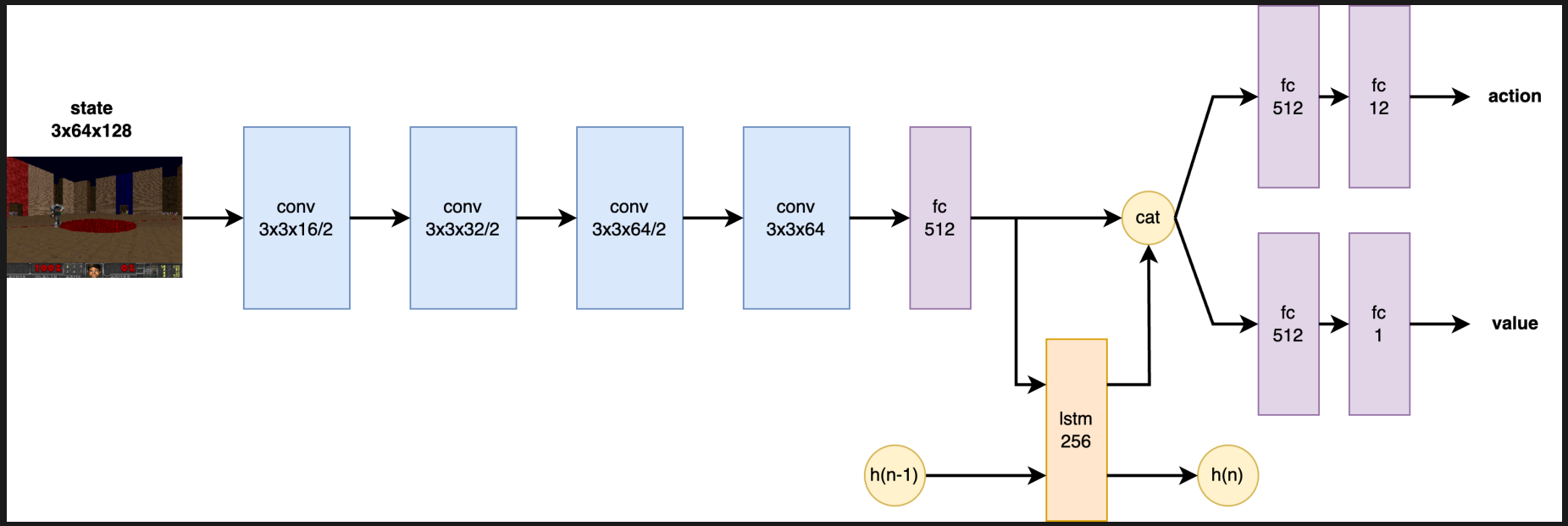
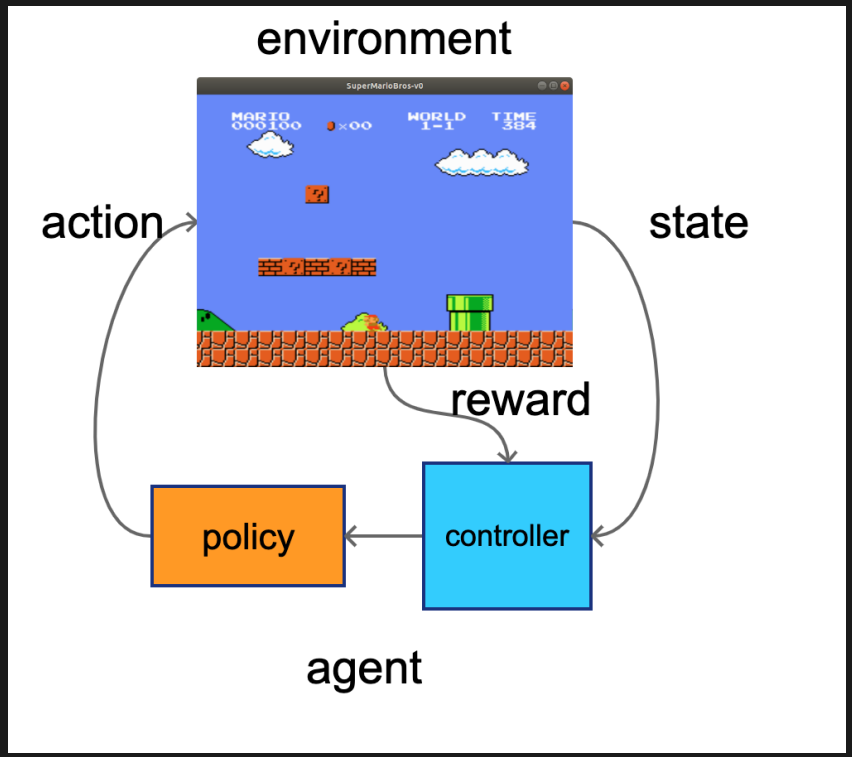
reinforcement learning with self supervised learning - Conquista of Montezuma's Revenge

Michal CHOVANEC, PhD.

net of doom - doom playing model



reinforcement learning



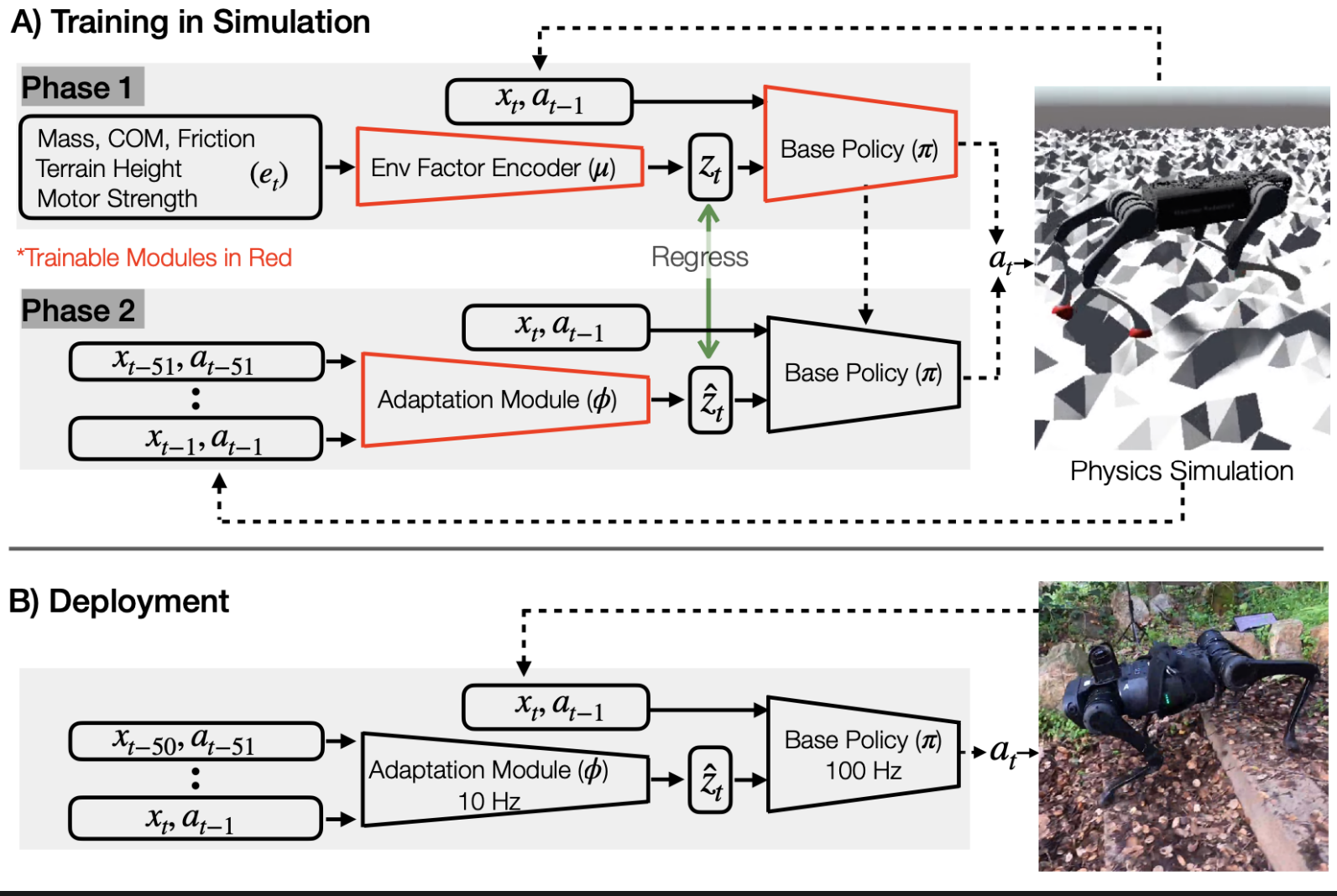
1. **obtain state** - observation
2. **choose action** - policy
3. **receive reward**
4. **learn from experiences**

