

# Credit Distribution in Relational Scientific Databases

Dennis Dosso<sup>a</sup>, Susan B. Davidson<sup>b</sup>, Gianmaria Silvello<sup>a</sup>

<sup>a</sup>*Department of Information Engineering, University of Padua, Italy*

<sup>b</sup>*Department of Computer and Information Science, University of Pennsylvania, USA*

---

## Abstract

Digital data is an important form of research product for which citation, and the generation of credit or recognition for authors, is still not well understood. The notion of *data credit* has therefore recently emerged as a new metric, defined and based on data citation theory.

Data credit is a real value that represents the importance of data cited by a paper or by another research entity. Credit can be used to annotate data contained in a curated scientific database, and then used as a measure for the importance and impact of that data in the research world. As such, it is a new method that, together with traditional citations, helps recognize the value of data and its creators.

In this paper we explore the problem of Data Credit Distribution, the process by which credit is distributed to the database parts responsible for the production of data being cited by a research entity.

We adopt as use case the IUPHAR/BPS Guide to Pharmacology (GtoPdb), a widely-used curated scientific relational database. We define four new distribution strategies, the first two based on two forms of data provenance, why-provenance and how-provenance, the third based on the concept of responsibility, the fourth on the Shapley value.

Using these distribution strategies we show how credit can highlight frequently used database areas and how it can be used as a new bibliometric measure for data and their corresponding curators. In particular, credit rewards data and authors based on their research impact, not merely on the number of citations. We also show how these distribution strategies vary in their sensitivity to the role of an input tuple in the generation of the output data, and reward input tuples differently.

*Keywords:* Data Citation, Data Credit, Provenance, Causality and Responsibility, Shapley value

---

## 1. Introduction

Citations are an essential component of scientific research, enabling research products to be found as well as the relationships between them to be created and understood. They form a basis on which to give credit to authors, papers, and venues [20, 21, 64]. Citations are used, among other things, to decide on tenure, promotion, hiring, and funding of grants for researchers [22, 35, 43, 47].

Science and research are increasingly digital, and there are numerous curated databases that are at the core of scientific research efforts [12]. It is therefore generally accepted that data must be cited and citable [15, 44], and that data citations should contribute to the scientific reputation of researchers, scientists, data curators, and creators [4, 59]. It is also accepted that data citations should be counted alongside of traditional citations, and contribute to bibliometrics indicators [7, 51].

A central problem in the data citation process is how to attribute credit to data creators and curators [11]. How to handle and count the credit generated by data citation, and how it contributes to traditional and new bibliometrics, are long-standing research issues [9, 30]. However, even when correctly applied, data citations and the bibliometrics computed using them do not always fully reward the creators of data used in a database. Data, in fact, is often cited at the “database level” or the “webpage level”. In the first case, the whole database is cited and therefore all credit goes to the key personnel of the database. In the second case, the database has a website with webpages that can be individually cited. The webpages use data extracted from the database, which is aggregated by topic and built to resemble a traditional research paper. Often the creators and curators of the webpage’s data are not credited or only marginally credited for their work [3].

Recently, the idea of *Data Credit Distribution* (DCD) [29, 41, 63] has emerged, built on top of methodologies for data citation. Data credit is a value that is computed based on the importance of the data being cited in a paper, and is a proxy for the impact of the data on the citing paper. The DCD problem consists of distributing this credit to elements in the databases in the citation graph that are responsible for the generation of the data being cited. The goal of DCD is to improve and expand the reach of data citation,

36 rather than being an alternative to it.

37 In this paper, we consider data credit as a measure of value for data in  
38 a (curated) scientific database. Credit is a real value that can be assigned  
39 to data of any kind and at any level of granularity. Therefore the concept  
40 of “data” is left intentionally vague, although in this paper we focus on  
41 relational databases. Credit acts as a proxy for the value of data based on  
42 the measure of citations, accesses, clicks, downloads, or other surrogates for  
43 data use.

44 We define DCD as *the process, method, or algorithm used to assign credit*  
45 *to a given datum or dataset*. It differs from the traditional citation setting  
46 since:

- 47 1. When a paper  $p_1$  cites another paper  $p_2$ , a +1 citation “credit” is given  
48 to  $p_2$ , and to all its authors. It does not matter why or how paper  
49  $p_1$  cites paper  $p_2$ <sup>1</sup>, the result is always +1 to the citation count of  $p_2$   
50 and of its authors. A different credit distribution strategy can assign a  
51 quantity of credit to  $p_2$  and its authors that is *proportional* to the role  
52 played by  $p_2$  in  $p_1$ . Hence, we can weight the importance of the cited  
53 entities and assign credit according to their role.
- 54 2. Traditional citations are *atomic*: a citation from  $p_1$  to  $p_2$  can never  
55 be broken into pieces and assigned in part to  $p_2$  and in part to other  
56 papers or data that contributed to  $p_2$ . In contrast, with data credit,  
57 we use a *non-atomic* real value, which can be divided and distributed  
58 to multiple components of a database.
- 59 3. Credit can be *transitive*, that is, it can be propagated through one  
60 cited entity to other entities cited by it that contributed to its content.  
61 Citations, traditionally, are not.

62 We study the DCD problem in the context of relational databases (RDBs)  
63 since they are widely used<sup>2</sup> and are the main focus of current work in data  
64 citation methods [12, 14, 52]. RDBs are also frequently a test-bed for new  
65 methods that can be adapted to other databases, e.g., graphs or document  
66 databases. The “portions” of data in an RDB that can be credited can be  
67 defined at different levels of granularity, in particular: (i) the whole database,  
68 (ii) tables, (iii) tuples, and (iv) attributes. The ability to specify different

---

<sup>1</sup>Note that there is vast research on this topic and many alternative proposals, but none of them currently work at a large scale.

<sup>2</sup>The “relational database market alone has revenue upwards of \$50B” [1].



Figure 1: Overview of the credit distribution pipeline.

69 levels of granularity in a relational database allows us to define the DCD  
70 problem at a particular level of granularity. In this paper, we focus on DCD  
71 at the tuple level.

72 The DCD process that we use is summarized in Figure 1:

73 **Step 1** Scientists and experts contribute the curated information contained  
74 in a scientific database. These are called the “Data Curators”.

75 **Step 2** Other researchers use the data in their research, and when possible,  
76 cite them.

77 **Step 3** The citation to the data generates credit, that can be used as a  
78 proxy for the impact of the data on the citing paper. This credit is  
79 represented as a real value  $k \in \mathbb{R}_{>0}$ .

80 **Step 4** Given the database instance  $I$  and the query  $Q$ , the *data prove-*  
81 *nance* of  $Q(I)$  is computed. The data provenance of  $Q(I)$  is a form of  
82 metadata that captures how  $Q$  used  $I$  to generate the output [17].

83 **Step 5** Provenance is input to the *Credit Distribution Strategy* (CDS, also  
84 referred only as *Distribution Strategy*, DS). CDS is a function  $f$  that

85 takes as input the credit value  $k$ , divides it and distributes it to the  
 86 data in the input database  $I$ , and is defined on the basis of citation  
 87 policies decided at the database administration level or at the domain  
 88 community level.

89 **Step 6** Once the CDS is computed, it is used to distribute the given credit  
 90  $k$  to the parts of the database that are responsible for the generation  
 91 of  $Q(I)$ . Transitively, this credit is also divided and given to the corre-  
 92 sponding authors of those data.

93 This paper expands the work in [26] where we first defined the problem  
 94 of DCD in relational databases, and proposed a viable Distribution Strategy  
 95 (DS) based on *lineage* – the simplest form of *data provenance*. The lineage  
 96 of a tuple  $t$  in the output  $Q(I)$  is defined as the set of all and only the tuples  
 97 in the database instance  $I$  that are “relevant” to the production of  $t$ . The  
 98 corresponding strategy equally redistributes the credit  $k$  to the tuples in the  
 99 lineage set, thus each tuple receives credit  $k/|L_t|$ , where  $L_t$  is the lineage set  
 100 of  $t$ .

101 One may argue that this DS is too simplistic, since lineage does not convey  
 102 any information about the role or importance of input tuples in the query.  
 103 Therefore, one may desire to give more credit to the tuples that are more  
 104 *important* to the production of the output, i.e. those tuples that, if removed,  
 105 would prevent the output tuple from appearing in the final result, or those  
 106 tuples used more than once by the query.

107 Therefore, in this paper, we expand the ideas in [26] by proposing new  
 108 DSs based on two other forms of data provenance: why-provenance [13] and  
 109 how-provenance [32]. We also propose other two DS based on the concepts  
 110 of responsibility [48] and the Shapley value [25, 45]. We show how these DS  
 111 differ from each other and to the one based on lineage, and discuss why one  
 112 may be preferred to another depending on the application and its goals. In  
 113 particular, we show that the proposed new DSs are more sensitive than the  
 114 lineage-based one to the *role* of a tuple in a query, i.e. how many times the  
 115 tuple is used and how it is used. We also show that the DSs based on why-  
 116 provenance and responsibility give more credit to tuples that are essential to  
 117 the production of the result set, whereas the how-provenance-based DS takes  
 118 into consideration the different ways in which a tuple is used. Finally, the DS  
 119 based on the Shapley value sees the process of distribution as a competitive  
 120 game in which tuples that contribute more to the generation of the output  
 121 are correspondingly rewarded more..

122 We use a well-known curated database called the IUPHAR/BPS<sup>3</sup> Guide  
 123 to Pharmacology [34], also known as GtoPdb<sup>4</sup>, to evaluate the DSs. GtoPdb  
 124 contains expertly curated information about diseases, drugs, cellular drug  
 125 targets, and their mechanisms of action. We chose GtoPdb for two main  
 126 reasons: (i) it is a widely-used and valuable curated relational database, (ii)  
 127 many papers in the literature use, and cite, its data (i.e., families, ligands,  
 128 and receptors). Real queries used in papers can therefore be seen as data  
 129 citations which, in turn, can be used to assign data credit.

130 We perform four sets of experiments. In the first, real queries are ex-  
 131 tracted from papers published in the British Journal of Pharmacology (BJP),  
 132 that represent data citations to GtoPdb, and are used to distribute credit in  
 133 the database using the three different provenance-based DSs. In the second  
 134 and third experiment we analyze the behavior of the different DS when com-  
 135 plex citation queries are employed. In the fourth set of experiments we use  
 136 both real and synthetic queries to assess the difference between traditional  
 137 citation and the notion of credit distribution in terms of rewarding those  
 138 responsible for the data, e.g. data curators.

139 **Contributions** of this work include:

- 140 • Four new Distribution Strategies based on why-provenance, how-provenance,  
 141 responsibility and the Shapley value.
- 142 • An in-depth analysis of the effects of credit distribution on real-world  
 143 curated data and of the differences between the five proposed Distri-  
 144 bution Strategies.
- 145 • A comparison between the behavior of traditional citations and data  
 146 credit in rewarding data curators.

147 **Outline.** The rest of the paper is organized as follows: Section 2 presents  
 148 background material and related work. Section 3 describes the GtoPdb use  
 149 case. Section 4 briefly presents the forms of provenance used in the paper.  
 150 Section 5 describes the credit distribution problem and the proposed dis-  
 151 tribution strategies. In Section 6 we present the experimental evaluation,  
 152 followed by a discussion of our design decisions in Section 7. Section 8 draws  
 153 some conclusions and outlines future work.

---

<sup>3</sup>International Union of Basic and Clinical Pharmacology/British Pharmacology Soci-  
 ety

<sup>4</sup><https://www.guidetopharmacology.org/>

## 154 2. Background

155 *Data in Research.* The world of research is rapidly transitioning towards the  
156 *fourth paradigm of science* [36], that is, data-intensive scientific discovery,  
157 where data are important for scientific advances as well as for traditional  
158 publications [6].

159 The scientific community is promoting an *open research culture* [50],  
160 founded on methods and tools to share, discover, and access experimental  
161 data. The community has identified the FAIR principles (Findable, Acces-  
162 sible, Interoperable, and Reusable) [61], that should be enforced by every  
163 database. In particular, data should be accessible from the articles, journals,  
164 and papers that cite or use them [20]. Aspects such as the need for the *repro-*  
165 *ducibility* of experiments through the used data; the *availability* of scientific  
166 data; the *connections* between data and the scientific results are all needed  
167 aspects for the fourth paradigm, and are all relevant to the domain of *data*  
168 *citation* [37].

169 *Data Citation: Principles and Motivations.* Data Citation principles were  
170 proposed in [19], and later summarized and endorsed by the Joint Declaration  
171 of Data Citation Principles (JDDCP) [46]. The principles are divided into  
172 two groups [57]. The first group contains principles concerning the role of  
173 data citation in scholarly and research activities such as the (i) *importance*  
174 of data (why data citation is important and why data should be considered  
175 as first-class citizens); (ii) *credit* and *attribution* to the creators and curators  
176 of the data; (iii) *evidence*; (iv) *verifiability*; and *interoperability*, with these  
177 last three requiring data citation methods to be flexible enough to operate  
178 through different communities. The second group defines the main guidelines  
179 to establish a data citation systems, and contains principles such as the (i)  
180 *unique identification* of the data being cited; (ii) *(open) access* to data; (iii)  
181 guarantee of *persistence* and *availability* of citations even after the lifespan  
182 of the cited entity; the (iv) *specificity* of a citation, i.e. it must lead to the  
183 data set originally cited.

184 The main motivations for data citation are outlined in [57] and range from  
185 data attribution and connection to data sharing, impact and reproducibility.

### 186 2.1. Data Citation in Relational Databases

187 Relational databases have been the target of data citation methods since  
188 the surge of the data-centric research paradigm. The RDA “Working Group

189 on Data Citation: Making Dynamic Data Citable”<sup>5</sup> [53] has developed guide-  
190 lines for citing large, dynamic, and changing datasets which have now moved  
191 on into adoption phase. The datasets considered by the Working Group are  
192 often relational.

193 In one of its most recent sessions [54], the Working Group (WG) on  
194 Data Citation reported that there are various implementations of its guide-  
195 lines for Data Citation on MySQL/Postgres relational databases. Some of  
196 these databases are: DEXHELPP<sup>6</sup> (Social Security Records); NERC (ARGO  
197 Global Array); EODC (Earth Observation Data Centre) [31]; LNEC (River  
198 dam monitoring); MDS (Million Song Database) [8]; CBMI<sup>7</sup> (Center for  
199 Biomedical Informatics); VMC (Vermont Monitoring Cooperative); CCA<sup>8</sup>  
200 (Climate Change Center Austria); VAMDC (Virtual Atomic and Molecular  
201 Data Center) [27, 65].

202 More examples of work on data citation in relational databases are [2,  
203 12, 24, 62]. The website <https://fairsharing.org/> keeps an updated list  
204 of curated and scientific databases (many of which are relational or graph-  
205 based) following FAIR guidelines. These databases are citable since they are  
206 compliant with the most recent guidelines, and they are in the vast majority  
207 of cases accessible via dynamically created Webpages. In all these databases  
208 it is, therefore, possible to implement DCD on top of the existing infrastruc-  
209 tures for citing data.

210 Data citation techniques are primarily applied to relational databases  
211 because of their pervasiveness as well as the “identifiability” of the portions  
212 of data that are to be cited: the whole database, a relation, a tuple, or  
213 even an attribute. Many papers [2, 10, 12] consider more complex citable  
214 units, recognizing that often the *views* of a database are the ones to be cited.  
215 Generally, a *view* is a query on the database. To this end, [62] suggested  
216 decomposing the database into a set of views, where each view is associated  
217 with its citation.

218 At present, the most common practices to cite databases include:

- 219 1. A database cited as a whole, even though only parts of the databases  
220 are used in the papers or datasets. Alternatively, the so-called “data pa-

---

<sup>5</sup><https://www.rd-alliance.org/groups/data-citation-wg.html>

<sup>6</sup><http://www.dexhelpp.at/>

<sup>7</sup>[https://medicine.missouri.edu/centers-institutes-labs/  
center-for-biomedical-informatics](https://medicine.missouri.edu/centers-institutes-labs/center-for-biomedical-informatics)

<sup>8</sup><https://ccca.ac.at/startseite>



pers” are cited, being traditional papers that describe a database [16]. In this case, all the credit from the citations goes to the database administrators or to the authors of the data papers.

