

# Big Data in official statistics Using Machine Learning as Statistical Methods.

Marco Puts



# Quality of Official Statistics

- **Relevance**
- **Accuracy**
- **Accessibility**
- **Clarity**
- **Coherence**
- **Comparability**

# Quality of Official Statistics

- **Relevance**
- **Accuracy**
- **Accessibility**
- **Clarity**
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- **Comparability**

**Methods used in Official Statistics also have to meet these quality standards!**

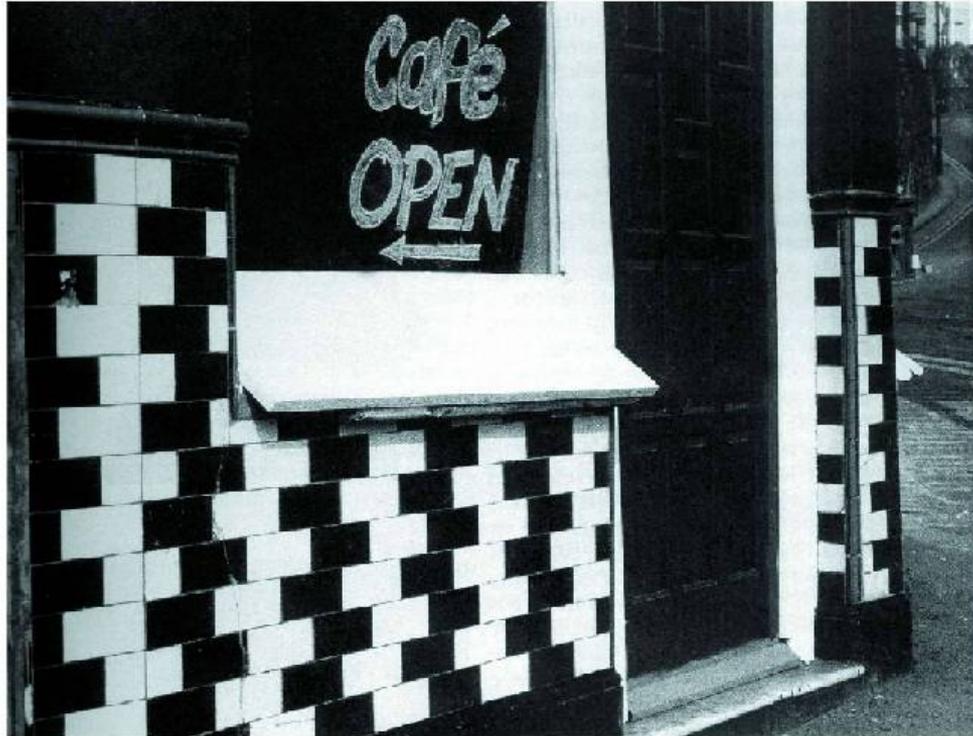
# Using Machine Learning in Official Statistics

