

Загрузите из keras.datasets набор данных CIFAR10 small images classification dataset (<https://keras.io/api/datasets/cifar10/>).

Оставьте в наборе изображения четырех классов предметов с метками, соответствующими четырем разным последним цифрам Вашего студенческого билета (например, если номер студбилета 1032259319, то последние четыре разные цифры – это 1, 3, 5, 9).

Выберите какую-либо размерность латентного пространства, создайте и обучите на обучающей выборке вариационный автокодировщик с размерностью скрытого представления, равной выбранной размерности латентного пространства.

Выберите в наборе данных два изображения разных классов, определите точки в скрытом пространстве, соответствующие этим изображениям, выполните трансформацию между двумя выбранными изображениями и визуализируйте полученные переходные изображения.

```

1
2 import os
3 os.environ["KERAS_BACKEND"] = "tensorflow"
4
5 import tensorflow as tf
6 import keras
7 from keras import layers
8 from keras.datasets import cifar10
9 import numpy as np
10 import math
11 import random
12 import matplotlib.pyplot as plt
13
14
15 print(f"TF: {tf.__version__} | Keras: {keras.__version__} | Backend: {keras.backend.backend()}")
16

```

TF: 2.19.0 | Keras: 3.10.0 | Backend: tensorflow

```

1 # User-configurable hyperparams
2 STUDENT_DIGITS = [5, 8, 6, 9]
3 LATENT_DIM = 8
4 BATCH_SIZE = 128
5 EPOCHS = 10
6 LEARNING_RATE = 1e-3
7 INTERP_STEPS = 12          # number of frames between A and B (inclusive)
8 INTERP_MODE = "slerp"      # "lerp" or "slerp"
9
10 # two classes for interpolation
11 CLASS_A = 5
12 CLASS_B = 9
13
14 SEED = 1337
15 np.random.seed(SEED)
16 tf.random.set_seed(SEED)
17 random.seed(SEED)
18
19 # CIFAR-10 label names
20 CIFAR10_LABELS = [
21     "airplane", "automobile", "bird", "cat", "deer",
22     "dog", "frog", "horse", "ship", "truck"
23 ]
24

```

```

1 # Utility functions
2 def slerp(p0, p1, t, eps=1e-7):
3     """Spherical linear interpolation in latent space.
4     Falls back to LERP when angle ~ 0.
5     """
6     p0 = np.asarray(p0, dtype=np.float32)
7     p1 = np.asarray(p1, dtype=np.float32)
8     p0_norm = p0 / (np.linalg.norm(p0) + eps)
9     p1_norm = p1 / (np.linalg.norm(p1) + eps)
10    dot = np.clip(np.dot(p0_norm, p1_norm), -1.0, 1.0)
11    omega = np.arccos(dot)
12    if np.abs(omega) < 1e-3:
13        return (1.0 - t) * p0 + t * p1
14    so = np.sin(omega)
15    return np.sin((1.0 - t) * omega) / so * p0 + np.sin(t * omega) / so * p1
16
17
18 def lerp(p0, p1, t):
19     """Linear interpolation in latent space."""
20     return (1.0 - t) * np.asarray(p0) + t * np.asarray(p1)

```

```

21
22
23 def make_grid(images, n_cols=8, titles=None, suptitle=None, w=2.0, h=2.0):
24     """Plot a grid of images."""
25     images = np.asarray(images)
26     n = len(images)
27     n_cols = min(n_cols, n)
28     n_rows = int(np.ceil(n / n_cols))
29     plt.figure(figsize=(w * n_cols, h * n_rows))
30     for i in range(n):
31         ax = plt.subplot(n_rows, n_cols, i + 1)
32         ax.imshow(images[i])
33         ax.axis("off")
34         if titles is not None and i < len(titles) and titles[i] is not None:
35             ax.set_title(titles[i], fontsize=9)
36     if suptitle:
37         plt.suptitle(suptitle, y=0.98)
38     plt.tight_layout()
39     plt.show()
40
41
42 def to_float01(x):
43     """Convert uint8 images to float32 in [0,1]."""
44     return x.astype("float32") / 255.0
45
46
47 def pick_first_by_label(x, y, label):
48     """Return the first image with a given label."""
49     idx = np.where(y == label)[0]
50     if len(idx) == 0:
51         raise ValueError(f"No sample found with label={label}")
52     return x[idx[0]]
53
54

