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Mini Review **Open Access**

Image Compression by Object-Based Vector Quantization (VQ)

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Vector quantization, VQ, is the process of picking suitable set of representative vectors, code book, to an extremely larger set. The use of representatives or their indices was widely applied in communication and multimedia compression. VQ techniques, for example k-means, adapt the code book vectors location in space to minimize representative's overall bin distortion. The VQ techniques treat boundary vectors contribution to distortion as any other point that leads to the possibility of forming clusters across the boundary of the classes or objects. The study highlights the possibility of having representatives that observe classes or objects boundaries. The code book generated is out of learning process to the classes or the connected regions. Consequently, the code book is not only effective in compression but also suitable for applications such as classifications and recognition. The proposed code book generation process is composed of three phases: Initialization, iterative, and finalization. In the initialization, the min-max algorithm is used to pick the initial code book. The min-max algorithm enables the choice of the code book size based on ceiling to the expected distortion. In the second phase, adapted LBG iterates on the code book, starting with the initial, to learn classes or objects boundaries. The iterative process focuses on using the miss-represented points to attract the right representative and repels the current. In the finalization phase, code book point that does not contribute to correct decoding is dropped from consideration in the final code book.

Vector quantization (VQ) is a classical quantization technique from signal processing that allows the modeling of probability density functions by the distribution of prototype vectors. It was originally used for data compression. It works by dividing a large set of points (vectors) into groups having approximately the same number of points closest to them. Each group is represented by its centroid point, as in k-means and some other clustering algorithms.

The density matching property of vector quantization is powerful, especially for identifying the density of large and high-dimensioned data. Since data points are represented by the index of their closest centroid, commonly occurring data have low error, and rare data high error. This is why VQ is suitable for lossy data compression. It can also be used for lossy data correction and density estimation.

Vector quantization is based on the competitive learning paradigm, so it is closely related to the self-organizing map model and to sparse coding models used in deep learning algorithms such as auto encoder.

Training

A simple training algorithm for vector quantization is:

1. Pick a sample point at random
2. Move the nearest quantization vector centroid towards this sample point, by a small fraction of the distance
3. Repeat

A more sophisticated algorithm reduces the bias in the density matching estimation, and ensures that all points are used, by including an extra sensitivity parameter:

1. Increase each centroid's sensitivity by a small amount
2. Pick a sample point at random
3. Find the quantization vector centroid with the smallest <distance-sensitivity>

a. Move the chosen centroid toward the sample point by a small fraction of the distance

b. Set the chosen centroid's sensitivity to zero

4. Repeat

It is desirable to use a cooling schedule to produce convergence: see simulated annealing. Another (simpler) method is LBG which is based on K-Means.

The algorithm can be iteratively updated with 'live' data, rather than by picking random points from a data set, but this will introduce some bias if the data are temporally correlated over many samples. A vector is represented either geometrically by an arrow whose length corresponds to its magnitude and points in an appropriate direction, or by two or three numbers representing the magnitude of its components.

Applications

Vector quantization is used for lossy data compression, lossy data correction, pattern recognition, density estimation and clustering.

Lossy data correction, or prediction, is used to recover data missing from some dimensions. It is done by finding the nearest group with the data dimensions available, and then predicting the result based on the values for the missing dimensions, assuming that they will have the same value as the group's centroid.

For density estimation, the area/volume that is closer to a particular centroid than to any other is inversely proportional to the density (due to the density matching property of the algorithm).

Vector quantization, also called "block quantization" or "pattern matching quantization" is often used in lossy data compression. It works by encoding values from a multidimensional vector space into a finite set of values from a discrete subspace of lower dimension. A lower-space vector requires less storage space, so the data is compressed. Due to the density matching property of vector quantization, the compressed data has errors that are inversely proportional to density.

The transformation is usually done by projection or by using a codebook. In some cases, a codebook can be also used to entropy code the discrete value in the same step, by generating a prefix coded variable-length encoded value as its output.

The set of discrete amplitude levels is quantized jointly rather than each sample being quantized separately. Consider a k-dimensional vector {\displaystyle [x_{1},x_{2},...,x_{k}]} of amplitude levels. It is compressed by choosing the nearest matching vector from a set of n-dimensional vectors {\displaystyle [y_{1},y_{2},...,y_{n}]} , with n < k.

All possible combinations of the n-dimensional vector {\displaystyle [y_{1},y_{2},...,y_{n}]} form the vector space to which all the quantized vectors belong.

Only the index of the codeword in the codebook is sent instead of the quantized values. This conserves space and achieves more compression.

Twin vector quantization (VQF) is part of the MPEG-4 standard dealing with time domain weighted interleaved vector quantization.