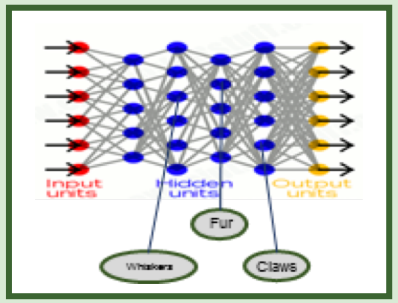
## XAI Goal

Create a suite of machine learning techniques that produce more explainable models, while maintaining a high level of learning performance

## Learning Techniques (today)

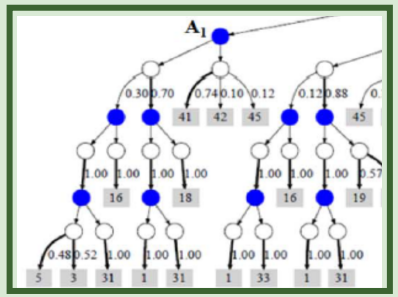


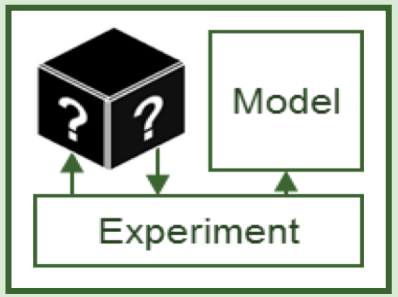

### Deep Explanation

Modified deep learning techniques to learn explainable features



### Interpretable Models

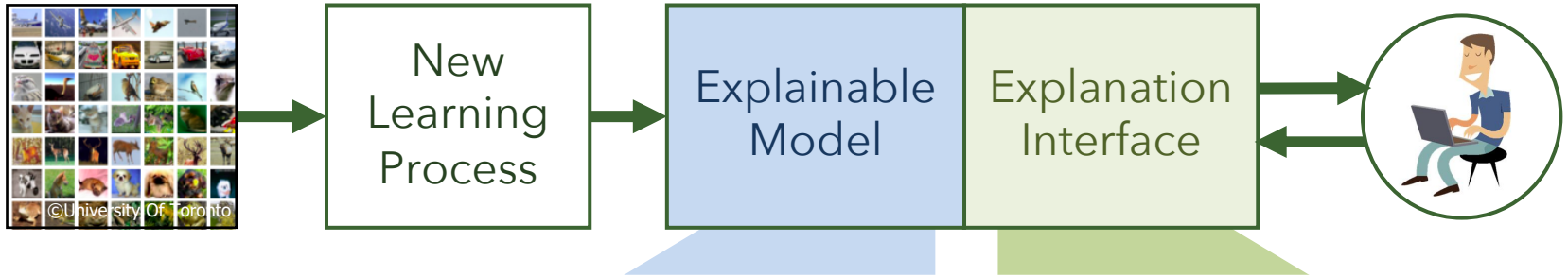
Techniques to learn more structured, interpretable, causal models



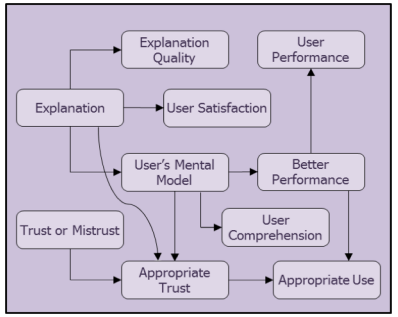

### Model Induction

Techniques to infer an explainable model from any model as a black box

# XAI Developers and Technical Approaches



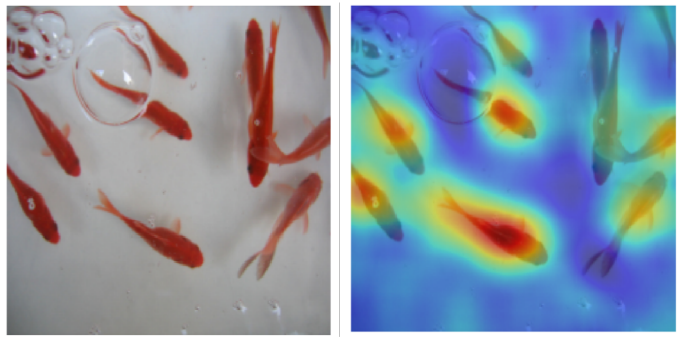

| CP | Performer | Explainable Model | Explanation Interface |
|---|---|---|---|
| Both | UC Berkeley | Deep Learning | Reflexive and Rational |
| | Charles River | Causal Modeling | Narrative Generation |
| | UCLA | Pattern Theory+ | 3-level Explanation |
| Autonomy | Oregon State | Adaptive Programs | Acceptance Testing |
| | PARC | Cognitive Modeling | Interactive Training |
| | CMU | Explainable RL (XRL) | XRL Interaction |
| Analytics | SRI International | Deep Learning | Show and Tell Explanation |
| | Raytheon BBN | Deep Learning | Argumentation and Pedagogy |
| | UT Dallas | Probabilistic Logic | Decision Diagrams |
| | Texas A&M | Mimic Learning | Interactive Visualization |
| | Rutgers | Model Induction | Bayesian Teaching |



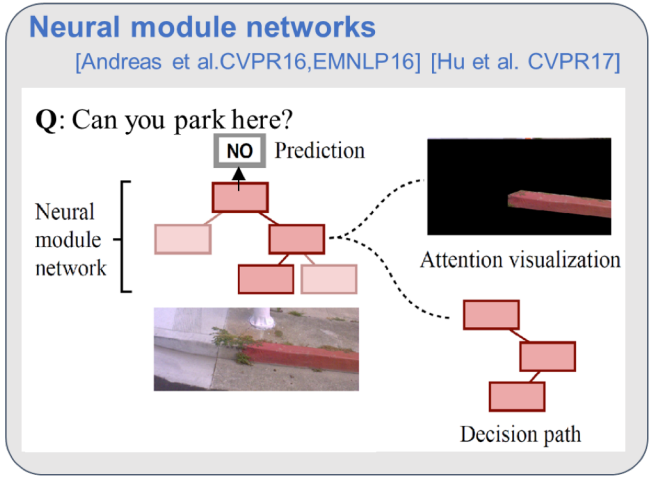

IHMC Psychological Models of Explanation

# Approaches to Deep Explanation

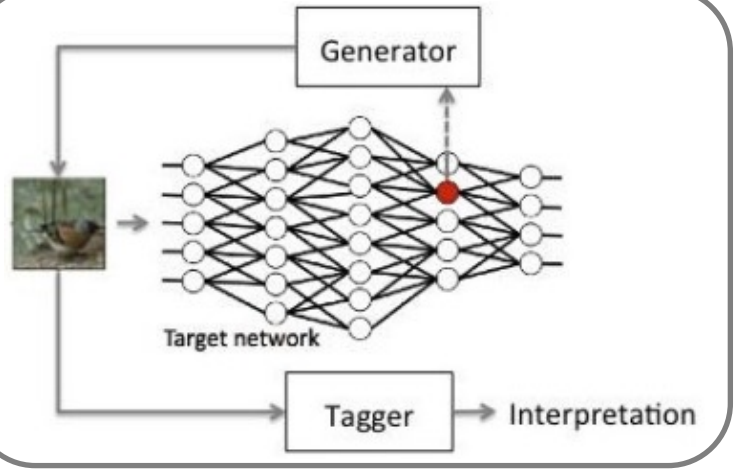
## Attention Mechanisms



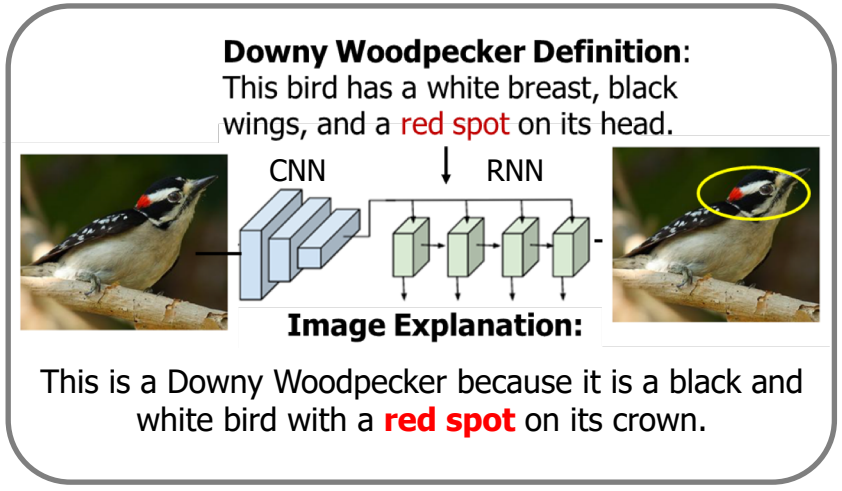

## Modular Networks




## Feature Identification




## Learn to Explain



# Deeply Explainable Artificial Intelligence

## UC Berkeley, Boston U., U. Amsterdam, Kitware

### Explainable Model

**Deep Learning**

- Post-hoc explanations by training additional DL models
- Explicit introspective explanations (Neural Module Networks)
- Reinforcement Learning
  - Informative rollouts
  - Explicit modular agent

### Explanation Interface

**Reflexive and Rational**

- Reflexive explanations (arise from the model)
- Rational explanations (come from reasoning about user's beliefs)
- Evaluation criteria
  - Human interpretability
  - Predictive behavior
  - Appropriate trust

### Challenge Problem

**Autonomy**

- Vehicle control (BDD-X, CARLA)
- Strategy games (StarCraft II)

