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*Aims and Scope*
The manifestos from Dagstuhl Perspectives Workshops are published in the *Dagstuhl Manifestos* journal. Each manifesto aims for describing the state-of-the-art in a field along with its shortcomings and strengths. Based on this, position statements and perspectives for the future are illustrated. A manifesto typically has a less technical character; instead it provides guidelines and roadmaps for a sustainable organisation of future progress.



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Manifesto from Dagstuhl Perspectives Workshop 14022

# Connecting Performance Analysis and Visualization to Advance Extreme Scale Computing

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## Abstract

In the first week of January 2014 Schloss Dagstuhl hosted a Perspectives Workshop on "Connecting Performance Analysis and Visualization to Advance Extreme Scale Computing". The workshop brought together two previously separate communities – from Visualization and Performance Analysis for High Performance Computing – to discuss a long term joint research agenda. The goal was to identify and address the challenges in using visual representations to understand and optimize the performance of extreme-scale applications running on today's most powerful computing systems like climate modeling, combustion, material science or astro-physics simulations.

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## 1 Executive Summary

The need for predictive scientific simulation has driven the creation of increasingly powerful supercomputers over the last two decades. No longer the simple, single-processor machines of the 1970's and 1980's, modern supercomputers comprise millions of cores connected through deep on-node memory hierarchies and complex network topologies. In contrast to the direction that mainstream application development has taken, where rapid development is prioritized and hardware details are often an afterthought, simulation science thrives only through high performance. Increasingly, *more* knowledge of esoteric hardware details is





required to exploit the performance of modern machines. The algorithms implemented by large simulations are already dauntingly complex, and the set of skills required to integrate domain science, numerical algorithms, and computer science is easily beyond the capability of any single scientist.

Performance analysis is a subfield of computer science that, for many years, has focused on the development of tools and techniques to quantify the performance of large-scale simulations on parallel machines. There are now a number of widely used tools and APIs to collect a wide range of performance data at the largest scales. This includes counts of micro-architectural events such as cache misses or floating point and integer operations, as well as timings of specific regions of code. The success of these tools has created a new challenge: the resulting data is too large and too complex to be analyzed in a straightforward manner. Existing tools use only rudimentary visualization and analysis techniques. They rely on users to infer connections between measurements and observed behavior. The raw data is abstract and unintuitive, and it is often poorly understood as much of the hardware details are undocumented by vendors. Automatic analysis approaches must be developed to allow application developers to intuitively understand the multiple, interdependent effects their algorithmic choices have on the final performance.

The natural first step towards automatic analysis is to visualize collected data. This provides insight into general trends. Visualization helps both application developers and performance experts form new hypotheses on causes of and solutions of performance problems. The HPC community has traditionally been associated with researchers in *scientific* visualization, but performance data is not necessarily a good fit for this model. The data is non-spatial, highly abstract, and often categorical. While some early attempts at including visualizations in performance tools have been proposed, these are rudimentary at best and have not found widespread adoption. The information visualization (info-vis) community is growing rapidly, focused on developing techniques to visualize and analyze complex, non-spatial data. There is a large body of work on general visualization design principles, color spaces, and user interfaces as well as a wide array of common techniques to tackle a broad range of applications. Unfortunately, there has so far been little overlap between the info-vis and performance analysis communities.

This Dagstuhl Perspectives Workshop, for the first time, gathered leading experts from both the fields of visualization and performance analysis for joint discussions on existing solutions, open problems, and the potential opportunities for future collaborations. The week started with a number of keynote sessions from authorities from each field to introduce the necessary background and to form a common baseline for later discussions. It became apparent that there is a significant overlap in the common tasks and challenges in performance analysis and the abstract problem definitions and concepts common in visualization research. The workshop continued with short talks focusing on various more specific aspects existing challenges and potential solutions, interspersed with increasingly longer group discussions. Theses extensive, inclusive, and in-depth exchanges ultimately shaped the second half of the workshop. This was only possible through Dagstuhl's unique collaborative discussion environment.

Ultimately, the workshop has spawned a number of collaborations and research projects between previously disparate fields, with potential for significant impact in both areas. Participants developed three high-level recommendations: First, joint funding for the various open research questions; second, support to build and foster a new community at the intersection of visualization and performance analysis; and third, the need to integrate performance visualization into the workflow of parallel application developers from design to optimization and production.

In this Dagstuhl Manifesto we summarize the discussions and results of the Dagstuhl Perspectives Workshop. At the end, the workshop led to four major results:

- The attendees summarized the state-of-the-art and its gaps for both performance analysis and information visualization. At the same time, this information functioned as education for the attendees of the other field and provided an introduction into the respective fields (Section 2).
- The group outlined the common challenges in bringing the two fields together (Section 3).
- One of the major obstacles identified during this activity was the need for a common understanding of the data being collected and visualized, which then lead to the definition of a general data model and a discussion on how existing tools can be mapped to it (Section 4).
- Finally, the workshop produced a set of next steps and recommendations to closer align the two fields. This has the potential to significantly further the performance visualization for large scale systems (Section 5).

Overall, these results and the manifesto based on them will result in closer collaboration between the fields of performance analysis and visualization, creating a vibrant new field of performance visualization.

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# 2 Background

The characterization, modeling, analysis, and tuning of software performance has been a central topic in High Performance Computing (HPC) since its early beginnings. The overall goal is to make HPC software run faster on particular hardware, either through better scheduling, on-node resource utilization, or more efficient distributed communication. The first step in optimizing is typically to collect some data about the program's behavior at runtime. Collecting and displaying this data to diagnose particular types of performance problems is the forte of current tools. The difficulty, and a long-standing open problem in performance analysis, is that for large parallel programs, there is simply too much performance data. Even a simple, single-threaded sequential program run on one processors can generate instruction traces comprising *millions* of execution events.

In a large parallel program, where data is collected from multiple threads on each node and potentially hundreds of thousands of nodes, the data becomes extremely unwieldy. Locating and identifying a performance culprit in such data is often like finding a needle in a hay stack, and it is typically not known in advance which data might help in the diagnosis, or which processes/threads it might be from. Visualization has therefore been used for the initial, high-level analysis of performance data for purely practical reasons: we delegate the task of finding the problem to the user.

During the workshop it became apparent that HPC performance analysts and InfoVis experts are both dealing with *visualizing and analyzing complex data*, and that there is great potential for collaboration between the two fields. InfoVis experts have developed many techniques to extract meaning from very high dimensional unstructured data, and to search it for correlations. Performance analysts have a strong focus on very large, relatively structured data sets that need to be studied in light of irregularities or known deficiencies. Much of this data, particularly with respect to networking and performance counters, is high dimensional and unstructured.

This section summarizes the state-of-the-art analysis and visualization in the performance analysis field and provides background for the common data model we propose later in Section 4.

## 2.1 Profiling Tools

The most basic performance measurement tools are *profilers*, which record, for some execution of a program, the parts of the source or binary code in which a program spent its time. A profile is essentially a histogram, binned by region in the code, of elapsed time spent executing. The key difference among profilers is *how* they bin locations in the source code.

1. **Flat profilers.** So-called *flat* profilers consider source code entirely statically, and bin source code by function names, source file and line number, or raw instruction addresses in a binary. While this is a simple way to consider source code, it ignores the *calling context* of the code. For example, a flat profiler will accumulate time into a single bin for the `MPI_Send()` function regardless of whether it was called directly by the application or from a library. Simple call graph profilers like IBM's Xprofiler include static call information in their display, but they are still flat profilers because they do not include any dynamic calling context information.
2. **Call-tree profilers** add information to a flat profile by binning code by calling context, i.e., by the contents of the runtime stack it was called from. The unique bins in such a

profile comprise a *calling context tree* or *call tree*, typically rooted at the `main` function or one of its ancestors. Binning based on dynamic runtime information can differentiate different uses of the same call, especially for library functions. It can also differentiate uses of different functions through the same callsite, e.g., in the case where a function is called indirectly through a pointer. Open|SpeedShop, Scalasca, TAU, and HPCToolkit all support this mode of profiling.

3. **Function profilers** such as mpiP intercept and time only certain function calls. mpiP in particular is a profiler tailored to the MPI interface, and because it only accesses certain functions, it can bin MPI operations according to their parameter values in addition to calling context. It is, however, unaware of time spent out side the MPI interface. Darshan is another example of an interface profiler that targets POSIX I/O commands.

In addition to the way they account for source locations, profilers differ in the metrics they can display, i.e. the metrics accumulated in each bin of the histogram. For example, HPCToolkit and Open|SpeedShop can both be configured to accumulate floating point instruction executions, cache misses, or other events instead of simply CPU cycles or time. In practice, profilers incorporate many aspects of the above traits. For example, mpiP incorporates calling context in addition to function parameters, and a call tree profiler can be used to generate a flat profiler with post-processing.

**Handling Parallelism.** When profiling a parallel program each process or thread typically generates its own copy of the profiling histogram. The task of aggregating profile data in large parallel programs is currently either handled by writing a single file per monitored task, or by aggregating this data. Parallel statistical techniques such as clustering have been proposed, but none of these techniques is used consistently in production tools to isolate problems, at least not for simple profiling. More often, data is averaged or summed across all processes, losing load imbalance information and any other heterogeneity in the profiled data.

**Visualizing Profiles.** The profilers above display their results in many different ways. HPCToolkit, Open|SpeedShop, Scalasca and TAU offer GUI tree widget views that show source locations and the percentage of total time spent in each. These views allow users to collapse and expand nodes of the calling context tree. Flat profilers typically provide a simple table, possibly grouped into categories for organization, e.g., by library or by source file. mpiP and Open|SpeedShop provide simple human-readable text output, and Darshan provides a web interface for visualizing its results. Some profilers provide mechanisms for zooming in on data based on some relevance criteria, for example, HPCToolkit allows a user to zoom in on the "hot path" in the profile by iteratively expanding a child with a large percentage of total time up to some threshold. IBM's XProfiler and TAU's callgraph view adjusts the size of call graph nodes based on the time spent in them, but aside from this, none of the current crop of tools provides visual metaphors to emphasize particular nodes in the tree or graph beyond simple coloring.

