Lightweight, low-overhead, high-performance: machine learning directly in C++

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Atlanta, GA
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Geographical Origin: *Atlanta*

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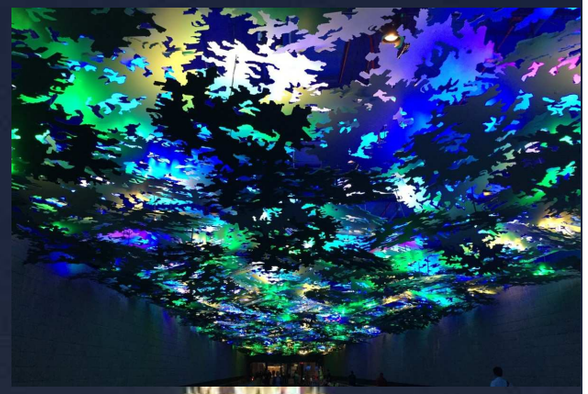
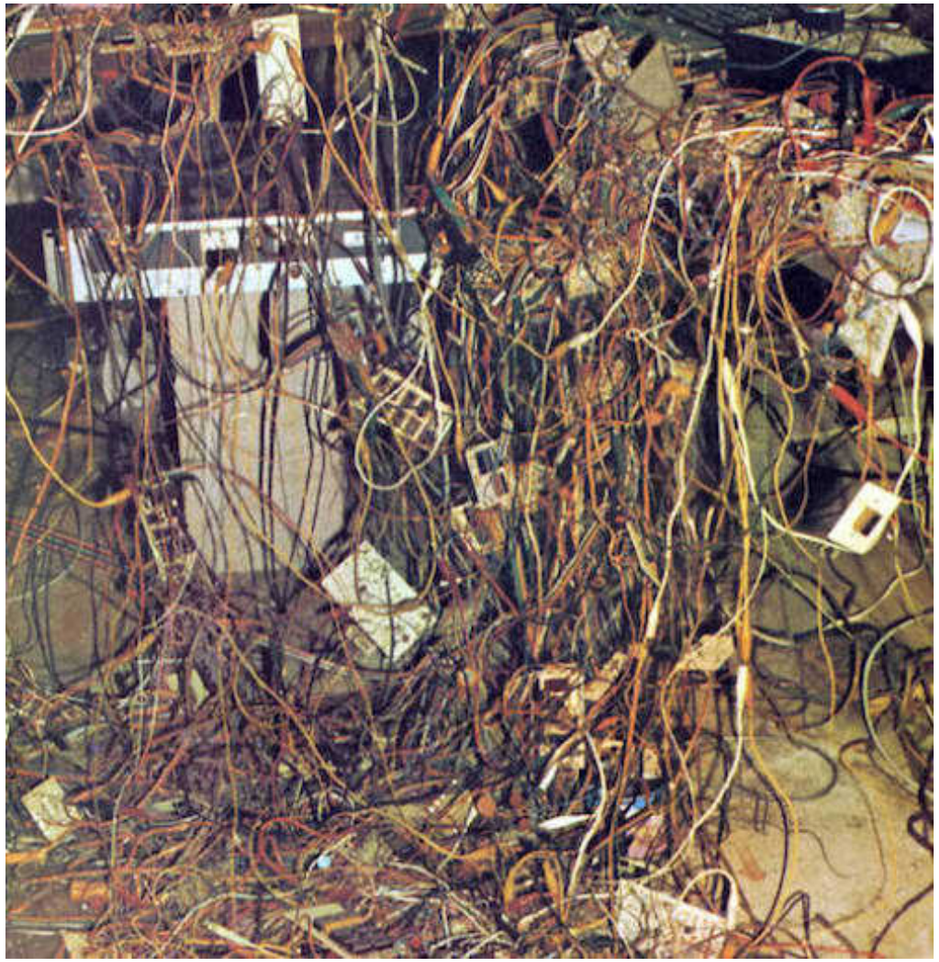


Atlanta quick tips:

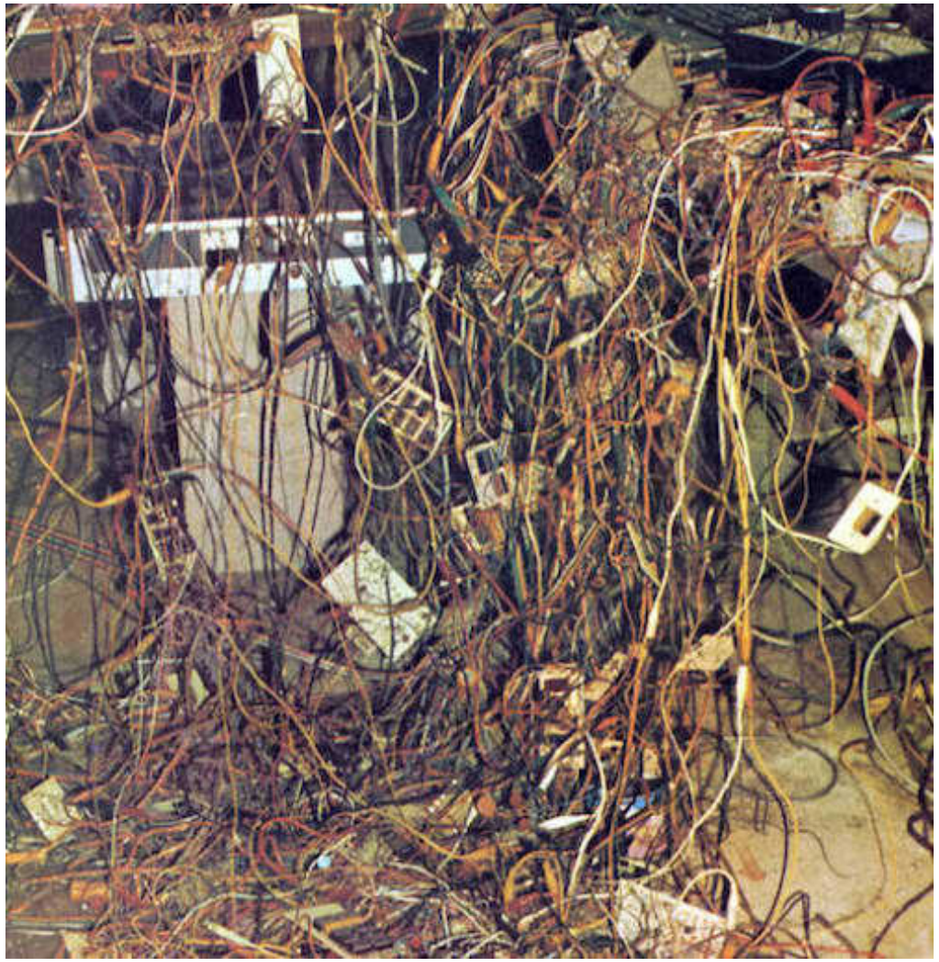
- Use the Plane Train unless traveling between concourses A and B
- Be hungry
- Do not go to the Varsity
- Check out the Laser Light Show at Stone Mountain and bring lots of cheap beer

