Duplicate Packet Suppression in Multi-Access NDN Network using Reinforcement Learning

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INTRODUCTION

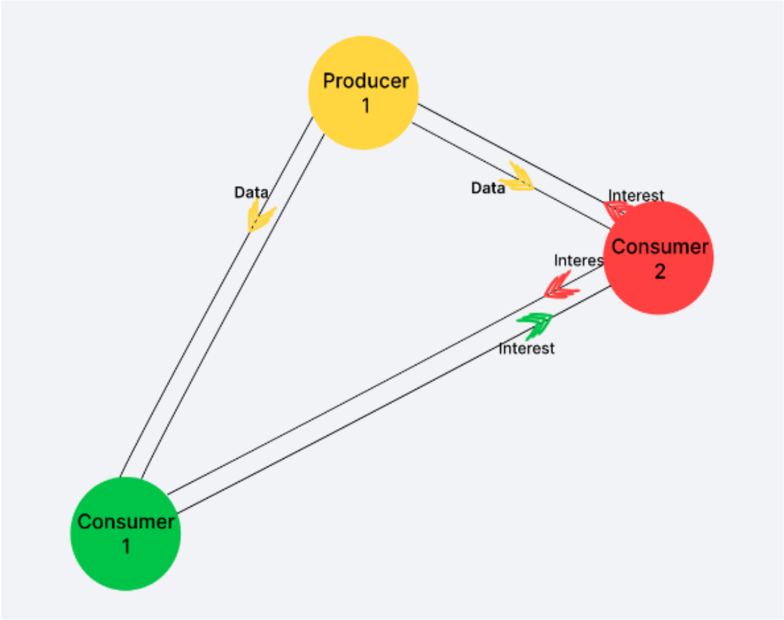
- Data-centric communication is more suitable for today's applications than host-centric communication.
  - vehicular networks
  - video conferencing
  - social networking
- Named Data Networking is a promising Internet architecture that focuses on data rather than location of host.
  - Built-in data multicast
  - In-network caching
  - Multipath forwarding
  - Secured data

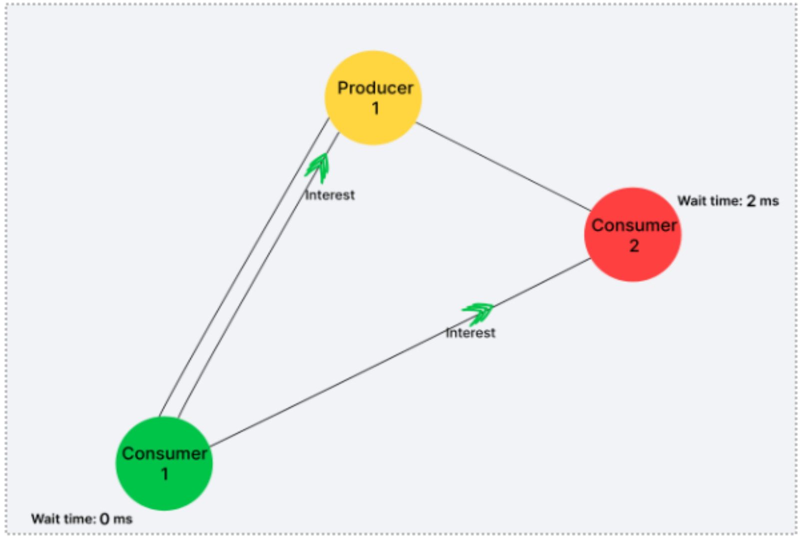
Problem Statement

- Multicasting in multi-access networks (e.g. Wifi) supports group communication and reduces unnecessary transmission

- Without proper coordination, many Interest and Data packets may flow across the network
- Even with just **two consumers**, **multiple Interest packets** can be generated for the **same data**, and increasing the number of nodes can cause **packet flooding**
- The same applies to **Data packets**, leading to further redundancy

- If nodes **briefly wait before forwarding packets**, they may suppress duplicates and **reduce network overhead**





