

Rational Concept Analysis

introducing the KLM framework to FCA

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Overview

1. **Formal Concept Analysis**
2. **The KLM framework**
3. **Rational Concept Analysis**

Introduction

- A lattice-theoretic framework for reasoning about concepts, objects, and properties.
- Its used for data-mining, knowledge discovery, ontologies, etc.
- Concepts are extracted from a data-structure called a formal context, a triple $\mathbb{K} = (G, M, I)$ of objects G , attributes M , and a relation $I \subseteq G \times M$ indicating when an object 'has' and attribute

\mathbb{K}	bird	mammal	reptile	aerial	aquatic	terrestrial	oviparous	viviparous	limbs
Chameleon			x			x		x	x
Crow	x			x			x		x
Ostrich	x					x	x		x
Penguin	x				x	x	x		x
Platypus		x			x	x	x		x
Snake			x			x	x		
Swallow	x			x			x		x
Whale		x			x			x	

Table: A formal context of animals and some of their properties

Derivation Operators

Definition (Derivation Operators)

In a formal context (G, M, I) the derivation operators are two maps $(\cdot)^\uparrow : G \mapsto M$ and $(\cdot)^\downarrow : M \mapsto G$ such that if $X \subseteq G$ and $Y \subseteq M$

$$X^\uparrow := \{m \in M \mid \forall g \in X : (g, m) \in I\}$$

$$Y^\downarrow := \{g \in G \mid \forall m \in Y : (g, m) \in I\}$$

- The derivation operators (\uparrow, \downarrow) allow us to move from sets of objects to attributes, and vice versa
- Given some set of objects X , its derivation is the set of attributes which are common to all objects in X

Concepts

- A **concept** in a formal context is defined by its extension, and intension
- It is a pair (X, Y) of sets $X \subseteq G$ and $Y \subseteq M$ such that
 - Y consists of the attributes which all objects in X share
 - X consists of those objects which have all attributes in Y

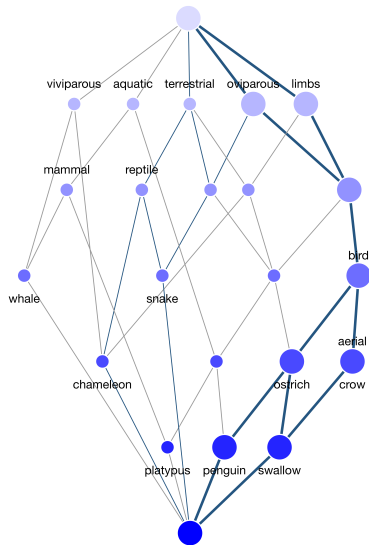
Definition (Formal Concept)

In a formal context (G, M, I) a concept is an object-attribute pair (X, Y) such that $X^\uparrow = Y$ and $Y^\downarrow = X$.

- Two concepts $C_1 = (X_1, Y_1)$ and $C_2 = (X_2, Y_2)$ can be ordered such that $C_1 \leq C_2$ iff. $X_1 \subseteq X_2$ iff. $Y_2 \subseteq Y_1$. Then C_1 is a **subconcept** of C_2 .
- This is a partial order, which corresponds to a complete lattice we call the **concept lattice**.

Concept Lattices

- We can represent the data in a context as a **concept lattice**
- Each node represents a concept
- Concepts inherit attributes from above, and contain objects from below



Implications I

Derivation operators also enable us to find correspondence between (sets of) attributes

1. $\mathbb{K} \models \text{bird} \rightarrow \text{oviparous}$
2. $\mathbb{K} \models \{\text{aquatic}, \text{terrestrial}\} \rightarrow \text{oviparous}$
3. $\mathbb{K} \not\models \text{bird} \rightarrow \text{aerial}$

Why?

