LABEL RANKING FOR ELECTION OUTCOME PREDICTION

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Presentation Structure

1. Introduction
2. Election Prediction
3. Association Rules Mining
4. Label Ranking
5. Pairwise Association Rules
6. Experimental setup
7. Results and Analysis
8. Conclusions

1 Introduction

Introduction

Context	Problem	Motivation / Goals

Introduction

Context

Election prediction and approaches

Problem

Motivation / Goals

Introduction

Context

Problem

Current methods face complex challenges

Motivation / Goals

Introduction

Context

Problem

Motivation / Goals

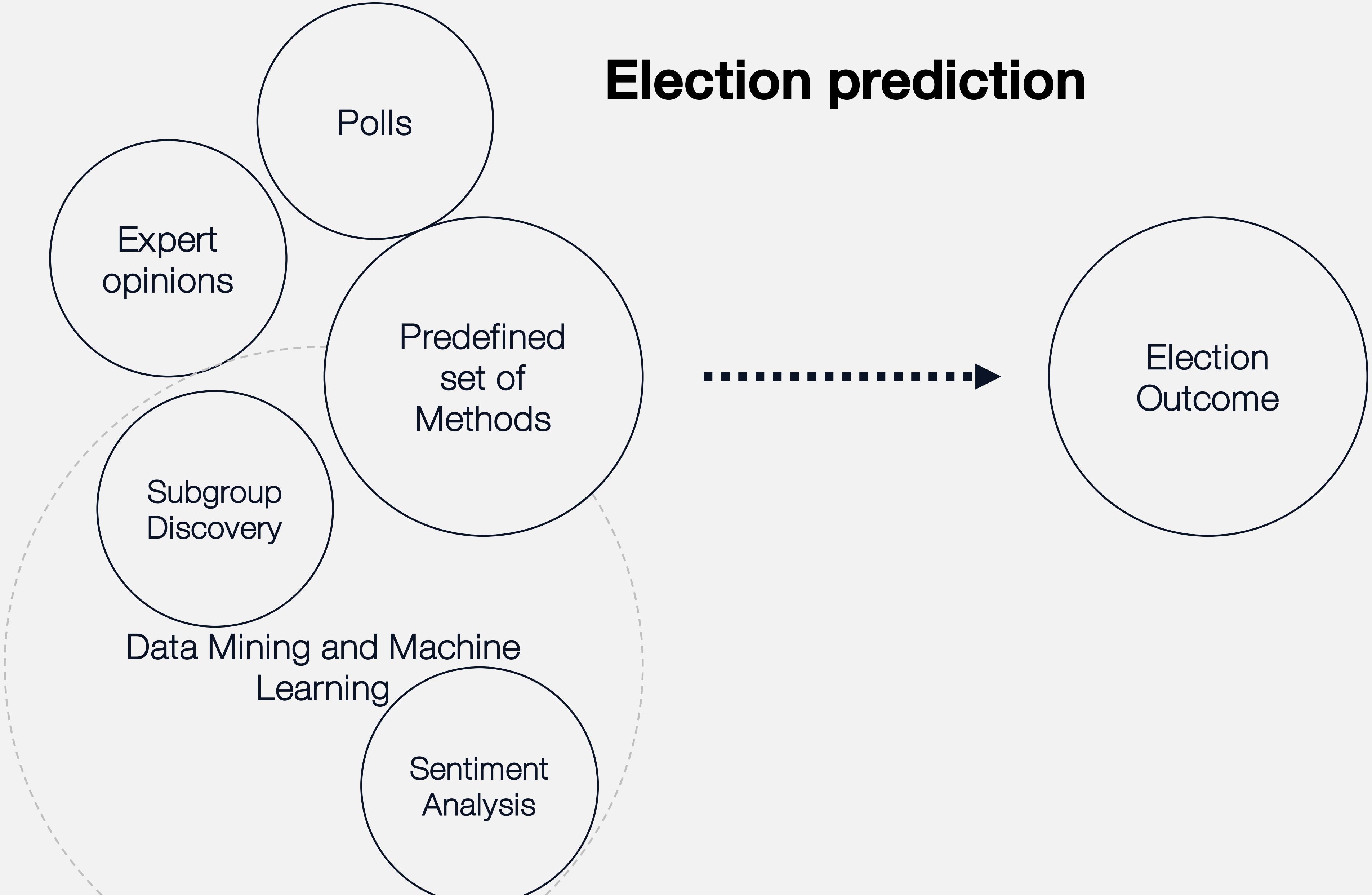
LR for Election Outcome Prediction

Adapt PAR for prediction

Study the accuracy trade-off between the prediction of complete rankings vs incomplete rankings

2 Election Prediction

Election prediction



3 Association Rules Mining

Formalization

$$A \longrightarrow C$$

i	instance	A	antecedent
$\mathbb{X}$	instance space	C	consequent
desc($\mathbb{X}$)	descriptors of $\mathbb{X}$ i.e. ⟨attribute, value⟩ pairs	$A \cap C = \emptyset$	
$\mathcal{A}$	independent variable	$A, C \subseteq desc(\mathbb{X})$	
x_i	vector of values of $\mathcal{A}$ that describe i		
D $\{\langle x_i \rangle\}$	data		

Example

i	instance	region of Porto
$\mathbb{X}$	instance space	all the regions in Portugal
desc($\mathbb{X}$)	descriptors of $\mathbb{X}$	{⟨ unemployment, high ⟩,…}
$\mathcal{A}$	independent variable	unemployment
x_i	vector of values of $\mathcal{A}$ that describe i	Porto: {⟨ unemployment, high ⟩,…}
D $\{\langle x_i \rangle\}$	data	{Porto: {…}, Lisbon: {…},…}

Example

(For instance i_1 = Porto)

