Video Coding for Deep Learning-Based Machine-to-Machine Communication in an Autonomous Driving Scenario

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Agenda

1. Motivation Video Coding for Machines
2. Evaluation Framework
3. Classic Coding Performance vs. Video Coding for Machines
4. Feature-based Rate-Distortion Optimization
5. Conclusions

Common Video Coding Scenario

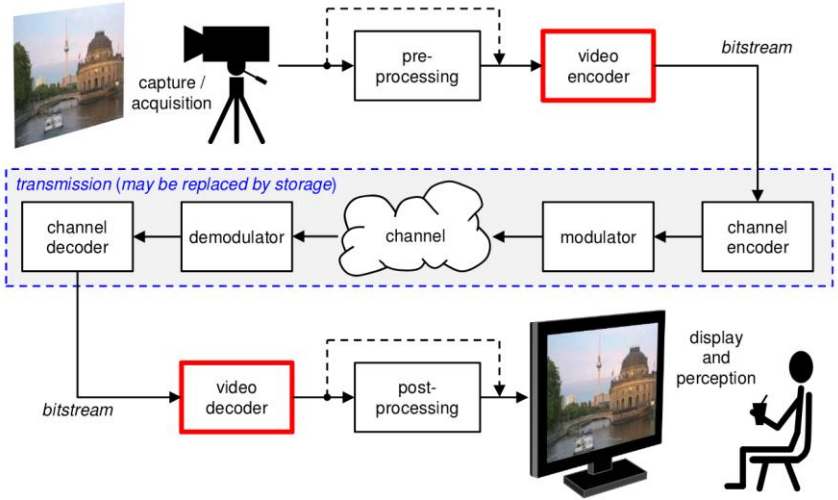
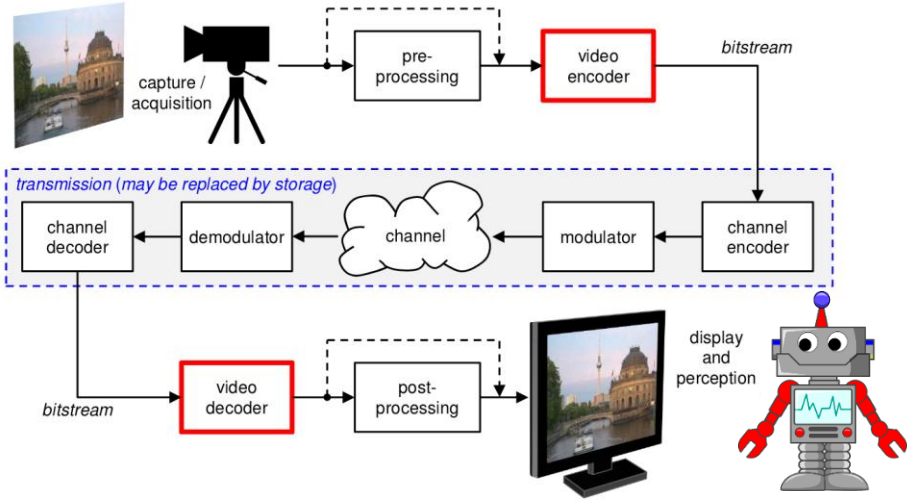


Image Credit: Schwarz and Wiegand: „Video Coding: Part II of Fundamentals of Source and Video Coding“, 2016

Machine-to-Machine (M2M) Communication



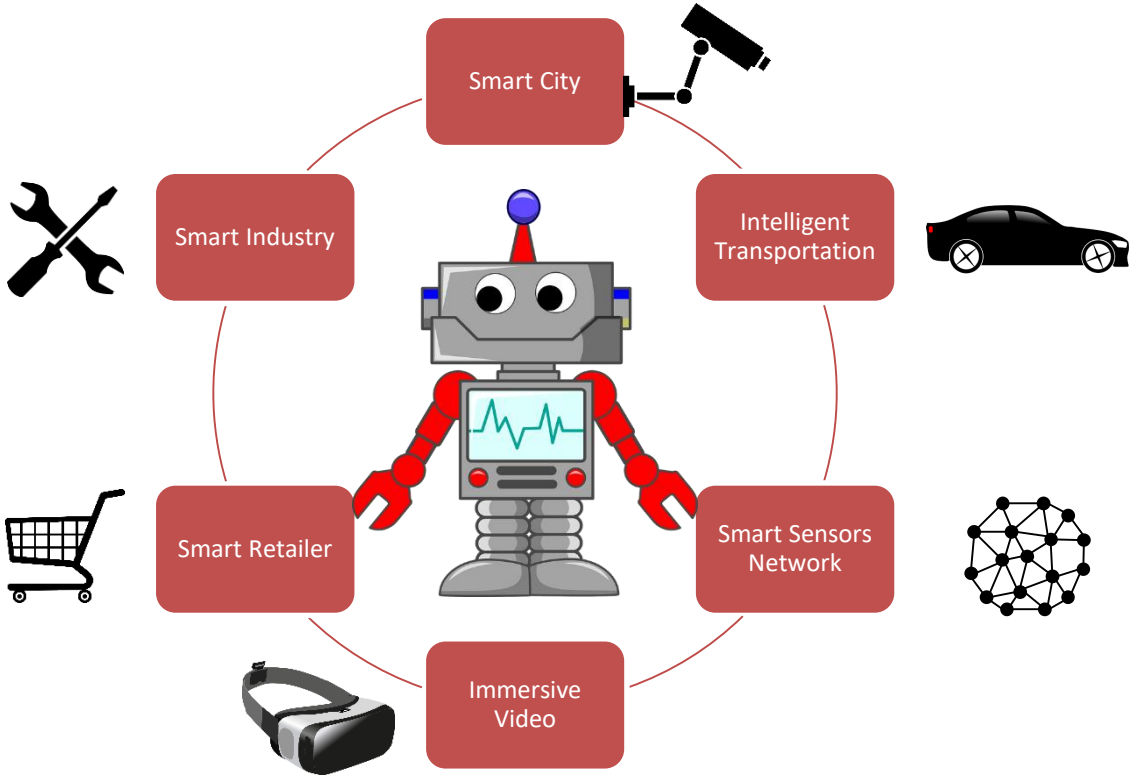
- Compressed image is analyzed by machine instead of human
- Target: Bitrate reduction at high detection rates
- Problem: Traditional codecs optimized for human observer

→ New coding methods have to be found

→ Targeted by MPEG "Video Coding for Machines (VCM)" ad-hoc group

VCM: Zhang et al., "MPEG-M49944: Report of the AhG on VCM," *MPEG*, 2020.
Image Credit: Schwarz and Wiegand: „Video Coding: Part II of Fundamentals of Source and Video Coding", 2016 (adapted)

VCM Use Cases



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Signal Flow Video Coding for Machines

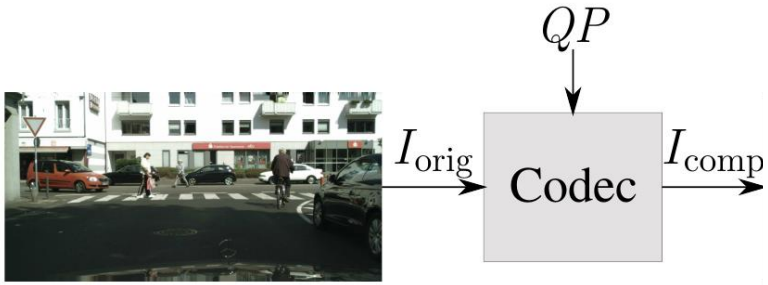
I_{orig}: Input image

Cityscapes Dataset

- Stereo data observing urban scenes
- 5000 uncompressed images
- 2048x1024 pixels
- Pixel-wise labeled data for object detection and segmentation
- 8 object categories considered like car, person, truck, etc.