1. All objects that are birds are oviparous,
 $\text{bird}^\downarrow \subseteq \text{oviparous}^\downarrow$

2. $\text{oviparous} \subseteq \{\text{aquatic}, \text{terrestrial}\}^\uparrow$

3. penguin is a bird but not aerial

\mathbb{K}	bird	mammal	aerial	aquatic	terrestrial	oviparous	viviparous
Crow	x		x			x	
Ostrich	x				x	x	
Penguin	x			x	x	x	
Platypus		x		x	x	x	
Snake					x	x	
Swallow	x		x			x	
Whale		x		x			x

Table: Slightly reduced context

Implications II

- But implications which do not hold in a context might still represent useful information
- We might be dealing with error-prone data, or want to tolerate exceptions
- Existing work tackles this problem through use of association rules (with *support*, *confidence*)
- But these metrics are unintuitive to settle on, and difficult to explain
- We look for an approach which has a clearer pattern of reasoning, i.e., the KLM framework

KLM Framework

- Kraus, Lehmann, and Magidor (KLM) argue that a logic for non-monotonic should be able to express something like *birds usually fly (even though some may not)*

$$b \sim f$$

- Expressed as a consequence relation satisfying certain properties (so called Rationality Postulates)

1. **Reflexivity:** $\frac{\alpha \rightarrow \alpha}{}$

3. **RW:** $\frac{\alpha \rightarrow \varphi, \gamma \vdash \alpha}{\gamma \vdash \varphi}$

5. **Or:** $\frac{\alpha \vdash \varphi, \gamma \vdash \varphi}{\alpha \vee \gamma \vdash \varphi}$

7. **CM:** $\frac{\alpha \vdash \gamma, \alpha \vdash \varphi}{\alpha \wedge \varphi \vdash \gamma}$

2. **LLE:** $\frac{\alpha \equiv \varphi, \alpha \vdash \gamma}{\varphi \vdash \gamma}$

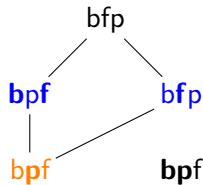
4. **And:** $\frac{\alpha \vdash \varphi, \alpha \vdash \gamma}{\alpha \vdash \varphi \wedge \gamma}$

6. **Cut:** $\frac{\alpha \wedge \gamma \vdash \varphi, \alpha \vdash \gamma}{\alpha \vdash \varphi}$

8. **RM:** $\frac{\alpha \vdash \varphi, \alpha \not\vdash \neg \gamma}{\alpha \wedge \gamma \vdash \varphi}$

Semantics

- The semantics for a statement like $b \sim f$ rest on the idea of ordering valuations \mathcal{V} by preference (*typicality*)¹



- Any *minimal* $v \in \mathcal{V}$ where birds is true, $v \models f$
- So, also $p \sim \neg f$

¹**boldface** indicates false

How do we develop a rational consequence relation in FCA?

Extending the Language

- In FCA, implications are defined over sets of attributes
- We do not naturally have a way of expressing \vee or \neg
- Even if we want to restrict ourselves to these inexpressive implications, we need to show that the pattern of non-monotonic reasoning corresponds to a rational consequence relation
- So we extend the language to **compound attributes**

Definition (The Language \mathcal{L}_M)

$$\phi := m \mid \phi_1 \wedge \phi_2 \mid \neg\phi \mid \phi_1 \vee \phi_2$$

$$m^\downarrow = \{g \mid (g, m) \in I\}$$

$$(\phi_1 \wedge \phi_2)^\downarrow = \phi_1^\downarrow \cap \phi_2^\downarrow$$

$$\neg\phi^\downarrow = G \setminus \phi^\downarrow$$

$$(\phi_1 \vee \phi_2)^\downarrow = \phi_1^\downarrow \cup \phi_2^\downarrow$$

Compound Attributes: Example

$(G, M, I) =$

	Republican	Quaker	Pacifist
Nixon	×	×	
Bush	×		
Penn		×	×

- $R^\downarrow = \{\text{Nixon}, \text{Bush}\}, Q^\downarrow = \{\text{Nixon}, \text{Penn}\}, P^\downarrow = \{\text{Penn}\}$
- *Those objects that are not republicans, or pacifists*
- $(\neg R \vee P)^\downarrow = (G \setminus R^\downarrow) \cup P^\downarrow = \{\text{Penn}\}$

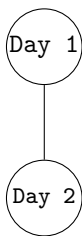
Cont.

$(G, M \cup \neg R \vee P, I) =$

	Republican	Quaker	Pacifist	$\neg R \vee P$
Nixon	×	×		
Bush	×			
Penn		×	×	×

Preferential Context

- An analogue to the view of a partial order over valuations representing preference is to order the objects in \mathbb{K}
- A preferential context $\mathbb{P} = (G, M, I, \preceq)$ where \preceq is a partial-order over G .

