

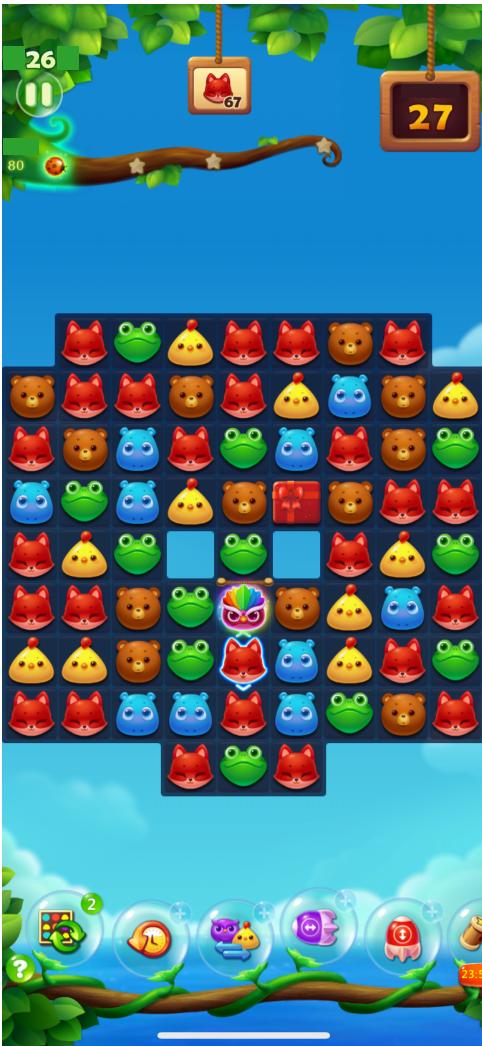


**MAKE  
THE  
WORLD  
HAPPY**

# **Generating the Best Game Experience through AI**

**Rein Houthooft**

# Introduction

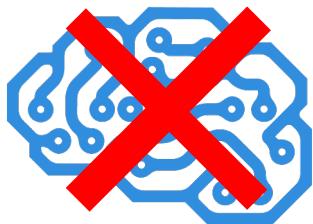


- Company focus: **casual** mobile games
- Main product: “**Anipop**” 
- Extremely popular (>**100M** users/month)
- Generates **TBs** of data each day
- **AI Lab** founded 1 year ago

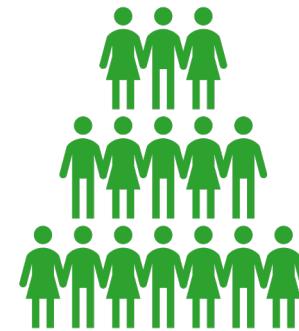


# AI Lab: Goals & Strategy

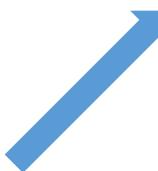
# Open-loop to Closed-loop Game Design



Sparse feedback



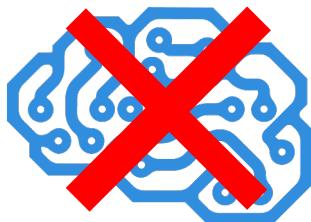
Little Optimization



# Open-loop to Closed-loop Game Design

- Product-player preferences mismatch
- Designers slow in adapting to changing player behavior
- Lower player satisfaction

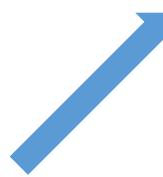
# Open-loop to Closed-loop Game Design



Dense feedback



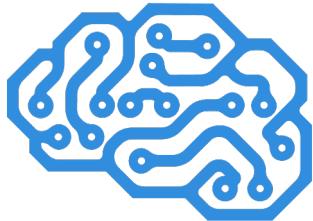
Rule-based Optimization



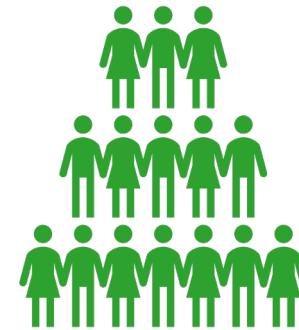
# Open-loop to Closed-loop Game Design

- Some adaptation to changing player preferences
- Low granularity
- Hard to maintain over time

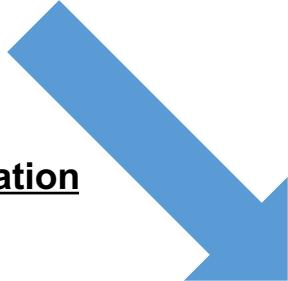
# Open-loop to Closed-loop Game Design



Dense feedback



ML-based Optimization



# Open-loop to Closed-loop Game Design

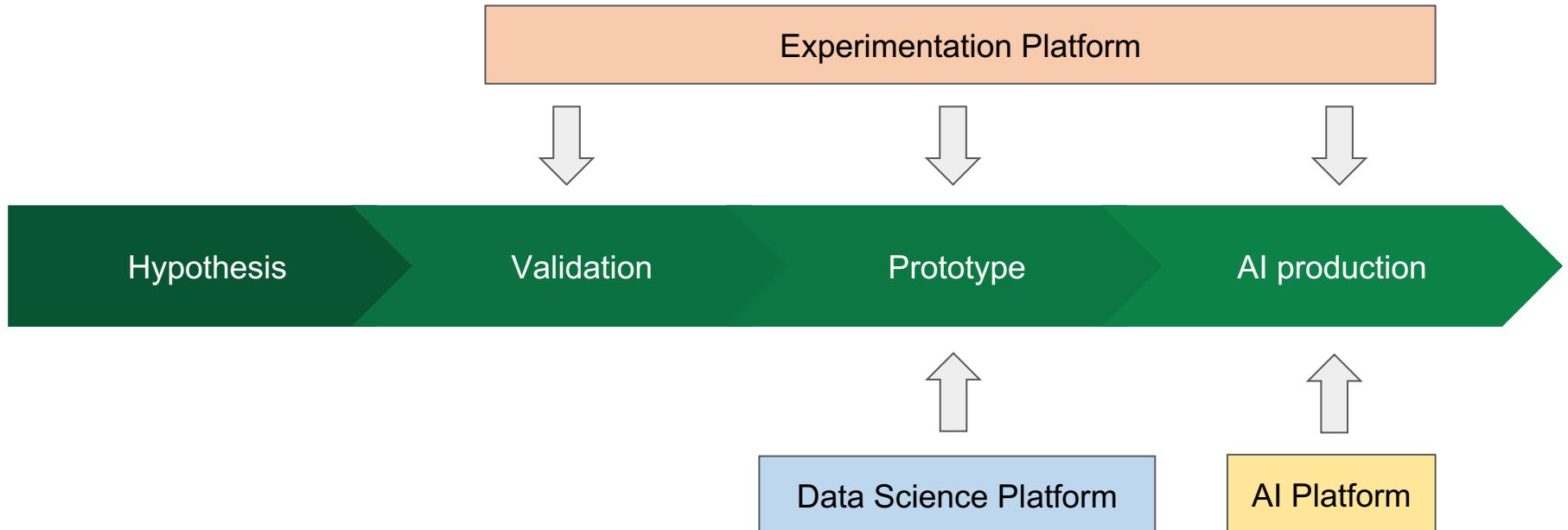
- Immediate adaptation to changing player preferences
- High granularity
- Maintains itself through objective function optimization



# **Sample AI Lab Project:**

## **Deep Learning for Game Difficulty Adjustment**

# From Hypothesis to Production



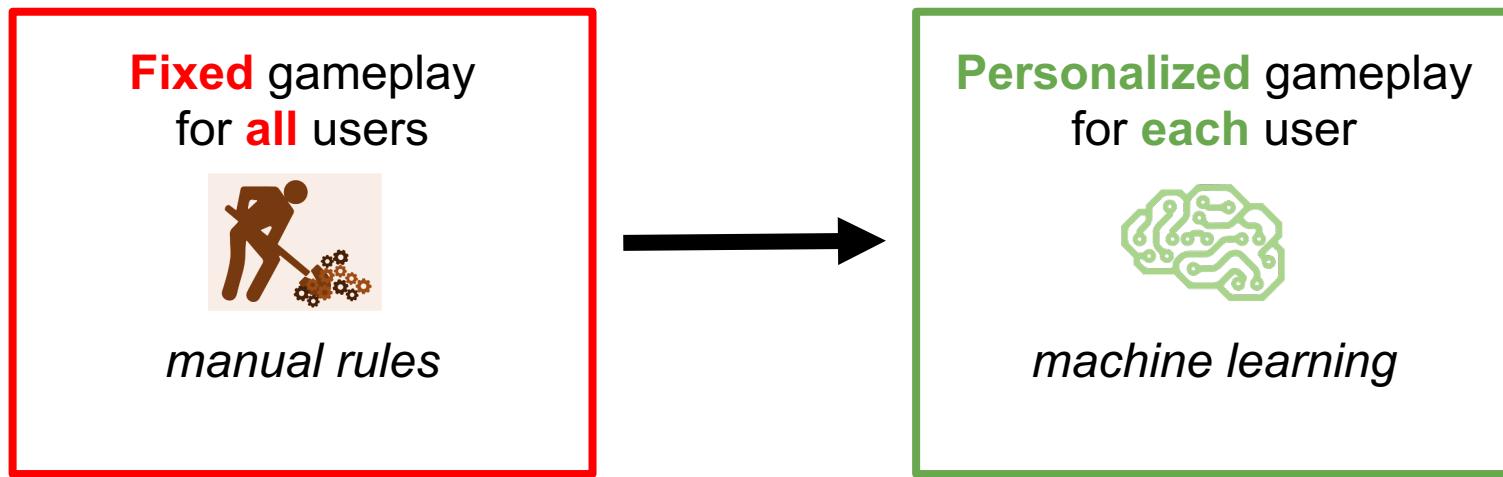
# Game Difficulty Adjustment

- Hypothesis: preferred difficulty varies across users & time.
- Validation: difficulty correlates with LTV/retention.
- Prototype + Production: adjust difficulty dynamically via ML.