Existing Solution

- Some researchers [1,2, 3] used random wait time between fixed [min, max] interval before sending the Interest/Data packets
  - If interest is overheard during the wait time, the interest transmission is canceled
  - Not adaptive to the number of consumers and producers
- Dulal et. al. introduced Adaptive suppression mechanism [4] that relies solely on observation of duplicate packet counts.
  - Unclear how to tune ADS parameters like duplicate threshold, smoothing factor, multiplicative factor etc. for different networks

Design Goal and Solution

- Goal: Reduce redundant NDN traffic in multi-access networks without negatively impacting data transfer time (one-hop scenario)
- Solution: Reinforcement Learning (RL) is suitable for dynamic environments.
  - Each node experiments with different suppression time and learns a policy that reduces duplicates under varying network conditions.
  - The reward guides the node to increase or decrease the suppression time based on the network state

System Design

- Two main components:
  - NDN Forwarding Daemon
  - Node with RL module
- NFD handles the NDN packets across the network managing FIB, PIT and CS
- Node with RL module acts as **agent** that waits briefly before forwarding packets

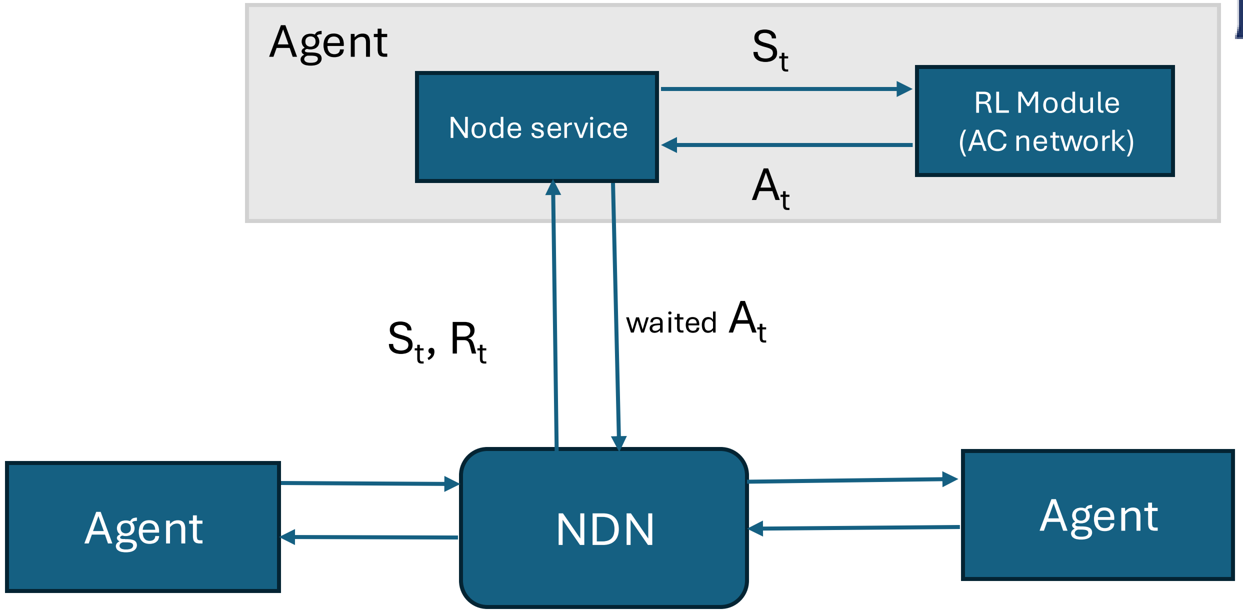


Fig: Computation of Suppression time as RL task

- The Agent observes the current state (S_t)
- Takes the action (A_t) which is to wait for the computed suppression time
- Environment is transitioned to next State (S_{t+1}).
- The Agent receives reward (R_t) based on outcome

RL Module (Actor Critic Network)

- **State** captures important environment information the agent needs to decide how long to wait before forwarding packet
  - **np –** Name Prefix
  - **st –** Suppression Time waited by agent
  - **dc –** Duplicate Count
  - **p –** Packet Type
  - **wf –** Boolean status indicating if the node forwarded the packet
- NDN represents the **Environment**

