Optimizing Machine Learning with Tensorflow, ActivePython and Intel

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ActiveState

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Machine Learning

- Transforming almost every business
- Exploding ecosystem of tools, making it more accessible to even non-experts
- TensorFlow, by Google has become the most popular package in this ecosystem

TensorFlow

- Google's library for ML
- Expresses calculations as a computation graph
- Many language bindings
- Supports/provides pre-trained models
- 72K stars on GitHub!

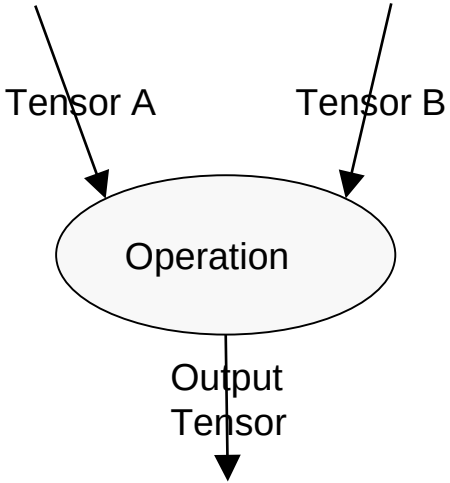
Tensorflow

- Official bindings for Python, C, Java, Go
- Library is written in C++
- Used as a ‘back end’ in wrapper libraries

Keras

TensorFlow

- Computation Graph is a graph where the nodes are operators (add, sub, multiply, etc.)
- Edges are tensors
- Tensors are effectively N-dimensional arrays



Tensors

- N-dimensional arrays
- Types of operations:
  - Matrix operations
  - Linear algebra
  - Vector math

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Optimization Cases

- Training neural networks
- Large data sets
- Complex deep learning networks
- Real-time Inference



Optimizing TensorFlow

- Data storage
  - Allocations, Conversions, Layout, etc.
- Parallelization
  - Taking advantage of cores, etc.
- Instruction optimization
  - MKL style operation optimization



Intel Optimizations

- Intel provides optimizations to take maximum advantage of their hardware

- For example, Intel MKL (Math Kernel Library) provides impressive results on fundamental math operations

Intel Optimizations

- ActivePython includes MKL, and work to include additional optimizations as they become available

- TensorFlow specific optimizations offer dramatic speed increases for commercial applications

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Simple MKL Performance Example

```
for nSize in range(0, 10):
    a = np.random.rand(nSize,nSize)
    result = np.linalg.eig(a);
```

A simple test that computes the eigenvalues and normalized eigenvectors of a random square matrix of increasing size.

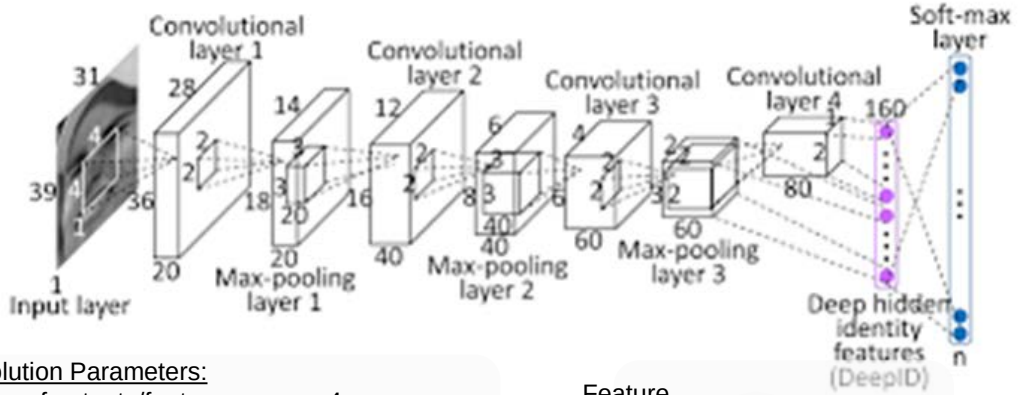


Linear Algebra Test - NumPy w/ Intel® MKL

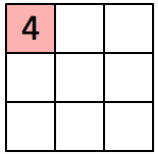
Optimizing TensorFlow

- *Mohammad Ashraf Bhuiyan - Intel Artificial Intelligence Group, Senior Software Engineer*
  - 10+ years in software in various roles
  - GitHub: mbhuiya

