Trusted AI:
Addressing Bias, Explainability and Robustness in Machine Learning Models

June 3, 2021

The session starts at 12:00pm.

Trusted AI

Addressing Bias, Explainability and Robustness in Machine Learning Models

Topics

- **Trust in AI**
- Cloud Pak for Data
- Lab Overview/Lab-1 Setup Environment
- Lab-2 Model Fairness
  - AIF360 Toolkit
- Lab-3 Model Explainability
  - AIX360 Toolkit
- Lab-4 Model Robustness
  - Adversarial Robustness Toolbox
- Lab-5 Watson OpenScale

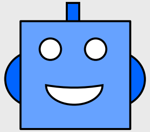
What is Machine Learning?

"Computer that learn without being explicitly programmed"

data
data data
data data data

Historical + Outcome
Data

Training



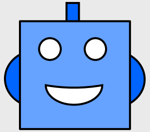
Trained
model

Algorithm

1 A machine learning model is trained to recognize patterns in historical data

data
data data
data data data

New
Data



Trained
model

prediction
or
classification

2 The model is then shown new data and asked to predict or classify it. If the patterns In the new data match the training data then the model makes accurate predictions.

Machine Learning is used in many high-stakes decision-making applications

Credit

Employment

Healthcare

Self-Driving Cars

Rising concerns over trust in AI

YouTube sued for using AI to racially profile content creators

They claim YouTube's algorithms discriminate against black users

BlackRock shelves unexplainable AI liquidity models

Risk USA: Neural nets beat other models in tests, but results could not be explained

Data science during COVID-19: Some reassembly required

Most likely, the assumptions behind your data science model or the patterns in your data did not survive the coronavirus pandemic. Here's how to address the challenges of model drift

Can AI models respond to black swan events like COVID-19?

Sections

The Washington Post

Democracy Dies in Darkness

Get 1 year for $29

Apple Card algorithm sparks gender bias allegations against Goldman Sachs

RETAIL OCTOBE

Amazon scraps secret AI recruiting tool that showed bias against women

EFF to HUD: Algorithms Are No Excuse for Discrimination

BY JAMIE WILLIAMS, SAIRA HUSSAIN, AND JEREMY GILLULA | SEPTEMBER 26, 2019

Enterprises must consider Regulatory Compliance

USA

SR 11–7 requires model risk management for all models in financial services

2019—Proposal for Algorithmic Accountability Act

2021 – US Govt. National AI Initiative Act

Canada

2017—National AI Strategy launched

2020—All public agencies must do an impact analysis for AI models

European Union

2021 – Draft regulation for trust in AI

2019—Guidelines for AI development

Mexico

2018—General principles for AI development in the government

Partnerships on AI

Partnership between tech companies to study best practices and impact of AI

AI Now Institute

NYU research center focused on social implications of AI

Aspects of Trustworthy AI

Fair

Impartial and addressing bias

Are privileged groups at a systematic advantage compared to other groups?

Robust

Handle exceptional conditions effectively

Can we evaluate and defend against a variety of threats?

Privacy

High integrity data and business compliance

How do we ensure owners retain control of data and insights?

Explainable

Easy to understand outcomes/decisions

Why did the AI arrive at an outcome? When would it have been different?

Transparent

Open to inspecting facts and details

Can we increase understanding of why and how AI was created?

Topics

- Trust in AI
- **Cloud Pak for Data**
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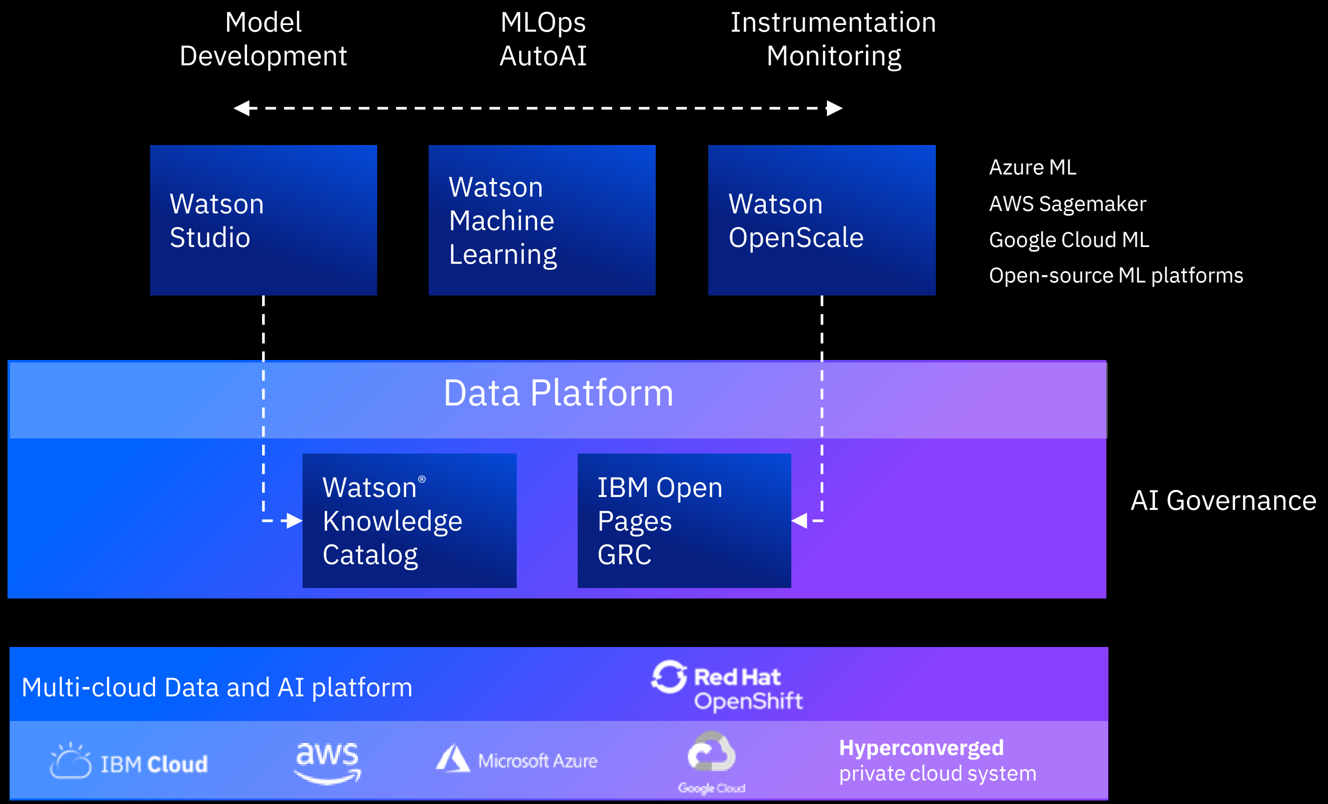
- Lab-5 Watson OpenScale

IBM Cloud Pak for Data enables a Governed, Automated AI Lifecycle



Topics

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Lab Overview - www.github.com/bleonardb3/TR_POT_06-03-2021

When deploying machine learning models, other factors besides the accuracy of the model needs to be considered. Is the model biased? Can the decisions made by the model be explained?. Is the model robust to adversarial attacks? IBM has developed 3 toolkits to help address these questions.

