SDN Based prioritized bandwidth scheduling using Reinforcement learning

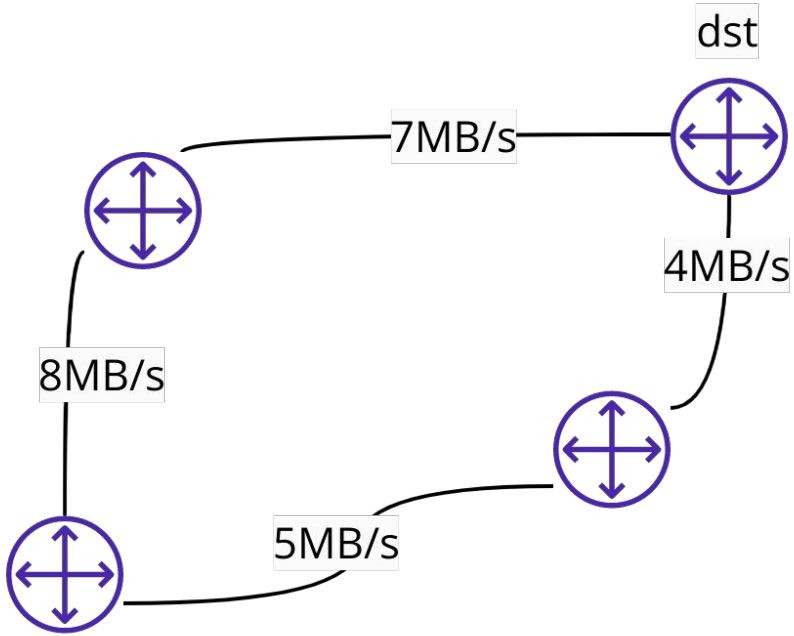
Manoj S (2019506048)

Aravinth Kumar A M (2019506012)

Vimal V(2019506114)

