Reinforcement Learning for Query Pricing in The Graph

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SEMIOTIC LABS

Outline

- **Introduction**
  - About Semiotic Labs
- **Automated Price Discovery: AutoAgora**
  - Problem Formulation: Dynamic Pricing
- **Reinforcement Learning 101**
- **Agent-Based Modeling** for
  - Testing system properties and outcomes
  - Single- and multiple-agent setup
- **AutoAgora in production**
- **Summary**

Team effort! Special shout outs to **Alexis Asseman** and **Matt Deible**

Section 1

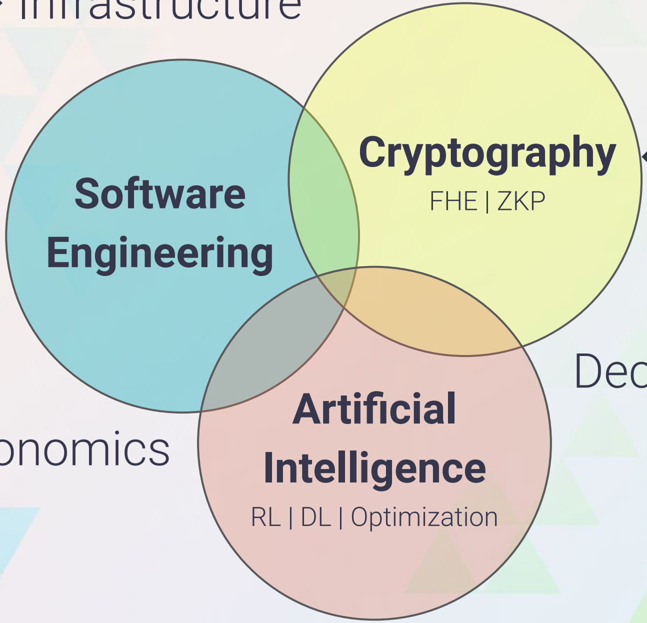
Introduction

About SEMIOTIC LABS

- Founded in 2020 by AI & Cryptography researchers
- Funding from NSF, DARPA, The Graph Foundation and Infinity Ventures
- Focus on Applied Research
- Core Developer of the graph Protocol
- Developer of ODOS the Optimal DEX Aggregator

SEMIOTIC LABS Expertise & Interests

Infrastructure



Decentralized Finance

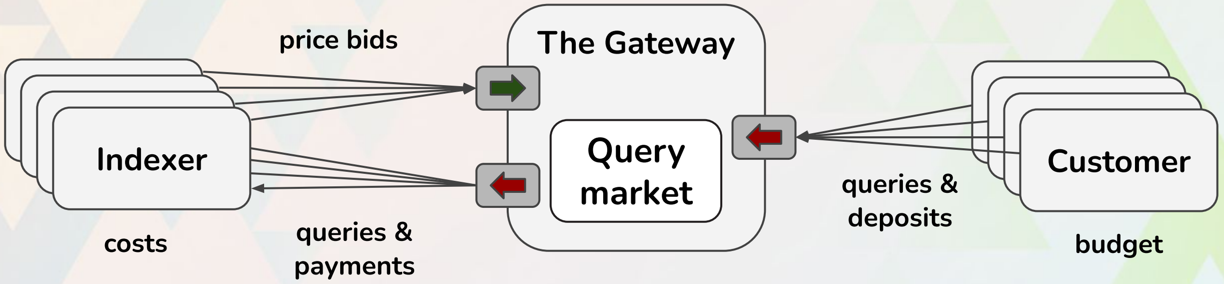
ODOS

Cryptoeconomics

Section 2

Automated Price Discovery: AutoAgora

Automated Price Discovery: The Scenario



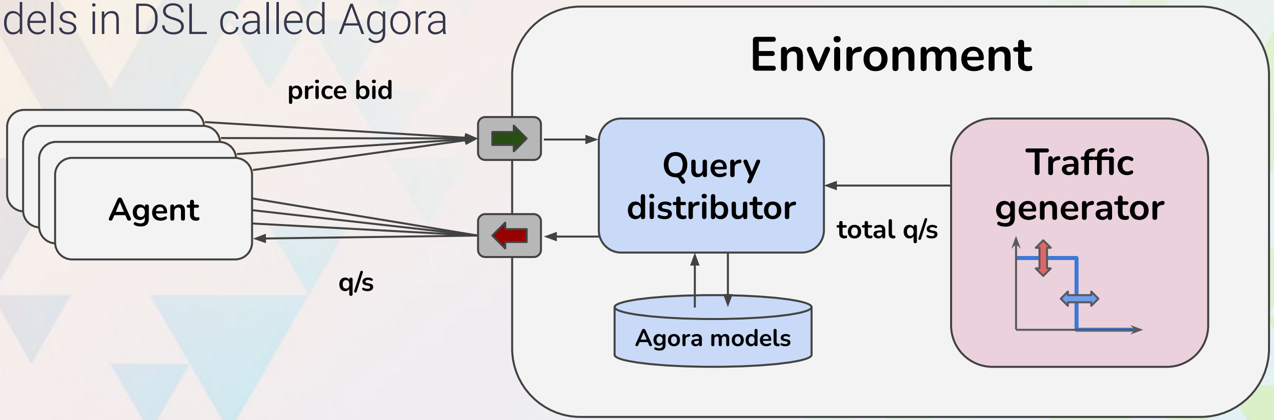
- **Customers** send queries to **The Gateway**
- **The Gateway** distributes queries between **indexers**
  - The decision is based on each indexer's price-bid and it's quality of service
- **Indexers** earn money by serving queries
  - **Indexers** can control the prices of served queries

- **AutoAgora** = **Dynamic pricing** based on query volume received by an indexer

Agent Based Modeling

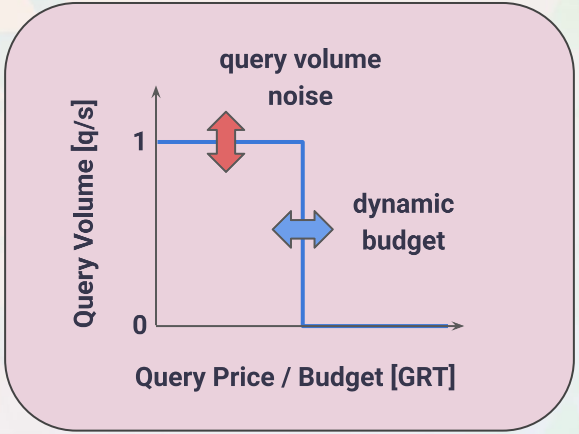
- Queries distributed amongst agents depending on their price bids

- Price bids expressed as models in DSL called Agora



- Queries simulated as a **total query volume** (q/s)

Assumptions (selected)



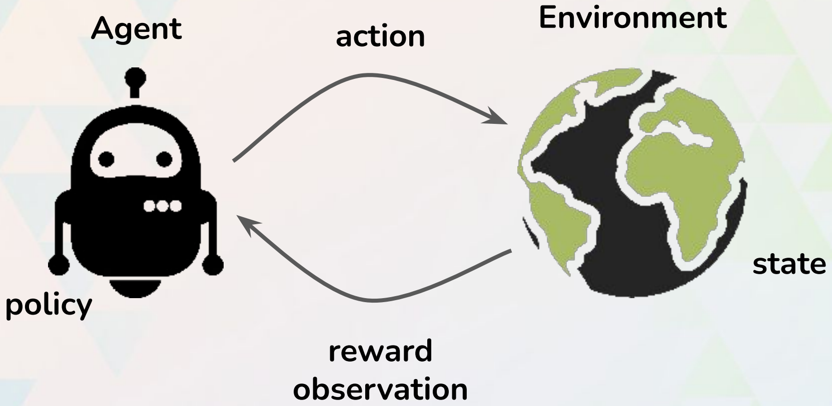
- **Normalized** query volume **with noise** (additive white Gaussian noise)
- Customers have **limited budget** that can change over time
- Query serving **costs** are not considered => agents operate purely on **revenue**

- **Game:** Agent's **revenue maximization** vs Gateway's **quality of service**

Section 3

Reinforcement Learning 101

Reinforcement Learning 101



- **Agent** interacts with the **Environment** by executing an **action**
- Agent's actions change the **state** of the **Environment**
- Agent gets a **reward** and **observes** the new state of the Environment
- Agent updates its **policy** based on the received **reward**

Image credits: Lilian Weng (2018). A (Long) Peek into Reinforcement Learning [link]

Agents and algorithms

- **Types of agents** used in our simulations
  - Trainable (RL) vs Rule-based (i.e. with predefined behaviors)
  - Deterministic vs Stochastic

- **Types of RL algorithms** (update rules):

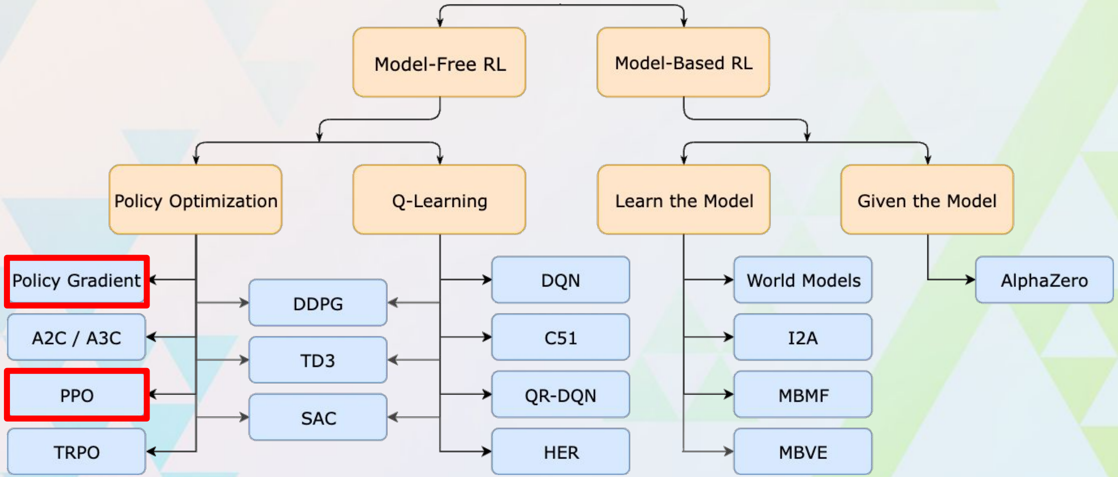
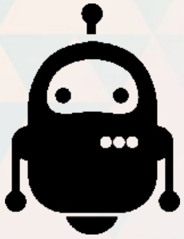


Image credits: OpenAI (2018), Spinning Up [link]

Gaussian bandits

$$\theta = [\mu, \sigma]^\top$$

$$\pi(a|\theta) \doteq \frac{1}{\sigma\sqrt{2\pi}} \exp^{-\frac{(a-\mu)^2}{2\sigma^2}}$$



