Video compression dataset and benchmark of learning-based video-quality metrics

Anastasia Antsiferova^{1,2*}, Sergey Lavrushkin^{1,2*}, Maksim Smirnov^{3*}, Alexander Gushchin^{3*}, Dmitriy Vatolin^{1,2,3*}, Dmitriy Kulikov^{2,3*} ISP RAS Research Center for Trusted Artificial Intelligence¹ MSU Institute for Artificial Intelligence² Lomonosov Moscow State University³ {aantsiferova, sergey.lavrushkin, maxim.smirnov.2025, alexander.gushchin, dmitriy, dkulikov}@graphics.cs.msu.ru

Abstract

Video-quality measurement is a critical task in video processing. Nowadays, many implementations of new encoding standards — such as AV1, VVC, and LCEVC — use deep-learning-based decoding algorithms with perceptual metrics that serve as optimization objectives. But investigations of the performance of modern video- and image-quality metrics commonly employ videos compressed using older standards, such as AVC. In this paper, we present a new benchmark for video-quality metrics that evaluates video compression. It is based on a new dataset consisting of about 2,500 streams encoded using different standards, including AVC, HEVC, AV1, VP9, and VVC. Subjective scores were collected using crowdsourced pairwise comparisons. The list of evaluated metrics includes recent ones based on machine learning and neural networks. The results demonstrate that new no-reference metrics exhibit high correlation with subjective quality and approach the capability of top full-reference metrics.

1 Introduction

Video constitutes the largest part of the world's Internet traffic, and its volume has increased because of the Covid lockdowns. The network load has also increased, making efficient video compression extremely important. Development and comparison of new video encoders greatly relies on quality measurement, and many new compression standards implement machine-learning- and neural-network-based approaches. But traditional image- and video-quality metrics, such as PSNR and SSIM, emerged long before recent compression standards, and they did not account for neural-network-related artifacts. VMAF [26], a well-known video-quality metric from Netflix, was also trained using only H.264/AVC-compressed videos. Thus, quality measurement for new video-encoding standards is even more vital. The number of new image- and video-quality metrics has increased, and many recent algorithms employ learning-based approaches. Industry leaders have also created their own quality metrics: Apple's Advanced Video Quality Tool (AVQT) [2], Tencent's Deep Learning-Based Video Quality Assessment (DVQA) [1], and the aforementioned VMAF. Only a few of these metrics demonstrate high performance on independent benchmarks, however, and some new ones, including AVQT and DVQA, still await detailed analysis. A concern associated with

36th Conference on Neural Information Processing Systems (NeurIPS 2022) Track on Datasets and Benchmarks.

^{*}A. Antsiferova designed methodology and performed results analysis, led the benchmark and the paper preparation, S. Lavrushkin performed results analysis and the paper preparation, M. Smirnov developed the benchmark of no-reference metrics, A. Gushchin developed the benchmark of full-reference metrics, both of them performed the dataset research, results analysis and contributed to the paper preparation, D. Vatolin and D. Kulikov coordinated the benchmark and the dataset creation



Figure 1: Crops from video sequences encoded using old and new standards relative to ground truth (GT). LCEVC employs super-resolution, which allows restoration of more details and creates new kinds of artifacts.

metric-result reproducibility and verification is the outdated datasets for measuring video-compression quality. Most datasets containing compressed videos and subjective scores only employ H.264/AVC compression. In-lab tests were the source of subjective scores for many such videos. Owing to the complexity and high cost of subjective comparisons, those tests involved a small number of viewers and garnered only a few scores per video.

Quality-metric development seldom takes into account artifacts produced by video encoders that implement contemporary standards. For example, super-resolution in LCEVC and in new neural-network-based encoders yields distortions that traditional metrics are unable to handle. Fig. 1 demonstrates the difference between frame crops of x265-encoded video and lcevc_x265-encoded video: the latter contains more detail despite its lower PSNR and SSIM scores. Existing benchmarks for image- and video-quality metrics do not consider artifacts produced by new compression standards. Our research therefore analyzed metric performance on videos with various compression artifacts.

The goal of our investigation was to evaluate new and state-of-the-art image- and video-quality metrics independently, using a large dataset representing diverse compression artifacts from different video encoders. We thus propose a new dataset of 2,486 compressed videos and subjective scores collected using a crowdsourced comparison with nearly 11,000 participants. We also present a new benchmark² based on that dataset, which we divide into open and hidden parts. This paper provides our assessment results for the open part as well as for the whole dataset.

2 Related Work

2.1 Video-Quality Datasets

Video-quality datasets with subjective scores break down into two types: legacy synthetically distorted (mainly through compression and transmission distortions, capture impairments, processing artifacts, and Gaussian blur), and authentic user-generated content (UGC). The former [43, 11, 42, 7, 32, 27, 37, 19] apply synthetic distortions to the original videos. The latter [14, 39, 36, 16, 44, 50] are gaining popularity, as videos produced today by amateurs often suffer from a wide variety of distortions. Many new video-quality metrics have undergone testing only for UGC videos. The latest studies employ a nearly identical pool of subjective video-quality datasets, summarized in Tab. 1.

2.2 Video-Quality Benchmarks

Most comparisons of IQA and VQA have appeared in papers that present new methods and a few benchmarks accept new methods for evaluation. Often, these comparisons either include an evaluation using open video datasets, for which existing metrics may have been tuned, or employ just a few methods. The authors of [39] published a comparison for a wide variety of datasets but evaluated only four methods. In [41] the authors compared no-reference VQA models using three UGC datasets

²https://videoprocessing.ai/benchmarks/video-quality-metrics.html

Dataset	Original videos	Average duration (s)	Distorted videos	Distortion	Subjective framework	Subjects	Answers
MCL-JCV (2016) [42]	30	5	1,560	Compression	In-lab	150	78K
VideoSet (2017) [43]	220	5	45,760	Compression	In-lab	800	-
UGC-VIDEO (2020) [25]	50	> 10	550	Compression	In-lab	30	16.5K
CVD-2014 (2014) [36]	5	10-25	234	In-capture	In-lab	210	-
LIVE-Qualcomm (2016) [14]	54	15	208	In-capture	In-lab	39	8.1K
GamingVideoSET (2018) [9]	24	30	576	Compression	In-lab	25	-
KUGVD (2019) [8]	6	30	144	Compression	In-lab	17	-
KoNViD-1k (2017) [16]	1,200	8	1,200	In-the-wild	Crowdsource	642	205K
LIVE-VQC (2018) [39]	585	10	585	In-the-wild	Crowdsource	4,776	205K
YouTube-UGC (2019) [44]	1,500	20	1,500	In-the-wild	Crowdsource	>8,000	600K
LSVQ (2020) [50]	39,075	5-12	39,075	In-the-wild	Crowdsource	6,284	5M
Our dataset: open part (2022)	36	10, 15	1,022	Compression (32 codecs)	Crowdsource	10,800	320K
Our dataset: hidden part (2022)	36	10, 15	1,464	Compression (51 codecs)	Crowdsource	10,800	446K
Our dataset (2022)	36	10, 15	2,486	Compression (83 codecs)	Crowdsource	10,800	766K

Table 1: Summary of subjective video-quality datasets and our new dataset.

Benchmark	Total number of videos	Total number of VQA methods	Total number of subjects	Distortion
Z. Sinno and A. Bovik (2018) [39]	585	4	4,776	In-the-wild videos, 80 mobile cameras, 18 resolutions
Y. Li et al. (2020) [24]	550	15	28	H.264, H.265 compression, QP: 22, 27, 32, 37, 42
UGC-VQA (2021) [41]	3,108 (LIVE-VQC, YouTube-UGC, KoNViD-1k)	13	>13,000	Compression, transmission
Our benchmark (2022)	2,486	26	10,800	Compression (H.264, H.265, AV1, VVC, etc.)

Table 2: Summary of video-quality-measurement benchmarks and our new benchmark.

and various experiments. They analyzed metrics applied to videos with different content types, resolution and quality subsets, temporal pooling, and computational-complexity-evaluation methods. Compression artifacts, however, played a minor role in that study. The main idea of [24] was to compare full- and no-reference metrics through subjective evaluation of UGC videos transcoded using different compression standards and levels, but this work only tested a few no-reference methods and codecs.

3 Benchmark

3.1 List of Metrics

This study aimed to evaluate new and state-of-the-art neural-network-based video- and image-quality metrics on a compression-oriented video dataset. We excluded several well-known metrics such as BRISQUE [33] and VIIDEO [34] because of their low correlations in many other studies [50, 22, 24].

3.1.1 No-Reference Video-Quality Metrics

The no-reference video-quality metric **VIDEVAL** (2021) [41] chooses 60 features (related to motion, certain distortions, and aesthetics) from previously developed quality models. It performs well on existing UGC datasets, but it may suffer from overfitting, as users must set many of its parameters.

Most recent quality-assessment papers emphasize deep-learning-based approaches. **MEON** (2017) [29] is a model consisting of two sub-networks: a distortion-identification one and a quality-prediction one. It can also determine the distortion type.

VSFA (2019) [20] employs a pretrained ResNet-50 [15] as well as a deep content-aware feature extractor followed by a temporal-pooling layer for temporal memory. It performed poorly in the cross-dataset evaluation, so the authors proposed an enhanced version, **MDTVSFA** (2021) [22]. This enhanced version follows a mixed-dataset training strategy and may have high computational complexity owing to recurrent layers and full-size-image inputs.

PaQ-2-PiQ (2020) [51] uses a deep region-based architecture trained on a large subjective imagequality dataset of 40,000 pictures. **KonCept512** (2020) [17] is based on InceptionResNetV2 and was trained on the proposed KonIQ-10k dataset. **SPAQ** (2020) [13] implements three extra modifications of its baseline model: EXIF-data processing (MT-E), image-attribute observation (MT-A), and observation of a scene's high-level semantics (MT-S). The creators of **Linearity** (2020) [21] introduced their own loss function, "norm-in-norm", which converges 10 times faster than the MAE and MSE loss functions. **NIMA** (2018) [40] was trained on the large-scale Aesthetic Visual Analysis (AVA) dataset and predicts a quality-rating distribution.

3.1.2 Full-Reference Video-Quality Metrics

PSNR and **SSIM** [45] are among the most popular image- and video-quality metrics. We compared variations of SSIM and **MS-SSIM** [46] in our benchmark; the latter is an advanced version of the former calculated over multiple scales using subsampling.

LPIPS (2019) [52] is based on AlexNet and VGG. We chose a VGG-based version for testing because it serves as a generalization of "perceptual loss" [18]. **DISTS** (2020) [12] was designed to tolerate texture resampling and to be sensitive to structural differences. It combines structure- and texture-similarity measurements for corresponding image embedments and is based on a pretrained VGG network.

Tencent's **DVQA** (2020) [1] is based on the C3DVQA network [49]. It uses 3D convolutional layers to learn spatiotemporal features and 2D convolutional layers to extract spatial information.

The main feature of **FovVideoVDP** (2021) [31] is consideration of peripheral visual acuity. This method models the human visual system's response to temporal changes across the visual field. It can estimate flickering, juddering, and other temporal distortions, as well as spatiotemporal artifacts such as those appearing at different degrees of peripheral vision.

ST-GREED (2021) [30] can quantify reference and distorted videos of different frame rates without temporal preprocessing. It offers two primary features: SGreed and TGreed. The latter quantifies the statistics of temporal bandpass responses to both spatial and temporal distortions. The former obtains spatial bandpass responses using a local filtering scheme. Calculation of the final ST- GREED value employs the support-vector regressor.

Nowadays **VMAF** (2018) [26] is one of the most popular VQA metrics. It computes three base features—the detail-loss metric (DLM) [23], visual-information fidelity (VIF) [38], and temporal information (TI)—and combines them with a support-vector regressor. We also evaluated **AVQT** (2021) [2], developed by Apple, but the company has yet to publish any technical information.

3.2 Video Dataset

To analyze the relevance of quality metrics to video compression, we collected a special dataset of videos exhibiting various compression artifacts. For video-compression-quality measurement, the original videos should have a high bitrate or, ideally, be uncompressed to avoid recompression artifacts. We chose from a pool of more than 18,000 high-bitrate open-source videos from www.vimeo.com. Our search included a variety of minor keywords to provide maximum coverage of potential results—for example "a," "the," "of," "in," "be," and "to." We downloaded only videos that were available under CC BY and CC0 licenses and that had a minimum bitrate of 20 Mbps. The average bitrate of the entire collection was 130 Mbps. We converted all videos to a YUV 4:2:0 chroma subsampling. Our choice employed space-time-complexity clustering to obtain a representative complexity distribution. For spatial complexity, we calculated the average size of x264-encoded I-frames normalized to the uncompressed frame size. For temporal complexity, we calculated the average P-frame size divided by the average I-frame size. We divided the whole collection into 36 clusters using the K-means algorithm [28] and, for each cluster, randomly selected up to 10 candidate videos close to the cluster center. From each cluster's candidates we manually chose one video, attempting to include different





Figure 2: Bitrate distribution of videos in our dataset.

Figure 3: PSNR (range and uniformity) comparison for our dataset versus other video datasets.

genres in the final dataset (sports, gaming, nature, interviews, UGC, etc.). The result was 36 FullHD videos for further compression.

We obtained numerous coding artifacts by compressing videos through several encoders: 11 H.265/HEVC encoders, 5 AV1 encoders, 2 H.264/AVC encoders, and 4 encoders based on other standards. To increase the diversity of coding artifacts, we also used two different presets for many encoders: one that provides a 30 FPS encoding speed and the other that provides a 1 FPS speed and higher quality. The list of settings for each encoder is presented in the supplementary materials. Not all videos underwent compression using all encoders. We compressed each video at three target bitrates — 1,000 kbps, 2,000 kbps, and 4,000 kbps — using a VBR mode (for encoders that support it) or with corresponding QP/CRF values that produce these bitrates. Major streaming-video services recommend at most 4,500–8,000 kbps for FullHD encoding [3, 4, 5]. We avoided higher target bitrates because visible compression artifacts become almost unnoticeable, hindering subjective comparisons. Fig. 2 shows the distribution of video bitrates for our dataset. The distribution differs from the target encoding rates because we used the VBR encoding mode, but it complies with the typical recommendations.

The dataset falls into two parts: open and hidden (40% and 60% of the entire dataset, respectively). We employ hidden part only for testing through our benchmark to ensure a more objective comparison of future applications. This approach may prevent learning-based methods from training on the entire dataset, thereby avoiding overfitting and incorrect results. To divide our dataset, we split the codec list in two; the encoded videos each reside in the part corresponding to their respective codec. We also performed x265-lossless encoding of all compressed streams to simplify further evaluations and avoid issues with nonstandard decoders.