(For independent variable $\mathcal{A}_1$ = unemployment)

$$\mathcal{A}_1 = \text{high} \longrightarrow \text{left-wing party wins elections}$$

Interest Measures

support percentage of instances in D that contain A and C

confidence percentage of instances that contain C from the set of instances that contain A

lift measures the independence of the consequent, C, relative to the antecedent, A

Interest Measures

Improvement measure of the *improvement (difference in confidence)* that a certain rule yields in comparison to it's predecessor

e.g. *improvement* = 2

Rule 1

$\mathcal{A}_1 = \mathrm{a} \longrightarrow \mathrm{C}$ *confidence = 90%*

Rule 2

$\mathcal{A}_1 = \mathrm{a}\ \&\ \mathcal{A}_2 = \mathrm{b} \longrightarrow \mathrm{C}$ *confidence =* ***91%***

Rule 1

$\mathcal{A}_1 = \mathrm{a} \longrightarrow \mathrm{C}$ *confidence = 90%*

Rule 2

$\mathcal{A}_1 = \mathrm{a}\ \&\ \mathcal{A}_2 = \mathrm{b} \longrightarrow \mathrm{C}$ *confidence =* ***92%***

Rules Generation

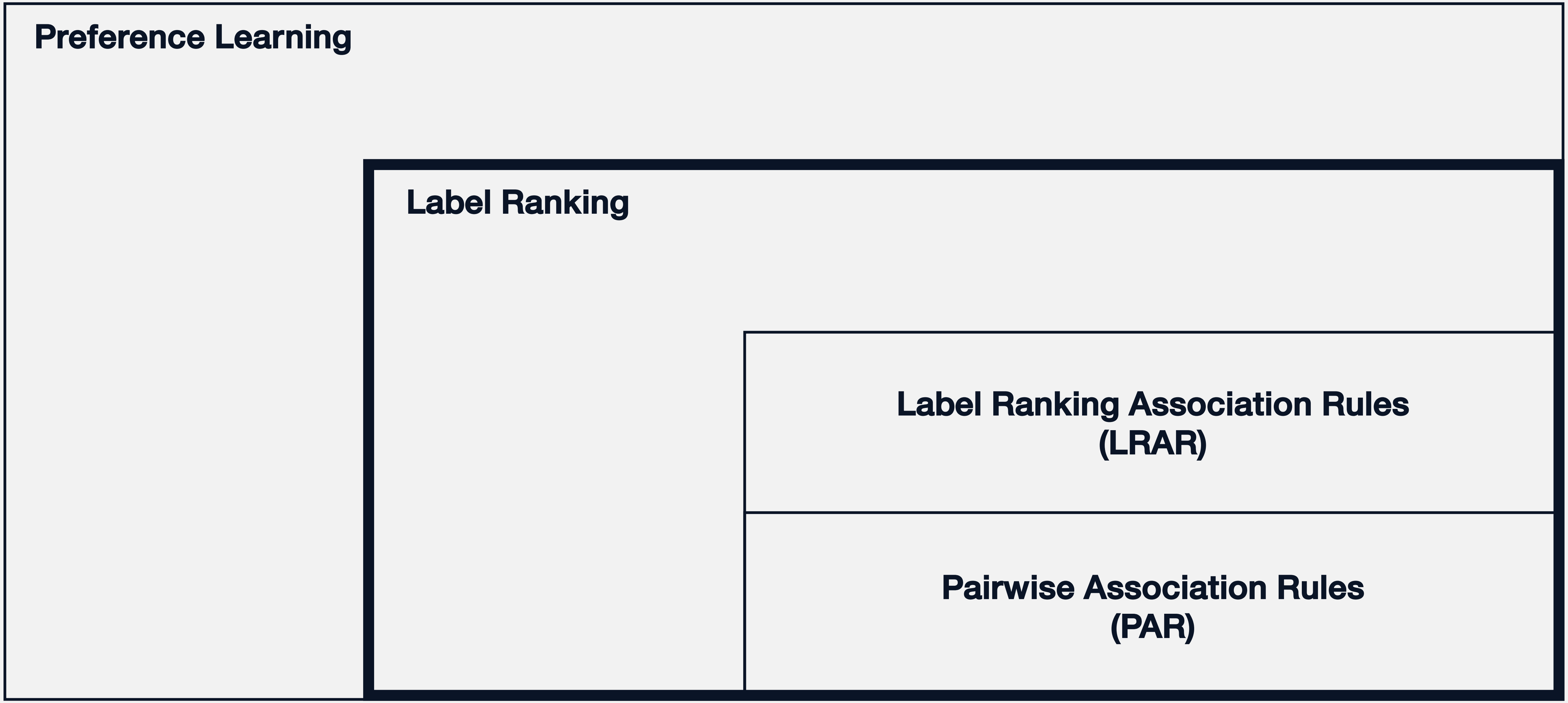
Item-set based

- APRIORI
- hashing
- Dynamic itemset countin
- Parallel and distributed mining
- ...

Rule based

- FP-Growth
- ...

4 Label Ranking


Preference Learning
Label Ranking
Label Ranking Association Rules (LRAR)
Pairwise Association Rules (PAR)

Formalization

goal : find the $\hat{\boldsymbol{\pi}}$ of $\mathcal{L}$ associated with x

$\boldsymbol{\pi}$	ranking
$\hat{\boldsymbol{\pi}}$	predicted ranking
x	instance in $\mathbb{X}$
$\mathcal{L}$	predefined set of classes $\{\lambda_1,\ldots, \lambda_k\}$
Ω	permutation space

Formalization

ranking

- complete
- partial
- incomplete

Formalization

ranking $\xrightarrow{\text{can be represented as an}}$ order

Formalization

ranking

complete	partial	incomplete
strict total order	***non-strict total order***	***non-strict partial order***
$\lambda_2 \succ \lambda_3 \succ \lambda_1 \succ \lambda_4$	$\lambda_1 = \lambda_2 \succ \lambda_3 \succ \lambda_4$	$\lambda_1 \succ \lambda_3 \succ \lambda_4$
$\boldsymbol{\pi} = (3,1,2,4)$	$\boldsymbol{\pi} = (1,1,2,3)$	$\boldsymbol{\pi} = (1,0,2,3)$

Label Ranking methods

Decomposition

- PAR
- Rule-Based Label Ranking
- ...

