MAX uid evi Ur (e) (i) (i) (i) (i) (i) (i) (i) (i	= 0.001 = 0.02 ence_w = 0.5 ce = "cuda:0" Inctionality for loading and visualizing dataset nave provided some functionality for loading and visualizing the dataset. You may add more cells/functions here. B]: rom 0-1 to -1-1 sform = Compose([ToTensor(), Lambda(lambda x: (x - 0.5) * 2)] set = MNIST("./datasets", download=True, train=True, transform=transform) er = DataLoader(dataset, batch_size, shuffle=True) I]: function plots images in a grid. Input is a Tensor. show_images(images, title=""): images = images.detach().cpu().numpy()
÷ h	<pre>images = images.detach().cpu().numpy() fig = plt.figure(figsize=(4, 4)) cols = math.ceil(len(images) *** (1 / 2)) rows = math.ceil(len(images) / cols) for r in range(rows): for c in range(cols): idx = cols * r + c ax = fig.add_subplot(rows, cols, idx + 1) ax.axis('off') if idx < len(images): ax.imshow(images[idx][0], cmap="gray") fig.suptitle(title, fontsize=18) plt.show() e gnerate the 10*n_sample conditioned images, so we resize it to the same size in the plt show_images_custom(images, title=""): images = images.detach().cpu().numpy() fig = plt.figure(figsize=(4, 8)) rows = 11 cols = math.ceil(len(images) / rows) for r in range(rows): for c in range(cols): plot_idx = r * cols + c ax = fig.add_subplot(rows, cols, plot_idx + 1) ax.axis('off') img_idx = plot_idx if img_idx < len(images): ax.imshow(images[img_idx][0], cmap="gray")</pre>
rcl 1 4 6 2 6 9 7 / 6	fig. suptitle(title, fontsize=18) pltt.show() show_first_batch(loader); for batch_feats, batch_labels in loader: print(batch_labels) print(ba
ass	s Forward_pass: def _init_(setf) -> None: #number of steps self.N = N
	<pre>2: torch.FloatTensor, t: torch.LongTensor, > Tuple[torch.FloatTensor, torch.FloatTensor]: # Sample from q(z_t z_0) mean = selfq_mean(z, t) std = selfq_std(z, t) epsilon = torch.randn_like(z) z_t = epsilon * std + mean return z_t, epsilon ##for training, sample random n timesteps for each input, return the repeated features, times-steps saidef q_sample_random(self, z: torch.FloatTensor, lables: torch.FloatTensor, n_timesteps = 5, > Tuple[torch.FloatTensor, torch.FloatTensor, torch.IntTensor, torch.IntTensor]: # Sample from q(z_t z_0) #we use the same times steps for all the samples in this batch for simplicity times = list(torch.randint(0, self.N-l, (n_timesteps,))) print(times) times_tist = [torch.Tensor([i]).repeat(z.shape[0]).to(torch.int64) for i in times] times_repeated = torch.cat(times_list) lables_repeated = torch.cat(times_list) mean = selfq_mean(z_repeated, times_repeated) #shape=(batch_size*5, 1, 28, 28) mean = selfq_std(z_repeated, times_repeated) epsilon = torch.randn_like(z_repeated) z_out = epsilon * std + mean return z_out, epsilon, times_repeated, lables_repeated ##for training, sample randomly one timestep for each img, return the repeated features, times-steps sidef q_sample_random2(self, z: torch.FloatTensor, lables: torch.FloatTensor,</pre>
ei ne ny	<pre>tables: torch.FloatTensor,</pre>
