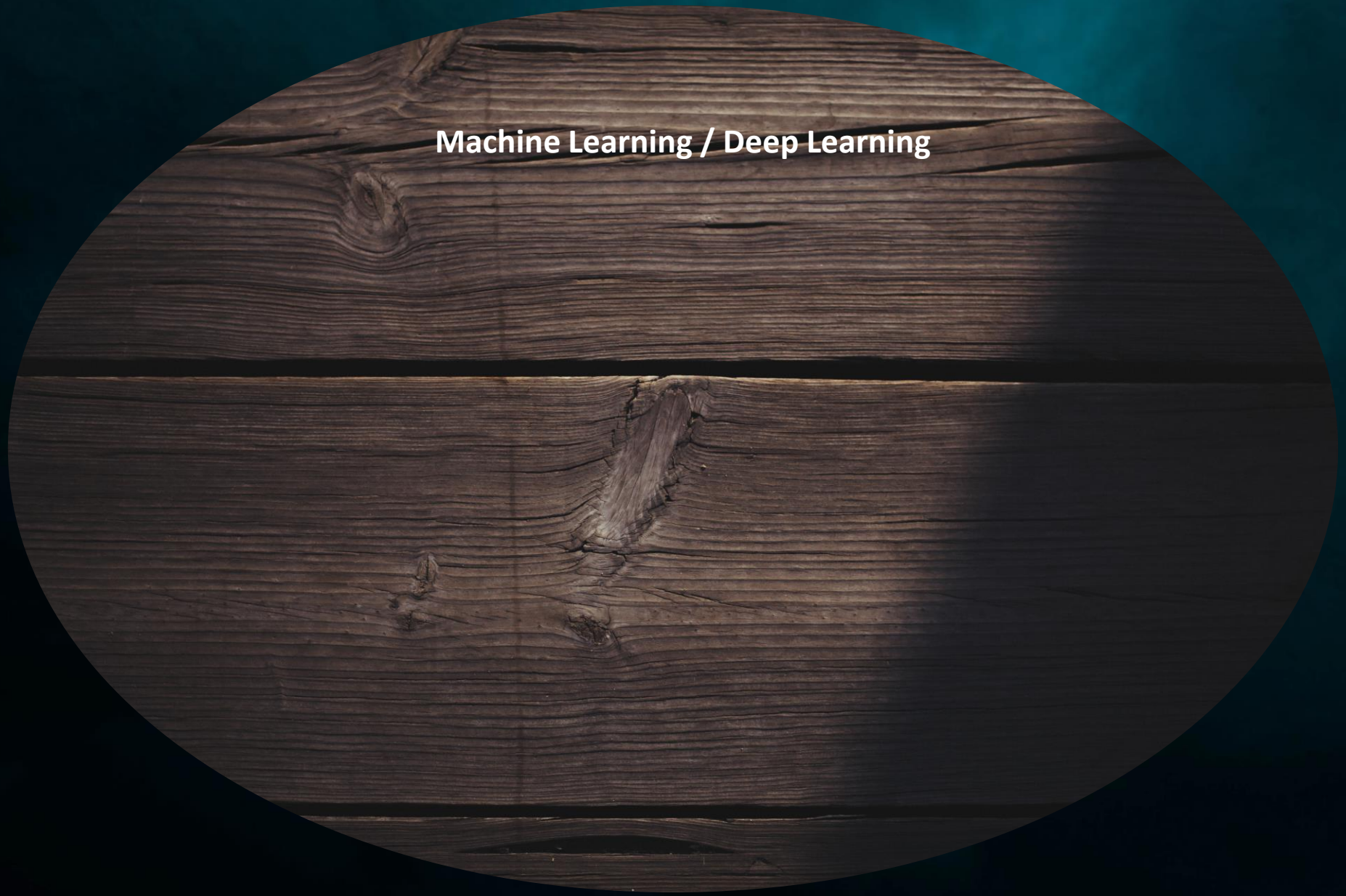
