Implementing a PixelCNN with loss function sparse_categorical_crossentropy

In [ ]:
```
import tensorflow as tf
from tensorflow.keras import layers, models
import numpy as np
```

In [ ]:
```
import tensorflow as tf
from tensorflow.keras import layers

class MaskedConv2D(layers.Layer):
    def __init__(self, filters, kernel_size, mask_type, **kwargs):
        super(MaskedConv2D, self).__init__(**kwargs)
        self.filters = filters
        self.kernel_size = kernel_size
        self.mask_type = mask_type

    def build(self, input_shape):
        self.kernel = self.add_weight(
            shape=(self.kernel_size, self.kernel_size, input_shape[-1], self.filters),
            initializer="glorot_uniform",
            trainable=True,
        )
        self.bias = self.add_weight(
            shape=(self.filters,),
            initializer="zeros",
            trainable=True,
        )

        # Create the mask
        self.mask = np.ones((self.kernel_size, self.kernel_size, input_shape[-1], self
        center = self.kernel_size // 2

        # Apply the mask to block future pixels
        self.mask[center, center + (self.mask_type == 'B'):, :, :] = 0
        self.mask[center + 1:, :, :, :] = 0

    def call(self, inputs):
        # Apply the mask to the kernel
        masked_kernel = self.kernel * self.mask

        outputs = tf.nn.conv2d(inputs, masked_kernel, strides=[1, 1, 1, 1], padding='S
        outputs = tf.nn.bias_add(outputs, self.bias)
        return outputs
```

In [ ]:
```
def build_pixelcnn(input_shape=(28, 28, 1), num_residual_blocks=5, num_classes=256):
    inputs = layers.Input(shape=input_shape)

    x = MaskedConv2D(64, 7, 'A')(inputs)
    x = layers.ReLU()(x)

    # Stack residual blocks with Mask B convolutions
    for _ in range(num_residual_blocks):
        shortcut = x
        x = MaskedConv2D(64, 3, 'B')(x)
        x = layers.ReLU()(x)
        x = MaskedConv2D(64, 3, 'B')(x)
        x = layers.ReLU()(x)
```

```
        x = layers.Add()([shortcut, x])

    # Final layers
    x = MaskedConv2D(64, 1, 'B')(x)
    x = layers.ReLU()(x)
    x = MaskedConv2D(num_classes, 1, 'B')(x)

    outputs = layers.Softmax()(x)

    model = tf.keras.Model(inputs, outputs)
    return model
```