Deep Learning: Example



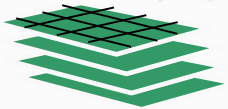
Image

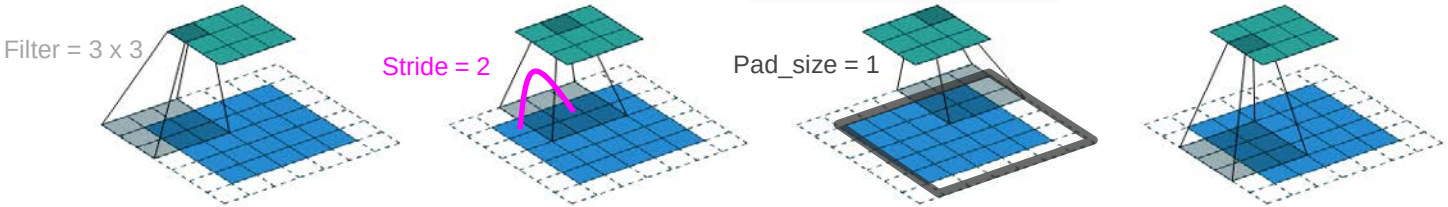


Convolved Feature

Convolution Parameters:
Number of outputs/feature-maps: < 4 >
Filter size: < 3 x 3 >
Stride: < 2 >
Pad_size (for corner case): <1>

Feature maps



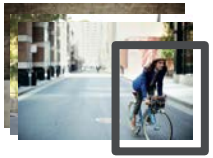


Deep Learning: Train Once Use Many Times

Step 1: Training

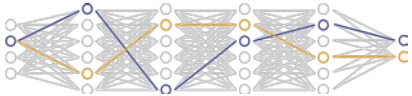
(Over Hours/Days/Weeks)

Input data



Person

Create deep network



Output classification

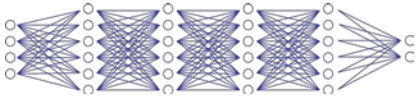
90% person
8% traffic light

Trained Model

Step 2: Inference

(Real Time)

New input from camera and sensors

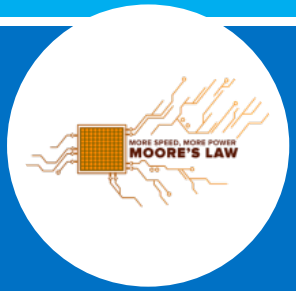


Trained neural network model

97% person

Output classification

Deep Learning: Why Now?

Bigger Data	Better Hardware	Smarter Algorithms
		
Image: 1000 KB / picture Audio: 5000 KB / song Video: 5,000,000 KB / movie	Transistor density doubles every 18 months Cost / GB in 1995: $1000.00 Cost / GB in 2015: $0.03	Advances in algorithm innovation, including neural networks, leading to better accuracy in training models

TensorFlow

- **2nd generation open source machine learning framework from Google***
- **Widely used across Google in many key apps – search, Gmail, photos, translate, etc.**
- **General computing mathematical framework used on:**
  - Deep neural network
  - Other machine learning algorithm

- **Core system provides set of key computational extendable kernel**
- **Core in C++, front end wrapper is in python**
- **Multi-node support using proprietary GRPC, VERBS, MPI protocols**

