Preference Learning: A Tutorial Introduction

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What is Preference Learning ?

- Preference learning is an emerging **subfield of machine learning**
- Roughly speaking, it deals with the **learning of (predictive) preference models** from observed (or extracted) preference information

MACHINE LEARNING ⟷ **Preference Learning** ⟷ PREFERNCE MODELING and DECISION ANALYSIS

computer science
artificial intelligence

operations research
social sciences (voting and choice theory)
economics and decision theory

Workshops and Related Events

- NIPS–01: New Methods for Preference Elicitation
- NIPS–02: Beyond Classification and Regression: Learning Rankings, Preferences, Equality Predicates, and Other Structures
- KI–03: Preference Learning: Models, Methods, Applications
- NIPS–04: Learning With Structured Outputs
- NIPS–05: Workshop on Learning to Rank
- IJCAI–05: Advances in Preference Handling
- SIGIR 07–10: Workshop on Learning to Rank for Information Retrieval
- **ECML/PDKK 08–10: Workshop on Preference Learning**
- NIPS–09: Workshop on Advances in Ranking
- American Institute of Mathematics Workshop in Summer 2010: The Mathematics of Ranking

Preferences in Artificial Intelligence

More generally, „preferences“ is a key topic in current AI research

User preferences play a key role in various fields of application:

- recommender systems,
- adaptive user interfaces,
- adaptive retrieval systems,
- autonomous agents (electronic commerce),
- games, …

Preferences in **AI research**:

- **preference representation** (CP nets, GAU networks, logical representations, fuzzy constraints, …)
- **reasoning** with preferences (decision theory, constraint satisfaction, non-monotonic reasoning, …)
- **preference acquisition** (preference elicitation, **preference learning**, ...)

AGENDA

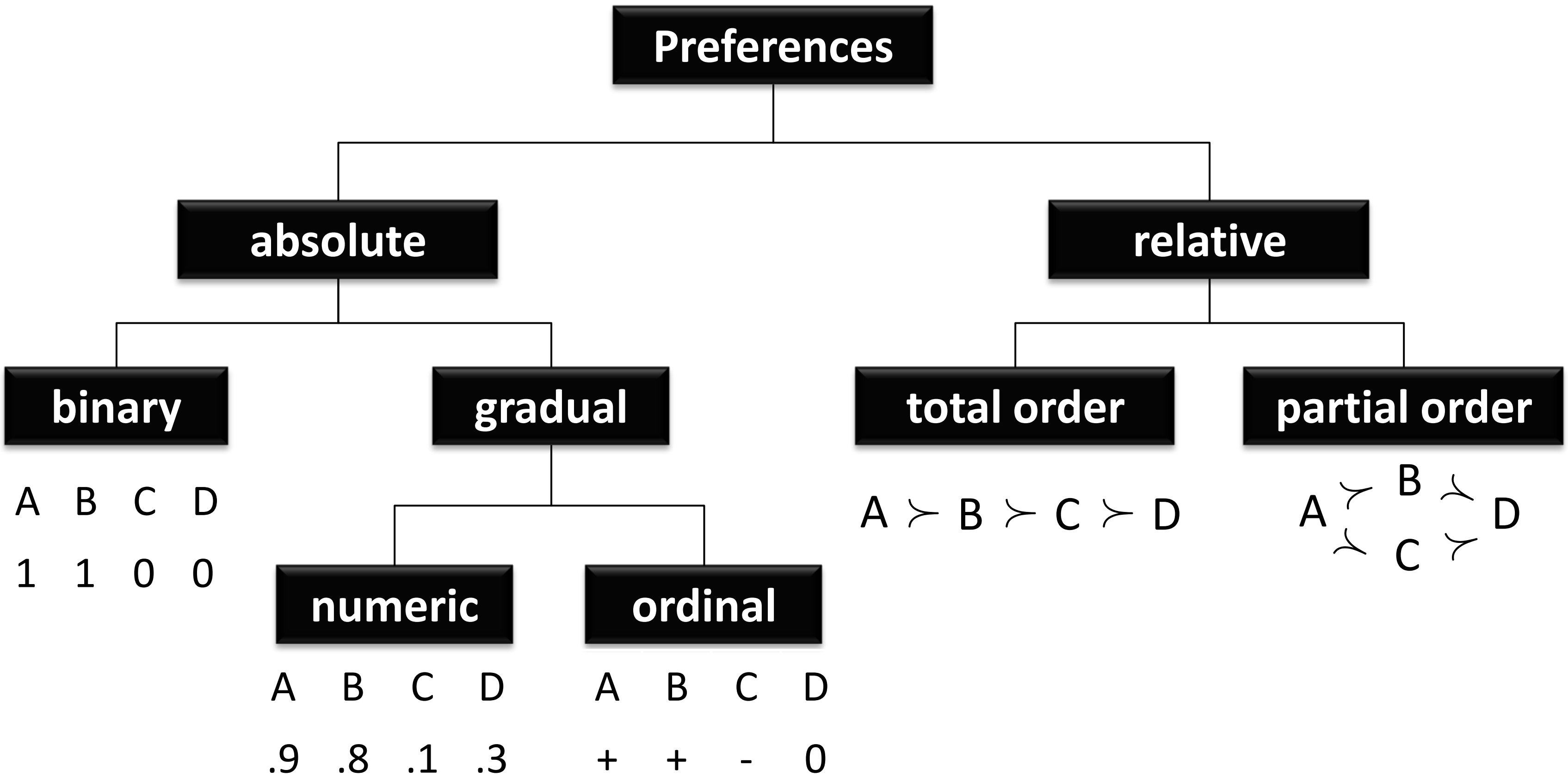
1. Preference Learning Tasks (Eyke)
2. Loss Functions (Johannes)
3. Preference Learning Techniques (Eyke)
4. Complexity of Preference Learning (Johannes)
5. Conclusions

