LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN
FAKULTÄT FÜR MATHEMATIK, INFORMATIK UND STATISTIK
INSTITUT FÜR INFORMATIK
LEHRSTUHL FÜR DATENBANKSYSTEME UND DATA MINING

Inferring Process Performance Models from Interval Events using the Performance Skyline

Master Thesis, Munich Germany

Andrea Maldonado

30th March 2020

DBS

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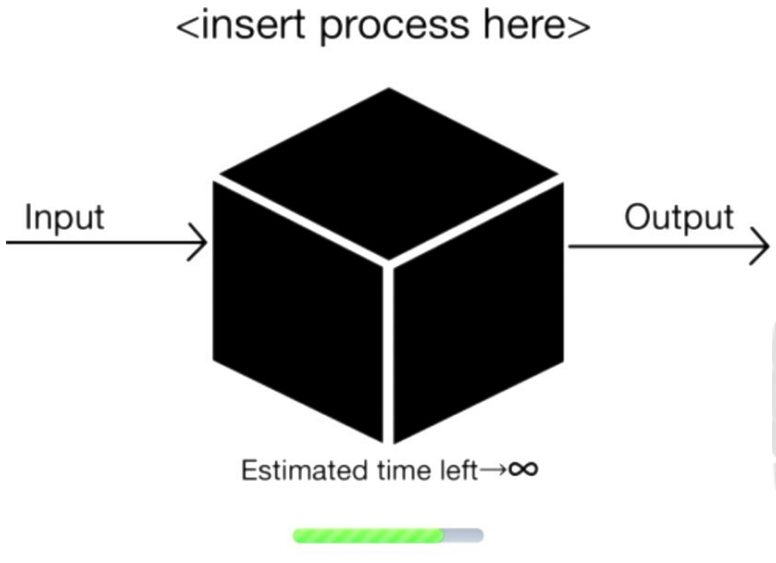
Agenda

- Introduction
- Background Knowledge and Related Work
- Performance Models Contribution
  - Interval Events
  - Performance Skyline
- Experiments
  - Dataset Description
  - Anomaly Detection
- Final Thoughts and Conclusion

Introduction: Motivation

- Process Enhancement requires understanding the process
- Deviation detection of described vs. prescribed processes
- Business processes and information systems' alignment requires continuous attention
- Processes are constantly changing



Introduction: Challenge

How to extract knowledge and model performance of processes containing (interval) events?

Related Work

Related Work: Process Mining

```
$ cat nfs/processmining/pm4pyexample/running-example-just-two-cases.csv
Case ID;Event ID;dd-MM-yyyy:HH.mm;Activity;Resource;Costs
1;35654423;30-12-2010:11.02;register request;Pete;50
