JEG-Hybrid

Framework for reproducible objective video quality research with case study on PSNR implementations

AHMED ALDAHDOOH
ENRICO MASALA
GLENN VAN WALLENDAEL
MARCUS BARKOWSKY

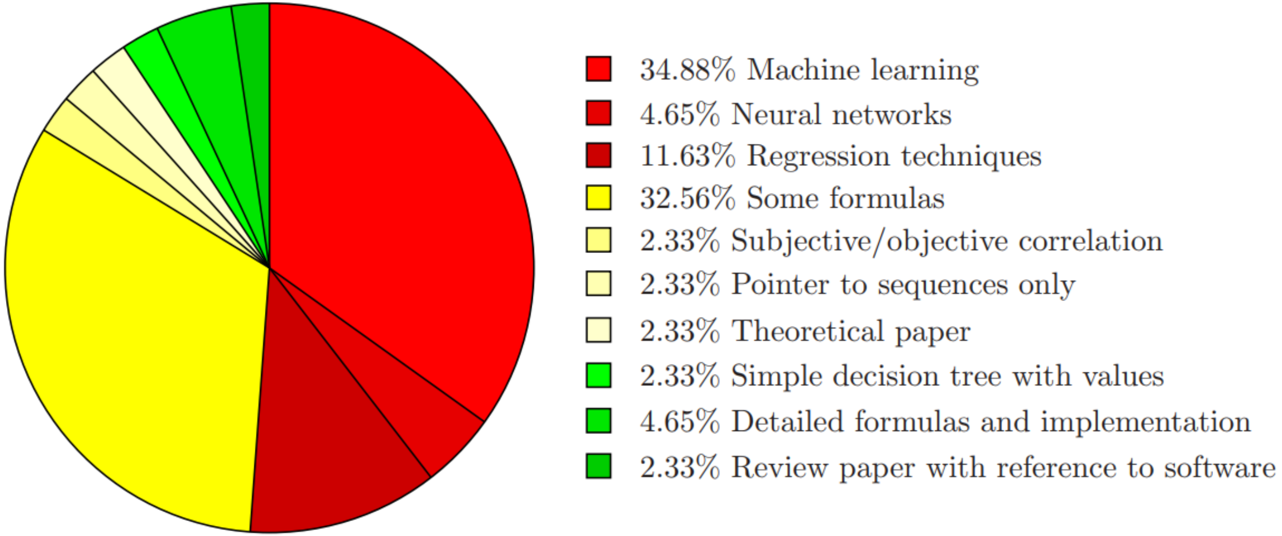
Reproducibility

- algorithms are complex,
- depend on specific implementations in software packages
- their parameters need to be trained on a particular dataset

- Textual descriptions:
  - lack the required detail
  - even for the simple Peak Signal to Noise Ratio (PSNR)

