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Department of Computer Science and Technology

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AAAI-23
Continual Causality Bridge Program

ODTÜ METU
Department of Computer Engineering

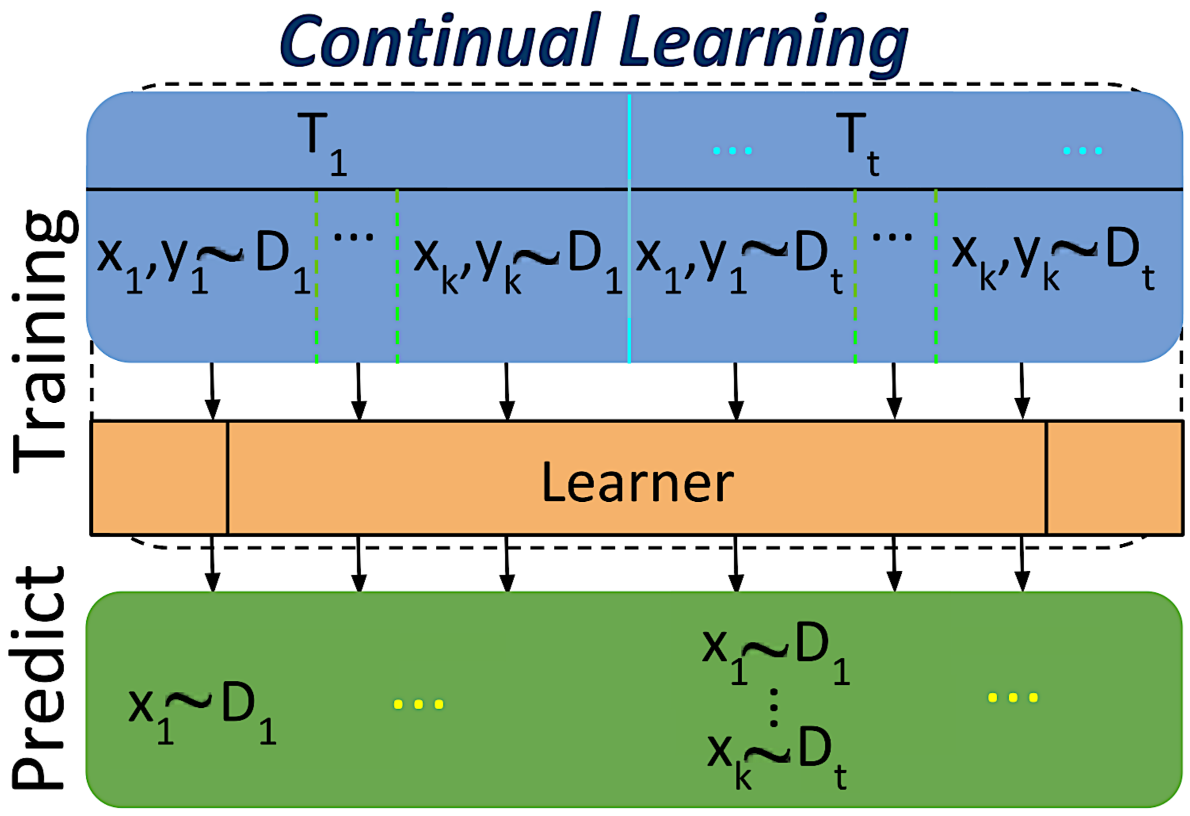
Towards Causal Replay for Knowledge Rehearsal in Continual Learning