## 2.2 Tracing Tools: Performance Timelines

*Tracing* tools record a *sequence* of parallel events per process. These events might include entering a particular function, exiting a function, sending a message, receiving a message, etc. Each event is recorded, typically with a timestamp, and possibly also with a set of metric counts for the time of the event. Unlike a profile, where individual event records are

discarded to conserve space and to build up an aggregate histogram, traces store the *entire* event trace. They can thus grow much larger than profiles, but can reveal phenomena that profiles cannot.

Traces are useful when program behavior depends on temporal information. In these cases, determining the root cause of a problem from a profile may not be possible. Conditions depend on the order of events as they execute at runtime, and the performance of many distributed communication operations depends on the order in which messages are passed among parallel processes. In thread-parallel programs, shared memory data exchange and locking is used for communication and synchronization, but the idea is the same.

Tracing tools are most typically used with MPI parallel applications. JumpShot, VampirTrace, Scalasca, Score-P, and TAU all provide the ability to measure the time an application enters and exits MPI calls, as well as the endpoints of parallel communication operations like sends and receives. Many also provide instrumenting compilers that allow the entries into and exits from local computation routines.

**Handling Parallelism.** Tracing tools, like profilers, record a series of events on every parallel task. Depending on the granularity of measurement, traces can grow very large very quickly, as their space complexity is proportional to the product of execution time and event frequency. Aggregating large amounts of trace data is difficult, though some tools like ScalaTrace have been developed to analyze trace data for similarity for purposes of compression (but not for analysis). Most trace tools simply dump per-process, compressed trace records, which makes their scalability lower than that of profilers for common usage.

**Visualizing Trace Data.** Trace data is typically visualized as a long timeline, or Gantt chart, with time on the horizontal axis and tasks (processes or threads) on the vertical axis. Colors are used to denote different communication and computation routines, and messages are shown as lines drawn between processes. Users can zoom into sub-regions of the full trace to expand complex behavior on short time scales. JumpShot and VNG both provide this type of visualization for trace data. ScalaTrace does not provide a visualizer. The HPCTraceViewer tool combines call tree profiling with tracing by displaying a fully dynamic call tree event view. This is a two-dimensional view of the 3D space of tasks vs. time vs. call trees, and the user can select a call tree level in advance and view the traditional 2-D trace view. Each element in this trace view is a sampled call path – there are no metrics recorded on the callpath elements in HPCTraceViewer's view.

## 2.3 Traditional Plots

In addition to profiles and traces, standard two- or multi-variate plot-based visualizations have been employed by performance tools. Bar charts, pie charts, and standard histograms are used by TAU, Vampir, ParaProf, and Cube to visualize binned data in arbitrary metric domains. Scalasca can use BoxPlots to show variation and distribution of timing and other metric values.

Often, a plot is the best way to display a relationship between a small number of values, but the user must know in advance what to plot, and exploring all possibilities is typically tedious. Visualization and analysis techniques are typically necessary to guide the user towards the right set of metrics to plot. PerfExplorer allows curves to be fit to scatter plots, and it can automate the generation of large numbers of plots for high-dimensional data, but the user must still scroll through a large array of bad curve fits to find the interesting ones.

## 2.4 Projected Views

Recently, many performance tools have begun to explore the idea of mapping, or *projecting* performance data onto spatial, logical, or other domains to show correlations and topological relationships.

The Cube tool allows a user to visualize metrics associated with each process in a large, parallel Blue Gene, Cray or K computer job to be displayed in the logical topology the tasks comprise at runtime. Blue Gene machines, as well as other supercomputers, employ cartesian *torus* or *mesh* shaped networks, and this view allows us to visualize processes in a projection that clearly displays their communication locality.

The PAVE project at the Lawrence Livermore National Laboratory (LLNL) has projected performance data into the simulated application domain, then used traditional scientific visualization techniques to display the resulting data. This revealed that for some fluid dynamics codes, there are correlations between performance metrics and particular domain data. Scalasca has been used to show a similar visualization of climate simulation data projected onto a visualization of the globe, and the TAU tool provides a similar projection tool that allows data to be projected onto an arbitrary 3D geometric shape to show correlations. These techniques allow users to understand data-dependent performance problems, and to identify what part of the source code cause data-dependent delays in the overall computation.

The Boxfish tool at LLNL was developed to generalize the idea of projecting performance data onto domain-specific views. For example, given a rendering of a 2-D, 3-D, or 5-D torus network, Boxfish can display per-process data projected onto the nodes and links of the network. It can also project the same data onto a custom 2-D network visualization, and display the same data with less clutter. Or, it can project this data onto a representation of the simulated physical domain, such as a material patch view for Adaptive Mesh Refinement (AMR) applications. Boxfish is structured so that the elements of the view to be colored or labeled are exposed for *any* performance data to be projected, which allows a user to explore correlations and relationships between performance measured in one domain with elements in some other domain, assuming a suitable view plugin has been developed for the domain.

## 2.5 Information Visualization for Performance Analysis

Most of the visualization techniques discussed above have been driven directly by specific needs of performance analysis. This has made these tools intuitive to use and well integrated into the HPC workflow. Unfortunately, these visualizations rarely consider aspects such as appropriate color selection, screen space usage, more abstract visual metaphors, or the advantage of interactive linked-view interfaces. This often results in cluttered displays, misleading visualizations, unscalable representations, and static plots not suited for an interactive exploration driven by the end user.

On the contrary, the field of information visualization has a long history of research in all these aspects. For example, there exist a number of taxonomies to classify different visualization tasks [3, 11, 8], extensive research on the use of color in visualization [1, 2, 9], and accepted practices on the design of visualization systems [4]. Unfortunately, due to the large amount of domain knowledge necessary to collect and interpret performance data only comparatively little research in the information visualization community has focused on performance data. Nevertheless, these include a number of interesting new concepts such as novel layouts for networks [10, 7] or the memory topology [5] and a different perspective on how to depict time [15]. However, these tools have found only very limited adoption as they

either do not directly or completely address the users needs, are limited in scale, or have simply proven to unintuitive for most HPC researchers. As a result a recent survey in related work on performance visualization [6] finds a large body of research that appears split into a set of widely used tools with often limited visualization capabilities and a set of advanced techniques, graphical layouts, and systems that is predominantly academic in nature.

## 2.6 Future Direction for Performance Visualization

One immediate result of even the first day of the Dagstuhl workshop was the realization that the combination of advanced visualization techniques with state of the art performance analysis technology has the potential for significant impact in virtually all areas of HPC. However, it also became clear that each area individually will have difficulty addressing the open challenges adequately. Instead, we need an exchange of knowledge in both direction with the visualization community becoming more familiar with HPC problems, techniques, and existing tools and the performance analysis community adapting more advanced visual encodings, integrated interfaces, and interactive tools. The data model described in Section 4 is a first step in this direction by describing, for the first time, a holistic view of performance data starting from the collection of raw measurements and ending and interactive visualization tools. As discussed in Section 4.6 many of the existing tools are well described by this model and recent developments designed to project data from one domain into the other can be see as an initial attempt at a complete realization of this model. Nevertheless, during the workshop it became apparent that to allow the techniques used in scientific and information visualization to be applied to performance tools, there will need to be more common nomenclature and more standardization in the way performance data is stored and exchanged.

# 3 Challenges

One of the central challenges of parallel performance analysis is the extreme volume and variety of measurements that can be gathered from parallel performance tools. Performance analysts have struggled with devising ways to gather and analyze this data for many years. Information and Scientific Visualization techniques have the potential to offer performance analysts an entirely new set of tools to analyze this data, but it was determined at the workshop that several obstacles impede collaboration between the performance analysis and visualization communities.

**Domain Knowledge.** First, there are knowledge and terminology gaps. Performance tools are often designed for experts. Understanding the measurements they generate can require a full-stack understanding of a supercomputer, making them opaque to most visualization experts. For example, identifying code regions may require knowledge of compilers and language implementation, as this determines how symbols are represented at runtime. Further, understanding many measurements, e.g., network performance measurements, likely requires knowledge of the network on a particular supercomputer machine. Finally, understanding the types of analyses likely to reveal performance problems typically requires knowledge of how particular instructions and code executes on specific hardware.

**Measurement Complexity.** In addition to complex data formats, complexities of performance measurement have made it difficult to easily relate data from one tool to that of

another. As mentioned, tools like profilers typically aggregate data in very specific ways, e.g., by building a histogram according to a code representation with a specific granularity. Other tools, such as AutomaDeD, may aggregate data on the fly at runtime, e.g., to build a stochastic model of control flow or to only record timing for specific functions (e.g., MPI calls). There are no readily available tools to relate aggregate data to exhaustive data, or to project (lossy or otherwise) data in one domain to another.

**Data Formats.** Because of the complexity of performance measurement, data collected by existing performance measurement tools are often stored in a manner closely tied to a particular performance tool's implementation. This is done for efficiency, either because the format was the easiest structure to use for *collecting* measurements, or simply because the designers of the measurement tool only envisioned their data being consumed by a single, bespoke performance visualization tool. The profusion of performance tool formats and the lack of documentation on them for non-experts makes exchanging data with visualization researchers hard, as accessing the data may require implementing a new parser or translator to even begin working with the data.

**Evaluation.** Once the collaboration between performance tool developers and information visualization experts is successful, and new data analysis or visualization functionality is being added to performance tools, the challenge remains how to evaluate the effectiveness of the new approach. Given the extreme diversity of parallel machine, application architecture and application domains, it will be very difficult to assess the usefulness of a new approach. If a new approach was successful highlighting a performance problem in one or two cases this does not automatically mean it is useful in general. On the other hand, if various experiments with a new approach have not produced any interesting performance result it does not necessarily follow that the approach is not useful: the experiments might just have picked the wrong application examples or parameters which (by luck) just work fine. Therefore, developing general purpose metrics and benchmarks for evaluating new approaches for parallel performance methods and tools will be difficult.