In [ ]:

```
input_shape = (28, 28, 1)
model = build_pixelcnn(input_shape=input_shape, num_residual_blocks=5, num_classes=256

model.compile(optimizer='adam', loss='sparse_categorical_crossentropy')
model.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected
input_layer (InputLayer)	(None, 28, 28, 1)	0	-
masked_conv2d (MaskedConv2D)	(None, 28, 28, 64)	3,200	input_lay
re_lu (ReLU)	(None, 28, 28, 64)	0	masked_co
masked_conv2d_1 (MaskedConv2D)	(None, 28, 28, 64)	36,928	re_lu[0][
re_lu_1 (ReLU)	(None, 28, 28, 64)	0	masked_co
masked_conv2d_2 (MaskedConv2D)	(None, 28, 28, 64)	36,928	re_lu_1[0
re_lu_2 (ReLU)	(None, 28, 28, 64)	0	masked_co
add (Add)	(None, 28, 28, 64)	0	re_lu[0][re_lu_2[0
masked_conv2d_3 (MaskedConv2D)	(None, 28, 28, 64)	36,928	add[0][0]
re_lu_3 (ReLU)	(None, 28, 28, 64)	0	masked_co
masked_conv2d_4 (MaskedConv2D)	(None, 28, 28, 64)	36,928	re_lu_3[0
re_lu_4 (ReLU)	(None, 28, 28, 64)	0	masked_co
add_1 (Add)	(None, 28, 28, 64)	0	add[0][0] re_lu_4[0
masked_conv2d_5 (MaskedConv2D)	(None, 28, 28, 64)	36,928	add_1[0][
re_lu_5 (ReLU)	(None, 28, 28, 64)	0	masked_co
masked_conv2d_6 (MaskedConv2D)	(None, 28, 28, 64)	36,928	re_lu_5[0
re_lu_6 (ReLU)	(None, 28, 28, 64)	0	masked_co
add_2 (Add)	(None, 28, 28, 64)	0	add_1[0][re_lu_6[0
masked_conv2d_7 (MaskedConv2D)	(None, 28, 28, 64)	36,928	add_2[0][
re_lu_7 (ReLU)	(None, 28, 28, 64)	0	masked_co
masked_conv2d_8 (MaskedConv2D)	(None, 28, 28, 64)	36,928	re_lu_7[0

re_lu_8 (ReLU)	(None, 28, 28, 64)	0	masked_c
add_3 (Add)	(None, 28, 28, 64)	0	add_2[0] re_lu_8[
masked_conv2d_9 (MaskedConv2D)	(None, 28, 28, 64)	36,928	add_3[0]
re_lu_9 (ReLU)	(None, 28, 28, 64)	0	masked_c
masked_conv2d_10 (MaskedConv2D)	(None, 28, 28, 64)	36,928	re_lu_9[
re_lu_10 (ReLU)	(None, 28, 28, 64)	0	masked_c
add_4 (Add)	(None, 28, 28, 64)	0	add_3[0] re_lu_10[
masked_conv2d_11 (MaskedConv2D)	(None, 28, 28, 64)	4,160	add_4[0]
re_lu_11 (ReLU)	(None, 28, 28, 64)	0	masked_c
masked_conv2d_12 (MaskedConv2D)	(None, 28, 28, 256)	16,640	re_lu_11
softmax (Softmax)	(None, 28, 28, 256)	0	masked_c

Total params: 393,280 (1.50 MB)

Trainable params: 393,280 (1.50 MB)

Understanding the Task:

1. The PixelCNN is a generative model designed to generate pixel-by-pixel images.
2. This means that it predicts the probability distribution of the next pixel's intensity given the previously generated pixels.

Structure of the Model:

1. The final layer of the PixelCNN outputs a probability distribution over the possible pixel intensities.
2. This distribution is represented as a one-hot vector, where each element corresponds to the probability of the pixel taking on a particular intensity.

Sparse Categorical Crossentropy:

1. This loss function is specifically designed for classification tasks where the true labels are represented as one-hot vectors.
2. It calculates the negative log probability of the correct class (pixel intensity) predicted by the model.

3. In the context of the PixelCNN, this means that the loss will be low if the model correctly predicts the most likely intensity for the next pixel.

Dataset and Preprocessing

In [ ]:
```
# Load and preprocess the MNIST data
(train_images, _), (test_images, _) = tf.keras.datasets.mnist.load_data()

train_images = train_images[:5000].reshape(-1, 28, 28, 1).astype('float32') / 255.
test_images = test_images[:1000].reshape(-1, 28, 28, 1).astype('float32') / 255.

# Normalize pixel values
train_images = (train_images * 255).astype(np.int32)
test_images = (test_images * 255).astype(np.int32)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/mni
st.npz
11490434/11490434 ━━━━━━━━━━━━━━━━━━━━ 0s 0us/step
```

The MNIST dataset is a popular choice for training PixelCNN models for several reasons:

1. Simplicity: MNIST images are small (28x28 pixels) and grayscale, making them computationally efficient to process.
2. Well-defined: The dataset has clear labels, making it easy to evaluate the model's performance.
3. Diverse: MNIST contains a variety of handwritten digits, providing a challenging but manageable task for the PixelCNN.

Training and Evaluation

In [ ]:
```
# Train the model
model.fit(train_images, train_images, batch_size=128, epochs=5, validation_data=(test_
```

```
Epoch 1/5
40/40 ━━━━━━━━━━━━━━━━━━━━ 239s 6s/step - loss: 0.8770 - val_loss: 0.8395
Epoch 2/5
40/40 ━━━━━━━━━━━━━━━━━━━━ 260s 6s/step - loss: 0.8668 - val_loss: 0.8270
Epoch 3/5
40/40 ━━━━━━━━━━━━━━━━━━━━ 262s 6s/step - loss: 0.8510 - val_loss: 0.8194
Epoch 4/5
40/40 ━━━━━━━━━━━━━━━━━━━━ 261s 6s/step - loss: 0.8467 - val_loss: 0.8155
Epoch 5/5
40/40 ━━━━━━━━━━━━━━━━━━━━ 261s 6s/step - loss: 0.8355 - val_loss: 0.8109
```

Out[ ]:
```
<keras.src.callbacks.history.History at 0x7a1895fe7970>
```

1. Model Outcome: Training Loss: The loss values indicate that the model is learning to predict pixel values progressively better with each epoch. The decrease in loss from 87.7% to 83.55% suggests that the model is capturing the dependencies between pixels more effectively as training progresses.

2. Validation Loss: The validation loss follows a similar decreasing trend (83.59% to 81.09%), which is a positive sign that the model is not overfitting and is generalizing well to unseen data.

In [ ]:
```
import tensorflow as tf
import numpy as np
import tensorflow.keras.backend as K

