First Time Experiences Using SciPy for Computer Vision Research

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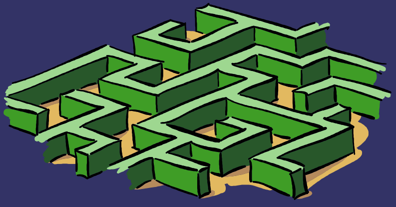
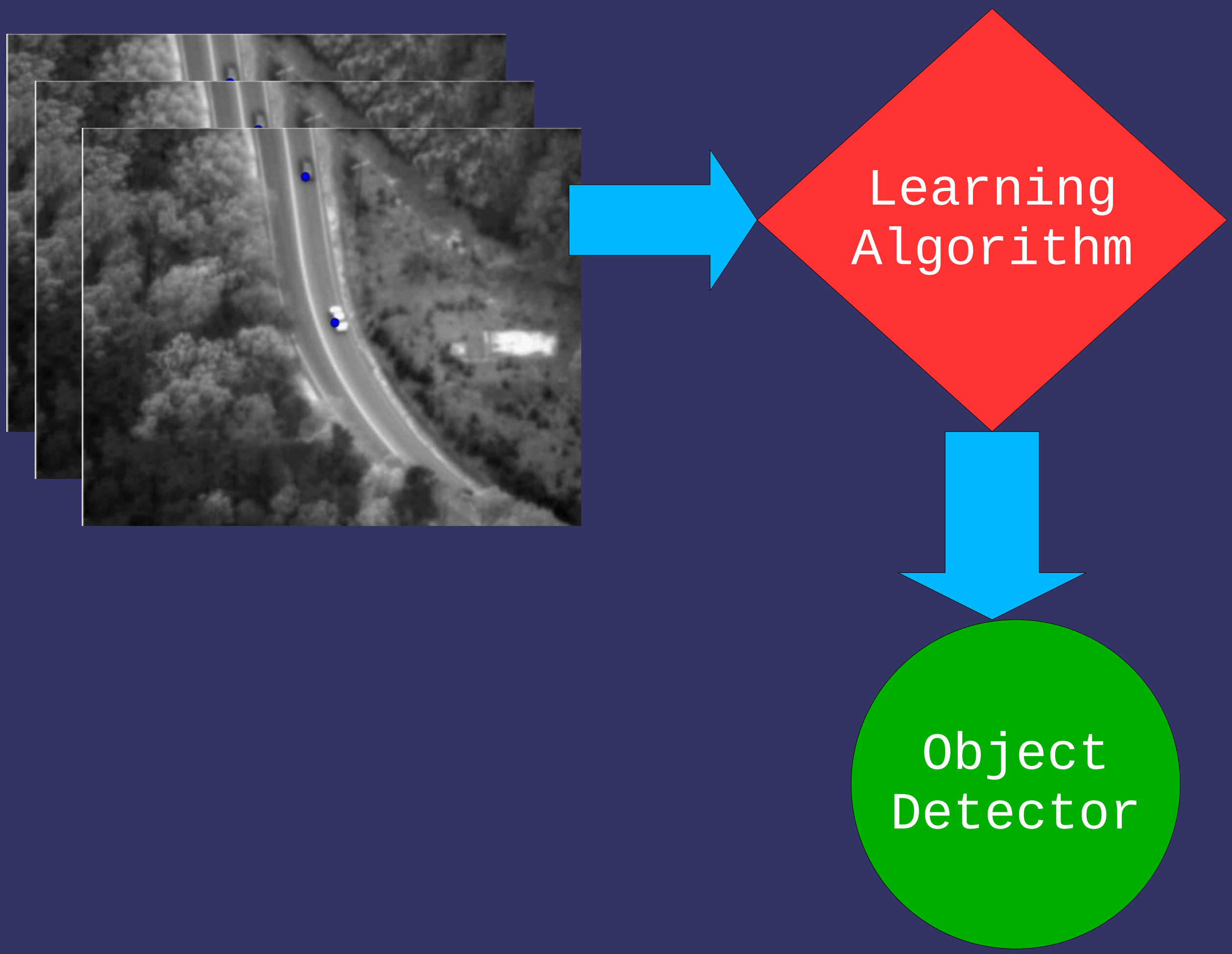


