Chapter 5

Static dynamic bridge

In the programming world, there are three main families of programming language [28]. There are (i) *compiled* programming languages, such as C, C++, Rust or Go, (ii) *interpreted* programming languages, such as Python, PHP, Lisp or Javascript, and (iii) hybrid programming languages, such as Java or C#. The latter have a fast compilation pass that compiles the source code into an intermediate bytecode. Then, this bytecode is interpreted via an interpreter on the host (runner) machine.

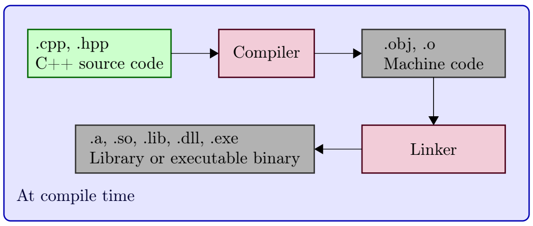
5.1 Introducing the static and dynamic bridge

Many studies have been carried out to compare the advantages and disadvantages of each family of programming languages [4]. In this thesis we focus mainly on comparing the burden that are shouldered by the maintainers and the end-user.

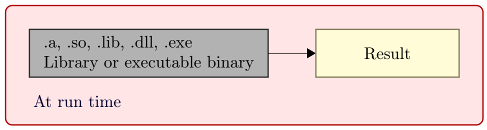
5.1.1 Languages types

Rework arguments for compiled and interpreted languages.

Compiled languages From the maintainer point of view, there is a lot of burden to shoulder. First is the binary generation which can be problematic in itself. Indeed, to generate a binary, there are many steps, as illustrated in fig. 5.1. First the compiler does a pass to generate machine code for each translation unit. There can be as many machine code as there are architecture and/or operating system supported. The maintainer may want to support different operating systems (last two windows and OSX version, a handful linux or unix distributions, maybe mobile phone portages). Each of these OS requires its own bundle. Additionally, the hardware may change, or the maintainer may want to take advantage of some specific hardware when available (like vectorized SIMD instructions such as SSE4, XOP, FMA4, AVX-512, etc.): this also requires the maintainer to multiply the number of binaries he compiles and distributes. Finally, the linker resolves the dependencies of the program and assembles the final binary. At that time the maintainer has to sort out how he wants to bundle the dependencies of his program. Should he statically link them alongside the binary and distribute them, at the risk of having the size of his binary exploding? Or should he state that the user has to install the dependencies on his system (via a package manager for instance) so that the binary can run? The burden of handling the dependencies is then shifted to the end-user when installing the program. Usually the package manager, such as *apt*, *yum* or *pacman*, solves this transparently for the end-user and the programs works "out-of-the-box" once installed, as illustrated in fig. 5.1. The downside is that the maintainer has to publish many bundles of his package where he wants it to be available.



(a) Compile-time



(b) Run-time

Figure 5.1: Compiled languages: compile-time (a) vs. run-time (b).

Interpreted languages From the maintainer point of view, this is the ideal standpoint. It is easier to distribute software via an interpreted language because only the source code and, a dependency tree and the assets are released in the bundle. All the burden about resolving the dependencies and installing the framework to run the script is shouldered by the end-user that is using the program. Indeed, as shown in fig. 5.2, everything happens at runtime. The main advantage of this approach is to build a very rich ecosystem as distributing, maintaining and using programs is very easy once integrated in a package manager (often delivered alongside the language SDK natively, e.g. pip for python). However, the most notable disadvantage is the performance which is explained by the fact that the source code is not compiled into optimized assembly code ready to be executed by the computer. Instead, the interpreter must do all the work in one go and very often this is slow (at least the first pass). Nowadays, interpreters differentiate two use cases. One is opening the console interpreter from the command line and typing commands to get the immediate interpreted results. This use-case usually does not provide heavy optimization because the user is likely prototyping his script and thus does not need it in the first place. The second use case is when the interpreter parses files and/or libraries as a whole. In this use-case, it is likely that the file will not change, but they will be used a lot. It is then relevant to pay a pass to generate intermediate bytecode that can be interpreted faster for the future passes onward. As an example, the Python programming language has several implementations: CPython, PyPy, Jython or IronPython. CPython generate intermediate bytecode in `*.pyc` files while Jython IronPython and PyPy embed a Just-In-Time (JIT) compiler to generate resp. JVM bytecode, CLR (.NET) bytecode, a large variety of bytecode format.

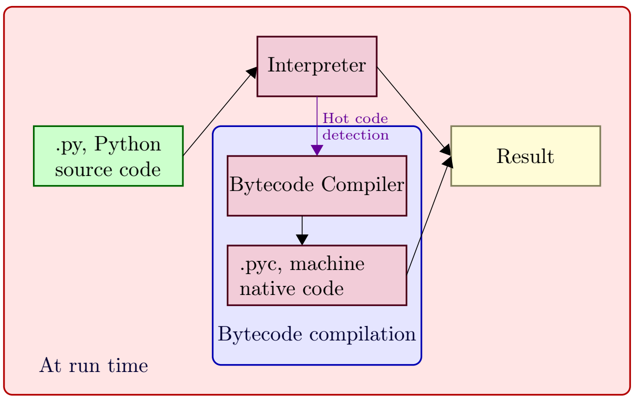


Figure 5.2: Interpreted languages: run-time

Hybrid languages The burden is shared evenly between the maintainer and the user, while remaining minimal. Indeed, languages such as Java or C# are in this category. Those programming languages need a compiling pass which is designed to be fast, so that the feedback loop while prototyping remains fast. The result of the compilation is bytecode which is then executed on an hosting Virtual Machine (VM) that the user must install on his computer. The main advantages of this solution are the portability and the small distributed binary size. Indeed, in theory, any machine supporting the VM may also support the program. Also, the as the VM execute the bytecode and resolve system dependencies, the distributed binary does not need to embed any system dependency. Finally, the user has the advantage of running a compiled program which provides fast user experience. The goal of hybrid languages is to ally advantages of both compiled and interpreted languages; no dependency management for the user, one small binary to distribute for the maintainer, good execution performance, and fast feedback loop when prototyping (fast incremental compilation), while minimizing the downsides; usually a garbage collector is working inside the VM to handle memory allocations and de-allocations. In this regard, both Java and C# manage to achieve this feat quite elegantly. In theory, VM can further increase performances by implementing hot code detection which would compile the bytecode into native optimized machine code. This area is still a field of research to this day (c.f. Java HotSpot [155, 64, 104]).

To summarize Interpreted and hybrid programming languages produces more portable artefacts and therefore are easier to deploy in a dynamic environment. We summarize in fig. 5.3 the different approaches in order to be able to execute a binary from source code.