This session will provide a brief overview of the toolkits and 1 lab on each toolkit. In addition, a lab on Watson Openscale which monitors accuracy, bias, and model drift will also be included. The attendees will use Watson Studio to complete the labs.

Lab-1 - This lab will walk through the steps to create a Watson Studio project. A Watson Studio project is a way to organize your data and analytical assets for an analytics project.

Lab-2 - This lab will feature IBM's AI Fairness 360 (AIF360), a comprehensive open-source toolkit of metrics to check for unwanted bias in datasets and machine learning models, and state-of-the-art algorithms to mitigate such bias.

Lab-3 - This lab will feature IBM's AI Explainability 360 (AIX360), a comprehensive open source toolkit of state-of-the-art algorithms that support the interpretability and explainability of machine learning models.

Lab-4 - This lab will feature IBM's Adversarial Robustness Toolbox (ART). ART is a library dedicated to adversarial machine learning. Its purpose is to allow rapid crafting and analysis of attacks and defense methods for machine learning models. ART provides an implementation for many state-of-the-art methods for attacking and defending classifiers.

Lab-5 - This demo will feature IBM Watson OpenScale. IBM Watson OpenScale is an open platform that helps remove barriers to enterprise-scale AI by supporting bias mitigation, accuracy, and explainability of outcomes among other features.

Lab Overview - www.github.com/bleonardb3/TR_POT_06-03-2021

Lab-1: Setup Environment

Introduction:

This lab will set up the Watson Studio environment for subsequent labs and introduce you to the Project features of Watson Studio. Watson Studio is an integrated platform of tools, services, data, and meta-data to help companies and agencies accelerate their shift to be data driven organizations. The platform enables data professionals such as data scientists, data engineers, business analysts, and application developers collaboratively work with data to build, train, deploy machine learning and deep learning models at scale to infuse AI into business to drive innovation. Watson Studio is designed to support the development and deployment of data and analytics assets for the enterprise.

Objectives:

Upon completing the lab, you will have:

1. Created a project
2. Associated a Machine Learning service with the project
3. Created a Deployment space
4. Created an instance of Watson OpenScale

Step 1. Please click on the link below to download the instructions to your machine.

Watson Studio Projects

Making Data Science a Team Sport

Watson Studio provides the environment and tools to collaborate on business problems.

Watson Studio is centered around the *Analytics Project.* Data scientists and business analysts use analytics projects to organize resources and analyze data with various tools.

Analytics projects

Collaborators

- Admin
- Editor
- Viewer

Data assets

- Data files
- Connections
- Connected data

Analytical assets

- Notebooks
- Experiments
- Dashboards
- Flows
- Models
- Scripts
- Shiny apps

Tools for doing these tasks

- Prepare data
- Visualize data
- Build models
- Automate AI experiments
- Train neural networks
- Schedule jobs
- Manage compute
- Script actions

Your data sources ↑ **Catalogs** ↕ **Deployment spaces** ↓ **Other services** ↑

Please work on Lab-1. We will return to present on the AIF360 Toolkit at 1:15pm EST

Topics

- Trust in AI
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- **Lab-2 Model Fairness**
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Model Fairness

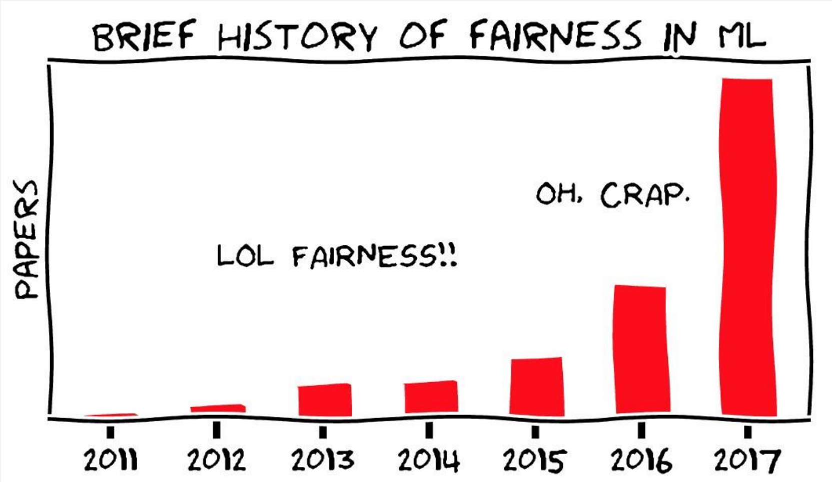
Machine Learning is a form of statistical discrimination by nature

Sometimes this discrimination becomes objectionable or possibly illegal

- Systematically favoring privileged groups like Caucasian male

Mitigating bias can be done on:

- training data*: pre-processing*
- the learned model: *in-processing*
- the model outcomes: post-processing



Source: [A Tutorial on Fairness in Machine Learning]

Example - Hiring

Source: A Tutorial on Fairness in Machine Learning

XING, a job platform similar to Linked-in, was found to rank less qualified male candidates higher than more qualified female candidates

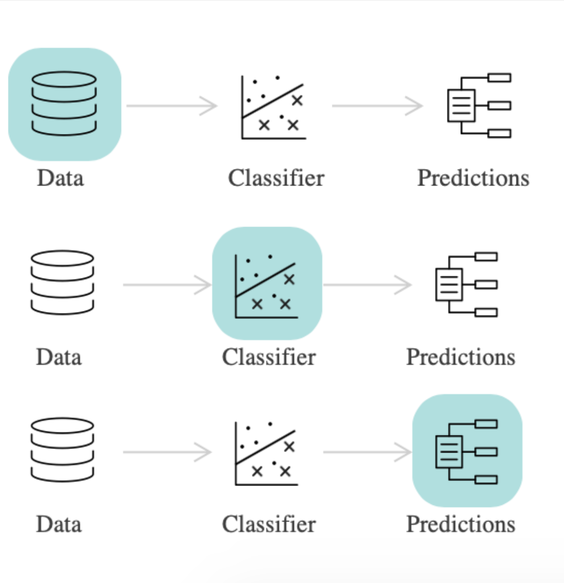
Search query	Work experience	Education experience	Profile views	Candidate	Xing ranking
Brand Strategist	146	57	12992	male	1
Brand Strategist	327	0	4715	female	2
Brand Strategist	502	74	6978	male	3
Brand Strategist	444	56	1504	female	4
Brand Strategist	139	25	63	male	5
Brand Strategist	110	65	3479	female	6
Brand Strategist	12	73	846	male	7
Brand Strategist	99	41	3019	male	8
Brand Strategist	42	51	1359	female	9
Brand Strategist	220	102	17186	female	10

TABLE II: Top k results on www.xing.com (Jan 2017) for the job serach query "Brand Strategist".

AIF360 Toolkit

- Provides fairness metrics to examine each stage of ML pipeline

- Provides bias mitigation in all stages



Pre-Processing: improve training data to remove bias from it

In-Processing: modify ML algorithm. Often in form of adding extra regularizations

Post-Processing: modify the prediction. Treats the ML model as a black box

For more information ...

AI Fairness 360

This extensible open source toolkit can help you examine, report, and mitigate discrimination and bias in machine learning models throughout the AI application lifecycle. We invite you to use and improve it.

