

A quick introduction to Tensorflow

Probabilistic Modeling Fall 2019



Many ML libraries:



P Y T  R C H

 Microsoft
CNTK

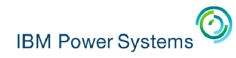
Which One to Learn:



Vs. **PYTORCH**

Current Trending:

- Tensorflow still dominating Industry



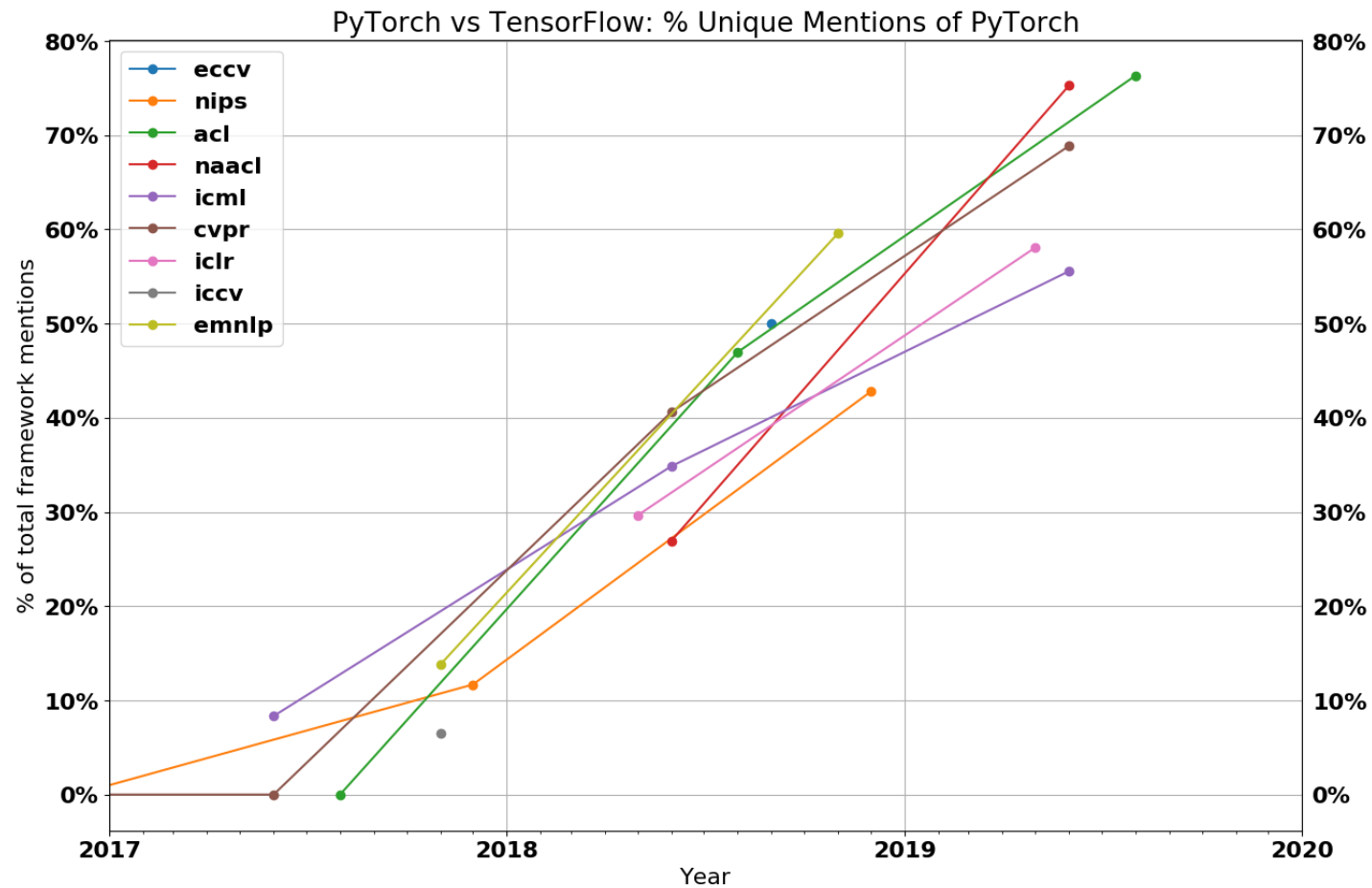
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Current Trending:

- PyTorch getting increasingly popular in Academia



An open-source library by Google:

TensorFlow:

Large-Scale Machine Learning on Heterogeneous Distributed Systems

(Preliminary White Paper, November 9, 2015)

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng
Google Research*

Further reading:

- Official website: <https://www.tensorflow.org/>

If want to master every details.

- *Deep Learning with Python* by Francois Chollet

Focus on Keras

- Hands-On Machine Learning with Scikit-Learn and TensorFlow

Tensorflow part is somewhat outdated. (Though this book is published in 2017, second edition was published at October 15 2019)

Core Functionalities:

- Augmented tensor operations (nearly identical to numpy)

Seamless interfaces with existing programs.

- Automatic differentiation

The very core of Optimization based algorithms.

- Parallel(CPU/GPU/TPU) and Distributed(multi-machine) Computing

Essential for large(industrial level) applications.

Implemented in C++/CUDA. Highly Efficient.

Automatic differentiation: Through back-propagation

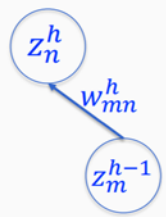
- Only operations with “sub-gradient” can be applied on Tensor

In general

For convenience, we generalize the notation h is the layer number, w_{mn}^h connects m -th node in layer $h-1$ (i.e., z_m^{h-1}) to the n -th node in layer h (i.e., z_n^h)

To compute each $\frac{\partial L}{\partial w_{mn}^h}$

1. Initialize $\frac{\partial L}{\partial w_{mn}^h} \leftarrow 0$
1. Find all the paths from z_n^h to the output node y
2. For each path s
 - 2.1 For each node z in s
 - Compute the partial derivative of z 's parent over z if the node is the output node y , then compute $\frac{\partial L}{\partial y}$
 - Multiply all the partial derivatives along the path s to obtain g_s
 - Add to the derivative: $\frac{\partial L}{\partial w_{mn}^h} \leftarrow \frac{\partial L}{\partial w_{mn}^h} + g_s \frac{\partial z_n^h}{\partial w_{mn}^h}$



63

Automatic differentiation: Through back-propagation

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Arithmetic: $+$, $-$, $*$, $/$

Elementary functions: \exp , \log , \max , \sin , \tan

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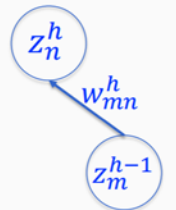
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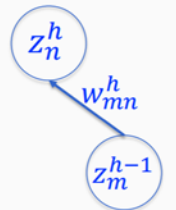
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- What operations are not “differentiable”?

For example: “Vanilla” sampling

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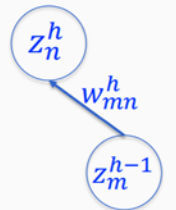
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Static vs Eager Mode

- Eager mode(PyTorch, Tensorflow 2.0)

Just like using numpy

- Static mode(Tensorflow 1.x version)

Predefine tensors and computation graphs then let TF engine to execute the graphs. Similar to defining Python functions.