Nikhil Churamani*, Jiaee Cheong*, Sinan Kalkan and Hatice Gunes

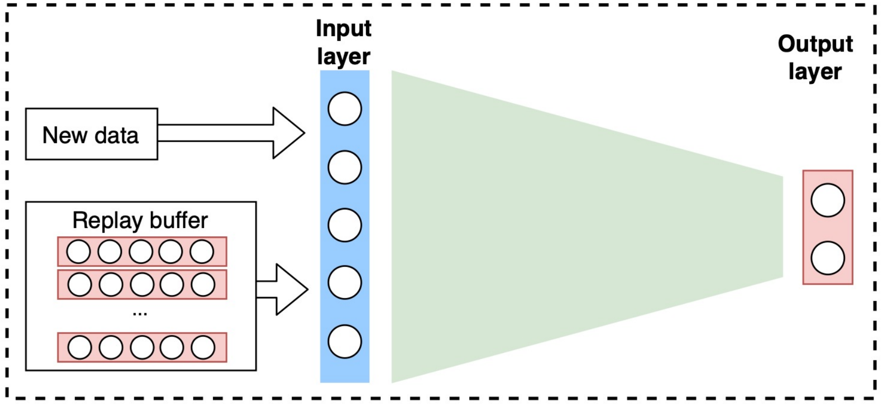
* Equal Contribution

The Alan Turing Institute
UKRI Engineering and Physical Sciences Research Council

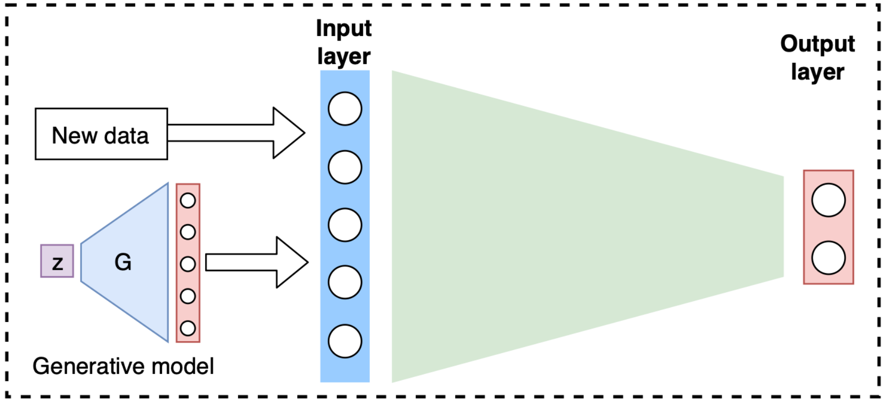
Motivation



Rehearsal



Pseudo-Rehearsal



De Lange, M, et al. A Continual Learning Survey: Defying Forgetting in Classification Tasks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 44(7):3366–3385, 2022.

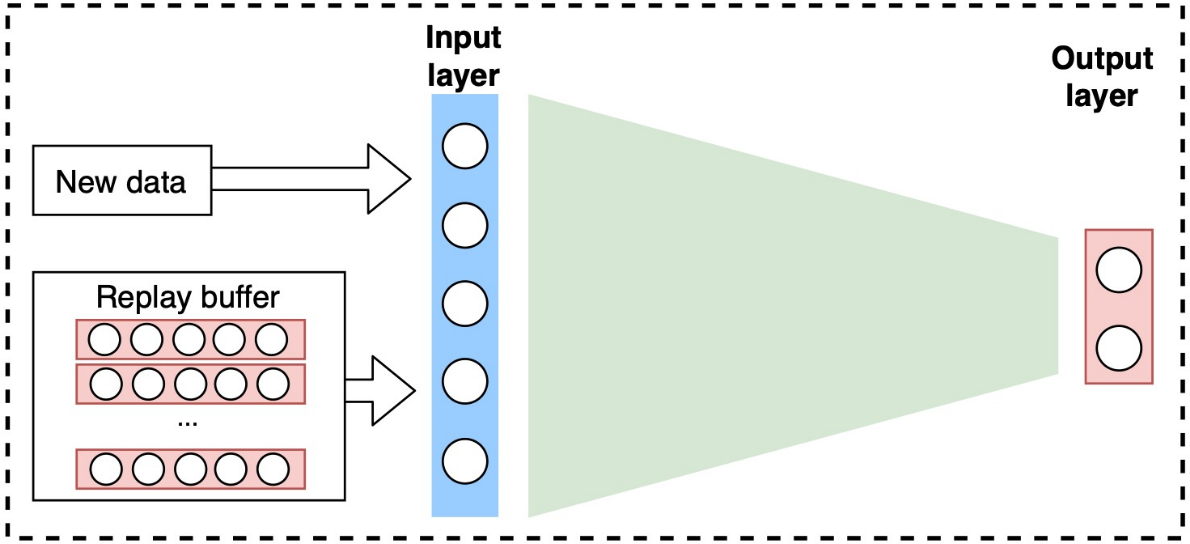
Stoychev, S., et al. Latent Generative Replay for Resource-Efficient Continual Learning of Facial Expressions. IEEE International Conference on Automatic Face and Gesture Recognition (FG), 2023

Challenges for Replay-based Continual Learning

Rehearsal:

- Maintaining a ‘*large enough*’ memory buffer inefficient.

