Visual data compression: beyond conventional approaches

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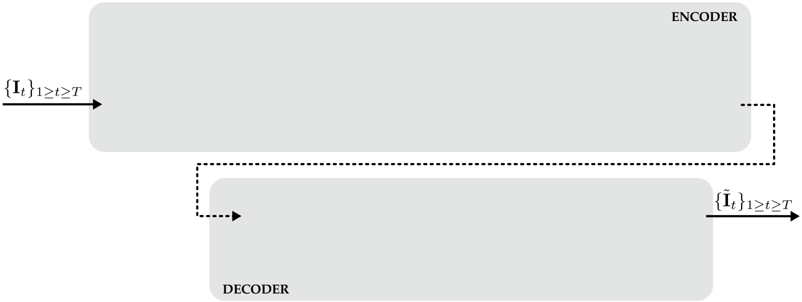
Conventional compression pipeline



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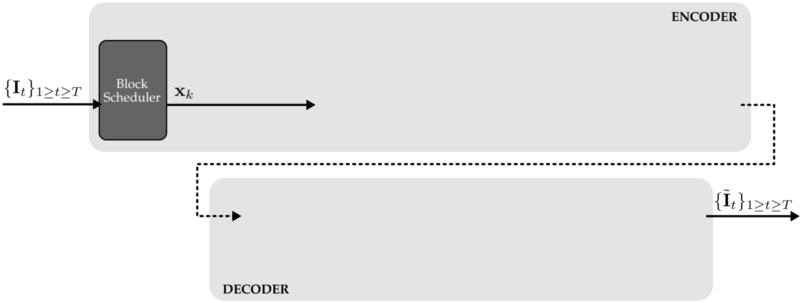

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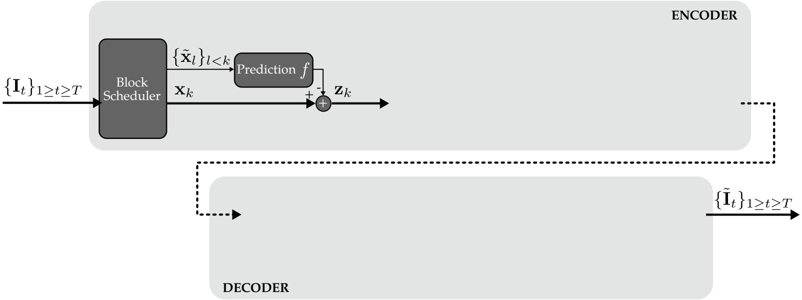

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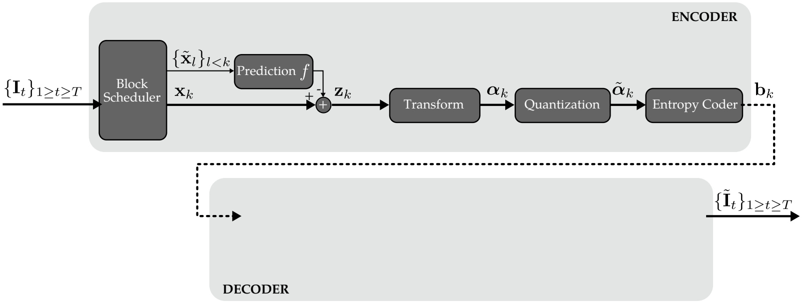

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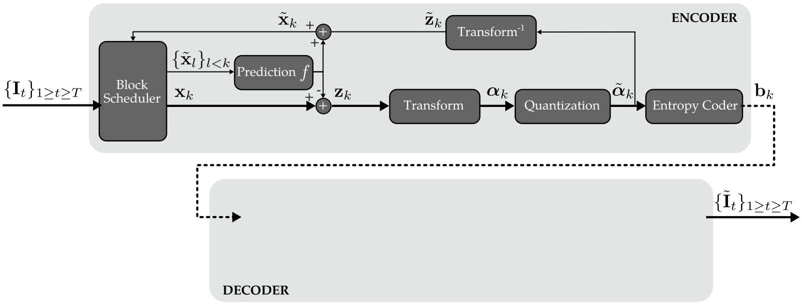

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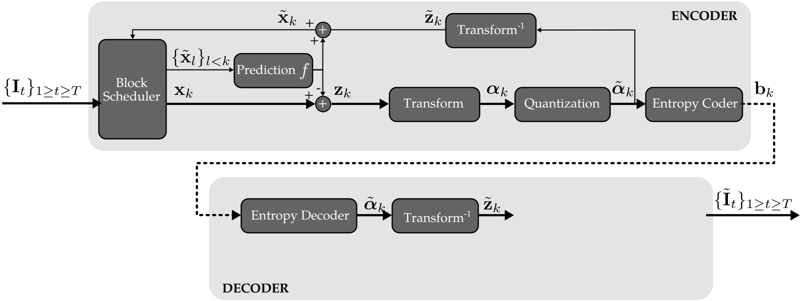

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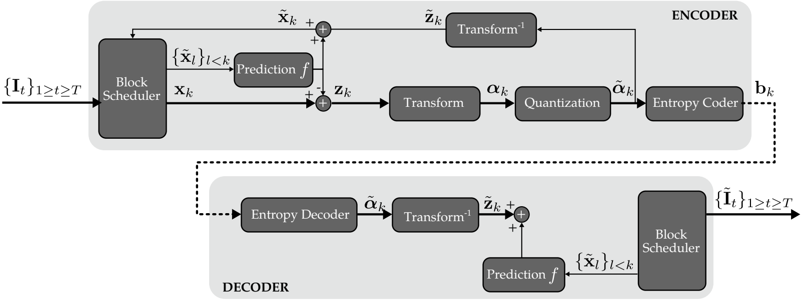

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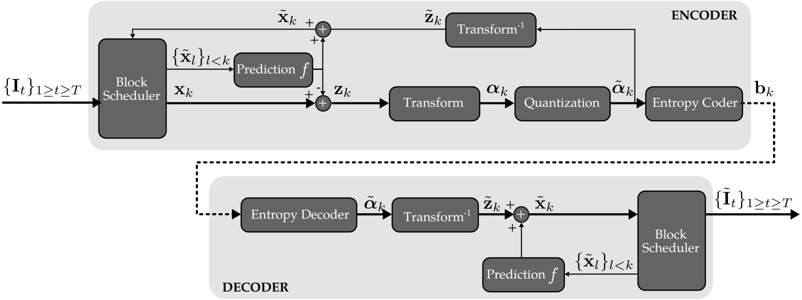

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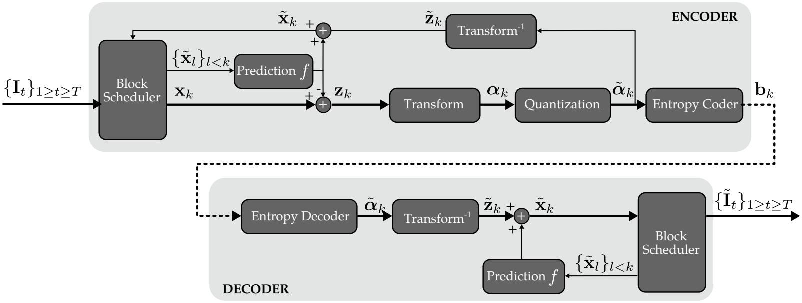


To simplify, the conventional compression pipeline is:

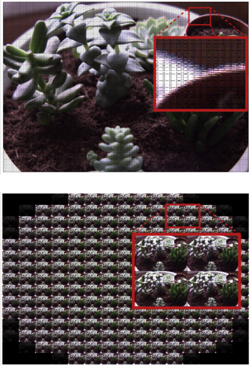
block subdivision $\rightarrow$ prediction $\rightarrow$ transform $\rightarrow$ quantization $\rightarrow$ entropy coding

and targets $\min R + \lambda D$ where $R = |\mathbf{b}_k|$ and $D = ||\mathbf{x}_k - \tilde{\mathbf{x}}_k||_2^2$

Raising of new 3D image modalities

Omnidirectional images/videos

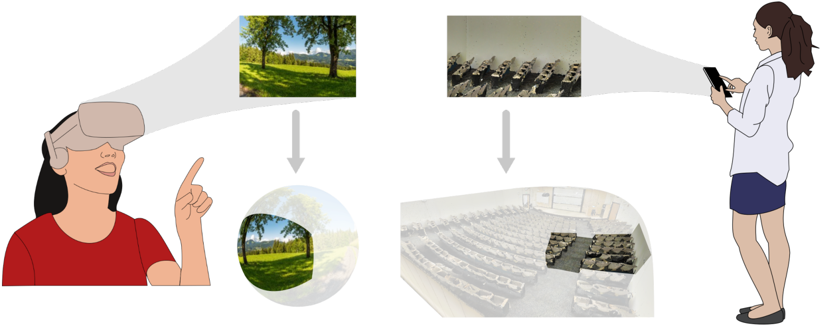
Light Field images/videos



Point Cloud / 3D Mesh

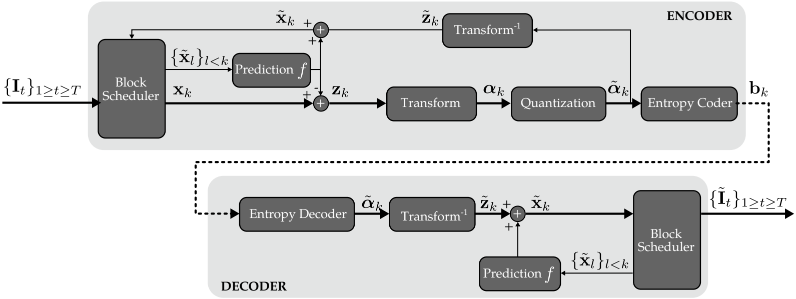
Two peculiarities of 3D data (among others)

