OPTIMIS

Framework for optimal control of a message in social media using deep reinforcement learning

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MOTIVATION

Motivation

➔ EnFVe: An Ensemble Fact Verification Pipeline is a recently published paper
➔ The four stages of fact checking according to FullFact
➔ The ‘Create and publish’ block of the pipeline is the focus for this thesis.

Four stages of fact-checking [1]

INTRODUCTION

Business Use-case

"A product marketing associate has a need to maximize the visibility of the product in social media"

High Level Overview

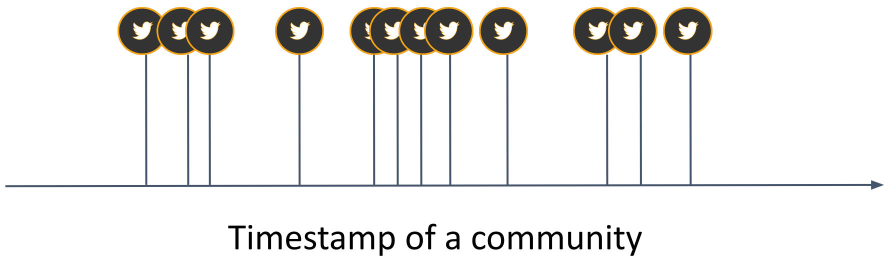
Problem

High Level Overview

Problem

High Level Overview

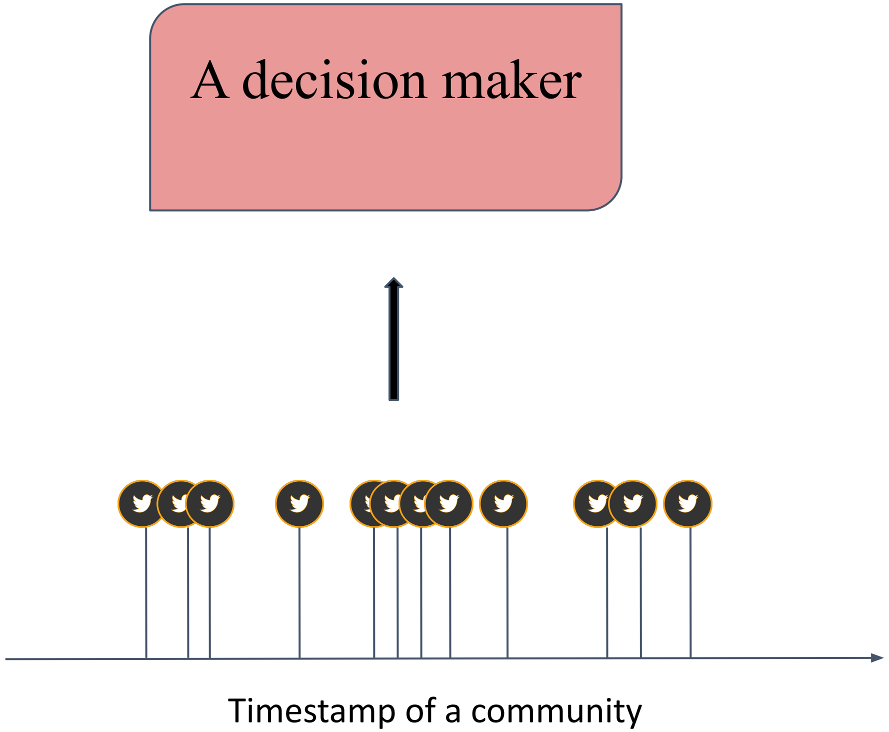
Problem



Solution

High Level Overview

Problem



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High Level Overview

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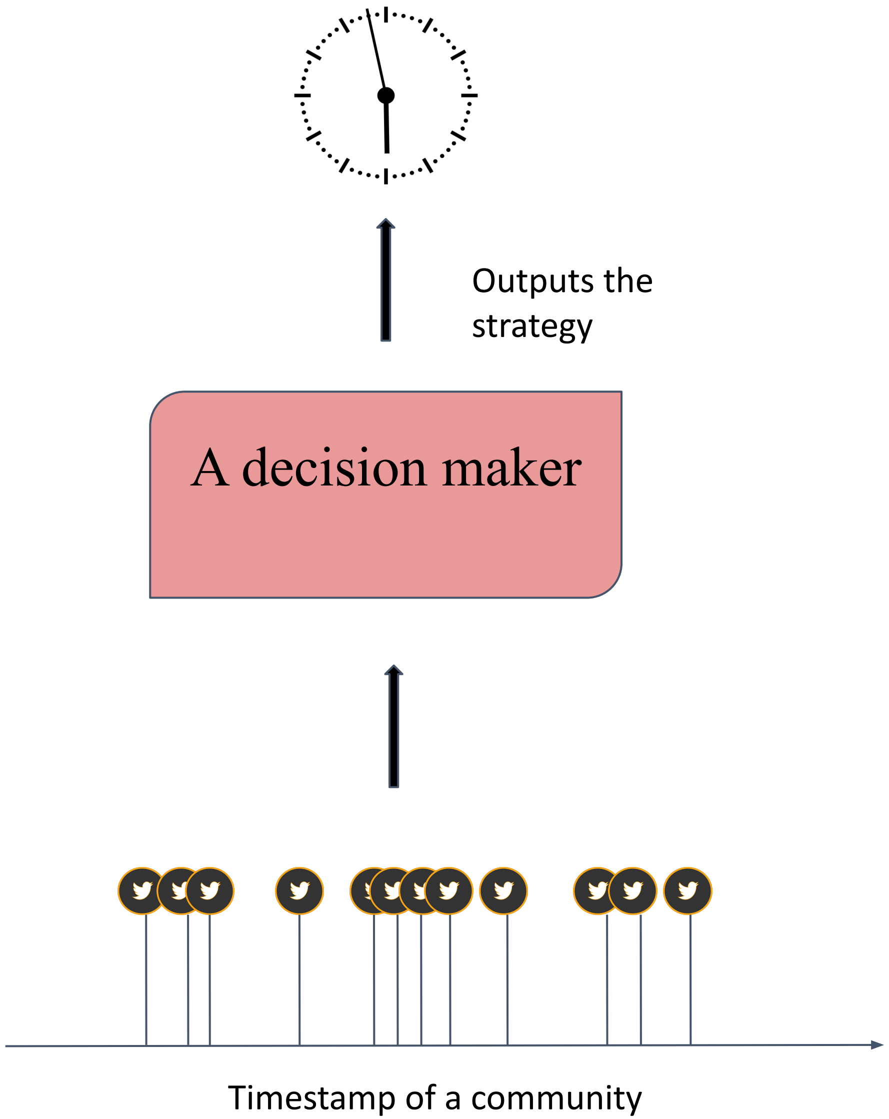