```

```

1 # Load & filter CIFAR-10
2 (x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
3 y_train = y_train.squeeze()
4 y_test = y_test.squeeze()
5
6 # Filter to selected classes (digits)
7 def filter_classes(x, y, keep):
8     mask = np.isin(y, keep)
9     return x[mask], y[mask]
10
11 x_train_f, y_train_f = filter_classes(x_train, y_train, STUDENT_DIGITS)
12 x_test_f, y_test_f = filter_classes(x_test, y_test, STUDENT_DIGITS)
13
14 print("Train filtered:", x_train_f.shape, y_train_f.shape)
15 print("Test filtered:", x_test_f.shape, y_test_f.shape)
16
17 # Normalize to [0,1]
18 x_train_f = to_float01(x_train_f)
19 x_test_f = to_float01(x_test_f)
20
21 # Simple train/val split from train_f (90/10)
22 n = len(x_train_f)
23 perm = np.random.permutation(n)
24 split = int(0.9 * n)
25 train_idx, val_idx = perm[:split], perm[split:]
26 x_tr, x_val = x_train_f[train_idx], x_train_f[val_idx]
27 y_tr, y_val = y_train_f[train_idx], y_train_f[val_idx]
28
29 # Build tf.data datasets (labels unused for VAE training)
30 train_ds = tf.data.Dataset.from_tensor_slices(x_tr).shuffle(4096, seed=SEED).batch(BATCH_SIZE).prefetch(tf.data.AUTOTUNE)
31 val_ds = tf.data.Dataset.from_tensor_slices(x_val).batch(BATCH_SIZE).prefetch(tf.data.AUTOTUNE)
32
33 # Show class counts for sanity
34 def class_counts(y):
35     counts = {d: int((y == d).sum()) for d in sorted(set(y))}
36     return {f"{d} ({CIFAR10_LABELS[d]})": c for d, c in counts.items()}
37 print("Train class counts:", class_counts(y_tr))
38 print("Val class counts:", class_counts(y_val))
39 print("Test class counts:", class_counts(y_test_f))
40

```

```

Train filtered: (20000, 32, 32, 3) (20000,)
Test filtered: (4000, 32, 32, 3) (4000,)
Train class counts: {'5 (dog)': 4491, '6 (frog)': 4489, '8 (ship)': 4497, '9 (truck)': 4523}
Val class counts: {'5 (dog)': 509, '6 (frog)': 511, '8 (ship)': 503, '9 (truck)': 477}
Test class counts: {'5 (dog)': 1000, '6 (frog)': 1000, '8 (ship)': 1000, '9 (truck)': 1000}