Direct

- LRAR
- k-Nearest Neighbors
- ...

Label Ranking Association Rules

$$A \longrightarrow \boldsymbol{\pi}$$

$$A \subseteq \mathbb{X}$$
$$\boldsymbol{\pi} \in \Omega$$

Label Ranking Association Rules

Example

$$\mathcal{A}_1 = \text{high} \wedge \mathcal{A}_2 = \text{low} \longrightarrow \text{C} \succ \text{A} \succ \text{B} \succ \text{D}$$

5 Pairwise Association Rules

Formalization

$$A \longrightarrow \{\boldsymbol{\lambda}_a \succeq \boldsymbol{\lambda}_b \oplus \boldsymbol{\lambda}_b \succeq \boldsymbol{\lambda}_a \oplus \boldsymbol{\lambda}_a = \boldsymbol{\lambda}_b \oplus \boldsymbol{\lambda}_a \perp \boldsymbol{\lambda}_b \mid \boldsymbol{\lambda}_a, \boldsymbol{\lambda}_b \in \mathcal{L}\}$$

Pairwise Association Rules

Example

$$\mathcal{A}_1 = \text{high} \wedge \mathcal{A}_2 = \text{low} \longrightarrow \boldsymbol{\lambda}_3 \succ \boldsymbol{\lambda}_1 \wedge \boldsymbol{\lambda}_2 \succ \boldsymbol{\lambda}_4$$

Example Comparison

LRAR

$$\mathcal{A}_1 = \mathrm{high} \wedge \mathcal{A}_2 = \mathrm{low} \longrightarrow \boldsymbol{\lambda}_3 \succ \boldsymbol{\lambda}_1 \succ \boldsymbol{\lambda}_2 \succ \boldsymbol{\lambda}_4$$

PAR

$$\mathcal{A}_1 = \mathrm{high} \wedge \mathcal{A}_2 = \mathrm{low} \longrightarrow \boldsymbol{\lambda}_3 \succ \boldsymbol{\lambda}_1 \wedge \boldsymbol{\lambda}_2 \succ \boldsymbol{\lambda}_4$$

Evaluation

LRAR

Kendall Tau normalized difference between the number of concordant and discordant pairs

PAR

Gamma measure of correlation between two incomplete rankings or between 2 incomplete and complete or partial rankings

PAR for prediction

Rule selection

Maximum Pairwise

Completeness

PAR for prediction

Rule selection

$\boldsymbol{x}$ instance

$\mathcal{R}$ generated rules

↓

applicableRules($\boldsymbol{x}$)

Maximum Pairwise

Completeness

PAR for prediction

Rule Selection

Maximum Pairwise

$$max_{pairwise}(k) = \frac{k!}{2!\,(k-2)!}$$

=1 $A \longrightarrow \lambda_1 \succ \lambda_2$

=2 $A \longrightarrow \lambda_1 \succ \lambda_2 \land \lambda_3 \succ \lambda_4$

Completeness

PAR for prediction

Rule Selection

Maximum Pairwise

Completeness

$$completeness = \frac{pairs}{max_{pairwise}(k)}$$

6 Experimental setup

Data

Table 4.1: LR datasets

dataset	type	# instances	# features	# labels
bodyfat	B	252	7	7
cpu-small	B	8192	6	5
glass	A	214	9	6
housing	B	506	6	6
iris	A	150	4	3
stock	B	950	5	5
vehicle	A	846	18	4
wine	A	178	13	3

Table 4.2: Election Datasets

dataset	# instances	# features	# labels
germany 2005	412	29	5
germany 2009	412	29	5
portugal 2009	308	20	5
portugal 2013	308	20	5
portugal 2017	308	20	5

Table 4.7: Subset of Socio-economic variables of the election datasets

id	description
$\mathcal{A}_1$	Unemployment below 25 years
$\mathcal{A}_2$	Residents between 15 and 64 years
$\mathcal{A}_3$	Elderly Population
$\mathcal{A}_4$	Average Monthly Income
$\mathcal{A}_5$	Employees in Construction
$\mathcal{A}_6$	Employees in Administration and Services
$\mathcal{A}_7$	Employees in Agriculture
$\mathcal{A}_8$	Employees in Transformation Industries
$\mathcal{A}_9$	Employees in Gross and Retails Markets
$\mathcal{A}_{10}$	Employees in Banks
$\mathcal{A}_{11}$	Employees in other Economic Sectors
$\mathcal{A}_{12}$	Population without Education
$\mathcal{A}_{13}$	Registered Web Domains
$\mathcal{A}_{14}$	Population with no school degree

Experimental setup

min support = 1%

A minimum support

1. generates better predictions
2. minimizes the use of the *default ranking*

***min confidence* = 70%**

We do not want to limit the rules generation

However

Predicting with a high confidence is desired *min improvement* = 0

We do not want to limit the generation of sub-rules

Generation of PAR and Prediction

CAREN

↓

$\mathcal{R}$ rules

Consequent e.g.: $\lambda_2 \succ \lambda_1 \wedge \lambda_2 \succ \lambda_4$

$$\begin{array}{lcr} \lambda_{\text{line}} > \lambda_{\text{column}} & \Rightarrow & 1 \\ \lambda_{\text{line}} < \lambda_{\text{column}} & \Rightarrow & -1 \\ \lambda_{\text{line}} = \lambda_{\text{column}} & \Rightarrow & 0 \\ \lambda_{\text{line}} \perp \lambda_{\text{column}} & \Rightarrow & NA \end{array}$$

