

Multi-Modal Semantic Communication Through Transformer-Aided Compression

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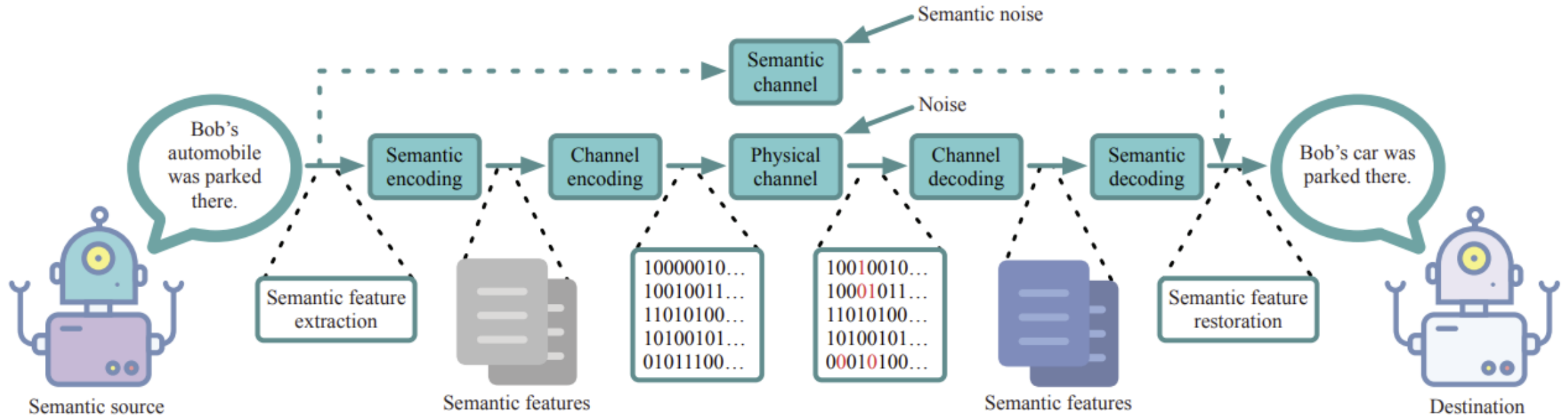
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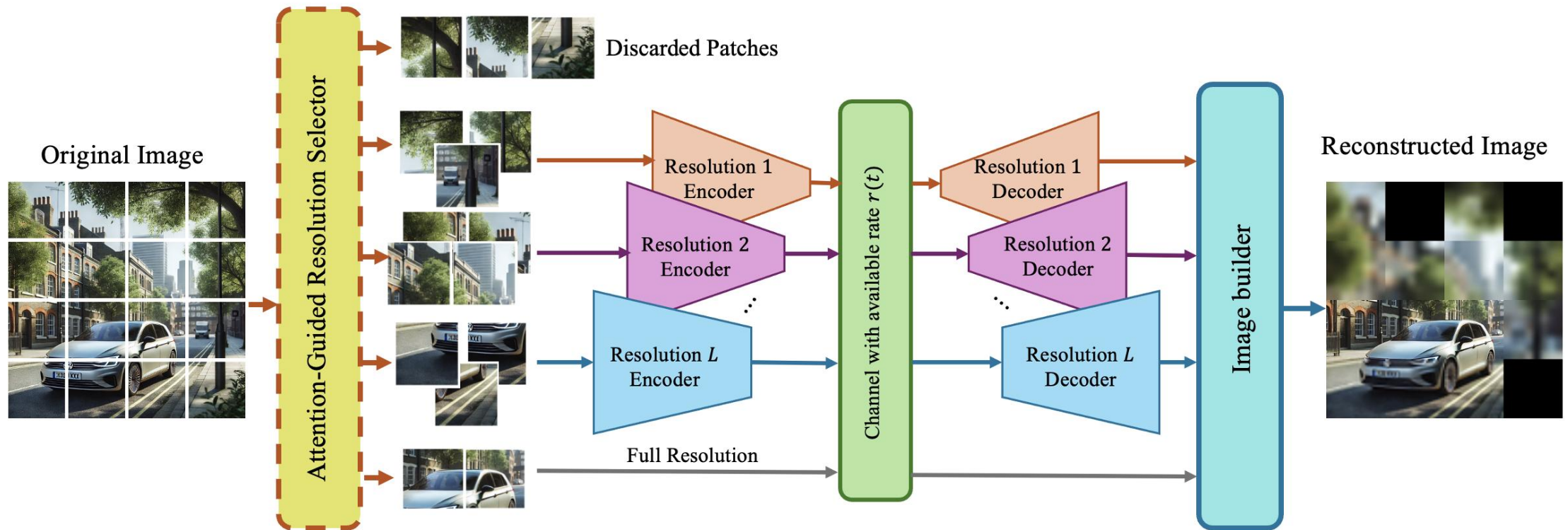
Introduction

