Parsimony Principles for Software Components and Metalanguages

[Extended Abstract]

Todd L. Veldhuizen
Electrical and Computer Engineering
University of Waterloo, Canada
tveldhui@acm.org

Abstract

Software is a communication system. The usual topic of communication is program behavior, as encoded by programs. Domain-specific libraries are codebooks, domain-specific languages are coding schemes, and so forth. To turn metaphor into method, we adapt tools from information theory—the study of efficient communication—to probe the efficiency with which languages and libraries let us communicate programs. In previous work we developed an information-theoretic analysis of software reuse in problem domains. This new paper uses information theory to analyze tradeoffs in the design of components, generators, and metalanguages. We seek answers to two questions: (1) How can we judge whether a component is over- or under-generalized? Drawing on minimum description length principles, we propose that the best component yields the most succinct representation of the use cases. (2) If we view a programming language as an assemblage of metalanguages, each providing a complementary style of abstraction, how can these metalanguages aid or hinder us in efficiently describing software? We describe a complex triangle of interactions between the power of an abstraction mechanism, the amount of reuse it enables, and the cognitive difficulty of its use.

Categories and Subject Descriptors D.2.13 [Software Engineering]: Reusable Software; D.2.10 [Software Engineering]: Design

General Terms Design, Theory

1. Introduction

"Metaphor is an invitation to see the world anew.... Metaphor transfers meaning from one domain into another and thereby enriches and enhances both domains.” [4]

The design theorist Donald Schon wrote extensively on the role of metaphor in design. One of his most famous ideas is that of generative metaphor [14], which describes a frame or perspective carried over from one domain to another to produce new insights. A consciously embraced metaphor can be enabling, but an unacknowledged (tacit) metaphor can cast a ‘spell’ over problem solvers, restricting their ability to see problems objectively.

Consciously or not, in software engineering we inevitably find ourselves invested in generative metaphors. Particularly prominent is McIlroy’s fecund metaphor of “mass-produced software components,” which spawned multiple generations of research on software factories, software product lines, software assembly lines, software robots, and so forth.

In this paper we explore the three generative metaphors for software components:

1. Software as communication;
2. Component design as statistical model-fitting;
3. Software abstractions as computable functions.

Software as communication. A fruitful viewpoint for understanding the role of abstractions in design is that of software as a communication system. The subject of the communication is program behaviors, as encoded in a programming language. Communication systems are a primary object of study in the field of information theory, and so information theory can rightly be expected to have much to say about abstractions and their role in design.

Efficient communication can be achieved by identifying frequently-occurring patterns or motifs in messages. Messages can then be compressed on average by assigning shorter codes to motifs. For instance, in spoken English the term “automobile carriage” was supplanted in the 20th century by “car,” a more efficient form that reflects its increased use frequency. These ideas carry over in a straightforward way to software. Good software abstractions capture commonly occurring motifs, and we can represent our programs more concisely (i.e., compress them) by referring to predefined abstractions, rather than describing them anew for each program. Abstractions also compress the design process itself, allowing us to discuss and reason about designs in terms of recognizable, high-level chunks.

The suggested correspondence between software design and information theory is summarized by the following table:

| Software Design | Information theory |
|-----------------|--------------------|
| Problem domain  | Random process     |
| Program         | Message            |
| Programming language | Encoding scheme |
| Library         | Codebook           |
| Abstraction     | Motif              |
| Code reuse      | Compression         |

In previous work we developed an information-theoretic view of software libraries [22]. This paper extends this work by using an information-theory perspective to analyze tradeoffs in the design
of components and domain-specific languages. We investigate two questions:
1. In designing a library for a problem domain, how can we evaluate whether a component is undergeneralized, overgeneralized, or ‘just right’?
2. How and why should we strike a tradeoff between the power of abstraction mechanisms in languages, their ease of use, and the amount by which they allow program length to be reduced?