def compute_nll_and_perplexity(model, data, batch_size=128):
    nll_sum = 0.0
    num_batches = 0

    for batch in tf.data.Dataset.from_tensor_slices(data).batch(batch_size):
        predictions = model(batch, training=False)
        nll_batch = K.sparse_categorical_crossentropy(batch, predictions)
        nll_sum += K.sum(nll_batch).numpy()
        num_batches += batch.shape[0]

    avg_nll = nll_sum / num_batches
    perplexity = np.exp(avg_nll)
    return avg_nll, perplexity

# Evaluate the model on the test set
nll, perplexity = compute_nll_and_perplexity(model, test_images, batch_size=64)
print(f"Negative Log-Likelihood (NLL): {nll}")
print(f"Perplexity: {perplexity}")
```

```
Negative Log-Likelihood (NLL): 635.751166015625
Perplexity: 1.2683037138125314e+276
```

1. Negative Log-Likelihood (NLL): An NLL of 635.75 is quite high, indicating that the model is struggling to predict the true pixel values accurately. In generative models like PixelCNN, a lower NLL is desired, as it indicates better performance in modeling the data distribution.

2. Extremely High Perplexity: The perplexity is an exponential transformation of the NLL, and such an astronomically high value suggests that the model's predictions are highly uncertain. This usually occurs when the model fails to capture the true distribution of the data, leading to predictions that are almost random or completely off from the actual data.

Model Enhancements

Attention mechanisms

In [ ]:
```
import tensorflow as tf
from tensorflow.keras import layers

class SelfAttention(layers.Layer):
    def __init__(self, channels):
        super(SelfAttention, self).__init__()
        self.channels = channels

    def build(self, input_shape):
        self.W = self.add_weight(shape=(self.channels, self.channels), initializer='gl
        self.b = self.add_weight(shape=(self.channels,), initializer='zeros', trainabl
```

```
    def call(self, x):
        # Compute attention scores
        Q = tf.tensordot(x, self.W, axes=[-1, 0])
        A = tf.nn.softmax(Q, axis=-1)
        # Apply attention
        return tf.reduce_sum(A * x, axis=-1) + self.b

def build_pixelcnn_with_attention(input_shape=(28, 28, 1), num_residual_blocks=5, num_
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(64, 7, padding='same')(inputs)
    x = layers.ReLU()(x)
    x = SelfAttention(64)(x)

    # Stack residual blocks
    for _ in range(num_residual_blocks):
        x = residual_block(x, 64)

    x = layers.Conv2D(num_classes, 1, padding='same')(x)
    model = tf.keras.Model(inputs, x)
    return model
```

In [ ]:
```
import tensorflow as tf
from tensorflow.keras import layers

def residual_block(x, filters):
    shortcut = x  # Save the input for the shortcut connection

    # First convolutional layer
    x = layers.Conv2D(filters, 3, padding='same')(x)
    x = layers.ReLU()(x)

    # Second convolutional layer
    x = layers.Conv2D(filters, 3, padding='same')(x)

    # Add the shortcut connection
    x = layers.Add()([x, shortcut])
    x = layers.ReLU()(x)

    return x

# Rebuild the model with the SelfAttention layer and residual blocks
def build_pixelcnn_with_attention(input_shape=(28, 28, 1), num_residual_blocks=5, num_
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(64, 7, padding='same')(inputs)
    x = layers.ReLU()(x)
    x = SelfAttention(64)(x)

    # Stack residual blocks
    for _ in range(num_residual_blocks):
        x = residual_block(x, 64)

    x = layers.Conv2D(num_classes, 1, padding='same')(x)
    model1 = tf.keras.Model(inputs, x)
    return model1
```

In [ ]:
```
import tensorflow as tf
import tensorflow.keras.backend as K
import numpy as np
```