The Problem



Typical machine learning deployment

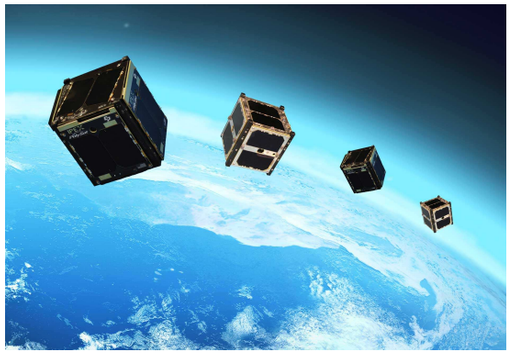
The Problem

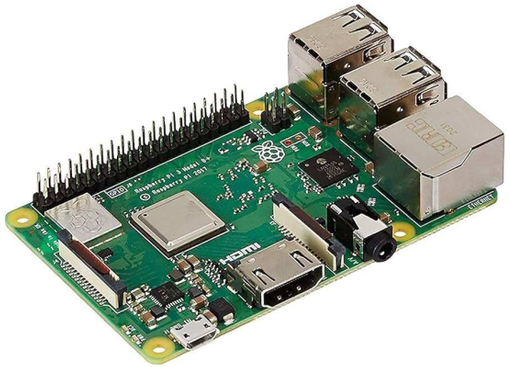


Typical machine learning deployment

$\sim$**60** packages needed for a basic miniconda scikit-learn or TensorFlow environment...

Size Is Not Always Cheap





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A Collection Of Hellos World

C++:

```cpp
#include <cstdio>

int main() { printf("Hello world!\n"); }
```

Python:

```python
print("Hello world!")
```

R/Julia:

```
print("Hello world!")
```

Scala:

```
object hello {
  def main(args: Array[String]) = {
    println("Hello world!")
  }
}
```

How big is your Hello World?

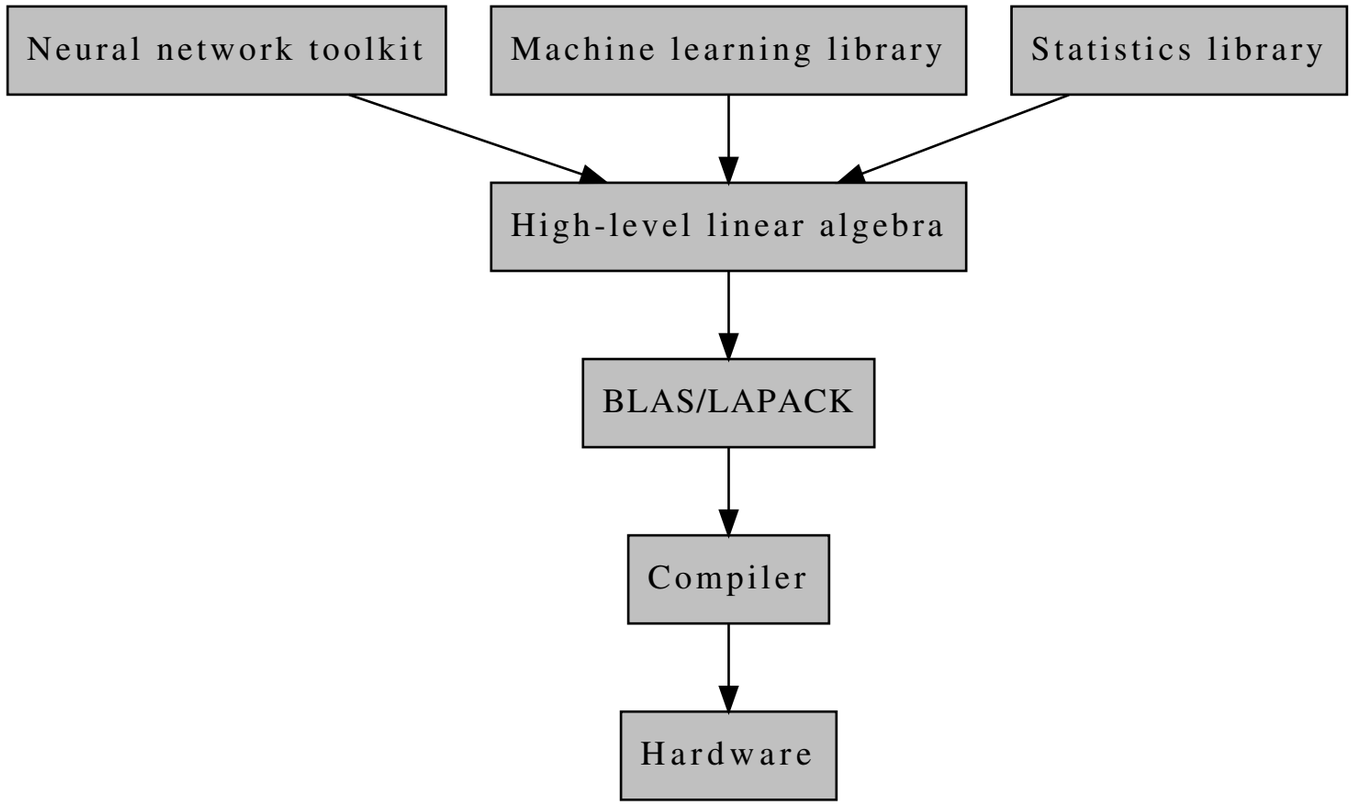
Containers only contain hello world script and minimal environment needed to run.

```
$ docker images
REPOSITORY                  TAG       IMAGE ID       CREATED          SIZE
hello_world_r               latest    ee64478b9235   35 seconds ago   811MB
hello_world_scala           latest    53fc54fa84a9   3 minutes ago    751MB
hello_world_jl_alpine       latest    15aecf1e9146   14 minutes ago   535MB
hello_world_jl_full         latest    eaca21a0a0e0   14 minutes ago   606MB
hello_world_py_full         latest    090088f4972d   16 minutes ago   1.02GB
hello_world_py_slim         latest    cfdbf9ffce45   17 minutes ago   130MB
hello_world_py_alpine       latest    a0ffd6653f17   18 minutes ago   51.8MB
hello_world_cpp             latest    6ebe01398789   22 minutes ago   7.71MB
hello_world_cpp_distroless  latest    32ae3c33e2f2   25 minutes ago   2.7MB
```

Built using base containers: `r-base`, `openjdk:22-slim`, `julia:1`, `julia:1-alpine`, `python:3-full`, `python:3-slim`, `python:3-alpine`, `alpine`, `distroless/static-debian11`.

More size optimization possible for C++, I didn't try too hard...

