Autoencoders (1)

November 13, 2023

1 Tutorial 8: Deep Autoencoders

In this tutorial, we will take a closer look at autoencoders (AE).

The main purpose of an autoencoder is to encode an input signal such as an image (using an encoder) into a smaller feature vector, which is inturn, then used to reconstruct the signal back (using a decoder). The feature vector is called the "bottleneck" of the network as we aim to compress the input data into a smaller amount of features. This property is useful in many applications, in particular in compressing data or comparing images on a metric beyond pixel-level comparisons. For the decoder, we will make use of 'deconvolutions' or 'transposed' convolutions for scaling up feature maps in height and width.

[1]:
```
## Standard libraries
import os
import json
import math
import numpy as np

## Imports for plotting
import matplotlib.pyplot as plt
%matplotlib inline
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('svg', 'pdf') # For export
from matplotlib.colors import to_rgb
import matplotlib
matplotlib.rcParams['lines.linewidth'] = 2.0
import seaborn as sns
sns.reset_orig()
sns.set()

## Progress bar
from tqdm.notebook import tqdm

## PyTorch
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.utils.data as data
```

```python
import torch.optim as optim
# Torchvision
import torchvision
from torchvision.datasets import CIFAR10
from torchvision import transforms

import torch.multiprocessing
torch.multiprocessing.set_sharing_strategy('file_system')

# PyTorch Lightning
try:
    import pytorch_lightning as pl
except ModuleNotFoundError: # Google Colab does not have PyTorch Lightning␣
↪installed by default. Hence, we do it here if necessary
    !pip install --quiet pytorch-lightning>=1.4
    import pytorch_lightning as pl
from pytorch_lightning.callbacks import LearningRateMonitor, ModelCheckpoint

# Tensorboard extension (for visualization purposes later)
from torch.utils.tensorboard import SummaryWriter
%load_ext tensorboard

# Path to the folder where the datasets are/should be downloaded (e.g. CIFAR10)
DATASET_PATH = "data"
# Path to the folder where the pretrained models are saved
CHECKPOINT_PATH = "tutorial8"

# Setting the seed
pl.seed_everything(42)

# Ensure that all operations are deterministic on GPU (if used) for␣
↪reproducibility
torch.backends.cudnn.deterministic = True
torch.backends.cudnn.benchmark = False

device = torch.device("cuda:0") if torch.cuda.is_available() else torch.
↪device("cpu")
print("Device:", device)
```

```
<ipython-input-1-8f1f46869188>:11: DeprecationWarning: `set_matplotlib_formats`
is deprecated since IPython 7.23, directly use
`matplotlib_inline.backend_inline.set_matplotlib_formats()`
  set_matplotlib_formats('svg', 'pdf') # For export
INFO:lightning_fabric.utilities.seed:Seed set to 42
```

```
Device: cuda:0
```

In this tutorial, we work with the CIFAR10 dataset. CIFAR10 dataset contains 50,000 training and 10,000 validation images with each image having 3 color channels and 32x32 pixels large.

[2]:
```
# Transformations applied on each image => only make them a tensor
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.
 ↪5,),(0.5,))])

# Loading the training dataset. We need to split it into a training and␣
 ↪validation part
train_dataset = CIFAR10(root='data', train=True, transform=transform,␣
 ↪download=True)
pl.seed_everything(42)
train_set, val_set = torch.utils.data.random_split(train_dataset, [45000, 5000])

# Loading the test set
test_set = CIFAR10(root='data', train=False, transform=transform, download=True)

# We define a set of data loaders that we can use for various purposes later.
train_loader = data.DataLoader(train_set, batch_size=256, shuffle=True,␣
 ↪drop_last=True, pin_memory=True, num_workers=4)
val_loader = data.DataLoader(val_set, batch_size=256, shuffle=False,␣
 ↪drop_last=False, num_workers=4)
test_loader = data.DataLoader(test_set, batch_size=256, shuffle=False,␣
 ↪drop_last=False, num_workers=4)

def get_train_images(num):
    return torch.stack([train_dataset[i][0] for i in range(num)], dim=0)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
data/cifar-10-python.tar.gz

100%|      | 170498071/170498071 [00:03<00:00, 45591459.91it/s]

Extracting data/cifar-10-python.tar.gz to data

INFO:lightning_fabric.utilities.seed:Seed set to 42

Files already downloaded and verified

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557:
UserWarning: This DataLoader will create 4 worker processes in total. Our
suggested max number of worker in current system is 2, which is smaller than
what this DataLoader is going to create. Please be aware that excessive worker
creation might get DataLoader running slow or even freeze, lower the worker
number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
```

