

# Applying Process Mining to User Behaviour Analysis: The Event-Case Attribution Problem

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# Agenda

## **Introduction**

Approach

Evaluation

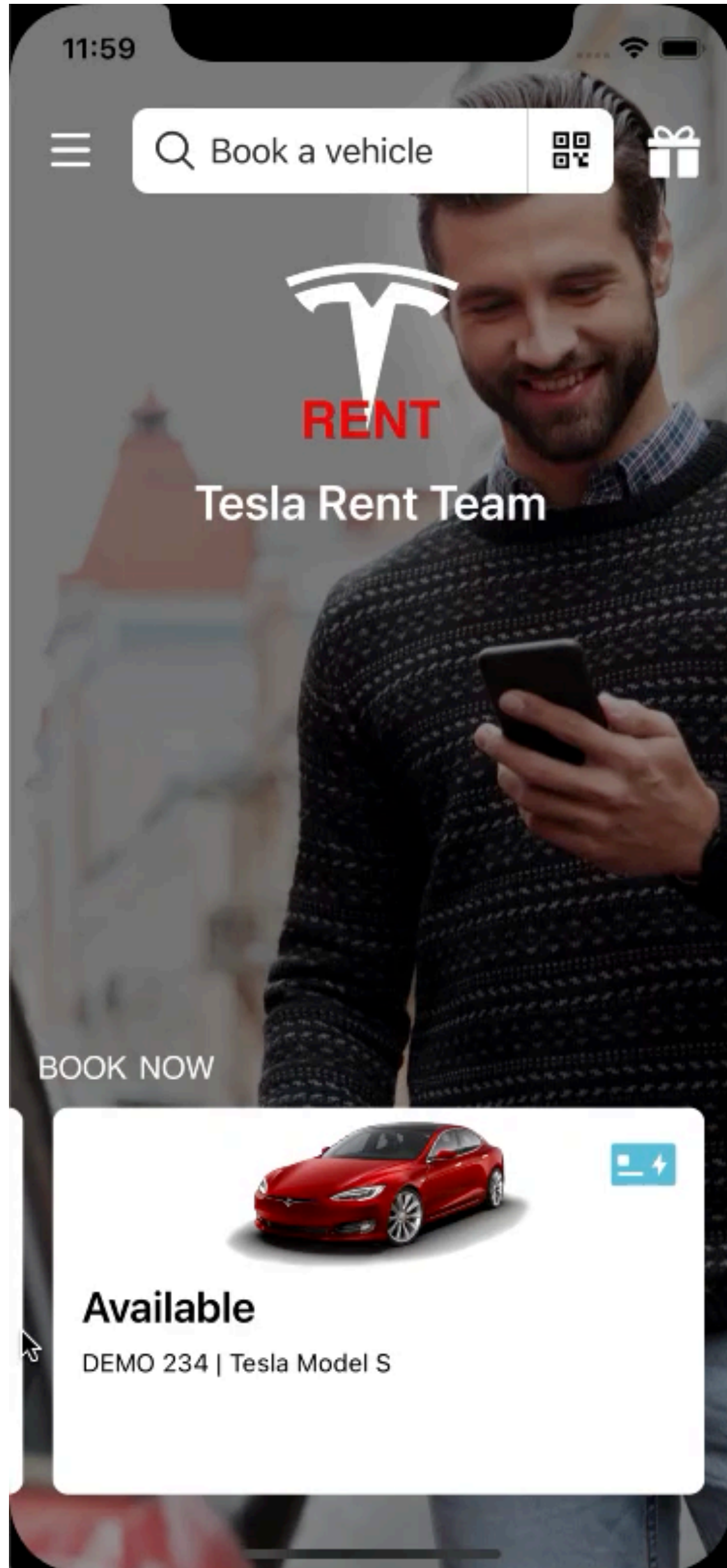
- Baseline Approaches

- Case / User Study

Conclusion

# Problem Statement

*"Applying **process mining** techniques to user **interaction recordings** in order to analyze the **real usage** of a software system."*



# Example Interaction Log

station_based_dashboard	11:59:10	ac2F	e4D2	iOS
search	11:59:11	ac2F	e4D2	iOS
date_time_picker	11:59:13	ac2F	e4D2	iOS
search_results	11:59:17	ac2F	e4D2	iOS
pre_booking	11:59:18	ac2F	e4D2	iOS
confirm_booking	11:59:19	ac2F	e4D2	iOS
booking	11:59:21	ac2F	e4D2	iOS
booking_started	11:59:23	ac2F	e4D2	iOS

# Example Interaction Log

	Screen	Timestamp
1	station_based_dashboard	11:59:10
2	search	11:59:11
3	date_time_picker	11:59:13
4	search_results	11:59:17
5	pre_booking	11:59:18
6	confirm_booking	11:59:19
7	booking	11:59:21
8	booking_started	11:59:23



# Revised Problem Statement

*"Given a user interaction log with **no case information**, find the **best segmentation** of the log, such that every user interaction belongs to **exactly one case**."*

→ Event-Case Attribution / Correlation Problem [4]

# Related Use Cases

- Marrella et al. 2018 [1]
- Measuring learnability of software system using UI recordings
- Predefined start / end events
- Jlaiaty et al. 2017 [2]
- Using emails as events, no connection to process instances
- Mail attributes (sender, receiver, ...)
- Linn et al. 2018 [3]
- Mine user interaction data as the basis for RPA applications
- User marks start / end

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## Measuring the Learnability of Interactive Systems Using a Petri Net Based Approach

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**ABSTRACT**  
A learnable system allows a user to know how to perform correctly any task of the system after having executed it a few times in the past. In this paper, we propose an approach to measure the learnability of interactive systems during their daily use. We rely on recording in a user log the user actions that take place during a run of the system and on replaying them over the system interaction models, which describe the expected ways of executing system tasks. Our approach identifies deviations between the interaction models and the user log and assesses their weight through a fitness value. By measuring the rate of the fitness value for subsequent executions of the system we are able not only to understand if the system is learnable with respect to its tasks, but also to quantify its degree of learnability over time and to identify potential learning issues.

**Author Keywords**  
Learnability; Usability; Quantitative Method; Interaction Design; Human-Computer Dialog; Petri nets; HCI Theory

**ACM Classification Keywords**  
H.5.2. User Interfaces: Theory and methods

**INTRODUCTION**

Starting from this general idea of learnability, the work [12] surveys the existing learnability research spanning over the past four decades, and shows that there is *no consistent agreement* on how learnability of a system should be defined, evaluated and improved. Several accepted metrics exist for measuring learnability, but they are scattered across various research papers and limited to measure specific aspects of the interaction. A classification of these metrics is presented in [12]. Some of them suffer from *evaluation subjectivity*, as they rely on associating learnability to the “quality” of the interaction through a score given by an external evaluator or by analyzing the user feedbacks after the interaction has happened [22, 20, 11]. *Mental metrics* – though more abstract and complex to be evaluated – are used to understand which cognitive processes drive the user behavior during the interaction with the system, in order to make it more learnable [31, 29, 33]. Finally, there are also *quantitative* metrics that allow to measure in an *objective* way the performances of a user executing a relevant task through the system (such as completion times, error rates and percentage of functionality understood) [26, 23, 7].

Since all the above measurements are mainly performed in (controlled) lab environments under the guidance of an external evaluator, they have been proven to be particularly suitable for measuring the first time interaction with a system (i.e. the mental learnability). Although the measurement of mental learn-

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## Business Process Instances Discovery from Email Logs

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**Abstract**—Email is a reliable, confidential, fast, free and easily accessible form of communication. Due to its wide use in personal, but most importantly, professional contexts, email represents a valuable source of information that can be harvested for understanding, reengineering and repurposing undocumented business processes of companies and institutions. Few researchers have investigated the problem of extracting and analyzing the process-oriented information contained in emails. In this paper, we go forward in this direction by proposing a new method to discover business process instances from email logs that uses unsupervised classification techniques. The approach is composed of two clustering steps. The first one uses a powerful semantic similarity measurement method, Word2vec, while the second one uses a similarity measure combining several email attributes. Experimental results are detailed to illustrate and prove our approach contributions.

**Index Terms**—Email analysis, Word2vec, process instance discovery, process mining, process analysis

**I. INTRODUCTION**

While its initial use focused on exchanging (personal) messages between individuals, email is nowadays used for complex activities ranging from organization of events, to marketing and sales campaigns, to recruitment, to customer

emails of the same process instance. However, using only one attribute for similarity estimation is not always sufficient to group emails of the same process instance.

To overcome the limits of related work and to take advantage of the many available process mining tools, our long-term goal is to propose a framework able to extract process-related information from email logs. This requires associating each email with a process model, a process instance and an activity type identifier. In this paper, we propose a new method able to associate each email with a process model and a process instance identifier, by leveraging unsupervised machine learning techniques. Discovering business process instances from email logs is useful in itself for several analysis questions like the following:

- What is the average duration of a business process? This can be computed by averaging the time taken by all process instances of the same process.
- Which process instances took the longest time to be achieved? This may help in identifying the reason behind some time delays.
- How many business process instances were generated?

Christian Czarnecki et al. (Hrsg.): Workshop der INFORMATIK 2018, Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2018 245

## Desktop Activity Mining - A new level of detail in mining business processes

Christian Linn<sup>1</sup>, Phileas Zimmermann<sup>2</sup>, Dirk Werth<sup>3</sup>

**Abstract:**

New analysis and automation technologies are significantly changing the way how business process management is performed. Especially Robotic Process Automation (RPA) is rapidly gaining importance as a method to automate office processes. An efficient automation of office processes however requires detailed information about all user activities related to the process. While process mining techniques can in principle be used to discover processes in a data driven way, the existing approaches are not able to gather information in a level of detail required for automation purposes. That is why in particular the configuration of RPA systems is a labor and knowledge-intensive task that is based on a human expert, modeling all process variations in detail. In this paper, we present Desktop Activity Mining as a new approach to mine detailed process activity data. The concept is to record the detailed desktop activities of all users performing an office process and consolidate the process variations with process

# Existing Approaches

- Pérez-Castillo et al. 2012 [4]
- Process mining for non process-aware software systems
- Correlation based on attributes

- ✓ Good accuracy
- ✓ Little additional input
- ✗ Requires additional event attributes
- ✗ Quadratic runtime

- Pourmirza et al. 2017 [5]
- Quadratic programming problem based on directly-follows relations
- Optimize based on time heuristic

- ✓ Good accuracy
- ✓ No additional input
- ✗ Cannot handle cyclic processes
- ✗ Long Runtime

- Bayomie et al. 2019 [6]
- Process model as input
- Simulated annealing, optimizing variance of activity execution times

- ✓ Very good accuracy
- ✓ Cyclic processes
- ✗ Requires detailed process model
- ✗ Long Runtime



