Business 4720 - Class 9

Process Analytics

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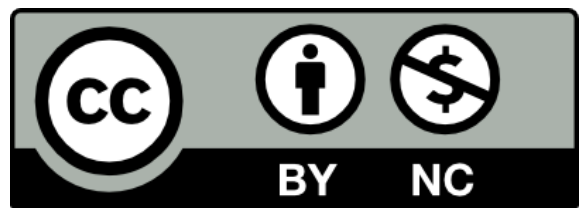

This Class

What You Will Learn:

- Introduction to Process Data
- Introduction to Process Analytics
  - Process Discovery
  - Process Conformance Analysis
  - Process Performance Analysis

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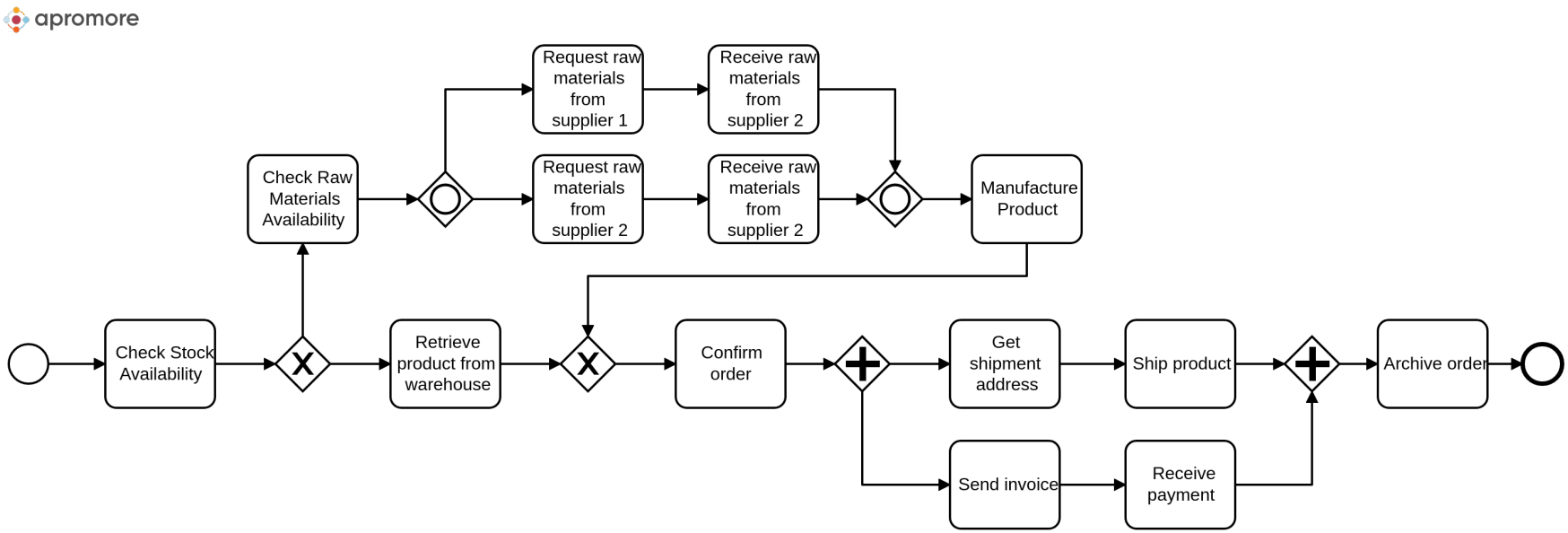
Business Processes

- Sequence of activities in a defined order
- Models describe processes
- Typically related to the processing of one type of business object
  - e.g. an order, a prescription, a complaint, etc.
- Standard notation: BPMN (”Business Process Modeling Notation”)

Basic BPMN

- Events (circles)
- Activities (boxes)
- Gateways (diamonds)
  - Exclusive (”X”) split and merge
  - Parallel (”+”) split and merge
  - Inclusive (”O”) split and merge

BPMN Example Process Model



Business Process Instances and Process Data

Case

- One instance of a business process
- Related to one particular business object (e.g. order 123, prescription R456, complaint C6789, etc.)

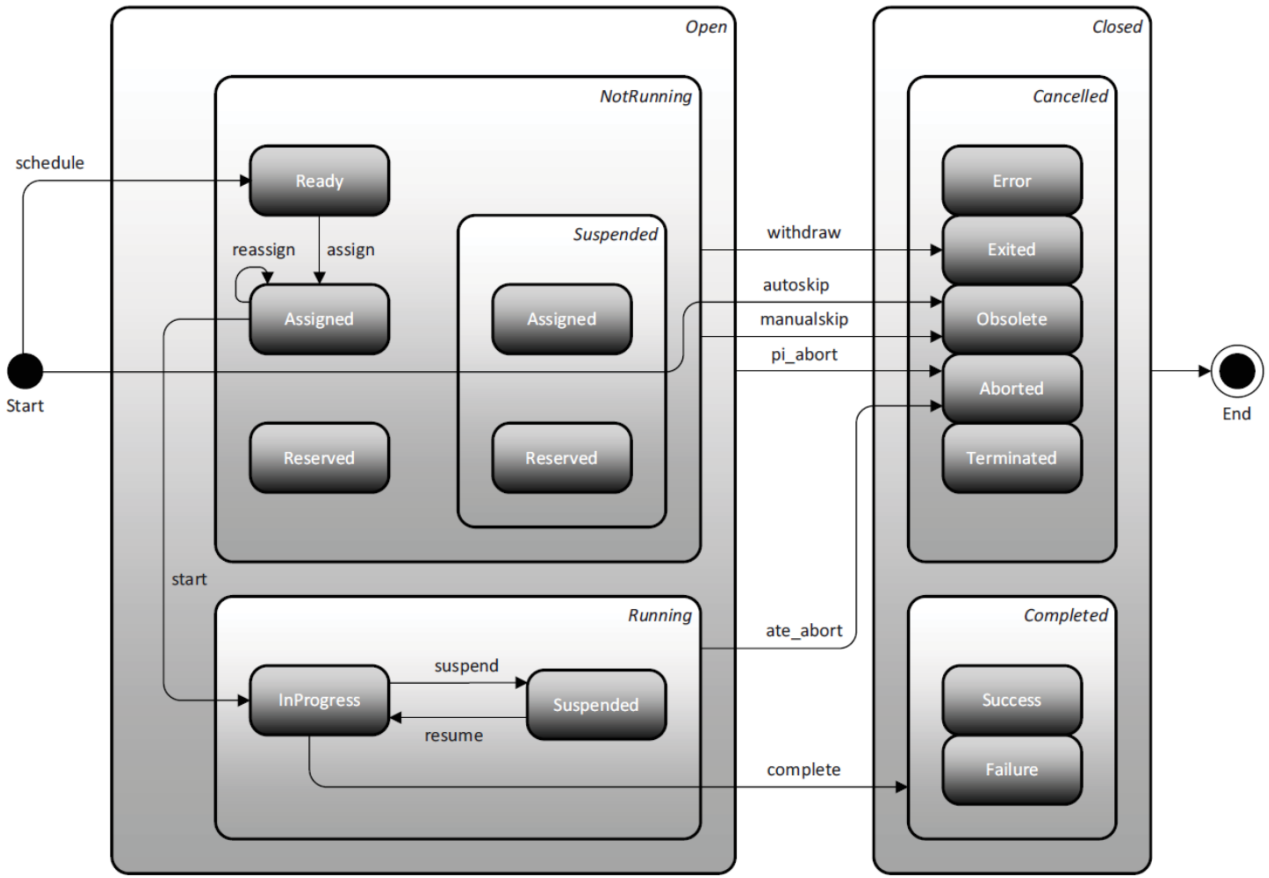
Trace

- Event data sequence for one case
- May includes attributes for the case and for each event
- May include resource information for each event
- May include timestamps for events

Event Log

- Set of traces for one process
- May include incomplete cases, may be sampled, etc.

Activity Lifecycle – Example



https://www.tf-pm.org/resources/xes-standard/about-xes/standard-extensions/lifecycle/standard

Event Log Data

Sources

- Process aware information systems
- Web server data
- ...

