

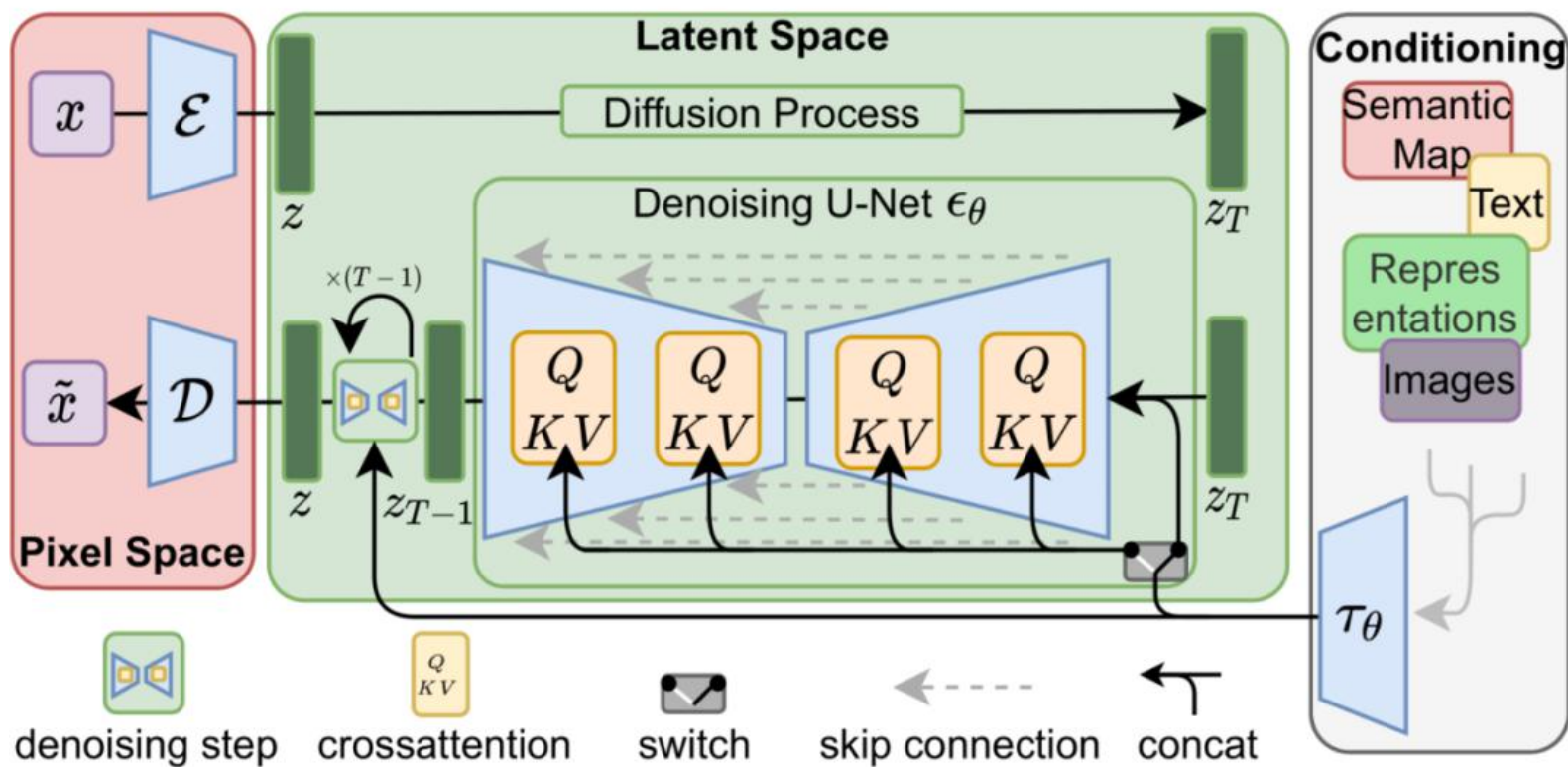
*Code is “cheap”, show me the PROMPT!*

*Stable Diffusion*基本原理与Keras简单示例

林嵩

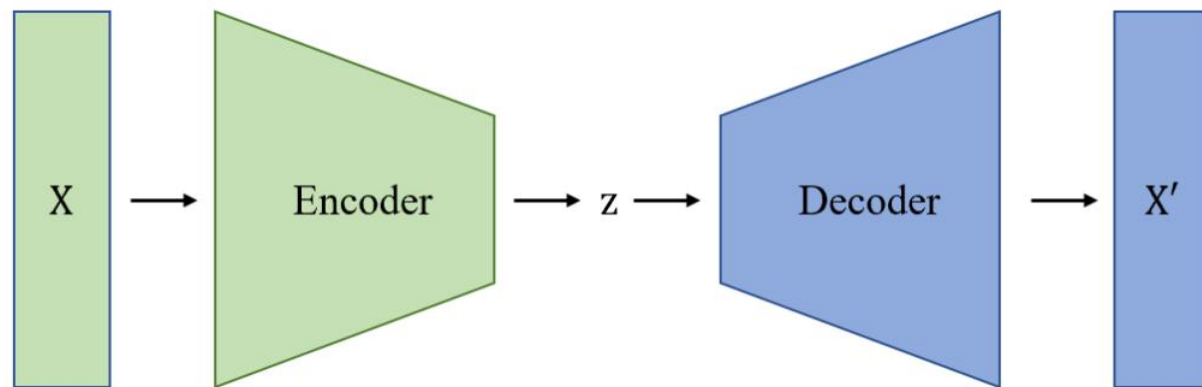
# 目录

Autoencoder  
diffusion  
U-net  
text embedding  
cross attention

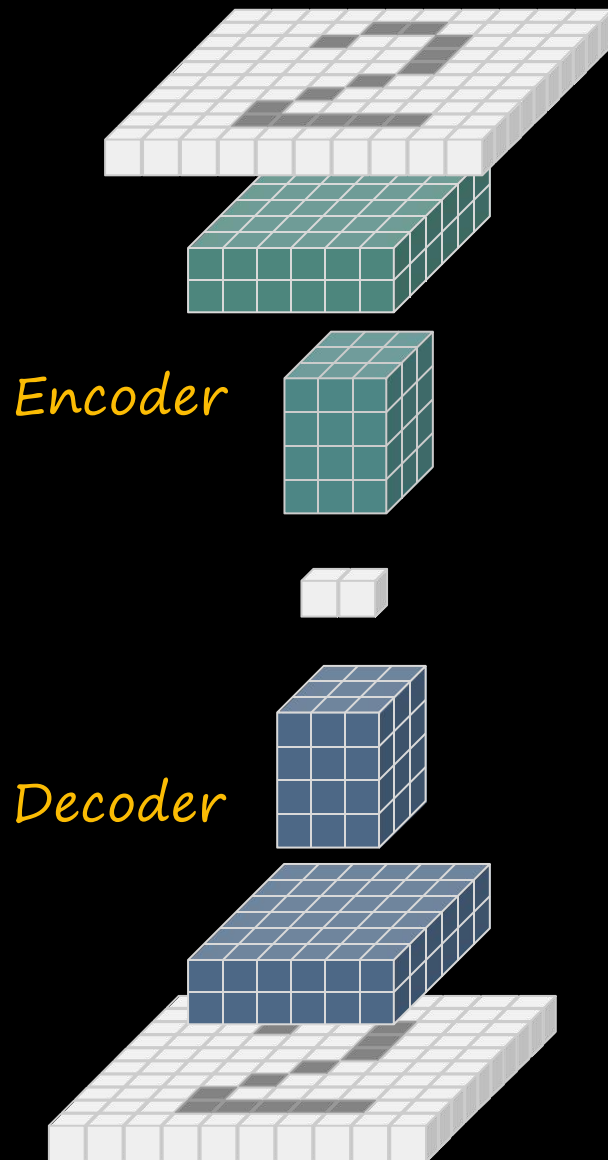


# AE

自动编码器（*Auto Encoder*, *AE*）是早期较为简单的生成模型，通过一个编码器将输入编码成隐变量，再通过一个解码器解码成重构样本。



# Autoencoder

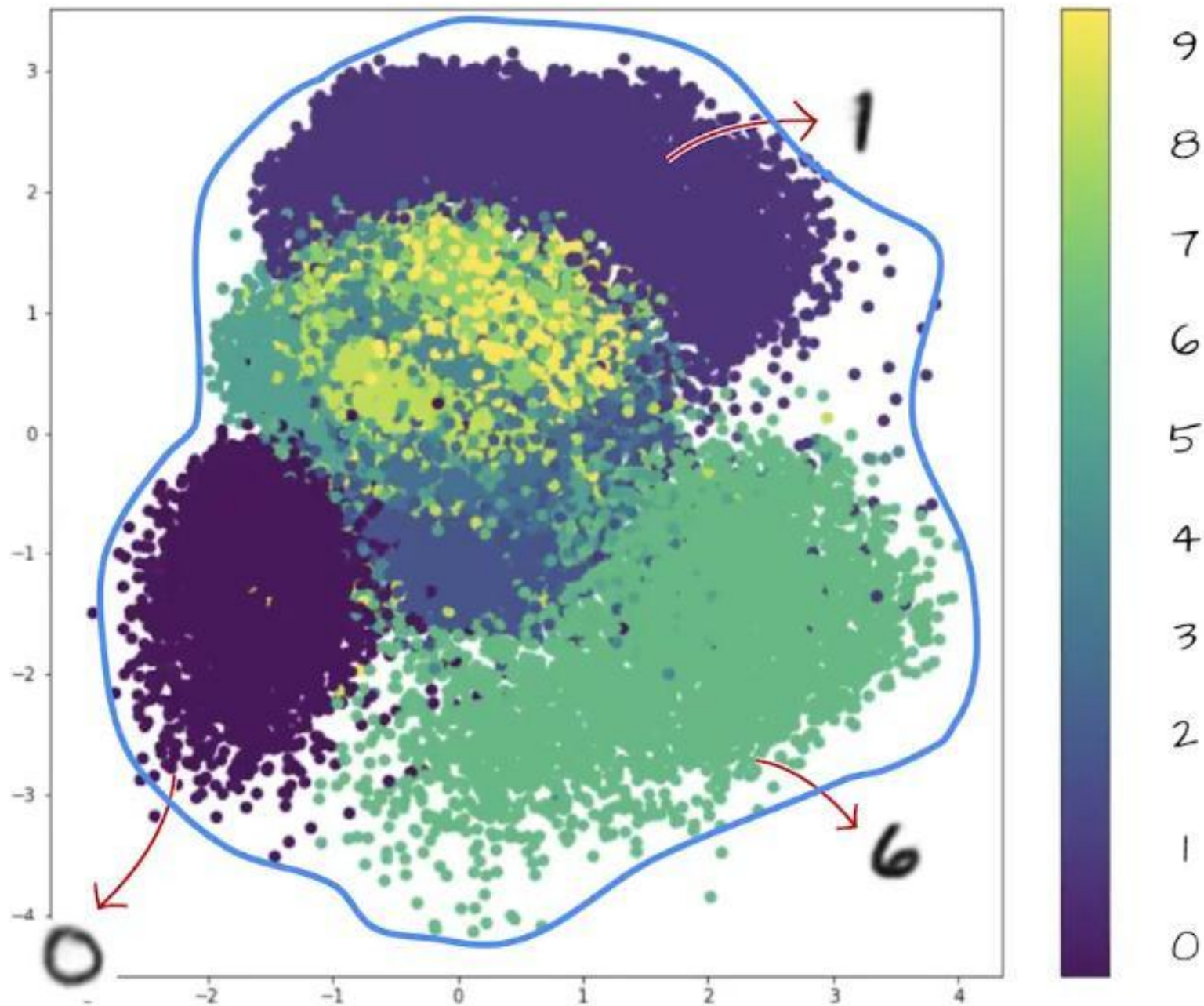


```
autoencoder = tf.keras.Sequential([  
  
    layers.Conv2D(32, 3, strides=2,  
                  activation="relu", padding="same"),  
    layers.Conv2D(64, 3, strides=2,  
                  activation="relu", padding="same"),  
    layers.Flatten(),  
    layers.Dense(latent_dim), # latent_dim=2  
  
    layers.Dense(7 * 7 * 64, activation="relu"),  
    layers.Reshape((7, 7, 64)),  
    layers.Conv2DTranspose(32, 3, strides=2,  
                           activation="relu", padding="same"),  
    layers.Conv2DTranspose(1, 3, strides=2,  
                           activation="sigmoid", padding="same")  
])
```