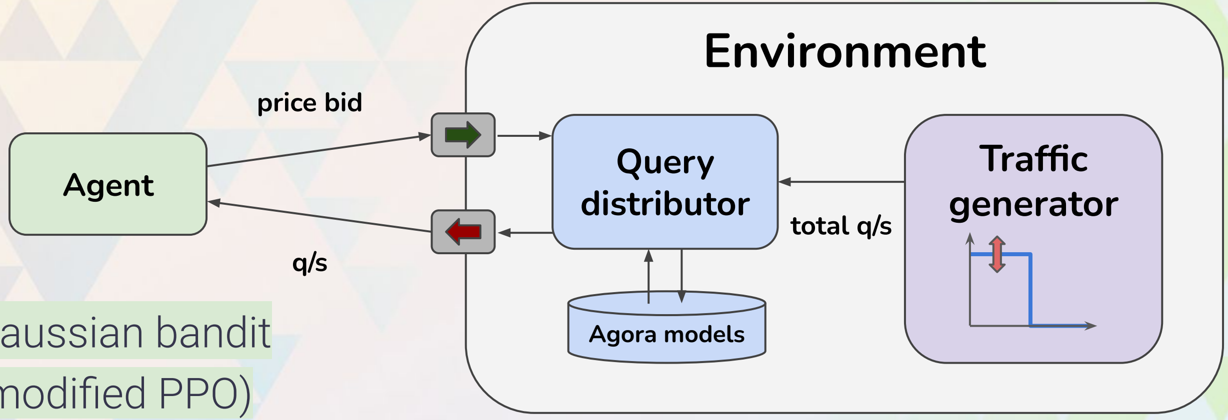
- **Gaussian bandits** = trainable, stochastic agents with:
  - **Policy** is represented as a **gaussian distribution** over the possible query prices
  - **Action** is sampled from the **policy distribution** (continuous action space)
  - No internal representation of the environment (bandit)

Section 4

Testing Properties with Agent-Based Modeling

Experiment 1.1

- Distribution inversely-proportional to price bids (inverse softmax)



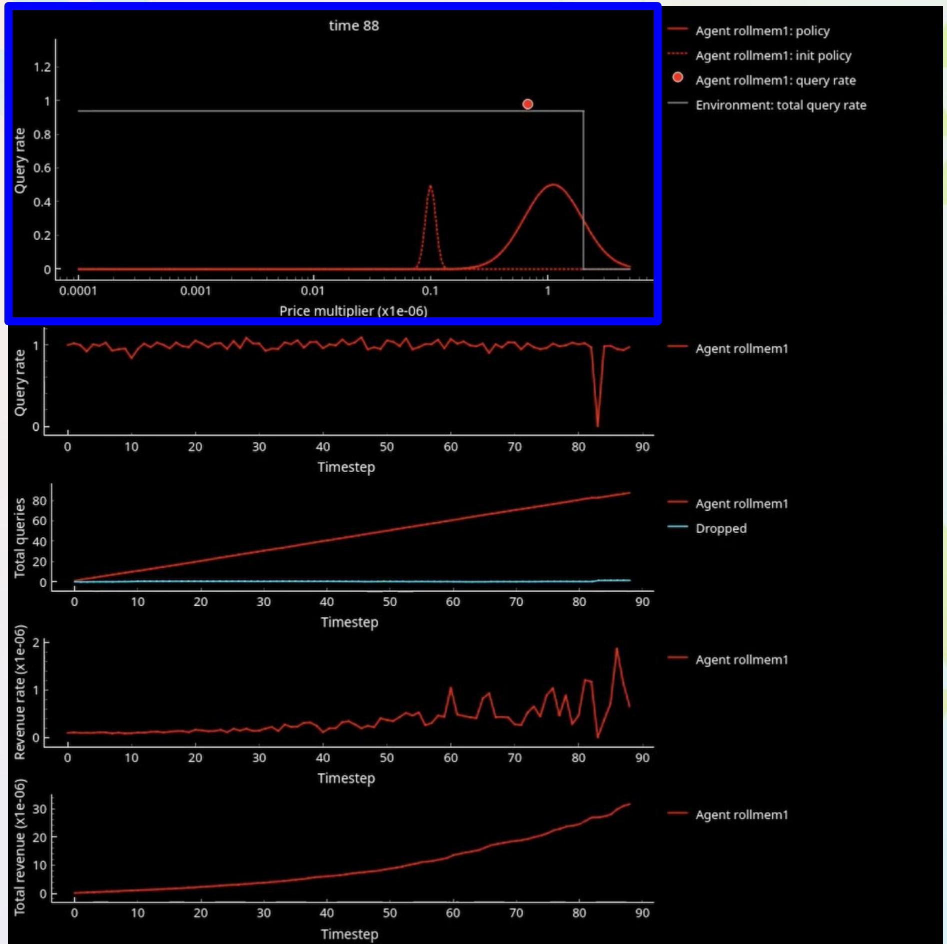
- Gaussian bandit (modified PPO)

- **Fixed** customer budget, with noise

- **Market Conditions**: Fixed customer budget
- **Bandit property tested:** Customer budget discovery

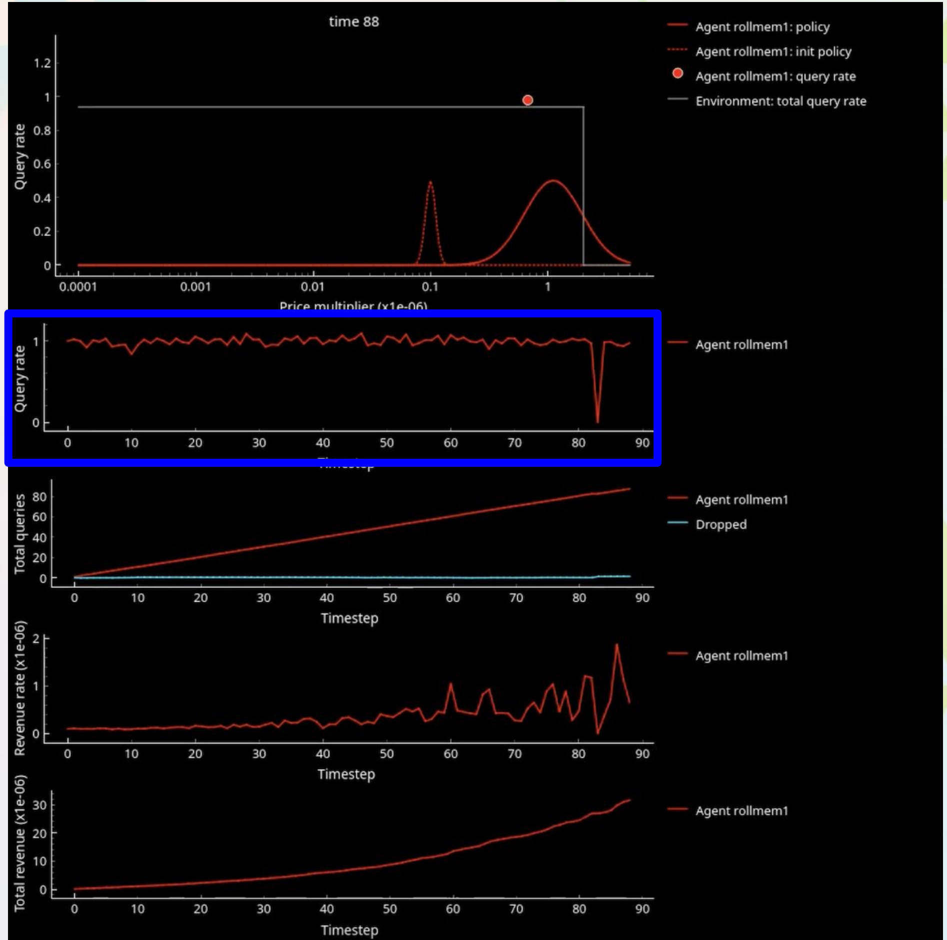
Experiment 1.2

- Query volume + consumer budget (white)
- Agent’s initial policy (dashed red)
- Agent’s current policy (red)



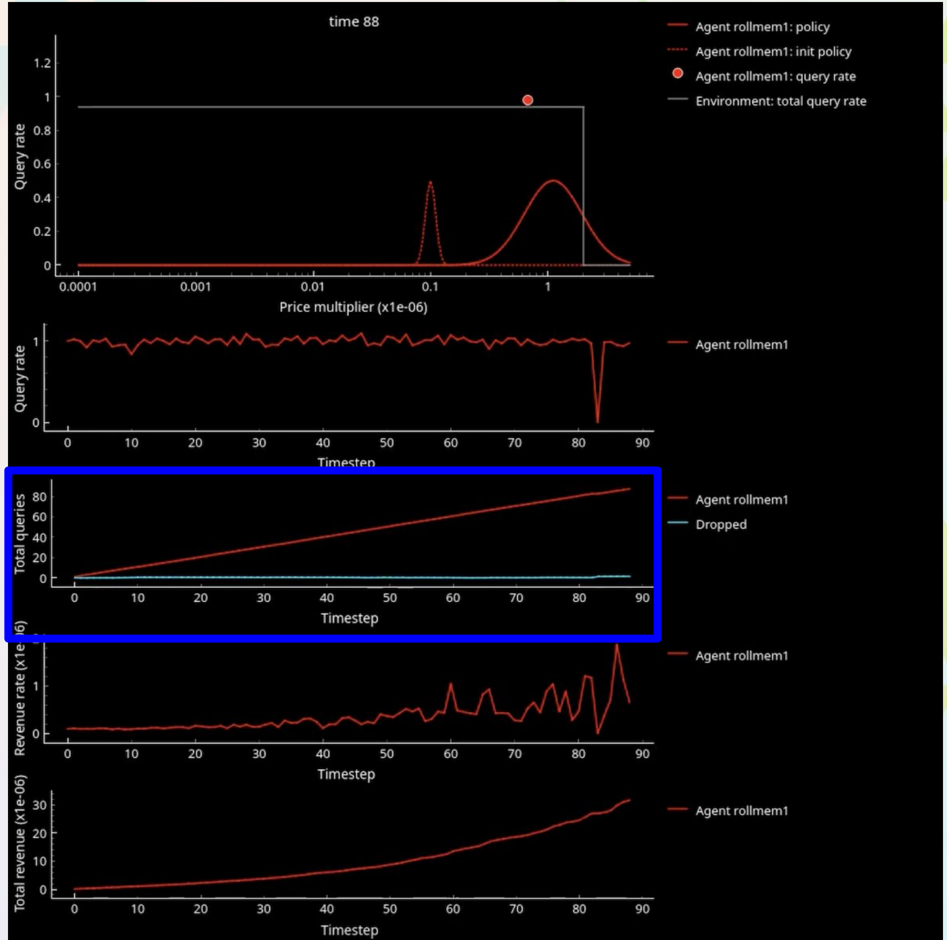
Experiment 1.2

- Query volume served by the agent



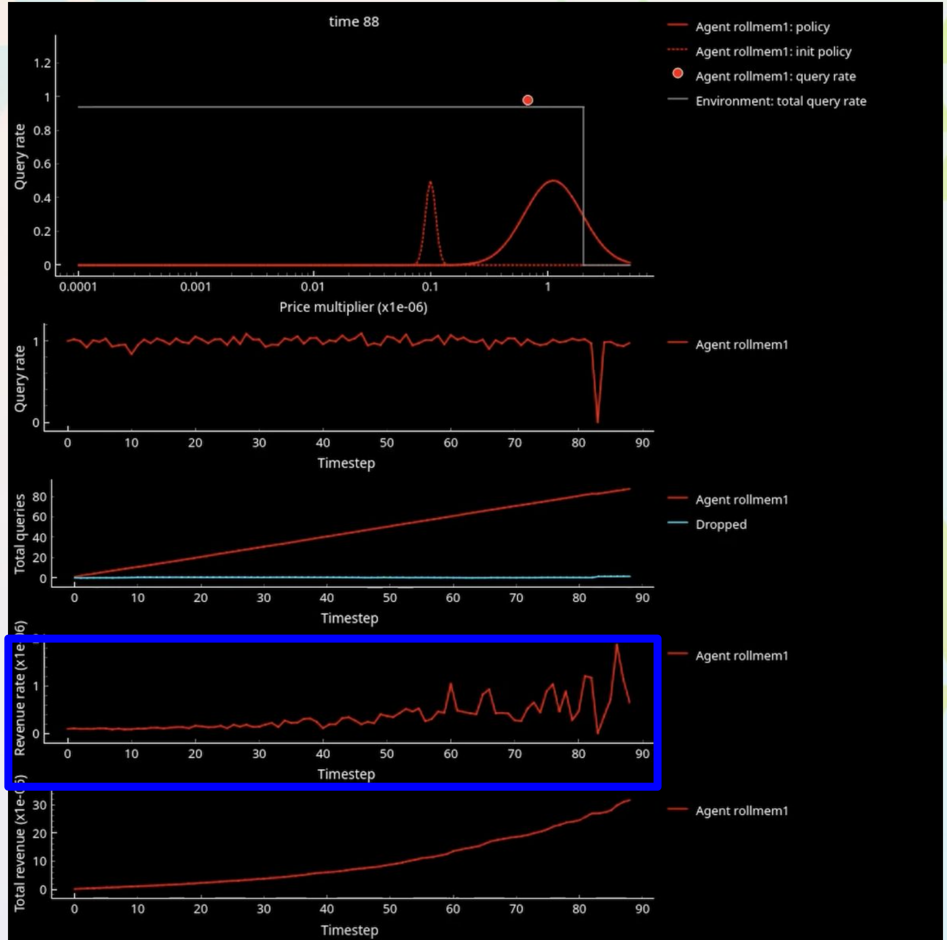
Experiment 1.2

- Aggregated query volume served by the agent (red)
- Aggregated volume of unserved queries (cyan)