## 4 The Foundation: A Common Data Model

One of the most significant results of this Dagstuhl workshop has been the joint realization that virtually all existing performance data collection and analysis routines can be defined in and described by a rather simple, yet general data model. Both performance analysts and visualization experts agreed that formally specifying a data model with which to describe performance results would allow for better communication and data exchange between the two communities. Making data more accessible, both in terms of a common format and in terms of the common structure needed to *explain* the format to others, will lower significant barriers to collaboration. In addition to the obvious benefit of giving InfoVis researchers access to performance data, it will facilitate exchange of data among performance researchers. This has the potential to allow measurements from different tools to be combined in ways not possible before, enabling new types of performance analysis.

We expect that a common data model will also go a long way towards solving the first problem of domain knowledge as phrased in a common language, performance data will become easier to understand for visualization experts. The resulting collaborations will serve to educate both communities about how best to visualize, analyze, and understand this data. The key, as this workshop has demonstrated, is lowering the barriers to entry that obstruct the speedy exchange of information.

## 4.1 The Anatomy of Performance Data

At a high level, parallel performance data can be said to describe the state of a dynamic system, usually a parallel supercomputer or some part of it. Typically, this data is recorded at runtime during the execution of some parallel application, as this is how most performance tools store their data. However, performance data may also include data recorded by tools or system logging daemons that run continuously, and that persist beyond the lifetime of a single parallel run. Further, it may include data that describes properties of the system or application – that is, metadata. Structurally, there is no particular distinction between recorded data and metadata. Semantically, metadata typically describes some static aspect of the system, like the dimensions of a network, or system configuration information particular to a single application execution, and recorded data represents dynamic measurements.

## 4.2 Notional Example

Before we delve into the details of the model, we will start with a notional example to illustrate the kinds of data we are dealing with. Suppose we have a performance tool that records, for each function in some application, the time spent in the function during each time step, the number of floating point operations executed by the function, and the number of cache misses incurred by the function's execution. We might represent this as a simple table:

| FunctionName | Time | FP | CM |
|---|---|---|---|
| hydro | 395 | 452 | 64 |
| checkpoint | 12342 | 0 | 7249 |
| solve | 19234 | 2097 | |

Each row in this table is a **record** written by some process. If we wanted to also record the 3-D torus network coordinates of the node where the measurement was taken, along with its rank in the MPI process, we would add columns to the table to get data that looks like this:

| FunctionName | x | y | z | rank | Time | FP | CM |
|---|---|---|---|---|---|---|---|
| hydro | 0 | 1 | 2 | 0 | 395 | 452 | 64 |
| checkpoint | 0 | 1 | 2 | 0 | 12342 | 0 | 7249 |
| solve | 0 | 1 | 2 | 0 | 19234 | 2097 | |

We can now see above that each record was taken on rank 0, which is located on node $(0, 1, 2)$ on the network. If we wanted to measure this data over multiple time steps we would further disambiguate them with a time step column, e.g.:

| FunctionName | Time | x | y | z | rank | Time | FP | CM |
|---|---|---|---|---|---|---|---|---|
| hydro | 0 | 0 | 1 | 2 | 0 | 395 | 452 | 64 |
| checkpoint | 0 | 0 | 1 | 2 | 0 | 12342 | 0 | 7249 |
| solve | 0 | 0 | 1 | 2 | 0 | 19234 | 2097 | |
| hydro | 1 | 0 | 1 | 2 | 0 | 395 | 452 | 64 |
| checkpoint | 1 | 0 | 1 | 2 | 0 | 12342 | | 7248 |
| solve | 1 | 0 | 1 | 2 | 0 | 19224 | 2107 | 224 |

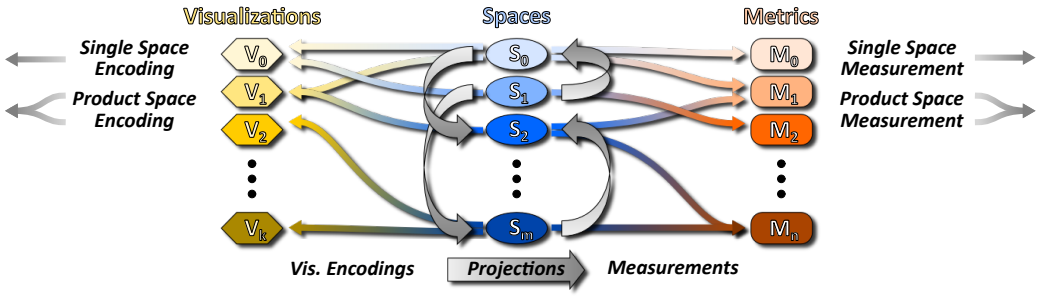



**Figure 1** A generic data model that captures the relationships between metrics being collected by a performance tool, the spaces on which theses metrics are defined and the visualization and analysis tools to explore the data. Performance tools typically implement a *measurement* that collects metrics such as FLOP counts on some domain defined by either a single or a cross product of *spaces*. Visualization tools are tailored to (cross-products of) spaces, i.e., the MPI rank space for communication graphs, and can analyze data defined on the corresponding domain. To expand the type of data applicable to any one analysis technique the model contains *mappings* between spaces.

This is a very general representation of the data. Each record represents a single fact recorded about the system. We might read the first record as the fact that "the hydro function took 395 nanoseconds, executed 452 FLOPS, and incurred 64 cache misses, on rank 0, on node $(0, 1, 2)$". Each record is simply a tuple of related *attribute values*. An **attribute** is simply the name by which we refer to a column header, along with an associated **type** for it values. Here all of the attribute have integer-types values, except FunctionName, which uses a string. A type can be a primitive type, such as an integer or real number, or it can be a structured data type as might be commonly used in programming languages. We do not restrict the types of attribute values, but in practice they are likely limited by the data store used. For each measurement, not every attribute must have a value. Tools are free to store as little or as much data as is available when they take their measurements.

## 4.3 A Generalized Data Model for Performance Tools

Following this notional example, we develop a generalization and formalization of our data model. Figure 1 provides a high-level sketch of the concepts explained below.

### 4.3.1 Spaces

At the core of the abstraction are a set of spaces. Each space is represented by a finite set of tuples and has a crossproduct of types associated with it, such that each type describes one element of the tuple. For example, the MPI rank space used above, uses a single integer to describe a location with respect to the communication graph and the triple of $x,y,\ z$ coordinates describes the physical coordinates in a torus network. The number of spaces is not limited. Time and code (represented by calling context trees [16]) are treated the same as any other space.

### 4.3.2 Metrics

Metrics are units for individual data points. Examples are floating point operations and MPI message counts. Metrics are typically represented by infinite sets, as not to restrict what can be measured, but may in individual cases be a finite set of possible outcomes.

### 4.3.3 Measurements

Measurements capture the data acquisition in performance tools. They are represented as mappings of a crossproduct of spaces – the domain the performance data is collected in – to a metric, the set of possible values for this measurement. To make reasoning about measurements easier, we define a measurement as a unique mapping or function, i.e., for each element of the measurement domain the measurement only maps to at most one element in the metric set. If this is not the case for an experiment, e.g., in tracing tools that provide multiple data points for each element of a space over time, the domain needs to be modified to allow for this uniqueness, in the example by adding a space representing real or virtual time to the crossproduct that forms the domain.

### 4.3.4 Comparison to Traditional Database Models

Thus far our data model is extremely general, and is closely related to many data models already in the literature. In particular, our model is very similar to the time-honored relational model, used in many database management systems. In the relational model, data is grouped into tuples, much like our records. A **relation** is a set of tuples with particular, common attributes – a **table** in database terms.

One key difference between our model and the relational model is that we do not restrict all records to have the same set of columns. Our model is designed to consume data from many different performance tools, each of which may have its own set of attributes, and each of which may even provide records with missing data. In this regard, we do not have *relations* in the same sense that a relational database does.

Recent NoSQL data stores such as Google's BigTable and Apache Cassandra are more flexible than a relational database with respect to columns. These stores represent their data as a large, multi-dimensional, sorted, distributed map. Our data most resembles this model because of the freedom to create new columns/attributes on demand and because of the lack of a rigid schema.

As will be described in more detail in the subsequent sections, a key aspect of our model is *projections* between data spaces, as well as the concept of *measurement functions*. While a traditional relational database is designed to do efficient queries on data with a known schema, our model may create new data by projecting existing values into new spaces, effectively creating new columns in the model. Adding attributes based on analysis is key to our model of visualizing performance data, and the fact that our model includes both structured computation in addition to data storage and retrieval differentiates it from the relational model, as well as recent NoSQL data stores.

## 4.4 Projections

In performance data analysis, and particularly in performance visualization, it is very useful to be able to project data from one domain to another. As mentioned in Section 2.4, several recent tools have begun to adopt projections and similar operations to visualize correlations between different types of performance data.

### 4.4.1 Projections in the Notional Example

Let us revisit our notional example and consider the following data, this time in terms of links rather than nodes on the network:

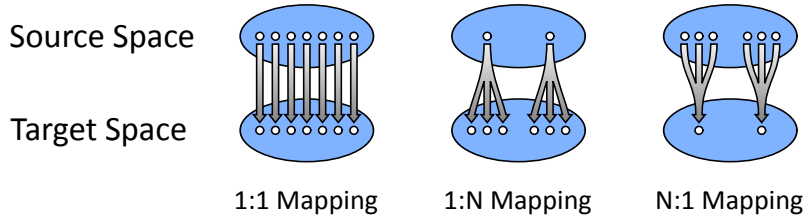



**Figure 2** Three different types of projections between spaces.

| FunctionName | sx | sy | sz | dx | dy | dz | bytes |
|---|---|---|---|---|---|---|---|
| hydro | 0 | 1 | 2 | 0 | 2 | 2 | 100 |
| checkpoint | 0 | 1 | 2 | 0 | 2 | 2 | 100 |
| solve | 0 | 1 | 2 | 0 | 0 | 2 | 50 |

Each of these records now represents bytes sent, e.g., to a neighbor in the torus network by a particular node in a particular function. A network link is identified by a source $(sx, sy, sz)$ triple and a destination $(dx, dy, dz)$ triple.

