

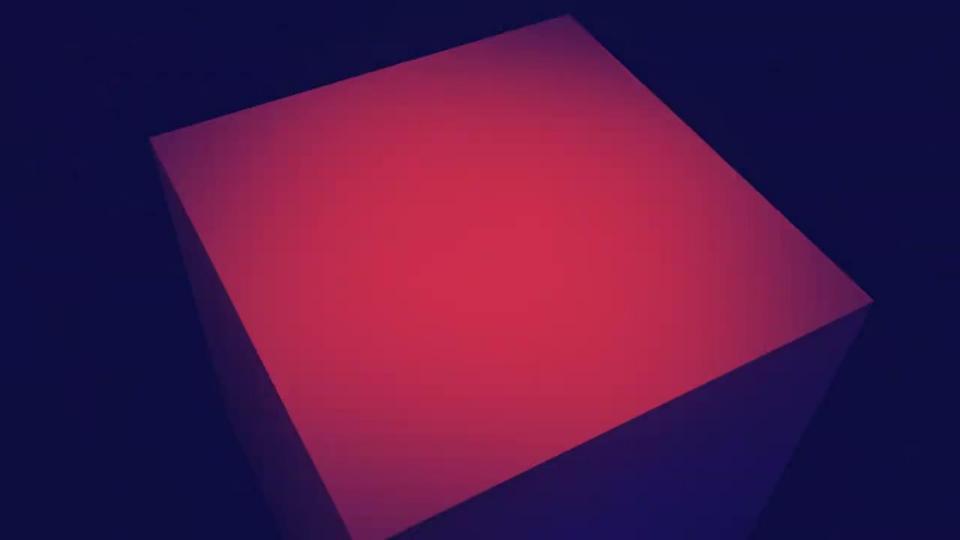
SEED // SEARCH FOR EXTRAORDINARY EXPERIENCES DIVISION

# **ML in Game Production**

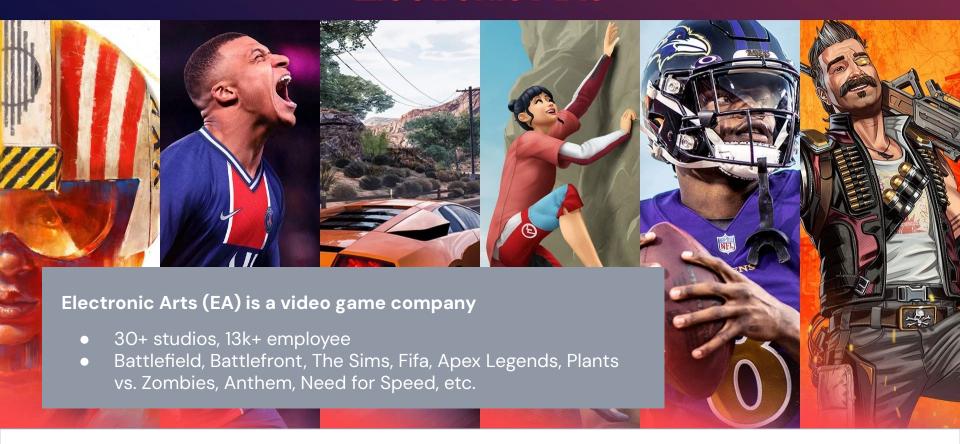
Linus Gisslén - ML Technical Director SEED - EA

# Purpose with this talk

- To show interesting challenges and solutions using ML in games and game production.
- To show why **ML is, and will continue to be important** for game production in the future.
- Present some **opportunities** for research in this domain and to foster even more **collaboration** between academia and industry.
- Excite you about the possibilities to work with this!



# **Electronic Arts**





## SEED

## **Search for Extraordinary Experiences Division**

SEED is an advanced R&D department at EA. Our mission is **to explore**, **build**, **and help define the future of interactive entertainment** 

Locations: Stockholm // San Francisco // LA // Vancouver // Montreal // Remote

#### We exist to:

- Explore risky topics
- Research new technologies for innovative concepts to emerge
- Empower EA to create even greater experiences for our players





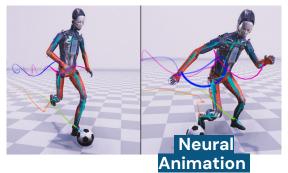
## **About SEED: Our different research vectors**













# **SEED partnerships**

## Current academic partnerships:

- BAIR: Pieter Abbeel, Trevor Darrell, Angjoo Kanazawa
- KTH: TMH, Robotics, Digital Future, etc.
- University of Houston
- University of Florence: Andy Bagdanov
- WASP WARA Media & Language

Bridge between academia and industry.





