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Experiences tuning SYCL libraries

John Lawson

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Auto-tuning compute kernels

- Parameterized kernels allow performance to be tuned for a range of hardware
- Automatically tuning these parameters reduces developer effort and increases effectiveness
- Auto-tuners work out the best set of kernel parameters for a given set of inputs...
- ... but general purpose libraries want to provide performance on all possible input sizes

Auto-tuning OpenCL

- OpenCL kernels are provided as source code, with parameters set using the preprocessor
- Cost of using different kernel parameters is only JIT compilation time

Required steps

1. Use auto-tuning to find kernel parameters for a representative range of input sizes
2. Provide a system to choose optimal kernel parameters for unseen input sizes

Existing implementations

- CLBlast
  - Provides a database of devices and tuning scripts
  - Uses a single best configuration for each device
- clBlas
  - Provides a number of different kernels generated for library targets
- ARM Compute Library
  - Hardcodes kernels and kernel parameters for the library targets

SYCL

- SYCL is a single-source heterogeneous parallel programming model maintained by the Khronos Group
- Allows developers to write compute kernels in C++

Providing kernels in a SYCL library

- SYCL kernels compiled to bitcode (SPIR, SPIR-V, PTX, GCN,...)
- Each tuned kernel a binary blob embedded in the library
- More kernels = better performance, but also larger binaries

SYCL required steps

1. Use auto-tuning to find kernel parameters for representative input sizes
2. Choose a subset of kernel parameters to deploy in library
3. Create a system to choose optimal kernel parameters for unseen inputs

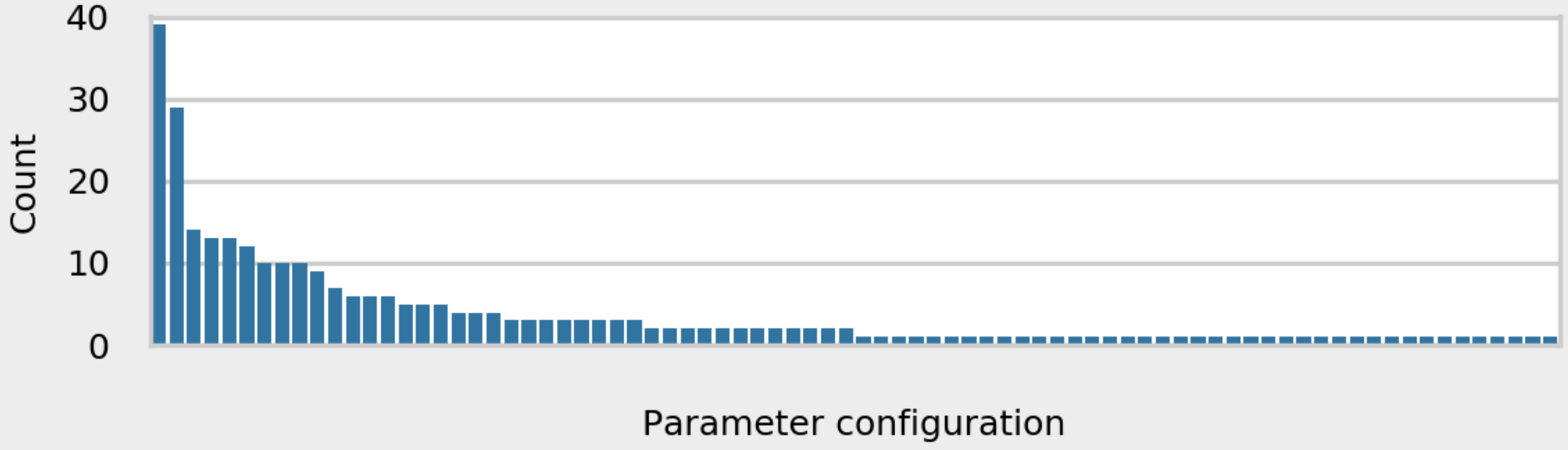
Matrix multiply case study

```
template <typename T, typename Index, bool TransposeLHS, bool TransposeRHS,
          int RowTile, int AccTile, int ColTile>
struct MatmulKernel;
```