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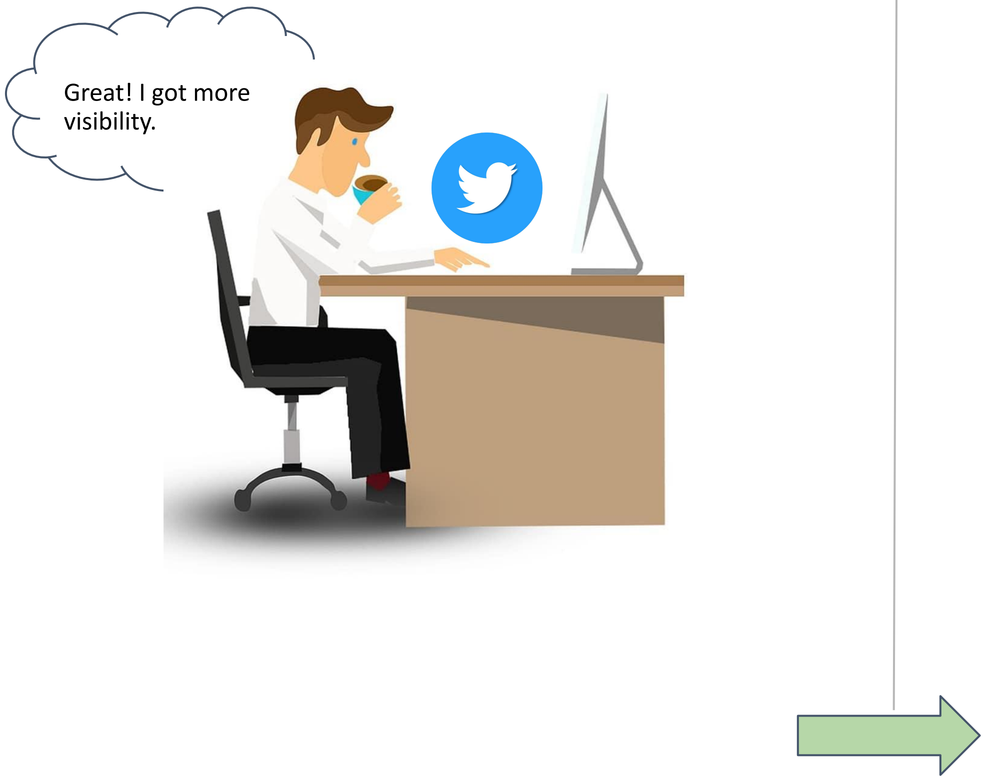
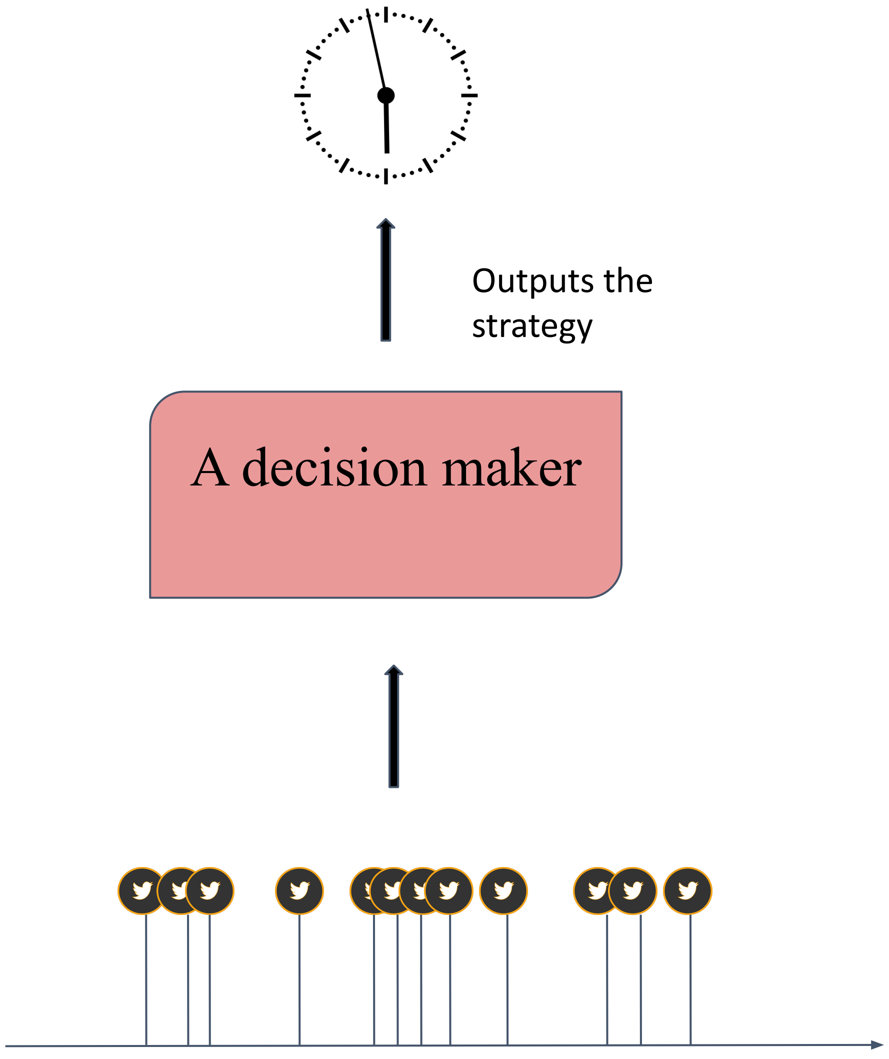
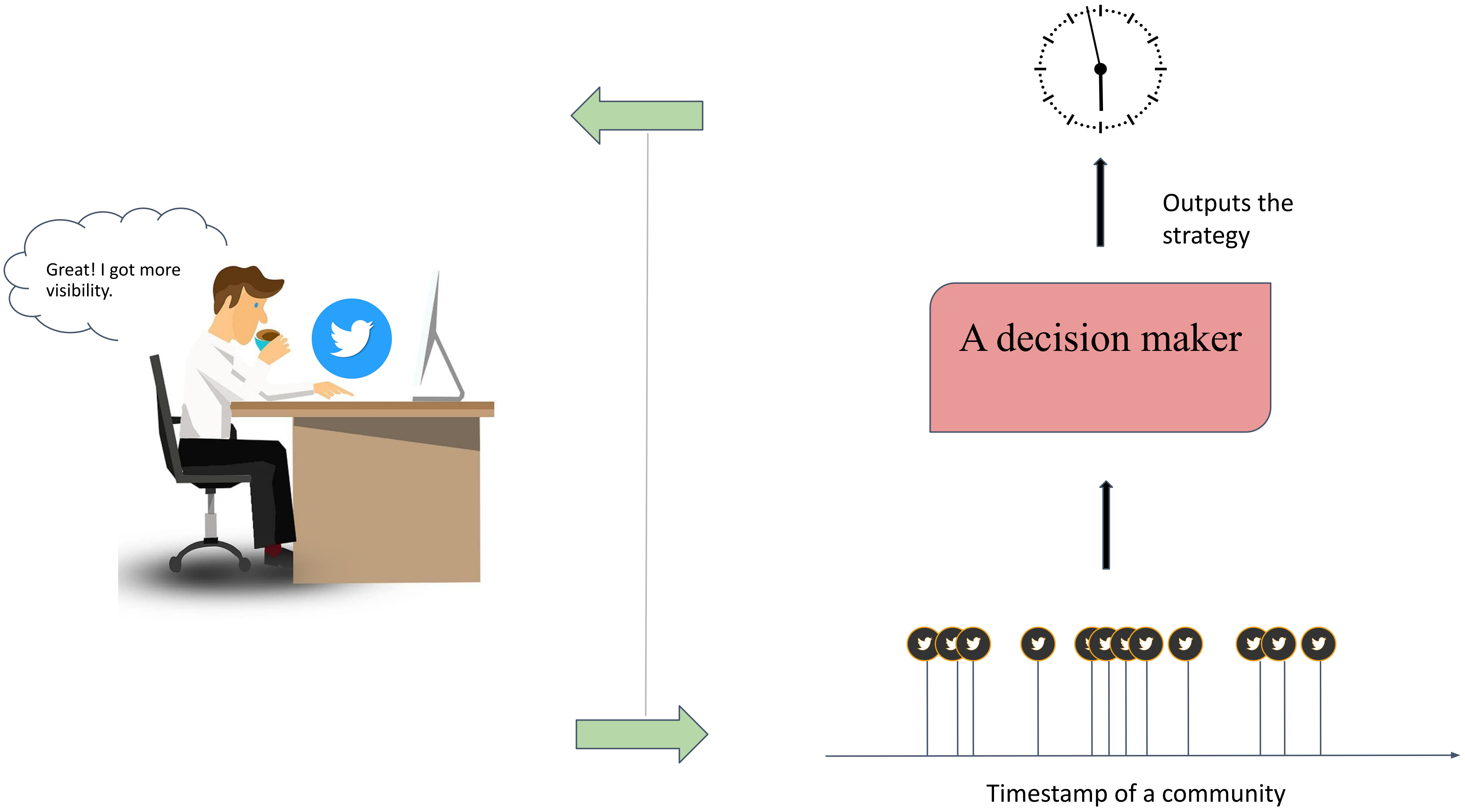
High Level Overview



Problem



Solution

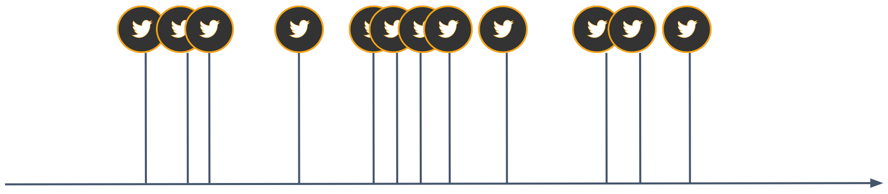


Problem

Solution

LITERATURE REVIEW

Point processes & its applications



Tweets timestamps

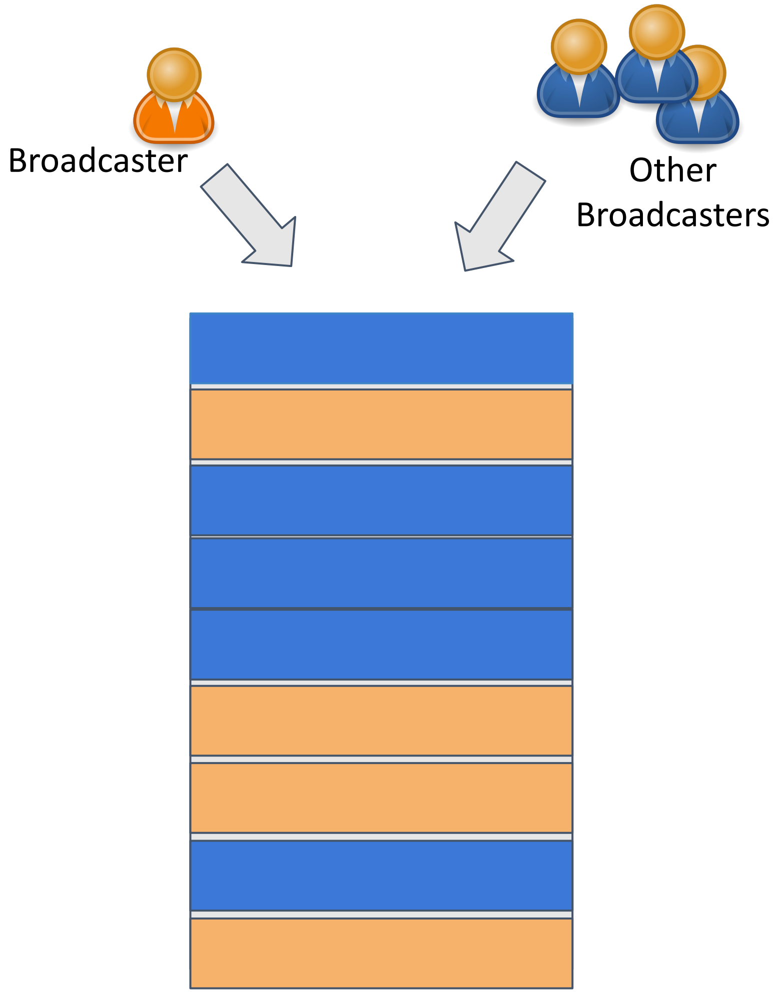
- ➔ Tweets are basically the temporal points.
- ➔ Typical domains where point processes exist: Trading, disease prevention, influence maximization, etc.
- ➔ The “when-to-post” problem is essentially the problem of influence maximization.

<u>The scope of the thesis is centered around influence maximisation</u>

Influence maximization

- ➔ Influence maximization encompasses a broad class of applications: effective broadcasting, ad placement, viral marketing, etc
- ➔ IM can be thought of as a decision making mechanism on point process where the broadcaster decides when to post to maximize her post visibility.
- ➔ Reinforcement learning is a good candidate for modeling on decision making processes.