**Encoder** output  
on training data

**Decoder** output  
from latent space

0 1 2 3 6

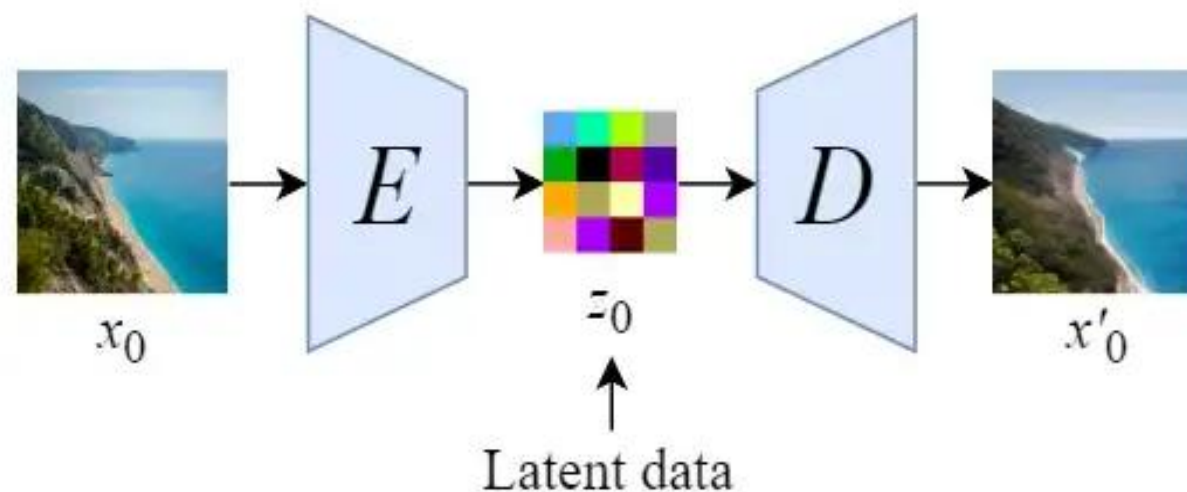
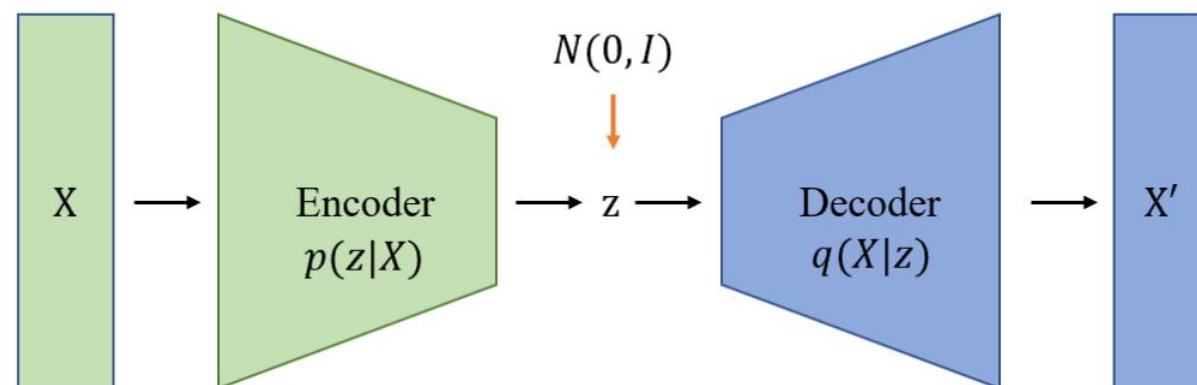


# VAE – 有点像但不多

## VAE (Variational Auto Encoder)

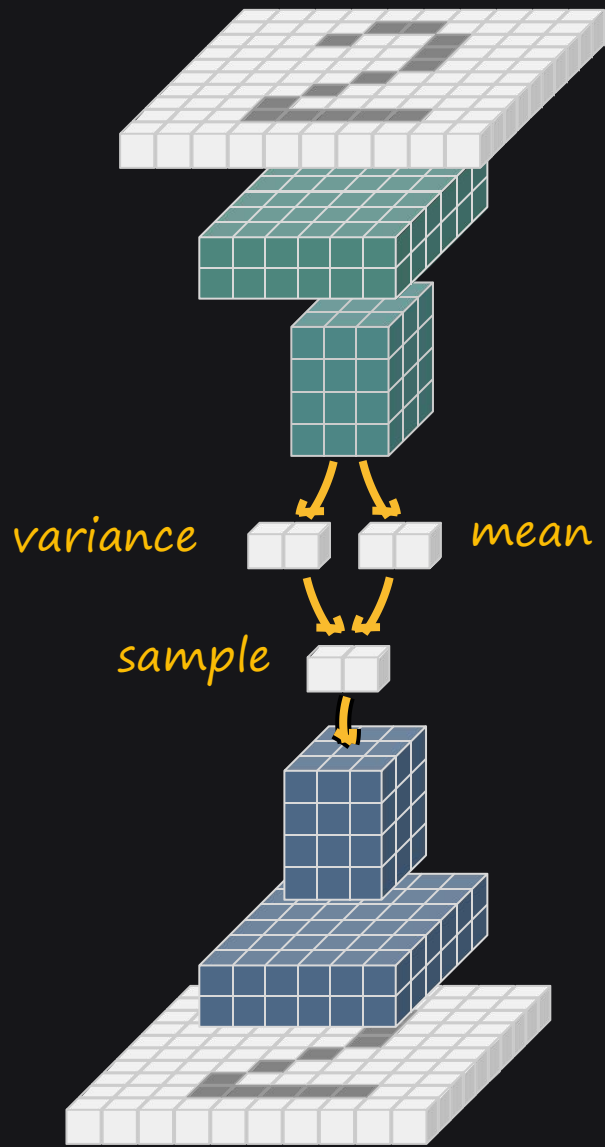
生成类似于输入样本，但是不完全一样的新东西，在合理范围内变花样。

在 $latent$ 上操作而不需要 $encoder$ ，直接得到 $decoder$ 的输出。

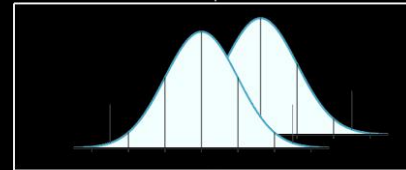




# Variational Autoencoder



Input image



Probabilistic representation



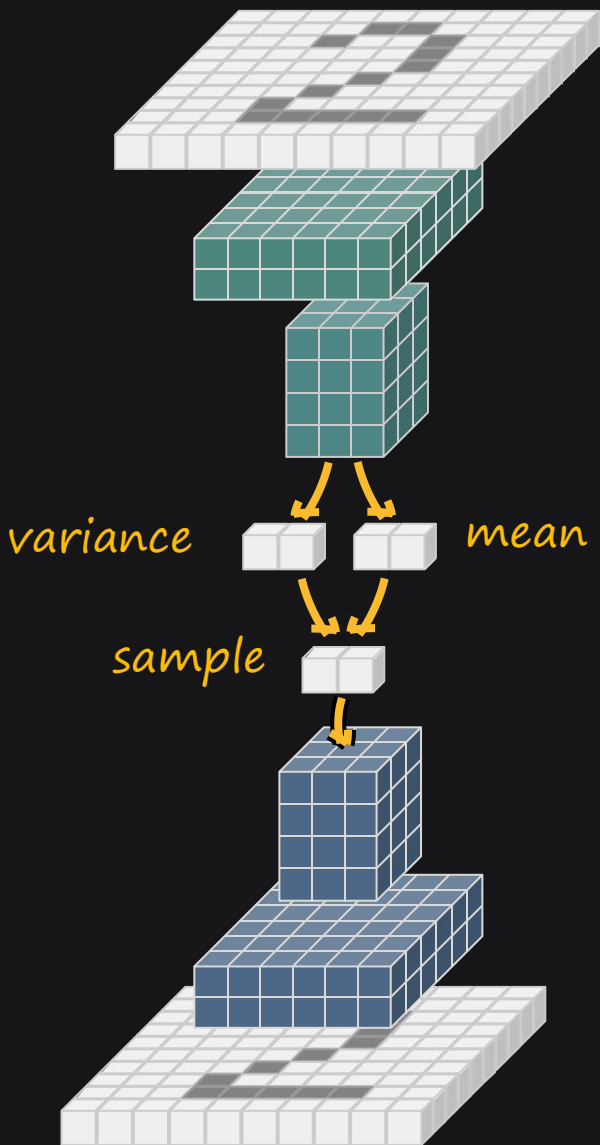
Reconstructed image

VAE part #1  
sampling layer

VAE part #2  
variational encoder

VAE part #3  
regularization loss

VAE part #4  
reconstruction loss



```
encoder_input = keras.Input(shape=(28, 28, 1))
```

```
x = layers.Conv2D(32, 3, strides=2,
                  activation="relu",
```

```
padding="same")(encoder_input)
```

```
x = layers.Conv2D(64, 3, strides=2, activation="relu",
padding="same")(x)
```

```
x = layers.Flatten()(x)
```

```
# latent_dim = 2
```

```
z_mean = layers.Dense(latent_dim, name="z_mean")(x)
```

```
z_log_var = layers.Dense(latent_dim, name="z_log_var")(x)
```

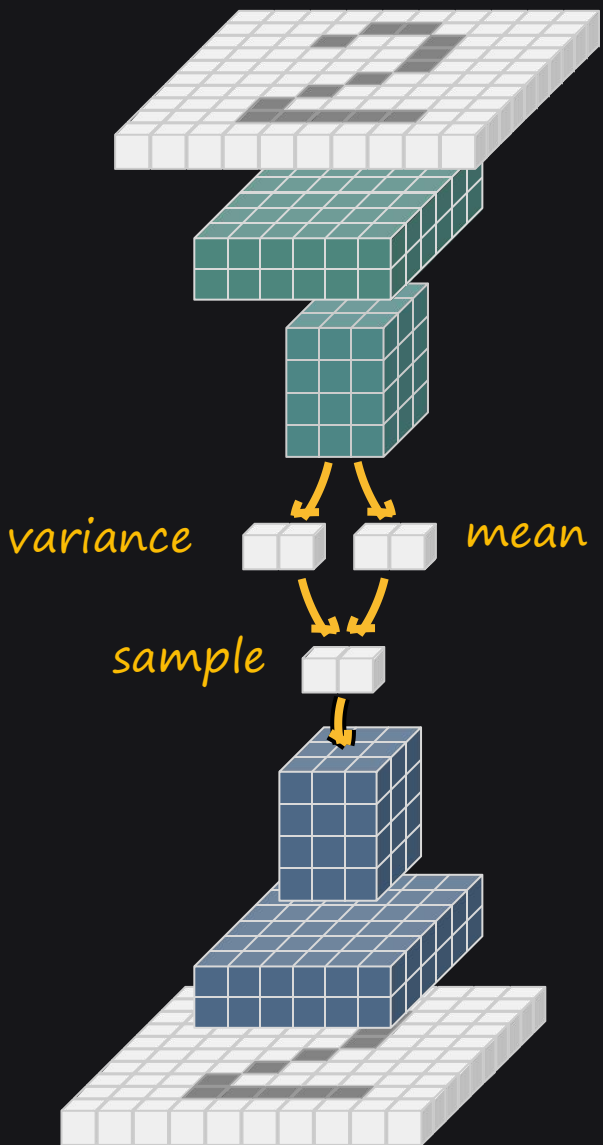
```
z = Sampling()(z_mean, z_log_var)
```

```
encoder = keras.Model(encoder_input, [z_mean, z_log_var, z])
```

Functional  
model

VAE part #2  
variational  
encoder





# Model Composition

```
latent_input = keras.Input(shape=(latent_dim,))
y = layers.Dense(7 * 7 * 64, activation="relu")(latent_input)
y = layers.Reshape((7, 7, 64))(y)
y = layers.Conv2DTranspose(32, 3, strides=2,
                           activation="relu", padding="same")(y)
y = layers.Conv2DTranspose(1, 3, strides=2,
                           activation="sigmoid", padding="same")(y)
```

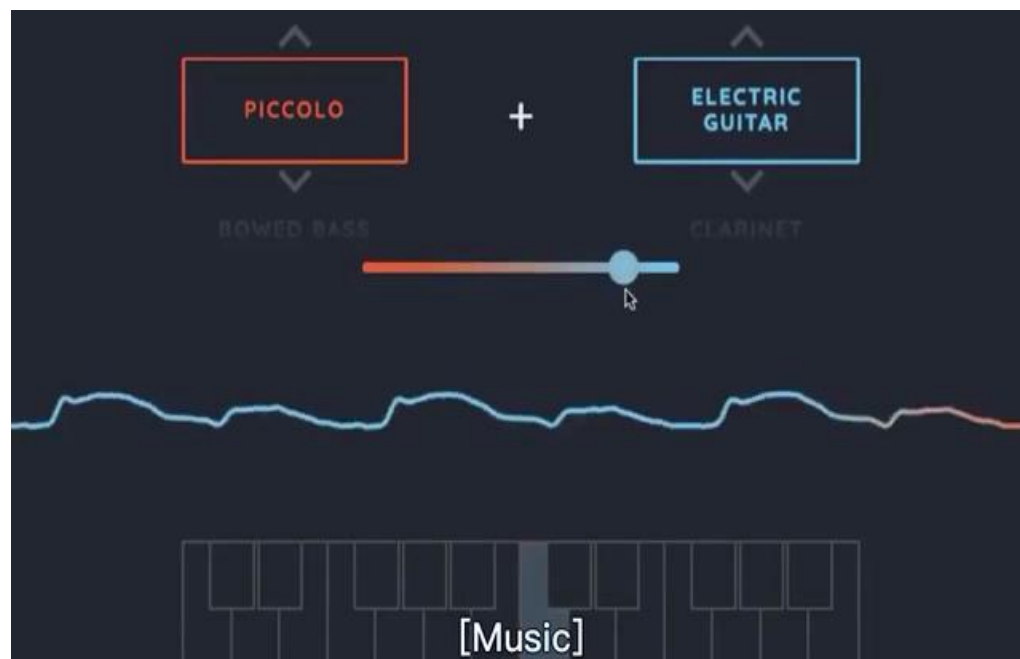
```
decoder = keras.Model(latent_input, y)
```

```
z_mean, z_log_var, z = encoder(encoder_input)
decoder_output = decoder(z)
```

```
vae = keras.Model(encoder_input, decoder_output)
```

应用场景:

- 降噪
- 异常检测
- *renlian*生成
- 曲风变化



```

(x_train, _), (x_test, _) = fashion_mnist.load_data()

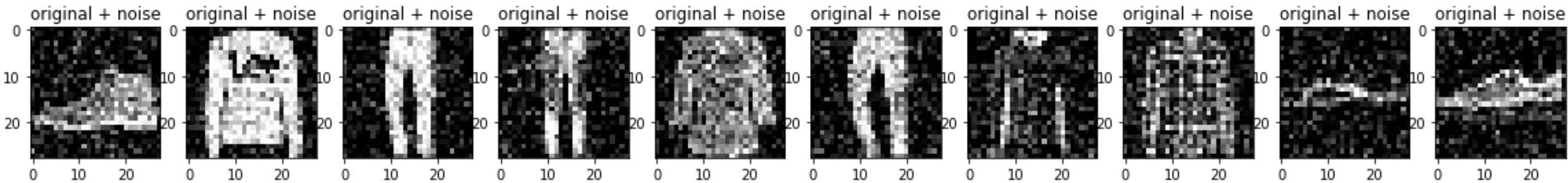
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.

x_train = x_train[..., tf.newaxis]
x_test = x_test[..., tf.newaxis]

noise_factor = 0.2
x_train_noisy = x_train + noise_factor * tf.random.normal(shape=x_train.shape)
x_test_noisy = x_test + noise_factor * tf.random.normal(shape=x_test.shape)

x_train_noisy = tf.clip_by_value(x_train_noisy, clip_value_min=0., clip_value_max=1.)
x_test_noisy = tf.clip_by_value(x_test_noisy, clip_value_min=0., clip_value_max=1.)