1.1 Building the autoencoder

In general, an autoencoder consists of an **encoder** that maps the input x to a lower-dimensional feature vector z, and a **decoder** that reconstructs the input $\hat{x}$ from z. We train the model by comparing x to $\hat{x}$ and optimizing the parameters to increase the similarity between x and $\hat{x}$. See below for a small illustration of the autoencoder framework.

We first start by implementing the encoder. The encoder effectively consists of a deep convolutional network, where we scale down the image layer-by-layer using strided convolutions. After downscaling the image three times, we flatten the features and apply linear layers. The latent representation z is therefore a vector of size d which can be flexibly selected.

2 Encoder

Conv2d(hid,3,1,2) -> Act Fn -> Conv2d(hid,3,1, 2) -> Act Fn -> Conv2d($2 * hid$,3,1) -> Act Fn -> Conv2d($2 * hid$,3,1,2) -> Act Fn -> Linear(latent_dim)

Legends: Conv2d - Convolutional2dlayer Conv2d(x,y,z,w) - x = out_chanels | y = kernel_size | z = padding | w = stride Act Fn - Activation function that is passed as asrguments to the

[3]:
```
class Encoder(nn.Module):

    def __init__(self,
                 num_input_channels : int,
                 base_channel_size : int,
                 latent_dim : int,
                 act_fn : object = nn.GELU):
        """
        Inputs:
            - num_input_channels : Number of input channels of the image. For␣
↪CIFAR, this parameter is 3
            - base_channel_size : Number of channels we use in the first␣
↪convolutional layers. Deeper layers might use a duplicate of it.
            - latent_dim : Dimensionality of latent representation z
            - act_fn : Activation function used throughout the encoder network
        """
        super().__init__()
        c_hid = base_channel_size
        self.net = nn.Sequential(
            nn.Conv2d(num_input_channels, c_hid, kernel_size = 3, padding = 1,␣
↪stride = 2),
            act_fn(),
            nn.Conv2d(c_hid, c_hid, kernel_size = 3, padding = 1, stride = 2),
            act_fn(),
            nn.Conv2d(c_hid, 2*c_hid, kernel_size = 3, padding = 1,),
            act_fn(),
            nn.Conv2d(2*c_hid, 2*c_hid, kernel_size = 3, padding = 1, stride =␣
↪2),
            act_fn(),
            nn.Flatten(),
            nn.Linear(4*4*2*c_hid, latent_dim)
        )
```

```
    def forward(self, x):
        return self.net(x)
```

We obtain the decoder by just taking the mirror image/ flipping the encoder. The only difference is that the vanilla convolutional layers are replaced with transposed convolutions to upscale the features. Transposed convolutions can be imagined as adding the stride to the input instead of the output, and can thus upscale the input. For an illustration of a `nn.ConvTranspose2d` layer with kernel size 3, stride 2, and padding 1, see below (figure credit - Vincent Dumoulin and Francesco Visin):

Overall, the decoder can be implemented as follows:

3 Decoder

Linear($2 * hid$) -> Act. Fn. -> ConvTrans($2 * hid$, 3, 1, 1, 2) -> Act. Fn. -> ConvTrans($2 * hid$, 3, 1) -> Act. Fn. -> ConvTrans(hid, 3, 1, 1, 2) -> Act. Fn. -> ConvTrans(3, 3, 1, 1, 2) -> Tanh()

Legends:

ConvTrans - ConvTranspose2d layer ConvTrans(x, y, z, w, a) - x = out_channels | y = kernel_size | z = padding | w = output_padding | a = stride

