Extricating IoT Devices from Vendor Infrastructure with Karl

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Abstract
Most consumer IoT devices are vertically integrated with cloud-side infrastructure. Such architectures present enormous risk to user data, exacerbated by vendor heterogeneity and the inability for users to audit cloud-side activity. A more promising approach would be to leverage local hardware, providing users control over how their data is processed and why it can be shared with other devices or the Internet.

Karl is a new smart-home framework designed to host IoT computation and storage on user-chosen devices. A key insight in Karl’s modular programming model is that a familiar interface (inspired by serverless) can capture most modern cloud-side IoT components under a single framework, which executes modules agnostic of hardware location. While local hosting eliminates many flows, modularity enables all remaining flows to be justified using fine-grained primitives. We introduce two IoT security mechanisms: pipeline permissions that permit device data to be shared given some justification and exit policies that block flows unless specific conditions are met. We evaluate Karl through two end-to-end applications.

1 Introduction
This paper presents Karl, a new smart home framework that eliminates dependence on vendor services by making local hosting practical. The tight integration between vendor services, companion apps, and modern IoT devices has increased the size of the smart home attack surface [2]. For example, most smart speakers parse audio commands such as “turn on the light” using a cloud service, even when they pertain only to local devices; doorbell cameras send video to the cloud; and even smart locks work through cloud services. Many devices are hard to update or lose vendor support over time, leaving them with software vulnerabilities. The need for devices to interoperate through “hubs” like HomeKit [4, 16, 49] can enable cross-device attacks. Overall, the dependency on vendor services has led to a large range of attacks on smart home devices [3, 8, 22, 23, 33, 34, 39, 43, 47].

Theoretically, an architecture in which user data never leaves user hardware offers better privacy and security. For many functions, such as turning on the light by voice, there is no need to send data remotely. Indeed, enterprise-grade IoT devices often have purely local control. Unfortunately, the consumer setting creates several challenges to local hosting: Devices are typically inexpensive and computationally constrained. Home networks prevent incoming connections, making it hard to connect companion apps directly to a device such as a camera. Users are less sophisticated, unable to configure servers or firewalls, and have difficulty understanding the security implications of configuration choices. And of course the lower price point of consumer devices makes almost any level of individual customer support untenable. The result is an over-reliance on vendor services, to the point that even locally hosted controllers such as Home Assistant [26] have a depressingly high fraction of integrations going through the cloud to communicate with local devices.

Fig. 1 shows Karl’s architecture. Karl leverages local hardware to move processing and storage out of devices and centralized vendor services and onto a user-controlled device such as an old PC. It offers a simple but expressive programming model based on modules that process data, such as speech-to-intent, and communicate with each other through a key-value data store. Each module executes in isolation, similarly to a serverless function [6], and each data and network access is validated by the locally-hosted Karl hub. The hub also serves Karl apps directly to the user’s phone.

While existing IoT hubs enable access control between different devices and the Internet, this has proven too coarse-
We additionally co-design functionality and policies in Karl to support complex device and service interactions. Karl executes its modules locally and also hosts the data store on local hardware. The Karl hub also runs and serves companion apps directly to a user’s phone through a user’s router. Flows that use an external service, such as downloading firmware updates, can still contact those services but only if the user allows them with Karl policies. These basic abstractions enable most device-to-device and companion app interactions to run on Karl-controlled hardware.

### Usable Privacy Policies

The second challenge is expressing privacy policies when a device must access the Internet. Existing techniques are either obfuscated in cloud infrastructure or based on coarse-grained security primitives such as device-to-device access control. In comparison, local hosting enables Karl to enforce ubiquitous policies that consider all components of modern IoT functionality, as opposed to blindly trusting multiple vendors. Modules also enable finely-grained privacy policies with semantic meaning such as requiring audio data to be converted to text. Thus Karl’s programming model empowers users to express and enforce policies that correspond to more intuitive privacy guarantees.

We additionally co-design functionality and policies in Karl such that modifying one reflects in the other. In particular,

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**Table 1: Classifying device network accesses and their justifications.**

| Category          | Justification                             | Smart Speaker Example                                                                 |
|-------------------|-------------------------------------------|---------------------------------------------------------------------------------------|
| Offload computation | weak local hardware                      | ML e.g., speech to intent                                                             |
| Offload storage    | scalability, fault tolerance              | record notable audio events                                                           |
| Remote access      | minimize system administration of NAT and firewalls | listen to remote audio feed                                                          |
| Pull data          | data not available at production, Internet-scale knowledge | weather queries, firmware updates                                                    |
| Push data          | aggregate analytics on data               | bug reports, training data, analytics                                                |

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**Figure 2:** The pipeline permission shows that the speaker wishes to send all outgoing data through the `speech_to_intent` module, which converts speech to text intent; then weather-related intents go to `weather.com`. Separately, the user could add an exit policy saying “all speech commands need to go through `speech_to_intent`.”

(a) Example dataflow graph (b) A generated pipeline permission and a user-specified exit policy.

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Karl tackles four major challenges to achieve its goals of eliminating dependence on vendor services and enabling expressive privacy policies on all remaining network accesses:
Karl enforces user privacy policies by modifying the dataflow graph that represents device functionality to comply with pipeline permissions and exit policies, such as by disabling network access or deleting an edge. Karl treats the generated graph as a declarative policy, automatically labeling data with non-hierarchical tags in the data store and enforcing mandatory access control on the edges. This mechanism combines the power of information flow with the simplicity of access control to enforce useful privacy policies at a fine granularity.

**Performance** A third challenge is maintaining performance for real-time interactions and compute-heavy tasks without amortizing costs on cloud hardware. By using local hardware, Karl can minimize latencies for many interactions [45] and even outperform cloud-based services. For heavy compute tasks such as ML, which typically run as long-lived services in the cloud, Karl accounts for the high initialization times of its stateless modules using a variant of speculative execution. Overall, we find that Karl has acceptable performance.

