Abstract

Visual inference over a transmission channel is increasingly becoming an important problem in a variety of applications. In such applications, low latency and bit-rate consumption are often critical performance metrics, making data compression necessary. In this paper, we examine feature compression for support vector machine (SVM)-based inference using quantized randomized embeddings. We demonstrate that embedding the features is equivalent to using the SVM kernel trick with a mapping to a lower dimensional space. Furthermore, we show that universal embeddings - a recently proposed quantized embedding design - approximate a radial basis function (RBF) kernel, commonly used for kernel-based inference. Our experimental results demonstrate that quantized embeddings achieve 50\% rate reduction, while maintaining the same inference performance. Moreover, universal embeddings achieve a further reduction in bit-rate over conventional quantized embedding methods, validating the theoretical predictions.

Data Compression Conference (DCC), 2015
Kernel Machine Classification Using Universal Embeddings

Petros T. Boufounos and Hassan Mansour
Mitsubishi Electric Research Laboratories
Cambridge, MA 02139, USA, \{petrosb, mansour\}@merl.com

Visual inference over a transmission channel is increasingly becoming an important problem in a variety of applications. In such applications, low latency and bit-rate consumption are often critical performance metrics, making data compression necessary. In this paper, we examine feature compression for support vector machine (SVM)-based inference using quantized randomized embeddings.

Specifically, we consider universal embeddings [1], namely transformations of the form \( \phi(x) = Q(Ax + e) \), where \( A \in \mathbb{R}^{M \times N} \) is a randomly generated matrix with i.i.d. standard normal entries, \( e \in \mathbb{R}^M \) is a random dither with elements drawn from an i.i.d. distribution uniform in \([0, \Delta]\), \( Q(y) \) is a non-monotonic scalar quantizer applied element-wise to its vector input, mapping \( y \) to 1 if \( y \in [2k, 2k + 1) \) and to -1 otherwise, \( \Delta \) is a scaling parameter, and \( x \in \mathbb{R}^N \) is the vector being embedded—typically a feature vector or a signal to be classified.

Universal embeddings have been shown to satisfy

\[
\begin{align*}
g(\|x - x'\|_2) - \tau & \leq d_H(\phi(x), \phi(x')) \leq g(\|x - x'\|_2) + \tau, \\
\end{align*}
\]

(1)

where \( d_H(\cdot, \cdot) \) is the Hamming distance of the embedded signals and \( g(d) \) is the map

\[
g(d) = \frac{1}{2} - \sum_{i=0}^{+\infty} \frac{e^{-\left(\frac{(xi(2i+1))d}{\sqrt{2}\Delta}\right)^2}}{(\pi(i+1/2))^2} \approx \begin{cases} 
\frac{d}{\Delta} \sqrt{\frac{2}{\pi}}, & \text{if } d \leq \frac{\Delta}{2} \frac{\sqrt{\pi}}{\sqrt{2}}, \\
0.5, & \text{otherwise}
\end{cases}
\]

(2)

with overwhelming probability, and \( \tau \) decreasing as \( 1/\sqrt{M} \).

We demonstrate that SVM kernels based on universal embeddings are very good approximations of radial basis function (RBF) kernels commonly used in classification. Thus, embedding features to a lower dimensional space is equivalent to using the SVM kernel trick with a kernel that approximates an RBF kernel.

**Proposition.** Let \( \phi(x) : \mathbb{R}^N \to \{-1, 1\}^M \) be a mapping function defined as above, with \( q = \phi(x) \). The kernel function \( K(x, x') \) given by \( K(x, x') = \frac{1}{2M} q^T q' \) is shift invariant and approximates the radial basis function \( K(x, x') \approx \frac{1}{2} - g(\|x - x'\|_2) \), with \( g(d) \), as defined in (2). Furthermore, this RBF approximates the Gaussian RBF.

Our experimental results on an 8-class image database using histogram-of-gradients (HOG) features demonstrate that quantized embeddings achieve 50% rate reduction over quantization of the feature vectors, while maintaining the same inference performance. Moreover, universal embeddings also achieve a reduction in bit-rate over conventional quantized embedding methods, validating the theoretical predictions.