★ Only a **subpart** of the visual data can be watched at a given time



★ The pixels lie on **non-euclidean domain**

Incompatibilities of conventional approaches



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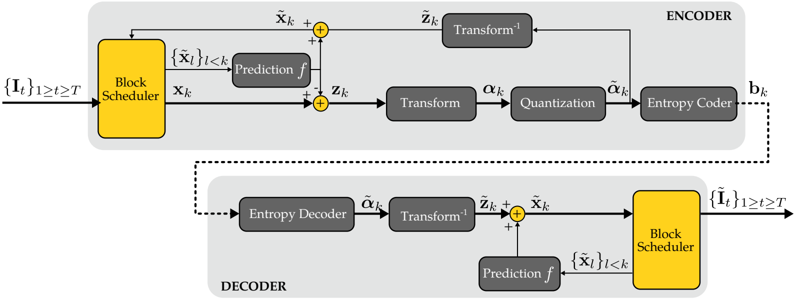
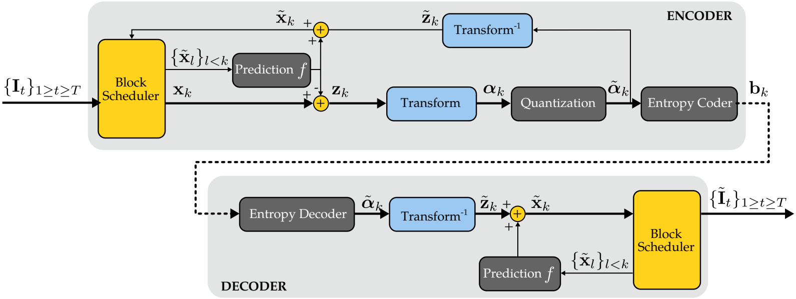


Coding steps incompatible with Random Access

Incompatibilities of conventional approaches



Coding steps incompatible with Random Access

Coding steps incompatible with Irregular Topologies

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2. Compression with Graph-based Transforms
3. Perspectives

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1 **Compression with random access**

2 Compression with Graph-based Transforms

3 Perspectives

Definition

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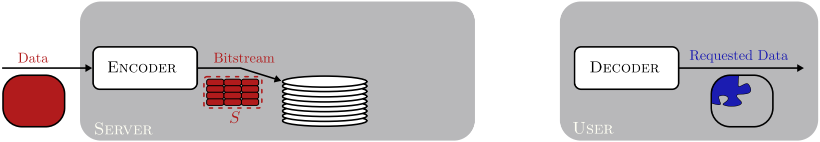
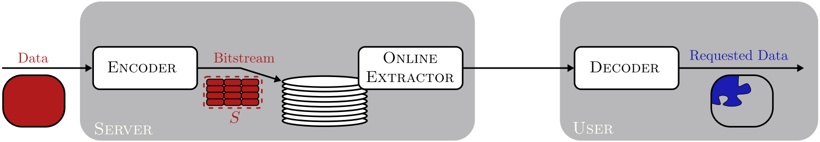
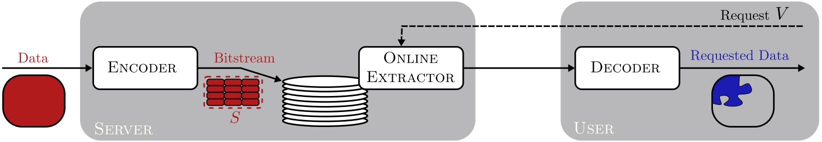

Data
Encoder
Bitstream
S
Server
Decoder
Requested Data
User

Definition



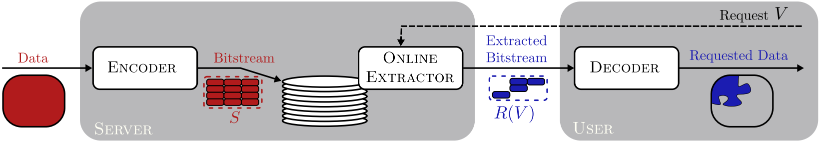
Data
Encoder
Bitstream
S
Online Extractor
Server
Decoder
Requested Data
User

Definition



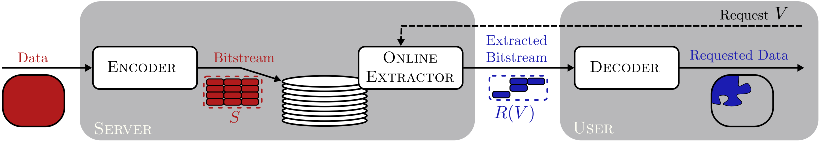
Request V
Data
ENCODER
Bitstream
ONLINE EXTRACTOR
DECODER
Requested Data
S
SERVER
USER

Definition



Request V
Data
ENCODER
Bitstream
S
ONLINE EXTRACTOR
Extracted Bitstream
$R(V)$
DECODER
Requested Data
SERVER
USER

Definition



The rate is split into two quantities:

- the **storage** rate S
- the **transmission** rate R:

$$R = \mathbb{E}_{V \sim p_V}[R(V)]$$

Common solution: data segmentation / tiling

e.g., [Zare16], [Rossi17], [Hosseini16]

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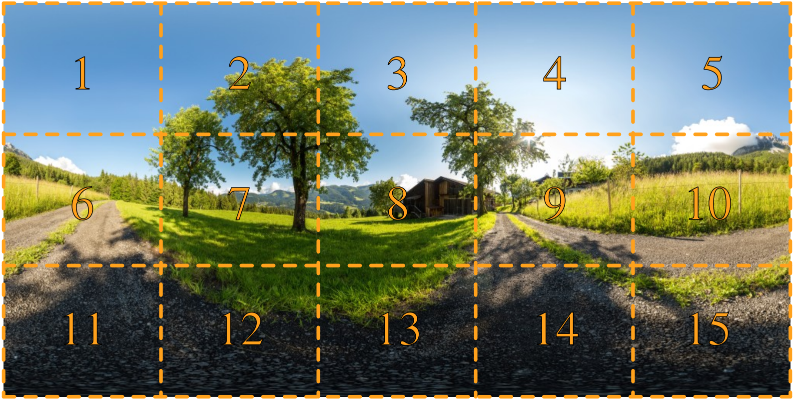

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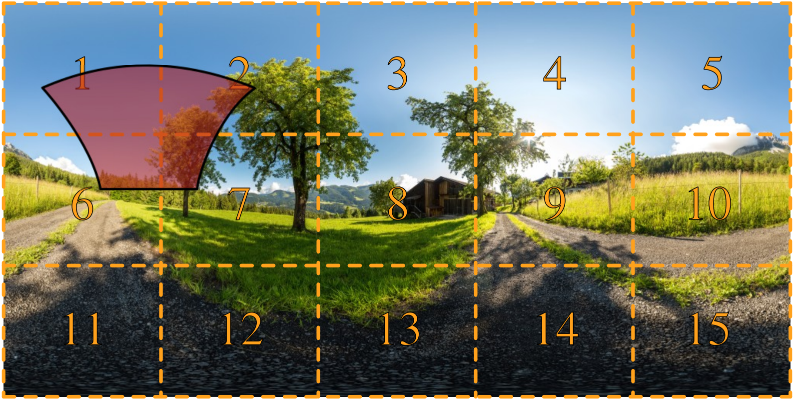

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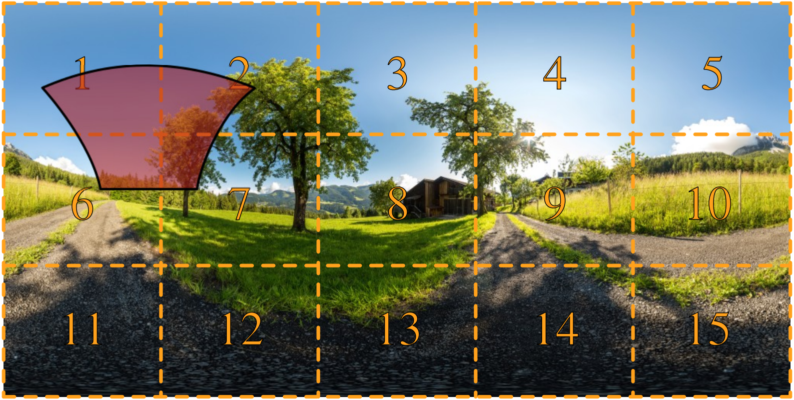


Do tile-based solutions minimize R and S ?

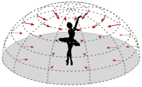
e.g., [Zare16], [Rossi17], [Hosseini16]

Research achievements

Tile-based / **Incremental**

Tiles for 6DoF ?

