# Uncertainty in
# Recurrent Decision Tree Classifiers

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Explainable Machine Learning

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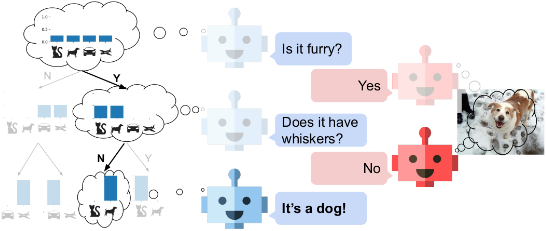
# What?

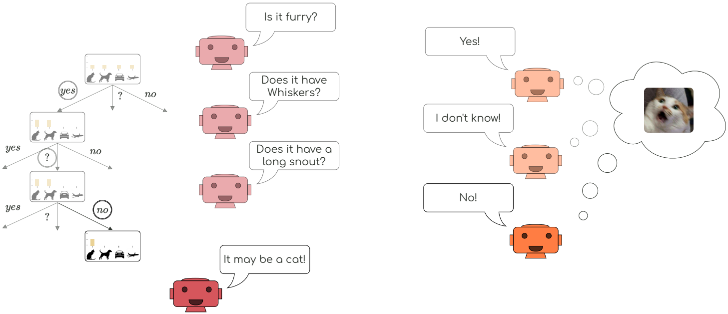
## Setting

- There are a lot of architectures that perform great on image classification tasks
- Maybe, most prominently: ResNet
- However, they only yield a classification
- In many settings a classification is not worth much without the reasoning behind it

# What?
## Recap




- Two agents
- One is asking questions and one is answering them
- The unfolding decision process is an interpretable tree

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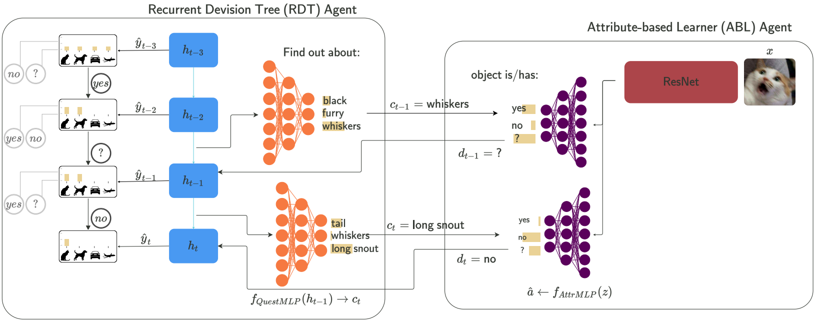
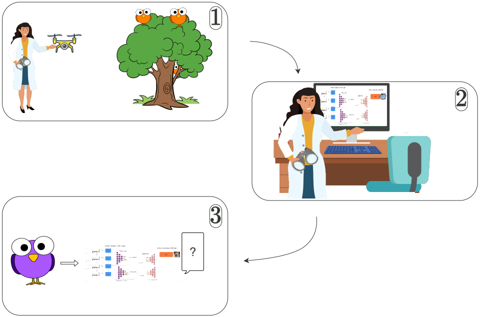
# What?
## Introducing Uncertainty

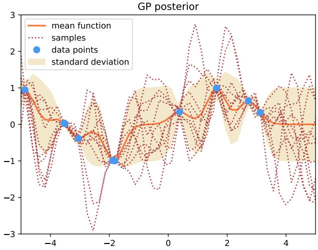


# Why do we need uncertainty?

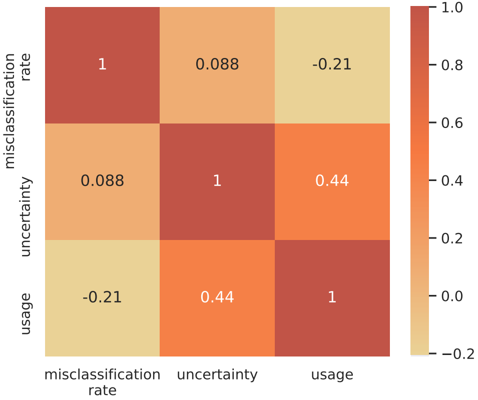
## A Practical Example...



