nofu – A Lightweight No-Reference Pixel Based Video Quality Model for Gaming Content.

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Motivation – Gaming Streams

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- beside classical video streams → gaming content:
  - e.g. Youtube Gaming, Twitch, ...
- gaming videos →
  - additional requirements /properties: *Zadtootaghaj et al.* [9]
  - live streaming, low delay, low stalling,
  - high video quality, cgi content, streaming technology
- focus on video quality of gaming streams

→ gaming qoe and gaming video quality

Gaming QoE and video quality

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- several influencing factors: *Möller, Schmidt, and Zadtootaghaj* [8]
  - video quality factors: content (cgi), encoding (fast),
  - interaction: delay, ...
- objective full-reference metrics: good results: *Barman et al.* [1, 2, 3]
  - VMAF best; problem: reference usually not available
- for live/adaptive encoding:
  - fast, accurate, no-reference quality estimation

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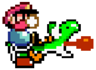

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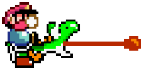

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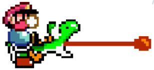

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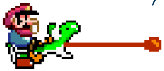

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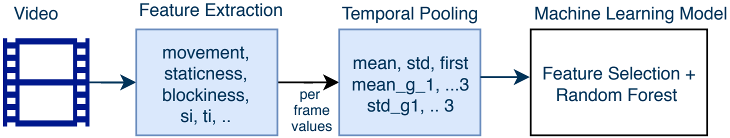

- features:
  - $si^I + ti^M$ [6], fft^I [7], $staticness^I$, $blockiness^I$ [5],
  - cubrow-$\{first,last\}^M$, cubcol-$\{first,last\}^M$, $blockmotion^M$ [5]
- speedup: 360p center crop of input video
- temporal pooling: 12 feature values per frame
  - *first*, *mean*, *std*, groups $g = [1, 2, 3]$: $mean_g$, std_g
  - $\rightarrow$ duration independent 108 values per sequence
- ML algorithm: feature selection + RF
- additional no-ref model: brisque+niqe features, similar pipeline

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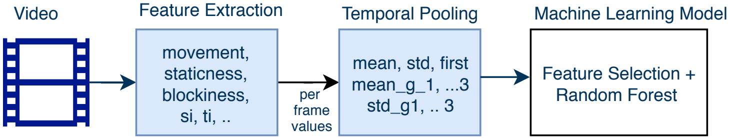

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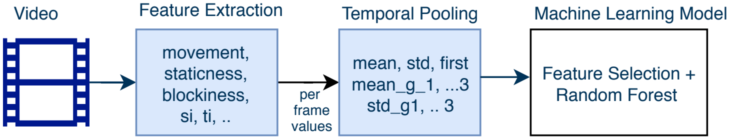

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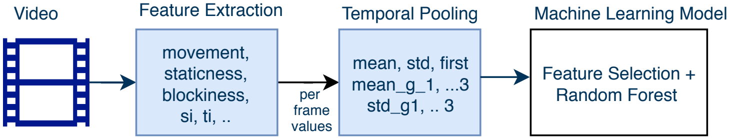

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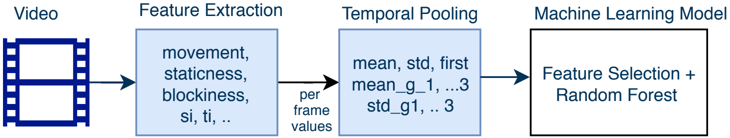

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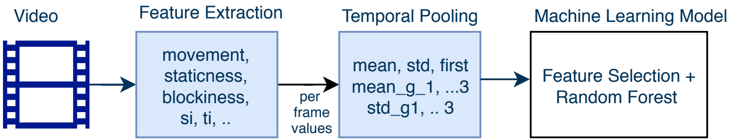

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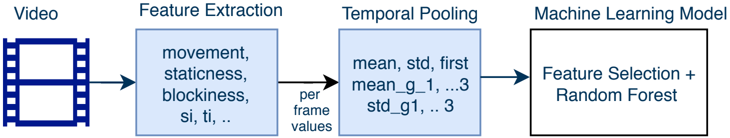

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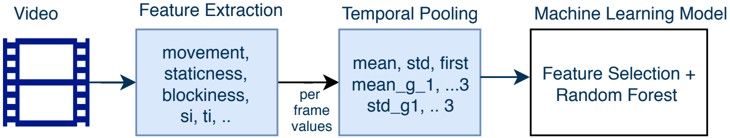

