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Measuring the Importance of Database Elements

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Importance of Database Tuples

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From Explanation to Responsibility Attribution

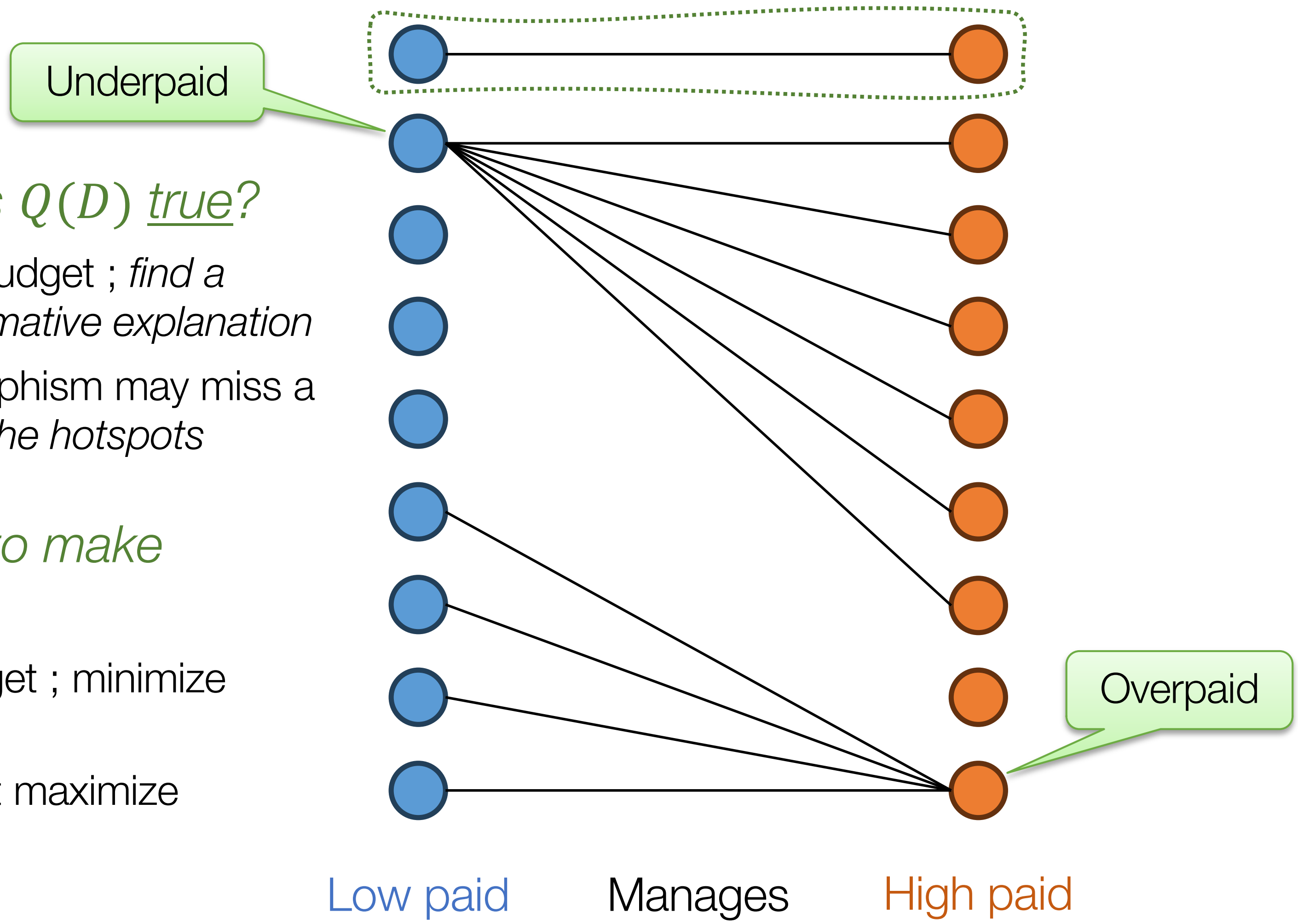
$$\exists x, y \; [\, \text{Salary}(x, \text{low}) \wedge \text{Salary}(y, \text{high}) \wedge \text{Manages}(x, y) \,]$$

Descriptive: *Why is $Q(D)$ true?*

- Limited attention budget ; *find a compact and informative explanation*
- Arbitrary homomorphism may miss a bigger story ; *find the hotspots*

Prescriptive: *How to make $Q(D)$ false?*

- Limited repair budget ; minimize the *extent* of $Q(D)$
- Find the tuples that maximize the benefit of fixing



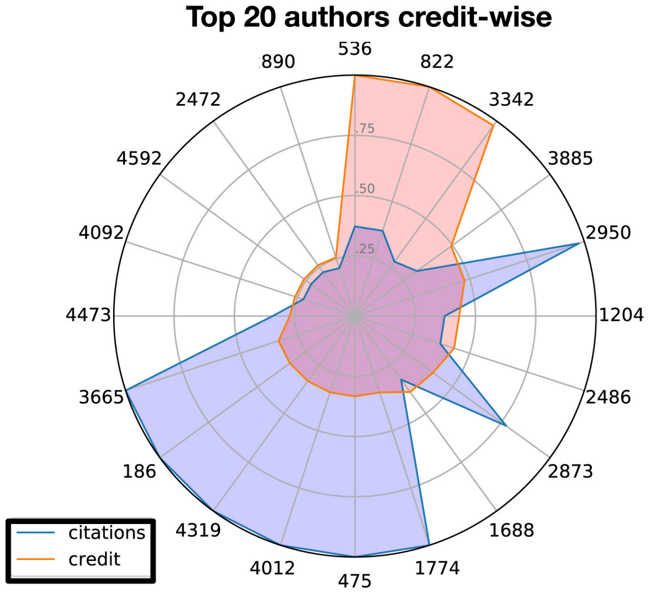
Beyond simple degrees, e.g., $\text{Manages}(x, y) \wedge \text{Manages}(y, z) \wedge \text{Family}(x, z)$

Another Example (Data Credit Distribution)

[Dosso-Davidson-Silvello22]



Credit to tuples of curated data based on references from *British Journal of Pharma.*



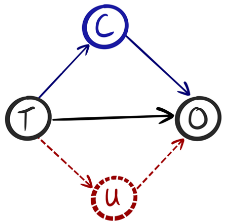
Credit to data curators (vs. their citation scores)

* Dennis Dosso, Susan B. Davidson, Gianmaria Silvello: *Credit distribution in relational scientific databases, Information Systems*, Volume 109, 2022.

