

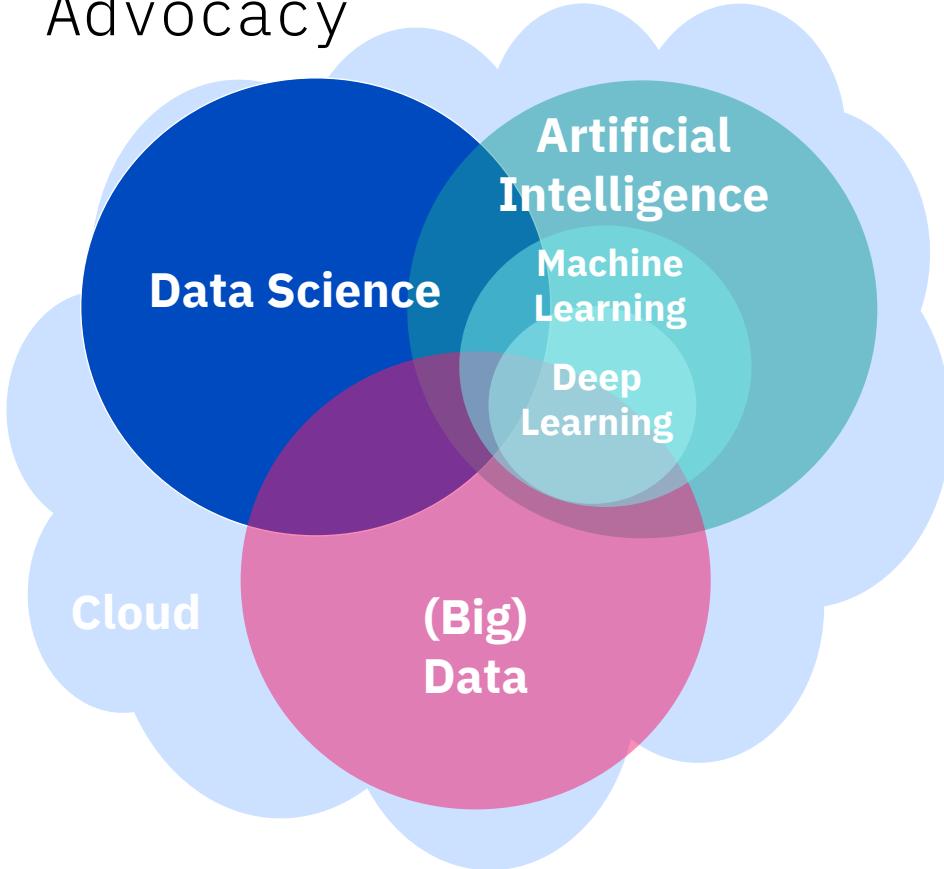
Fair and Explainable AI

Dr. Margriet Groenendijk

Data Science & AI Developer Advocate

IBM

Data & AI Developer Advocacy



@MargrietGr

Build Smart.
Build Secure.

More than 100 open source projects, a library of knowledge resources, developer advocates ready to help, and a global community of developers. What will you create?

Search IBM Developer



AI



Analytics



Node.js



Blockchain



Containers



Java

developer.ibm.com

Code patterns
Tutorials
Blogs, articles
Models, data
Open source projects
Events, podcasts, videos

What is the A-level algorithm? How the Ofqual's grade calculation worked - and its effect on 2020 results explained

The algorithm which used school data to calculate A-level grades has been accused of widening inequality

<https://inews.co.uk/news/education/a-level-algorithm-what-ofqual-grades-how-work-results-2020-explained-581250>

An Algorithm Determined UK Students' Grades. Chaos Ensued

This year's A-Levels, the high-stakes exams taken in high school, were canceled due to the pandemic. The alternative only exacerbated existing inequities.



PHOTOGRAPHY: TOLGA AKMEN/AFP/GETTY IMAGES

<https://www.wired.com/story/an-algorithm-determined-uk-students-grades-chaos-ensued/>

Why did the A-level algorithm say no?



Sean Coughlan
Education correspondent

🕒 14 August 2020

Exam results 2020



A protest over A-level results gathered in Westminster

<https://www.bbc.co.uk/news/education-53787203>

AI is used in many decision-making applications



Credit



Employment



Admission



Sentencing



Healthcare

Fair and explainable AI pipelines

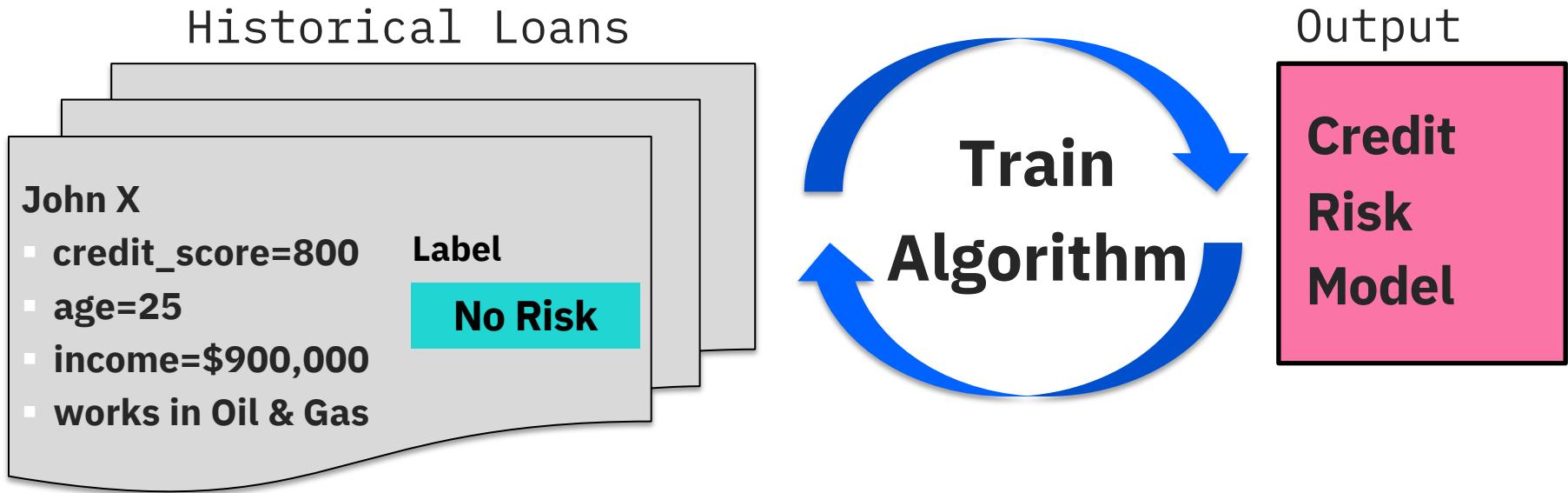
Machine learning
Algorithm selection

Deep learning
Neural network design

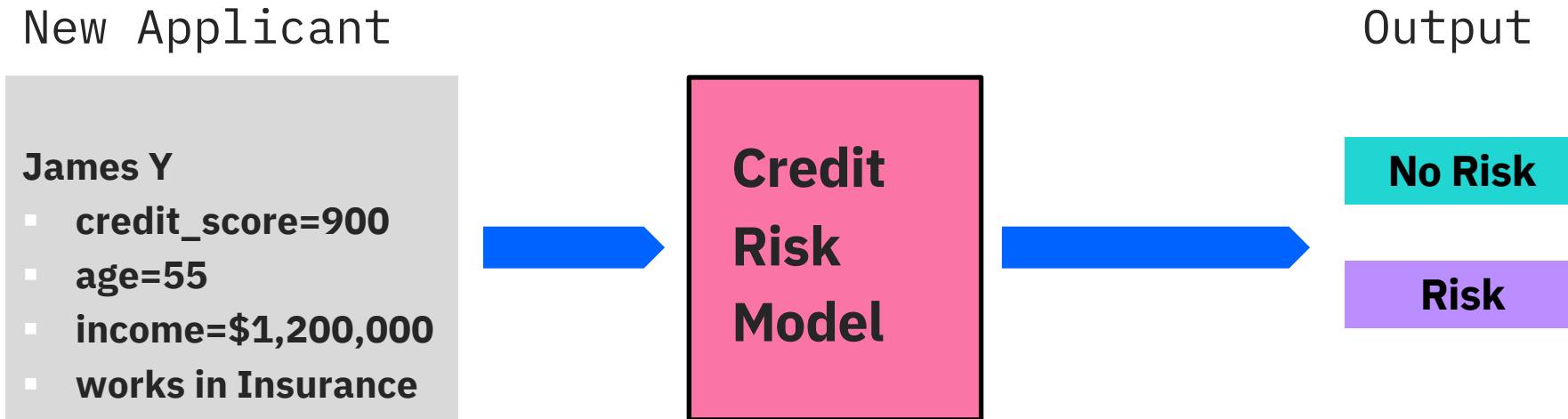
Natural Language Processing
Interactions between computers and
human languages