Using Reinforcement learning on Influence Maximisation is a promising idea



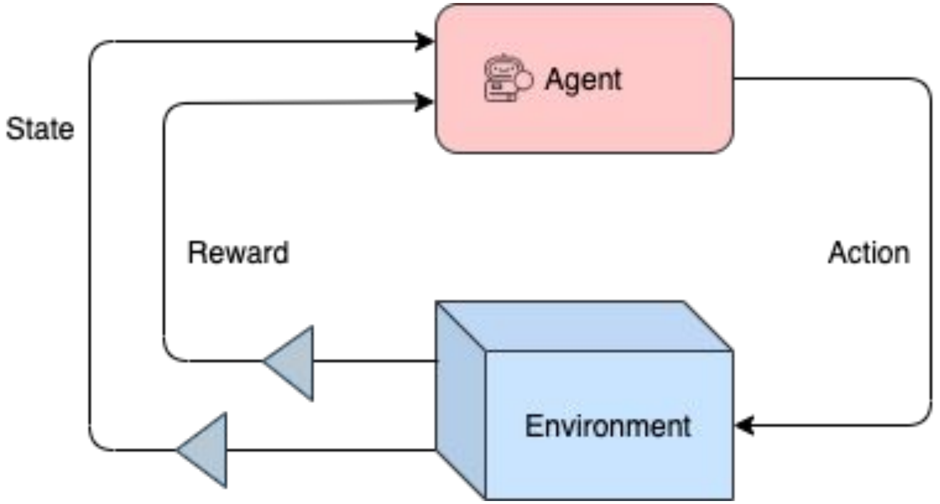
A user's feed

A short walkthrough of RL

Reinforcement learning is the idea of making the optimal sequence of actions in an environment in order to maximize reward.

Consists of two primary components:

- **The agent** is basically the brain of the framework, which learns a policy to act upon.
- **The environment** provides the agent with the state to act upon, and also given the reward for informing future actions.



Reinforcement Learning cycle [5]

The current research focus and gaps

Agents

- The main focus is on building the RL agents
- For Influence maximization, Deep RL approaches that employs complex policy gradient methods like TPPRL [2]

Environments

- Mostly game-like environments exist out there (atari)
- For time series, support is very limited as well. Especially in trading such as tensortrade library [3]
- Interesting environments simulating heat dynamics of a building [4].

Takeaway

Not much research in RL for temporal point processes

Problem

There exists no environments for enabling decision-making problems that involve influence maximisation

Solution

A custom RL environment that can support various influence maximisation strategies.

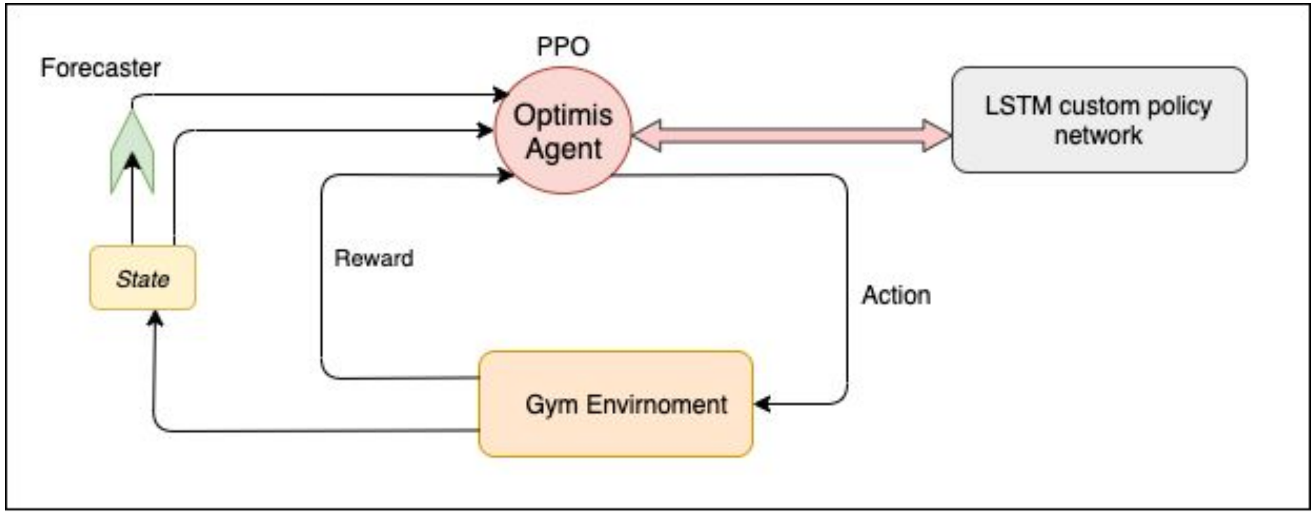
Contribution

Enables rapid development of influence-maximisation-based applications as well as accelerating research in the domain

IMPLEMENTATION OF THE OPTIMIS FRAMEWORK

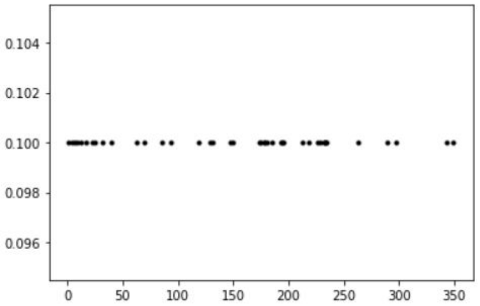
Architecture overview

- ➔ The framework consists of two primary components:
  - ◆ the environment
  - ◆ agent
- ➔ the environment is the highlight of the framework
- ➔ the agent is employed to illustrate its application of the environment
- ➔ The API layer enables users to customize various strategies

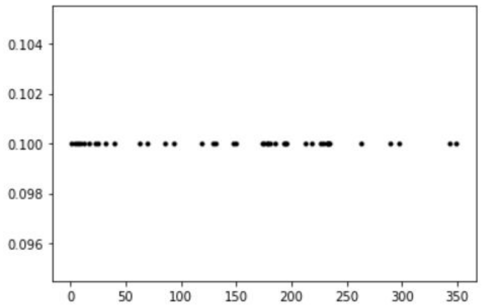


OPTIMIS FRAMEWORK

Preprocessing



Preprocessing: first order time difference



First-order time difference

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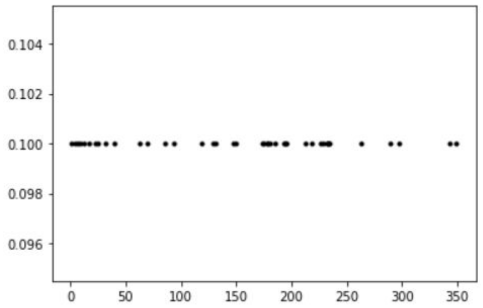

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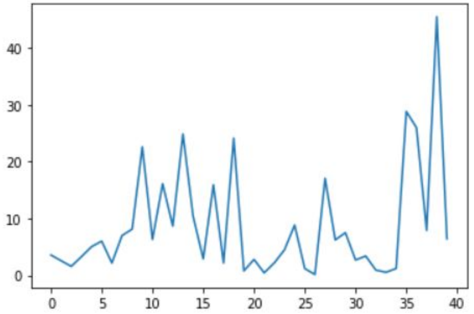
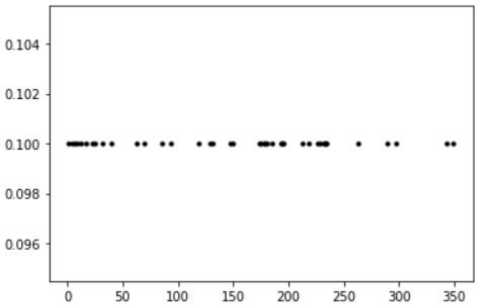


transformed values

Forecaster module



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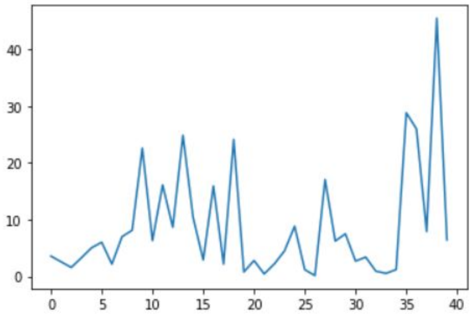
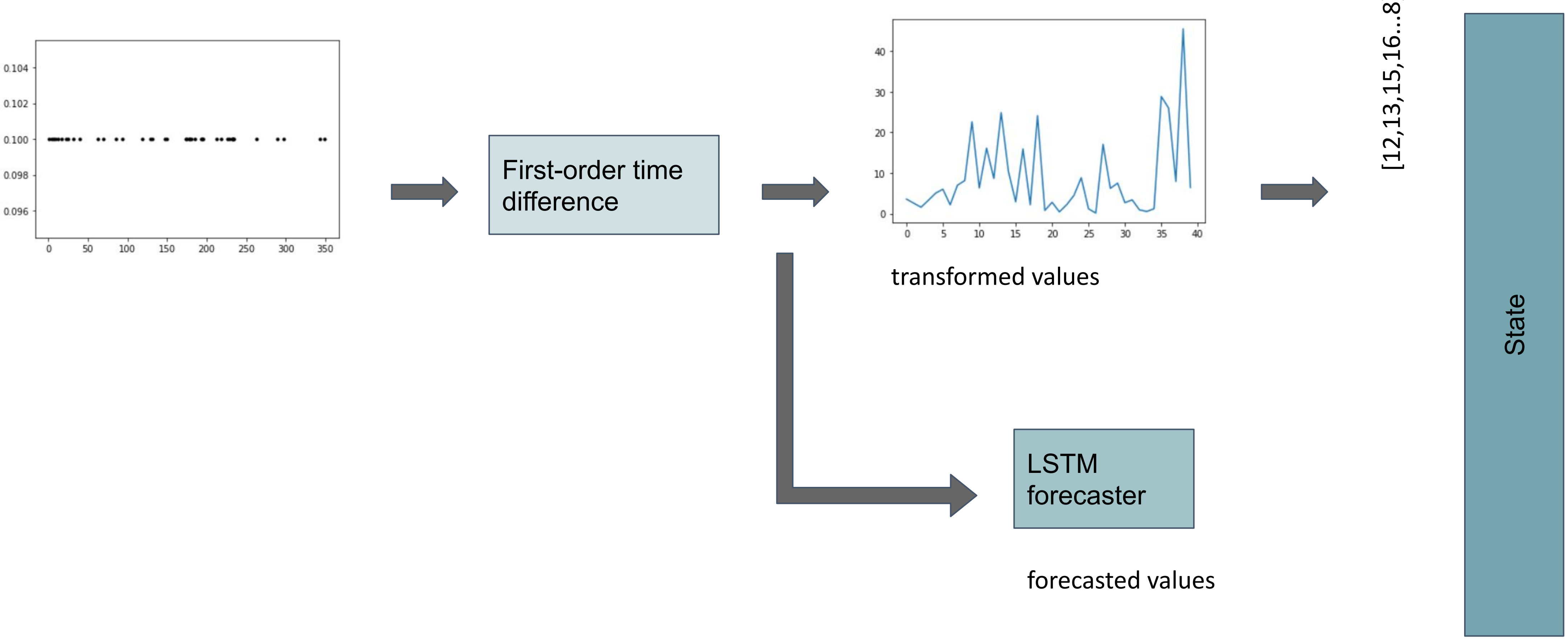


transformed values

[12,13,15,16...8]