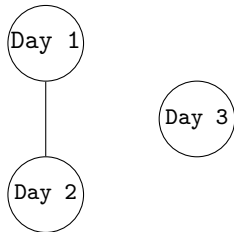


	Sun	Rain	Wind	Hot
Day 1	×	×	×	×
Day 2				×
Day 3	×		×	×

Defeasible Implications in FCA

Definition (Defeasible Implication over \mathcal{L}_M)

A defeasible implication $A \sim B \in \mathcal{L}_M$ holds in a preferential context \mathbb{P} iff. the minimal objects $\underline{A}^\downarrow \subseteq \underline{B}^\downarrow$

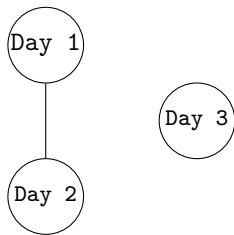


	Sun	Rain	Wind	Hot
Day 1	×	×	×	×
Day 2				×
Day 3	×		×	×

- $\text{Hot} \sim \neg \text{Rain}$ then holds in \mathbb{P} since $\underline{\text{Hot}}^\downarrow \subseteq \underline{\neg \text{Rain}}^\downarrow$
- A partial order doesn't guarantee Rational Monotonicity

Rational Monotonicity

$$\text{Rational Monotonicity} = \frac{\alpha \sim \varphi, \alpha \not\sim \neg\gamma}{\alpha \wedge \gamma \sim \varphi}$$



	Sun	Rain	Wind	Hot	¬Rain
Day 1	×	×	×	×	
Day 2				×	×
Day 3	×		×	×	×

1. $\mathbb{P} \models \text{Hot} \sim \neg\text{Rain}$
2. $\mathbb{P} \models \text{Hot} \not\sim \neg\text{Wind}$
3. $\mathbb{P} \not\models \text{Hot} \wedge \text{Wind} \sim \neg\text{rain}$ (because of Day 1)

Ranked Context

Definition

A ranked context $\mathbb{R} = (G, M, I, R, \Delta)$ is a formal context with a ranking function $R : G \mapsto \mathbb{N}$, where the partial order imposed by R is *modular*, and Δ is a set of (defeasible) constraints we place over (G, M, I) .

- Object g is more “typical” than g' iff. $R(g) < R(g')$
- *Modularity* enforces that if two objects are incomparable then they occupy the same rank
- Δ represents some external domain knowledge about how we expect objects in a context to behave (i.e. *that mammals are usually viviparous*)
- We derive R by a translated BaseRank algorithm (not shown)

Ranked Context

R	K	bird	mammal	reptile	aerial	aquatic	terrestrial	oviparous	viviparous	limbs
0	Swallow	x			x			x		x
	Crow	x			x			x		x
1	Ostrich	x					x	x		x
	Penguin	x				x	x	x		x
2	Snake			x			x	x		
	Whale		x			x			x	
3	Chameleon			x			x		x	x
	Platypus		x			x	x	x		x

Table: A ranked context of some vertebrates

- $\text{bird} \sim \text{aerial}$
- $\text{terrestrial} \wedge \text{bird} \sim \neg \text{aerial}$

Recap

- We argued that FCA could benefit from “softer” rules, enabling it to reason with error-prone, or exceptional data
- Proposed KLM-style defeasible implications as an attempt to do this
- Requires a change from implications over attributes to implications over compound attributes
- And that we place some order, encoding a view of typicality, over the object set
- Have an algorithm to determine this order, given some background information about the context (not shown)

Future Work & Paper

- If we accept that defeasible implications contain useful information, it would be nice to have consistency w.r.t concepts
- i.e. if $\text{bird} \sim \text{fly}$ then the concept derived from `bird` should contain `fly`
- This is the notion of a *typical concept*
- We would obviously like to then have a concept lattice for the set of typical concepts
 - this is the tricky part
- If you are interested, we have a paper “Non-monotonic Extensions to Formal Concept Analysis via Object Preferences”
- Also, Ding, Yiwen, et al. “Defeasible Reasoning on Concepts.” arXiv preprint arXiv:2409.04887 (2024)

Thanks



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