Context-aware encoding and dynamic encoding ladders

Machine Learning for Per-Title Encoding

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Outline

- ❑ Resolution Switching and convex hull
- ❑ Subjective and Objective Quality Assessment
- ❑ Problem
- ❑ Dataset and data preprocessing
- ❑ Training the model
- ❑ Results and discussion

One-Size-Fits-All encoding

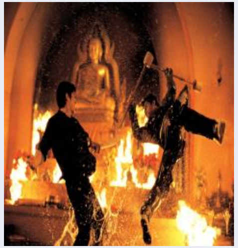
- Motion → Low vs High
- Texture → Plain vs Noisy (Complex)

- **Downside**
- For the scenes with high complexity → Blockiness
- For simple content like cartoons → Waste the bitrate

Bitrate (kbps)	Resolution
235	320x240
375	384x288
560	512x384
750	512x384
1050	640x480
1750	720x480
2350	1280x720
3000	1280x720
4300	1920x1080
5800	1920x1080

bitrate ladder

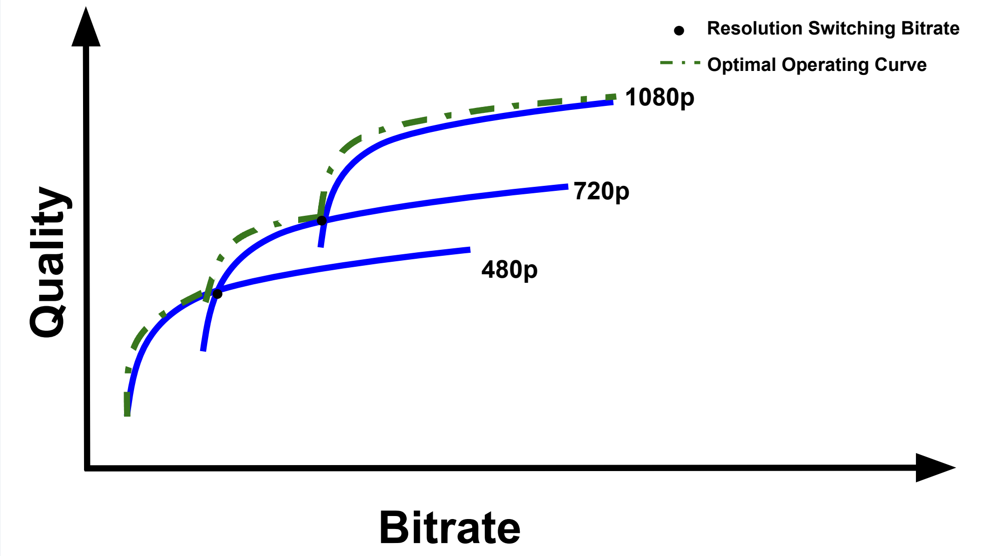
Low Complexity



High Complexity

Resolution Switching

- **At a certain resolution, bitrate can increase the quality to a certain point, after that point the quality gets saturated**
  - We need to increase the resolution



Subjective Quality Assessment

- **Typically subjective rating used to find out the resolution switching points**
  - Subjective tests are expensive
  - Subjective ratings are not always available
- **Objective metrics can be an alternative**
  - Cons: Adding the errors due to prediction errors
  - Pros: it can be applied simply to every encoded videos

Objective Quality Assessment

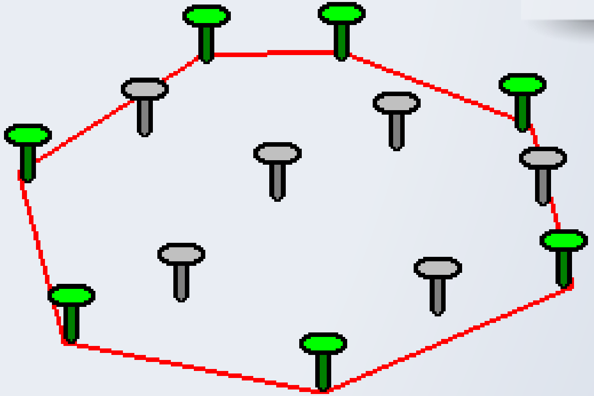
- **Signal based models**
  - Full reference, reduced reference, no reference
  - **Cons**: the video has to be encoded first
- **Parametric based models**
  - Based on the network and **encoding parameters**
  - **Cons:** Less accuracy as content information is not available
  - **Pros**: no need to encode the video
- **Hybrid models**

Resolution switching using objective metrics

- **Typically full-reference metrics are used**
  - **PSNR** (Peak Signal-To-Noise Ratio)
    - The most commonly used metric in video compression.
  - **VMAF** (Video Multi-Method Assessment Fusion)
    - Perceptual quality metric developed by Netflix
  - **Still expensive** procedure as the videos needed to be encoded in several bit-resolution pairs to get the curves
    - Can be replaced by parametric-based models

What is the Convex Hull ?

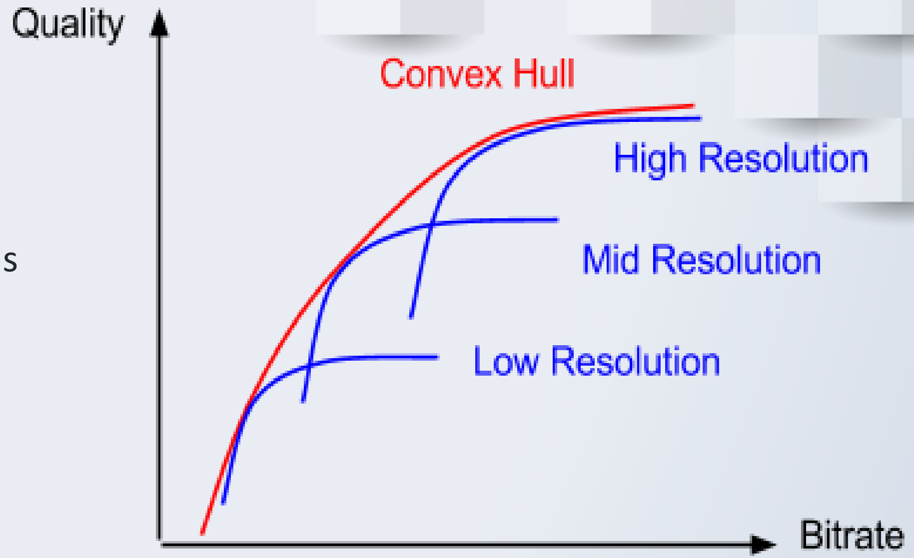
Rubber band



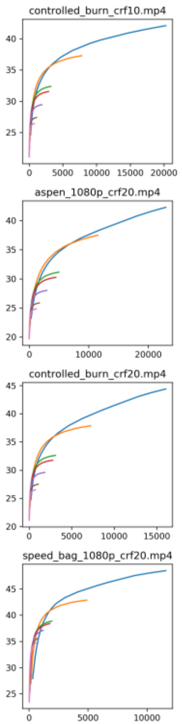
Convex Hull

What is the Convex Hull ?