**System Administration** Though Karl is best hosted on local hardware for privacy, end users may prefer the durability and scalability of the cloud. We show it is feasible to deploy Karl in the cloud but on user-managed hardware, a similar approach to DIY Hosting [40]. The cloud deployment increases network latency and costs money, but self-hosting Karl in the cloud (e.g., using Amazon Web Services) is still comparable in cost to popular IoT cloud subscriptions, and improves privacy because the user need only trust their own cloud provider rather than vendors and their providers.

We implement and evaluate a functioning prototype of Karl. We port 4 home IoT devices—a security camera, smart speaker, light bulb, and occupancy sensor. We implement several applications in which these devices interact with each other and third parties outside the home network. We analyze several privacy properties that users may desire but cannot be enforced in existing frameworks, and demonstrate how they are intuitive to express in Karl. In addition, we demonstrate that Karl offers reasonable performance and can improve the latency of some interactive applications. Finally, we analyze the tradeoffs of self-hosting Karl in the cloud.

In summary, our contributions are:

- We introduce Karl’s modular programming model, which makes it practical to support the rich interactions of modern devices on local, user-managed hardware.

- We introduce **pipeline permissions**, which restrict devices to justifiable data flows based on finer-grained primitives with semantic meaning.

- We introduce **exit policies** as a way to capture end-to-end confidentiality policies users care about and avoid unintended consequences of pipeline permissions.

- We present and evaluate an implementation of Karl on applications spanning 4 devices and 10 modules.

## 2 Security Properties

The stakeholders in the Karl ecosystem are hardware vendors, module developers, and end users. We assume end users properly install Karl, configure secure login credentials (through the Karl hub UI), and that Karl can mediate all Internet traffic. Some hardware vendors and module developers may be compromised or negligent, however, leading to vulnerable components. Attackers attempt to leverage these vulnerable components—possibly in collusion with their compromised creators—so as to violate end-user privacy or actuate smart-home controls in undesired ways.

Karl’s security guarantee is that it restricts inter-component communication to the dataflow graph specified by the user’s pipeline permissions and exit policies. The benefit of this model is that the presence of a few secure modules can significantly restrict the consequences of compromised components. For instance, the only path through which training data can leave the network may go through a “statistics” module that restricts communication to a trusted vendor’s analytics endpoint. In this case, a camera with malicious firmware cannot leak video to outside parties on the wide-area network.

Some vendors may host cloud services, but this will be apparent in the pipeline permission. In many cases, the communication can be mediated by simple, well-known, and trustworthy modules that provide meaningful security guarantees. For example, firmware updates should be mediated by a data pump module that ensures devices receiving firmware cannot send large amounts of locally recorded data back upstream.

Pipeline policies enable visual verification that devices gain approximately least privilege, simplifying the process of determining that the permissions suit the functionality. In practice, only a small fraction of users may actually object to unwarranted permissions, but the hope is that this is enough to flag dangerous devices for the rest of the ecosystem.

Karl does not prevent covert channels that leak information through resource utilization. Nor does it prevent side-channel attacks, such as cache timing, microarchitectural data leaks, or network timing attacks. However, such attacks are typically difficult to disguise in plausibly legitimate source code. Hence, we assume most hardware vendors and module developers are well-intentioned with reputations to uphold, and would not risk wall-banging attacks in production code.

## 3 Motivating Examples

To motivate the need for a modern smart home framework with strong privacy guarantees, we start with a comparison of popular IoT frameworks in industry (Samsung SmartThings), the open-source community (Home Assistant), and research (FlowFence). We base our comparison off the smart speaker example from the introduction and discuss several privacy properties a user might desire. For each framework, we ana-
lyze how a developer would implement the smart speaker, and how the user would enforce the following privacy properties:

1. The speaker can share data with weather.com if I ask about the weather, but not the raw audio.
2. The speaker can share data with the light if I ask it to turn the light on or off, but not the raw audio.
3. No one (except me) should access raw audio data unless it has been transformed from speech to an intent.
4. The vendor can't switch my light on or off.

In existing frameworks, developers bear the burden of protecting user data, and users cannot verify their privacy guarantees:

1) Samsung SmartThings. SmartThings [49] is an industry home automation framework that can connect hundreds of brands and thousands of devices. The platform is centered around the SmartThings Cloud, which remotely manages devices, data, automations, and more. Devices connect to the Cloud through a phone, hub, WiFi, or third-party cloud. Vendors write integrations for simple devices such as a light bulb or sensor based on a schema that also provides authentication and a consistent UI. Devices with more complex automation logic, such as a smart speaker, must implement SmartApps, connectors that run on AWS Lambda or another vendor-hosted server and send events back to the Cloud.

Vendor Perspective. Amazon Alexa and Google Home are both smart speakers with SmartThings compatibility. However, they primarily use SmartThings to proxy commands to hub-connected devices that use different protocols or schemas. The devices are still connected to their original cloud services, which they depend on for remote access and tasks like speech-to-text. While larger companies may appreciate the flexibility of being able to integrate their existing cloud infrastructure, smaller vendors face high liability and startup costs.

User Perspective. Allowing devices unrestricted network access requires total trust in the vendor. Network traffic is typically encrypted, so privacy settings in the companion app are not verifiable. Raw audio data could be leaked through vulnerabilities in the smart speaker, SmartApp, Cloud, or the light bulb the speaker turns on. The user can restrict communication between different devices through the SmartThings Cloud, but devices that require additional cloud communication to provide functionality are outside the scope of the framework. None of the four properties can be enforced.

2) Home Assistant. Home Assistant (HA) [26] is an open-source smart home framework with a focus on local control and privacy. The HA architecture depends on an event bus that fires and listens to events such as state changes and services. Developers write integrations (e.g., image processing, light, Z-Wave) that extend the core architecture with small pieces of home automation logic. Integrations are limited to Python scripts and can access the network. HA is highly programmable, and users have the option of self-hosting the framework on local hardware such as a Raspberry Pi.

