Prediction-based Resource Allocation using LSTM and minimum cost and maximum flow algorithm

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Contents

Introduction

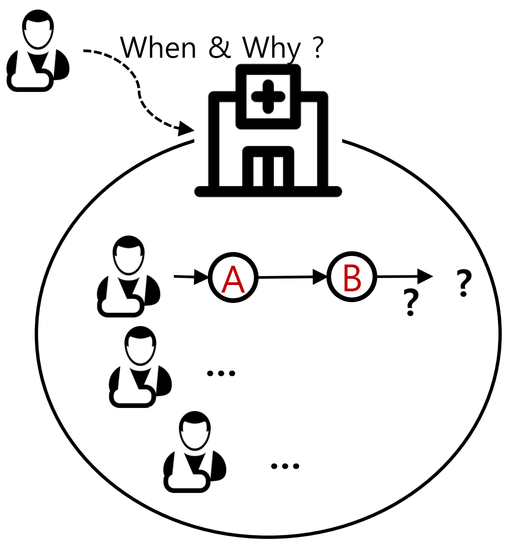
- Research Background
- Objective

Introduction – Research Background

- **Resource allocation in business process management (BPM)**
  - Resource allocation in BPM **aims at allocating appropriate resources to tasks at the correct time**, to balance the demand for process executions against the availability of these resources.
  - It has been recognized as an important issue in BPM since **efficient resource allocation improves productivity, balances resource usage, and reduces execution costs.**
  - In a more general perspective, it shares commonalities with **job-shop scheduling problem in operations research.**
    - This problem finds the job sequences on machines to achieve an objective (e.g., minimizing total completion time), which is NP-hard and computationally intractable combinatorial problem.
    - There has been considerable research in the area of job shop scheduling over the past years.
      - ✓ Dispatching rules (Huang et al., 2015)
      - ✓ Shifting bottleneck heuristics (Braune et al., 2016)
      - ✓ Local Search (Kuhpfahl et al., 2016)

Introduction – Research Background

- **Resource allocation in business process management (BPM)**
  - Among the techniques, **dispatching rules** receive massive attention from practical viewpoint since it is useful to find **a reasonably good solution in a relatively short time**.
  - However, they are applicable **only if the required parameters** such as the release time, the processing time, and the sequence of operations of jobs **are known in advance**.
  - Instead, we have **limited information** about the scheduling parameters in many circumstances.



<Emergency department>

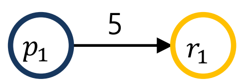
Unaware of,
1. When and why a patient would come into the department
2. Clinical procedures
3. Processing time taken to finish an operation

Non-clairvoyant Online Job Shop Scheduling Problem

Prediction can play a key role in this problem

Introduction – Research Background

- **Motivating example**
  - Suppose we find optimal resource allocation (in terms of **total weighted completion time**) for "MRI" operation in emergency department.