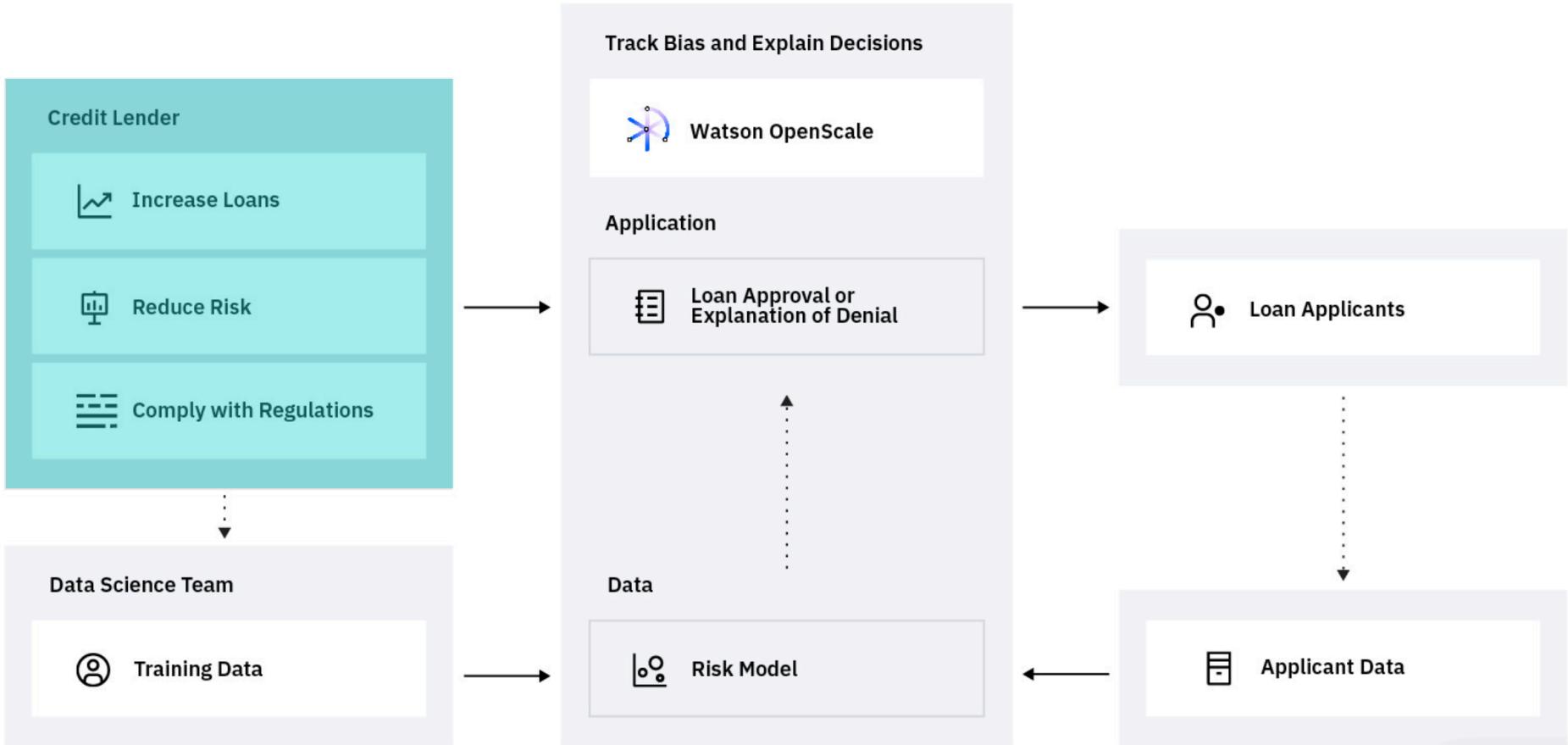
Artificial intelligence
Systems architecture