Vendor Perspective. HA allows vendors flexibility to execute functionality locally or in the cloud. HA offers smart speaker functionality through a combination of multiple integrations. Almond [11] is an open, privacy-preserving virtual assistant integration that acts as the text-to-intent backend. Almond also has a repository of apps, called Thingpedia, such as an app that retrieves the weather. Other integrations handle speech: Ada [46] is powered by Microsoft Cognitive Services, and Rhasspy [42] is an offline voice assistant. Thus smaller vendors can easily contribute to some or all parts of a device simply by writing software integrations. HA is also compatible with Alexa and Google Home, which similarly use HA as a hub to access devices like in SmartThings.

User Perspective. Programmability and the option to self-host make it feasible for HA to implement the majority of functionality on local hardware, but in the remaining cases it is hard to verify privacy guarantees. HA does not sandbox integrations. For example, Ada necessarily talks to the Microsoft API, but it is unclear if or when other integrations such as a speech-to-intent integration access the network. The combination of services, state changes, and other events make it difficult to manually trace which data might have been exfiltrated and where. In addition, part of the dataflow for asking the weather is in a non-ephemeral Almond server rather than an HA integration. Devices such as the Alexa have similar privacy concerns as in SmartThings. Thus while the user can take steps to run mostly privacy-preserving software, it is still difficult to justify every network access that may contain data. None of the four properties can be enforced.

3) FlowFence. FlowFence is a research framework for smart homes that takes a dataflow approach to privacy instead of access control. In FlowFence, IoT apps consist of functions that compute on sensitive data (quarantined modules or QMs), and code that does not compute on sensitive data. QMs execute inside Java sandboxes on the hub, which can run on an Android phone. QMs access sensitive data via opaque handles, monitored by the hub according to flow policies. Also, QMs communicate via event channels or a key-value store. Developers declare intended dataflows of sensitive data to other devices or the network, which users approve via UI prompts when a flow is first required.

Vendor Perspective. It is straightforward for vendors to modularize existing device-side logic and port it to QMs in FlowFence, similar to other app-based frameworks. However, FlowFence does not explicitly consider how to integrate companion apps into the framework, such as to remotely turn on a light, as evidenced by the example flow that sends door state to the Internet for the user to view. It also does not consider how to express policies that use cloud services such as machine learning, which are not as easily modularized while preserv-
ing performance given high initialization times, and may not fit within the Java programming model. Vendors must also consider how to set and interpret taint labels within module code. Thus FlowFence complicates device-side logic while still requiring vendors to manage their own infrastructure.

**User Perspective.** Unlike the previous frameworks, FlowFence requires all network connections involving sensitive data to go through the hub. The user can enforce P1 and P2 by approving flows that correspond to the properties. However, it may be difficult for users to understand and approve every flow, particularly because a device also includes flows for cloud services and companion apps, which can negate P4. FlowFence does not have the concept of restricting categories of flows such as in P3. Furthermore, some of the suggested flow policies are overly permissive because they do not include the application semantics in the QM pipeline. For example, the flow from a speaker to the lock means a malicious QM could send raw audio to the lock, even if only a subset of that information is required.

4) **Karl.** Karl provides privacy through local hosting that captures all the rich interactions that modern IoT devices have with cloud services, companion apps, and other devices; and modularity that enables enforceable, fine-grained privacy policies. Karl’s programming model is based off the familiar serverless interface that is easy for existing vendors to adopt.

**Vendor Perspective.** The vendor splits device functionality into firmware for the device, and modules that cannot run on the device, because they require too much computation or storage or because they run on a user’s phone. The vendor programs an initial dataflow graph into the firmware, representing the device’s functionality. Instead of creating a mobile app, the vendor creates a Karl app, which the hub serves from the user’s machine to the user’s phone. The hub downloads modules from a Karl package manager and executes the modules on local hardware. The vendor no longer needs to host any cloud infrastructure or user data.

**User Perspective.** The user installs a device, which locates the Karl hub on the local network, and sends the initial dataflow graph. The user gets a notification that a new device is available and approves it. As part of approving the device, the user reviews a set of pipeline permissions corresponding to P1 and P2, showing which device data may be shared and why. The user may also assign exit policies such as P3 to device and application data, preventing sensitive data from being shared under certain conditions regardless of pipeline permissions. The user is guaranteed P4 due to local hosting of companion apps, since the light does not need network access.

In the following sections, we describe the programming model for Karl and illustrate how Karl can enforce novel privacy guarantees that existing frameworks cannot.

### Table 2: Example specification of the light_switch module that maps a JSON intent to a state the light bulb can understand.

| Field     | Value |
|-----------|-------|
| Name      | light_switch |
| Inputs    | intent – JSON of the form { type: “light”, state: <state> }, where the state is “on” or “off” |
| Outputs   | state – 1-bit to turn on and 0-bit to turn off |
| Domains   | N/A   |

```
class ModuleAPI:
    def read(input, lower_timestamp, upper_timestamp)
    def read_last_n(input, n)
    def read_event(input)
    def push(output, bytes)
    def network(domain, request)
```

Listing 1: API used by module code to read and push to the data store in various ways, and make HTTPS requests. The API wraps gRPC calls to the sandbox, which forwards authorized requests.

### 4 Programming Model

Karl’s programming model is intentionally similar to existing event-driven programming models to provide a familiar interface to IoT developers. Unlike existing programming models, Karl’s is designed to eliminate vendor dependence on cloud infrastructure—cloud services, companion apps, hardware—using the simplest abstractions for compute and storage.

In this section, we describe our abstractions for compute and storage, and the Karl app UI. Karl expresses all functionality as modules that interact with a persistent data store and Karl web apps. We then describe the dataflow graphs that represent device functionality, and discuss example graphs for three different IoT devices that handle sensitive data.

**Serverless modules.** Similar to the serverless programming model, a module is a self-contained program that executes code given some inputs. Modules can take multiple inputs and return multiple outputs. Each input and output is named and associated with a particular data type, and is part of the module specification (Table 2). The module must also specify any domain names with which it requires network access.

