



**MAKE
THE
WORLD
HAPPY**

Generating the Best Game Experience through AI

Rein Houthooft

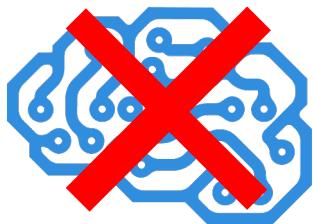
Introduction



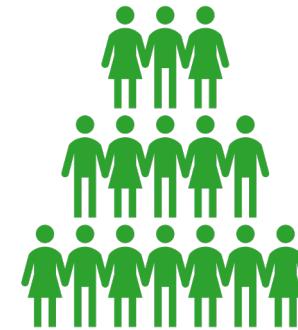
- Company focus: **casual** mobile games
- Main product: “**Anipop**” 
- Extremely popular (>**100M** users/month)
- Generates **TBs** of data each day
- **AI Lab** founded 1 year ago

AI Lab: Goals & Strategy

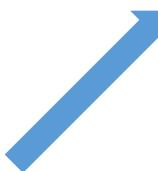
Open-loop to Closed-loop Game Design



Sparse feedback



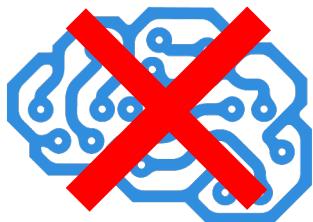
Little Optimization



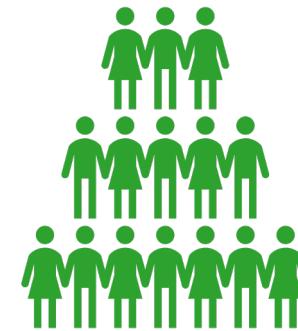
Open-loop to Closed-loop Game Design

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

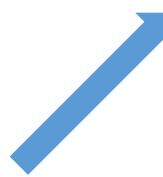
Open-loop to Closed-loop Game Design



Dense feedback



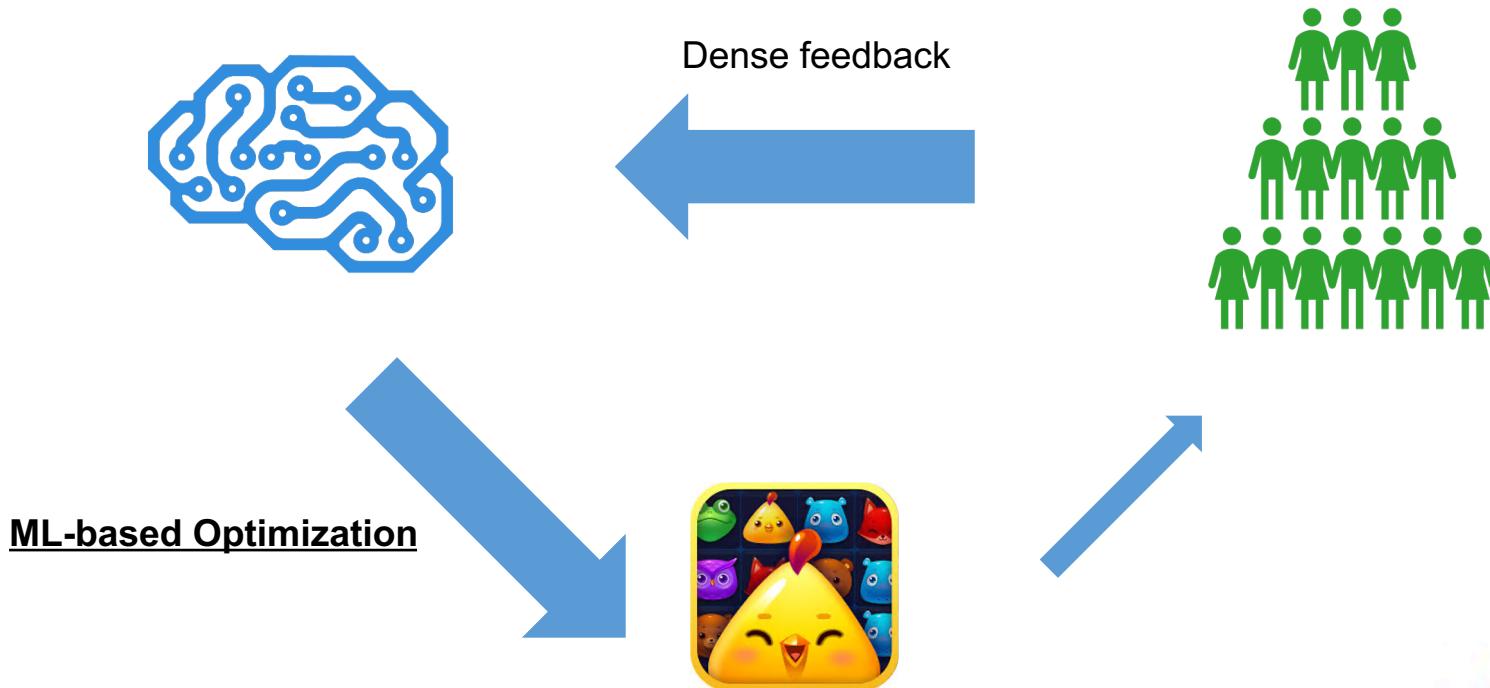
Rule-based Optimization



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



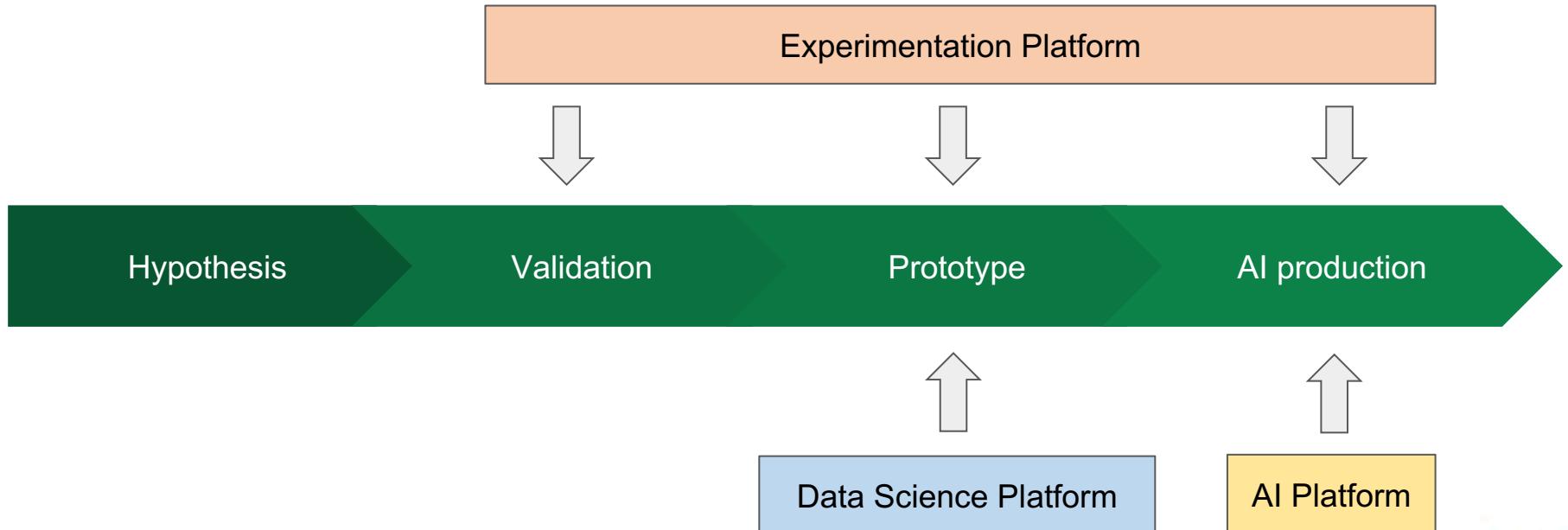
Open-loop to Closed-loop Game Design

- 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



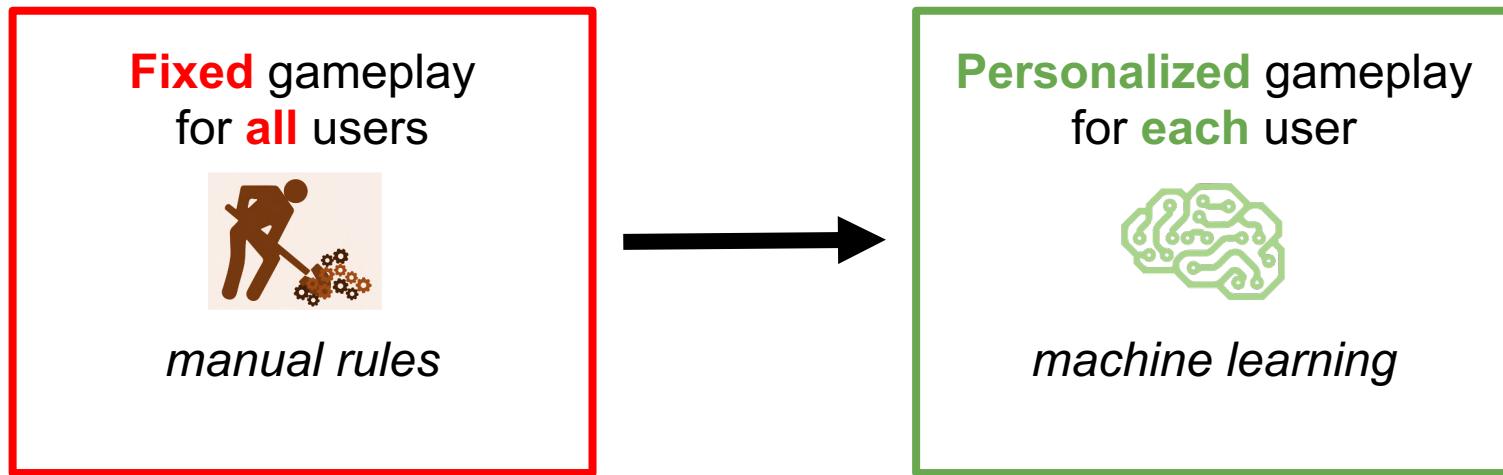
Game Difficulty Adjustment

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

Problem Formulation

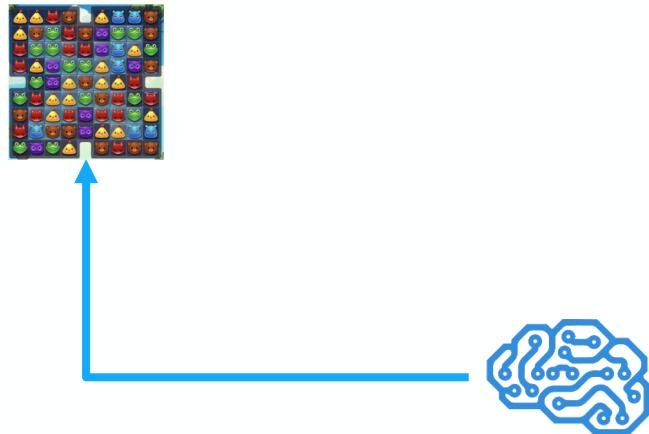


Problem Formulation



Problem Formulation

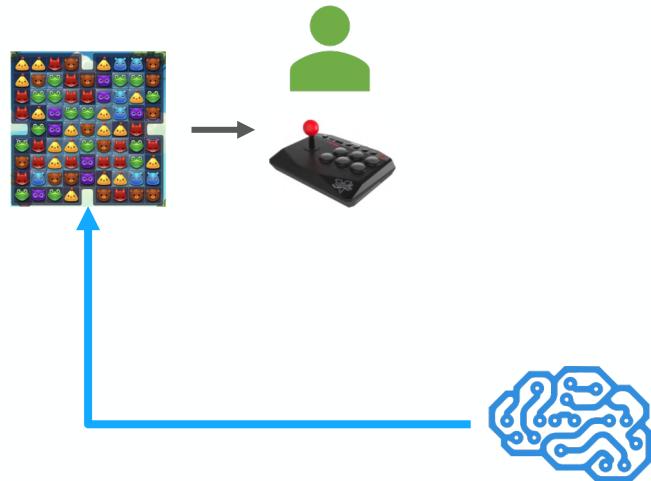
Gameplay modification: Action sequences



Objective: Rewards = player revenue/retention

Problem Formulation

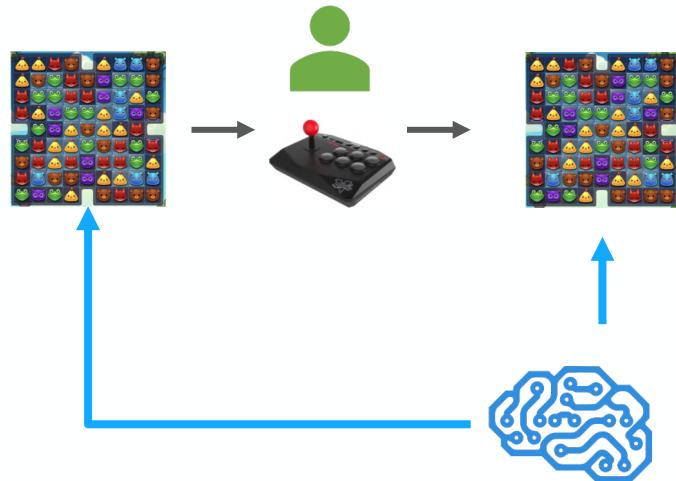
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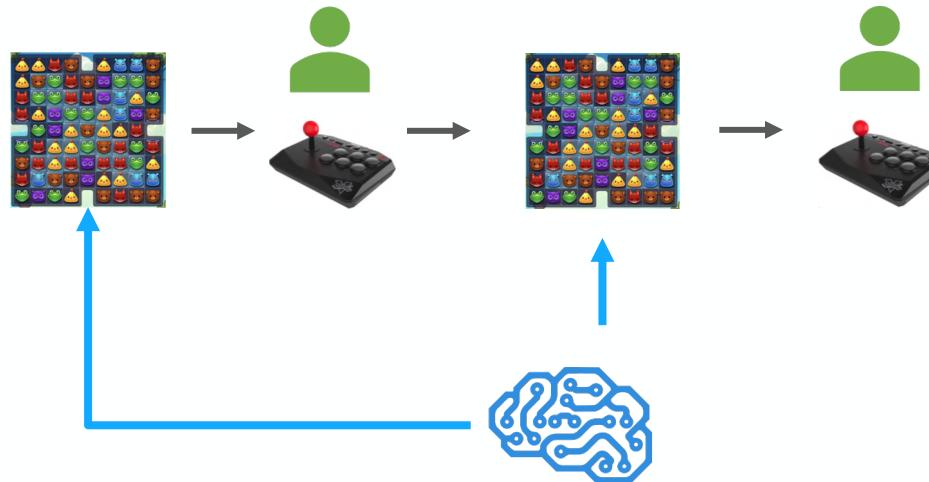
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Problem Formulation