[4]:
```
class Decoder(nn.Module):

    def __init__(self,
                 num_input_channels : int,
                 base_channel_size : int,
                 latent_dim : int,
                 act_fn : object = nn.GELU):
        """
        Inputs:
            - num_input_channels : Number of channels of the image to␣
↪reconstruct. For CIFAR, this parameter is 3
            - base_channel_size : Number of channels we use in the last␣
↪convolutional layers. Early layers might use a duplicate of it.
            - latent_dim : Dimensionality of latent representation z
            - act_fn : Activation function used throughout the decoder network
        """
        super().__init__()
        c_hid = base_channel_size
        self.linear = nn.Sequential(
            nn.Linear(latent_dim, 2*16*c_hid),
            act_fn()
        )
        self.net = nn.Sequential(
            nn.ConvTranspose2d(2*c_hid, 2*c_hid, kernel_size = 3, padding = 1,␣
↪output_padding = 1, stride = 2),
```

```
            act_fn(),
            nn.ConvTranspose2d(2*c_hid, 2*c_hid, kernel_size = 3, padding = 1,␣
↪),
            act_fn(),
            nn.ConvTranspose2d(2*c_hid, c_hid, kernel_size = 3, padding = 1,␣
↪output_padding = 1, stride = 2),
            act_fn(),
            nn.ConvTranspose2d(c_hid, num_input_channels, kernel_size = 3,␣
↪padding = 1, output_padding = 1, stride = 2),
            nn.Tanh()
        )

    def forward(self, x):
        x = self.linear(x)
        x = x.reshape(x.shape[0], -1, 4, 4)
        x = self.net(x)
        return x
```

The encoder and decoder networks we chose here are relatively simple. Usually, more complex networks are applied, especially when using a ResNet-based architecture. For example, see VQ-VAE and NVAE (although the papers discuss architectures for VAEs, they can equally be applied to standard autoencoders).

In a final step, we add the encoder and decoder together into the autoencoder architecture. We define the autoencoder as PyTorch Lightning Module to simplify the needed training code:

[5]:
```
class Autoencoder(pl.LightningModule):

    def __init__(self,
                 base_channel_size: int,
                 latent_dim: int,
                 encoder_class : object = Encoder,
                 decoder_class : object = Decoder,
                 num_input_channels: int = 3,
                 width: int = 32,
                 height: int = 32):
        super().__init__()
        # Saving hyperparameters of autoencoder
        self.save_hyperparameters()
        # Creating encoder and decoder
        self.encoder = encoder_class(num_input_channels, base_channel_size,␣
↪latent_dim)# Fill your code here
        self.decoder = decoder_class(num_input_channels, base_channel_size,␣
↪latent_dim)# Fill your code here
        # Example input array needed for visualizing the graph of the network
        self.example_input_array = torch.zeros(2, num_input_channels, width,␣
↪height)
```

```python
    def forward(self, x):
        """
        The forward function takes in an image and returns the reconstructed␣
↪image
        """
        z = self.encoder(x)# Fill your code here
        x_hat = self.decoder(z)# Fill your code here
        return x_hat

    def _get_reconstruction_loss(self, batch):
        """
        Given a batch of images, this function returns the reconstruction loss␣
↪(MSE in our case)
        """
        x, _ = batch # We do not need the labels
        x_hat = self.forward(x)# Fill your code here
        loss = F.mse_loss(x, x_hat, reduction = 'none')# Fill your code here␣
↪using torch.functional.MSE Loss
        loss = loss.sum(dim=[1,2,3]).mean(dim=[0])
        return loss

    def configure_optimizers(self):
        optimizer = optim.Adam(self.parameters(), lr=1e-3)
        # Using a scheduler is optional but can be helpful.
        # The scheduler reduces the LR if the validation performance hasn't␣
↪improved for the last N epochs
        scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer,
                                                         mode='min',
                                                         factor=0.2,
                                                         patience=20,
                                                         min_lr=5e-5)
        return {"optimizer": optimizer, "lr_scheduler": scheduler, "monitor":␣
↪"val_loss"}

    def training_step(self, batch, batch_idx):
        loss = self._get_reconstruction_loss(batch)
        self.log('train_loss', loss)
        return loss

    def validation_step(self, batch, batch_idx):
        loss = self._get_reconstruction_loss(batch)
        self.log('val_loss', loss)

    def test_step(self, batch, batch_idx):
        loss = self._get_reconstruction_loss(batch)
        self.log('test_loss', loss)
```

For the loss function, we use the mean squared error (MSE). However, MSE has also some considerable disadvantages. Usually, MSE leads to blurry images where small noise/high-frequent patterns are removed as those cause a very low error.