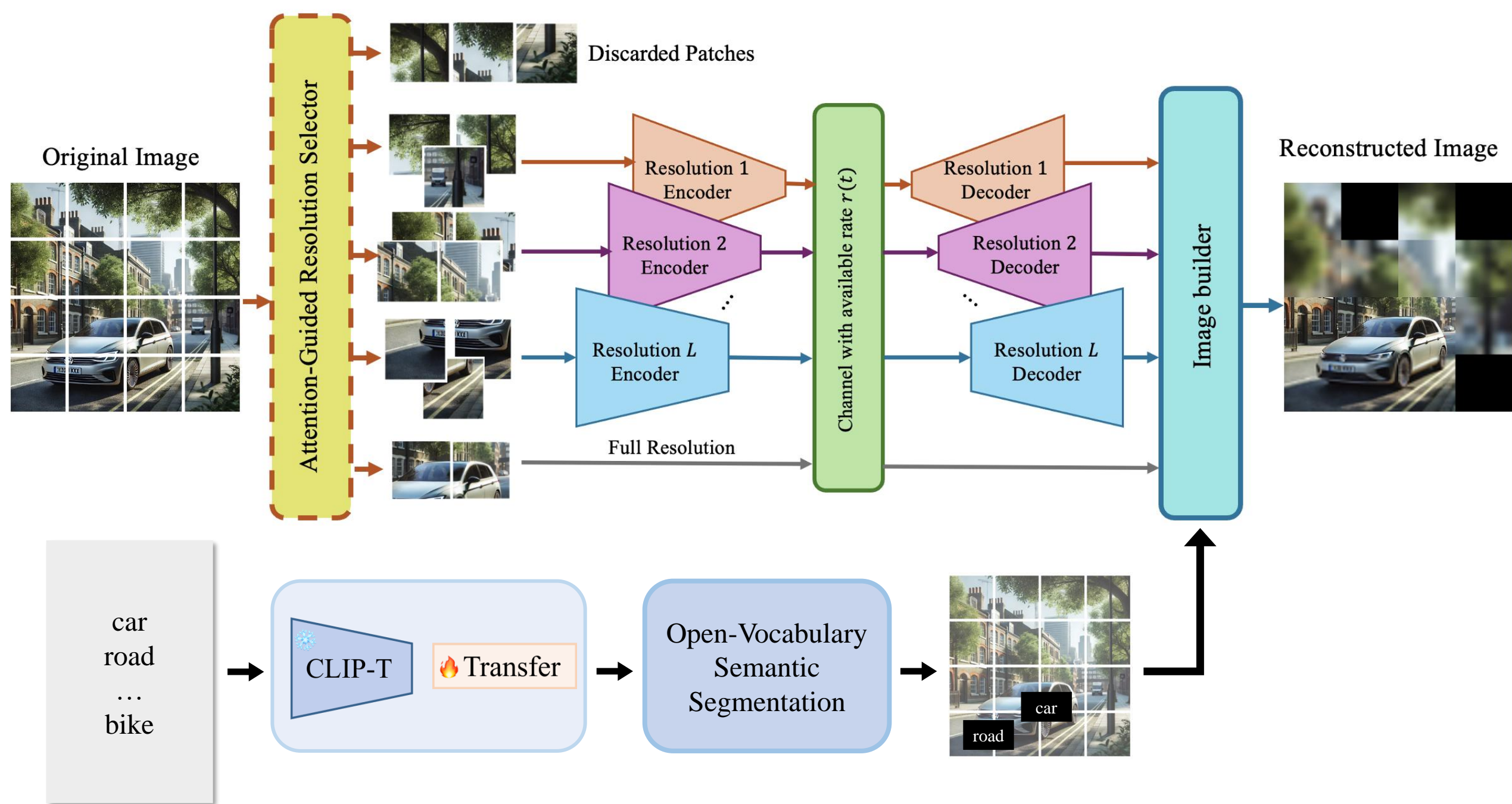
- Semantic communications is to extract the “meanings” or “features” of sent information from a source and “interpret” the semantic information at a destination.



Introduction

- Goal: Transmit multi-resolution data in limited bandwidth conditions.
- Developed a transformer-based framework for channel-adaptive communication.