# Agenda

Introduction

**Approach**

Evaluation

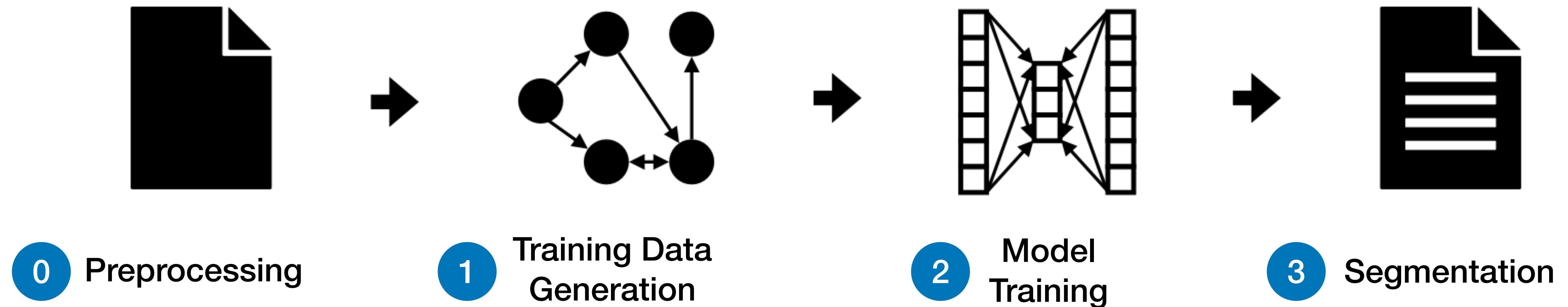
Baseline Approaches

Case / User Study

Conclusion

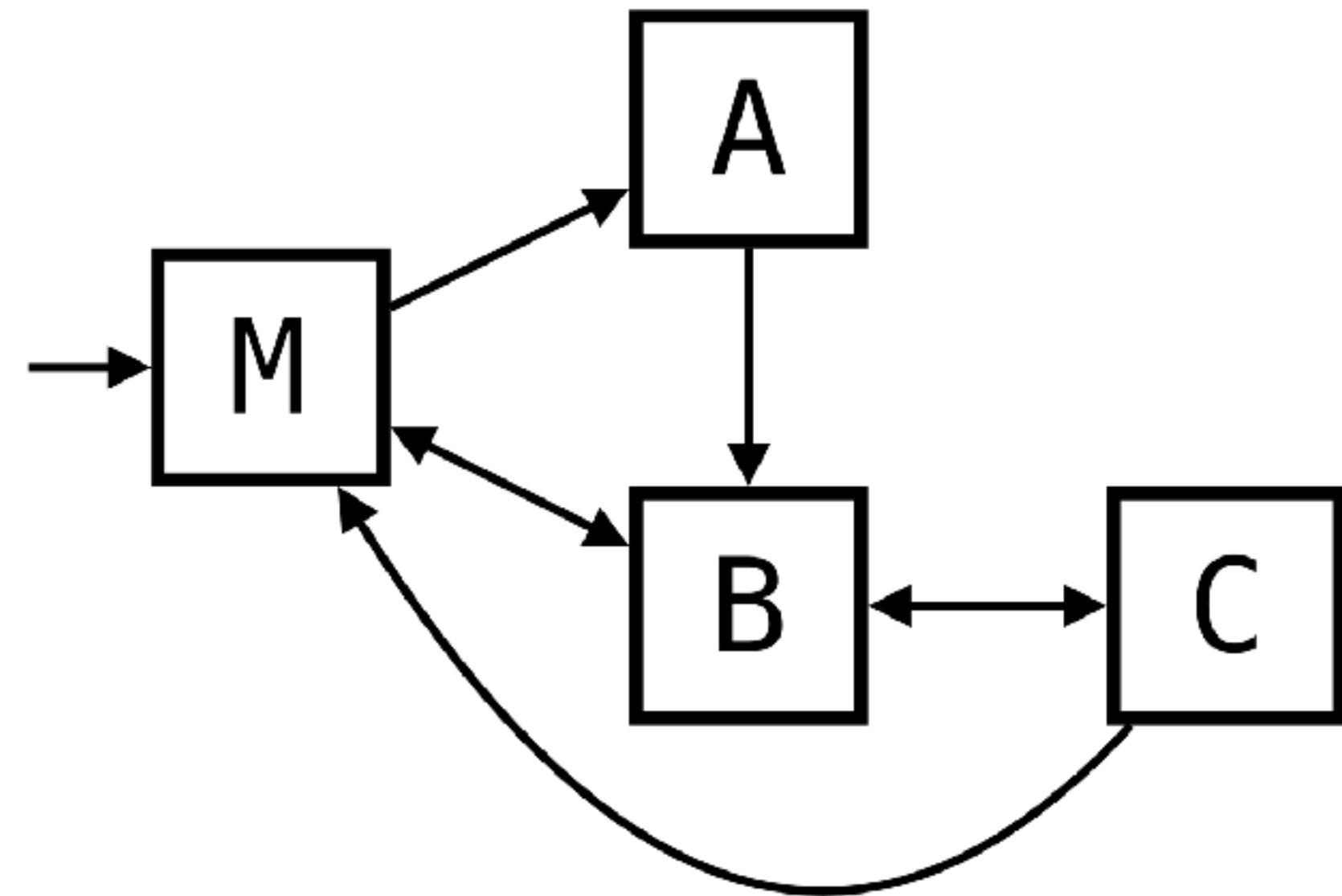
# Proposed Approach

- Perform log segmentation using word2vec [7, 8] models
  - Inspired by Lakhani et. al 2019 [9]
- Considers the special properties of interaction data & Supports cycles



# Running Example

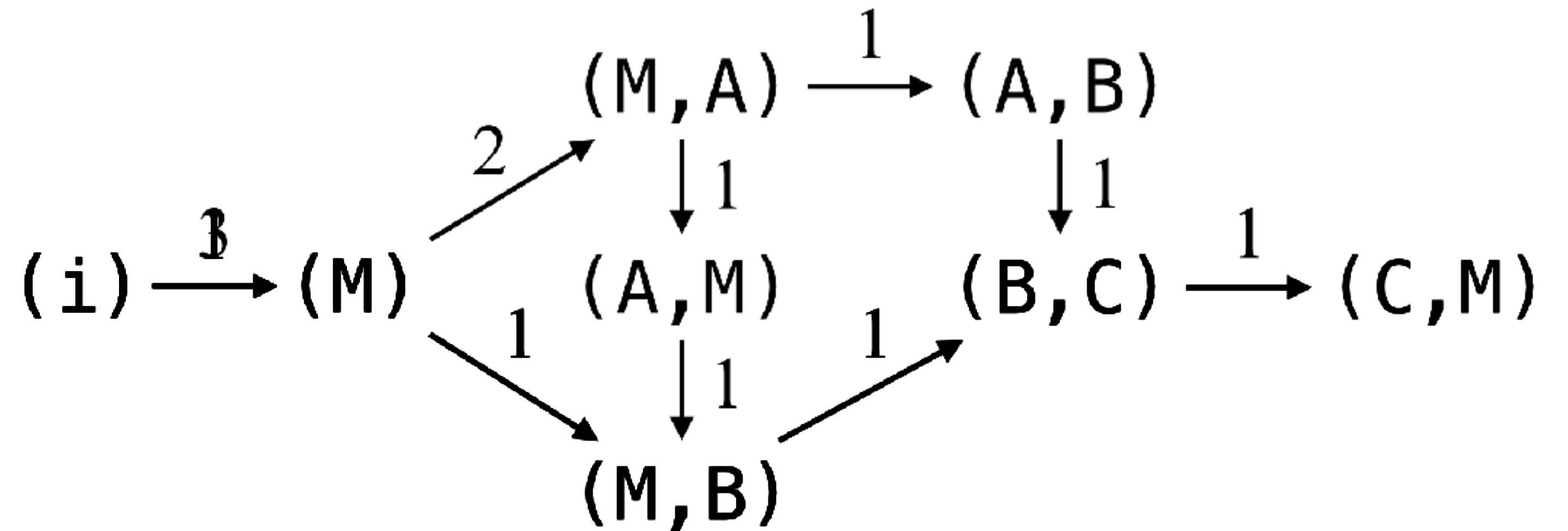
- Four actions
  - M (menu)
  - A, B, C (features)
- Three users
  - $\langle M, A, M, B, C \rangle$
  - $\langle M, B, C, M \rangle$
  - $\langle M, A, B, C \rangle$



