Data Provenance: What next?

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ABSTRACT
Research into data provenance has been active for almost twenty years. What has it delivered and where will it go next? What practical impact has it had and what might it have? We provide speculative answers to these questions which may be somewhat biased by our initial motivation for studying the topic: the need for provenance information in curated databases. Such databases involve extensive human interaction with data; and we argue that the need continues in other forms of human interaction such as those that take place in social media.

1. INTRODUCTION
The purpose of this paper is neither to define provenance nor to provide a survey of the relevant research; there are numerous contributions to the literature that do this [19, 18, 25, 45, 49, 71, 28]. What we hope to do here is to draw out new strands of research and to indicate what we can do practically on the basis of what we now know about provenance. A good starting point is to state two generally held but conflicting observations: first that the more provenance information one can collect the better; second that it is impossible in practice to record all relevant provenance information.

Before narrowing our discussion to data provenance, let us look at these two observations. Imagining the impossible, suppose we could record all the provenance associated with some process or artefact (digital or otherwise). In what would be a massive amount of provenance data, would we be able to answer simple questions such as where some data was copied from or whether a process invoked a particular piece of software? Such questions may involve the querying of huge data sets and complex code. So simply recording total provenance, even if it were possible, still requires complex analysis. It requires us to extract simple explanations from a massive and complex structure of data and code. What are those explanations?

Being more realistic, in practice, we only have resources to record a limited amount of provenance information. So what do we record? We may – as is the case with physical artefacts – have some standard attributes (ownership, location etc.) but for computational processes and data can we predict what will be asked of provenance? Again we have to understand what kinds of explanation we are likely to want. Is there any minimal requirement on what we should record or how we should record it?

For most purposes, what we should record is application dependent. For example, if an application is targeting to answer the provenance of a sales figure reported in a company earnings report, then the data provenance that consists of the source data and the program or query that was used to generate the report are likely to be sufficient. However, sometimes, intermediate sales results from specific regions are combined with other data sources or results from other regions to generate the final report. In this case, to provide a comprehensive understanding of the sales figure in the company earnings report, it may also be necessary to track the programs that were used to generate the intermediate results.

In yet another type of application, it is important that the results are repeatable and reproducible. This is true of experiments in chemistry and physics where it is not only crucial that one can obtain the same results by running the experiments but also by running it at other locations. Software repeatability and reproducibility have also become an important topic. To enable software reproducibility, it is typically necessary to document the hardware, the version of operating system and software libraries used, in addition to the program and data used to execute the experiment.

Insofar as data provenance is separable from other forms of provenance [8, 26] we focus on provenance that has to do with data: databases, data sets, file systems etc. In the Background section that follows, we summarise some of the important research contributions to data provenance, the motivation behind the research and the practical applications of it. In Section 3, we then look at possible applications of provenance in other areas of computer science.
2. BACKGROUND

As often happens, the first paper that addressed provenance [78] in databases had to be “rediscovered” several years after it was written. This paper introduced a form of tagging or annotation to describe the source of elements of a relational database, a form of where-provenance. Then in the later 1990s under various names the study started in earnest. In [79] a method based on inverse functions was used to visualize the lineage of data in scientific programming; and in [21, 22], in the context of data warehouses, an operational definition was given of what tuples in some source data “contributed to” a tuple in the output of a relational query — perhaps a form of why-provenance.

The authors’ interest in the topic was sparked by their collaboration with biologists [44] involved in the Human Genome Project who were building curated databases of molecular sequence data. While a curated database resembles a data warehouse in the integration of existing databases, it also involves the manual correction and augmentation of the source data, and it cannot simply be characterized as a data warehouse or view. The biologists complained that they were losing track of where their data had come from. Now biologists are, by training, quite meticulous in keeping a record of what they have done — in this case what queries they have made or what manual additions or corrections were made, so in some sense the provenance of some small element of data — a number or a tuple — was available. However extracting the information they needed from a complex workflow of updates and queries on other databases was proving difficult. What they appeared to need was a simple explanation e.g.: “this number was entered by ... on ...” (where-provenance); or “this tuple was formed by joining tuple $t_1$ from $R_1$ to tuple $t_2$ from $R_2$” (how-provenance); or “this tuple is in the result because some other tuple was in the input” (why-provenance).