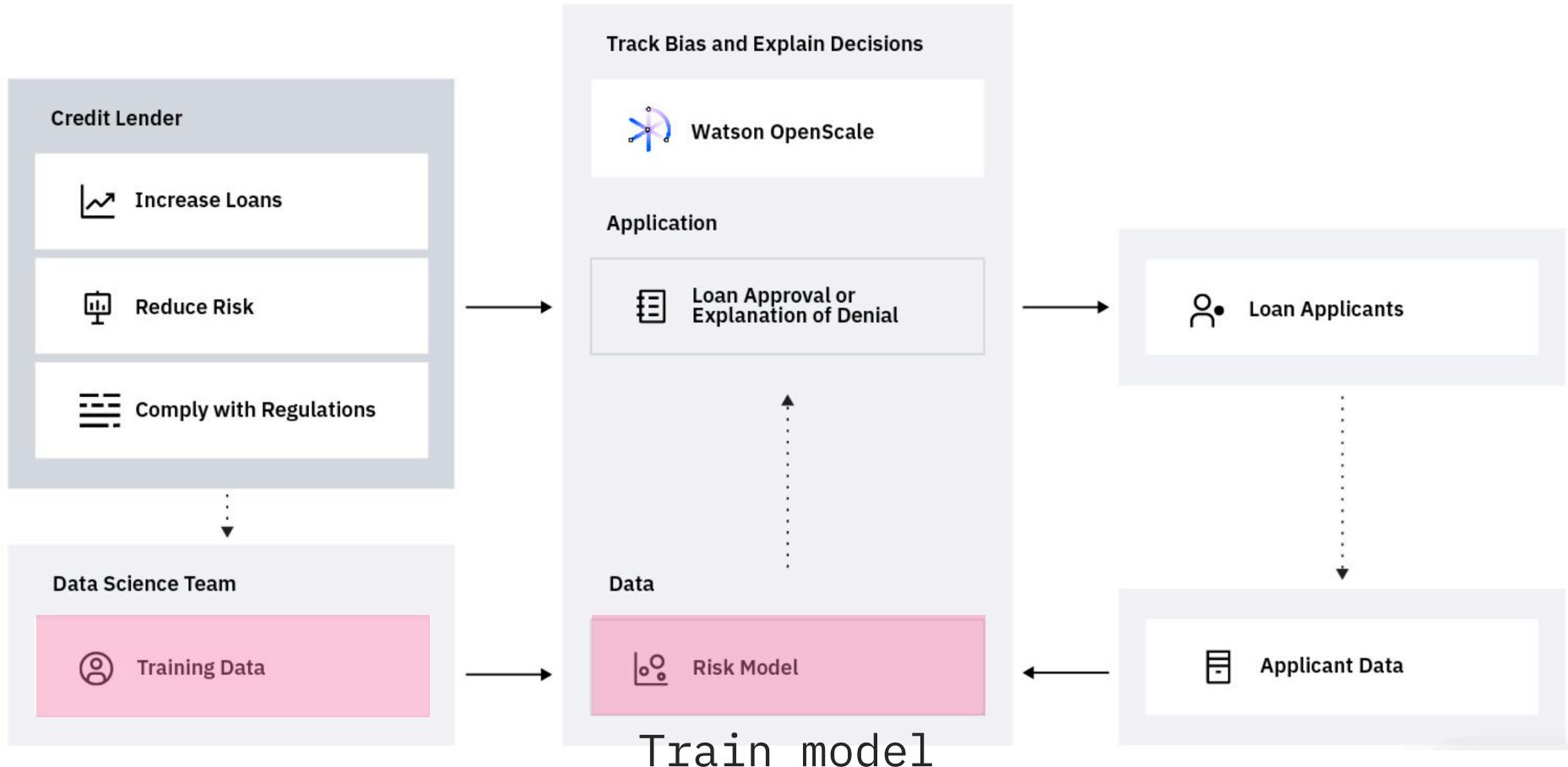
Example: credit risk

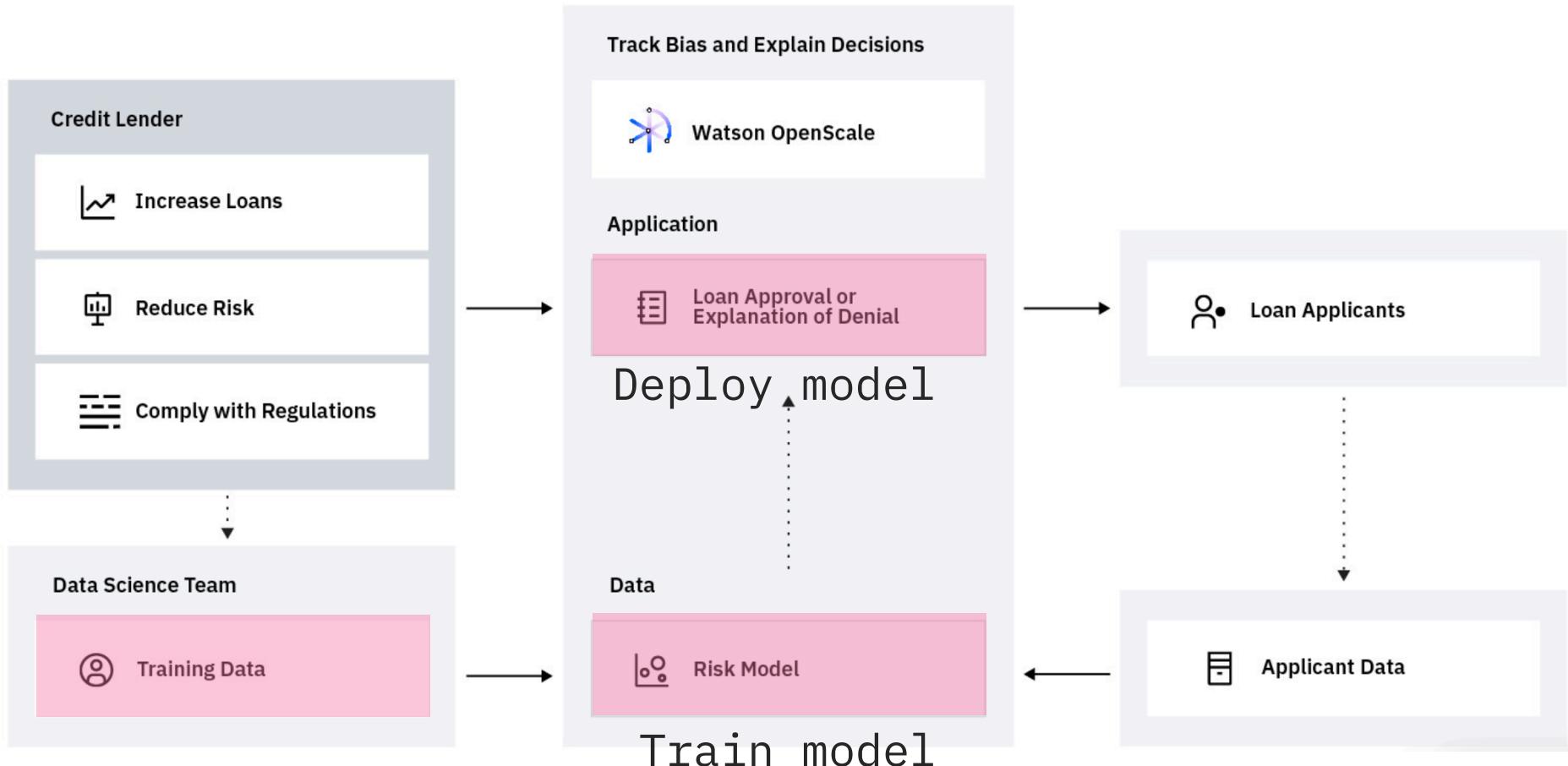


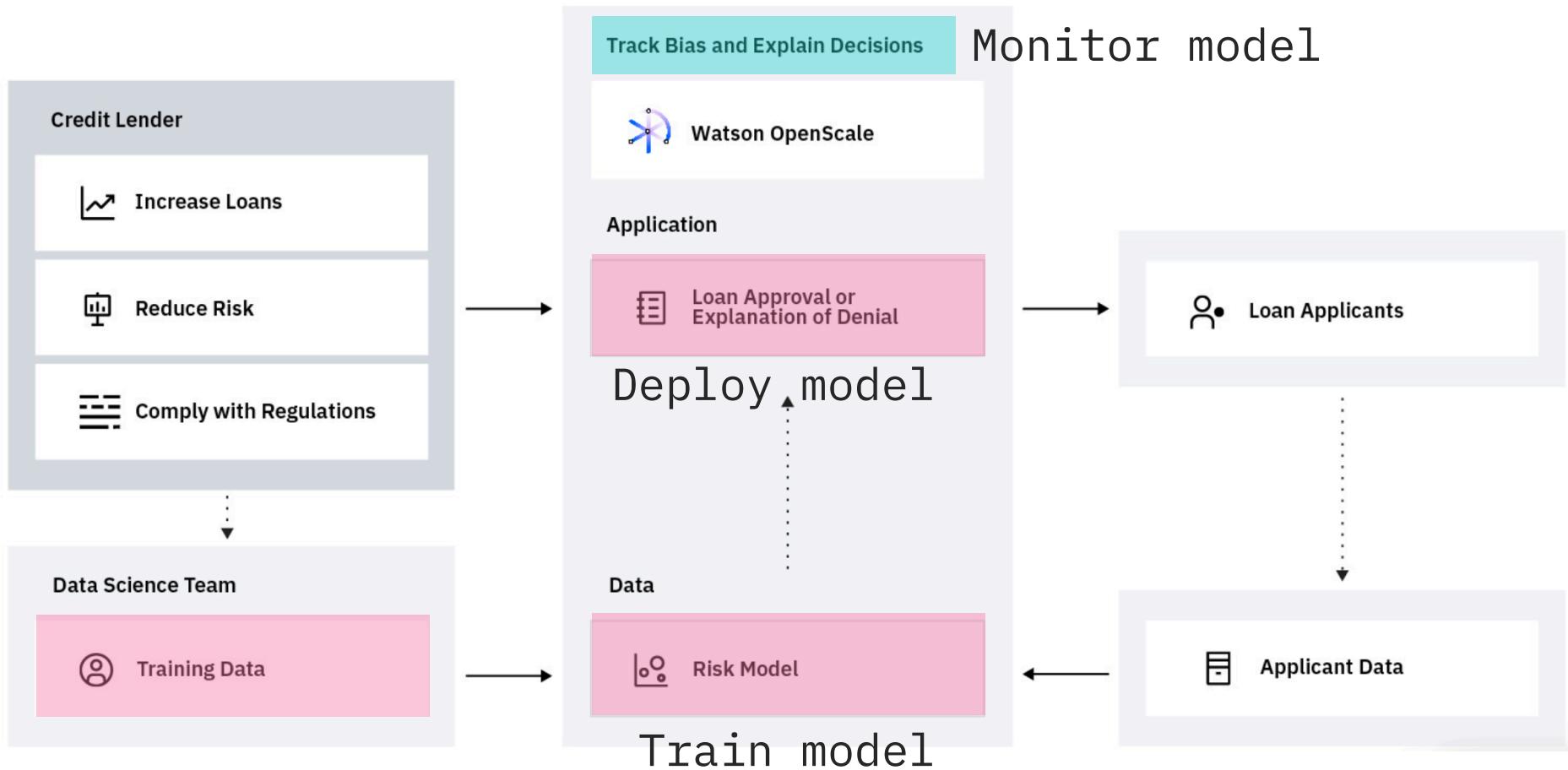
Example: credit risk

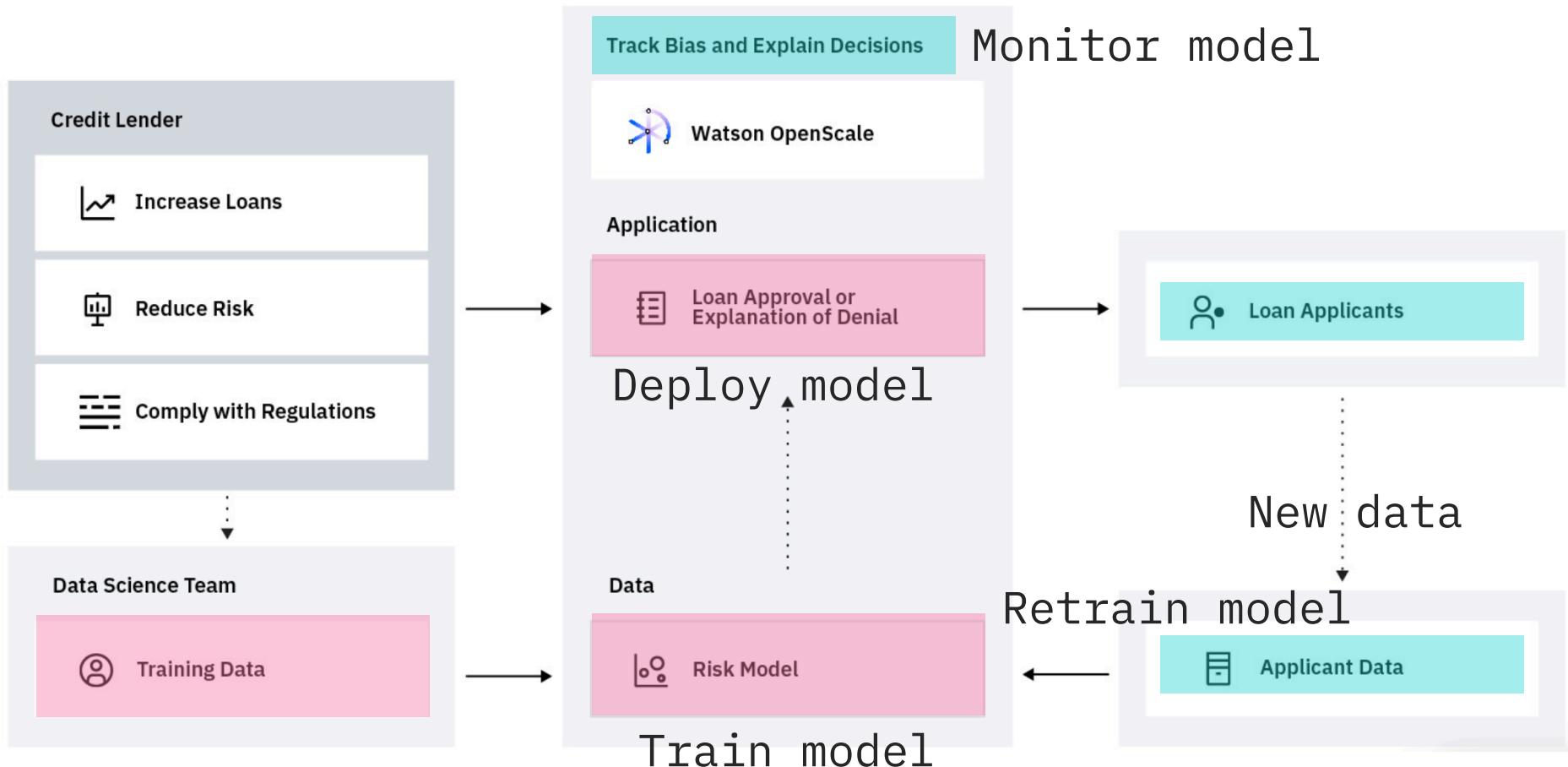




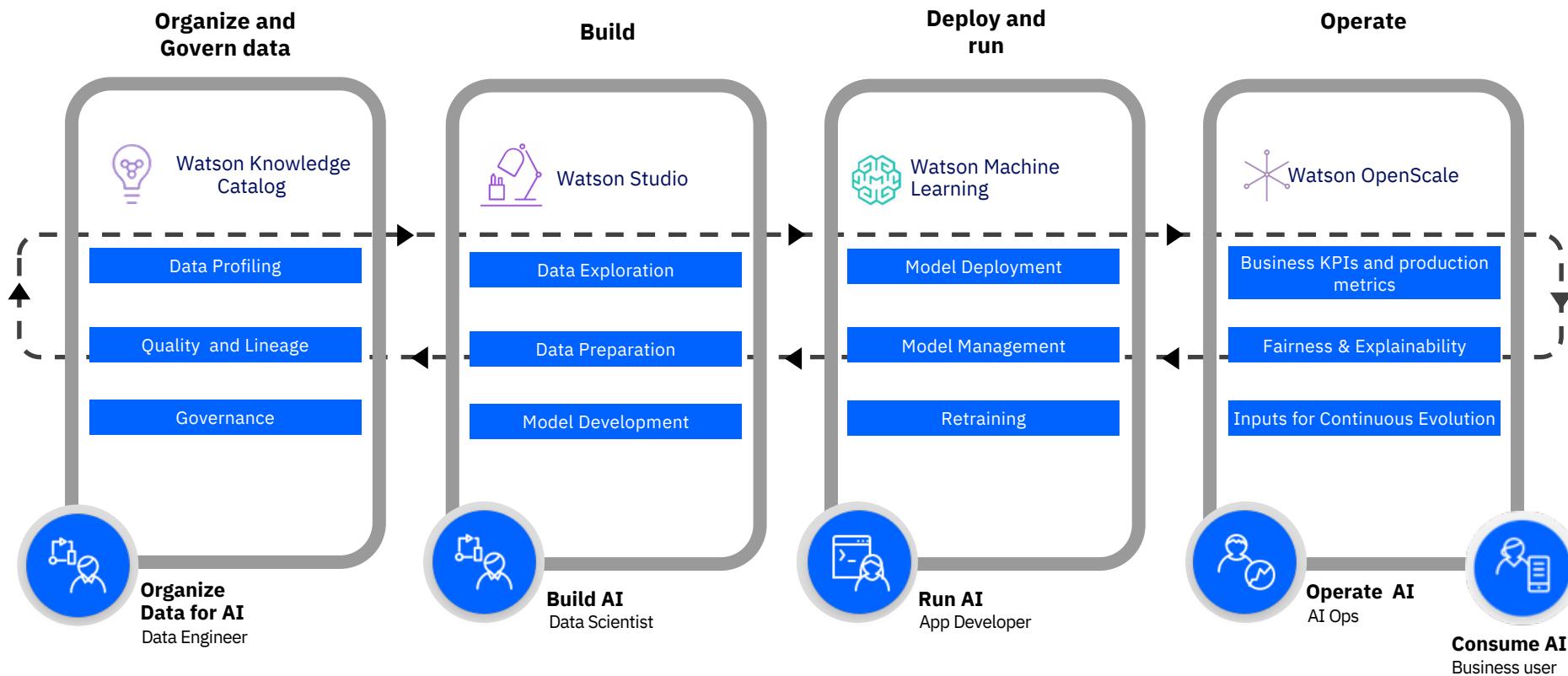








AI pipeline



IBM Cloud Pak for Data

Fully-integrated data and AI platform



Cloud Pak for Data...