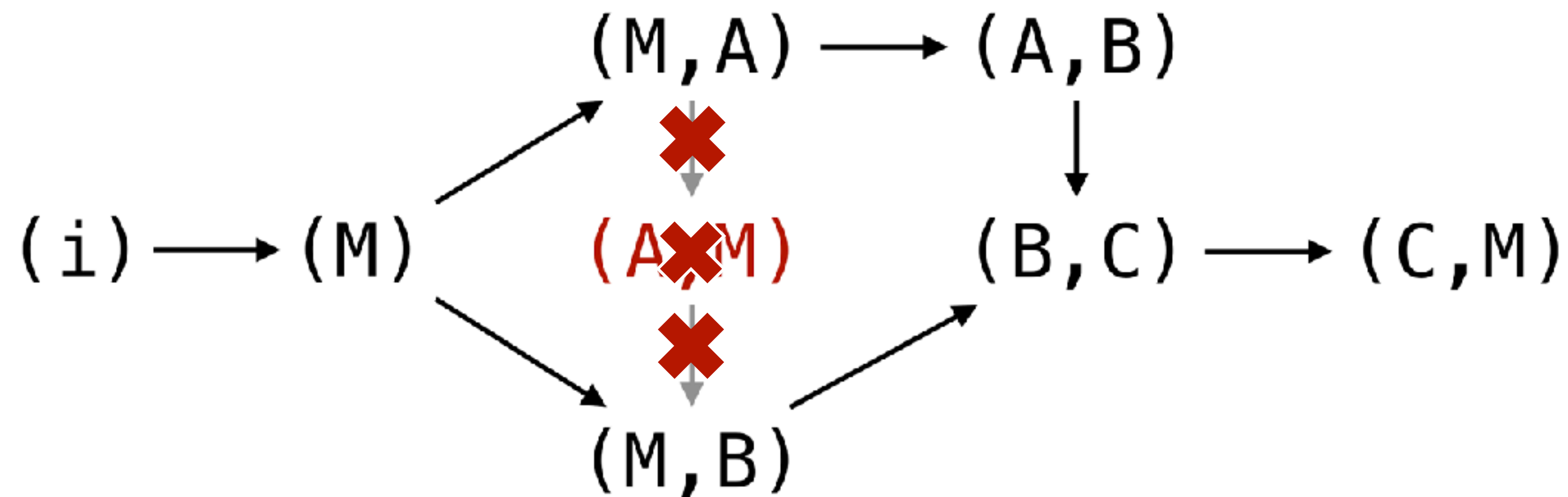
**Directly-Follows Graph**

# 1 Transition System Generation

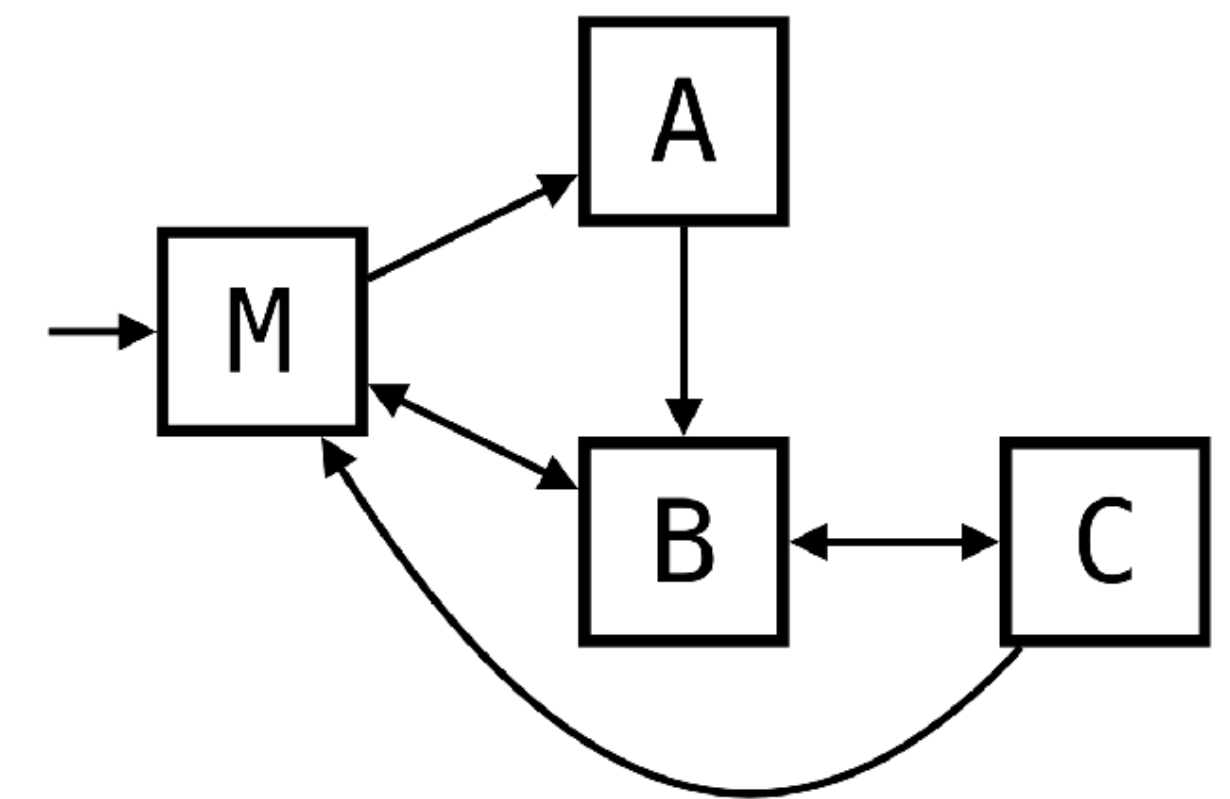
M A B C  
□ M B C M  
M A M B C



# 1 Transition System Generation



Remove Illegal Transitions

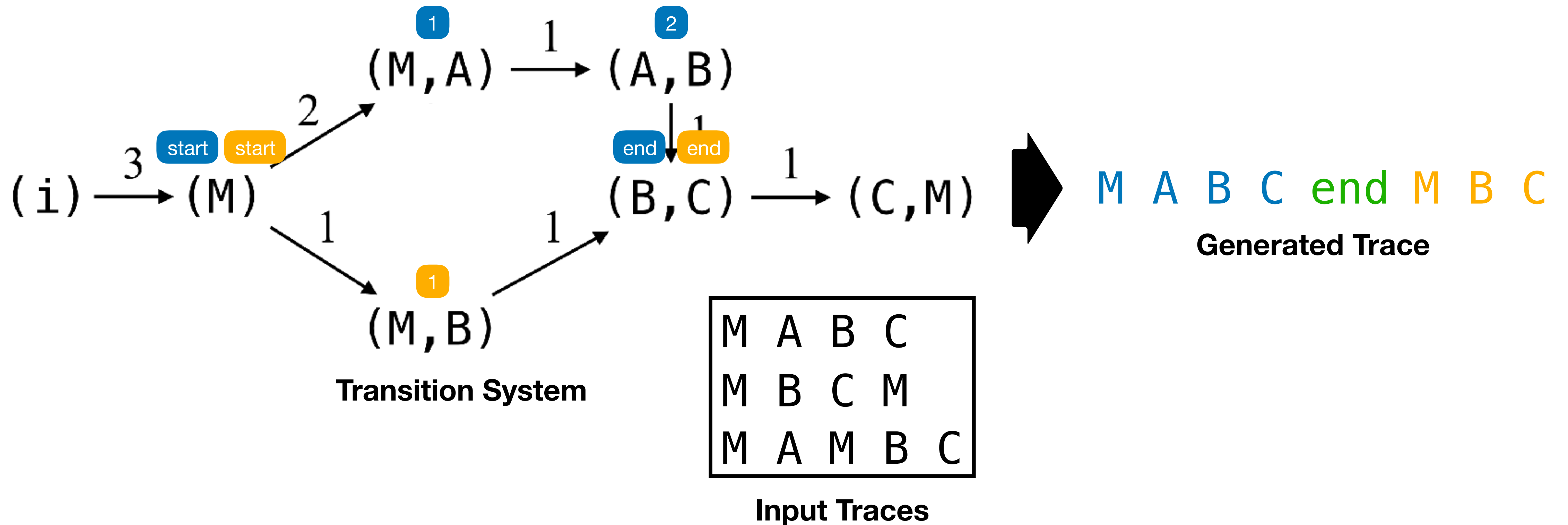


DFG

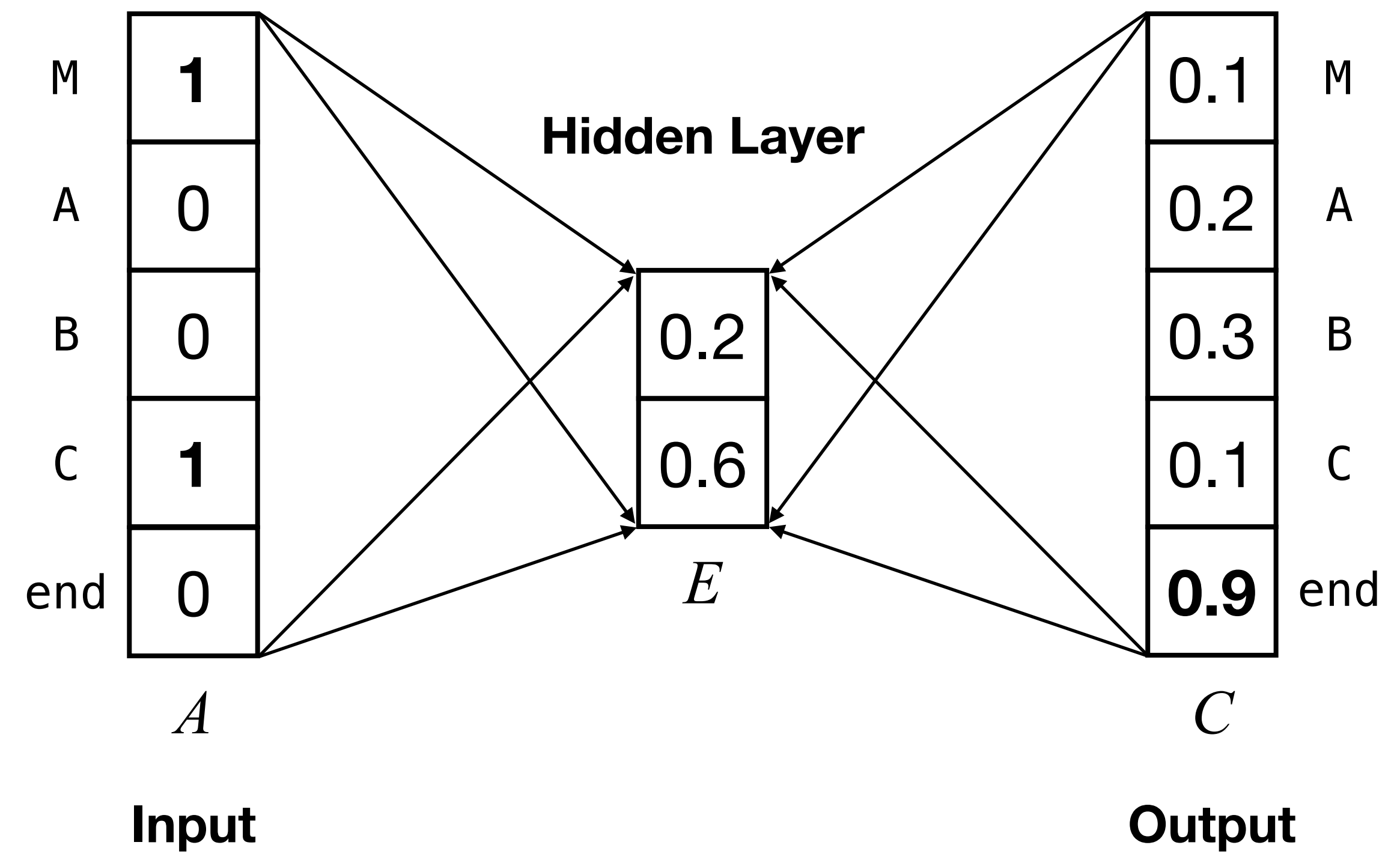
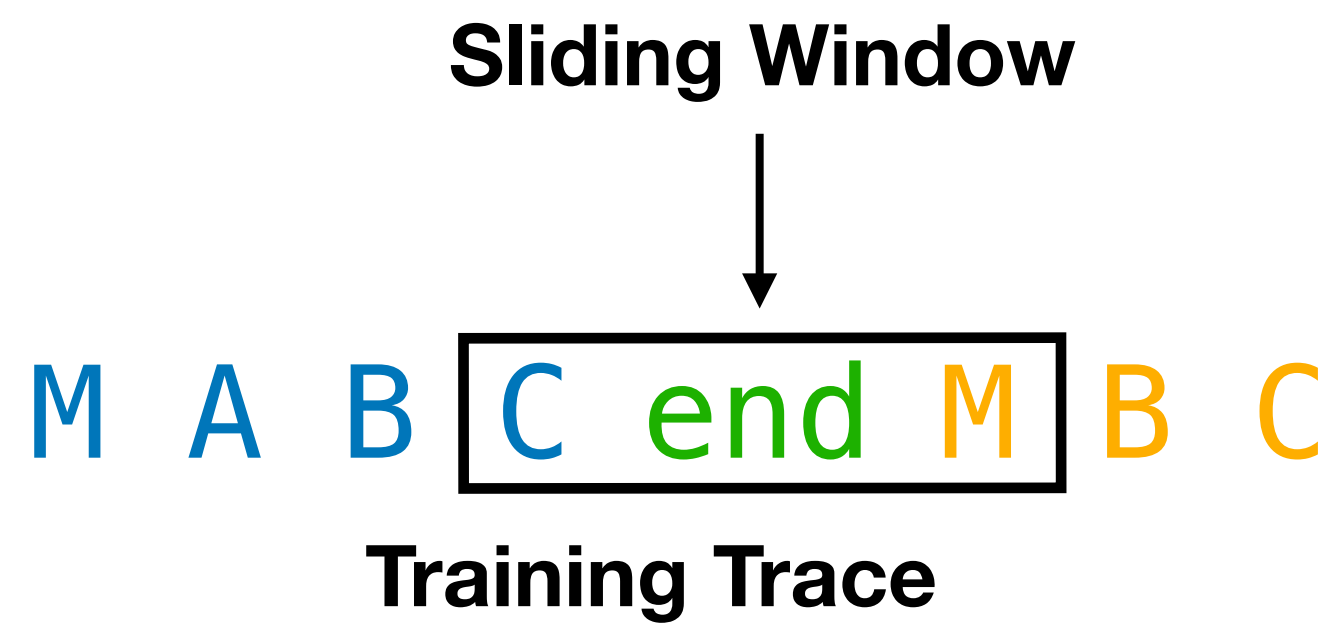
# 1 Trace Generation