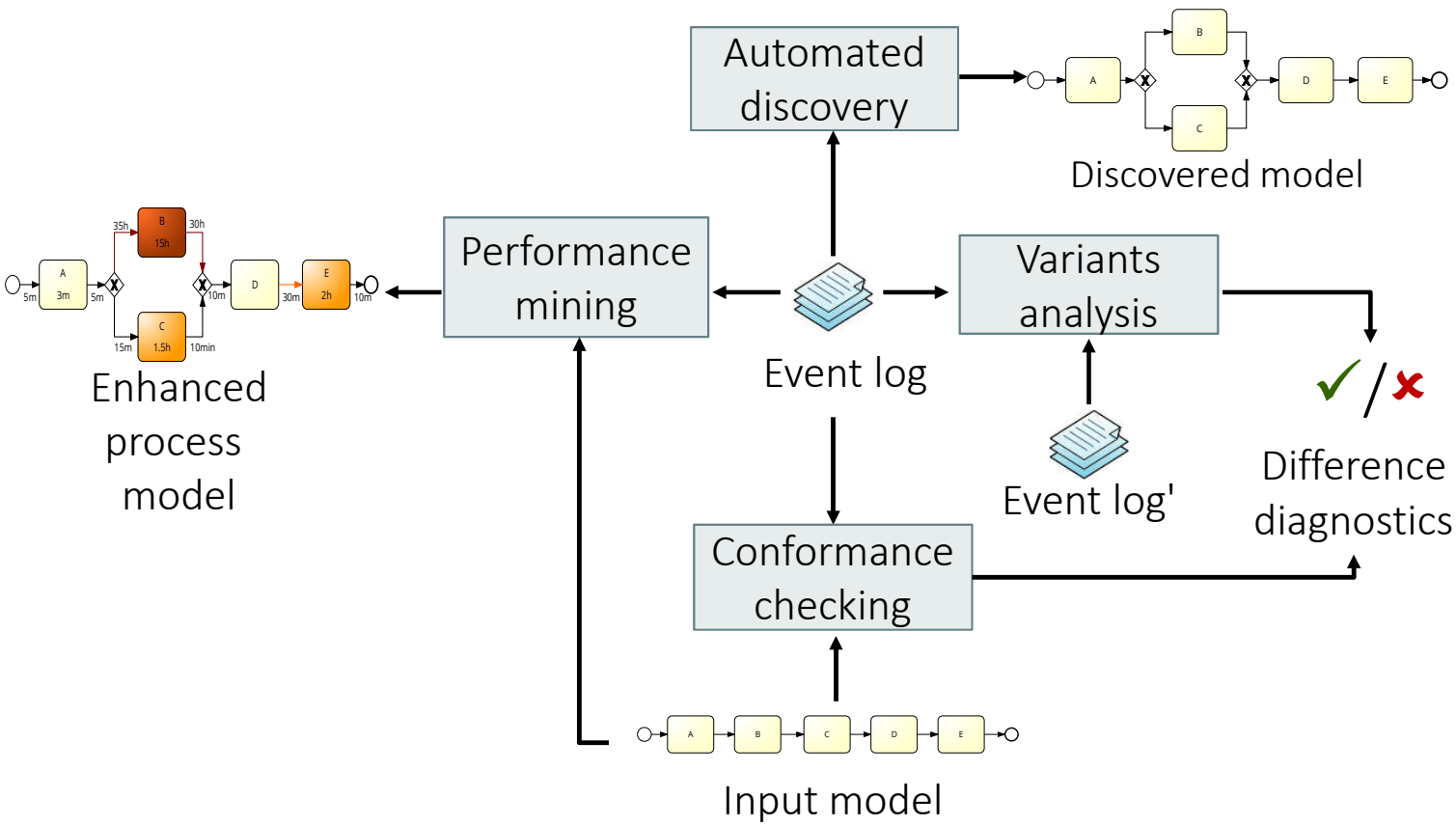
Formats

- CSV (one line per event)
- MXML (older XML format)
- XES ("eXtensible Event Stream") (current XML format)

Challenges

- Event correlation from multiple systems
- Noise, incompleteness
- Timestamping, batch processing
- Abstraction levels

Process Analytics



Source: Marlon Dumas, Marcello La Rosa, Jan Mendling, Hajo A. Reijers (2018) "Fundamentals of Business Process Management", 2nd edition, Springer Verlag, Germany

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Process Analytics

Purpose

- Discover actual operations
- Check actual process against desired process
- Identify operational (performance) problems
- Improve operational processes
- External compliance analysis and reporting
- Identify implicit or de-facto organizational groups and relationships

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Process Analytics in R

BupaR

- Hasselt University
- Open source R library
- Development since 2020
- Process visualization (DFG)
  - Frequencies metrics
  - Performance metrics
- Control flow analysis
- Rule-based conformance analysis
- Performance metrics
- Organizational analysis

`https://bupar.net/`

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Process Analytics in Python

PM4PY

- Fraunhofer Institute for Applied Information Technology
- Open source python package, since 2018
- Process discovery
  - *Techniques*: Inductive miner, Heuristics miner, ...
- Conformance checking
  - *Techniques*: Token-based replay, Cost-based alignment, ...
- Log–Model Comparison
  - *Metrics*: Fitness, Precision, Generalization, Complexity, ...
- Decision mining
- Trace clustering
- LTL checking
- Social network discovery

`https://processintelligence.solutions/pm4py`

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Read a CSV dataset:

Python

```python
import pandas as pd
import pm4py

# Load the event log and parse date columns
log = pd.read_csv('https://evermann.ca/busi4720/\
   PurchasingExample.csv',
   parse_dates=['Start Timestamp', 'Complete Timestamp'],
   infer_datetime_format=True)

# Tell PM4PY about which columns represent case ID,
# activity name, and timestamp. Case ID and activity
# names must be string type
log['case:concept:name']=log['Case ID'].astype('string')
log['concept:name']=log['Activity'].astype('string')
log['time:timestamp']=log['Complete Timestamp']
log['org:resource']=log['Resource']
```

PM4PY Basics

Reading an XES file is easy:

Python

```
log2 = pm4py.read_xes('BPI_Challenge_2012.xes.gz')
```

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PM4PY Basic Statistics

Python

```python
num_cases = len(log['Case ID'].unique())
num_events = log.shape[0]

pm4py.get_start_activities(log)
pm4py.get_end_activities(log)

pm4py.get_all_case_durations(log)

# Useful only or XES-based event logs
pm4py.get_event_attributes(log)
pm4py.get_trace_attributes(log)
```

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PM4PY Basic Statistics

- Variants are sets of traces with the same sequence of events

Python

```python
varients = pm4py.get_variants(log)
# Returns a dict with keys and values
list(variants.keys())
list(variants.values())

# Split the log into sub-logs
for variant, subdf in pm4py.split_by_process_variant(log):
    print(variant)
    print(subdf)
```

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Process Discovery – DFG

Directly-Follows Graph (Dependency Graph) (Process Map)

- Shows how often one activity directly follows another

Python

```
dfg, start, end = pm4py.discover_dfg(log)

pm4py.view_dfg(dfg, start, end, rankdir='LR')

pm4py.save_vis_dfg(dfg=dfg,
    start_activities=start,
    end_activities=end,
    file_path='dfg.png', rankdir='TB')
```