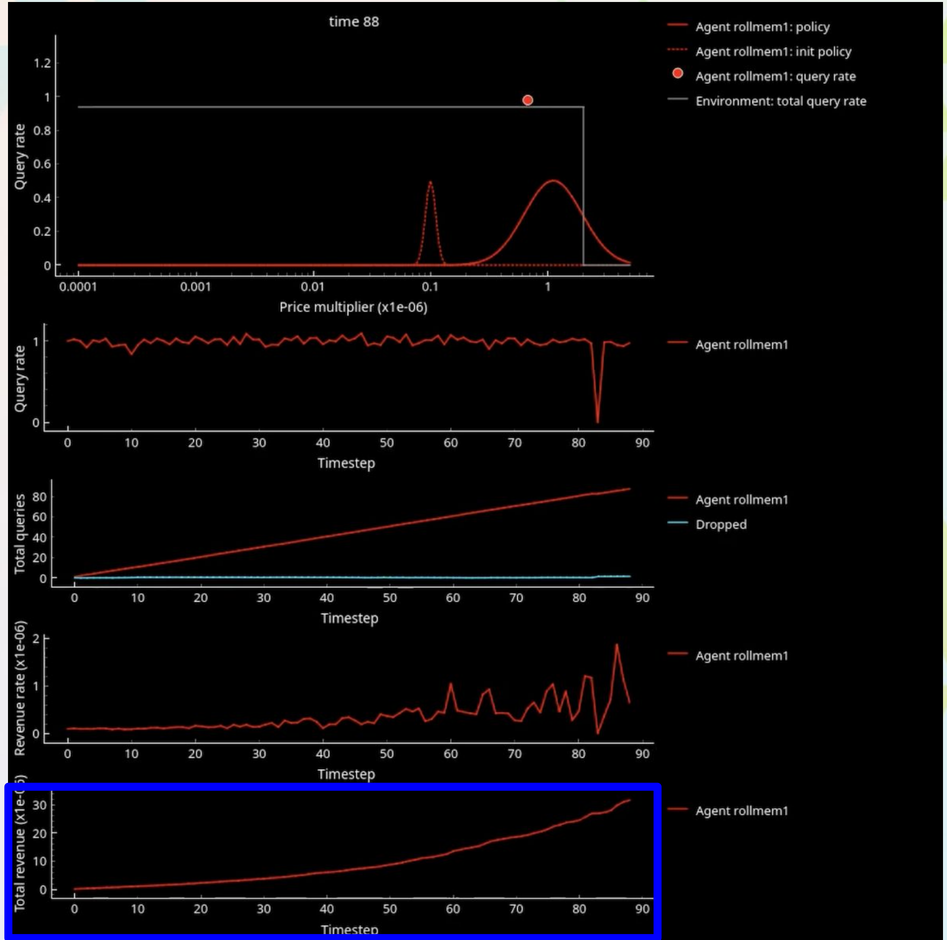


Experiment 1.2

- Agent's revenue

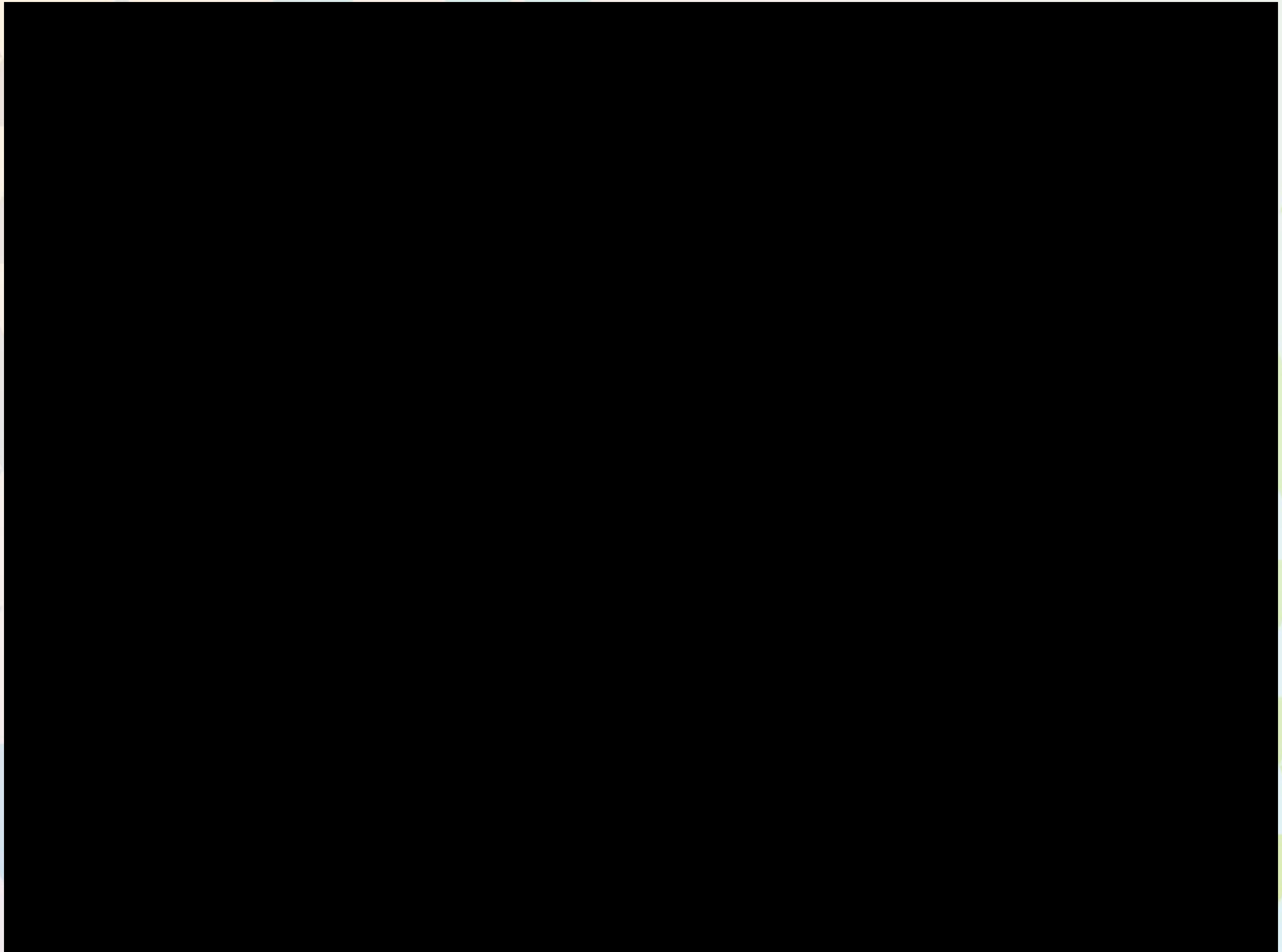


Experiment 1.2



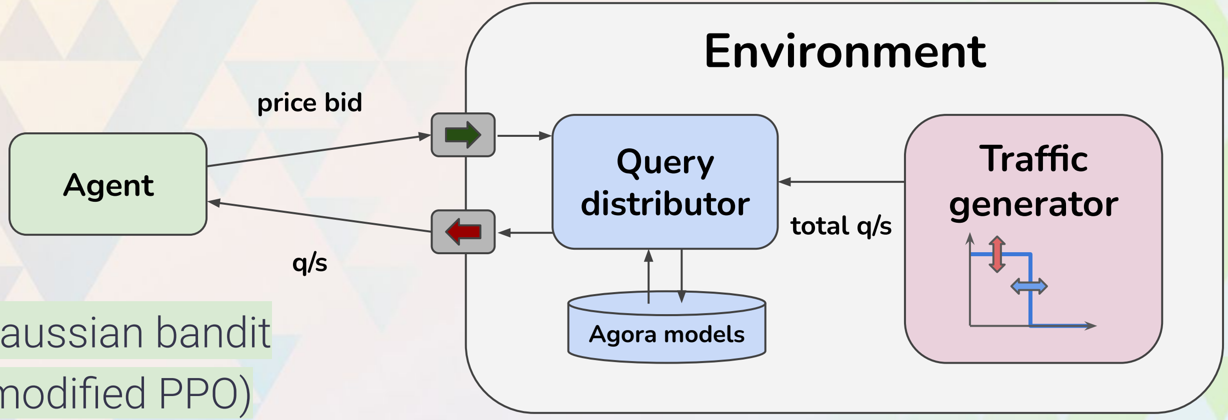
- Aggregated agent's revenue

Experiment 1.3



Experiment 2.1

- Distribution inversely-proportional to price bids (inverse softmax)