Research Problem

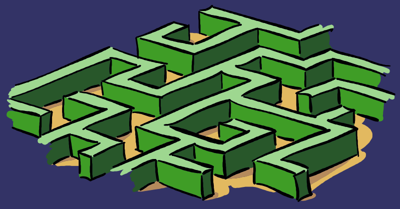
- Find the cars

Algorithm Workflow



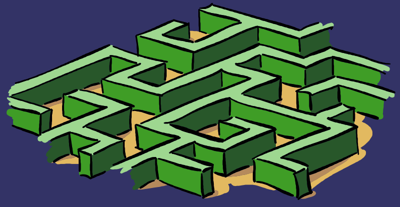
New Research Project

- New government research project in 2007
- Learn object detectors from example data
- Explore new algorithms
- Requirements: short deadlines, must work on Windows and Linux, algorithms exploration, and production system.
- Extensive knowhow with MATLAB and C++
- No experience with SciPy
- Chose Scipy: *risk*



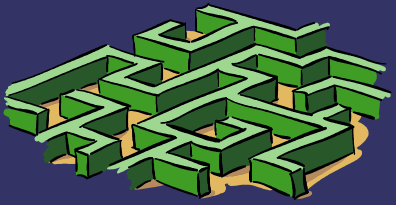
Postmortem

- SciPy: a superior choice
- nice learning curve: useful in a few hours
- effective for research and production codes
- universal language (Python)
- easy to rework prototypes into deployable applications



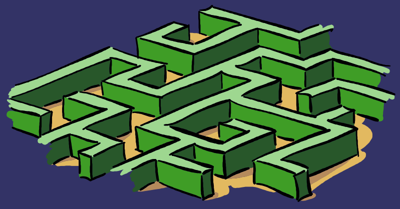
SciPy: good for prototyping

- Easy to vectorize
- Succinct syntax (thanks to Python's extensive support for operator overloading)
- Slicing with views: avoids copying!
- Unlike MATLAB, R and Octave: Python is a *universal language*
  - Separation of concerns:
    - **Python group**: the language
    - **SciPy group**: scientific codes
  - Larger corpora of libraries, more subcommunities: GUI, database, file unpacking, etc.



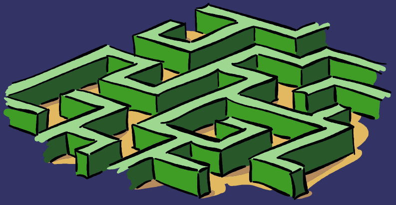
What this talk is about...

- Topic 1. Extensions
  - Have large data sets
  - Can't always vectorize
- Topic 2. C++
  - Lots of anti-C++ people
  - Static efficiency
  - How to interface?



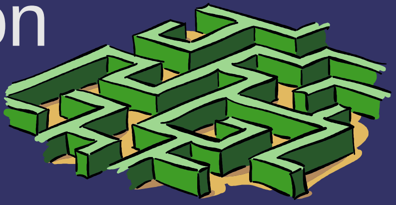
Why we need C++?

- A lot of Computer Vision code can't be vec-torized
  - Python “for” loops: cost prohibitive for very large data sets.
- C++:
  - “for” loops are efficient
  - lots of serial algorithms and data structures, e.g. sets, queues, heaps, multimaps, etc.
  - static efficiency
  - you can do more in-place



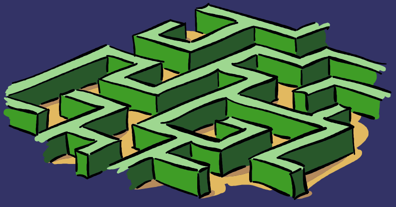
Computer Vision Codes

- large data sets and significant computation
  - efficiency is important
  - Avoid unnecessary duplication
    - Can slow things down,
    - Or hose you!
- used LIBCVD: a C++ library
  - Cambridge Video Dynamics Library
  - Frame-rate real time implementations of many computer vision algorithms
  - Essential for our work
  - Need to interface C++ library with Python