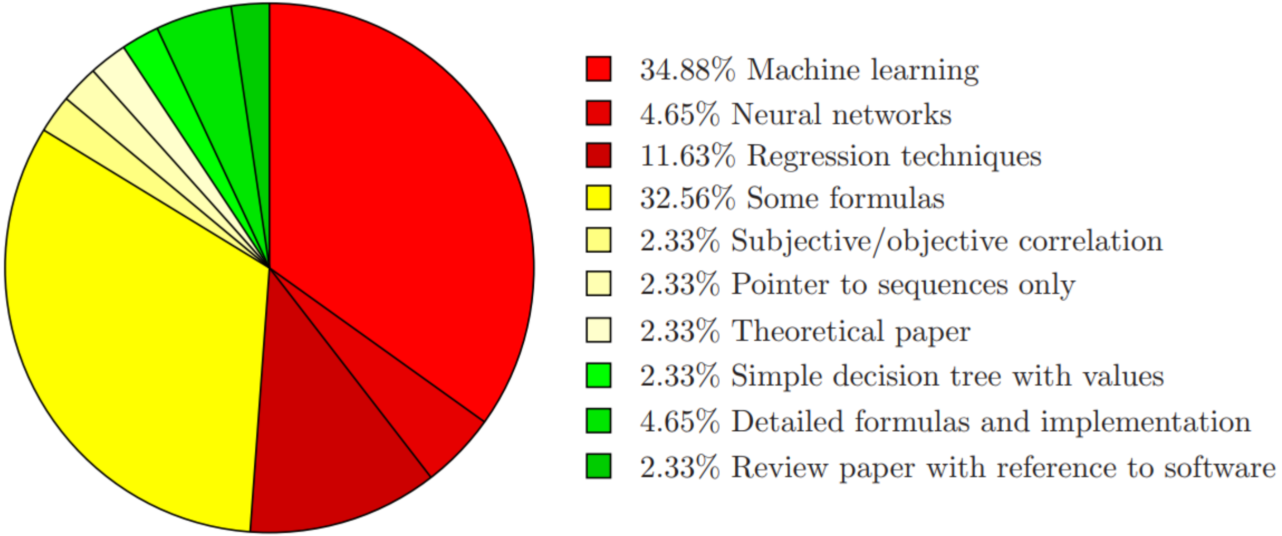
Reproducibility: a sample example

- Search three terms in IEEEXplore: video, quality, and prediction
- 59 hits
- 16: no new algorithm → discarded



Reproducibility: a sample example

- Green: 9.31% out of the 43 papers: comes with source code allowing reproducibility
- Yellow: 39.53% of the works seem to provide reasonably detailed information
- Red: 51.16% rely on some sort of learning technique (no dataset, no code)



Reproducibility: PSNR

- peak value
  - ITU-R BT.601: 235
  - 8 bit: 255

$$20 \log_{10} \frac{235}{255} \approx -0.71$$

- temporal alignment
  - overestimates the quality when ignoring
    - Stalling
    - Skipping
    - Reduced frame rate
- color alignment
  - brightness, contrast, and color changes may even improve quality
- temporal pooling
  - averaging the Mean Squared Error (MSE)
  - averaging the PSNR values per frame
  - squared mean of the PSNR values: emphasizing degradations

Temporal pooling

$$MSE_f = \sum_{i=1}^{X}\sum_{j=1}^{Y}(\hat{p}_{ij} - p_{ij})^2$$

$$PSNR_f = 10\log_{10}\frac{\text{peak}^2}{MSE_f}.$$

- $PSNR_A$ (arithmetic mean): MSE_f is averaged over all frames
- $PSNR_G$ (geometric mean): the mean of the $PSNR_f$

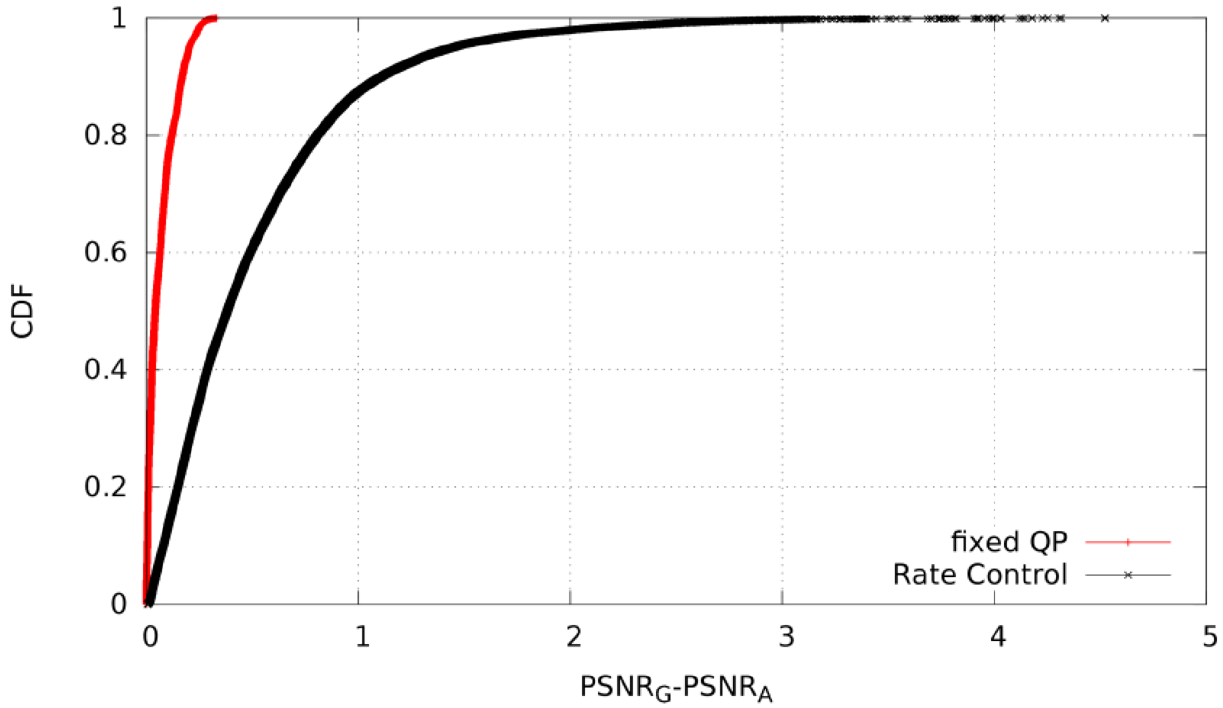
$$PSNR_A = 10\log_{10}\frac{255^2}{\frac{1}{N}\sum_{k=1}^{N} PSNR_{f_k}}$$