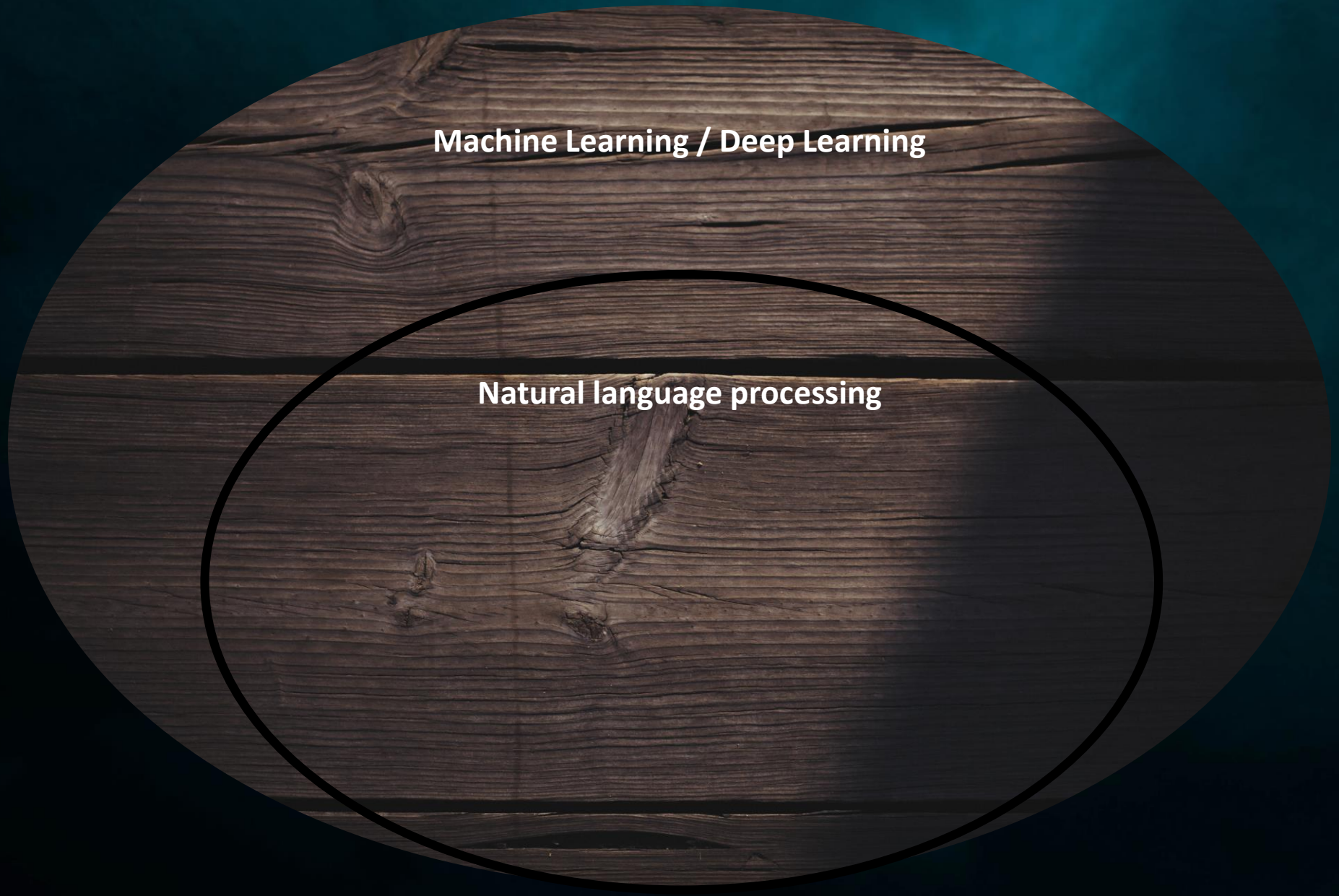