1;35654424;31-12-2010:10.06;examine thoroughly;Sue;400
1;35654425;05-01-2011:15.12;check ticket;Mike;100
1;35654426;06-01-2011:11.18;decide;Sara;200
1;35654427;07-01-2011:14.24;reject request;Pete;200
4;35654641;06-01-2011:15.02;register request;Pete;50
4;35654643;07-01-2011:12.06;check ticket;Mike;100
4;35654644;08-01-2011:14.43;examine thoroughly;Sean;400
4;35654645;09-01-2011:12.02;decide;Sara;200
4;35654647;12-01-2011:15.44;reject request;Ellen;200
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Related Work: Process Mining

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Case id	Activity id	Timestamp
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1	check ticket	05-01-2011:15.12
1	decide	06-01-2011:11.18
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⋮	⋮	⋮

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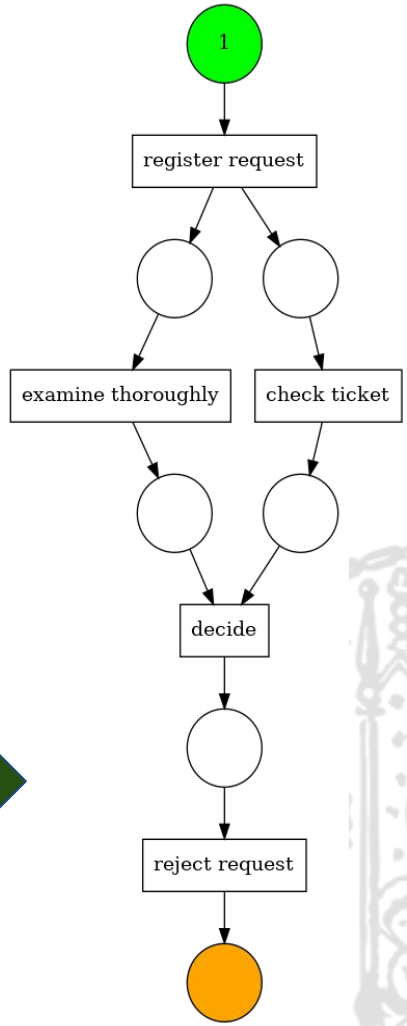
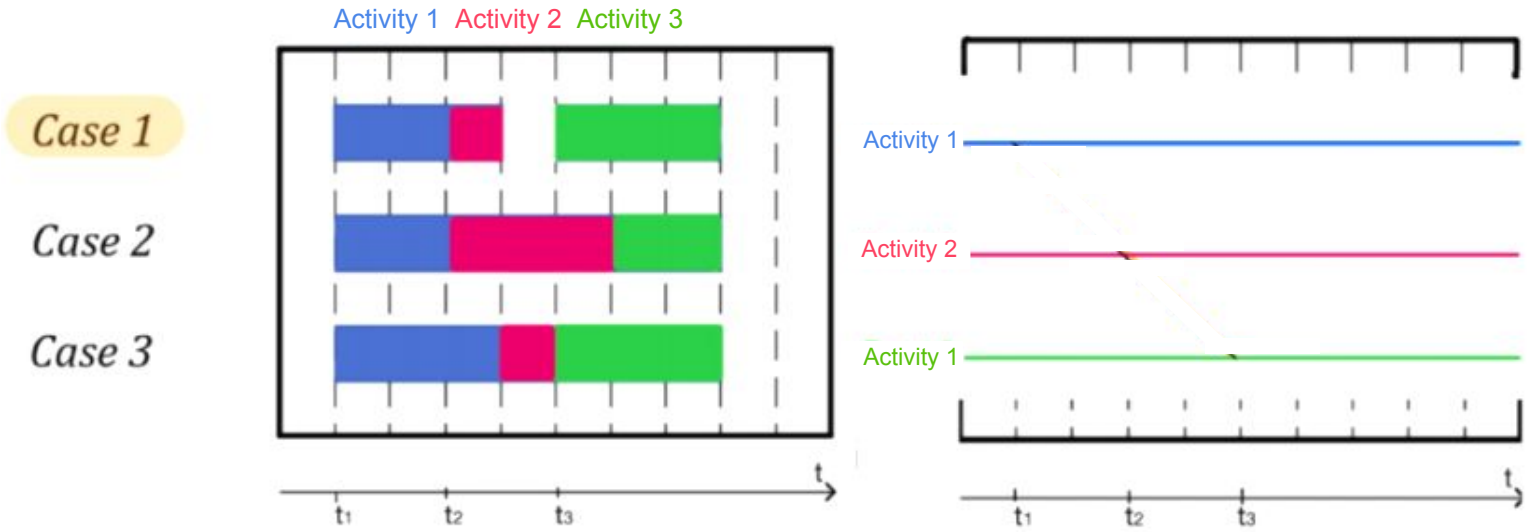


Related Work: Performance Spectrum



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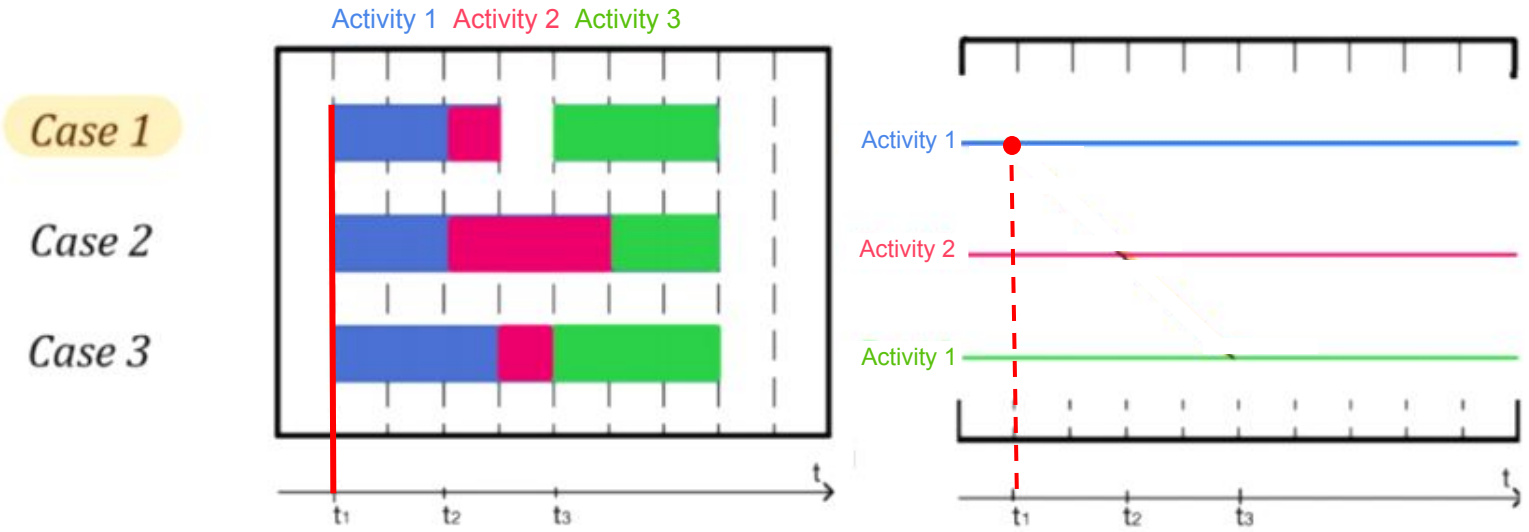

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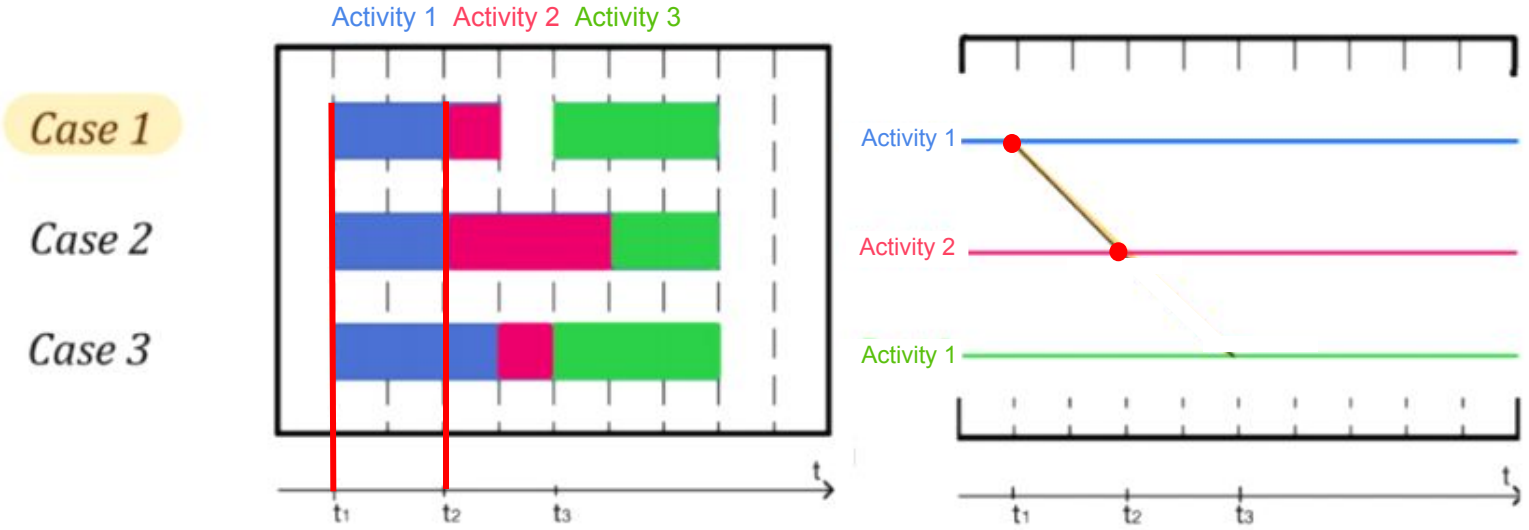

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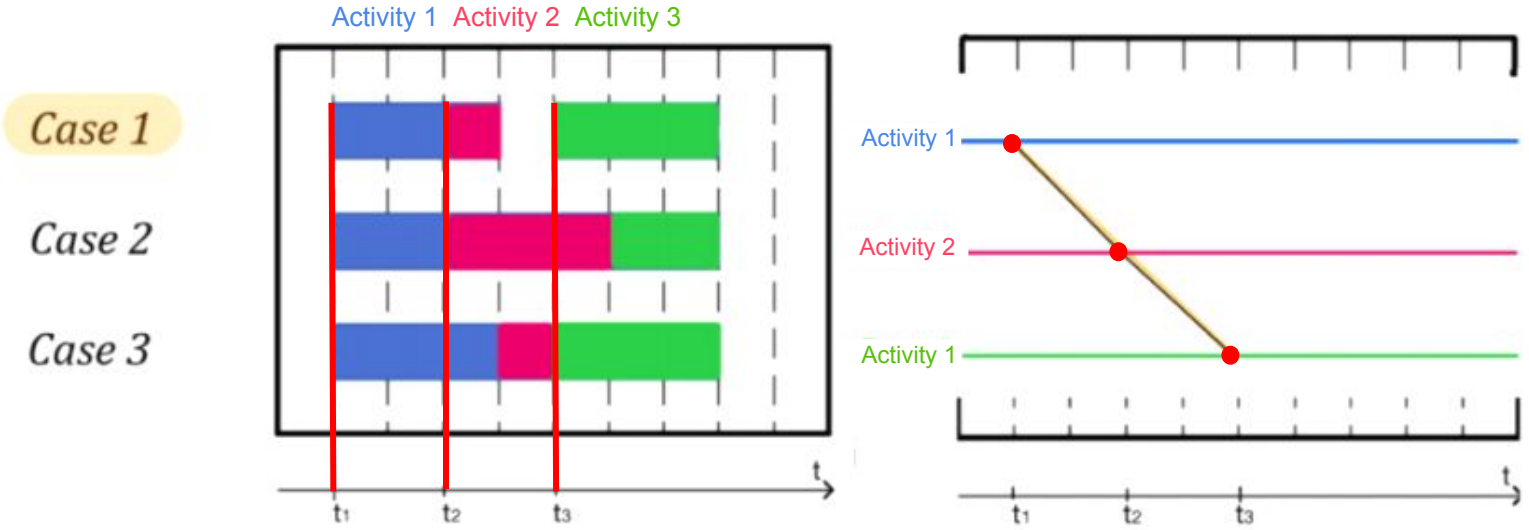

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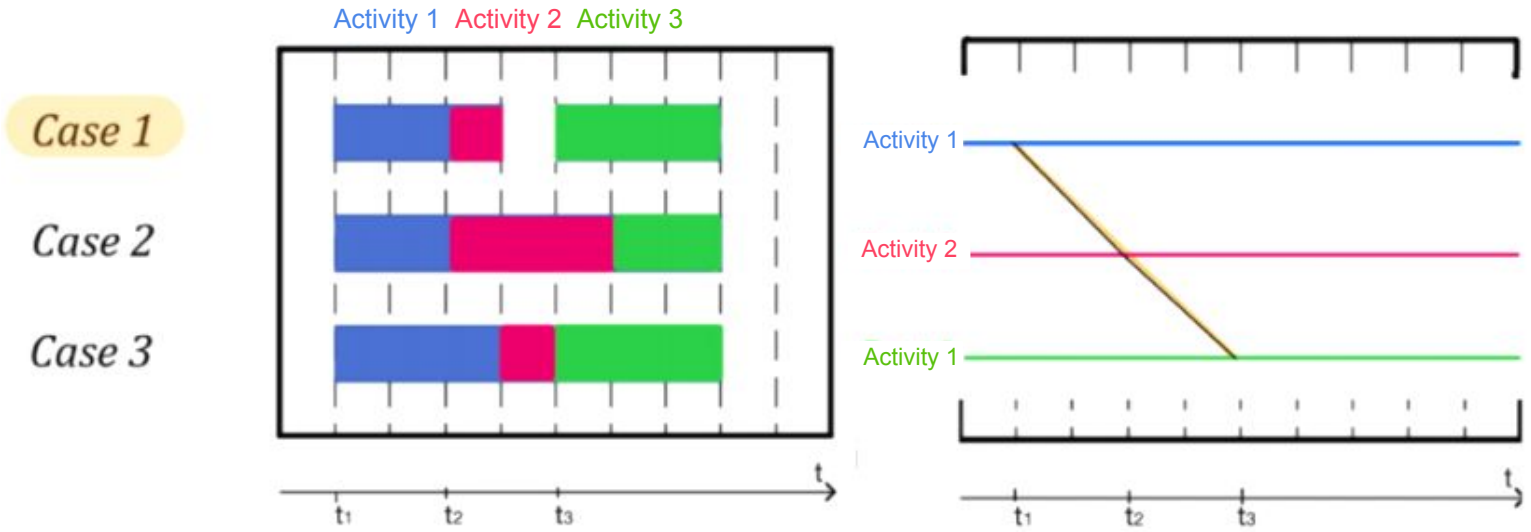