Modules execute inside sandboxes managed by the Karl hub. The module has a single network connection to a sandbox, which proxies data and network accesses (Listing 1) to the data store and the Internet. The sandbox decides which accesses are allowed, forwarding data accesses to a controller and HTTPS requests to the requested domain. Note that data accesses are keyed by the names in the module specification, agnostic of how data is used outside the module.

**Persistent data store.** The data store extends the key-value store, a common data structure for stateful FaaS [48, 50]. In
Figure 3: Example dataflow graphs. The gray boxes are devices and white boxes are modules. The smaller boxes inside are input and output nodes. Edges connect nodes and represent data dependencies. Solid edges are stateless, while dashed edges are stateful. Blue edges flow to a module, while red edges flow to a device. Green headers represent modules with network access. The clock indicates a fixed interval schedule.

Listing 2: Example implementation of the module in Table 2.

```python
import karl
intent = karl.read_event("intent")
if intent["state"] == "on":
    karl.push("state", [1])
else:
    karl.push("state", [0])
```

Karl web apps. The Karl hub includes a per-user web interface for reading and pushing to the data store, and configuring and spawning modules. Vendors can write static pages with JavaScript (i.e. single-page apps) called Karl apps that wrap these features to replicate the functionality of mobile companion apps. For example, instead of serving sensitive photos from vendor-managed cloud storage, the page can visualize data associated with the corresponding tag in the data store. Instead of forwarding a request to view a live video feed through the cloud, the page can spawn a module that turns on the livestream feature and then visualize data associated with a livestream tag. It would be a simple extension to also support a stateful webserver running as a module.

4.1 Dataflow Graph

Each IoT device proposes an initial dataflow graph where data flows from the device, through modules, and to other devices and the Internet (Fig. 3). Though we discuss a visual graph, devices send their graphs to the hub using JSON. Karl downloads the requested modules from a Karl package manager. Vendors can either upload their own modules or use existing modules based on their specifications.

The boxes in the dataflow graph are modules and devices, while nodes are their inputs and outputs. For example, the light bulb in Fig. 3a outputs its state and intensity, and has...
inputs that change the same state. Each node corresponds to a tag, and edges represent stateless or stateful data dependencies between nodes. When the set_true module pushes to its output that is connected to a single input, the controller automatically adds the tag for each node: set_true.true and #light.state. Modules spawn on three different schedules: when data is pushed to a stateless edge, at a fixed time interval, or when manually spawned by the user. Some modules require network access, which implies a flow to the Internet.

In addition to data processing flows, the graph includes the flows needed for Karl apps. Fig. 4a is the light bulb’s Karl app. The app visualizes the light state and intensity by reading the sensor output tags. It sets the intensity by pushing to the #light.intensity input. It switches the light on or off by spawning a module that pushes a 1-bit or 0-bit to the #light.on input. These interactions go through user hardware, so the light bulb state is guaranteed to be private.

We provide example dataflow graphs for two, more complex devices: a smart speaker (Fig. 3b) and a security camera (Fig. 3c). The smart speaker requires network access to pull weather data, while the camera pulls firmware updates and pushes analytics. The smart speaker also expresses control flow logic using modules. The camera uses a stateful edge to process a query over recorded motion events, and spawns a firmware update module using a fixed interval schedule.

The initial device dataflow graph provides a starting point for users who introduce new devices to their home. Users can configure devices to interact with each other, such as by enabling the smart speaker to turn on the light bulb with a voice command. The user can also add privacy-preserving modules between sensitive data and the network to reduce the fidelity of data before sharing it with the Internet. We imagine a frontend for privacy settings and automation logic, such as IFTTT [28] or the Home Assistant frontend, that automatically maps user configurations to the underlying dataflow graph. For example, the frontend could suggest edges based on corresponding data types or recognize devices from the

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**Figure 4:** Example Karl apps that correspond with the dataflow graphs in Fig. 3. The user can set and visualize light state. In the camera, they can see motion detection events and toggle the livestream.

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**Figure 5:** Example privacy properties a user might desire.

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5 Privacy Policies

The modular dataflow graph provides a convenient foundation for privacy policies based on fine-grained application semantics. Karl can regulate the flow of sensitive data from source to sink based on the semantics of the pipeline of modules in between. Recall the justifications for IoT network access in Table 1. Karl can provide compute, storage, and connectivity using local hardware, but devices should still justify when they must fundamentally pull or push data to the Internet.

Karl provides the framework for users to monitor these dataflows based on two concepts. **Pipeline permissions** specify why and to whom data can flow based on the pipeline of modules from source to sink. They serve to ensure that dataflows match users’ intuitions, and that devices and modules do not engage in unnecessary communication. However, seemingly plausible pipeline permissions can still have unintended consequences. **Exit policies** capture end-to-end data policies that block flows unless specific conditions based on modules are met, regardless of pipeline permissions.

In this section, we discuss how the privacy properties in Fig. 5 map to pipeline permissions and exit policies, apply these concepts to modify the dataflow graph as a declarative policy, and describe how Karl compiles the graph to a non-hierarchical form of mandatory access control.

### 5.1 Pipeline Permissions

When a user registers a device with Karl for the first time, appending its dataflow graph, they must approve any new sensitive dataflows as **pipeline permissions** (Fig. 6). These permissions ensure there are not any unintended effects from introducing a new device into a complex ecosystem. Karl
An automation frontend links light_switch.state A-D in Fig. 5, detected from the dataflow graphs in Fig. 3. These permissions represent tradeoffs between privacy and because it improves the product for future use.

client-side protection of data [10, 13, 18, 29, 32]. In this case, such as E or F (Fig. 7). There are many such techniques for to make it clear that they use data in an anonymized form the user’s trust, the vendor might add a module in the pipeline share statistics that could include raw image data. To gain the given permission B, the user may not think it necessary to

the camera firmware because it is a trusted vendor.

Exhibit 3: Pipeline permissions that correspond to privacy properties A-D in Fig. 5, detected from the dataflow graphs in Fig. 3.