Tensorflow Optimizations at Intel

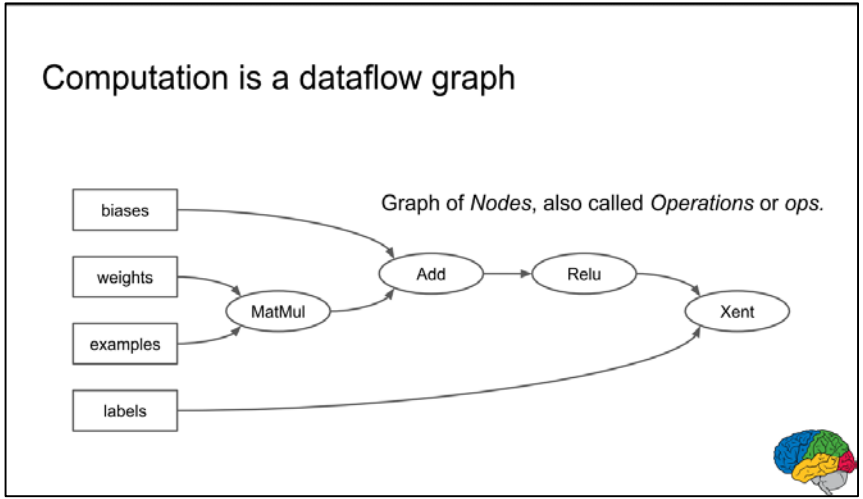
1. Operator-level optimizations in TensorFlow* for Intel® Architectures
   - Intel® MKL integration

2. Graph-level optimizations in TensorFlow* for Intel® Architectures
   - Data layout conversion optimization
   - Node merging optimization
   - Memory allocation
   - Load balancing

Operator-level optimization

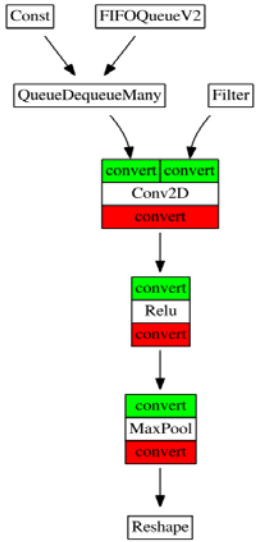
- **Intel® MKL has optimized common set of primitives**
- **Call Intel® MKL API for executing Tensorflow operation**
- **Require Data layout conversion:**

> TF code
> TF layout to MKL layout
> Call MKL API
> MKL layout to TF layout
> TF code



Operator-level optimizations: Example

```
class MklConv2DOp : public OpKernel {
  void Compute (OpKernelContext* context) override {
   const Tensor& tf_input = context->input(0);
   const Tensor& tf_filter = context->input(1);
   Tensor* output = context->allocate_output(..);
   mkl_input = convert_to_mkldnnlayout(tf_input);
   mkl_filter = convert_to_mkldnnlayout(tf_filter);
   mkl_output = mkldnn_conv2d_fwd(mkl_input, mkl_filter,…);
   *output = convert_to_tflayout(mkl_output);
  }
 };
```



Graph optimizations address the overhead of data layout conversion

Tensorflow* Operations optimized for Intel® Architectures

Forward	Backward
• Conv2D • Relu • MaxPooling • AvgPooling • LRN • FusedBatchNorm • MatMul • MklToTF (convert)	• Conv2DGrad • ReluGrad • MaxPoolingGrad • AvgPolingGrad • LRNGrad • FusedBatchNormGrad • TransposeCpu • Reshape