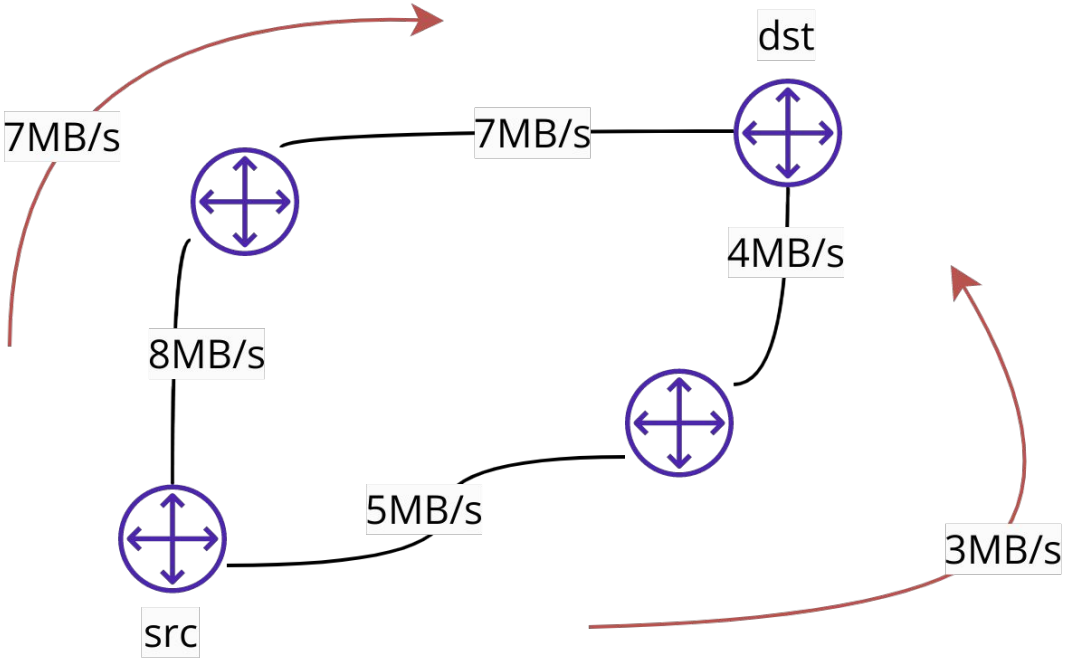
Supervised by

Dr. S Umamaheswari



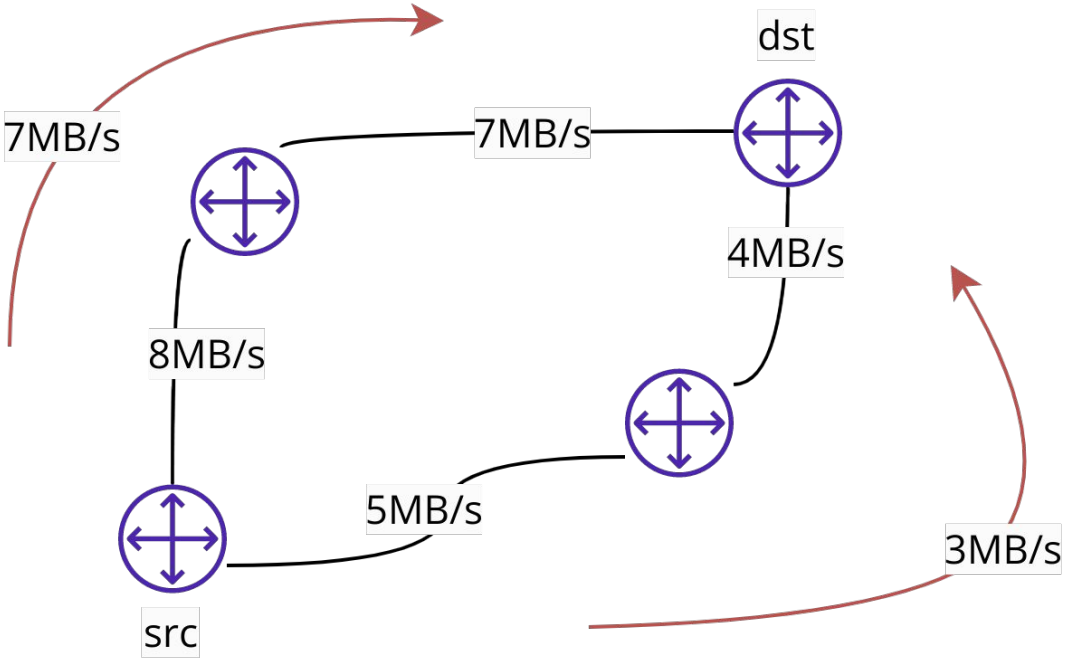
Maximum 7MB/s can be allotted using traditional algorithms

10MB/s required