Preference Learning

Preference learning problems can be distinguished along several **problem dimensions**, including

- **representation of preferences, type of preference model**:
  - utility function (ordinal, cardinal),
  - preference relation (partial order, ranking, …),
  - logical representation, …
- **description of individuals/users and alternatives/items**:
  - identifier, feature vector, structured object, …
- **type of training input**:
  - direct or indirect feedback,
  - complete or incomplete relations,
  - utilities, …
- …

Preference Learning



→ (ordinal) regression

→ classification/ranking

Structure of this Overview

(1) Preference Learning as an extension of **conventional supervised learning**: Learn a mapping

$$\mathcal{X} \rightarrow \mathfrak{P}$$

that maps instances to preference models (→ structured/complex output prediction).

(2) Other settings (object ranking, instance ranking, CF, …)

Structure of this Overview

(1) Preference Learning as an extension of **conventional supervised learning**: Learn a mapping

$$\mathcal{X} \rightarrow \mathfrak{P}$$

that maps instances to preference models (→ structured/complex output prediction).

Instances are typically (though not necessarily) characterized in terms of a feature vector.

The output space consists of preference models over a fixed set of alternatives (classes, labels, …) represented in terms of an identifier
→ *extensions of multi-class classification*

Multilabel Classification [Tsoumakas & Katakis 2007]

Training

X1	X2	X3	X4	A	B	C	D
0.34	0	10	174	0	**1**	**1**	0
1.45	0	32	277	0	**1**	0	**1**
1.22	1	46	421	0	0	0	1
0.74	1	25	165	0	**1**	**1**	**1**
0.95	1	72	273	**1**	0	**1**	0
1.04	0	33	158	**1**	**1**	**1**	0

Binary preferences on a fixed set of items: liked or disliked

Prediction

0.92	1	81	382	**0**	**1**	**0**	**1**

LOSS

Ground truth

0.92	1	81	382	**1**	**1**	**0**	**1**

Multilabel Ranking

Training

X1	X2	X3	X4	A	B	C	D
0.34	0	10	174	0	**1**	**1**	0
1.45	0	32	277	0	**1**	0	**1**
1.22	1	46	421	0	0	0	1
0.74	1	25	165	0	**1**	**1**	**1**
0.95	1	72	273	**1**	0	**1**	0
1.04	0	33	158	**1**	**1**	**1**	0

Binary preferences on a fixed set of items: liked or disliked

Prediction

$B \succ D \succ C \succ A$

0.92	**1**	**81**	**382**	**4**	**1**	**3**	**2**

A ranking of all items

LOSS

Ground truth

0.92	**1**	**81**	**382**	**1**	**1**	**0**	**1**

Graded Multilabel Classification [Cheng et al. 2010]