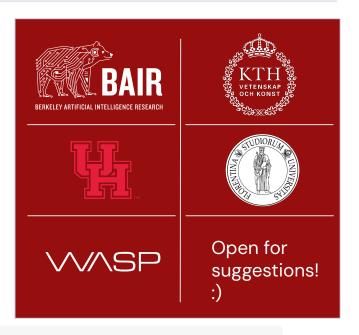












# ML for game production



# Motivation for ML in game production

Today's games are often huge and requires years of development

Case study: Red Dead Redemption 2

• Cost: ~\$500M

• Time: ~8 years of development

Staff: ~2000 persons



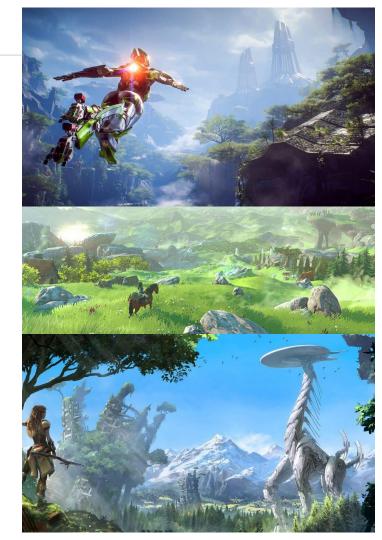
# **Trend in games**

## Trend in AAA games:

- Open world
- Higher quality assets, more detail
- Deeper interactions

Trend continues for industry and EA. Automation and tools to create new generation of games is crucial.

ML is ideal for this and in this talk I will give some example of research in this direction.





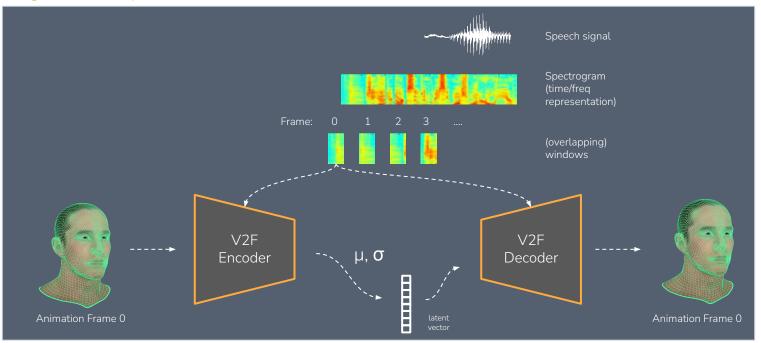
## **Automated facial animations**

### Motivation

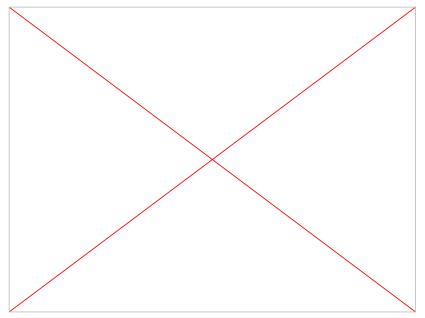
- Creating facial animations is very tedious, takes days to do minutes of animations
- Existing automated (non-ML) methods are not very good
- E.g. Real-time animation on player speech would unlock new experiences

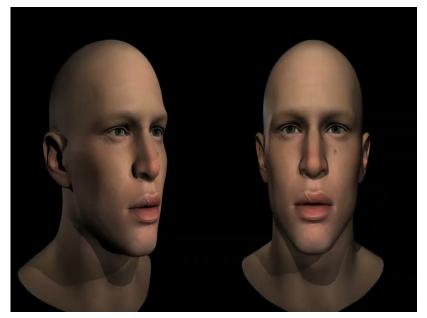
## Voice2Face

## Generating Facial Expressions from Voice



## Voice2Face





Results: English Non-English

Voice2Face: Audio-driven Facial and Tongue Rig Animations with cVAEs Aylagas MV, Leon HA, Teye M, Tollmar K Computer Graphics Forum 2022 BATTLEFIELD