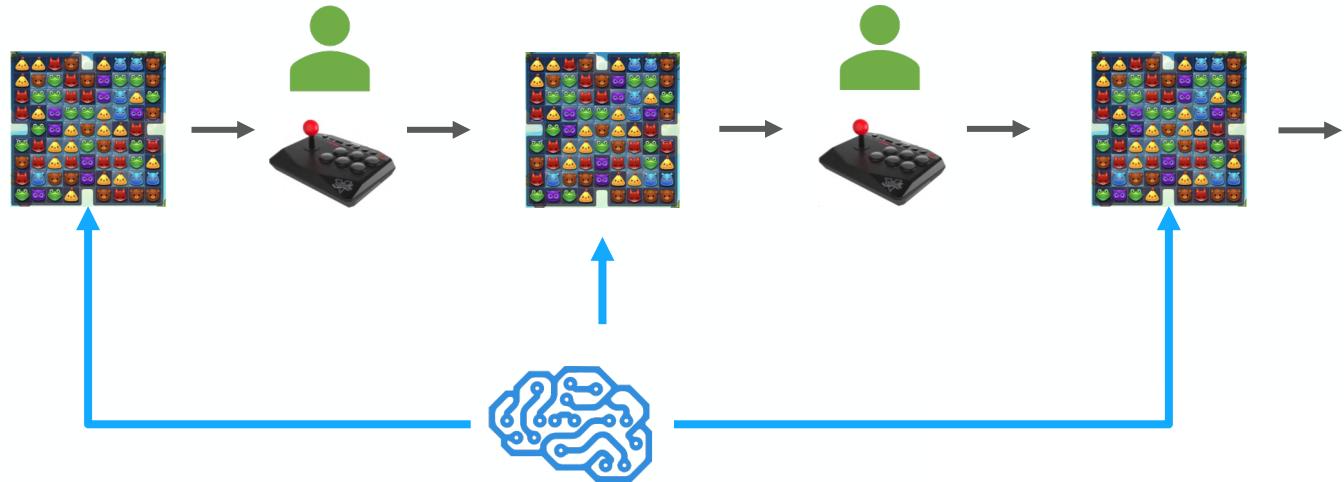
Gameplay modification: Action sequences



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Problem Formulation

Gameplay modification: Action sequences



Objective: Rewards = player revenue/retention

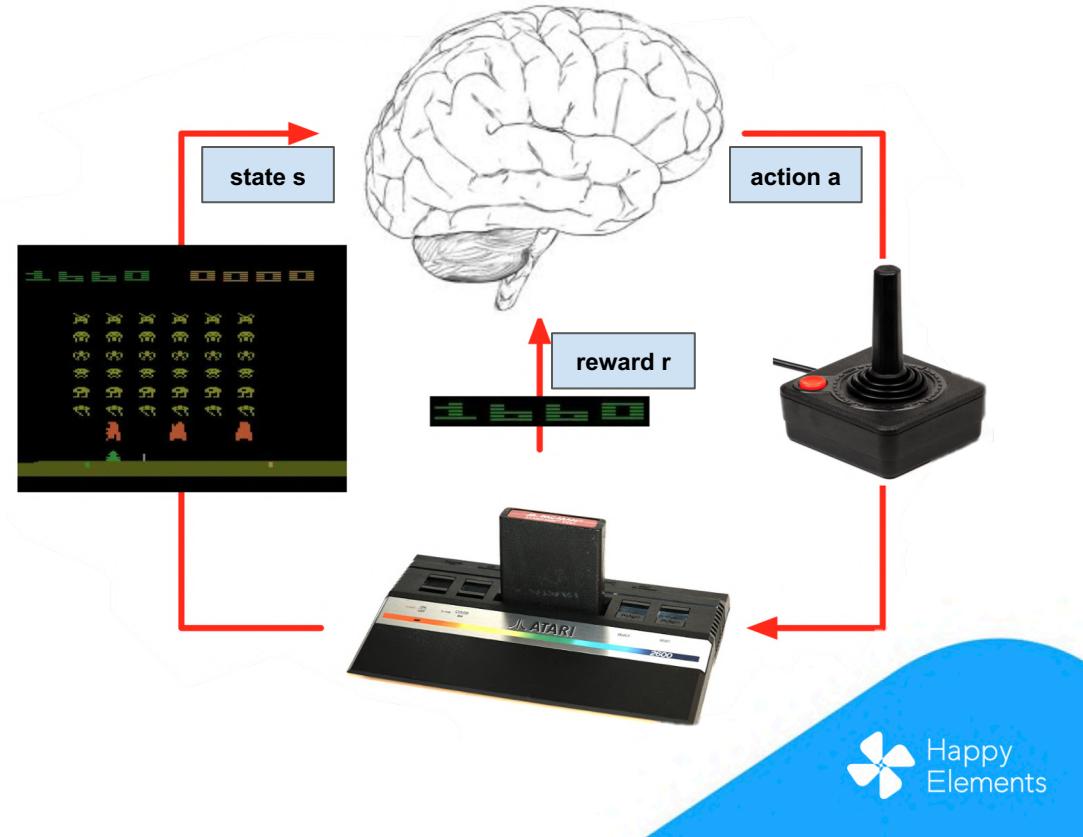
Deep Reinforcement Learning

- 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:

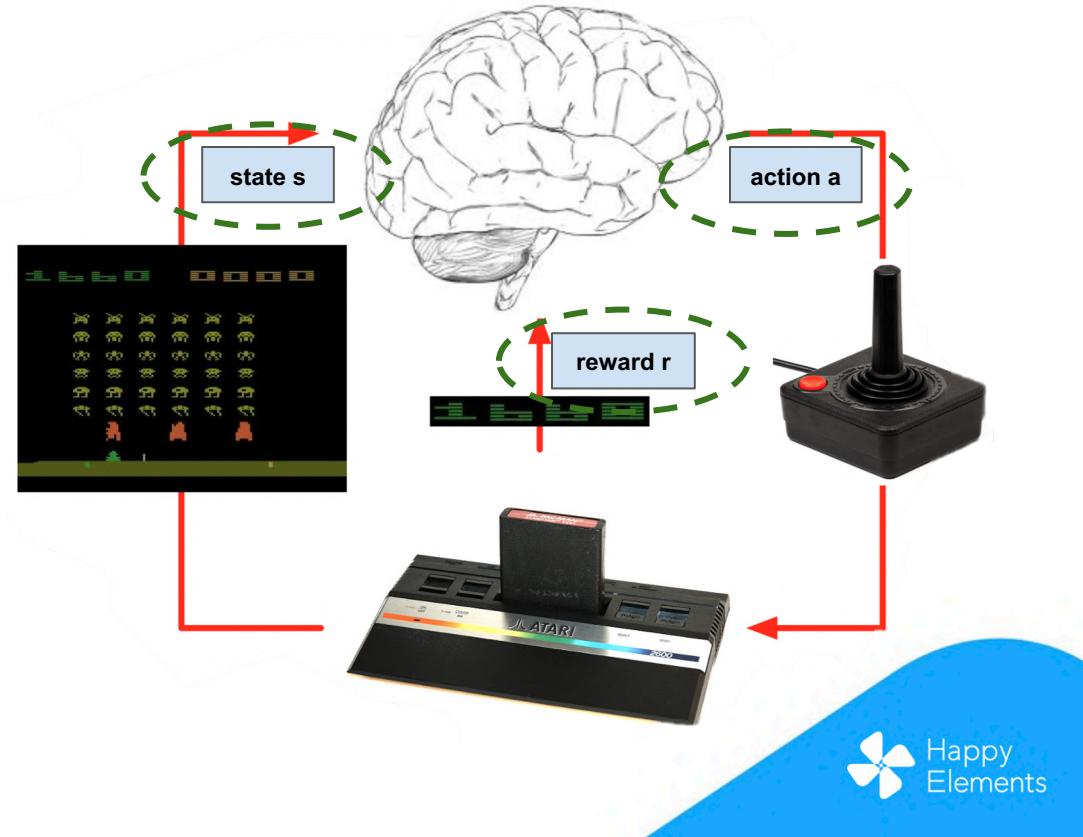
- What **action a** to take in **state s** to **optimize** the expected **reward $E[r]$** ?
- For example, video game:
 - state s = screen
 - action a = controller
 - reward r = score



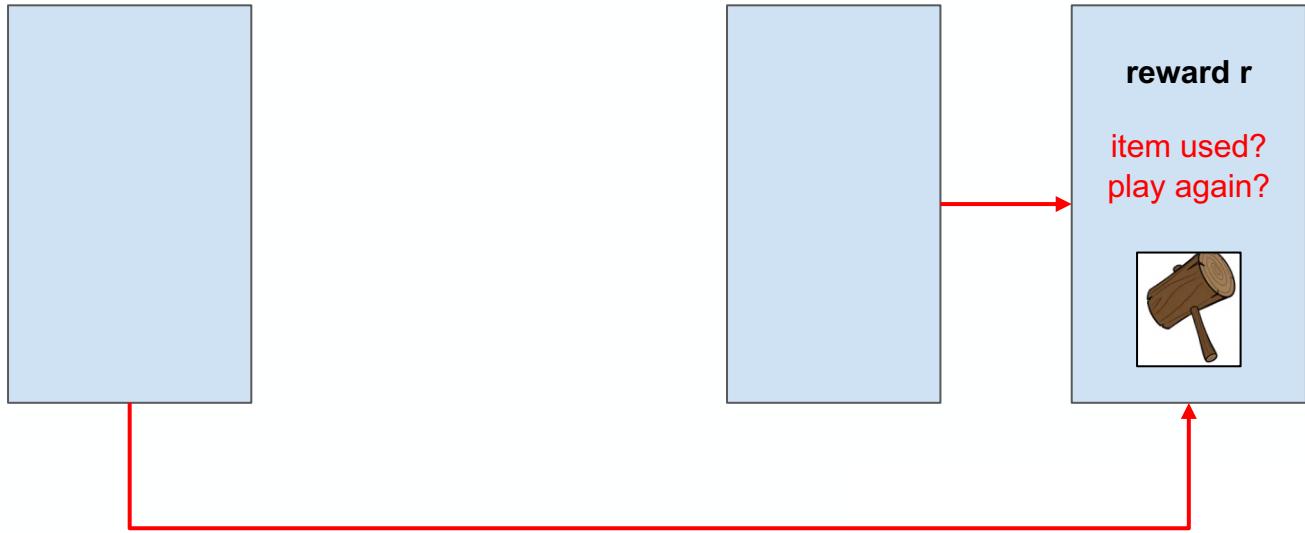
Problem Formulation

Reinforcement Learning:

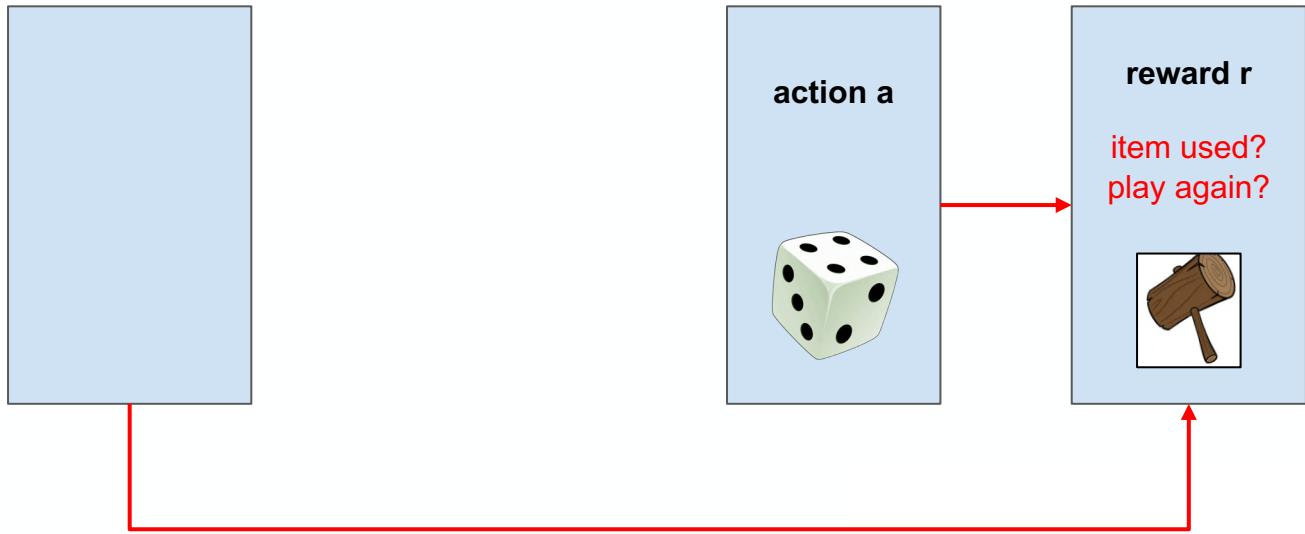
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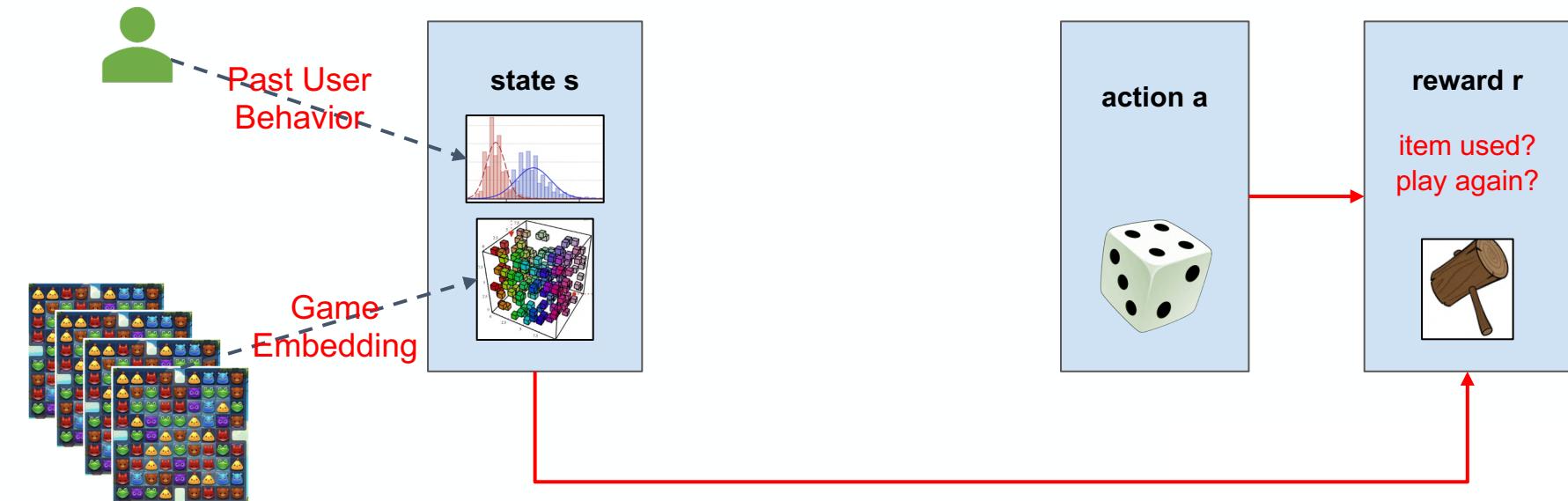
Reinforcement Learning



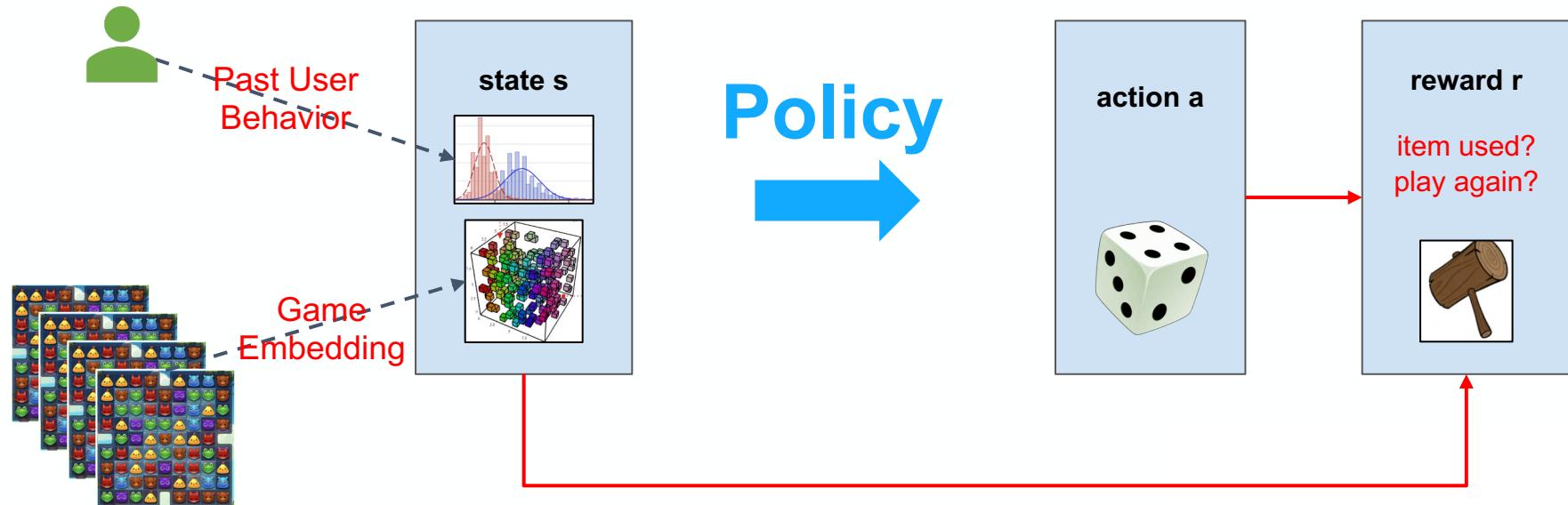
Reinforcement Learning



Reinforcement Learning



Reinforcement Learning

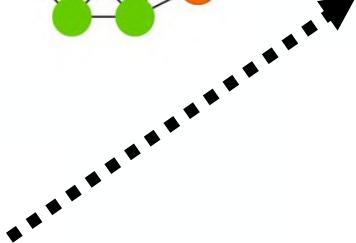
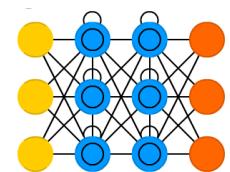
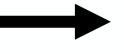
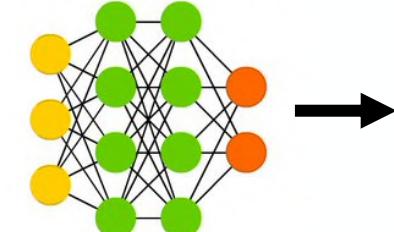
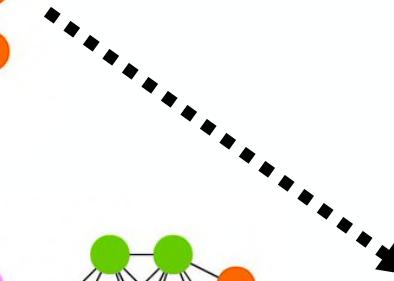
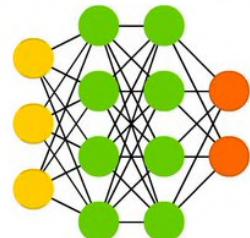
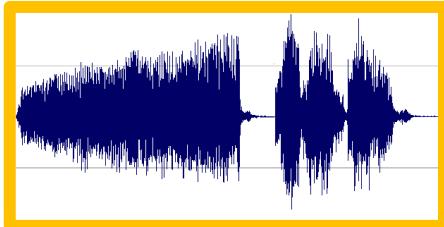