2. Subsets of data, obtained by issuing queries to a database, are individually cited. This is the solution adopted by the *Resource Data Alliance* (RDA) working group on Data Citation [53]. In this case, the credit generated from citations is distributed among the contributors of the portions of data being cited, and/or to the database administrators.
3. The database is accessible via a series of Webpages that arrange the content of the database by topic or theme. Examples in the life science domain include the Reactome Pathway database [40], the GtoPdb [34], and the VAMDC [65]. Every single Webpage is unequivocally identifiable and can be individually cited.

## 2.2. Data Credit

Data credit is related to data citation: they both aim to recognize the work of data creators and curators. Data credit can therefore also be seen as a by-product of data citation, since credit attribution is impossible without the presence of data citations.

Katz [41] suggests the need for a *modified citation system* that includes the idea of *transient* and *fractional credit*, to be used by developers of research products as software and data. Two considerations are made: (i) research objects such as data and software are currently not formally rewarded or recognized by the community; (ii) even in traditional papers, the contribution of each author to the work is hard to understand, unless explicitly specified in the paper. This is even more true for data, where different groups of people work on the same database.

In [41] credit is defined as a “quantity” that describes the importance of a research entity, such as papers, software, or data, mentioned in a citation. It also proposed the idea of a *distribution* of credit from research entities, such as papers or data, to other research entities through citations. *Therefore, when discussing data credit, we need to consider credit computation – i.e., the process to compute the quantity of credit generated by the citation – and credit distribution – i.e., the process to distribute credit and to assign it to the entities that contributed to the creation/curation of the cited data. In this paper we focus on the latter.*

*These two processes are done by exploiting the structure of the citation graph, a directed graph whose nodes are publications and edges are citations.*

258 This graph is the model at the core of systems such as Google Scholar and  
259 the Web of Science. We add to this that the concept of credit can be built  
260 on top of the existing infrastructure handling traditional and data citations.

261 Katz [41] further explores the idea of a *distribution* of credit from research  
262 entities (i.e., papers and data) to other research entities through citations  
263 that connect them. Thanks to traditional citations and now also to data  
264 citations, this distribution is finally possible, at least between papers and  
265 data. Some problems related to traditional citations can thus be solved by  
266 citations:

- 267 1. Credit rewards research entities that to date are not (formally) recog-  
268 nized (a goal shared with data citation).
- 269 2. Credit can reward authors *proportionally* to their role in generating the  
270 entity. The more an author contributes to a paper, the more credit is  
271 given to him. Zou and Peterson [64] work on something similar with  
272 their zp-index, which includes in its formulation the position (and thus  
273 the role) of a publication author to represent its impact in the work  
274 itself.
- 275 3. Credit can be *transitively* channeled through a chain of papers citing  
276 each other, thus enabling the rewarding of older papers that are no  
277 more cited, since other papers summarize or report their content but  
278 are nevertheless crucial in a research area for the influence of their  
279 content.

280 Fang [29] presents a framework to distribute the credit generated by a  
281 paper to its authors and to the papers in its reference list in a transitive way.  
282 Let us consider the *citation graph* as the graph where the nodes are papers  
283 and the links are the citations among them. In this graph, every paper is  
284 a source of credit, which is then transferred to the neighboring nodes. The  
285 quantity of credit received by each cited paper depends on its impact/role  
286 in the citing paper. So far, this theoretical framework is limited to papers,  
287 but it can be easily extended to a citation graph including both papers and  
288 data.

289 Zeng et al. [63] proposes the first method to compute credit within a net-  
290 work of papers citing data. Adopting a network flow algorithm, they simulate  
291 a random walker to estimate a score for each dataset, leveraging real-world  
292 usage data to compute the credit. This is the first step towards an automatic  
293 credit computation procedure. This proposal is, however, limited to assign-  
294 ing credit to whole datasets, and it does not deal with the granularity of data.

295 It does not work to assign credit to a single research entity within a dataset.  
 296 Differently from Zeng et al. [63], we do not treat the credit computation  
 297 process, but we focus on the distribution process.

### 298 2.3. Data Provenance

299 To distribute credit, we base two of our methods on *data provenance*.  
 300 Data provenance is information that describes the origin and the process of  
 301 creation of data. It can also be seen as metadata pertaining to the derivation  
 302 history of the data. It is particularly useful to help users to understand  
 303 where data are coming from, and the process they went through. Data  
 304 citation and data provenance are closely linked [3] since both are forms of  
 305 annotations on data retrieved through queries. Data provenance has been  
 306 widely studied in different areas of data management. In this paper, we  
 307 focus on provenance for database management systems (DBMS). For further  
 308 details on data provenance, please refer to surveys like [17] and [58].

309 Cheney et al. [17] presents four main types of data citation for DBMS: *lin-*  
 310 *age* [23], *why-provenance* [13], *how-provenance* [32] and *where-provenance* [13].

311 Let us start with the first three provenances. Given a database instance  
 312  $I$ , a query  $Q$ , and the result  $Q(I)$ , consider one tuple  $t$  of the output. Its  
 313 provenance is information about its generation through the tuples of the  
 314 input that are used by  $Q$ . Different types of provenance convey different  
 315 levels of information. Since these three provenances are computed for each  
 316 tuple of the output, they are also referred to as *tuple-based*.

317 Where-provenance, differently from the other three, is *attribute-based*, so  
 318 we do not take it into account in this work since we consider the tuple as the  
 319 finest citable unit.

### 320 2.4. Causality and Responsibility

321 We also consider the notions of causality and responsibility, as defined  
 322 in [48]. Causality is an enrichment of lineage, and it is the attribution of  
 323 a certain degree of importance to the tuples of the lineage based on their  
 324 role in the generation of the output. Responsibility is a value given to the  
 325 tuples of the lineage to rank them based on their degree of causality (the  
 326 more important the role of a tuple in generating the output, the higher its  
 327 responsibility).

328 While computing responsibility for general queries is hard [18], Meliou  
 329 et al. [48] proved a dichotomy result for conjunctive queries: for each query  
 330 without self-joins, either its responsibility can be computed in PTIME in the

331 size of the database or checking if it has a responsibility below a given value  
332 is NP-hard.

### 333 2.5. Shapley value

334 The Shapley value was introduced in 1952 [56], framed as a *cooperative*  
335 *game* played by a set  $A$  of players, and defined by a *wealth function*  $v$  that  
336 assigns to each coalition set  $B \subseteq A$  the wealth  $v(B)$ . The question behind the  
337 Shapley Value is how to quantify the contribution of each player to the overall  
338 wealth. Informally, the Shapley value is defined as follows [45]: assume that  
339 we select players randomly one by one and without replacement, starting  
340 with the empty set. Every time a player  $a$  is selected, its addition to the  
341 coalition  $B$  produces a change in the wealth of the coalition from  $v(B)$  to  
342  $v(B \cup \{a\})$ . The Shapley value of  $a$  is the expectation of change that  $a$  causes  
343 in this probabilistic process.

344 The Shapley value has been widely used, e.g. in economics, law, envi-  
345 ronmental science, and network analysis, and has strong theoretical justifica-  
346 tions. However, its use in databases as a metric for quantifying the influence  
347 of a tuple on the output of a query (thereby presenting an alternative to  
348 responsibility) has only recently been considered [45]. The initial theoretical  
349 analysis in [45] showed mainly lower bounds on the complexity of the prob-  
350 lem, and did not suggest a feasible implementation. However, very recently,  
351 an efficient implementation for Boolean queries has been provided [25], both  
352 in terms of an exact computation (which in practice works well for most  
353 queries) and in inexact one (which is extremely fast and provides the same  
354 ranking of tuples as the exact computation, but not necessarily the same  
355 values).

## 356 3. Use Case: GtoPdb

357 The IUPHAR/BPS Guide to Pharmacology [34] (GtoPdb<sup>9</sup>) is a well-  
358 known and well structured scientific relational database that contains ex-  
359 pertly curated information about diseases, drugs in clinical use, their cellular  
360 targets, and the mechanisms of action on the human body. It is curated and  
361 maintained by the GtoPdb Committee and 96 subcommittees, comprising  
362 512 scientists collaborating with in-house curators who draw the information

---

<sup>9</sup><https://www.guidetopharmacology.org/>

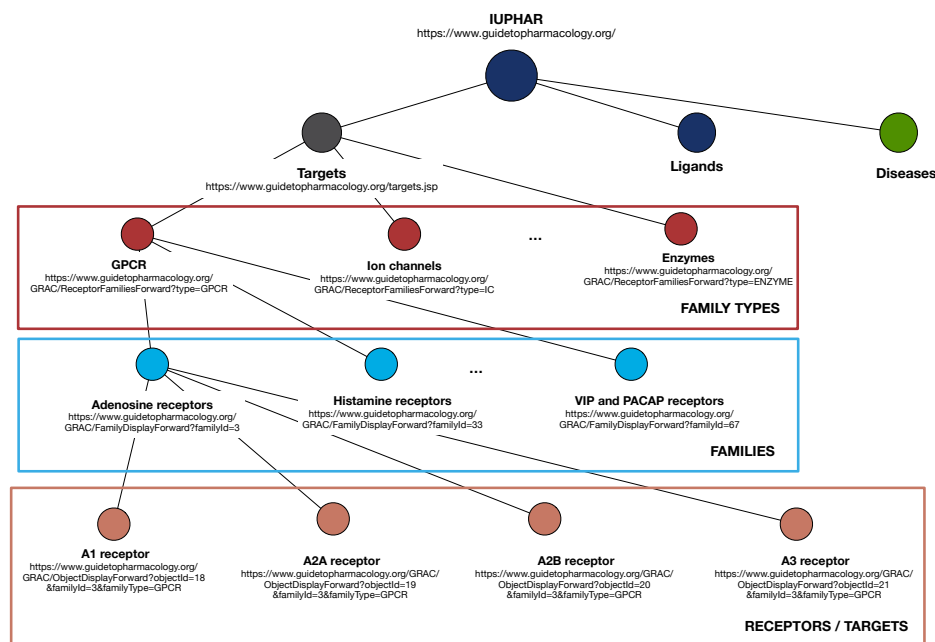


Figure 2: Partial map of the GtoPdb hierarchical structure grouping the targets into families and family types.

contained in the database from high-quality pharmacological and medicinal chemistry literature. Roughly 1000 researchers from all over the world have contributed to the database, and the curators wanted to give recognition to these contributors. This led to some early work on data citation [10].

GtoPdb is relational, but its logical structure is hierarchical as shown in Figure 2. The information contained in the database is also organized into webpages focused on specific diseases, targets or ligands, and families for easier access by users. As depicted in Figure 2, the database can be thought of as a tree where the root is the database; the first level consists of all targets, ligands, and diseases; and the lower levels consists of specific targets, ligands and diseases. In this paper, we focus on targets; thus the figure at the third level shows examples of family types, at the fourth level of specific families of targets (a finer level of granularity), and finally, at the last level, the single targets (also known as receptors).

GtoPdb provides access to the webpages corresponding to all these nodes through URLs. The webpages corresponding to target families all present a similar structure, as shown in Figure 3 for the “Adenosine receptors” family.

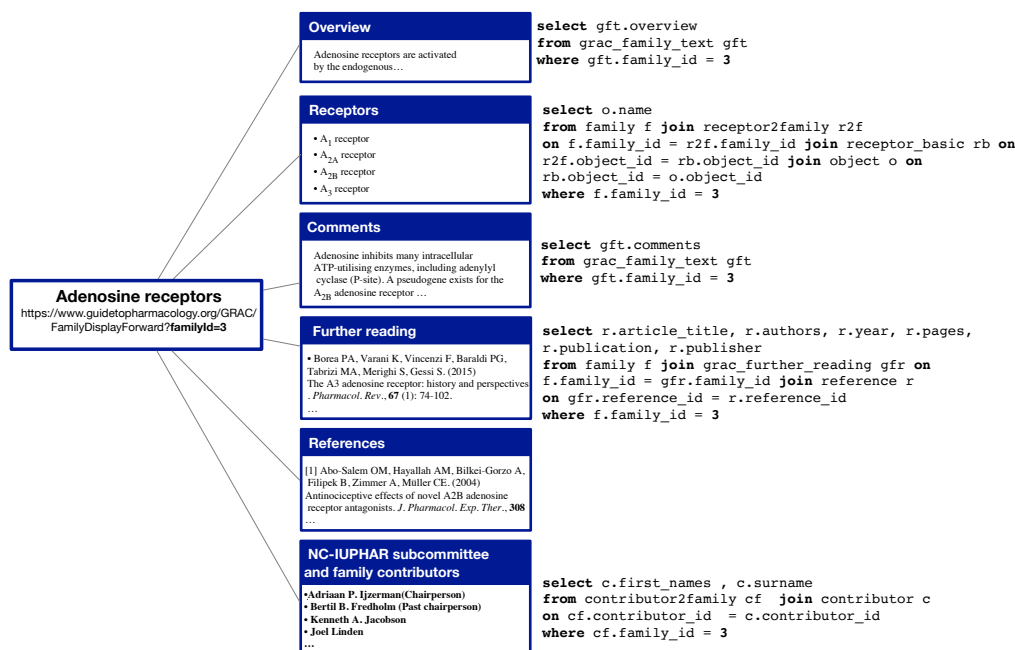


Figure 3: Basic web-page structure of “Adenosine receptors” family (ID 3), with queries used to retrieve the information contained in every section, except references.

Each page has an *Overview*, a brief text describing the content of the page; a list of *Receptors* comprising the family; a section of *comments* about the family; the *References*, a list of the papers consulted by the curators of the page, similar to a reference list of a paper; the *further reading* list, reporting papers that an interested reader may want to consult to obtain more insight on the family; and a final section called *How to cite this family page*, containing text snippets useful to cite the specific page or the whole database. Figure 3 shows the SQL code that retrieves the information used to build the corresponding sections (apart from the References section). Therefore, each family page can be considered a full-fledged traditional publication, consisting of title, authors, abstract (the overview), content, and references.

In practice, many papers in the literature only reference GtoPdb (the root) without including a reference to the specific page being cited. That is, they only cite a paper describing GtoPdb as a whole (e.g., [34]) and refer to targets, ligands, diseases, etc. only by name. Thus, citations to specific families are *de-facto* “hidden” to citation systems such as Google Scholar, and useless for the computation of bibliometrics.

family			contributor2family		
id	name	type	id	family_id	contributor_id
$f_1$	Dopamine Receptors	gpcr	$c2f_1$	$f_1$	$c_1$
$f_2$	Bile Acid Receptor	gpcr	$c2f_2$	$f_1$	$c_2$
$f_3$	FAK Family	enzyme	$c2f_3$	$f_2$	$c_3$
$f_4$	YANK Family	enzyme	$c2f_4$	$f_4$	$c_1$

contributor		
id	Name	Country
$c_1$	John Smith	UK
$c_2$	Jim Doe	UK
$c_3$	Hans Zimmerman	Germany
$c_4$	Roberta Rossi	Italy

Table 1: Example of a database consisting of three tables. **family** contains receptor families; **contributor** contains the name and country of contributors; **contributor2family** connects contributors to the families they contributed to.

397 In certain “lucky” cases, as with papers available in PDF and published  
398 in the British Journal of Clinical Pharmacology <sup>10</sup> (BJCP), when a family,  
399 ligand, receptor name, etc. are used, they have a hyperlink pointing to the  
400 corresponding webpage in GtoPdb. Therefore, the citations to the families  
401 can be detected and counted using the URLs reported in the papers. How-  
402 ever, these citations to GtoPdb webpages are not counted as such by citation  
403 systems, so they are not converted into credit for curators and collaborators.