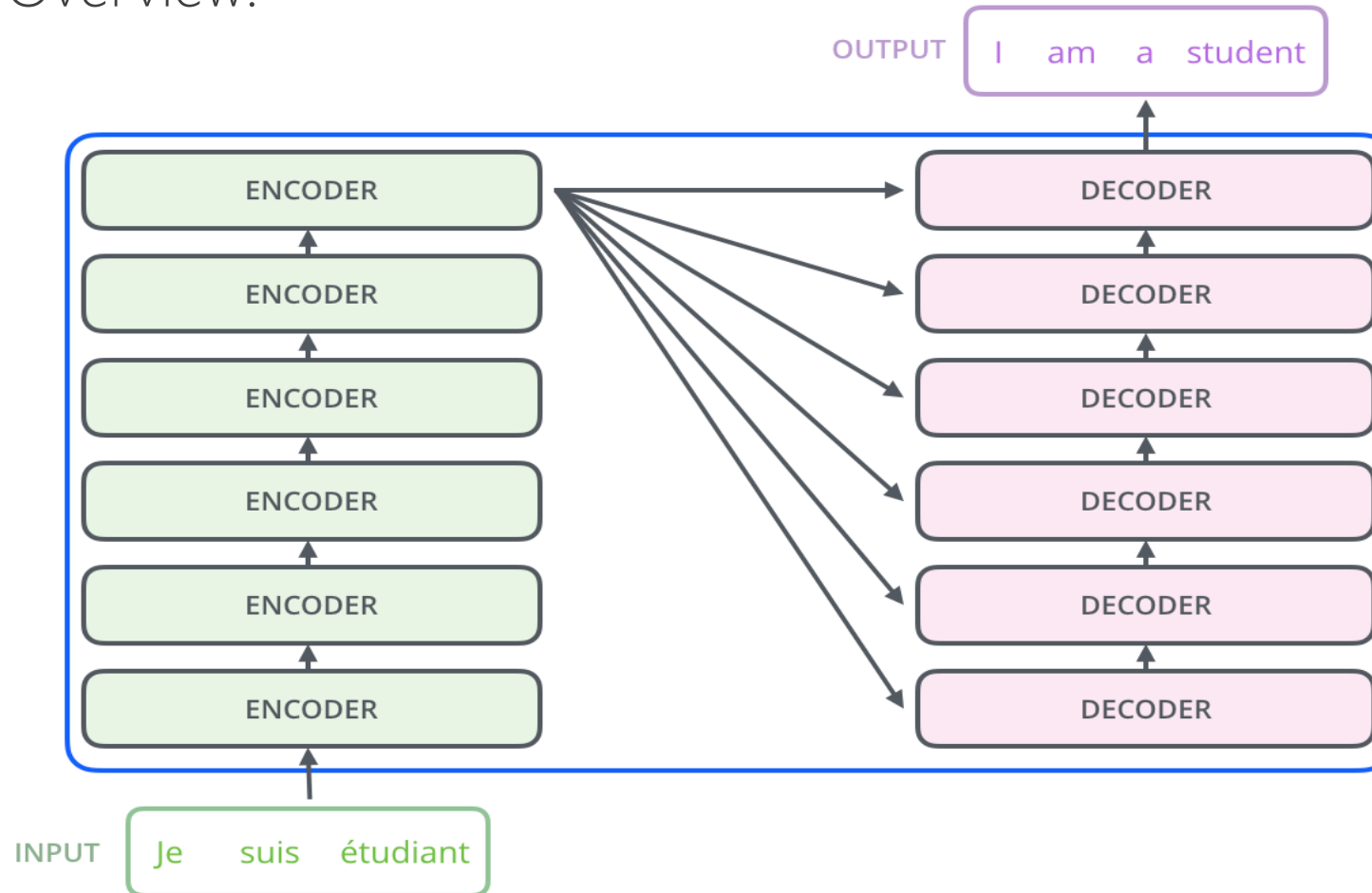




Background

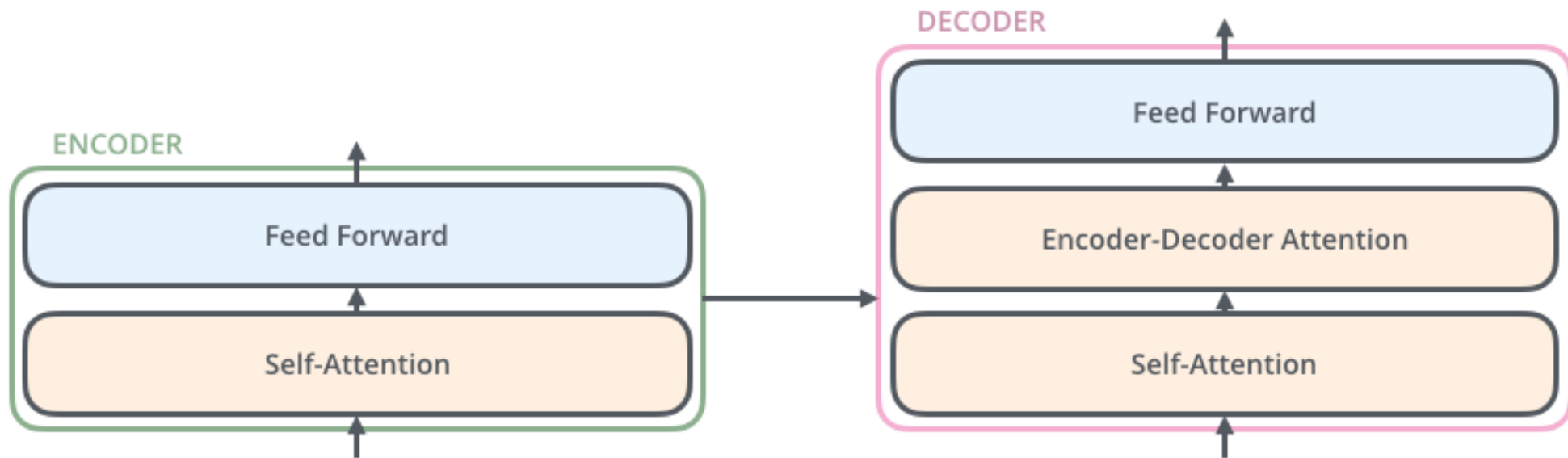
Background (Transformer)

