Reliable JPEG Forensics via Model Uncertainty

Detecting the training-test mismatch with Bayesian logistic regression

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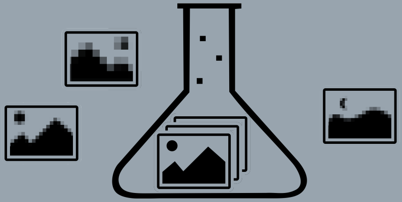

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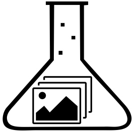

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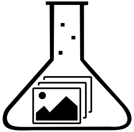

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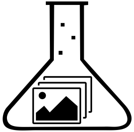

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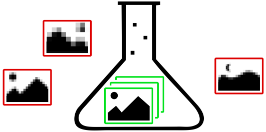

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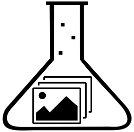

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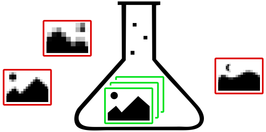

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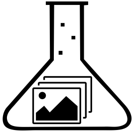

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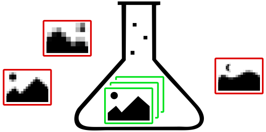

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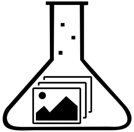

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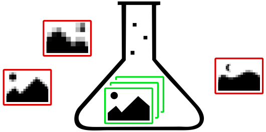

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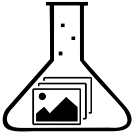

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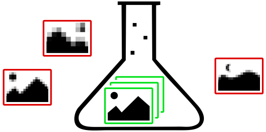

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Current approaches to mitigating the training-test mismatch

1. Create more robust detectors with broad applicability (open challenge)
2. Create several detectors specialized to a narrow range of JPEG settings (not fool-proof)

Contribution: Detect training-test mismatch with Bayesian detector

Our proposal: **Create reliable detectors that express uncertainty in unfamiliar situations**

$\Rightarrow$ Quantify when to trust the model's predictions

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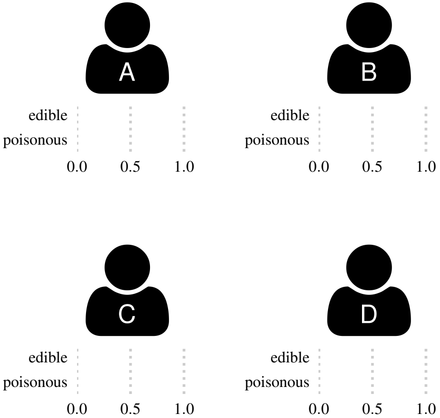
Experiments

- Detect JPEG double compression based on first-digit features
- Uncertainty measure allows anticipating misclassifications when test image is not aligned with the training data
  - Mismatch in JPEG quality factors
  - Mismatch in quantization tables $\leftarrow$ this talk
  - Mismatch in DCT implementation

Data and model uncertainty



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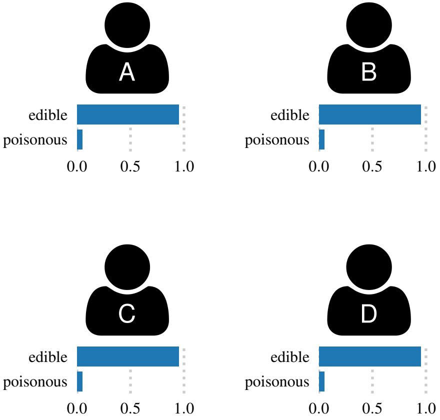

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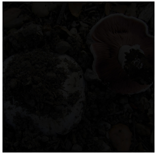

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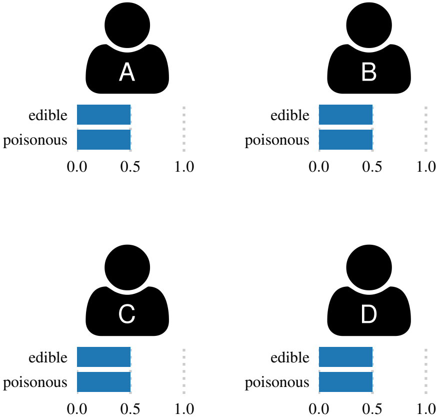

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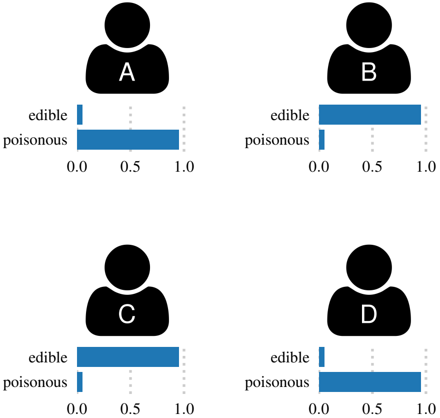

1. No uncertainty: All experts agree
2. Data uncertainty: All experts are uncertain
3. **Model uncertainty: Experts have different opinions**

Bayesian logistic regression

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- Express uncertainty about decision boundary by modeling weights as probability distributions