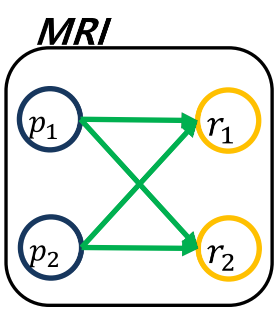
<Notation>

	p_1	p_2	p_3
Weight	1	1	10

<patient weights (Urgency)>

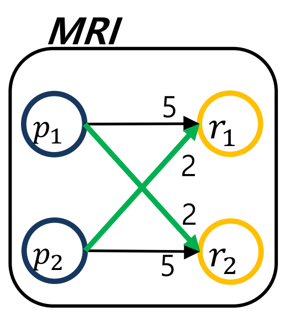
Initial Setting

At $T = t$,



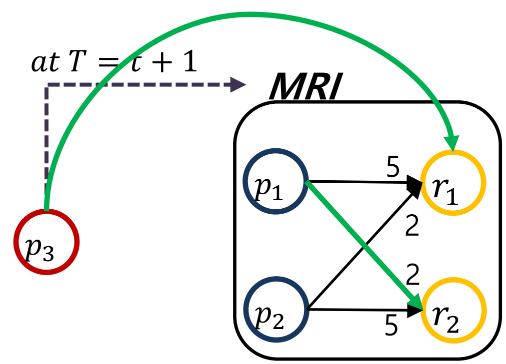
Allocation

Predicting the processing time → Assigning most efficient resource



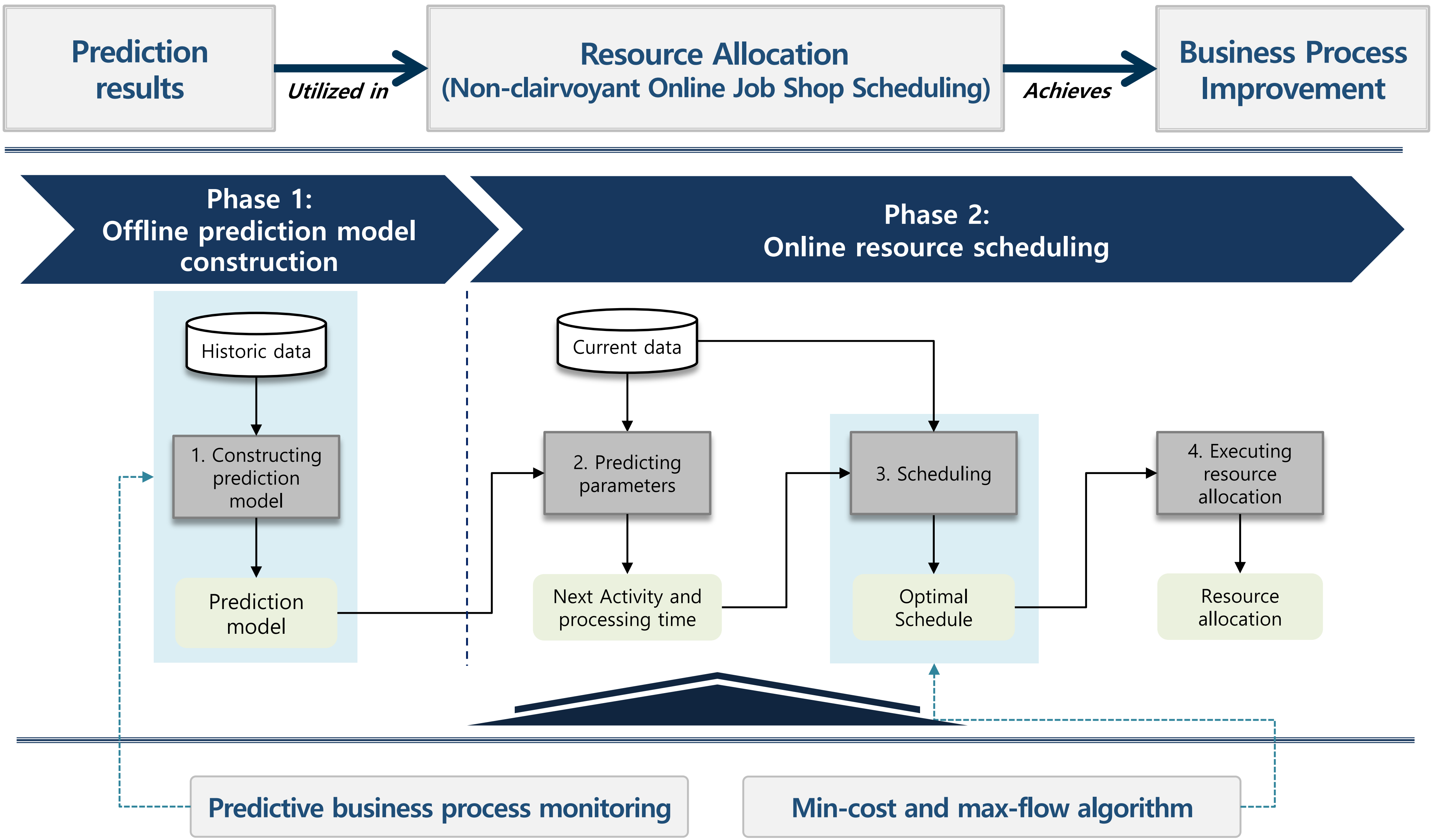
Allocation

Predicting that p_3 will require "MRI" → Reserving r_1 for p_3



Allocation

Introduction – Objective

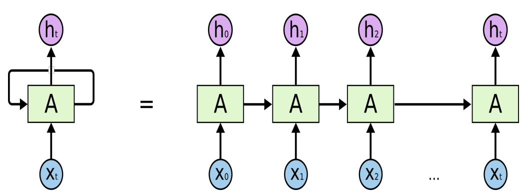


Background

- Preliminaries
- Problem Statement
- Baseline approach

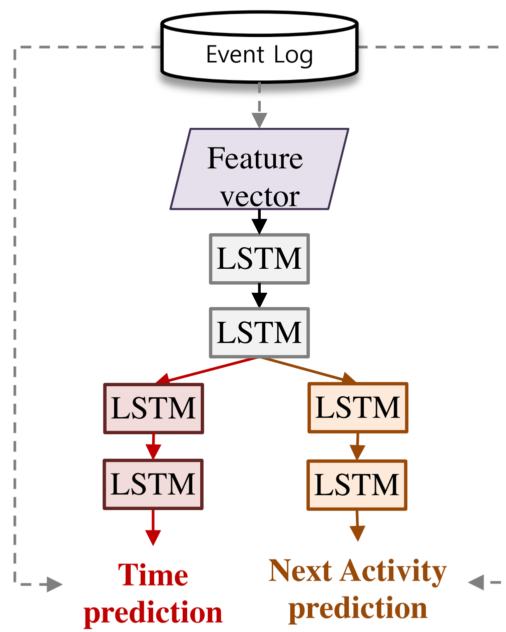
Background – Preliminaries

- **Predictive business process monitoring**
  - Predictive business process monitoring aims at **providing timely information** that enable **proactive and corrective actions** to improve process performance and mitigate risks.
    - Next event prediction: predicting the next event of a running instance such as **next activity**.
    - Time prediction: predicting time-related properties of a running instance such as **remaining time and processing time**.
  - Tax et al. (2017) propose an approach that predicts both the next activity and its timestamp using LSTM (Long-Short Term Memory Neural Network).