Tab. 1 shows the characteristics of the final parts of the dataset. Links to source videos and additional details about the collection process are in the supplementary materials. We also compared the statistics of PSNR uniformity and range for our dataset using the approach in [47]. As Fig. 3 shows, this dataset provides wide quality and compression-rate ranges.

3.3 Subjective-Score Collection

We collected subjective scores for our video dataset through the Subjectify.us crowdsourcing platform. Subjectify.us is a service for pairwise comparisons; it employs a Bradley-Terry model to transform the results of pairwise voting into a score for each video. A more detailed description of the method is at www.subjectify.us.

Because the number of pairwise comparisons grows exponentially with the number of source videos, we divided the dataset into five subsets by source videos and performed five comparisons. Each subset contained a group of source videos and their compressed versions. Every comparison produced and

evaluated all possible pairs of compressed videos for one source video. Thus, only videos from the same source were in each pair. The comparison set also included source videos. Participants viewed videos from each pair sequentially in full-screen mode. They were asked to choose the video with the best visual quality or indicate that the two are of the same quality. They also had an option to replay the videos. Each participant had to compare a total of 12 pairs, two of which had an obviously higher-quality option and served as verification questions. All responses from those who failed to correctly answer the verification questions were discarded.

To increase the relevance of the results, we solicited at least 10 responses for each pair. In total, we collected 766,362 valid answers from nearly 11,000 individuals. After applying the Bradley-Terry model to a table of pairwise ranks, we received subjective scores that are consistent within each group of videos compressed from one reference video. A detailed description of the subjective-comparison process, as well as collected statistics, is in the supplementary materials. Tab. 1 summarizes the parameters of our dataset.

3.4 Methodology

We used public source code for all metrics without additional pretraining, and we selected the default parameters to avoid overfitting. To get a video's quality score using the IQA method, we compared the given distorted sequence and the reference video frame by frame, then averaged the resulting per-frame quality scores for each video. VQA methods generate a score for the whole distorted sequence and require no additional averaging.

Because the subjective scores are based on pairwise comparisons of videos produced from the same original sequence, they are comparable only within their respective groups. Each group size is three (the number of encoding bitrates) times the number of codecs applied to the reference video. For each reference-video/preset pair (resulting in one distorted-video group), we calculated Spearman and Kendall correlation coefficients (SROCC and KROCC, respectively) between the metrics and subjective scores. We then selected only those values calculated for groups whose number of samples exceed a threshold (15 for SROCC and 6 for KROCC) to provide more-statistically-reliable results. Our next step was to use the Fisher Z-transform [10] (inverse hyperbolic tangent) and average the results, weighted proportionally to group size. The inverse Fisher Z-transform yielded a single correlation for the entire dataset. We provide the link to code example in Sec. 4.

To analyze metric performance in more detail, we added a few mutually nonexclusive categories with videos from the dataset: User-Generated Content, Shaking, Sports, Nature, Gaming / Animation, Low Bitrate (up to 1,000 Kbps), and High Bitrate (above 6,000 Kbps). To assign each video to one of these categories, we conducted a subjective survey of five people from our laboratory.

3.5 Results

We examined the results for the open part of the dataset as well as for the whole dataset, including the hidden part. Tab. **3** shows the Spearman and Kendall correlation coefficients for the metrics we analyzed, along with subjective quality scores. For the whole dataset, VMAF and its variations calculated using different chroma-component ratios exhibited the highest correlations. VMAF was originally to be calculated only using the luma component, but here we proved that YUV-VMAF performs better. Also, VMAF NEG (a no-enhancement-gain version [6]) correlated less well with subjective quality than the original version did. MDTVSFA and Linearity had the highest correlations among no-reference methods: about 0.93, nearly matching the top results of full-reference metrics (VMAF at 0.94). For the open dataset, SSIM and PSNR showed the highest correlations in addition to VMAF, followed by a recently-released AVQT by Apple.

We compared metrics using different video subsets: videos with low and high bitrates; videos encoded using HEVC/H.265, AV1, and VVC/H.266 (Tab. 4); and videos with different content types — UGC, Shaking, Sports, Nature, and Gaming/Animation (Tab. 5).

"High bitrate" and "Low bitrate" encoding. All metrics showed their lowest correlations for videos encoded at 6,000 Kbps or higher. The reason may be the low confidence of the subjective scores for this category. As we described in Sec. 3.2, viewers apparently have difficulty spotting compression artifacts in videos that employ high-quality encoding. The no-reference MDTVSFA, VSFA, and

Dataset	All Dataset (2486	Open+Hidden) videos	Open I 1022	Dataset videos	Dataset	All Dataset (2480	Open+Hidden) 5 videos	Open Dataset 1022 videos		
Metric	SROC	KROC	SROC	KROC	Metric	SROC	KROC	SROC	KROC	
No-Reference MEON [29]	0.507	0.376	0.554	0.350	Full-Reference FOV VIDEO [31]	0.527 (0.521, 0.534)	0.375 (0.370, 0.380)	0.565 (0.551, 0.579)	0.492 (0.477, 0.507)	
Y-NIQE [35]	(0.495, 0.518) 0.599 (0.586, 0.611)	(0.367, 0.384) 0.421 (0.411, 0.431)	(0.534, 0.574) 0.701 (0.679, 0.721)	(0.333, 0.366) 0.557 (0.541, 0.573)	LPIPS [52]	0.749 (0.742, 0.756) 0.763	0.567 (0.561, 0.573) 0.579	0.787 (0.774, 0.799) 0.774	0.667 (0.655, 0.679) 0.683	
VIDEVAL [41]	0.729 (0.719, 0.738)	0.541 (0.532, 0.551)	0.719 (0.700, 0.737)	0.558 (0.540, 0.575)	GREED [30]	(0.756, 0.770) 0.764 (0.759, 0.769)	(0.572, 0.585) 0.588 (0.582, 0.593)	(0.762, 0.786) 0.790 (0.782, 0.797)	(0.670, 0.695) 0.644 (0.634, 0.654)	
KonCept512 [17]	0.836 (0.831, 0.841)	0.661 (0.655, 0.666)	0.861 (0.853, 0.868)	0.696 (0.688, 0.703)	Y-VQM [48]	0.821 (0.815, 0.827)	0.644 (0.637, 0.651)	0.881 (0.870, 0.890)	0.767	
NIMA [40]	0.849 (0.844, 0.854)	0.675 (0.668, 0.681)	0.868 (0.860, 0.875)	0.729 (0.719, 0.738)	DISTS [12]	0.847 (0.842, 0.851)	0.671 (0.667, 0.676)	0.873 (0.866, 0.879)	0.753 (0.744, 0.761)	
PaQ-2-PiQ [51]	0.871 (0.866, 0.875)	0.708 (0.702, 0.714)	0.901 (0.894, 0.908)	0.752 (0.743, 0.761)	AVQT [2]	0.876 (0.872, 0.879)	0.720 (0.716, 0.725)	0.889 (0.882, 0.896)	0.792 (0.784, 0.800)	
SPAQ MT-A [13]	0.879 (0.875, 0.884)	0.715 (0.709, 0.720)	0.912 (0.905, 0.919)	0.796 (0.786, 0.805)	YUV-PSNR	0.883 (0.879, 0.887) 0.906	0.728 (0.722, 0.733) 0.756	(0.949 (0.946, 0.952) 0 948	0.849 (0.844, 0.854) 0 897	
SPAQ BL [13]	0.880 (0.875, 0.884)	0.711 (0.704, 0.717)	0.912 (0.905, 0.918)	0.789 (0.780, 0.798)	YUV-SSIM	(0.902, 0.909) 0.909	(0.750, 0.761) 0.756	(0.945, 0.951) 0.946	(0.872, 0.917) 0.841	
SPAQ MT-S [13]	0.882 (0.878, 0.886)	0.719 (0.713, 0.724)	0.912 (0.906, 0.918)	0.787 (0.778, 0.796)	Y-VMAF NEG [26]	(0.905, 0.912) 0.914	(0.751, 0.760) 0.765	(0.943, 0.949) 0.945	(0.835, 0.847) 0.841	
VSFA [20]	0.905 (0.901, 0.908)	0.748 (0.743, 0.753)	0.891 (0.886, 0.897)	0.758 (0.750, 0.766)	YUV-VMAF NEG [26]	(0.911, 0.917) 0.917 (0.014, 0.020)	(0.760, 0.769) 0.769 (0.765, 0.774)	(0.942, 0.948) 0.947 (0.044, 0.050)	(0.836, 0.846) 0.894	
Linearity [21]	0.910 (0.907, 0.913)	0.759 (0.754, 0.763)	0.905 (0.899, 0.911)	0.783 (0.774, 0.791)	Y-VMAF (v061) [26]	(0.914, 0.920) 0.942 (0.940, 0.944)	0.809 (0.805, 0.813)	(0.944, 0.950) 0.945 (0.942, 0.948)	0.888 (0.861, 0.910)	
MDTVSFA [22]	<u>0.929</u> (0.927, 0.931)	0.788 (0.784, 0.792)	<u>0.930</u> (0.927, 0.934)	<u>0.813</u> (0.806, 0.819)	YUV-VMAF (v061) [26]	<u>0.943</u> (0.941, 0.945)	0.810 (0.806, 0.814)	0.948 (0.945, 0.951)	0.895 (0.870, 0.916)	

Table 3: Results for SROCC and KROCC on the full dataset and on the open part.

Linearity metrics performed better than the full-reference alternatives. The leaders for "Low Bitrate" remain the same as for the whole dataset supplemented by no-reference NIMA.

HEVC, AV1, and VVC encoding. Metric correlation for "H.265 encoding" is higher than for other standards. Because H.265 is older and more popular than newer standards, quality-assessment models may have been tuned to it. For the new VVC standard, the leaders differ relative to other encoding standards: the best no-reference metric is Linearity and the best full-reference one is SSIM. This result is unexpected, but SSIM's good performance may owe to its versatility. Also, the sample for this category is small, so further analysis of the best metrics for estimating VVC encoding quality would likely require a larger dataset.

Leaders by video content category: "UGC", "Shaking", "Sports", "Nature", and "Gaming/Animation". VMAF retained its lead in all categories, but its original luma-only (Y-VMAF) version performed better on "UGC" and "Shaking" content; its modified version using chroma components (YUV-VMAF) is the best for other categories. The no-reference MDTVSFA metric leads in "UGC", "Shaking" and "Nature"; Linearity is ahead in "Sports"; and VSFA is best for "Gaming/Animation". PaQ-2-PiQ also achieves to precisely estimate gaming-content quality.

We performed a one-sided Wilcoxon rank-sum test on SROCC, which we computed for most of the methods in Tab. 4 and Tab. 5 using different groups of videos from our dataset to get the average correlation value. A table of results appears in the supplementary materials. Different versions of SPAQ (BL, MT-S, and MT-A) behaved in a statistically equal manner—except in the "Sports" and "Low Bitrate" categories, where SPAQ BL was superior. In addition, VMAF, the top full-reference metric in average SROCC for the full dataset, yielded to MDTVSFA, the leading no-reference metric, only on videos encoded using AV1 and videos with a high bitrate. A rarely used encoding standard for training quality-assessment methods, VVC was difficult for these methods to handle, and videos encoded using it form the only part of our dataset where MDTVSFA fell short of Linearity. Among related metrics, the test revealed that VMAF NEG and VSFA were statistically worse than or equal to VMAF (v061) and MDTVSFA, respectively, depending on the subset. AVQT was superior to most metrics for the "Low Bitrate" and "Shaking" categories, making it valuable when predicting subjective quality.

Tab. 6 shows the computational complexity of the metrics we studied.

Fig. 4 shows the distribution of normalized metric scores for our dataset. Many metrics have a nonuniform "real-life" distribution of values resulting from compression artifacts. For example, the average SSIM is about 0.85, which corresponds with common statistics (an SSIM of 0.5 does not mean average quality, and values below 0.5 seldom appear in real situations).