Static vs Eager Mode

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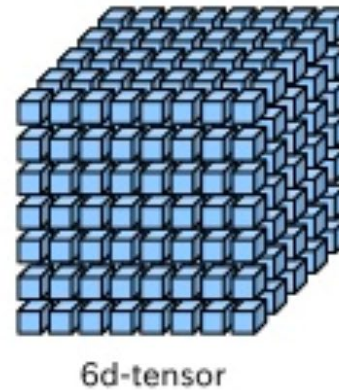
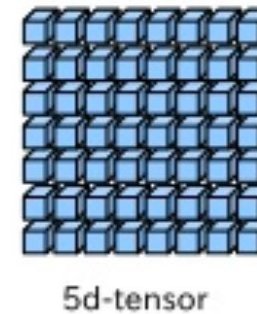
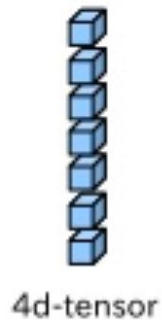
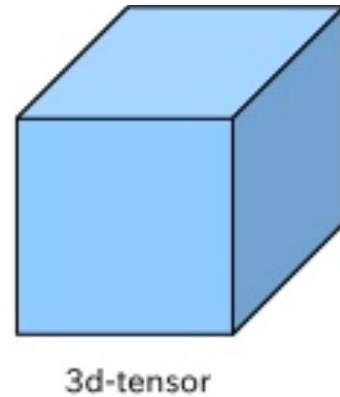
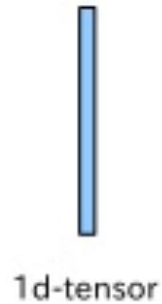
- Static mode(Tensorflow 1.x version)

We focus solely on this mode in this tutorial

Subtlety appears here.

