

Affective Computing

Bringing humans and machines closer
through emotions



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- ❖ **Miles** | hakan.silfvernagel@miles.no

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Håkan Silfvernagel

- ❖ Manager AI and Big Data at Miles AS
- ❖ HMI for Process Automation and Robotics
- ❖ MSc in Electrical Engineering
- ❖ Master in Behavioural Science



/in/hakansilfvernagel

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sessionize.com/hakan-silfvernagel

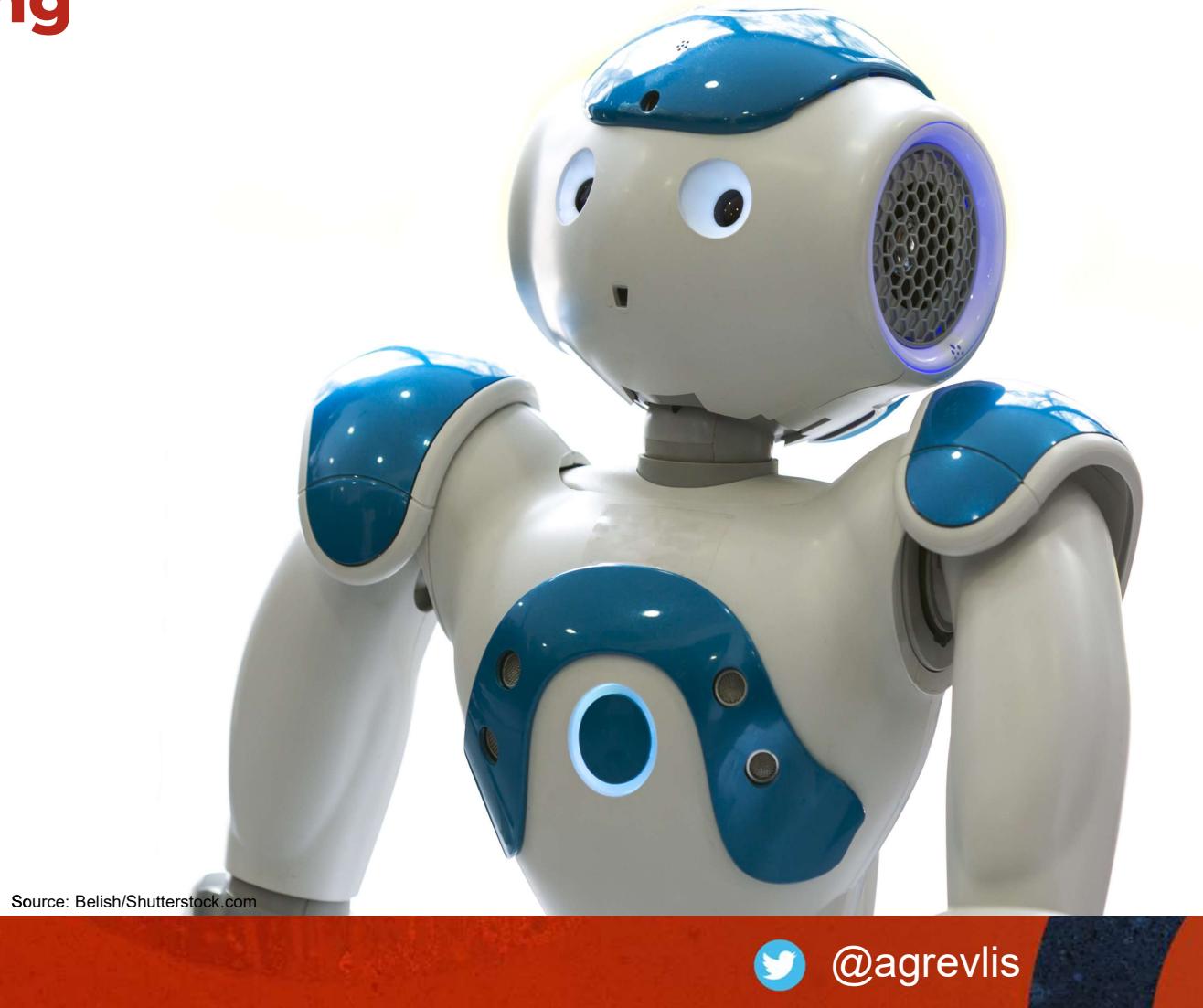
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What is it?



Source: Belish/Shutterstock.com

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What is an emotion?



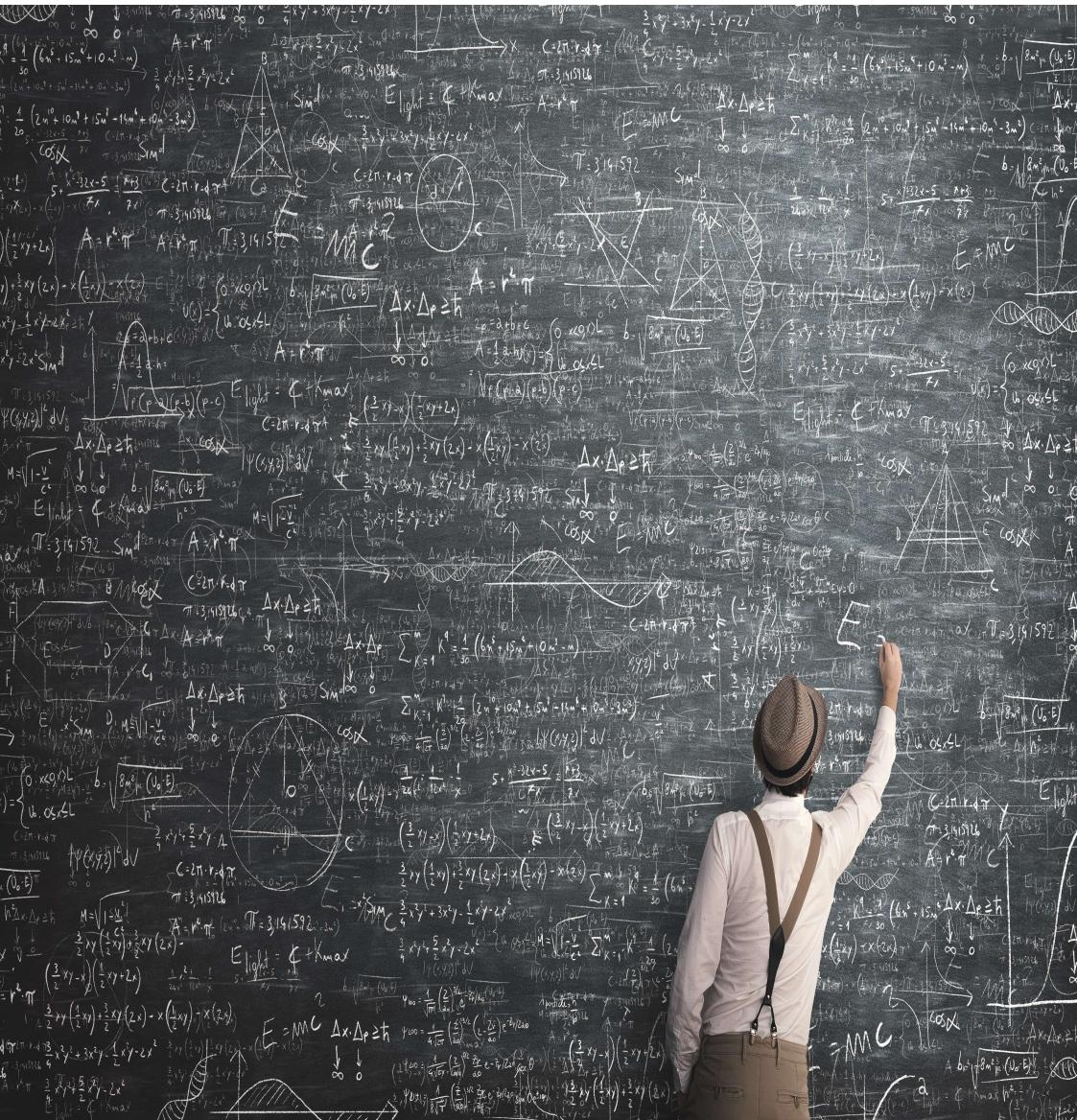
What is an emotion?