# Problem Formulation

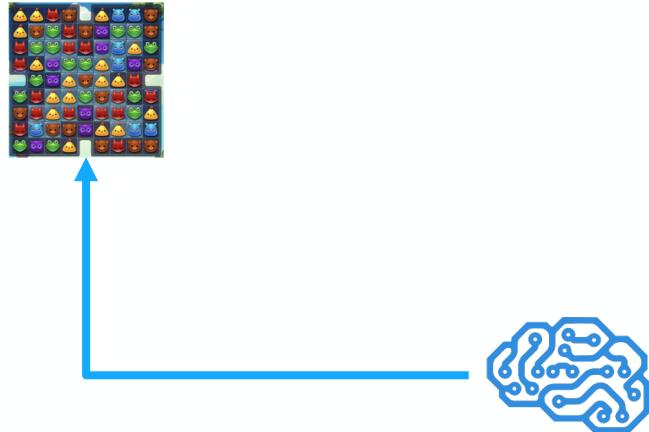


# Problem Formulation



# Problem Formulation

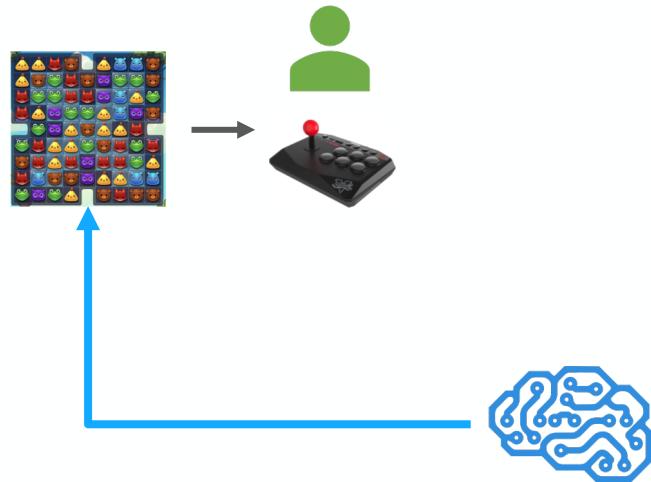
Gameplay modification: Action sequences



Objective: Rewards = player revenue/retention

# Problem Formulation

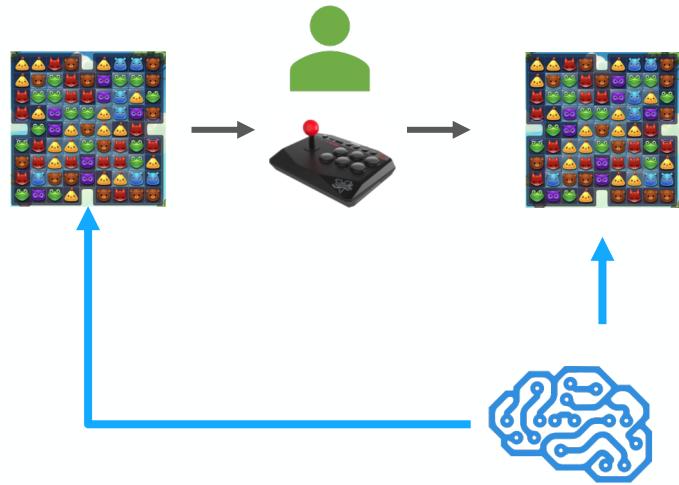
Gameplay modification: Action sequences



Objective: Rewards = player revenue/retention

# Problem Formulation

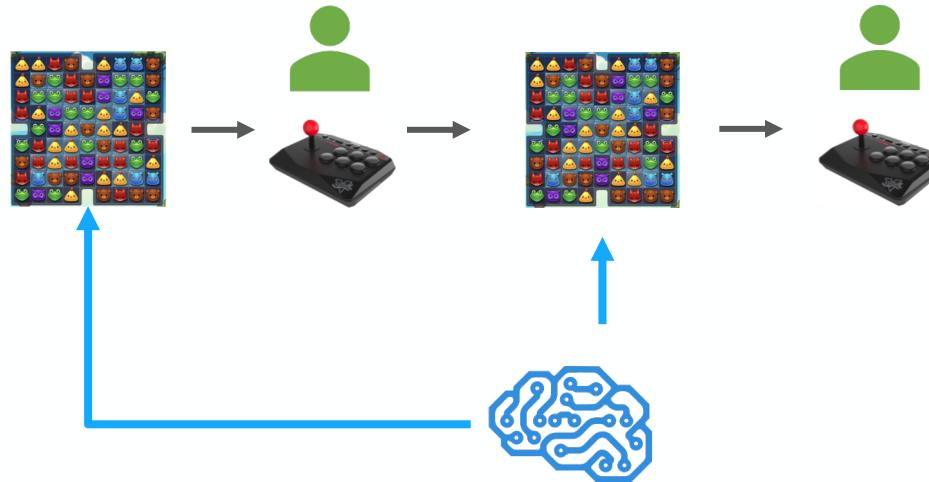
Gameplay modification: Action sequences



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# Problem Formulation

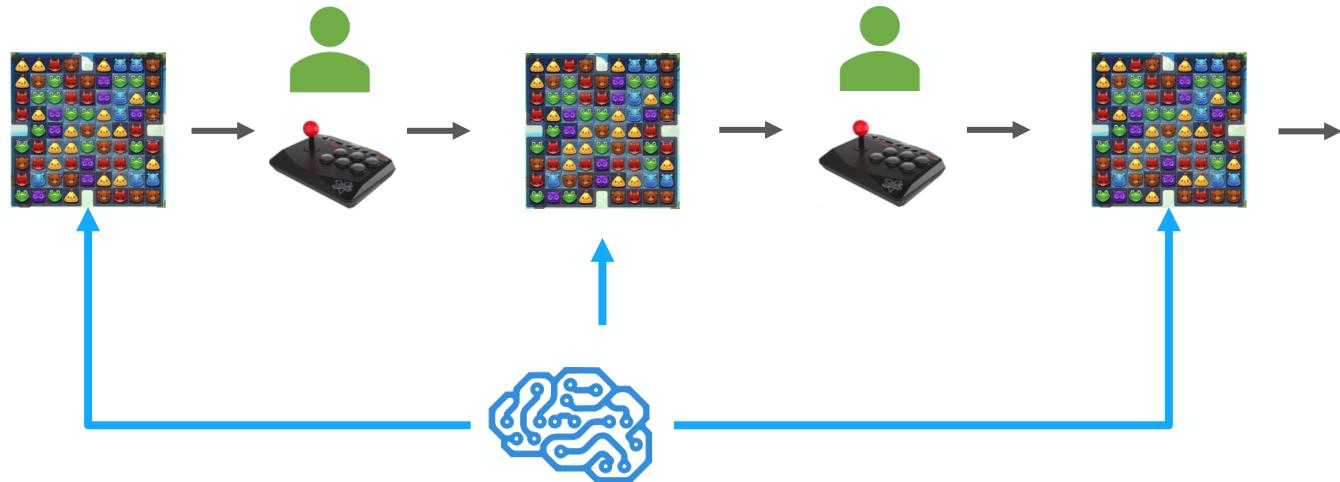
Gameplay modification: Action sequences



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# Problem Formulation

Gameplay modification: Action sequences



Objective: Rewards = player revenue/retention

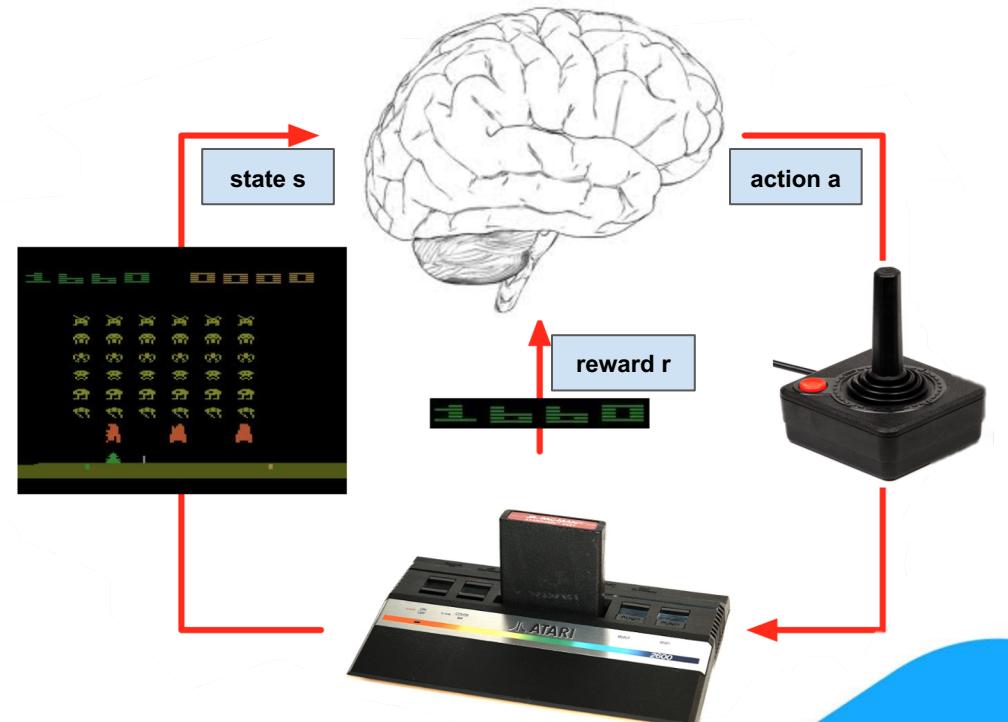
# Deep Reinforcement Learning

- Reinforcement learning defines problem via high-level **objective**
- Deep learning is a **paradigm** for building flexible **solutions**
- Deep reinforcement learning integrates both above points

# Problem Formulation

## Reinforcement Learning:

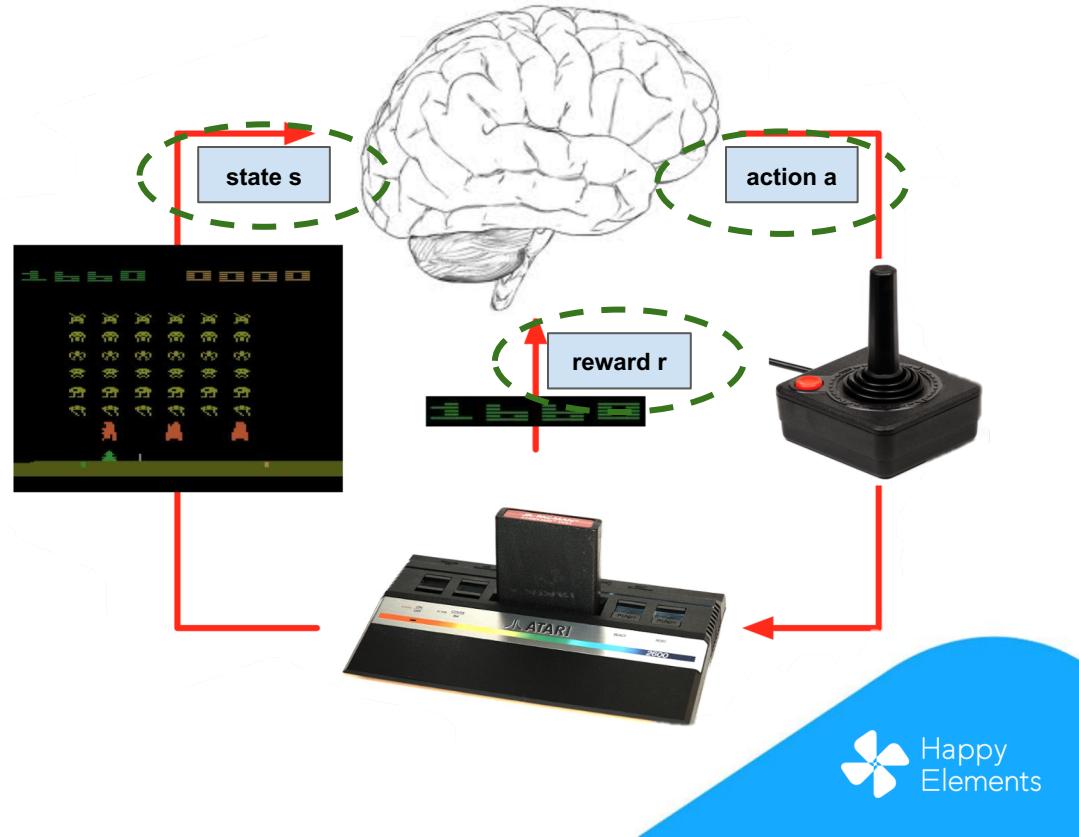
- What **action  $a$**  to take in **state  $s$**  to **optimize** the expected **reward  $E[r]$** ?
- For example, video game:
  - state  $s$  = screen
  - action  $a$  = controller
  - reward  $r$  = score



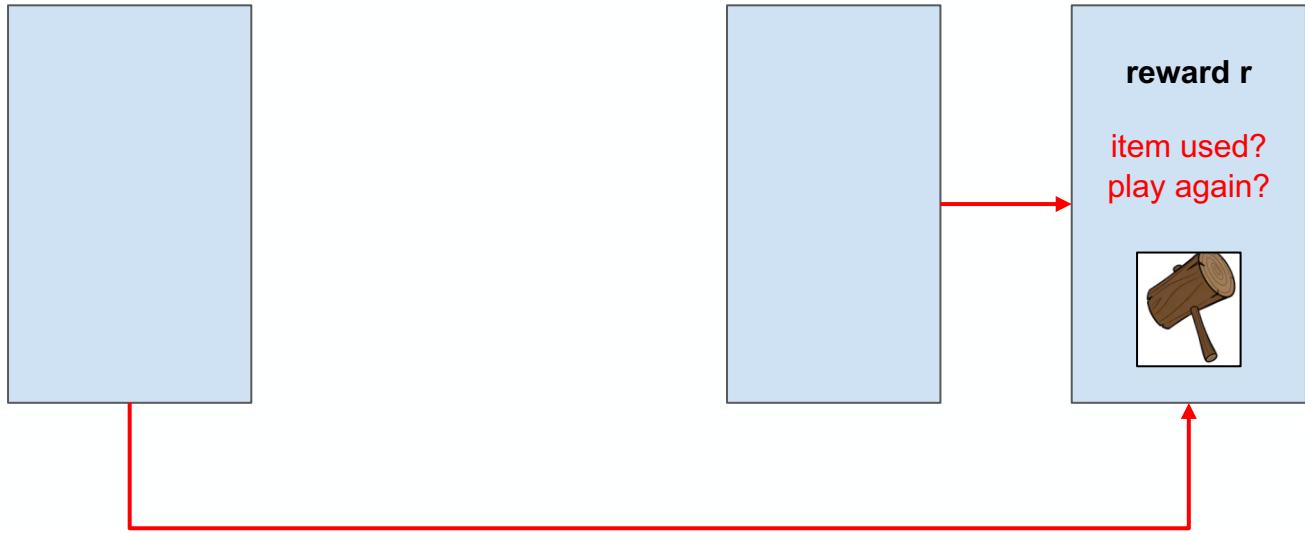
# Problem Formulation

## Reinforcement Learning:

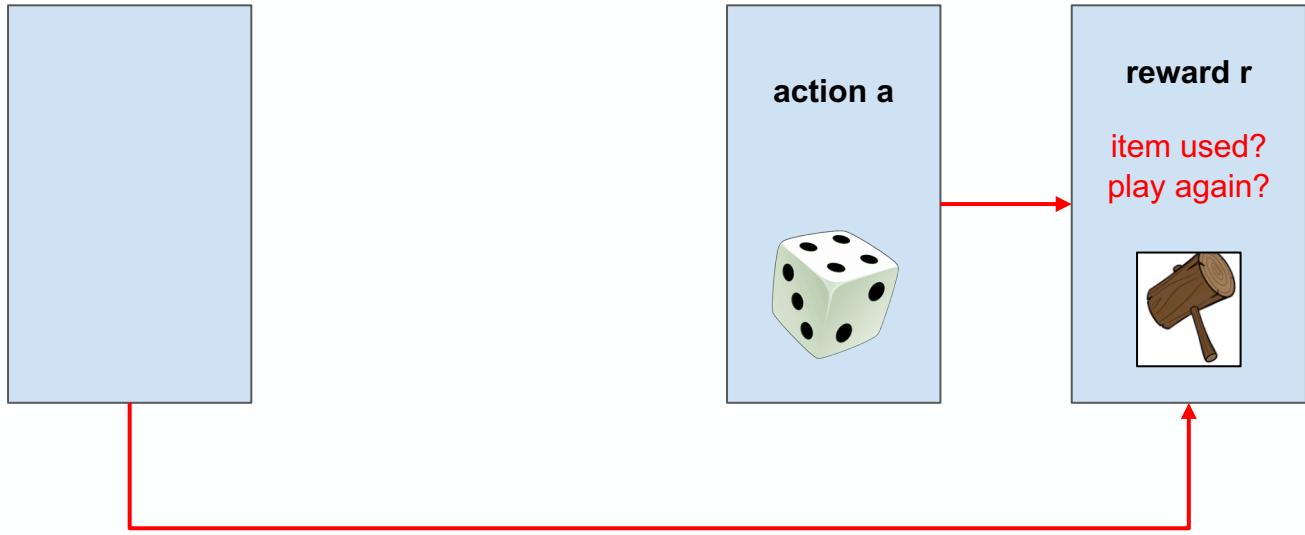
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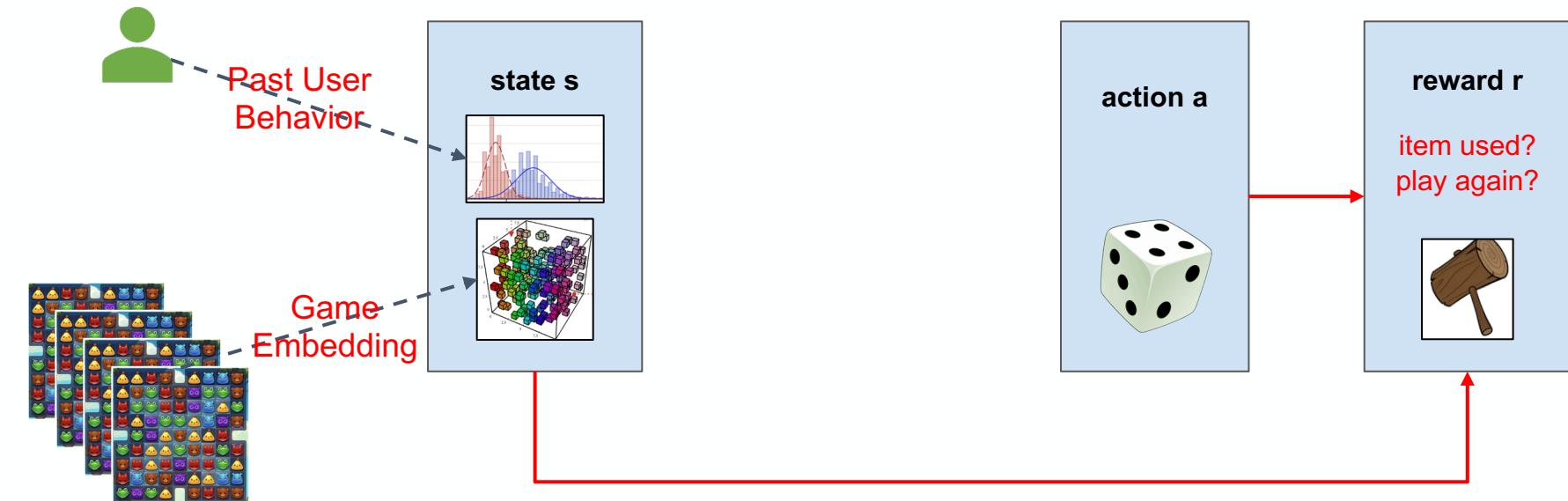
# Reinforcement Learning



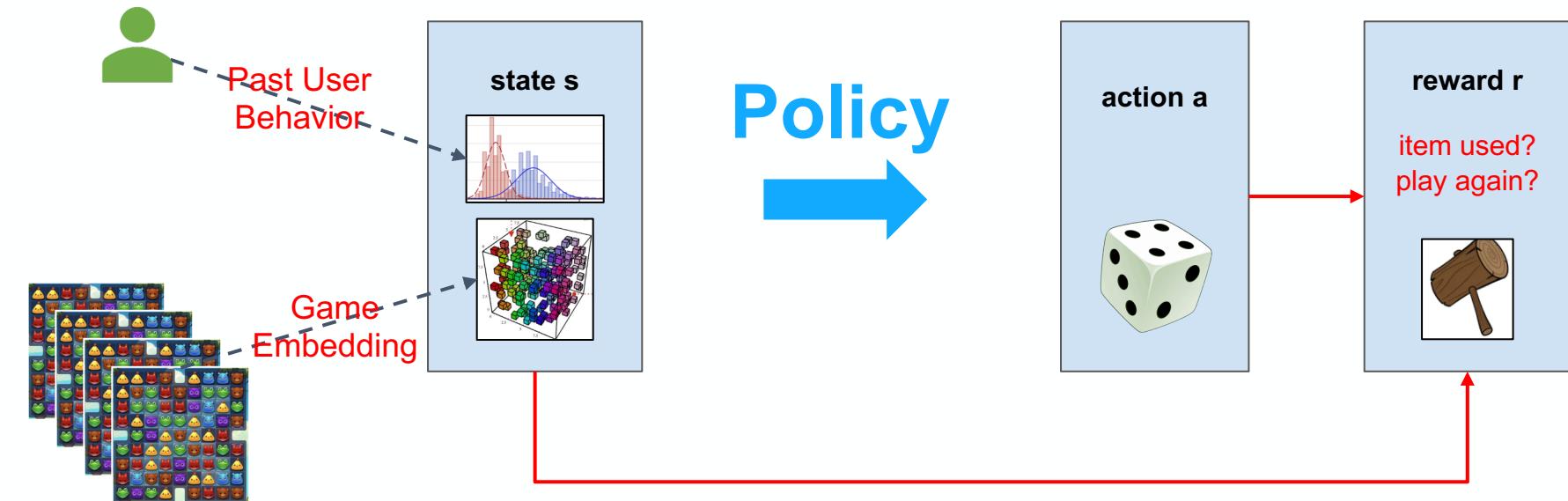
# Reinforcement Learning



# Reinforcement Learning



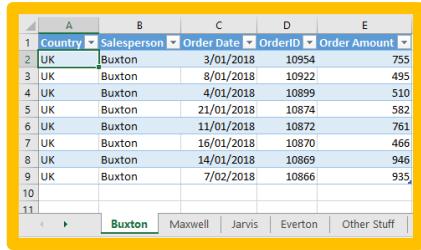
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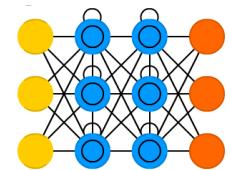
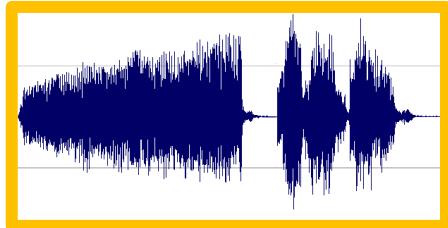
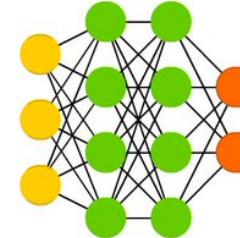
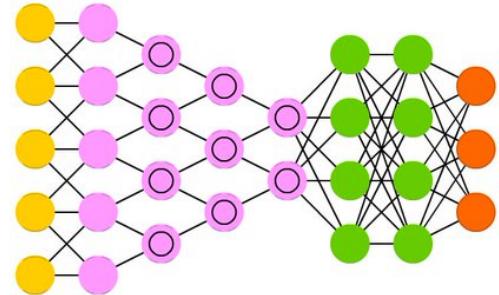
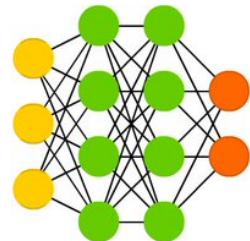
# Deep Learning