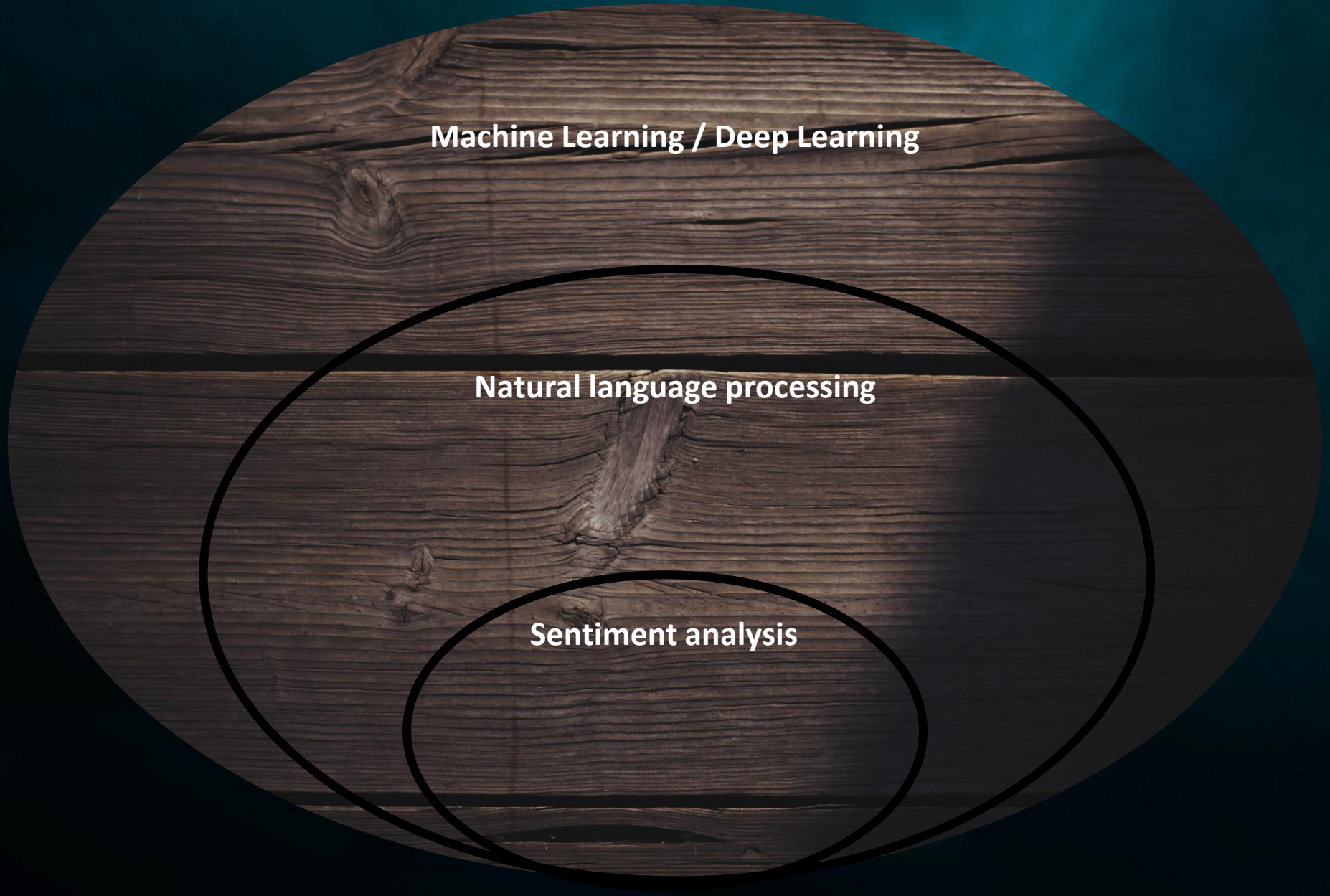
Sarcasm detection