Dataset	Low I (up to 1,0 477 v	Bitrate 000 kbps) videos	High I (above 6,0 384 v	Bitrate 000 kbps) ideos	H.265 E	incoding videos	AV1 Er 482 v	ncoding rideos	VVC E	ncoding ideos
Metric	Metric SROC		SROC	KROC	SROC	KROC	SROC	KROC	SROC	KROC
No-Reference										
MEON [29]	0.039	0.069	0.127	0.107	0.834	0.703	0.800	0.734	0.709	0.535
	(0.000, 0.093)	(0.032, 0.106)	(0.097, 0.158)	(0.089, 0.125)	(0.825, 0.842)	(0.661, 0.740)	(0.768, 0.828)	(0.625, 0.815)	(0.662, 0.750)	(0.492, 0.576)
	0.313	0.214	0.027	0.013	0.722	0.519	0.629	0.640	0.389	0.271
Y-NIQE [35]	(0.263, 0.361)	(0.181, 0.246)	(0.000, 0.063)	(0.000, 0.040)	(0.706, 0.736)	(0.431, 0.597)	(0.574, 0.678)	(0.501, 0.747)	(0.311, 0.462)	(0.218, 0.323)
VIDEVAL [41]	(0.580, 0.647)	(0.387, 0.441)	(0.256, 0.322)	(0.189, 0.229)	(0.791, 0.817)	(0.576, 0.731)	(0.707, 0.794)	(0.596, 0.653)	(0.576, 0.688)	(0.444, 0.533)
KonCept512 [17]	(0.883, 0.899)	(0.708, 0.729)	(0.149, 0.259)	(0.136, 0.192)	(0.898, 0.909)	(0.837, 0.907)	(0.793, 0.842)	(0.972, 0.996)	(0.819, 0.874)	(0.658, 0.725)
NIMA [40]	(0.895, 0.913) 0.880	(0.751, 0.776) 0.689	(0.315, 0.405) 0.402	(0.232, 0.280) 0 291	(0.872, 0.886)	(0.748, 0.828) 0.861	(0.774, 0.835) 0.870	(0.901, 0.978) 0.978	(0.648, 0.765) 0.888	(0.486, 0.589) 0 749
PaQ-2-PiQ [51]	(0.871, 0.888) 0.842	(0.675, 0.703)	(0.343, 0.457)	(0.261, 0.321)	(0.906, 0.915) 0.898	(0.823, 0.891)	(0.851, 0.886)	(0.949, 0.991) 0.957	(0.865, 0.908) 0 894	(0.717, 0.777)
SPAQ MT-A [13]	(0.835, 0.849) 0.844	(0.677, 0.702)	(0.356, 0.430) 0.401	(0.286, 0.331) 0.332	(0.892, 0.904) 0.901	(0.777, 0.849) 0.820	(0.853, 0.886) 0.875	(0.909, 0.980) 0.888	(0.869, 0.915) 0.887	(0.689, 0.760) 0.729
SPAQ BL [13]	(0.835, 0.852)	(0.659, 0.685)	(0.358, 0.442)	(0.307, 0.356)	(0.894, 0.907)	(0.781, 0.852)	(0.858, 0.890)	(0.812, 0.935)	(0.862, 0.908)	(0.694, 0.760)
	0.810	0.648	0.417	0.344	0.891	0.808	0.882	0.959	0.908	0.764
SPAQ MT-S [13]	(0.804, 0.816)	(0.640, 0.656)	(0.382, 0.450)	(0.319, 0.368)	(0.883, 0.897)	(0.767, 0.842)	(0.867, 0.896)	(0.914, 0.981)	(0.886, 0.926)	(0.731, 0.793)
	0.894	0.757	0.517	0.370	0.927	0.790	0.914	0.989	0.846	0.694
V SFA [20]	(0.890, 0.898)	(0.748, 0.764)	(0.467, 0.565)	(0.339, 0.401)	(0.922, 0.932)	(0.782, 0.799)	(0.900, 0.927)	(0.973, 0.996)	(0.818, 0.870)	(0.662, 0.723)
	0.900	0.731	0.470	0.336	0.932	0.902	0.906	0.993	0.919	0.791
Linearity [21]	(0.894, 0.906)	(0.721, 0.740)	(0.424, 0.514)	(0.311, 0.361)	(0.928, 0.936)	(0.870, 0.926)	(0.892, 0.918)	(0.981, 0.997)	(0.903, 0.933)	(0.768, 0.812)
	0.943	0.818	0.560	0.363	0.945	0.871	0.932	0.997	0.882	0.746
MD1 V3FA [22]	(0.940, 0.946)	(0.811, 0.824)	(0.511, 0.606)	(0.331, 0.394)	(0.941, 0.948)	(0.843, 0.895)	(0.919, 0.943)	(0.991, 0.999)	(0.859, 0.902)	(0.718, 0.772)
Full-Reference										
FOV VIDEO [31]	0.526	0.372	0.158	0.116	0.558	0.403	0.381	0.539	0.281	0.211
	(0.512, 0.539)	(0.361, 0.384)	(0.135, 0.182)	(0.100, 0.133)	(0.544, 0.571)	(0.393, 0.413)	(0.349, 0.414)	(0.377, 0.670)	(0.243, 0.319)	(0.185, 0.238)
LPIPS [52]	0.774	0.577	0.270	0.179	0.814	0.815	0.532	0.477	0.464	0.356
	(0.761, 0.786)	(0.565, 0.589)	(0.246, 0.293)	(0.160, 0.198)	(0.803, 0.824)	(0.757, 0.860)	(0.499, 0.563)	(0.452, 0.502)	(0.422, 0.504)	(0.325, 0.387)
DVQA [1]	0.781	0.584	0.103	0.100	0.786	0.828	0.458	0.466	0.503	0.366
	(0.766, 0.794)	(0.572, 0.596)	(0.075, 0.130)	(0.088, 0.113)	(0.775, 0.797)	(0.767, 0.874)	(0.434, 0.482)	(0.435, 0.495)	(0.446, 0.555)	(0.327, 0.403)
GREED [30]	0.823	0.642	0.210	0.145	0.805	0.808	0.593	0.682	0.593	0.448
	(0.811, 0.834)	(0.628, 0.656)	(0.189, 0.231)	(0.128, 0.162)	(0.796, 0.815)	(0.748, 0.854)	(0.562, 0.621)	(0.557, 0.777)	(0.554, 0.630)	(0.417, 0.478)
Y-VQM [48]	0.752	0.586	0.265	0.149	0.842	0.833	0.787	0.589	0.843	0.700
	(0.721, 0.779)	(0.559, 0.611)	(0.213, 0.315)	(0.117, 0.181)	(0.833, 0.851)	(0.780, 0.873)	(0.754, 0.816)	(0.565, 0.613)	(0.804, 0.874)	(0.656, 0.740)
DISTS [12]	0.901	0.731	0.417	0.245	0.866	0.873	0.711	0.731	0.626	0.460
	(0.896, 0.906)	(0.723, 0.739)	(0.397, 0.436)	(0.229, 0.260)	(0.860, 0.873)	(0.828, 0.908)	(0.695, 0.726)	(0.621, 0.812)	(0.601, 0.650)	(0.440, 0.478)
AVQT [2]	0.923	0.784	0.176	0.075	0.894	0.872	0.857	0.926	0.842	0.698
	(0.918, 0.927)	(0.777, 0.791)	(0.129, 0.222)	(0.042, 0.107)	(0.889, 0.899)	(0.831, 0.903)	(0.833, 0.877)	(0.858, 0.962)	(0.812, 0.867)	(0.665, 0.728)
YUV-PSNR	0.907 (0.901, 0.912)	0.869 (0.814, 0.908)	0.239 (0.184, 0.293)	0.119 (0.085, 0.152)	0.893 (0.886, 0.898)	0.911 (0.874, 0.937)	0.813 (0.786, 0.837)	0.641 (0.616, 0.664)	0.900 (0.878, 0.919)	0.773 (0.743, 0.800)
YUV-SSIM	0.937 (0.935, 0.940)	0.820 (0.813, 0.826)	0.302 (0.256, 0.347)	0.177 (0.144, 0.209)	0.915 (0.910, 0.920)	0.921 (0.888, 0.944)	0.869 (0.848, 0.887)	0.874 (0.788, 0.926)	(0.891, 0.929)	(0.776, 0.832)
Y-MS-SSIM [46]	<u>0.952</u>	0.897	0.259	0.134	0.910	0.901	0.860	0.819	0.905	0.778
	(0.950, 0.955)	(0.854, 0.928)	(0.211, 0.306)	(0.102, 0.166)	(0.905, 0.914)	(0.864, 0.928)	(0.839, 0.879)	(0.741, 0.876)	(0.882, 0.923)	(0.747, 0.805)
Y-VMAF NEG [26]	0.946	0.823	0.268	0.163	0.910	0.902	0.863	0.957	0.880	0.731
	(0.943, 0.948)	(0.818, 0.827)	(0.215, 0.320)	(0.128, 0.197)	(0.905, 0.915)	(0.865, 0.928)	(0.842, 0.881)	(0.909, 0.980)	(0.855, 0.900)	(0.700, 0.759)
YUV-VMAF NEG [26]	0.945	0.836	0.245	0.146	0.920	0.925	0.861	0.884	0.896	0.766
	(0.942, 0.947)	(0.831, 0.841)	(0.196, 0.293)	(0.113, 0.179)	(0.915, 0.925)	(0.894, 0.947)	(0.840, 0.880)	(0.806, 0.933)	(0.873, 0.915)	(0.736, 0.793)
Y-VMAF (v061) [26]	0.932	0.803	0.453	0.366	0.940	0.922	0.905	0.997	0.874	0.732
	(0.928, 0.936)	(0.798, 0.809)	(0.405, 0.499)	(0.337, 0.394)	(0.937, 0.944)	(0.893, 0.943)	(0.890, 0.919)	(0.992, 0.999)	(0.849, 0.895)	(0.701, 0.760)
YUV-VMAF (v061) [26]	<u>0.952</u> (0.950, 0.954)	0.846 (0.841, 0.851)	0.274 (0.225, 0.322)	0.216 (0.186, 0.246)	(0.942, 0.949)	(0.914, 0.957)	0.910 (0.894, 0.924)	0.996 (0.988, 0.999)	0.897 (0.874, 0.916)	0.767 (0.737, 0.794)

Table 4: Results for SROCC and KROCC on five subsets of our dataset (by encoding category).



Figure 4: Distribution of metric scores. Each metric appears on a separate axis.

4 Conclusion

We created a new diverse dataset containing 2,486 videos compressed by various encoding standards, including AVC, HEVC, AV1, and VVC. We used it to analyze the correlation between new learningbased objective-quality metrics and subjective-quality scores. Our analysis revealed that some new no-reference metrics, such as MDTVSFA, have already caught up with full-reference metrics. At the same time, VMAF showed the highest correlation with subjective scores, making it the best full-reference option for assessing video-compression quality. The open part of the dataset is available publicly ³. The code, with an example metric launch running on that part of the dataset, is also available ⁴.

³https://videoprocessing.ai/datasets/vqa.html

⁴https://github.com/msu-video-group/MSU_VQM_Compression_Benchmark

Dataset	User-Genera 203 v	ated Content rideos	Sha 594 v	king ideos	Sp 582 v	orts videos	Na 1216	ture videos	Gaming / A 204 vi	Animation
Metric	SROC	KROC	SROC	KROC	SROC	KROC	SROC	KROC	SROC	KROC
No-Reference										
No-Kelerence	0.072	0.102	0.221	0.176	0.645	0.490	0.524	0.405	0.707	0.531
MEON [29]	(0.021_0.122)	(0.061_0.143)	(0.201_0.241)	(0.162, 0.190)	(0.625, 0.665)	(0.473_0.507)	(0.508, 0.539)	(0 393 0 416)	(0.677, 0.734)	(0.503_0.557)
	0.232	0 164	0.473	0.332	0.672	0.485	0.621	0.443	0.810	0.623
Y-NIQE [35]	(0.148, 0.312)	(0.102, 0.223)	(0.437, 0.507)	(0.305, 0.358)	(0.658, 0.685)	(0.474, 0.496)	(0.604 0.638)	(0.429, 0.457)	(0 794, 0 826)	(0.602, 0.644)
	0.422	0.304	0.535	0.386	0.836	0.645	0.739	0.548	0.923	0.773
VIDEVAL [41]	(0.365, 0.475)	(0.260, 0.346)	(0.511, 0.559)	(0.367, 0.406)	(0.827, 0.844)	(0.634, 0.655)	(0.726, 0.751)	(0.536, 0.560)	(0.912, 0.933)	(0.751, 0.792)
W G	0.789	0.629	0.833	0.651	0.843	0.669	0.809	0.642	0.755	0.565
KonCept512[17]	(0.771, 0.805)	(0.612, 0.646)	(0.819, 0.847)	(0.634, 0.666)	(0.836, 0.849)	(0.661, 0.676)	(0.802, 0.816)	(0.634, 0.649)	(0.732, 0.777)	(0.543, 0.587)
NIMA 1401	0.826	0.674	0.849	0.677	0.837	0.656	0.792	0.609	0.814	0.637
INIMA [40]	(0.809, 0.842)	(0.654, 0.693)	(0.838, 0.859)	(0.664, 0.689)	(0.831, 0.843)	(0.649, 0.664)	(0.783, 0.801)	(0.599, 0.618)	(0.804, 0.823)	(0.628, 0.645)
PaO 2 PiO [51]	0.801	0.659	0.807	0.643	0.908	0.753	0.827	0.658	0.963	0.855
1 aQ-2-1 IQ[51]	(0.778, 0.822)	(0.637, 0.679)	(0.792, 0.821)	(0.627, 0.659)	(0.903, 0.913)	(0.745, 0.761)	(0.818, 0.835)	(0.648, 0.667)	(0.961, 0.965)	(0.851, 0.860)
SPAO MT-A [13]	0.786	0.624	0.797	0.607	0.848	0.678	0.857	0.690	0.942	0.801
51 AQ M1-A [15]	(0.733, 0.829)	(0.570, 0.672)	(0.776, 0.816)	(0.585, 0.629)	(0.841, 0.854)	(0.671, 0.684)	(0.848, 0.864)	(0.680, 0.700)	(0.937, 0.947)	(0.793, 0.810)
SPAO BL [13]	0.764	0.608	0.797	0.603	0.869	0.699	0.865	0.693	0.924	0.773
51112 52 [13]	(0.709, 0.810)	(0.553, 0.657)	(0.773, 0.818)	(0.578, 0.627)	(0.864, 0.875)	(0.693, 0.706)	(0.856, 0.872)	(0.683, 0.704)	(0.921, 0.926)	(0.769, 0.778)
SPAO MT-S [13]	0.780	0.619	0.756	0.568	0.890	0.727	0.863	0.693	0.954	0.830
	(0.739, 0.815)	(0.575, 0.661)	(0.735, 0.776)	(0.546, 0.589)	(0.884, 0.895)	(0.720, 0.734)	(0.855, 0.871)	(0.683, 0.703)	(0.949, 0.958)	(0.819, 0.839)
VSFA [20]	0.852	0.690	0.830	0.654	0.911	0.758	0.873	0.708	0.975	0.881
	(0.843, 0.861)	(0.678, 0.702)	(0.818, 0.841)	(0.640, 0.667)	(0.905, 0.916)	(0./50, 0./65)	(0.867, 0.878)	(0./01, 0./16)	(0.9/2, 0.9/8)	(0.8/3, 0.889)
Linearity [21]	0.893	0./55	0.864	0.088	0.931	0.787	0.904	0./54	0.964	0.856
	(0.882, 0.903)	(0./38, 0./6/)	(0.852, 0.874)	(0.6/4, 0.702)	(0.927, 0.936)	(0./80, 0./95)	(0.899, 0.909)	(0./4/, 0./61)	(0.961, 0.967)	(0.849, 0.862)
MDTVSFA [22]	(0.001.0.018)	(0.762, 0.799)	(0.899.0.005)	(0.720, 0.754)	(0.020, 0.028)	(0.772.0.797)	(0.012.0.021)	(0.766, 0.778)	(0.068, 0.072)	(0.860.0.872)
·	(0.904, 0.918)	(0.705, 0.708)	(0.000, 0.905)	(0.729, 0.754)	(0.920, 0.920)	(0.775, 0.767)	(0.915, 0.921)	(0.700, 0.770)	(0.900, 0.975)	(0.000, 0.072)
Full-Reference										
FOULTIPEO	0.625	0.464	0.540	0.387	0.560	0.401	0.516	0.373	0.566	0.396
FOV VIDEO [31]	(0.596, 0.651)	(0.441, 0.486)	(0.528, 0.553)	(0.378, 0.397)	(0.546, 0.574)	(0.389, 0.412)	(0.506, 0.527)	(0.365, 0.380)	(0.550, 0.581)	(0.384, 0.408)
I DIDG	0.724	0.587	0.639	0.473	0.854	0.674	0.746	0.565	0.785	0.597
LPIPS [52]	(0.692, 0.753)	(0.565, 0.609)	(0.617, 0.660)	(0.455, 0.490)	(0.846, 0.861)	(0.665, 0.683)	(0.734, 0.758)	(0.554, 0.576)	(0.772, 0.798)	(0.586, 0.608)
DVOA	0.847	0.689	0.708	0.528	0.841	0.653	0.783	0.600	0.883	0.709
DVQA[I]	(0.824, 0.867)	(0.664, 0.711)	(0.687, 0.727)	(0.510, 0.545)	(0.832, 0.849)	(0.642, 0.663)	(0.772, 0.792)	(0.590, 0.610)	(0.872, 0.894)	(0.694, 0.723)
GREED (20)	0.719	0.572	0.726	0.551	0.805	0.640	0.748	0.580	0.828	0.643
OKEED [50]	(0.685, 0.749)	(0.543, 0.600)	(0.712, 0.740)	(0.538, 0.564)	(0.800, 0.811)	(0.634, 0.645)	(0.739, 0.755)	(0.573, 0.588)	(0.812, 0.842)	(0.624, 0.662)
V VOM [48]	0.809	0.656	0.810	0.634	0.867	0.689	0.848	0.677	0.930	0.779
1- v Qivi [46]	(0.787, 0.830)	(0.637, 0.675)	(0.798, 0.822)	(0.620, 0.647)	(0.857, 0.877)	(0.675, 0.702)	(0.841, 0.855)	(0.669, 0.685)	(0.922, 0.936)	(0.766, 0.791)
DISTS [12]	0.854	0.694	0.794	0.613	0.893	0.726	0.834	0.657	0.896	0.727
21010[12]	(0.831, 0.874)	(0.668, 0.718)	(0.780, 0.807)	(0.599, 0.627)	(0.888, 0.898)	(0.719, 0.733)	(0.826, 0.841)	(0.649, 0.665)	(0.888, 0.902)	(0.717, 0.737)
AVOT [2]	0.919	0.791	0.849	0.684	0.902	0.757	0.877	0.719	0.913	0.772
	(0.908, 0.928)	(0.774, 0.807)	(0.838, 0.860)	(0.669, 0.698)	(0.896, 0.908)	(0.748, 0.765)	(0.871, 0.883)	(0.712, 0.727)	(0.910, 0.915)	(0.768, 0.776)
YUV-PSNR	0.770	0.638	0.810	0.645	0.935	0.793	0.868	0.710	0.944	0.807
	(0./40, 0./9/)	(0.616, 0.658)	(0.797, 0.822)	(0.632, 0.658)	(0.928, 0.937)	(0.785, 0.801)	(0.860, 0.876)	(0./01, 0./19)	(0.938, 0.950)	(0./95, 0.818)
YUV-SSIM	(0.750, 0.805)	(0.618, 0.665)	(0.707.0.824)	(0.622.0.662)	(0.048, 0.057)	0.020	(0.900	(0.730	(0.051_0.064)	(0.837
	(0.750, 0.805)	0.746	(0.797, 0.824)	0.680	(0.946, 0.957)	(0.818, 0.857)	(0.893, 0.907)	0.746	(0.951, 0.904)	(0.823, 0.830)
Y-MS-SSIM [46]	(0.882, 0.907)	(0.720, 0.762)	(0.841_0.862)	(0.666, 0.693)	(0.038 0.047)	(0.800.0.817)	(0.805_0.007)	(0.738, 0.754)	(0.950, 0.960)	(0.821.0.841)
	0.916	0.779	0.861	0.688	0.945	0.810	0.909	0.757	0.960	0.841
Y-VMAF NEG [26]	(0.907, 0.925)	(0.765, 0.791)	(0.851, 0.870)	(0.675, 0.700)	(0.940, 0.949)	(0.802.0.818)	(0.903, 0.914)	(0.749, 0.765)	(0.956, 0.964)	(0.832, 0.849)
MUN ANA FNES	0.916	0.773	0.861	0.691	0.947	0.815	0.913	0.763	0.968	0.860
YUV-VMAF NEG [26]	(0.907, 0.924)	(0.761, 0.785)	(0.851, 0.870)	(0.678, 0.703)	(0.942, 0.951)	(0.807, 0.823)	(0.908, 0.918)	(0.756, 0.771)	(0.965, 0.970)	(0.854, 0.866)
V VMAE (061) rec	0.946	0.835	0.891	0.730	0.959	0.836	0.942	0.810	0.967	0.860
1-VMAF (V001) [26]	(0.940, 0.952)	(0.822, 0.846)	(0.882, 0.900)	(0.717, 0.743)	(0.955, 0.962)	(0.828, 0.843)	(0.939, 0.946)	(0.803, 0.816)	(0.964, 0.969)	(0.854, 0.866)
VIIV VMAE (v061) roct	0.942	0.820	0.879	0.716	0.961	0.843	0.944	0.813	0.972	0.872
10, 10, 10, 10, 10, 10, 10, 10, 10, 10,	(0.935, 0.948)	(0.807, 0.832)	(0.870, 0.888)	(0.703, 0.729)	(0.958, 0.964)	(0.836, 0.850)	(0.941, 0.947)	(0.806, 0.819)	(0.971, 0.974)	(0.868, 0.876)

