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International Telecommunication Union
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Recommendation

ITU-T F.748.18 (12/2022)

SERIES F: Non-telephone telecommunication services

Multimedia services

Metric and evaluation methods for AI-enabled multimedia application computing power benchmark

ITU-T F-SERIES RECOMMENDATIONS

NON-TELEPHONE TELECOMMUNICATION SERVICES

TELEGRAPH SERVICE	
Operating methods for the international public telegram service	F.1–F.19
The gentex network	F.20–F.29
Message switching	F.30–F.39
The international telemessage service	F.40–F.58
The international telex service	F.59–F.89
Statistics and publications on international telegraph services	F.90–F.99
Scheduled and leased communication services	F.100–F.104
Phototelegraph service	F.105–F.109
MOBILE SERVICE	
Mobile services and multidestination satellite services	F.110–F.159
TELEMATIC SERVICES	
Public facsimile service	F.160–F.199
Teletex service	F.200–F.299
Videotex service	F.300–F.349
General provisions for telematic services	F.350–F.399
MESSAGE HANDLING SERVICES	F.400–F.499
DIRECTORY SERVICES	F.500–F.549
DOCUMENT COMMUNICATION	
Document communication	F.550–F.579
Programming communication interfaces	F.580–F.599
DATA TRANSMISSION SERVICES	F.600–F.699
MULTIMEDIA SERVICES	**F.700–F.799**
ISDN SERVICES	F.800–F.849
UNIVERSAL PERSONAL TELECOMMUNICATION	F.850–F.899
ACCESSIBILITY AND HUMAN FACTORS	F.900–F.999

For further details, please refer to the list of ITU-T Recommendations.

Recommendation ITU-T F.748.18

Metric and evaluation methods for AI-enabled multimedia application computing power benchmark

Summary

Recommendation ITU-T F.748.18 provides an artificial intelligence (AI) computing power benchmark framework, evaluation metrics and methods, and a guideline for technical testing for AI clusters. Facing more diverse AI computing systems, users hope to have a unified evaluation metric for the system that provides AI computing power. The establishment of relevant real application performance evaluation benchmarks can objectively reflect the current state of the AI computing ability by providing objective metrics and comparison dimensions.

History

Edition	Recommendation	Approval	Study Group	Unique ID*
1.0	ITU-T F.748.18	2022-12-14	16	11.1002/1000/15195

Keywords

AI computing power, benchmark, metric, training.

* To access the Recommendation, type the URL http://handle.itu.int/ in the address field of your web browser, followed by the Recommendation's unique ID. For example, http://handle.itu.int/11.1002/1000/11830-en.

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Table of Contents

Recommendation ITU-T F.748.18

Metric and evaluation methods for AI-enabled multimedia application computing power benchmark

1 Scope

This Recommendation provides the artificial intelligence (AI) computing power benchmark framework, evaluation metrics and methods, and a guideline for technical testing for the cluster.

It addresses the following subjects:

a) Architecture framework of AI computing power benchmark;

b) Metrics of AI computing power benchmark;

c) Evaluation method of AI computing power benchmark;

d) Technical testing of AI computing power benchmark.

2 References

The following ITU-T Recommendations and other references contain provisions which, through reference in this text, constitute provisions of this Recommendation. At the time of publication, the editions indicated were valid. All Recommendations and other references are subject to revision; users of this Recommendation are therefore encouraged to investigate the possibility of applying the most recent edition of the Recommendations and other references listed below. A list of the currently valid ITU-T Recommendations is regularly published. The reference to a document within this Recommendation does not give it, as a stand-alone document, the status of a Recommendation.

None.

3 Definitions

3.1 Terms defined elsewhere

This Recommendation uses the following terms defined elsewhere:

3.1.1 benchmark [b-ITU-T F.748.11]: Benchmark is an evaluation method with a long-term application in the entire computer field. Example: As computer architecture advanced, it became more difficult to compare the performance of various computer systems simply by looking at their specifications. Therefore, tests were developed that allowed the comparison of different architectures (i.e., providing benchmarks).

3.1.2 deep learning software framework [b-ITU-T F.748.12]: A tool that uses a set of pre-built and optimized components to define a model to achieve the encapsulation of artificial intelligence algorithms, data calls, and the use of computing resources.

3.1.3 machine learning (ML) [b-ITU-T Y.3172]: Processes that enable the computational system to understand data and gain knowledge from it without necessarily being explicitly programmed.