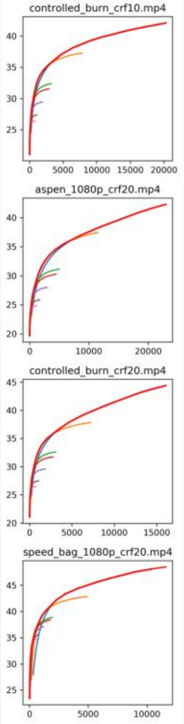
- Mathematically, the convex hull or convex envelope or convex closure of a set X of points in the Euclidean plane or in a Euclidean space is the smallest convex set that contains X.



Convex Hull & Complexity Analysis (For each Movie/Clip)

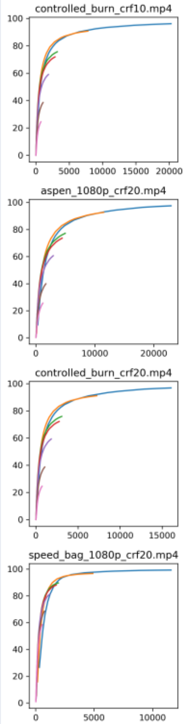


RD Curves

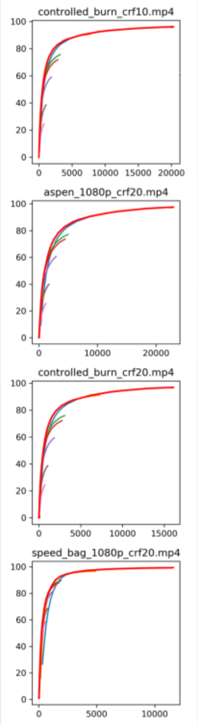


Convex Hull

PSNR



RD Curves



Convex Hull

VMAF

Problem

- **Predict VMAF based on the encoding parameters as well as video information**
  - Pros: There will no need for encoding the video anymore
  - Challenge: the prediction strongly affected by content complexity
    - Temporal and spatial complexity

Dataset tables

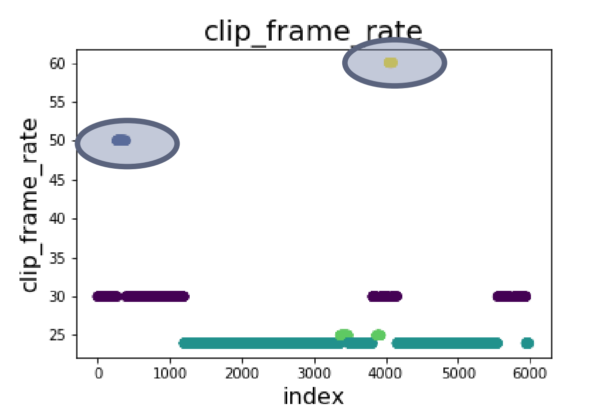
- **Clip**: attributes of a clip.
- **Encode**: describes a single test encode with used encoding parameters (e.g. crf, resolution, etc) and derived quality metrics (VMAF, PSNR) of an encode.
- **Scene Change**: Scene changes indicate a change of the setting/scene in a video.
  - complex content has a lot scene changes
- **Label**: Labels for each source video which are tagged using machine learning classifiers like Tensorflow Mobilenet to define labels and categories for the content.

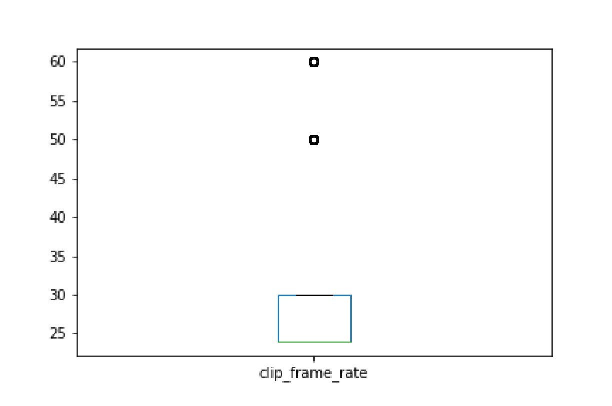
Data preprocessing

- **Missing values**
  - Nan values are removed
- **Outliers are removed**
  - We used ITU-T recommendation p.1401
    - It is designed for subjective rating, but found it to be useful
- **Categorical data handling**
  - Dummy Coding
- **Normalizing the data**
  - It is required as the features have different ranges

