

Shapley Values for Relational Databases

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L'équipe LINKS (Linking Dynamic Data)

Joint team between Inria Lille, university of Lille, and the CNRS CRIStAL lab. Members :

- 9 permanent members (1 *directeur de recherche*, 2 *professeurs*, 5 *maîtres de conférence*, 1 *chargé de recherche*)
- 5 PhD students
- 1 research engineer

Research themes

- Store, query, update, integrate **heterogeneous data**...
 - relational databases, graph databases, RDF, hybrid formats, etc.
- that can be **linked** and **constrained**...
 - *schema mappings*, integrity constraints, *ontologies*, etc.
- that is potentially **voluminous**...
 - “big data”, *streaming* algorithms, usage of RDBMS for graphs, etc.
- and can also contain **uncertainty**
 - databases with missing values, *probabilistic* databases

The Shapley value

Cooperative games

Notion from **cooperative game theory**. Let X be a set of **players** and $\mathcal{G} : 2^X \rightarrow \mathbb{R}$ be a function defined on subsets of X (\mathcal{G} will be called a **game on X**). We wish to assign to every player $p \in X$ a **contribution** $s_X(\mathcal{G}, p)$. Some reasonable axioms:

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2. **Symmetry**: For every game \mathcal{G} on X and players $p_1, p_2 \in X$, if we have $\mathcal{G}(S \cup \{p_1\}) = \mathcal{G}(S \cup \{p_2\})$ for every $S \subseteq X \setminus \{p_1, p_2\}$, then $s_X(\mathcal{G}, p_1) = s_X(\mathcal{G}, p_2)$

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3. **Linearity**: For every $a, b \in \mathbb{R}$, games $\mathcal{G}_1, \mathcal{G}_2$ on X and player p we have $s_X(a\mathcal{G}_1 + b\mathcal{G}_2, p) = a \cdot s_X(\mathcal{G}_1, p) + b \cdot s_X(\mathcal{G}_2, p)$

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4. **Efficiency**: For every game \mathcal{G} on X we have $\sum_{p \in X} s_X(\mathcal{G}, p) = \mathcal{G}(X)$

The Shapley value

Theorem [Shapley, 1953]

There is a unique function $s_X(\cdot, \cdot)$ that satisfies all four axioms.

$$\text{Shapley}_X(\mathcal{G}, p) \stackrel{\text{def}}{=} \sum_{S \subseteq X \setminus \{p\}} \frac{|S|!(|X| - |S| - 1)!}{|X|!} (\mathcal{G}(S \cup \{p\}) - \mathcal{G}(S))$$

Shapley values in databases: explaining query results

Shapley values for databases

- Framework introduced by Livshits, Bertossi, Kimelfeld, and Sebag [LBKS'20]
- Let D be a relational database, that we see as a set of facts of the form $R(a_1, \dots, a_k)$, and q be a Boolean query that takes as input a database D and outputs $q(D) \in \{0, 1\}$.

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- We want to define the “contribution” of every fact $f \in D$ for the (non-)satisfaction of q . We use the Shapley value where the players are the facts of D and the game maps $S \subseteq D$ to $q(S) \in \{0, 1\}$

$$\text{Shapley}(q, D, f) \stackrel{\text{def}}{=} \sum_{S \subseteq D \setminus \{f\}} \frac{|S|!(|D| - |S| - 1)!}{|D|!} (q(S \cup \{f\}) - q(S)).$$

Complexity?

When can it be computed efficiently?

Definition: problem $\text{Shapley}(q)$

Input: A database D and a fact $f \in D$

Output: The value $\text{Shapley}(q, D, f)$

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We consider the **data complexity** (query q is *fixed*)

Theorem [LBKS'20]

Let q be a self-join-free conjunctive query. If q is **hierarchical** then $\text{Shapley}(q)$ is PTIME, otherwise it is $\text{FP}^{\#P}$ -hard

Link to probabilistic databases?

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This is the same dichotomy as for probabilistic query evaluation...
Is there a more general connection?

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This is the same dichotomy as for probabilistic query evaluation...
Is there a more general connection?

Answer: yes, we show that $\text{Shapley}(q)$ reduces to probabilistic query evaluation, for every Boolean query q

Tuple-independent probabilistic database (TID)

Probabilistic databases

Tuple-independent probabilistic database (TID)

			<hr/>		
			WorksAt		
			<hr/>		
				π	
$D =$	Bob	Inria	0.9		
	Alice	CNRS	0.5		
	John	ENS	0.7		
	Mary	Inria	0.2		

Probabilistic databases

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$$\Pr(D') = (1 - 0.9) \times 0.5 \times (1 - 0.7) \times 0.2$$

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$q = \llcorner$ there are two people who work at the same institution \lrcorner

Probabilistic databases

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$D =$

$q =$ « there are two people who work at the same institution »

$$\Pr((D, \pi) \models q) = \sum_{\substack{D' \subseteq D \\ D' \models q}} \Pr(D')$$

PQE(q) and Shapley(q)

Definition: problem PQE(q)

Input: A tuple-independent database (D, π)

Output: The probability $\Pr((D, \pi) \models q)$ that (D, π) satisfies q

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Theorem (ours)

For every Boolean query q , Shapley(q) reduces in PTIME to PQE(q)

→ In particular, this implies that Shapley(q) is PTIME whenever PQE(q) is PTIME (and we know a lot about this)

Next: proof of this result

Reduction from Shapley(q) to PQE(q) (1/4)