E. camera.motion → person.detection (+ occupancy_sensor.at.home) → boolean → statistics → statistics.com
F. camera.motion → person.detection → prio → a.statistics.com
G. camera.motion → statistics → camera.livestream
H. camera.motion → camera.livestream
I. speaker.speech_command → speech_to_intent → #light.state
J. person_detection.image → true
K. person_detection.image → speech_to_intent
L. person_detection.image → boolean → a.statistics.com
M. person_detection.image → a.statistics.com
N. person_detection.image → a.statistics.com
O. person_detection.image → a.statistics.com
P. person_detection.image → a.statistics.com
Q. person_detection.image → a.statistics.com
R. person_detection.image → a.statistics.com
S. person_detection.image → a.statistics.com
T. person_detection.image → a.statistics.com
U. person_detection.image → a.statistics.com
V. person_detection.image → a.statistics.com
W. person_detection.image → a.statistics.com
X. person_detection.image → a.statistics.com
Y. person_detection.image → a.statistics.com
Z. person_detection.image → a.statistics.com

Note that the dataflows that access the network need only be those that fundamentally pull and push data. This reduces the number of policies the user must consider. For example, rather than sending the light state to the Internet to visualize in the companion app, the state goes directly to the Karl app and the flow does not need to be authorized. Rather than sending raw audio to a cloud service to process the speech command, Karl translates the audio locally.

It may be difficult for users to accurately judge every permission, a common issue in user-driven policies [19, 44]. It will be important to conduct user studies to determine how best to present pipeline permissions in the UI. But even if the user approves all dataflows, Karl can still provide auditable logs because it captures every network access and its provenance. To provide additional reassurances about sensitive data, we combine the allow approach of pipeline permissions with the deny approach using exit policies, in the next section.

5.2 Exit Policies

| Tag                        | Exit Policy |
|----------------------------|-------------|
| G. light.state             | false       |
| H. camera.livestream       | false       |
| I. speaker.speech_command | speech_to_intent |
| J. person_detection.image  | boolean | prio |

Table 3: Exit policies proposed by a user for the devices in Fig. 3, corresponding to privacy properties G-J in Fig. 5. The policy defaults to true if unspecified, deferring to pipeline permissions.

Even if a user mistakenly approves a pipeline permission, modularity enables the user to define exit policies on categories of data (Table 3). Karl’s data store groups data under tags corresponding to the device it comes from or its downstream modules. The user then defines conditions under which this data category can be exfiltrated to the network or another device. These conditions are at the granularity of Karl’s serverless modules, enabling expressive, high-level policies.

Tags enable data-centric policies on important categories of data, rather than policies on devices and apps that use the data. In Karl, devices distinguish the different types of data they push at the source, such as camera.motion or camera.livestream. Tags also represent the inputs and outputs of downstream modules, such as indoor_person_detection.training_data for outputs of a module that runs person detection specifically on indoor cameras. This distinction between tags is built into Karl’s modular programming model, tightly integrating vendor-defined functionality with policy enforcement.

We provide a simple policy language defined in terms of modules for specifying conditions under which tags can be exfiltrated. The language consists of three operators: &, |, and >. The & and | operators represent conjunctions and disjunctions, while > represents ordering. Note that true implies the exit policy is met in all conditions and allows all pipelines,
while \textit{false} implies the opposite. We expect this policy language to be expressive and intuitive to developers, though a simpler alternative could use only singular modules.

For example, defining the exit policy \((\text{boolean } | \text{prio}) > \text{statistics}\) on the tag \text{camera.motion}\) indicates that the camera’s motion detection data can only be exfiltrated in a pipeline that includes one of the anonymization modules, and then the statistics module. The boolean module forwards data along one input if the other input indicates a condition has been met, while the \text{prio}\) module is a technique for ensuring data is analyzed in aggregate.

Pipeline permissions and exit policies are most useful in combination. Pipeline permissions enable device functionality given a privacy tradeoff, while exit policies restrict the conditions under which data can be exfiltrated. When two permissions conflict, the stricter one is enforced. For example, Permission B in Fig. 6 conflicts with the exit policy J in Table 3. The UI then alerts the user of this conflict to either remediate the existing pipeline or accept a loss in functionality.

### 5.3 Enforcement Mechanism

The primary goal of the enforcement mechanism is simplicity for the vendors, developers, and users of the framework. Vendors no longer bear the burden of protecting user data because the data is locally stored and processed. Module developers are agnostic of data labels such that they can write modular functions without considering their global implications. Karl also uses a simple, non-hierarchical data storage format, as opposed to accumulating labels as data flows through the graph. At a high level, Karl creates a modified version of the original dataflow graph to comply with user-defined policies, then treats the modified graph as a declarative policy of permitted dataflows, enforcing access control at the edges.

Karl determines how to modify the dataflow graph based on pipeline permissions and exit policies. Karl denies the permissions explicitly denied by the user, and the ones that conflict with exit policies. For each denied permission, Karl either revokes network access or removes the edge to the device input. These changes are applied in a secondary layer, ensuring the list of permissions presented to the user remains the same. Denying one permission may affect an allowed permission, such as if the path overlaps. In this case, Karl can attempt to duplicate the overlapping graph such that the policies are independent. If Karl were to identify the pipeline permissions in the modified graph, they would include none of the denied permissions and as many of the allowed permissions as possible, while following exit policies.

We treat the final dataflow graph as a declarative policy of permitted dataflows between devices, modules, and the Internet. The resulting graph nicely integrates vendor-defined functionality with user-defined policies. Given the final graph, the sandbox enforces access control rules on the API calls in Listing 1. When a module pushes data, the sandbox adds tags for the module’s output and the inputs on connected edges.

When a module reads data, it can only read the tags for its inputs. If the read is along a stateless edge, the module cannot read data previously pushed to that tag, a property aided by the ephemerality of modules. The sandbox allows network accesses only to the domains specified for that module.

