CONTINUAL LEARNING FOR AFFECTIVE ROBOTICS

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https://www.cl.cam.ac.uk/~hg410
https://cambridge-afar.github.io

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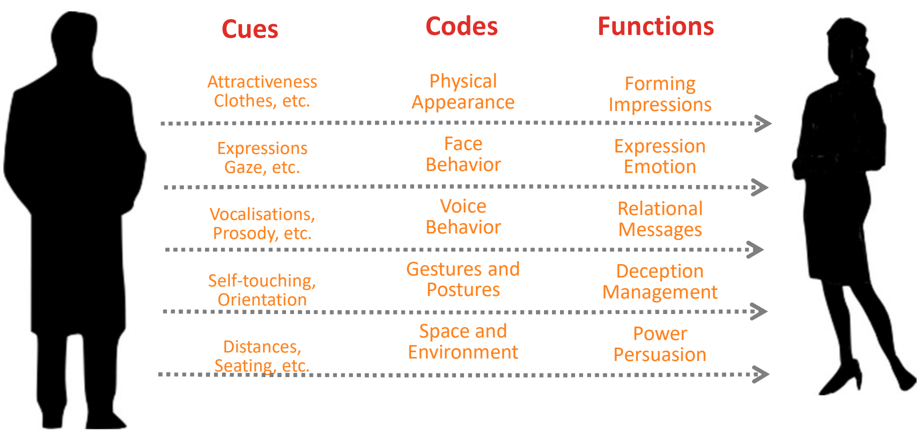
NONVERBAL SOCIAL SIGNALS



Slide credit: A. Vinciarelli & H. Hung

Richmond and McCroskey, "*Nonverbal Behaviors in Interpersonal Relations*", Allyn and Bacon, 1995

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NONVERBAL SOCIAL SIGNALS

Cues	Codes	Functions
Attractiveness Clothes, etc.	Physical Appearance	Forming Impressions
Expressions Gaze, etc.	Face Behavior	Expression Emotion
Vocalisations, Prosody, etc.	Voice Behavior	Relational Messages
Self-touching, Orientation	Gestures and Postures	Deception Management
Distances, Seating, etc.	Space and Environment	Power Persuasion

Image credit: https://www.festo.com/group/en/cms/11921.htm

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Image credit: https://www.festo.com/group/en/cms/11921.htm

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Continual Learning for Affective Robotics

Why, What and How?

Nikhil Churamani, Sinan Kalkan and Hatice Gunes

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Acknowledgement

Nikhil Churamani

Sinan Kalkan

Hatice Gunes

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Hatice Gunes is supported by the EPSRC (grant ref. EP/R030782/1) and the Alan Turing Institute Faculty Fellowship (G102185).

S. Kalkan is supported by Scientific and Technological Research Council of Turkey (TUBITAK) through BIDEB 2219 International Postdoctoral Research Scholarship Program.

UKRI Engineering and Physical Sciences Research Council

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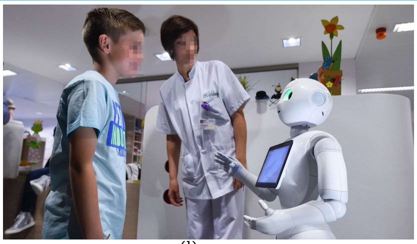
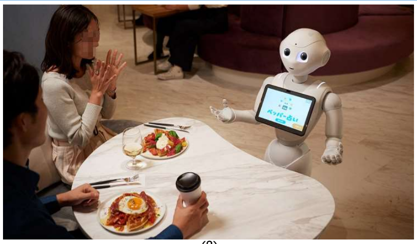
Affective Robots

Healthcare



(1)

Service



(2)

Elderly care

(3)

Companion

(4)

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(1) http://abovewhispers.com/2016/06/14/robot-receptionists-introduced-at-hospitals-in-belgium/
(2) https://interestingengineering.com/softbank-is-opening-a-cafe-where-pepper-robots-will-work-alongside-humans
(3) https://www.thetimes.co.uk/article/robot-carers-for-the-elderly-are-now-a-reality-in-japan-but-do-we-want-them-here-mw8zpw0zd
(4) https://customerthink.com/4-ways-social-robots-improve-customer-experience-in-retail-stores/

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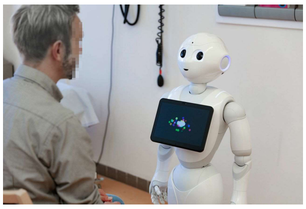
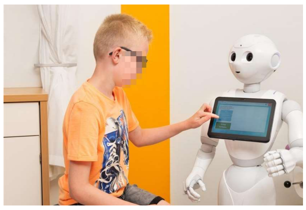
Need for Adaptation



(a)

(b)



(c)

…

Equipped with Learning Models → Interact and adapt. → Extend learning with other users. → Adapt to different user demographics. →

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(a) Boumans R, van Meulen F, Hindriks K, *et al* Robot for health data acquisition among older adults: a pilot randomised controlled cross-over trial *BMJ Quality & Safety* 2019;**28:**793-799.
(b) https://www.scmp.com/lifestyle/health-wellness/article/3024028/how-robot-nurses-could-help-care-worlds-elderly-and
(c) https://eindhovennews.com/news/2018/06/robot-pepper-helps-children-hospital-visits/

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Traditional Approaches vs. Continual Learning

Traditional Approaches

- Models **trained in isolation** on benchmark datasets.
- Large datasets enable **generalisation** across contexts.
- Training data might be very **different** from application scenarios.
- Generalisation comes **at the cost** of learning individual differences.
- **Cumbersome** to retrain and update models.

Continual Learning

- Agents **acquire** and **integrate** knowledge **incrementally** about changing environments.
- Data only made available **sequentially**.
- Highly **sensitive** towards changing data conditions.
- **Adaptations** in learning to avoid forgetting.
- CL Problem Formulation:

New Data Task Updated Experience

$$A_i^{CL} : \langle h_{i-1}, Tr_i, M_{i-1}, t_i \rangle \rightarrow \langle h_i, M_i \rangle$$

Model Experience Improved Model

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T. Lesort *et al.*, "Continual learning for robotics: Definition, frame- work, learning strategies, opportunities and challenges," *Information Fusion*, vol. 58, pp. 52–68, 2020.