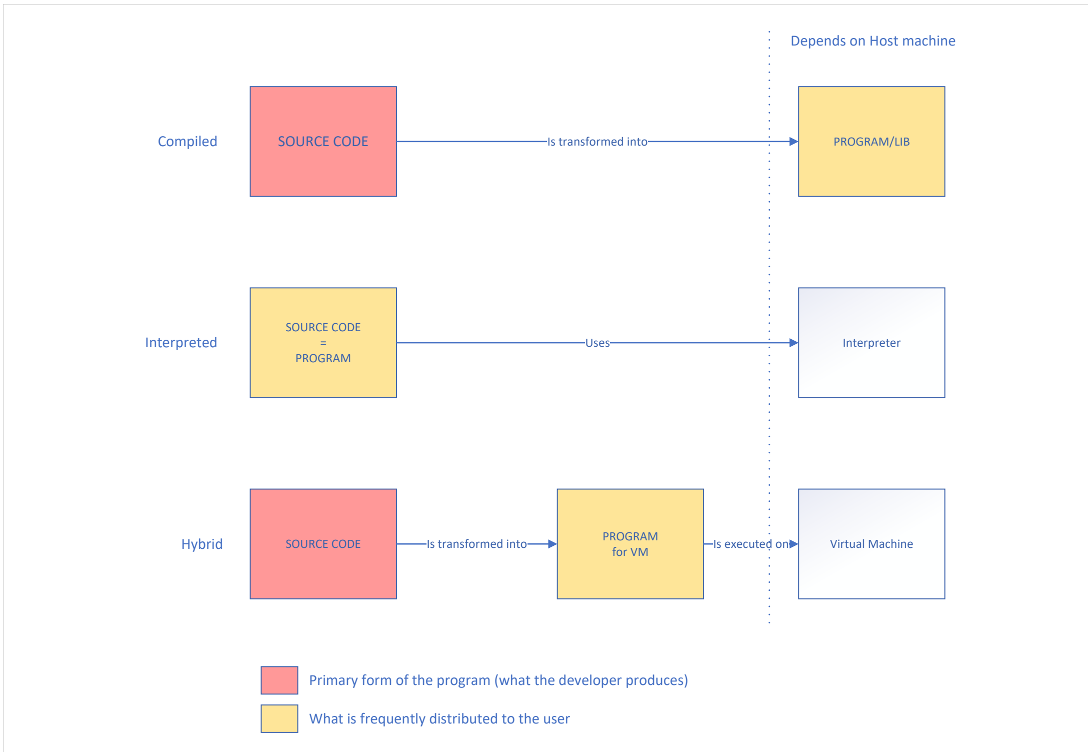


Figure 5.3: Languages types: summary diagram

5.1.2 Static and dynamic informations

Compiles programming languages usually have poor support of introspection facilities. At best, static reflection is available at compile-time, but dynamic reflection is not an option. The structure of the program does not change at runtime. Some flexibility exists when delving into the area of hot-swapping dynamic libraries at run-time, however this techniques drags alongside security-related issues that injecting possible foreign machine code into one's program may generate. Interpreted programming languages usually have very developed introspection facilities. Dynamic reflection at runtime is possible and some language, such as Common Lisp, even go further by allowing the developer to mutate the program Abstract Syntax Tree (AST) at runtime (macro). This allows very powerful integrations such as defining one's own DSL as if it was part of the core language itself. Hybrid programming languages usually offers very good static and dynamic introspection facility at both compile-time and runtime, even if it means that runtime facilities will hurt performances. Also, those languages are usually designed to be able to hot-swap code at runtime. It is then possible to have the application running, recompile part of the binary of the application, replace the old running binary by the new compiled one, all the while the application is running.

The next important step is to classify what information is known at *compile-time* (machine/bytecode code generation): we call it *static* information; and what information is known at *runtime* (program execution): we call it *dynamic* information. In image processing, we have, on the one hand, knowledge about the following static informations:

- Image's value type (unit8, rgb8, complex, etc.),
- Image's dimension size (1D, 2D, 3D, etc.),
- Architecture of the hardware hosting the program (x86, ARM, PowerPC, GPU, etc.).

This means that, while the information may not be known at compile-time, we are able to write (or, more accurately, generate) code dedicated for those common types that we know constitutes a large portion of the use cases. Furthermore, we can write optimized portion of code dedicated to handle some particular known types that the program will use when it encounters them at run-time. On the other hand, the following informations are always dynamic:

- Image's actual values,
- Image's actual size,
- Architecture of the hardware hosting the program (x86, ARM, PowerPC, GPU, etc.).

The library needs both information type (static and dynamic) however, even if some informations are missing, it is not a fatality and the library can still recover and work efficiently at runtime.

On another note, we notice that the architecture hosting the program is both an information which is static and dynamic. This translates the complexity of this information. Indeed, the maintainer needs to guess the array of architectures he wants to support and generate binaries for them (static). Also, the program needs to detect at runtime (dynamically) on which hardware he is running to possibly take advantage of it to increase performances. This is an area of research on its own called heterogeneous computing [122, 123].

5.1.3 Introducing our hybrid solution

Image processing communities like to have bridges with interpretable language such as Python or Matlab, to interface with their favorite tools, algorithms and/or facilities. As an example, with Python, the module NumPy [57] is a community standard which is heavily used. Henceforth, to broaden the usage of our library, we should be able to provide a way to communicate between our library and NumPy. There is always a need for genecity in both C++ and Python. Indeed, in C++ genericity is achieved via template programming, which is static, whereas in Python genericity is achieved via duck typing, which is dynamic, as shown in fig. 5.4.

On the one hand, static polymorphism induces no indirection in the generated code as the type is known at compile-time. It is then possible to generate optimized code for specific types. It is not possible to add a new supported type at runtime as the code has already been compiled. On the other hand, the dynamic polymorphism implies that there will be indirections when executing the code. Indeed, the code first needs to dispatch onto the appropriate function handling the input types to perform the operation properly. Nevertheless, it is possible to add new supported type at runtime without recompiling the library binary.

```cpp
template <typename T>
T add(T a, T b) {
  return a + b;
}
```

(a) C++ static genericity

```python
def add(a, b):
  return a + b
```

(b) Python dynamic genericity

Figure 5.4: C++ Static (a) vs. Python Dynamic (b) genericity.

From the maintainer point of view, however, only distributing the C++ templated source code is a showstopper to the usability of his library by a Python user, because he does not hand over binaries. Indeed, one caveat of using C++ template programming is that the C++ compiler cannot generate a binary until it knows which type (of image, of value) will be used. But the maintainer does not know this information and the user (on Python's end) does not want to recompile the generic library code each time he has another set of types to exercise against. From here, there are still multiple ways to achieve our goal.

The first option is to embed and distribute, alongside the library, a JIT compiler whose job would be to generate the binaries and bindings just as they are used. This solution brings speed (excluding the first run that includes the compilation time) and unrestrained genericity. However it bounds both user and maintainer to the specificities of a compiler vendor and loose platform portability.

Another option is to type-erase (dynamic polymorphism) our types to enable the use of various concrete types through a single generic interface. This would translate into a class hierarchy whose concrete classes are the leaves (thus, whose value-types and dimensions are known). This induces a non-negligible performance overhead but enables us to keep the genericity and portability at the cost of maintaining the class hierarchy.

Type generalization can also be considered. It is possible to cast everything into a super-type that is suitable for the vast majority of cases. For instance, we could say that we have a super-type `image4D<double>` into which we can easily promote sub-types such as `image2D<int>` or `image3D<float>`. Of course we would loose the generic aspect and induce non negligible speed cost. Although portability is kept.

And finally there is the dynamic dispatch. It consists in embedding dynamic information at runtime about types, and dispatch (think of switch/case) to the correct facility which can handle those types. The obvious caveat is the cost of maintenance induced by the genericity as we would have a number of possible dispatches that grow in a multiplicative way with the number of handled types. Which is not very generic. On the other hand there is almost no speed loss and the portability is guaranteed. Theoretical models exist that could bring solutions to lower the number of dispatcher to write, such as multi-method [70]. Unfortunately they are currently not part of C++.