Ane Berasategi


Machine Learning / Deep Learning


Machine Learning / Deep Learning
Natural language processing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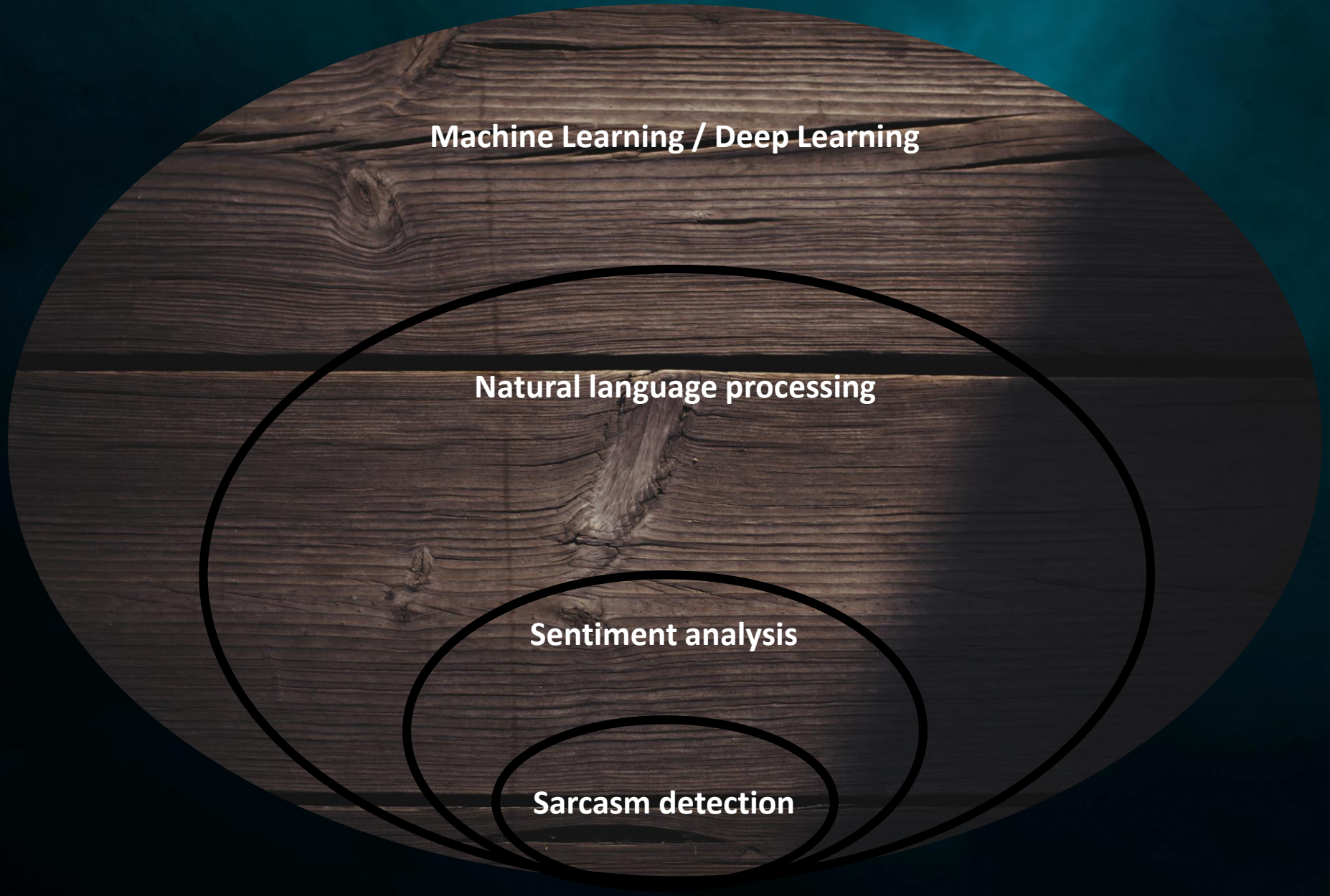
Sentiment analysis


Machine Learning / Deep Learning
Natural language processing
Sentiment analysis
Sarcasm detection

- Task: detect if a text is sarcastic or not
- But what is **sarcasm**?