404 For our running example, consider Table 1. This simplified version of  
405 GtoPdb contains three tables: **family**, **contributor** and **contributor2family**.  
406 The first table, **family**, has tuples representing families with three attributes:  
407 the id of the family, its name, and type. Table **contributor** contains peo-  
408 ple who have helped generate the data in the database. The third table,  
409 **contributor2family**, serves as a link between the families and the people  
410 who contributed to them. For instance, “John Smith” ( $c_1$ ) contributed to  
411 “Dopamine Receptors” ( $f_1$ ) as well as to the “YANK Family” ( $f_4$ ). Through-  
412 out the rest of the paper, we will use the **id** attribute of these tables as the  
413 *provenance token* of its corresponding tuples, that is, as a symbol that serves  
414 to identify a tuple when talking about provenance.

---

<sup>10</sup><https://bpspubs.onlinelibrary.wiley.com/journal/13652125>

$I$	database instance
$L_t$	lineage set of an output tuple $t$
$\Gamma$	contingency set
$\rho_t$	responsibility of tuple $t$
$Q$	a query
$\bar{Q}_o$	Boolean query such that $\bar{Q}_o(I) = 1$ if $o$ is present in $Q(I)$
$\mathcal{W}$	witness basis
$W$	a witness set
$\gamma(\mathcal{W}, t)$	set of witnesses in $\mathcal{W}$ containing $t$
$\mathcal{H}$	provenance polynomial
$M_i$	a monomial in $\mathcal{H}$
$t_j$	a tuple in $M_i$
$c(\mathcal{H})$	sum of $\mathcal{H}$ 's coefficients
$e(M_i)$	sum of $M_i$ 's exponents
$mc(M_i)$	$M_i$ 's coefficient
$te(t_j, M_i)$	exponent of $t_j$ in $M_i$
$\gamma(t_j, \mathcal{H})$	set of monomials in $\mathcal{H}$ containing $t_j$

Table 2: Notations used in this paper.

#### 4. Provenance, Responsibility, and Shapley

We now describe the three types of provenance used in this paper – lineage, why-provenance, and how-provenance – as well as the notion of causality and responsibility, and the Shapley value function.

##### 4.1. Lineage

Lineage is the simplest form of provenance. It was first introduced by Cui et al. [23], and can be thought of as the set of all tuples that are used by the query to generate the output [17].

As an example, consider the following SQL query **Q1**, applied to the database described in Table 1, asking for the names of families curated by researchers based in the United Kingdom (UK):

```

Q1: SELECT DISTINCT f.name
FROM family AS f JOIN contributor2family AS c2f
ON f.id = c2f.family_id
JOIN contributor AS c ON c2f.contributor_id = c.id
WHERE c.country = 'UK'
```



id	name	lineage
$o_1$	Dopamine Receptors	$\{f_1, c2f_1, c_1, c2f_2, c_2\}$
$o_2$	YANK Family	$\{f_4, c2f_4, c_1\}$

Table 3: Result of Q1 over the database instance in Table 1 with the lineage of each output tuple. Attribute `id` is not part of the output, and was added to identify each tuple.

Table 3 shows the query output, which consists of two tuples. We add an extra attribute `id` so that we can easily refer to each result tuple. The lineage for tuple  $o_1$  is the set  $\{f_1, c2f_1, c_1, c2f_2, c_2\}$ , since the tuple  $f_1$  was joined with  $c2f_1$  and then with  $c_1$ , and was also joined with  $c2f_2$  and  $c_2$ . No other tuple is used in the database to produce  $o_1$ . For tuple  $o_2$  the lineage is  $\{f_4, c2f_4, c_1\}$ . Lineage is defined for each tuple of the output, and can differ between tuples.

#### 4.2. Why-Provenance

Why-Provenance was first defined in terms of a deterministic semistructured data model and query language [13]. We use here its definition in terms of the relational model [17].

While lineage aims to find all and only the tuples in the input relevant to the production of an output tuple, why-provenance aims to find sub-instances of the input that “witness” a part of the output. Given a tuple  $t$  in the query’s output  $Q(I)$ , a *witness* is any sub-instance of the database that produces  $t$ , i.e., a set that guarantees the existence of  $t$  in  $Q(I)$ . In particular, the whole database and the lineage of  $t$  are both examples of witnesses of  $t$ . Since the definition of witness allows for the presence of “irrelevant” tuples, the set of all witnesses is finite (since the database instance  $I$  is finite), but it is potentially exponentially large [17].

Buneman et al. [13] defined the why-provenance of an output tuple  $t$  in the result  $Q(I)$  as a special *subset* of the set of witnesses called the *witness basis*. The witnesses of the basis exclude tuples that are irrelevant to  $t$  being produced by  $Q$ , and thus the basis tends to be very small compared to the set of all possible witnesses [17].

In a sense, each witness in the witness basis captures one possible way in which a tuple in the output was generated by the query. To better understand this, consider the example in Table 4, where each tuple in the result of query Q1 is annotated with its why-provenance.

id	name	why-provenance
$o_1$	Dopamine Receptors	$\{\{f_1, c2f_1, c_1\}, \{f_1, c2f_2, c_2\}\}$
$o_2$	YANK Family	$\{\{f_4, c2f_4, c_1\}\}$

Table 4: Result of Q1 over the database instance in Table 1 with the why-provenance of each output tuple.

460 The why-provenance of output tuple  $o_2$  has only one witness, which co-  
461 incides with its lineage. This happens because there is only one way this  
462 output tuple can be produced, i.e., for tuple  $f_4$  to be joined with  $c2f_4$  and  $c_1$ .  
463 On the other hand,  $o_1$  has a witness basis of two witnesses, since there are  
464 two possible ways in which the query can generate  $o_1$ . One possibility is that  
465  $f_1$  is joined with  $c2f_1$  and  $c_1$  (the first witness), and the second possibility  
466 is that  $f_1$  is joined with  $c2f_2$  and  $c_2$  (the second witness). This means that  
467 to generate  $o_1$ , it is sufficient that only one of the two witnesses is present in  
468 the input database.

#### 469 4.3. How-Provenance

470 While why-provenance describes the source tuples that witness an output  
471 tuple in the result of the query, it leaves out information about how the source  
472 tuples are used. How-provenance was therefore defined in [32] to capture  
473 this information using a *semiring* algebraic structure. It takes the form of  
474 a polynomial, called *provenance polynomial*, where the variables are taken  
475 from the set  $X$  of identifiers of the tuples (provided that each tuple in  $I$  has  
476 an identifier) and the coefficients are drawn from the set of natural numbers  
477  $\mathbb{N}$ .<sup>11</sup>

478 The key idea in Green et al. [32] is to use the two operators  $+$  and  $\cdot$  to  
479 represent two basic transformations that source tuples undergo as a result  
480 of applying a relational query to a database [17]. Two tuples may either  
481 be joined together (a join is represented with the  $\cdot$  operator) or merged via  
482 union or projection (represented with the  $+$  operator).

483 Table 5 shows the two output tuples of our running example annotated  
484 with their respective how-provenances. Tuple  $o_2$  was produced by a join of  
485 the input tuples  $f_4, c2f_4$ , and  $c_1$ . The three provenance tokens are therefore  
486 “multiplied” together. The case of  $o_1$  is slightly more complex, as already  
487 discussed. It can be obtained by the joins of two different sets of tuples,

---

<sup>11</sup>This semiring is commonly referred as  $\mathbb{N}[X]$  in the literature.

id	name	how-provenance
$o_1$	Dopamine Receptors	$f_1 \cdot c2f_1 \cdot c_1 + f_1 \cdot c2f_2 \cdot c_2$
$o_2$	YANK Family	$f_4 \cdot c2f_4 \cdot c_1$

Table 5: Result of Q1 over the database instance in Table 1 with the how-provenance polynomial of each output tuple.

so there are two monomials combined by + representing these alternative derivations. Each monomial corresponds, in a way, to the witnesses of the why-provenance of  $o_1$ .

Provenance polynomials may also have monomials whose exponents and/or coefficients are greater than one, for example,  $3f_1 \cdot c2f_1 \cdot c_1 + f_1 \cdot c2f_2^3 \cdot c_2^3$ . This is a polynomial of a tuple produced by a query where the result of the join between the tuples  $f_1$ ,  $c2f_1$ , and  $c_1$  is produced three times and then merged (e.g. as the result of a union), and the tuples  $c2f_2$  and  $c_2$  are used three times in the operation described by the second monomial (e.g., with nested queries).

#### 4.4. Causality and Responsibility

A formal study of causality was introduced in [18, 33] and later expanded by Meliou et al. [48] to explain the causes of answers and non-answers to queries. In the following, we refer to the definition of causality and responsibility provided in [48]. In particular, we only focus on answers to a query since non-answers are not relevant in our context.

There are two types of “cause” tuples: counterfactual and actual. Let  $o$  be a tuple in the result of query  $q$  on the database instance  $I$ , and  $t$  a tuple in its lineage. We call  $t$  a *counterfactual cause* if, by removing  $t$  from  $I$ ,  $o$  is also removed from the output (i.e.,  $t$  is essential for the generation of  $t$ ). We call  $t$  an *actual cause* if there is a set of tuples  $\Gamma \subseteq I$  called a *contingency set*, such that  $t$  is a counterfactual cause in  $I - \Gamma$ . In other words,  $t$  is an actual cause if, even when removed from  $I$ , there is another set of tuples of the lineage that guarantees the presence of  $o$ .

Computing the causality of tuples is NP-complete for general queries [28], but for conjunctive queries can be computed in PTIME, as showed by Meliou et al. [48].

The notion of *responsibility* measures the degree of causality as a function of the size of the smallest contingency set [18]. This allows us to rank lineage

id	name	responsibility
$o_1$	Dopamine Receptors	$f_1 = 1, c_2f_1 = 0.5, c_2f_2 = 0.5, c_1 = 0.5, c_2 = 0.5$
$o_2$	YANK Family	$f_4 = 1, c_2f_4 = 1, c_1 = 1$

Table 6: Result of Q1 over the database instance in Table 1 with the responsibilities of lineage tuples.

518 tuples based on their degree of causality in generating the output.

**Definition 4.1.** *Responsibility* [48]

Let  $o$  be an output tuple in the result of query  $Q$  on  $I$ , and let  $t$  be a cause for  $o$ . The responsibility of  $t$  for the answer  $o$  is:

$$\rho_t = \frac{1}{1 + \min_{\Gamma} |\Gamma|}$$

519 where  $\Gamma$  ranges over all contingency sets for  $t$ .

520 Note that a counterfactual cause will have the maximum responsibility  
521 of 1, and that the larger the minimum contingency of an actual cause is, the  
522 smaller its responsibility will be since there are alternatives to guarantee the  
523 presence of the answer  $o$ .

524 As an example, consider Table 5, where we reported the result set of Q1  
525 and the tuples of the lineages with their responsibility values. Focusing on  
526  $o_1$ : the lineage tuple  $f_1$  is a counterfactual cause, since its contingency set is  
527 empty (when removed from the database,  $o_1$  disappears from the result set).  
528 Consequently, its responsibility is 1. All the other tuples of the lineage are  
529 actual causes.  $c_1$ , for example, has as minimal contingency set  $\{c_2f_2\}$ , thus  
530 its responsibility is 0.5. For the output tuple  $o_2$ , all the tuples of the lineage  
531 are counterfactual causes, thus their responsibility is 1.

532

#### 533 4.5. Shapley value

534 We use the definitions provided in [25]: Let  $q$  be a Boolean query and  $f \in$   
535  $D$  be a fact, the Shapley value of  $f$  in  $D$  intuitively represents the contribution  
536 of  $f$  to the query result.<sup>12</sup> The higher the value, the more  $f$  helps in satisfying  
537  $q$ . Formally, the Shapley value is defined as follows:

---

<sup>12</sup>We ignore the distinction between endogenous and exogenous facts, since in our setting they are all assumed to be endogenous.

id	name	Shapley value
$o_1$	Dopamine Receptors	$f_1 = \frac{7}{15}, c_2 f_1 = \frac{2}{15}, c_2 f_2 = \frac{2}{15}, c_1 = \frac{2}{15}, c_2 = \frac{2}{15}$
$o_2$	YANK Family	$f_4 = \frac{1}{3}, c_2 f_4 = \frac{1}{3}, c_1 = \frac{1}{3}$

Table 7: Result of **Q1** over the database instance in Table 1 with the Shapley values of the tuples of the lineage. In this case  $D^n$  corresponds to the lineage.

$$Shapley(q, D, f) = \sum_{E \subseteq D \setminus \{f\}} \frac{|E|! (|D| - |E| - 1)!}{|D|!} \left( q(E \cup \{f\}) - q(E) \right)$$

The sum in this value is performed on all possible subsets of  $D$  that do not contain  $f$ . The value  $(q(E \cup \{f\}) - q(E))$  is the “wealth” brought by  $f$  when added to  $E$ . Thus, the Boolean query is used as a wealth function  $v$ : its value is 1 only when the set  $E \cup \{f\}$  makes the query true, and the set  $E$  makes it false, i.e., when the addition of the fact  $f$  is determinant to making the Boolean query true. The value  $|E|! (|D| - |E| - 1)!$  is the number of all the possible permutations over  $D$  where the facts in  $E$  come first, then  $f$  is added, and then all the remaining facts. Thus, the value  $\frac{|E|! (|D| - |E| - 1)!}{|D|!}$  can be thought as a weight for the wealth brought by  $f$  when added to  $E$ .

To extend this definition to non-Boolean queries, we adopt the approach in Deutch et al. [25]: the Shapley value of the fact  $f$  for the answer  $\bar{t}$  to  $Q(\bar{x})$  is the value  $Shapley(Q[\bar{x}/\bar{t}], D, f)$ , where  $Q[\bar{x}/\bar{t}]$  is the Boolean query defined by  $Q[\bar{x}/\bar{t}](D) = 1$  if and only if  $\bar{t}$  is in the output of  $Q(\bar{x})$  on  $D$ , and 0 otherwise. In other words, the definition of  $Shapley(q, D, f)$  is extended to queries  $Q(\bar{x})$  with free variables by considering the Boolean query  $Q[\bar{x}/\bar{t}]$  as a value function. This query can be seen as a function that takes as input a set of facts and returns 1 if this set is a witness for  $\bar{t}$ , and 0 otherwise.

As an example, consider Table 7, that shows the Shapley values for the lineage’s tuples of  $o_1$  and  $o_2$ , results of query **Q1**. We note that, to compute the Shapley value of an input tuple  $f$  it is sufficient to compute and sum the values  $\frac{|E|! (|D| - |E| - 1)!}{|D|!}$  for all the possible sets  $E$  such that  $E \cup \{f\}$  is a witness and  $E$  is not. Thus, suppose we want to compute the Shapley value of the tuple  $f_1$ . Let us call  $\bar{Q}_{1,o_1}$  the Boolean query such that  $\bar{Q}_{1,o_1}(D) = 1$  if and only if  $o_1$  is in the output of **Q1** on  $D$ , and  $L_{o_1}$  is the lineage of  $o_1$ . Then the Shapley value of  $f_1$  with respect of  $o_1$  is given by:

$$\begin{aligned} Shapley(\bar{Q}_{1,o_1}, L_{o_1}, f_1) &= \frac{2!2!}{5!} + \frac{2!2!}{5!} + \frac{3!}{5!} + \frac{3!}{5!} + \frac{3!}{5!} + \frac{3!}{5!} + \frac{4!}{5!} \\ &= \frac{7}{15} \end{aligned}$$

563 where for the first element of the sum the corresponding  $E$  is  $\{c2f_1, c_1\}$ , for  
 564 the second element it is  $\{c2f_2, c_2\}$ , for the third  $\{c2f_1, c2f_2, c_1\}$ , for the fourth  
 565  $\{c2f_1, c_1, c_2\}$ , for the fifth  $\{c2f_2, c_2, c_1\}$ , for the sixth  $\{c2f_1, c2f_2, c_2\}$ , and for  
 566 the seventh  $\{c2f_1, c2f_2, c_1, c_2\}$ . Every other possible subset  $E$  would make  
 567 the factor equal to 0. Note that in this case we consider  $D = L_{o_1}$ , the lineage  
 568 of  $o_1$ , since these are the only facts in all the database that contribute to the  
 569 generation of  $o_1$ .