- ❖ Emotions
- ❖ Feelings
- ❖ Mood & affect



Theories of emotion

- ❖ James-Lange
- ❖ Cannon-Bard
- ❖ Schacter-Singer
- ❖ Lazarus



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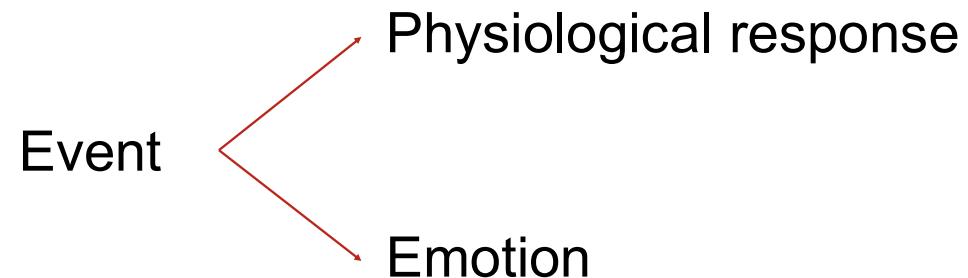
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Theories of emotion: James – Lange

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

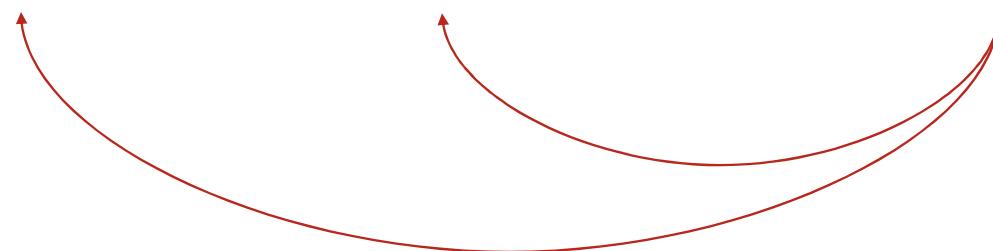


Theories of emotion: Cannon - Bard

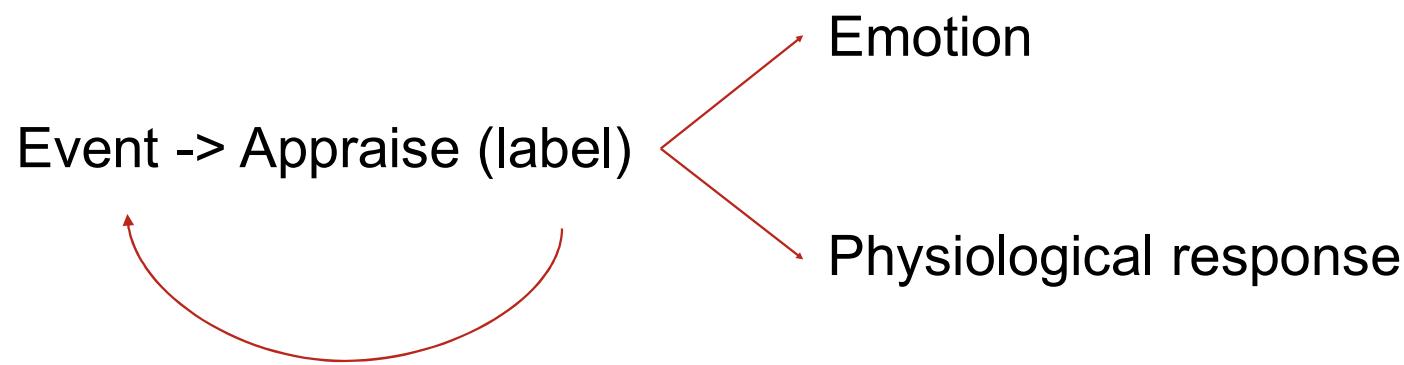


Theories of emotion: Schacter-Singer

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



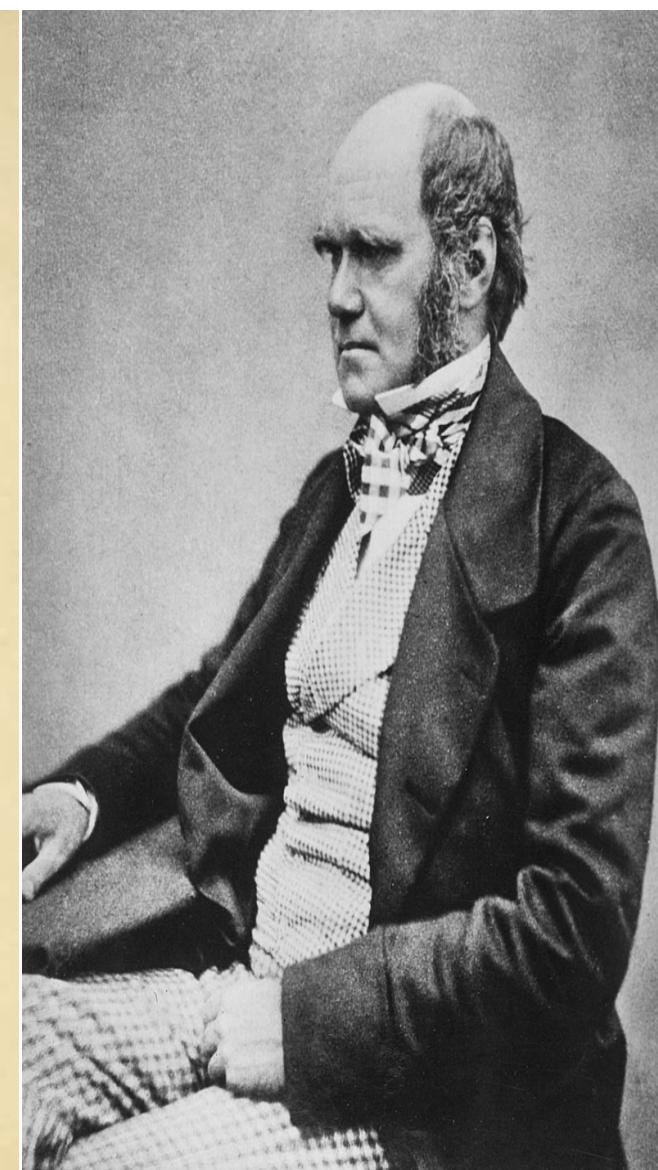
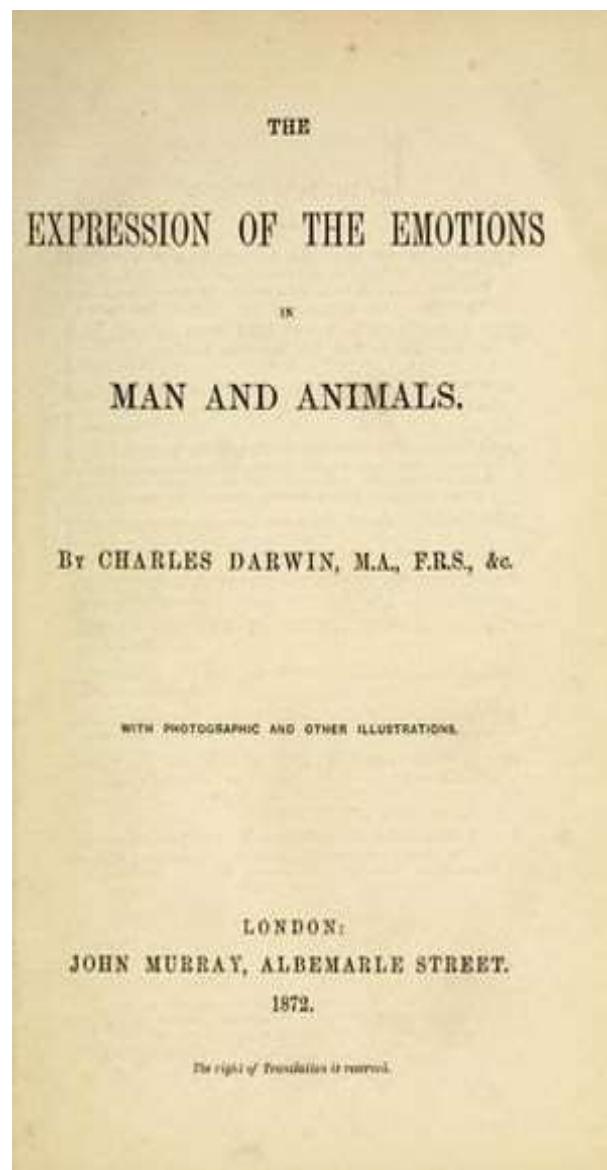
Theories of emotion: Lazarus



How do we measure emotions?



Universal emotions



Duchenne



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

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Paul Ekman



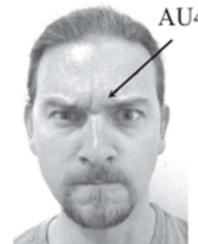
Source: <https://www.paulekman.com/people/paul-ekman>

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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, associated 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



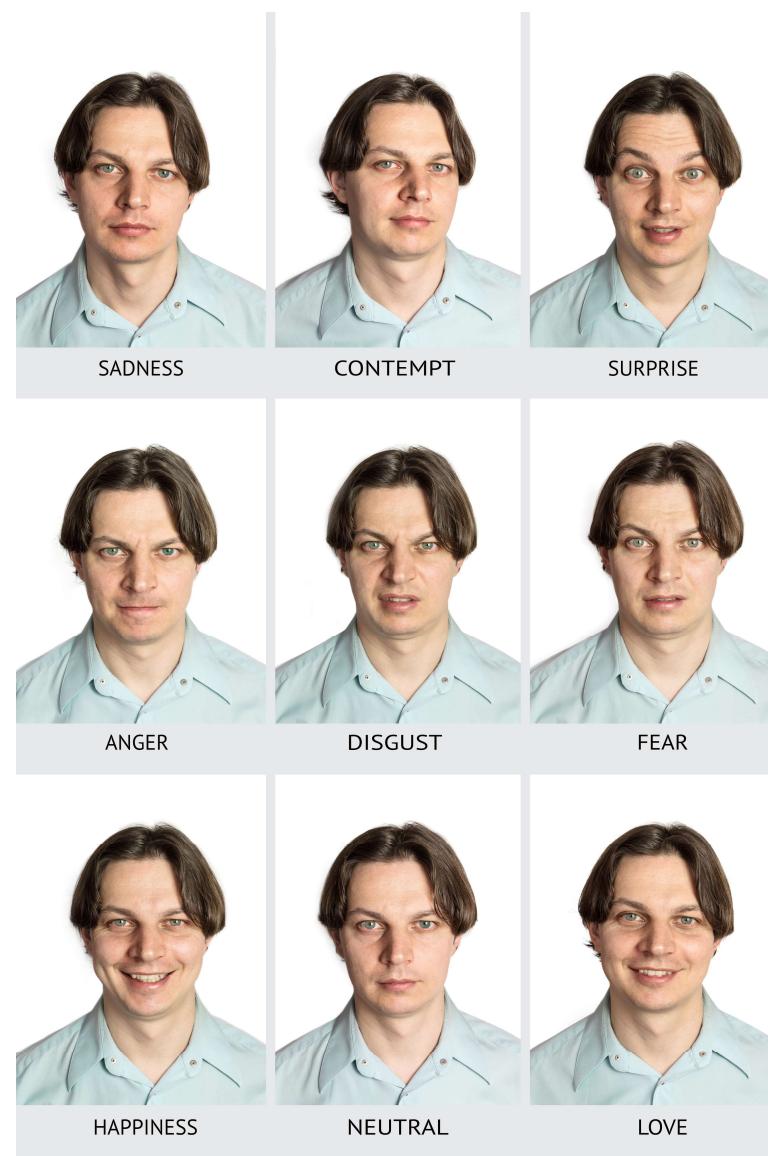
AUs 1+15, associated with Sadness



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

Detect emotions



Source: [Plateresca/Shutterstock.com](#)

