Conditions for Trustworthy AI:
Explainable Artificial Intelligence

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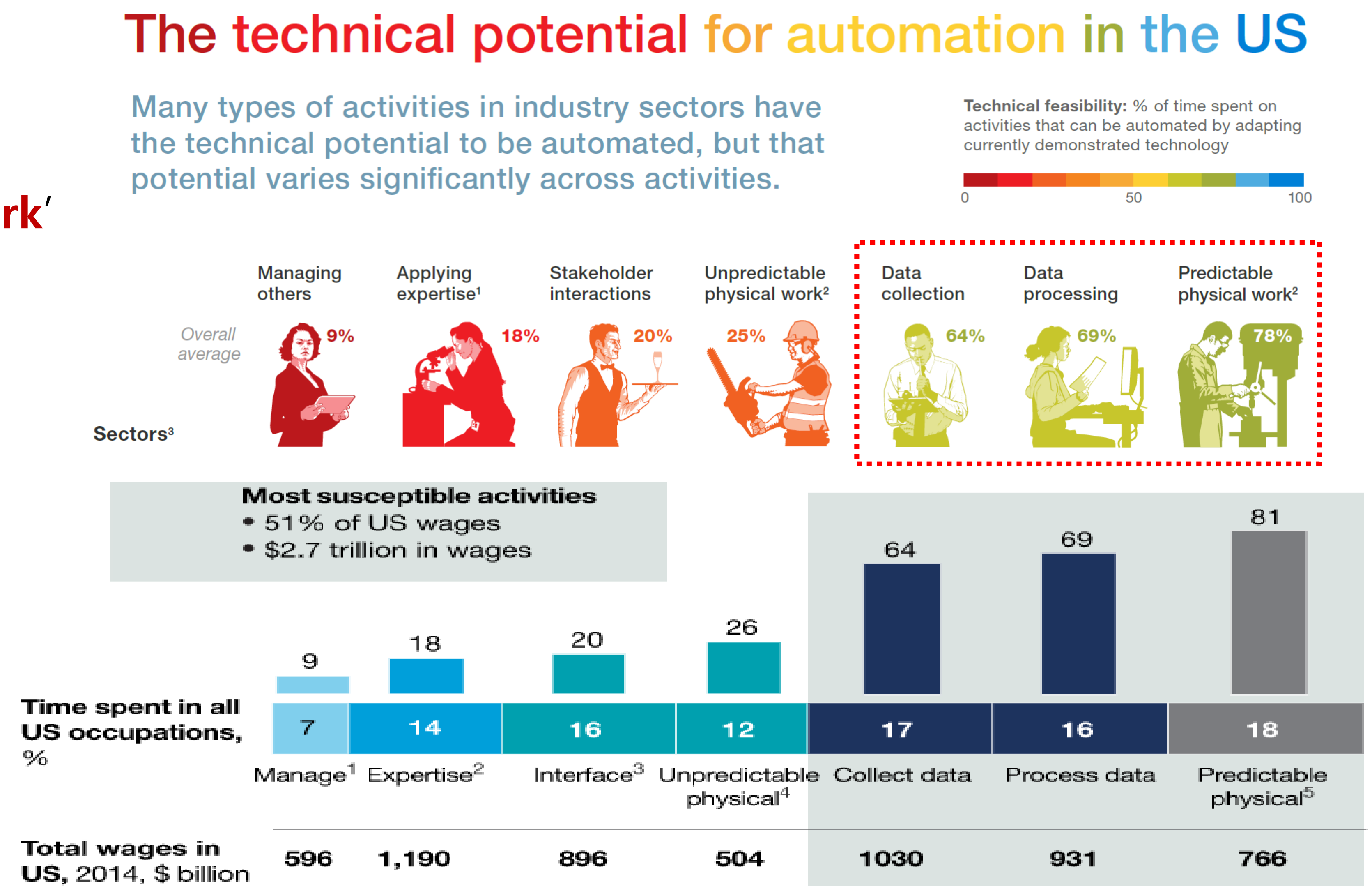
In 2025,
estimated economic impact of
‘**Automation of Knowledge work**’
may reach up to
6.7 trillion US dollar.

In US,
51% of US wages or
$2.7 trillion in wages
could be automated.



Automation of Knowledge Work [McKinsey 2013]

DARPA Grand Challenge 2005

Say Hello to Waymo 2016

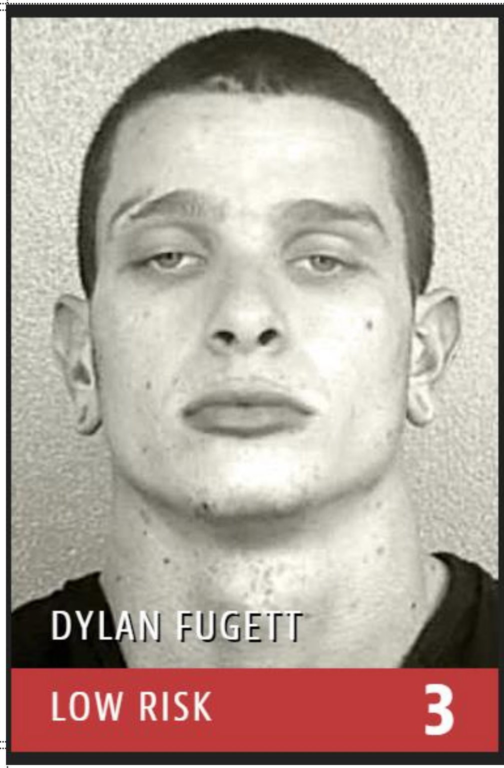
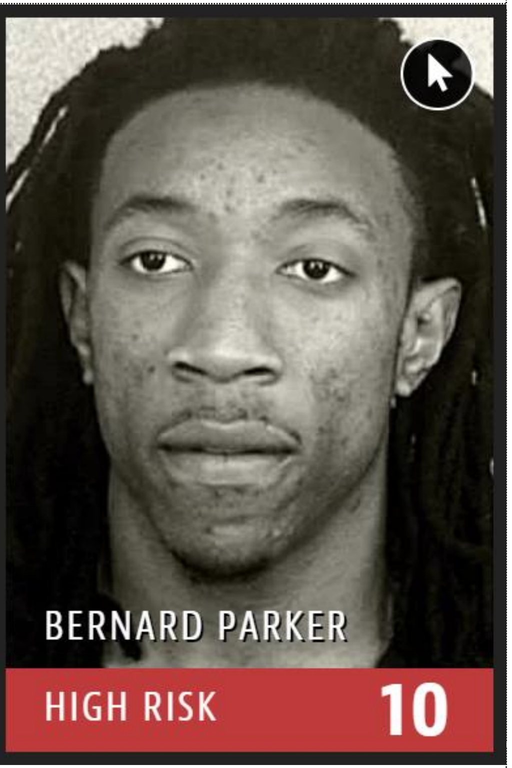
Uber's first car accident - [Death of Elaine Herzberg]

Many, complex AI systems are not transparent to see the mechanisms inside!