**Data Analytics**

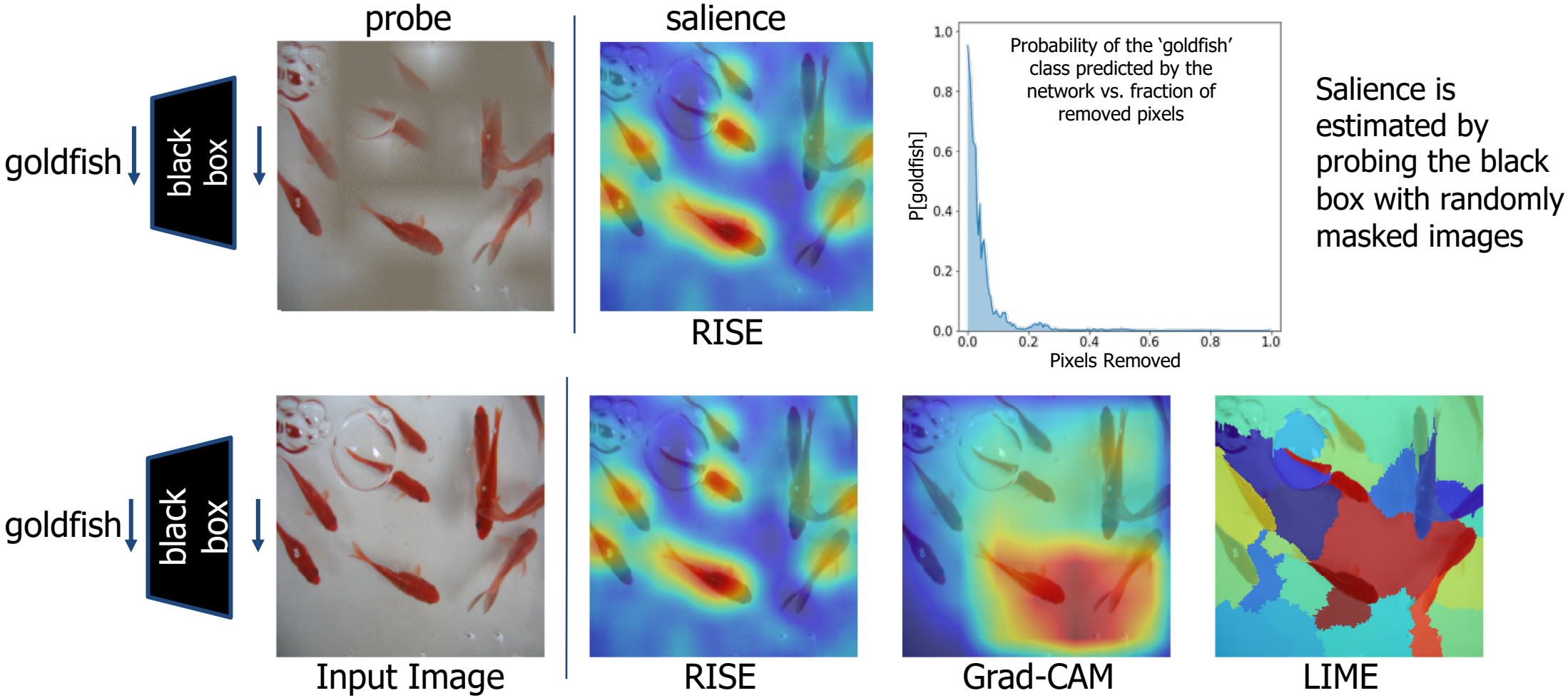
- Visual QA and filtering tasks (VQA-X, ACT-X, xView, DiDeMo, etc.)

- **PI**: Trevor Darrell (UC Berkeley)

- Pieter Abbeel (UC Berkeley)
- Tom Griffiths (UC Berkeley)
- Kate Saenko (Boston U.)
- Zeynep Akata (U. Amsterdam)
- Dan Klein (UC Berkeley)
- John Canny (UC Berkeley)
- Anca Dragan (UC Berkeley)
- Anthony Hoogs (Kitware)

# High Fidelity Visual Salience Model

## UC Berkeley, Boston U., U. Amsterdam, Kitware




Salience is estimated by probing the black box with randomly masked images

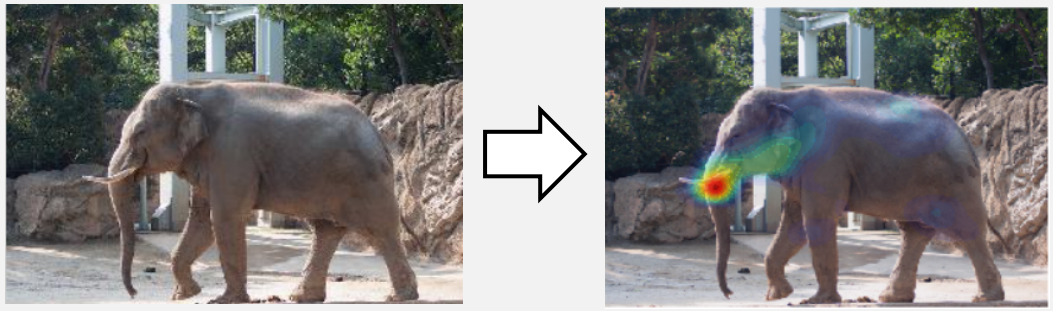
Petsiuk, Das and Saenko. RISE: Randomized Input Sampling for Explanation of Black-box Models, 2018

# Textual justification with grounding and pragmatics

## Given the multi-modal explanation generated by the model, do you think the system will answer correctly?

Question: *Does this elephant have tusks?*

*"because there are no bones sticking out from its mouth"*



Yes No

Incorrect! The system answered *"no"* when the ground-truth answer is *"yes"*

Question: *Is this a professional sporting event?*

*"because the players are wearing official jerseys"*

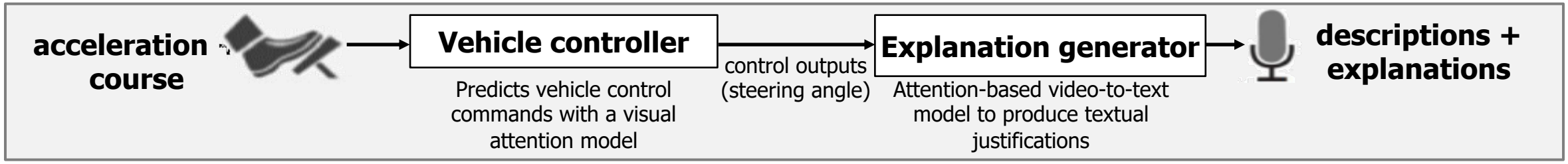
Yes No

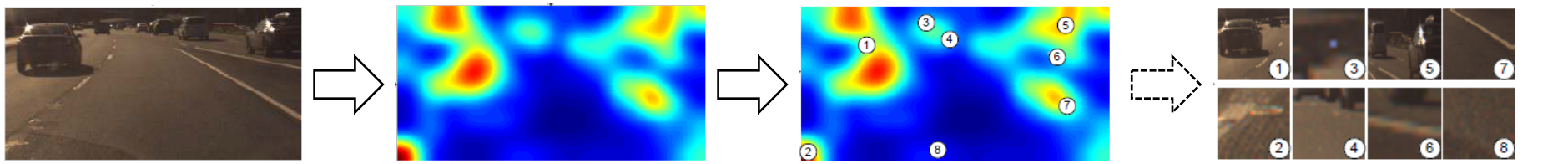
Correct! The system answered *"yes"* when the ground-truth answer is *"yes"*

| **Explanation Effectiveness** | Attention for Explanation Used? | Accuracy of Users Judgement |
|---|---|---|
| **Without explanation (existing SOTA)** | No | 57.5% |
| **UCB Model on descriptions** | Yes | 66.5% |
| **UCB Model without attention** | No | 61.5% |
| **UCB Model** | Yes | **70.0%** |

Dong Huk Park, Lisa Anne Hendricks, Zeynep Akata, Anna Rohrbach, Bernt Schiele, Trevor Darrell, and Marcus Rohrbach. Multimodal Explanations: Justifying Decisions and Pointing to the Evidence, 2018

# Causal Grounded Driving



**Input image stream** | **Attention heat map** | **Clustering analysis** | **Visual saliency detection and causality check**

*Kim and Canny, in ICCV, 2017*
*Kim, Rohrbach, Darrell, Canny, and Akata, in NIPS Interpretable ML Symposium, 2017*

# CAMEL: Causal Models to Explain Learning

## Charles River Analytics (CRA), U. Mass, Brown

### Explainable Model

**Causal Modeling**

- Experiment with the learned model (as a grey box) to learn an explainable, causal, probabilistic programming model

### Explanation Interface

**Narrative Generation**

- Interactive visualization based on the generation of temporal, spatial narratives from the causal, probabilistic models

### Challenge Problem

**Autonomy**

- Atari
- Starcraft

**Data Analytics**

- Pedestrian Detection (INRIA)
- Activity Recognition (ActivityNet)

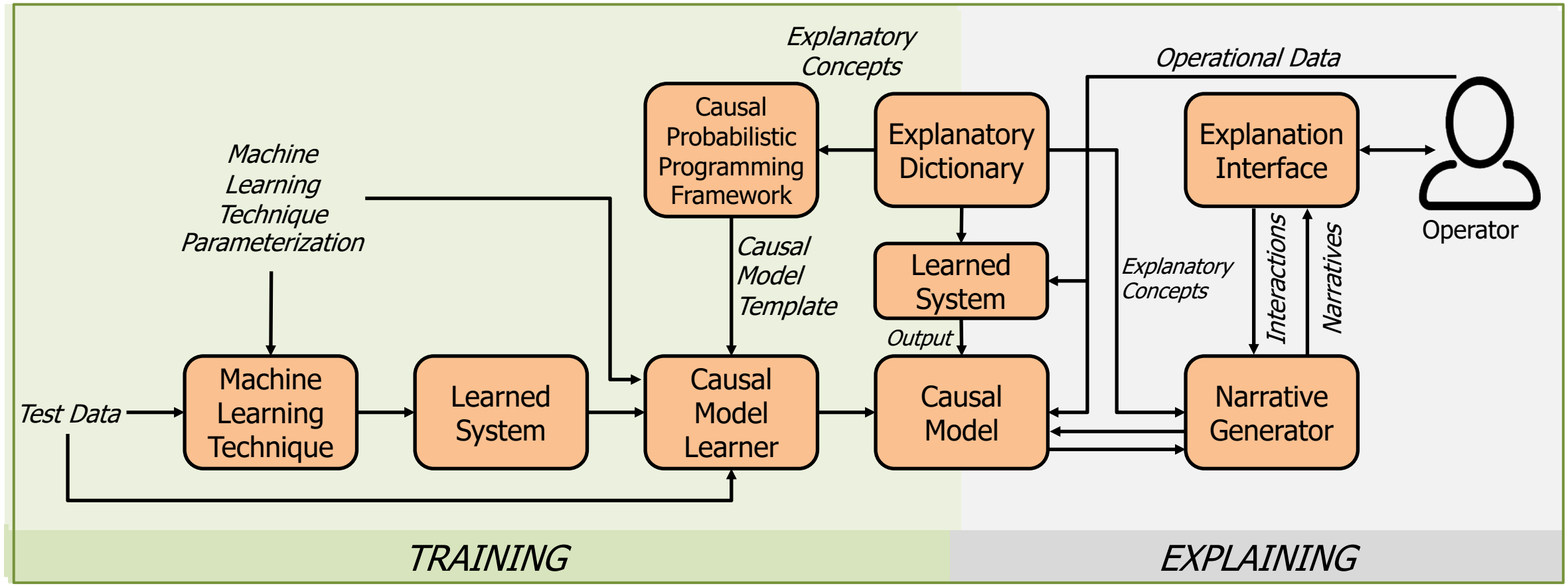
- **PI**: James Tittle (CRA)