- All samples may not be representative for the task. Possible redundancy.



Challenges for Replay-based Continual Learning

Rehearsal:

- Maintaining a '*large enough*' memory buffer inefficient.
- All samples may not be representative for the task. Possible redundancy.
- Noisy samples may negatively impact model learning.
- Need for ***prioritising*** samples to be replayed.

Zhang, Z, et al. "Learning social relation traits from face images." Proceedings of the IEEE International Conference on Computer Vision. 2015.

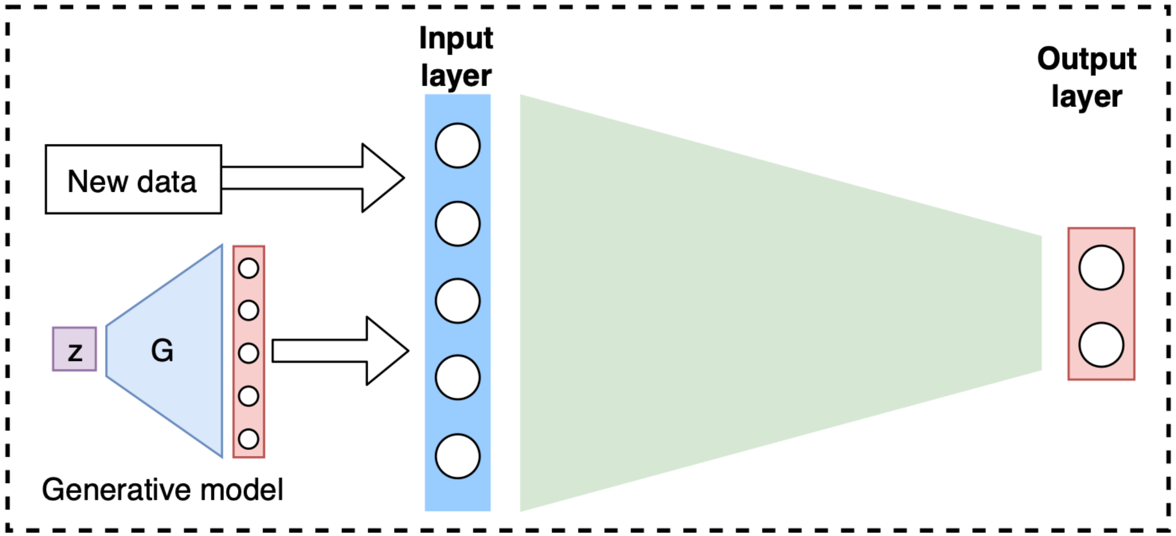
Zhang, Z., et al. From Facial Expression Recognition to Interpersonal Relation Prediction. Int J Comput Vis 126, 550–569 (2018).

Challenges for Replay-based Continual Learning

Pseudo-Rehearsal:

- Generative models harder to train for high-dimensional data, e.g. images.

- Difficult to extract task-discriminative features for a large number of tasks.



Challenges for Replay-based Continual Learning

Pseudo-Rehearsal:

- Generative models harder to train for high-dimensional data, e.g. images.
- Difficult to extract task-discriminative features for a large number of tasks.
- Spurious features may be learnt, negatively impacting pseudo-rehearsal.
- ***Prioritising*** features that contribute most to the task.

N. Churamani and H. Gunes, "CLIFER: Continual Learning with Imagination for Facial Expression Recognition," 2020 15th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2020), Buenos Aires, Argentina, 2020, pp. 322-328.