reinforcement learning - success story

Mastering the game of Go with deep neural networks and tree search, Nature, 2016

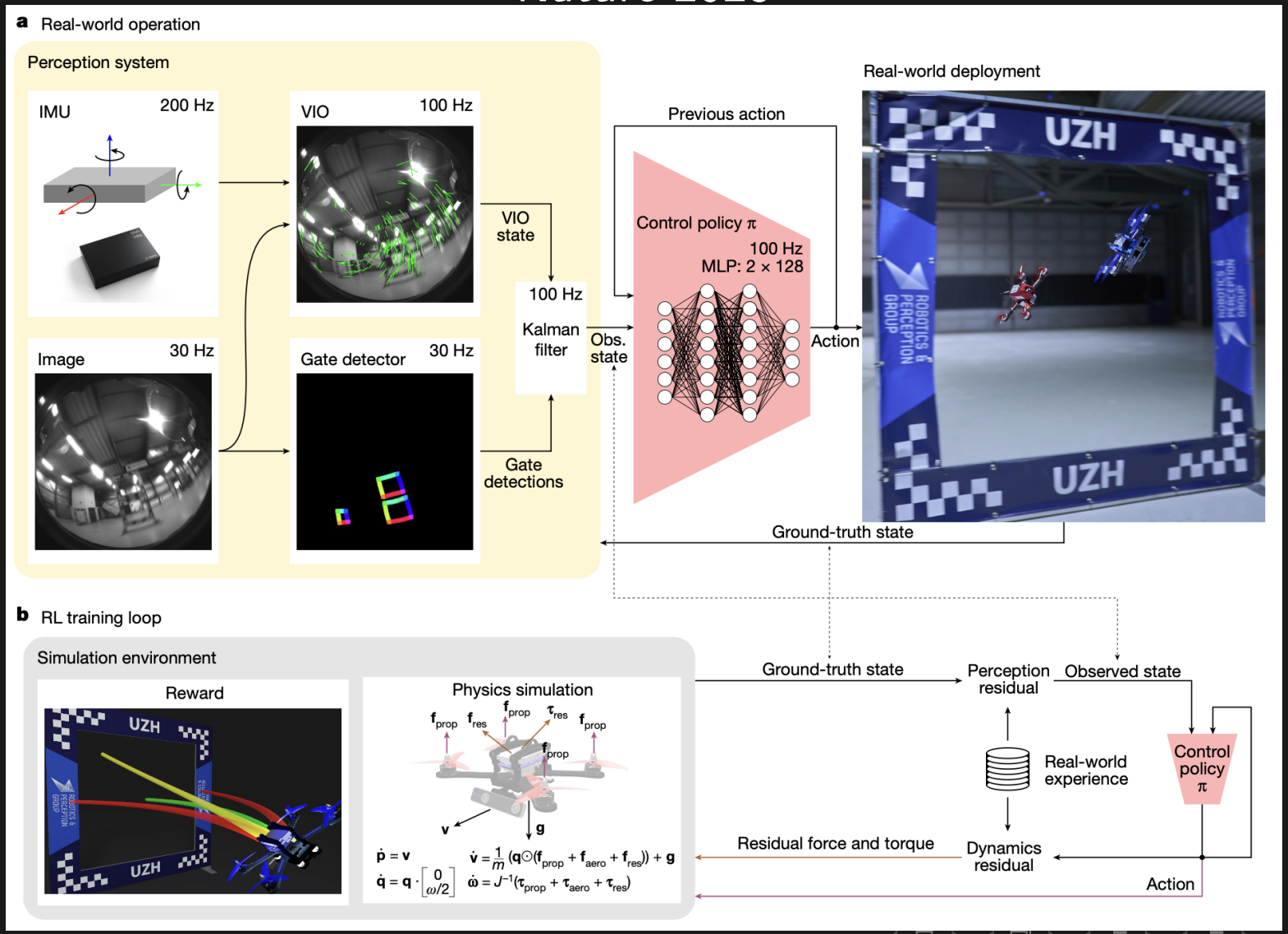
reinforcement learning - success story

RMA: Rapid Motor Adaptation for Legged Robots



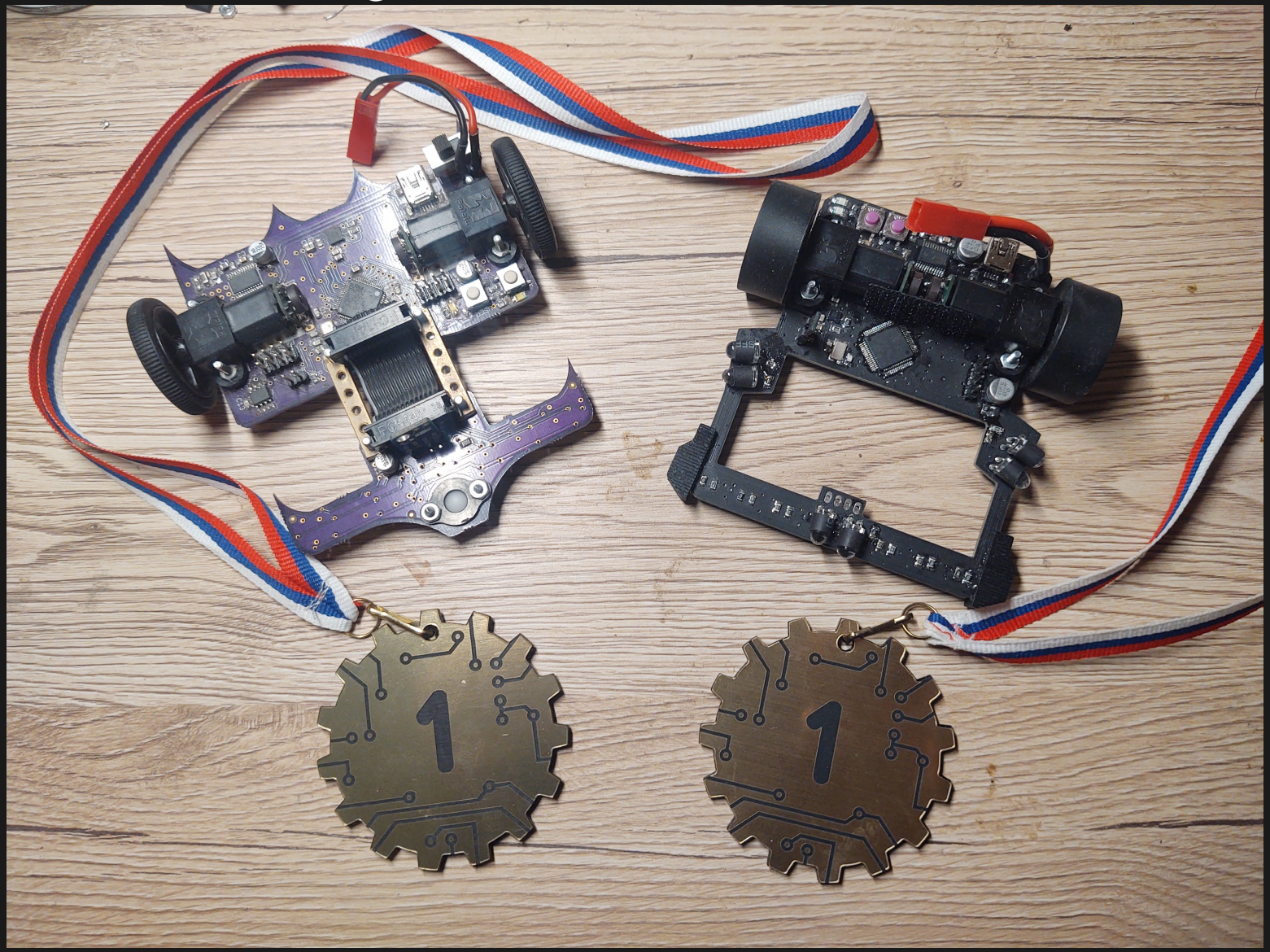
reinforcement learning - success story

Champion-level drone racing using deep reinforcement learning, Nature 2023



reinforcement learning - success story

Motoko line following robot



reinforcement learning - success story

$$\mathcal{L} = \int_0^\infty x^T Q x \, dt + u^T R u \, dt$$
$$s.t. \, dx = Ax + Bu$$