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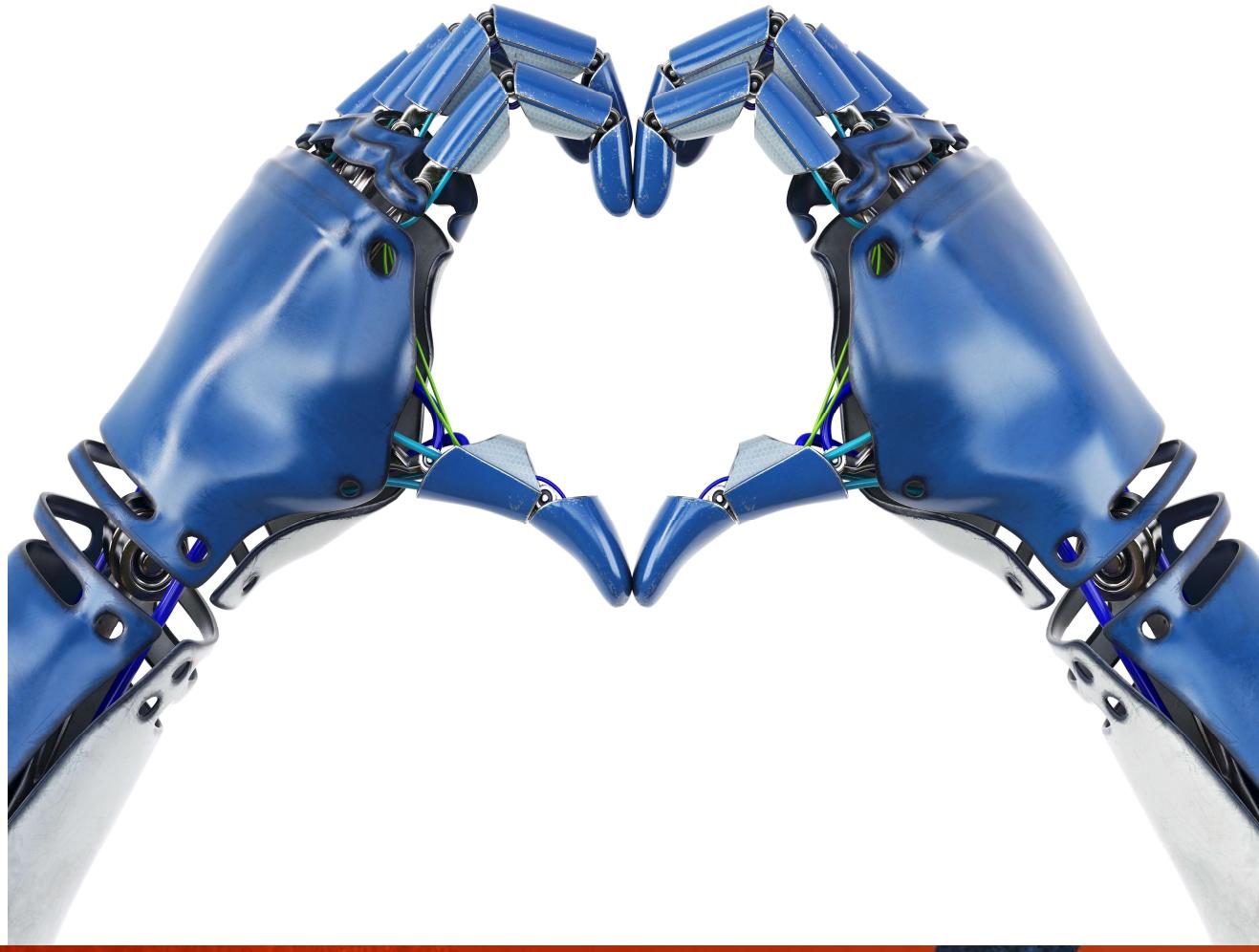


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Emotions in machines

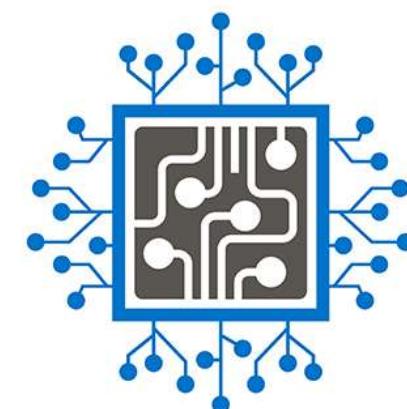
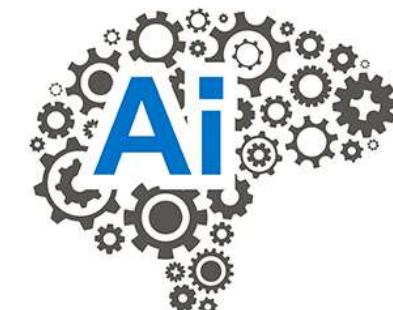


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Enabling technologies

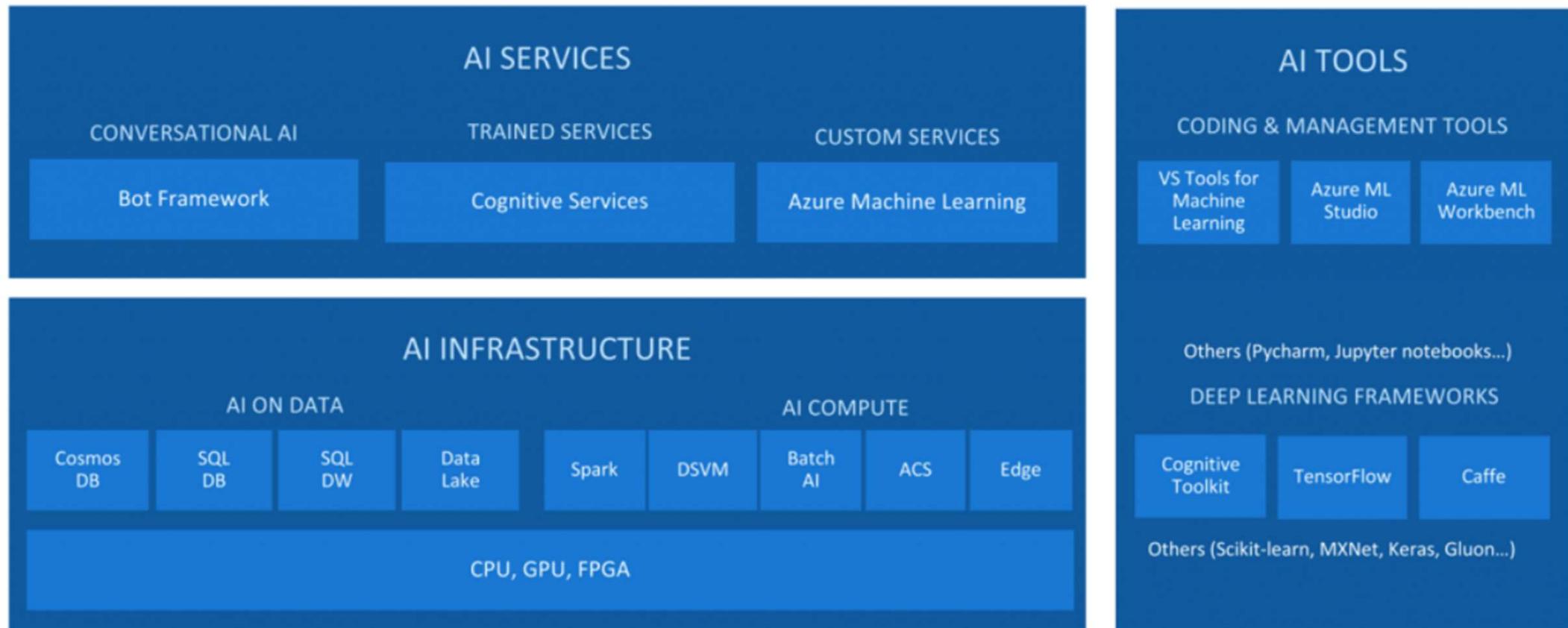


Source: Panchenko Vladimir/Shutterstock.com

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Microsoft AI Services



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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

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
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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

