# Affective Computing

## Bringing humans and machines closer through emotions


- Håkan Silfvernagel
- Miles | hakan.silfvernagel@miles.no


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# Håkan Silfvernagel

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- HMI for Process Automation and Robotics
- MSc in Electrical Engineering
- Master in Behavioural Science


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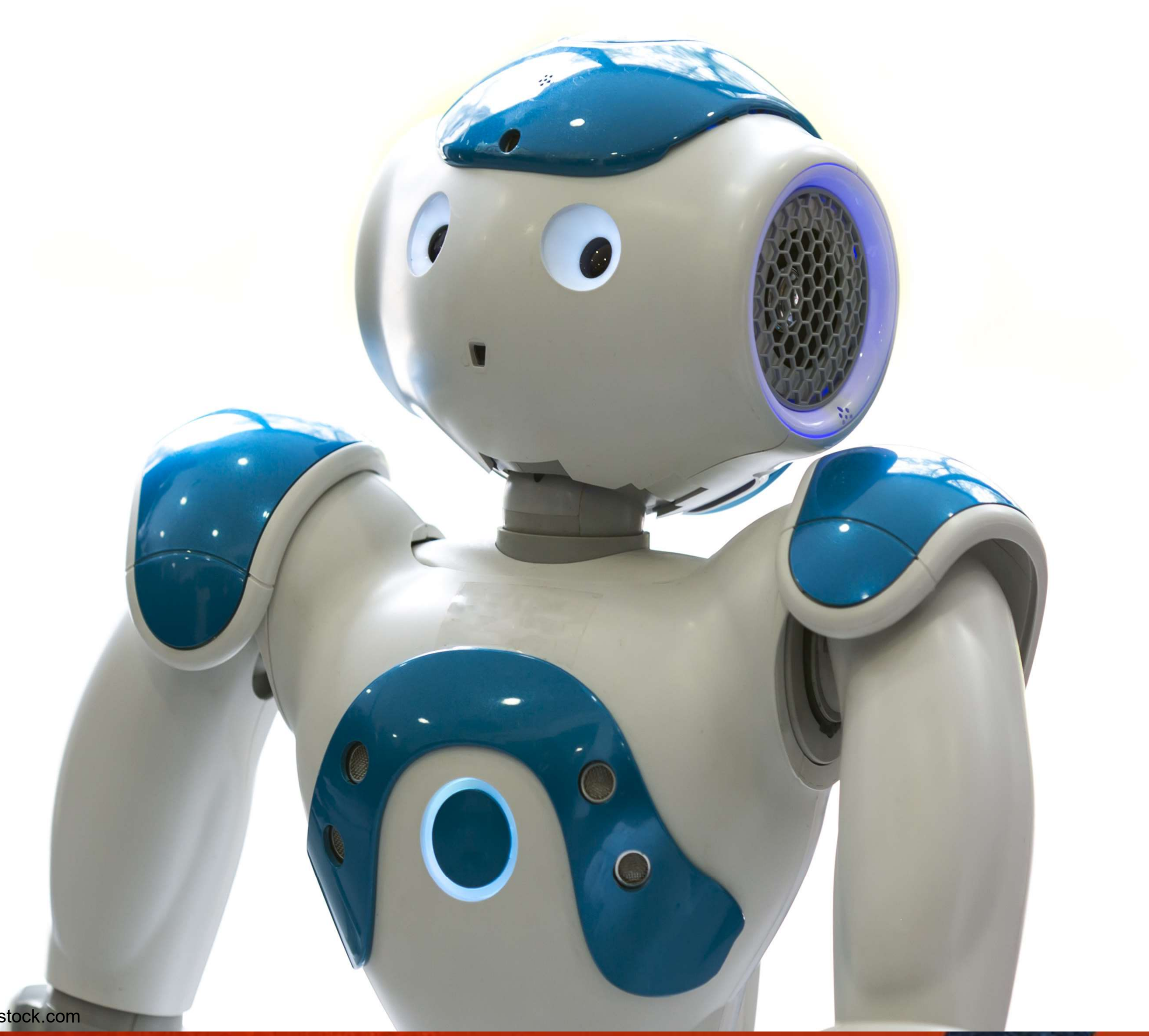
# Affective Computing

What is it?



Source: Belish/Shutterstock.com

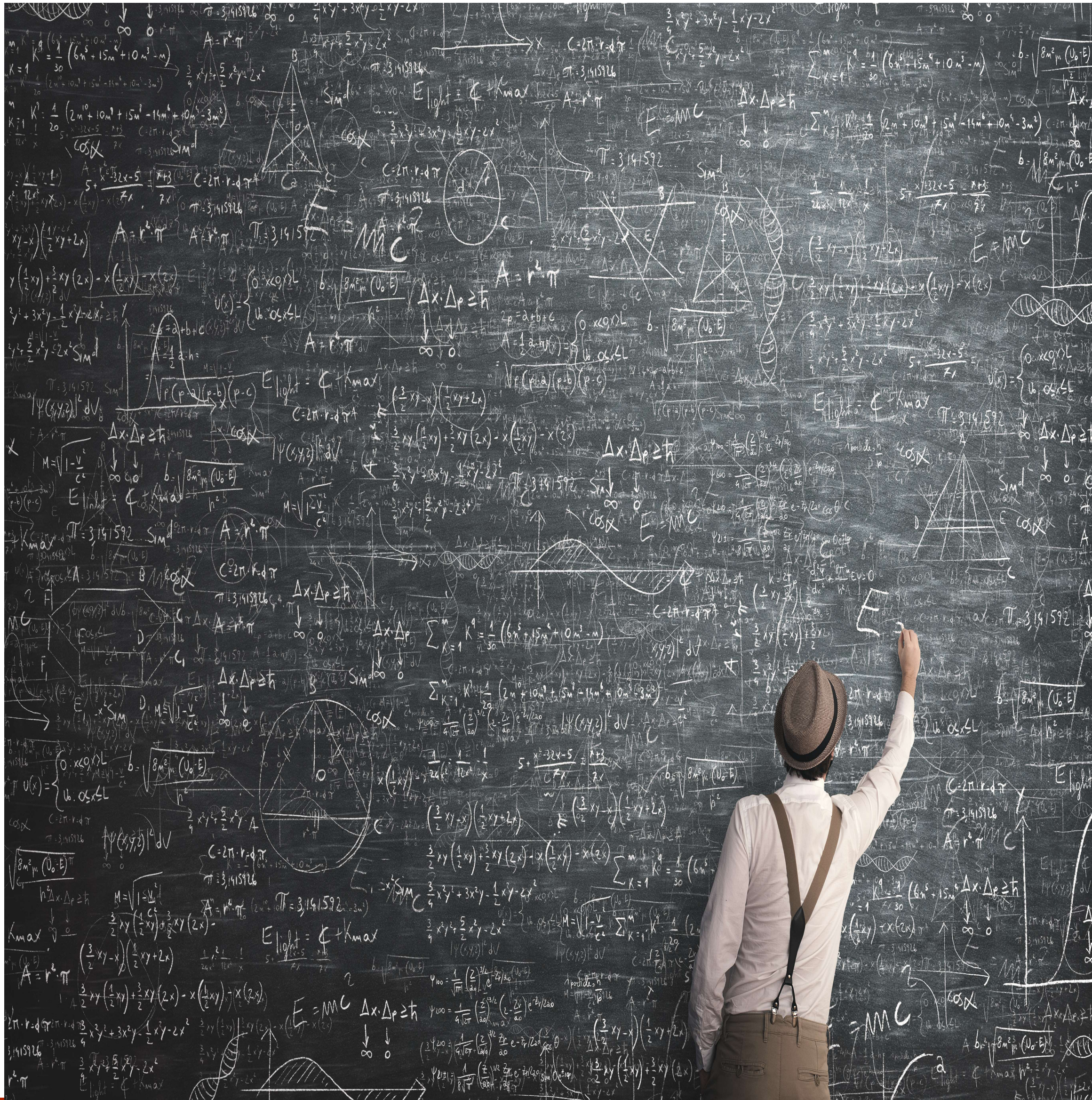
# What is an emotion?

# What is an emotion?

- Emotions
- Feelings
- Mood & affect

# Theories of emotion

- James-Lange
- Canon-Bard
- Schacter-Singer
- Lazarus



# Theories of emotion: James – Lange

Event -> Physiological Response -> Interpretation of -> Emotion

# Theories of emotion: Cannon - Bard

Physiological response

Event

Emotion

# Theories of emotion: Schacter-Singer

Event -> Physiological Response -> Indentity the reason for -> Emotion

# Theories of emotion: Lazarus

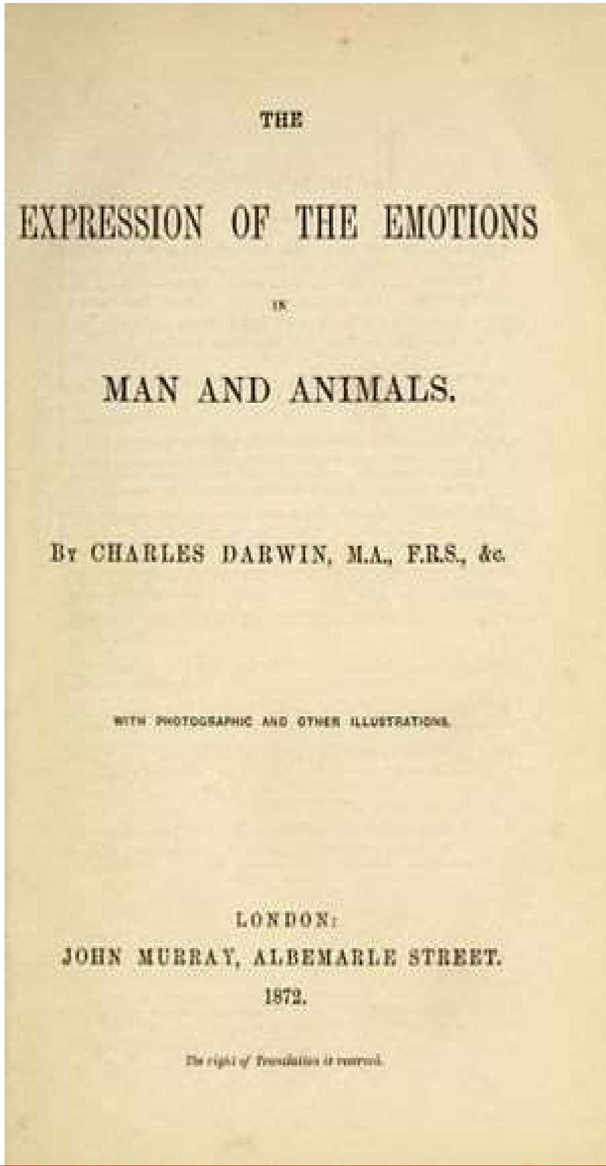
Emotion

Event -> Appraise (label)

Physiological response

# How do we measure emotions?

# Universal emotions


THE

EXPRESSION OF THE EMOTIONS

IN

MAN AND ANIMALS.