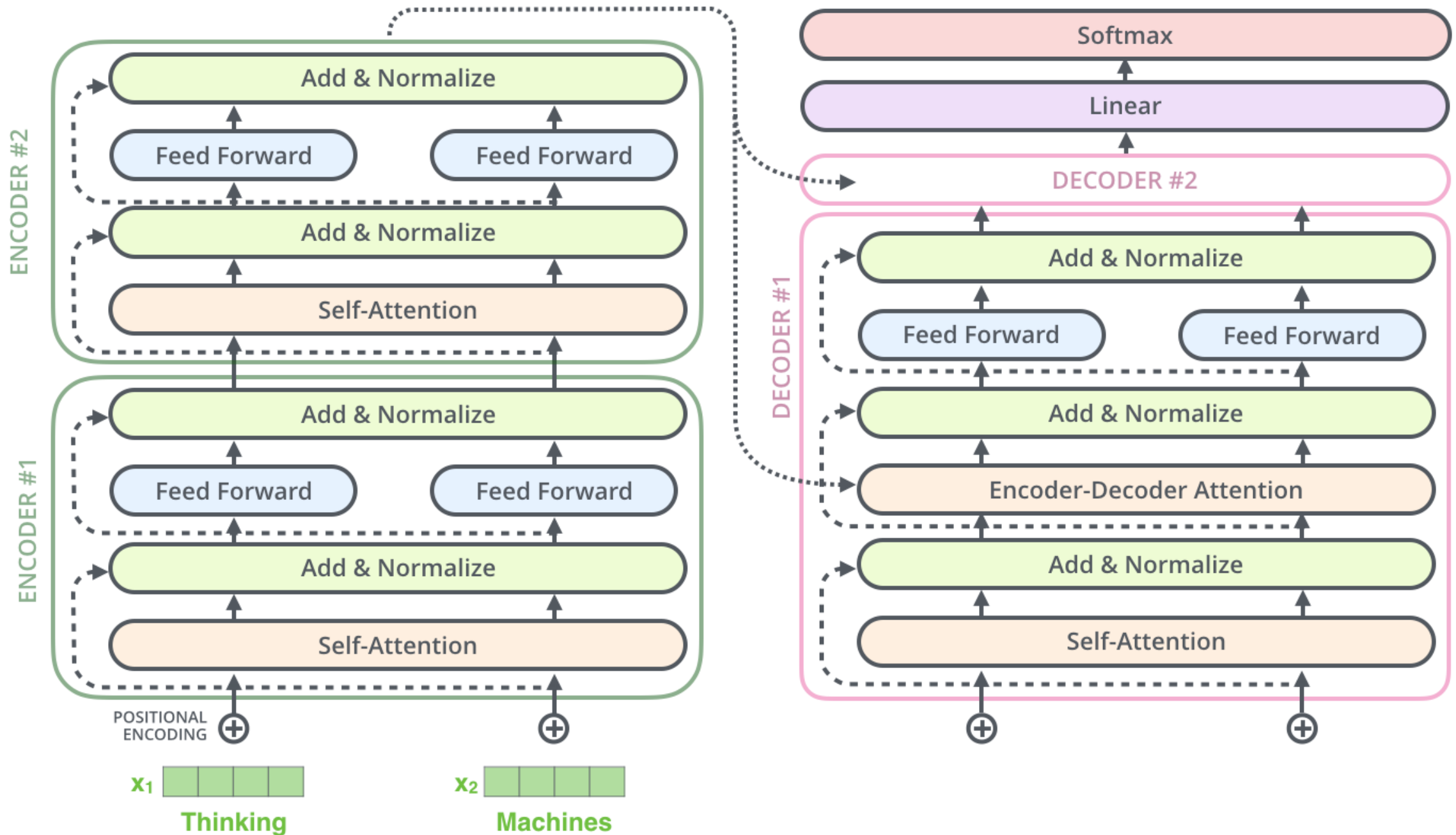
- Transformer Overview:



Background (Transformer)

- Transformer Overview:
 - A deep learning architecture with self-attention mechanisms.
 - Enables focus on key elements in complex data.