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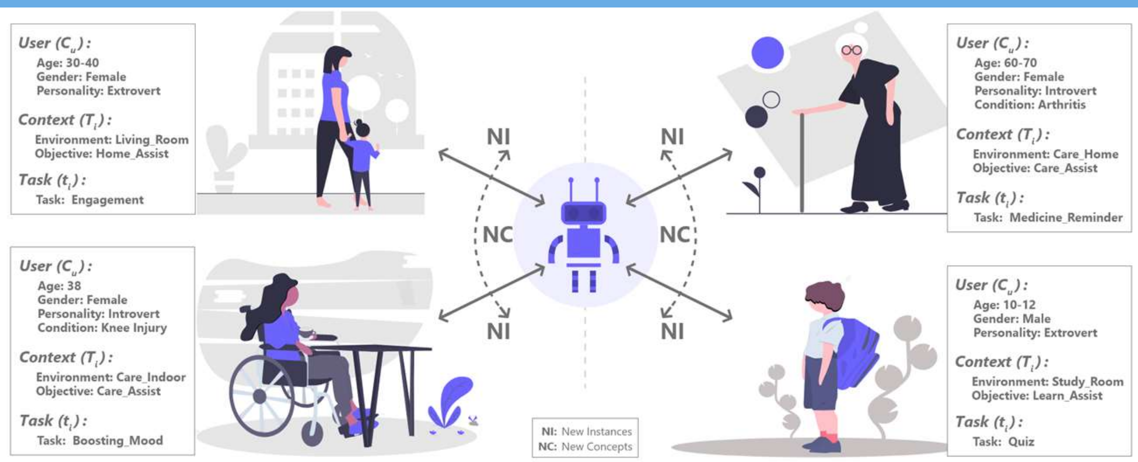
Continual Learning for Affective Robotics



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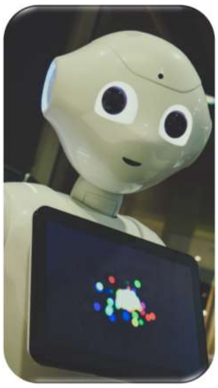
Challenges and Recommendations



Gathering Person-specific Data

Why?

- **Interactions** are the only source of data.
- Initial interactions impacted due to **slow learning**.
- User specific **data unavailable** before any interaction.

How?

- Conduct **introductory interaction rounds** enable collecting additional data.
- Use a generative model to **simulate** additional person-specific data for **augmenting** learning.

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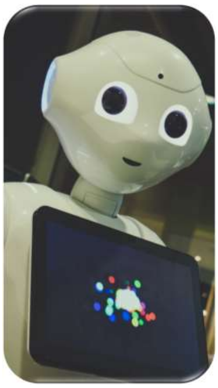
Challenges and Recommendations



Obtaining Ground Truth

Why?

- Human affect is **subjective**.
- Ground truth **changes** with users and contexts.
- Unsupervised learning may be **intractable** in real-time.

How?

Learn Normative Baselines

- Contextually neutral interactions provide a **baseline** for measuring human behaviour.

Learn Semantic Associations

- Group users based on person-specific attributes to **speed up** learning.

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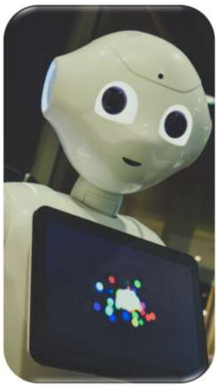
Challenges and Recommendations



Learning without Task Boundaries

Why?

- Human interactions are fluid and **toggle** between contexts.
- Robots need robust and quick **context-switching**.
- Contextual attributions required for learning may **overlap**.

How?

Learn Contextual Attributions

- Context-aware embeddings enable **distinguishing** between task boundaries.
- Context attributes (e.g. environment) facilitate **context-switching**.

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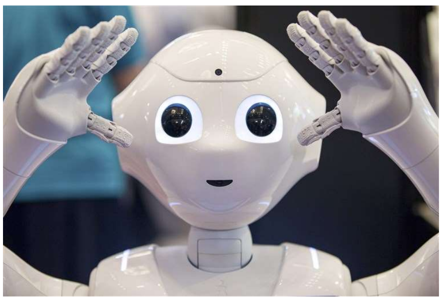
Conclusion

- **Real-world** interactions are **complex** and **unpredictable**
- Affective Robots need to **adapt on-the-fly**
  - **personalisation** and behaviour **adaptation**
- *Continual Learning* enables **perpetual evolution** of robot capabilities



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https://www.nbcnews.com/tech/tech-news/we-re-entering-age-friendly-robots-n703336

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Learning Social Appropriateness of Robot Actions

Jonas Tjomsland[1], Sinan Kalkan[1,2], and Hatice Gunes[1]

[1] Department of Computer Science and Technology, University of Cambridge, Cambridge, UK

[2] Department of Computer Engineering, Middle East Technical University, Ankara, Turkey

2020 IEEE RO-MAN Workshop on Lifelong Learning for Long-term Human-Robot Interaction (LL4LHRI)

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Sinan Kalkan is with the Department of Computer Engineering, Middle East Technical University, Ankara, Turkey, and was a visiting researcher at the Department of Computer Science and Technology, University of Cambridge, UK.

He is supported by Scientific and Technological Research Council of Turkey(TUBITAK) through BIDEB 2219 International Postdoctoral Research Scholarship Program.

Jonas Tjomsland and **Hatice Gunes** are with the Department of Computer Science and Technology, University of Cambridge.

Their work has been partially supported by the EPSRC under grant ref: EP/R030782/1.