	λ_1	λ_2	λ_3	λ_4	λ_5
λ_1	0	-1	*NA*	*NA*	*NA*
λ_2	1	0	*NA*	1	*NA*
λ_3	*NA*	*NA*	0	*NA*	*NA*
λ_4	*NA*	-1	*NA*	0	*NA*
λ_5	*NA*	*NA*	*NA*	*NA*	0

Prediction $\Rightarrow$ best rule

Evaluation

Table 4.4: Accuracy measures comparison

π	$\hat{\pi}$	Kendall Tau	gamma	accuracy
$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	1	1	1
$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \boldsymbol{\lambda_5 \succ \lambda_4}$	0.8	0.8	0
$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	$\boldsymbol{\lambda_5 \succ \lambda_4 \succ \lambda_3 \succ \lambda_2 \succ \lambda_1}$	-1	-1	0
$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	$\lambda_1 \succ \lambda_2 \wedge \lambda_2 \succ \lambda_3 \wedge \lambda_3 \succ \lambda_4$	NA	1	1
$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	$\boldsymbol{\lambda_2 \succ \lambda_1} \wedge \lambda_2 \succ \lambda_3 \wedge \lambda_3 \succ \lambda_4$	NA	0.33(3)	0
$\lambda_1 \succ \lambda_2 \succ \lambda_3 \succ \lambda_4 \succ \lambda_5$	$\boldsymbol{\lambda_2 \succ \lambda_1} \wedge \lambda_2 \succ \lambda_3 \wedge \boldsymbol{\lambda_4 \succ \lambda_3}$	NA	-0.33(3)	0

7 Results and Analysis

Experimental results with typical LR datasets

Table 4.5: Experimental results using the common LR datasets

	baseline	IB-PL	IB-Mal	Lin-PL	Lin-LL	LRAR	1 Pair	2 Pairs	3 Pairs	4 Pairs
bodyfat	-.04	.23	.23	.27	.27	.02	.33	.19	-.37	-.58
cpu-small	.23	.50	.50	.43	.42	.45	.81	.74	.61	.33
glass	.68	.84	.84	.83	.82	.71	.97	.98	.95	.94
housing	.05	.71	.74	.66	.63	.69	1	.99	.97	.91
iris	.09	.96	.93	.83	.82	.86	.95	.95	.89	-
stock	.06	.92	.93	.71	.70	.82	.99	.99	.99	.95
vehicle	.18	.86	.86	.84	.78	.82	.95	.95	.94	.83
wine	.33	.95	.94	.95	.94	.92	.88	.87	.5	-