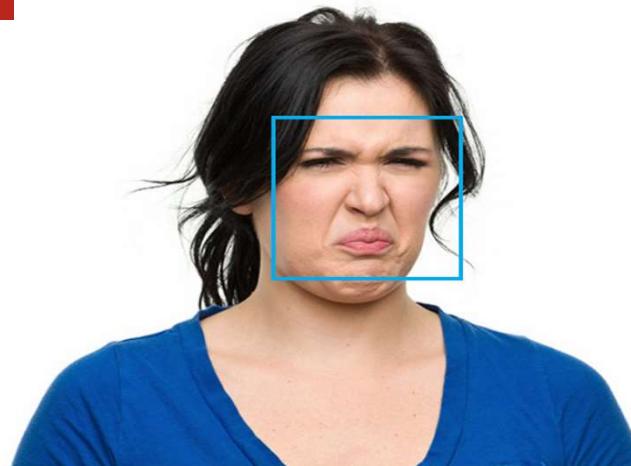


Search

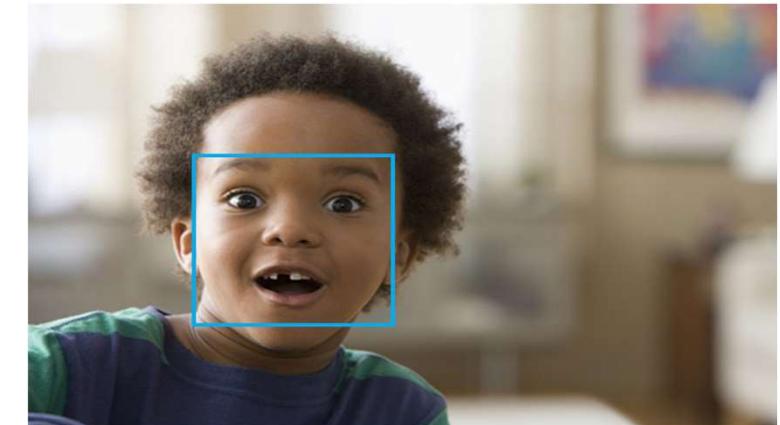
Ad-free web, news, image, and video search results
Trends for video, news
Image identification, classification and knowledge extraction
Identification of similar images and products
Named entity recognition and classification
Knowledge acquisition for named entities
Search query autosuggest
Ad-free custom search engine creation

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/>

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Demo: Face detection



Application scenarios



Retail



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A photograph of a man with a beard lying in a hospital bed, looking up at a female doctor in scrubs. The doctor is leaning over him. The background shows a modern hospital room with large windows.

Medical

Retail

Medical

Education

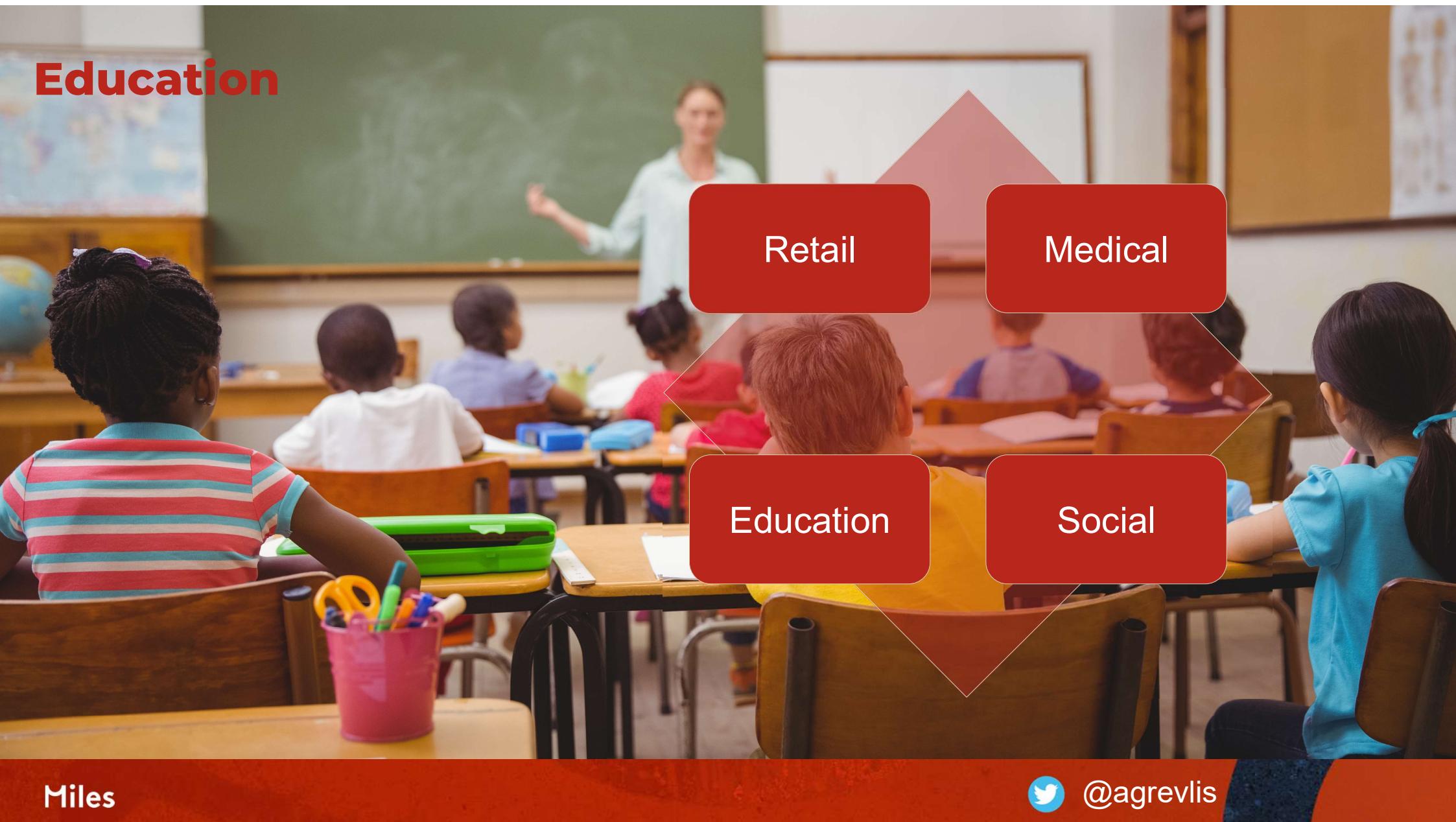
Social

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Education



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Social



Retail

Medical

Education

Social

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What is in the front line?