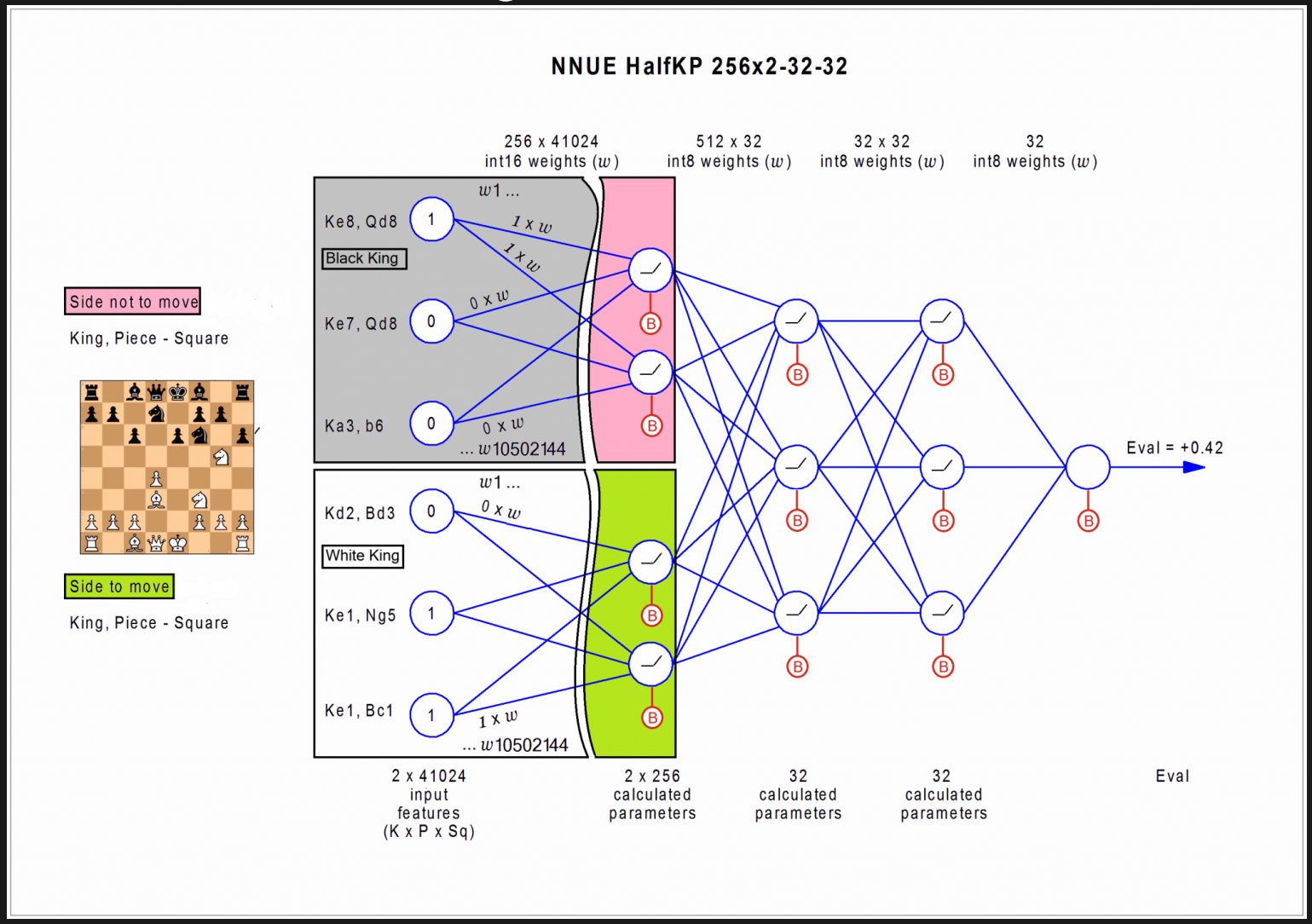
solution :

- quadratic programming for constrained x, u
  - model predictive contol (MPC)
- algebraic Riccati equation

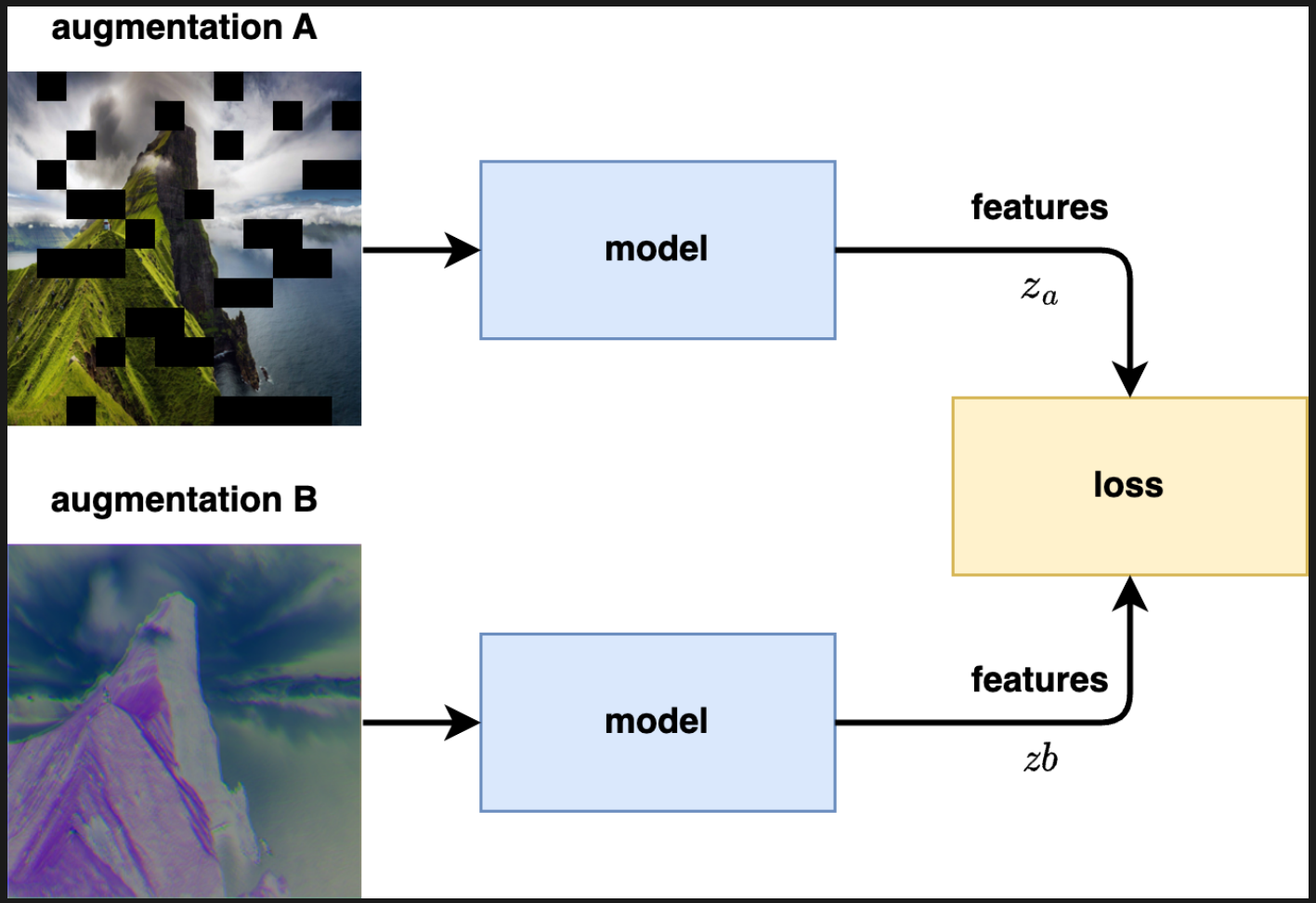
$$0 = A^T P + PA - PBR^{-1}B^T P + Q$$
$$K = R^{-1}B^T P$$
$$u = -Kx$$

