

MathDNN Homework 8

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Problem 1

Since \mathcal{T} is a 2×2 average pool operator with stride 2, A will be given as

$$A = \begin{bmatrix} \frac{1}{4} & \frac{1}{4} & 0 & \cdots & 0 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots \\ 0 & 0 & \frac{1}{4} & \frac{1}{4} & 0 & \cdots & 0 & 0 & 0 & 0 & \frac{1}{4} & \frac{1}{4} & 0 & \cdots & 0 & 0 & \cdots \\ \vdots & & & & \ddots & \ddots & & & & & & \ddots & \ddots & & & & \cdots \\ 0 & 0 & 0 & 0 & \cdots & 0 & \frac{1}{4} & \frac{1}{4} & 0 & 0 & 0 & 0 & \cdots & 0 & \frac{1}{4} & \frac{1}{4} & \cdots \\ & & & & & & & & & & & & & & & & \ddots \\ & & & & & & & & & & & & & & & & \ddots \end{bmatrix}.$$

and

$$[\mathcal{T}(X)]_{i,j} = \frac{1}{4} \left([X]_{2i-1,2j-1} + [X]_{2i-1,2j} + [X]_{2i,2j-1} + [X]_{2i,2j} \right).$$

So by the definition of \mathcal{T}^\top , we can calculate

$$\begin{aligned} \sum_{i=1}^{m/2} \sum_{j=1}^{n/2} [Y]_{i,j} [\mathcal{T}(X)]_{i,j} &= \sum_{i=1}^{m/2} \sum_{j=1}^{n/2} \frac{1}{4} [Y]_{i,j} \left([X]_{2i-1,2j-1} + [X]_{2i-1,2j} + [X]_{2i,2j-1} + [X]_{2i,2j} \right) \\ &= \sum_{i=1}^m \sum_{j=1}^n \frac{1}{4} [Y]_{\lceil i/2 \rceil, \lceil j/2 \rceil} [X]_{i,j} = \sum_{i=1}^m \sum_{j=1}^n [\mathcal{T}^\top(Y)]_{i,j} [X]_{i,j}. \end{aligned}$$

Therefore we can compute \mathcal{T}^\top by calculating $[\mathcal{T}^\top(Y)]_{i,j} = \frac{1}{4} [Y]_{\lceil i/2 \rceil, \lceil j/2 \rceil}$. This is equivalent to $\frac{1}{4}$ times the nearest neighbor upsampling.

Problem 2

```
# Using Nearest Neighbor Upsampling
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```
layer = nn.Upsample(scale_factor=r, mode='nearest')
```

```
# Using Transpose Convolution
```

```
layer = nn.ConvTranspose2d(in_channels, out_channels, kernel_size=r, stride=r)
```

```
layer.weight.data = torch.ones(layer.weight.data.shape)
```

The two implementations above are equivalent. Transpose convolution with same kernel size and stride can be understood as nearest neighbor upsampling where all elements of the weight tensor are 1.

Problem 3

(a) Since f is a convex function, we can apply Jensen's inequality to f , which gives

$$\begin{aligned} D_f(X||Y) &= \int f\left(\frac{p_X(x)}{p_Y(x)}\right) p_Y(x) dx = \mathbf{E}\left[f\left(\frac{p_X(Y)}{p_Y(Y)}\right)\right] \\ &\geq f\left(\mathbf{E}\left[\frac{p_X(Y)}{p_Y(Y)}\right]\right) = f\left(\int \frac{p_X(x)}{p_Y(x)} p_Y(x) dx\right) = f(1) = 0. \end{aligned}$$

(b) If $f(t) = -\log t$,

$$D_f(X||Y) = \int -\log\left(\frac{p_X(x)}{p_Y(x)}\right) p_Y(x) dx = \int \log\left(\frac{p_Y(x)}{p_X(x)}\right) p_Y(x) dx = D_{\text{KL}}(Y||X).$$

If $f(t) = t \log t$,

$$D_f(X||Y) = \int \left(\frac{p_X(x)}{p_Y(x)}\right) \log\left(\frac{p_X(x)}{p_Y(x)}\right) p_Y(x) dx = \int \log\left(\frac{p_Y(x)}{p_X(x)}\right) p_X(x) dx = D_{\text{KL}}(X||Y).$$

Problem 4

We should show $G(u) \leq x \Leftrightarrow u \leq F(x)$ for all $u \in (0, 1)$ and $x \in \mathbb{R}$.