Using group services we can split the bandwidth

10MB/s required



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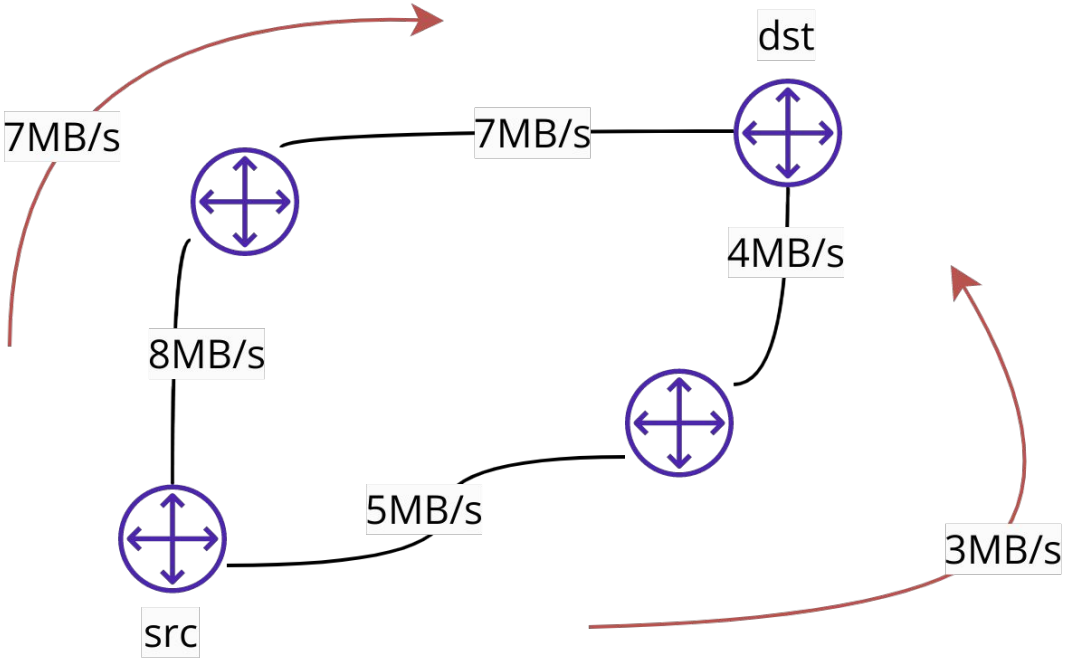
There are 2 problems

