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

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Introduction

- Research Background
- Objective
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.

![Diagram](image)

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.

\[
\begin{array}{c|c|c|c}
\text{Weight} & p_1 & p_2 & p_3 \\
\hline
1 & 1 & 10 \\
\end{array}
\]

\(p_1 \rightarrow r_1\)  
\(<\text{Notation}>\)  
\(<\text{patient weights (Urgency)}>\)

Initial Setting

At \(T = t\),

Predicting the processing time → Assigning most efficient resource

Predicting that \(p_3\) will require “MRI” → Reserving \(r_1\) for \(p_3\)
Introduction – Objective

Phase 1: Offline prediction model construction

1. Constructing prediction model
   - Historic data

Phase 2: Online resource scheduling

2. Predicting parameters
   - Current data

3. Scheduling
   - Next Activity and processing time

4. Executing resource allocation
   - Optimal Schedule

Prediction results

Utilized in

Resource Allocation (Non-clairvoyant Online Job Shop Scheduling)

Achieves

Business Process Improvement

Predictive business process monitoring

Min-cost and max-flow algorithm

Achieves
Background

- Preliminaries
- Problem Statement
- Baseline approach
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 $T = t \rightarrow$ We don’t know the processing time.
    - $I_5$ is currently doing its 2\textsuperscript{nd} operation (i.e., $wi_{5,2}$) at $T = t \rightarrow$ We don’t know the next activity (and required resource).

\begin{tabular}{|c|c|c|c|c|}
\hline
 & $I_1$ & $I_2$ & $I_3$ & $I_4$ & $I_5$ \\
\hline
\textbf{Weight} & 1 & 1 & 1 & 5 & 10 \\
\hline
\end{tabular}

\begin{tikzpicture}
  \node[fill=blue!20] (wi1) at (0,0) {$wi_{1,1}$};
  \node[fill=blue!20] (wi2) at (0,-1) {$wi_{2,1}$};
  \node[fill=blue!20] (wi3) at (0,-2) {$wi_{3,1}$};
  \node[fill=blue!20] (wi4) at (0,-3) {$wi_{4,1}$};
  \node[fill=blue!20] (wi5) at (0,-4) {$wi_{5,3}$};

  \node[fill=blue!20] (r1) at (2,0) {$r_1$};
  \node[fill=blue!20] (r2) at (2,-1) {$r_2$};
  \node[fill=blue!20] (r3) at (2,-2) {$r_3$};

  \draw[->] (wi1) -- (r1);
  \draw[->] (wi2) -- (r2);
  \draw[->] (wi3) -- (r2);
  \draw[->] (wi3) -- (r3);
  \draw[->] (wi4) -- (r3);
  \draw[->] (wi5) -- (r3);

  \node[draw=none,fill=white,inner sep=5pt] at (0,-5) {To be released};
  \node[draw=none,fill=white,inner sep=5pt] at (2,-5) {Released at $T = t$};
\end{tikzpicture}
**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.

<table>
<thead>
<tr>
<th></th>
<th>$I_1$</th>
<th>$I_2$</th>
<th>$I_3$</th>
<th>$I_4$</th>
<th>$I_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Weight</strong></td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>10</td>
</tr>
</tbody>
</table>

<Instance weights>

At $T = t$,

Released at $wi_{5,3}$

Released at $t = t$

Allocation

Here

<Result of resource allocation based on **WeightGreedy**>

<table>
<thead>
<tr>
<th></th>
<th>$t$</th>
<th>$t+1$</th>
<th>$t+2$</th>
<th>$t+3$</th>
<th>$t+4$</th>
<th>$t+5$</th>
<th>$t+6$</th>
<th>$\Sigma w_iC_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_1$</td>
<td>$wi_{1,1}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>65</td>
</tr>
<tr>
<td>$r_2$</td>
<td></td>
<td>$wi_{2,2}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5</td>
</tr>
<tr>
<td>$r_3$</td>
<td>$wi_{4,1}$</td>
<td>$wi_{3,1}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>15</td>
</tr>
</tbody>
</table>

85
Method

- Overview
- Steps
Method – Overview

Phase 1: Offline prediction model construction

1. Constructing prediction model
   - Historic data

   Prediction model

Phase 2: Online resource scheduling

2. Predicting parameters
   - Current data

3. Scheduling
   - Next Activity and processing time

4. Executing resource allocation
   - Optimal Schedule

   Resource allocation
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 2\textsuperscript{nd} 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.

  **We know,**

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

  **Cost function is designed to minimize total weighted completion time**

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

  **Optimal allocation**
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 $T = t,$

\[
\begin{align*}
wi_{1,1} & \quad r_1 \\
wi_{2,2} & \quad r_2 \\
wi_{3,1} & \quad r_3 \\
wi_{4,1} & \quad r_4
\end{align*}
\]

Not available at the moment

\[
\begin{align*}
wi_{5,3} & \quad r_5
\end{align*}
\]

Here

<table>
<thead>
<tr>
<th>t</th>
<th>t+1</th>
<th>t+2</th>
<th>t+3</th>
<th>t+4</th>
<th>$\Sigma w_i C_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_1$</td>
<td>$wi_{5,3}$</td>
<td>$wi_{2,2}$</td>
<td>25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r_2$</td>
<td>$wi_{1,1}$</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$r_3$</td>
<td>$wi_{4,1}$</td>
<td>$wi_{3,1}$</td>
<td>15</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<Result of resource allocation>
Evaluation

- Artificial event log
- Real-life 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

- Evaluation
  - Registration
  - Triage and Assessment
  - Blood Test
  - Urine Test
  - Diagnosis
  - Admission
  - Intravenous
  - X-ray
  - MRI
  - Evaluation
  - Discharge
  - Patient Arrives
  - Patient Leaves
Evaluation – Artificial event log

• Results

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

  - Baseline: 28,393
  - Suggested: 24,804 (-14%)

High computation for prediction
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
    - According to the case attribute “AMOUNT_REQ”, we assign the weight (1~10) to each instance.

- Log split
  - Historic data: events before 10\textsuperscript{th} Mar. 2012
  - Current data: 10\textsuperscript{th} 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>

<table>
<thead>
<tr>
<th>Method</th>
<th>Total weighted completion time</th>
<th>Computation time(secs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>1479</td>
<td>7.6</td>
</tr>
<tr>
<td>Suggested</td>
<td>1038 (-42%)</td>
<td>115.6</td>
</tr>
</tbody>
</table>

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