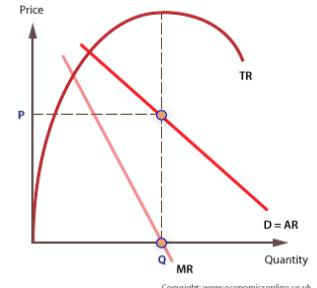
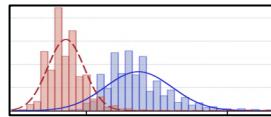
Deep Learning

- 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**

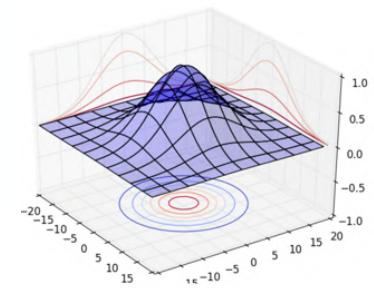
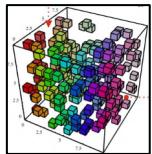
Deep Learning

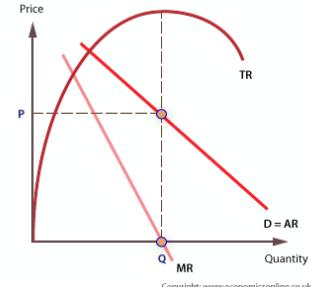
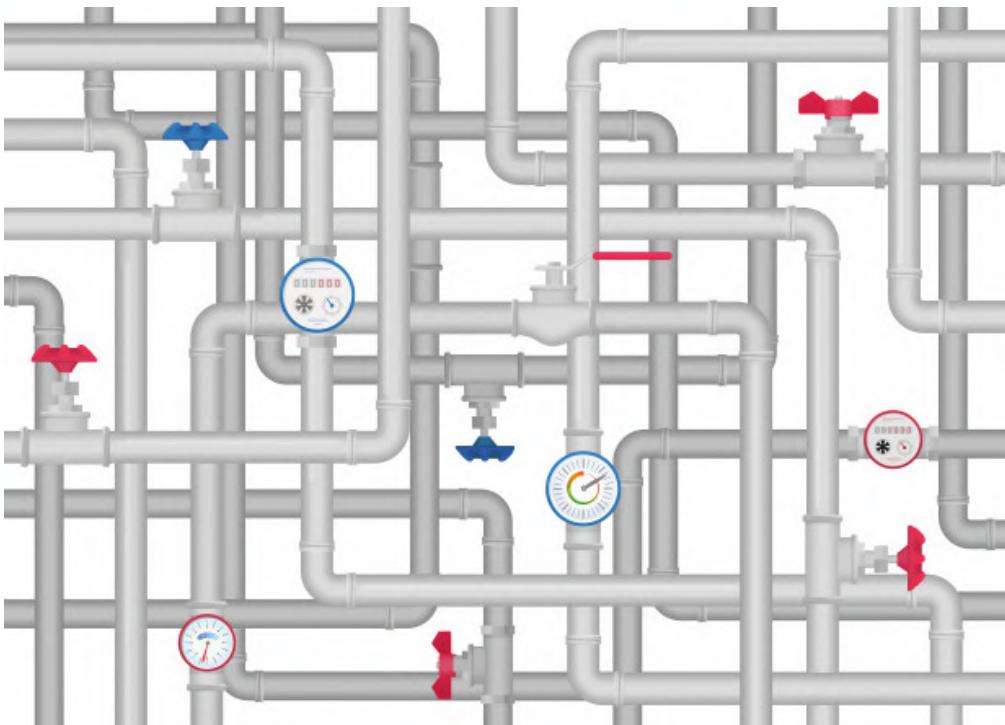
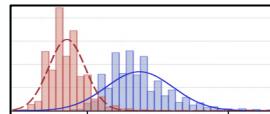
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UK	Buxton	4/01/2018	10899	510
UK	Buxton	21/01/2018	10874	582
UK	Buxton	11/01/2018	10872	761
UK	Buxton	16/01/2018	10870	466
UK	Buxton	14/01/2018	10869	946
UK	Buxton	7/02/2018	10866	935



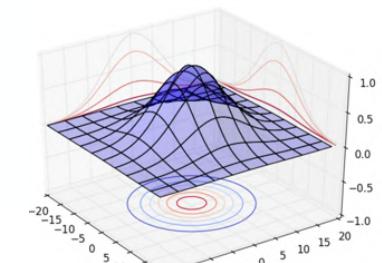
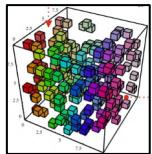


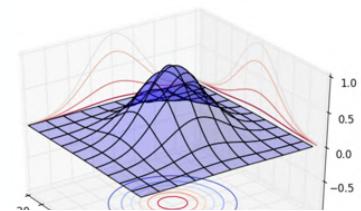
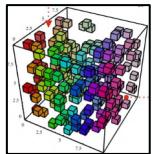
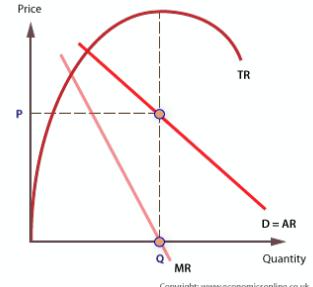
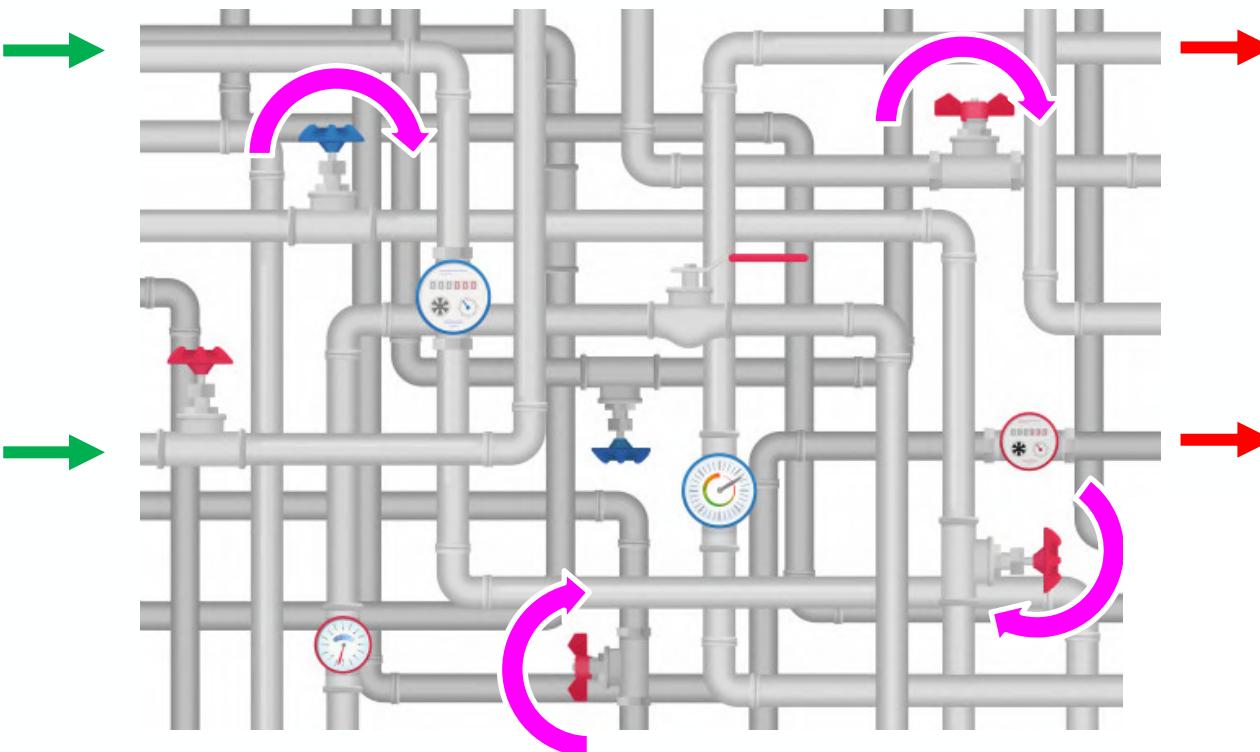
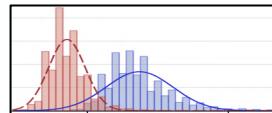
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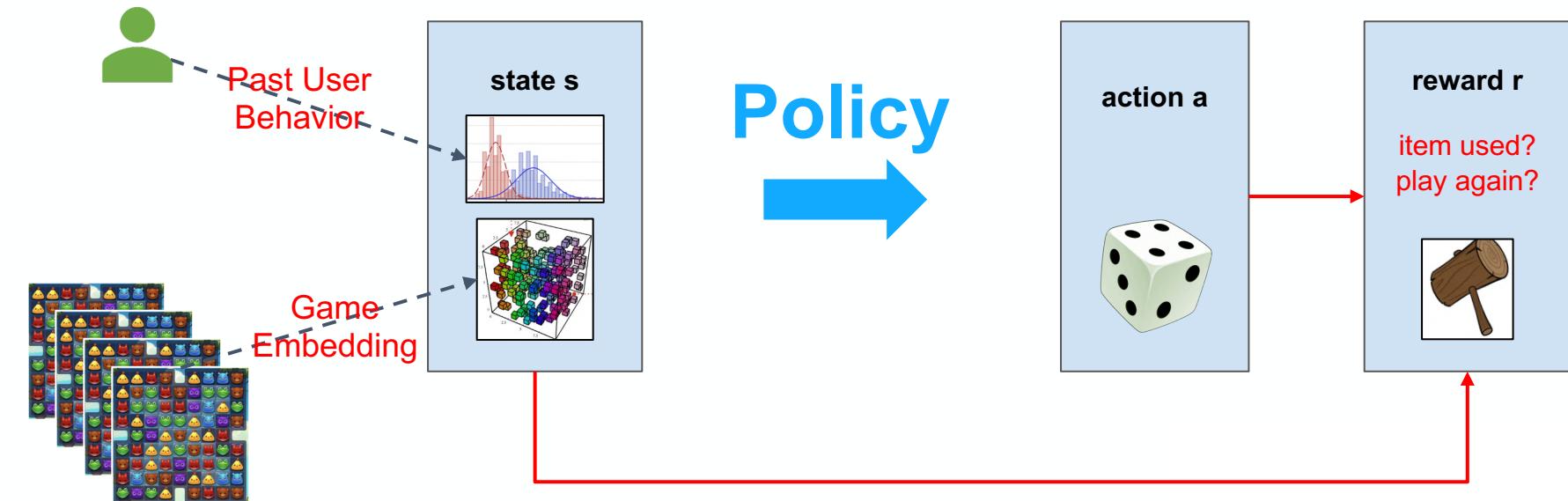


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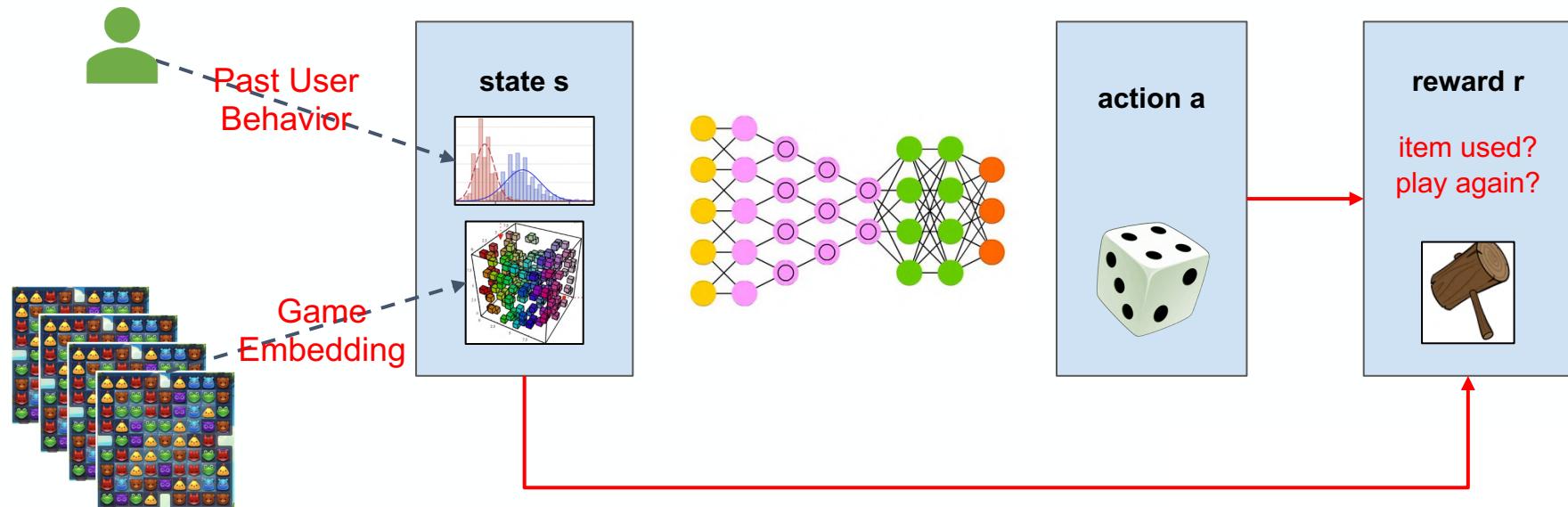




Reinforcement Learning



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:

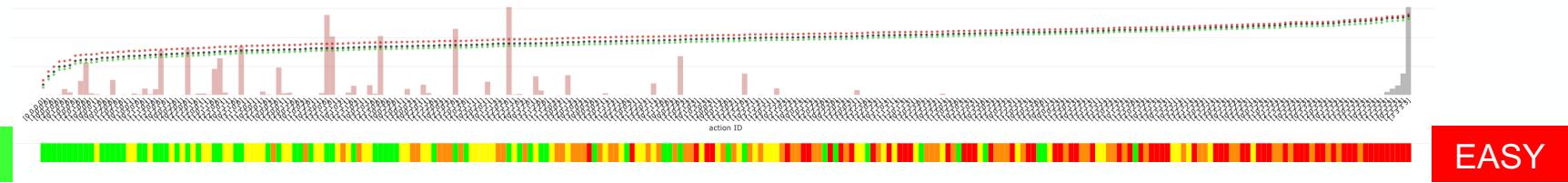
What when the data regime is highly non-stationary?