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Social Appropriateness of Domestic Actions

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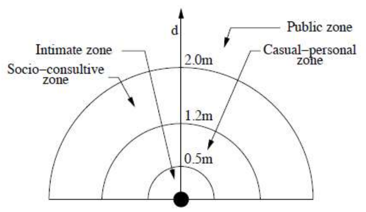
Use of Space in Social Interactions



concentric zones around each individual associated to different kinds of interaction

Source: Vinciarelli, Pantic, and Bourlard 2009

a) *Circular* arrangement b) *Vis-a-vis* arrangement c) *L*-arrangement d) *Side-by-side* arrangement

Free standing conversations (F-formations)

Source: http://profs.sci.univr.it/~cristanm/ssp/

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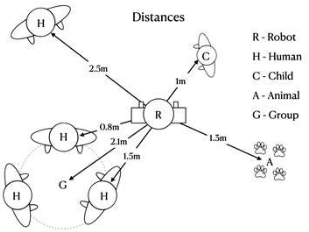
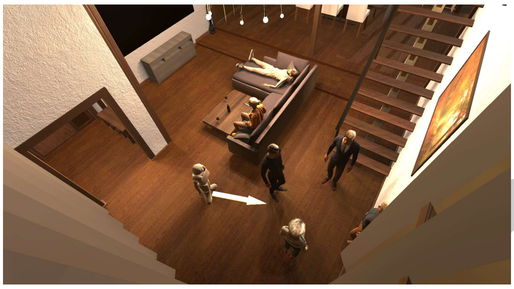
Synthetic Dataset Generation

Feature	*Variable type*	*Range*
Operating within circle	Int	0 or 1
Radius of action circle	Float	$0.5 \rightarrow 3$
Operating in the direction of an arrow	Int	0 or 1
Number of humans	Int	$0 \rightarrow 9$
Number of children	Int	$0 \rightarrow 2$
Distance to closet child	Float	$0.4 \rightarrow 6$
Number of animals	Int	0 or 1
Distance to animal	Float	$0.4 \rightarrow 6$
Number of people in a group	Int	$2 \rightarrow 5$
Group radius	Float	$0.50 \rightarrow 1$
Distance to group	Float	$0 \rightarrow 6$
Robot within group?	Int	0 or 1
Robot facing group?	Int	0 or 1
Distance to 3 closest humans	3 x Float	$0.3 \rightarrow 5$
Direction robot to 3 closest humans	3 x Float	$0.0 \rightarrow 360.0$
Direction closest human to robot	Float	$0.0 \rightarrow 360.0$
Robot facing 3 closest humans?	3 x Int	0 or 1
3 closest humans facing robot?	3 x Int	0 or 1
Number of people sofa	Int	$0 \rightarrow 2$
Playing music?	Int	0 or 1
Total number of agents in scene	Int	$1 \rightarrow 11$





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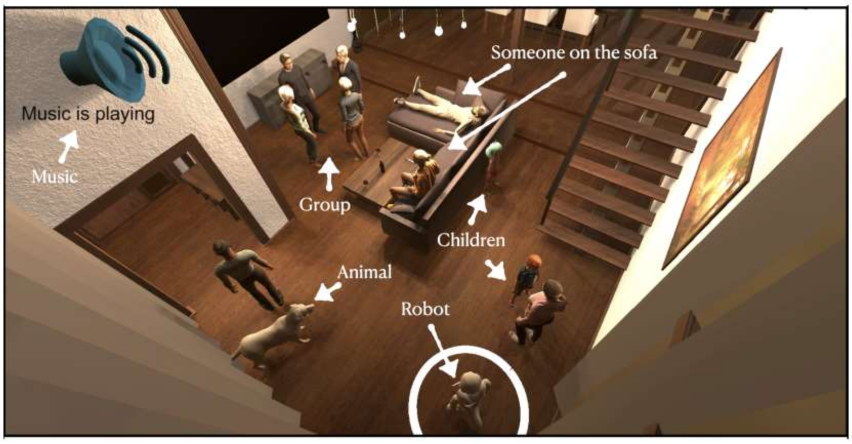
Synthetic Data Generation



An example scene of the simulated living room environment.

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Robot Actions

Within a circle

- Vacuum cleaning
- Mopping the floor
- Carry warm food
- Carry cold food
- Carry drinks
- Carry big objects
- Carry small objects
- Cleaning (Picking up stuff)

In the direction of an arrow

- Vacuum cleaning
- Mopping the floor
- Carry warm food
- Carry cold food
- Carry drinks
- Carry big objects
- Carry small objects
- Starting conversation

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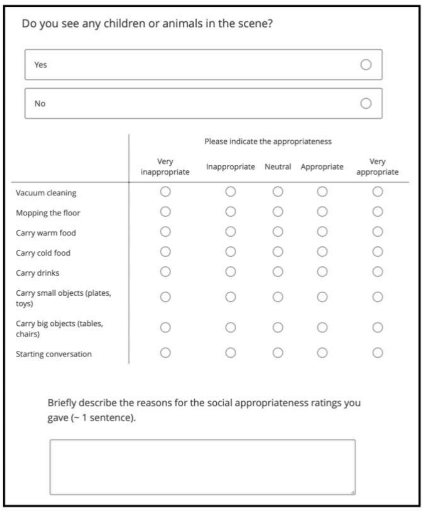
Dataset Annotation



Do you see any children or animals in the scene?

- Yes
- No

	Please indicate the appropriateness				
	Very inappropriate	Inappropriate	Neutral	Appropriate	Very appropriate
Vacuum cleaning	○	○	○	○	○
Mopping the floor	○	○	○	○	○
Carry warm food	○	○	○	○	○
Carry cold food	○	○	○	○	○
Carry drinks	○	○	○	○	○
Carry small objects (plates, toys)	○	○	○	○	○
Carry big objects (tables, chairs)	○	○	○	○	○
Starting conversation	○	○	○	○	○

Briefly describe the reasons for the social appropriateness ratings you gave (~ 1 sentence).

The task as shown to the annotators on the crowd-sourcing platform.