reinforcement learning - success story

Stockfish NNUE Chess engine

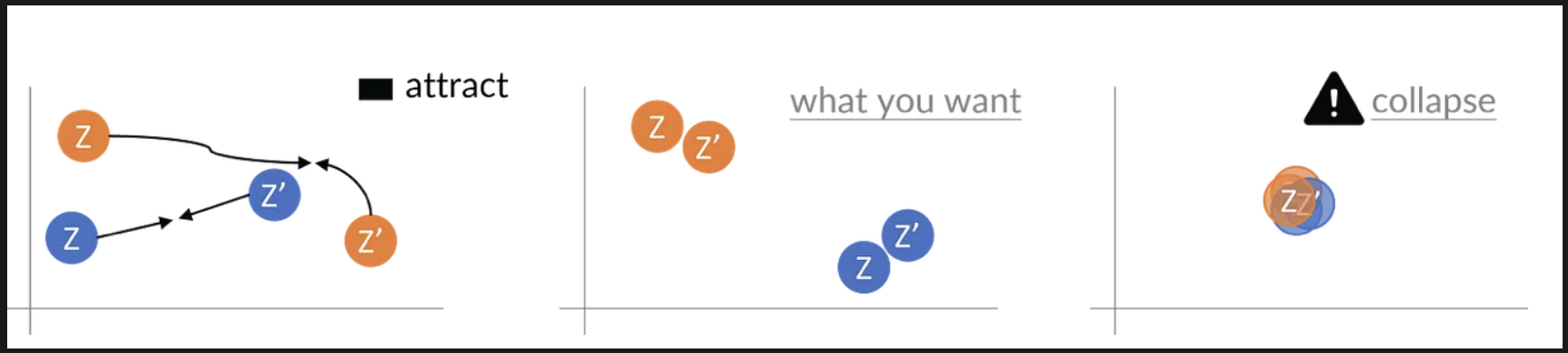


self supervised learning

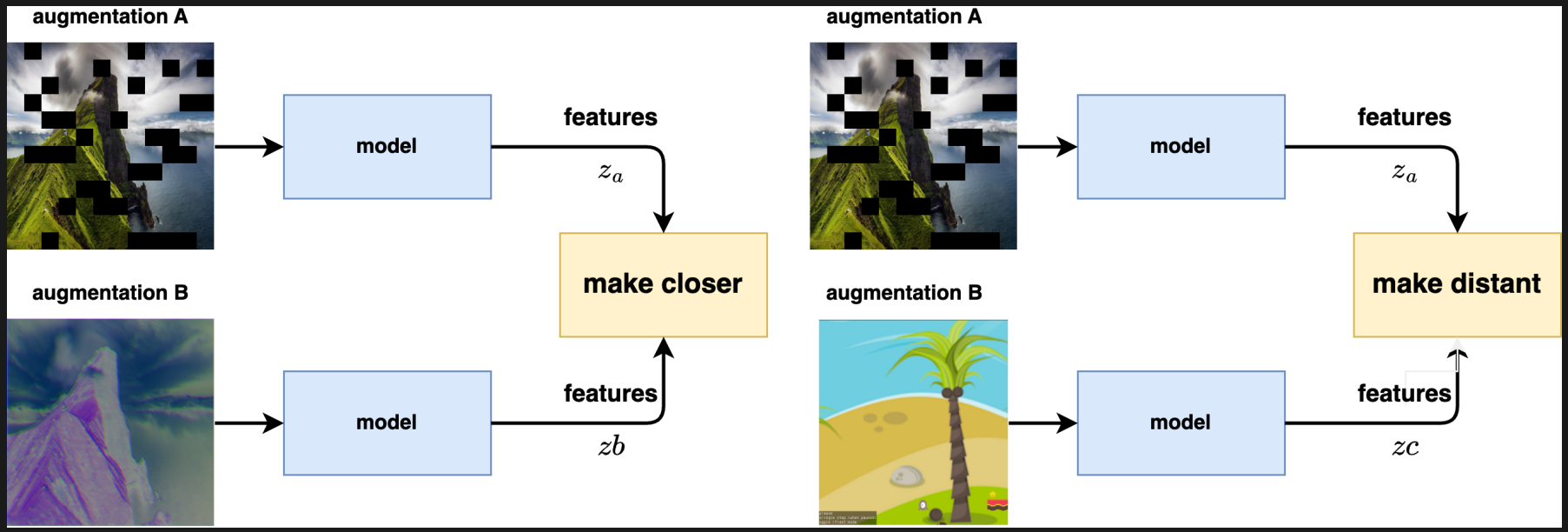


$$\mathcal{L} = |z_a - z_b|_2^2$$

self supervised learning - loss collapse



self supervised learning - contrastive loss



$$\mathcal{L} = |z_a - z_b|_2^2 - |z_a - z_c|_2^2$$

VICReg - non contrastive supervised learning

- VICReg: Variance-Invariance-Covariance Regularization for Self-Supervised Learning
- Yann LeCun: Dark Matter of Intelligence and Self-Supervised Learning