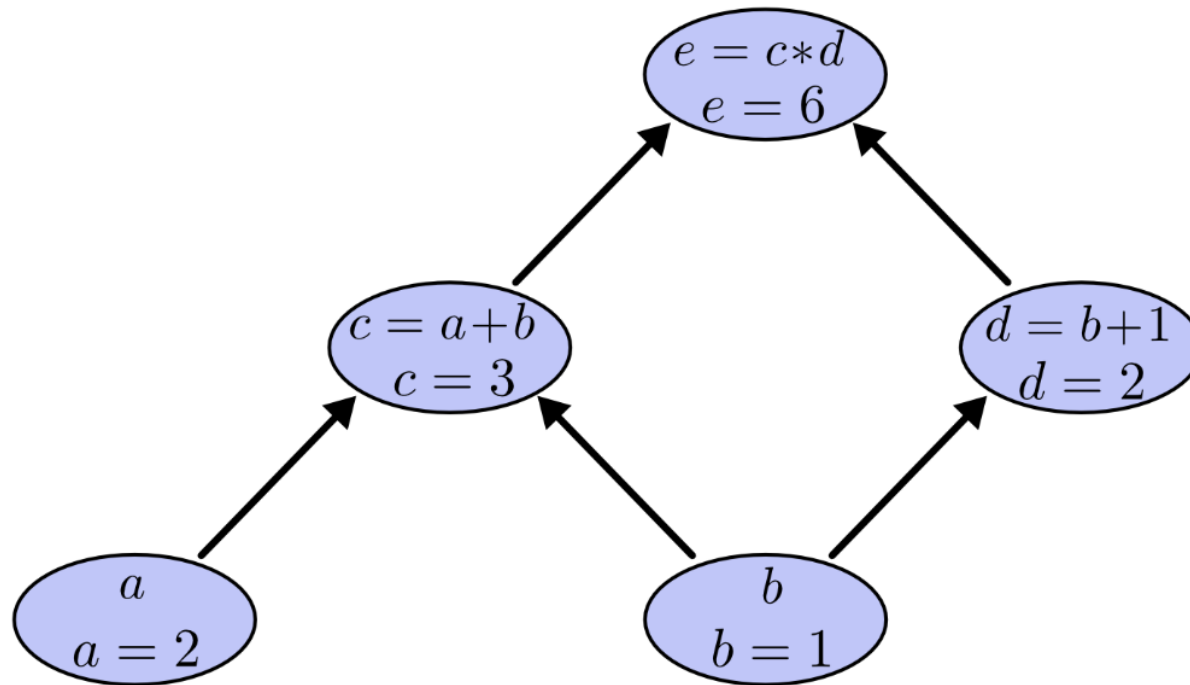
Working process: Tensor, Flow

- Tensor: multi-dimension array



Working process: Tensor, Flow

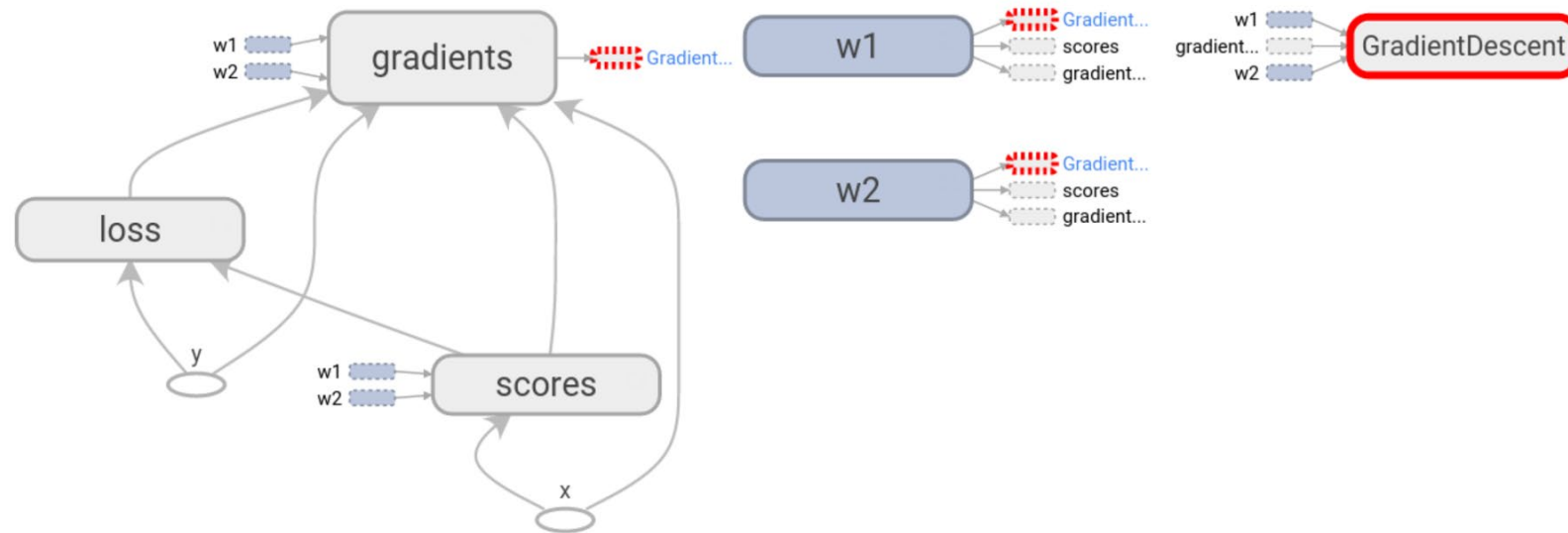
- flow: computation graph



Working process: Tensor, Flow

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Can be visualize by tensorboard



3 levels of tensorflow:

- **Primitive tensorflow**: lowest, finest control and most flexible
Suitable for most machine learning and deep learning algorithms.
We work at this level in this course.
- Keras(Mostly for deep learning):highest, most convenient to use, lack flexibility
- Tensorflow layers (Mostly for deep learning): somewhere at the middle.

General pipeline:

- Define inputs and variable tensors(weights/parameters).

*Keras will take care of these for you.

- Define computation graphs from inputs tensors to output tensors.

- Define loss function and optimizer

Once the loss is defined, the optimizer will compute the gradient for you!

- Execute the graphs.