Additionally, comparing two images using MSE does not necessarily reflect their visual similarity. For instance, suppose the autoencoder reconstructs an image shifted by one pixel to the right and bottom. Although the images are almost identical, we can get a higher loss than predicting a constant pixel value for half of the image (see code below).

[7]:
```
def compare_imgs(img1, img2, title_prefix=""):
    # Calculate MSE loss between both images
    loss = F.mse_loss(img1, img2, reduction="sum")
    # Plot images for visual comparison
    grid = torchvision.utils.make_grid(torch.stack([img1, img2], dim=0),␣
 ↪nrow=2, normalize=True)
    grid = grid.permute(1, 2, 0)
    plt.figure(figsize=(4,2))
    plt.title(f"{title_prefix} Loss: {loss.item():4.2f}")
    plt.imshow(grid)
    plt.axis('off')
    plt.show()

for i in range(2):
    # Load example image
    img, _ = train_dataset[i]
    img_mean = img.mean(dim=[1,2], keepdims=True)

    # Shift image by one pixel
    SHIFT = 1
    img_shifted = torch.roll(img, shifts=SHIFT, dims=1)
    img_shifted = torch.roll(img_shifted, shifts=SHIFT, dims=2)
    img_shifted[:,:1,:] = img_mean
    img_shifted[:,:,:1] = img_mean
    compare_imgs(img, img_shifted, "Shifted -")

    # Set half of the image to zero
    img_masked = img.clone()
    img_masked[:,:img_masked.shape[1]//2,:] = img_mean
    compare_imgs(img, img_masked, "Masked -")
```

Shifted - Loss: 205.40

Masked - Loss: 158.48

Shifted - Loss: 418.47

3.0.1 Training the model

During the training, we want to keep track of the learning progress by seeing reconstructions made by our model. For this, we implement a callback object in PyTorch Lightning which will add reconstructions every N epochs to our tensorboard:

[8]:
```
class GenerateCallback(pl.Callback):

    def __init__(self, input_imgs, every_n_epochs=1):
        super().__init__()
        self.input_imgs = input_imgs # Images to reconstruct during training
        self.every_n_epochs = every_n_epochs # Only save those images every N␣
↪epochs (otherwise tensorboard gets quite large)

    def on_epoch_end(self, trainer, pl_module):
        if trainer.current_epoch % self.every_n_epochs == 0:
            # Reconstruct images
            input_imgs = self.input_imgs.to(pl_module.device)
            with torch.no_grad():
                pl_module.eval()
                reconst_imgs = pl_module(input_imgs)
                pl_module.train()
            # Plot and add to tensorboard
            imgs = torch.stack([input_imgs, reconst_imgs], dim=1).flatten(0,1)
            grid = torchvision.utils.make_grid(imgs, nrow=2, normalize=True,␣
↪range=(-1,1))
            trainer.logger.experiment.add_image("Reconstructions", grid,␣
↪global_step=trainer.global_step)
```

[11]:
```
def train_cifar(latent_dim):
    # Create a PyTorch Lightning trainer with the generation callback
    trainer = pl.Trainer(default_root_dir=os.path.join(CHECKPOINT_PATH,␣
↪f"cifar10_{latent_dim}"),
```

```
                        accelerator="gpu" if str(device).startswith("cuda")␣
↪else "cpu",
                        devices=1,
                        max_epochs=10,
                        callbacks=[ModelCheckpoint(save_weights_only=True),
                                   GenerateCallback(get_train_images(8),␣
↪every_n_epochs=10),
                                   LearningRateMonitor("epoch")])
    trainer.logger._log_graph = True         # If True, we plot the computation␣
↪graph in tensorboard
    trainer.logger._default_hp_metric = None # Optional logging argument that␣
↪we don't need

    # Check whether pretrained model exists. If yes, load it and skip training
    pretrained_filename = os.path.join(CHECKPOINT_PATH, f"cifar10_{latent_dim}.
↪ckpt")
    if os.path.isfile(pretrained_filename):
        print("Found pretrained model, loading...")
        model = Autoencoder.load_from_checkpoint(pretrained_filename)
    else:
        model = Autoencoder(base_channel_size=32, latent_dim=latent_dim)
        trainer.fit(model, train_loader, val_loader)
    # Test best model on validation and test set
    val_result = trainer.test(model, val_loader, verbose=False)
    test_result = trainer.test(model, test_loader, verbose=False)
    result = {"test": test_result, "val": val_result}
    return model, result
```