Optimization Horizon

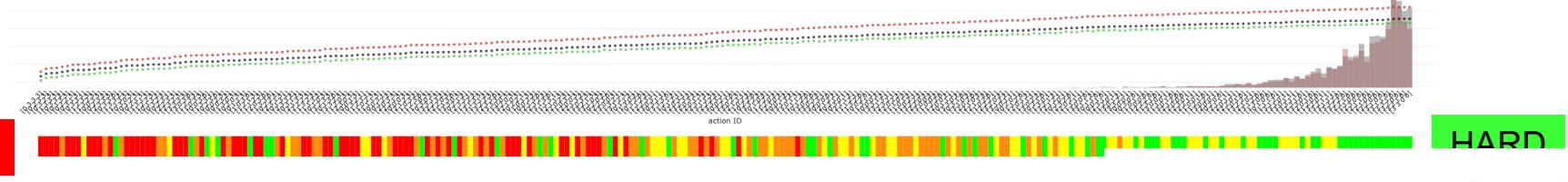
- Often it is easy to define **short-term targets**:
Did the user play another in-game level?
Did the user make an in-app purchase?
- But how does this lead to **long-term objectives**?
User engagement over the next year
Life-time value of player

Optimization Horizon

Retention

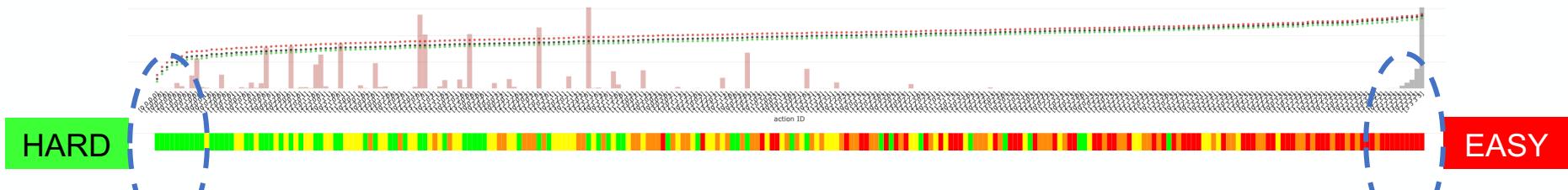


Revenue

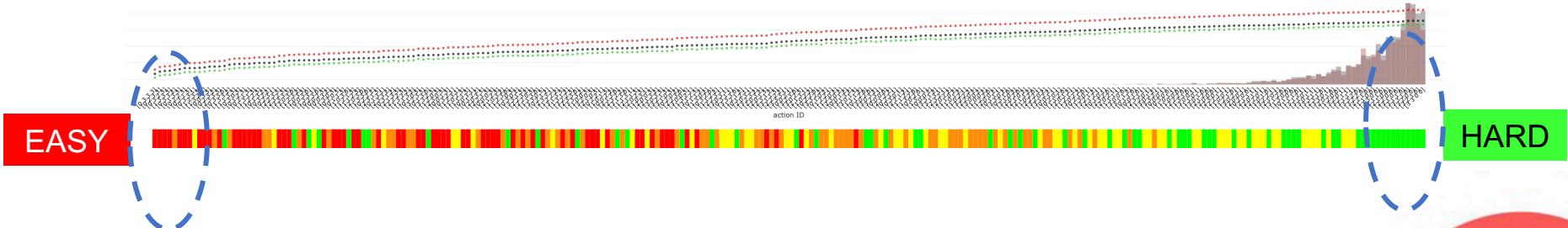


Optimization Horizon

Retention



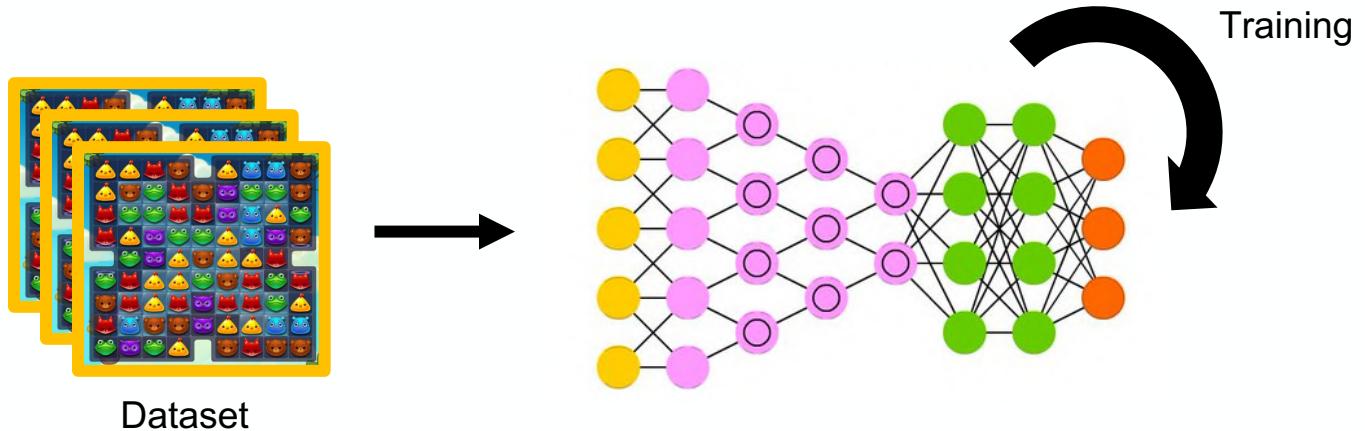
Revenue



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

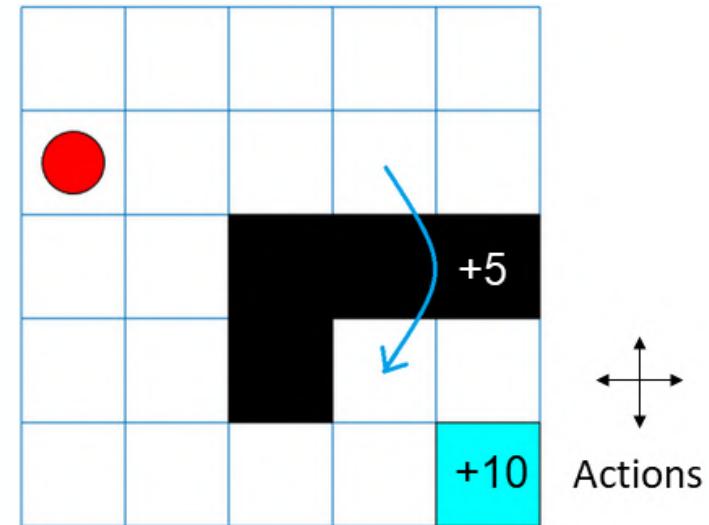
Exploration – Exploitation Duality



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

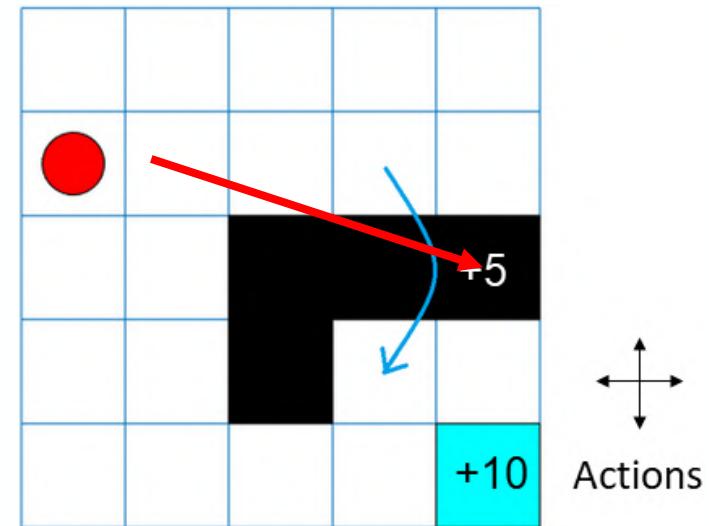
Exploration – Exploitation Duality

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



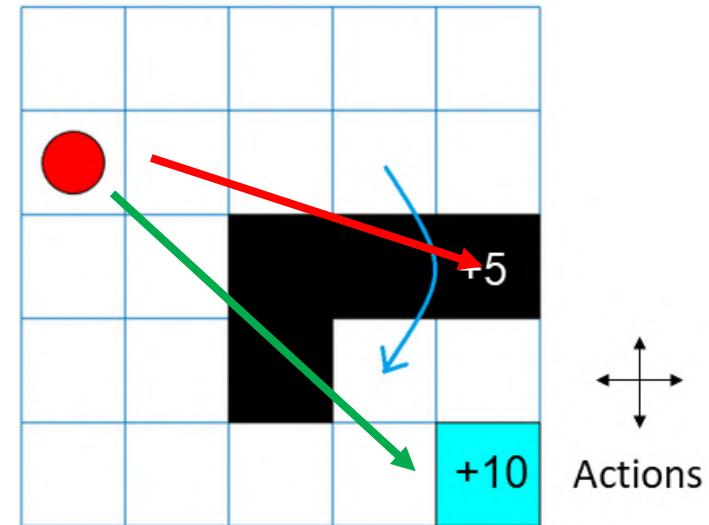
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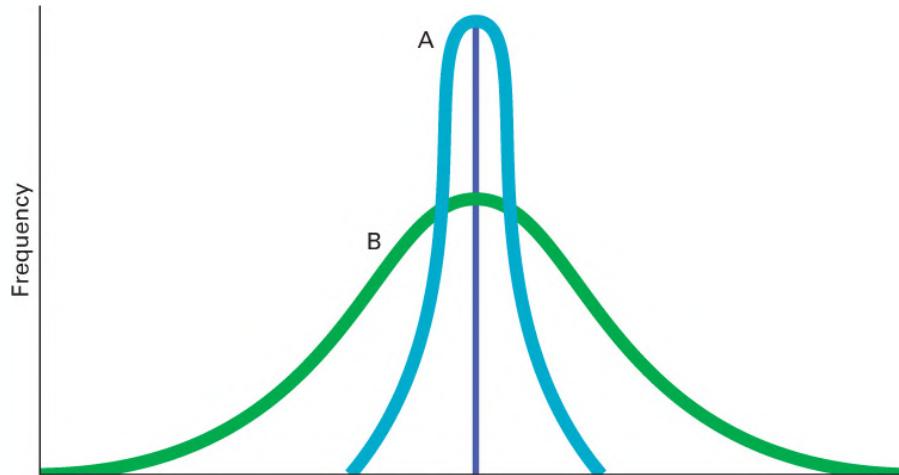
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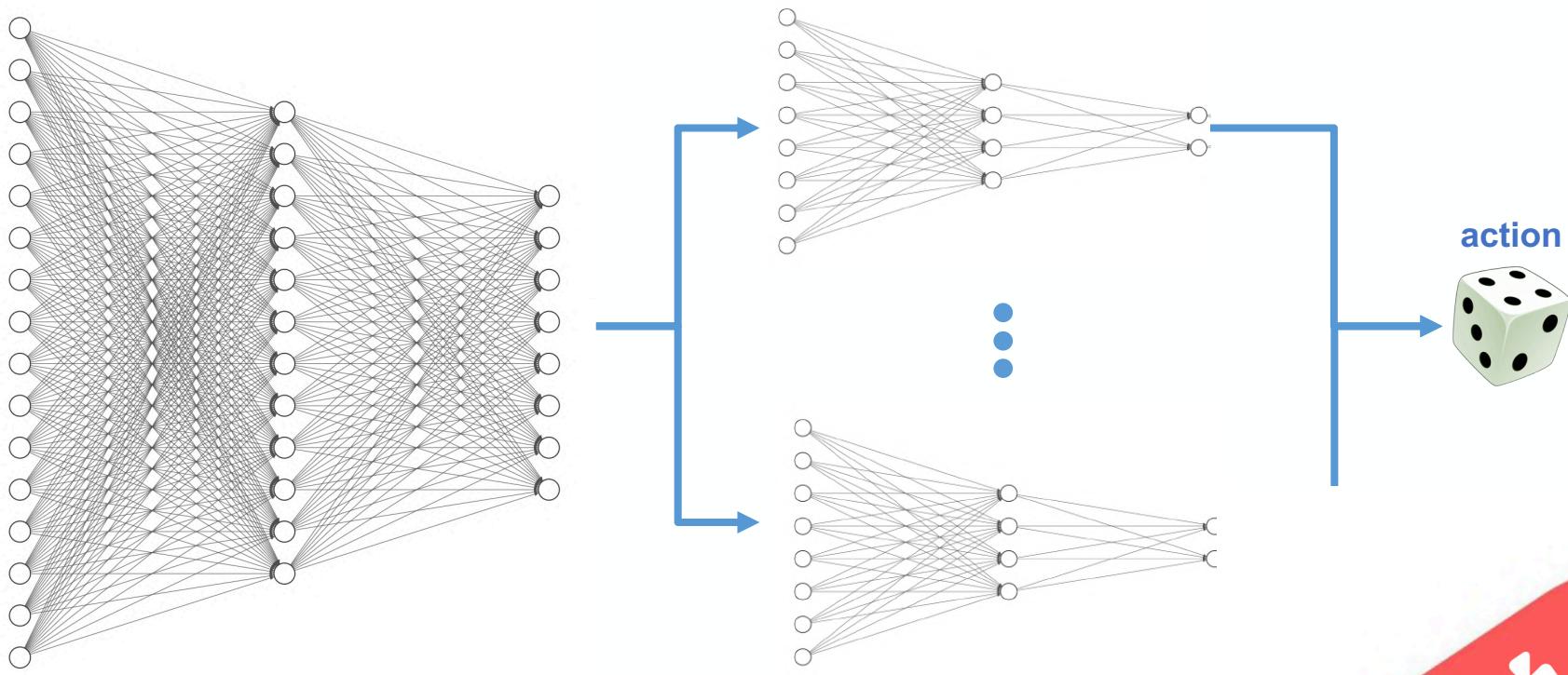


Exploration – Exploitation Duality

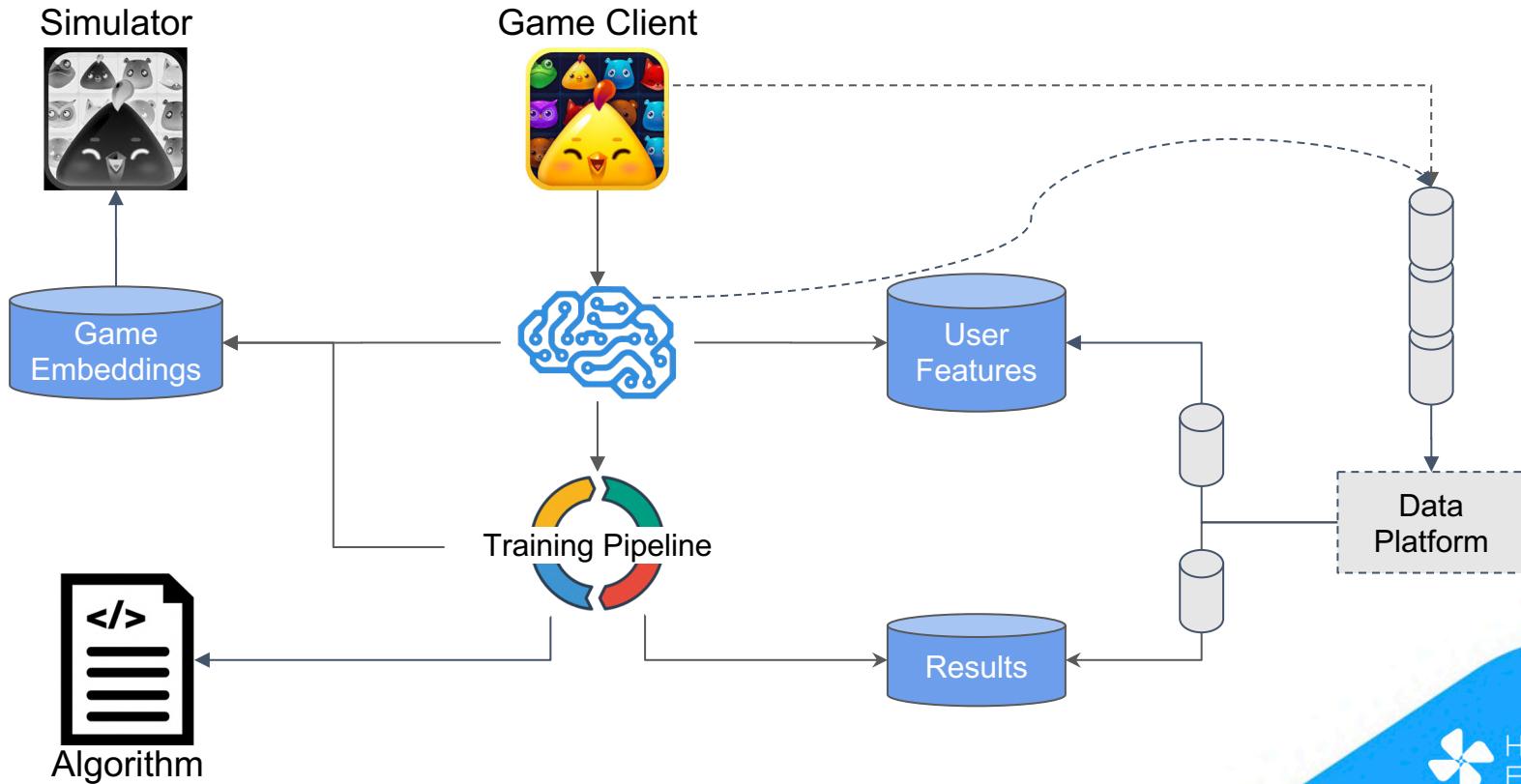
- Approximate Bayesian approach to capture **model uncertainty**
- Solving exploitation (A) vs. exploration (B) problem.