```



```

class Denoise(Model):
    def __init__(self):
        super(Denoise, self).__init__()
        self.encoder = tf.keras.Sequential([
            layers.Input(shape=(28, 28, 1)),
            layers.Conv2D(16, (3, 3), activation='relu', padding='same',
strides=2),
            layers.Conv2D(8, (3, 3), activation='relu', padding='same',
strides=2)])

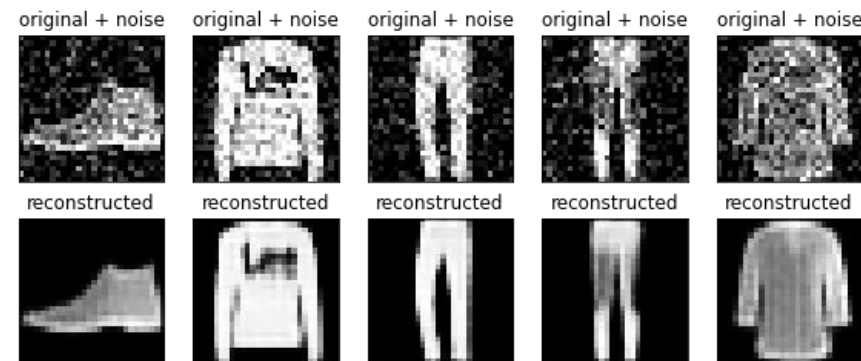
        self.decoder = tf.keras.Sequential([
            layers.Conv2DTranspose(8, kernel_size=3, strides=2,
activation='relu', padding='same'),
            layers.Conv2DTranspose(16, kernel_size=3, strides=2,
activation='relu', padding='same'),
            layers.Conv2D(1, kernel_size=(3, 3), activation='sigmoid',
padding='same')])

    def call(self, x):
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)
        return decoded

autoencoder = Denoise()

autoencoder.fit(x_train_noisy, x_train, epochs=10,
                shuffle=True, validation_data=(x_test_noisy,
x_test))

```



```

class AnomalyDetector(Model):
    def __init__(self):
        super(AnomalyDetector, self).__init__()
        self.encoder = tf.keras.Sequential([
            layers.Dense(32, activation="relu"),
            layers.Dense(16, activation="relu"),
            layers.Dense(8, activation="relu")])

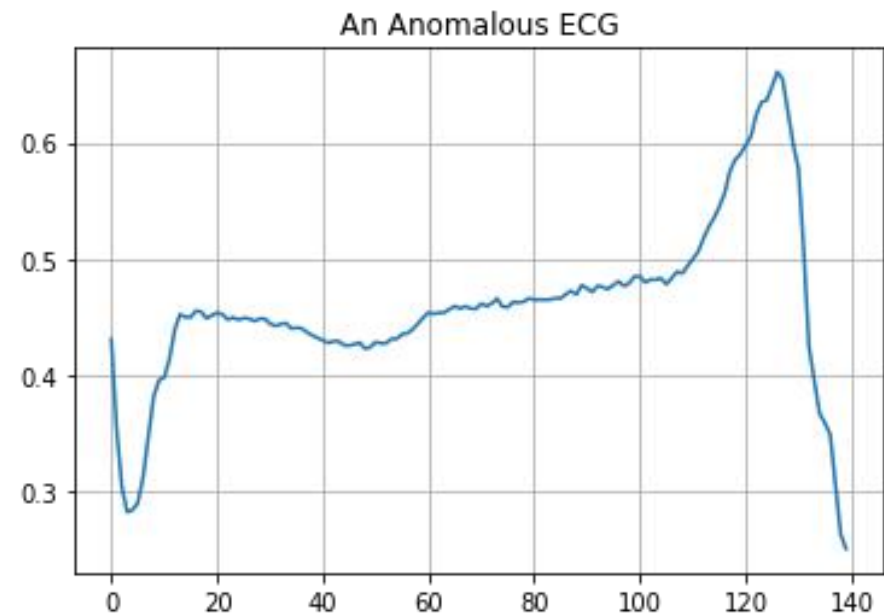
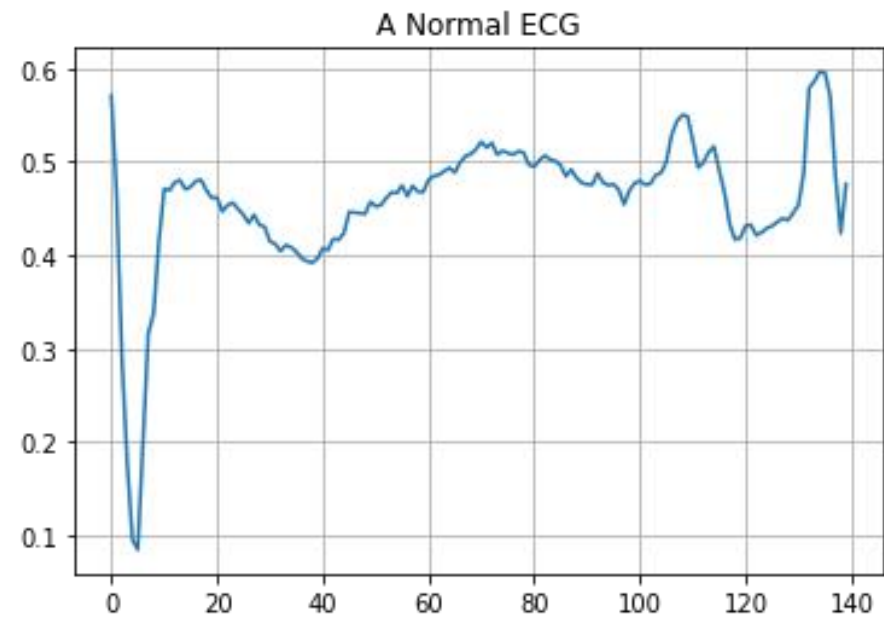
        self.decoder = tf.keras.Sequential([
            layers.Dense(16, activation="relu"),
            layers.Dense(32, activation="relu"),
            layers.Dense(140, activation="sigmoid")])

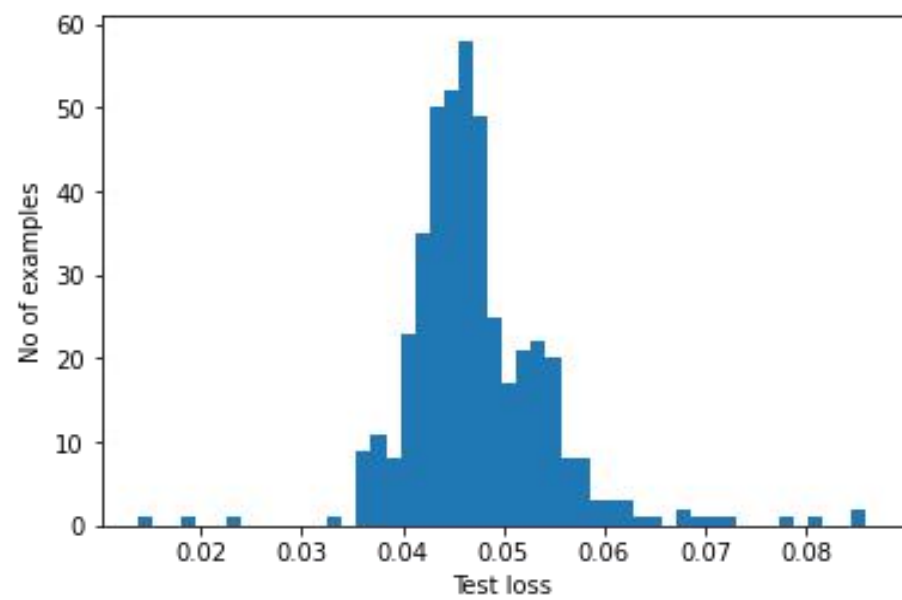
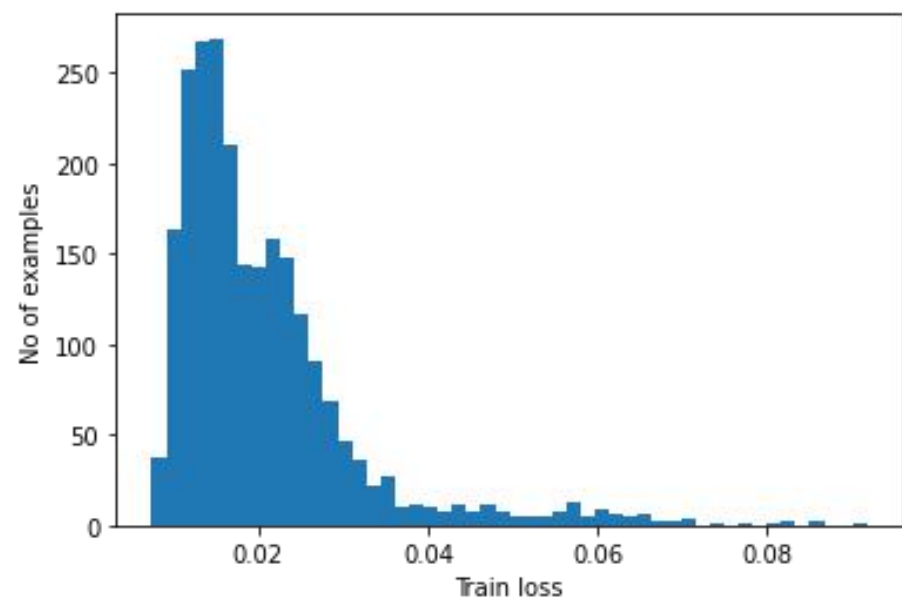
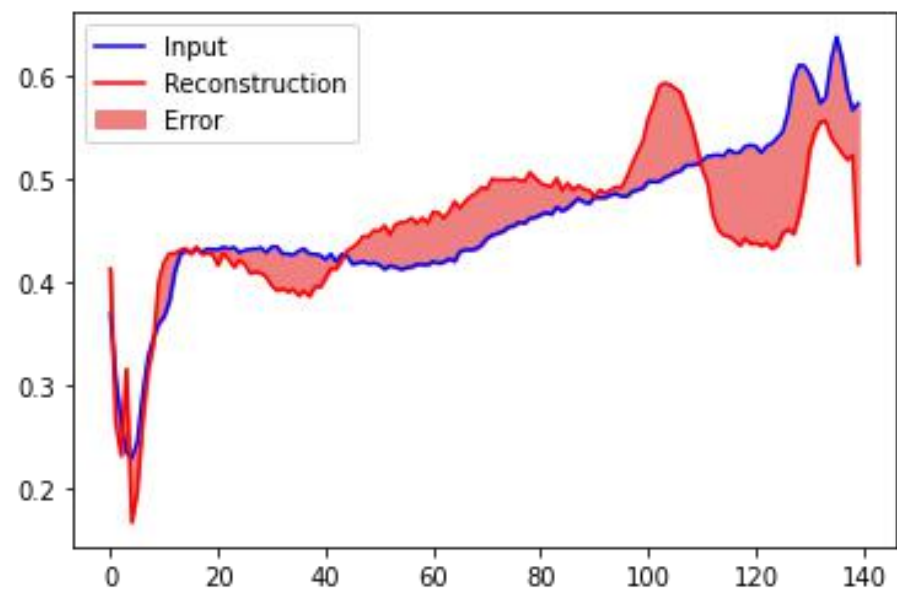
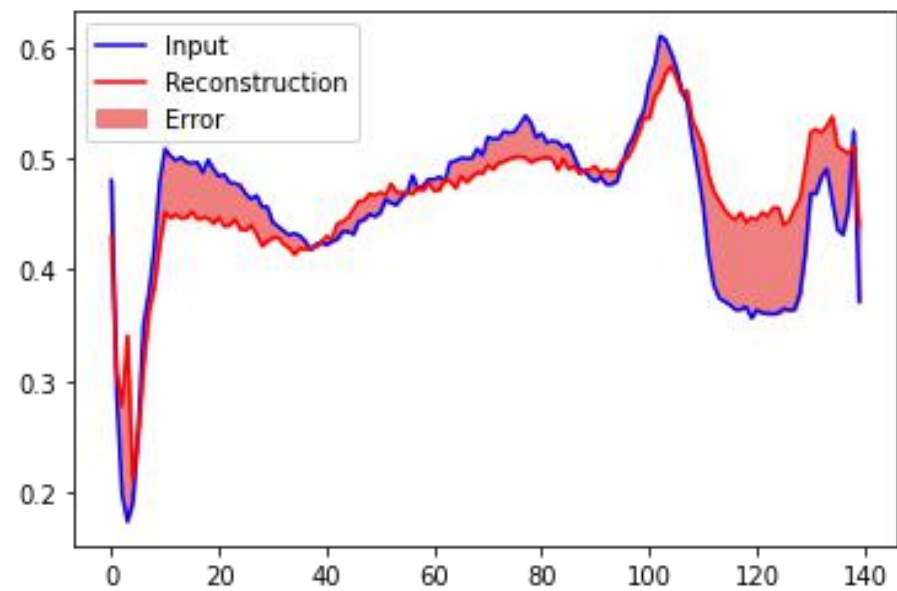
    def call(self, x):
        encoded = self.encoder(x)
        decoded = self.decoder(encoded)
        return decoded

autoencoder = AnomalyDetector()
autoencoder.compile(optimizer='adam', loss='mae')

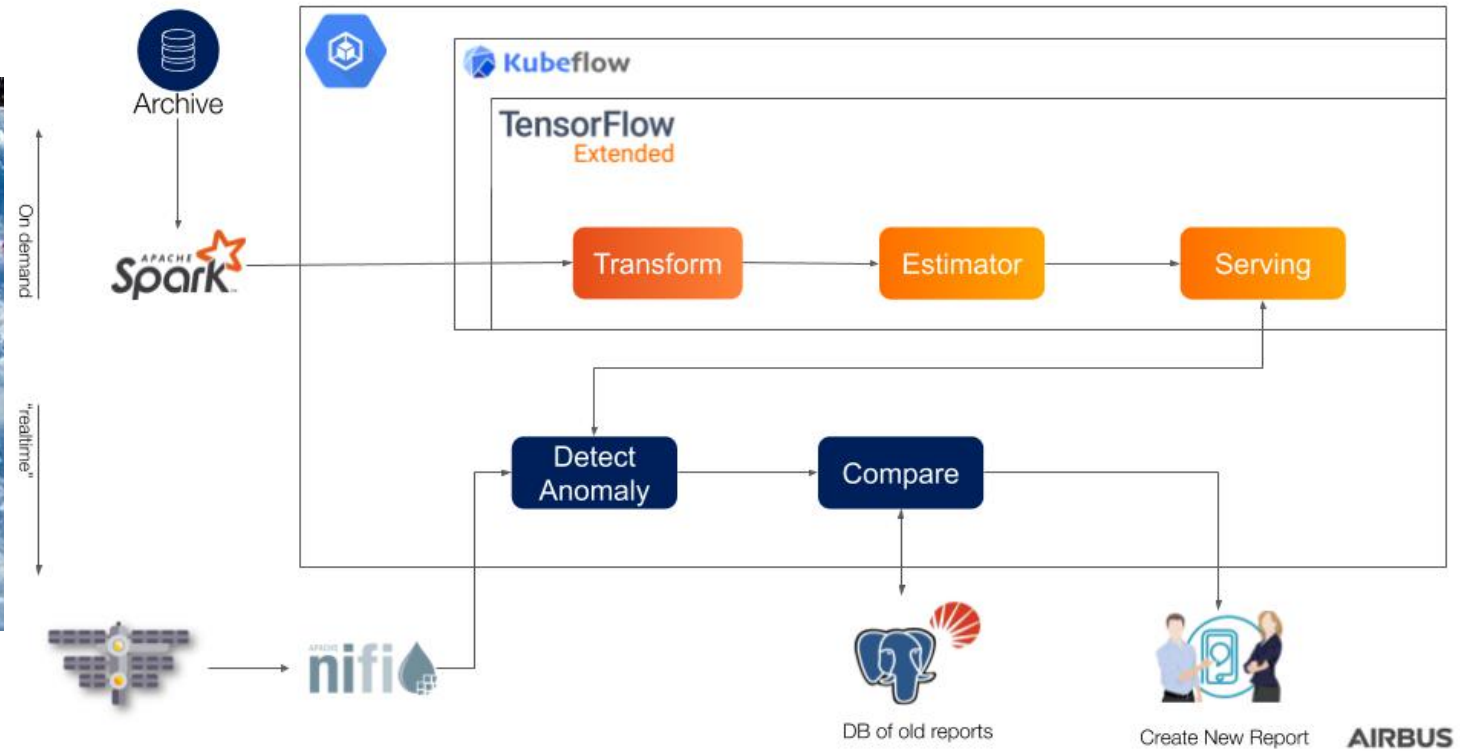
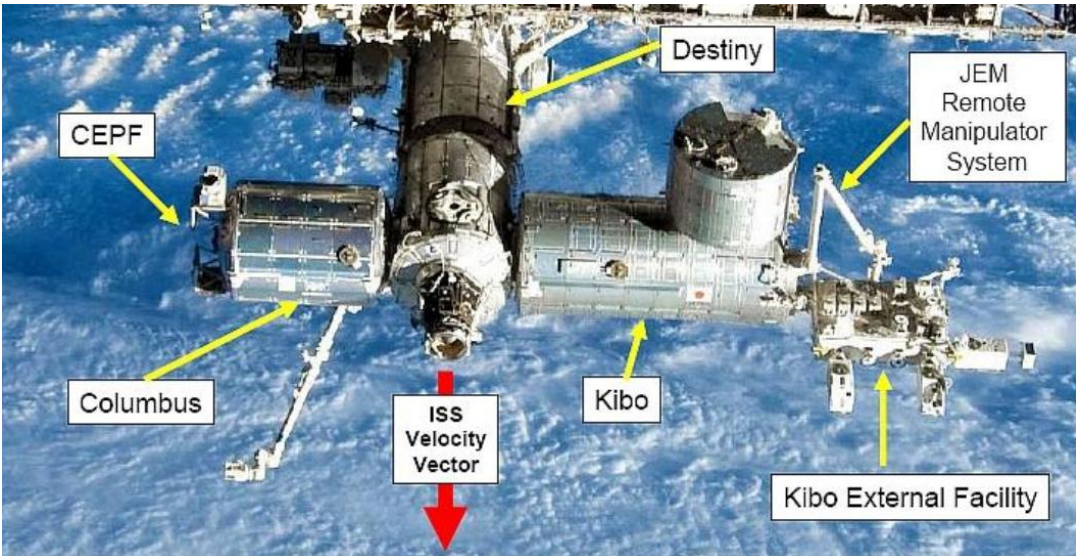
history = autoencoder.fit(normal_train_data, normal_train_data,
                          epochs=20, batch_size=512,
                          validation_data=(test_data, test_data), shuffle=True)