The example in Figure 1 illustrates the types of provenance described above. Consider a Friend relation, a Profile relation, and a query that joins the two relations to find pairs of friends with identical occupations (shown below).

```
select f.name1, f.name2
from Friend f, Profile p1, Profile p2
where f.name1 = p1.name and
      f.name2 = p2.name and
      p1.occupation = p2.occupation
```

The value “Carl” in the result is derived from the value “Carl” in the Friend relation. Hence, if there were an annotation on who entered that information and when, this information can propagate to the result according to where-provenance. The figure also illustrates that the how-provenance of the output tuple is the result of joining three tuples (Carl, Bob), (Bob, 30, analyst), and (Carl, 50, analyst) from the input. The why-provenance of the output consists of the same three source tuples. We will discuss the finer differences between the latter two types of provenance in Section 2.1. However, it is important to note that to fully explain why the output tuple exists, one must also account for the query. That is, these three tuples satisfy all the equality condition in the where clause of the query.

What we should again emphasize is that the purpose of data provenance is to extract relatively simple explanations for the existence of some piece of data from some complex workflow of data manipulation. In this sense it has a similar purpose to program slicing which seeks to provide an explanation for a part of the output of some complex program to a small part of the input — an explanation that is much simpler than the program itself.

Given that provenance is about explanation of some part of a complex process, it is natural to ask whether there is a unified language or model for describing provenance. PROV is a W3C recommendation for a model or ontology in which one can describe provenance [60, 58]. The intention is to produce a general model for any kind of provenance such as that associated with artefacts or some general computational process. At its core, PROV can be used to describe causal relationships between entities and activities, and in doing this can naturally describe the evaluation of a workflow. Because of this the term “workflow provenance” has sometimes been used to distinguish the ambit of PROV from that of data provenance. Worse, the terms “fine-grained” and “coarse-grained” have been used for this distinction. We do not believe these distinctions to be helpful. While it is straightforward to use PROV to describe basic aspects of data provenance, we do not do so in this paper because it does not add much to the formalisms that have been found useful in the context of databases. Conversely, there is no reason why the formalisms developed for “fine-grained” data manipulation cannot be used in a larger context as we shall see in Section 3.1.

2.1 Annotation and provenance

From the beginning it was recognized that provenance should be expressed as a form of annotation. This was precisely the purpose of the Polygen model [78]: to annotate data elements with their provenance. However, there is a much more fundamental connection between the two topics, which again shows up in curated databases. Much of curated data is about annotation of existing data structures. Sometimes this annotation is expressed in the primary tables in a relational database, but sometimes important information about the currency or validity of some data is held in an auxiliary table or –
in the case of semistructured data – some additional sub-
trees in a hierarchy or some additional edges in a graph
representation. In fact, annotation data is semistructured
by nature and often lives in some kind of auxiliary data-
bases. Queries over the “core” data often do not recog-
nize this annotation, and this is one of the main sources
of misleading or dirty data in both data warehouses and
curated databases.

The basic question is then how do annotations prop-
agate through database queries? This is a question that
is closely related to data provenance and one that has
driven much of the most interesting research on data
provenance since its inception.

**Annotation.** The Polygen model [78] inspired the sub-
sequent system DBNotes [6, 20] and other following
work (e.g., [35, 10]). For each relational algebra oper-
ator, DBNotes provided a rule to propagate annotations
based on where data is copied from. These rules are sen-
sitive to the way the query is formulated: even though
two queries are equivalent in the normal sense of always
producing the same result the way the rules propagate
annotations through the two queries may differ. Another
propagation scheme that is agnostic to the way equiva-

tent queries are formulated was also proposed to propa-
gate the same annotations to the result.

That provenance may be sensitive to query formula-

tion is seen in [10] which discusses update languages
and uses a propagation scheme that is an extension of
that in DBNotes. From a theoretical perspective, rela-
tional update languages, such as the update fragment of
SQL, are often regarded as uninteresting because they
are no more expressive than query languages. Consider
the action of an SQL update: it replaces a version of
the database with a new version. If we think of the old
version as the input and the new version of the output,
then that transformation from input to output can be ex-
pressed as a query in relational algebra. For example,
Figure 2.1 shows a simple update query and an equiva-
lent – in the sense that it produces the same output –
query that doesn’t involve updates. The backwards ar-
rows show where all components of the table, values
tuples and the table itself, come from. While the two
queries produce the same answer, the provenance is dif-
ferent. The first update query only affects the where-
provenance of the cell that the number “5” belongs to in
the output. All the other components of the result table
“come from” the corresponding component of the input
table. On the other hand the more complicated query not
only creates a new value 5, and a new tuple containing
that value and a new table. In the figure the components
that are created by the query are outlined in dotted red;
the components that are copied are outlined on black.