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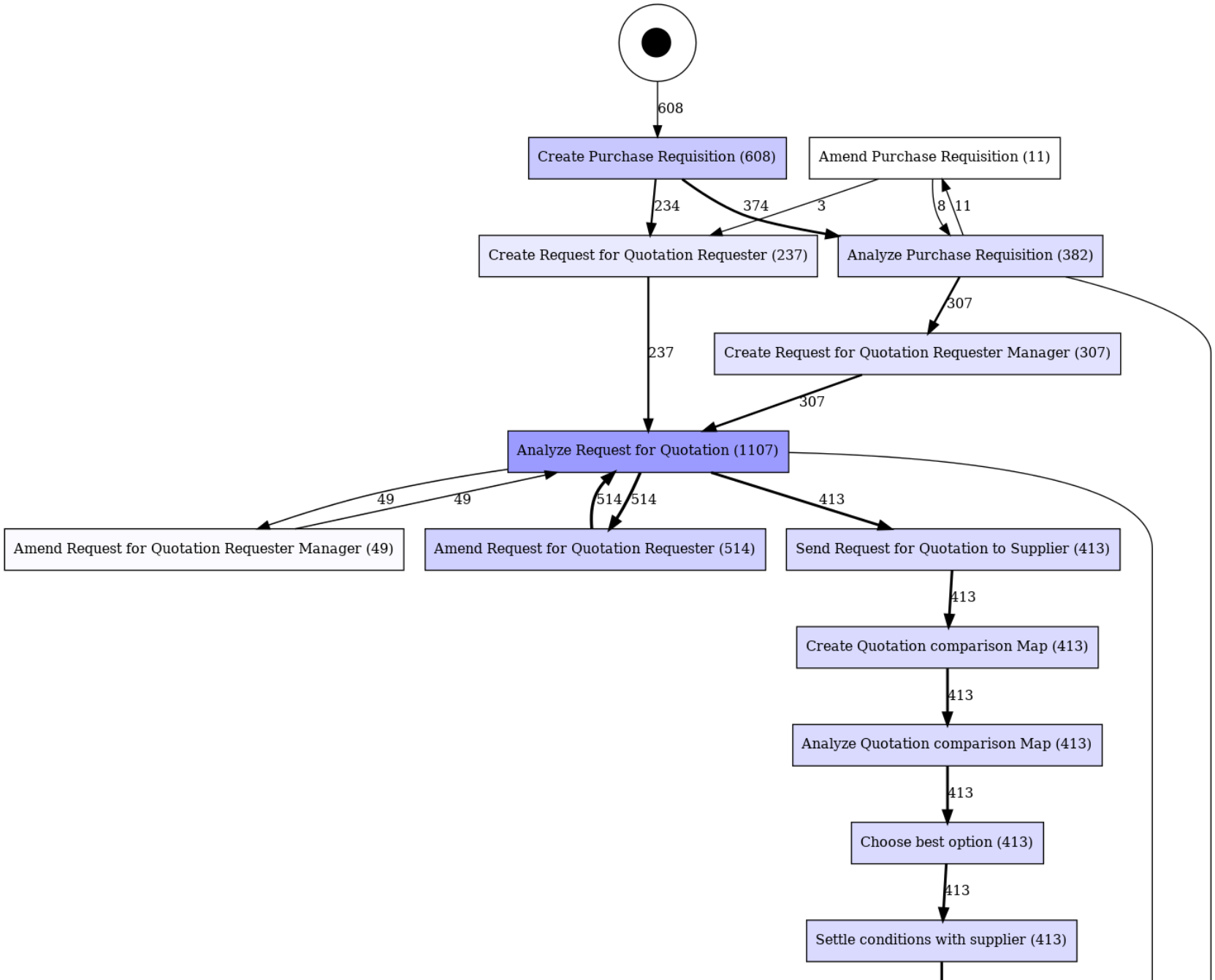
Process Discovery



Hands-On Exercises

Use the event log from
`https://evermann.ca/busi4720/BPI_Challenge_2012.csv`

1. Read the data into a Pandas data frame using `read_csv()`. Parse the `Start Timestamp` and `Complete Timestamp` columns as dates.
2. Create the `case:concept:name`, `concept:name`, `time:timestamp`, `org:resource` columns as in the example above.
3. Create and visualize a directly-follows-graph (DFG)
4. How many variants are there? What is the most frequent variant?

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Process Discovery – Inductive Miner

Principles

- Identifies subsets of activities by repeatedly ”cutting” the DFG
- Filter infrequent activities to deal with noise
- Mines a process tree that can be transformed to BPMN

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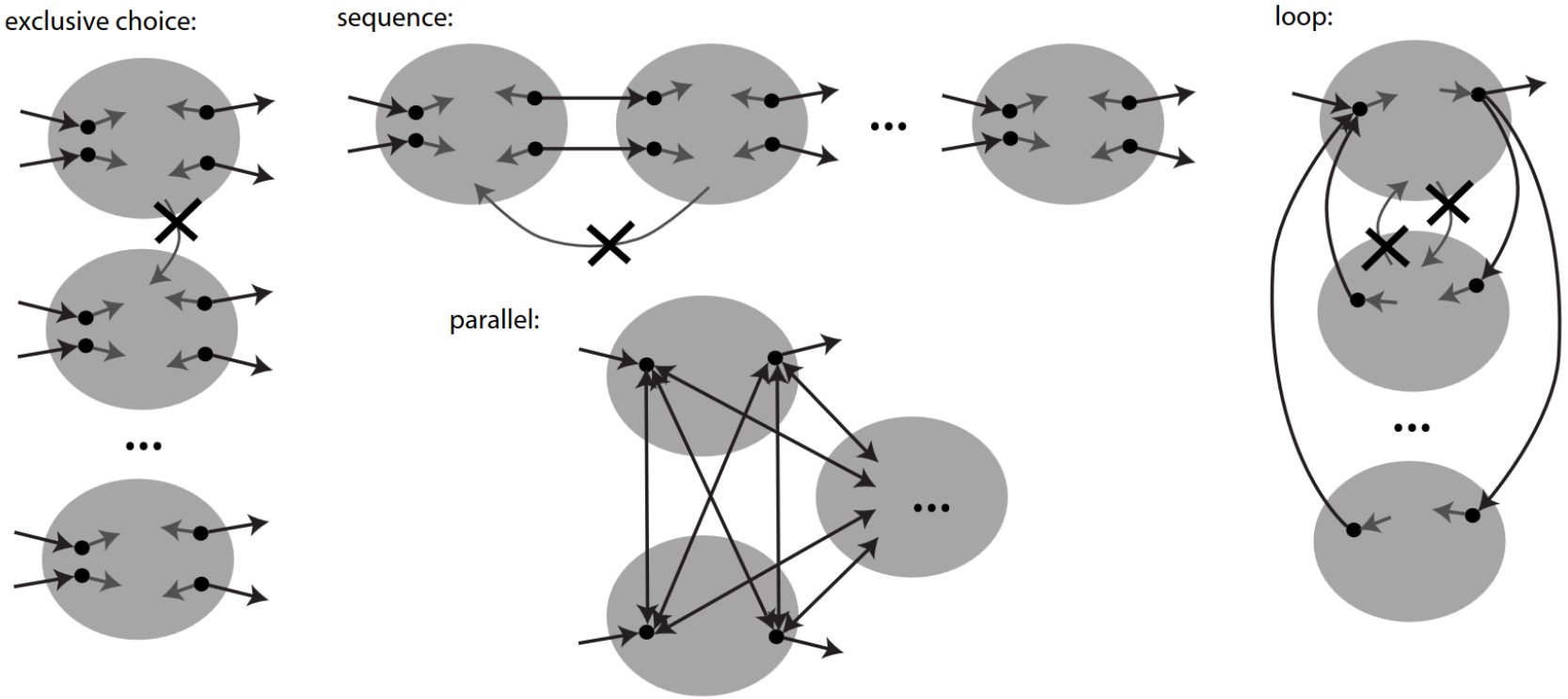
Process Discovery – Inductive Miner



Source: Leemans, S.J.J., Fahland, D., van der Aalst, W.M.P. (2013). Discovering Block-Structured Process Models from Event Logs - A Constructive Approach. In: Colom, JM., Desel, J. (eds) Application and Theory of Petri Nets and Concurrency. PETRI NETS 2013. Lecture Notes in Computer Science, vol 7927. Springer, Berlin, Heidelberg.

