Adaptive Routing with Guaranteed Delay Bounds using Safe Reinforcement Learning

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Problem Statement

- Route packets through a real-time network
- Give guarantees on total transmission delay
- Use reinforcement learning(**RL**) to explore the state-space

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DAG with worst case link delay

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Eliminate need for complex routing tables

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DAG with worst case link delay

dline D_F

Real-time routing requires guarantees

- RL is simple but powerful.
- RL is inherently stochastic.

- Ro
- Gi
- Us … space

Eliminate need for complex routing tables

- Route packets through a real-time network
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- Use reinforcement learning (**RL**) to explore the state-space

Try the algorithm yourself

https://github.com/AdaptiveRouting-using-RL/AdaptiveRoutingUsingRL

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- Typical transmission time over link varies over time

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- Real-time solution [1]

[1] S. Baruah, “Rapid routing with guaranteed delay bounds,” in 2018 IEEE Real-Time Systems Symposium (RTSS) , December 2018

Motivation

- Typical transmission time over link varies over time
- Classical RL based solutions
  - Reduce total transmission times
  - Do not provide guarantees
- Real-time solution [1]
  - Provide Guarantees
  - Depends on complex routing tables
  - Does not react to disturbances

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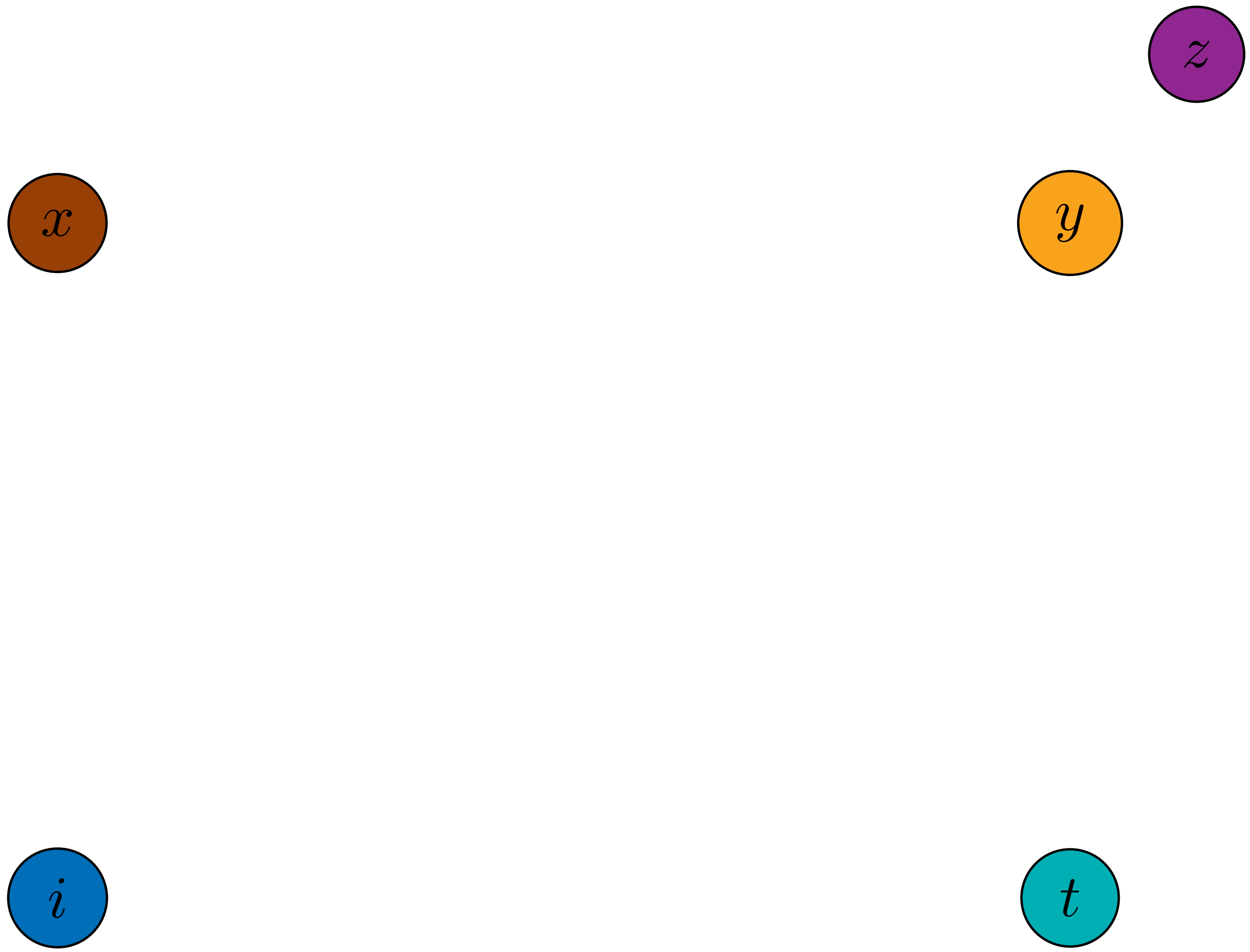
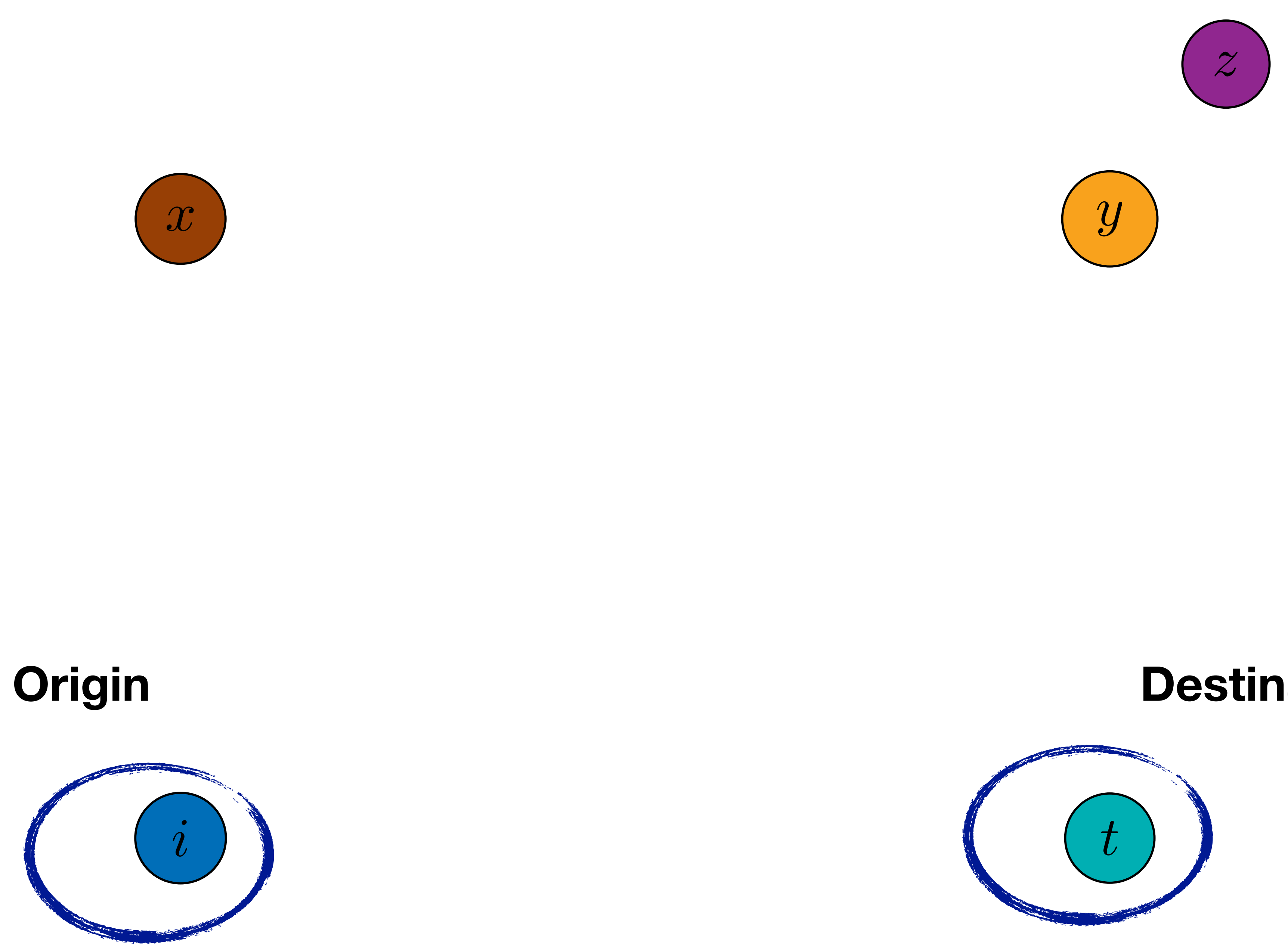
Example Network Overview



Example Network Overview



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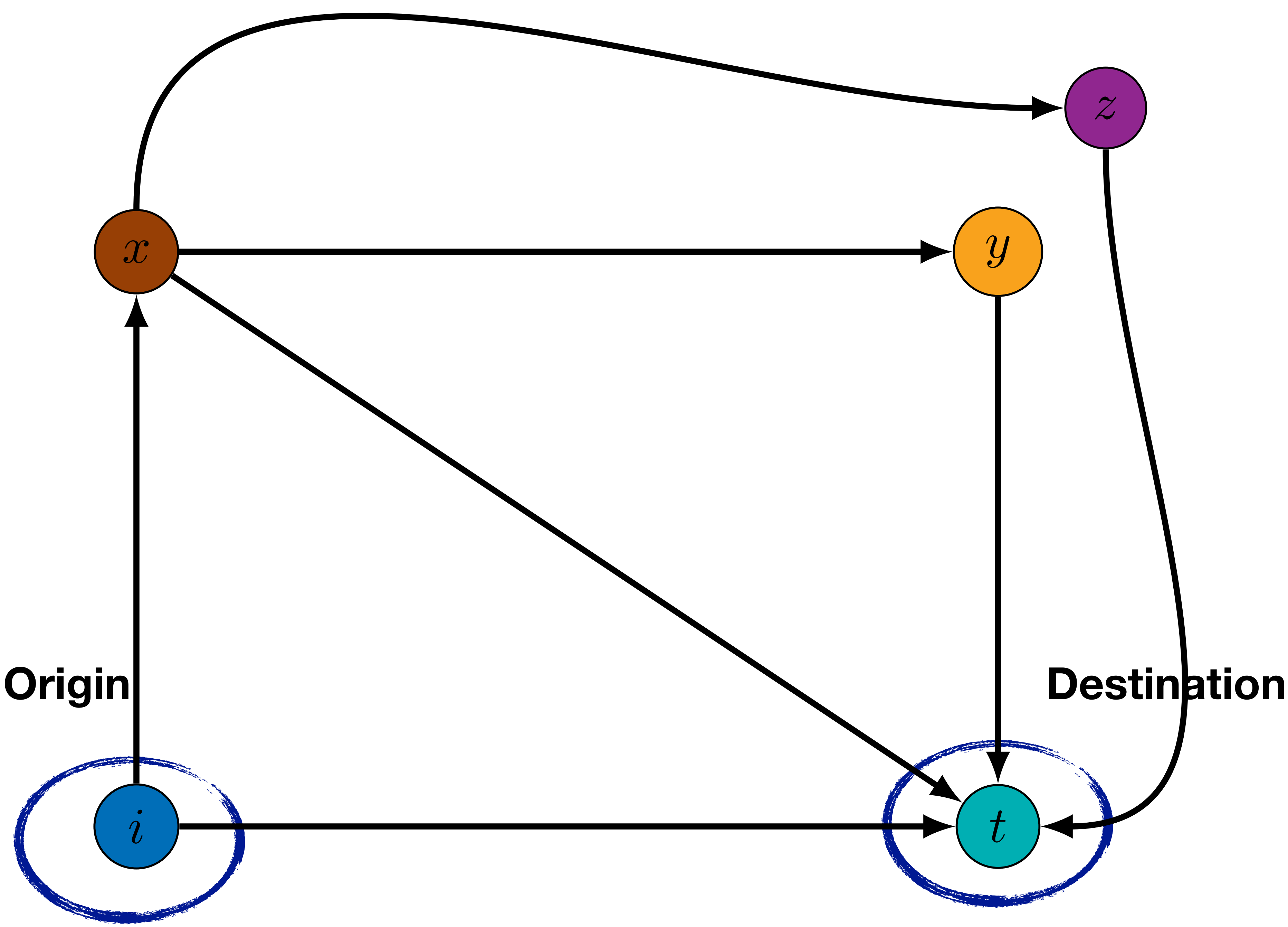
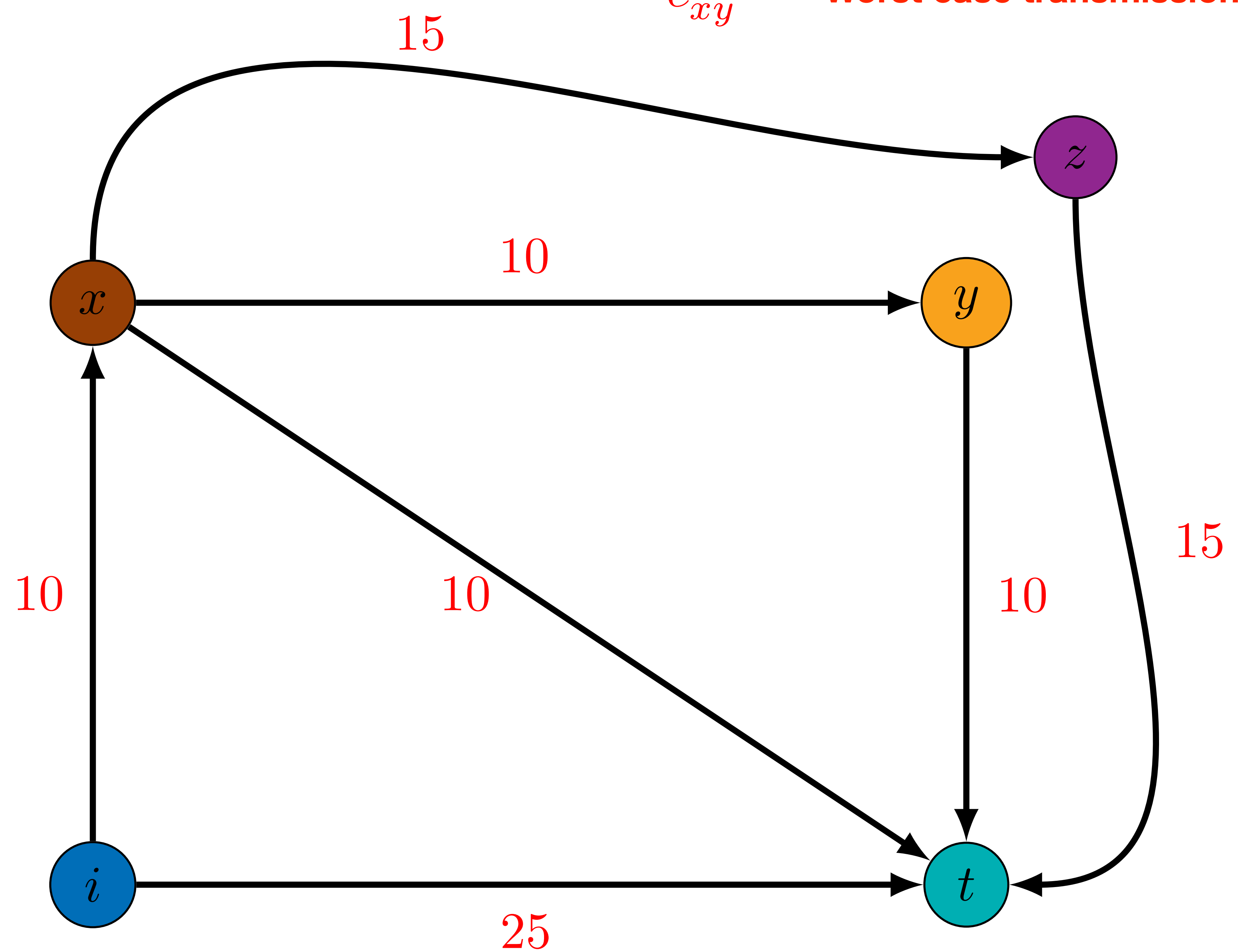


Example Network Overview

c^{W}_{xy} = Worst case transmission time over x,y



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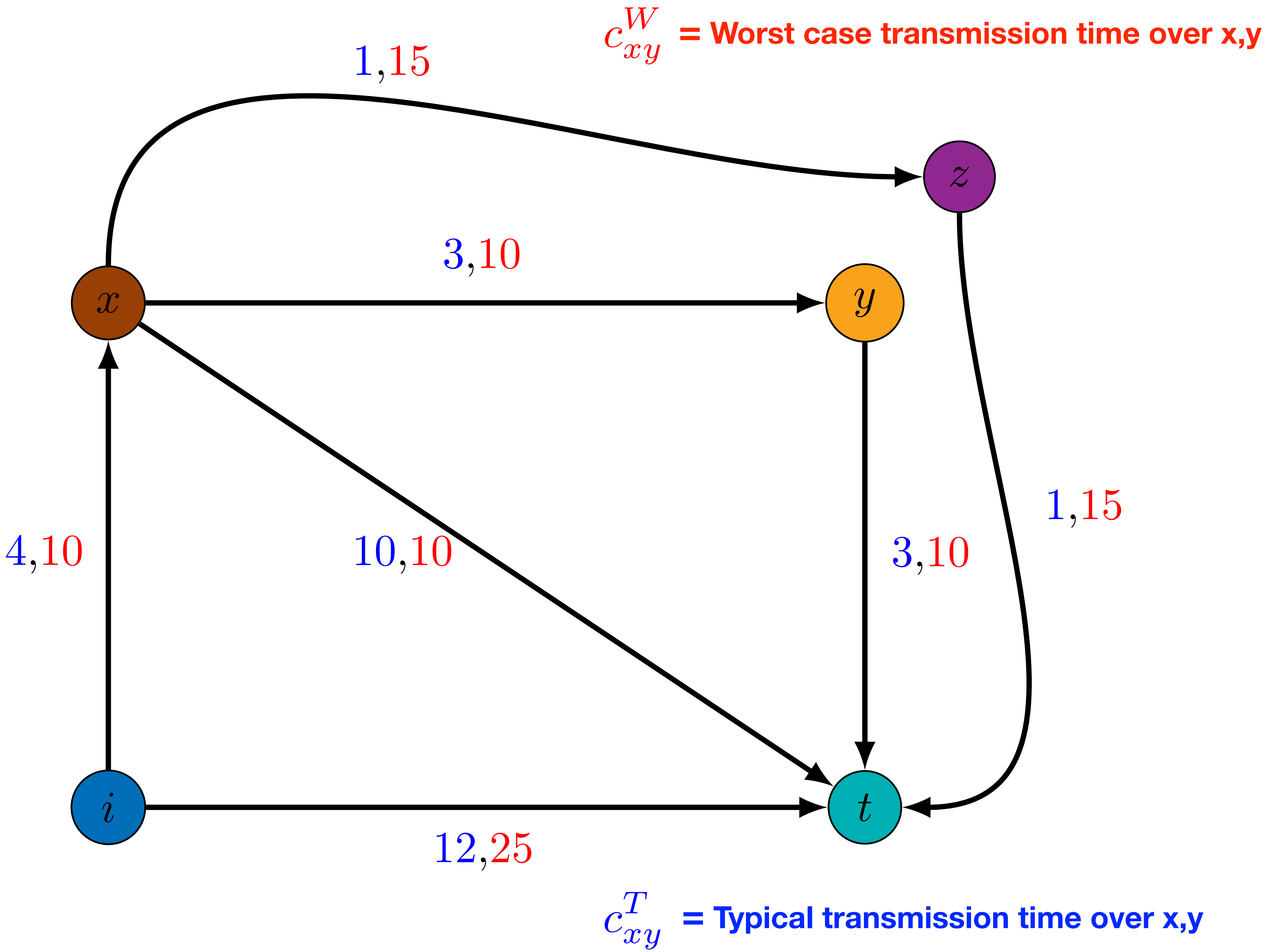

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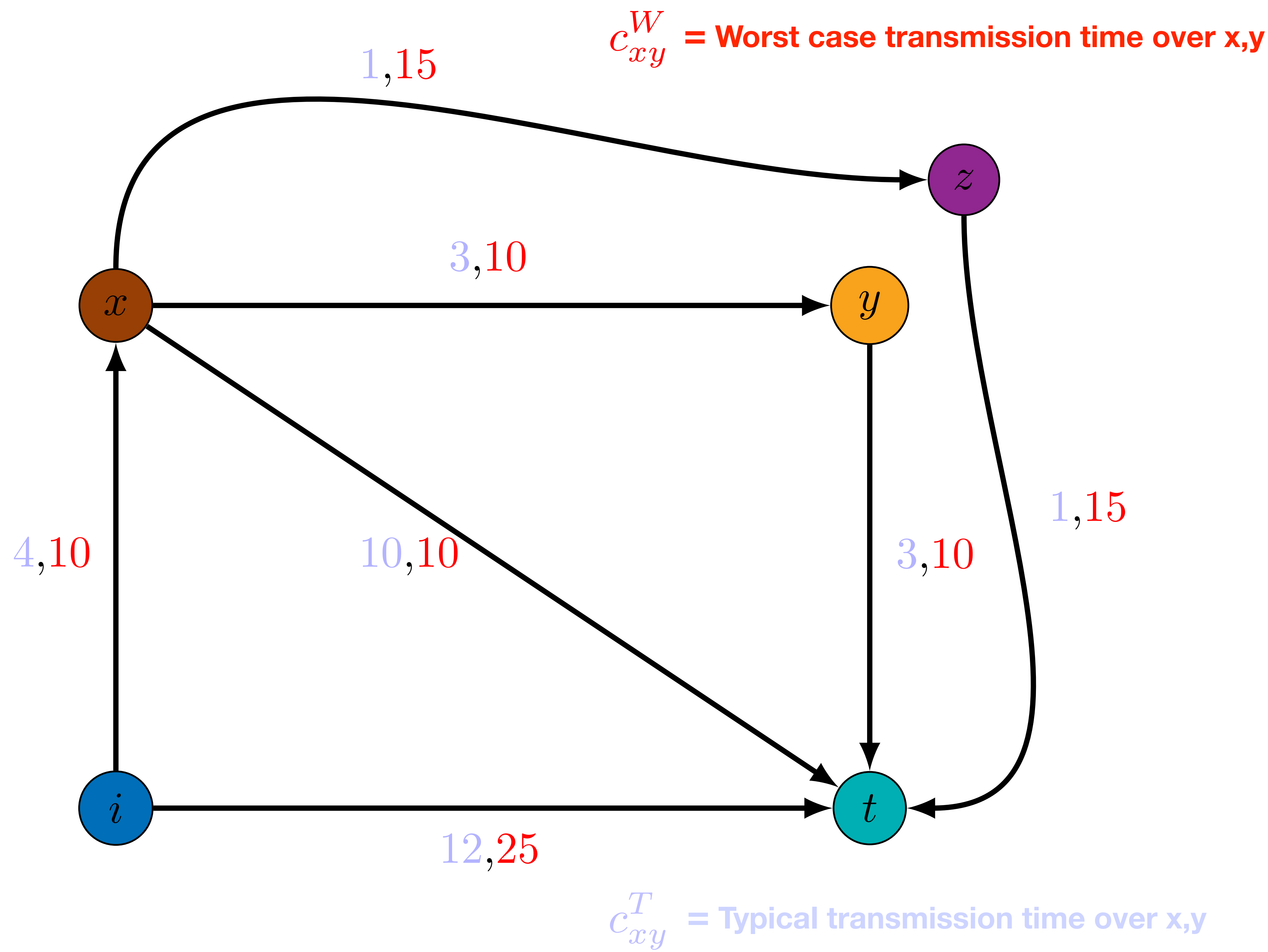

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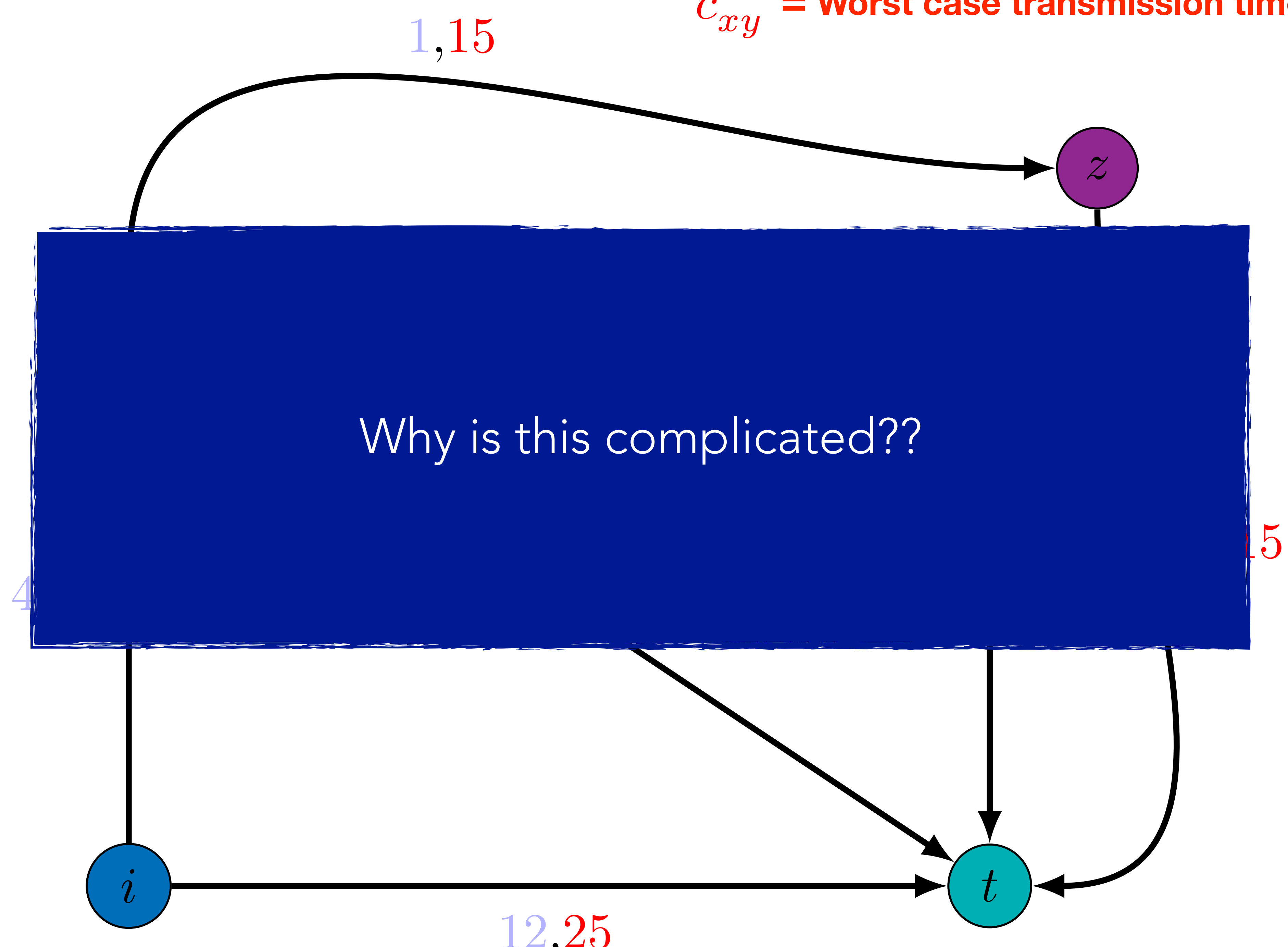


Why is this complicated??

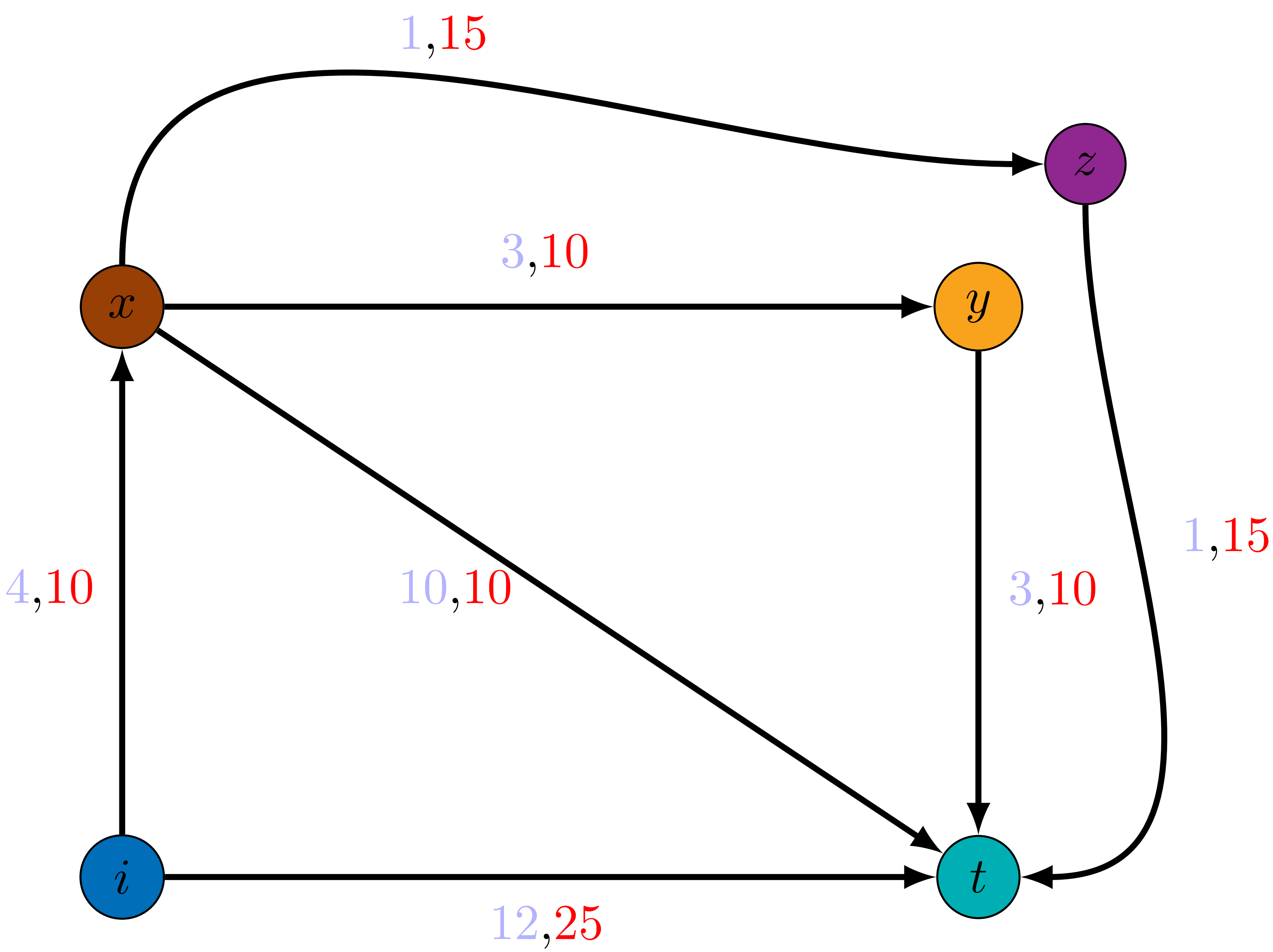
c^T_{xy} = Typical transmission time over x,y

Example Network Overview

Deadline

Typical delay to t

PATH	δ	D_F

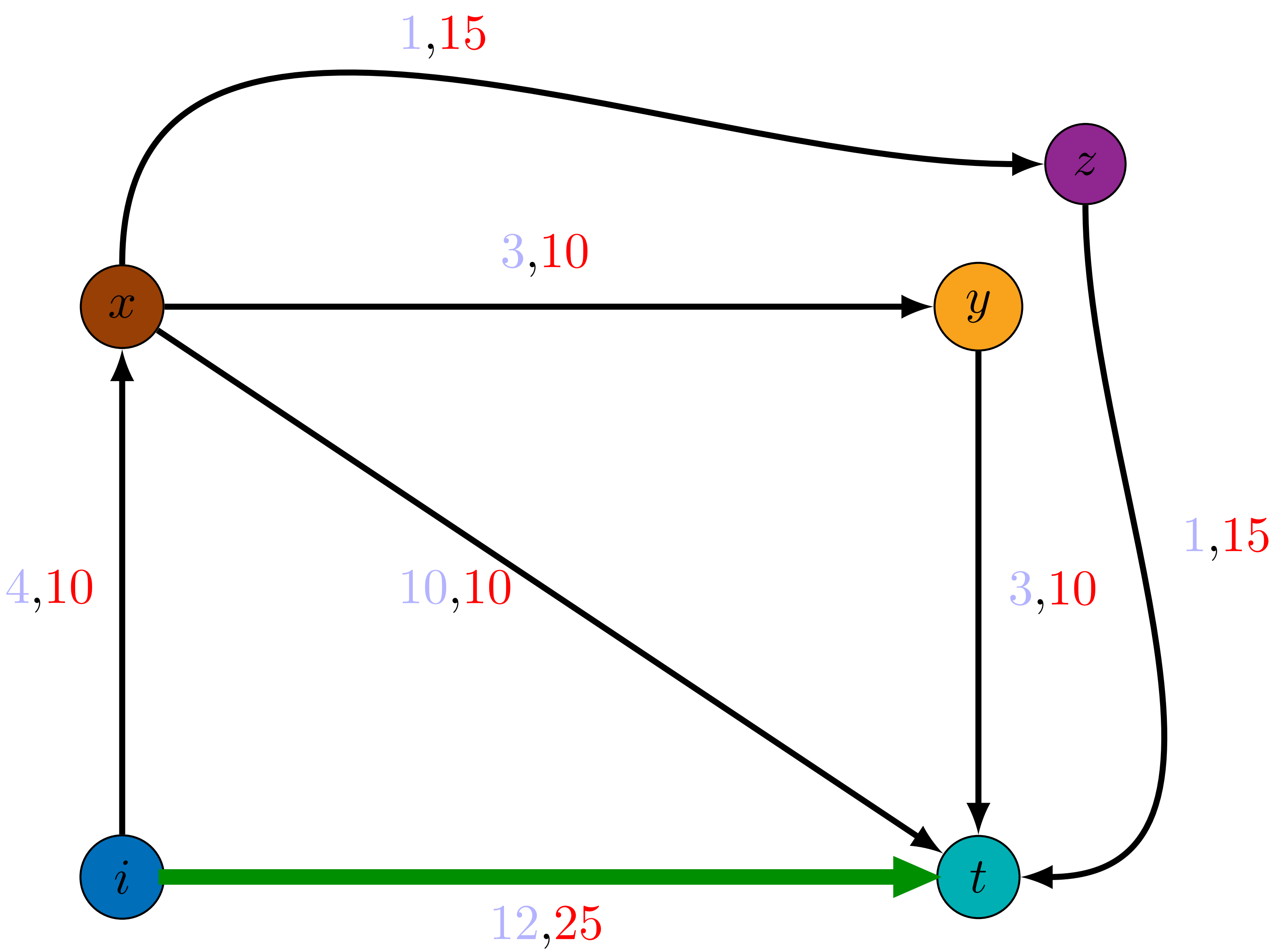


Example Network Overview

Deadline

Typical delay to t

PATH	δ	D_F
$i \rightarrow t$	12	25

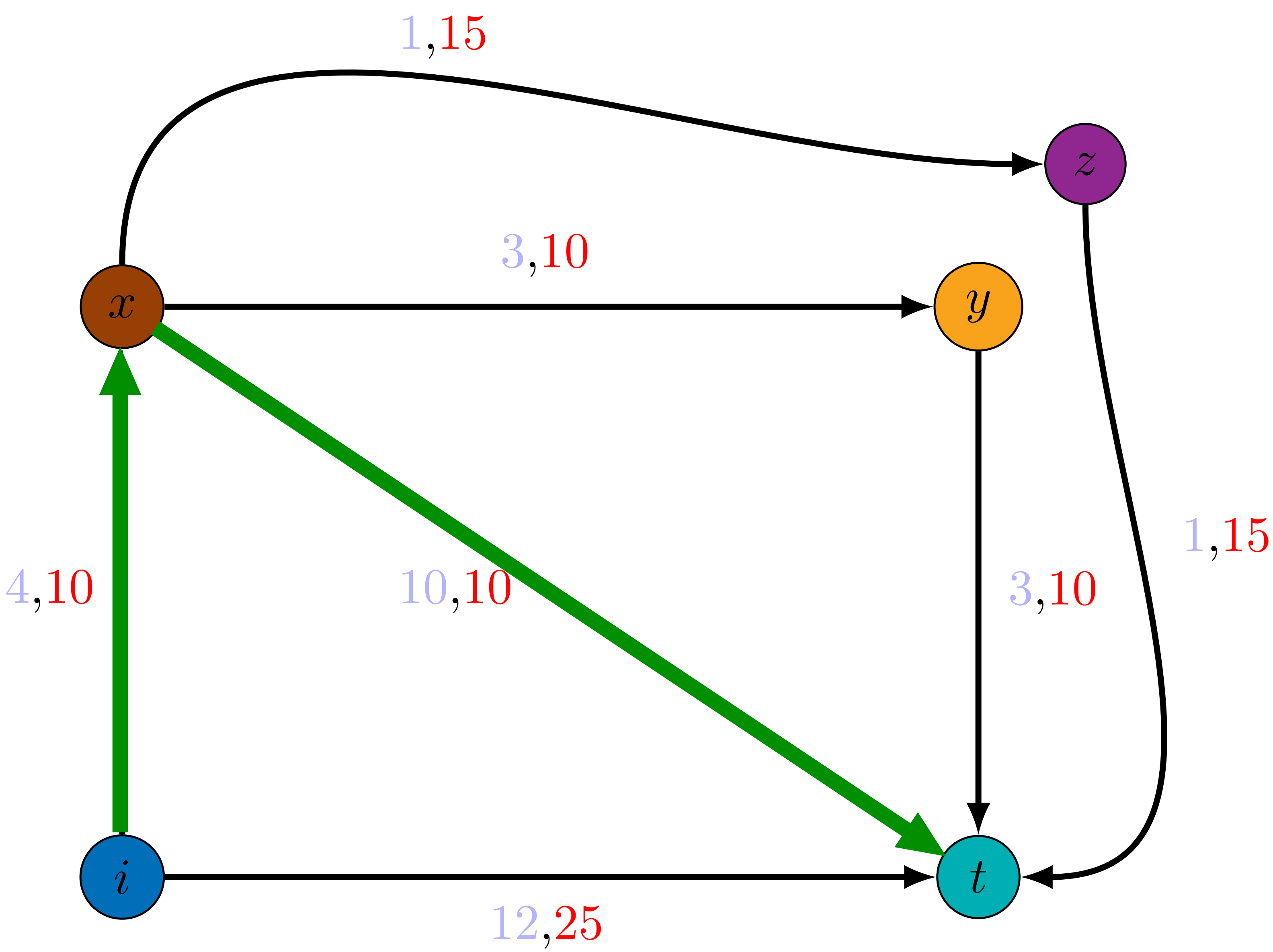


Example Network Overview

Deadline

Typical delay to t

PATH	δ	D_F
$i \to t$	12	25
$i \to x \to t$	14	20



Example Network Overview

Deadline

Typical delay to t

PATH	δ	D_F
$i \to t$	12	25
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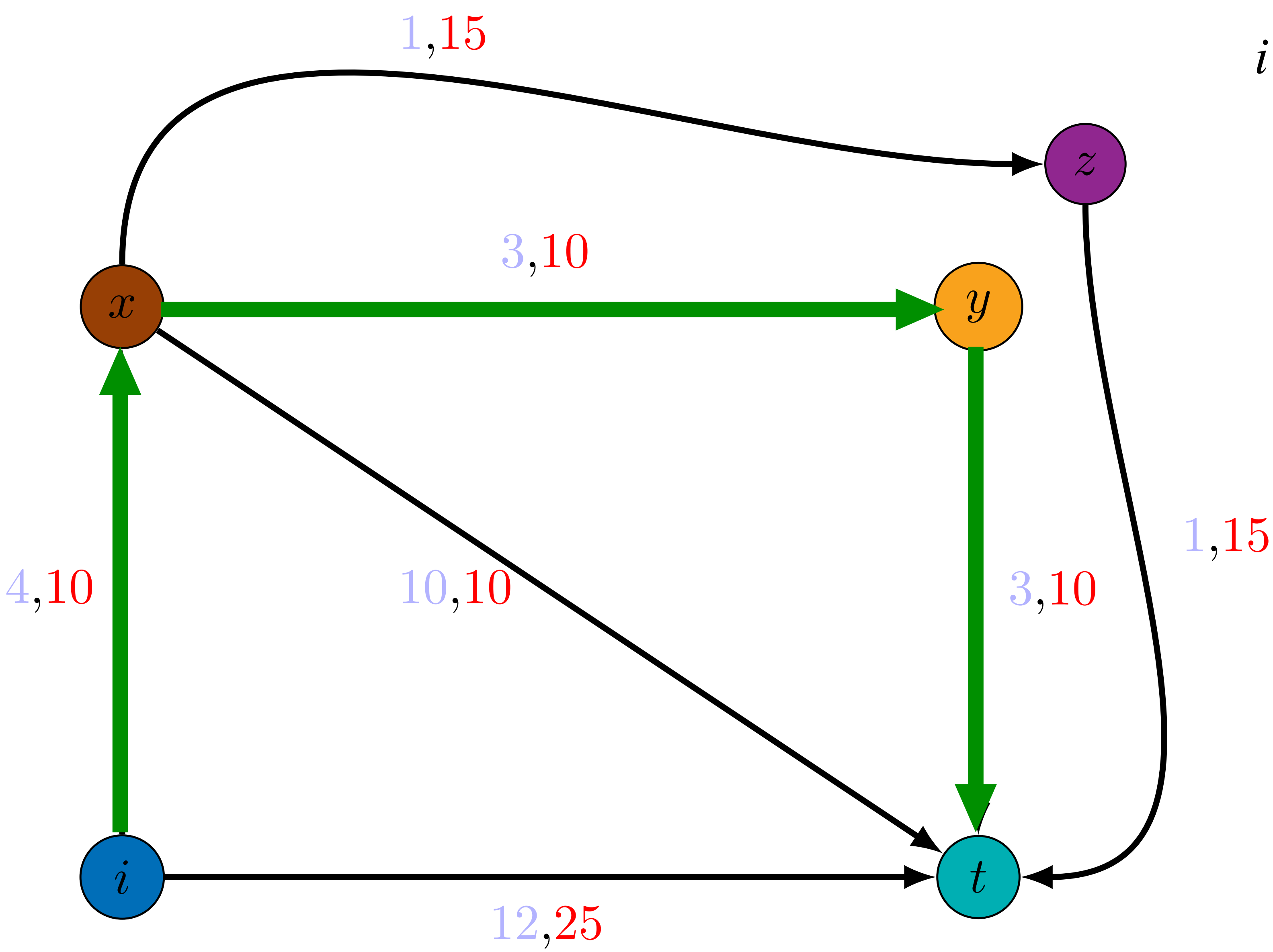
$i \to x \to y \to t$	10	30



