Agora: Towards An Open Ecosystem for Democratizing Data Science & Artificial Intelligence

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ABSTRACT

Data science and artificial intelligence are driven by a plethora of diverse data-related assets including datasets, data streams, algorithms, processing software, compute resources, and domain knowledge. As providing all these assets requires a huge investment, data sciences and artificial intelligence are currently dominated by a small number of providers who can afford these investments. In this paper, we present a vision of a data ecosystem to democratize data science and artificial intelligence. In particular, we envision a data infrastructure for fine-grained asset exchange in combination with scalable systems operation. This will overcome lock-in effects and remove entry barriers for new asset providers. Our goal is to enable companies, research organizations, and individuals to have equal access to data, data science, and artificial intelligence. Such an open ecosystem has recently been put on the agenda of several governments and industrial associations. We point out the requirements and the research challenges as well as outline an initial data infrastructure architecture for building such a data ecosystem.

1. INTRODUCTION

The ongoing digitalization has a profound impact on industry, science, and society as a whole. The access to and the processing capabilities of data (by virtue of data science and AI algorithms) constitute a critical control point. They are crucial for economic success as well as for scientific and, in the end, for the societal progress of individuals, organizations, and even nations. In this context, we now talk of a completely new economy based on data\textsuperscript{1}. Economists and business leaders talk about the 4th industrial revolution\textsuperscript{2}. In sciences, the term 4th paradigm is used to derive scientific insights based on the analysis of large datasets generated from large scientific experiments\textsuperscript{31}.

The truth is that data has become a fundamental factor of production. It is usually curated and subsequently exploited, using data science and AI algorithms, to produce new insights to better understand (or solve) a problem. It has been identified that data and data science & AI technology are competitive differentiators in the data economy: Companies proficient at using them grow faster and perform better than their peers\textsuperscript{2}. Therefore, owning data and mastering data science as well as AI technologies are the key factors for future competitiveness.

Unfortunately, there are only a few players who have the control (“monopoly”) over most digital data. As owning data means owning intelligence, these few companies are then in a better position than anybody else. As a result, the data economy develops a strong dependency on a few companies only, which implicitly causes lock-in effects on customers. For instance, customers often have to stick to one cloud provider as cloud providers do not effectively interoperate among them. Such lock-in effects, in turn, might cause customers to use suboptimal solutions.

If data and data science & AI technologies are the production factors of the future, it is clear that they must be accessible by everyone. We must build a data ecosystem, where one can have access to (i) high-quality data, (ii) state-of-the-art data science and AI technology and expertise, and (iii) computing and storage resources. Having such an ecosystem would not only foster innovation by reducing the cost of getting new insights but also would have a benefit in data literacy for the population as a whole.

Academia and industry have made important progress to share data\textsuperscript{3}, AI algorithms\textsuperscript{4, 5}, expertise (services)\textsuperscript{6, 7, 8, 9}, or computational resources\textsuperscript{10}. However, we are still far from a unified data ecosystem, where different assets (e.g., data, algorithms, ML models, systems, services, or compute resources) are seamlessly combined to gain new insights or offer new services. For example, a social scientist, who has no expertise in data science techniques and does not own any data, has no chance to validate her assumptions about a social phenomenon, even if the required data and technology exists. Our envisioned ecosystem enables non-expert users to gain insights or enhance their businesses based on existing assets and enables asset providers to offer their assets to a broader audience. As a result, the ecosystem makes data and tools accessible to everyone.

The problem is that we are missing the data infrastructure to make such a data ecosystem possible. This problem has caught the attention of society and many governments, which are now willing to invest in building a data infrastructure\textsuperscript{13, 14, 15, 36}. We need a data infrastructure that provides the means for: (i) asset sharing and discovering; (ii) assets privacy and security; (iii) assets interoperability; (iv) query language independence; and (v) hardware independence.

In this paper, we layout our vision towards realizing a data ecosystem. We first present our motivation (Section 2), then introduce the infrastructure of the envisioned ecosystem (Section 3), and outline research challenges and possible solutions (Section 4). We discuss related work in Section 5 and summarize benefits and implications in Section 6.