- Runs on Red Hat OpenShift and is a fully-integrated data and AI platform
- Supports multi-cloud environments such as AWS, Azure, Google Cloud, IBM Cloud, and private clouds
- Allows you to build, deploy, and manage ML models that scale throughout the organization and automates the AI lifecycle
- Enables integrations to popular open source and cloud native tools, as well as IBM application middleware and development services

Developer benefits...

- Full control over your data and its privacy
- Seamless integration of developer tools -- streamlines work by creating a pipeline for collecting, organizing, analyzing, and consuming data
- Single platform for data management and analysis, allowing developers to easily manage data connections and access to analysis tools
- Core operational services provided, including logging, monitoring, and security

<https://ibm.biz/cpd-experiences>

Build once. Deploy anywhere.

Consulting Services

Strategy	Migration	Development	Management

ISV Applications/Solutions

Advanced Technologies

AI	Analytics	Blockchain	IoT	Quantum

Cloud Paks

Cloud Pak for Applications	Cloud Pak for Data	Cloud Pak for Integration	Cloud Pak for Automation	Cloud Pak for Multicloud Management	Cloud Pak for Security
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Foundation



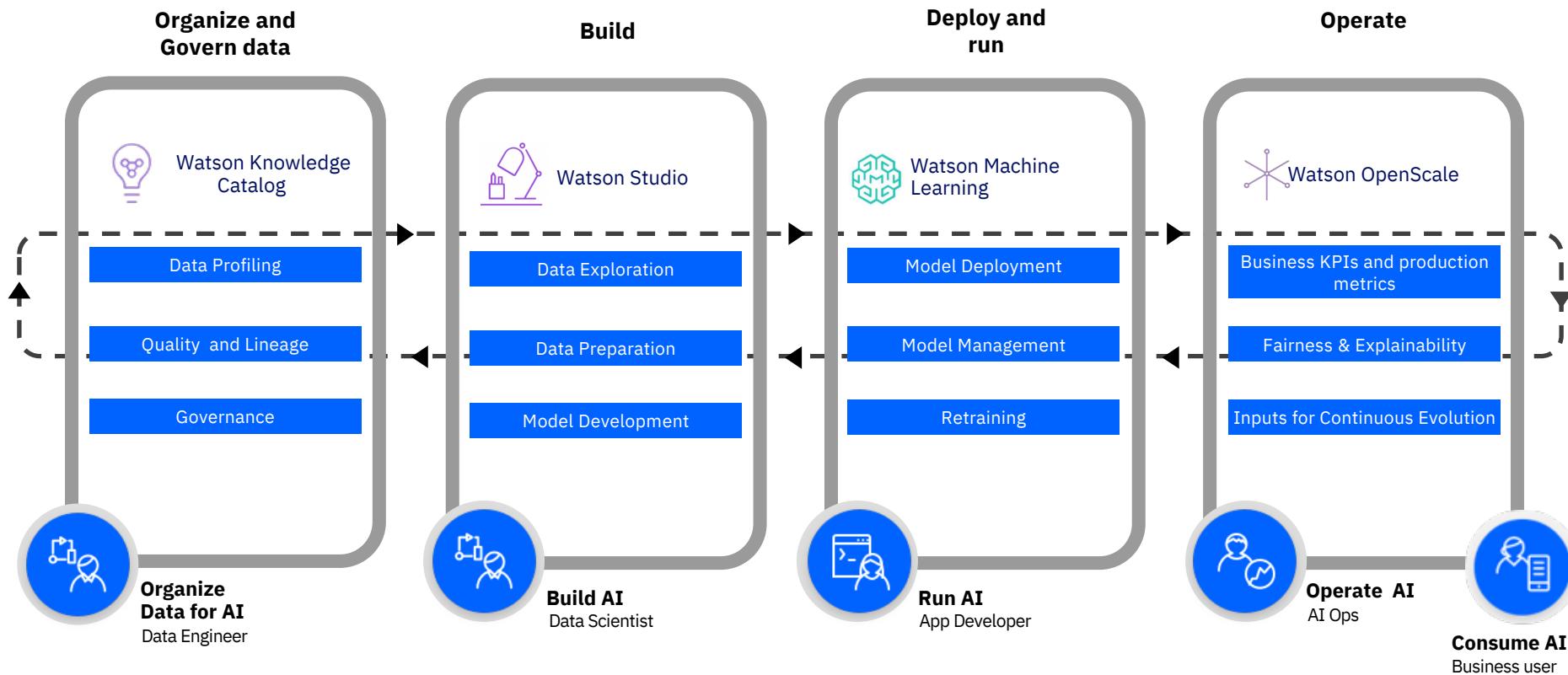
Open Hybrid Multicloud Platform



Infrastructure

IBM public cloud	AWS	Microsoft Azure	Google Cloud	Private	IBM Z IBM LinuxOne IBM Power IBM Storage	Endpoints

AI pipeline in Cloud Pak for Data (aaS)



Fair and explainable AI pipelines

Is your model treating different classes fairly?

WILL KNIGHT BUSINESS 11.19.2019 09:15 AM

The Apple Card Didn't 'See' Gender—and That's the Problem

The way its algorithm determines credit lines makes the risk of bias more acute.

MONEYBOX

Amazon Created a Hiring Tool Using A.I. It Immediately Started Discriminating Against Women.

By JORDAN WEISSMANN

OCT 10, 2018 • 4:52 PM

@MargrietGr

Two Petty Theft Arrests



Borden was rated high risk for future crime after she and a friend took a kid's bike and scooter that were sitting outside. She did not reoffend.



Jerome Pesenti
@an_open_mind

#gpt3 is surprising and creative but it's also unsafe due to harmful biases. Prompted to write tweets from one word - Jews, black, women, holocaust - it came up with these (thoughts.sushant-kumar.com). We need more progress on #ResponsibleAI before putting NLG models in production.

Can you explain your model results?

Why did the A-level algorithm say no?



Sean Coughlan
Education correspondent

⌚ 14 August 2020



Exam results 2020

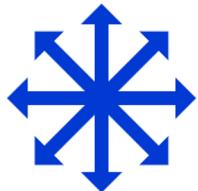


A protest over A-level results gathered in Westminster

Trusted AI Lifecycle through Open Source

Pillars of trust, woven into the lifecycle of an AI application

Did anyone
tamper with it?



ROBUSTNESS

Is it fair?



FAIRNESS

Is it easy to
understand?



EXPLAINABILITY

Is it accountable?



LINEAGE

Adversarial
Robustness 360

↳ (ART)

github.com/IBM/adversarial-robustness-toolbox

art-demo.mybluemix.net

AI Fairness
360

↳ (AIF360)

github.com/IBM/AIF360

aif360.mybluemix.net

AI Explainability
360

↳ (AIX360)

github.com/IBM/AIX360

aix360.mybluemix.net

AI FactSheets
360

↳ (AIFS360)

aifs360.mybluemix.net

Agenda

08:45 - 09:00: Enrolment & Setup

09:00 - 09:10: Introductory remarks

09:10 - 09:30: Fair and Explainable AI

09:30 - 10:15: Remove Unfair Bias in Machine Learning

10:15 - 10:30: Break

10:30 - 11:05: Explain Machine Learning Models

11:05 - 11:40: Build a machine learning model and monitor the performance, bias and drift

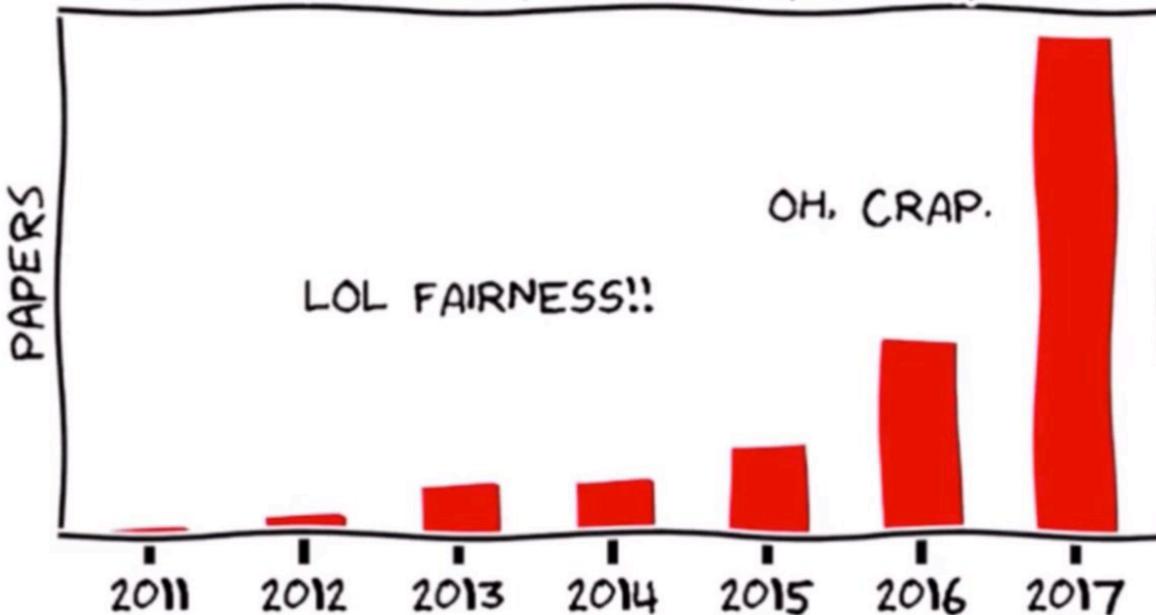
11:40 - 11:50: Summary & Next Steps including Q&A

11:50 - 12:00: Closing remarks

[https://margriet-groenendijk.
gitbook.io/trusted-ai-workshop](https://margriet-groenendijk.gitbook.io/trusted-ai-workshop)

Part 1: Remove Unfair Bias in Machine Learning

BRIEF HISTORY OF FAIRNESS IN ML



What is Fairness?