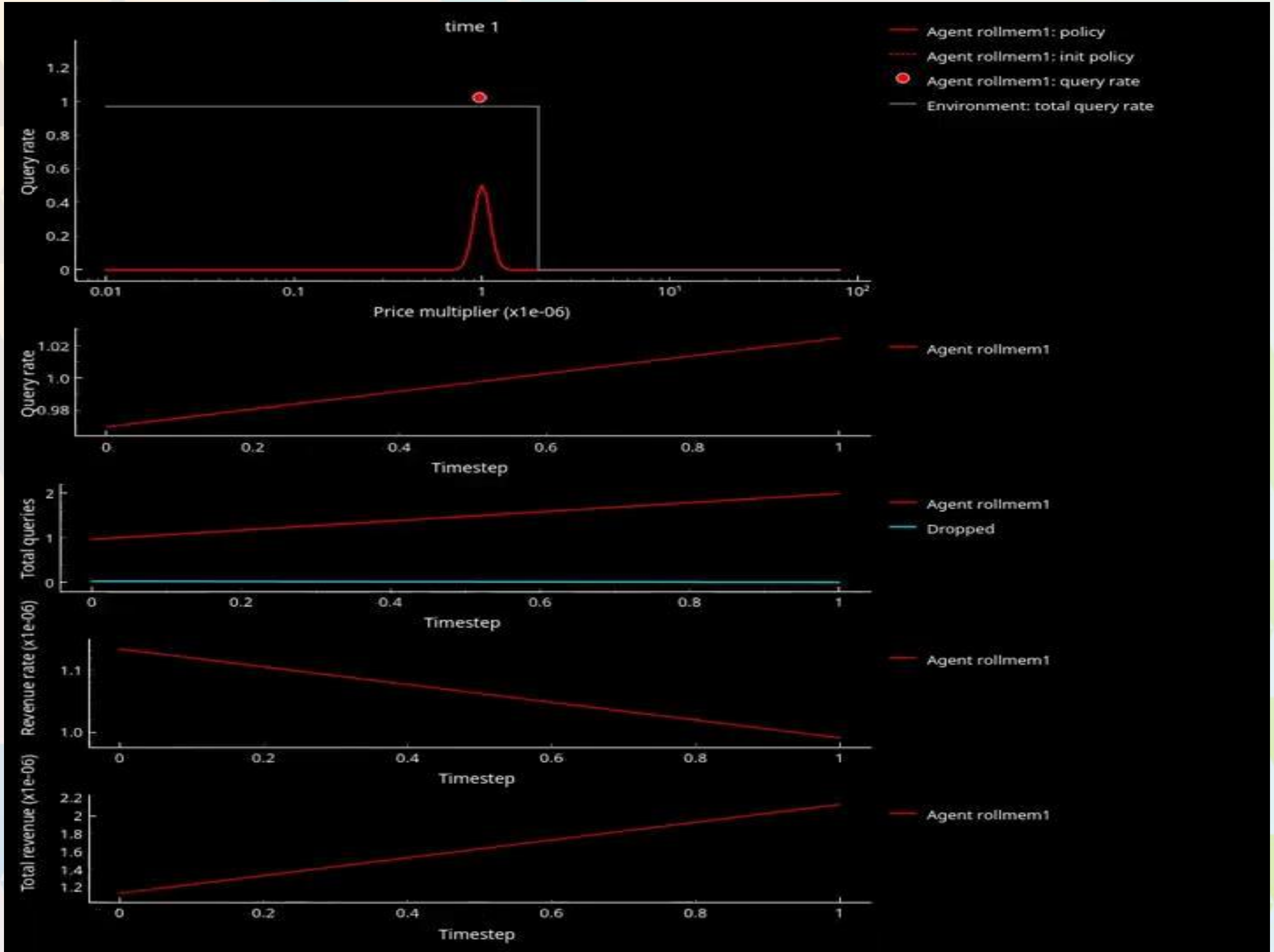


- Gaussian bandit (modified PPO)

- **Dynamic** customer budget, with noise

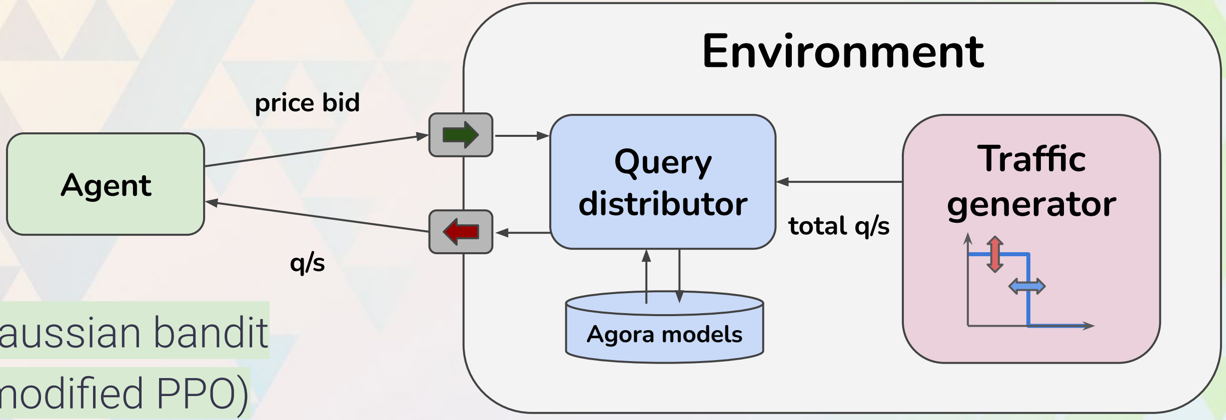
- **Market Conditions**: Dynamic customer budget
- **Bandit property tested:** Customer budget discovery

Experiment 2.2



Experiment 3.1

- Distribution inversely-proportional to price bids (inverse softmax)

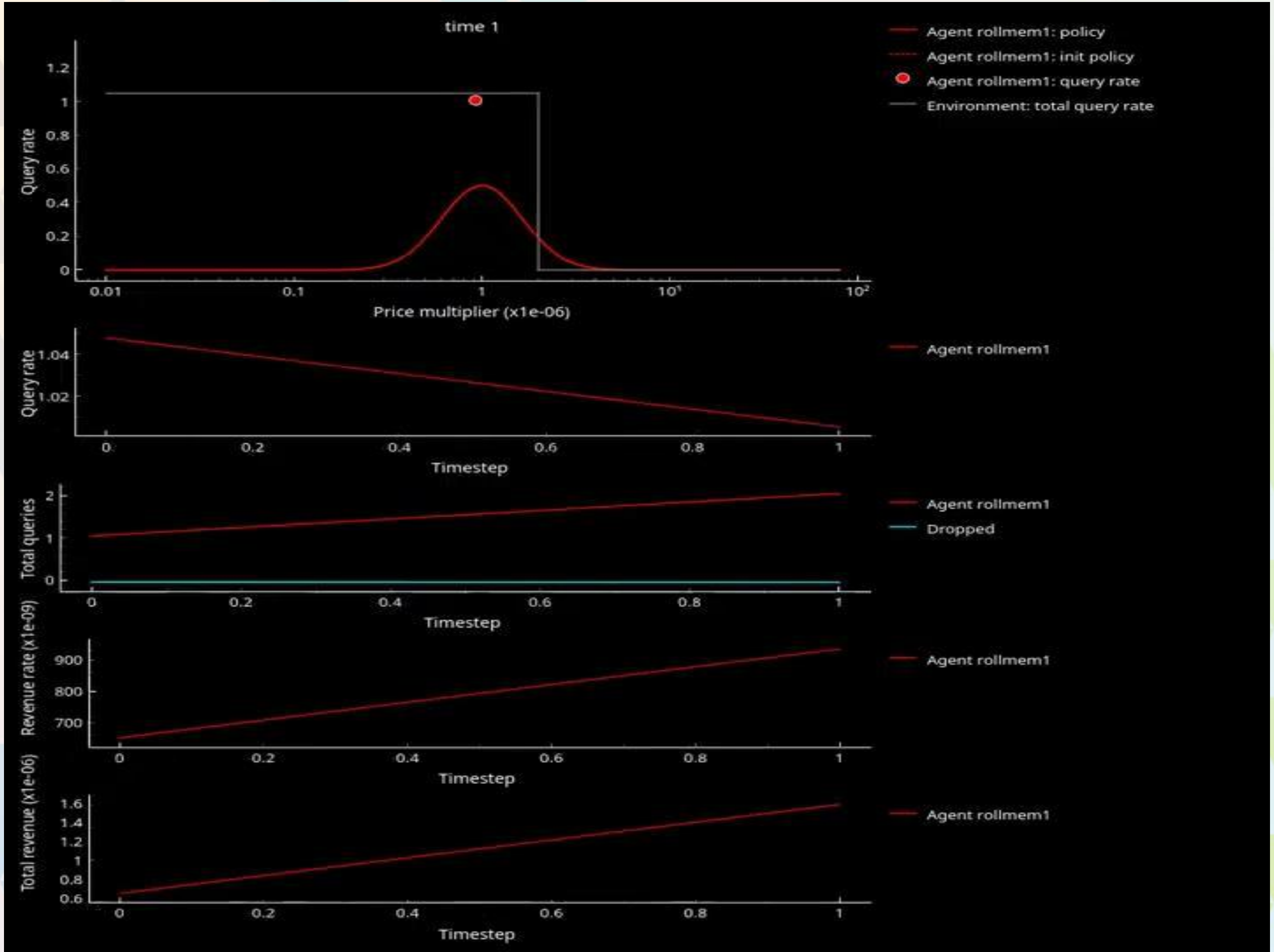


- Gaussian bandit (modified PPO)

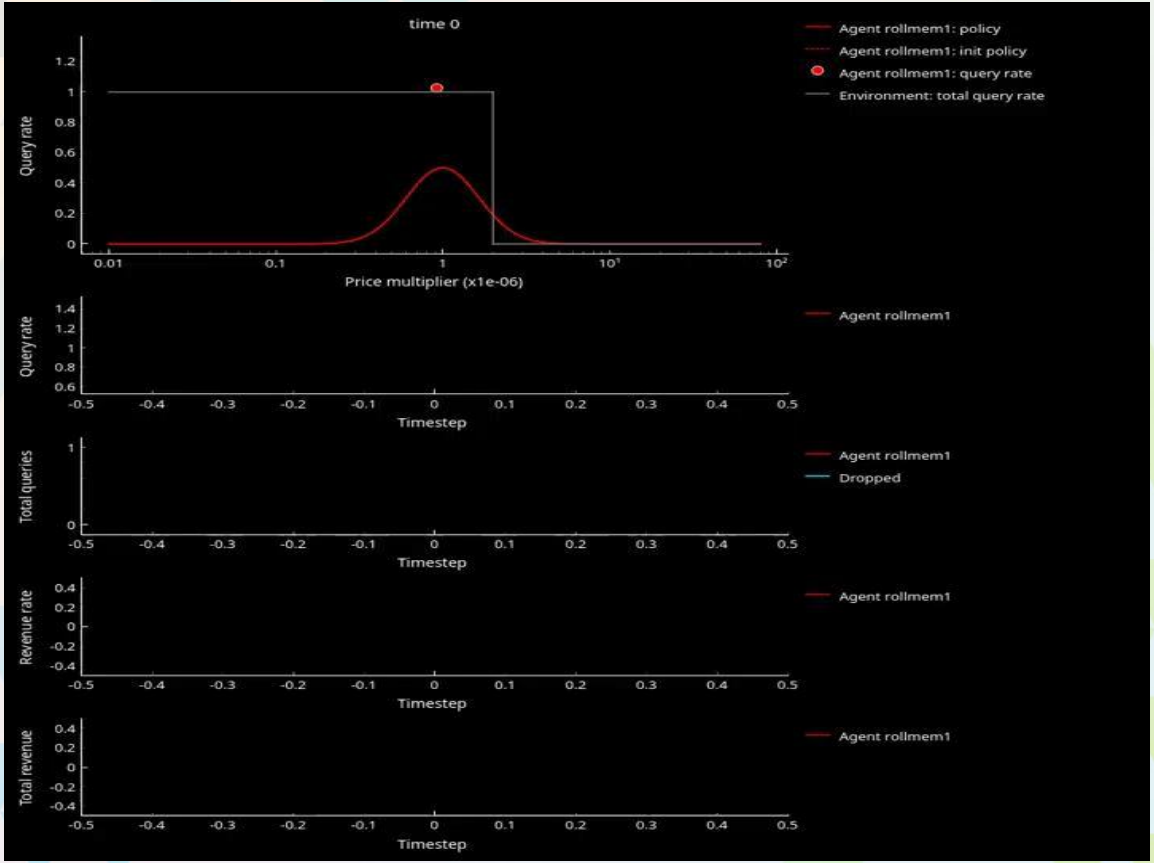
- **Dynamic** customer budget, with noise

- **Market Conditions**: No demand
- **Bandit property tested:** Fallback and recovery