- Jeff Druce (CRA)
- Avi Pfeffer (CRA)
- David Jensen (U. Mass)
- Michael Littman (Brown U.)
- James Niehaus (CRA)
- Emilie Roth (Roth Cognitive Engineering)
- Joe Gorman(CRA)
- James Tittle (CRA)

# Causal Models to Explain Learning (CAMEL)

## Charles River Analytics, U. Mass, Brown

Generate causal explanations of ML operation and present them to the user as intuitive narratives in an interactive, easy-to-use interface grounded in cognitive engineering theories



# Learning and Communicating Explainable Representations

## UCLA, Oregon State, Michigan State

### Explainable Model

**Pattern Theory+**

Interpretable representations
- STC-AOG: spatial, temporal, and causal models
- STC-PG: scene and event interpretations in analytics
- STC-PG$^{+}$: task plans in autonomy

Theory of mind representations
- User's beliefs
- User's mental model of agent

### Explanation Interface

**3-Level Explanation**
- Concept compositions
- Causal and counterfactual reasoning
- Utility explanations

Explanation representations:
- X-AOG: explanation model
- X-PG: explanatory parse graph as dialogue
- X-Utility: priority and loss for explanations

### Challenge Problem

**Autonomy**
- Robot executing daily tasks in physics-realistic VR platform
- Autonomous vehicle driving (GTA5 game engine)

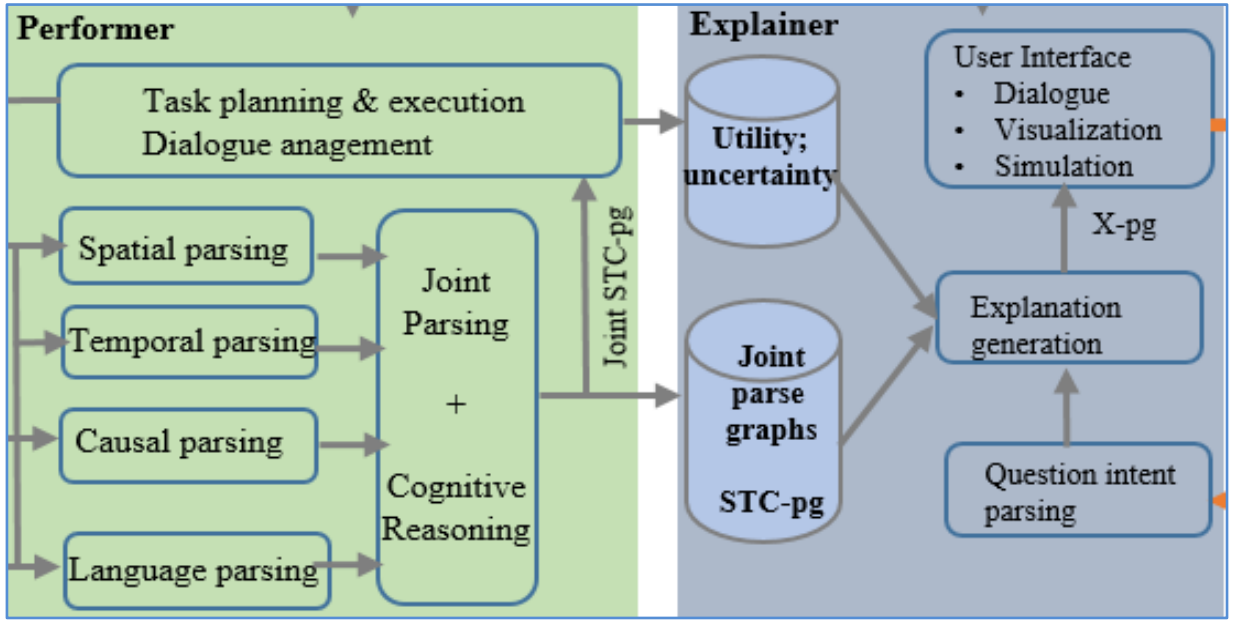
**Data Analytics**
- Network of video cameras for scene understanding and event analysis

- **PI**: Song-Chun Zhu (UCLA)

- Ying Nian Wu (UCLA)
- Sinisa Todorovic (OSU)
- Joyce Chai (Michigan State)

## UCLA, Oregon State, Michigan State

### System Architecture



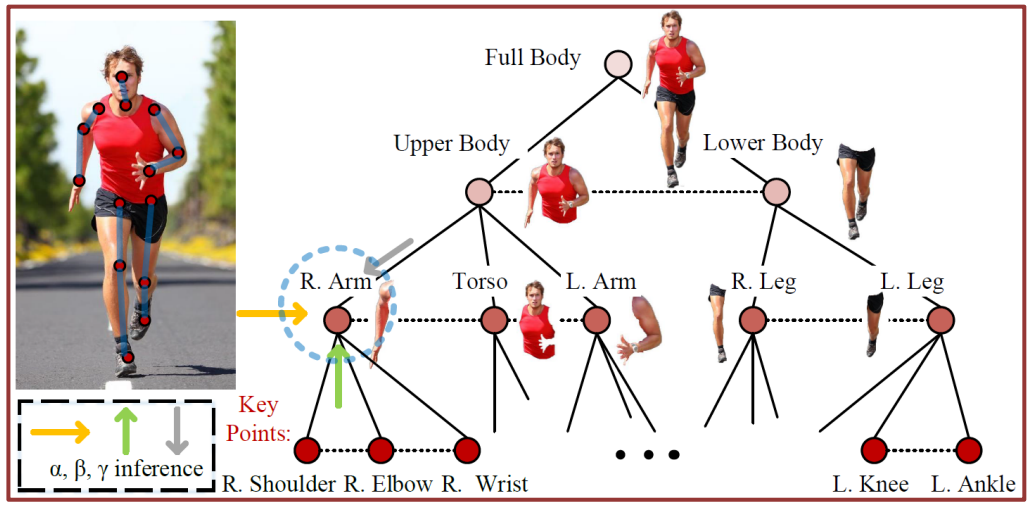

**Performer**

Outputs interpretable representations in a spatial, temporal, and causal parse graph (STC-PG)

**Explainer**

Outputs an explanatory parse graph (X-PG) in a dialogue process

### STC Parse Graph




An attributed parse graph for a running person. Each node has 3 computing channels:

- $\alpha$: grounding the node on DNN features;
- $\beta$: bottom-up;
- $\gamma$: top-down.

An explanation is represented as parse graph X-pg

# xACT: Explanation-Informed Acceptance Testing of Deep Adaptive Programs

## Oregon State University

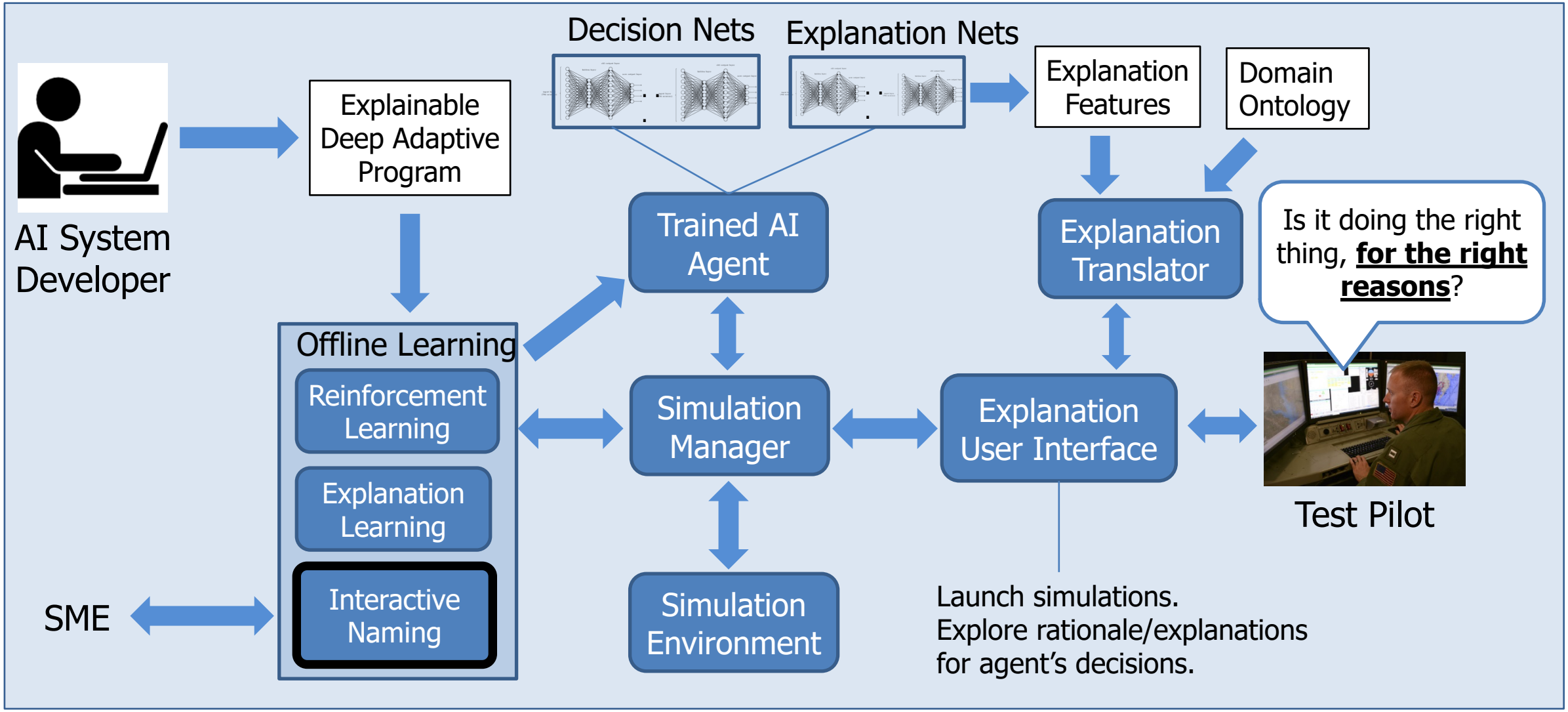
| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Adaptive Programs**<br>• Explainable Deep Adaptive Programs (xDAPs) – a new combination of Adaptive Programs, Deep Learning, and explainability | **Acceptance Testing**<br>• Provides a visual and Natural Language explanation interface for acceptance testing by test pilots based on Information Foraging Theory | **Autonomy**<br>• Real-time Strategy Games based on custom designed game engine designed to support explanation<br>• Starcraft II |