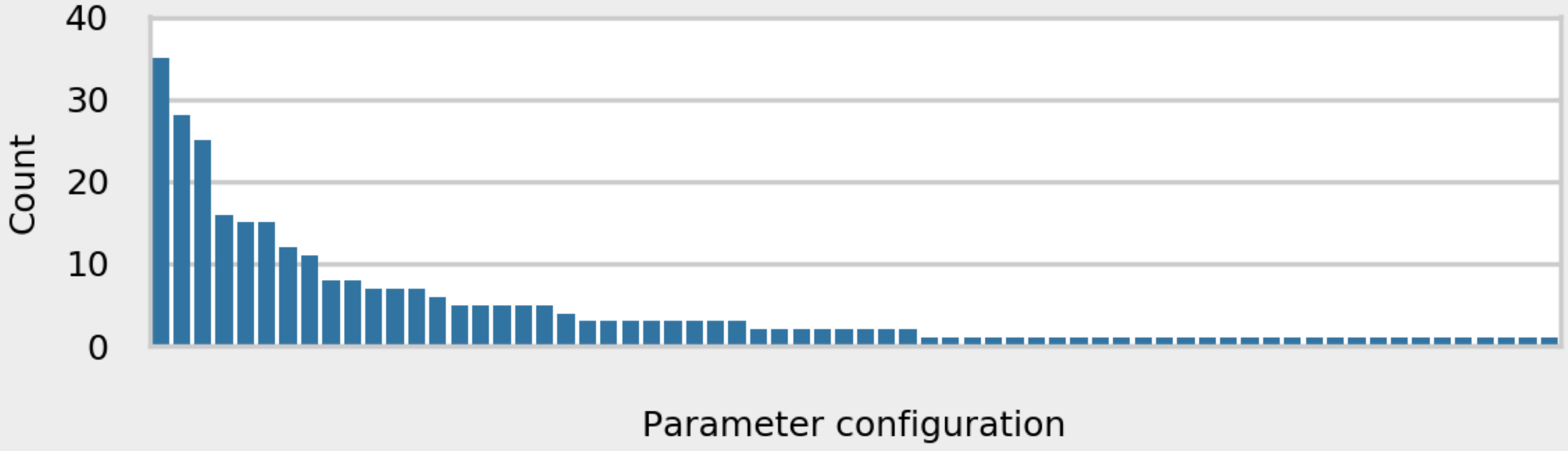
- 640 possible kernel configurations
  - Tile sizes 1, 2, 4 and 8
  - Work-group sizes of 1, 8, 16, 32 and 128
- Recorded average execution time and flops for 300 matrix sizes on AMD R9 Nano GPU and Intel i7-6700K CPU.