Possible definitions:

- The **opposite of what you mean** in order to make fun of someone
- It has an **implied negative** sentiment, but a **positive surface** sentiment

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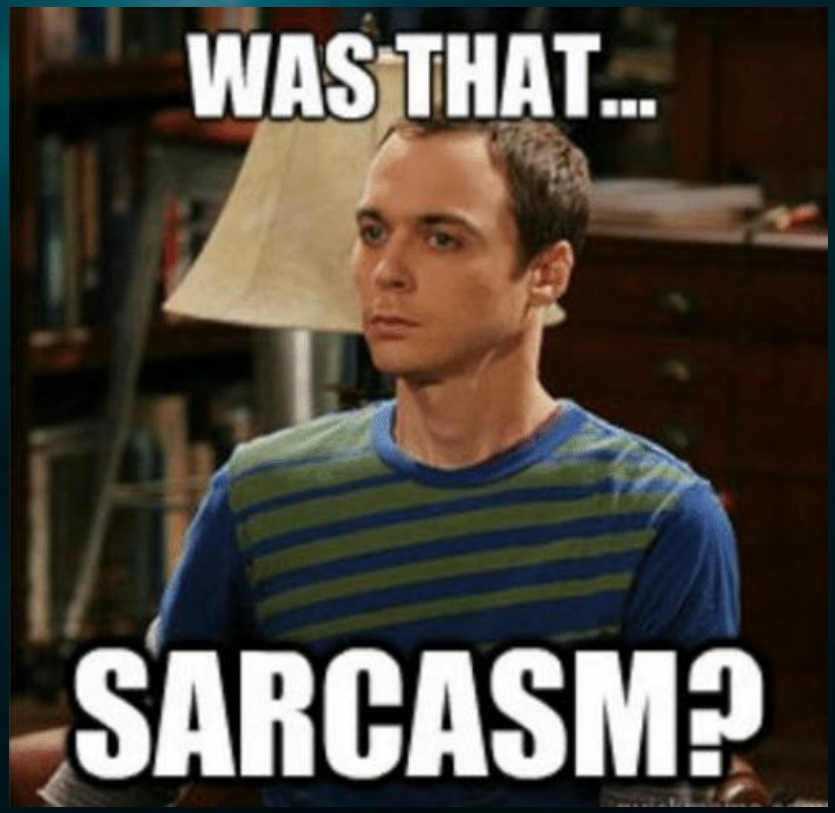
- Intended sarcasm != detected sarcasm



Plan

Part 1: Overview

- Datasets overview
- Feature overview
- Model overview

Part 2: Analysis

- Analysis
- Current stand
- Future research

2.1. Datasets overview

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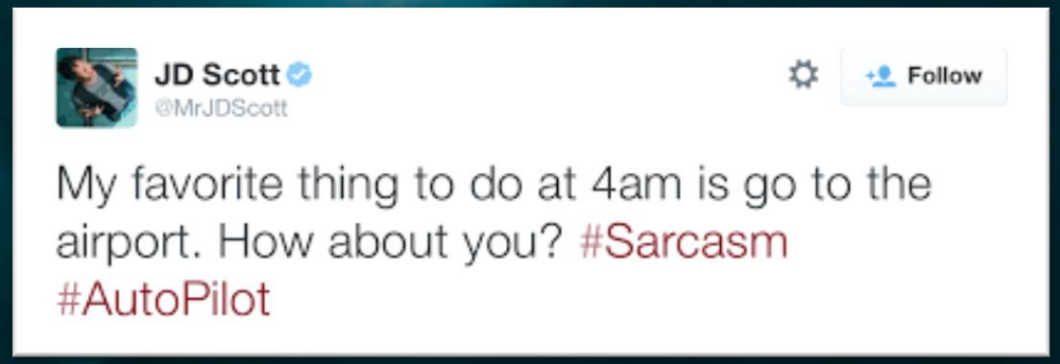
- Nature of the examples
  - Intended sarcasm vs. perceived sarcasm