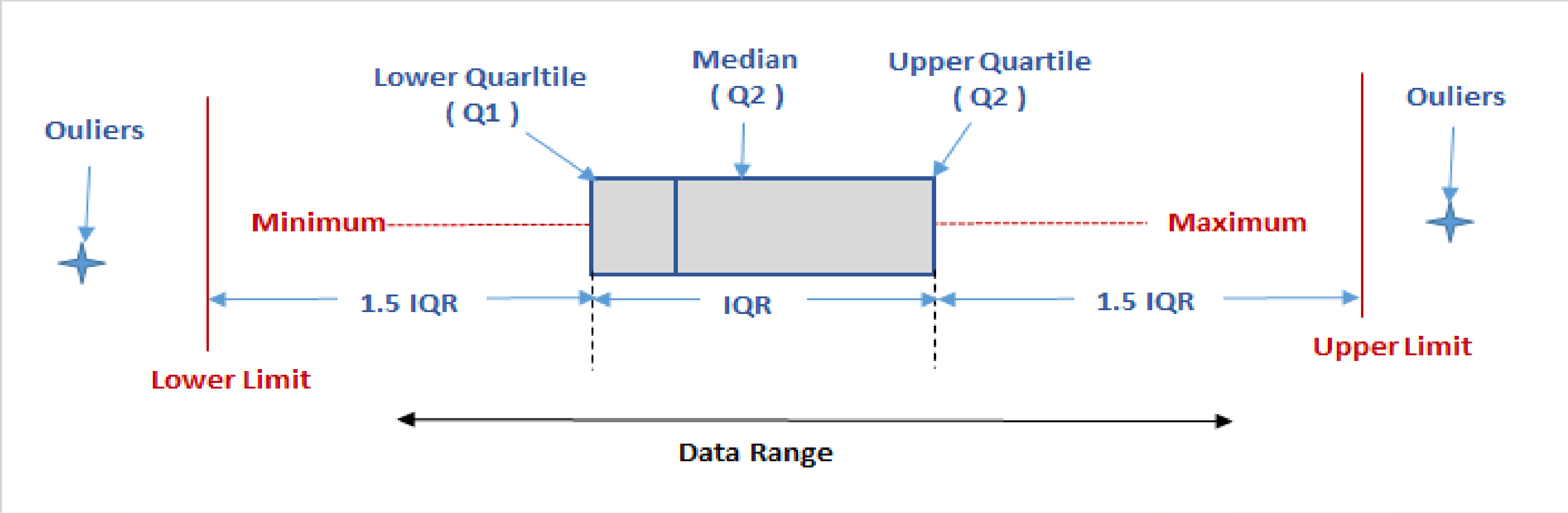
Data preprocessing

- **Data preparation**
  - **e.g. Framerate:** Change from 30000/1001 to 30 fps
  - Nan values are removed
- **Outliers are removed**
  - Check them in simple scatter plot first
  - Box-and-whisker-plot as similar to ITU-T p.1401 the outlier are removed





Outlier detection: Box-and-whisker-plot



Plot from Quality and Usability Seminar

Training data

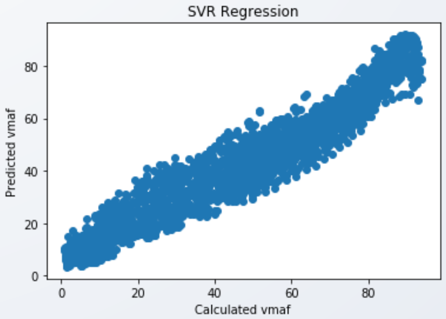
- **Train set and test set**
  - **Blind cross validation**
    - Really good results, but probably biased to the training set
  - **Split dataset**: 25% of source videos (based on clip table) are chosen to be test and 75% training set
  - **Leave-one-out cross validation**: every time one source video was out trained based on the other sequences, then tested based on the holdout sequence
- **Four regressions are used:**
  - Linear regression, SVR (rbf kernel), random forest, XGBoost

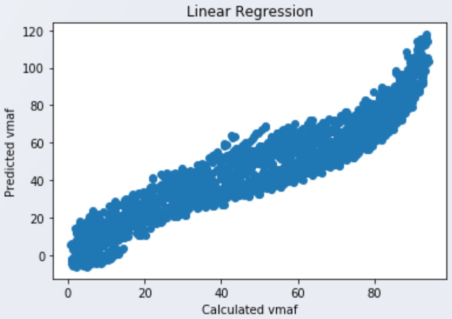
Predicting VMAF
[Clip_Encode] table

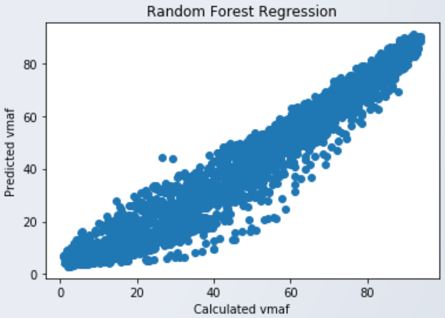
- **Predict VMAF purely based on the encoding parameters**
  - **Cons**: missing information about the video complexity
    - Assume that videos have similar complexity level
- **Features used for training**
  - **Clip table:**
    - clip_duration, clip_frame_rate, clip_height, clip_size
  - **Encode table:**
    - encode_WidthHeight, encode_bitrate_video, encode_crf

Training and results

- Split dataset [Clip_Encode tables]







	SVR	Linear	Random Forest
MSE	86.1827	101.0071	86.9497
RMSE	9.2834	10.0502	9.3246
Pearson Correlation	0.9588	0.9344	0.9654

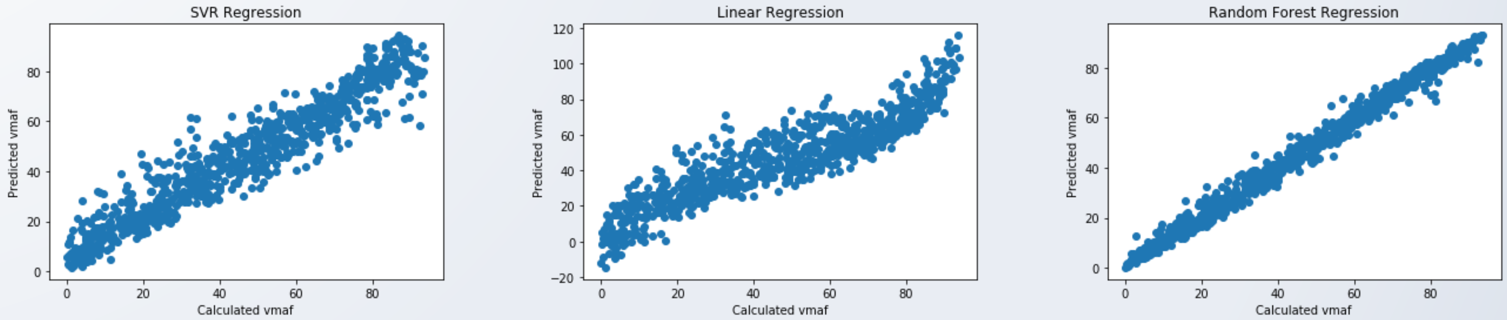
Predicting VMAF

[Clib_Encode_scenechange] table

- **Predict VMAF based on the encoding parameters and scene change percentage**
  - **Pros:** taking into account the temporal video complexity
  - **Cons**: missing information about the spatial video complexity
    - Assume that videos have similar spatial complexity (texture) level
- **Features used for training**
  - **Clip table:**
    - clip_duration, clip_frame_rate, clip_height, clip_size
  - **Encode table:**
    - encode_WidthHeight, encode_bitrate_video, encode_crf
  - **Scene change table**: percentage of scene change in 1 second