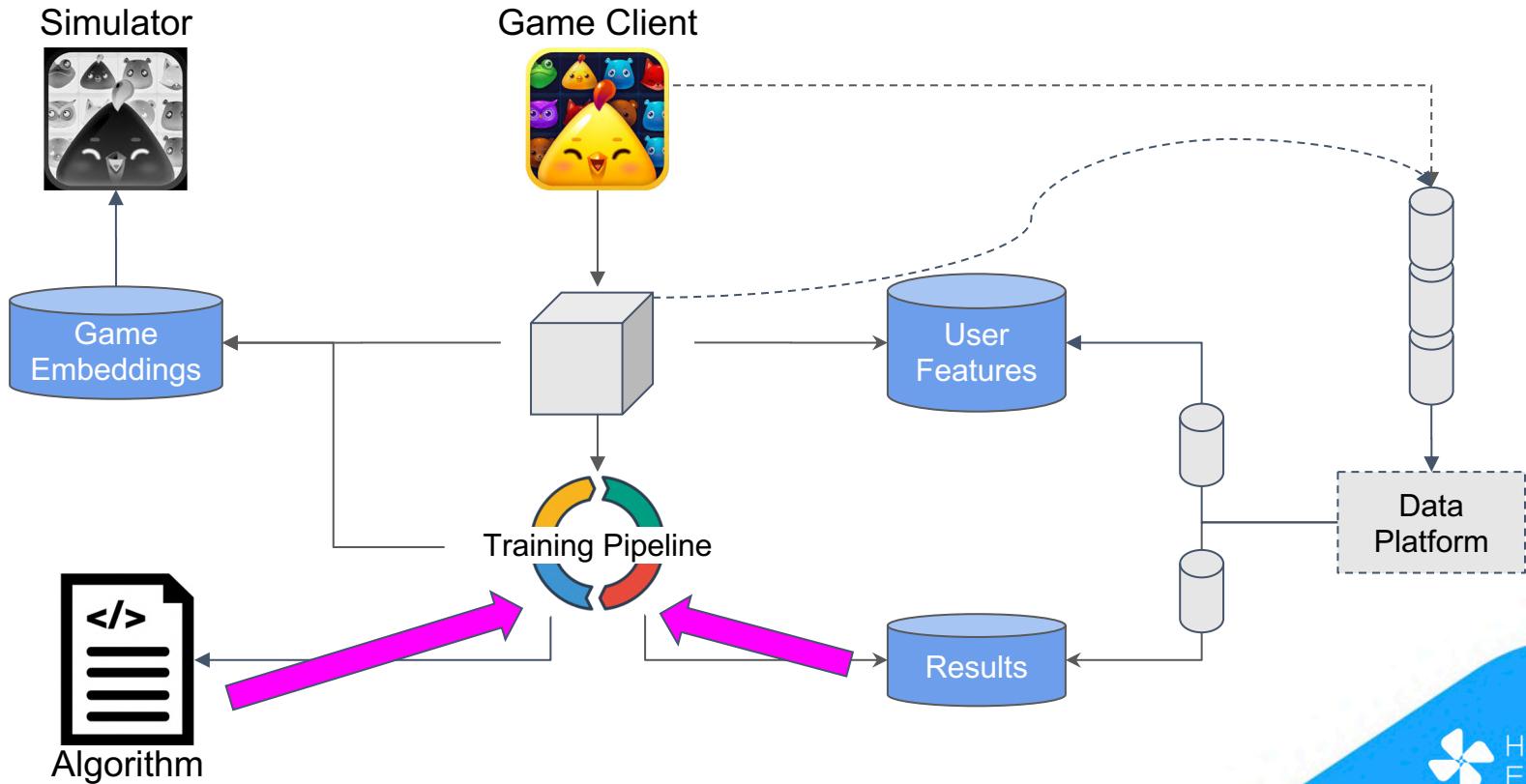
Model: Bootstrapped Contextual Bandits



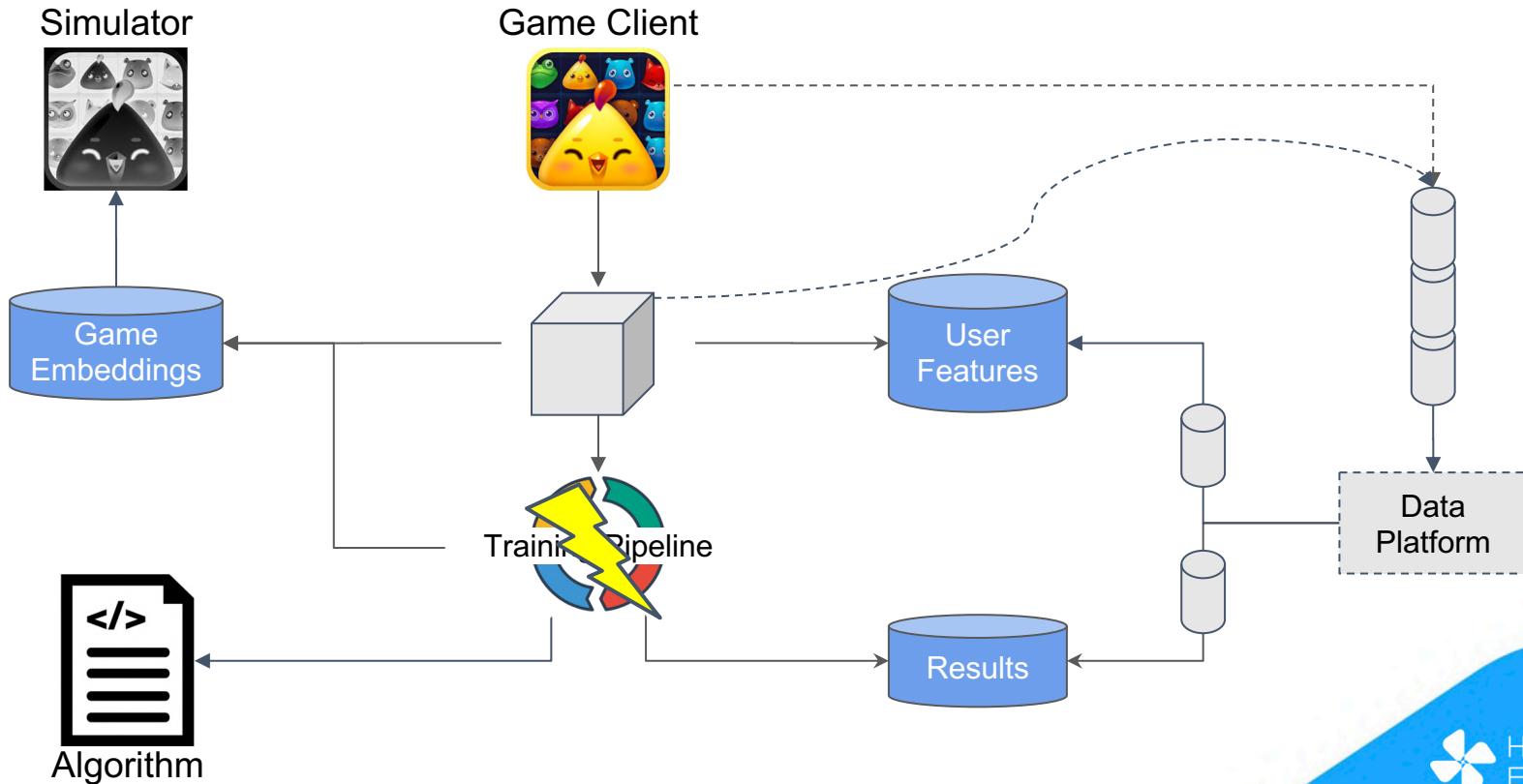
System Architecture



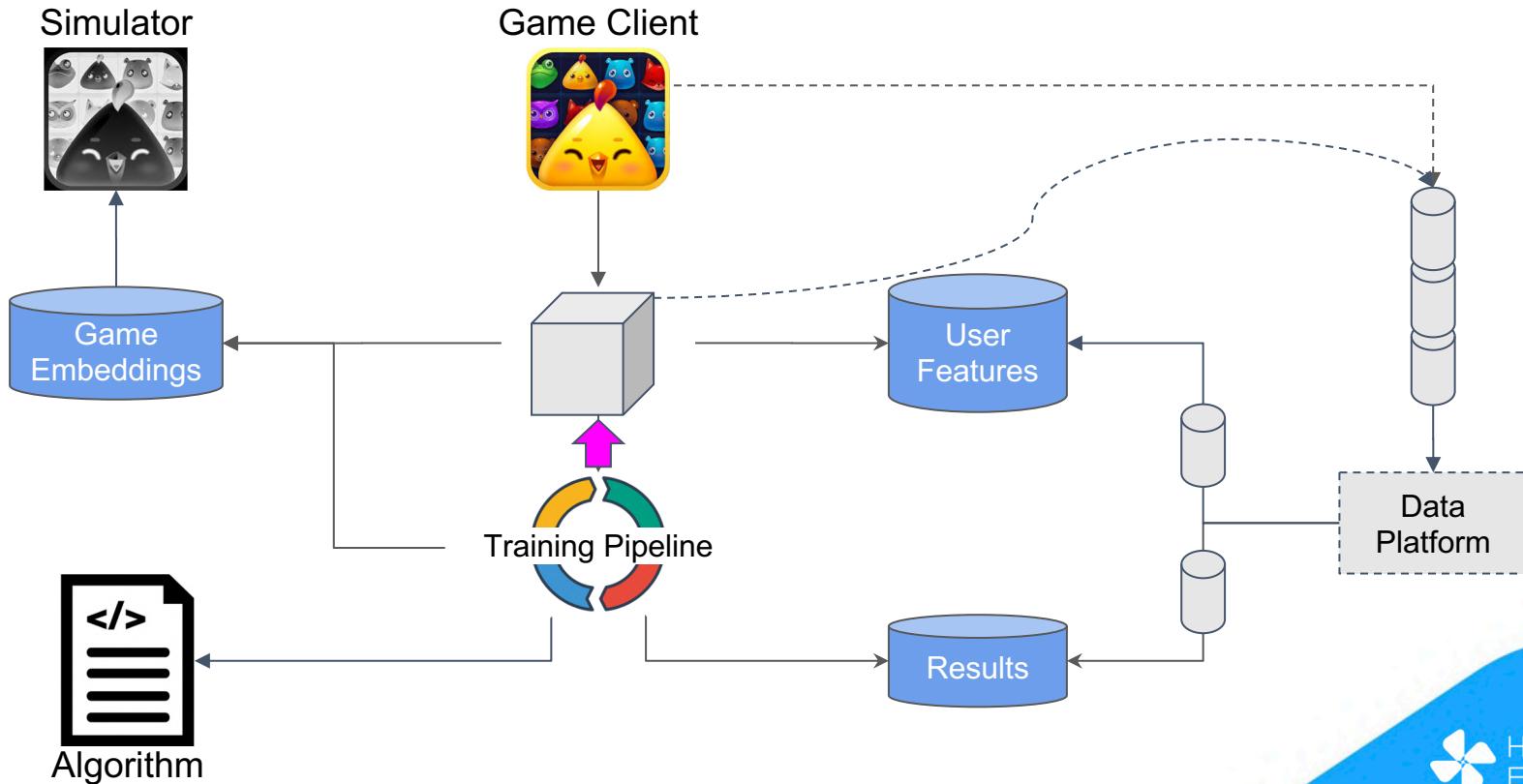
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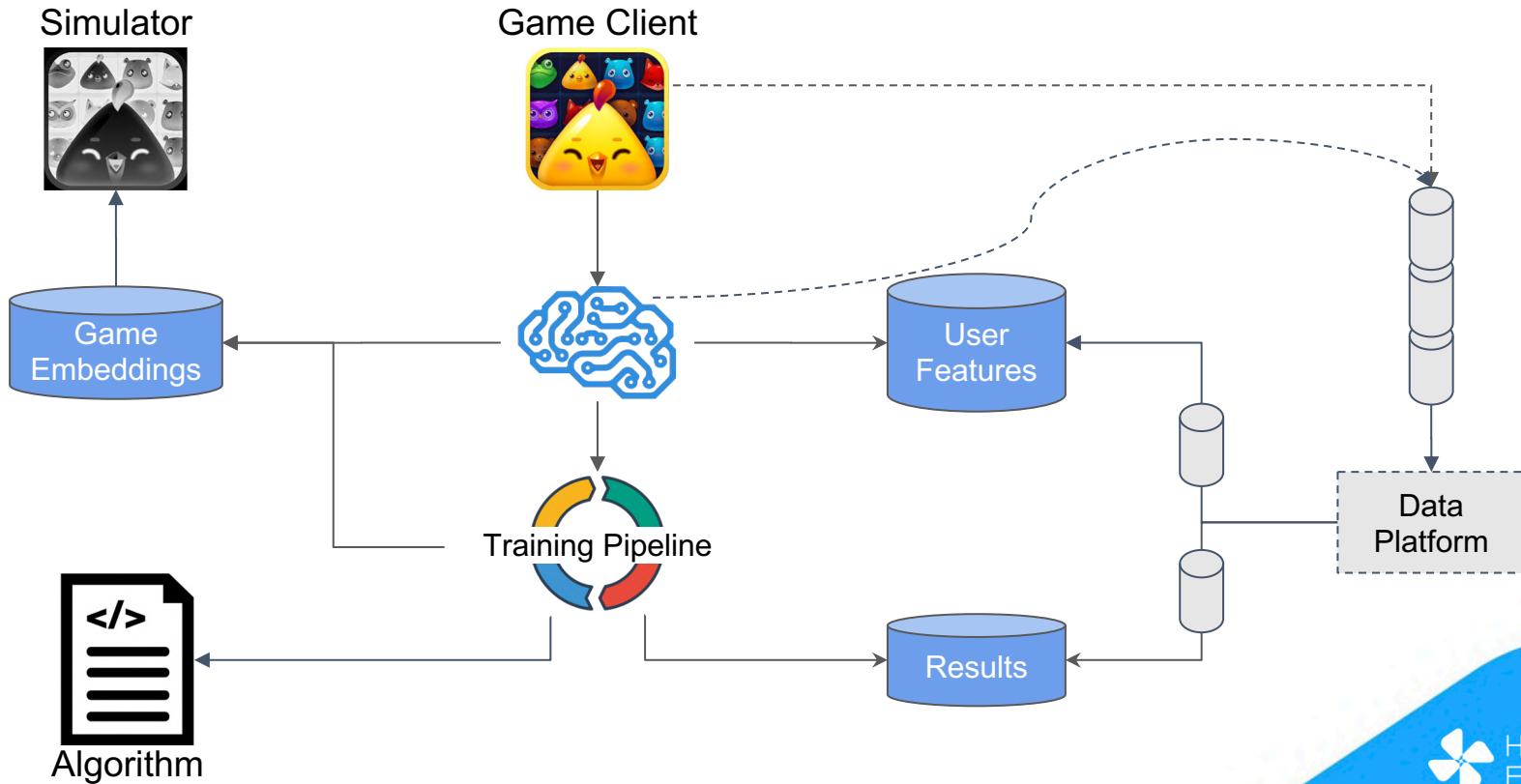
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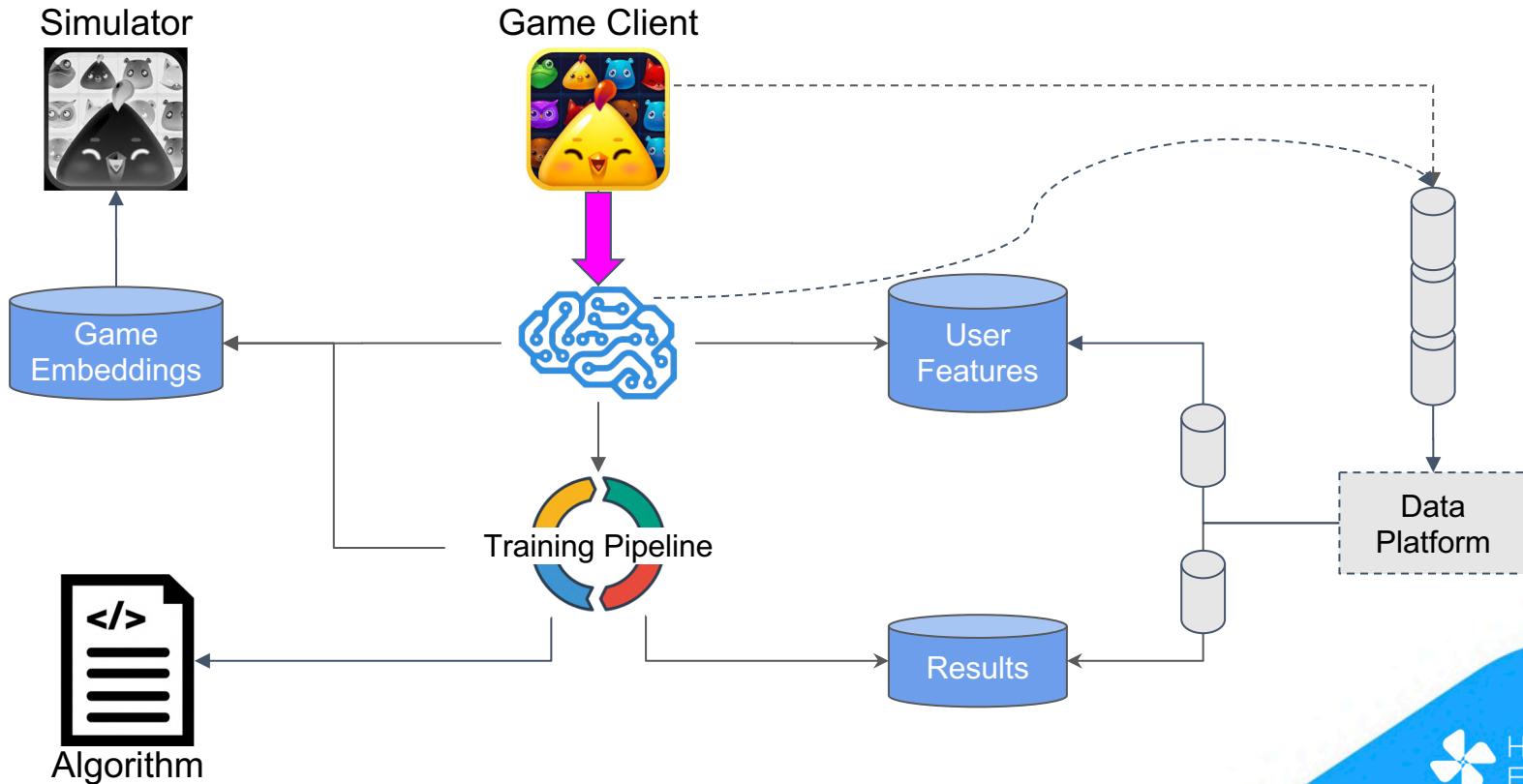
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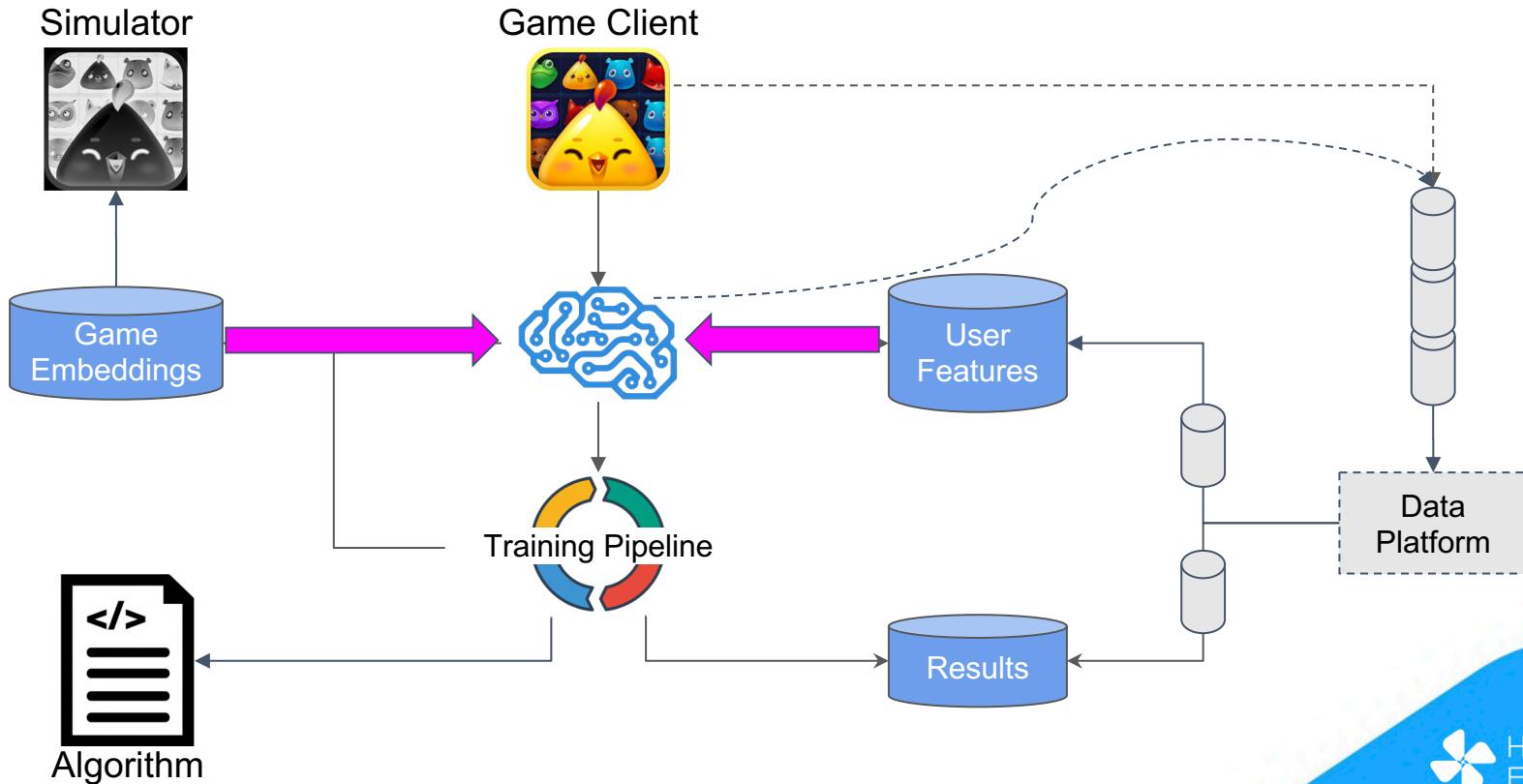
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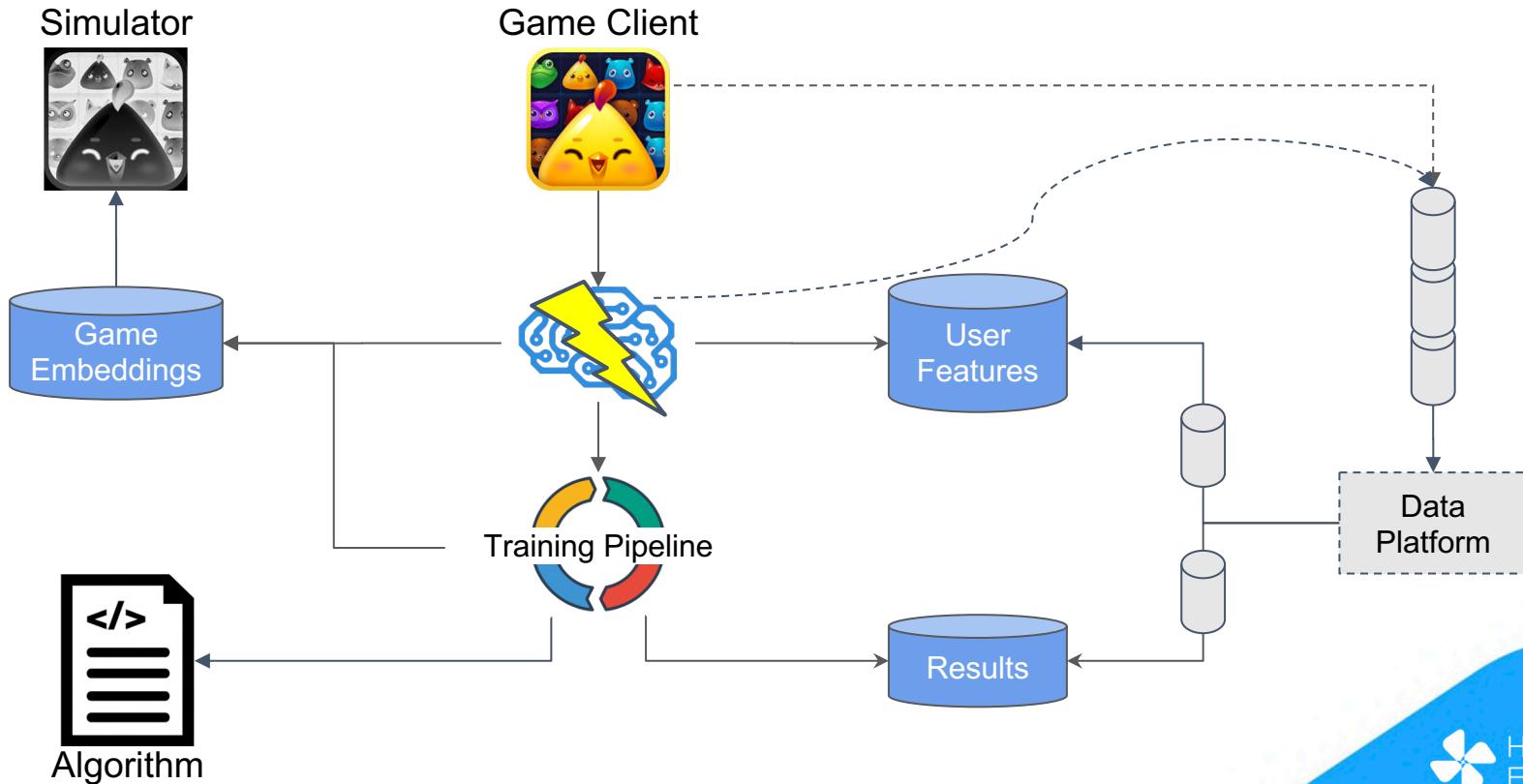