Table 5: Results for SROCC and KROCC on five subsets of our dataset (by content type).

No-Reference Metric	VIDEVAL1 (CPU)	MEON1 (CPU)	Linearity1	KonCept5121	SPAQ MT-S1	SPAQ BL ¹	SPAQ MT-A ¹	NIMA ¹	MDTVSFA ¹	VSF ¹ A	PaQ-2-PiQ1	NIQE ¹
Computation Complexity (FPS)	0.62	2.27	3.41	4.18	6.48	6.49	6.66	7.24	9.12	9.26	11.10	80.00
Full-Reference Metric	LPIPS ¹	DVQA ¹	GREED ¹	DISTS1	FOV VIDEO1	AVQT (CPU)2	VMAF ¹	MS-SSIM1	SSIM ¹	VQM ¹	PSNR ¹	
Computation Complexity (FPS)	3.20	5.75	7.10	8.65	37.57	37.66	52.62	99.36	160.58	280.00	371.96	

Table 6: FPS evaluation for videos from the dataset. The metric testing used a configuration with two Intel Xeon Silver 4216 processors running Ubuntu 20.04 at 2.10 GHz with a Titan RTX GPU, and another configuration with an Intel Core i9 processor running at 2.3 GHz with 16 GB of RAM and AMD Radeon Pro 5500M 4 GB graphics card.

Our proposed dataset will be useful for researchers and developers of image- and video-quality metrics that evaluate video-compression artifacts. It can serve in training models that assess video-compression quality to achieve more-precise results and higher correlation with subjective scores. Our benchmark will remain an unbiased test of compression quality for new image- and video-quality metrics.

We are accepting new methods for evaluation using our benchmark⁵. During the few months since its publication, we have already received several submissions, as well as good reviews and requests for further development. Our plan is to further increase the number of original videos and add new encoders. Because the subjective tests are expensive, we estimate our current dataset cost about \$15,000. We are open to collaboration and sponsorship to improve the dataset more quickly and to provide more-reliable and more-valuable results.

⁵https://videoprocessing.ai/benchmarks/video-quality-metrics.html

4.1 Limitations

We did not retrain the tested metrics on the open part of our dataset. We used already trained models without tuning their parameters. This approach allowed us to prevent metrics from overfitting on our dataset. Nevertheless, some methods are not fitted for data that was absent from the training set (for instance, compression artifacts) or simply underwent training on small datasets. As a result, these metrics may show weak performance on our dataset. Future work will therefore include metric retraining on open part of the dataset and assessment of their quality on the hidden part.

4.2 Acknowledgments

The work received support through a grant for research centers in the field of artificial intelligence (agreement identifier 000000D730321P5Q0002, dated November 2, 2021, no. 70-2021-00142 with the Ivannikov Institute for System Programming of the Russian Academy of Sciences).

References

- [1] Dvqa deep learning-based video quality assessment. https://github.com/Tencent/DVQA. Accessed: 2022-08-06. 1, 4, 7, 8, 9
- [2] Evaluate videos with the advanced video quality tool. https://developer.apple.com/videos/play/ wwdc2021/10145. Accessed: 2022-08-06. 1, 4, 7, 8, 9
- [3] Recommended encoding settings for ibm watson media. https://support.video.ibm.com/hc/ en-us/articles/207852117-Internet-connection-and-recommended-encoding-settings. Accessed: 2022-08-12. 5
- [4] Recommended encoding settings for twitch streaming. https://stream.twitch.tv/encoding/. Accessed: 2022-08-12. 5
- [5] Recommended encoding settings for youtube. https://support.google.com/youtube/answer/ 2853702. Accessed: 2022-08-12. 5
- [6] Toward a better quality metric for the video community, netflix technology blog. https: //netflixtechblog.com/toward-a-better-quality-metric-for-the-video-community\ -7ed94e752a30. Accessed: 2022-08-17. 6
- [7] Christos George Bampis, Zhi Li, Anush Krishna Moorthy, Ioannis Katsavounidis, Anne Aaron, and Alan Conrad Bovik. Study of temporal effects on subjective video quality of experience. *IEEE Transactions* on *Image Processing*, 26(11):5217–5231, 2017. 2
- [8] Nabajeet Barman, Emmanuel Jammeh, Seyed Ali Ghorashi, and Maria G Martini. No-reference video quality estimation based on machine learning for passive gaming video streaming applications. *IEEE* Access, 7:74511–74527, 2019. 3
- [9] Nabajeet Barman, Saman Zadtootaghaj, Steven Schmidt, Maria G Martini, and Sebastian Möller. Gamingvideoset: a dataset for gaming video streaming applications. In 2018 16th Annual Workshop on Network and Systems Support for Games (NetGames), pages 1–6. IEEE, 2018. 3
- [10] David Corey, William Dunlap, and Michael Burke. Averaging correlations: Expected values and bias in combined pearson rs and fisher's z transformations. *Journal of General Psychology - J GEN PSYCHOL*, 125:245–261, 07 1998. 6
- [11] Francesca De Simone, Marco Tagliasacchi, Matteo Naccari, Stefano Tubaro, and Touradj Ebrahimi. A h. 264/avc video database for the evaluation of quality metrics. In 2010 IEEE International Conference on Acoustics, Speech and Signal Processing, pages 2430–2433. IEEE, 2010. 2
- [12] Keyan Ding, Kede Ma, Shiqi Wang, and Eero Simoncelli. Image quality assessment: Unifying structure and texture similarity. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PP:1–1, 12 2020. 4, 7, 8, 9
- [13] Yuming Fang, Hanwei Zhu, Yan Zeng, Kede Ma, and Zhou Wang. Perceptual quality assessment of smartphone photography. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3677–3686, 2020. 4, 7, 8, 9
- [14] Deepti Ghadiyaram, Janice Pan, Alan C Bovik, Anush Krishna Moorthy, Prasanjit Panda, and Kai-Chieh Yang. In-capture mobile video distortions: A study of subjective behavior and objective algorithms. *IEEE Transactions on Circuits and Systems for Video Technology*, 28(9):2061–2077, 2017. 2, 3
- [15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 770–778, 2016.
 4
- [16] Vlad Hosu, Franz Hahn, Mohsen Jenadeleh, Hanhe Lin, Hui Men, Tamás Szirányi, Shujun Li, and Dietmar Saupe. The konstanz natural video database (konvid-1k). In 2017 Ninth international conference on quality of multimedia experience (QoMEX), pages 1–6. IEEE, 2017. 2, 3