Affectiva

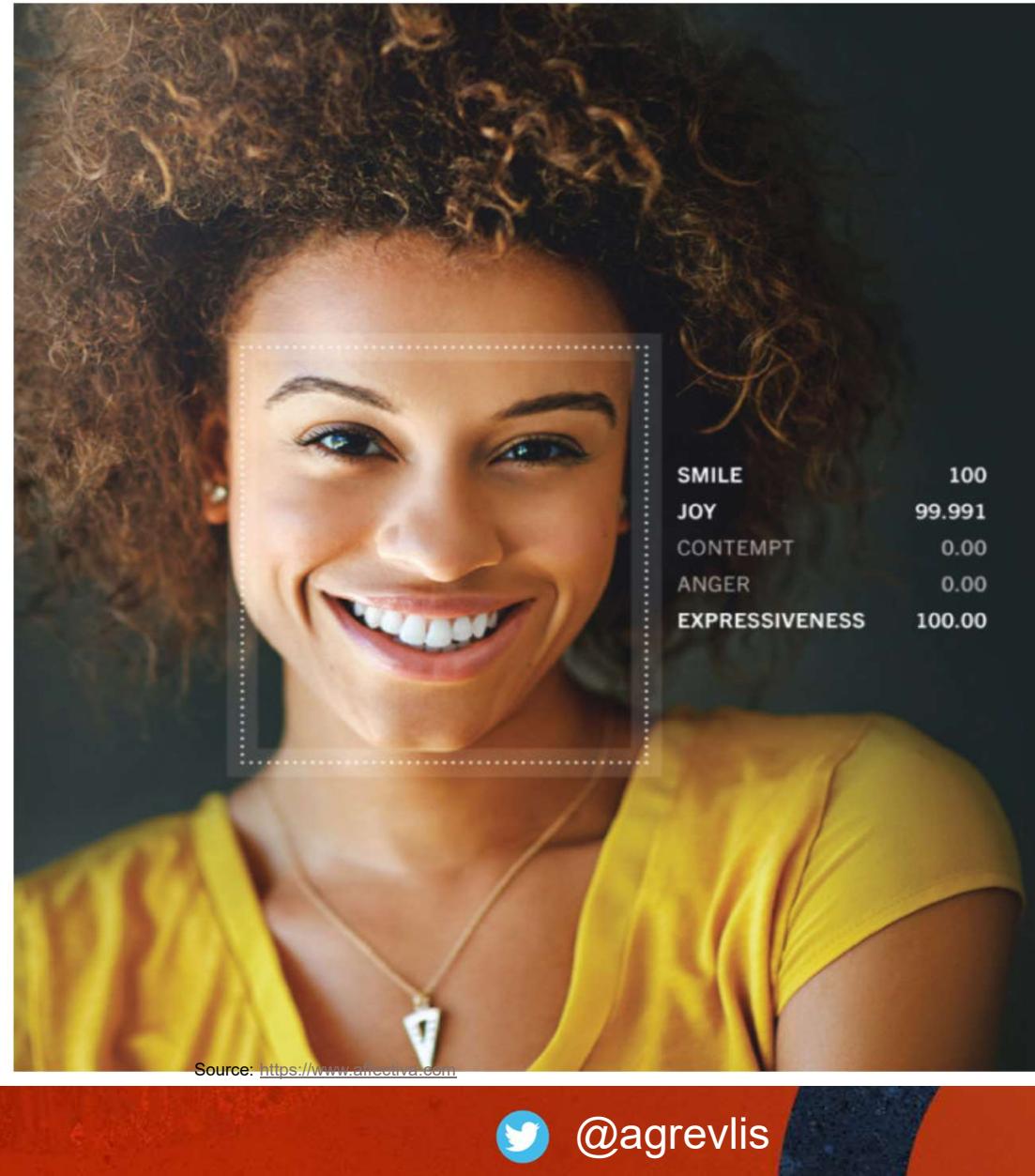


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Emotion as a Service



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Pepper



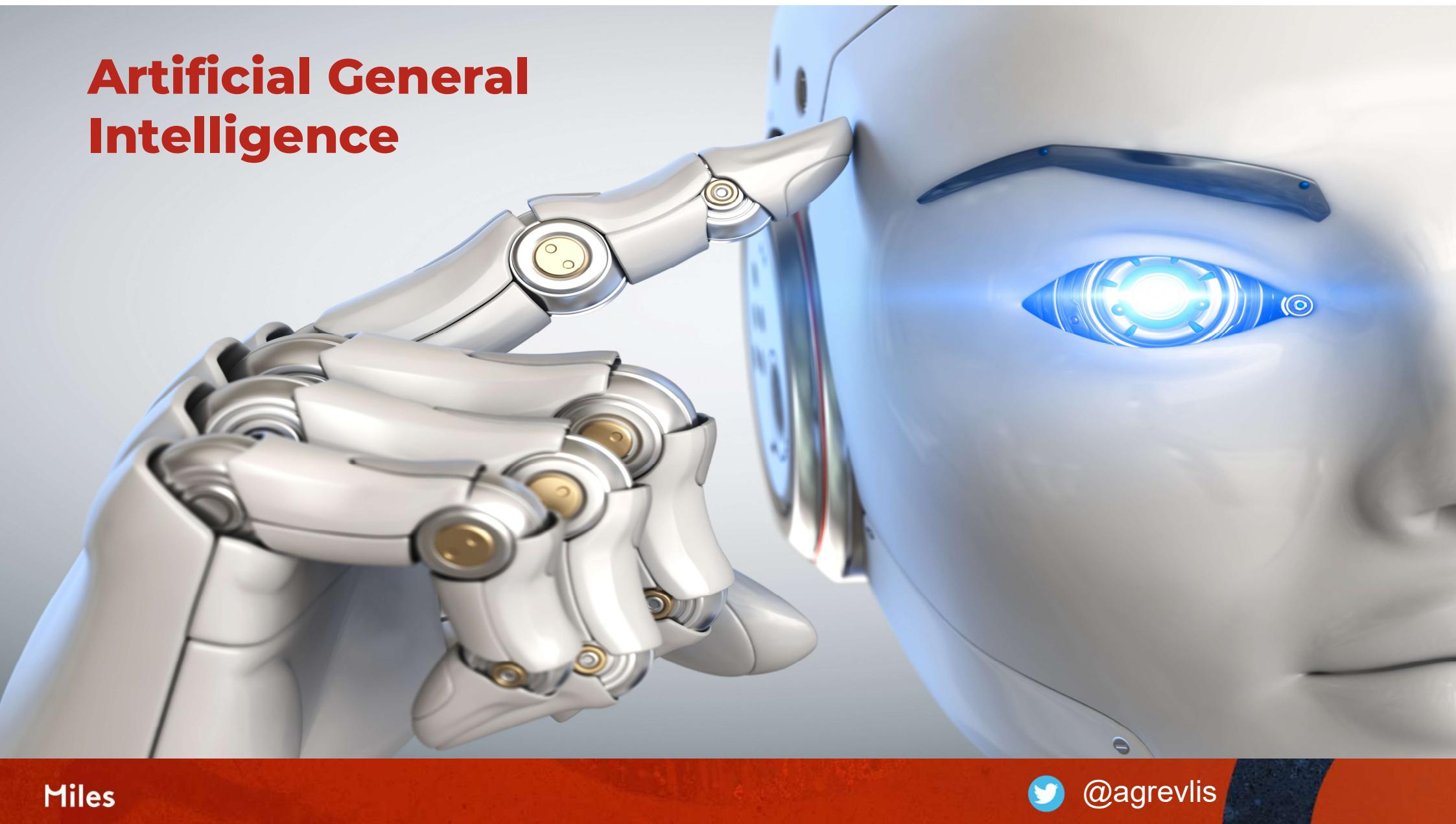
Source: VTT Studio/Shutterstock.com

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Artificial General Intelligence

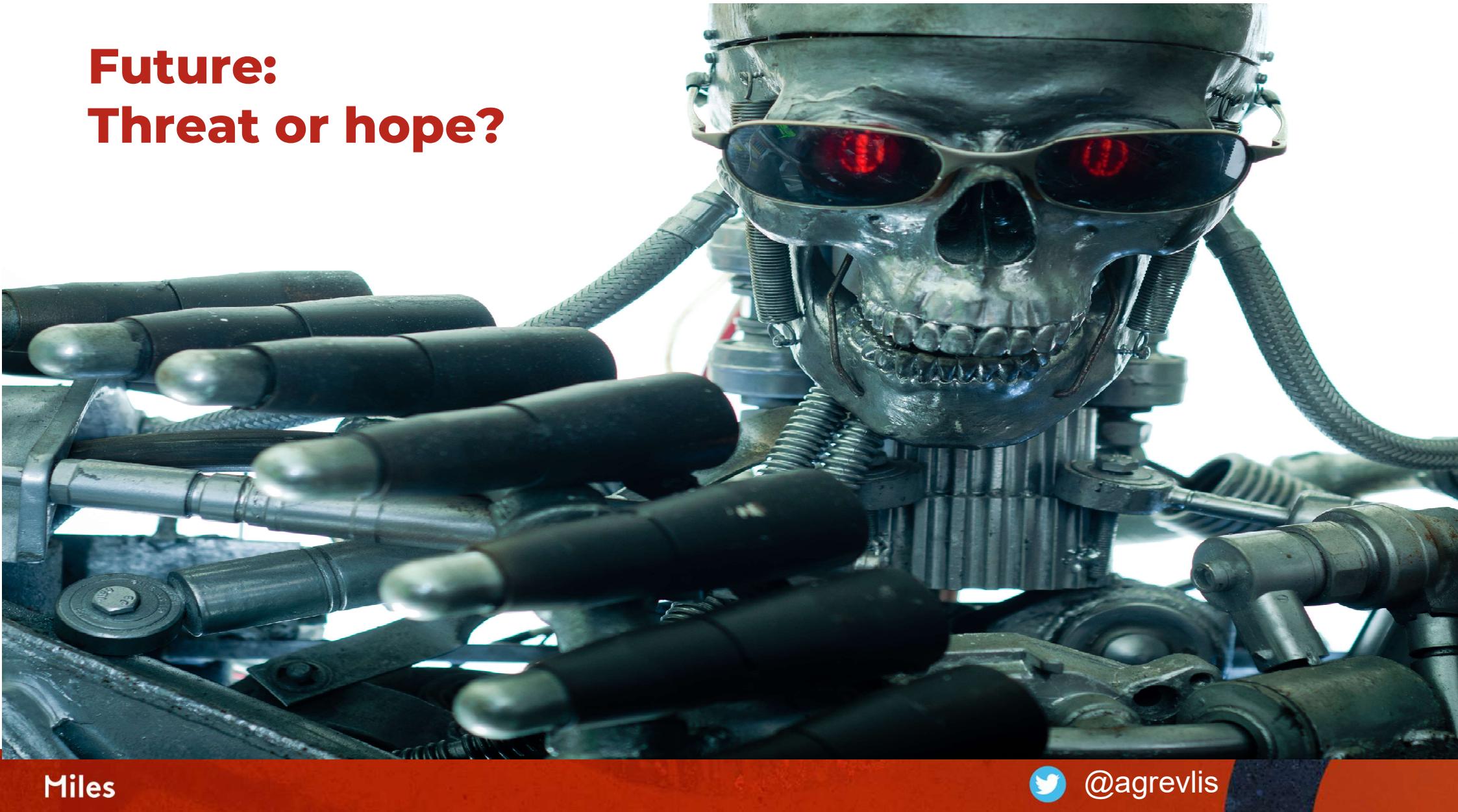


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Future: Threat or hope?



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When will AI surpass human level?

Never

In 300 years

In 100 years

In 50 years

In a few decades

In a few years

Techno skeptics

Beneficial AI movement

Digital utopians

Luddites

Virtually nobody

Definitely
bad

Probably
bad

Highly
uncertain

Probably
good

Definitely
good

If superhuman AI appears, will it be a good thing?