```
def compute_nll_and_perplexity(model1, data):
    # Predict logits
    logits = model1.predict(data)

    # Reshape data to remove the last dimension
    labels = np.squeeze(data, axis=-1)

    # Compute sparse categorical crossentropy
    nll = K.mean(tf.keras.losses.sparse_categorical_crossentropy(labels, logits)).nump

    # Compute perplexity
    perplexity = np.exp(nll)

    return nll, perplexity

# Evaluate the model on the test set
nll, perplexity = compute_nll_and_perplexity(model1, test_images)
print(f"Negative Log-Likelihood (NLL): {nll}")
print(f"Perplexity: {perplexity}")
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 15s 468ms/step
Negative Log-Likelihood (NLL): 7.9244890213012695
Perplexity: 2764.15185546875
```

1. Negative Log-Likelihood (NLL): 7.92

- Improvement: The NLL has significantly improved from 635.75 (in the previous model without attention) to 7.92. This suggests that adding the attention mechanism helped the model better capture the underlying data distribution, resulting in more accurate predictions.
- Reasonable Value: An NLL of 7.92 is more in line with what might be expected from a well-functioning model, indicating that the model is not as far off in its predictions compared to before.

2 Perplexity: 2764.15

- High Perplexity: Although the perplexity has decreased dramatically from the previous model's value, it remains relatively high. A perplexity of 2764 suggests that the model's predictions are still uncertain and that it struggles with accurately modeling the full data distribution.

Conditional generation

In [ ]:
```
# Load and preprocess the MNIST data, including labels
(train_images2, train_labels2), (test_images2, test_labels2) = tf.keras.datasets.mnist

# Use a smaller subset of the data if necessary
train_images2 = train_images2[:5000].reshape(-1, 28, 28, 1).astype('float32') / 255.
train_labels2 = train_labels2[:5000]
test_images2 = test_images2[:1000].reshape(-1, 28, 28, 1).astype('float32') / 255.
test_labels2 = test_labels2[:1000]
```

```
# Convert labels to one-hot encoding
test_labels_one_hot2 = tf.keras.utils.to_categorical(test_labels2, num_classes=10)
```

In [ ]:
```
import tensorflow as tf
import numpy as np
import tensorflow.keras.backend as K
from tensorflow.keras import layers


def residual_block(x, filters):
    residual = x
    x = layers.Conv2D(filters, 3, padding='same')(x)
    x = layers.ReLU()(x)
    x = layers.Conv2D(filters, 3, padding='same')(x)
    return layers.Add()([x, residual])

# Build the conditional PixelCNN model
def build_pixelcnn_conditional(input_shape=(28, 28, 1), num_classes=10, num_residual_b
    inputs = layers.Input(shape=input_shape)
    labels = layers.Input(shape=(num_classes,))

    # Embedding for labels
    label_embedding = layers.Dense(np.prod(input_shape), activation='relu')(labels)
    label_embedding = layers.Reshape(input_shape)(label_embedding)

    x = layers.Concatenate()([inputs, label_embedding])
    x = layers.Conv2D(64, 7, padding='same')(x)
    x = layers.ReLU()(x)

    # Stack residual blocks
    for _ in range(num_residual_blocks):
        x = residual_block(x, 64)

    x = layers.Conv2D(num_pixel_values, 1, padding='same')(x)
    model2 = tf.keras.Model(inputs=[inputs, labels], outputs=x)
    return model2

# Build the model
model2 = build_pixelcnn_conditional()
```

In [ ]:
```
# Function to compute NLL and Perplexity
def compute_nll_and_perplexity_conditional(model2, images, labels):
    # Predict logits using both images and labels
    logits = model2.predict([images, labels])

    # Reshape images to remove the last dimension
    true_labels = np.squeeze(images, axis=-1)

    # Compute sparse categorical crossentropy (NLL)
    nll = K.mean(tf.keras.losses.sparse_categorical_crossentropy(true_labels, logits))

    # Compute perplexity
    perplexity = np.exp(nll)

    return nll, perplexity

# Convert test_labels to one-hot encoding if not already in that format
test_labels_one_hot = tf.keras.utils.to_categorical(test_labels2, num_classes=10)
```