2. Background
2.1 Information theory of design
The development of a design discipline around a problem domain can be understood as a process whereby people solving design problems in a new domain identify recurring motifs in their successful designs, which they abstract into reusable form. As the domain matures, the most useful abstractions form a design canon that represents the core knowledge of the design community. From an information-theoretic perspective, the design canon is a codebook defined to compress (provide terse representations of) design solutions.

We have proposed that a problem domain be associated with a probability distribution on programs, where the distribution reflects the likelihood that someone working in the problem domain will set out to realize a particular program. Many interesting questions about design can be reduced, via information theory, to properties of this distribution: the scale of abstraction at which we can work, the limits of software reuse, and the rates at which software components can be reused. For instance, information theory dictates that the extent to which software reuse can occur is governed by the ‘entropy parameter’ $H$ of this distribution. In “low-entropy” problem domains (with $H$ near 0), programs are highly similar to one another and we can design at a high level of abstraction. For problem domains with $H$ near 1, the potential for reuse is low and each program requires substantial quantities of new code. We developed this viewpoint in the paper [22].

Tradeoffs in abstraction mechanisms Programming languages provide a variety of abstraction mechanisms that serve to capture common patterns in designs. Critical to developing good design notations and programming languages is understanding the tradeoffs between various forms of abstraction in terms of succinctness, safety properties, complexity, and so forth. A preliminary investigation of such tradeoffs from the perspective of computability theory has identified useful avenues of exploration [23]. In this work we develop the understanding of such tradeoffs further, extending our analysis to encompass connections with the psychology of programming, and develop means to communicate such results to practitioners and language designers in a meaningful way. One way to summarize tradeoffs is to sketch “tradeoff curves” for forms of abstraction, as commonly used in engineering design. Such curves give an intuitive appreciation of the tradeoffs inherent in selecting forms of abstraction.

3. Minimum Description Length Principles
Good component design must strike a balance between over- and under-generalization. In this section we describe how the Minimum Description Length (MDL) principle, pioneered for choosing statistical models, also provides a useful framework for reasoning about the best level of generalization for a component.

3.1 The generality problem
Generality of software components plays a key role in their reusability: A general-purpose component is more likely to be reused. This has been known since the dawn of time (in software terms): describing in 1952 the first major subroutine library for the Cambridge EDSAC, the late David Wheeler wrote:

'It may be desirable to code [the subroutine] in such a manner that the operation is generalized ... [24]

If a component is ‘not general enough,’ we call it undergeneralized. The development of polymorphism, generics, metaprogramming, and so forth has led to languages in which a reasonable level of generality is easy to achieve. The ease with which components can be generalized occasionally leads to the problem of overgeneralization. Components pay for their generality (or, more correctly, their users pay) by requiring too much work to configure, glue, adapt, and so forth. As a slightly facetious example we mention that the ultimate generalized subroutine in C++ is something such as

```cpp
template< typename Inputs ,
          typename Outputs ,
          typename Operation >
void do( Inputs& in , Outputs& out ,
        Operation& op )
{
    op(in , out);
}
```

This function can be made to do most anything one might want; however, to specialize this function to a specific purpose, one has to do as much (or more) work than required by a direct implementation. (For functional languages, something of the form $\lambda x.\lambda y.\lambda z.\lambda x y z$ is analogous.)

For a more realistic example, consider matrix multiplication. The standard Basic Linear Algebra Subroutines (BLAS) function for this is called DGEMM. Rather than being merely a matrix multiply, DGEMM is generalized to carry out an operation of the form

$$C = aAB + \beta C$$

and optionally, one may transpose any subset of the matrices. This broad functionality is paid for by a somewhat unwieldy interface. The C binding is:

```c
void dgemm( char transa, char transb, int m ,
            int n, int k, double alpha, double *a,
            int lda, double *b, int ldb, double beta,
            double *c, int ldc);
```

The parallel version (from ScaLAPACK) has even more parameters:

```c
void pcgemm( char transa, char transb, int m ,
            int n, int k, double alpha, double *a,
            int ia, int ja, int *desca, double *b,
            int ib, int jb, int *descb, double beta,
            double *c, int ic, int jc, int *descd);
```

Let me emphasize that this is not gratuitous overdesign; there are situations in which this flexibility is needed. However, using such interfaces requires great concentration from the uninitiate. Similarly unwieldy interfaces were commonplace when C++ templates were first introduced, and the fashion was to anticipate every possible variation with a template parameter.