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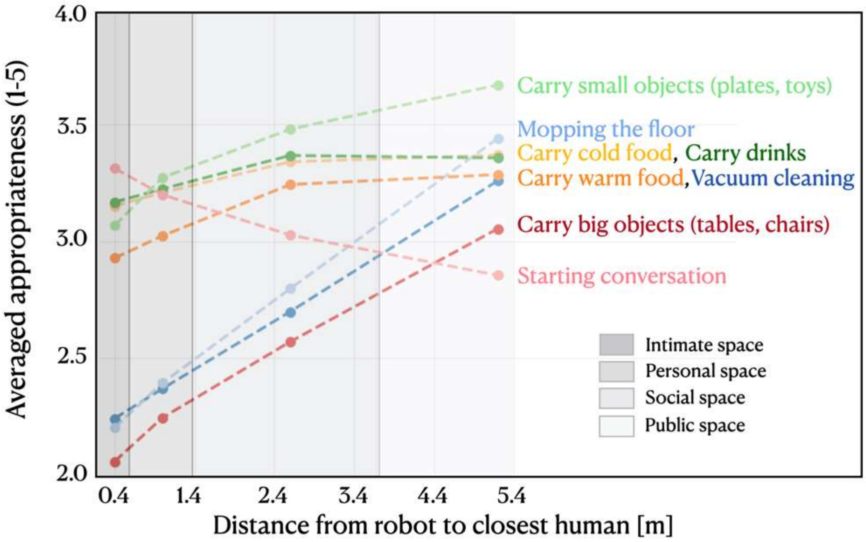
Appropriateness w.r.t. Distance



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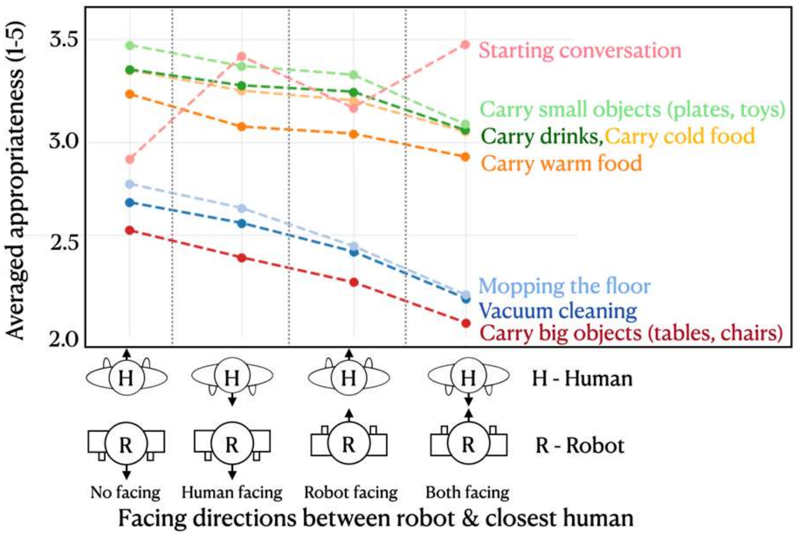
Appropriateness w.r.t Orientation



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Visual Examples

Action:	Vacuum cleaning	Mopping the floor	Carry warm food	Carry cold food	Carry drinks	Carry small objects	Carry big objects	Cleaning
Actual label:	4.36	4.29	3.29	3.21	3.14	4.21	4.29	4.43

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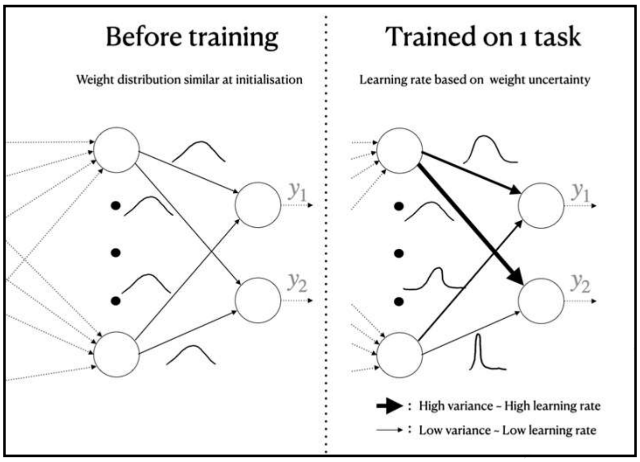
Continual Learning

Baseline | BNN

2-tasks model | BNN-2CL

16-tasks model | BNN-16CL



Ebrahimi, Sayna, et al. "Uncertainty-guided Continual Learning with Bayesian Neural Networks." ICLR 2019

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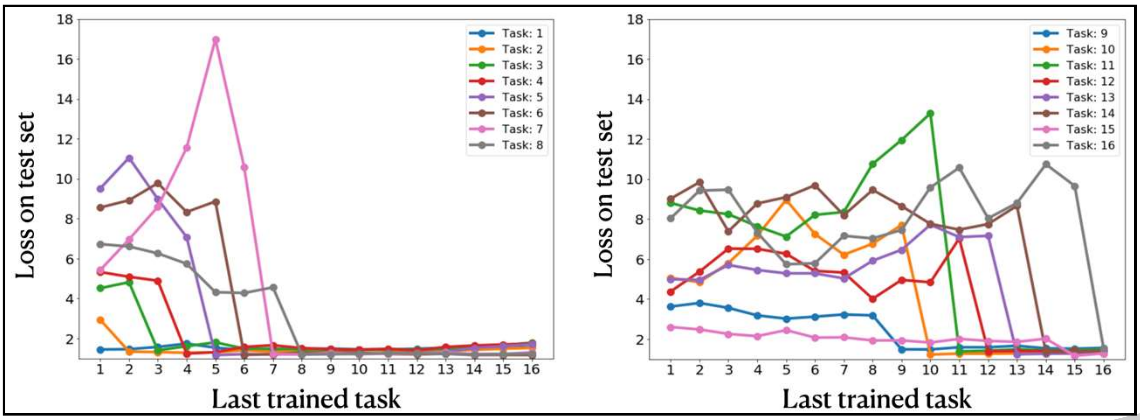
Results



16 task model: RMSE 0.63 (on test set)