The machine learning stack



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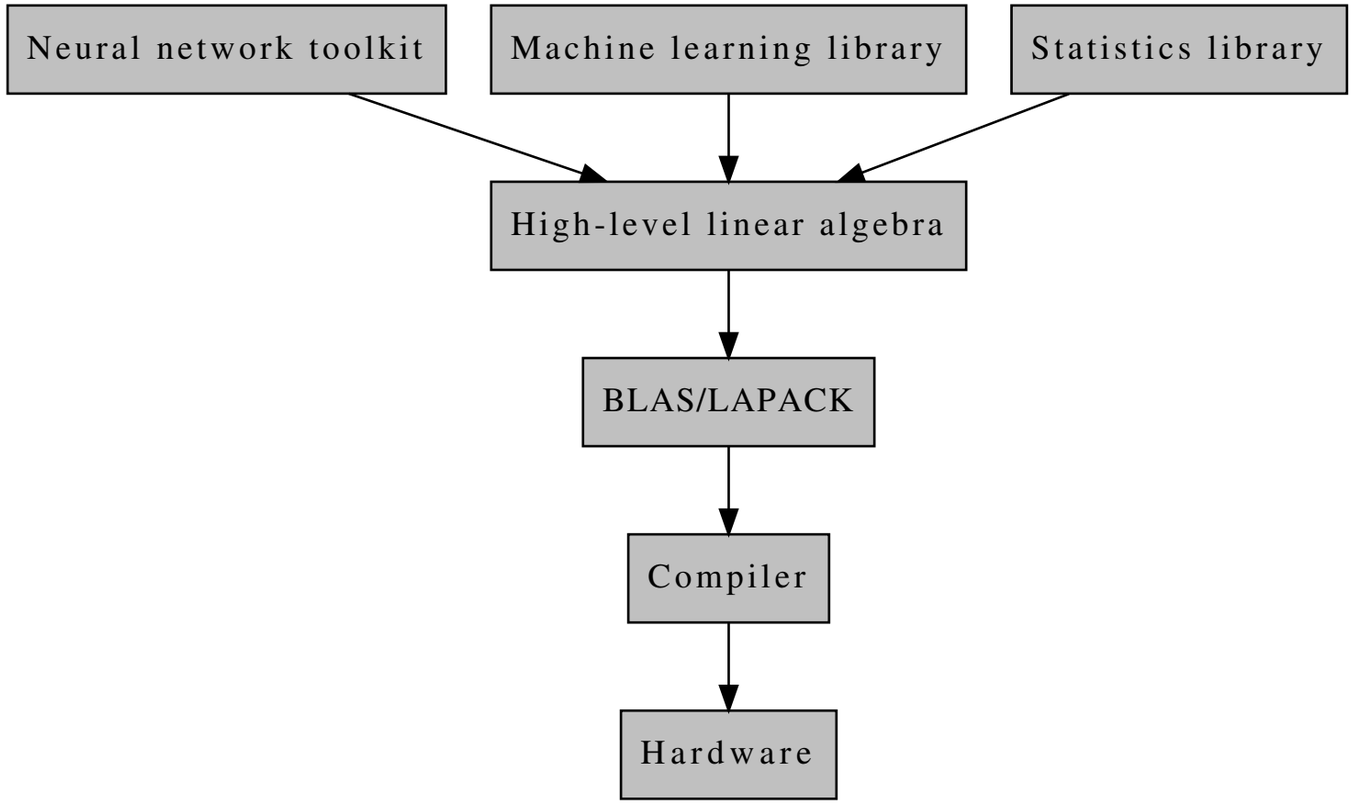

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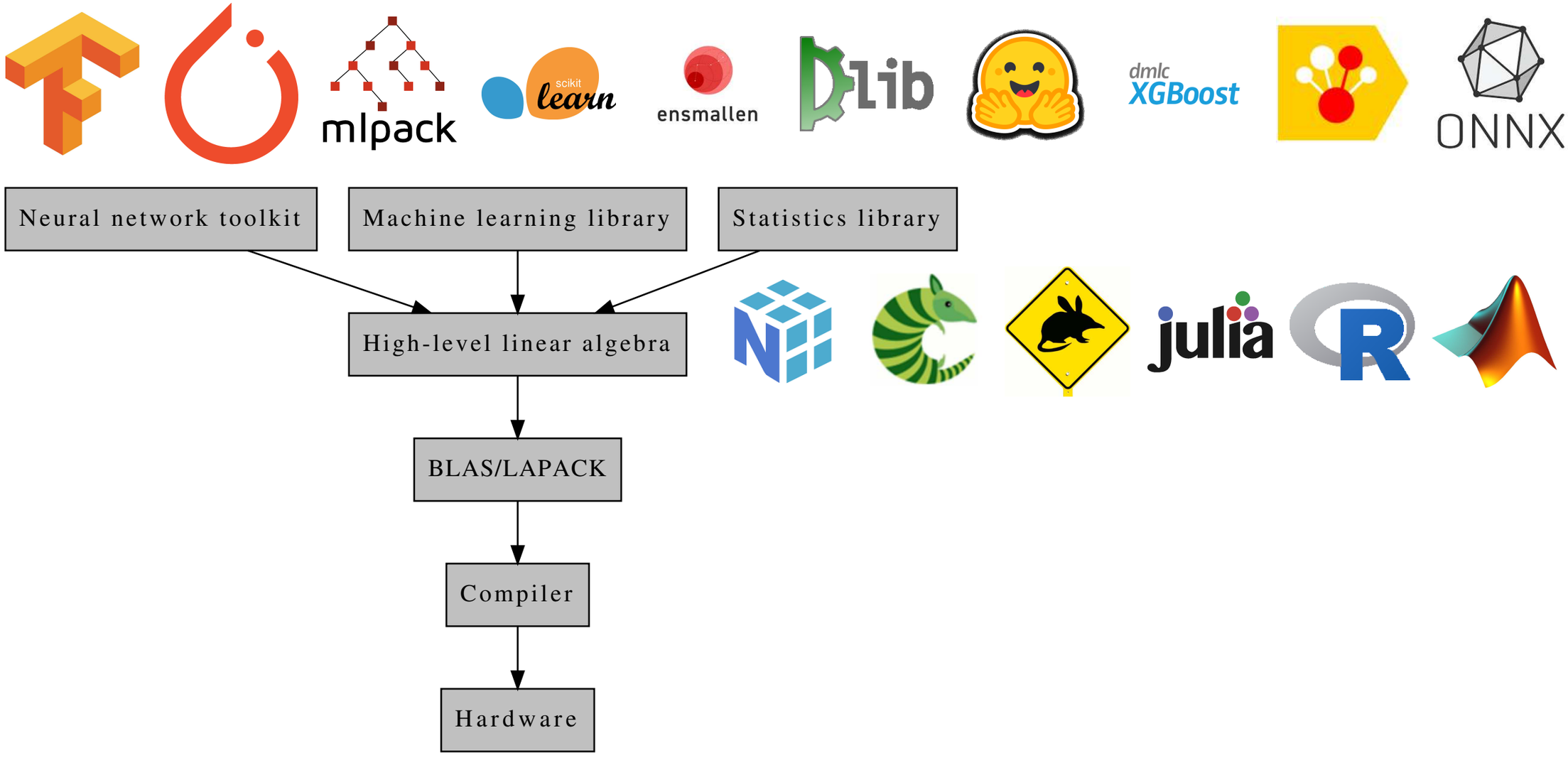