- [17] Vlad Hosu, Hanhe Lin, Tamas Sziranyi, and Dietmar Saupe. Koniq-10k: An ecologically valid database for deep learning of blind image quality assessment. *IEEE Transactions on Image Processing*, 29:4041–4056, 2020. 4, 7, 8, 9
- [18] Justin Johnson, Alexandre Alahi, and Li Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In *European conference on computer vision*, pages 694–711. Springer, 2016. 4
- [19] Christian Keimel, Arne Redl, and Klaus Diepold. The tum high definition video datasets. In 2012 Fourth international workshop on quality of multimedia experience, pages 97–102. IEEE, 2012. 2
- [20] Dingquan Li, Tingting Jiang, and Ming Jiang. Quality assessment of in-the-wild videos. In Proceedings of the 27th ACM International Conference on Multimedia, pages 2351–2359, 2019. 4, 7, 8, 9
- [21] Dingquan Li, Tingting Jiang, and Ming Jiang. Norm-in-norm loss with faster convergence and better performance for image quality assessment. In *Proceedings of the 28th ACM International Conference on Multimedia*, pages 789–797, 2020. 4, 7, 8, 9
- [22] Dingquan Li, Tingting Jiang, and Ming Jiang. Unified quality assessment of in-the-wild videos with mixed datasets training. *International Journal of Computer Vision*, 129(4):1238–1257, 2021. 3, 4, 7, 8, 9
- [23] Songnan Li, Fan Zhang, Lin Ma, and King Ngan. Image quality assessment by separately evaluating detail losses and additive impairments. *IEEE Transactions on Multimedia*, 13:935–949, 10 2011. 4
- [24] Yang Li, Shengbin Meng, Xinfeng Zhang, Meng Wang, Shiqi Wang, Yue Wang, and Siwei Ma. Usergenerated video quality assessment: A subjective and objective study. *IEEE Transactions on Multimedia*, 2021. 3
- [25] Yang Li, Shengbin Meng, Xinfeng Zhang, Shiqi Wang, Yue Wang, and Siwei Ma. Ugc-video: Perceptual quality assessment of user-generated videos. In 2020 IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), pages 35–38, 2020. 3
- [26] Zhi Li, Christos Bampis, Julie Novak, Anne Aaron, Kyle Swanson, Anush Moorthy, and JD Cock. Vmaf: The journey continues. *Netflix Technology Blog*, 25, 2018. 1, 4, 7, 8, 9
- [27] Joe Yuchieh Lin, Rui Song, Chi-Hao Wu, TsungJung Liu, Haiqiang Wang, and C-C Jay Kuo. Mcl-v: A streaming video quality assessment database. *Journal of Visual Communication and Image Representation*, 30:1–9, 2015. 2
- [28] Stuart Lloyd. Least squares quantization in pcm. *IEEE transactions on information theory*, 28(2):129–137, 1982.
- [29] Kede Ma, Wentao Liu, Kai Zhang, Zhengfang Duanmu, Zhou Wang, and Wangmeng Zuo. End-to-end blind image quality assessment using deep neural networks. *IEEE Transactions on Image Processing*, 27(3):1202–1213, 2017. 3, 7, 8, 9
- [30] Pavan C Madhusudana, Neil Birkbeck, Yilin Wang, Balu Adsumilli, and Alan C Bovik. ST-GREED: Space-time generalized entropic differences for frame rate dependent video quality prediction. *IEEE Trans. Image Process.*, 2021. 4, 7, 8, 9
- [31] Rafał K Mantiuk, Gyorgy Denes, Alexandre Chapiro, Anton Kaplanyan, Gizem Rufo, Romain Bachy, Trisha Lian, and Anjul Patney. Fovvideovdp: A visible difference predictor for wide field-of-view video. ACM Transactions on Graphics (TOG), 40(4):1–19, 2021. 4, 7, 8, 9
- [32] Xiongkuo Min, Guangtao Zhai, Jiantao Zhou, Mylene CQ Farias, and Alan Conrad Bovik. Study of subjective and objective quality assessment of audio-visual signals. *IEEE Transactions on Image Processing*, 29:6054–6068, 2020. 2
- [33] Anish Mittal, Anush Krishna Moorthy, and Alan Conrad Bovik. No-reference image quality assessment in the spatial domain. *IEEE Transactions on image processing*, 21(12):4695–4708, 2012. 3
- [34] Anish Mittal, Michele A Saad, and Alan C Bovik. A completely blind video integrity oracle. *IEEE Transactions on Image Processing*, 25(1):289–300, 2015. 3
- [35] Anish Mittal, Rajiv Soundararajan, and Alan C Bovik. Making a "completely blind" image quality analyzer. *IEEE Signal processing letters*, 20(3):209–212, 2012. 7, 8, 9
- [36] Mikko Nuutinen, Toni Virtanen, Mikko Vaahteranoksa, Tero Vuori, Pirkko Oittinen, and Jukka Häkkinen. Cvd2014—a database for evaluating no-reference video quality assessment algorithms. *IEEE Transactions on Image Processing*, 25(7):3073–3086, 2016. 2, 3
- [37] Pradip Paudyal, Federica Battisti, and Marco Carli. A study on the effects of quality of service parameters on perceived video quality. In 2014 5th European Workshop on Visual Information Processing (EUVIP), pages 1–6. IEEE, 2014. 2
- [38] Hamid Sheikh, Alan Bovik, and Gustavo Veciana. An information fidelity criterion for image quality assessment using natural scene statistics. *Image Processing, IEEE Transactions on*, 14:2117–2128, 01 2006. 4
- [39] Zeina Sinno and Alan Conrad Bovik. Large-scale study of perceptual video quality. *IEEE Transactions on Image Processing*, 28(2):612–627, 2018. 2, 3
- [40] Hossein Talebi and Peyman Milanfar. Nima: Neural image assessment. IEEE Transactions on Image Processing, 27(8):3998–4011, 2018. 4, 7, 8, 9
- [41] Zhengzhong Tu, Chia-Ju Chen, Yilin Wang, Neil Birkbeck, Balu Adsumilli, and Alan C Bovik. Video quality assessment of user generated content: A benchmark study and a new model. In 2021 IEEE International Conference on Image Processing (ICIP), pages 1409–1413. IEEE, 2021. 2, 3, 7, 8, 9

- [42] Haiqiang Wang, Weihao Gan, Sudeng Hu, Joe Yuchieh Lin, Lina Jin, Longguang Song, Ping Wang, Ioannis Katsavounidis, Anne Aaron, and C-C Jay Kuo. Mcl-jcv: a jnd-based h. 264/avc video quality assessment dataset. In 2016 IEEE International Conference on Image Processing (ICIP), pages 1509–1513. IEEE, 2016. 2, 3
- [43] Haiqiang Wang, Ioannis Katsavounidis, Jiantong Zhou, Jeonghoon Park, Shawmin Lei, Xin Zhou, Man-On Pun, Xin Jin, Ronggang Wang, Xu Wang, et al. Videoset: A large-scale compressed video quality dataset based on jnd measurement. *Journal of Visual Communication and Image Representation*, 46:292–302, 2017. 2, 3
- [44] Yilin Wang, Sasi Inguva, and Balu Adsumilli. Youtube ugc dataset for video compression research. In 2019 IEEE 21st International Workshop on Multimedia Signal Processing (MMSP), pages 1–5. IEEE, 2019. 2, 3
- [45] Zhou Wang, Alan Bovik, Hamid Sheikh, and Eero Simoncelli. Image quality assessment: From error visibility to structural similarity. *Image Processing, IEEE Transactions on*, 13:600 – 612, 05 2004. 4
- [46] Zhou Wang, Eero P Simoncelli, and Alan C Bovik. Multiscale structural similarity for image quality assessment. In *The Thrity-Seventh Asilomar Conference on Signals, Systems & Computers, 2003*, volume 2, pages 1398–1402. Ieee, 2003. 4, 7, 8, 9
- [47] Stefan Winkler. Analysis of public image and video databases for quality assessment. *IEEE Journal of Selected Topics in Signal Processing*, 6(6):616–625, 2012. 5
- [48] Feng Xiao et al. Dct-based video quality evaluation. Final Project for EE392J, 769, 2000. 7, 8, 9
- [49] Munan Xu, Junming Chen, Haiqiang Wang, Shan Liu, Ge Li, and Zhiqiang Bai. C3dvqa: Full-reference video quality assessment with 3d convolutional neural network. In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 4447–4451. IEEE, 2020. 4
- [50] Zhenqiang Ying, Maniratnam Mandal, Deepti Ghadiyaram, and Alan Bovik. Patch-vq:'patching up'the video quality problem. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14019–14029, 2021. 2, 3
- [51] Zhenqiang Ying, Haoran Niu, Praful Gupta, Dhruv Mahajan, Deepti Ghadiyaram, and Alan Bovik. From patches to pictures (paq-2-piq): Mapping the perceptual space of picture quality. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3575–3585, 2020. 4, 7, 8, 9
- [52] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 586–595. IEEE, 2018. 4, 7, 8, 9

Supplementary materials: Video compression dataset and benchmark of learning-based video-quality metrics

Anastasia Antsiferova^{1,2}, Sergey Lavrushkin^{1,2*}, Maksim Smirnov^{3*}, Alexander Gushchin^{3*}, Dmitriy Vatolin^{1,2,3*}, Dmitriy Kulikov^{2,3*} ISP RAS Research Center for Trusted Artificial Intelligence¹ MSU Institute for Artificial Intelligence² Lomonosov Moscow State University³ {aantsiferova, sergey.lavrushkin, maxim.smirnov.2025, alexander.gushchin, dmitriy, dkulikov}@graphics.cs.msu.ru

1 Appendix

1.1 Metric Calculations

Below we describe the steps for calculating metrics. To avoid overfitting on our dataset, we used already fitted image- and video-quality-assessment models with public source code. We left the default parameters of all metrics unchanged.



Figure 1: Metric-calculation process.

We tested some metrics (VMAF, PSNR, SSIM, MS-SSIM, VQM, and NIQE) on each color component (Y, U, and V) in addition to averaging the components using different weights. For example, one possibility is SSIM calculated solely on the Y component with a 6:1:1 weighted average.

Below are the steps for calculating different versions of such metrics.

1.2 IQA-Method Calculation

We used mean temporal pooling as a way to aggregate scores from multiple frames. Previous research showed no significant difference between pooling methods, and our tests confirmed that finding.

Therefore, to get a quality score for a whole video using an IQA method, we compared a given distorted sequence frame by frame with the corresponding reference video and then averaged the scores. We intend to include more data on this research in future publications.

To perform lossless conversion between file formats, we used the following commands:

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Figure 2: Metric calculation using different weights.

1. .yuv -> .mp4

```
ffmpeg -f rawvideo -vcodec rawvideo -s {width}x{height}
-r {FPS} -pix_fmt yuv420p -i {video name}.yuv -c:v libx265
-x265-params "lossless=1:qp=0" -t {hours:minutes:seconds}
-vsync 0 {video name}.mp4
```

2. .mp4 -> .png

ffmpeg -i {sequence name}.mp4 {images dir}/image_%05d.png

1.3 Metric-Speed Measurement

We also measured the metric-speed performance, expressed in FPS (the execution time of a full model divided by the number of sequence frames).

- The calculation used the following:
 - Five reference videos compressed using the x264 codec (three target bitrates).
 - Three metric calculations for each distorted video.
 - In total, 15 compressed videos and 45 total measurements.
- Output: maximum FPS among three calculations for the given video.
- Calculations employed the following hardware:
 - Nvidia Titan RTX GPU
 - 64-CPU cluster based on Intel Xeon Silver 4216 processor @ 2.10GHz

1.4 Metric Correlation for Different Categories



Figure 3: SROCC values on full dataset.



Figure 4: KROCC values on full dataset.



Figure 5: SROCC values for "Low Bitrate" category.



Figure 6: KROCC values for "Low Bitrate" category.



Figure 7: SROCC values for "High Bitrate" category.



Figure 8: KROCC values for "High Bitrate" category.



Figure 9: SROCC values for "User-Generated Content" category.



Figure 10: KROCC values for "User-Generated Content" category.



Figure 11: SROCC values for "Shaking" category.



Figure 12: KROCC values for "Shaking" category.



Figure 13: SROCC values for "Sports" category.



Figure 14: KROCC values for "Sports" category.



Figure 15: SROCC values for "Nature" category.



Figure 16: KROCC values for "Nature" category.



Figure 17: SROCC values for "Gaming / Animation" category.



Figure 18: KROCC values for "Gaming / Animation" category.

1.5 Metrics Correlation for Different Compression Standards



Figure 19: SROCC values for AV1 encoding standard.



Figure 20: KROCC values for AV1 encoding standard.



Figure 21: SROCC values for H.265 encoding standard.



Figure 22: KROCC values for H.265 encoding standard.



Figure 23: SROCC values for VVC encoding standard.



Figure 24: KROCC values for VVC encoding standard.