Training

X1	X2	X3	X4	A	B	C	D
0.34	0	10	174	--	+	++	0
1.45	0	32	277	0	++	--	+
1.22	1	46	421	--	--	0	+
0.74	1	25	165	0	+	+	++
0.95	1	72	273	+	0	++	--
1.04	0	33	158	+	+	++	--

Ordinal preferences on a fixed set of items: liked or disliked

Prediction

0.92	**1**	**81**	**382**	**--**	**+**	**0**	**++**

A ranking of all items

LOSS

Ground truth

0.92	**1**	**81**	**382**	**0**	**++**	**--**	**+**

Graded Multilabel Ranking

Training

X1	X2	X3	X4	A	B	C	D
0.34	0	10	174	--	+	++	0
1.45	0	32	277	0	++	--	+
1.22	1	46	421	--	--	0	+
0.74	1	25	165	0	+	+	++
0.95	1	72	273	+	0	++	--
1.04	0	33	158	+	+	++	--

Ordinal preferences on a fixed set of items: liked or disliked

Prediction

$B \succ D \succ C \succ A$

0.92	**1**	**81**	**382**	**4**	**1**	**3**	**2**

A ranking of all items

LOSS

Ground truth

0.92	**1**	**81**	**382**	**0**	**++**	**--**	**+**

Label Ranking [Hüllermeier et al. 2008]

Training

X1	X2	X3	X4	Preferences
0.34	0	10	174	$A \succ B$, $B \succ C$, $C \succ D$
1.45	0	32	277	$B \succ C$
1.22	1	46	421	$B \succ D$, $A \succ D$, $C \succ D$, $A \succ C$
0.74	1	25	165	$C \succ A$, $C \succ D$, $A \succ B$
0.95	1	72	273	$B \succ D$, $A \succ D$,
1.04	0	33	158	$D \succ A$, $A \succ B$, $C \succ B$, $A \succ C$

Instances are associated with pairwise preferences between labels.

Prediction

$B \succ D \succ C \succ A$

0.92	**1**	**81**	**382**	**4**	**1**	**3**	**2**

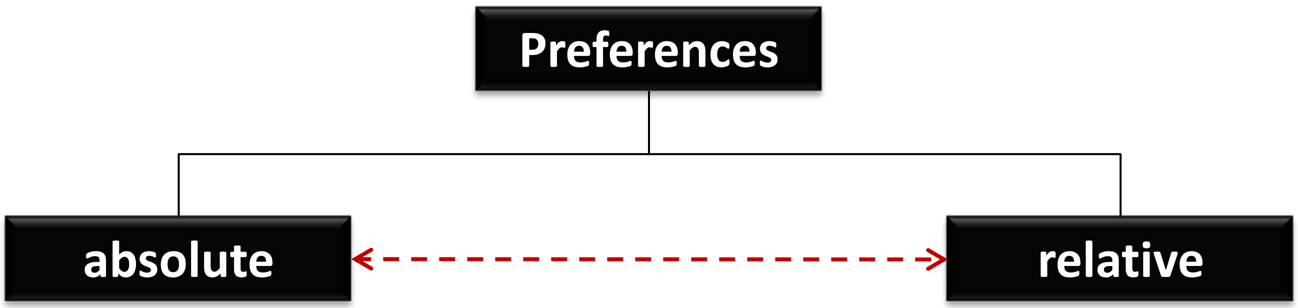
A ranking of all items

LOSS

Ground truth

0.92	**1**	**81**	**382**	**2**	**1**	**3**	**4**

Calibrated Label Ranking [Fürnkranz et al. 2008]



Combining absolute and relative evaluation:

$$\underbrace{a \succ b \succ c}_{\text{relevant / positive / liked}} \;|\; \underbrace{d \succ e \succ f \succ g}_{\text{irrelevant / negative / disliked}}$$

Structure of this Overview

(1) Preference Learning as an extension of conventional supervised learning: Learn a mapping

$$\mathcal{X} \rightarrow \mathfrak{P}$$

that maps instances to preference models (→ structured output prediction).

(2) Other settings

object ranking, instance ranking („no output space“)
collaborative filtering („no input space“)

Object Ranking [Cohen et al. 99]

Training

$$
\begin{array}{ccc}
(0.74, 1, 25, 165) & \succ & (0.45, 0, 35, 155) \\
(0.47, 1, 46, 183) & \succ & (0.57, 1, 61, 177) \\
(0.25, 0, 26, 199) & \succ & (0.73, 0, 46, 185) \\
(0.95, 0, 73, 133) & \succ & (0.25, 1, 35, 153) \\
(0.68, 1, 55, 147) & \succ & (0.67, 0, 63, 182)
\end{array}
$$

Pairwise preferences between objects (instances).