3.2 Terms defined in this Recommendation

This Recommendation defines the following term:

3.2.1 artificial intelligence computing power: A metric of computing power capacity of a system that includes AI accelerators.

NOTE – The metric is defined based on the performance of the system and the AI model accuracy.

4 Abbreviations and acronyms

This Recommendation uses the following abbreviations and acronyms:

AI	Artificial Intelligence
ASIC	Application-Specific Integrated Circuit
BLEU	Bilingual Evaluation Understudy
CNN	Convolutional Neural Network
DUT	Device Under Test
FP	Forward Propagation
FPGA	Field Programmable Gate Array
GAN	Generative Adversarial Network
GPU	Graphics Processing Unit
HPC	High Performance Computing
HPO	Hyper-Parameter Optimization
MAC	Multiply-Accumulate
MIoU	Mean Intersection over Union
NAS	Neural Architecture Search
NFS	Network File System
NPU	Neural Processing Unit
OPS	Operations Per Second
PSNR	Peak Signal to Noise Ratio
PSU	Power Supply Unit
RAM	Random-Access Memory
RNN	Recurrent Neural Network
SSIM	Structural Similarity Index Measure

5 Conventions

The following conventions are used in this Recommendation:

– The keywords "**is required to**" indicate a requirement that must be strictly followed and from which no deviation is permitted, if conformance to this Recommendation is to be claimed.

– The keywords "**is recommended**" indicate a requirement that is recommended but which is not absolutely required. Thus, this requirement need not be present to claim conformance.

6 Overview of AI computing power benchmark

6.1 Evaluation object

AI computing systems could provide strong computing support for multimedia applications, data centres, or edge computing scenarios powered by artificial intelligence (AI) algorithms and software. As an artificial intelligence device is equipped with a graphics processing unit (GPU), field programmable gate array (FPGA), application-specific integrated circuit (ASIC), and other acceleration chips, the device under test (DUT) could be a PC, workstation high performance computing (HPC) data centre, etc.

6.2 Evaluation principle

6.2.1 Practicality

Benchmarking methods should be built based on the representative artificial intelligence applications and be able to produce robust results. Benchmarking methods are recommended to cover commonly used AI models or algorithms in practical applications such as convolutional neural network (CNN), recurrent neural network (RNN), generative adversarial network (GAN), autoencoder, transformer, vision transformer, and conventional machine learning algorithms. The benchmark is performed by evaluating the training speed of the above models or algorithms.

6.2.2 Fairness

Benchmarking methods should provide a fair comparison by specifying rules and metrics and be based on objective scientific test data during the evaluation process. As the architecture of AI hardware platforms varies, different AI hardware utilizes different accelerating methods or even different precision formats to maximize computing efficiency. In this case, the accelerating method and precision format for each benchmarking score must be explicitly noted for a fair comparison. In addition to the total score, it is also necessary to demonstrate the sub-scores of each evaluation item to reflect the advantages or disadvantageous of each AI platform for particular scenarios.

6.2.3 Scalability

Benchmarking methods should provide variable scale workloads to make full use of the computing resources of the artificial intelligence computing system to reflect its computing power. The benchmarking methods can run on a single-node device with relatively lower computational performance, as well as the ability to run on a large-scale cluster with multiple nodes or units in a highly parallelized fashion.

6.2.4 Repeatability

Benchmarking methods should ensure that the error of measurement results is within a certain controllable range while using the same benchmark implementation under the same configurations on multiple trials. The benchmarking score needs to be calculated by averaging the results of multiple runs instead of the result of a single run.

6.3 Evaluation mechanism

The benchmarking program uses a representative and auto-adaptive or scalable workload to establish an end-to-end benchmark suite for the AI computing power system. Once the benchmark process is complete, an overall score representing the computational power and stability, and the sub-scores representing the individual computing power of different application scenarios are demonstrated.

7 Architecture framework of AI computing power benchmark

The benchmarking framework consists of three parts, as shown in Figure 1, which are 1) workload as the input part, 2) AI computing power benchmark with a specific evaluation environment, and 3) metric as the output part with the benchmark score.