Source: *Life 3.0*, Max Tegmark

Ethical AI

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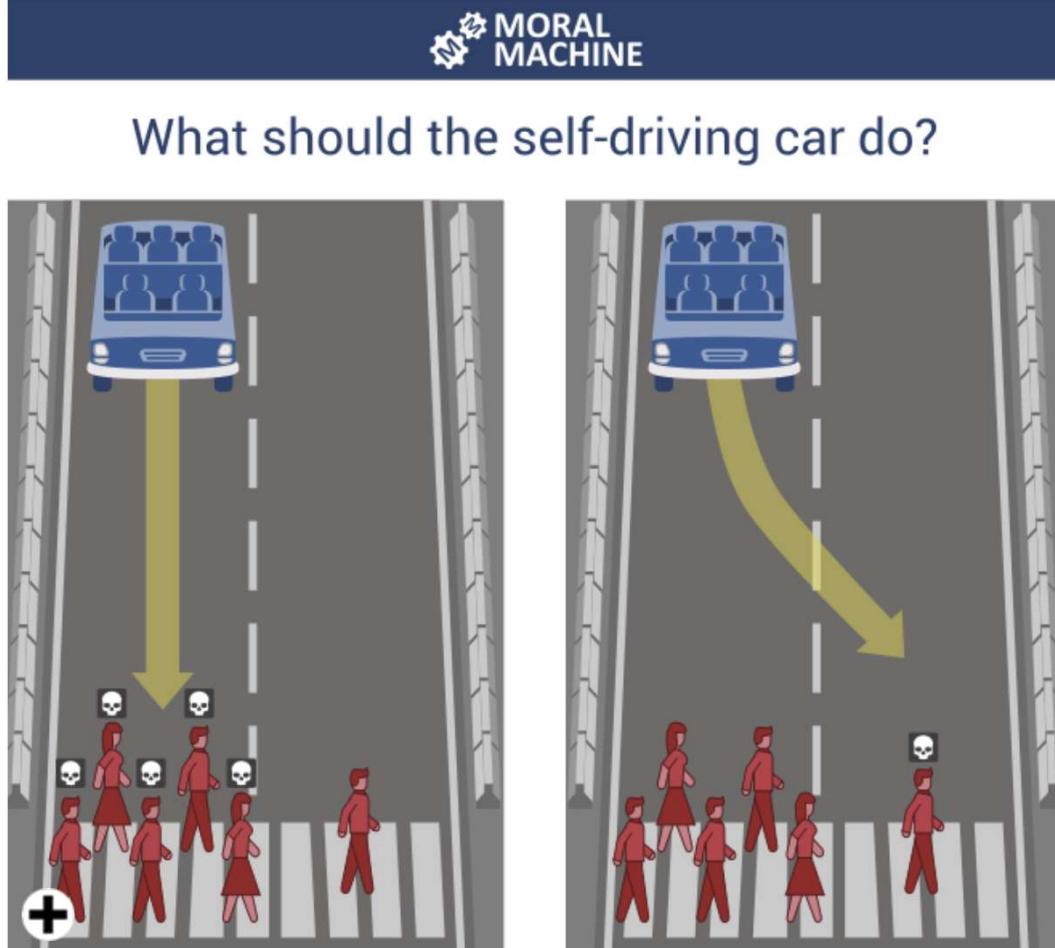


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The Moral Machine

- ❖ 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

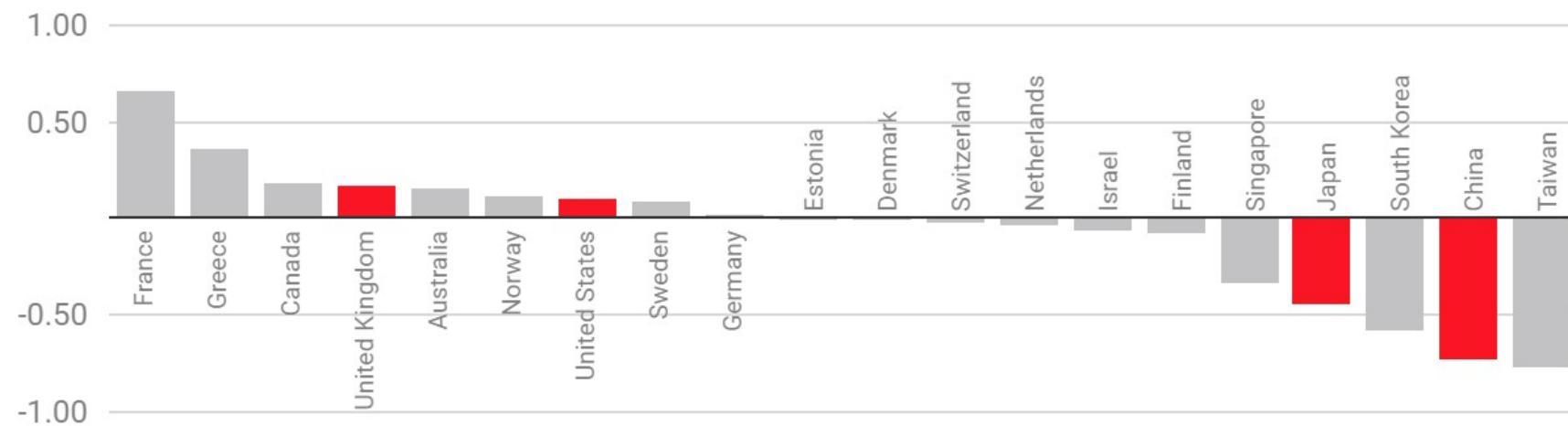
Source: <https://www.technologyreview.com/s/612341/a-global-ethics-study-aims-to-help-ai-solve-the-self-driving-trolley-problem/>

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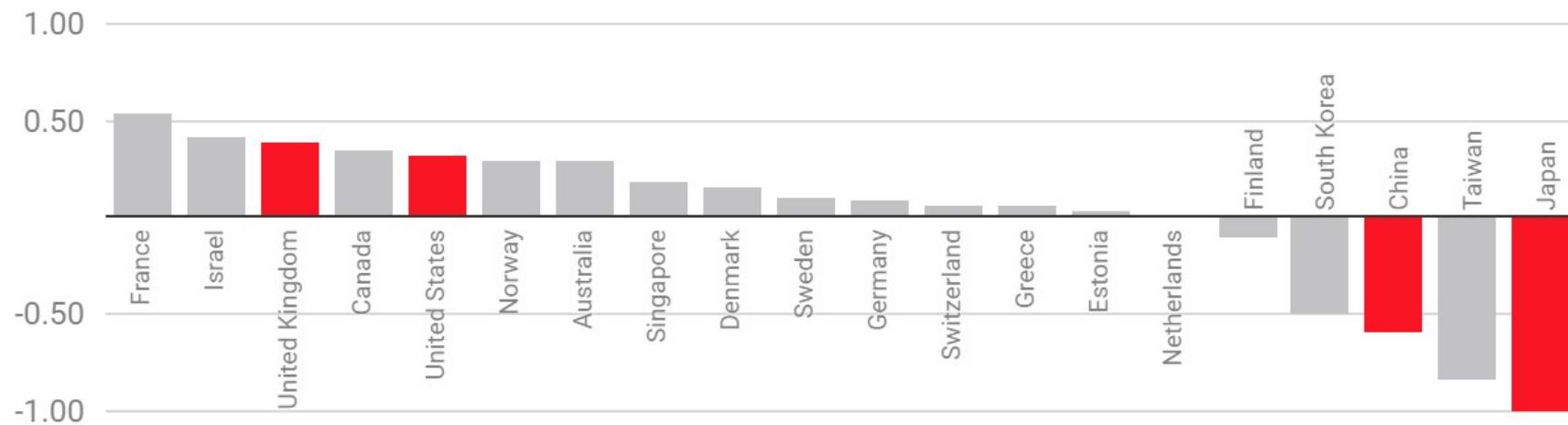
Countries with more individualistic cultures are more likely to spare the young



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/>

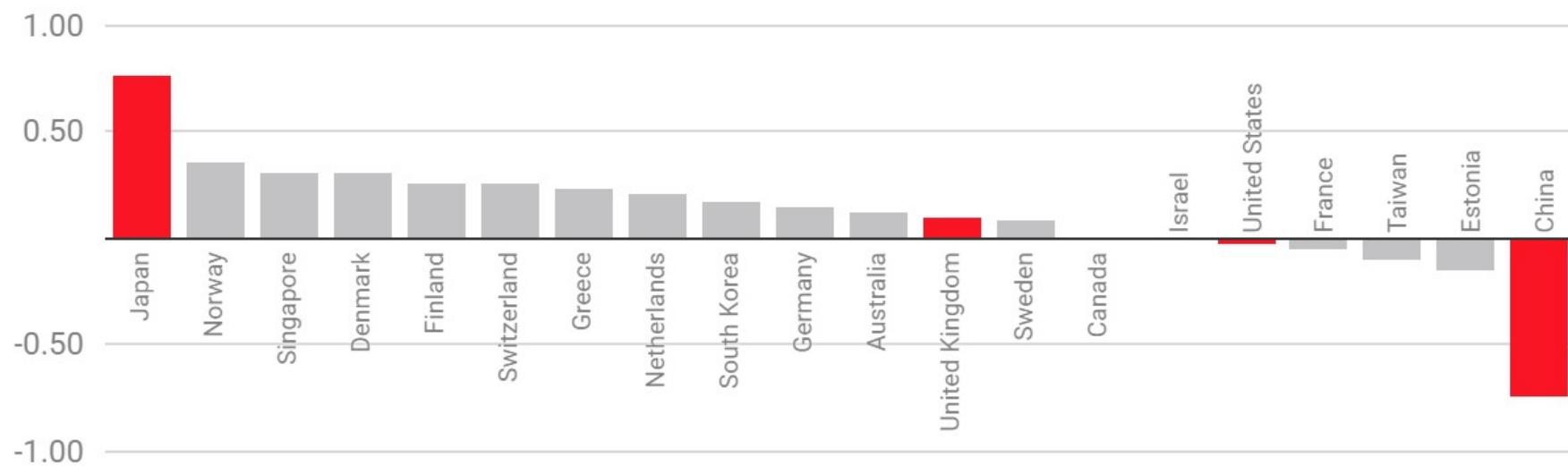
Countries with more individualistic cultures are more likely to spare more lives