Clearly, we must tradeoff the generality of an abstraction against the difficulty of applying it. Too specific, and the abstraction has limited applicability. Too general, and it becomes arduous to adapt. We call the problem of finding the right amount of generality for a component ‘the generality problem.’

We propose a solution for the generality problem based on the ‘Minimum Description Length’ principle that has proven so infor-
The best explanation of the data is the one that minimizes
the sum of
1. the number of bits required to describe the model; and
2. the number of bits required to encode the data relative to the
model.

For example, to encode data with a linear regression model, one
would first encode the slope and offset of the line, and then encode
the deviations of the data points from that line. If this encoding
were more succinct than, say, an encoding using a quadratic model,
the linear model would be considered a better fit.

A similar principle can clarify the tradeoff in software design
between over- and under-generalization. The proposed correspon-
dence is as follows:

| Statistics       | Software design          |
|------------------|--------------------------|
| Model parameters | Parameters and glue code |
| Model            | Abstraction              |
| Model class      | Abstraction mechanism    |
| Data point       | Use scenario             |
| Underfit         | Under-generalization      |
| Overfit          | Over-generalization       |

We paraphrase the principle for software components:

The best level of generality of a software component is that
which minimizes the sum of:
1. the code length required to implement the component; and
2. the code length required to adapt the component to the
desired use cases.

In the next sections we describe how this can work in practice, and
what the implications of adopting this principle are.

3.3 Applying the MDL Principle for components

The MDL principle requires modification to yield sensible results
for software components. Our starting point is a set of use cases
$U_1, \ldots, U_n$ and a set of candidate components $C_1, \ldots, C_k$. We
assume the abstractions are ordered from least to most general, in
the sense that the functionality of $f_{i+1}$ is a superset of $f_i$. 

```c++
double sum(double x, int n)
{
    double s = 0.0;
    for (int i=0; i < n; ++i)
        s += x[i];
    return s;
}
``` 

```
#template<typename T>
T sum(T x, int n)
{
    T s = 0;
    for (int i=0; i < n; ++i)
        s += x[i];
    return s;
}
``` 

```
#template<typename T, typename Iter>
T sum(Iter x, int n)
{
    T s = 0;
    for (; x.hasNext(); ++x)
        s += *x;
    return s;
}
``` 

```
#template<typename T, typename Iter, typename Op, typename Unit>
T sum(Iter x, Iter end, Op op, T unit)
{
    T s = unit;
    for (; x != end; ++x)
        s = op(s,*x);
    return s;
}
``` 

Figure 1. Four functions that can be used to sum elements of a numeric array.
To apply the MDL principle we need an appropriate measure of code length. Using bits, as in Rissanen’s formulation for statistics, would select the component that best compressed the use cases. However, this would favour cryptically terse implementations over more readable ones. What we need is a code length measure that moderates the notion of succinctness with a nod toward usability. In preliminary experiments, we have found that the token count provides reasonable results. The token count is invariant under symbol renamings, comments, whitespace, and so forth, so that one cannot make a component ‘better’ (with respect to the MDL principle) by stripping comments and choosing one-letter variable names.

We have found that the following approach yields sensible results:

1. For each component and use case combination, write code that uses the component to implement the use case. If the component cannot be adapted to the use case, then write the simplest possible implementation of the use case without the component.
2. For each component, count the tokens required to:
   (a) implement the component; and
   (b) adapt it to each use case.
3. The MDL principle, as adapted for components, suggests that the component minimizing the count of (2) possesses the ‘right’ level of generality.