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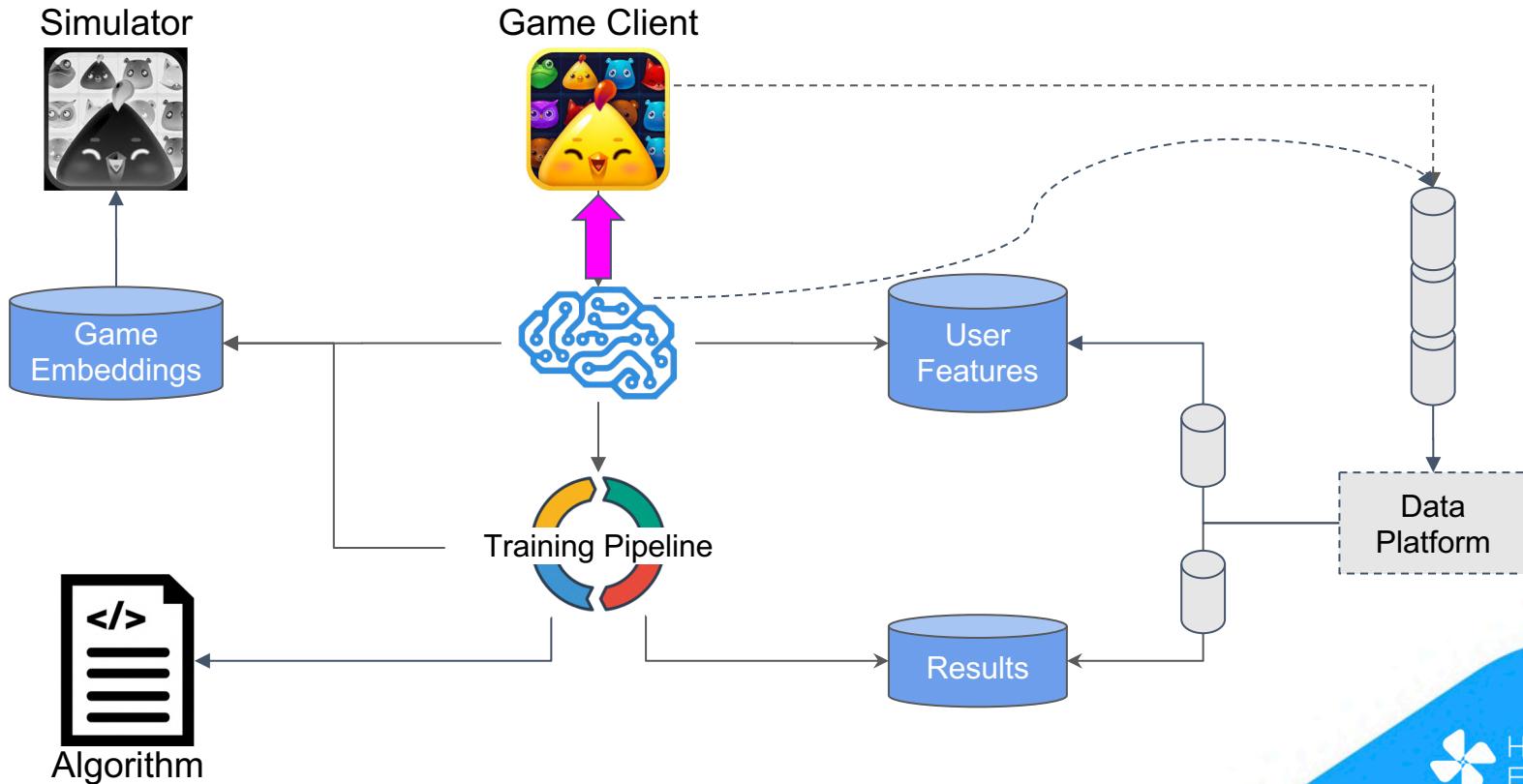
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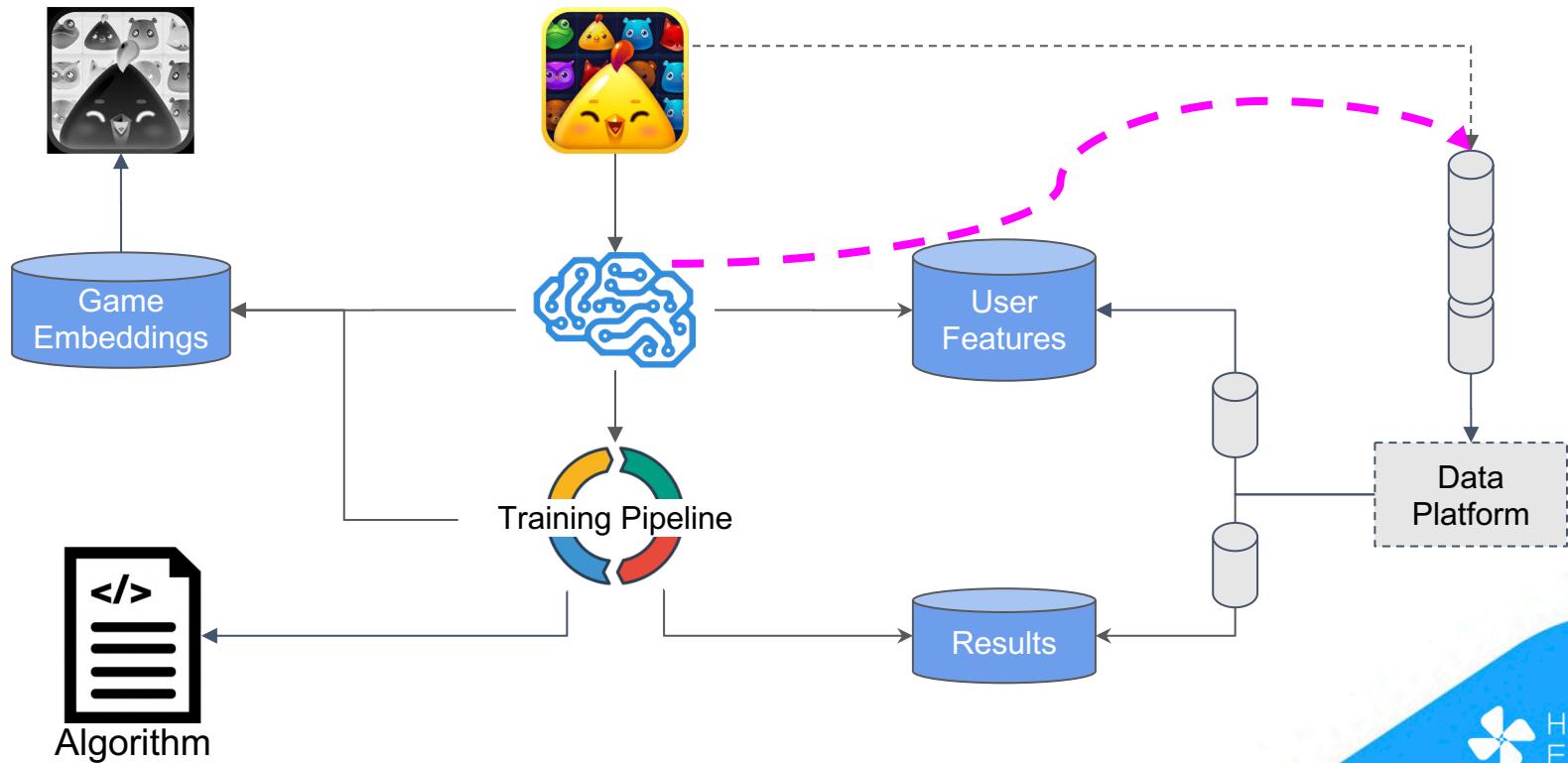
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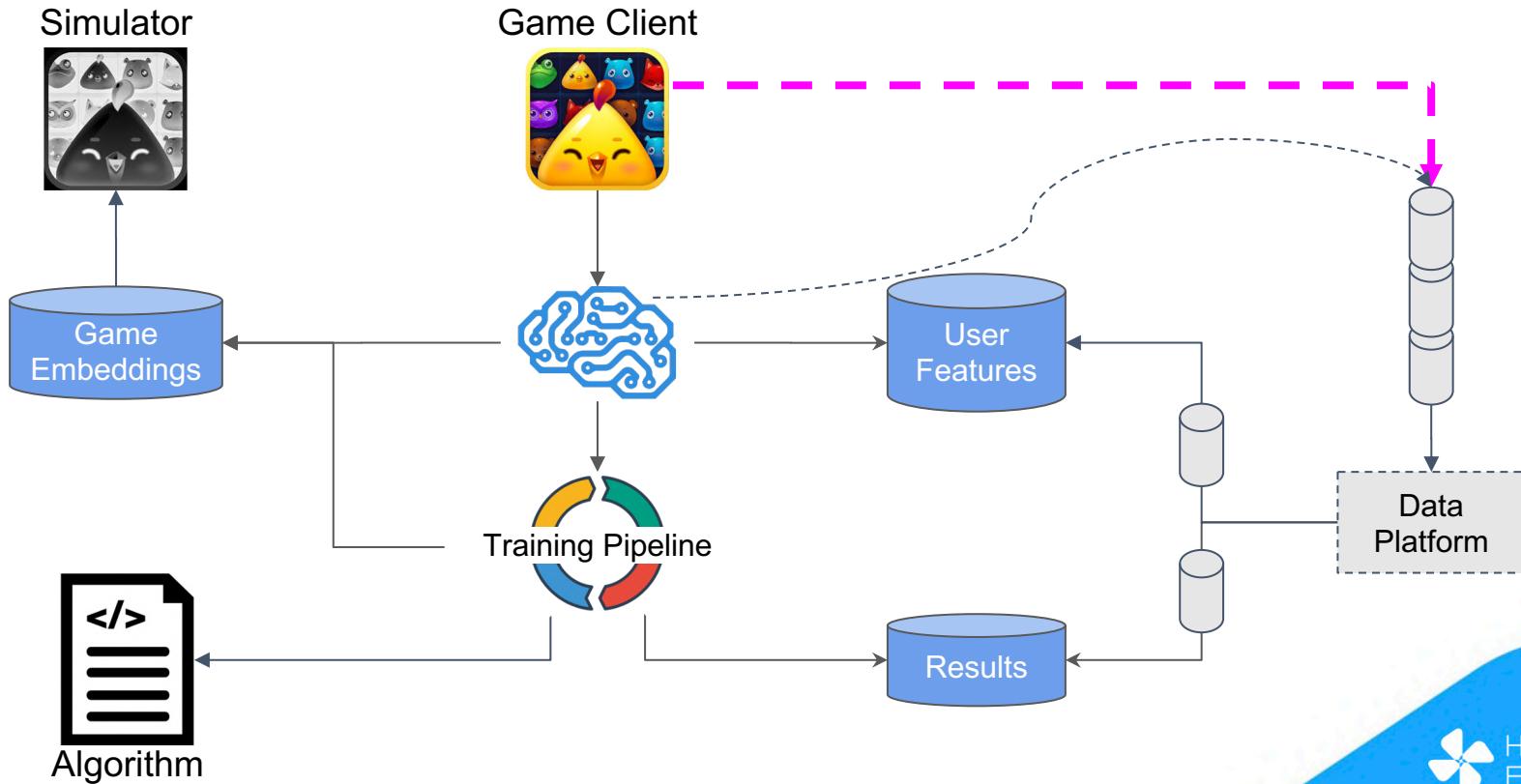
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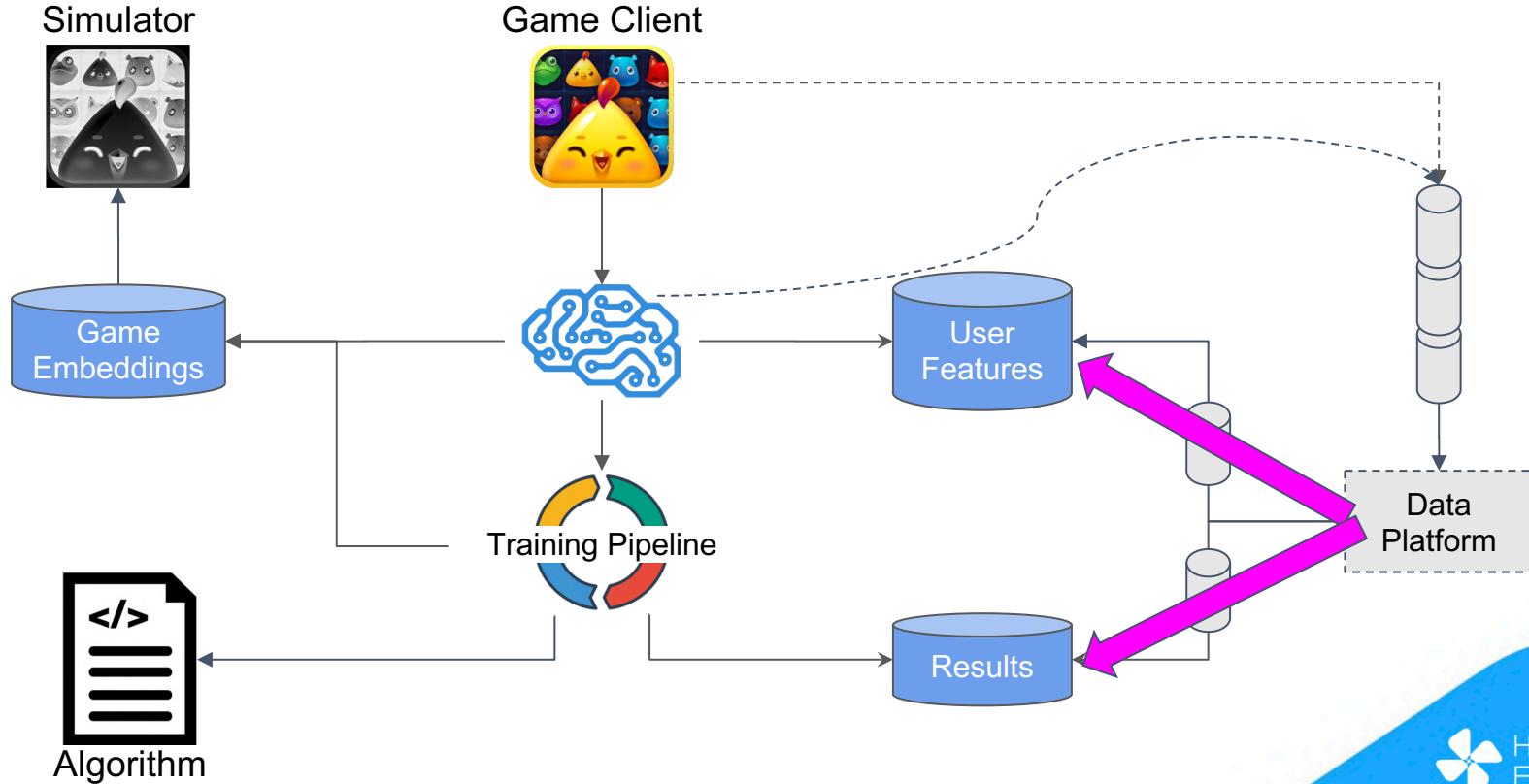
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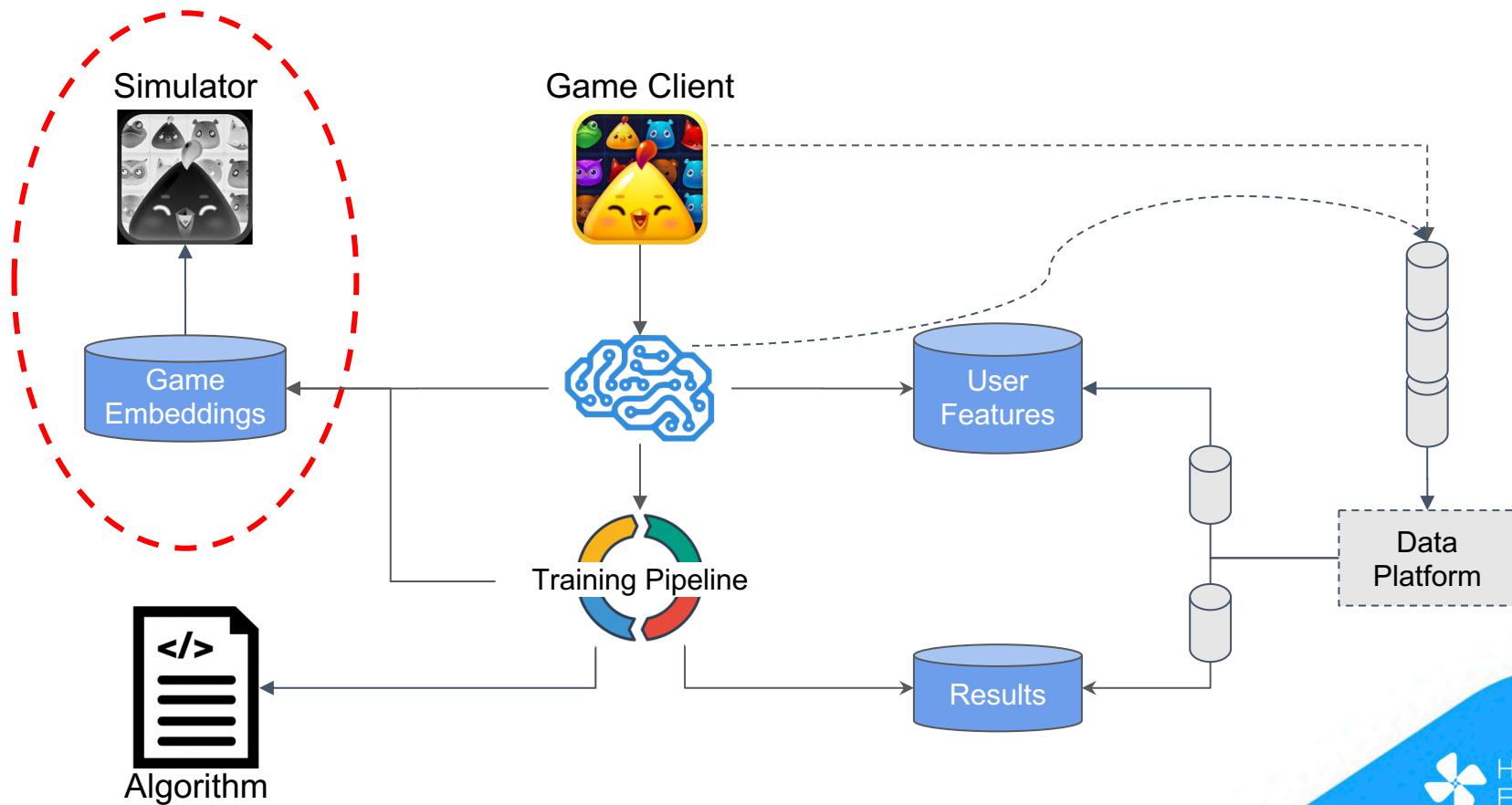
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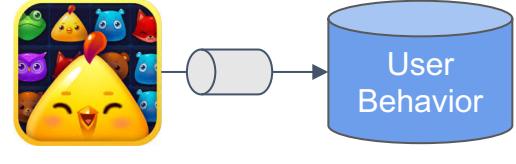
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System Architecture