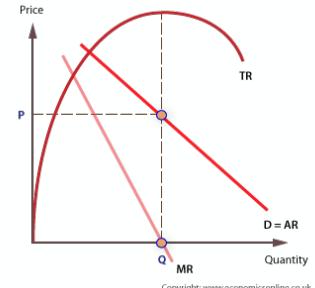
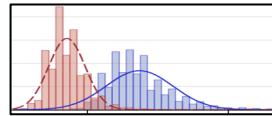
- Paradigm shift rather than new technique
- Ability to **optimize any sort** of target using **any type** of data flow
- Extremely **flexible** in fusing and integrating **heterogeneous data**

# Deep Learning

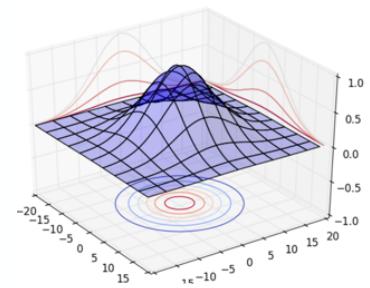
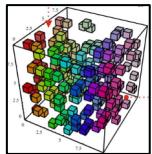


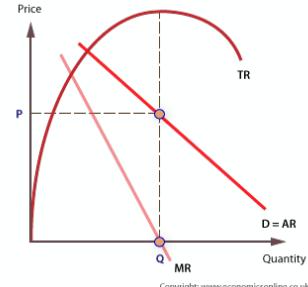
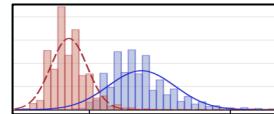
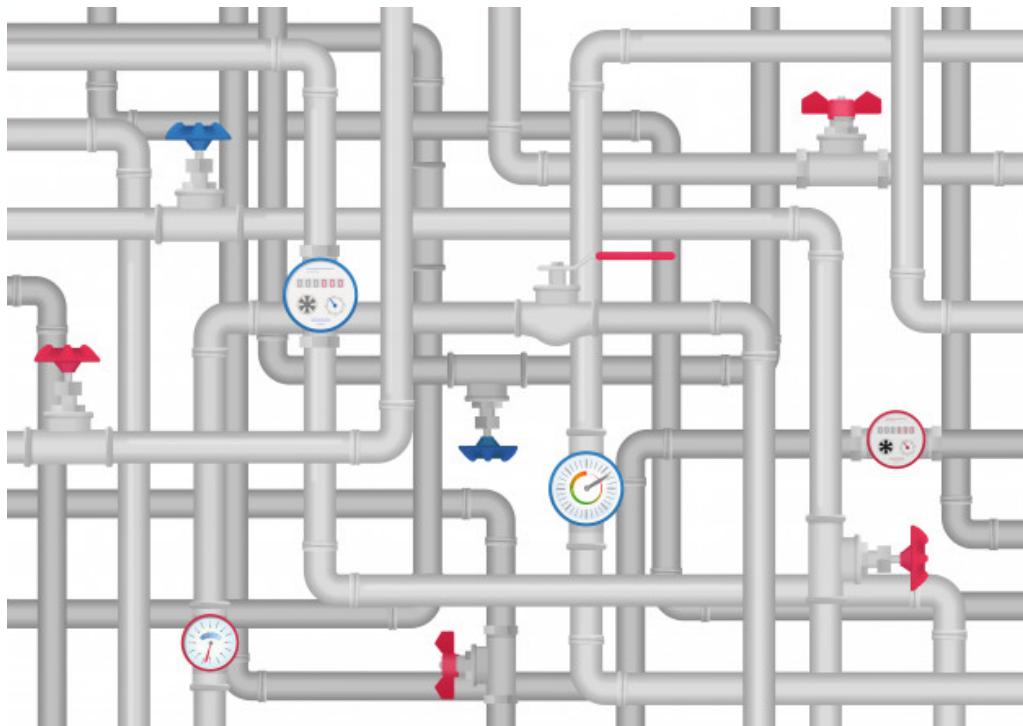
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UK	Buxton	21/01/2018	10874	582
UK	Buxton	11/01/2018	10872	761
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UK	Buxton	7/02/2018	10866	935



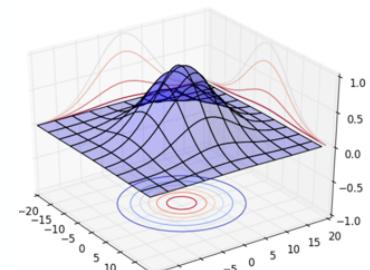


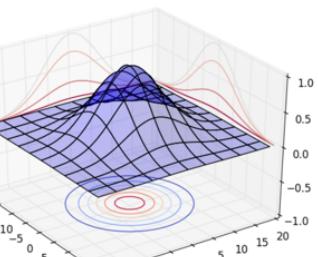
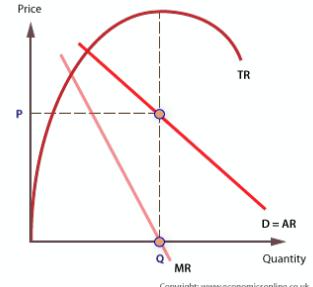
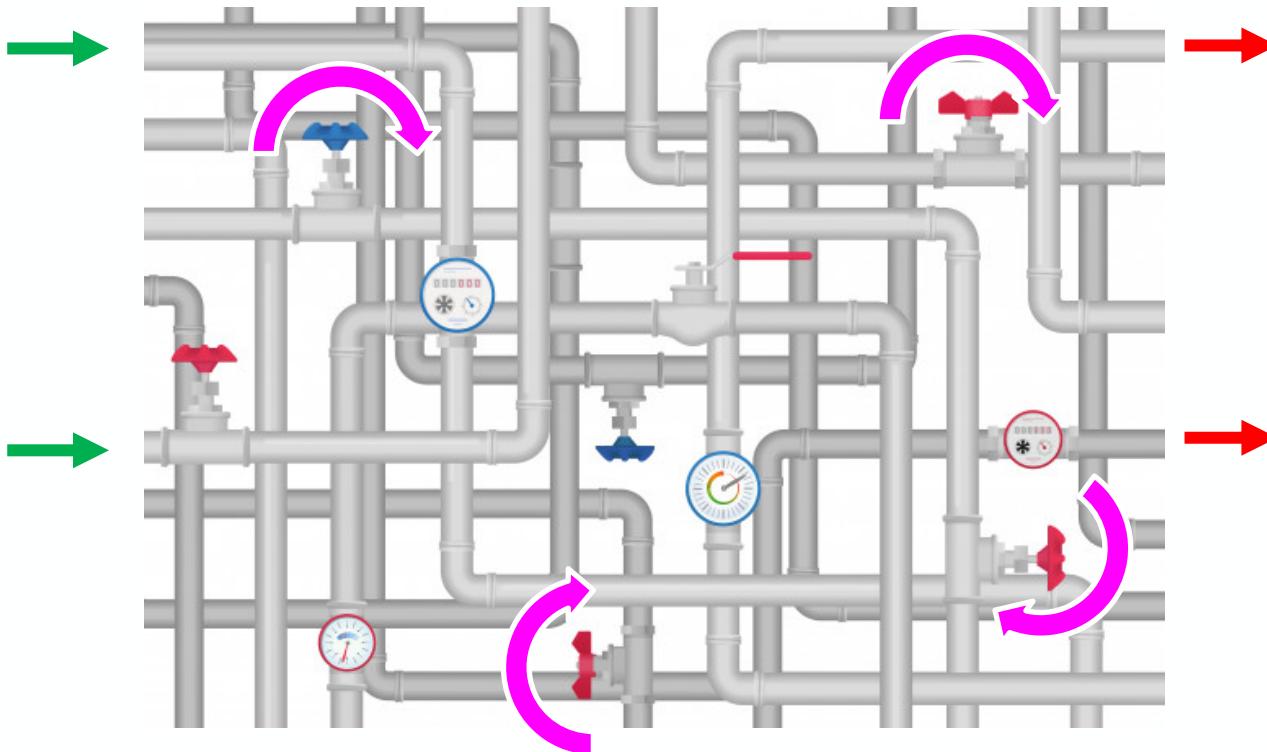
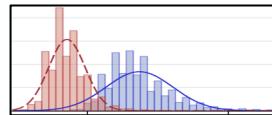
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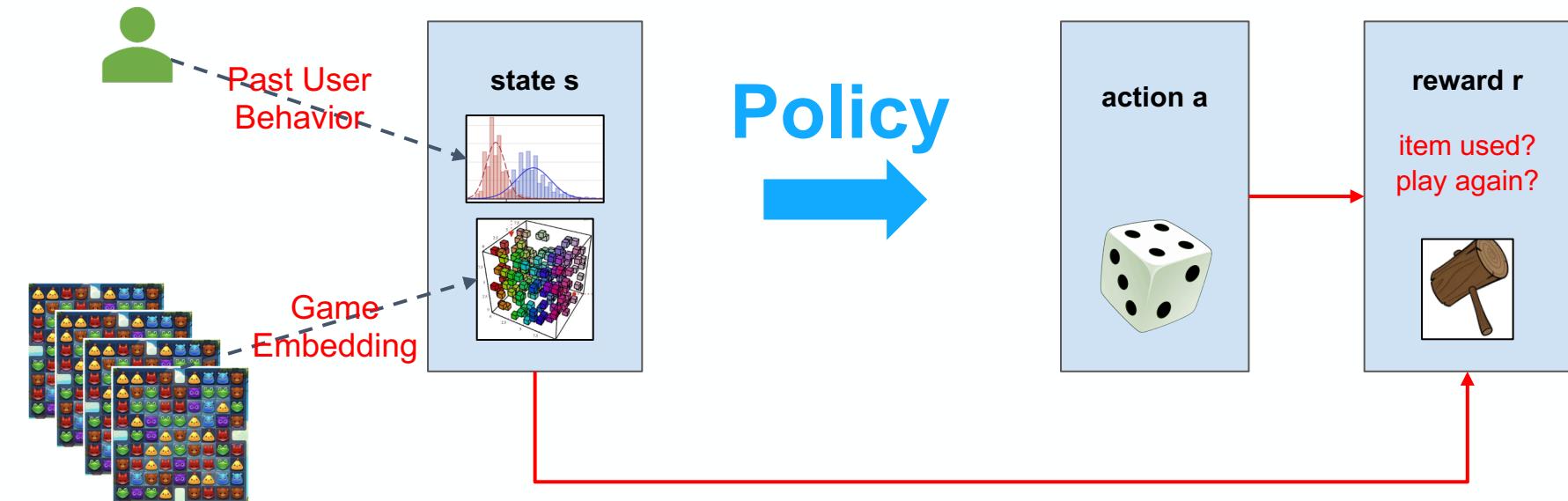


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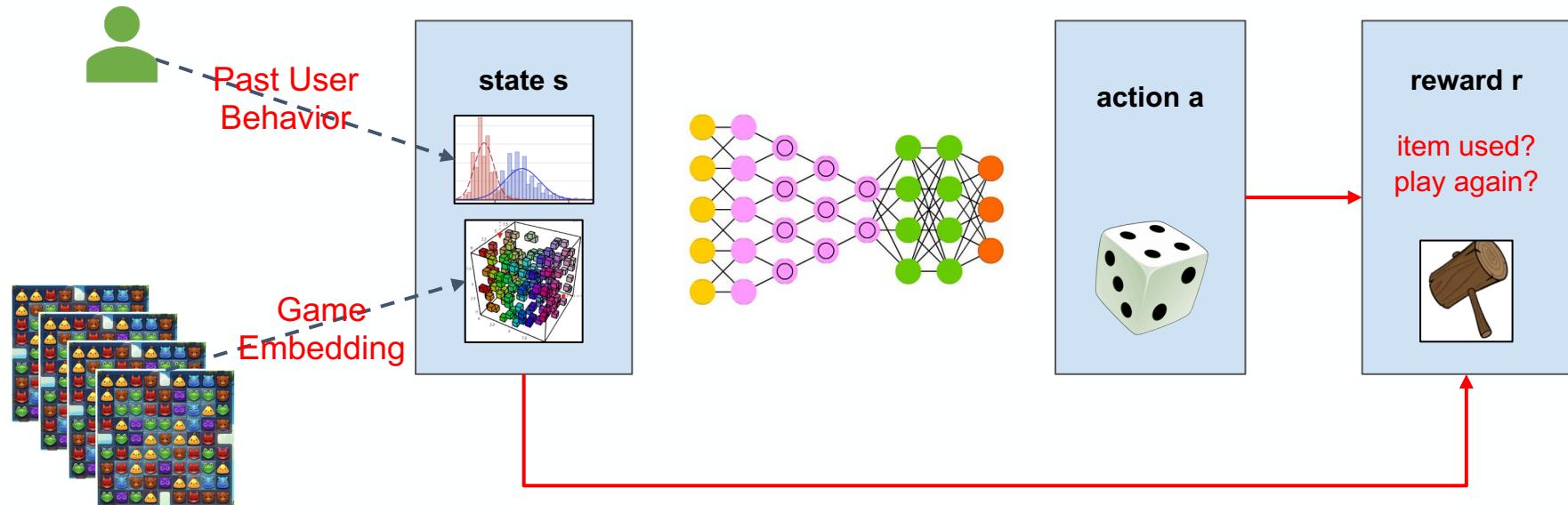




# Reinforcement Learning



# Deep Reinforcement Learning



# In Practice: Key Problems

- ML good at optimizing short-term targets:

*How do short-term targets relate to long-term objectives?*

- ML good at optimizing on fixed dataset:

*What when the data regime is highly non-stationary?*

# Optimization Horizon

- Often it is easy to define **short-term targets**:

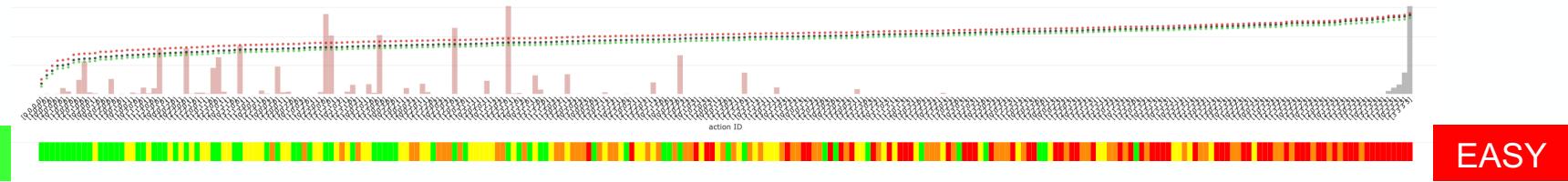
Did the user play another in-game level?  
Did the user make an in-app purchase?

- But how does this lead to **long-term objectives**?