Uber's self-driving car killed a pedestrian (Marc 18th, 2018)
The 'safety driver' was watching a TV show (June 22th, 2018)

Do We Understand AI Systems Enough?

COMPAS: Prediction of Crime

<table>
<tr><td>Prior Offense</td><td>1 attempted burglary</td><td>1 resisting arrest without violence</td></tr>
<tr><td>COMPAS' decision</td><td>
</td><td>
</td></tr>
<tr><td>Subsequent Offenses</td><td>3 drug possessions</td><td>None</td></tr>
</table>

AI algorithms are exposed to

(1) data bias,
(2) model bias, and
(3) algorithmic bias

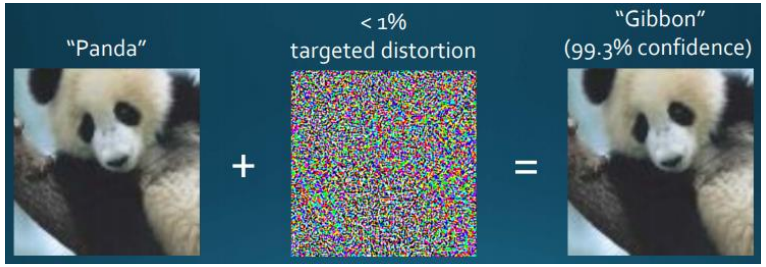
Do We Understand AI Systems Enough?

Article	Contents
13-14. **Right to explanation**	A data subject has the right to "**meaningful information about the logic involved**" when decision is made automatically.
EU administration	When violated **4% of global revenue** will be fined.
Enact	**May 28th, 2018**

EU General Data Protection Regulation (GDPR)

DESCRIBE	CATEGORIZE	EXPLAIN
Handcrafted Knowledge	*Statistical Learning*	*Contextual Adaptation*

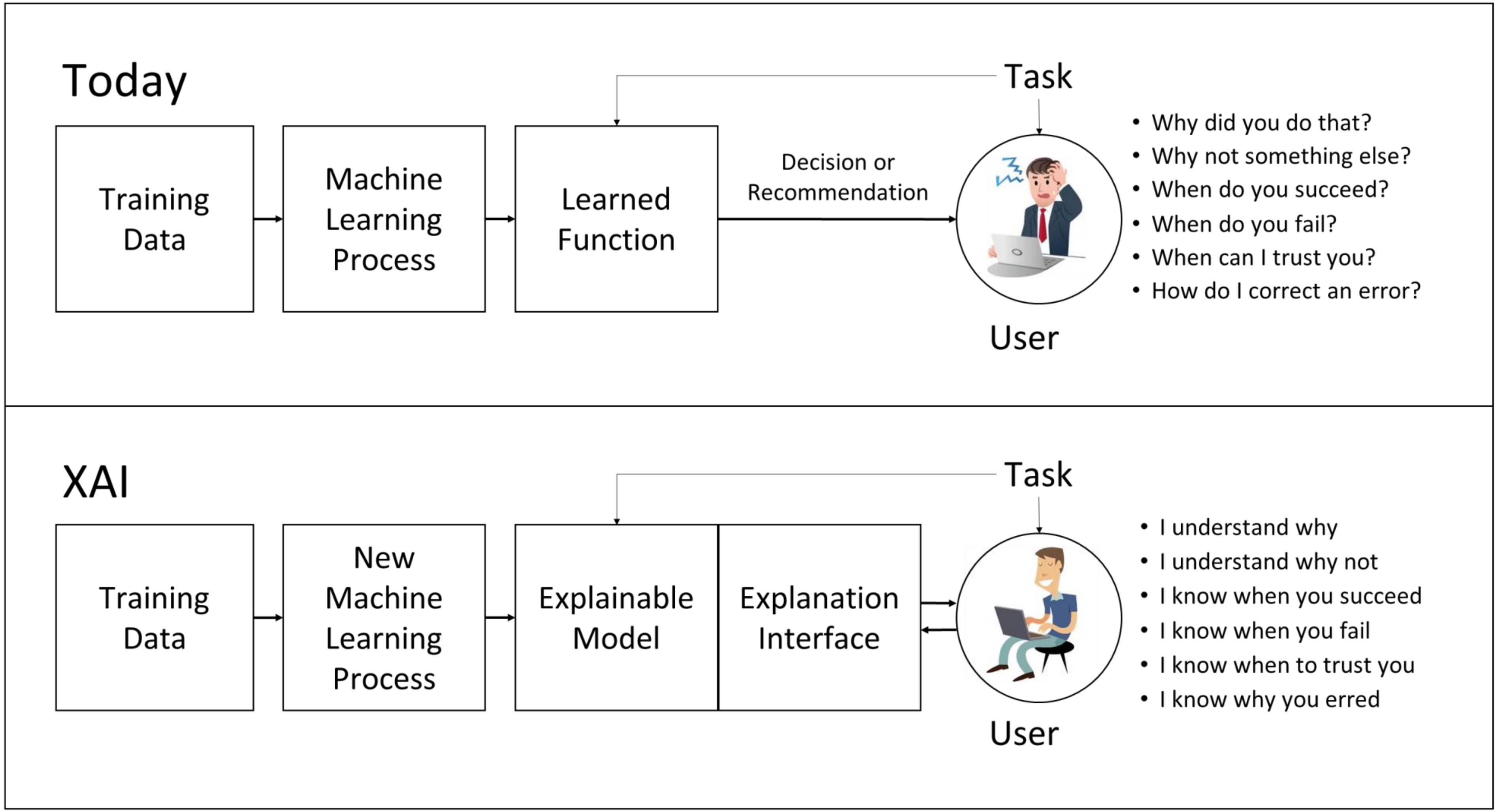
Statistically impressive, but individually unreliable