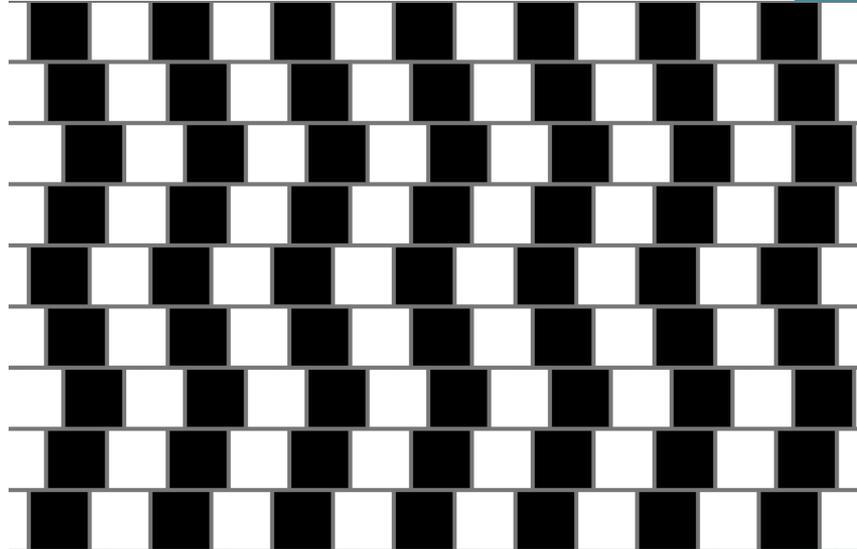
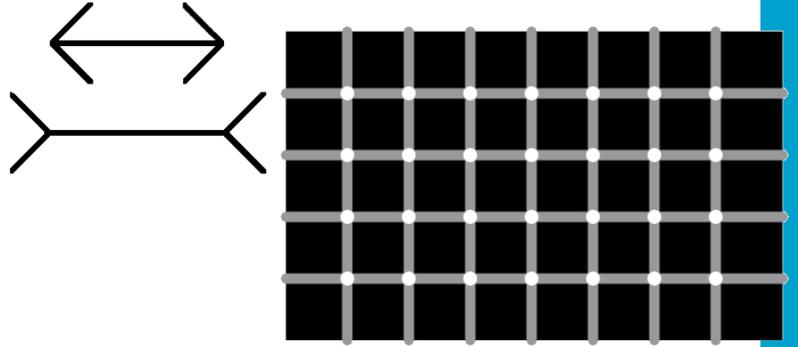
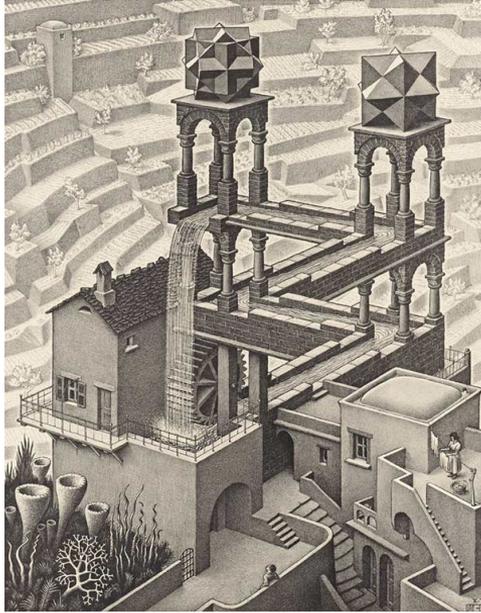
- Induction, Deduction and Abduction
- Machine Learning
- Classification
- The asymptotical behavior towards annotated data
- Representativity of training sets
- Explainable AI

# Induction, Deduction and Abduction



# Inductive Research





# Theory vs. Data driven

- Inductive vs. deductive

- **Deductive**

- Theory

- Hypothesis

- Observation

- Interpretation

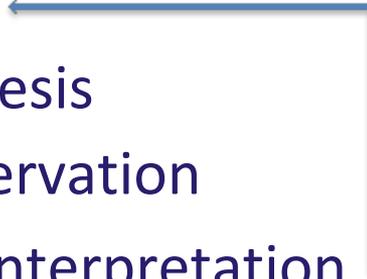
- **Inductive**

- Observation(Data)