- **Definition** of Navigation segments
- **Representation** of Navigation segments
- **Optimal** tiling



(C17,18,29) (J3,8,13,18,23)

What achievable performance ?

- New **formulation** of the problem
- User access **modeling**: navigation graph
- **Derivation** of Optimal performance

(C28) (J19)

Proof of Concept

- First **experimentation** on toy graph
- **Achievement** of optimal performance

(J22)

Practical 3D image coder

- **Coder development** for 360° data
- **Coder development** for 3D mesh

(C41,43) (J24)

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Incremental

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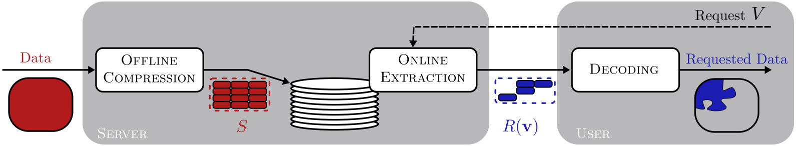

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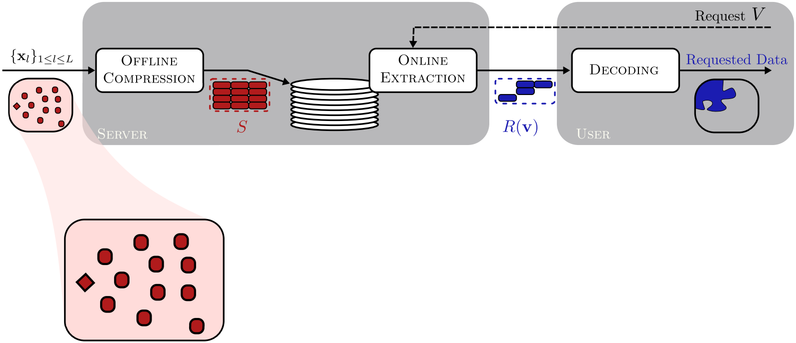

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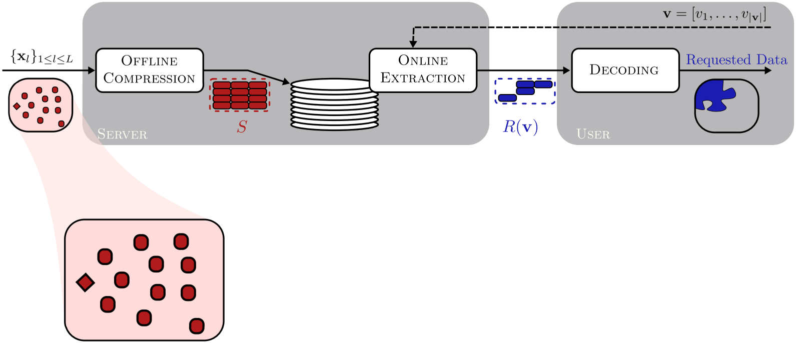

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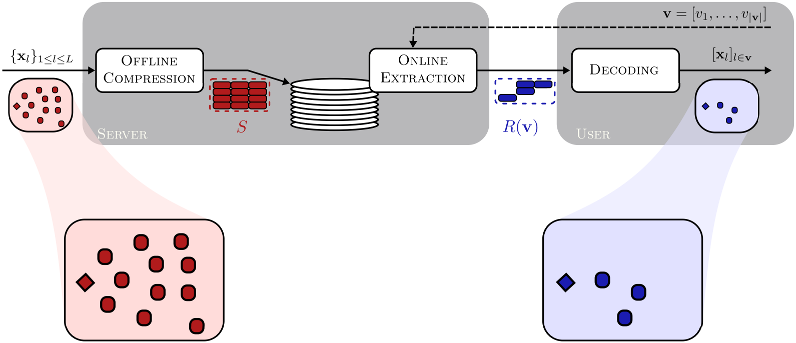

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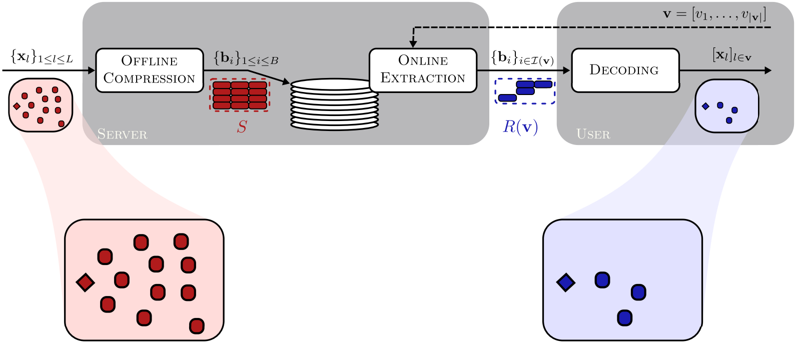

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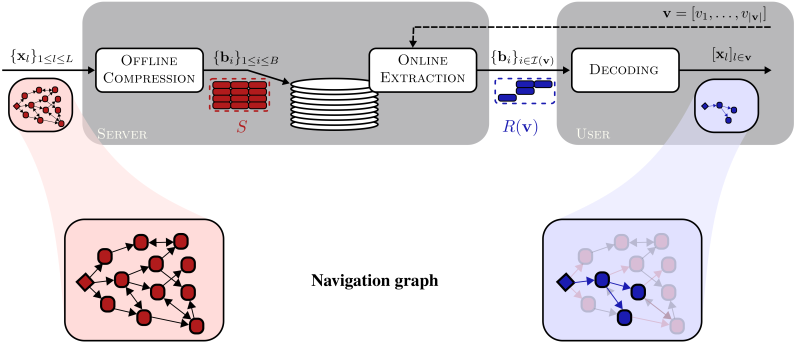

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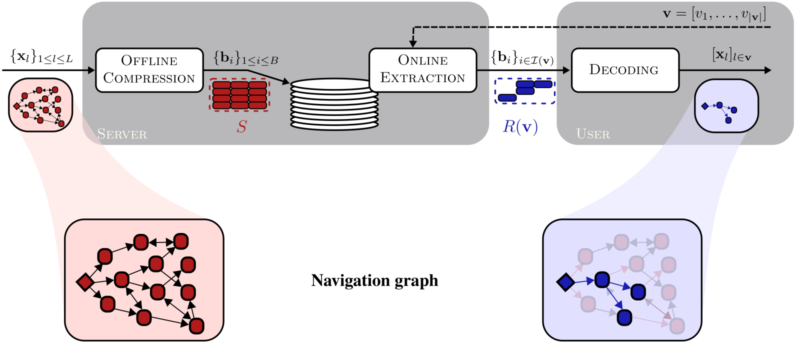

$$S = \sum_{i=1}^{B} |\mathbf{b}_i| \text{ and } R(\mathbf{v}) = \sum_{i\in\mathcal{I}(\mathbf{v})} |\mathbf{b}_i|$$

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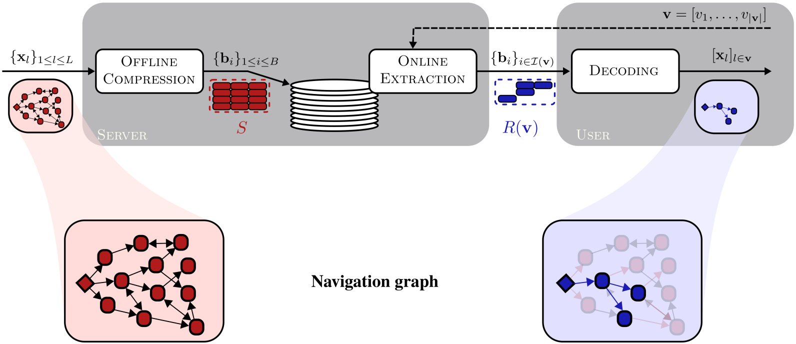

$S = \sum_{i=1}^{B} |\mathbf{b}_i|$ and $R(\mathbf{v}) = \sum_{i\in\mathcal{I}(\mathbf{v})} |\mathbf{b}_i|$

What are the achievable S and $R(\mathbf{v})$?