Cityscapes: Cordts et al., "The Cityscapes Dataset for Sementic Urban Scene Understanding," *CVPR*, 2016.

Signal Flow Video Coding for Machines



I_{orig}: Input image
I_{comp}: Compressed image
QP: Quantization parameter

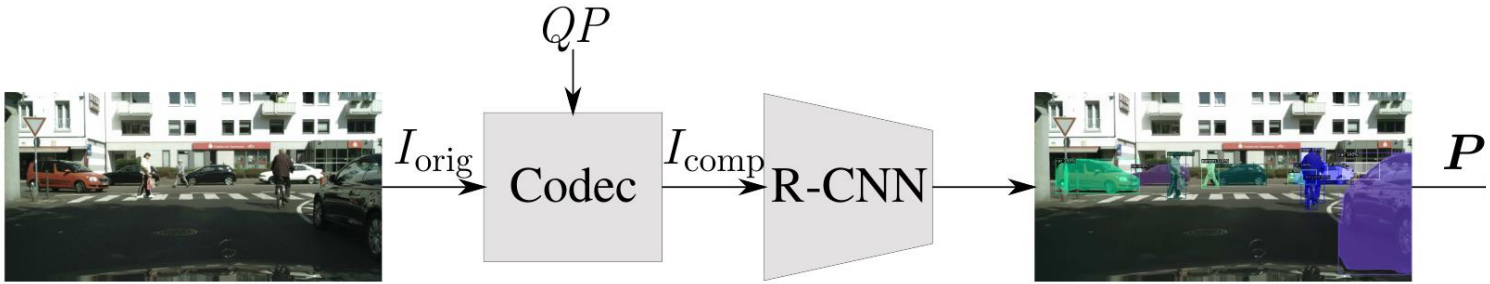
R-CNN: Region-based convolutional neural network
P: Predicted objects
G: Ground-truth objects
AP: Average precision

Coding Framework

- HEVC test model (HM-16.18)
- VVC test model (VTM-6.0)
- All-intra configuration
- QP from 2 to 47 in steps of 5
- Coded 500 images from Cityscapes validation set
- Transformation from RGB to YCbCr 4:2:0 and vice versa with Ffmpeg

HEVC: Sullivan et al., "Overview of the high efficiency video coding (HEVC) standard," *TCSVT*, 2012.
VVC: Chen et al., "JVET-O2002: Algorithm description for versatile video coding and test model 6 (VTM 6)," *Tech. Rep.*, 2019.

Signal Flow Video Coding for Machines

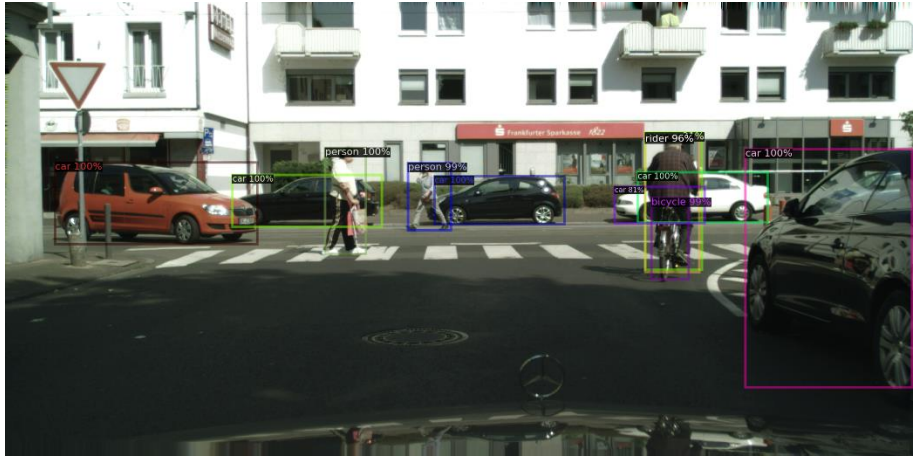


I_{orig}: Input image
I_{comp}: Compressed image
QP: Quantization parameter

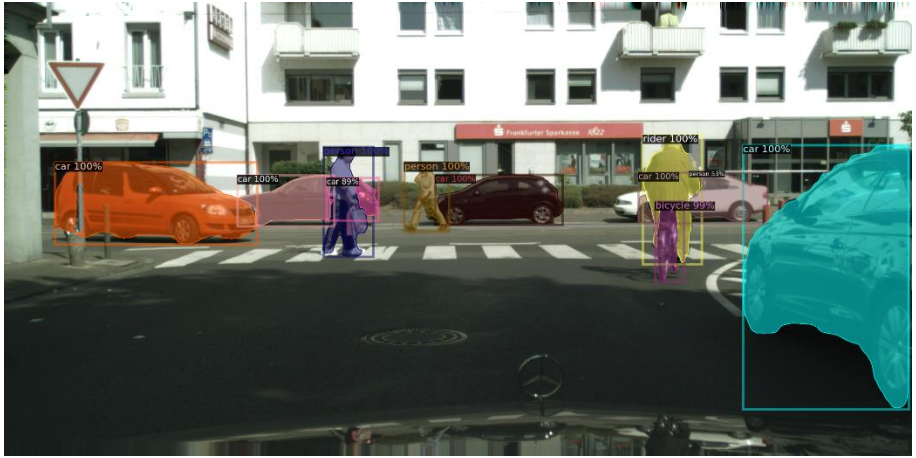
R-CNN: Region-based convolutional neural network
P: Predicted objects