BY CHARLES DARWIN, M.A., F.R.S., &c.

WITH PHOTOGRAPHIC AND OTHER ILLUSTRATIONS.

LONDON:
JOHN MURRAY, ALBEMARLE STREET.
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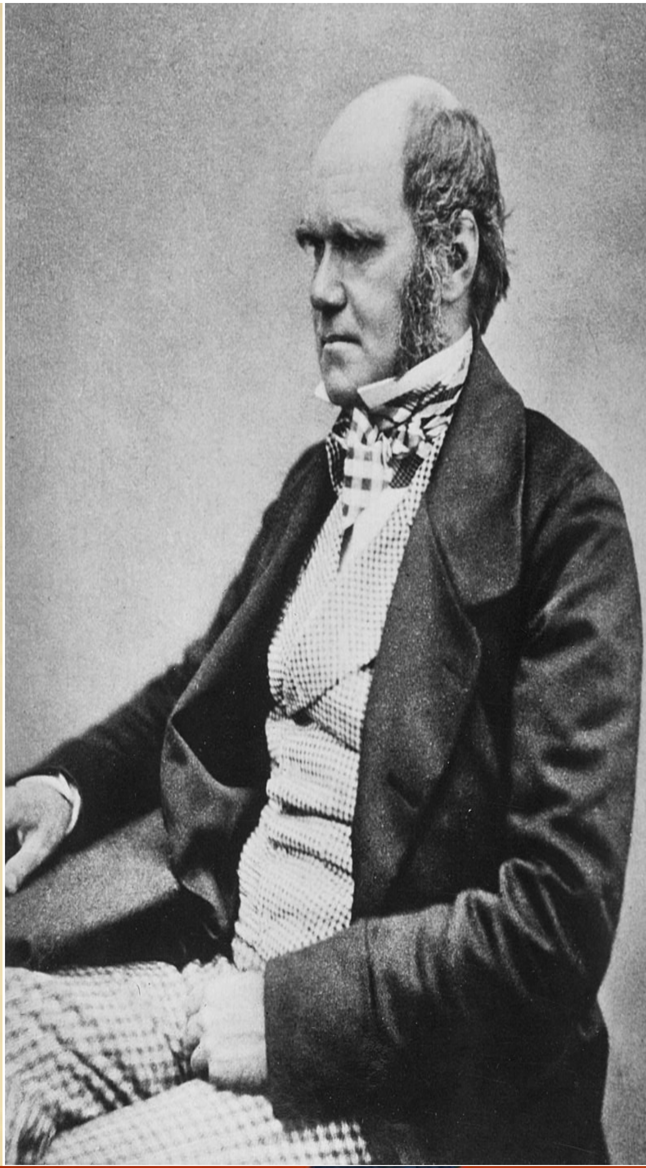


# Duchenne

Source: https://en.wikipedia.org/wiki/Duchenne_de_Boulogne

# Paul Ekman

Source: https://www.paulekman.com/about/paul-ekman/

# Facial expressions


AUs 4+5, with lip press, associated with Anger, Criticism, Contempt

Unilateral AU14, associated with Contempt

Unilateral AU14 with eye roll, associated with Contempt

AUs 4+10, associated with Disgust and Contempt

AU 2 ("the horns"), associated with Domineering

AU 2 ("the horns") with head forward, associated with Domineering


AUs 1+2+5, with cheek biting, associated with Fear / Tension

AUs 1+2+4+5+20, assocated with high intensity Fear / Tension (exaggerated here).

Slight AUs 6+12, associated with Neutral, Interest, Affection, and Validation.

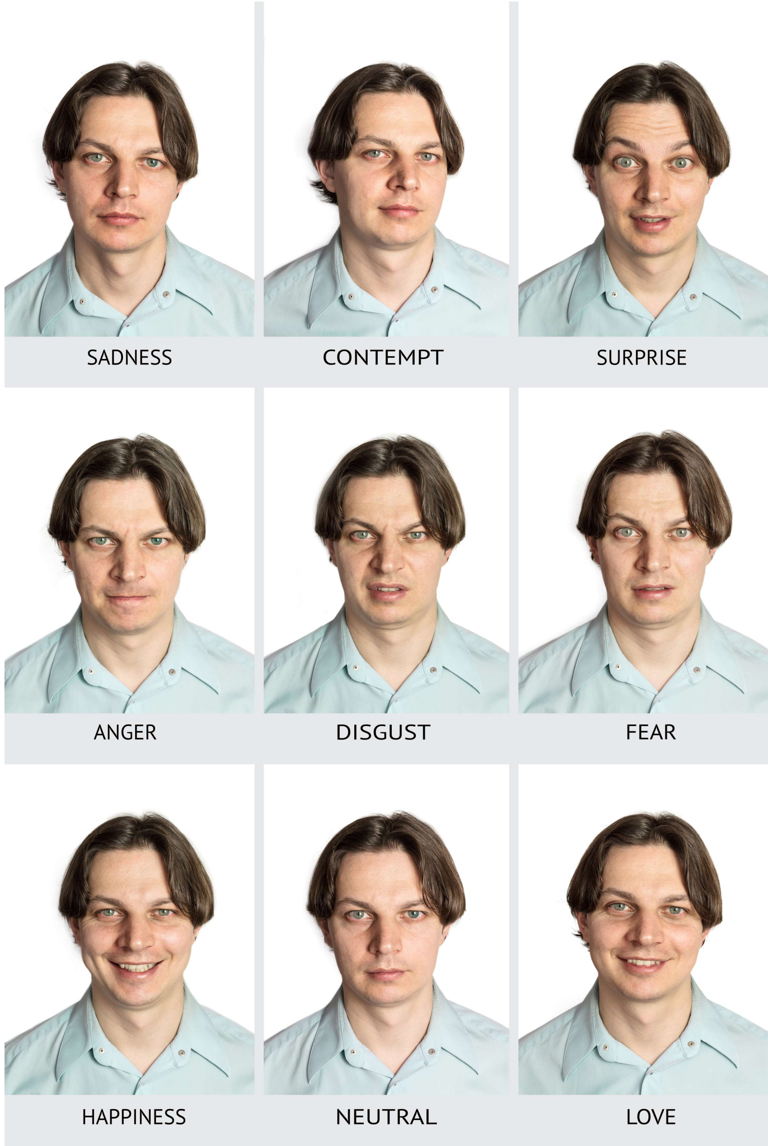
AUs 6+12, associated with Interest, Affection, Validation, Humor and Enthusiasm

AUs 1+15, associated with Sadness

AUs 1+6+15, associated with Sadness

Source: https://www.researchgate.net/profile/James_Coan/publication/230676408_The_Specific_Affect_Coding_System_(SPAFF)/links/09e41502d44ad3450e000000.pdf