- Pattern

- Possible hypothesis

- Theory



# Machine learning



# Machine Learning

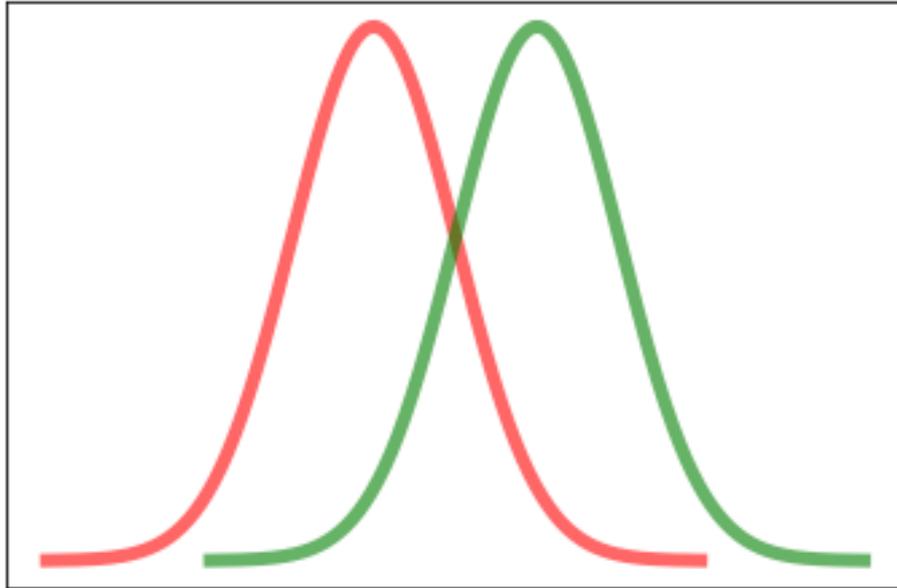
Subfield of Artificial Intelligence

“Learning strategies for Computers”

- **Unsupervised learning**
  - **Clustering**
- **Supervised learning**
  - **Classification**
  - **Regression**