### 3.4 Example

We illustrate the application of the MDL principle by considering three use cases for the candidate components of Figure 1:

1. Summing an array of double-precision floating point numbers (doubles);
2. Summing an array of integers;
3. Summing an array of floats.

In this scenario many experienced programmers would opt for the component of Figure 1(b) that abstracts over the data type. Abstracting over the data structure or operation provides no benefit for these use scenarios, although might be appropriate depending on anticipated future needs.

To determine what the MDL principle suggests, we implemented four versions of these use scenarios, one for each component in Figure 1. For Figure 1(a) we merely duplicated the code three times, and edited to change the datatypes. For the remaining components we ‘adapted’ them to each use scenario by providing appropriate template parameters and arguments.

Figure 2 shows the code for component Figure 1(d) and the code needed to adapt it to the three use scenarios. Using an automated tool to count the number of tokens, we obtain the following results:

| Component | Tokens | Adaptation Tokens | Total Tokens |
|-----------|--------|-------------------|-------------|
| (a)       | 41     | 82                | 123         |
| (b)       | 46     | 60                | 106         |
| (c)       | 42     | 66                | 108         |
| (d)       | 56     | 121               | 177         |

These results are plotted in Figure 3. From the math one expects a convex (U-shaped) function, and this can be seen in Figure 3. If the component is too specific, it cannot be used for all the use cases. If the component is too general, then it is arduous to adapt. And, in between the two extremes, we expect a component with the ‘right’ level of generality, which the MDL principle recommends to us.
3.5 Discussion

The proposed MDL principle for components can be summarized as: ‘the best component yields the most succinct representation of the use cases.’

We propose this not as an absolute, but rather as a guiding principle. Among the advantages of following this principle are:

1. Choosing abstractions according to the MDL principle yields succinct programs. If we presume a correlation between program length and development/maintenance costs, this suggests following MDL principles in component design would be beneficial.

2. The MDL principle weeds out components that are overgeneralized. Overgeneralized components typically have numerous parameters not needed in ordinary usage. These parameters can make the component harder to use for novice users, and the possibility of variation may, in practice, translate into a possibility of error.

3. The MDL principle provides a quantitative, non-subjective criterion for choosing the right level of generality.

However, in practice it would be an unreasonable amount of work to approach the design of every component by applying the strategy described in Section 3.3, i.e., implement all the components and use cases and evaluating the description length. We do not advocate the MDL principle as a day-to-day design tool, but rather for the following uses:

1. As a teaching tool, a mindset, an exemplar of ‘optimal’ design that can be used to guide more informal decision-making.

2. As a retrospective tool with which to evaluate existing library APIs, with the aim of extracting general design principles and recommendations. In a forthcoming paper we apply the MDL principle to evaluating the API of some existing generic libraries, notably the STL, with use cases gleaned from open source projects. Our preliminary results suggest the STL is overgeneralized with respect to the use cases for which it is most commonly employed.

Finally, we note that the MDL principle suggests that the ‘right’ level of generality can only be gauged with respect to a set of use cases. These use cases might be chosen to guide the design of a component for a specific project, or they may be chosen to represent typical usage in a problem domain. In the latter case we can think of the use cases as sampling the distribution of programs associated with the problem domain.

4. Abstraction mechanisms

Modern programming languages support multiple forms of abstraction, each with a distinct sublanguage in which they are defined. For example, in the language C++ there are distinct sublanguages for defining classes, functions, generic functions, and macros. The evolution of programming languages can be seen in part as an ongoing quest to identify useful forms of abstraction and formalize them as language features.

The difficulty of adapting or instantiating an abstraction for a particular use scenario relates directly to the computational complexity of the problem of inverting the abstraction. The cognitive difficulty of spotting common motifs in programs that can be abstracted away appears to be closely related to the computational complexity of compressing the program with respect to a class of abstractions.

In this section we explore the tradeoff between the power of abstraction mechanisms, the degree of succinctness they offer, and the cognitive difficulty of their use.