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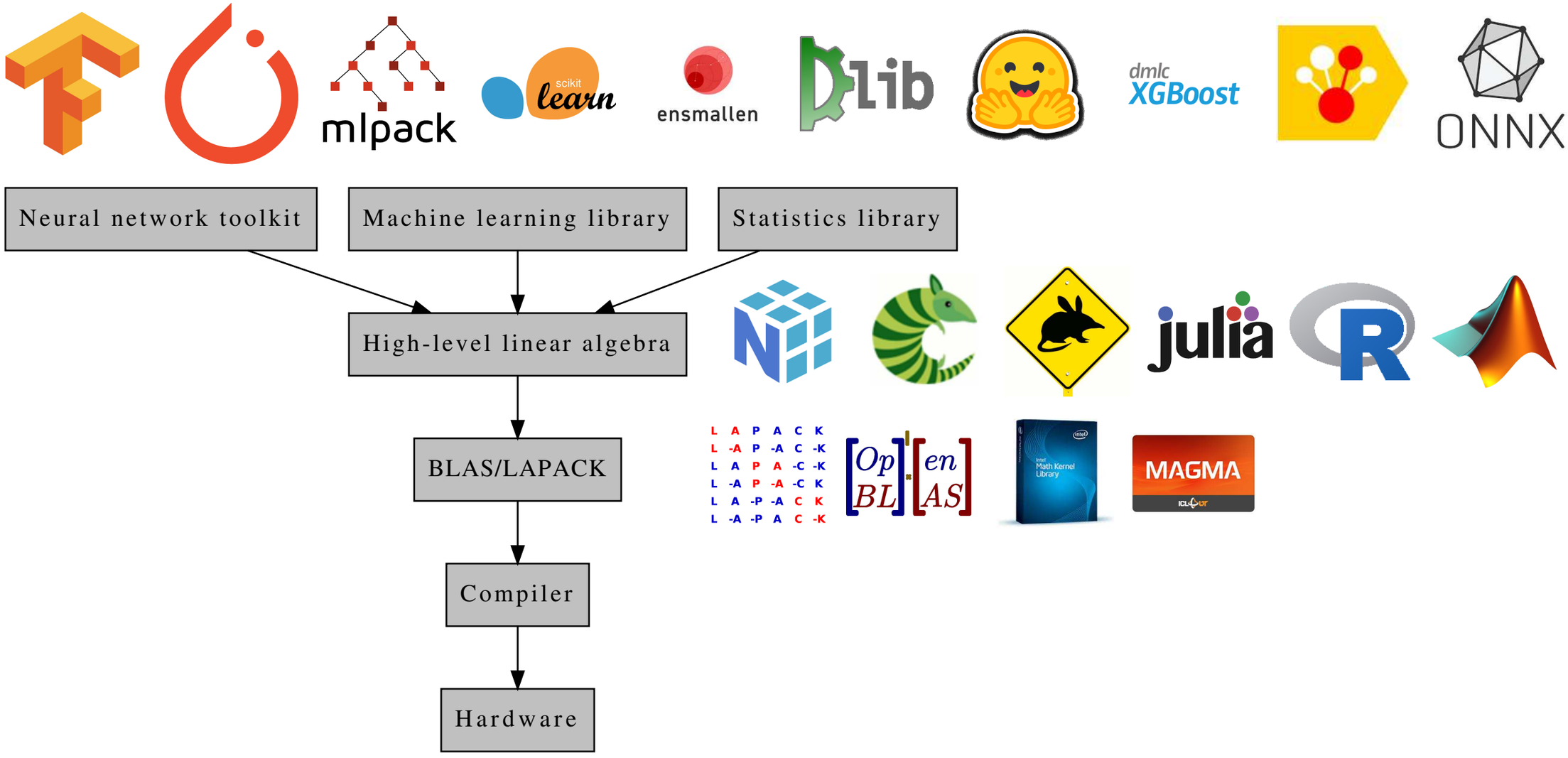

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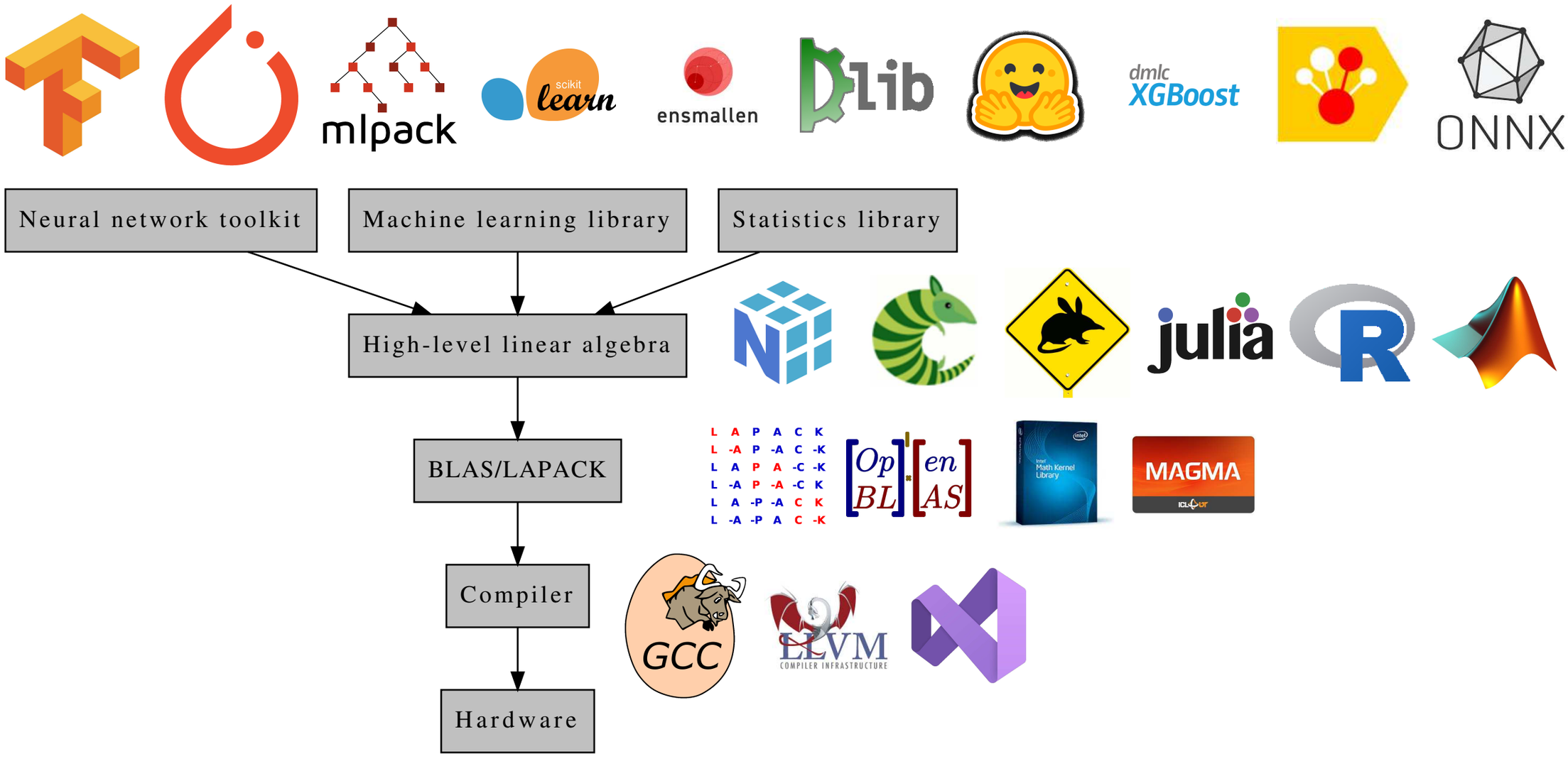