$$l_{\text{trans}}(s_1, a, s_2) = \frac{\omega(s_1, a, s_2)}{\sum_{t' \in T_{\text{out}}(s_1)} \omega(t')}$$

$$l(\langle s_1, \dots, s_m \rangle) = l_{\text{start}}(s_1) \cdot \prod_{i=1}^{m-1} l_{\text{trans}}(s_i, a, s_{i+1}) \cdot l_{\text{end}}(s_m)$$

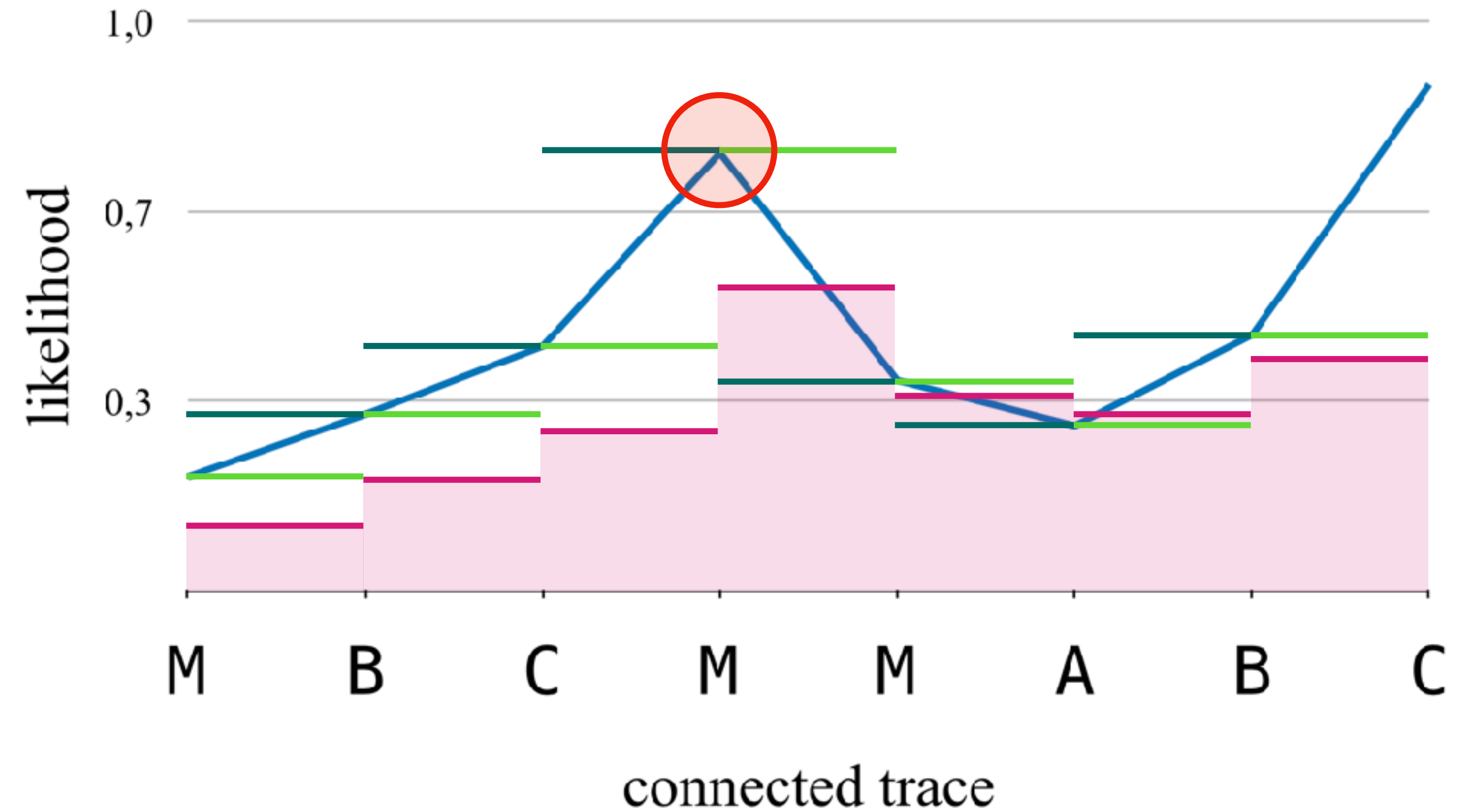


# 2 Model Training



# 3 Scoring & Segmentation

- 1  $s_i > b_1 \cdot s_{i-1}$
- 2  $s_i > b_2 \cdot s_{i+1}$
- 3  $s_i > \frac{b_3}{k} \cdot \sum_{j=(i-k-1)}^{i-1} s_j$





# Agenda

Introduction

Approach

**Evaluation**

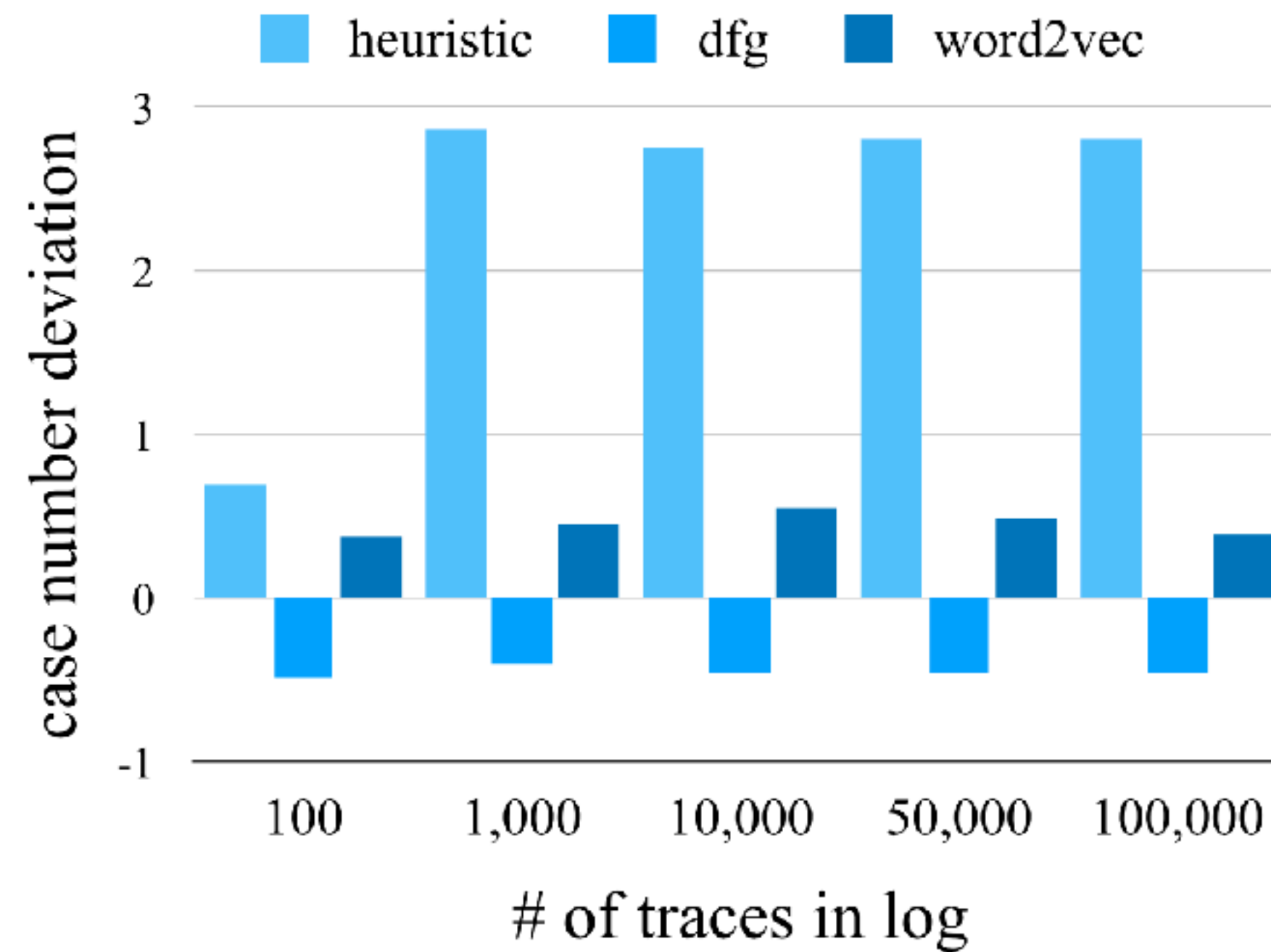
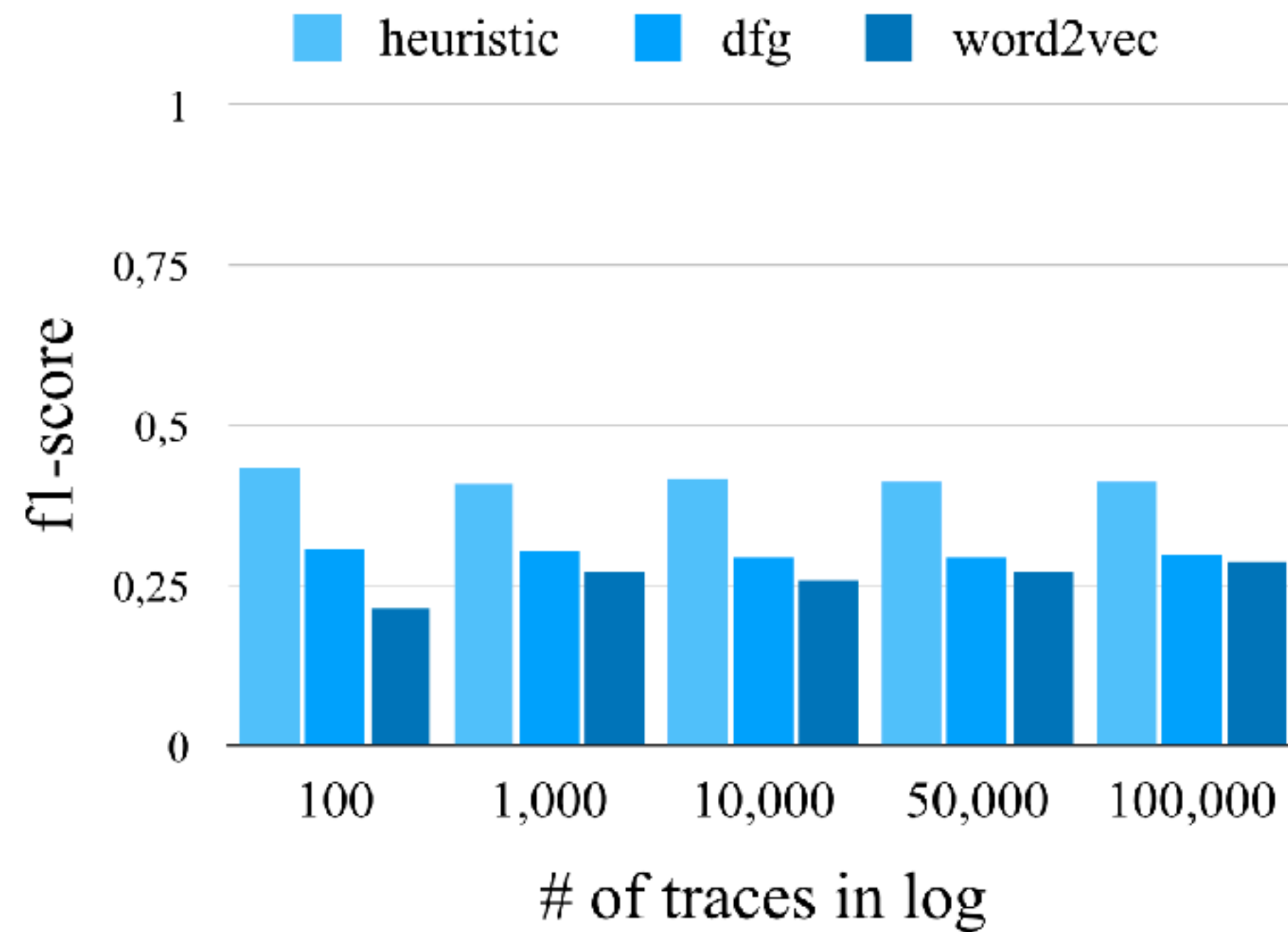
Baseline Approaches