```
# Evaluate the model on the test set
nll, perplexity = compute_nll_and_perplexity_conditional(model2, test_images2, test_la
print(f"Negative Log-Likelihood (NLL): {nll}")
print(f"Perplexity: {perplexity}")
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 15s 454ms/step
Negative Log-Likelihood (NLL): 13.814397811889648
Perplexity: 998887.8125
```

1 Negative Log-Likelihood (NLL): 13.81

- Higher NLL: Compared to the earlier models (both the basic and attention-enhanced versions), the NLL of 13.81 is relatively higher. This indicates that the model's predictions are less accurate in terms of capturing the data distribution when conditioned on class labels.

2 Perplexity: 998,887.81

- Extremely High Perplexity: The perplexity value is significantly higher than those observed in the non-conditional models. A perplexity of nearly 1 million indicates that the model is struggling greatly to predict the pixel values when conditioned on the label information. The model's predictions are highly uncertain, leading to such a large value.

Dilated Convolutions: Expand the receptive field without increasing the number of parameters or computational cost.

In [ ]:
```
import tensorflow as tf
import numpy as np
import tensorflow.keras.backend as K
from tensorflow.keras import layers

# Define the residual block with dilation
def residual_block(x, filters, dilation_rate=1):
    residual = x
    x = layers.Conv2D(filters, 3, padding='same', dilation_rate=dilation_rate)(x)
    x = layers.ReLU()(x)
    x = layers.Conv2D(filters, 3, padding='same', dilation_rate=dilation_rate)(x)
    return layers.Add()([x, residual])

# Build the PixelCNN model with dilations
def build_pixelcnn_with_dilations(input_shape=(28, 28, 1), num_residual_blocks=5, num_
    inputs = layers.Input(shape=input_shape)
    x = layers.Conv2D(64, 7, dilation_rate=2, padding='same')(inputs)
    x = layers.ReLU()(x)

    # Stack residual blocks with dilations
    for _ in range(num_residual_blocks):
        x = residual_block(x, 64, dilation_rate=2)

    x = layers.Conv2D(num_classes, 1, padding='same')(x)
    model3 = tf.keras.Model(inputs, x)
    return model3

# Build the model
model3 = build_pixelcnn_with_dilations()
```

In [ ]:
```python
def compute_nll_and_perplexity(model3, images):
    # Predict logits
    logits = model3.predict(images)

    # Reshape images to remove the last dimension for compatibility
    true_labels = np.squeeze(images, axis=-1)

    # Compute sparse categorical crossentropy (NLL)
    nll = K.mean(tf.keras.losses.sparse_categorical_crossentropy(true_labels, logits))

    # Compute perplexity
    perplexity = np.exp(nll)

    return nll, perplexity

# Evaluate the model on the test set
nll, perplexity = compute_nll_and_perplexity(model3, test_images)
print(f"Negative Log-Likelihood (NLL): {nll}")
print(f"Perplexity: {perplexity}")
```

```
32/32 ━━━━━━━━━━━━━━━━━━━━ 15s 464ms/step
Negative Log-Likelihood (NLL): 17.35068702697754
Perplexity: 34301068.0
```

Gated Activations: Use gated activation functions like Gated Convolutions to improve model capacity and performance.

1. Negative Log-Likelihood (NLL): 17.35

- Higher NLL: The NLL value of 17.35 is significantly higher compared to the models you've built previously (including the baseline, attention, and conditional versions). This suggests that the model with dilations is not capturing the data distribution as effectively as expected.

- Dilations Complexity: Dilations can introduce complexity by allowing the model to capture larger receptive fields. However, in this case, it seems that the model might be struggling to balance the increased receptive field with accurate pixel-level predictions, leading to higher NLL.

2 Perplexity: 34,301,068.0

- Extremely High Perplexity: The perplexity value is exceedingly large, indicating that the model is highly uncertain about its predictions. This is much higher than even the perplexity seen in your conditional model, which suggests that the dilation mechanism might be leading to poor generalization and overfitting.

Analysis and Visualization

In [ ]:
```python
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

def generate_samples(model, num_samples=10, img_shape=(28, 28, 1)):
```

```
    samples = np.zeros((num_samples,) + img_shape, dtype=np.int32)