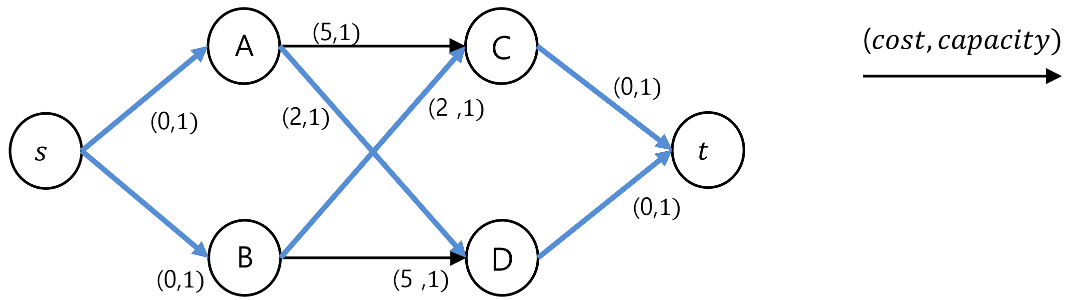
LSTM
(Long-Short Term Memory)

- Sequence learning tasks (e.g., Natural language processing (NLP))
- Learning temporal dynamics



Background – Preliminaries

- **Minimum cost and maximum flow problem**
  - Minimum cost and maximum flow problem is a way of **minimizing the cost required to deliver maximum amount of flow possible in the network**.
    - E.g., A directed graph $G = (V, E)$ with a source node $s \in V$ and a sink node $t \in V$, where each edge $(u, v) \in E$ has cost and capacity.



<Minimum cost and maximum flow of G>

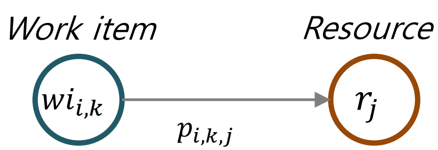
  - It can be solved in polynomial time using the network simplex algorithm.

Background – Problem Statement

- **Non-clairvoyant Online Job Shop Scheduling Problem**
  - Given a set of instances I, this problem **finds an optimal scheduling of all operations** within instances while **minimizing total weighted completion time $\Sigma_i w_i C_i$**,
    - w_i: weight of I_i
    - C_i: difference between the finish time F_i and start time S_i of an instance I_i.
  - Assumptions:
    1. **Unaware of the information** regarding an instance **except the weight** of it.
    2. Find out the **next operation of an instance** only if the instance finishes its current operation.
    3. Each operation has **a specific set of resources** with whom it needs to be processed.
    4. **Only one operation** within an instance can be processed at a given time.
    5. Once processing begins on an operation, **it cannot be stopped** until completion.

Background – Problem Statement

- **Running Example**
  - Suppose there are 5 instances and 3 resources in the process.
    - $I_1, \ldots, I_4$ are ready for the allocation at $T = t$ → We don't know the processing time.
    - I_5 is currently doing its 2nd operation (i.e., $wi_{5,2}$) at $T = t$ → We don't know the next activity (and required resource).



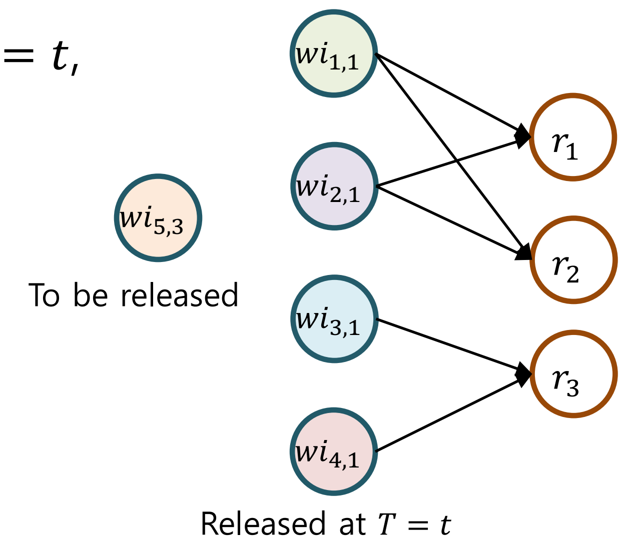
<Notation>

→ $\boldsymbol{wi_{i,k}}$ (k^{th} operation of instance I_i) can be processed by $\boldsymbol{r_j}$ in $\boldsymbol{p_{i,k,j}}$ (processing time)

	I_1	I_2	I_3	I_4	I_5
Weight	1	1	1	5	10

<Instance weights>

At $T = t$,



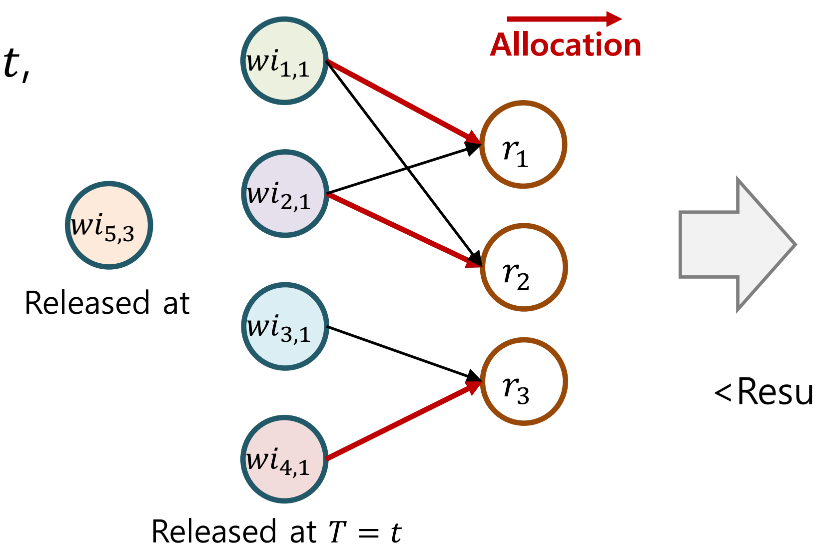
Background – Baseline approach

- **Baseline Approach (*WeightGreedy*)**
  1. Each work item is assigned to an available resource in a "**first come, first served**" manner.
  2. If there exist conflicting demands for the same resource, the work item with **higher weight is served first**.
  3. If the competing work items have the same instance weights, the **tie is broken at random**.

