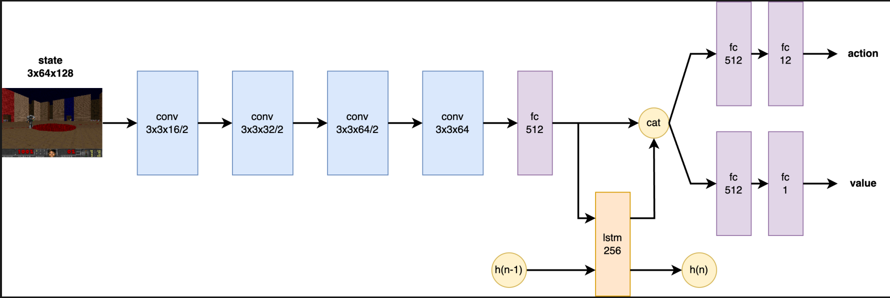
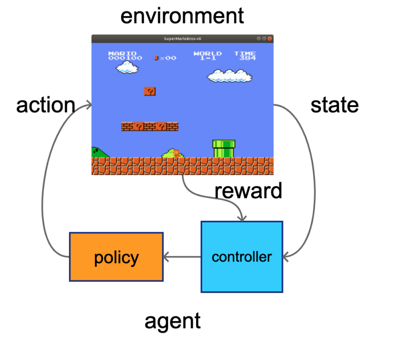
# reinforcement learning with self supervised learning - Conquista of Montezuma's Revenge

Michal CHOVANEC, PhD.

# net of doom - doom playing model



# reinforcement learning



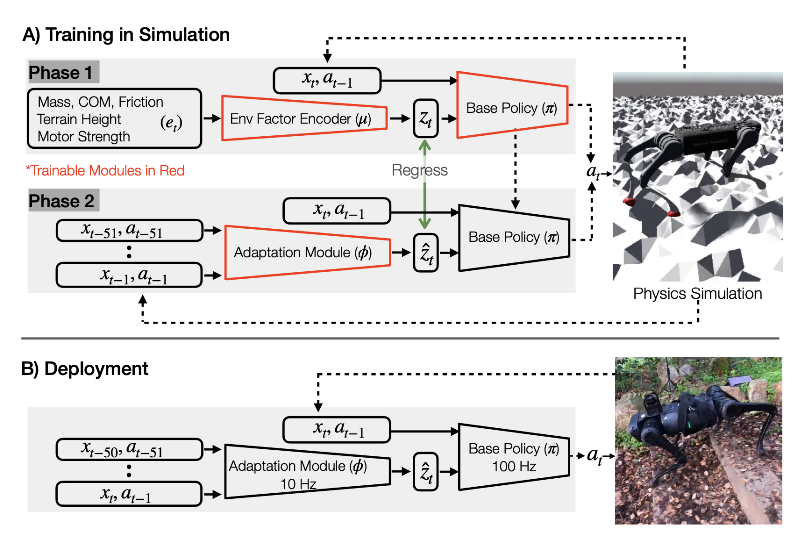

1. **obtain state** - observation
2. **choose action** - policy
3. **receive reward**
4. **learn from experiences**

# reinforcement learning - success story

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

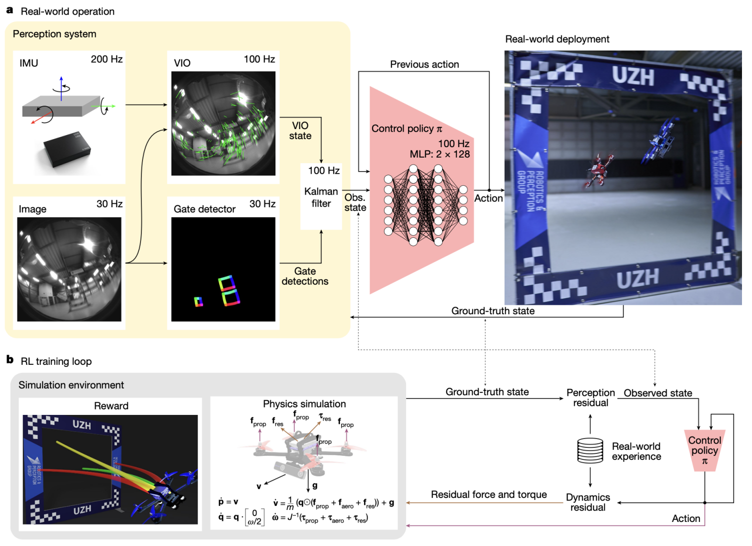
# reinforcement learning - success story