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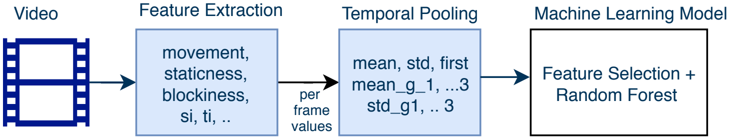

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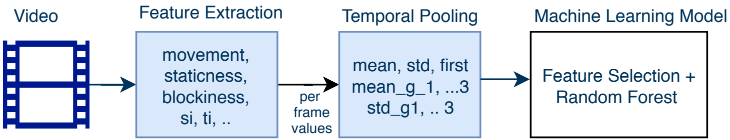

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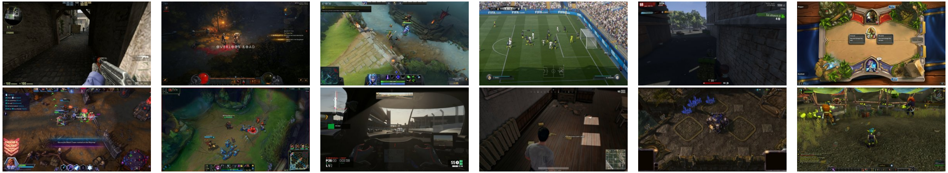

- GamingVideoSET: *Barman et al.* [4]:
  - 24 full-HD sources, 576 distorted videos, 90 with subjective scores
- two main evaluations: 10-fold cross validation and source fold:
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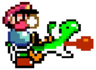
  → MOS prediction



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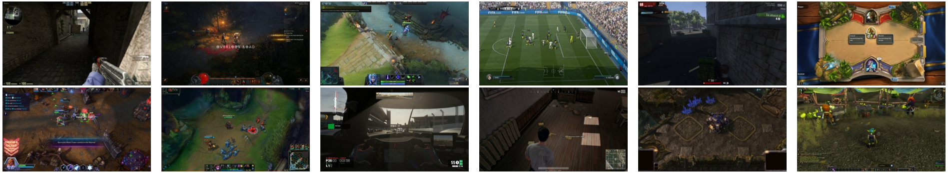

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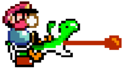

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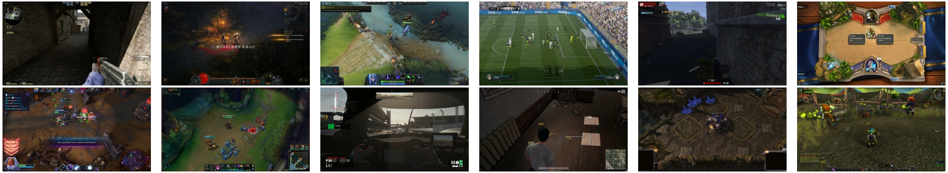

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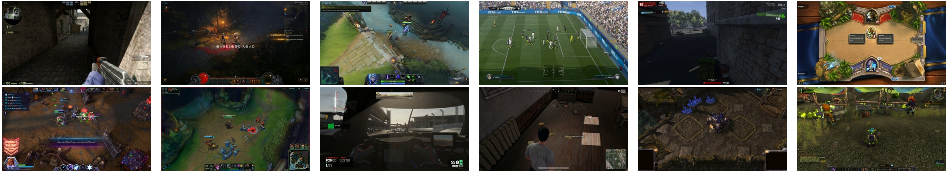

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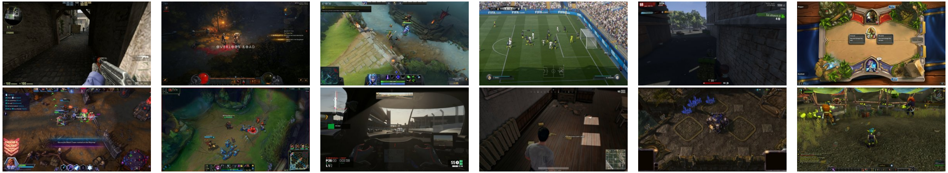

