Trustworthy Al

SAS network for women 27. September 2023

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Agenda







- Diversity leads to more varied perspectives, more innovation and ideas
- Role Models
- Female Market Insights
- Navigate cultural differences in a globalized world
- Greater gender diversity in IT has economic benefits

"There is a need for Women everywhere – but also in Technology" (Margrethe Vestager, on international Women's day 8.3.2023)



https://www.aldeparty.eu/vestager we need women everywhere



If your training data set looks like this...



It won't extrapolate to a population that includes



Examples of Gender Bias in Al

Debat | Chefen er en mand, kvinden er sekretær - tænker du også bias i AI?



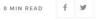
Vi bad det billedgerende AI-værktøj Midjourney om lave et billede af "manager in modern office" og "secretary in modern office", og dette var resultatet. Illustration: Illustration: Midjourney/Aslak



RETAIL OCTOBER 11, 2018 / 1:04 AM / UPDATED 5 YEARS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

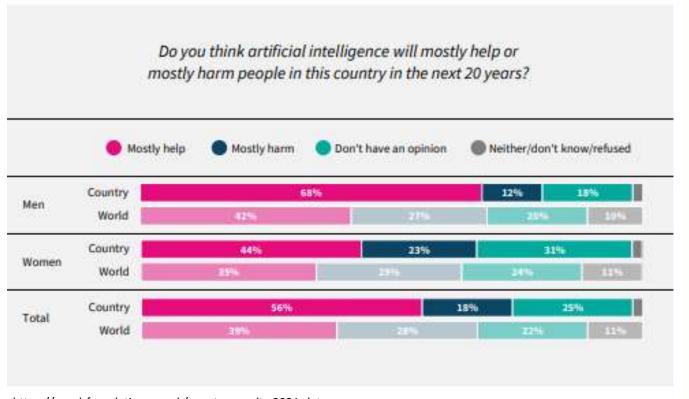
By Jeffrey Dastin





World AI Risk Pool 2021:

68% of Norwegian men think that AI will mostly help compared to 44% of Norwegian women



https://wrp.lrfoundation.org.uk/country-results-2021-data-ai/world_risk_poll_results_2021_data_ai_norway.pdf



Why is regulation of Al needed from a diversity perspective?

Al is everywhere, it affects us all already and some of it is biased

Algorithms can affect:

- Whether you are invited to a job interview or not
- Whether you can buy a house or not
- What adds you see and what news you read
- What insurance premium you pay
- Whether you get an insurance claim approved or not and how fast

Examples of Bias

- White applicants are called for interviews twice as often as black applicants with the same resume
- Men paid higher salaries than women in the same position
- Medical students in the 1900s for medical research
- Tech employees in the 1990s used for facial recognition



Sensitive Variables

- Race
- Gender
- Religion
- Sexual orientation
- Ethnicity
- Country of Origin
- Mother tongue



Risk of Al

- AI HAS THE POTENTIAL TO SIGNIFICANTLY IMPACT INDIVIDUALS AND SOCIETY
- Al can perpetuate and amplify biases
- Al can be **OPAQUE** and difficult to understand
- Al raises ethical concerns
- CREATE TRUST IN AI





Definition of Al

Al definitions

"artificial intelligence system" (Al system) means a machine-based system that is designed to operate with varying levels of autonomy and that can, for explicit or implicit objectives, generate outputs such as predictions, recommendations, or decisions, that influence physical or virtual environments;

 European Parliament proposal for rules for regulation of Artificial Intelligence <u>draft from June 2023</u> Artikel 3 nr. 1

"An AI system is a machine-based system that is capable of influencing the environment by producing an output (predictions, recommendations or decisions) for a given set of objectives. It uses machine and/or human-based data and inputs to (i) perceive real and/or virtual environments; (ii) abstract these perceptions into models through analysis in an automated manner (e.g., with machine learning), or manually; and (iii) use model inference to formulate options for outcomes. Al systems are designed to operate with varying levels of autonomy."