The interesting observation is that if we take prove-

going into account, that is the query or update is a func-
tion that not only produces a result but also produces
where-provenance associated with the values and tuples
in a table, update languages become *more* expressive
than query languages. Moreover [10] provides a com-
pleteness result: if the where-provenance can be expressed
in (nested) relational algebra, then there is an update
query in which the same where-provenance is implicit.

**Semiring provenance** The seminal work of [40] de-
scribes a formalism of data provenance that captures and
extends previous formalisms such as why-provenance
of [14] and lineage described in the Trio system [5].

A *commutative semiring* is a quintuple \((K, 0, 1, \oplus, \otimes)\).
Here, \(K\) is a set of elements containing the distinguished
elements 0 and 1, \(\oplus\) and \(\otimes\) are two binary operators that
are both commutative and associative and 0 and 1 are
the identities of \(\oplus\) and \(\otimes\) respectively. In addition, \(\otimes\) is
distributive over \(\oplus\) and \(0 \otimes t = t \otimes 0 = 0\).

We assume that every tuple in the source database has
a tuple identifier, and \(I \subseteq K\) is the set of all such source
tuple identifiers. The provenance of an element in an
output table is expressed as a polynomial, an expres-
sion built up from \(I, 0, 1, \oplus\) and \(\otimes\). The provenance
of an output tuple for each relational operator (select,
project, cross product, union, rename) is obtained from
the provenance polynomial of each input tuple. The sim-
plest case is selection in which the provenance of an out-

put tuple is the same as the provenance of the (unique) corresponding input tuple. For join, suppose that tuple is the same as the provenance of the (unique) tuple was constructed – by “joining” (jection, the provenance is the polynomial \( e \circ e \)). We can think of the polynomial as a description of each tuple in the output of a query are built up inductively by these rules and others described in [40]. We can think of the polynomial as a description of how each tuple was constructed – by “joining” (\( \circ \)) and “merging” (\( \oplus \)) other tuples.

The example below shows a query in SQL over the Friend relation of Figure 1. The query finds all people who share a friend with someone. In some sense the query is trivial because everyone shares a friend with themselves, however the provenance is interesting.

Query:

```sql
select f1.name1
from Friend f1, Friend f2
where f1.name2 = f2.name2
```

Assume that the tuples (Ann, Bob), (Carl, Bob), and (Frank, Dan) are annotated with \( i_1, i_2 \), and respectively, \( i_3 \). The result of the query is shown below alongside with annotations of the corresponding provenance polynomials and why-provenance.

<table>
<thead>
<tr>
<th>name1</th>
<th>provenance</th>
<th>why-provenance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann</td>
<td>( i_1 \circ i_1 \oplus i_1 \circ i_2 )</td>
<td>{( {i_1}), {( i_1, i_2}}}</td>
</tr>
<tr>
<td>Carl</td>
<td>( i_2 \circ i_2 \oplus i_1 \circ i_2 )</td>
<td>{( {i_2}), {( i_1, i_2}}}</td>
</tr>
<tr>
<td>Frank</td>
<td>( i_3 \circ i_3 )</td>
<td>{( {i_3}}}</td>
</tr>
</tbody>
</table>

For example, the provenance polynomial for Ann is \( i_1 \circ i_1 \oplus i_1 \circ i_2 \) showing that \( i_1 \) and \( i_2 \) itself is one way of deriving the output tuple and another uses \( i_1 \) and \( i_2 \).

The remarkable property of these polynomials is that they unify many other generalizations of relational algebra such as bag semantics, C-tables and probabilistic databases. For bag semantics simply assign the “identifier” \( 1 \) to each tuple in the input and use the semiring \((\mathbb{N}, 0, +, \times)\). The evaluation of the polynomial attached to a tuple gives the multiplicity of that tuple.