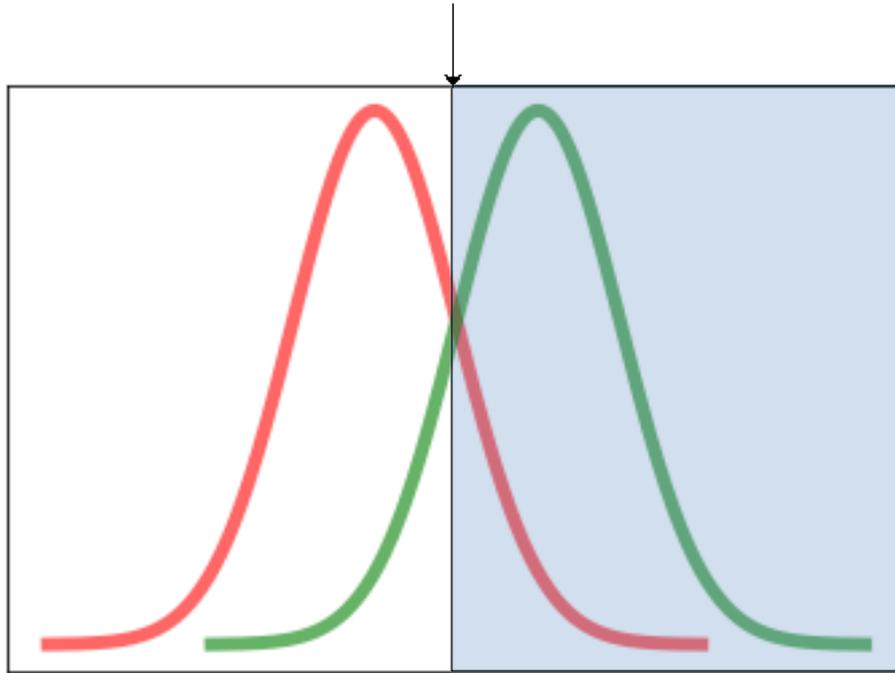
# Machine Learning

## Classification Explained



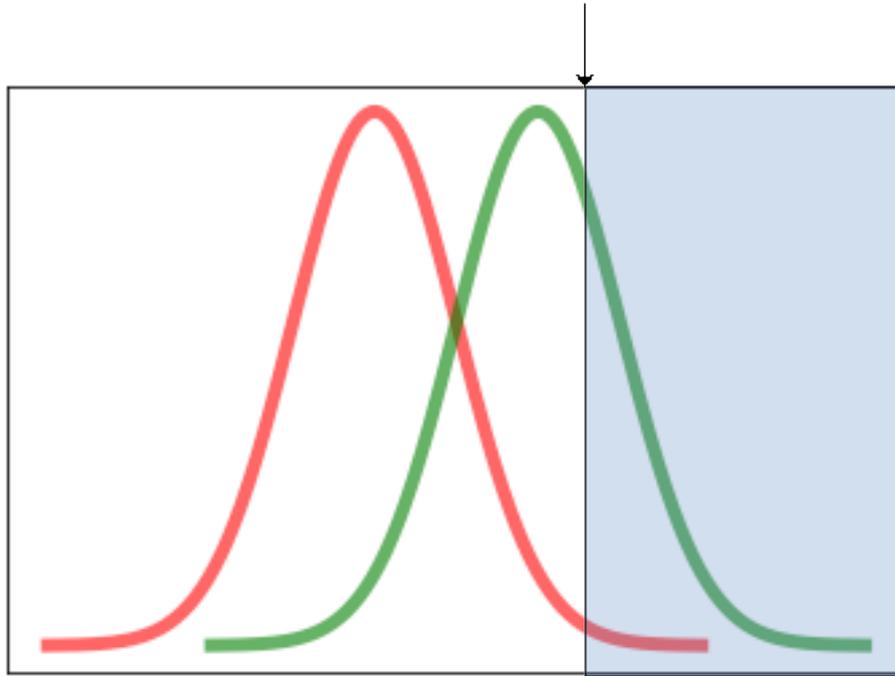
# Machine Learning

## Threshold



# Machine Learning

## Threshold

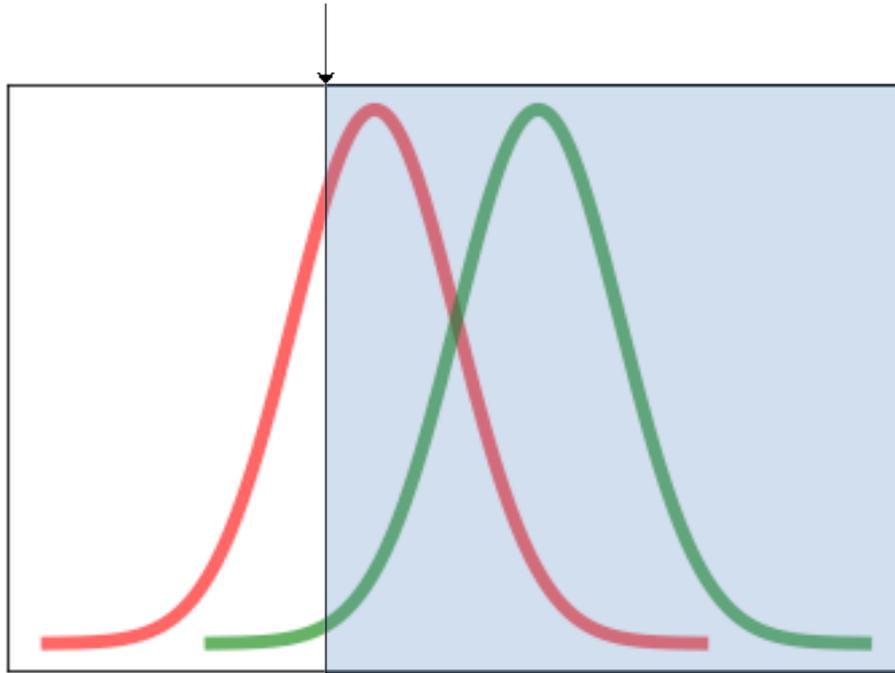


High Precision  
Low Recall



# Machine Learning

## Threshold



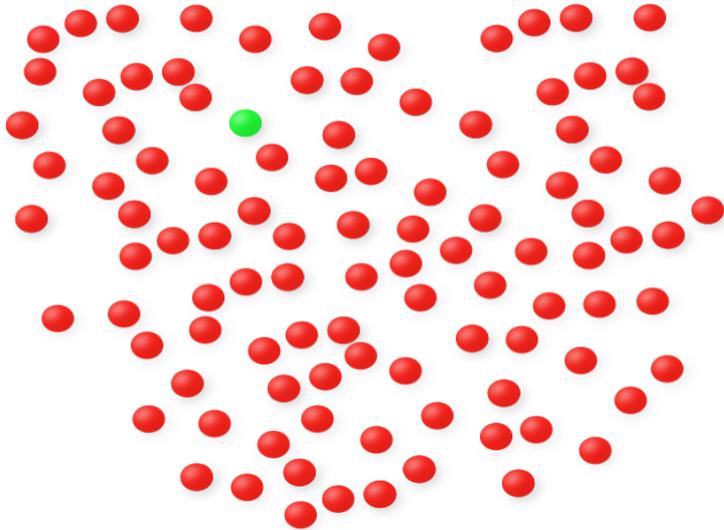
Low Precision  