5.2 Designing the hybrid solution

In Pylene we have chosen a hybrid solution between type-erasure and dynamic dispatch. The aim is to have a set of known types for which we have no speed cost as well as continuing to handle other types to remain generic. In [125] we provide a facility to expose our generic code to Python. As seen in the previous chapter, it is not possible to bind C++ source code to Python. We need to have a compiled binary implementing Python binding (we chose Pybind11 [114]) in order to be able to call C++ code from Python. In order to achieve the binding without sacrificing the genericity and the performances, we have designed a solution in two steps. We do not want to provide an abstract interface that will resolve the calls to access data on the call-site via virtual call because it would be very slow when the C++ code is executed. This would defeat the purpose of having to rely on C++ in a first place. However, it is possible to convert an abstract class into an instantiated concrete generic class whose template parameter are known. This requires, however, to enumerate all the possible cases. With modern C++, it has become possible to design $n * n$ dispatch without gigantic switch-case clauses.

5.2.1 First step: converting back and forth

The first step of our solution consists in designing a buffer class that holds all the informations about an image: dimension, underlying type, strides and pointer to data buffer. This class is named `ndimage_buffer`. When interfacing with Python, it is necessary to convert the Python image which is a `NumPy.array` into our image type and vise versa, converting our C++ image type back into a python image. The purpose of this buffer image is to holds all the information from the `NumPy.array` to then instantiate a concrete C++ type. This process is illustrated in fig. 5.5. The first pitfall here is due to a limitation from the abstraction interface used in Python. Indeed, when using, for instance *Scikit-Image*, it is not possible to differentiate a 2D multichannel image from a 3D grayscale image. Indeed, the image is always broken down to its most simple value and a 2D multichannel image is turned into a 3-dimensional `NumPy.array` containing a single 8-bits channel, the last dimension contains only 3 elements at max but can theoretically contain more. Indeed, there is no limitation embed in the used abstraction which does not prevent that. To prevent this confusion, the C++ wrapper code may chose between two strategies; first is to consider all 3D/1-channel image as 2D/RGB images by default, second is to let the user give the information. For the sake of simplicity, we have chosen the first strategy.

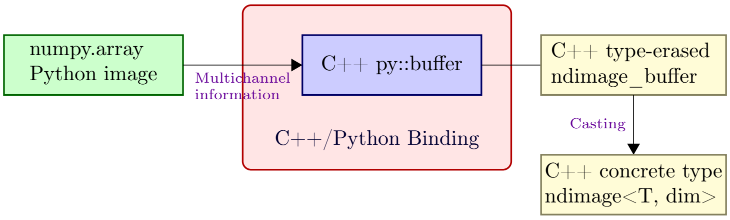


Figure 5.5: Bridge from Python to C++ via Pybind11 and a type-erased C++ class.

From the point of view of a practitioner, the code on the call-site (python side) should be as follow:

```
from skimage import data
import numpy as np
import Pylena as pln # our python binding
img = data.astronaut() # 2D-rgb8 image -> Numpy.array(ndim=3, dtype='uint8')
# pln.<any_algorithm>(img)
```

The C++ code contains lots of glue code necessary to expose the module to Python. In this thesis we have chosen to work with Pybin11 [114] which provides a modern API and is actively being maintained and improved. The glue code exposing the Python module from C++ is given in appendix C.4. In order to have a seamless interaction between Python's `numpy.array` and C++, we need to define a proper strategy to convert the Python type into the C++ type without copying all data around. Pybind offers us two possibilities to achieve this. The first one is to use the buffer protocol to pass around numpy's buffer information to C++ in way so that C++ can properly bind the data into a proper C++ class. The second one is to use a custom type-caster to implicitly convert the python type into a C++ type each time it is needed.

With the first method, one would need to write the following code on python's side:

```
np_img = data.astronaut() # 2D-rgb8 image -> Numpy.array(ndim=3, dtype='uint8')
pln_img = pln.ndimage(np_img) # conversion into the C++ image type
pln_img_ret = pln.<any_algorithm>(pln_img) # call to algorithm
np_img_ret = pln_img.to_numpy(); # convert back into numpy.array
# use np.<...>(np_img_ret) # use resulting image with numpy
```

Whereas the second method would require the user to write the following code on python's side:

```
np_img = data.astronaut() # 2D-rgb8 image -> Numpy.array(ndim=3, dtype='uint8')
np_img_ret = pln.<any_algorithm>(np_img) # implicit conversion with custom type-caster on C++ side
# use np.<...>(np_img_ret) # use resulting image with numpy
```

Removing this conversion step is the major reason we have chosen the second method: the custom type-caster. The C++ code for this part is given in appendix C.1.

We are now all set and are able to convert back-and-forth a python image into a C++ image and vice versa.

5.2.2 Second step: multi-dispatcher (a.k.a. $n * n$ dispatch)

The second step of our hybrid solution is to dispatch the abstract buffer type coming from Python to an efficient generic code. The naive way of doing so would be to include a gigantic switch-case clause in each algorithm implementation and dispatch to the correct instantiated generic algorithm from there. Aside from being a nightmare to maintain, the size of those clauses would grow several fold depending on the cardinality of the generic implementation. For instance, for a generic dilation, there are 3 axis of cardinality: the underlying type, the dimension and the structuring element shape. In the case where the library support 5 different structuring element shape, 10 underlying types and 6 dimension for the image, the switch-case statement would need to dispatch over 300 clauses. Also, each supported algorithm would need to have dispatcher. This solution defeat the purpose of genericity which is to write less code in the first place. We needed to design a solution to implement those dispatchers while keeping our code short and efficient. The idea we took to solve this problem comes from the design of a C++ feature, the variant, and especially the visitor, applied to image processing, as in [72] for instance. We need to have a way to write the implementation of the algorithm once while enumerating all the possible cases. Also, if possible, the list of supported types should be written once at one place for maintenance purpose.

Simple dispatcher We then had the idea of writing a dispatcher. This dispatcher lists all the supported types and call the given callbacks forwarding the given arguments by instantiating a specific type. Let us try to expose to python, for instance, the generic existing algorithm for thresholding a binary image. The Python call-site code will look like this:

```
img_grayscale = skimage.data.grass()
pln.operators.binary_threshold(img_grayscale)
```

On the C++ side, we want to avoid writing code that looks like this:

```
mln::ndbuffer_image binary_threshold(mln::ndbuffer_image input) {
  auto dim = input.dim();
  auto tid = input.tid();
  switch(dim) {
    case 1: // 1D image
      switch(tid) {
        case UINT8:
          if(auto* image_ptr = input.template cast_to<uint8_t, 1>(); image_ptr)
            return mln::binary_threshold(*image_ptr);
        case RGB8:
          // error support only RGB8 images
      }
      break;
    case 2: // 2D image
      // ...
      break;
    // ... 3D, 4D, ...
  }
}
```

Instead, it is possible to separate the dispatching code and the logical code entirely by using a templated operator, the same way we use lambdas in the pattern `std::variant/std::visit`. For our binary threshold example, the operator be implemented just by writing the following code:

```
// Operator templated by the dimension
template <auto Dim>
struct binary_threshold_op_t {
  // Function templated by the image type
  template <typename Img>
  mln::ndbuffer_image operator()(Img&& img) const {
    // Cast to a grayscale (information known) of the correct dimension
    if (auto* image_ptr = std::forward<Img>(img).template cast_to<std::uint8_t, Dim>(); image_ptr)
      // ACTUAL call to the generic algorithm
      return mln::binary_threshold(*image_ptr);
    else {
      std::runtime_error("Unable to convert the image to the required type.");
      return {};
    }
  }
};
```