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/>

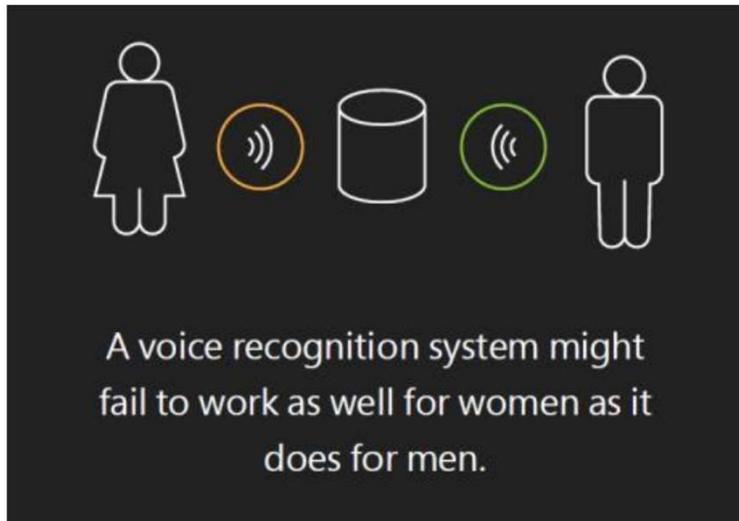
Fairlearn

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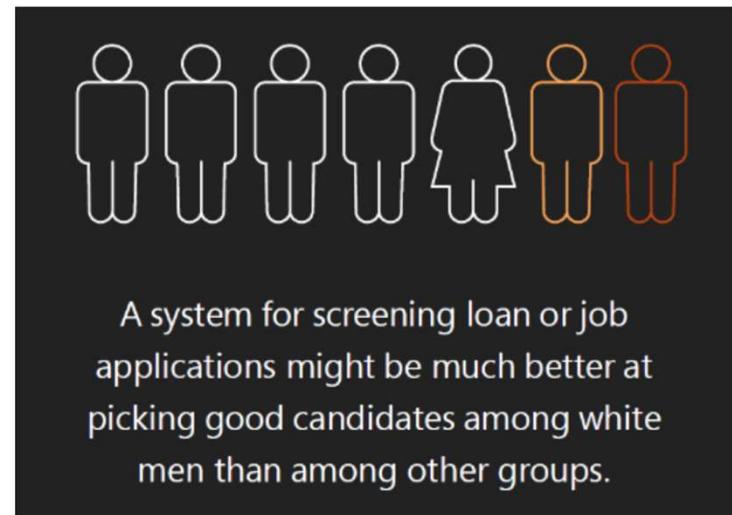
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Fairlearn



A voice recognition system might fail to work as well for women as it does for men.

Quality of service harm



A system for screening loan or job applications might be much better at picking good candidates among white men than among other groups.

Allocation harm

Visualization dashboard

Fairlearn

Welcome to the Fairlearn dashboard

The Fairlearn dashboard enables you to assess tradeoffs between performance and fairness of your models

To set up the assessment, you need to specify a sensitive feature and a performance metric.

01 Sensitive features

Sensitive features are used to split your data into groups. Fairness of your model across these groups is measured by disparity metrics. Disparity metrics quantify how much your model's behavior varies across these groups.

02 Performance metric

Performance metrics are used to evaluate the overall quality of your model as well as the quality of your model in each group. The difference between the extreme values of the performance metric across the groups is reported as the disparity in performance.

→ Get started

Fairlearn

Sensitive features Performance metric

Along which features would you like to evaluate your model's fairness?

Data statistics
1 sensitive feature
48842 instances

Fairness is evaluated in terms of disparities in your model's behavior. We will split your data according to values of each selected feature, and evaluate how your model's performance metric and predictions differ across these splits.

Sensitive features

Subgroups

sex

Male
Female

This feature has 2 unique values

Next

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Visualization dashboard

Fairlearn

Sensitive features Performance metric Performance metric

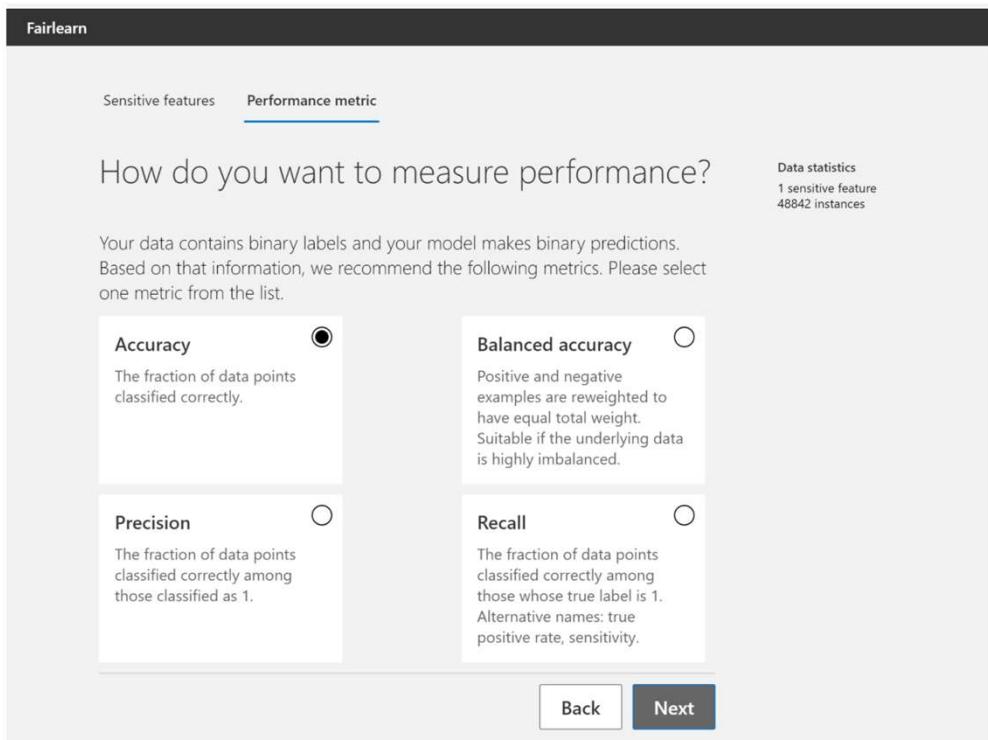
How do you want to measure performance?

Your data contains binary labels and your model makes binary predictions. Based on that information, we recommend the following metrics. Please select one metric from the list.

Accuracy <input checked="" type="radio"/>	Balanced accuracy <input type="radio"/>
The fraction of data points classified correctly.	Positive and negative examples are reweighted to have equal total weight. Suitable if the underlying data is highly imbalanced.
Precision <input type="radio"/>	Recall <input type="radio"/>
The fraction of data points classified correctly among those classified as 1.	The fraction of data points classified correctly among those whose true label is 1. Alternative names: true positive rate, sensitivity.