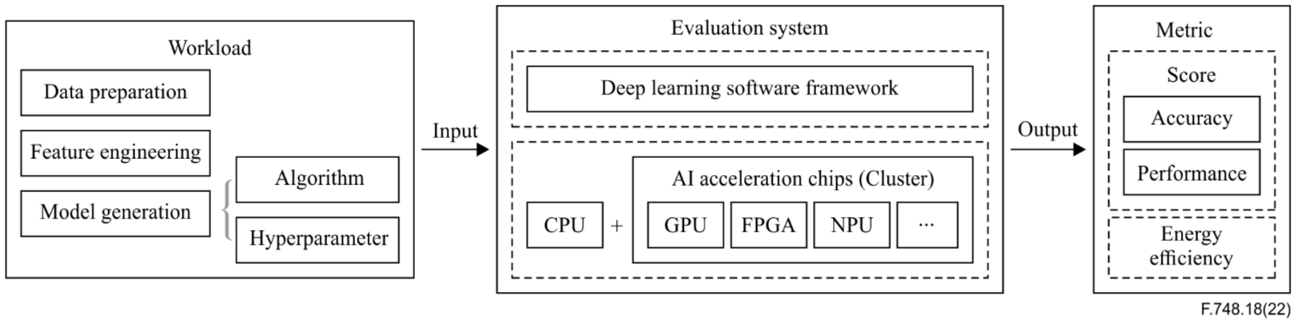

Figure 1 – Architecture framework of AI computing power benchmark

7.1 Workload

A representative AI application is used as the workload which contains the critical components regarding the primary computing operations (e.g., sparse matrices multiplication), calculation precision (in a single-precision floating-point, half-precision floating-point, or other precision formats), and workflow in real AI scenarios (e.g., computer vision, neural language processing, speech recognition). The reference of the benchmark workloads can be found in Appendix III.

7.1.1 Data preparation

Data preparation involves data collection, data cleaning and data argumentation. To perform the benchmark objectively, the process of data preparation, input, and output dimensions of the data preparation in the AI benchmark should be similar to the actual application scenarios. Actual data instead of the matrix is recommended.

7.1.2 Feature engineering

Feature engineering involves feature selection, feature construction and feature extraction. They depend on the application scenarios and are irrelevant to the machine computing power, therefore it is not considered in the benchmark.

7.1.3 Model generation

Model generation involves algorithms and hyper-parameters. An algorithm means using specific approaches to generate the neural architecture and hyper-parameter optimization (HPO) is essentially the optimization of the loss function over the complex configuration space. Evaluation of models and algorithms in all kinds of real application scenarios is recommended to comprehensively evaluate the AI computing power of an AI computing hardware.

7.2 Metrics

Operations per second (OPS) or samples per second is used as the benchmark metric to describe the performance. The OPS here represents the number of computing operation counts that certain hardware can complete in the benchmark testing items. The samples per second is a result-oriented metric that can evaluate the computing efficiency of an AI hardware in practice. The benchmark score is required to be the weighted summation of each testing item (including training of each AI model or algorithm).

7.2.1 AI computing power score

The benchmark scoring metric is constructed based on not only the computing efficiency but also the reduction of the AI model accuracy. Therefore, a penalty factor is recommended to demonstrate this effect. An example of the benchmark metric is shown below:

$$Score_{total} = \sum_{i=1}^{test\ items}[\lambda_{sub_i} \cdot Score_{sub_i}] \tag{1}$$

And the sub-scores can be formulated as:

$$Score_{sub_i} = accuracy^2 \cdot performance, performance = OPS \; or \; \frac{samples}{second} \quad (2)$$

Where *accuracy* will be:

$$accuracy = 1 - reduction \quad (3)$$

And *reduction* will be:

$$reduction = \chi(error) \cdot error, \; \chi(x): \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (4)$$

And *error* will be:

$$error = \frac{metric_{theoretical} - metric_{tested}}{metric_{theoretical}} \quad (5)$$

Here, $Score_{sub_i}$ *is* the performance score of training in the i-th benchmark testing item which can be measured by OPS or samples per second. λ_{sub_i} is the weighting parameters corresponding to the scores. The $reduction$ is calculated by the $error$ which is a penalty factor to reflect the accuracy reduction of models or algorithms. The $error$ here is the ratio of the difference between test results and theoretical results and the theoretical results are the accuracy result of the models or algorithms demonstrated in original papers or official benchmarks of certain datasets. The resulting metric can be any type of metric (such as accuracy, F1-score, mean intersection over union (MIoU), peak signal to noise ratio (PSNR), structural similarity index measure (SSIM), or bilingual evaluation understudy (BLEU)) corresponding to specific tasks. Once the benchmark process is completed, both the $Score_{total}$ represents the overall AI performance and the $Score_{sub_i}$ represent the AI performance for each specific task that should be demonstrated. This AI computational power metric example considers both the computational power of various practical AI tasks and the accuracy degradation in AI computational acceleration or optimization. This example can be used as a reference for the setting of the AI computing metric.