Inherent flaws can be exploited

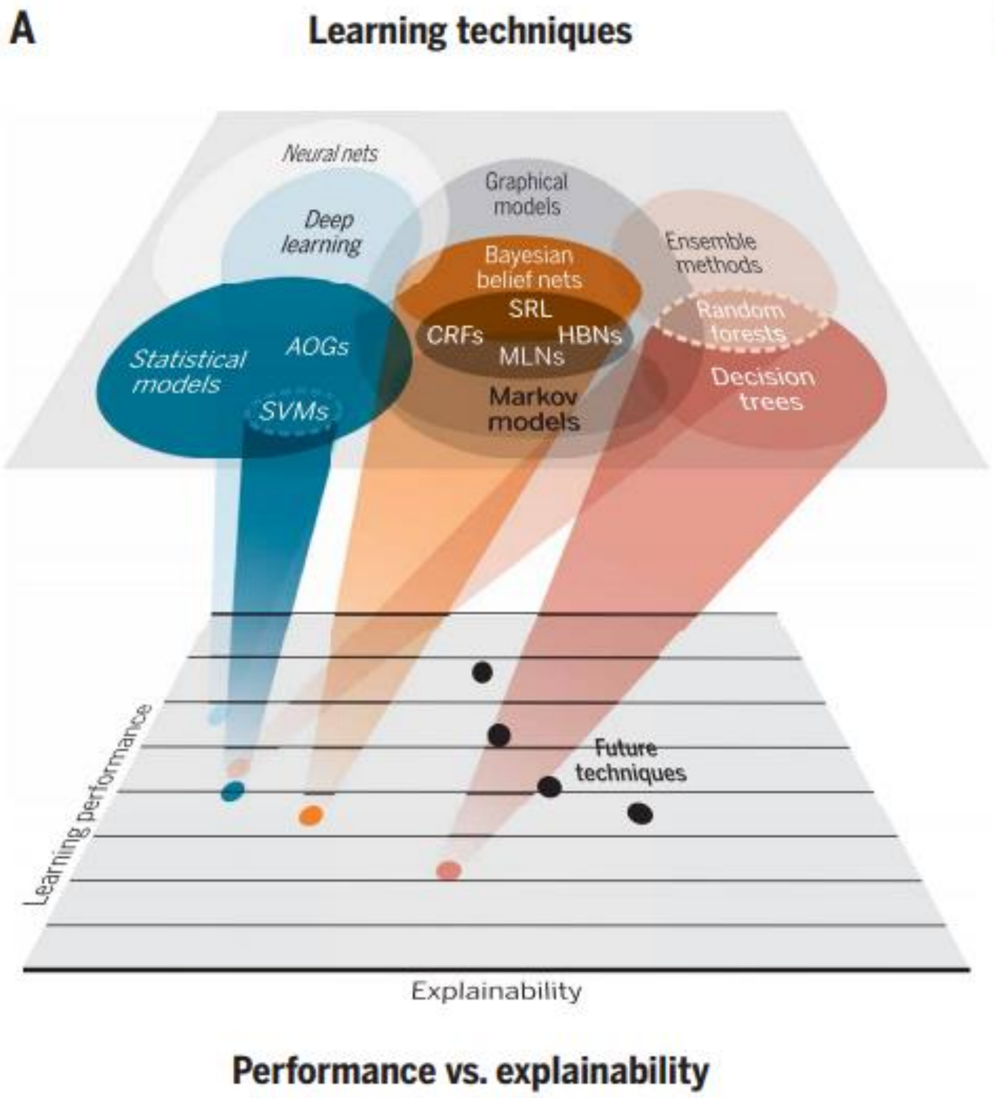
Skewed training data creates Maladaptation

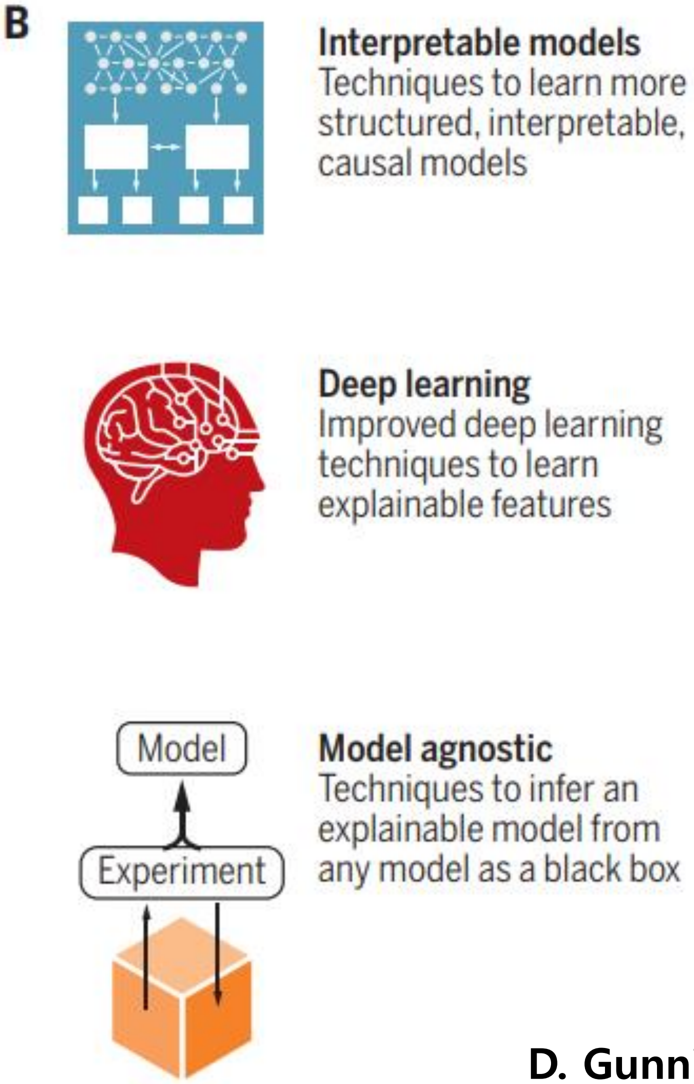
A DARPA Perspective on AI – Three Waves of AI