Annotation vs. Contribution

- Opposite flows:
  - Annotated DBs: annotate output tuples according to the annotation of input tuples
  - Tuple contribution: annotate input tuples according to their impact on output tuples
- Abstractly – *how does each input annotation contribute to the output annotation?*
  - Useful abstraction for aggregate queries (e.g., sum)
- Relationship between the two… to be explored

Approaches to Contribution Measurement



- **Causality** (level of responsibility)
  - Idea: *Query answers depend causally on tuples ; to what degree?*
  - *Counterfactual dependence* under contingency [Meliou-Gatterbauer-Moore-Suciu10] [Meliou-Roy-Suciu15]
    - Based on [Chockler-Halpern04]: "*… minimal number of changes […] to obtain a contingency where B counterfactually depends on A*"
    - Here, min #tuples to delete so the answer depends on the tuple's existence
  - *Causal effect* [Salimi-Bertossi-Suciu-VanDenBroeck16]
    - Based on Pearl's degree of responsibility [Pearl09]
    - $\mathbb{E}[Q|\ \text{tuple}] - \mathbb{E}[Q|\ \neg\text{tuple}]$ when the DB is considered a probabilistic DB
    - Similar to earlier ideas [Kanagal-Li-Deshpande11]

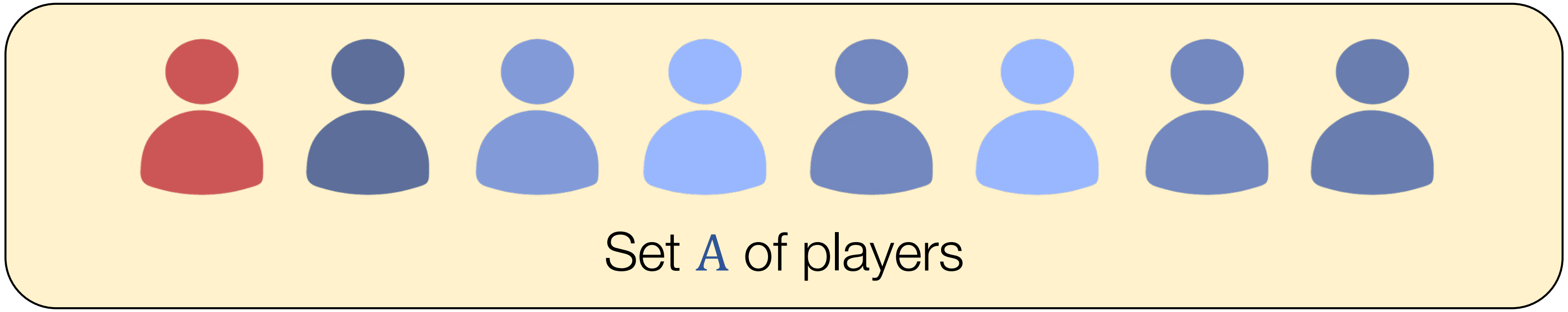
- **Cooperative Games** (profit sharing)
  - Idea: *tuples cooperate towards the answer ; what is their "share"?*
  - The Shapley value [Livshits-Bertossi-K-Sebag20] (next…)
  - The Banzhaf Power Index (= causal effect) [Abramovich-Deutch-Frost-Kara-Olteanu23]

The Shapley Value

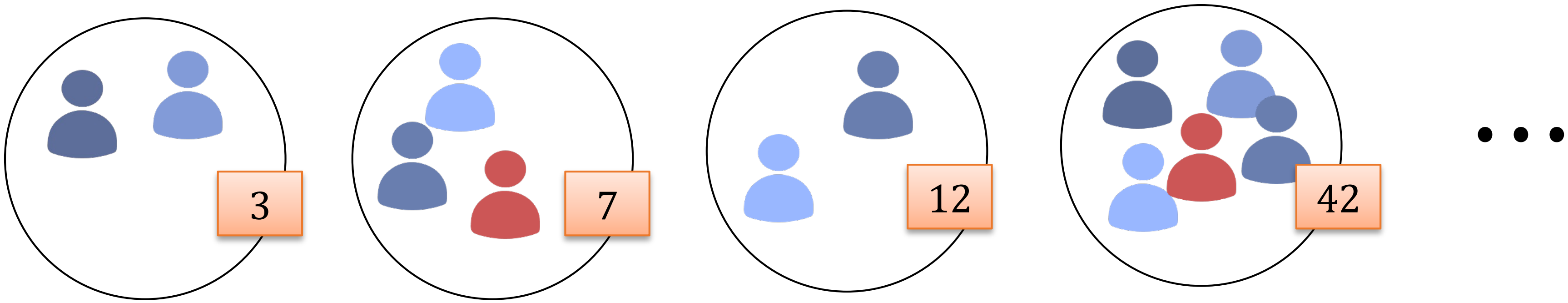
Lloyd Shapley
[1923-2016]

- Widely known profit-sharing formula in cooperative game theory by Shapley
  - [L.S. Shapley: *A value for n-person games*, 1953]
- Theoretical justification: **unique under axioms of rationality** (symmetry, linearity, efficiency, null player)
- Many application areas
  - Pollution responsibility in environmental management
  - Influence measurement in social networks
  - Identifying candidate autism genes
  - Bargaining foundations in economics
  - Takeover corporate rights in law
  - Explanations (local) in machine learning
  - Explanations in databases
  - …