### 4.4.2 Formalization of Projections

A projection, in the sense of the data model, maps one or more spaces (the origin domain) to one or more spaces (the target domain). This allows measurements represented in the target domain to be used in analysis operations on the origin domain. In general, we can distinguish three types of projections, which are also illustrated in Figure 2:

- **1:1 Projections:** Each element of the origin domain is mapped to exactly one element of the target domain. An example of such a 1:1 projection is the mapping between node coordinates in a network to node IDs, since both domains describe the same physical entity, but using different names or numbering schemes. 1:1 projections allow a direct translation of measurements in one domain to another.
- **1:N Projections:** Each element of the origin domain is mapped to one or more elements of the target domain. An example for a such a 1:N projection is the mapping from node IDs in a system to process or MPI rank, since multiple ranks can be on each node. When mapping measurements using a 1:N projection, a measurement from an element in the target domain must be distributed or spread over all elements in the origin domain that map to it. The semantics of this operation depends on the semantics of the domains. For example, the same measured value could be attributed to each element in the origin domain in full, or the value could be split up based on a distribution function.
- **N:1 Projections:** Each element of the origin domain is mapped to at most one, not necessarily unique, element of the target domain. An example for a such a N:1 projection is the mapping of MPI ranks to nodes in a system, since multiple ranks can be on each node. When mapping measurements using a N:1 projection, measurements from all elements in target domain that map to a single element in the origin domain have to be combined using an aggregation operation. This can be as simple as a sum or average, but can also be a more complex operation such as clustering or statistical outlier detection.

Projections can further be combined into new projections, allowing a translation over multiple domains from an origin to a target domain. This could also lead to situations in which multiple translations between two domains using different compositions, i.e., a different route

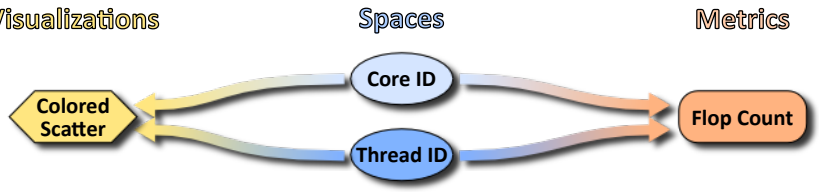



**Figure 3** A simple context of a two-dimensional colored scatterplot with two spaces, core-id and thread-id, and a single metric FLOP count.

through the set of available domains, are possible. Note, though, that not all combined mappings between the same domains carry the same semantics. For example, a 1:1 projection between two domains may also be representable by a combination of a N:1 and a 1:N mapping, but the latter would include a loss of information by first aggregating measured values before spreading them out again. Choosing the right combination of projections based on the intended analysis is therefore crucial.

## 4.5 Contexts and Visual Representations

The previous sections describe three fundamental aspects that can be used to describe performance data: the space in which samples are taken which allows to identify and attribute samples to different software or hardware entities; the metrics which are collected to describe the behavior of the system; and the potential projections that allow comparing and correlating information related to different portions of the system. While having a generic and thus portable description of performance data solves only part of the overarching problem. In particular, given a specific problem or analysis task one still must decide what portion of the data to consider and in what *context*. We consider a context to be a (collection of) space(s) together with a means to analyze or visualize values defined on these spaces. A context may be as simple as a plot of, for example, FLOP count per MPI process or as complex as a network visualization.

In particular, the more complex contexts such as a visualization showing the physical network have a *native* domain – in this case the node ids – and may require additional meta-information such as whether the network forms a mesh, a torus, a dragonfly etc.. Combined with the data model described above this now allows to describe a virtually arbitrary analysis task as a simple combination of what metrics are of interest, on which spaces are the corresponding samples defined an in what context should these be analyzed. Figure 3 shows a diagram of a simple analysis such as a colored scatterplot expressed in this way. In the example, the FLOP count is recorded on the space of core-id and thread-id and the colored scatterplot context shows the data and potential relationships.

However, the true power of the new data model emerges when one considers projections. For example, Figure 4 shows a schematic of some context depending on MPI rank showing the number of packets per network switch. One way to analyze the packets in the context of the MPI ranks is to first project the samples from the space of the network switch to node ids and subsequently to MPI ranks. Assuming each node has its own switch the first projection is 1:1 but requires additional meta-information indicating which switch belongs to which node. The second projection from nodes to MPI requires the node mapping that was active for the corresponding run and is likely 1:N. Therefore, the user must decide how to process the packet counts further. For example, one could assign the packets evenly to all MPI ranks on a node or proportional to other say FLOP counts.

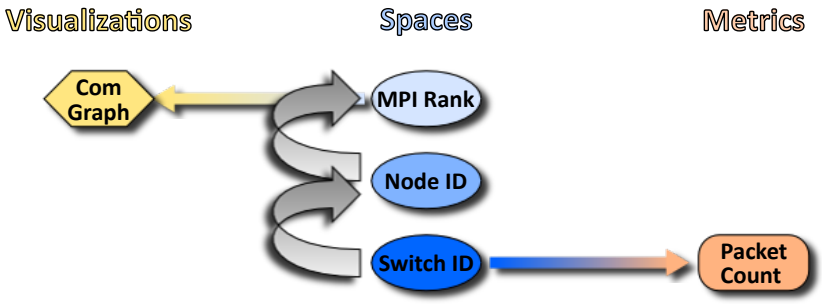



**Figure 4** A more complex context example of a communication graph operating on MPI ranks that shows network packets collected on a per network switch bases. The count is first projected to node ids according to the hardware configuration and subsequently to MPI ranks via the node mapping file stored at runtime.

In the language of this data model, open challenges in performance analysis can now be classified as one of three areas: first, how to collect data, i.e., how to define measurements and collect samples in an efficient and scalable manner; second, how to attribute and connect data from different spaces, i.e., how to project samples collected on one space, e.g., AMR patch id, into another, e.g., core id; and third how to analyze or visualize data, i.e., by developing new useful contexts. Furthermore, the data model now decouples these tasks to the extent possible. For example, developing a new context like a new visual metaphor for a complex network topology becomes a well defined and independent task with a clearly defined native domain on which is operates. Any samples that can be projected into this native domain (potentially another independent research challenge) can use this context and thus tools and techniques can easily be combined. Finally, the data model is well suited to support the complex interconnected analysis likely to be required to understand future systems. Through the projections many tools, data sources, and contexts can be combined and connected, for example, to form the linked viewed interfaces an advanced visual analytics solution.

## 4.6 Examples of Existing Tools

The model introduced above can be used to reason about any kind of performance data. In the following we describe how it can be mapped to a selection of existing tools and how it can be used to describe their data. These tools cover the three major types of performance measurement approaches (sampling, profiling, and tracing) showing the generality of the base model.

### 4.6.1 Open|SpeedShop (Sampling)

Open|SpeedShop is a performance tool set, which includes both tracing and sampling experiments within a single tool and workflow [13]. For the following, we concentrate on the sampling experiments (the tracing parts are equivalent to the Vampir tool covered below).

Sampling, or statistical sampling, is a technique to approximate the time spent by an application in various code segments. The execution of an application is repeatedly interrupted using a timer interrupt and during every interruption the tool records the program counter

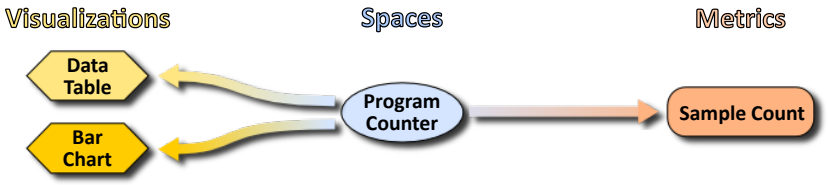



**Figure 5** Open|SpeedShop described in the generic data model.

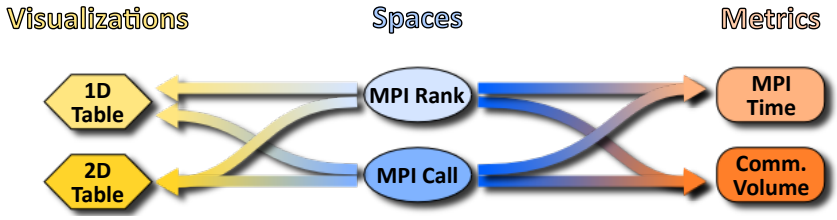



**Figure 6** mpiP described in the generic data model.

the application was executing at that time [1] and attributes the time since the last interrupt to that program counter location. If this is repeated often enough and with a fine enough granularity between interrupts, one can achieve a fairly accurate overview of which code pieces (identified by their program counter location) are executed for how long. As such, sampling tools provide an easy and low-overhead way to gain an overview of an application's performance.

This kind of performance tool essentially provides a histogram of times attributed to each program counter location, or, in other words, an association of number of sample counts (represented by the time associated with them) to PC locations. This can be represented by a single space, covering the PC locations, and a metric space representing number of samples (see Figure 5). The data is then displayed as a big table or in the form of a bar chart. In both cases, the tool directly shows the histogram.

### 4.6.2 mpiP (Profiling)

mpiP is a profiling tool for MPI communication [17]. It tracks all calls to the MPI library, records the time spent in the MPI library and aggregates the information. At the end of the execution, mpiP then produces a report that shows the time spent inside the MPI library and in each type of MPI call or (when used together with stack trace information) each call path for all MPI call sites in the code. Additionally, mpiP keeps track of how much data is communicated and maps this data to the same entities as the timing data. Combined, this provides users with a basic, yet powerful overview of the communication characteristics of their application and can help to identify MPI routines that contribute to execution delays.