DARPA

Explainable AI – Performance vs. Explainability





D. Gunning et al., Science Robotics, 2019

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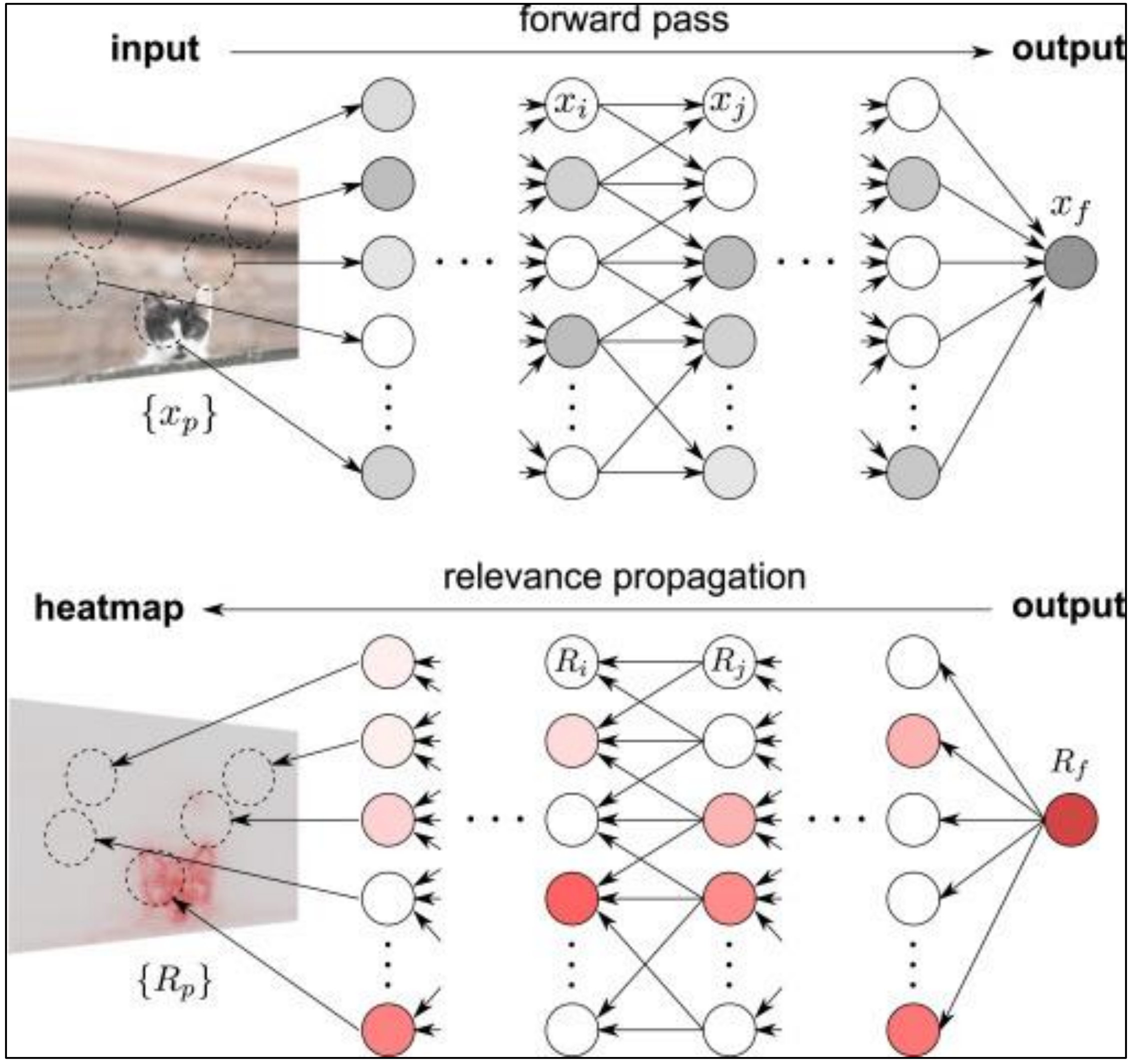
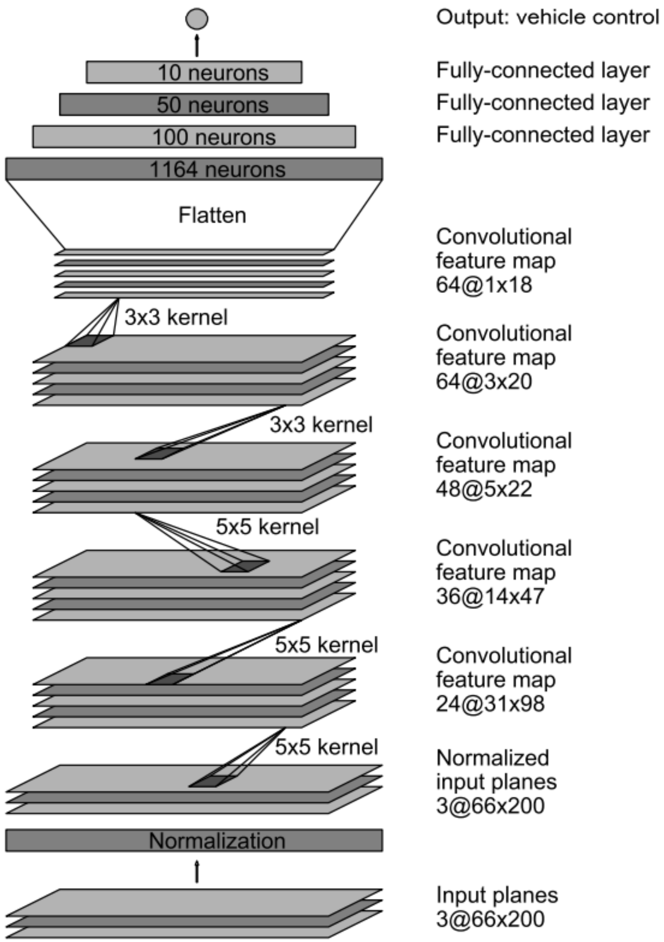


[Image courtesy of Klaus Muller]