High Recall



# Bias in Classifications

## Thought experiment

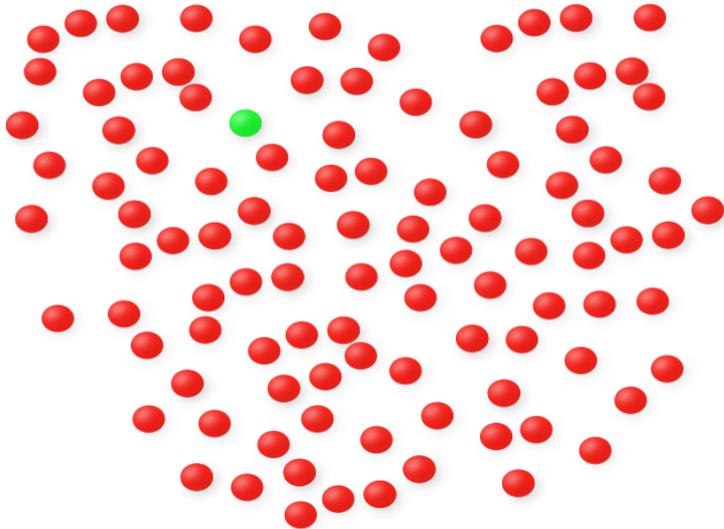
- 99 red marbles and 1 green marble
- Which model can predict the color correctly in 99% of the cases?



# Bias in Classifications

## Thought experiment

- 99 red marbles and 1 green marble
- Which model can predict the color correctly in 99% of the cases?