Example of navigation graph

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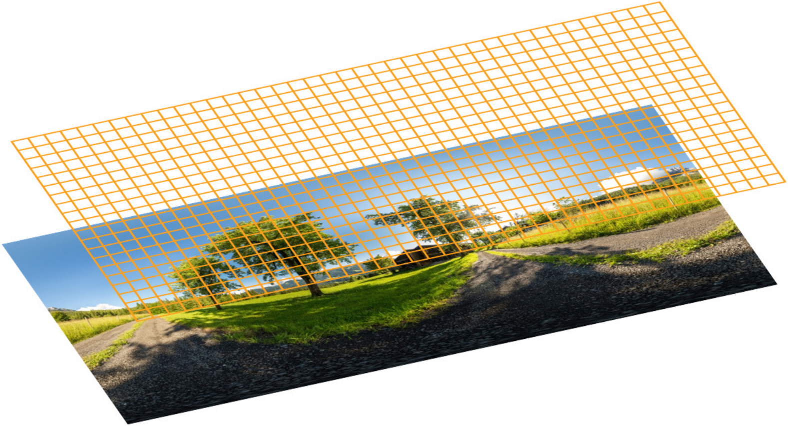

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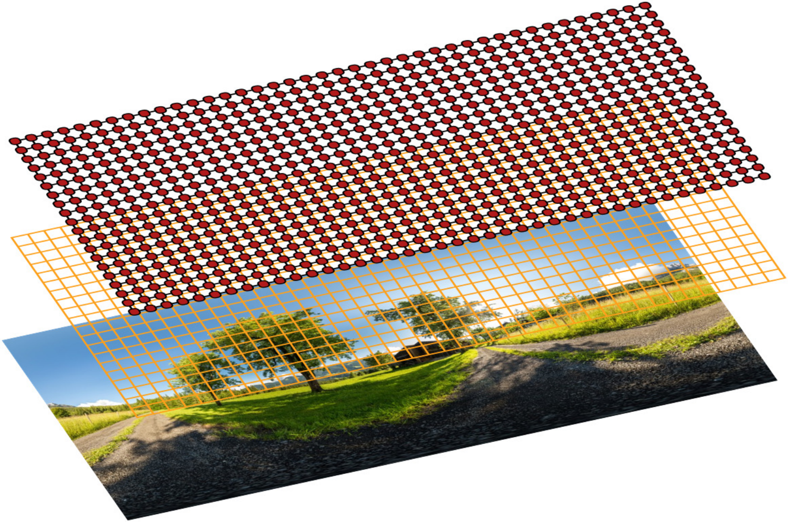
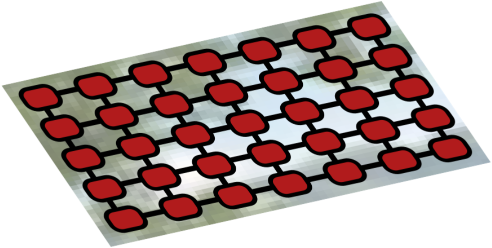
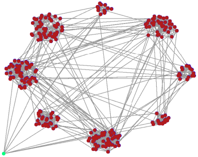


Coding cost evaluation





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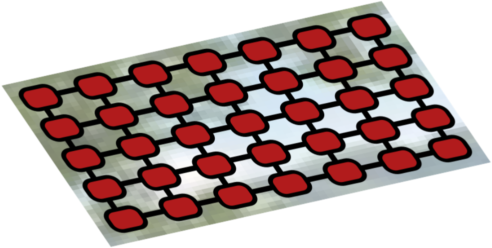
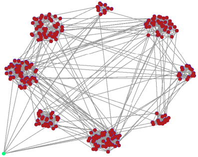


Hypothesis 1
Sources are coded individually
($\neq$ independently)



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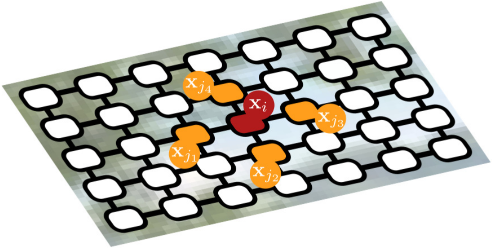
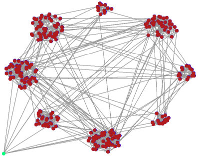


Hypothesis 2
When coding source $\mathbf{x}_i$,
at least one neighbor
$(\mathbf{x}_{j_1}, \mathbf{x}_{j_2}, \mathbf{x}_{j_3}, \mathbf{x}_{j_4})$ is available



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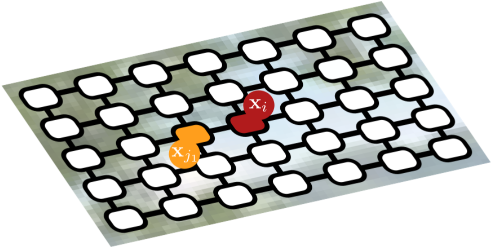
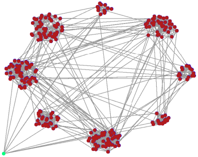


Hypothesis 3
When coding source $\mathbf{x}_i$,
based on source $\mathbf{x}_j$
the rate is:

$$h_{i|j} = H(X_i|X_j)$$



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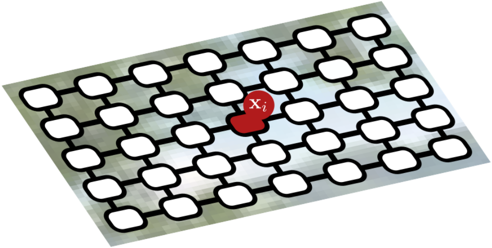
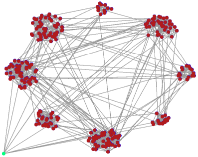


All Intra (AI)
The source $\mathbf{x}_i$
is coded independently

$$S_{AI} = h_i$$

$$R_{AI} = h_i$$



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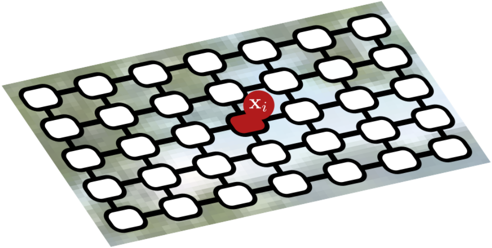

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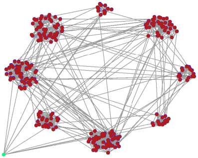

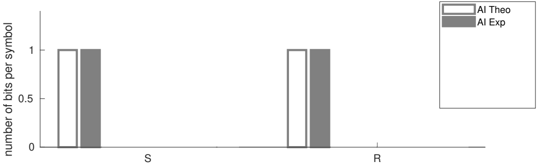

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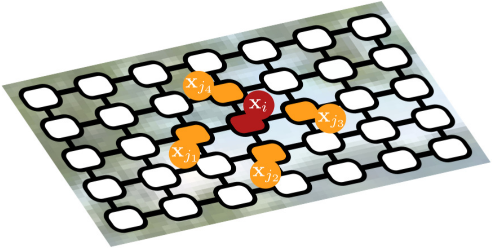
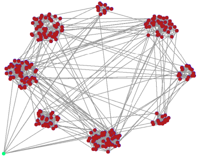
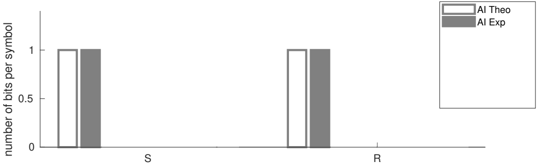


Multiple Prediction (MP)
Each residual $\mathbf{x}_i - f(\mathbf{x}_j)$ is stored

$$S_{MP} = \sum_j h_{i|j}$$

$$R_{MP} = h_{i|j}$$





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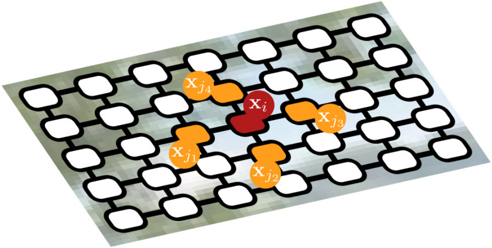

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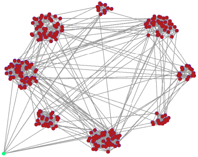

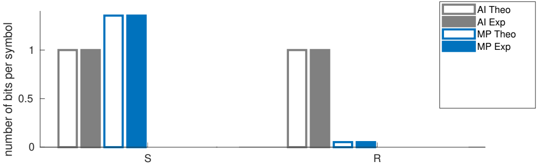

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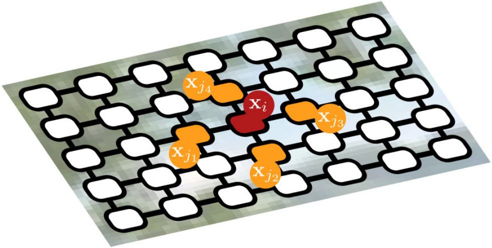
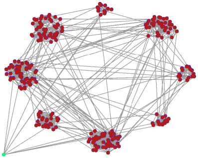
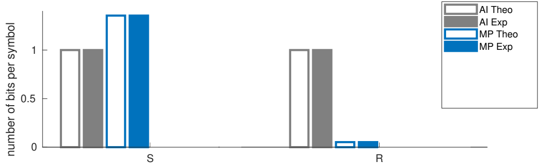


Compound (C) [Cheung11]
A parity codeword able
to decode any prediction

$$S_C = \max_j h_{i|j}$$

$$R_C = \max_j h_{i|j}$$





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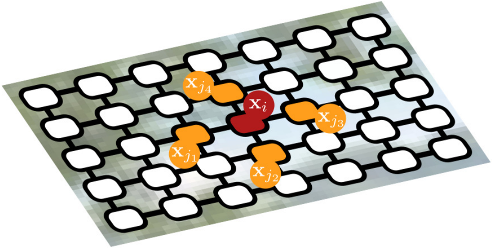

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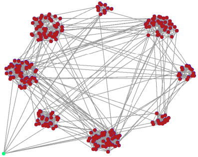
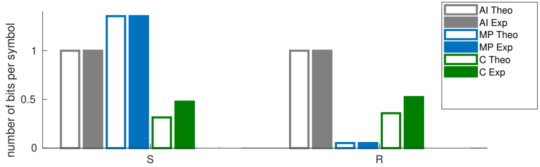
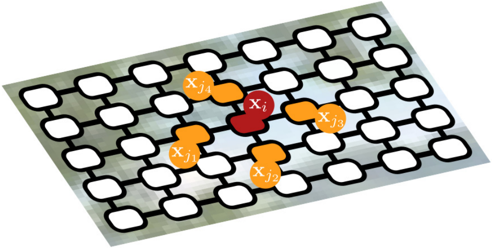
$$R_C = \max_j h_{i|j}$$





(C28) Roumy and TM, 2015, (J19) Dupraz, TM, Roumy, Kieffer, 2019, (J22) TM, Roumy, Dupraz, Kieffer, 2020.