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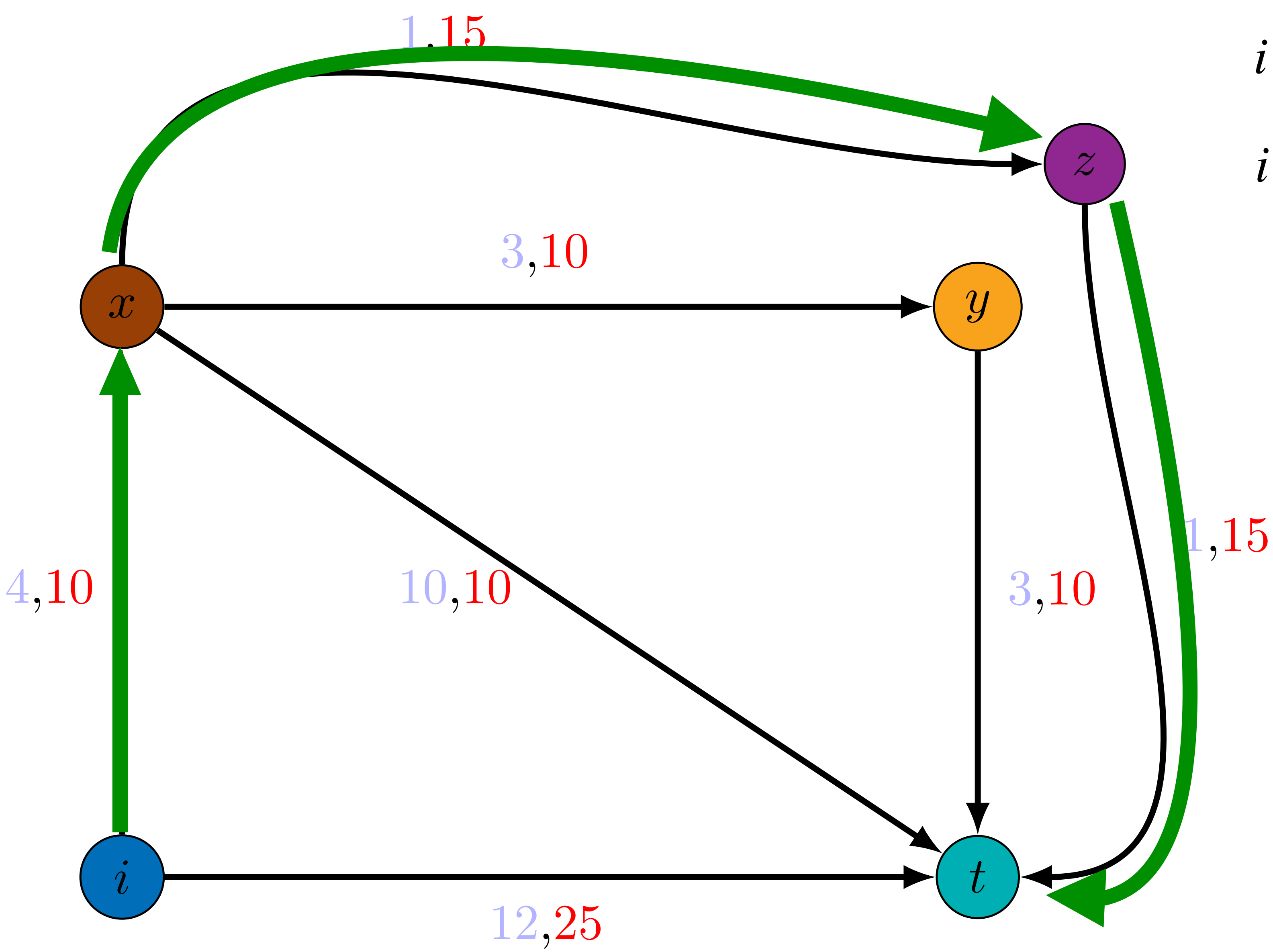
Deadline

Typical delay to t

PATH	δ	D_F
$i \to t$	12	25
$i \to x \to t$	14	20
$i \to x \to y \to t$	10	30
$i \to x \to z \to t$	6	40



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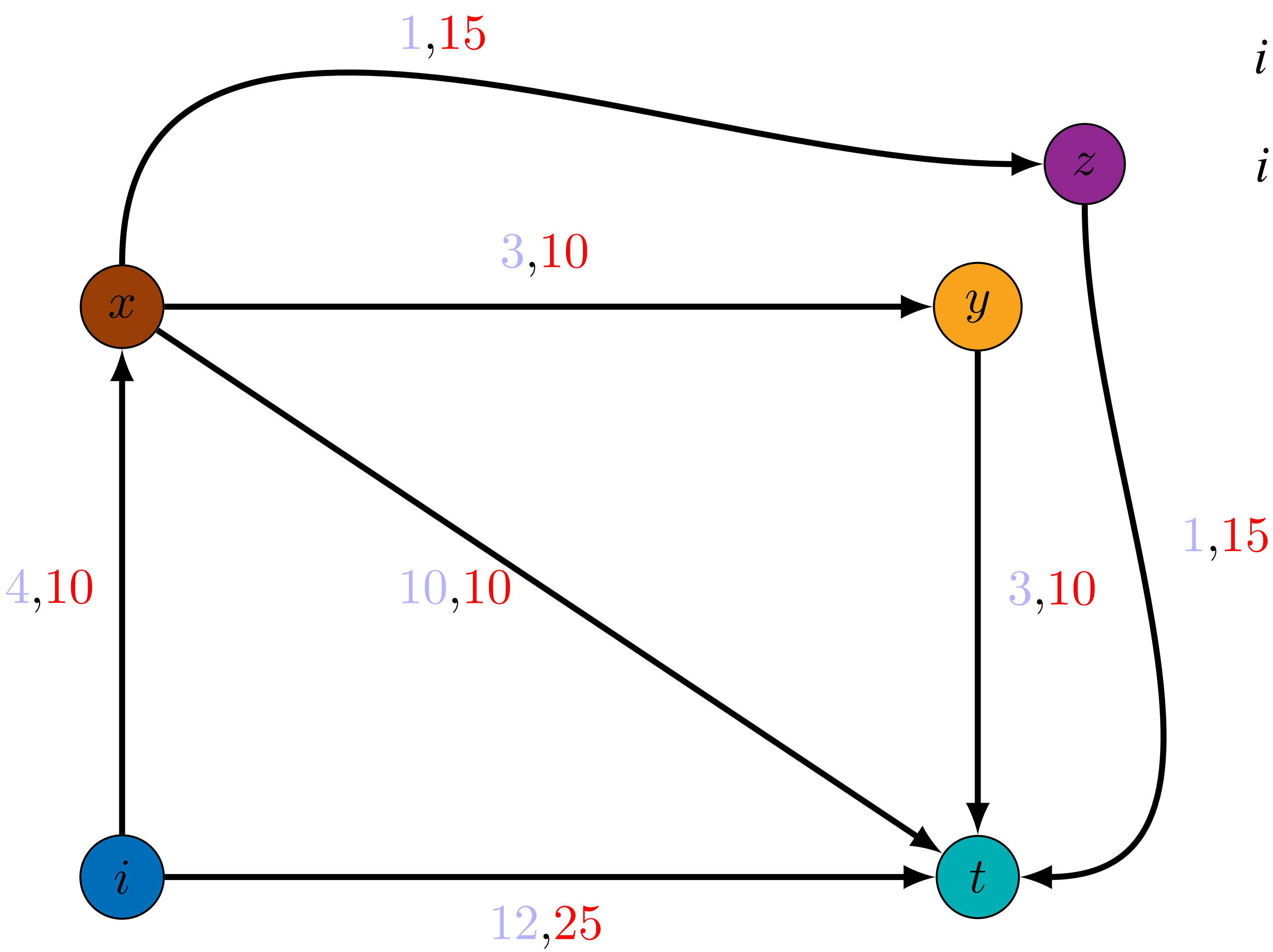


The Beginning

Subject: Your talk today
Date: Wed, 12 Dec 2018 17:14:25 +0100
From: Karlerik karl-erik.arzen@control.lth.se
To: baruah@wustl.edu

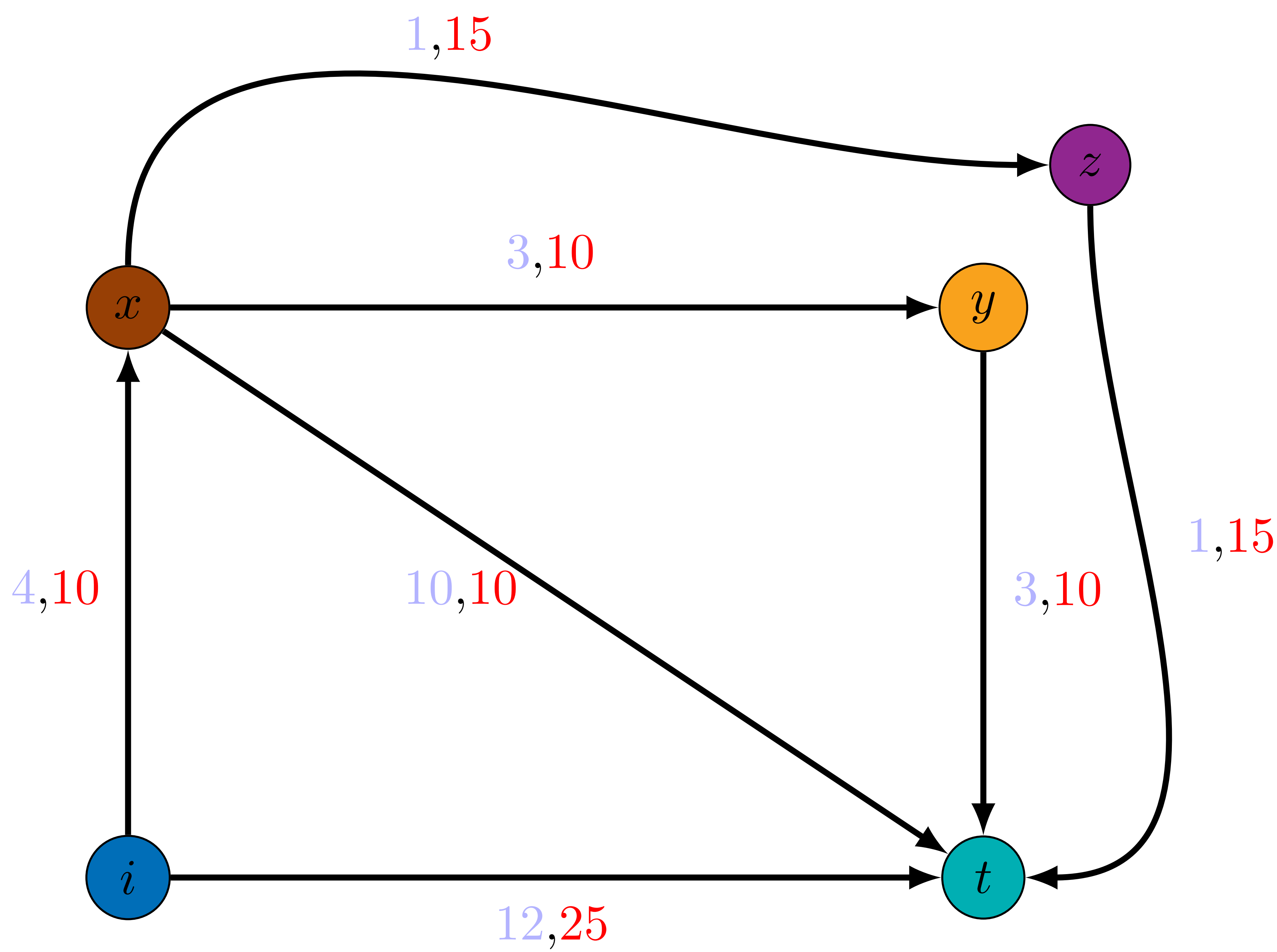
Sanjoy

Very interesting talk. I am currently trying to learn Reinforcement learning (RL). When I heard your talk I felt many similarities between what you are doing and policy learning and q-learning in RL. There might be an interesting connection.

Best

Karl-Erik

Previous work [1]



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Previous work [1]

Remaining delay bound

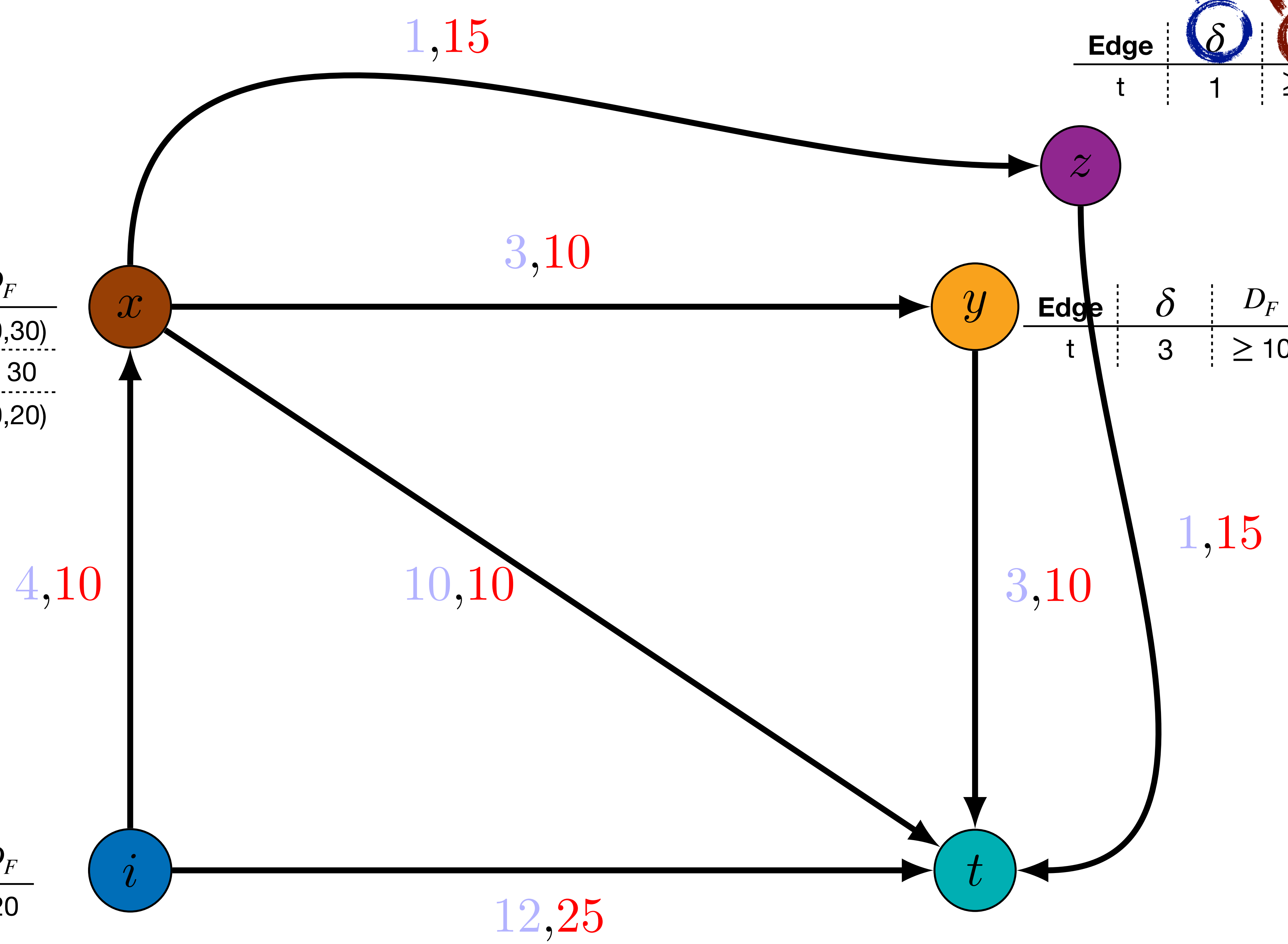
Typical delay to t

Edge	δ	D_F
t	1	$\geq$ 15

Edge	δ	D_F
y	6	[20,30)
z	2	$\geq$ 30
t	10	[10,20)

Edge	δ	D_F
t	3	$\geq$ 10

Edge	δ	D_F
x	10	$\geq$ 20



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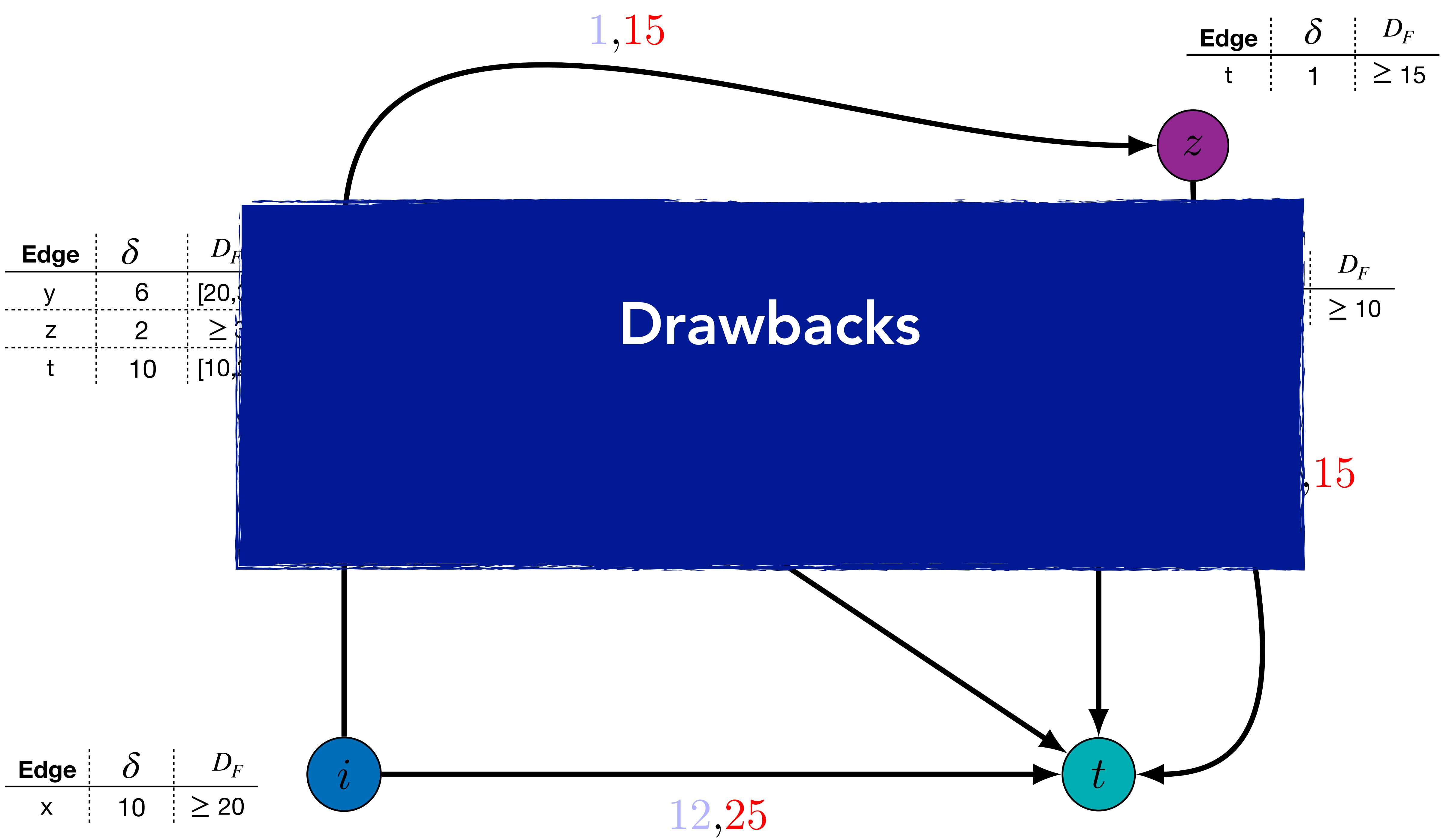

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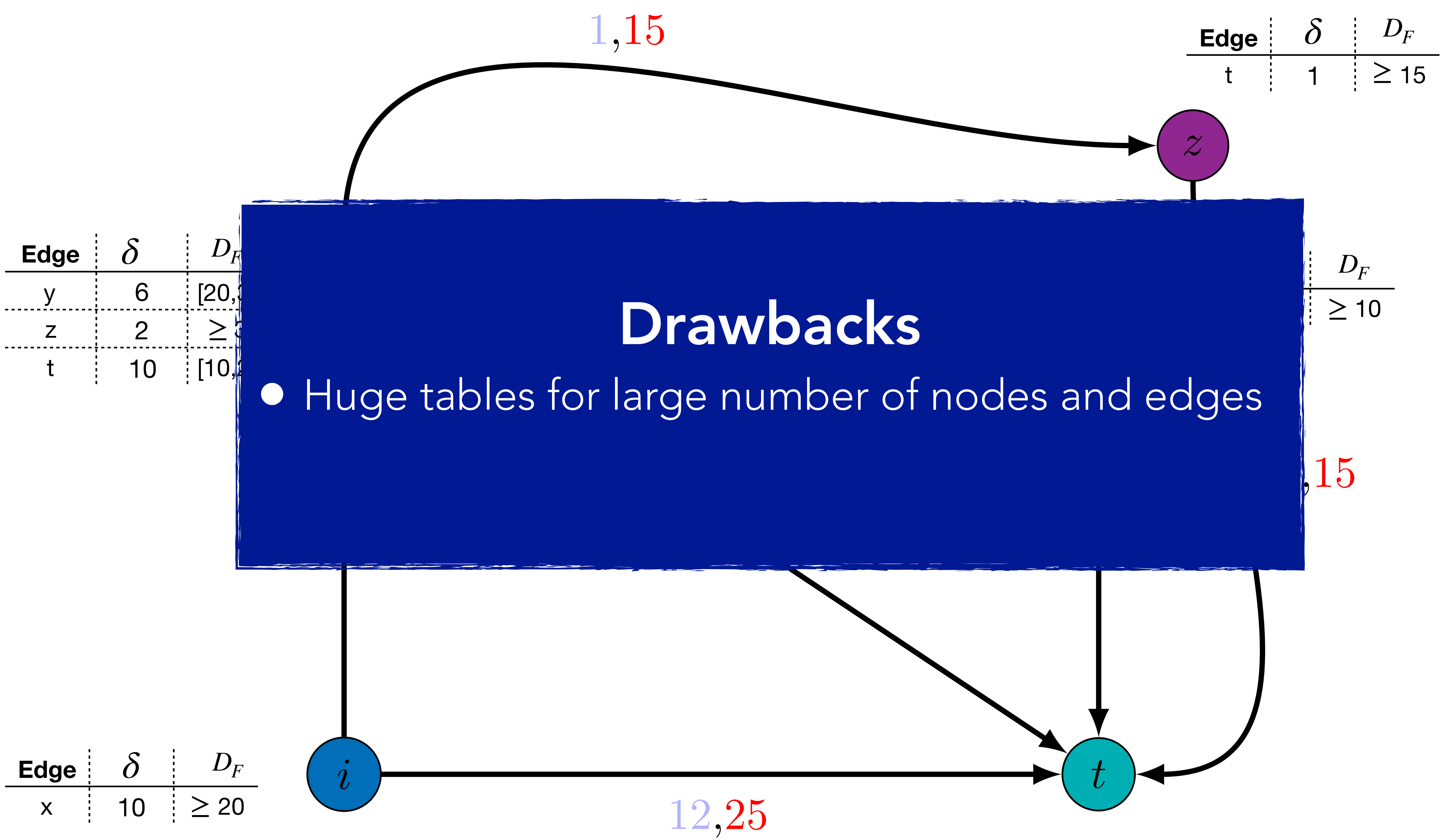

Drawbacks

- Huge tables for large number of nodes and edges

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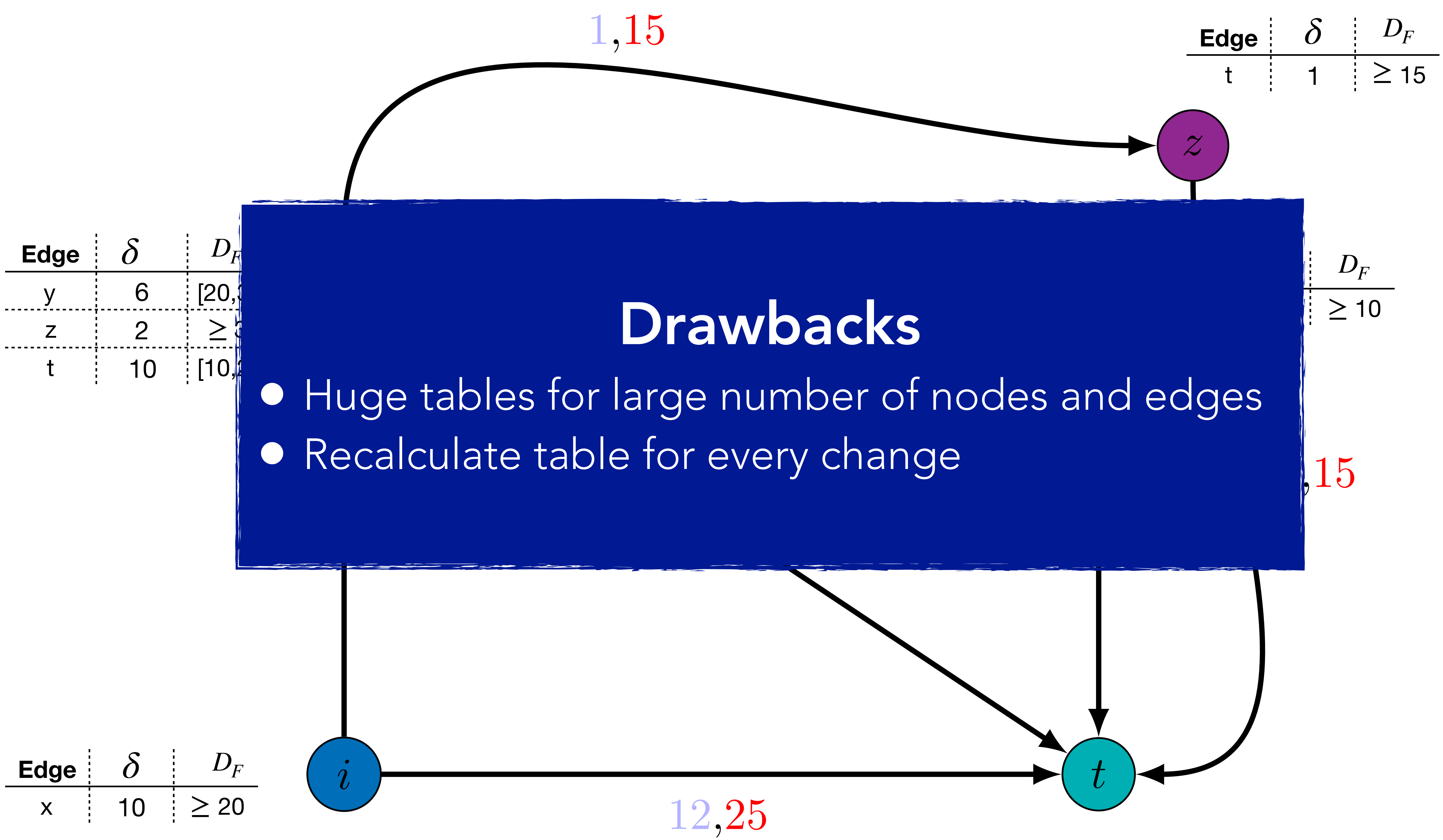

Drawbacks

- Huge tables for large number of nodes and edges
- Recalculate table for every change

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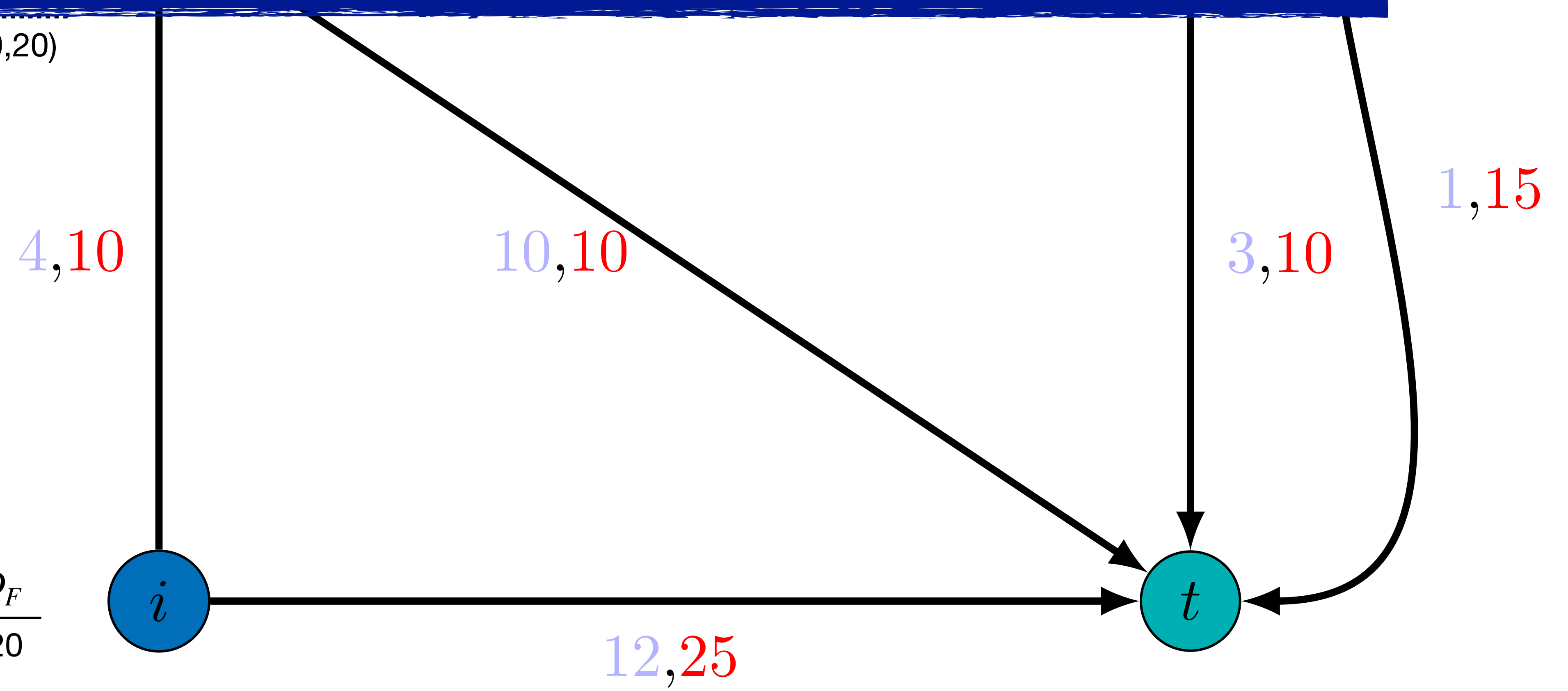
Previous work [1]

Our solution?

e	δ	D_F
	1	≥ 15

Edge	δ	
y	6	
z	2	
t	10	[10,20)

δ	D_F
3	≥ 10



Edge	δ	D_F
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Our solution?
Use Reinforcement Learning

...e	δ	D_F
	1	$\geq$ 15

Edge	δ	
y	6	
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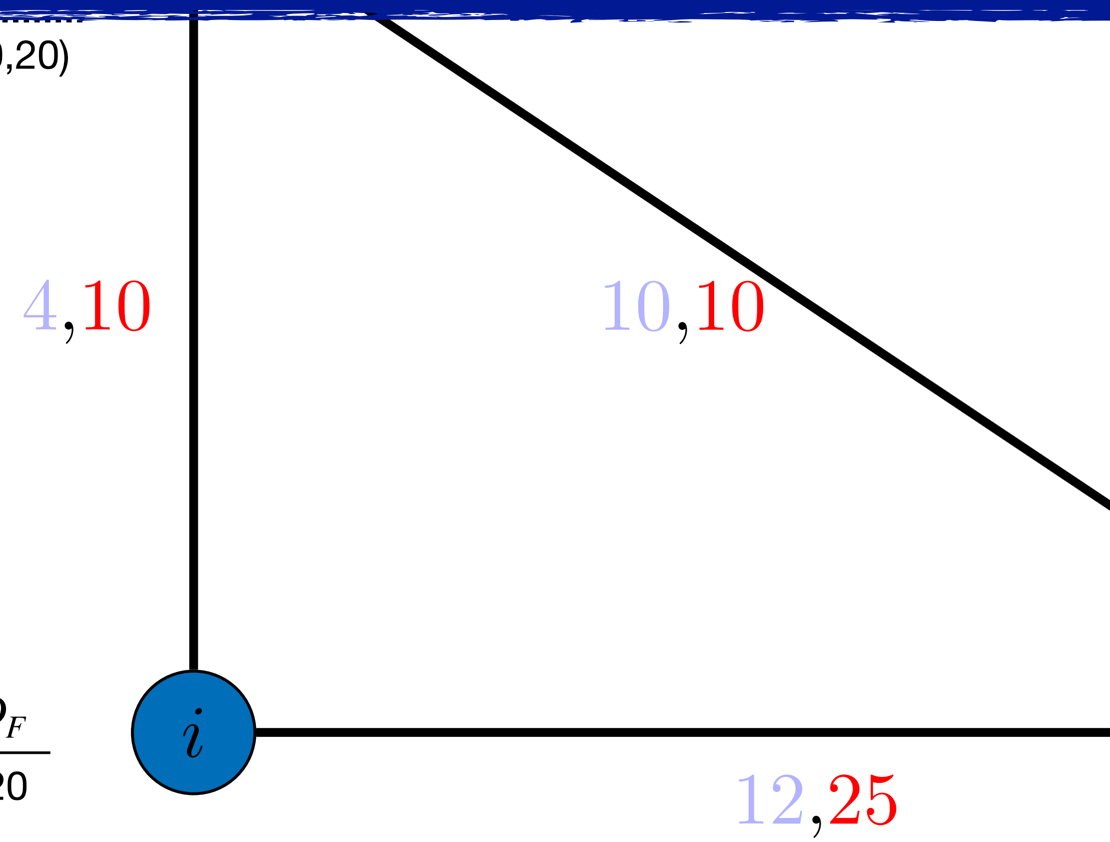
t	10	[10,20)

	δ	D_F
	3	$\geq$ 10



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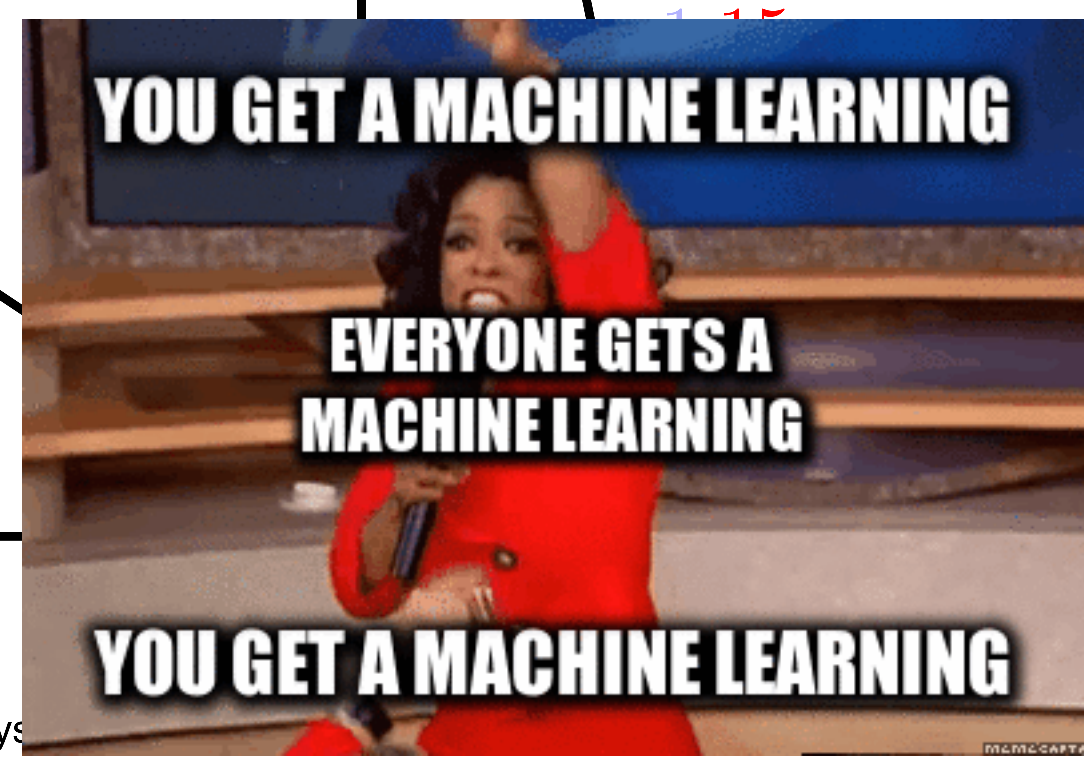

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Reinforcement Learning

- Branch of machine learning that is unsupervised

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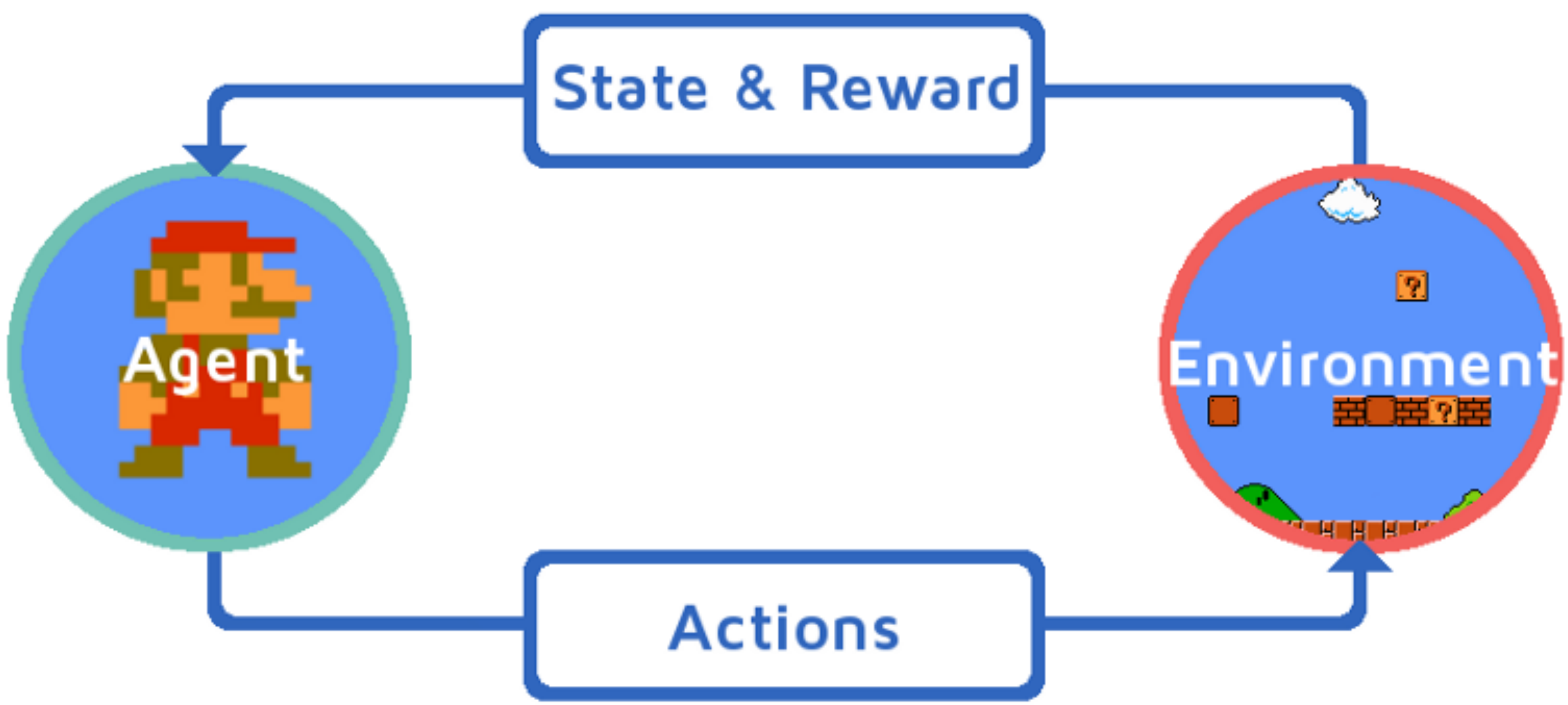
- Branch of machine learning that is unsupervised
- Agent teaches itself how to behave by trial and error in episodic manner
- Learns to maximise a reward returned by the environment



	Lunch	Mario	Routing

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Agent	You	Mario/Luigi	Node

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Policy (π) (Exploitation vs Exploration)	Greedy, ϵ- greedy		
	• Stick to Inspira • Try the new restaurant	• Jump on the goomba • Go down the pipe	• Choose the path with lowest delay • Explore an edge

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Q-Value (Q)	Similar to V but maps state-action pairs to rewards.		