7.2.2 Energy efficiency

Energy efficiency, which is the ratio of AI computing power to electric power assumption, is also a key factor for AI computing systems. The computing power is evaluated by the AI benchmark process of various AI tasks in OPS and the electric power assumption is measured by a power meter in watts.

7.3 AI computing power benchmark

AI computing power benchmark includes the testing environment with hardware specification and evaluation environment.

7.3.1 Hardware specification

Hardware specification involves the information of the processor, AI accelerator, storage, and the Ethernet network. The configuration (including clock speed of GPU, CPU, random-access memory (RAMs) and other components, cooling systems, and power supply unit (PSU) systems) of the hardware applied in the benchmark needs to be identical to the mass production version. Hardware parameters and configurations must be indicated and cheating designed for the benchmark is prohibited.

7.3.2 Evaluation environment

The evaluation environment involves the information of the system, deep learning framework, and the related software. Since the environment configuration and acceleration method significantly impacts the benchmark results, the settings of the test environment and acceleration method need to be indicated.

8 Technical testing for AI computing power benchmark

The workflow of an end-to-end benchmark suite utilizing the automated machine learning (AutoML) as a workload to evaluate the performance of a heterogeneous AI computing power system is shown in Figure 2.

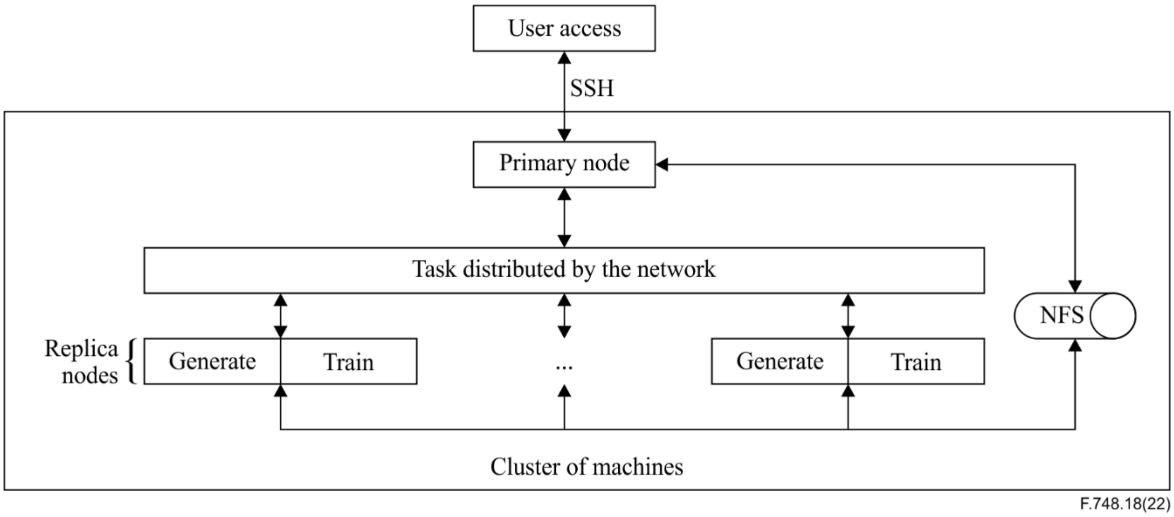

Figure 2 – Schematic diagram of the benchmark workflow

The benchmark workflow is described as follows, to ensure the utilization of the AI accelerator, steps 3 and 4 are usually run in parallel. Steps 3-4 are cycled until the running terminates once the condition is satisfied (e.g., reaching user-defined time):

Step 1: The user accesses the primary node through the secure shell (SSH) and collects the information about replica nodes.

Step 2: Primary node dispatches workloads by the network to the replica nodes corresponding to the requested and available resources, parallelly and asynchronously.

Step 3: The CPUs on the replica nodes search for new architectures based on the current historical model list, which contains detailed model information and accuracy on the test dataset, then store the candidate architecture in the buffer (e.g., network file system (NFS)) for later training.

Step 4: The AI accelerators on replica nodes load the candidate architecture and data, utilize data parallelism to train along with the hyper-parameter optimization (HPO), and then store the results in the historical model list.