```

```

1 # Build VAE (Conv encoder/decoder)
2 # Encoder
3 def build_encoder(latent_dim=LATENT_DIM, input_shape=(32, 32, 3)):
4     """Convolutional encoder producing z_mean, z_log_var, and sampled z."""
5     inputs = layers.Input(shape=input_shape)
6     x = inputs
7     # downsampling conv blocks
8     x = layers.Conv2D(32, 3, strides=2, padding="same", activation="relu")(x) # 16x16
9     x = layers.Conv2D(64, 3, strides=2, padding="same", activation="relu")(x) # 8x8
10    x = layers.Conv2D(128, 3, strides=2, padding="same", activation="relu")(x) # 4x4
11    x = layers.Flatten()(x)
12    x = layers.Dense(256, activation="relu")(x)
13    z_mean = layers.Dense(latent_dim, name="z_mean")(x)
14    z_log_var = layers.Dense(latent_dim, name="z_log_var")(x)
15
16    # Reparameterization trick
17    def sampling(args):
18        z_m, z_lv = args
19        eps = tf.random.normal(shape=tf.shape(z_m))
20        return z_m + tf.exp(0.5 * z_lv) * eps
21
22    z = layers.Lambda(sampling, name="z")([z_mean, z_log_var])
23    return keras.Model(inputs, [z_mean, z_log_var, z], name="encoder")
24
25 # Decoder
26 def build_decoder(latent_dim=LATENT_DIM, output_shape=(32, 32, 3)):
27     """Convolutional decoder that maps z -> x_hat in [0,1]."""
28    latent_inputs = layers.Input(shape=(latent_dim,))
29    x = layers.Dense(4 * 4 * 128, activation="relu")(latent_inputs)
30    x = layers.Reshape((4, 4, 128))(x)
31    x = layers.Conv2DTranspose(128, 3, strides=2, padding="same", activation="relu")(x) # 8x8
32    x = layers.Conv2DTranspose(64, 3, strides=2, padding="same", activation="relu")(x) # 16x16
33    x = layers.Conv2DTranspose(32, 3, strides=2, padding="same", activation="relu")(x) # 32x32
34    outputs = layers.Conv2D(3, 3, padding="same", activation="sigmoid")(x)
35    return keras.Model(latent_inputs, outputs, name="decoder")
36
37 encoder = build_encoder(LATENT_DIM)
38 decoder = build_decoder(LATENT_DIM)
39
40 # Custom VAE model with explicit loss reporting
41 class VAE(keras.Model):
42     """VAE model that handles KL + reconstruction losses in train/test_step."""
43     def __init__(self, encoder, decoder, **kwargs):
44         super().__init__(**kwargs)
45         self.encoder = encoder
46         self.decoder = decoder
47         self.total_loss_tracker = keras.metrics.Mean(name="loss")
48         self.recon_loss_tracker = keras.metrics.Mean(name="recon_loss")
49         self.kl_loss_tracker = keras.metrics.Mean(name="kl_loss")
50
51     @property
52     def metrics(self):
53         return [self.total_loss_tracker, self.recon_loss_tracker, self.kl_loss_tracker]
54
55     def train_step(self, data):
56         x = data # data is images only
57         if isinstance(x, tuple):
58             x = x[0]
59         with tf.GradientTape() as tape:
60             z_mean, z_log_var, z = self.encoder(x, training=True)
61             x_hat = self.decoder(z, training=True)
62
63             # Reconstruction loss (MSE sum over pixels), averaged over batch
64             recon_loss = tf.reduce_mean(tf.reduce_sum(tf.square(x - x_hat), axis=[1, 2, 3]))
65
66             # KL divergence loss
67             kl_loss = -0.5 * tf.reduce_mean(tf.reduce_sum(1 + z_log_var - tf.square(z_mean) - tf.exp(z_log_var), axis=
68
69             total = recon_loss + kl_loss
70
71         grads = tape.gradient(total, self.trainable_variables)
72         self.optimizer.apply_gradients(zip(grads, self.trainable_variables))
73
74         self.total_loss_tracker.update_state(total)
75         self.recon_loss_tracker.update_state(recon_loss)
76         self.kl_loss_tracker.update_state(kl_loss)
77         return {"loss": self.total_loss_tracker.result(),
78                 "recon_loss": self.recon_loss_tracker.result(),
79                 "kl_loss": self.kl_loss_tracker.result()}
80
81     def test_step(self, data):
82         x = data

```

```

83     if isinstance(x, tuple):
84         x = x[0]
85     z_mean, z_log_var, z = self.encoder(x, training=False)
86     x_hat = self.decoder(z, training=False)
87     recon_loss = tf.reduce_mean(tf.reduce_sum(tf.square(x - x_hat), axis=[1, 2, 3]))
88     kl_loss = -0.5 * tf.reduce_mean(tf.reduce_sum(1 + z_log_var - tf.square(z_mean) - tf.exp(z_log_var), axis=1))
89     total = recon_loss + kl_loss
90     self.total_loss_tracker.update_state(total)
91     self.recon_loss_tracker.update_state(recon_loss)
92     self.kl_loss_tracker.update_state(kl_loss)
93     return {"loss": self.total_loss_tracker.result(),
94           "recon_loss": self.recon_loss_tracker.result(),
95           "kl_loss": self.kl_loss_tracker.result()}
96
97 vae = VAE(encoder, decoder)
98 vae.compile(optimizer=keras.optimizers.Adam(learning_rate=LEARNING_RATE))

```

```

1 # Train
2 history = vae.fit(
3     train_ds,
4     validation_data=val_ds,
5     epochs=EPOCHS,
6     verbose=2
7 )