It could be interesting future work to explore how to enforce Karl’s policies using IFC labels instead of non-hierarchical mandatory access control. Exit policies as Boolean predicates would work nicely with Boolean labeling schemes \((51)\). In this model, one might allow module developers to view the data labels, though developers could then leak information through the labels. This design choice could allow greater flexibility in enforcing policies based on data provenance, at the cost of complexity \((21, 27)\). It remains interesting to provide a theoretically-grounded approach to enforcing high-level policies in a dataflow graph.

### 6 Karl Hub

The disaggregation of storage and compute from the IoT device allows functionality to exist outside the device in a \textit{Karl hub}. In contrast, typical frameworks spread the functionality across local device state, companion apps, and cloud services, in addition to the hub.

In this section, we describe how to deploy the hub on local network cloud hardware managed by the user and discuss the tradeoffs. We then describe how caching and data locality optimizations in the scheduler improve the performance of Karl, particularly for resource-constrained environments.

#### 6.1 Deployment

The Karl hub consists of sandboxes that execute Karl modules, and a controller that schedules computation onto sandboxes (Fig. 8). The controller manages the data store, and the webserver through which users configure and interact with the smart home using Karl apps. All data and network accesses from a module must go through the controller.

**Local Deployment.** The recommended deployment uses local hardware to best moderate data exfiltration outside the network boundary. To use the hub, users install a program for the controller on a local server such as an old laptop. The program can also come pre-installed on dedicated hardware.
Then users install sandbox programs on the same server (or others), making up the computational capacity of the hub.

Cloud Deployment. If resources are limited and scalability is an issue, it is possible to host the hub on cloud hardware that is still managed by the user. The user can rent a cloud server that meets the smart home’s computational demands at comparable cost to IoT cloud subscriptions, with better privacy. In future work, we hope to provide controller drivers for any backend that implements the data store and module abstractions. This can include serverless platforms like AWS Lambda or even community Karl sandboxes. Then the smart home can primarily leverage local hardware but rollover to other hardware in the event of resource constraints.

6.2 Scheduler

To improve performance in resource-constrained environments, we provide a scheduler that optimizes for the smart home. In particular, writing stateful cloud services with large data dependencies, such as person detection and other ML tasks, as serverless modules results in high initialization and data transfer times. In response, we implement data caching optimizations and modify the scheduler to consider data locality to reduce the impact of these modules on end user latency.

Cold-cache. The cold-cache optimization mitigates the effect of large data dependencies on increased network latencies. ML modules may contain large models, particularly if they were offloaded to obviate IoT space constraints. Modules written in interpreted languages may also contain large code dependencies. The sandbox unpacks the files in a local filesystem cache, and mounts repeated modules using aufs, an overlay filesystem, to not modify the root. To avoid sending repeat dependencies, the controller tracks which modules it has spawned on which sandboxes. If the sandbox has evicted the module, the controller takes note and tries again.

Warm-cache. The warm-cache optimization minimizes long initialization times by preemptively launching slow modules and pausing until the first data or network access. The sandbox then waits for the controller to spawn the same module and continues executing at this point. An ML module might preemptively load its model in the initialization phase, and handle an inference request as soon as the module is re-spawned. Modules cannot be long-running services themselves, as they would be unnecessarily stateful and leak data across invocations.

The scheduler manages a queue of modules that are ready to be spawned and decides which sandbox to send each module to. Modules enter the queue based on the schedule assigned to the module: when data is pushed to a particular tag, at a regular interval (e.g., daily), or when manually triggered through the webserver. Given a module, the scheduler selects a sandbox without an active request, prioritizing those with the module cached. If a request does not return after a certain timeout, the scheduler cancels the request and retries on a different sandbox with an exponentially increasing timeout.

Though our scheduler prioritizes caching and availability, the scheduler could consider many other factors to best utilize the resources available to it. One example is to collect statistics about which sandboxes are fastest for specific modules, and map modules to that sandbox. This is particularly important on heterogeneous hardware. If Karl used a combination of local and cloud hardware, the scheduler could account for privacy concerns on cloud hardware, and data locality for latency. The scheduler could balance modules based on whether the request needs real-time latency for a user interaction or better hardware for a computationally expensive task.

7 Implementation

We build a prototype of Karl in Rust, with SDKs in Rust and Python, in ~7000 LOC. The controller, sandboxes, devices, and modules communicate over gRPC. The webserver passes tags and module names to Karl web apps via the Handlebars templating language, authenticates each app with cookies, and isolates app data from the Internet using Content Security Policy. Module sandboxes use Firejail, an SUID program based on jails and namespaces, and a Netfilter firewall.

We implemented 4 devices—a smart speaker, a light, a camera and an occupancy sensor—and 10 modules ranging from ML to multi-device interactions, shown in Table 4. We use Mask R-CNN [25] for person detection and Picovoice [41] for speech-to-intent. We modeled devices as programs that push data to the hub at a fixed interval. The camera pushes 156KB PNG images, and the microphone pushes 172KB WAV audio files. We were able to put Karl camera firmware on a hacked WyzeCam v2 [55], and a Karl smart speaker on a Raspberry Pi v4 with hardware accessories.

We combined these devices and modules in two end-to-end applications to highlight the range of functionality that Karl can express (Fig. 9). The first application supports speech commands to a smart speaker that looks up the weather or turns on a light. The second runs person detection when motion is detected from the camera, sends training data to the Internet only when the user is not home, and allows the camera to check for firmware updates.