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# **Expressive Voice2Face**



Comparison, different emotions



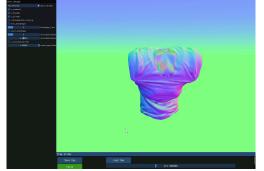
## Swish: Neural Cloth Simulation on Madden 21-24

### Adding wrinkles in Jerseys with ML

- Training data:
  - Plausible poses extracted from game
  - Cloth generated in Marvelous Designer was paired with the pose. Post-processing with Maya to optimize for speed.
- Train a simple neural network pose -> mesh
- Inference time; 140  $\mu$ s -> Cheaper than standard real-time cloth deformation



Visual target



Training data sample

## Swish: Neural Cloth Simulation on Madden 21-24

Adding wrinkles in Jerseys with ML

#### Swish: Neural Network Cloth Simulation on Madden NFL 21

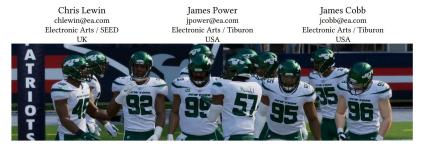
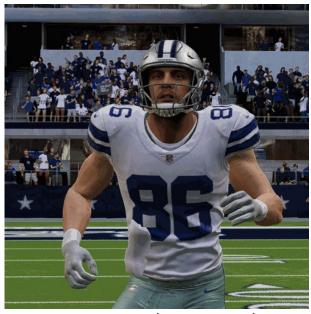


Figure 1: Player jerseys in Madden NFL 21 simulated using our system.

Swish: Neural Network Cloth Simulation on Madden NFL 21. C. Lewin, J. Power, J. Cobb. ACM SIGGRAPH 2021.



Results in-game (Madden 21)

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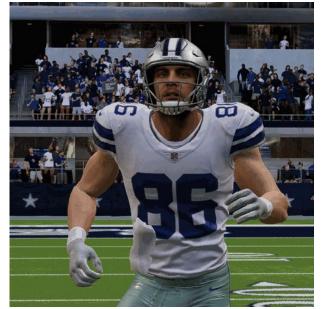
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## Swish: Neural Cloth Simulation on Madden 21-24

Adding wrinkles in Jerseys with ML

#### Potential future research:

- More loosely fit garment: dresses, capes, scarves, etc.
- Other cloth objects such as flags and tents
- Other types such as trees, grass, waves, etc.



Results in-game (Madden 21)

Swish: Neural Network Cloth Simulation on Madden NFL 21. C. Lewin, J. Power, J. Cobb. ACM SIGGRAPH 2021.



# **Self-Learning Agents**

Data driven behaviour generation

Benefits over traditional methods (scripting):

- No scripting/programming needed: more accessible to everyone
- Re-train instead of re-script: Less manual work
- Automated (can run overnight): potentially faster
- Can solve problems that scripting can not: adds functionality



# **Self-Learning Agents for Game Al**

Some lessons learned from adding RL to Battlefield 2018:

- Artists needs explicit control over behaviours/visuals
- Inference (run-time) took too much resources
- Player facing ML is difficult, no room for failures
- It did not fit in into the existing pipeline of game creation
- Expertise on the "receiving" end did not exist, i.e. hard to retrain when needed



\*RL agents playing Battlefield 1



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<sup>\*</sup>Imitation Learning with Concurrent Actions in 3D games, J Harmer, et. al CoG 2018

# **Self-Learning Agents for Game Testing**

- No artist needs to see the failures
- No run time needed, at least not critical
- Not player facing
- Needs to fit into existing pipeline
- Expertise on the "receiving" end needed

3/5 is not too bad odds!



Test-bed for game testing algorithms



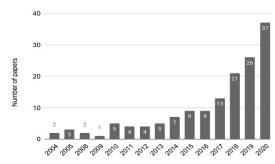
# First use-case: Automated Game Testing

"In Battlefield V testing all maps and modes for 1 hour requires 2304h of testing. **288**people to test that every day. If we add more maps and modes this number will be larger."