Describing mpiP's data in the generic data model discussed above requires a more complex set of spaces. In its finest granularity data can be shown per MPI process (represented by the its rank in MPI_COMM_WORLD) and per MPI call. As shown in Figure 6, we represent both as a separate space and their crossproduct defines the domain for mpiP measurements.

[1] More advanced sampling techniques also record the call stack and/or sample on other events than time, e.g., cache misses or remote memory access – with loss of generality, we limit our discussion here to pure program counter sampling to keep the description simpler.

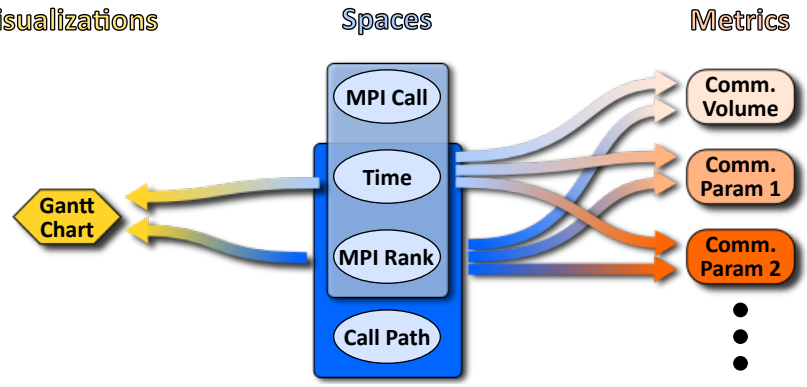



**Figure 7** Score-P/Vampir described in the generic data model.

The latter has two metrics, one for time spent in MPI and one for communication volume, both defined on the entire domain. The visualization in the current tool is simple and consists only of text output of the raw data covering both dimensions of the underlying domain.

Additionally, mpiP reports the spent in each call site aggregated across all MPI processes. This can be represented in our general mode with a 1:N projection from the space representing call sites to the complete domain combined with an aggregation function, in this case a simple addition. This creates "implicit" measurements from the "call" domain to the same metrics. This information is again printed in textual form, but this time has just a single dimension. Going even further, mpiP also reports the total time spent (across all processes and across all call sites), which can again be represented with a 1:N mapping from a new domain, represented by a single identifier representing the application run, to the entire measurement domain. This allows us to extract the total time spent in MPI (and the total data volume) which is then simply printed as a scalar.

### 4.6.3 Score-P/Vampir (Tracing)

The tracer component of Score-P [14] is an MPI tracer that, like mpiP, intercepts and records every call to the MPI library and stores the collected data. Unlike mpiP, though, every invocation is stored separately without aggregation. This enables user to collect and subsequently analyze a complete trace of all communication events. Additionally, Score-P optionally uses compiler-based instrumentation to track invocations of functions and records this information in the same way as invocations to the MPI library. Both traces (computation functions and MPI invocations) are then combined and can be visualized using the Vampir tool set using a Gantt chart like display [12].

In order to represent the data in our model, we start with the model used by mpiP, but add additional spaces. Namely, Score-P also records a time stamp for each measurement as well as a full call path. These four spaces are combined into two different domains: The MPI Call × MPI Rank × Time domain describing which MPI rank communicated when and using what MPI call; and the Call Path × MPI Rank × Time domain, which describes in which function the communication occurred. Conceptually, all measurements taken are recorded with respect to both domains independently though for efficiency reasons they are likely stored more compactly. Both domains are then combined in a Gantt chart which typically uses the first domain as primary axes, showing MPI ranks on the y-axis and time on the x-axis and the second domain to color entries by various metrics or function types.

Note, that as with mpiP, Score-P/Vampir can aggregate data by any of the three

dimensions, which again can be presented with corresponding 1:N projections. We omit these in the figure to keep the diagram legible, though. In particular, aggregating from the time space allows tracing data to be reduced to profiling data, equivalent to the data reported by mpiP. This is one example of how this model can help to map data between tools and their corresponding visualization approaches. Further, the "function" space used here and the PC space introduced earlier during the discussion of Open|SpeedShop, are related – each PC is associated with one function. We can therefore also provide a projection between those two spaces, making it possible with our model to bride the gap between sampling and tracing/profiling tools.

### 4.7 Discussion

One of the immediate impacts already apparent during the workshop itself has been to provide a common framework for both communities to discuss ideas and solutions. In particular, the ability to describe existing tools on both sides in terms of the data model and the relevant projections has greatly facilitated communications. Even though the model will likely be refined by both communities in coming years this represents a significant and lasting impact. Furthermore, we believe that the model can serve as a blueprint for general, interoperable, and cross-community tools. The three main ingredients of the model, measuring data, visualizing/analyzing data, and projecting data directly correspond to a set of well defined and to a large extent independent tasks. Assuming appropriate interfaces, techniques and implementations in any of these three areas can be combined in a variety of ways. For example, many projections between non-trivial spaces, e.g., MPI rank vs. network port, require detailed machine-specific knowledge and sophisticated low-level tools to extract it. As a result this functionality will be challenging for visualization researchers to implement. At the same time mappings are crucial to expand the type of data that can be display beyond the native domain of a visualization and to provide linked views. For example, understanding how a feature in the communication graph is expressed in or caused by the underlying network hardware could be tremendously helpful. However, this functionality requires the projection from MPI ranks to ports. Going forward we anticipate targeted tools to be developed for individual tasks, described with respect to the model, which allows them to be used more readily to assemble more powerful solutions.

## 5 Recommendations

By all accounts, the workshop has been a great success and has already led to a number of new collaborations, joint proposals, and a very successful workshop at the 2014 Supercomputing conference with 18 strong submissions. The second installation of the workshop is scheduled for Supercomputing 2015 and we expect a similar response. Nevertheless, much remains to be done to establish a subfield of performance visualization at the intersection of HPC performance analysis and information visualization. In particular, we have two specific recommendations to advance this new area of research and a number of suggestions to ensure a broader impact of the resulting work.

## 5.1 Recommendation I: Dedicated Funding for Joint Research

While all the participants of the workshop agreed that combining forces has significant potential for future impact, this only came after intense personal discussions to overcome "language" and "cultural" differences between the two communities. At this point the greatest concern is that the core competencies of both areas are too far apart to organically grow closer. In particular, finding funding for the required long term collaborative teams necessary to make progress will likely be difficult in the current climate. At this moment few solicitations in performance analysis will consider visualization research within scope nor will program managers or reviewers fully appreciate the resources required to design new visual metaphors or interactive tools or the potential impact of these efforts. Similarly, solicitations in the area of information visualization typically do not consider research in the specific application area to be within scope nor does the corresponding community have sufficient insight into HPC problems to recognize the need for new techniques to collect and organize performance data. Nevertheless, it is our opinion that ultimately progress will crucially depend on close collaborations between experts of both fields over long periods of time as the initial start-up cost of such an effort will likely be substantial. As a result we recommend the creation of a dedicated funding stream contributed from both communities specifically designed for collaboration in the area of performance visualization to foster and encourage the foundational research necessary to establish this subarea.

This should include not only the wide range of topics associated with the core topic of turning the massive amounts of performance data into insightful visual representations, but also include support areas such as more structured data acquisition, interoperable data stores, visualization toolkits specialized to performance data, or (semi-) automatic analysis algorithm to enable novel visualizations. Further, underlying to all these efforts should a goal of scalability, in terms of number processing cores used by application, data volume collected and stored, as well as throughput of analysis steps.

As an additional remark, this workshop has shown that both communities are highly international covering multiple countries and even continents. This is already evident from the list of attendees and their widely varying geographic background. However, current funding opportunities are often highly localized and intercontinental funding is an absolute rarity, which hinders collaborations. Approaches to overcome this deficit would be extremely valuable in supporting this new field and would likely lead to a series of new and highly fruitful collaborations.

## 5.2 Recommendation II: Building a Community

Another important aspect of establishing performance visualization as viable subfield is the creation of a research community. Maybe the most significant outcome of the Dagstuhl workshop has been the personal connections between researchers of both communities. Unfortunately, only a small fraction of interested researchers could attend and organizing similar events in the future has the potential for significant impact by simply making researchers on either side aware of the needs and abilities of the other. Further, support for dedicated publication outlets, like the workshop at Supercomputing 2014 and 2015 by the Dagstuhl organizers, would make this area of research more attractive, especially to junior researchers.

Closely connected to the remarks on funding above, but going beyond the monetary aspect, this area more than many others would benefit substantially from international project

support. HPC systems, especially at the high end, are often unique resources available only at a small number of location. Remote access by researchers in other countries is often a difficult and in some cases (e.g., Japan) even prohibited by law. Overcoming these restrictions and providing an avenue for international teams to exchange machine access, system knowledge and leverage software infrastructure could greatly improve the pace of research.

Finally, at this moment one of the greatest obstacle for new research is the difficulty in provide or getting access to meaningful data to drive the develop of new techniques. Therefore, establishing an infrastructure by which the new community could share data, problem descriptions, benchmarks, etc., would allow a much larger number of researchers to participate in the process.

### 5.3 Recommendations for Broader Impact

Improving the performance of large scale codes can have a significant positive impact on HPC centers and their users and performance visualization can contribute substantially towards this goal. At the same time, performance visualization (both of individual applications and complete systems and facilities) can help raise awareness for this problem in the first place. Performance analysis is often seen as a second class citizen, as an activity to be done after the development of the code is (near) complete. This limits the impact performance analysis can have and results in inefficient executions and wasted performance or throughput – we get less science done than we could/should for the huge investments made in HPC centers.

