Stochastic Optimization of Vector Quantization Methods in Application to Speech and Image Processing

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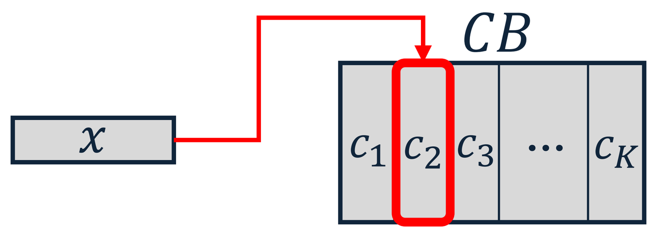
1. Vector Quantization (VQ)

- A data compression technique similar to k-means algorithm
- Quantizes the input vector x to the closest codeword within the codebook (CB)

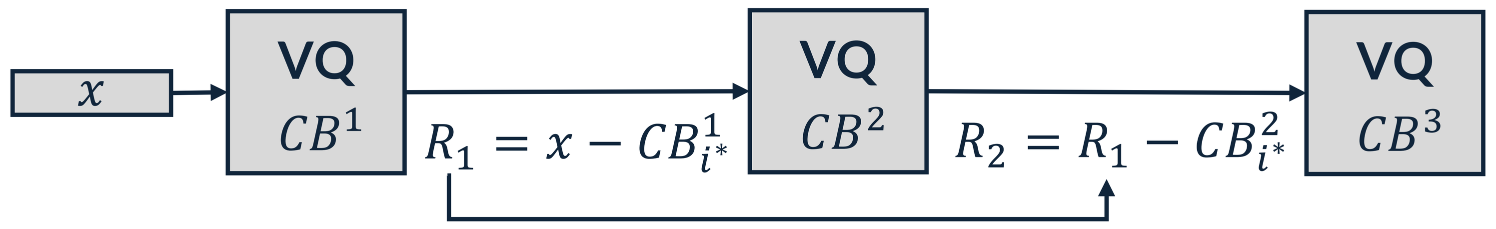


$$x_{quantized} = c_{i^*} \, ; \, i^* = \arg\min_i \|x - c_i\|^2 \, ; i \in \{1, \ldots, K\} \quad (1)$$

- **Challenge:** computationally complex for a large codebook
- **Solution:** employ variants of VQ; Residual VQ, Product VQ, and Additive VQ

2. Residual Vector Quantization (RVQ)

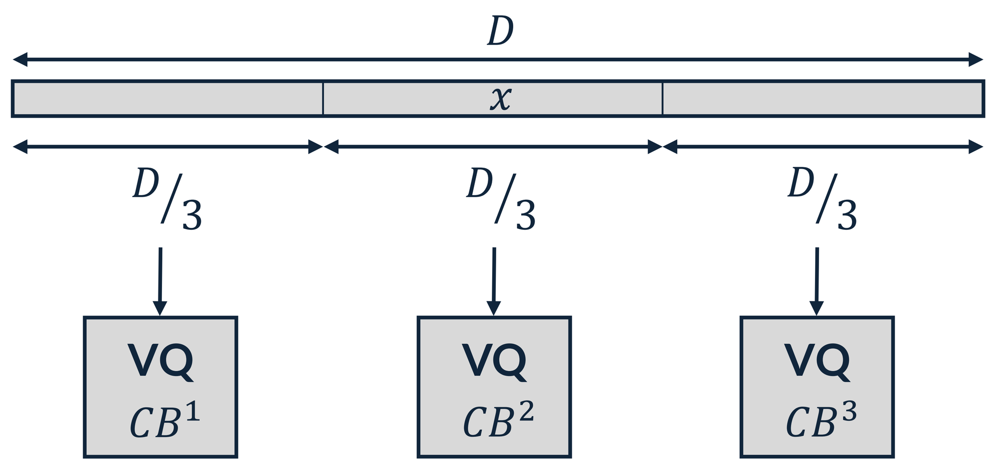
- Quantizes the input vector x by M consecutive VQ modules
- Quantizes x as a summation of M codewords
- Suppose $M = 3$:



$$x_{quantized} = CB^1_{i^*} + CB^2_{i^*} + CB^3_{i^*}$$

3. Product Vector Quantization (PVQ)

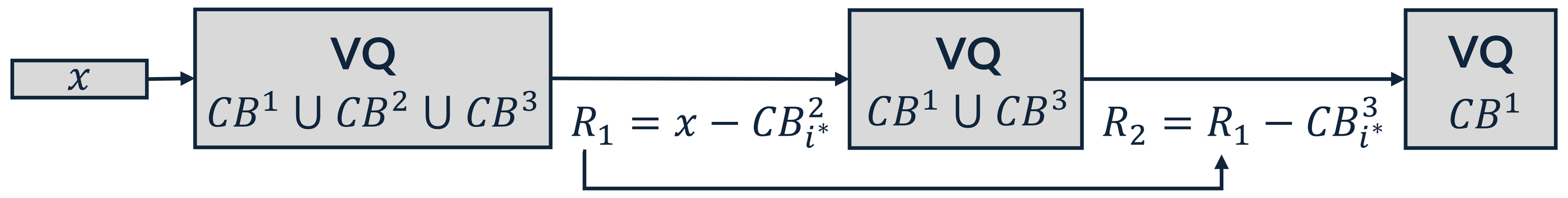
- Splits the input vector x of dimension D to M independent subspaces of dimension D/M
- Applies M independent VQ modules to the existing subspaces
- Quantizes x as a concatenation of M closest codewords
- Suppose $M = 3$:



$$x_{quantized} = concatenate[CB^1_{i^*}, CB^2_{i^*}, CB^3_{i^*}]$$

4. Additive Vector Quantization (AVQ)

- Applies beam searching [1] to find the closest codewords
- Quantizes the input vector x by M consecutive VQ modules
- Quantizes x as a summation of M codewords
- Suppose $M = 3$:



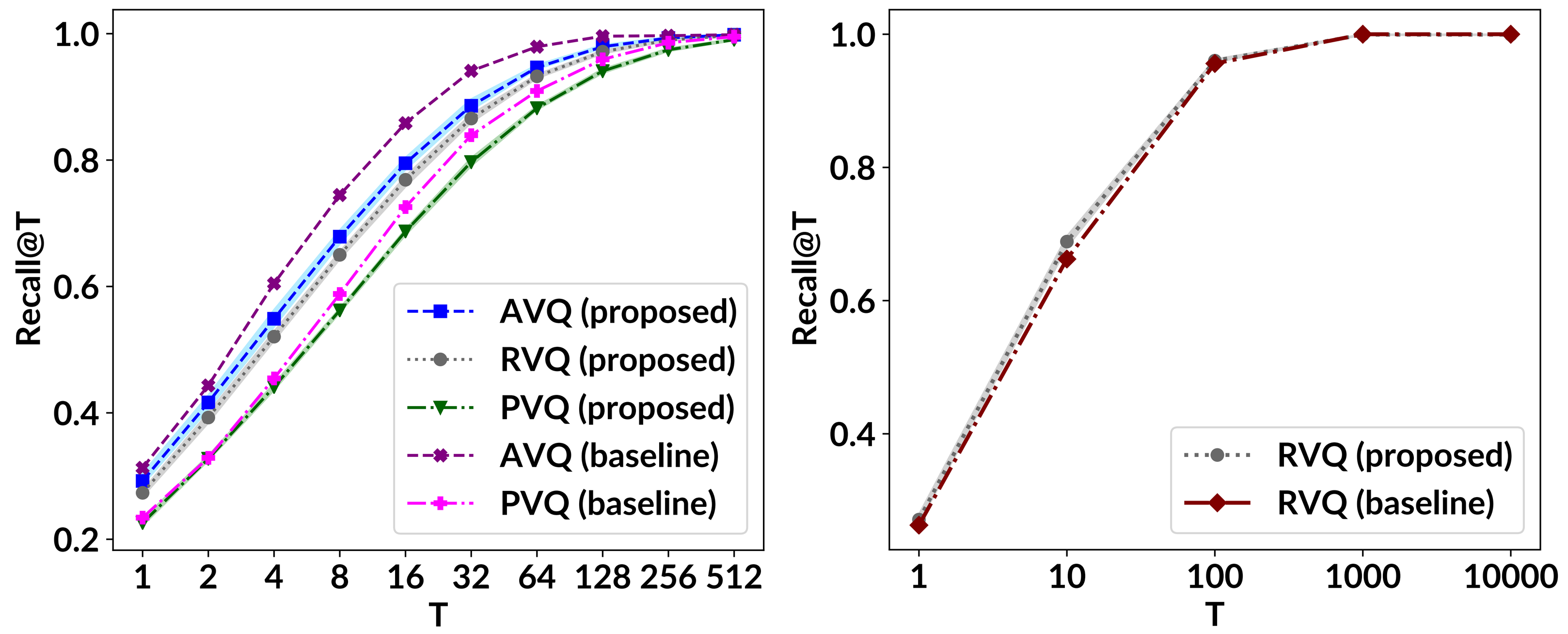
$$x_{quantized} = CB^2_{i^*} + CB^3_{i^*} + CB^1_{i^*}$$