State

Forecaster module



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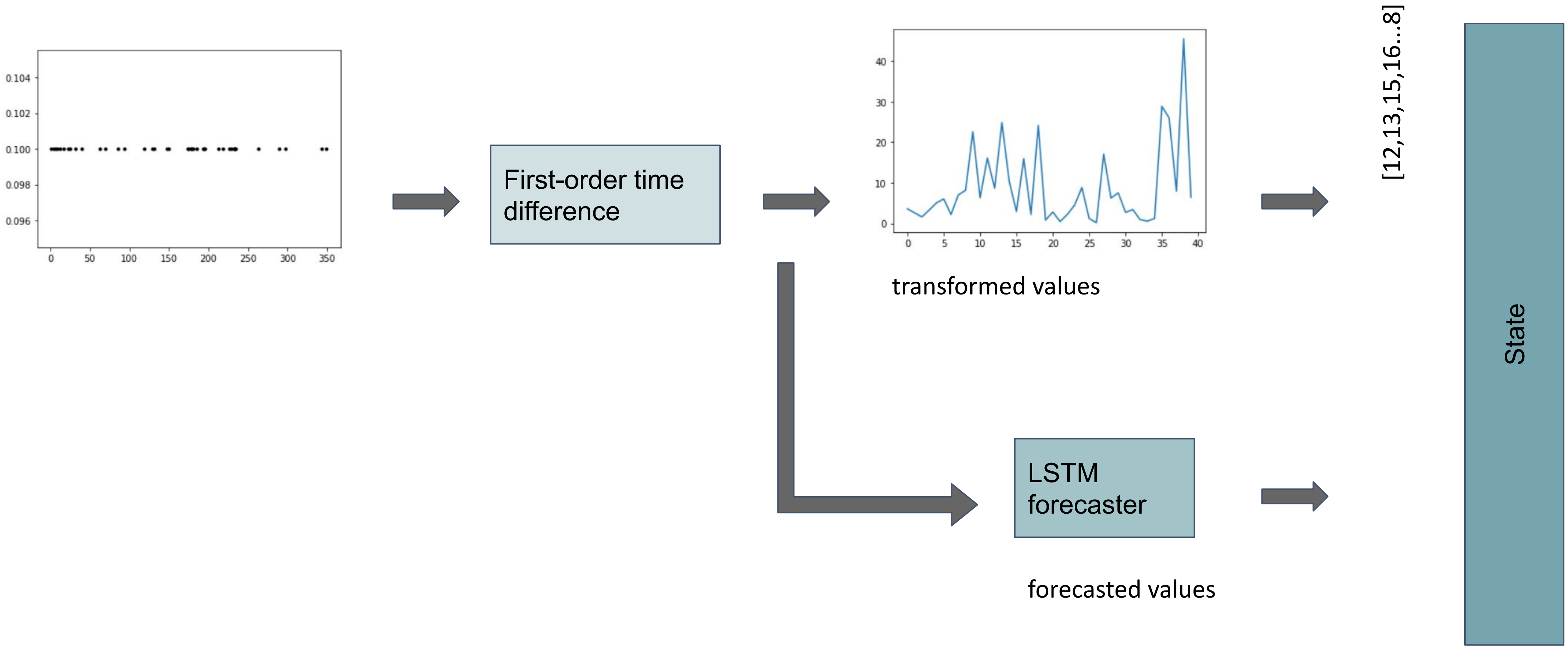

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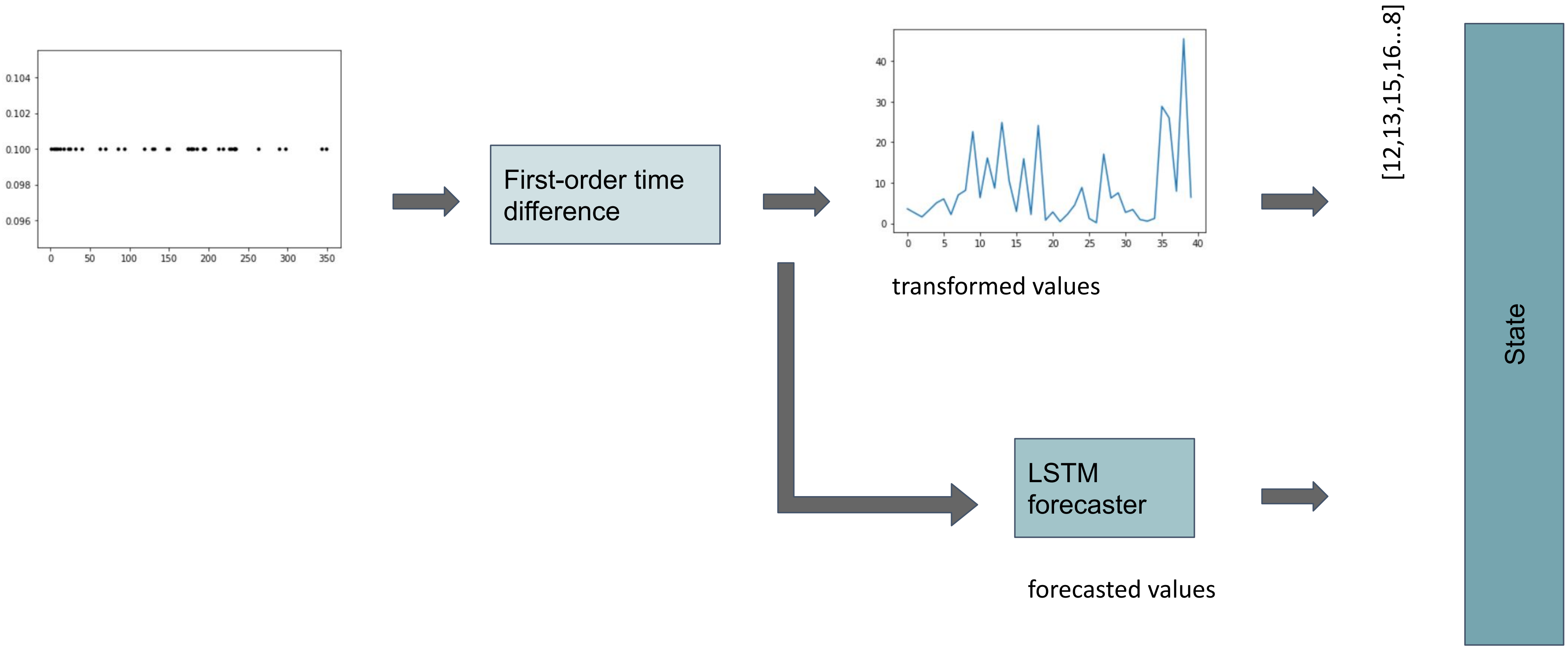


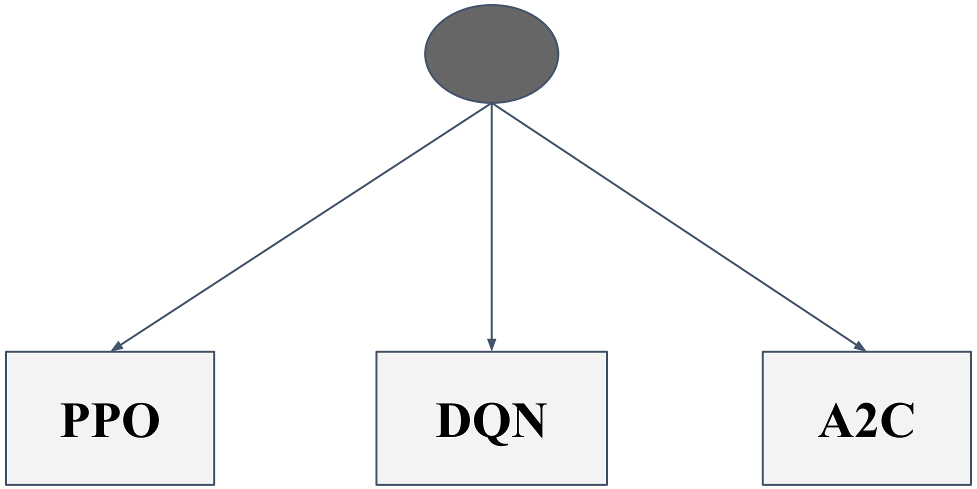
User has the control over which preprocessing step to be used and which ones to be omitted

Agents

- Basic support for agents are included, with stable baselines and rllib environments which has the algorithms

- The algorithms are chosen as they support discrete actions as outputs

- The code shows an implementation of how a PPO agent can be used through RLLib.




```
from ray import tune
from ray.rllib.agents.ppo import PPOTrainer
#Running the PPO with recurrent policy
Optimis = tune.run(PPOTrainer, config={"env":'my_env',
                            'num_workers': 1, 'num_gpus': 1,
                            "model": {"use_lstm": True}})
```

Description of environment

Based on Open AI gym environment

Reward function:
Reward = future_timestamp - current timestamp - action_penalty

Episode termination conditions:
- If the current step exceeds the total episode length
- If the actions made by the agent is more than the allowed actions
- If the current time step exceeds the allowed time limit