Investigated Object Detection R-CNNs

Faster R-CNN

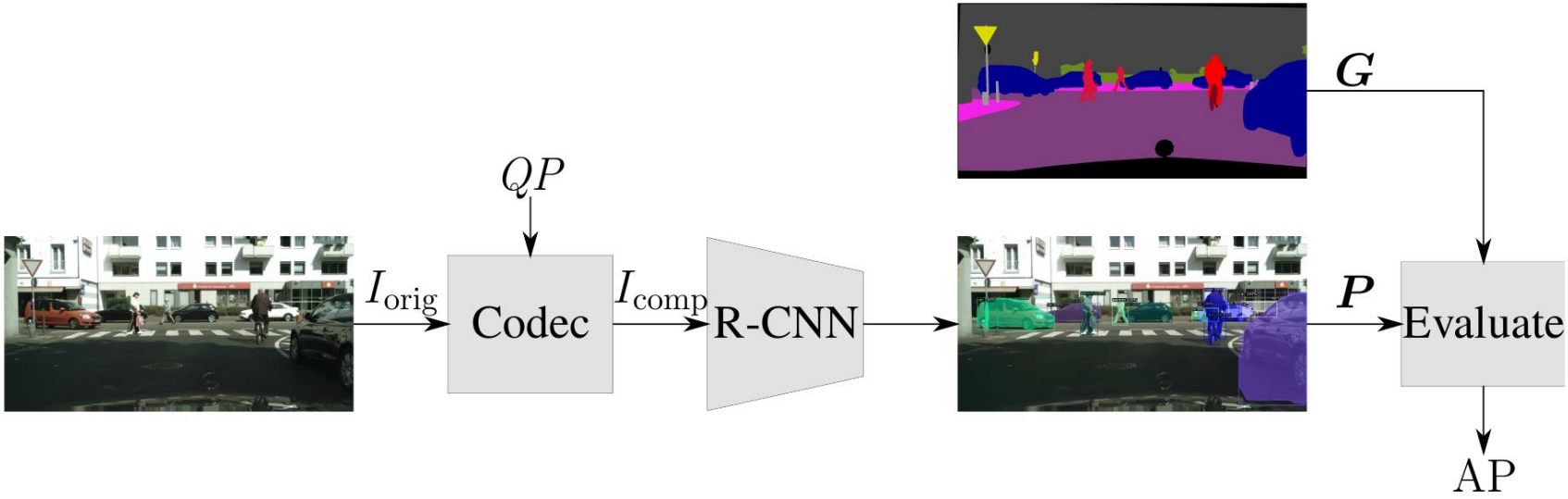


Mask R-CNN



Faster R-CNN: Ren et al., “Faster R-CNN: Towards real-time object detection with region proposal networks,” *TPAMI*, 2017.
Mask R-CNN: He et al., “Mask R-CNN,” *ICCV*, 2017.

Signal Flow Video Coding for Machines

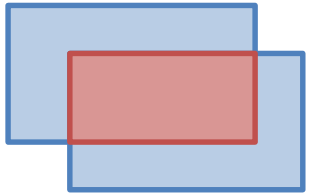


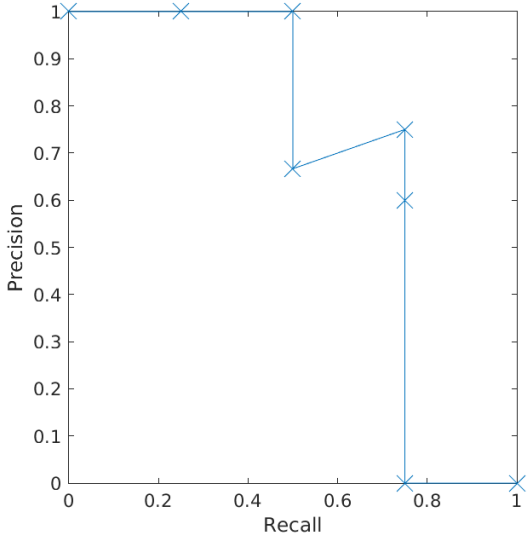
I_{orig}: Input image
I_{comp}: Compressed image
QP: Quantization parameter

R-CNN: Region-based convolutional neural network
P: Predicted objects
G: Ground-truth objects
AP: Average precision

Mean Average Precision (mAP)

- Metric to evaluate accuracy of object detection
- mAP used as proposed for Cityscapes
- Derive True Positives for certain Intersection over Union (IoU) thresholds
- Calculate precision and recall
- mAP is the mean over the AP of each class
- Modification: mAP is calculated as weighted average depending on the number of instances of each class in the dataset ➔ weighted AP (wAP)





Cityscapes Scripts: Cordts et al., "The cityscapes dataset," https://github.com/mcordts/cityscapesScripts, 2017.

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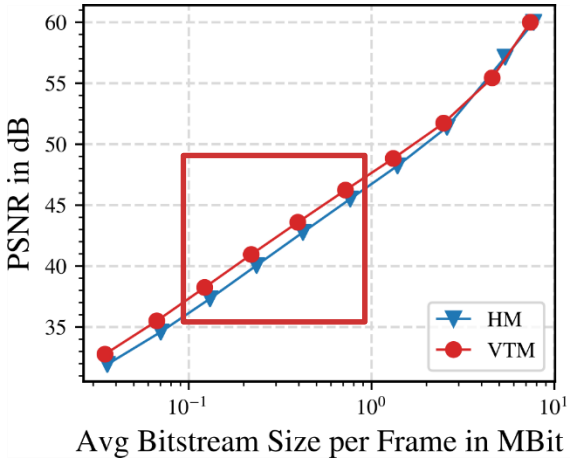
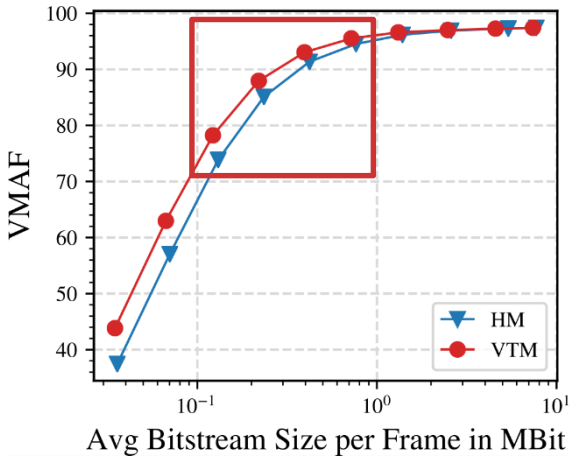
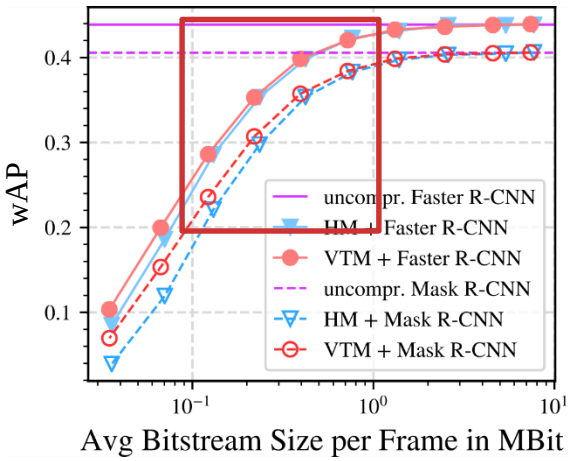
Comparison HEVC vs. VVC







Bjøntegaard Delta Rate (BDR) Savings in %	PSNR	VMAF
Faster R-CNN	-22.17	-25.55
Mask R-CNN		

QP = {22, 27, 32, 37}
Anchor: HM

Fischer et al., "On intra video coding and in-loop filtering for neural object detection networks," *ICIP*, 2020.