Similarly, for tuple  $c_1$  (and the other tuples of the lineage), the computation is:

$$\begin{aligned} \text{Shapley}(\bar{Q}_{1,o_1}, L_{o_1}, c_1) &= \frac{2!2!}{5!} + \frac{3!}{5!} + \frac{3!}{5!} \\ &= \frac{2}{15} \end{aligned}$$

570 It can be seen that for all the tuples of  $o_2$ 's lineage the corresponding  
 571 Shapley values are equal to  $1/3$ , since they are all equally responsible for  
 572 the generation of the output. Thus the sum of the Shapley values of all the  
 573 tuples in an output tuple's lineage is always equal to 1 when using a Boolean  
 574 query as wealth function.

## 575 5. Credit Distribution and Distribution Strategies

576 We now give formal definitions of data credit and Data Credit Dis-  
 577 tribution (DCD), and present three different Distribution Strategies (DSs)  
 578 based on the forms of provenance discussed earlier: Lineage-based DS, Why-  
 579 Provenance-based DS, How-Provenance-based DS, **responsibility-based DS,**  
 580 **and the Shapley value-based DS.** We also show how these strategies distribute  
 581 credit in the IUPHAR example discussed earlier.

### 582 5.1. Data Credit and Data Credit Distribution

583 Given a database instance  $I$ , a *recipient of credit* is a unit of information  
 584 within  $I$ . In the case of relational databases, recipients may be (i) the whole  
 585 database; (ii) a table; (iii) a tuple; or (iv) an attribute.

586 *Data credit* is a value  $k \in \mathbb{R}_{>0}$ . Every recipient in a database is annotated  
 587 with a quantity of credit as a proxy for its importance. In this paper, we  
 588 focus on *tuples* as recipients of credit.

589 Given a *distribution strategy* (DS), *Data Credit Distribution* (DCD) takes  
 590 a database instance  $I$ , a quantity of credit  $k$ , and query  $Q$  over  $I$ , and it splits  
 591  $k$  among the recipients of credit in  $I$ .

592 In the following, we use the notation in Cheney et al. [17]: Given a  
 593 database instance  $I$ , a *tuple location*  $(R, t)$  is a tuple  $t$  in relation  $R$ . With  
 594 reference to the running example,  $(\text{family}, \langle f_1, \text{Dopamine Receptors},$

595 `gpcr`) is the tuple location of the first tuple in the `family` relation. The set  
 596 of all tuple locations in  $I$  is called *TupleLoc*. We use this to formally define  
 597 DCD at the *tuple level*.

598 **Definition 5.1. Tuple Level Data Credit Distribution (DCD)** [26]  
 599 *Given a query  $Q$  over  $I$  and  $k \in \mathbb{R}_{>0}$ , DCD is defined by the function  $f_{I,Q} :$   
 600  $\text{TupleLoc} \times \mathbb{R}_{>0} \rightarrow \mathbb{R}_{\geq 0}$  such that  $f_{I,Q}(t, k) = h$  where  $0 \leq h \leq k$  and  
 601  $\sum_{t \in \text{TupleLoc}} f_{I,Q}(t, k) = k$ . The function  $f_{I,Q}$  is the distribution strategy (DS).*

602 As we can see, the DS is a function that annotates each tuple in the  
 603 database with a real value, which is a fraction of the given quantity  $k$ . The  
 604 only constraint is that the sum of the credit annotations on tuples must be  
 605  $k$ , i.e. that no credit is generated or destroyed during the distribution. Given  
 606  $I$  and  $Q$ , many different DSs may be defined as long as they sum up to  $k$ .

607 In what follows, we use information provided by data provenance to de-  
 608 fine distribution functions. For simplicity, we assume that the credit  $k$  is  
 609 distributed equally across the set of output tuples (i.e. the result of a query),  
 610 and discuss how the credit of one output tuple  $o$ ,  $k_o$ , is distributed across the  
 611 instance  $I$ .

## 612 5.2. A Lineage-based Distribution Strategy

613 In the lineage-based distribution strategy, each tuple in the output of  
 614 a query distributes credit equally to each input tuple that appears in its  
 615 lineage. More formally:

**Definition 5.2. Lineage-based Distribution Strategy** [26]

*Let  $I$  be a database instance,  $Q$  a query over  $I$ ,  $o \in Q(I)$  an output tuple and  
 $k_o$  the credit associated to  $o$ . Let  $L$  be the lineage of  $o$  and  $t$  be a tuple in  $I$ ,  
 then  $t$  receives credit equal to:*

$$f_{I,Q}(t, k_o) = \begin{cases} 0 & \text{if } t \notin L \\ \frac{k_o}{|L|} & \text{if } t \in L \end{cases}$$

616 Note that lineage-based DS distributes credit only to input tuples that  
 617 have a role in creating  $o$  by the query  $Q$ , and that each receives an equal  
 618 share of credit. Thus, the more tuples in a lineage set, the less credit each  
 619 tuple receives.

620 As an example, consider the output tuples of Table 3, and assume that  
 621 each output tuple has credit  $k_o = 1$ . The lineage of the first tuple,  $o_1$ , is

the set  $\{f_1, c2f_1, c_1, c2f_2, c_2\}$ . Therefore, each tuple in this set receives credit 1/5. The other tuples of the database receive zero credit. The lineage of the second output tuple is  $\{f_4, c2f_4, c_1\}$ , therefore each of these tuples receives credit 1/3.

At the end of the process, tuples  $f_1$ ,  $c2f_2$  and  $c_2$  each receive credit 1/5, tuples  $f_4$  and  $c2f_4$  receive 1/3, while tuple  $c_1$  receives 8/15. Note that if a tuple appears in more than one lineage set, then it will accumulate credit from the distribution associated with each one of these sets, implying that it has a more significant role in the context  $Q$ , as is the case with  $c_1$  in this example.

Not all of the tuples in the lineage of an output tuple are necessary to be present at the same time for the output tuple to appear in the query results. For example, if the database only had the set of tuples  $\{f_1, c2f_1, c_1\}$  or the set  $\{f_1, c2f_2, c_2\}$ , the existence of  $o_1$  would still be guaranteed. In other words, while  $f_1$  is always needed for  $o_1$  to appear in the output, only one of the sets of tuples  $\{c2f_1, c_1\}$  and  $\{c2f_2, c_2\}$  is required. One could therefore argue that it would be more fair for  $f_1$  to receive more credit than the other four tuples, given its role in producing  $o_1$ .

This highlights one limitation of the lineage-based DS: while able to find all and only the relevant tuples of the output, it does not distinguish the *importance* of tuples in the query computations. We therefore present four other, more sophisticated, forms of distribution strategies based on why-provenance, how-provenance, **responsibility**, and **Shapley value**.

### 5.3. A Why-Provenance-Based Distribution Strategy

The distribution strategy based on why-provenance first equally distributes the credit  $k_o$  among the witnesses of the witness basis for  $o$ , and then equally divides the credit of a witness among the tuples in the witness. Since a tuple may appear in more than one witness, it will receive more than one portion of credit from the same distribution. More formally:

#### Definition 5.3. Why-Provenance-based Distribution Strategy

Let  $I$  be a database instance,  $Q$  a query over  $I$ ,  $o \in Q(I)$  an output tuple and  $k_o$  the total credit associated to  $o$ . Let  $\mathcal{W} = \text{Why}(Q, I, o)$  be the witness basis of  $o$  according to  $Q$  and  $I$ , and  $W \in \mathcal{W}$  be a witness.

Then tuple  $t$  in  $I$  receives credit equal to:

$$f_{I,Q}(t, k_o) = \frac{k_o}{|\mathcal{W}|} \sum_{W \in \gamma(\mathcal{W}, t)} \frac{1}{|W|}$$



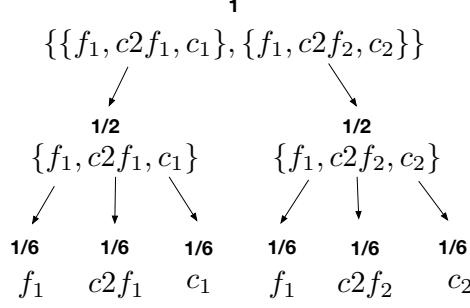


Figure 4: Distribution of credit using why-provenance-based DS for tuple  $o_1$ .

where  $\gamma$  is a function which returns all witnesses  $W$  in which  $t$  appears:

$$\gamma(\mathcal{W}, t) = \{W \in \mathcal{W} : t \in W\}$$

Figure 4 shows the distribution of credit with why-provenance-based DS for tuple  $o_1$ . The credit is first equally divided between the two witnesses, so that both receive credit  $1/2$ . The credit is then further divided among the tuples in each witness. Since each witness has three tuples, each tuple in a witness receives  $1/6$  of credit. At the end of the distribution,  $f_1$  receives a total credit of  $1/3$ , and the other tuples receive  $1/6$  each. This distribution better reflects the role of  $f_1$  in the generation of  $o_1$  since, as discussed earlier, it is the only mandatory tuple for  $o_1$  to appear in the output; only one of the two other pairs of tuples are necessary for  $o_1$  to appear in the result.

This example illustrates that why-provenance can better reward input tuples depending on their role. Tuples that appear in more than one witness are rewarded more than others.

#### 5.4. A How-Provenance Based Distribution Strategy

The how-provenance-based DS first distributes the credit to the monomials of the polynomial accordingly to the weight represented by their coefficients, then to the tuples of each monomial accordingly to the weights represented by their exponents.

To define the DS more formally, we introduce some notation and illustrate it using the provenance polynomial  $\mathcal{H}$  shown in Figure 5. This notation is also shown in Table 2 for easy reference.

We call  $c$  the function that, given a polynomial, returns the sum of its coefficients; thus  $c(\mathcal{H}) = 3 + 1 = 4$ . We call  $e$  the function that, given a

$$\begin{aligned}
\mathcal{H} &= \underbrace{3f_1 \cdot c2f_1 \cdot c_1}_{M_1} + \underbrace{f_1 \cdot c2f_2^3 \cdot c_2^3}_{M_2} \\
c(\mathcal{H}) &= 4 & e(M_2) &= 7 \\
mc(M_1) &= 3 & mc(M_2) &= 1 \\
te(c_2, M_2) &= 3 & \gamma(c_1, \mathcal{H}) &= \{M_1\} \\
\gamma(f_1, \mathcal{H}) &= \{M_1, M_2\}
\end{aligned}$$

Figure 5: Illustration of notation used to define the how-provenance based DS

677 monomial, returns the sum of its exponents, thus  $e(M_2) = 1 + 3 + 3 = 7$ .  
678  $mc$  is the function that takes as input a monomial and returns its coefficient; thus  $mc(M_1) = 3$ .  $te$  is a function that takes as input a tuple and a  
679 monomial, and returns the exponent of the tuple in the monomial, if present;  
680 thus  $te(c_2, M_2) = 3$ . Finally,  $\gamma$  takes as input a tuple and the whole polynomial,  
681 and returns a set of monomials containing that tuple, if present in the  
682 polynomial; thus  $\gamma(f_1, \mathcal{H}) = \{M_1, M_2\}$ ,  $\gamma(c_2, \mathcal{H}) = \{M_2\}$ .  
683

**Definition 5.4.** *How-Provenance-Based Distribution Strategy*

Let  $I$  be a database instance,  $Q$  a query over  $I$ ,  $o \in Q(I)$  an output tuple,  $\mathcal{H}$  be the provenance polynomial for  $o$ , and  $k_o$  the credit given to  $o$ . The credit given to tuple  $t$  in  $I$  is:

$$f_{I,Q}(t, k_o) = \frac{k_o}{c(\mathcal{H})} \sum_{M \in \gamma(t, \mathcal{H})} mc(M) \frac{te(t, M)}{e(M)}$$

684 Going back to the example of Table 5, consider  $o_1$  with provenance poly-  
685 nomial  $f_1c2f_1c_1 + f_1c2f_2c_2$ . The how-provenance-based DS firstly divides  
686 the credit between the two monomials. Since the coefficients of each mono-  
687 mial are 1, the credit is split in half. If they were, for example, 1 and 2  
688 respectively, 1/3 of the credit would go to the first monomial, and 2/3 to  
689 the second. Since in our example each variable has exponent 1, the credit is  
690 further divided equally among the three variables. Thus, at the end of the  
691 computation,  $f_1$  receives 1/3, and the other tuples receive 1/6.

692 In this specific example, the how-provenance-based DS has the same out-  
693 come as the one based on why-provenance. We therefore consider another  
694 query over GtoPdb, Q2, that asks for the families of type **gpcr** that have as  
695 contributor a researcher located in the UK:

id	name
$oxs_1$	Dopamine Receptors

lineage	why-provenance	how-provenance
$\{f_1, c2f_1, c_1, c2f_2, c_2\}$	$\{\{f_1, c2f_1, c_1\}, \{f_1, c2f_2, c_2\}\}$	$f_1^2 c2f_1 c_1 + f_1^2 c2f_2 c_2$

Table 8: Result of query Q2 applied on the database of Table 1 and its different provenances. The reported numbers are the credit distributed through the process.

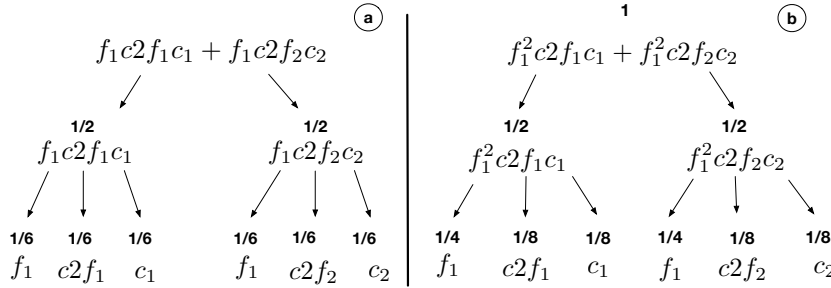


Figure 6: Comparison of different distributions obtained with the how-provenance-based DS with queries Q1 and Q2.

```

696 Q2: SELECT DISTINCT F.name
697 FROM family as F JOIN
698 (SELECT DISTINCT f.name AS name
699 FROM family AS f JOIN contributor2family AS c2f ON f.id = c2f.family_id
700 JOIN contributor AS c ON c2f.contributor_id = c.id
701 WHERE c.country = "UK") AS R ON F.name = R.name
702 WHERE F.type = "gpcr"

```

The result of Q2 is shown in Table 8, and consists of one tuple,  $oxs_1$ , annotated with each of the three provenances. As can be seen, lineage and why-provenance are identical to those of the tuple  $o_1$  in the previous example. The how-provenance, however, is different since tuple  $f_1$  is used twice: first in the join of the inner query, and second in the join of the outer query. This information is lost in the first two forms of provenances since they are sets, but it is captured in how-provenance through the use of the operator ‘.’.

Figure 6 shows the differences between the three DS for the tuple  $o_1$  of Table 8. Subfigure 8.a uses lineage, sub-figure 8.b uses why-provenance, and sub-figure 8.c uses how-provenance. The DS based on the provenance polynomial gives credit 1/2 to  $f_1$ , and 1/8 to the other tuples. This is reasonable since Q2 relies on  $f_1$  even more than Q1 does. The distribution

715 based on how-provenance rewards  $f_1$  more, showing that how-provenance is  
 716 even more sensitive to the tuples' role in a query than why-provenance. This  
 717 is a direct consequence of the fact that, as proven in [32], how-provenance is  
 718 more general than why-provenance and lineage, in the sense that it contains  
 719 more information.

720

### 721 5.5. Responsibility-based Distribution Strategy

722 As described in Section 4.3, causality and responsibility is new informa-  
 723 tion that is added to lineage. One possible option for defining a distribution  
 724 strategy using responsibility is to simply assign the responsibility of each tu-  
 725 ple in the lineage of an output tuple as its credit. In this way, responsibility  
 726 is both a way to compute credit and to distribute it. Using the example of  
 727 Table 6, in the case of output tuple  $o_1$ ,  $f_1$  receives credit 1 and the other  
 728 tuples receive credit 0.5.