Shapley Definition



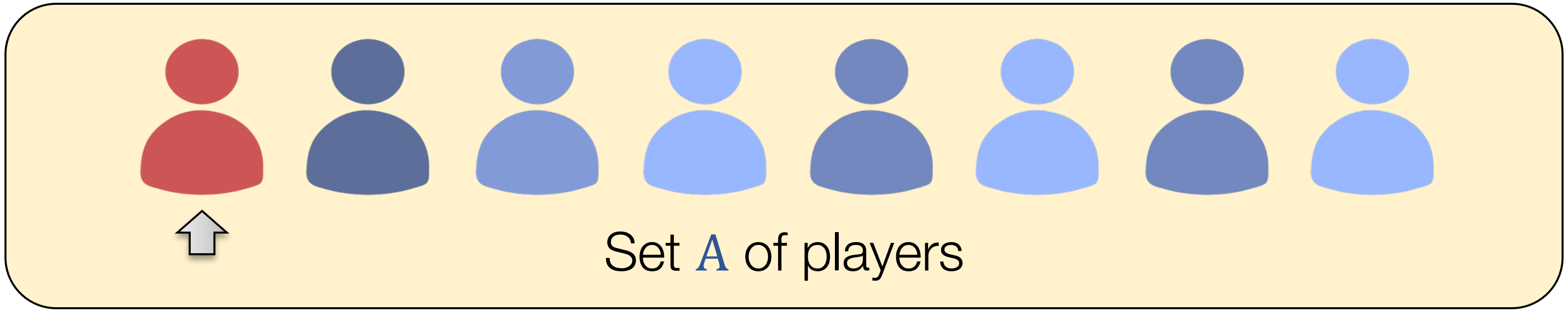
Wealth function $v: \mathcal{P}(A) \longrightarrow \mathbb{R}$ maps each coalition to a utility

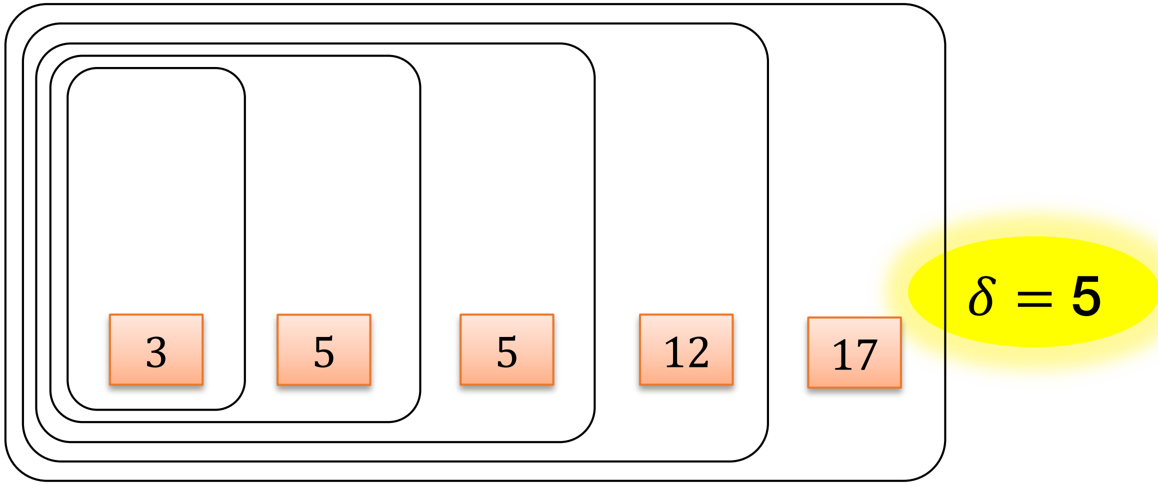


How to share the wealth among the players?

$$\text{Shapley}(A, v, a) = \sum_{B \subseteq A \setminus \{a\}} \frac{|B|!\,(|A| - |B| - 1)!}{|A|!} \big(v(B \cup \{a\}) - v(B)\big)$$