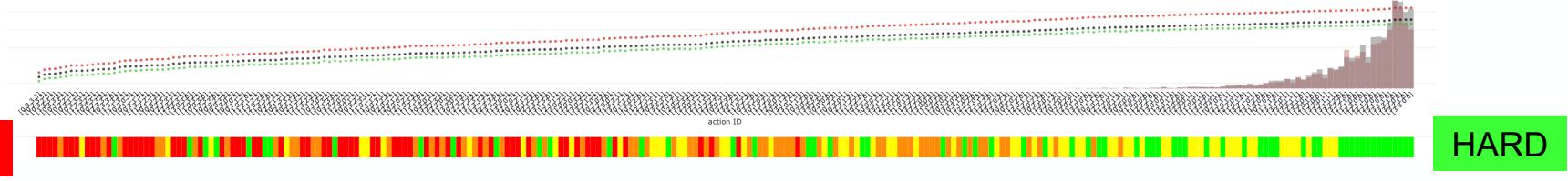
User engagement over the next year  
Life-time value of player

# Optimization Horizon

Retention

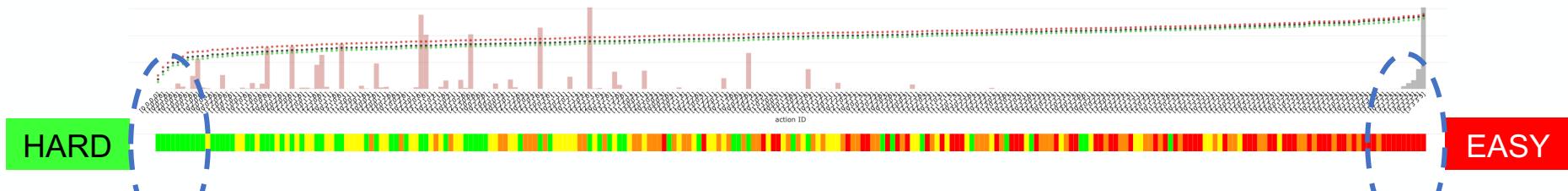


Revenue

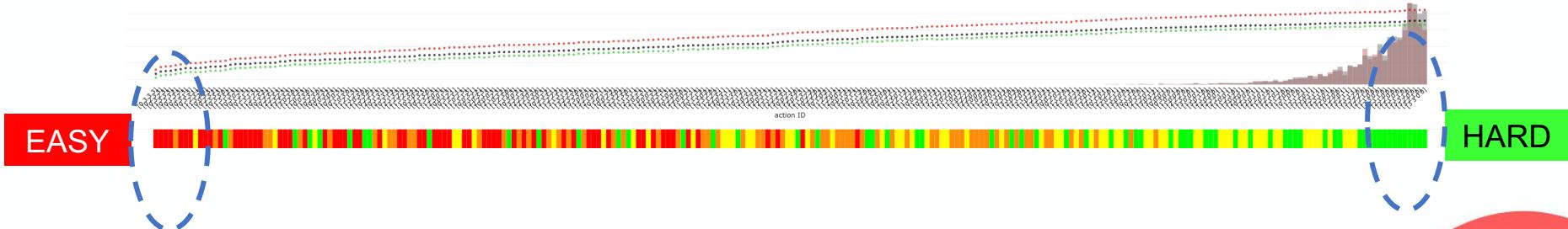


# Optimization Horizon

Retention



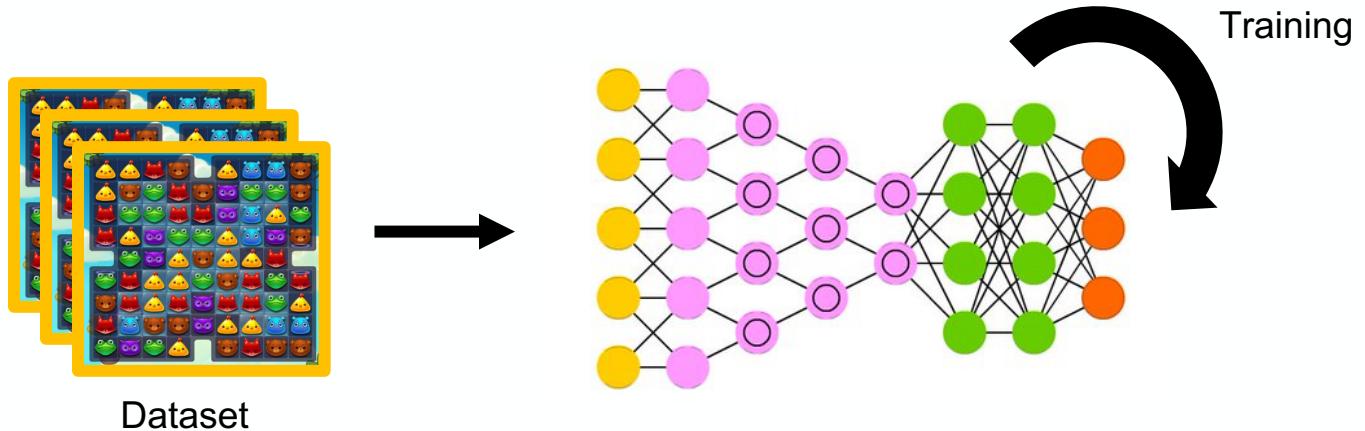
Revenue



# Optimization Horizon

- This can be solved through **RL** by **formulating the right objective**
- Objective is a **sum of individual short-term targets** over a time horizon
- However problem remains in **how to accurate model** this objective

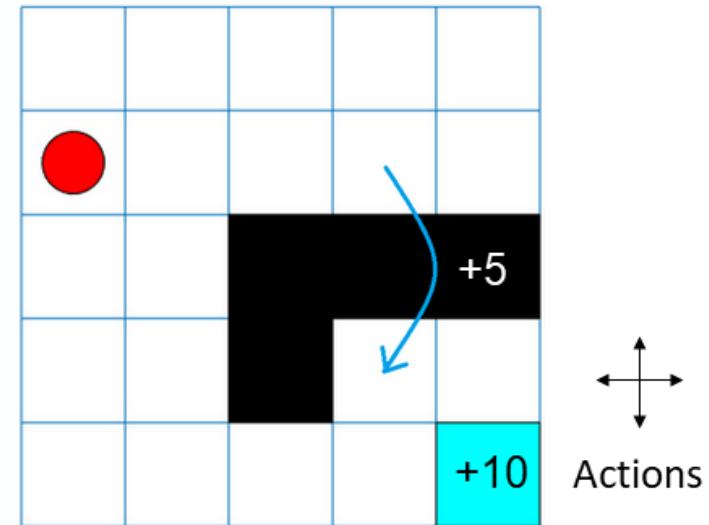
# Exploration – Exploitation Duality



- Traditionally, ML works on a **fixed dataset**
- Practical RL in **constant motion**: model generates future dataset

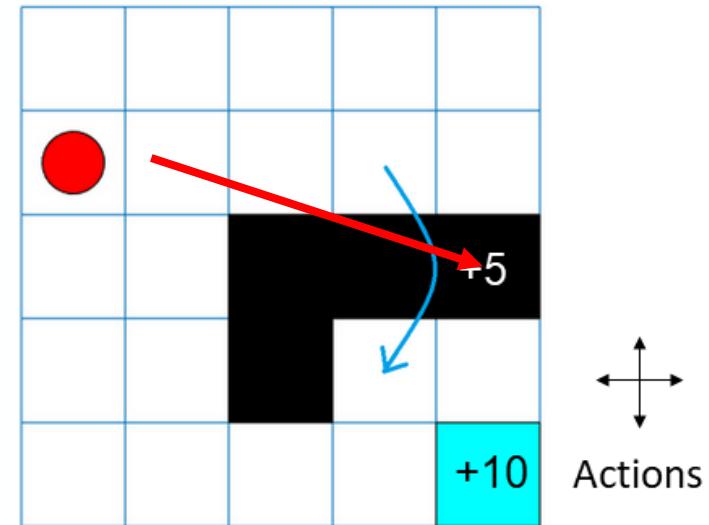
# Exploration – Exploitation Duality

- Rewards might be **sparse**: learn from long-term signal
- + **dynamic interaction** with players: inherently **nonstationary** data regime
- Core problem: trading off **exploration vs exploitation**



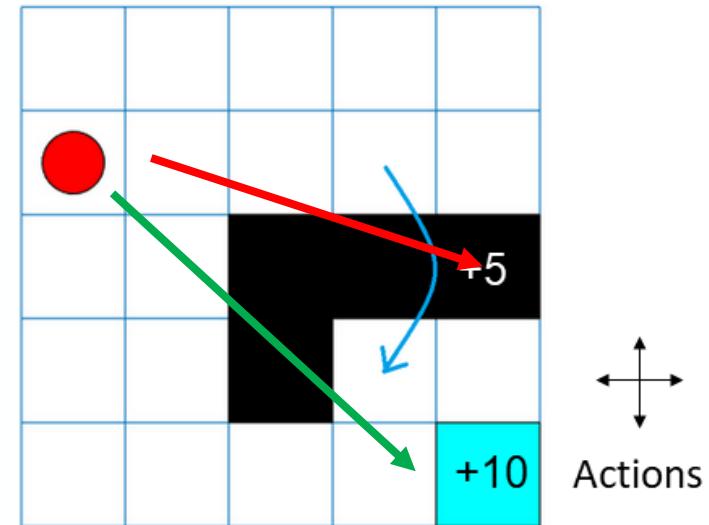
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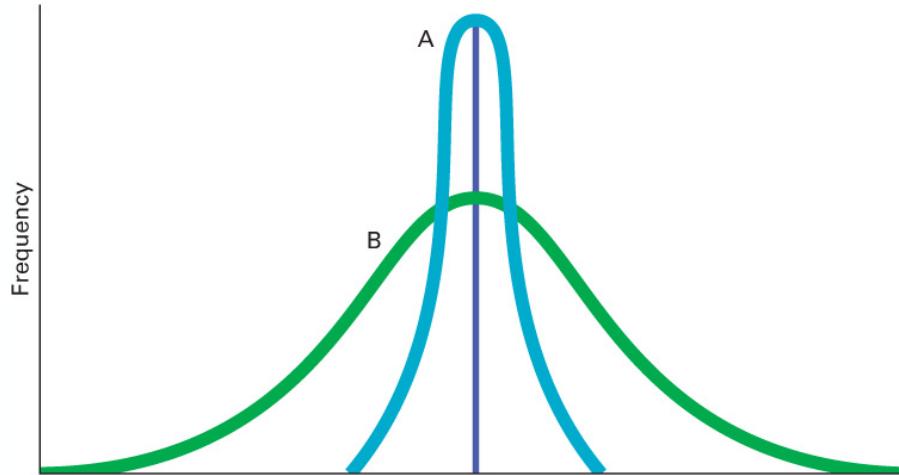
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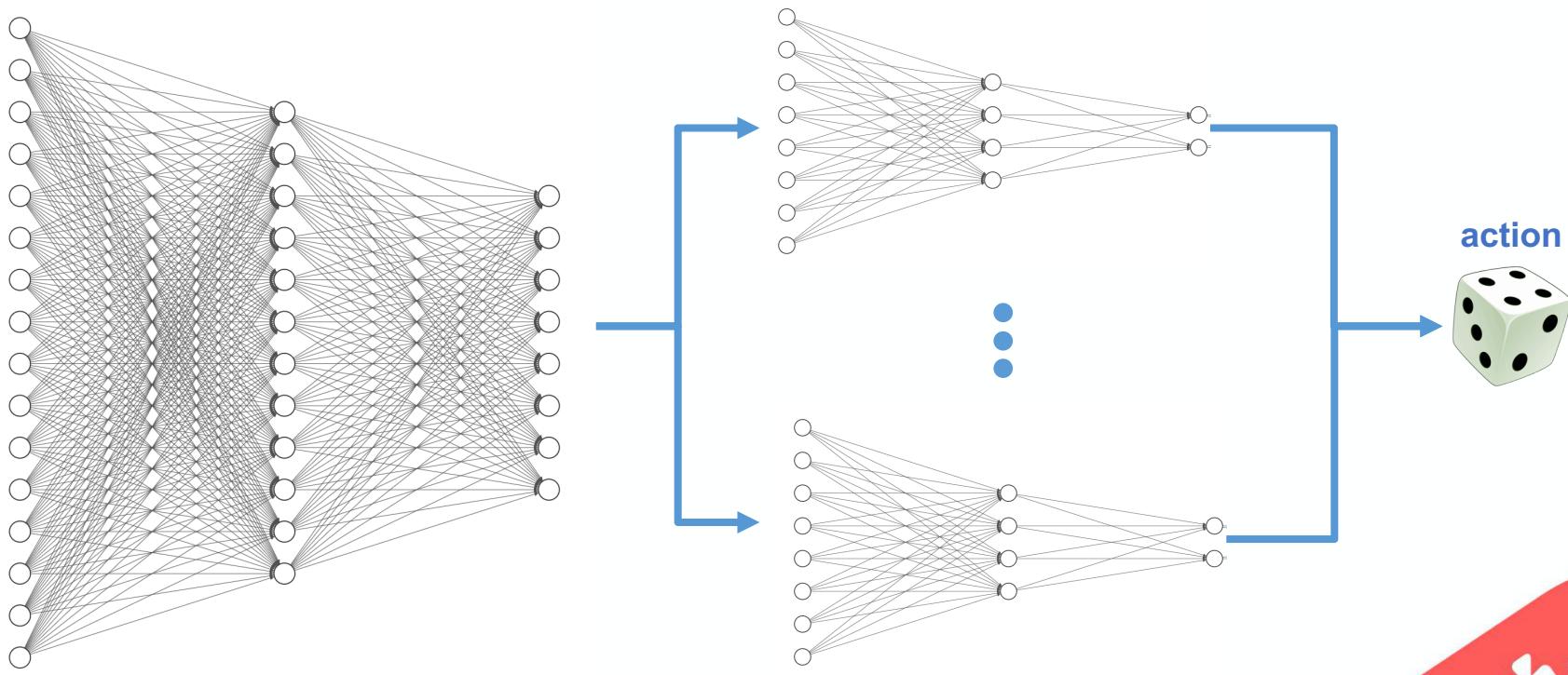


# Exploration – Exploitation Duality

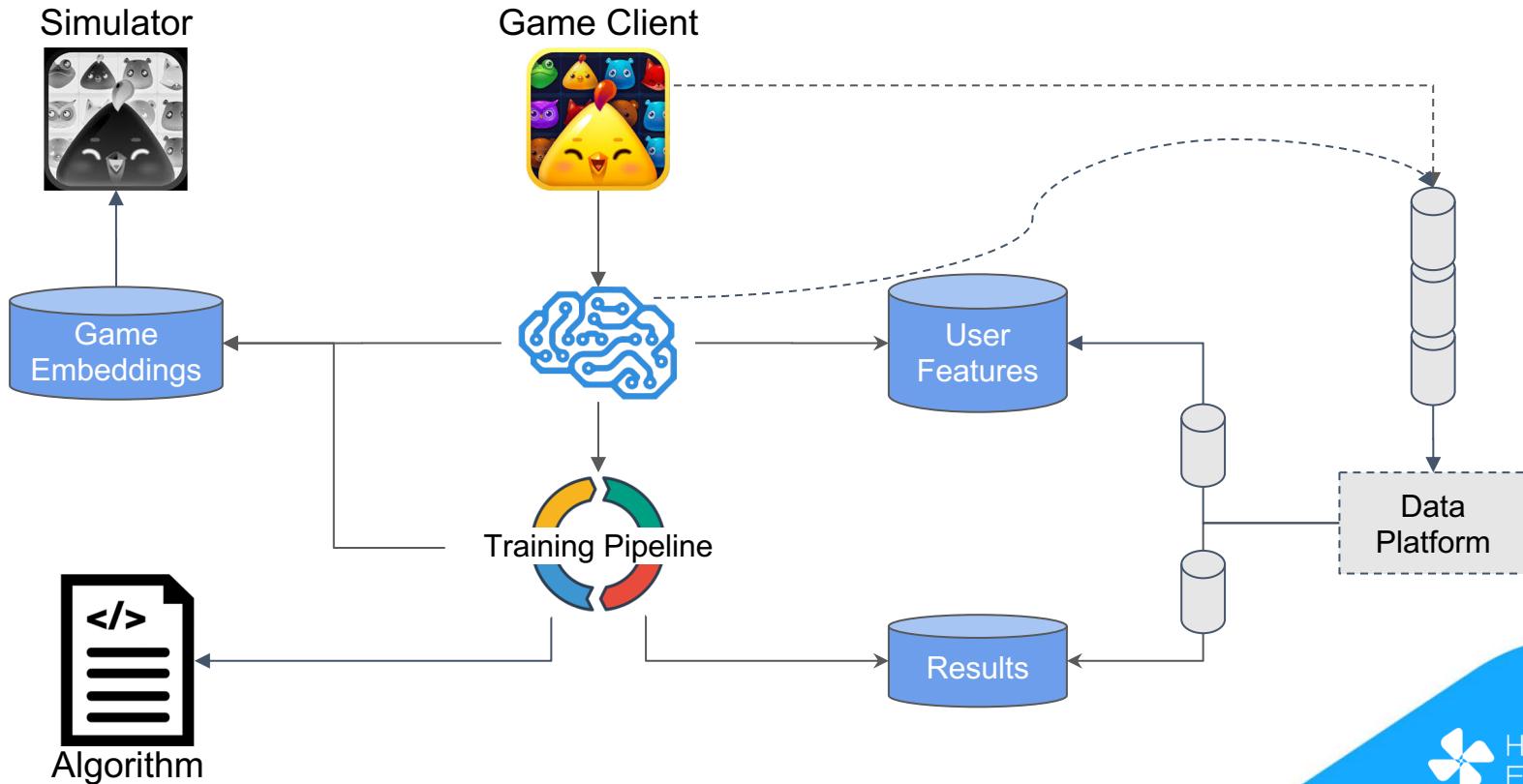
- Approximate Bayesian approach to capture **model uncertainty**
- Solving exploitation (A) vs. exploration (B) problem.