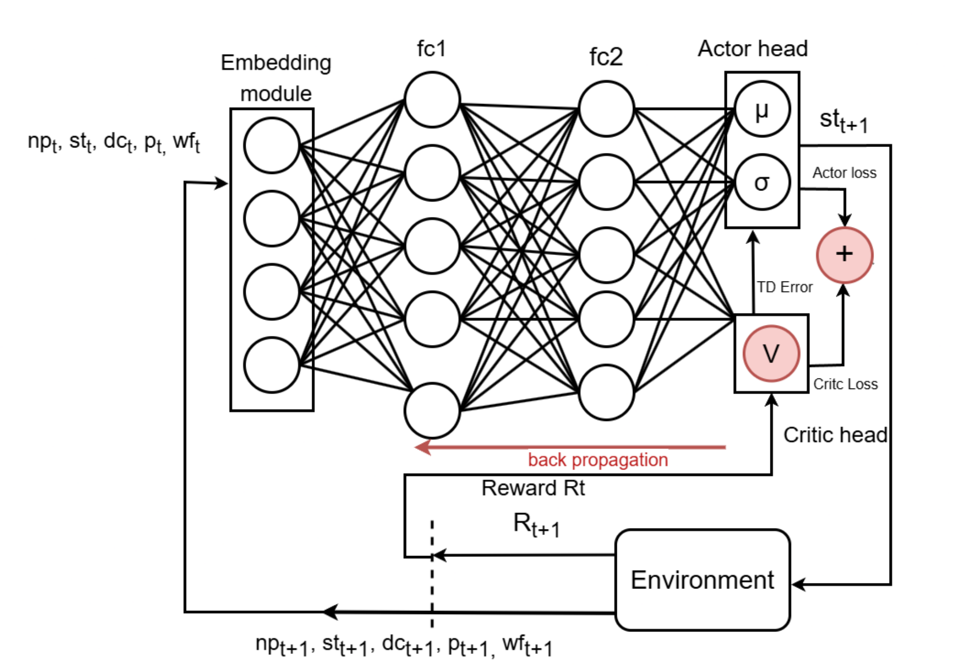


Fig: Actor Critic Network

- Embedding layer converts the input state to dense vector representation
- Fully connected layers extract relevant features from the input
- Actor head computes the suppression time (action to take)
- Critic head evaluates the action by providing feedback to the Actor head, indicating how good the action was.

Model Learning

- Initialize the weights of the neural network
- Collect Experience (sequence of S_t, A_t, R_t, S_{t+1},…)
- After taking action, Critic evaluates action using TD Error:

  TD Error (δ) = Rt + $\gamma V(S_{t+1}) - V(S_t)$

  where V(S) represents how good it is to be in the state S and γ is the discount factor
- Update the Actor's policy using gradient ascent method:

$$\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi(a|s;\theta)\delta$$

  where Θ are parameters of actor, α is learning rate, $\nabla_\theta \log \pi(a|s;\theta)$ is the gradient of the log-probability of taking action a in state s.
- Critic is updated to minimize mean squared error between the predicted value ($V(S_t)$) and actual outcome ($R + \gamma V(S_{t+1})$)

$$\phi \leftarrow \phi - \alpha \nabla_\phi(\delta^2)$$

  where ϕ is critic parameter

Measurement Module

- RL module retrieves current state of environment from the Measurement table
- Measurement table stores:
  - Name prefix
  - Number of duplicate packets
  - Forwarded status of the packet
- Suppression time is computed when a measurement table entry is removed
- Data measurement entry is removed when its record expires
- An Interest measurement entry is removed either:
  - When it is satisfied by a Data packet
  - When the record is expired

