# GluonCV and GluonNLP: Deep Learning in Computer Vision and Natural Language Processing

Jian Guo GJIAN@UMICH.EDU

University of Michigan MI, USA

He He
Tong He
HEHEA@AMAZON.COM
HTONG@AMAZON.COM
Leonard Lausen
\*Mu Li
MLI@AMAZON.COM
HAIBILIN@AMAZON.COM

Amazon Web Services, CA, USA

Xingjian Shi xshiab@connect.ust.hk

Hong Kong University of Science and Technology, Hong Kong, China

Chenguang WangCHGWANG@AMAZON.COMJunyuan XieERIC.JY.XIE@GMAIL.COMSheng ZhaZHASHENG@AMAZON.COMAston ZhangASTONZ@AMAZON.COMHang ZhangHZAWS@AMAZON.COMZhi ZhangZHIZ@AMAZON.COMZhongyue ZhangZHONGYUE@AMAZON.COM

Amazon Web Services, CA, USA

Shuai Zheng szhengac@cse.ust.hk

Hong Kong University of Science and Technology, Hong Kong, China

#### Abstract

We present GluonCV and GluonNLP, the deep learning toolkits for computer vision and natural language processing based on Apache MXNet (incubating). These toolkits provide state-of-the-art pre-trained models, training scripts, and training logs, to facilitate rapid prototyping and promote reproducible research. We also provide modular APIs with flexible building blocks to enable efficient customization. Leveraging the MXNet ecosystem, the deep learning models in GluonCV and GluonNLP can be deployed onto a variety of platforms with different programming languages. Benefiting from open source under the Apache 2.0 license, GluonCV and GluonNLP have attracted 100 contributors worldwide on GitHub. Models of GluonCV and GluonNLP have been downloaded for more than 1.6 million times in fewer than 10 months.

**Keywords:** Machine Learning, Deep Learning, Apache MXNet, Computer Vision, Natural Language Processing

<sup>\*.</sup> Mu Li is the corresponding author.

# 1. Introduction

Deep learning, a sub-field of machine learning research, has driven the rapid progress in artificial intelligence research, leading to astonishing breakthroughs on long-standing problems in a plethora of fields such as computer vision and natural language processing. Tools powered by deep learning are changing the way movies are made, diseases are diagnosed, and play a growing role in understanding and communicating with humans.

Such development is made possible by deep learning frameworks, such as Caffe (Jia et al., 2014), Chainer (Tokui et al., 2015), CNTK (Seide and Agarwal, 2016), Apache (incubating) MXNet (Chen et al., 2015), PyTorch (Paszke et al., 2017), TensorFlow (Abadi et al., 2016), and Theano (Bastien et al., 2012). These frameworks have been crucial in disseminating ideas in the field. Specifically, imperative tools, arguably spearheaded by Chainer, are easy to learn, read, and debug. Such benefits make imperative programming interface quickly adopted by the Gluon API of MXNet (while can be seamlessly switched to symbolic programming for high performance), PyTorch, and TensorFlow Eager.

Leveraging the imperative Gluon API of MXNet, we design and develop the GluonCV and GluonNLP (referred to as GluonCV/NLP hereinafter) toolkits for deep learning in computer vision and natural language processing. To the best of our knowledge, GluonCV/NLP are the first open source toolkits for deep learning in both computer vision and natural language processing that simultaneously i) provide modular APIs to allow customization by re-using efficient building blocks; ii) provide pre-trained state-of-the-art models, training scripts, and training logs to enable fast prototyping and promote reproducible research; iii) leverage the MXNet ecosystem so that models can be deployed in a wide variety of programming languages including C++, Clojure, Java, Julia, Perl, Python, R, and Scala.

# 2. Design and Features

In the following, we describe the design and features of GluonCV/NLP.

## 2.1 Modular APIs

GluonCV/NLP provide access to modular APIs to allow users to customize their model design, training, and inference by re-using efficient components across different models. Such common components include (but are not limited to) data processing utilities, models with individual components, initialization methods, and loss functions.

To elucidate how the modular API facilitates efficient implementation, let us take the data API of GluonCV/NLP as an example, which is used to build efficient data pipelines with popular benchmark data sets or those supplied by users. In computer vision and natural language processing tasks, inputs or labels often come in with different shapes, such as images with a varying number of objects and sentences of different lengths. Thus, the data API provides a collection of utilities to sample inputs or labels then transform them into mini-batches to be efficiently computed. Besides, users can access a wide range of popular data sets via the data API, including (but are not limited to) ImageNet of image classification, VOC of object detection, COCO of instance segmentation, SQuAD of question answering, and SST of sentiment analysis.

## 2.2 Model Zoo

Building upon those modular APIs, GluonCV/NLP provide pre-trained state-of-the-art models, training scripts, and training logs via the model zoo to enable fast prototyping and promote reproducible research. As of the time of writing, GluonCV/NLP have provided over 100 models for common computer vision and natural language processing tasks, such as image classification, object detection, semantic segmentation, instance segmentation, pose estimation, word embedding, language model, machine translation, sentiment analysis, natural language inference, dependency parsing, and question answering.