Python API Docs ↗ | Get Python Code ↗ | Get R Code ↗

Not sure what to do first? Start here!

Read More

Learn more about fairness and bias mitigation concepts, terminology, and tools before you begin.

Try a Web Demo

Step through the process of checking and remediating bias in an interactive web demo that shows a sample of capabilities available in this toolkit

Watch Videos

Watch videos to learn more about AI Fairness 360.

Read a paper

Read a paper describing how we designed AI Fairness 360.

Use Tutorials

Step through a set of in-depth examples that introduces developers to code that checks and mitigates bias in different industry and application

http://aif360.mybluemix.net/

https://github.com/IBM/AIF360

Lab 2 - README.md

Machine learning models are increasingly used to inform high stakes decisions about people. Although machine learning, by its very nature, is always a form of statistical discrimination, the discrimination becomes objectionable when it places certain privileged groups at systematic advantage and certain unprivileged groups at systematic disadvantage. Biases in training data, due to either prejudice in labels or under-/over-sampling, yields models with unwanted bias.

AI Fairness 360 is an open source toolkit developed by IBM Research, that can help you examine, report, and mitigate discrimination and bias in machine learning models throughout the AI application lifecycle. The goal of this lab is to introduce its bias detection functionalities and help mitigate the bias in the machine learning model using Adversarial Debiasing technique.

For more information see links below:

```
AIF360 Demo: https://aif360.mybluemix.net
AIF360 GitHub: https://github.com/IBM/AIF360
AIF360 API Docs: https://aif360.readthedocs.io/en/latest/
```

Objectives

In this notebook you will utilize AIF360 to detect and mitigate bias on Compas dataset which is used to assess the likelihood that a criminal deefendant will reoffend.

Upon completing this lab you will learn:

```
1. How to add a Notebook to a project
2. How to load datasets from the toolkit package    1.
3. How to use AIF360 to check the dataset for bias
4. How to use AIF360 to mitigate existing bias by using Adversarial Debiasing technique
5. How to train on both original and corrected dataset and compare results
```

Step 1. Please click on the link below to download the instructions to your machine.

Please work on Lab-2.

We will return to present on the AIX360 Toolkit at 2:00 pm EST

Topics

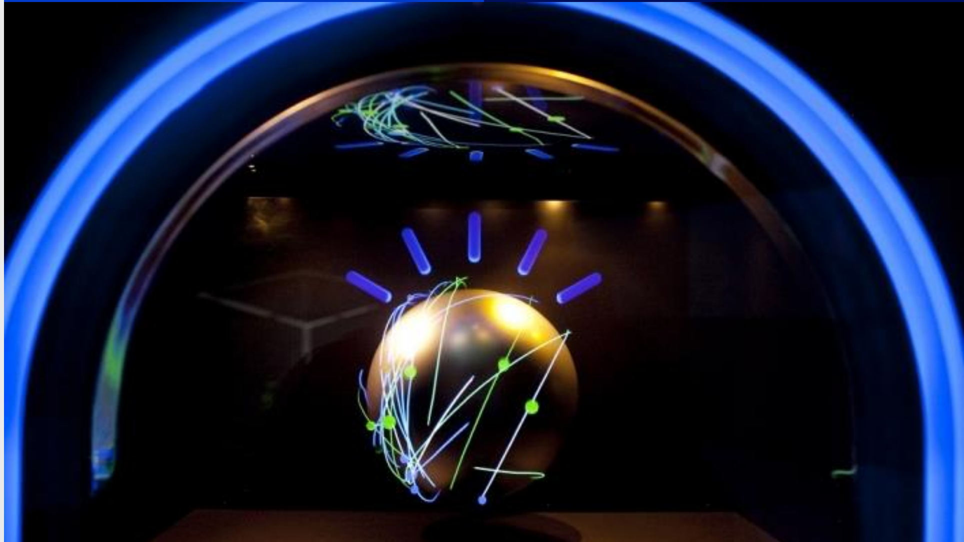
- Trust in AI
- Cloud Pak for Data
- Model Fairness
  - AIF360 Toolkit
- **Model Explainability**
  - AIX360 Toolkit
- Model Robustness
  - Adversarial Robustness Toolbox
- Watson OpenScale
- Lab Overview

Model Explainability

- To explanation our decisions in daily life, we use expressive vocabulary and several examples
- Must do the same with algorithmic decisions

Produce more explainable models, while maintaining a high level of learning performance (prediction accuracy)

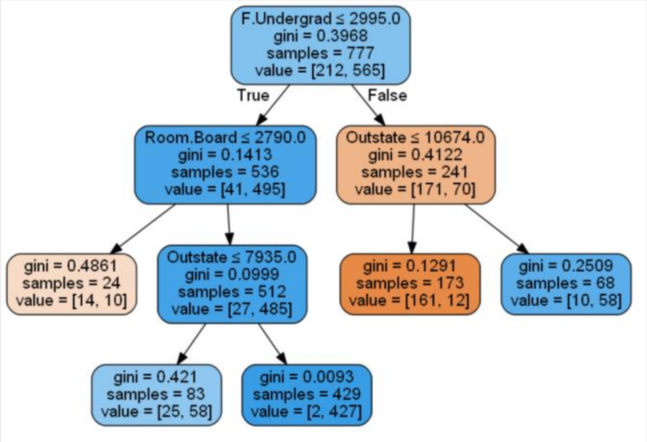
Enable human users to understand, trust, and effectively manage the emerging generation of artificially intelligent partners.

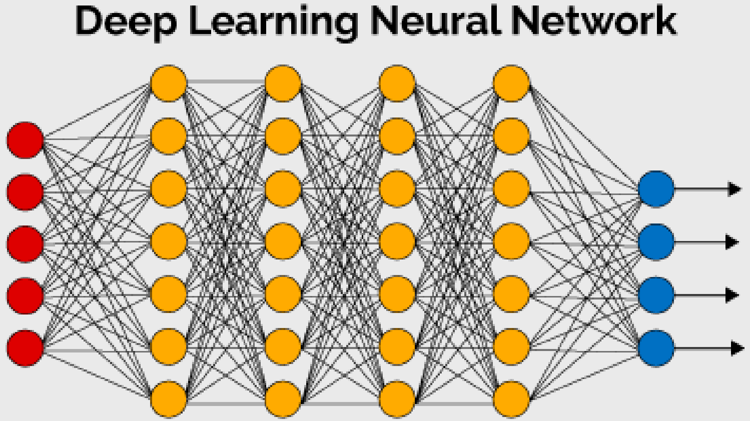


What is going on in The Black Box?

Source: If applicable, describe source origin

- Black box ML models cannot be understood by people
- The more powerful a model gets, the harder it is to understand





Which model's decision is easier to explain?

Example – Healthcare

AI System Diagnoses a patient with heart disease

Explain to the Doctor

What symptoms contributed to such diagnosis? What was similar/ different between this patient and the ones who where diagnosed before?

Explain to the Patient

What could have she done to prevent the illness?

AIX360 Toolkit

- Comprehensive toolkit of state-of-the-art algorithms
- Support the interpretability and explainability of machine learning models
- Open-source library written in python

Data Scientists

Interested in technical details of why a model works the way it does.