- **PI**: Alan Fern (OSU)

- Tom Dietterich (OSU)
- Fuxin Li (OSU)
- Prasad Tadepalli (OSU)
- Weng-Keen Wong (OSU)
- Margaret Burnett (OSU)
- Martin Erwig (OSU)
- Liang Huang (OSU)

# xACT: Explanation-Informed Acceptance Testing of Deep Adaptive Programs

## Oregon State University



# COGLE: Common Ground Learning and Explanation

**PARC, CMU, U. Edinburgh, U. Michigan, USMA, IHMC**

| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Cognitive Model**<br>3-layer architecture<br>• Learning Layer (DNNs)<br>• Cognitive Layer (ACT-R Cognitive Model)<br>• Explanation Layer (HCI) | **Interactive Training**<br>• Interactive visualization of states, actions, policies, and values<br>• Module for test pilots to refine and train the system | **Autonomy**<br>• MAVSim wrapper over ArduPilot simulation environment<br>• Value of Explanation framework for measuring explanation effectiveness |

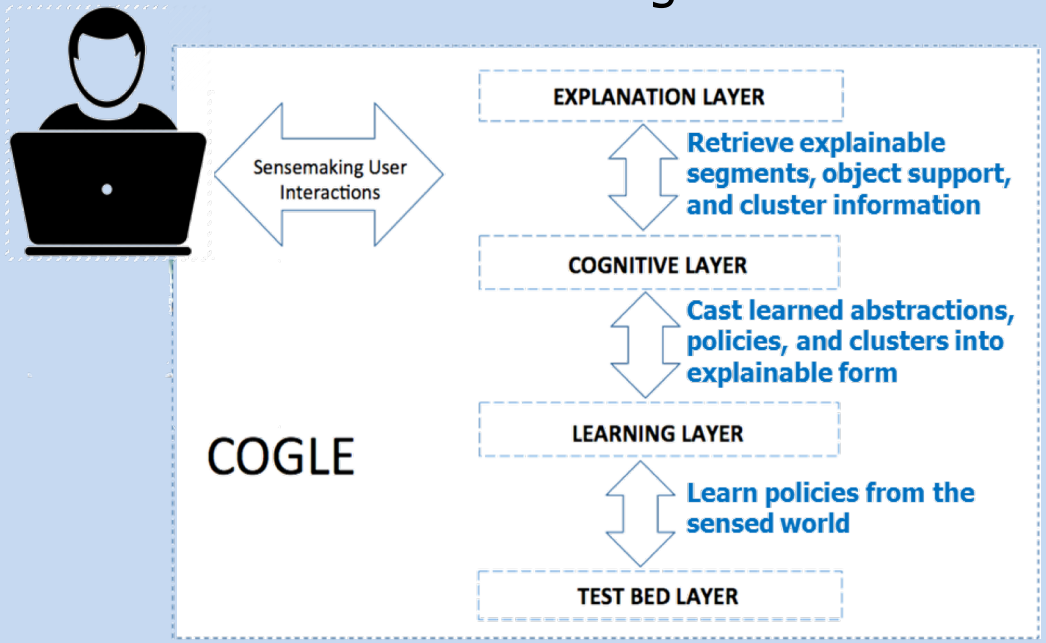
- **PI**: Mark Stefik (PARC)

- Honglak Lee (U. Michigan)
- Subramanian Ramamoorthy (U. Edinburgh)
- Christian Lebiere (CMU)
- John Anderson (CMU)
- Robert Thomson (USMA)
- Michael Youngblood (PARC)

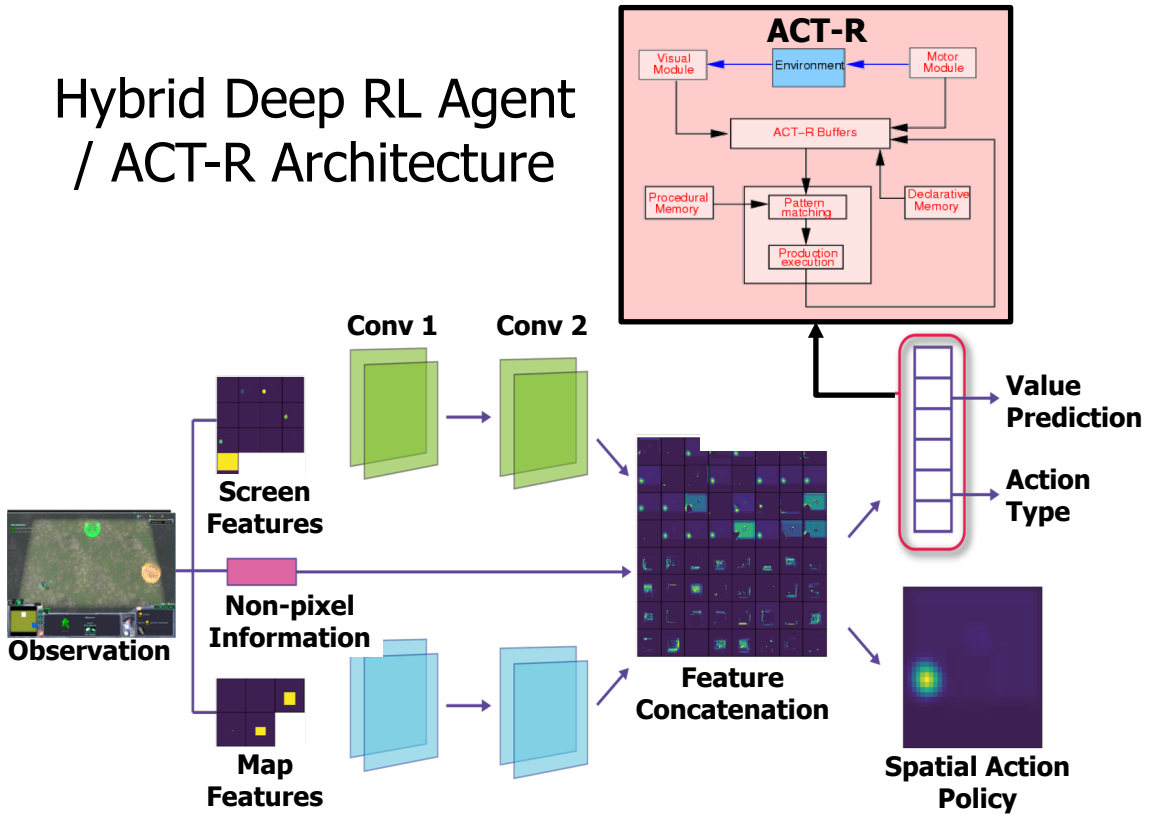
# COGLE: Common Ground Learning and Explanation

## PARC, CMU, U. Edinburgh, U. Michigan, USMA, IHMC

### Layered Cognitive Architecture to Partition Explanation And Learning




### Hybrid Deep RL Agent / ACT-R Architecture



# XRL: Explainable Reinforcement Learning

## Carnegie Mellon University

| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Explainable RL (XRL)**<br>• Create a new scientific discipline for Explainable Reinforcement Learning with work on new algorithms and representations | **XRL Interaction**<br>• Interactive explanations of dynamic systems<br>• Human-machine interaction to improve performance | **Autonomy**<br>• Open AI Gym<br>• Autonomy in the electrical grid<br>• Mobile service robots<br>• Self-improving educational software |

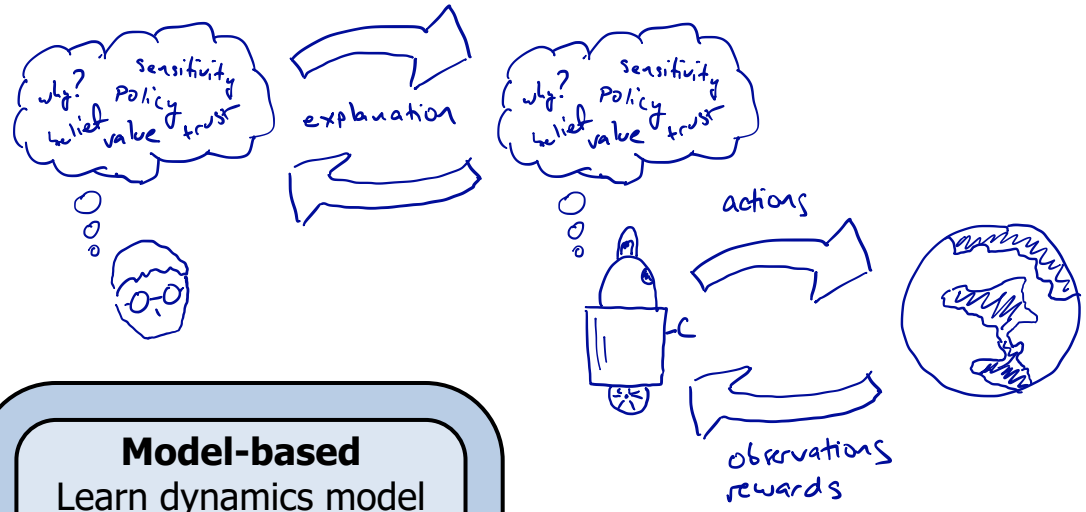
- **PI**: Zico Kolter (CMU)