There are 21 definitions of fairness

Many of the definitions conflict

The way you define fairness impacts bias

AI Fairness 360

↳ (AIF360)

<https://github.com/IBM/AIF360>

Toolbox

Fairness metrics (70+)

Fairness metric explanations

Bias mitigation algorithms (10+)

<http://aif360.mybluemix.net/>

**Extensible
Toolkit for
Detecting,
Understanding, &
Mitigating
Unwanted
Algorithmic Bias**

Leading Fairness
Metrics and
Algorithms from
Industry &
Academia

Designed to **translate new research**
from the **lab to industry practitioners**
(using Scikit Learn's fit/predict
paradigm)

Fairness Terms

Protected Attribute – an attribute that partitions a population into groups whose outcomes should have parity (ex. race, gender, caste, and religion)

Privileged Protected Attribute – a protected attribute value indicating a group that has historically been at systemic advantage

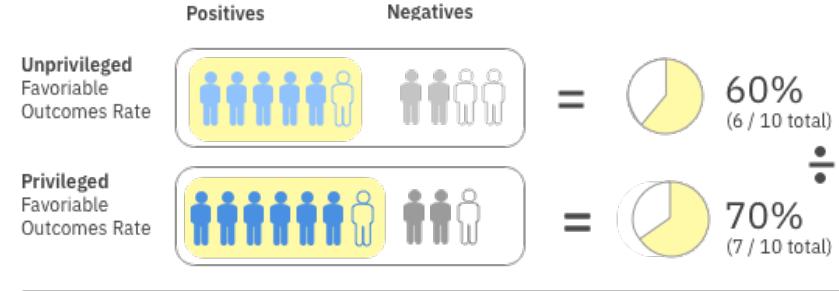
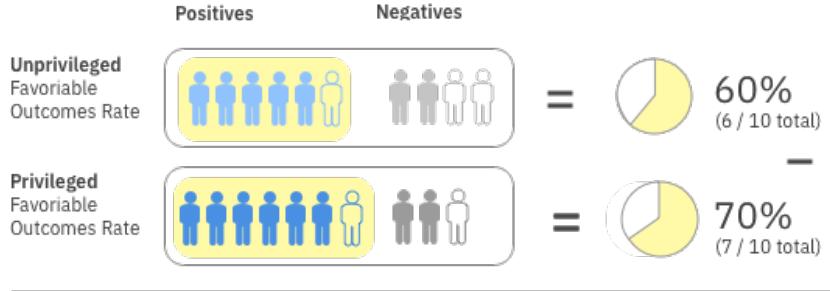
Group Fairness – Groups defined by protected attributes receiving similar treatments or outcomes

Individual Fairness – Similar individuals receiving similar treatments or outcomes

Fairness Metric – a measure of unwanted bias in training data or models

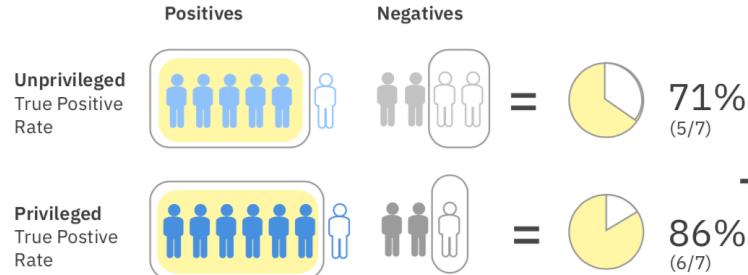
Favorable Label – a label whose value corresponds to an outcome that provides an advantage to the recipient

How To Measure Fairness - Some Group Fairness Metrics



Statistical Parity Difference = -10%

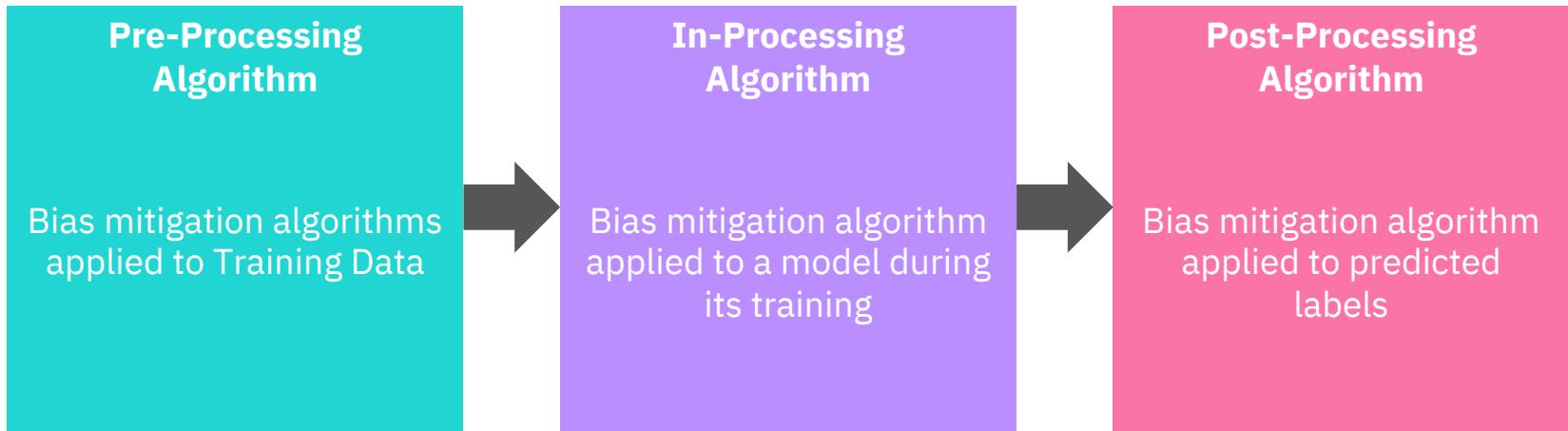
Disparate Impact = 0.86



Equal Opportunity Difference = -15%

LEGEND	
Positives	Negatives
TRUE	FALSE
TRUE	FALSE

Where Can You Intervene in the Pipeline?



- If you can modify the Training Data, then pre-processing can be used
- If you can modify the Learning Algorithm, then in-processing can be used
- If you can only treat the learned model as a black box and can't modify the training data or learning algorithm, then only post-processing can be used

Tradeoffs - Bias vs. Accuracy

1. Is your model doing good things or bad things to people?
 - If your model is sending people to jail, may be better to have more false positives than false negatives
 - If your model is handing out loans, may be better to have more False Negatives than False Positives
2. Determine your threshold for accuracy vs. fairness based upon your legal, ethical and trust guidelines

LEGAL

Doing what is legal is top priority (Penalties)

ETHICAL

What's your company's Ethics (Amazon Echo)

TRUST

Losing customer's Trust costly (Facebook)



Preventing Bias Is Hard!

Work with your stakeholders early to define fairness, protected attributes & thresholds

Apply the earliest mitigation in the pipeline that you have permission to apply

Check for bias as often as possible using any metrics that are applicable

Caveat: AIF360 should only be used with well defined data sets & well-defined use cases

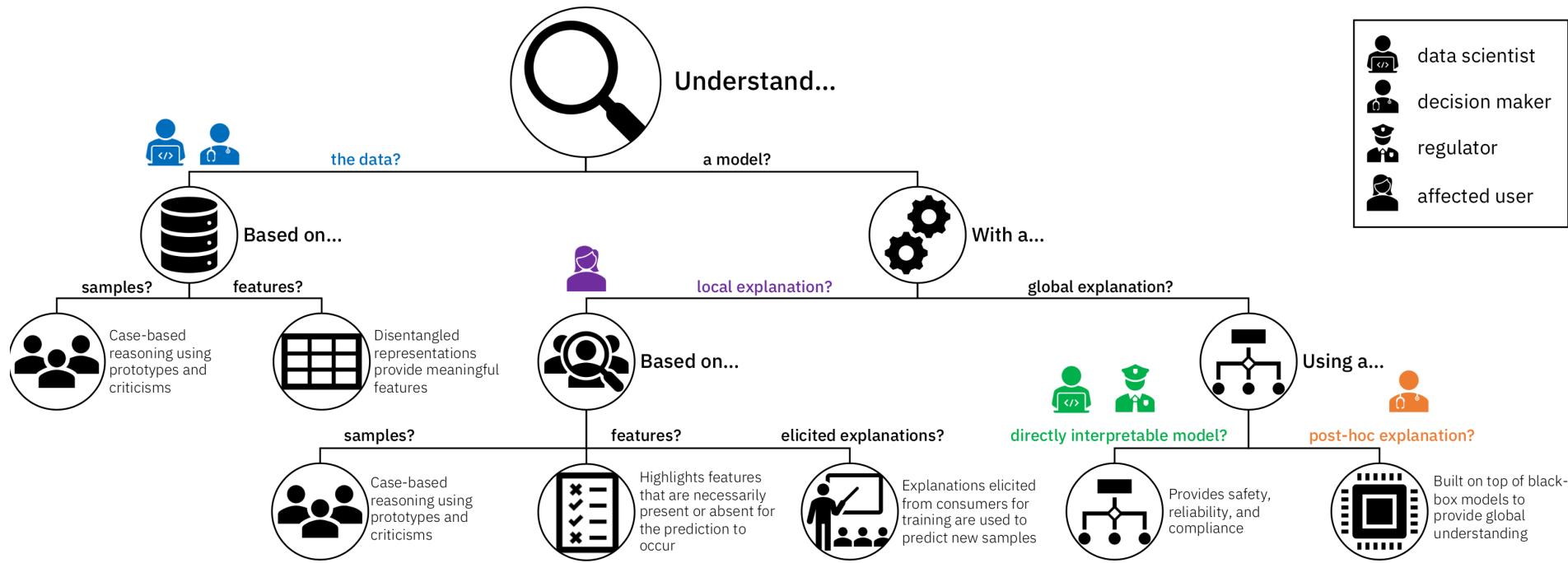
Part 1: Remove Unfair Bias in Machine Learning