2. MOTIVATION

We aim at designing an asset-centric ecosystem where everyone can offer and access all kinds of data-related assets and combine them to novel applications without any required expertise. Assets cover the whole data science pipeline ranging...
from sensor data streams over machine learning models to specialized algorithms and from processing systems to compute and storage resources. Such a fine-grained and easy exchange of assets leads to two major benefits for the ecosystem community:  

(1) **Secondary use of existing assets.** We enable reuse of existing assets such as code reuse and data reuse:

**Example 2.1 (Secondary use of assets)**
A company that develops a navigation system records videos of test drives to improve their software. This same data can be used for many other applications such as planning of road maintenance and cataloging parking spots. The data provider benefits from a financial reward and the data consumer gets cheap access to high-quality data which would not be available otherwise.

Especially in Europe, small and medium-sized companies build the backbone of the economy. These companies own a plethora of highly valuable assets. However, because these assets are fragmented across companies, their economical potential remains unused as secondary asset usage is extremely rare. A fine-grained asset sharing allows for combining existing resources to derive new insights and services.

(2) **Leveraging specializations.** We leverage an ecosystem of highly specialized asset providers who focus on a particular set of assets and can provide their assets in very high quality. Such an ecosystem is comparable with the automotive industry where many companies specialize in specific parts (e.g., brakes, tires, or lights), which get combined to one high-quality car.

**Example 2.2 (Specialized asset providers)**
One company can specialize in operating a network of weather stations and providing accurate weather data in real-time. Another company can develop a highly efficient stream join. Yet another company combines both assets to correlate weather data with its sales data in order to predict revenues and estimate required logistics based on weather conditions.

Such highly specialized providers can only operate economically if they can offer their assets through an open ecosystem without massive overhead. We want to provide an easy way to offer, buy, and combine data, algorithms, software components and other data-related assets. This allows small and medium-sized companies to offer data and software components that they would not be able to bring to market otherwise. The ecosystem prevents the need for individual negotiations between providers and consumers, which allows for building applications combining assets from multiple vendors. Currently, many companies replicate the same fundamental software components and suffer from the non-availability of sufficiently large training data. Our ecosystem aims to join forces to overcome these problems and to provide cheap and easy access to data science and AI for everyone.

3. **BUILDING A DATA ECOSYSTEM**

We now layout the data infrastructure we propose for building our envisioned data ecosystem. Our infrastructure builds around data-related units of production (Assets) and consists of two core components: Marketplaces and Operations Managers.

3.1 **Ecosystem Overview**

The key-idea of our vision is that the ecosystem offers both, the resources and the infrastructure, required to run any data-driven application. Providers and consumers meet in the data ecosystem to exchange data, algorithms, models and any other data-related assets. All users form a community that creates, rates, and uses assets. Anyone who offers an asset can benefit from shared revenues through open marketplaces.

Figure 1: Data Ecosystem Overview.
(5) Storage and compute: The data ecosystem accommodates storage and compute nodes, which can be offered by cloud providers, organizations, or individuals. Compute nodes can be virtual machines or dedicated servers and storage resources can be random access memory, disks, or network-attached storage.

(6) Applications: An application incubates systems, pipelines, algorithms, and, optionally, data sources and storage/compute nodes to offer a complete ready-to-use solution. The components that constitute the application can be assets from the data ecosystem or private resources. Typical applications include web applications, interactive dashboards, and home automation systems.

(7) Operation service: Reliably operating and tuning processing systems requires expertise and continuous monitoring, which is an asset per se. This asset bridges the gap between system vendors and providers of compute and storage resources.

(8) Expertise and consultancy: Combining existing assets to build new data-driven applications regularly requires a broad knowledge of available assets, compatibilities, SLAs, and price-performance ratios. Thus, the process of building applications from existing assets also becomes an asset in the data ecosystem.

Specification of Assets. As users might combine different assets to create new assets, pipelines, or applications, it is important to have a standard (asset specification layer in Figure 1) that provides a unified view of the different types of assets. Thus, asset providers comply with this specification when sharing their assets. They should be able to specify their assets logically, i.e., the asset can run on any runtime engine, or physically, i.e., the asset can only run on a specific runtime engine.