729 However, we want a DS that is also a function of the input credit value  
 730  $k$  in order to be comparable with the other three strategies proposed so far.  
 731 We define a new DS based on responsibility that is a function of the quantity  
 732 of credit  $k_o$  that assigns to each tuple of the lineage a portion of this credit  
 733 weighted by its normalized quantity of responsibility. This will give a bigger  
 734 portion of credit to tuples that are higher in the responsibility ranking. For-  
 735 mally:

736

#### **Definition 5.5.** *Responsibility-based Distribution Strategy*

*Let  $I$  be a database instance,  $Q$  a query over  $I$ ,  $o \in Q(I)$  an output tuple,  $L$  the lineage of  $o$ , and  $k_o$  the credit given to  $o$ . The credit given to tuple  $t$  in  $I$  is:*

$$f_{I,Q}(t, k_o) = k_o \frac{\rho_t}{\sum_{t' \in L} \rho_{t'}}$$

737 where  $\rho_j$  is the responsibility of tuple  $j$  as in Definition 4.1.

738 Note that only the tuples that belong to the lineage will receive a quantity  
 739 of credit  $> 0$ . Furthermore, the more important the tuple is, i.e., the higher  
 740 its responsibility, the larger the quantity of credit received.

741 Figure 7 shows the responsibility and credit assigned to the tuples of the  
 742 lineage of the output tuple  $o_1$  of Table 6. Assuming that  $k_{o_1} = 1$ ,  $f_1$  receives  
 743 credit  $1/3$ , while the others receive credit  $1/6$ . As we see, the DS in this  
 744 case returns the same distribution as that obtained using why-provenance as

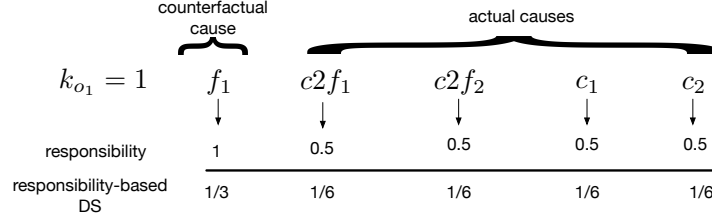


Figure 7: Example of distribution of credit using the responsibility-based DS, assuming  $k_o = 1$ .

745 shown in Figure 6. This is not always the case though, as we show in the  
 746 example of Section 6.2.

747

#### 748 5.6. Shapley value-based Distribution Strategy

749 As with responsibility, the Shapley value can be seen both as a method  
 750 to generate and distribute credit. Moreover, it can be seen that, using the  
 751 definition of Shapley value for Boolean queries given in Section 4.3, the sum  
 752 of the Shapley values of all the tuples of the lineage  $L$  of an output tuple  $o$   
 753 is 1. Thus, the definition of a Shapley value-based distribution strategy is  
 754 straightforward:

**Definition 5.6.** *Shapley Value-Based Distribution Strategy*

*Let  $I$  be a database instance,  $Q$  a query over  $I$ ,  $o \in Q(I)$  an output tuple, and  $k_o$  the credit given to  $o$ . The credit given to tuple  $t$  in  $I$  is:*

$$f_{I,Q}(t, k_o) = k_o \cdot \text{Shapley}(\bar{Q}_o, I, t)$$

755 where  $\bar{Q}_o$  is the Boolean query such that, given the set of facts  $D$ ,  $\bar{Q}_o(D) = 1$   
 756 if and only if  $o$  is in the output of  $Q$  on  $D$ .

757 As shown in Table 7, tuple  $f_1$  in  $o_1$ 's lineage takes credit 7/15 when  
 758  $k_{o_1} = 1$ , while the other tuples of the lineage take credit 2/15. This DS still  
 759 rewards  $f_1$  more than the other tuples, since it is more important than the  
 760 other tuples of the lineage. This DS thus behaves differently from all the  
 761 other four previous strategies. In particular,  $f_1$  is rewarded more with this  
 762 DS than with the others.

763 In the case of  $o_2$  there is only one witness set, thus this DS behaves like  
 764 all the others, distributing 1/3 of credit to each tuple in the lineage.

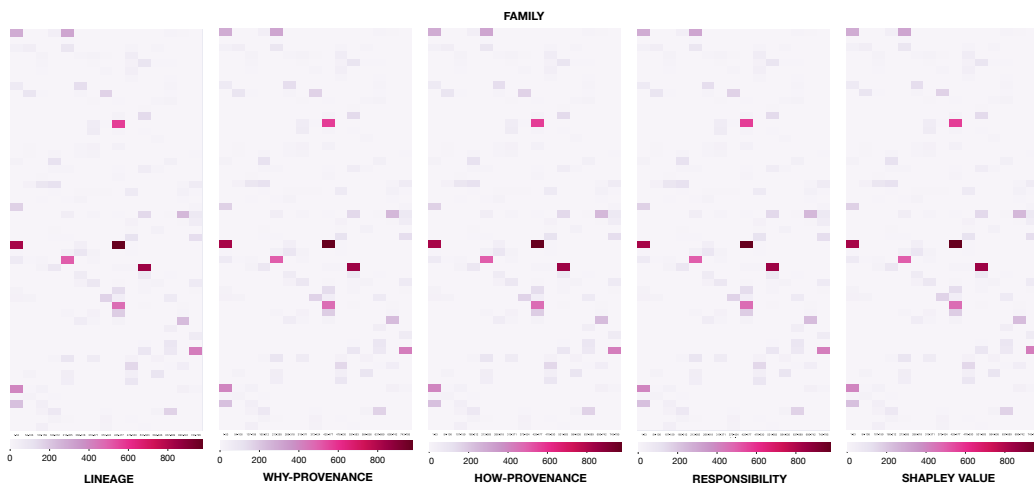


Figure 8: Comparison of four DS on the same table `family` using the distribution given by the queries retrieved from papers. Each cell is a tuple.

## 6. Experimental Evaluation

To understand the trade-offs between these Distribution Strategies (DSs), we perform four sets of experiments using queries over target families presented on the GtoPdb website. The first set of experiments use real queries extracted from citations to GtoPdb published in the British Journal of Pharmacology. The second set uses synthetically produced provenance polynomials, corresponding to more complex queries, in order to better highlight the differences between the DSs. The third set of experiments considers the accrual of credit over time by the three strategies, again using synthetic queries. The fourth set of experiments shows how the DSs compare to traditional citations in giving credit to data curators using both real and synthetic queries.

The source code for the experiments is written in Java and supported by a PostgreSQL database. For purposes of reproducibility, the code we used for our experiments and all queries are available here: [https://bitbucket.org/dennis\\_dosso/credit\\_distribution\\_project](https://bitbucket.org/dennis_dosso/credit_distribution_project).

## 781 6.1. Real-world queries

782 Examples of real queries are drawn from papers published in the British  
 783 Journal of Pharmacology (BJP) <sup>13</sup>. Each time a paper in this journal cites a  
 784 webpage from GtoPdb, it reports the URL of the page. From this URL, the  
 785 query used to obtain the webpage data can be determined. We considered all  
 786 889 papers in BJCP citing the IUPHAR/BPS Guide to pharmacology [34]  
 787 as of October 2020, and extracted all webpage URLs to GtoPdb contained  
 788 within the paper.<sup>14</sup>

789 The queries that we inferred are those used to build target family web-  
 790 pages within GtoPdb. An example was given in Figure 3, where we show  
 791 how the structure of the “Adenosine receptors” family can be mapped into  
 792 queries over the underlying database. In GtoPdb, all target family pages  
 793 share a similar structure; the only difference is that individual sections, such  
 794 as “contributors” or “further readings”, may be missing. Therefore, the same  
 795 queries can be used to build all of the target family pages by changing the  
 796 family id used in the query (for example, in Figure 3, it is 3). Note that  
 797 the queries are fairly simple SQL queries, and fall into a class called “select-  
 798 project-join” or “SPJ” queries. A total of more than 12K different queries  
 799 were built in this way. Without loss of generality, we give each tuple in the  
 800 output of a query a credit of 1.

801 *Results.* Figure 8 shows the heat-maps obtained by the distribution of credit  
 802 according to the **five** DS on one of the tables in the underlying database,  
 803 **family**, which is often joined with other tables in the database to build the  
 804 webpages. Each cell in a heat-map represents a tuple of the **family** table  
 805 and the color indicates the amount of credit attributed to such tuple. It can  
 806 be seen that the result of credit distribution over **family** is the same for all  
 807 **five** strategies. The same result is also obtained with the other tables of the  
 808 database used by the queries shown in Figure 3.

809 The reason why credit distribution is the same for all **five** strategies is that  
 810 the queries are all simple SPJ queries, which use each table only once and  
 811 do joins on key attributes. Under these conditions, each tuple of the output  
 812 presents: (i) a how-provenance that is a single monomial with coefficient

---

<sup>13</sup><https://bpspubs.onlinelibrary.wiley.com>

<sup>14</sup>The IUPHAR/BPS Guide is a journal that describes the structure and evolution of GtoPdb. At the time of writing, it had received more than 1200 citations on Google Scholar.

one and exponent one in each variable; (ii) a why-provenance with only one witness; (iii) a lineage that is the same of the witness in the basis, (iv) all tuples are counterfactual causes when considering responsibility, and (v) all tuple have the same importance in the production of the output tuples according to their Shapley value. Hence, for these queries, the five DSs behave in the same way: credit is uniformly distributed among the tuples of the lineage.

To illustrate this, consider one of the queries in Figure 3 which is used to build the output webpage:

```
Q3: SELECT c.first_names, c.surname
FROM contributor2family AS cf JOIN contributor AS c ON
cf.contributor_id = c.contributor_id
WHERE f.family_id = 3
```

Q3 returned 10 tuples from the version of GtoPdb used. The first tuple, <Bertil B., Fredholm>, has  $c_{939} \cdot c_{2f_{496}}$  as its provenance polynomial.  $c_{939}$  represents the provenance token of a tuple in `contributor`, and  $c_{2f_{496}}$  the provenance token of a tuple in table `contributor2family`. The why-provenance of this tuple is  $\{\{c_{939}, c_{2f_{496}}\}\}$ , its lineage is  $\{c_{939}, c_{2f_{496}}\}$ , both these tuples are counterfactual causes and have a responsibility of one. Therefore, the credit assigned to these tuples is 1/2 using all five DS. This happens for all the tuples in the output of each query of GtoPdb, thus making the distributions equivalent over all outputs.

However, this is not the case with more complex queries. As we showed in the previous section, when two or more tuples are merged as a result of a projection or union, the credit distributions will differ between the strategies.

## 6.2. Synthetic queries

To see what happens with more complex queries, we synthetically generated provenance polynomials in which the coefficients and exponents could be greater than one, and picked them at random from a uniform distribution. The queries involve three GtoPdb tables: `family`, `contributor2family`, and `contributor`. The polynomials were generated as follows: first, the number of monomials was decided by randomly choosing a number between one and six. Then, we randomly chose a tuple from the `family` table, one from the `contributor2family` table and one from the `contributor` table; these are the variables of the monomial. We then chose a coefficient for the monomial (between one and three) and an exponent for each tuple (between one and



**How-provenance:**  $3f_1^3c_2f_1^2c_1^2 + 2f_1c_2f_2^3c_2^3 + 4f_5c_2f_{17}^4c_{18}^3$

**Credit distribution:**

$$f_1 = \frac{59}{315}, f_5 = \frac{1}{18}, c_2f_1 = \frac{2}{21}, c_2f_2 = \frac{2}{15}, c_2f_{17} = \frac{2}{9}, c_1 = \frac{2}{21}, c_2 = \frac{2}{15}, c_{18} = \frac{1}{6}$$

**Why-provenance:**  $\{\{f_1, c_2f_1, c_1\}, \{f_1, c_2f_2, c_2\}, \{f_5, c_2f_{17}, c_{18}\}\}$

**Credit distribution:**

$$f_1 = \frac{2}{9}, f_5 = \frac{1}{9}, c_2f_1 = \frac{1}{9}, c_2f_2 = \frac{1}{9}, c_2f_{17} = \frac{1}{9}, c_1 = \frac{1}{9}, c_2 = \frac{1}{9}, c_{18} = \frac{1}{9}$$

**Lineage:**  $\{f_1, f_5, c_2f_1, c_2f_2, c_2f_{17}, c_1, c_2, c_{18}\}$

**Credit distribution:**

$$f_1 = \frac{1}{8}, f_5 = \frac{1}{8}, c_2f_1 = \frac{1}{8}, c_2f_2 = \frac{1}{8}, c_2f_{17} = \frac{1}{8}, c_1 = \frac{1}{8}, c_2 = \frac{1}{8}, c_{18} = \frac{1}{8}$$

**Causality:** counterfactual causes:  $\emptyset$ ,

actual causes:  $\{f_1, f_5, c_2f_1, c_2f_2, c_2f_{17}, c_1, c_2, c_{18}\}$

**Responsibility:**

$$f_1 = \frac{1}{2}, f_5 = \frac{1}{2}, c_2f_1 = \frac{1}{3}, c_2f_2 = \frac{1}{3}, c_2f_{17} = \frac{1}{2}, c_1 = \frac{1}{3}, c_2 = \frac{1}{3}, c_{18} = \frac{1}{2}$$

**Credit distribution:**

$$f_1 = \frac{3}{20}, f_5 = \frac{3}{20}, c_2f_1 = \frac{1}{10}, c_2f_2 = \frac{1}{10}, c_2f_{17} = \frac{3}{20}, c_1 = \frac{1}{10}, c_2 = \frac{1}{10}, c_{18} = \frac{3}{20}$$

**Shapley value:**

$$f_1 = 0.258\bar{3}, f_5 = \frac{1}{8}, c_2f_1 = 0.091\bar{6}, c_2f_2 = 0.091\bar{6}, c_2f_{17} = \frac{1}{8}, c_1 = 0.091\bar{6}, c_2 = 0.091\bar{6}, c_{18} = \frac{1}{8}$$

Figure 9: Sample synthetic provenance polynomial (how-provenance) and corresponding why-provenance, lineage, responsibility, and Shapley values, together with the corresponding credit distributions. The sum of Shapley values is equivalent to the quantity of credit being distributed (assuming that the input credit is equal to 1).

849 four). For the next monomial, we decided if we wanted to keep the same  
 850 tuple from the table family as first tuple of the new monomial. To do so, we  
 851 generated a random float number between zero and one. If the number was  
 852 above 0.2, we changed the family tuple.

853 An example can be found in Figure 9, which shows a sample synthetic  
 854 provenance polynomial (the how-provenance), the corresponding why-provenance,  
 855 lineage, the causality of the tuples of the lineage, together with their respon-  
 856 sibility, and, finally, the Shapley values of the lineage tuples. The resulting  
 857 credit distribution for each DS is also shown.

858 As an example of how the distribution strategies behave with these syn-

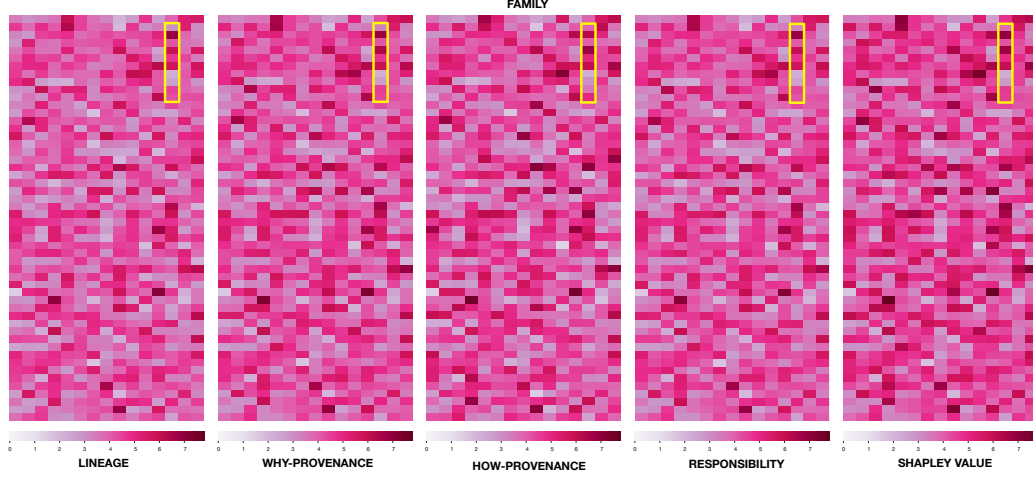


Figure 10: Comparison of three DS on the same table **family** after the distribution computed using 10K synthetic and randomly generated provenance polynomials. The tuples in the blue rectangles are used as example in the discussion connected to Figure 11.