Shapley Explained

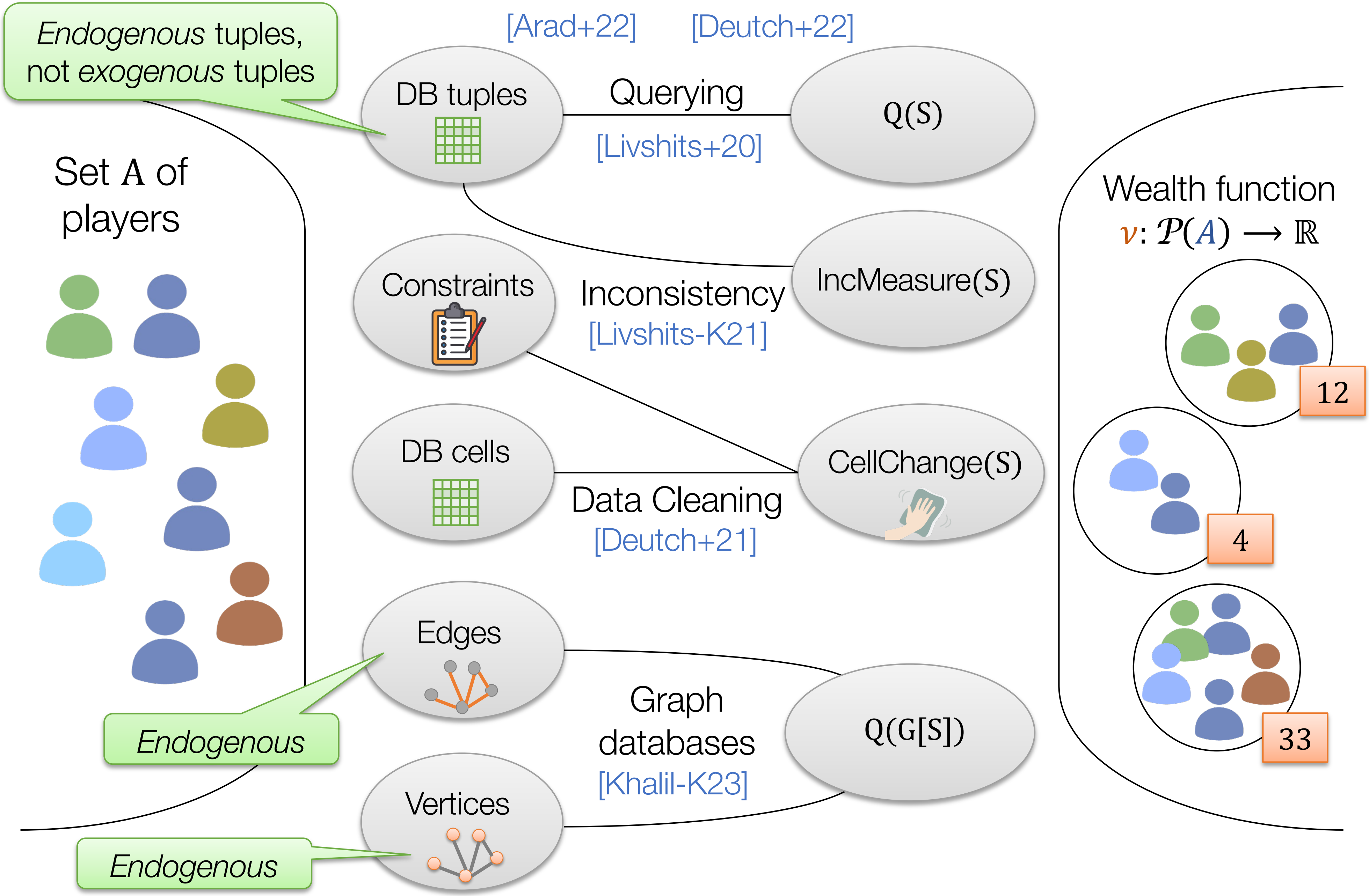




$$\text{Shapley}(A, v, a) = \sum_{B \subseteq A \setminus \{a\}} \frac{|B|!\,(|A| - |B| - 1)!}{|A|!} \big(v(B \cup \{a\}) - v(B)\big)$$

Shapley value: expected δ

Examples of Database Usage



Computation Techniques

- Factorization through linearity of expectation
  - Example: Inconsistency measure #violations under functional dependencies, #problematic tuples [Livshits-K21]
- Reduction to queries over probabilistic DBs
  - General result [Deutch-Frost-K-Monet22]
- Knowledge compilation (to d-DNNF)
  - *Daniel's talk…* [Deutch-Frost-K-Monet22]
- Approximation via sampling [Reshef-K-Livshits20] [Livshits-K21] [Khalil-K23]
  - Additive approx gives multiplicative approx via the *gap property*: the Shapley value is either zero or large

Reduction to PQE

For every Boolean query Q, Shapley[Q] reduces in PTime to Eval[Q] over tuple-independent databases [Deutch-Frost-K-Monet22]

- Proof idea:
  1. Reduce Shapley to the problem of counting the size-k-sets of tuples that satisfy the query
  2. Produce from the database multiple TIDs, each with a different (uniform) probability for the endogenous tuples
  3. Each probability gives a linear combination over the counts of size-k-sets ; all linearly independent (Vandermonde)

  ⇒ Solve equation system to find the counts

- Similar to a known reduction for the SHAP score [VandenBroeck-Lykov-Schleich-Suciu21]

Other Direction?

- The other direction is open: we do not know whether Shapley[Q] and PQE[Q] have the same complexity
- Solved positively for the class CQs w/o self-joins
  - For both, *the tractable CQs are the hierarchical CQs* [Livshits+20]

Importance of Query Parameters

(preliminary work, unpublished yet)