	I_1	I_2	I_3	I_4	I_5
Weight	1	1	1	5	10

<Instance weights>

At $T = t$,



Here

	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$\sum w_i C_i$
r_1	$wi_{1,1}$					$wi_{5,3}$		65
r_2	$wi_{2,2}$							5
r_3	$wi_{4,1}$		$wi_{3,1}$					15

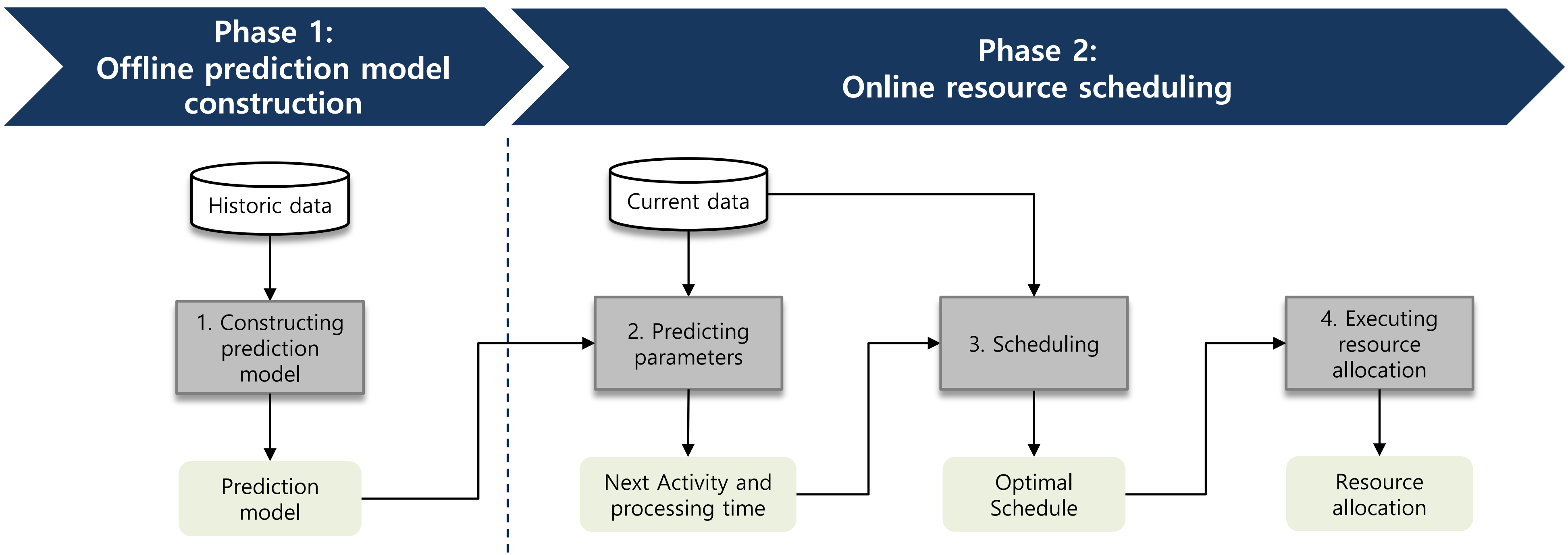
85

<Result of resource allocation based on *WeightGreedy*>

Method

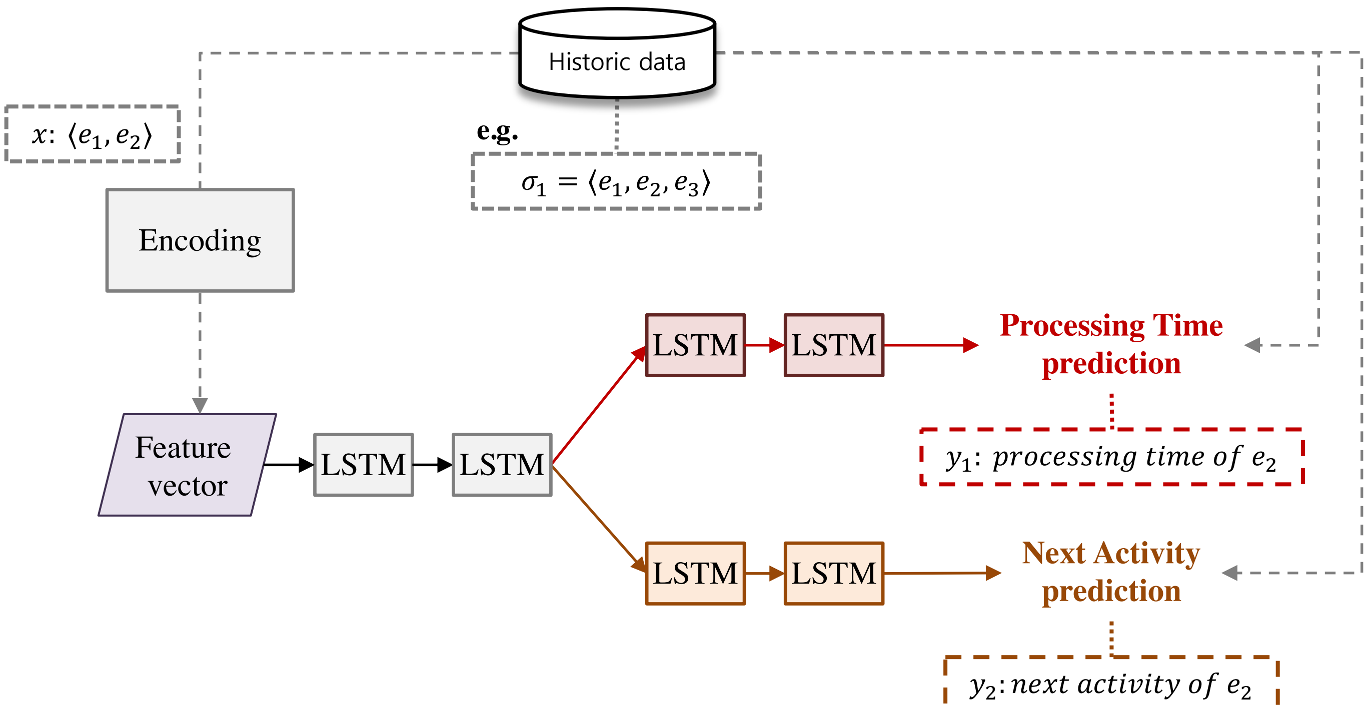
- Overview
- Steps

Method – Overview



Method – Phase 1

- **Step 1: Constructing Prediction Model**
  - In this step, we aim at building a model to predict the **processing time** and the **next activity** of a running instance, which is based on LSTM (Tax et al, 2017).