$$PSNR_G = \frac{1}{N}\sum_{k=1}^{N} PSNR_{f_k}.$$

Impact of temporal pooling

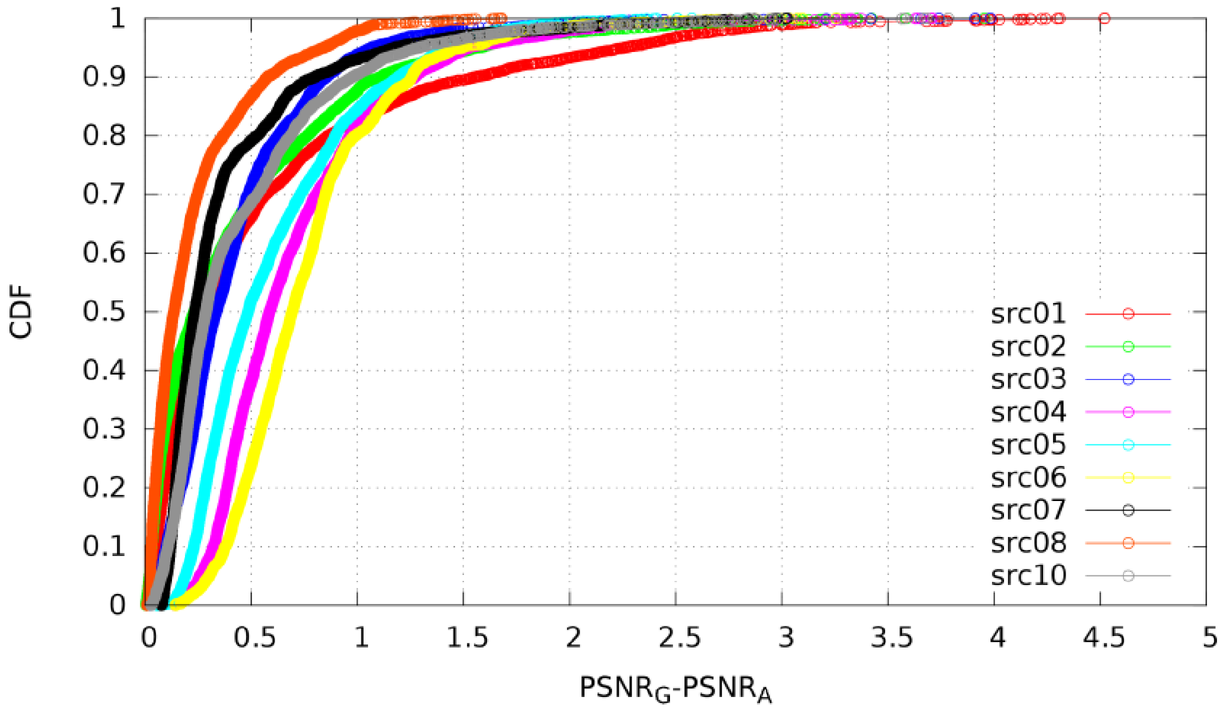
Difference in PSNR up to 4dB depending on temporal pooling.