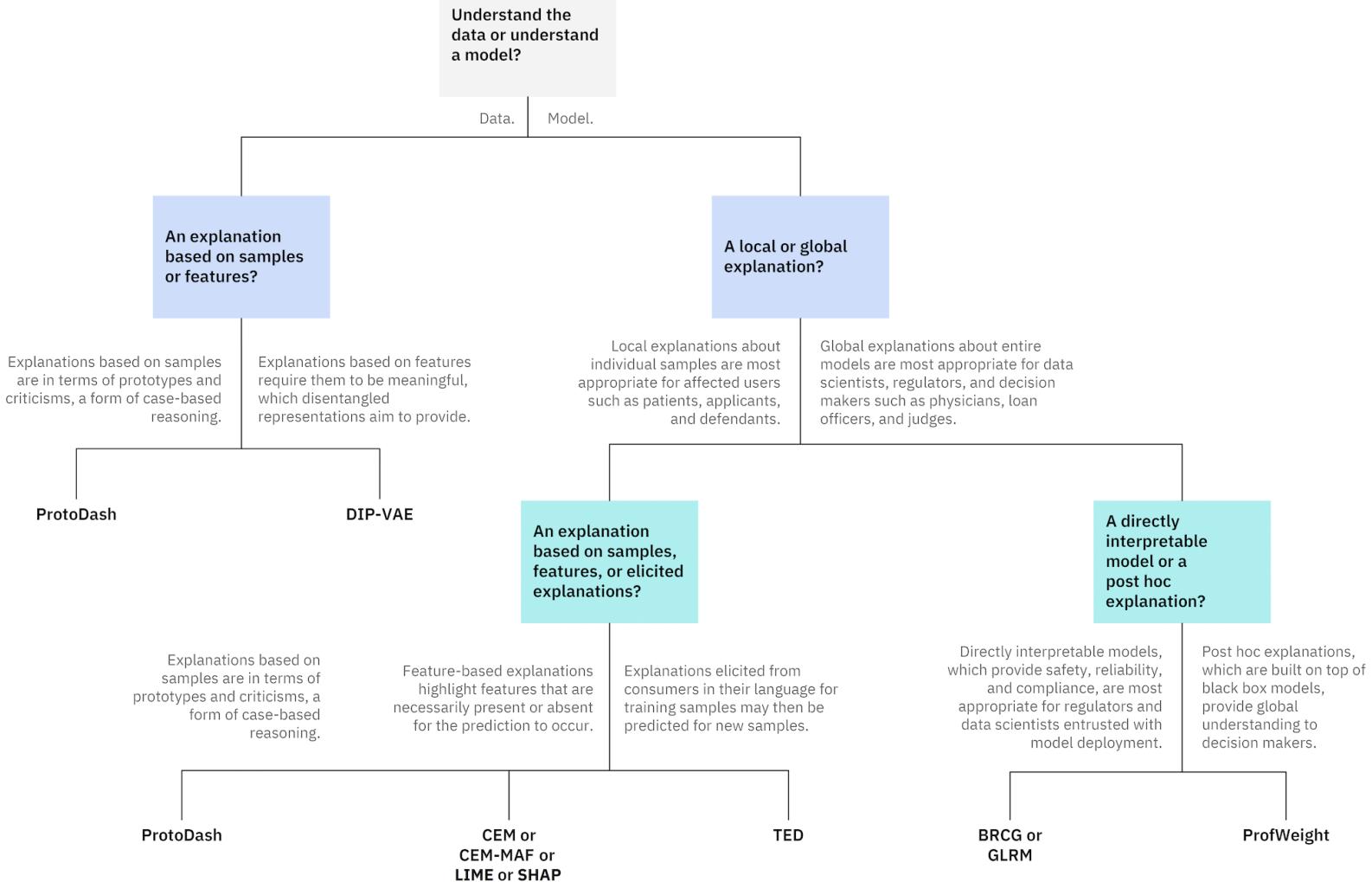
Hands-on

Break
until
10:30



Part 2: Explain Machine Learning Models





FICO Explainable Machine Learning Challenge dataset

<http://aix360.mybluemix.net/>

Use the information about the applicant in their credit report to predict whether they will make timely payments over a two-year period

Choose a consumer type

-  **Data Scientist**
must ensure the model works appropriately before deployment
-  **Loan Officer**
needs to assess the model's prediction and make the final judgement
-  **Bank Customer**
wants to understand the reason for the application result



A Data Scientist wants to understand:

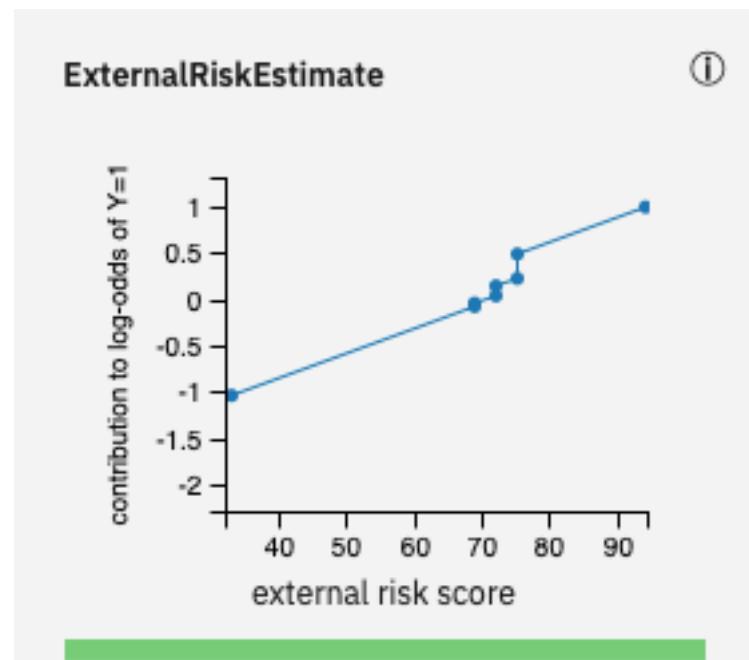


What is the overall logic of the model in making decisions?

Is the logic reasonable, so that we can deploy the model with confidence?

ExternalRiskEstimate is an important feature **positively correlated with good credit risk.**

The jumps in the plot indicate that applicants with above average ExternalRiskEstimate (the mean is 72) get an additional boost.

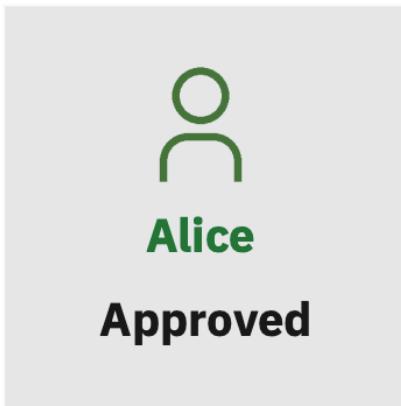




A Loan Officer wants to understand:

Why is the model recommending this person's credit be approved or denied?

How can I inform my decision to accept or reject a line of credit by looking at similar individuals?



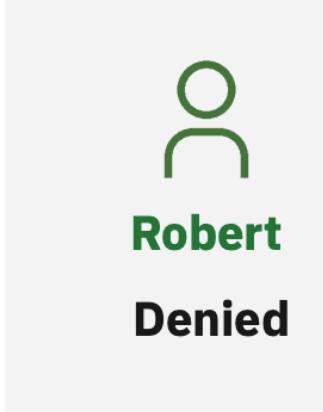
	Alice	Mia	Kate	Cal
Outcome	-	Paid	Paid	Paid
Similarity to Alice (from 0 to 1)	-	0.765	0.081	0.065
ExternalRiskEstimate	82	85	80	89
MSinceOldestTradeOpen	280	223	382	379
MSinceMostRecentTradeOpen	13	13	4	156
AverageMInFile	102	87	90	257
NumSatisfactoryTrades	22	23	21	3
NumTrades60Ever2DerogPubRec	0	0	0	0
NumTrades90Ever2DerogPubRec	0	0	0	0
PercentTradesNeverDelq	91	91	95	100
MSinceMostRecentDelq	26	26	69	0



A Loan Officer wants to understand:

Why is the model recommending this person's credit be approved or denied?

How can I inform my decision to accept or reject a line of credit by looking at similar individuals?



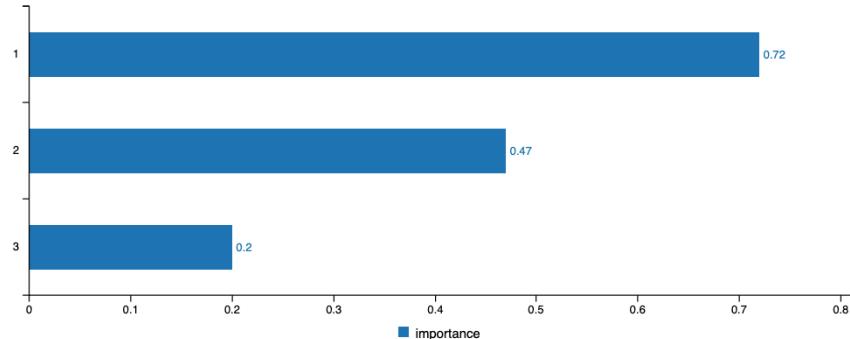
	Robert	James	Danielle	Franklin
Outcome	-	Defaulted	Defaulted	Defaulted
Similarity to Robert (from 0 to 1)	-	0.690	0.114	0.108
ExternalRiskEstimate	78	71	72	69
MSinceOldestTradeOpen	82	95	166	193
MSinceMostRecentTradeOpen	5	1	12	12
AverageMInFile	54	43	74	167
NumSatisfactoryTrades	33	33	37	36
NumTrades60Ever2DerogPubRec	0	0	1	0
NumTrades90Ever2DerogPubRec	0	0	1	0
PercentTradesNeverDelq	100	100	95	100
MSinceMostRecentDelq	0	0	7	0

A Bank Customer wants to understand:



Why was my application rejected?

What can I improve to increase the likelihood my application is accepted?