as	<pre>s ResidualConvBlock(torch.nn.Module): definit(</pre>
as	<pre>out = x + x2 else: out = x1 + x2 return out / 1.414 else: x1 = self.conv1(x) x2 = self.conv2(x1) return x2 s UnetDown(torch.nn.Module): definit(self, in_channels, out_channels): super(UnetDown, self)init() process and downscale the image feature maps layers = [ResidualConvBlock(in_channels, out_channels), torch.nn.MaxPool2d(2)] self.model = torch.nn.Sequential(*layers) def forward(self, x): return self.model(x) s UnetUp(torch.nn.Module): definit(self, in_channels, out_channels): super(UnetUp, self)init() process and upscale the image feature maps layers = [torch.nn.ConvTranspose2d(in_channels, out_channels, 2, 2),</pre>
as	ResidualConvBlock(out_channels, out_channels), ResidualConvBlock(out_channels, out_channels), self.model = torch.nn.Sequential(*layers) def forward(self, x, skip): x = torch.cat((x, skip), 1) x = self.model(x) return x self.input_dim, emb_dim): super(EmbedFC, self)init() init(self, input_dim, emb_dim); self.input_dim = input_dim layers = [torch.nn.Linear(input_dim, emb_dim), torch.nn.Linear(emb_dim, emb_dim), self.model = torch.nn.Sequential(*layers) def forward(self, x): x = x.view(-1, self.input_dim) return self.model(x) self.modelBackbone(torch.nn.Module):
	<pre>definit(self, in_channels = 1, hidden_channels = 256, image_size = 28, n_classes=11, num_timesteps super(ConditionedBackbone, self)init() self.in_channels = in_channels self.in_feat = hidden_channels self.inage_size = image_size self.num_timesteps = num_timesteps self.num_timesteps = num_timesteps self.n_classes = n_classes #the classes are 0-9 plus a "empty/unconditional" lable, they are encon ## trainable embeddings for lable and time, not working if using a simple linear transformation, so #self.time_emb = torch.nn.Linear(1, self.n_feat*2) #self.lable_emb = torch.nn.Linear(self.n_classes, self.n_feat*2) self.time_emb = EmbedFC(1, self.n_feat * 2) self.lable_emb = EmbedFC(self.n_classes, self.n_feat * 2) self.init_conv = ResidualConvBlock(in_channels, self.n_feat, is_res=True) self.down1 = UnetDown(self.n_feat, self.n_feat) self.down2 = UnetDown(self.n_feat, 2 * self.n_feat) self.to_vec = torch.nn.Sequential(torch.nn.AvgPool2d(7), torch.nn.GELU()) self.up0 = torch.nn.Sequential(torch.nn.ConvTranspose2d(6 * self.n_feat, 2 * self.n_feat, 7, 7), torch.nn.GroupNorm(8, 2 * self.n_feat), torch.nn.ReLU(),) self.up1 = UnetUp(4 * self.n_feat, self.n_feat) self.up2 = UnetUp(2 * self.n_feat, self.n_feat) self.up2 = UnetUp(2 * self.n_feat, self.n_feat)</pre>