VICReg - non contrastive self supervised learning

- VAriance

$$\mathcal{L}_{variance} = \frac{1}{N} \sum_{n} \max(0, 1 - std(z^*_{n,:}))$$

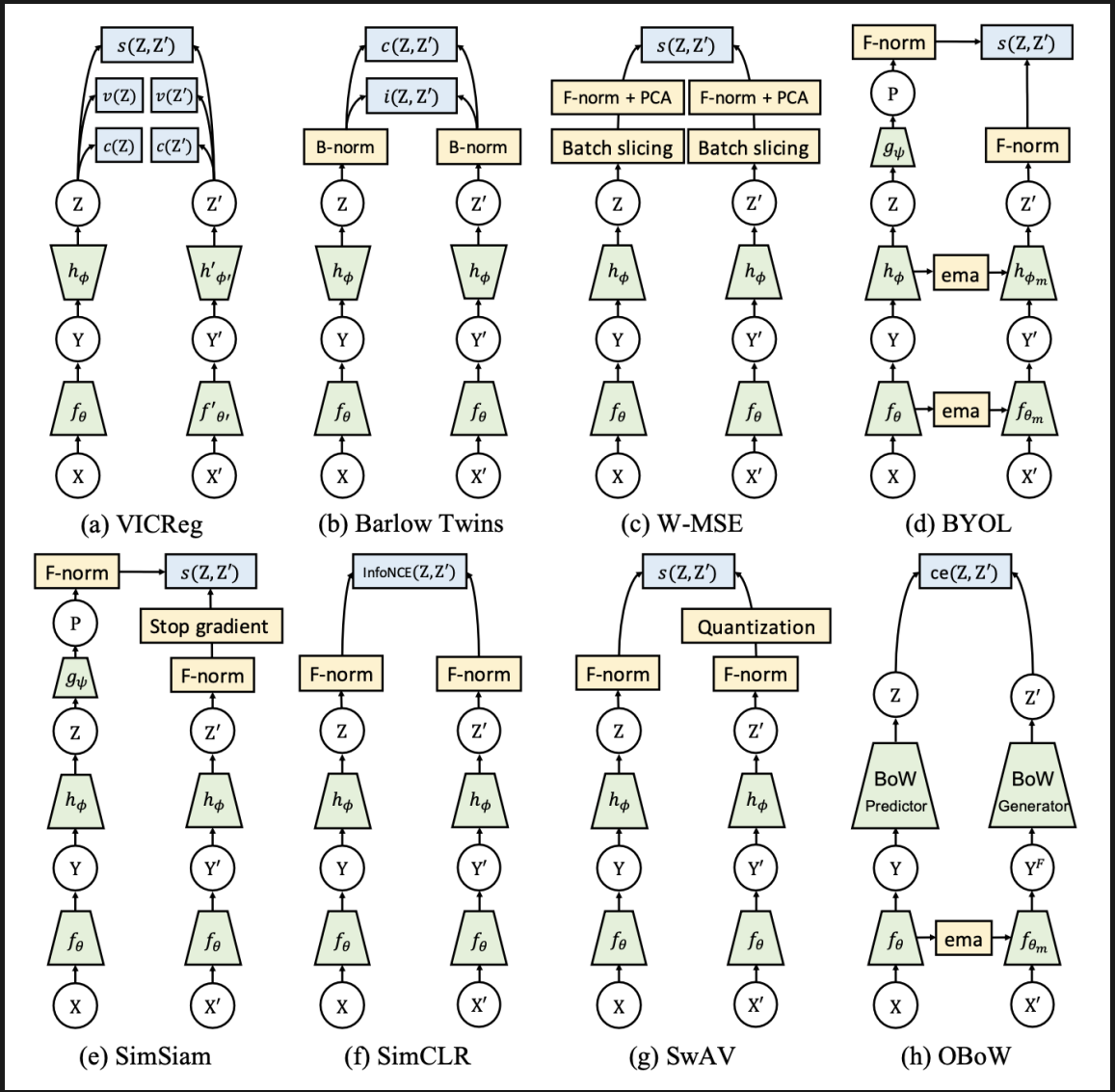
- INvariance

$$\mathcal{L}_{invariance} = \frac{1}{N} \sum_{n} |z^a_{n,:} - z^b_{n,:}|_2^2$$

- Covariance

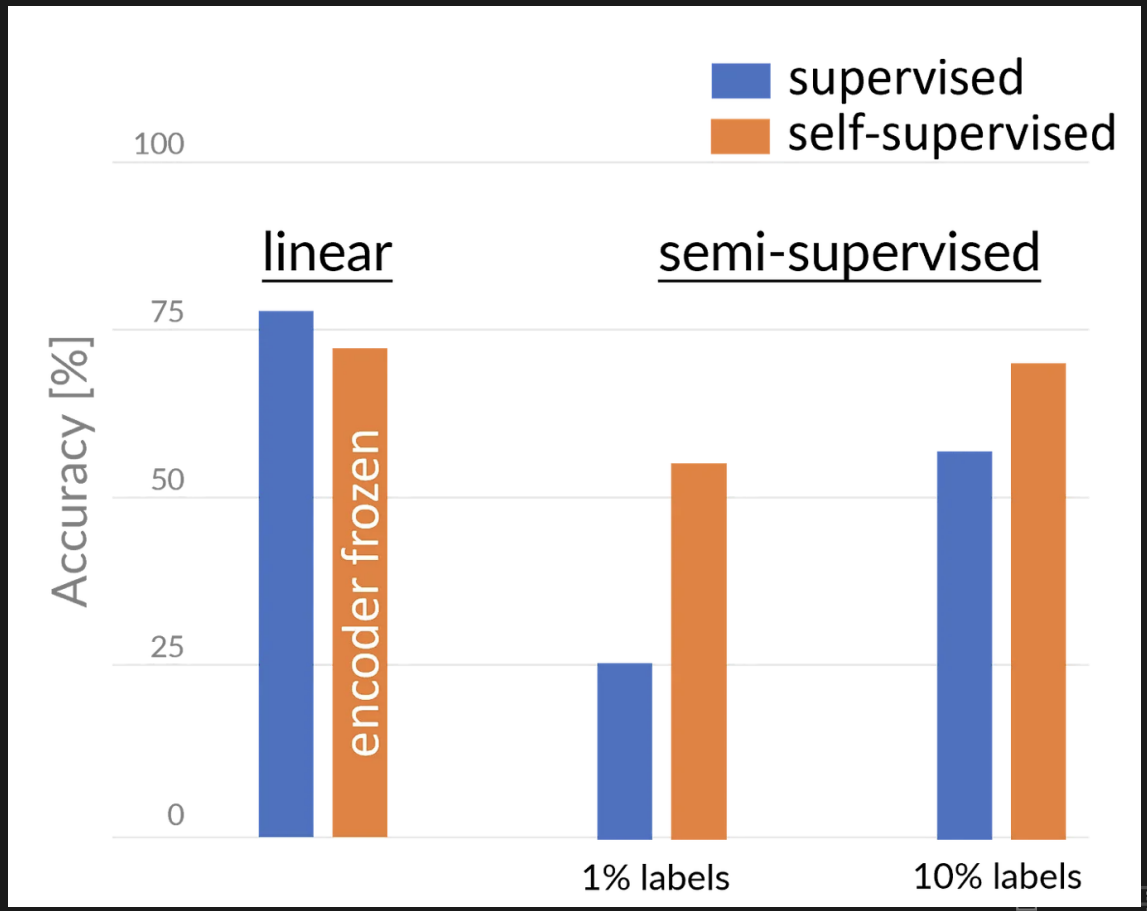
$$\mathcal{L}_{covariance} = \frac{1}{F} \sum_{i \neq j} cov(z^*_{:,i}, z^*_{:,j})$$

another loss examples



applications

- face, signature matching
- anomaly detection
- e-shop similar goods finding
- searching by image - Google lens
- less labeled data for self supervised training



fresh news

- I-JEPA : The first AI model based on Yann LeCun's vision for more human-like AI
- MAST : Masked Augmentation Subspace Training for Generalizable Self-Supervised Priors

Montezuma's revenge - 10 years of tears?

source : `https://paperswithcode.com/sota/atari-games-on-atari-2600-montezumas-revenge`

year	name	score
2013	Playing Atari with Deep Reinforcement Learning	0
2015	Deep Reinforcement Learning with Double Q-learning	0
2017	Curiosity-driven Exploration by Self-supervised Prediction [a]	0
2021	MuZero	2500
2018	Count-Based Exploration with Neural Density Models [b]	3705
2019	**Exploration by Random Network Distillation [c]**	**8152**
2021	GoExplore* [d]	43 000

*** requires environment state saving/loading**

[a] https://arxiv.org/abs/1705.05363
[b] https://arxiv.org/abs/1703.01310
[c] https://arxiv.org/abs/1810.12894
[d] https://arxiv.org/abs/2004.12919

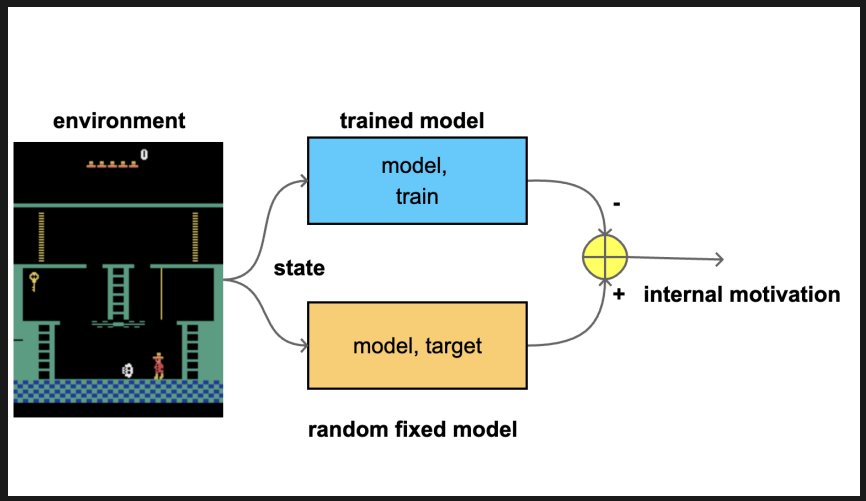
sample efficiency

- RND [1] $4.5 * 10^9$ samples, score 8152 on MR
- Never give up [2] $3.5 * 10^{10}$ samples, score 10 000 on MR
- SND $1.28 * 10^8$ samples with score 25 000

NGU on my machine means **740 days** !!!