Prediction (ranking a new set of objects)

$$\mathcal{Q} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \boldsymbol{x}_4, \boldsymbol{x}_5, \boldsymbol{x}_6, \boldsymbol{x}_7, \boldsymbol{x}_8, \boldsymbol{x}_9, \boldsymbol{x}_{10}, \boldsymbol{x}_{11}, \boldsymbol{x}_{12}, \boldsymbol{x}_{13}\}$$

$$\boldsymbol{x}_{10} \succ \boldsymbol{x}_4 \succ \boldsymbol{x}_7 \succ \boldsymbol{x}_1 \succ \boldsymbol{x}_{11} \succ \boldsymbol{x}_2 \succ \boldsymbol{x}_8 \succ \boldsymbol{x}_{13} \succ \boldsymbol{x}_9 \succ \boldsymbol{x}_3 \succ \boldsymbol{x}_{12} \succ \boldsymbol{x}_5 \succ \boldsymbol{x}_6$$

Ground truth (ranking or top-ranking or subset of relevant objects)

$$\boldsymbol{x}_{11} \succ \boldsymbol{x}_7 \succ \boldsymbol{x}_4 \succ \boldsymbol{x}_2 \succ \boldsymbol{x}_{10} \succ \boldsymbol{x}_1 \succ \boldsymbol{x}_8 \succ \boldsymbol{x}_{13} \succ \boldsymbol{x}_9 \succ \boldsymbol{x}_{12} \succ \boldsymbol{x}_3 \succ \boldsymbol{x}_5 \succ \boldsymbol{x}_6$$

$$\boldsymbol{x}_{11} \succ \boldsymbol{x}_7 \succ \boldsymbol{x}_4 \succ \boldsymbol{x}_2 \succ \boldsymbol{x}_{10}$$

$$\mathcal{P} = \{\boldsymbol{x}_{11}, \boldsymbol{x}_7, \boldsymbol{x}_4, \boldsymbol{x}_2, \boldsymbol{x}_{10}, \boldsymbol{x}_1\} \qquad \mathcal{N} = \{\boldsymbol{x}_8, \boldsymbol{x}_{13}, \boldsymbol{x}_9, \boldsymbol{x}_{12}, \boldsymbol{x}_3, \boldsymbol{x}_5, \boldsymbol{x}_6\}$$

Instance Ranking [Fürnkranz et al. 2009]

Training

	X1	X2	X3	X4	class
$\boldsymbol{x}_1$	0.34	0	10	174	--
$\boldsymbol{x}_2$	1.45	0	32	277	0
$\boldsymbol{x}_3$	0.74	1	25	165	++
	…	…	…	…	…
$\boldsymbol{x}_n$	0.95	1	72	273	+

Prediction (ranking a new set of objects)

$$\mathcal{Q} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3, \boldsymbol{x}_4, \boldsymbol{x}_5, \boldsymbol{x}_6, \boldsymbol{x}_7, \boldsymbol{x}_8, \boldsymbol{x}_9, \boldsymbol{x}_{10}, \boldsymbol{x}_{11}, \boldsymbol{x}_{12}, \boldsymbol{x}_{13}\}$$