Structural Causal Model (SCM)

M: (U,V,F) such that:

1. U is a set of latent background or exogeneous variables which affect the model but yet are not represented within the model.
2. $V = \{V_1, ..., V_n\}$ is the set of observable or endogeneous variables within the model.
3. F is the set of functions $\{f_1, ..., f_n\}$, one for each $V_i \in V$, such that $V_i = f_i(pa_i, U_{pa_i})$, $pa_i \subseteq V \backslash \{V_i\}$, $U_{pa_i} \subseteq U$.

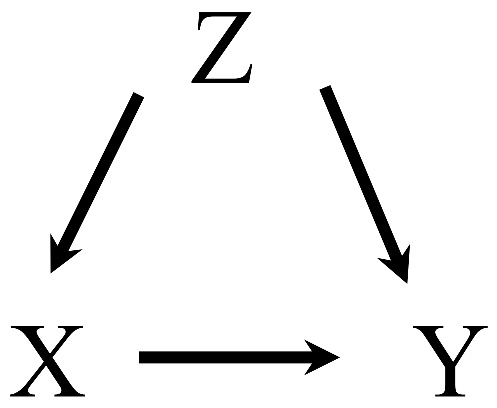
Tools in Causal Research:

- Graphical models
- Do-operator do(x)
- Counterfactuals
- Structural Equations

We focus on:

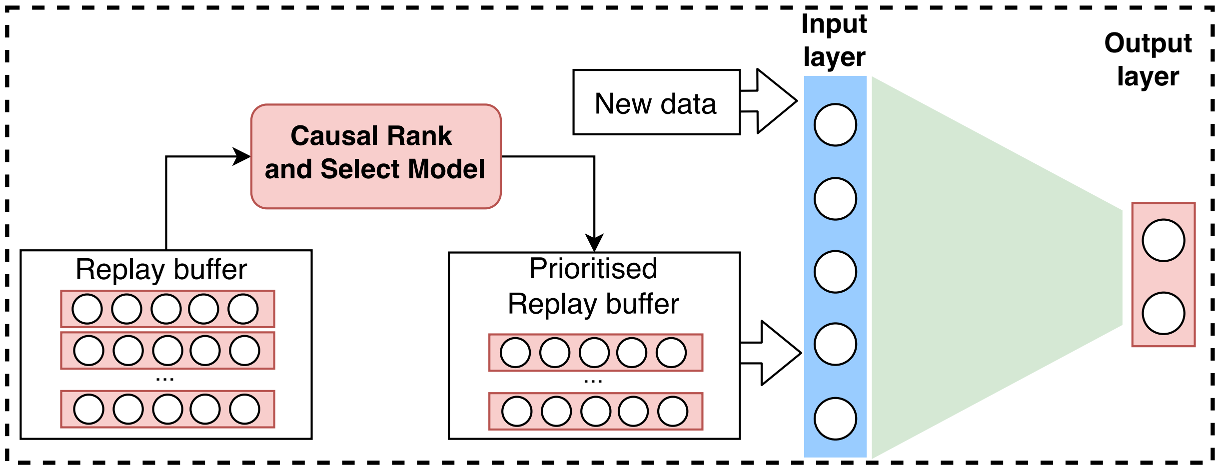
- Causal Interventions
- Causal Structure Discovery