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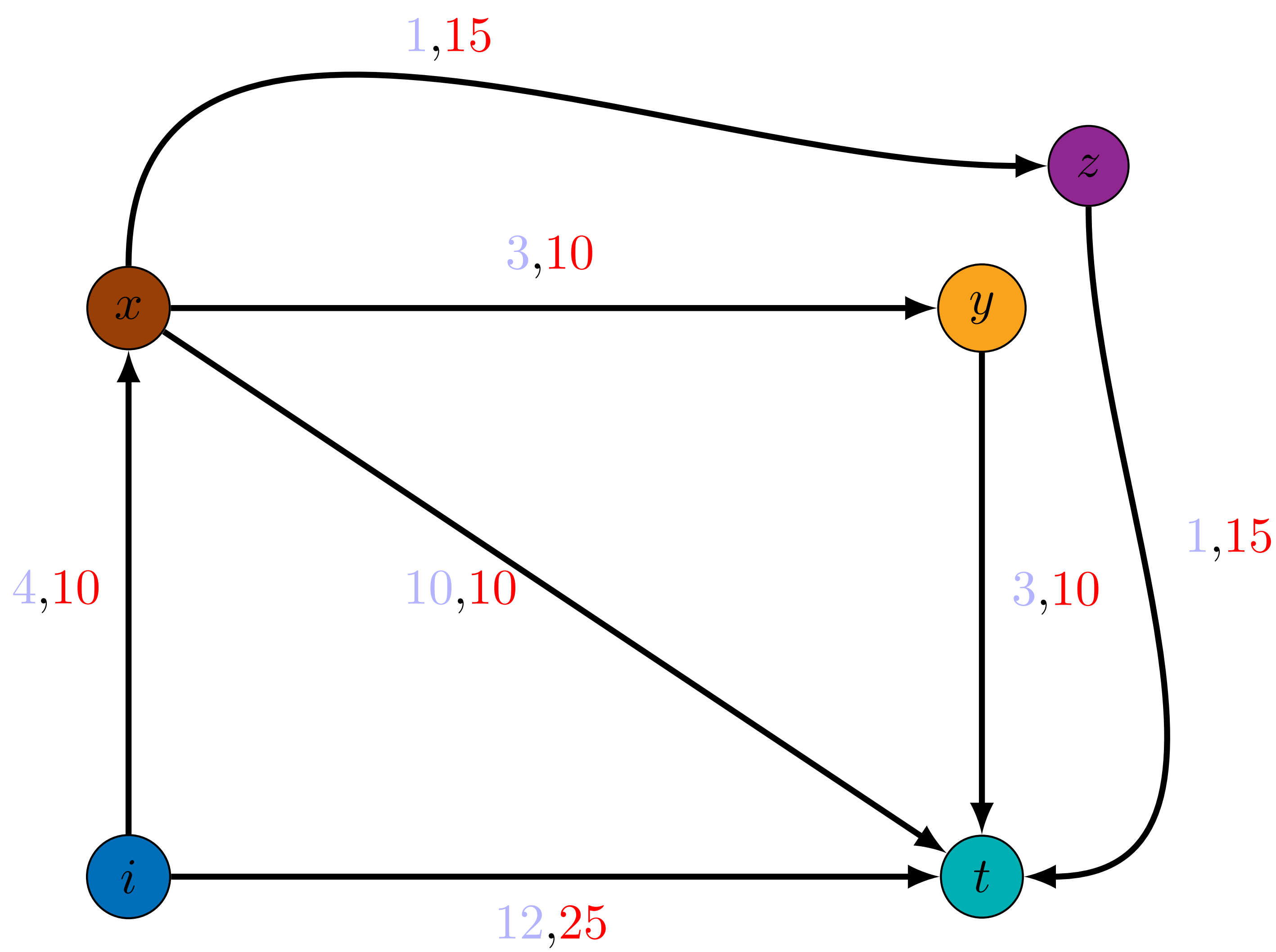
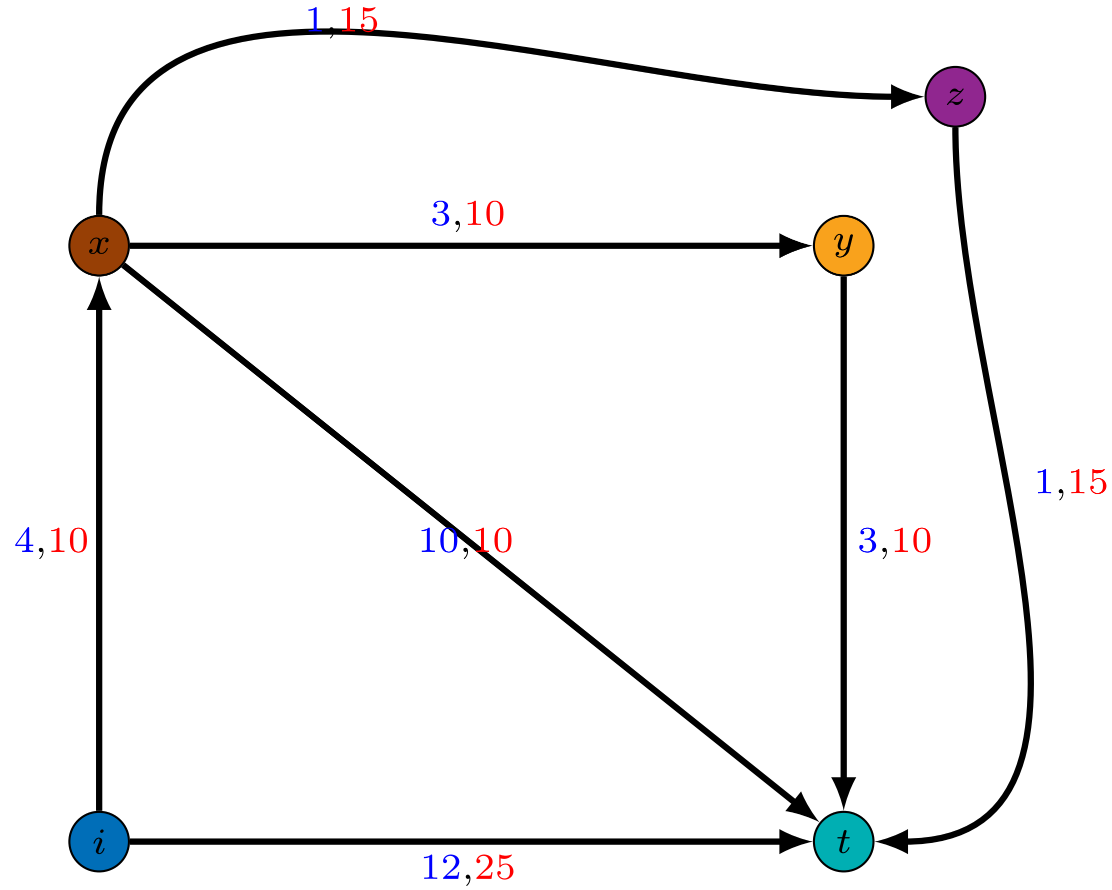
  - Rewards from each state (**R**)
- In our state space, we encode the current vertex and total time elapsed from the beginning

State-Space Example

- Consider a scenario with :-
    - Source node **i**, destination node **t**
    - Maximum admissible time, $D_F = 25$

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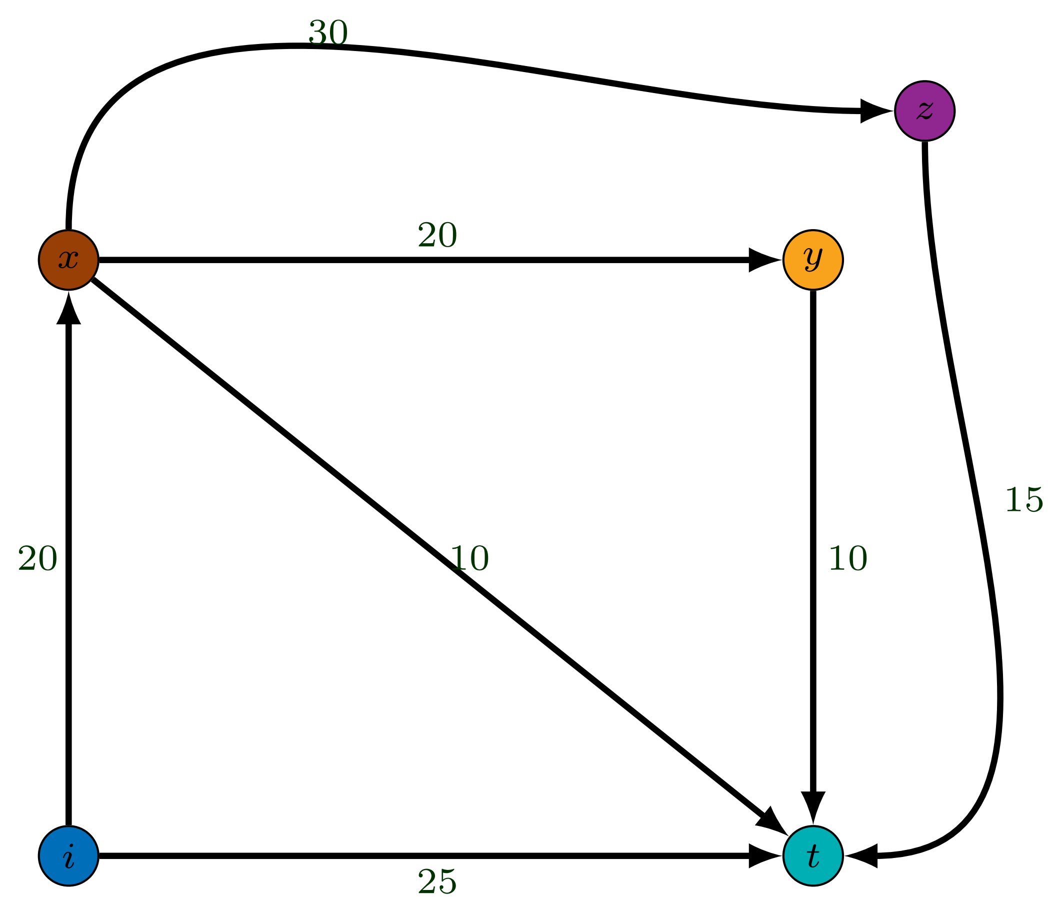
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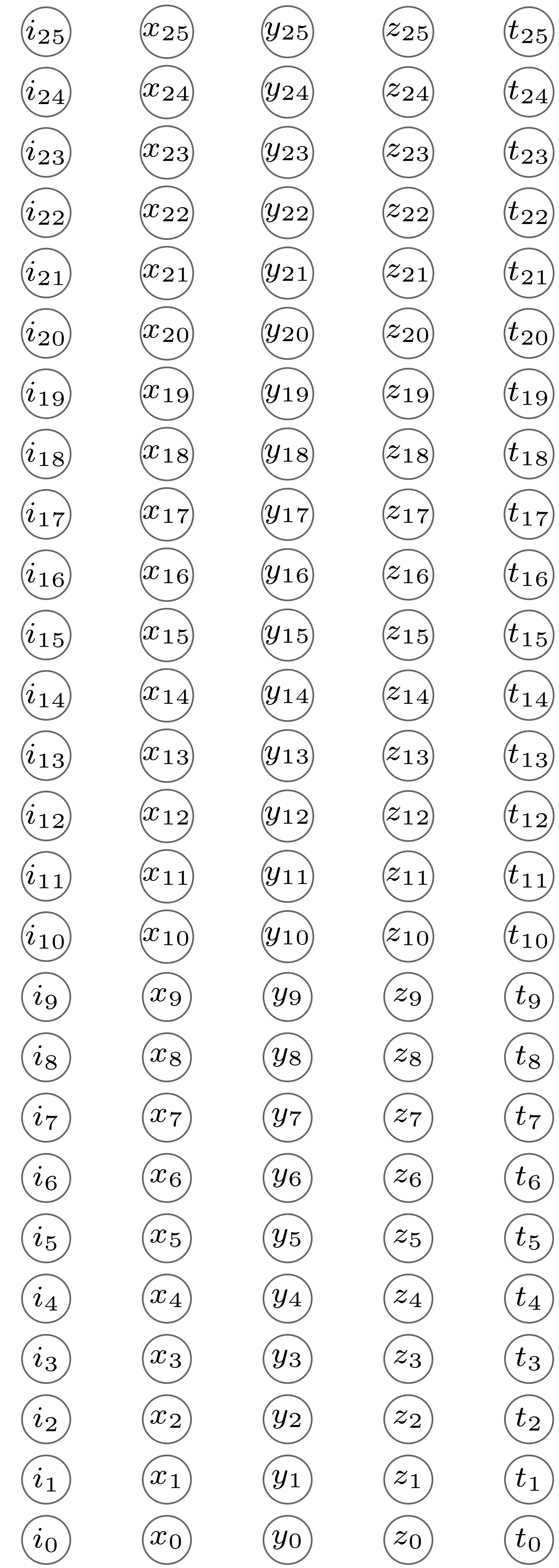
i_{25} x_{25} y_{25} z_{25} t_{25}
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i_{21} x_{21} y_{21} z_{21} t_{21}
i_{20} x_{20} y_{20} z_{20} t_{20}
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i_{4} x_{4} y_{4} z_{4} t_{4}
i_{3} x_{3} y_{3} z_{3} t_{3}
i_{2} x_{2} y_{2} z_{2} t_{2}
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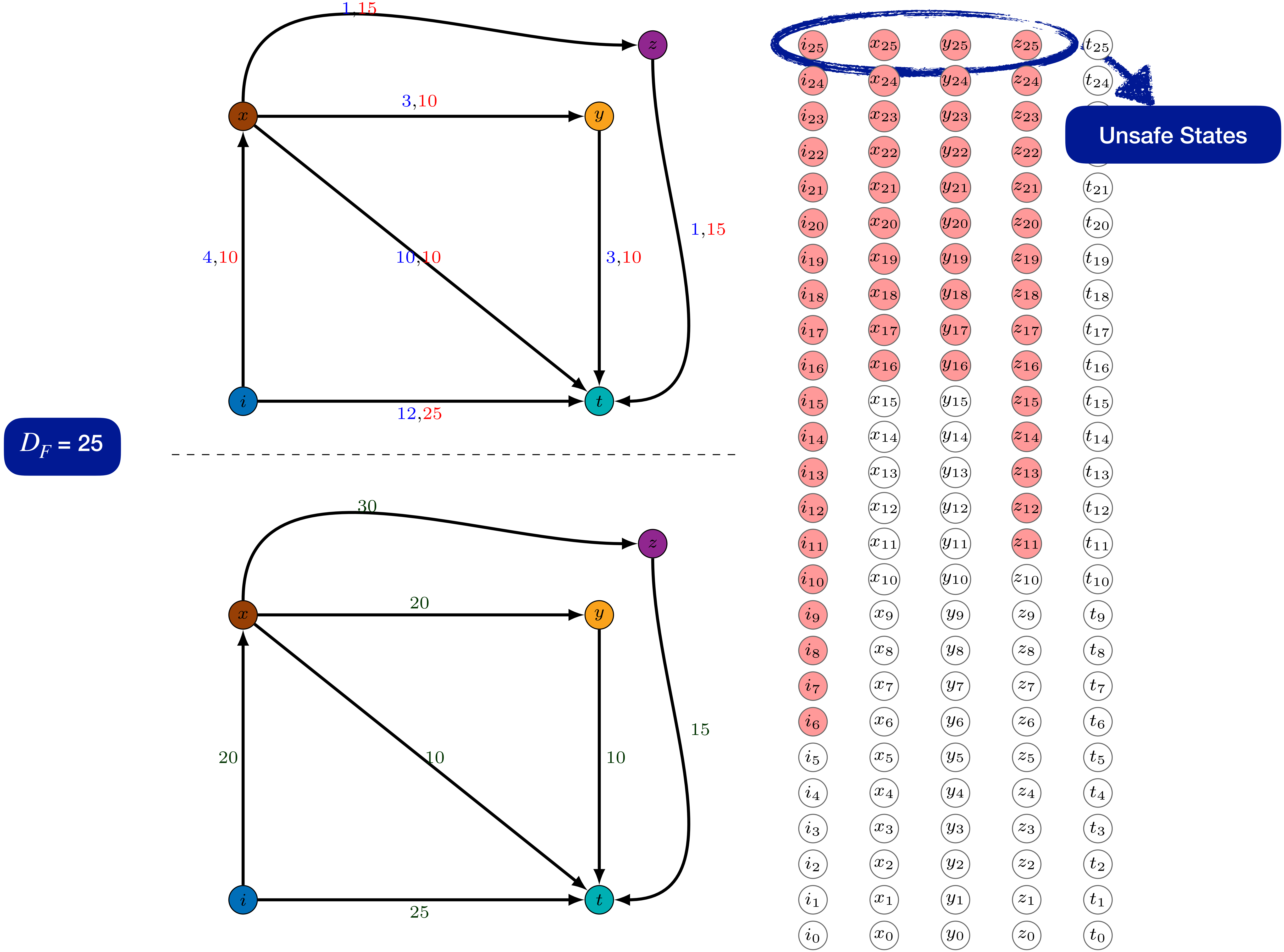
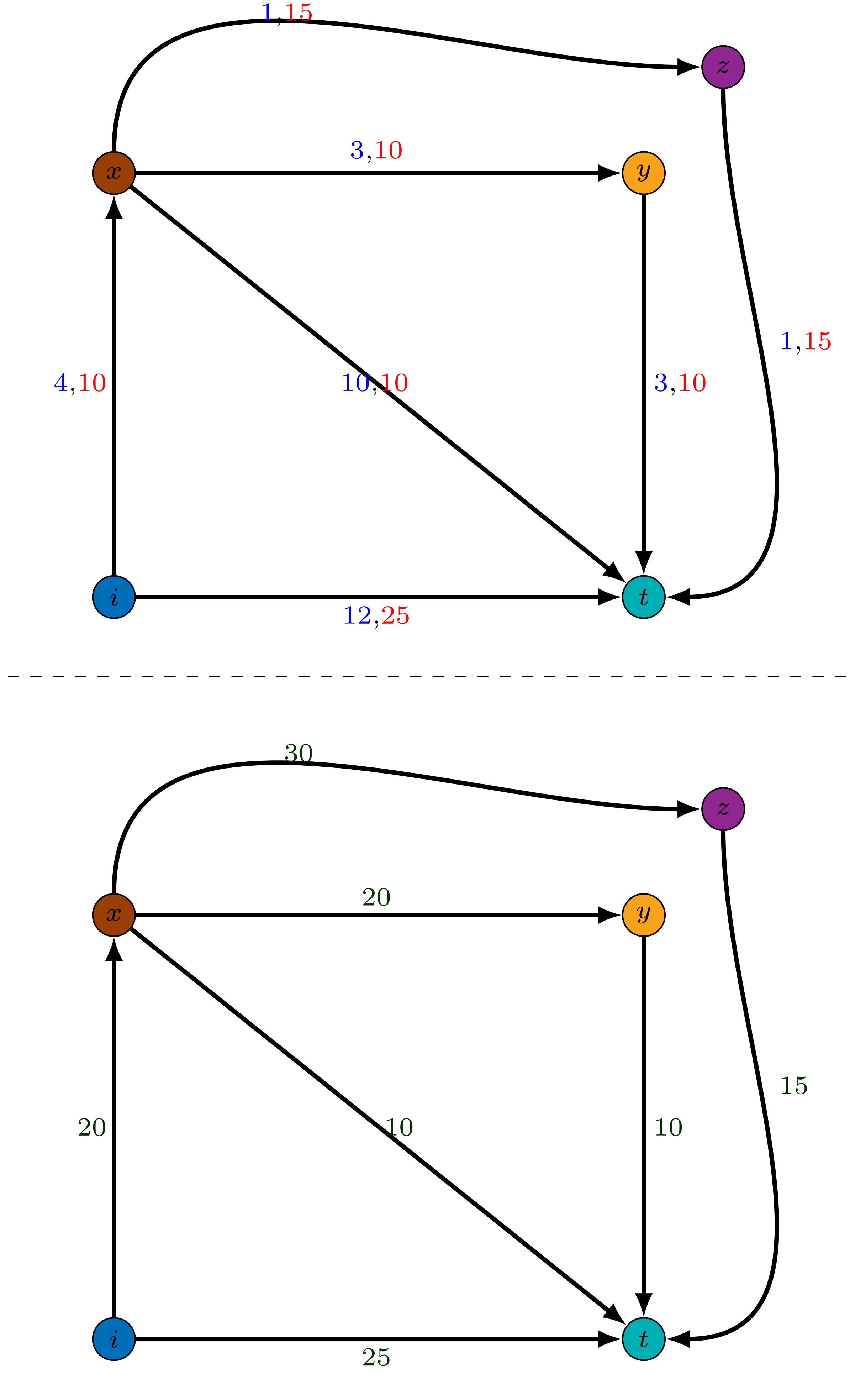


Unsafe States
D_F = 25

D_F = 25



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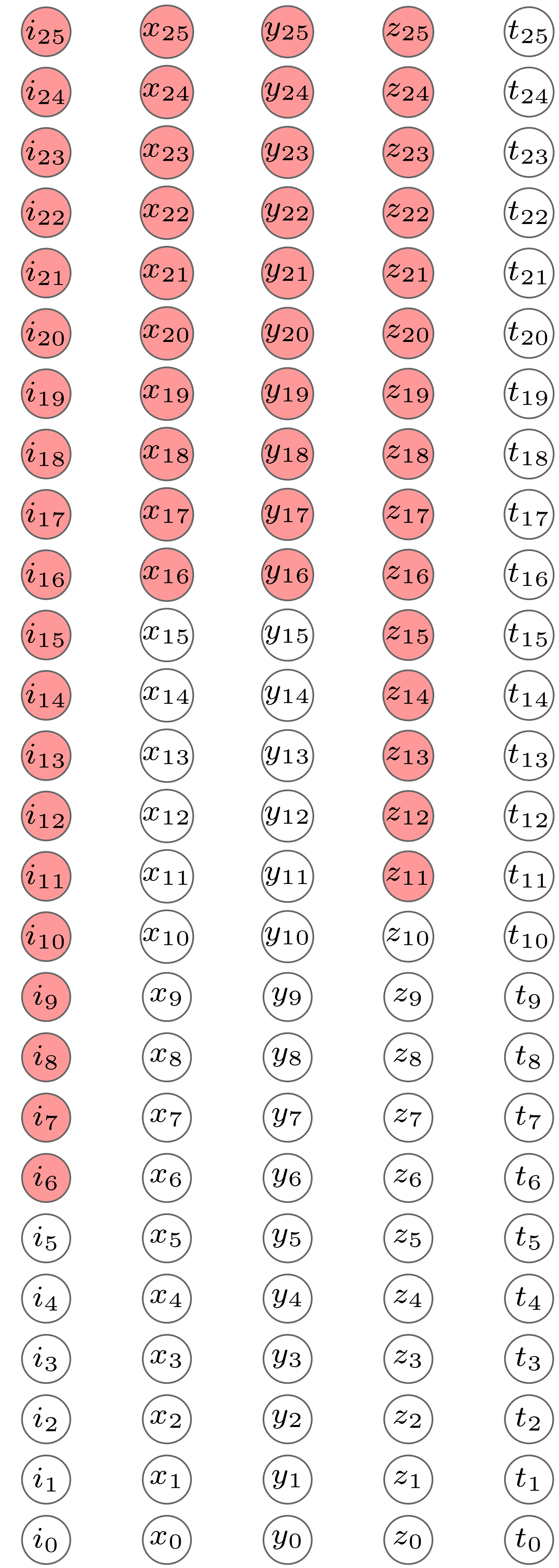

i_{25} x_{25} y_{25} z_{25} t_{25}
i_{24} x_{24} y_{24} z_{24} t_{24}
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i_{22} x_{22} y_{22} z_{22} t_{22}
i_{21} x_{21} y_{21} z_{21} t_{21}
i_{20} x_{20} y_{20} z_{20} t_{20}
i_{19} x_{19} y_{19} z_{19} t_{19}
i_{18} x_{18} y_{18} z_{18} t_{18}
i_{17} x_{17} y_{17} z_{17} t_{17}
i_{16} x_{16} y_{16} z_{16} t_{16}
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i_8 x_8 y_8 z_8 t_8
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i_6 x_6 y_6 z_6 t_6
i_5 x_5 y_5 z_5 t_5
i_4 x_4 y_4 z_4 t_4
i_3 x_3 y_3 z_3 t_3
i_2 x_2 y_2 z_2 t_2
i_1 x_1 y_1 z_1 t_1
i_0 x_0 y_0 z_0 t_0

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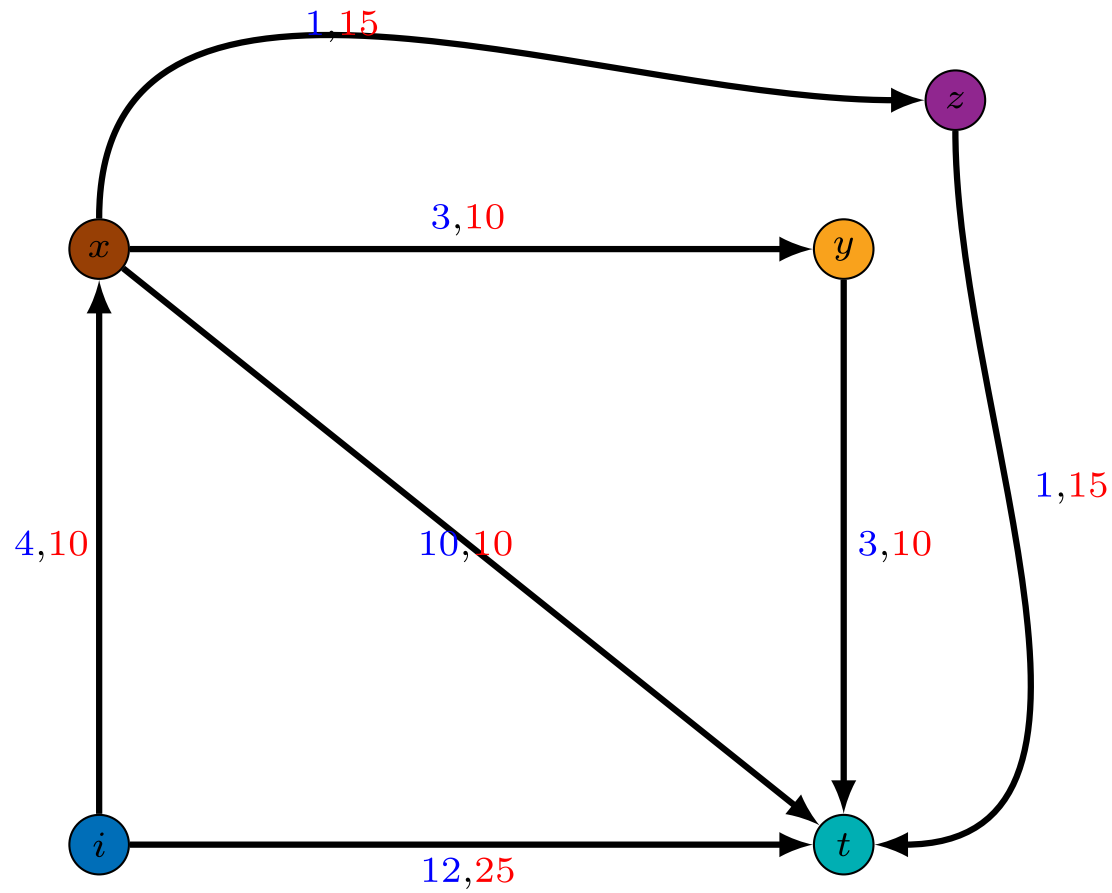
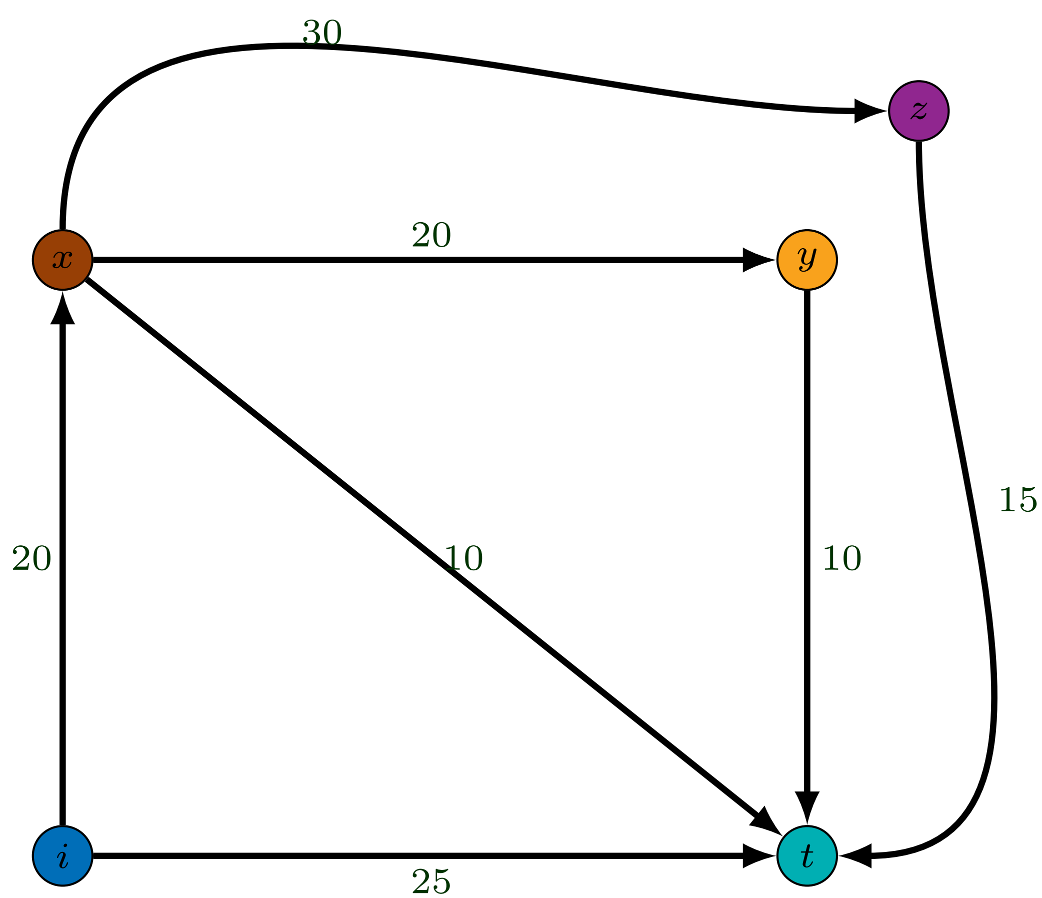
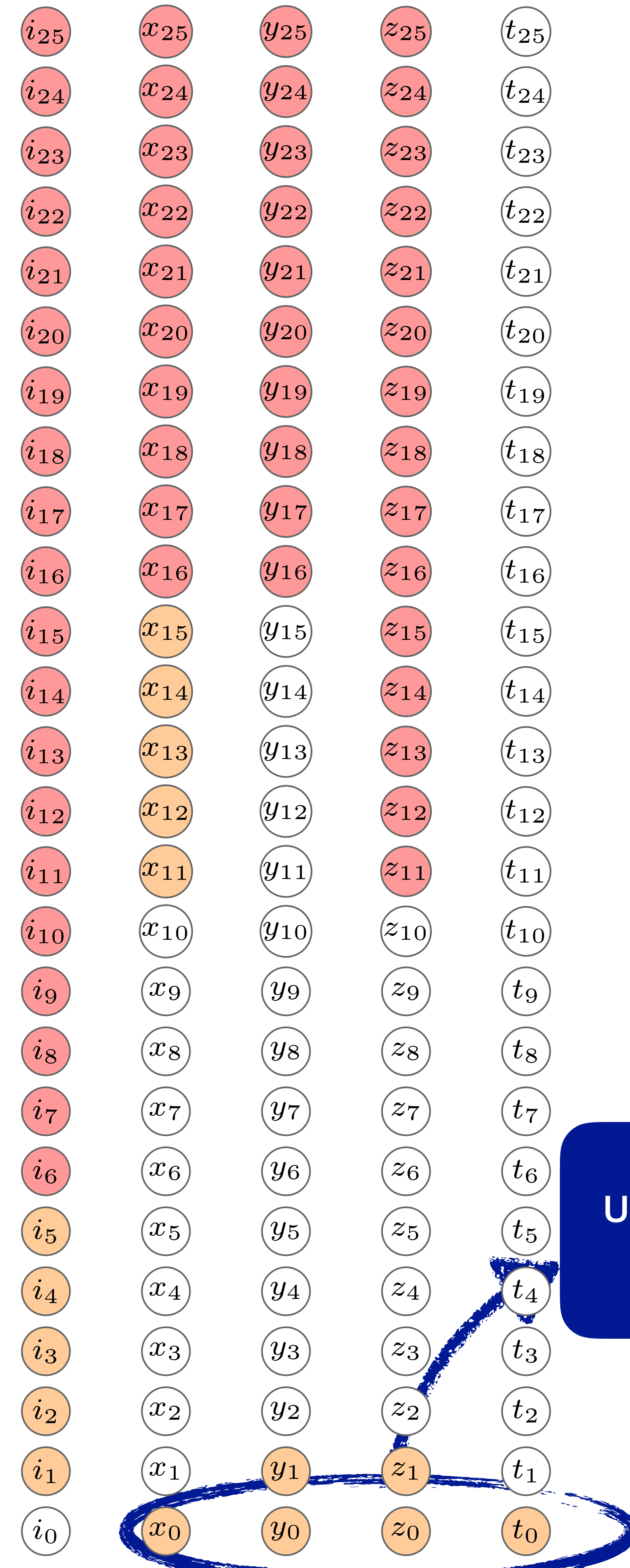
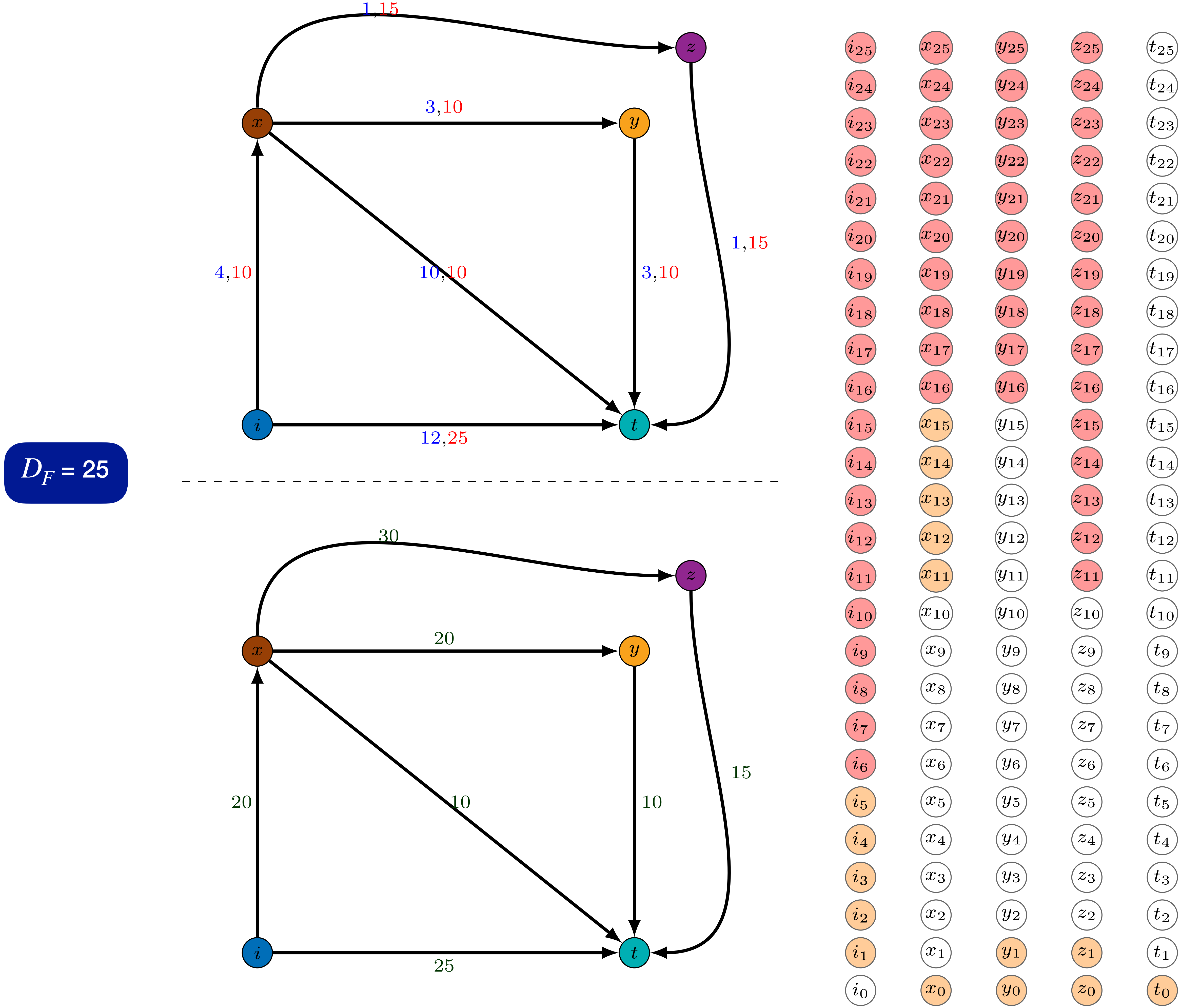






Unreachable states



D_F = 25
1,15
3,10
4,10
10,10
3,10
1,15
12,25
30
20
20
10
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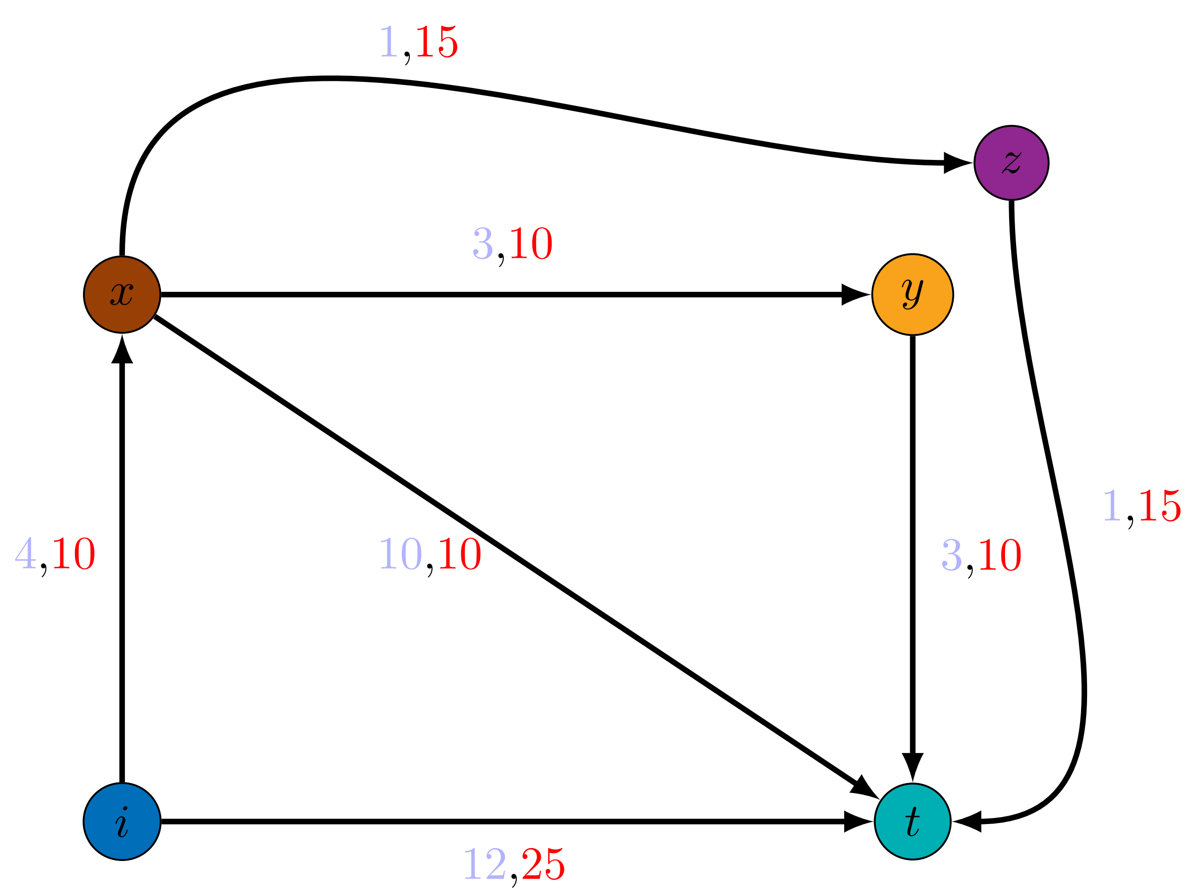
15
25
i_{25} x_{25} y_{25} z_{25} t_{25}
i_{24} x_{24} y_{24} z_{24} t_{24}
i_{23} x_{23} y_{23} z_{23} t_{23}
i_{22} x_{22} y_{22} z_{22} t_{22}
i_{21} x_{21} y_{21} z_{21} t_{21}
i_{20} x_{20} y_{20} z_{20} t_{20}
i_{19} x_{19} y_{19} z_{19} t_{19}
i_{18} x_{18} y_{18} z_{18} t_{18}
i_{17} x_{17} y_{17} z_{17} t_{17}
i_{16} x_{16} y_{16} z_{16} t_{16}
i_{15} x_{15} y_{15} z_{15} t_{15}
i_{14} x_{14} y_{14} z_{14} t_{14}
i_{13} x_{13} y_{13} z_{13} t_{13}
i_{12} x_{12} y_{12} z_{12} t_{12}
i_{11} x_{11} y_{11} z_{11} t_{11}
i_{10} x_{10} y_{10} z_{10} t_{10}
i_9 x_9 y_9 z_9 t_9
i_8 x_8 y_8 z_8 t_8
i_7 x_7 y_7 z_7 t_7
i_6 x_6 y_6 z_6 t_6
i_5 x_5 y_5 z_5 t_5
i_4 x_4 y_4 z_4 t_4
i_3 x_3 y_3 z_3 t_3
i_2 x_2 y_2 z_2 t_2
i_1 x_1 y_1 z_1 t_1
i_0 x_0 y_0 z_0 t_0

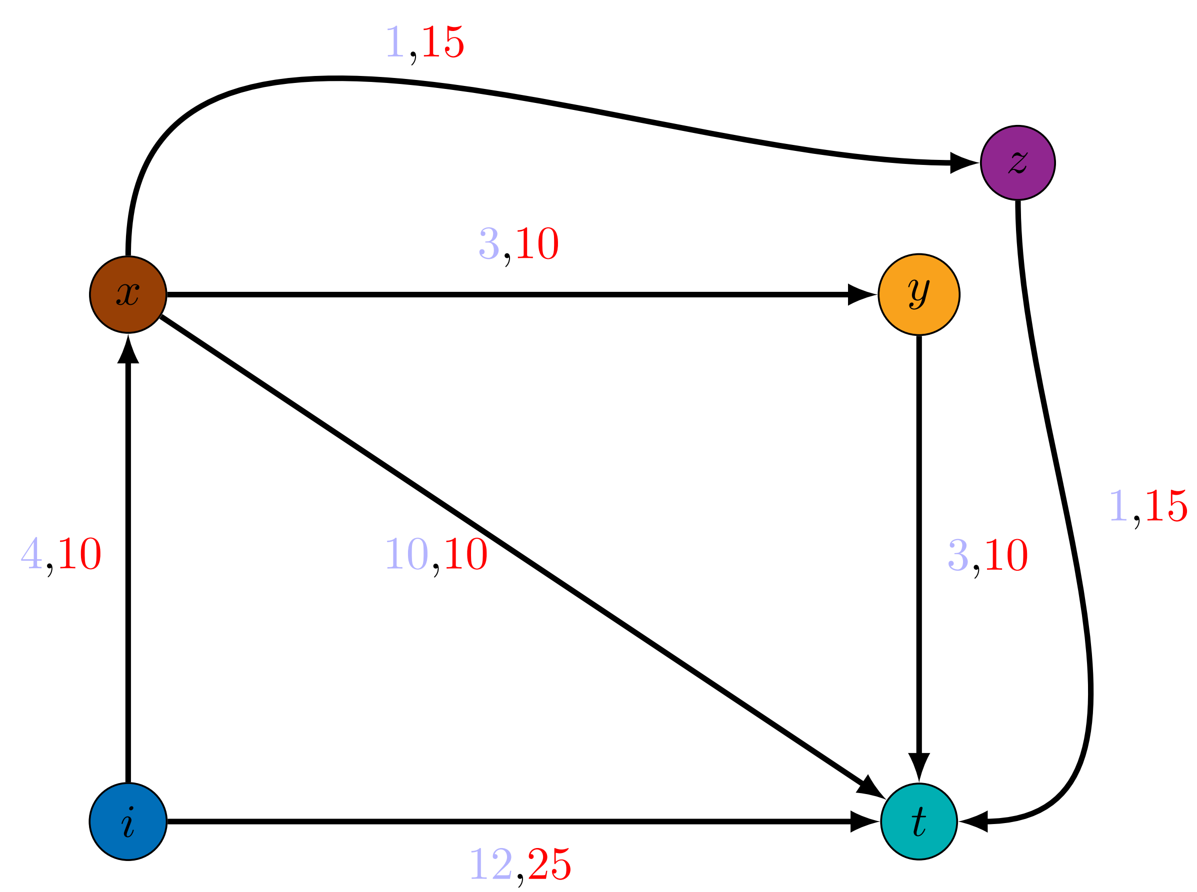
Dijkstras shortest path

- Versatile algorithm to find shortest path from starting to target node in a weighted graph



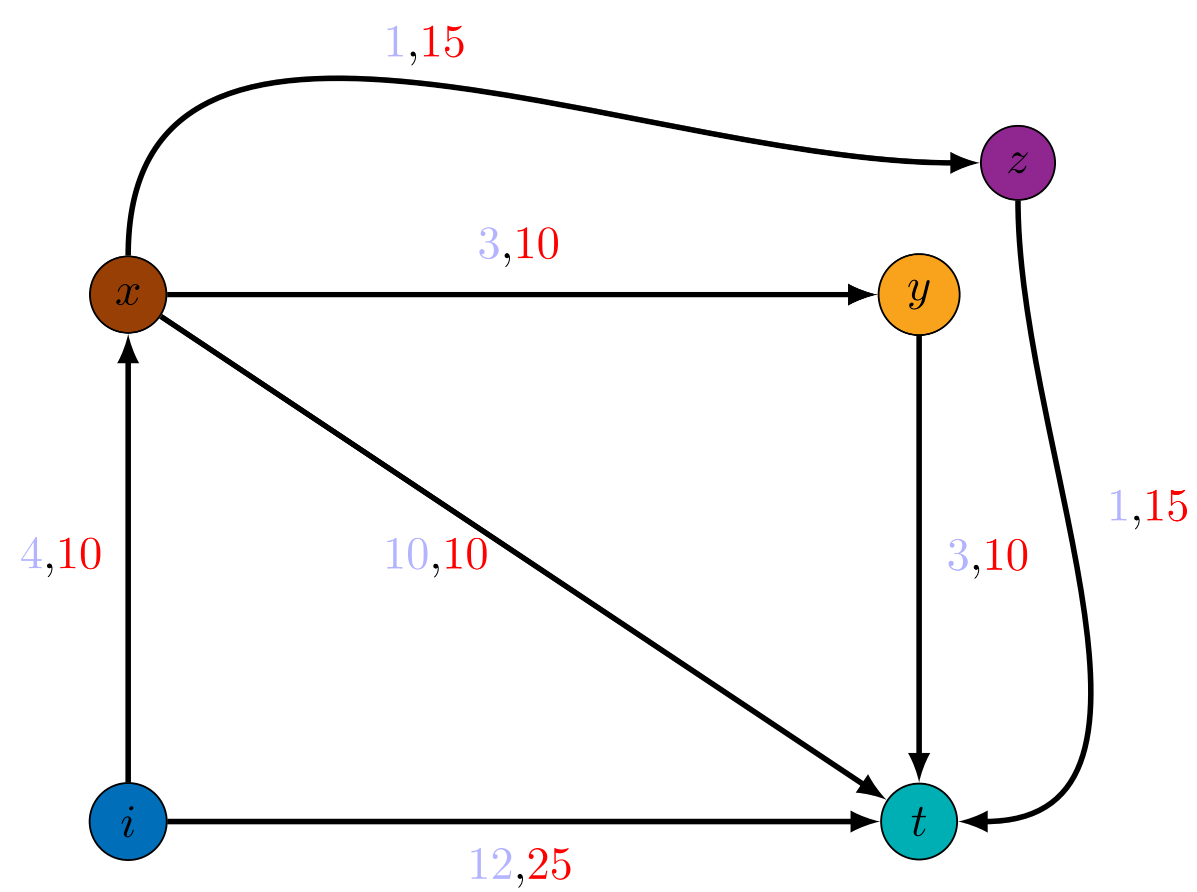
Dijkstras shortest path

- Versatile algorithm to find shortest path from starting to target node in a weighted graph
- Forms the basis of pre-processing stage