```

```

ms/step - kl_loss: 4.8104 - loss: 159.0787 - recon_loss: 154.2683 - val_kl_loss: 8.2439 - val_loss: 126.3577 - val_recon_loss:
/step - kl_loss: 11.1903 - loss: 102.0919 - recon_loss: 90.9016 - val_kl_loss: 11.5080 - val_loss: 96.0340 - val_recon_loss:
1ms/step - kl_loss: 11.4078 - loss: 94.8011 - recon_loss: 83.3933 - val_kl_loss: 11.3436 - val_loss: 93.2746 - val_recon_loss:
ms/step - kl_loss: 11.9832 - loss: 91.8405 - recon_loss: 79.8573 - val_kl_loss: 12.6454 - val_loss: 90.3489 - val_recon_loss:
ms/step - kl_loss: 12.2456 - loss: 89.6006 - recon_loss: 77.3549 - val_kl_loss: 12.6252 - val_loss: 88.9898 - val_recon_loss:
ms/step - kl_loss: 12.3630 - loss: 88.8623 - recon_loss: 76.4993 - val_kl_loss: 12.2501 - val_loss: 88.8979 - val_recon_loss:
ms/step - kl_loss: 12.3483 - loss: 88.2468 - recon_loss: 75.8985 - val_kl_loss: 12.4982 - val_loss: 88.4009 - val_recon_loss:
ms/step - kl_loss: 12.3753 - loss: 87.9085 - recon_loss: 75.5331 - val_kl_loss: 12.3049 - val_loss: 87.8378 - val_recon_loss:
ms/step - kl_loss: 12.3862 - loss: 87.6579 - recon_loss: 75.2717 - val_kl_loss: 12.6682 - val_loss: 87.9028 - val_recon_loss:
ms/step - kl_loss: 12.4079 - loss: 87.3556 - recon_loss: 74.9477 - val_kl_loss: 12.8632 - val_loss: 87.8530 - val_recon_loss:

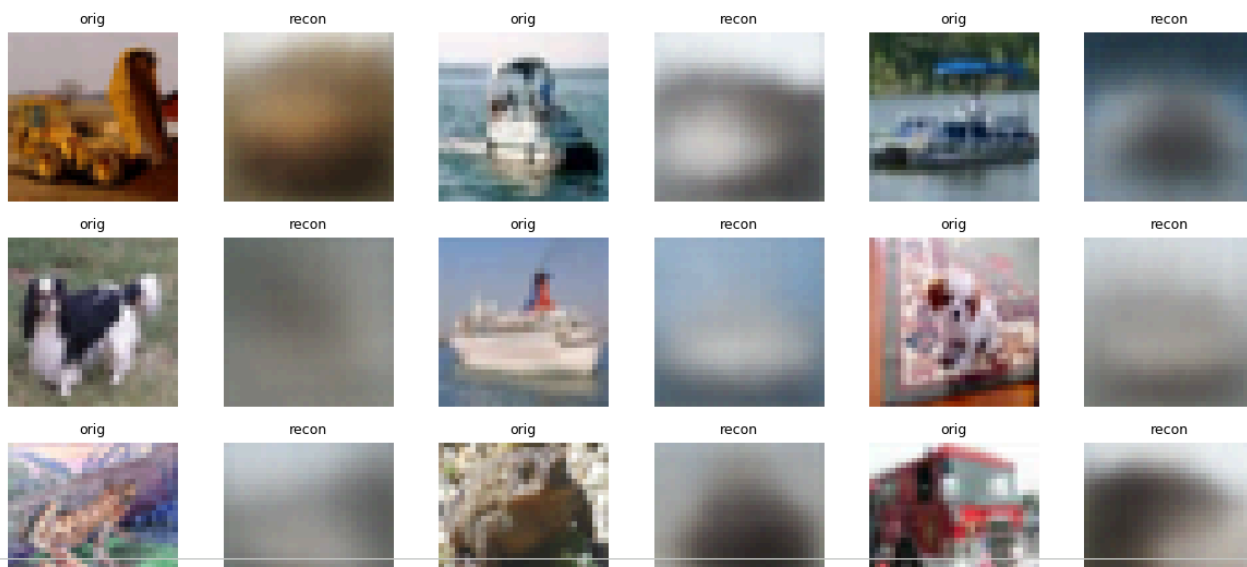
```

```

1 # Reconstructions on test set
2 n_show = 12
3 idx = np.random.choice(len(x_test_f), size=n_show, replace=False)
4 x_sample = x_test_f[idx]
5 z_mean, z_log_var, z = encoder.predict(x_sample, verbose=0)
6 x_recon = decoder.predict(z, verbose=0)
7
8 # Clip for safety
9 x_recon = np.clip(x_recon, 0.0, 1.0)
10
11 # Interleave originals and reconstructions for visualization
12 pairs = []
13 titles = []
14 for i in range(n_show):
15     pairs.append(x_sample[i])
16     titles.append(f"orig")
17     pairs.append(x_recon[i])
18     titles.append(f"recon")
19 make_grid(pairs, n_cols=6, titles=titles, suptitle="Originals (odd) / Reconstructions (even)")
20