Experiment 3.2



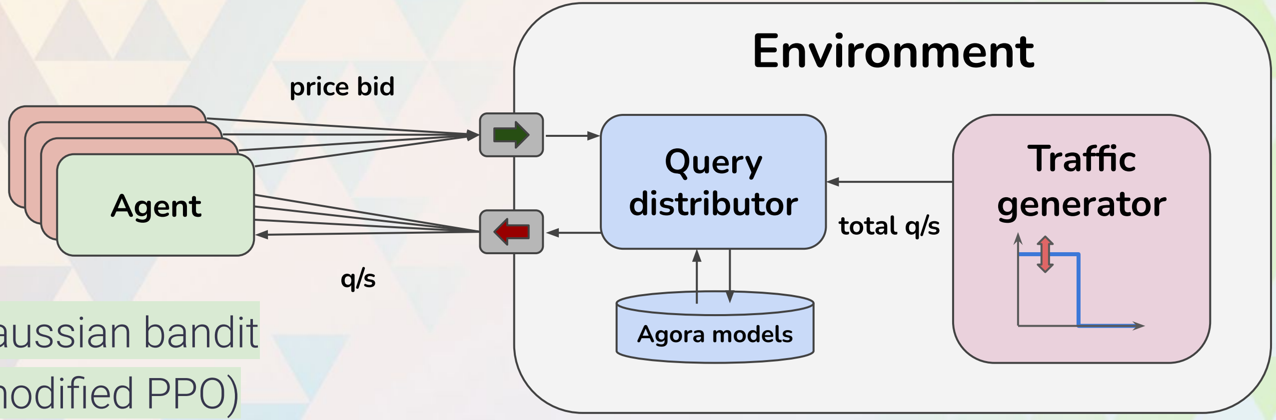
Experiment 3.3



- **Graceful Init Pull!**

Experiment 4.1

- Distribution inversely-proportional to price bids (inverse softmax)

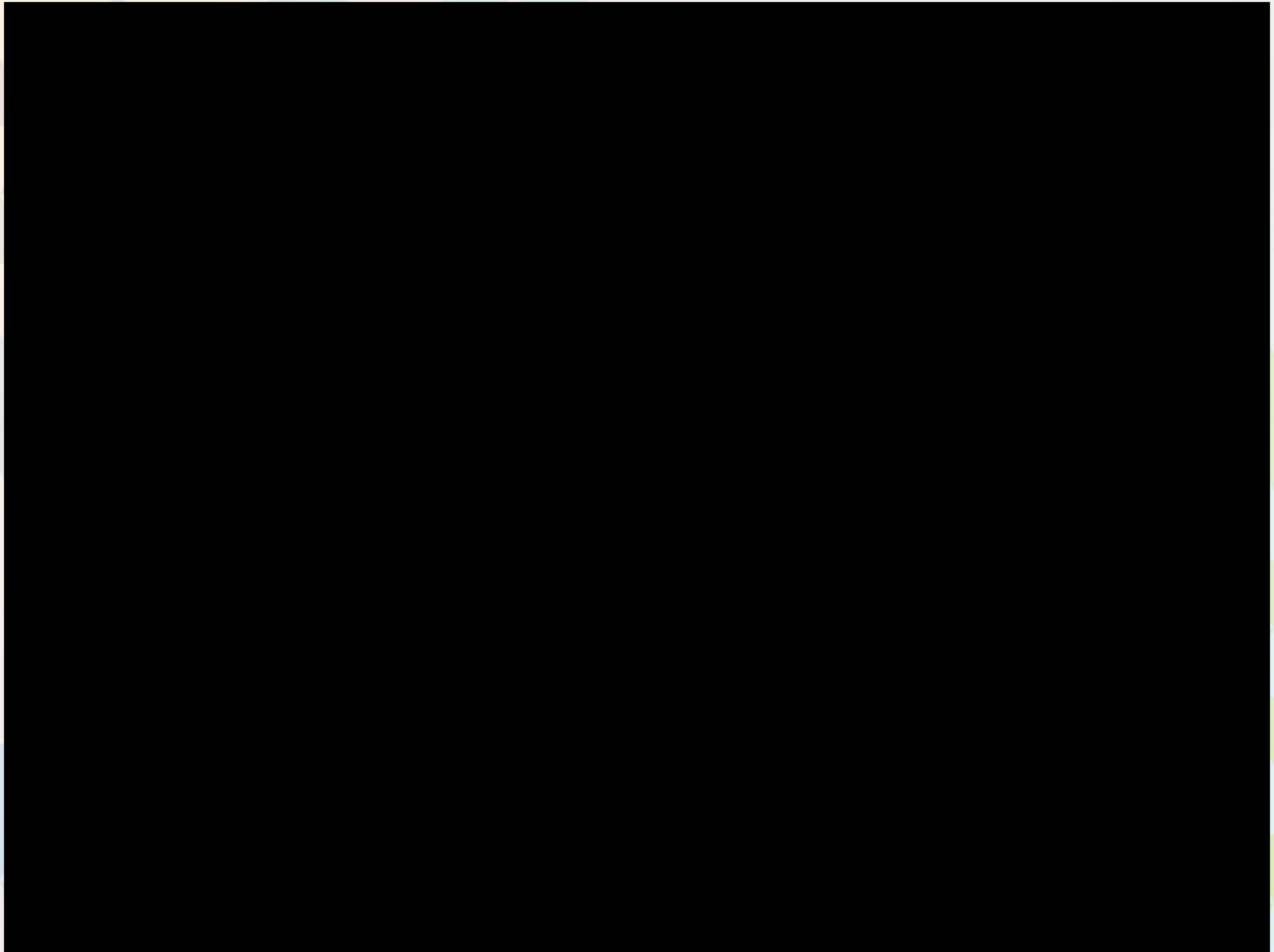


- Gaussian bandit (modified PPO)
- Deterministic agents (rule-based, no update)

- **Static** customer budget, with noise

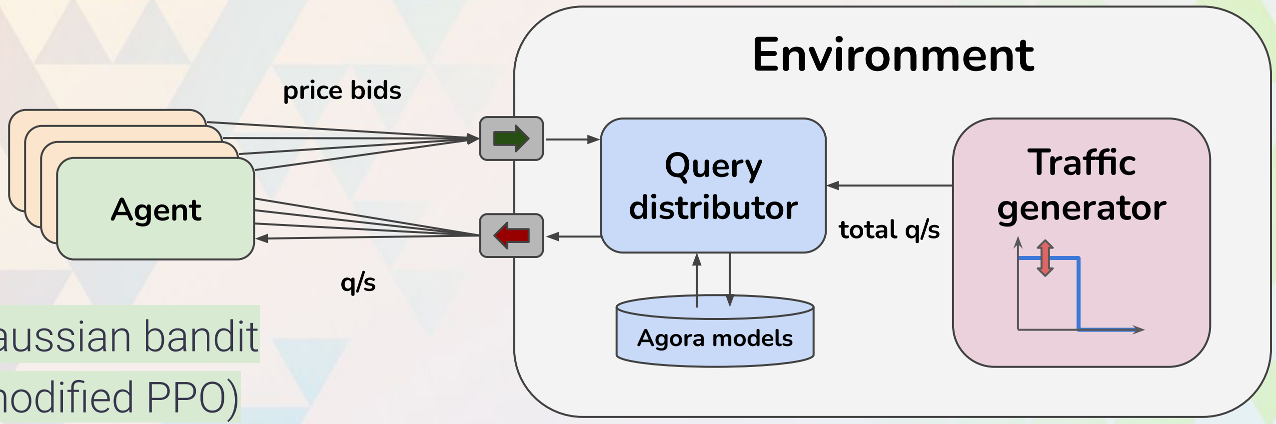
- **Market Conditions**: Competition with deterministic agents
- **Bandit property tested:** Discovery of price bids of competitive agents

Experiment 4.2



Experiment 5.1

- Distribution inversely-proportional to price bids (inverse softmax)

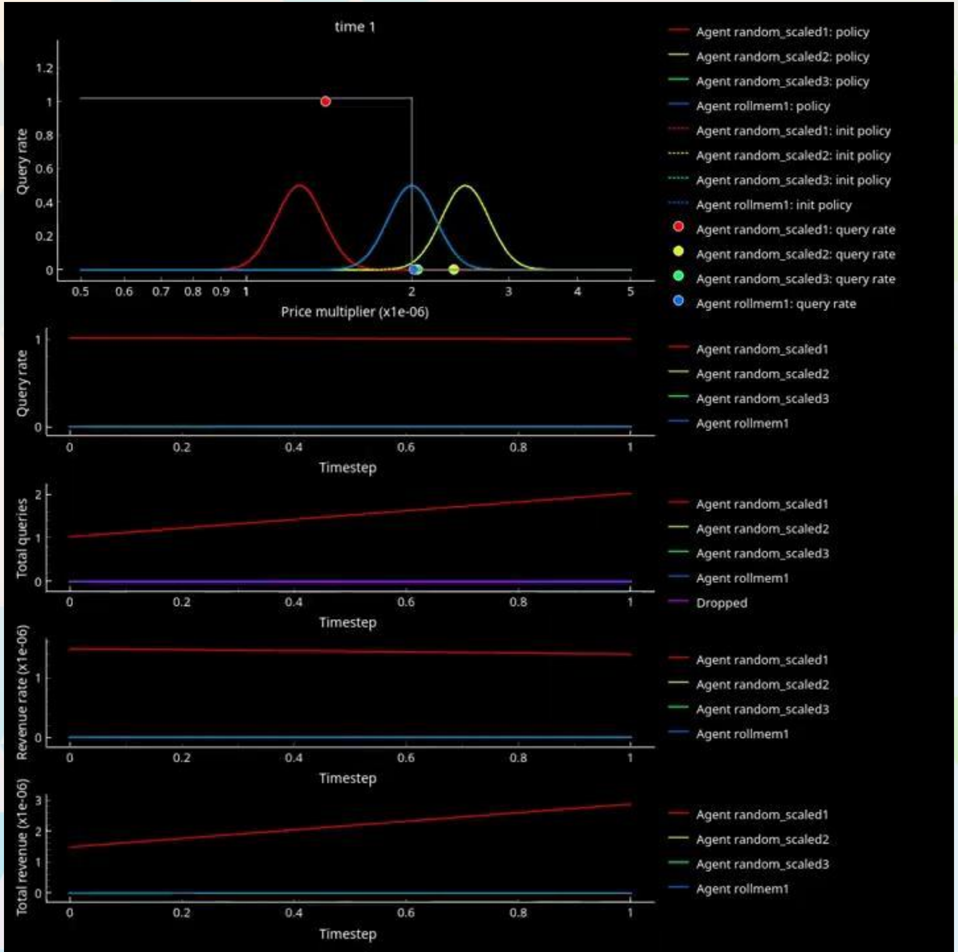


- Gaussian bandit (modified PPO)
- Stochastic agents (rule-based, no update)