# Detect emotions



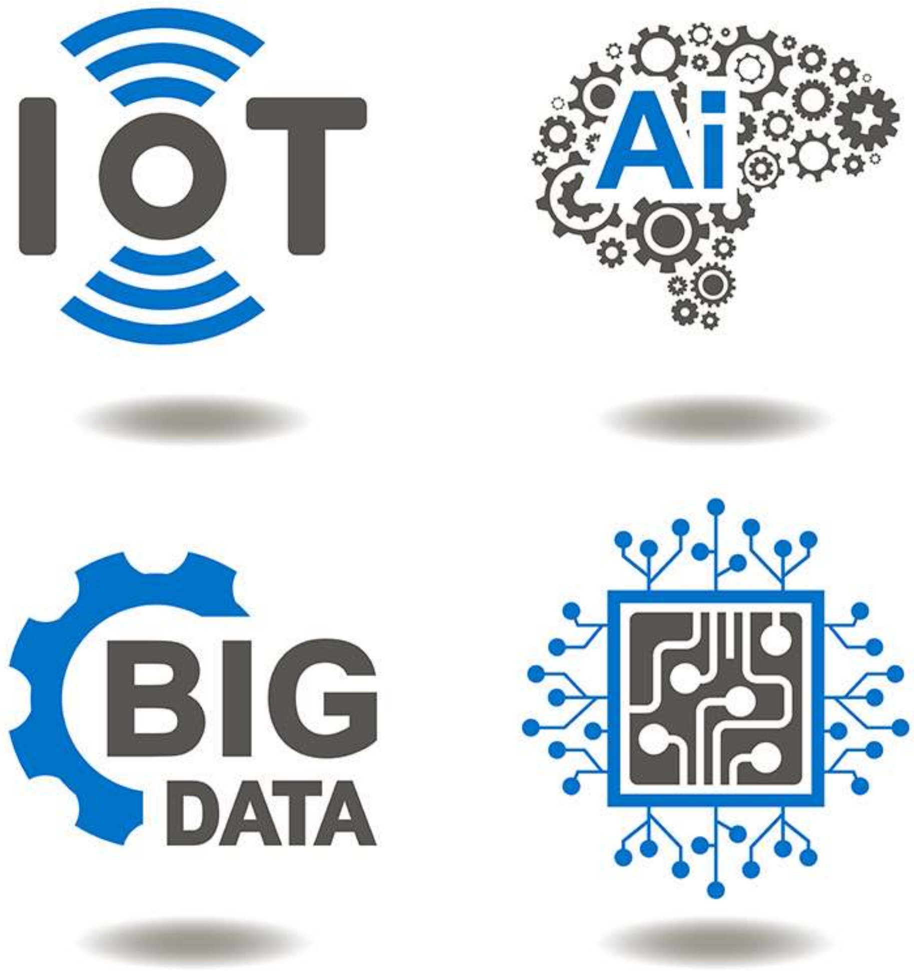

Source: Plateresca/Shutterstock.com

# Affective Computing

# Affective Computing

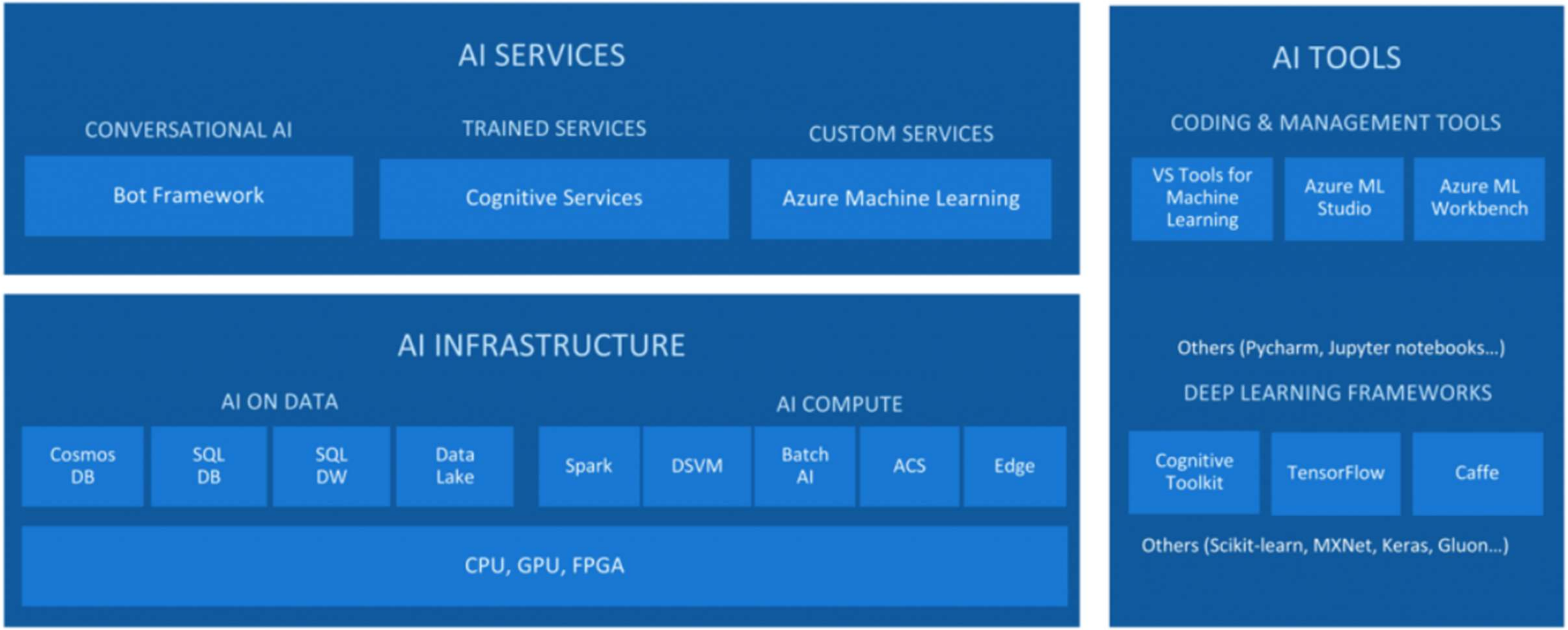

# Emotions in machines

# Enabling technologies




Source: Panchenko Vladimir/Shutterstock.com

# Microsoft AI Services



# Azure Cognitive Services

## Vision

Object, scene, and activity detection

Face recognition and identification

Celebrity and landmark recognition

Emotion recognition

Text and handwriting recognition (OCR)

Video metadata, audio, and keyframe extraction and analysis

Explicit or offensive content moderation

Custom image recognition

## Speech

Speech transcription (Speech-to-text)

Speech Synthesis (Text-to-speech)

Real-time speech translation

Speaker identification and verification

Custom Speech models for transcription and translation

Custom voice

## Language

Language detection

Text sentiment analysis

Key phrase extraction

Entity recognition

Spell checking

Explicit or offensive text content moderation, PII detection

Text translation

Customizable text translation

Contextual language understanding

## Knowledge

Q&A extraction from unstructured text

Knowledge base creation from collections of Q&As

Semantic matching for knowledge bases

Customizable content personalization learning

## Search

Ad-free web, news, image, and video search results

Trends for video, news

Image identification, classification and knowledge extraction

Identification of similar images and products

Named entity recognition and classification

Knowledge acquisition for named entities

Search query autosuggest

Ad-free custom search engine creation

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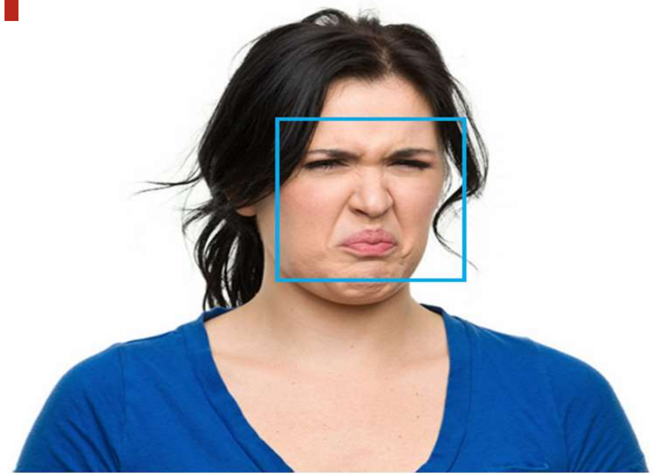
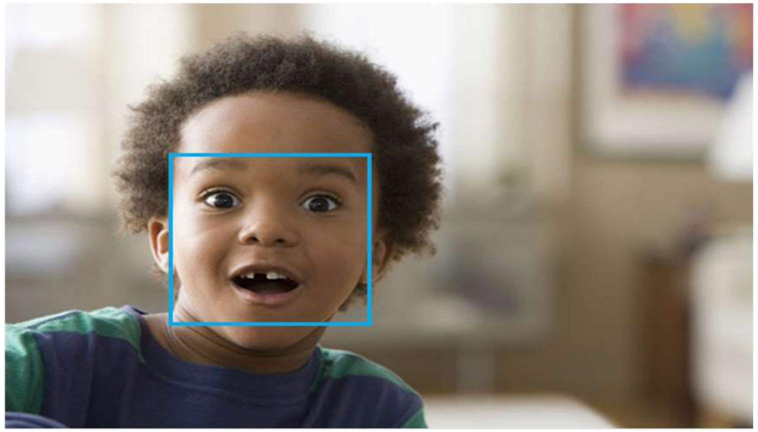
# Face Detection API

- Happiness
- Sadness
- Surprise
- Anger
- Fear
- Contempt
- Disgust
- Neutral




```
Detection result:
1 faces detected

 JSON:
 [
  {
    "faceRectangle": {
      "top": 127,
      "left": 250,
      "width": 163,
      "height": 163
    },
    "scores": {
      "anger": 0.09557262,
      "contempt": 0.003917685,
      "disgust": 0.684764564,
      "fear": 4.03712329E-06,
      "happiness": 8.999826E-08,
      "neutral": 0.002147009,
      "sadness": 0.213587672,
      "surprise": 6.34691469E-06
    }
  }
]
```


```
Detection result:
1 faces detected

 JSON:
 [
  {
    "faceRectangle": {
      "top": 141,
      "left": 130,
      "width": 162,
      "height": 162
    },
    "scores": {
      "anger": 9.29041E-06,
      "contempt": 0.000118981574,
      "disgust": 3.15619363E-05,
      "fear": 0.000589638,
      "happiness": 0.06630674,
      "neutral": 0.00555004273,
      "sadness": 7.44669524E-06,
      "surprise": 0.9273863
    }
  }
]
```