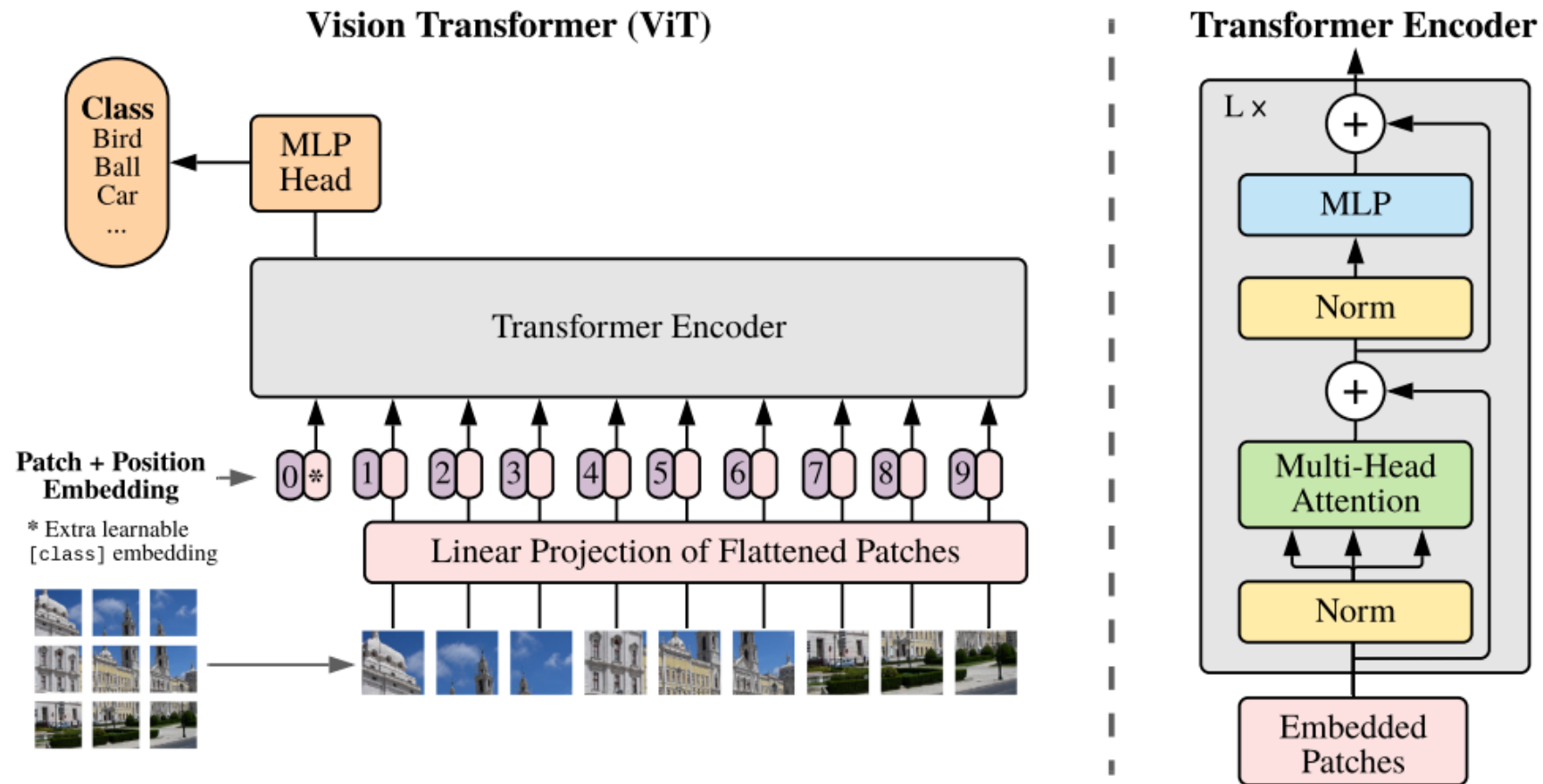


Background (Transformer)

- Key Features:
 - Multi-head attention
 - Positional encodings
 - Encoder-decoder structure
- Application for the paper:
 - Image patches encoded and compressed based on semantic content.

Background (Vision Transformer)

- Vision Transformer (ViT)



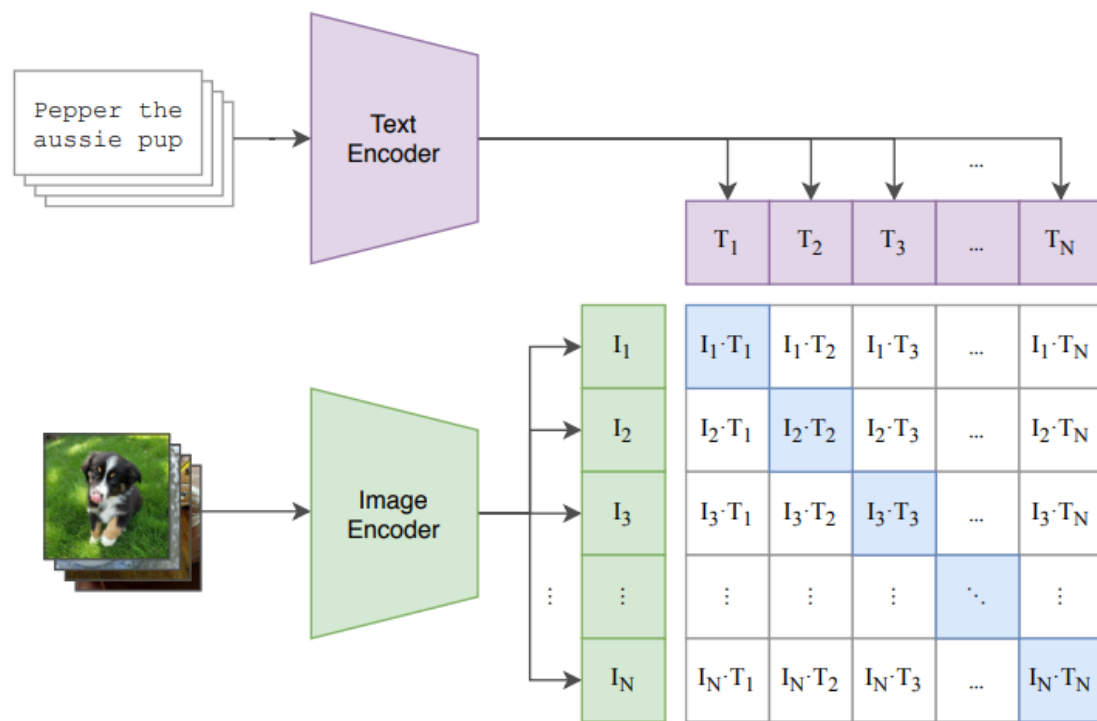
Background (Vision Transformer)

- Vision Transformer (ViT):
 - Image Patching: The input image is divided into fixed-size patches, typically 16x16 pixels.
 - Patch Embedding: Each patch is flattened and linearly embedded into a lower-dimensional vector.
 - Positional Encoding: Positional embeddings are added to retain spatial information.
 - Transformer Encoder: The sequence of patch embeddings is processed by a standard Transformer encoder.
 - Classification: A special "classification token" is added to the sequence for final prediction