Graphical Model G

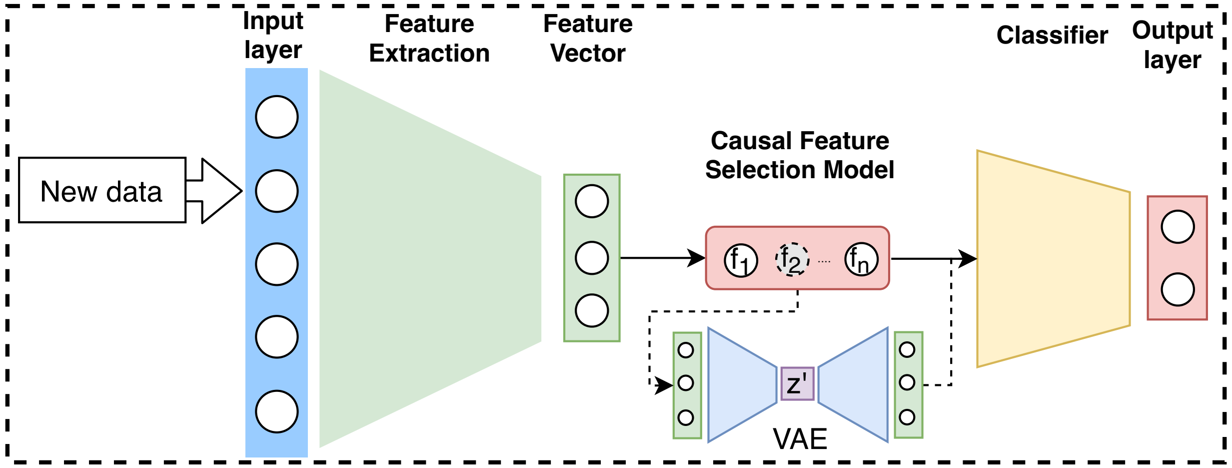


Causal-Replay for Knowledge Rehearsal

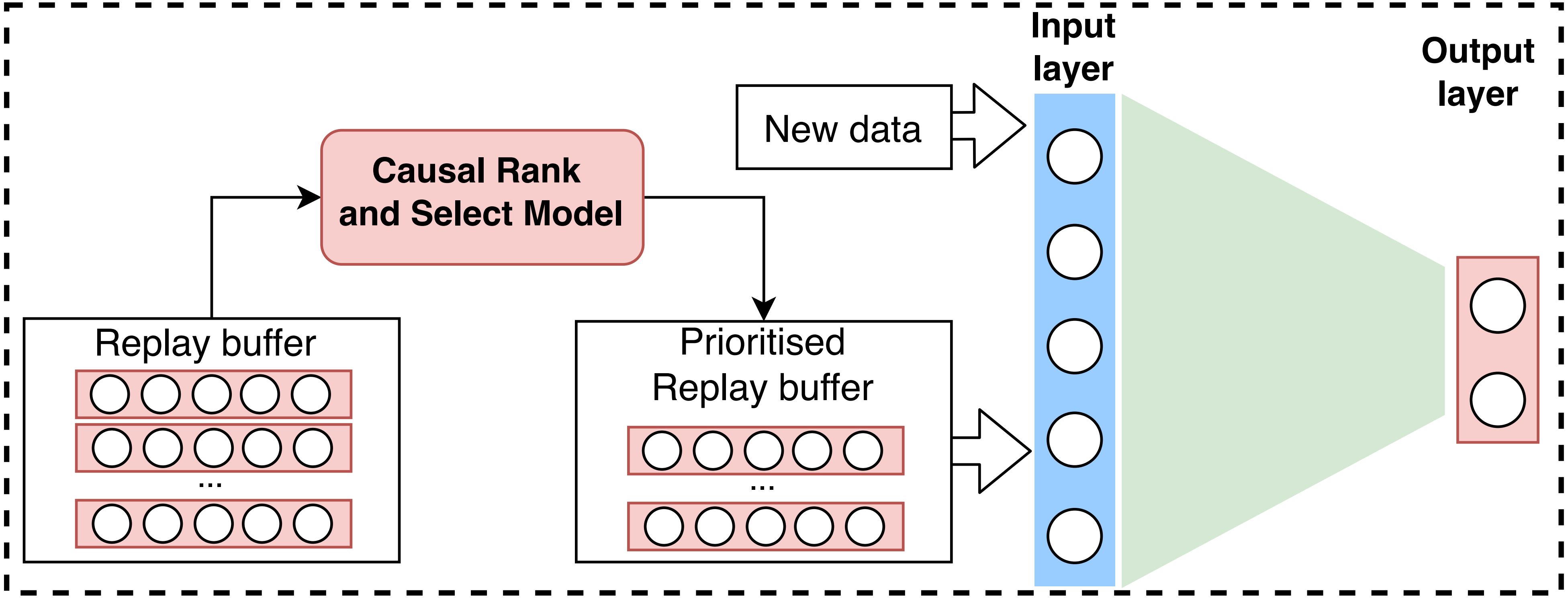
Causal Rehearsal



Causal Pseudo-Rehearsal



Causal Rehearsal



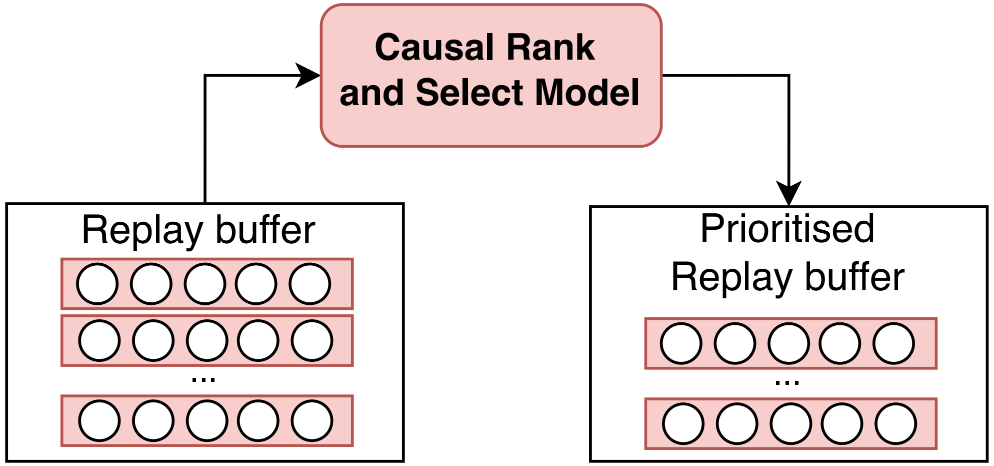
- **Goal:** Rank/Prioritise replay buffer samples for efficient rehearsal.
- **Leverage on:** Causal-Scoring: Samples with strong causal relationships are prioritised.

Causal Rehearsal

Prioritising Replay Buffers

Step 1: Rank buffer samples for a given task using causal scoring/discovery tools such as *Rank and Select.*

Step 2: Implement a threshold for the Causal Ranking and prune replay buffer to only include ‘high-ranking’ samples. Use the pruned replay buffer for training the model.