Which path to choose

% to split for each path



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Reinforcement Learning

% to split for each path

Linear programming

Designing Inputs / state

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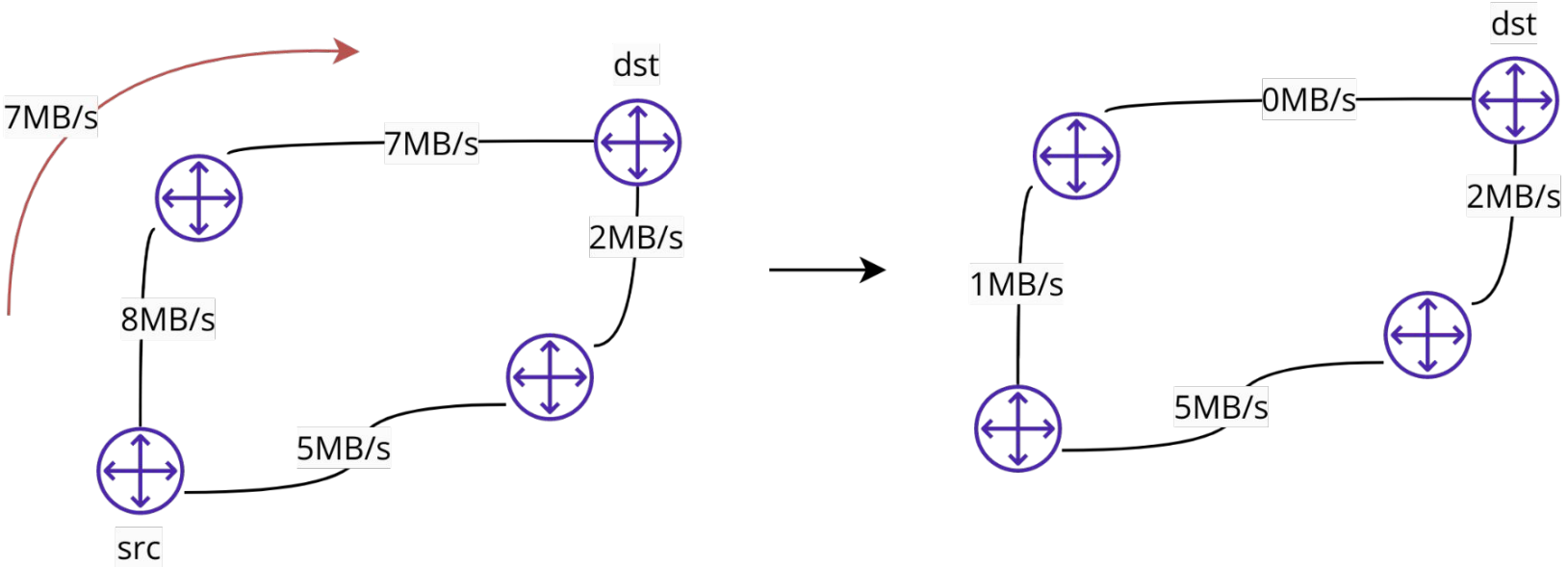
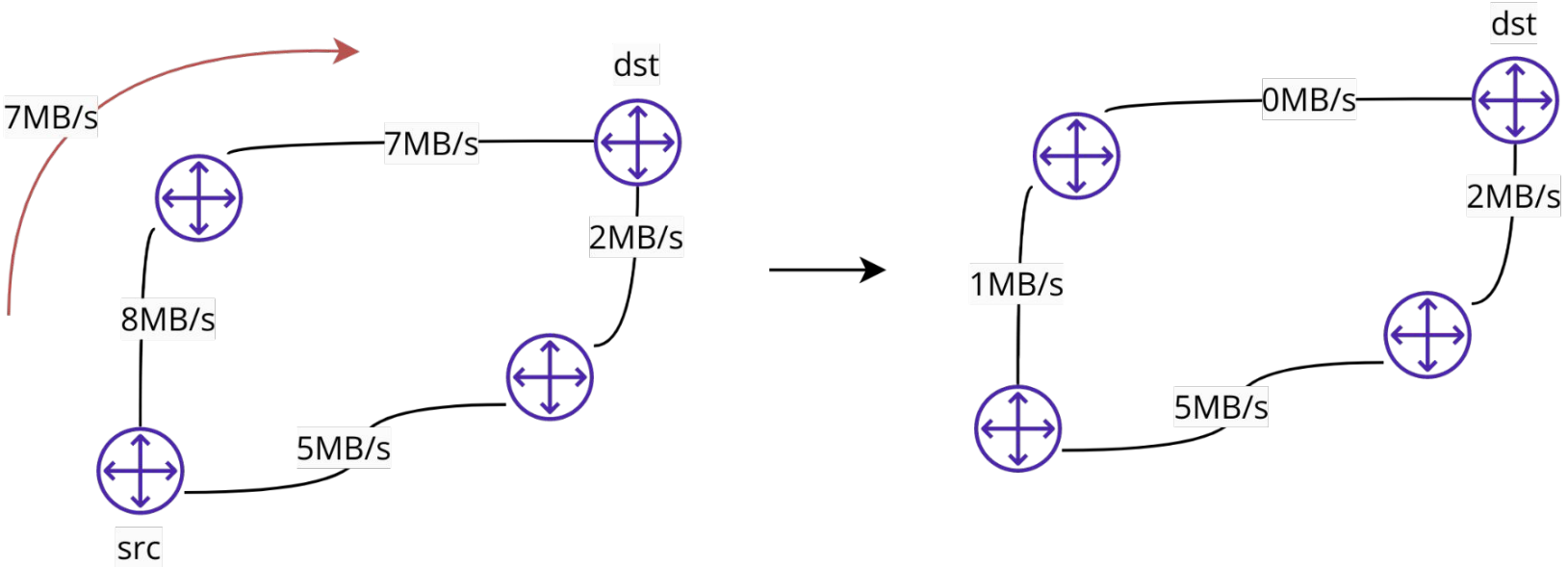
Fix on Action