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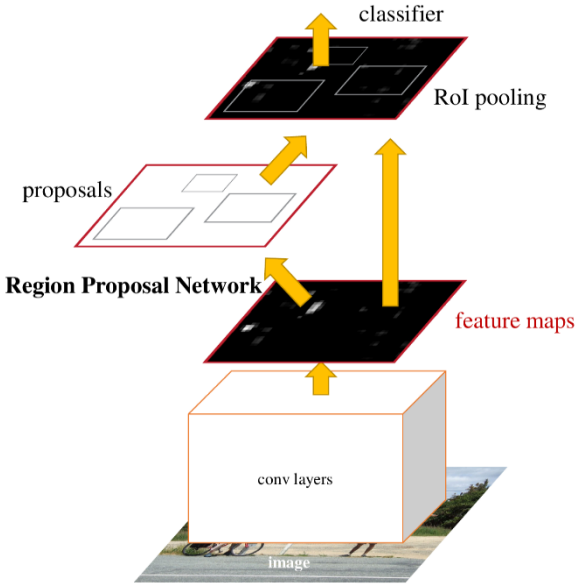
Feature-Based Rate Distortion Optimization (FRDO)



- Feature space is created by convolution layers from input image
- For VCM, high feature fidelity is required
- High feature fidelity does not necessarily depend on a high pixel fidelity

→ This gap is exploited by standard-compliant FRDO for block partitioning in VVC

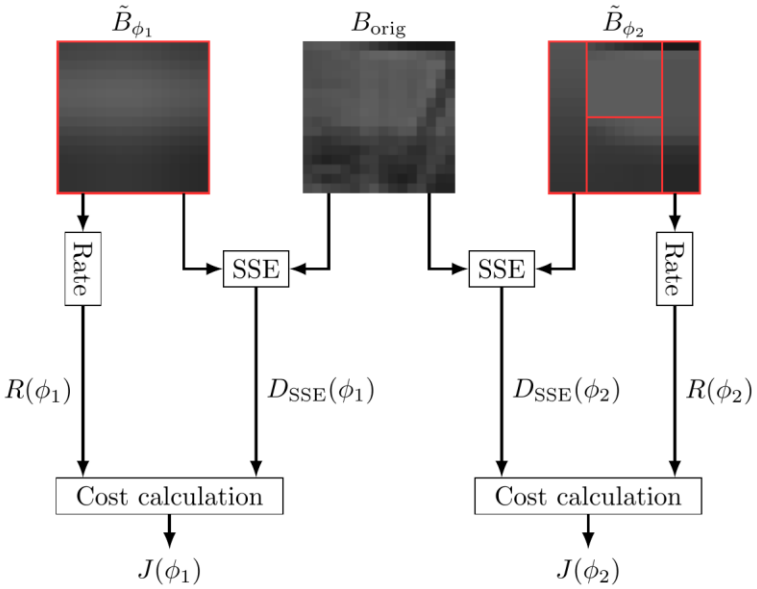
FRDO: Fischer et al., "Video Coding for Machines with Feature-Based Rate-Distortion Optimization," *MMSP*, 2020.
Image credit: Ren et al., "Faster R-CNN: Towards real-time object detection with region proposal networks," *TPAMI*, 2017

Classic Rate-Distortion Optimization (RDO)

- Calculating costs J
  - For parameter configuration ϕ
  - Rate R
  - Distortion D
  - Lagrange multiplier λ

$$J(\phi) = D(\phi) + \lambda \cdot R(\phi)$$

- Commonly, sum of squared errors (SSE) used as distortion
- ϕ resulting in reconstructed block $\tilde{B}$ with lowest costs is selected



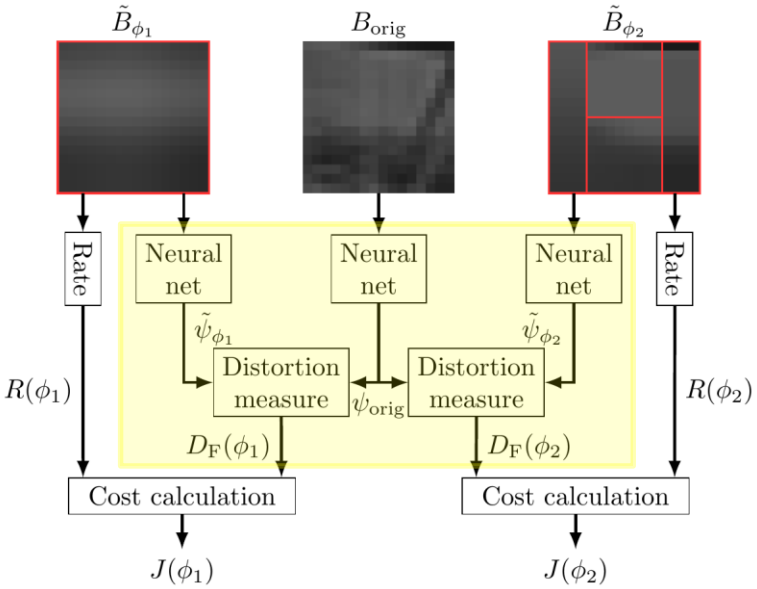
Feature-Based RDO

- Replacing SSE measure in pixel space with distortion measured in feature-space of each block ψ_ϕ

$$\psi_\phi = f(B_\phi)$$

$$D_{\mathrm{FSSE}}(\phi) = \sum_{(x,y,c)\in\psi} \left(\psi_{\mathrm{orig}}(x,y,c) - \tilde{\psi}_\phi(x,y,c)\right)^2$$

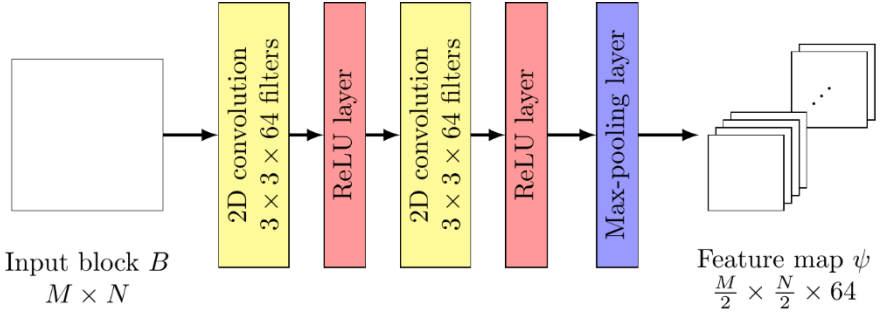
$$D_{\mathrm{FSAD}}(\phi) = \sum_{(x,y,c)\in\psi} \left|\psi_{\mathrm{orig}}(x,y,c) - \tilde{\psi}_\phi(x,y,c)\right|$$



FRDO: Fischer et al., "Video Coding for Machines with Feature-Based Rate-Distortion Optimization," *MMSP*, 2020.

Simulation Setup

- Added FRDO to VVC Test Model software VTM 8.0
- Hybrid FRDO (HFRDO) combining SSE and feature-based distortion
- QP from 12 to 27 in steps of 5
- First five layers of VGG-16 model used to obtain feature space



VTM: Bross et al., "JVET-Q2001: Versatile video coding (draft 8)," *JVET*, 2020.
VGG: Simonyan et al., "Very deep convolutional networks for large-scale image recognition," *Tech. Rep.*, 2015.