State:
- A sliding window of past n timesteps
- Forecaster is added to the state

API interface

```
# loading twitter data
#returns a list of timestamps
data = load_twitter_data()

#initialise the optimis environment
env = OptimisEnv()

#load the temporal points into the environment
env.set_timestamps(data)

#helper function to display information about the data
env.display_data_stats()

#setting strategies
env.set_constraints(action_penalty=30,
                    max_allowed_actions=None)

#train forecaster
env.train_forecaster(num_steps=18, num_epochs=350)

#enable or disable preprocessing techniques
env.settings(use_forecaster=True,
             use_previous_timestamps=False,
             first_difference=True)
```

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env.settings(use_forecaster=True,
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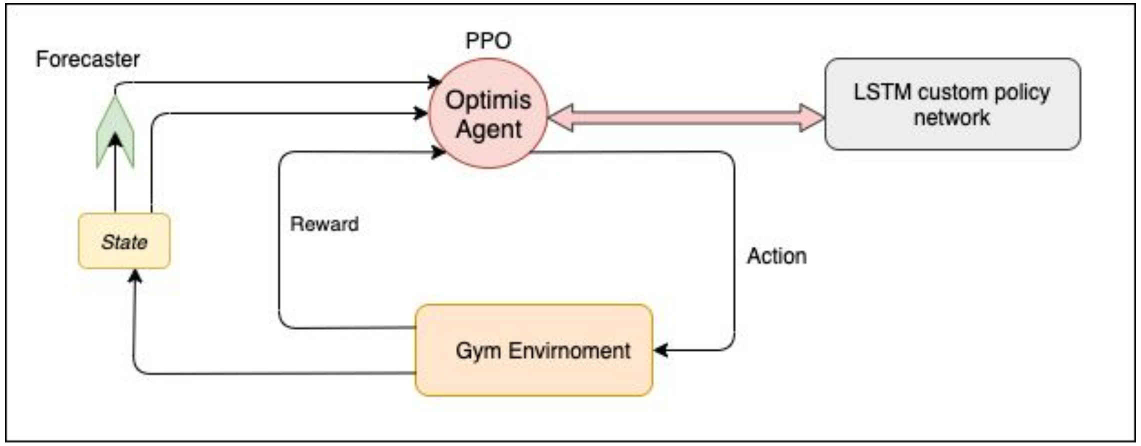
#training the model
model = env.train_agent(policy='PPO', iterations=50_000)
```

Summary

The Optimis framework consists of:

- Data preprocessing for handling point processes
- A high-level API that lets users set strategies
- A list of RL policies



OPTIMIS FRAMEWORK

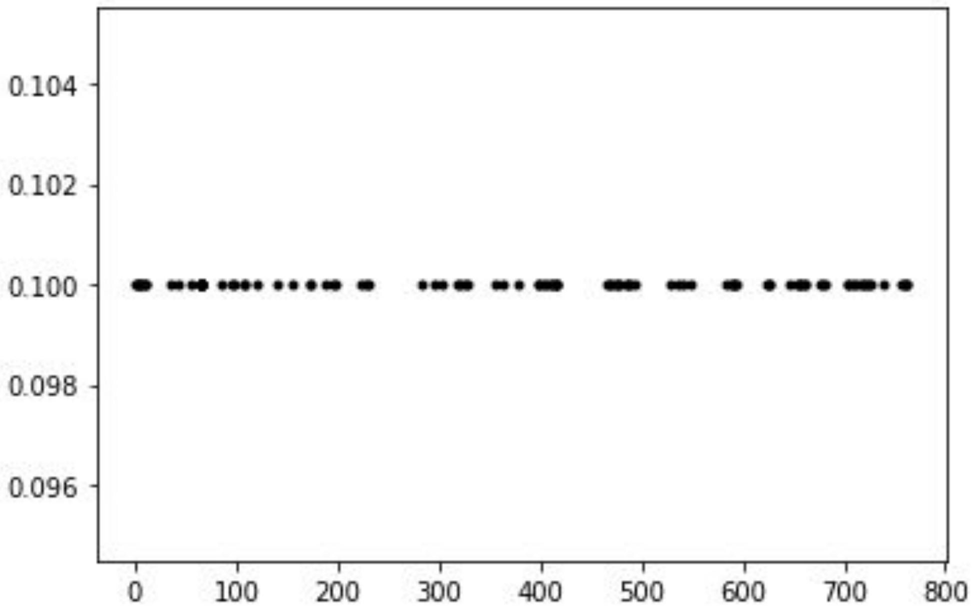
EVALUATION

Evaluation: on twitter dataset

Collected 1913 tweets over 5 days

average interval between two points: 3.76 minutes

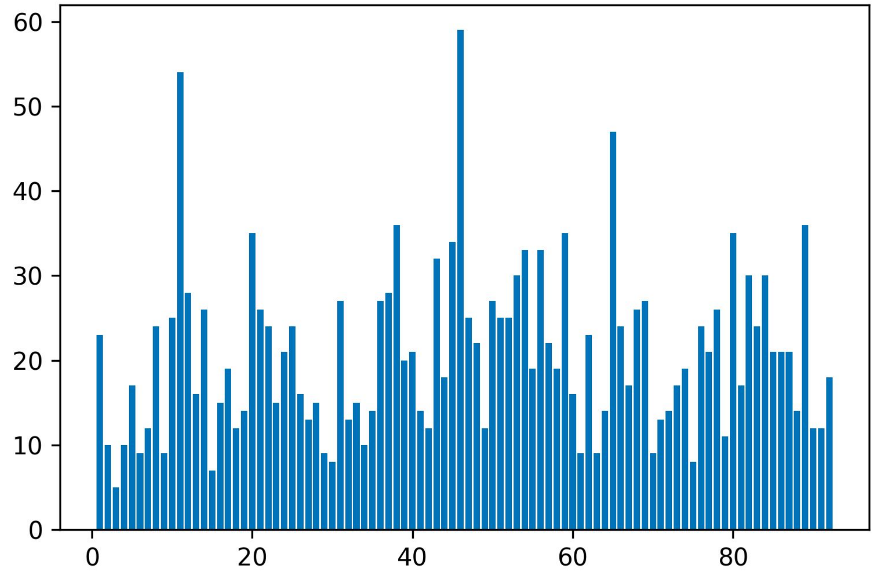
Top 10 intervals:[42.4, 41.6, 38.47, 35.33, 35.33, 33.76, 32.98, 30.62, 30.62, 29.83] minutes



interesting pattern of increasing and decreasing intensities can be observed

Evaluation

- Fetched tweets related to #machinelearning
- Total number of tweets: 1913
- Duration: 2.5 hours
- Average interval between two points: 4.79 secs
- Top 5 intervals found in the dataset: 54.0, 53.0, 49.0, 45.0, 45.0 secs



Algorithm	No preprocessing	First-order time difference	Forecaster	Forecaster+FO
DQN	(-32.3) N/A	(7.1) N/A	(8.5) 32.9	(11.2) 34.1
A2C	(-12.8) N/A	(-13.4) N/A	(-4.8) N/A	(-4.2) N/A
PPO	(8.6) 35.7	(42.6) 45.1	(56.9) 44.9	(63.2) 45.8

RUNNING EXAMPLE

Consider these scenarios

"I want to make a post that lasts at least half an hour on social media"

"I want to maximize the visibility of the three posts that I have"

"I want to make 3 posts in the next hour and make sure that they gets an average airtime of at least 30 seconds"

Posting strategy

"I want to make 3 posts in the next hour and make sure that it gets an airtime of at least 30 seconds"

User wants to post:

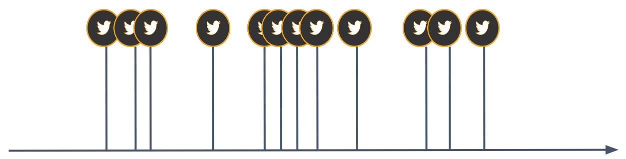
No of posts → 3 times

Time limit → in the next hour

Post time should be minimum → 30 seconds