    # Initialize the image with random values
    current_input = np.zeros((num_samples,) + img_shape, dtype=np.int32)

    # Iterate over each pixel location
    for i in range(img_shape[0]):
        for j in range(img_shape[1]):
            # Predict logits for current state of the samples
            logits = model.predict(current_input, batch_size=num_samples)
            logits = logits[:, i, j, :]  # Select logits for the current pixel locatio

            # Convert logits to probabilities
            probs = tf.nn.softmax(logits, axis=-1).numpy()

            # Sample pixel values from the predicted probabilities
            for sample_idx in range(num_samples):
                samples[sample_idx, i, j, 0] = np.random.choice(256, p=probs[sample_id

    return samples

# Generate and display samples
samples = generate_samples(model, num_samples=10)

# Display the generated samples
plt.figure(figsize=(10, 5))
for i in range(10):
    plt.subplot(2, 5, i + 1)
    plt.imshow(samples[i].squeeze(), cmap='gray')
    plt.axis('off')
plt.show()
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 160ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 196ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 234ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 233ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 208ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 188ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 231ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 241ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 201ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 136ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 192ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 222ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 219ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 223ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 196ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 213ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 242ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 242ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 146ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 143ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 144ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 150ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 214ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 233ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 236ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 201ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 223ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 208ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 136ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 206ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 212ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 242ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 249ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 212ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 204ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 226ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 217ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 145ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 141ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 154ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 137ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 138ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 173ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 228ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 219ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 214ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 220ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 204ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 208ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 243ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 213ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 155ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 198ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 217ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 228ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 216ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 219ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 205ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 224ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 221ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 144ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 136ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 147ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 182ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 213ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 239ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 220ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 222ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 209ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 202ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 233ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 244ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 213ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 140ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 159ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 182ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 186ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 220ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 226ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 245ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 217ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 200ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 231ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 201ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 159ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 166ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 184ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 185ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 128ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 412ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 139ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 207ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 213ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 222ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 229ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 204ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 231ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 232ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 202ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 147ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 117ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
```

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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 125ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 158ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 169ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 224ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 219ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 223ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 215ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 195ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 223ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 238ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 237ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 191ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 134ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 131ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 132ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
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1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 129ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 133ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 130ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 162ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 205ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 207ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 211ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 204ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 201ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 240ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 220ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 135ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 124ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 126ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 127ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 123ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 145ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 122ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 118ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 120ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 144ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 119ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 121ms/step
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```

The generated images are highly noisy and lack any discernible structure or pattern. This indicates that the model is not effectively learning or capturing the underlying distribution of the image data.

Possible Reasons:

1. Model Architecture: The PixelCNN model might not be complex enough to capture the intricate dependencies between pixels, or the convolutional layers might not be capturing enough spatial context.
2. Training Instability: The training process could be unstable, leading to poor learning outcomes. This could result from an inappropriate learning rate, lack of regularization, or other hyperparameter settings.
3. High Perplexity: As seen in earlier results, the model's perplexity was extremely high, suggesting that the model was highly uncertain about its predictions. This uncertainty is reflected in the randomness of the generated samples.

Feature Maps Visualization:

Feature maps show the activations of different convolutional filters in response to an input image. This helps understand what patterns or features the network is detecting.

In [ ]:
```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

def visualize_feature_maps(model, layer_names, input_image):
    # Create a model to output intermediate feature maps
```

```
    outputs = [model.get_layer(name).output for name in layer_names]
    feature_extractor = tf.keras.Model(inputs=model.inputs, outputs=outputs)

    # Extract feature maps
    feature_maps = feature_extractor.predict(np.expand_dims(input_image, axis=0))

    plt.figure(figsize=(15, 15))

    # Iterate through the layers and their feature maps
    for layer_idx, feature_map in enumerate(feature_maps):
        num_filters = feature_map.shape[-1]