Figure 4.1: Completeness vs Accuracy in the LR datasets

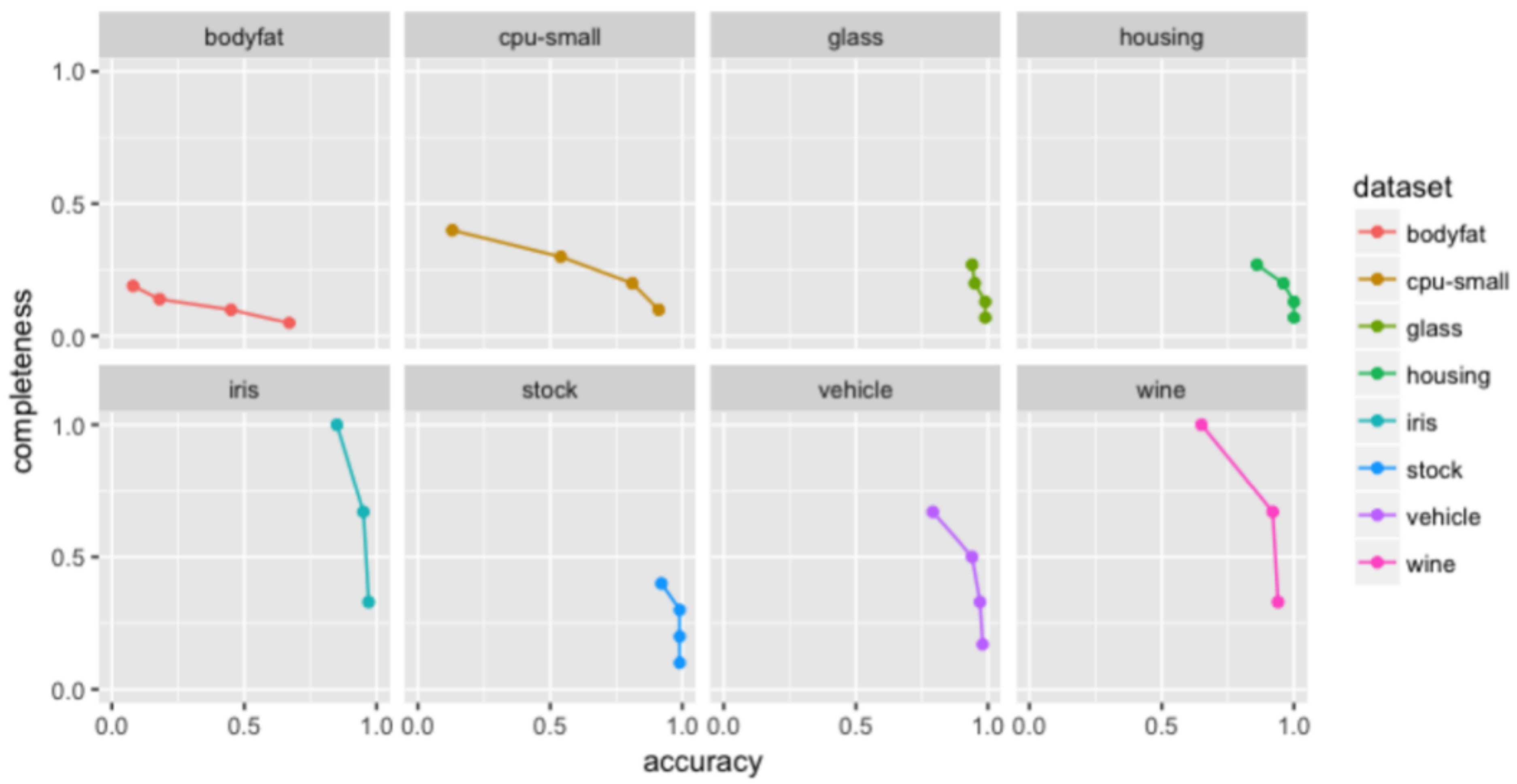


Figure 4.2: Completeness