- Geoff Gordon (CMU)
- Pradeep Ravikumar (CMU)

# XRL: Explainable Reinforcement Learning

## Carnegie Mellon University

Create a new discipline of explainable RL to enable dynamic human-machine interaction and adaptation for maximum team performance

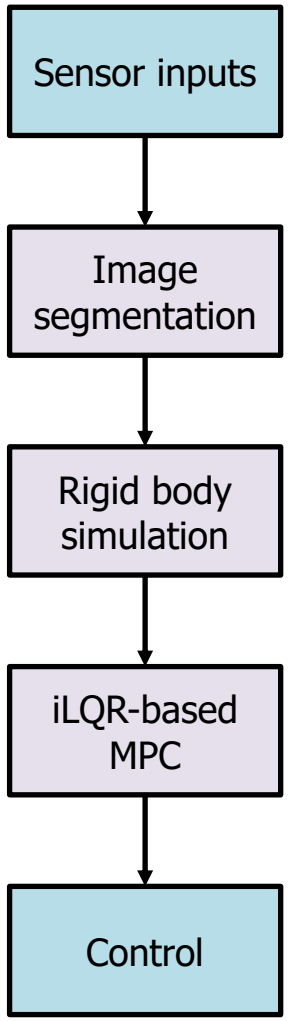



**Model-based**
Learn dynamics model of environment, plan actions in model, and execute in real system

→ Improve model learning/ creation for RL agents to capture benefits of model-based approach

**Model-free**
Directly learn value and/or policy for the environment

→ For any type of RL approach, provide an explanation of why an agent acted in a certain way




**Differentiable Physics -** Applies implicit differentiation to solutions of LCP to analytically derive a backpropagation update of next state with respect to previous state, control, and model parameters

# DARE: Deep Attention-based Representations for Explanation

## SRI International, U. Toronto, UCSD, U. Guelph

### Explainable Model

**Deep Learning**

Multiple deep learning techniques
- Attention-based mechanisms
- Compositional NMNs
- GANs

### Explanation Interface

**Show & Tell Explanation**
- DNN visualization
- Query evidence that explains DNN decisions
- Generate natural language justifications

### Challenge Problem

**Data Analytics**
- VQA
  - Visual Gnome
  - Flickr30
- MovieQA

- **PIs**: Giedrius Burachas (SRI), Mohamed Amer (SRI)

- Xiao Lin (SRI)
- Ryan Villamil (SRI)
- Dejan Jovanovic (SRI)
- Avi Ziskind (SRI)
- Michael Wessel (SRI)

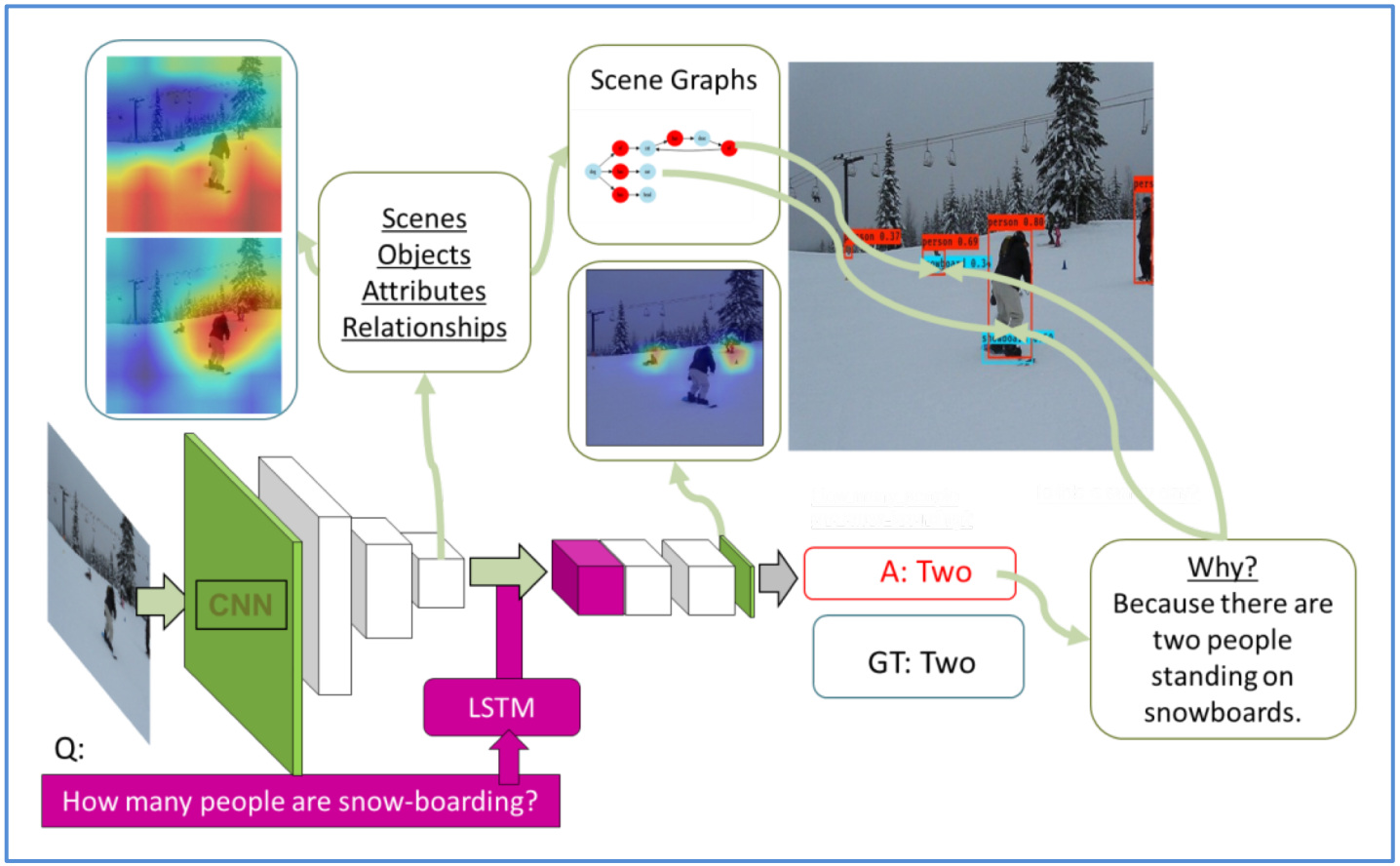
Richard R. Zemel (U. Toronto)
Sanja Fidler (U. Toronto)
David Duvenaud (U. Toronto)
Graham Taylor (U. Guelph)

- Jürgen Schulze (UCSD)

# DARE: Deep Attention-based Representations for Explanation

## SRI International, U. Toronto, UCSD, U. Guelph

Interpretable, Scene Graph-based VQA System with Active Attention




- Generate "show-and-tell" explanations with justifications of decisions accompanied by visualizations of input data used to generate inferences
- Scene and Situation Graphs, inferred from images and videos, support rich multimodal data analytics and explanations
- Scene Graphs guide attentional scanning for interpretable analytics