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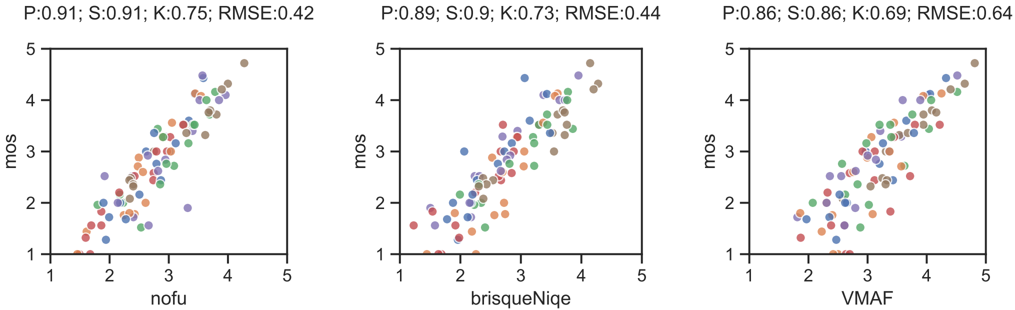

pearson (P), spearman (S), kendall (K) and RMSE

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- source video fold evaluation: nofu > brisque+niqe

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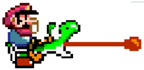

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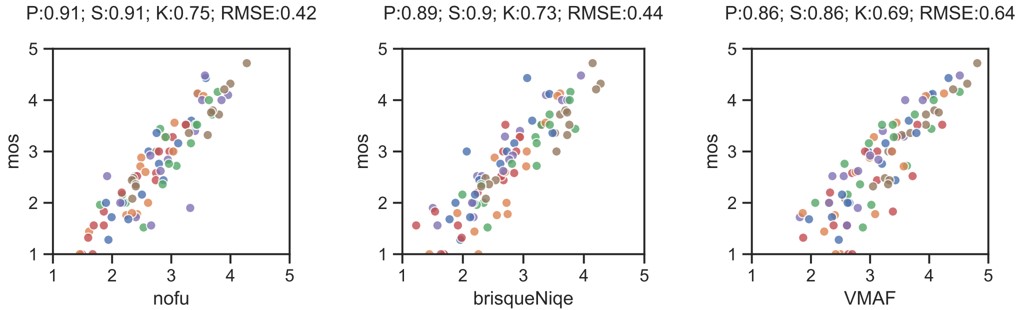

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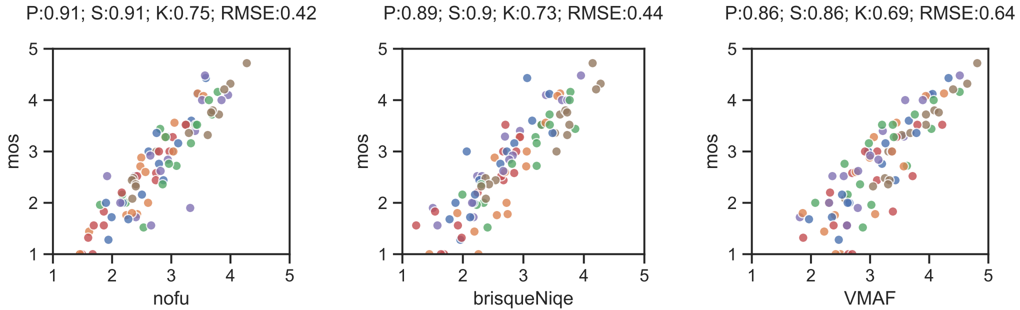

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  - **features**: quality-related and gaming-specific
  - **temporal pooling + 360p center crop**
  - machine learning based
- evaluation using GamingVideoSET [4]
  - **nofu** outperforms other no-ref models + VMAF
  - per source fold: promising results
- open and next steps:
  - include delay/latency, bitstream features, combine **nofu**+brisque+niqe
  - use features/approach for different tasks

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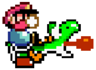

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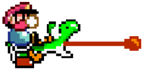
Conclusion, Summary and Future Work

- introduced **nofu**: no-reference model for gaming video quality
  - **features**: quality-related and gaming-specific
  - **temporal pooling + 360p center crop**
  - machine learning based
- evaluation using GamingVideoSET [4]
  - **nofu** outperforms other no-ref models + VMAF
  - per source fold: promising results
- open and next steps:
  - include delay/latency, bitstream features, combine **nofu**+brisque+niqe
  - use features/approach for different tasks



Thank you for your attention

...... are there any questions?

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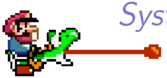

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