*Keras will take care of this for you as well

Getting started today:

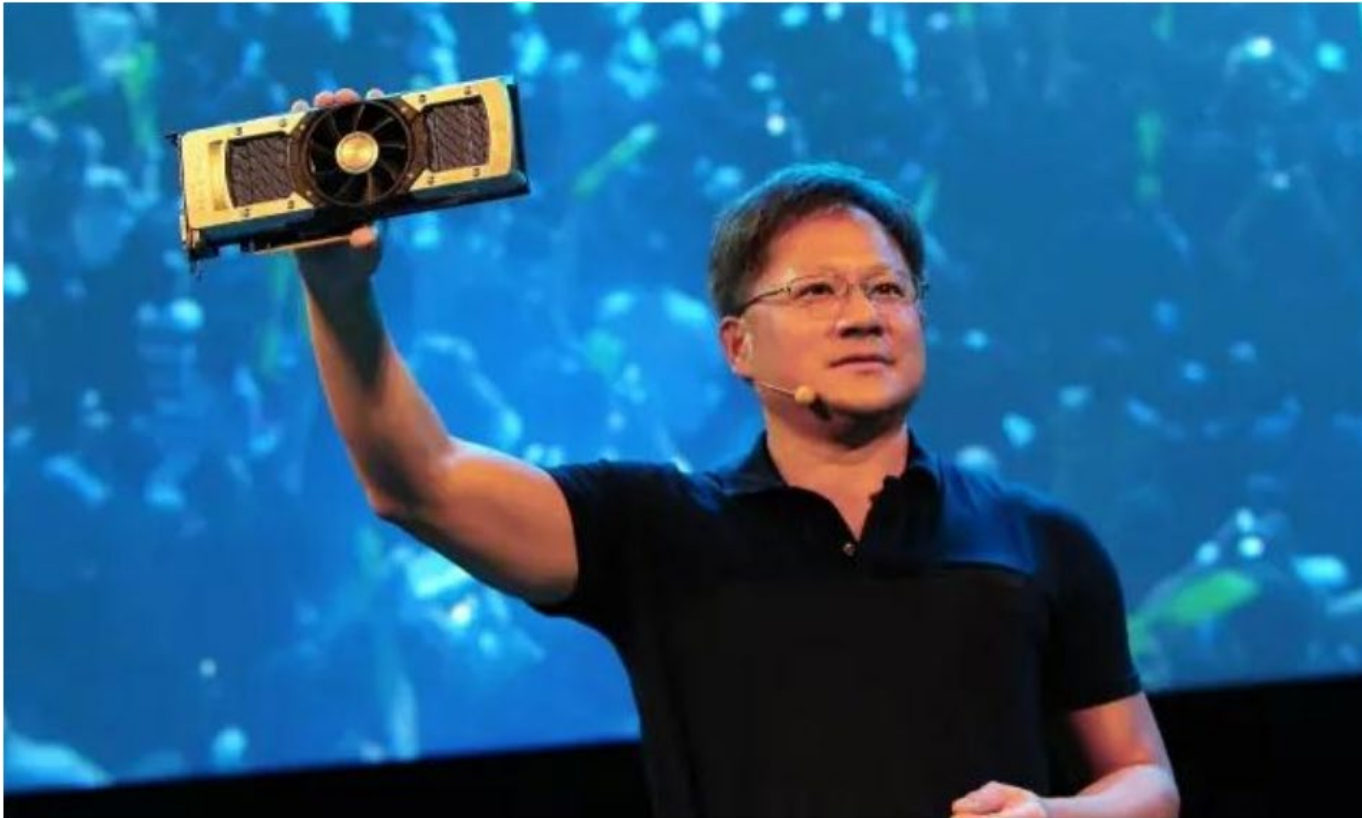
- GPU acceleration
- Installation
- Demos
 - Arithmetic and tensor operations
 - Newton Raphson Logistic Regression
 - Tensorflow Style Logistic Regression

GPU acceleration:

- Literally need one if training on non-toy models and datasets.