4.1 Metalanguages as classes of functions

To examine the differences between forms of abstraction, we need a common framework in which to compare them. We believe a useful viewpoint is that of abstraction mechanisms as classes of functions, in particular, as classes of partial computable functions. The rationale is as follows. An abstraction represents a set of concrete instances. For example, a generic linked list class List(T) can be instantiated to instances such as List(int) and List(string); we can associate with List(T) a function mapping the parameter T to instances. Similarly, a macro can be associated with a map that substitutes parameters into the macro definition; a subroutine can be associated with an abstraction function that substitutes arguments for variables and inlines the function body; a class definition can be associated with a function that imbues subclasses with its functionality; a parser generator can be associated with a map from grammar specifications to parser implementations.

This gives abstraction mechanisms an operational interpretation, e.g., the activity a compiler would carry out to reduce the abstraction to a lower-level representation. Alternately, we can think of abstraction mechanisms as defined by a denotational meaning, e.g., we associate with each abstraction a function from parameters to object language semantics. In either case, we can associate with each abstraction an abstraction function that gives it meaning, either operationally or denotationally.

An abstraction mechanism can then be viewed as a class of abstraction functions, as enumerated by some restricted language we call a metalanguage, following the usual terminology of metaprogramming. Programming languages can be regarded as an assemblage of metalanguages, each offering a distinct form of abstraction.

To fit metalanguages into the framework of computability, complexity theory, and subrecursive languages, we use the following correspondences:

| Software design | Theory idea |
|-----------------|-------------|
| Abstraction     | Partial computable function |
| Abstraction mechanism | Class of p.c. functions, a metalanguage |
| Parameters/glue code | Input |
| Instantiation   | Evaluation of p.c. function |
| Instance of an abstraction | Output of p.c. function |
| Adaptation      | Inversion of p.c. function |

4.2 Facets of abstraction mechanisms

The fact that programming languages provide a variety of abstraction mechanisms (i.e., metalanguages) suggests that there is no single best ‘universal abstraction mechanism.’ Instead we find that metalanguages offer a broad variety of tradeoffs between desirable facets, namely:

- The expressive power of the metalanguage, i.e., what abstractions are definable in it.
- The safety properties we are guaranteed about instances. For example, an ongoing concern in programming language design is finding metalanguages that can generalize over types in a safe way, e.g., generics |
- Succinctness, that is, how long the description of an abstraction must be, and how long parameters must be to produce instances of interest.

1 For historical accuracy one might regard a programming language as a pastiche of metalanguages.
The time and space complexity of instantiating an abstraction (i.e., how intensive the compilation process must be.)

The difficulty of finding parameters to an abstraction that will produce a particular instance, i.e., inversion of an abstraction.

The effort required to devise an appropriate abstraction, given an instance or class of instances over which we wish to generalize.

In previous work we used tools from computability theory and the theory of subrecursive languages to study tradeoffs between succinctness (code length) and safety properties [23].

In the present work we examine tradeoffs between the expressive power of abstractions, the amount of ‘compression’ they allow, and the cognitive effort required to use them.

4.3 Tradeoffs and cognitive tasks of design

In designing a compression algorithm, one is interested in the tradeoff between the degree of compression achieved and the computational cost of compression and decompression. In programming languages, humans do the compression and compilers do the decompression, so to speak. In designing a programming language, the tradeoff is largely between the succinctness a language offers (i.e., amount of compression) and the cognitive difficulty of recognizing and exploiting motifs (i.e., the cost of compression).

Perhaps not surprisingly, the difficulty of cognitive tasks we encounter in design appears to correlate with the computational complexity of abstraction mechanisms [23]. For instance, a crucial design activity is deciding whether an abstraction can be adapted to a use scenario. To support rapid design work, the cognitive task ought to be simple — abstractions that require great deviousness to adapt are unlikely to be used frequently. The equivalent problem in our formalism is deciding whether there exist parameters for the abstraction function that will cause it to produce a desired output — the problem of inverting the abstraction function (not to be confused with inverting a runtime computation, an altogether different problem.)