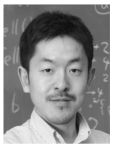
By providing user friendly and intuitive representations, application developers are more likely to overcome the initial startup barrier and learning curve conventional tools often have and facilities can get an easier overview on how well their systems are used by which codes and have a chance to react. Such raised awareness for the need of performance analysis and optimization coupled with a new generation of tools that helps address existing performance bottlenecks, will go a long way in improving the efficiency of our large scale compute resources and will ultimately be critical to the underlying computational missions.

## 6 Workshop Participants

The following section lists all participants of the Dagstuhl workshop “Connecting Performance Analysis and Visualization to Advance Extreme Scale Computing”, which was held January 6–10, 2014, all of which contributed to this report either by writing or through the extensive discussions during the workshop. We have grouped them by one of four self-assigned categories and for each include two keywords describing key projects or other relevant keywords.

## Developers of Performance Tools

Todd Gamblin
Lawrence Livermore National Lab
*Keywords*: Topology, Boxfish



Naoya Maruyama
RIKEN
*Keywords*: GPUs, K Computer

Matthias Müller
RWTH Aachen
*Keywords*: Virtual Reality, Validation Tools

Martin Schulz
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Judit Gimenez
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Holger Brunst
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Chris Muelder
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SPPEXA

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- Hans-Joachim Bungartz
TU München, DE
- Remco Chang
Tufts University, US
- Hank Childs
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- Markus Geimer
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- Hans Hagen
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- Daniel A. Keim
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## References


1 D. Borland and R. M. Taylor. Rainbow color map (still) considered harmful. *Computer Graphics and Applications, IEEE*, 27(2):14–17, March 2007.

2 David Borland and Alan Huber. Collaboration-specific color-map design. *IEEE Comput. Graph. Appl.*, 31(4):7–11, July 2011.

3 Matthew Brehmer and Tamara Munzner. A multi-level typology of abstract visualization tasks. *IEEE Trans. on Visualization and Computer Graphics*, 19(12):2376–2385, 2013.

4 Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman, editors. *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1999.

5 A. N. M. Imroz Choudhury and Paul Rosen. Abstract visualization of runtime memory behavior. In *VISSOFT*, pages 1–8. IEEE, 2011.

6 K. E. Isaacs, A. Giménez, I. Jusufi, T. Gamblin, A. Bhatele, M. Schulz, B. Hamann, and P.-T. Bremer. State of the Art of Performance Visualization. *Comput. Graph. Forum*, pages 141–160, 2014.

7 A. G. Landge, J. A. Levine, K. E. Isaacs, A. Bhatele, T. Gamblin, M. Schulz, S. H. Langer, P.-T. Bremer, B. Hamann, and V. Pascucci. Visualizing network traffic to understand the performance of massively parallel simulations. *IEEE Transactions on Visualization and Computer Graphics*, 18(12):2467–2476, 2012.

8 Zhicheng Liu and John Stasko. Mental models, visual reasoning and interaction in information visualization: A top-down perspective. *IEEE Transactions on Visualization and Computer Graphics*, 16(6):999–1008, November 2010.

9 Kenneth Moreland. Diverging color maps for scientific visualization. In *Proceedings of the 5th International Symposium on Advances in Visual Computing: Part II*, ISVC'09, pages 92–103, Berlin, Heidelberg, 2009. Springer-Verlag.

10 Christopher Muelder, Carmen Sigovan, Kwan-Liu Ma, Jason Cope, Sam Lang, Kamil Iskra, Pete Beckman, and Robert Ross. Visual Analysis of I/O System Behavior for High-end Computing. In *Proceedings of the Third International Workshop on Large-scale System and Application Performance*, LSAP'11, pages 19–26, New York, NY, USA, 2011. ACM.

11 Tamara Munzner. A nested model for visualization design and validation. *IEEE Transactions on Visualization and Computer Graphics*, 15(6):921–928, November 2009.

12 W. E. Nagel, A. Arnold, M. Weber, H. C. Hoppe, and K. Solchenbach. VAMPIR: Visualization and analysis of MPI resources. *Supercomputer*, 12(1):69–80, 1996.

13 Martin Schulz, Jim Galarowicz, Don Maghrak, William Hachfeld, David Montoya, and Scott Cranford. Open|speedshop: An open source infrastructure for parallel performance analysis. *Scientific Programming*, 16(2-3):105–121, 2008.

14 Score-P User Manual. https://silc.zih.tu-dresden.de/scorep-current/pdf/scorep.pdf, 2015.

15 Carmen Sigovan, Chris W. Muelder, and Kwan-Liu Ma. Visualizing large-scale parallel communication traces using a particle animation technique. In *Proceedings of the 15th Eurographics Conference on Visualization*, EuroVis'13, pages 141–150, Aire-la-Ville, Switzerland, Switzerland, 2013. Eurographics Association.

16 Nathan R. Tallent, Laksono Adhianto, and John M. Mellor-Crummey. Scalable identification of load imbalance in parallel executions using call path profiles. In *Proceedings of IEEE/ACM Supercomputing'10*, November 2010.

17 Jeffrey Vetter and Chris Chambreau. mpiP: Lightweight, Scalable MPI Profiling. http://mpip.sourceforge.net.

Manifesto from Dagstuhl Perspectives Workshop 14401

# Privacy and Security in an Age of Surveillance

**Edited by**

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## Abstract

Before the Snowden revelations about the scope of surveillance by the NSA and its partner agencies, most people assumed that surveillance was limited to what is necessary and proportionate for these agencies to fulfil their prescribed role. People assumed that oversight mechanisms were in place to ensure that surveillance was appropriately constrained. But the Snowden revelations undermine these beliefs. We now know that nations are amassing personal data about people's lives at an unprecedented scale, far beyond most people's wildest expectations.

The scope of state surveillance must be limited by an understanding of its costs as well as benefits. The costs are not limited to financial ones but also include eroding personal rights and the degradation to the integrity, vibrancy, or fundamental character of civil society.

This manifesto stems from a Dagstuhl Perspectives Workshop held in late 2014. The meeting was a four-day gathering of experts from multiple disciplines connected with privacy and security. The aim was to explore how society as a whole, and the computing science community in particular, should respond to the Snowden revelations. More precisely, the meeting discussed the scope and nature of the practice of mass-surveillance, basic principles that should underlie reforms, and the potential for technical, legal, and other means to help stem or restore human rights threatened by ubiquitous electronic surveillance.

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## Executive Summary

While intelligence services play a role in protecting democratic societies against their enemies, their capabilities and methods must respect both human rights and the rule of law. Many people have assumed that intelligence agencies did indeed confine themselves to what was necessary to their task – for example, that surveillance was done only on "targeted" individuals, and that a variety of oversight mechanisms ensured this. But the Snowden revelations have made clear that the "Five Eyes" organisations, and by extension other national intelligence agencies, routinely go beyond what most would regard as proportionate and necessary for



the execution of their duties: they electronically surveil most inhabitants of the planet, and have been active in undermining the security of the internet. Oversight mechanisms have been ineffectual.

The Snowden revelations raise issues of immense significance to the information society: how can we resolve the tension that exists between maintaining the effectiveness of intelligence services in protecting society on the one hand, and the need to respect essential privacy rights on the other? The difficulty is aggravated by the impossibility of making the activities and capabilities of intelligence services totally transparent. More subtle approaches are required, and any solutions to this conundrum must involve a mix of legal and technical mechanisms.

To understanding the gravity of the problem one needs to realize that privacy is not just an individual right: it is essential to the health of a democratic society. Society benefits from the ability of people to exercise their rights and freedoms. It *needs* people to do so. Yet privacy rights, like most other rights, are not absolute. Someone for whom there are sound grounds for suspicion of involvement in a serious crime or terrorist activity might forfeit privacy rights with regard to investigations of the purported offences. Still, any such breaches of privacy, and the methods used to accomplish them, must be accountable and transparent.

How can society as a whole be provided strong assurance that intelligence services are "playing by the rules" while at the same time allowing them sufficient secrecy to fulfil their institutional role? It seems possible that technical mechanisms can contribute to solving this problem. One might imagine that something analogous to a zero-knowledge proof might help demonstrate that intelligence agencies are following appropriate rules while not revealing details of those activities. Or one might strive to make public and technically verifiable the total *amount* of surveillance done, but without revealing the targets. One might imagine that a specified limit is placed on the proportion of internet or telephone data and metadata made available to intelligence services. The effect would be to force the agencies to be selective in their choice of targets. In a different direction, the crypto and security communities can strive to make the internet much more secure, hoping to make population-wide surveillance technically or economically infeasible, understanding that modest amounts of targeted surveillance will always be technically and economically feasible.

The problems addressed here have vast implications for society. It would not be reasonable to expect a small group of people, not representative of society as a whole, to produce solutions in the course of less than four days. Our goal was to air technical, legal, and social issues connected to mass surveillance, and to propose a number of guiding principles and ways forward. In the following pages, we do so.

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## 1 Introduction

The world's communication infrastructure wasn't designed to be robust against nation-state adversaries – and it isn't. Working with industry or in secret, governments track who searches for what, who calls whom and says what, who emails what to whom, who buys what, who goes where, and so on. Using automated means, they can do this on a population-wide scale, surveilling virtually everyone. The surveillance is not entirely passive. When technology is being standardised, governments can exert such weight on standards bodies so as to virtually ensure that the ability to surveil is woven into our technological infrastructure.

The contours of contemporary governmental surveillance did not arise from the leaks of Edward Snowden: they began surfacing several years earlier, from the work of prior whistle blowers and journalists. Still, for many people – even researchers in computer security and cryptography – it was indeed the Snowden revelations that brought home the scope of contemporary surveillance. It was no longer feasible to regard mass surveillance as the fringe concern of conspiracy theorists.

It was in the wake of the Snowden revelations, then, that the organizers felt it important to gather a group at Schloss Dagstuhl. We assembled in September/October of 2014 for four days of discussion. We wanted to explore how society as a whole, and the computing science community in particular, should respond to the Snowden revelations. We aimed to discuss the scope and nature of mass-surveillance, basic principles that should underlie reforms, and potential means to address the problem of ubiquitous surveillance.