Graph optimizations

Graph optimizations in TensorFlow* for Intel® Architectures

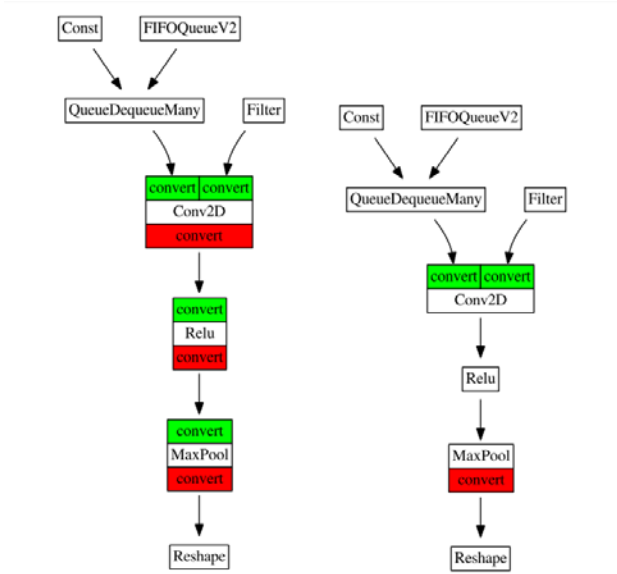
- **Graph has complete view of the operations and their context.**
- **Enable cross-operation optimizations**

- **Graph optimizations**
  1. Data layout conversion optimizations
  2. Node merging (also called Fusion)
  3. Memory allocation
  4. Load balancing

Data Layout Conversion Optimization

Data layout conversion optimization - Example

- **Layout conversions are expensive data shuffling operations.**
- **The challenge is how to avoid unnecessary conversions**
- **Optimizations:**
  - Find out sub-graphs that contain all operators supported by Intel® MKL.
  - Then introduce layout conversions on the boundary of the subgraphs.



(a) Graph with input and output conversions

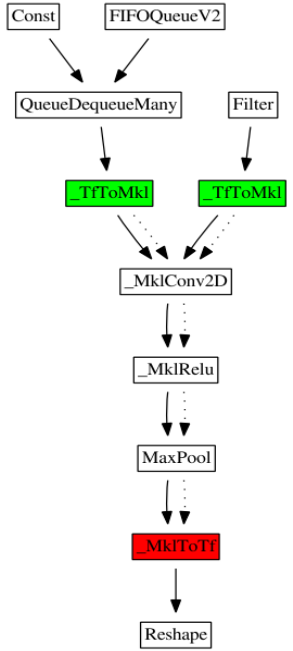
(b) Graph with optimized conversions

Layout conversion optimization

- **Based on Google's suggestions, our current implementation emits Intel® MKL layout as an extra output tensor.**

- **Example: if X = Conv2D(A, B) was earlier operator, then X_mkl = _MklConv2D(A, B, A_m, B_m) is a new operator.**

✓ A_m, B_M are MKL layout of A and B



Need Graph Rewrite Pass : Rewrite TF op to MKL op

- **Example:**
  - Conv2D takes 2 inputs and produces 1 output.
  - We want Conv2D to accept 4 inputs and produce 2 output.
  - That is why we need new Conv2D operator (_MklConv2D).
- A graph pass rewrite ***TF operators*** into ***MKL operators***.