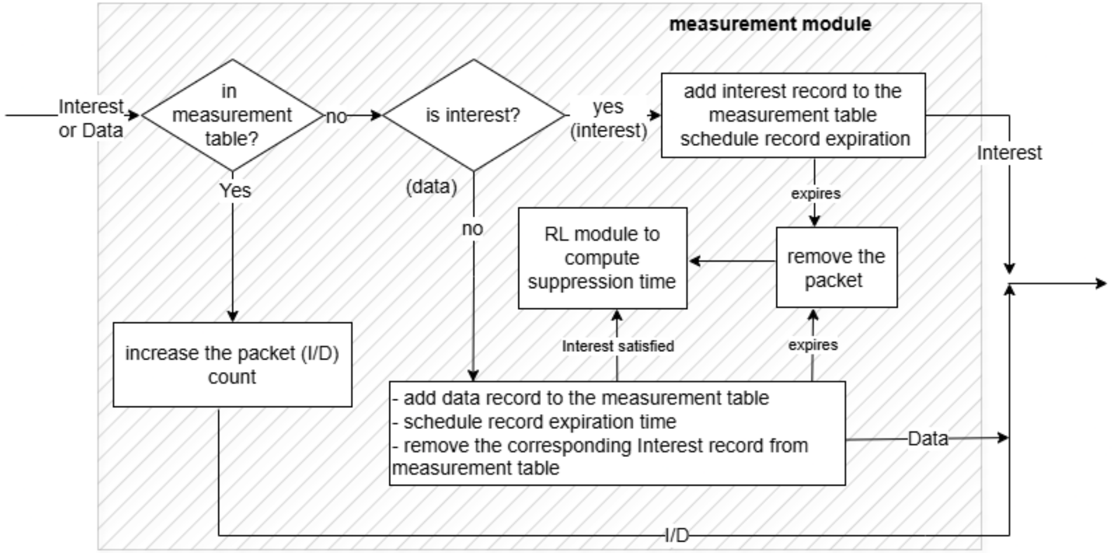


Fig: Measurement Module

Overview of packet processing pipeline

Incoming packet processing pipeline

- The incoming packet is checked if the same packet is scheduled for the transmission
- If yes, cancel the schedule, this decrease duplicate interest packet or data packet

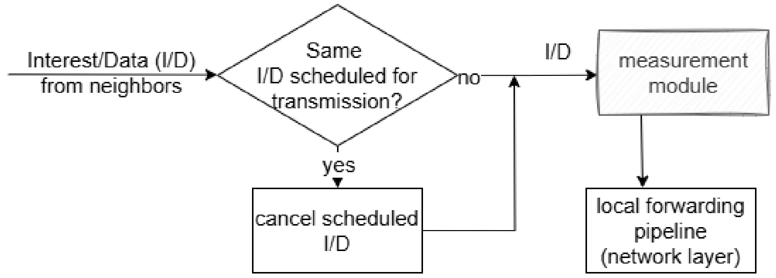


Fig: Incoming Packet Processing Pipeline

Outgoing packet processing pipeline

- Before forwarding the packet, check if the packet is already in measurement table, indicating if it had been recently forwarded (by this node or others)
- If yes, drop the forwarding, decreasing the possible duplicates