1.6 Wilcoxon Test

	WISS-SW-2	6-VMAF NEG	6-VMAF (v061)	(UV-VMAF (v061)	/UV-VMAF NEG	WQT	MQV-	/SFA	ADTVSFA	6-NIQE	/IDE VAL	aQ-2-PiQ	conCept512	INEARITY	spaq BL	SPAQ VIT-S	SPAQ AT-A	AEON	VIMA	BREED	DISTS	SdId	ADVQA	/UV-PSNR	WISS-AU
Y-MS-SSIM		0,-,- -,-,- 0,0,-	0,1,0 0,0,1 0,0,- 0,-	0,-,- 0,0,- 0,0,0 0,0	0,-,- 0,-,- 0,0,- 0	1,1,- 1,-,1 0,-,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	-,1,- -,0,- -,-,-	0,-,0 0,0,- -,-,- 0,0	1,1,- 1,1,1 1,1,1 1,1	1,1,- 1,1,1 1,1,1 1,1	1,1,- -,-,- -,1,1 1,-	1,1,- -,-,- -,-,1 1,-	-,1,- 0,0,- -,-,- -,0	1,1,- -,-,- -,1,1	1,1,- -,-,1 -,1,1 1,-	1,1,- -,-,1 -,1,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	1,1,- -,-,1 -,-,1 1,1	1,1,- 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	1,1,- 1,1,1 -,1,1 1,-	1,1,- 1,1,- 1,1,- 1,-	1,1,0 -,-,0 1,1,0
Y-VMAF NEG	1,-,- -,-,- 1,1,-	-	0,1,0 0,0,- 0,-,0	0,-,- 0,0,- -,-,0 0,0	0,-,- 0,-,- -,-,-	1,1,- 1,-,- -,-,1	1,1,1 1,1,1 1,1,1 1,1,1	-,1,- -,0,- -,1,-	0,-,- 0,0,- -,-,-	1,1,- 1,1,1 1,1,1 1,1	1,1,- 1,1,1 1,1,1	1,1,- -,-,- 1,1,1	1,1,- -,-,- 1,1,1 1 1	-,1,- 0,0,0 -,-,-	1,1,- -,-,- -,1,1	1,1,- -,-,- 1,1,1 1 -	1,1,- -,-,- 1,1,1 1 1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,-,- -,-,1 1 1	1,1,- 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1	1,1,- 1,1,0 1,1,-	1,-,- -,-,0 1,1,-
Y-VMAF v061	, 1,0,1 1,1,0 1,1,-	1,0,1 1,1,- 1,-,1	-	-,0,1 0,-,- -,1,-	1,0,1 1,1,- 1,1,-	1,-,1 1,1,- -,1,1 1 1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,-,- 1,1,1	, 1,-,- -,-,1 -,-,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,-,- 1,1,1	1,1,1 1,1,- 1,1,1 1,1,1	, 1,1,- 1,-,0 1,1,1	1,1,- 1,-,- 1,1,1 1,1	1,1,- 1,-,- 1,1,1	1,1,- 1,-,- 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,-,- 1,1,- 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,-,1 1,-,1 1,1,0 1,1,1	1,-,- 1,1,0 1,1,-
YUV-VMAF v061	1,-,- 1,1,- 1,1,1 1,1	1,-,- 1,1,- -,-,1	-,1,0 1,-,- -,0,-		1,-,- 1,1,- -,1,1	1,1,- 1,1,1 1,1,1 -,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,0 1,-,- 1,1,1	1,-,0 -,0,- -,-,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,-,- 1,1,1	1,1,- 1,1,- 1,1,1 1,1,1	1,1,0 1,-,- 1,-,1	1,1,- 1,-,1 1,1,1 1,1	1,1,0 1,-,- 1,1,1	1,1,- 1,-,- 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,- 1,-,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,1,- 1,1,1 1,1,1	1,-,- 1,1,- 1,1,-
YUV-VMAF NEG	1,-,- 1,-,- 1,1,-	1,-,- 1,-,- -,-,-	0,1,0 0,0,- 0,0,- 0,-	0,-,- 0,0,- -,0,0 0.0	-	1,1,- 1,-,1 -,1,1	1,1,1 1,1,1 1,1,1 1,1,1	-,1,- -,0,- -,1,- 1,-	-,-,0 0,0,- -,-,-	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- -,-,- 1,1,1	1,1,- -,-,- 1,1,1 1,1	-,1,- -,0,0 -,-,1	1,1,- -,-,1 -,1,1 1,1	1,1,- 1,-,- 1,1,1 1,-	1,1,- -,-,- 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,-,- -,-,1 1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,1,- 1,1,1 1,1	1,-,0 -,-,- 1,1,- 1,-
AVQT	0,0,- 0,-,0 1,-,0	0,0,- 0,-,- -,-,0	0,-,0 0,0,- -,0,0	0,0,- 0,0,0 -,0,0	0,0,- 0,-,0 -,0,0		1,1,1 1,1,1 1,1,1 1,1,1	0,1,0 0,0,- -,-,-	, 0,-,0 0,0,- -,-,0	1,1,- 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1	-,1,- -,-,- -,1,- 1.0	1,1,- -,-,- 1,-,1	0,-,- 0,0,0 -,-,0	-,1,- -,-,- -,1,-	-,1,- -,0,- -,1,-	-,1,- -,-,- -,-,-	1,1,1 1,1,1 1,1,1 1,1,1	1,-,- -,-,- -,-,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1	-,-,- -,1,0 1,1,0	-,-,0 0,0,0 1,1,0
Y-VQM	, 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0	-	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,- 0,-,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	, 0,0,0 0,0,0 0,0,0	0,0,- -,-,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	-,-,- -,-,- -,-,-	0,-,- 0,0,0 -,0,- 0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	, 0,0,0 0,0,0 0,0,0
VSFA	-,0,- -,1,- -,-,-	-,0,- -,1,- 0,0,- 0 -	0,0,- 0,-,- 0,0,0	0,0,1 0,-,- 0,0,0 0 -	-,0,- -,1,- 0,0,- 0,-	1,0,1 1,1,- -,-,-	1,1,1 1,1,1 1,1,1 1,1,1		0,0,- 0,-,- 0,0,-	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1	1,-,1 -,-,- -,-,- 1,-	0,0 1,-,1 -,-,- -,-,1 1,1	-,-,- -,-,- 0,-,- 0 -	1,1,- 1,-,- -,1,-	1,1,- 1,-,- -,1,-	1,1,- 1,-,- -,-,-	1,1,1 1,1,1 1,1,1 1,1,1	1,-,- 1,1,- -,-,1	1,1,1 1,1,1 -,-,1	, 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 -,1,-	1,-,- 1,1,- 1,-,-	-,0,- -,-,- -,-,-
MDTVSFA	, 1,-,1 1,1,- -,-,-	1,-,- 1,1,- -,-,-	0,-,- -,-,0 0,-	0,-,1 -,1,- -,-,0	-,-,1 1,1,- -,-,-	, 1,-,1 1,1,- -,-,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,-,- 1,1,-		1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,1 1,1,- 1,1,- 1,1,-	1,1,1 1,1,- 1,1,1 1,1,1	1,1,- 1,-,0 -,1,-	,, 1,1,- 1,1,- 1,1,1 1 1	, 1,1,- 1,1,- 1,1,-	, 1,1,- 1,1,- 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,1,- 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	,, 1,1,- 1,1,- 1,1,-	, 1,-,- 1,1,- 1,1,-
Y-NIQE	0,0,- 0,0,0 0,0,0 0,0,0	, 0,0,- 0,0,0 0,0,0 0.0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	, 0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0,0	1,1,- 1,-,1 1,1,1 1,1	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0	-	0,0,0 0,0,0 -,0,0 0.0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	-,-,1 1,1,1 -,-,-	0,0,0 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0	1,1,1 1,-,1 1,1,1 1,2	1,1,1 1,-,- 1,1,1 1,-	0,0,- 0,0,0 0,0,0 0,0,0	0,0,- 0,0,0 0,0,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0,0
VIDEVAL	0,0,- 0,0,0 0,0,0 0,0,0	0,0,- 0,0,0 0,0,0 0,0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,-	1,1,1 1,1,1 1,1,1 1,1,1	0,0,0 0,0,0 0,0,0 0,0,0	0,0,- 0,0,0 0,0,0 0,0	1,1,1 1,1,1 -,1,1		0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,-,0 0,0,- 0,-	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,- 0,-	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,- 0,-	, 1,1,1 1,1,1 1,1,1 1,1	0,0,- 0,-,- 0,0,- 0,-	0,0,- -,-,- 0,0,-	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	0,0,1 -,1,- 0,0,- 0,-	0,0,- 0,-,0 0,0,0 0,-	0,0,- 0,0,0 0,0,0 0,0,0
PaQ-2-PiQ	0,0,- -,-,- -,0,0 0,-	0,0,- -,-,- 0,0,0 0,-	0,0,- 0,-,- 0,0,0 0,-	0,0,- 0,-,- 0,0,0 0,0	0,0,- -,-,- 0,0,0 0,-	-,0,- -,-,- 0,0,- 0,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	0,-,0 -,-,- -,-,- 0,-	0,0,0 0,0,- 0,0,- 0,-	1,1,1 1,1,1 1,1,1 1,1,1 1,1	1,1,- 1,1,1 1,1,1 1,1		1,-,- -,-,- -,-,1 -,1	0,-,- 0,0,- -,0,0 0,-	-,-,- -,-,- -,-,- -,1	-,-,- -,-,- -,1,-	-,1,- -,-,- -,-,- -,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	-,1,1 -,1,1 -,-1	1,-,- 1,1,1 -,-,1 -,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	1,1,1 1,1,1 -,-,1 -,1	-,0,- -,1,- -,-,0 -,1	0,0,- -,-,- -,-,0 0,-
KonCept512	0,0,- -,-,- -,-,0 0,0	0,0,- -,-,- 0,0,0 0,0	0,0,0 0,0,- 0,0,0 0,0	0,0,- 0,0,- 0,0,0 0,0	0,0,- -,-,- 0,0,0 0,0	0,0,- -,-,- 0,-,0 0,0	1,1,1 1,1,1 1,1,1 1,1,1 1,1	0,-,0 -,0,- -,-,0 0,0	0,0,0 0,0,- 0,0,0 0,0	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,-,1 1,1,- 1,-	0,-,- -,-,- -,-,0 -,0		0,-,0 0,0,0 0,0,0 0,0	0,-,0 -,0,- -,-,- 0,0	0,1,0 1,0,- -,-,0 0,0	0,1,0 -,0,- -,-,- -,0	1,1,1 1,1,1 1,1,1 1,1,1 1,1		1,-,- 1,1,1 -,-,-	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 -,-,- 0	0,-,- -,-,- -,-,0	0,0,- -,-,- -,-,0 0,-
LINEARITY	-,0,- 1,1,- -,-,-	-,0,- 1,1,1 -,-,-	0,0,- 0,-,1 0,0,0 0,-	0,0,1 0,-,- 0,-,0 0,0	-,0,- -,1,- -,-,0	1,-,- 1,1,1 -,-,1 1,-	1,1,1 1,1,1 1,1,1 1,1,1	-,-,- -,-,- 1,-,- 1,-	0,0,- 0,-,1 -,0,- -,0	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1	1,-,- 1,1,- -,1,1 1,-	1,-,1 1,1,1 1,1,1 1,1	-	1,1,- 1,1,1 1,1,1 1,-	1,1,- 1,1,1 1,1,- 1,-	1,1,- 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,-,- 1,1,1 1,-,1 1,1	1,-,- 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 -,1,1 1,1	1,-,- 1,1,- 1,1,- 1,1	1,0,- 1,1,- 1,1,0 1,-
SPAQ BL	0,0,- -,-,- -,0,0	0,0,- -,-,- -,0,0 0,0	0,0,- 0,-,- 0,0,0 0,0	0,0,- 0,-,0 0,0,0 0,0	0,0,- -,-,0 0,0,0 0,0	-,0,- -,-,- 0,0,-	1,1,1 1,1,1 1,1,1 1,1,1	0,0,- 0,-,- -,0,- -,0	0,0,- 0,0,- 0,0,0 0,0	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,- 1,-	-,-,- -,-,- -,-,- -,0	1,-,1 -,1,- -,-,- 1,1	0,0,- 0,0,0 0,0,0 0,-		-,1,- -,-,- -,-,-	-,-,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1	-,-,- -,1,- -,0,- -,1	1,-,1 1,1,1 -,-,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,-,1 1,1,1 -,-,-	-,0,- -,-,- -,0,0	-,0,- -,-,- -,0,0
SPAQ MT-S	0,0,- -,-,0 -,0,0 0	0,0,- -,-,- 0,0,0 0,-	0,0,- 0,-,- 0,0,0 0.0	0,0,- 0,-,- 0,0,0 0.0	0,0,- 0,-,- 0,0,0 0,-	-,0,- -,-,- 0,0,-	1,1,1 1,1,1 1,1,1 1,1,1	0,0,- 0,-,- -,0,- - 0	0,0,- 0,0,- 0,0,- 0.0	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,-	-,-,- -,0,-	1,0,1 0,1,- -,-,1	0,0,- 0,0,0 0,0,- 0,0	-,0,- -,-,- -,-,-	-	-,-,- -,0,1	1,1,1 1,1,1 1,1,1 1,1,1	-,0,- -,1,- -,0,- -,1	1,-,1 1,1,1 -,-,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,-,1 1,1,1 -,-,-	-,0,- -,1,- -,0,0	-,0,- -,-,0 -,0,0
SPAQ MT-A	0,0,- -,-,0 -,0,0	0,0,- -,-,- 0,0,0 0,0	0,0,- 0,-,- 0,0,0 0,0	0,0,- 0,-,- 0,0,0 0,0	0,0,- -,-,- 0,0,0 0,0	-,0,- -,-,- -,0,-	1,1,1 1,1,1 1,1,1 1,1,1 1,1	0,0,- 0,-,- -,-,- -,0	0,0,- 0,0,- 0,0,0 0,0	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,- 1,-	-,0,- -,-,- -,-,- -,0	1,0,1 -,1,- -,-,- -,1	0,0,- 0,0,0 0,0,0 0,0	-,-,- -,-,0	-,-,- -,-,0		1,1,1 1,1,1 1,1,1 1,1,1	-,-,- -,0,- -,1	1,-,- 1,1,1 -,-,- 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,-,1 1,1,1 -,-,-	-,0,- -,-,- -,-,0	-,0,- -,-,0 -,-,0
MEON	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	1,1,- -,-,1 1,1,1 1,1	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	-,-,0 0,0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0		0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	1,1,1 -,-,- 1,1,1 1,-	1,1,- -,0,- 1,1,1 1,-	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0,0
NIMA	0,0,- -,-,0 -,-,0 0,0	0,0,- 0,-,- 0,-,0 0,0	0,-,- 0,0,- 0,0,0 0,0	0,0,- 0,0,- 0,0,0 0,0	0,0,- 0,-,- 0,-,0 0,0	0,-,- -,-,- -,-,0 0,0	1,1,1 1,1,1 1,1,1 1,1	0,-,- 0,0,- -,-,0 0,0	0,0,- 0,0,0 0,0,0 0,0	1,1,1 1,1,1 1,1,1 1,1	1,1,- 1,-,- 1,1,- 1,-	-,-,- -,0,0 -,-,- -,0	-,-,- -,-,- -,-,- -,-,-	0,-,- 0,0,0 0,-,0 0,0	-,-,- -,0,- -,1,- -,0	-,1,- -,0,- -,1,- -,0	-,-,- -,-,- -,-,- -,0	1,1,1 1,1,1 1,1,1 1,1	-	1,1,- 1,1,- -,-,-	1,1,1 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1	1,1,1 1,1,- -,-,- -,0	-,-,0	-,0,0 -,-,0
GREED	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	1,1,1 1,1,1 1,1,1 1,1	0,0,0 0,0,0 -,-,0 0,0	0,0,- 0,0,0 0,0,0 0,0	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- -,-,- 1,1,- -,0	0,-,0 0,0,0 -,-,0 -,0	0,-,- 0,0,0 -,-,-	0,-,0 0,0,0 0,0,0 0,0	0,-,0 0,0,0 -,-,0 0,0	0,-,0 0,0,0 -,-,0 0,0	0,-,- 0,0,0 -,-,- 0,0	1,1,1 1,1,1 1,1,1 1,1,1 1,1	0,0,- 0,0,- -,-,-	-	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	-,-,- -,1,1 0,-,- -,0	0,0,- 0,0,0 -,-,0 0,0	0,0,- 0,0,0 -,-,0 0,0
DISTS	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	-,-,0 -,-,- -,-,-	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,-,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 -,-,- 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	-	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0
LPIPS	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	1,-,- 1,1,1 -,1,- 1,1	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,-,- 0,0,0 0,-	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,- -,1,- 0,0,0 0,-	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	1,1,1 1,1,1 1,1,1 1,1		0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0	0,0,0 0,0,0 0,0,0 0,0
DVQA	0,0,- 0,0,0 -,0,0 0,-	0,0,- 0,0,0 0,0,0 0,-	0,0,0 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,0	0,0,- 0,0,0 0,0,0 0,-	1,1,1 1,1,1 1,1,1 1,1	0,0,0 0,0,0 -,0,- 0,0	0,0,0 0,0,0 0,0,0 0,0	1,1,- 1,1,1 1,1,1 1,1	1,1,0 -,0,- 1,1,- 1,-	0,0,0 0,0,0 -,-,0 -,0	0,0,- 0,0,0 -,-,-	0,0,0 0,0,0 -,0,0 0,0	0,-,0 0,0,0 -,-,-	0,-,0 0,0,0 -,-,-	0,-,0 0,0,0 -,-,-	1,1,- 1,1,1 1,1,1 1,1	0,0,0 0,0,- -,-,-	-,-,- -,0,0 1,-,- -,1	1,1,1 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1	-	0,0,- 0,0,0 -,-,0 -,-	0,0,0 0,0,0 -,-,0 0,-
YUV-PSNR	0,0,- 0,0,- 0,0,- 0,-	0,0,- 0,0,1 0,0,- 0,0	0,-,0 0,0,1 0,0,0 0,0	0,0,- 0,0,- 0,0,0 0,0	0,0,- 0,0,- 0,0,0 0,0	-,0,1 0,0,1 0,-	1,1,1 1,1,1 1,1,1 1,1	0,-,0 0,0,- 0,-,- -,0	0,0,0 0,0,- 0,0,- 0,0	1,1,- 1,1,1 1,1,1 1,1	1,1,- 1,-,1 1,1,1 1,-	-,-,- -,0,- -,-,1 -,0	1,-,- -,-,- -,-,1 -,-	0,-,- 0,0,- 0,0,- 0,0	-,1,- -,0,- -,-,1	-,1,- -,0,- -,1,1	-,1,- -,0,- -,-,1	1,1,1 1,1,1 1,1,1 1,1,1 1,1		1,1,- 1,1,1 -,-,1 1,1	1,1,1 1,1,1 1,1,1 1,1	1,1,1 1,1,1 1,1,1 1,1	1,1,- 1,1,1 -,-,1 -,-		0,0,0 0,0,- -,-,0 0,-
YUV-SSIM	0,0,1 -,-,1 0,0,1	0,-,- -,-,1 0,0,-	0,-,- 0,0,1 0,0,-	0,-,- 0,0,- 0,0,-	0,-,- -,-,- 0,0,-	-,-,1 1,1,1 0,0,1	1,1,1 1,1,1 1,1,1 1,1,1	-,1,- -,-,- -,-,-	0,-,- 0,0,- 0,0,- 0,0	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 1,1,1 1,1,1	1,1,- -,-,- -,-,1	1,1,- -,-,- -,-,1	0,1,- 0,0,- 0,0,1	-,1,- -,-,- -,1,1	-,1,- -,-,1 -,1,1	-,1,- -,-,1 -,-,1	1,1,1 1,1,1 1,1,1 1,1,1	-,1,1 -,0,1	1,1,- 1,1,1 -,-,1 1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,1 1,1,1 1,1,1 1,1,1	1,1,- 1,1,1 -,-,1	1,1,1 1,1,- -,-,1	-

Table 1: Results of one-sided Wilcoxon rank-sum test performed on SROCC values for the methods compared above. For each pair of methods, the table shows values for 11 subsets of our dataset: in the first row are the entire dataset, Low Bitrate, and High Bitrate; in the second are H.265 Encoding, AV1 Encoding, and VVC Encoding; in the third are User-Generated Content, Shaking, and Sports; and in the fourth are Nature and Gaming/Animation. A value of 1 indicates the method for that row is statistically superior to the method for that column. A 0 value indicates the opposite: the method for that column is statistically better than the one for that row. A hyphen (-) indicates they are statistically indistinguishable.