Simulation Results

Bjøntegaard delta rate with standard VTM-8.0 as anchor

	Quality Metric	
Optimization Method	**PSNR**	**wAP Mask R-CNN**
FRDO-SSE	4.30 %	-0.50 %
FRDO-SAD	3.02 %	-3.99 %
HFRDO-SSE	1.63 %	-4.55 %
HFRDO-SAD	1.26 %	-5.49 %

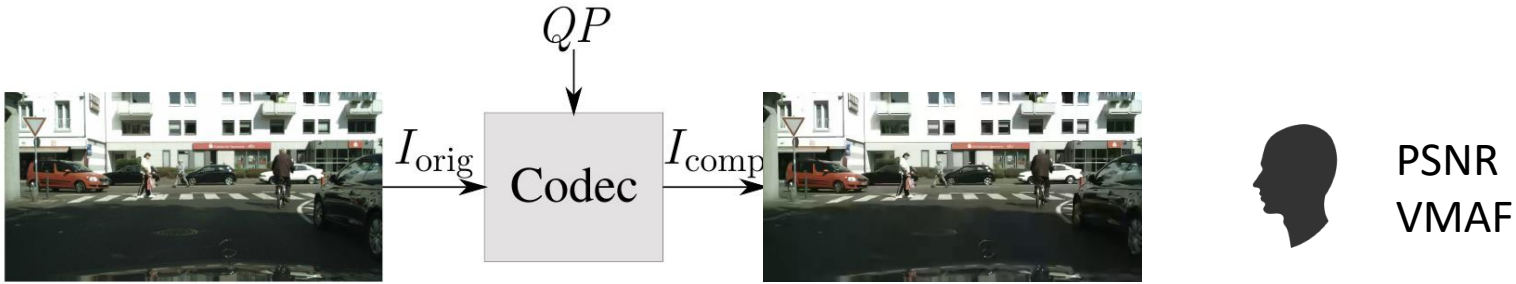
FRDO: Fischer et al., "Video Coding for Machines with Feature-Based Rate-Distortion Optimization," *MMSP*, 2020.

Conclusions

- Rising interest in video coding for machine scenarios
- Demands for optimized frameworks and codecs
- Coding gains of VTM over HM for VCM scenarios significantly lower
  - Above 22 and 25% BDR savings of VVC over HEVC for PSNR and VMAF, respectively
  - Only 5 to 14% BDR savings for VCM use case with Faster and Mask R-CNN
- FRDO to obtain coding gains over standard VTM-8.0
  - Standard-compliant optimization for block partitioning
  - Saves up to 5.5% bitrate at the same Mask R-CNN detection accuracy
- Future work: confirm results for video data

BACKUP

Signal Flow Video Coding for Humans

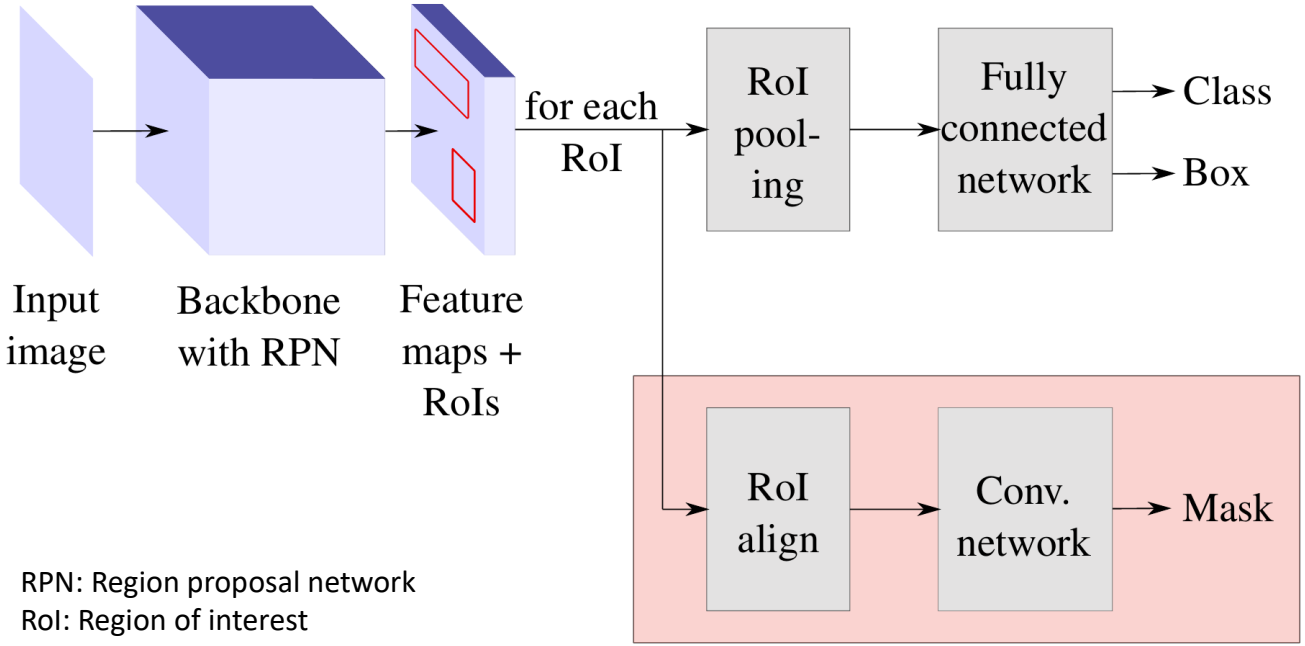


I_{orig}: Input image
I_{comp}: Compressed image
QP: Quantization parameter

PSNR: Peak-signal-to-noise ratio
VMAF: Video multi-method assesment fusion

VMAF: Netflix Inc., "VMAF – video multi-method assessment fusion," https://github.com/Netflix/vmaf, 2016.

Investigated Object Detection R-CNNs



RPN: Region proposal network
RoI: Region of interest

Faster R-CNN: Ren et al., "Faster R-CNN: Towards real-time object detection with region proposal networks," *TPAMI*, 2017.
Mask R-CNN: He et al., "Mask R-CNN," *ICCV*, 2017.