Mostly below 0.5dB



Impact of temporal pooling

- Only considering rate control:

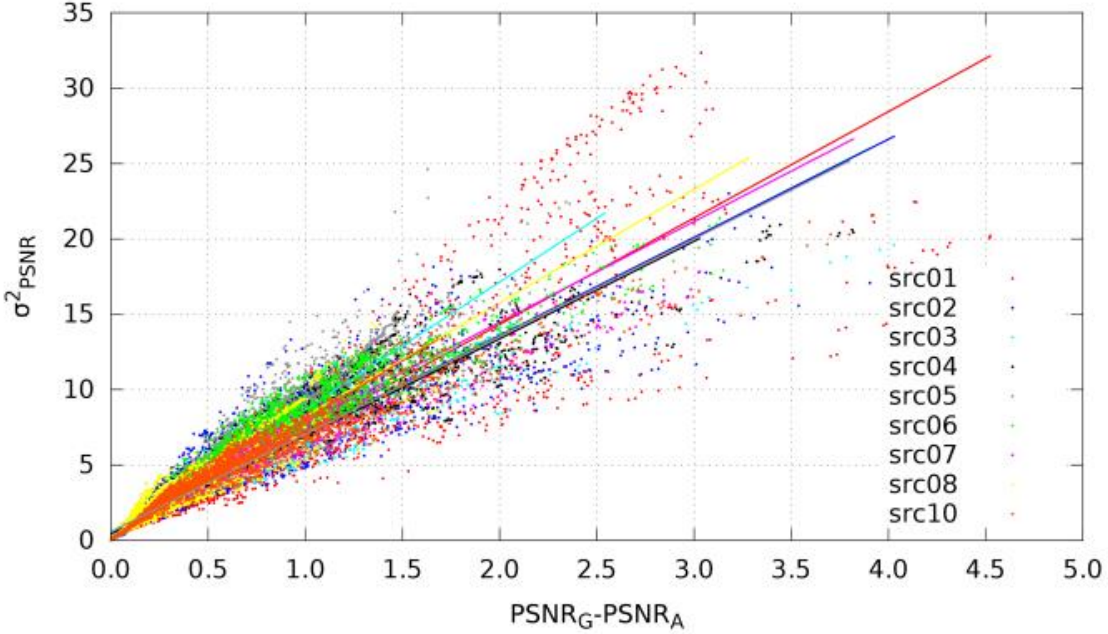


Variance as an extra indicator

Higher σ^2_{PSNR} yields to higher difference

if σ^2_{PSNR} it is lower than 2
PSNR difference < 0.5 dB

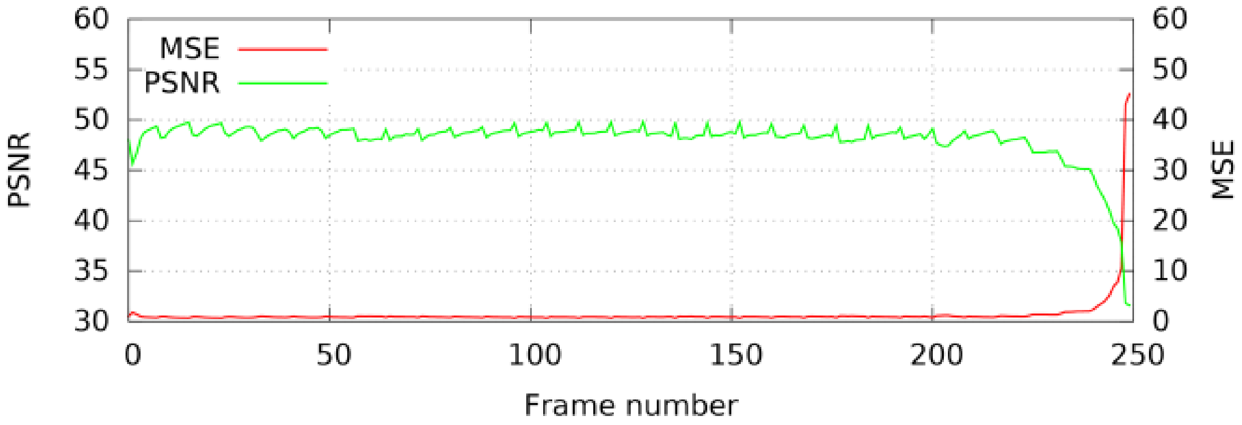
if σ^2_{PSNR} it is higher than 4
PSNR difference can be 1.5 dB