All for Testing: The Development of Bots that Play 'Battlefield V' Jonas Gillberg - GDC 2019

#### Problem statement:

- Automatic testing is difficult, requires scripting of bots
- Large game and open world games with procedural content doesn't scale well with current solutions
- Testing of user generated content requires new solutions, something that can adapt



Trend in research: exponential growth in published papers on "Automated game testing"\*

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<sup>\*</sup>Towards Automated Video Game Testing: Still a Long Way to Go C. Politowski, YG Guéhéneuc, F Petrillo, ICSE Workshop on Games 2022 Electronic Arts

# **Automated Game Testing with Reinforcement Learning (RL)**

Goal for RL is to maximize reward -> exploitation

Finding exploits without being "told" (see right)

Algorithm learns, therefore:

- No scripting required
- Retrain instead of rewriting scripts
- Unpredictable and teachable: more "human like" control
- Explorative: by figuring out how to play it covers more game states

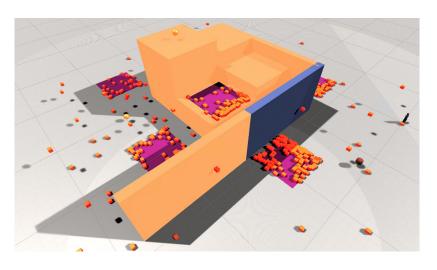


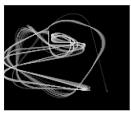
Courtesy: Open Al blog Faulty reward functions in the wild



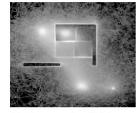
## **Automated Game Testing**

High game state coverage -> more bugs found -> better testing. A RL case study.

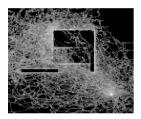




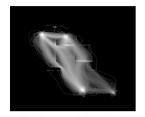
(a) Scripted NavMesh agent.



(c) RL agent after 30 M steps.



(b) RL agent after 5 M steps.



(d) RL agent fully trained.

Augmenting automated game testing with deep reinforcement learning J Bergdahl, C Gordillo, K Tollmar, L Gisslén. CoG 2020

# Problem: RL does not always generalize well

## Inspiration:

- Idea: That training on procedurally generated content improves generalization in RL agents\*
- Idea: That RL can be used for PCG\*\*
- 3. Idea: Posing increasingly difficult (progressive PCG) problems increase learning capacity\*\*\*

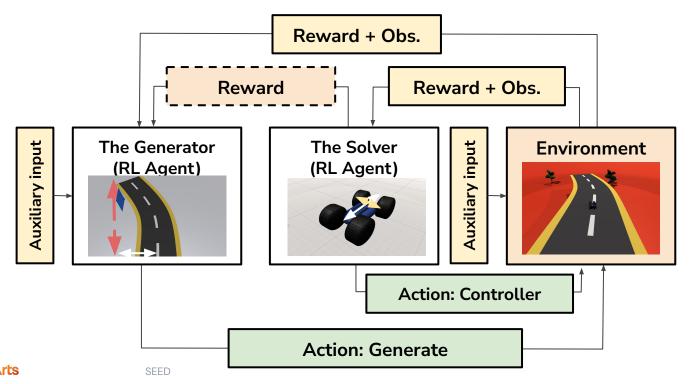
Proposed solution: Generator RL and Solver RL pair. With the feedback from the Solver the Generator can learn to make difficult but not impossible maps.

<sup>\*</sup> Increasing Generality in ML through PCG. Risi S & Togelius J Nature Machine Intelligence 2020

<sup>\*\*</sup> Pcgrl: Procedural content generation via reinforcement learning Khalifa A, Bontrager P, Earle S, Togelius J. AlIDE 2020

<sup>\*\*\*</sup> Illuminating generalization in deep reinforcement learning through procedural level generation Justesen, Niels, et al. ArXiv 2018

## **ARLPCG: Adversarial RL for Procedural Content Generation**



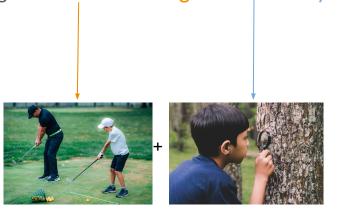
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# Automatic Gameplay Testing with Curiosity-Conditioned Proximal Trajectories

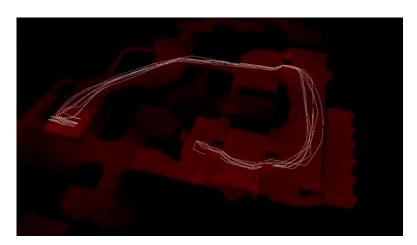
Combining Imitation Learning and Curiosity for guided exploration.