Normalizing Feature-Based Distortion with SSE

Classic RDO

$$J(\phi) = D_{\mathrm{SSE}}(\phi) + \lambda \cdot R(\phi)$$

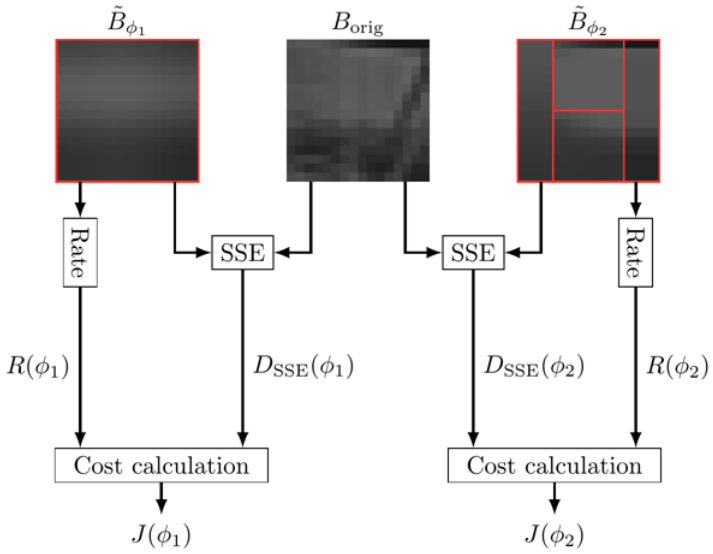
Feature-Based RDO

$$J(\phi) = D_F(\phi) + \lambda \cdot R(\phi)$$

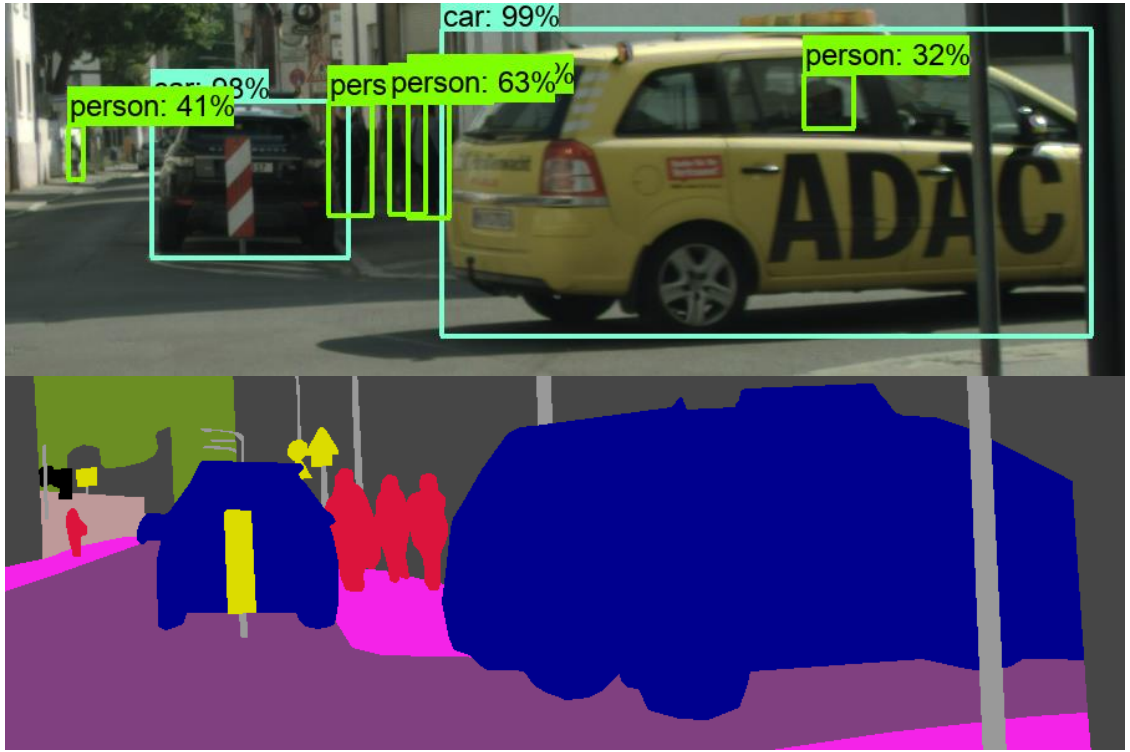
➔ $D_F(\phi)$ should be in same range as $D_{\mathrm{SSE}}(\phi)$

$$D_F^*(\phi_1) = D_F(\phi_1) \cdot \frac{D_{SSE}(\phi_1)}{D_F(\phi_1)} = D_{SSE}(\phi_1)$$

$$D_F^*(\phi_2) = D_F(\phi_2) \cdot \frac{D_{SSE}(\phi_1)}{D_F(\phi_1)}$$

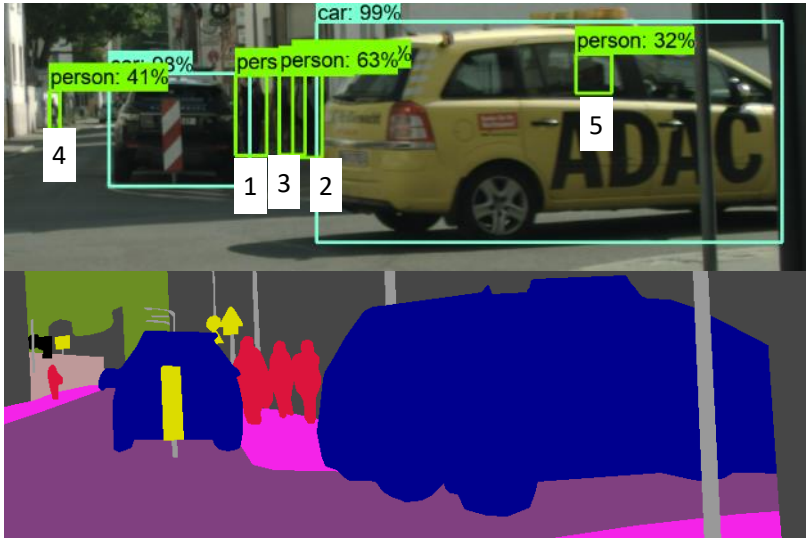


Example AP for Class Person and IoU=0.5



- 4 ground truth objects of class “Person”
- Convert ground truth data from pixelwise to boxes

Example AP for Class Person and IoU=0.5



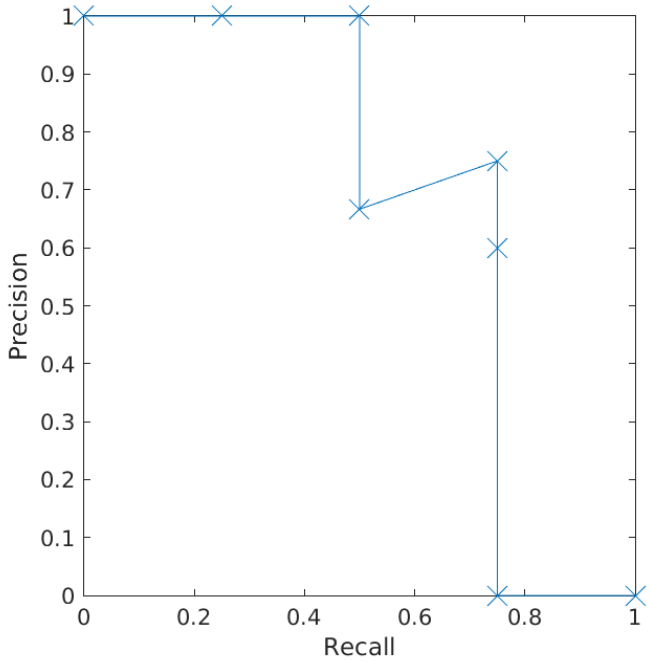
Rank	Score	Correct
1	0.93	True
2	0.91	True
3	0.63	False
4	0.41	True
5	0.32	False

