

Intelligent Assistance for Expert-Driven  
Subpopulation Discovery in High-Dimensional  
Time-Stamped Medical Data

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# Contents

Structure . . . . .	5
<b>1 Thesis overview</b>	<b>7</b>
1.1 Motivation . . . . .	7
1.2 Medical applications . . . . .	7
1.3 Open challenges . . . . .	7
1.4 Structure and summary of contributions . . . . .	7
<b>I SUBPOPULATION DISCOVERY IN HIGH-DIMENSIONAL DATA</b>	<b>9</b>
<b>2 Interactive discovery and inspection of subpopulations</b>	<b>11</b>
2.1 Motivation and comparison with related work . . . . .	11
2.2 The SHIP dataset . . . . .	11
2.3 Subpopulation discovery workflow and interactive mining assistant	11
2.4 Experiments and findings . . . . .	11
2.5 Benefits of our workflow . . . . .	11
<b>3 Identifying diverse subpopulations</b>	<b>13</b>
3.1 Motivation and comparison with related work . . . . .	13
3.2 Finding diverse classification rules . . . . .	13
3.3 Experiments and findings . . . . .	13
3.4 Benefits our our method . . . . .	13

<b>II</b>	<b>EXPLOITING TEMPORAL INFORMATION</b>	<b>15</b>
<b>4</b>	<b>Constructing evolution features to capture change over time</b>	<b>17</b>
4.1	Motivation and comparison with related work . . . . .	17
4.2	Overview of the mining workflow . . . . .	17
4.3	Generating evolution features . . . . .	17
4.4	Experiments and findings . . . . .	17
4.5	Benefits our our method . . . . .	17
<b>5</b>	<b>Feature extraction from short temporal sequences for clustering</b>	<b>19</b>
5.1	Motivation and comparison with related work . . . . .	19
5.2	The diabatic foot dataset . . . . .	19
5.3	Overview of the mining workflow . . . . .	19
5.4	Experiments and findings . . . . .	19
5.5	Benefits our our method . . . . .	19
<b>III</b>	<b>POST-MINING FOR INTERPRETATION</b>	<b>21</b>
<b>6</b>	<b>Post-hoc interpretation of classification models</b>	<b>23</b>
6.1	Motivation and comparison with related work . . . . .	23
6.2	The aneurysm dataset . . . . .	23
6.3	The tinnitus dataset . . . . .	23
6.4	Overview of the mining workflow . . . . .	23
6.5	Experiments and findings on aneurysm data . . . . .	23
6.6	Experiments and findings on tinnitus data . . . . .	23
6.7	Benefits our our method . . . . .	23
<b>IV</b>	<b>SUMMARY</b>	<b>25</b>
<b>7</b>	<b>Conclusion and future work</b>	<b>27</b>
7.1	Research results for medical expert-guided knowledge discovery .	27
7.2	Future work . . . . .	27

## Structure

- 1 Thesis Overview
  - 1.1 Motivation
  - 1.2 Medical Applications
  - 1.3 Open Challenges
  - 1.4 Structure and Summary of Contributions

### PART I SUBPOPULATION DISCOVERY

- 2 Interactive discovery and inspection of subpopulations
  - 2.1 The SHIP dataset
  - 2.2 Motivation and comparison with related work
  - 2.3 Subpopulation discovery workflow and interactive mining assistant
  - 2.4 Experiments and findings
  - 2.5 Benefits of our workflow

- 3 Identifying diverse subpopulations
  - 3.1 Motivation and comparison with related work
  - 3.2 Finding diverse classification rules
  - 3.3 Experiments and findings
  - 3.4 Benefits our our method

### PART II EXPLOITING TEMPORAL INFORMATION

- 4 Constructing evolution features to capture change over time
  - 4.1 Motivation and comparison with related work
  - 4.2 Overview of the mining workflow
  - 4.3 Generating evolution features
  - 4.4 Experiments and findings
  - 4.5 Benefits our our method
- 5 Feature extraction from short temporal sequences for clustering
  - 5.1 The diabatic foot dataset
  - 5.1 Motivation and comparison with related work 5.2 Overview of the mining workflow
  - 5.3 Experiments and findings
  - 5.4 Benefits our our method

### PART III POST-MINING FOR INTERPRETATION

- 6 Post-hoc interpretation of classification models
  - 6.1 Motivation and comparison with related work
  - 6.2 The aneurysm dataset
  - 6.3 The tinnitus dataset
  - 6.2 Overview of the mining workflow
  - 6.3 Experiments and findings on aneurysm data
  - 6.4 Experiments and findings on tinnitus data
  - 6.5 Benefits our our method

## **PART IV SUMMARY**

- 7 Conclusion and future work
  - 7.1 Research results for medical expert-guided knowledge discovery
  - 7.2 Future work

## **PART V APPENDIX**

- Bibliography
- List of publications
- Abbreviations

# Chapter 1

## Thesis overview

1.1 Motivation

1.2 Medical applications

1.3 Open challenges

1.4 Structure and summary of contributions





Part I

**SUBPOPULATION  
DISCOVERY IN  
HIGH-DIMENSIONAL  
DATA**



## Chapter 2

# Interactive discovery and inspection of subpopulations

Based on: [1]

**2.1 Motivation and comparison with related work**

**2.2 The SHIP dataset**

**2.3 Subpopulation discovery workflow and interactive mining assistant**

**2.4 Experiments and findings**

**2.5 Benefits of our workflow**



## Chapter 3

# Identifying diverse subpopulations

Based on: [2]

**3.1 Motivation and comparison with related work**

**3.2 Finding diverse classification rules**

**3.3 Experiments and findings**

**3.4 Benefits of our method**



## Part II

# EXPLOITING TEMPORAL INFORMATION





## Chapter 4

# Constructing evolution features to capture change over time

Based on: [3]

- 4.1 Motivation and comparison with related work
- 4.2 Overview of the mining workflow
- 4.3 Generating evolution features
- 4.4 Experiments and findings
- 4.5 Benefits of our method



## Chapter 5

# Feature extraction from short temporal sequences for clustering

### 5.1 Motivation and comparison with related work

Based on: [4]–[6]

### 5.2 The diabatic foot dataset

### 5.3 Overview of the mining workflow

### 5.4 Experiments and findings

### 5.5 Benefits our our method



## Part III

# POST-MINING FOR INTERPRETATION



## Chapter 6

# Post-hoc interpretation of classification models

Based on: [7]–[10]

**6.1 Motivation and comparison with related work**

**6.2 The aneurysm dataset**

**6.3 The tinnitus dataset**

**6.4 Overview of the mining workflow**

**6.5 Experiments and findings on aneurysm data**

**6.6 Experiments and findings on tinnitus data**

**6.7 Benefits of our method**





**Part IV**

**SUMMARY**



## Chapter 7

# Conclusion and future work

7.1 Research results for medical expert-guided knowledge discovery

7.2 Future work



## Part V

# APPENDIX



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