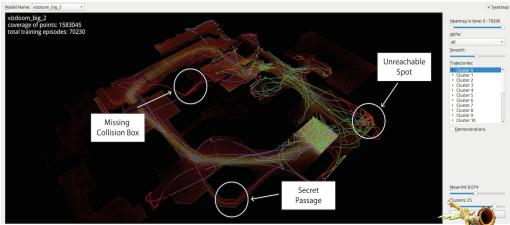


# Automatic Gameplay Testing with Curiosity-Conditioned Proximal Trajectories

Combining Imitation Learning and Curiosity for guided exploration.



Human demonstration in VizDoom



Algorithm exploration includes a unknown passage

Automatic Gameplay Testing with Curiosity-Conditioned Proximal Trajectories





# Technical Challenges of Deploying Reinforcement Learning Agents for Game Testing in AAA Games

• Time: 13:50, Wednesday August 23rd. Location: ISEC 102



Technical Challenges of Deploying Reinforcement Learning Agents for Game Testing in AAA Games J Gillberg, J Bergdahl, A Sestini, A Eakins, L Gisslén. Conference on Games (CoG) 2023

## **Self-learning Agents for Game Design**

#### The Problem

- Game testing is today often a long process with long lead times. Testing happens often in another phase than design phase.
- Test results comes too late for it to be efficient use of data, and sometimes too late for corrections to be added in production.

### Proposed solution

- Let expert (game designers) demonstrate how level should be played.
- ML agents learn from that data, and plays the game accordingly.
- Move the testing "upstream" i.e. in the hands of the creators/designers.



### **Self-Learning Agents for Game Design**

#### Requirements for this use-case

- End-user (game designers, etc.) does not know ML (so reward shaping is difficult)
- No, or little, exploration and exploitation is desirable
- Speed: Has to be fast enough to be used in production
- Generalization: Small changes should not lead to re-training
- Controllability: Human Personas is important in game design. This should be incorporated.



## **Imitation Learning for Game Design**





# Towards Informed Design and Validation Assistance in Computer Games Using Imitation Learning

• 11:00, Thursday August 24th. Location: ISEC 140

## Towards Informed Design and Validation Assistance in Computer Games Using Imitation Learning

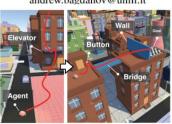
Alessandro Sestini<sup>1</sup>, Joakim Bergdahl<sup>1</sup>, Konrad Tollmar<sup>1</sup>, Andrew D. Bagdanov<sup>2</sup>, Linus Gisslén<sup>1</sup>

\*\*ISEED - Electronic Arts (EA), <sup>2</sup>Università degli Studi di Firenze

\*\*{asestini, jbergdahl, ktollmar, lgisslen}@ea.com

\*\*andrew.bagdanov@unifi.it\*





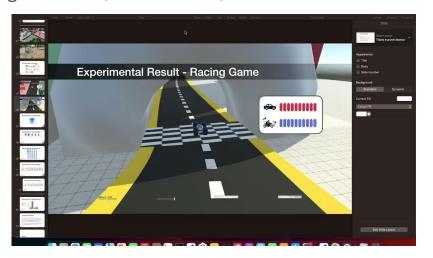


Towards Informed Design and Validation Assistance in Computer Games Using Imitation Learning A Sestini, J Bergdahl, A Bagdanov, K Tollmar, L Gisslén. Conference on Games (CoG) 2023

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# Generating Personas for Games with Multimodal Adversarial Imitation Learning

• 09:40 Thursday August 24th (Best of CoG). Location: ISEC 102



Generating Personas for Games with Multimodal Adversarial Imitation Learning W Ahlberg, A Sestini, K Tollmar, L Gisslén Conference on Games (CoG) 2023

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## Potential use cases/research for ML in games





### Caveat

### My prediction (in 2011, when I started in AI):

2025

Unloading dishwasher Cleaning Self-driving cars



SEED

2050

Poetry Art Music



#### Caveat

## The NeverEnding Game: How Al Will Create a New Category of Games

by Jonathan Lai

#### Reality (now):

2025

Poetry Art Music



2050

Unloading dishwasher Cleaning Self-driving cars



## Future of ML in games and game production Dialogues with NPCs



GPT4 for NPCs demo from May 2023 Courtesy: NVIDIA

#### Possible use-cases for LLMs:

- NPC dialogue (see video)
- Player coach
- Brainstorm tool
- Side-quest generator
- Game commentator
- Etc. etc.