Dijkstras shortest path

- Versatile algorithm to find shortest path from starting to target node in a weighted graph
- Forms the basis of pre-processing stage
- Gives the tightest deadline D_F that can be guaranteed over each link



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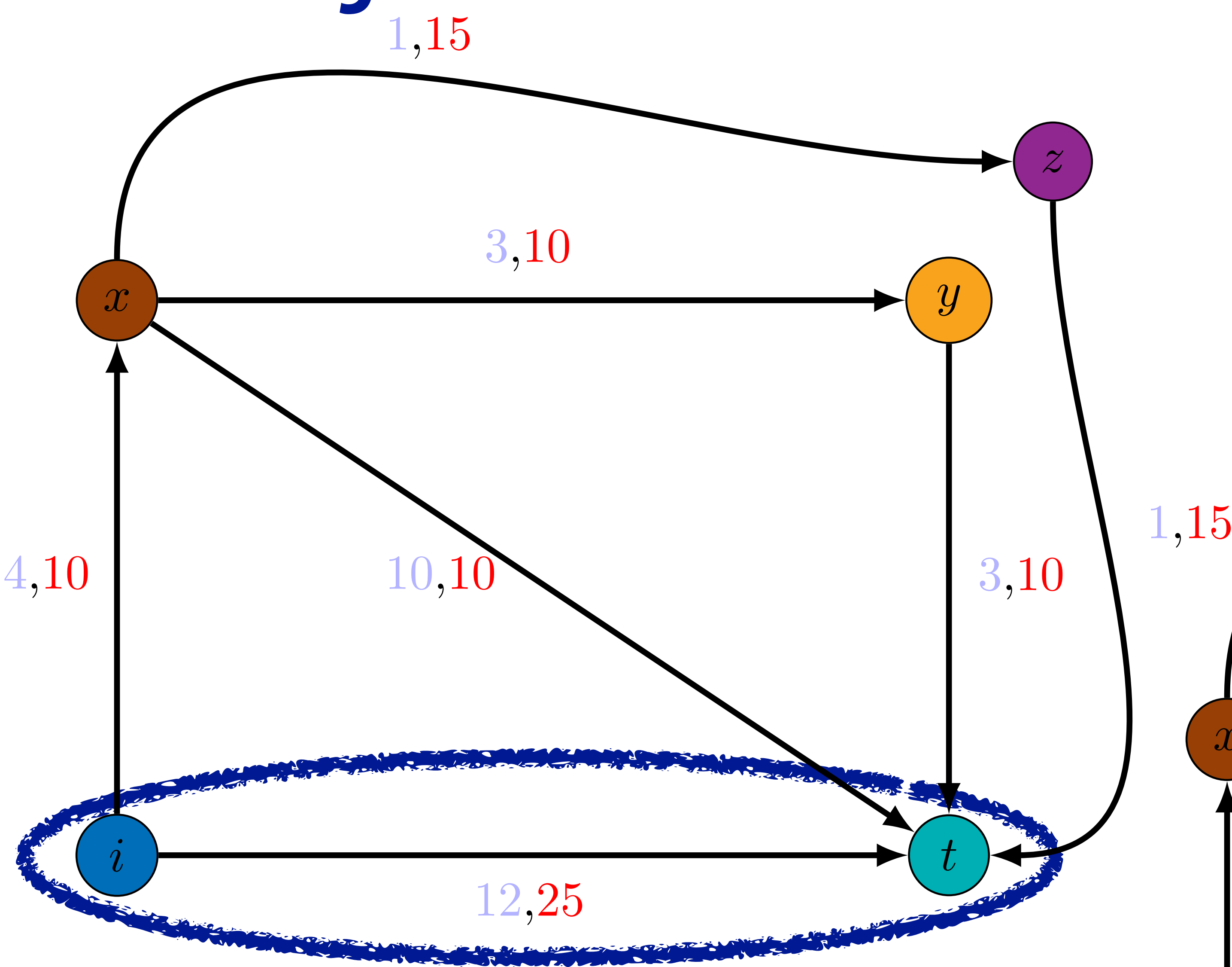

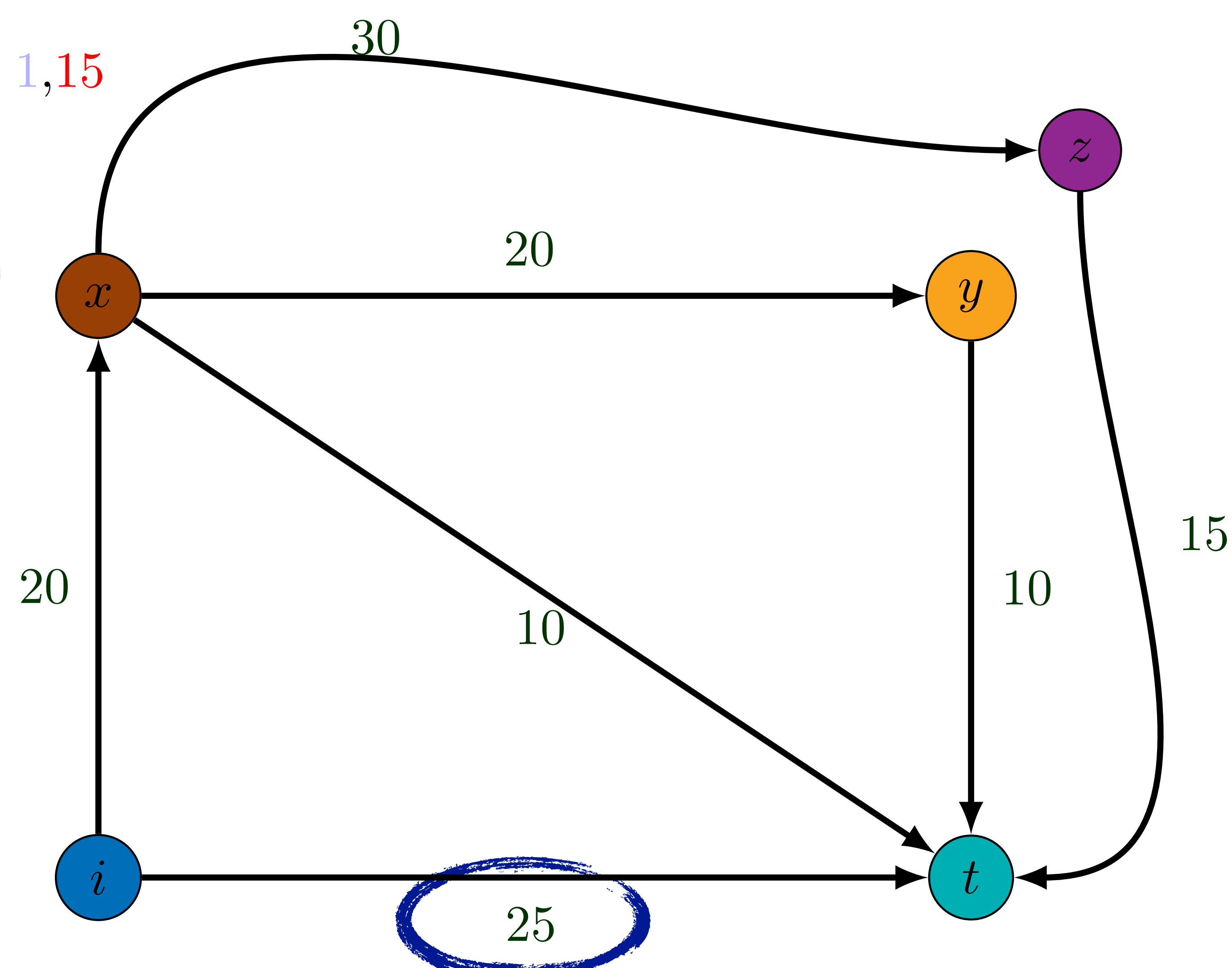

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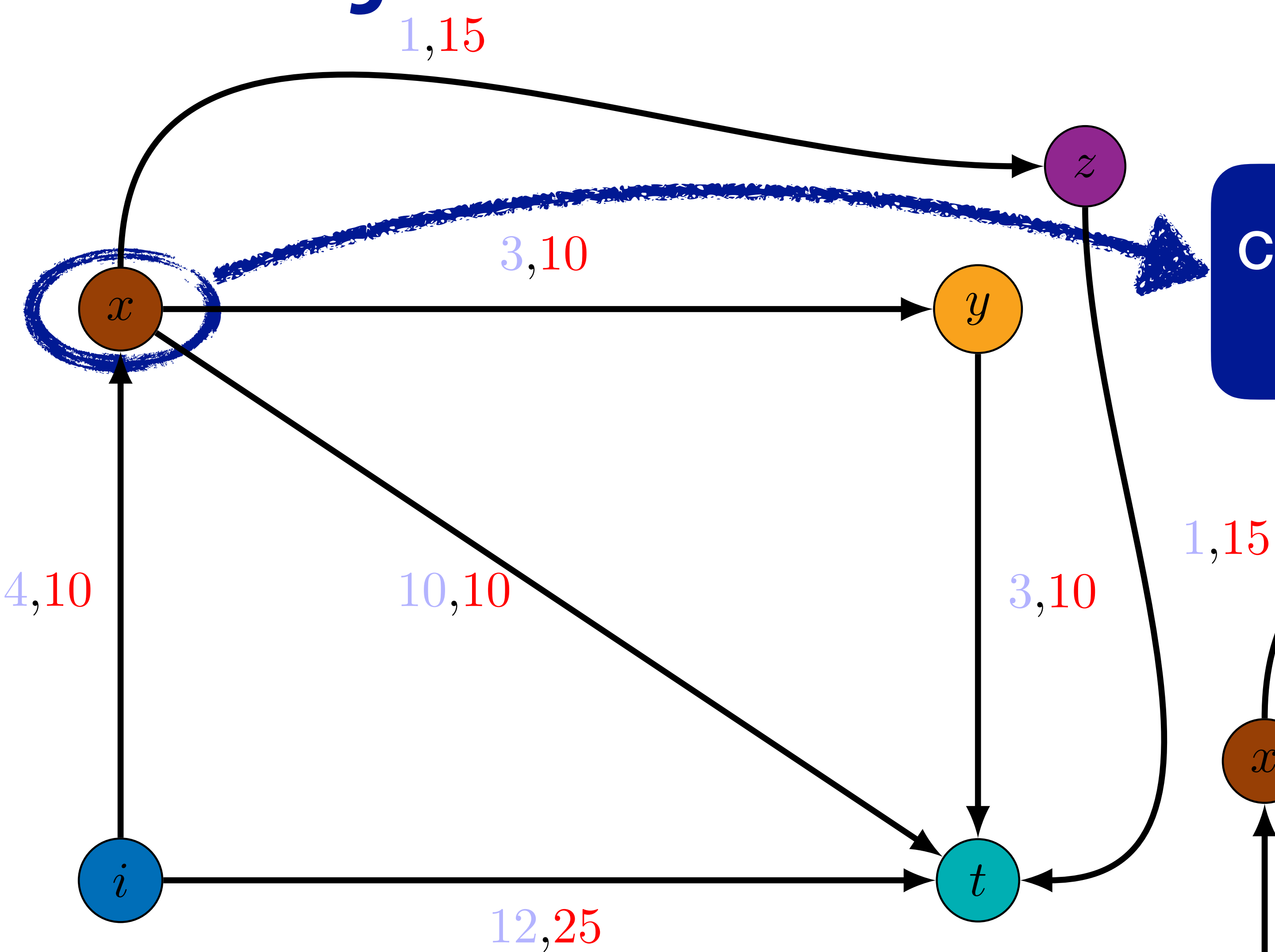
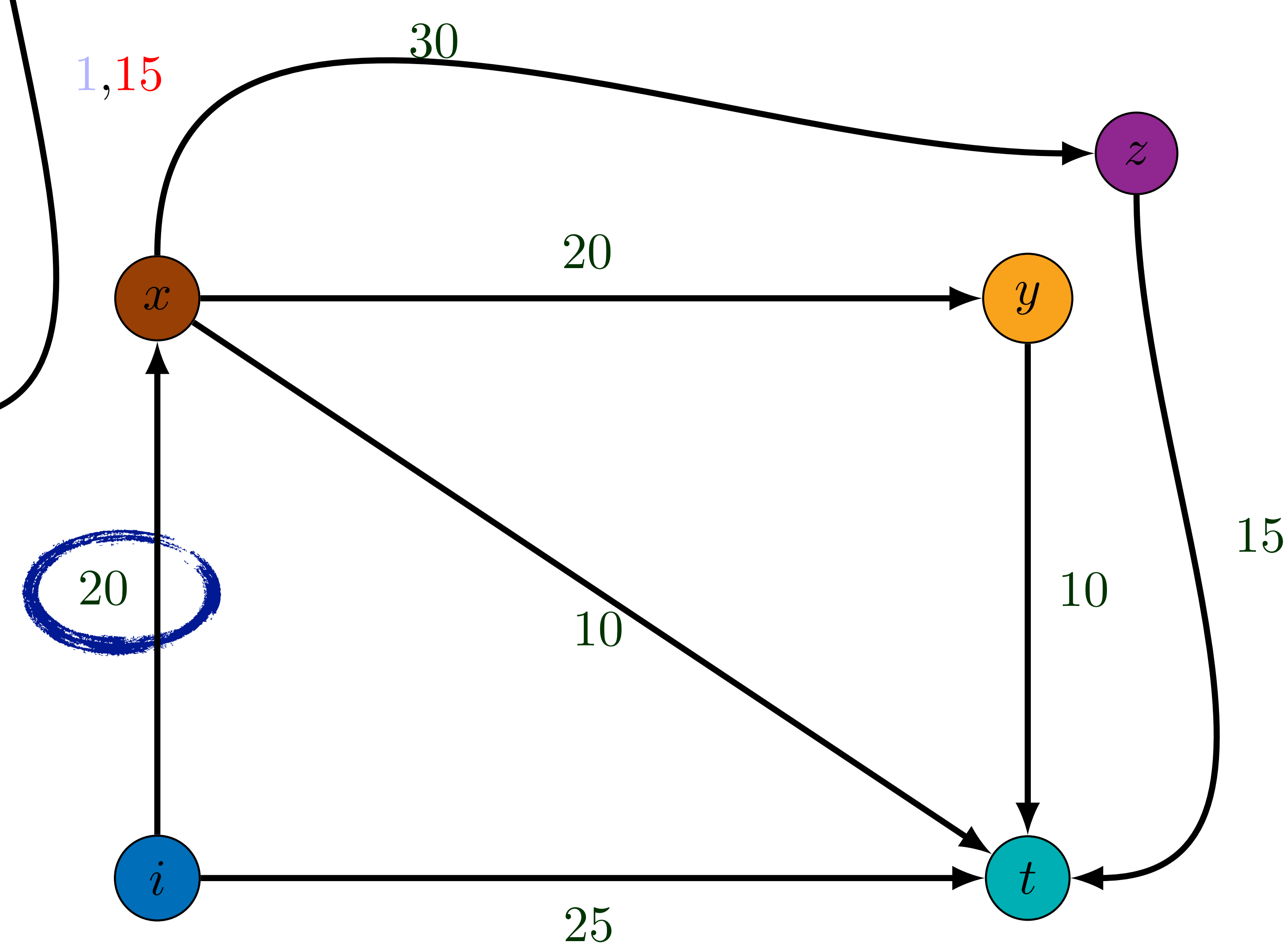
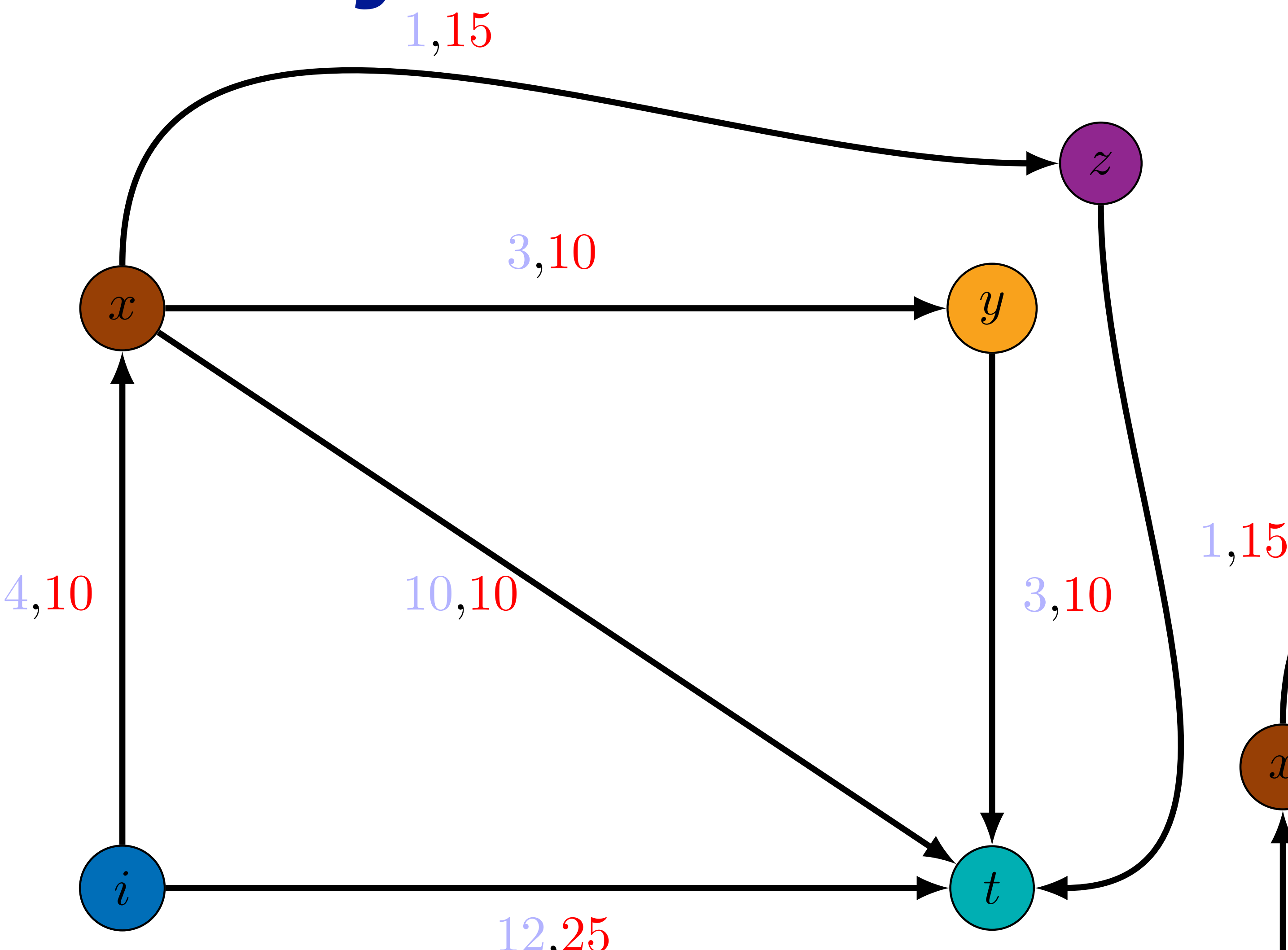
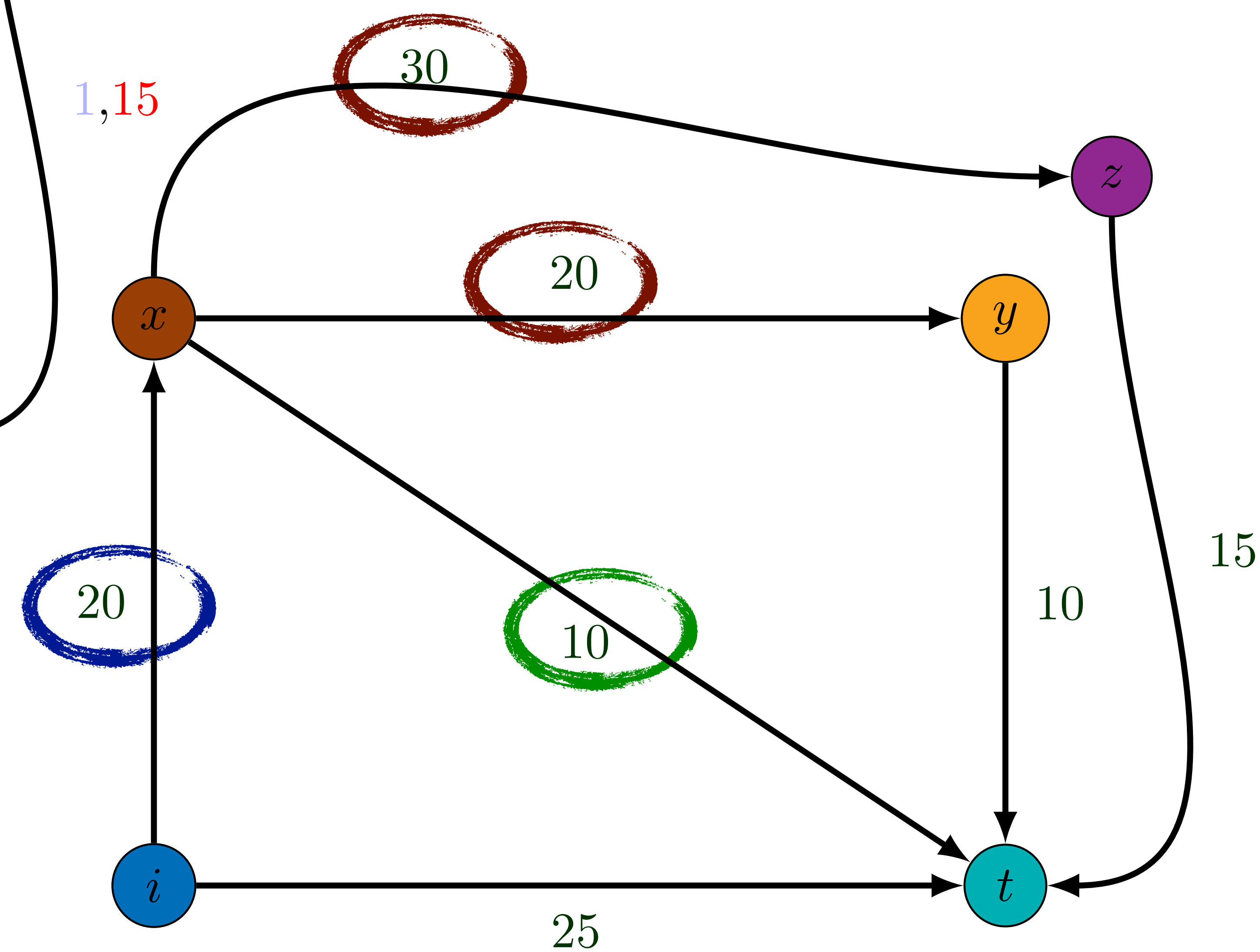


Calculate shortest path from next node to destination



Dijkstras shortest path





Reduced computation when run from destination to source

Pre-processing phase

- Required irrespective of the algorithm used to provide guarantees

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Routing with safe reinforcement learning

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- Chooses optimal path in dynamic environmental conditions

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- While ensuring never to violate deadline restrictions

Thanks to the truncated state-space

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Routing with safe reinforcement learning

- Chooses optimal path in dynamic environmental conditions
- While ensuring never to violate deadline restrictions
- Algorithm has two phases
    - Pre-processing phase (Dijkstras algorithm)
    - Run-time phase
- The environment returns the reward after each episode

Routing with safe reinforcement learning

- Value iteration updates a value of being in a state, improving future episodes

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- Popular Methods
  - Monte Carlo value estimation
  - Temporal Difference(TD) Learning

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- Exploration using ϵ-greedy approach

  - Taking only safe edges ensures safe learning

Value Update

- Monte-Carlo Methods

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Value Update

- Monte-Carlo Methods
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- Temporal Difference(TD) Learning
  - Learning without waiting for episode to end
  - Special case TD(0) depends only on the value of current and next state-action pairs
  - $Q(s,a) = Q(s,a) + \alpha \cdot (R + \max(\gamma Q(s',a')) - Q(s,a))$

Exploration

- ϵ-greedy exploration gives stochastic convergence guarantees
- Ensures that all feasible paths in the network will eventually be explored

Run-time phase

- Run at every node when a packet arrives

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Algorithm 1 Node Logic (u)

for Every packet **do**
    if u = source node i **then**
        $D_u = D_F$ // Initialise the deadline for each episode
        $\delta_{it} = 0$ // Initiliaze total delay for packet = 0
    for each edge $(u \rightarrow v)$ **do**
        if $c_{uv} > D_u$ **then** // Unsafe Edge
            $P(u|v) = 0$
        else if $Q(u, v) = max(Q(u, a \in A))$ **then**
            $P(u|v) = (1 - \epsilon)$
        else
            $P(u|v) = \epsilon/(size(\mathcal{F} - 1))$
    Choose edge $(u \rightarrow v)$ with P
    Observe δ_{uv}
    δ_{it} += δ_{uv}
    $D_v = D_u - \delta_{uv}$
    R = Environment Reward Function(v, δ_{it})
    $Q(u, v)$ = Value iteration from Equation
    if $v = t$ **then**
        DONE

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        DONE

Reward Function

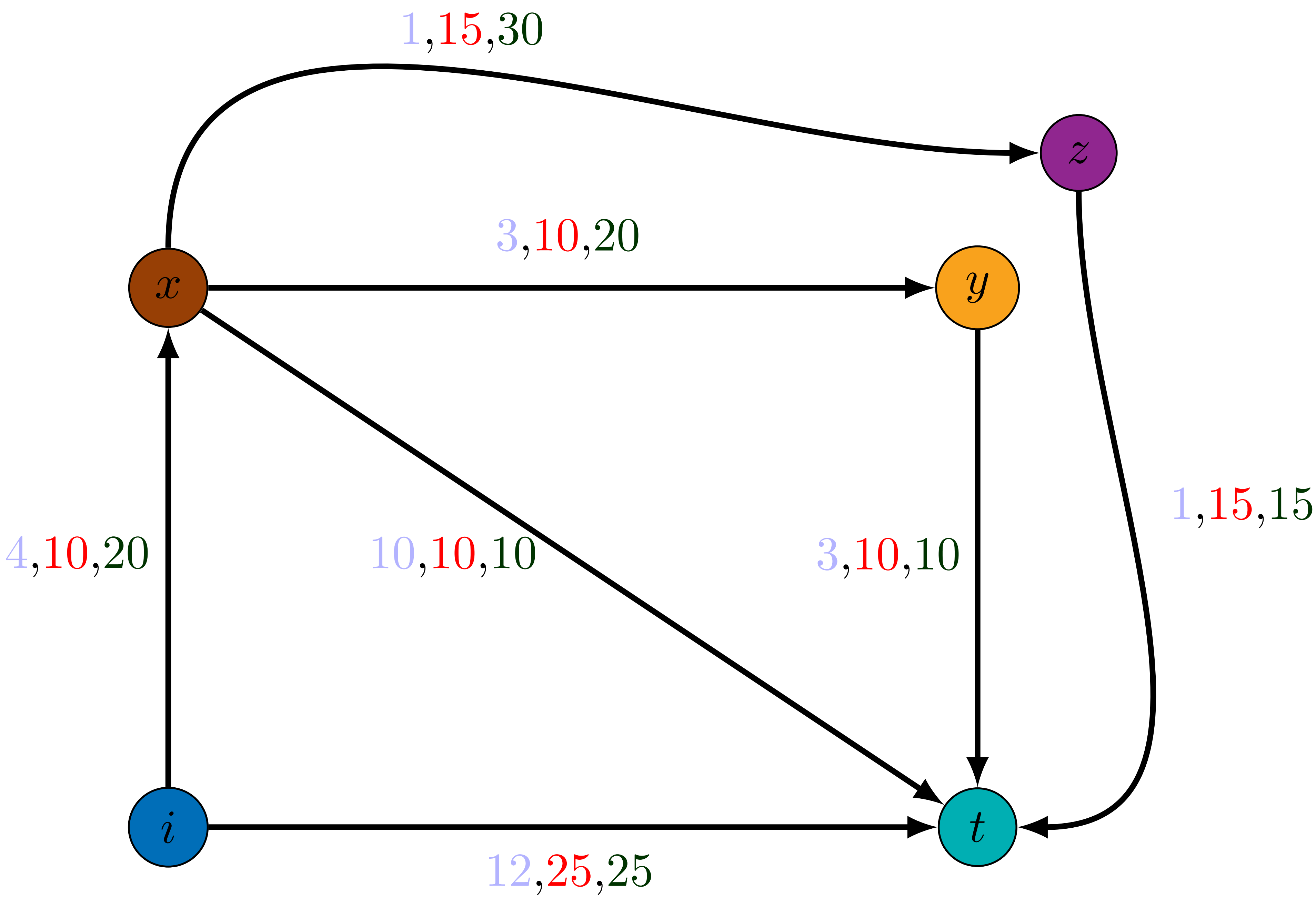
- Reward assigned by the environment
- At the end of every episode/packet transmission
- Propagates to other nodes through TD(0)

Algorithm 1 Environment Reward Function(v, δ_{it})

1: Assigns the reward at the end of transmission
2: **if** $v = t$ **then**
3: $\quad R = D_F - \delta_{it}$
4: **else**
5: $\quad R = 0$

An Example. $D_F = 25$

Episode	Path	Transmission Time



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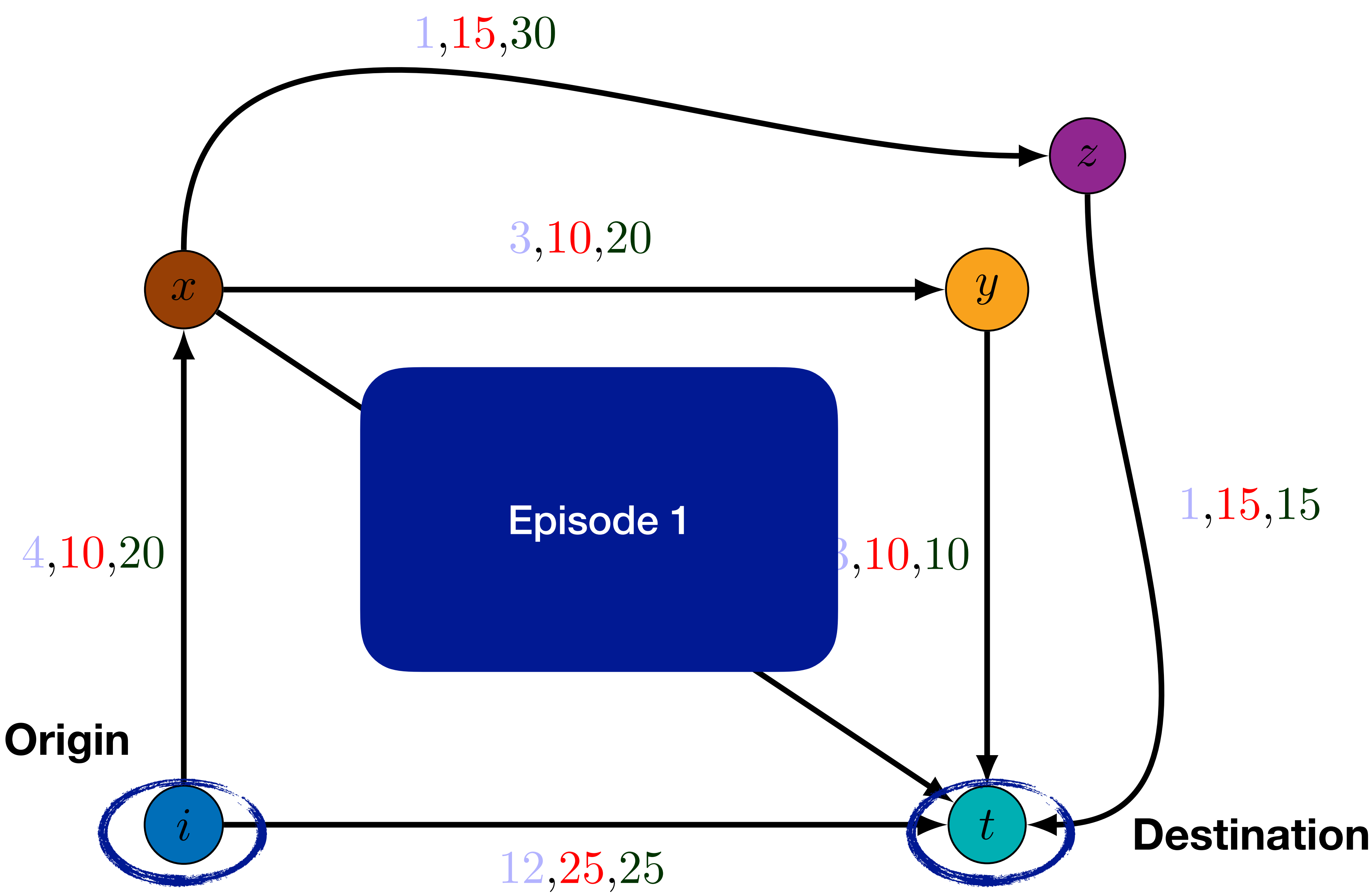

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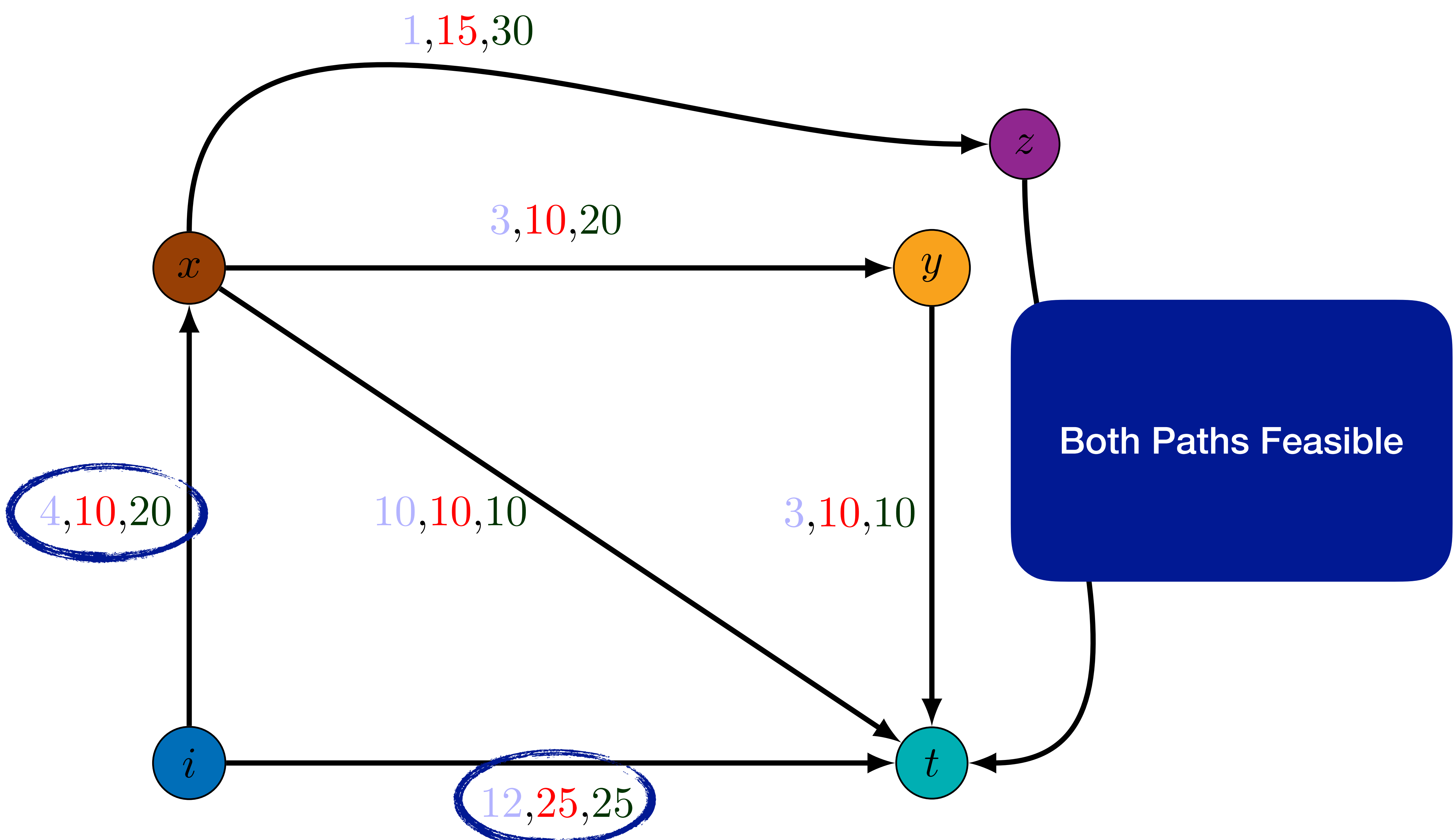
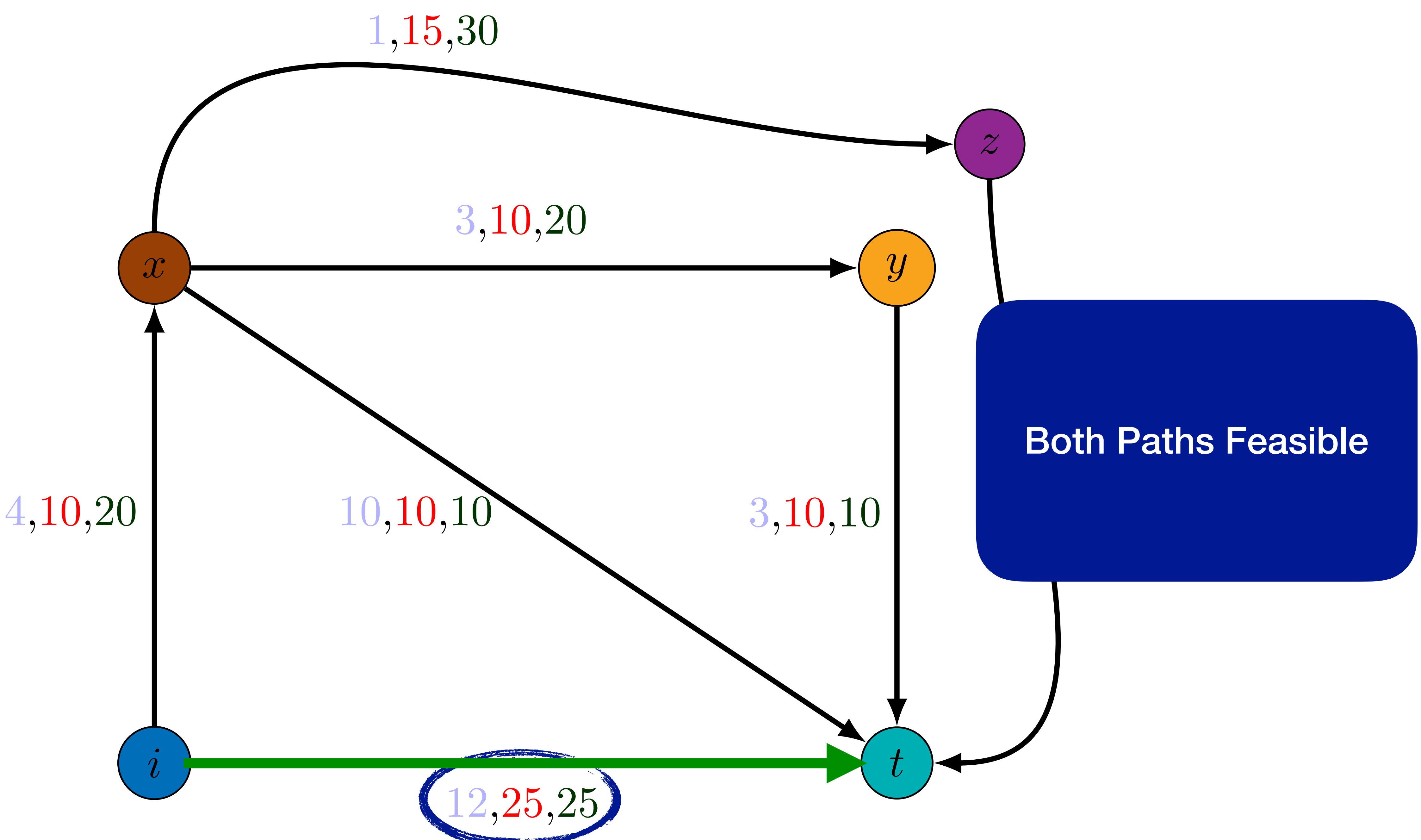


An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12



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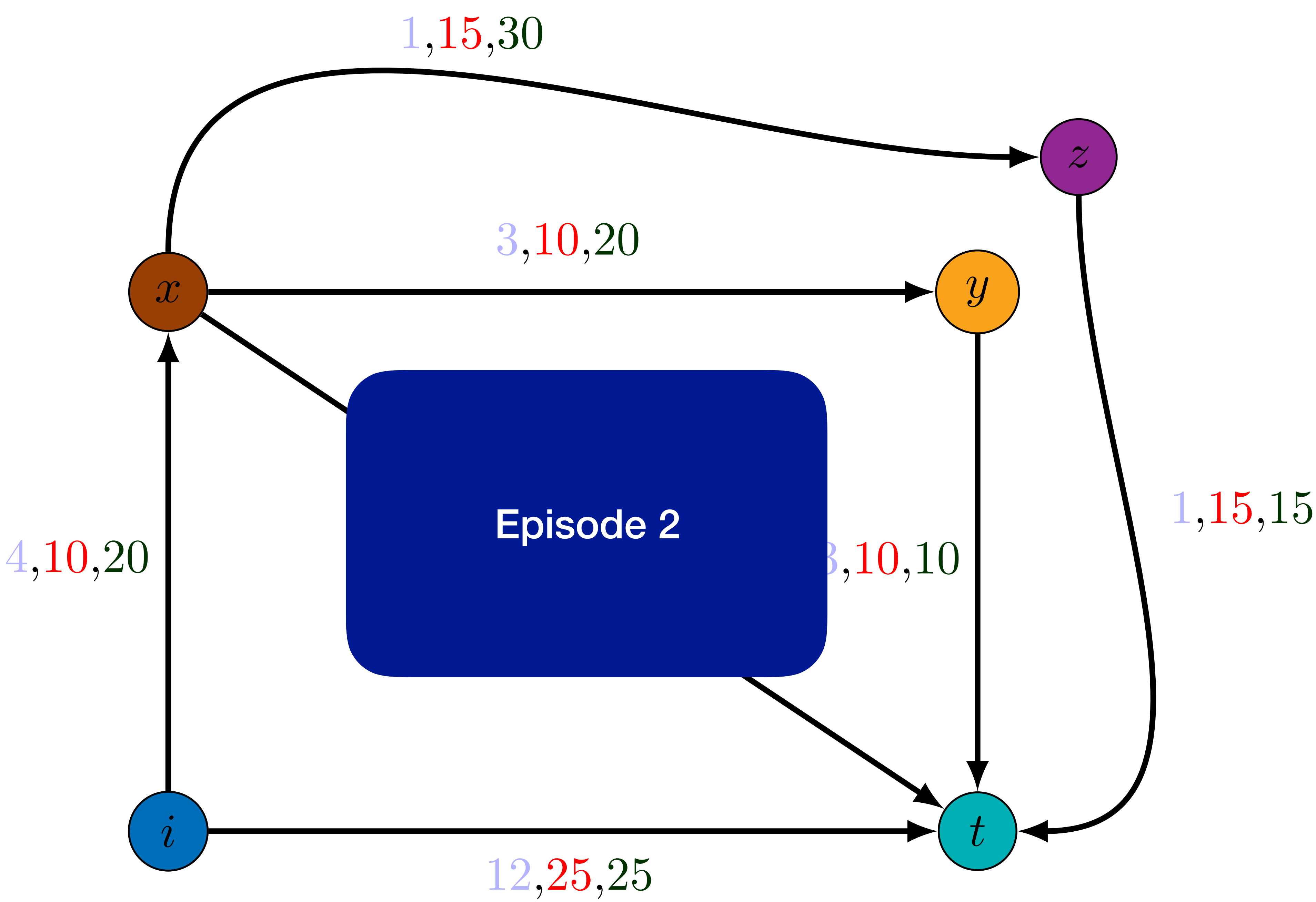