vs Accuracy in the LR datasets - Merged

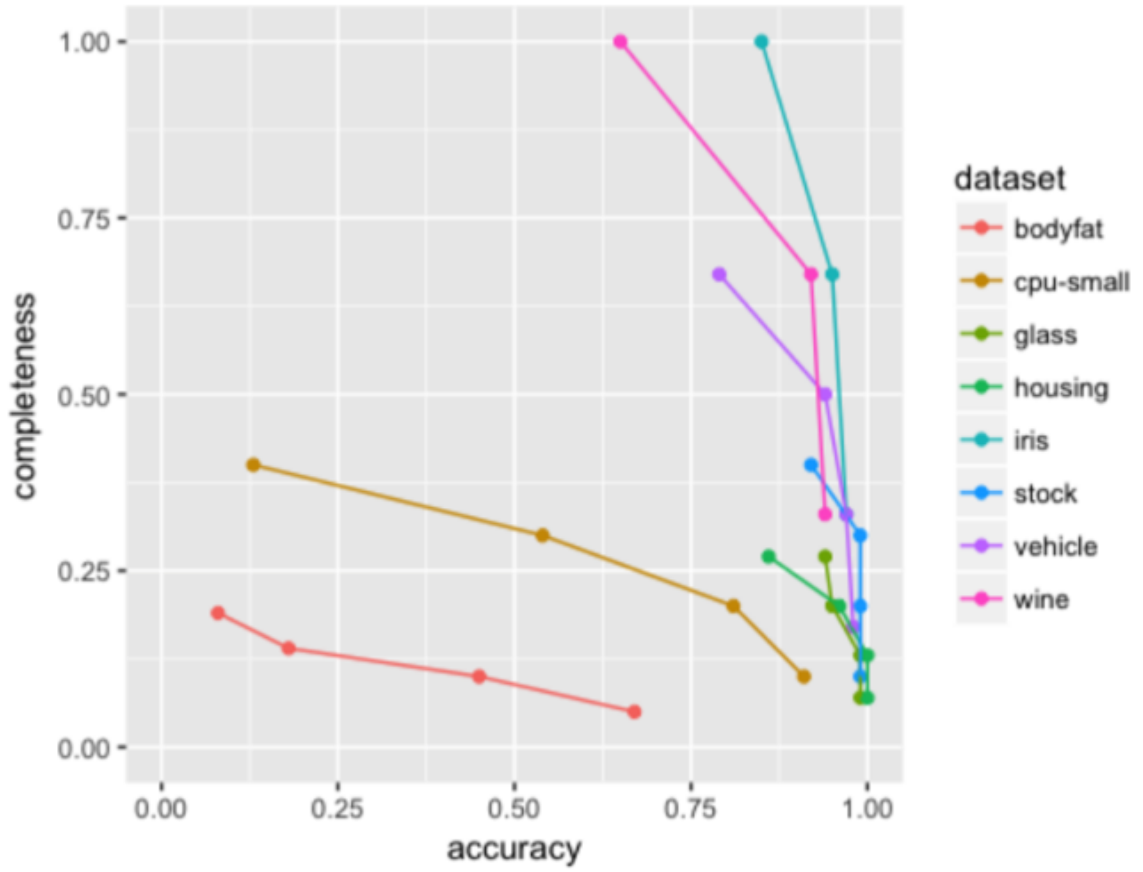
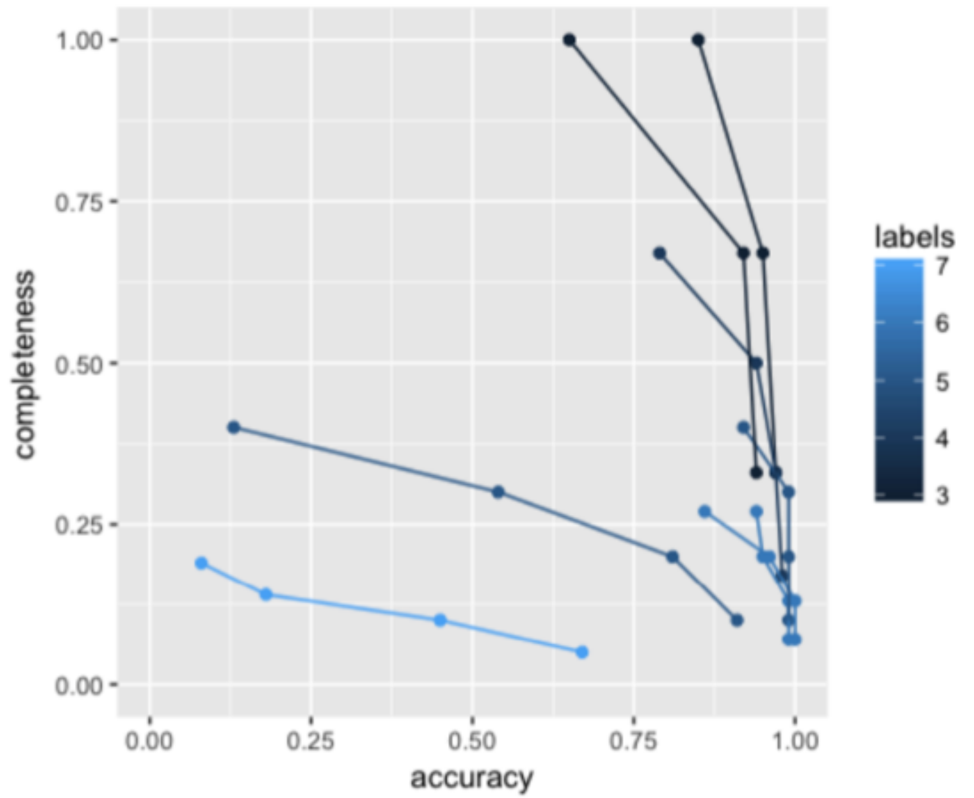