[1] Burda et al. 2018
[2] Badia et al. 2020

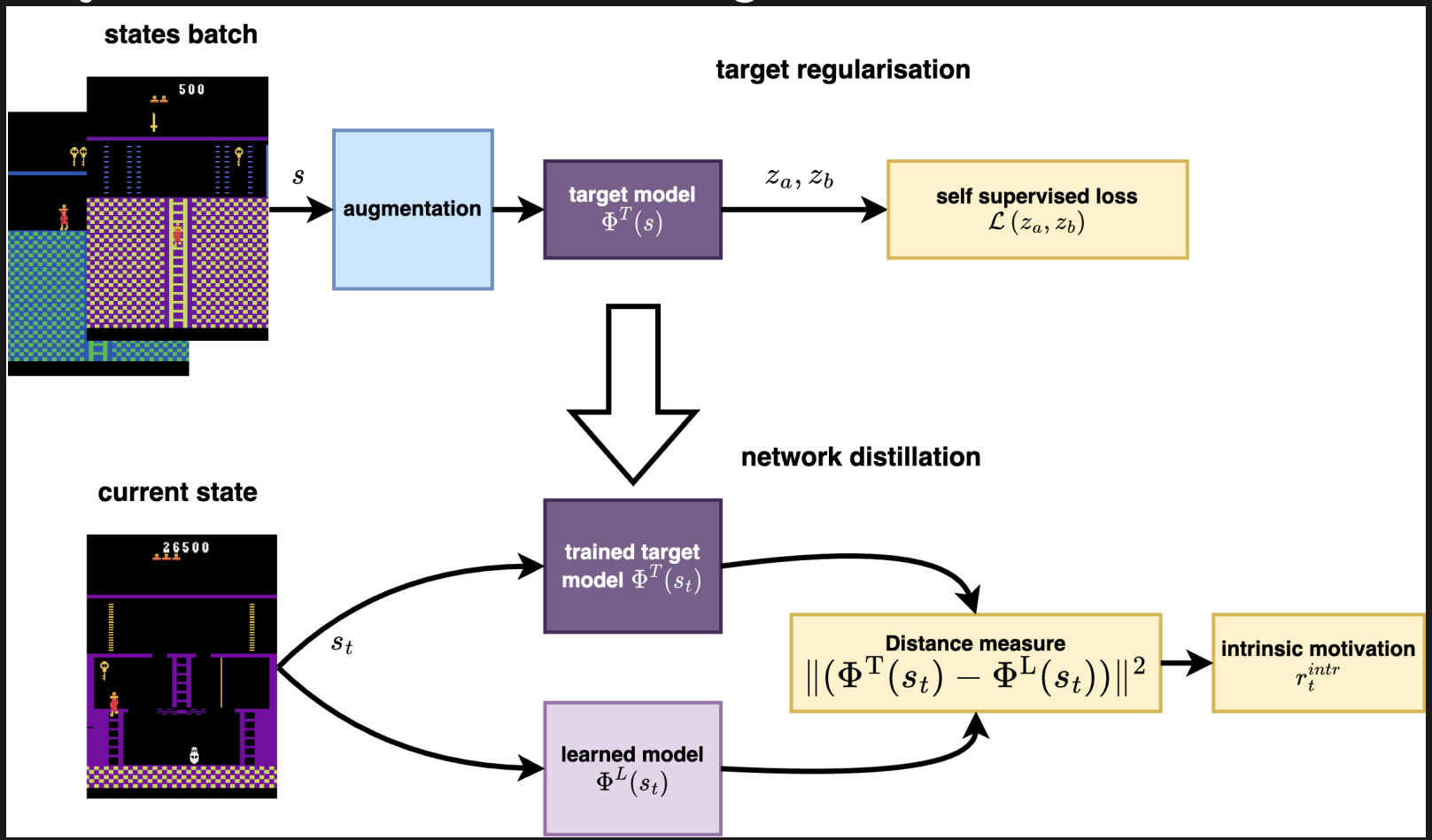
random network distillation



- neural network works as **novelty detector**
- model learns to imitate random (target) model
- **less visited states produce bigger motivation signal**
- orthogonal weights initialisation ($g = 2^{0.5}$) for strong signal
- lot of fully connected layers **to avoid generalisation**

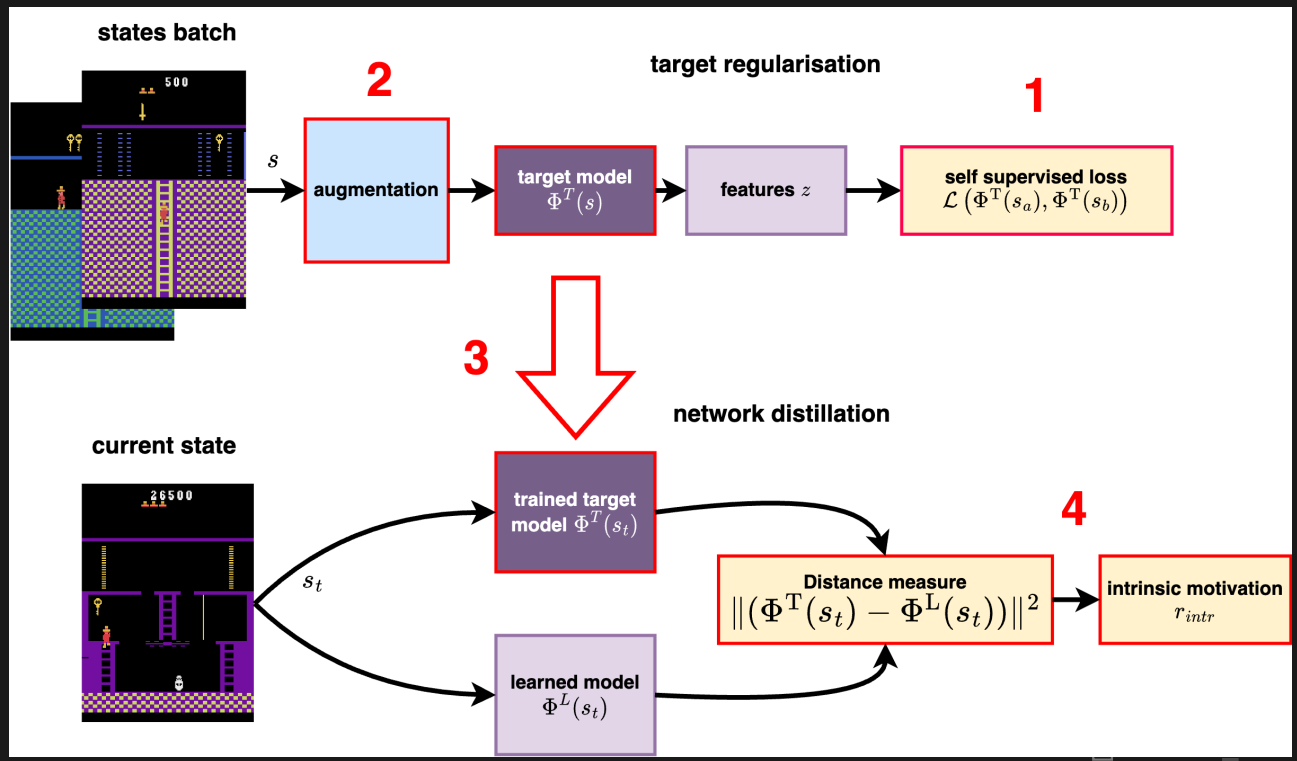
Exploration by self supervised-exploitation

Matej Pecháč, Michal Chovanec, Igor Farkaš



Exploration by self supervised-exploitation

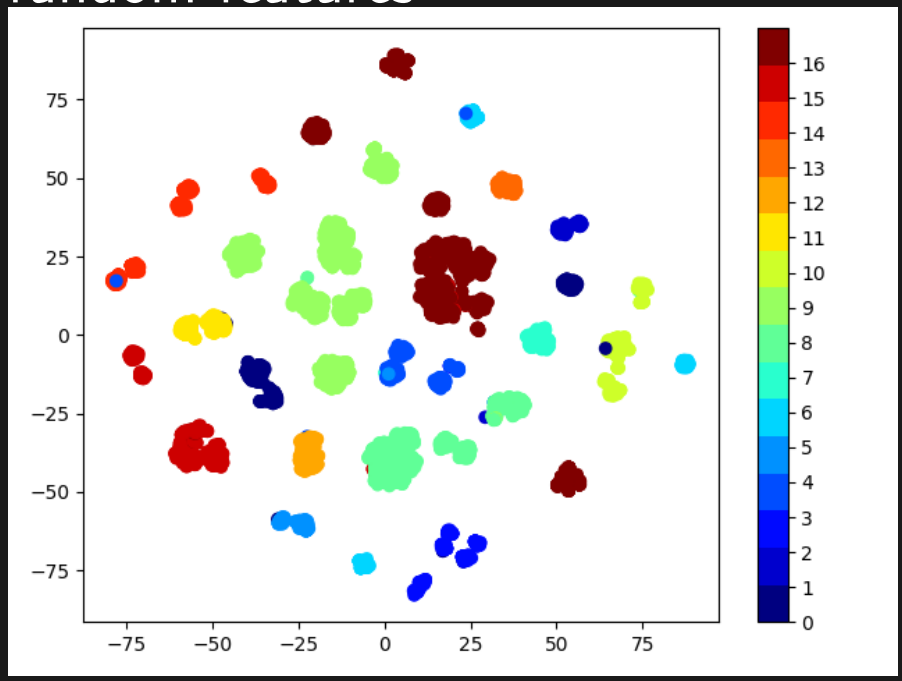
- we extended existing idea of Random Network Distillation
- 1 : for target model, self supervised training is used
- 2 : augmented states are used to train target model
- 3 : target model is used as distillation source
- 4 : distillation error is used for intrinsic motivation