Case / User Study

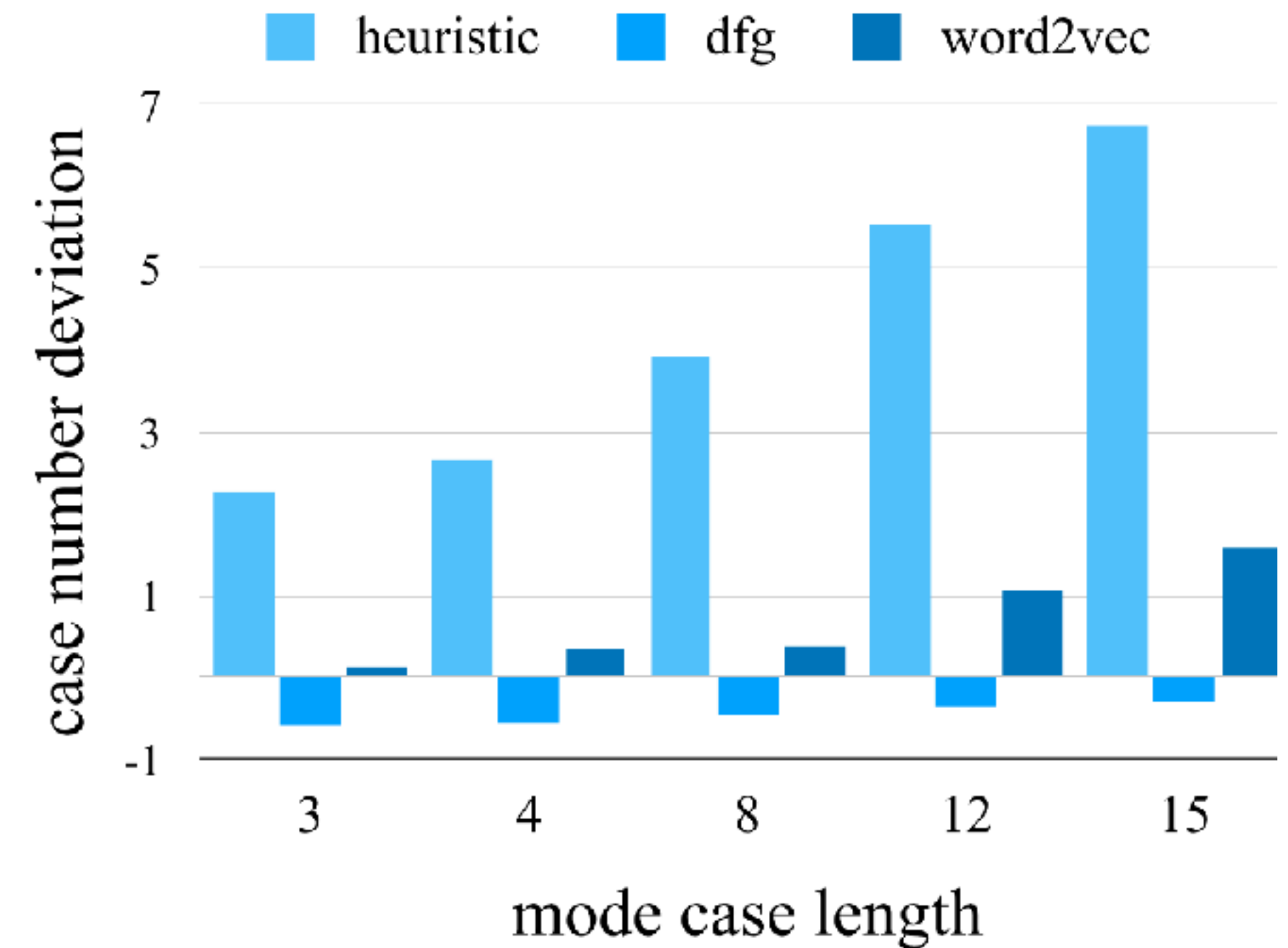
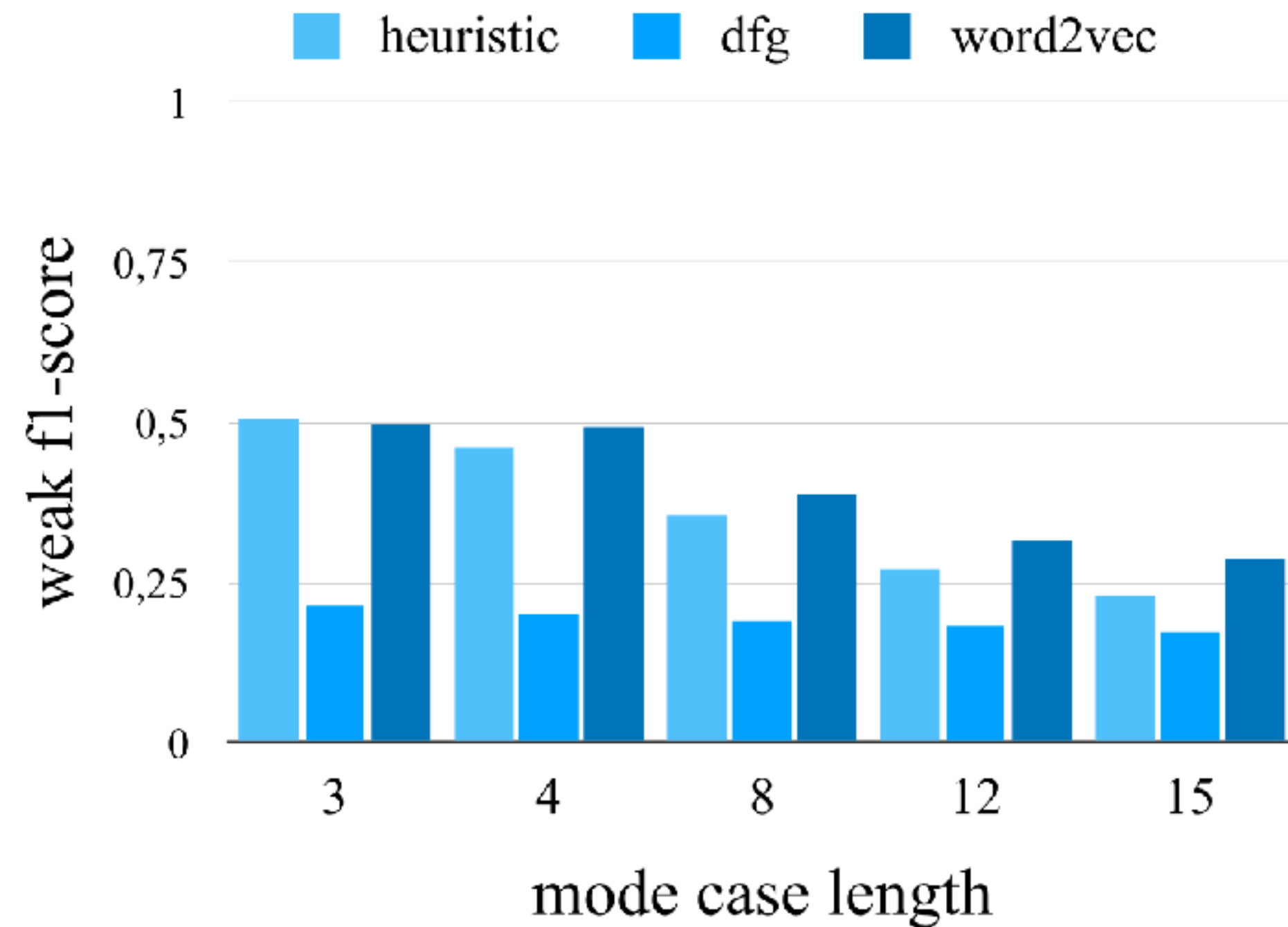
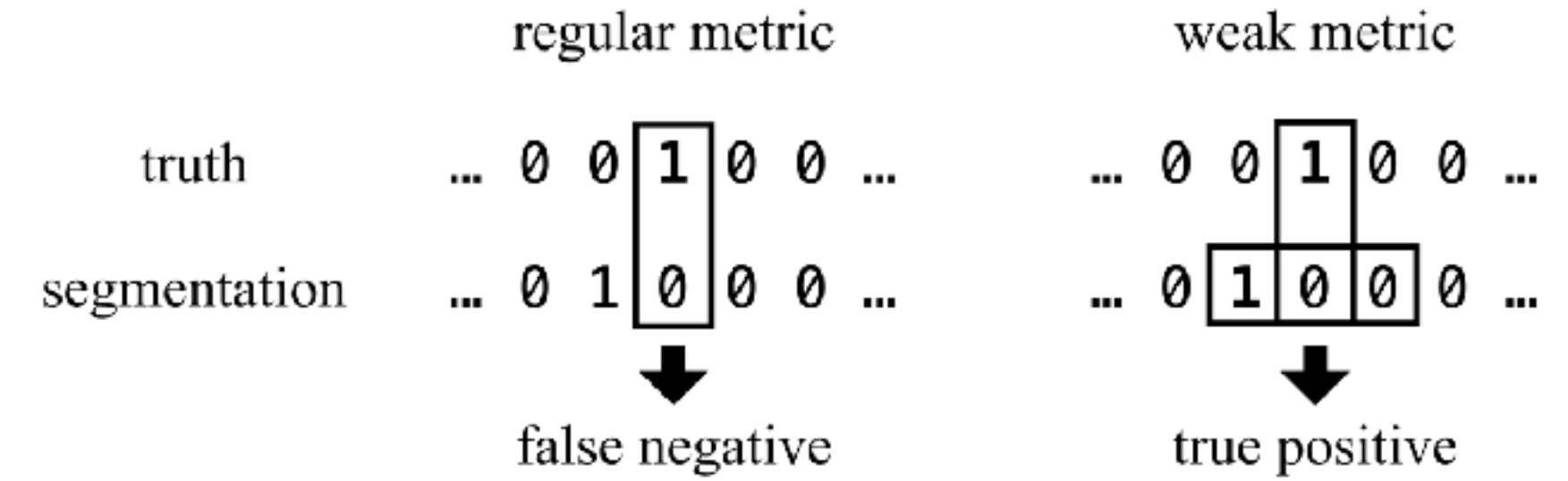
Conclusion & Outlook