  - We learn the model with all traces in the historic data.
    - E.g., Training with a trace $\sigma_1 = \langle e_1, e_2, e_3 \rangle$

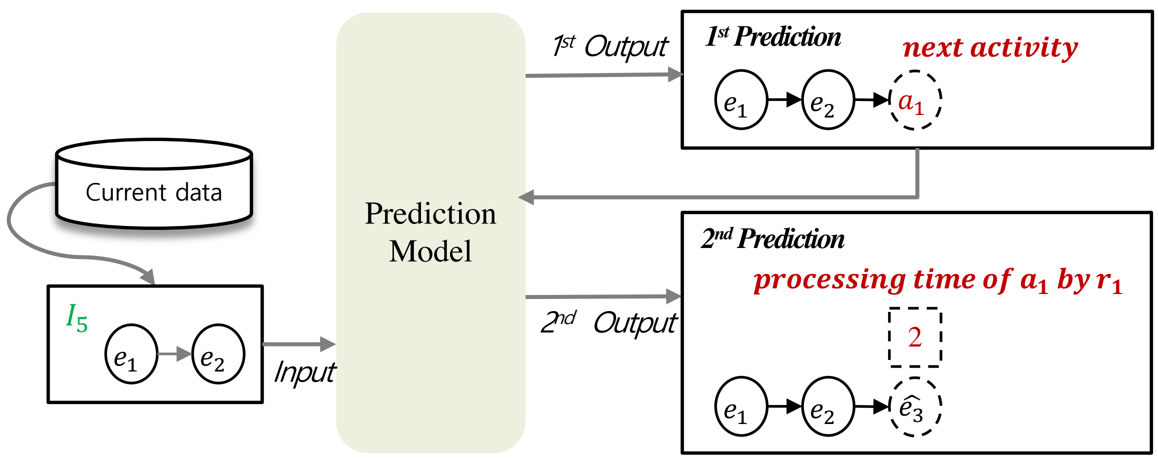


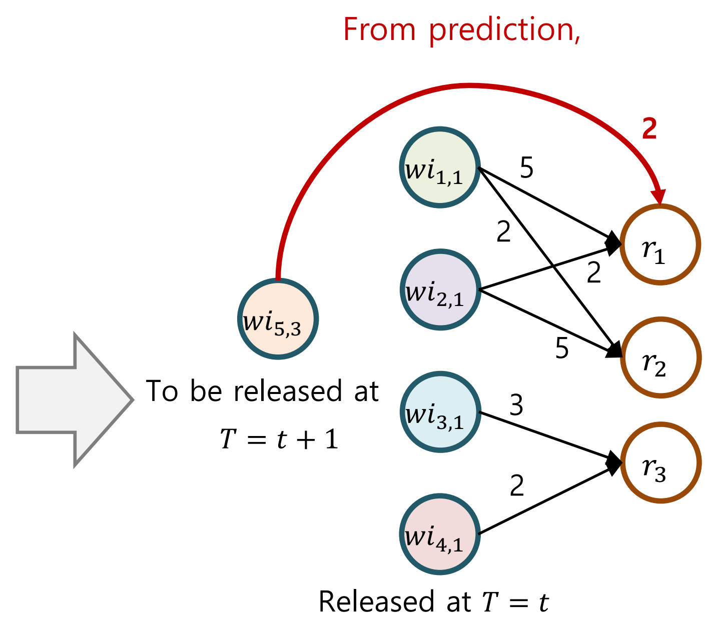
Method – Phase 2

- **Step 2: Predicting parameters**
  - Based on the prediction model we construct in the previous step, we predict the **next activity and processing time** of ongoing instances from the current data.
  - We conduct **two consecutive predictions** for a running instance.
    1. Predict the next activity of it.
    2. Predict the processing time of the activity by available resources.

