Deep Learning

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Outline

Stochastic Gradient Descent

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Do you see problems in finding minimum of these functions using GD?

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Do you see problems in this optimization method?

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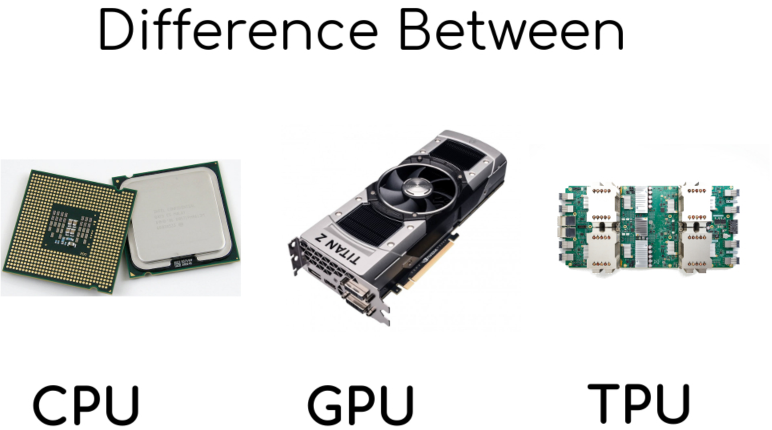
  - For $i = 1, 2, ..., \lceil \frac{n}{B} \rceil$, do

$$w \leftarrow w - \alpha \frac{1}{B} \sum_{k=(i-1)\cdot B+1}^{i \cdot B} L_k(w).$$

Outline

CPU vs GPU vs TPU



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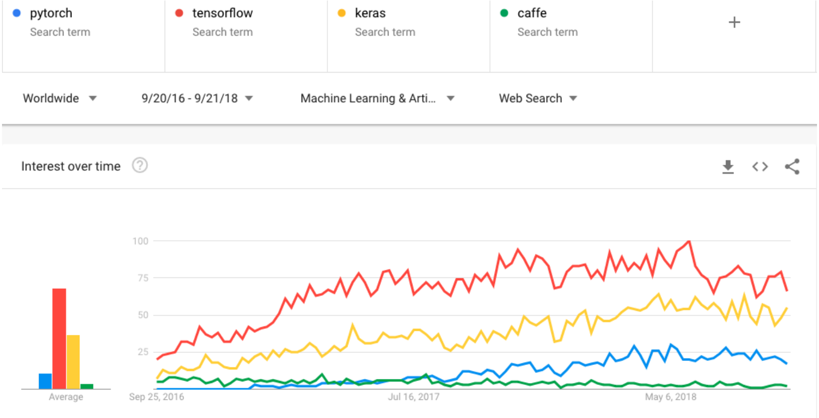
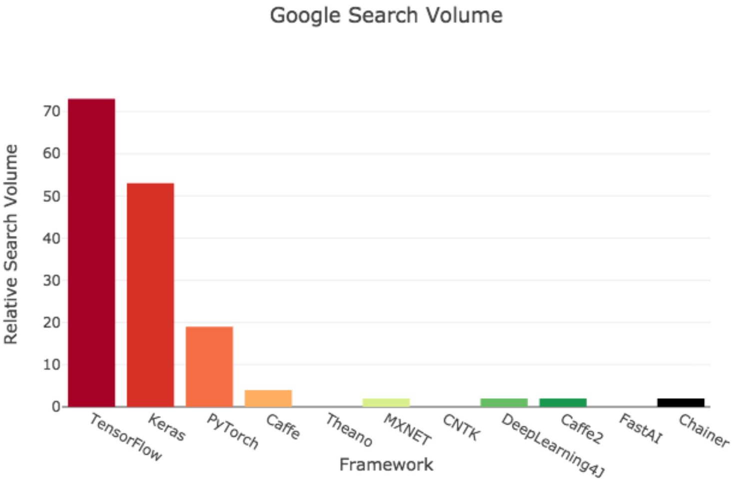
- Tensor Processing Unit is a custom-built integrated circuit developed specifically for machine learning and tailored for TensorFlow, Google's open-source machine learning framework. TPU's have been powering Google data centers since 2015.

Why Tensorflow?