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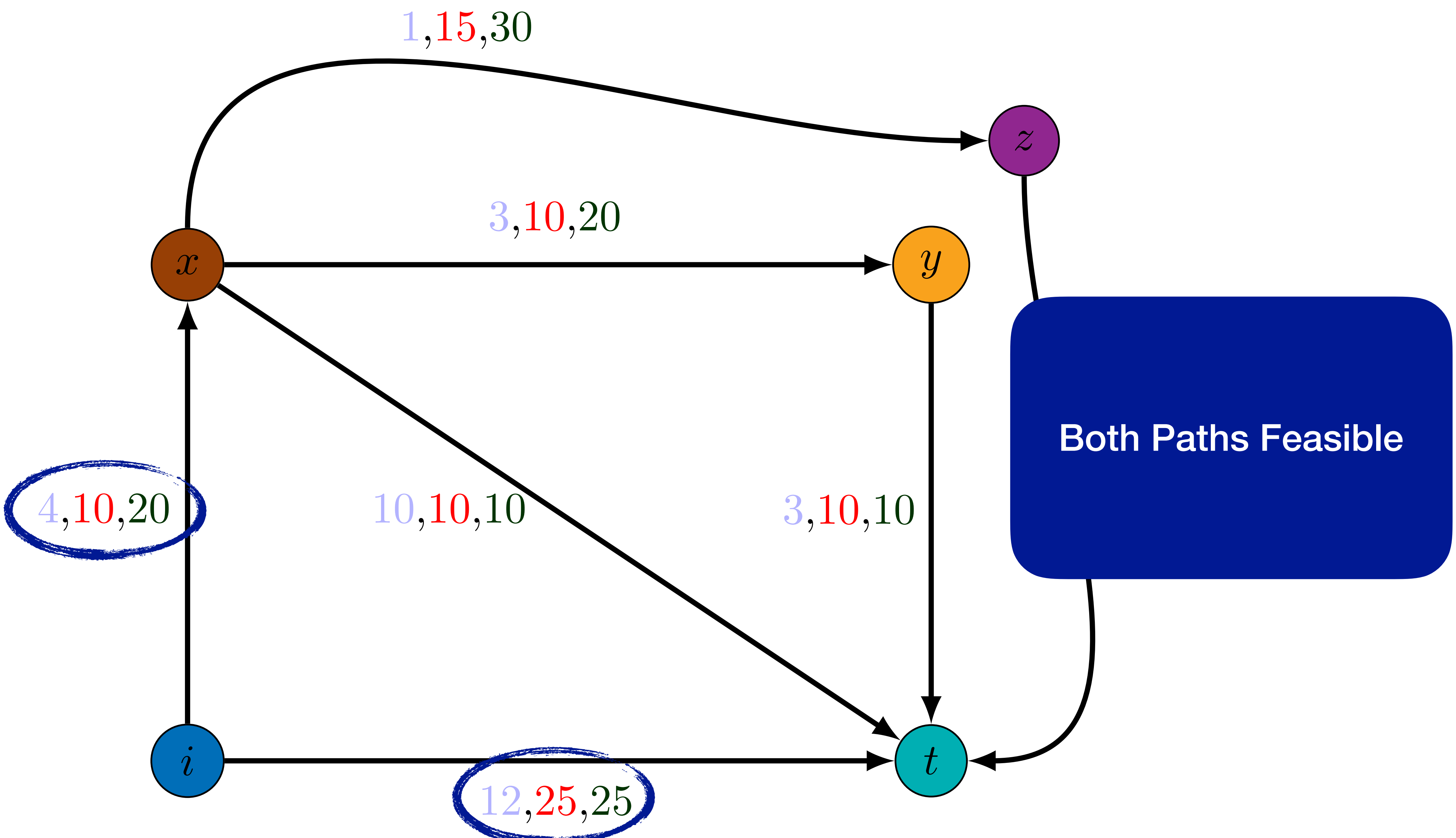
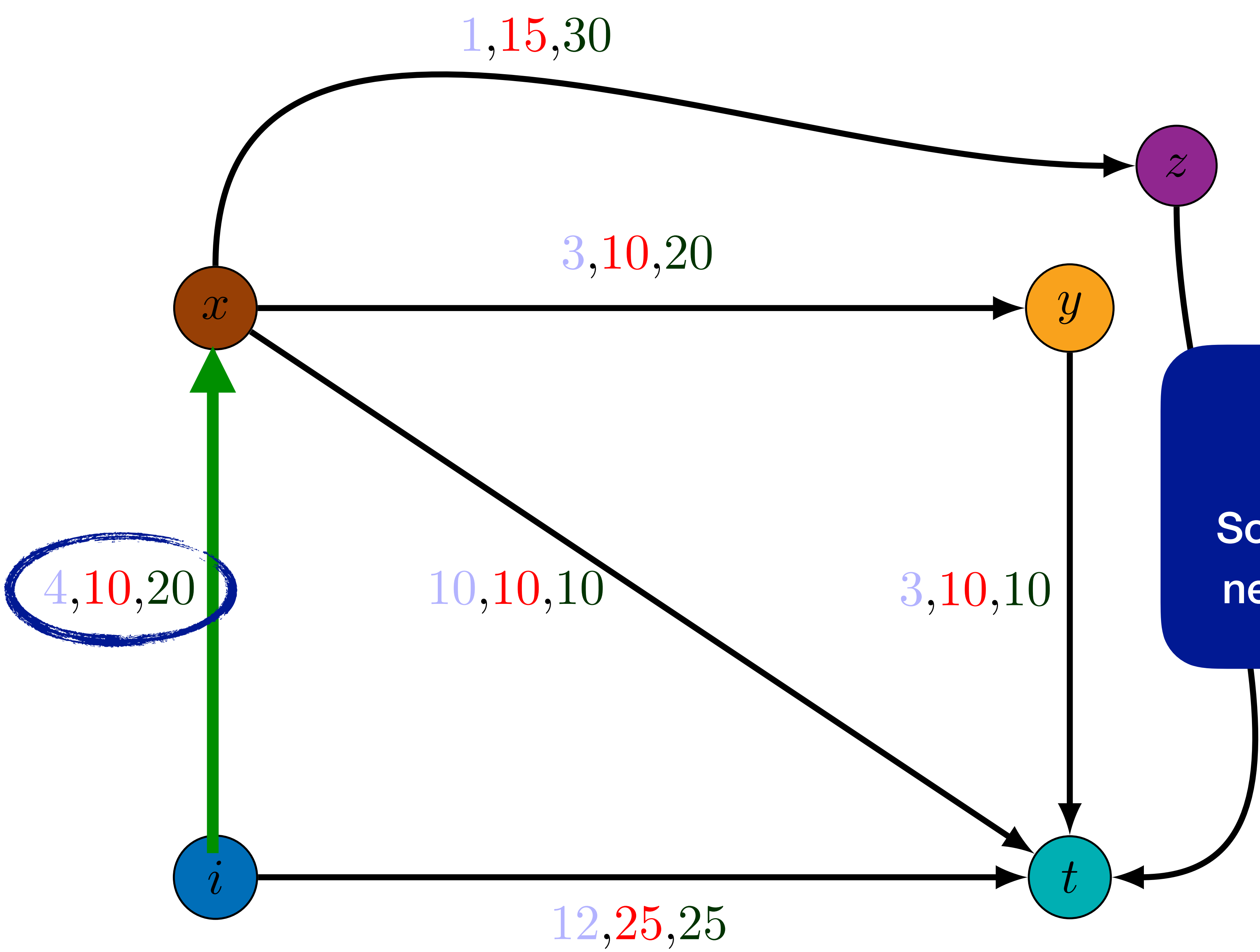


An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, -]	4

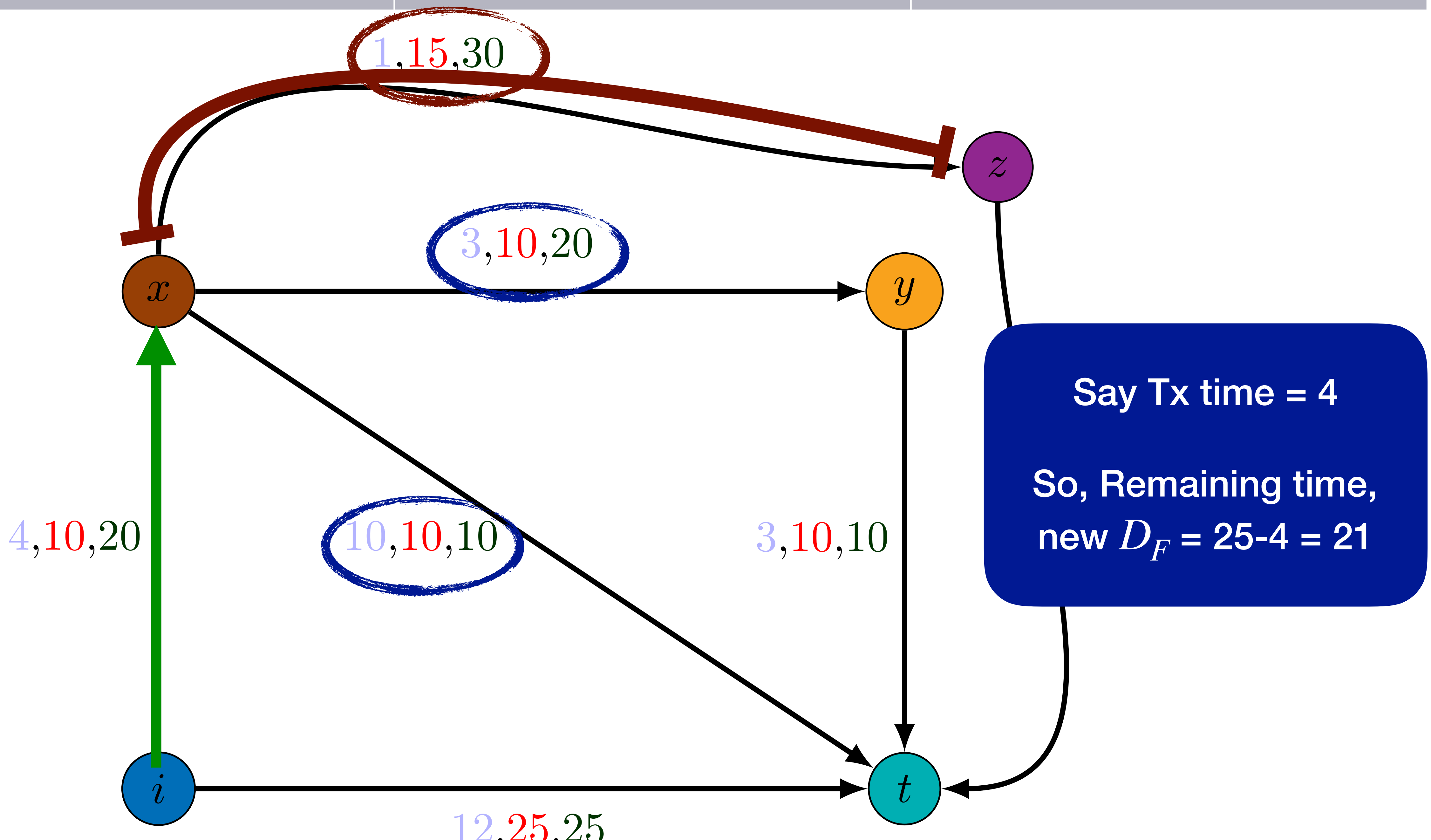


Say Tx time = 4

So, Remaining time, new D_F = 25-4 = 21

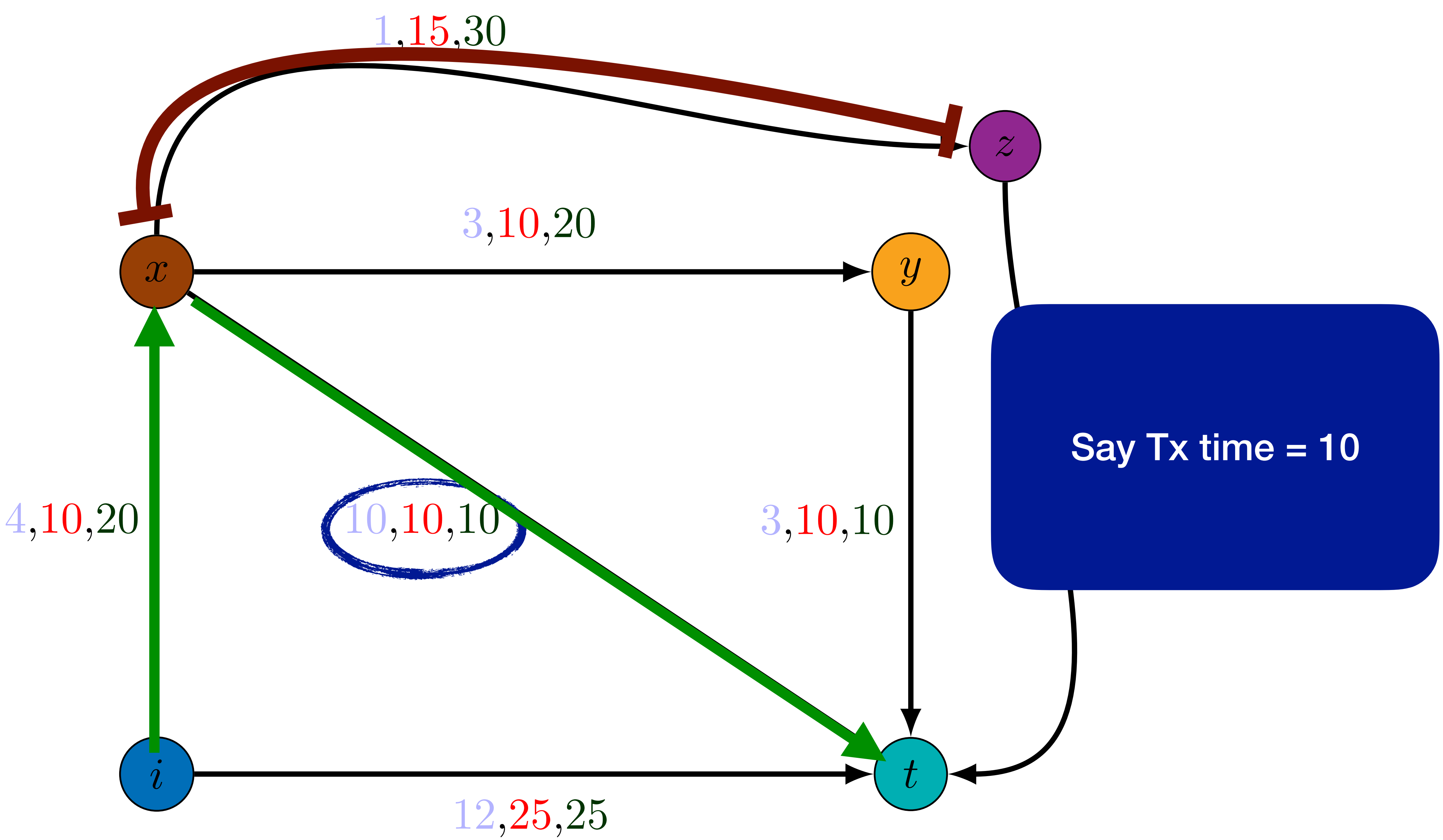
An Example. D_F = 25

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, -]	4



An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14



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Episode	Path	Transmission Time
1	[i, t]	12
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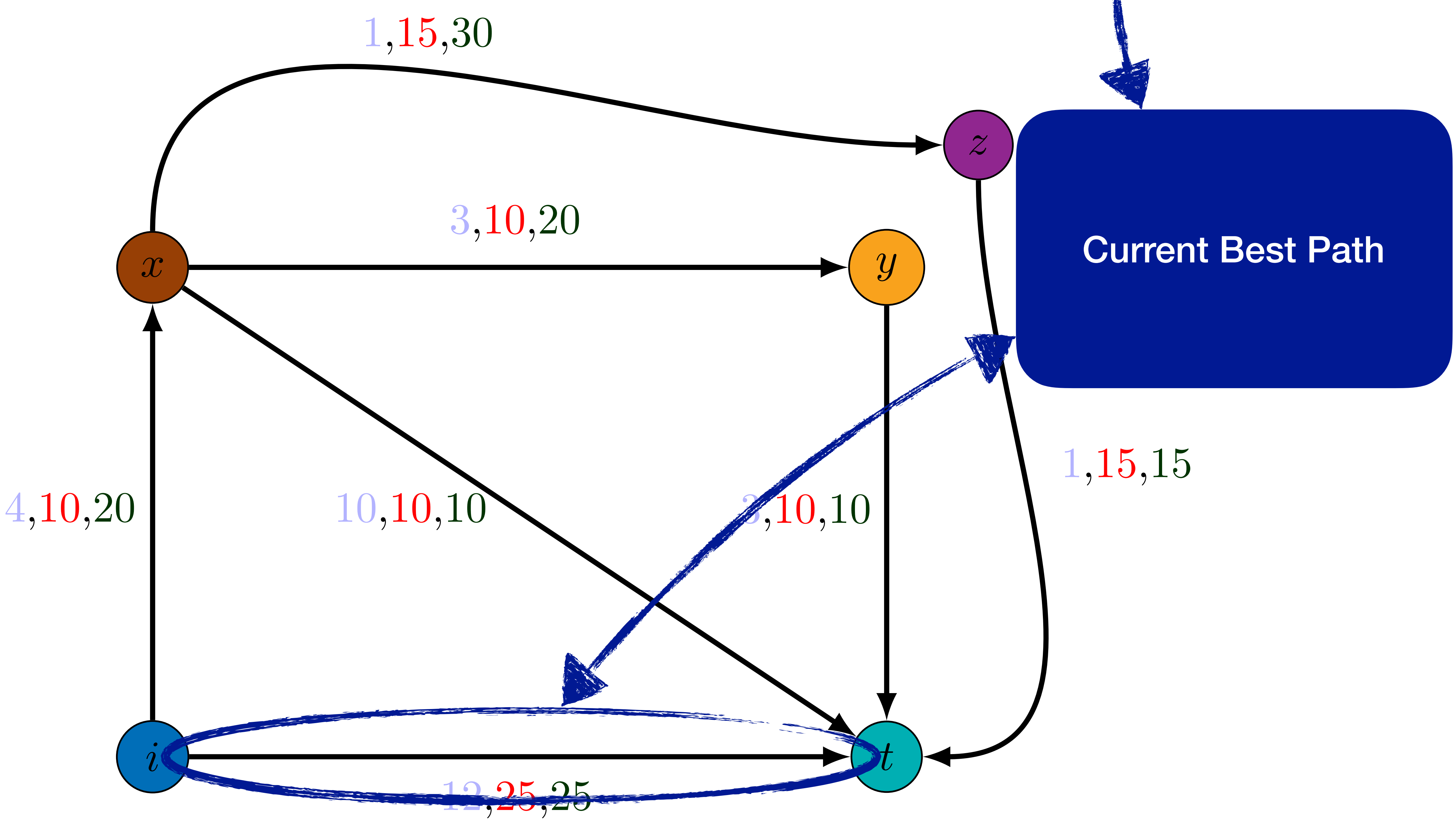
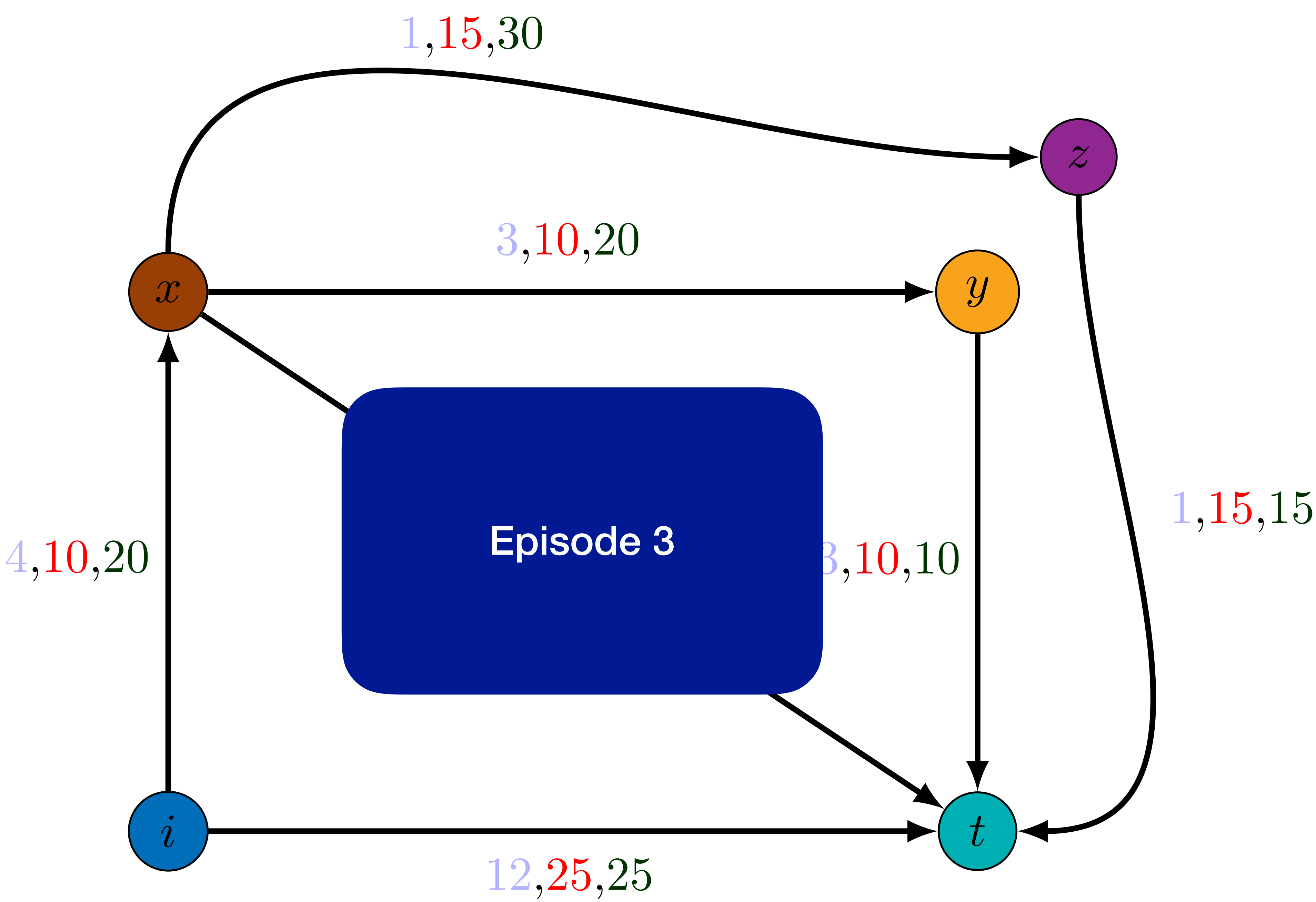


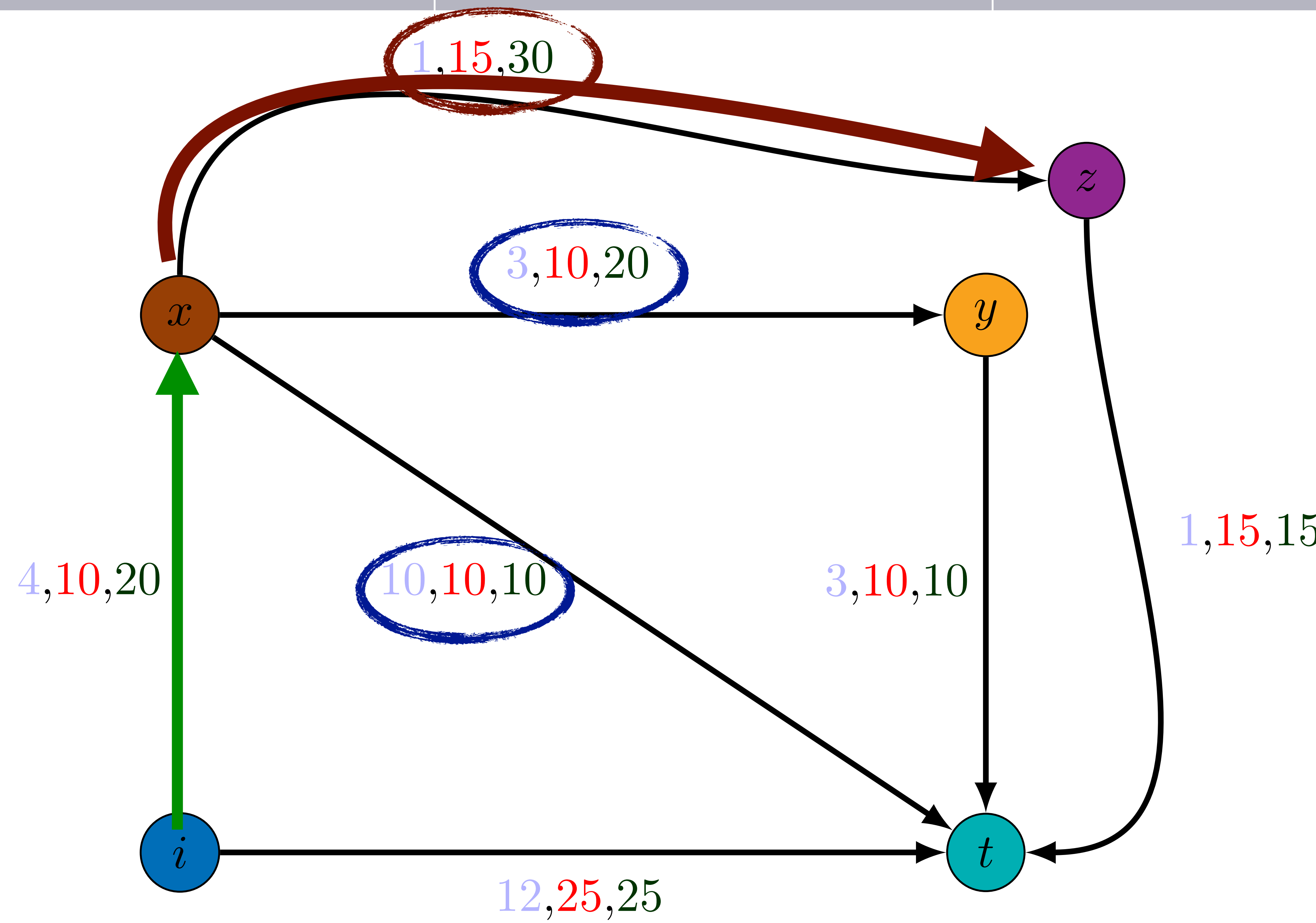
An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14



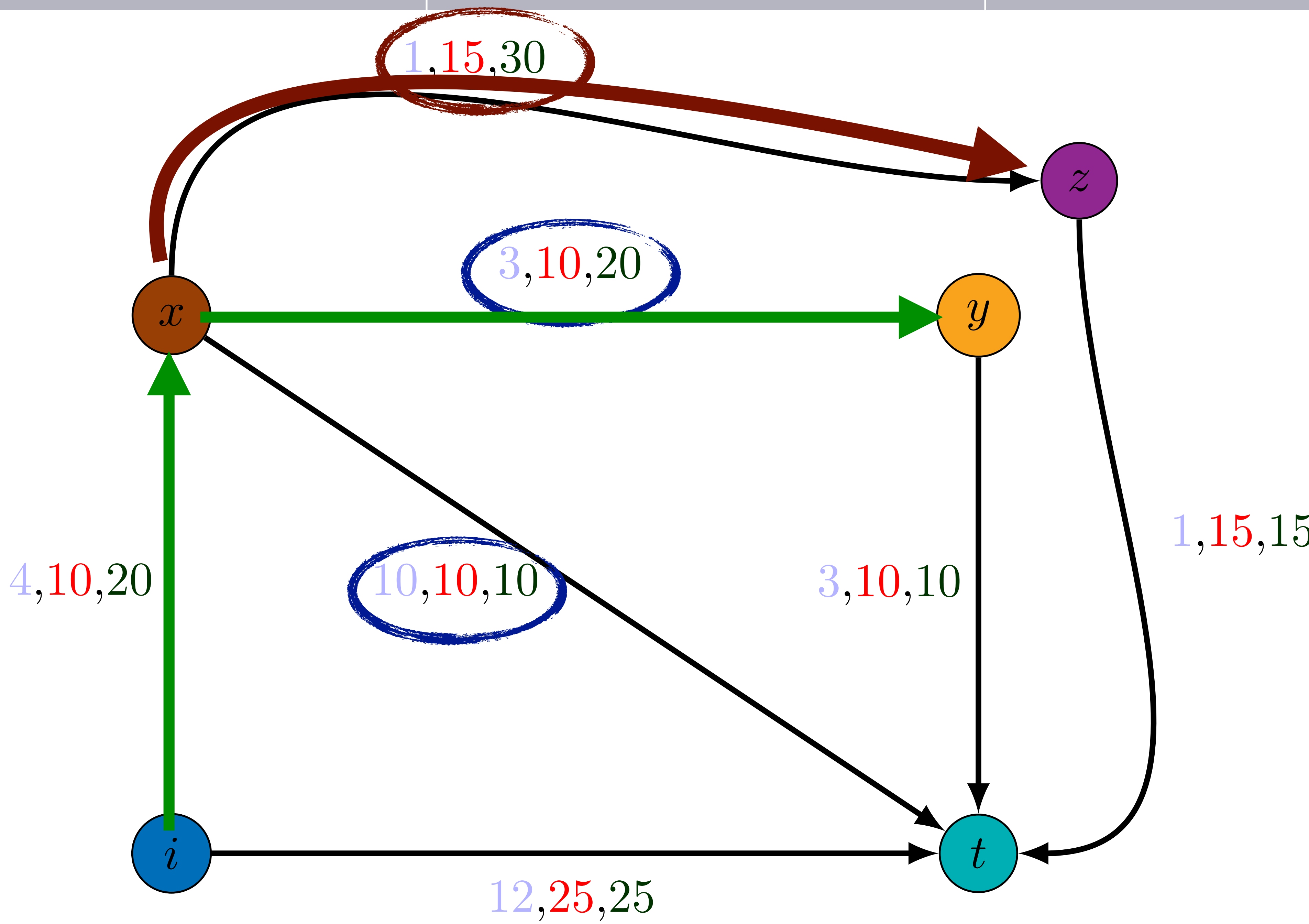
An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14
3	[i, x, -]	4



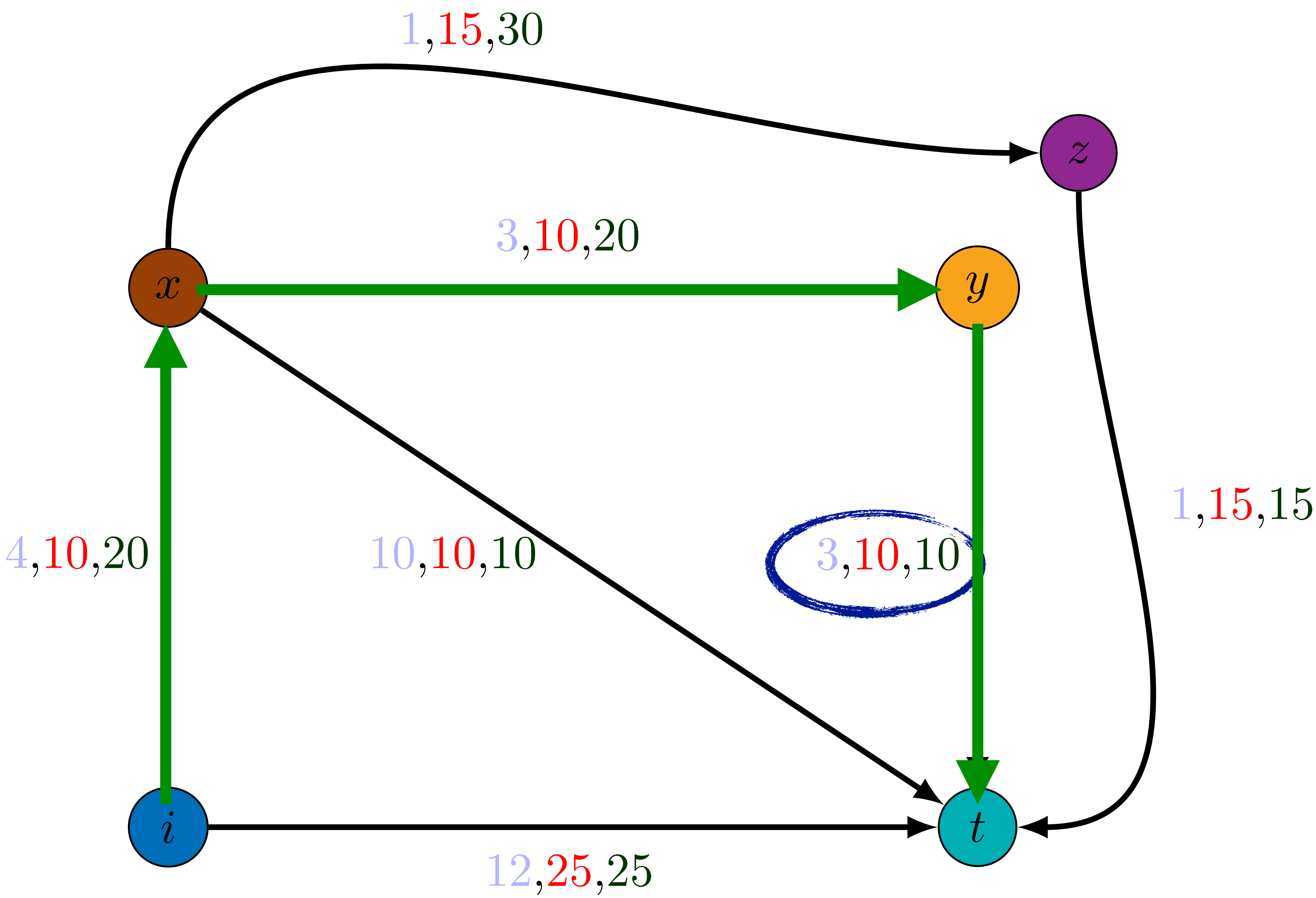
An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14
3	[i, x, y]	7



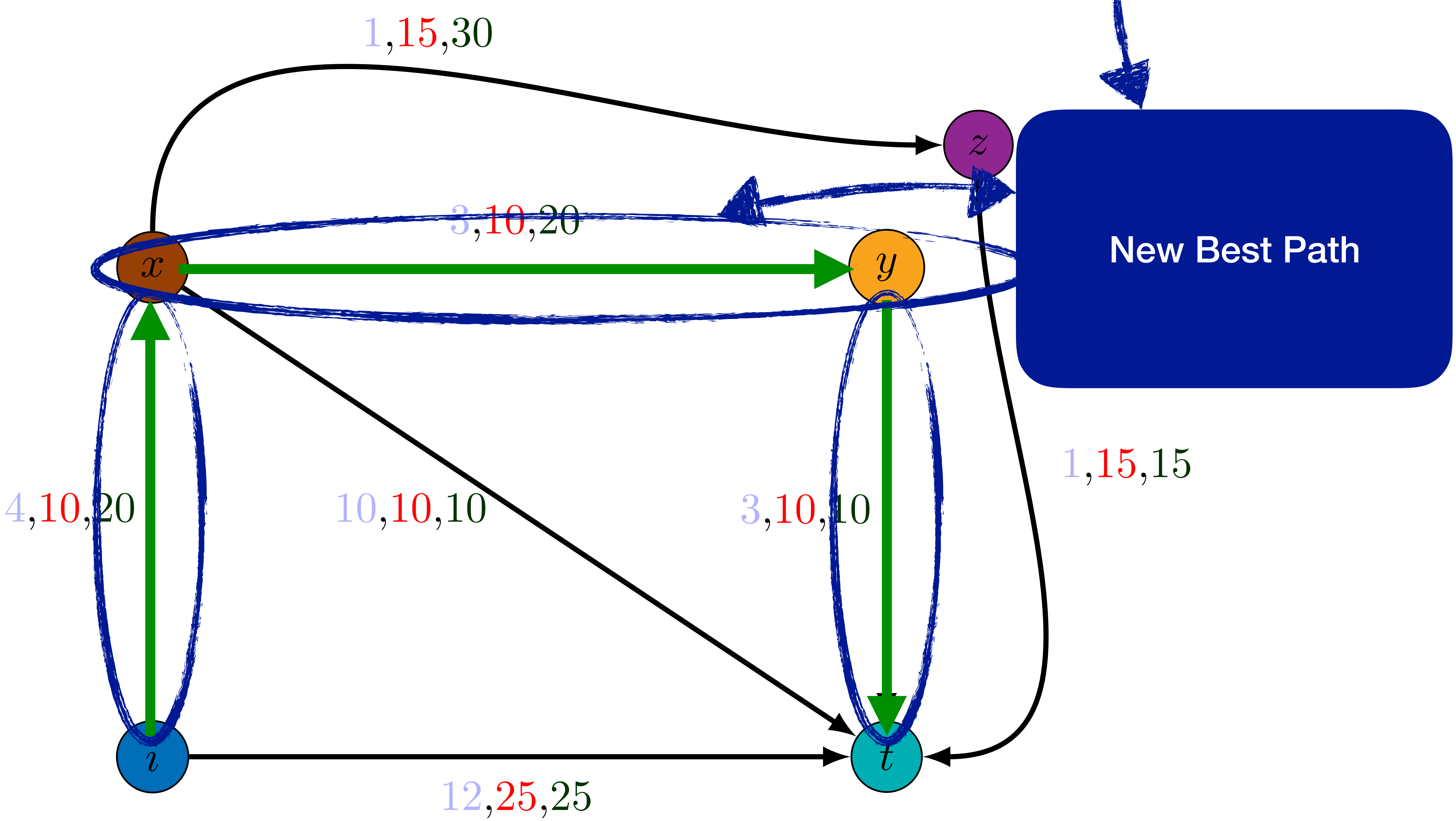
An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14
3	[i, x, y, t]	10



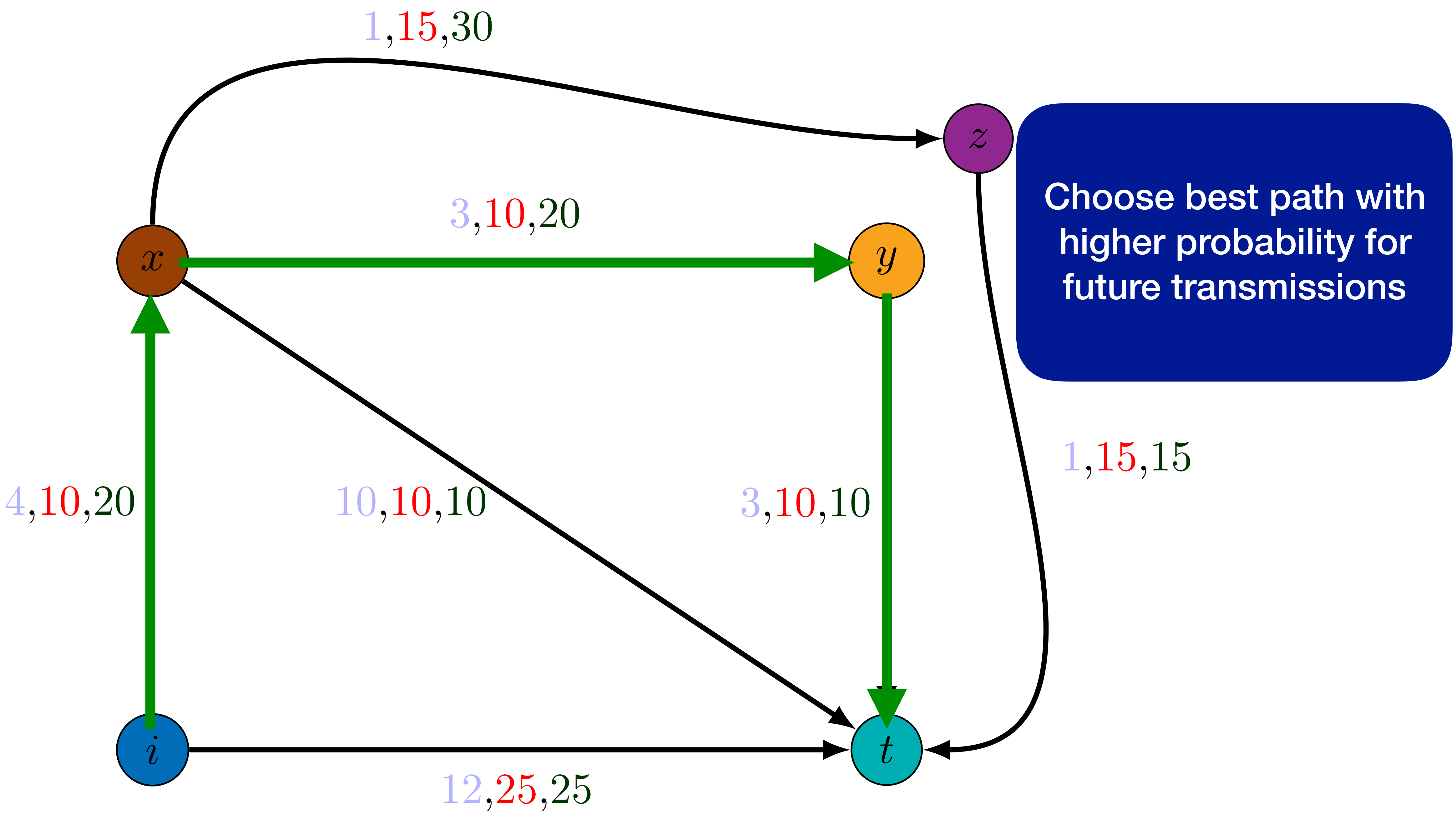
An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14
3	[i, x, y, t]	10



An Example. $D_F = 25$

Episode	Path	Transmission Time
1	[i, t]	12
2	[i, x, t]	14
3	[i, x, y, t]	10
4	[i, x, y, t]	10



Evaluation

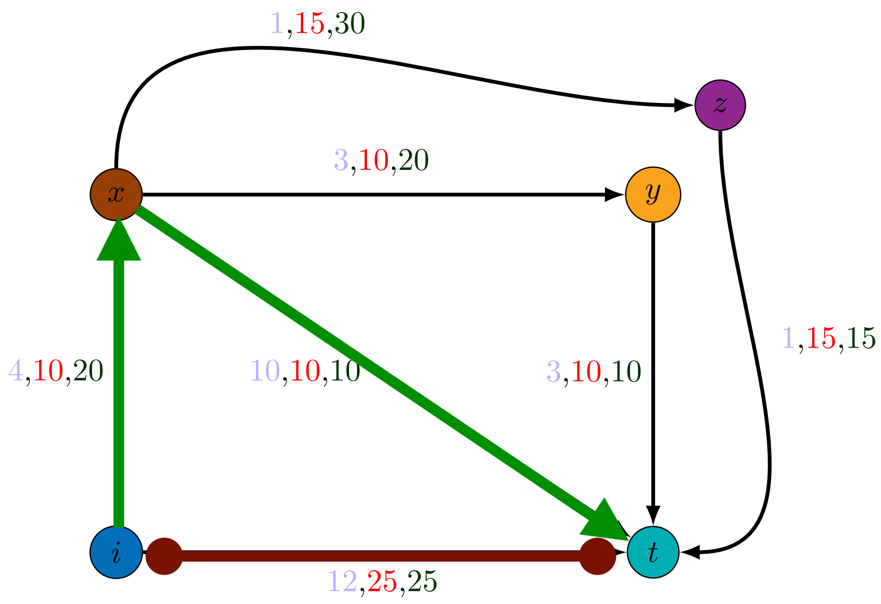
- Implemented using NetworkX[1]
- Python graph generator package
- Compare our algorithm to Rapid Routing[2] and classical RL