Step 5: The final results are calculated based on the recorded metrics and then reported.

Appendix I

OPS calculation

(This appendix does not form an integral part of this Recommendation.)

Table I.1 and Table I.2 give the analytical operation counts of each layer (per image) in the forward propagation (FP) and backward propagation (BP) respectively.

The analytical operation counts each layer (per image) in the FP. For the convolutional layer, the input image dimension is $H_i \times W_i \times C_i$, the output dimension is $C_o \times W_o \times C_o$, and the kernel (filter) size is $K \times K$. For the dense layer, the input is $C_i$and the output is C_o.

Table I.1 – The analytical operation counts in FP

Layer	Operation in the FP
Convolutional layer	$MAC = K \times K \times C_i \times H_o \times W_o \times C_o$
Dense layer	$MAC = C_i \times C_o$
Batch normalization	$MAC = Add = Div = H_i \times W_i \times C_i$
ReLU	$Comparison = H_o \times W_o \times C_o$
Add layer	$Add = H_o \times W_o \times C_o$
Max-pooling layer	$Comparison = K \times K \ H_o \times W_o \times C_o$
Global-pooling layer	$Add = H_i \times W_i \times C_i \ ; \ Div = C_i$
Softmax layer	$Exp = Add = Div = C_o$

The analytical operation counts each layer (per image) in the BP. The meanings of the symbols are the same as in Table I.1. The total operation needed for calculating the gradients and updating the parameters are summed.

Table I.2 – The analytical operation counts in BP

Layer	Operation in the BP
Convolutional layer	$MAC = 2 \times (K \times K \times C_i \times H_o \times W_o \times C_o)$ $+(K \times K \times C_i \times C_o)$
Dense layer	$MAC = 2 \times C_i \times C_o + (C_i + 1) \times C_o$

Appendix II

Fixed and customizable configurations

(This appendix does not form an integral part of this Recommendation.)

Table II.1 gives the summarized configurations. These fixed and customizable configurations allow users to optimize the performance.

To ensure fairness in the benchmark, key parameters in the benchmark are required to be fixed in each testing item. The following table takes a neural architecture search (NAS)-based AutoML task as an example to demonstrate the parameter settings in the benchmark process.

Table II.1 – Summarized configurations

Configuration	Fixed and customizable setups
Server arrangement	Fixed: Primary-replica
NAS method	Fixed: Network morphism
HPO method	Fixed: Bayesian optimization
Dataset	Fixed: ImageNet
DL framework	Default: TensorFlow
Initial architecture	Fixed: ResNet-50
Initial weight	Default: Method in
Batch size	Default: 448
Optimizer	Default: Gradient descent with momentum
Learning rate	Default: 0.1 with linear decay
Loss function	Default: Categorical cross entropy
Maximum epoch	Default: 60
Parallelism	Default: Synchronous all-reduce
Parallel data transformation	Default: 48
Minimum precision	Fixed: Half-precision floating-point
Maximum error	Fixed: 30%

Appendix III

Reference of the benchmark workloads

(This appendix does not form an integral part of this Recommendation.)

Table III.1 gives references to benchmark workloads, which include the application scenarios, datasets and models.

Table III.1 – Benchmark workloads

No.	Application scenarios	Dataset	Model
1	Image classification	ImageNet	ResNet-50 and ResNet-101, the architecture and implementation can be found in [b-He]
			MobileNetV3, the architecture and implementation can be found in [b-Howard]
			Swin transformer, the architecture and implementation can be found in [b-Liu]
2	Object detection	COCO	Faster, the architecture and implementation can be found in [b-Ren]
			HRNet, the architecture and implementation can be found in [b-Sun]
			YOLOv5, the architecture and implementation can be found in [b-Zhu]
3	Segmentation	ADE20K	DeepLabV3+, the architecture and implementation can be found in [b-Chen]
			SegFormer, the architecture and implementation can be found in [b-Xie]
			BiSeNetV2, the architecture and implementation can be found in [b-Yu]
4	Super-resolution	IXI Dataset	Residual dense network for image super-resolution, the architecture and implementation can be found in [b-Zhang], [b-Wang] and [b-Ledig]
5	Face recognition	CelebA	FaceNet, the architecture and implementation can be found in [b-Schroff]
6	Machine translation	WMT 2014	T5-11B, the architecture and implementation can be found in [b-Raffel]
7	Question answering	SQuAD1.1	LUKE, the architecture and implementation can be found in [b-Yamada]
8	Recommendation	MovieLens	Graph convolutional matrix completion, the architecture and implementation can be found in [b-Berg.]