- **File:** core/graph/mkl_layout_pass.cc

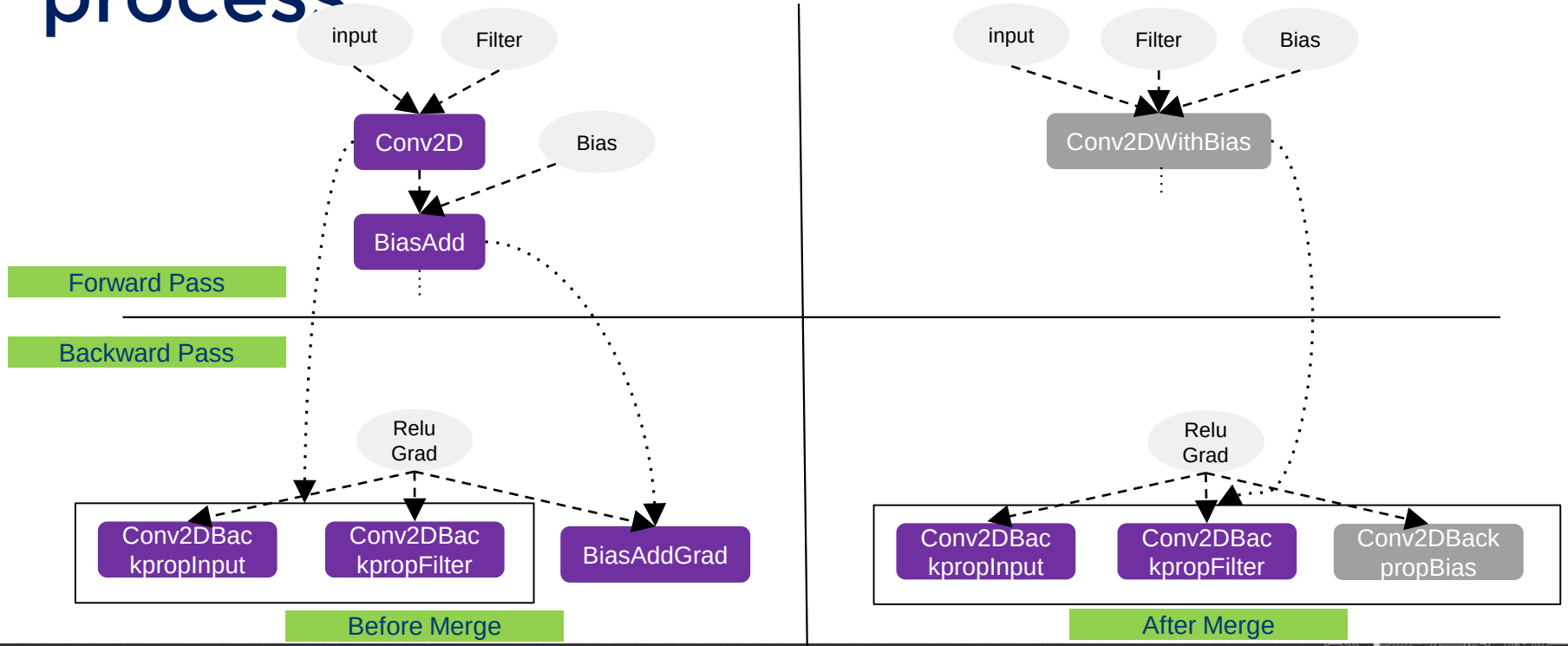
Data: G: Input operation graph
Result: G'': output operation graph with optimized layout conversions
$G_t \leftarrow topological\_sort(G)$;
$G' \leftarrow []$
/* Loop below implements first task of graph rewrite pass. */
for $\forall$ *operation* O *in* G_t **do**
  if $is\_mkldnn\_op(O)$ **then**
    $O'_{inputs} \leftarrow [] ;$
    for *every input* I *of* O **do**
      $O'_{inputs} \leftarrow O'_{inputs} \cup I ;$
      /* I_{mkl} is extra input that carries MKL-DNN layout. */
      $O'_{inputs} \leftarrow O'_{inputs} \cup I\_mkl$
    end
    $O' \leftarrow O'_{inputs} ;$
    $G' \leftarrow G' \cup O' ;$
    delete O;
  else
    $G' \leftarrow G' \cup O ;$
  end
end

Node fusion optimization

Fusion optimization

- **Identify common pattern of operators that arise in most deep learning models**
- **Merge matching subgraph for the pattern to produce smaller graph nodes**
- **Currently, we merge Conv2D+Bias to new node _MklConv2DWithBias.**
- **Implementation**
  - Perform in the same graph rewrite pass that rewrites nodes for data layout conversion optimization

Conv2D and BiasAdd: Merge process



Memory Allocation


Optimization: Memory Allocation

- **Most NN operators allocate huge chunk of memory (Conv2D ~ hundred of MBs)**
- **Default CPU allocator in TensorFlow -> frequent allocs/deallocs of huge chunk of memory -> frequent mmap/unmap -> unnecessary page clears**

- **We developed Custom Pool Allocator using existing Pool allocator.**
  - Allocator holds on to released memory rather than releasing to OS directly.
  - Code: tensorflow/core/common_runtime/mkl_cpu_allocator.h

Load Balancing

Thread Pool and Parallelism

- **Tensorflow is a data-flow graph.**
- **It offers excellent opportunity for exploiting parallelism**

✓ Between operators.