E.g.,

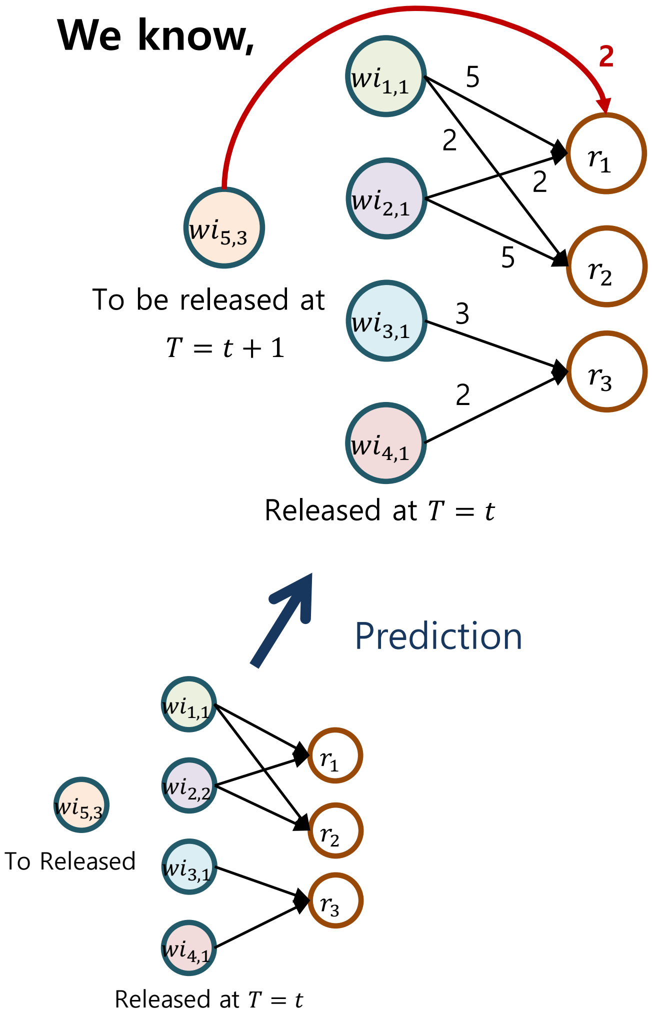
- I_5 is currently at its 2nd operation.
- We first predict its next activity a_1
- Next, we predict the processing time of a_1 by resource r_1.





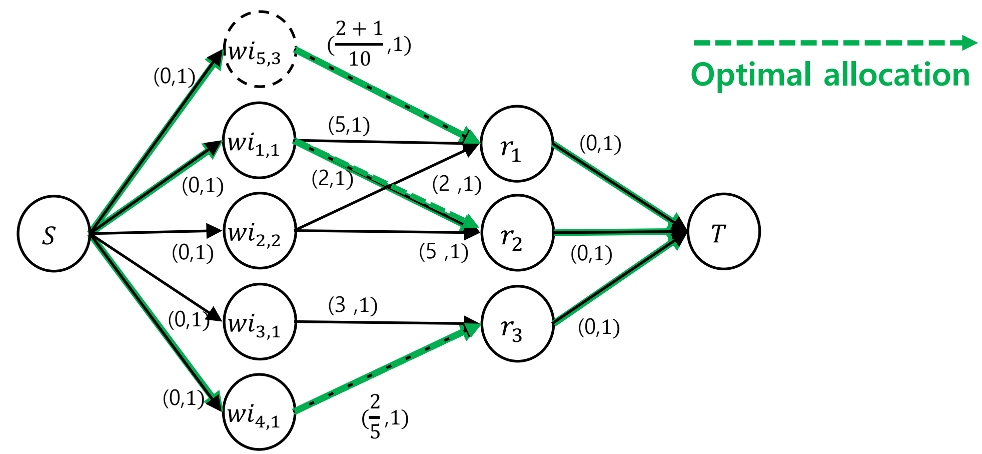
Method – Phase 2

- **Step 3: Scheduling**
  - In this step, we find an optimal scheduling by solving a min-cost max-flow network problem.