Figure 4.3: Completeness vs Accuracy in the LR datasets grouped by number of labels



Experimental results with LR elections datasets

Table 4.6: Experimental results using the elections datasets

	baseline	LRAR	1 Pair	2 Pairs	3 Pairs	4 Pairs	5 Pairs
germany 2005-2009	.72	.64	.82	.75	.84	.86	.89
portugal 2009-2013	.65	.6	.92	.82	.79	.66	.67
portugal 2013-2017	.44	.47	.75	.75	.63	.63	.62

Figure 4.4: Completeness vs Accuracy in the Elections datasets

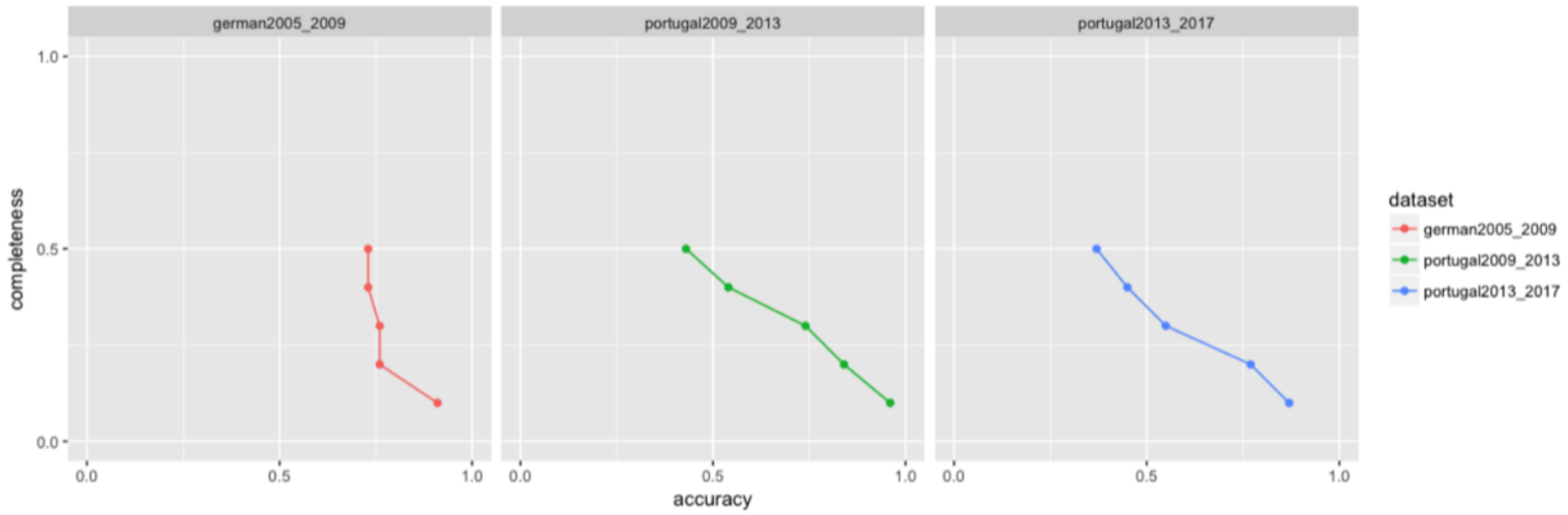
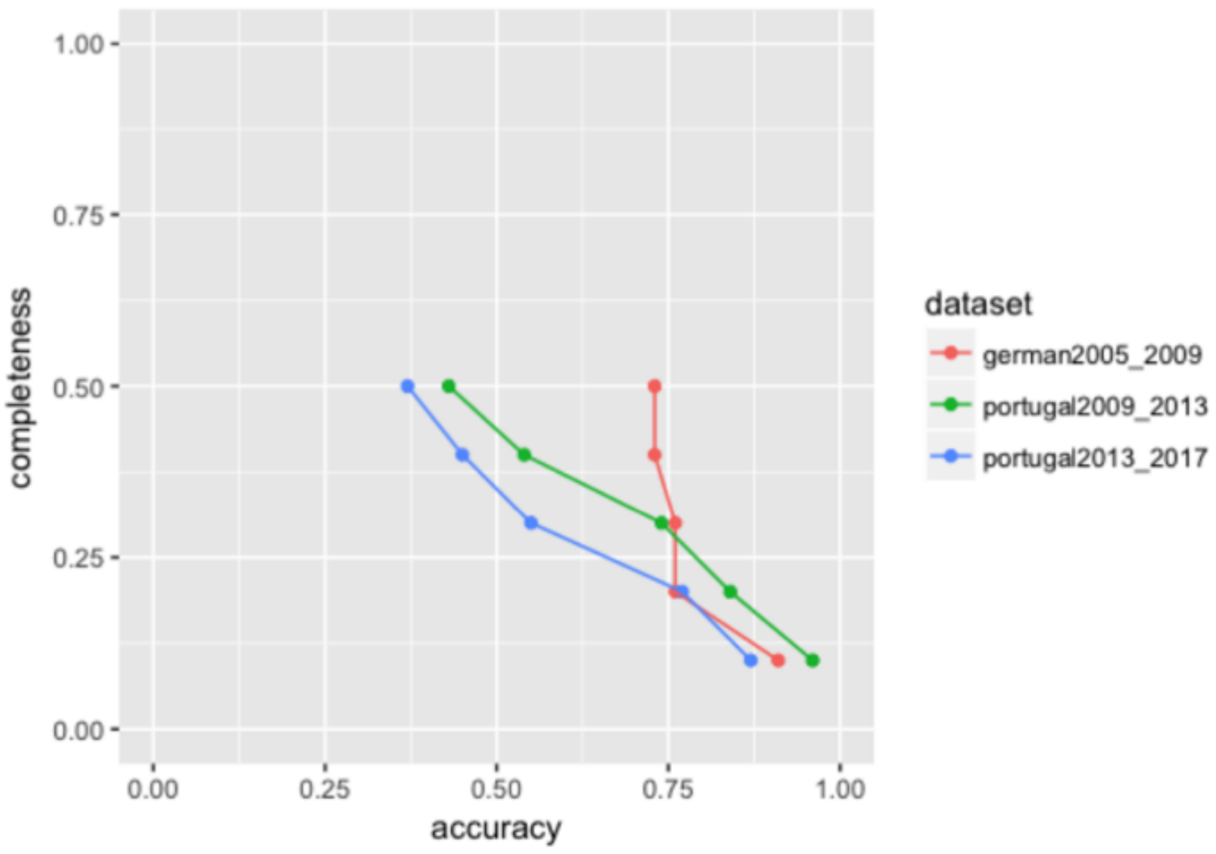
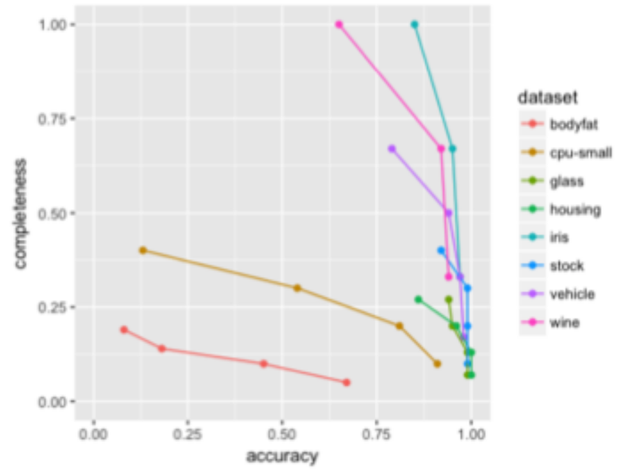
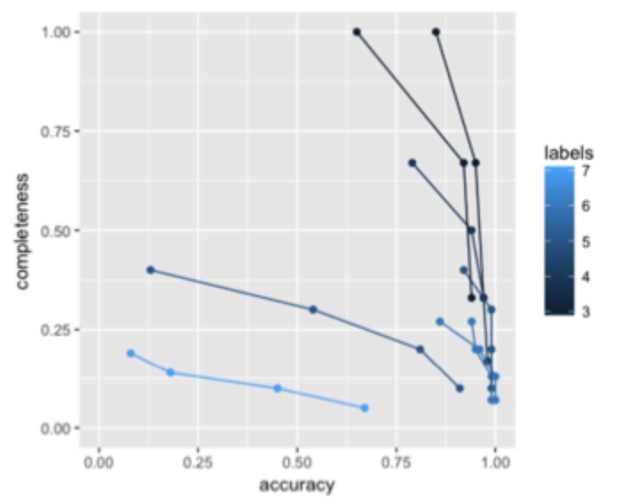