- OECD's definition of an Al system

Artificial intelligence (AI) makes it possible for machines to learn from data and human experience, adjust to new inputs, and enable data-driven decisions that are both effective and efficient. SAS defines Artificial Intelligence as "the science of designing ethical and transparent systems to support and accelerate human decisions and actions."

SAS



Machine Learning and Artificial Intelligence video

1950's

Artificial Intelligence

Traditional AI/ML systems recognize patterns and make predictions

1959 Machine Learning and **Neural Networks**

Machine learning is a specific subset of AI that trains a machine how to learn 2017 Deep Learning

Deep learning is a subset of machine learning that focuses on deep neural networks with multiple hidden layers. It has been particularly successful in tasks involving image and speech recognition, natural language processing, and

2021 Generative AI:

learn real-world data to *generate* data – *like* text, images, audio, tabular data, simulated data, code

- Large Language Models (LLMs) is a type of Natural Language Processing Model (NLP) that is designed to process and generate natural language text
 - November 2022 CHATGPT





EU Al Act is coming

disclaimer: we are not giving legal advice here

EU AI Act is coming

Overview - draft

On April 21 2021 the European Commission proposed the first legal framework on AI ever, which addresses the risks of AI and positions the European Union to play a leading role globally. It aims to regulate the development and use of AI in the EU. The act aims to address various aspects of AI, including ethics, safety, privacy, fairness, transparency, and accountability. but also to stimulate innovation in Europe



WHAT DOES IT FOCUS ON?

- Classification of AI systems
- Risk-based approach
- Human centered



WHO DOES IT APPLY TO?

- Providers, Users, Importers and Distributers of AI systems inside of the EU
- All sectors, except
 Al systems exclusively developed or used for military purposes



WHEN WILL IT APPLY?

- The Parliament is currently negotiating with the EU Council and the European Commission in the trilogue process. And expected to conclude in regulation end of 2023/start of 2024
- Then 2-3 years after this the legislation will enter into force, ie. End of 2025/2026



WHY SHOULD I CARE?

- You might already have AI systems in place
- Non-compliance can lead to fees up up to €20 million or 4% turnover, whichever is higher (Use of high-risk AI systems without solid data governance or violation of transparency requirements)

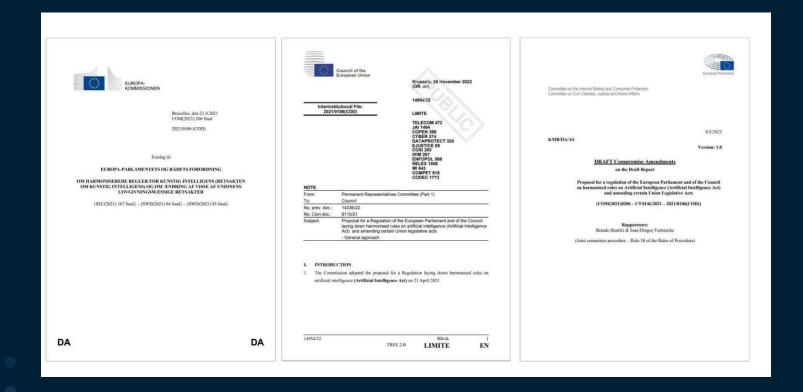


WHAT SHOULD WE DO NOW?

- First and foremost, know the rules in your industry, GDPR and the proposed AI regulation etc.
- Get an overview of the Al-systems you already use or are thinking about using – to which Risk category do they belong?
- Start thinking about the requirements from the AI act – wrt. Development, vendors etc.
- Start the build-up of a Responsible Al Governance Program
- Education and awareness about the proposed rules ("Al literacy")

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3 drafts exist currently wrt EU AI Act





EU AI Act Risk Based Approach

Draft still under negotiation

I. The use of Unacceptable-Risk AI systems is simply banned.

Examples: Real-time remote biometric identification in public places (Article 5)