These polynomials also capture why-provenance with the semiring \((\text{Why}(K), \emptyset, \{\emptyset\}, \cup, \ominus)\), where \( x \cup y \) denotes the pairwise union of all sets in the two collections \( x \) and \( y \). The evaluation of the provenance polynomial will give rise to the set of sets shown on the rightmost column above. Indeed, if we interpret each tuple identifier as a set of a singleton set, then the provenance polynomial of Ann \( i_1 \circ i_1 \oplus i_1 \circ i_2 \) is \( \{\{i_1\}\} \cup \{\{i_1\}\} \ominus \{\{i_1\}\} \circ \{\{i_2\}\} \) which is \( \{\{i_1\}\} \cup \{\{i_1, i_2\}\} \) and gives rise to the why-provenance \( \{\{i_1\}, \{i_1, i_2\}\} \).

Observe that the why-provenance describes what tuples in the source are sufficient for deriving the output according to the query. Indeed, either \( i_1 \) alone or both \( i_1 \) and \( i_2 \) are sufficient for generating the output tuple Ann according to the query. It is easy to see that the why-provenance can be derived from the provenance polynomial but not the other way round; the provenance polynomial is more informative.

Semirings for propagating comments or beliefs can also be derived from the semiring framework. For example, the semiring \((\text{Lin}(K), \bot, \emptyset, \cup, \ominus)\) which captures the lineage described in [22] can also be used to model how comments should propagate. Intuitively, the element \( \bot \) denotes no lineage while \( \emptyset \) denotes empty lineage, and \( \cup \) is the usual union operator \( \cup \) except that \( \bot \cup X = X \cup \bot = \bot \).

The figure above exemplifies the “comments” semiring. The first source tuple (Ann, Bob) has two comments \( C_1 \) and \( C_3 \) and the second source tuple (Carl, Bob) has a single comment \( C_2 \) each of the first two tuples has all three comments in the result.

On the other hand, the belief of an output tuple can be captured with the following semiring \((\text{Belief}(K), \bot, \emptyset, \cup, \ominus)\).
which takes the intersection of the beliefs of the source
tuples on a relational join.

<table>
<thead>
<tr>
<th>Friend (F)</th>
<th>name1</th>
<th>name2</th>
<th>name1</th>
<th>name2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann</td>
<td>Jane</td>
<td>Tim</td>
<td>Ann</td>
<td>Jane</td>
</tr>
<tr>
<td>Carl</td>
<td>Bob</td>
<td>Sue</td>
<td>Carl</td>
<td>Jane</td>
</tr>
<tr>
<td>Frank</td>
<td>Dan</td>
<td>Zoe</td>
<td>Frank</td>
<td>Sue</td>
</tr>
</tbody>
</table>

Hence, \{Jane, Sue\} are the only remaining believers after the relational join operation.

Today, several database systems have been developed to support the propagation and querying of provenance such as Perm [37], LogicBlox, and Orchestra [39]. More recent implementations such as [2] provides a provenance-aware middleware implementation which can be used with different database back-ends and also supports **provenance for transactions**. Provenance support has also been implemented outside database systems. For example, in network provenance [82, 81], provenance is maintained and queryable at Internet-scale for diagnosing network errors in a distributed setting.

### 2.2 Provenance, repeatability, versioning

The ability to reproduce an experiment is essential to the credibility of the results of that experiment. The same is true for any kind of computational analysis or workflow that has been used to derive some data: the analysis must be repeatable. Whatever is needed to ensure repeatability is often regarded as provenance. The ability to record, reproduce, and query some computational process underlies “system-level” provenance [62], the provenance “challenge” [61] and at least one view of data citation [66]. Now almost all such analyses use some kind of external data source – this is obvious in the case of data citation, where the data source is the source being cited. The problem in all these cases is that the data source, and even its structure, is likely to evolve over time.

In curated databases we see a similar problem. When external data is incorporated, it is common to provide a link to source data as part of the provenance. While this requirement seems rather straightforward, there are at least two caveats to ensure a proper “implementation” that meets this requirement. First, the link should be a stable reference to the correct version of the database even if the database evolves. Most curated databases have a link which serves as a citation to its entire database. Web pages follow a similar organization where its URL refers to the latest version of the web page. When the database changes, the new database replaces the old database and hence, the link, which now refers to the new database, is no longer a valid reference for the previous database. The second issue is that the link is typically a coarse-grain approximation to a specific part of the database where the reference is typically intended for. While the HTML structure of web pages can be exploited to pinpoint to specific portions of the website, it is less obvious how specific portions of a database can be precisely referenced.