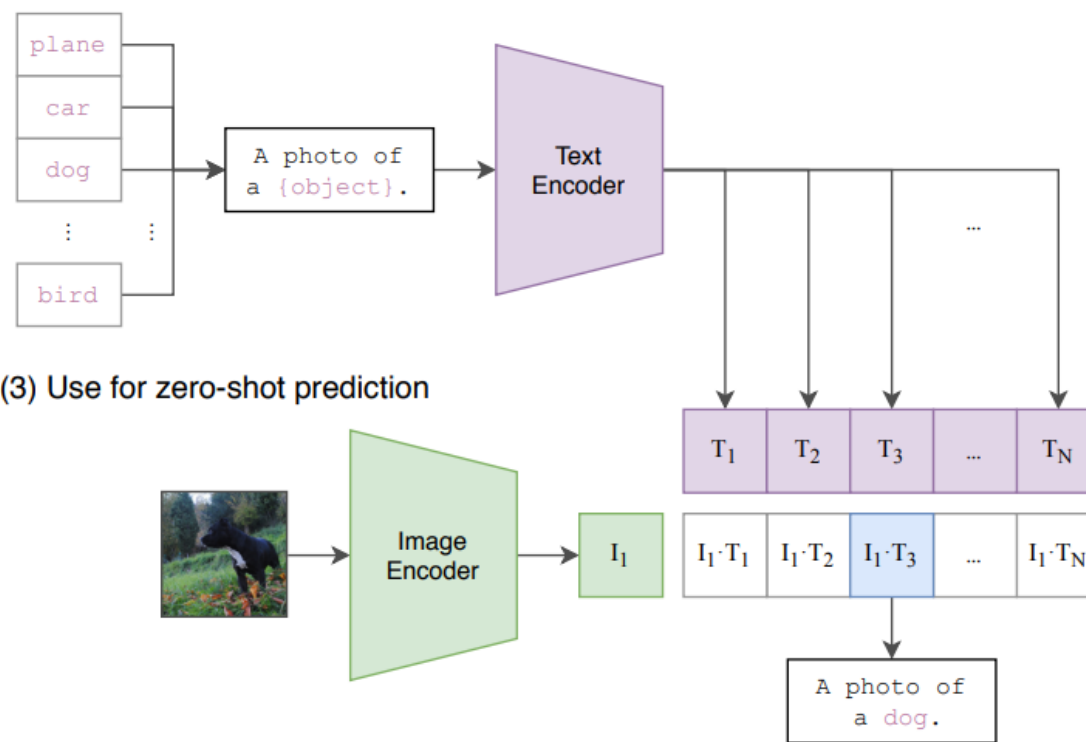
Background (CLIP)

- Contrastive Language–Image Pretraining (CLIP)
 - A model that predicts image-text similarity