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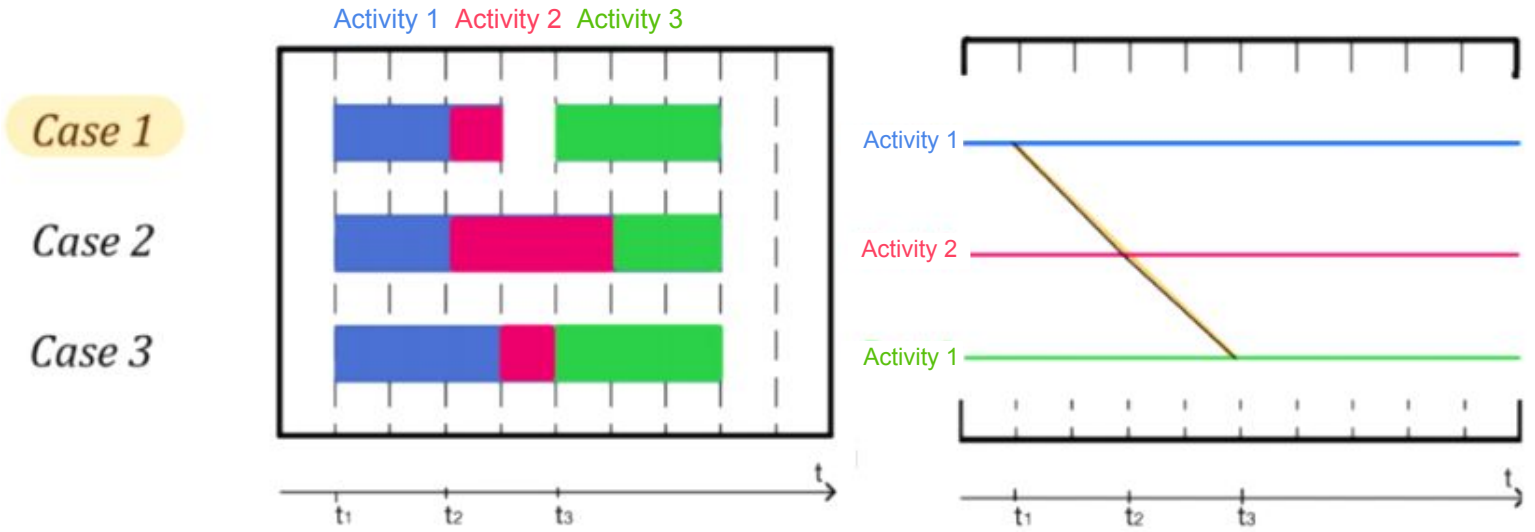
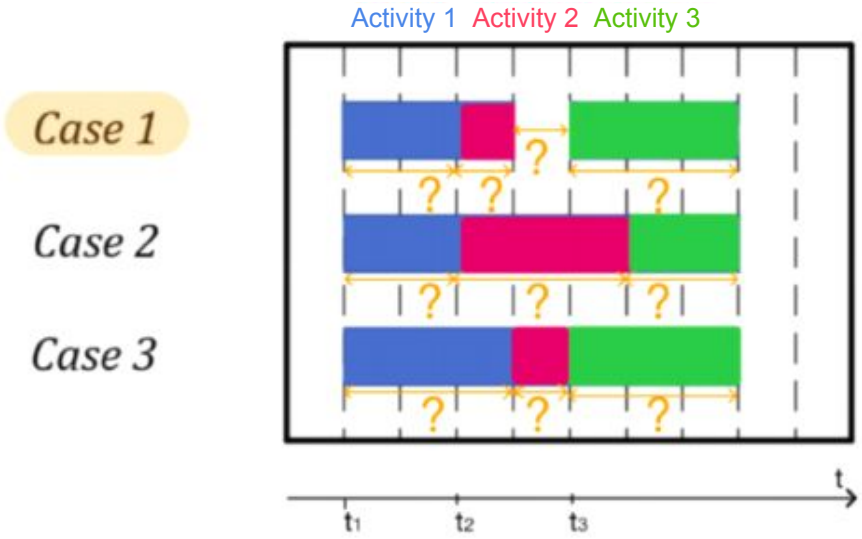
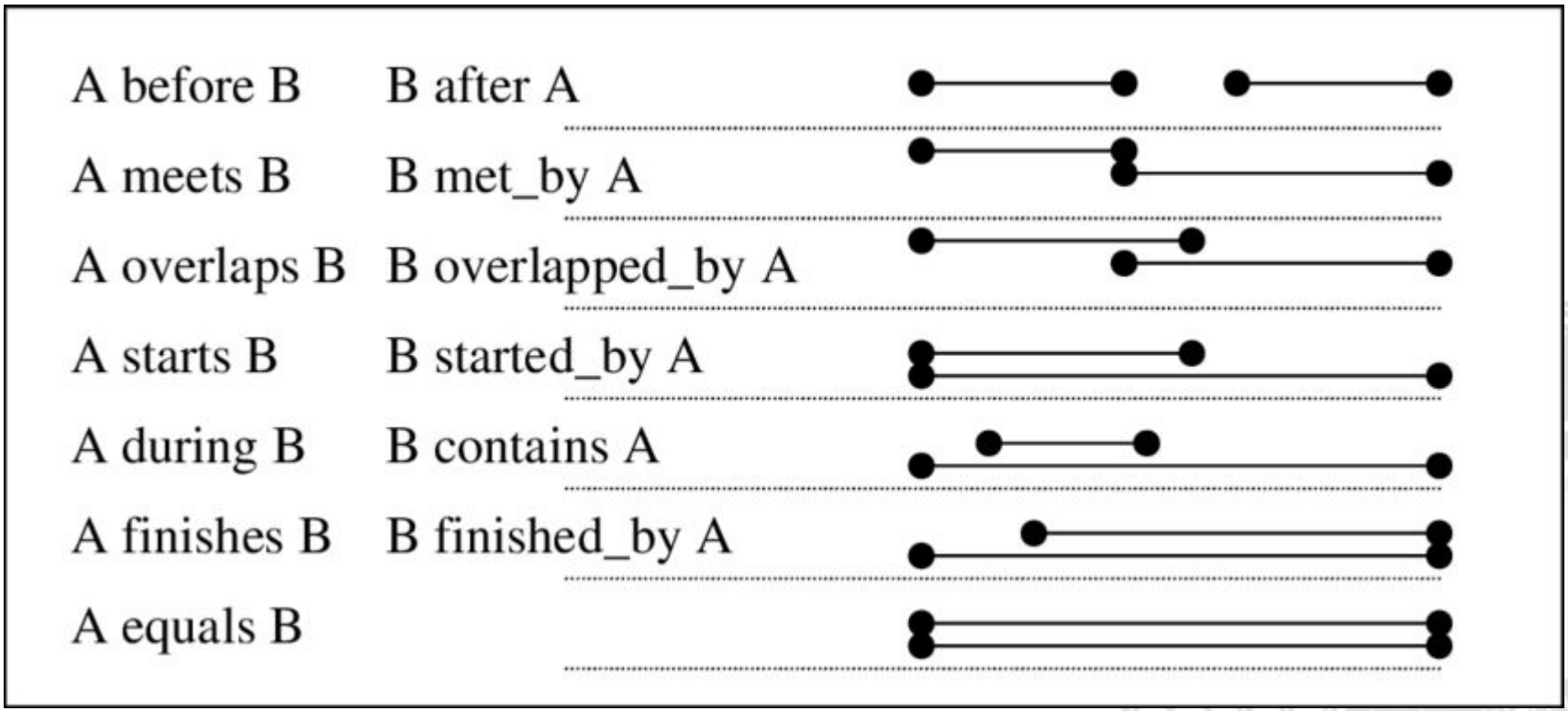


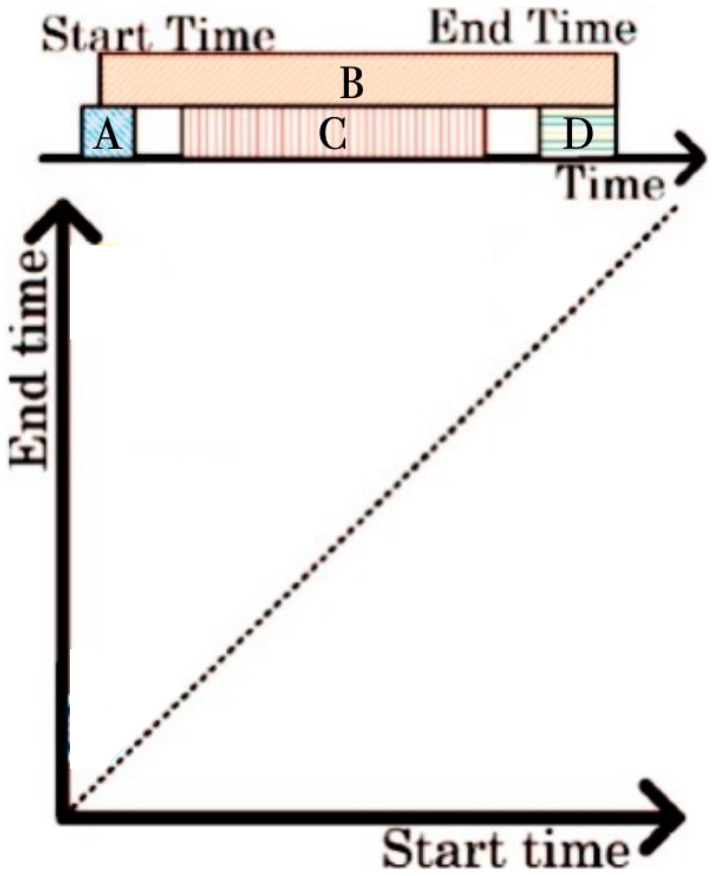


Related Work: Allen's Interval Algebra

- Deals with temporal intervals *{A},{B}*:
  with starting at *{A+},{B+}* and ending at *{A-},{B-}*



Related Work: Sequence Pattern Mining



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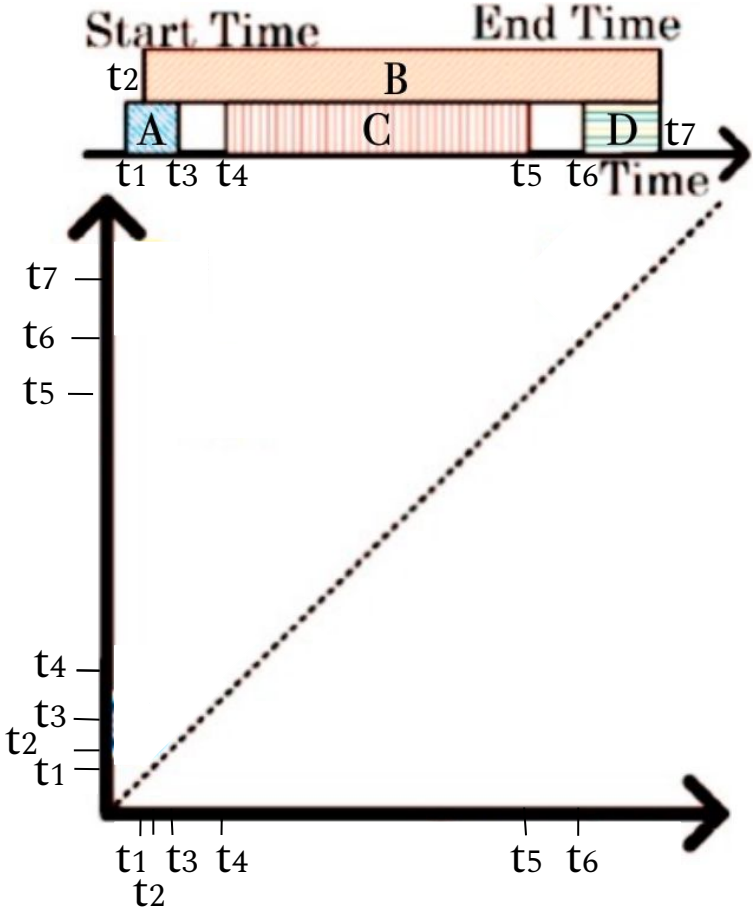
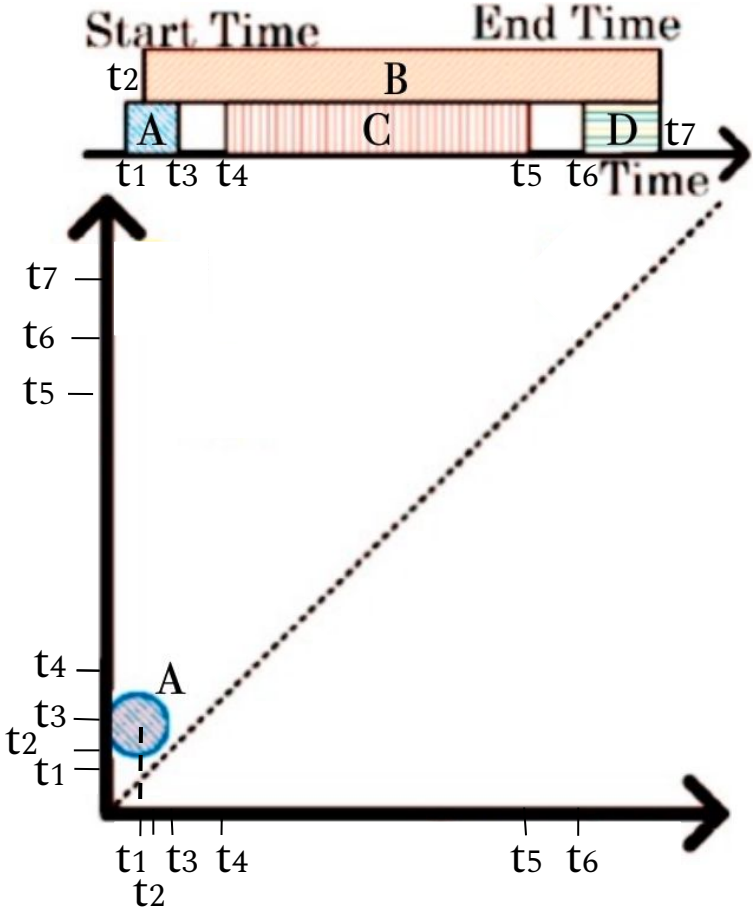


- Interval Geometric Representation:
  {A+}=t1; {A-}=t3

Related Work: Sequence Pattern Mining



- Interval Geometric Representation:
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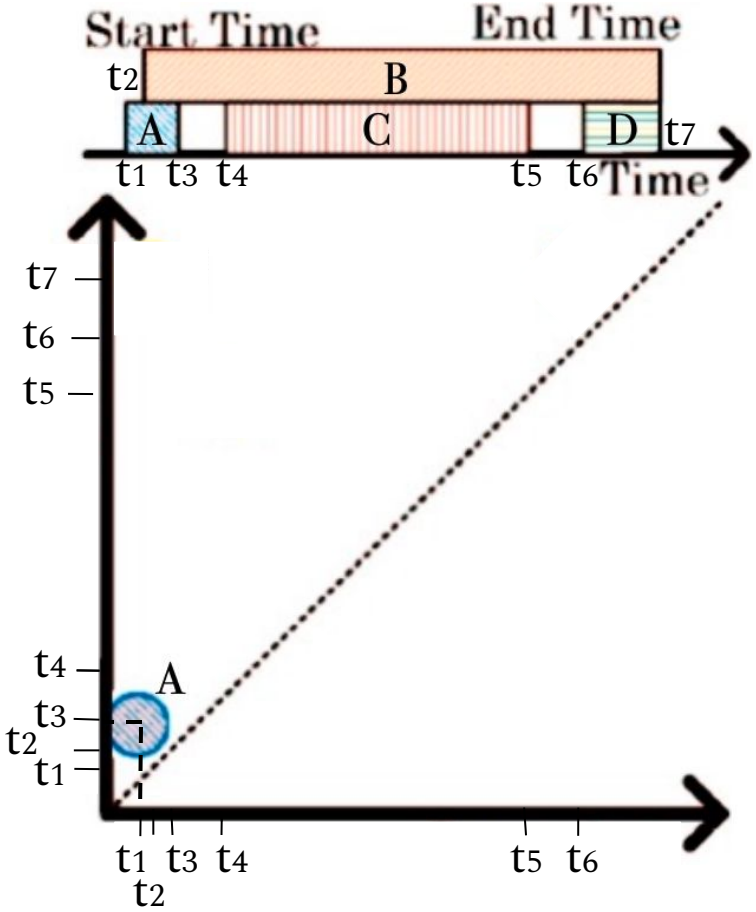
Related Work: Sequence Pattern Mining



- Interval Geometric Representation:
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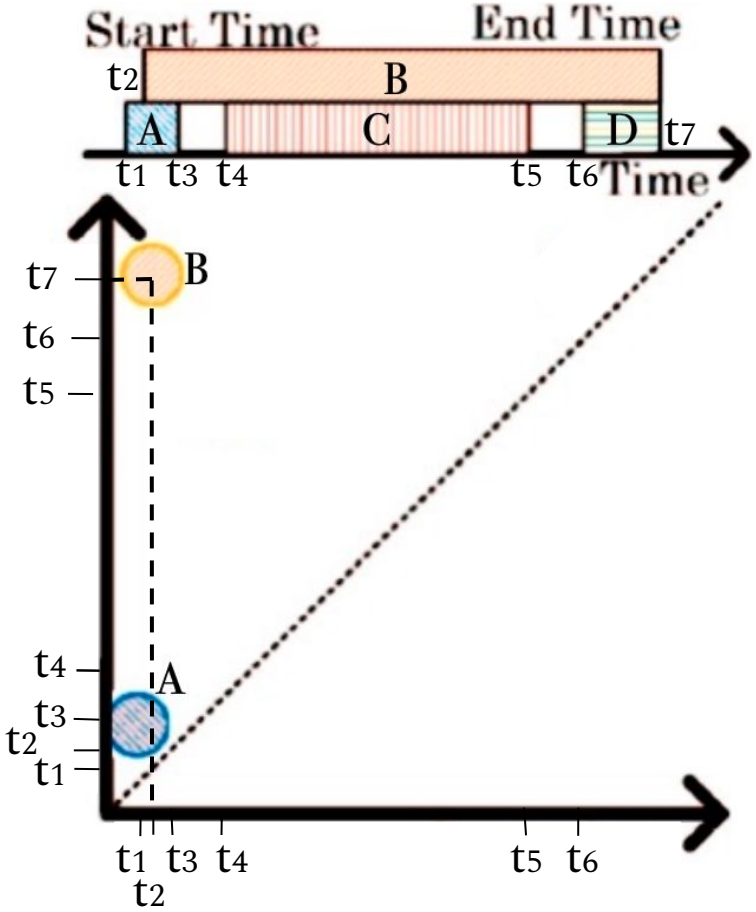
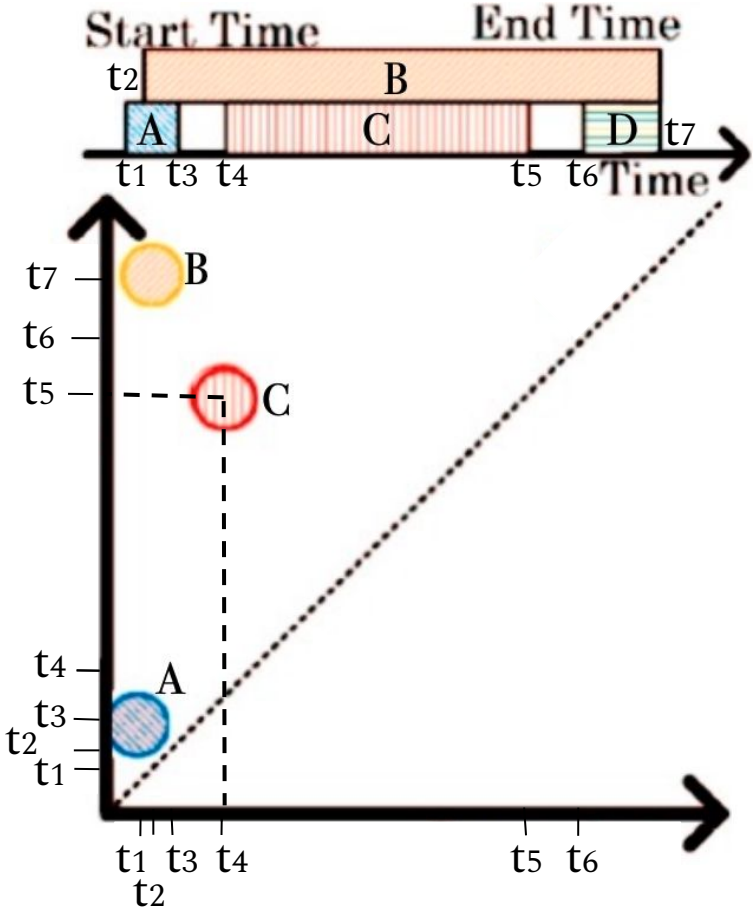


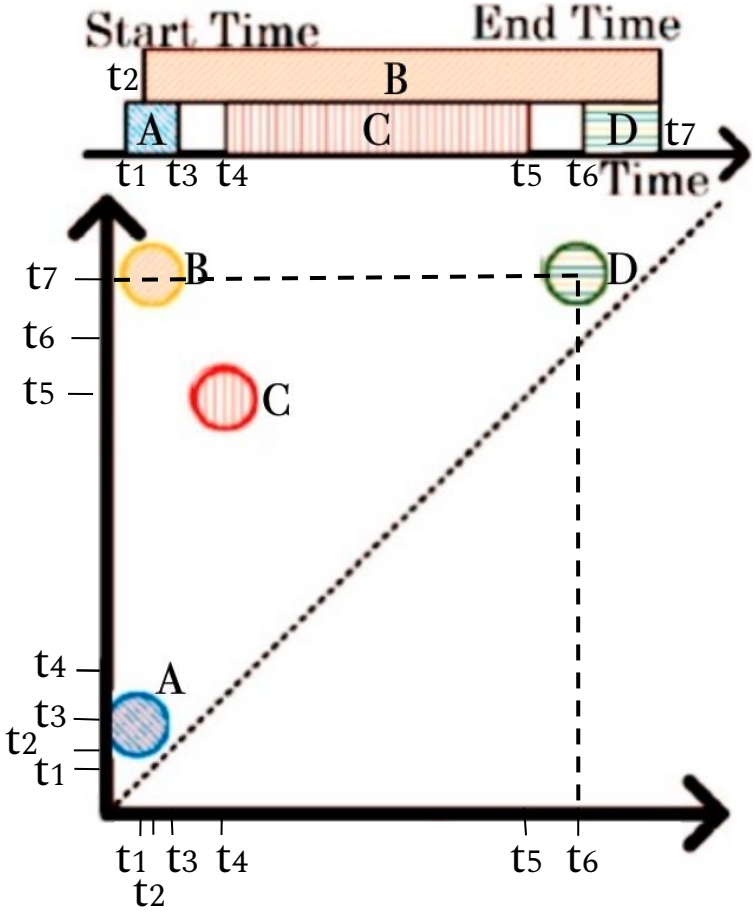
- Interval Geometric Representation:
  {A+}=t1; {A-}=t3
  {B+}=t2; {B-}=t7

Related Work: Sequence Pattern Mining



- Interval Geometric Representation:
  {A+}=t1; {A-}=t3
  {B+}=t2; {B-}=t7
  {C+}=t4; {C-}=t5