[1] Aric A. Hagberg, Daniel A. Schult and Pieter J. Swart, "Exploring network structure, dynamics, and function using NetworkX"

[2] S. Baruah, "Rapid routing with guaranteed delay bounds," in 2018 IEEE Real-Time Systems Symposium (RTSS) , December 2018

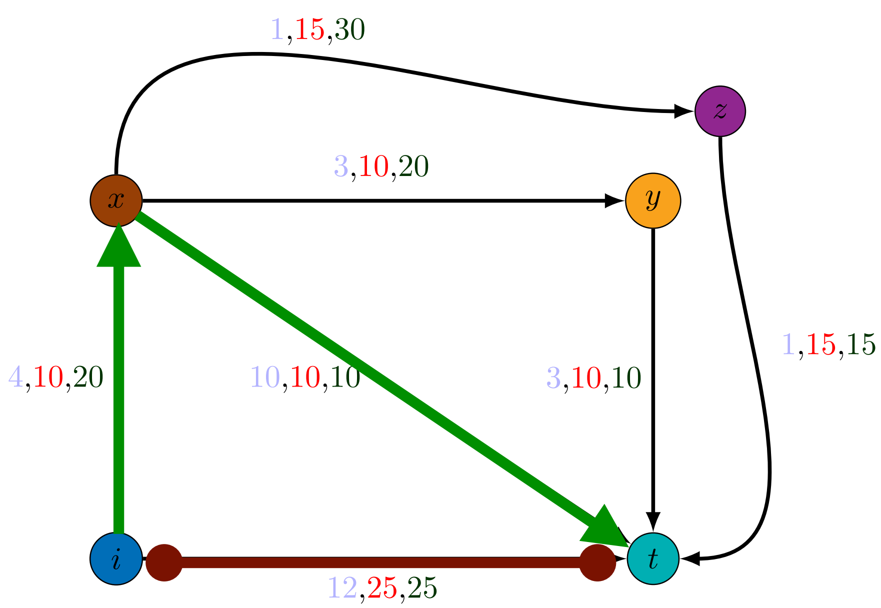
Deadline	Path	No Variance Tx Time
20	[i, x, t]	14

D_F = **20**

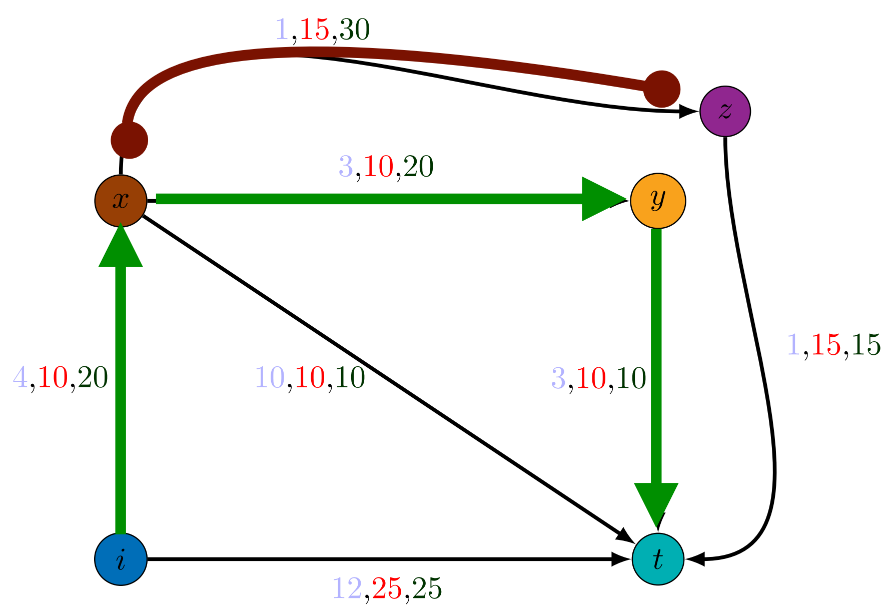


Deadline	Path	No Variance Tx Time
20	[i, x, t]	14
25	[i, x, y, t]	10

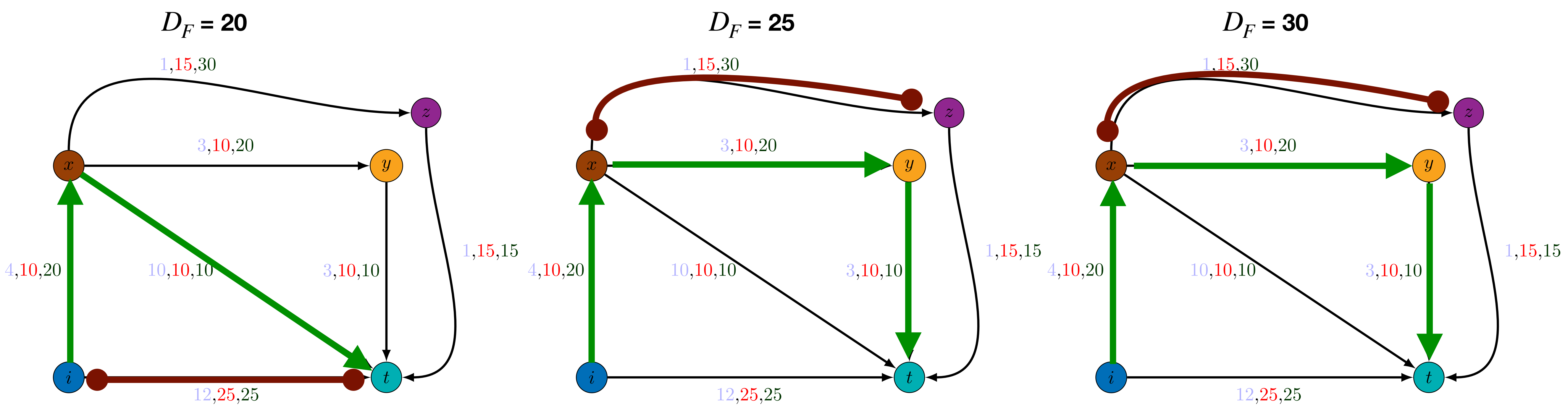
D_F = **20**



D_F = **25**

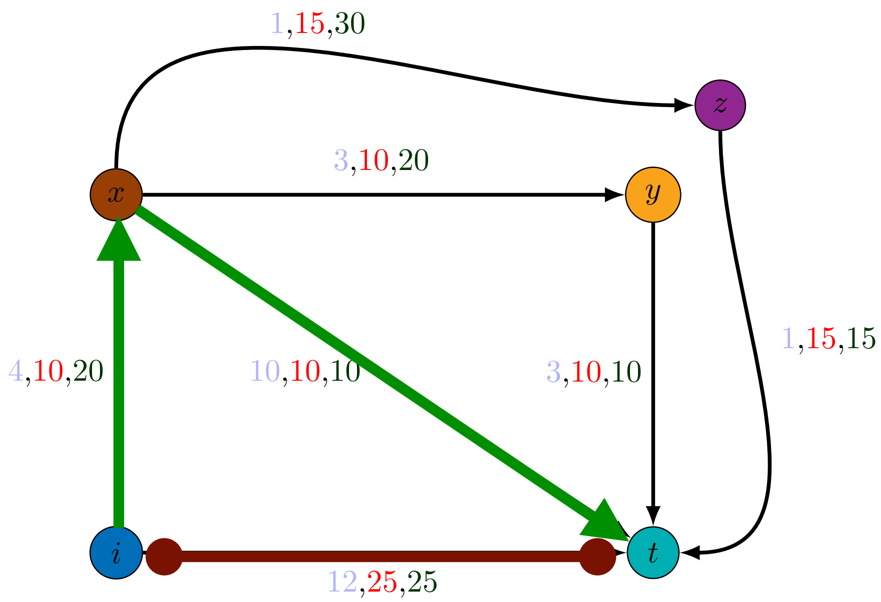


Deadline	Path	No Variance Tx Time
20	[i, x, t]	14
25	[i, x, y, t]	10
30	[i, x, y, t]	10

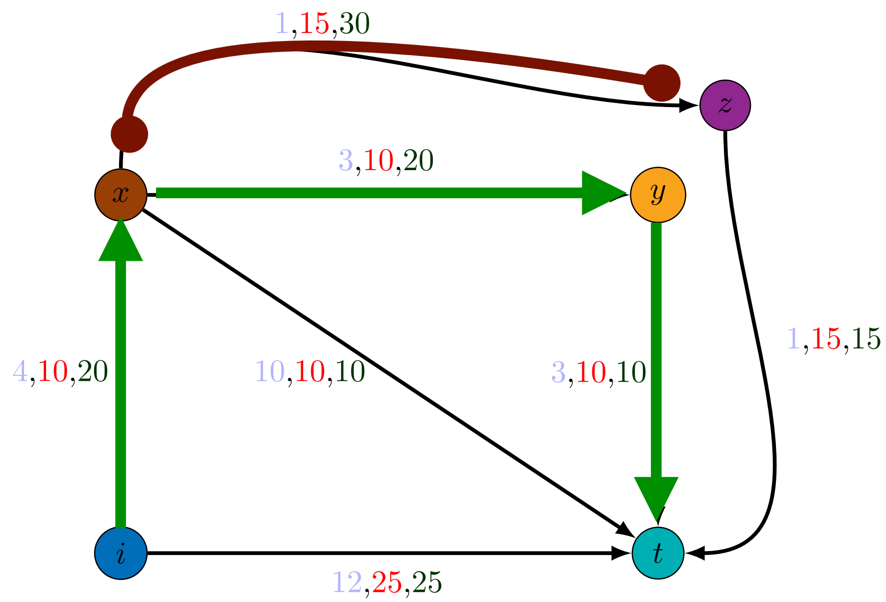


Deadline	Path	No Variance Tx Time
20	[i, x, t]	14
25	[i, x, y, t]	10
30	[i, x, y, t]	10
35	[i, x, z, t]	6

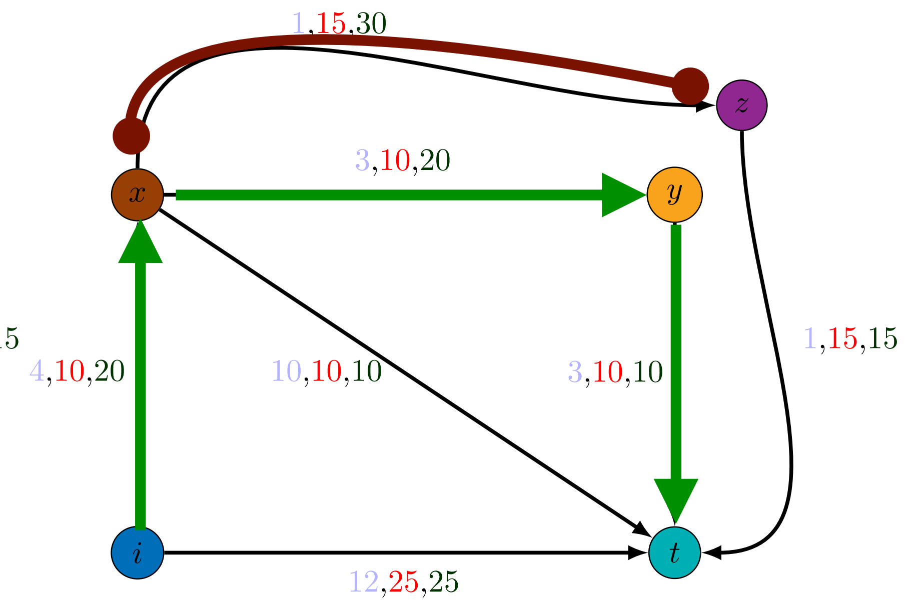
D_F = **20**



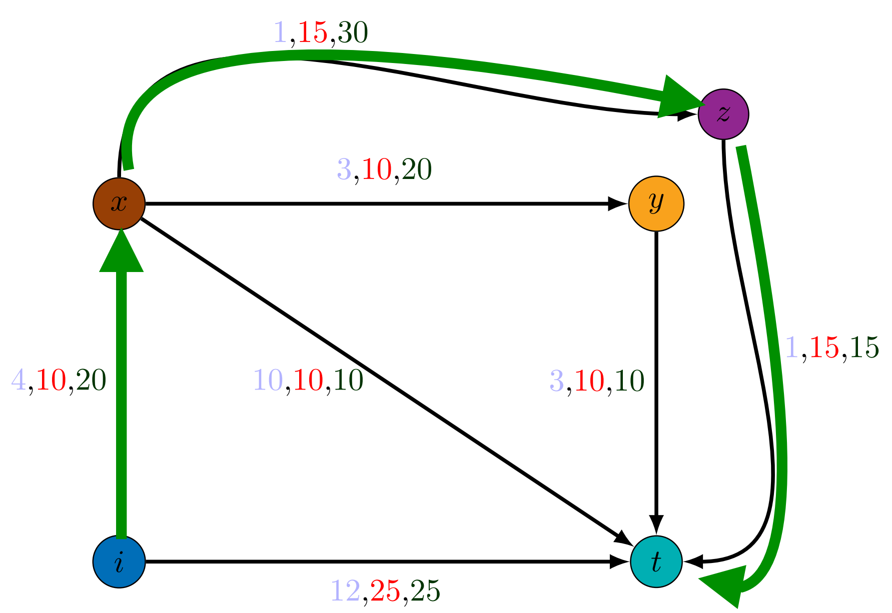
D_F = **25**



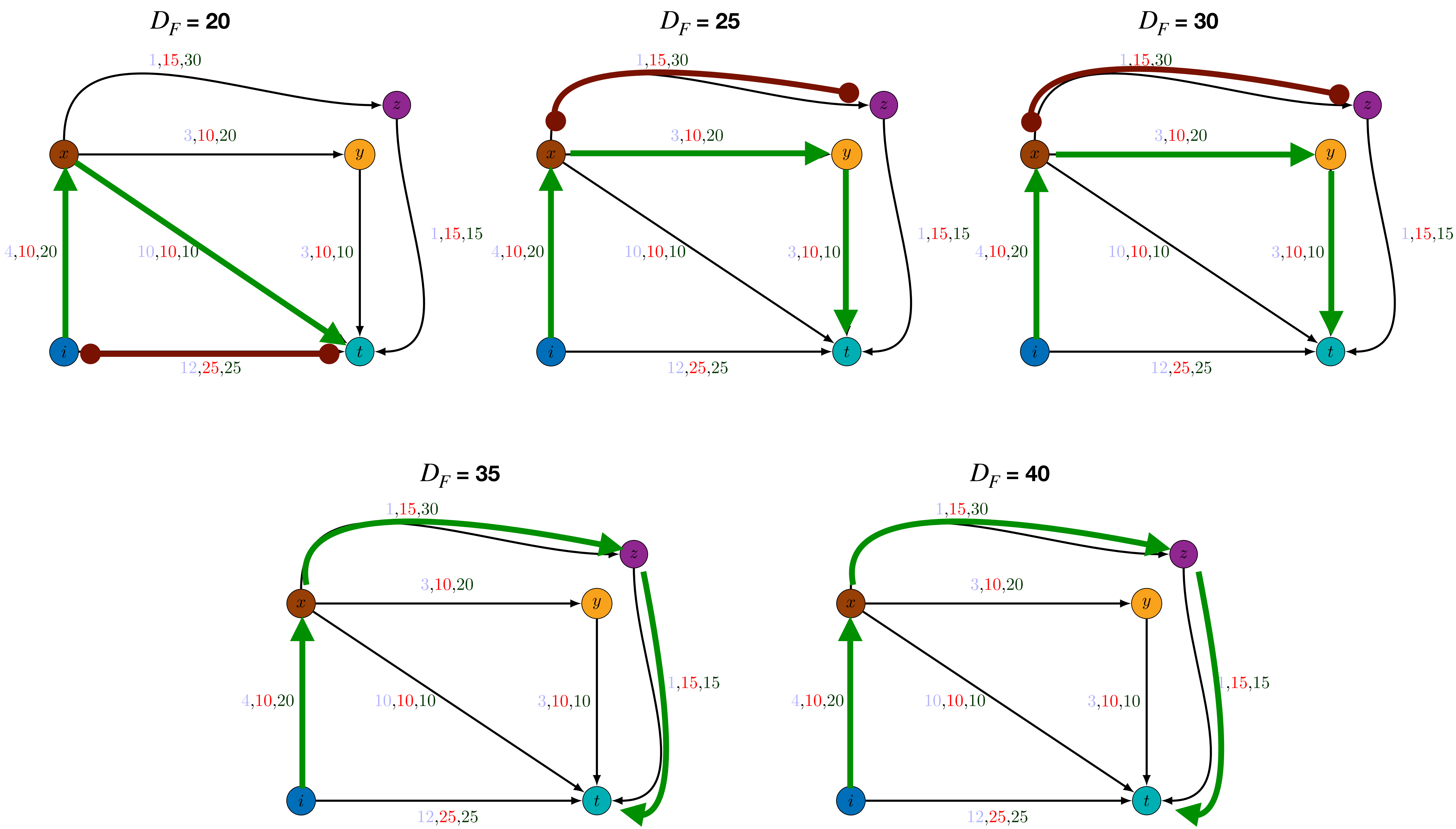
D_F = **30**



D_F = **35**



Deadline	Path	No Variance Tx Time
20	[i, x, t]	14
25	[i, x, y, t]	10
30	[i, x, y, t]	10
35	[i, x, z, t]	6
40	[i, x, z, t]	6



Experiment 1: No Variance. $\delta = c_{xy}^{T}$

- No Variance in the typical transmission times

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- Paths taken by both Rapid Routing and Safe RL converge to the same

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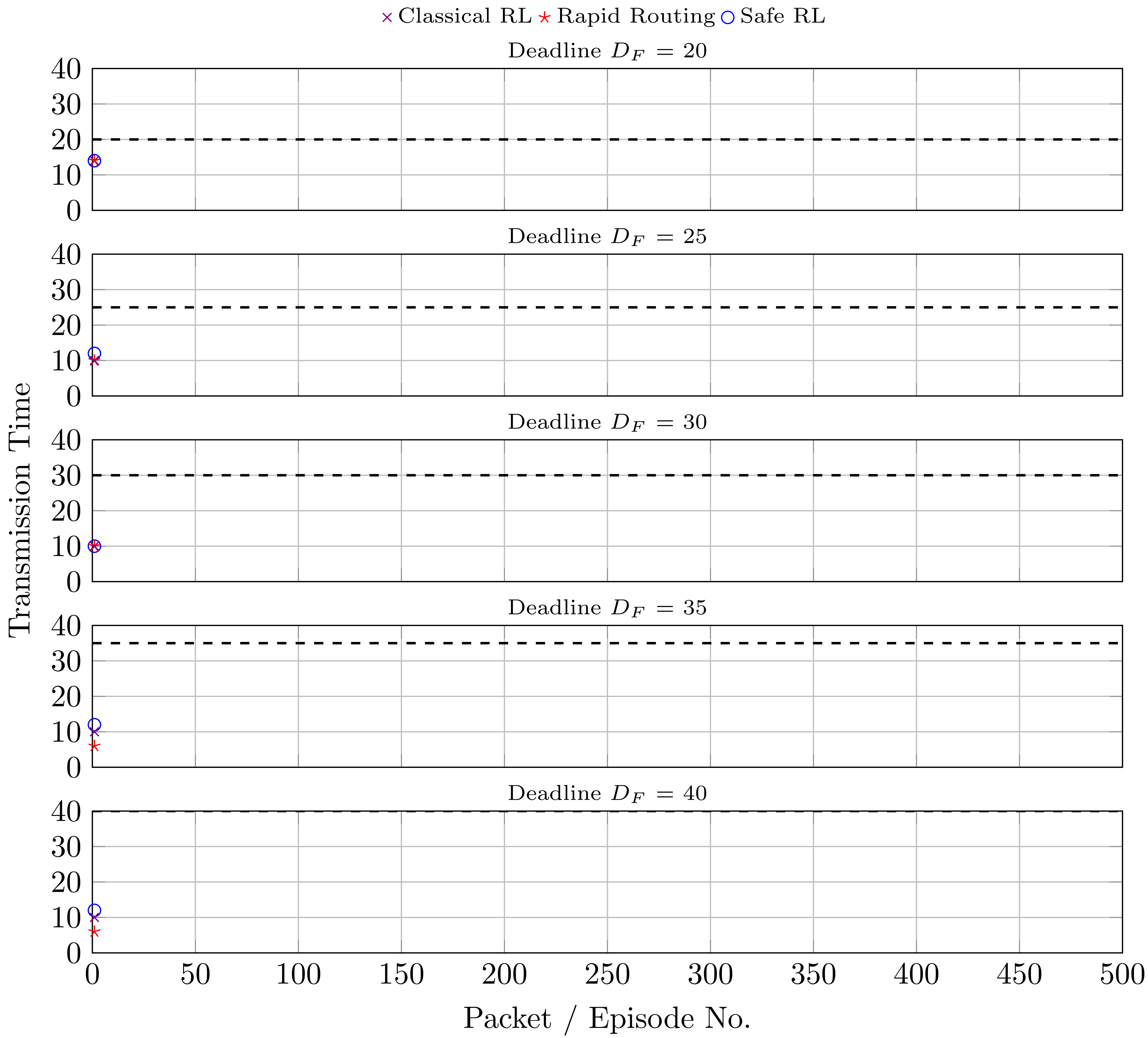
- No Variance in the typical transmission times
- Paths taken by both Rapid Routing and Safe RL converge to the same
- Average delays are slightly higher for Safe RL due to exploration

Table 1: Optimal Path for Different Deadlines

D_F	Optimal Path	Delays, Rapid Routing	Average Delays (1000 episodes)
15	Infeasible	-	-
20	{i,x,t}	14	14
25	{i,x,y,t}	10	10.24
30	{i,x,y,t}	10	10.22
35	{i,x,z,t}	6	6.64
40	{i,x,z,t}	6	6.55

Experiment 1: No Variance. $\delta = c_{xy}^T$



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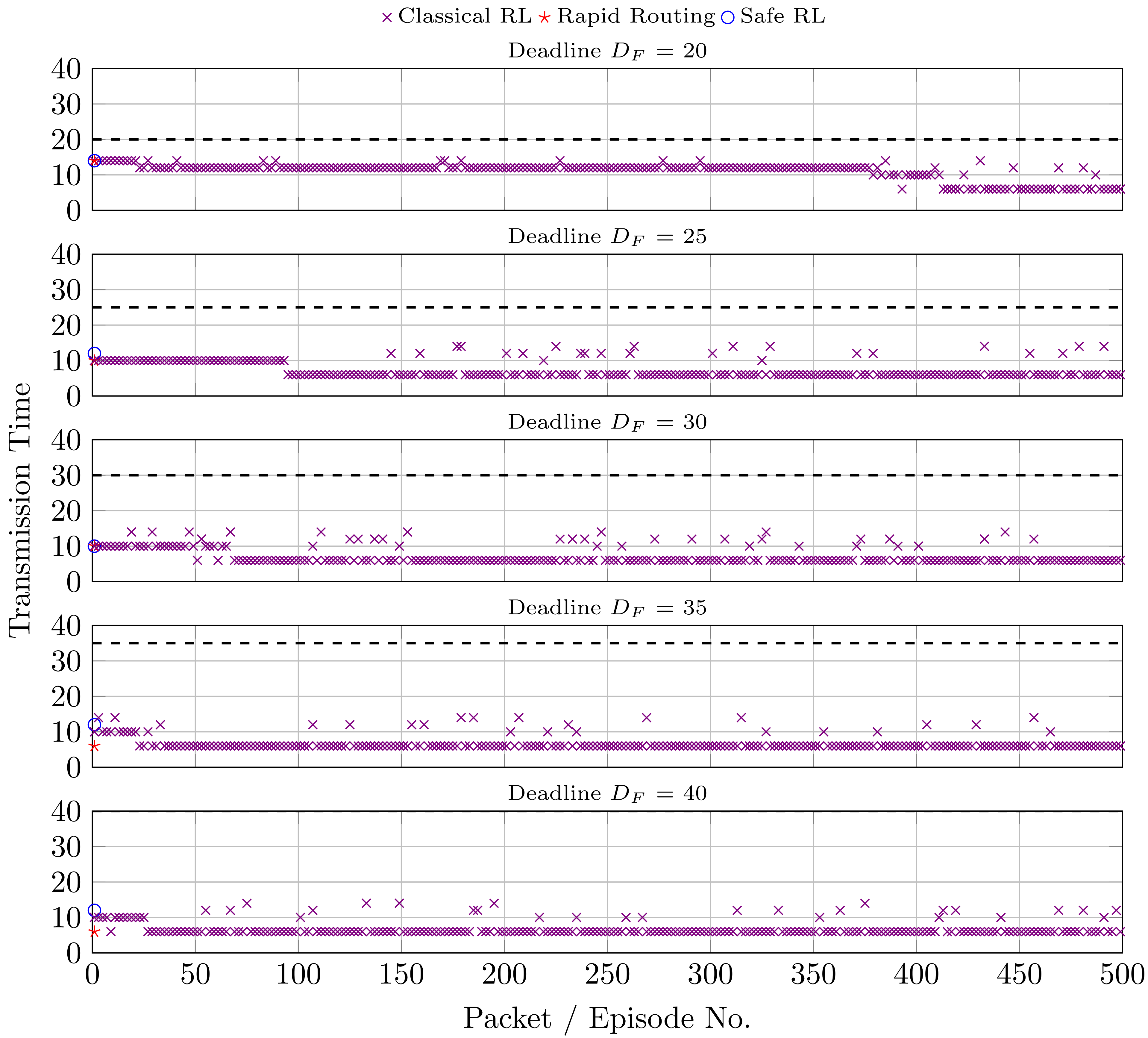
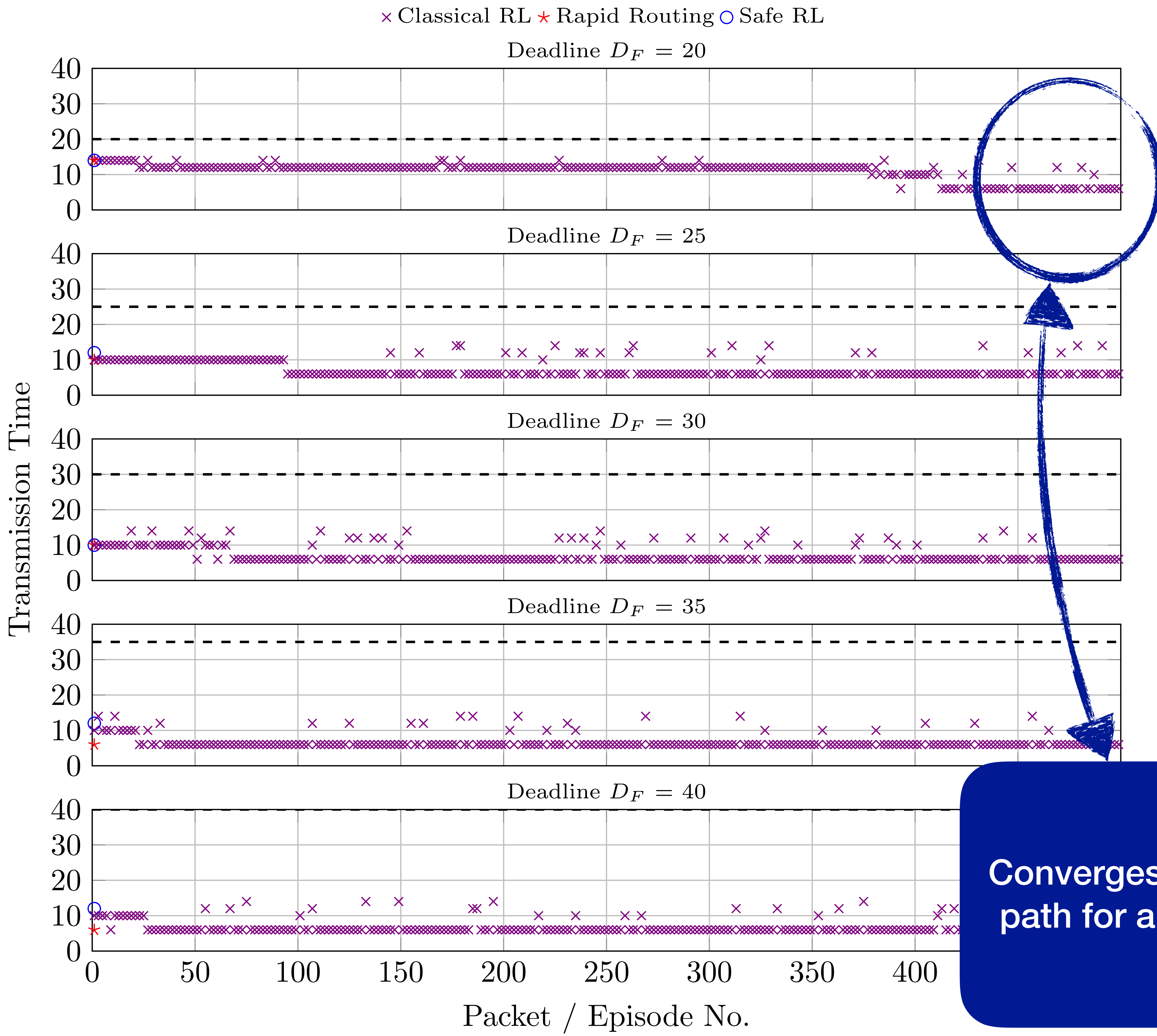
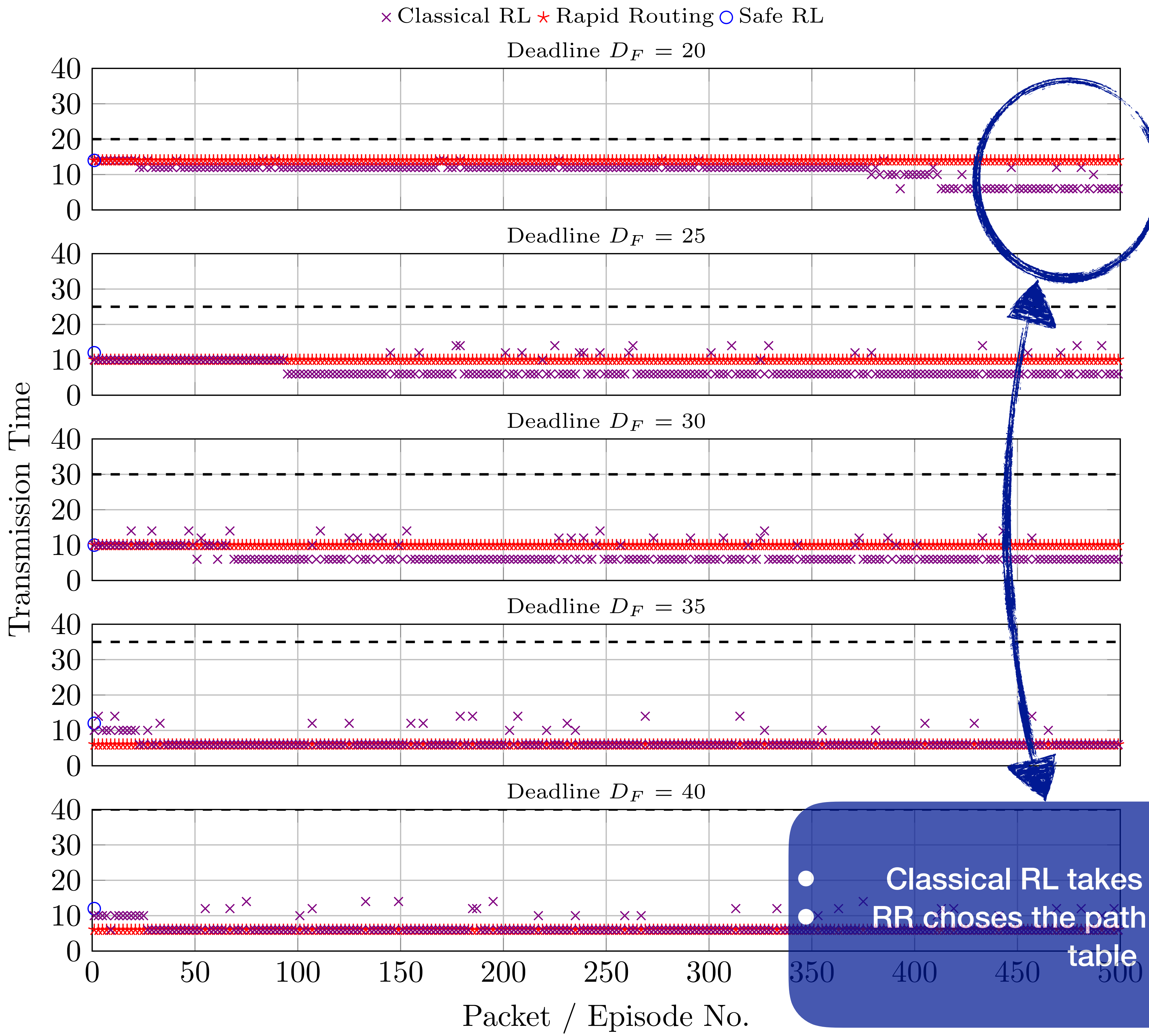


Experiment 1: No Variance. $\delta = c_{xy}^{T}$



Converges to the best path for all deadlines

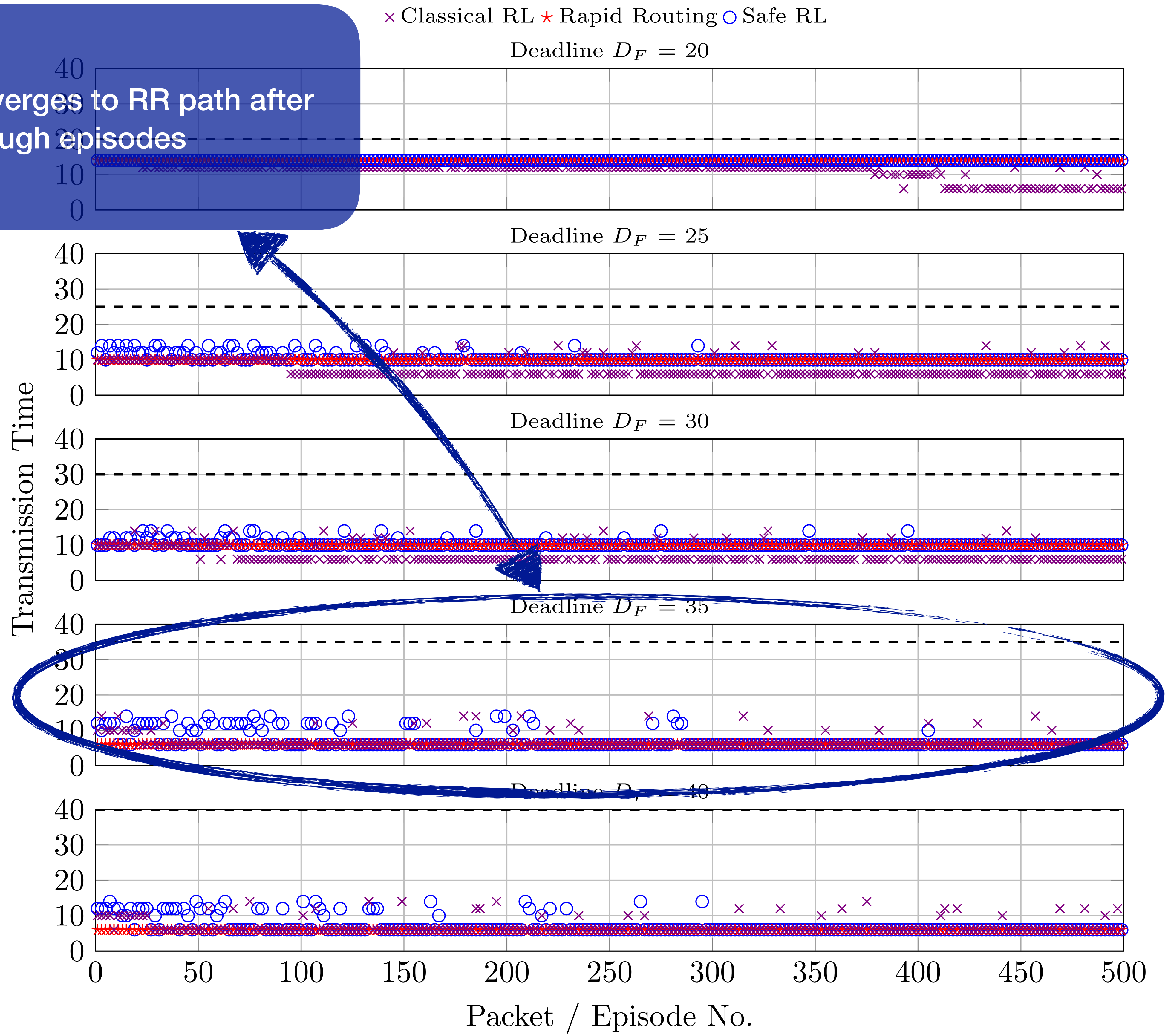
Experiment 1: No Variance. $\delta = c_{xy}^T$



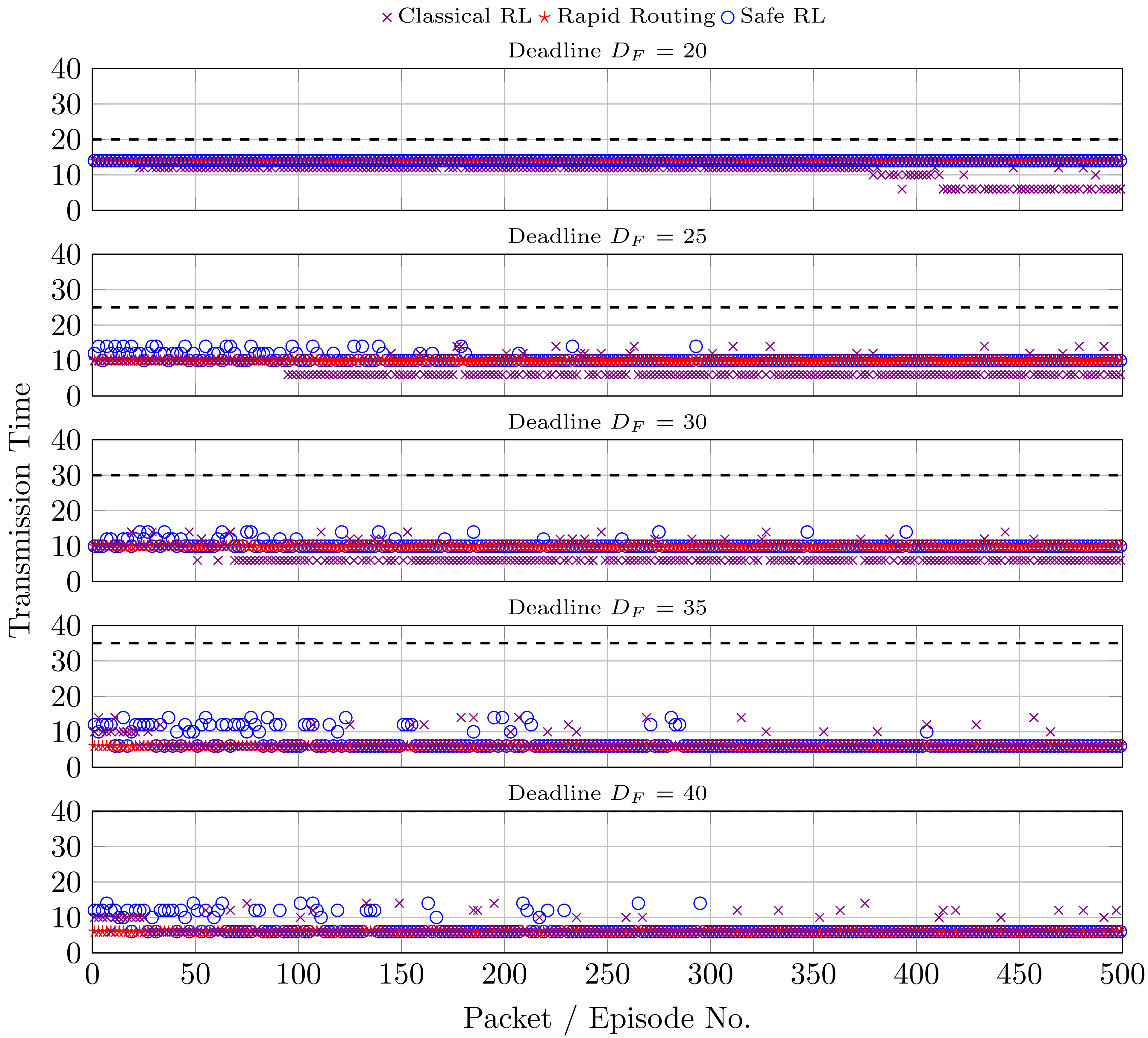
- Classical RL takes unsafe path
- RR choses the path according to table

Experiment 1: No Variance. $\delta = c_{xy}^T$

Safe RL converges to RR path after enough episodes



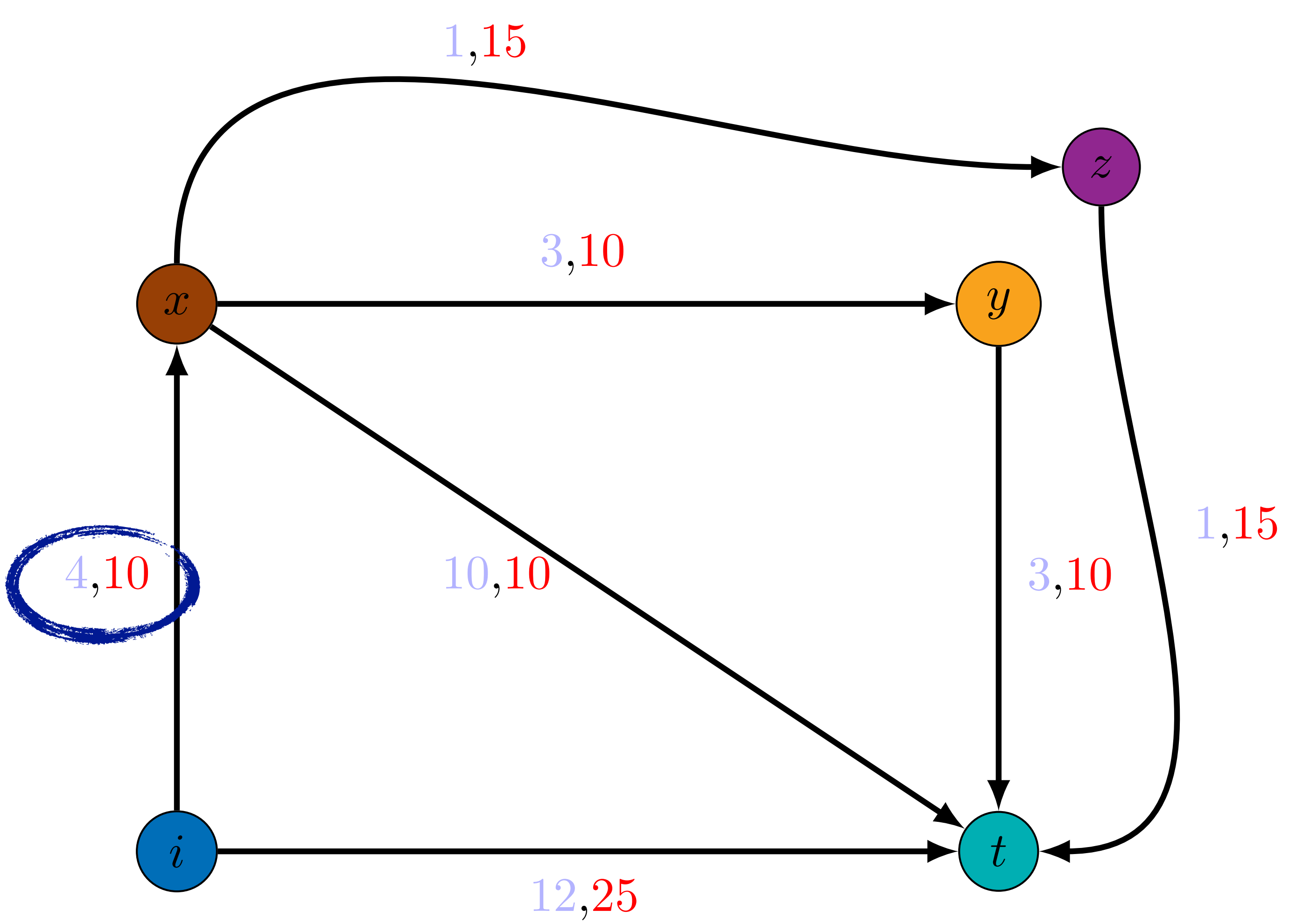
Experiment 1: No Variance. $\delta = c_{xy}^T$