**Best Model:**

**Always predict that the marble is  
RED**

# Bayesian Ideal Observer Model

## A Bayesian view on Classifiers

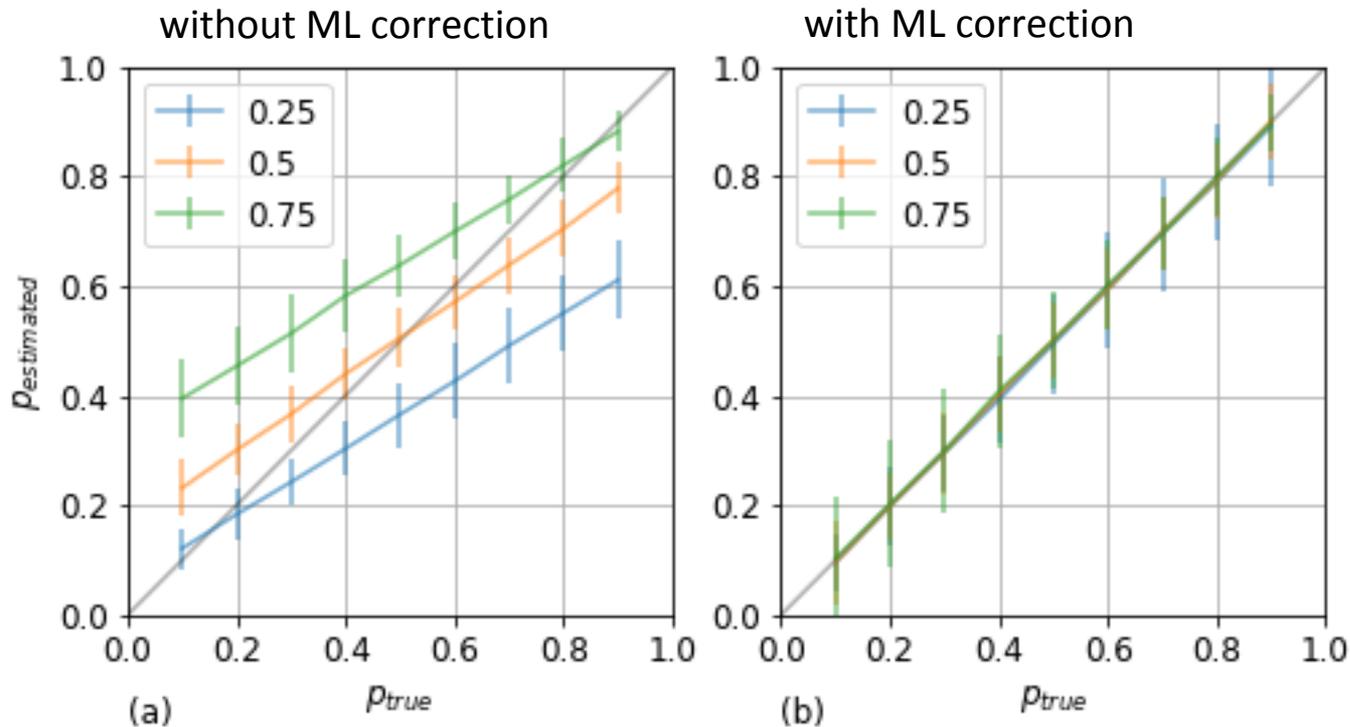
$$P(c = C|\bar{x}) = \frac{P(\bar{x}|c = C)P(c = C)}{P(\bar{x})}$$

- The prior introduces a Bias!

- $$P(\bar{x}) = \sum_{e \in \bar{C}} P(\bar{x}|e)P(e)$$

# Bias in Classifications

Simulated dataset



# Classification vs. Quantification

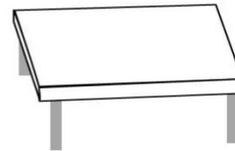
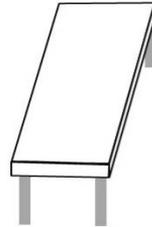
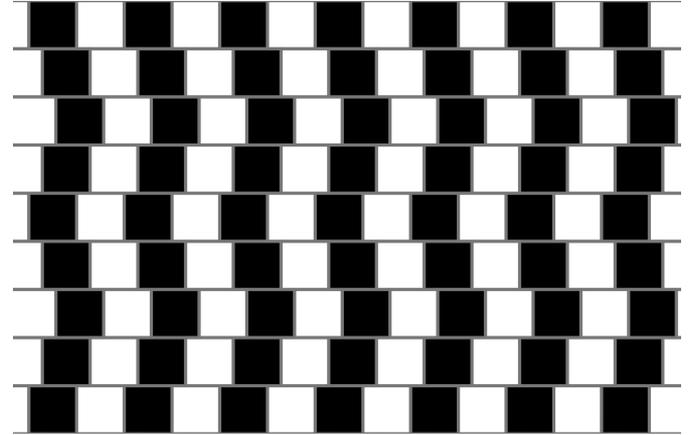
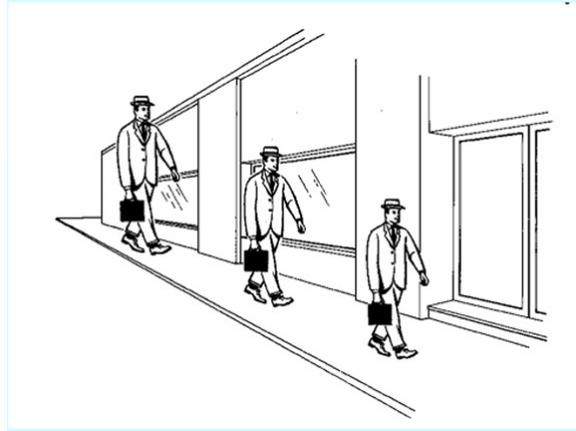
**Two ways of using a classifier:**