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Pros of C++:

- No runtime other than what the system already has

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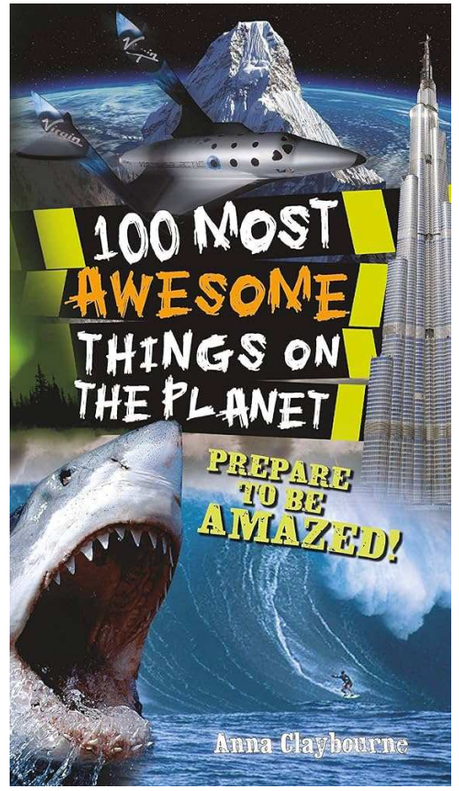

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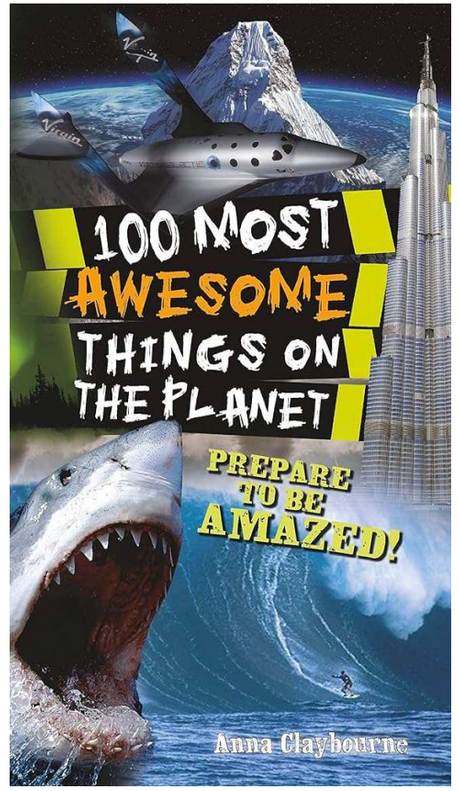

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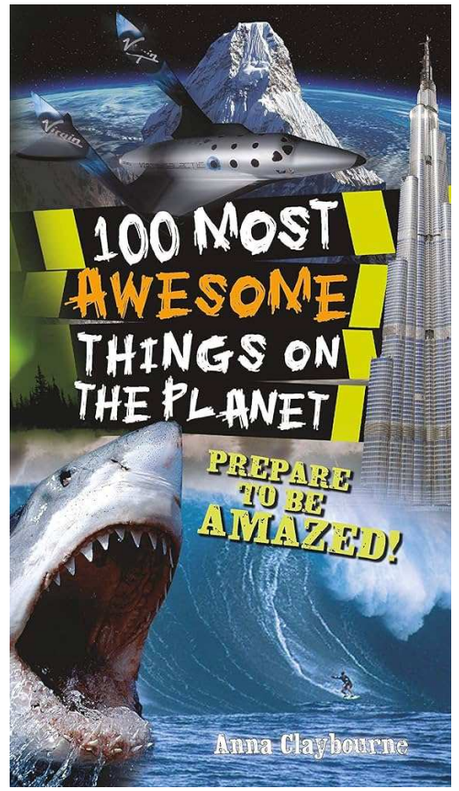

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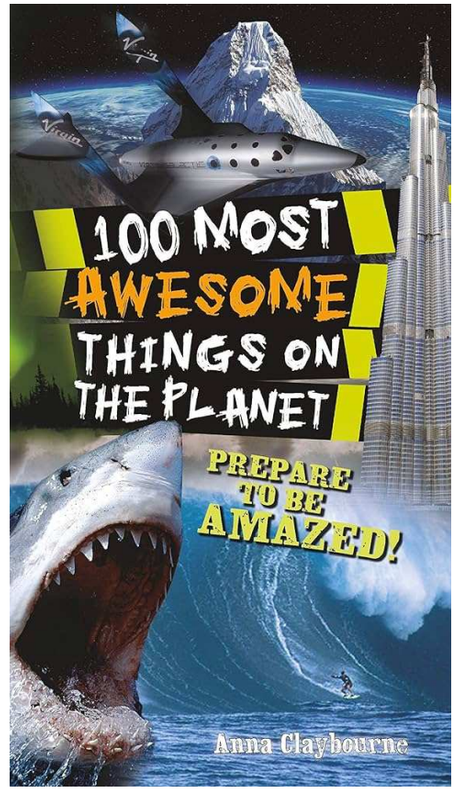
- Low-level memory management for fine-grained control
- Readily runs on all reasonable modern systems
- Fast! Small!



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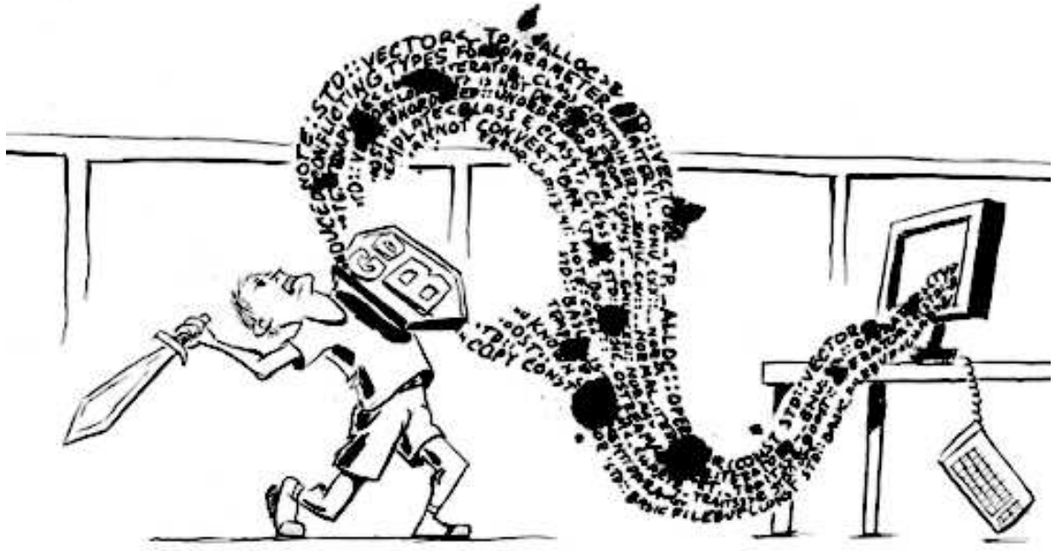