#### Data Versioning

To ensure proper citation, some curated databases simply keep all past versions of the data. The onus is on the user to cite the correct (portions of the) version and to answer queries over multiple versions of data. For example, longitudinal queries such as “what are all the changes in the last five versions?”, or “when was this entry made?” would be difficult to answer without going through each of the relevant database versions at least once.

Another approach, which is more economical on storage, stores only the changes (or deltas) between consecutive versions. However, the need to go through every relevant version for certain types of longitudinal queries such as “return all versions where a particular entry exists” is still unavoidable.

The archiving method of [13] strikes a balance between the two approaches described above; it keeps all database versions intact and economically by “merging”, to the extent possible, different database versions together. Conceptually, every version is assumed to be in a hierarchical format such as in a JSON file format or XML. Every node has an associated set of intervals which captures the versions by which the node exists (the fat node method of persistent data structures [32]). Furthermore, if, as frequently happens, a node’s interval set is identical to that of its parent one can save storage by taking the lack of an interval set to indicate that the interval set should be inherited. For biological databases such as those described in [13], it was observed that the dominant change is the addition of a node in the hierarchy, and that node modifications are relatively infrequent. This allows significant space savings, and a year’s history of a database typically requires only a small percentage overhead in storage.

The main challenge with the archiving strategy is that it is not obvious how to match and merge nodes of a version into nodes of an existing database archive. In [13], a critical assumption is that there are keys for nodes in a hierarchical structure [12]. The keys are paths of labels or values and identify nodes in a version. Hence, they also help identify which nodes in the database archive to match and merge into. If a node in the version does not exist in the database archive, then it is a node that is new to the version and will be created as a new node in the database archive with a new interval. Conversely, if a node in the database archive has no corresponding node in the database version, then that node no longer exists and its interval of versions is terminated accordingly. Otherwise, the node is merged into the node in the database archive and its interval of versions is extended,
In temporal databases, much of the effort is dedicated to the tuple is actually valid in the real world (valid time). Transaction time distinguishes these two types of time; transaction time change is recorded in the database. Bi-temporal databases of when a tuple has changed coincides with when the change is recorded in the database. Therefore, managing and querying [52] these two notions of time efficiently.

Most versioning work and temporal databases has focused on recording data changes and there are relatively little that directly tackles the problem of managing both data and schema changes [68, 59, 23]. When the schema changes, can we easily query which data has changed (or not) across different versions? Can we effectively answer longitudinal queries across the versions? Can we seamlessly answer and even visualize the provenance of data that may consist of tuples from different versions, which may in turn be the result of another query on a database and so on?

### 3. WHAT IS NEXT?

So far, we have described, and asked questions about, existing work on data provenance that was largely motivated by curated databases. Next, we look at potential applications of provenance in data citation and in other areas of computer science, such as machine learning, social media, blockchain technology and privacy.

#### 3.1 Provenance and data citation

Because so much knowledge is now disseminated through some form of database, there has been an increasing demand [34, 67] for these databases to be properly cited for the same reasons that we use citations for conventional publications. There is a problem in that data of interest is usually extracted from the database by some form of query. What citation should one associate with
interpretability is quite different from interpretability of the predication so that a programmer can debug the model of interpretability. For example, the requirements for provenance, different users have different requirements. Hence, understanding the foundations by which a decision has been made can help build further trust in the system’s performance and understand the foundations by which a decision has been made.

In machine learning research, the problem of deriving explanations of machine learning models is called interpretability. Somewhat ironically, there is less consensus on what the exact interpretation of interpretability [31, 64] should be. However, the reason for the lack of consensus should not be surprising. Like the situation in provenance, different users have different requirements of interpretability. For example, the requirements for interpretability so that a programmer can debug the model is quite different from interpretability of the prediction of a crop yield. In the latter, one may only need to explain that it is because the estimated rainfall is high/low but in the former, one may need to understand how many rounds of simulation have been applied, the parameters and software modules used.