1.7 How to Submit an Algorithm for Benchmarking

To submit an algorithm for benchmarking, send an email to vqa@videoprocessing.ai with the following information:

- Method name, which we will use in our benchmark
- Method-launch script with the following options (or their analogs):
 - -ref—path to reference video (for full-reference metrics)
 - -dist-path to distorted video
 - output—path to algorithm's output
 - -t--threshold, if algorithm requires it
- Any other helpful information about the method (optional):
 - Desired parameters
 - Link to any papers about the method
 - Architectural characteristics

Our policy:

- We won't publish the results for a method without the submitter's permission.
- We share only the open part of our dataset; the rest is hidden.

2 Dataset Documentation

Here we provide documentation for our dataset in the common datasheets format [2].

2.1 Motivation

For what purpose was the dataset created? Was there a specific task in mind? Was there a specific gap that needed to be filled?

We produced the dataset to evaluate full- and no-reference video-quality metrics. To the best of our knowledge, it is the biggest compressed-video dataset that includes new encoding standards and subjective scores. Investigations of the performance of modern video- and image-quality metrics commonly employ videos compressed with older standards, such as AVC. Our goal was to create a dataset that uses numerous compression standards.

Who created the dataset (for example, which team, research group) and on behalf of which entity (for example, company, institution, organization)?

The dataset was a joint effort by Anastasia Antsiferova, Sergey Lavrushkin, Alexander Gushchin, Maksim Smirnov, Dmitriy Kulikov, Egor Sklyarov, Mikhail Erofeev, and Dmitriy Vatolin . The authors are researchers affiliated with the MSU Graphics and Media Lab.

Who funded the creation of the dataset? If there is an associated grant, please provide the name of the grantor and the grant name and number.

Part of the dataset was collected for the annual MSU Video Codecs Comparisons project [1].

The work received support through a grant for research centers in the field of artificial intelligence (agreement identifier 000000D730321P5Q0002, dated November 2, 2021, no. 70-2021-00142 with the Ivannikov Institute for System Programming of the Russian Academy of Sciences). Anastasia Antsiferova was supported by "Intellect", a noncommercial fund for science and educational development.

2.2 Composition

What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)? Are there multiple types of instances (for example, movies, users, and ratings; people and interactions between them; nodes and edges)?

The instances represent video files with corresponding subjective scores. Each video was produced by compressing the original with a specific encoder.

How many instances are there in total (of each type, if appropriate)?

The dataset has a total of 2,486 compressed videos with corresponding subjective scores. The open part contains 1,022 videos; the hidden part contains 1,464.

Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)?

The dataset contains all generated instances. But since it also includes reference videos, the dataset can be extended using new video encoders. Original videos were chosen based on SI-TI characteristics; they cover most possible cases of spatial and temporal complexity.

What data does each instance consist of? "Raw" data (for example, unprocessed text or images) or features?

Each instance is a video file in .mp4 format. Each subjective score is a floating-point number.

Is there a label or target associated with each instance?

Each instance has a corresponding subjective score that represents relative video quality compared with other instances generated from the same original video.

Is any information missing from individual instances?

No.

Are relationships between individual instances made explicit (for example, users' movie ratings, social network links)?

We divided the videos into groups on the basis of a reference video, which is compressed using different encoders and bitrates to generate a group.

Are there recommended data splits (for example, training, development/validation, testing)?

We recommend splitting data according to the original videos. This way, all videos that are compressed representations of a given reference video will fall into the same group. Also, when obtaining the subjective scores, compressed versions of a given reference video were shown to crowdworkers, so correlations of video-quality-metric values with subjective scores apply only within a group.

Are there any errors, sources of noise, or redundancies in the dataset?

No.

Is the dataset self-contained, or does it link to or otherwise rely on external resources (for example, websites, tweets, other datasets)?

The dataset is self-contained.

Does the dataset contain data that might be considered confidential (for example, data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)?

We allow free distribution of the dataset's open part. The hidden part contains confidential information that we must withhold.

Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?

No.

2.3 Collection Process

How was the data associated with each instance acquired? Was the data directly observable (for example, raw text, movie ratings), reported by subjects (for example, survey responses), or indirectly inferred/derived from other data (for example, part-of-speech tags,

model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified?

We formed the dataset using 36 reference clips chosen from more than 18,000 open-source highbitrate videos (licensed under CCBY or CC0). They include recordings by professionals and amateurs. Almost half contain scene changes and high dynamism. Moreover, the ratio of synthetic to natural lightning is approximately 1:3.

Content types: nature, sports, humans close up, gameplay, music video, water or steam, and CGI. Effects and distortions: shaking, slow motion, grain/noise, overly dark/bright regions, macro shooting, captions (text), and extraneous objects on or near the camera lens. Such content diversity helps better simulate realistic conditions.

- 1. Resolution: 1,920×1,080—the most popular video resolution today (likely to increase over time)
- 2. Format: yuv420p.
- 3. FPS: 24, 25, 30, 39, 50, and 60.
- 4. Video duration: 10, 15 seconds (most cases).

We divided the video collection into 36 clusters using the K-means method. For each cluster, we randomly selected one to six candidate videos that were close to the cluster center and that had an appropriate license. From each set of candidates, we manually chose one video and attempted to include videos of different semantics in the final dataset.



Figure 25: Selection of reference videos using the K-means clustering method.

Tab. 2 lists URLs for the original videos.

Details about the crowdsourced study:

- Screen resolutions were from 640×320 to 3,840×1,080. Tab. 3 shows the most popular ones.
- Participants were from 78 countries.
- Participant ages ranged from 18 to 85 with an average of 36. Fig. 26 shows the distribution.

What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated?

The subjective assessment (labeling) involved pairwise comparisons using Subjectify.us. Each pair, which was shown to hired participants, consisted of two samples of the same test video encoded by

Video URL	Author
https://vimeo.com/202290580	Currently Unavailable
https://wimeo.com/87156909	Al Caudullo Productions
100pB., / Vimeo.com/ 0/100000	(https://vimeo.com/alfredcaudullo)
https://vimeo.com/192252473	IA Film Group
h	(https://vimeo.com/ianimgroup)
nttps://vimed.com/90230210	Xinh org Video Test Media
https://media.xiph.org/video/derf/(crowd_run)	[derf's collection]
https://wedie.wigh.eng/widee/denf/(treator)	Xiph.org Video Test Media
https://media.xiph.org/video/defi/(dactor)	[derf's collection]
https://vimeo.com/312309391	krautmovies (https://vimeo.com/krautmovies)
https://vimeo.com/78721233	SantaMarta and Astorga
•	Animal Factory Films
https://vimeo.com/259826267	(https://vimeo.com/animalfactoryfilms)
https://media.withyoutube.com/(gaming 71a5)	Youtube UGC Dataset
https://media.withyoutube.com/(livemusic_3549)	Youtube UGC Dataset
https://media.withyoutube.com/(Vlog_1080P-35cd)	Youtube UGC Dataset
https://media.withyoutube.com/(CoverSong_1080p-5430)	Youtube UGC Dataset
https://media.withyoutube.com/(Vlog_1080P-52fe)	Youtube UGC Dataset
https://media.withyoutube.com/(Gaming_1080P-6db2)	Youtube UGC Dataset
https://media.withyoutube.com/(Vlog_1080P-5904)	Youtube UGC Dataset
https://media.withyoutube.com/(CoverSong_1080P-1b0c)	Youtube UGC Dataset
https://media.withyoutube.com/(Vlog_1080P-23cD)	Youtube UGC Dataset
https://media.withyoutube.com/(Vlog_1080P-4921)	Youtube UGC Dataset
https://media.withyoutube.com/ (Vlog_1080P-2113)	Youtube UGC Dataset
https://media.withyoutube.com/ (Vlog_1080P-2600)	Youtube UGC Dataset
((10 <u>5</u> 10001 2000)	Christopher Stoney
https://vimeo.com/198898016	(https://vimeo.com/cstoney)
https://vimeo.com/150329182	Andrew Jones (/https://vimeo.com/jones3)
https://vimeo.com/163746200	JTwo.tv (https://vimeo.com/jtwo)
https://vimeo.com/207154158#t=0	niko (https://vimeo.com/igwana)
https://vimeo.com/204297495#t=140	Scott (https://vimeo.com/slee1000)
https://vimeo.com/218791521#t=0	Pyranha (https://vimeo.com/pyranhakayaks)
https://vimeo.com/280135236#t=347	Currently Unavailable
https://vimeo.com/311282786#t=18	Harold Aune (https://vimeo.com/haroldaune)
https://vimeo.com/245154516#t=42	Rest Of My Family
$\frac{1}{2082005144-0}$	(https://vimeo.com/restormyramity)
https://vimeo.com/300029951#t=172	Currently Unavailable
https://vimeo.com/18939352/# $t=175$	Kona Bikes (https://vimeo.com/konaworld)
100ps.,, vimeo.com/100/00/0#0-00	Keith W Roe
https://vimeo.com/130709443#t=49	(https://vimeo.com/user10596573)
	George Manolis
nttps://vimeo.com/219044636#t=63	(https://vimeo.com/user7033472)

Table 2: URLs for original videos.

various codecs at various bitrates. For each pair, participants were asked to choose the one with better visual quality. They also had the option to play the videos again or to indicate the videos have equal quality. Fig. 27 depicts the subjective experiment's general process.

Because the necessary number of pairwise comparisons grows exponentially with the number of source videos, we divided the dataset into five subsets by source videos and performed five comparisons. Each subset contained a group of source videos and their compressed versions. In each comparison, all possible pairs of compressed videos for one source video were generated and

Resolution	Number of users
1366x768	10926
1920x1080	8421
1536x864	3397
1280x1024	2285
1600x900	2262
1440x900	1014
1280x720	984
1680x1050	677
1360x768	584
1280x800	420

Table 3: Most popular screen resolutions among crowdworkers.







Figure 27: Subjective-assessment scheme.

evaluated. Thus, only videos from the same source were in each pair. The comparison set also included source videos. Participants saw videos from each pair sequentially in full-screen mode. They were asked to choose the one with the best visual quality or indicate that the two are of the same quality. They also had an option to replay the videos. Their task was to evaluate a total of 12 video pairs, two of which had an obviously superior-quality option and served as verification questions. Responses from participants who failed either or both of these questions were discarded.

To increase the relevance of the results, we solicited at least 10 responses for each pair. In total, we were able to collect 766,362 valid answers from nearly 11,000 individuals.

After applying the Bradley-Terry model to a table of pairwise ranks, we received subjective scores that are consistent within each group of videos compressed from a single reference video.

If the dataset is a sample from a larger set, what was the sampling strategy (for example, deterministic, probabilistic with specific sampling probabilities)?

The open part is a sample of our full dataset. It includes all nonconfidential material. The hidden part contains confidential information and cannot be published. We employ the former only for our benchmark testing to allow a more objective comparison of future algorithms. This approach may prevent learning-based methods from training on the entire dataset, avoiding overfitting and, thus, incorrect results. The full dataset is not a sample of a larger set.

Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?

The subjective scores were collected through the www.subjectify.us crowdsourcing platform. The average payment to crowdworkers per pair of sequences was \$0.05. We estimate the overall cost of the subjective tests was \$15,000.

Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)?

Collection of the dataset took place over four years, but the timeframe is immaterial in our case.

Were any ethical review processes conducted (for example, by an institutional review board)?

No, such processes were unnecessary in our case.

2.4 Preprocessing/Cleaning/Labeling

Was any preprocessing/cleaning/labeling of the data done (for example, discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)?

We encoded all samples using x264 with a constant quantization parameter and then calculated the temporal and spatial complexity of each scene. In our definition, spatial complexity is the average size of the I-frame normalized to the sample's uncompressed frame size, while temporal complexity is the average size of the P-frame divided by the average size of the I-frame. Eventually, we added another preprocessing step to unify the chroma subsampling of videos, which affected evaluation complexity . All videos were converted to a YUV 4:2:0 chroma subsample.

For the open part of the dataset, we used 13 codecs implementing five compression standards (H.264, AV1, H.265, VVC, etc.) to encode the original videos. Each video had three target compression bitrates: 1,000 Kbps, 2,000 Kbps, and 4,000 Kbps. Each also had different real-life encoding modes: constant quality (CRF) and variable bitrate (VBR). Our chosen range of bitrates simplifies the subjective comparison, since video quality is more difficult to distinguish visually at high bitrates. Tab. 4 shows command lines that we used to compress videos.