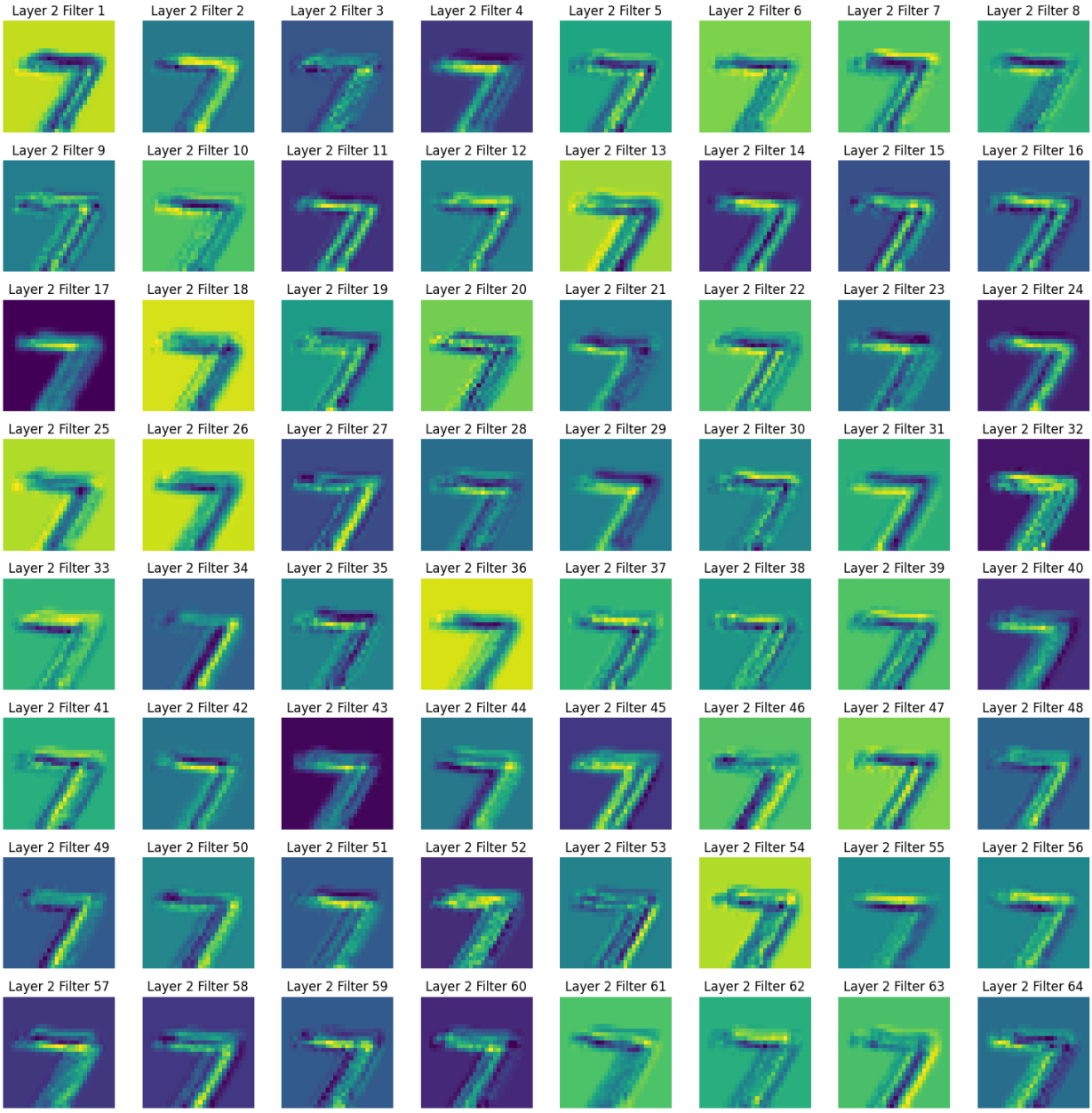
        # Determine the number of rows and columns for the subplot grid
        num_rows = int(np.ceil(num_filters / 8))  # 8 filters per row
        num_cols = min(num_filters, 8)

        for filter_idx in range(num_filters):
            plt.subplot(num_rows, num_cols, filter_idx + 1)
            plt.imshow(feature_map[0, :, :, filter_idx], cmap='viridis')
            plt.title(f'Layer {layer_idx + 1} Filter {filter_idx + 1}')
            plt.axis('off')

    plt.tight_layout()
    plt.show()