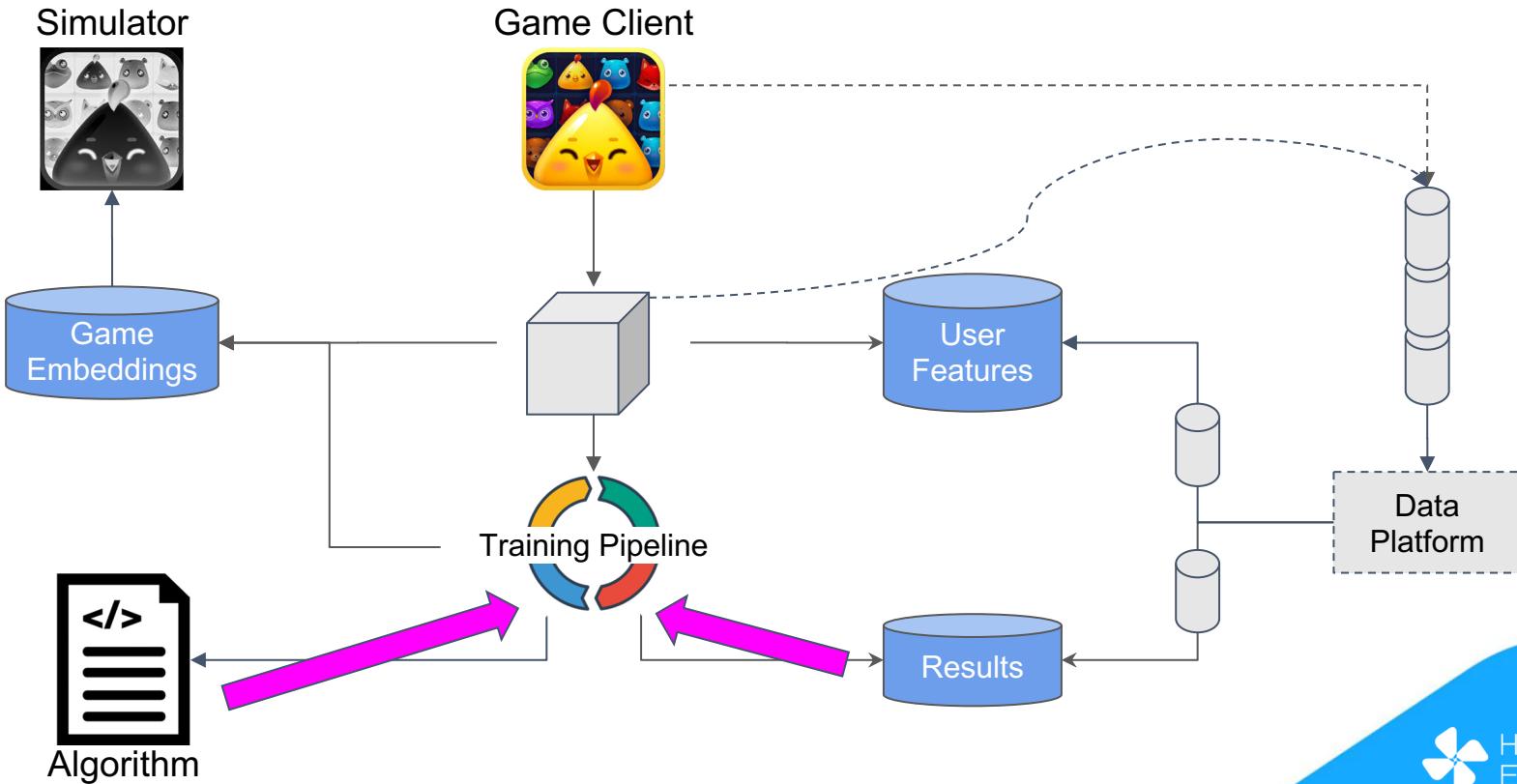
# Model: Bootstrapped Contextual Bandits



