

Solutions to Problem Set 9

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Data Compression With And Without Deep Probabilistic Models

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Course materials available at <https://robamler.github.io/teaching/compress22/>

Problem 9.1: Simple Variational Autoencoder (VAE)

The accompanying jupyter notebook guides you through the implementation of a simple (toy) variational autoencoder. Follow the instructions in the notebook to complete the implementation.

Problem 9.2: Random Sampling by Decoding Random Bit Strings

In this problem, we show that decoding some message from a uniformly distributed random bit string with an entropy coder that is optimal for some probabilistic model is equivalent to drawing a random sample from the same probabilistic model.

As a reminder, this issue came up in the lecture on June 23 when we derived the connection between the (modified) bits-back coding algorithm and variational inference. The encoding process of our modified bits-back coding algorithm started with decoding z from some existing bit string, where the entropy model for the coder was the variational distribution $Q_\phi(Z | \mathbf{X} = \mathbf{x})$. Since the existing bit string was not under our control, we wanted to average over all possible bit strings, and we claimed that this averaging was equivalent to taking the expectation under $z \sim Q_\phi(Z | \mathbf{X} = \mathbf{x})$. You will provide the proof for this claim in this exercise.

Since the equivalence between sampling and decoding from a uniformly distributed random bit string holds in general and not just for bits-back coding, we won't use the letters z and Q here and we will instead follow our usual naming conventions and consider the case of decoding a message $\mathbf{x} \in \mathfrak{X}^k$ that is a sequence of k symbols $x_i \in \mathfrak{X}$ from some discrete alphabet \mathfrak{X} using a model $P(\mathbf{X})$. For simplicity, we'll assume that $P(\mathbf{X})$ models the symbols as i.i.d., i.e., $P(\mathbf{X}) = \prod_{i=1}^k P(X_i)$ where $P(X_i)$ is the same probability distribution for all $i \in \{1, \dots, k\}$.

- (a) Let's first convince ourselves that the claim holds for the concrete case of decoding with Asymmetric Numeral Systems (ANS). Assume you have a string of statistically independent and uniformly distributed random bits, and you decode the first symbol x_1 from it using ANS with the model $P(X_1)$.

Recall how decoding with ANS works and argue why x_1 will be distributed (almost) as $x_1 \sim P(X_1)$ (with the only deviation coming from the fact that ANS approximates $P(X_1)$ in fixed point arithmetic). You may assume that the random

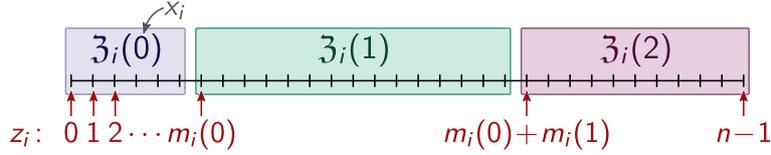


Figure 1: Reminder of how ANS works (for Problem 9.2 (a)).

bit string is at least `precision` bits long so that ANS doesn't run out of bits. You may want to refer to Figure 1 for your argument.

Solution: The ANS algorithm executes the following three steps for decoding a symbol x_i from some bit string:

1. consume `precision` bits from the bit string and interpret them as the binary representation of a number $z_i \in \{0, 1, \dots, n - 1\}$ where $n = 2^{\text{precision}}$;
2. identify the unique symbol x_i that satisfies $z_i \in \mathfrak{Z}_i(x_i)$; here, $\mathfrak{Z}_i(x_i)$ is a subset of the range $\{0, 1, \dots, n - 1\}$ with size $|\mathfrak{Z}_i(x_i)| = n Q(X_i = x_i)$ where $Q(X_i)$ approximates of the entropy model $P(X_i)$ in `precision`-bit fixed point arithmetic;
3. encode the position of z_i within $\mathfrak{Z}_i(x_i)$ back onto the bit string.