## RMA: Rapid Motor Adaptation for Legged Robots



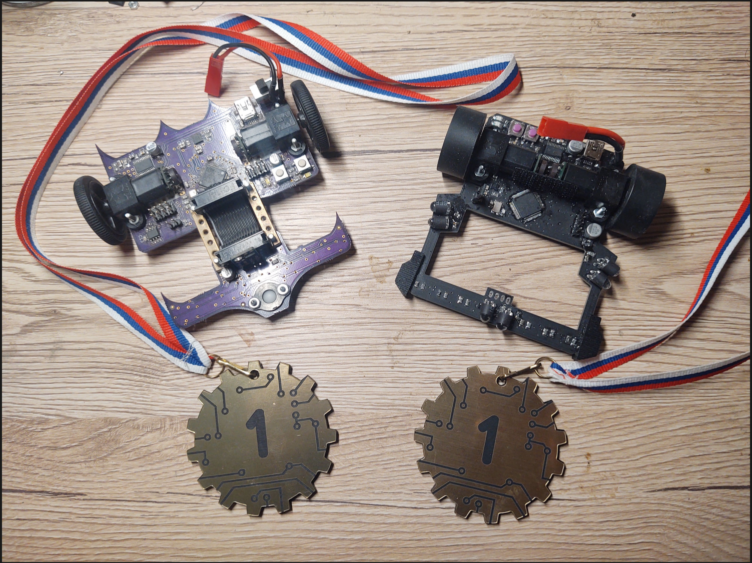
# reinforcement learning - success story

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



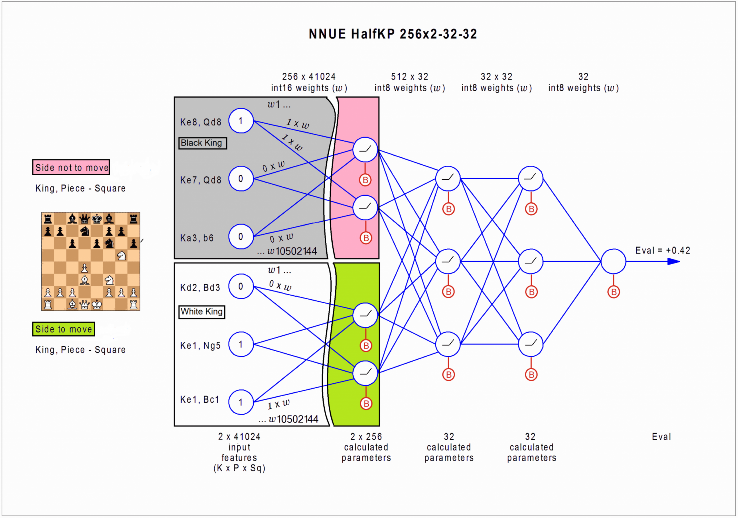
# reinforcement learning - success story