```
#setting strategies
#unit of time is seconds
env.set_constraints(action_penalty=30,
                    max_allowed_actions=3,
                    time_limit=3600)
```

How each timestep works



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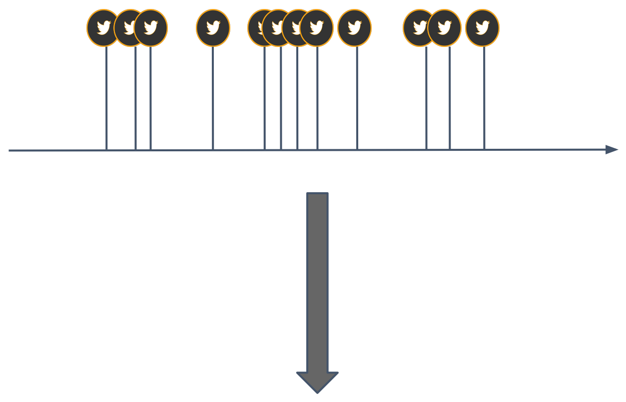

[1.0, 3.0, 4.0, 5.0, 6.0, 7.0, 10.0, 11.0, 36.0, 42.0]

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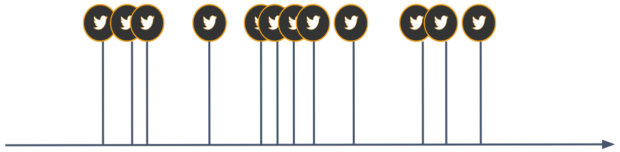
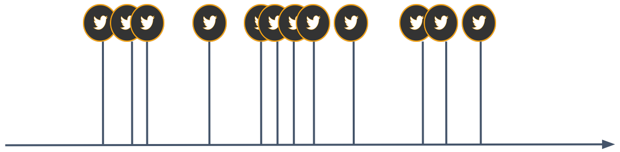


[1.0, 3.0, 4.0, 5.0, 6.0, 7.0, 10.0, 11.0, 36.0, 42.0]

[3., 0., 1., 1., 2., 3., 1., 25., 6.]

How each timestep works



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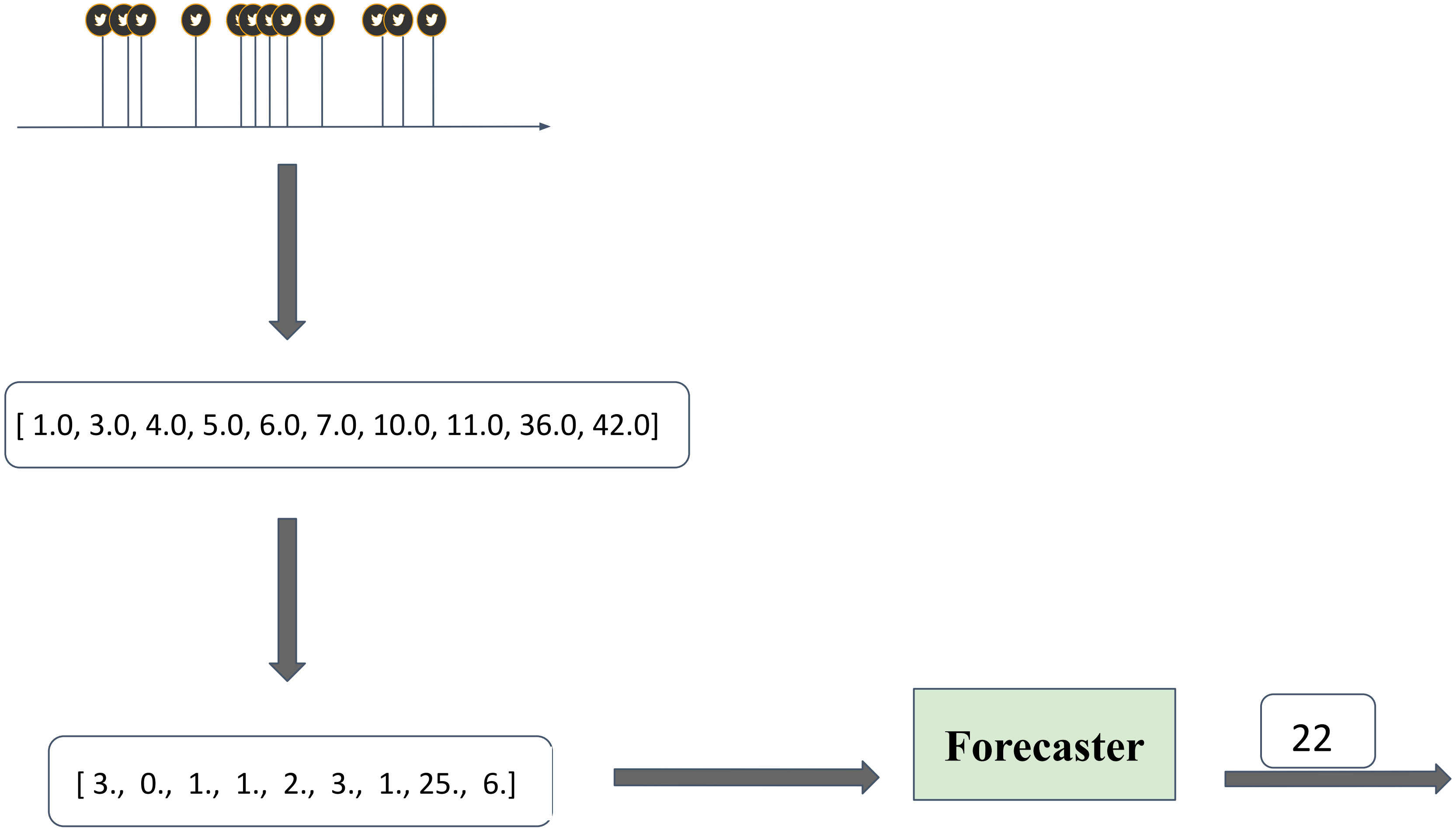
[3., 0., 1., 1., 2., 3., 1., 25., 6.]

Forecaster

How each timestep works