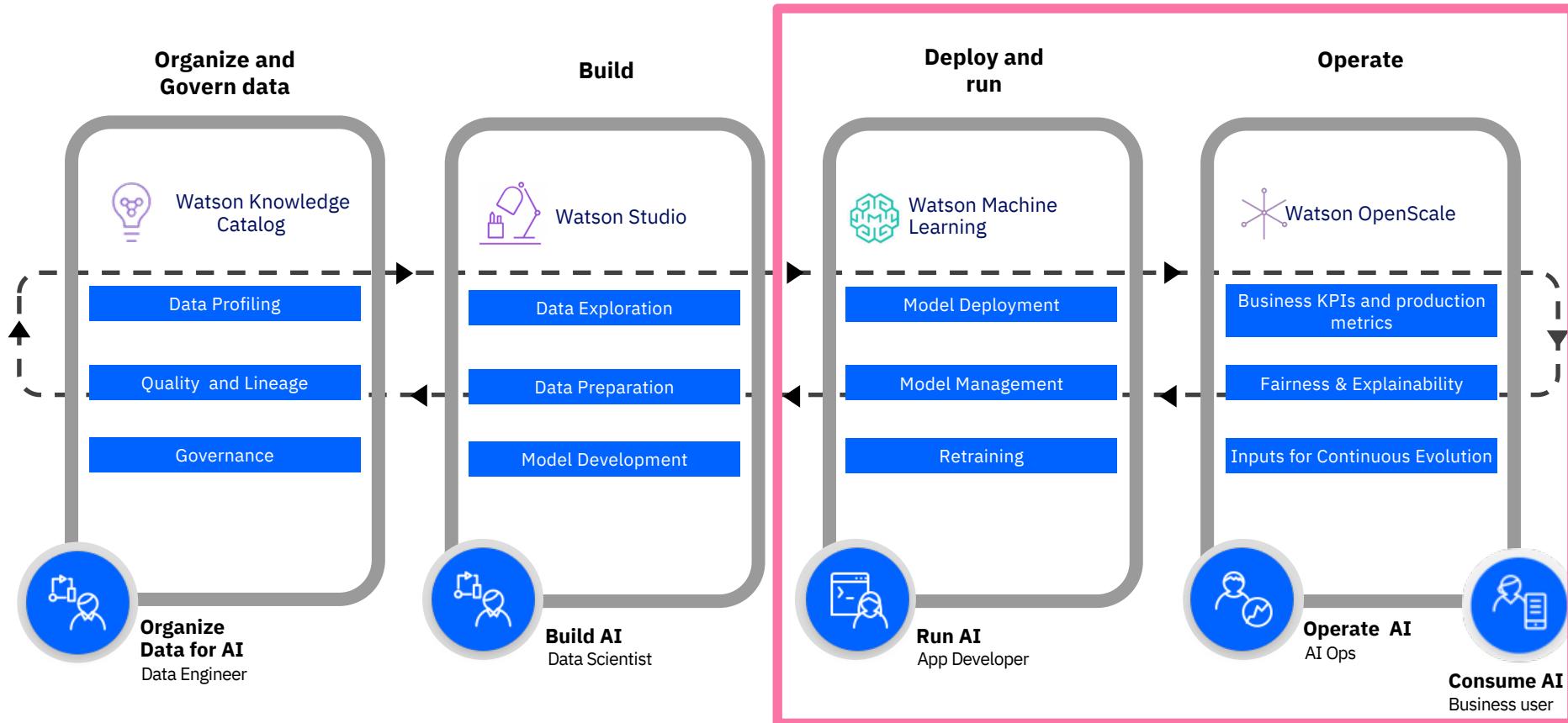
1. The value of **Consolidated risk markers** is **65**. It needs to be around **72** for the application to be approved.
2. The value of **Average age of accounts in months** is **52**. It needs to be around **68** for the application to be approved.
3. The value of **Months since most recent credit inquiry not within the last 7 days** is **2**. It needs to be around **3** for the application to be approved.

Part 2: Explain Machine Learning Models

Hands-on

Part 3: Monitor
the performance,
bias and drift

AI pipeline in Cloud Pak for Data (aaS)



Part 3: Monitor the performance, bias and drift

Hands-on



Insights Dashboard

Application Monitors *beta*

0

Model Monitors

1

Deployments

Monitored

1

Quality

Alerts

1

Fairness

Alerts

1

Drift

Alerts

0

Quality and Fairness metrics update every hour. Drift metrics update every 3 hours.

Watson Machine Learning

Spark German Risk Deployment

Issues

2

QUALITY

BIAS

Quality

67%

Fairness

95%

Drift

0%

1 alerts

Evaluated 5 minutes ago

Date range

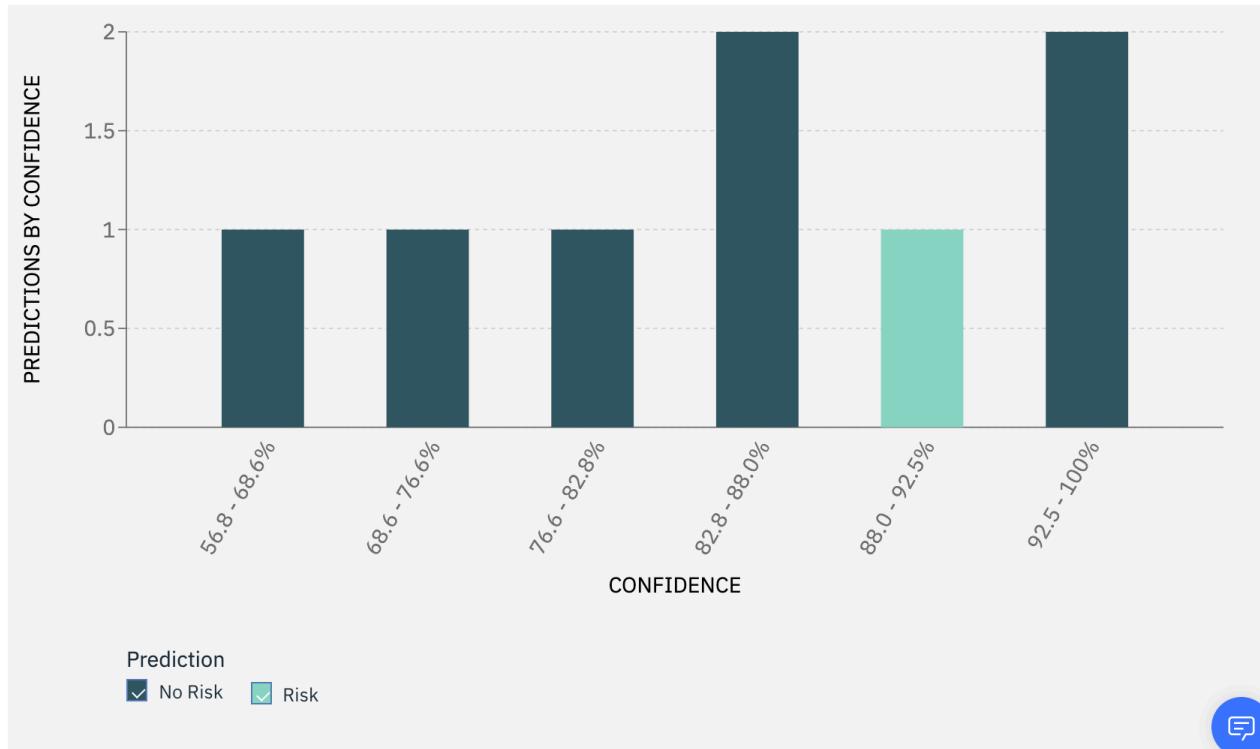
Past 3 months

Past week

Yesterday

Today

Custom range



Fairness

Sex



Age

Drift

Drop in accuracy

Performance

Throughput

Analytics

Predictions by Confidence

Chart Builder

Fairness for Sex

The models propensity to deliver favorable outcomes to one group over another. [Learn more.](#)

Time frame

Hourly

Daily

Weekly

Date range

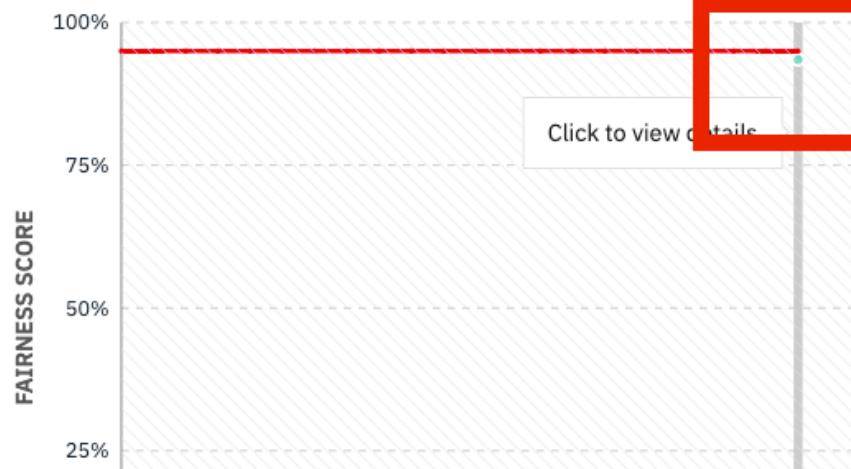
Past 3 months

Past week

Yesterday

Today

Custom range



Fairness Score for Sex

94%

1% below threshold

Sat, Oct 26, 2019, 9:00 PM EDT

■ Threshold

Monitored Groups

Average

female

BIAS

⬅ Spark German Risk Deployment: Transactions

Data Set [i](#)

Payload + Perturbed

Payload

Training

Debiased

Monitored Feature

Sex

Date and Time

 10/26/2019

9:00 PM

Monitored groups [i](#)

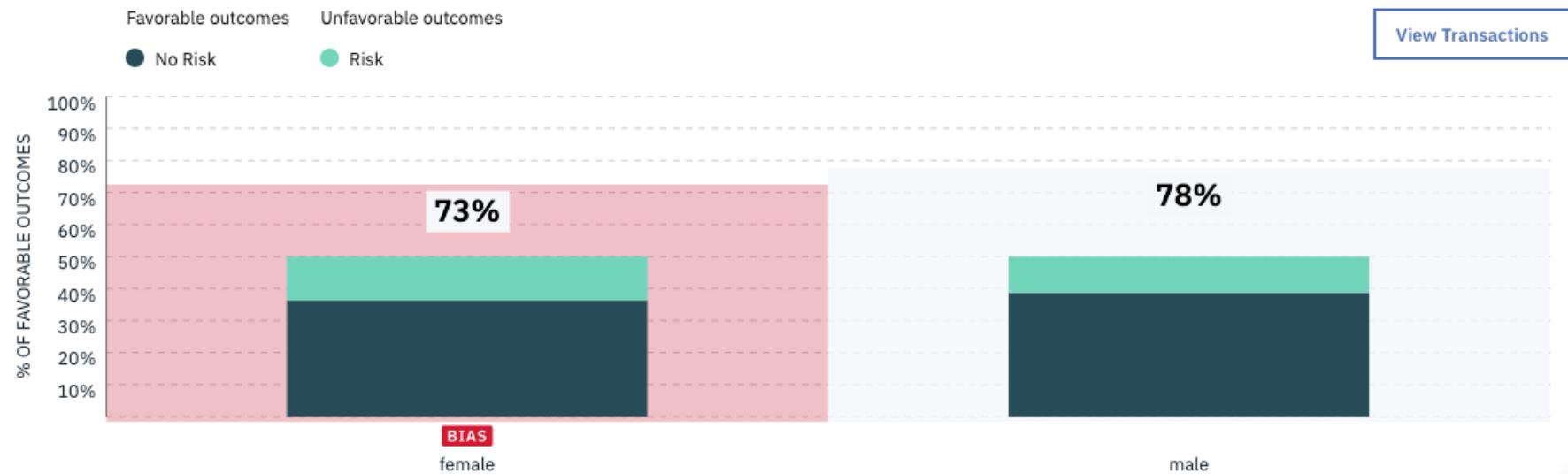
73% of the group **female**
received favorable outcomes.