Constraints of Assets. Additionally, it is important that providers can specify how they want their assets to be shared and executed. Thus, the data infrastructure allows providers to define constraints on their assets. Such constraints include technical, non-technical, and functional requirements. Technical requirements cover particular hardware requirements (such as GPU and CPU architectures), main-memory requirements, and required software environments (such as specific operating systems and installed processing systems). Non-technical requirements cover location restrictions (e.g., do not share or transfer data outside the USA), vendor restrictions (e.g., run only on nodes provided by Microsoft), and other arbitrary certificates (e.g., SLAs for security standards or for using renewable energy). Functional requirements are restrictions concerning financial costs, processing latency, and execution times. In the full version of this paper, we will describe each asset, the resulting user roles, the benefits for asset providers, and the combination of assets in more detail by providing end-to-end examples.

3.3 Marketplace: Sharing Assets

The marketplace is an essential component of the data infrastructure to support our envisioned data ecosystem. It is in a marketplace that assets are published to be shared. A typical example of an online marketplace is a vacation rental marketplace where there are different kinds of offers (e.g., houses, rooms, adventures, and restaurants) and two types of users (hosts and guests). Similarly, a data-related asset marketplace offers a wide variety of assets (as discussed in Section 3.2) and has two types of users (providers and consumers). Providers access a marketplace to share their assets either for free or at a given cost and consumers access a marketplace to use assets. While a provider goes directly to a marketplace to publish her assets, a consumer can also go to an asset search engine to find and combine assets from multiple marketplaces. In the latter case, the asset search engine matches the request of the consumer with the assets from all marketplaces it can contact. Here, the asset search engine is similar to a vacation rental metasearch website (e.g., trip.com), which proposes rentals from multiple websites.

Figure 2: The Operations Manager.

The data infrastructure provides the marketplace as an open software component to allow anyone to set up her own asset market for private or public use. For example, universities, companies, and individuals can operate their own marketplace to manage their assets and share them with selected partners.

3.4 Operations Manager: Deploying Assets

Once a consumer has combined a set of assets from the marketplaces to an application, she may decide to proceed in an offline or online fashion. If offline, she downloads the application (combined assets) and executes it outside the data ecosystem, using her own storage and compute resources. If online, she executes the application by using the storage and compute resources (assets) shared in the data ecosystem. In either case, it is an instance (implementation) of the operations manager that is responsible for launching the set of assets on storage and compute nodes. The operations manager has four main functionalities as depicted in Figure 2: (i) It matches the assets constraints with the properties of storage and compute nodes; (ii) It splits the set of assets into non-blocking sequences of assets and decides the distribution, parallelization, and physical implementation for each sequence (data- or pipeline-parallelism); (iii) It optimizes the assignment of the sequence of assets based on the assets constraints, e.g., location of data/nodes and financial costs; and (iv) It orchestrates the execution and manages usage statistics for pay-per-use assets.

Similarly to the marketplace, the data infrastructure provides the operation manager as an open software component to allow anyone to set up her own instance. A user could use her operation manager instance privately in her premises or publicly in the data ecosystem. In the full version of this paper, we will describe each task of the operations manager and discuss the respective functionalities in more detail.

4. RESEARCH CHALLENGES

Our envisioned data ecosystem opens up many opportunities for data, algorithms, and software exchange. However, there are numerous research challenges that we have to tackle. In the following, we discuss these research challenges by outlining the most prominent requirements of each of the three core components in the envisioned data ecosystem: the marketplace, the asset specification, and the operations manager.

4.1 Asset Marketplaces

A marketplace provides three basic operations: publishing, discovering, and composing assets. Still, providing these basic operations effectively has several requirements, which raise many challenges and require novel solutions.
Asset sharing. A marketplace, at its core, exists mainly for sharing assets in the data ecosystem. Yet, sharing assets in a data ecosystem is challenging for several reasons:

1. **Constraints**: Determining how to express asset constraints is not only hard because of the asset heterogeneity but also because of the different constraint granularities, e.g., an entire dataset (or application) or parts of it (single algorithms).

2. **Pricing**: Our ecosystem should not only allow providers to define a price for their assets but also propose a price. However, how can we bring the entire data ecosystem supply and demand together? At the same time, how can it avoid malicious effects like arbitrage? Additionally, the pricing mechanism should be dynamic and adapt to the state of the data ecosystem. Ideas from query-based pricing and economic models for the cloud can be investigated and adapted to fit a more general data ecosystem.