This code allows us to dispatch over any number of dimensions. We are required to pass a grayscale image for the algorithm so here the example is limited to dispatching over just one cardinality: the dimension. Let us now take a look at how we can implement the dispatcher for our example to work. The dispatcher must take the dimension as first parameter and any number of arguments to forward to the instantiated operator. The dispatcher then looks like the following code:

```
template <template <auto> class Op, typename... Args>
auto dispatch_v(std::size_t dim, Args&&... args) {
  switch (dim) {
    case (1):
      return Op<1>{}(std::forward<Args>(args)...);
    case (2):
      return Op<2>{}(std::forward<Args>(args)...);
    case (3):
      return Op<3>{}(std::forward<Args>(args)...);
    /* ... */
  }
}
```

The operator `Op` is instantiate with the correct dimension number and the the `operator()` (parenthesis) is called while being forwarded the correct arguments. In our case, it will instantiate the type `binary_threshold_op_t<2>` and then call the function `binary_threshold_op_t<2>.operator()(input)`, forwarding the input image to the underlying algorithm. Indeed, using the dispatcher is as simple as writing `dispatch_v<binary_threshold_op_t>(input.dim(), input);`

The main advantage of this approach is that we respect all the requirements. First the logical code is bounded in the operator, second, the supported types are all listed in one place, once. Also, while our example is limited to one cardinality, any number of dispatcher can be piped to one after another to achieve the cardinality wanted.

Double dispatcher Let us push our example to implement the mathematical morphology operator dilation. We now have two more generic axis to cover: the structuring element shape and the underlying datatype. First, let us take a look at what the Python code may look like:

```
img_grayscale = skimage.data.grass()
rect = pln.se.rect2d(width=3, height=3)
img_dil = pln.operators.dilate(img_grayscale, se)
```

The first thing to notice is the need to add additional bindings to expose our C++ structuring elements. The glue code to achieve this is given in appendix C.2. Let us take a look at our dilation operator:

```
template <auto Dim, typename T>
struct dilate_operator_t {
  template <typename Img, typename SE>
  mln::ndbuffer_image operator()(Img&& img, SE se) const {
    if (auto* image_ptr = std::forward<Img>(img).template cast_to<T, Dim>(); image_ptr)
      // ACTUAL call to the generic algorithm
```

```
      return mln::dilation(*image_ptr, se);
    else {
      std::runtime_error("Unable to convert the image to the required type.");
      return {};
    }
  }
};
```

This operator needs double dispatch over two cardinalities: the dimension `Dim` and the value type `T`. We can skip the dispatch of the structuring element's shape as we have made a `std::variant` of all the supported structuring element supported for the sake of simplicity. Dispatching over the supported structuring elements can then be offloaded upstream from the call to the double dispatch, just by calling `std::visit`. We can immediately notice that there is an issue with our dilation operator. Indeed, there are two template parameters and our dispatcher `dispatch_v` does only handle one. We solve this issue by writing another intermediate operator dispatcher `dilate_operator_intermediate_t` serving as trampoline operator that will partially instantiate the final operator `dilate_operator_t` along the dimension template parameter to feed it to the last dispatcher, `dispatch_t`:

```
template <auto Dim>
struct dilate_operator_intermediate_t {
  template <typename Img, typename SE>
  mln::ndbuffer_image operator()(Img&& img, SE&& se) const {
    // Partial instantiation
    return double_dispatch_t<dilate_operator_t, Dim>(
            input.sample_type(), std::forward<Img>(input), std::forward<SE>(se));
  }
};
```

Dispatching the operator alongside two cardinalities (even three including the structuring element handled by `std::variant`) would then become as simple as calling:

```
// dispatch the structuring elements through using std::visit for std::variant
return std::visit(
[&input](const auto& se_) { // dispatch over the trampoline
    return dispatch_v<dilate_operator_intermediate_t>(input.dim(), input, se_);
  }, se);
```

In order for this to work, we need to piece together the final part of our puzzle, which is the double dispatch function that will handle the last dispatch along the underlying data while forwarding the first dispatch along the dimension. This dispatcher works the same as the simple one (`dispatch_v`) but take an additional template parameter (here `Dim`) that will be forwarded as-is to the given operator `Op`. The implementation then looks like this:

```
template <template <auto, typename> class Op, auto Dim, typename... Args>
auto double_dispatch_t(type_id tid, Args&&... args) {
  switch (tid) {
    case (type_id::INT8):
      return Op<Dim, std::int8_t>{}(std::forward<Args>(args)...);
    case (type_id::UINT8):
      return Op<Dim, std::uint8_t>{}(std::forward<Args>(args)...);
    case (type_id::DOUBLE):
      return Op<Dim, double>{}(std::forward<Args>(args)...);
      /* ... */
  }
}
```

We have now presented all the techniques and design required to build operators that are agnostic from the supported data-types, dimensions and/or additional data such as structuring elements. Indeed, the maintainer has gathered all the logic about listing the supported data types and dimension in one place: the custom dispatcher. He just needs to maintain those to enable full support for all exposed algorithm, by default. This hybrid solution mixes type-erasure and modern C++ facilities to allow maximum performance. Indeed, the dispatch is done before entering algorithms and the custom type-caster facility allows us to plug directly into the

Python image without having any unnecessary copies. The only caveat would be the code bloat incurred by all the explicit instanciation leading to compiling a larger and larger binary the more algorithms are being exposed. This can lead to performances issues due to pre-fetching memory optimization missed and code locality issues [32]. Another point not covered right now would be a way to support arbitrary data types, possibly injected from Python, into C++. Indeed, our hybrid solution only support the types provided by the library and listed in the dispatchers. It will instantiate all the code relative to them and support all of the combinations but the user may be tempted to plug a user-defined type from Python as an underlying image data-type. To allow this use-case, we introduce a new concept: the *value-set*. The value-set is a standard way manipulate the underlying values. Through type-erasure, we can either manipulate known underlying value type with native facilities (near-zero overhead), or fallback to a virtual call that may report an error, or callback user-provided Python routine to manipulate unknown user values.

5.2.3 Third and final step: type-erasure & the value-set

rework motivation of this part: what do we want to write and why.

As common thread in this section, we will work on the *stretch* algorithm which is naively defined in fig. 5.6.

```
template <class T>
mln::image2d<float> naive_stretch(const mln::image2d<T>& src) {
  mln::image2d<float> res  = mln::transform(src, [](auto val) -> float {
    auto max = std::numeric_limits<T>::max();
    return static_cast<float>(val) / static_cast<float>(max);
  });
  return res;
}
```

Figure 5.6: Stretch algorithm, naive C++ version.

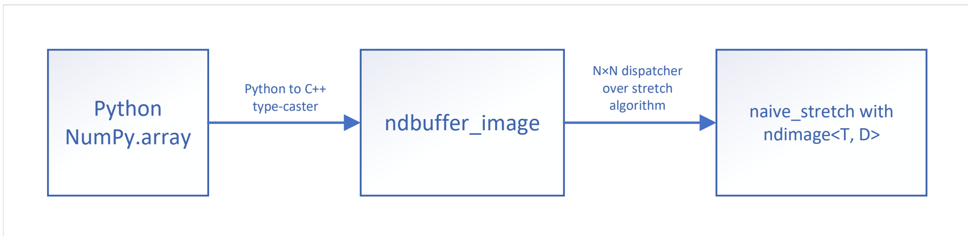


Figure 5.7: Python to C++ pipeline algorithm through the $n * n$ dispatcher.