Related Work: Sequence Pattern Mining



- Interval Geometric Representation:
  {A+}=t1; {A-}=t3
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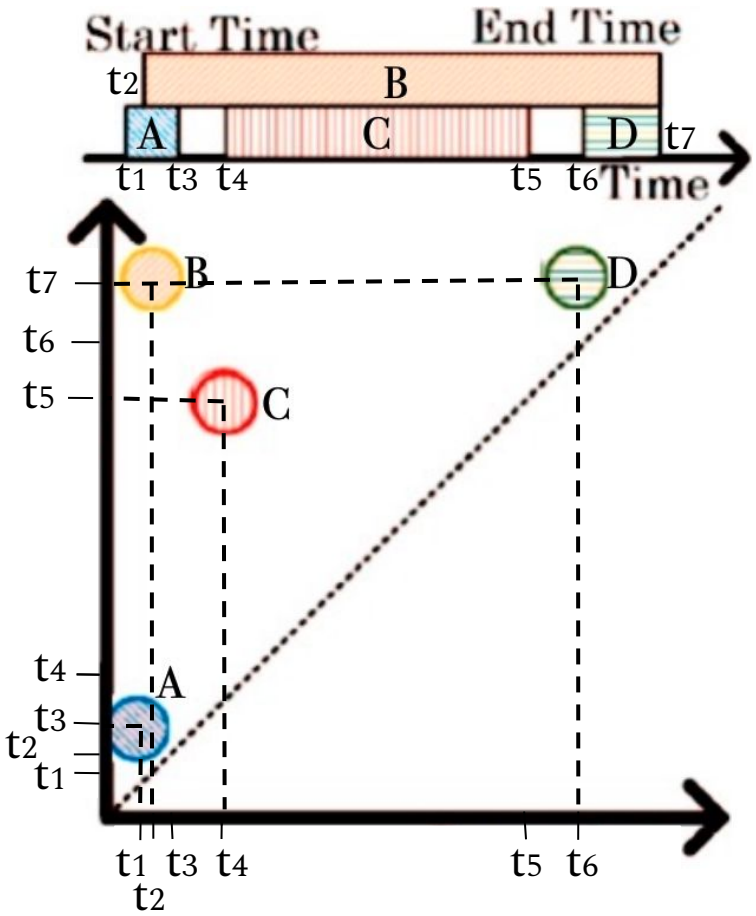
  {C+}=t4; {C-}=t5
  {D+}=t6; {D-}=t7

Related Work: Sequence Pattern Mining



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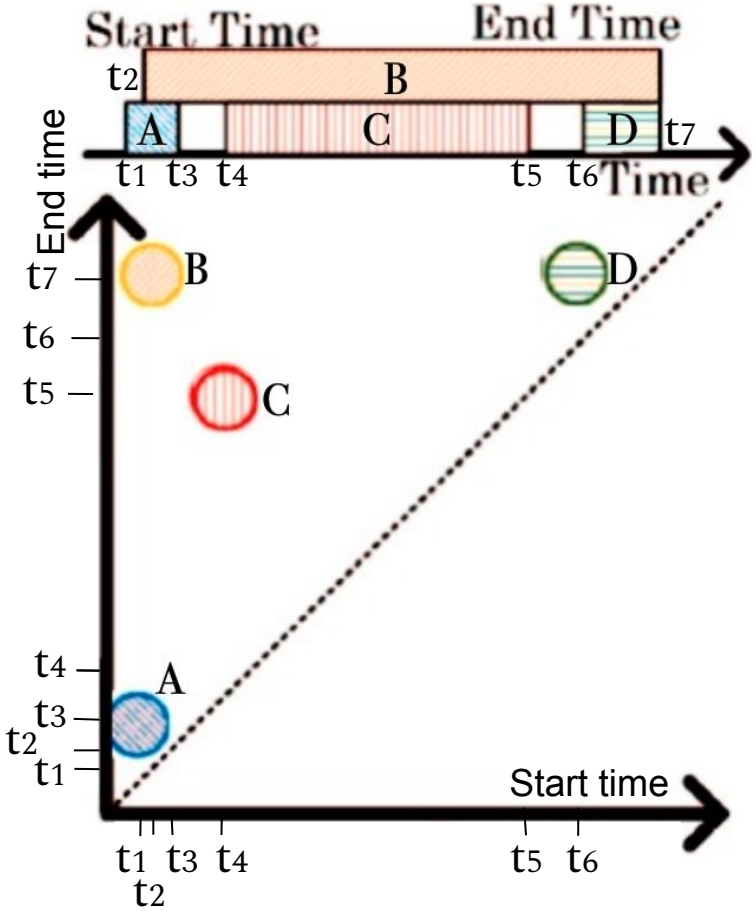

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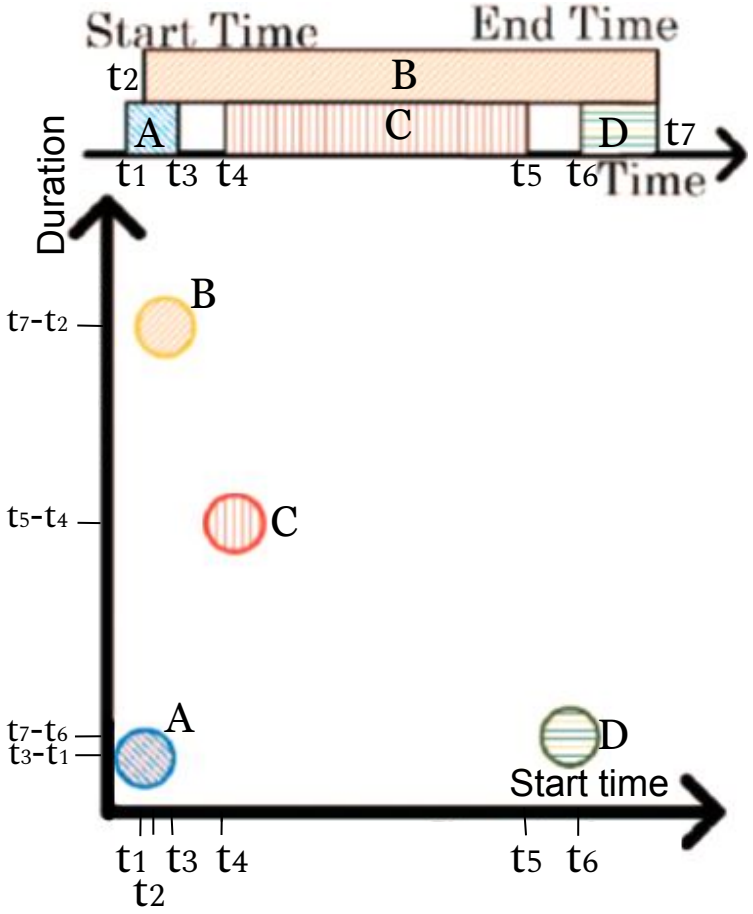

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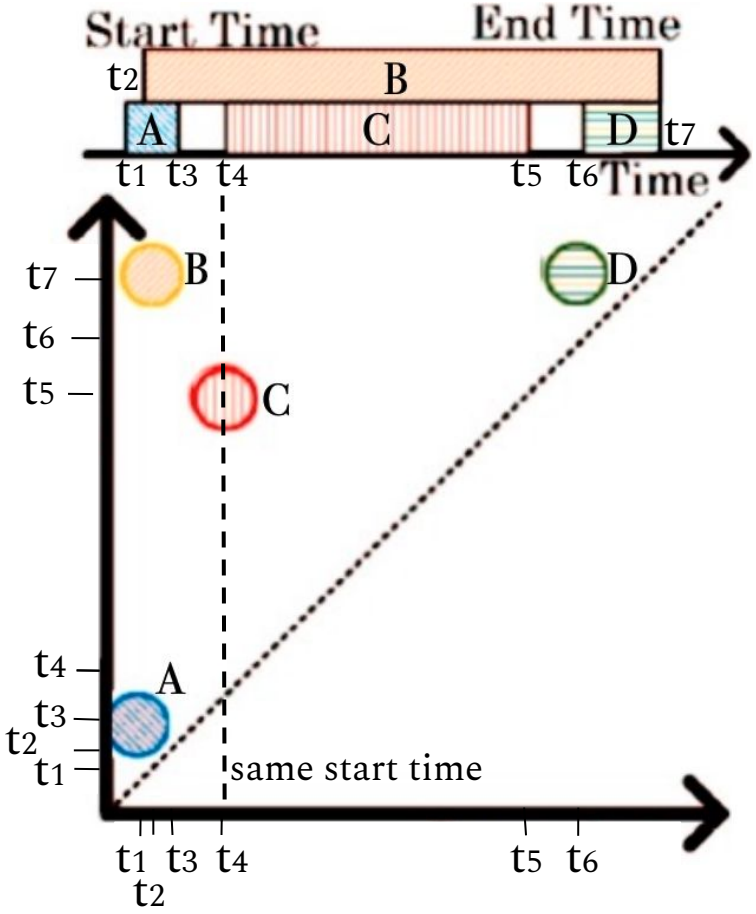
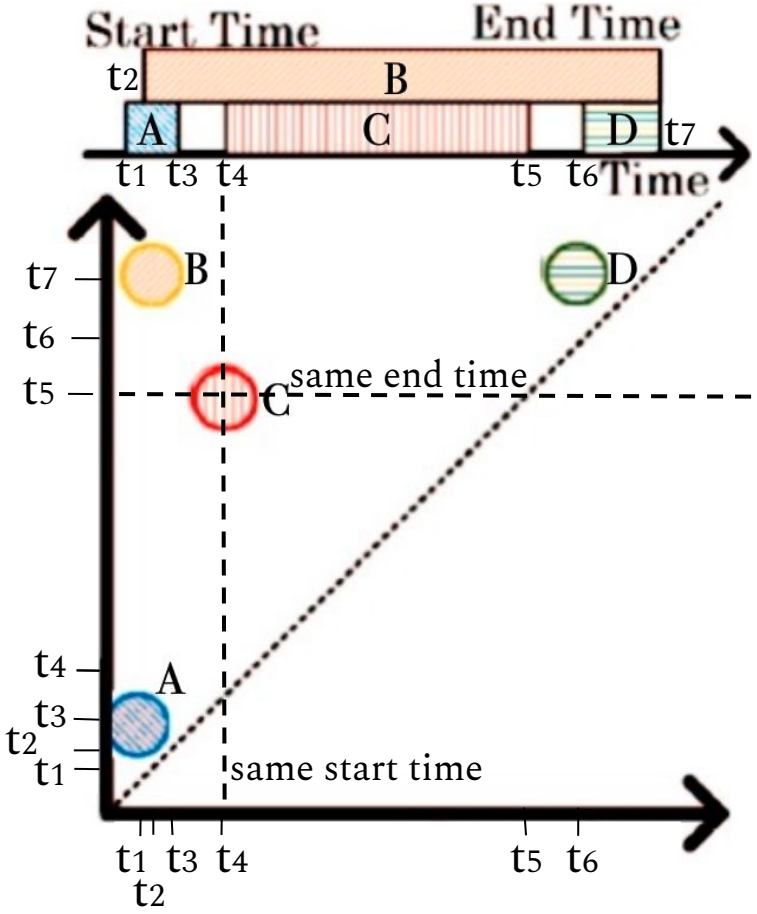


- Interval Geometric Representation for **C**: *{C+}=t4; {C-}=t5*
- Allen's Interval Algebra

Related Work: Sequence Pattern Mining



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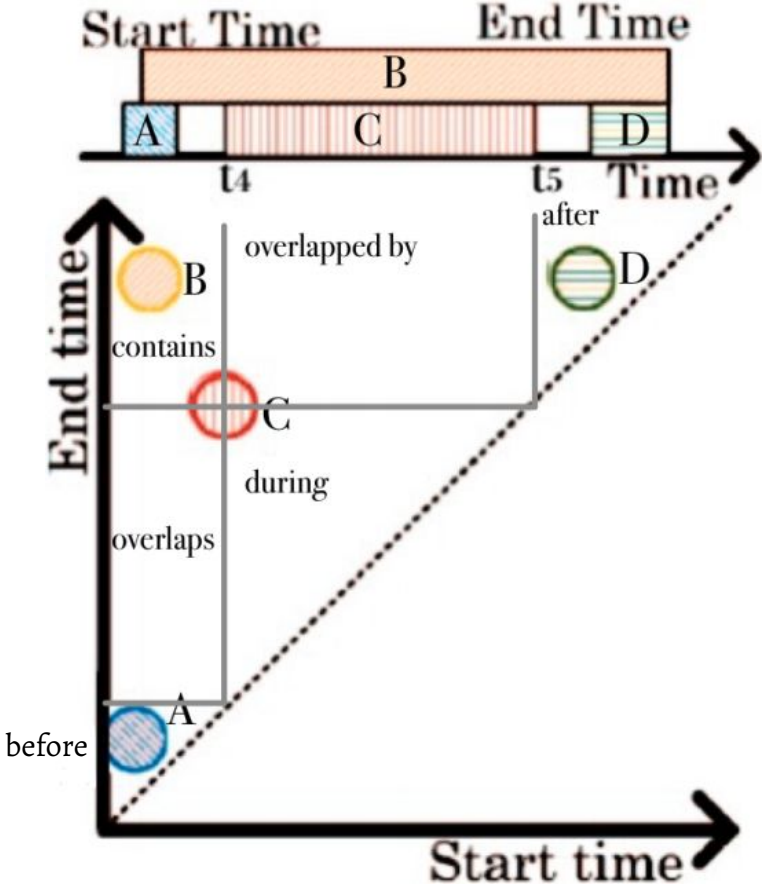

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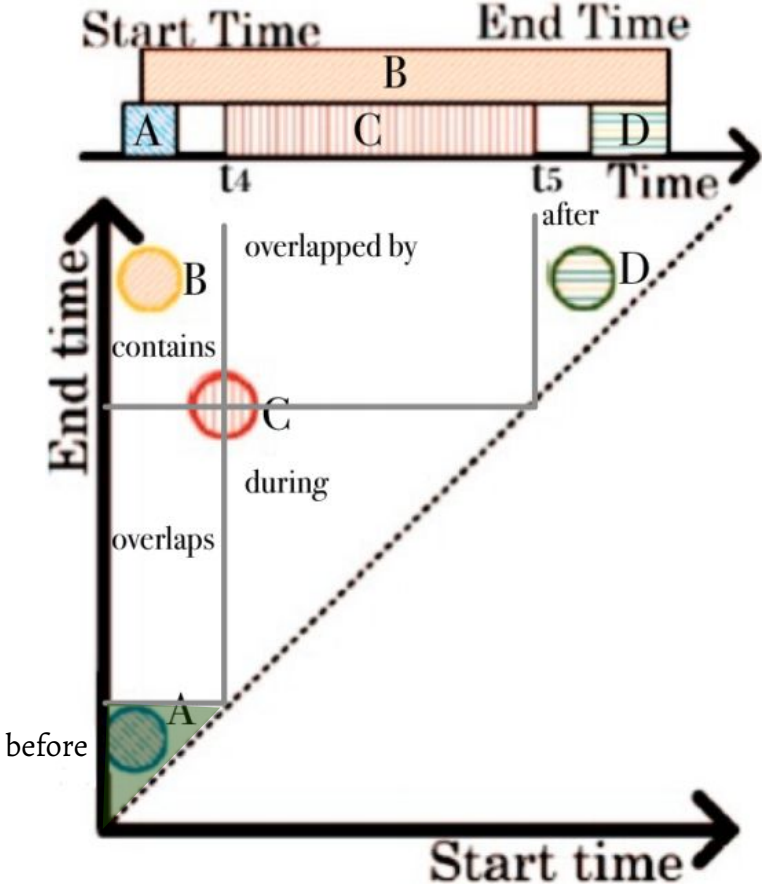
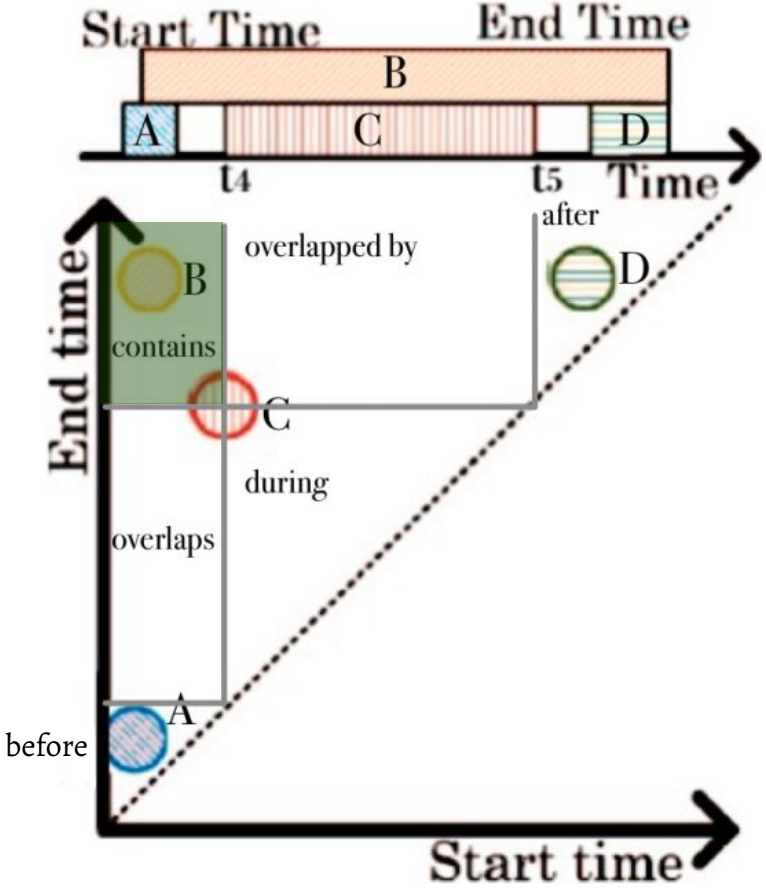


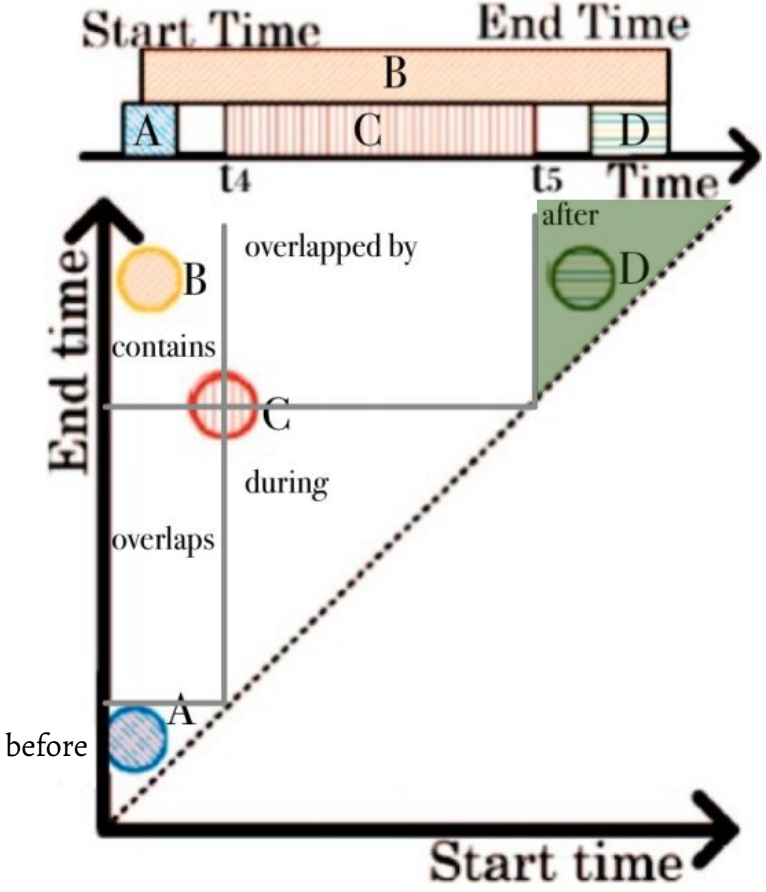
- Interval Geometric Representation for *C*: *{C+}=t4; {C-}=t5*
- Allen's Interval Algebra
  - *A* before *C*

Related Work: Sequence Pattern Mining



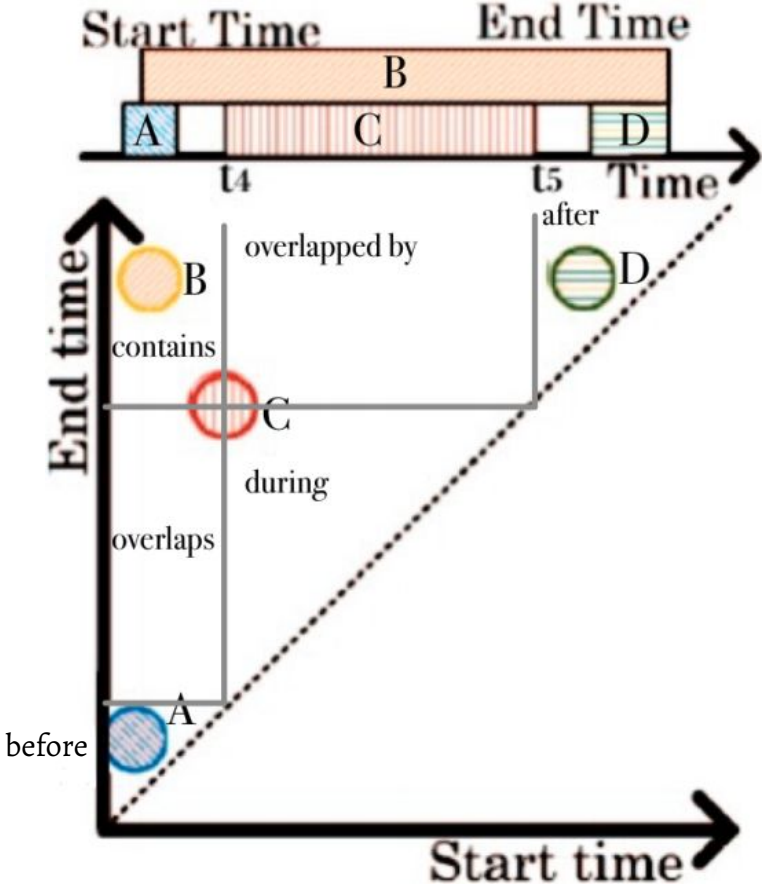
- Interval Geometric Representation for *C*: *{C+}=t4; {C-}=t5*
- Allen's Interval Algebra