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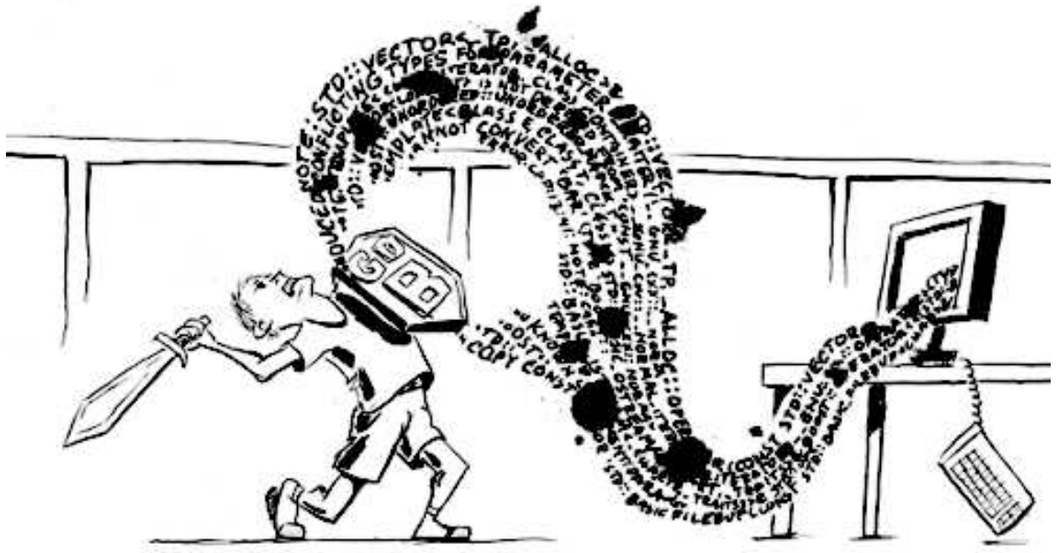

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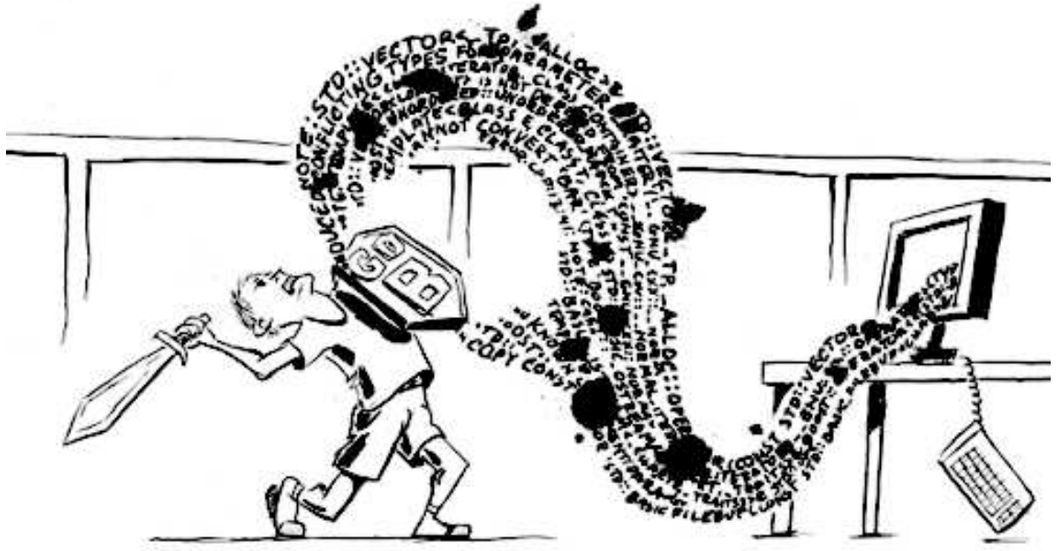

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- Memory bugs are easy to introduce.
- The new language revisions are not making the language any simpler...

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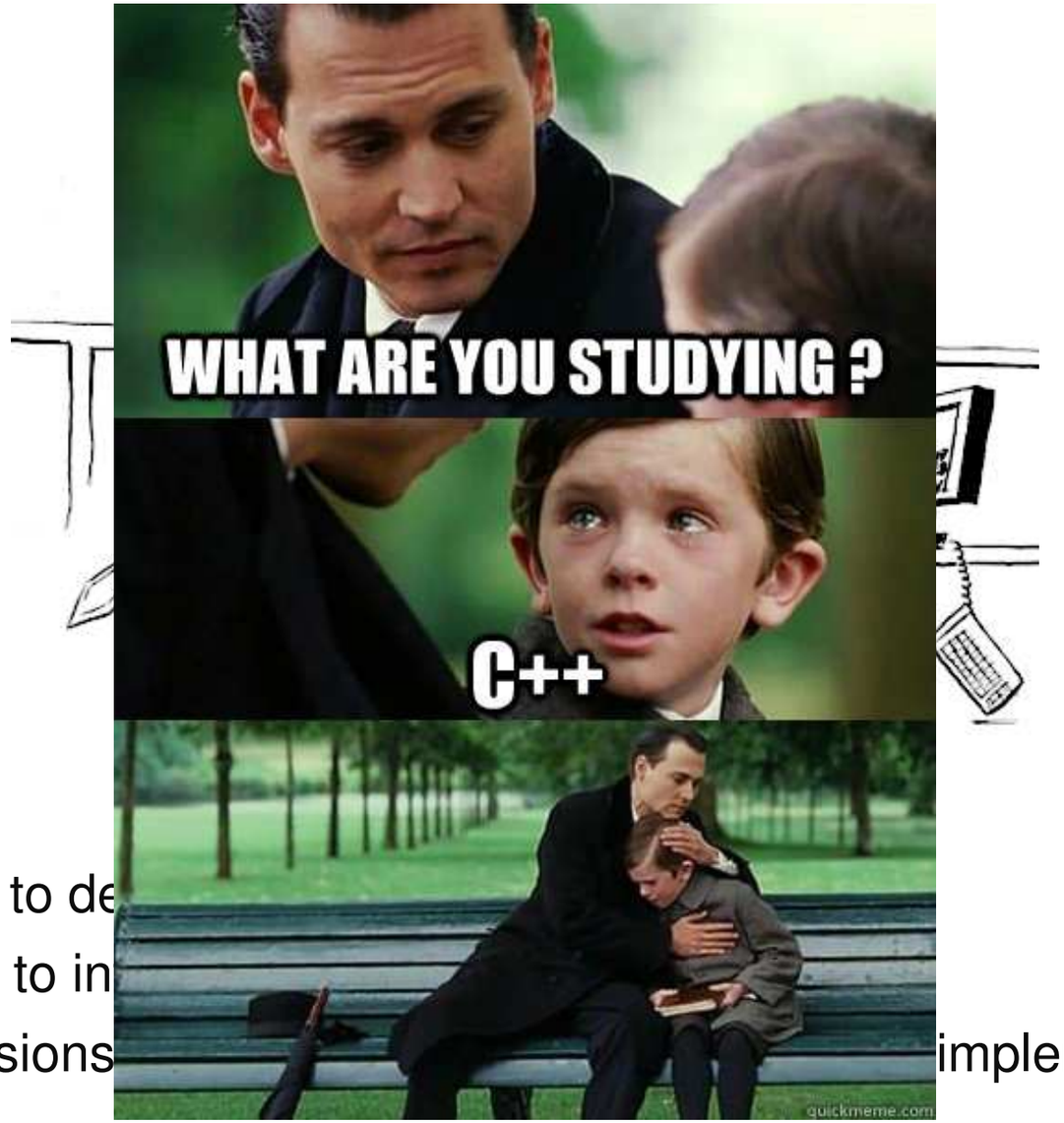