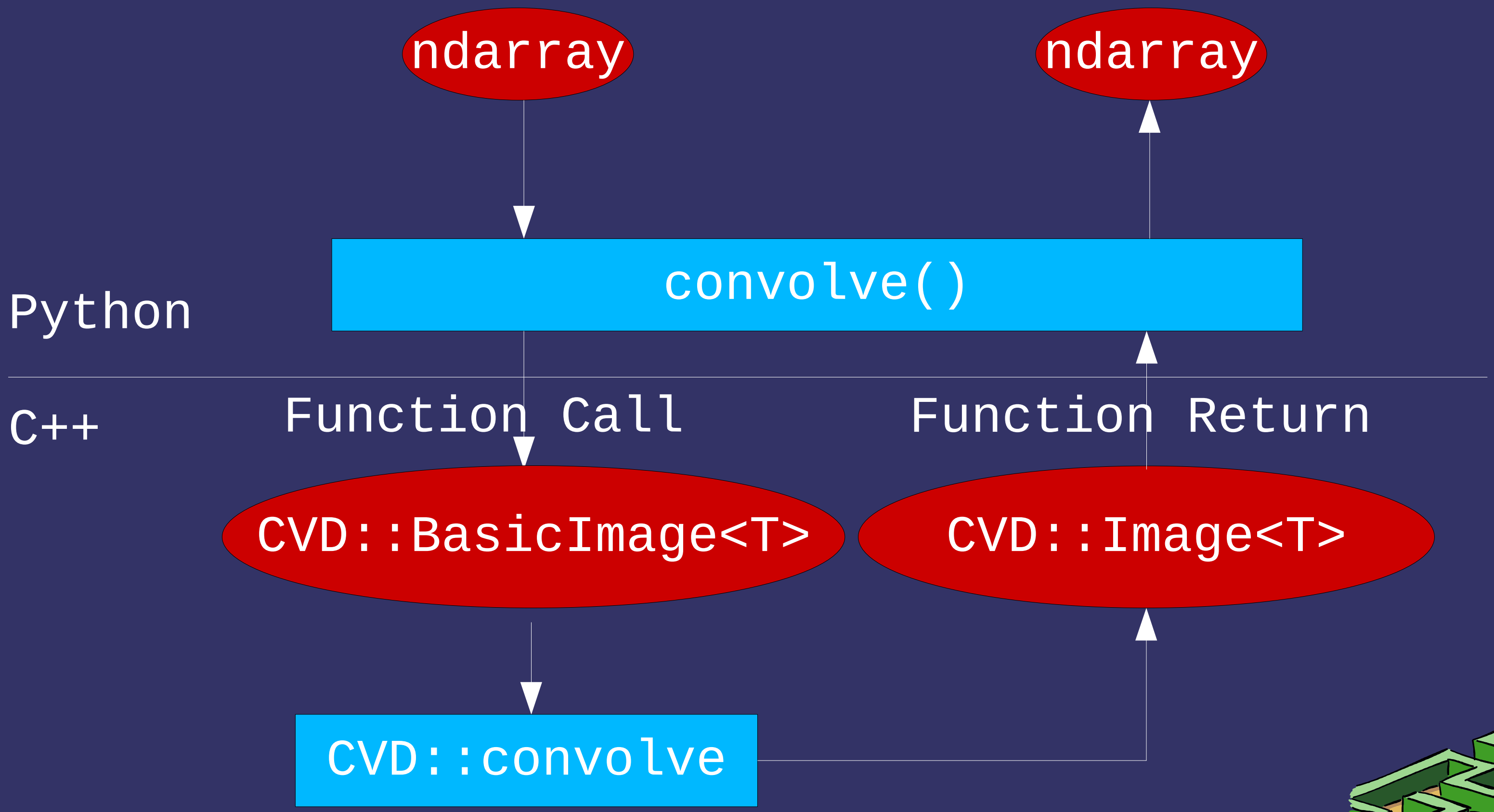
Basic LIBCVD Data Structures

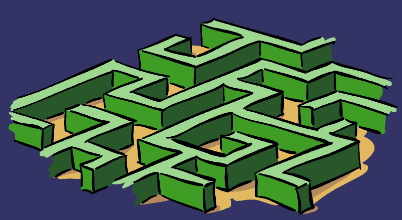
- BasicImage<T>: an image object that does not manage its memory
- Image<T>: a new image object whose memory is allocate when created
- SubImage<T>: region of an image
- ImageRef: coordinates in an image; has two members: x and y.



What we want?

- Call LIBCVD function, pass a numpy array and get back a numpy array.
- Hide the LIBCVD infrastructure!