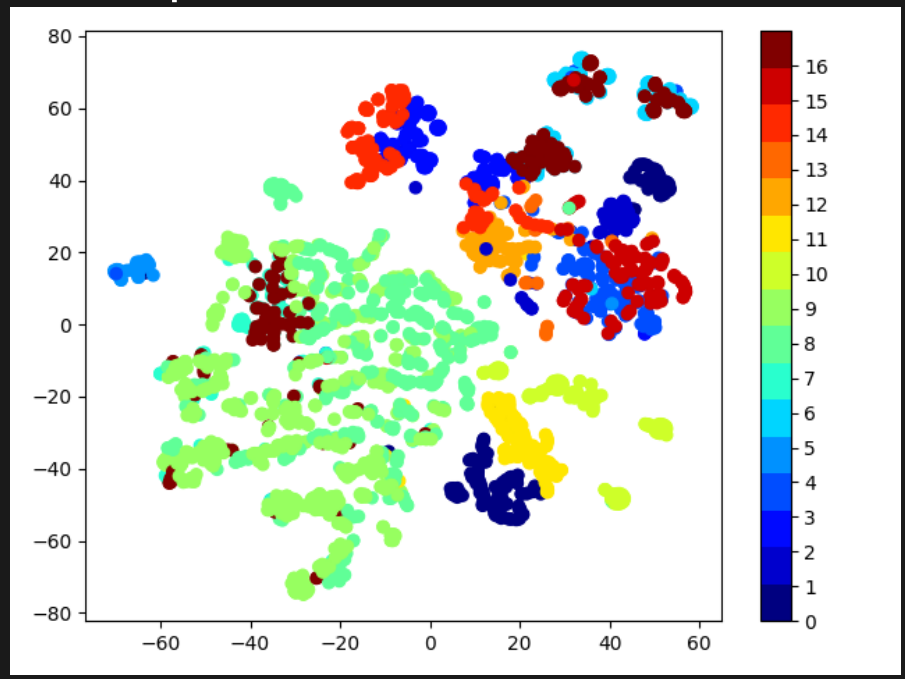
Trained features

- t-SNE features projection for random and trained models
- color represents different rooms in Atari Montezuma's Revenge
- self supervised features provides much bigger variance
- preventing agent to stuck

random features



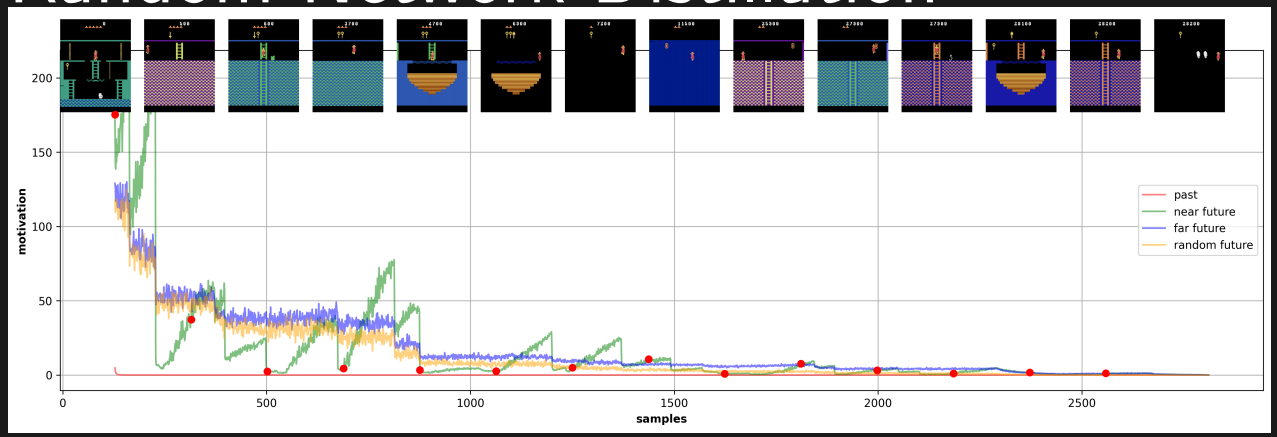
self supervised trained features



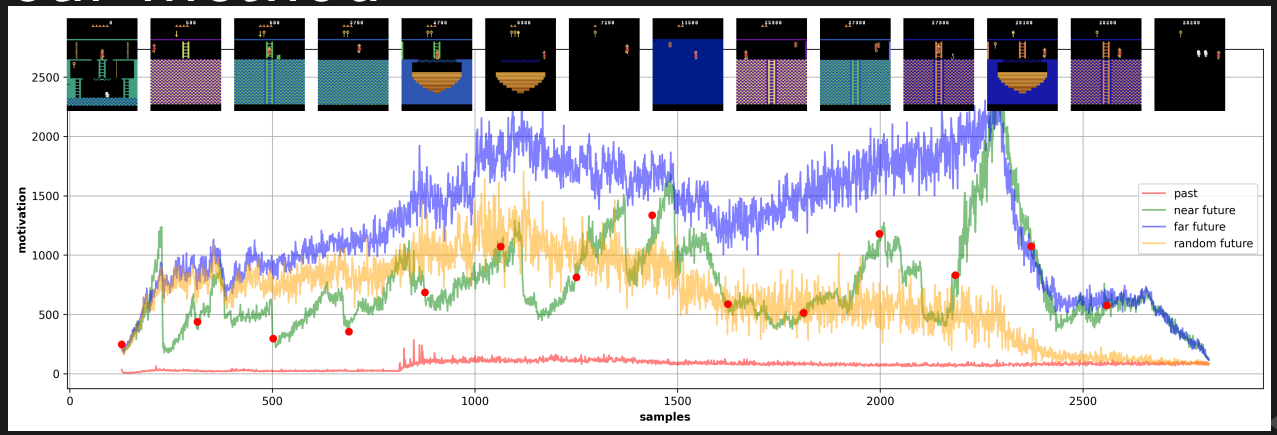
Exploration signal

- Random Network Distillation signal decrease over time
- our method provides more informative signal