3.0.2 Comparing latent dimensionality

When training an autoencoder, we need to choose a dimensionality for the latent representation z. The higher the latent dimensionality, the better we expect the reconstruction to be. However, the idea of autoencoders is to *compress* data. Hence, we are also interested in keeping the dimensionality low. To find the best tradeoff, we can train multiple models with different latent dimensionalities. The original input has $32 \times 32 \times 3 = 3072$ pixels. Keeping this in mind, a reasonable choice for the latent dimensionality might be between 64 and 384:

[12]:
```
model_dict = {}
for latent_dim in [64, 128, 256, 384]:
    model_ld, result_ld = train_cifar(latent_dim)
    model_dict[latent_dim] = {"model": model_ld, "result": result_ld}
```

```
INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda), used:
True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False, using: 0 TPU
cores
INFO:pytorch_lightning.utilities.rank_zero:IPU available: False, using: 0 IPUs
```

```
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False, using: 0 HPUs
WARNING:pytorch_lightning.loggers.tensorboard:Missing logger folder:
tutorial8/cifar10_64/lightning_logs
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]
INFO:pytorch_lightning.callbacks.model_summary:
  | Name    | Type    | Params | In sizes       | Out sizes
----------------------------------------------------------------------
0 | encoder | Encoder | 131 K  | [2, 3, 32, 32] | [2, 64]
1 | decoder | Decoder | 159 K  | [2, 64]        | [2, 3, 32, 32]
----------------------------------------------------------------------
290 K     Trainable params
0         Non-trainable params
290 K     Total params
1.164     Total estimated model params size (MB)

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557:
UserWarning: This DataLoader will create 4 worker processes in total. Our
suggested max number of worker in current system is 2, which is smaller than
what this DataLoader is going to create. Please be aware that excessive worker
creation might get DataLoader running slow or even freeze, lower the worker
number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:`Trainer.fit` stopped:
`max_epochs=10` reached.
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]
```

```
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda), used:
True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False, using: 0 TPU
cores
INFO:pytorch_lightning.utilities.rank_zero:IPU available: False, using: 0 IPUs
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False, using: 0 HPUs
WARNING:pytorch_lightning.loggers.tensorboard:Missing logger folder:
tutorial8/cifar10_128/lightning_logs
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]
INFO:pytorch_lightning.callbacks.model_summary:
  | Name    | Type    | Params | In sizes       | Out sizes
----------------------------------------------------------------------
0 | encoder | Encoder | 196 K  | [2, 3, 32, 32] | [2, 128]
1 | decoder | Decoder | 225 K  | [2, 128]       | [2, 3, 32, 32]
----------------------------------------------------------------------
422 K     Trainable params
0         Non-trainable params
422 K     Total params
1.688     Total estimated model params size (MB)

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:`Trainer.fit` stopped:
`max_epochs=10` reached.
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]
```

```
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda), used:
True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False, using: 0 TPU
cores
INFO:pytorch_lightning.utilities.rank_zero:IPU available: False, using: 0 IPUs
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False, using: 0 HPUs
WARNING:pytorch_lightning.loggers.tensorboard:Missing logger folder:
tutorial8/cifar10_256/lightning_logs
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]
INFO:pytorch_lightning.callbacks.model_summary:
  | Name    | Type    | Params | In sizes       | Out sizes
----------------------------------------------------------------------
0 | encoder | Encoder | 327 K  | [2, 3, 32, 32] | [2, 256]
1 | decoder | Decoder | 356 K  | [2, 256]       | [2, 3, 32, 32]
----------------------------------------------------------------------
684 K     Trainable params
0         Non-trainable params
684 K     Total params
2.737     Total estimated model params size (MB)

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:`Trainer.fit` stopped:
`max_epochs=10` reached.
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]
```

```
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:GPU available: True (cuda), used:
True
INFO:pytorch_lightning.utilities.rank_zero:TPU available: False, using: 0 TPU
cores
INFO:pytorch_lightning.utilities.rank_zero:IPU available: False, using: 0 IPUs
INFO:pytorch_lightning.utilities.rank_zero:HPU available: False, using: 0 HPUs
WARNING:pytorch_lightning.loggers.tensorboard:Missing logger folder:
tutorial8/cifar10_384/lightning_logs
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]
INFO:pytorch_lightning.callbacks.model_summary:
  | Name    | Type    | Params | In sizes       | Out sizes
----------------------------------------------------------------------
0 | encoder | Encoder | 459 K  | [2, 3, 32, 32] | [2, 384]
1 | decoder | Decoder | 487 K  | [2, 384]       | [2, 3, 32, 32]
----------------------------------------------------------------------
946 K     Trainable params
0         Non-trainable params
946 K     Total params
3.786     Total estimated model params size (MB)

Sanity Checking: |          | 0/? [00:00<?, ?it/s]

Training: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

Validation: |          | 0/? [00:00<?, ?it/s]

INFO:pytorch_lightning.utilities.rank_zero:`Trainer.fit` stopped:
`max_epochs=10` reached.
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]

Testing: |          | 0/? [00:00<?, ?it/s]
```

```
INFO:pytorch_lightning.accelerators.cuda:LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES:
[0]
```

```
Testing: |          | 0/? [00:00<?, ?it/s]
```