While some models lend themselves well to some form of interpretability (e.g., generalized additive models [15]), other models, especially neural networks, are opaque. An approach to overcome the opaque nature of neural networks is to learn another less opaque model based on the predictions of the original model.

The goals of data provenance and interpretability are clearly similar. Both seek to find explanations, at different levels of granularity, for the output of a program or a process. A major difference is that in database provenance, the program and process that have been considered by researchers are typically not opaque as in machine learning models.

A promising area of cross-fertilization between provenance and interpretability is the following: Instead of learning models that are interpretable based on the predictions of the original model, one can learn rules or program (in some language) that can approximate a machine learning model or special cases of it. The problem of deriving rules from the model predictions is closely related to the problem of reverse engineering queries, which is to derive the specification from known behaviors such as known input and output mappings (e.g., [7, 75, 48] to name some recent work). These rules can be further abstracted to provide human friendly explanations for the model [74]. Interestingly, the process of reverse engineering often involves developing a machine learning model to learn a query for the given input and output data, which itself may require explanations.

### 3.2 Provenance and machine learning

Machine learning and artificial intelligence have become an indispensable part in our daily lives. Machine learning methods are commonly used to automate everyday decision making in all aspects of our lives; from predicting email spams [42] to predicting crop yields [76], loan application, autonomous driving [17], disease identification and recommendation of medical treatments [51]. Even if machine learning models perform very well in practice, it is natural to question why a certain decision or prediction has been made, especially when decisions are critical. Explanations of a model’s output can help build further trust in the system’s performance and understand the foundations by which a decision has been made.

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### 3.3 Provenance and social media

Social media, such as Facebook, Instagram, Twitter etc., are an effective vehicle for disseminating news at scale. They provide an easy platform for users to continuously communicate and network with one another. The continuity and scale are critical characteristics that set it apart from traditional forms of communications such as phones, television, or newspapers. Unfortunately, its effectiveness for disseminating information has also been exploited for disseminating fake news and fake claims.

There has been substantial interest lately in how to detect fake news articles or fake claims (e.g., see [1, 4, 16, 47, 80, 77]), and having adequate provenance is seen as an essential part of this process. We discuss some potential directions for further work and argue that building a mechanism for understanding the provenance of news obtained through the social network is an important part of determining fake news or fake claims.

As with data provenance, the provenance of a piece
of information found in an article or statement in social media should explain why that information is there and how it was created. One method of achieving this is to ensure that provenance is disseminated along with news propagation. We should also discredit news without mechanisms for authenticating its provenance. When an article is first created, it should include information such as the authorship and attribution to sources. The social network software responsible for disseminating the news should add the identity of the receiver into the chain of provenance information. Furthermore, there should be tamper-proof mechanisms built into the software to prevent the identity from being modified.

If provenance information may not be immediately available from an article, can we infer the provenance with social media network? For example, [72] identifies the source of rumor when all recipients are known (rumor-centrality). In [53], the effectors are determined under the independent cascade propagation model and in [65], the NetSleuth approach [65] estimates the sources under the assumption of the Susceptible Infected information propagation model. As shown in [33, 41], some provenance attributes can also be recovered from various social media websites and can lead to better knowledge of the sources.

A promising area for further research is to incorporate provenance into the fact checking problem. Fact checking originated from the data journalism community and refers to the problem of determining whether or not factual claims in media content are true. Today, there are websites\(^1\) dedicated to analyzing and reasoning about facts. Google also supports an API for reviewing claims\(^2\). Note that whether a fact is true or not is actually independent of its provenance. However, since a trusted source tends to produce articles that are free of wrong facts, a property for judging whether a claimed fact is true or not can be based on the trustworthiness of the sources. In turn, this requires knowledge of the provenance attributes of these sources. Can we use provenance to as a reliable signal for determining whether a fact is true or not? Some recent work has begun to incorporate such information in determining the truth of news/facts [69]. Another promising direction is to incorporate trust and reputation management into social media. Can we maintain a reputation rating for different sources based on their history of the authenticity of news articles and correct facts that are wrongly reported and shared. In turn, these reputation ratings can be used as another signal for fact checking and checking for fake news [29]. Regardless of the method used to determine sources of fake news or fake claims, it is crucial that provenance about the sources can be obtained or inferred. It is also critical to create standards to institute a minimum set of attributes that should be provided before an author can publish or responsibly propagate an article on any social media platform.