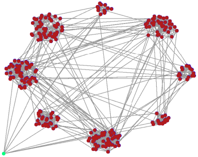
Coding cost evaluation

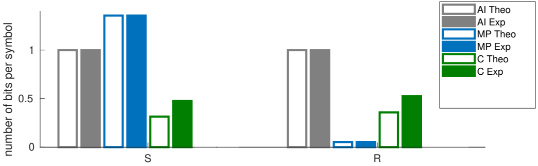


Our result
We have proven that theoretically

$$S^* = \max_j h_{i|j}$$

$$R^* = h_{i|j}$$





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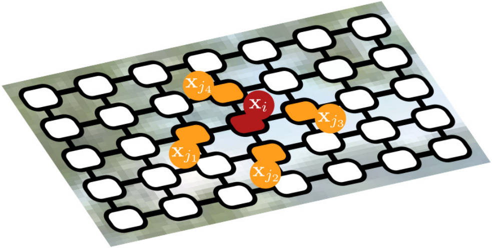

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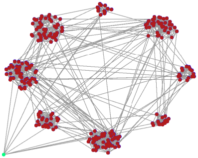

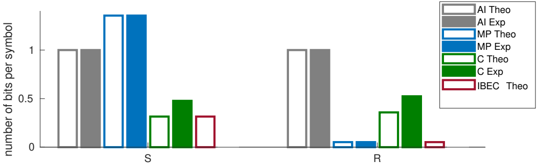

(C28) Roumy and TM, 2015, (J19) Dupraz, TM, Roumy, Kieffer, 2019, (J22) TM, Roumy, Dupraz, Kieffer, 2020.

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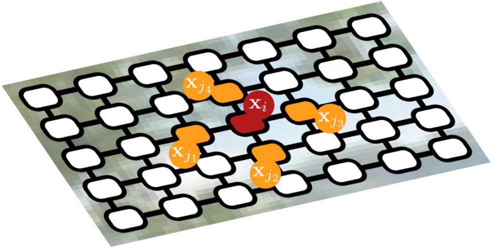

Our result
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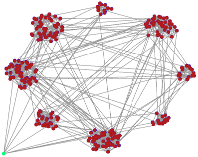
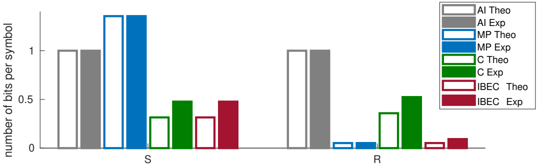
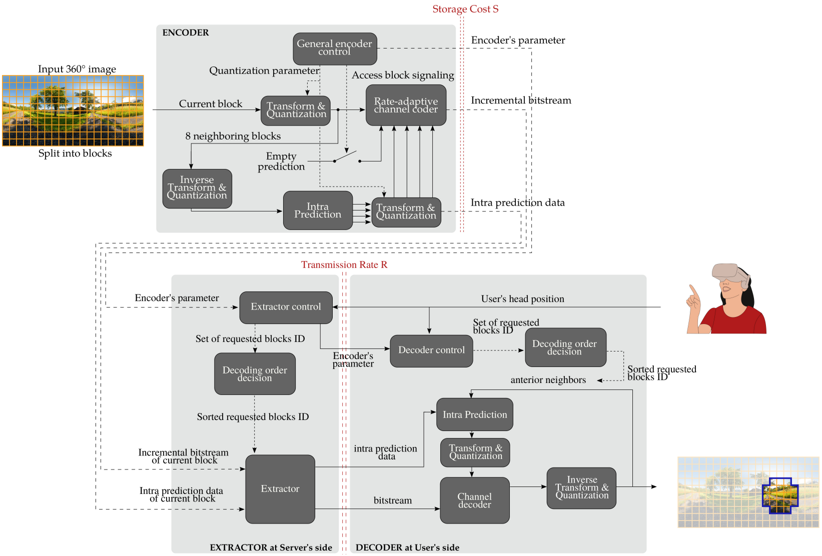
Achievable in practice





(C28) Roumy and TM, 2015, (J19) Dupraz, TM, Roumy, Kieffer, 2019, (J22) TM, Roumy, Dupraz, Kieffer, 2020.

Complete Coding Scheme



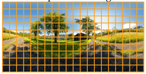
(J24) Mahmoudian Bidgoli, TM, Roumy 2020

Coding Scheme: step by step

Storage Cost S

ENCODER

Input 360° image



Split into blocks

Transmission Rate R

EXTRACTOR at Server's side

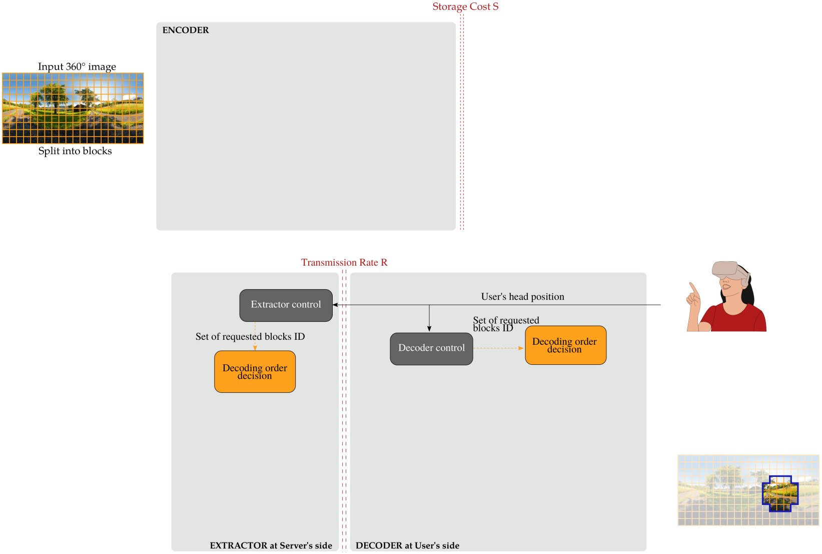
DECODER at User's side

(J24) Mahmoudian Bidgoli, TM, Roumy 2020

Coding Scheme: step by step

(J24) Mahmoudian Bidgoli, TM, Roumy 2020

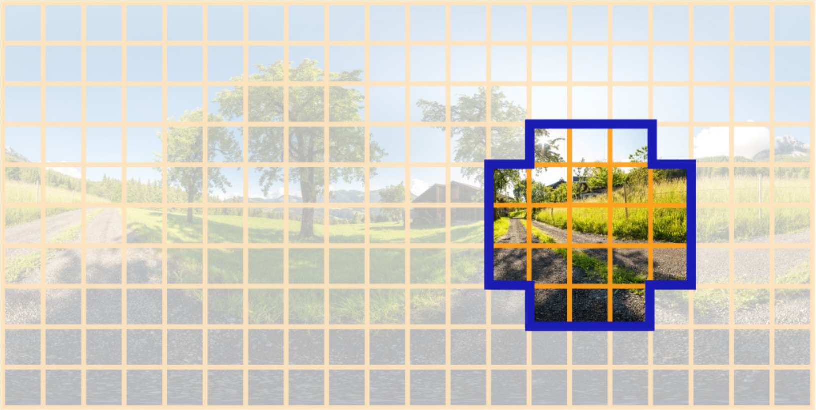
Coding Scheme: step by step



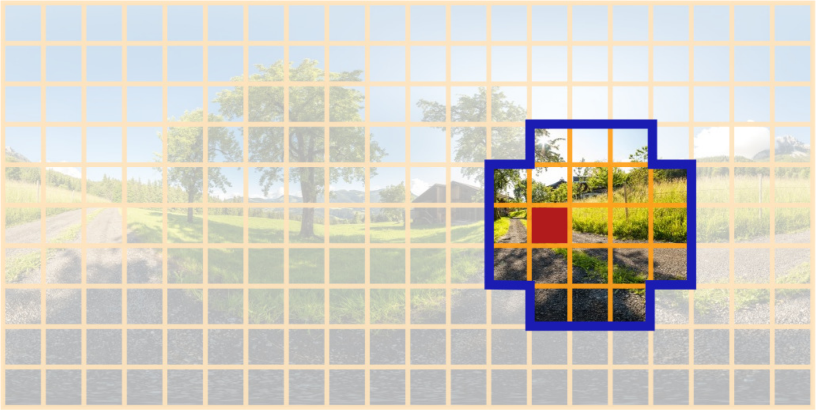
(J24) Mahmoudian Bidgoli, TM, Roumy 2020