(1) Contrastive pre-training



(2) Create dataset classifier from label text

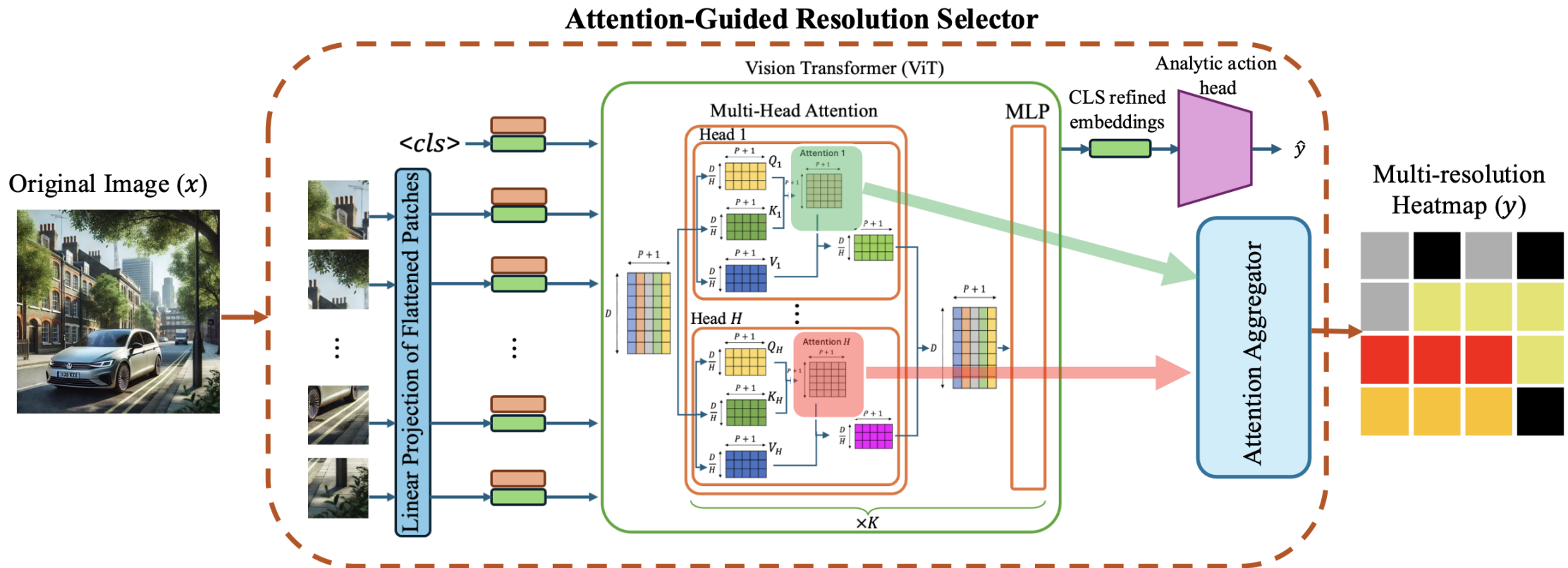


(3) Use for zero-shot prediction

System Model

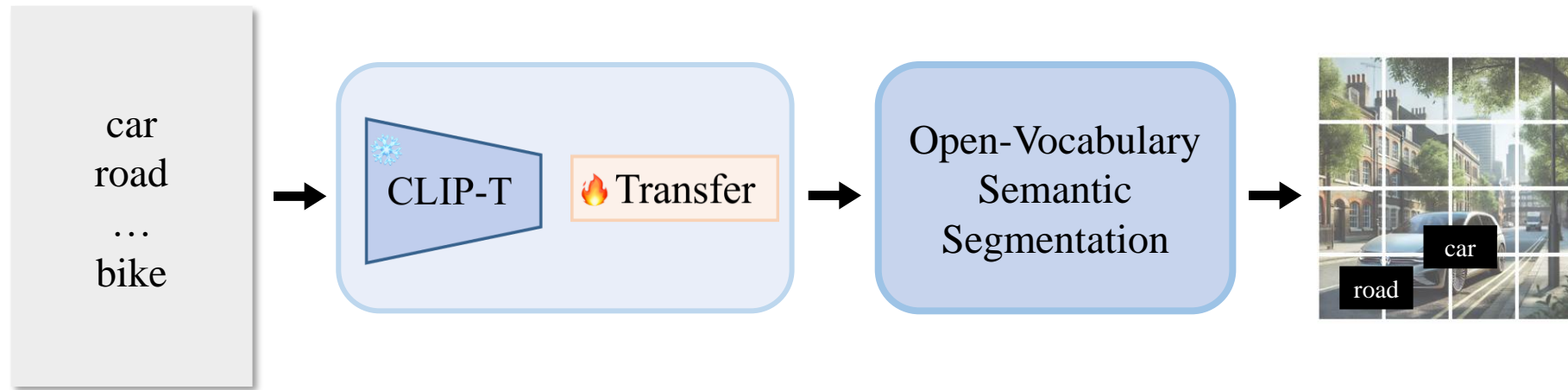
System Model

- Attention-Guided Resolution Selector determines the encoding resolution for each patch based on its semantic importance and available channel rate.



System Model

- Open-vocabulary segmentation framework find an attention score of images based on the text input

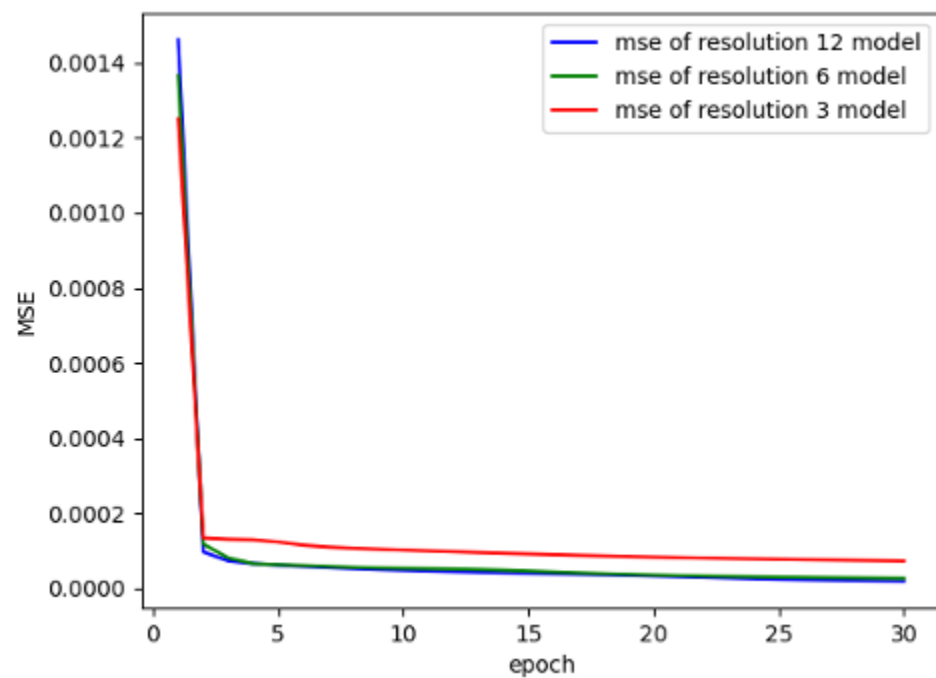


System Model

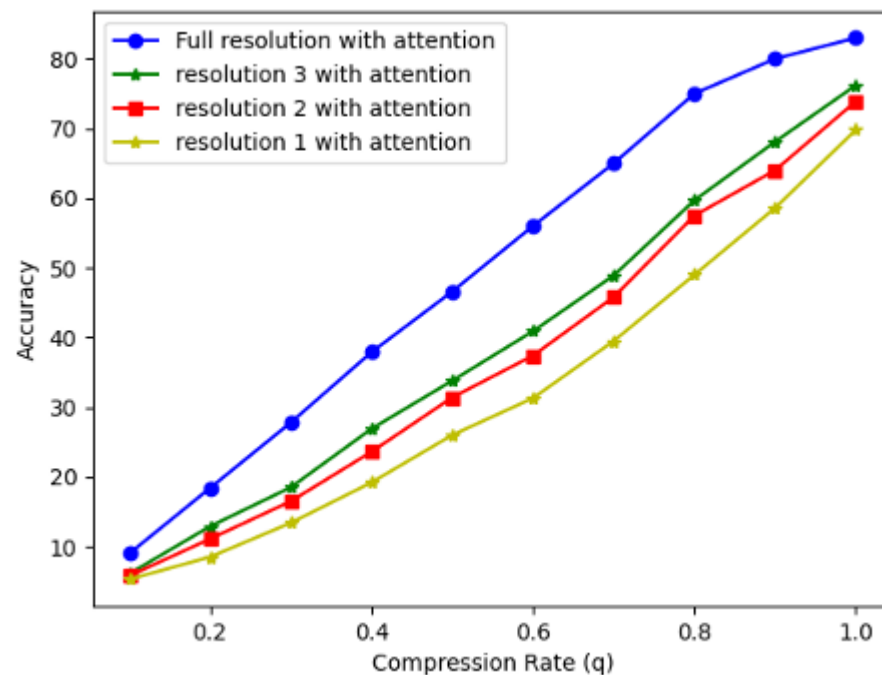
- Key contributions:
 - Multi-resolution encoding for preserving semantic fidelity.
 - Dynamic adaptation to varying channel conditions.
- Results:
 - Optimized bandwidth utilization.
 - Maintained high task accuracy and data quality.