$$Precision = \frac{true_pos}{true_pos + false_pos}$$

$$Recall = \frac{true_pos}{true_pos + false_neg}$$

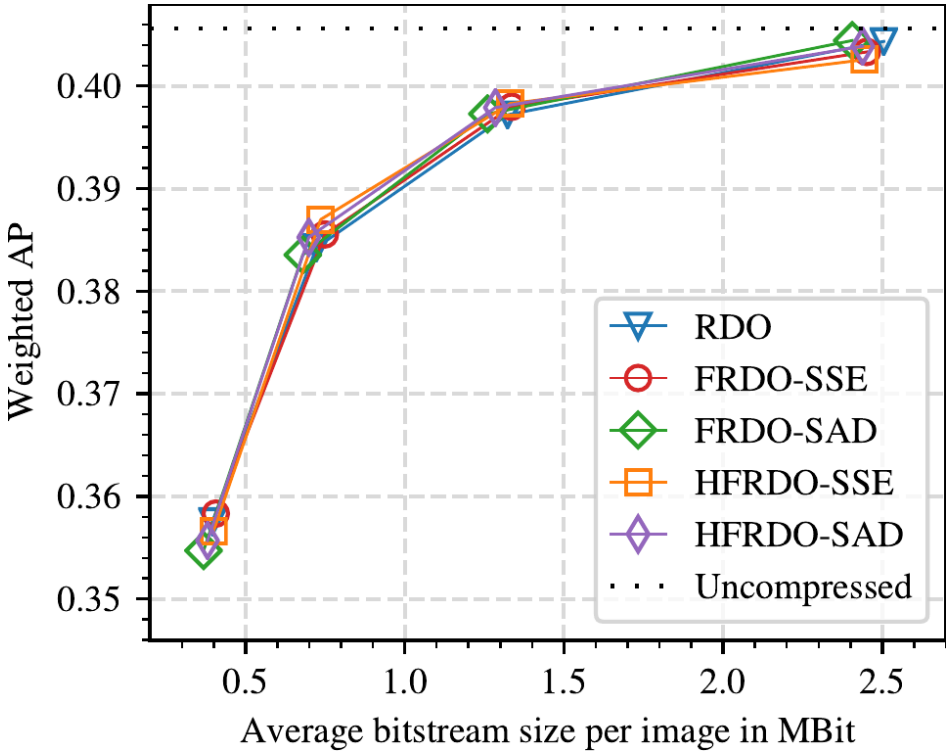
Example AP for Class Person and IoU=0.5

Rank	Score	Correct	Precision	Recall
1	0.93	True	$\frac{1}{1+0} = 1$	$\frac{1}{1+3} = 0.25$
2	0.91	True	$\frac{2}{2+0} = 1$	$\frac{2}{2+2} = 0.5$
3	0.63	False	$\frac{2}{2+1} = 0.67$	$\frac{2}{2+2} = 0.5$
4	0.41	True	$\frac{3}{3+1} = 0.75$	$\frac{3}{3+1} = 0.75$
5	0.32	False	$\frac{3}{3+2} = 0.6$	$\frac{3}{3+1} = 0.75$



➔ AP is area under Precision/Recall curve; here: AP=0.6771

Simulation Results



Simulation Results Allowing Delta QP

Bjøntegaard delta rate with standard VTM as anchor w/o delta QP

	Quality Metric	
Optimization Method	**PSNR**	**Weighted AP**
RDO with delta QP	-0.36 %	-1.15 %
FRDO-SAD with delta QP	4.55 %	-5.35 %
HFRDO-SAD with delta QP	1.01 %	-9.95 %