Cost function is designed to minimize total weighted completion time

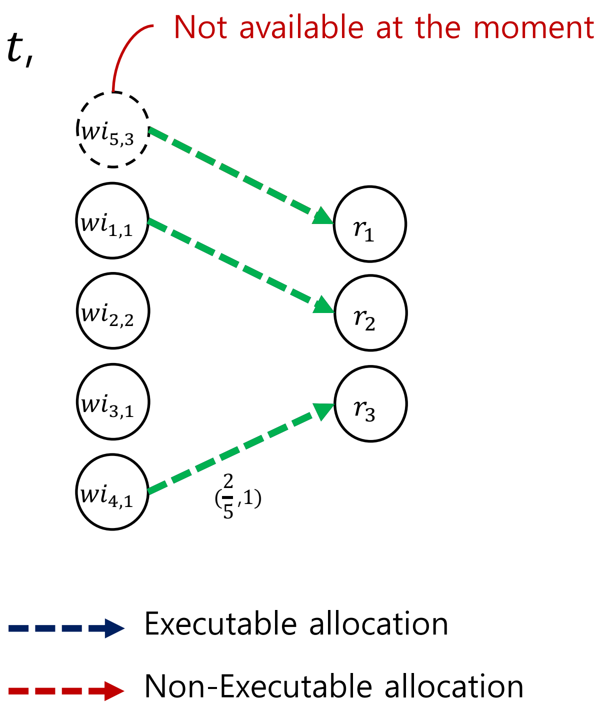
1. Connect source(sink) node to $\widehat{WI}(\hat{R})$. Edges have cost of 0 and capacity of 1.
2. If a work item can be processed by a resource, add edges with (*cost*, *capacity=1*).
3. Apply min-cost max-flow algorithm to find the optimal allocations.



Method – Phase 2

- **Step 4: Executing resource allocation**
  - In this step, we classify the optimal allocations into **executable and non-executable allocations** and then execute only the executable allocations.
    - *Executable allocation* : both instance and resource are available at the moment
    - *Non-executable allocation* : either instance or resource is not available at the moment

At $T = t$,



	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$\sum w_i C_i$
r_1	$wi_{1,1}$					$wi_{5,3}$		65
r_2	$wi_{2,2}$							5
r_3	$wi_{4,1}$		$wi_{3,1}$					15

85

improve

Here

	t	$t+1$	$t+2$	$t+3$	$t+4$	$\sum w_i C_i$
r_1		$wi_{5,3}$		$wi_{2,2}$		25
r_2	$wi_{1,1}$					2
r_3	$wi_{4,1}$		$wi_{3,1}$			15

42

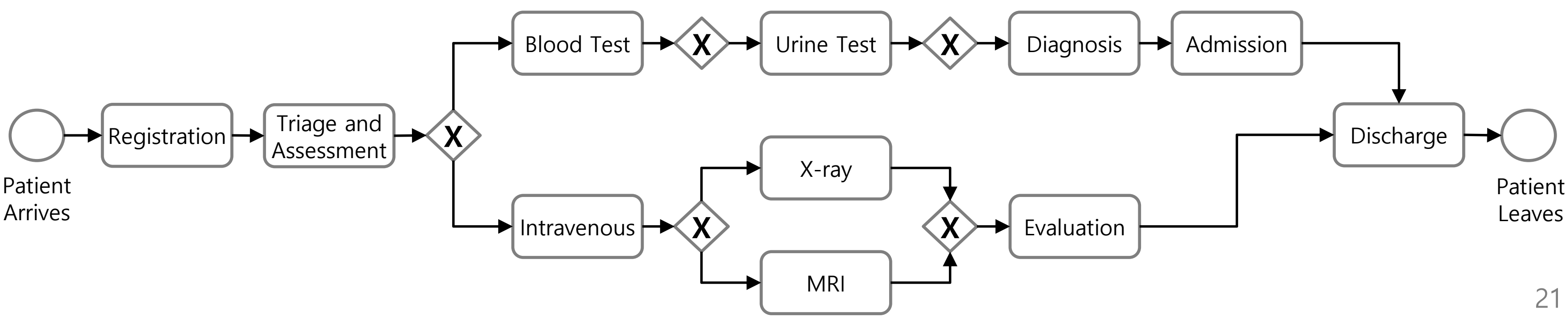
<Result of resource allocation>

Evaluation

- Artificial event log
- Real-life event log

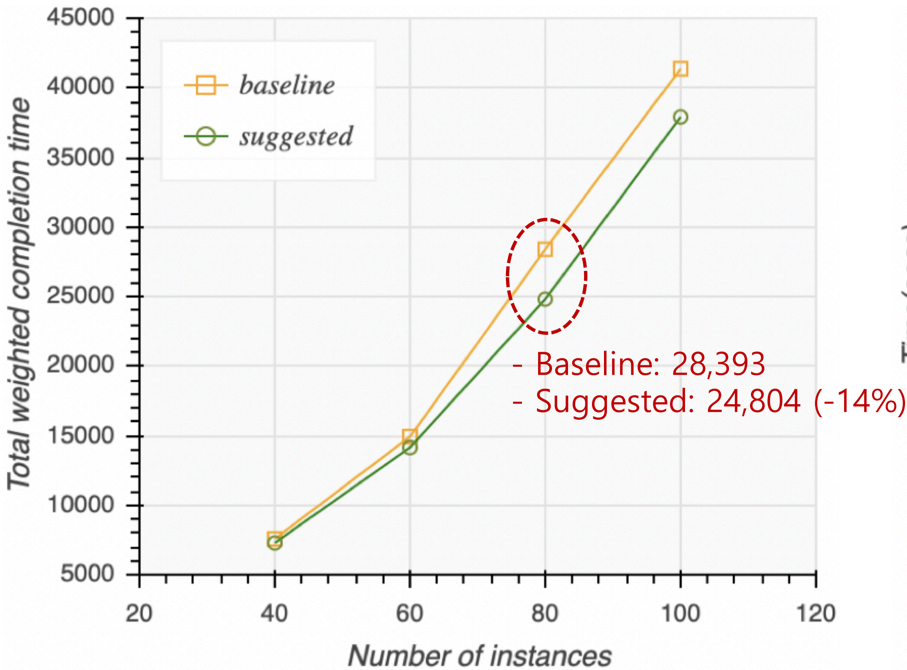
Evaluation – Artificial event log

- **Experimental design**
  - Procedure
    1. Design a business process and generate historic data and current data by simulating it.
    2. Compare our proposed method with baseline approach in terms of **total weighted completion time and computation time by varying the number of instances**.
  - Process description
    - Emergency treatment process at a hospital with 11 activities and 25 resources
    - Each resource has different skills and proficiency level.
    - Patients with different weights (1~10) come into the process in a regular interval.
  - Log Generation
    - Historic data: 7 days, 1,000 instances
    - Current data: 6 hours, 40~120 instances