Decision Makers

(e.g. Doctors)

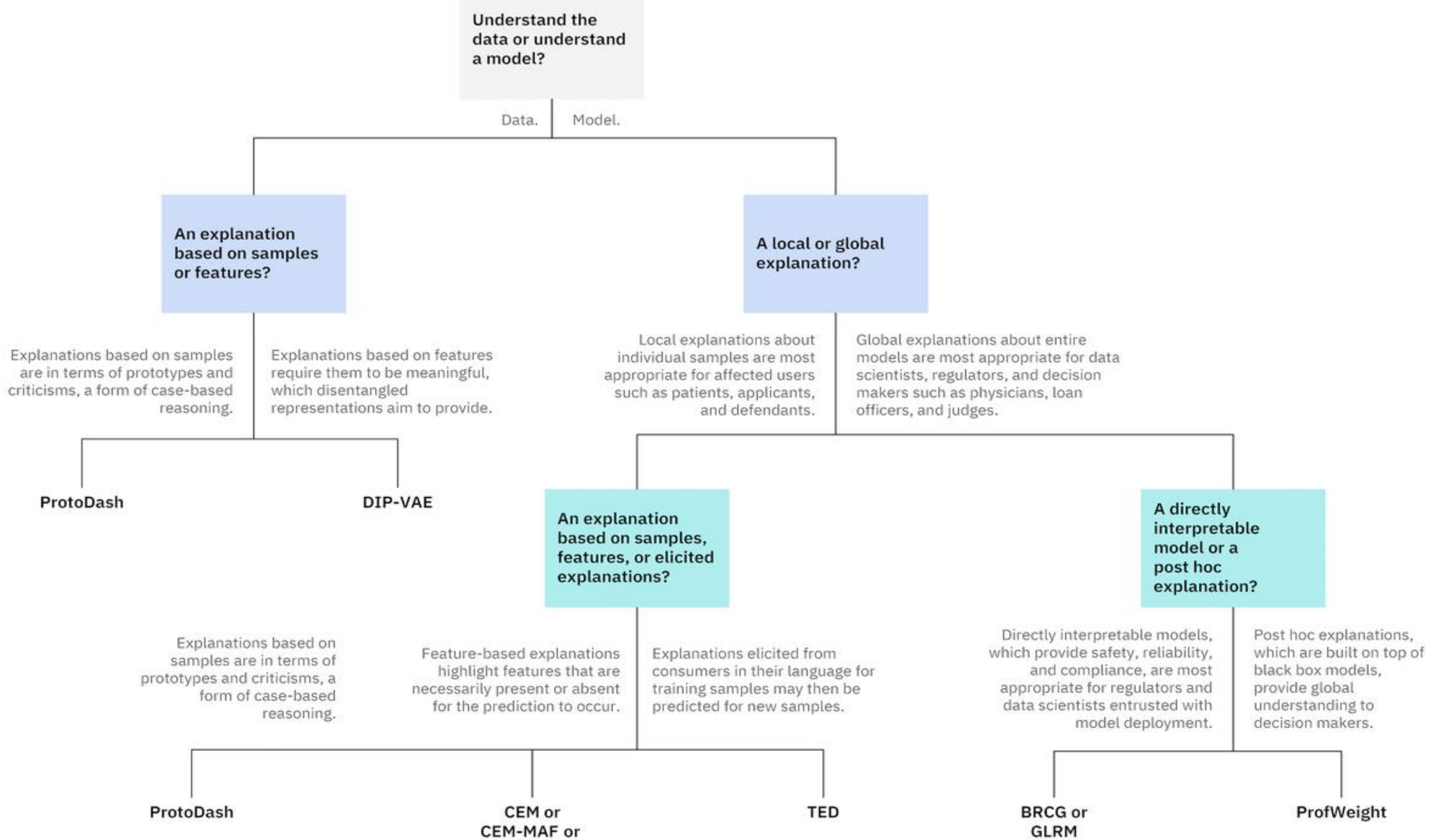
Interested in understanding the entire decision-making process and ensure its safety, reliability, or compliance.

Affected Users

(e.g. Patients)

Need to understand the decision about them in simple terms.

Explainability Algorithms Guidance



For more information ....

AI Explainability 360

This extensible open source toolkit can help you comprehend how machine learning models predict labels by various means throughout the AI application lifecycle. We invite you to use it and improve it.

API Docs ↗ Get Code ↗

Not sure what to do first? Start here!

Read More

Learn more about explainability concepts, terminology, and tools before you begin.

Try a Web Demo

Step through the process of explaining models to consumers with different personas in an interactive web demo that shows a

Watch Videos

Watch videos to learn more about AI Explainability 360 toolkit.

Read a Paper

Read a paper describing how we designed AI Explainability 360 toolkit.

Use Tutorials

Step through a set of in-depth examples that introduce developers to code that explains data and models in different industry

http://aix360.mybluemix.net/#

https://github.com/IBM/AIX360

Lab 3 - README.md

Introduction

Black box machine learning models that cannot be understood by people, such as deep neural networks and large ensembles, are achieving impressive accuracy on various tasks. However, as machine learning is increasingly used to inform high stakes decisions, explainability and interpretability of the models is becoming essential.

AI Explainability 360 is an open source toolkit developed by IBM Research, that can help explain why a machine learning model came to a decision. This toolkit includes algorithms that span the different dimensions of ways of explaining along with proxy explainability metrics.

For more information see links below:

```
AIX360 Demo: https://aix360.mybluemix.net
AIX360 GitHub: https://github.com/IBM/AIX360/
AIX360 API Docs: https://aix360.readthedocs.io/en/latest/
```

Objectives

Upon completing the lab, you will learn how to:

1. Add a notebook to a Watson Studio project
2. Load a dataset using a download link
3. Create, train, and evaluate a XGBoost model
4. Use Protodash Algorithm to extract similar examples and compare with the current patient's case

Step 1. Please click on the link below to download the instructions to your machine.

Instructions.

Please work on Lab-3.

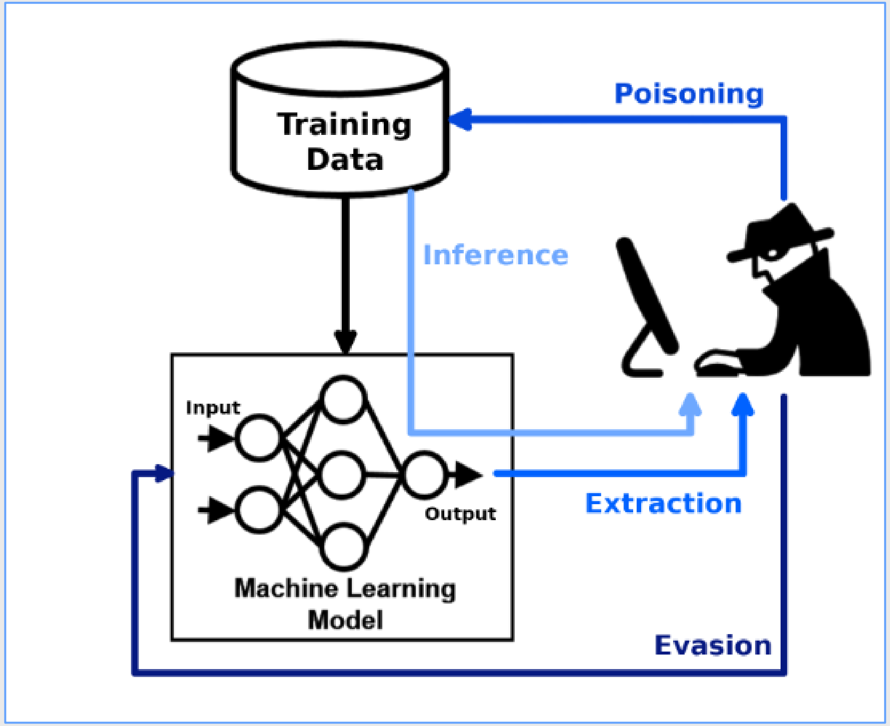
We will return to present on the ART Toolbox at 3:00 pm EST