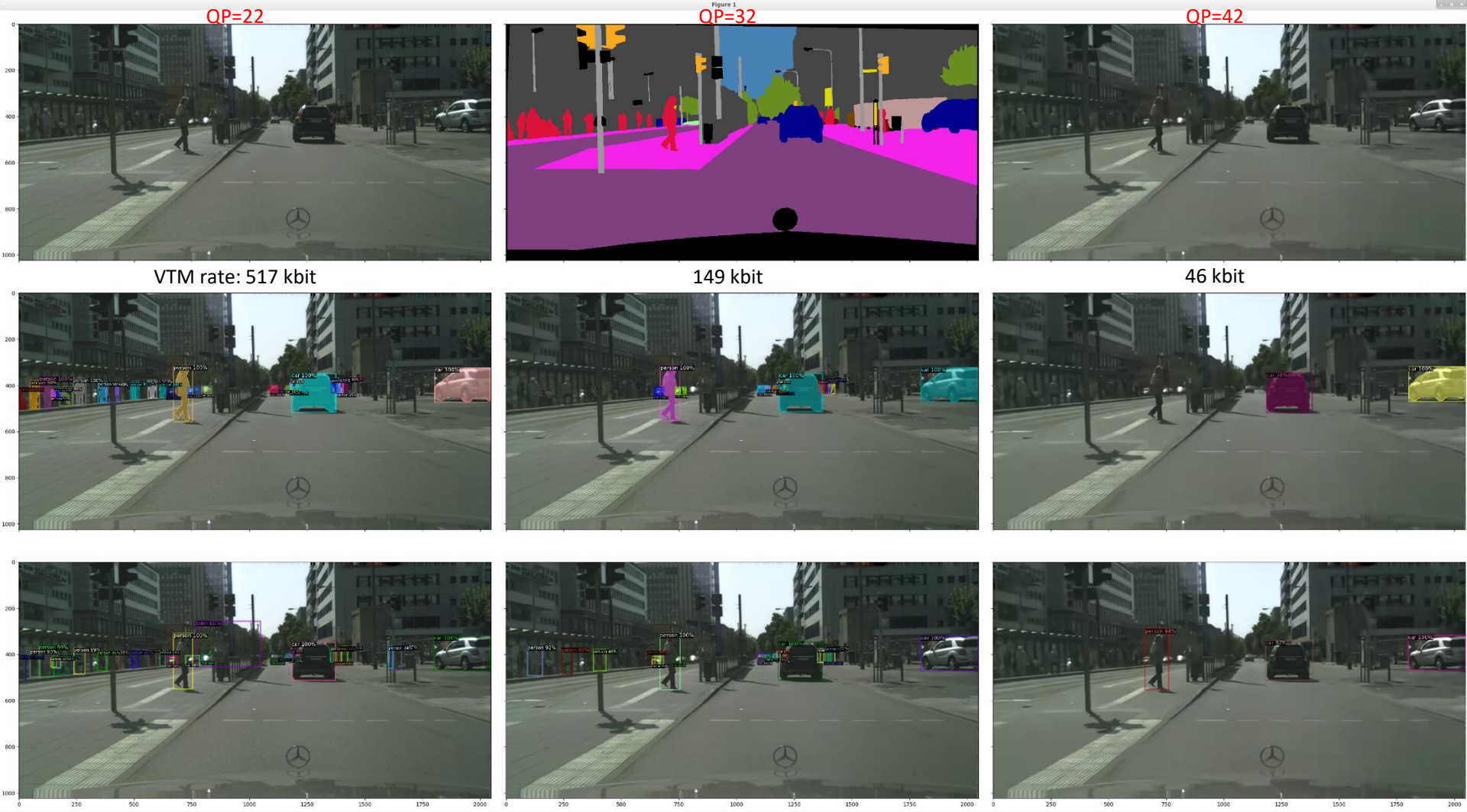
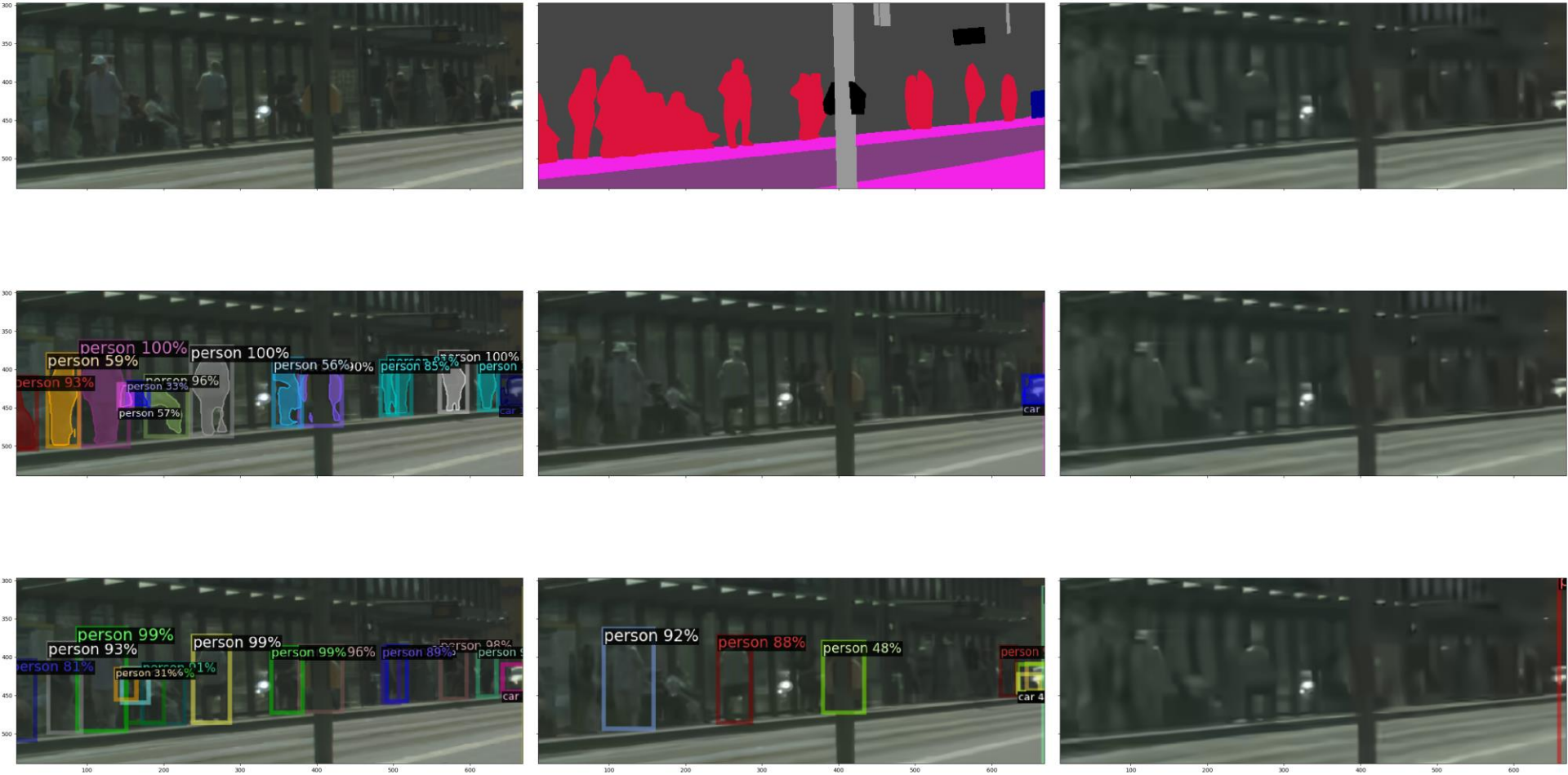
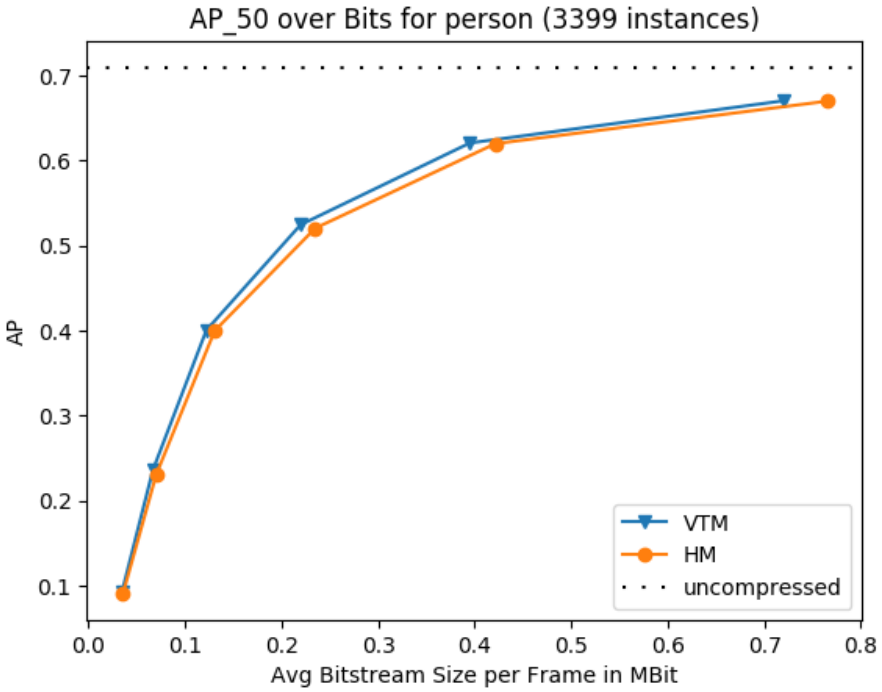
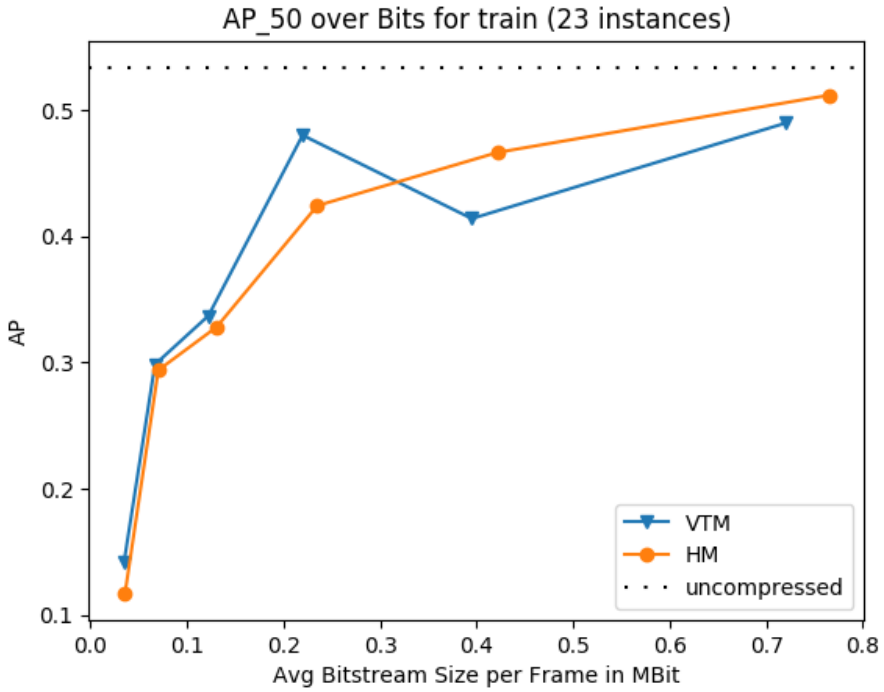


Figure 1
QP=22
QP=32
QP=42
VTM rate: 517 kbit
149 kbit
46 kbit

QP=22 QP=32 QP=42



Results AP_50 HM vs. VTM Faster R-CNN



Results AP_50 HM vs. VTM Faster R-CNN