# EQUAS: Explainable QUestion Answering System

## Raytheon BBN, Georgia Tech, UT Austin, MIT

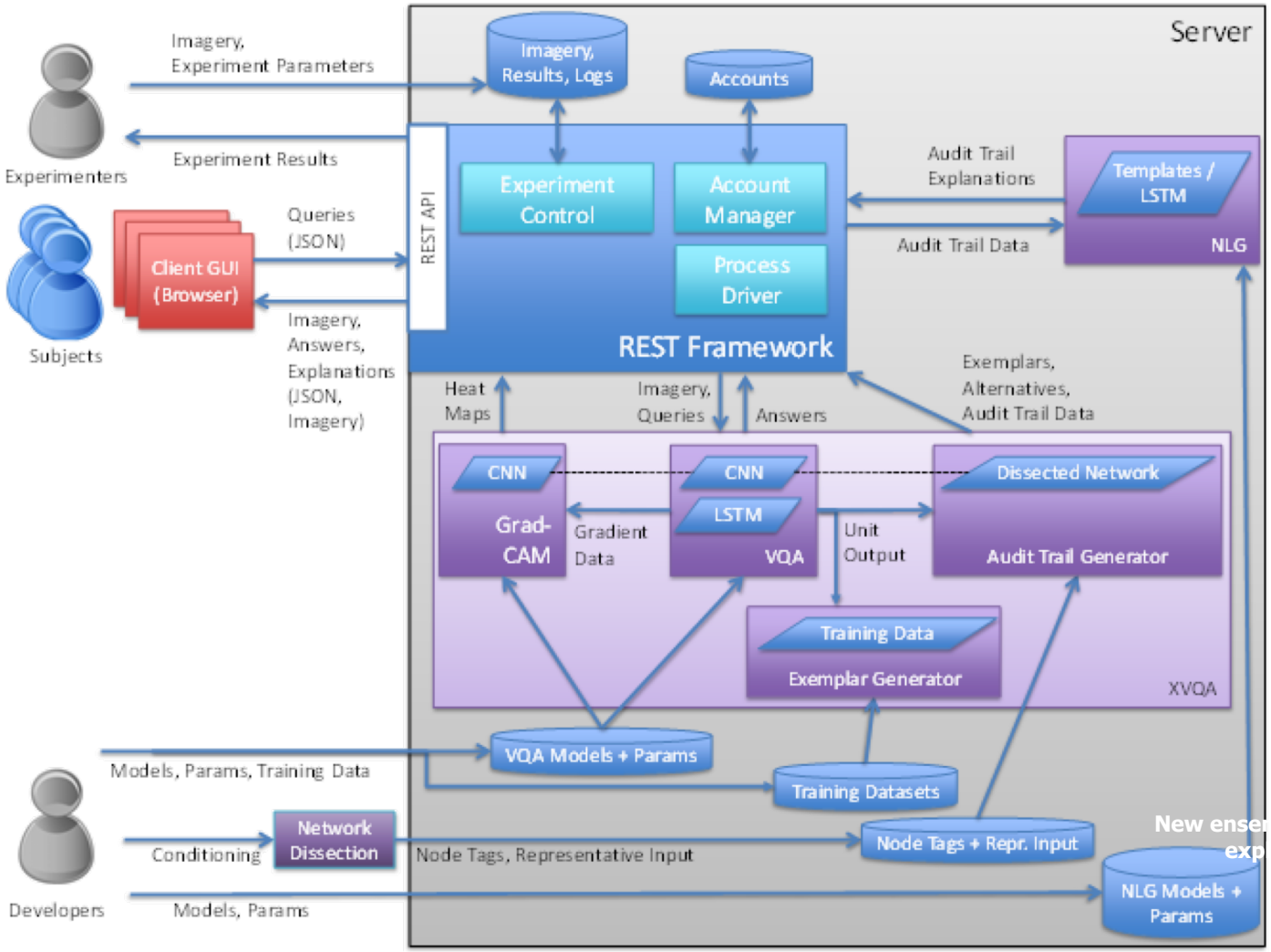
| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Deep Learning**<br>• Semantic labelling of DNN neurons<br>• DNN audit trail construction<br>• Gradient-weighted Class Activation Mapping | **Argumentation Theory**<br>• Comprehensive strategy based on argumentation theory<br>• NL generation<br>• DNN visualization | **Data Analytics**<br>• VQA for images and video |

- **PI**: William Ferguson (Raytheon BBN)

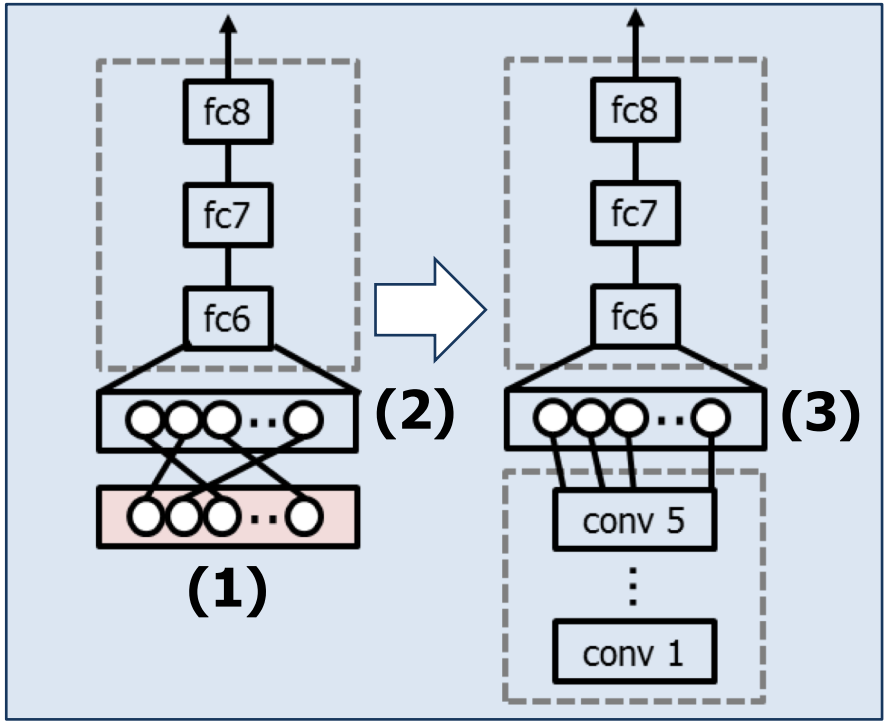
- Antonio Torralba (MIT)
- Ray Mooney (UT Austin)
- Devi Parikh (Georgia Tech)
- Dhruv Batra (Georgia Tech)

# EQUAS: Explainable QUestion Answering System

## Raytheon BBN, Georgia Tech, UT Austin, MIT




Improve the interpretability of units using a **new conditioning method** to retrain the network to intentionally include *concept detectors*




1) **Pick units from standard vocabulary**
2) **Train top part of net**
3) **Use top to train bottom**

# Tractable Probabilistic Logic Models

## UT Dallas, UCLA, Texas A&M, Indian Institute of Technology

| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Probabilistic Logic**<br>• Tractable Probabilistic Logic Models (TPLMs) – an important class of (non-deep learning) interpretable models | **Decision Diagrams**<br>• Enables users to explore and correct the underlying model as well as add background knowledge | **Data Analytics**<br>• Infer activities in multimodal data (video and text)<br>• Wetlab (biology) and TACoS (cooking) datasets |

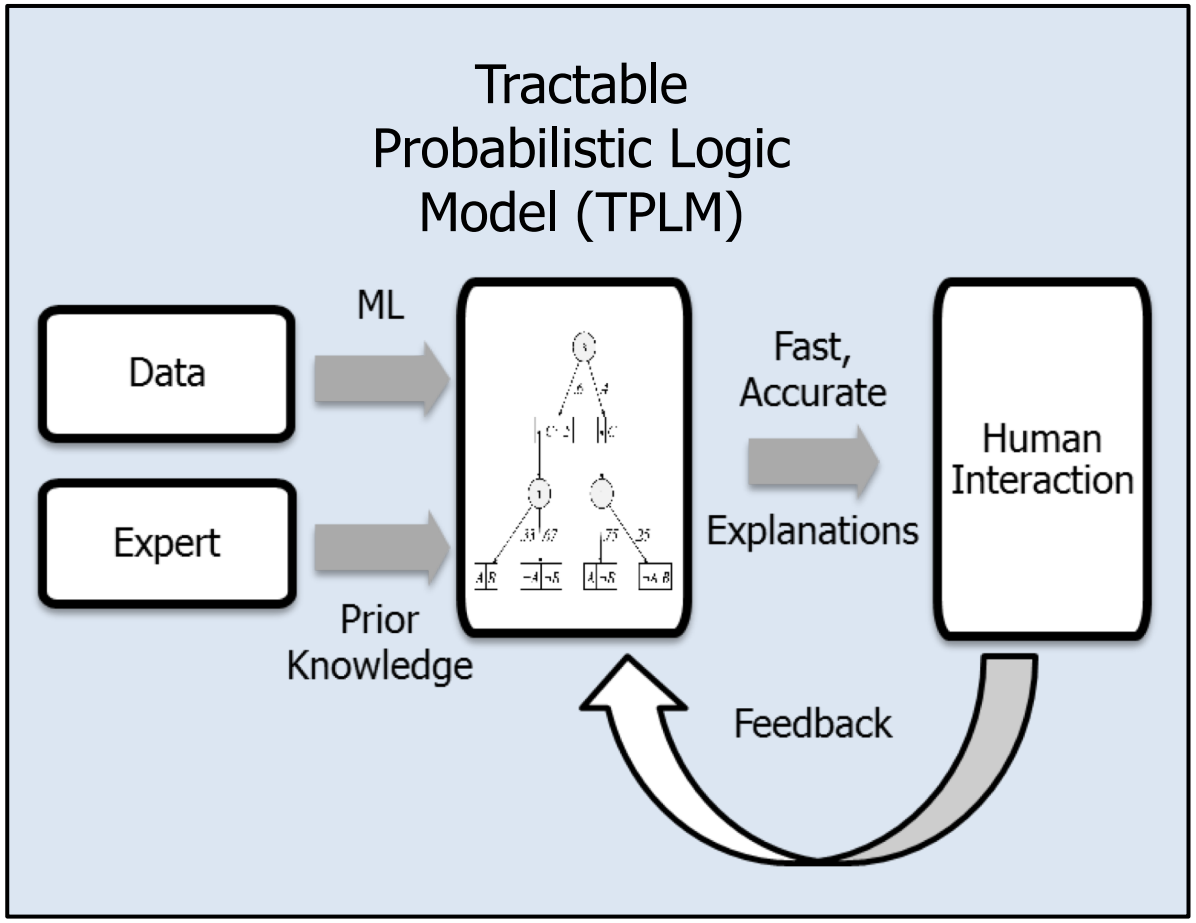
- **PI**: Vibhav Gogate (UT Dallas)

- Adnan Darwiche (UCLA)
- Guy Van Den Broeck (UCLA)
- Nicholas Ruozzi (UT Dallas)
- Eric Ragan (Texas A&M)
- Parag Singla (IIT-Delhi)

# Tractable Probabilistic Logic Models

## UT Dallas, UCLA, Texas A&M, Indian Institute of Technology

Use interpretable and tractable models based on well-founded principles from logic and probability theory




**Find all videos in which a person peels oranges**
(explanations are captions generated by TPLMs)

Person using his hands to peel oranges. I can see the orange skin

Person using his hands. I can see the orange skin and skinless orange

Person using his hands to peel oranges. I can see the orange skin on the table and peeled oranges

# Transforming Deep Learning to Harness the Interpretability of Shallow Models

## Texas A&M, Washington State

| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Mimic Learning**<br>• Mimic learning framework combines DL models for prediction and shallow models for explanations<br>• Interpretable learning algorithms extract knowledge from DNNs for relevant explanations | **Interactive Visualization**<br>• Interactive visualization over multiple views, using heat maps and topic modeling clusters to show predictive features | **Data Analytics**<br>• Multiple tasks using data from Twitter, Facebook, ImageNet, and news websites |