Designing Inputs / state

Fix on Action

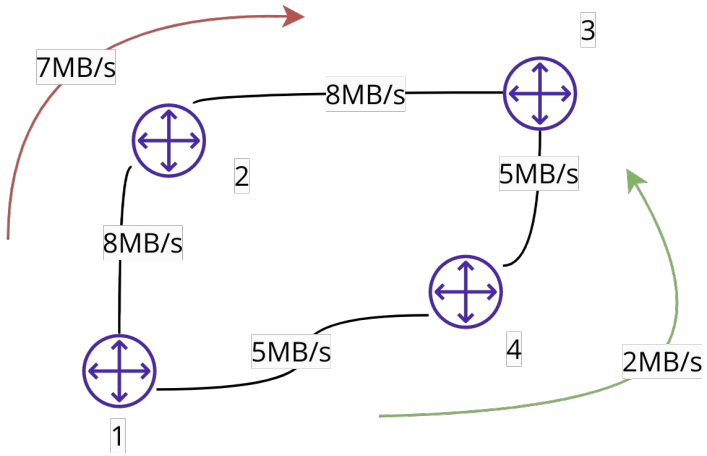


state1

Change in residual bandwidth is captured as state

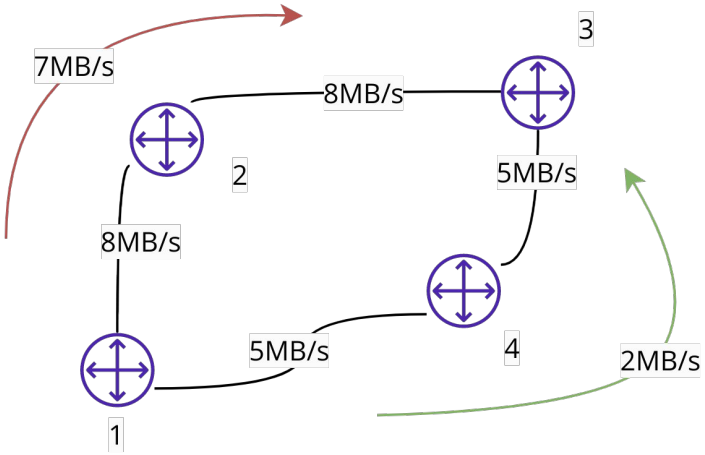
state2

Rewards



Another 4MB/s
from 1 to 2 ?

Rewards



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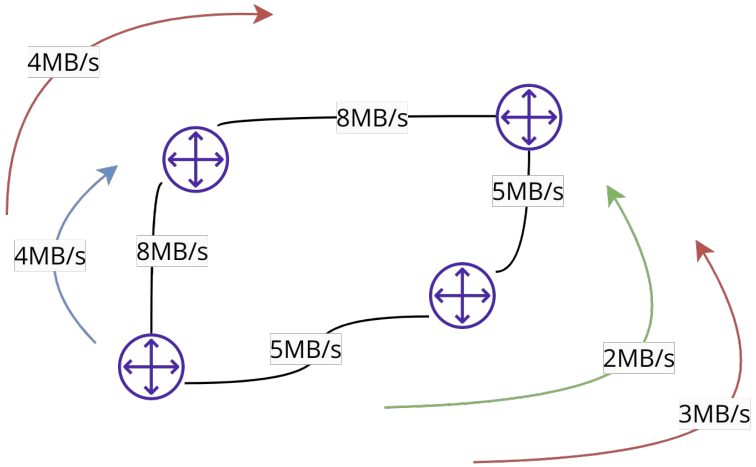

Rewards

	Technique 1	Technique 2
Step 1	7	3 + 4 = 7
Step 2	7 + 2 = 9	3 + 4 + 2 = 9
Step 3	9	9 + 4 = 12
Expected at step 1	7 + y*9 + y*y*9	7 + y*9 + y*y*12
	22.39	24.82

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Predict Expected Reward

Choose paths until it crosses certain threshold

Why is Linear Programming required

- Assigning one flow higher bw can cause disruption to many other
- Compromising 1 flow might give higher advantage to many other
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Constraints in Linear Programming

- For every request the sum of bandwidth assigned to multiple paths should be less than requirement
- For every link the sum of bandwidths assigned from different requests and paths should be less than capacity

$Let,$

$l\ be\ the\ number\ of\ requests\ arrived$

$m\ be\ the\ number\ of\ all\ possible\ paths$

$k\ be\ the\ total\ number\ of\ links$

$F_{ijk} = 1\ \ if\ in\ the\ i^{th}\ request\ j^{th}\ path\ is\ chosen\ and$

$represents\ link\ k\ else\ 0$

$B_{ijk}\ represents\ the\ bandwidth\ of\ the\ link\ to\ be\ assigned$

$$\forall_k \left[\sum_{i=0}^{l} \sum_{j=0}^{m} (B_{ijk} * F_{ijk}) < Capacity_k \right]$$

$$\forall_i \left[\sum_{j=0}^{m} \sum_{k=0}^{n} (B_{ijk} * F_{ijk}) < Required\ Bandwidth_i \right]$$

$$let\ P_i\ represent\ the\ priority\ of\ flow\ i$$

$$max\left(\sum_{i=0}^{l} \sum_{j=0}^{m} \sum_{k=0}^{n} (B_{ijk} * F_{ijk} * P_{ijk}) \right)$$