  - *A* before *C*
  - *B* contains *C*

Related Work: Sequence Pattern Mining



- Interval Geometric Representation for *C*: *{C+}=t4; {C-}=t5*
- Allen's Interval Algebra
  - *A* before *C*
  - *B* contains *C*
  - *D* after *C*

Related Work: Sequence Pattern Mining



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  - *A* before *C*
  - *B* contains *C*
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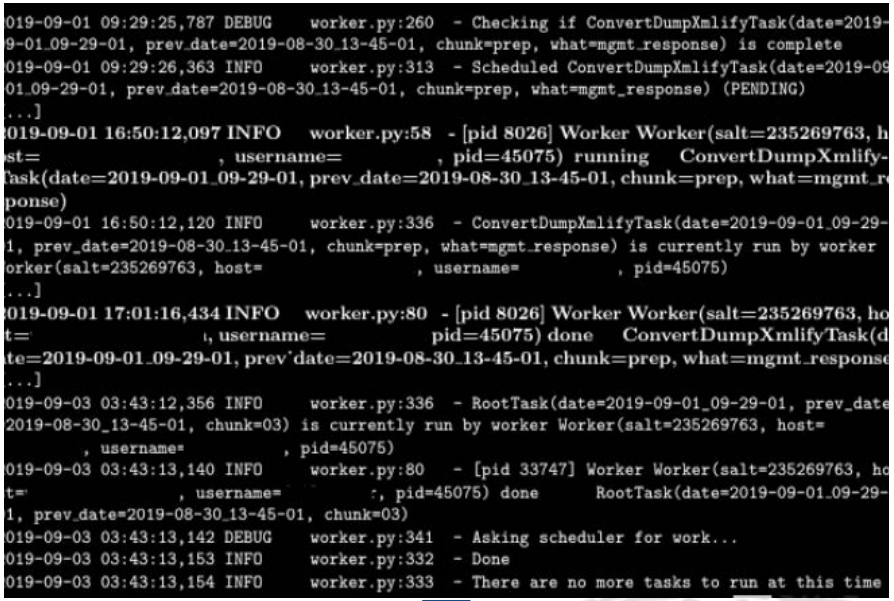
Performance Models Contribution

- Interval Events
- Performance Skyline

Interval Events

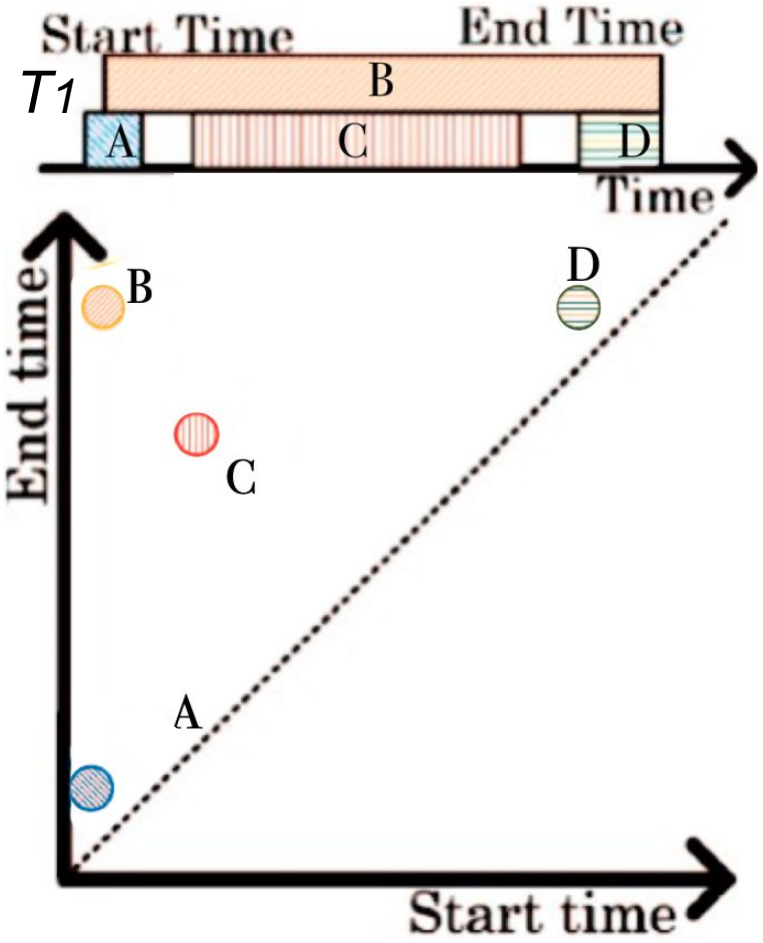
$$e = (c, a, t^+, t^-) \epsilon \mathbb{N} \times A \times \mathbb{N} \times \mathbb{N}$$

- Case id
- Activity id
- Timestamp (start)
- Timestamp (end)



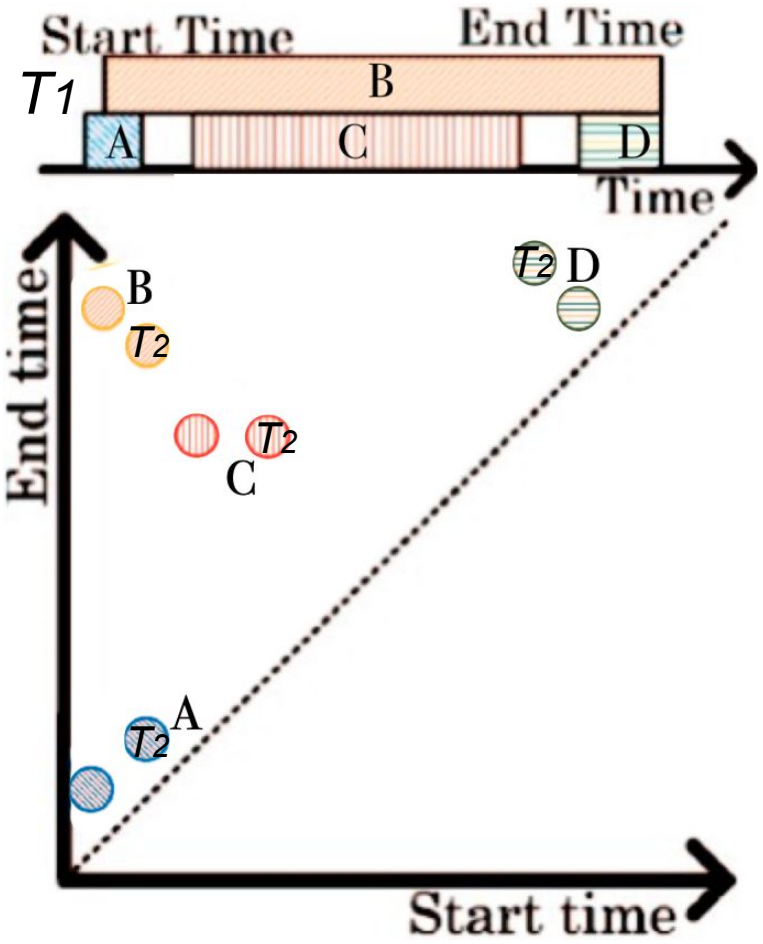
case id	activity id	start time	end time
example-process. 2019-09-01	ConvertDumpXmlifyTask (what=mgmt_response)	2019-09-01 16:50:12	2019-09-01 17:01:16
example-process. 2019-09-01	ConvertDumpXmlifyTask (what=source)	2019-09-01 14:13:56	2019-09-01 14:17:03
example-process. 2019-09-03	ConvertDumpXmlifyTask (what=source)	2019-09-03 07:33:56	2019-09-03 07:37:24

Performance Skyline



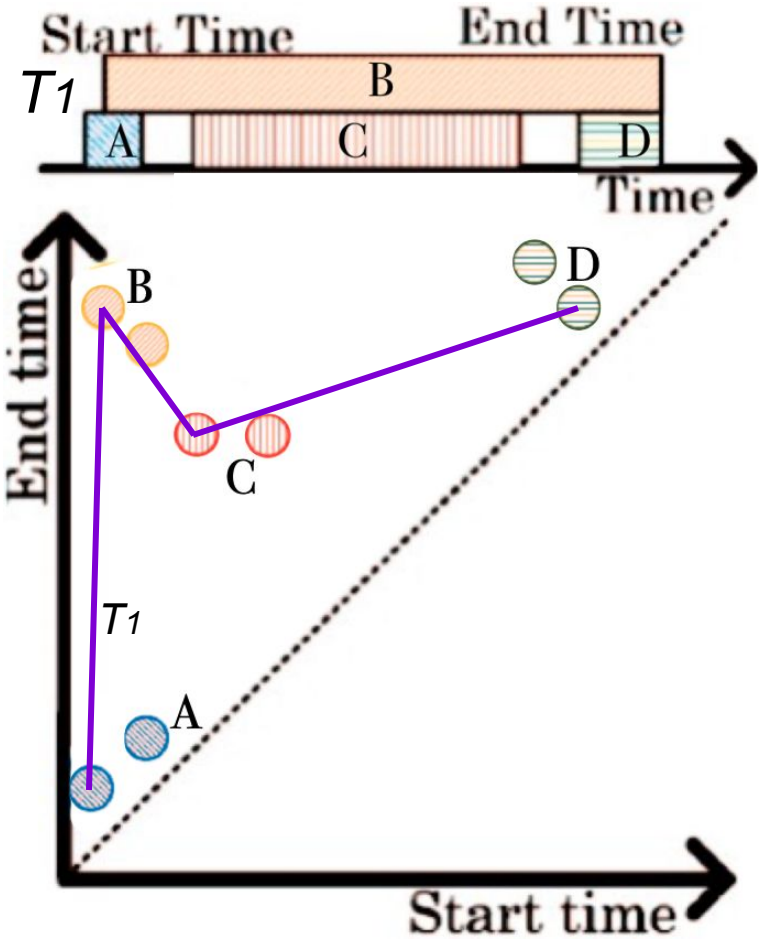
- Process Geometrical Representation
  - Traces *T1* has 4 events
  - Activity ids: *A*, *B*, *C*, *D*