Training and results

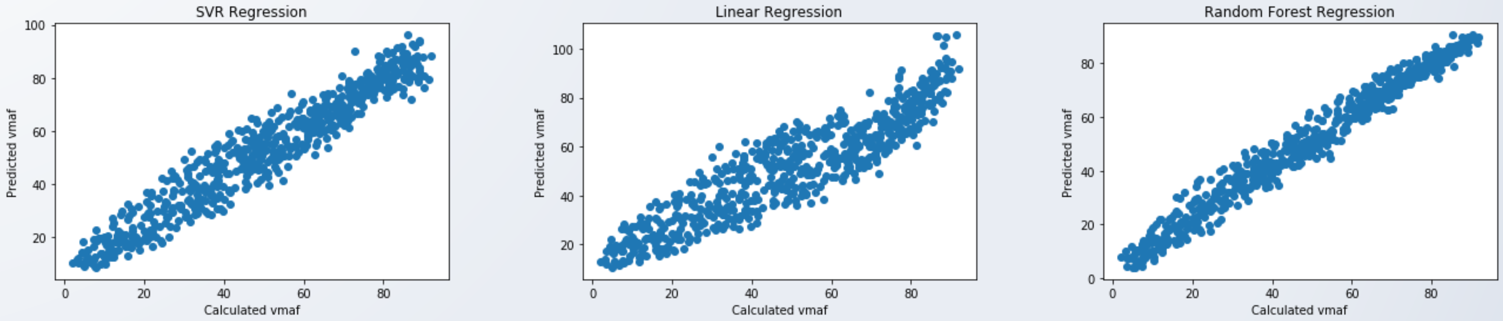
- Blind cross validation [Clip_Encode_Scene change tables]



	SVR	Linear	Random Forest
MSE	66.4030	119.8154	8.8470
RMSE	8.1488	10.9460	2.9743
Pearson Correlation	0.9534	0.9095	0.9936

Training and results

- Split dataset [Clip_Encode_Scene change tables]

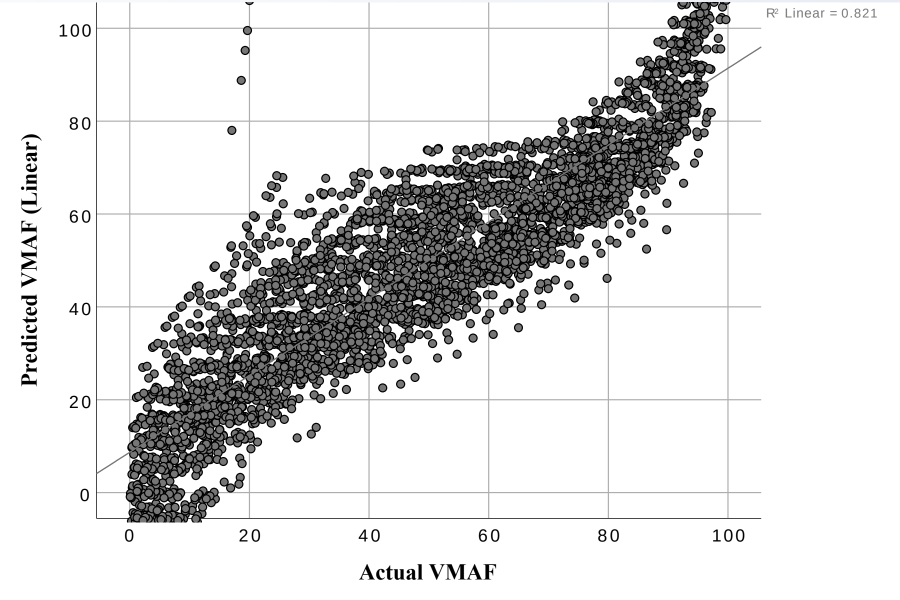


	SVR	Linear	Random Forest
MSE	48.6618	99.7779	19.8211
RMSE	6.9758	9.9888	4.4520
Pearson Correlation	0.9647	0.9146	0.9857

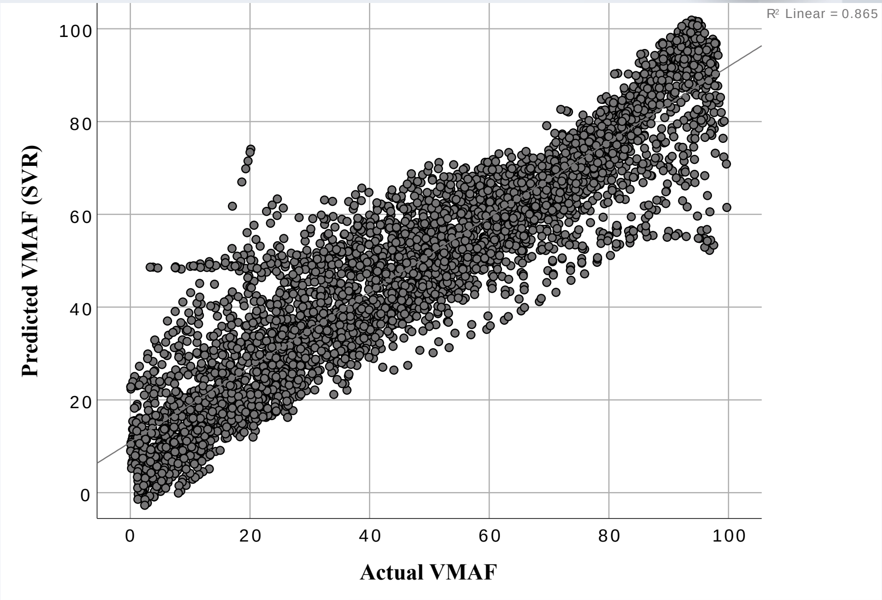
Promised Work

- **One-Leave-out cross validation**
- Improving the results by adding content labels (Mobilenet labels)
- Importance of features for training
  - Based on XGBoost
  - Based on Information Gain
- Predicting Convex hull using our trained model