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- Nvidia GPUs Only



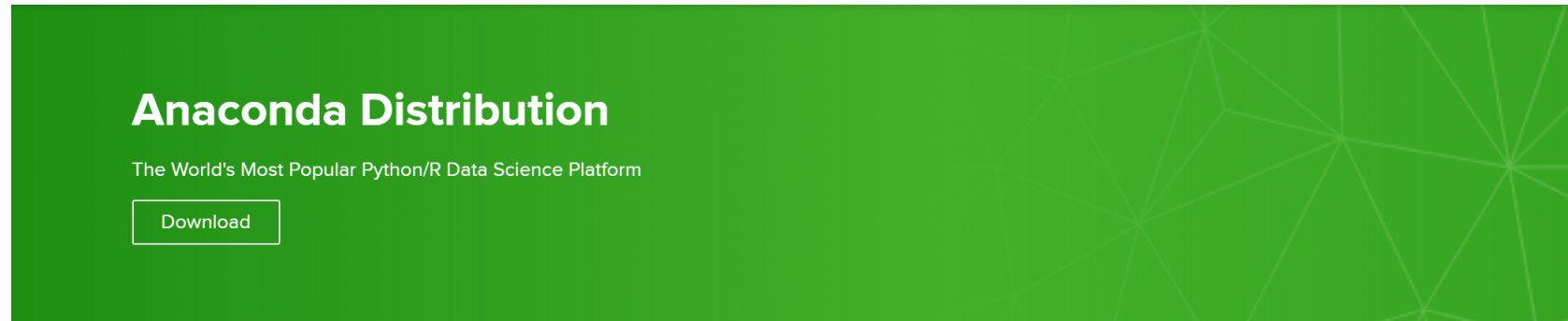
Where to find (free) computing resources:

- Your own Gaming PC
- CHPC(University) , CADE (Collage of Engineering)
- AWS/Google Cloud Platform: First time coupon.
- Google Colab: Always free, equipped with GPU and TPU!

Installation: Anaconda

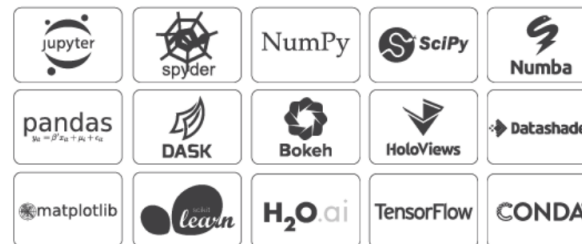
- Installing with Anaconda could save you much work.

<https://www.anaconda.com/>



The open-source **Anaconda Distribution** is the easiest way to perform Python/R data science and machine learning on Linux, Windows, and Mac OS X. With over 11 million users worldwide, it is the industry standard for developing, testing, and training on a single machine, enabling *individual data scientists* to:

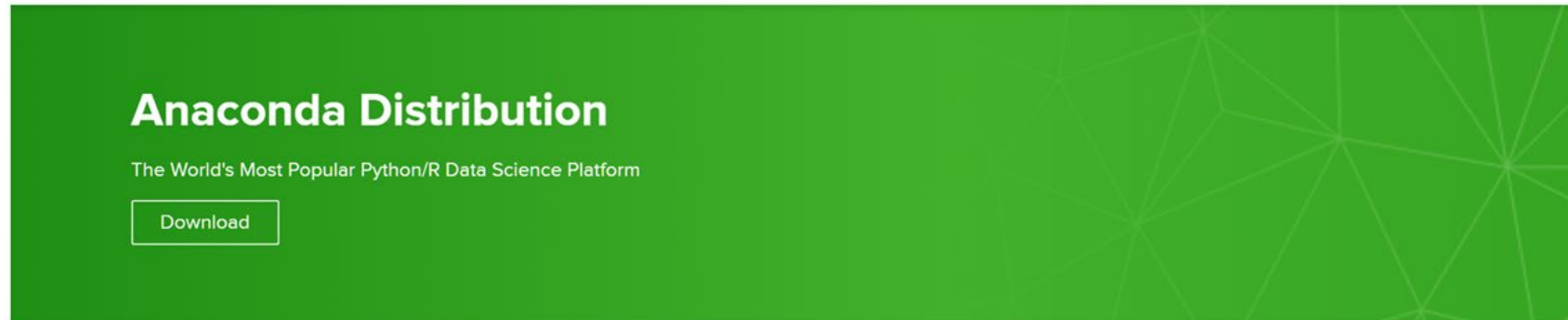
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