Source: https://azure.microsoft.com/en-us/services/cognitive-services/emotion/

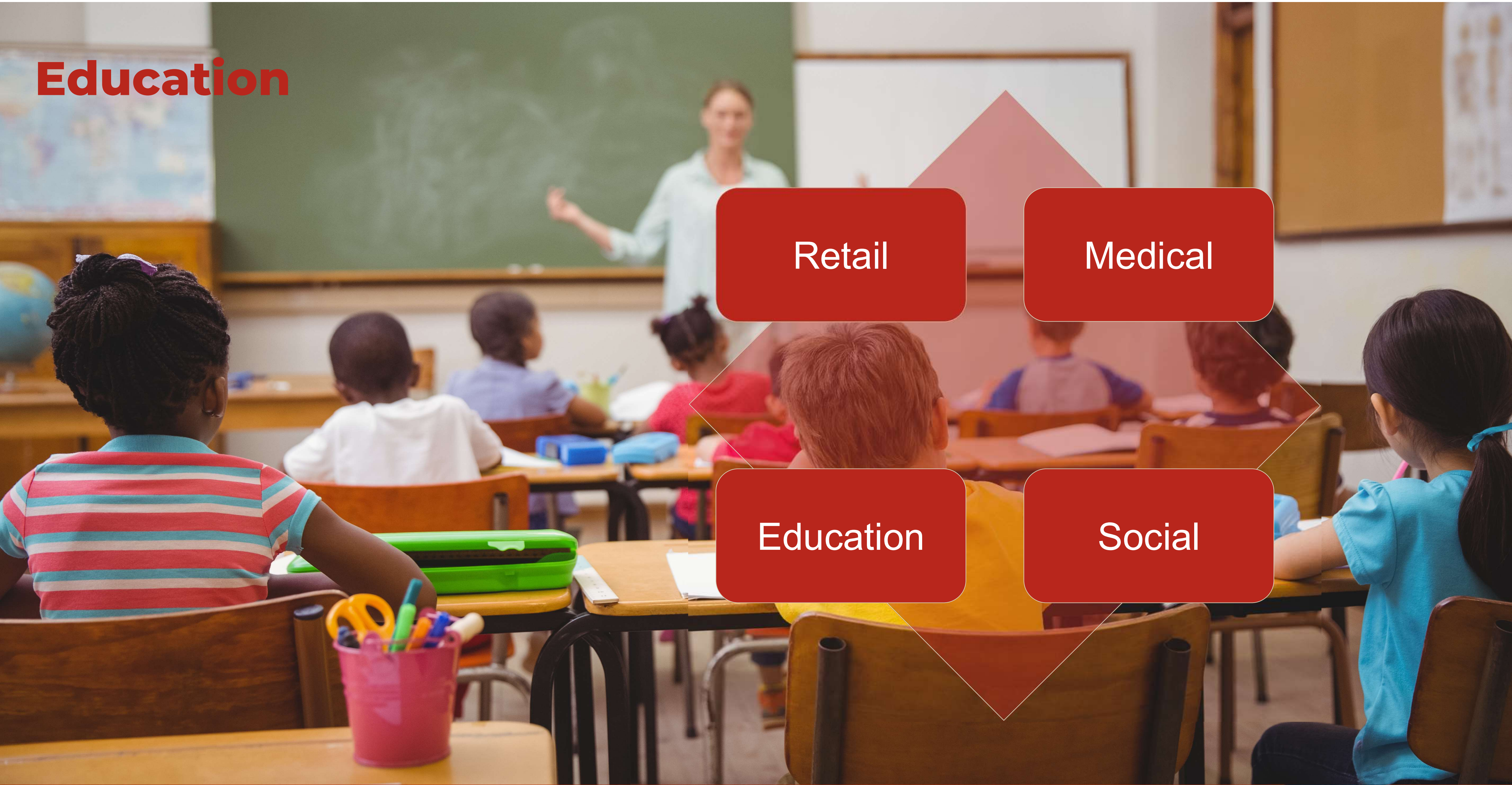
# Demo: Face detection

# Application scenarios

# Retail

# Medical

# Education



# Social

Retail

Medical

Education

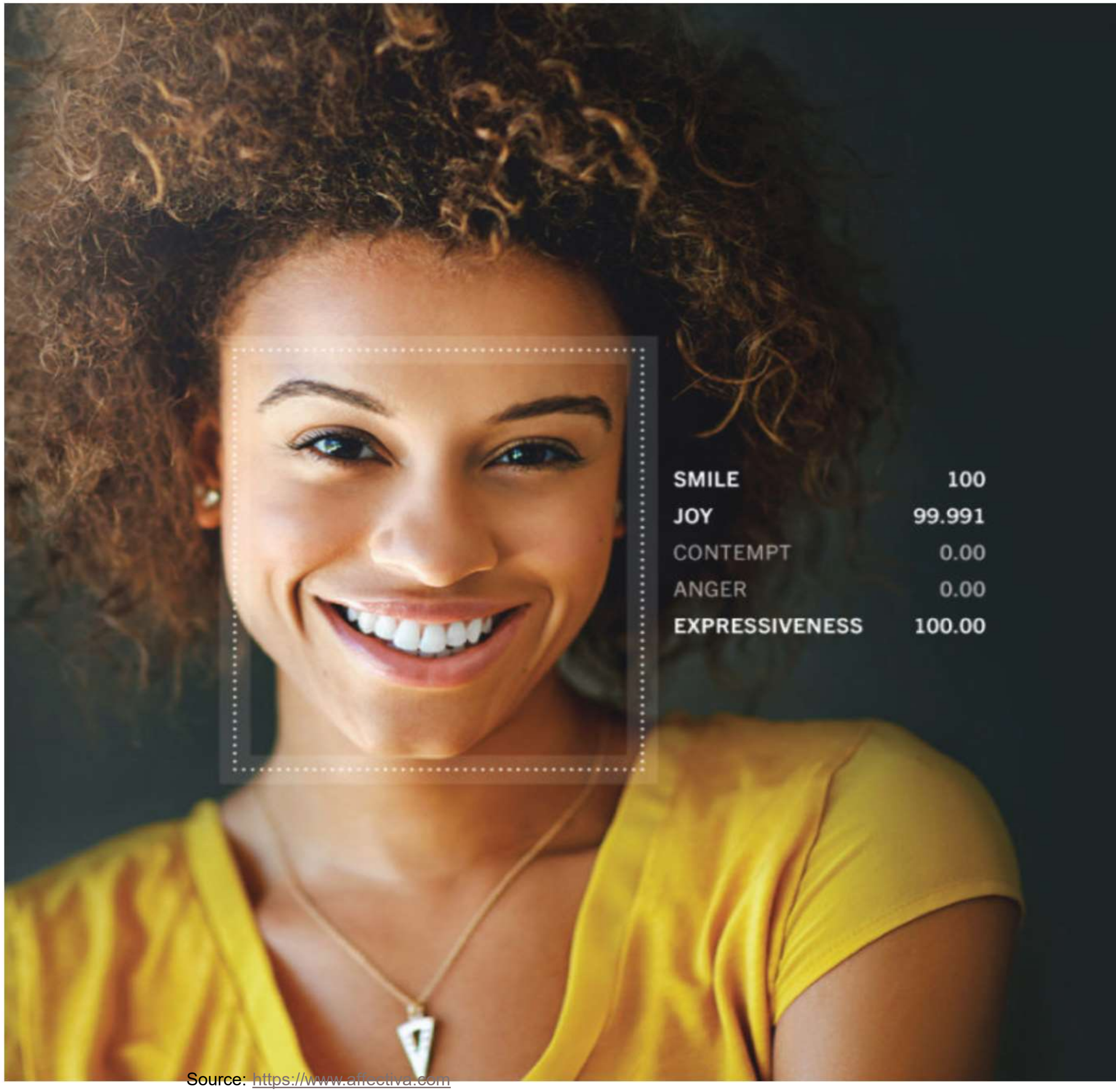
Social

# What is in the front line?

# Affectiva


Source: https://www.affectiva.com

# Emotion as a Service

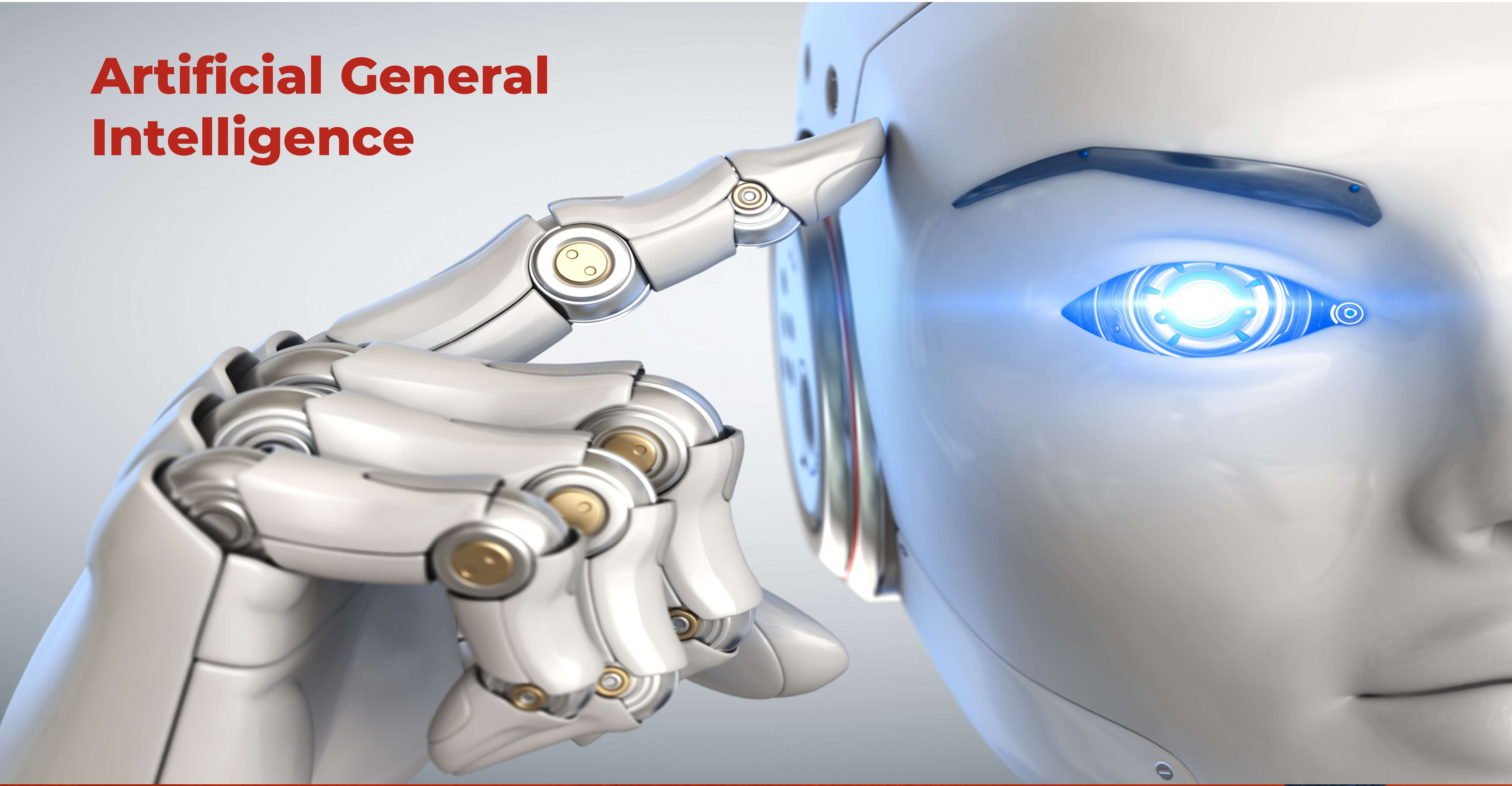



Source: https://www.affectiva.com

# Pepper

Source: VTT Studio/Shuterstock.com

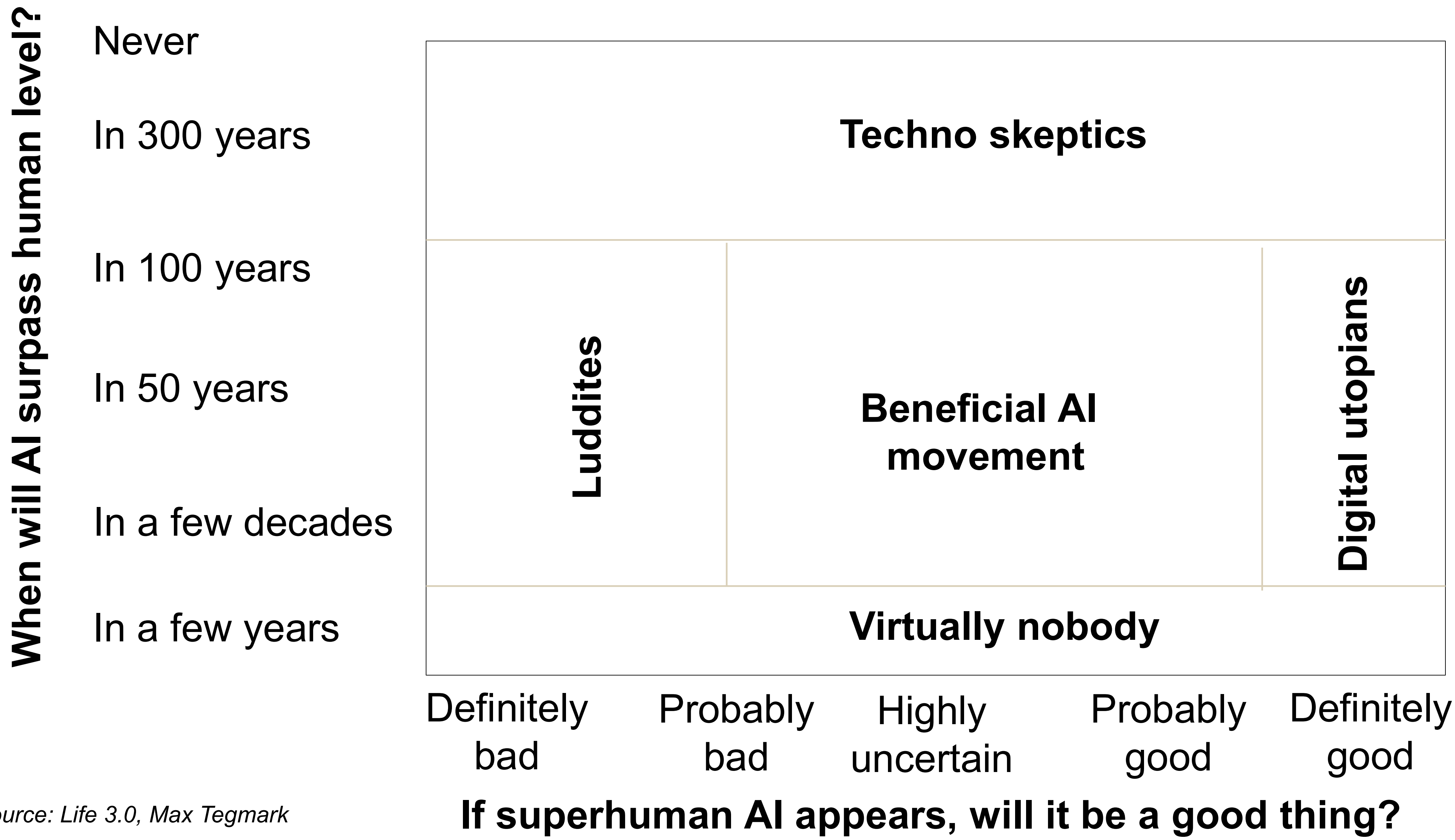
# Artificial General Intelligence



Miles

@agrevlis

# Future:
# Threat or hope?



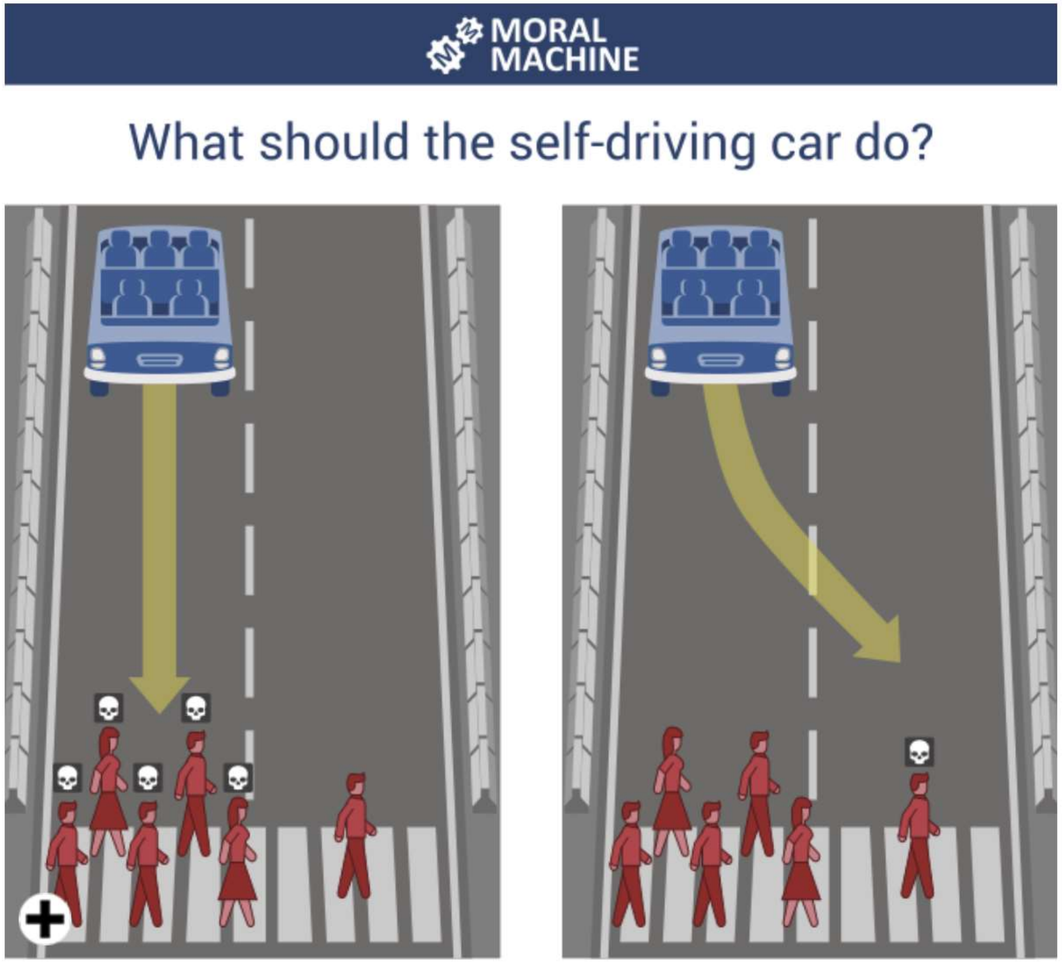

*Source: Life 3.0, Max Tegmark*

# Ethical AI

# The Moral Machine

- Humans over pets
- Passenger over pedestrians