```

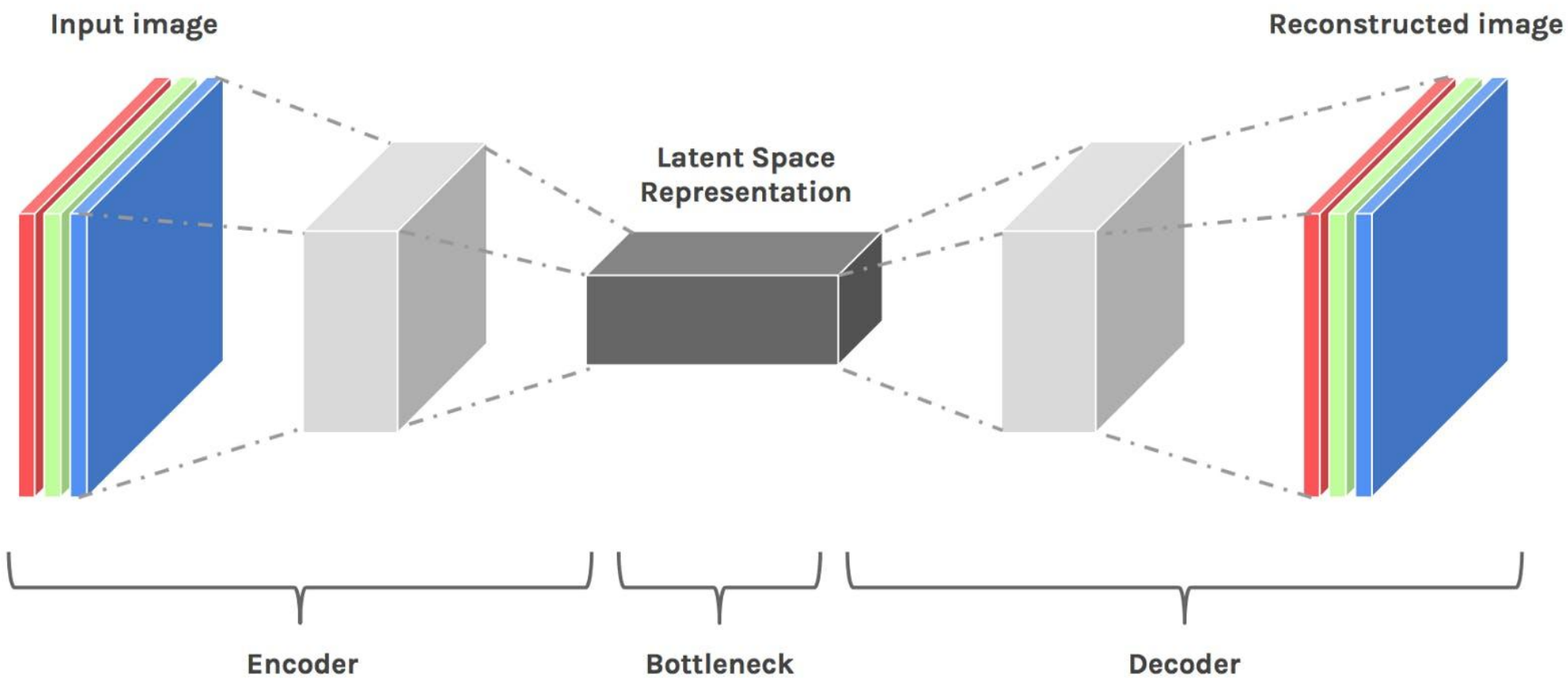


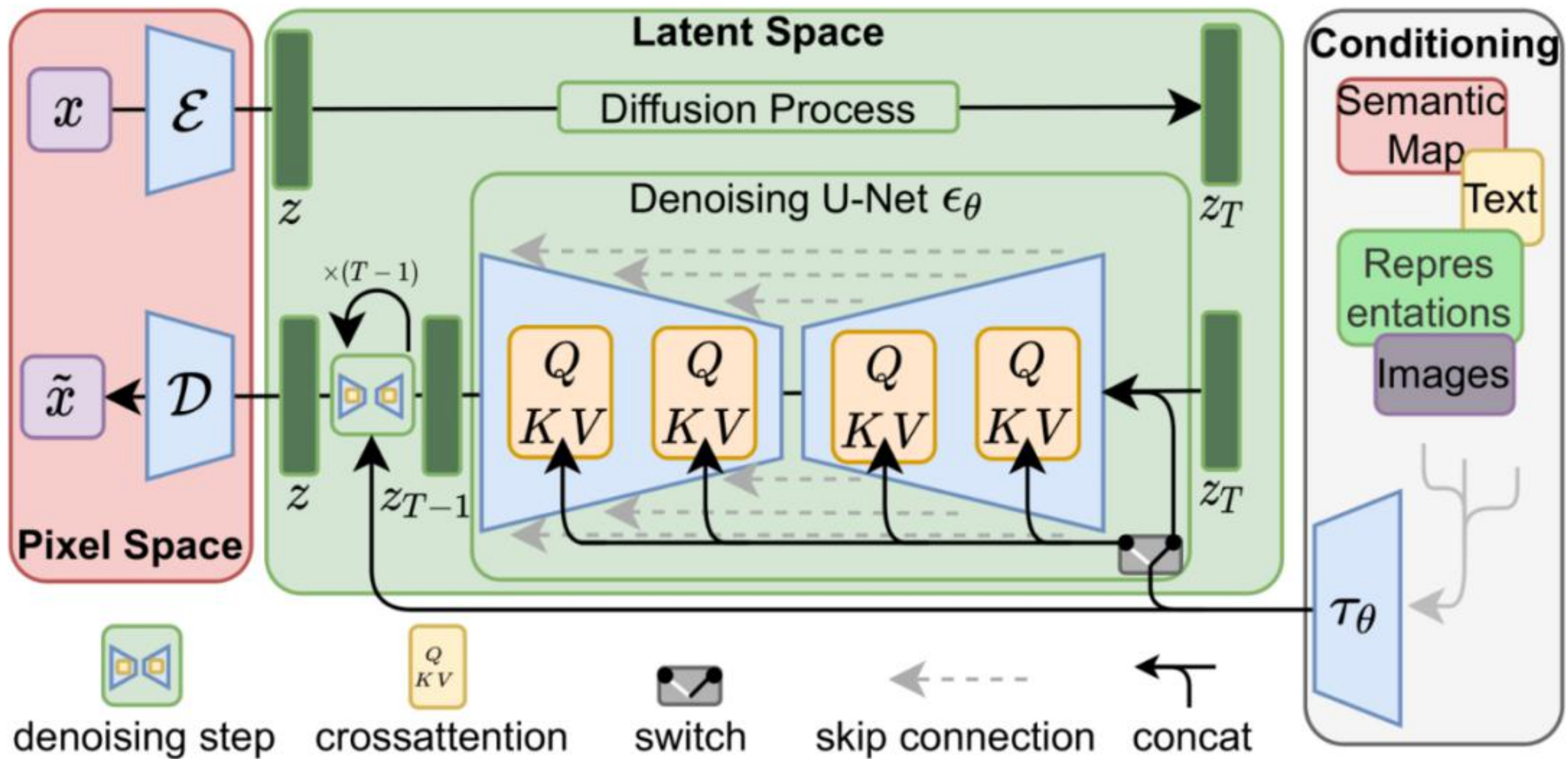






# AE机制的核心-latent



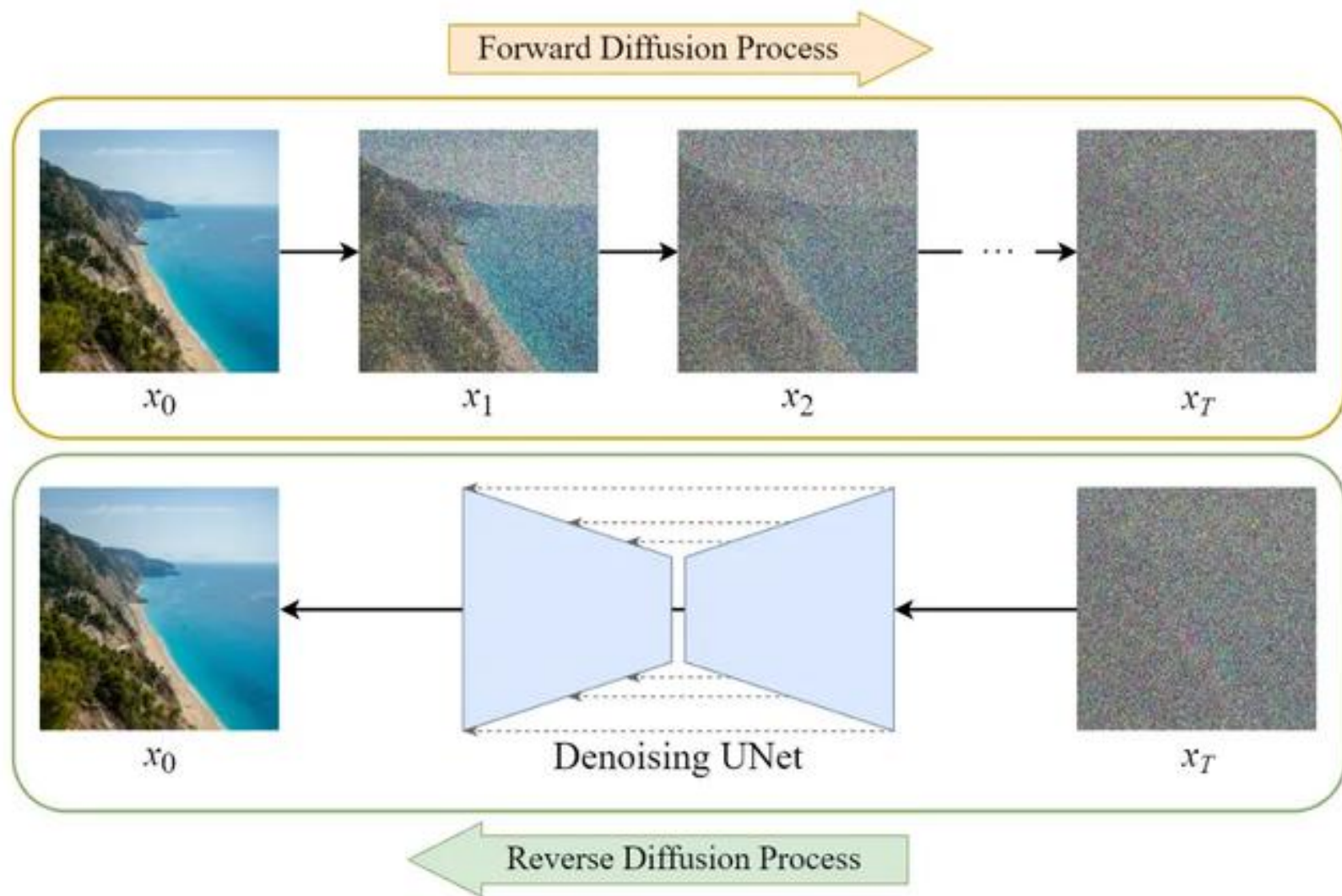


# diffusion

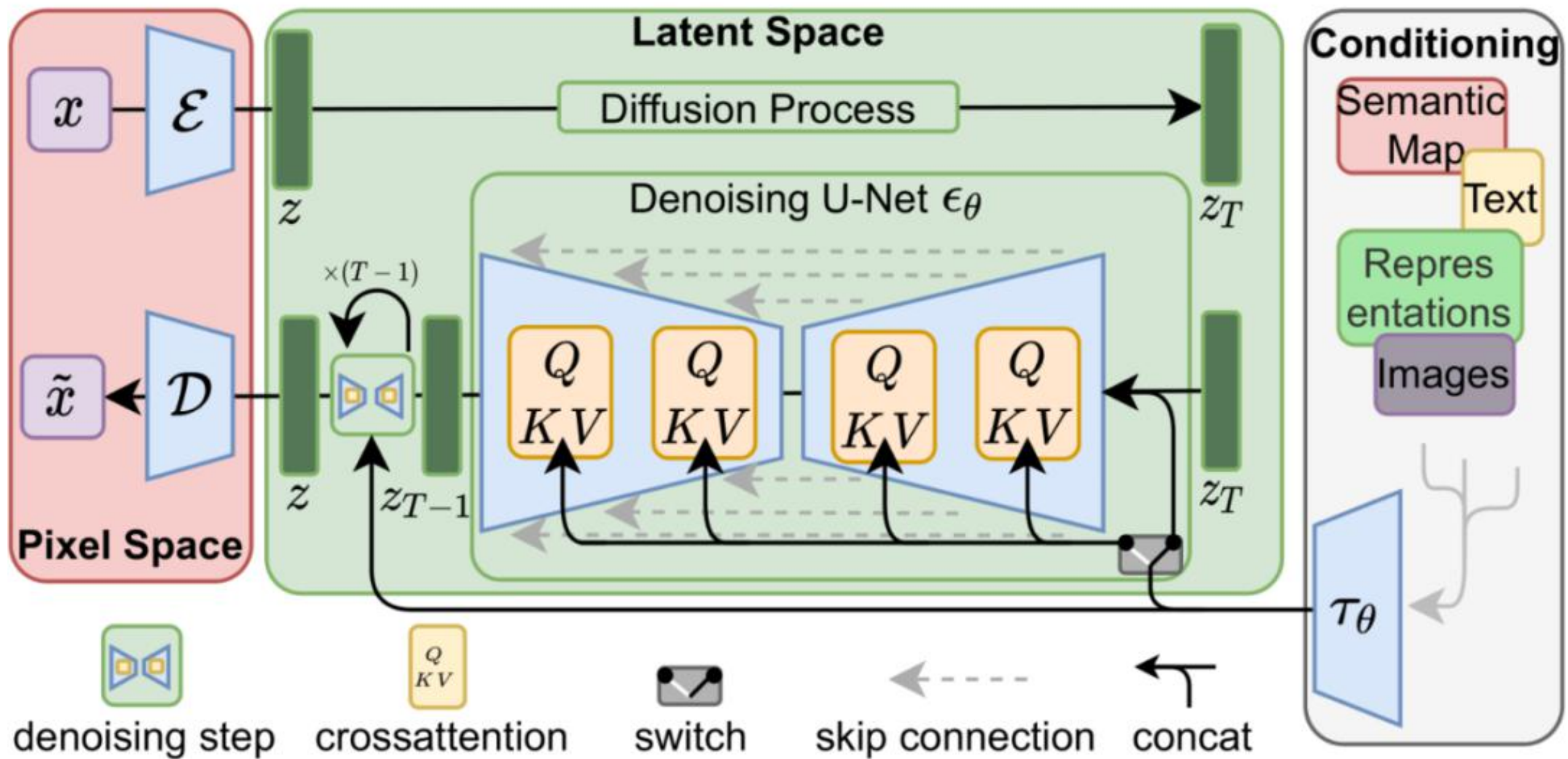
正向：水里加盐

逆向：慢镜头分步倒放

一个模型的状态转移如果符合马尔科夫链的状态转移矩阵，当状态转移到一定次数时，模型状态最终收敛于一个平稳分布。