### 3.4 Provenance and blockchain technology

Blockchain technology, or more generally, Distributed Ledger Technology (DLT) has been developed to keep a distributed immutable ledger of financial transactions. The ledger can be seen as a provenance record of, say, bitcoins; and it is therefore entirely unsurprising that DLT could be used to record provenance in other settings. There is some commercial interest in using DLT to record supply side provenance – for example the farm from which a lamb chop originated [56, 73], and there have been suggestions that it could be used for valued artefacts [70]. Superficially this kind of provenance looks rather like where-provenance for digital artefacts. Indeed there is at least one system [55] that has been developed to record data provenance at the level of file systems. The system-level provenance [62] operations on files such as read, write, share and modify are recorded using DLT.

Whether the cost of current DLT justifies its use for these applications or whether there are sufficient financial incentives to maintain a distributed ledger for the provenance of artefacts are questions well beyond the scope of this paper. However there is one interesting observation regarding data provenance. DLT was developed [63] in part to prevent “double spending”: the same coin cannot be given to two parties, and a similar constraint holds for the provenance of artefacts. In nearly all forms of data provenance, it is understood that data gets copied, thus we do not need this constraint. Whether this will allow us to to develop simpler or less costly distributed ledgers for data provenance is an open question.

### 3.5 Provenance and privacy

On the face of it, provenance negates privacy. Gaining knowledge of where some piece of clinical data has come from is exactly what techniques such as differential privacy are designed to prevent. This contradiction itself poses some interesting questions because there are many situations in which we want both provenance and privacy. Imagine, for example that we have some clinical patient records provided by a hospital H and a research group R that wants to analyze some of the data in those records. H writes programs to export anonymized data to R and R writes some analysis programs. H and R interact, and both H and R keep provenance associated with their activities perhaps for repeatability as described in Section 2.2. In what sense have they kept

\(^1\)https://www.factcheck.org, https://www.truthvalue.org

\(^2\)https://developers.google.com/search/docs/data-types/factcheck
enough provenance to describe the combined interaction?

This raises some interesting issues with provenance models. In what sense can we compose the provenance descriptions of two interacting activities. In the simple world of database queries, composition is a natural requirement and is usually satisfied. The provenance of the composition of two queries can be easily derived from the provenance of each of those queries. However, it is not clear how in, for example, PROV [60] one might glue together two provenance graphs of interacting activities, and whether this would be a satisfactory model of the combined activity. In our example of medical records, supposed R discovered some anomaly that indicated that H had a patient at risk. Would one have enough information to identify that patient? Also, suppose that neither R nor H wanted to reveal their individual provenance data, could some secure multi-party computation algorithm be used to identify the patient?

4. CONCLUSIONS

We have attempted to describe some areas in which data provenance is finding applications and is opening up new lines of research. There is no doubt that the theory of provenance, annotation in relational databases, and versioning will continue to develop and will be developed for other data models. Some examples of recent work in these areas include [36], where semirings are extended to capture the semantics of SPARQL queries (with OPTIONAL) on annotated RDF data and [38] where semirings are extended to deal with negation.

However the developments that will have the most impact will, we believe, stem from the public understanding of provenance. For example, we have seen how provenance can be understood and exploited in the social media, but there are even simpler situations in which one could develop useful applications of provenance. Consider the apparently innocuous copy and paste operations and how much provenance has been lost in their use. It would surely be a relatively simple matter to instrument these operations to carry some kind of provenance token that is generated for the source data (document, spreadsheet etc.) and for this to be carried across, along with the data being copied into a provenance repository associated with the target. In experimental environments for curated databases, such a mechanism has already been shown to be workable [9] and not at all costly in resources.

Today, the prevalence of open data [3] makes it even more compelling for data providers and consumers alike to instrument such provenance-aware generation and copy-paste mechanisms. Just as we prefer to read documents with proper authorship and from trusted sources, shouldn’t we place higher value on documents that contain provenance or are generated by editors that are provenance-aware? Isn’t it time to instrument good “provenance manners” to practice for the mass market by enabling documents to generate provenance tokens and editors to be provenance-aware?

5. REFERENCES


[67] Research Data Alliance (RDA), Data Citation WG.


[77] Research Data Alliance (RDA), Data Citation WG.