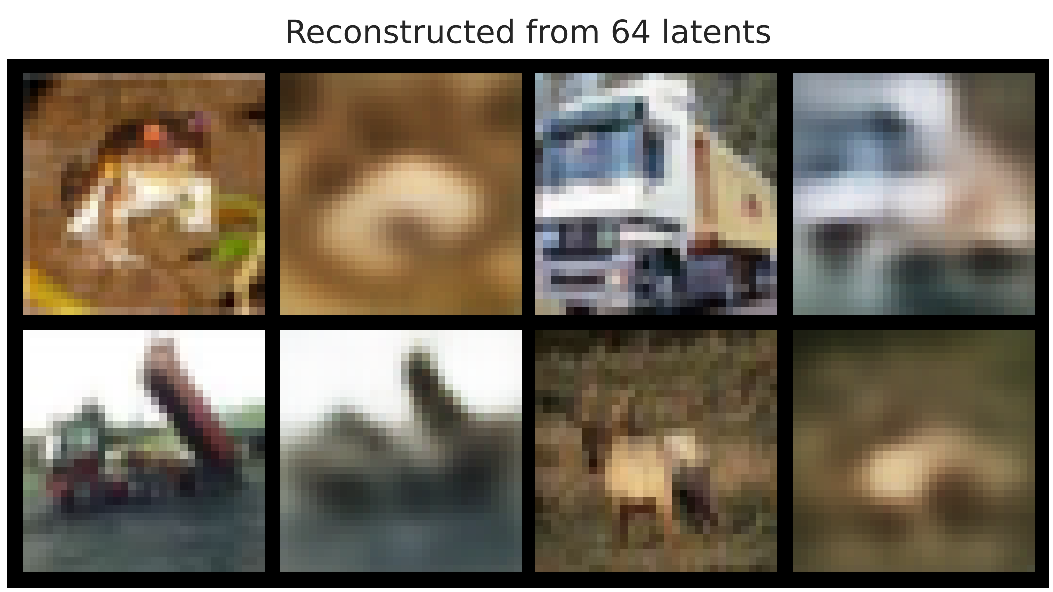
After training the models, we can plot the reconstruction loss over the latent dimensionality to get an intuition how these two properties are correlated:

[13]:
```
latent_dims = sorted([k for k in model_dict])
val_scores = [model_dict[k]["result"]["val"][0]["test_loss"] for k in␣
 ↪latent_dims]

fig = plt.figure(figsize=(6,4))
plt.plot(latent_dims, val_scores, '--', color="#000", marker="*",␣
 ↪markeredgecolor="#000", markerfacecolor="y", markersize=16)
plt.xscale("log")
plt.xticks(latent_dims, labels=latent_dims)
plt.title("Reconstruction error over latent dimensionality", fontsize=14)
plt.xlabel("Latent dimensionality")
plt.ylabel("Reconstruction error")
plt.minorticks_off()
plt.ylim(0,100)
plt.show()
```

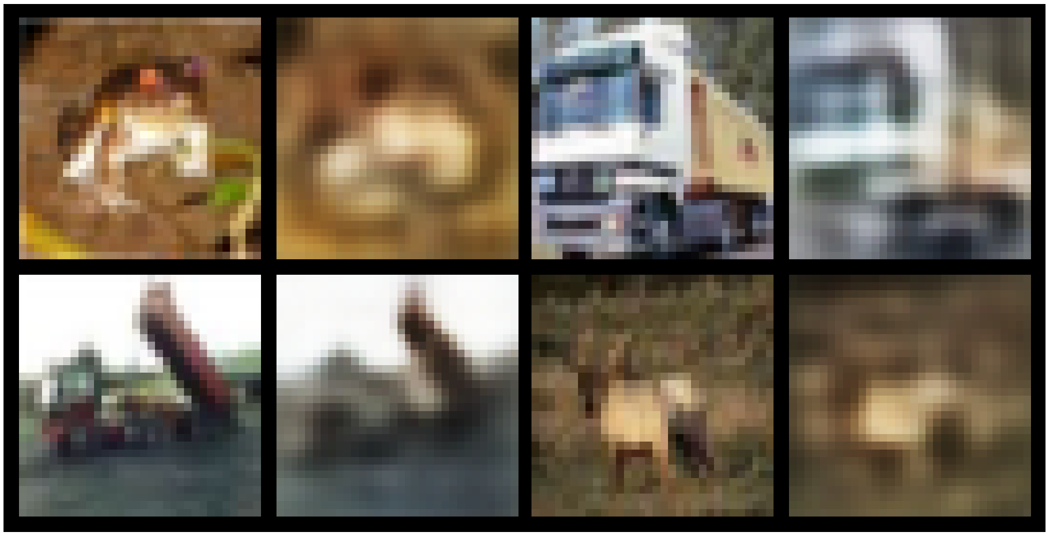
As we initially expected, the reconstruction loss goes down with increasing latent dimensionality. For our model and setup, the two properties seem to be exponentially (or double exponentially) correlated. To understand what these differences in reconstruction error mean, we can visualize example reconstructions of the four models:

[16]:
```
def visualize_reconstructions(model, input_imgs):
    # Reconstruct images
    model.eval()
    with torch.no_grad():
        reconst_imgs = model(input_imgs.to(model.device))
    reconst_imgs = reconst_imgs.cpu()

    # Plotting
    imgs = torch.stack([input_imgs, reconst_imgs], dim=1).flatten(0,1)
    grid = torchvision.utils.make_grid(imgs, nrow=4, normalize=True)
    grid = grid.permute(1, 2, 0)
    plt.figure(figsize=(7,4.5))
    plt.title(f"Reconstructed from {model.hparams.latent_dim} latents")
    plt.imshow(grid)
    plt.axis('off')
    plt.show()
```