Decoding order

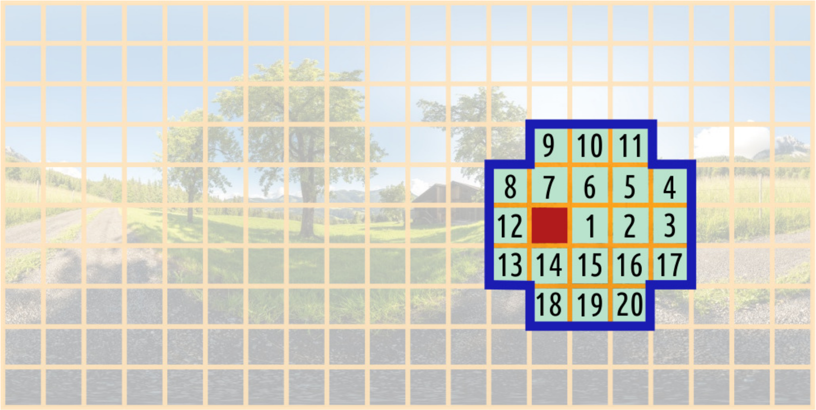
Decoding order



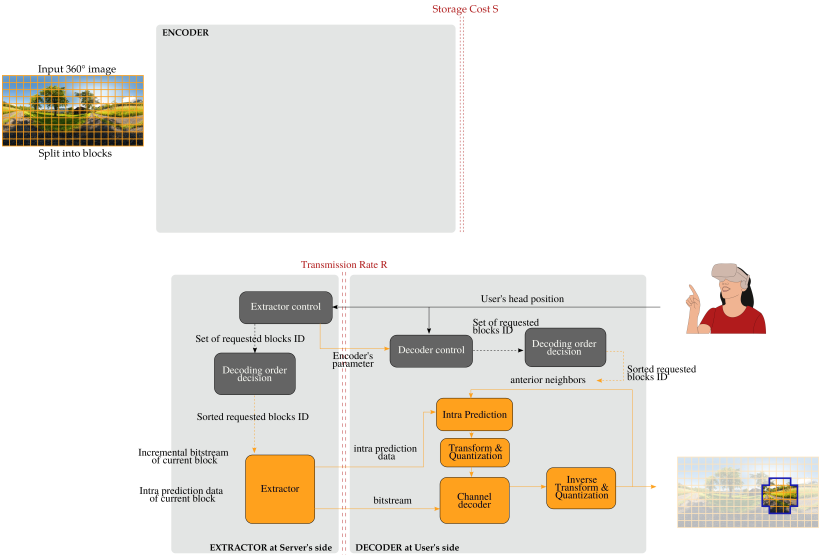
Decoding order



Decoding order



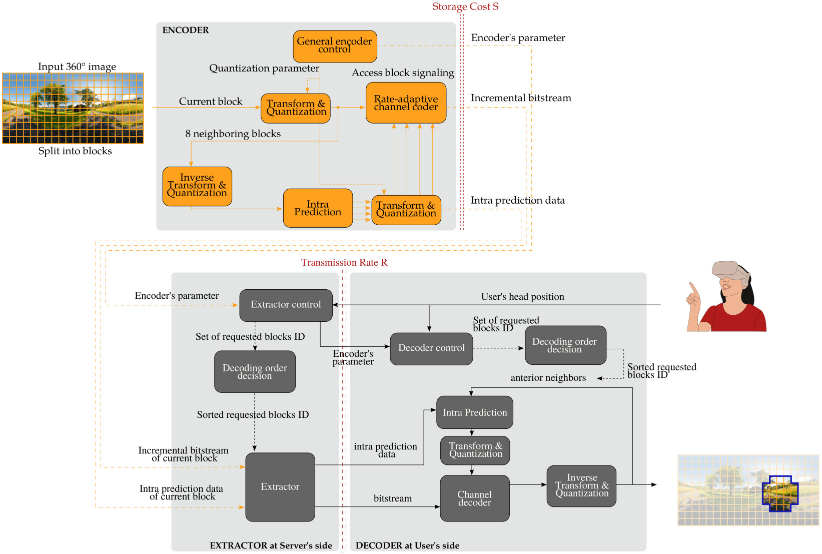
Coding Scheme: step by step



(J24) Mahmoudian Bidgoli, TM, Roumy 2020

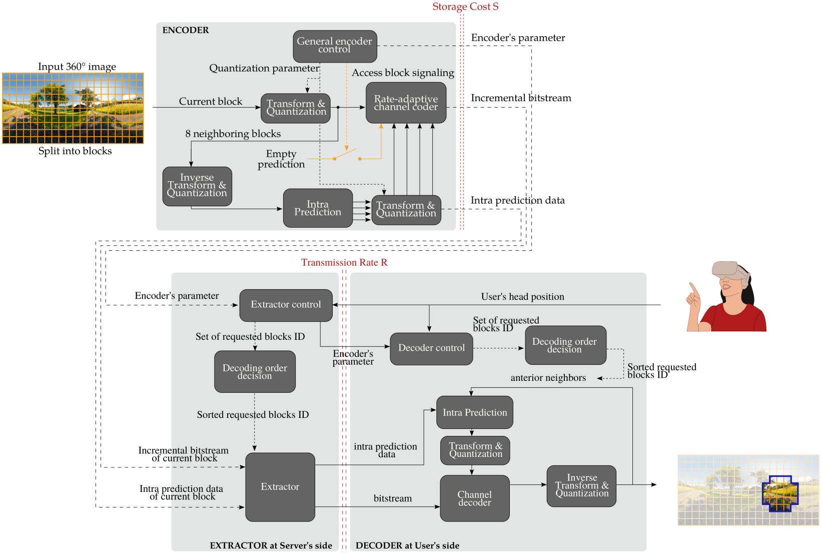
8 possible *intra predictions* (*e.g.*, those of VVC [Pfaff21]) have to be anticipated:

Coding Scheme: step by step

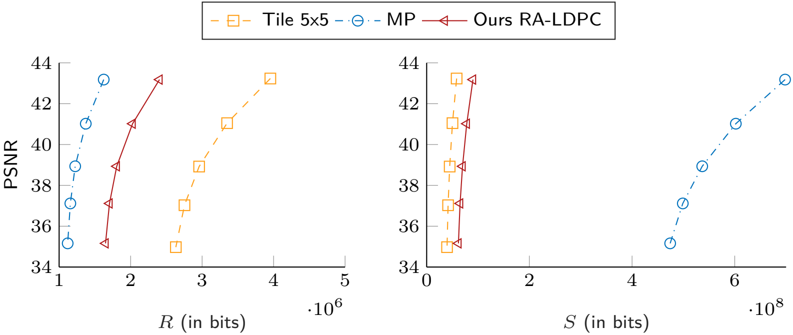


(J24) Mahmoudian Bidgoli, TM, Roumy 2020

Coding Scheme: step by step



(J24) Mahmoudian Bidgoli, TM, Roumy 2020


Tile 5x5
MP
Ours RA-LDPC
PSNR
44
42
40
38
36
34
1
2
3
4
5
$\cdot 10^6$
R (in bits)
0
2
4
6
$\cdot 10^8$
S (in bits)

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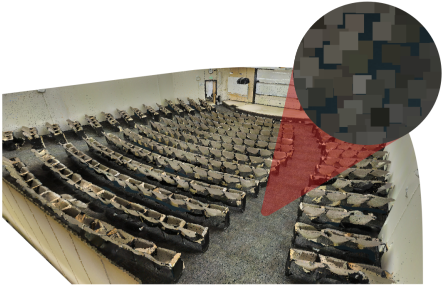
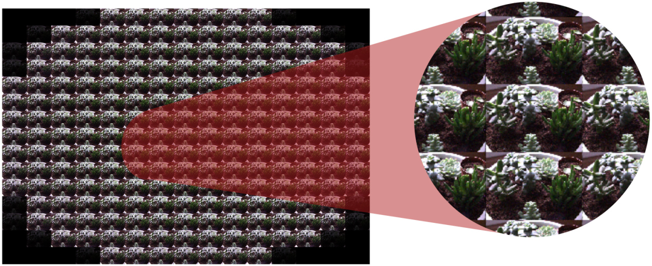
1 Compression with random access

2 Compression with Graph-based Transforms

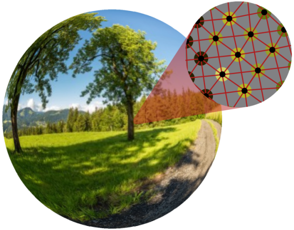
3 Perspectives

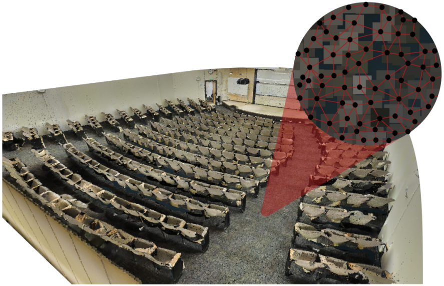
Dealing with irregular topology





Dealing with irregular topology





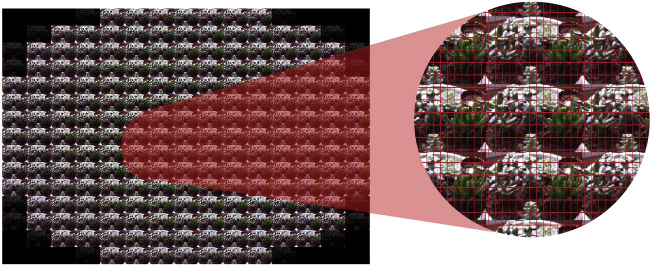


Image on a graph

Graphs represent a pairwise relationship between the pixels.

