Recover Subjective Quality Scores from Noisy Measurements

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VQEG Kraków 2017
Background - Acknowledgements

- Netflix has invested significant resources in video quality
  - VMAF (algorithmic development, subjective testing, OSS)

- Collaboration with research universities to address open problems
  - University of Nantes (Patrick Le Callet)
  - University of Southern California (C.-C. Jay Kuo)
  - University of Texas at Austin (Al Bovik)
  - More to come
Raw opinion scores are noisy and unreliable

Would MOS or DMOS be good enough?

Partial remedies

- Z-scoring - can only partially compensate subject bias
- Subject rejection
Algorithm 1 Subject rejection [8]

- Input: $x_{e,s}$ for $s = 1, ..., S$ and $e = 1, ..., E$.
- Initialize $p(s) \leftarrow 0$ and $q(s) \leftarrow 0$ for $s = 1, ..., S$.
- For $e = 1, ..., E$:
  - Let $Kurtosis_e = \frac{m_4,e}{m_2,e}$.
  - If $2 \leq Kurtosis_e \leq 4$, then $\epsilon_e = 2$; otherwise $\epsilon_e = \sqrt{20}$.
  - For $s = 1, ..., S$:
    * If $x_{e,s} \geq \mu_e + \epsilon_e \sigma_e$, then $p(s) \leftarrow p(s) + 1$.
    * If $x_{e,s} \leq \mu_e - \epsilon_e \sigma_e$, then $q(s) \leftarrow q(s) + 1$.
- Initialize $Set_{rej} = \emptyset$.
- For $s = 1, ..., S$:
  - If $\frac{p(s)+q(s)}{E} \geq 0.05$ and $\left| \frac{p(s)-q(s)}{p(s)+q(s)} \right| < 0.3$, then $Set_{rej} \leftarrow Set_{rej} \cup \{s\}$.
- Output: $Set_{rej}$.
BT.500 limitations

- All scores corresponding to rejected subjects are discarded -- an overkill
- Often only identifies a subset of outliers
  - In the example above, only subjects #26, #28 and #29 were identified
- Does not generalize well for selective sampling (i.e. missing data)
Can we do better?

Take into account subject characteristics

- Subject bias
  - Picky viewers tend to be biased toward lower scores
  - Not every subject has “golden eyes” - their sensitivity to impairment varies
  - Different sessions

- Subject inconsistency
  - Subjects may not rate consistently throughout a viewing session
  - Outliers - a special case with very large inconsistency

First need a model to capture these factors!!
Modeling raw opinion score

\[ X_{e,s} = x_e + B_{e,s}, \text{ for } e = 1, \ldots, E, s = 1, \ldots, S \]

where:

\[ B_{e,s} \sim N(b_s, \sigma^2_s) \]

Independently validated by:
L. Janowski and M. Pinson, “The accuracy of subjects in a quality experiment: A theoretical subject model,” IEEE Transactions on Multimedia, Dec 2015.
Proposed approach

Main idea: find unknown parameters to maximize likelihood function of the observations
- maximum likelihood estimation (MLE)

Example problem size

- # observations: 300 (PVS) * 30 (Subject) = 9000
- # unknowns:
  - True quality scores (300)
  - Subject Bias (30)
  - Subject inconsistency (30)
A solution based on Belief Propagation

\textbf{Algorithm 2} BP solution for the proposed MLE formulation

- Input:
  - $x_{e,s}$ for $s = 1, \ldots, S$ and $e = 1, \ldots, E$.
  - Refresh rate $\alpha$.
  - Stop threshold $\Delta x^{thr}$.
- Initialize $\{x_e\} \leftarrow \{\mu_e\}$, $\{b_s\} \leftarrow \{0\}$, $\{v_s\} \leftarrow \{\sigma_s\}$
- Loop:
  - $\{x_e^{prev}\} \leftarrow \{x_e\}$.
  - $b_s \leftarrow (1 - \alpha) \cdot b_s + \alpha \cdot b_s^{new}$ where $b_s^{new} = b_s - \frac{\partial L(\theta)}{\partial b_s} \frac{\partial^2 L(\theta)}{\partial b_s^2}$ for $s = 1, \ldots, S$.
  - $v_s \leftarrow (1 - \alpha) \cdot v_s + \alpha \cdot v_s^{new}$ where $v_s^{new} = v_s - \frac{\partial L(\theta)}{\partial v_s} \frac{\partial^2 L(\theta)}{\partial v_s^2}$ for $s = 1, \ldots, S$.
  - $x_e \leftarrow (1 - \alpha) \cdot x_e + \alpha \cdot x_e^{new}$ where $x_e^{new} = x_e - \frac{\partial L(\theta)}{\partial x_e} \frac{\partial^2 L(\theta)}{\partial x_e^2}$ for $e = 1, \ldots, E$.
  - If $\left( \sum_{e=1}^{E} (x_e - x_e^{prev})^2 \right)^{\frac{1}{2}} < \Delta x^{thr}$, break.
- Output: $\{x_e\}$, $\{b_s\}$, $\{v_s\}$

Implementation at: \url{github.com/Netflix/vmaf/tree/master/python/src/vmaf/mos}
Algorithm Validation: Synthetic Data

Synthetic data generation

- Randomly generate parameters according to $x_e \sim U[1, 5]$, $b_s \sim N(0, 1)$, $v_s \sim U[0, 1)$
- Randomly generate observations according to parameters and model
Sample recover results

Raw Opinion Scores ($x_{cs}$)

Recovered Quality Score ($x_q$)

Subject Bias ($b_s$)

Subject Inconsistency ($v_s$)
Resistance to outliers

**Proposed Approach**

- MOS
- SR_MOS
- ZS_SR_MOS
- MLER

Y-axis: RMSE w.r.t. clean case

- ZS - Z-scoring
- SR - Subject rejection

Worse

Better
Selective sampling in the presence of outliers

Y-axis: RMSE w.r.t. clean case

Proposed Approach

Worse

Better

ZS - Z-scoring
SR - Subject rejection
Conclusions

Jointly estimating quality scores with subject characteristics yields more robust recovery against outliers than the BT.500 recommendation, and tighter confidence intervals.

Recovered side information provides additional insight on subjects’ bias and inconsistency.
Work in progress: content ambiguity

\[ X_{e,s} = x_e + B_{e,s} + A_{e,s} \text{ for } e = 1, \ldots, E, s = 1, \ldots, S \]

\[ B_{e,s} \sim N(b_s, \nu_s^2) \]

\[ A_{e,s} \sim N(0, a_{c:c(e)=c}^2) \]
Thank you

Source code at:
github.com/Netflix/vmaf/tree/master/python/src/vmaf/mos

Will also release a stand-alone version soon.
More datasets
Yonsei UHD ACR Dataset

Raw Opinion Scores ($x_{es}$)

Recovered Quality Score ($x_e$)
Yonsei UHD ACR Dataset (Cont’d)

Subject Bias ($b_s$)

Subject Inconsistency ($v_s$)
VQEG HD3 Dataset

Raw Opinion Scores ($x_{es}$)

Test Subjects ($s$)

Recovered Quality Score ($x_e$)

Impaired Video Encodes ($e$)
VQEG HD3 Dataset (Cont’d)

Subject Bias ($b_s$)

Subject Inconsistency ($v_s$)