Motoko line following robot

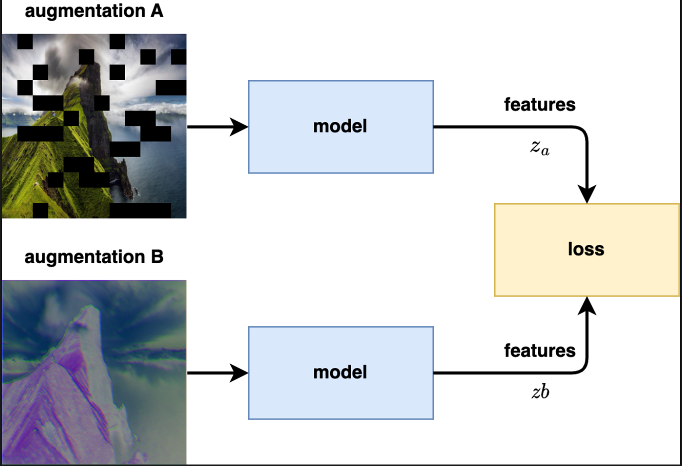


# reinforcement learning - success story

## Stockfish NNUE Chess engine

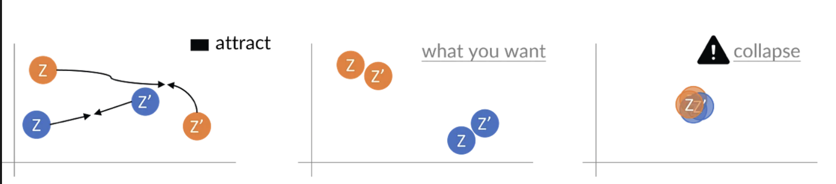


# self supervised learning

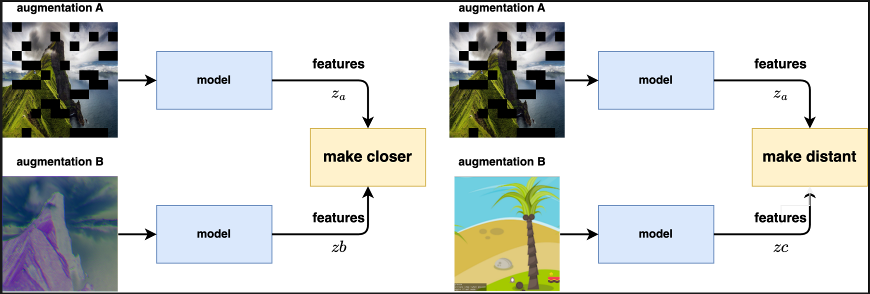



$$\mathcal{L} = |z_a - z_b|_2^2$$

# 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

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

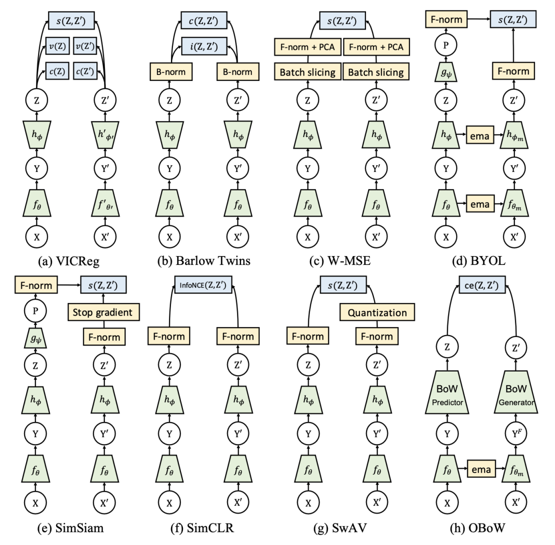
- INvariance

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

- Covariance

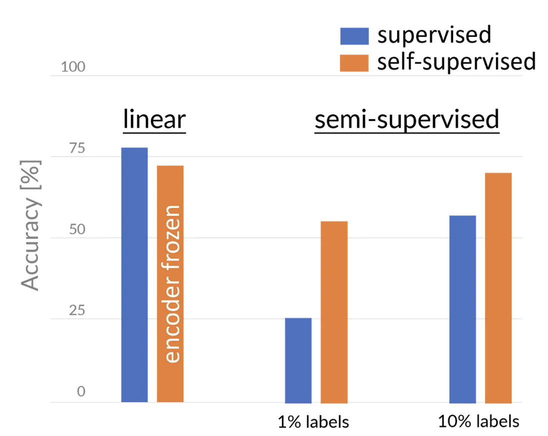
$$\mathcal{L}_{covariance} = \frac{1}{F} \sum_{i \neq j} cov(z^*_{:,i}, z^*_{:,j})$$