```

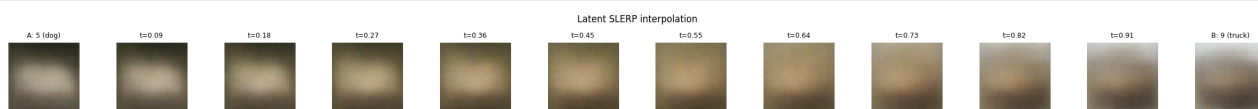
Originals (odd) / Reconstructions (even)



```

1
2 # Latent interpolation between two images of different classes
3 if CLASS_A not in STUDENT_DIGITS or CLASS_B not in STUDENT_DIGITS or CLASS_A == CLASS_B:
4     raise ValueError("CLASS_A and CLASS_B must be two distinct values from STUDENT_DIGITS.")
5
6 img_a = pick_first_by_label(x_test_f, y_test_f, CLASS_A)
7 img_b = pick_first_by_label(x_test_f, y_test_f, CLASS_B)
8
9 # Encode to latent means (we use mean for deterministic interpolation)
10 z_mean_a, _, _ = encoder.predict(img_a[None, ...], verbose=0)
11 z_mean_b, _, _ = encoder.predict(img_b[None, ...], verbose=0)
12 za = z_mean_a[0]
13 zb = z_mean_b[0]
14
15 # Build interpolation path
16 ts = np.linspace(0.0, 1.0, INTERP_STEPS)
17 zs = []
18 for t in ts:
19     if INTERP_MODE.lower() == "slerp":
20         zt = slerp(za, zb, t)
21     else:
22         zt = lerp(za, zb, t)
23     zs.append(zt)
24 zs = np.stack(zs, axis=0)
25
26 # Decode sequence
27 interp_imgs = decoder.predict(zs, verbose=0)
28 interp_imgs = np.clip(interp_imgs, 0.0, 1.0)
29
30 # Show interpolation with endpoints labeled
31 titles = [f"t={t:.2f}" for t in ts]
32 titles[0] = f"A: {CLASS_A} ({CIFAR10_LABELS[CLASS_A]})"
33 titles[-1] = f"B: {CLASS_B} ({CIFAR10_LABELS[CLASS_B]})"
34 make_grid(interp_imgs, n_cols=INTERP_STEPS, titles=titles, suptitle=f"Latent {INTERP_MODE.upper()} interpolation")
35

```



```

1
2 # Op: 2D latent scatter if LATENT_DIM == 2
3 if LATENT_DIM == 2:
4     print("LATENT_DIM == 2 -> projecting test set means...")
5     # Take a subset for speed
6     max_pts = min(3000, len(x_test_f))
7     x_sub = x_test_f[:max_pts]
8     y_sub = y_test_f[:max_pts]
9     z_means, _, _ = encoder.predict(x_sub, verbose=0)
10    # Basic scatter
11    plt.figure(figsize=(6, 5))
12    for d in sorted(set(y_sub)):
13        mask = (y_sub == d)
14        plt.scatter(z_means[mask, 0], z_means[mask, 1], s=8, alpha=0.7, label=f"{d}:{CIFAR10_LABELS[d]}")
15    plt.legend(markerscale=2, fontsize=8)

```

```
16 plt.title("Latent space (z_mean) by class")
17 plt.xlabel("z1"); plt.ylabel("z2")
18 plt.tight_layout()
19 plt.show()
20
21 print("Done.")
22
```

Done.