- Threshold/Argmax (classification)
- Expected value by adding up probabilities (quantification)

# The asymptotical behavior towards annotated data

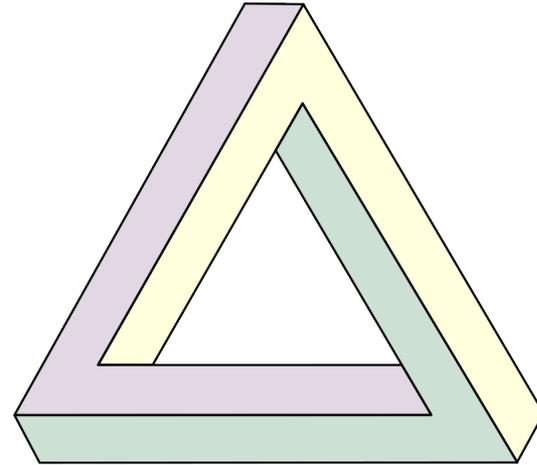


# The asymptotical behavior towards annotated data



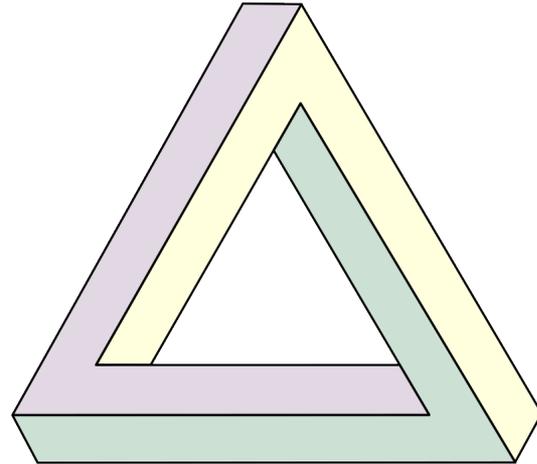
# The asymptotical behavior towards annotated data

To what extent is the “observed Ground Truth” real?



# The asymptotical behavior towards annotated data

The ML algorithm can never outperform the annotator, since it will learn the mistakes of the annotator.

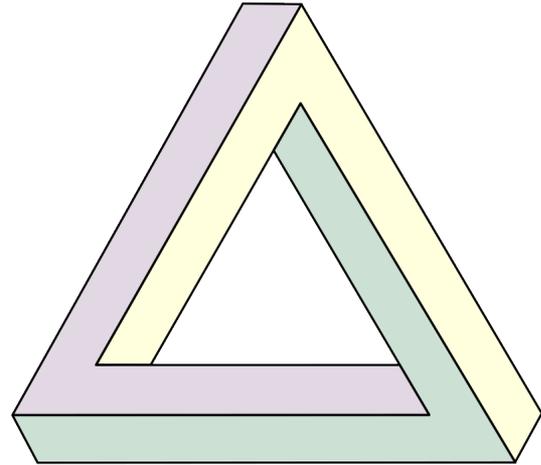


# The asymptotical behavior towards annotated data

Mistakes are present in:

- Training set
- Test set
- Validation set

So how to detect these errors?



