## **Explainable Machine Learning**

Application Perspectives

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# General Data Protection Regulation

#### Motivation



recusers nave choices too — \$650 billion market, we have 6%.

Break up FB?: US tech companies key asset for America; break up strengthens Chinese companies. GDPR [Don't say we already do what GDPR requires]

- People deserve good privacy tools and controls wherever they live.
- We build everything to be transparent and give people control. GDPR does a few things. Provides control over data use -- what we've done for a few years.
- o Requires consent -- done a little bit, now doing more in Europe and around the world. Get special consent for sensitive things e.g. facial recognition. Support privacy legislation that is practical, puts people in control and allows for innovation.

#### Background

- Enforcement date: 25 May 2018
- · Regulation instead of Directive
  - ⇒ Similar to national laws
- Fines up to €20 million or 4% of global revenue
- Regardless of company location



#### Goals

#### Basis for processing

- · Consent must be explicit for purpose
  - · e.g. calls recorded for training
- Records of processing activities
  - purpose
  - operator



#### Goals

#### Responsibility and accountability

- · Explanation of algorithmic decision
  - · recommendation systems
  - credit/insurance
- Human intervention (at least safeguards)
- · Respect data subjects rights/freedom
- Non-discriminating



#### Goals

- · Right of access
  - · e.g. Facebook export tool
- · Right to erasure
- Data breaches
  - · 72 h disclosure time
- Pseudoanonymisation
  - $\cdot$  encryption keys stored on other system



#### Overview

- · Data Protection Officer for every organization
- Responsibility and accountability
- · Lawful basis for processing
- Pseudoanonymisation
- Handling of data breaches
- Right of access
- · Right to erasure
- ⇒ Data protection and privacy by design
- ⇒ Overhaul of standard algorithmic techniques

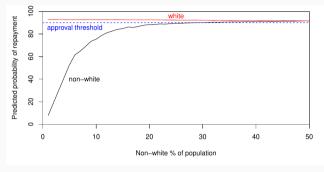


#### **Problems**

- · Fines only enforceable with international treaties
- · Blockchain vs. right to erasure
- · No official "checklist"
- · Big Data is not neutral
  - · side-channels even if features removed
  - biases from training set

#### Example: Unintended Discrimination

- Favor groups
- · Data size 500
- Default 95% probability
- Representation of non-white
- Less uncertainty



Discriminating underrepresented groups in training set with a risk avers logistic regression classifier.

#### Examples

- · Postal code
  - · revealing racial information
  - · info on loan defaulting
- $\cdot$  Consumer buying history o comparable to medical exam for life insurance
- ⇒ Meaningful solutions require understanding how result was inferred.

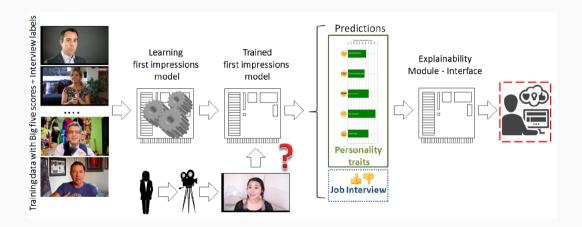
#### Outlook

- · Companies are planning since years
- · Chance to rectify current algorithms
- · Better than human counterparts after this?
- · Have to start planning algorithms with GDRP in mind

collect less data ← better predictions

Explainable Learning Challenge

#### Challenge Overview



### Design of an Explainable Learning Challenge for Video Interviews – Objectives

#### Explainability/interpretability:

- · Why is decision preferred over others
- · How confident is the algorithm
- · How were parameters selected
- Provide text description of reasoning





#### Challenge

#### Video:

- Gestures
- Facial expressions

#### Spoken word:

- Intonation
- · Pitch
- Transcript of video

⇒ "job-interview" prediction
 social characteristics – Extraversion, Agreeableness, Conscientiousness,
 Neuroticism and Openness

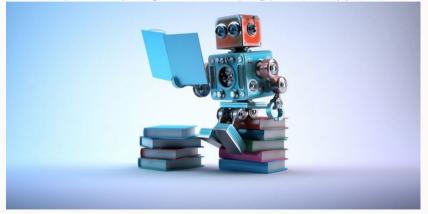
#### **Applications**

- Recruiters
   ⇒ need explanation of decision
- Negotiators
- Security gates
- Surveillance
- Military



#### Pro & Con Compared to Human Decision

Would you accept algorithms denying your job applications?