$\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$, where

- $\mathcal{V}$ are the nodes (indexed from 1 to N)
- $\mathcal{E}$ are the edges
- $\mathcal{W}$ are the weights on the edges

An image on a graph: assign a color to each node

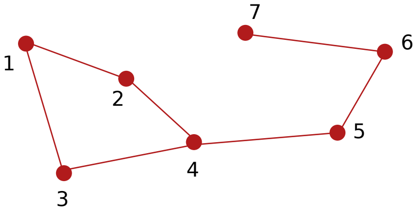


Image on a graph

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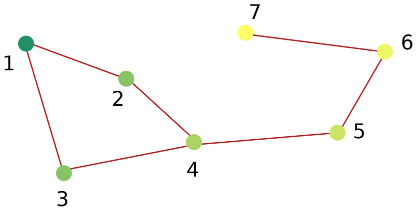
An image on a graph: assign a color to each node $\longrightarrow$ **a vector $\mathbf{z}$**



Useful definitions

Adjacency matrix $\mathbf{A}$:

$$a_{ij} = \begin{cases} 1 \text{ if } e_{i,j} \in \mathcal{E} \\ 0 \text{ otherwise} \end{cases}$$

Degree matrix $\mathbf{D}$:

$$d_{ij} = \begin{cases} \mathrm{degree}(v_i) \text{ if} i = j \\ 0 \text{ otherwise} \end{cases}$$

Laplacian matrix $\mathbf{L}$:

$$\mathbf{L} = \mathbf{D} - \mathbf{A}$$

Graph Fourier Transform

Compute the Laplacian matrix:

$$\mathbf{L} = \mathbf{D} - \mathbf{A}$$

Find the eigenvectors and the eigenvalues:

$$\mathbf{L} = \mathbf{U}\boldsymbol{\Lambda}\mathbf{U}^\top$$

Project the signal z on the eigenvectors to get the transformed coefficients:

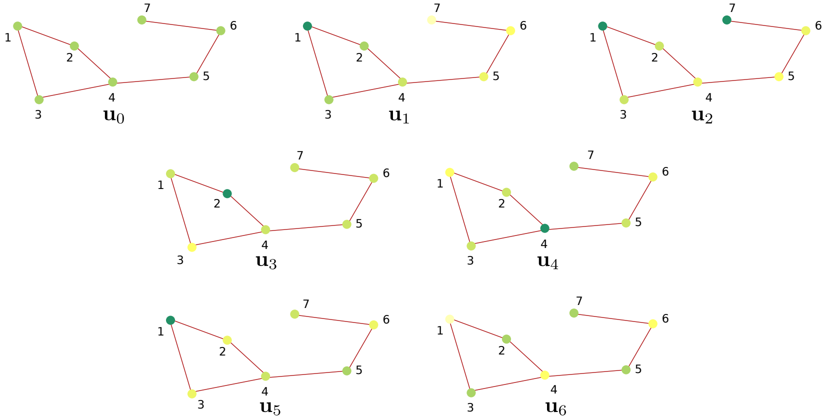
$$\boldsymbol{\alpha} = \mathbf{U}^\top \mathbf{z}$$

The inverse transform is:

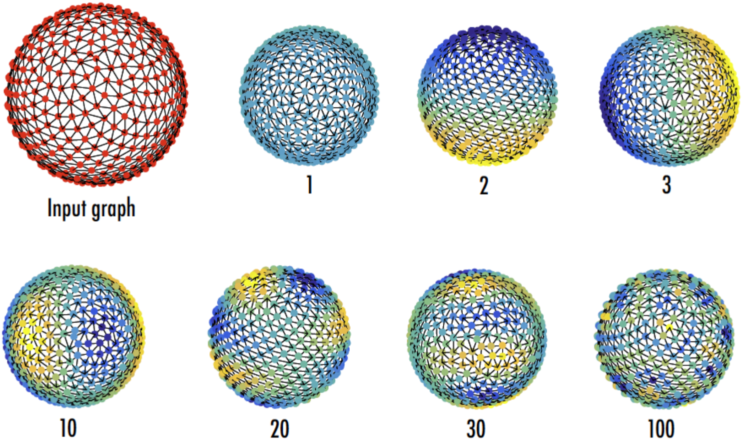
$$\mathbf{z} = \mathbf{U}\boldsymbol{\alpha}$$

More details in *e.g.*, [Shuman13] [Cheung18] [Hu21]

Frequency in the graph



Graph Transforms on the sphere



Research achievements

How to construct the graph ?

How to reduce GFT complexity ?

Graph for 3D modalities

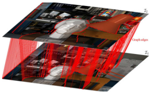
Graph construction:

- 360°
- 3D mesh
- Light Fields

(C32, 39,44)

Graph describing the 3D geometry

- GBR **construction**
- Color **compression**
- **Generalization** to any camera config.



(C19,20,21,24,30) (J10,16)

Graph segmentation

- Rate-distortion oriented **partitioning**

(C35,36) (J21)

Separable transform

- graph **separation**
- eigenvector **alignment**

(J20)

Graph reduction

- graph **coarsening**
- **optimal** graph reduction

(J28)

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(J28)

GFT complexity issue

$\mathbf{L} =$ 

(a) Full Laplacian

GFT complexity issue

(a) Full Laplacian

(b) Segmentation

Light-field super-ray

A graph applied on each super-ray (estimated *e.g.*, with [Hog17]):

(C32)

Light-field super-ray

A graph applied on each super-ray (estimated *e.g.*, with [Hog17]):

(C32)

A graph applied on each super-ray (estimated *e.g.*, with [Hog17]):

(C32)

$$\mathbf{L} =$$

(a) Full Laplacian

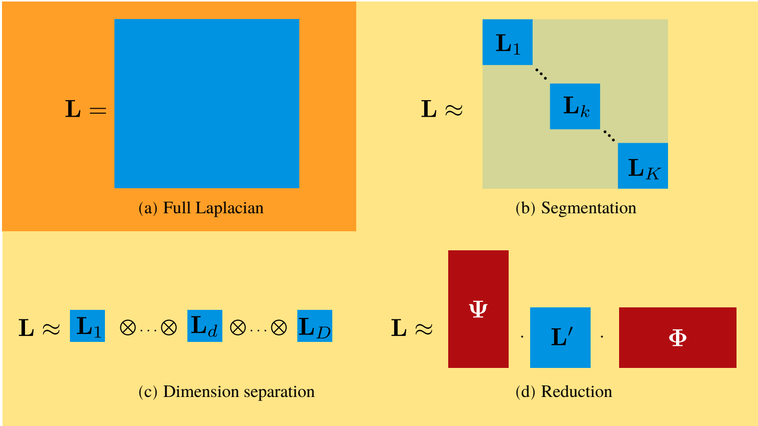
$$\mathbf{L} \approx \begin{bmatrix} \mathbf{L}_1 & & & & \\ & \ddots & & & \\ & & \mathbf{L}_k & & \\ & & & \ddots & \\ & & & & \mathbf{L}_K \end{bmatrix}$$

(b) Segmentation

$$\mathbf{L} \approx \mathbf{L}_1 \otimes \cdots \otimes \mathbf{L}_d \otimes \cdots \otimes \mathbf{L}_D$$

(c) Dimension separation

GFT complexity issue



(a) Full Laplacian

(b) Segmentation

(c) Dimension separation

(d) Reduction

Laplacian interpretation

2^{nd} derivative, it says how much a z_i value can be estimated by the linear combination of its neighbors:

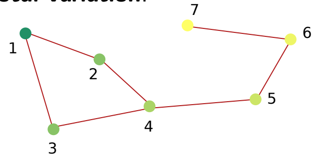
$$\mathbf{Lz} \longrightarrow \begin{pmatrix} \vdots \\ d_i z_i - \sum_{j \in \mathcal{N}(\mathrm{i})} w_{i,j} z_j \\ \vdots \end{pmatrix}$$

Laplacian interpretation

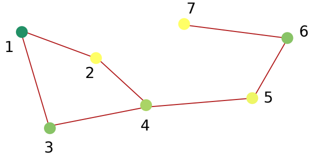
2^{nd} derivative, it says how much a z_i value can be estimated by the linear combination of its neighbors:

$$\mathbf{L}\mathbf{z} \longrightarrow \left(\begin{array}{c} \vdots \\ d_i z_i - \sum_{j \in \mathcal{N}(\mathrm{i})} w_{i,j} z_j \\ \vdots \end{array} \right)$$

Total variation:



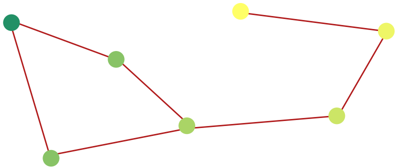
$$\mathrm{TV}_{\mathbf{L}}(\mathbf{z}_1) = \mathbf{z}_1^\top \mathbf{L} \mathbf{z}_1 = 60$$