- More lives over fewer
- Women over men
- Young over old
- Fit over sick
- Higher social status
- Law abiders

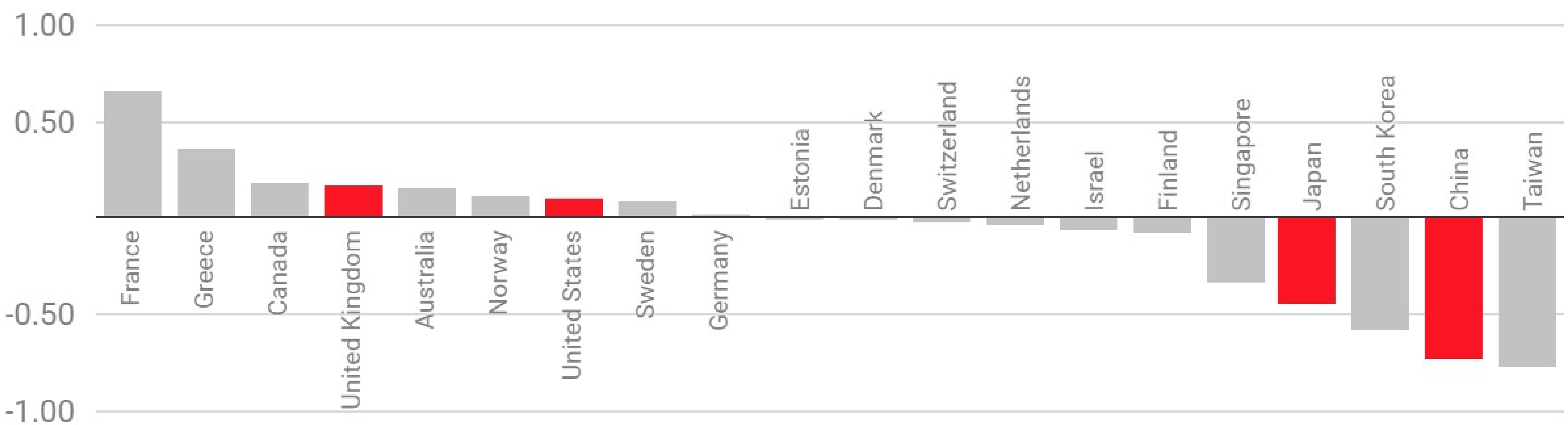
- Should the car take action or not




An example question posed to Moral Machine participants.
MORAL MACHINE

*Source: https://www.technologyreview.com/s/612341/a-global-ethics-study-aims-to-help-ai-solve-the-self-driving-trolley-problem/*

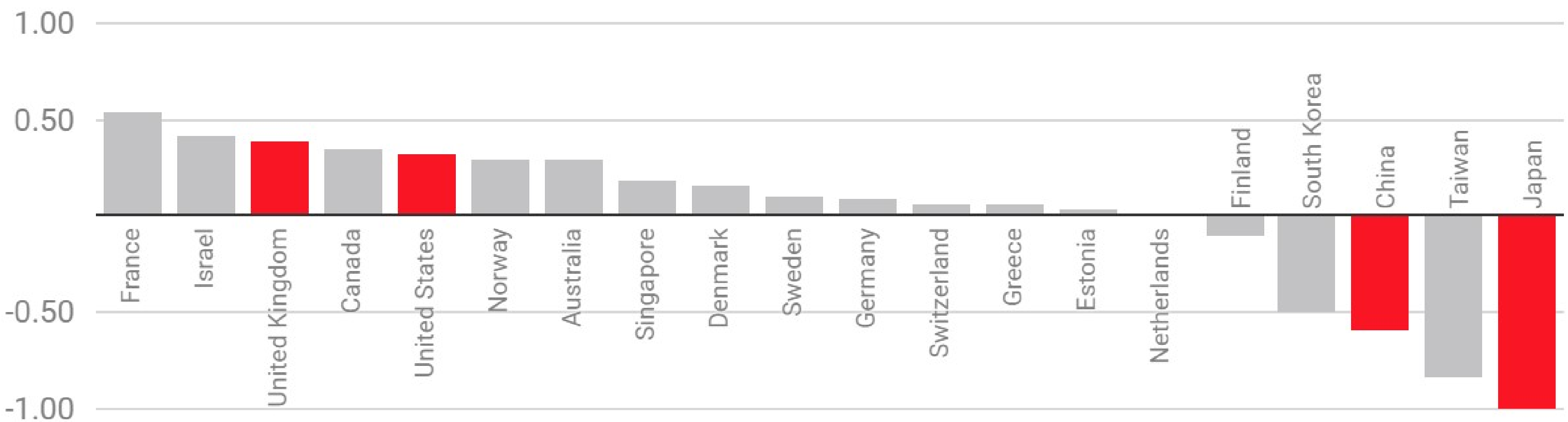
## Countries with more individualistic cultures are more likely to spare the young




*A comparison of countries piloting self-driving cars: If the bar is closer to 1, respondents placed a greater emphasis on sparing the young; if the bar is closer to -1, respondents placed a greater emphasis on sparing the old; 0 is the global average.*