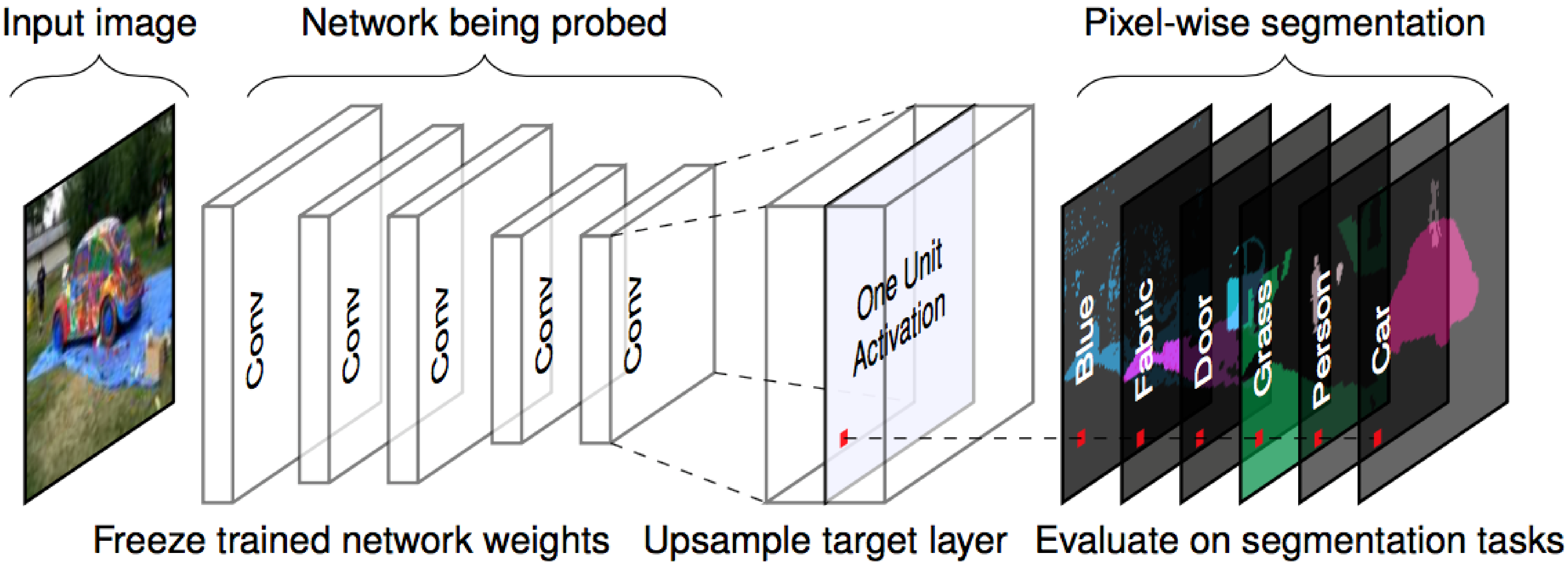
Input Attribution Methods



PilotNet Architecture, NVIDIA/Google, 2017

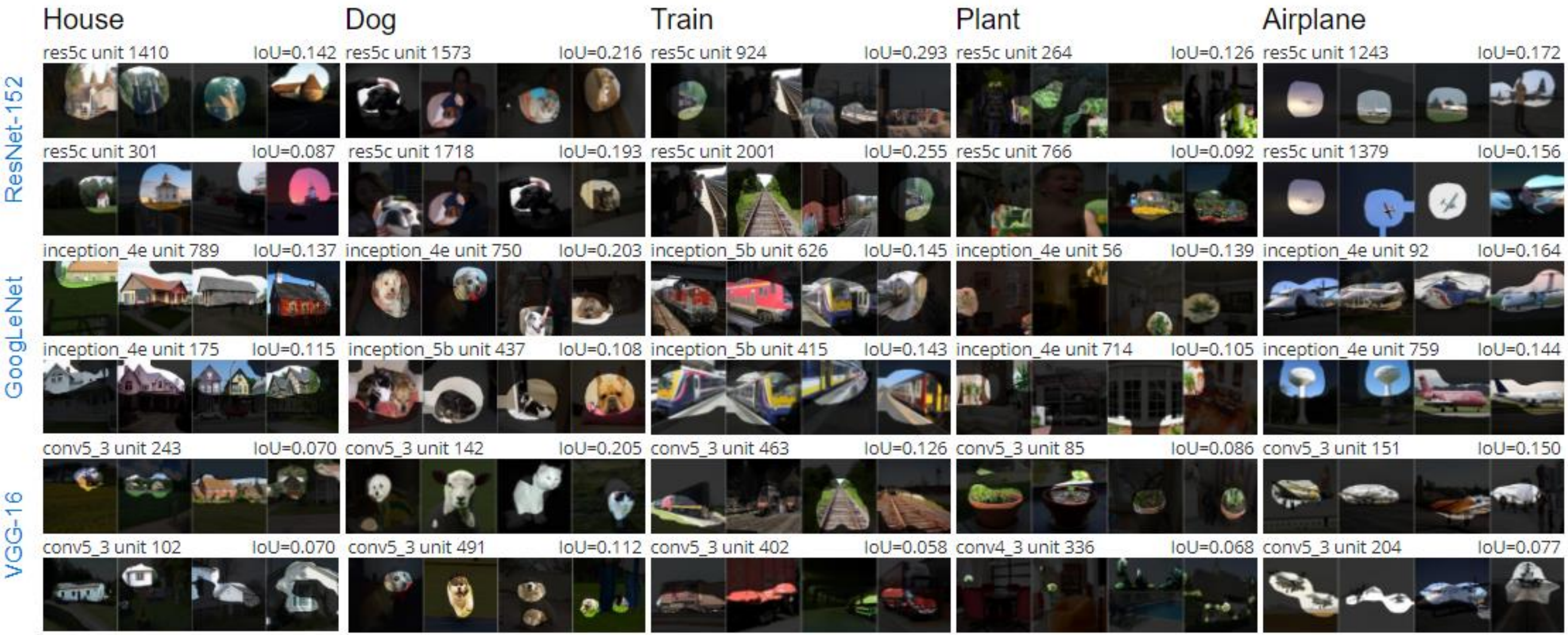
Input Attributions of PilotNet

Explaining Decision of Autonomous Driving



Network Dissection

D. Bau et. al., CVPR, 2017
D. Bau et. al., PNAS, 2020



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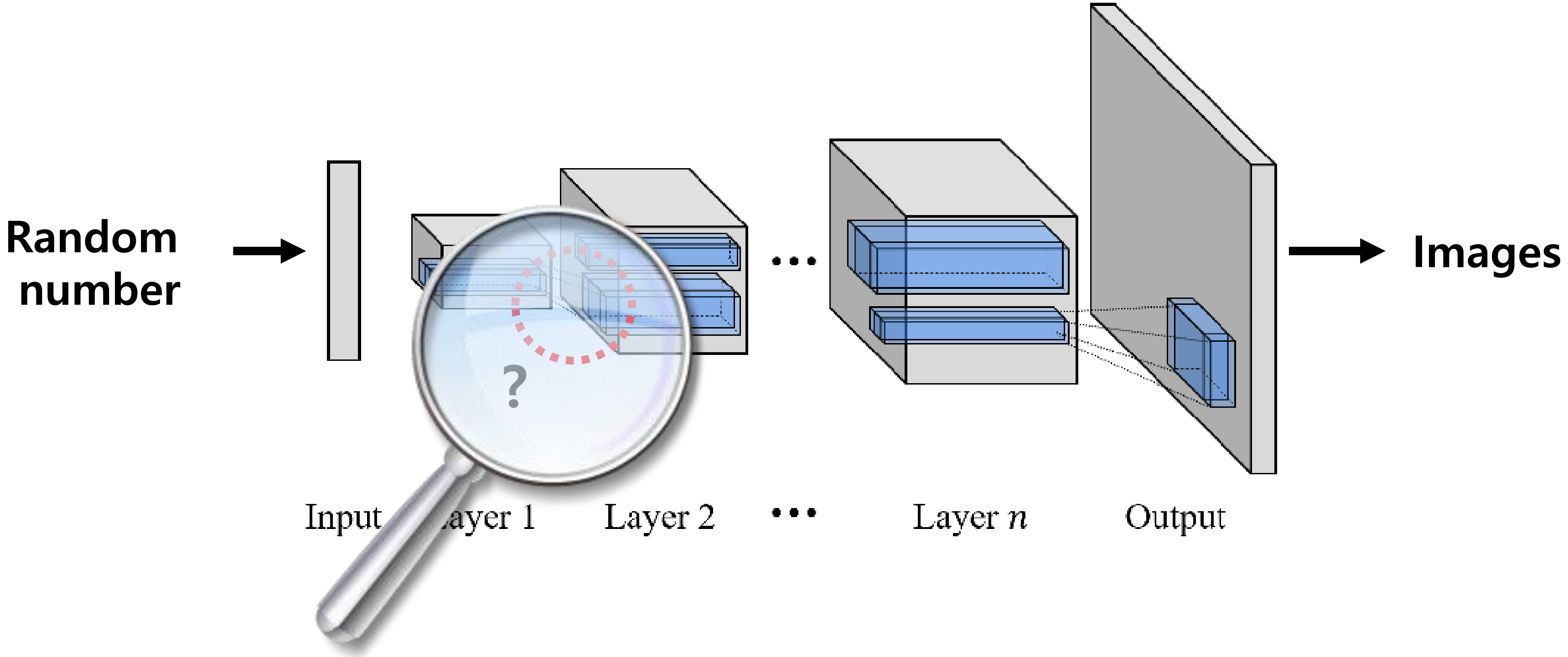
A Generative Neural Network (GNN)