For example, macros and subroutines are forms of abstraction “instantiated” by substitution of arguments for variables. Consider the function hypot of Figure 4. For the function hypot to be useful, it must be possible for us to recognize places in our design where it might be used, and to determine what parameters will make it do what we want: given the fragment

```c
double hypot(double a, double b) {
    return a*a + b*b;
}
```

Figure 4. A simple abstraction that is easy to “invert.”

4.4 Viscosity and Lipschitz abstractions

Cognitive tradeoffs in design notations have been summarized by Thomas Green and colleagues in the popular Cognitive Dimensions of Notations framework [11, 12]. Green argues that programming languages are properly regarded as a medium in which we hash out design decisions, not just record them after the fact. Human design work — even that of experts — has been shown in numerous studies to be disorderly, characterized by false starts, frequent rewriting, and simultaneous attacks on the problem at many levels of abstraction: “design is redesign, programming is reprogramming.” [11].

To support the way humans design, notations must be malleable — it must be possible to quickly evolve code to match our changing understanding of the design. In the cognitive dimensions framework this quality is dubbed viscosity: the resistance of a notation to change. One way to evaluate the ‘viscosity’ of an abstraction mechanism is to analyze how sensitive the input of the abstraction function is to small changes in its desired output. Returning to our earlier hypot() example, consider a small change in the use scenario from \(r + f(s) + f(s)\) to \(r + r + f(s + 1) + f(s + 1)\). This change requires only a minor change to the parameters: from hypot(r, f(s)) to hypot(r, f(s + 1)).

This can be formalized by examining the relation between tree edit distance [12] of the inputs and outputs to the abstraction function. Roughly speaking, tree edit distance measures how many “editing operations” would be required to transform a term \(t\) to a term \(t’\), giving a distance metric \(d(t, t’)\) on terms. If making small changes in the instantiated code requires large changes to the parameters, we expect the notation to be “viscous” in the sense of Green, resisting our efforts to evolve our design. The cognitive dimensions framework suggests that small changes in the instantiation should be realizable by small changes in parameters. This is illustrated in Figure 5.

We can formalize this intuition in terms of Lipschitz continuity. A Lipschitz condition on a real function \(f : \mathbb{R} \to \mathbb{R}\) is a requirement of the form

\[|f(a) - f(b)| \leq K|a - b|\]

where \(K \geq 0\). A function satisfying this condition is said to be Lipschitz, and \(K\) its Lipschitz constant. The notion generalizes easily to metric spaces: given a metric space \((T, d)\), and a function \(f : T \to T\), we can call \(f\) Lipschitz if

\[d(f(a), f(b)) \leq Kd(a, b)\]

for some \(K \geq 0\). Viewing abstractions as functions from terms to terms, and tree edit distance as the distance metric, we can make the following conjecture:

The ease with which an abstraction can be used in design work is strongly influenced by whether it is Lipschitz, and if so, the magnitude of its Lipschitz constant.

Again, it seems significant that the abstraction mechanisms we find useful in practice usually satisfy this requirement. For instance, with substitution (the abstraction mechanism for subroutines), the edit distance between parameters is at most the edit distance between instantiations. This property does not hold in general for abstraction mechanisms that lie in higher computational complexity classes, so again we return to the observation that useful abstraction mechanisms tend to be computationally very simple.