Frequency that one kernel is best

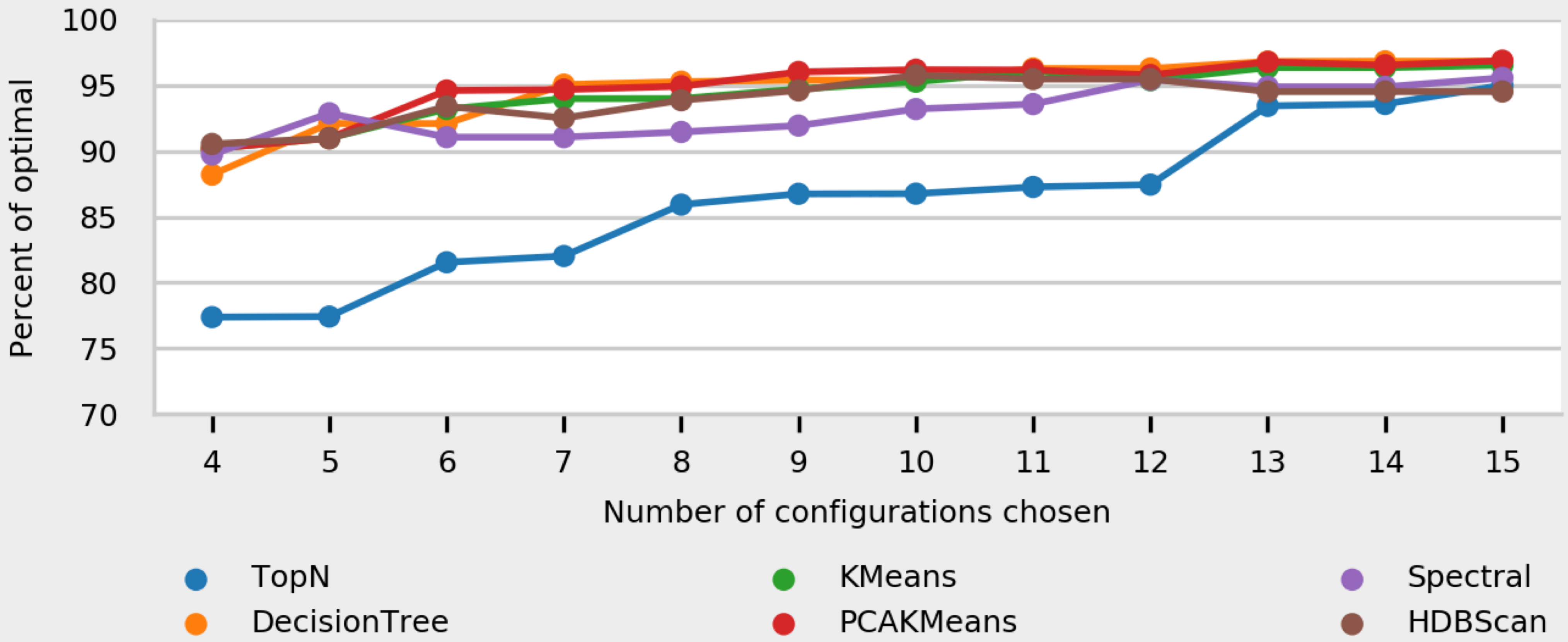
GPU:



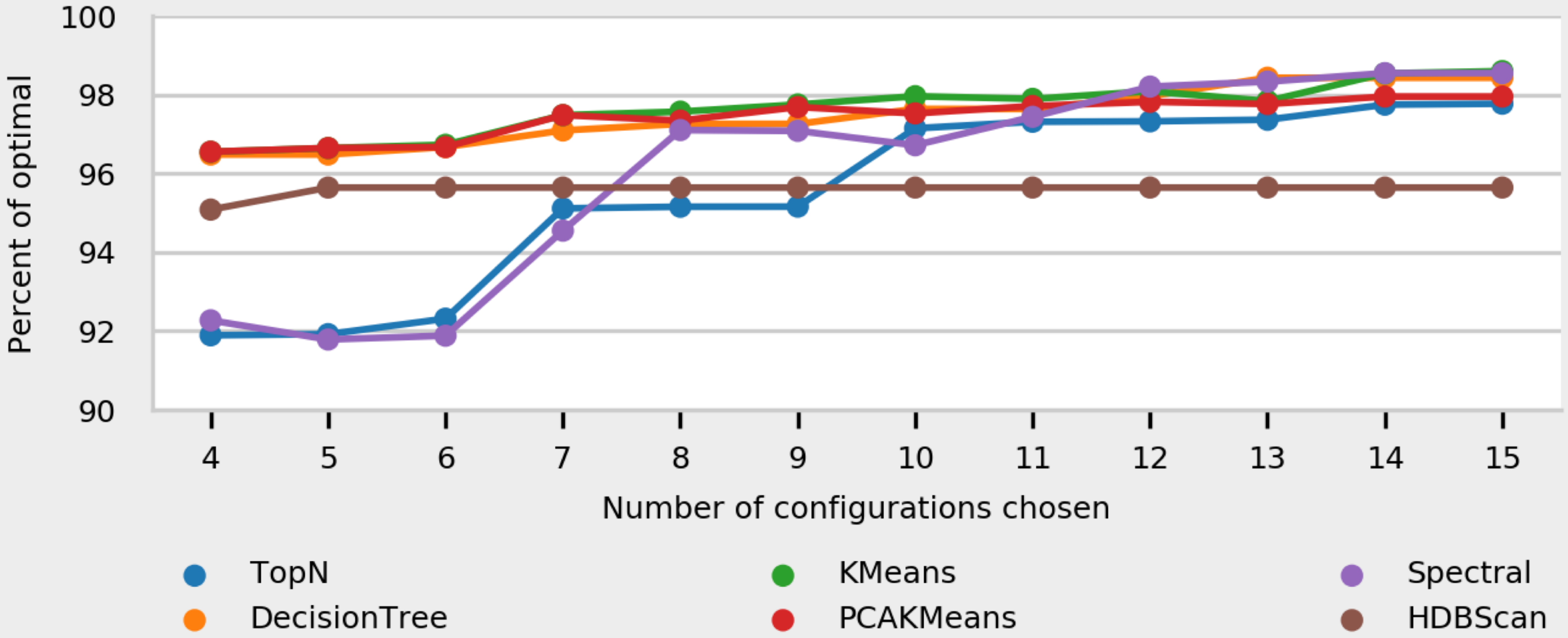
CPU:



Selecting a subset of kernels (GPU)

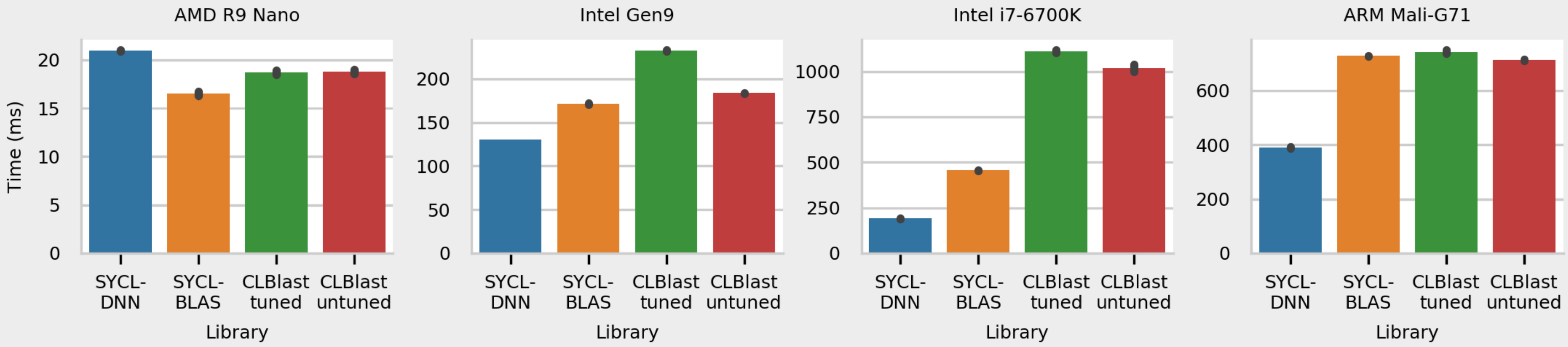


Selecting a subset of kernels (CPU)



Selecting kernels at runtime

Performance on machine learning model



Time for one image inference of a SYCL-DNN implementation of VGG16 with different matrix multiplication libraries.

Conclusions

- Unsupervised machine learning techniques provide easy and effective methods to select a subset of kernels to deploy in a SYCL library.
- A decision tree gives reasonable performance when selecting which of these kernels to use at runtime.
- This system extracts portable performance from parameterized SYCL kernels, beating other tuned libraries.

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info@codeplay.com

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