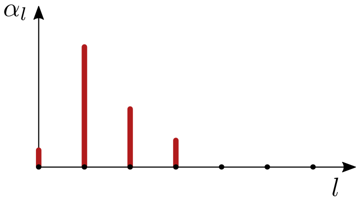


$$\mathrm{TV}_{\mathbf{L}}(\mathbf{z}_2) = \mathbf{z}_2^\top \mathbf{L} \mathbf{z}_2 = 120$$

Link with compression

Smooth signal $\longrightarrow$ compact energy





A small number of coefficients sufficient to describe the signal

$\longrightarrow$ Decrease the graph size

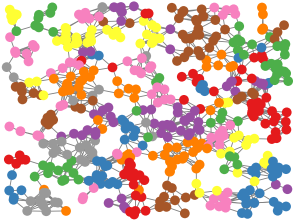
Graph coarsening

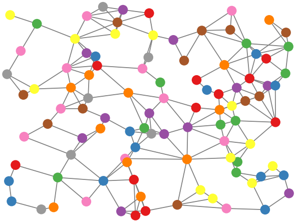
In [Loukas 2019], a projection matrix $\mathbf{P}$:

$$\mathbf{z}' = \mathbf{P}\mathbf{z}$$

$$\mathbf{L}' = \mathbf{P}^{\mp}\mathbf{L}\mathbf{P}^{+}$$

$$\tilde{\mathbf{z}} = \mathbf{P}^{+}\mathbf{z}'$$



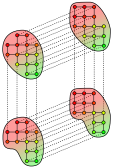


Theoretical link between $\mathrm{TV}_{\mathbf{L}}(\mathbf{z})$ and $||\mathbf{z} - \tilde{\mathbf{z}}||_2^2$

Application to Light Field compression

Signal-oriented decision

Super-ray

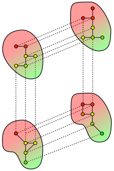


$\mathbf{L} =$

Full Laplacian

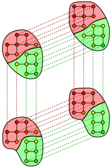
$$\mathbf{L} \approx \mathbf{P}^{+} \cdot \mathbf{L_c} \cdot \mathbf{P}^{\mp}$$

Graph coarsening



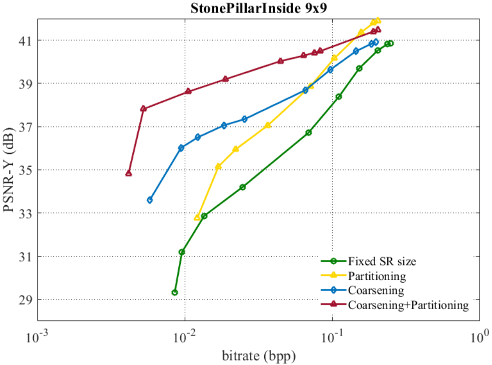
$$\mathbf{L} \approx \begin{bmatrix} \mathbf{L_1} & \\ & \mathbf{L_2} \end{bmatrix}$$

Graph partitioning



(J28) Rizkallah, TM, Guillemot, 2019

Results



(J28) Rizkallah, TM, Guillemot, 2019

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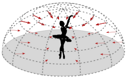
Interactive coding dissemination

Tile-based

Incremental

Tiles for 6DoF ?

- **Definition** of Navigation segments
- **Representation** of Navigation segments
- **Optimal** tiling



(C17,18,29) (J3,8,13,18,23)

What achievable performance ?

- New **formulation** of the problem
- User access **modeling**: navigation graph
- **Derivation** of Optimal performance

(C28) (J19)

Proof of Concept

- First **experimentation** on toy graph
- **Achievement** of optimal performance

(J22)

Practical 3D image coder

- **Coder development** for 360° data
- **Coder development** for 3D mesh

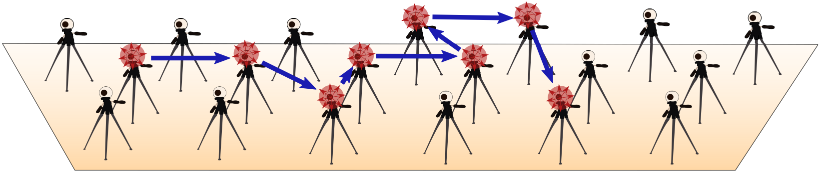
(C41,43) (J24)

Coder transfer

- open-source **implementation**
- **demonstrator**
- **extension** to video streaming optim.

Sebastien Bellenous (Research engineer), Reda Kaafarani (PhD)

Multi-view 360° view synthesis



User is able to make discrete translation in the scene

At every discrete camera position, the user is able to watch every direction

Learning on the Sphere

Geometric Deep Learning

Graph for 3D modalities

Graph construction:

- 360°
- 3D mesh
- Light Fields

(C32, 39,44)

Graph describing the 3D geometry

- GBR **construction**
- Color **compression**
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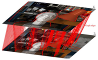

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(J20)

Graph reduction

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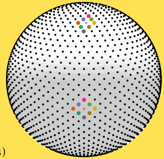
- **optimal** graph reduction

(J28)

OSLO toolbox

- On-the-Sphere learning toolbox

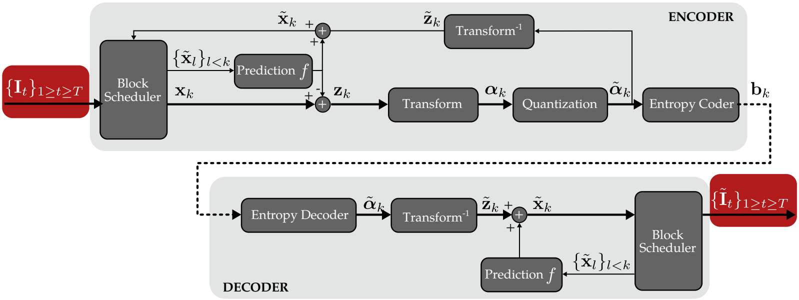


(J31s)

Anax Start-up

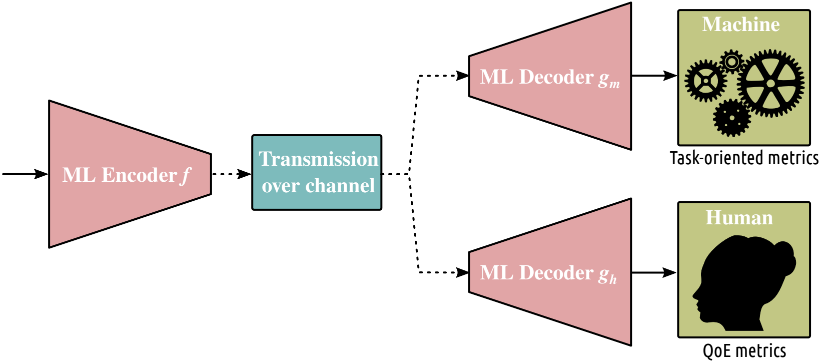
- 360° image editing using AI

Another conventional coding limitation

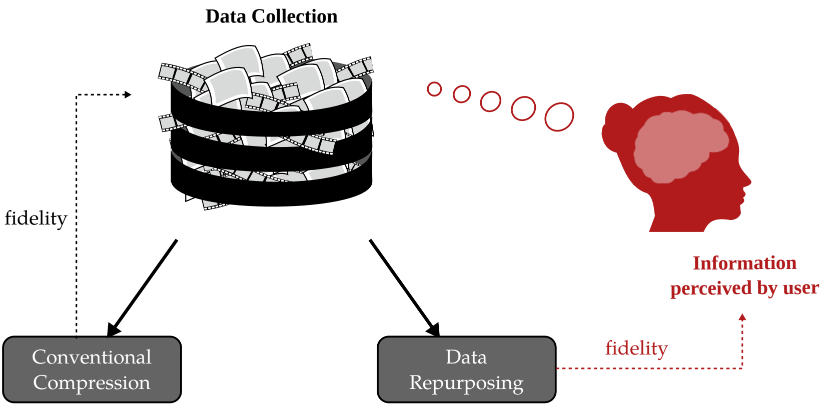


Compression gain limited by the **fidelity criterion**

Coding for machine



Data Repurposing



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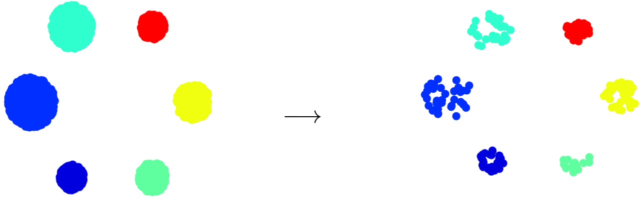
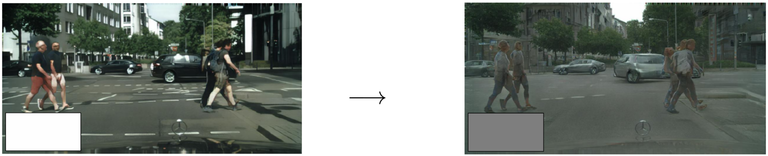
Data Repurposing

★ **Sampled** data collection



★ **Generative compression**: content **regenerated** from a digest [Agustsson19]



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Thank you

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