2.1. Two Twitter datasets



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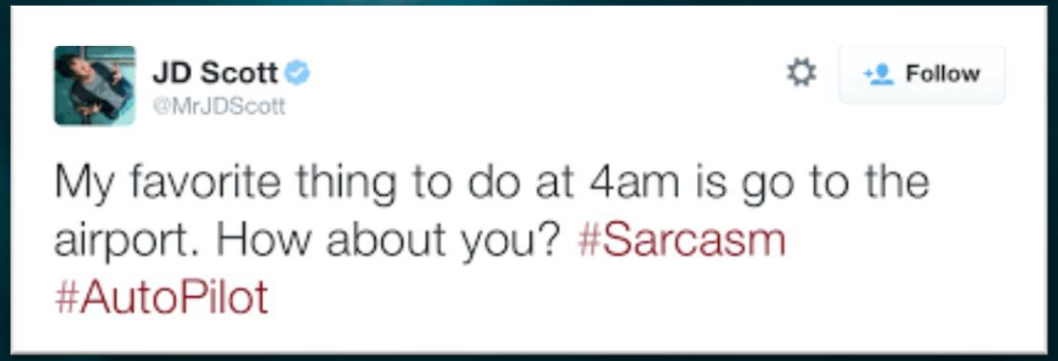
Riloff et al.[1]:

- 35k tweets with #sarcasm
- 140k random tweets



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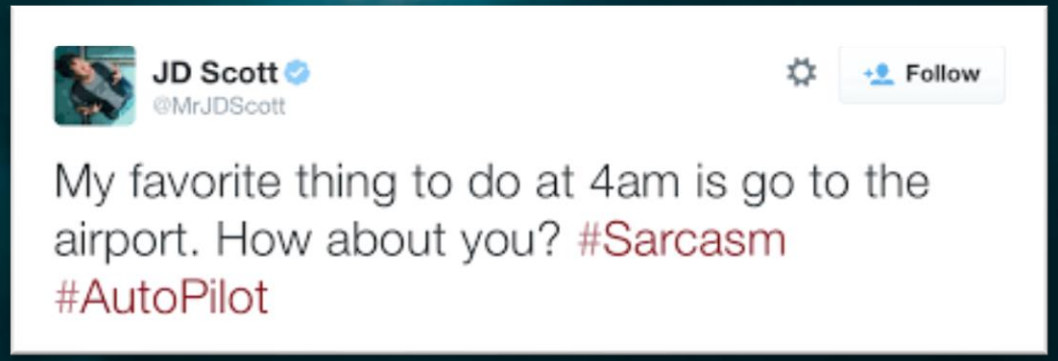

Ptáček et al.[2]:

- 7k tweets manually annotated
- 7k random tweets

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Can we provide more information/features to help the models?

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- User embeddings[6]: stylometric and personality features from the user

2.3. Model overview

- Until ~2017 mostly ML models
  - They need manual engineering
- From 2017 LSTMs, Transformers
  - They capture long-range dependencies better

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- Models perform better on Riloff, not so well on Ptacek
- Riloff: intended, Ptacek: perceived sarcasm

3.4. Current stand

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- Performance way below human performance
- False negatives (sarcastic texts not detected)
  - world knowledge is lacking

3.5. Future research?

- Bigger datasets: but very time intensive
- Incorporate world knowledge: but how?
- Something else?

References

1. Sarcasm as Contrast between a Positive Sentiment and Negative Situation, Riloff et al., 2013
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3. Identifying sarcasm in twitter: A closer look, González-Ibáñez et al., 2015
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5. Detecting Sarcasm is Extremely Easy ;-), Parde and Nielsen, 2018
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8. Towards Multimodal Sarcasm Detection (An Obviously Perfect Paper), Castro et al., 2019

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