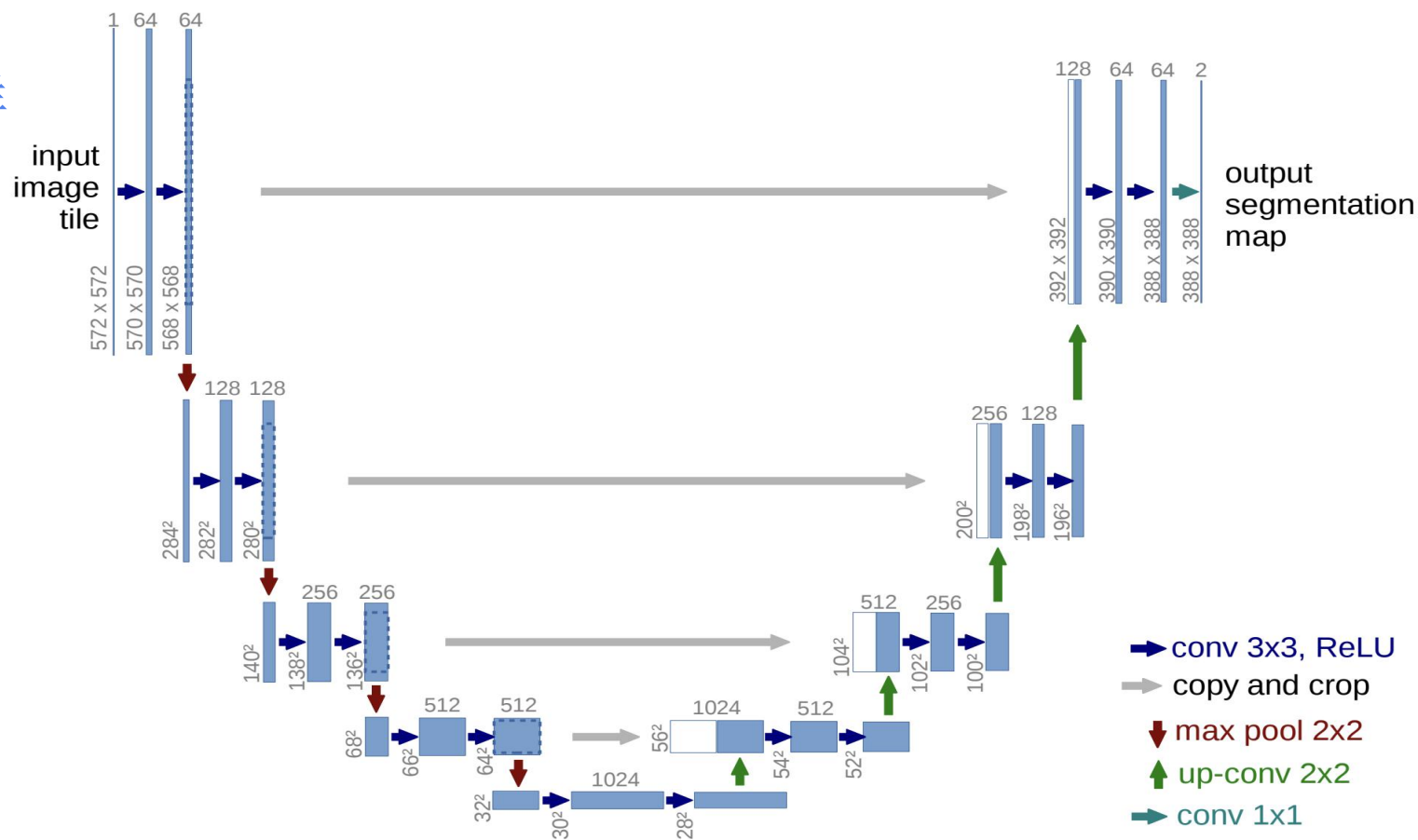




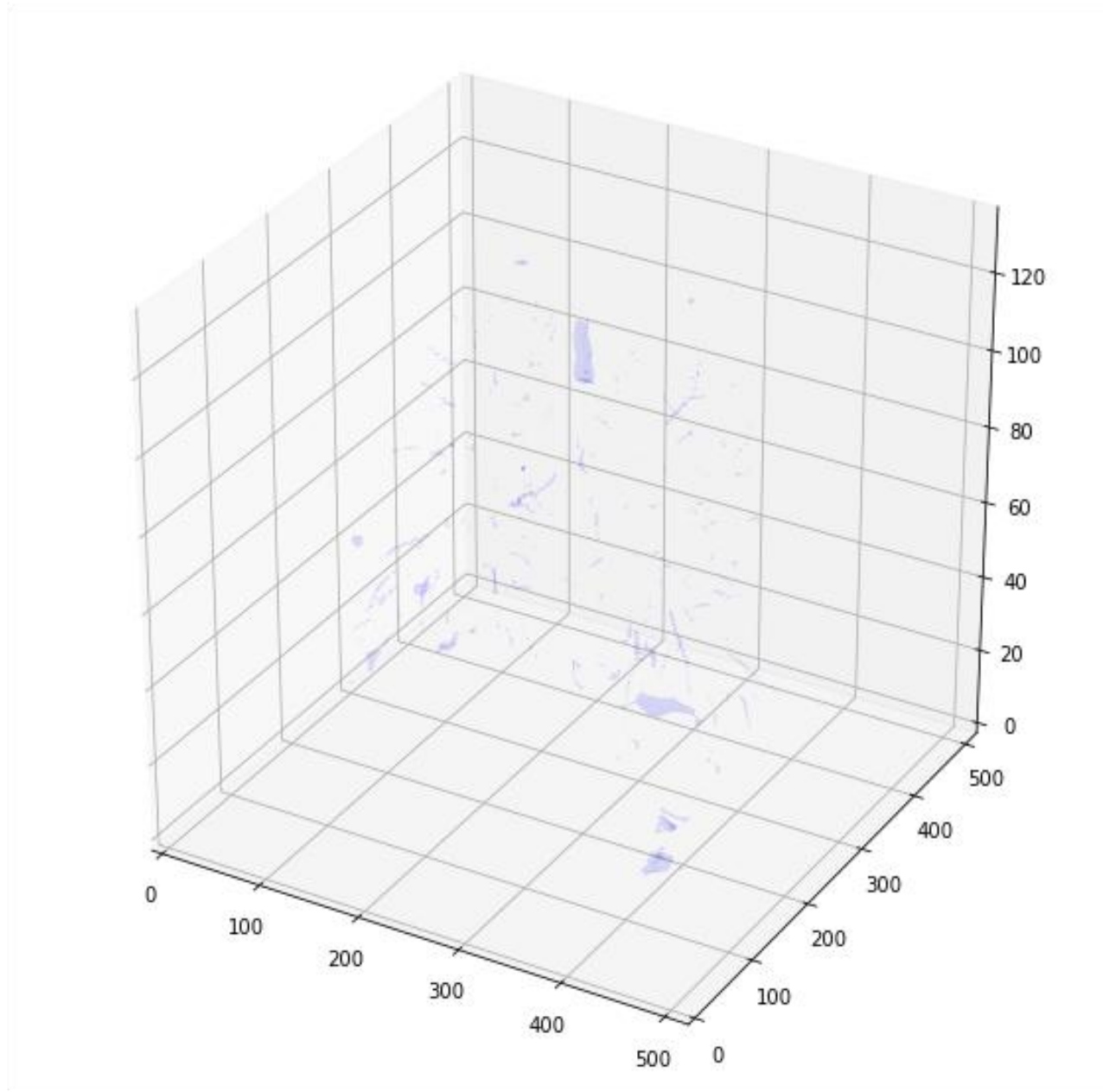
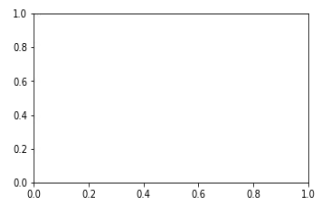
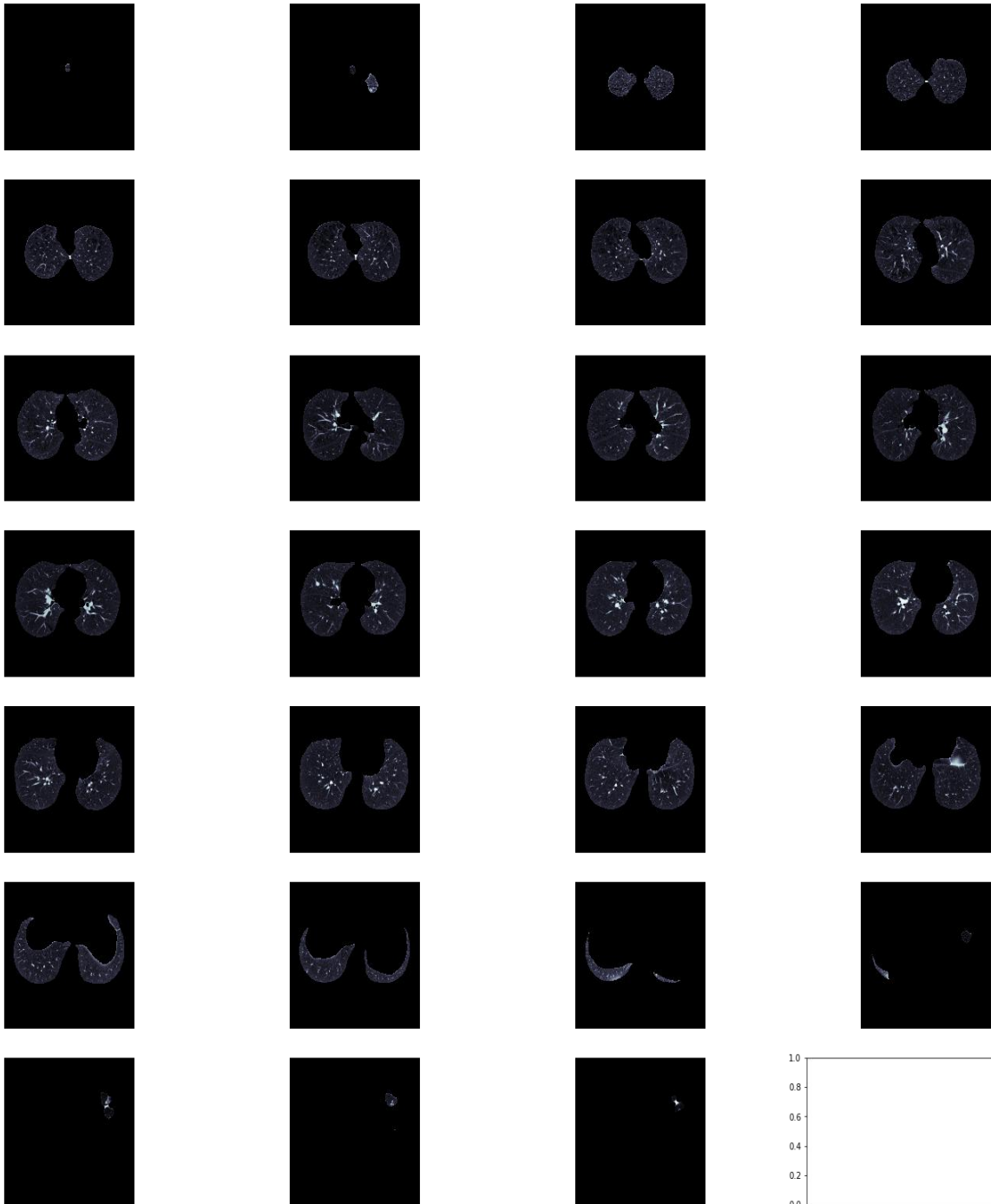
# U-net

下采样提取目标特征，上采样  
对其像素点进行分类。

*skip connection*帮助解决下  
采样丢失掉的细节损失。









(a) 实验原图