First, if $G(u) \leq x$, we obtain $F(G(u)) \leq F(x)$ since F is nondecreasing. Also, since F is right continuous and $\lim_{x \rightarrow -\infty} F(x) = 0$, $G(u)$ exists such that $u \leq F(G(u))$. Therefore $u \leq F(G(u)) \leq F(x)$, so $u \leq F(x)$.

Next, if $u \leq F(x)$, we obtain $G(u) \leq x$ from the definition of $G(u)$.

Therefore we obtain $G(u) \leq x \Leftrightarrow u \leq F(x)$, so

$$\Pr(G(U) \leq t) = \Pr(U \leq F(t)) = F(t).$$

Problem 5

From the relation $Y = \varphi(X) = A^{-1}(X - b)$, we obtain the following.

$$\begin{aligned} p_X(x) &= p_Y(A^{-1}(x - b)) \left| \det \frac{\partial A^{-1}(x - b)}{\partial x}(x) \right| \\ &= \frac{1}{\sqrt{(2\pi)^n}} e^{-\frac{1}{2} \|A^{-1}(x-b)\|^2} |\det A^{-1}| = \frac{1}{\sqrt{(2\pi)^n}} e^{-\frac{1}{2} \|A^{-1}(x-b)\|^2} |\det A|^{-1} \\ &= \frac{1}{\sqrt{(2\pi)^n}} e^{-\frac{1}{2} (A^{-1}(x-b))^{\top} (A^{-1}(x-b))} \frac{1}{\sqrt{\det A A^{\top}}} \\ &= \frac{1}{\sqrt{(2\pi)^n \det A A^{\top}}} e^{-\frac{1}{2} (x-b)^{\top} A^{-1\top} A^{-1} (x-b)} = \frac{1}{\sqrt{(2\pi)^n \det A A^{\top}}} e^{-\frac{1}{2} (x-b)^{\top} A^{\top} A^{-1} (x-b)} \\ &= \frac{1}{\sqrt{(2\pi)^n \det A A^{\top}}} e^{-\frac{1}{2} (x-b)^{\top} (A A^{\top})^{-1} (x-b)} \end{aligned}$$

Problem 6

All indices in the pseudocode start from 1.

Algorithm 1 Inverse Permutation

procedure INVERSEPERMUTATION(σ)

$\sigma' = []$

▷ Empty List

while $i = 1, 2, \dots, n$ **do**

while $j = 1, 2, \dots, n$ **do**

if $\sigma(j) = i$ **then**

$\sigma'(i) = j$

break

end if

end while

end while

return σ'

end procedure

Problem 7

(a) For any $x \in \mathbb{R}^n$,

$$(P_\sigma x)_i = e_{\sigma(i)}^\top x = x_{\sigma(i)}.$$

(b) Since the rows of P_σ are standard unit vectors, they are orthonormal and P_σ is an orthogonal matrix.

Therefore $P_\sigma P_\sigma^\top = P_\sigma^\top P_\sigma = I$, and $P_\sigma^\top = P_\sigma^{-1}$. Also, for all $i = 1, \dots, n$, $[P_\sigma]_{i, \sigma(i)} = 1$ and all other elements are 0. Then for P_σ^\top , we can say $[P_\sigma^\top]_{\sigma(i), i} = 1$ for all $i = 1, \dots, n$, which is equivalent to stating $[P_\sigma^\top]_{j, \sigma^{-1}(j)} = 1$ for all $j = 1, \dots, n$. This gives $P_\sigma^\top = P_{\sigma^{-1}}$. Therefore $P_\sigma^\top = P_\sigma^{-1} = P_{\sigma^{-1}}$.

(c) $\det P_\sigma = (-1)^t \det I = (-1)^t$, where t is the number of row changes. Therefore $|\det P_\sigma| = 1$.