VMAF Prediction vs Actual VMAF

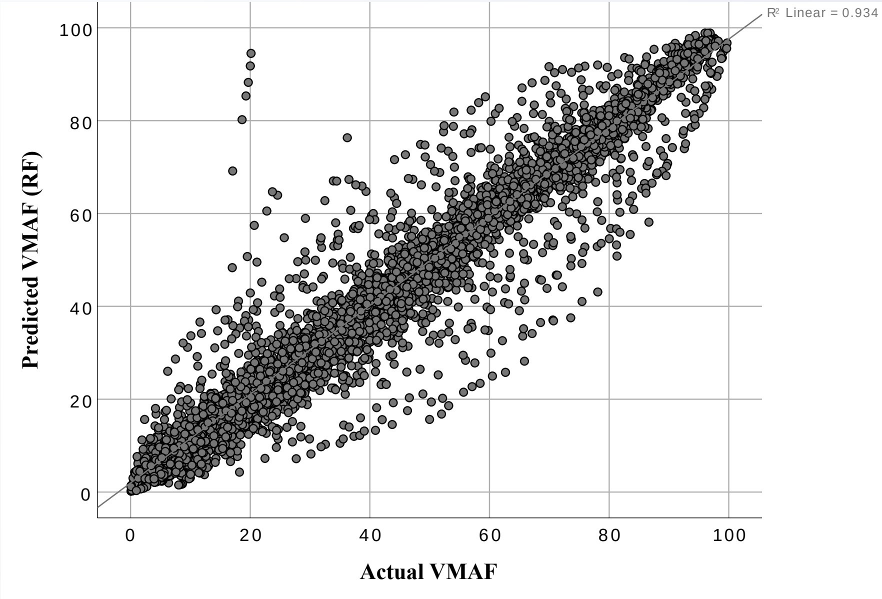


Corr=0.91
Rmse=11.97

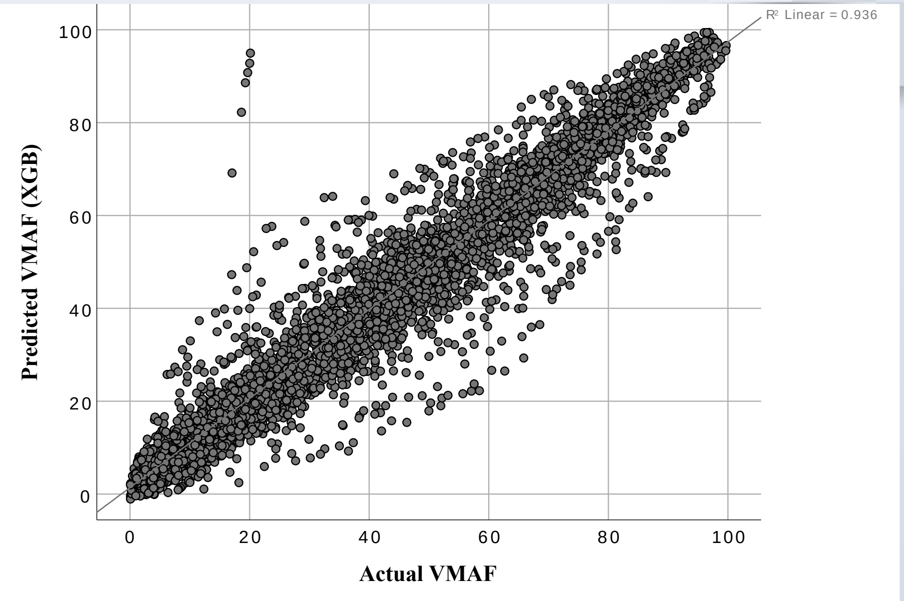


Corr = 0.93
Rmse = 10.59

RF and XGB Prediction vs Actual VMAF



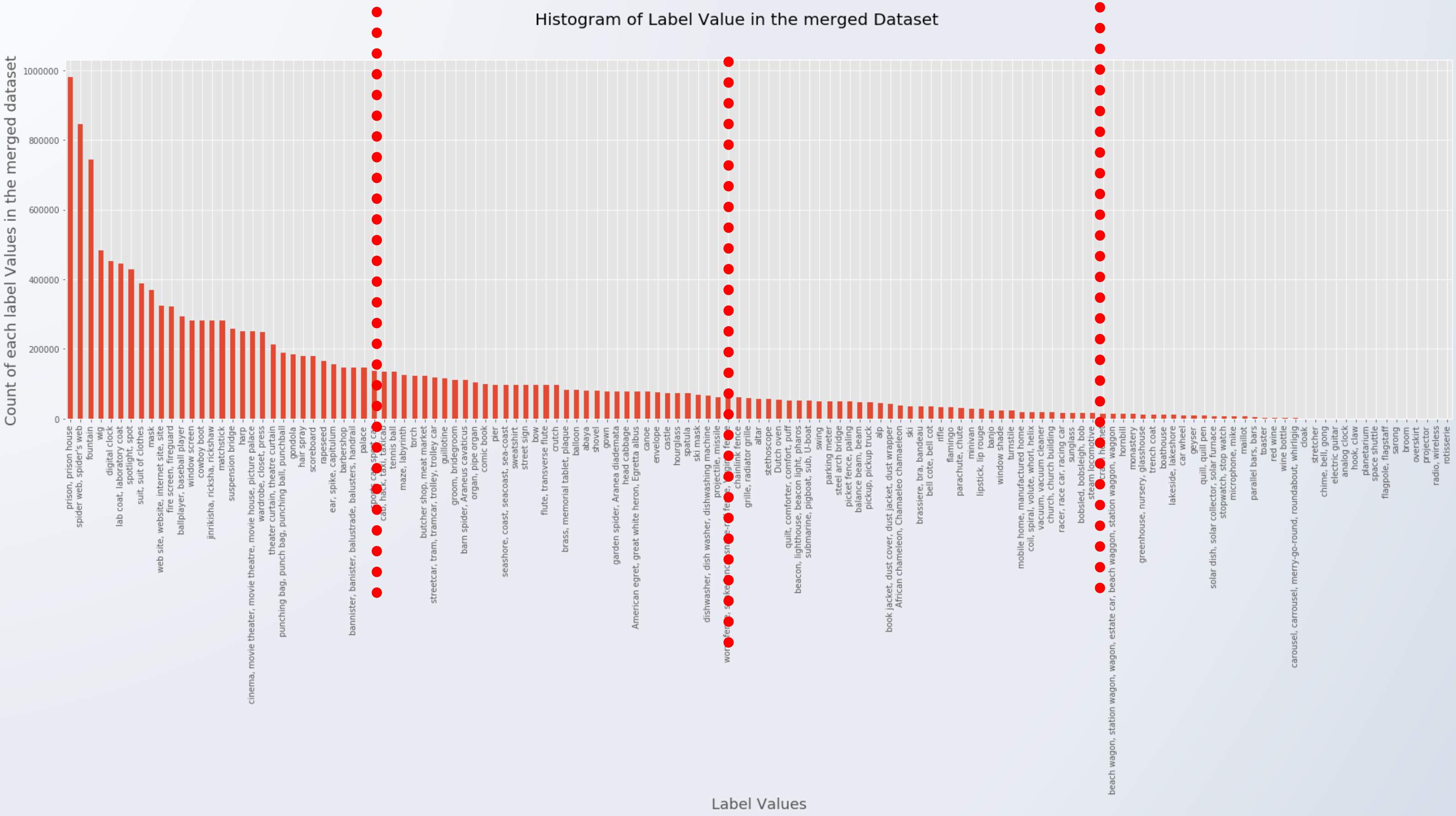
Corr=0.97
Rmse=7.3



Corr=0.97
Rmse=7.2

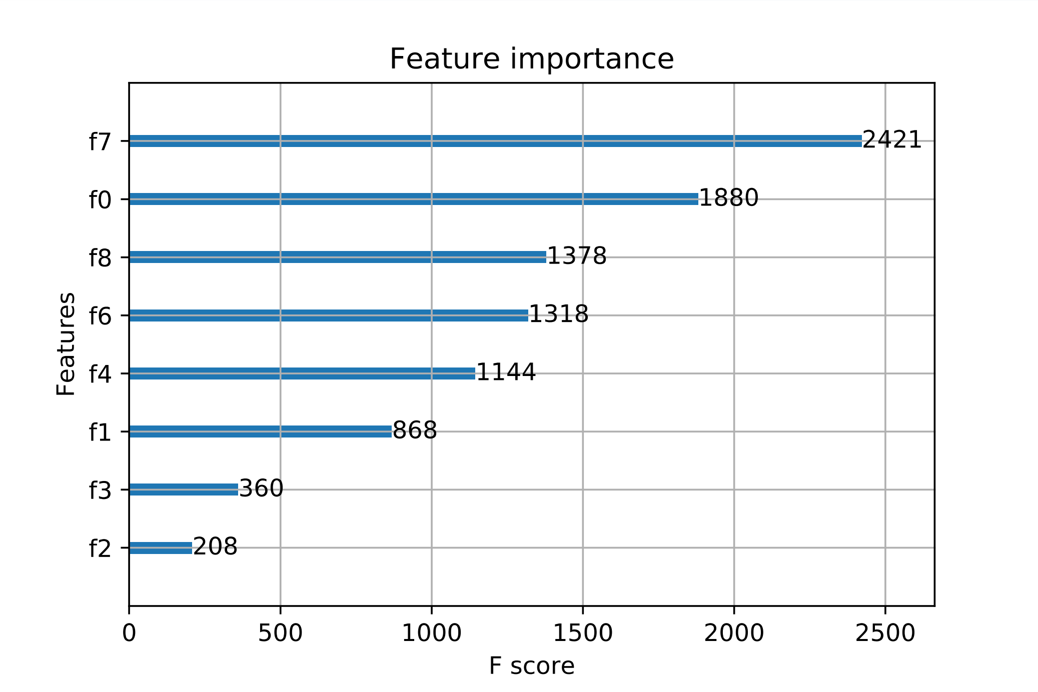
Promised Work

- ❑ One-Leave-out cross validation ✔
- ❑ **Improving the results by adding content labels (Mobilenet labels)**
- ❑ Importance of features for training
  - ❑ Based on XGBoost
- ❑ Predicting Convex hull using our trained model


Histogram of Label Value in the merged Dataset
Count of each label Values in the merged dataset
1000000
800000
600000
400000
200000
0
prison, prison house
spider web, spider's web
fountain
wig
digital clock
lab coat, laboratory coat
spotlight, spot
suit, suit of clothes
mask
web site, website, internet site, site
fire screen, fireguard
ballplayer, baseball player
window screen
cowboy boot
jinrikisha, ricksha, rickshaw
matchstick
suspension bridge
harp
cinema, movie theater, movie theatre, movie house, picture palace
wardrobe, closet, press
theater curtain, theatre curtain
punching bag, punch bag, punching ball, punchball
gondola
hair spray
scoreboard
rapeseed
ear, spike, capitulum
barbershop
bannister, banister, balustrade, balusters, handrail
palace
cab, hack, taxi, taxicab
tennis ball
maze, labyrinth
torch
butcher shop, meat market
streetcar, tram, tramcar, trolley, trolley car
guillotine
groom, bridegroom
barn spider, Araneus cavaticus
organ, pipe organ
comic book
pier
seashore, coast, seacoast, sea-coast
sweatshirt
street sign
bow
flute, transverse flute
crutch
brass, memorial tablet, plaque
balloon
abaya
shovel
gown
garden spider, Aranea diademata