3. **Pricing models**: A provider should determine the pricing model of her asset. In software licensing, there are three fundamentally different pricing models: pay-once, subscription, and pay-per-use. With pay-once, a user buys a license once and can use the licensed software forever. Subscription models are similar to the pay-once model, with the difference that licenses may expire and have to be renewed. The pay-per-use model is common for cloud services where users pay per function call to an API (e.g., Twitter API). A provider could adopt any of these models. For instance, pay-per-use can be used for algorithms (e.g., pay $1 per thousand calls) and for the compute resources (e.g., pay $5 per hour).

4. **Payments**: Ensuring a safe way for providers to charge and consumers to pay the use of assets is crucial for the data ecosystem health. Although there exist different ways, such as online payment systems (e.g., Paypal), in-house payment systems, and micro-transaction systems (e.g., IOTA), these solutions need to be evaluated, to derive the right transaction platform(s) for payments in the data ecosystem.

5. **Lego-style API**: The infrastructure should offer not only basic building blocks, such as datasets, algorithms, and models but also assets composed of multiple assets. To achieve this, a lego-style API that allows interoperability among assets is required. Defining a lego-style API is challenging because it should be (i) flexible enough to enable building complex pipelines and systems, (ii) general enough to support all operations and multiple query languages, and (iii) easy enough for lay users.

Asset discovery. A factor of success for a data ecosystem is how easily one can find the right assets for a given request. A good solution benefits consumers, but also providers by making their assets reachable to the masses. Providing easy asset discovery comes with several challenges:

1. **User interfaces**: A marketplace, as well as an asset search engine, should provide an intuitive interface for different types of users (e.g., lay users, data scientists, and developers). This can be a graphical user interface, where lay users can browse the assets or use keyword search. Besides, more advanced users should be able to use a declarative query language to quickly describe the assets they want. The design of such a graphical interface or declarative language is highly interesting research challenges.

2. **Asset matchmaking**: A marketplace (and an asset search engine) should be able to effectively and efficiently identify all assets related to a given consumer’s request. A research challenge here is to determine or define (i) the best-suited data model to describe the characteristics of the assets in a meaningful way and (ii) a query language that can match a request with the characteristics of the assets. One could get inspired by semantic web services matchmakers which solve a similar problem for web services.

3. **Composing assets**: In many cases, a single asset may not be sufficient to satisfy a consumer’s request. In this case, several assets should be combined to achieve the consumer’s goal. For this reason, an asset marketplace, and an asset search engine should be able to integrate different assets into one combined asset that satisfies the consumer’s request. Solutions for automated web service composition provide a starting point for this challenge.

Marketplace regulation. Whoever decides to create a marketplace also needs to decide how the marketplace will be regulated. Several questions need to be answered to provide a marketplace regulation: Will there be a central entity to control who can join the marketplace? How will the supply and demand be handled? Can the marketplace receive payments or there should be direct payments from consumers to producers?

Asset search engine. An asset search engine should be able to discover public marketplaces so that it uses assets from different places. For example, a search engine could have agreements with specific marketplaces from which it gets the assets (similarly to the vacation rentals metasearch). Another idea is that the marketplaces are organized in a peer-to-peer fashion and the search engine takes advantage of such an architecture to discover marketplaces or assets.

Privacy. In general, the actions and identity of users in the marketplace must be protected to not reveal business secrets. For example, a company should be able to search for assets on the marketplace without revealing its business strategy. When a company combines assets to offer a new service, the combination of assets becomes a business secret by itself which should be protected to prevent plagiarism. Thus, marketplaces should provide the means to anonymize the activity of users.

4.2 Asset standardization and certification

Recall, an asset search engine typically (and a marketplace might) use assets from other marketplaces to satisfy a consumer’s request. Therefore, there is a need for a unified specification for asset sharing, discovery, and billing among different markets. Marketplaces should comply with a publicly available specification (a standard) for the assets they offer. The challenge here is that there are different types of assets: from datasets and stream sources to complex algorithms or data management systems. The standard should take all these different types of assets into consideration as well as their combinations while keeping as much simplicity as possible.

Another challenge resides in the standardization of certificates and application requirements. Only this way the operations manager can match applications (or parts of applications) with compute and storage resources. To this end, our key idea is to democratize the certification of properties such as security standards and the locations of nodes. Everyone can become a certification authority and everyone can decide which authorities to trust. For example, the EU could certify that a compute node is located in the EU and therefore become a certification authority. The requirement specification of an application can define the node location as a requirement and specify the EU as a trusted certification authority. In the full version of this paper, we will present in detail how one can issue, validate, and match arbitrary certificates, which represent node and service properties.