# 2.3 Leveraging the MXNet Ecosystem

GluonCV/NLP have benefitted from the MXNet ecosystem through use of MXNet. At the lowest level, MXNet provides high-performance C++ implementations of operators that are leveraged by GluonCV/NLP; thus, improvements in low-level components of MXNet often result in performance gains in GluonCV/NLP. Same as any other model implemented with MXNet, GluonCV/NLP can be used to train models on CPU, GPU (single or multiple), and multiple machines. In sharp contrast to building upon other deep learning frameworks, through the unique hybridizing mechanism by MXNet (Zhang et al., 2019), usually GluonCV/NLP models can be deployed with no or minimal configuration in a wide spectrum of programming languages including C++, Clojure, Java, Julia, Perl, Python, R, and Scala. There are also ongoing efforts to bring more quantization (int8 and float16 inference) benefits from MXNet to GluonCV/NLP to further accelerate model inference.

The documentation https://gluon-cv.mxnet.io/ and http://gluon-nlp.mxnet.io/ of GluonCV/NLP include installation instructions, contribution instructions, open source repositories, extensive API reference, and comprehensive tutorials. As another benefit of leveraging the MXNet ecosystem, the GluonCV/NLP documentation is supplemented by the interactive open source book *Dive into Deep Learning* (based on the Gluon API of MXNet) (Zhang et al., 2019), which provides sufficient background knowledge about GluonCV/NLP tasks, models, and building blocks. Notably, some users of *Dive into Deep Learning* have later become contributors of GluonCV/NLP.

## 2.4 Requirement, Availability, and Community

GluonCV/NLP are implemented in Python and are available for systems running Linux, macOS, and Windows since Python is platform agnostic. The minimum and open source package (e.g., MXNet) requirements are specified in the documentation. As of the time of writing, GluonCV/NLP have reached version 0.6 and 0.4 respectively, and have been open sourced under the Apache 2.0 license. Since the initial release of the source code in April 2018, GluonCV/NLP have attracted 100 contributors worldwide. Models of GluonCV/NLP have been downloaded for more than 1.6 million times in fewer than 10 months.

## 3. Performance

We demonstrate the performance of GluonCV/NLP models in various computer vision and natural language processing tasks. Specifically, we evaluate popular or state-of-the-art models on standard benchmark data sets. In the experiments, we compare model performance

Table 1: Comparison of model performance (in percentage) on the validation data sets between GluonCV/NLP and other open source implementations (OOSI) across popular computer vision and natural language processing tasks and data sets.

Task	Data set	Model	Measure	GluonCV/NLP	OOSI
Image Classification	ImageNet	ResNet-50	top-1 acc.	79.2	75.3 <sup>[a]</sup>
Image Classification	ImageNet	ResNet-101	top-1 acc.	80.5	$76.4^{[a]}$
Image Classification	ImageNet	MobileNet 1.0	top-1 acc.	73.3	$70.9^{[b]}$
Object Detection	COCO	Faster R-CNN	mAP	40.1	$39.6^{[c]}$
Instance Segmentation	COCO	Mask R-CNN	mask AP	33.1	$32.8^{[c]}$
Pose Estimation	COCO	Simple Pose (f)	OKS AP	74.2	N.A.
Sentiment Analysis	TREC	textCNN	acc.	92.8	$92.2^{[e]}$
Sentiment Analysis	SST-2	$BERT_{BASE}$	acc.	93.0	$92.7^{[e]}$
Question Answering	SQuAD 1.1	$BERT_{BASE}$	F1/EM	88.5/81.0	$88.5/80.8^{[e]}$
Question Answering	SQuAD 1.1	$BERT_{LARGE}$	F1/EM	91.0/84.1	$90.9/84.1^{[e]}$
Natural Language Inference	MNLI-m	$BERT_{BASE}$	acc.	84.6	$84.4^{[e]}$
Paraphrasing	MRPC	$\mathrm{BERT}_{\mathrm{BASE}}$	acc.	88.7	86.7 <sup>[e]</sup>

<sup>[</sup>a] https://github.com/KaimingHe/deep-residual-networks (in Caffe)

between GluonCV/NLP and other open source implementations with Caffe, Caffe2, Theano, and TensorFlow, including ResNet (He et al., 2016) and MobileNet (Howard et al., 2017) for image classification (ImageNet), Faster R-CNN (Girshick, 2015) for object detection (COCO), Mask R-CNN (He et al., 2017) for instance segmentation, Simple Pose (Xiao et al., 2018) for pose estimation (COCO), textCNN (Kim, 2014) for sentiment analysis (TREC), and BERT (Devlin et al., 2018) for question answering (SQuAD 1.1), sentiment analysis (SST-2), natural language inference (MNLI-m), and paraphrasing (MRPC). Table 1 shows that the GluonCV/GluonNLP implementation matches or outperforms the compared open source implementation for the same model evaluated on the same data set.

# 4. Conclusion

GluonCV/NLP provide modular APIs and the model zoo to allow users to rapidly try out new ideas or develop downstream applications in computer vision and natural language processing. GluonCV/NLP are in active development and our future works include further enriching the API and the model zoo, and supporting deployment in more scenarios.

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<sup>[</sup>b] https://github.com/tensorflow/models/blob/master/research/slim/nets/mobilenet\_v1.md (in TensorFlow)

<sup>[</sup>c] https://github.com/facebookresearch/Detectron (in Caffe2)

<sup>[</sup>d] https://github.com/yoonkim/CNN\_sentence (in Theano)

<sup>[</sup>e] https://github.com/google-research/bert (in TensorFlow)

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