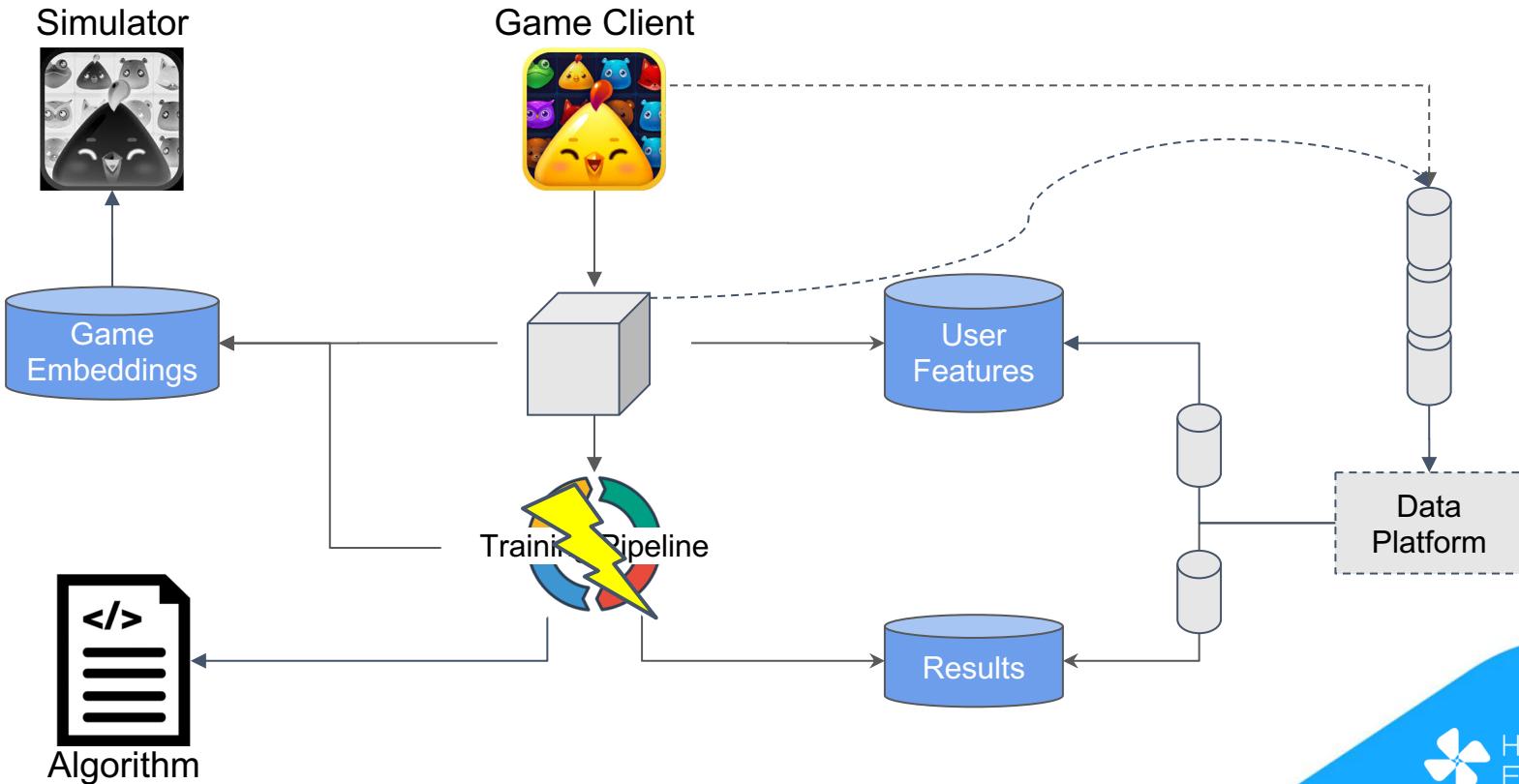
# System Architecture



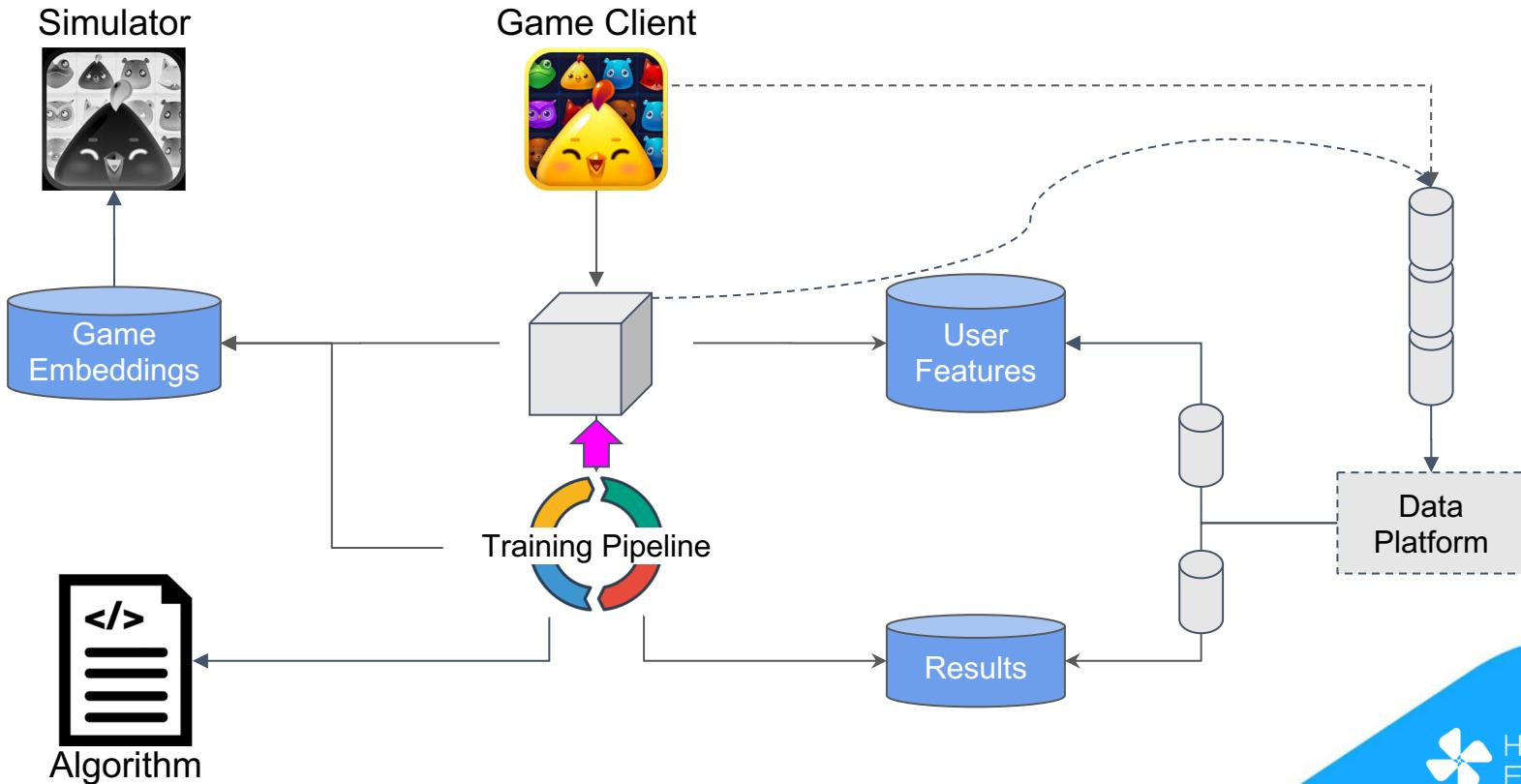
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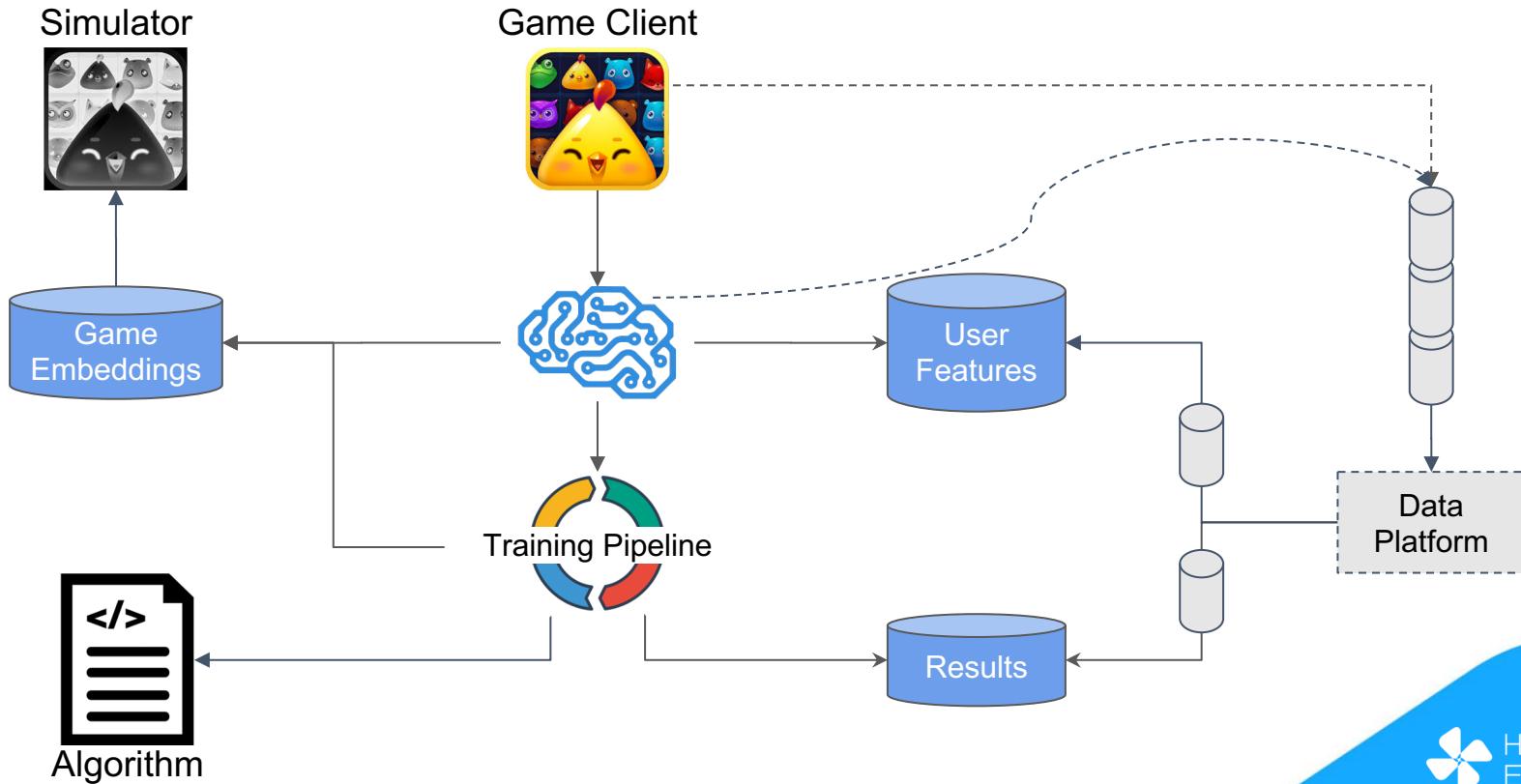
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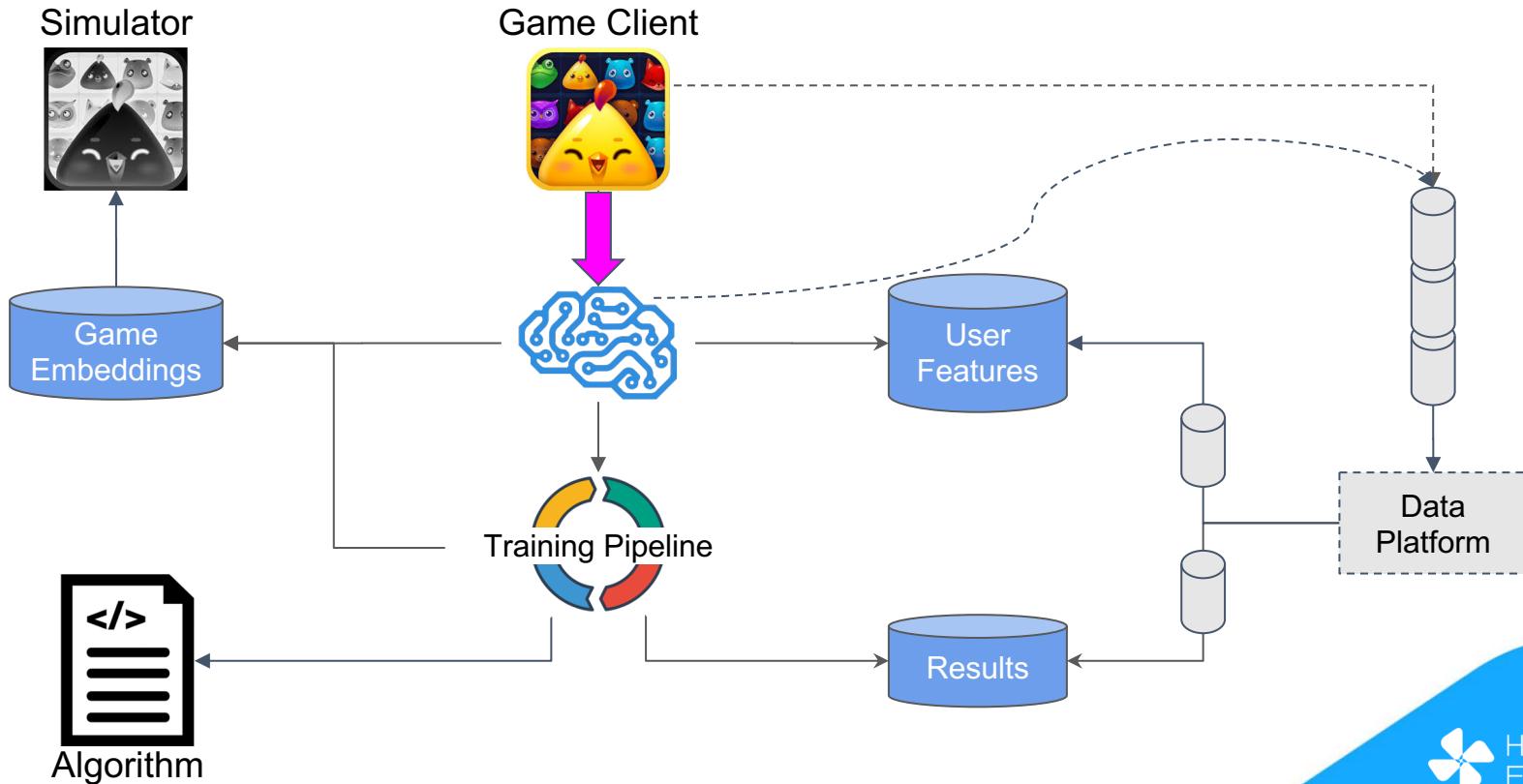
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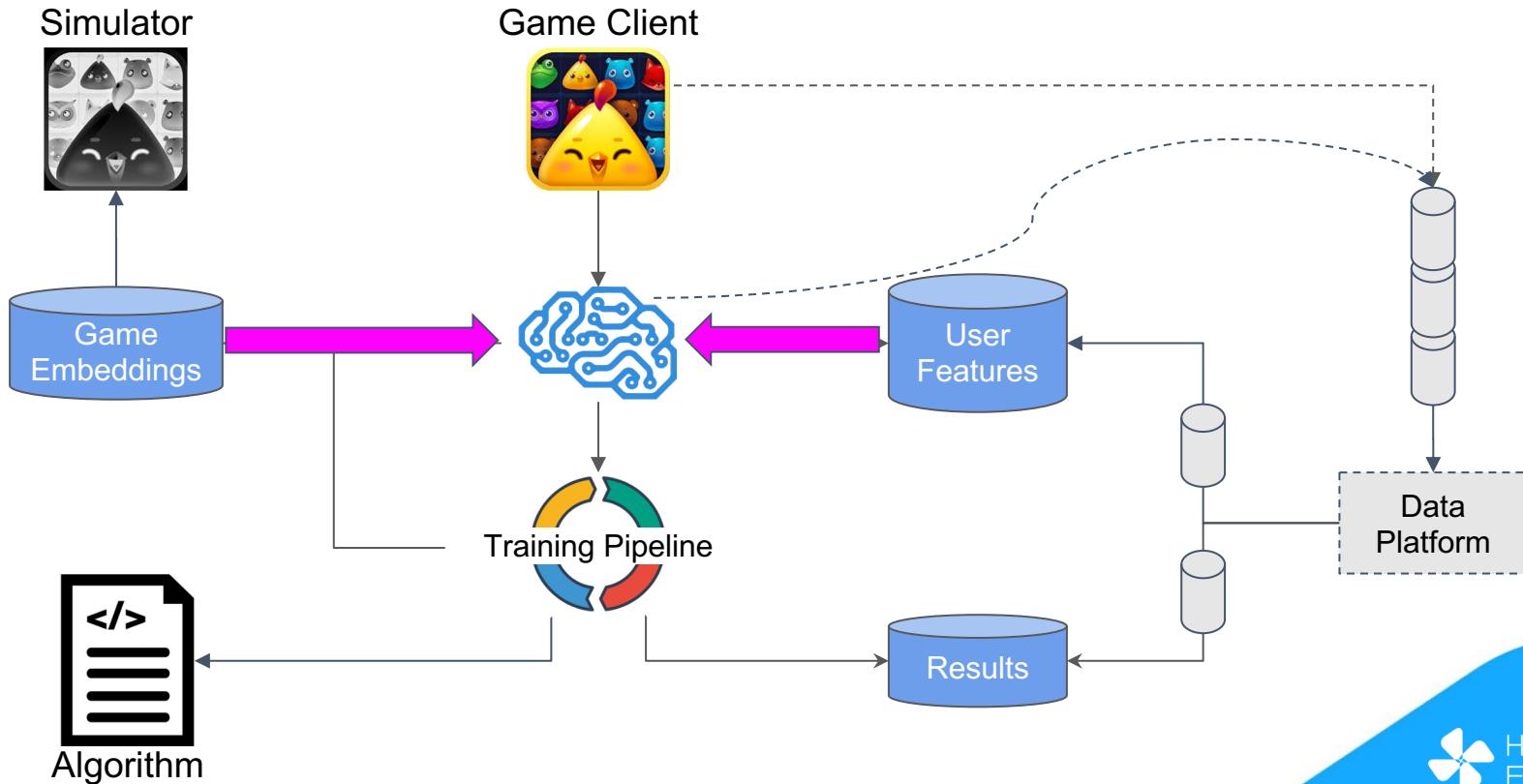
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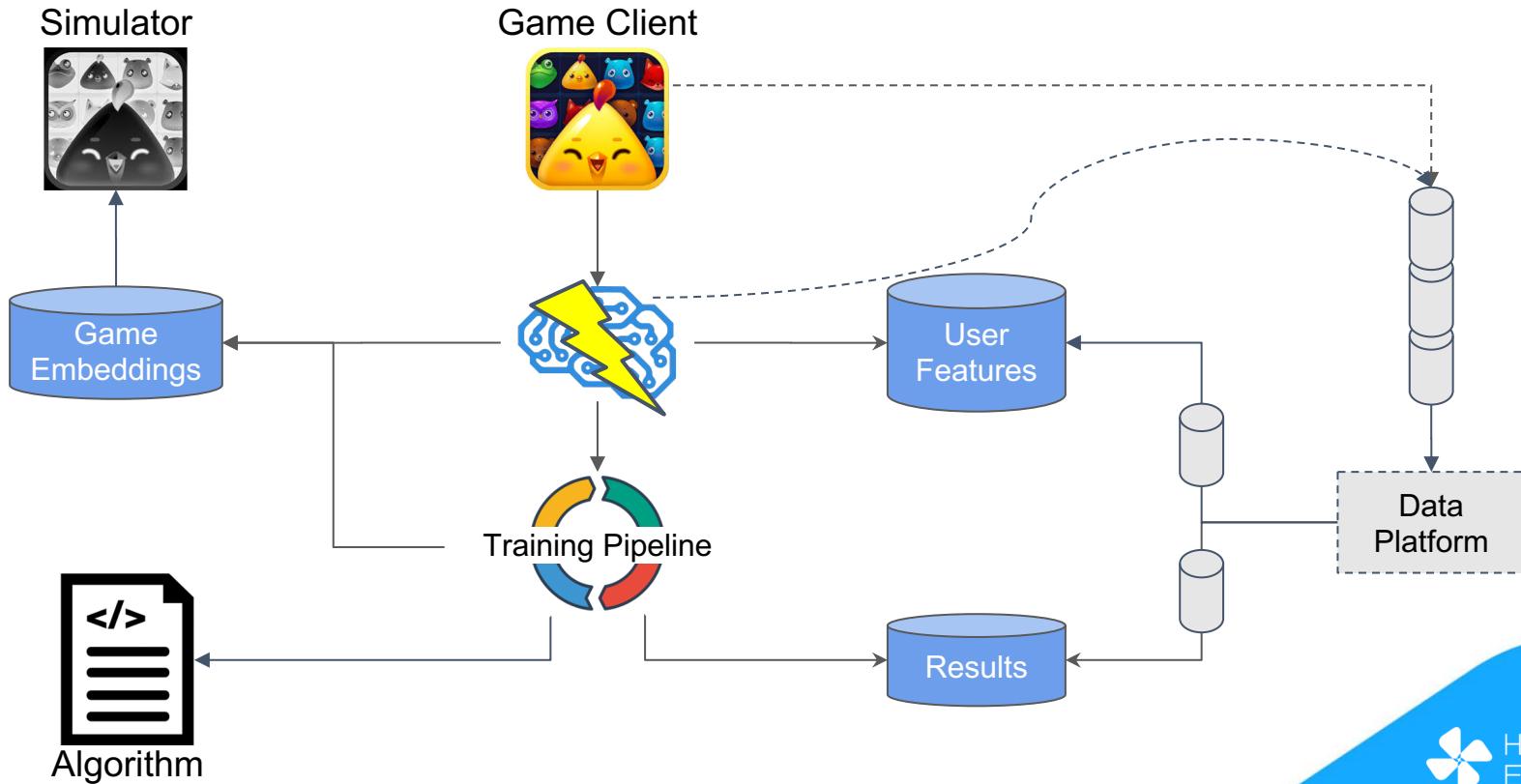
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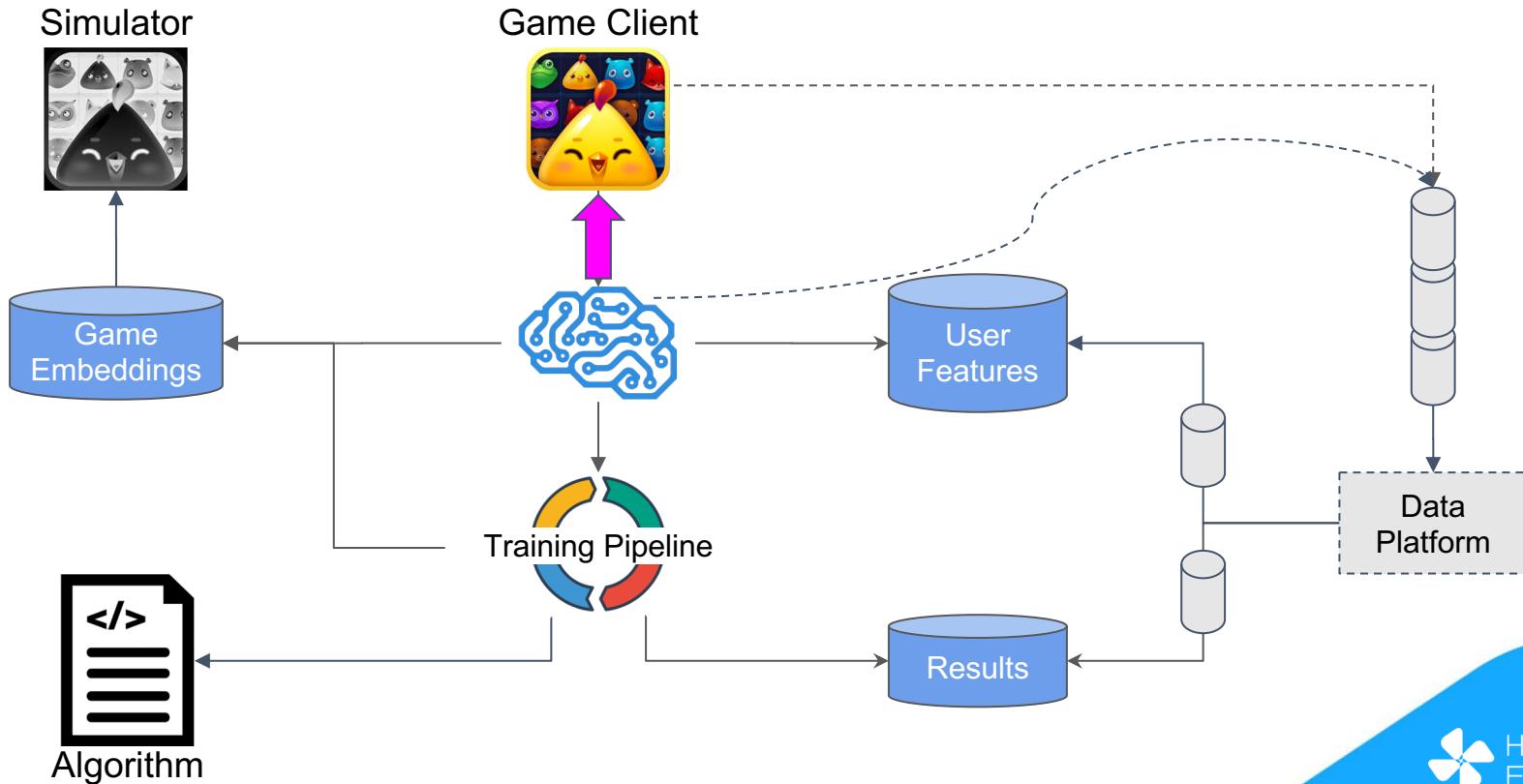
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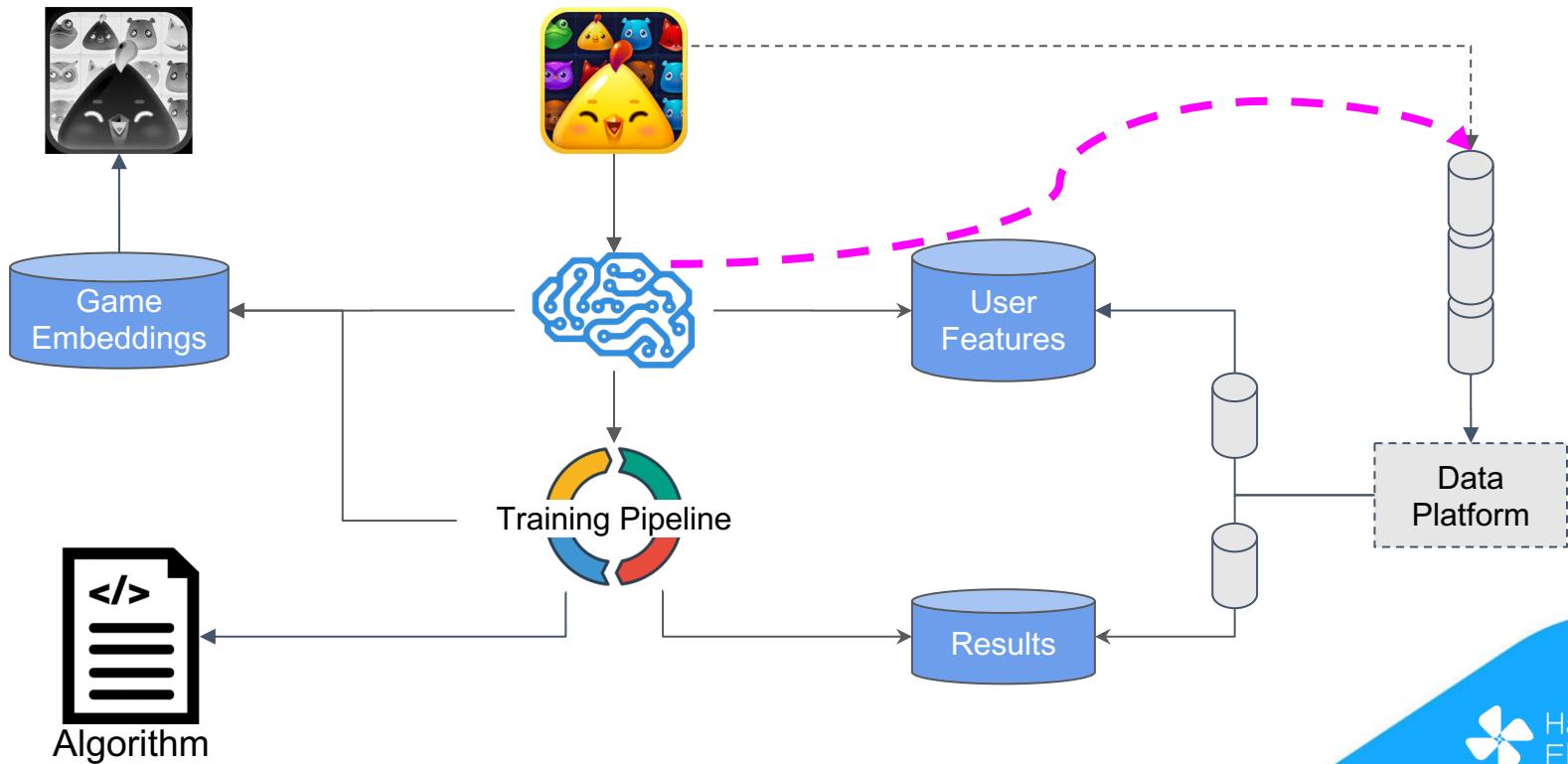
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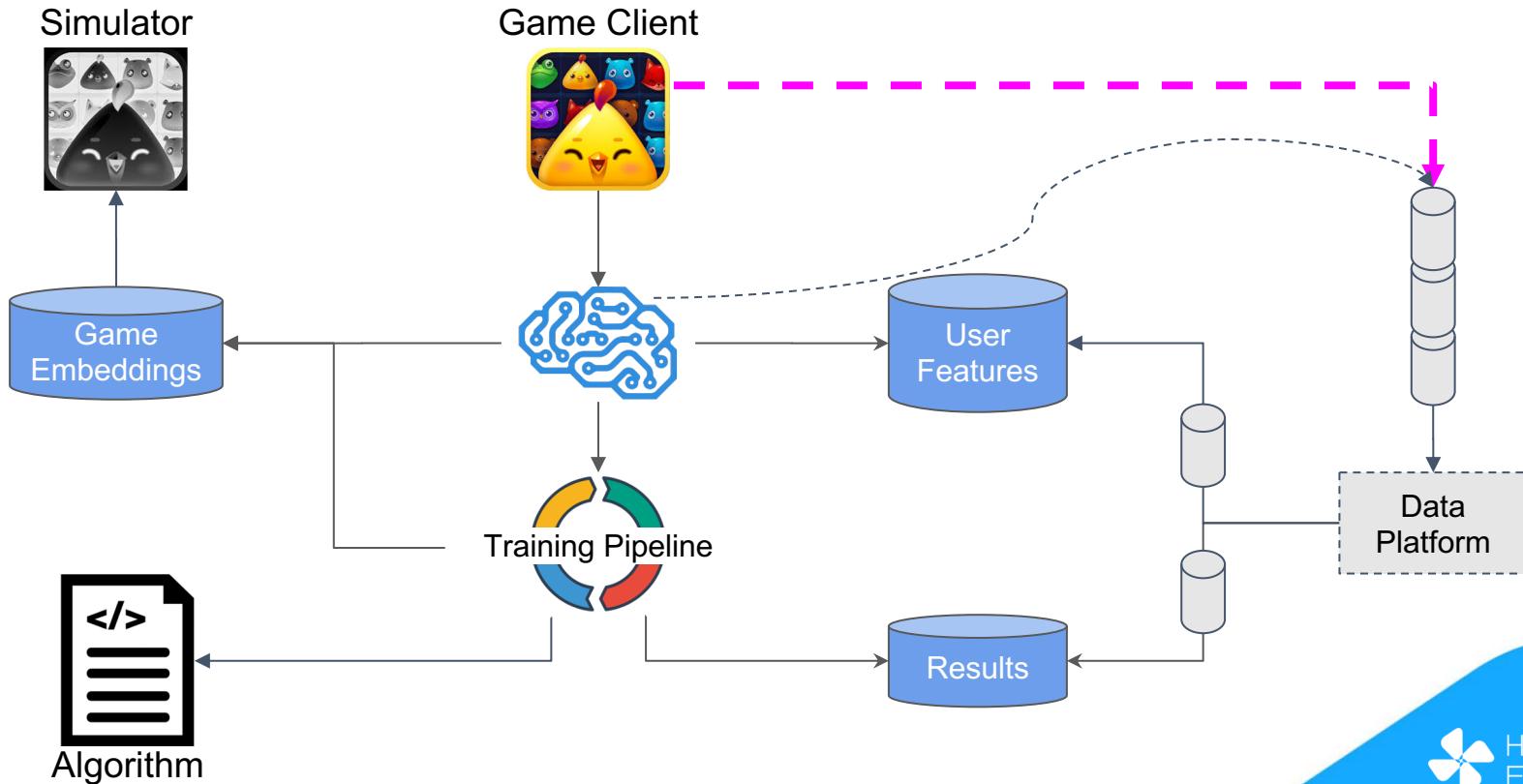
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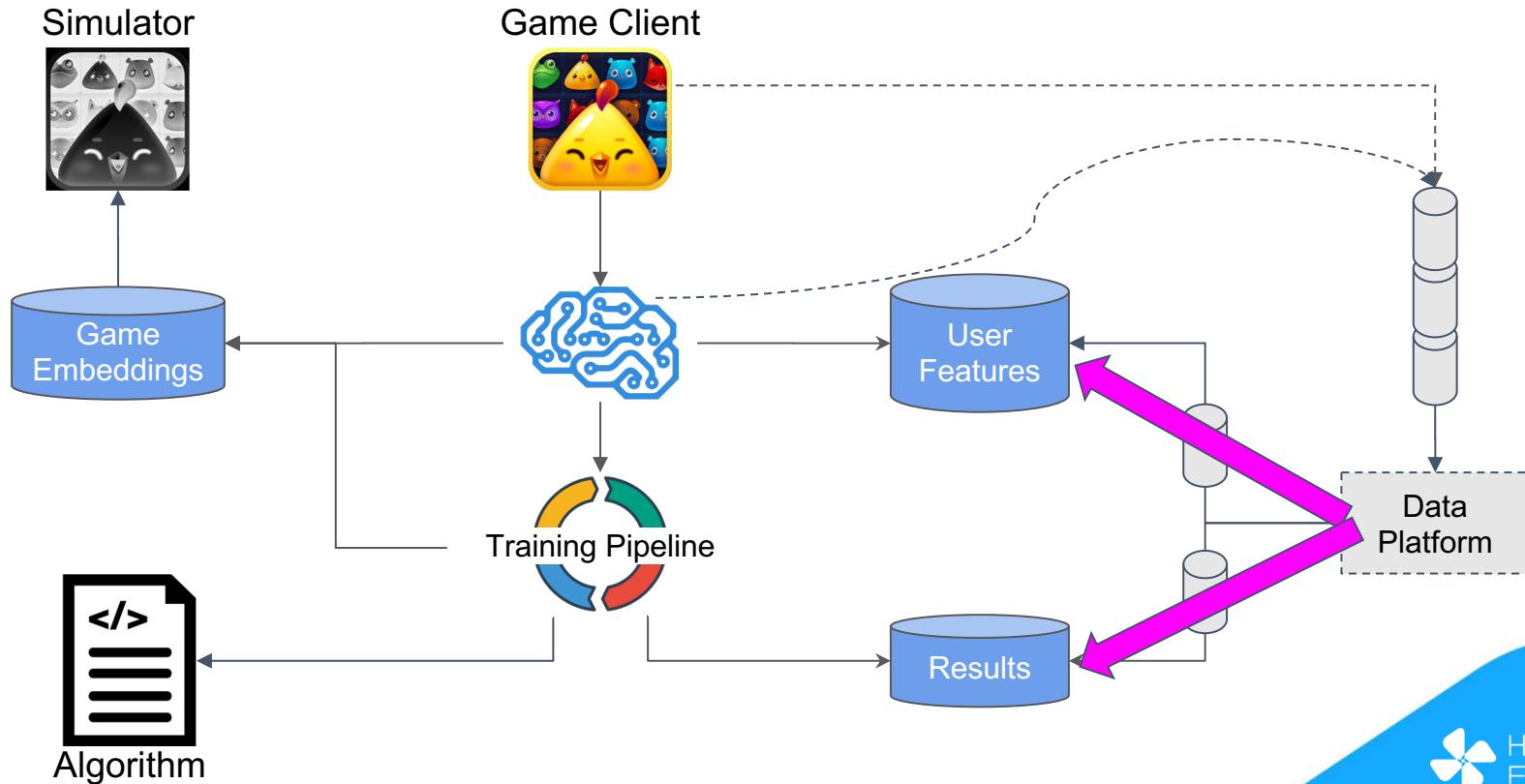
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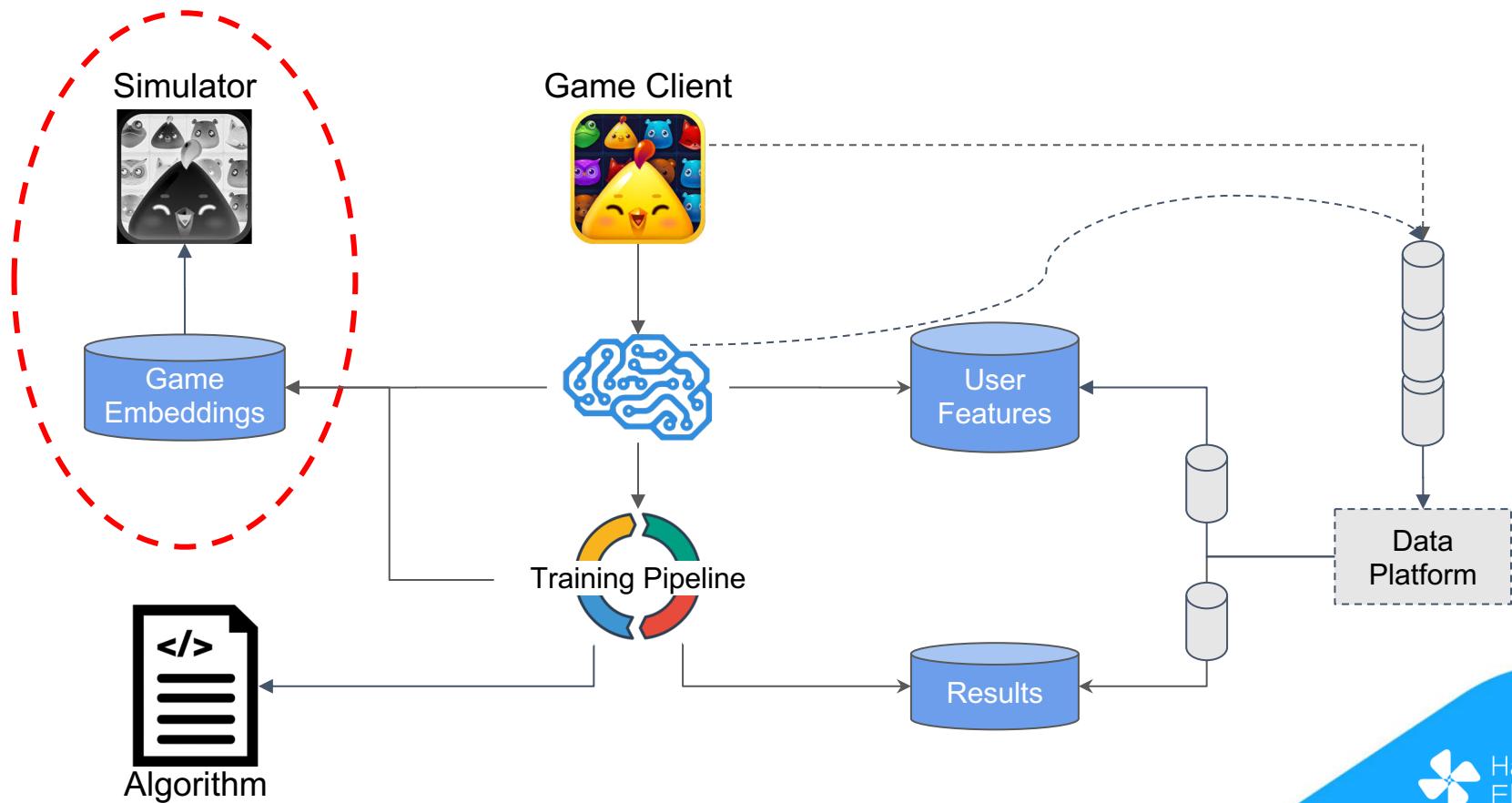
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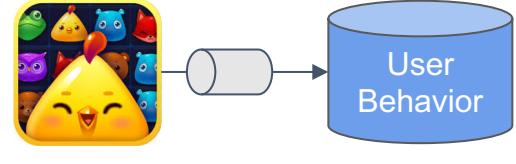
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# System Architecture