	<pre>self.out = torch.nn.Sequential() torch.nn.Conv2d(2 * self.n_feat, self.n_feat, 3, 1, 1), torch.nn.GroupNorm(8, self.n_feat), torch.nn.ReLU(), torch.nn.Conv2d(self.n_feat, self.in_channels, 3, 1, 1),) def forward(self, x, lables, t) -> float: # x is (noisy) image batch (from the Forward_pass for training and from the N(0,1) for sampling), # diff_noise are the corresponding noise in the forward pass, #labels are the numbers from 0-10, 10 represents the unconditioned sample, t is the timestep usual x = self.init_conv(x) down1 = self.down1(x) down2 = self.down2(down1) hiddenvec = self.to_vec(down2) #I tried several embedding methods, the concatenation seems to be the best #map to the vector size time_emb = self.time_emb(t.type(torch.float32).view(-1,1)).view(-1, self.n_feat * 2, 1 ,1) lable_one_hot = torch.nn.functional.one_hot(lables, num_classes=self.n_classes).type(torch.float) lable_emb = self.lable_emb(lable_one_hot).view(-1, self.n_feat * 2, 1 ,1) #hiddenvec = hiddenvec + lable_emb up1 = self.up0(torch.cat((time_emb, lable_emb, hiddenvec), 1))</pre>
	<pre>up2 = self.up1(up1, down2) up3 = self.up2(up2, down1) e_pred = self.out(torch.cat((up3, x), 1)) return e_pred s Reverse_pass(torch.nn.Module): definit(self, model, alphas, alpha_bars, betas, num_classes = 11) -> None: super()init() self.model = model.to(device) self.N = N self.num_classes = num_classes ##for computing the samples self.alphas = alphas self.sqrt_1_minus_alpha_bars = torch.sqrt(1-alpha_bars) ##we use the simpler version of sigma for the reverse pass self.sigmas = torch.sqrt(betas) #loss self.mse = torch.nn.MSELoss() def sample(self, n_samples = 3, image_size = 28, guidence_w = guidence_w): ## sample "n" samples for each number "0-9" (including the unditional label "10") using 'Classifie with torch.no_grad():</pre>
	<pre>#sample noised images and arrange labels batch_size = n_samples*self.num_classes #x_batch = torch.randn(batch_size, 1, image_size, image_size).to(device) x_batch = torch.randn(batch_size, 1, image_size, image_size).to(device) ##labels = [0,0,0,1,1,1,2,2,2] labels = [torch.tensor([i], device=device).repeat(n_samples) for i in range(self.num_classes) #labels = torch.cat(labels).to(device) labels = torch.cat(labels) for interpolation (label = 10) labels_uncon = torch.full_like(labels, self.num_classes-1) labels = torch.cat((labels, labels_uncon)) last_batch = x_batch for i in range(self.N, 0, -1): print(f'sampling timestep {i}\n') #current_t = torch.tensor([i]).to(device) current_t = torch.tensor([i-1],device=device) #i-1 for one-hot encoding t_batch = current img for unconditioned sampling x_doubled = last_batch.repeat(2,1,1,1) #(2*batch_size) # duplicate the current img for unconditioned sampling x_doubled = t_batch.repeat(2) #(2*batch_size) # predict the diffusion noise, and interpolate diff_noise = self.model(x_doubled, labels, t_doubled) diff_con = diff_noise[:batch_size] diff_noise_final = (1+guidence_w)*diff_con - guidence_w*diff_uncon</pre>
ho nis la de	<pre># predict x_t-1 #observation_noise = torch.randn(batch_size, 1, image_size, image_size).to(device) if i > . observation_noise = torch.randn(batch_size, 1, image_size, image_size).to(device) if i > .</pre>
ve	<pre>s,alphas_alpha_bars = forward.ret_coefs() rse = Reverse_pass(model, alphas, alpha_bars, betas) rn_batch = reverse.sample(n_samples=5) _images_custom(return_batch, "Images generated from the untrained model")</pre>