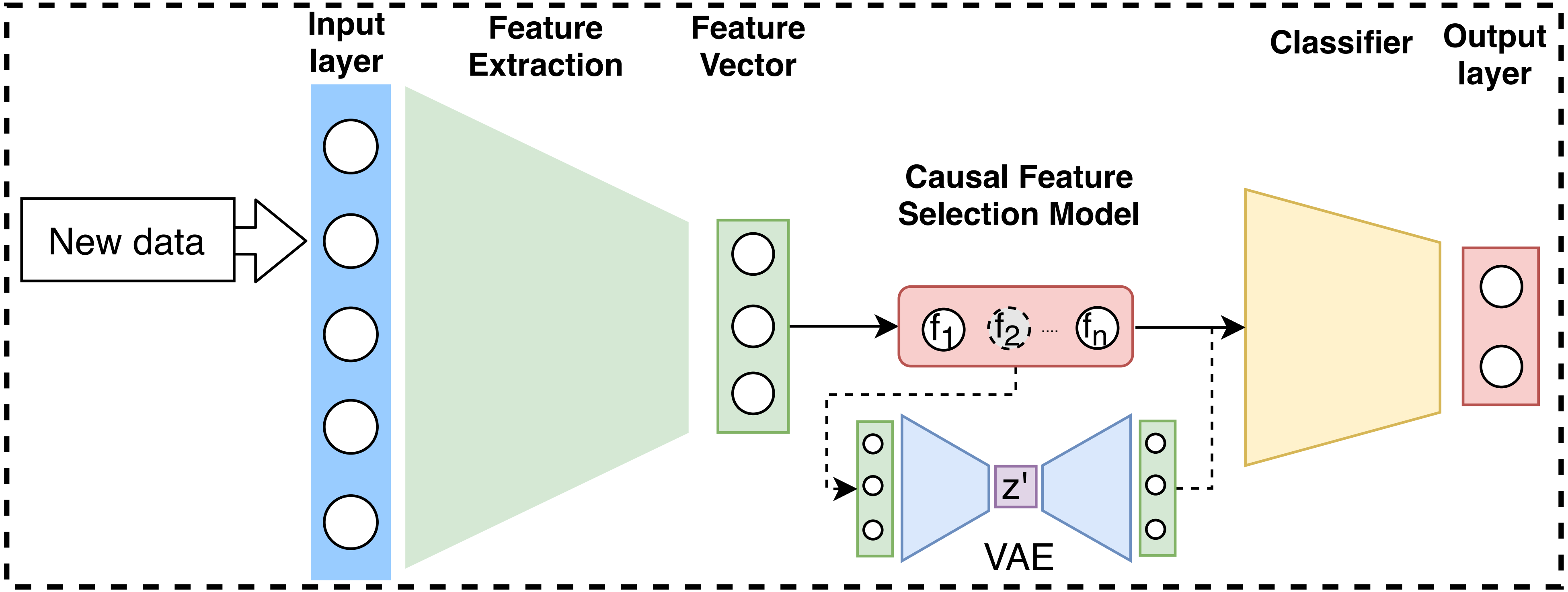


Step 3: Update the *Rank and Select* model based on the pruned replay buffer.

Glymour, C.; Zhang, K.; and Spirtes, P. 2019. Review of causal discovery methods based on graphical models. Fron- tiers in genetics, 10: 524.

Javed, K.; White, M.; and Bengio, Y. 2020. Learning causal models online. arXiv preprint arXiv:2006.07461.

Causal Pseudo-Rehearsal



- **Goal:** Rehearse data in a principled manner
- **Leverage on:** interventions (both hard and soft)

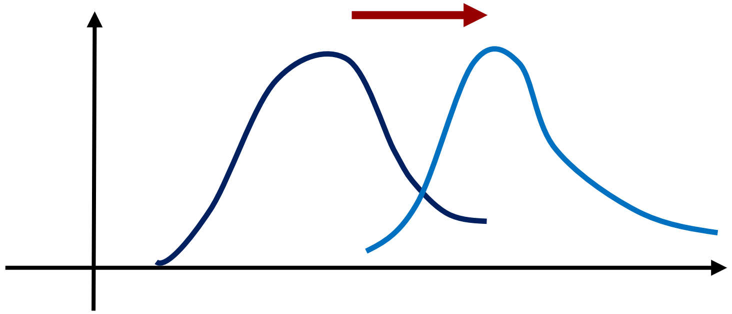
Causal Pseudo-Rehearsal

Sample Generation from Intervened Distribution

Step 1: Train a generative model.

Step 2: Causally update the generative model's original distribution P(y|x) by inducing an intervention P(y|do(x)).

Step 3: Generate samples from the updated distribution which has been 'intervened' upon.



Original Distribution
P(y|x)

Intervened Distribution
P(y|do(x))

Summary and Next Steps

Summary

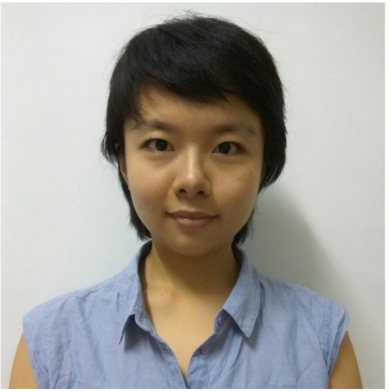
- Benefiting from Causality-driven knowledge rehearsal.
- Causal Replay by prioritising and pruning replay buffer samples.
- Causal Pseudo-rehearsal by extracting *strongest* task-discriminative features.
- Continually updating causal models as new data is acquired.

Next Steps

- Cross-dataset evaluations across popular computer vision benchmarks.
- Application towards Continual Facial Expression Recognition (FER).
- Subject-specific learning and personalisation for fairer FER.
- Deep-dive into causal discovery and inference for improved Causal Replay.

Acknowledgement

Nikhil Churamani



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