# Log Size

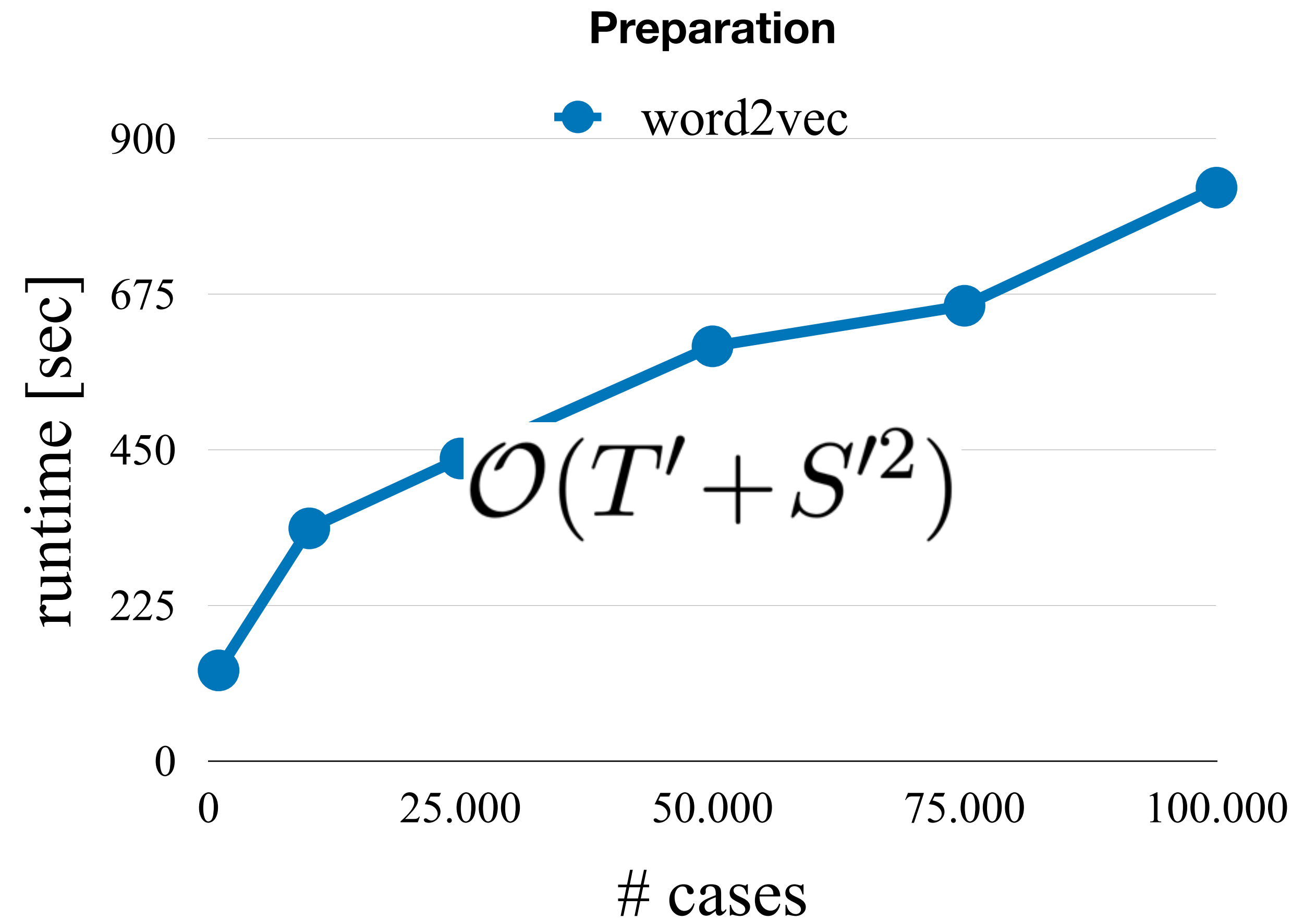
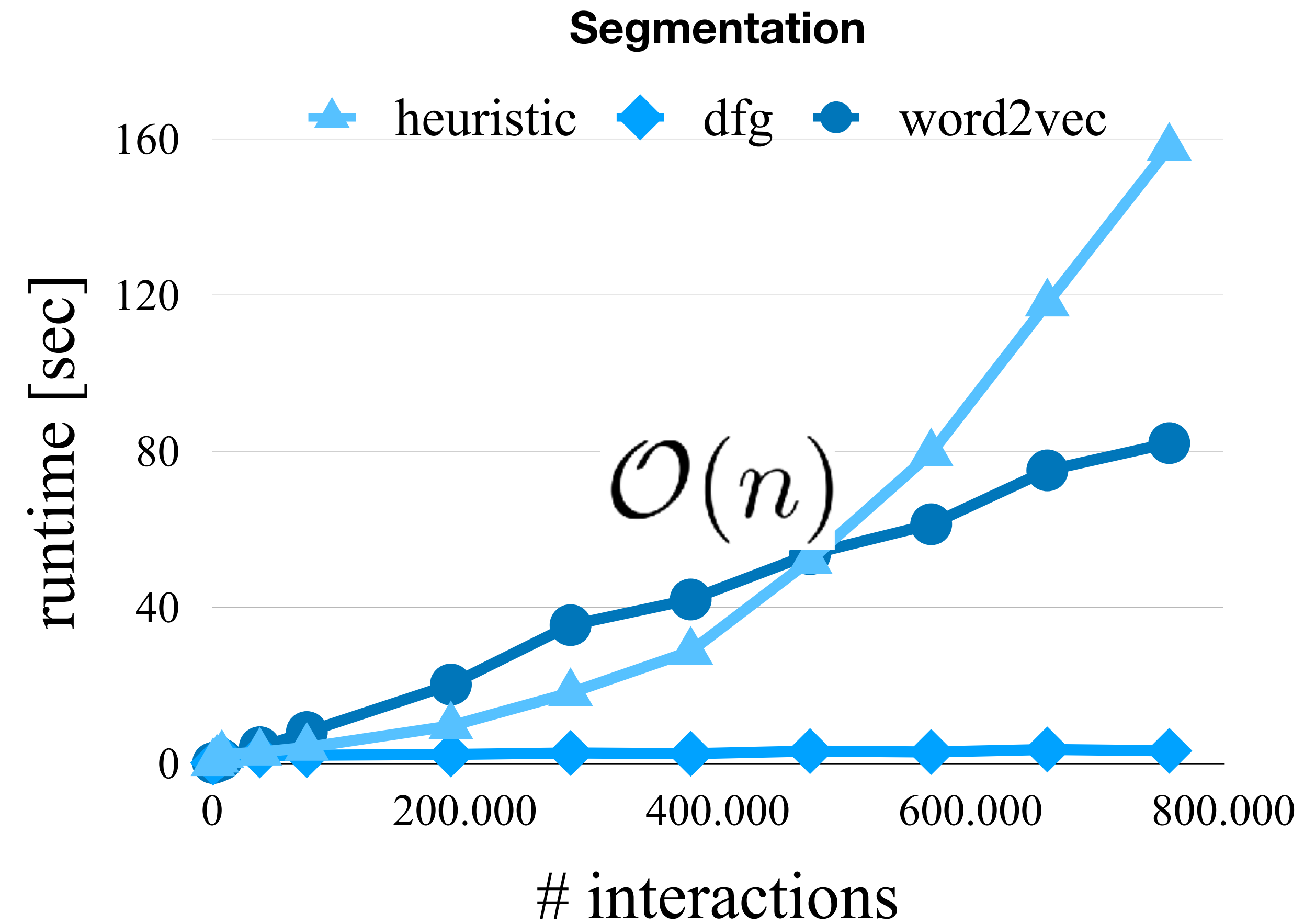
$$cnd = \frac{\# \text{ of predicted cases} - \# \text{ of real cases}}{\# \text{ of real cases}}$$