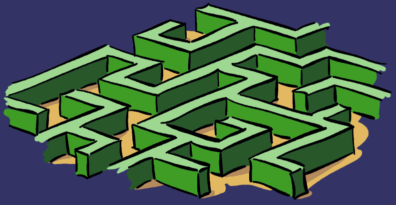


C++ and Python

- Semantic differences can be painful
  - Both want to manage their own memory
  - Example: when resizing an array, there is no way to tell Python to look at a different buffer
  - Fortunately, LIBCVD has numpy-like semantics
  - Can't always preallocate: size of the buffer might not be known *a priori*
- Hard to examine C++ data structures from Python, e.g. std::vector

ctypes

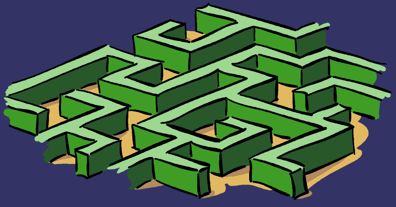
- Call functions by name from shared libraries
- *Distutils won't compile* shared libraries properly on windows and Mac OS X
- Does not understand C++ name mangling or template instantiation
  - Hard to translate C++ data structures into Python ones



ctypes

- C wrapper function. Can call it like a Python function with C-types.

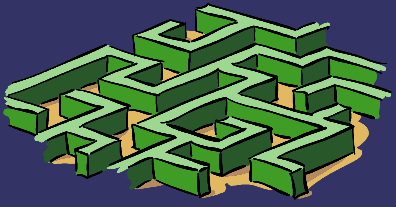
```
extern   C   int* wrap_find_objects(const float *image,
                                    int m, int n,
                                    int *size) {
    BasicImage <float> cpp(image, ImageRef(m, n));
    vector <ImageRef> cpp_refs;
    find_objects(cpp, cpp_refs);
    *size = cpp_refs.size();
    return convertToC(cpp_refs);
}
```



ctypes

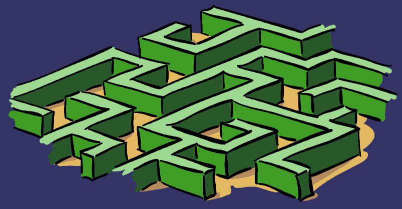
- Converts a C++ vector of (x,y) points to a C-array so it can be understood by c-types

```
int *convertToC(vector <ImageRef> &xy_pairs,
                int *num) {
  int *retval = new int[xy_pairs.size()*2];
  *num = xy_pairs.size();
  for (int i = 0; i < xy_pairs.size(); i++) {
    retval[i*2] = xy_pairs[i].x;
    retval[i*2+1] = xy_pairs[i].y;
  }
  return retval;
}
```



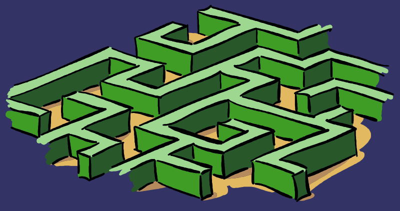
ctypes

- Type checking cannot always be done
  - can cause core dumps.
  - Python wrapper may be needed
- **three wrappers per C++ function!**
- **more wrappers to write, more bugs**
- ctypes inappropriate for our purposes!



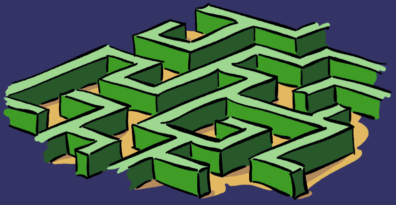
ctypes

- Appropriate for wrapping
  - numerical C codes where buffer sizes are known *a priori*
  - non-numerical C codes with simple interfaces
- Not appropriate for C++.



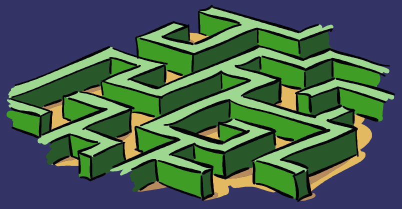
weave

- can write C++ and C programs in Python as multi-line strings!
- hashes C++ program strings to map to compiled code
- properly handles iteration over strided ar-rays
- *pseudo-templated*: changing types of input variables causes recompile



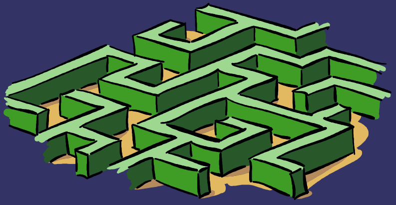
weave

- Pros
  - Great for prototyping “high risk” code
  - Seems to work on both platforms
- Cons
  - Compiler errors can be somewhat cryptic.
  - Code translation: somewhat opaque
  - Released binary requires compiler