Only steps 1 and 2 are relevant for decoding the first symbol x_1 . If the `precision` bits that we consume in step 1 are statistically independent and uniformly distributed, then z_1 is uniformly distributed over the range $\{0, 1, \dots, n - 1\}$, i.e., the probability for any given z_1 in this range is $\frac{1}{n}$. Thus, the probability that $z_1 \in \mathfrak{Z}_1(x_1)$ for some given x_1 is $|\mathfrak{Z}_1(x_1)|/n = Q(X_1 = x_1)$. This is almost equal to the probability of x_1 under our entropy model $P(X_1)$ except for tiny rounding errors due to the fact that ANS approximates $P(X_1)$ in fixed point arithmetic. ■

The equivalence between decoding from a random bit string and sampling from the employed entropy model is actually not just a special property of ANS but holds for all optimal entropy coders. Roughly speaking, the argument for this is that *encoding* symbols that are distributed according to the employed entropy model must result in a bit string of maximum entropy (i.e., independent and uniformly distributed bits) because otherwise the bit string could be further compressed and thus the coder is not optimal. Therefore, *decoding* from independent and uniformly distributed random bits must reverse the process and result in samples from the model. However, formalizing this argument is a bit more subtle because the length of the resulting bit string depends on the encoded symbols.

Let C be an encoder for symbols $x_i \in \mathfrak{X}$ that can append to some existing bit string. For concreteness, we'll assume that encoding and decoding operate with "stack" semantics (i.e., "last in first out", as in ANS). Thus, $C : (\{0, 1\}^*, \mathfrak{X}) \rightarrow \{0, 1\}^*$ is an injective function that maps some existing bit string $s \in \{0, 1\}^*$ and a symbol $x_i \in \mathfrak{X}$ to a new bit string $C(s, x_i) \in \{0, 1\}^*$. The decoding operation C^{-1} inverts this pro-

cess and recovers both the encoded symbol x_i as well as the original bit string s , i.e., $C^{-1}(C(s, x_i)) = (s, x_i)$.

We further introduce the shorthands $\ell_{\min} := \min_{x_i \in \mathfrak{X}} [-\log_2 P(X_i = x_i)]$ and $\ell_{\max} := \max_{x_i \in \mathfrak{X}} [-\log_2 P(X_i = x_i)]$ for the minimum and maximum information content per symbol and we assume, for simplicity, that our model P has $\ell_{\min} > 0$ and $\ell_{\max} < \infty$.

- (b) Assume we are given some initial random bit string S_0 with some fixed length $|S_0|$, where the bits are independent and uniformly distributed. We now use the coder C to decode some number k of symbols X_k from S . Since the bit string S is random, we have to treat the decoded symbols X_k also as random variables, and we denote the probability distribution that is induced by decoding from S as $P_{\text{dec}}(X_1, \dots, X_k)$ to distinguish it from our model P .

In detail, we decode one symbol after the other:

$$\begin{aligned} (S_1, X_1) &:= C^{-1}(S_0); \\ (S_2, X_2) &:= C^{-1}(S_1); \\ (S_3, X_3) &:= C^{-1}(S_2); \\ &\vdots \\ (S_k, X_k) &:= C^{-1}(S_{k-1}). \end{aligned} \tag{1}$$

We assume that the coder C is an optimal stream code for the model $P(\mathbf{X}) = \prod_{i=1}^k P(X_i)$ in the sense that decoding some specific message $\mathbf{x} \in \mathfrak{X}^k$ consumes $-\log_2 P(\mathbf{X}=\mathbf{x}) + \varepsilon$ bits, where $\varepsilon \in [-\gamma, \gamma]$ with some constant γ takes into account that the stream code amortizes fractional information contents over multiple bits (e.g., in ANS, we have $\gamma = \text{precision}$). In particular, this means that

$$|S_0| - |S_k| > -\log_2 P(\mathbf{X}=\mathbf{x}) - \gamma \quad \forall \mathbf{x} \in \mathfrak{X}^k \quad \text{with} \quad k \leq (|S_0| - \gamma)/\ell_{\max}. \tag{2}$$

where $|\cdot|$ denotes the length of a bit string and we assumed that the original bit string S_0 is long enough so that we don't run out of bits, i.e., $|S_0| \geq k \ell_{\max} + \gamma$.

Use Eq. 2 to show that¹

$$P_{\text{dec}}(\mathbf{X}=\mathbf{x}) < 2^{\gamma+1} P(\mathbf{X}=\mathbf{x}) \quad \forall \mathbf{x} \in \mathfrak{X}^k \quad \text{with} \quad k \leq (|S_0| - \gamma)/\ell_{\max}. \tag{3}$$

Hint: How many initial bit strings S_0 are there at most that decode to a given message \mathbf{x} given that C^{-1} is injective, and how many total bit strings of the (fixed) length $|S_0|$ are there?