5. Codebooks Optimization

- **Traditional approach:** Optimization by k-means algorithm
- **Problem with machine learning optimization:** argmin function in Eq. 1 is not differentiable
- **Solutions:**
  1. Proposed: Noise Substitution in Vector Quantization (NSVQ) [2]. models the quantization error by noise addition
  2. Conventional: Straight Through Estimator (STE) [3]. copies the gradients over VQ module ($VQ_{gradient} = 1$)
- **Advantages of NSVQ over STE:** 1) More accurate gradients. 2) Faster convergence. 3) No additional hyper-parameter tuning for VQ training.

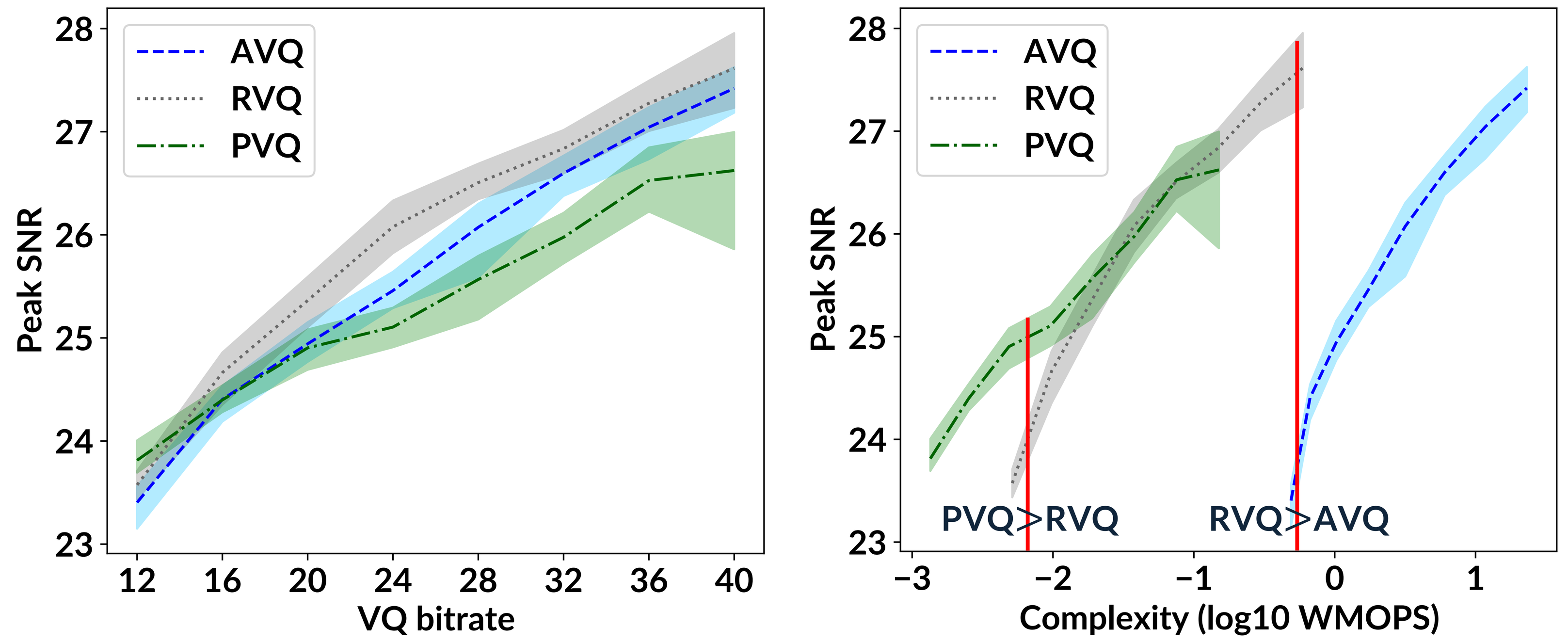
6. Experiments: Approximate Nearest Neighbor (ANN) Search