Peter
Lindner

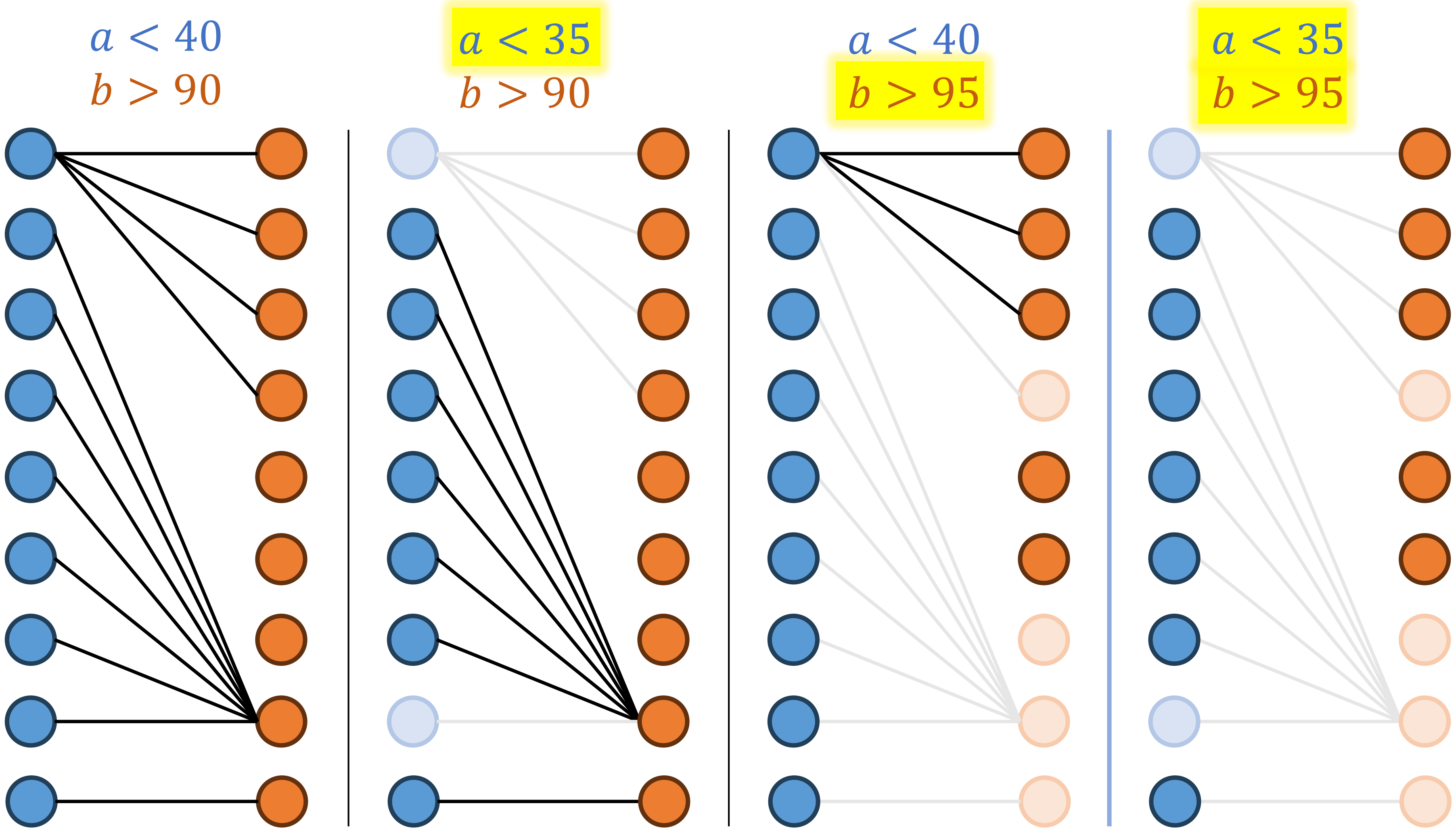
Christoph
Standke

Martin
Grohe

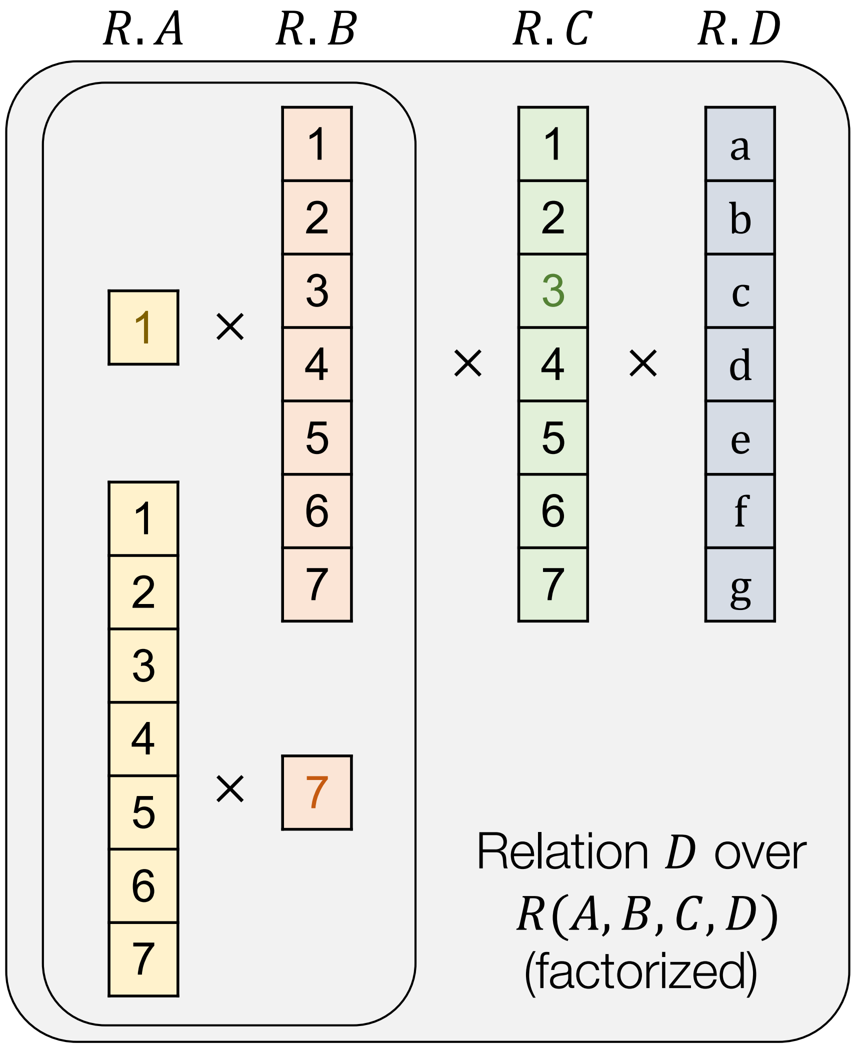
$$\exists x, y \ [\,\text{Salary}(x, a) \wedge \text{Salary}(y, b) \wedge \text{Manages}(x, y) \wedge a < 40 \wedge b > 90\,]$$

How critical are the exact parameter values?

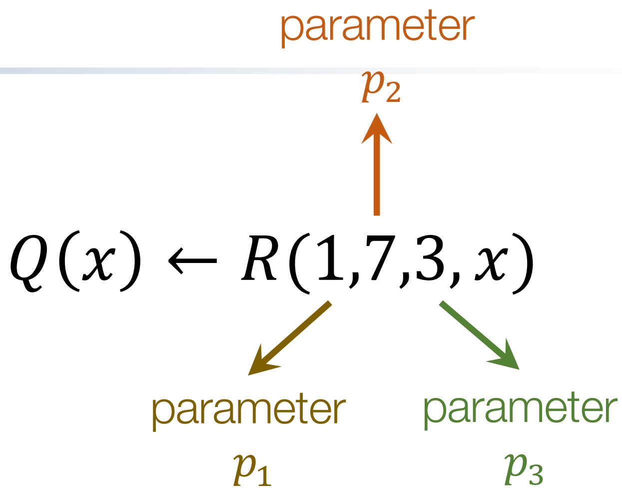
Maybe they are chosen arbitrarily… does it matter?



Another Example



$$Q(D) \coloneqq \{\mathrm{a, b, c, d, e, f, g}\}$$



How arbitrary is the choice of parameter values?