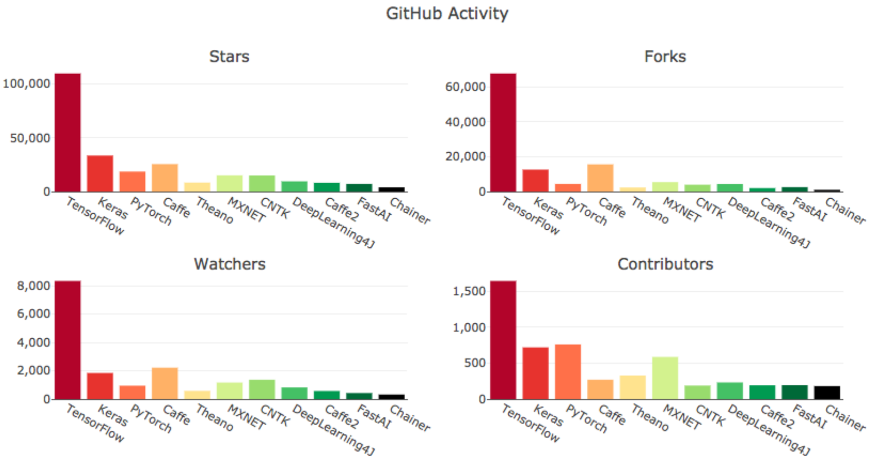
Interest Over Time



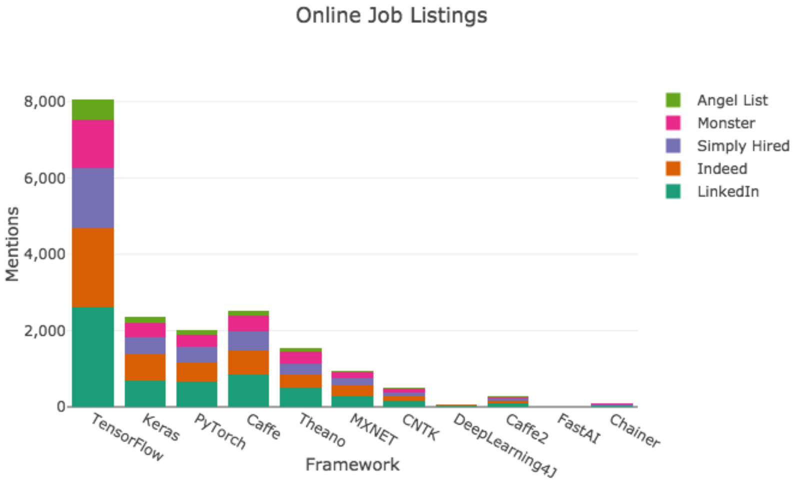
Google Search Activity



GitHub Activity



Online Job Listings



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- TensorFlow gives the best performance with an ability to iterate quickly, train models faster and run more experiments.
- TensorFlow runs on nearly everything: GPUs and CPUs—including mobile and embedded platforms—and tensor processing units (TPUs), which are specialized hardware to do the tensor math on.

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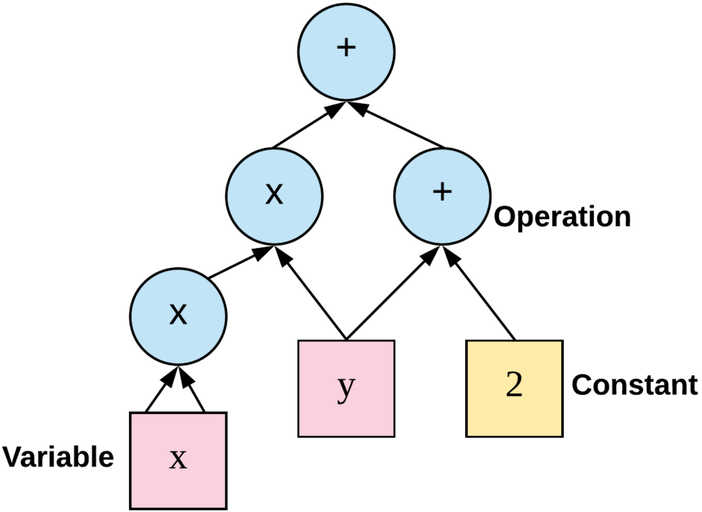
- This is the basic approach, there is also a dynamic approach implemented in the recently introduced eager mode.

Computational Graphs



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- Ops are functions on tensors.

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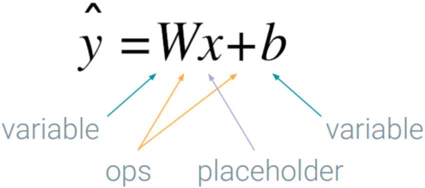

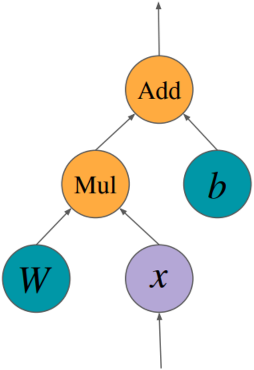

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>>> op1 = tf.add(a, b)
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Tensor("Const:0", shape=(), dtype=int32)
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- Upon op execution, only the subgraph (required for calculating its value) is evaluated

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   - Run the optimizer over batches.

Tensorboard