(b) 目视解译图



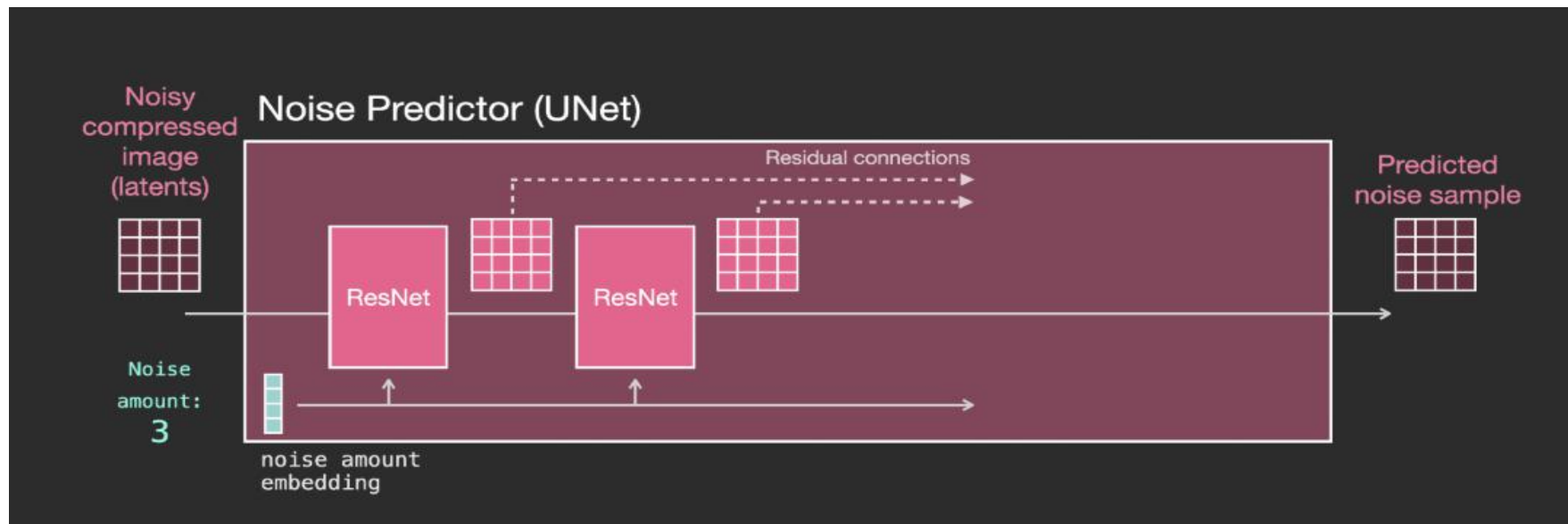
(c) 道路提取图



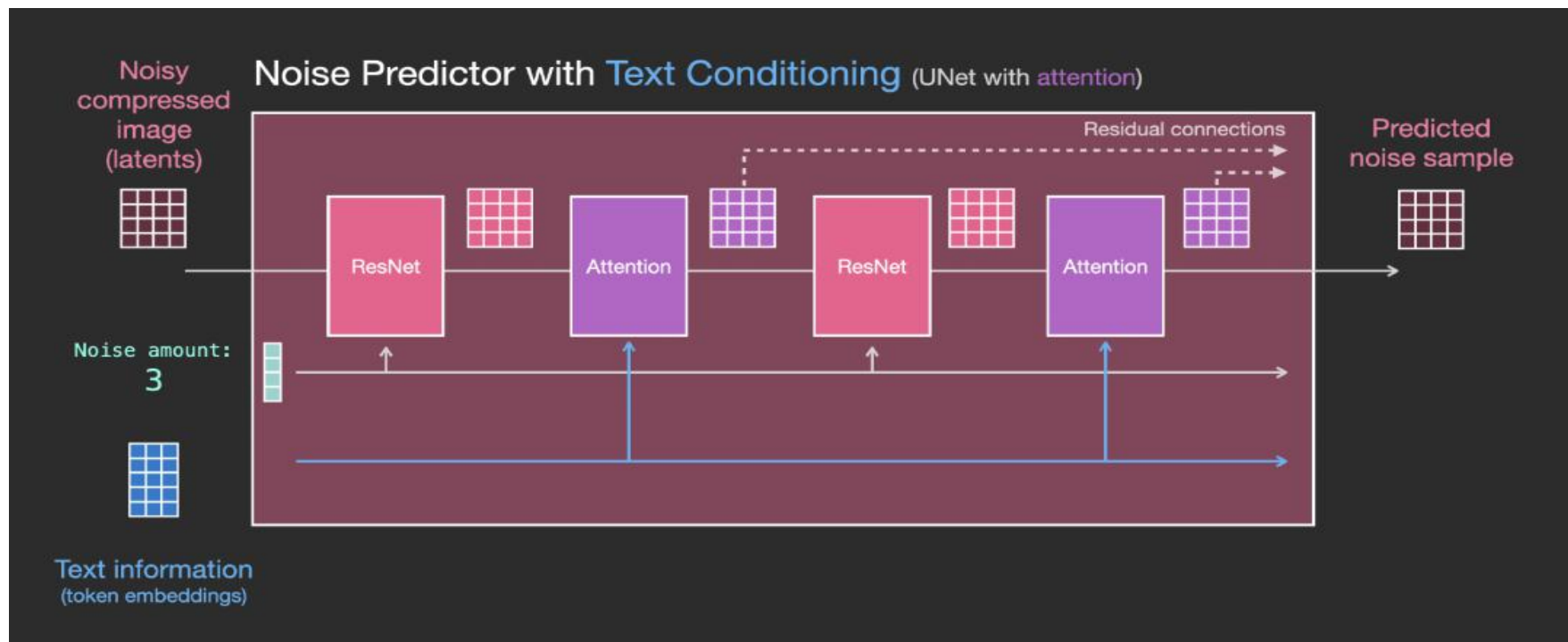
(d) 道路叠加图

# U-net

一般降噪：  
*ResNet*块添加噪声。



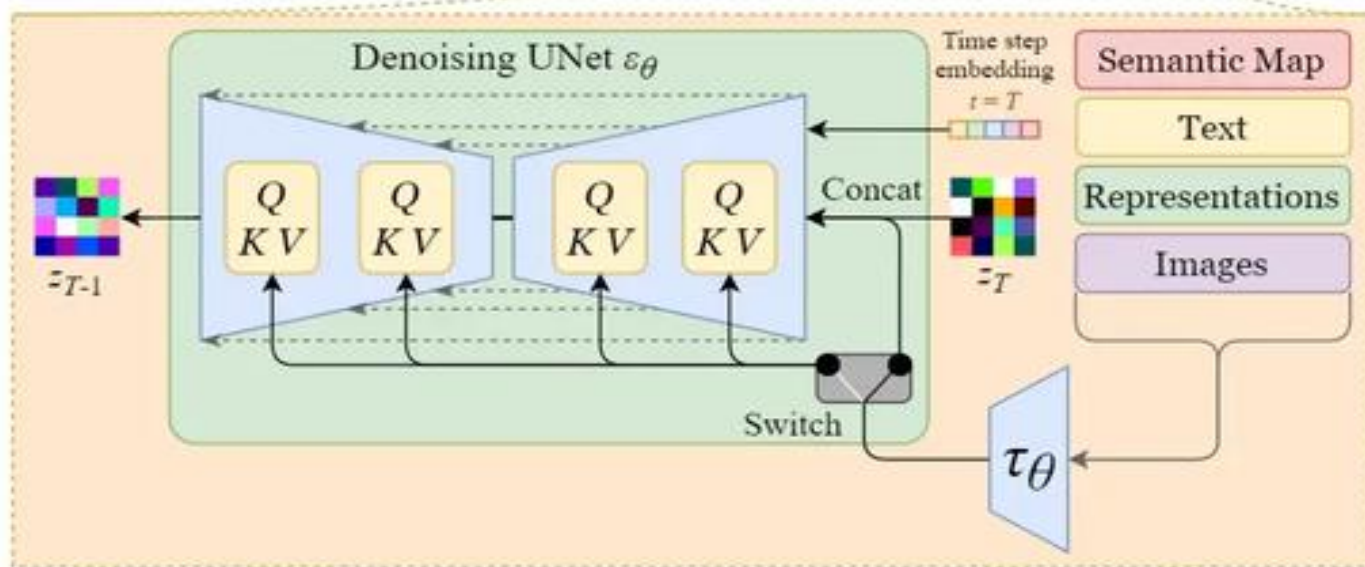
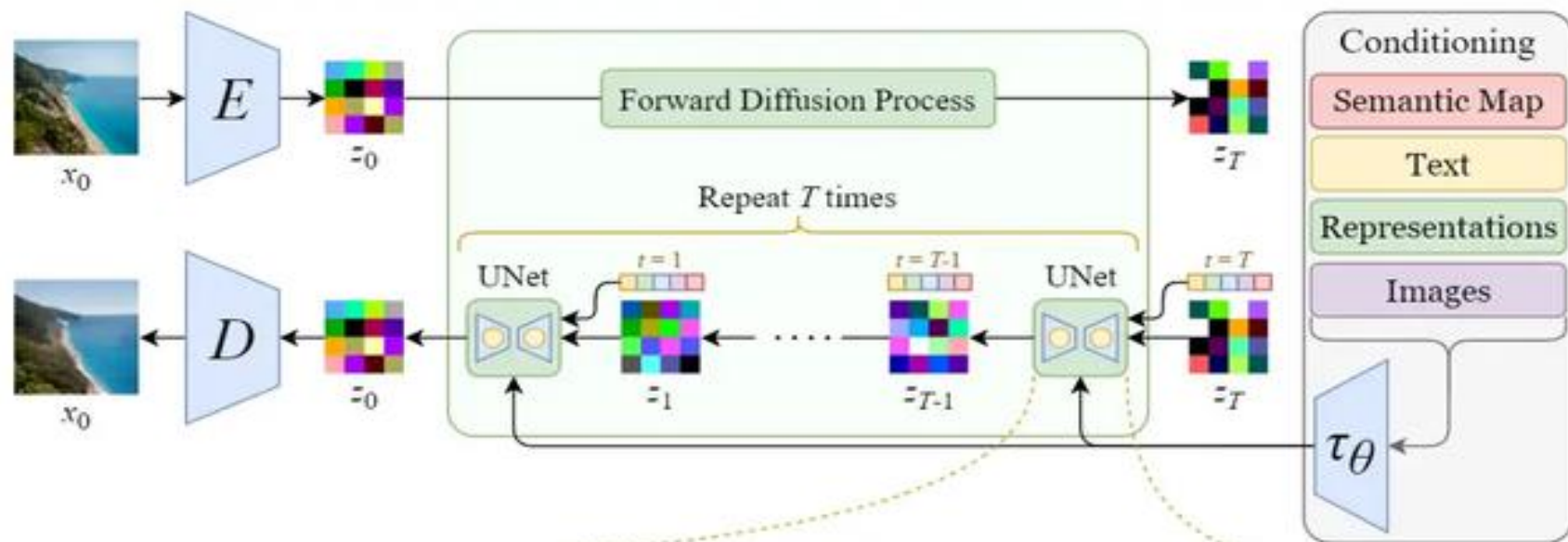
带文本降噪：  
*ResNet*块之间添加  
*Attention*层。