859 thetic queries, consider tuple  $f_5$  in Figure 9. This tuple receives the highest  
 860 quantity of credit using responsibility-based distribution and less credit us-  
 861 ing, in order, lineage, the Shapley value, why- and how-provenance. On the  
 862 other hand, tuple  $f_1$  is rewarded more by the Shapley value, then, in order,  
 863 by why-provenance, how-provenance, responsibility, and finally lineage. This  
 864 difference is explained considering the different role of the tuples in the gener-  
 865 ation of the output and the characteristics of the distributions. Generally  
 866 speaking, the more complex the distribution (e.g., the how-provenance), the  
 867 more credit is given to tuples that are more frequently used or more critical in  
 868 the production of the output. Depending on the situation, i.e. on the syntax  
 869 of the query, the distributions may differ among them. Responsibility creates  
 870 a ranking among lineage's tuples describing the importance of their role in  
 871 generating the output. As such, the responsibility-based DS gives more credit  
 872 to  $f_1$ ,  $f_5$ ,  $c_2f_{17}$  and  $c_{18}$  due to their higher responsibility values. “Importance”  
 873 is connected to their corresponding minimal contingency sets. For example,  
 874  $f_1$  has a minimal contingency set (one of the many)  $\{f_5\}$ , with cardinality  
 875 1. On the other hand,  $c_1$  has, as minimal contingency set (one of the many)  
 876  $\{f_5, c_2\}$ , with cardinality two. This means that  $c_1$  is the “least important”  
 877 amongst the tuples with minimal contingency sets of lower cardinality, and  
 878 this is reflected in the different quantities of credit being distributed.

Table 9: Results of the pairwise Kendall Tau confidence value on all the DSs on the **family** table (the p-values are all below 0.05).

	lineage	why	how	resp.	Shapley
lineage	1.0	0.88	0.73	0.91	0.81
why	0.88	1.0	0.75	0.93	0.92
how	0.73	0.75	1.0	0.74	0.74
resp.	0.91	0.93	0.74	1.0	0.89
Shapley	0.81	0.91	0.74	0.89	1.0

879 The Shapley value behaves similarly, but it rewards tuple  $f_1$  the most and  
880 then  $f_5$ ,  $c2f_{17}$ ,  $c_{18}$ , and last all the other tuples of the lineage. Although both  
881 Responsibility and the Shapley value create a ranking of the tuples based on  
882 their role in the generation of the output, the corresponding functions behave  
883 differently due to the syntax of the query; for this reason each different distri-  
884 bution strategy highlights a slightly different aspect that can be considered  
885 as “important” when distributing the credit.

886 Despite being synthetic, these provenance polynomials are realistic: they  
887 can be obtained by any nested query with join and union operations that use  
888 the same tuple multiple times (in which case the exponents are larger than  
889 one), and the same combination of operations more than once (in which case  
890 the coefficients of monomials are larger than one).

891 *Results.* The results of credit distribution on the **family** table using 10K  
892 randomly generated synthetic provenance polynomials are shown in Figure  
893 10. We set the maximum value in the heat maps to the highest value reached  
894 by a tuple in all **five** distributions (i.e., 7.7, with the Shapley value-based DS).

895 There is a certain amount of consistency between the strategies in that  
896 tuples which are highly rewarded by one strategy are also highly rewarded by  
897 the others. This shows that the four DSs consistently reward certain tuples  
898 more than others.

899 Table 9 reports the pairwise Kendall  $\tau$  correlation values<sup>15</sup> for the five  
900 DSs computed on the **family** table. As we see, there are certain DS that  
901 are correlated to others, such as lineage with why-provenance, responsibility

---

<sup>15</sup>The Kendall’s  $\tau$  coefficient is a statistic used to measure the ordinal association between two measured quantities [42]. Intuitively, it is high between two variables when observation have a similar rank.

902 and lineage, or responsibility and why-provenance. The others are mildly  
 903 correlated, such as the Shapley value with how-provenance, responsibility  
 904 and how-provenance, or why-provenance and lineage with how-provenance.  
 905 We see, therefore, that the DS based on how-provenance is the one that  
 906 correlates the least with the other DSs.

907 Note that lineage-based DS gives the least credit to tuples in the **family**  
 908 table, indicated by an overall lighter hue. This is because the DS distributes  
 909 credit equally to all tuples appearing in the lineage. Since these queries also  
 910 use two other tables, credit is distributed to tuples in those tables.

911 Moving to why-provenance-based DS, we see that more credit is given to  
 912 tuples in the **family** table than with the previous strategy. This is because  
 913 the DS considers the different ways that a tuple is used, e.g. in joins with  
 914 other tuples. If the same tuple is present in more than one witness, it will  
 915 draw more credit and take it from other tuples in the witness basis. In this  
 916 case, tuples in **family** drew more credit, taking it from tuples in the other  
 917 two tables, due to the role that **family** tuples played in the queries that were  
 918 executed.

919 Consider the how-provenance-based DS heat-map. As with why-provenance,  
 920 more credit is typically given to tuples in **family** compared to lineage-based  
 921 DS, since it recognizes the role of these tuples in the queries, and the over-  
 922 all hue is deeper. The two distributions appear similar, although on closer  
 923 inspection, slight differences can be seen. This is because how-provenance  
 924 also considers the frequency with which tuples are used, not only the ways in  
 925 which they are used. Therefore, although the overall distribution is similar,  
 926 there are small differences due to the presence of exponents and coefficients  
 927 in the provenance polynomials, influencing the distribution of credit.

928 The responsibility-based distribution strategy has a distribution that is  
 929 also quite similar to the one provided by why-provenance (which is also visible  
 930 from Table 9). It is often the case, for example when the witnesses of the  
 931 why provenance share one common tuple, that the two distributions behave  
 932 similarly.

933 Finally, the heat-map reporting the distribution produced by the Shapley  
 934 value is the one that, at a closer inspection, shows many differences. Although  
 935 the tuples that receive the biggest quantities of credit are the same, the hue  
 936 of this tuple is different. The Shapley value in certain circumstances differs  
 937 greatly from the other DSs, thus showing its ability to weight differently the  
 938 roles of the tuples.

939 We note that the lineage-based DS gives an average credit of 3.92 to each

940 tuple in the table, while the DS based on why-provenance assigns 4.19, how-  
 941 provenance 4.18, the one based on responsibility 4.13, and the one based on  
 942 the Shapley value 4.40. Moreover, lineage distributed a total of about 3121  
 943 units of credit to the `family` table, why-provenance 3333, how-provenance  
 944 3331, while responsibility assigned 3290, and the Shapley value 3505. Thus,  
 945 the Shapley value is the method that accumulates the highest quantity of  
 946 credit in this table.

947 To better understand the differences between DSs, in the next subsection  
 948 we consider the accrual of credit over time. In doing so, we will focus on the  
 949 ten tuples shown within the large yellow rectangles in Figure 11. Each small  
 950 rectangle within a large yellow rectangle is a tuple, and we number them  
 951 from 1 (top) to 10 (bottom). These ten tuples were cherry-picked because  
 952 they allow us to see the evolution of the distribution of credit through time.  
 953 There are other tuple sets that could have been selected driving us to the  
 954 same considerations.

### 955 6.3. Credit accrual over time

956 Since credit accrues over time, we simulate the passage of time by varying  
 957 the number of queries executed, and look at the “snapshots” of credit for each  
 958 of the strategies using synthetic queries. The results are shown in Figure 11.

959 In this figure, four groups of heat-maps are shown. Each group represents  
 960 a “snapshot” taken after 1K, 2K, 5K and 10K provenance polynomials have  
 961 been considered for credit distribution. The ten tuples in each heat-map are  
 962 those highlighted in the yellow boxes of Figure 10 from the `family` table.

963 The polynomials used are the same as the experiment of the previous  
 964 section. The range of credit in each map goes from 0 (no credit) to 7 (the  
 965 maximum quantity of credit reached – using how-provenance – on one of the  
 966 tuples of the considered window at the “snapshot” with 10K queries). The  
 967 color hue of the legend, as can be seen, still ranges from 0 to 7.7.

968 By the end of 1K queries, credit differentials between tuples as well as  
 969 between strategies can be seen. For example, tuple 3 is usually rewarded  
 970 the most credit by all five strategies. Moreover, it can be seen that tuples 1  
 971 receives a higher quantity of credit when how-provenance is adopted, show-  
 972 ing how this form of provenance behaves differently from the others in this  
 973 context. Moving to 2K queries, it is possible to see that tuple 3 and 7 are  
 974 still the most rewarded by the strategies.

975 By the end of 5K queries, tuple 7 emerges with the highest value of  
 976 credit with all five DSs, a position which is strengthened with 10K queries.

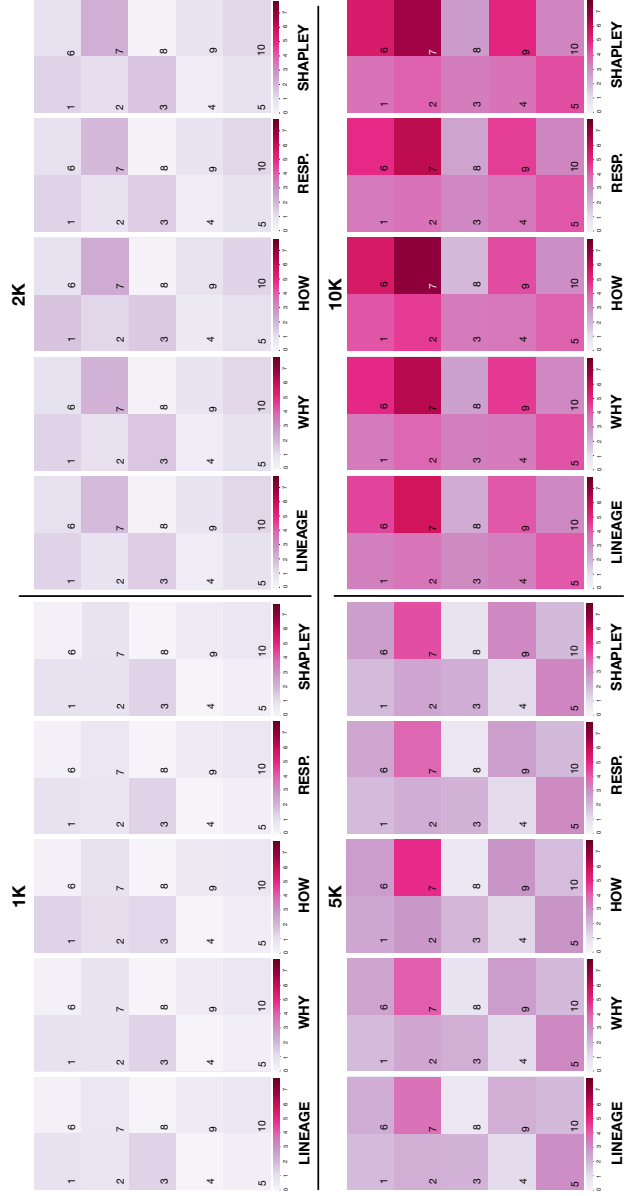


Figure 11: Comparison of the distribution of credit performed by the five DSs on a subset of 10 tuples taken from the `family` table, simulating the passing of time. The number at the top of each group of heat-maps represents the number of polynomials whose credit has been distributed.

Moreover, with the passing of time, tuple 3 ceases to be one of the most rewarded ones and new tuples, such as 6 and 9, emerge as being particularly rewarded at 5K, while at 10K tuples 6 and 7 are the most rewarded from the distributions. This is because tuple 7 is used several times within queries being executed, which is rewarded strongly by why- and how-provenance. We also note that the responsibility-based distribution confirms its trend of being similar to why-provenance, although not identical. This is more evident at step 10K, where tuple 7 is slightly less rewarded using responsibility (6.12) with respect to why-provenance (6.24). The responsibility that rewards the more tuple 7 is the one based on how-provenance (credit 7.03), followed by the Shapley value (credit 6.64). This is due to the fact that tuple 7 had, among some of the polynomials being used for the experiments, a high responsibility but it did not appear in all witnesses. This changed slightly the distribution.

While the relative value of credit “positions” of tuples within a DS strategy depends on what queries are being executed, the important thing to notice is the difference between the DSs over time: overall, lineage gives less credit to tuples in the `family` table than the other strategies since credit is shared with tuples in other tables. The other strategies recognize the more important role being played by the `family` tuples than those in the other tables. The differences between why- and responsibility-based DS are, for the most times, negligible. The differences between the why- and how-provenance-based DSs are also relatively minor in most cases. However, there are certain situations in which the role of a tuple is particularly critical in a query, and in this case the difference in the value of credit assigned is notably higher for how-provenance and the Shapley value, as we saw with tuple 7 in the example of Figure 11.

To sum up, the DS based on lineage is sufficient to highlight which tuples in the database are used by a query, and distributes credit equally to these tuples. The resulting distribution rewards tuples that are used by more queries, but does not reward how many times tuples are used in the same query. However, a DS based on why-provenance, responsibility, Shapley value or how-provenance may be better if the queries are complex, since they reward more tuples that have a critical role in generating the output. In particular, these four DSs may be useful for finding “hotspots” in the database based on the role of tuples, with the how-provenance-based and Shapley value-based DSs being preferable if a higher sensitivity to the role of a tuple in queries is required.

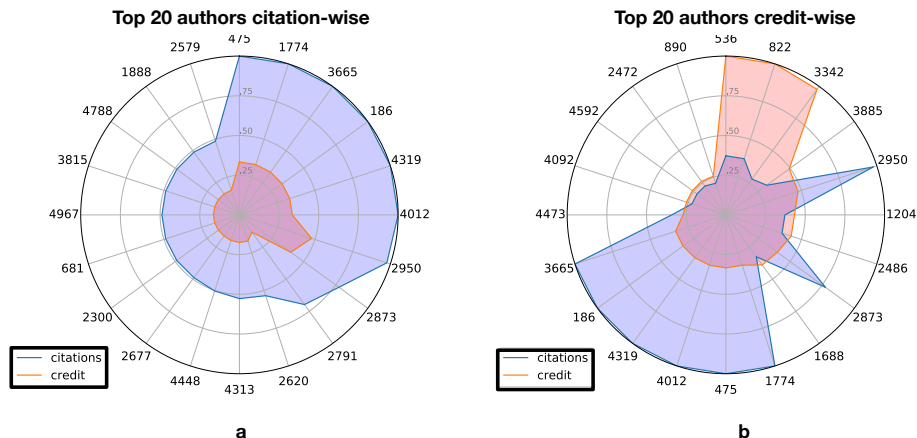


Figure 12: Radars presenting the top 20 authors citation-wise and credit wise, together with their (normalized between 0 and 1) values of citations and credit.

#### 6.4. Credit vs Citations

In the last set of experiments, we compare traditional citations to the proposed credit distribution strategies to see the difference in reward for data authors and curators. Using both real-world and synthetic queries, we distribute credit to the authors responsible for the data under the different strategies. Our results show that credit rewards authors of data that is cited fewer times, but that has a higher impact on the query results.

To do so, we need to identify a set of authors and queries that cite data curated by them. Considering GtoPdb, each target family page has a list of curators, representing the people who are co-creators and curators of the data comprising the page. This list can be obtained using the last query shown in Figure 3. Each time a target family page is cited, we assign one *citation* to each author associated with the page. The authors also receive *credit* in the amount assigned to the data used by the query to construct the webpage, equally divided between the authors of the webpage.

*Results: Real-world queries.* As described in Section 6.1, we consider real-world queries taken from papers published in the BJP which reference web-pages in GtoPdb. Since for these queries there is no difference in the distribution of credit between the DSs, only one value for credit is used.