- **Static** customer budget, with noise

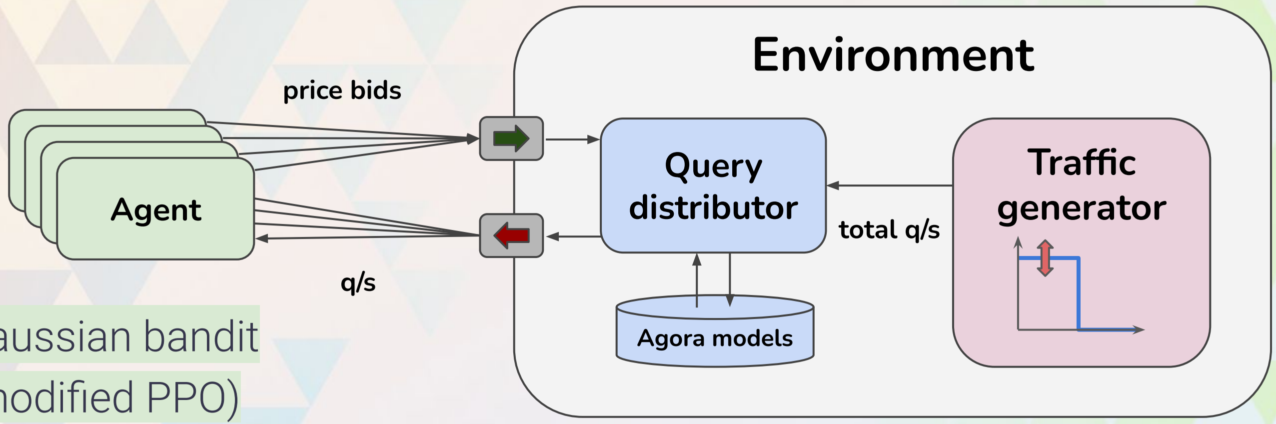
- **Market Conditions**: Competition with stochastic agents
- **Bandit property tested:** Discovery of price bids of competitive agents

Experiment 5.2



Experiment 6.1

- Distribution inversely-proportional to price bids (inverse softmax)

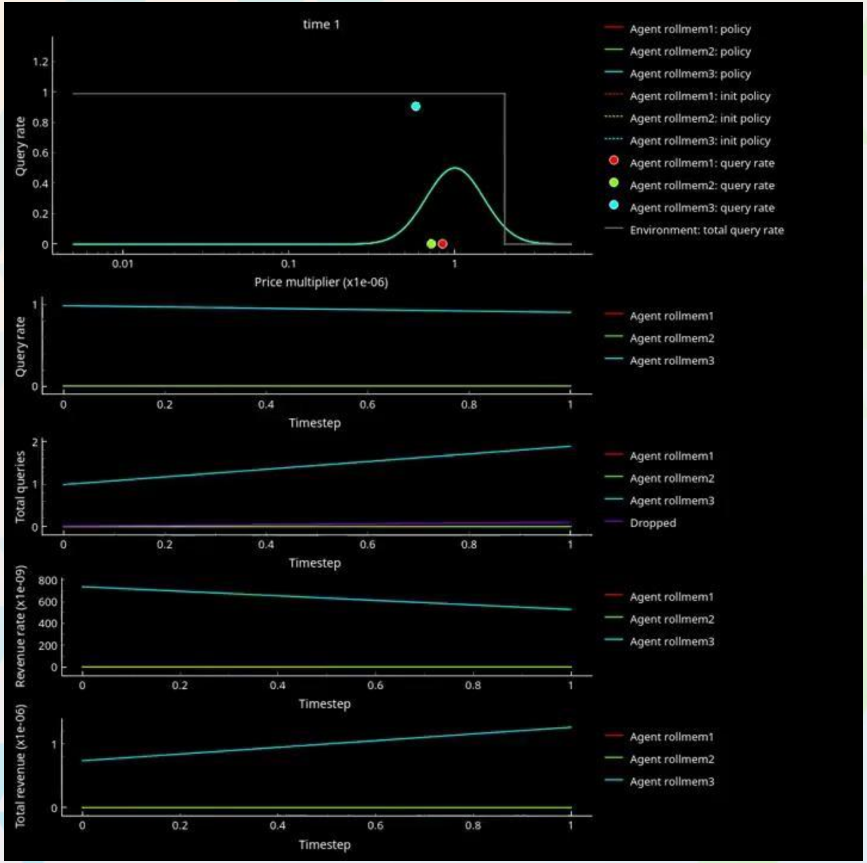


- Gaussian bandit (modified PPO)

- **Static** customer budget, with noise

- **Market Conditions**: Competition with Gaussian bandits
- **Bandit property tested:** Discovery of price bids of competitive agents

Experiment 6.2



- **Race to the bottom!**

On the Expected Outcomes

- **Agents** and **Environment** form a **Game**
  - When Agents' rewards are driven purely by query volume (x price) and
  - Environment naively distributes the queries based on the price bids, then

Race to the bottom is the expected outcome!

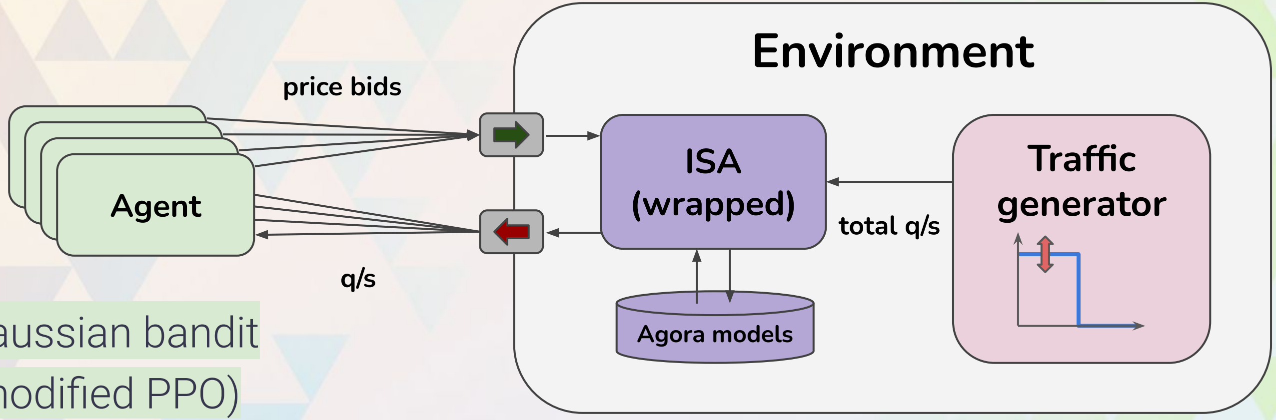
- Different outcomes can be achieved in various ways

- The Graph protocol desired features and outcomes (selected):
  - All Indexers should have freedom with their pricing models
  - All Indexers should be able to make (some) profit
  - Conclusion: **The Gateway** should implement the anti-domination rules

So happens it already does!

Experiment 7.1

- **Indexer Selection Algorithm (ISA)**
  (wrapped one of components of The Graph's Gateway)

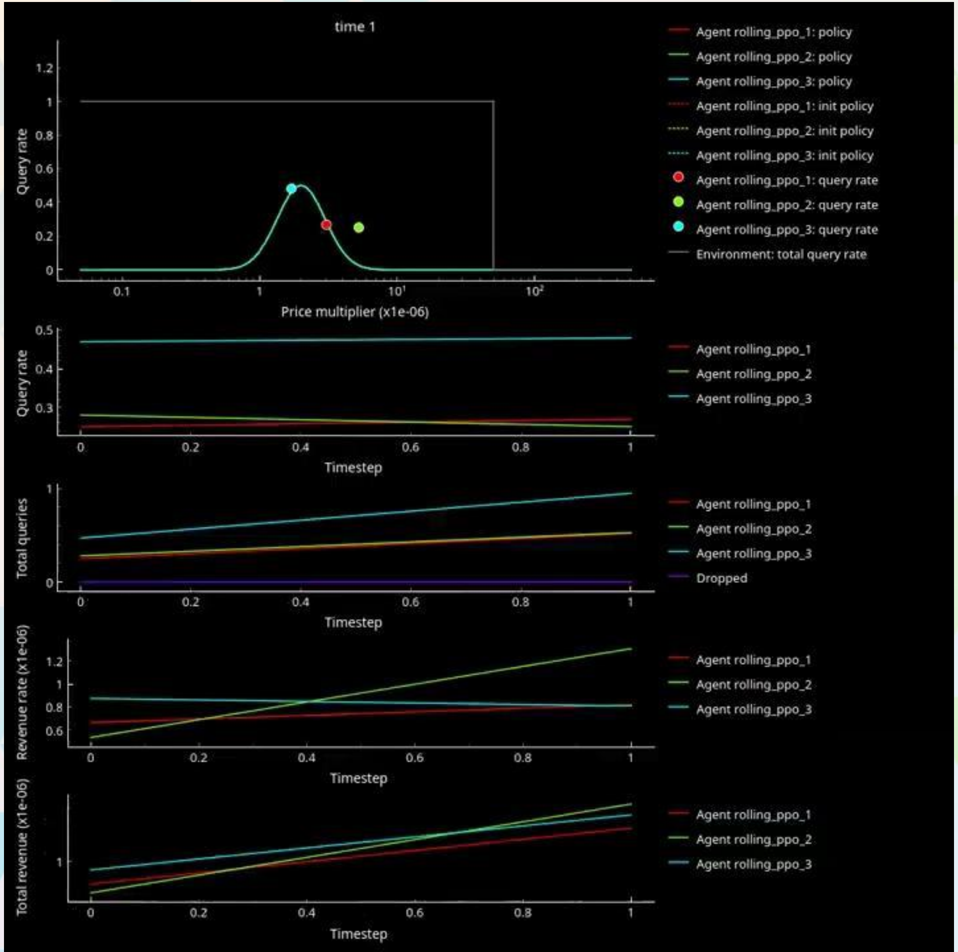


- Gaussian bandit
  (modified PPO)

- **Static** customer budget,
  with noise

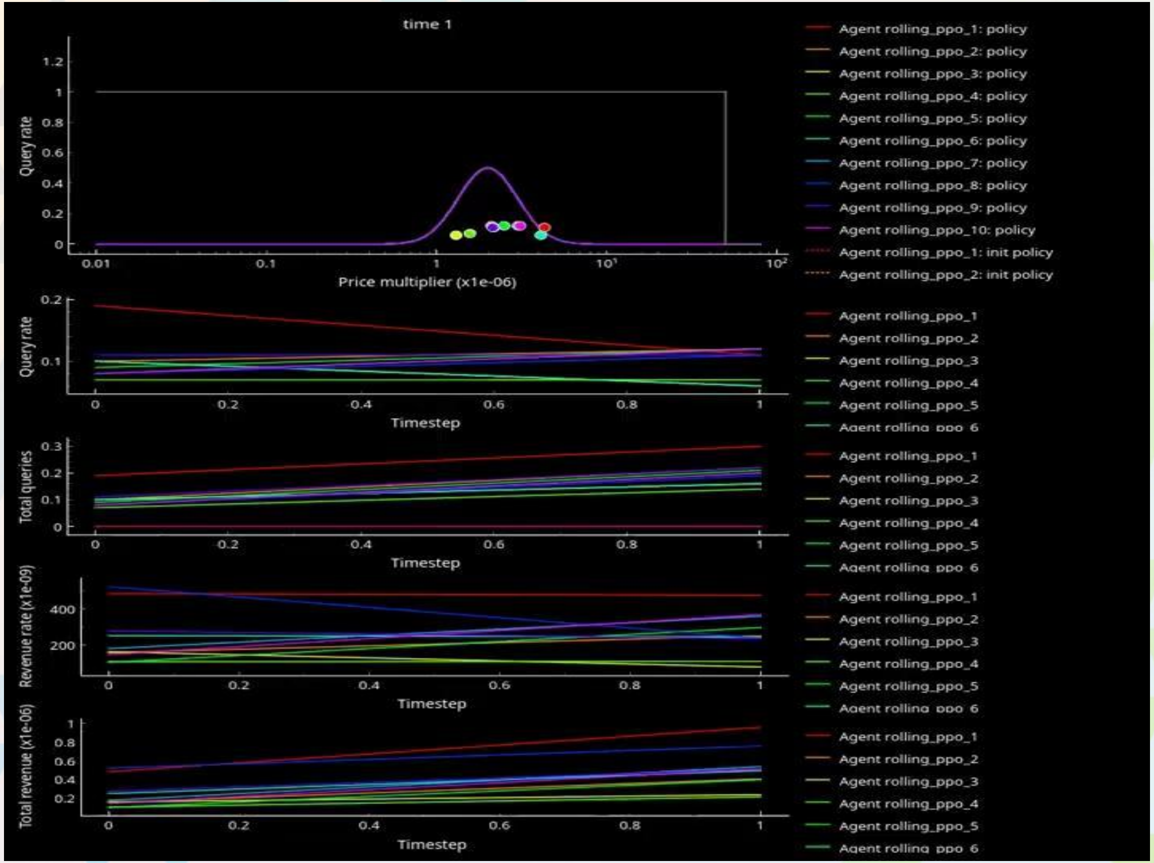
- **Market Conditions**: Competition with Gaussian bandits
- **Bandit property tested:** Discovery of price bids of competitive agents