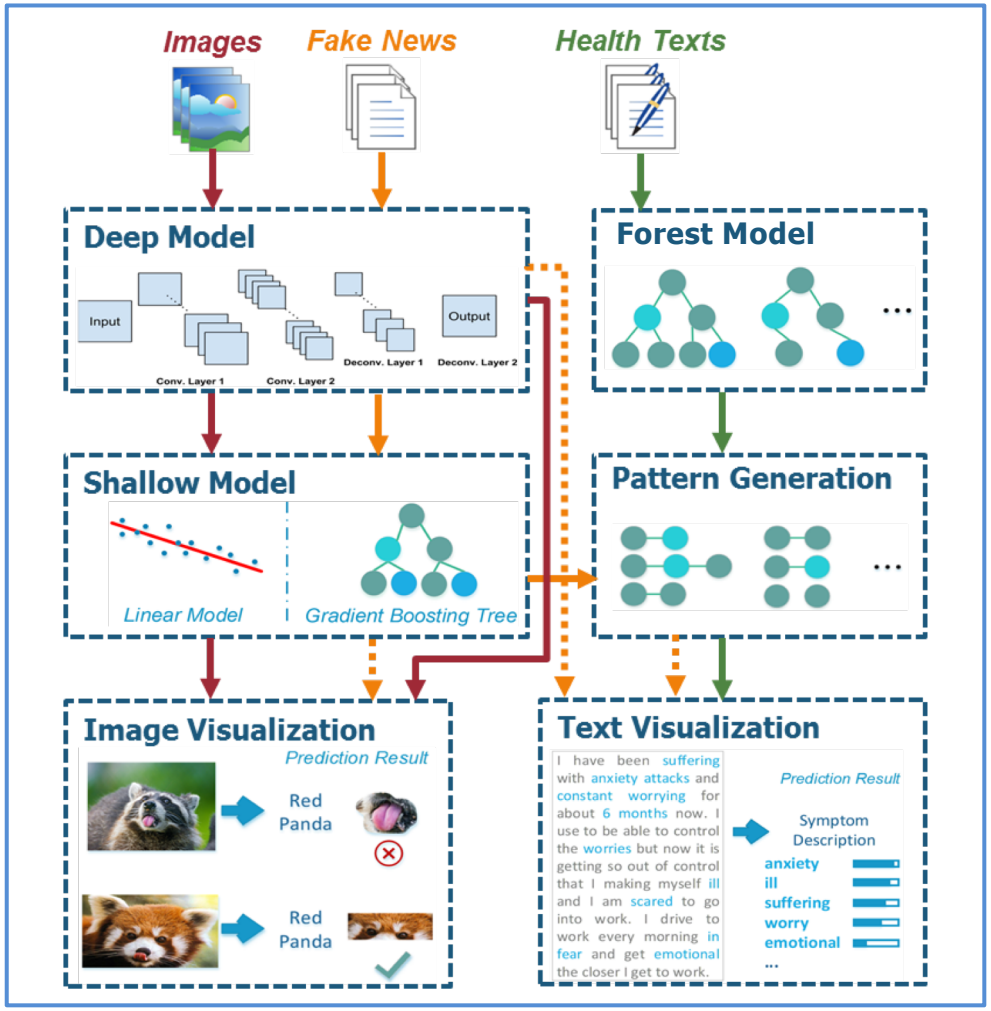
- **PI**: Xia Hu (Texas A&M)

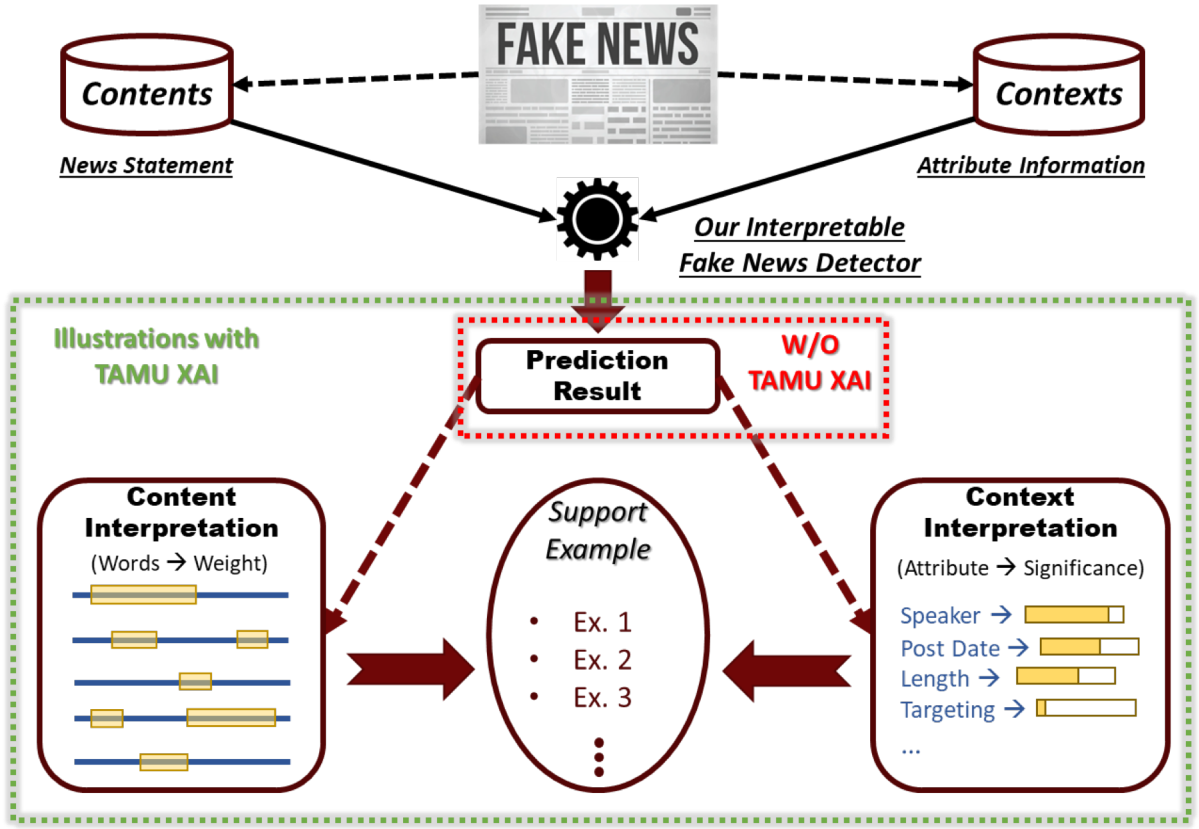
- Shuiwang Ji (Wash. State)
- Eric Ragan (Texas A&M)

# Transforming Deep Learning to Harness the Interpretability of Shallow Models

## Texas A&M, Washington State

Develop an end-to-end interpretable deep learning infrastructure with image and text datasets



# Model Explanation by Optimal Selection of Teaching Examples

## Rutgers University

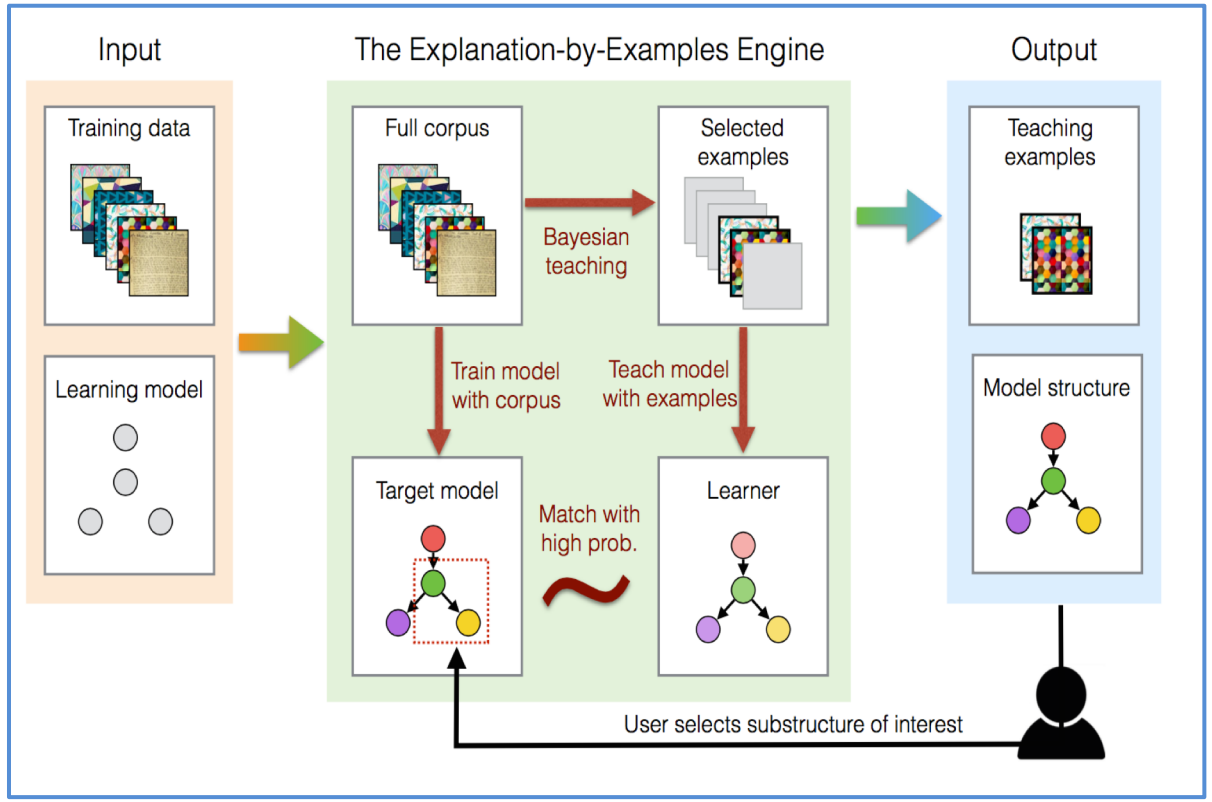
| Explainable Model | Explanation Interface | Challenge Problem |
|---|---|---|
| **Model Induction**<br>• Select the optimal training examples to explain model decisions based on Bayesian Teaching | **Bayesian Teaching**<br>• Example-based explanation of<br>  • Full model<br>  • User-selected sub-structure<br>  • User submitted examples | **Data Analytics**<br>• Image processing<br>• Text corpora<br>• VQA<br>• Movie events |