head cabbage
American egret, great white heron, Egretta albus
canoe
envelope
castle
hourglass
spatula
ski mask
dishwasher, dish washer, dishwashing machine
projectile, missile
chainlink fence
grille, radiator grille
altar
stethoscope
Dutch oven
quilt, comforter, comfort, puff
beacon, lighthouse, beacon light, pharos
submarine, pigboat, sub, U-boat
swing
parking meter
steel arch bridge
picket fence, paling
balance beam, beam
pickup, pickup truck
alp
book jacket, dust cover, dust jacket, dust wrapper
African chameleon, Chamaeleo chamaeleon
ski
brassiere, bra, bandeau
bell cote, bell cot
rifle
flamingo
parachute, chute
minivan
lipstick, lip rouge
banjo
window shade
turnstile
mobile home, manufactured home
coil, spiral, volute, whorl, helix
vacuum, vacuum cleaner
church, church building
racer, race car, racing car
sunglass
bobsled, bobsleigh, bob
steam locomotive
beach wagon, station wagon, wagon, estate car, beach waggon, station waggon, waggon
hornbill
monastery
greenhouse, nursery, glasshouse
trench coat
boathouse
lakeside, lakeshore
car wheel
geyser
quill, quill pen
solar dish, solar collector, solar furnace
stopwatch, stop watch
microphone, mike
maillot
parallel bars, bars
toaster
red wine
wine bottle
carousel, carrousel, merry-go-round, roundabout, whirligig
cloak
stretcher
chime, bell, gong
electric guitar
analog clock
hook, claw
planetarium
space shuttle
flagpole, flagstaff
sarong
broom
overskirt
projector
radio, wireless
rotisserie
Label Values

Promised Work

- ❑ One-Leave-out cross validation ✔
- ❑ Improving the results by adding content labels (Mobilenet labels) ✔
- ❑ **Importance of features for training**
  - ❑ **Based on XGBoost**
- ❑ Predicting Convex hull using our trained model