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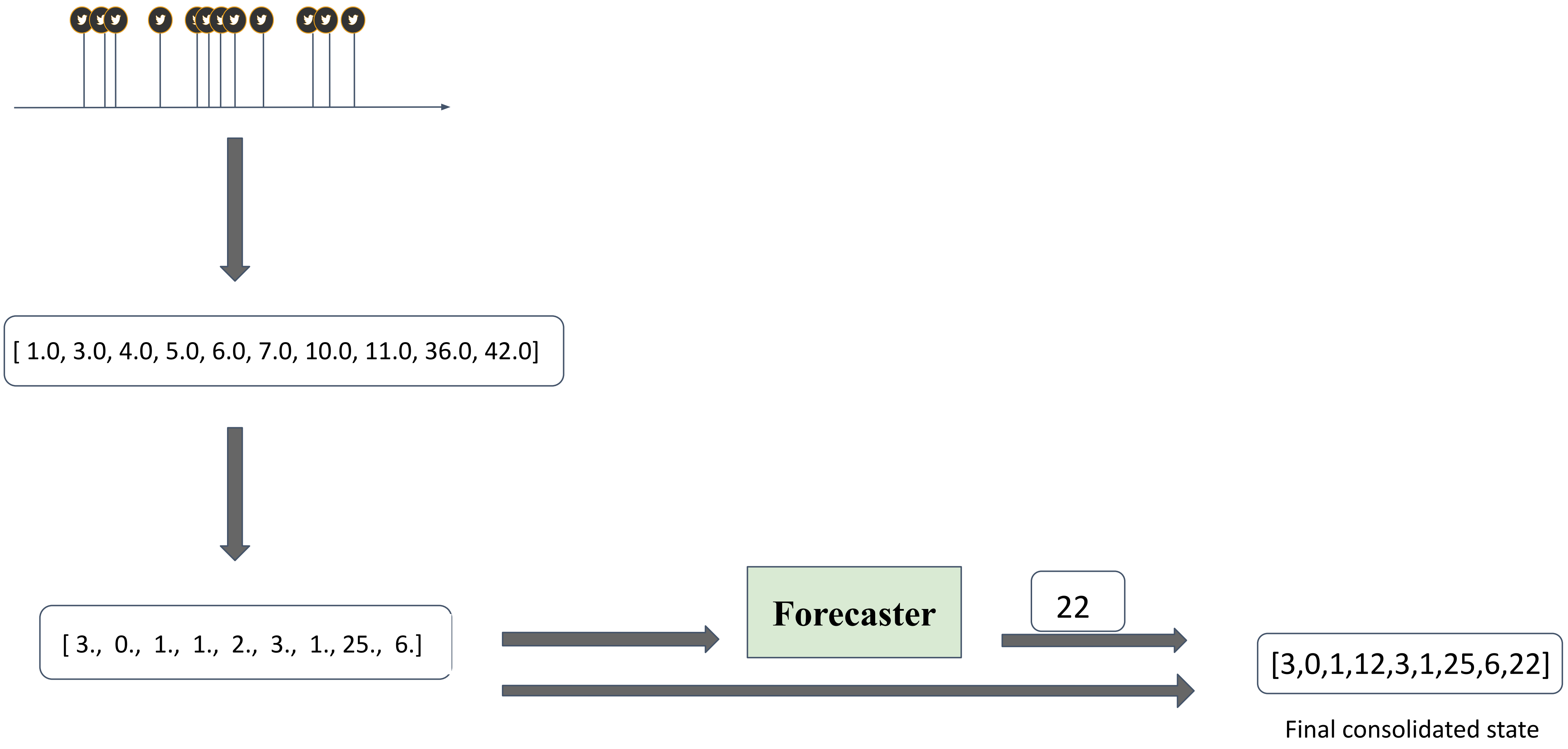

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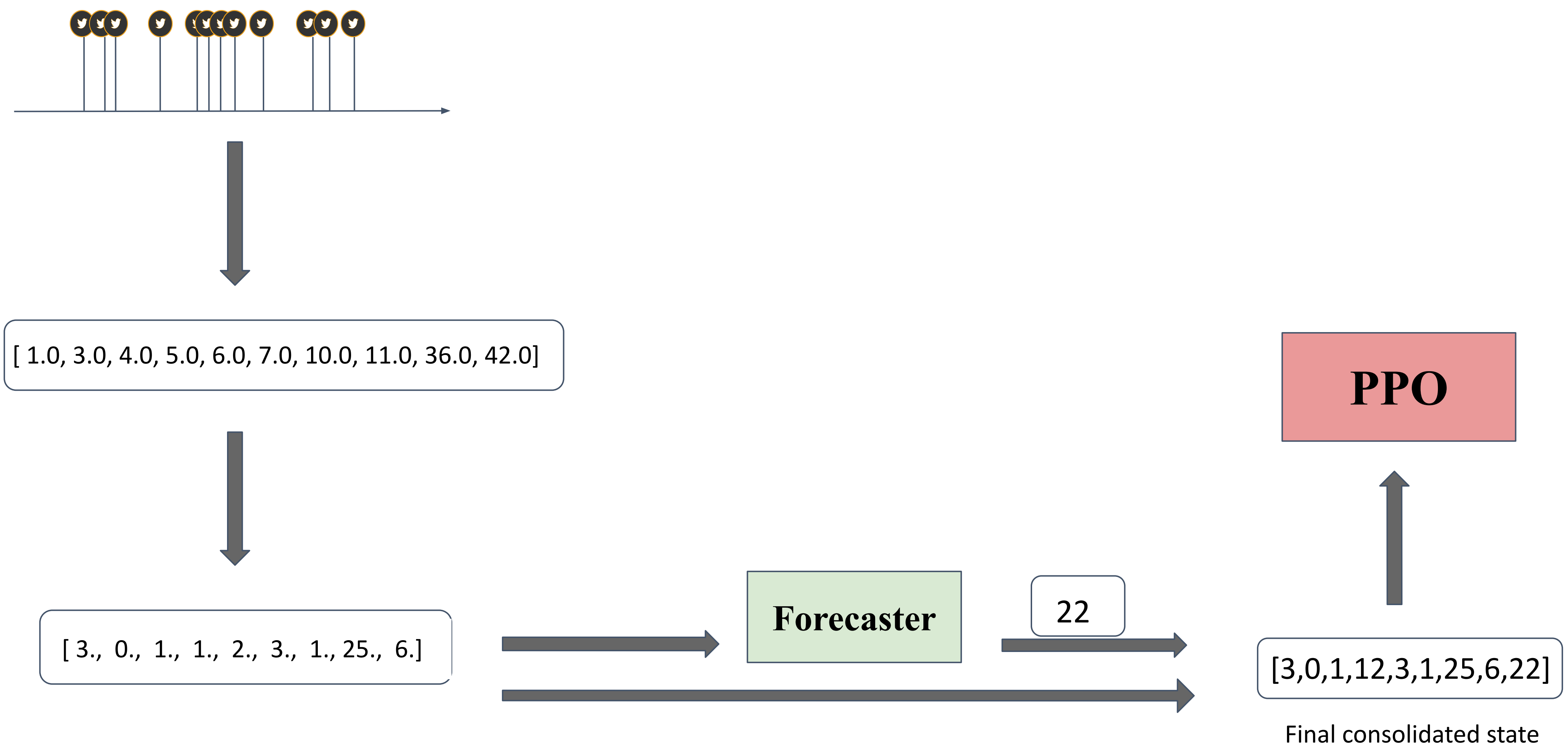

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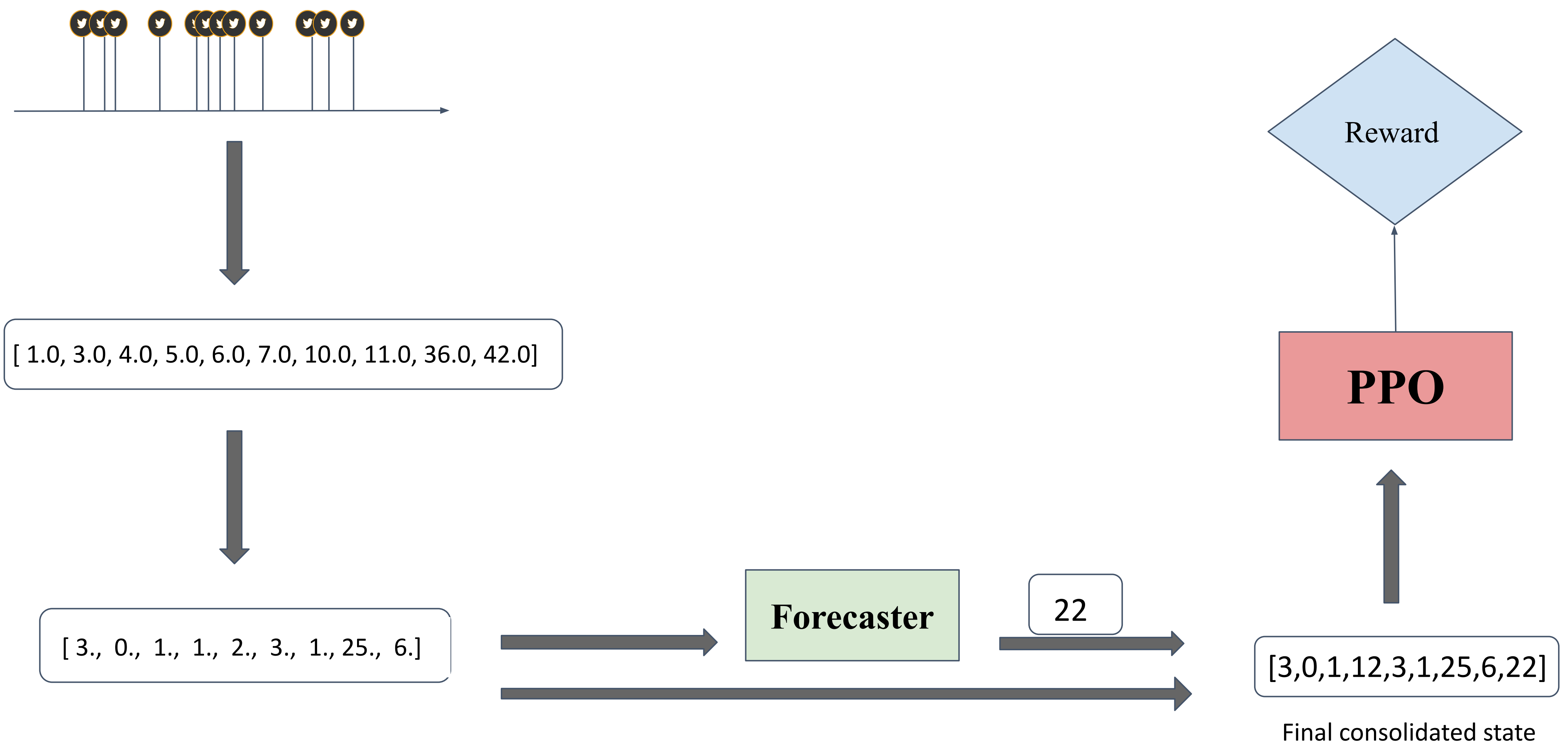

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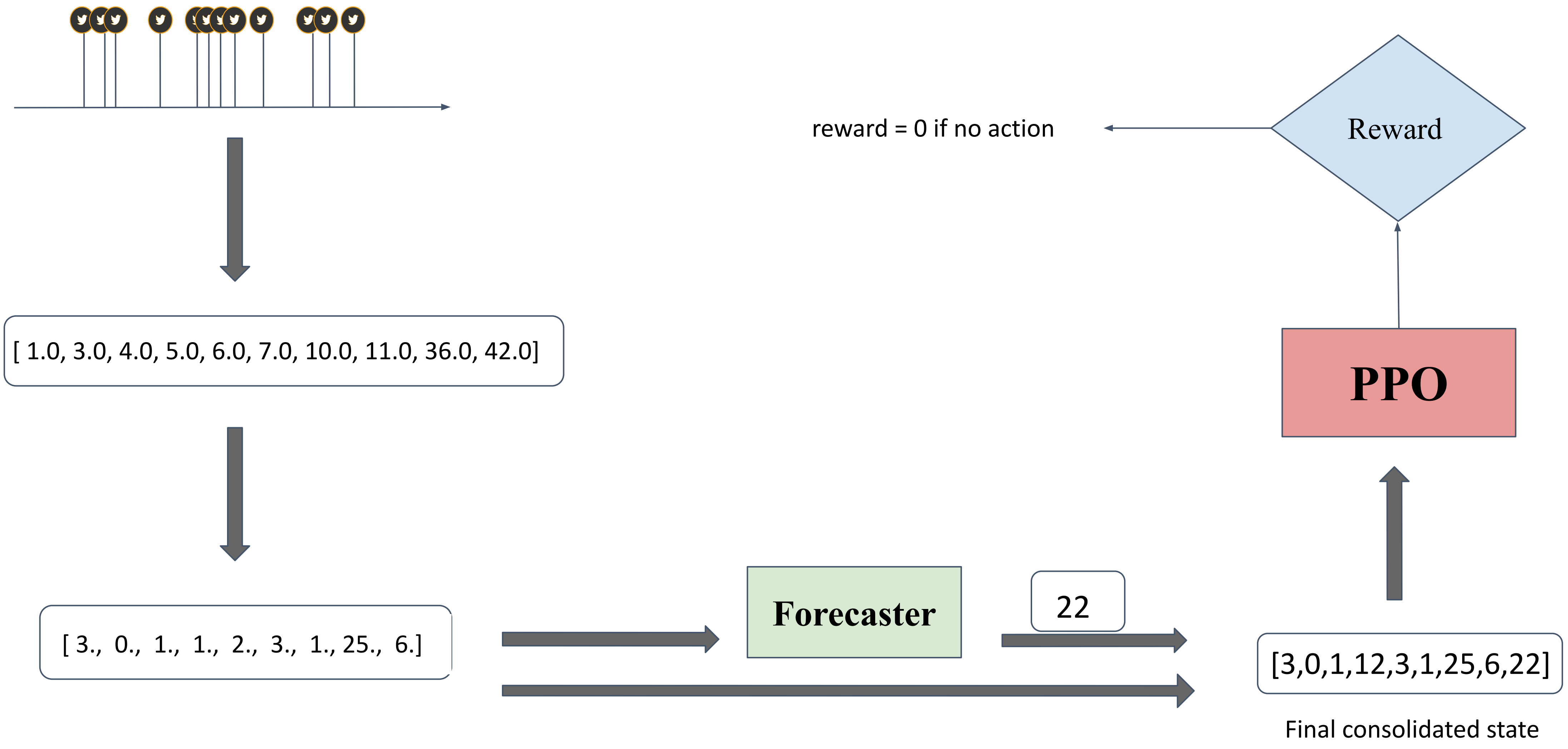

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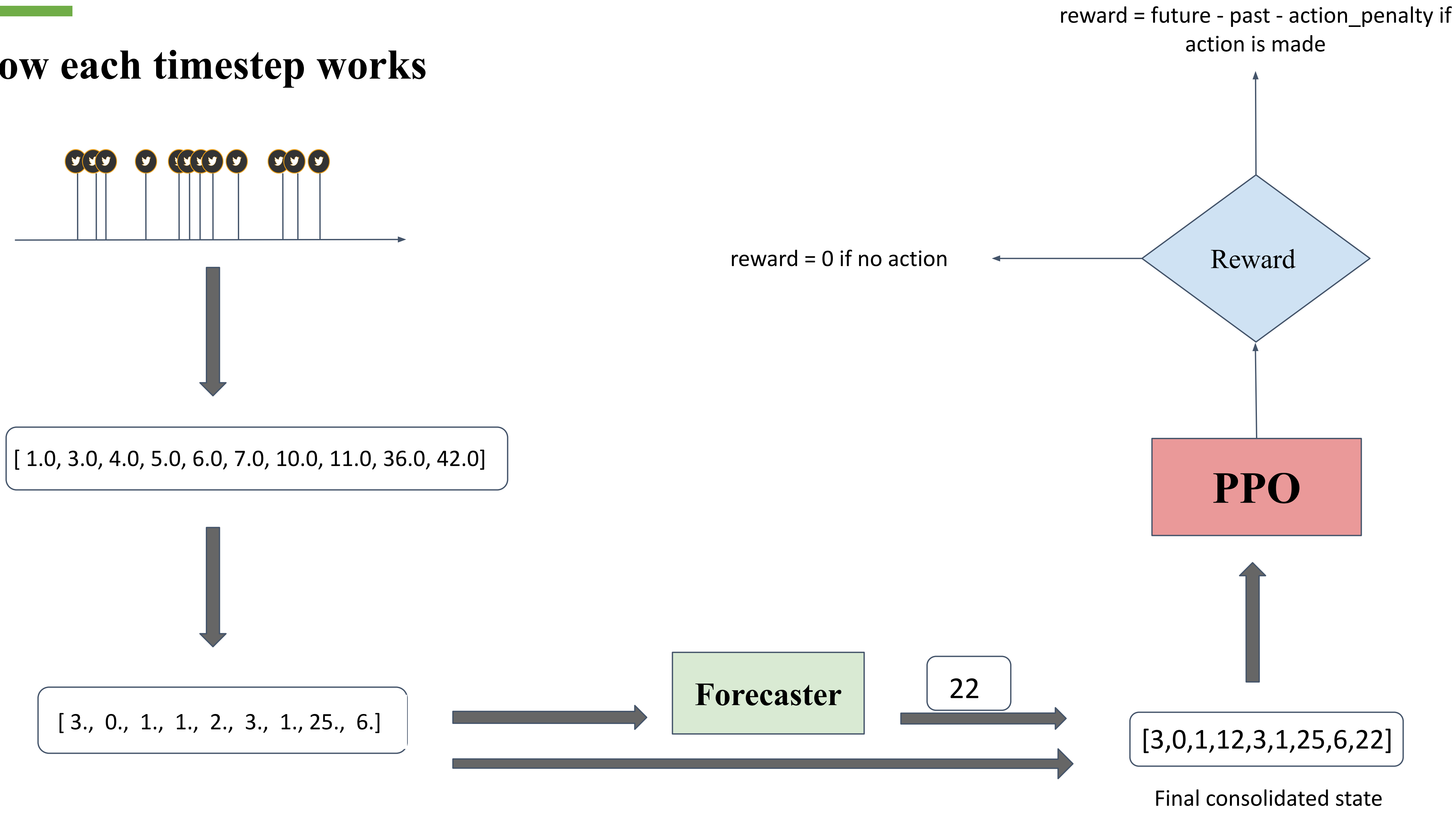
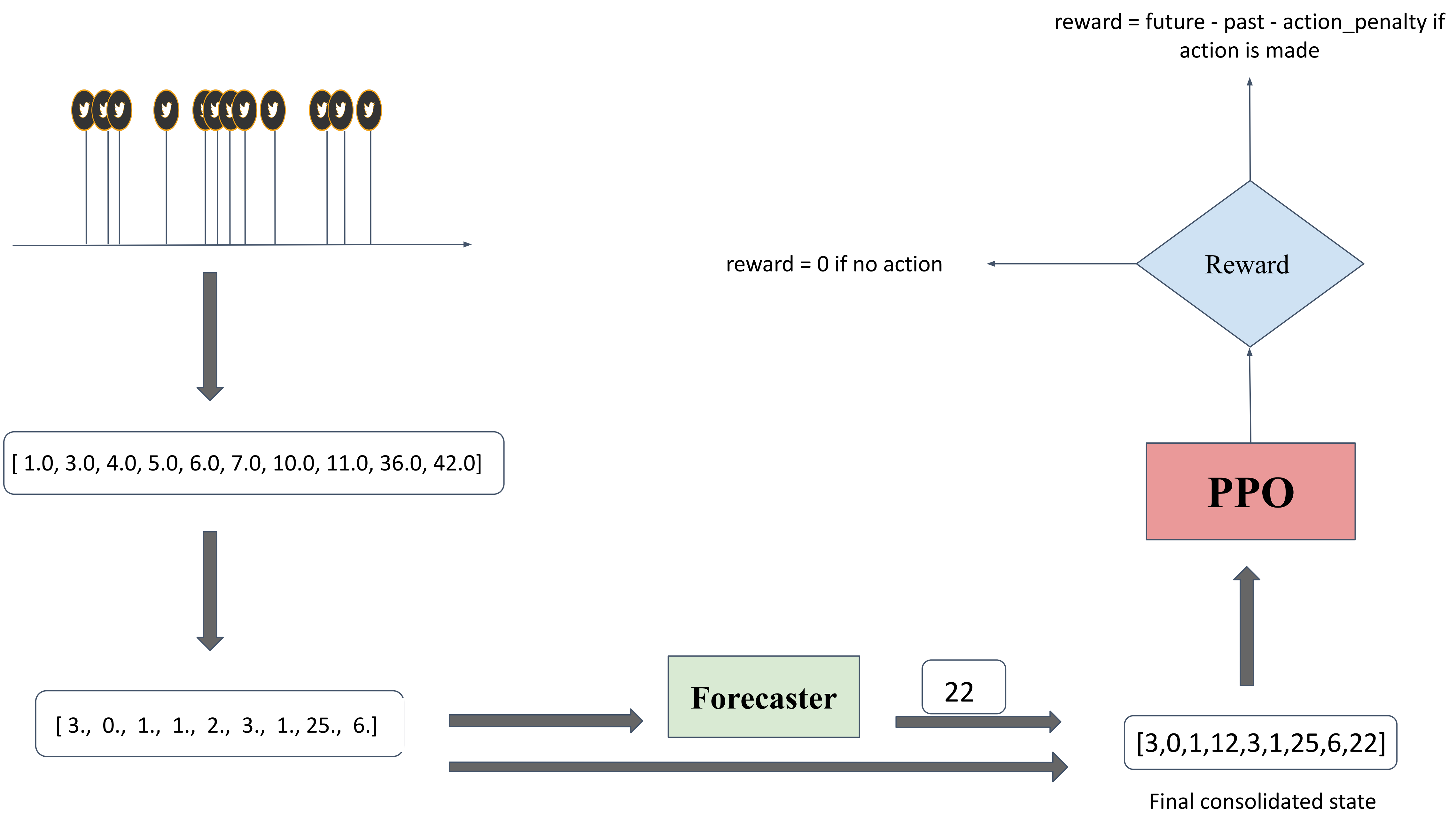
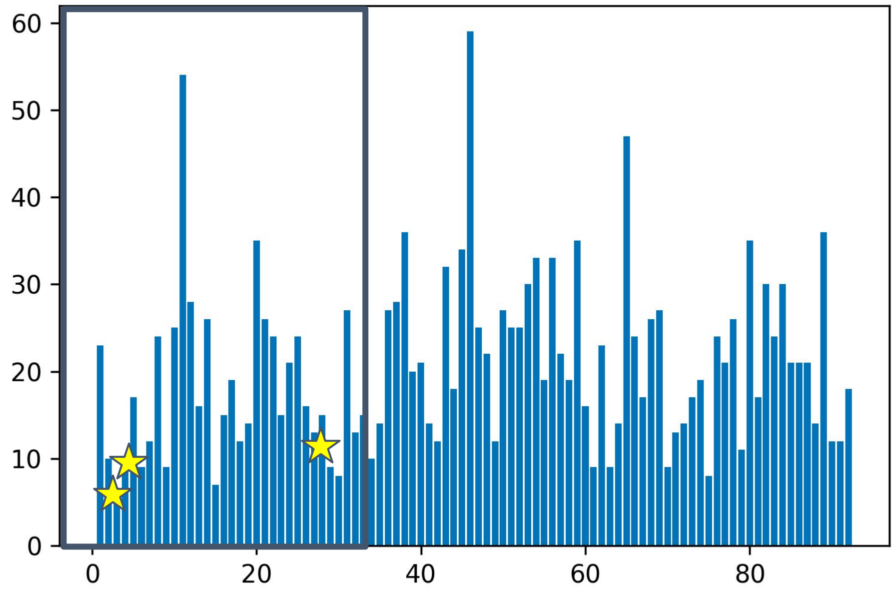



reward = future - past - action_penalty if action is made
reward = 0 if no action
Reward
[1.0, 3.0, 4.0, 5.0, 6.0, 7.0, 10.0, 11.0, 36.0, 42.0]
PPO
Forecaster
22
[3., 0., 1., 1., 2., 3., 1., 25., 6.]
[3,0,1,12,3,1,25,6,22]
Final consolidated state

Results