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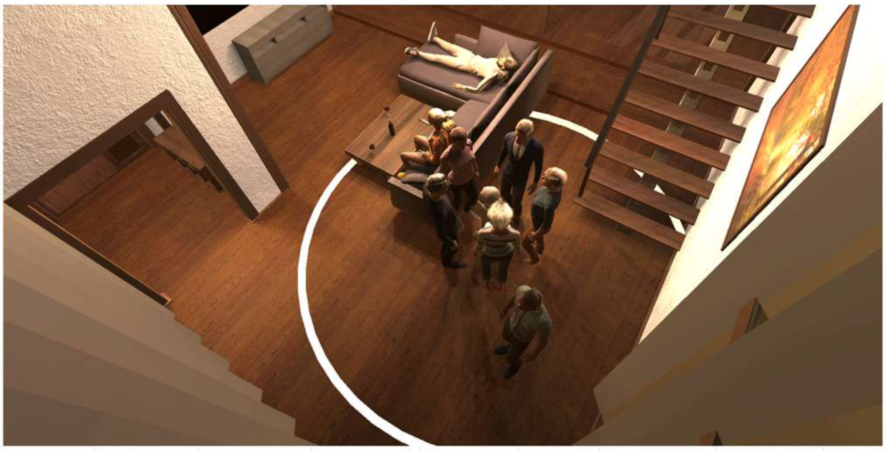
Testing



Action:	Vacuum cleaning	Mopping the floor	Carry warm food	Carry cold food	Carry drinks	Carry small objects	Carry big objects	Cleaning
Actual label:	1.57	1.57	2.50	3.00	3.07	2.79	1.64	2.43
BNN:	1.51	1.35	3.37	3.45	3.68	3.24	1.83	2.63
BNN-2CL:	1.07	1.16	3.46	2.67	3.89	2.99	1.91	2.04
BNN-16CL:	1.36	2.37	3.06	3.03	2.98	3.27	1.67	2.30

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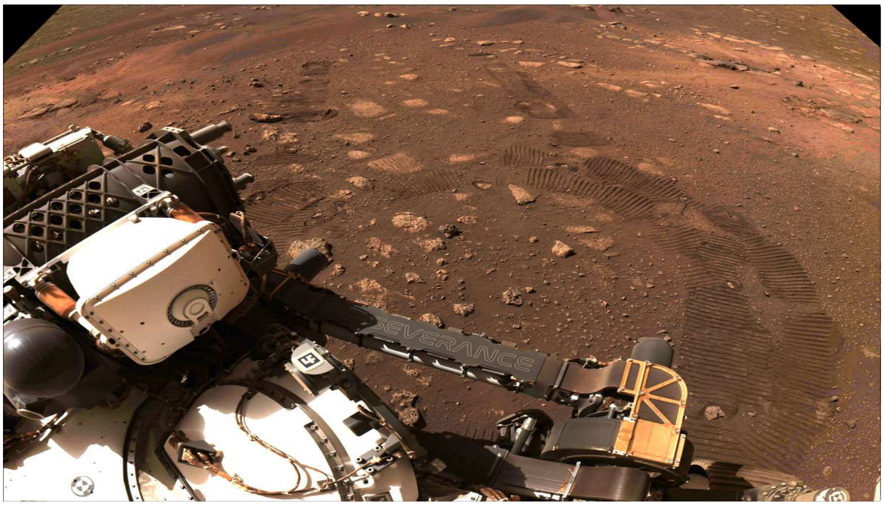
Conclusions & Future Work



https://mars.nasa.gov/resources/25689/perseverance-is-roving-on-mars/

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Domain-incremental Continual Learning for Mitigating Bias in Facial Expression and Action Unit Recognition

Ozgur Kara Nikhil Churamani Hatice Gunes

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Investigating Bias and Fairness in Facial Expression Recognition

Tian Xu[1], Jennifer White[1], Sinan Kalkan[2], and Hatice Gunes[1]

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[2] Department of Computer Engineering, Middle East Technical University, Ankara, Turkey

2020 ChaLearn Looking at People workshop ECCV: Fair Face Recognition and Analysis

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Jiaee Cheong


Tian Xu


Jennifer White


Sinan Kalkan


Hatice Gunes

WORKINGAGE

Jiaee Cheong is funded by the Alan Turing Institute. Tian Xu and Hatice Gunes are funded by WorkingAge Project (EU H2020 Programme): https://www.workingage.eu/

Sinan Kalkan is supported by Scientific and Technological Research Council of Turkey (TUBITAK) through BIDEB 2219 International Postdoctoral Research Scholarship Program.

HORIZON 2020

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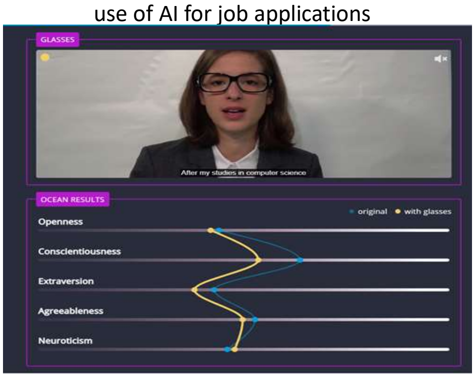
BIAS IN VISION-BASED AI MODELS

- Dataset bias
- Algorithmic bias

use of AI for job applications



https://web.br.de/interaktiv/ki-bewerbung/en/

gender classification error rate by skin color

	TYPE I	TYPE II	TYPE III	TYPE IV	TYPE V	TYPE VI
Microsoft	1.7%	1.1%	3.3%	0%	23.2%	25.0%
FACE++	11.9%	9.7%	8.2%	13.9%	32.4%	46.5%
IBM	5.1%	7.4%	8.2%	8.3%	33.3%	46.8%

Buolamwini & Gebru FAT* 2018, Slides from Joy Buolamwini

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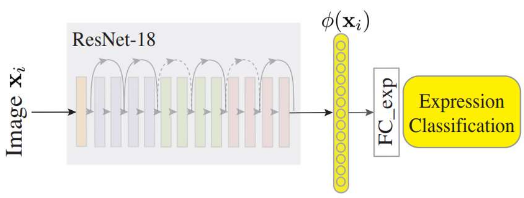
FAIRNESS IN EXPRESSION RECOGNITION

- Baseline approach
- Fairness through **awareness**
- Fairness through **unawareness**

- **Model**: 18-Layer Residual Network (ResNet-18)
- **Task**: Expression Classification
- **Loss Function**: Cross Entropy



T. Xu, J. White, S. Kalkan & H. Gunes, "Investigating bias andfairness in facial expression recognition," in Computer Vision –ECCV 2020 Workshops, pp. 506–523.