# 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

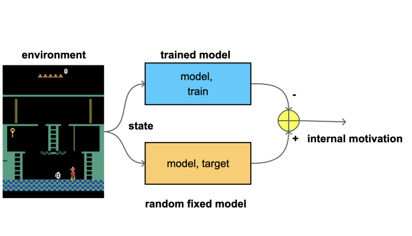
# sample efficiency

- 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

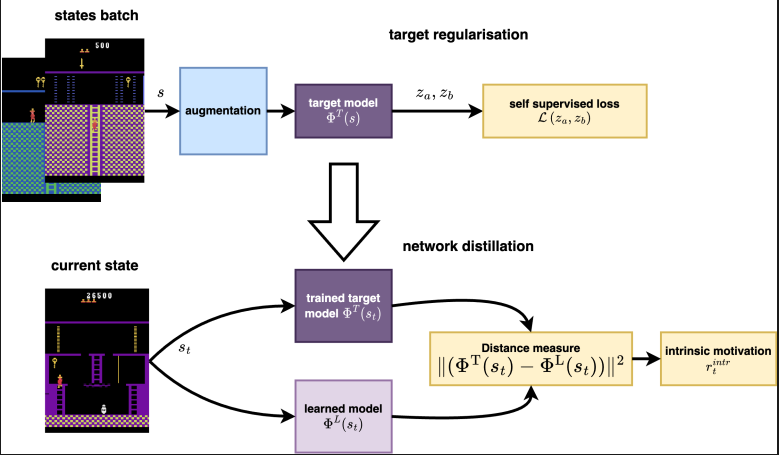
# random network distillation




- 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**

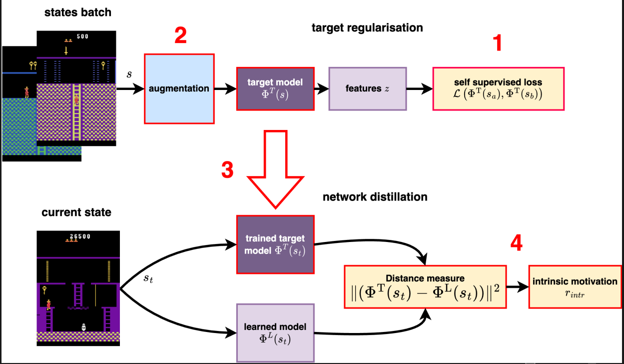
# Exploration by self supervised-exploitation

Matej Pecháč, Michal Chovanec, Igor Farkaš



# Exploration by self supervised-exploitation

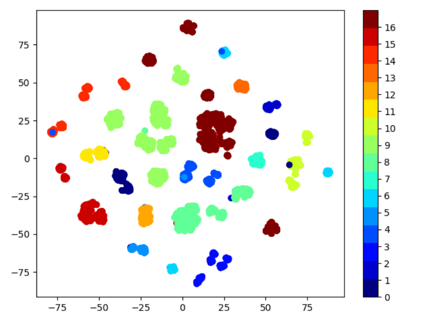
- we extended existing idea of Random Network Distillation
- 1 : for target model, self supervised training is used
- 2 : augmented states are used to train target model
- 3 : target model is used as distillation source
- 4 : distillation error is used for intrinsic motivation