# U-net

训练过程：  
文本引导下的  
*latent*生成

主打参数占比大



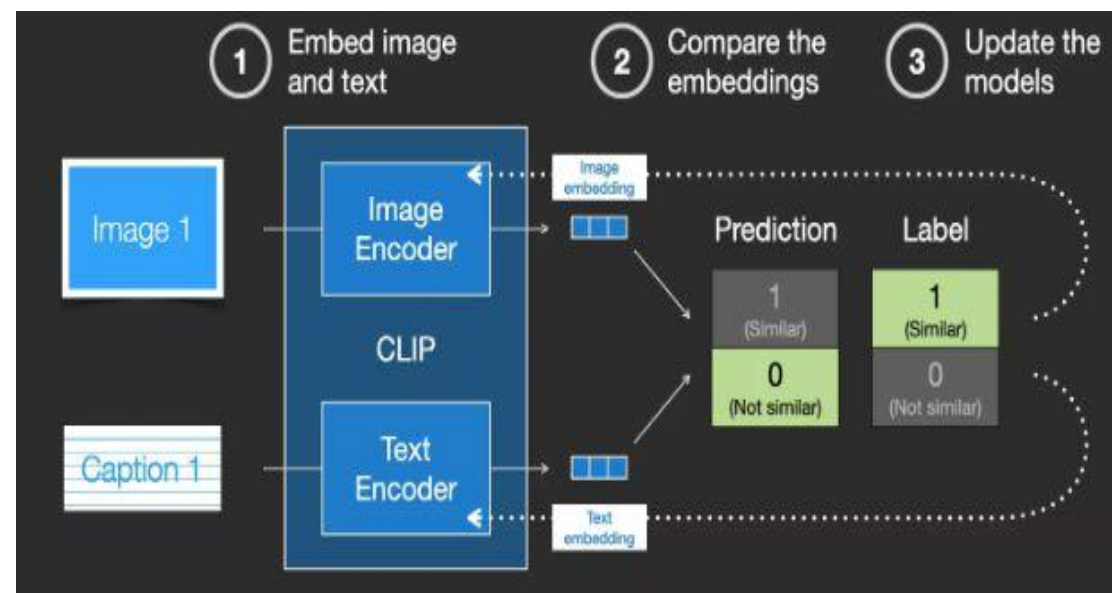


# text embedding

维度匹配：以OpenAI所开源的CLIP模型clip-vit-large-patch14为例，CLIP的text encoder是一个只有encoder模块的transformer模型，层数为12，特征维度为768。

长度约束：对于输入text，送入CLIP text encoder后得到最后的hidden states（即最后一个transformer block得到的特征），其特征维度大小为77x768（77是token的数量）

输入text的tokens数量超过77后，将进行截断，如果不足则进行paddings。



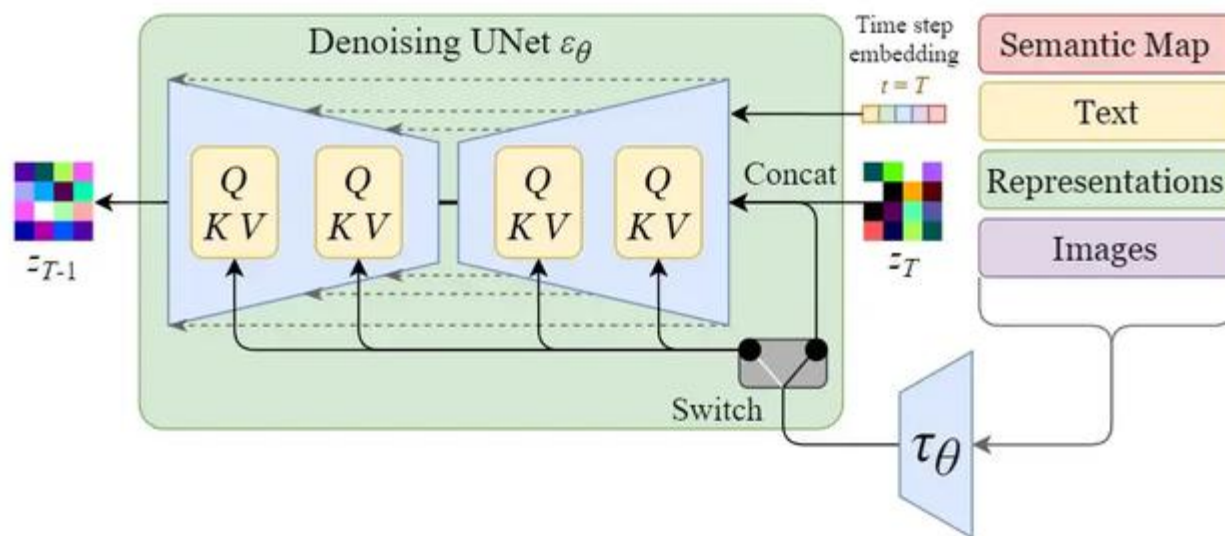
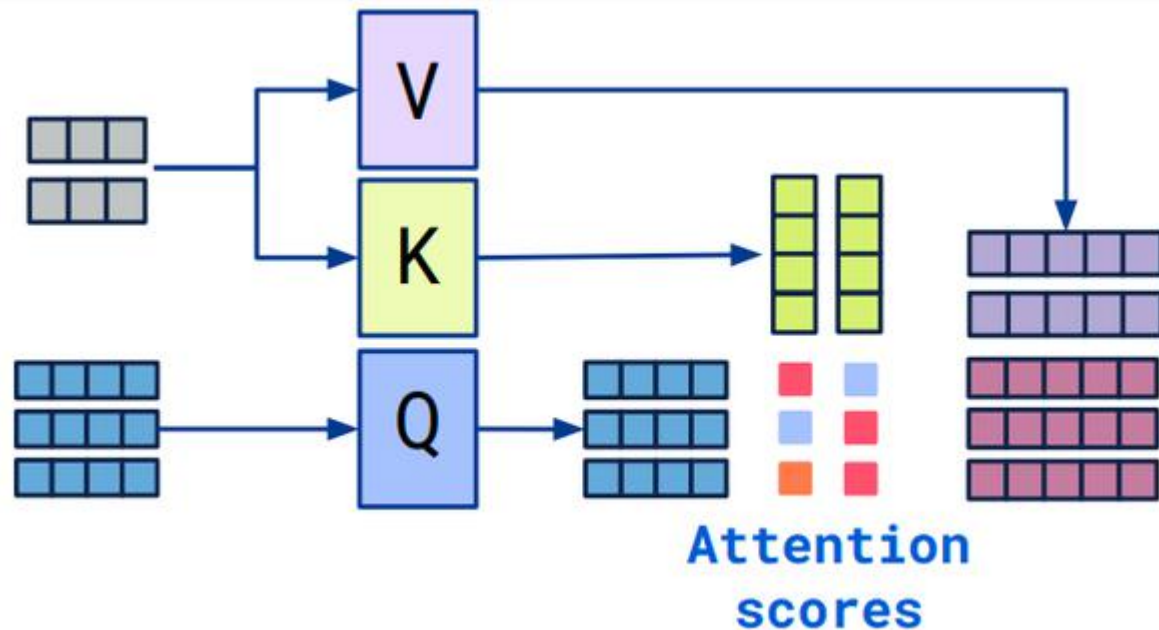
# cross attention