Topics

- Trust in AI
- Cloud Pak for Data
- Model Fairness
  - AIF360 Toolkit
- Model Explainability
  - AIX360 Toolkit
- **Model Robustness**
  - Adversarial Robustness Toolbox
- Watson OpenScale
- Lab Overview

Adversarial Robustness Toolbox (ART)

- Provides tools to defend and evaluate Machine Learning models against the adversarial threats of Evasion, Poisoning, Extraction, and Inference.
- Supports all popular machine learning frameworks (TensorFlow, Keras, PyTorch, MXNet, scikit-learn, XGBoost, LightGBM, CatBoost, GPy, etc.)
- Supports all data types (images, tables, audio, video, etc.)
- Supports machine learning tasks (classification, object detection, speech recognition, generation, etc.).



Adversarial Robustness Toolbox (ART)

- IBM Research team in Ireland developed the toolbox to help defend Machine Learning models against adversarial attacks
- Open-source software library written in Python
- It creates adversarial examples AND provides methods for defending Machine Learning models against those.

Model Robustness

- Check if the mode is vulnerable to adversaries

Model Hardening

- Make sure the model will not be fooled

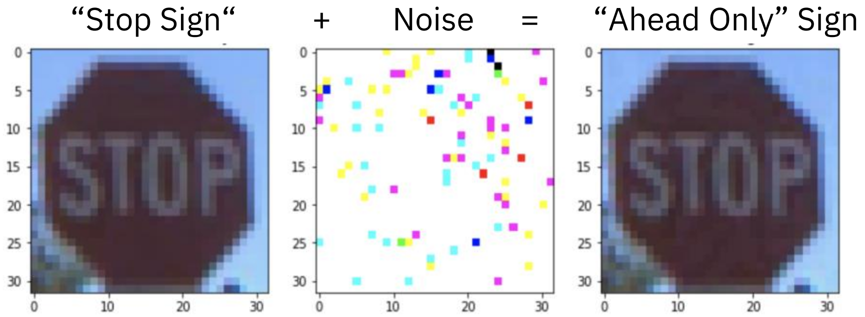
Runtime Detection

- Flag any input that an adversary tampered with

Adversarial Images

- Adversarial examples are inputs (say, images) which have deliberately been modified to produce a desired response by a VR system.

- Often, the target of adversarial examples is misclassification or a specific incorrect prediction which would benefit an attacker.

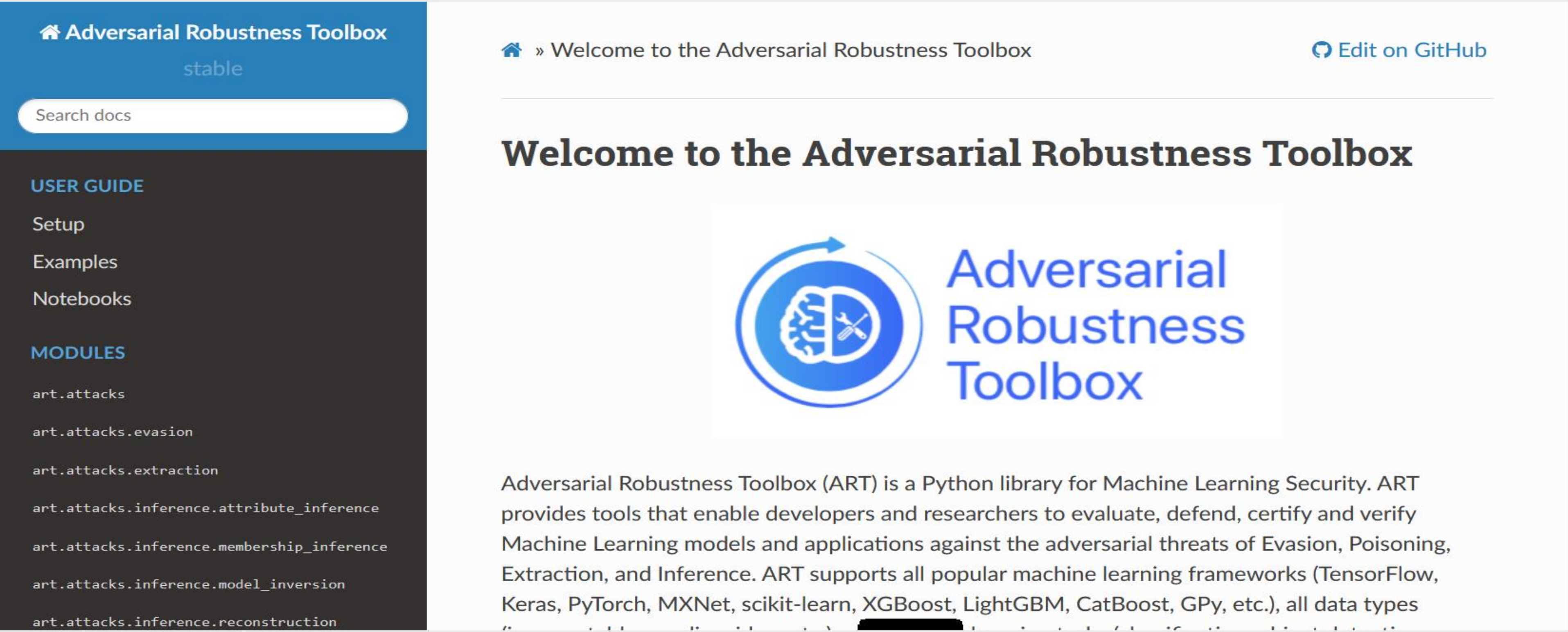


Why are they dangerous?