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Process Discovery – Inductive Miner

Python

```
bpmn_model = \
    pm4py.discover_bpmn_inductive(log, noise_threshold=0.5)

pm4py.view_bpmn(bpmn_model, rankdir='LR')

pm4py.save_vis_bpmn(bpmn_model,
   file_path='bpmn.png', rankdir='TB')
```

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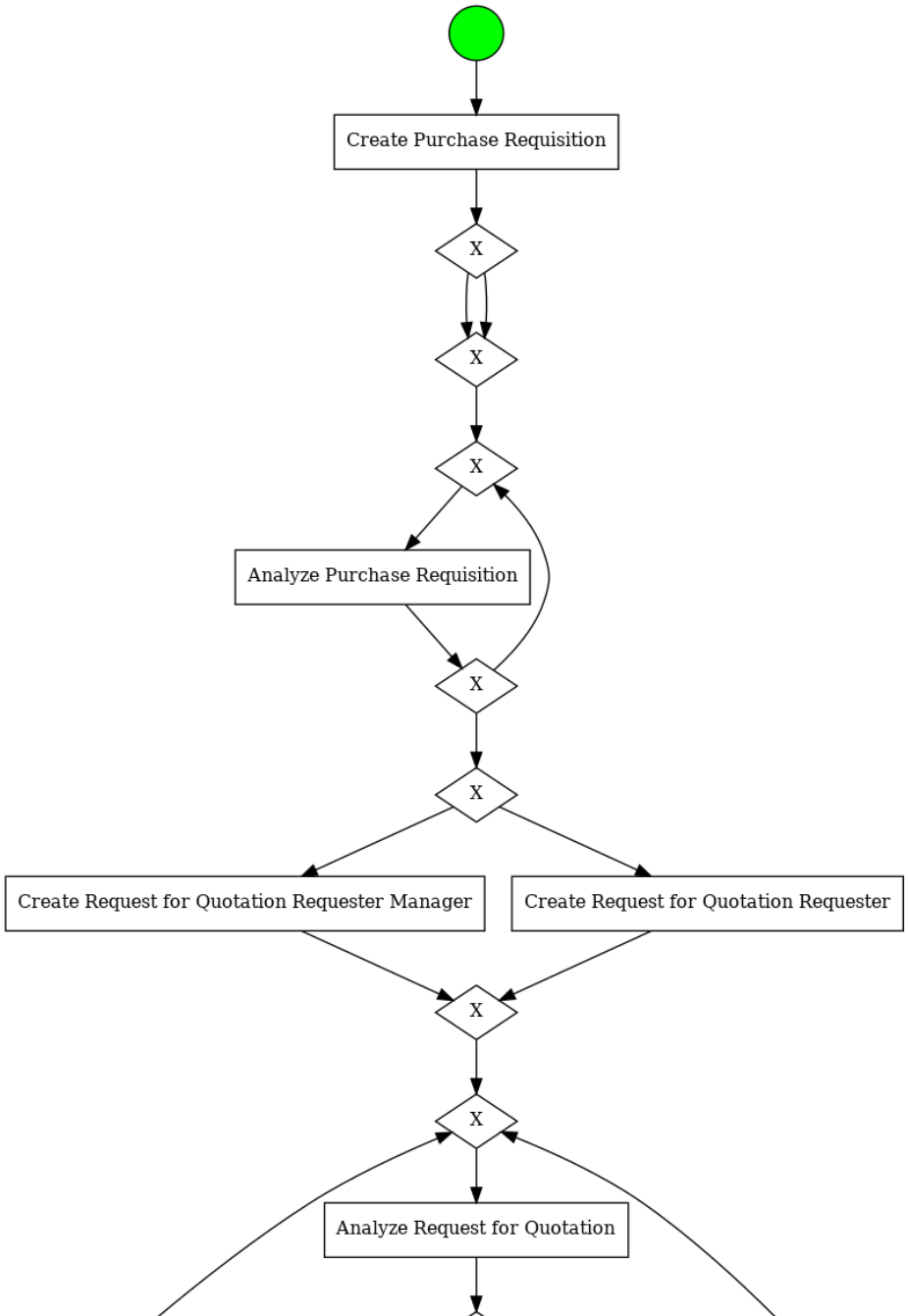
Process Discovery – Inductive Miner



Process Discovery – Heuristics Net

Principles

- Remove noise by frequency threshold on dependency graph
- Identifies loops of length 1 and length 2
- Identifies long-distance dependencies
- Removes non-observable activities

Frequencies in DFG

$$a \Rightarrow b = \left(\frac{|a > b| - |b > a|}{|a > b| + |b > a| + 1} \right)$$

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Process Discovery – Heuristics Net

```python
petri_net, initial_marking, final_marking = \
    pm4py.discover_petri_net_heuristics(log,
        dependency_threshold=0.6,
        and_threshold=0.65,
        loop_two_threshold=0.4)

pm4py.view_petri_net(petri_net)

bpmn_model2 = pm4py.convert_to_bpmn(
    petri_net, initial_marking, final_marking)

pm4py.view_bpmn(bpmn_model2)
pm4py.save_vis_bpmn(bpmn_model2, 'bpmn2.png', rankdir='TB')
```

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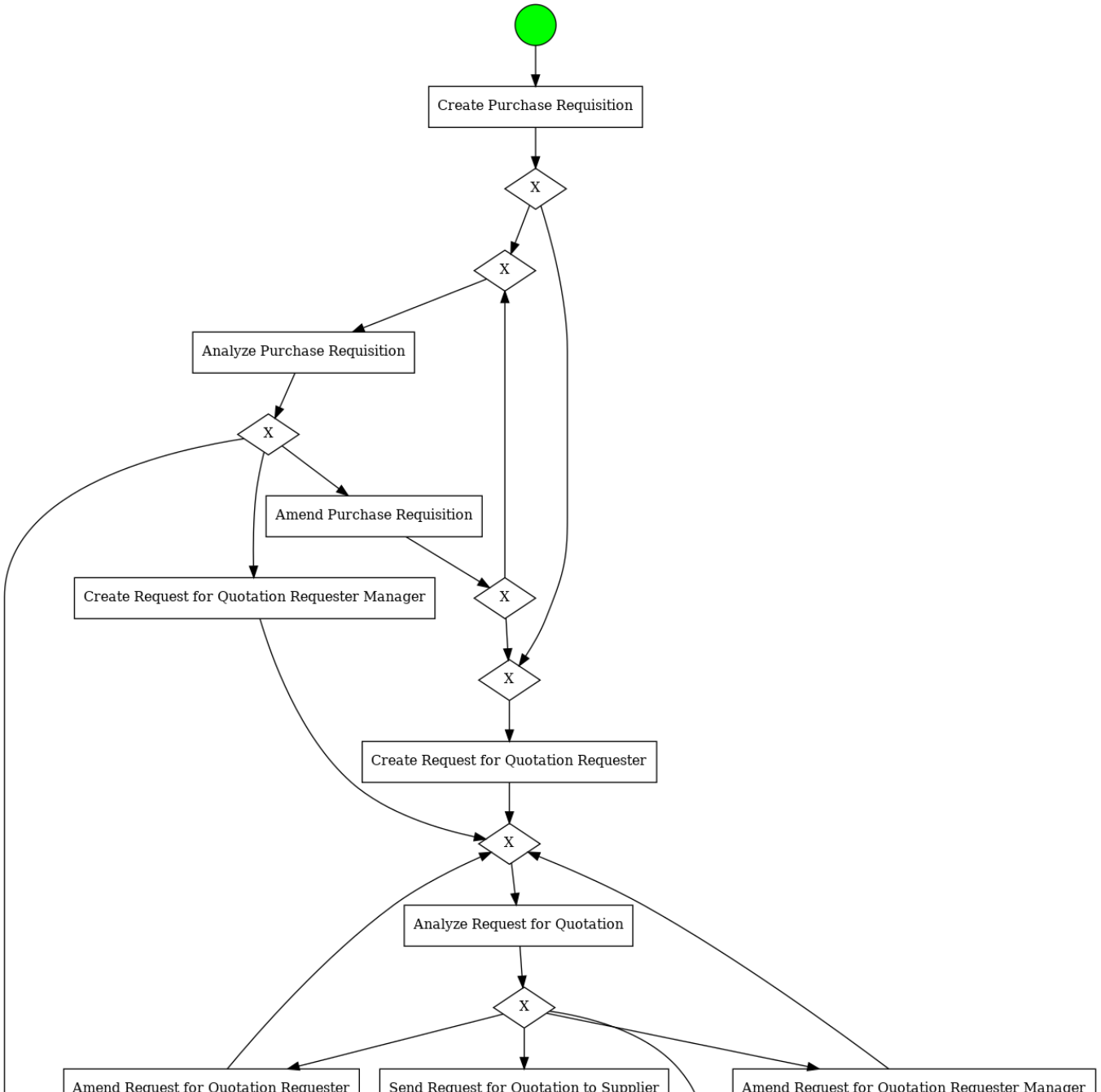
Process Discovery – Heuristics net



Process Discovery

Quality of Discovered Models

- **Fitness**: Can the model generate all traces in log?
- **Precision**: Does the model only generate traces in log?
- **Generalization**: Can the model generalize to ”sensible” traces not seen in log?
- **Complexity**: Is the model too complex to understand?