Explorative Generative Boundary Aware Sampling (E-GBAS)

G. Jeon et. al., AAAI, 2020

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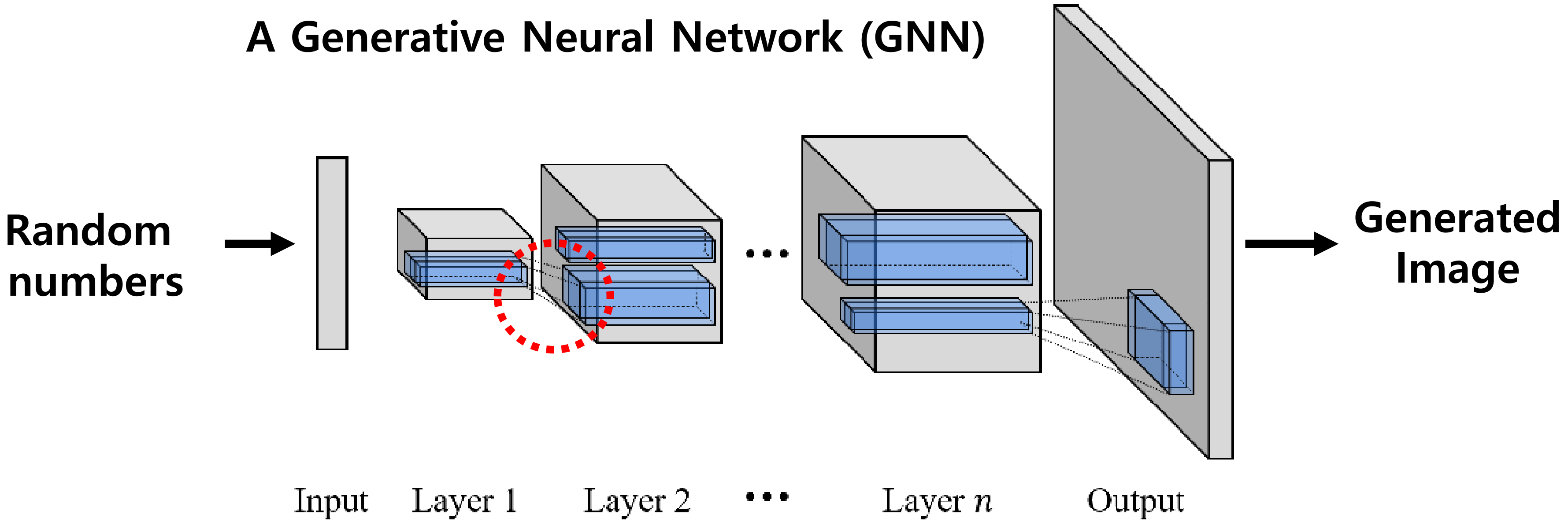
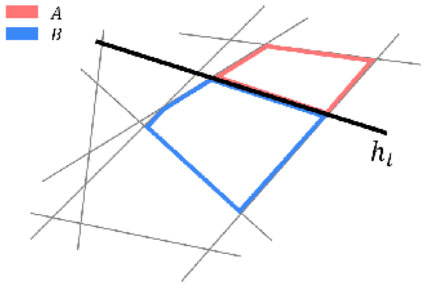
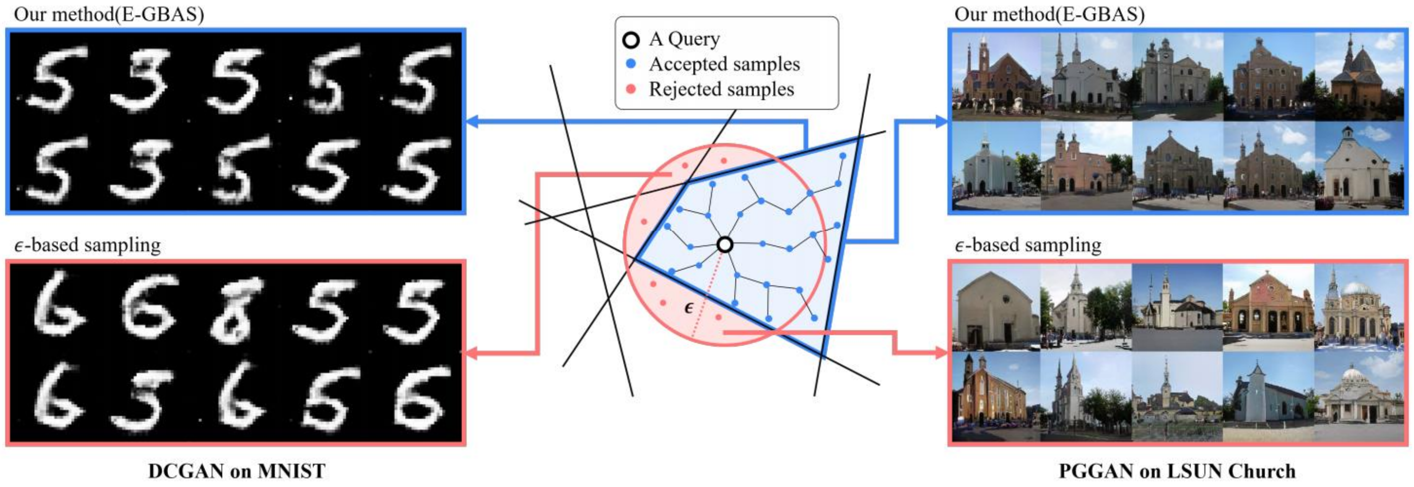




Generative boundaries

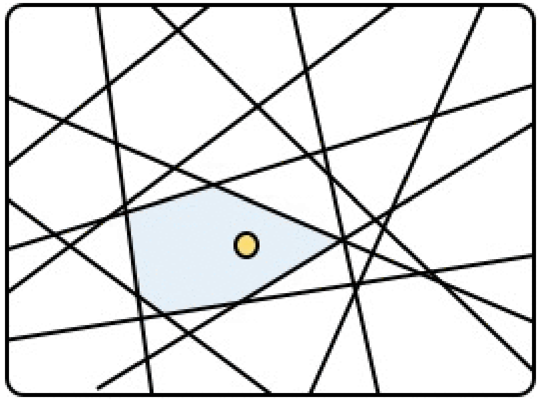


Explorative Generative Boundary Aware Sampling (E-GBAS)