- Changing each of the three alone does not change $Q(D) \coloneqq \{\mathrm{a}, \dots, \mathrm{g}\}$
- The value of p_3 really makes no difference
- What about p_1 and p_2?
  - Changing each *separately* makes no difference
  - … even if p_3 changed in parallel
  - Changing *both* empties the result

Concepts of Sensitivity to Parameters

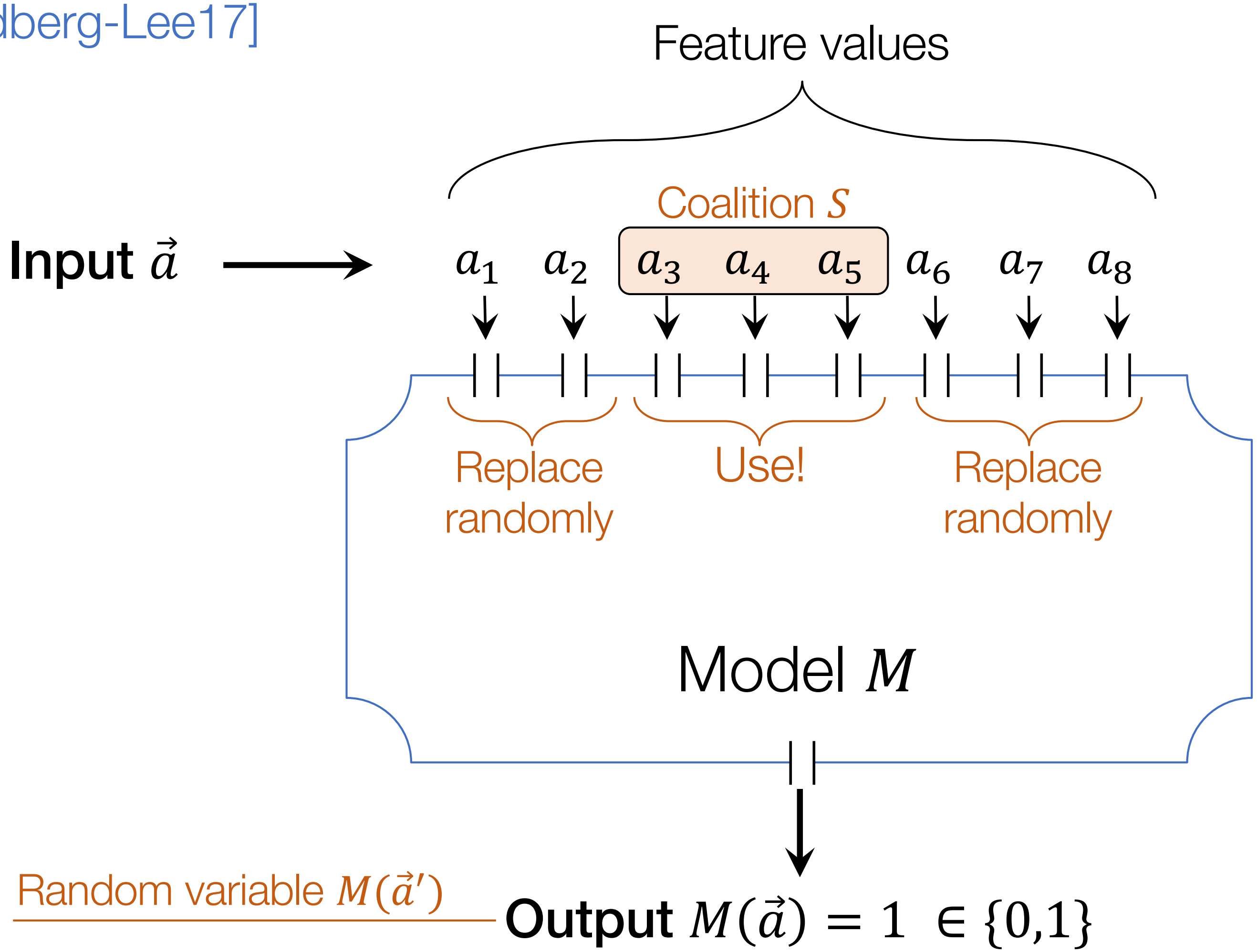
- The *empty-answer* problem: which small param changes cause the result to be nonempty?
  - [Koudas+06] [Mottin+13]
- Parameter perturbations to explain non-answers
  - [Chapman-Jagadish09] [Tran-Chan10]
- Fact checking, cherry-picked queries
  - [Wu+17] [Lin+21]
- We study the application of the Shapley value to assess the contribution of parameters

Parameter Contribution as Coop. Game

- Goal: *assess the contribution of individual parameter values to the outcome*
- What is the cooperative game here?
- Unlike other settings, we cannot just *throw away* parameters outside of the coalition ; what else?
- Similar situation in feature contribution for ML classifiers
  - ⇒ The SHAP score [Lundberg-Lee17]
- We apply a similar approach

The SHAP Score for ML Classifiers

[Lundberg-Lee17]