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Fitness & Precision

Token-Based Replay

- Replays each trace of an event log on a process model
- Discovers missing and surplus tokens, i.e. model activities that cannot be executed, or model activities that are executed too often
- Percentage of traces that fit perfectly, average fitness

Alignments

- Aligns traces to process model
- ”sync move”: Activity in both trace and model
- ”move on log”: Activity in trace but not in model
- ”mode on model”: Activity in model but not in trace
- Percentage of traces that fit perfectly, average fitness

Fitness

Python

```
petri_net, initial_marking, final_marking = \
    pm4py.discover_petri_net_inductive(log,
        noise_threshold=0.5)

fitness_alignments = pm4py.fitness_alignments(log,
    petri_net, initial_marking, final_marking)
print(fitness_alignments)

fitness_tbr = pm4py.fitness_token_based_replay(log,
    petri_net, initial_marking, final_marking)
print(fitness_tbr)
```

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Precision

Python

```
precision_alignments = pm4py.precision_alignments(log,
    petri_net, initial_marking, final_marking)
print(precision_alignments)

precision_tbr = pm4py.precision_token_based_replay(log,
    petri_net, initial_marking, final_marking)
print(precision_tbr)
```

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Log Filtering

- Focus on subsets of logs
- Identify differences
- Simplify discovered models

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Example Filters

`filter_activities_rework`	Keep cases where the specified activity occurs at least n times
`filter_case_size`	Keep cases having a length between n and m events
`filter_case_performance`	Keep cases having a duration between n and m seconds
`filter_directly_follows_relation`	Keep cases where A is followed immediately by B
`filter_end_activities`	Keep cases that end with the specified activity
`filter_event_attribute_values`	Keep cases or events in cases that satisfy the specified condition
`filter_eventually_follows_relation`	Keep cases where A is eventually followed by B
`filter_start_activities`	Keep cases that start with the specified activity
`filter_time_range`	Keep events occurring between two timestamps
`filter_trace_attribute_values`	Keep cases that satisfy the specified condition

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Hands-On Exercises

Use the log from `https://evermann.ca/busi4720/PurchasingExample.csv'` and answer the following questions:

1. What are the types of activities in the log?
   - Use `unique()`
2. How often does each activity occur in the log?
   - Use `value_counts()`
3. Filter complete cases, that is, cases that end with activity "Pay invoice"
   - Use `pm4py.filtering.filter_end_activities`
4. Plot the case durations. What do you notice?
   - Use `pm4py.stats.get_all_case_durations`
   - Put case durations into a `pd.DataFrame`
   - 1 day = 86400 seconds
   - Use `px.histogram` or `pm4py.vis.view_case_duration_graph`

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Hands-On Exercises [cont'd]

5. What is the mean case duration?
   - Use `mean()`
6. Split the log on the mean case duration
   - Use `pm4py.filtering.filter_case_performance`
7. Create BPMN models for each partial log and compare them. How do they differ?
8. Create a BPMN model for the total log. Compare the fitness and precision values compared to the partial logs.

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Hands-On Exercises

9. What is the activity with the longest mean time?
   - Activities taking a long time may be bottle-neck in the process flow
   - Create a new column as the difference between the 'Complete Timestamp' and 'Start Timestamp' columns
   - Use `groupby()` and `mean()` on the data frame
10. What is the mean number of activities for each case?
   - Long cases may indicate problems
   - Calculate the number of activities for each case using `groupby()` and `count()` on the dataframe

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Hands-On Exercises

11. Which activities are carried out more than once for some case
    - Repeated activities may indicate re-work or fixing of mistakes
    - Calculate the number of instances for each case for each activity using `groupby()` and `count()` on the dataframe
12. Are there cases that contain activity 'Pay invoice' but do not contain activity 'Send invoice'?
    - Non-compliant cases may represent a problem with controls and compiance
    - Use `pm4py.filtering.filter_eventually_follows_relatio`

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Performance Mining — DFG

- Identify median (mean, min, max, sum, stdev) waiting times

Python

```
perf_dfg, start_activities, end_activities = \
    pm4py.discover_performance_dfg(log)

pm4py.view_performance_dfg(perf_dfg,
    start_activities, end_activities,
    aggregation_measure='median')
pm4py.save_vis_performance_dfg(perf_dfg,
    start_activities, end_activities,
    file_path='perfdfg.png', rankdir='TB')
```

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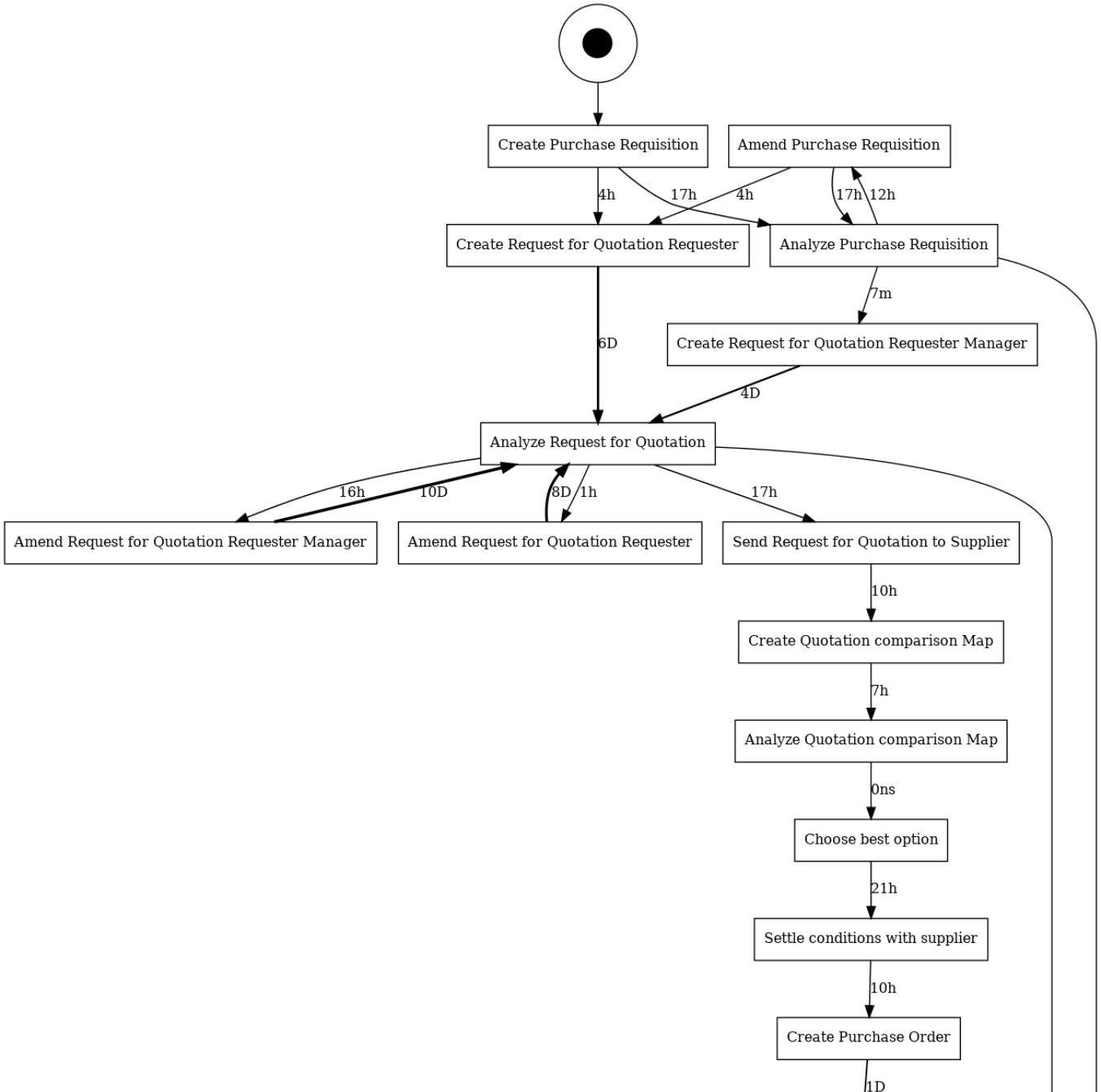
Performance Mining — DFG



Performance Mining — Dotted Chart

- Identify batching of activities
- Identify different variants
- Case arrival and case finishing rates