The results are shown in the radar plots of Figure 12, in which each number on the outer circle (e.g. 475, 1774 and 3665) represents an author



(id) and the blue (red) line represents the normalized value of credit generated by citations (credit), respectively. The first radar plot, Figure 12.a, shows the top 20 authors in terms of *citations*, ordered in a clockwise direction, whereas Figure 12.b orders the authors based on *credit*. Comparing the author ids used in the outer circles of these two plots, it can immediately be seen that the “top authors” are very different using these two metrics, although there is some overlap (for example, authors 1774, 475, and 4012).

Diving a bit deeper to focus on the red and blue areas in each of the plots reveals that there is a significance difference between citations and credit: The top 20 authors in terms of citations do not have the highest values of credit (Figure 12.a). Conversely, the authors with the highest values of credit do not necessarily have a large number of citations (Figure 12.b). For example, author 536 has the highest value of credit, but is not even in the top 20 authors in terms of citations. This means that authors like 536, 822, and 3342 in Figure 12.b receive much more credit from their relatively few citations than authors like 475, who receives the largest number of citations. That is, the data underlying certain webpages is more “valuable” in terms of credit than a citation to the webpage.

The reason for the difference between citation and credit is partly due to the experimental setup: each output tuple carries a credit of 1, and there can be many tuples used to generate a webpage. Thus a webpage that is created from more tuples will have a higher credit value than one created from fewer tuples. Furthermore, authors who collaborated with fewer people will receive a biggest share of the equally divided credit. However, all authors will receive a citation of one.

Credit distribution therefore rewards authors differently than traditional citations: an author who has curated larger quantities of cited data and collaborated with fewer co-authors, will receive larger quantities of credit. Thus, credit rewards them for their larger contribution to the database.

*Results: Synthetic queries.* We used the same synthetic polynomials described in Section 6.2, and we distributed credit with the first 100, 1K, and 10K of them. Since these polynomials are created by randomly selecting tuples from three tables, they usually correspond to a set of data curated by authors who, in reality, did not collaborate. To make the size of the author set more realistic, we therefore created 20 synthetic authors, and randomly assigned one author to blocks of consecutive tuples in the database, with the size of each block varying between 10 and 40, to simulate different quantities

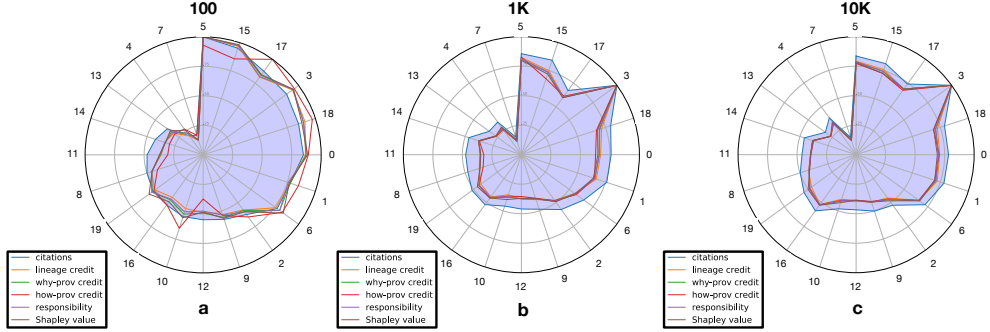


Figure 13: Radars presenting the 20 synthetic authors with corresponding citation and quantities of credit distributed through the 4 DSs (all values normalized between 0 and 1) through different numbers of polynomials (respectively, 100, 1K and 10K). The order is the one defined by figure a, i.e. descending order of citations obtained from 100 polynomials.

of work performed by an author. Every time an author appears as curator of one or more tuples used in a polynomial, we assign them one citation. They also receive four kinds of credit, each one using a different DS.

Figure 13 shows three radar plots, one for the results obtained with 100 polynomials, one with 1K polynomials, one with 10K polynomials. Each plot shows the top 20 authors in terms of citations (hence the authors and clockwise ordering is the same in each of the plots), and additionally shows the the normalized values of citation (blue line), lineage-based credit (yellow line), why-provenance-based credit (green line), how-provenance-based credit (red line), responsibility-based credit (violet line), and the Shapley value-based credit (brown line).

As can be seen, given the synthetic nature of the queries, the correlation between the number of citations and the quantity of credit assigned to the authors appears to be a much stronger than with the real-world queries of Figure 12. In fact, for Figure 13.a the linear correlation between the citation number and all four types of credit is always above 0.94 with p values in the order of  $3e-8$ . The credit distributed via lineage is closest to the number of citations (a linear correlation of 0.99, p value of  $2e-16$  in Figure 13.a), while the other three types of credit behave slightly differently (a linear correlation of around 0.95 or above in all other four cases in Figure 13.a). Similar observations can be made for Figure 13.b and 13.c.

What these figures show is that, in certain cases, authors who do not have a large number of citations receive more credit than others, as for example au-

thors 17, 18 and 10 in Figure 13.a, and especially when credit is distributed using how-provenance. This again shows how credit gives a different perspective on the role of data and authors by going beyond the limitations of traditional citations.

It is worth noting that, when scaling up to  $1K$  and  $10K$  polynomials, the credit distributions become almost identical (the linear correlation for the values of Figure 13.c is more than 0.99 with a p-value of  $1.32e-32$ ). This is consistent with what we observed in Figure 10.

## 7. Discussion

Before concluding, we discuss some design decisions: the focus on Credit Distribution (as opposed to Credit Generation), and the choice of Distribution Strategies.

### 7.1. Credit Generation

In this paper we focused on Credit Distribution, the problem of distributing credit generated by a citation to the parts of the database referenced by the query. A different problem is Credit Generation, the task of generating credit which is then distributed. Credit Generation presents a series of issues which are shared by traditional citation practices. For instance, defining the quantity of credit to be generated for a given citation is still an open problem. Different types of citations may generate different quantities of credit. Data cited as previous work or as useful for previous work may generate less credit than other data extensively used to produce the results presented in a paper. The computation of credit could be done manually (although we must consider the complexity of the task, human biases and the resources required to carry it out) or automatically, but it must be based on a shared definition of impact which is still not agreed upon for data or for traditional citation. For this reason, we used a uniform credit assignment.

There is also the problem of *transitive credit distribution*, i.e., how to transitively propagate credit from one cited unit to another unit that was used to produce the one being cited. For this, a graph of cited units that propagate credit between the units depending on influence could be used. How to propagate credit is an open and non-trivial problem that needs to consider the importance and impact of a citation in a work, be it a paper or data, and how to eventually compute the quantity of credit to be propagated.

1129 Finally, in our experiments we assumed that the credit carried by an  
 1130 output tuple is one. Thus, each tuple in the output has equal importance.  
 1131 As described above, this assumption may be revised and different credit to  
 1132 different output tuples could be assigned. Note that from the distribution  
 1133 model viewpoint no change is required since the DCD is defined for a generic  
 1134 value  $k$ .

## 1135 7.2. Choice of Distribution Strategies

1136 In this paper we presented four different DSs, so the natural question is  
 1137 which one to use. This depends on the task at hand. When we want to  
 1138 highlight the tuples being used in the database by a workload, the lineage-  
 1139 based DS may be sufficient. When we also want to know the relative impact  
 1140 of tuples in the context of the query, the other DSs should be used since they  
 1141 give a better understanding of the importance of data.

1142 In the real-world based experiments, the four DSs behaved the same,  
 1143 which was due to the specific nature of the data and the queries being used.  
 1144 However, the why-provenance of a query will differ from the lineage of the  
 1145 same query whenever the output tuples can be computed in more than one  
 1146 way by the query, i.e., if there is more than one witness. This is usually true  
 1147 when join and projection operators are used in the query.

1148 To address the question of what types of queries are likely to extract  
 1149 cited data, we turn to the results of published studies on the characteristics  
 1150 of query workloads and the complexity of their queries [38, 55, 60]. These  
 1151 studies show that operations such as inner-/outer-joins and projections occur  
 1152 in a significant number of queries. Therefore why- and how-provenances may  
 1153 become quite complex in certain cases and provide a distribution of credit  
 1154 that is significantly different from the one obtained with lineage.

1155 From a computational complexity standpoint, all five DSs are similar  
 1156 since we focused on SPJ queries. Going beyond SPJ queries, Green et al.  
 1157 [32] proposed the provenance semiring framework for SPJRU (Select, Project,  
 1158 Join, Rename, and Union queries), and Amsterdamer et al. [5] showed how  
 1159 to extend the framework to aggregate queries. Since lineage and why-  
 1160 provenance can be computed starting from how-provenance, it is possible to  
 1161 apply the first three DSs proposed in this paper to SPJRU and aggregation  
 1162 queries. Causality and subsequently Responsibility are harder to compute  
 1163 (NP-complete [48]) for general queries. Credit Distribution is more con-  
 1164 cerned with Responsibility, which is in general hard to compute [18]. Meliou  
 1165 et al. [48] proved a dichotomy result for conjunctive queries: for each query

without self-joins, either its responsibility can be computed in PTIME in the size of the database, or checking if it has a responsibility below a given value is NP-hard. Queries with self-joins are NP-hard in general. This makes responsibility harder to be utilized for credit distribution in a real-world application, since for this problem it is necessary to actually know the responsibility value, not simply the ranking amongst tuples.

As for the Shapley Value, Livshits et al. [45] studied the computational complexity of calculating the Shapley values in query answering. They originally showed mainly lower bounds on the complexity of the problem, with the exception of the sub-class of self-join free SPJ queries called *hierarchical* queries, where they gave a polynomial-time algorithm. Very recently, Deutch et al. [25] proved that the Shapley value can be efficiently (polynomial-time) reduced to probabilistic query answering. This not only applies to hierarchical queries, but to general SPJ queries. This means that one can compute Shapley values using a query engine for probabilistic databases, for example, the practically effective *Knowledge Compilation* [39], making it a viable solution for Credit Distribution via SPJ queries.

## 8. Conclusions and Future Work

This paper defines four new distribution strategies based on why-provenance, how-provenance, responsibility, and the Shapley Value, and it compares them against the lineage-based distribution strategy defined in [26]. The first, why-provenance-based DS, uses the concept of a witness, and gives more credit to tuples that appear in more than one witness. In this way, tuples that are more important to the query and are used in different ways are rewarded more. The second, how-provenance-based DS, considers the frequency with which a tuple or combination of tuples is used in the query through the information contained in a provenance polynomial. In this case, the how-provenance-based DS is more sensitive than the why-provenance-based DS to the role and importance of tuples. The third DS exploits the notion of responsibility, a real value that ranks the lineage tuples based on their degree of causality in generating the output. The responsibility-based DS was shown to behave similarly to the why-provenance based DS. The fourth DS uses the Shapley value function, used to rank the facts of the database, seen as players, in producing the required result. To do so, the wealth function in the Shapley value's definition was adapted for general free-variable queries on the database.

1202 To show the differences between the five DSs, we performed extensive  
1203 experiments based on GtoPdb, a curated scientific relational database, using  
1204 both real and synthetic queries. In the first set of experiments, we used select-  
1205 project-join (SPJ) queries extracted from citations to webpages in GtoPdb  
1206 found in papers published in the British Journal of Pharmacology. Using  
1207 these “real” queries, we distributed credit to tuples in different tables of the  
1208 database, highlighting tuples that were more frequently used. We showed  
1209 that, with these queries, the five strategies produce the same distribution.  
1210 This is because the SPJ queries were fairly simple, and did not use self-joins.  
1211 Therefore the formulas underlying the different DSs had the same output.

1212 In the second set of experiments, we synthetically produced more com-  
1213 plex provenance polynomials, corresponding to more complex queries, that  
1214 resulted in exponents and coefficients in the provenance polynomials that  
1215 were greater than (or equal to) 1. These experiments highlighted the differ-  
1216 ences between the five DSs. While the DS based on lineage rewards all the  
1217 tuples used by a query equally, the strategies based on why-provenance and  
1218 responsibility give more credit to tuples that are more critical to the query.  
1219 In particular, why-provenance considers the different ways in which a tuple  
1220 is used in a query, while responsibility considers the relative importance of  
1221 a tuple in the generation of the output. The DS based on the Shapley value  
1222 similarly rewards the tuples based on their participation. The more impactful  
1223 the role of a tuple, the higher its reward in credit. This distribution proved  
1224 to be different from the previous two and to reward even more tuples that  
1225 are used in more than one witness. How-provenance is even more sensitive  
1226 to the tuple’s role: it also considers the frequency with which a tuple or a  
1227 set of tuples is used.

1228 In the third set of experiments, we showed how the differences between  
1229 the DS are compounded over time, i.e. when more and more queries are  
1230 processed by the system.

1231 In the fourth set of experiments we compared traditional citations to  
1232 authors to the credit accrued to them via the DSs. We showed how, in  
1233 both real-world and synthetic scenarios, credit rewards authors who con-  
1234 tribute/curate data that has the highest impact, and therefore receives the  
1235 biggest quantity of credit, and not necessarily the data with the highest ci-  
1236 tation count. In this sense, credit appears to be an useful new measure to  
1237 discover data and their corresponding curators that have a high impact in  
1238 the research world, even when they are cited few times or do not appear at  
1239 all in the data that are cited (i.e. the case of data used to build the output

of a query but that is not visualized in the output itself).

In future work, we plan to explore different strategies to generate and distribute credit. In this paper we assumed that each output tuple carries credit 1. In more sophisticated scenarios we can employ different strategies to compute credit, that reflect the importance of cited data. Other, more sophisticated, strategies could also be used to decide how credit is distributed between the authors, beyond the uniform distribution used here, in a way to reflect the work performed by them on the cited data. There are also a number of other intriguing applications for credit over relational databases. One such application is *data pricing*, which gives a price to a query submitted by a user who wants to buy the produced information. Currently, a common strategy used for data pricing is based on query rewriting: A database stores a set of views with their price. When a new query arrives, the system rewrites it using the stored views to obtain a query price, a process that can be computationally expensive. We plan to distribute credit through carefully planned and representative queries, and use credit information to define a new, faster, and potentially more flexible pricing function.

Another application is *data reduction* [49], which addresses the problem of reducing the vast – and rapidly expanding – amount of data that is being produced. Data credit can help address this problem by identifying “hotspots” and “coldspots” of data. A hotspot is data in a database (e.g. a tuple) with a high quantity of credit, which is therefore valuable for the set of queries that execute frequently over the data and distribute the credit. A coldspot is data with a low quantity of credit which can therefore be considered as less important, and could be deleted, summarized, or moved to cheaper and/or less efficient memory.

## Acknowledgement

The work was partially supported by the ExaMode project, as part of the European Union H2020 program under Grant Agreement no. 825292.