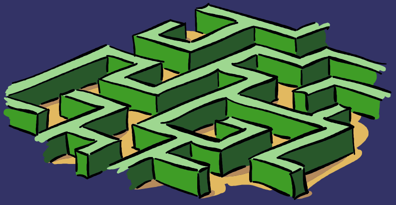
Boost::Python

- Large, powerful, and mature library for interfacing C++ code with Python.
- Steep learning curve: Large investment of time up-front
- Protection can be annoying
  - C++ objects are copied prior to being returned to Python space: avoid problems
  - Hard to avoid copying
  - Excessive copying: either quite costly or a show stopper!



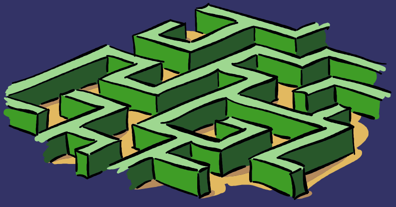
Python C Extensions (PythonExt)

- Eventually settled on PythonExt
- Conversion from Numpy to CVD and vice versa is easy: helper functions
- Error handling is easy!
  - Aggressive type checking with templated helpers
  - Throw exception
- Only a single wrapper function needed.
  - Wrapper in Python space was unnecessary
- Easy to parse complicated argument tuples!
- Great framework!



PythonExt

- Wrote suite of C++-templated helper functions
  - Numpy to C++/CVD
    - BasicImage <T> to_cvd<T>(PyObject *np)
    - void np_to_irvec<T>(PyArrayObject *obj, vector <ImageRef> &out)
  - C++/CVD to Numpy
    - PyArrayObject *from_cvd<T>(BasicImage <T> &img)
    - PyArrayObject *irvec_to_np<T>(vector <ImageRef> &points)

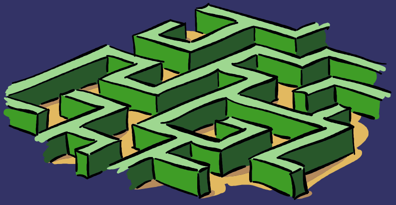


PythonExt: type checking

```
#define CODE(Type, PyType) \
template<> struct Code<Type>\
{\
   static const int   type = PyType;\
   static string name(){ return #Type;}\
   static char code(){ return PyType##LTR;}\
}
```

PythonExt: type checking

```
CODE(unsigned char , NPY_UBYTE );
CODE(char          , NPY_BYTE  );
CODE(short         , NPY_SHORT );
CODE(unsigned short, NPY_USHORT);
CODE(int           , NPY_INT   );
CODE(unsigned int  , NPY_UINT  );
CODE(float         , NPY_FLOAT );
CODE(double        , NPY_DOUBLE);
```

PythonExt: type checking

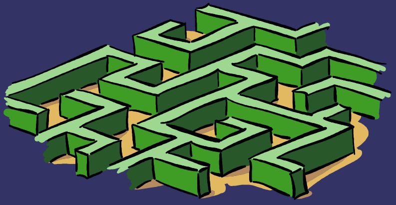
```
template<class I, class P> BasicImage<I>
pyobject_to_basic_image(P* p, const string& n="") {
  if (!PyArray_Check(p) || PyArray_NDIM(p) != 2
      || !PyArray_ISCONTIGUOUS(p)
      || PyArray_TYPE(p) != Code<I>::type)
   throw string(n + " must be a contiguous array of " +
   Code<I>::name() + " (type code " + Code<I>::code() +
   ")!");

  PyArrayObject* image = (PyArrayObject*)p;
  int sm = image->dimensions[1];
  int sn = image->dimensions[0];
  BasicImage <I> img((I*)image->data,
                         ImageRef(sm, sn));
  return img;
}
```

PythonExt: error checking

```
PyObject* wrapper(PyObject* self,
                  PyObject* args) {
  try {
    if(!PyArg_ParseTuple(...))
       return 0;

    //C++ code goes here.
  }
  catch(string err) {
    PyErr_SetString(PyExc_RuntimeError,
                    err.c_str());
    return 0;
  }
}
```