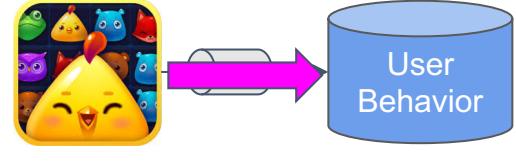


System Architecture: Gameplay Embeddings



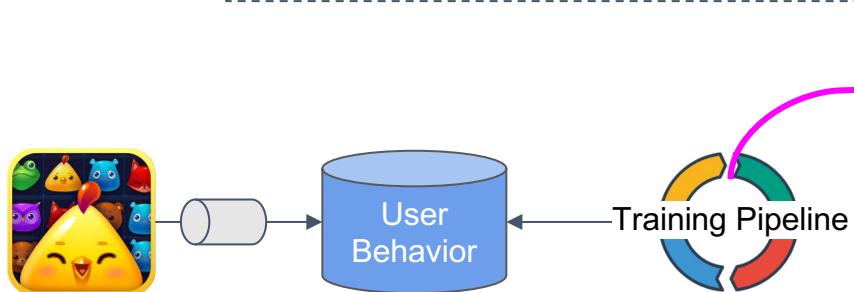
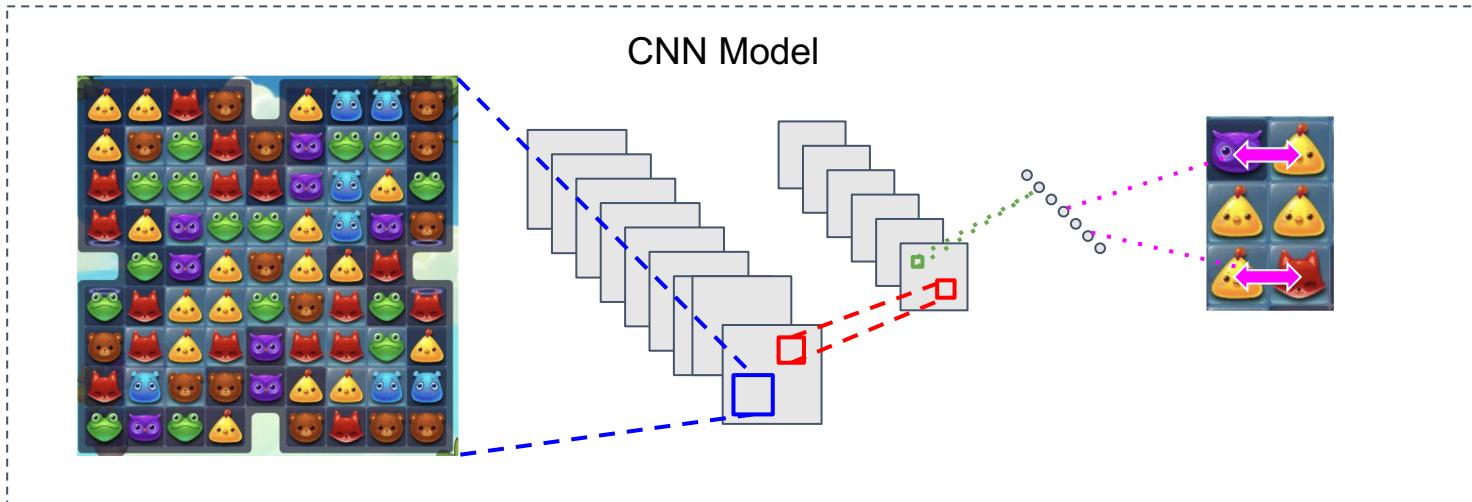
Game Client