## References

- [1] Abadi, D., Ailamaki, A., Andersen, D., Bailis, P., Balazinska, M., Bernstein, P., Boncz, P., Chaudhuri, S., Cheung, A., Doan, A., Dong, L., Franklin, M. J., Freire, J., Halevy, A., Hellerstein, J. M., Idreos, S., Kossmann, D., Kraska, T., Krishnamurthy, S., Markl, V., Melnik, S., Milo,

- 1274 T., Mohan, C., Neumann, T., Chin Ooi, B., Ozcan, F., Patel, J., Pavlo,  
1275 A., Popa, R., Ramakrishnan, R., Ré, C., Stonebraker, M., and Suciu, D.  
1276 (2020). The seattle report on database research. *SIGMOD Rec.*, 48(4):44–  
1277 53.
- 1278 [2] Alawini, A., Davidson, S. B., Hu, W., and Wu, Y. (2017). Automating  
1279 data citation in citedb. *PVLDB*, 10(12):1881–1884.
- 1280 [3] Alawini, A., Davidson, S. B., Silvello, G., Tannen, V., and Wu, Y.  
1281 (2018). Data citation: A new provenance challenge. *IEEE Data Eng.*  
1282 *Bull.*, 41(1):27–38.
- 1283 [4] Altman, M., Borgman, C. L., Crosas, M., and Martone, M. (2015). An  
1284 Introduction to the Joint Principles for Data Citation. *Bulletin of the*  
1285 *Association for Information Science and Technology*, 41(3):43–45.
- 1286 [5] Amsterdamer, Y., Deutch, D., and Tannen, V. (2011). Provenance for ag-  
1287 gregate queries. In Lenzerini, M. and Schwentick, T., editors, *Proceedings*  
1288 *of the 30th ACM SIGMOD-SIGACT-SIGART Symposium on Principles*  
1289 *of Database Systems, PODS 2011*, pages 153–164. ACM.
- 1290 [6] Bechhofer, S., Buchan, I. E., De Roure, D., Missier, P., Ainsworth, J. D.,  
1291 Bhagat, J., Couch, P. A., Cruickshank, D., Delderfield, M., Dunlop, I.,  
1292 Gamble, M., Michaelides, D. T., Owen, S., Newman, D. R., Sufi, S., and  
1293 Goble, C. A. (2013). Why linked data is not enough for scientists. *Future*  
1294 *Gener. Comput. Syst.*, 29(2):599–611.
- 1295 [7] Belter, C. W. (2014). Measuring the Value of Research Data: A Citation  
1296 Analysis of Oceanographic Data Sets. *PLoS ONE*, 9(3):e92590.
- 1297 [8] Bertin-Mahieux, T., Ellis, D., Whitman, B., and Lamere, P. (2011). The  
1298 million song dataset. In *Proceedings of the 12th International Conference*  
1299 *on Music Information Retrieval (ISMIR 2011)*, pages 591–596.
- 1300 [9] Borgman, C. L. (2016). Data Citation as a Bibliometric Oxymoron. In  
1301 Sugimoto, C. R., editor, *Theories of Informetrics and Scholarly Commu-*  
1302 *nication*, pages 93–116. De Gruyter Mouton.
- 1303 [10] Buneman, P. (2006). How to cite curated databases and how to make  
1304 them citable. In *18th International Conference on Scientific and Statistical*  
1305 *Database Management, SSDBM*, pages 195–203. IEEE Computer Society.



- [11] Buneman, P., Christie, G., Davies, J. A., Dimitrellou, R., Harding, S. D., Pawson, A. J., Sharman, J. L., and Wu, Y. (2020). Why data citation isn't working, and what to do about it. *Database J. Biol. Databases Curation*, 2020.
- [12] Buneman, P., Davidson, S. B., and Frew, J. (2016). Why data citation is a computational problem. *Commun. ACM*, 59(9):50–57.
- [13] Buneman, P., Khanna, S., and Tan, W. C. (2001). Why and where: A characterization of data provenance. In *Database Theory - ICDT 2001, 8th International Conference*, pages 316–330.
- [14] Buneman, P. and Silvello, G. (2010). A rule-based citation system for structured and evolving datasets. *IEEE Data Eng. Bull.*, 33(3):33–41.
- [15] Callaghan, S., Donegan, S., Pepler, S., Thorley, M., Cunningham, N., Kirsch, P., Ault, L., Bell, P., Bowie, R., Leadbetter, A. M., Lowry, R. K., Moncoiffé, G., Harrison, K., Smith-Haddon, B., Weatherby, a., and Wright, D. (2012). Making Data a First Class Scientific Output: Data Citation and Publication by NERC's Environmental Data Centres. *International Journal of Digital Curation*, 7(1):107–113.
- [16] Candela, L., Castelli, D., Manghi, P., and Tani, A. (2015). Data Journals: A Survey. *Journal of the Association for Information Science and Technology*, 66(9):1747–1762.
- [17] Cheney, J., Chiticariu, L., and Tan, W. (2009). Provenance in databases: Why, how, and where. *Foundations and Trends in Databases*, 1(4):379–474.
- [18] Chockler, H. and Halpern, J. Y. (2004). Responsibility and blame: A structural-model approach. *J. Artif. Intell. Res.*, 22:93–115.
- [19] CODATA-ICSTI Task Group on Data Citation Standards and Practices (2013). *Out of Cite, Out of Mind: The Current State of Practice, Policy, and Technology for the Citation of Data*, volume 12.
- [20] Cousijn, H., Feeney, P., Lowenberg, D., Presani, E., and Simons, N. (2019). Bringing citations and usage metrics together to make data count. *Data Science Journal*, 18(1).

- 1337 [21] Cronin, B. (1984). *The Citation Process. The Role and Significance of*  
1338 *Citations in Scientific Communication*. London: Taylor Graham.
- 1339 [22] Cronin, B. (2001). Hyperauthorship: A postmodern perversion or evi-  
1340 dence of a structural shift in scholarly communication practices? *JASIST*,  
1341 52(7):558–569.
- 1342 [23] Cui, Y., Widom, J., and Wiener, J. L. (2000). Tracing the lineage of  
1343 view data in a warehousing environment. *ACM Trans. Database Syst.*,  
1344 25(2):179–227.
- 1345 [24] Davidson, S. B., Deutch, D., Milo, T., and Silvello, G. (2017). A model  
1346 for fine-grained data citation. In *CIDR 2017, 8th Biennial Conference on*  
1347 *Innovative Data Systems Research*. [www.cidrdb.org](http://www.cidrdb.org).
- 1348 [25] Deutch, D., Frost, N., Kimelfeld, B., and Monet, M. (2021). Computing  
1349 the shapley value of facts in query answering.
- 1350 [26] Dosso, D. and Silvello, G. (2020). Data credit distribution: A  
1351 new method to estimate databases impact. *Journal of Informetrics*,  
1352 14(4):101080.
- 1353 [27] Dubernet, M. L., Antony, B. K., Ba, Y. A., et al. (2016). The vir-  
1354 tual atomic and molecular data centre (VAMDC) consortium. *Journal of*  
1355 *Physics B: Atomic, Molecular and Optical Physics*, 49(7):074003.
- 1356 [28] Eiter, T. and Lukasiewicz, T. (2002). Complexity results for structure-  
1357 based causality. *Artif. Intell.*, 142(1):53–89.
- 1358 [29] Fang, H. (2018). A discussion of citations from the perspective of the  
1359 contribution of the cited paper to the citing paper. *JASIST*, 69(12):1513–  
1360 1520.
- 1361 [30] Garfield, E. (1999). Journal impact factor: a brief review. *Can. Med.*  
1362 *Assoc.*, 979-980.
- 1363 [31] Gößwein, B., Miksa, T., Rauber, A., and Wagner, W. (2019). Data  
1364 identification and process monitoring for reproducible earth observation  
1365 research. In *2019 15th International Conference on eScience (eScience)*,  
1366 pages 28–38. IEEE.

- 1367 [32] Green, T. J., Karvounarakis, G., and Tannen, V. (2007). Provenance  
1368 semirings. In *Proceedings of the twenty-sixth ACM SIGMOD-SIGACT-*  
1369 *SIGART symposium on Principles of database systems*, pages 31–40. ACM.
- 1370 [33] Halpern, J. Y. and Pearl, J. (2013). Causes and explanations: A  
1371 structural-model approach — part 1: Causes. *CoRR*, abs/1301.2275.
- 1372 [34] Harding, S. D., Sharman, J. L., Faccenda, E., Southan, C., Pawson,  
1373 A. J., Ireland, S., Gray, A. J. G., Bruce, L., Alexander, S. P. H., Anderton,  
1374 S., Bryant, C., Davenport, A. P., Doerig, C., Fabbro, D., Levi-Schaffer, F.,  
1375 Spedding, M., Davies, J. A., and Nc-Iuphar (2018). The IUPHAR/BPS  
1376 guide to PHARMACOLOGY in 2018: updates and expansion to encom-  
1377 pass the new guide to IMMUNOPHARMACOLOGY. *Nucleic Acids Re-*  
1378 *search*, 46(Database-Issue):D1091–D1106.
- 1379 [35] Hartley, J. (2017). Authors and their citations: a point of view. *Scien-*  
1380 *tometrics*, 110(2):1081–1084.
- 1381 [36] Hey, T., Tansley, S., and Tolle, K. M. (2009). Jim Gray on eScience: a  
1382 transformed scientific method.
- 1383 [37] Honor, L. B., Haselgrove, C., Frazier, J. A., and Kennedy, D. N. (2016).  
1384 Data citation in neuroimaging: proposed best practices for data identifi-  
1385 cation and attribution. *Frontiers in neuroinformatics*, 10:34.
- 1386 [38] Jain, S., Moritz, D., Halperin, D., Howe, B., and Lazowska, E. (2016).  
1387 Sqlshare: Results from a multi-year sql-as-a-service experiment. In *Pro-*  
1388 *ceedings of the 2016 International Conference on Management of Data*,  
1389 pages 281–293.
- 1390 [39] Jha, A. K. and Suciu, D. (2013). Knowledge compilation meets database  
1391 theory: Compiling queries to decision diagrams. *Theory Comput. Syst.*,  
1392 52(3):403–440.
- 1393 [40] Joshi-Tope, G., Gillespie, M., Vastrik, I., D’Eustachio, P., Schmidt, E.,  
1394 de Bono, B., Jassal, B., Gopinath, G. R., Wu, G. R., Matthews, L., Lewis,  
1395 S., Birney, E., and Stein, L. (2005). Reactome: a knowledgebase of bio-  
1396 logical pathways. *Nucleic Acids Research*, 33(Database-Issue):428–432.

- 1397 [41] Katz, D. (2014). Transitive credit as a means to address social and  
1398 technological concerns stemming from citation and attribution of digital  
1399 products. *Journal of Open Research Software*, 2(1).
- 1400 [42] Kendall, M. G. (1938). A new measure of rank correlation. *Biometrika*,  
1401 30(1/2):81–93.
- 1402 [43] Kosten, J. (2016). A classification of the use of research indicators.  
1403 *Scientometrics*, 108(1):457–464.
- 1404 [44] Lawrence, B., Jones, C., Matthews, B., Pepler, S., and Callaghan, S.  
1405 (2011). Citation and Peer Review of Data: Moving Towards Formal Data  
1406 Publication. *International Journal of Digital Curation*, 6(2):4–37.
- 1407 [45] Livshits, E., Bertossi, L. E., Kimelfeld, B., and Sebag, M. (2020). The  
1408 shapley value of tuples in query answering. In Lutz, C. and Jung, J. C.,  
1409 editors, *23rd International Conference on Database Theory, ICDT 2020,*  
1410 *March 30-April 2, 2020, Copenhagen, Denmark*, volume 155 of *LIPICs*,  
1411 pages 20:1–20:19. Schloss Dagstuhl - Leibniz-Zentrum für Informatik.
- 1412 [46] Martone, M. (2014). Joint declaration of data citation principles.  
1413 *FORCE11. San Diego CA. Data Citation Synthesis Group*. [https://www.](https://www.force11.org/datacitationprinciples)  
1414 [force11.org/datacitationprinciples](https://www.force11.org/datacitationprinciples), online September 2020.
- 1415 [47] Meho, L. I. and Yang, K. (2007). Impact of data sources on citation  
1416 counts and rankings of LIS faculty: Web of science versus scopus and  
1417 google scholar. *Journal of the american society for information science*  
1418 *and technology*, 58(13):2105–2125.
- 1419 [48] Meliou, A., Gatterbauer, W., Moore, K. F., and Suciu, D. (2010). The  
1420 complexity of causality and responsibility for query answers and non-  
1421 answers. *Proc. VLDB Endow.*, 4(1):34–45.
- 1422 [49] Milo, T. (2019). Getting rid of data. *Journal of Data and Information*  
1423 *Quality (JDIQ)*, 12(1):1–7.
- 1424 [50] Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D.,  
1425 Breckler, S. J., Buck, S., Chambers, C. D., Chin, G., Christensen, G.,  
1426 Contestabile, M., Dafoe, A., Eich, E., Freese, J., Glennerster, R., Goroff,  
1427 D., Green, D. P., Hesse, B., Humphreys, M., Ishiyama, J., Karlan, D.,  
1428 Kraut, A., Lupia, A., Mabry, P., Madon, T., Malhotra, N., Mayo-Wilson,

- 1429 E., McNutt, M., Miguel, M., Paluck, E. L., Simonsohn, U., Soderberg, C.,  
 1430 Spellman, B. A., Turitto, J., VandenBos, G., Vazire, S., Wagenmakers,  
 1431 E. J., Wilson, R., and Yarkoni, T. (2015). Promoting an open research  
 1432 culture. *Science*, 348(6242):1422–1425.
- 1433 [51] Peters, I., Kraker, P., Lex, E., Gumpenberger, C., and Gorraiz, J.  
 1434 (2016). Research data explored: An extended analysis of citations and  
 1435 altmetrics. *Scientometrics*, 107(2):723–744.
- 1436 [52] Pröll, S. and Rauber, A. (2013). Scalable data citation in dynamic,  
 1437 large databases: Model and reference implementation. In *Proceedings of*  
 1438 *the 2013 IEEE International Conference on Big Data, 6-9 October 2013,*  
 1439 *Santa Clara, CA, USA*, pages 307–312.
- 1440 [53] Rauber, A., Ari, A., van Uytvanck, D., and Pröll, S. (2016). Identi-  
 1441 fication of Reproducible Subsets for Data Citation, Sharing and Re-Use.  
 1442 *Bulletin of IEEE Technical Committee on Digital Libraries, Special Issue*  
 1443 *on Data Citation*, 12(1):6–15.
- 1444 [54] Rauber, A., Asmi, A., van Uytvanck, D., and Proell, S. (2015). Data  
 1445 citation of evolving data: Recommendations of the working group on data  
 1446 citation (wgdc). *Result of the RDA Data Citation WG*, 20.
- 1447 [55] Remil, Y., Bendimerad, A., Mathonat, R., Chaleat, P., and Kaytoue,  
 1448 M. (2021). ” what makes my queries slow?”: Subgroup discovery for sql  
 1449 workload analysis. *arXiv preprint arXiv:2108.03906*.
- 1450 [56] Shapley, L. S. (1954). A value for n-person games. In Kuhn, H. W. and  
 1451 Tucker, A. W., editors, *Contributions to the Theory of Games II*, pages  
 1452 307–317. Princeton University Press, Princeton.
- 1453 [57] Silvello, G. (2018). Theory and practice of data citation. *J. Assoc. Inf.*  
 1454 *Sci. Technol.*, 69(1):6–20.
- 1455 [58] Simmhan, Y., Plale, B., and Gannon, D. (2005). A survey of data  
 1456 provenance in e-science. *SIGMOD Record*, 34(3):31–36.
- 1457 [59] Spengler, S. (2012). Data Citation and Attribution: A Funder’s Per-  
 1458 spective. In of Sciences’ Board on Research Data, N. A. and Information,  
 1459 editors, *Report from Developing Data Attribution and Citation Practices*

- 1460     *and Standards: An International Symposium and Workshop*, pages 177–  
1461     178. National Academies Press: Washington DC.
- 1462     [60] Vogelsgesang, A., Haubenschild, M., Finis, J., Kemper, A., Leis, V.,  
1463     Mühlbauer, T., Neumann, T., and Then, M. (2018). Get real: How bench-  
1464     marks fail to represent the real world. In *Proceedings of the Workshop on*  
1465     *Testing Database Systems*, pages 1–6.
- 1466     [61] Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G.,  
1467     Axton, M., Baak, A., Blomberg, N., Boiten, J., da Silva Santos, L. B.,  
1468     Bourne, P. E., et al. (2016). The fair guiding principles for scientific data  
1469     management and stewardship. *Scientific data*, 3.
- 1470     [62] Wu, Y., Alawini, A., Davidson, S. B., and Silvello, G. (2018). Data  
1471     citation: Giving credit where credit is due. In *Proceedings of the 2018*  
1472     *International Conference on Management of Data, SIGMOD*, pages 99–  
1473     114.
- 1474     [63] Zeng, T., Wu, L., Bratt, S., and Acuna, D. E. (2020). Assigning credit to  
1475     scientific datasets using article citation networks. *Journal of Informetrics*,  
1476     14(2).
- 1477     [64] Zou, C. and Peterson, J. B. (2016). Quantifying the scientific output of  
1478     new researchers using the zp-index. *Scientometrics*, 106(3):901–916.
- 1479     [65] Zwölf, C. M., Moreau, N., and Dubernet, M.-L. (2016). New Model for  
1480     Datasets Citation and Extraction Reproducibility in VADMC. *Journal of*  
1481     *Molecular Spectroscopy*, 327:122–137.