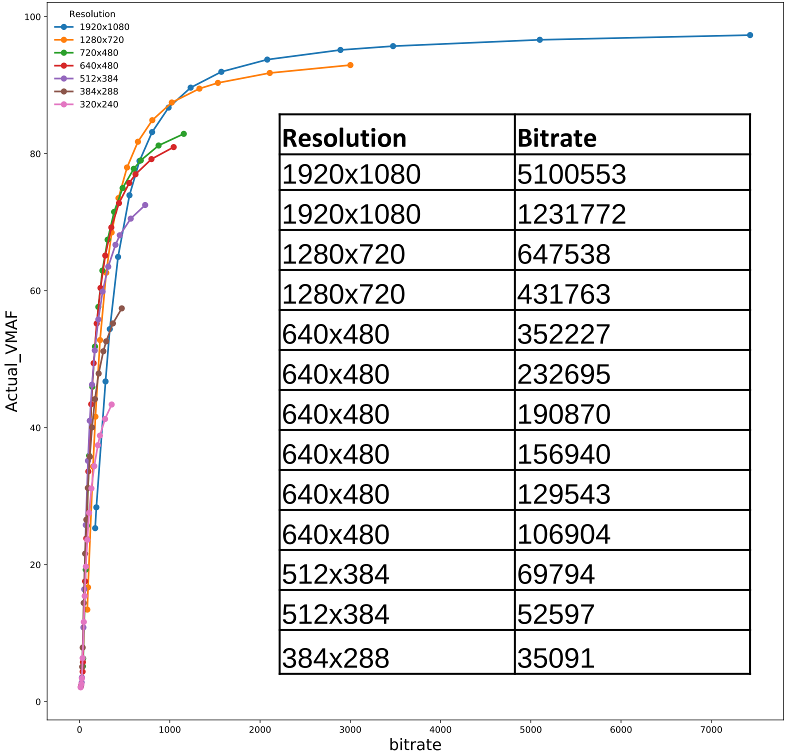
F0: Avg Scene Change
F1: Clip Duration
F2: Frame Rate
F3: Clip Hight
(Reference Video)
F4: Clip Size
F5: Profile (Dummy Value)
F6: Resolution
(Number of pixel)
F7: Encoding Bitrate
F8: Constant Rate Factor (CRF)

Promised Work

- One-Leave-out cross validation
- Improving the results by adding content labels (Mobilenet labels)
- Importance of features for training
  - Based on XGBoost
- **Predicting Convex hull using our trained model**

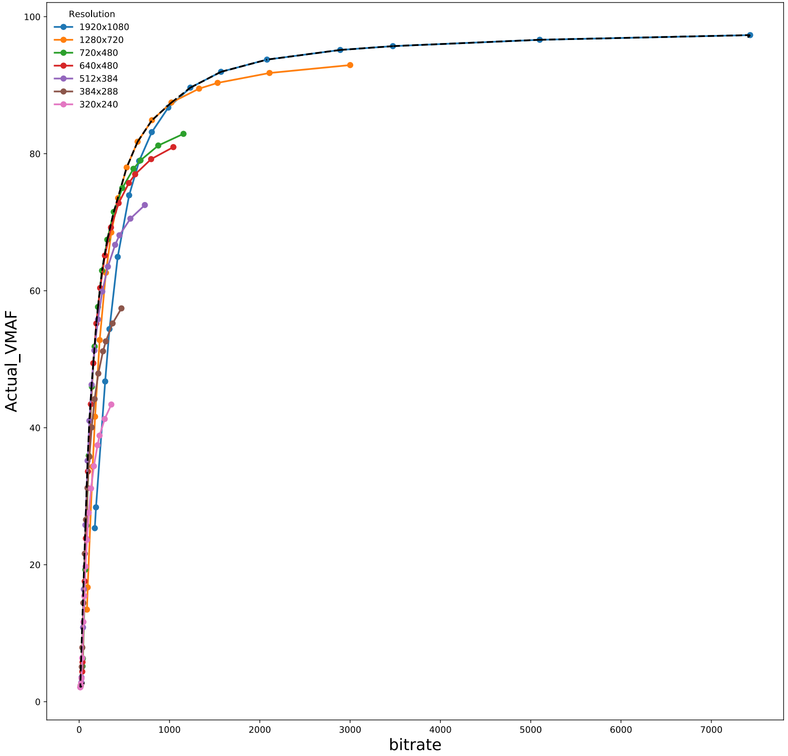
Main Goal

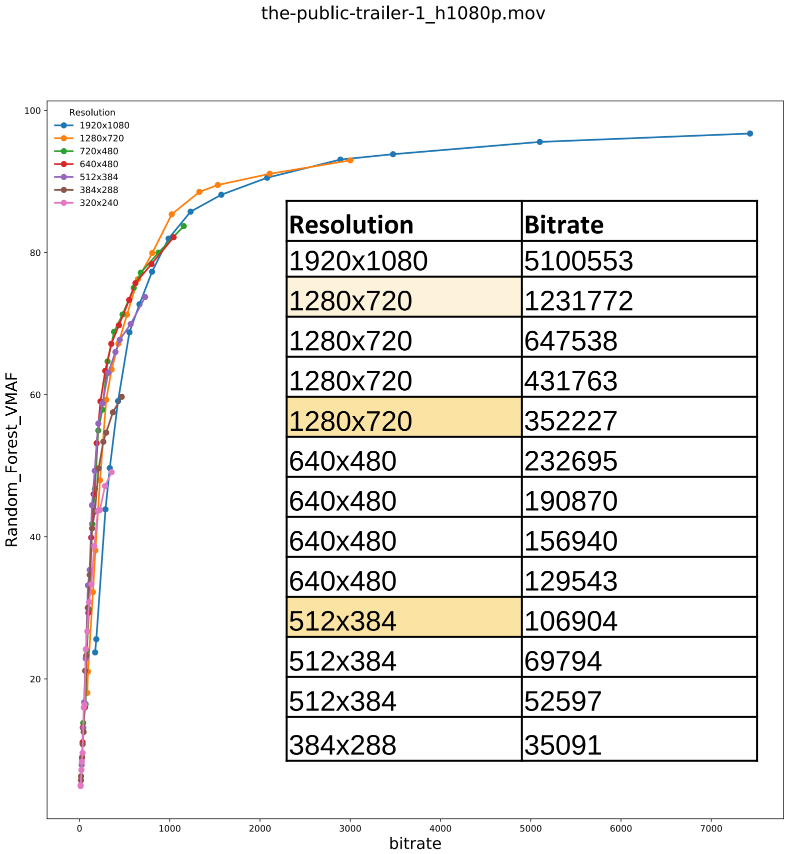
the-public-trailer-1_h1080p.mov



Resolution	Bitrate
1920x1080	5100553
1920x1080	1231772
1280x720	647538
1280x720	431763
640x480	352227
640x480	232695
640x480	190870
640x480	156940
640x480	129543
640x480	106904
512x384	69794
512x384	52597
384x288	35091