Python

```
pm4py.view_dotted_chart(log, show_legend=False)
pm4py.save_vis_dotted_chart(log,
    'dottedchart.png', show_legend=False)
```

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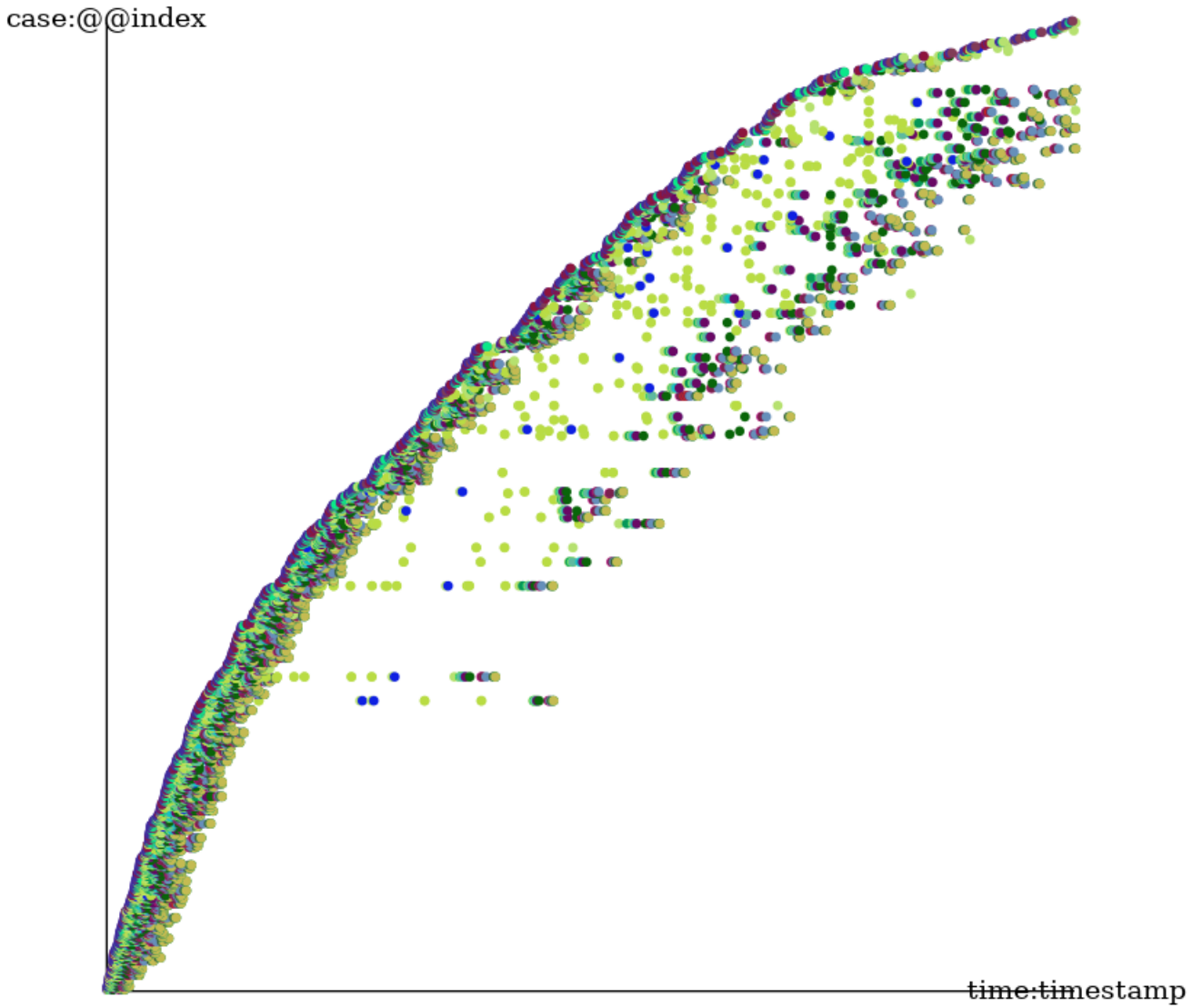
Performance Mining — Dotted Chart



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Performance Mining — Performance Spectrum

- Identify variations in wait times

Python

```
pm4py.view_performance_spectrum(log,
    ['Send invoice', 'Pay invoice'])
pm4py.save_vis_performance_spectrum(log,
    ['Send invoice', 'Pay invoice'],
    'perfspectrum.png')
```

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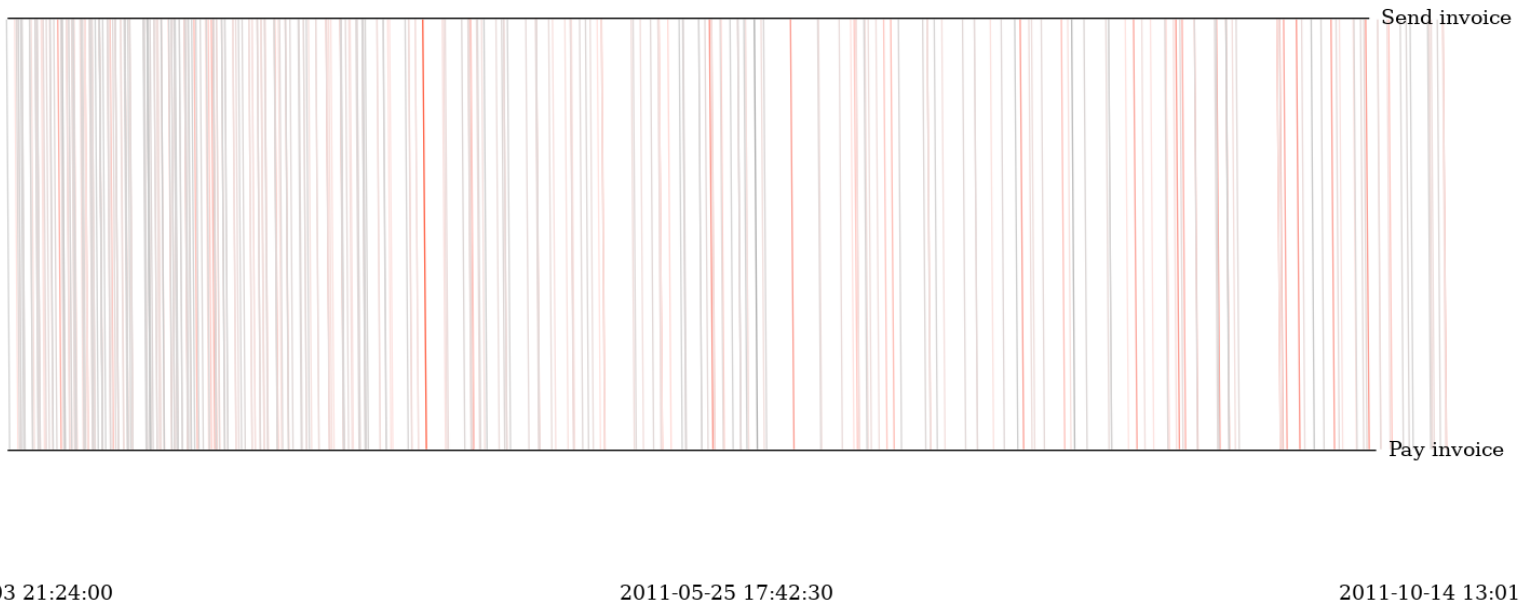
Performance Mining — Performance Spectrum



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Performance Mining — Event Distribution

- Identify distribution of when events/activities occur

Python

```
pm4py.view_events_distribution_graph(log, 'days_week')
pm4py.view_events_distribution_graph(log, 'days_month')
pm4py.view_events_distribution_graph(log, 'months')
pm4py.view_events_distribution_graph(log, 'weeks')
```