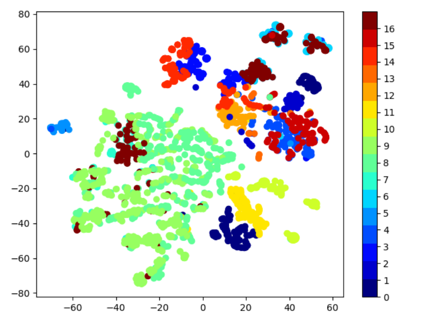
# Trained features

- 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



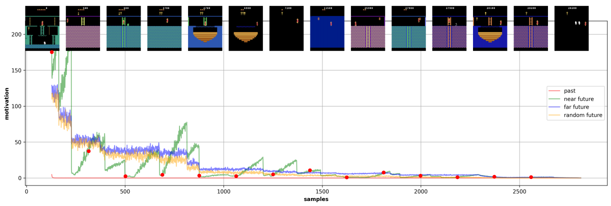

self supervised trained features



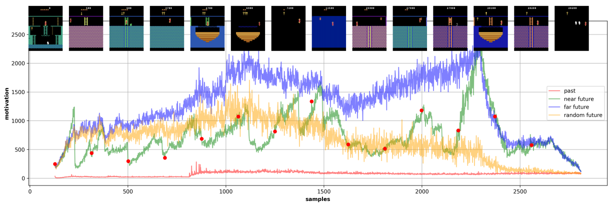
# Exploration signal

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

## Random Network Distillation

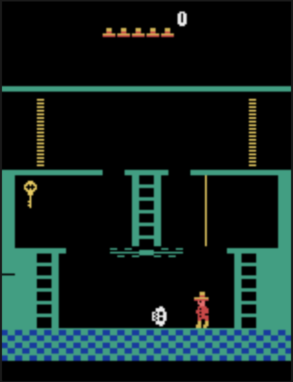



## our method



# Results

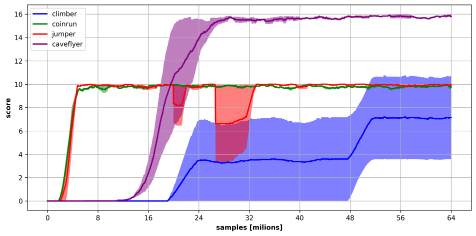
- Montezuma's Revenge, with score 25 000+
- Private Eye, with score 12 000+
- Venture, Gravitar
- 128M samples total - only single GPU needed




# 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

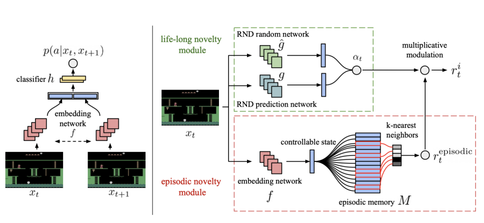
- not working on REAL hard exploration problems
- Super Mario is special case - moving forward is close to optimal policy
- inverse ICM model - why they didn't shown accuracy (my results arround only 40% !!!)
- how predicted state looks ?

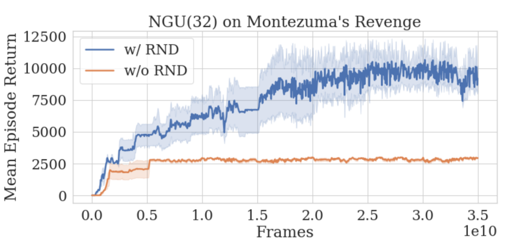
| | Gravitar | Montezuma's Revenge | Pitfall! | PrivateEye | Solaris | Venture |
|---|---|---|---|---|---|---|
| RND | **3,906** | **8,152** | -3 | 8,666 | 3,282 | **1,859** |
| PPO | 3,426 | 2,497 | 0 | 105 | 3,387 | 0 |
| Dynamics | 3,371 | 400 | 0 | 33 | 3,246 | 1,712 |
| SOTA | 2,209[1] | 3,700[2] | **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

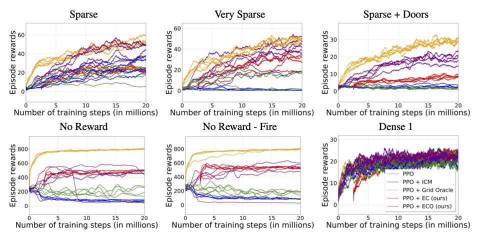
nice looking score, but on cost of $3.5 * 10^{10}$ samples !!!



# 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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