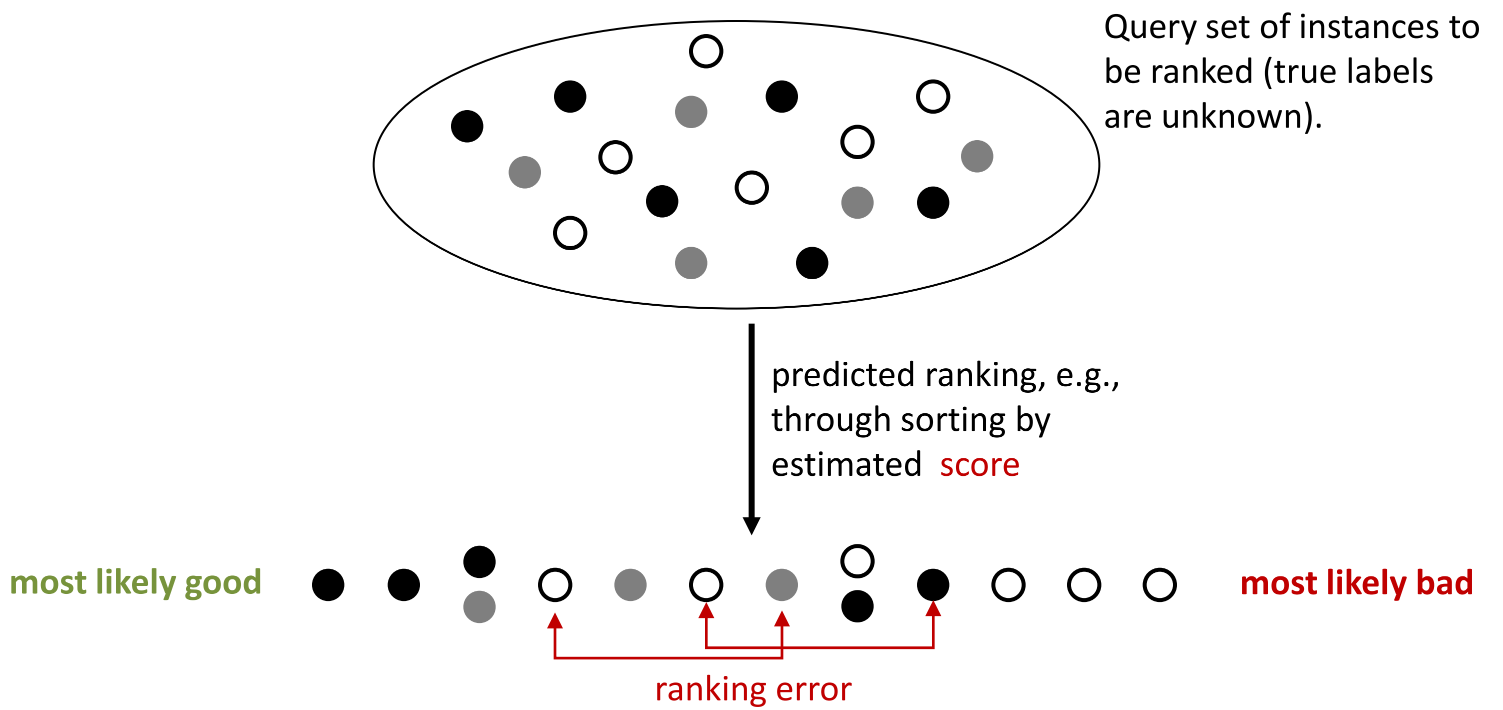
$$\boldsymbol{x}_{10} \succ \boldsymbol{x}_4 \succ \boldsymbol{x}_7 \succ \boldsymbol{x}_1 \succ \boldsymbol{x}_{11} \succ \boldsymbol{x}_2 \succ \boldsymbol{x}_8 \succ \boldsymbol{x}_{13} \succ \boldsymbol{x}_9 \succ \boldsymbol{x}_3 \succ \boldsymbol{x}_{12} \succ \boldsymbol{x}_5 \succ \boldsymbol{x}_6$$

Ground truth (ordinal classes)

$\boldsymbol{x}_{10}$	$\boldsymbol{x}_4$	$\boldsymbol{x}_7$	$\boldsymbol{x}_1$	$\boldsymbol{x}_{11}$	$\boldsymbol{x}_2$	$\boldsymbol{x}_8$	$\boldsymbol{x}_{13}$	$\boldsymbol{x}_9$	$\boldsymbol{x}_3$	$\boldsymbol{x}_{12}$	$\boldsymbol{x}_5$	$\boldsymbol{x}_6$
+	0	++	++	--	+	0	+	--	0	0	--	--

Instance Ranking [Fürnkranz et al. 2009]

Extension of AUC maximization to the polytomous case, in which instances are rated on an ordinal scale such as { **`bad, medium, good`** }



Collaborative Filtering [Goldberg et al. 1992]

PRODUCTS

USERS

	P1	P2	P3	…	P38	…	P88	P89	P90
U1	1		4	…		…		3	
U2		2	2	…		…	1		
…				…		…			
U46	?	**2**	?	…	?	…	?	?	**4**
…				…		…			
U98	5			…		…	4		
U99			1	…		…		2	

1: very bad, 2: bad, 3: fair, 4: good, 5: excellent

Inputs and outputs as identifiers, absolute preferences in terms of ordinal degrees.