Solution: Since we assume that the original bit string S_0 is uniformly distributed over $\{0, 1\}^{|S_0|}$, each possible initial bit string s_0 has probability $P(S_0 = s_0) =$

¹An earlier version of this problem set wrongfully stated the bound as $2^\gamma P(\mathbf{X}=\mathbf{x})$, without the “+1” in the exponent. This error had no impact on any arguments that build on Eq. 3 since the “+1” can be absorbed in a redefinition of γ .

$1/|\{0, 1\}^{|S_0|}| = 2^{-|S_0|}$. The probability $P_{\text{dec}}(\mathbf{X}=\mathbf{x})$ of decoding a given message \mathbf{x} is therefore given by $2^{-|S_0|}$ times the number of initial bit strings s_0 that decode to \mathbf{x} . We can bound this number by using the fact that the decoder C^{-1} of an optimal lossless code is injective. Therefore, its composition in Eq. 1, which maps S_0 to the tuple (S_k, \mathbf{X}) , is also injective, i.e., each initial bit string S_0 that decodes to a given message $\mathbf{X}=\mathbf{x}$ must leave a different remainder S_k . Thus, the number of original bit strings S_0 that decode to a given message $\mathbf{X}=\mathbf{x}$ cannot exceed the number of possible outcomes for the remaining bit string S_k .

In order to derive a bound on the number of possibilities for S_k , we first derive upper bound on its length by solving Eq. 2 for $|S_k|$:

$$|S_k| < |S_0| - (-\log_2 P(\mathbf{X}=\mathbf{x})) + \gamma := L_{k,\max}.$$

How many distinct bit strings are there whose length is less than $L_{k,\max}$? For any given length ℓ' , there are $2^{\ell'}$ distinct bit strings of that length. Thus, the number of bit strings that are shorter than $L_{k,\max}$ is

$$\begin{aligned} |\{\text{bit strings } S_k \text{ with } |S_k| < L_{k,\max}\}| &= |\{\text{bit strings } S_k \text{ with } |S_k| \leq \lceil L_{k,\max} \rceil - 1\}| \\ &= \sum_{\ell'=0}^{\lceil L_{k,\max} \rceil - 1} 2^{\ell'} = 2^{\lceil L_{k,\max} \rceil} - 1 \\ &< 2^{L_{k,\max}+1} = 2^{|S_0|+\gamma+1} P(\mathbf{X}=\mathbf{x}). \end{aligned}$$

As discussed above, the probability $P_{\text{dec}}(\mathbf{X}=\mathbf{x})$ of decoding \mathbf{x} is $2^{-|S_0|}$ times the number of bit strings S_0 that decode to \mathbf{x} . Thus, $P_{\text{dec}}(\mathbf{X}=\mathbf{x}) < 2^{\gamma+1} P(\mathbf{X}=\mathbf{x})$. ■

(c) Use Eq. 3 to derive an upper bound on the Kullback-Leibler (KL) divergence

$$\Delta_k := D_{\text{KL}}(P_{\text{dec}}(X_1, \dots, X_k) \parallel P(X_1, \dots, X_k)) \leq \text{const} \quad (4)$$

from the model $P(X_1, \dots, X_k) = P(X_1)P(X_2) \cdots P(X_k)$ to the probability distribution $P_{\text{dec}}(X_1, \dots, X_k)$ that is induced by decoding from the random bit string S_0 .

Solution: We write out the definition of the KL-divergence and apply Eq. 3:

$$\begin{aligned} \Delta_k &:= D_{\text{KL}}(P_{\text{dec}}(X_1, \dots, X_k) \parallel P(X_1, \dots, X_k)) \\ &= \mathbb{E}_{P_{\text{dec}}} \left[\log_2 \frac{P_{\text{dec}}(X_1, \dots, X_k)}{P(X_1, \dots, X_k)} \right] \leq \gamma + 1. \end{aligned}$$

■

Eq. 4 holds for all $k \leq (|S_0| - \gamma) / \ell_{\max}$ and the bound that you should find is a constant (independent of k). Therefore, you might already be convinced that the KL-divergence must actually be zero since, if it wasn't it should grow for growing k . The remaining parts of this problem formalize this argument.