- Can be crafted even if the attacker doesn’t have exact knowledge of the architecture of the Machine Learning Model
- Adversarial attacks can be launched in the physical world
  - adversaries could evade face recognition systems by wearing specially designed glasses
  - defeat visual recognition systems in autonomous vehicles by sticking patches to traffic signs

* Pictures from paper: Kevin Eykholt, et al. “Robust Physical-World Attacks on Deep Learning Visual Classification”

For more information …


Adversarial Robustness Toolbox
stable
Search docs

USER GUIDE
Setup
Examples
Notebooks

MODULES
art.attacks
art.attacks.evasion
art.attacks.extraction
art.attacks.inference.attribute_inference
art.attacks.inference.membership_inference
art.attacks.inference.model_inversion
art.attacks.inference.reconstruction

» Welcome to the Adversarial Robustness Toolbox
Edit on GitHub

Welcome to the Adversarial Robustness Toolbox

Adversarial Robustness Toolbox (ART) is a Python library for Machine Learning Security. ART provides tools that enable developers and researchers to evaluate, defend, certify and verify Machine Learning models and applications against the adversarial threats of Evasion, Poisoning, Extraction, and Inference. ART supports all popular machine learning frameworks (TensorFlow, Keras, PyTorch, MXNet, scikit-learn, XGBoost, LightGBM, CatBoost, GPy, etc.), all data types [redacted]

https://art-demo.mybluemix.net/

https://github.com/IBM/AIF360

Lab 4 - README.md

```
ART Demo: https://art-demo.mybluemix.net
ART Blog: https://www.ibm.com/blogs/research/2018/04/ai-adversarial-robustness-toolbox/
ART Github: https://github.com/IBM/adversarial-robustness-toolbox
```

In this lab, you will work with the Adversarial Robustness Toolbox (ART) and implement an adversarial attack and its defense on a trained model. You will work with a model trained on the German Traffic Signs dataset (see Citation below) and get the model to misclassify a stop sign.

Dataset Citation

J. Stallkamp, M. Schlipsing, J. Salmen, and C. Igel. The German Traffic Sign Recognition Benchmark: A multi-class classification competition. In Proceedings of the IEEE International Joint Conference on Neural Networks, pages 1453–1460. 2011.

@inproceedings{Stallkamp-IJCNN-2011, author = {Johannes Stallkamp and Marc Schlipsing and Jan Salmen and Christian Igel}, booktitle = {IEEE International Joint Conference on Neural Networks}, title = {The {G}erman {T}raffic {S}ign {R}ecognition {B}enchmark: A multi-class classification competition}, year = {2011}, pages = {1453--1460} }

Objectives

Upon completing the lab, you will learn how to:

1. Add a notebook to a Watson Studio project
2. Load a Tensorflow trained model
3. Create an ART classifier object using the loaded model
4. Perfom an adversarial attack
5. Perfom a defense to make sure manipulated images can still be classified correctly

Step 1. Please click on the link below to download the instructions to your machine.

Please work on Lab-4.

We will return to present on Watson OpenScale at 4:00 pm EST

Topics

- Trust in AI
- Cloud Pak for Data
- Model Fairness
  - AIF360 Toolkit
- Model Explainability
  - AIX360 Toolkit
- Model Robustness
  - Adversarial Robustness Toolbox
- **Watson OpenScale**
- Lab Overview

Watson OpenScale

Trust and Transparency

- Intelligently delivers bias mitigation help
- Provides traceability & auditability of AI predictions made in production applications
- Tracks AI accuracy in applications
- Explains an outcome in business terms
- Provides drift detection

Automation

- Automatically detects and mitigates bias in model output, without affecting currently deployed model or outcomes

Open by Design

- Monitor models deployed on third party mode server engines
- Deploy behind enterprise firewall or on IaaS provider.

Model build / train frameworks

TensorFlow
scikit learn
Keras
PYTORCH
Caffe2
APACHE Spark

Model serving environments

IBM Cloud
aws

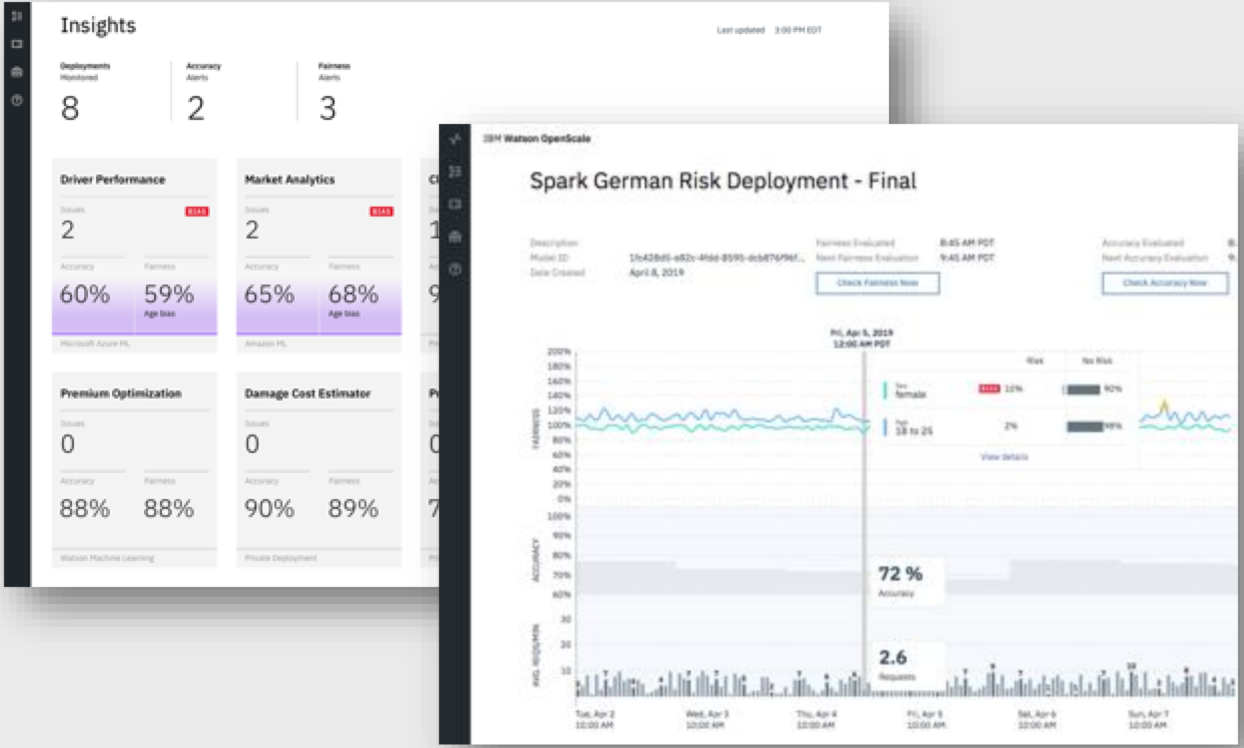
OpenScale Operations Dashboard

Description:

Monitor deployed models in a single dashboard that can be filtered by deployment making it easy to manage AI in apps

Value:

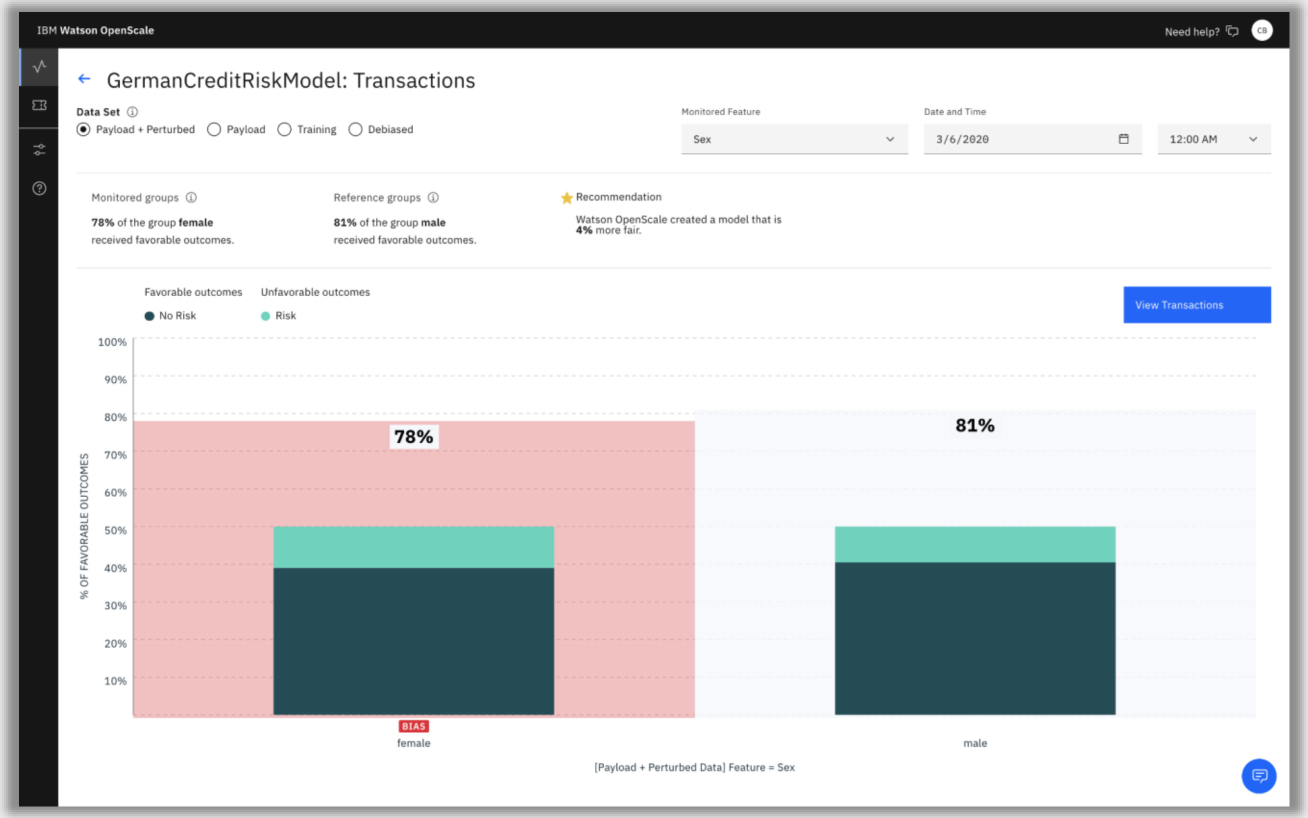
- Configure alerts or actions to be triggered when KPIs exceed threshold, ensuring model quality for improve business outcomes
- Measure model accuracy as it pertains to it’s ability to deliver outcomes more accurate than knowledge workers
- Provides “continuous evolution” for your models



Bias Mitigation – Original Model Output

Credit Risk Example Model

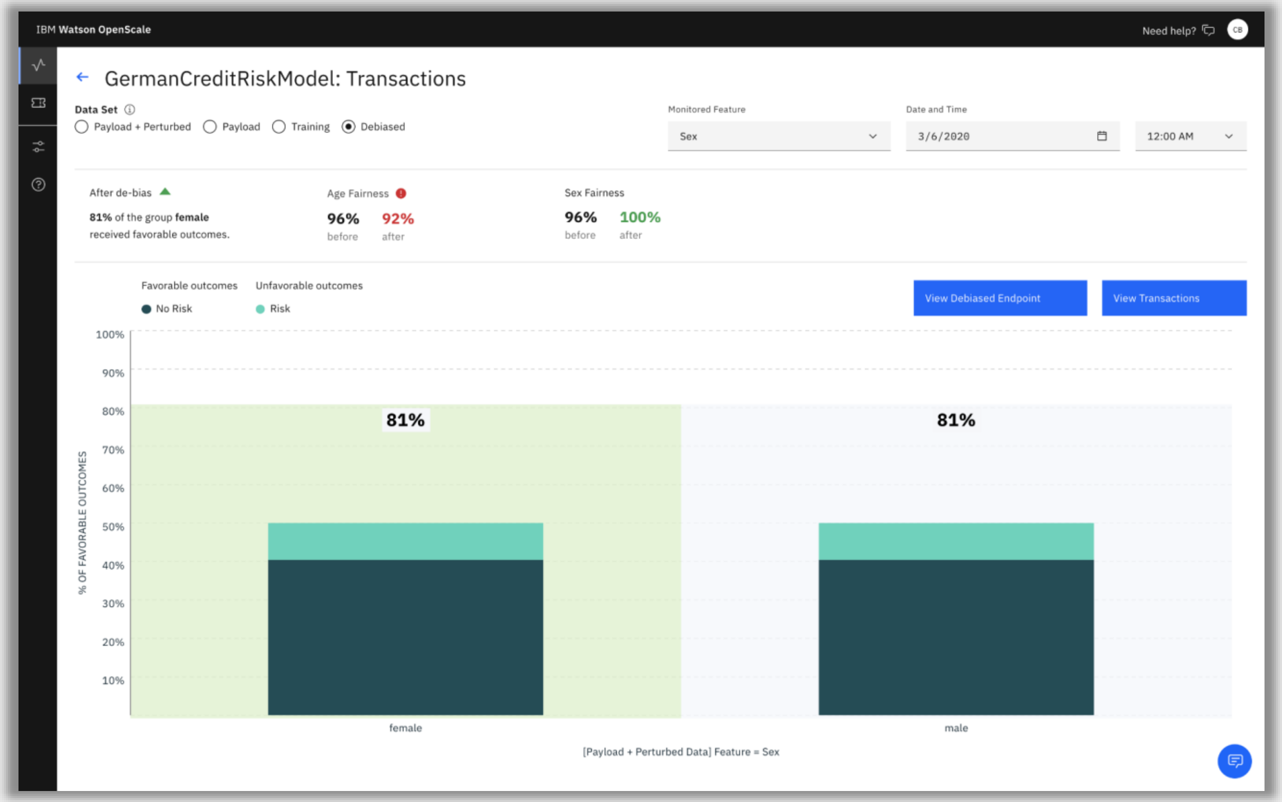
- 78% of the protected group (female) have a favorable output
- 81% of the reference group (male) get a favorable output
- Disparate impact Value: 96%