混合两个不同嵌入序列的注意机制

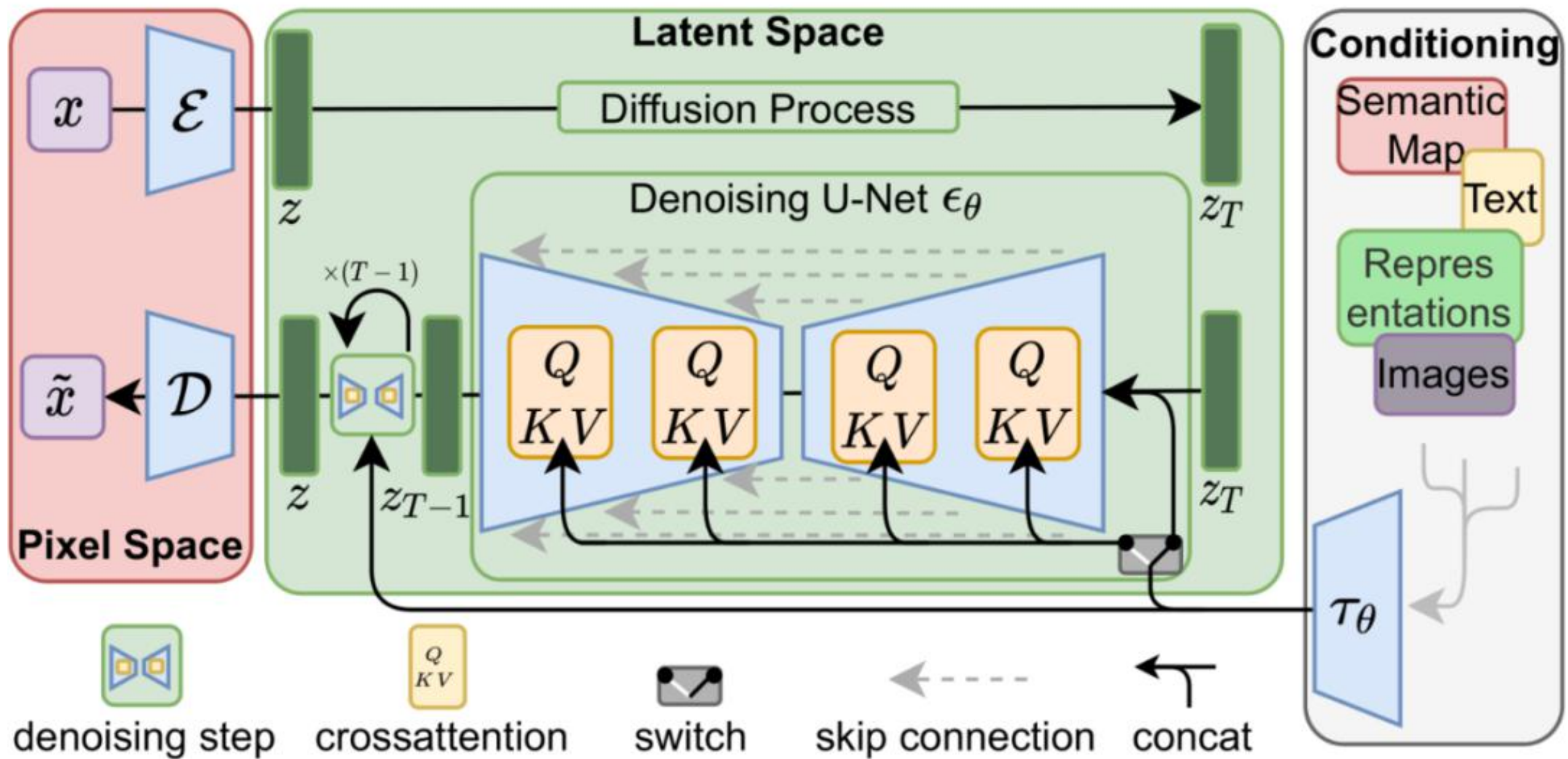
两个序列必须具有相同的维度

两个序列可以是不同的形式（文本、图像、声音）

*concat*（三角函数）







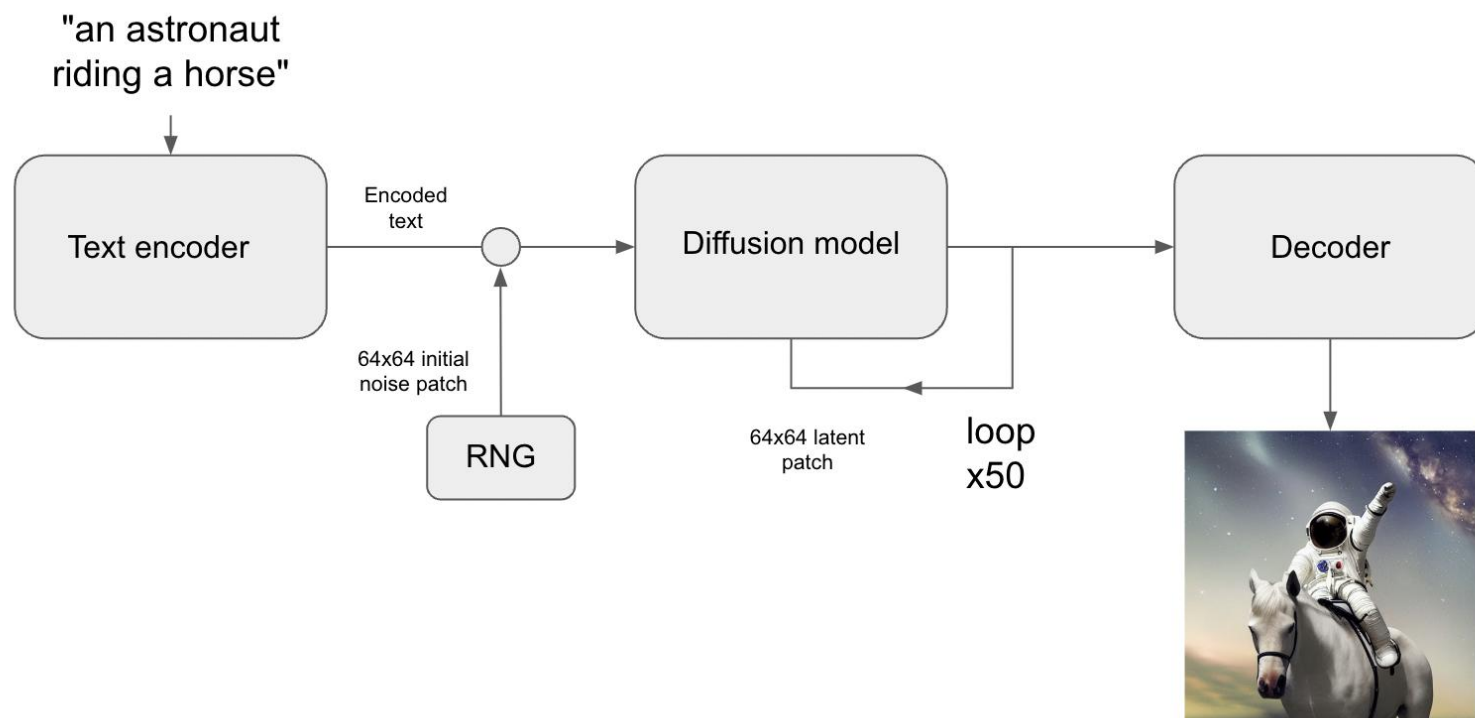
# 推理流程

根据输入`text`用`text encoder`提取`text embeddings`,

初始化随机噪音`noise`（维度匹配），

送入`U-net`中生成去噪后的`latent`,

最后送入`decoder`得到生成的图像。



# 已有改进

SD本身

*Fine-tuning: Textual Inversion, Aesthetic Embedding, Dreambooth, Hypernetworks, LoRA, ControlNet*

Keras实现

*XLA compilation via jit\_compile = True* 进行 XLA 编译

*Support for mixed precision computation* 混合精度运算

# 混合精度 + XLA 编译设置

```
keras.mixed_precision.set_global_policy("mixed_float16")
model = keras_cv.models.StableDiffusion(jit_compile=True)
images = model.text_to_image(
    "Teddy bears conducting machine learning research",
    batch_size=3,
)
```



# 架构小结

Autoencoder

diffusion

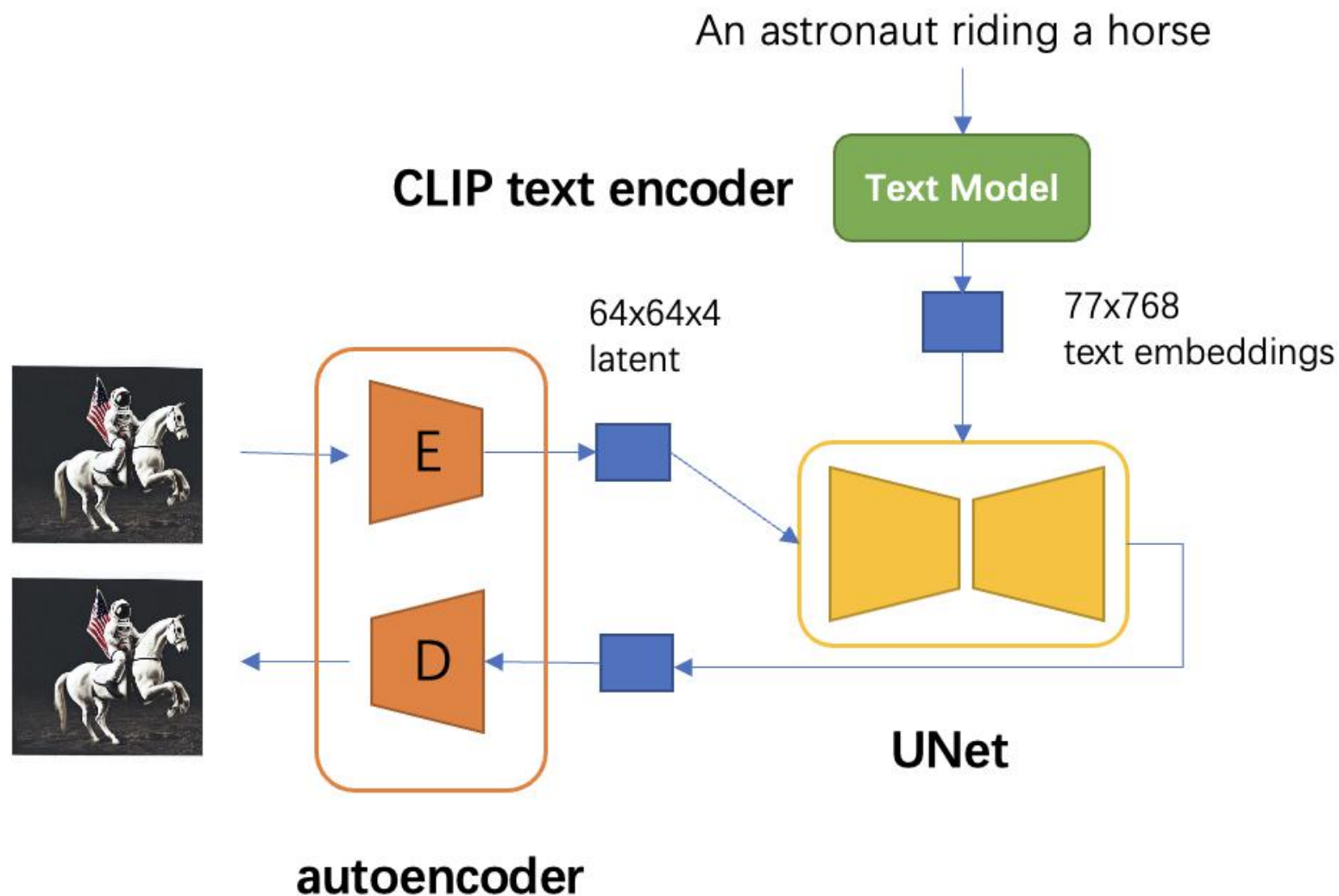
U-net

text embedding

cross attention

启示:

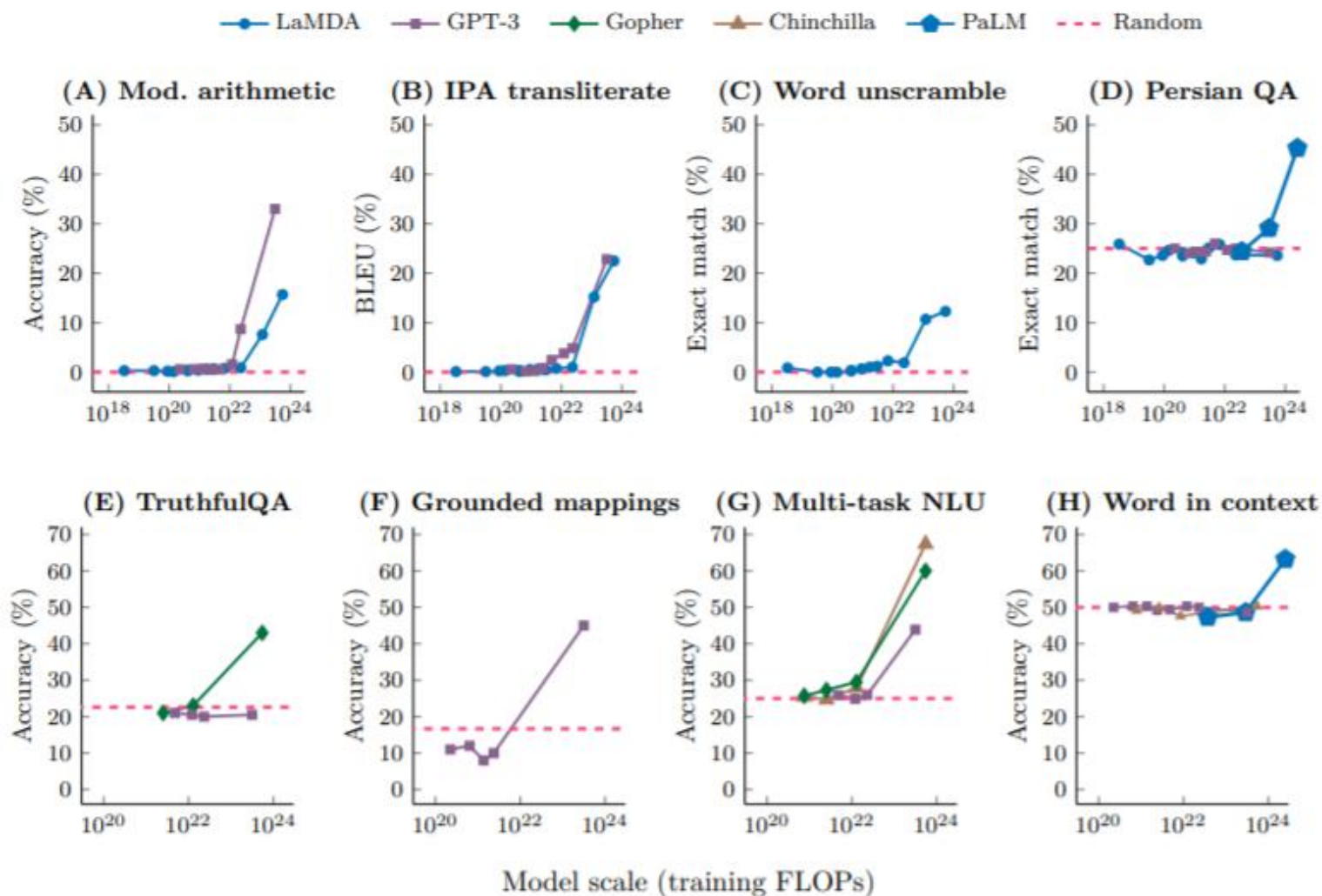
- 集成创新
- *code*的内涵并不cheap





# 涌现能力 (*Emergent Abilities*)

模型大  
+  
语料库大  
=  
厚积薄发





# 可能的发展方向

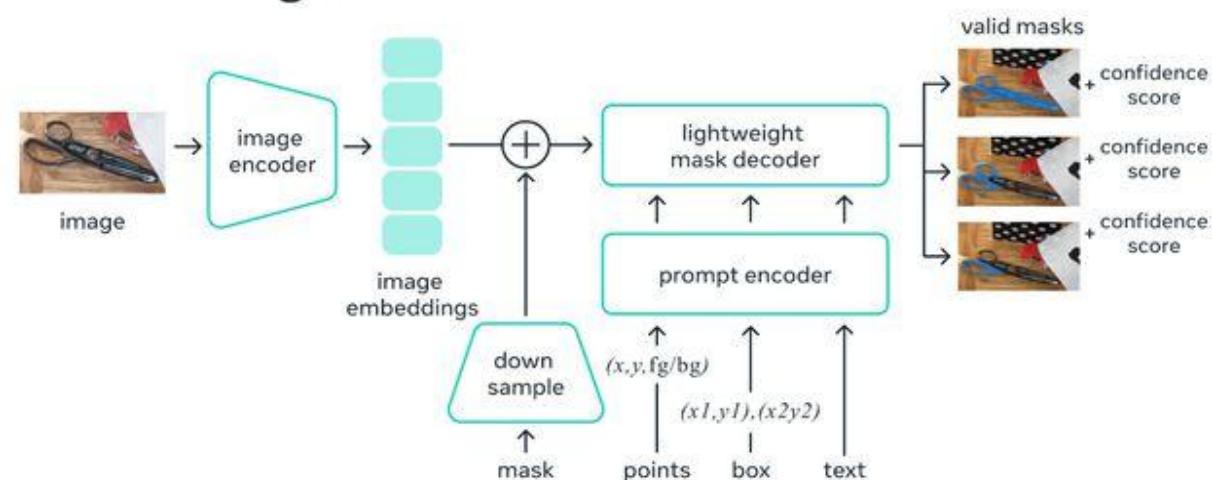
## 通用

- （可以实现的）模型更大？
- （实现某个功能的）模型更小？
- 实时在线获取新知识？
- 输入字数更多？
- 输入数据格式更丰富？
- 节能？
- 同时发生！

## 专用

- 许多细分领域

## Universal segmentation model



## Common carbon footprint benchmarks

in lbs of CO2 equivalent

Roundtrip flight b/w NY and SF (1 passenger)

1,984

Human life (avg. 1 year)

11,023

American life (avg. 1 year)

36,156

US car including fuel (avg. 1 lifetime)

126,000

Transformer (213M parameters) w/  
neural architecture search

626,155

# 郑重提示

利用生成式人工智能生成的内容应当体现社会主义核心价值观

-- 《生成式人工智能服务管理办法（征求意见稿）》

[http://www.cac.gov.cn/2023-04/11/c\\_1682854275475410.htm](http://www.cac.gov.cn/2023-04/11/c_1682854275475410.htm)

*tf.yyds.thanks!*