Data statistics
1 sensitive feature
48842 instances

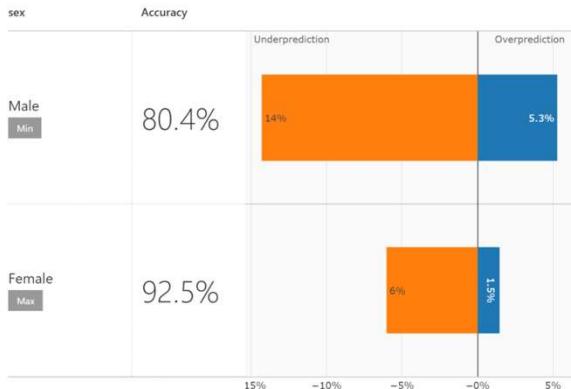
Back Next



Visualization dashboard

Disparity in accuracy

84.4% Is the overall accuracy | 12.1% Is the disparity in accuracy

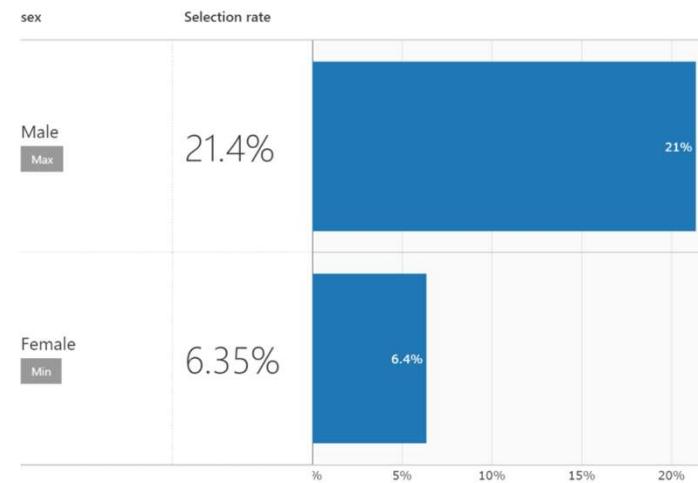


Disparity in predictions

16.4% Is the overall selection rate | 15% Is the disparity in selection rate

Disparity in predictions

16.4% Is the overall selection rate | 15% Is the disparity in selection rate



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
```



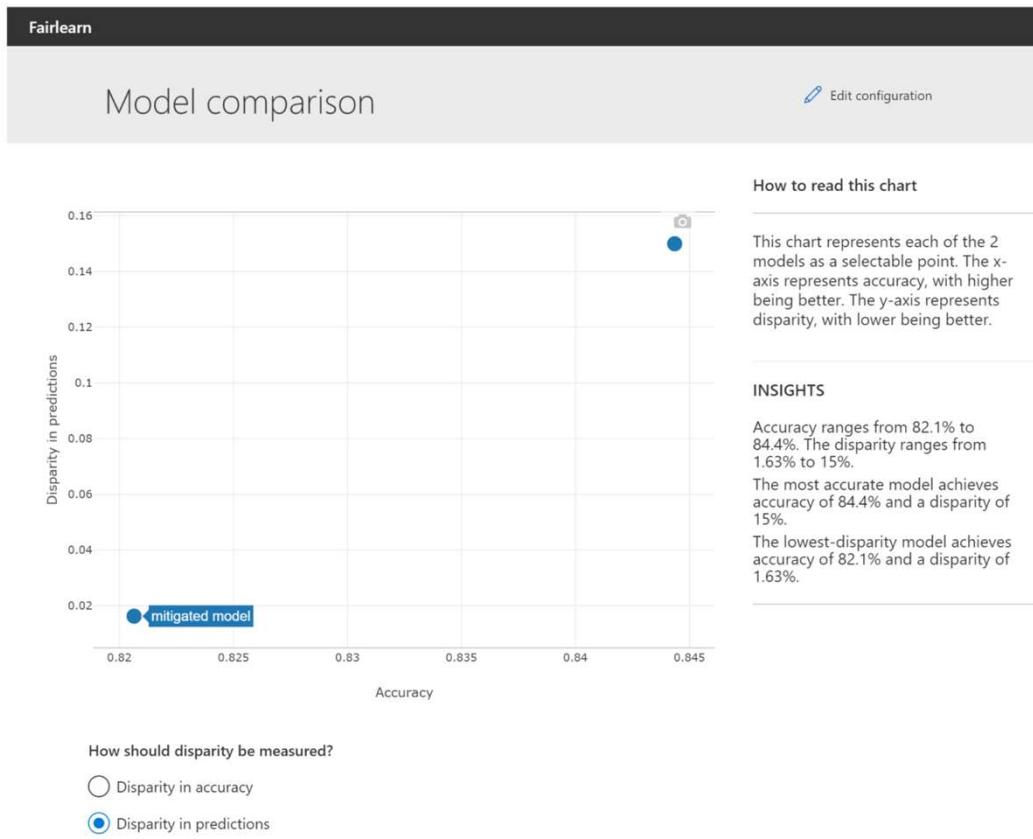
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0.1661...
>>> print(sr_mitigated.by_group)
sex
Female    0.1552...
Male      0.1715...
Name: selection_rate, dtype: object
```

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



Mitigation



Integrated with Azure Machine Learning

The screenshot shows the Microsoft Azure Machine Learning interface. The top navigation bar includes 'Preview' (highlighted in orange), 'Microsoft Azure Machine Learning', and various icons for settings, help, and user profile. The main title is 'Run 3 Completed'. Below the title are buttons for 'Refresh', 'Resubmit', and 'Cancel'. A navigation menu on the left lists 'New', 'Home', 'Author', 'Assets', 'Datasets', 'Experiments' (selected), 'Pipelines', 'Models', 'Endpoints', 'Manage', 'Compute', 'Datastores', and 'Data Labeling'. The main content area displays 'Fairness metrics are used to understand model fairness with respect to sensitive attributes. Learn more'. It shows a dropdown menu with 'Upload MutiAsset Census with all models | binary_classification | April 29, 2020 10:40 PM'. A large panel titled 'Fairlearn' contains tabs for 'Sensitive features' (selected) and 'Accuracy metric'. The text 'Along which features would you like to evaluate your model's fairness?' is displayed. At the bottom, it says 'Fairness is evaluated in terms of disparities in your model's behavior. We will split your data according to values of each selected feature, and evaluate how your model's accuracy and'.

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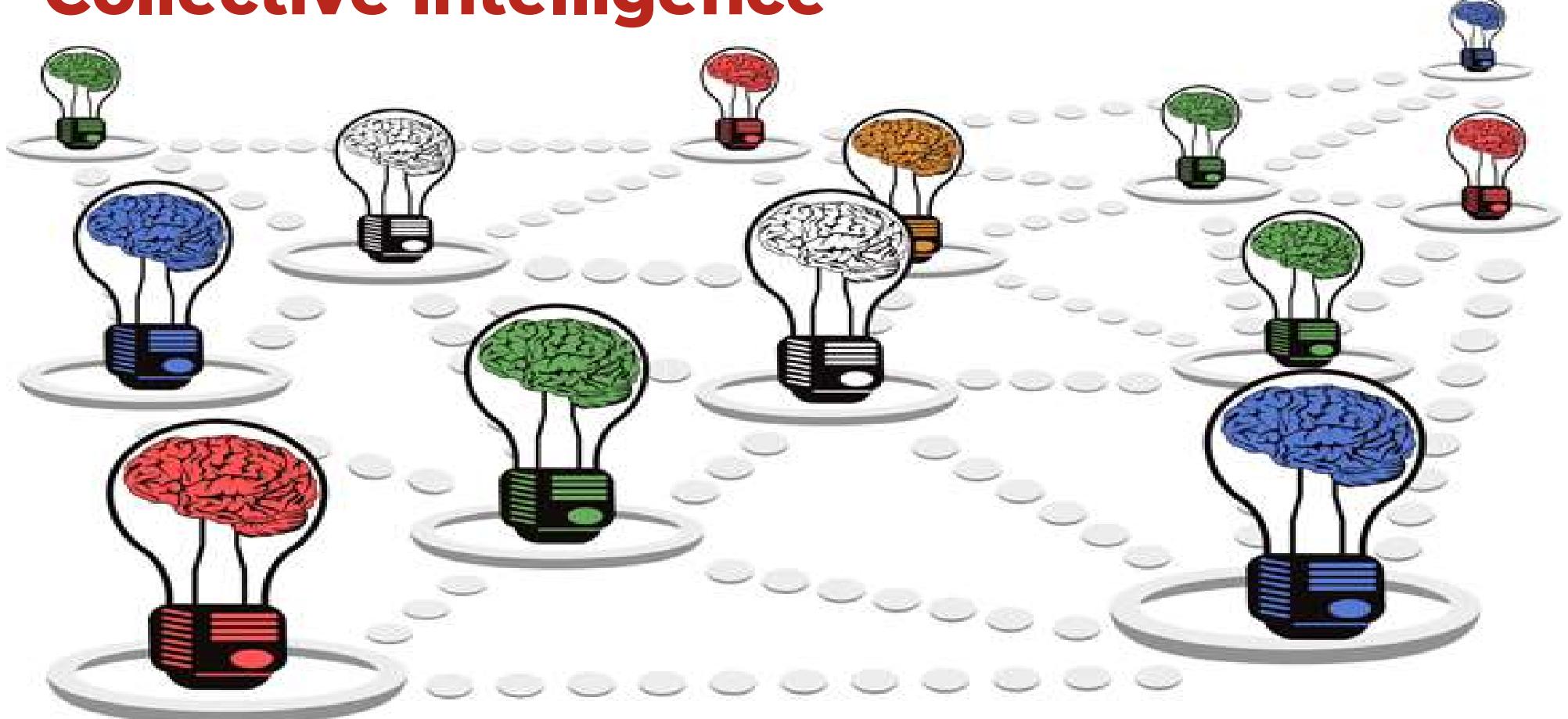
Collective Intelligence

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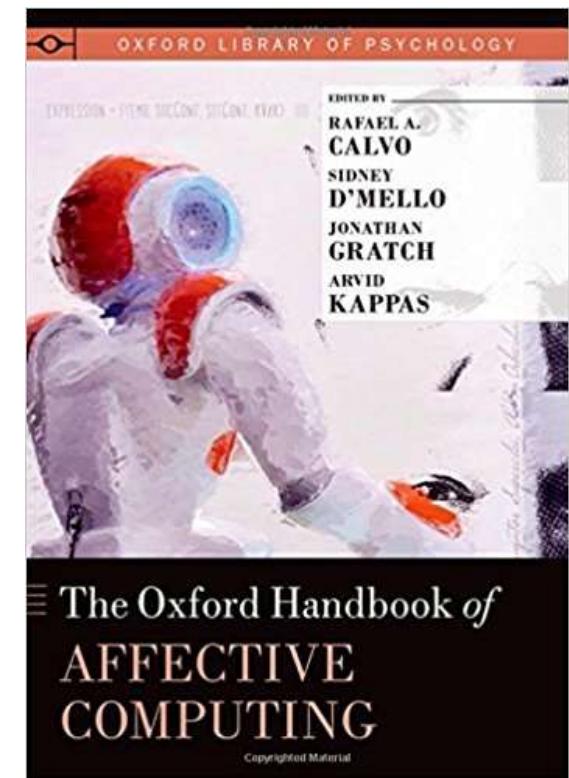
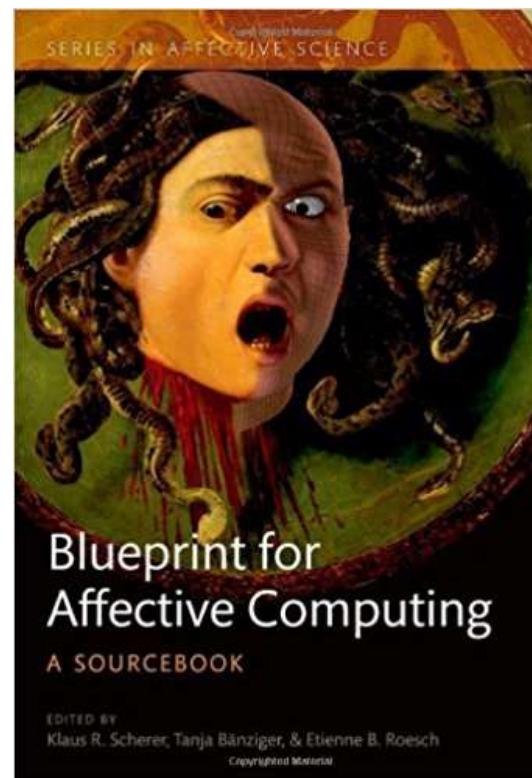
Collective intelligence



References



References



Thank you!



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hakan.silfvernagel@miles.no

A large audience of people is seated in rows, facing towards the left side of the frame. They appear to be in a conference room or lecture hall. A blue-tinted overlay covers the entire background.

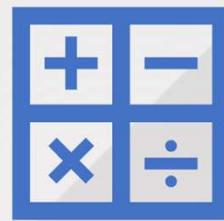
Tusen takk!

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