Performance Skyline



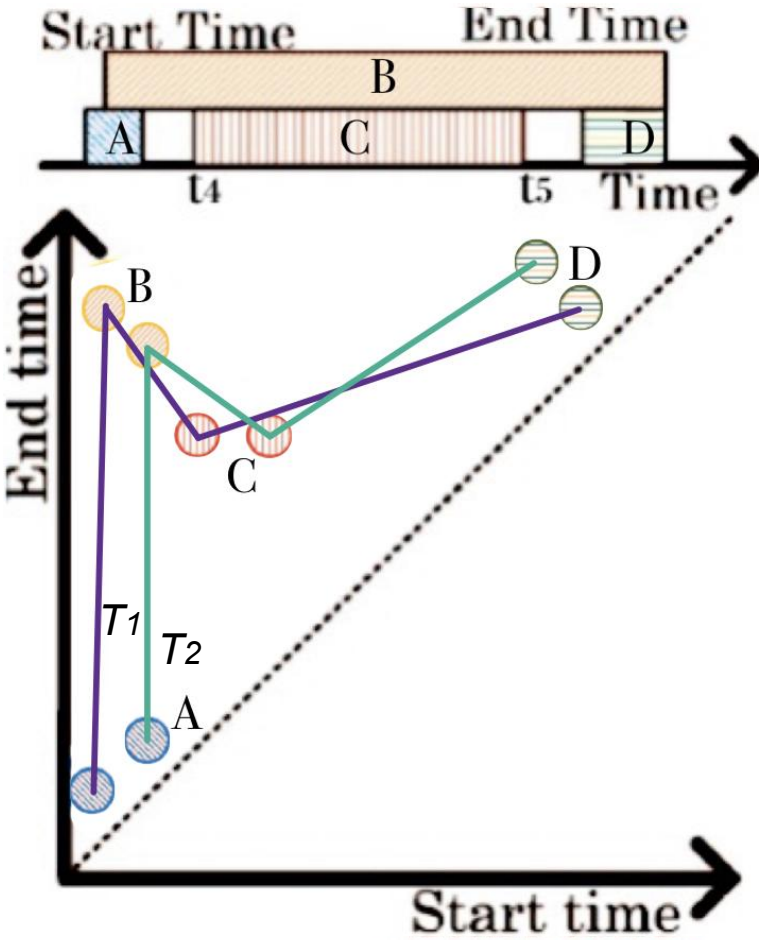
- Process Geometrical Representation
  - Traces *T1* and *T2* have four events each
  - Events of activity ids: *A*, *B*, *C*, *D*

Performance Skyline



- Process Geometrical Representation
  - Traces *T1* and *T2* have four events each
  - Events of activity ids: *A*, *B*, *C*, *D*

Performance Skyline



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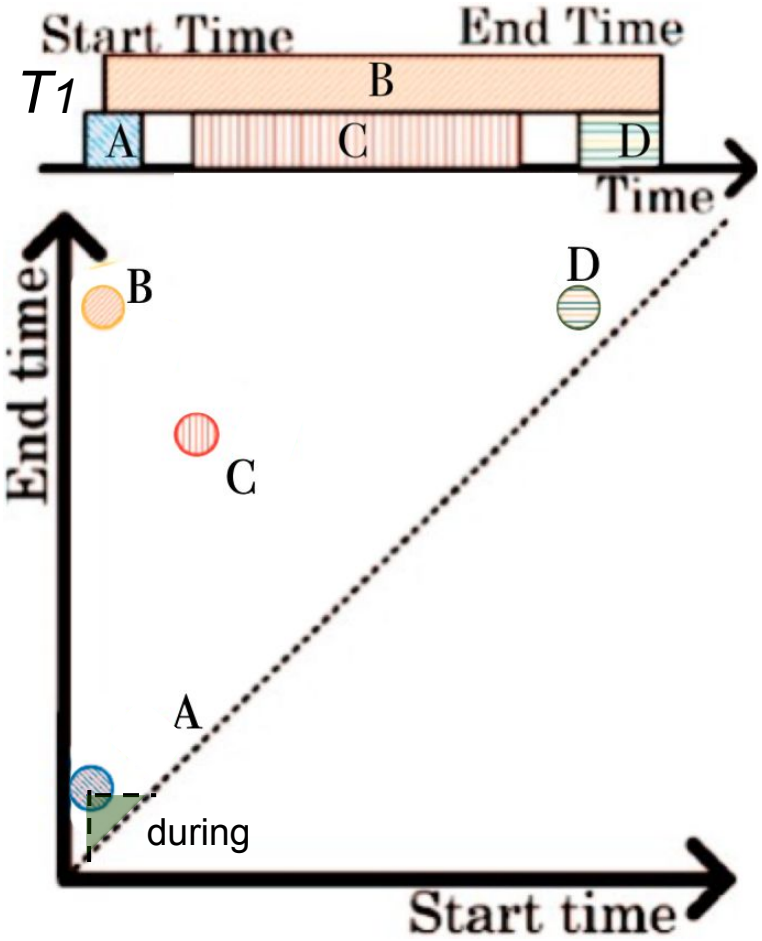
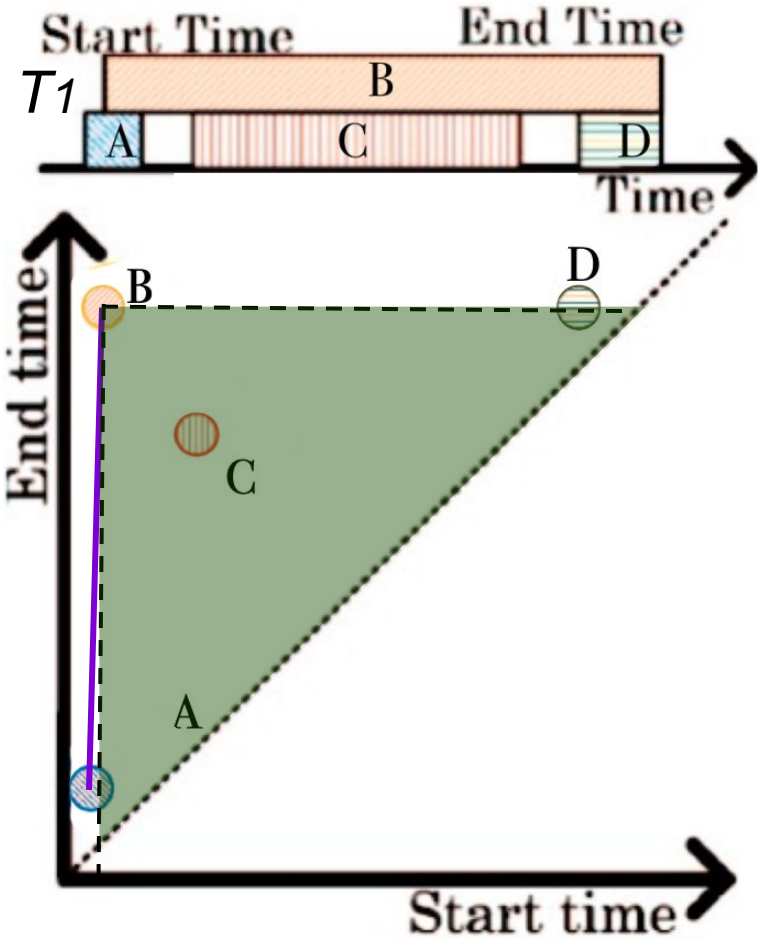
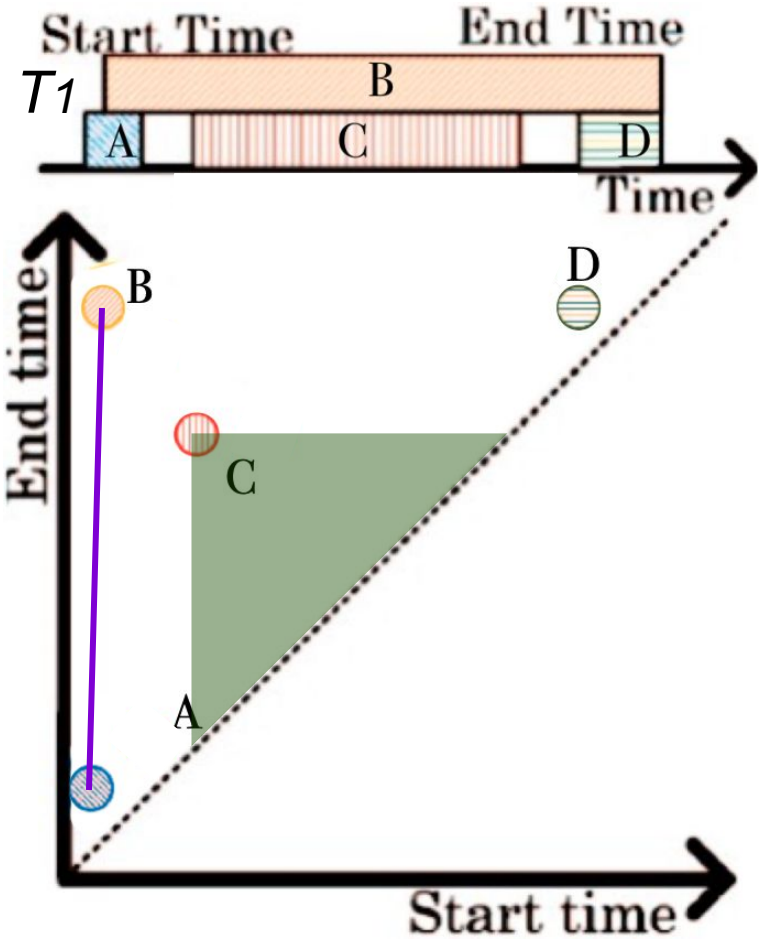


Performance Skyline



Performance Skyline



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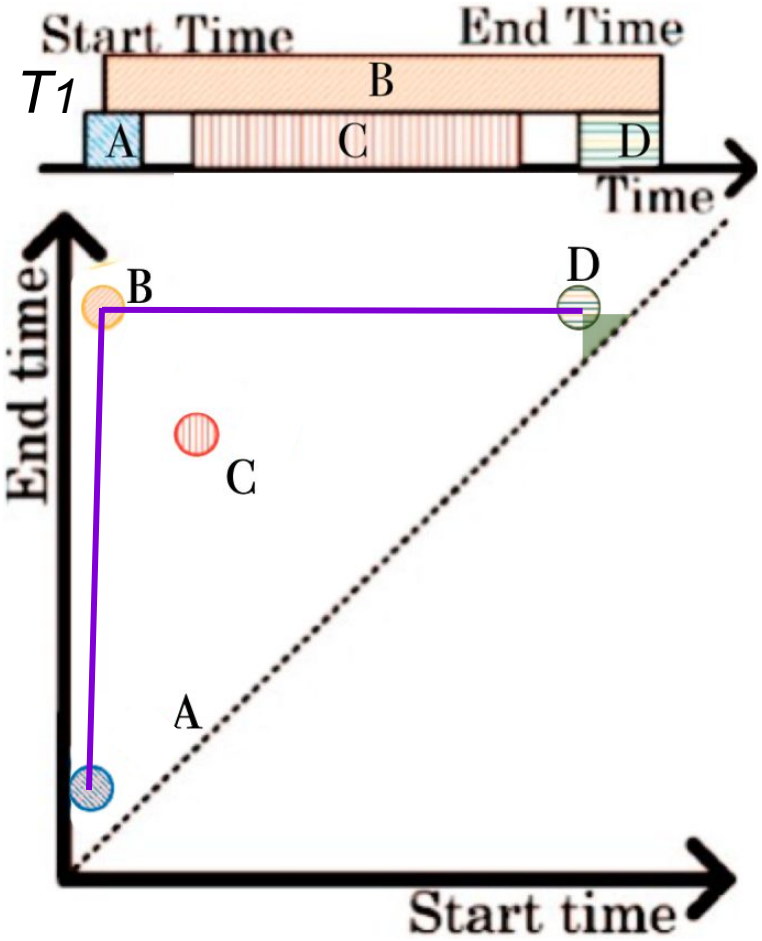

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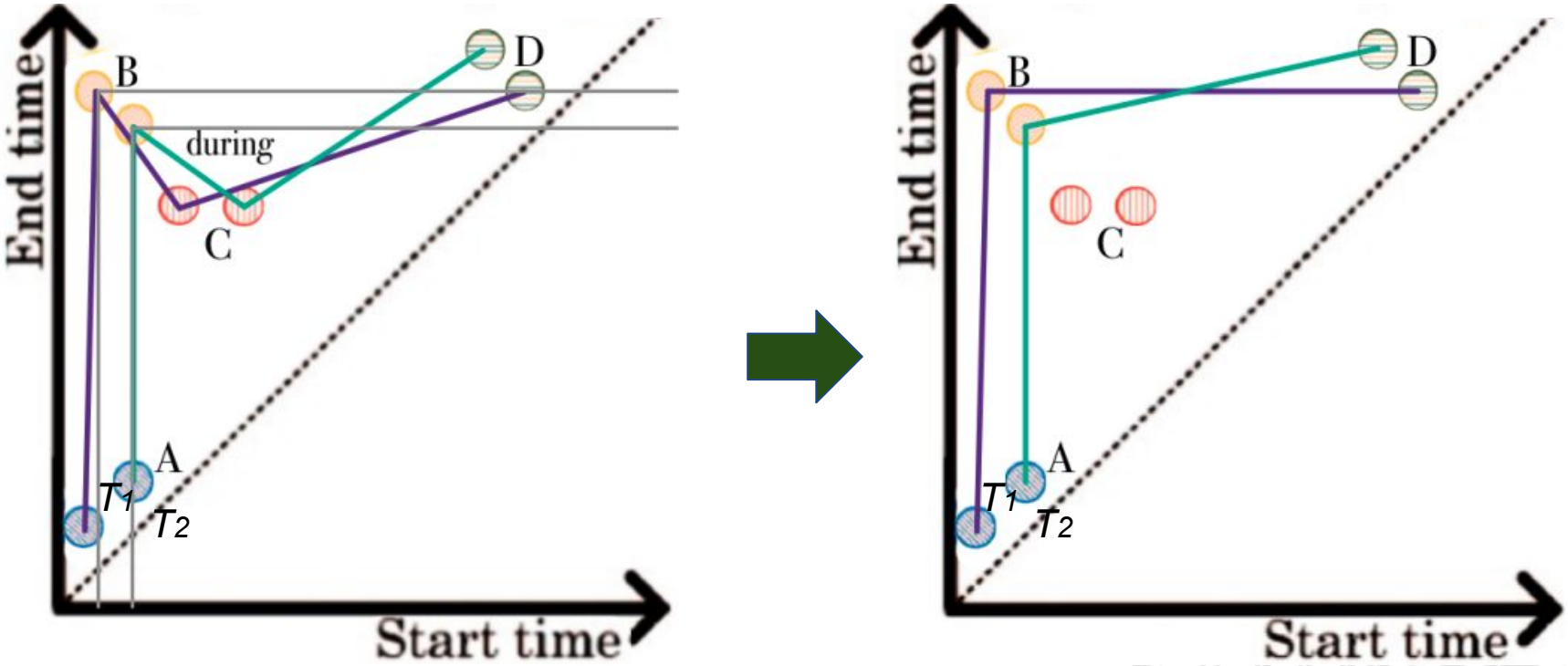

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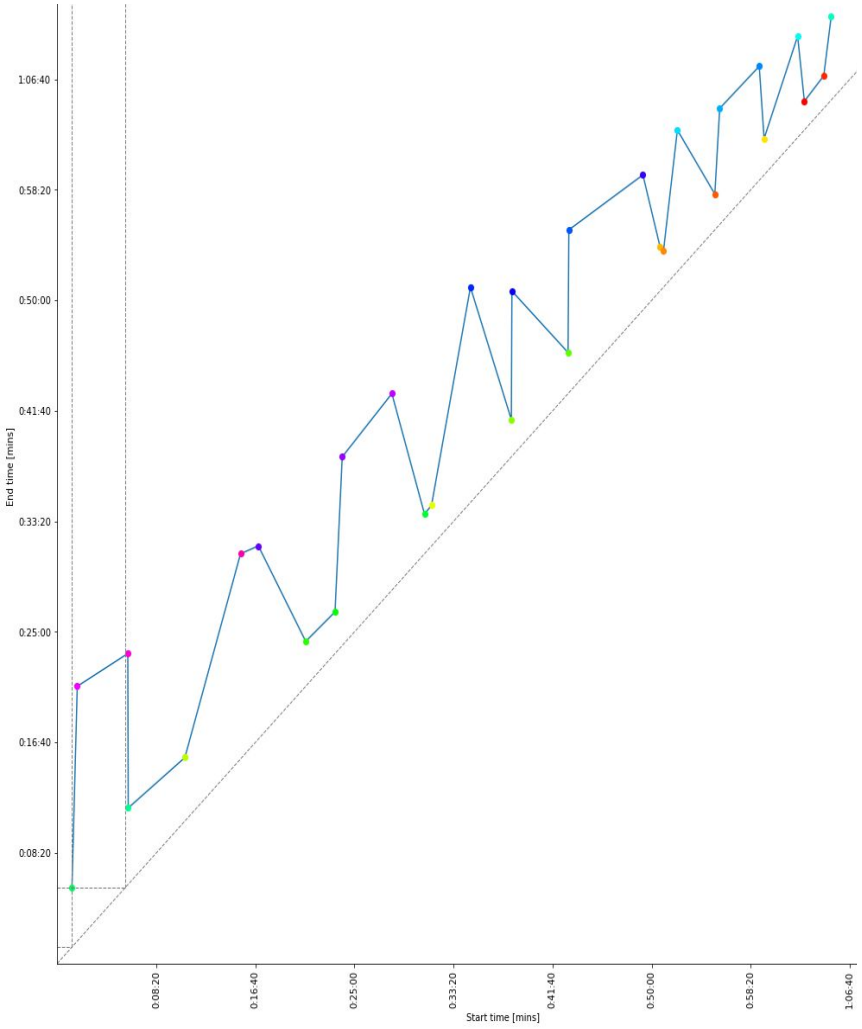

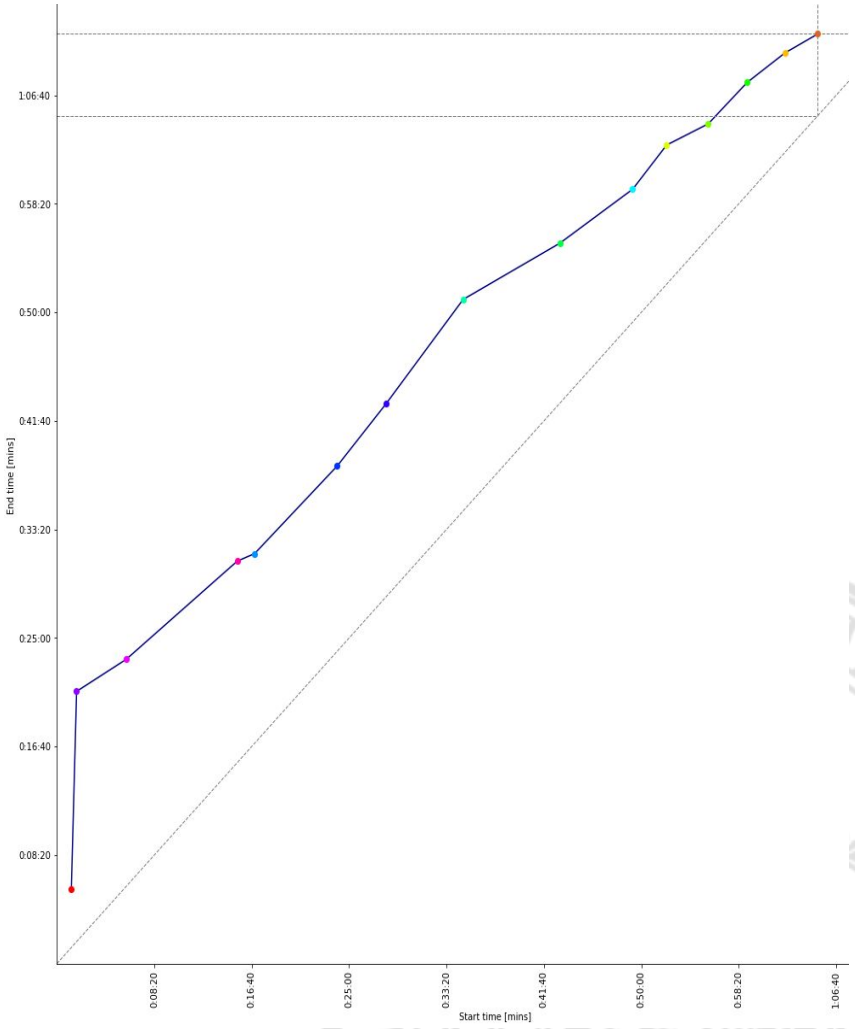

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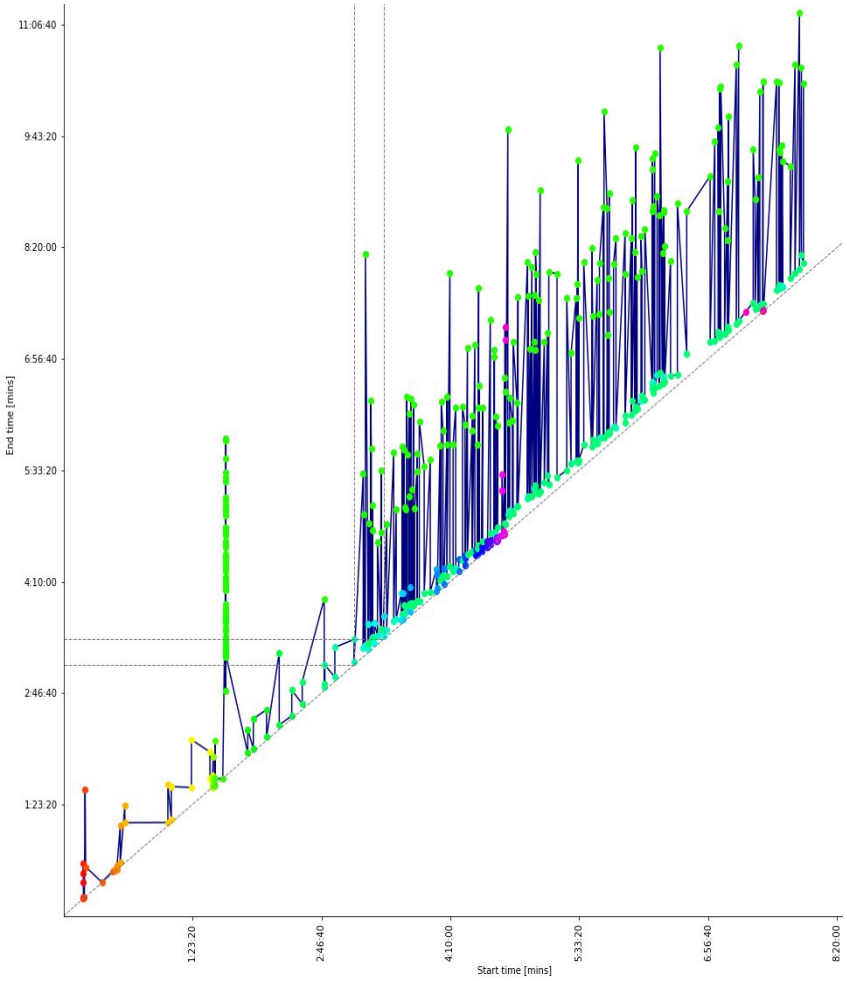

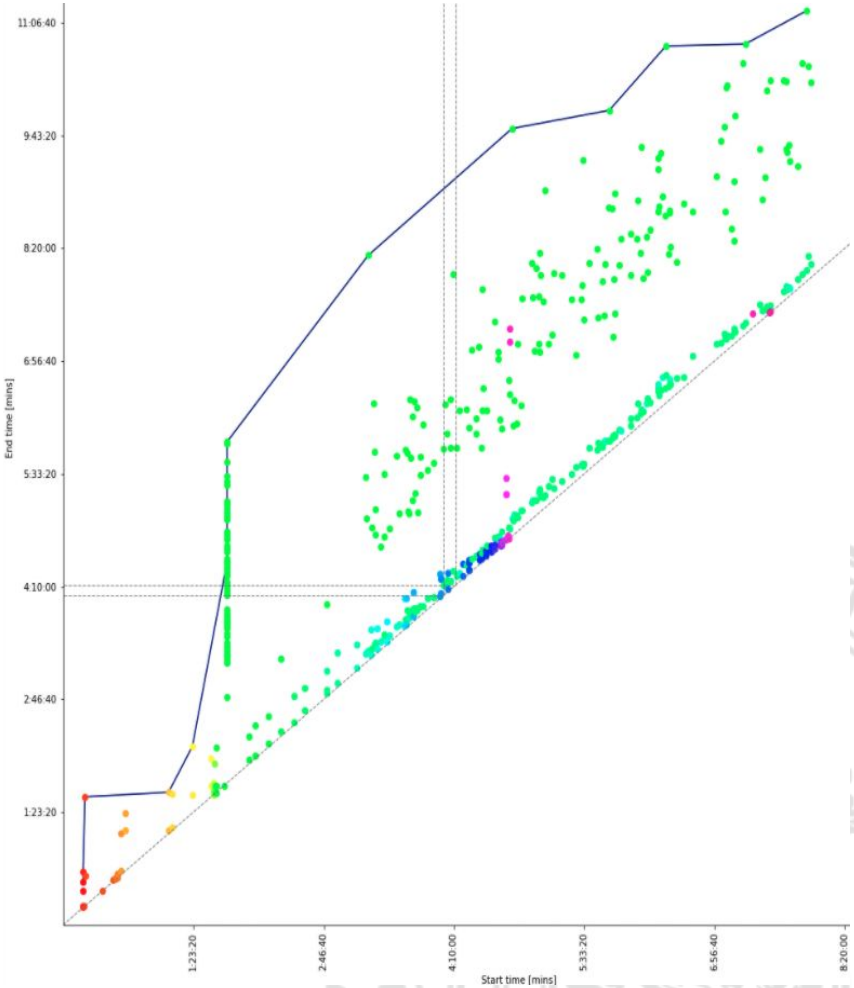

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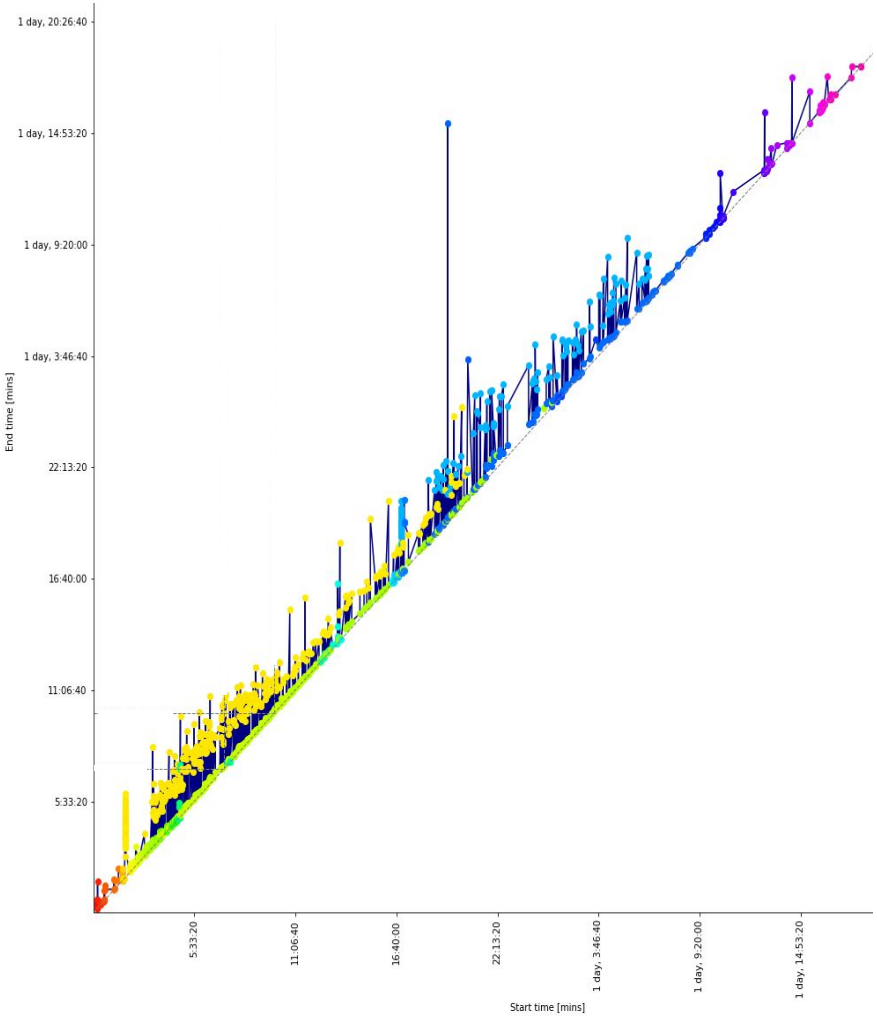
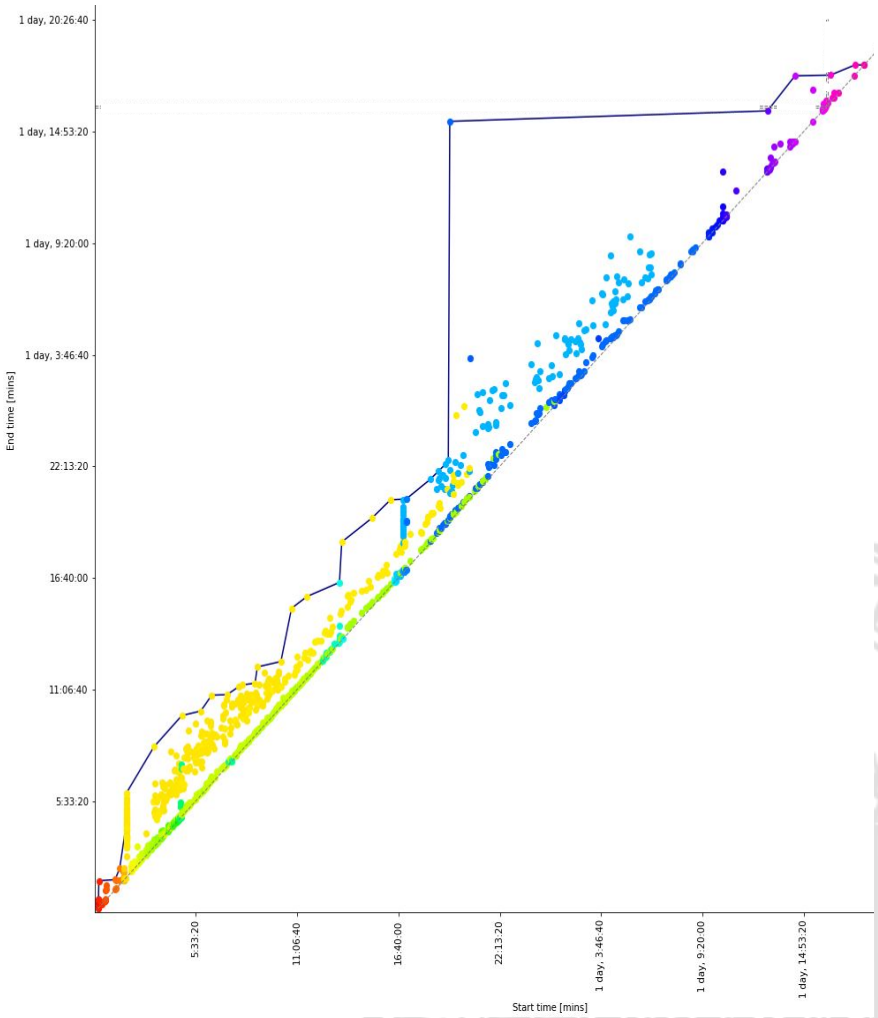


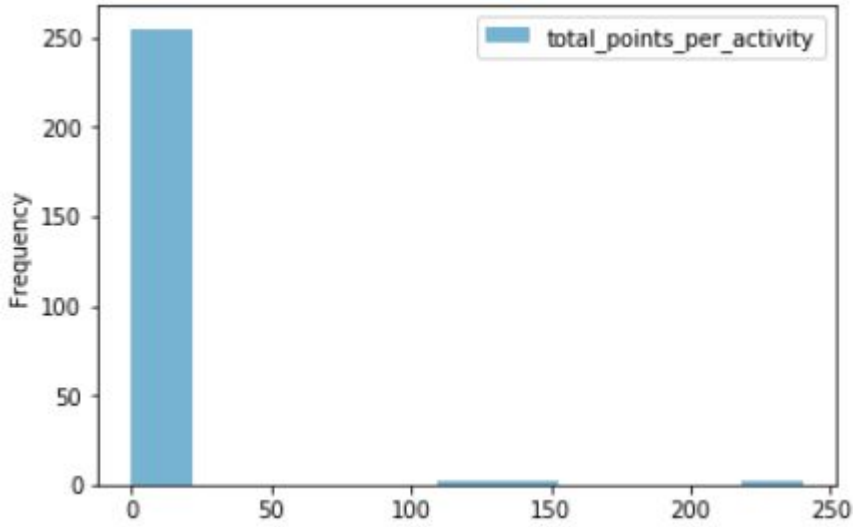


Computational Experiments:

- Trace Set Description
- Anomaly Detection

Experiments: Data Description

- 61864 events (~1238 on average)
- 50 traces
- 261 activities



Experiments: Data Description

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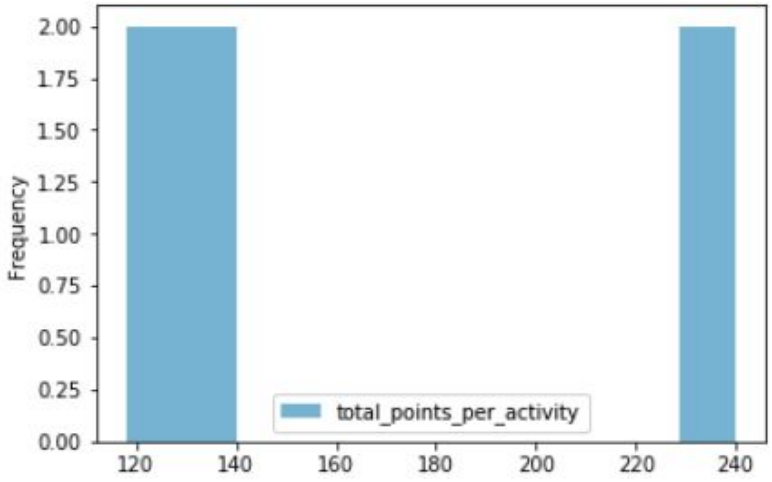

	activity	total_points_per_activity
72	CrawlTask(crawler=creepy-crawly)(chunk=01)	240
133	ExtractTask(crawler=creepy-crawly)(chunk=01)	240
135	ExtractTask(crawler=creepy-crawly)(chunk=03)	139
74	CrawlTask(crawler=creepy-crawly)(chunk=03)	138
134	ExtractTask(crawler=creepy-crawly)(chunk=02)	118
73	CrawlTask(crawler=creepy-crawly)(chunk=02)	118

Anomaly Detection

- Number of Events in Trace
- Percentage of Events on Skyline
- Skyline Activity Set
- Number of Events per Activity on Skyline
- Number of Events in Skyline of Unexpected Duration

Anomaly Detection

- Number of Events in Trace
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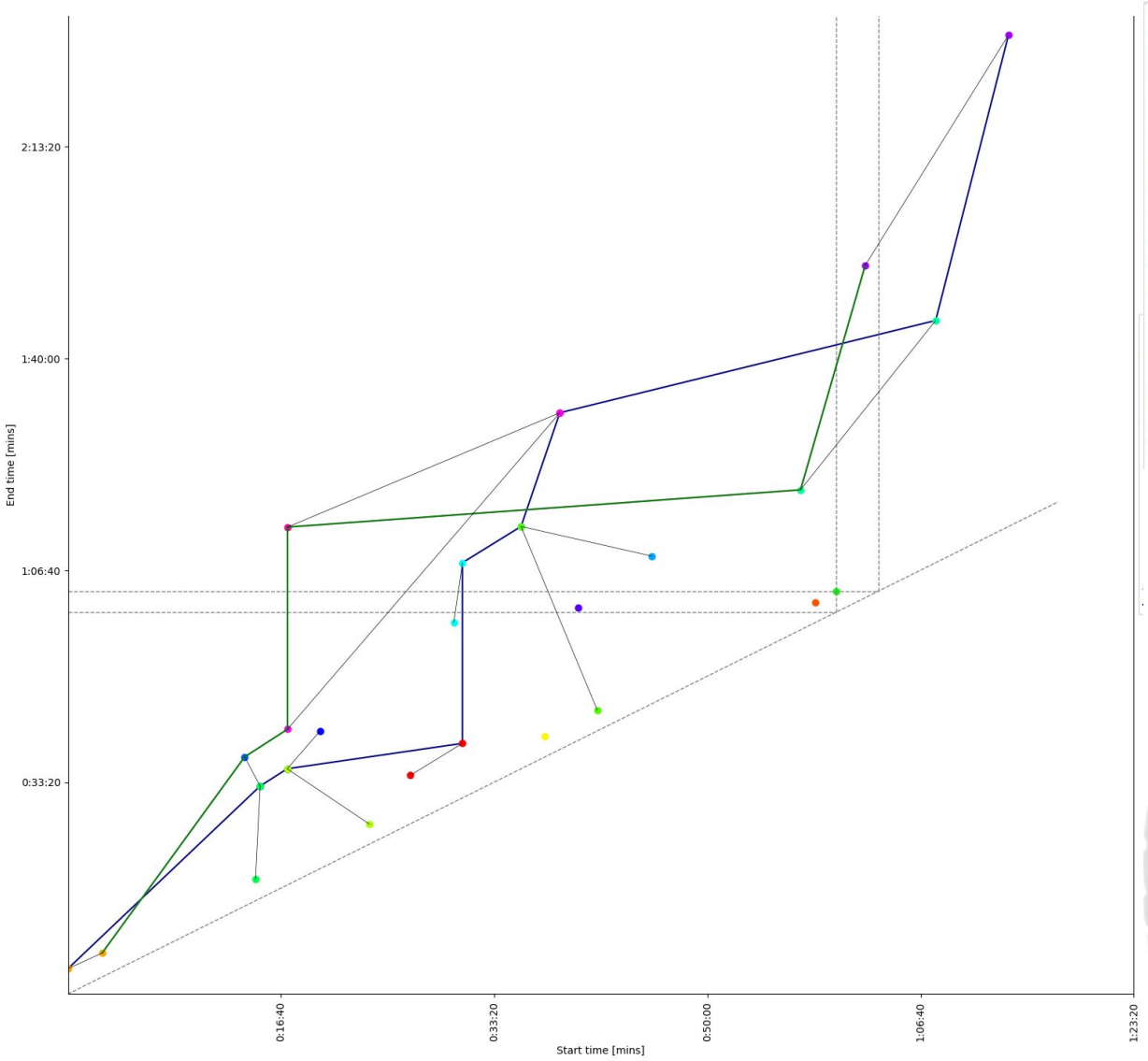
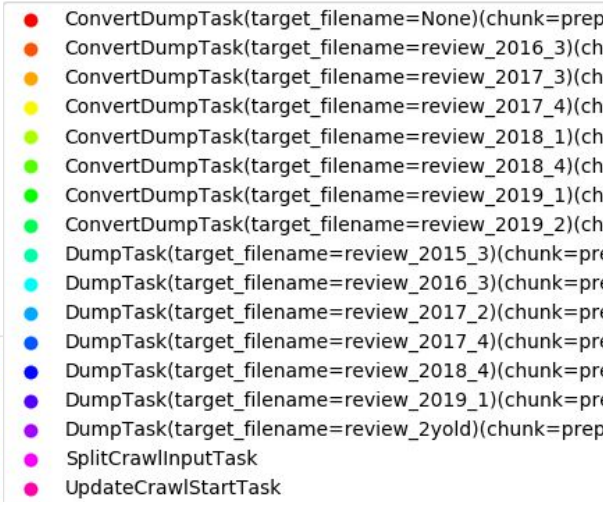
Anomaly Detection: Results

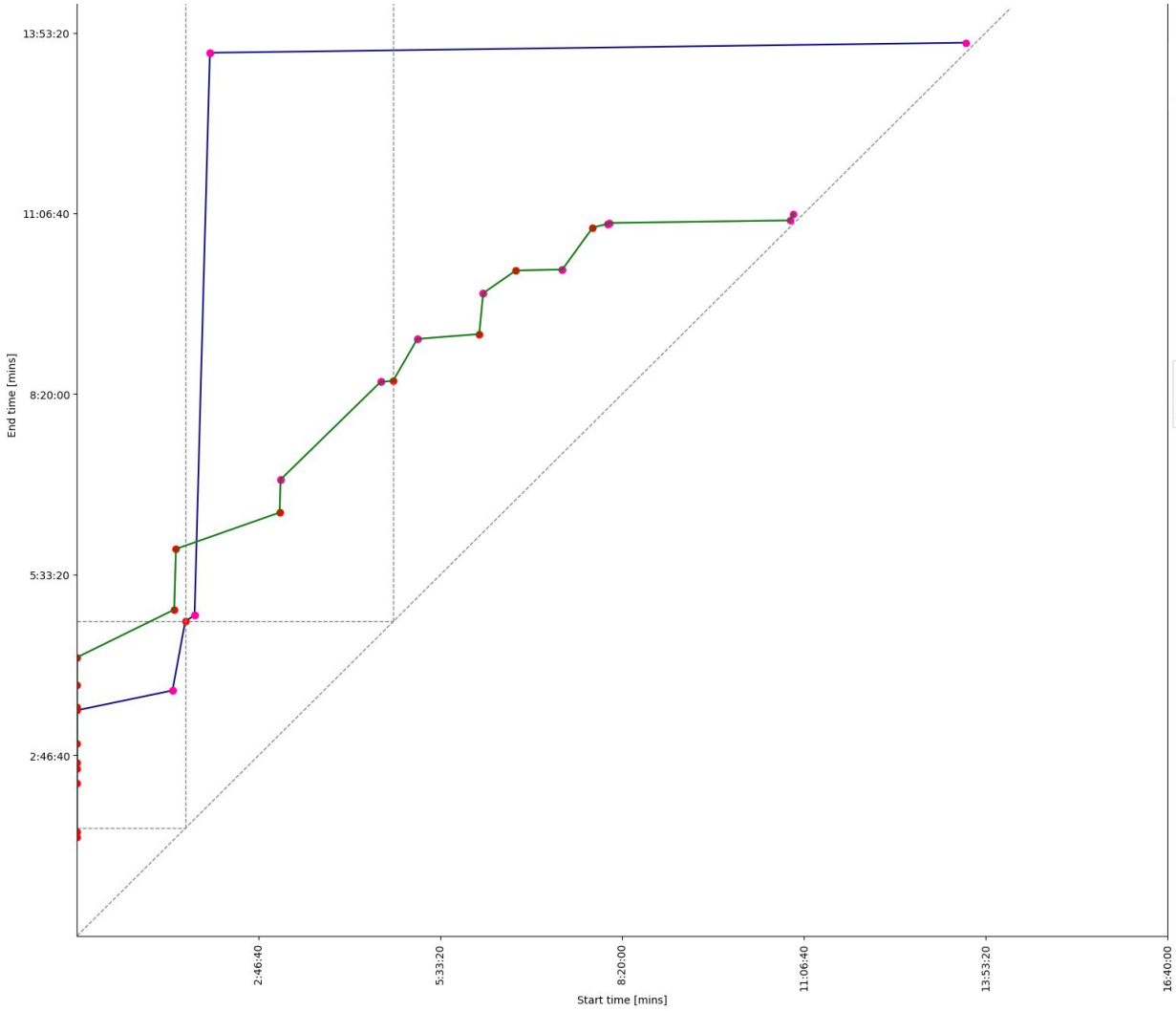
Anomaly Trace Type	**Tolerance Threshold**		**Number of Anomaly Traces**
	Average	Deviation	
Number of Events in Trace	1238	**±1*71.62**	**1**
		±1.5*71.62	1
		±2.25*71.62	1
		±3.375*71.62	1
Percentage of Events in Skyline	5.22	±1*1.38	11