We can represent the pipeline calling this algorithm from Python in fig. 5.7.

Introducing the value-set The *value-set* is an abstraction layer around common operations needed when implementing an image processing algorithm such as an addition, a multiplication, a type conversion, getting the maximum etc. It can be defined in C++ as a class template whose parameter is the manipulated type. The following code shows how to define a value-set:

```
template <class T = void>
struct value_set {
  template <class U>
  U cast(T v) const { return static_cast<U>(v); }

  T max() const noexcept { return std::numeric_limits<T>::max(); }
  T min() const noexcept { return std::numeric_limits<T>::min(); }
  /* inf, sup, ... */

  T add(T l, T r) const noexcept { return l + r; }
```

```
  T sub(T l, T r) const noexcept { return l - r; }
  /* mod, pow, min, max, ... */
};
```

We can see that the default parameter of the class template is `void`. Indeed, we are inspired by what was implemented in the standard library for `std:less` and providing a default (void) specialization in order to improve the usability. The following code shows how to implement this specialization:

```
template <>
struct value_set<void> {
  template <class U, class T>
  U cast(T&& t) const { return static_cast<U>(std::forward<T>); }

  template <class T, class U>
  auto add(T&& l, U&& r) const noexcept { return std::forward<T>(l) + std::forward<U>(r); }
  template <class T, class U>
  auto sub(T&& l, U&& r) const noexcept { return std::forward<T>(l) - std::forward<U>(r); }
  /* ... */
};
```

The full code of the value-set is given in appendix C.3.2. The template parameter is shifted from the class to the member functions. It is also important to note that the member function are not static, which requires to instantiate the `value-set` before using it. It may sound like a disadvantage at first glance but it can be turned into an advantage later on. Indeed, this design allows a subclass to hold member variables which will be crucial for injecting user-types from python.

Now that we have designed how our value-set is intended to work, we can deduce that an image is able to provide its own value-set. Indeed, an image knows what values it holds and thus is able to instantiate the proper value-set corresponding to this type. The member function returning the value-set in the class template `ndimage<T, D>` is then implemented as follow:

```
template <class T, std::size_t D>
class ndimage {
  /* ... */
  auto get_value_set() const noexcept {
    return value_set<T>{};
  }
};
```

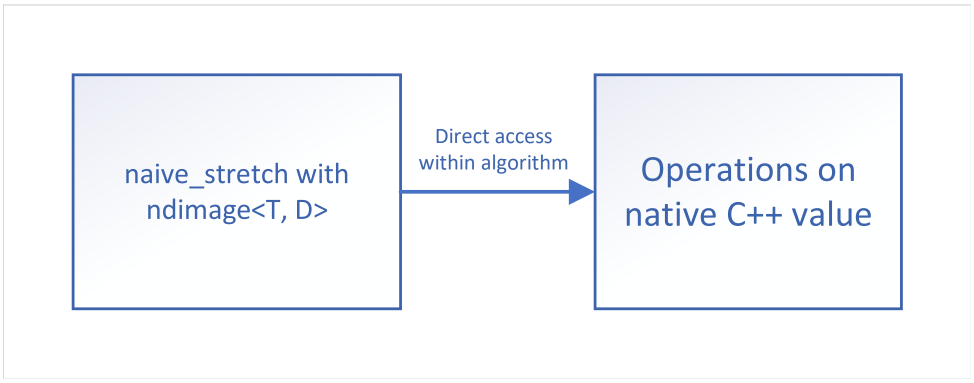


Figure 5.8: Naive stretch algorithm, pipeline to perform operations on values.

Let us recall our naive stretch algorithm presented earlier. The pipeline representing the operations on values inside the algorithm is presented in fig. 5.8. Typically, this algorithm performs three operations that are the responsibility of a value-set: getting the max, performing a cast, and performing a division. The first step is then to use the value set shown above to abstract away those operations. The new algorithm is shown in fig. 5.9.

```cpp
1  template <class T>
2  mln::image2d<float> fast_stretch(const mln::image2d<T>& src) {
3    auto                vs   = src.get_value_set();     // value-set for T
4    auto                vs_f = mln::value_set<float>{}; // fast value-set for float
5    mln::image2d<float> res  = mln::transform(src, [&vs, &vs_f](auto val) -> float {
6      auto max  = vs.max();                         // returns T
7      auto fval = vs.template cast<float>(val); // returns float
8      auto fmax = vs.template cast<float>(max); // returns float
9      return vs_f.div(fval, fmax);              // div directly returns float
10   });
11   return res;
12 }
```

Figure 5.9: Stretch algorithm, fast C++ version.

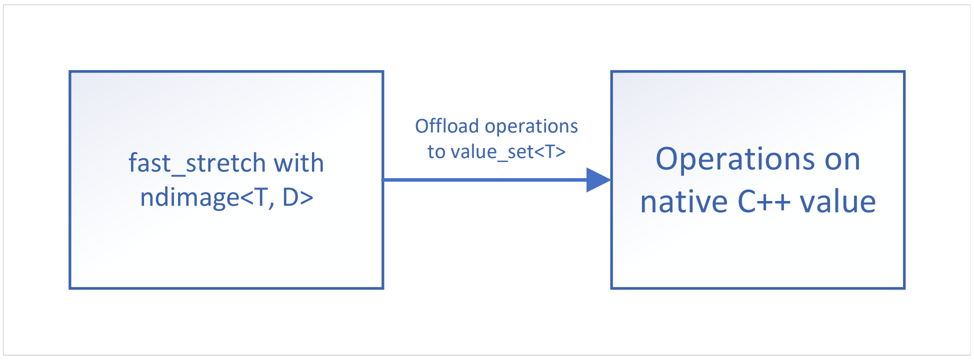


Figure 5.10: Fast stretch algorithm, pipeline to perform operations on values.

We instantiates the value-set we will need (for `T` values and `float` values) on lines 3 and 4. Then the maximum value is obtained via the value-set of `T` on line 6. Then a cast is performed via the value-set to get floating point value on lines 7 and 8. Finally a floating point division is performed on line 9 via the formerly instantiates floating point value-set defined on line 4. Indeed, using the value-set instantiated for `T` would have performed an Euclidean division and which would have resulted in a bug. Calling this algorithm from python is as simple as `ret = pln.fast_stretch(input)` once exposed. The pipeline representing the actual operations in the algorithm to access values is shown in fig. 5.10. The glue code to expose this algorithm is given in appendix C.3.3.