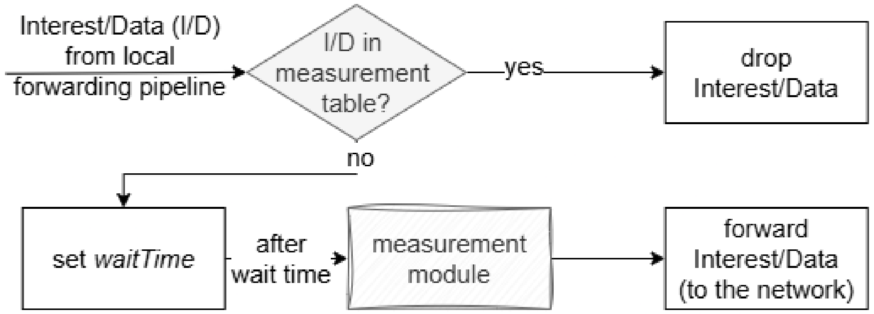


Fig: Outgoing Packet Processing Pipeline

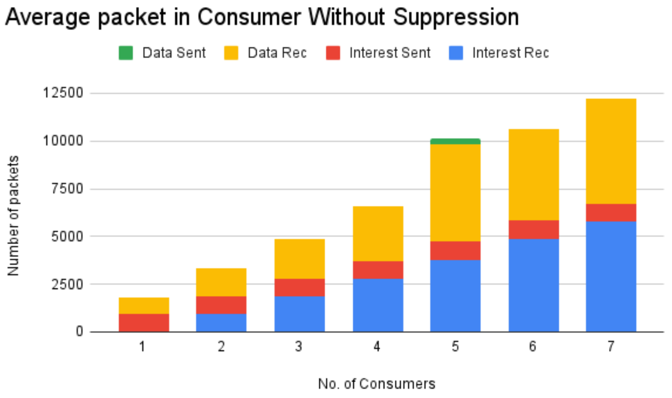
Experiment

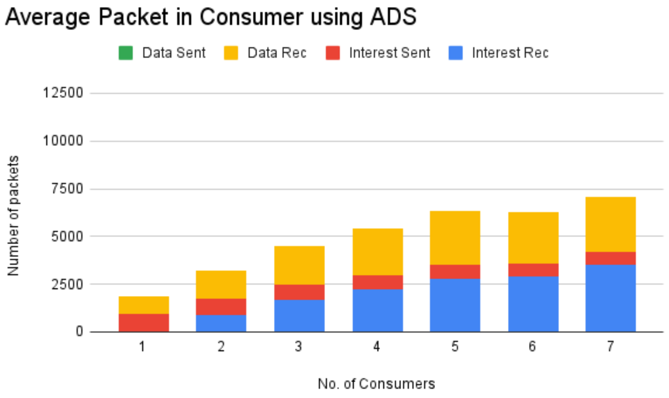
- Topology of the experiment:
  - 1 producer, 1-7 consumer
  - File size: 1 MB
  - One hop scenario, multi-access network

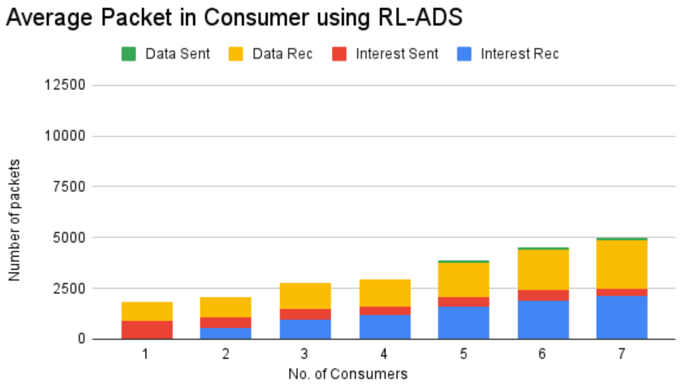
- Emulator: Mini-NDN Wifi
- Use catchunks/putchunks over multi-access link to publish and fetch packets

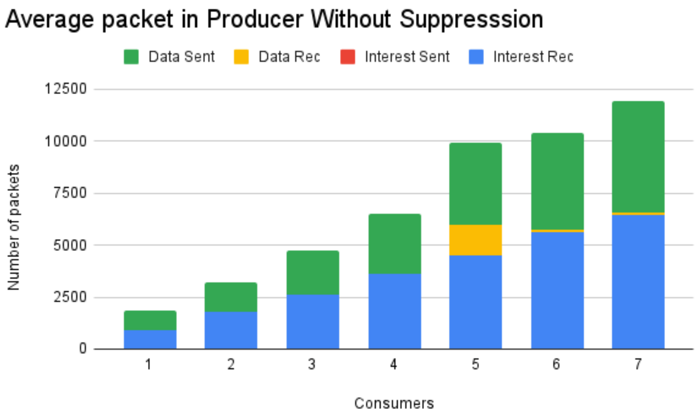
Result

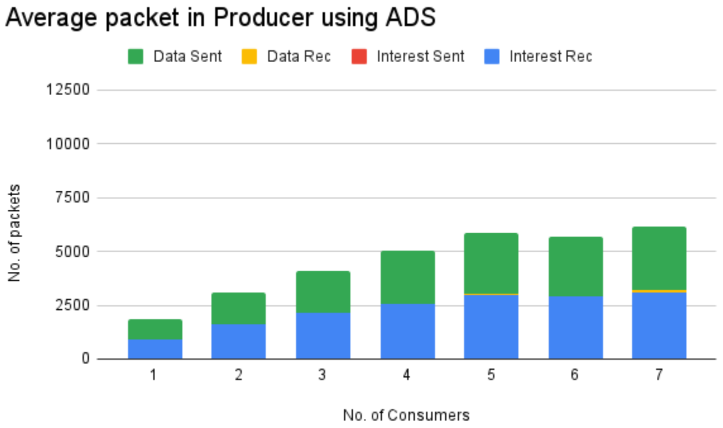
- As the number of nodes in the network increases, RL-ADS reduces the number of packets more effectively.