Experiment 7.2



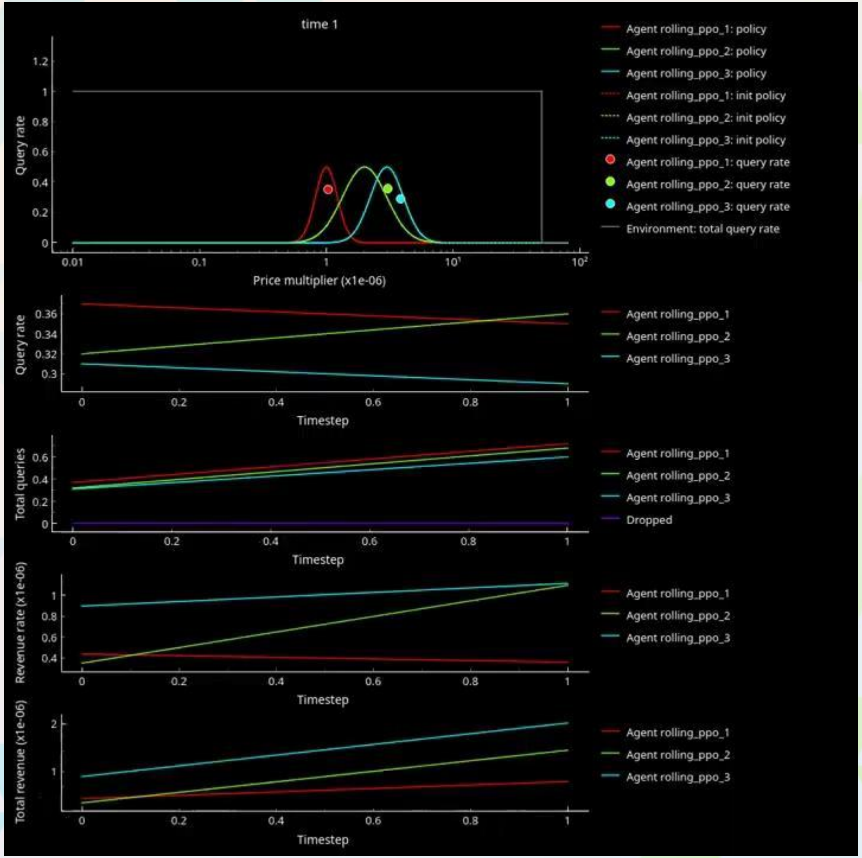
✅

Experiment 7.3



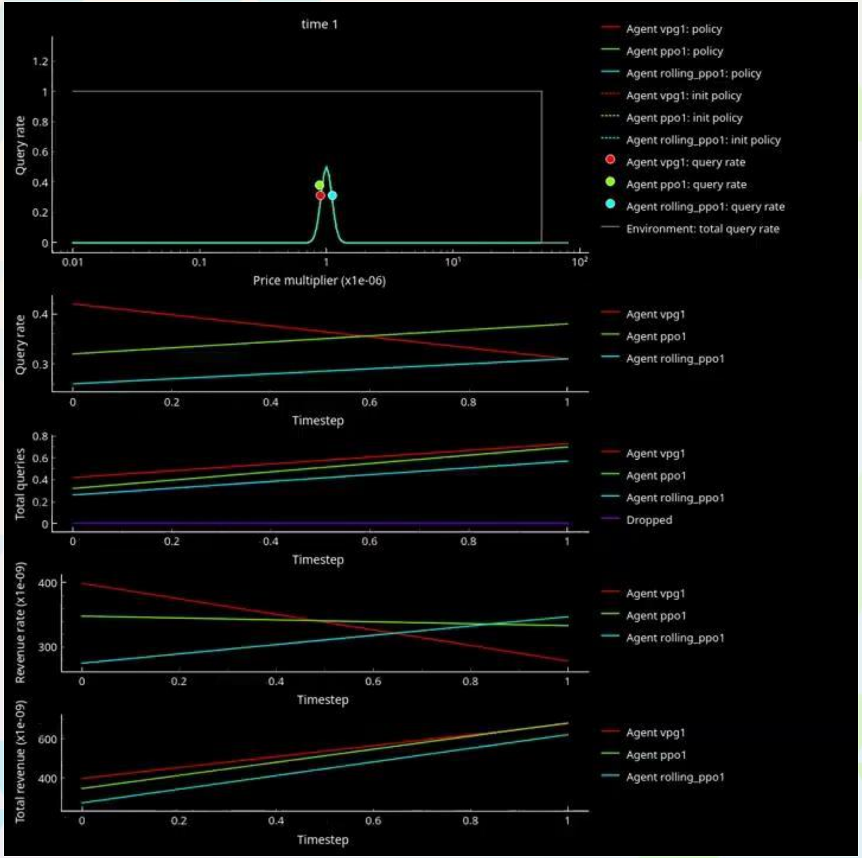
- **Market Conditions**: Competition with Gaussian bandits (more agents)

Experiment 7.4



- **Market Conditions**: Competition with Gaussian bandits (different init conditions)

Experiment 7.5

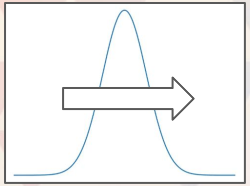


- **Market Conditions**: Competition with Gaussian bandits (weaker/stronger update rules)

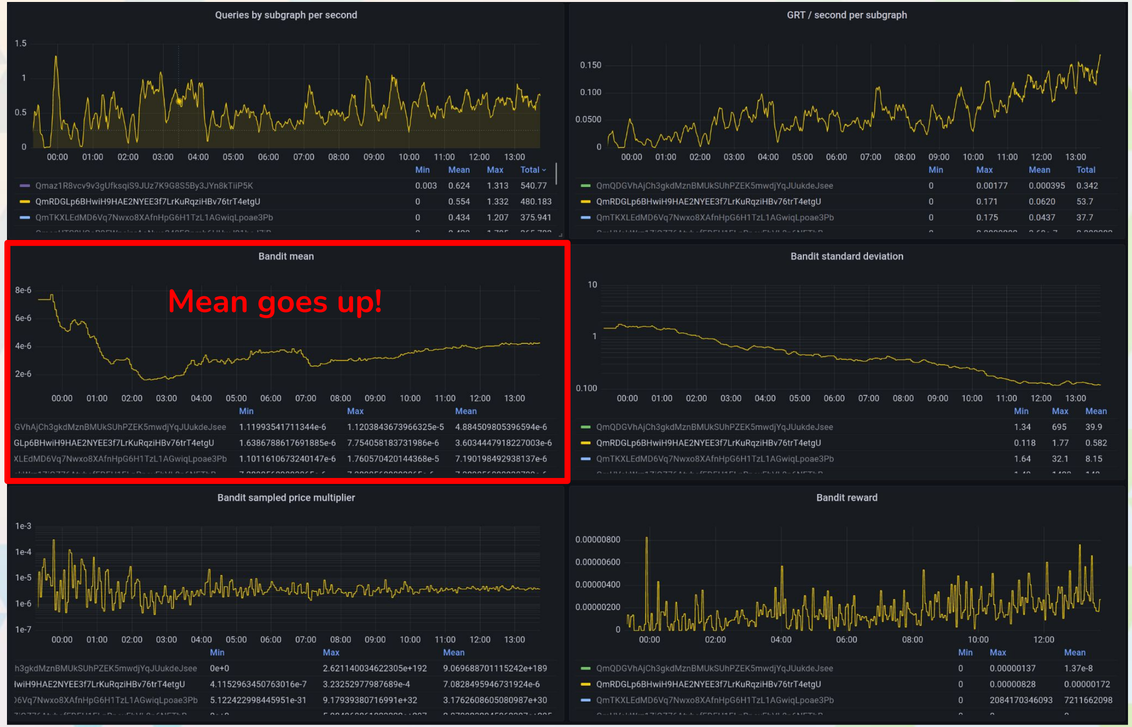
Section 5

AutoAgora In Production

AutoAgora in production 1

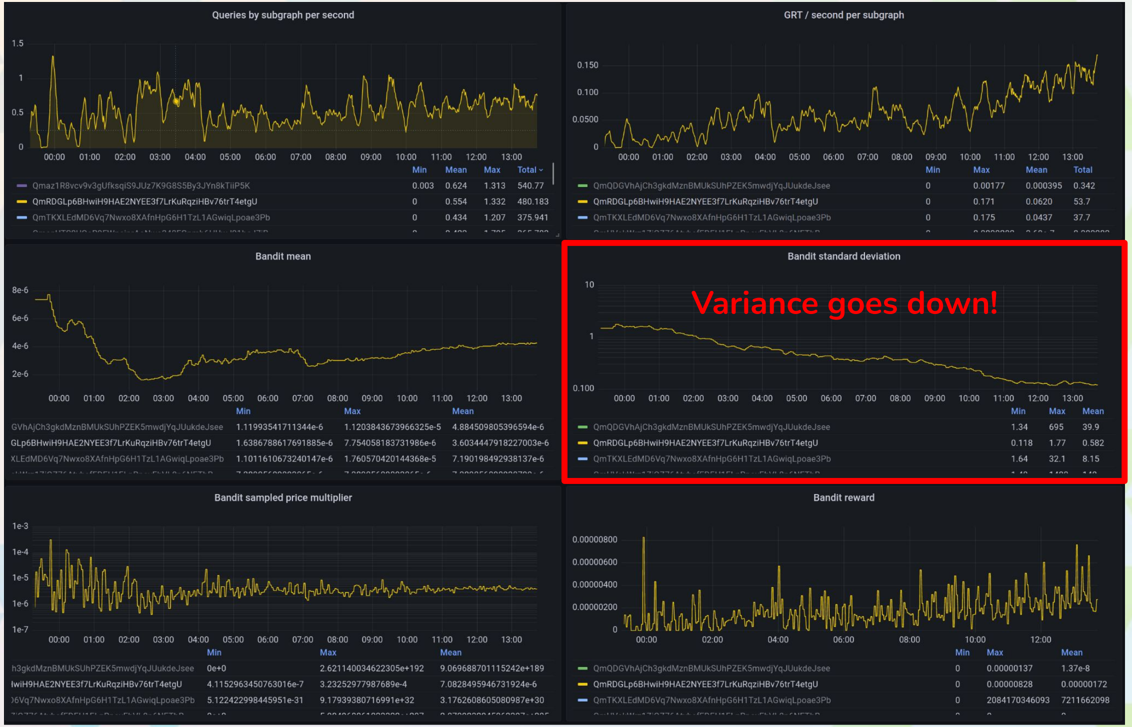


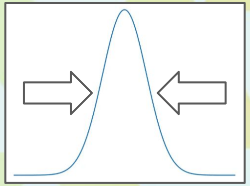
Gaussian moves right!