Type-erasure interface for value-set Moving one step further, we ultimately want to be able to dynamically inject a value-set into our algorithm. In order to achieve this feat, we need to design an abstract value-set as an interface so that a user can sub-class it and provide his own value set. This abstract value-set needs to work with `std::any` as input value-type in order to provide a generic interface. Here, the genericity is achieved via type-erasure (the input value is type-erased into a `std::any`). The interface would look like (full code is given in appendix C.3.2):

```cpp
struct abstract_value_set {
  virtual ~abstract_value_set() {}

  virtual std::any max() const = 0;
  /* min, sup, inf, ... */

  virtual std::any add(const std::any& l, const std::any& r) const  = 0;
  virtual std::any div(const std::any& l, const std::any& r) const  = 0;
  /* sub, mult, ... */
};
```

The important part here is to notice that all values (returned and passed as argument) are now type-erased behind a `std::any`. From this interface, it is trivial to define the canonical sub-classes for trivial types. We do this by defining the class template `concrete_value_set` which is able to generate a concrete interface for every given template type. The implementation will look like this:

```
template <typename T>
struct concrete_value_set : abstract_value_set {
  ~concrete_value_set() override {}

  template <class U>
  std::any cast(std::any v) const { return {static_cast<U>(std::any_cast<T>(v))}; }

  std::any max() const override { return {std::numeric_limits<T>::max()}; };
  /* min, sup, inf, ... */

  std::any add(const std::any& l, const std::any& r) const override {
    return {std::any_cast<T>(l) + std::any_cast<T>(r)};
  }
  std::any div(const std::any& l, const std::any& r) const override {
    return {std::any_cast<T>(l) / std::any_cast<T>(r)};
  }
  /* sub, mult, ... */
};
```

This concrete value-set implement simple dispatch via casting the type-erased `std::any` into the wanted value type to properly perform the operation. Thanks to this implementation, we are able to rewrite our stretch algorithm using this value-set to perform its operations. The new algorithm is shown in fig. 5.11.

```
1   template <class T>
2   mln::image2d<float> virtual_dispatch_stretch(const mln::image2d<T>& src) {
3     auto                vs   = mln::concrete_value_set<T>{};     // value-set for T
4     auto                vs_f = mln::concrete_value_set<float>{}; // value-set for float
5     mln::image2d<float> res  = mln::transform(src, [&vs, &vs_f](auto val) -> float {
6       auto anymax  = vs.max();                                 // returns std::any
7       auto fanyval = vs.template cast<float>(val);             // cast to float in std::any
8       auto fanymax = vs.template cast<float>(anymax);          // cast to float in std::any
9       return std::any_cast<float>(vs_f.div(fanyval, fanymax)); // div returns float
10    });
11    return res;
12  }
```

Figure 5.11: Stretch algorithm, virtual dispatch version.

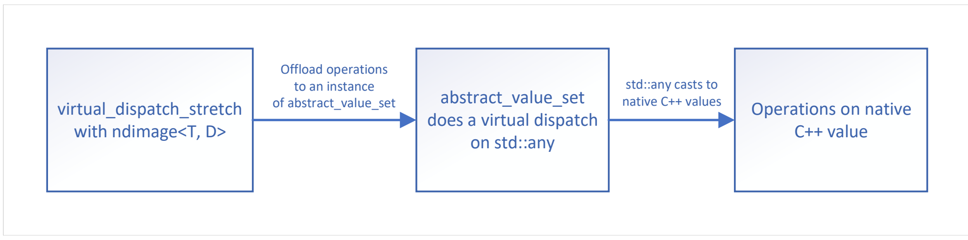


Figure 5.12: Virtual dispatch stretch algorithm, pipeline to perform operations on values.

This algorithm uses two value sets (l.3 and l.4), one to get the maximum value with regard of the original underlying value type in the image `T` (l.6) and to properly cast the values into float values (l.7-8). The other one is used to perform the floating point division (l.9). This algorithm is almost identical to the one given for `fast_stretch` earlier. Only the lines instantiating the value-set changes (l. 3-4) as well as the line handing over the result (l. 9) where we added a downcast from `std::any`. The pipeline presenting the operations needed to access values is presented in fig. 5.12.

Going forward: type-erasing the value entirely The need may arise where the user wants to handle images where the input value is abstracted away behind a type-erased type. This happens when handling image with heterogeneous value-type (different channel number from one value to another, optional information embed with the value, etc.). In order to work, this value-type needs to be aware of its own value-set to perform operations. To achieve this, the value must embed the value set (as a pointer for instance) directly alongside the value. This embedding would allow writing such code possible:

```
class type_erased_value {
  type_erased_value add(const type_erased_value& rhs);
  /* ... */
};

void my_algo(ndimage<type_erased_value, Dim> img1,
              ndimage<type_erased_value, Dim> img2) {
  ndimage<type_erased_value, Dim> img_out = /* ... */;
  for (auto [v1, v2, out] : zip(img1.values(), img2.values(), img_out.values())) {
    out = v1.add(v2); // the value knows how to perform the addition
  }
}
```

This code enables fallback when all the supported values have been exhausted. For instance, when considering the previously defined `abstract_value_set`, when attempting to dispatch over all the supporting native C++ type unwrapped from the given `std::any`, if no type is matched, we can attempt one final unwrap to this type-erased value which is aware itself of how to perform the operation. In pseudo-code it breaks down to the following logic:

```
1  std::any value_set<type_erased_value>::add(const std::any& lhs, const std::any& rhs){
2    abstract_value_set* vs = lhs.get_embedded_vs();
3    if (lhs.type() == typeid(int) && rhs.type() == typeid(int)) {
4      auto ret = std::any_cast<int>(lhs) + std::any_cast<int>; // unwrap, do the work
5      return std::any{ret}; // rewrap with the vs
6    } else if (lhs.type() == typeid(float) && rhs.type() == typeid(float)) {
7      /* ... same ... */
8    } else {
9      auto te_lhs = std::any_cast<type_erased_value>(lhs); // last attempt
10     return lhs.add(rhs); // fallback on embedded value-set
11   }
12 }
```

First step is to conditionally attempt to cast the type-erased value over the supported native values (lines 3 and 6). When the type is supported then we unwrap it and perform the operation before rewrapping it in a `std::any` and returning it. If we could not unwrap the value into a supported value-type, we make a last attempt on line 9 into our type-erased value-type. If this attempt succeeds, we rely on the fact that this value-type is aware of its own value-set and embed it to perform the required operation on line 10. The full code of the implementation for this value-set aware value-type is given in appendix C.3.2. We have relied on metaprogramming techniques in order to efficiently write the code that will do the work.

Thanks to this technique, we are able to write another version of our stretch algorithm which is shown in fig. 5.13.

This version is verbose because we do not yet support `mln::image2d<type_erased_value>` as a proper image type. Thus we need to first convert the value of type `T` into the value-set aware type-erased value type. This work is done on lines 8 to 12. Then on lines 13 to 20 we perform the actual work on the values. This is where the dispatch mechanic, whose pipeline is shown in detail in fig. 5.14, will happen. Finally, on lines 22 and 23, we unwrap the previously wrapped type-erased value into a float to return for the algorithm.

Everything comes to a full circle: injecting a value-set from Python We have seen how to write an algorithm independently from ths its underlying types on C++ side thanks to relying on an abstraction layer: the value-set. This enables one fundamental feature which is code injection from Python. Indeed, if we suppose every python value is a `pybind11::object`,

```
template <class T>
mln::image2d<float> stretch_virtual_dispatch_type_erased_value(const mln::image2d<T>& src) {
  auto                vs   = mln::concrete_value_set<T>{};     // value-set for T
  auto                vs_f = mln::concrete_value_set<float>{}; // value-set for float
  mln::image2d<float> res  = mln::transform(src, [&vs, &vs_f](auto val) -> float {
    // simulate having an image<type_erased_value>
    auto anyval = std::any{val}; // std::any of T
                                  // type_erased_value of std::any of T aware of value-set of T
    auto abs_anyval = mln::type_erased_value{anyval, vs};
    // instantiate a value-set for type_erased_value
    auto abs_vs = mln::value_set<mln::type_erased_value>{abs_anyval};
    auto anyabs_anymax =
        abs_vs.max(); // returns std::any of type_erased_value
                      // cast underlying std::any of type_erased_value of std::any of T into
                      // std::any of type_erased_value of std::any of float aware of value-set for float
    auto anyabs_fanyval = abs_vs.template cast<T, float>(std::any{abs_anyval}, &vs_f);
    auto anyabs_fanymax = abs_vs.template cast<T, float>(anyabs_anymax, &vs_f);
    // dispatch on known type, find a type_erased_value, then call
    // anyabs_fanyval.div(anyabs_fanymax) to perform division which will call
    // the underlying value-set for float for this operation
    auto anyabs_fanyret = abs_vs.div(anyabs_fanyval, anyabs_fanymax);
    // convert result back into float for returning to the image
    auto anyfret = std::any_cast<mln::type_erased_value>(anyabs_fanyret).val();
    return std::any_cast<float>(anyfret);
  });
  return res;
}
```

Figure 5.13: Stretch algorithm, virtual dispatch with a type-erased value version.