✓ Within operators.

- **Thread pool parameters:**
  1. **Inter_op_parallelism_threads =** max number of operators that can be executed in parallel
  2. **Intra_op_parallelism_threads =** max number of threads to use for executing an operator
  3. **MKL Threads =** operators controlled using OMP_NUM_THREADS. OMP_NUM_THREADS is conceptually same as intra_op_parallelism_threads.

Current Threading Issues & Solution

> Problem:

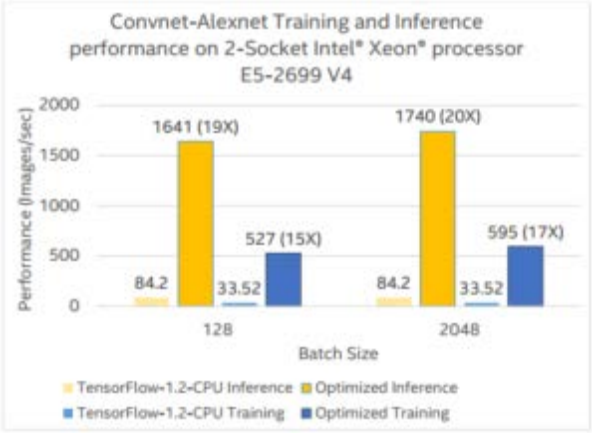
- Incorrect setting of `inter_op_threads` and `intra_op_threads` can lead to over- or under-subscription, leading to poor performance.

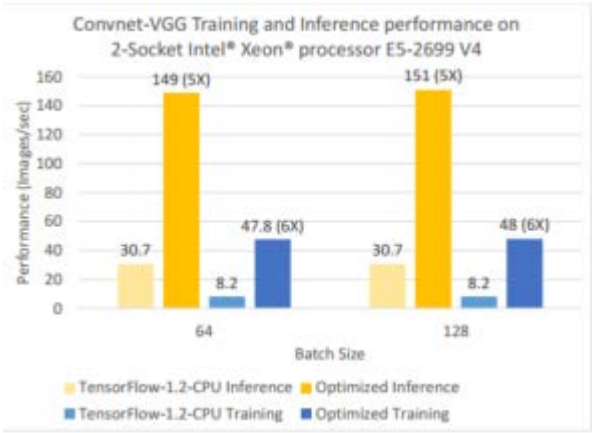
> Solution:

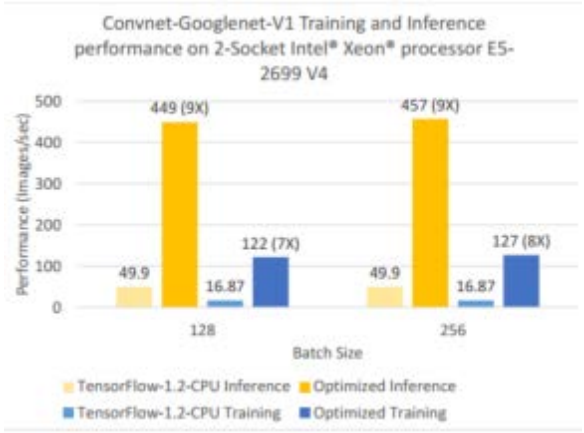
- Settings for `inter_op`, `intra_op` and `OMP_NUM_THREADS` were explored to get the best performance . Typically:
  - Intra_op = OMP_NUM_THREADS = # of physical cores in CPU
  - inter_op = # of sockets in a system
  - Google performance guide: https://www.tensorflow.org/performance/performance_guide
- No changes to Tensorflow code; changes to the run command.