```
{'current_step': 35, 'current_post_time': 231.0, 'next_post_time': 284.0}
reward: 2.5704999999999956
{'current_step': 54, 'current_post_time': 416.0, 'next_post_time': 465.0}
reward: -1.4295000000000044
{'current_step': 511, 'current_post_time': 2707.0, 'next_post_time': 2752.0}
reward: -5.429500000000004
episode end
```



CONCLUSION

Conclusion

Contributions	How the Framework achieves them
1. A custom RL environment that can work with temporal point processes, and can **accommodate the needs of various influence maximization strategies.**	➔ By adding a layer of customization over the API like action penalty, max allowed action and time limit, many high-level posting strategies are possible
2. The RL environment enables the use of simple policy models in discrete domain so that they can be **implemented with ease by application developers & researchers.**	➔ By implementing an environment with preprocessing techniques that make point processes suitable for simple in-built agents like PPO, DQN, and A2C.

Limitations

- ➔ Marks could be added for additional complexity of strategies
- ➔ The API could be extended to enable custom reward function (this could greatly extend the application)
- ➔ Various other preprocessing techniques could be investigated

Future scope

There can be several applications that can be built on top of Optimis:

- ➔ Fake news mitigation as a direct consequence of influence maximisation
- ➔ Viral marketing applications

References

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THANK YOU