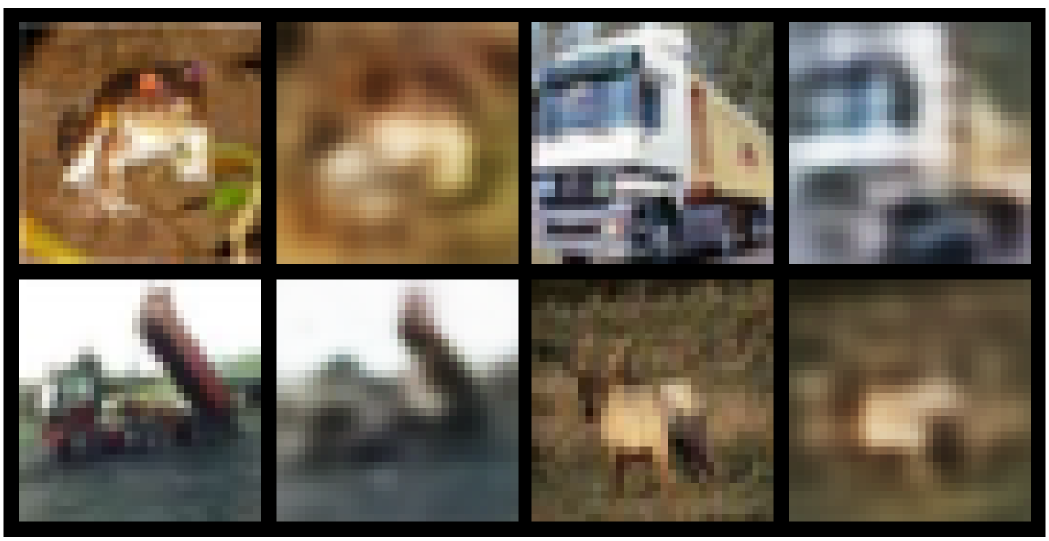
[17]:
```
input_imgs = get_train_images(4)
for latent_dim in model_dict:
    visualize_reconstructions(model_dict[latent_dim]["model"], input_imgs)
```

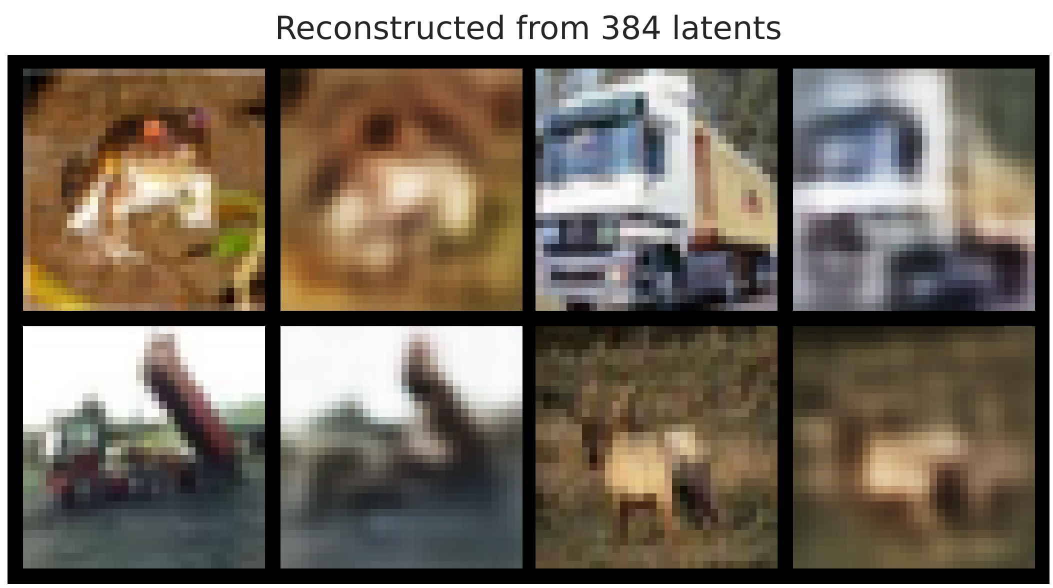


Reconstructed from 128 latents



Reconstructed from 256 latents





Clearly, the smallest latent dimensionality can only save information about the rough shape and color of the object, but the reconstructed image is extremely blurry and it is hard to recognize the original object in the reconstruction. With 128 features, we can recognize some shapes again although the picture remains blurry. The models with the highest two dimensionalities reconstruct the images quite well. The difference between 256 and 384 is marginal at first sight but can be noticed when comparing, for instance, the backgrounds of the first image (the 384 features model more of the pattern than 256).

3.1 Conclusion

In this tutorial, we have implemented our own autoencoder on small RGB images and explored various properties of the model.

Repeat the process for latent dimensions of 128 and 256 and compare the properties observed in the above applications.