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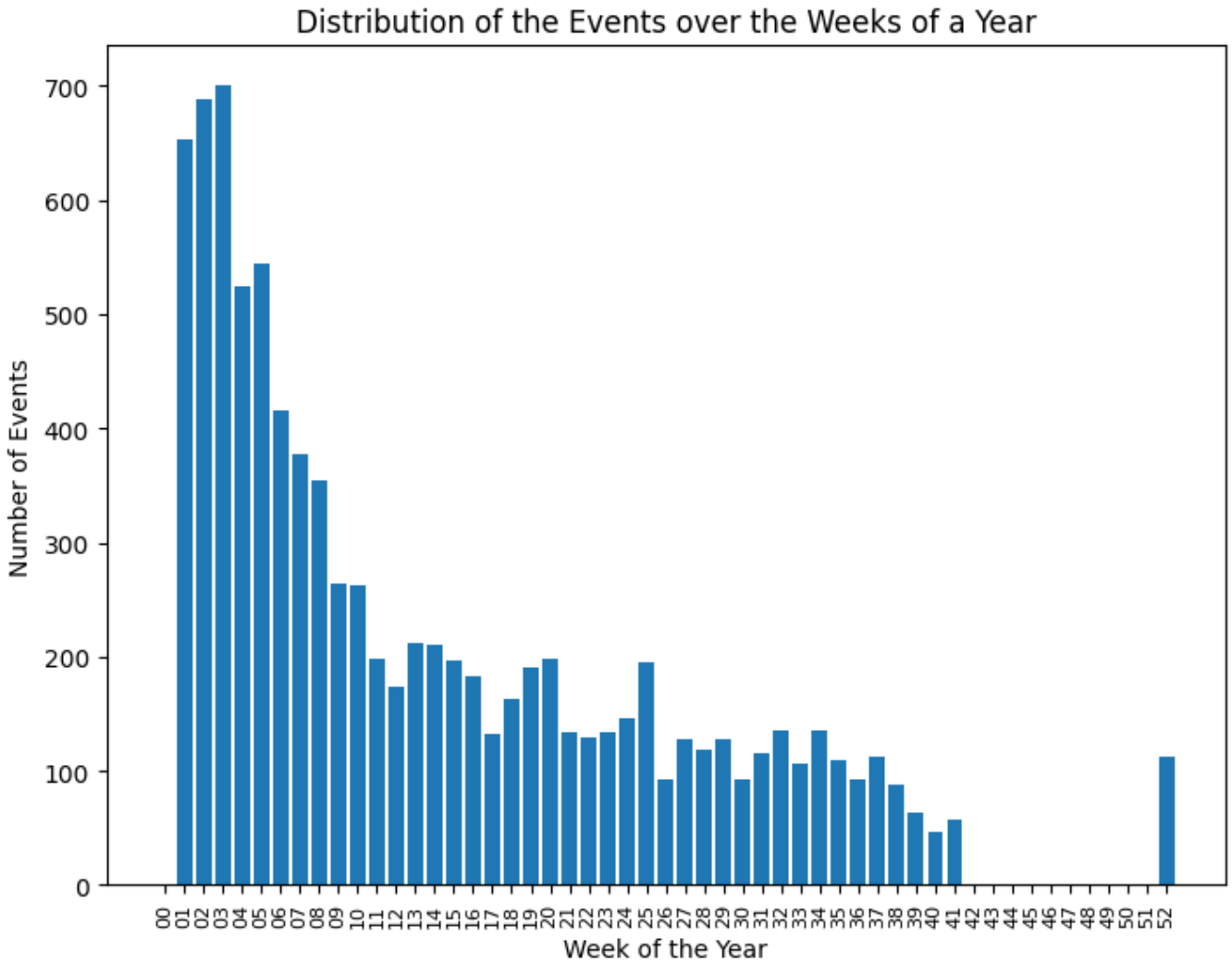
Performance Mining — Event Distribution



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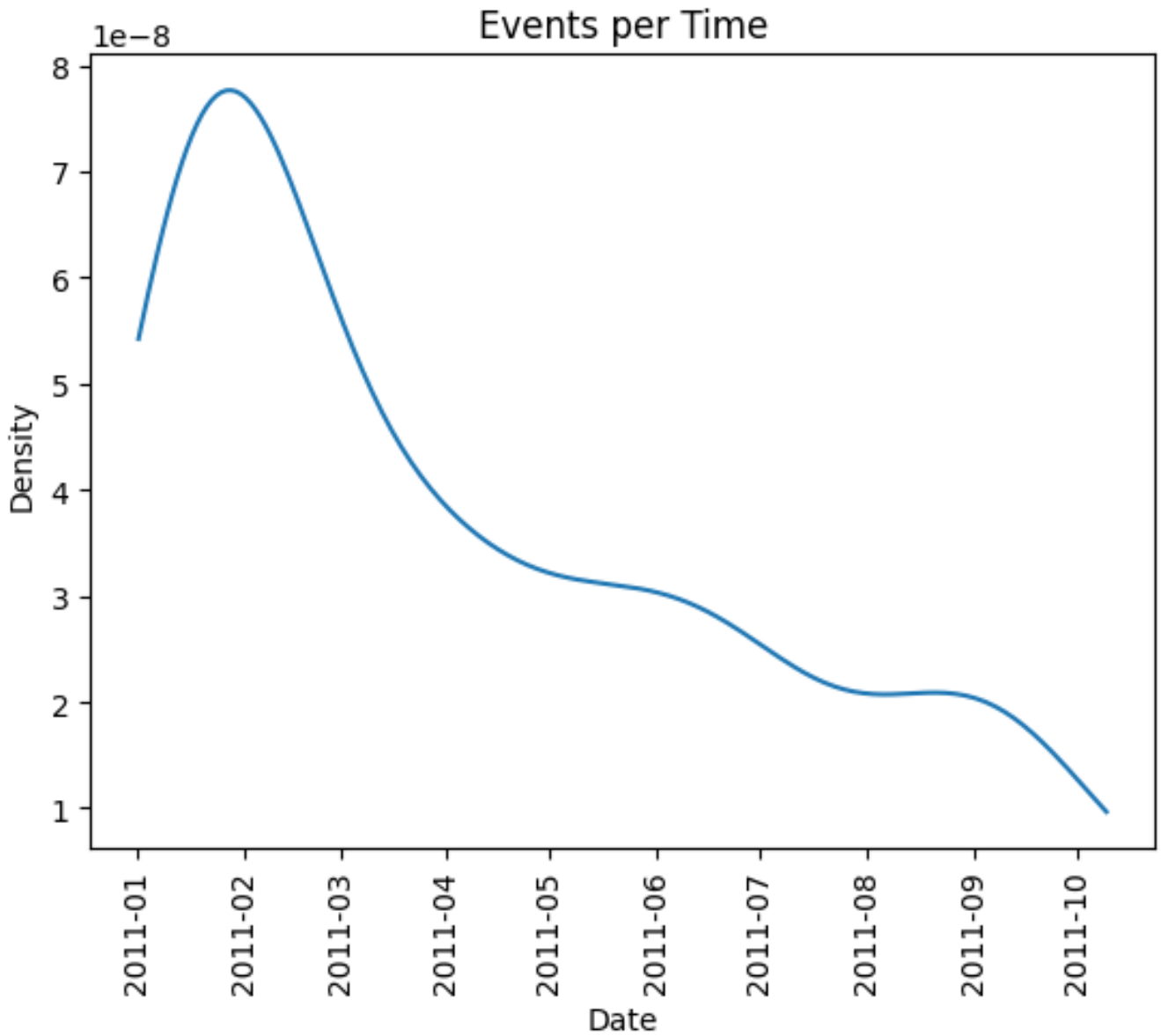
Performance Mining — Events per Time

```Python
pm4py.view_events_per_time_graph(log)
pm4py.save_vis_events_per_time_graph(log, 'eventspertime.png')
```

Performance Mining — Events per Time



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Activity-Based Resource Similarity

- Identify similar resources based on the set of activities they perform

Python

```
sna_graph = \
 pm4py.discover_activity_based_resource_similarity(log)

pm4py.view_sna(sna_graph, variant_str='networkx')
pm4py.view_sna(sna_graph, variant_str='pyvis')

pm4py.save_vis_sna(sna_graph, 'ressimilarity.png',
    variant_str='networkx')
```