Use case: NPC dialogue (pauses are cut).

GPT3 demo from Feb 2021. Courtesy: Lee Vermeulen



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- The industry is moving from manual and scripted to data driven methods
- Data driven content generation + data driven behaviour.
- As ML tools becomes more available -> domain knowledge will be more important



Courtesy: Midjourney Al Art

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#### Challenges for data driven solutions

- **Curation:** how do we filter? Guard-rails for player facing ML.
- **Speed:** Generation might be expensive and slow, especially in real-time applications.
- Control: How can we control the output and make sure it fits with the narrative
- **Data:** Acquisition or generation of data is a non-trivial process and highly affects the quality of the models

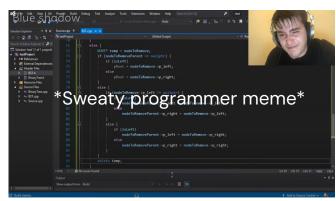


## SPECULATIVE: Game creation will change significantly in 5–10 years

- As algorithm becomes more "intelligent" game devs and designers role will become more a of a movie director rather than to explicit instruct/create
- Devs will be able to instruct by natural language and show by examples

#### **Current state**

- Programming of behaviours
- Largely manually creation of assets



"If(playerDistance < attackDistance) Attack(player);"

#### **Future**

- Demonstrating behaviours
- Showing examples to generate new assets
- Instructing through natural language



"Attack the player when they come too close"



## Summary

We believe that ML and AI has the potential to radically change the way we create games

So far the industry have only explored a fraction of what's possible using ML/AI

Change is coming to game production, you better **be prepared**:)



## Thank you for listening!

seed.ea.com

Contact: Linus Gisslén (lgisslen@ea.com)

#### References

- 1. Generating Personas for Games with Multimodal Adversarial Imitation Learning W Ahlberg, A Sestini, K Tollmar, L Gisslén Conference on Games (CoG) 2023
- 2. Technical Challenges of Deploying Reinforcement Learning Agents for Game Testing in AAA Games J Gillberg, J Bergdahl, A Sestini, A Eakins, L Gisslén. Conference on Games (CoG) 2023
- 3. Towards Informed Design and Validation Assistance in Computer Games Using Imitation Learning A Sestini, J Bergdahl, A Bagdanov, K Tollmar, L Gisslén. Conference on Games (CoG) 2023
- 4. Neural Synthesis of Sound Effects Using Flow-Based Deep Generative Models S Andreu, M Villanueva Aylagas AllDE 2022
- 5. Voice2Face: Audio-driven Facial and Tongue Rig Animations with cVAEs Monica Villanueva Aylagas, Hector Anadon Leon, Mattias Teye, Konrad Tollmar
- 6. Swish: Neural Network Cloth Simulation on Madden NFL 21. C. Lewin, J. Power, J. Cobb. ACM SIGGRAPH 2021.
- 7. Imitation Learning with Concurrent Actions in 3D games, J Harmer, L Gisslén, J del Val, H Holst, J Bergdahl, T Olsson, K Sjöö, M Nordin. Conference on Computational Intelligence and Games 2018
- 8. Augmenting automated game testing with deep reinforcement learning J Bergdahl, C Gordillo, K Tollmar, L Gisslén. Conference on Games CoG 2020
- 9. Improving Playtesting Coverage via Curiosity Driven Reinforcement Learning Agents C Gordillo, J Bergdahl, K Tollmar, L Gisslén. CoG 2021
- 10. Automated Gameplay Testing and Validation with Curiosity-Conditioned Proximal Trajectories A Sestini et. al 2022
- 11. Adversarial Reinforcement Learning for Procedural Content Generation L Gisslén, A Eakins, C Gordillo, J Bergdahl, K Tollman
- 12. Automatic Testing and Validation of Level of Detail Reductions Through Supervised Learning, Tamm et. al CoG 2022
- 13. Using deep convolutional neural networks to detect rendered glitches in video games, C. Ling, K. Tollmar, L. Gisslén AIIDE 🐲