4.3 Operations Manager

As a marketplace, the operations manager is at the core of the data ecosystem. Several research challenges need to be tackled for enabling the operations manager to carry out the tasks it is responsible for. We layout these challenges.

Constraints satisfaction. Depending on the language designed for expressing assets’ constraints, the operations manager...
should be able to match these constraints with the characteristics of the processing or data nodes. The challenge here lies in the architectural design of the operations manager. Putting everything in a single catalog may not be the most efficient and scalable solution due to the different number of constraints and the large number of storage and compute resources.

**Optimization.** The operations manager is responsible to split an application into a sequence of assets and parallelize them, if necessary. However, assets may be attached to monetary costs. Thus, there is a need not only for optimizing runtime but also monetary costs while satisfying the constraints too. Another research challenge is the trade-off between bringing the computation close to the data or moving the data close to the computing resources. This trade-off combined with the monetary costs and constraints opens new research directions.

**Determining the execution environment.** A user may decide to use a specific dataset with a specific algorithm from a marketplace and wishes to execute it inside the data ecosystem. However, she specifies neither the processing system nor the computer architecture (e.g., GPU or CPU). The operations manager should be able to determine the execution environment, i.e., the processing system and computer architecture, for any given consumer’s request. It should then allocate the request to compute nodes accordingly. For example, if it is a batch processing job, the operations manager might decide to run it on Flink, while if it is a reinforcement learning algorithm, it may decide to run it on Rya. Identifying the type of algorithms and where they should be executed is a very challenging task. Although the first step towards this has been done with Rheem [23], it is still an open research problem for more diverse workloads.

**Asset usage tracking.** To ensure fair asset payments, the operations manager should be able to track the usage of the assets. However, tracking fine-granular operations in a set of assets (e.g., in a pipeline), which may run in parallel, is not an easy task. It requires not only an aggregation component but it also depends on the trustworthy honesty of the nodes that report the usage tracking. In Figure 3, we depict a possible mechanism for usage tracking. This mechanism provides a common API that allows for calling a tracking function from the asset source code (to track the use of assets) or as an operator (to track the use of pipelines). As this usage tracking function is called many times (e.g., per processed tuple), an aggregation component is required to propagate aggregated usage counters (e.g., once per minute) instead of individual function calls. The operations manager can additionally aggregate the usage counters from several compute nodes before forwarding the overall counters to the relevant marketplaces, which take care of the billing. Still, such a usage tracking mechanism does work only if compute nodes honestly report usages counters. We, thus, allow for restricting the execution of operators and pipelines to specific nodes, which fulfill certification requirements. For instance, compute node providers can obtain a certificate that proves that their nodes report usage statistics according to the ecosystem standard. Then, consumers and providers can restrict the execution of assets to happen only on certified compute nodes.

**Privacy and security.** In an open ecosystem, it is important that users can exchange data among them in a secure way. In this context, secure means that (i) all data transmission is encrypted to prevent unauthorized access, (ii) the integrity of the data is guaranteed and can be validated by receivers, and (iii) sender and receiver can use an escrow service to secure data trading. One of the challenges is that data can be arbitrarily large and data streams often have high bandwidths. Senders should thus send the data directly to the receivers and the operations manager should act as a coordinator only, which renders both privacy and security an issue. In Figure 4, we outline a possible way, which fulfills all requirements stated above, for data exchange in the data ecosystem. The key idea is that users exchange encrypted data while the operations manager acts as a mediator to pass the hash value and key of the encrypted data from the sender to the receiver.

5. RELATED WORK

The closest works to our vision are OpenAI [16], ML Bazaar [43], Ocean Protocol [3], Enigma [12], Datum [17], and Nebula [40]: OpenAI promotes “openness” in AI so that its benefits touch all of humanity; ML Bazaar proposes a unified ML API to ease the development and sharing of ML algorithms; Ocean Protocol [3] aims at enabling data sharing for AI; Enigma [12] focuses on enabling computational resources sharing in a decentralized manner; Datum [17] strives to allow anyone to store structured data securely in a decentralized way; and Nebula [40] forms a cloud of edge computers to perform distributed data-intensive computing. Although all these efforts are going in the right direction for building a data ecosystem, it is still hard to combine them for devising new solutions. Our work envisions a single data ecosystem where data, data science & AI technologies, and storage and compute resources can easily be combined to give birth to new data insights or technologies.