- Compress the SIFT1M dataset (128-D image descriptors)
- Evaluate recall metric: whether the actual nearest neighbor (from groundtruth) exists in the T computed nearest neighbors



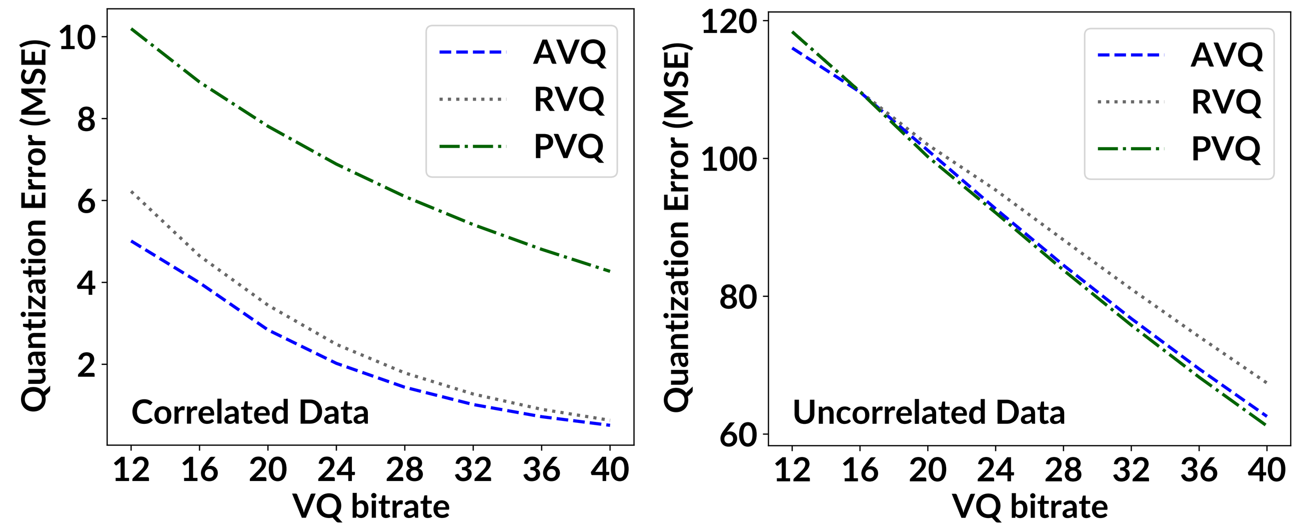
7. Experiments: Image Compression using VQ-VAE

- Compress CIFAR10 dataset with vector quantized variational autoencoder (VQ-VAE)
- Evaluate peak signal to noise ratio (Peak SNR) and complexity



8. Experiments: Toy Example Datasets

- Compress correlated and uncorrelated toy datasets
- Evaluate accuracy with respect to correlation in the data



9. Conclusions

- Variants of VQ are desirable for higher bitrates and dimensions
- Machine learning optimization of codebooks using our recently proposed NSVQ technique [2]
- Achieve comparable results to the baselines in ANN search
- Study the trade-offs between bitrate, accuracy, complexity
- Using our open source implementation [4] enables choosing the most suitable VQ method

References

[1] A. Babenko and V. Lempitsky, "Additive Quantization for Extreme Vector Compression," in *Proc. CVPR*, 2014.
[2] M. H. Vali and T. Bäckström, "NSVQ: Noise Substitution in Vector Quantization for Machine Learning," *IEEE Access*, 2022.
[3] Y. Bengio, N. Léonard, and A. Courville, "Estimating or Propagating Gradients Through Stochastic Neurons for Conditional Computation," *arXiv preprint arXiv:1308.3432*, 2013.
[4] https://gitlab.com/speech-interaction-technology-aalto-university/vq-variants.