DT8122 - Assignment

DDPM: https://arxiv.org/abs/2006.11239

Install necessary libraries

name.

Deadline: 2023 August 15 AoE (Anywhere on Earth)

be able to generate 28x28 grayscale handwritten image of said digit.

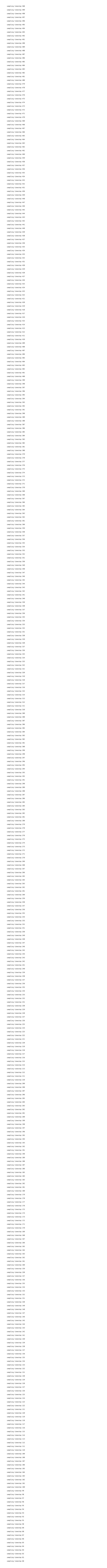
Classifier-free conditional DDPM: https://arxiv.org/abs/2207.12598

You can add additional cells anywhere in the notebook to make your code more readable.

Send a zip file with the notebook both as a .ipynb and as a .pdf file to dt8122@idi.ntnu.no. Label the file with your full

The task is to implement conditional DDPM for MNIST images. Your implementation should take as input a digit and

The notebook should be run when it is turned in so all plots are visible. All code should be contained in the notebook.



sampling times	tep 50 tep 49 tep 48 tep 47
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ampling times	generated from the untrained model
	training loop There should be some indication of how long the model took to train, both total and per enoch
For good result expect to see s n [9]: lef train_cond print(f"{s optimizer for i in r	I here. There should be some indication of how long the model took to train, both total and per epoch. s you will want to train the model for several epochs, but with a good implementation you should comething that looks like digits after only a single epoch. ditionedDDPM(n_epochs = 10, learning_rate = le-4): sum(p.numel() for p in reverse.parameters() if p.requires_grad)} parameters to train") = torch.optim.Adam(reverse.parameters(), lr=learning_rate) range(n_epochs):
print(progre total_ for ba op #5 #2 Z_ lo	<pre>(f"Training epoch: {i+1}") ess_loader = tqdm(loader) _loss = 0 etch_feats,batch_labels in progress_loader: etimizer.zero_grad() sample with forward pass e_out, epsilon_target, times, labels= forward.q_sample_random(batch_feats, batch_labels) _out, epsilon_target, times, labels= forward.q_sample_random2(batch_feats, batch_labels) ess = reverse.compute_loss(z_out, epsilon_target, times, labels)</pre>
to lo op print(otal_loss += loss oss.backward() otimizer.step() (f'Loss for the current epoch is {total_loss}') /isualize the model
n [10]: nodel = Condit forward = Forw petas,alphas,a reverse = Reve	alpha_bars = forward.ret_coefs() erse_pass(model, alphas, alpha_bars, betas) onedDDPM(n_epochs = 10)
raining epoch 00% oss for the c raining epoch oss for the c raining epoch	469/469 [00:27<00:00, 17.12it/s] urrent epoch is 43.41958236694336 : 2 469/469 [00:27<00:00, 16.85it/s] urrent epoch is 24.419374465942383
raining epoch 00% coss for the c raining epoch 00% coss for the c raining epoch 00% coss for the c	<pre>: 4</pre>
oss for the craining epoch oss for the craining epoch oss for the craining epoch	469/469 [00:28<00:00, 16.37it/s] urrent epoch is 17.489013671875 : 8 469/469 [00:28<00:00, 16.67it/s] urrent epoch is 17.0726318359375 : 9 469/469 [00:28<00:00, 16.75it/s] urrent epoch is 16.6922550201416
oss for the c n [12]: return batch1	<pre># 10 # 469/469 [00:27<00:00, 16.78it/s] # urrent epoch is 16.3807373046875 # reverse.sample(n_samples = 5, guidence_w = 0.5) ## ustom(return_batch1, "Imgs from 0-9, the last row is the unconditioned sampling")</pre>

sampling timestep 79

sampling timestep 78

sampling timestep 77

sampling timestep 76

sampling timestep 75

sampling timestep 74

sampling timestep 73

sampling timestep 72

sampling timestep 71

sampling timestep 70

sampling timestep 69

sampling timestep 68

sampling timestep 67

sampling timestep 66

sampling timestep 65

sampling timestep 64

sampling timestep 63

sampling timestep 62

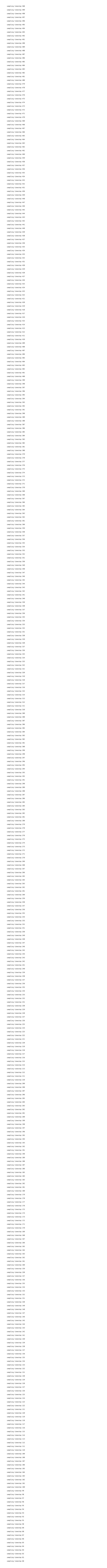
sampling timestep 61

sampling timestep 60

sampling timestep 59

sampling timestep 58

sampling timestep 57



sampling timestep 74 sampling timestep 73 sampling timestep 72 sampling timestep 71 sampling timestep 70 sampling timestep 69			
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sampling timestep 1	the last row is the	ne unconditioned	sampling
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	0 8 5		

sampling timestep 79

sampling timestep 78

sampling timestep 77

sampling timestep 76

sampling timestep 75