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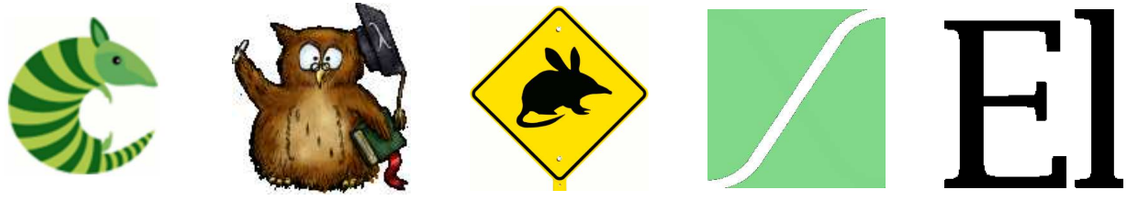
The C++ data science ecosystem



- **Linear algebra**: Armadillo, Eigen, Bandicoot (GPU), XTensor, `std::mdspan`, GGML...

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The Armadillo library gives us good linear algebra primitives:

```
using namespace arma;
mat x(100, 100, fill::randu);
mat y(100, 100, fill::randn);
mat z = (x + y) * chol(x) + 3 * chol(y.t());
```

The C++ data science ecosystem





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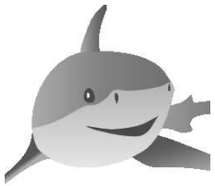


- **Machine learning**: mlpack, ensmallen, dlib-ml, PyTorch, XGBoost, LIBLINEAR, Shark, Shogun, darknet, `llama.cpp`, Vowpal Wabbit, TensorFlow, OpenCV, Catboost...

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- **Linear algebra**: Armadillo, Eigen, Bandicoot (GPU), XTensor, `std::mdspan`, GGML...

- **Machine learning**: mlpack, ensmallen, dlib-ml, PyTorch, XGBoost, LIBLINEAR, Shark, Shogun, darknet, `llama.cpp`, Vowpal Wabbit, TensorFlow, OpenCV, Catboost...
- **More**: `xeus-cling`, Jupyter, `xplot`, `xframe`, support libraries for whatever else...

Quick Linear Algebra Benchmark #1

Task 1: $z = 2(x' + y) + 2(x + y')$.

```
extern int n;
mat x(n, n, fill::randu);
mat y(n, n, fill::randu);
mat z = 2 * (x.t() + y) + 2 * (x + y.t()); // only time this line
```

n	**arma**	**numpy**	**octave**	**R**	**Julia**
1000	0.029s	0.040s	0.036s	0.052s	**0.027s**
3000	0.047s	0.432s	0.376s	0.344s	**0.041s**
10000	**0.968s**	5.948s	3.989s	4.952s	3.683s
30000	**19.167s**	62.748s	41.356s	*fail*	36.730s

Quick Linear Algebra Benchmark #2

Task 2: $z = a'(\mathrm{diag}(b)^{-1})c$.

```
extern int n;
vec a(n, fill::randu);
vec b(n, fill::randu);
vec c(n, fill::randu);
double z = as_scalar(a.t() * inv(diagmat(b)) * c); // only time this line
```

n	**arma**	**numpy**	**octave**	**R**	**Julia**
1k	**8e-6s**	0.100s	2e-4s	0.014s	0.057s
10k	**8e-5s**	49.399s	4e-4s	0.208s	18.189s
100k	**8e-4s**	*fail*	0.002s	*fail*	*fail*
1M	0.009s	*fail*	0.024s	*fail*	*fail*
10M	0.088s	*fail*	0.205s	*fail*	*fail*
100M	0.793s	*fail*	1.972s	*fail*	*fail*
1B	8.054s	*fail*	19.520s	*fail*	*fail*

Two Points (That I Hope To Convince You Of)

1. **It isn’t ugly.** It’s easy to write and read and maintain.

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1. **It isn't ugly.** It's easy to write and read and maintain.

2. **The code is deployable** and you can compile it to be really small. *No bloat.*

a more organized machine learning deployment

Language Detection: A Simple Model

- **Input:** user gives a string

  `“Ihr Spracherkennungsmodell ist sehr schlecht.”`

- **And then:** magic occurs

- **Output:** user receives a language

  `“de”`

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  Use machine learning model to predict language (as a number)

  Turn number into language

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Language Detection: A Simple Model

- **Input:** user gives a string

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- **And then:**

  Convert string into numbers; features:

  256 byte counts

  768 of the most common 2-byte sequences in the training data

  Normalize resulting 1024-dimensional vector

  Use machine learning model to predict language (as a number)

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  Number of classes = number of languages

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  Turn number into language

  Map class id back into name of language

- **Output:** user receives a language

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n-gram computation code (or a simplification)

```
void ComputeNGrams(const vector<string>& stringData, mat& ngrams)
{
  // Resize the matrix to the right size.
  // This uses 256 dimensions for the single-byte features.
  // Armadillo and mlpack use column-major data, so each string is a *column*.
  ngrams.zeros(256, stringData.size());
  for (size_t i = 0; i < stringData.size(); ++i)
  {
    for (size_t j = 0; j < stringData[i].size(); ++j)
    {
      // Add one to the count of times we've seen this byte.
      ++ngrams((unsigned char) stringData[i][j], i);
    }

    // Now normalize.  (Important since not all strings are the same length.)
    ngrams.col(i) /= accu(ngrams.col(i));
  }
}
```

NGramLangDetectModel

```
class NGramLangDetectModel
{
 public:
  // Train the model on the given data.
  void Train(const vector<string>& data, const vector<string>& labels,
             const size_t bigramsToKeep = 768);

  // Classify a single string, or a set of strings.
  string Classify(const string& point) const;
  void Classify(const vector<string>& data, vector<string>& predictions) const;

  // Serialize the model to/from disk.
  template<typename Archive> void serialize(Archive& ar, const unsigned int /* version */);

 private:
  // The actual trained model.
  mlpack::SoftmaxRegression model;
  // The set of 2-byte sequences we are using as features.
  unordered_map<uint16_t, size_t> bigramDimensionMap;
  // The names of each class.
  vector<string> classNames;
};
```

Train()

```
void NGramLangDetectModel::Train(const vector<string>& data, const vector<string>& labels,
                                 const size_t bigramsToKeep)
{
  // Convert data to numeric data via n-gramming.
  mat trainData;
  ComputeNGrams(data, bigramDimensionMap, trainData, bigramsToKeep);
  // Convert labels to numeric data.  We also have to keep track of the class names.
  Row<size_t> trainLabels(trainData.n_cols);
  unordered_map<string, size_t> classMappings; // Stores language -> class index mappings.
  for (size_t i = 0; i < labels.size(); ++i)
  {
    // If we haven't seen this label before, assign the next index to this label.
    if (classMappings.count(labels[i]) == 0)
    {
      classMappings[labels[i]] = classMappings.size();
      classNames.push_back(labels[i]); // Add the label to the list of class labels.
    }
    trainLabels[i] = classMappings[labels[i]];
  }

  // Train the model.  It would be possible to set some hyperparameters here.
  model = mlpack::SoftmaxRegression(trainData, labels, classNames.size());
}
```