- Deployed AutoAgora on our Graph indexer agent (semiotic-indexer.eth) [graphscan]

AutoAgora in production 2

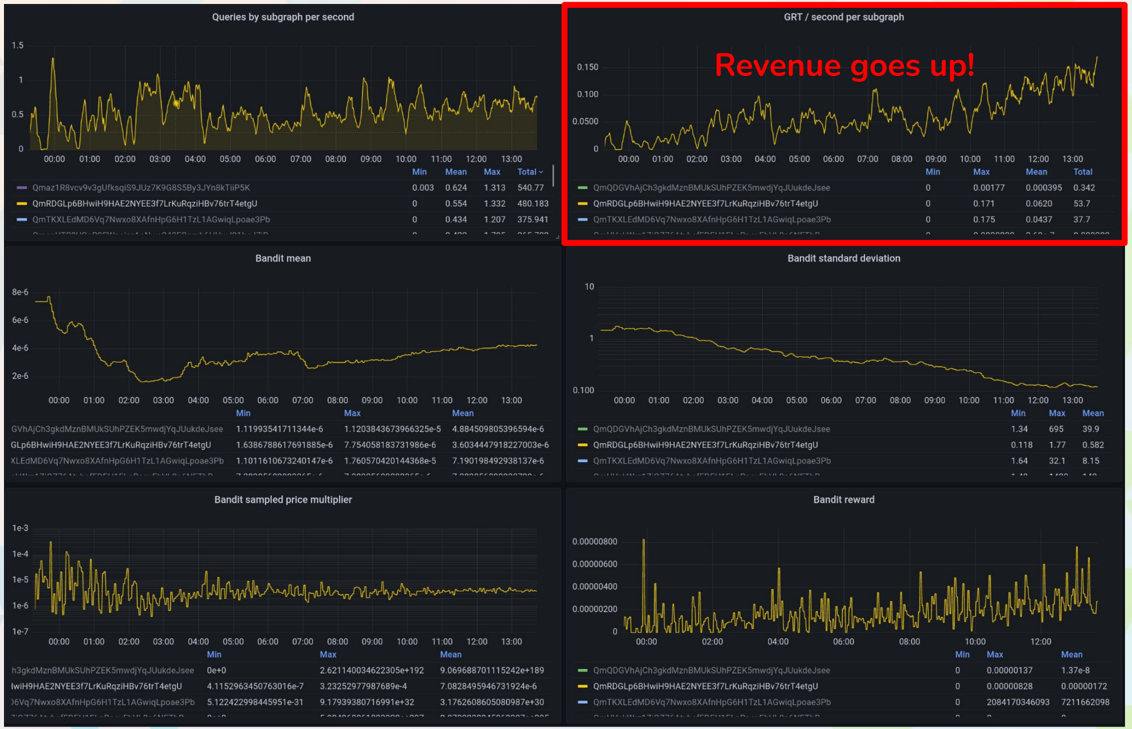




Gaussian gets narrower!

AutoAgora In Production 3

AutoAgora In Production 4



Section 6

Summary

Summary

- Agent-based Modelling (ABM) for cryptoeconomics
  - Focus on Dynamic Pricing applied to Automated Price Discovery
  - Focus on agents using reinforcement learning for revenue maximization
- We have shown how to use ABM for
  - Testing the properties of the protocol
  - Discovering (and designing!) the outcomes of the game
- Finally, we have deployed AutoAgora in a real Graph indexer!

Summary 2

- **Feature works**
  - Better update rules/policies
  - Agents with multiple rewards (taking QoS into account)
  - Modelling and putting consumer agents into play
  - Redesigning the game (e.g. perfect information)

- **AutoAgora resources**
  - A. Asseman (2022): "Automated Query Pricing in The Graph" [blogpost]
  - A. Asseman (2022), Special Graph Hack Episode: "Automated Cost Modeling" [youtube]
  - AutoAgora GitHub Repository (**open-source!**) [link]

Oct 12th, 10:00am, Matt: "**Overview of AMM mechanisms**" ODOS

Oct 12th, 11:30am, Seve: **"A SNARK's Tale: A Story of Building SNARK Solutions on Mainnet"**

We are hiring | full time & interns | remote & Los Altos, California

- **AI Researchers** (RL, DL)
- **Cryptographers** (SNARKs, ZK proofs, FHE)
- **Developers** (general | web3, Rust, Solidity)
- **DevOps Engs** (infrastructure, CI, real-time services, AWS)
- **Data Scientists** (general | arbitrage strategy and capture)
- **BizDev Officers**(general | web3)

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Thank you!

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Appendix

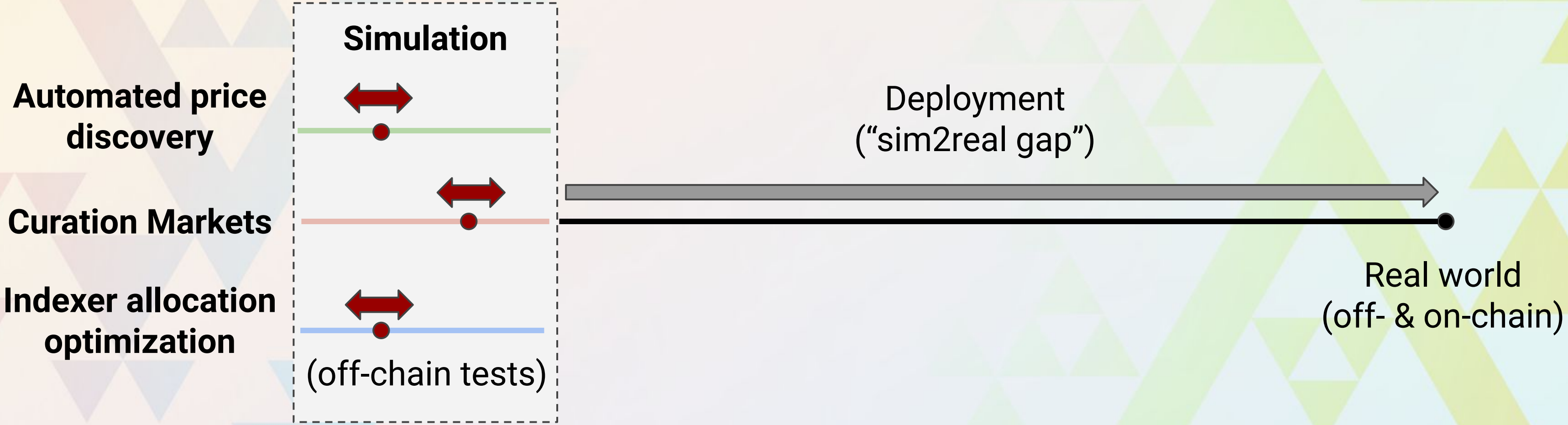
Agent-Based Simulation (in Protocol Economics)

Dynamic Pricing In Competitive Markets

- **Dynamic pricing** happens where the **price is flexible**
  - **Flexibility:** price can be based on demand, supply, competition price, and/or subsidiary product prices
  - **Personalization**: Price may change from customer-to-customer based on their purchase habits

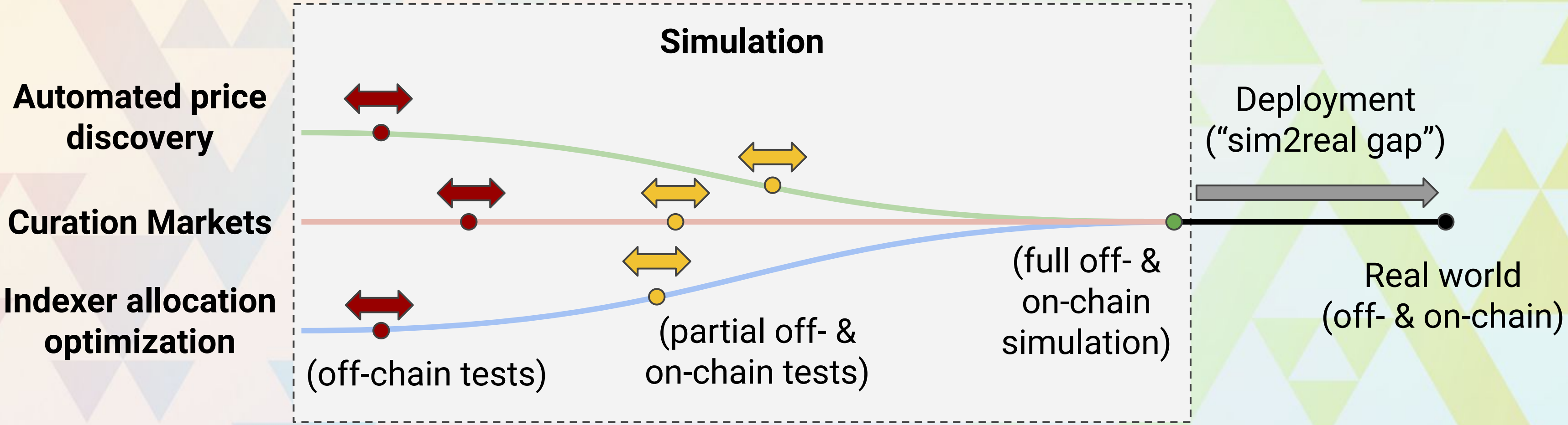
- Protocols like RAI and Filecoin already rely on Dynamic Pricing
- **Reinforcement Learning** is often cited as a **future option** for automated decision-making in web3 protocols

Independent simulations



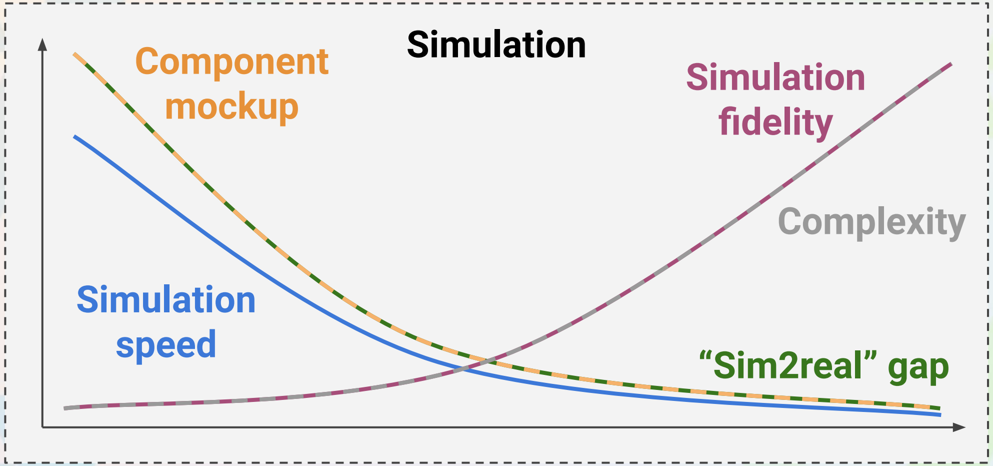
- Fast: good for rapid prototyping, unit testing etc.
- Huge "sim2real gap": deployment is *the actual testing*

Multi-fidelity Simulation 1



- Reduction of the sim2real gap
- Modeling off- & on-chain with varying "realism"

Multi-fidelity Simulation 2



Testing new ideas
(off-chain tests)

Verification
(partial off- & on-chain tests)

E2E testing
(full off- & on-chain simulation)