Surveillance is by no means limited to governments; industry too is an eager player. Industry and government surveillance are deeply intertwined: governments exploit the capabilities of industry to surveil the users of the ubiquitous electronic services that they provide, while industry exploits the laissez-faire regulatory environment that helps maximize both profits and information of governmental interest. Still, there are significant differences between governmental surveillance and industry surveillance, beginning with the fact that, presumably, only governments, employ surveillance data for assassinations and the suppression of dissent.

This Dagstuhl Manifesto gathers participant views expressed at a Dagstuhl Perspectives Workshop. We assembled a mix of people with expertise in the legal, social-scientific, and technological aspects of privacy and surveillance. We invited members of the intelligence services, but those invitees declined to attend (in most cases failing to even reply). We had more success getting positive replies from members of the technical community than members of the legal or regulatory communities. In the end, the makeup of the workshop was not as balanced as we had hoped. Nonetheless, we felt that we did achieve a healthy mix, which resulted in plenty of lively debate. Indeed the issues addressed by this workshop were unusually contentious for a Dagstuhl workshop, and discussions were, at times, highly animated, even heated. In editing this manifesto, we did not attempt or expect to get every workshop participant to agree to every view we set forth. That would not have been possible.

We have organized this manifesto in three sections. We begin with some basic principles we heard expressed. Our enumeration of principles is rather different from prior ones we have seen. Then we discuss some research problems in this space. It is a diffuse and multidisciplinary area, and the list of research areas we give is similarly diffuse. Finally, we propose some strategies to help redress the balance in favour of the rights to privacy.

Our workshop was the first gathering at Dagstuhl on this contentious topic. It was a relatively rare instance in which computer scientists and others come together to discuss something inherently political associated with our work. The starting point is the decision

to take the problem seriously. "Communications surveillance should be regarded as a highly intrusive act that interferes with human rights" says the Necessary and Proportionate document [1]; therefore, one *should* treat the topic with corresponding seriousness. There is an inherently normative core to any serious consideration of privacy and surveillance.

## 2 Principles

There have been many attempts to enumerate basic principles associated with privacy and surveillance. Prominent examples include the Fair Information Practice (FIP) principles [2], versions of which underlie all information privacy legislation; the list of questions suggested by Gary Marx [3]; the Necessary and Proportionate principles [1]; and the Reform Government Surveillance principles [4]. Our own attempt to compile a list of principles is informed by such works, but includes principles with a more technical slant, as well as those with clear political overtones. Our list takes the form of short imperatives and maxims.

Like most rights, privacy rights are not absolute. For example, when we say that "Every person has the right to communicate privately and securely with every other person" we do not mean that there are *no* circumstances under which it would be legitimate for a state to abridge this right for a given pair of communicants. We mean that the right is the norm and that its abridgment would not be legitimate if carried out *en masse*, without warrant, or outside of a known legal framework.

We begin with high-level maxims on privacy, security, and surveillance (Principles 1–9). Next we list some imperatives that speak more specifically to the design, construction, and operation of privacy-relevant technological systems (Principles 10–15). We end with some imperatives directed to individuals and organisations on the conduct of their work (Principles 16–17).

### Basic Privacy Principles

1. **Right to secure communication and services.** Every person has the right to communicate privately and securely with every other person, no matter where they are located. Every person has the right to interact securely and privately with electronic services.
2. **Universality.** With respect to privacy, security, and surveillance, all persons in any jurisdiction have the right to equal treatment without regard to citizenship.
3. **Privacy can enhance security.** Privacy and security are often construed as in conflict and zero-sum. But enhancing privacy often *enhances* security. Sometimes these goals are mutually antagonistic but, just as often, they are mutually supportive.
4. **Privacy is a social good.** Privacy is often positioned as a *personal* value while security is positioned as a *societal* need. But privacy is also a social value and a public good, not just an individual right.
5. **Metadata is data.** There is no significant distinction between *data* and *metadata* from a privacy perspective. Labeling bits as "metadata" does not change the privacy implications of collecting or analyzing it, nor the applicability of the principles enumerated in this document.
6. **Machine interception is interception.** The technology-driven shift from human-mediated to machine-mediated surveillance does not negate the applicability of surveillance principles. A communication is collected when it is captured, processed, or retained for intelligence or law-enforcement purposes even if no human is directly involved as an agent in these processes.

7. **Oversight.** Where targeted and proportionate surveillance is performed, there should be meaningful and independent oversight.
8. **No secret law.** Governments must eschew secret laws, secret interpretations of laws, and secret legal definitions.
9. **No proxy surveillance.** A government must not obtain information that its own laws would forbid it to collect by getting it from another entity not covered by those laws.
10. **Building privacy in.** Privacy protection should be built into technology. Good privacy defaults, including ubiquitous encryption and anonymity, will not prevent governments from spying on targeted individuals, but can inhibit mass surveillance.
11. **No backdoors.** Technical features to facilitate and routinize law enforcement or intelligence agency requests should not be built into computing and communication technology. Systems should not embed privacy-relevant features undesired by or unknown to users.
12. **Privacy impact assessments.** Governments should require that information technology with surveillance implications be subjected before deployment to an assessment of its implications for human rights and social values, including privacy. The assessment must be made public and potential adverse consequences mitigated. The sale and use of systems for population-wide phone or internet surveillance should be illegal.
13. **Fair Information Practices (FIP).** The FIP principles [2] are still relevant and important, but need updating to be applicable to contemporary conditions of technology, law, commerce, state action, and public policy.
14. **Reversed privacy policy.** People should be able to create a machine-readable privacy policy, and companies should be required to retrieve the policies and to comply with them (when they are legal and compliance is technically feasible).
15. **No race to the bottom.** In creating technological artefacts for the international market, privacy protections must not be reduced in order to enter markets where privacy rights or their enforcement are weaker.
16. **No vulnerability stockpiling.** Anyone who discovers a vulnerability in a computer system should engage in a coordinated disclosure as quickly as practically possible. Minimising the window of opportunity for exploitation should be the primary goal. The sale of exploits for use as cyberweapons should in most cases be illegal. Exceptions should be regulated and monitored with democratic oversight.
17. **Duty of care.** Companies and governments, as well as computer scientists and relevant researchers, have a duty of care to uphold, promote, and protect the rights expressed in this enumeration of principles.

## 3 Research Directions

This section explores some research topics identified during the discussions. They have been grouped under four categories: mass surveillance, communications security, big data and centralised cloud infrastructures, and nation-state compromise of systems and standards. Here *systems* is a broad concept that includes not only hardware and software in end-user devices and routers, but also cryptographic systems. These topics are clearly not independent.

## 3.1 Mass Versus Targeted Surveillance

Security agencies operate a "funnel" in which bulk data collection is done population-wide, and this is used to inform them of targets of interest. Then deeper, more resource-intensive analysis is done on those targets. But the initial, bulk surveillance raises serious concerns about abuse and the limitations of state power. Most people have done nothing that would justify a forfeiture of their basic privacy rights. One might ask:

- Can researchers agree on definitions of *mass surveillance* and *targeted surveillance*?
- Are there any kinds of mass surveillance that can be considered legitimate?
- What alternatives to bulk collection exist for security agencies to identify targets of interest?

Typically, bulk collection is done on metadata, because it is more readily available and easier to process than content data. Metadata is the data that arises as a side effect of a user's intention. For example, a user wants to send a message (content), and as a side effect, records are created that a message was sent at a certain time, of a certain length, to a certain person (metadata). Metadata is just as privacy-sensitive as content data; in fact, because it is easier to collect and process, it can be considered more sensitive.

- How can we better protect metadata than is done by leading technologies such as Tor?

Some ways of making bulk collection more acceptable have been proposed. They aim to mitigate its bad effects, for example by trying to constrain the level of collection or processing, or make it accountable, or limit the possible outcomes. The *time capsule* approach gathers and stores everything but without processing it; the data can be opened at a later date if there are indications that crucial intelligence is buried in it. Another idea is to devise techniques that restrict the computations that can be done, for example, using functional encryption. It may be difficult to agree and specify the computations that are allowed; an alternative is to allow any computations, but limit their number or the amount of data they can access. Again, recognising the difficulty of agreeing any limit on the amount, one might just try to enforce that the amount will be known and verifiable. This would mean that there is no limit on how the data is used, but the nature and quantity of access to the data would be plain for all to see. In a democracy, one could imagine that discussion of the quantity becomes part of the political discourse, in a similar way to that taxation levels are debated.

- Are there ways of managing the collection of data so that *limitations on its use*, or *transparency of how it is used*, can be assured? Can technical means ever achieve that?
- What limitations or transparency measures are technically feasible?
- How could information about the nature and quantity of bulk surveillance carried out be presented to citizens in an *understandable and meaningful way*?

An asymmetry of the debate around mass surveillance arises because participants who are not "security cleared" are not allowed to know the details of surveillance carried out, and what, if any, are the tangible benefits that have accrued.

- Are there technical solutions that would enable auditors outside the intelligence community to audit surveillance outcomes, without viewing information that would compromise the purpose of the surveillance?
- In particular, can citizens be given access to verifiable quantitative correlation about the subjects of surveillance and the outcomes it has?

## 3.2 Communications Security

Securing communication content seems to be the "easy" problem, certainly in comparison to securing computations and devices. However, it has become apparent that, even if we have strong cryptography, most communications are unprotected and the threat models that have most often been considered so far are too weak. Moreover, protecting metadata – particularly who is communicating with whom – is challenging.

- Can we develop technical solutions that provide strong-end-to-end communications, offering protection of data against global adversaries that control part of the network, and control some of the endpoints?
- Can the protection of *metadata* be added to the solutions, resulting in *strongly-anonymous* communication systems? These systems should resist attackers that are able to eavesdrop on multiple points in the network, interfere with communication and control a significant number of the anonymising servers.
- Can we develop *key management* techniques that are easy to deploy and use and that offer support for forward secrecy, deniability, group sessions, multi-cast?
- Can we implement these solutions so that they interoperate seamlessly with complex network and IT environments, which include proxies, content-distribution networks, users and servers with multiple devices and instances, and so on?
- Can we develop *free and open-source software* for the above problems? A key element here is audit, usability and integration with existing applications.
- How can we encourage *universal deployment* of these solutions?