# Case Length

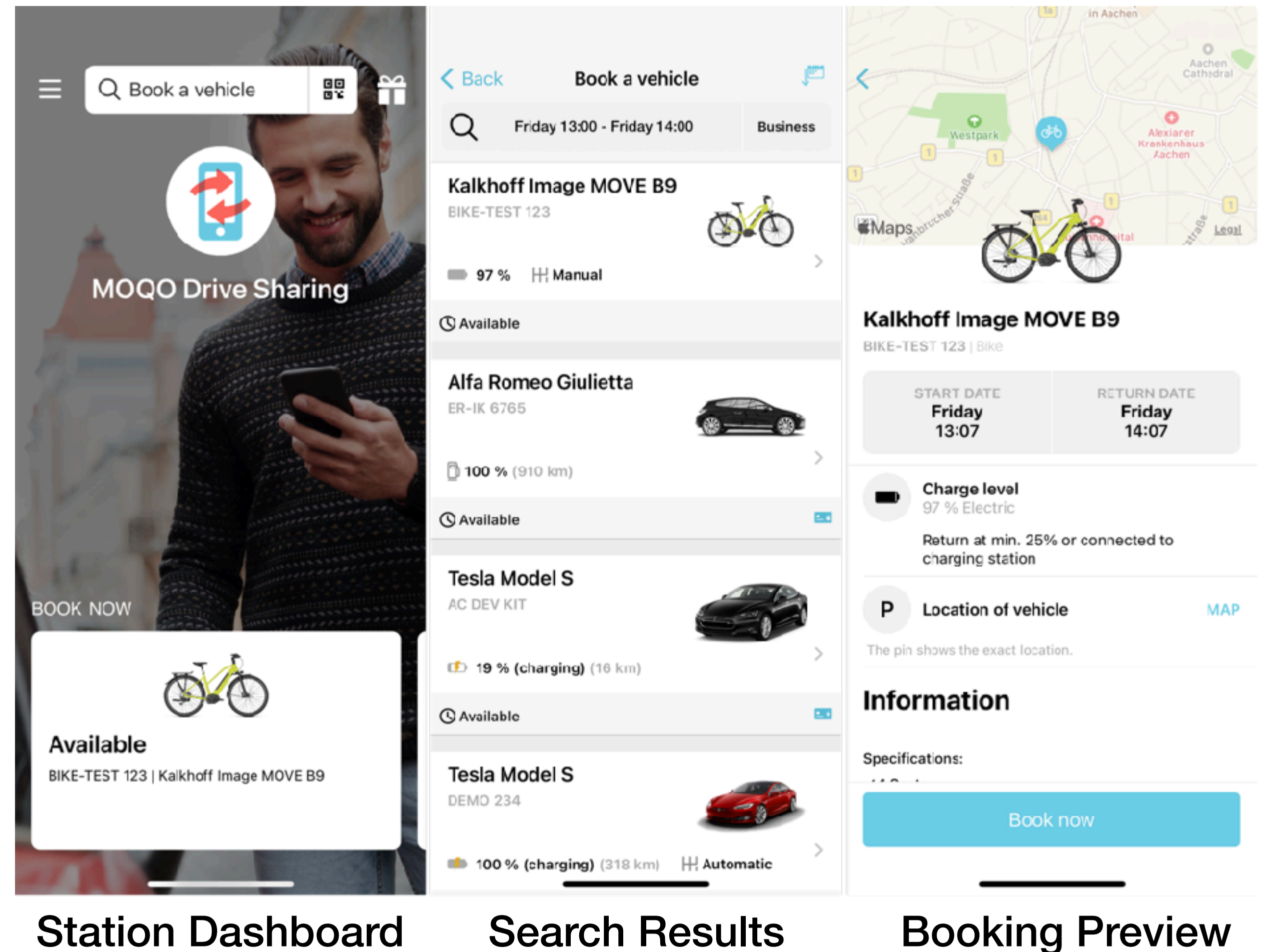


# Time Analysis



# Case / User Study

- Dataset from mobility sharing application
  - 990,000 events
  - 12,200 users
  - 78 activities
- Log analysis using process mining techniques
- Results were discussed with experts



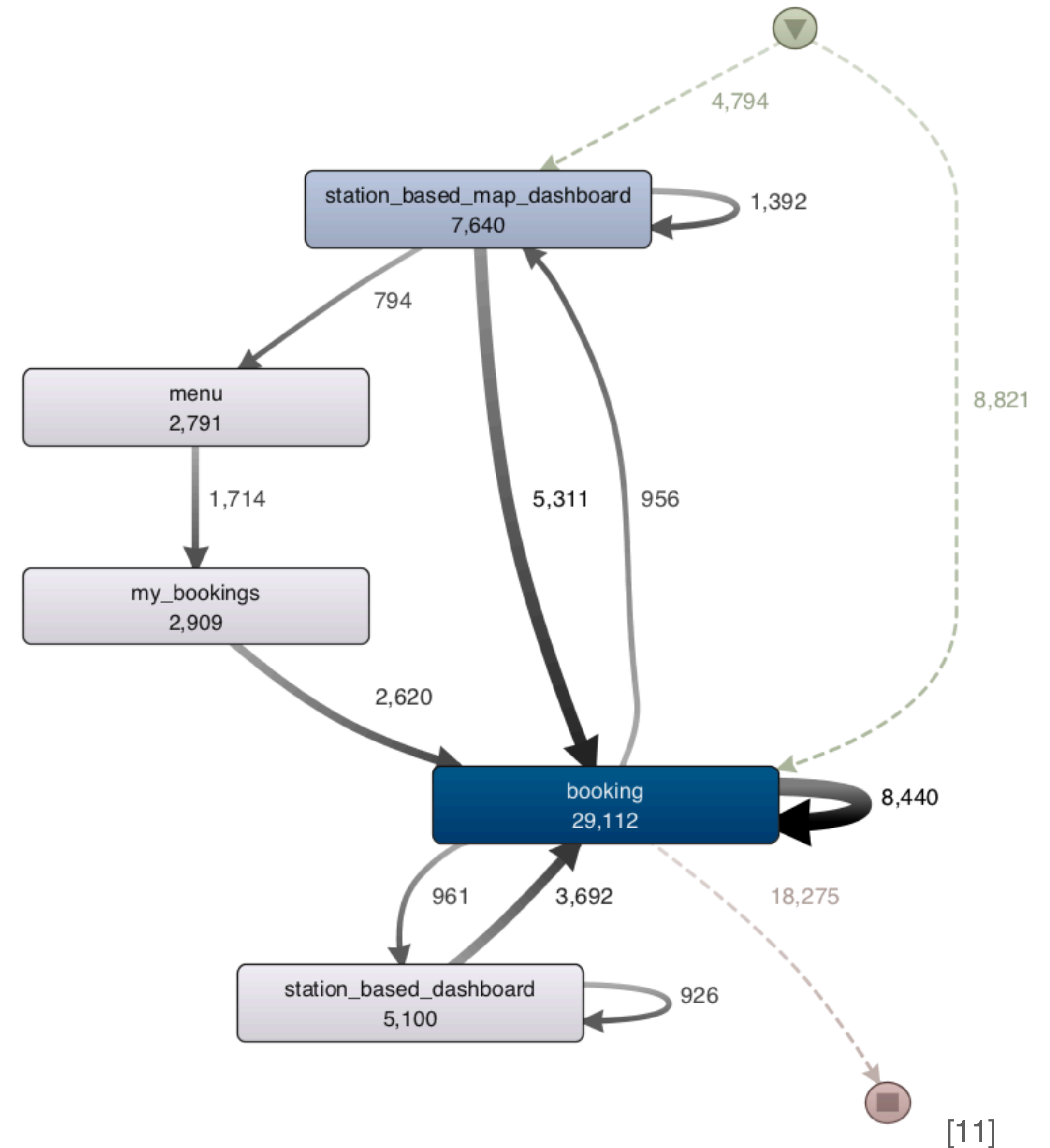
# Question 4 & 5

- *"What is the average length / median duration of an interaction with the App?"*
  - Experts significantly overestimate the length of interactions
  - Users spend more time on fewer screens
    - Experts: 5,6 s / screen
    - Method: 11,1 s / screen
- ➔ Screens might be too complex

Expert Answers	Proposed Method	5 Minute Threshold
50 screens / 240 s		
30 screens / 120 s		
12 screens / 90 s	4.8 screens / 53.4 s	6.7 screens / 14 s
10 screens / 60 seconds		
25.5 screens / 127.5 s		

# Question 10

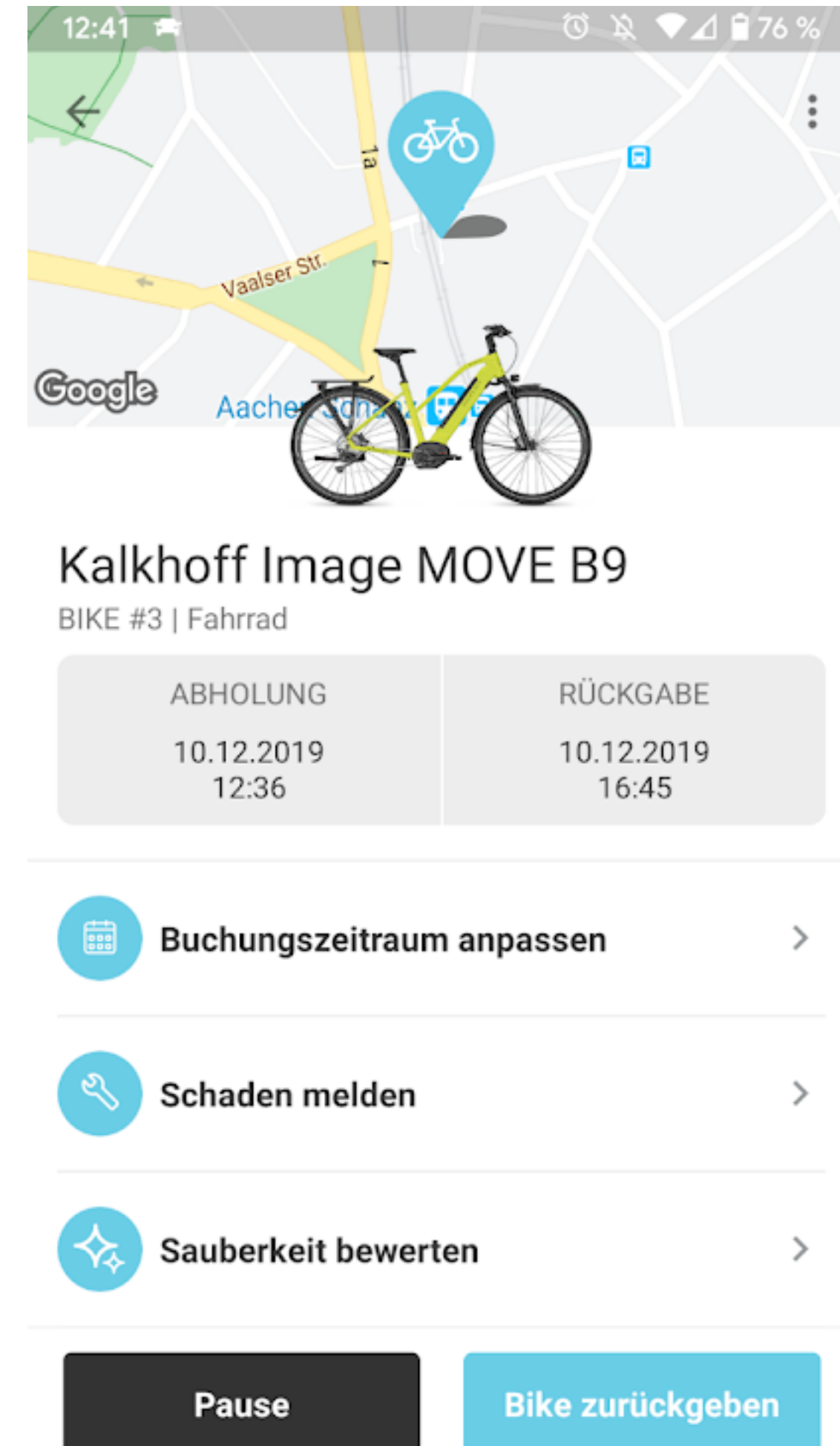
- "Given this process model that is based on interactions **ending on the booking screen**, what are your observations?"
- Frequent use of "map" dashboard
  - ➔ Focus efforts on this dashboard
- High number of users take a detour through the bookings list
  - Especially true for "map" dashboard
  - ➔ Button is not noticeable enough