Videos 1 and 2

Experiment 2: Congestion on link

- Tests the adaptability of our algorithm
- Simulate congestion of network
- At episode **40**, c_{ix}^{T} = **10** instead of c_{ix}^{T} = **4**



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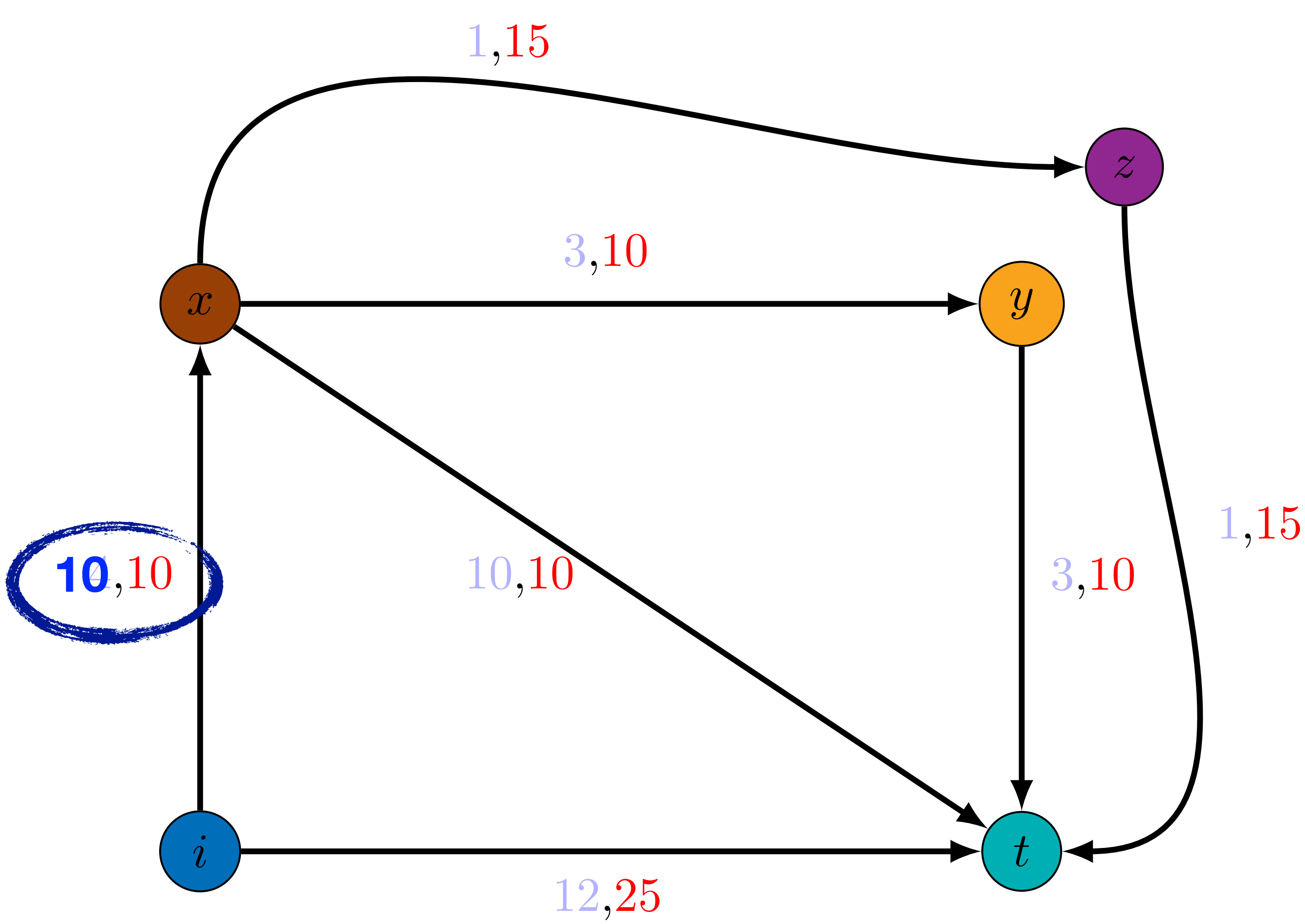
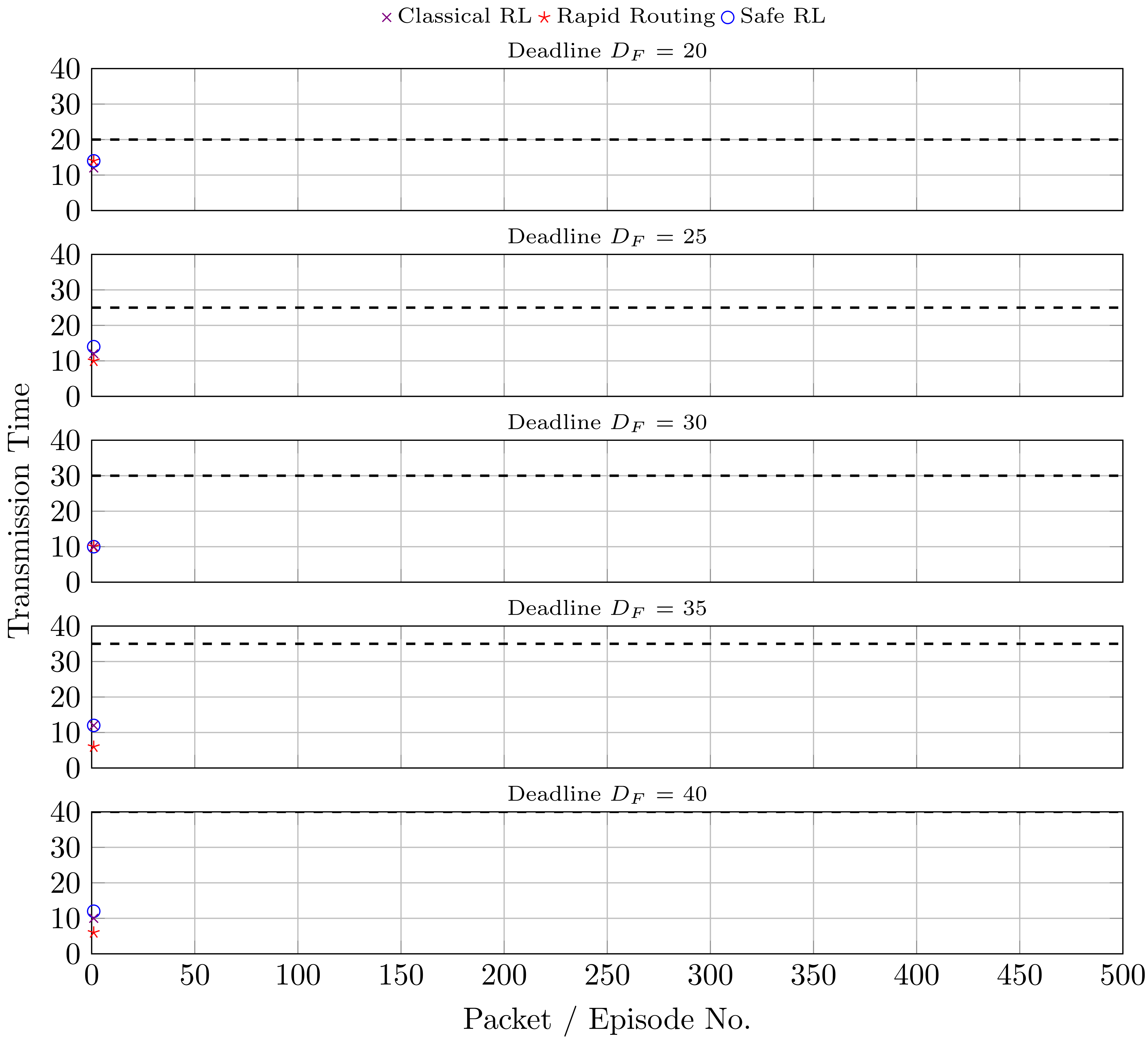


Experiment 2: Congestion on link.



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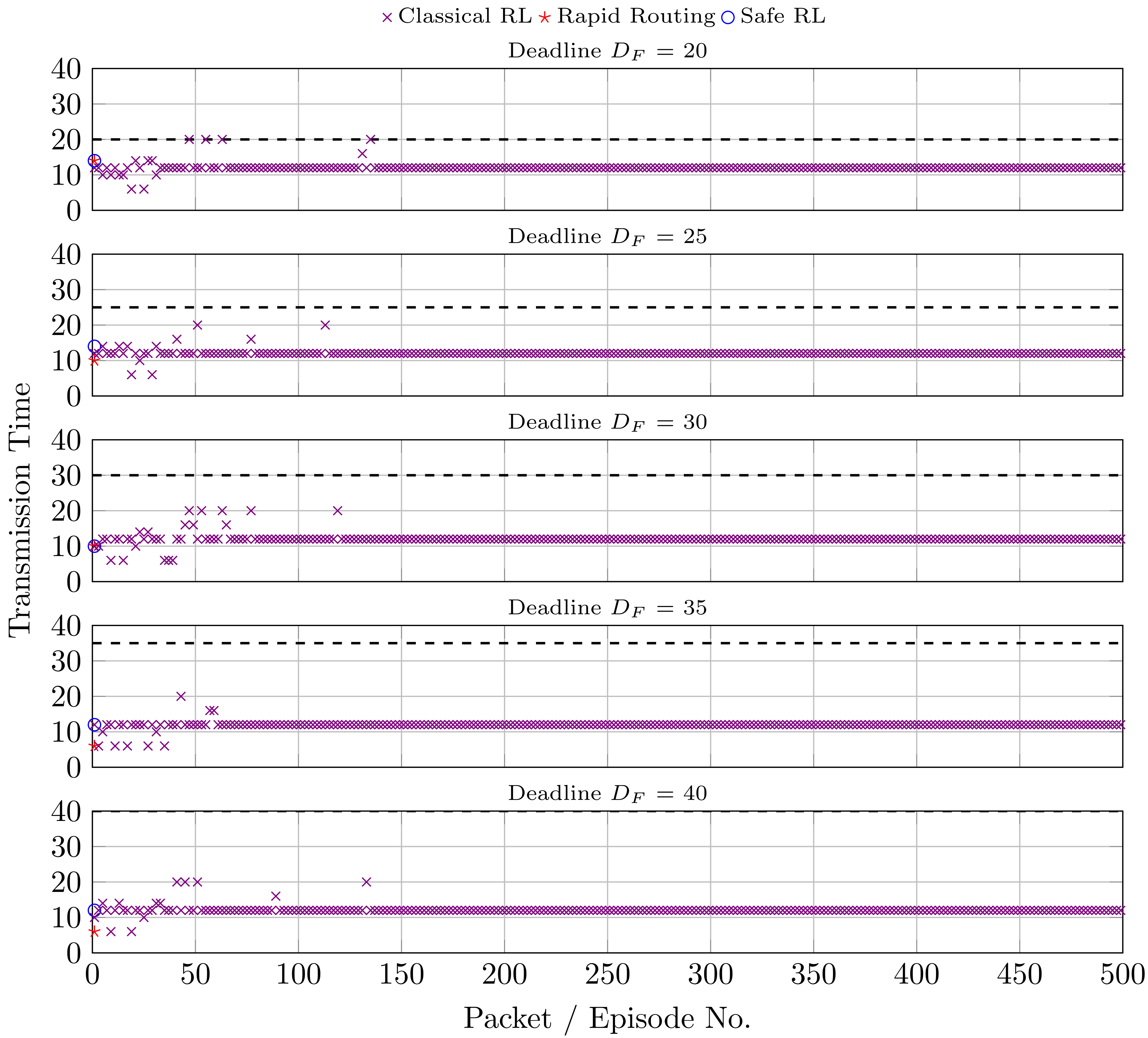

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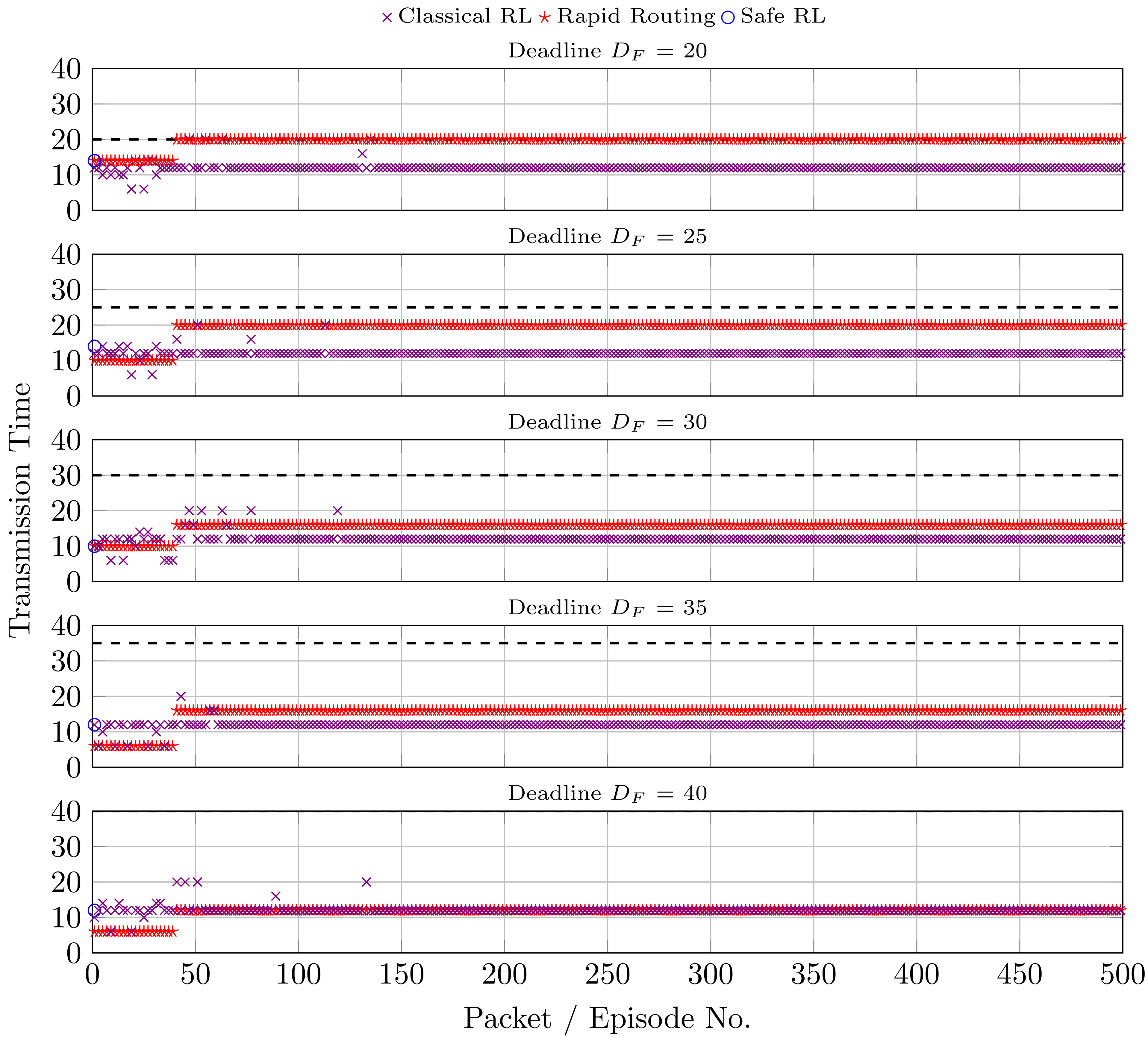

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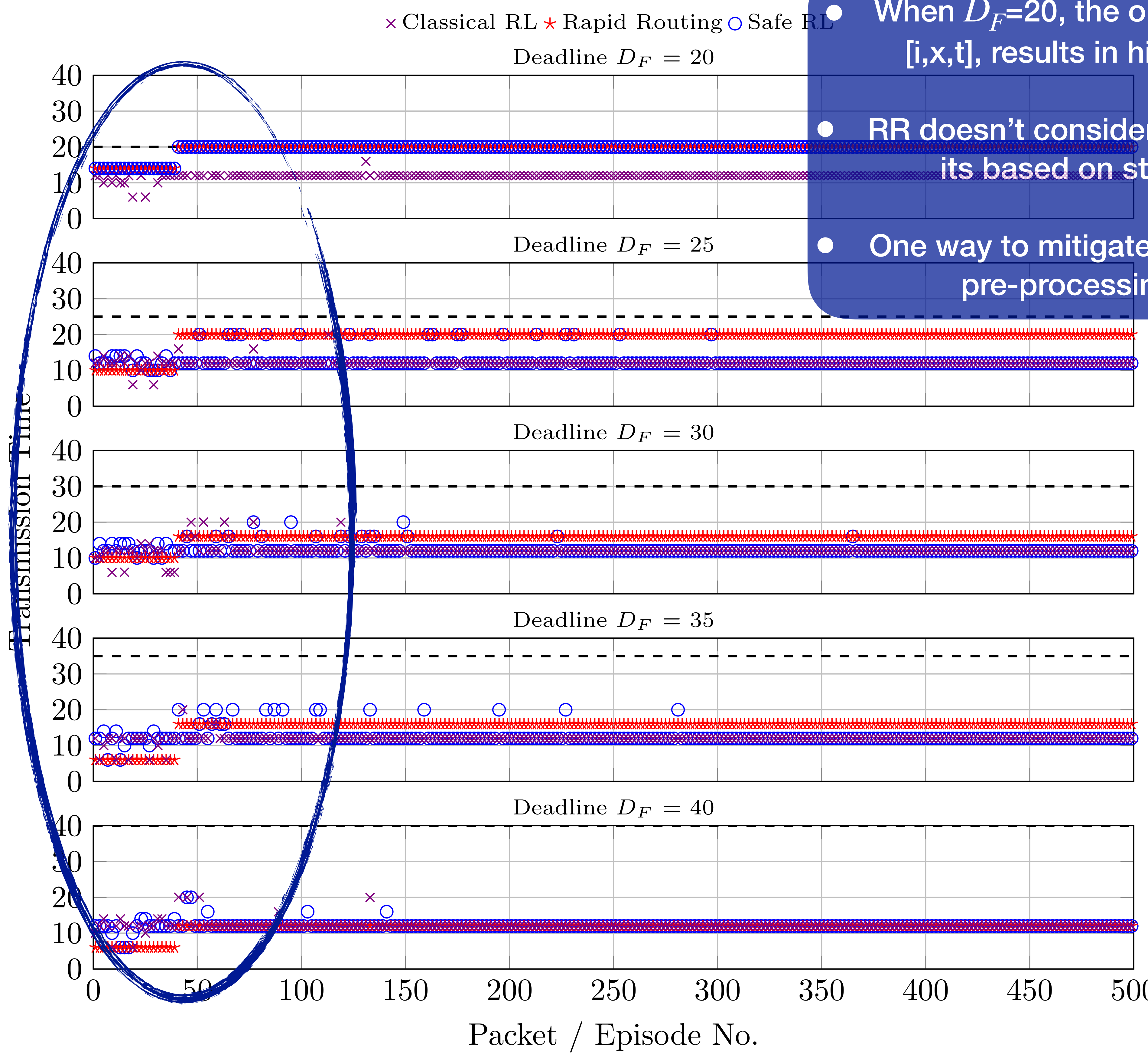
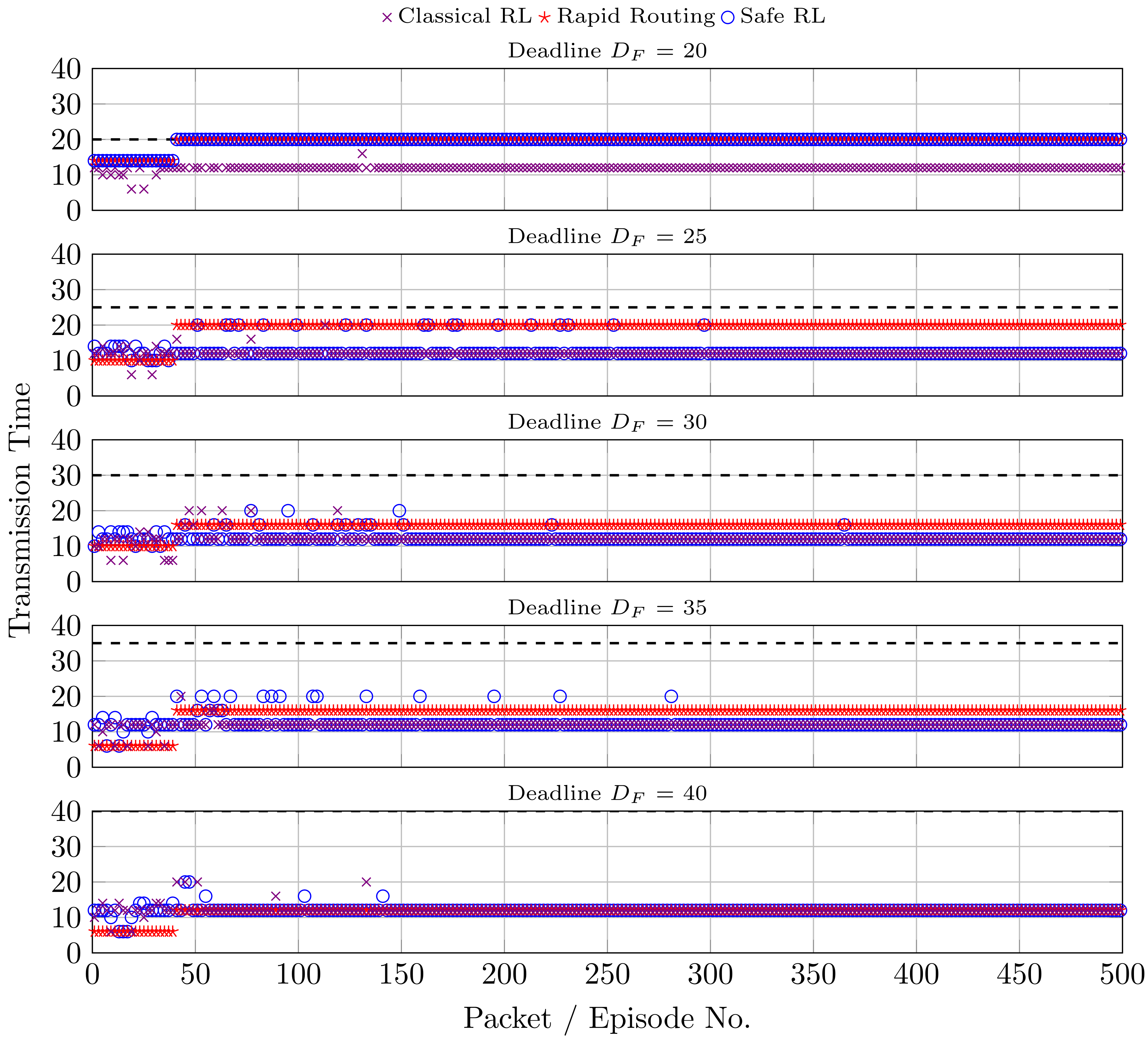


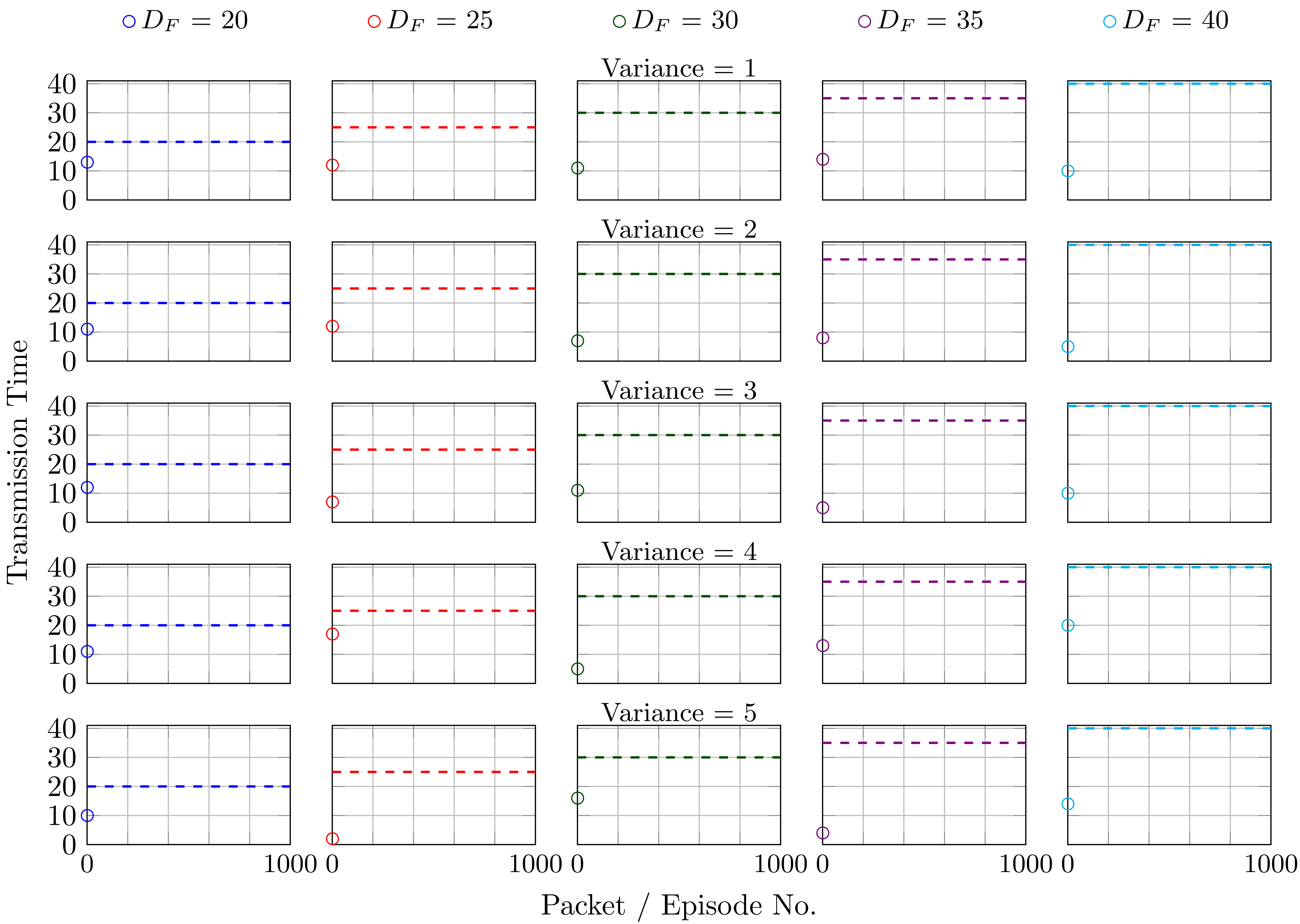
- When D_F=20, the only safe path is [i,x,t], results in higher tx times
- RR doesn't consider disturbance as its based on static tables.
- One way to mitigate it is to redo the pre-processing/tables

Experiment 2: Congestion on link



Video 3

Experiment 3a: Truncated Normal Distribution



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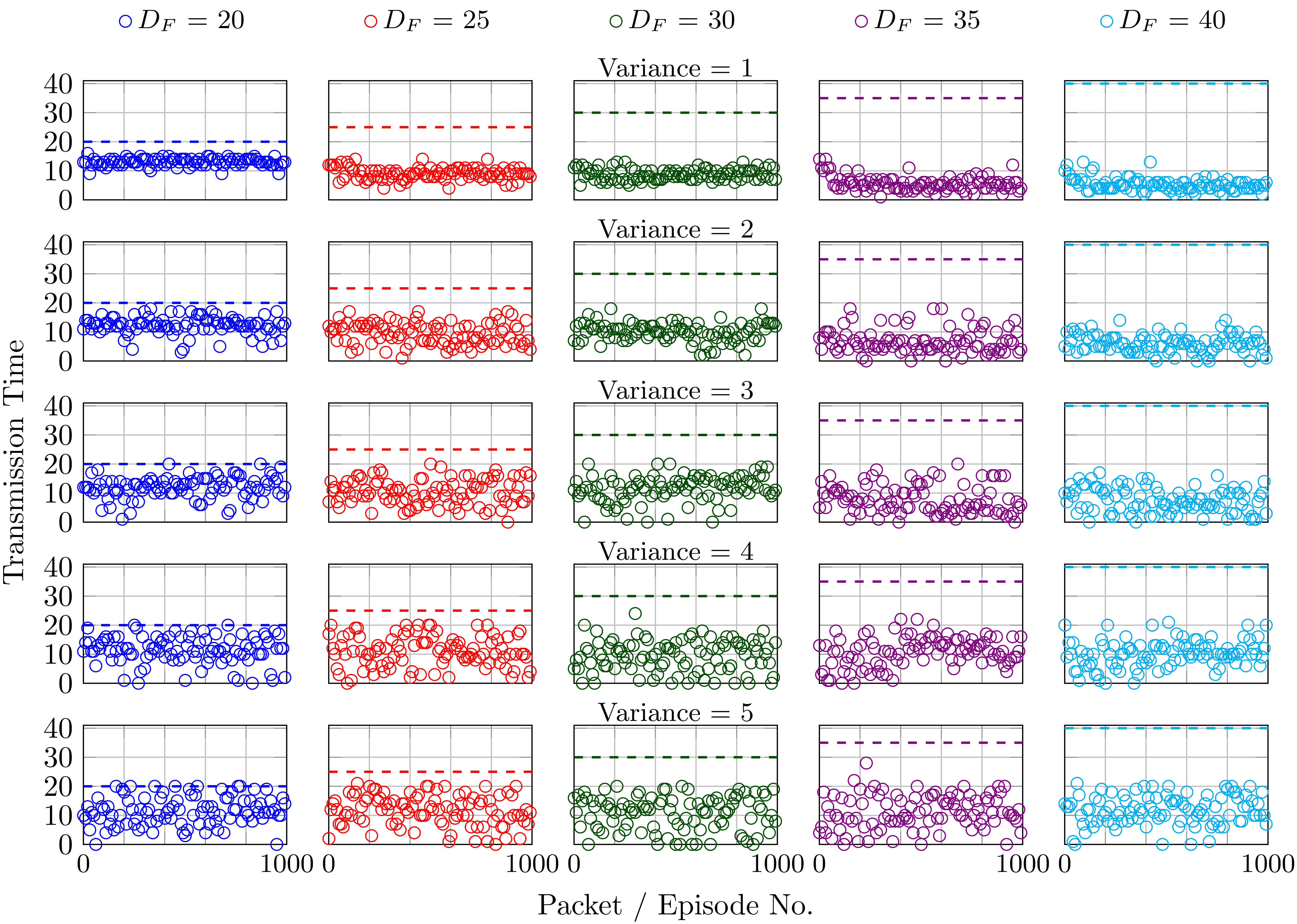
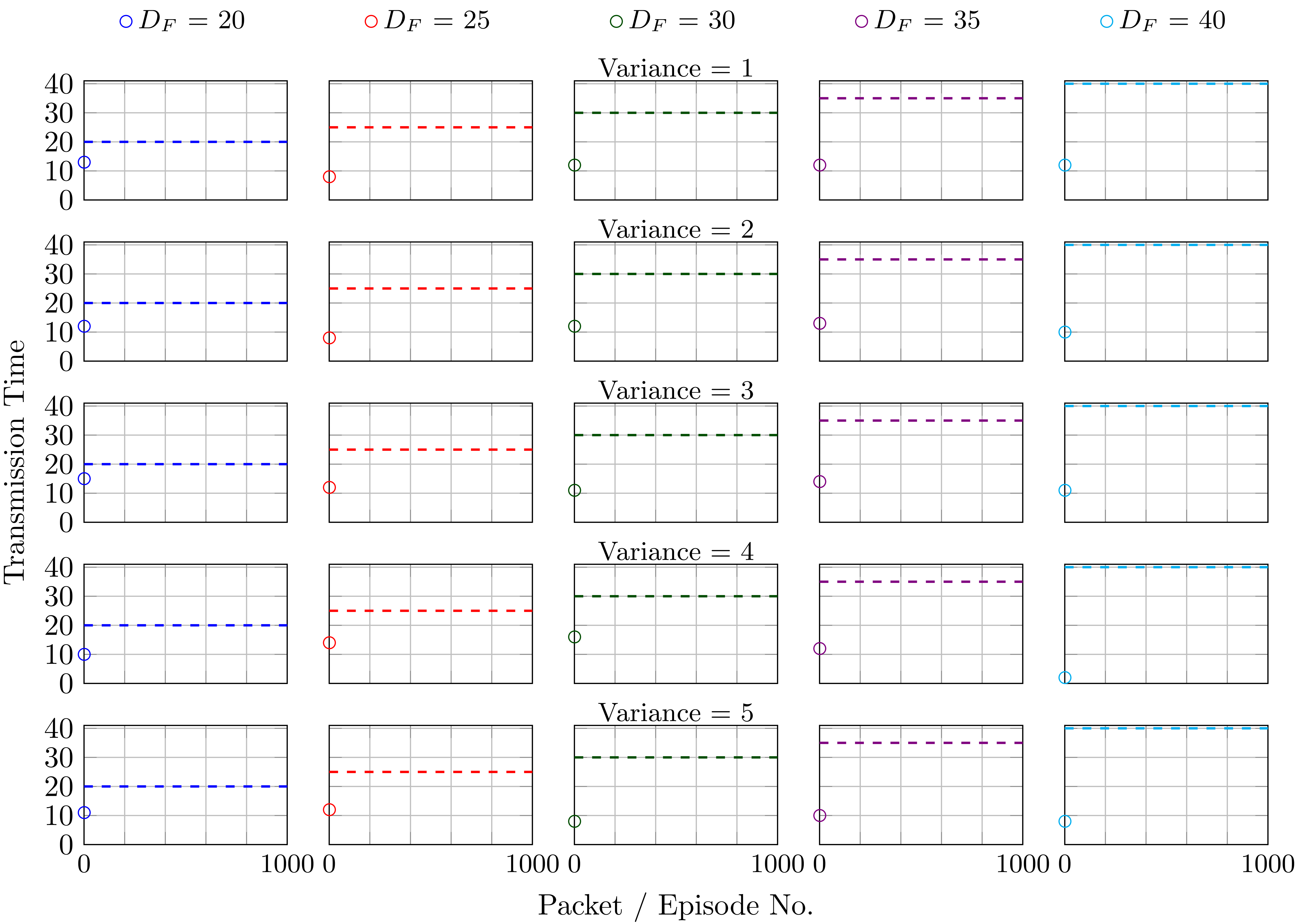


Experiment 3b: Uniform Distribution



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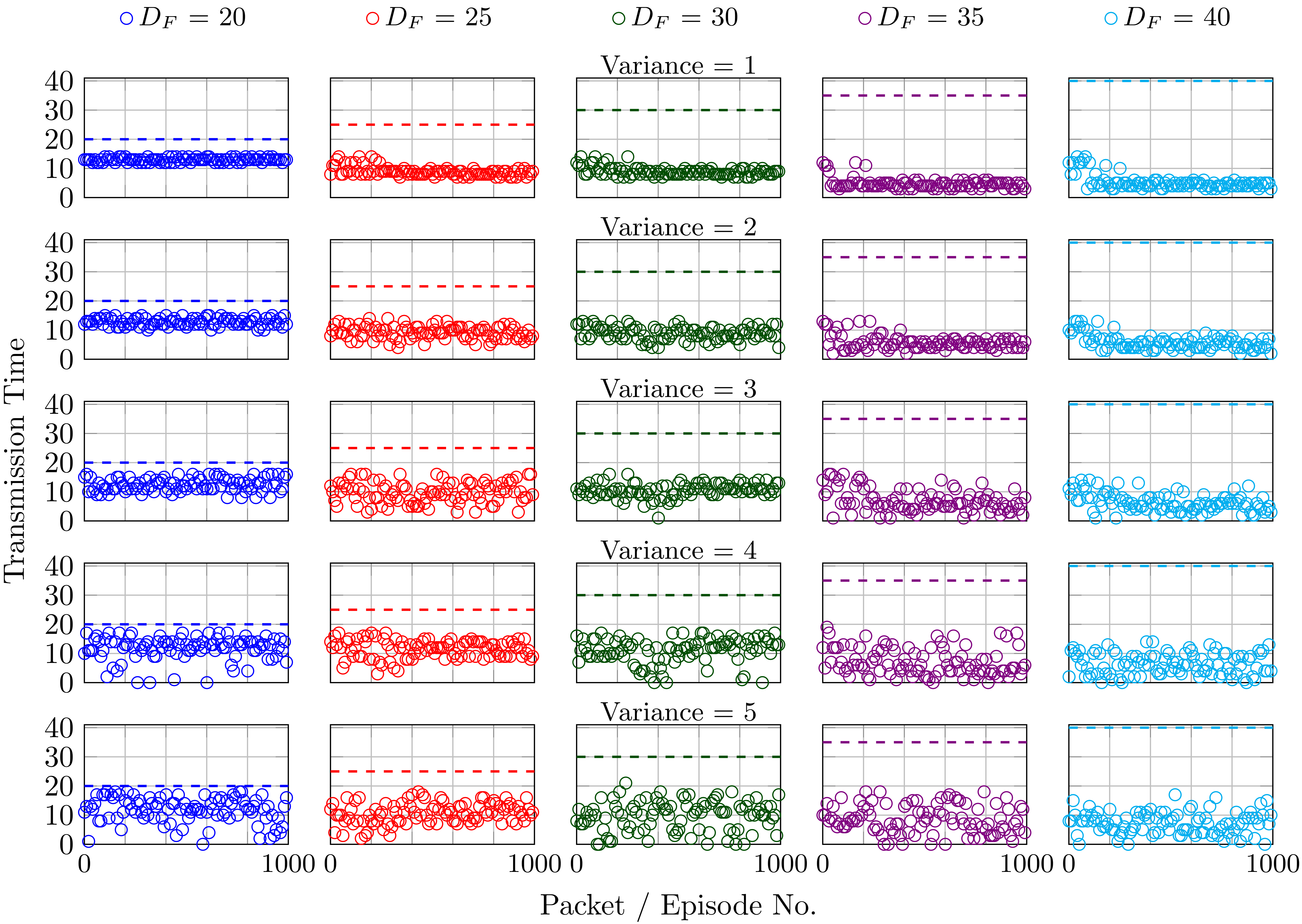
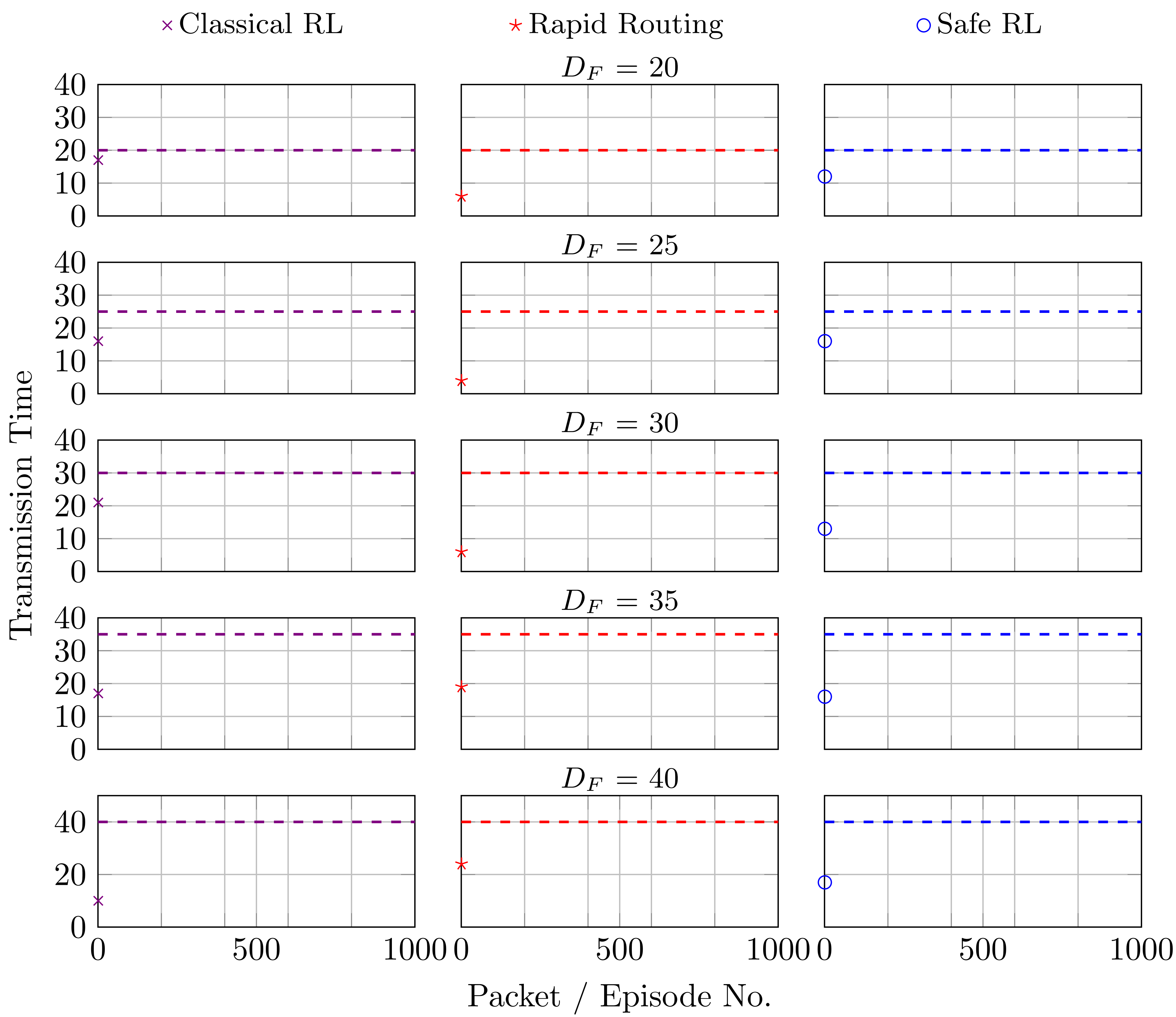