4.5 Tradeoff curves

The formalization of abstraction mechanisms as metalanguages lends itself to understanding tradeoffs between forms of abstrac-
Abstraction Parameters | Instance
---|---
\[x = (r, f(s))\] | \[y = r + r + f(s) \star f(s)\]
\[d(x,x')\] | \[d(y,y')\]
\[x' = (r, f(s+1))\] | \[y' = r + r + f(s+1) \star f(s+1)\]

Figure 5. Illustration of how abstractions interact with edit distance, ideally: a small change in the instantiation (from \(y\) to \(y'\)) can be achieved by a small change in the parameters (from \(x\) to \(x'\)), i.e., \(d(x,x') \leq d(y,y')\).

program size (thick line, left axis) decreases, tending to some optimal value greater than \(H(n)\), the entropy for the problem domain \(\mathbb{Q}\). (2)) It is possible we cannot achieve the maximum possible compression \(H(n)\) because there might be patterns in programs which are not exploitable in any effective way, leading to what is labeled the “computability gap” in Figure 6. To achieve the best possible compression, this curve suggests we ought to use a high level of abstraction power, i.e., arbitrary program generators. On the other hand, as the power of abstractions increases, the difficulty of using them in a given situation (the complexity of the inverse problem) increases rapidly, quickly becoming noncomputable (dashed line, right axis). Thus we have a tradeoff between the power of abstractions to generalize, and the difficulty of adapting them to a particular use scenario. The dotted line shows a tradeoff curve with a hypothetical ‘sweet spot’ that balances the complexity of abstractions against the program length achievable.

This graph illustrates why in practice we tend to use computationally weak forms of abstraction, and use complex forms of abstraction (e.g., program generators) sparingly, even though they might in principle allow us to achieve much shorter program lengths.

5. Conclusions
We have proposed using the MDL principle to answer the ‘generality problem,’ of how one chooses the right level of generality
for a software component. As applied to software components, the MDL principle suggests that ‘the best component yields the most succinct representation of the use cases.’ In forthcoming work we use this approach to retrospectively evaluate the interface design of generic libraries.

The second portion of this paper suggested an approach to understanding the tradeoff in programming language design between the power of abstraction mechanisms, their ability to reduce program length, and the cognitive difficulty of their use. We observed that almost all the abstraction mechanisms popular in practice lie in low computational complexity classes. A plausible explanation for this is that such mechanisms are easy to ‘invert,’ e.g., we can readily figure out what parameters to provide a macro to achieve a desired result. We connected Thomas Green’s notion of notational viscosity to the theoretical notion of Lipschitz continuity, which formalizes the bridge between cognitive difficulty and computational difficulty. Finally, we summarized the tradeoffs in abstraction mechanisms by sketching a curve illustrating the ‘sweet spot’ that balances the complexity of abstractions, their cognitive difficulty, and the amount by which they reduce program length.

Acknowledgments

The question of how to decide when components are over- or under-generalized was posed to me by Sibylle Schupp.

References

[1] D. Abrahams and A. Gurtovoy. C++ Template Metaprogramming: Concepts, Tools, and Techniques from Boost and Beyond. Addison-Wesley, 2004.

[2] A. Alexandrescu. Modern C++ Design: Generic Programming and Design Patterns Applied. Addison-Wesley, 2001.

[3] B. Barak, R. Shaltiel, and A. Wigderson. Computational analogues of entropy. In A. Arora, K. Jansen, J. D. P. Rolim, and A. Sahai, editors, RANDOM-APPROX, volume 2764 of Lecture Notes in Computer Science, pages 200–215. Springer, 2003.

[4] F. J. Barrett and D. L. Cooperider. Generative metaphor intervention: A new approach for working with systems divided by conflict and caught in defensive perception. The Journal of Applied Behavioral Science, 26(2):219–239, 1990.

[5] D. Bert, P. Drabik, R. Echahed, O. Declerfayt, B. Demeuse, P.-Y. Schobbens, and F. Wautier. LPG: A generic, logic and functional programming language. In H. Ganzinger, editor, ESOP’88, 2nd European Symposium on Programming, volume 300 of Lecture Notes in Computer Science, pages 376–377, Nancy, France, 21–24 Mar. 1988. Springer.

[6] A. F. Blackwell, C. Britton, A. Cox, T. Green, C. Gurr, G. Kadoda, M. S. Kutar, M. Loomes, C. L. Nehaniv, M. Petre, C. Roast, C. Roes, A. Wong, and R. M. Young. Cognitive dimensions of notations: Design tools for cognitive technology. Lecture Notes in Computer Science, 2117:325–341, 2001.