Reference groups [i](#)

78% of the group **male**
received favorable outcomes.

★ Recommendation

Watson OpenScale created a model that is
6% more fair.



Spark German Risk Deployment: Transactions

October 31, 2019, 2:00 AM

Sex ▾

View

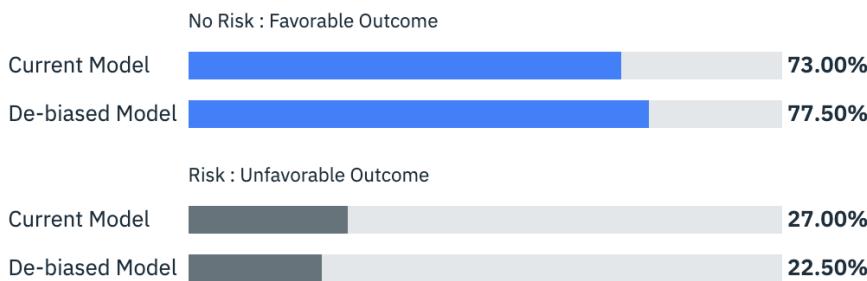
All transactions

Biased transactions

This subset of transactions received biased outcomes. Click the Explain link to determine how the monitored feature contributed to each unfavorable outcome. [i](#)

Transaction ID	Type	Outcome	Action
dc552a8ff80c6d30a1a15c875f7ed6c3-168	Original	Risk	Explain
dc552a8ff80c6d30a1a15c875f7ed6c3-53	Altered	Risk	Explain
dc552a8ff80c6d30a1a15c875f7ed6c3-199	Altered	Risk	Explain
dc552a8ff80c6d30a1a15c875f7ed6c3-37	Original	No Risk	Explain
dc552a8ff80c6d30a1a15c875f7ed6c3-101	Altered	No Risk	Explain

Fairness Correction Table [i](#) Manual_Labeling_430ce9f4-72c6-48fa-b98e-662a18211bdb



Details ⓘ

Transaction dc552a8ff80c6d30a1a15c875f7ed6c3-168
 Deployment Spark German Risk Deployment
 Model Name Spark German Risk Model
 Type Original

Minimum changes for No Risk outcome ⓘ

LoanDuration 21.0
 Sex male
 InstallmentPercent 3.0

Maximum changes allowed for the same outcome ⓘ

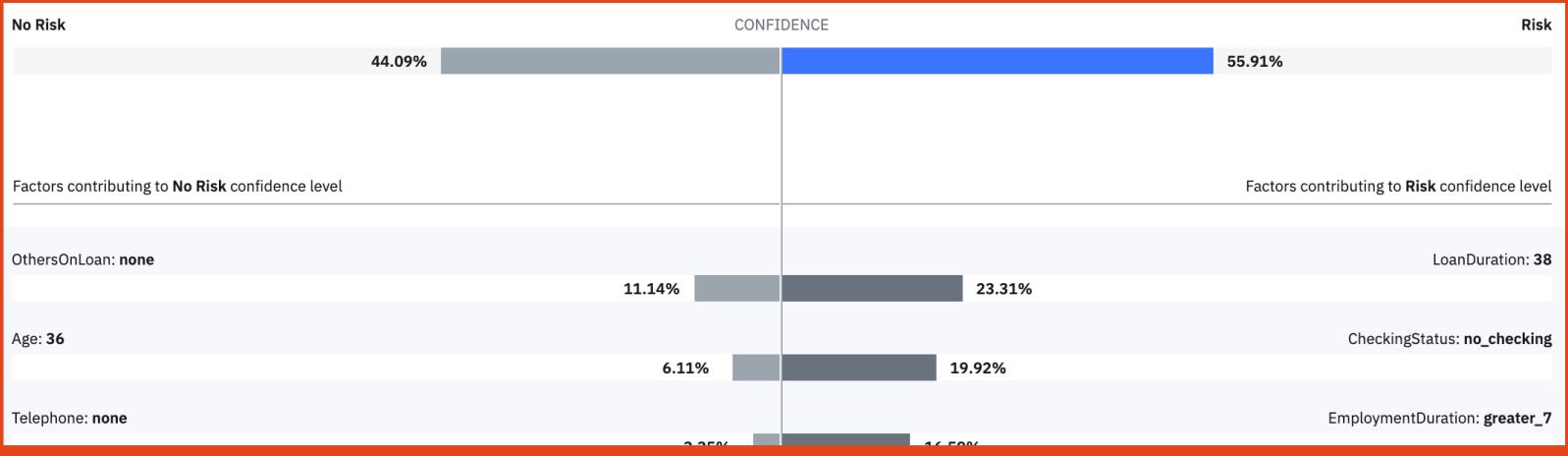
CheckingStatus no_checking
 LoanDuration 38.0
 CreditHistory credits_paid_to_date

How this prediction was determined

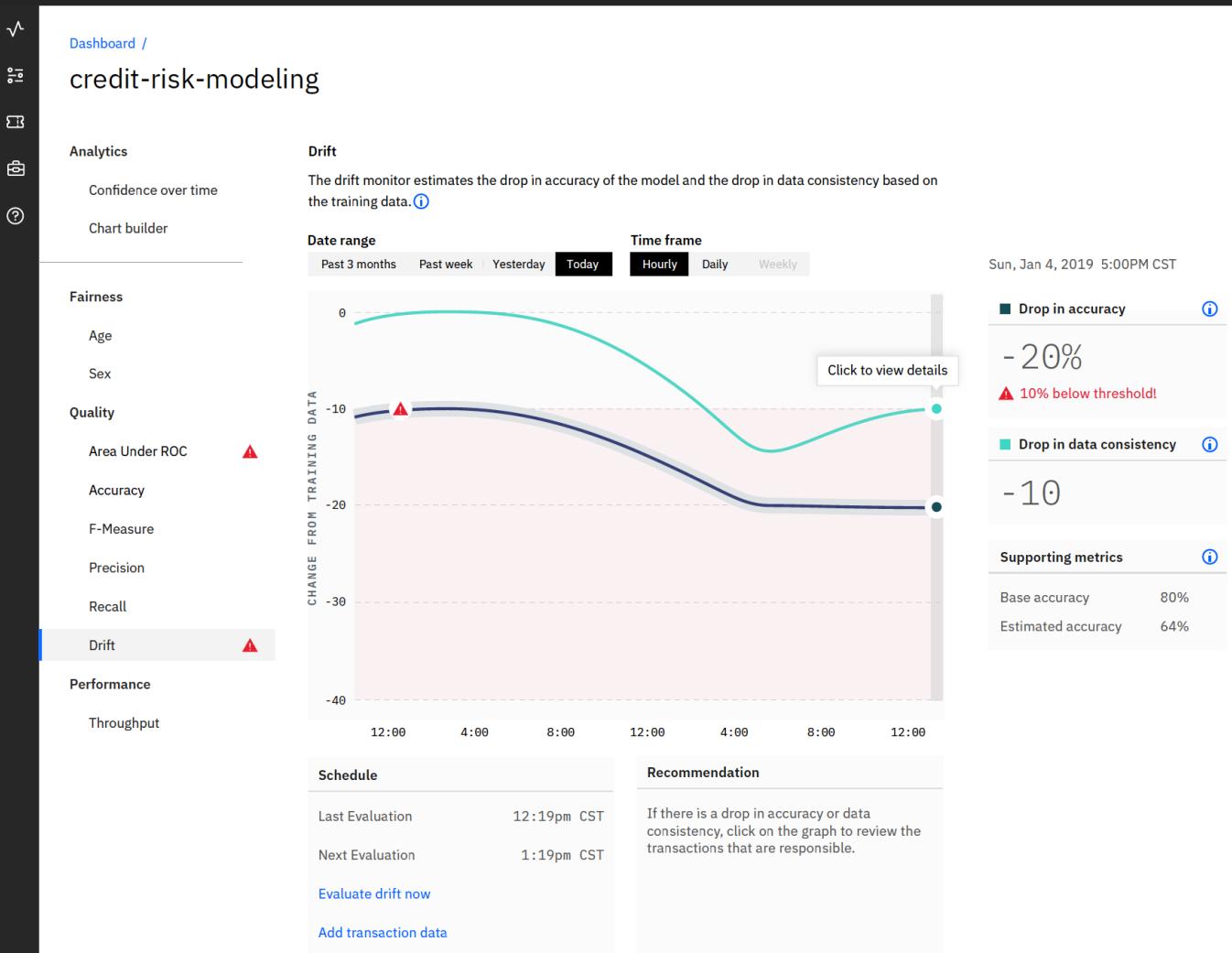
The **Spark German Risk Model** predicts **Risk** with 55.91% confidence. The following features were most important in determining this prediction: **LoanDuration** (23.31%), **CheckingStatus** (19.92%), and **EmploymentDuration** (16.59%).

Most important factors influencing prediction

Feature	Value	Weight
LoanDuration	38	23.31%
CheckingStatus	no_checking	19.92%
EmploymentDuration	greater_7	16.59%



Drift



Drift

Dashboard / Drift

credit-risk-modeling : Drift

View the transactions responsible for a drop in accuracy, a drop in data consistency, or both.

January 4, 2019 05:00 PM

Select a transaction set from the chart or list below

- Transactions responsible for drop in accuracy
- Transactions responsible for drop in accuracy and data consistency
- Transactions responsible for drop in data consistency

	200	80	200
Transactions responsible for drop in accuracy	200	80	200
Transactions responsible for drop in accuracy and data consistency	80	0	0
Transactions responsible for drop in data consistency	0	0	200

Transactions responsible for drop in accuracy

Number of transactions
200

Drop in accuracy
11%

Number of transactions
120

Features responsible for drop in accuracy
Profession
State

Influence on accuracy
Large influence
Some influence

Number of transactions
80

Features responsible for drop in accuracy and data consistency
CheckingStatus

Influence on accuracy
Large influence



Summary

Is it fair?



FAIRNESS

**Is it easy to
understand?**



EXPLAINABILITY

AI Fairness
360

↳ (AIF360)

[github.com/Trusted-
AI/AIF360](https://github.com/Trusted-AI/AIF360)

aif360.mybluemix.net

AI Explainability
360

↳ (AIX360)

[github.com/Trusted-
AI/AIX360](https://github.com/Trusted-
AI/AIX360)

aix360.mybluemix.net