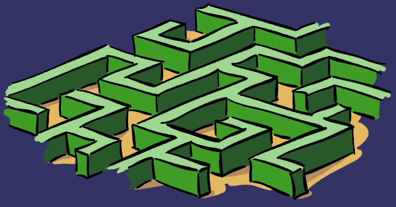
Type Generality: no if statements!

```
struct End{};

template<class C, class D> struct TypeList
{
  typedef C type;
  typedef D next;
};

typedef TypeList<char,
        TypeList<unsigned char,
        TypeList<short,
        TypeList<unsigned short,
        TypeList<int,
        TypeList<unsigned int,
        TypeList<float,
        TypeList<double, End> > > > > > > > CVDTypes;
```



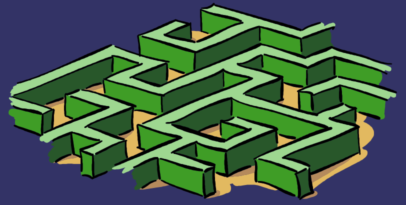
Type Generality: no if statements!

```
template<class List> struct load_image_by_type_letter
{
  static PyObject* load(const string& fname, char
   type_letter)
  {
    typedef typename List::type type;
    typedef typename List::next next;

    if(type_letter == Code<type>::code())
        return image_load_by_type<type>(fname);
    else
        return load_image_by_type_letter<next>::load(fname,
   type_letter);
  }
};
```



Type Generality: no if statements!

```
template<> struct load_image_by_type_letter<End>
{
  static PyObject* load(const string& fname,
                        char type_letter) {
    char L[2] = {type_letter, 0};
    throw string("Can't load image in to unknown type: ")+L;
  }
};
```

C++ Extensions

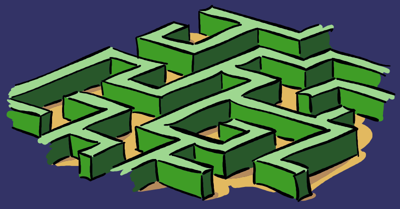
- ctypes
  - Three wrappers needed per function
  - Bug prone
  - Conversion code messy
- Boost::Python
  - Object lifetime issues
- PythonExt
  - templated greatness: type checking, type generality, clean conversion functions
  - easy error handling: throw an exception, catch in one place
  - is around to stay!

Comparison with mex

- separate source file for each function!
- No `PyArg_ParseTuple` or equivalent
- Opening mex with gdb
  - Cumbersome
  - Difficult to pin down segmentation faults
- Lacks succinctness and expressibility
  - Temptations to copy code: leads to bugs

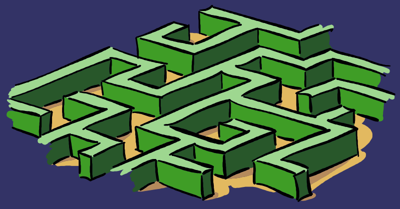
Windows Version

- Use Linux or Mac OS X whenever possible
  - Windows: not the best scientific computing OS
- Memory manager is *wimpy*
  - Allocation of large buffers: very problematic
  - Not aggressive about cleaning up data
- *Processing* does not work as well
  - Memory leaks
- Hard to get optimizations right
  - Core dumps optimized code requiring aligned memory – not a problem on linux
- Nice installers with *distutils*



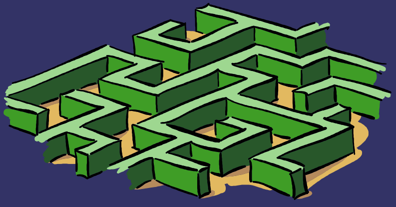
MATLAB

- MATLAB
  - object-oriented infrastructure
    - objects are immutable
    - one directory per class
    - one file per method
  - Pass-by-value: global variables
  - Not really good for production systems
  - Richer data structures often encoded with matrix
    - graphs
    - trees



Python: Production Capable

- Can code richer data structures
  - Graphs, trees, lists
- Good for organizing larger code bases
  - production systems
- Universal language
  - Lots of GUI toolkits, networking libraries, database suites, etc.
- MATLAB-like: simple calling conventions



Conclusion

- SciPy
  - A good choice!
  - Easy to implement extensions to handle large data sets
  - Python provides a nice extension framework
  - C++ templated helpers and exceptions do the job!
  - Easy to write prototype code in Python+Weave
  - Universality and Separation of Concerns
    - Lots of libraries out there when your app becomes more sophisticated!
    - Good quality code!