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Explanation Scores in Data Management

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Explanations in Databases

Receives	$R.1$	$R.2$
	s_2	s_1
	s_3	s_3
	s_4	s_3

Store	$S.1$
	s_2
	s_3
	s_4

- Query: Are there pairs of official stores in a receiving relationship?
- $\mathcal{Q}$: $\exists x \exists y (Store(x) \wedge Receives(x, y) \wedge Store(y))$

  The query is true in D: $D \models \mathcal{Q}$
- What tuples "cause" the query to be true?
- How strong are they as causes?
- We expect tuples $Receives(s_3, s_3)$ and $Receives(s_4, s_3)$ to be "causes"
- Explanations for a query result ...

- A DB system could provide *explanations*
- Explanations come in different forms

A Score-Based Approach: Responsibility

- Causality has been developed in AI for three decades or so
- In particular: Actual Causality
- Also the quantitative notion of Responsibility: a measure of causal contribution
- Both based on Counterfactual Interventions
- Hypothetical changes of values in a causal model to detect other changes: *"What would happen if we change ..."?*

  By so doing identify actual causes
- Do changes of feature values make the label change to "Yes"?
- We have investigated actual causality and responsibility in data management and ML-based classification
- Semantics, computational mechanisms, intrinsic complexity, logic-based specifications, reasoning, etc.

- There are other *local explanation scores*

  Also called "attribution scores"

- Assign numbers to, e.g., database tuples or features values to capture their causal, or, more generally, explanatory strength

- Some of them (in data management or ML)
  - Responsibility
  - The Causal Effect score
  - The Shapley value (as Shap in ML)

Example

- Database D with relations R and S below

$$\mathcal{Q}\colon\ \exists x \exists y (S(x) \wedge R(x,y) \wedge S(y)) \qquad \text{Here:}\quad D \models \mathcal{Q}$$

R	A	B
	a_4	a_3
	a_2	a_1
	a_3	a_3

S	A
	a_4
	a_2
	a_3

- Causes for $\mathcal{Q}$ to be true in D?
- $S(a_3)$ is counterfactual cause for $\mathcal{Q}$:
  If $S(a_3)$ is removed from D, $\mathcal{Q}$ is no longer an answer

  Its responsibility: $\frac{1}{1 + \text{ min. \# addit. changes}} = \frac{1}{1+|\emptyset|} = 1$
- $R(a_4, a_3)$: actual cause with contingency set $\{R(a_3, a_3)\}$

  If $R(a_3, a_3)$ is removed from D, $\mathcal{Q}$ is still true, but further removing $R(a_4, a_3)$ makes $\mathcal{Q}$ false
- Responsibility of $R(a_4, a_3)$: $= \frac{1}{1+1} = \frac{1}{2}$
- $R(a_3, a_3)$ and $S(a_4)$ are actual causes, with responsibility $\frac{1}{2}$

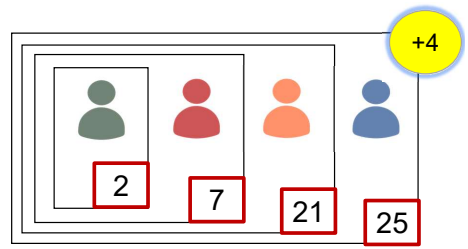
Coalition Games and the Shapley Value

- Initial motivation: By how much a database tuple contributes to the inconsistency of a DB? To the violation of ICs
- Similar ideas can be applied to the contribution to query results
- Usually *several tuples together* are necessary to violate an IC or produce a query result
- Like players in a coalition game, some may contribute more than others
- Apply standard measures used in game theory: the Shapley value of tuple

- Consider a set of players D, and a wealth-distribution (game) function $\mathcal{G}: \quad \mathcal{P}(D) \longrightarrow \mathbb{R}$ ($\mathcal{P}(D)$ the power set of D)
- The Shapley value of player p among a set of players D:

$$Shapley(D, \mathcal{G}, p) := \sum_{S \subseteq D \setminus \{p\}} \frac{|S|!(|D| - |S| - 1)!}{|D|!} (\mathcal{G}(S \cup \{p\}) - \mathcal{G}(S))$$

- $|S|!(|D| - |S| - 1)!$ is number of permutations of D with all players in S coming first, then p, and then all the others
- Expected contribution of player p under all possible additions of p to a partial random sequence of players followed by a random sequence of the rest of the players



- Database tuples and feature values can be seen as players in a coalition game

  Each of them contributing to a shared wealth function
- The Shapley value is a established measure of contribution by players to the wealth function
- It emerges as the only measure that enjoys certain desired properties
- For each game one defines an appropriate wealth or game function
- Shapley difficult to compute: #P-hard in general
- Evidence of difficulty: $\#SAT$ is #P-hard

  About counting satisfying assignments for propositional formulas

  At least as difficult as SAT

Shapley Values as Scores in DBs

- Database tuples can be seen as players in a coalition game
- Query $\mathcal{Q}$: $\exists x \exists y (Store(x) \wedge Receives(x, y) \wedge Store(y))$

  It takes values 0 or 1 in a database
- Game function becomes the value of the query
- A set of tuples make it true or not, with some possibly contributing more than others to making it true

$$Shapley(D, \mathcal{Q}, \tau) := \sum_{S \subseteq D \setminus \{\tau\}} \frac{|S|!(|D|-|S|-1)!}{|D|!} (\mathcal{Q}(S \cup \{\tau\}) - \mathcal{Q}(S))$$

- Quantifies the contribution of tuple τ to query result
- All possible permutations of subinstances of D
- Average of differences between having τ or not
- Counterfactuals implicitly involved and aggregated

- We investigated algorithmic, complexity and approximation problems
- A dichotomy theorem for Boolean CQs without self-joins

  Syntactic characterization: : PTIME vs. #P-hard
- Extended to aggregate queries
- It has been applied to measure contribution of tuples to inconsistency of a database
- Related and popular score: Banzhaf Power Index (order ignored)

$$\mathit{Banzhaf}(D, \mathcal{Q}, \tau) := \frac{1}{2^{|D|-1}} \cdot \sum_{S \subseteq (D \setminus \{\tau\})} (\mathcal{Q}(S \cup \{\tau\}) - \mathcal{Q}(S))$$

- Banzhaf also difficult to compute: #P-hard in general
- We proved "Causal Effect" coincides with the Banzhaf Index!

Some Research Directions

1. We have investigated the *Resp* score in the presence of ICs

   How does the Shapley score behave under ICs (or additional metadata)?

2. Some explanation scores appeal to a probability distribution over the data

   For example, the *Causal-Effect* score

   Only the case of the uniform distribution has been investigated

   What about other distributions?

   If we impose or use explicit and additional domain semantics or domain knowledge?

   Can we modify the score's definition and computation accordingly?

   Or the probability distribution?

3. Shapley values satisfy desirable properties for general coalition game theory

   Existing scores have been criticized or under-explored in terms of general properties

   Specific general and expected properties for Explanations Scores (in data management)?

4. Features (in ML and in general) may be hierarchically ordered according to categorical dimensions

   $$\text{address} \rightarrow \text{neighborhood} \rightarrow \textit{city} \rightarrow \cdots$$

   We may want to define and compute explanations (scores) at different levels of abstraction

   How to do this in a systematic way, possibly reusing results at different levels?

   Multi-dimensional explanations?

5. There is a need for principled and sensible algorithms for explanation score aggregation

   At the individual level as in Item 4. or at the group level, e.g. categories of instances

   Hopefully guided by a declarative and flexible specifications (about what to aggregate and at which level)

References (some publications for this presentation)

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