(d) Show that

$$\Delta_k - \Delta_{k-1} = H(P_{\text{dec}}(X_k), P(X_k)) - H_{P_{\text{dec}}}(X_k | X_1, X_2, \dots, X_{k-1}) \quad (5)$$

where, following our usual notation, the first term on the right-hand side denotes the cross entropy between the marginal distribution of X_k under P_{dec} and the marginal model distribution $P(X_k)$, and the second term on the right-hand side is the conditional entropy as defined in Problem 4.3 (c) on Problem Set 4.

Then show that

$$\Delta_k - \Delta_{k-1} \geq D_{\text{KL}}(P_{\text{dec}}(X_k) || P(X_k)). \quad (6)$$

Hint: Use the fact that the conditional entropy is smaller or equal to the entropy (recall: the difference between the two is the mutual information, which is nonnegative).

Solution: We have

$$\begin{aligned} \Delta_k - \Delta_{k-1} &= \mathbb{E}_{P_{\text{dec}}} \left[\log_2 \frac{P_{\text{dec}}(X_1, \dots, X_k)}{P(X_1, \dots, X_k)} \frac{P(X_1, \dots, X_{k-1})}{P_{\text{dec}}(X_1, \dots, X_{k-1})} \right] \\ &= \mathbb{E}_{P_{\text{dec}}} \left[-\log_2 \frac{P(X_1, \dots, X_k)}{P(X_1, \dots, X_{k-1})} + \log_2 \frac{P_{\text{dec}}(X_1, \dots, X_k)}{P_{\text{dec}}(X_1, \dots, X_{k-1})} \right]. \end{aligned}$$

Since we assumed that $P(\mathbf{X})$ models the symbols as i.i.d., i.e., $P(\mathbf{X}) = \prod_{i=1}^k P(X_i)$, we can simplify:

$$\begin{aligned} \Delta_k - \Delta_{k-1} &= \mathbb{E}_{P_{\text{dec}}} \left[-\log_2 P(X_k) + \log_2 P_{\text{dec}}(X_k | X_1, \dots, X_{k-1}) \right] \\ &= H(P_{\text{dec}}(X_k), P(X_k)) - H_{P_{\text{dec}}}(X_k | X_1, \dots, X_{k-1}) \\ &\geq H(P_{\text{dec}}(X_k), P(X_k)) - H_{P_{\text{dec}}}(X_k) \\ &= D_{\text{KL}}(P_{\text{dec}}(X_k) || P(X_k)) \end{aligned}$$

where we used $H_{P_{\text{dec}}}(X_k | X_1, \dots, X_{k-1}) = H_{P_{\text{dec}}}(X_k) - I_{P_{\text{dec}}}(X_k; (x_1, \dots, X_{k-1})) \leq H_{P_{\text{dec}}}(X_k)$ since the mutual information I is nonnegative. ■

(e) Finally, use the telescopic sum $\Delta_k = \Delta_1 + \sum_{i=2}^k (\Delta_i - \Delta_{i-1})$ and Eqs. 4 and 6 to show that

$$\sum_{i=1}^k D_{\text{KL}}(P_{\text{dec}}(X_i) || P(X_i)) \leq \Delta_k < \text{const} \quad (7)$$

and thus, that the average KL-divergence from $P(X_i)$ to $P_{\text{dec}}(X_i)$ per symbol X_i can be bounded by an arbitrarily small constant $\propto 1/k$ by considering increasingly long initial random bit strings S_0 .

Solution: The telescopic sum follows by simply writing out the terms and observing that all Δ_i with $i < k$ cancel. Thus,

$$\begin{aligned}\Delta_k &= \Delta_1 + \sum_{i=2}^k (\Delta_i - \Delta_{i-1}) \\ &\stackrel{(6)}{\geq} D_{\text{KL}}(P_{\text{dec}}(X_1) \parallel P(X_1)) + \sum_{i=2}^k D_{\text{KL}}(P_{\text{dec}}(X_i) \parallel P(X_i)) \\ &= \sum_{i=1}^k D_{\text{KL}}(P_{\text{dec}}(X_i) \parallel P(X_i)).\end{aligned}$$

Combining this with the bound $\Delta_k \leq \gamma + 1$ we find that the KL-divergence from $P(X_i)$ to $P_{\text{dec}}(X_i)$ *per symbol* goes to zero for long messages,

$$\frac{1}{k} \sum_{i=1}^k D_{\text{KL}}(P_{\text{dec}}(X_i) \parallel P(X_i)) \leq \frac{\gamma + 1}{k} \xrightarrow{k \rightarrow \infty} 0.$$

■