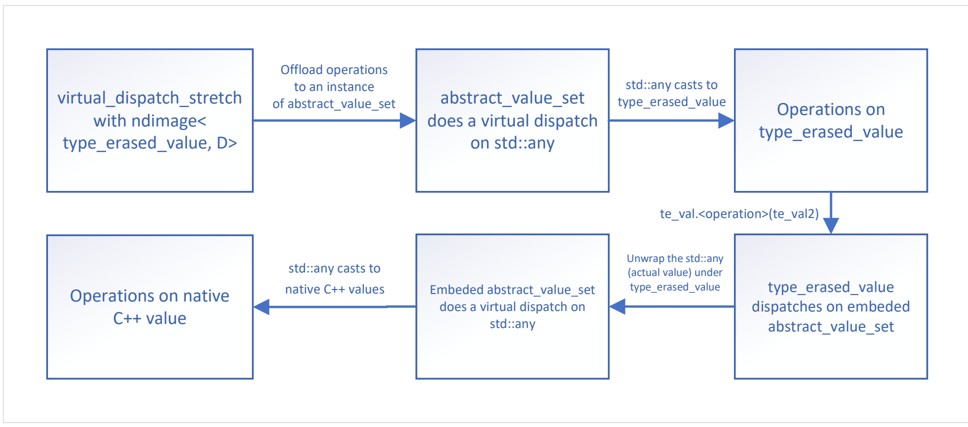


Figure 5.14: Virtual dispatch stretch algorithm with a type-erased value, pipeline to perform operations on values.

which is the generic way to refer to a non-trivially-convertible Python type we can write a value-set handling this value type. The value-set handling python data-type would then provide the following interface:

```
1  template <>
2  struct value_set<pybind11::object> : abstract_value_set
3  {
4    value_set(pybind11::object python_vs_instance): vs_instance_(python_vs_instance) {}
5    ~value_set() override {}
6
7    template <typename U>
8    std::any cast(const std::any& v) const { /* ... */ }
9
10   std::any max() const override { {vs_instance_.attr("max")()}; }
11   /* min, sup, inf, ... */
12
13   std::any add(const std::any& l, const std::any& r) const override {
14     auto pyl = std::any_cast<pybind11::object>(l);
15     auto pyr = std::any_cast<pybind11::object>(r);
16     return {vs_instance_.attr("add")(pyl, pyr)};
17   }
18   std::any div(const std::any& l, const std::any& r) const override {
19     auto pyl = std::any_cast<pybind11::object>(l);
20     auto pyr = std::any_cast<pybind11::object>(r);
21     return {vs_instance_.attr("div")(pyl, pyr)};
22   }
23   /* max, min, sub, mult, ... */
24 private:
25   pybind11::object vs_instance_;
26 };
```

In this code we can clearly see at lines 4 and 27 that we are storing our Python's value-set instance into our class. This is possible due to the fact that our value-set abstraction is not providing static class function but member function. Hence, it is possible to offload the work of the value-set to a member variable at lines 10, 15-17 and 21-23 that will call the Python's value-set and get the wanted result. Also, at line 8 we use multiples techniques at once to get the correct resulting cast from a Python type. Indeed, the cast is done on Python side before being casted back into the corresponding C++ type. As such, we have to translate the wanted C++ type information into Python type information to request the cast. Once the cast is done, we need to unwrap the python type into the corresponding C++ type and rewrap it into our, now favorite, `std::any`. The full implementation of this facility is given in appendix C.3.2.

On this particular matter, the user will find a Python abstract class to implement in order for his value-set to be usable by the library. This abstract class is defined by the following Python code:

```python
class AbstractValueSet(ABC):
  @abstractmethod
  def cast(self, value: Any, type_): pass
    if type_ in ["int", "float", "bool", "str"]:
      module = importlib.import_module('builtins')
      cls = getattr(module, type_)
      return cls(value)
    else:
      raise ValueError()
  @abstractmethod
  def max(self): return math.inf

  # ... min, sup, inf, ...

  @abstractmethod
  def add(self, lhs: Any, rhs: Any) -> Any: return lhs + rhs
  @abstractmethod
  def div(self, lhs: Any, rhs: Any) -> Any: return lhs / rhs

  # ... sub, mult, ...
```

This abstract class provide a facility to cast a value into a given type from its representation as a string. It also provides default/standard way of computing values. Those methods needs to be overridden by a child class as they are all tagged with the `@abstractmethod` attribute. The full code of this data structure is given in appendix C.5.

Let us assume our user wants to build an image whose value type are his own custom Python data structure. For the sake of this example, we will name this specific value type will be named `MyStruct`. The Python structure will look like this:

```
class MyStruct:
  v_: Any
  def __init__(self, v: Any): self.v_ = v
  def getV(self) -> Any:      return self.v_
  def setV(self, v: Any):     self.v_ = v
```

It is just a strong wrapper around a value with setters and getters. If we want to use this data structure as an image value-type and downstream it to our C++ library, we need to provide a value-set which is aware of how to handle this value type properly. If the user wants to write such a code:

```
img = np.array([MyStruct(1), MyStruct(2), MyStruct(6.5), MyStruct(3.14)] * 10, ndmin=2)
pln_img = pln.stretch(img) # Error, C++ does not know how to handle a value of type MyStruct
```

Then the user must provide his own value-set defined after the Python `AbstractValueSet` seen earlier. Such a value-set would look like this:

```
class MyValueSet(AbstractValueSet):
  def get_MyStruct__(self, v: Any):
    return v.getV() if isinstance(v, MyStruct) else v
  def cast(self, value: Any, type_):
    v = self.get_MyStruct__(value)
    return super().cast(v, type_)
  def max(self):
    return 255

  # ... min, sup, inf, ...

  def add(self, lhs: Any, rhs: Any) -> Any:
    l = self.get_MyStruct__(lhs)
    r = self.get_MyStruct__(rhs)
    return MyStruct(super().add(l, r))
  def div(self, lhs: Any, rhs: Any) -> Any:
    l = self.get_MyStruct__(lhs)
    r = self.get_MyStruct__(rhs)
    return MyStruct(super().div(l, r))

  # ... sub, mult, ...
```

The full code of this implementation is given in appendix C.5. With this information, we can now write the following Python code:

```
img = np.array([MyStruct(1), MyStruct(2), MyStruct(6.5), MyStruct(3.14)] * 10, ndmin=2)
pln_img = pln.stretch(img, value_set=MyValueSet()) # This works !
```

And this will work finely.

On the C++ side, the maintainer just needs to write another version of the stretch algorithm supporting the Python value-set which is shown in fig. 5.15.