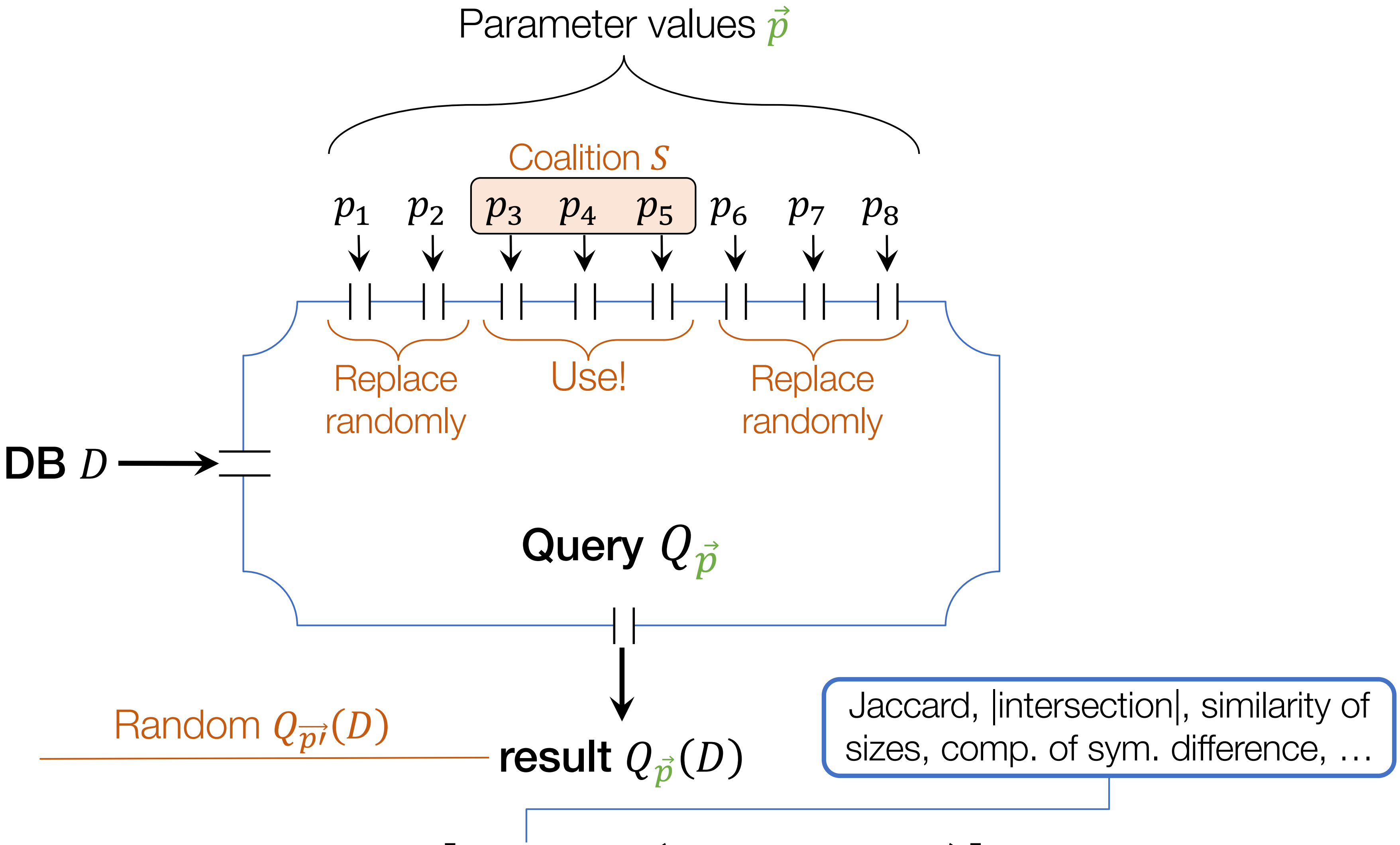
SHAP score: Shapley value for the utility $\nu(S) = \mathbb{E}[M(\vec{a}')]$

Idea: high utility $\Rightarrow$ *values of* S *lead to* $M(x) = 1$ *regardless of the rest*

Adapting SHAP to Query Parameters

- We treat parameters similarly to features
- Assume distributions over parameter values
  - Uniform, perturbations, ad-hoc, …
  - Hence, the query (and result) are random
- Unlike classifiers, the outcome is not binary, but a *set of tuples*
  - Different random changes have different impacts on this set
  - Hence, the utility function compares the random result with the actual result

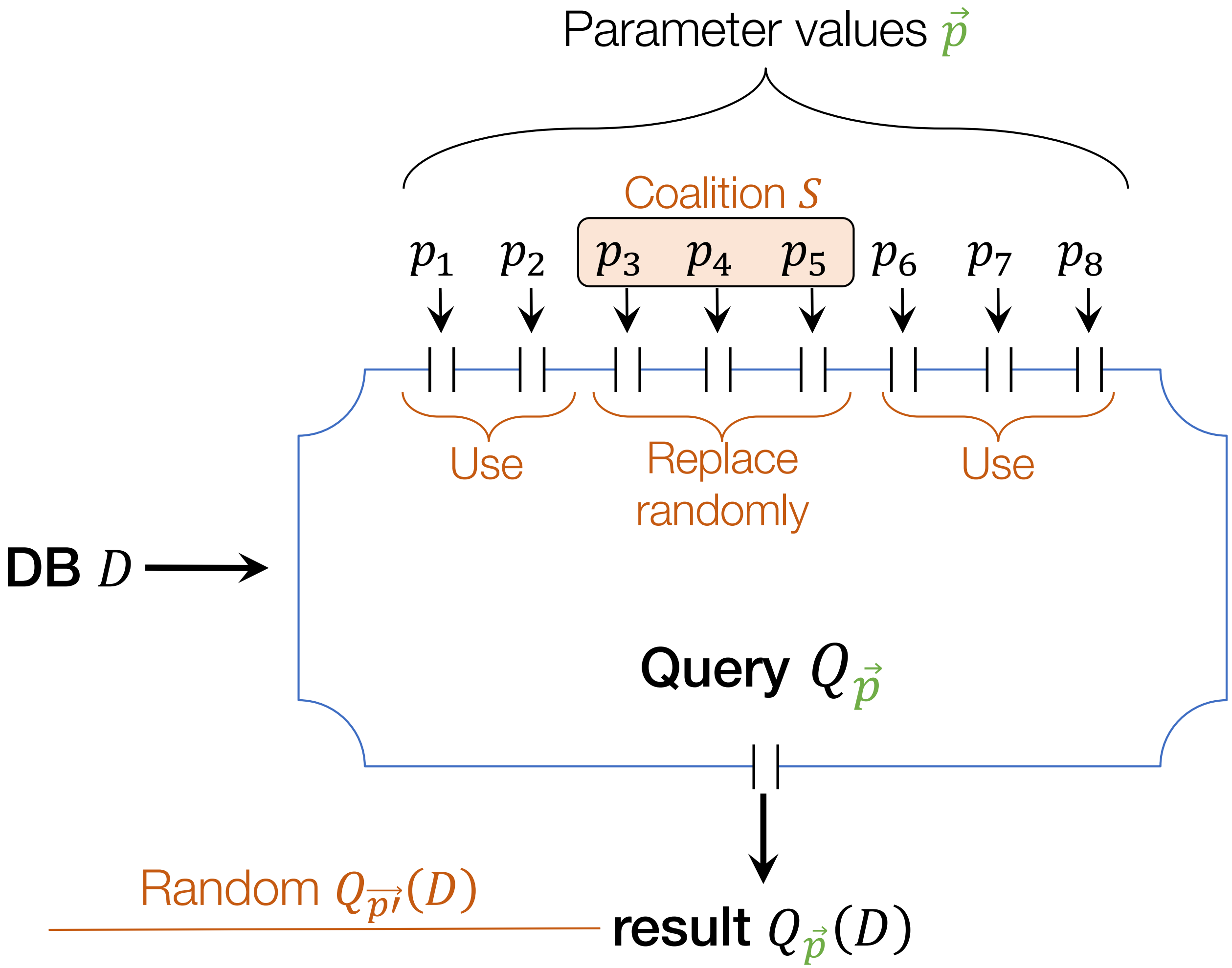
SHAP Score for Query Parameters



$$v(S) = \mathbb{E}\left[\text{similarity}\left(Q_{\vec{p}}(D)\,, Q_{\vec{p'}}(D)\right)\right]$$