*Source: https://www.technologyreview.com/s/612341/a-global-ethics-study-aims-to-help-ai-solve-the-self-driving-trolley-problem/*

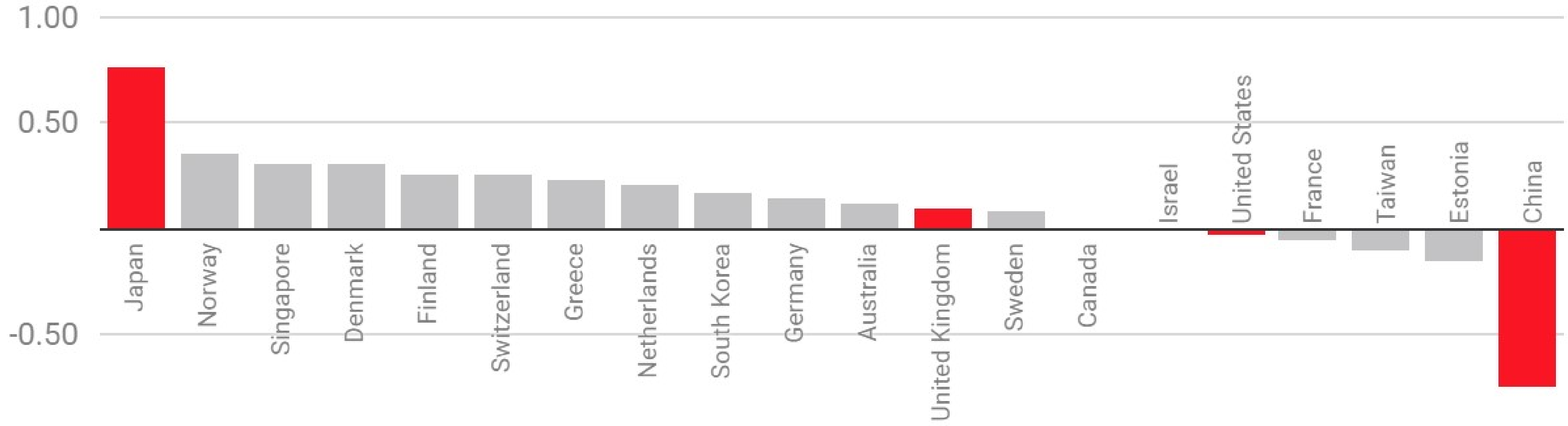
## Countries with more individualistic cultures are more likely to spare more lives




*A comparison of countries piloting self-driving cars: If the bar is closer to 1, respondents placed a greater emphasis on sparing more lives; if the bar is closer to -1, respondents placed a smaller emphasis on sparing more lives; 0 is the global average.*

*Source: https://www.technologyreview.com/s/612341/a-global-ethics-study-aims-to-help-ai-solve-the-self-driving-trolley-problem/*

# How countries compare in sparing pedestrians over passengers



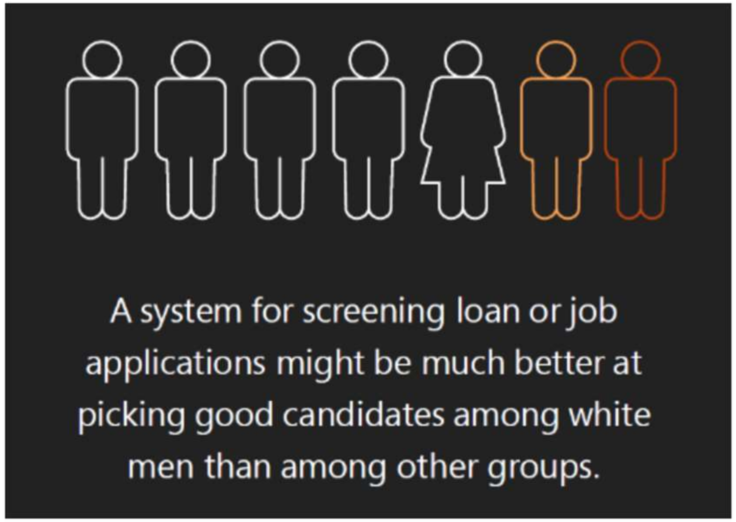

*If the bar is closer to 1, respondents placed a greater emphasis on sparing pedestrians; if the bar is closer to -1, respondents placed a greater emphasis on sparing passengers; 0 is the global average.*

*Source: https://www.technologyreview.com/s/612341/a-global-ethics-study-aims-to-help-ai-solve-the-self-driving-trolley-problem/*