Social scoring

II. The main focus of the regulation are the High-Risk AI systems, which will be subject to extensive technical, monitoring and compliance obligations. (Annex III)

Examples:

"5(b) Al systems intended to be used to evaluate the creditworthiness of natural persons or establish their credit score, with the exception of Al systems used for the purpose of detecting financial fraud"

"5(c) AI systems intended to be used for making decisions or materially influencing decisions on the eligibility of natural persons for health and life insurance"

III. & IV. Certain systems in the Low-Risk category are subject to transparency obligations. The low-risk category is encouraged to self-regulate by implementing codes of conduct for instance by adopting some of the requirements that are imposed on High-Risk AI systems. Examples: Simple recommendation engines, simple Chatbots used for basic customer support queries, such as answering frequently asked questions or providing information about products and services, spam filtre could be considered low risk.





European Commission Guidelines for Trustworthy Al



- 1 HUMAN AGENCY AND OVERSIGHT
- 2 TECHNICAL ROBUSTNESS AND SAFETY
- 3 PRIVACY AND DATA GOVERNANCE
- 4 TRANSPARANCY
- DIVERSITY, NON-DISCRIMINATION AND FAIRNESS
- 6 SOCIETAL AND ENVIRONMENTAL WELL-BEING
- 7 ACCOUNTABILITY

Focus today

Ssas

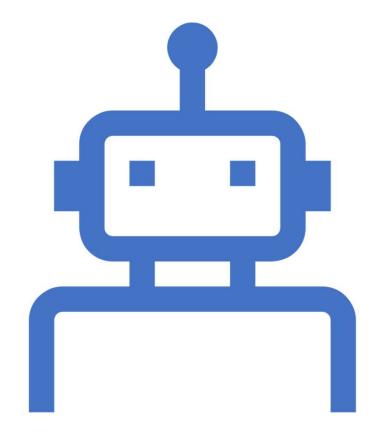
European Commission Guidelines for Trustworthy Al

- HUMAN AGENCY AND OVERSIGHT How do you guarantee that the AI system does not violate fundamental rights? How is the AI system augmenting human capabilities and how is it controlled?
- TECHNICAL ROBUSTNESS AND SAFETY Is the AI system resilient against attacks? Do you have a fallback plan? How do you measure accuracy, assess reliability and ensure reproducibility?
- PRIVACY AND DATA GOVERNANCE Is your AI system compliant with the relevant privacy regulations? How to you qualify the quality and integrity of data? Who can access the data?
- TRANSPARENCY Are you able to explain the results and decisions of the AI system? How do you ensure traceability? Are the users of the AI system aware that they are communicating with an AI system?
- DIVERSITY, NON-DISCRIMINATION AND FAIRNESS Unfair bias must be avoided, as it could could have multiple negative implications, from the marginalization of vulnerable groups, to the exacerbation of prejudice and discrimination. Fostering diversity, AI systems should be accessible to all, regardless of any disability, and involve relevant stakeholders throughout their entire life circle.
- SOCIETAL AND ENVIRONMENTAL WELL-BEING How do measure the environmental, societal and social impact of the Al system?
- ACCOUNTABILITY How do you facilitate auditability of the AI system? Is the AI system making unauthorized decisions on behalf of your organization? How do you minimize negative impact?