		±1.5*1.38	**4**
		±2.25*1.38	3
		±3.375*1.38	0
Skyline Activity Set	>70% activities of overall set are found		33
	>75%		**17**
	>80%		11
	>85%		8
	>90%		5
Number of Events per Activity on Skyline	>90% anomalous activities are found		10
	>80%		**3**
	>70%		2
	>60%		2
	>40%		1

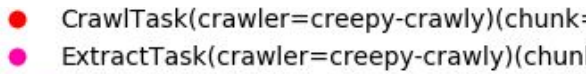
Percentage of Events on Skyline Anomaly



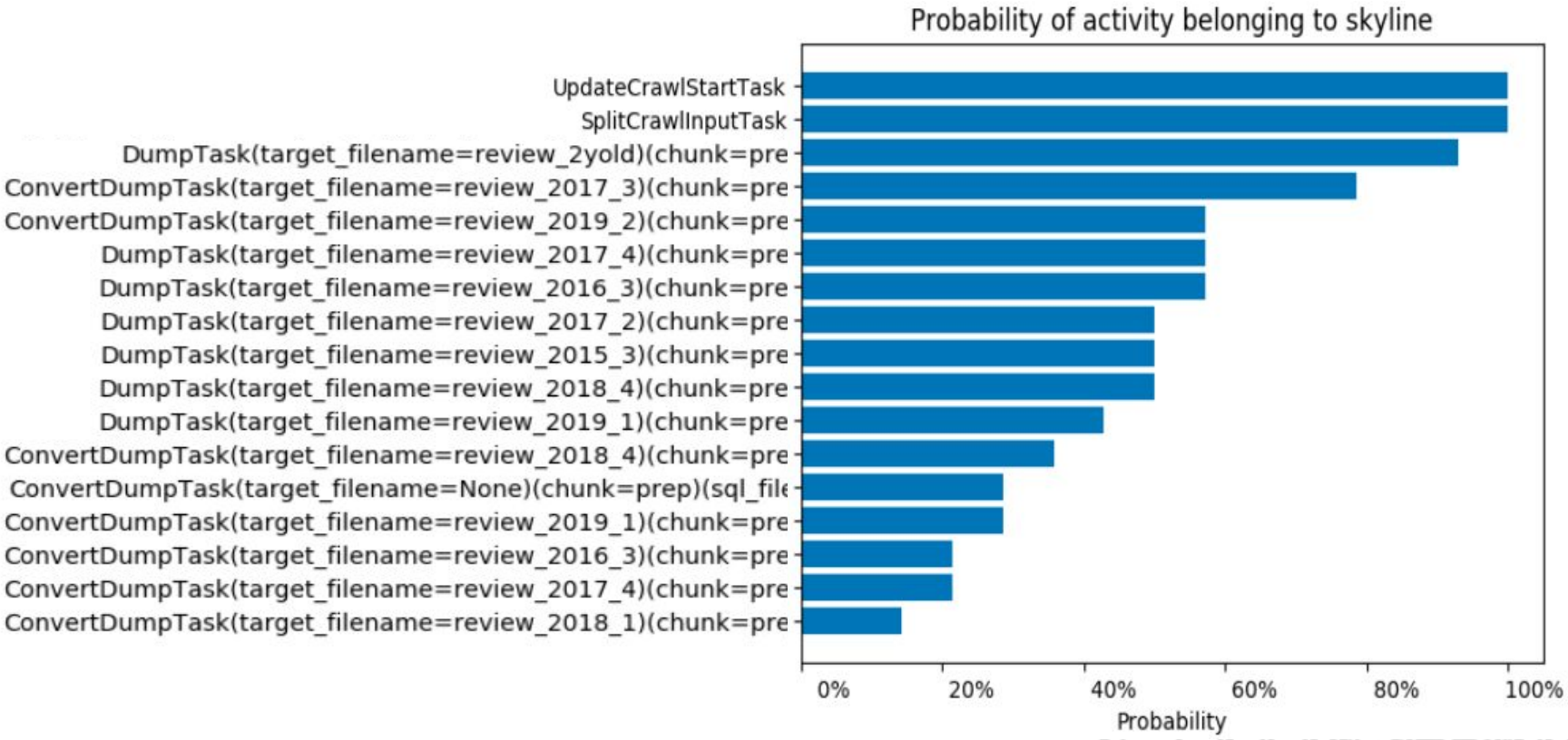


Anomaly Detection: Number of Events per Activity

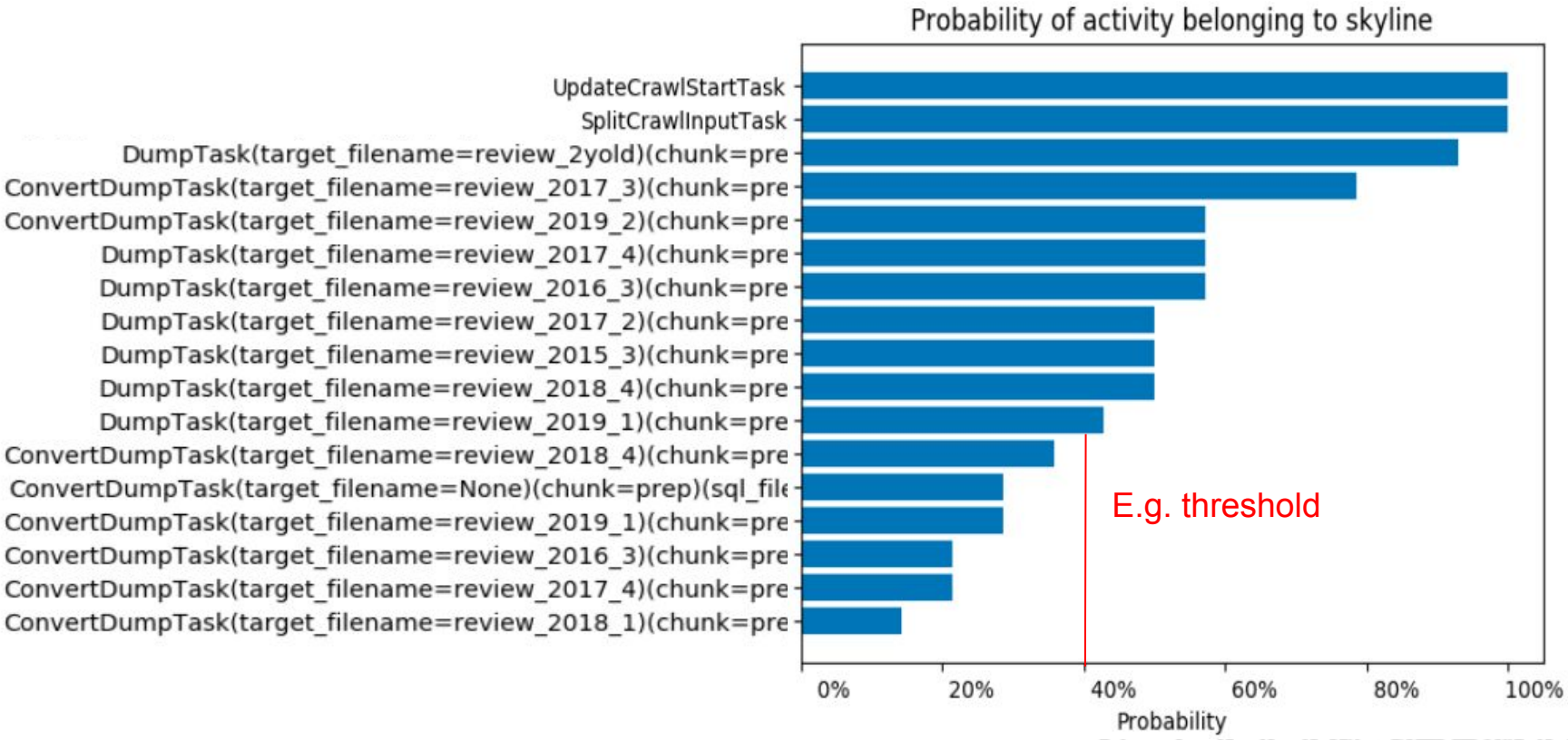




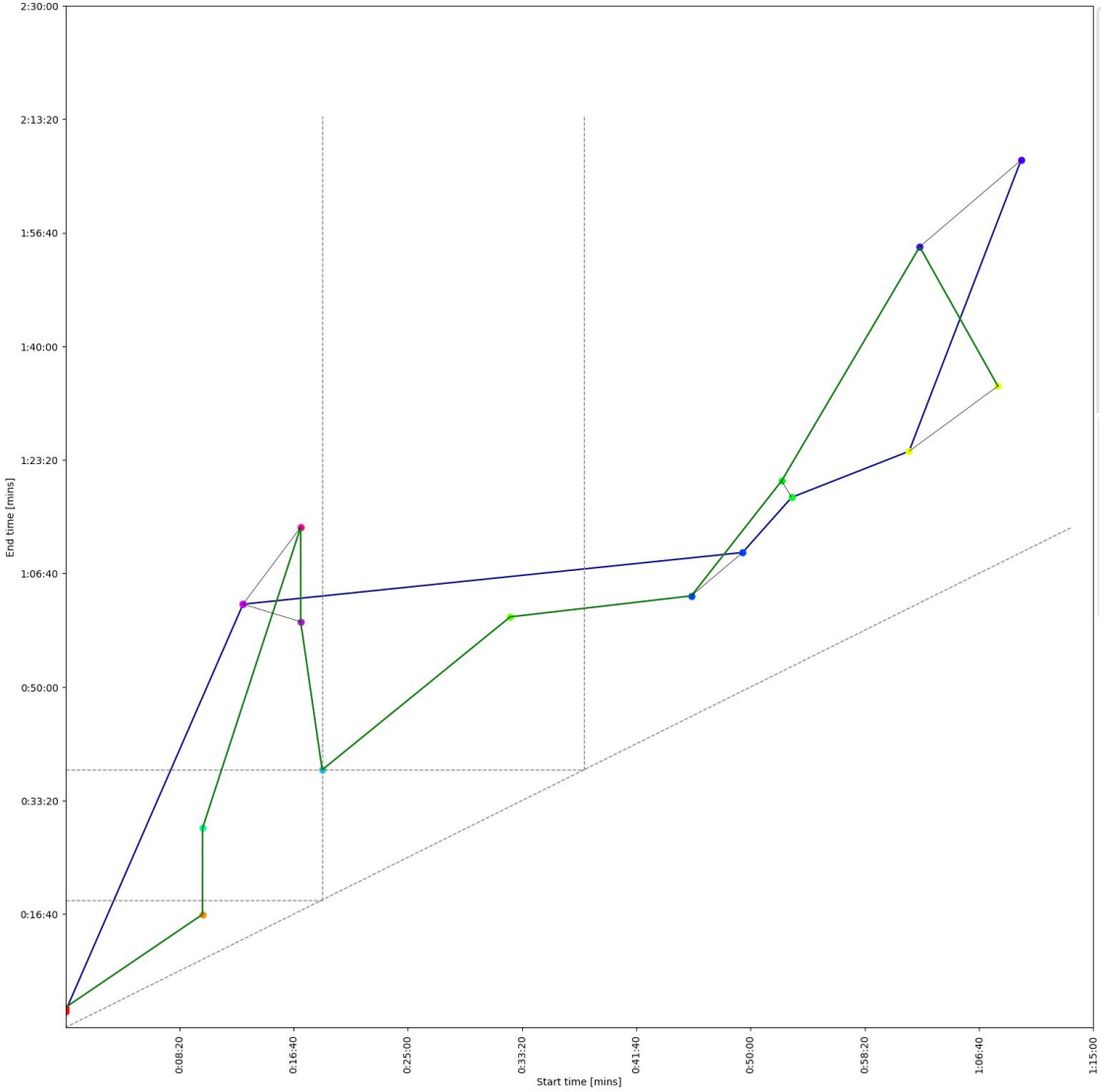
Activity Set Anomaly

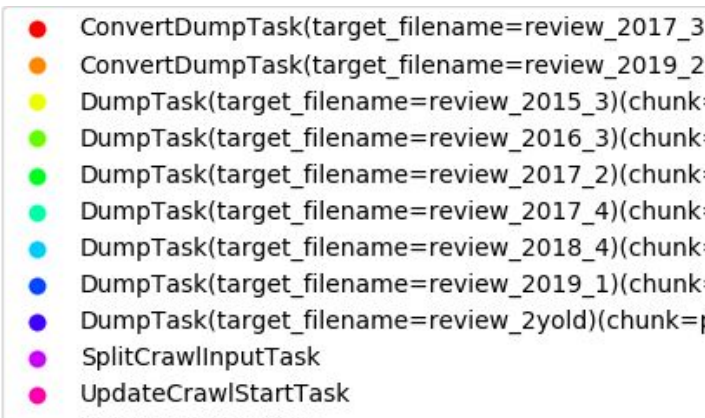


Activity Set Anomaly



Activity Set Anomaly





Final Thoughts & Conclusion

- Achievements:
  - Process performance notation for interval events
  - Visualization of real process event logs
  - Pattern Recognition: Time Variance Anomaly Detection
- Further work:
  - Process discovery: Extensions, alignment, clustering, etc.
  - Conformance checking: Predictions, drift recognition, skyline expectation maximization, etc.
  - Process Enhancement: Bottlenecks recognition, resource allocation, etc.

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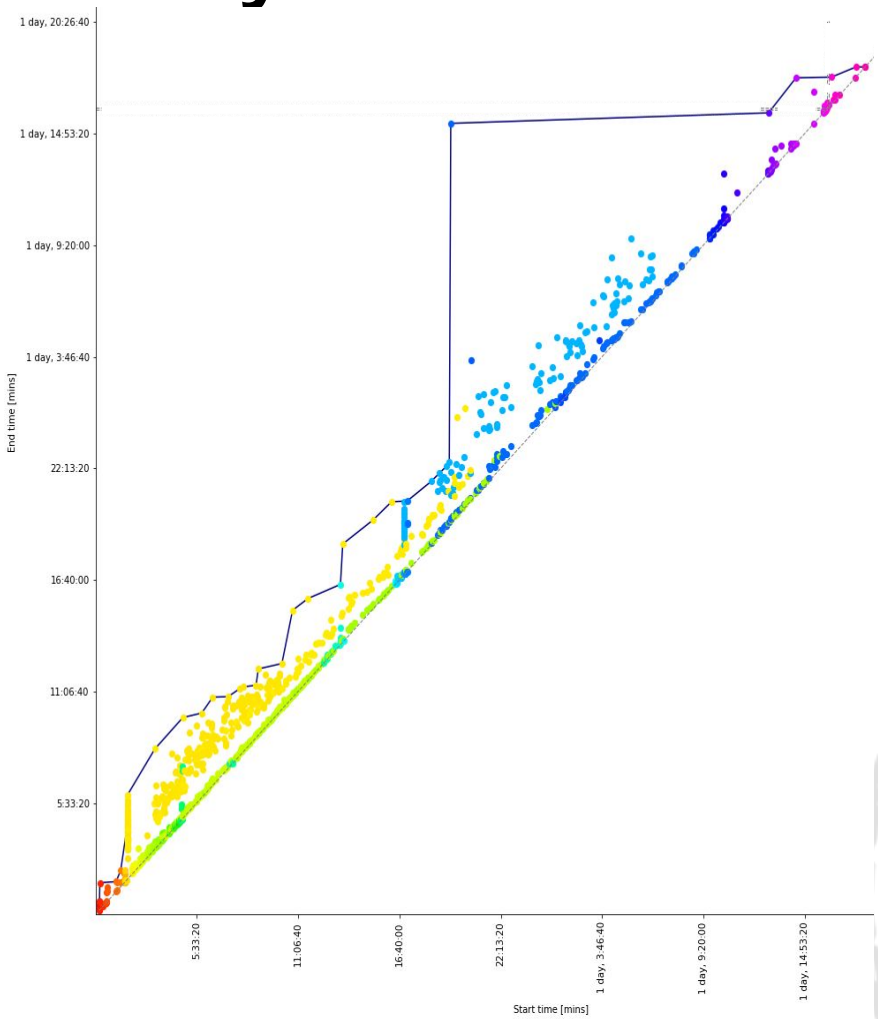
In summary…



Thank you!

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