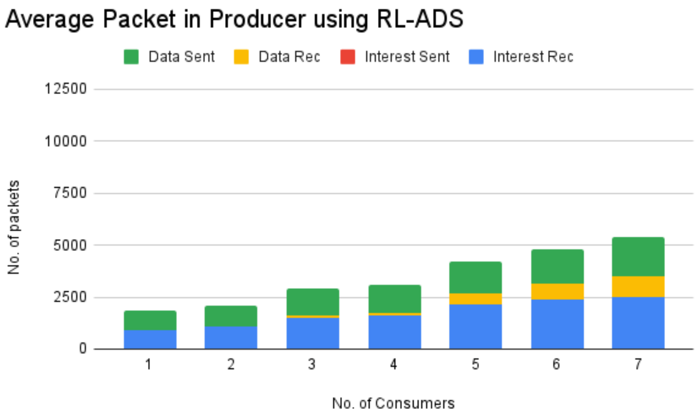






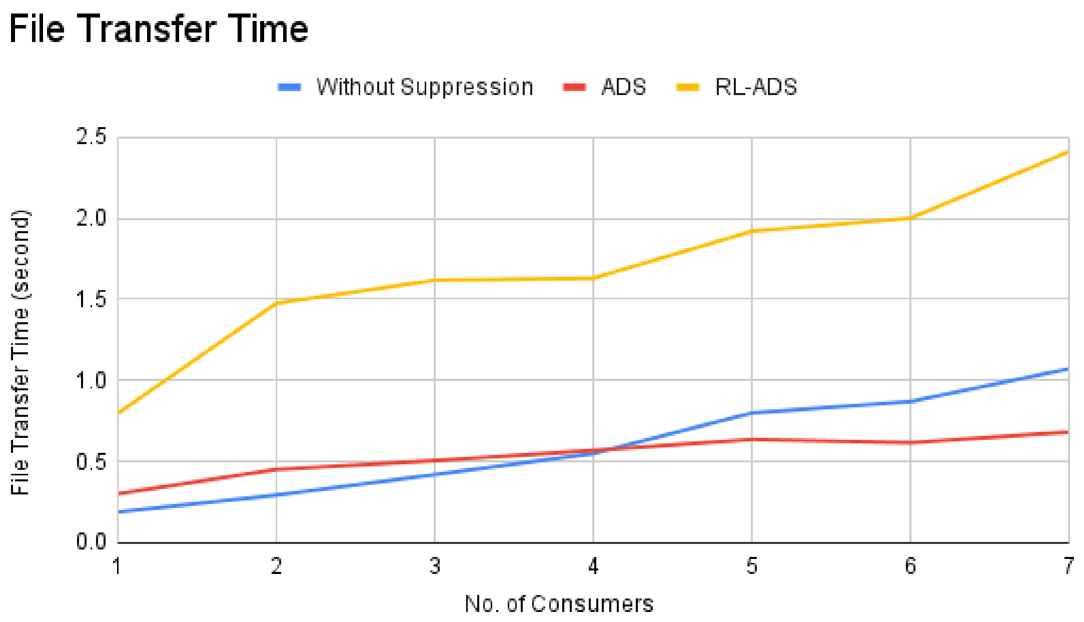






Result

- ADS is the most efficient approach for minimizing file transfer time as the number of consumers increases
- RL-ADS has the highest file transfer time:
  - FIFO-based communication between C++ and Python
  - Neural network computational overhead during decision-making also causes some delay
  - State does not include any observation related to round trip time. As a result, the reward does not file transfer time into account.



Conclusion

- Designed Reinforcement learning based suppression mechanism in NDN forwarding
- Implemented Actor Critic Algorithm to compute the suppression time
- Compared the performance of Actor Critic Algorithm with Adaptive Suppression Mechanism and No suppression Forwarding mechanism

Future work

- Online finetuning of the model to adapt in different network conditions
- Improve inter process communication
- Explore other RL algorithms

References

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Thank you