the-public-trailer-1_h1080p.mov





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512x384	52597
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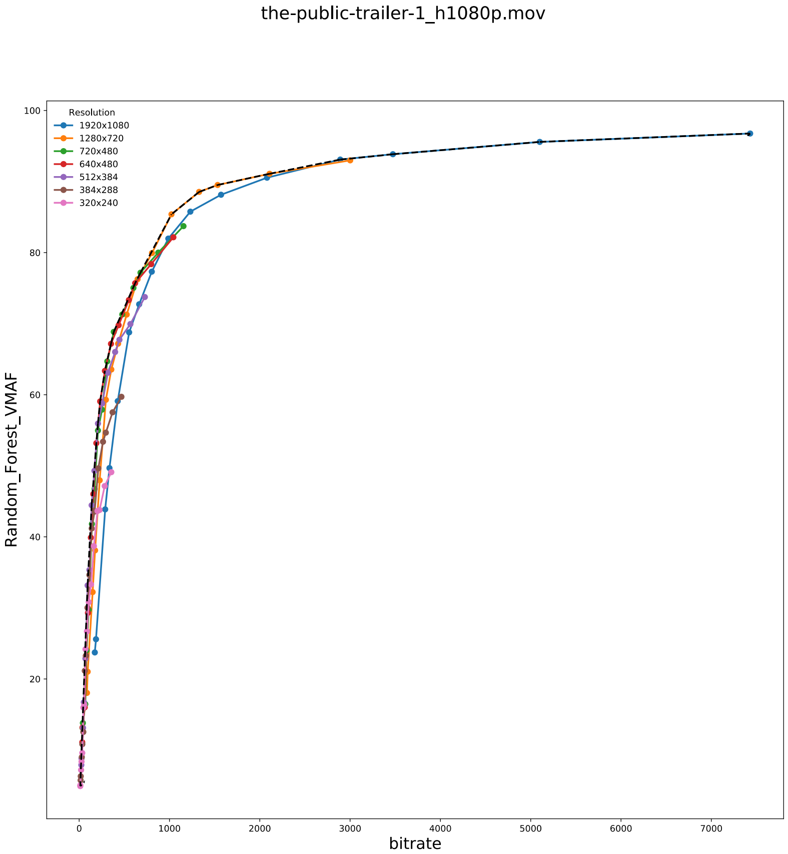
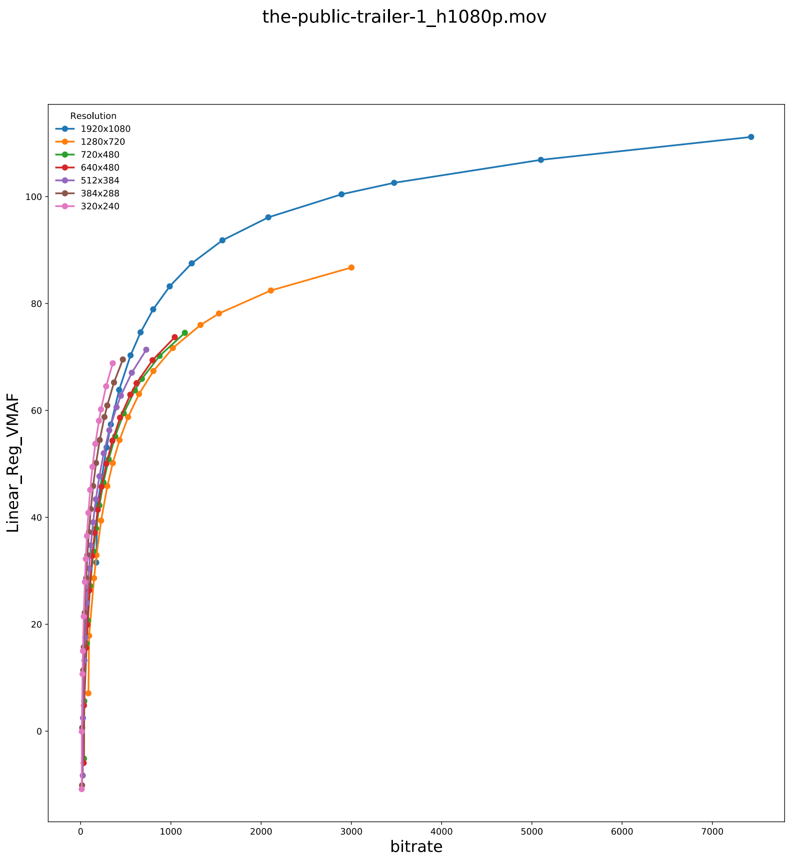
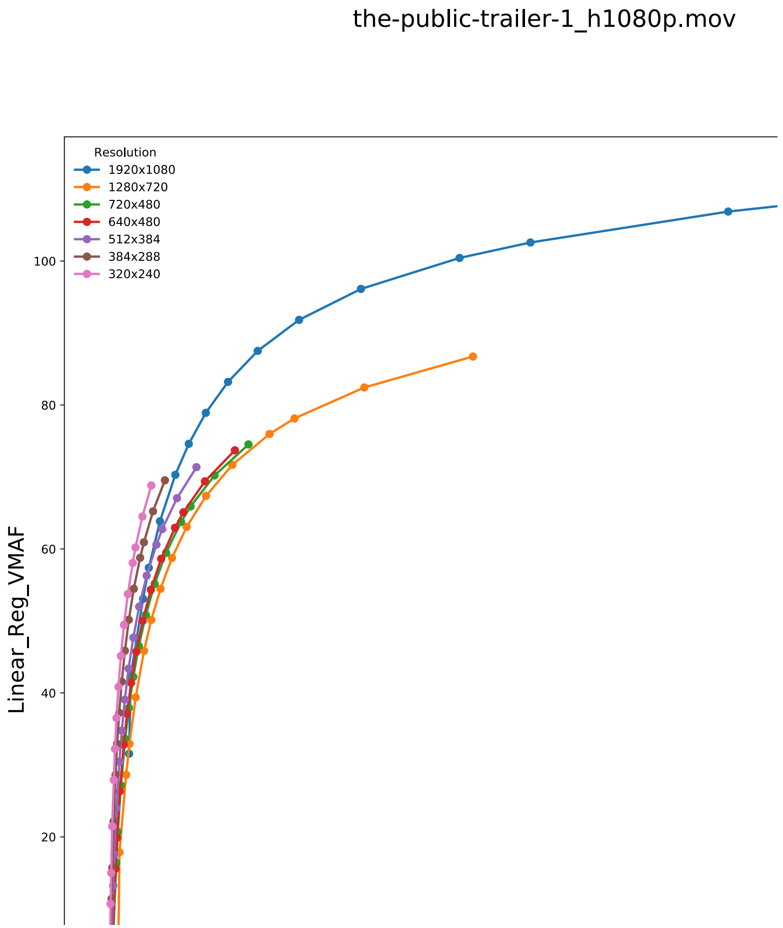



the-public-trailer-1_h1080p.mov
Resolution
1920x1080
1280x720
720x480
640x480
512x384
384x288
320x240
Linear_Reg_VMAF
bitrate
0
20
40
60
80
100
1000
2000
3000
4000
5000
6000
7000


the-public-trailer-1_h1080p.mov
Resolution
1920x1080
1280x720
720x480
640x480
512x384
384x288
320x240
Linear_Reg_VMAF
20
40
60
80
100

THANKS!

Any questions?