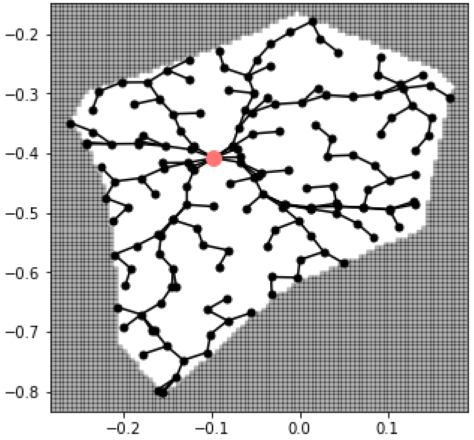
G. Jeon et. al., AAAI, 2020

Generative Boundary constrained Rapidly-exploring Random Tree (RRT)

- ☐ Given generative boundary as constraints,
  RRT is gives solution to search over the generative region.
- ☐ This explorative sampling always guarantee acceptance inside the region



Illustrative example



Example in nonconvex region

S. M. LaValle, “Rapidly-exploring random trees: A new tool for path planning”, 1998.

Explorative Generative Boundary Aware Sampling (E-GBAS)

G. Jeon et. al., AAAI, 2020

Explorative Generative Boundary Aware Sampling

- Accepted Cluster 1
- Accepted Cluster 2
- Accepted Cluster 3
- Rejected Sample

Explorative Generative Boundary Aware Sampling (E-GBAS)

G. Jeon et. al., AAAI, 2020

Leading method (Fisher-Vector / SVM Model) of PASCAL VOC challenge

Unmasking Clever Hans Predictors

W. Samek, Unmasking Clever Hans Predictors, Nature Communications, 2019

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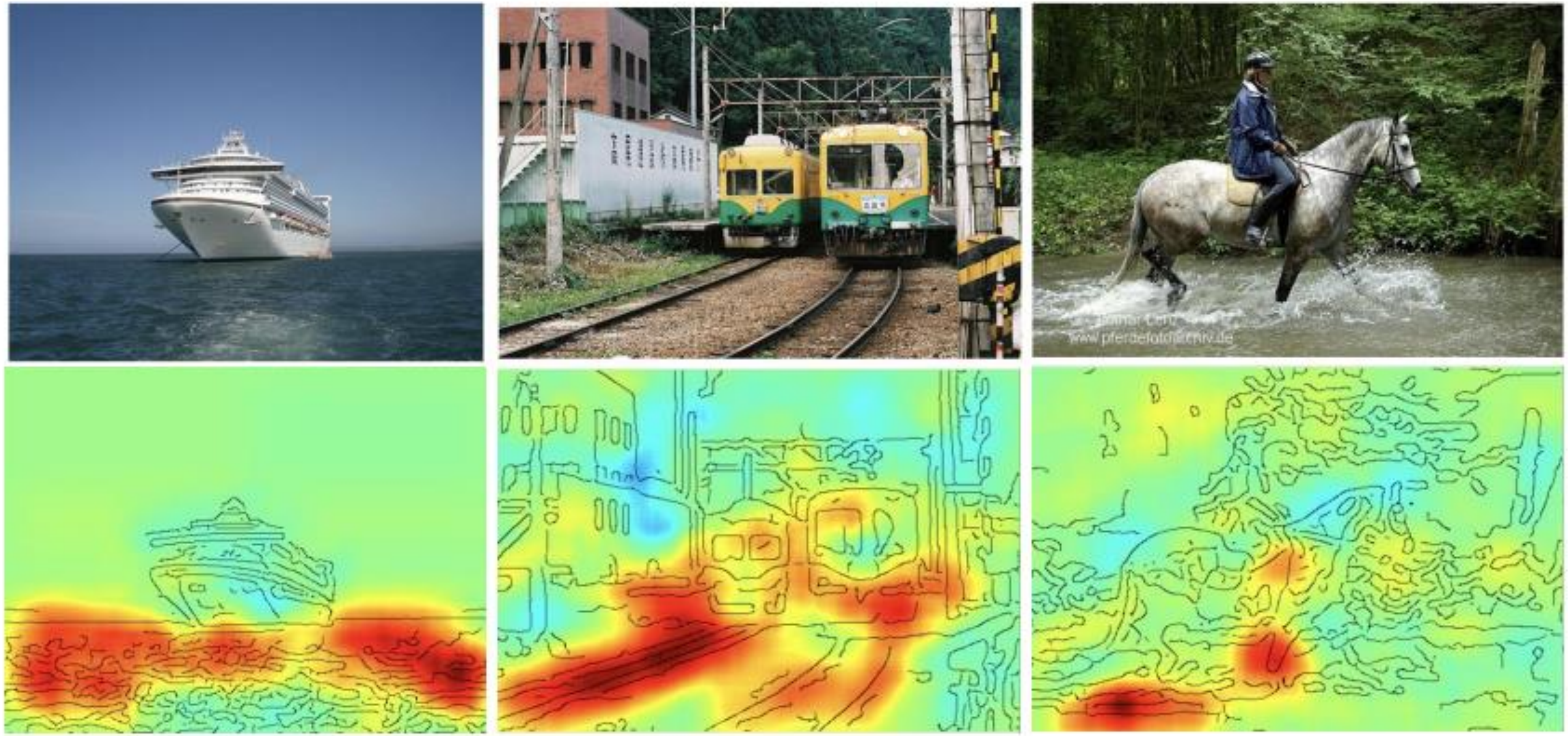