Performance Improvement

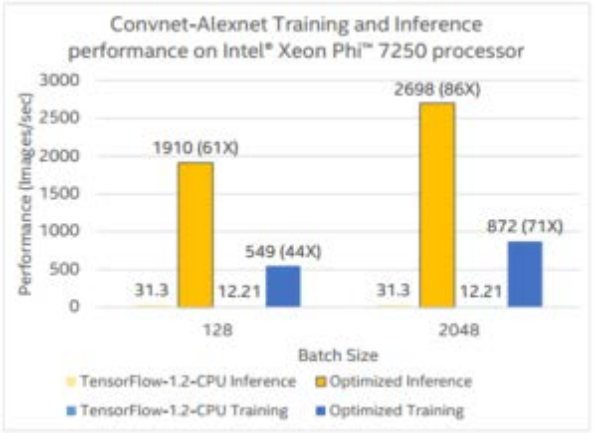
Optimized Tensorflow Performance on Intel® Xeon® processor

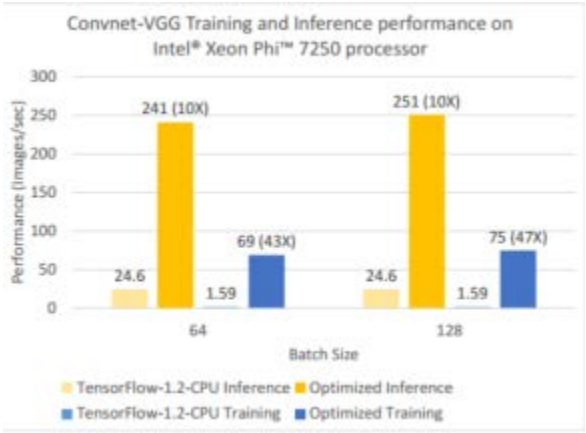


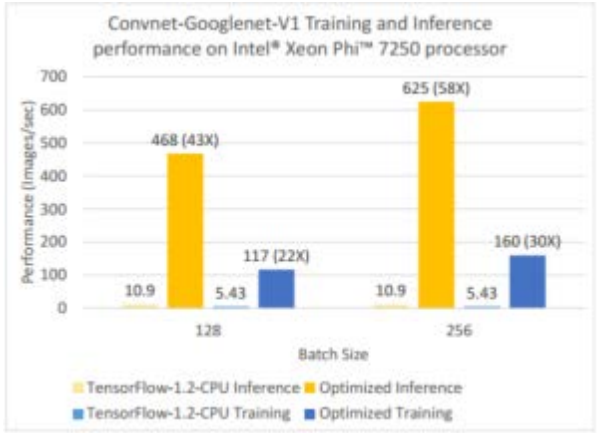




Optimized Tensorflow Performance on Intel® Xeon Phi® processor







How Do I Get Order of Magnitude CPU Speedup?

- Optimized TensorFlow on Intel architectures available from the public git.
  - git clone https://github.com/tensorflow/tensorflow.git
- Configure for best performance on CPU:
  - Run “./configure” from the TensorFlow source directory
- Building for best performance on CPU
  - Use following command to create a pip package that can be used to install the optimized TensorFlow wheel
  - bazel build --config=mkl --s --c opt //tensorflow/tools/pip_package:build_pip_package
  - Automatically downloads latest MKL-ML
- Install the optimized TensorFlow wheel
  - bazel-bin/tensorflow/tools/pip_package/build_pip_package ~/path_to_save_wheel
  - pip install --upgrade --user ~/path_to_save_wheel/wheel_name.whl

Summary

- **TensorFlow* is widely used DL and AI framework**
  - It has been slow on CPU until recently
- **Unique performance challenges addressed: MKL, data layout, inter/intra layer parallelization, etc.**
- **Significant performance gains from Intel optimization on Intel® Xeon and Xeon Phi processors**

- **Call to action:**
  - Use the right configuration for Tensorflow building
  - Find the best set of parameter for running models with Tensorflow
  - Get the orders of magnitude higher performance

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