The `mln::value_set<pybind11::object>` is constructed from the passed `value_set` argument on python side as it is a `pybind11::object`. The dispatcher then forward it to the algorithm as an additional parameter. We then have actual Python call on lines 4, 6 and 7. The line 5 just wrap the image value into a python object so that it can then be forwarded to the python code downstream, as described in the pipeline shown in fig. 5.16. The line 7 cast the python type into an actual C++ type (wrapped into our `std::any` wrapper). Finally, the line 8 unwrap the float for returning it to the algorithm.

```cpp
template <class T>
mln::image2d<float> slow_stretch(const mln::image2d<T>& src, const mln::value_set<pybind11::object>& py_vs) {
  mln::image2d<float> res = mln::transform(src, [&py_vs](auto val) -> float {
    auto anymax  = py_vs.max();                       // returns std::any of pybind11:object
    auto anyval  = std::any{pybind11::cast(val)};     // converts to std::any of pybind11::object
    auto anyret  = py_vs.div(anyval, anymax);         // returns std::any of pybind11::object
    auto anyfret = py_vs.template cast<float>(anyret); // returns std::any of float
    return std::any_cast<float>(anyfret);             // returns float
  });
  return res;
}
```

Figure 5.15: Stretch algorithm, injected value-set from Python version.

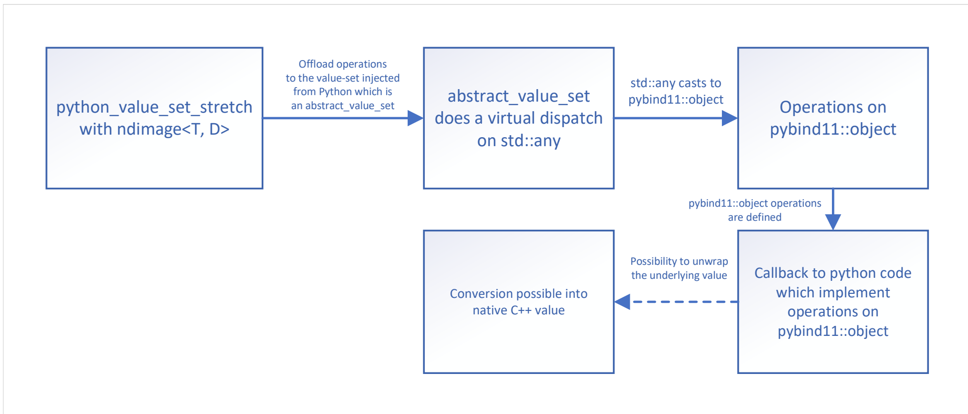


Figure 5.16: Stretch algorithm with an injected value-set from Python code, pipeline to perform operations on values.

5.3 Summary and continuation

5.3.1 Performances & overhead

In this chapter, we have designed many solutions to solve several kind of issues. However, layering one abstraction layer after another, or even calling Python code does come with performance cost. This is why we have run a benchmark to outline the cost of our solutions. The full code of the benchmark is given in appendix C.6. This benchmark compares the four version of our stretch algorithm. The result is shown in table 5.1.

Dispatch type	Compute Time	ΔCompute Time
Native value-set with native C++ value-type (baseline) 5.9	$0.0093s$	0
Value-set with virtual dispatch with native C++ value-type 5.11	$0.1213s$	×13
Value-set with virtual dispatch with C++ type-erased values 5.13	$1.0738s$	×115
Injected Python value-set with native C++ value-type 5.15	$21.5444s$	×2316

Table 5.1: Benchmarks of all our version of the stretch algorithm.

This benchmark shows that each time an abstraction layer is added on top of the baseline, the user must expect a 10× slowness factor in his code performance. Also, calling Python code is immensely slower (2300× !) than the baseline. This renew the interest there is to recompile the templated C++ library with an additional known type than injecting it from Python long time running code. Being able to inject Python code ease prototyping and increase the speed at which the user can write his code. However the benchmark shows that this is not a viable solution once the prototype needs to scale to a production environment.

5.3.2 Continuation: JIT-based solutions, pros. and cons.

Our hybrid solution certainly has advantages but the huge disadvantage is the slowness of injecting our own types from the Python side. There exists another solution that this thesis did not have the opportunity to study in-depth. This solution is based on a known technology: the Just-In-Time (JIT) compilation which has been previously illustrated in fig. 5.2. Indeed, it is a technology already used by interpreted languages such as Java or PHP to generate on-the-fly native and optimized machine code for the section of the source code that is considered "hot" by the interpreter. A source code is "hot" when it is executed a lot: the end-user would gain paying the compilation time once to have this code executed faster several times later on. When applying this strategy to our problematic, it would mean that the user must be able to compile native machine code from the templated generic C++ code by injected the requested type when it is used. Such an operation shift heavily the burden on the user and it is well-known that compiling C++ code is notably *complicated* and *slow*. In addition, the library needs to be able to auto-generate python-binding once the code is compiled. There are several solutions to achieve this process.

The first solution is to basically use system call to the compilers to actually *compile* C++ code once the templated types are known and explicitly instanciated in the source code. This solution requires careful code-generation design and that the user actually possess a compiler on his computer. Furtheremore, the user must resolve all the library dependencies, such as *freeimage* for IO etc. This solution was engineered in the library [88]. Indeed, each time the user declared a new automata in his jupyter notebook, corresponding source code is compiled in the foreground and then cached. It is a very perilous solution to implement when the final execution environment (OS, installed software) is not well-known in advance. Nowadays, the issue may be lesser, however, it still requires to maintain both the library and the container solution to use it.

The second solution is to use Cython [71]. It is a transpiling infrastructure which transform a Python source code directly into C-language source code so that it can be compiled by a standard C compiler just by linking against the Python/C API. This remove the burden of writting the careful code-generation routine, system-calls to the C++ compiler and removes the need to resolve all the dependencies. This infrastructure takes care of everything for the user. Also, by transpiling it into C code, it is faster because a C compiler is faster than a C++ compiler. Cython even support C++ template code [150] which is mandatory for our use-case.

The third solution consists in relying on recent projects that are all relying on the LLVM infrastructure. We can notably note Autowig [118], Cppyy [107] and Xeus-cling [147]. Autowig has in-house code based on LLVM/Clang to parse C++ code in order to generate and compile a Swig Python binding using the Mako templating engine. Autowig, coupled with Cython would permit the user to, for instance, generate C code related to a custom Python structure. Then a simple call to Autowig will parse the C code and inject it into the C++ library to generate the appropriate bindings for the user. As for Cppyy, it is based on LLVM/Cling, a C++ interpreter, and can directly interpret C++ code from a python string. This allow for easy injection of custom types, be they in Python code (transpiled with Cython) or C++ code (directly interpreted by Cling). Afterwards, the infrastructure generates the appropriate binding from the templated C++ library for the injected type. Finally, Xeus-cling is a ready-to-use jupyter kernel and allow the usage of C++ code directly from within a notebook. This completely bypass the need of a Python binding in the first place and allow the user to use the library from within the notebook as if he was using a Python library. However all those infrastructure come with a hefty cost in term of binary size. Indeed, a C++ compiler is not small and embarking it alongside the image processing library can easily impact greatly the final binary. Without the LLVM infrastructure the binary may weight around 3MB. With the LLVM infrastructure, the binary weight at the bare minimum 50MB. Also, these solutions may not be immediately faster. Indeed, when prototyping back and forth with a variety of types, the user may not be eager to wait for long compilations times each time he is testing with a an iteration of his work. Despite those facts, those solutions offers great avenue of research for the future and the author is eager to thread those paths.