# Representativity of training sets



# Representativity of training sets

## get the right set of features

Hard to find the correct set of features

- Rare cases
- Minor classes

Sampling methodology is a valid way to overcome this:

- (Stratified) Random Sampling in the population

# Representativity of training sets

get the right set of features

Finding strata:

- Clustering features
- Using background information

Apply stratification:

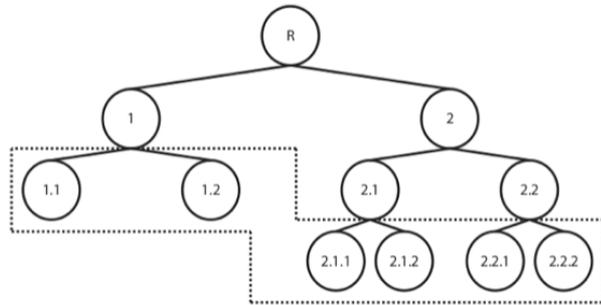
- Weighing
- multiple models

# Representativity of training sets

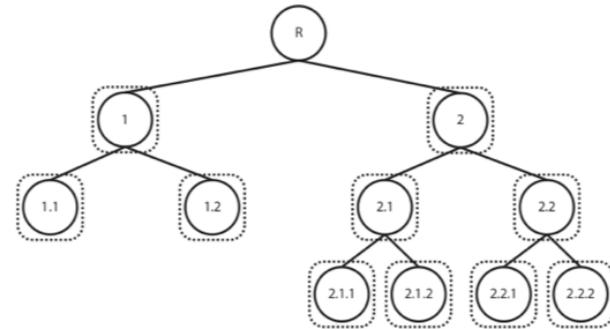
## Multiple models

Related model:

- Hierarchical Classification



vs.



Pedro Chaves, Hierarchical Classification – a useful approach for predicting thousands of possible categories, KDNuggets

# eXplainable AI



# eXplainable AI

## Three Stages

### Stages of AI explainability

<https://medium.com/@bahador.khaleghi>

#### Pre-modelling explainability

##### Goal

Understand/describe data used to develop models

##### Methodologies

- Exploratory data analysis
- Dataset description standardization
- Dataset summarization
- Explainable feature engineering

**The How of Explainable AI: Pre-modelling Explainability**

#### Explainable modelling

##### Goal

Develop inherently more explainable models

##### Methodologies

- Adopt explainable model family
- Hybrid models
- Joint prediction and explanation
- Architectural adjustments
- Regularization

**The How of Explainable AI: Explainable modelling**

#### Post-modelling explainability

##### Goal

Extract explanations to describe pre-developed models

##### Methodologies

- Perturbation mechanism
- Backward propagation
- Proxy models
- Activation optimization

**The How of Explainable AI: Post-modelling Explainability**



# eXplainable AI

## Validation

- The best way to validate a model is by understanding
- Marr (1982): Three levels at which an information -processing device should be described to be fully understood:
  - Computational Theory (How does the model relate to the reality?)
    - What is the goal?
    - Why is it appropriate?
    - Logic of the strategy?
  - Representation and algorithm (Design Pattern)
    - Input/output
    - Algorithm
  - (hardware) Implementation (How is it realized?)

# eXplainable AI

## Computational Theory (cf. Marr)

- "..., trying to understand perception by studying only neurons is like trying to understand bird flying by studying only feathers."
- In AI, the *how* question is often confused with the *why* question.
- "Why are these features selected" vs. "How are these features selected"
- Does it matter how complex the model is when we use this strategy?

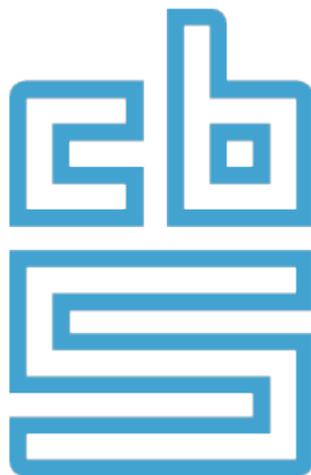
# Conclusion



# Quality of Official Statistics

- **Relevance**
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  - **Comparability**
- 
- **New research topics within machine learning appear due to applications in Official Statistics!**





**Facts that matter**