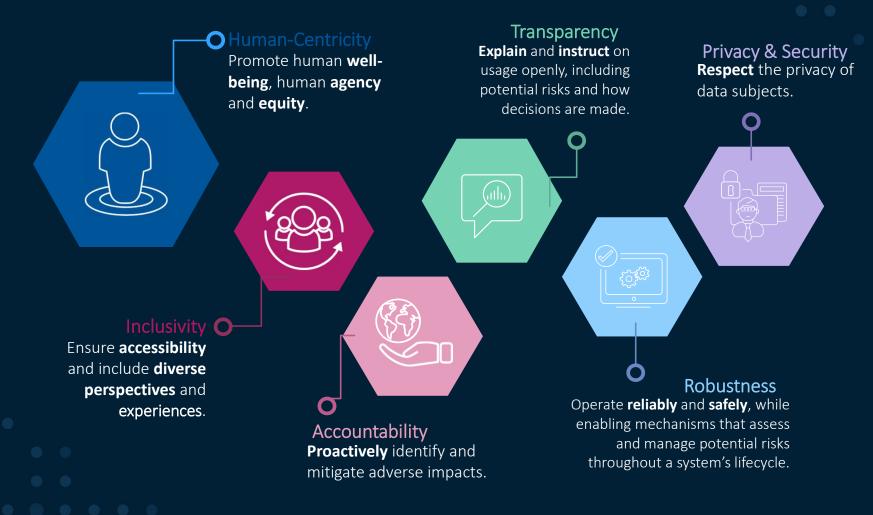
Focus today



SAS and Trustworthy Al



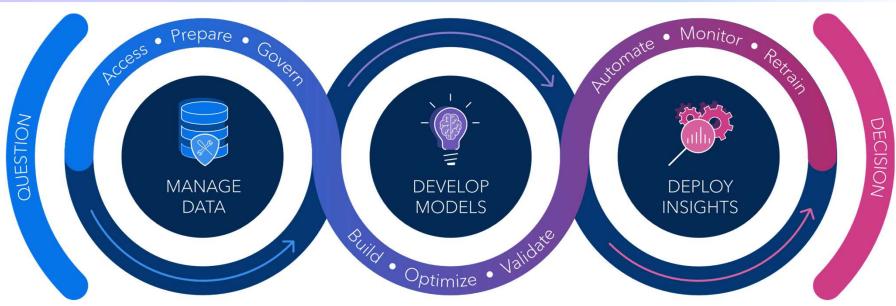
SAS and Trustworthy Al principles





How does SAS Viya support Trustworthy AI?

SAS Trustworthy AI CAPABILITIES



- Data Quality
- Data Exploration
- Information Privacy
- Data Masking (<u>1</u>) (<u>2</u>)
- <u>Data Suppression</u>
- <u>Data Lineage</u>

- Natural Language Insights (1) (2)
- Model Interpretability
- <u>Fairness Assessment</u> & <u>Bias Mitigation</u>
- Model Governance
- Model Monitoring
- Decision Accountability

Demo Today



ata Bias

Bias

Is the data representative?

Are sensitive variables or proxies used in model development?

Can you explain how a model arrives at a decision?

Is model accuracy better for specific populations or groups over others?

How do you monitor model bias over time?

Are the final decisions biased wrt to specific populations or groups?

- Explore data distributions across different groups and populations to identify data anomalies and potential bias.
- Automatically identify sensitive variables and proxies for sensitive variables.
- Assess model interpretability by group.
- Use AUC parity, predictive parity and equalized odds to evaluate model performance by group
- Set up fairness monitoring over time and define **automated alerts**.
- Test and monitor impact of end user decisioning.

Re-sampling / Re-weighing

Remove sensitive variables and proxies, adapt data collection strategy...

Use a segmentation strategy to optimize model's logic per group or population

Evaluate different cut-off thresholds per group by optimizing fairness statistics

Model re-training and re-optimization per group or population

Evaluate different business rule cut-off thresholds per group or population



How to Assess Model Fairness with SAS? fairAlTools.assessBias Action

```
Node
              Notes
      proc cas;
          fairAITools.assessBias /
 3
               modelTableType = "NONE",
               predictedVariables = {"P_high_low_flag0","P_high_low_flag1"}
 5
               response = "high low flag",
               responseLevels = {"0","1"}
               event = "1",
 8
               sensitiveVariable = "sex"
 9
               table = {name="adultScored",caslib="casuser"};
10
       run;
11
       quit;
```