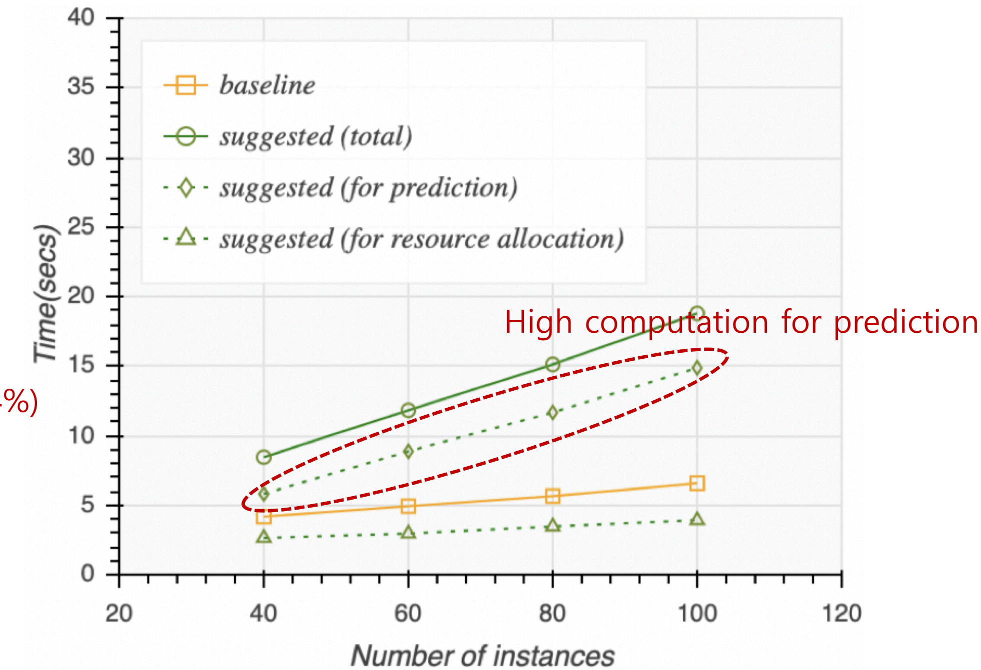


Evaluation – Artificial event log

- **Results**
  - Total weighted completion time and computation time, given the different number of instances.



<Total weighted completion time of varying |I|>



<Computation time of varying |I|>

Evaluation – Real-life event log

- **Experimental design**
  - Procedure
    1. Generate historic data and current data by splitting the real-life log.
    2. Compare our proposed method with baseline approach in terms of **total weighted completion time and computation time**
  - Process description
    - Application procedure for a personal loan at a global financing organization (BPIC'12)
    - 7 activities and 48 resources
    - 13,087 cases and 262,200 events from Oct. 2011 to Mar. 2012
    - According to the case attribute "*AMOUNT_REQ*", we assign the weight (1~10) to each instance.
  - Log split
    - Historic data: events before 10th Mar. 2012
    - Current data: 10th Mar. 2012
      - ✓ contains 110 instances, each conducting 3 activities on average

Evaluation – Real-life event log

- **Results**
  - Total weighted completion time and computation time.
    - Total weight completion time of the proposed method is **42 percent lower** than the one of baseline approach.
      - ✓ assigning the most efficient resources and reserving some resources for future allocation
    - The computation time is much higher in the proposed method.
      - ✓ each work item has many resource options → high computation for predicting the parameters (110.1 out of 115.6)

<Experimental result on real-life event log>

Method	Total weighted completion time	Computation time(secs)
Baseline	1479	7.6
Suggested	1038 (-42%)	115.6

For prediction: 110.1 secs
For scheduling: 5.5 secs

Conclusion

- Contribution
- Limitation
- Future works

Conclusion

- **Contribution**
  - In this paper, we suggest a **concrete method to improve a business process using results from predictive business process monitoring**.
  - To this end, we adopt **the time and next event prediction technique based on LSTM** and **min-cost max-flow algorithm** to optimize online resource scheduling.
  - We verify the effectiveness and efficiency of the proposed method on **both an artificial log and a real-life log**.

- **Limitation**
  - Our proposed method relies heavily on the **performance of the prediction model**.
  - The **computation time** is relatively higher than the baseline approach.

Conclusion

- **Future work**
  - We will conduct additional experiments such as **the effect of the prediction accuracy on the performance**.
  - We will extend this two-phase method to achieve **another goal** such as minimizing the potential risks in the business process **by predicting other relevant parameters and defining a relevant cost function of network arcs**.
  - Another direction for future work is to extend the proposed method by **adopting advanced dispatching techniques**.

Q&A

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