# Fairlearn

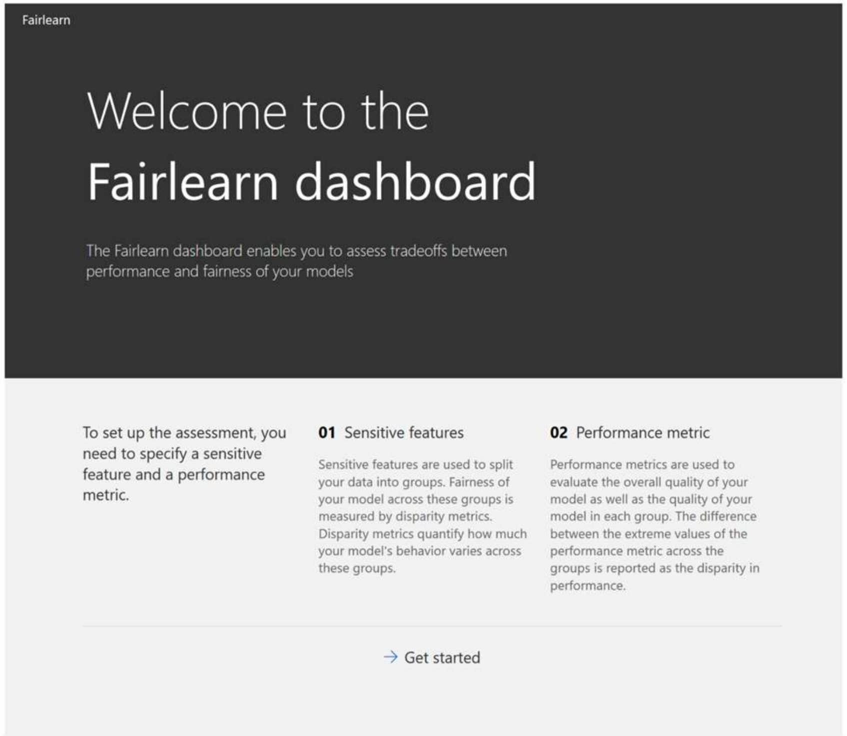
# Fairlearn

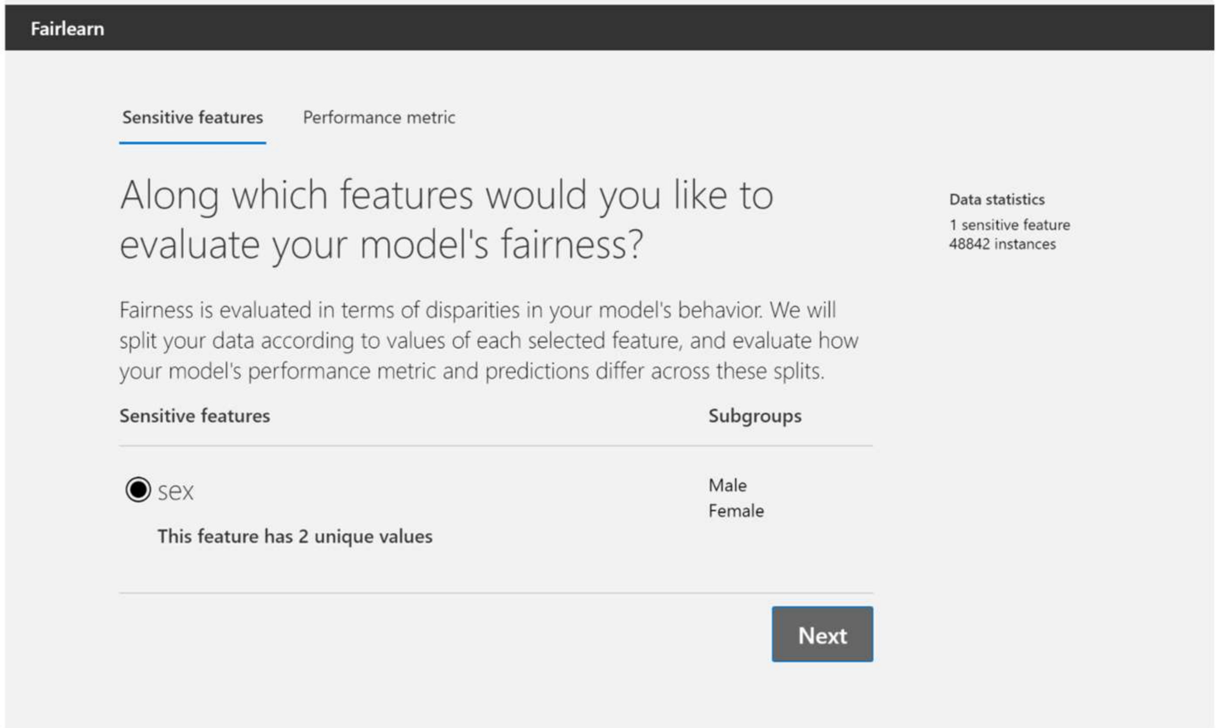

Quality of service harm



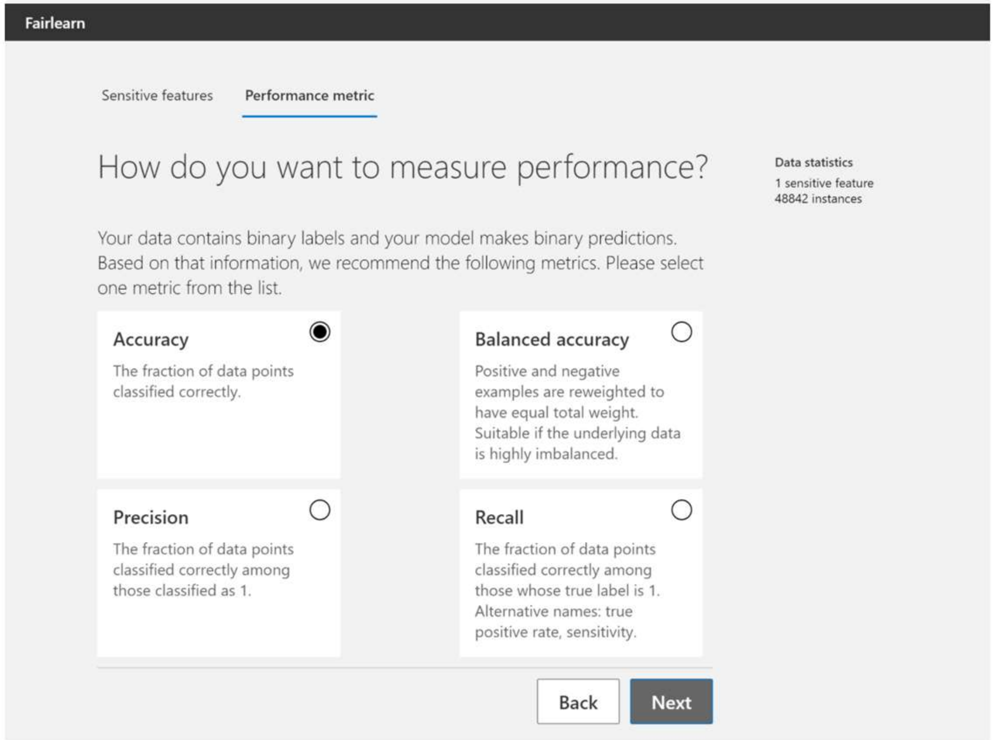

Allocation harm

# Visualization dashboard

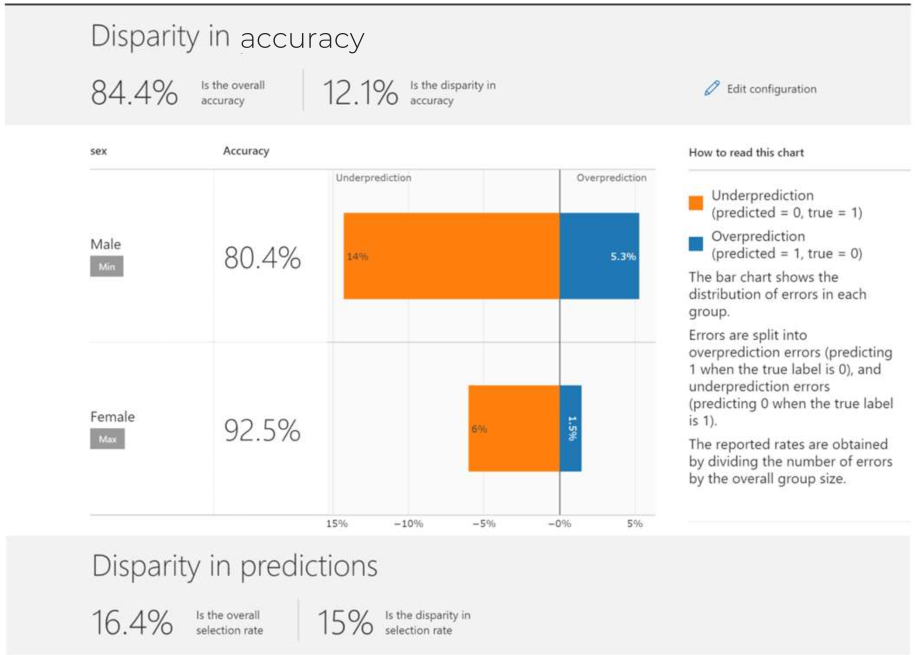


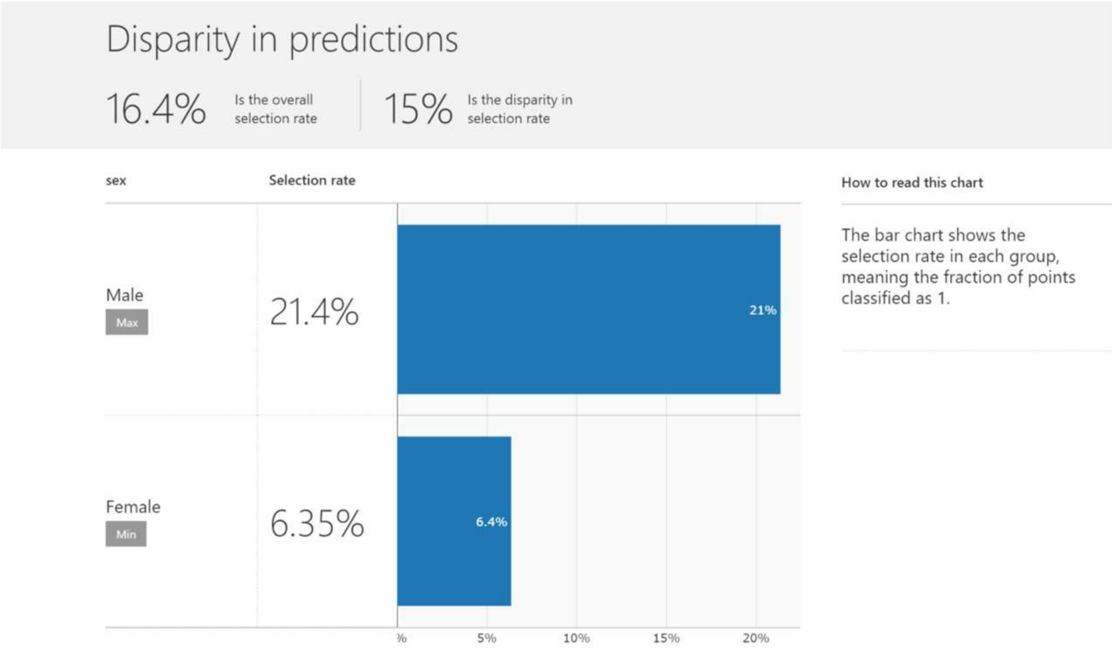



# Visualization dashboard



# Visualization dashboard



# Mitigated model

```
>>> from fairlearn.reductions import ExponentiatedGradient, DemographicParity
>>> np.random.seed(0)  # set seed for consistent results with ExponentiatedGradient
>>>
>>> constraint = DemographicParity()
>>> classifier = DecisionTreeClassifier(min_samples_leaf=10, max_depth=4)
>>> mitigator = ExponentiatedGradient(classifier, constraint)
>>> mitigator.fit(X, y_true, sensitive_features=sex)
>>> y_pred_mitigated = mitigator.predict(X)
>>>
>>> sr_mitigated = MetricFrame(selection_rate, y_true, y_pred_mitigated, sensitive_features=sex)
>>> print(sr_mitigated.overall)
0.1661...
>>> print(sr_mitigated.by_group)
sex
Female    0.1552...
Male      0.1715...
Name: selection_rate, dtype: object
```

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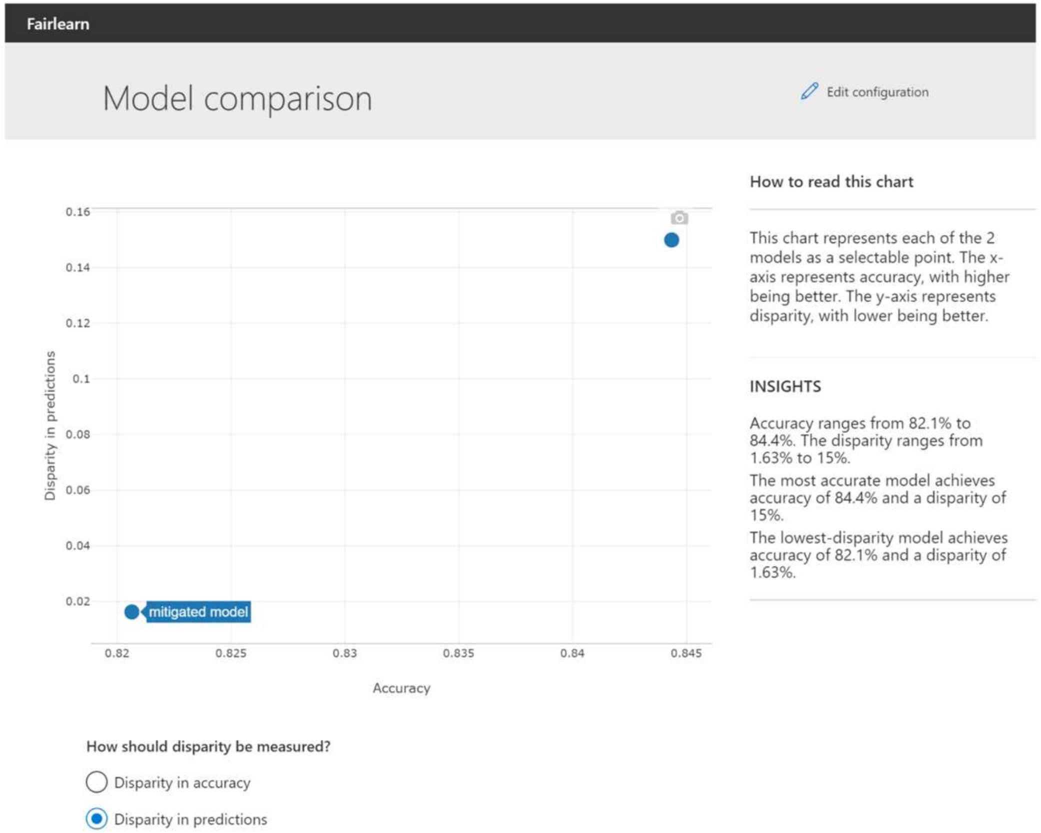
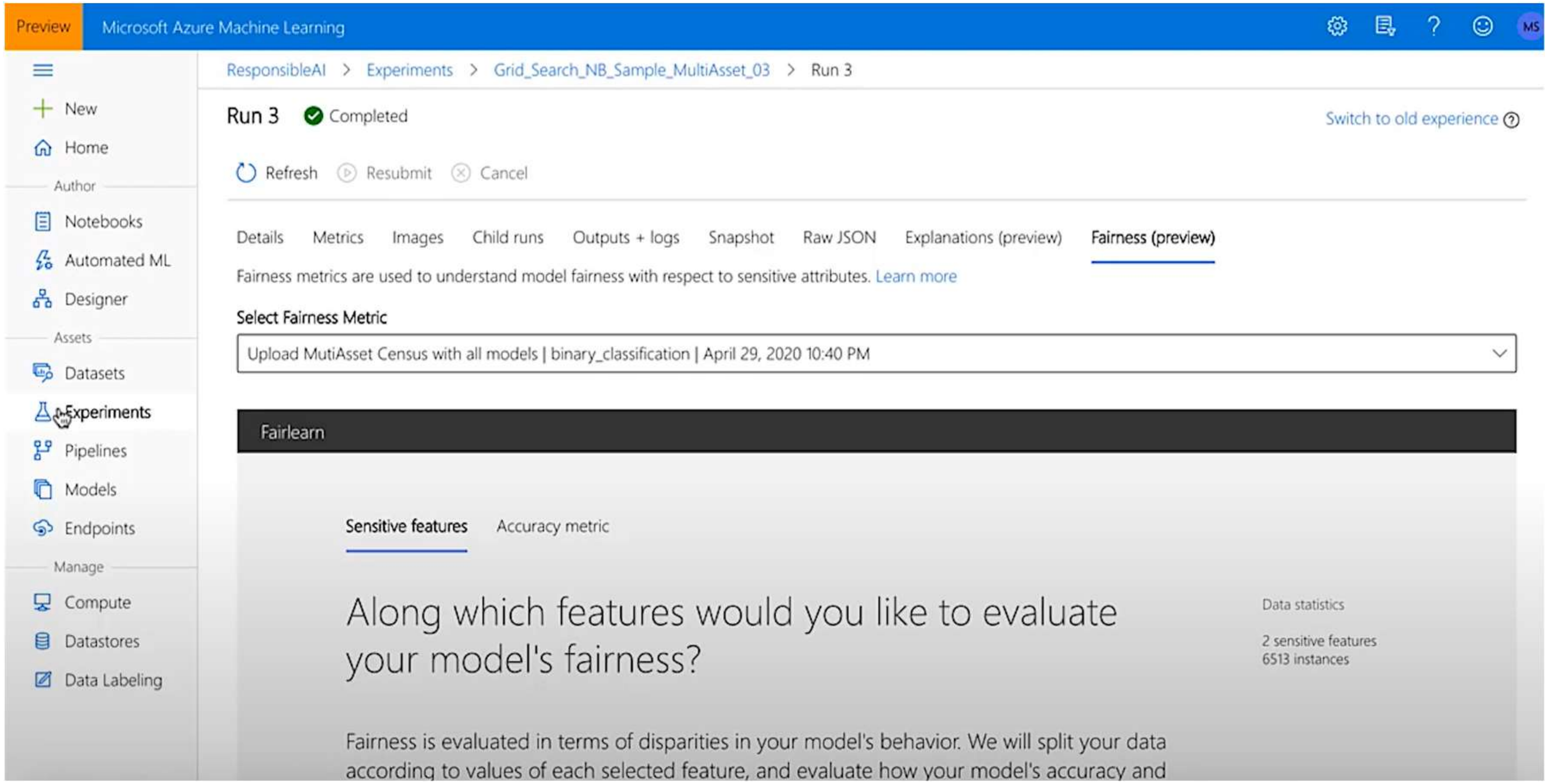
sex
Female    0.1552...
Male      0.1715...
Name: selection_rate, dtype: object
```