<u>link to</u> documentation

		Bias Metrics		
Bias Statistic	Bias Statistic Label	Bias Statistic Value	Base Level	Compare Leve
DemographicParity	Demographic Parity (Statistical Parity)	0.1783	Male	Female
PredictiveParity	Predictive Parity	0.1905	Male	Female
EqualAccuracy	Equal Accuracy	0.1007	Female	Male
EqualizedOdds	Equalized Odds	0.0786	Male	Female
EqualOpportunity	Equal Opportunity	0.0786	Male	Female



Example Fit Statistics to Measure Model Performance

Abbreviation	Fit Statistic Name	Better is:	
ASE	Average Squared Error	lower	
RASE	Root Average Squared Error	lower	
maxKS	Maximum Kolmogorov Smirnov statistic	higher	
MCLL	Multi-Class Log Loss	lower	
TPR	True Positive Rate	higher	
FPR	False Positive Rate	lower	
FNR	False Negative Rate	lower	
FDR	False Discovery Rate = FP/(FP + TP)	lower	
С	Area under ROC	higher	
F1	F1 score	higher	

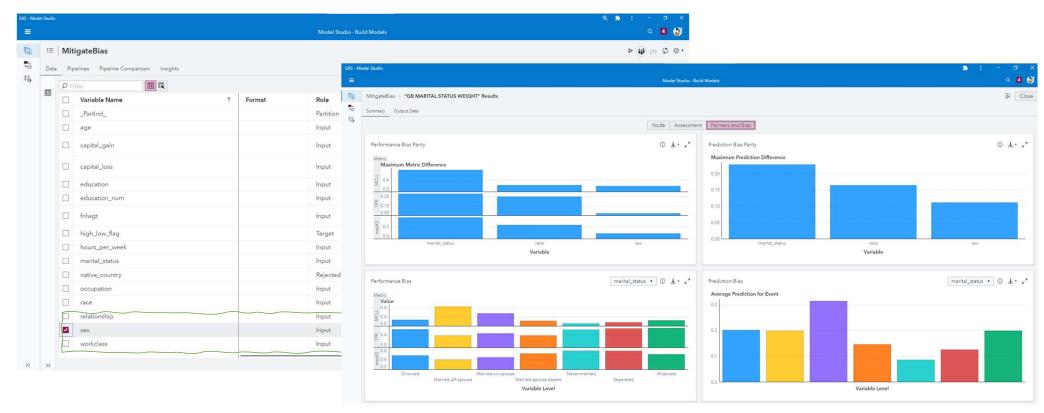


Using SAS Model Studio to Assess Bias

Assessing Bias				
Performance Bias	Fit statistics (e.g., ASE, RASE, MCLL, TPR & KS) grouped by each level of the sensitive variable			
Performance Bias Parity	Difference between the variable level with the highest value and the variable value with the lowest value for each of the fit statistics from the Performance Bias Chart			
Prediction Bias	Average predicted values for every level (including missing values) of the sensitive variable			
Prediction Bias Parity	Difference between the variable level with the highest average prediction for event value and the variable level with the lowest average prediction for event value			

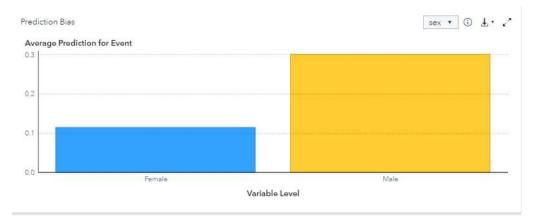


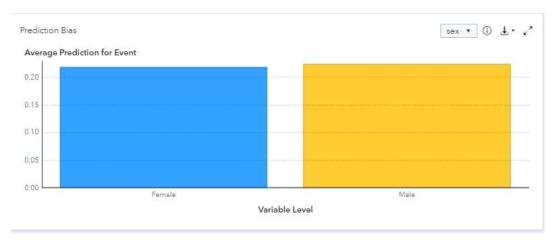
How to Assess Model Fairness with SAS?