[7] J. Carette. Understanding expression simplification. In ISSAC ’04: Proceedings of the 2004 international symposium on Symbolic and algebraic computation, pages 72–79, New York, NY, USA, 2004. ACM Press.

[8] K. Czarnecki and U. W. Eisenecker. Generative Programming: Methods, Tools, and Applications. Addison-Wesley, 2000.

[9] R. Garcia, J. Jarvi, A. Lumsdaine, J. Siek, and J. Willcock. A comparative study of language support for generic programming. In Proceedings of the 18th ACM SIGPLAN conference on Object-oriented programming, systems, languages, and applications, pages 115–134. ACM Press, 2003.

[10] J. A. Goguen. Principles of parameterized programming. pages 159–225. ACM Press, New York, NY, USA, 1989.

[11] T. R. G. Green. Cognitive dimensions of notations. In Proceedings of the HCI’89 Conference on People and Computers V, Cognitive Ergonomics, pages 443–460, 1989.

[12] P. N. Klein. Computing the edit-distance between unrooted ordered trees. In G. Bilardi, G. F. Italiano, A. Pietracaprina, and G. Pucci, editors, Proceedings of the 6th Annual European Symposium on Algorithms, ESA ’98 (Venice, Italy, August 24–26, 1998), volume 1461 of LNCS, pages 91–102. Springer-Verlag, Berlin, 1998.

[13] K. Knight. Unification: A multidisciplinary survey. ACM Computing Surveys, 21(1):93–124, Mar. 1989.

[14] B. Liskov, A. Snyder, R. Atkinson, and C. Schaffert. Abstraction mechanisms in CLU. Commun. ACM, 20(8):564–576, 1977.

[15] D. R. Musser and A. A. Stepanov. Algorithm-oriented generic libraries. Software: Practice and Experience, 24(7):632–642, July 1994.

[16] J. Rissanen. Stochastic Complexity in Statistical Inquiry, volume 15 of Series in Computer Science. World Scientific, 1989.

[17] D. Schön. Generative metaphor: A perspective on problem setting in social policy. In A. Ortony, editor, Metaphor and Thought. Cambridge University Press, 1978.

[18] M. Shaw, W. A. Wulf, and R. L. London. Abstraction and verification in Alphard: defining and specifying iteration and generators. Commun. ACM, 20(8):553–564, 1977.

[19] T. Sheard and J. Hook. Type safe meta-programming. Unpublished manuscript, Oregon Graduate Institute, November 1994.

[20] W. Taha and T. Sheard. MetaML and multi-stage programming with explicit annotations. Theoretical Computer Science, 248(1–2):211–242, Oct. 2000.

[21] T. L. Veldhuizen. Using C++ template metapgrams. C++ Report, 7(4):36–43, May 1995. Reprinted in C++ Gems, ed. Stanley Lippman.

[22] T. L. Veldhuizen. Software libraries and their reuse: Entropy, Kolmogorov complexity, and Zipf’s law. In S. Arora, K. Jansen, J. D. P. Rolim, and A. Sahai, editors, RANDOM-APPROX, volume 2764 of Lecture Notes in Computer Science, pages 51–62, Berlin, 2003. Springer.

[23] T. L. Veldhuizen. Tradeoffs in metaprogramming. In ACM SIGPLAN Workshop on Partial Evaluation and Semantics-Based Program Manipulation, Jan. 2006.

[24] D. J. Wheeler. The use of sub-routines in programmes. In ACM ’52: Proceedings of the 1952 ACM national meeting (Pittsburgh), pages 235–236. ACM Press, 1952.

[25] G. V. Wilson. Personal communication. December 2005.

[26] K. Zhang and D. Shasha. Simple fast algorithms for the editing distance between trees and related problems. SIAM J. Comput., 18:1245–1262, 1989.