Variance as an extra indicator

Higher σ^2_{PSNR} yields to higher difference

if σ^2_{PSNR} it is lower than 2 *PSNR* difference < 0.5 dB



Variance as an extra indicator

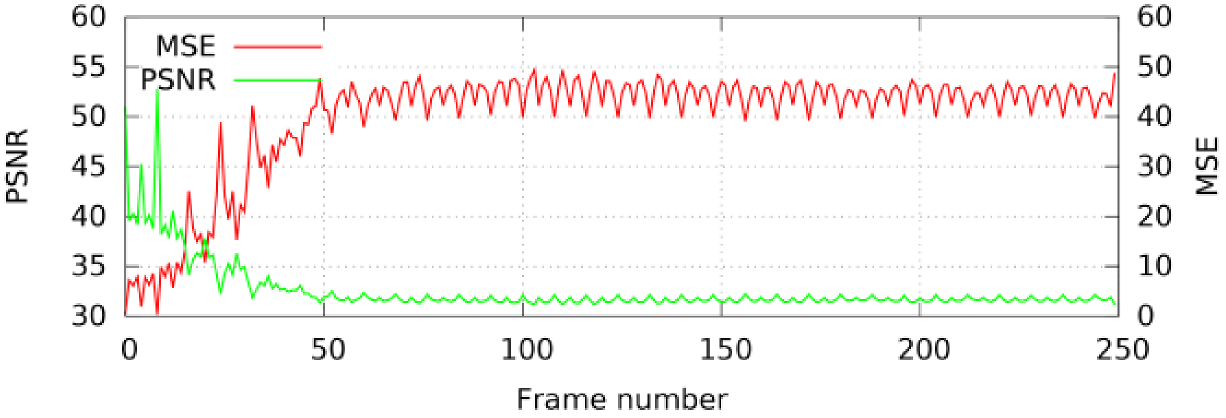
Higher σ^2_{PSNR} yields to higher difference

if σ^2_{PSNR} it is lower than 2

PSNR difference < 0.5 dB

if σ^2_{PSNR} it is higher than 4

PSNR difference can be 1.5 dB



JEG-Hybrid

Subset selection for the design of subjective experiments

AHMED ALDAHDOOH
ENRICO MASALA
GLENN VAN WALLENDAEL
MARCUS BARKOWSKY

Subset selection

- You do not want to select
  - different quality levels, i.e. different QPs
  - different bitrate budgets, nor
  - selecting different content types
- choose the HRCs that cover a wide range of the targets

Subset selection

- Quality/Bitrate-driven HRCs Subset
  - representing all ranges of PSNR and bitrates
- Content-driven HRCs Subset
  - algorithm for selecting the HRCs that behave differently with the contents

Goal-driven Large-scale Database Subset Generation

- predict the behavior of a full-reference quality measure (VQM)

		Tested on				
		Content-based	Quality/bitrate -based	Random 1	Random 2	Random 3
Trained on	Content-based	0.99	0.97	0.96	0.97	0.97
	Quality/bitrate -based	0.98	0.99	0.99	0.99	0.99
	Random 1	0.98	0.96	0.99	0.97	0.90
	Random 2	0.95	0.98	0.99	0.99	0.99
	Random 3	0.63	0.60	0.69	0.92	0.99