## 3.3 Big Data and Centralised Cloud Infrastructures

The separation between data collected by governments and private organisations is increasingly blurred. While it is the role of the government to regulate the collection of personal data/Personal Identifiable Information (PII) by private organisations, government agencies use a broad range of methods to get access to data collected by those organisations. Data in cloud infrastructure needs to be protected against mass surveillance by intelligence agencies.

- Can we deal with *compelled service providers?* The Snowden revelations tell us that Section 702 of the FISA Amendments Act of 2008 is used to compel US companies to grant access to data they hold on production of a court warrant. Is it technically possible for a service provider to provide a set of useful services, including mail, document storage, and search, while protecting themselves against a state that demands to see particular users' data?
- Can we enable citizens to exercise their rights? How can service providers offer more transparency about the economic benefits they derive from user's data and how they collect and use the data in an acceptable way? How can they enable users to exercise their rights (such as right of access and right to delete).
- How can privacy regulators mandate privacy-protective versions of services? What criteria would define "usable" or "privacy protective"? What are the economics of a privacy-protective set of offerings?
- Can we develop a better understanding of the *economics of privacy?* If the research community cannot find effective and efficient solutions to the above problem, can we find economic models under which privacy preserving solutions can thrive? What is the economic and social impact (the cost) of loss of privacy, and in particular of this

phenomenon (small number of corporations controlling huge collections of data)? What regulatory and financial/market mechanisms can protect against these concerns? Can we change liability rules for entities that store personal data/PII to create economic incentives to minimize personal data collection?

- Which services and infrastructure can we offer in a *decentralised mode with minimal centralised data collection and trust* and a high level of robustness?
- Can we develop *efficient cryptography for outsourced data?* Current practice in cloud environments is that most data is stored in cleartext form. Applications that only require storage allow for encryption, but this precludes any computation on this data. We have theoretical solutions enabling "computation on encrypted data", such as fully homomorphic encryption (FHE), secure multiparty computation (MPC), and functional encryption (FE).
  - Is it possible to enhance the *functionality* offered by currently deployed solutions (in terms of the computation that can be done "in the encrypted domain") whilst maintaining efficiency such that the overall cost to the service provider does not become exorbitant? This requires an exploration of tradeoffs.
  - Privacy preservation in the free service model: As a special case, are privacy-preserving *search, data mining and advertising* – at scale and with timing constraints – possible? This would be necessary to enable companies to be able to continue to provide their services for free whilst enhancing the privacy of users. For search, there is *Startpage*[1] , but because it deletes results immediately, it lacks certain capabilities (e.g., the ability to go back and continue the search). Does the lack of functionality matter?
  - One approach to deploy these technologies would be to perform computations on cleartext exclusively in the *browser*, and the service provider only sees ciphertext. *confichair.org* is a conference management system that aims to achieve this goal; can it be generalised?
  - What are the *limitations* of this approach? Is the idea of a privacy-protective version of *Google Now* even meaningful?
  - How do we make solutions, with all the attendant user interface and key management issues, *deployable?*

## 3.4 Nation-state Compromise of Systems and Standards

We have strong evidence that mass surveillance is not limited to passive eavesdropping. The NSA has compromised cryptographic standards (e.g., the Dual_EC_DRBG[2] random number generator), with an eye toward improving its ability to decrypt intercepted messages easily. Likewise, from the Snowden revelations, we understand that the NSA has a variety of capabilities to compromise computer hardware while it is being delivered from the manufacturer to an entity that would then be subject to surveillance. These issues are not exclusive to the NSA (e.g., similar accusations are leveled against a large router manufacturer). These issues raise a number of interesting research challenges:

- *Policy of software/hardware trapdoor operations.* What are the long-term implications of the current trend of exploitation of vulnerabilities, and even 'planting' of vulnerabilities,

[1] https://startpage.com
[2] http://en.wikipedia.org/wiki/Dual_EC_DRBG

by nation-states' offensive cyberwarfare organisations? Is there a better way, e.g., treaties or agreements on restrictions on such practices?

- *Re-architecting the Internet infrastructure.* How can we redesign and/or protect the Internet infrastructure (mainly routing and naming services) from sophisticated active attacks?
- *Supply chain integrity.* Outsourcing manufacturing leads to plants that might substitute malicious parts or components. Tools and techniques are required to detect this; it might include sampling techniques that would require disassembly and detailed analysis. Similar problems can occur during shipping of devices.
- *Base software integrity.* Techniques are needed to provide assurances that a platform is running "correct" software (i.e., software as distributed by the original vendor). These techniques often include "attestations" that can be verified by users or third parties, outside of the particular hardware device, that the software stack is "correct". These techniques must be extended to work under a stronger threat model, such as when the vendor itself might be compelled to produce customized software for a targeted attack against a specific individual.
- *Trustworthy user environment.* Investigate and develop trusted environment that allows handling sensitive operations, data etc., in a way which is secure even if the general operating system of the device is not secure. This is particularly relevant to mobile devices (smart phones).
- *Secure cryptography.* Having the current standards potentially compromised requires the research community to revisit currently deployed cryptographic systems and networking protocols and to devise new systems with public review.
- *Identifying the current obstacles to the widespread use of cryptography.* We need to facilitate mass use of cryptography by developing free and open-source, secure, user-friendly and free clients which bring cryptography closer to the ordinary citizens.
- The previous items have focused mostly on existing ICT environments and how they can be improved. One can expect that in the next decade the *Internet of Things* will become a reality: tens of billions of "smart" devices (i.e., equipped with a processor) will be connected to the Internet. One can think of sensors and actuators in buildings, cars, TVs, smart phones, and the human body. This creates a potential avenue for extremely invasive surveillance and presents enormous security and privacy challenges. How can we know (or regulate) who has access to data coming from the sensors (e.g., device manufacturers, app developers, cloud providers)? How can one define and enforce data sharing policies? How can users express consent for the data collection and processing by these sensors?
- Ways should be sought to prevent states from undermining the standardization processes for the security of the internet. These could include, as a minimum, the exclusion of members of intelligence agencies from the standards bodies.

## 4 Strategy

Having enumerated some privacy principles and research problems, we list some strategic possibilities towards realizing these aims. In the same sense that many of the enumerated principles were high-level and aspirational, so too are some of the strategic directions.

- We call on system developers to design easy-to-use cryptographic software to facilitate personal privacy and security.

- We call on funding agencies to fund research into hardware and software supporting security and privacy, as well as social, ethical and legal aspects of surveillance and counter-surveillance.
- We call on oversight and privacy regulatory bodies to develop sufficient technical expertise, in-house or on tap, to enable them to be effective in regulating and overseeing surveillance.
- We call on legislators to regulate more aggressively the collection and use of customer data by the private sector, and to regulate the exchange of data collected for monitoring purposes between public and private sectors, including the transfer of personal data from the private sector to law enforcement and intelligence agencies.
- We call on legislators to improve legal protections afforded to whistle-blowers.
- We call on governments and other stakeholders to devote immediate attention and resources to the negotiation, agreement and ratification of an international treaty on surveillance.
- We call on legislators to introduce laws that make it illegal for organisations to buy, sell or operate computing systems specifically designed to facilitate population-wide electronic surveillance.
- We call on countries and regions to help minimise the risk to personal data by promoting, encouraging and assisting companies offering national and regional privacy-friendly IT solutions, including cloud services.
- We call on cryptographers to attend more seriously to problems of anonymity, traffic analysis, and subversion.
- We call on governments to allocate funding for education about the value of privacy and the risks posed by surveillance, and about means of increasing personal privacy protection.
- We call on intelligence-agency insiders to "blow the whistle" if they are aware of illegal activities within their organisation and cannot find redress though other means.

## 5 Acknowledgements

Our deepest thanks to Matt Blaze, who co-organized this Dagstuhl Perspectives Workshop with us, but who was unable to attend for reasons beyond his control. Many thanks to Johana Hamilton for making available to us her documentary film *1971*, which we were delighted to screen during our workshop prior to its release in cinemas.

## 6 In Memoriam

This report is dedicated to our late colleague Caspar Bowden, who worked tirelessly to protect universal human rights, including people's right to privacy regardless of nationality. Well before the Snowden disclosures caught the attention of the world, Casper raised the problem of protecting privacy in the cloud to the European Parliament [6]. His voice will be sorely missed.

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## References


1 "Necessary and Proportionate Principles." International Principles on the Application of Human Rights to Communications Surveillance. Final version, May 2014. Available from https://necessaryandproportionate.org/

2 Federal Trade Commission (USA). Privacy Online: A Report to Congress. June 1998. Available from the FTC website.

3 Gary T. Marx. An Ethics for the New Surveillance. *The Information Society*, 14(3), pp. 171–186, 1998.

4 Global Government Surveillance Reform. Joint from AOL, Apple, Dropbox, Facebook, Google, Linkedin, Microsoft, Twitter, and Yahoo! https://www.reformgovernmentsurveillance.com/

5 Frank la Rue. Report of the Special Rapporteur on the promotion and protection of the right to freedom of opinion and expression. Report to the United Nations General Assembly, Human Rights Council. A/HRC/23/40

6 Didier Bigo, Gertjan Boulet, Caspar Bowden, Sergio Carrera, Julien Jeandesboz, Armandine Scherrer, "Fighting Cybercrime and Protecting Privacy in the Cloud," Directorate General for Internal Studies, Policy Department C: Citizens Rights and Constitutional Affairs, Study for the European Parliament, Oct. 2012. Available from http://www.europarl.europa.eu/meetdocs/2009_2014/documents/libe/dv/study_cloud_study_cloud_en.pdf