8 Evaluation

We evaluate Karl to answer four questions:

- Can Karl preserve existing device functionality in device-side logic, mobile companion apps, and cloud services?
- Can Karl enforce useful privacy policies that are difficult to enforce in existing frameworks?
- Does Karl provide reasonable latency for real-time interactions and ML applications on local hardware?
- How does hosting Karl on cloud hardware affect performance and cost?
Table 4: Module implementations and specifications. The Rust modules are ≈2.0MB because they all statically compile MUSL libc. The Python modules are larger because Python is an interpreted language with more dependencies.

| Module Name       | LOC | Size  | Language | Inputs                          | Outputs                      | Domains        |
|-------------------|-----|-------|----------|---------------------------------|------------------------------|----------------|
| boolean           | 27  | 2.0MB | Rust     | condition,input                 | output                       | -              |
| firmware_update   | 11  | 2.0MB | Rust     | -                               | firmware                     | firmware.com   |
| light_switch      | 24  | 2.0MB | Rust     | light_intent                    | state                        | -              |
| person_detection  | 46  | 981MB | Python   | image                           | training_data,count          | -              |
| speech_to_intent  | 75  | 38MB  | Python   | speech                          | weather_intent,light_intent  | -              |
| query             | 36  | 2.1MB | Rust     | image_data                      | result                       | -              |
| set_true          | 5   | 2.0MB | Rust     | -                               | true                         | -              |
| set_false         | 5   | 2.0MB | Rust     | -                               | false                        | -              |
| statistics        | 12  | 2.0MB | Rust     | data                           | -                            | statistics.com |
| weather           | 25  | 2.1MB | Rust     | weather_intent                 | weather                      | weather.com    |

Figure 9: End-to-end applications with a speaker and a light (left), and an occupancy sensor and two cameras (right).

We run the controller under Ubuntu 20.04 on a 10-year-old machine with two 4-core Xeon E5620 CPUs typical of discarded last-generation servers (CPUs $8/pair on eBay) and 48GiB of RAM (mostly unused, as seen in Table 7). We run a single sandbox and emulate the devices on the same server.

8.1 Does Karl’s serverless programming model preserve device functionality?

The applications we implemented in Fig. 9 demonstrate that Karl can preserve the functionality of existing IoT devices in its programming model. We are able to express device-side logic, companion apps, and cloud services using local hardware under a single framework, unlike existing systems where IoT devices are still tied to vendor infrastructure.

We found device-side logic to be modular and event-driven, fitting with Karl’s modules and stateless edges. We designed edges to use common data types such as image formats or JSON, such that even modules from different vendors could be compatible. Otherwise, one could implement connector modules that convert between formats. We used the boolean module to express control flow logic such as conditional policies on whether the home was occupied or the time of day.

We designed Karl apps to match existing companion apps without a cloud mediator. The light app lets the user adjust the light with low latency because it communicates on the local network. The camera app lets the user view a livestream on the user’s phone, preventing breaches where employees or hackers of a vendor service see the feed [9,53]. Storage is also controlled by the user and kept on local hardware.

We implemented two ML modules that typically run as stateful cloud services: speech-to-intent and person detection. When searching for ML implementations, we were pleasantly surprised by the variety of open-source options [24,25,41,42], depending on how users prioritize latency or accuracy. Though ML typically runs on dedicated CPU and GPU servers in the cloud, our experiments showed reasonable latency on our hub’s 10-year-old CPU. In general, we believe that ML applications previously thought to be too costly for local hardware will be cheaper to support in the future, as commodity hardware vendors are implementing ML acceleration, e.g. in Intel’s integrated GPUs and Apple’s Neural Engine.

8.2 Can Karl enforce useful privacy policies?

To determine what is considered “useful”, we analyzed Karl in terms of existing studies on smart home users. Zheng et al. [56] suggests that users care strongly about audio-visual data, would prefer sharing data in aggregate, and prioritize functionality over privacy. Dixon et al. [16] recommends time-based access control and extra sensitive devices as security primitives, and a central management layer. The Karl hub can enforce these properties with exit policies on tags for audio-visual or sensitive data, conditions based on anonymization or boolean modules for time-based policies, and a framework that that tightly integrates functionality and privacy.

We validated Karl’s generality by implementing all the privacy properties in Fig. 5. Existing research frameworks either cannot express or enforce all these policies (§3). Hubs integrate local devices, but do not account for data handled in companion apps and vendor services [21,52,54]. Another reason is the granularity at which frameworks define policies. Low-level IPCs lack semantic meaning [31], while high-level app descriptions do not directly match functionality [52].

Next, we discuss the enforcement mechanism and how it reflects the users’ privacy expectations. In many cases, denying
a pipeline permission does not affect other pipelines, such as when we denied the speaker from turning on the light bulb in Fig. 9. In other cases, it affects other permissions that the user has allowed, leading to unintended side effects. When we denied the occupancy sensor from sending data to statistics.com, Karl revoked network access from the statistics module, and the camera was no longer able to share training data. This side effect makes sense—when we decided not to leak metadata about our occupancy, the boolean module could no longer properly anonymize training data, so the camera pipeline was also denied. The UI indicates when pipeline permissions conflict with exit policies and each other to convey side effects to users, though user studies should be performed to improve the design. Karl still provides the foundation on which IoT hubs can build to express and enforce comprehensive privacy policies on modular application semantics.

8.3 How is performance on local hardware?

Fig. 10 demonstrates that Karl has reasonable end-to-end latency for real-time user interaction and computational tasks in a resource-constrained environment. We evaluated combinations of these two types of requests using the pipelines in Table 5. We measured end-to-end latency as the time from when a user interacts with system to when the user can observe its intended effect. Latencies are the average of 5 trials, after warmup. All performance optimizations are enabled.

We tested two real-time user interactions and observed they are within a reasonable human response time. We turned on a camera livestream through a Karl app in 2ms, and turned on a light through a speech command in 236ms. In comparison, we asked an Amazon Alexa the weather as a simple experiment 1s after finishing the command. Device usability relies on real-time interactions, an area where Karl’s local computation excels.

Computational tasks can be constrained by user hardware, though they do not necessarily require real-time latency. Person detection and post-processing took 8.1s, bottlenecked by the lack of AVX2 instructions in our hardware (it took 3.1s on cloud hardware with AVX2). Unless the Karl hub is fully saturated, we do not expect occasionally compute-heavy tasks like this to significantly impact user experience.