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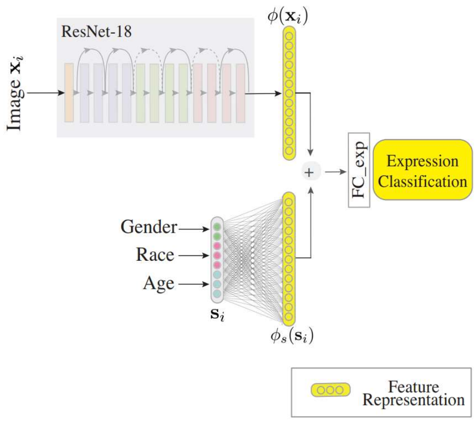
FAIRNESS IN EXPRESSION RECOGNITION

- Fairness through awareness
- **The Attribute-aware Approach**
  - Sensitive information as input



T. Xu, J. White, S. Kalkan & H. Gunes, "Investigating bias andfairness in facial expression recognition," in Computer Vision –ECCV 2020 Workshops, pp. 506–523.

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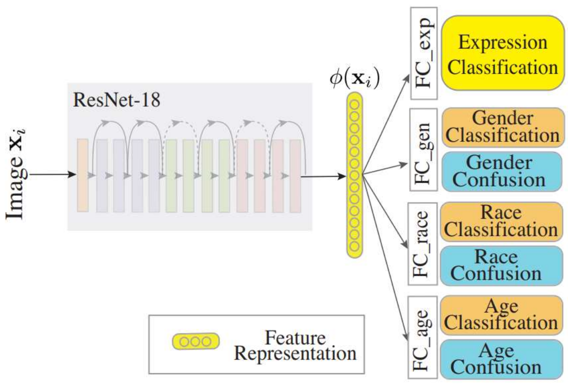
FAIRNESS IN EXPRESSION RECOGNITION

- Fairness through unawareness[1]
- **The Disentangle Approach**
  - Primary branch is for expression classification
  - Parallel branches
    - Confusion
    - Classification



[1] Kusner, Matt J., et al. "Counterfactual fairness." 2017

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DATASET

- **RAF-DB**[1]
  - **Expression**: Surprise, Fear, Disgust, Happy, Sad, Anger and Neutral
  - **Gender**: Male, Female
  - **Race**: Caucasian, African- American, Asian
  - **Age**: 0-3, 4-19, 20-39, 40-69, 70+

[1]Li, Shan, et al. "Reliable crowdsourcing and deep locality-preserving learning for expression recognition in the wild." 2017.

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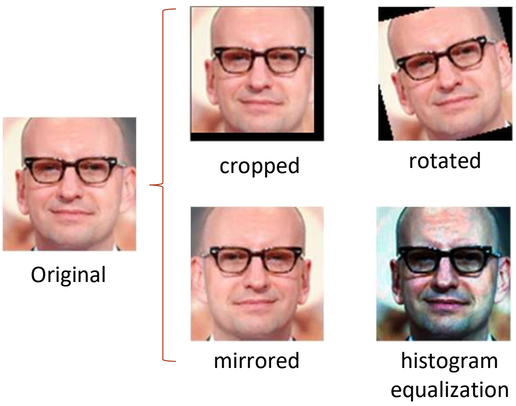
DATA AUGMENTATION



T. Xu, J. White, S. Kalkan & H. Gunes, "Investigating bias andfairness in facial expression recognition," in Computer Vision –ECCV 2020 Workshops, pp. 506–523.

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EVALUATION METRICS

- **Accuracy**
  - The fraction of the predictions that the model predicted correctly
- **Fairness**
  - Indicates whether a classifier is fair to the sensitive attributes
  - **Equal opportunity**: the classifier should ideally provide similar results (e.g. accuracy) across different demographic groups

$$\text{Fairness Measure} = \min\left\{\frac{\text{Acc. of demog. group A}}{\text{Acc. of Dominant group}}, \ldots, \frac{\text{Acc. of demog. group N}}{\text{Acc. of Dominant group}}\right\} \times 100\%$$

T. Xu, J. White, S. Kalkan & H. Gunes, "Investigating bias andfairness in facial expression recognition," in Computer Vision –ECCV 2020 Workshops, pp. 506–523.

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EXPERIMENTS: ATTRIBUTE-WISE ACCURACY

- The dataset is biased
- The disentangled approach with augmentation achieves the best accuracy

		Without Augmentation			With Augmentation		
%	Samples	Baseline	Attri-aware	Disentangl	Baseline	Attri-aware	Disentangl
Male	43.7%	65.3	67.4	62.5	72.3	73.7	**74.2**
Female	56.3%	63.5	64.9	61.0	74.1	74.1	**74.4**
Cau	77.4%	65.9	68.3	63.4	74.7	74.9	**75.6**
AA	7.1%	68.1	62.8	58.4	76.3	76.3	**76.6**
Asian	15.5%	60.0	59.8	54.4	67.8	69.9	**70.4**
0-3	5.5%	63.6	59.9	56.7	**80.2**	71.9	65.0
4-19	16.4%	59.5	58.8	57.0	61.1	63.7	**69.9**
20-39	57.5%	65.9	68.2	62.9	74.9	75.8	**76.4**
40-69	17.4%	65.0	63.4	60.1	73.8	**74.4**	72.1
70+	3.2%	51.3	53.6	51.6	60.8	54.3	**62.2**

Mean class-wise accuracy broken down by attribute labels

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EXPERIMENTS: FAIRNESS VALUES

- The attribute-aware and the disentangled approaches with augmentation mitigate bias
  - Effect is mild if the distribution across (sub)groups is even
  - The disentangled approach is the best one for mitigating demographic bias

%	Without Augmentation			With Augmentation		
	Baseline	Attri-aware	Disentangl	Baseline	Attri-aware	Disentangl
Gender	97.3	96.3	97.5	97.6	99.5	**99.7**
Race	88.1	87.5	85.8	88.8	91.6	**91.9**
Age	77.7	78.6	**82.1**	75.8	71.6	81.4
G-R	76.7	82.2	83.0	74.8	85.3	**87.7**

Fairness Measure broken down by attribute labels

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UNIVERSITY OF CAMBRIDGE
Department of Computer Science and Technology

2021 Virtual

BOĞAZİÇİ ÜNİVERSİTESİ 1863

Towards Fair Affective Robotics: Continual Learning for Mitigating Bias in Facial Expression and Action Unit Recognition



Ozgur Kara Nikhil Churamani Hatice Gunes

https://arxiv.org/abs/2103.09233

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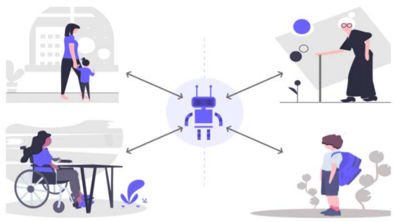
CONTINUAL LEARNING FOR FAIRNESS?