Results

Results

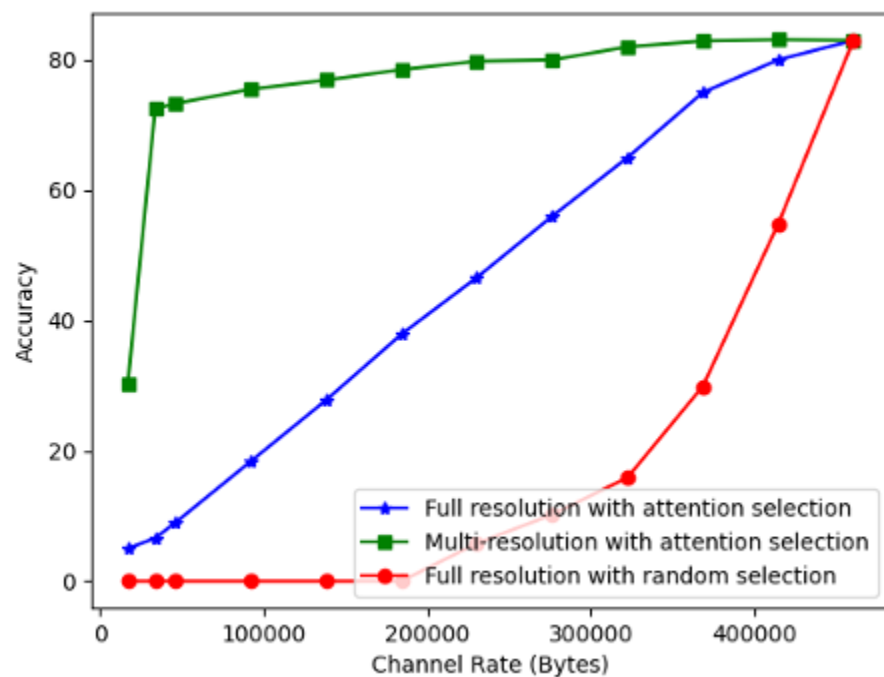


<Reconstruction result for three medium resolutions.>

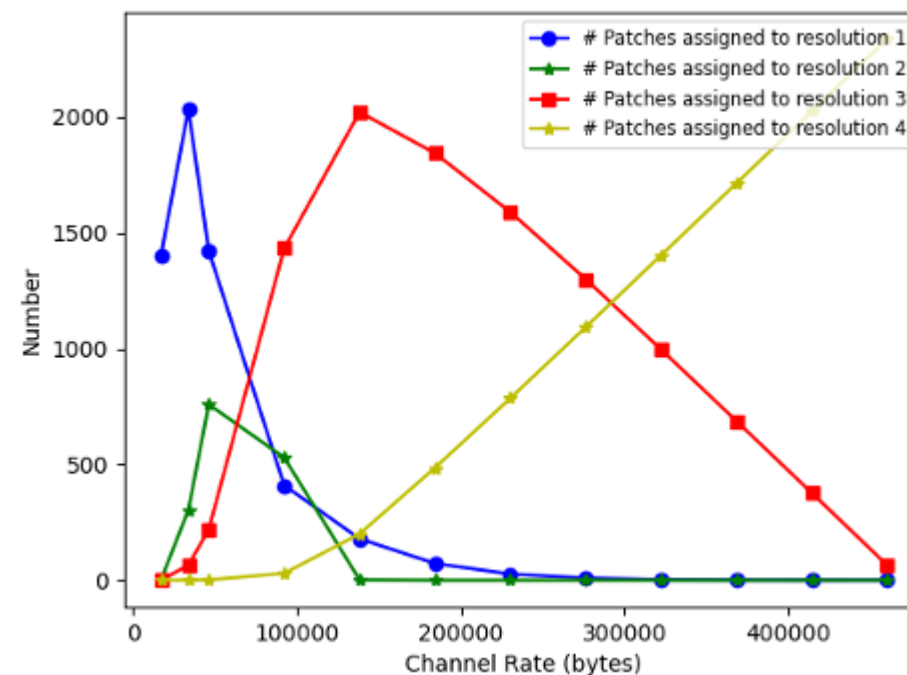


<Accuracy result for three medium resolutions.>

Results



<Accuracy result for adaptive multi-resolution semantic communication framework in various channel rates.>



<Resolution assignment to patches in different channel rate.>

Discussion and Conclusion

Discussion

- Potential Directions:
 - Extend to multimodal data (e.g., text and images together).
 - Extend to video data with recent techniques in computer vision fields
 - Develop task-specific optimization techniques for diverse domains (e.g., image anomaly detection).
- Key Challenges:
 - Efficient training of adaptive encoders.
 - Addressing latency in dynamic channel conditions.

Conclusion

- This work proposes a novel semantic communication framework that fuses open-vocabulary vision–language segmentation with transformer-based compression.
- We build on recent advances in open-vocabulary segmentation, which leverage large pre-trained vision–language models to break away from fixed label sets and segment arbitrary categories described by text prompts.