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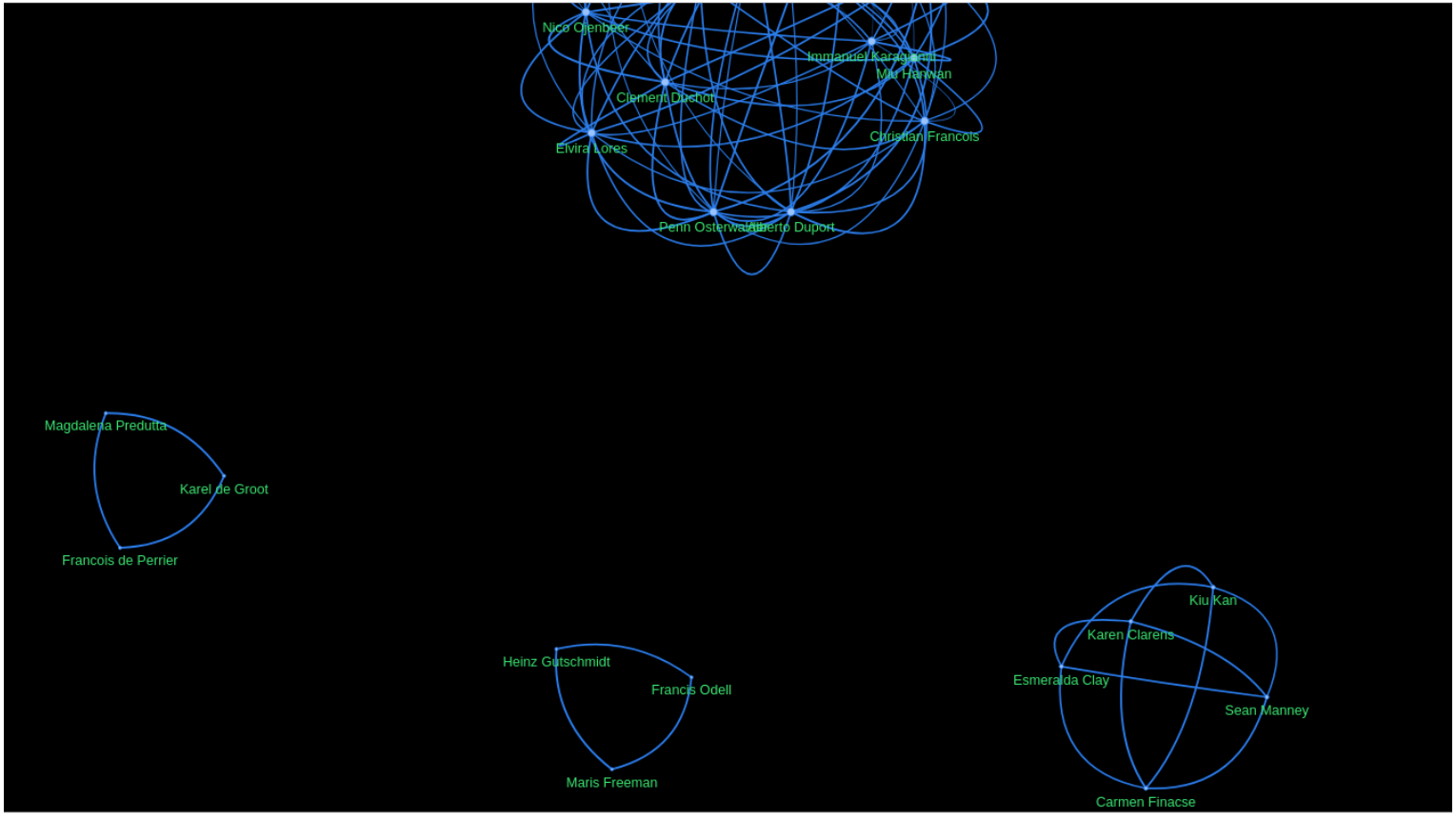
Organizational Mining

Activity-Based Resource Similarity



Handover of Work Network

- Identify resources that pass work from one to another
- A DFG for resources instead of activities

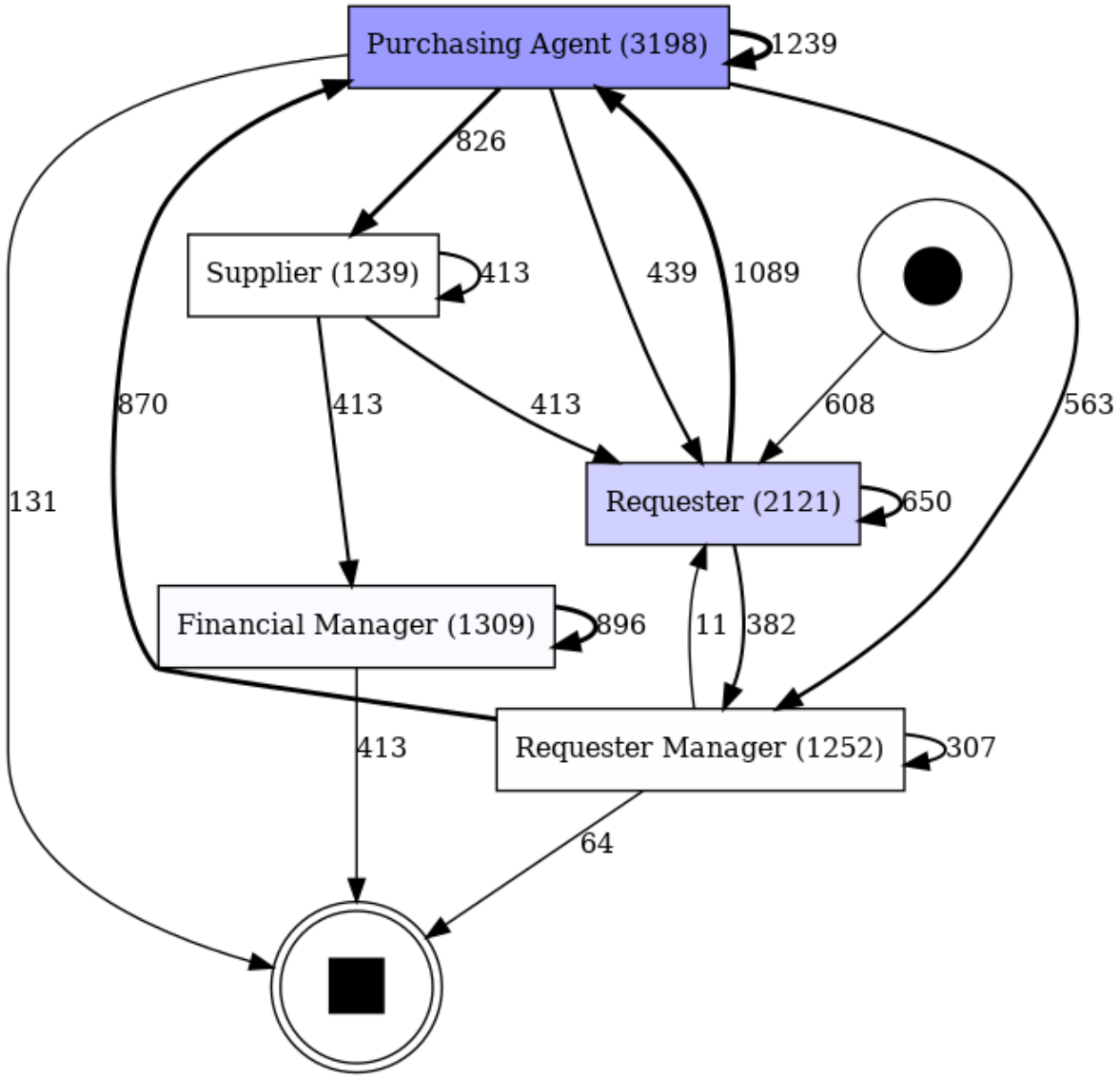
Python

```
dfg, start, end = pm4py.discover_dfg(log, activity_key='Role')
pm4py.view_dfg(dfg, start, end, rankdir='LR')

pm4py.save_vis_dfg(dfg=dfg,
    start_activities=start,
    end_activities=end,
    file_path='handover.png', rankdir='TB')
```

Organizational Mining

Handover of Work Network



Organizational Mining

Organizational Roles

- Identify similar resources based on the set of activities they perform

Python

```
roles = pm4py.discover_organizational_roles(log)
print(roles)
```

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Working-Together Network

- Resources work together, if they collaborate on some trace

Python

```
sna_graph = pm4py.discover_working_together_network(log,
   resource_key='Role')
pm4py.view_sna(sna_graph, variant_str='pyvis')
pm4py.view_sna(sna_graph, variant_str='networkx')
```

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Oganizational Mining

Working-Together Network