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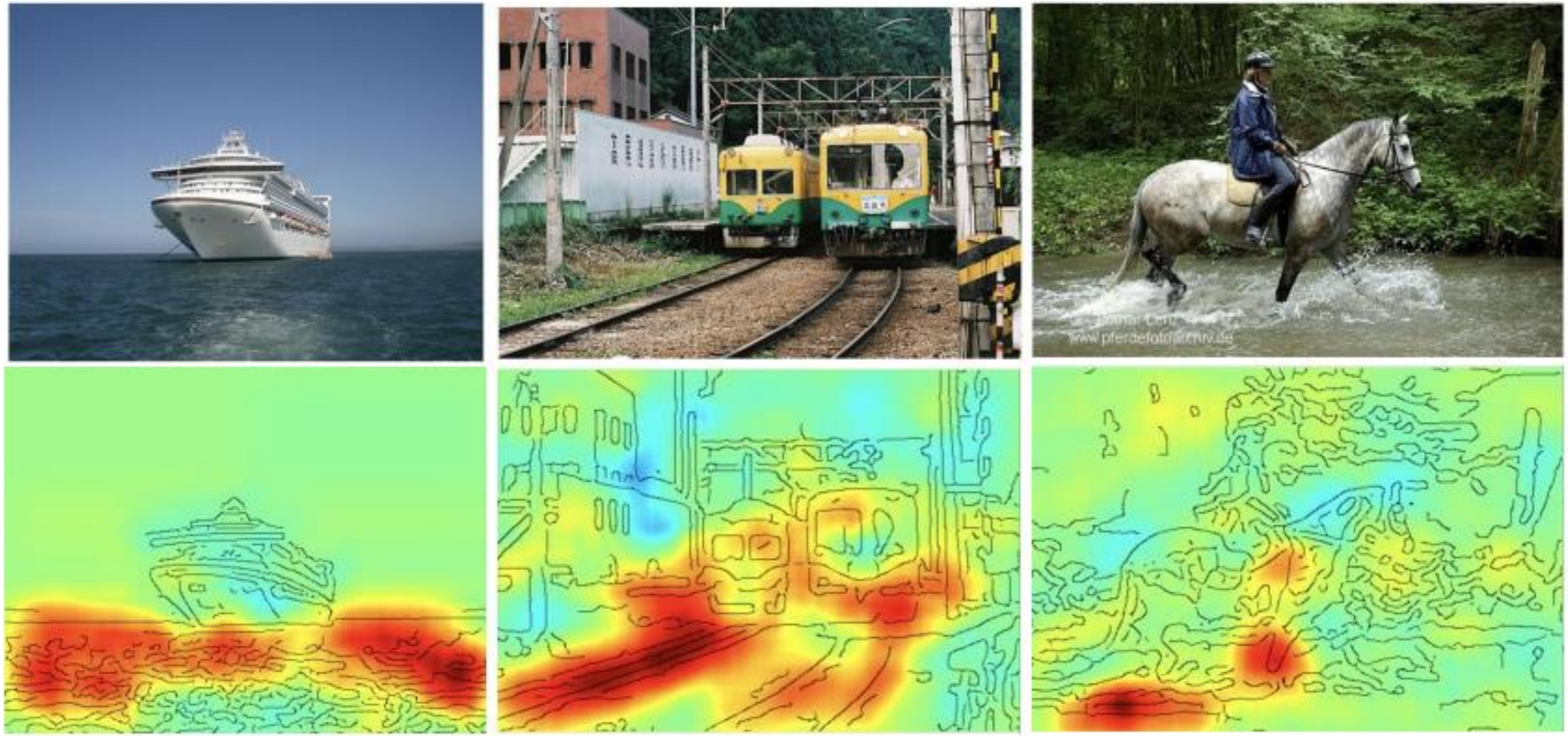

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This is a ***mallard*** because this is a brown and white bird with a green head and a yellow beak.

Explainable AI can improve the accuracy of AI system

T. Darrell, Recent progress towards XAI at UC Berkeley, 2019

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Explainable AI can improve the accuracy of AI system

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~~This is a ***mallard*** because this is a brown and white bird with a green head and a yellow bill.~~

This is a ***mallard*** because this bird has a brown head, orange feet, and a flat bill.

Explainable AI can improve the accuracy of AI system

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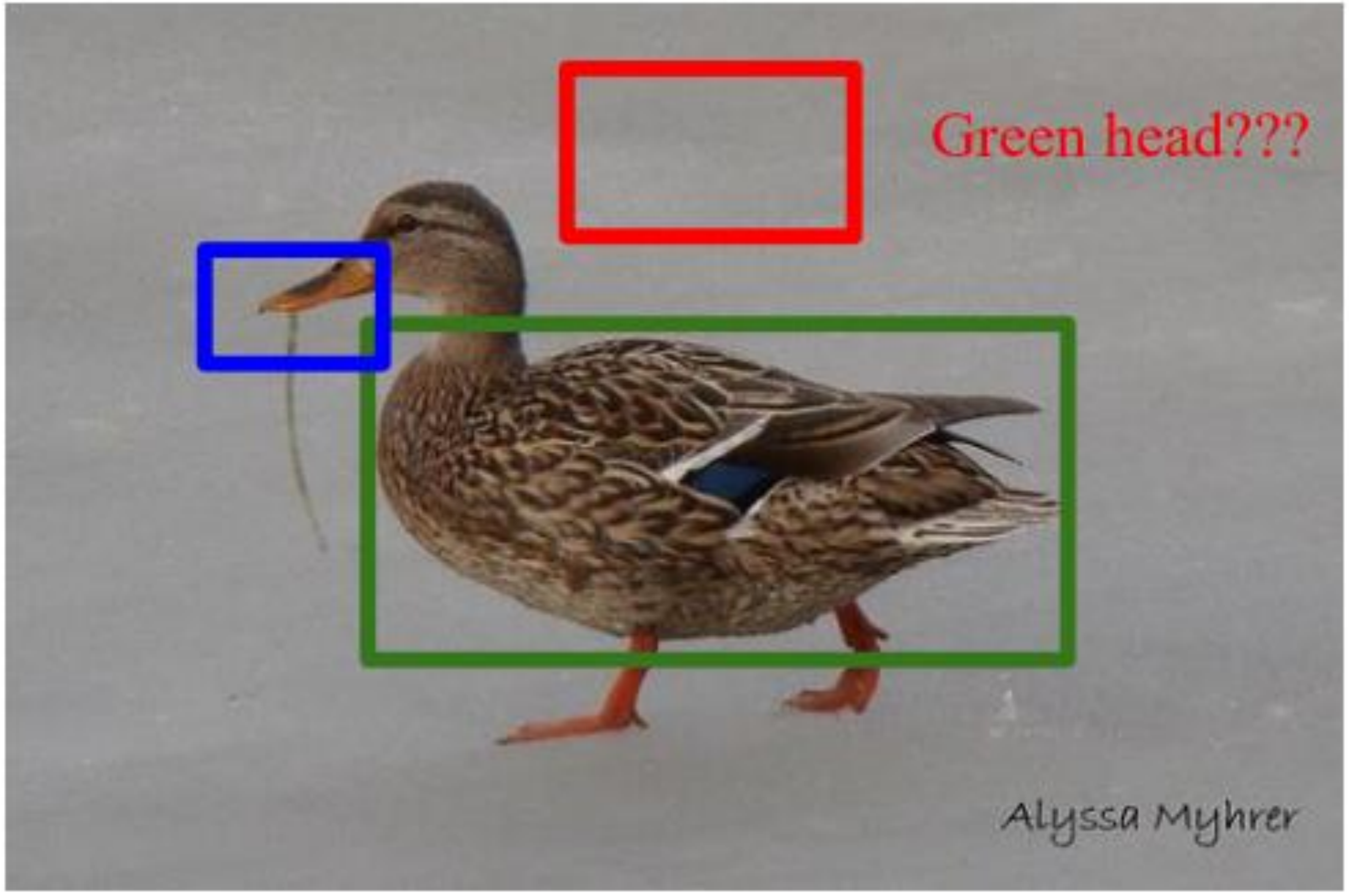

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Explainable AI can improve the accuracy of AI system

T. Darrell, Recent progress towards XAI at UC Berkeley, 2019

- Interpretable and explainable AI methods are **necessary for the coexistence of human and AI**.

- Recent advances in XAI can **analyze internal nodes of deep neural networks**.

- Some XAI methods help to **improve the performance of AI systems**.

Conclusions

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