Random Network Distillation

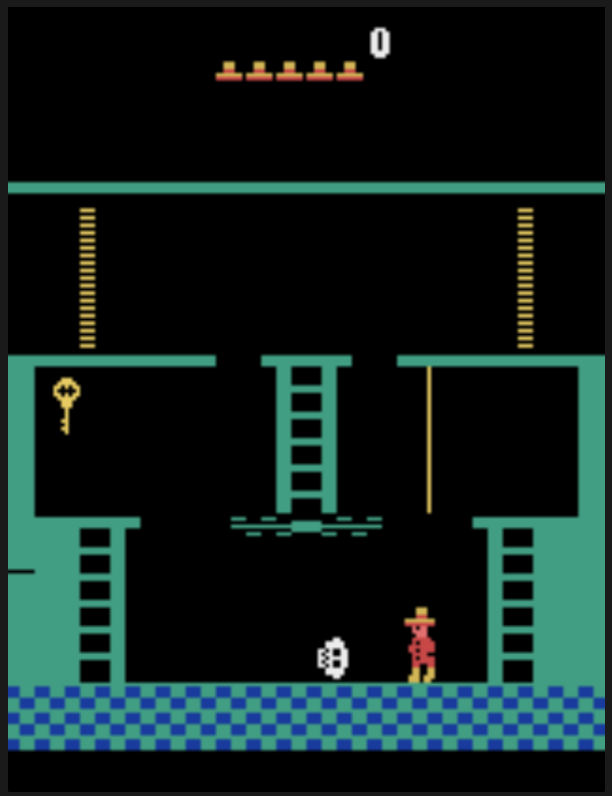


our method



Results

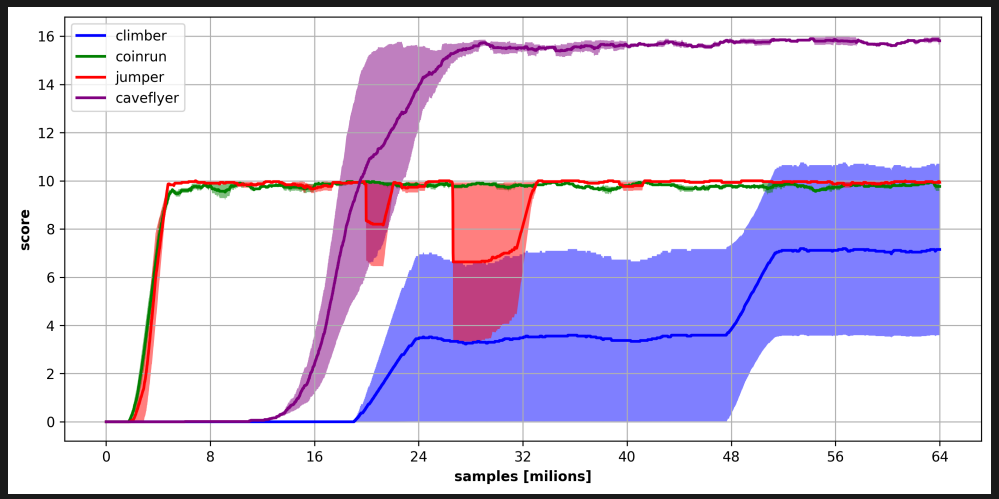
- Montezuma's Revenge, with score 25 000+
- Private Eye, with score 12 000+
- Venture, Gravitar
- 128M samples total - only single GPU needed



Results

solved Procgen hard exploration seeds

environments : Caveflyer, Climber, Coinrun, Jumper



misleading papers - Curiosity-driven Exploration by Self-supervised Prediction [a]

[a] Pathak et al. 2017

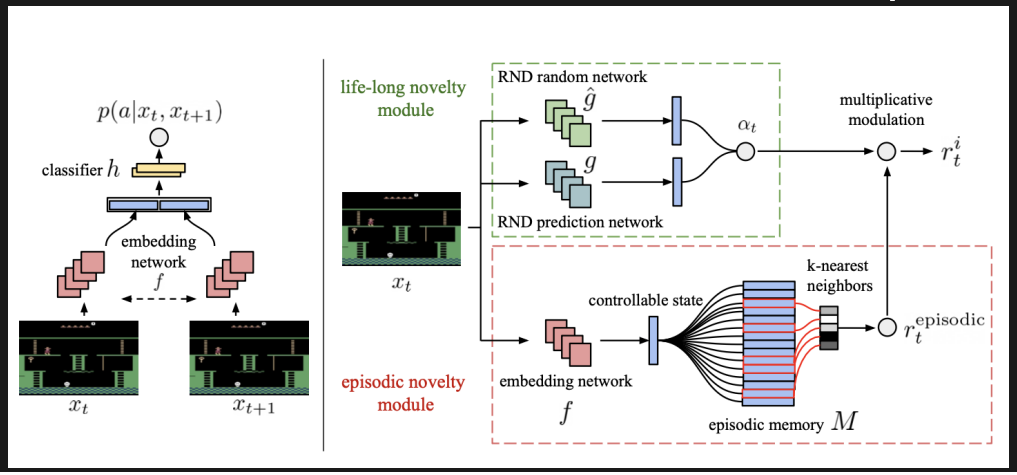
- not working on REAL hard exploration problems
- Super Mario is special case - moving forward is close to optimal policy
- inverse ICM model - why they didn't shown accuracy (my results arround only 40% !!!)
- how predicted state looks ?

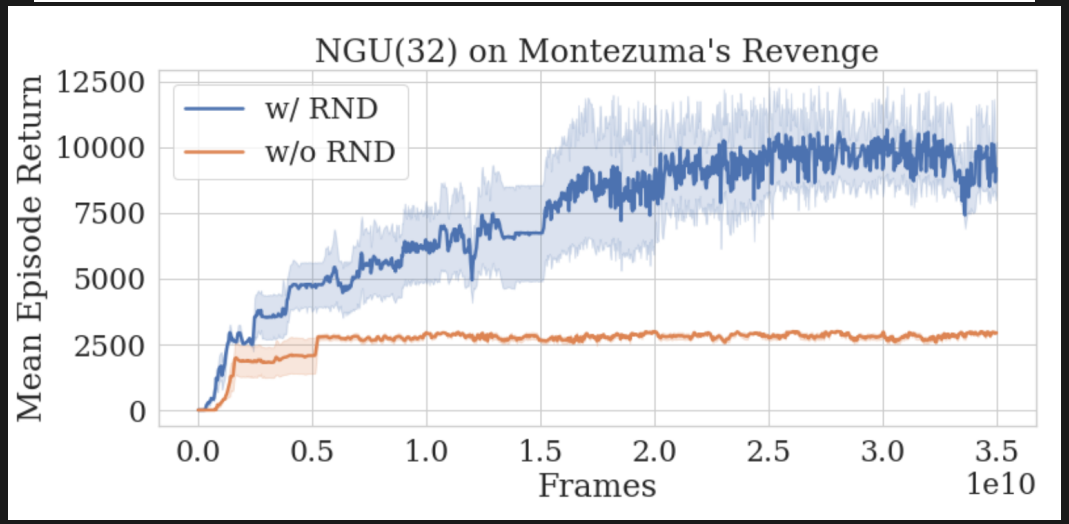
	Gravitar	Montezuma's Revenge	Pitfall!	PrivateEye	Solaris	Venture
RND	**3,906**	**8,152**	-3	8,666	3,282	**1,859**
PPO	3,426	2,497	0	105	3,387	0
Dynamics	3,371	400	0	33	3,246	1,712
SOTA	2,209[1]	3,700[2]	**0**	**15,806**[2]	**12,380**[1]	**1,813**[3]
Avg. Human	3,351	4,753	6,464	69,571	12,327	1,188

misleading papers - Never give up [a]

[a] Badia et al. 2020

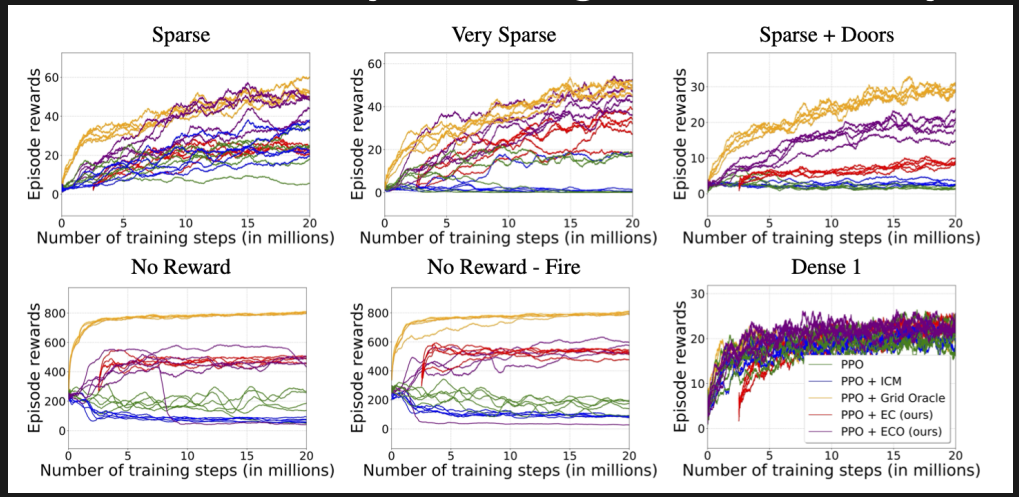
nice looking score, but on cost of $3.5 * 10^{10}$ samples !!!





other misleadings

avoiding comparing with SOTA or common benchmarks results : Episodic Curiosity Through Reachability, Savinov, 2019



many other :

- simple gridworld or toy environment experiments
- providing key prior information (e.g. possition)
- selecting only "good" results

Q&A

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- michal.nand@gmail.com