The Machine Learning Pipeline – A space for action

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We call it ADM

Automated Decision Making

- Rule-based algorithms
- Machine Learning
- Deep Learning / Neural Networks
ADM in a work context

Labour organization discussions

Think WFH means your boss isn’t watching you? Think again. (John Naughton)

Total numbers, work-related focus on labour organization’s activities on algorithmic transparency and accountability on a global scale. Study conducted by AW on behalf of ITUC, preliminary results.
From principles to advocacy
Contributions by Labour Organizations in Europe on Algorithmic Transparency and Accountability
ADM systems as black boxes

- Lack of transparency
- Unsupervised learning
- Potentially constantly changing systems

Finding entry points for worker advocacy
ML-Pipeline

1. Problem definition

2. Data

3. Model-Training

4. Deployment

5. Retraining
ML-Pipeline

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- “decrease the cost of finding good employees”
- “collect data of current workforce”
- “extract patterns from data into a model”
- “integrate this model into an ADMS”
- “ingest new data into the ADMS”
ML-Pipeline

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Common content
- problem and approach
- requirements
- resources

Common risks
- “subjective worldview”
- prediction != prescription
- power shifts

Safeguards
- representation and integration of employee’s interests
ML-Pipeline

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Common content
- Defining Entities, Attributes & Interconnections
- Measuring and transforming data

Common risks
- Arbitrary simplifications
- Privacy violations

Safeguards
- Measures for fair and de-biased data
- Data directly relating to employee’s interest
ML-Pipeline

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Common content
- Goal: extracting useful patterns from training data

Common risks
- Hard to prevent from learning harmful patterns?

Safeguards
- Interested-aligned algorithmic sub-components:
  - Objective function
  - Training algorithm
  - Metrics
Common content
- Model is integrated into a classical software
- General aspects:
  - Performance
  - User experience

Safeguards
- Provide info for the employees
  - Performance & uncertainty
  - Metrics & monitoring (logs, dashboards, alerts)
ML-Pipeline

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Shifting distributions:

Common Content
- Diverging distributions
- Deteriorating performance
- However: “degenerate feedback loops”

Safeguards
- Monitoring distributions and modeling the influence of the model itself
To conclude

ML-Pipeline can be a tool to advocate for employee’s interests

It’s technically possible to implement worker interests

Employer interests: find constructive compromises

Infrastructure to support formation and expression of employees’ interests

Political power to realize the implementation of these interests
Questions/Discussion