Experiment 4: WC-Uniform Distribution. $0 < \delta \leq c_{xy}^{W}$



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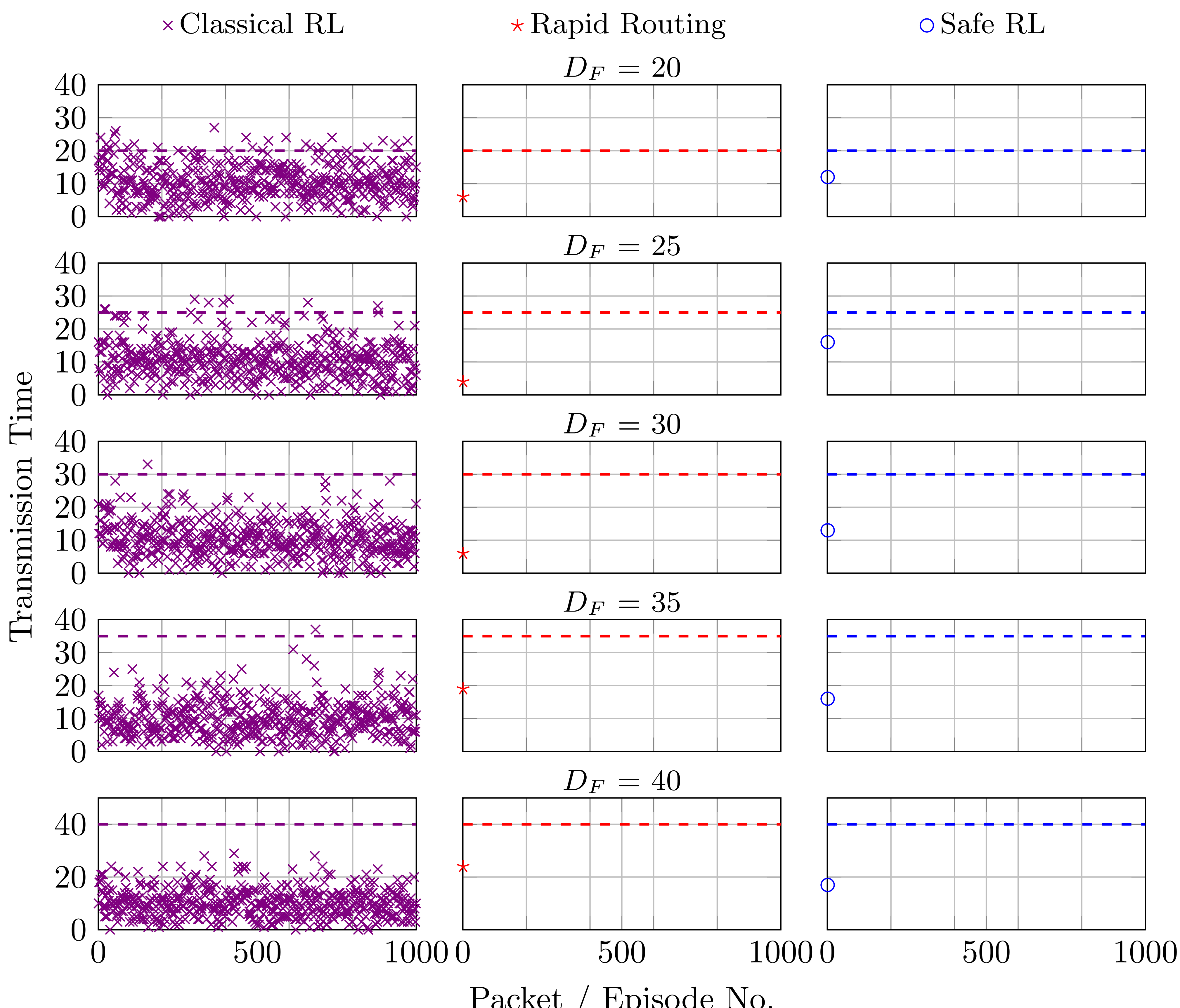

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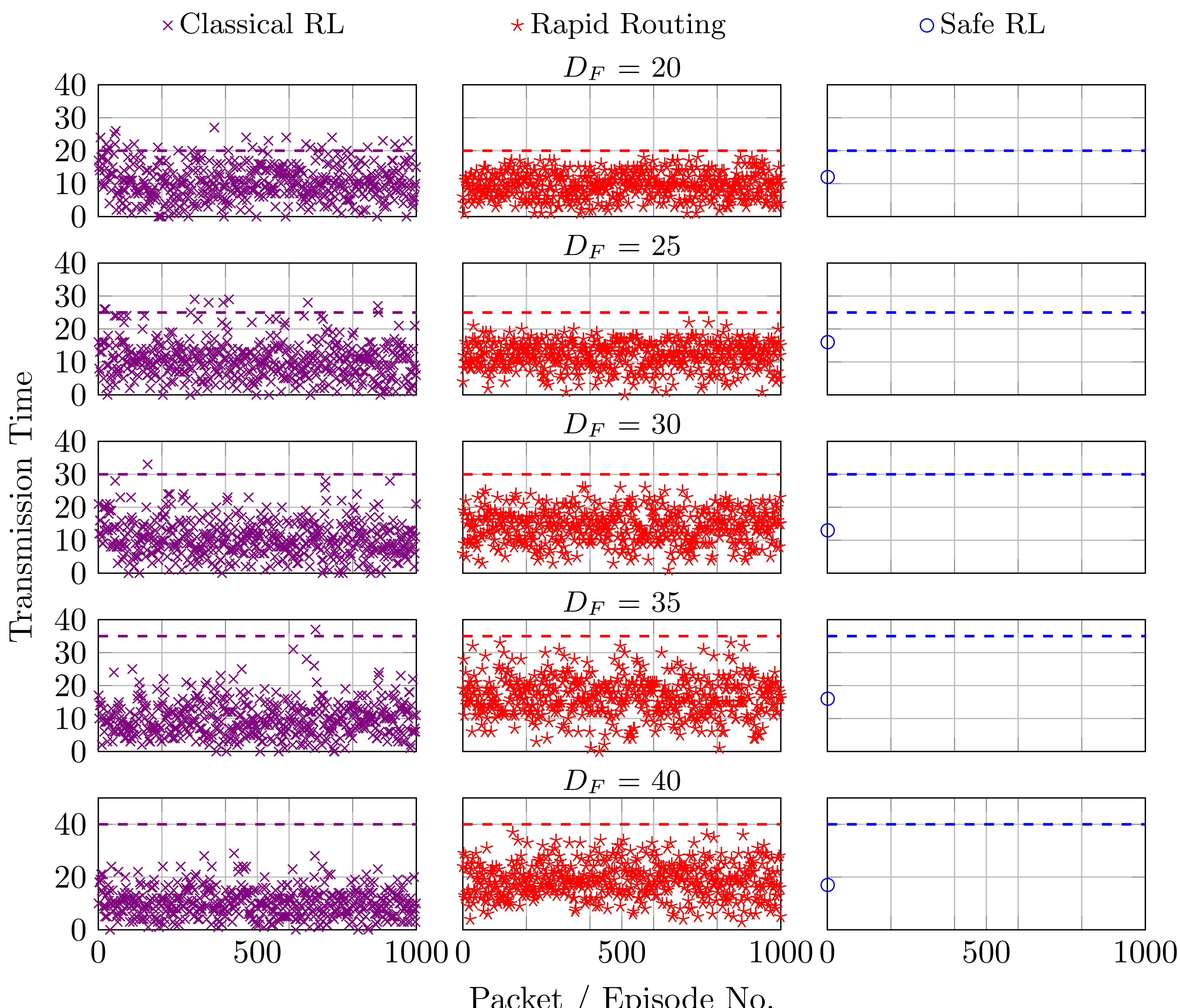

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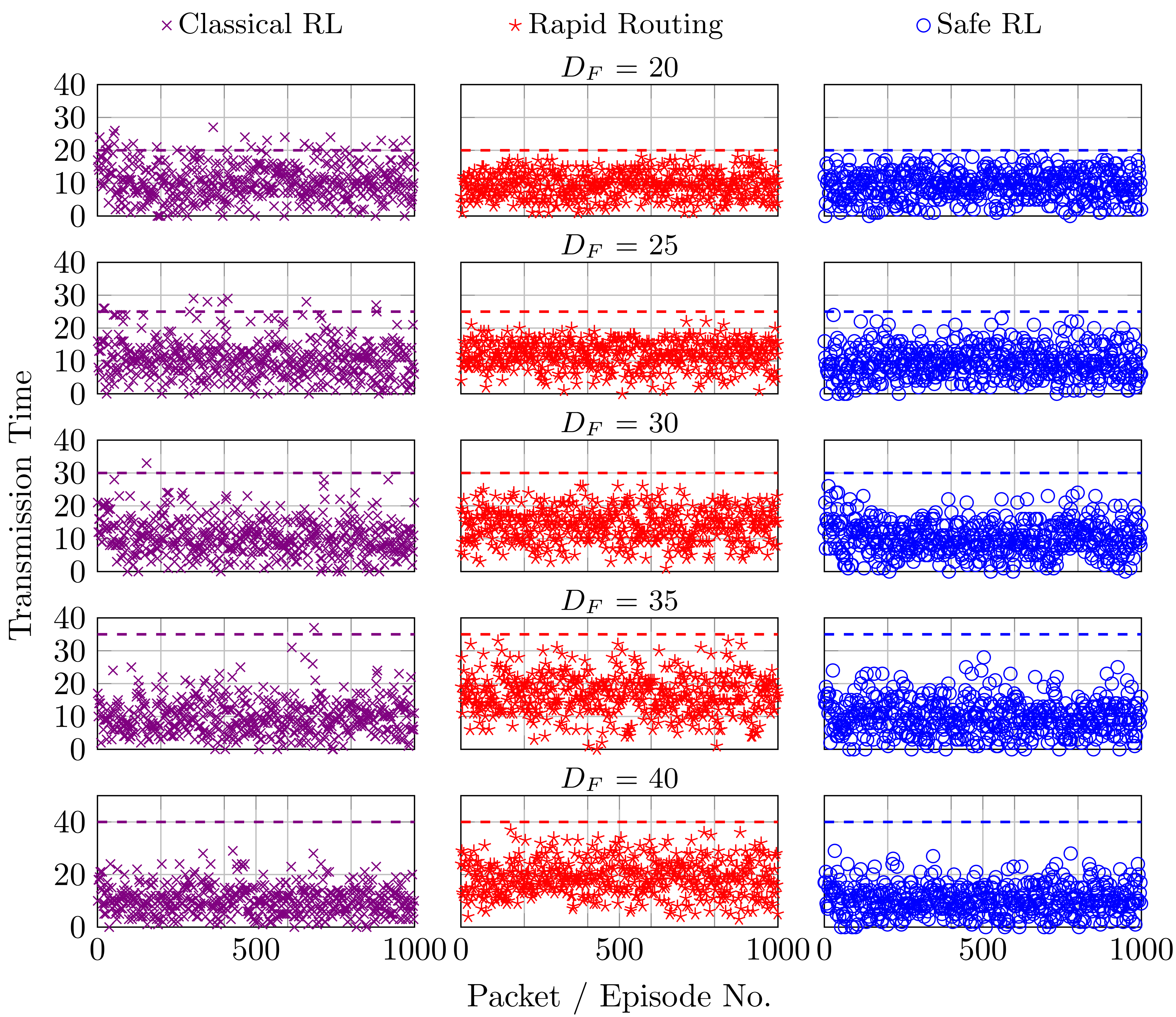
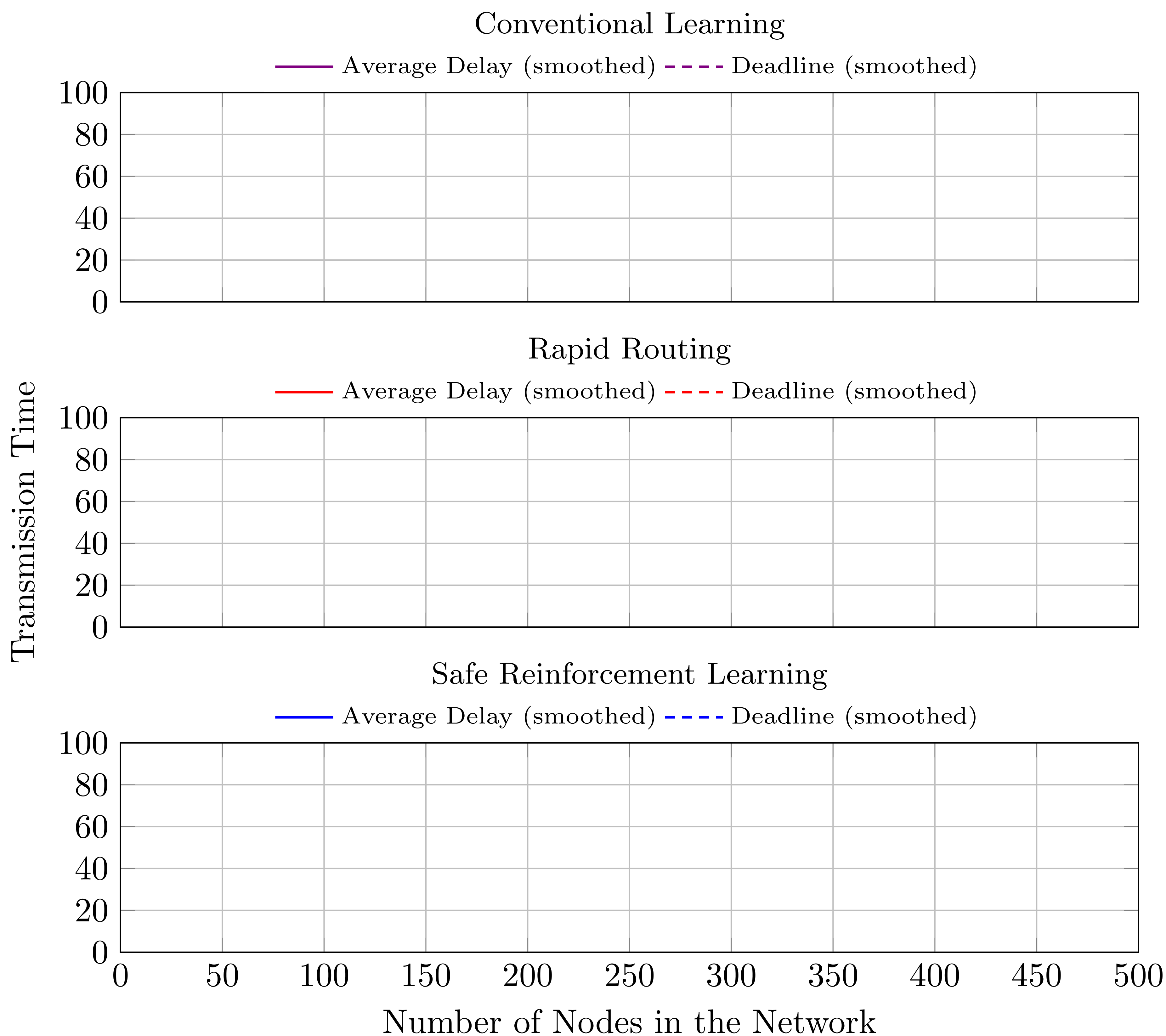


Video 4

Experiment 5: Large Networks



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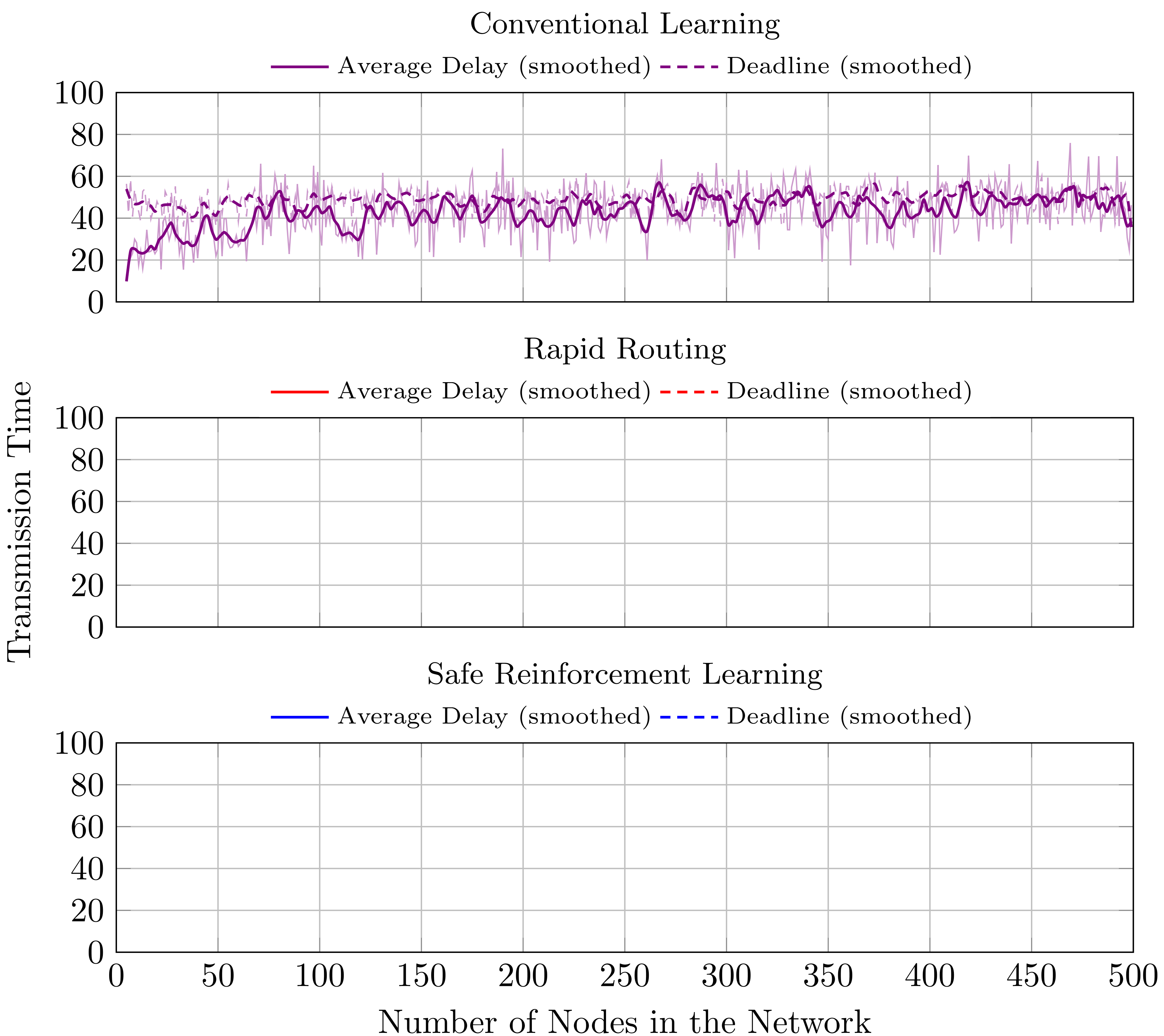

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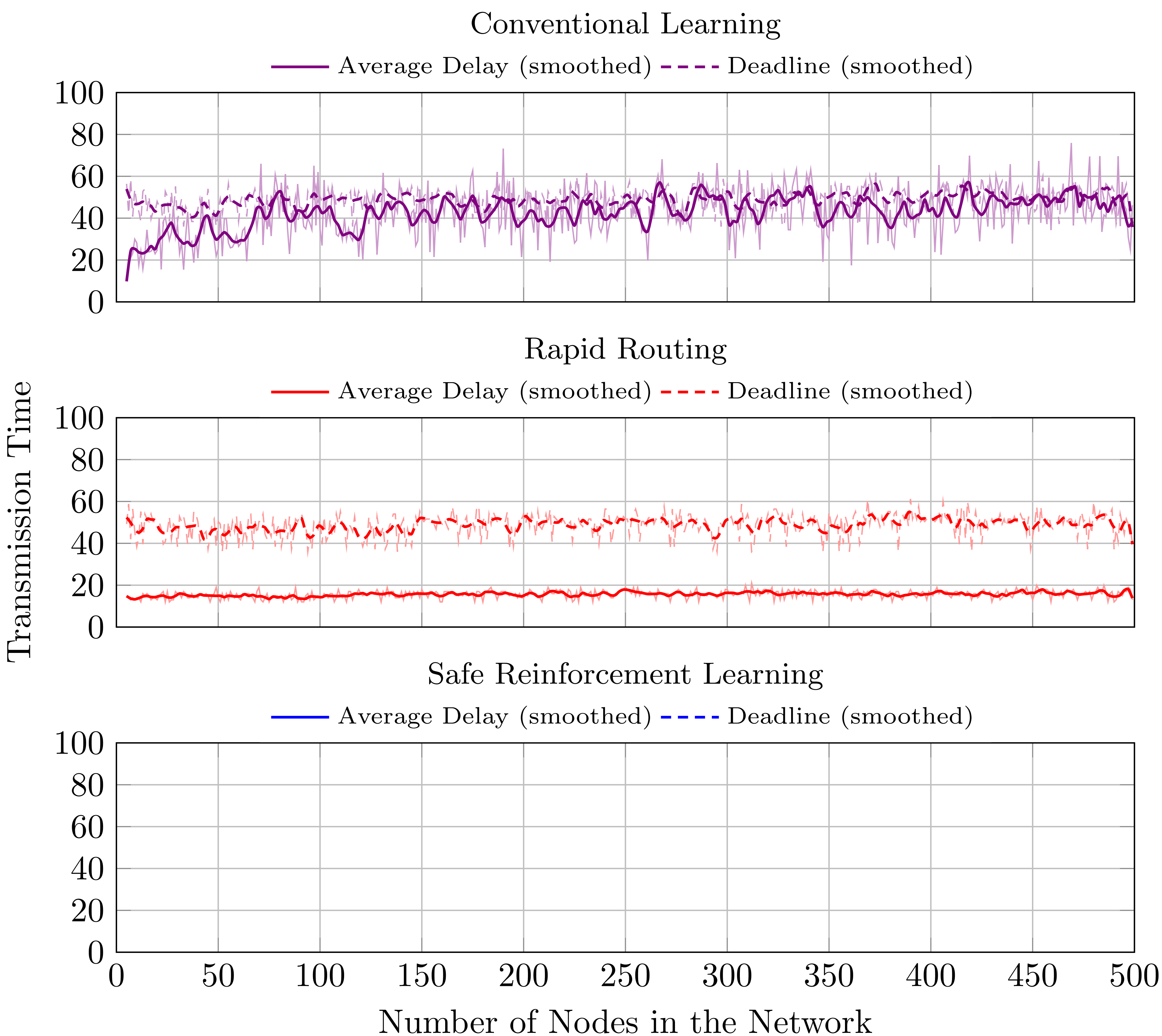

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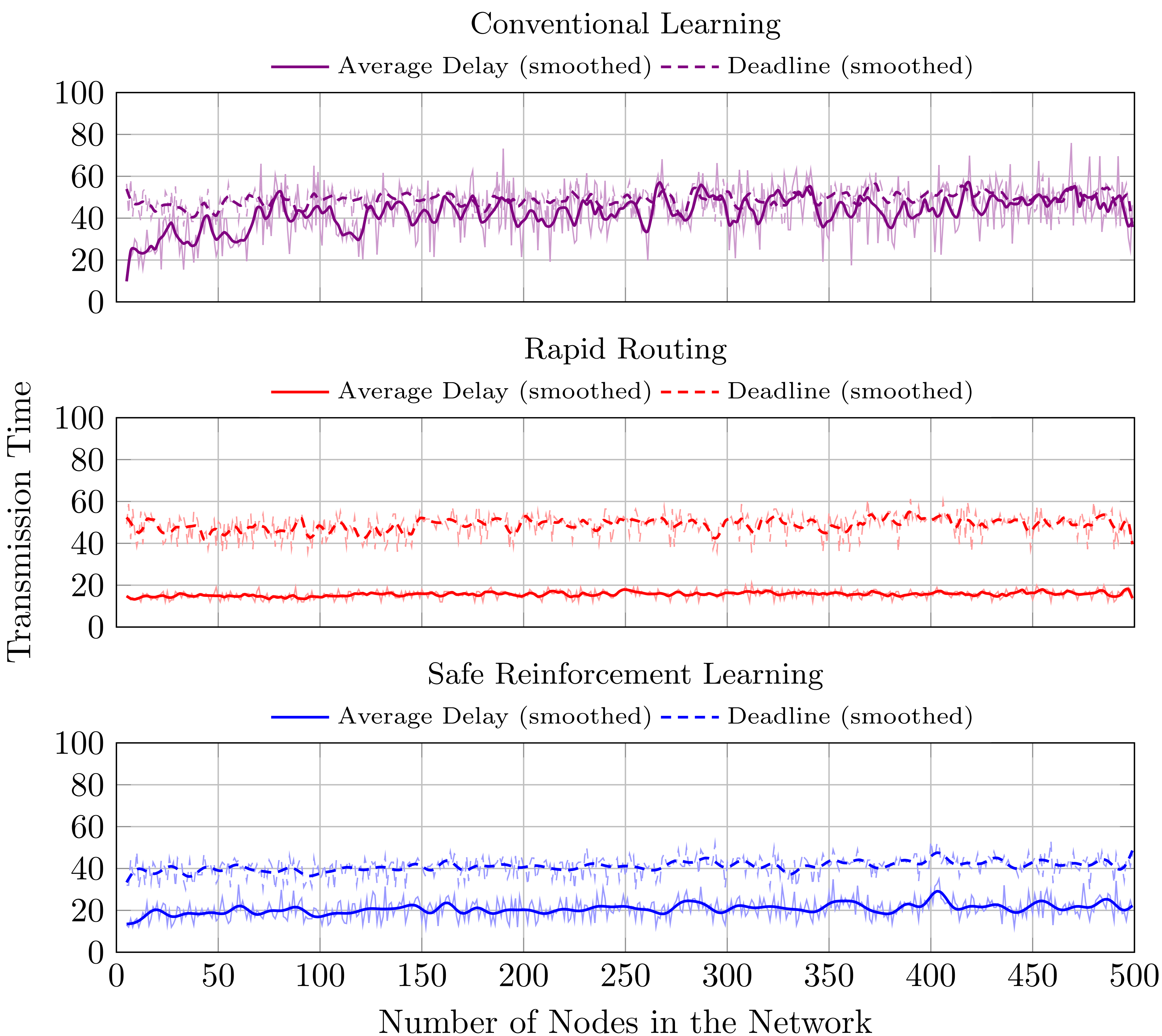
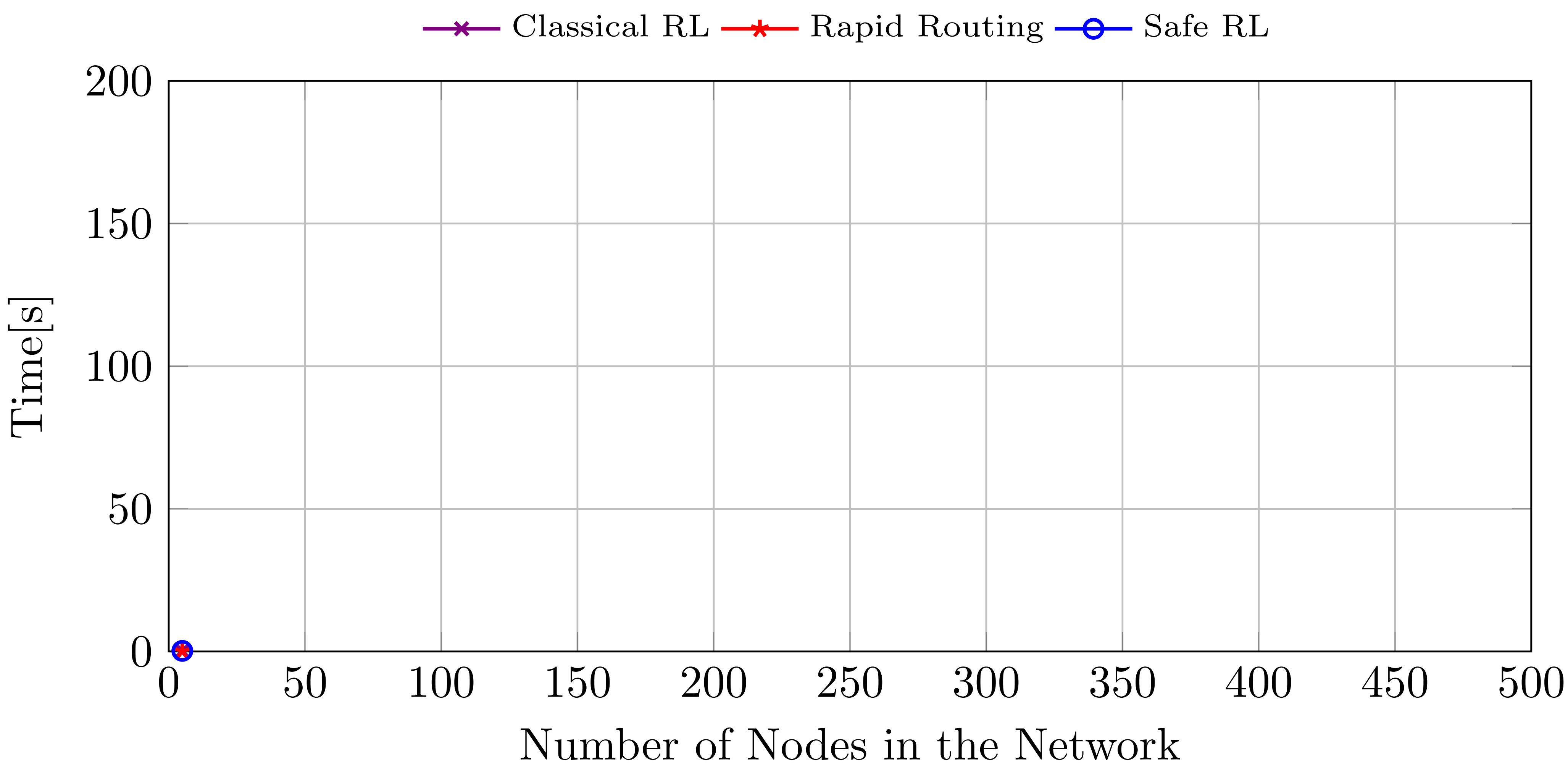
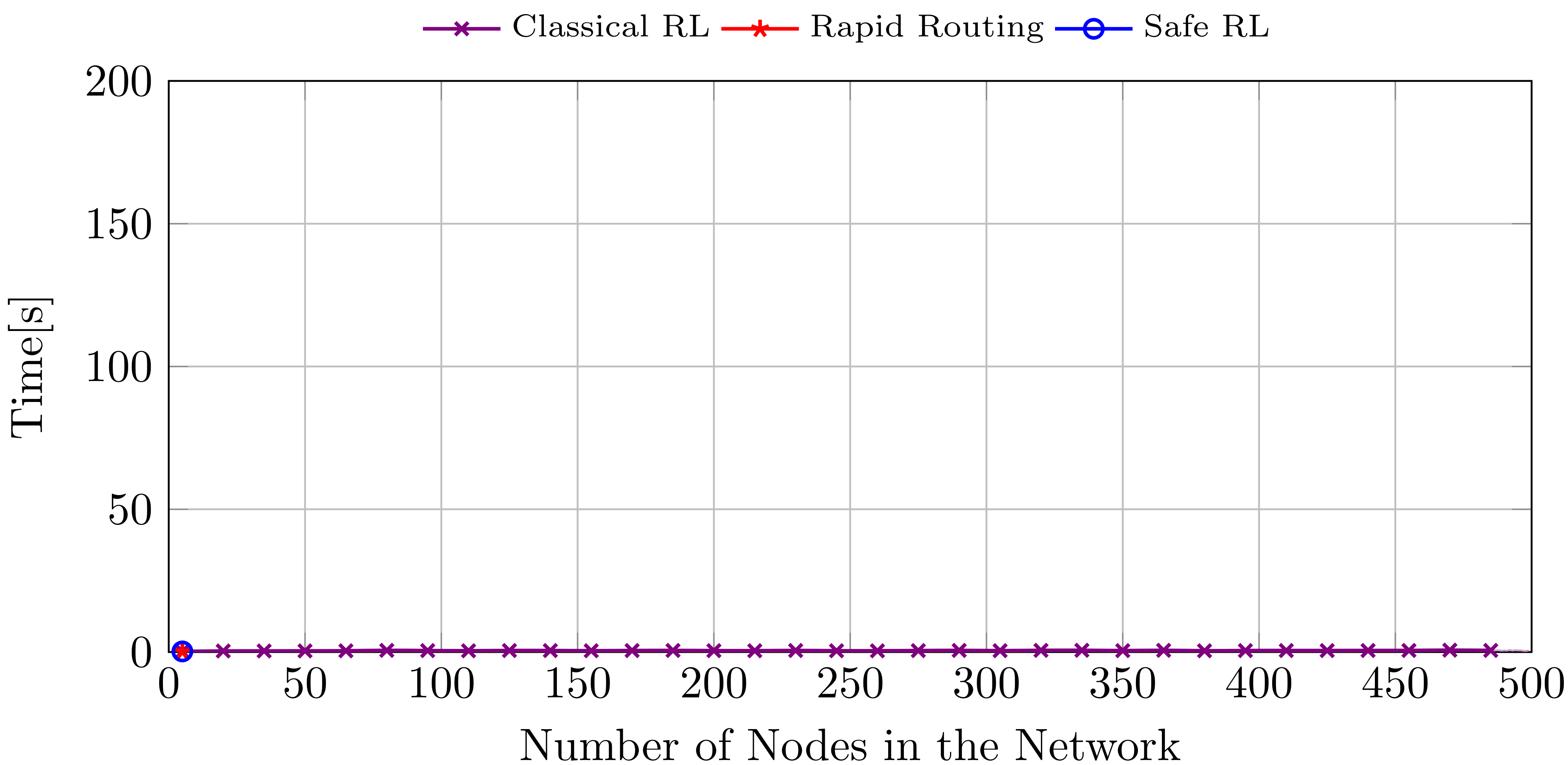


Experiment 5: Computational time



Experiment 5: Computational time

- Classical RL has low complexity (ms), but doesn't provide guarantees



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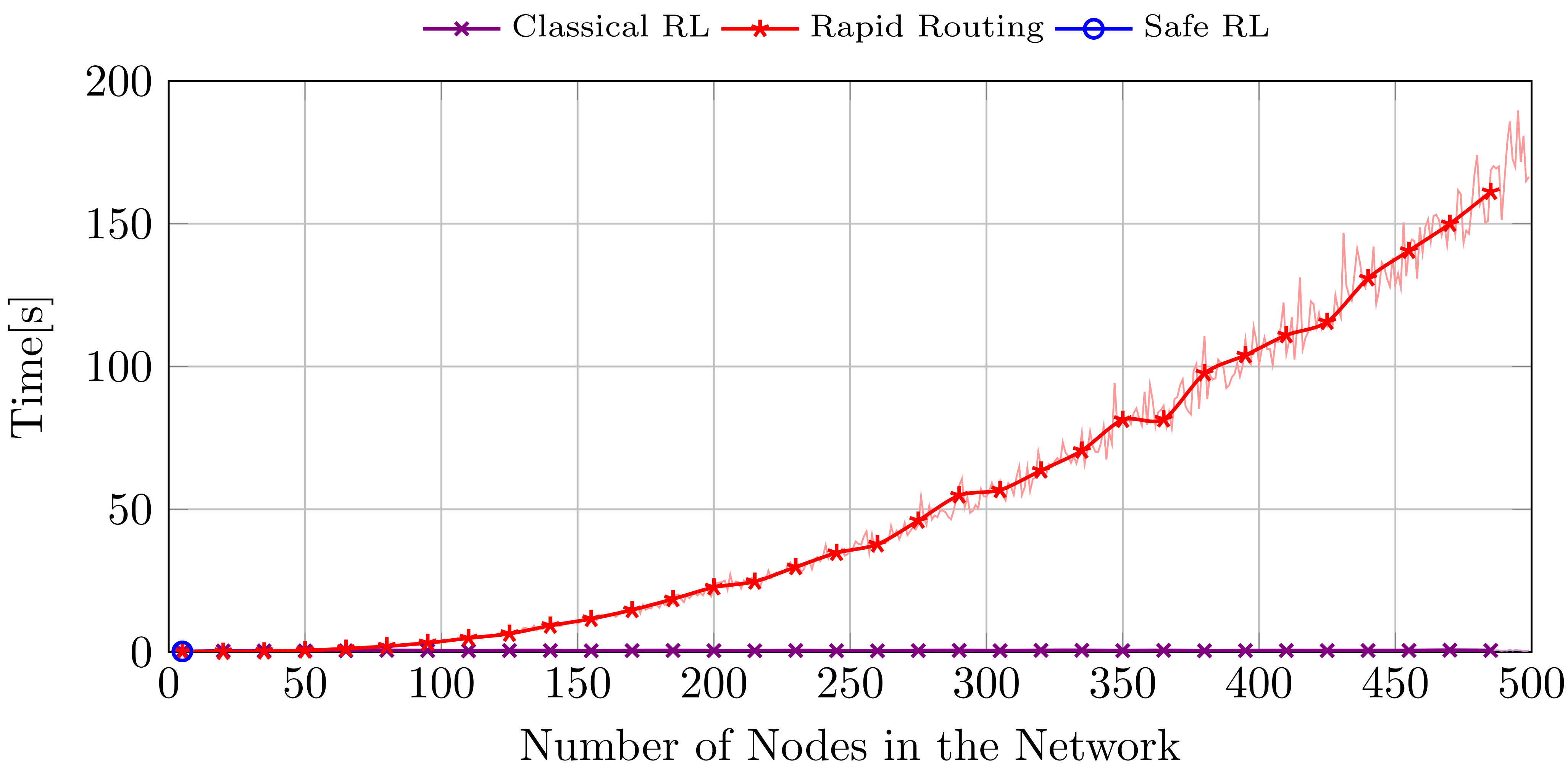

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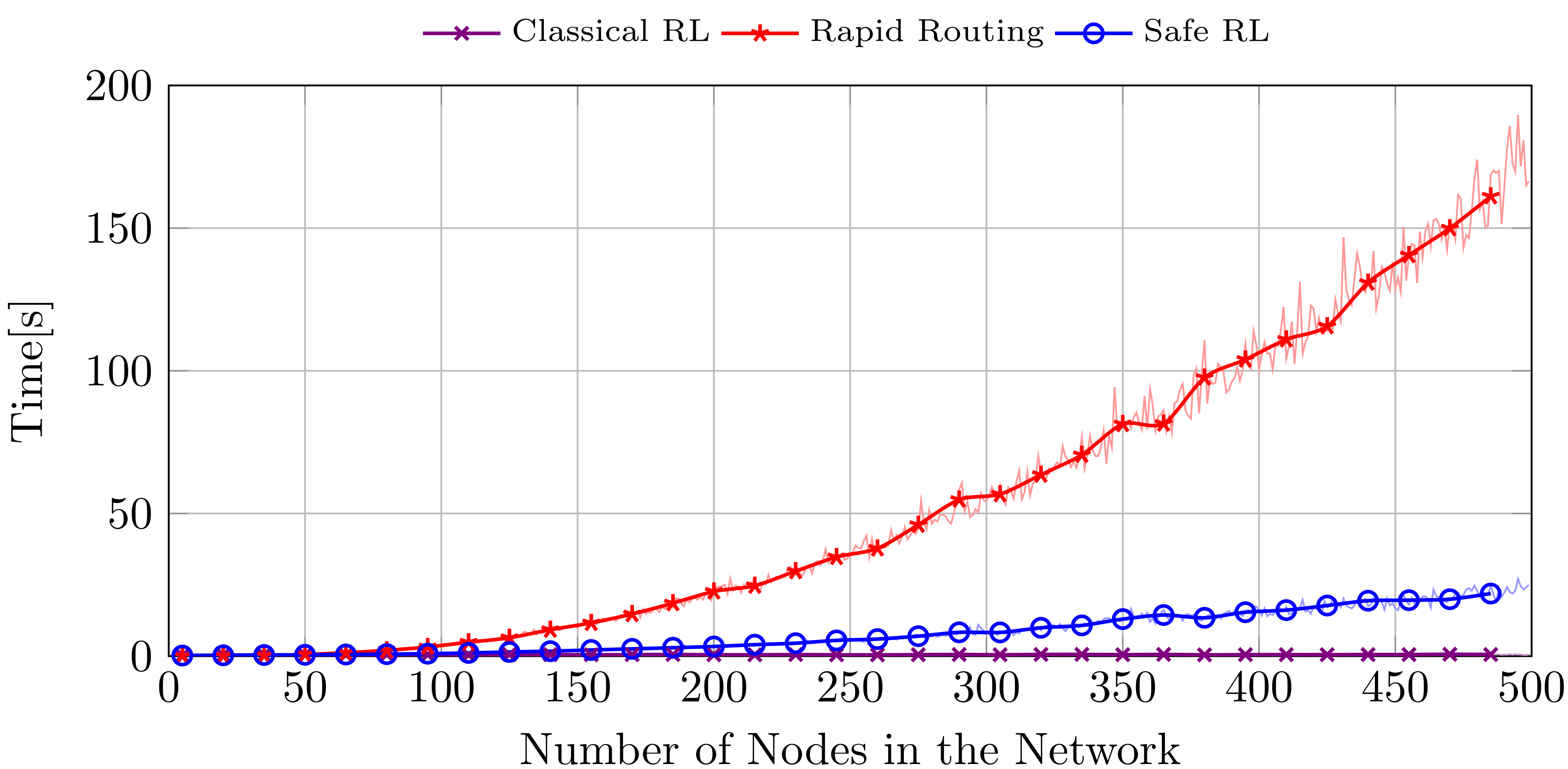

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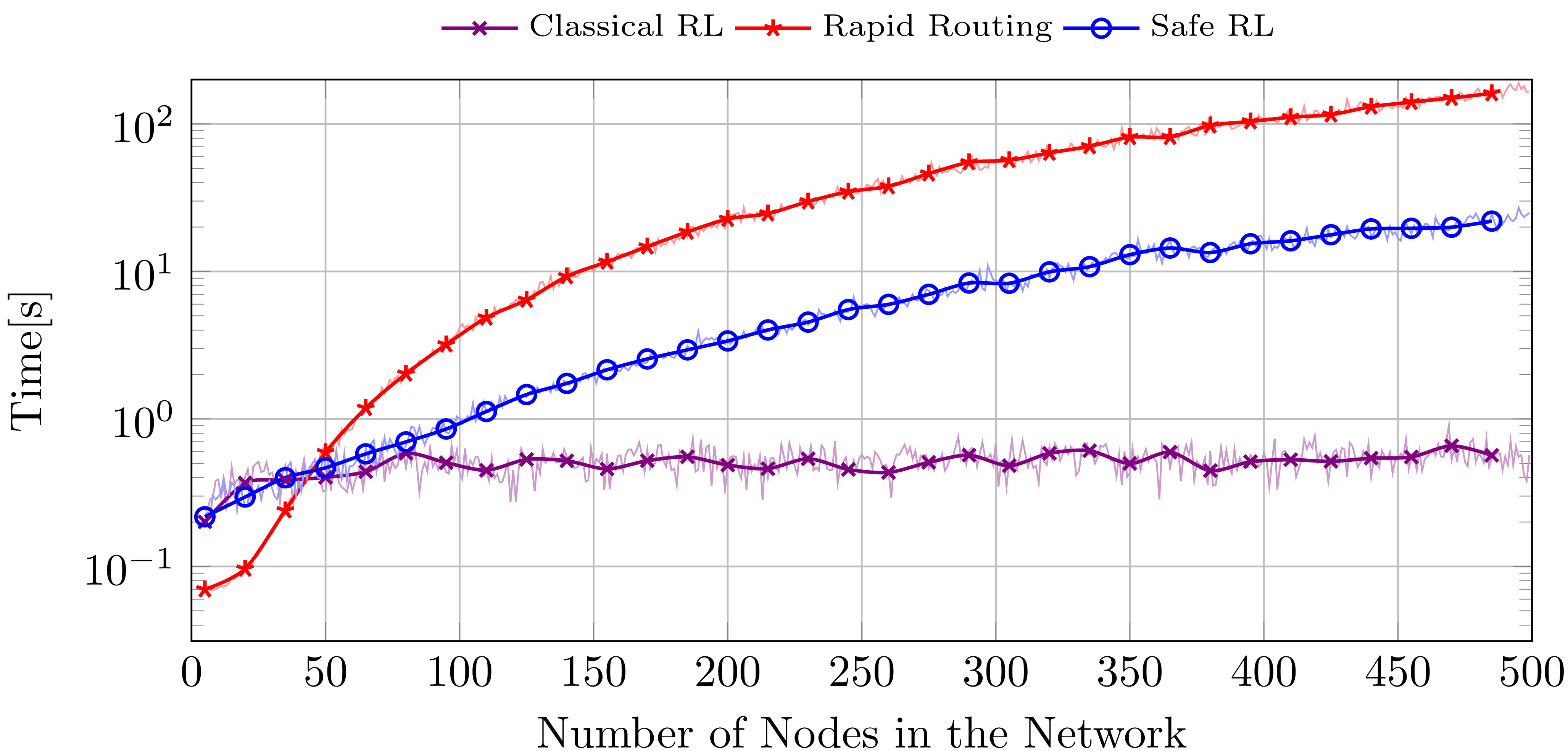

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- Augmented state-space allows safe exploration
- Constant adaptation to changes in typical transmission time
- Compared to classical RL, our algorithm is robust and does not violate any deadlines
- Compared to previous work, our algorithm
  - Adapts online to changes in typical transmission time
  - Is less computationally intensive

Future Work

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- Implement on a network emulator
    - Thank you Alex for pointers.

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Future Work

- Implement on a network emulator
    - Thank you Alex for pointers.
- Investigate probability propagation through network
- Is there anyway to guarantee safety if loops are present in the network?

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