- **PI**: Patrick Shafto (Rutgers)
- Scott Cheng-Hsin Yang (Rutgers)

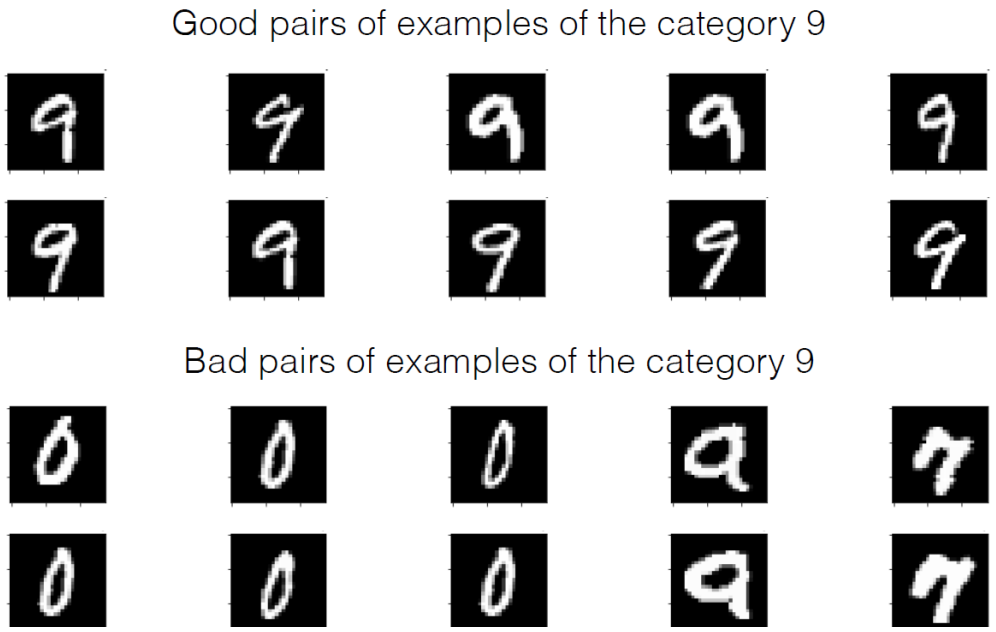
# Model Explanation by Optimal Selection of Examples

## Rutgers University

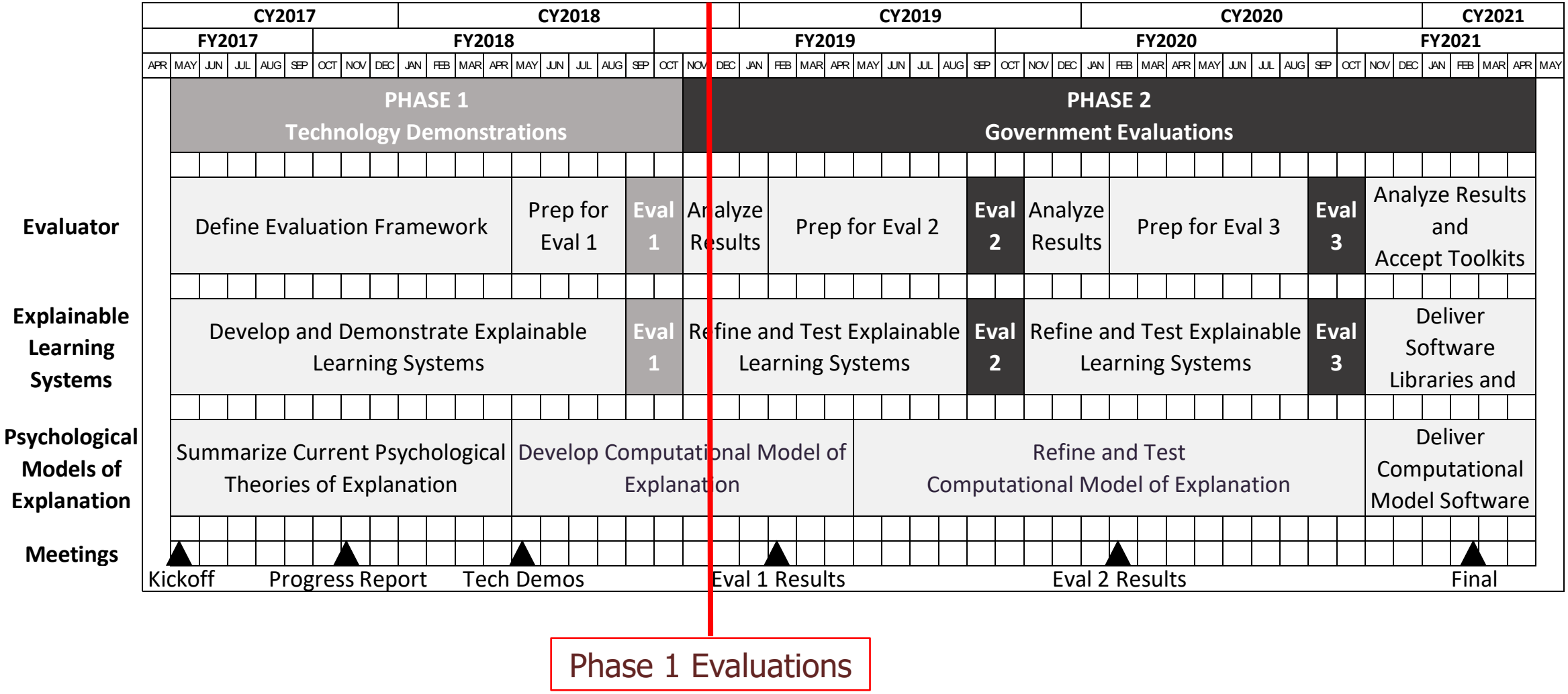
Extend Bayesian teaching to enable automatic explanation by selecting the subset of data that are most representative of the model's generative process




Good and bad examples for teaching a category (illustrates model strengths and weaknesses)

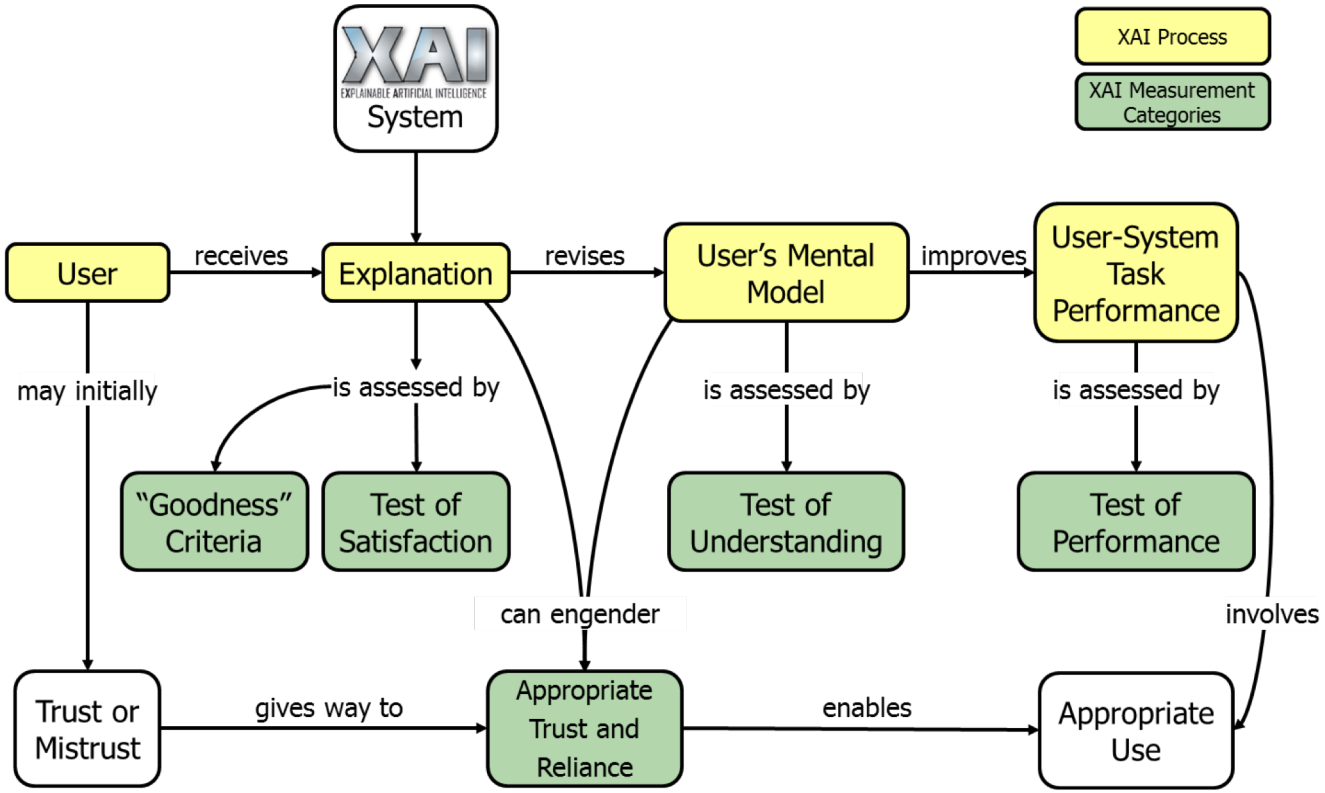


# XAI Program Schedule



# Evaluation Framework

## Explanation Process & Measures




## Experimental Conditions

***Without Explanation*** - The explainable learning system is used to perform a task without providing an explanation to the user

***With Explanation*** - The explainable learning system is used to perform a task and generates explanations for every recommendation or decision it makes, and every action it takes

***Partial Explanation*** - The explainable learning system is used to perform a task and generates only partial or ablated explanations (to assess various explanation features)

***Control*** - A baseline state-of-the-art non-explainable system is used to perform a task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