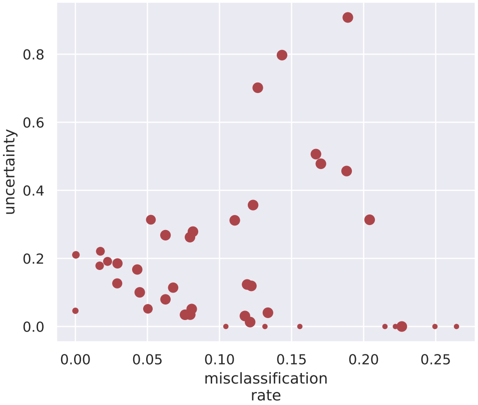

- The ornithologist is tasked to survey bird species, which she automates using a drone and computer vision software
- She uses our model to go through the vast amount of collected data
- Some bird species unknown to the model appear in the data. The model yields high uncertainty and the ornithologist can classify them manually



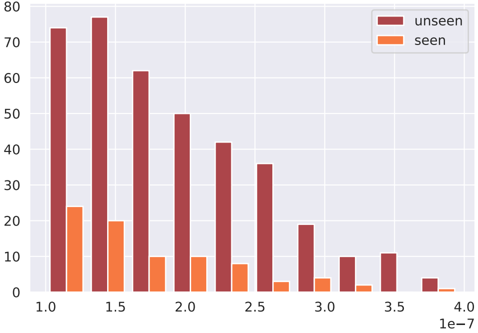

- Data points can be described by (infinitely) many functions
- A GP is a PDF over these functions
- Parameterized by mean function and covariance function
- The variance resembles the model uncertainty where no data is given
-



misclassification rate
uncertainty
usage
1
0.088
-0.21
0.088
1
0.44
-0.21
0.44
1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


uncertainty
0.0
0.2
0.4
0.6
0.8
0.00
0.05
0.10
0.15
0.20
0.25
misclassification
rate

# Experiments
## OOD Detection

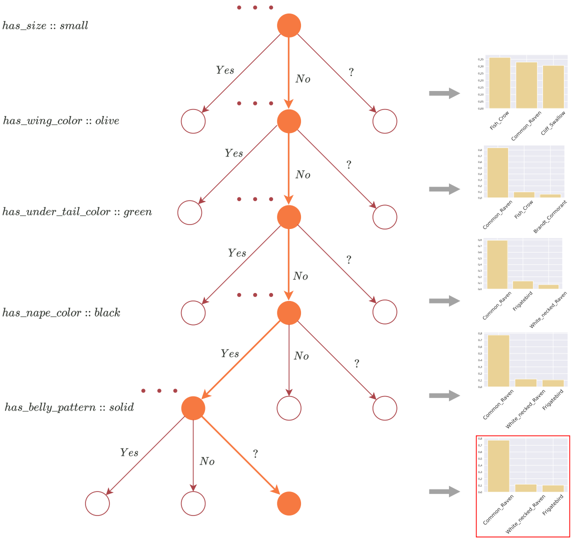


| | AWA2 | aPY | CUB |
|---|---|---|---|
| ResNet [HZRS16] | 98.2± 0.0 | 85.1± 0.6 | 79.0± 0.2 |
| DT | 78.0± 0.4 | 64.3± 0.6 | 19.3± 0.3 |
| dNDF[KFCRB15] | 97.6± 0.2 | 85.0± 0.6 | 73.8± 0.3 |
| RDTC[AA19] | 98.0± 0.1 | 85.7± 0.7 | 78.1± 0.2 |
| XDT | 73.9± 0.9 | 59.9± 1.5 | 4.9± 1.3 |
| aRDTC[AA19] | 98.6 | 86.1 | 77.9± 0.6 |
| remRDTC(ours) | 98.7 | 86.4 | 77.7 |
| extRDTC(ours) | 98.7 | 85.4 | 77.8 |

| | aRDTC [AA19] | Random Baseline | remRDTC | extRDTC |
|---|---|---|---|---|
| **AWA2** | | | | |
| Class | 98.6 | 98.5 | 98.7 | 98.7 |
| Attribute | 80.4 | 84.6 | 87.5 | 82.31 |
| **aPY** | | | | |
| Class | 86.1 | 86.5 | 86.4 | 85.4 |
| Attribute | 86.4 | 86.2 | 87.6 | 87.12 |
| **CUB** | | | | |
| Class | 77.9 | 76.8 | 77.7 | 77.8 |
| Attribute | 68.6 | 70.0 | 77.4 | 82.6 |

# Conclusions

## A qualitative Example



[AA19] Stephan Alaniz and Zeynep Akata. Explainable observer-classifier for explainable binary decisions. arXiv preprint arXiv:1902.01780, 2019.

[HZRS16] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.

[KFCRB15] Peter Kontschieder, Madalina Fiterau, Antonio Criminisi, and Samuel Rota Bulo. Deep neural decision forests. In Proceedings of the IEEE international conference on computer vision, pages 1467–1475, 2015.