## Pro & Con Compared to Human Decision

#### Advantages:

- objective assessment
- · replicable solution

#### Disadvantages:

- · algorithm must be explainable
- · built to mimic human decisions

#### **Employed Data Set**

- 10 000 of 15 s clips from 3000 Youtube Videos
- · Labeled by humans (Amazon Mechanical Turk)
- · Voice transcription (Human transcription service)



#### **Evaluation Process**

- 1. Interview recommendation
- 2. Explanatory mechanism
  - · Textual description why decision was made
  - · Understand-ability
  - · Rational and scientifically common?
- 3. Code sharing



#### Proposed Attempts for Explanation of Employed Algorithms



This is to evaluate the quality of participants submission (below in yellow). Please answer all questions on the scale 0-5, **5** is best.

- Clarity: Is the text understandable / written in proper English?
- Explainability: Does the text provide relevant explanations to the hiring decision made?
- Soundness: Are the explanations rational and, in particular, do they seem scientific and/or related to behavioral cues commonly used in psychology?



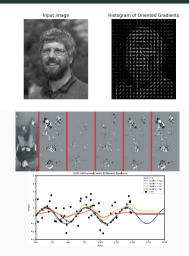
Submit

**Approaches** 

#### Example Parts of Pipelines Used

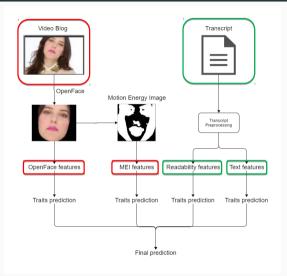
#### Selection of techniques used:

- · Face detection
- Frame differences
- · Support vector regression
- · Deep convolutional network



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#### Pipeline of the Winning Paper of the Second Round



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#### Presented Explanation of Winning Paper

```
************
```

\* ASSESSMENT REPORT FOR VIDEO 2c42A4Z7qPE.001.mp4: \*

\*\*\*\*\*\*\*\*\*\*\*\*

On a scale from 0.0 to 1.0, I would rate this person's interviewability as 0.497947.

Below, I will report on linguistic and visual assessment of the person.

Percentiles are obtained by comparing the person against scores of 6000 earlier assessed people.

\_\_\_\_\_

#### Presented Explanation of Winning Paper

```
****************

* USE OF LANGUAGE *

*****************
```

Here is the report on the person's language use:

\*\* FEATURES OBTAINED FROM SIMPLE TEXT ANALYSIS \*\*
Cognitive capability may be important for the job.
I looked at a few very simple text statistics first.

\*\*\* Amount of spoken words \*\*\*

This feature typically ranges between 0.000000 and 90.000000.

The score for this video is 29.000000 (percentile: 25).

In our model, a higher score on this feature typically leads to a higher overall assessment score.

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#### Presented Explanation of Winning Paper

```
*********

* VISUAL FEATURES *

**********

Here is the report on what I could "see":
```

\*\*\* Action Unit 12: how often was the lip corner pulled? \*\*\*
This feature typically ranges between 0.000000 and 1.000000.
The score for this video is 0.148148 (percentile: 82).

\*\*\* Action Unit 12: how much was the lip corner pulled on average? This feature typically ranges between 0.000000 and 2.880709. The score for this video is 0.333867 (percentile: 81).

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Conclusion

#### Explainability achieved?

- · Understandable for an expert
- · Unclear if really compliant with GDRP
- · Neural networks not explained
- · Most of the submitted entries did not use deep learning



#### Thanks!

#### Thank you for your attention!

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Support princip legislation that is practical, puts people in control and allows for Innovation.

#### References:

European Union regulations on algorithmic decision-making and a "right to explanation"; Goodman and Flaxman

Design of an explainable machine learning challenge for video interviews; Escalante et al.

Conclusion 23/23