Neural Network

Training should also be done in java

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Training should also be done in java

Replay Buffer would be used to store previous data

```
while (true):
      Replay Buffer -> rb
      for task_i in episode:          // each time new episode
            Buffer -> b
            If random < e:
                  take random action
            else:
                  take action as per neural net
            Store (state, reward) in b

      reward = 0
      for (st,rw) in reverse(b):
            reward = rw + γ*reward
            store( st, reward ) in rb
```

Neural Network

Training should also be done in java

Replay Buffer would be used to store previous data

Training would run periodically by sampling replay buffer

```
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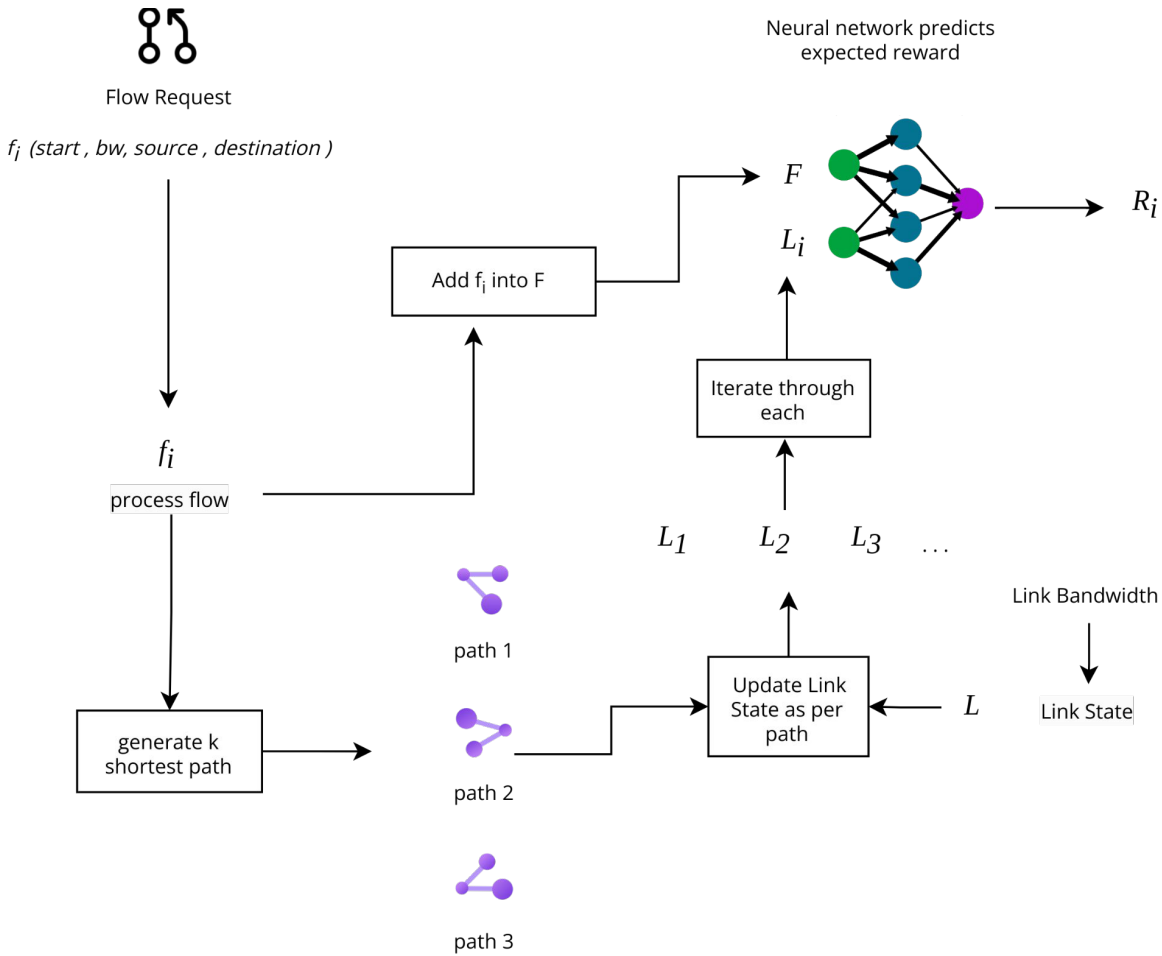
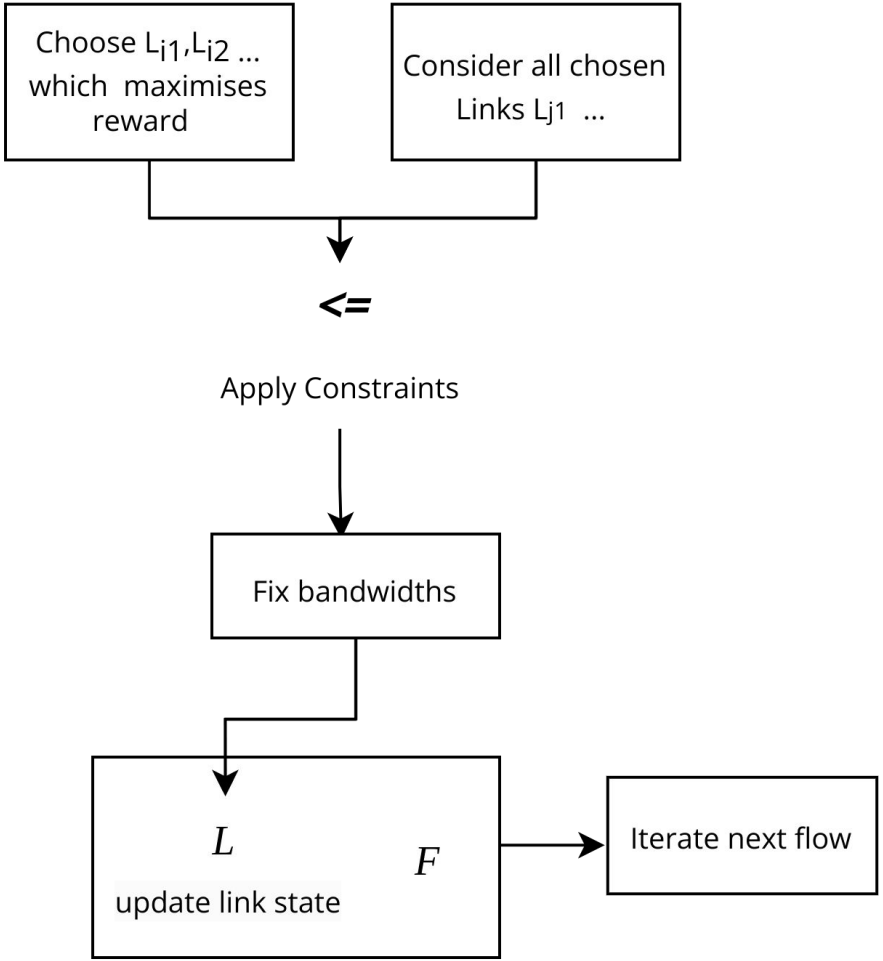

Flow Request
f_i (start , bw, source , destination)
Neural network predicts expected reward
F
L_i
R_i
Add f_i into F
Iterate through each
f_i
process flow
L_1
L_2
L_3
...
path 1
path 2
path 3
generate k shortest path
Update Link State as per path
L
Link Bandwidth
Link State


Choose L_{i1},L_{i2} ... which maximises reward
Consider all chosen Links L_{j1} ...
<=
Apply Constraints
Fix bandwidths
L
F
update link state
Iterate next flow

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