How to mitigate Bias with SAS Viya?





sex

Prediction bias represents how much greater the model's probability to predict the event is for one group over another on average. The bars in this plot represent the target event's average predicted probability for each level of the variable sex for the VALIDATE partition. Large differences in bar size indicate that the model predicts the event at considerably different rates for different levels of sex, and you should be aware of this before using your model. You can view the maximum prediction difference between levels of each Assess for Bias variable in the Prediction Bias Parity plot.





How to Mitigate Model Fairness with SAS? fairAlTools.mitigateBias Action

```
proc cas;
  fairAITools.mitigateBias result=rslt /
      biasMetric="PREDICTIVEPARITY",
      bound="625",
      event="1",
      learningRate="0.01",
      maxIters="10",
      predictedVariables={"P_high_low_flag0", "P_high_low_flag1"},
      response="high low flag",
      responseLevels={"0", "1"},
      sensitiveVariable="sex",
      table="adult train",
      tolerance="0.005",
      trainProgram="
           decisionTree.gbtreeTrain result=train res /
              table=table,
              weight=weight,
              target=""high_low_flag"",
              inputs= {
                       ""age"",
                       ""workclass"",
                       ""fnlwgt"",
                       ""education"",
                       ""occupation"",
                       ""relationship"",
                       ""capital gain"",
                       ""capital_loss"",
                       ""hours per week"",
                       ""native_country""
              nominals={""workclass"",""high_low_flag"",""education"",
              nBins=50,
```

Enter expression				
	(a) Iteration		⊕ PR	
1	1	Female	0.1443	
2	1	Male	0.2918	
3	2	Female	0.1657	
4	2	Male	0.2623	
5	3	Female	0.1926	
6	3	Male	0.2404	
7	4	Female	0.2065	
8	4	Male	0.2295	
9	5	Female	0.2156	
10	5	Male	0.2246	
11	6	Female	0.2186	
12	6	Male	0.2225	

Link to documentation



Demo

Creating Fairness in your AI models with SAS Viya

Assessing Bias in Visual Analytics

Assessing and Mitigating Bias in Model Studio

Demo scenario

- Background:
 - https://archive.ics.uci.edu/ml/datasets/census+income
 - Model Objective: The models predicts who ends up in the high (>50.000 usd) or low income <50.000 usd) group(binary variable)
- Data (32.561 obs): Marital_status, education, age,
 - Sensitive variable: sex , race, nationality



Try the demo yourself

- Start up a Viya environment
 - Free 14 day trial
- https://www.sas.com/en_us/trials/software/viya/viya-trial-form.html

Fetch for instance this dataset that I used – or use your own data (but should be non-sensitive, anonymized):

- https://archive.ics.uci.edu/ml/datasets/census+income
- Follow the steps in Tamara Fischer and Veronique Van Vlasselelaer's <u>webinar on Creating Fair Machine Learning Models</u>

More information

Trustworthy AI

5.10.2023: webinar on how to put Trustworthy Al into practice

https://www.sas.com/en_us/webinars/trustworthy-ai-using-sas.html

For the insurers

5.10.2023: webinar on AI and Explainable AI in a ratemaking content

https://www.sas.com/sas/webinars/actuarial-models.html

https://www.sas.com/content/dam/SAS/documents/marketing-whitepapers-ebooks/ebooks/en/a-

comprehensive-approach-to-trustworthy-ai-governance-113518.pdf

About the EU AI Act

The status of AI regulation in the US and elsewhere 24.8.2023

https://open.spotify.com/show/0hSfdnMthaAv3jFIWbxq5e

The Norwegian government position on the EU AI Act

https://www.regieringen.no/contentassets/939c260c81234eae96b6a1a0fd32b6de/norwegian-position-paper-on-the-ecs-proposal-for-a-regulation-of-ai.pdf

Bias

"Coded Bias" documentary from netflix https://lnkd.in/eHrzDzXq

https://kjonnsforskning.no/sites/default/files/rapporter/hva vet vi om kunstig intelligens og likestilling.pdf