```
>>> FairlearnDashboard(sensitive_features=sex,
...                    sensitive_feature_names=['sex'],
...                    y_true=y_true,
...                    y_pred={"initial model": y_pred, "mitigated model": y_pred_mitigated})
```

# Mitigation

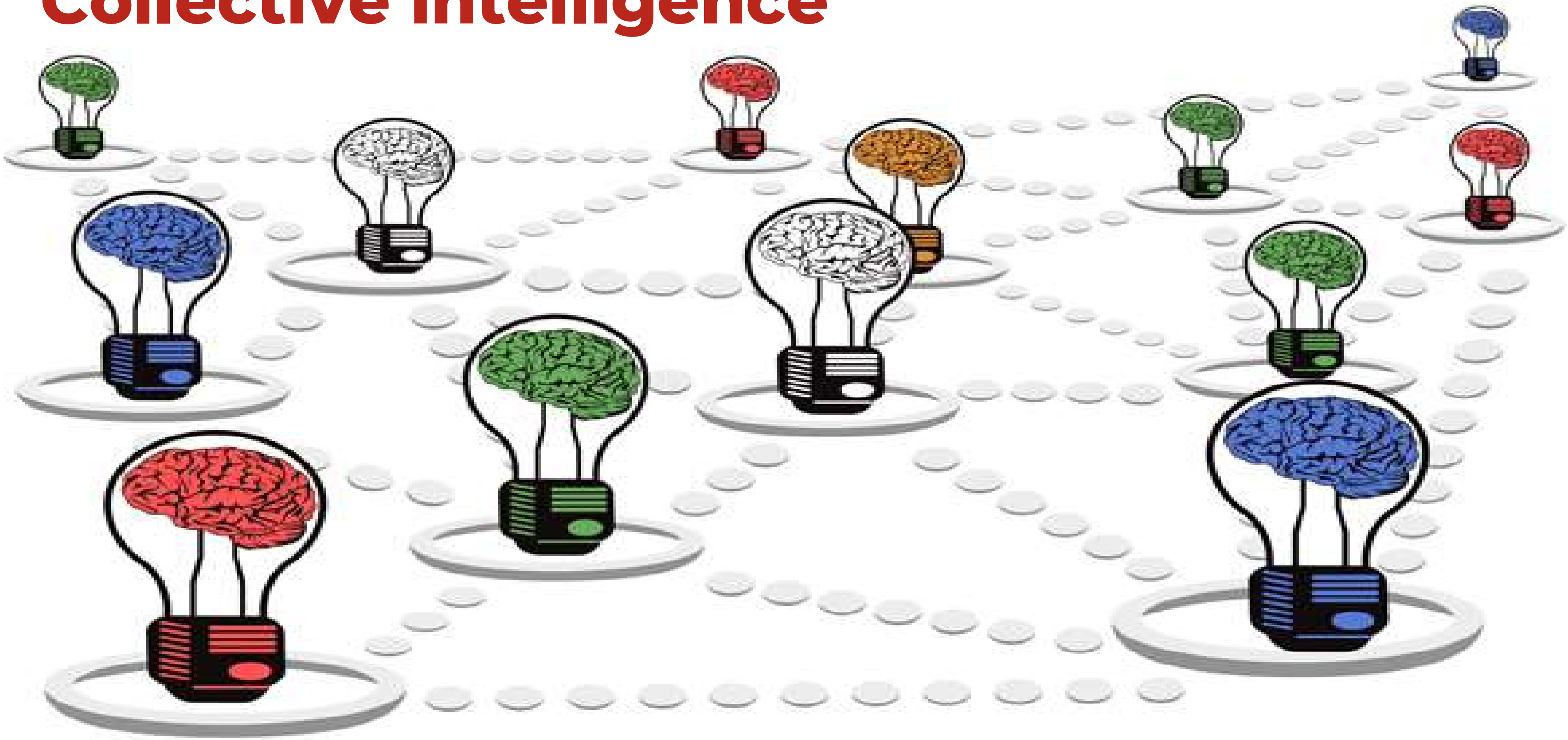

Fairlearn
Model comparison
Edit configuration
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
Disparity in predictions
mitigated model
0.82
0.825
0.83
0.835
0.84
0.845
Accuracy
How to read this chart
This chart represents each of the 2 models as a selectable point. The x-axis represents accuracy, with higher being better. The y-axis represents disparity, with lower being better.
INSIGHTS
Accuracy ranges from 82.1% to 84.4%. The disparity ranges from 1.63% to 15%.
The most accurate model achieves accuracy of 84.4% and a disparity of 15%.
The lowest-disparity model achieves accuracy of 82.1% and a disparity of 1.63%.
How should disparity be measured?
Disparity in accuracy
Disparity in predictions

# Integrated with Azure Machine Learning



# Collective Intelligence

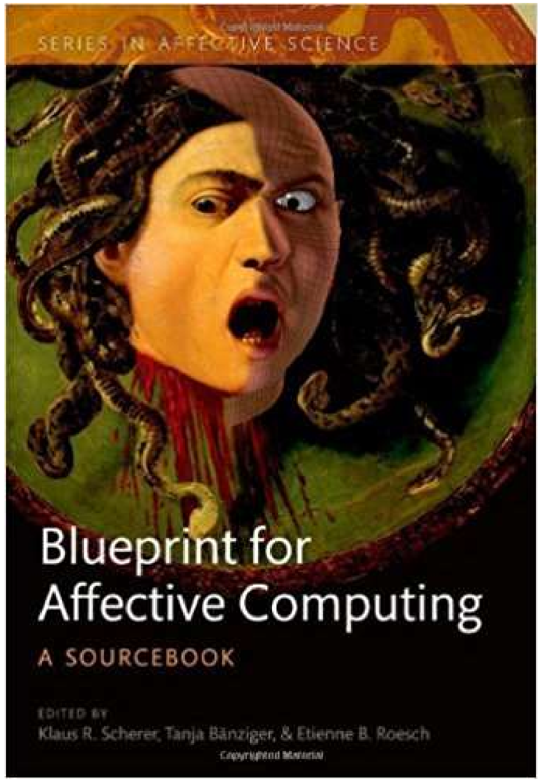
# Collective intelligence



# References

# References

AFFECTIVE COMPUTING
Rosalind W. Picard

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Blueprint for Affective Computing
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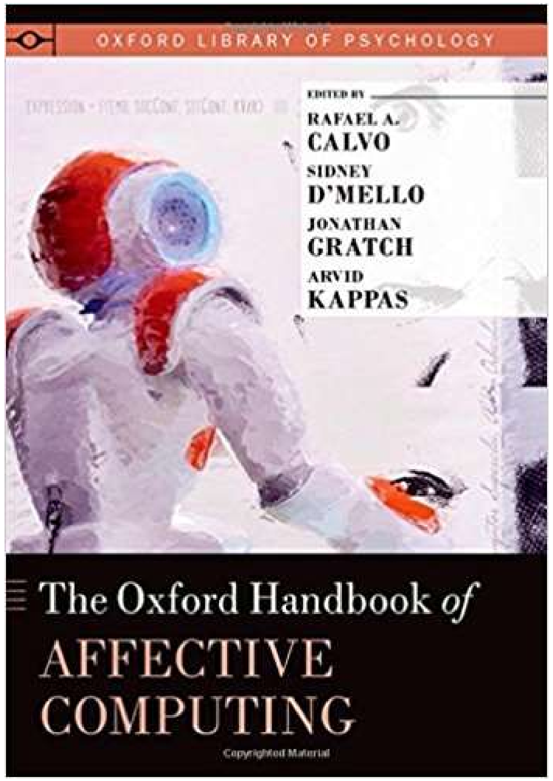

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MVP-Dagen

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