Idea: *high utility ⇒ values of S give the actual result, regardless of the rest*

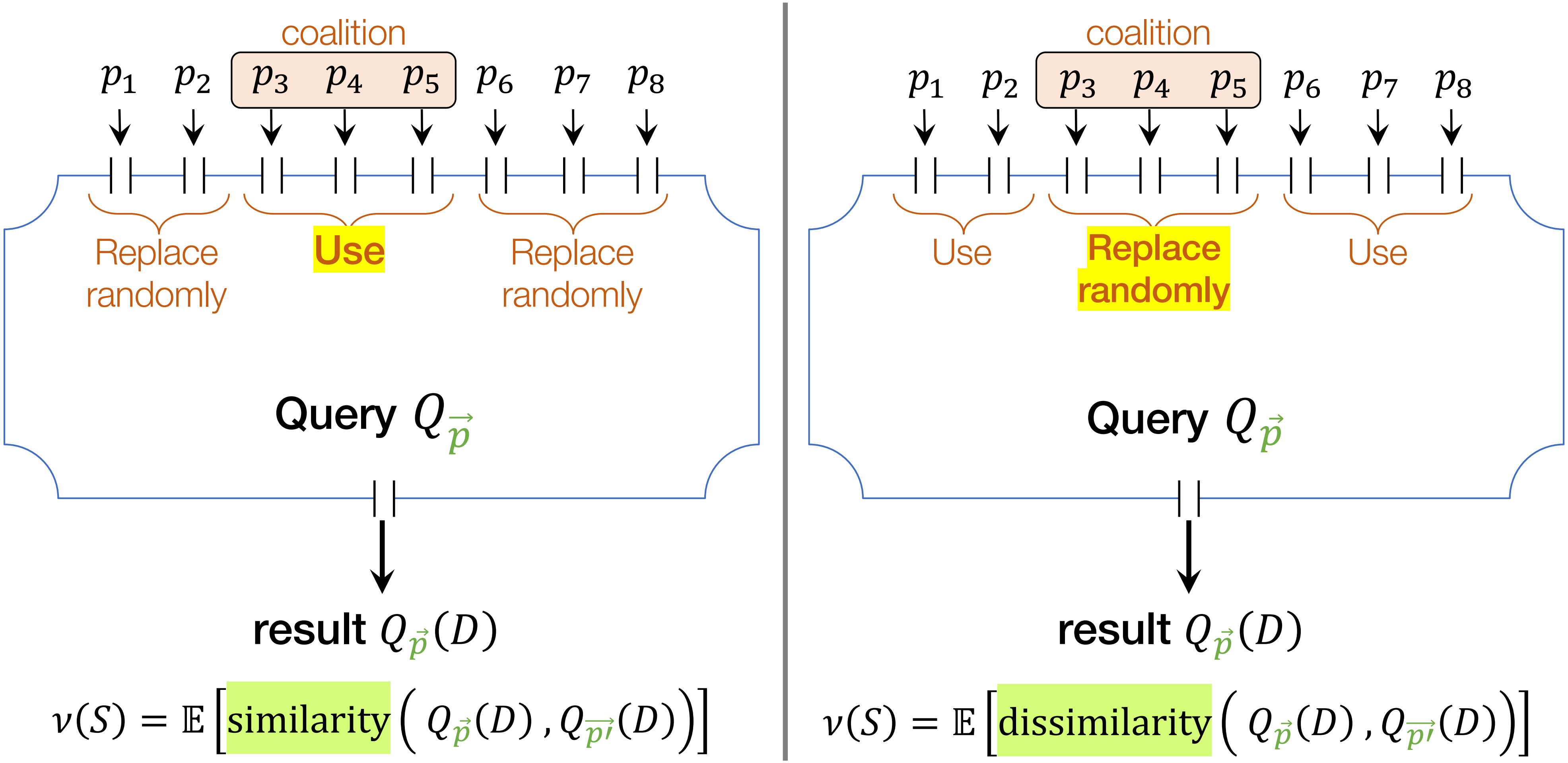
Alternative View



$$v(S) = \mathbb{E}\left[\text{dissimilarity}\left(Q_{\vec{p}}(D)\,, Q_{\vec{p'}}(D)\right)\right] = \mathbb{E}\left[K - \text{similarity}\left(Q_{\vec{p}}(D), Q_{\vec{p'}}(D)\right)\right]$$

Idea: high utility ⇒ changing S greatly impacts the result

Equivalent SHAP Definitions



The two cooperative games lead to the same Shapley value!

Complexity Study

- Algorithms use a general reduction of [Van den Broeck-Lykov-Schleich-Suciu22] from SHAP to expectation calculation
- Polynomial-time algorithms for full acyclic CQs
  - Extends to acyclic CQs with inequalities (e.g., $x < p$)
  - In contrast, even one existential variable can make an acyclic CQ #P-hard
- Efficient approximation scheme under general conditions
  - Conditions – we can efficiently sample parameters, evaluate queries, and calculate similarity

Conclusion

- Contribution measurement in databases: not new (e.g., past proposals based on causality)
- As done in other disciplines, recent efforts to deploy cooperative game theory, specifically the Shapley value
  - Also others, e.g., Banzhaff [Abramovich+23]
- Several deployments: queries, cleaning, …, query design
- Tight connections to probabilistic databases, not fully resolved yet
- Many other directions for future work
  - Database-specific axioms for contribution measures?
  - Non-monotonicity: negation [Reshef+20], non-tuples, non-answers
  - Connection to semiring annotation?
  - Tractability conditions on similarity functions?
  - …

Thank you!