There are also initiatives in providing marketplaces for sharing data [18, 19], data science [8, 20, 6], AI [6, 7, 8, 9], and services [10, 11]. The industry has also brought storage, computational, and cloud resources at the reach of the masses; Amazon EC2 [21], Microsoft Azure [6], and IBM Cloud [22] are just few examples of such efforts. Nevertheless, all these efforts provide lock-in solutions: Users must stick to one provider for the entire pipeline of their solutions. We envision an open data ecosystem where one can combine resources from different marketplaces easily without lock-in effects.

The research community has also proposed many solutions to facilitate data processing in general from different angles: such as scalable data processing systems [45, 23], declarative data querying [29, 38], intelligent systems [34], Internet-of-things systems [37], and cross-platform (a.k.a. polystore) processing [23, 27, 30], among others. All these works are orthogonal and complementary to our vision: one could see them as the assets being offered in the data ecosystem.

6. DEMOCRATIZING DATA SCIENCE & AI

As data access and data analysis expertise are the key factors for future competitiveness, there is a global consensus on the importance of democratizing data, data science, and AI
technologies. However, despite all our efforts in making data science, and AI easier and more explainable[23][22][25][35][24], we are still far from a true democratization of such production factors. Every single citizen should have equal rights of access to all such production factors. This is the only way one can achieve fairness in the data economy. Although having a data ecosystem is an important building block, governmental organizations must get involved too. They have to vote new laws and need to design policies and legal frameworks to guarantee equal access to everyone as well as to regulate the data ecosystem. Fortunately, the European Commission[15], state governments[14], and industrial associations[13] already reached a consensus that a data ecosystem is needed and needs to be supported. We believe that the database research community should drive the vision of such a democratized ecosystem and support politicians to define the right legal frames.

Such a joint effort for a truly democratized data ecosystem will have positive implications on society, economy, and science:

- **Society**: It would be used not only by economic operators but also by research institutions, universities, schools, and citizens, having a big benefit in data literacy. For example, students could be playfully introduced to programming, data analysis, and even potential business models. Lay people could also prepare chores, or even potential business models, by developing on top of the exposed data and analytics infrastructure. Most importantly, data, data science, and AI technologies could remain with their owners. Everyone could contribute to the big data ecosystem.

- **Economics**: It would provide a breeding ground for data-driven technology innovation by exposing data, data science, and AI technologies. This would reduce the cost of new insights or the establishment of new business models. In this way, it can become an innovation engine for education, business models, business start-ups, and data-driven value creation. It would also have a huge impact on small and medium-sized enterprises by having a lower entry threshold for the use of a data and analysis infrastructure. For example, it would enable a sports bar to predict how long they will stay open in a given evening in order to better plan human resources. Additionally, it would motivate a consistent implementation of open standards, which could break the current vendor lock-in effects.

- **Scientific**: It would make tools of the entire data value chain (processing, analysis, and visualization) re-usable and easy-to-use (web-based, plug & play, a combination of public and private data in an analysis). This would enable more researchers to derive insights from data without deep knowledge about data management and algorithms. It would also foster scientific innovation and algorithms by enabling researchers to easily share their data insights and technologies. Moreover, it would ignite new research in all sciences by providing scientists with access to a large amount of data and state-of-the-art data science and AI technologies.

### 7. CONCLUSION

We presented our vision for democratizing data science and artificial intelligence through a data ecosystem. Our proposed data infrastructure to support such an open ecosystem builds around assets, which are fine-grained data-related units of production. One can share assets through marketplaces and combine them to form novel data-driven applications and to derive new insights. We defined the different types of assets and pointed out research challenges as well as potential solutions with respect to asset classification, asset standardization, and flexible asset combinations. We explained the implications that such an open ecosystem would have for society, economy, and science. In the long version of this paper, we will provide a detailed description of the different user roles and asset types as well as their interaction. We will also add a description of the usage tracking and the data escrow in the open ecosystem. Last but not least, we will provide an end-to-end example with concrete assets in order to better highlight the benefits of having the envisioned data ecosystem. Building the data infrastructure for such an ecosystem will be a key focus of our future work.

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