Preference Learning Tasks

task	input	output	training	prediction	ground truth
	representation		type of preference information		
collaborative filtering	identifier	**identifier**	absolute ordinal	absolute ordinal	absolute ordinal
multilabel classification	feature	**identifier**	absolute binary	absolute binary	absolute binary
multilabel ranking	feature	**identifier**	absolute binary	ranking	absolute binary
graded multilabel classification	feature	**identifier**	absolute ordinal	absolute ordinal	absolute ordinal
label ranking	feature	**identifier**	relative binary	ranking	ranking
object ranking	**feature**	--	relative binary	ranking	ranking or subset
instance ranking	**feature**	identifier	absolute ordinal	ranking	absolute ordinal

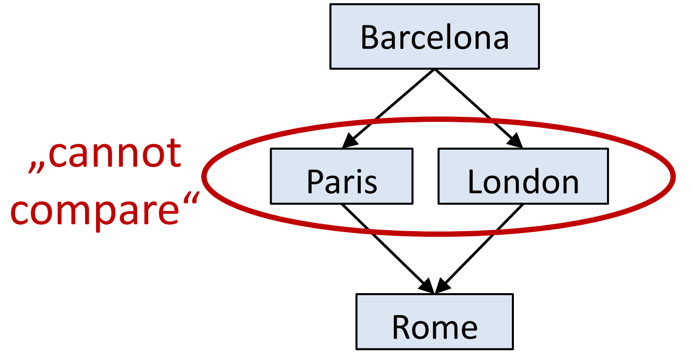
generalized classification

ranking

Two main directions: (1) Ranking and variants (2) generalizations of classification.

Beyond Ranking: Predicting Partial Oders [Chevaleyre et al. 2010, Cheng et al. 2010b]

- Rankings (strict total orders) can be generalized in different ways, e.g., through **indifference** (ties) or **incomparability**
- Predicting **partial orders** among alternatives:



- Learning conditional preference (CP) networks
- Two interpretations: **Partial abstention** due to uncertainty (target is a total order) versus prediction of **truly partial order** relation.

Loss Functions

Things to be compared:

absolute utility degree	⟷	absolute utility degree	standard comparison of scalar predictions
subset of preferred items	⟷	subset of preferred items	non-standard comparisons
fuzzy subset of preferred items	⟷	fuzzy subset of preferred items	
subset of preferred items	⟷	ranking of items	
ranking of items	⟷	ordered partition of items	
ranking of items	⟷	ranking of items	

References

- W. Cheng, K. Dembczynski and E. Hüllermeier. *Graded Multilabel Classification: The Ordinal Case*. ICML-2010, Haifa, Israel, 2010.
- W. Cheng and E. Hüllermeier. *Predicting partial orders: Ranking with abstention*. ECML/PKDD-2010, Barcelona, 2010.
- Y. Chevaleyre, F. Koriche, J. Lang, J. Mengin, B. Zanuttini. *Learning ordinal preferences on multiattribute domains: The case of CP-nets*. In: J. Fürnkranz and E. Hüllermeier (eds.) Preference Learning, Springer-Verlag, 2010.
- W.W. Cohen, R.E. Schapire and Y. Singer. *Learning to order things*. Journal of Artificial Intelligence Research, 10:243–270, 1999.
- J. Fürnkranz, E. Hüllermeier, E. Mencia, and K. Brinker. *Multilabel Classification via Calibrated Label Ranking*. Machine Learning 73(2):133-153, 2008.
- J. Fürnkranz, E. Hüllermeier and S. Vanderlooy. *Binary decomposition methods for multipartite ranking*. Proc. ECML-2009, Bled, Slovenia, 2009.
- D. Goldberg, D. Nichols, B.M. Oki and D. Terry. *Using collaborative filtering to weave and information tapestry*. Communications of the ACM, 35(12):61–70, 1992.
- E. Hüllermeier, J. Fürnkranz, W. Cheng and K. Brinker. *Label ranking by learning pairwise preferences*. Artificial Intelligence, 172:1897–1916, 2008.
- G. Tsoumakas and I. Katakis. *Multi label classification: An overview*. Int. J. Data Warehouse and Mining, 3:1–13, 2007.