We wish to compute $\text{Shapley}(q, D, f) \stackrel{\text{def}}{=}$

$$\sum_{S \subseteq D \setminus \{f\}} \frac{|S|!(|D| - |S| - 1)!}{|D|!} (q(S \cup \{f\}) - q(S)).$$

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For an integer $k \in \{0, \dots, |D|\}$, define

$$\#\text{Slices}(q, D, k) \stackrel{\text{def}}{=} |\{S \subseteq D \mid |S| = k \text{ and } q(S) = 1\}|.$$

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Regroup the terms by size to obtain $\text{SHAP}(q, D, f) =$

$$\sum_{k=0}^{|D|-1} \frac{k!(|D| - k - 1)!}{|D|!} \left(\#\text{Slices}(q_{+f}, D \setminus \{f\}, k) - \#\text{Slices}(q_{-f}, D \setminus \{f\}, k) \right).$$

In other words, $\text{Shapley}(q)$ reduces to the problem of computing $\#\text{Slices}(q)$, so it suffices to reduce $\#\text{Slices}(q)$ to $\text{PQE}(q)$

Reduction from Shapley(q) to PQE(q) (2/4)

We wish to compute $\#Slices(q, D, k) \stackrel{\text{def}}{=}$

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For $z \in \mathbb{Q}$, we define a TID database (D_z, π_z) as follows: D_z contains all the facts of D , and for a fact f of D we define $\pi_z(f) \stackrel{\text{def}}{=} \frac{z}{1+z}$.

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$$\begin{aligned} \Pr(q, (D_z, \pi_z)) &\stackrel{\text{def}}{=} \sum_{S \subseteq D_z \text{ s.t. } q(S)=1} \Pr(S) \\ &= \sum_{i=0}^{n \stackrel{\text{def}}{=} |D|} \sum_{\substack{S \subseteq D \text{ s.t.} \\ |S|=i \text{ and } q(S)=1}} \Pr(S) \end{aligned}$$

Reduction from Shapley(q) to PQE(q) (3/4)

$$\begin{aligned}\Pr(q, (D_z, \pi_z)) &= \sum_{i=0}^n \sum_{\substack{S \subseteq D \text{ s.t.} \\ |S|=i \text{ and } q(S)=1}} \Pr(S) \\ &= \sum_{i=0}^n \sum_{\substack{S \subseteq S \text{ s.t.} \\ |S|=i \text{ and } q(S)=1}} \left(\frac{z}{1+z}\right)^i \left(1 - \frac{z}{1+z}\right)^{n-i} \\ &= \sum_{i=0}^n \left(\frac{z}{1+z}\right)^i \left(\frac{1}{1+z}\right)^{n-i} \sum_{\substack{S \subseteq S \text{ s.t.} \\ |S|=i \text{ and } q(S)=1}} 1 \\ &= \frac{1}{(1+z)^n} \sum_{i=0}^n z^i \# \text{Slices}(q, D, i).\end{aligned}$$

Reduction from Shapley(q) to PQE(q) (3/4)

Hence we have

$$(1+z)^n \Pr(q, (D_z, \pi_z)) = \sum_{i=0}^n z^i \#Slices(q, D, i).$$

This suffices to conclude. Indeed, we now call an oracle to PQE(q) on $n+1$ databases D_{z_0}, \dots, D_{z_n} for $n+1$ arbitrary distinct values z_0, \dots, z_n , forming a **system of linear equations** as given by the relation above. Since the corresponding matrix is a **Vandermonde with distinct coefficients**, it is invertible, so we can compute in polynomial time the value $\#Slices(q, D, k)$.

So Shapley(q) reduces in PTIME to PQE(q).

Open problem

Do we have **the other direction**? We don't know

Open problem

For every Boolean query q , is it the case that $\text{PQE}(q)$ reduces in PTIME to $\text{Shapley}(q)$?

Using provenance and knowledge compilation to solve Shapley(q) (1/2)

- An approach to probabilistic query evaluation: compute the **provenance** of the query q on the database D in a formalism from **knowledge compilation**, and then use this representation to compute the probability.

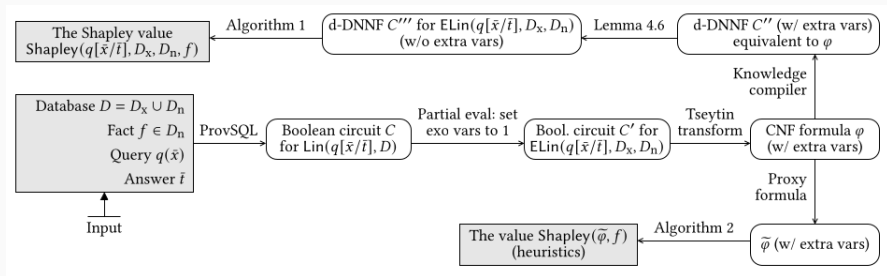
→ We can do the same for computing Shapley values

Proposition (ours)

Given as input a **deterministic and decomposable circuit** C representing the provenance, we can compute in time $O(|C| \cdot |D_n|^2)$ the value $\text{SHAP}(q, D_n, D_x, f)$.

Using provenance and knowledge compilation to solve $\text{Shapley}(q)$ (2/2)

Implementation, experiments on TPC-H and IMDB datasets.



The End

- Thanks for your attention!
- (Contact us for research internships)



Ester Livshits, Leopoldo E. Bertossi, Benny Kimelfeld, and Moshe Sebag.

The shapley value of tuples in query answering.

In *ICDT*, volume 155, pages 20:1–20:19. Schloss Dagstuhl, 2020.



Lloyd S Shapley.

A value for n-person games.

Contributions to the Theory of Games, 2(28):307–317, 1953.