- Lifelong and incremental learning has the potential for
  - robustness against biased attributes
  - balancing learning across different domains
    - leading to developing fairer models



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CONTINUAL LEARNING

- Domain incremental learning
  - Input data distribution changes or shifts, but
    - the task to be learnt does not change

Task: Classifying facial expressions

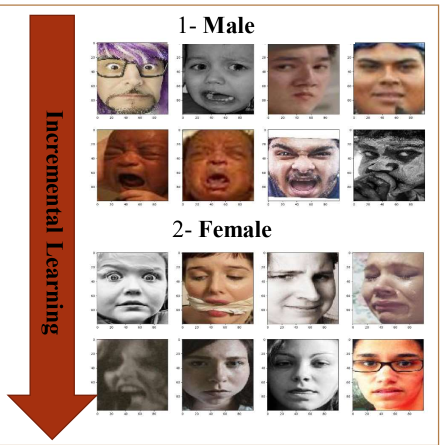
Attribute: Gender

Domains: Male & Female

Splits: Each split has samples from one domain

Training: Model encounters one split at a time and learns incrementally

Evaluation: Model is evaluated on each split after training



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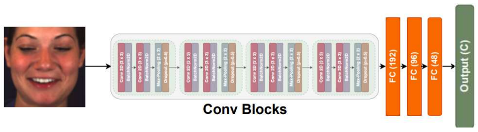
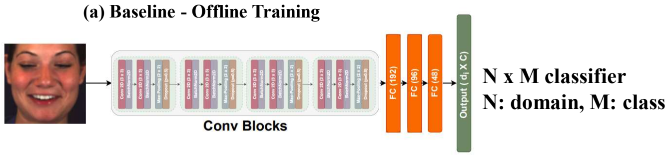
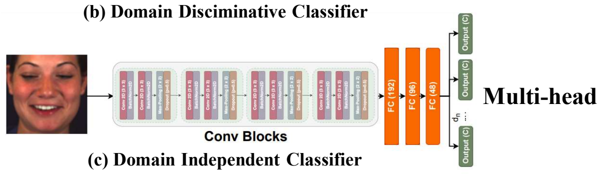
NON-CL BASED APPROACHES



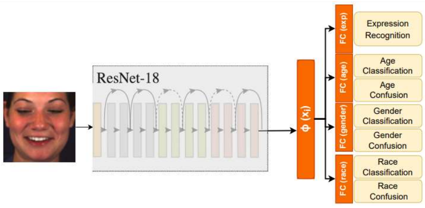
(a) Baseline - Offline Training



(b) Domain Disciminative Classifier



(c) Domain Independent Classifier



(d) The Disentangled Approach

$$L(\mathbf{y},\hat{\mathbf{y}}) = -\frac{1}{N}\sum_{i=1}^{N} \overset{\text{Weight}}{w_i} \sum_{s=1}^{S} y_s^{(i)} \log \hat{y}_s^{(i)}$$

(e) Strategic Sampling

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CL BASED APPROACHES

Elastic Weight Consolidation (EWC)

- Adds quadratic penalty on the difference between the parameters for the old and new tasks using a probabilistic perspective

EWC Online

- A modification is applied to EWC where instead of many quadratic terms, a single quadratic penalty is applied in an online fashion

Synaptic Intelligence (SI)

- Adds importance value to parameters of the network, more important parameters change less

Memory Aware Synapses (MAS)

- Enables importance weight estimation on an unsupervised held-out dataset, hence capable of user-specific data adaptation

Naive Rehearsal (NR)

- While training for a new task, each mini-batch is constructed by an equal amount of new data and the rehearsal data

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FAIRNESS MEASURE

- **Accuracy** & **Fairness** metrics for model comparisons
- **Fairness** defined as *equal opportunity* [1]
  - quantifies the largest score gap among different domains

$$\mathcal{F} = \min\left(\frac{f(\hat{\mathbf{y}}, \mathbf{y}, s_0, \mathbf{x})}{f(\hat{\mathbf{y}}, \mathbf{y}, d, \mathbf{x})}, \ldots, \frac{f(\hat{\mathbf{y}}, \mathbf{y}, s_n, \mathbf{x})}{f(\hat{\mathbf{y}}, \mathbf{y}, d, \mathbf{x})}\right)$$

x: input
y: ground truth label vector
ŷ: predicted label vector
f: calculating score with given parameters (Accuracy)
s: sensitive attribute
d: dominant attribute

	Black	Asian	White	Latino	Fairness
Method 1	0.659	0.720	0.771	0.764	0.855
Method 2	0.767	0.779	0.788	0.762	0.967

Green shows the minimum accuracy value

Blue shows the maximum accuracy value

Fairness = **Green** / **Blue** => largest gap

Example: Accuracy and fairness comparison for two methods evaluated on race attribute

[1] M. Hardt, E. Price, and N. Srebro, "Equality of opportunity insupervised learning," inAdvances in neural information processingsystems, 2016, pp. 3315–3323.