Figure 4.5: Completeness vs Accuracy in the Elections datasets - Merged





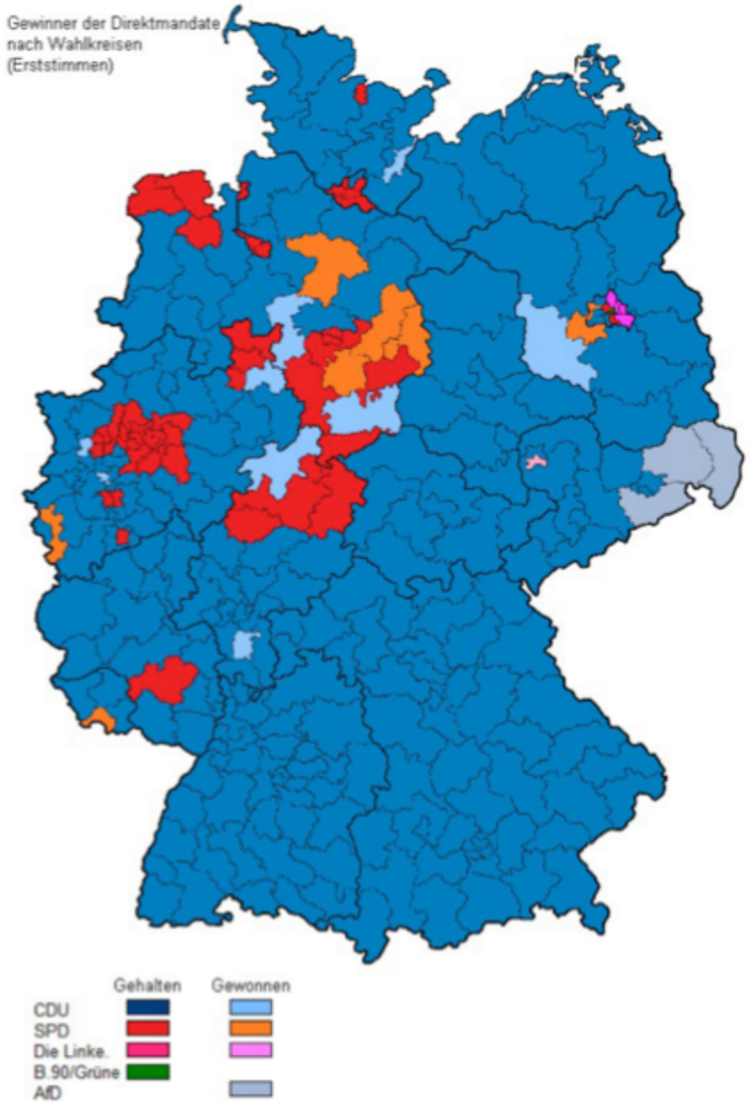


Rule analysis

Table 4.8: Top 5 Rules analysis

	antecedent	consequent	%sup	%conf
germany 2005	$\mathcal{A}_{13} > 74 \wedge \mathcal{A}_{14} < 10\%$	SPD $\succ$ FDP $\wedge$ SPD $\succ$ LEFT	81.31	100
	$\mathcal{A}_{13} > 74 \wedge \mathcal{A}_{14} < 10\%$	CDU $\succ$ FDP $\wedge$ SPD $\succ$ LEFT	81.31	100
	$\mathcal{A}_{13} > 74 \wedge \mathcal{A}_{14} < 10\%$	SPD $\succ$ GREEN $\wedge$ SPD $\succ$ LEFT	81.31	100
	$\mathcal{A}_{13} > 74 \wedge \mathcal{A}_{14} < 10\%$	CDU $\succ$ GREEN $\wedge$ SPD $\succ$ LEFT	81.31	100
	$\mathcal{A}_{3} < 30\%$	SPD $\succ$ FDP $\wedge$ SPD $\succ$ LEFT	80.58	100
portugal 2009	$\mathcal{A}_{5} \in [14\%, 27\%] \wedge \mathcal{A}_{11} < 1\%$	PS $\succ$ BE $\wedge$ PS $\succ$ CDS.PP	42.53	100
	$\mathcal{A}_{12} < 9\% \wedge \mathcal{A}_{6} < 7\% \wedge \mathcal{A}_{11} < 1\%$	PS $\succ$ BE $\wedge$ PS $\succ$ PCP.PEV	16.88	100
	$\mathcal{A}_{12} \in [15\%, 20\%] \wedge \mathcal{A}_{7} < 13\%$	PS $\succ$ BE $\wedge$ PS $\succ$ PCP.PEV	15.58	100
	$\mathcal{A}_{2} > 66\% \wedge \mathcal{A}_{6} < 7\% \wedge \mathcal{A}_{11} < 1\%$	PS $\succ$ BE $\wedge$ PS $\succ$ PCP.PEV	15.58	100
	$\mathcal{A}_{10} \in [1\%, 3\%] \wedge \mathcal{A}_{5} \in [14\%, 27\%]$	PS $\succ$ CDS.PP $\wedge$ PS $\succ$ PCP.PEV	10.06	100
portugal 2013	$\mathcal{A}_{5} < 14\% \wedge \mathcal{A}_{6} < 7\% \wedge \mathcal{A}_{10} < 1\%$	PCP.PEV $\succ$ BE $\wedge$ PS $\succ$ BE	24.03	100
	$\mathcal{A}_{1} \in [12\%, 17\%] \wedge \mathcal{A}_{8} < 16\% \wedge \mathcal{A}_{9} \in [17\%, 27\%]$	PCP.PEV $\succ$ BE $\wedge$ PS $\succ$ BE	18.18	100
	$\mathcal{A}_{4} \in [780, 1000] \wedge \mathcal{A}_{8} < 16\% \wedge \mathcal{A}_{9} \in [17\%, 27\%]$	PCP.PEV $\succ$ BE $\wedge$ PS $\succ$ BE	17.53	100
	$\mathcal{A}_{12} < 9\% \wedge \mathcal{A}_{6} < 7\%$	PSD $\succ$ BE $\wedge$ PS $\succ$ BE	17.21	100
	$\mathcal{A}_{8} \in [16\%, 31\%] \wedge \mathcal{A}_{4} \in [1000, 1730]$	PSD $\succ$ BE $\wedge$ PS $\succ$ BE	16.88	100

Figure 4.6: German regional elections map 2009 to 2017[4]



8 Conclusions

1. PAR are a solid alternative to solve complex LR problems
2. The completeness versus accuracy trade-off is clear
3. The less information it is required, the better PAR is at predicting without mistakes
4. In situations where it is more important to have an accurate rather than more complete prediction, PAR can provide a meaningful contribution
5. It appears that in smaller rankings the accuracy is less affected
6. We contributed to the Label Ranking community with 3 real-world label ranking datasets
7. PAR finding obvious information validates our approach but does not gives much valuable information for election prediction
8. Some parties clearly dominating the political scenario lead to unbalanced ranking data
9. Computationally heavy processes of discretization and mining of LRAR and PAR limit some experimental approaches
10. As future work in PAR, we suggest improving the generation of rules with multiple items in the consequent
11. Also in PAR, we suggest studying the aggregation of rules by their consequent
12. Lastly, we suggest the application of PAR for prediction in a more balanced real-world use-case

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Thank you

Obrigado