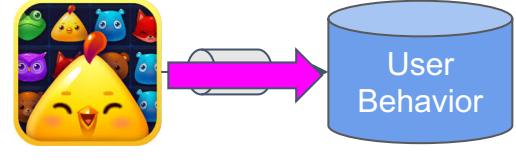


# System Architecture: Gameplay Embeddings



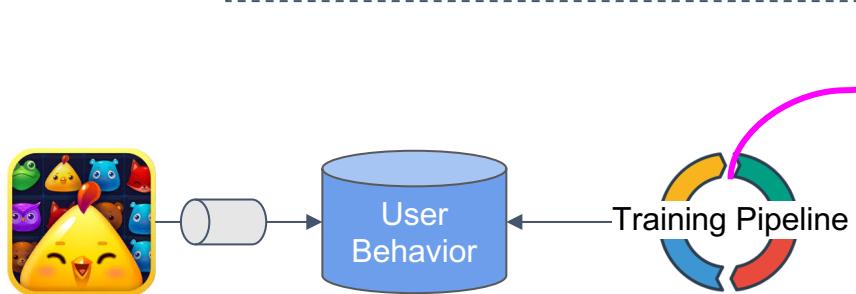
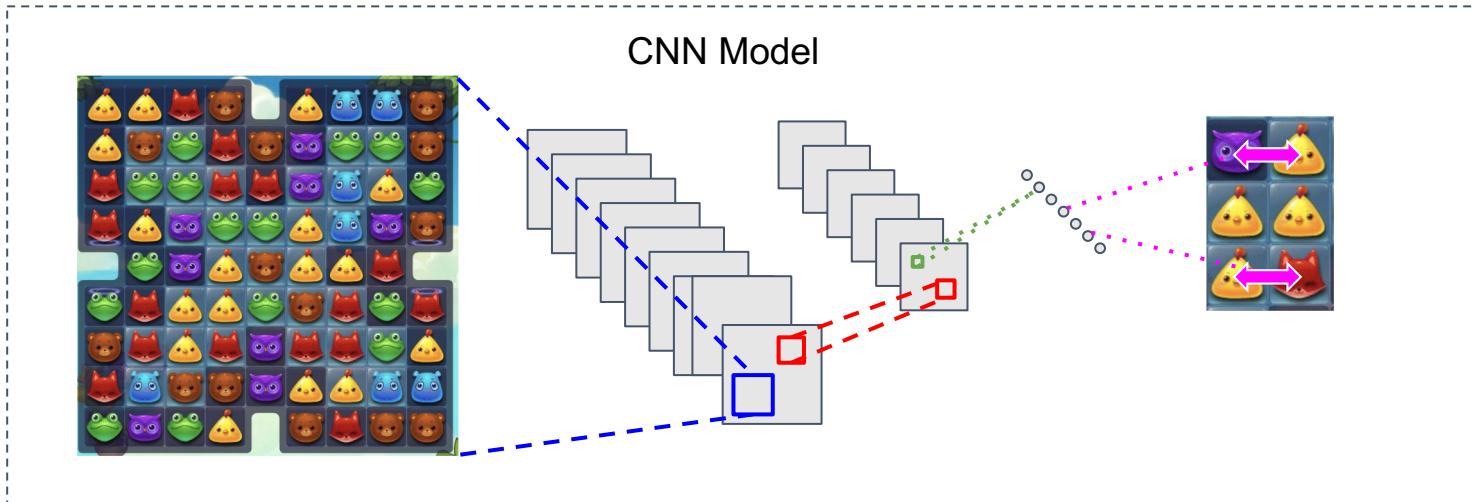
Game Client