[11]

# Question 14

- "2% of users use the intermediate lock functionality before ending a booking."
- This is not necessary and can introduce technical problems with the locks
- Wording in the interface might encourage this behaviour
- ➔ Reconsider the interplay between intermediate lock and vehicle return





# Agenda

Introduction

Approach

Evaluation

Baseline Approaches

Case / User Study

**Conclusion**

# Conclusion

- The Event-Case Attribution Problem is highly relevant in **other areas** (RPA)
- The proposed method is able to produce **usable** segmented logs
- It can be applied to **large user interaction logs** because of its linear time complexity during segmentation
- Process mining based analysis of UI logs produces **actionable findings** for process experts, showing the large potential of process mining for user behaviour analysis

# Questions

# References

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# Appendix - RPA

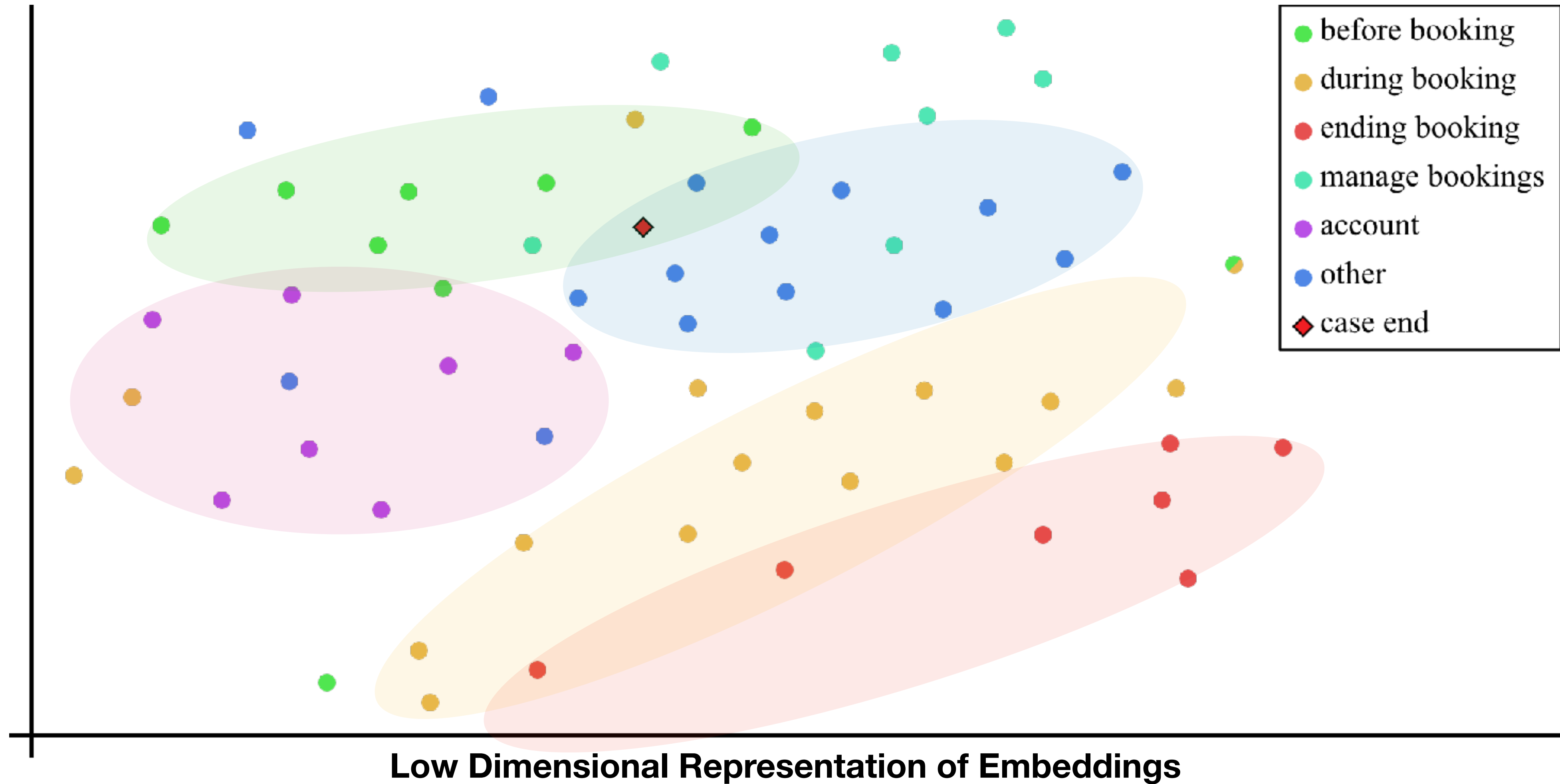
- Basis for RPA are detailed descriptions of the behaviour that should be automated
- There are API based and observation based approaches
- Aguirre et al. 2017: RPA is only applicable to *stable* processes because of the required modelling [A1]
- Syed et al. 2020: Automation of the early stages of RPA is one of the main challenges [A2]
- Montero et al. 2019: Missing case information is a challenge for automated testing in RPA [A3]

# Appendix - Outlook

- **Alternative approaches** to training log generation
- There exist no techniques to accurately **assess the quality** of log segmentations **without labeled data**
- Consider more **advanced** process mining techniques
  - Running case prediction
  - Root-cause analysis



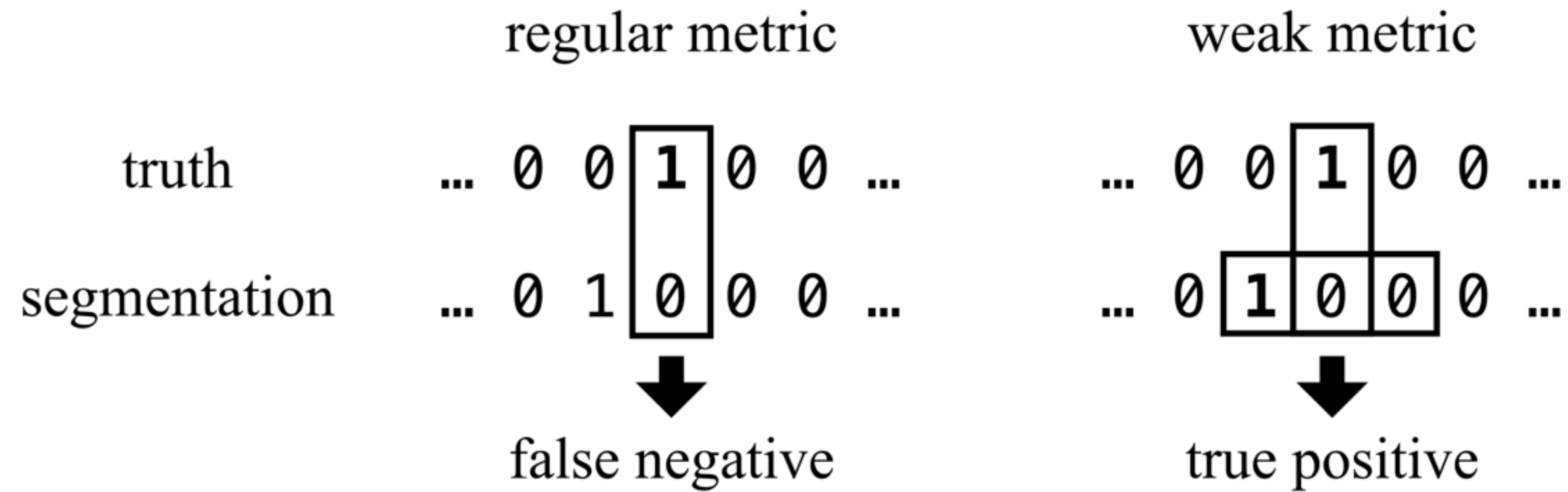
# Appendix - Embedding Vectors



# Appendix - Unclear Boundaries

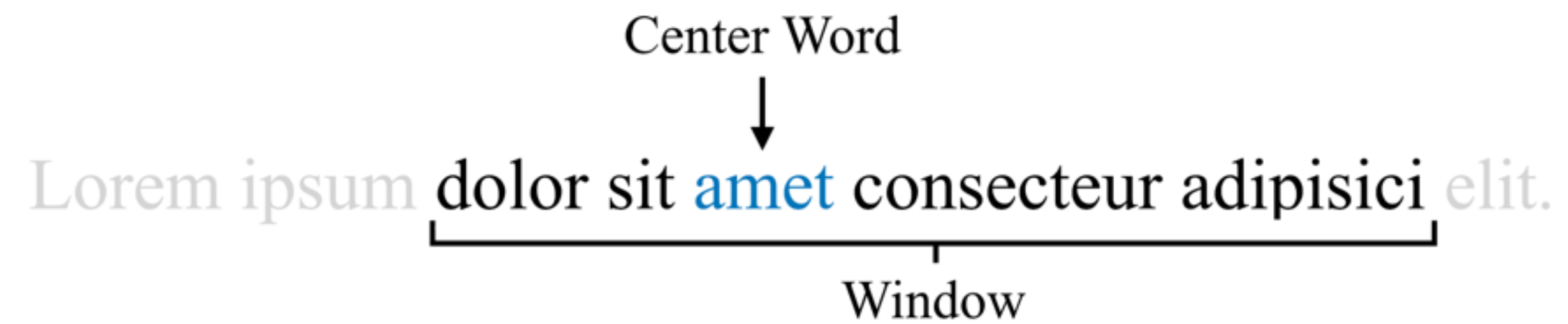
1. dashboard pre confirm booking | lock
2. dashboard pre confirm | booking lock
3. dashboard pre confirm booking | booking lock

# Appendix - Metrics



$$cnd = \frac{\# \text{ of predicted cases} - \# \text{ of real cases}}{\# \text{ of real cases}}$$

# Appendix - word2vec



# Appendix - Definition UI Log

**Definition 2.8** (User Interaction Log). [16] A *user interaction log (UI Log)*  $L$  is a collection of ordered user interactions. It is denoted by a tuple  $L = (I, \sigma)$  where  $I = \langle i_1, \dots, i_n \rangle$  is an ordered sequence of user interactions  $i_j = (u_j, a_j, t_j)$  with  $(u_j, a_j, t_j) < (u_k, a_k, t_k) \Rightarrow t_j \leq t_k$  and  $\sigma : I \rightarrow \mathbb{N}$  is a segmentation function that assigns a case identifier to every user interaction. Interactions with the same case identifier according to  $\sigma$  are belonging to the same case.

# Appendix - Segmentation Example