Classify()

```
// Predict the class of one string.
string NGramLangDetectModel::Classify(const string& point) const
{
  vec processedPoint;
  ComputeNGrams(point, processedPoint, bigramDimensionMap); // Turn string into numeric features.
  const size_t classIndex = model.Classify(processedPoint); // Use model to classify.
  return classNames[classIndex];
}

// Predict the class of a set of strings.
void NGramLangDetectModel::Classify(const vector<string>& data, vector<string>& predictions) const
{
  mat points;
  ComputeNGrams(data, points, bigramDimensionMap); // Turn strings into numeric features.
  Row<size_t> predictedClasses;
  model.Classify(points, predictedClasses); // Stores output class IDs in ‘predictedClasses‘.

  // Turn predictions back into string classes.
  predictions.clear();
  for (size_t i = 0; i < predictedClasses.n_elem; ++i)
    predictions.push_back(classNames[predictedClasses[i]]);
}
```

`serialize()` via Cereal

```
// This function is used by Cereal to save/load the model.
// We just serialize each of the members to ‘ar‘.
template<typename Archive>
void NGramLangDetectModel::serialize(Archive& ar, const unsigned int version /* unused */)
{
  ar(CEREAL_NVP(model));
  ar(CEREAL_NVP(bigramDimensionMap));
  ar(CEREAL_NVP(classNames));
}
```

Training program

```
#include <mlpack.hpp>
#include "ngram_langdetect_model.hpp"

using namespace std; using namespace arma; using namespace mlpack;

int main(int argc, char** argv)
{
  // blah blah blah, parse input options, load data, train/test split...

  NGramLangDetectModel m; // Create and train the model.
  m.Train(trainData, trainLabels, bigramsToKeep);

  // Now compute training and test accuracies.
  Row<size_t> trainPredictions, testPredictions;
  m.Classify(trainData, trainPredictions);
  m.Classify(testData, testPredictions);
  double trainAccuracy = 100.0 * ((double) accu(trainPredictions == trainLabels)) / trainLabels.n_elem;
  double testAccuracy = 100.0 * ((double) accu(testPredictions == testLabels)) / testLabels.n_elem;
  cout << "Training set accuracy: " << trainAccuracy << "\%." << endl;
  cout << "Test set accuracy:     " << testAccuracy << "\%." << endl;

  data::Save(modelFile, "model", m, true /* fatal on failure */);
}
```

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  double testAccuracy = 100.0 * ((double) accu(testPredictions == testLabels)) / testLabels.n_elem;
  cout << "Training set accuracy: " << trainAccuracy << "\%." << endl;
  cout << "Test set accuracy:     " << testAccuracy << "\%." << endl;

  data::Save(modelFile, "model", m, true /* fatal on failure */);
}
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Compilation is trivial:

```
$ g++ -O3 -o ngram_langdetect_train ngram_langdetect_train.cpp -larmadillo
```

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  NGram
  m.Tra

  // No
  Row<s
  m.Cla
  m.Classify(testData, testPredictions);
  double trainAccuracy = 100.0 * ((double) accu(trainPredictions == trainLabels)) / trainLabels.n_elem;
  double testAccuracy = 100.0 * ((double) accu(testPredictions == testLabels)) / testLabels.n_elem;
  cout << "Training set accuracy: " << trainAccuracy << "\%." << endl;
  cout << "Test set accuracy:     " << testAccuracy << "\%." << endl;

  data::Save(modelFile, "model", m, true /* fatal on failure */);
}
```

Then run it:

```
$ ./ngram_langdetect_train all_lang_data.csv all_lang_data.labels.csv
    all_lang_data_model.bin
Training set accuracy: 96.4473%.
Test set accuracy:     96.3722%.
```

Classification program

```
#include <mlpack.hpp>
#include "ngram_langdetect_model.hpp"

using namespace std; using namespace arma; using namespace mlpack;

int main(int argc, char** argv)
{
  // The first argument must be the model file.  (Error checking removed for slides...)
  NGramLangDetectModel m;
  data::Load(string(argv[1]), "model", m, true /* fatal */);

  while(true)
  {
    string line;
    getline(cin, line);
    if (cin.eof())
      return 0;

    // Classify the point and print the predicted language.
    cout << m.Classify(line) << endl;
  }
}
```

Demo time

This will never work!

Container size initial results

```
$ docker images
REPOSITORY                  TAG                 IMAGE ID            CREATED                  SIZE
langdetect_pytorch          latest              5b20c970aac9        39 seconds ago           6.48GB
langdetect_py_full          latest              2591cd3cc86d        34 minutes ago           1.28GB
langdetect_py_slim          latest              308af891fc36        5 minutes ago            394MB
langdetect_py_alpine        latest              4534971adb18        About a minute ago       327MB
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```

Compilation reformation

- When we link dynamically against OpenBLAS, we have to keep every single OpenBLAS symbol... most of which we don’t use.
- So we should link statically, and pass a number of options to gcc to strip unneeded code.

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```
g++ -Os -DNDEBUG -DARMA_DONT_USE_WRAPPER -DARMA_NO_DEBUG -fopenmp \
    -fdata-sections -ffunction-sections -fwhole-program \
    -fvisibility=hidden -fvisibility-inlines-hidden \
    -static-libgcc \
    -static-libstdc++ \
    ngram_langdetect_run.cpp -o ngram_langdetect_run \
    -Wl,-Bstatic -lopenblas \
    -Wl,--as-needed -Wl,--gc-sections -flto
```

More container size results

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langdetect_cpp_dynamic      latest              76c949b5ee22        3 hours ago              47.1MB
langdetect_cpp_static       latest              73eb70105ffd        3 hours ago              25.5MB
```

Just a little bit more...

- It turns out OpenBLAS is actually pretty large; linking against (singlethreaded) reference BLAS and LAPACK can save a lot of size.
- We can also use the distroless container to save even more space.

More container size results

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langdetect_cpp_static         latest    73eb70105ffd   3 hours ago          25.5MB
langdetect_cpp_distroless     latest    d69c6693cae8   34 seconds ago       3.96MB
```

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Hello world to langdetect, Python: 51.8MB $\rightarrow$ 327MB

Hello world to langdetect, C++: 2.7MB $\rightarrow$ 3.96MB

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```

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And the actual program and model:

```
$ ls -lh
-rw-r--r-- 1 ryan ryan 176K Oct 31 14:46 all_lang_data_model.bin
-rwxr-xr-x 1 ryan ryan 1.5M Oct 31 14:53 ngram_langdetect_run_static
```

There are a lot of additional size optimization possibilities...

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5. Check it out:

    `https://www.mlpack.org` — `https://www.ensmallen.org`
    `https://arma.sourceforge.net` — `https://coot.sourceforge.net`
    `https://github.com/rcurtin/lightweight_cpp_talk_code`

Questions and comments?

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