Table 6a demonstrates how our caching optimizations improved performance. The cold-cache optimization most benefited Pipeline III by eliminating the time to resend ML data dependencies and Python libraries over the network. The size of the person_detection module was $490 \times$ the size of the set_true module in Pipeline I, which benefited the least. The warm-cache optimization most benefited Pipeline I, which had long initialization times for mounting the filesystem and establishing a sandbox, relative to the remaining execution. In Pipeline III, warm-cache eliminated the pre-processing time of loading a model, reducing latency by 3.0s.

8.4 How does hosting Karl in the cloud affect performance and cost?

We compared the network latency of the same pipelines using Karl deployed on user-managed cloud hardware. We used an m510 CloudLab server with an Intel Xeon D-1548 processor with 8 cores and 64GiB RAM. We observed 16ms more latency from Pipeline I, which sent a request to the camera over the WAN with larger and more variable latencies. Module data accesses still went over the same LAN as the hub.

Another aspect of performance is the hardware. Notably, the processor on the CloudLab server supports AVX2. If the user has particular applications they want to run that rely on special hardware for performance, cloud platforms could give them flexibility in selecting exactly the resources they need.

A back-of-the-envelope calculation finds that we can deploy Karl in AWS for $14.80/month, which is comparable to IoT subscriptions like Ring Protect for $10/month with greater privacy. Most IoT traffic is frequent and low-bandwidth [38] similar to Pipeline I, so we assume the bottlenecks to involve ML. Given the CPU and memory usage statistics of each pipeline (Table 7), we select an instance that can handle Pipeline III. Even if multiple cameras handle 100 requests/day, these tasks are hardly enough to fully utilize a sandbox if they rarely overlap. On AWS, a t2.medium reserved instance with 2 vCPUs and 4.0 GiB RAM costs $14/month, and 10 GB of EBS storage is $0.80/month. We hope to reduce these costs in future work by leveraging serverless cloud platforms for Karl sandboxes instead [40].

9 Discussion

In this section, we discuss some of the more practical concerns about adopting Karl.

Administrative benefits of local hosting. We argue the convenience of cloud hosting is overstated. The Karl hub has the same uptime as the home router on which it depends for connectivity, and is not affected by cloud outages [1, 5, 15, 39]. Another issue Karl addresses is the heterogeneity of individual vendors [22, 33, 34], who can focus on building software and hardware rather than rebuilding the same infrastructure. Karl can integrate security best practices such as multi-factor authentication and encrypted network protocols directly into
Pipeline Real-time? ML?
LivestreamOn (I) set_true → camera.livestream → camera.livestream yes no
SpeechLight (II) speaker.speech_command → speech_to_intent → light_switch → light.state yes yes
PersonDet (III) camera.motion → person.detection (+ occupancy.sensor.at.home) → boolean no yes

Table 5: Evaluated pipelines for end-to-end latency.

| Pipeline    | Baseline | Cold-cache | Warm-cache |
|-------------|----------|------------|------------|
| LivestreamOn| 64ms     | 54ms (16%) | 2ms (97%)  |
| SpeechLight | 740ms    | 515ms (30%)| 236ms (68%)|
| PersonDet   | 17.0s    | 11.1s (34%)| 8.1s (53%) |

(a) Local deployment.

| Pipeline    | Baseline | Cold-cache | Warm-cache |
|-------------|----------|------------|------------|
| LivestreamOn| 126ms    | 99ms (21%) | 18ms (86%) |
| SpeechLight | 1110ms   | 894ms (19%)| 488ms (56%)|
| PersonDet   | 10.1s    | 5.2s (49%) | 3.1s (69%) |

(b) Cloud deployment.

Table 6: Effect of caching optimizations on end-to-end latencies of the three pipelines in Table 5, where the baseline is Karl with no optimizations. In parentheses, percent improvement over baseline.

the framework, and durability measures such as encrypted backups on cloud or decentralized storage [7, 37].

Vendor incentives to adopt Karl. Vendors can provide users lower latency for interactive applications and real-time processing in bandwidth-limited wide-area networks, similar to edge computing [45]. Smaller vendors in particular would benefit from lower upfront costs without having to recoup the costs of hosting cloud infrastructure, and not having to invest in complying with stricter legislation trends.

Business model other than data monetization. We imagine a world in which users are willing to pay a privacy premium for just hardware devices and software modules, without sacrificing their data. It is reasonable to run proprietary software on user hardware, as in the mobile app market. Karl also does not prevent vendors from collecting data, as long as they do it transparently and with justification. Karl is particularly compatible with client-side anonymization techniques [10, 13, 18, 29, 32].

Privacy legislation trends. There has been a trend towards stricter privacy laws such as GDPR [14, 36]. Karl automatically ensures privacy through local hosting so vendors without the security expertise to comply can focus on building software and hardware. In general, privacy laws need to strike a balance between what protects user data most and what is practical for vendors to implement. We hope Karl and future research can influence legislation by demonstrating the practicality of more privacy-friendly approaches.

Transition strategy. The easiest way to transition to Karl would be for existing frameworks such as SmartThings and Home Assistant to adopt its ideas. Karl’s event-driven programming model shares many similarities, but the difference is how these frameworks leverage local hosting and modularity to provide privacy guarantees. Existing frameworks should be more restrictive about their concept of a “module”, and its data and network privileges. They should determine all pathways for sensitive data to be leaked, including the companion apps, cloud services, and multi-device interactions of modern devices. Adopting these ideas can provide the foundation for privacy policies such as pipeline permissions and exit policies that can be enforced and expressed by the user.

10 Conclusion

IoT devices that belong to end users should not depend on vendor-maintained infrastructure to operate. Karl provides a better model that prioritizes privacy while preserving the functionality of modern devices: IoT devices outsource computation and storage to user-controlled hardware, on which Karl sandboxes software modules from different vendors. With Karl, vendors extricate themselves from hosting cloud infrastructure, and users can unilaterally enforce coherent security across devices and modules. Karl introduces two security mechanisms: pipeline permissions that permit device data to be shared given some justification and exit policies that block flows unless specific conditions are met. We demonstrate Karl’s viability through several IoT applications with comparable performance and much greater privacy.
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