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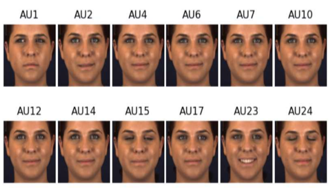
EXPERIMENTAL SETUP

- Evaluated fairness on two datasets for gender and race attributes
  - with and without data augmentation
- A Res-Net based CNN architecture for all models
  - except for Disentangled Approach
- All experiments are repeated 3 times and results are averaged

- ~15K facial images
- Labelled for : Surprise, Fear, Disgust, Happiness, Sadness, Anger, Neutral
- Gender and race attributes
  - Male – Female/ Caucasian – African American – Asian

RAF-DB



- 41 subjects performing 8 different tasks
- 12 most frequent Action Units (AU)
- Gender and race attributes
  Male – Female / Black – White – Latino - Asian

BP4D

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EXP 1: FACIAL EXPRESSION RECOGNITION

- Fairness scores across Gender and Race for the RAF-DB Dataset

Method	W/O Data-Augmentation		W/ Data-Augmentation	
	Gender	*Race*	*Gender*	*Race*
Baseline	0.834	0.943	0.816	0.937
Offline	0.944	0.925	0.954	0.974
Non-CL-based Bias Mitigation Methods				
DDC [44]	0.968	0.985	0.961	0.976
DIC [44]	0.938	0.989	0.962	0.965
SS [15]	0.955	0.961	0.954	0.975
DA [45]	0.975	0.858	[*0.997*]	0.919
Continual Learning Methods				
EWC [23]	0.972	0.987	0.983	0.990
EWC-Online [39]	0.970	0.987	0.974	0.990
SI [47]	**0.990**	**0.996**	**0.999**	**0.996**
MAS [2]	[*0.980*]	[*0.990*]	0.990	[*0.994*]
NR [22]	0.928	0.974	0.923	0.974

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EXP 2: FACIAL AU DETECTION

- Fairness scores across Gender and Race for the BP4D Dataset

Method	W/O Data-Augmentation		W/ Data-Augmentation	
	Gender	*Race*	*Gender*	*Race*
Baseline	0.962	0.855	0.941	0.858
Offline	0.984	0.878	[*0.994*]	0.901
Non-CL-based Bias Mitigation Approaches				
DDC [44]	[*0.990*]	0.920	0.991	0.924
DIC [44]	0.979	0.925	0.985	0.922
SS [15]	0.977	0.920	0.983	0.919
DA [45]	**0.994**	[*0.954*]	**0.995**	[*0.962*]
Continual Learning Approaches				
EWC [23]	0.981	0.949	0.992	0.943
EWC-Online [39]	0.976	0.937	[*0.994*]	0.957
SI [47]	0.986	0.946	0.965	0.954
MAS [2]	0.966	0.920	0.967	0.909
NR [22]	0.983	**0.966**	0.954	**0.974**

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CONCLUSIONS & FUTURE WORK

- Proposed the novel usage of continual learning for developing fairer models
- Highlighted how CL methods can help mitigate bias
  - CL methods can balance learning across different domains
  - CL methods outperform non-CL based approaches w.r.t fairness metric utilised
- Future work
  - will focus on incorporating CL-based FER systems for long-term HRI with users from different demographics

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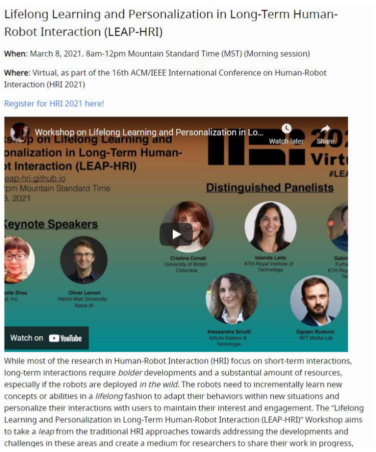
HRI'21 Workshop on Lifelong Learning and Personalization in Long-Term Human-Robot Interaction (LEAP-HRI)

https://leap-hri.github.io/


Lifelong Learning and Personalization in Long-Term Human-Robot Interaction (LEAP-HRI)

When: March 8, 2021. 8am-12pm Mountain Standard Time (MST) (Morning session)

Where: Virtual, as part of the 16th ACM/IEEE International Conference on Human-Robot Interaction (HRI 2021)

Register for HRI 2021 here!

While most of the research in Human-Robot Interaction (HRI) focus on short-term interactions, long-term interactions require *bolder* developments and a substantial amount of resources, especially if the robots are deployed *in the wild*. The robots need to incrementally learn new concepts or abilities in a *lifelong* fashion to adapt their behaviors within new situations and personalize their interactions with users to maintain their interest and engagement. The "Lifelong Learning and Personalization in Long-Term Human-Robot Interaction (LEAP-HRI)" Workshop aims to take a *leap* from the traditional HRI approaches towards addressing the developments and challenges in these areas and create a medium for researchers to share their work in progress,

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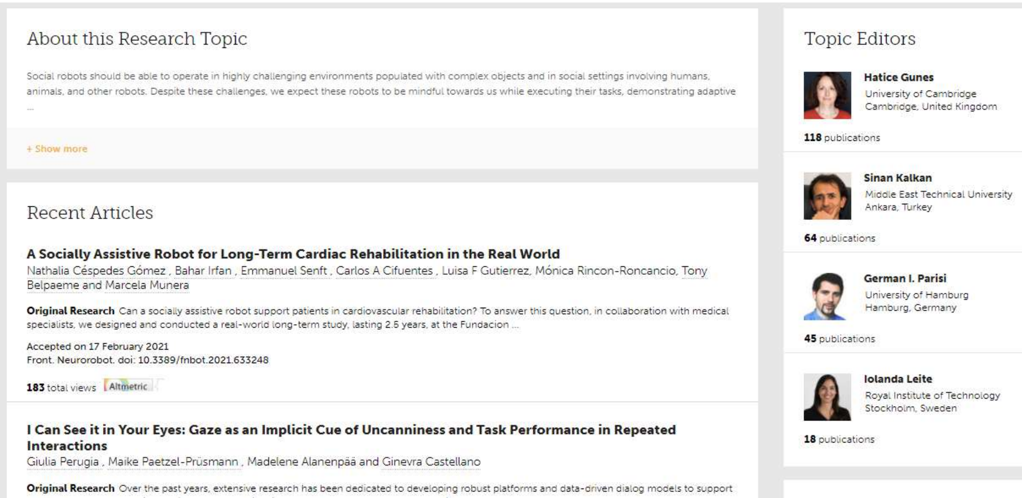
Research Topic in Frontiers Robotics & AI

Lifelong Learning and Long-Term HRI

https://www.frontiersin.org/research-topics/14495/lifelong-learning-and-long-term-human-robot-interaction



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