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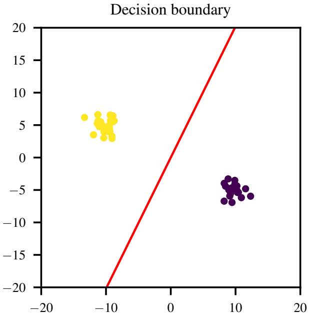
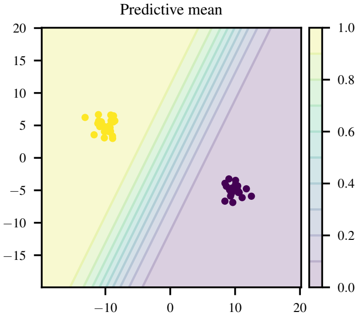
- $p(\boldsymbol{w} \mid \boldsymbol{x}_{\text{train}}, \boldsymbol{y}_{\text{train}})$ - posterior distribution over the weights after training data is seen

Toy example: Standard logistic regression





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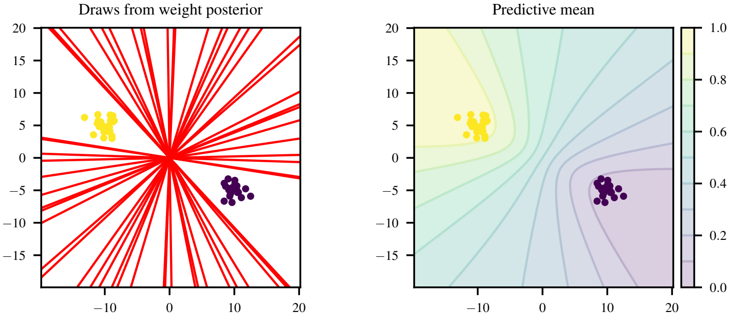

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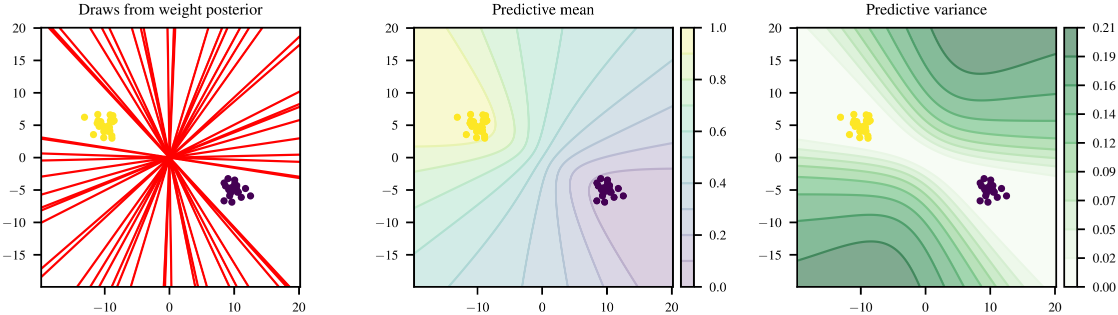

Experiments & Results

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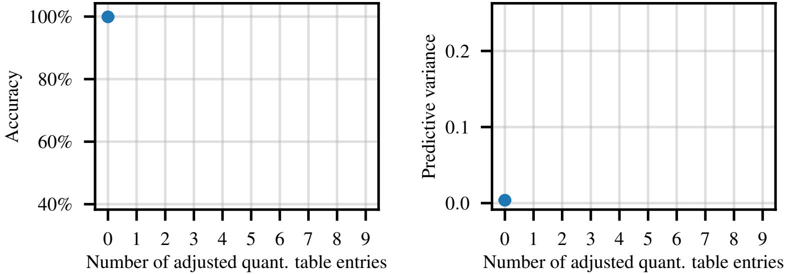

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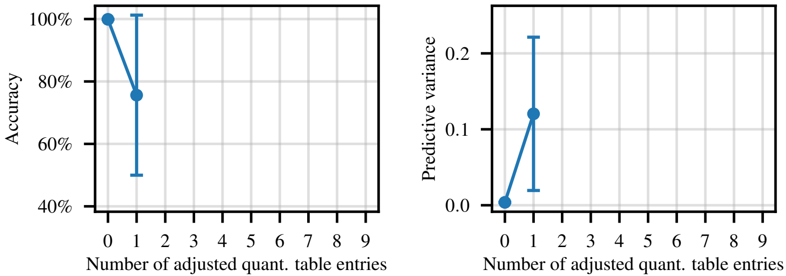

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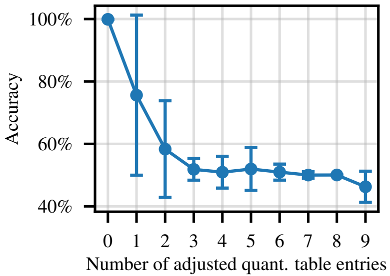
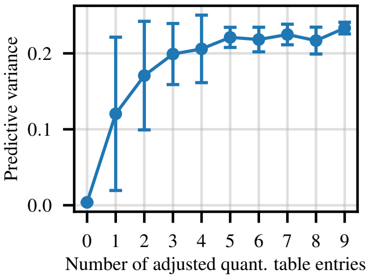
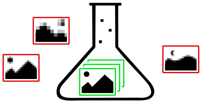




$\Rightarrow$ Bayesian detector anticipates misclassifications from quantization table mismatch

Conclusion

Conclusion: Reliable detectors from model uncertainty



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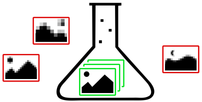

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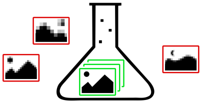

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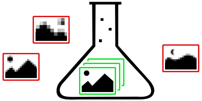

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Thank you

References

- Tube icon adapted from environmental science icon
- Mushroom photos from Wikipedia [1, 2]