To save repository space and prevent problems with nonstandard decoders, we transcoded YUV files to MP4 using lossless x265 encoding and the following command:

```
ffmpeg -f rawvideo -vcodec rawvideo -s {width}x{height}
-r {FPS} -pix_fmt yuv420p -i {video name}.yuv -c:v libx265
-x265-params "lossless=1:qp=0" -t {hours:minutes:seconds}
-vsync 0 {video name}.mp4
```

To decode videos back to YUV, we employed this command:

```
ffmpeg -i {video name}.mp4 -pix_fmt yuv420p -vcodec rawvideo
-f rawvideo {video name}.yuv
```

Because Bradley-Terry scores were calculated only for encoded streams with the same reference video, correlations were calculated separately for each reference video (and corresponding encoded streams). To compute a single correlation for a whole dataset, we used the Fisher Z-transform to average group correlations weighted proportionally to group size. The quality-control pairs consisted of test videos compressed by the x264 encoder at 1 Mbps and 4 Mbps; they protect the comparison against random answers and bots. Responses from participants who failed in these cases were excluded.

Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (for example, to support unanticipated future uses)?

If we interpret "raw" data as streams encoded before decoding them back to YUV and transcoding with x265, the answer is no. But we share ground-truth (or reference) videos, which are necessary when calculating full-reference metrics.

Is the software that was used to preprocess/clean/label the data available?

We obtained some metric scores (VMAF, VQM, PSNR, SSIM, etc.) through the VQMT, available at www.compression.ru/video/quality_measure/vqmt_download.html. Also, all data was labeled through the Subjectify.us crowdsourcing service, which is at www.subjectify.us.

2.5 Uses

Has the dataset been used for any tasks already?

The dataset has served in two separate projects:

- 1. Measurement of video-quality metrics for distorted videos along with calculation of the correlation between these scores and subjective scores (video-quality-metric benchmark).
- 2. Comparing the effects (artifacts) of different compression standards and codecs (codeccomparison project).

The second project held annual comparisons using different datasets, from which we assembled the dataset in our paper.

Is there a repository that links to any or all papers or systems that use the dataset?

Video-quality benchmark is available through www.videoprocessing.ai/benchmarks/ video-quality-metrics.html and the codec-comparison project through www.compression. ru/video/codec_comparison/index_en.html.

What (other) tasks could the dataset be used for?

The open part of the dataset can be used to train or validate a new metric and determine whether it can reliably meet most compression needs. Our video-quality-metric benchmark uses the hidden part to test submitted models.

Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? Is there anything a dataset consumer could do to mitigate these risks or harms?

One preprocessing stage is transcoding through the H.265 standard, which can affect bitstream-basedmodel performance. In addition, consumers cannot use subjective scores to directly compare distorted videos compressed from different original streams because of the subjective-evaluation procedure we employed for the dataset.

Are there tasks for which the dataset should not be used?

No.

2.6 Distribution

Will the dataset be distributed to third parties outside of the entity (for example, company, institution, organization) on behalf of which the dataset was created?

The open part of the dataset is available to everyone. The hidden part is only available to benchmarksupport personnel for testing metric performance.

How will the dataset be distributed (for example, tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?

The open part of the dataset is accessible through https://calypso.gml-team.ru:5001/ sharing/lxSWi6vtg using the password c943=R3/tJwVV%P%. The benchmark is at www. videoprocessing.ai/benchmarks/video-quality-metrics.html

When will the dataset be distributed?

We have already released the dataset as test data for our benchmark, and we are now accepting submissions.

Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?

The dataset is available under a CCBY license.

Have any third parties imposed IP-based or other restrictions on the data associated with the instances?

All original videos have CCBY and CC0 licenses.

Do any export controls or other regulatory restrictions apply to the dataset or to individual instances?

No.

2.7 Maintenance

Who will be supporting/hosting/maintaining the dataset?

The CMC MSU Graphics and Media Lab hosts the dataset. The team that works with codecs and video-quality assessment methods maintains it. Also, the authors of this paper support the video-quality-metric benchmark.

How can the owner/curator/manager of the dataset be contacted (for example, email address)?

Contact our team at vqa@videoprocessing.ai.

Is there an erratum?

No. The dataset has remained unchanged since the benchmark's release.

Will the dataset be updated (for example, to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (for example, mailing list, GitHub)?

We are planning to extend the dataset to ensure benchmark results with the highest statistical credibility. Such updates will be rare, as they involve subjective evaluation—a time-consuming task that requires extensive preparation. Also, we understand the problems that consumers can face during updates. But after updates become public, they will receive notification primarily through the mailing list, and all the new information will be on the benchmark website.

If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (for example, were the individuals in question told that their data would be retained for a fixed period of time and then deleted)?

No.

Will older versions of the dataset continue to be supported/hosted/maintained?

We do not intend to create a version history, as every relevant edition of the dataset will include all previous editions.

If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? Will these contributions be validated/verified? If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers?

We encourage everyone to share their ideas on extending our dataset to cover more compression cases and provide more-reliable results. Our method of subjective quality evaluation, however, is set; we recommend consumers contacting us by vqa@videoprocessing.ai to coordinate subjective

quality evaluation. Moreover, we can cover the costs of subjective scoring for videos that we find relevant to our research.

References

- [1] Msu codec comparison page. https://www.compression.ru/video/codec_comparison/index_en. html. Accessed: 2022-08-06. 16
- [2] Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. Datasheets for datasets. *Communications of the ACM*, 64(12):86–92, 2021. 16

Encoder name and version	Encoding commands
x265 v.3.0+1-ed72af837053	"x265.exe -input %SOURCE_FILE% -input-res %WIDTH%x%HEIGHT% -fps %FPS% -p veryslow -bitrate %BITRATE_KBPS% -psnr -ssim -tune=ssim -o %TARGET_FILE%"
x264 v.r2969-d4099dd	"x264 –preset placebo –me umh –merange 32 –keyint infinite –tune ssim –pass 1 –bitrate %BITRATE_KBPS% %SOURCE_FILE% –input-res %WIDTH%x%HEIGHT% –fps %FPS% -o NUL x264 –preset placebo –me umh –merange 32 –keyint infinite –tune ssim –pass 2 –bitrate %BITRATE_KBPS% %SOURCE_FILE% –input-res %WIDTH%x%HEIGHT% –fps %FPS% -o %TARGET_FILE%"
vp9 v1.8.0-424-ge50f4e411	<pre>"vpxenc.exe %SOURCE_FILE% -0 %TARGET_FILE% -codec=vp9 -good -p 2 -target-bitrate=%BITRATE_KBPS% -profile=0 -lag-in-frames=25 -min-q=0 -max-q=63 -auto-alt-ref=1 -passes=2 -kf-max-dist=9999 -kf-min-dist=0 -drop-frame=0 -static-thresh=0 -bias-pct=50 -minsection-pct=0 -maxsection-pct=2000 -arnr-maxframes=7 -arnr-strength=5 -sharpness=0 -undershoot-pct=100 -overshoot-pct=100 -frame-parallel=0 -row-mt=1 -width=%WIDTH% -height=%HEIGHT% -fps=%FPS_NUM%%FPS_DENOM% -tile-columns=0 -cpu-used=0 -threads=32"</pre>
xin265 1.0	"xin265_enc.exe -w %WIDTH% -h %HEIGHT% -f %FPS% -b %BITRATE_BPS% -o %TARGET_FILE% -p 4 -i %SOURCE_FILE%"
x264 r3018-db0d417	"x264.exe -preset placebo -me umh -merange 32 -keyint infinite -tune ssim -crf {TARGET_RC} {SOURCE_FILE} -input-res {WIDTH}x{HEIGHT} -fps FPS -o TARGET_FILE" "x264.exe -preset slow -subme 9 -bframes 8 -me umh -keyint infinite -tune ssim -crf TARGET_RC SOURCE_FILE -input-res WIDTHxHEIGHT -fps FPS -o TARGET_FILE"
x265 2020-04-13	"x265.exe -tune ssim -preset medium -crf TARGET_RC SOURCE_FILE -o TARGET_FILE -input-res WIDTHxHEIGHT -fps FPS" "x265.exe -tune ssim -pass 1 -preset veryslow-rof TARGET_RC SOURCE_FILE -o TARGET_FILE -input-res WIDTHXHEIGHT -fps FPS -vbv-bufsize 12000 -vbv-maxrate 12000 x265.exe -tune ssim -pass 2 -preset veryslow -crf TARGET_RC SOURCE_FILE -o TARGET_FILE -input-res WIDTHXHEIGHT -fps FPS -vbv-bufsize 12000 -vbv-maxrate 12000" x265.exe -tune ssim -pass 2 -preset veryslow -crf TARGET_RC SOURCE_FILE -o TARGET_FILE -input-res WIDTHXHEIGHT -fps FPS -vbv-bufsize 12000 -vbv-maxrate 12000" x265.exe -preset veryslow -tune ssim -rskip 0 -ref 5 -merange 92 -rc-lookahead 50 -crf TARGET_RC SOURCE_FILE -o TARGET_FILE -input-res WIDTHxHEIGHT -fps FPS"
rav1e	"rav le.exe –threads 12 –tiles 8 –min-keyint 25 –keyint 250 –speed 3 –quantizer TARGET_RC -o TARGET_FILE.ivf SOURCE_FILE"
SVT-AV1 v0.8.3	"SvtAv1EncApp.exe -i %SOURCE_FILE% -w %WIDTH% -h %HEIGHT% -fps %FPS% -rc 0 -q %BITRATE_KBPS% -preset 3 -b %TARGET_FILE%"
SVT-VP9 v0.2.0	"SvtVp9EncApp.exe -i %SOURCE_FILE% -w %WIDTH% -h %HEIGHT% -fps %FPS% -rc 0 -q %BITRATE_KBPS% -enc-mode 0 -b %TARGET_FILE%"
SVT-HEVC v1.4.3	"SvtHevcEncApp.exe -i %SOURCE_FILE% -w %WIDTH% -h %HEIGHT% -fps %FPS% -rc 0 -q %BITRATE_KBPS% -encMode 0 -b %TARGET_FILE%"
x264 0.160.3000 33f9e14	"x264-r3018-db0d417.exepreset placebome umh merange 32keyint infinitetune ssimcrf %BITRATE_KBPS% %SOURCE_FILE% input-res %WIDTH%x%HEIGHT%fps %FPS%o %TARGET_FILE%"
x265 3.3+21-6bb2d88029c2	"x265-64bit-8bit-2020-04-13.exe -tune ssim -preset ultrafast -crf %BITRATE_KBPS% %SOURCE_FILE% -o %TARGET_FILE% -input-res %WIDTH%x%HEIGHT% -fps %FPS%"
SVT-HEVC v1.5.1	"SvtHevcEncApp.exe -i SOURCE_FILE -w WIDTH -h HEIGHT -fps FPS -rc 1 -tbr TARGET_BITRATE -encMode 0 -b TARGET_FILE" "SvtHevcEncApp.exe -i SOURCE_FILE -w WIDTH -h HEIGHT -fps FPS -rc 1 -tbr TARGET_BITRATE -encMode 5 -b TARGET_FILE"
SVT-VP9 v0.3.0	"SvtVp9EncApp.exe -i SOURCE_FILE -w WIDTH -h HEIGHT -fps FPS -rc 1 -tbr TARGET_BITRATE -enc-mode 0 -b TARGET_FILE" "SvtVp9EncApp.exe -i SOURCE_FILE -w WIDTH -h HEIGHT -fps FPS -rc 1 -tbr TARGET_BITRATE -enc-mode 5 -b TARGET_FILE"
x264 r3065-ae03d92	"x264-r3065-ae03d92.exe –preset placebo –me umh –merange 32 –keyint infinite -tune ssim –bitrate TARGET_BITRATE SOURCE_FILE –input-res WIDTHxHEIGHT –fps FPS o TARGET_FILE" "SvtVp9EncApp.exe -i SOURCE_FILE = WIDTH -h HEIGHT -fps FPS -rc 1 -tbr TARGET_BITRATE -enc-mode 5 -b TARGET_FILE"
x265 3.5+1-ce882936d	"x265-8bit.exeinput SOURCE_FILEinput-res WIDTHxHEIGHTfps FPS bitrate TARGET_BITRATEpreset mediumlimit-saolimit-ref 0 -o TARGET_FILEpsnrssimtune=ssim" "x265-8bit.exeinput SOURCE_FILEinput-res WIDTHxHEIGHTfps FPS crf TARGET_RCvbv-bufsize 12000ptreset veryslowrskip 0 ref 5merange 92rc-lookahead 50 -o TARGET_FILEpsnrssimtune=ssim"
x265 3.5+1-f0c1022b6	"x265.exe -input SOURCE_FILE -input-res WIDTHxHEIGHT -fps FPS -preset medium -bitrate TARGET_BITRATE -psnr -ssim -tune=ssim -o TARGET_FILE -sao -limit-sao -ctu 64 -ref 3 -limit-ref 0" "x265.exe -input SOURCE_FILE -input-res WIDTHxHEIGHT -fps FPS -p placebo -bitrate TARGET_BITRATE -psnr -ssim -tune=ssim -o TARGET_FILE"
vvenc v1.0.0	"./vvencapppreset fast -i SOURCE_FILE -s WIDTHxHEIGHT -r FPS bitrate TARGET_BITRATE -o TARGET_FILE"
xin v1.0	"xin26x_test.exe -o TARGET_FILE -i SOURCE_FILE -w WIDTH -h HEIGHT -f FPS -n FRAMES_NUM -r 1 -b TARGET_BITRATE -p 3 -a 0" "xin26x_test.exe -o TARGET_FILE -i SOURCE_FILE -w WIDTH -h HEIGHT -f FPS -n FRAMES_NUM -r 1 -b TARGET_BITRATE -p 5 -intranxn 1 -transformskip 1 -a 0"
xin vvc v1.0	 "xin26x_test.exe -o TARGET_FILE -i SOURCE_FILE -w WIDTH -h HEIGHT -f FPS -n FRAMES_NUM -r 1 -b TARGET_BITRATE -p 1 -a 2" "xin26x_test.exe -o TARGET_FILE -i SOURCE_FILE -w WIDTH -h HEIGHT -f FPS -n FRAMES_NUM -r 1 -b TARGET_BITRATE -p 4 -a 2"
rav1e 0.5.0-alpha (p20210518)	"rav1e-ch.exe –threads 16 –tiles 8 –slots 2 –min-keyint 25 –keyint 250 –speed 3 –quantizer TARGET_RC –frame-rate FPS_NUM –time-scale FPS_DENOM -o TARGET_FILE.ivf SOURCE_FILE"

Table 4: Encoding commands used for creating compressed videos.