Bibliography

[b-ITU-T F.748.11] Recommendation ITU-T F.748.11 (2020), *Metrics and evaluation methods for a deep neural network processor benchmark*.

[b-ITU-T F.748.12] Recommendation ITU-T F.748.12 (2021), *Deep learning software framework evaluation methodology*.

[b-ITU-T Y.3172] Recommendation ITU-T Y.3172 (2019), *Architectural framework for machine learning in future networks including IMT-2020*.

[b-Berg] Berg, R.V.D., Kipf, T.N., and Welling, M. (2017), *Graph Convolutional Matrix Completion*. <https://arxiv.org/abs/1706.02263>

[b-Chen] Chen, L-C., Papandreou, G., Schroff, F., and Adam, H. (2017), *Rethinking Atrous Convolution for Semantic Image Segmentation*. <https://arxiv.org/abs/1706.05587>

[b-He] He, K., Zhang, X., Ren, S., and Sun, J. (2016), *Deep Residual Learning for Image Recognition*. <https://ieeexplore.ieee.org/document/7780459>

[b-Howard] Howard, A., Sandler, M., Chu, G., Chen, L-C., Chen, B., Tan, M., Wang, W., Zhu, Y., Pang, R., Vasudevan, V., Le, Q.V., and Adam, H. (2019), *Searching for MobileNetV3*. <https://arxiv.org/abs/1905.02244>

[b-Ledig] Ledig, C., Theis, L., Huszar, F., Caballero, J., Cunningham, A., Acosta, A., Aitken, A., Tejani, A., Totz, J., Wang, Z., and Shi, W. (2017), *Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network*. <https://arxiv.org/abs/1609.04802>

[b-Liu] Liu, Z., Lin, Y., Cao, Y., Hu, H., Wei, Y., Zhang, Z., Lin, S., and Guo, B. (2021), *Swin Transformer: Hierarchical Vision Transformer using Shifted Windows*. <https://arxiv.org/abs/2103.14030>

[b-Raffel] Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., and Liu, P.J. (2020), *Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer*. Journal of Machine Learning Research 21, 1-67. <https://jmlr.org/papers/volume21/20-074/20-074.pdf>

[b-Ren] Ren, S., He, K., Girshick, R., and Sun, J. (2016), *Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks*. <https://arxiv.org/abs/1506.01497>

[b-Schroff] Schroff, F., Kalenichenko, D., and Philbin, J. (2015), *FaceNet: A Unified Embedding for Face Recognition and Clustering*. <https://arxiv.org/abs/1503.03832>

[b-Sun] Sun, K., Xiao, B., Liu, D., and Wang, J. (2019), *Deep High-Resolution Representation Learning for Human Pose Estimation*. <https://arxiv.org/abs/1902.09212>

[b-Wang] Wang, X., Yu, K., Wu, S., Gu, J., Liu, Y., Dong, C., Chen, C.L., Qiao, Y., and Tang, X. (2018), *ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks*.
<https://arxiv.org/abs/1809.00219>

[b-Xie] Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J.M., and Luo, P. (2021), *SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers*.
<https://arxiv.org/abs/2105.15203>

[b-Yamada] Yamada, I., Asai, A., Shindo, H., Takeda, H., and Matsumoto, Y. (2020), *LUKE: Deep Contextualized Entity Representations with Entity-aware Self-attention*.
<https://arxiv.org/abs/2010.01057>

[b-Yu] Yu, C., Wang, J., Peng, C., Gao, C., Yu, G., and Sang, N. (2018), *BiSeNet: Bilateral Segmentation Network for Real-time Semantic Segmentation*.
<https://arxiv.org/abs/1808.00897>

[b-Zhang] Zhang, Y., Tian, Y., Kong, Y., Zhong, B., and Fu, Y. (2018), *Residual Dense Network for Image Super-Resolution.*
<https://arxiv.org/abs/1802.08797>

[b-Zhu] Zhu, X., Lyu, S., Wang, X., & Zhao, Q. (2021), *TPH-YOLOv5: Improved YOLOv5 Based on Transformer Prediction Head for Object Detection on Drone-captured Scenarios*.
<https://arxiv.org/abs/2108.11539>

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Series A	Organization of the work of ITU-T
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Series F	**Non-telephone telecommunication services**
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Series H	Audiovisual and multimedia systems
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