Bias Mitigation – De-biased Model Output

After De-biasing algorithms was applied

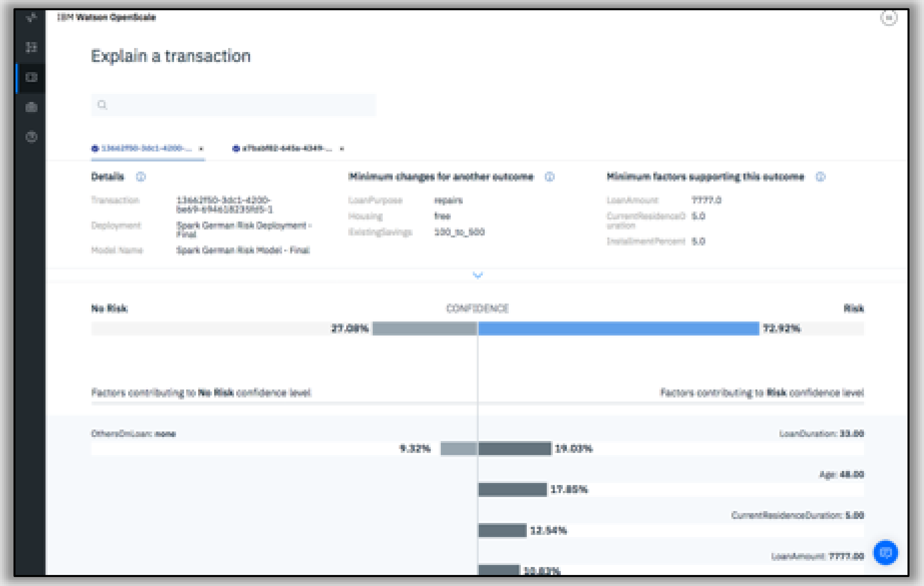
- Predictions are 4% more fair in this example
- 81% of the protected group (female) and of the reference group (male) get a favorable output
- Disparate impact Value: 100%



Explainability

OpenScale records every individual transaction and drills down into its working to explain how the model makes decisions

It provides a simple explanation that is user friendly and interactive



Value:

- Explain individual transaction level decisions made by the model in run time, including details about most important attributes and their values in order to assist in compliance and customer care situations
- Analyze individual transactions in a what-if manner in order to understand how model behavior will change in different business situations

LIME and Contrastive Explanations

Lime Output:

– Set of features which played a positive role or negative role in the prediction.

– Also identifies the feature weights which helps to identify the most important or least important features

Contrastive Explanation:

– Explains the behavior of the model in the vicinity of the data point whose explanation is being generated.

– Assumption:

- The most common value is the least interesting from an explanation point of view
- E.g., If median salary is between $70-90K, then someone who has a salary of $80K it is not very “interesting” or to say it differently it is “normal”.
- However, if someone has salary of $200K, it is very “interesting”

Drift Detection in OpenScale

Drift Monitor in OpenScale measures two types of drifts:

- **Drop in accuracy**: It estimates the drop in accuracy of the model at runtime. The model accuracy could drop if there is an increase in transactions similar to those which the model was unable to evaluate correctly in the training data.
- **Drop in data consistency**: It estimates the drop in consistency of the data at runtime as compared to the characteristics of the data at training time.

A drop in model accuracy and data consistency may lead to a negative impact on the business outcomes associated with the model.

OpenScale measures the drift without requiring labelled data. Accuracy computation using labelled data can be expensive and might not be comprehensive

OpenScale does Drift detection on the entire payload data

OpenScale will automatically detect drifted transactions and pinpoint datapoints that contribute to drift

Lab 5 - README.md

2. Track actionable metrics in a single console
3. Explain AI outcomes
4. Detect and mitigate harmful bias to improve outcomes
5. Track drift
6. Accept feedback to compute accuracy measures
7. Accelerate the integration of AI into existing business applications.

Objectives

The goal of this lab is to familiarize the user with the features of Watson OpenScale. Upon completing this lab, you will understand how to:

1. Import a machine learning model
2. Deploy the model
3. Provision Watson OpenScale
4. Configure the payload logging database and Machine Learning provider
5. Score Data
6. Prepare Deployed Model for Monitoring
7. Configure Payload Logging
8. Configure Quality
9. Configure Fairness
10. Configure Drift
11. Submit Feedback and View Quality Metrics
12. Score Data and View Fairness Metrics
13. Explain a Transaction.

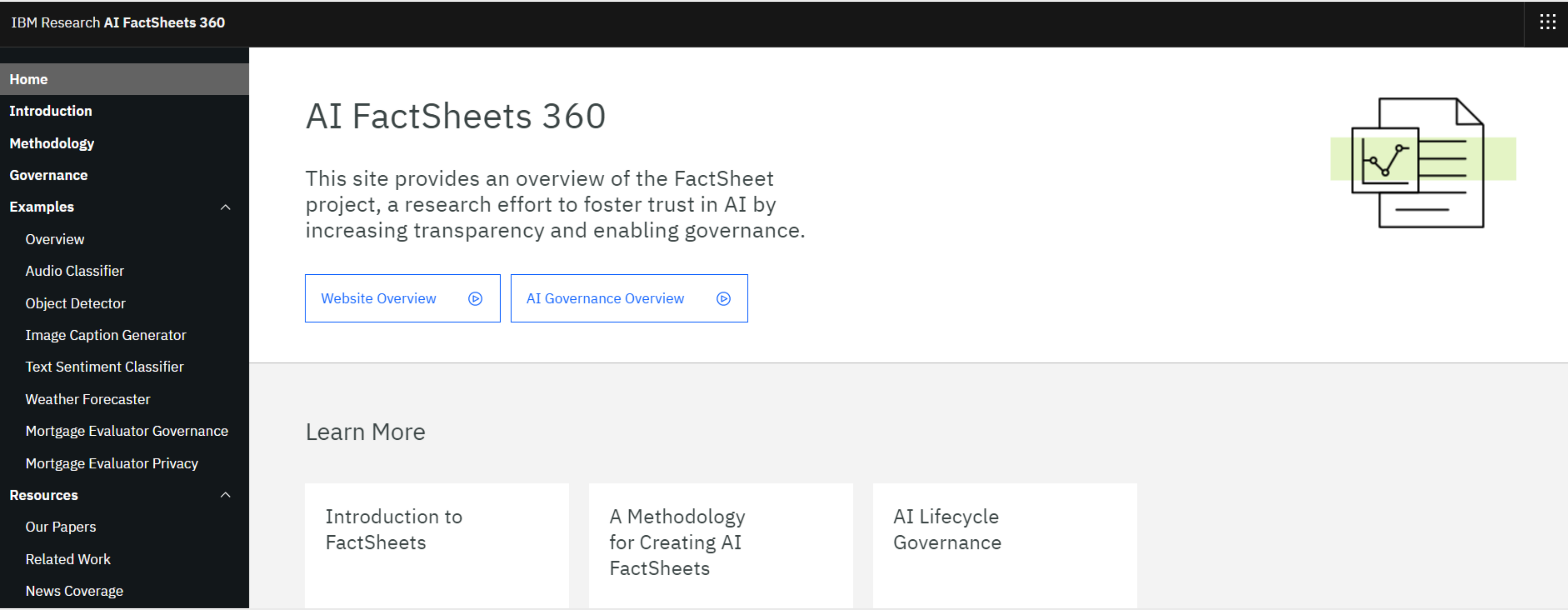
Step 1. Please click on the link to download the instructions to your machine

Instructions

Please work on Lab-5.

We will return to review the Watson OpenScale lab at 5:00 pm EST

AI Transparency: AI FactSheets



http://aifs360.mybluemix.net/#

Summary

- ✓ Trust in AI
- ✓ Cloud Pak for Data
- ✓ Model Fairness - AIF360 Toolkit
- ✓ Model Explainability - AIX360 Toolkit
- ✓ Model Robustness - Adversarial Robustness Toolbox
- ✓ Monitoring - Watson OpenScale

A3 Center Link:
https://www.ibm.com/industries/federal/analytics

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