System Architecture: Gameplay Embeddings

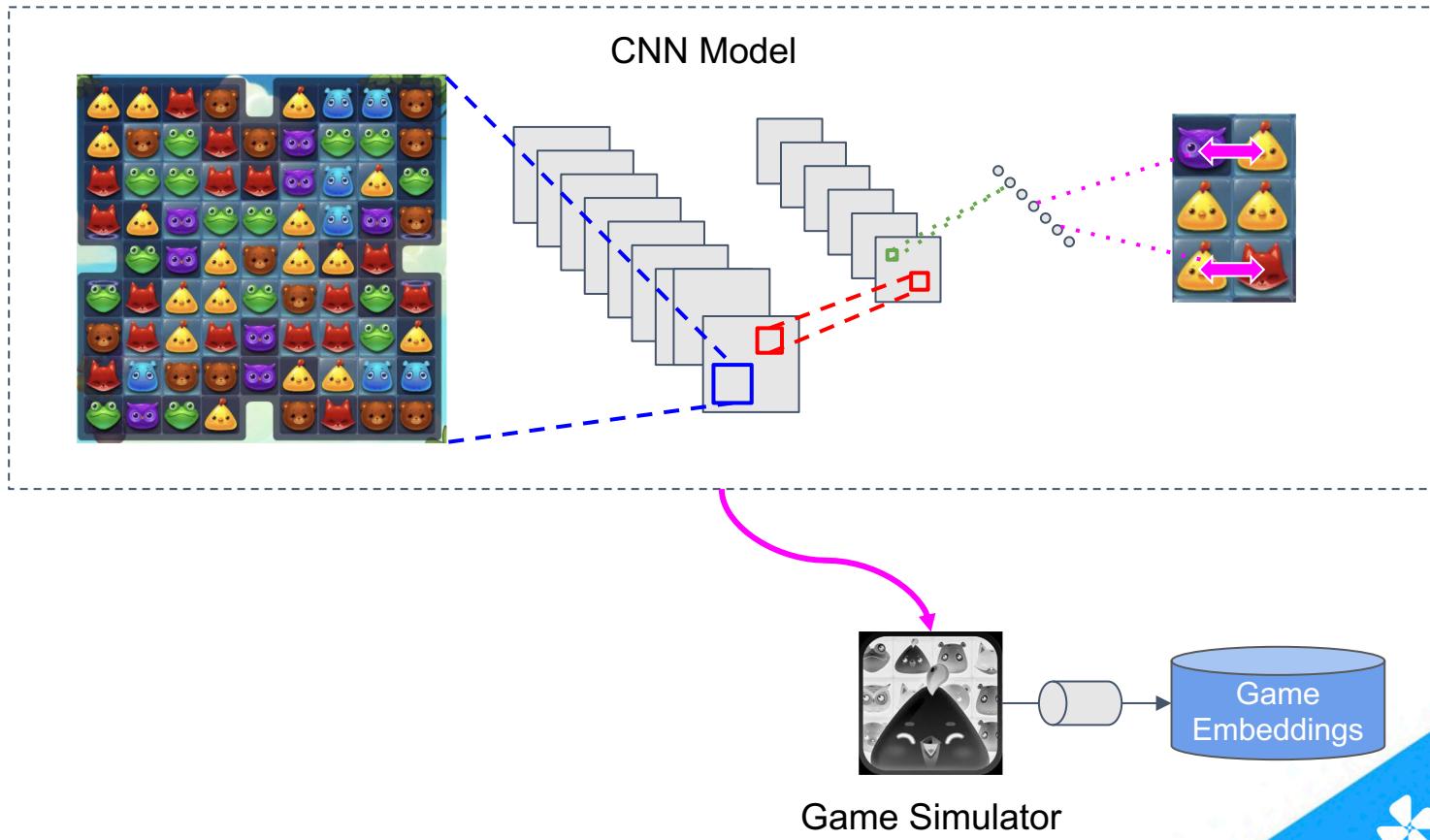


Game Client

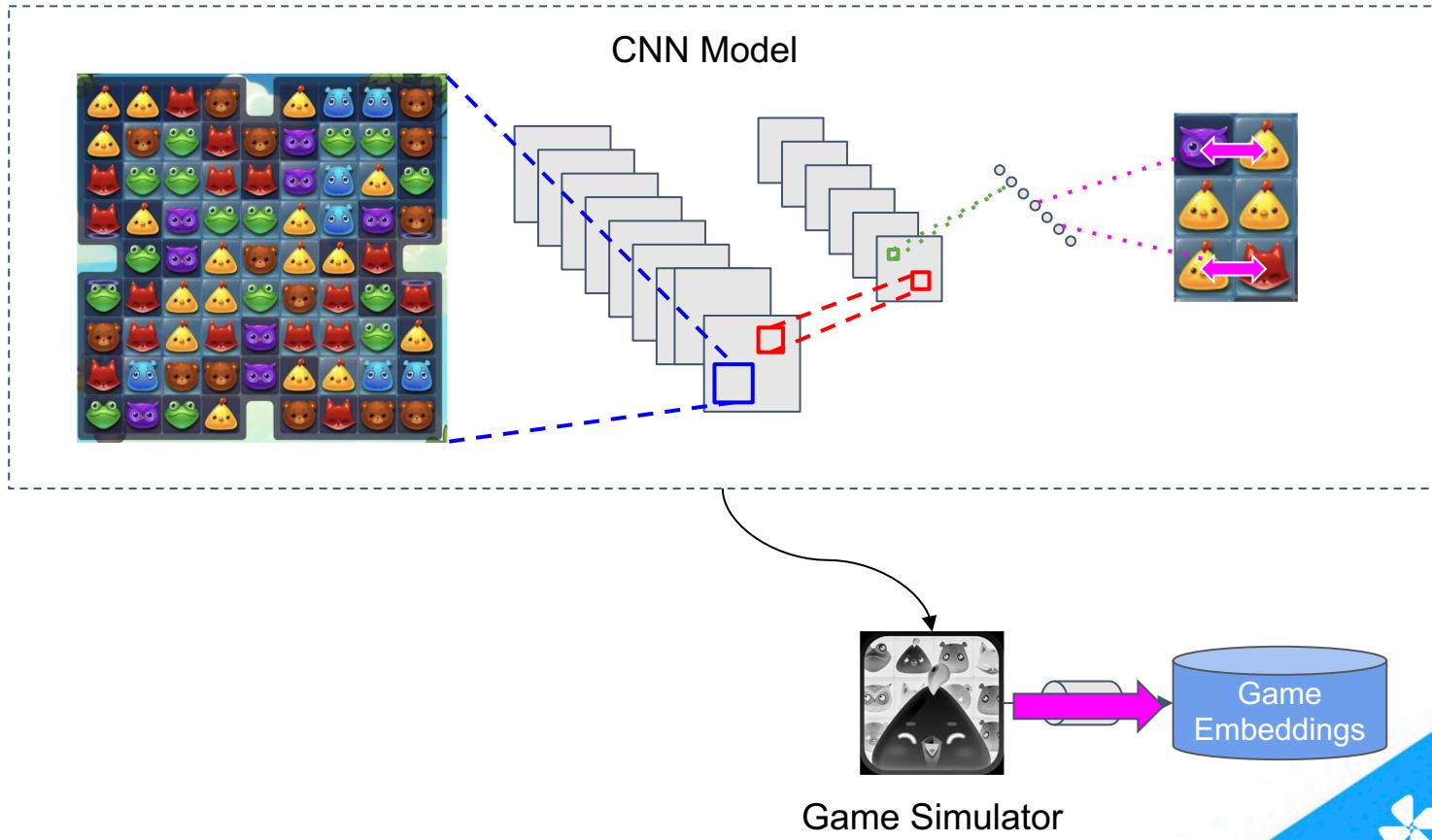
System Architecture: Gameplay Embeddings



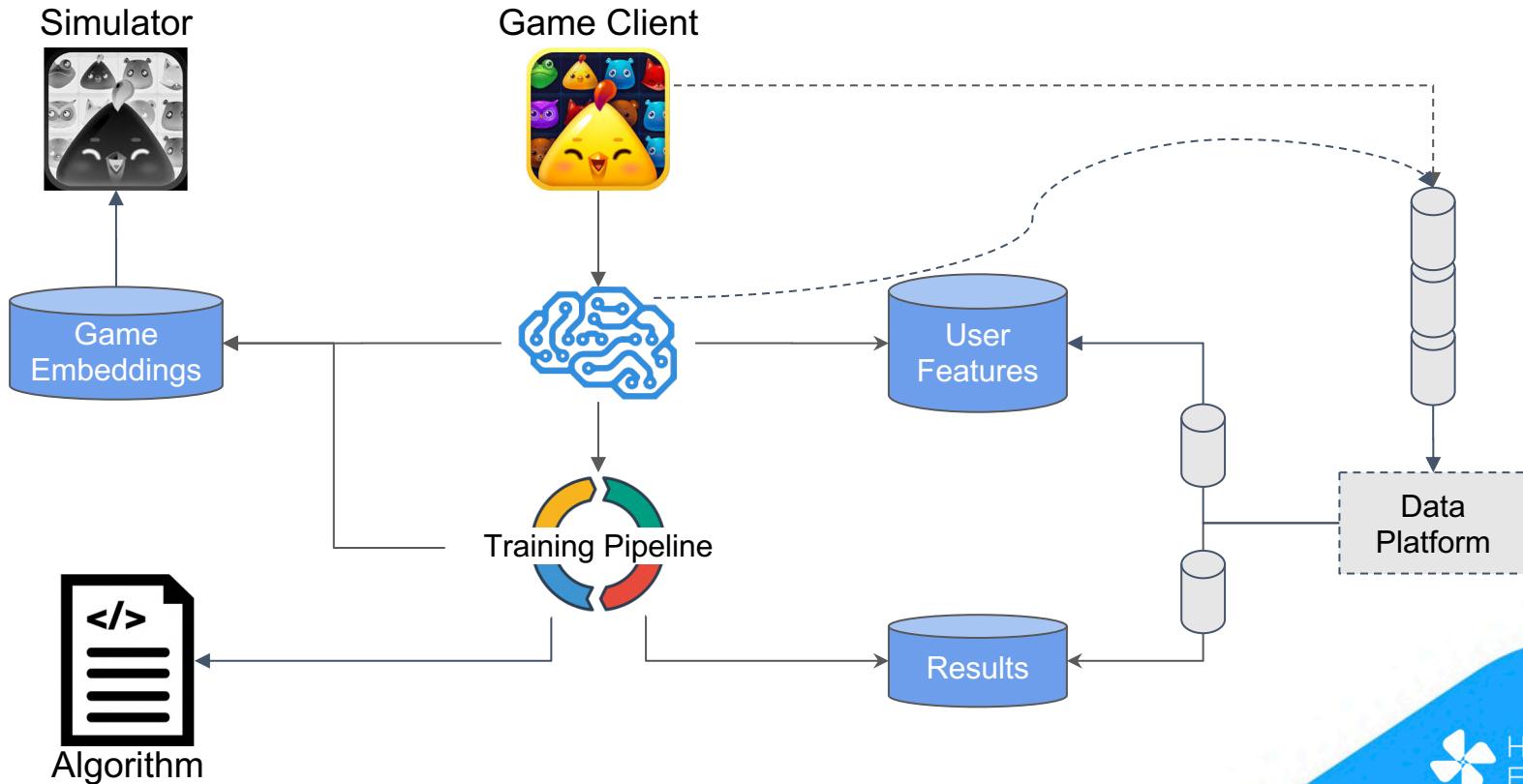
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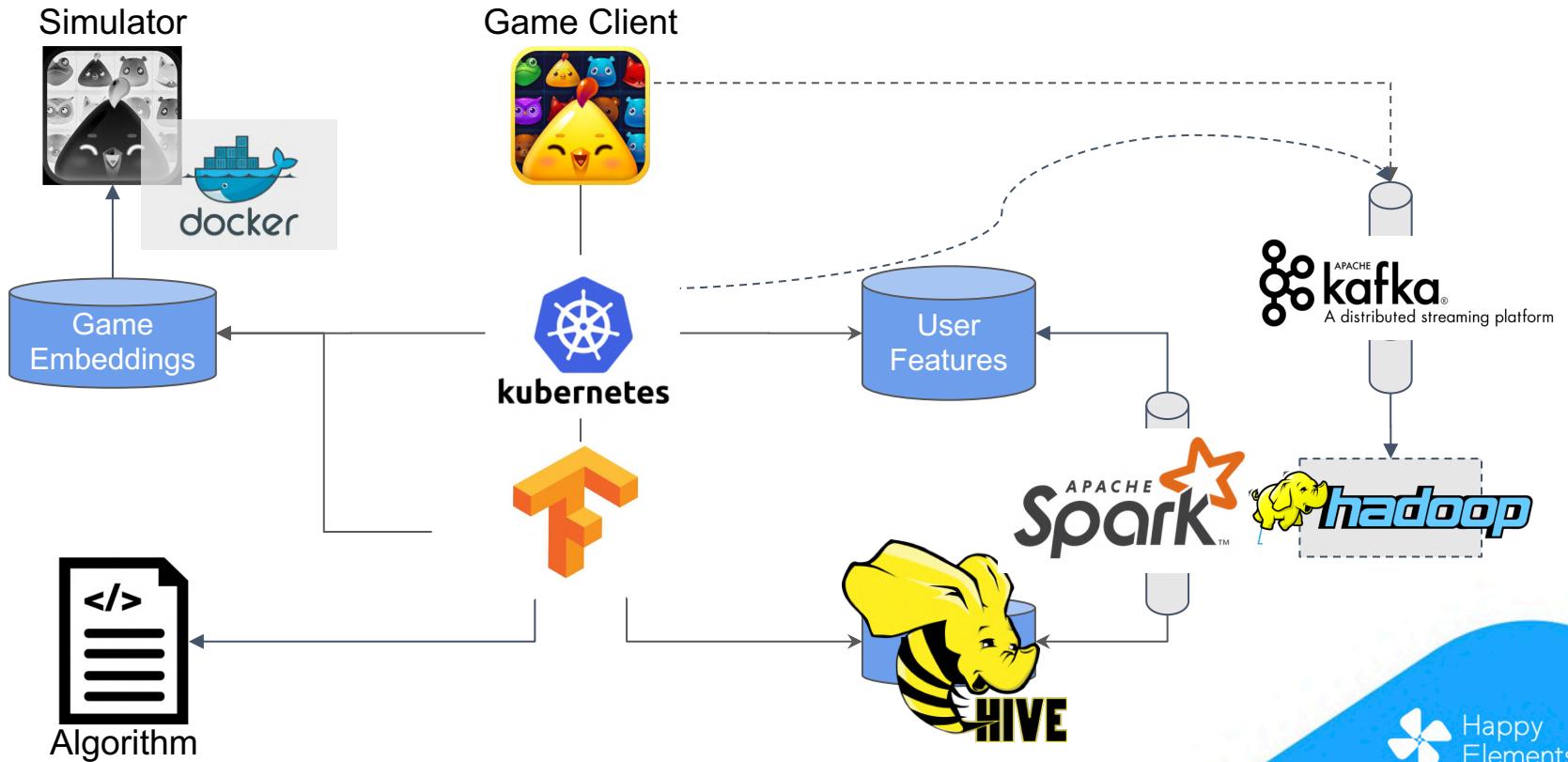
System Architecture: Gameplay Embeddings



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>