# System Architecture: Gameplay Embeddings

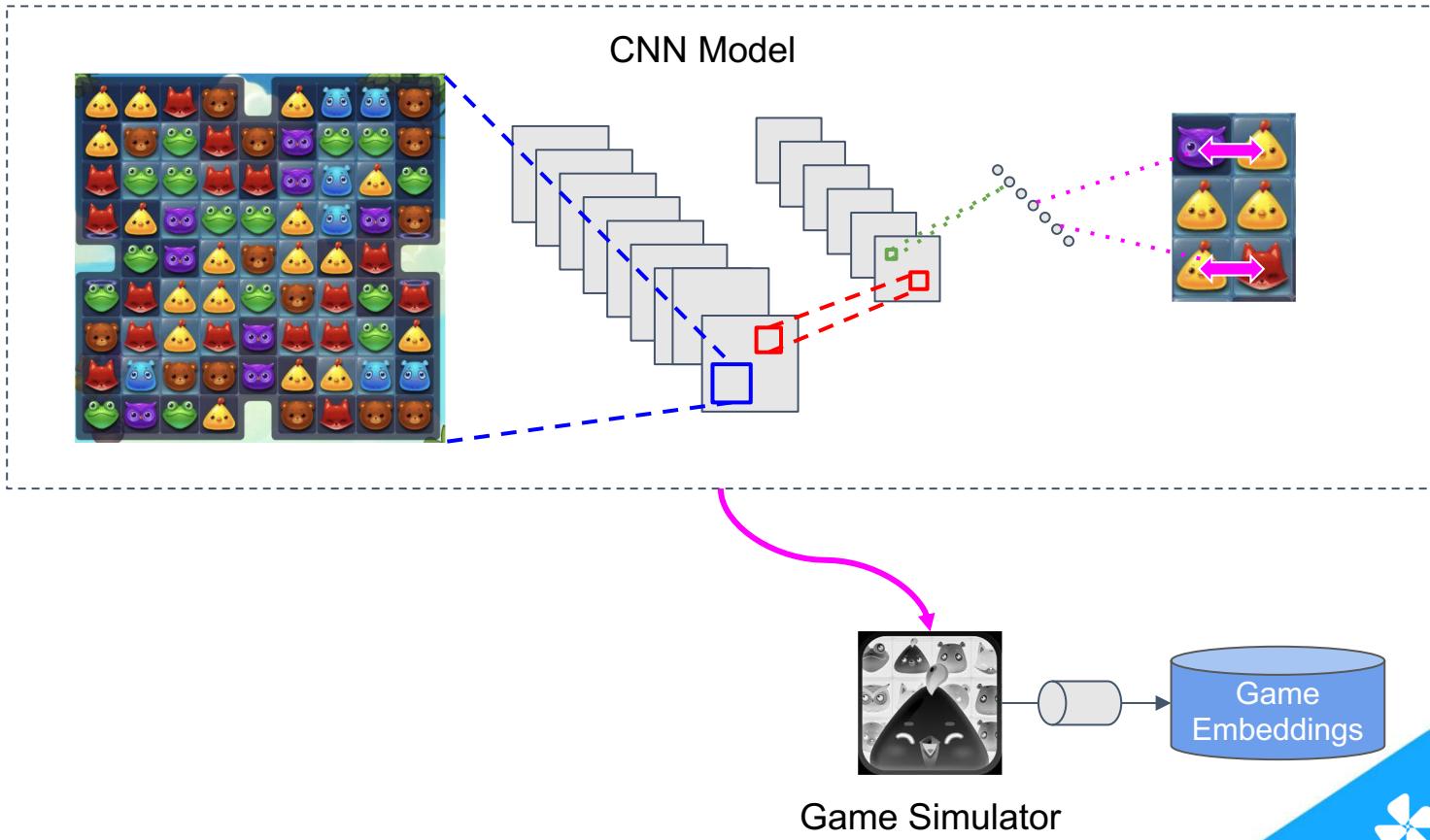


Game Client

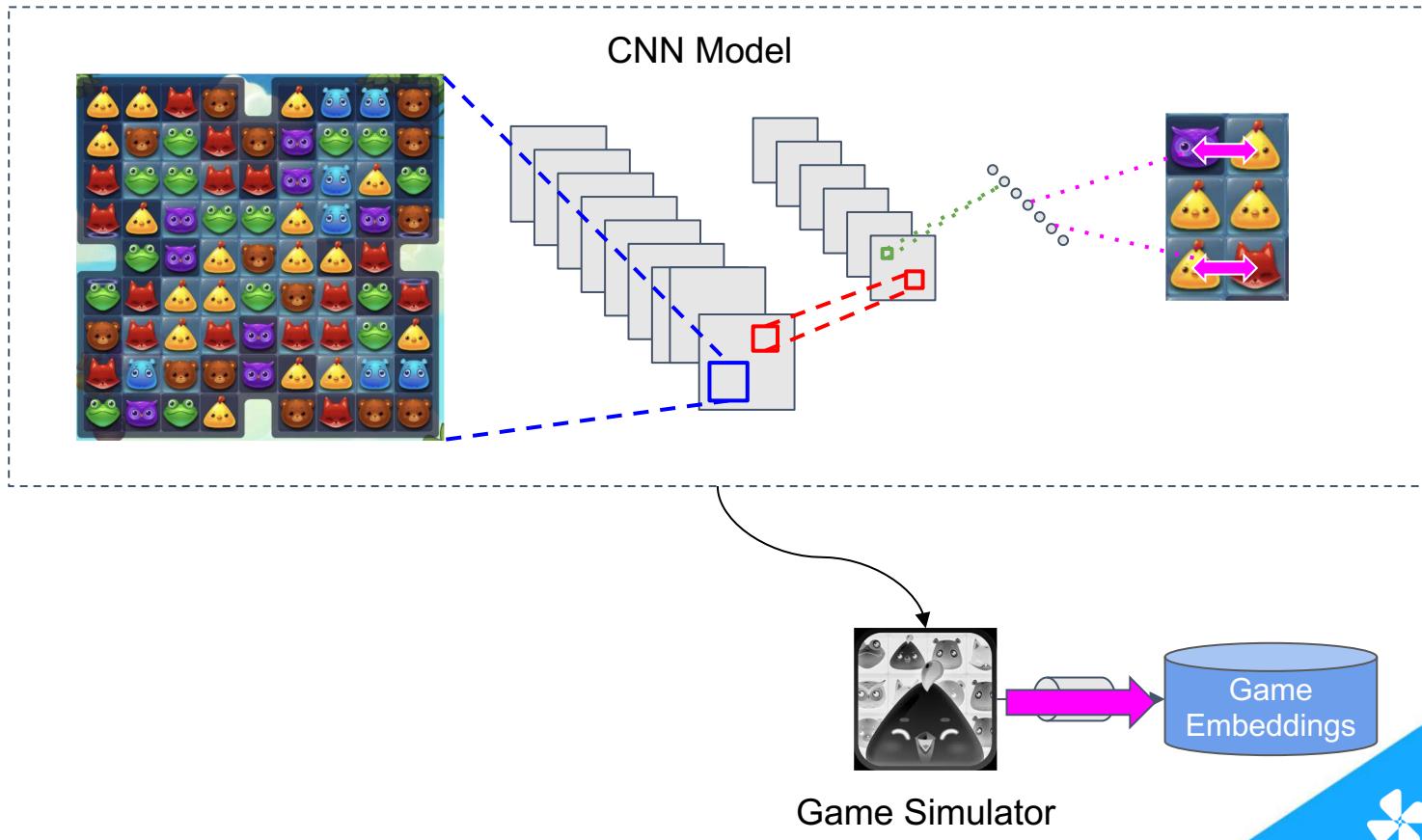
# System Architecture: Gameplay Embeddings



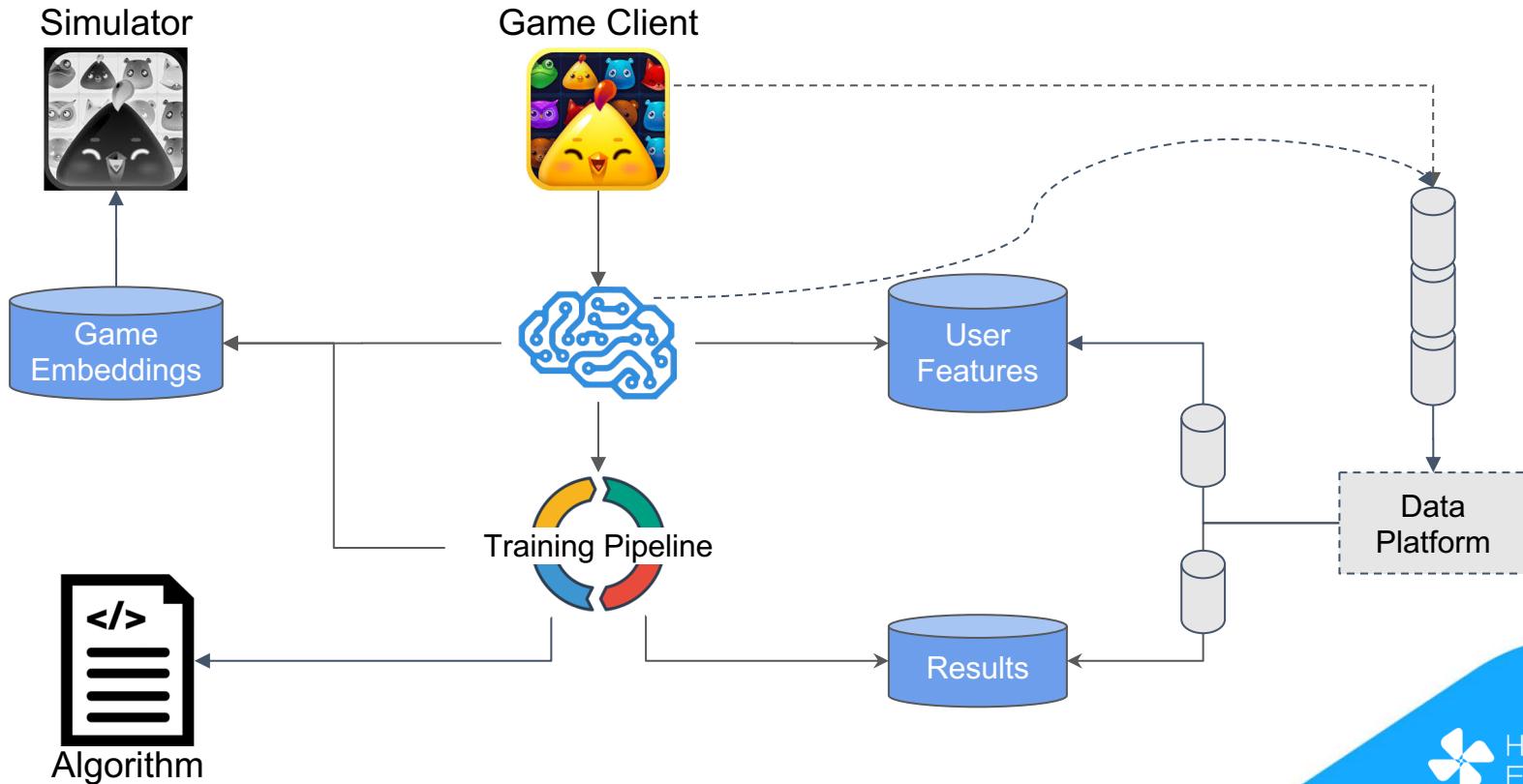
# System Architecture: Gameplay Embeddings



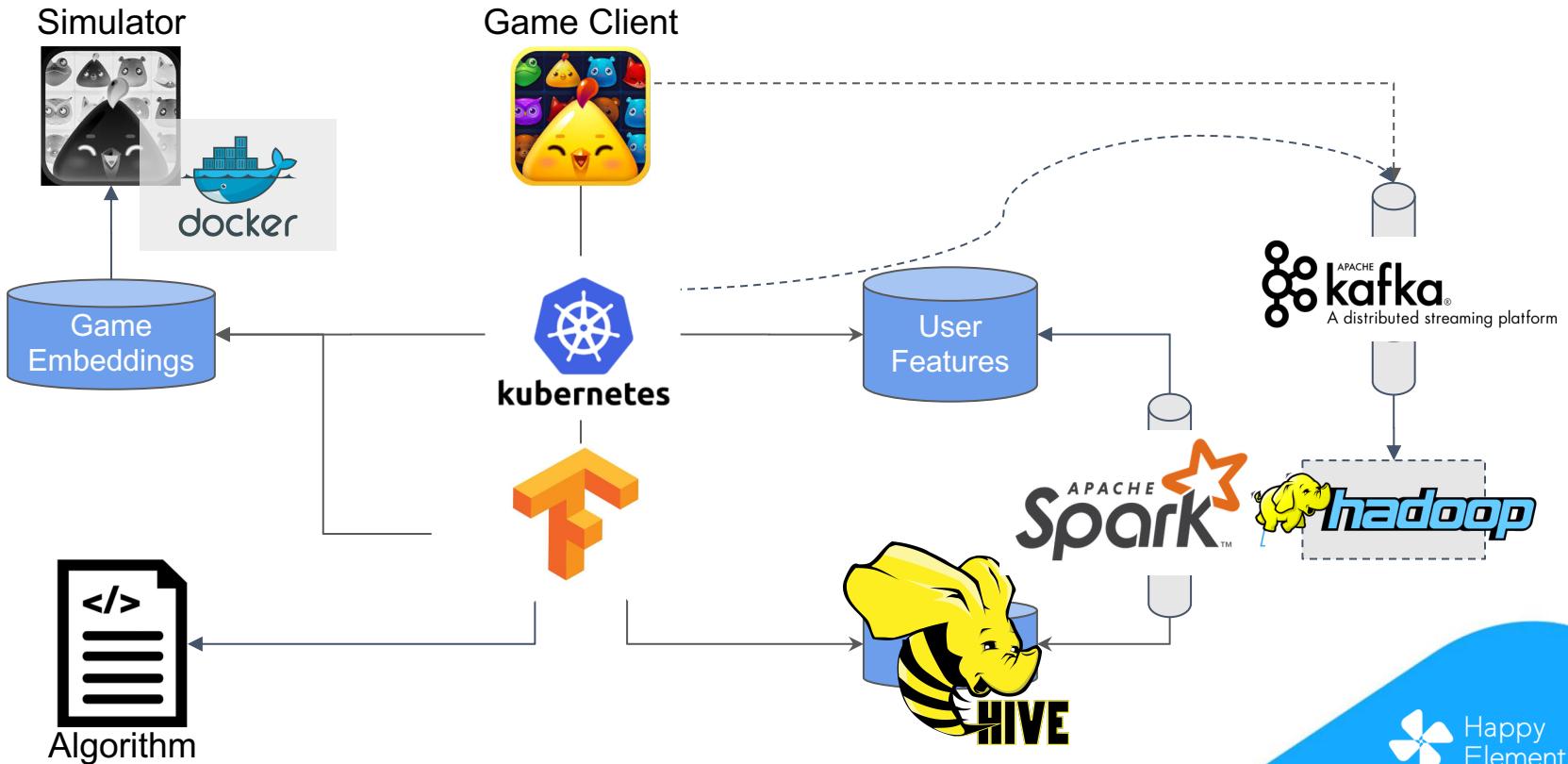
# System Architecture: Gameplay Embeddings



# System Architecture



# Technology Stack Samples



# Conclusions

- Deployment of ML can **significantly improve revenue and engagement**
- **Nonstationary** data presents **difficult optimization** problem
- **Relationship** between **short-term and long-term metrics** hard to identify



# THANKS

<http://en.happyelements.com/ai>