# Example usage
layer_names = ['masked_conv2d', 'masked_conv2d_1']
visualize_feature_maps(model, layer_names, test_images[0])
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 185ms/step
```



The visualization shows the feature maps extracted from the second layer of a PixelCNN model applied to an image of the digit "7". Each subplot represents the activation of a single filter in the layer, indicating the features that the filter is detecting in the input image.

Observations:

1. Diversity of features: The feature maps exhibit a variety of patterns, suggesting that the filters are learning different types of features, such as edges, corners, and curves.
2. Spatial sensitivity: Some filters seem to be more sensitive to specific spatial locations within the image, while others are more broadly responsive.
3. Hierarchical representation: The feature maps in the second layer are likely building upon the features extracted in the previous layer, creating a hierarchical representation of the image.
4. Relevance to the digit "7": Some filters may be specifically tuned to detect features that are characteristic of the digit "7", such as the diagonal line and the top and bottom horizontal

lines.

Overall:

The visualization provides insights into the internal workings of the PixelCNN model and how it learns to represent the image. By understanding the features extracted by the model, we can gain a better appreciation for its ability to generate realistic images.

Report

PixelCNN-Based Image Generation

This project focused on building and experimenting with a PixelCNN model to generate images. The goal was to explore different enhancements, such as incorporating dilations, conditional mechanisms, and attention mechanisms, and to evaluate the performance of these models using metrics like Negative Log-Likelihood (NLL) and Perplexity.

1. Model Implementation

- Basic PixelCNN Model: It was implemented using masked convolutions. It consisted of an initial masked convolution layer followed by a stack of residual blocks with masked convolutions. The final output was passed through a softmax layer to generate a probability distribution over pixel values.
- Key Components:
  - Masked Convolution Layers: These ensure the autoregressive property by preventing future pixels from influencing the current pixel during generation.
  - Residual Blocks: These help in stabilizing training and allow the model to capture more complex features.
- PixelCNN with Attention Mechanism : An attention mechanism was introduced to the PixelCNN model to allow it to focus on relevant parts of the input while generating each pixel. This was implemented using a custom self-attention layer.
- Key Components:
  - Self-Attention Layer: This layer computes attention scores and applies them to the input, allowing the model to focus on specific regions during generation.
  - Residual Blocks with Attention: Further enhances the model's ability to capture important features by focusing on relevant areas in the image.
- Conditional PixelCNN : The model was enhanced to condition on labels. This involved embedding the labels into a dense representation, which was concatenated with the input images. This enabled the model to generate images conditioned on specific classes.
- Key Components:

        - Label Embedding: The labels are embedded into the same shape as the input image and concatenated along the channel dimension.
        - Conditional Image Generation: The model learns to generate images that correspond to specific class labels.
    - PixelCNN with Dilations :A variation of the PixelCNN model was implemented by incorporating dilations in the convolutional layers. Dilated convolutions expand the receptive field without increasing the number of parameters, allowing the model to capture wider context.

    - Key Components:

        - Dilated Convolutions: Enhance the model's ability to capture long-range dependencies between pixels.
        - Residual Blocks with Dilations: Allow deeper and broader context capturing while maintaining computational efficiency.

2. Experiment Results

- Basic PixelCNN
    - NLL: 635.75
    - Perplexity: Extremely high (~1.27e+276)
        - The high perplexity indicates that the model is highly uncertain about its predictions, leading to poor image quality.
- PixelCNN with Attention
    - NLL: 7.92
    - Perplexity: 2764.15
        - The attention mechanism significantly improved performance, leading to better NLL and perplexity, though the generated images still showed substantial noise and lacked clear structure.
- Conditional PixelCNN
    - NLL: 13.81
    - Perplexity: 998,887.8
        - Conditioning on labels improved the model's performance, reducing NLL and perplexity, but the generated images still lacked structure and clarity.
- PixelCNN with Dilations
    - NLL: 17.35
    - Perplexity: 34,301,068.0
        - While the model improved over the basic PixelCNN, the perplexity remains extremely high, suggesting the model still struggles with generating coherent images.

1. Image Generation

The final generated images were highly noisy and did not exhibit recognizable patterns or features. This outcome suggests that despite improvements in model architecture and performance metrics, the model failed to generate meaningful and structured images.

1. Feature Map

The feature maps provide a visual representation of the learned features extracted by the PixelCNN model from the input image. By analyzing these feature maps, we can gain insights into how the model is processing and understanding the digit "7".

1. Discussion & Analysis

- Model Performance
    - The incorporation of dilations, conditional mechanisms, and attention mechanisms provided incremental improvements, as evidenced by decreasing NLL and perplexity.
    - However, even with these enhancements, the models struggled to generate coherent images, likely due to limitations in capturing the complex dependencies necessary for generating high-quality samples.

1. Challenges

    - Model Complexity: The PixelCNN architecture may not be sufficient to model the complex dependencies in image data, even with enhancements.
    - Training Stability: The extremely high perplexity in some models suggests potential instability during training, possibly due to inappropriate hyperparameter settings or insufficient training duration.

2. Recommendations

    - Further Architectural Enhancements: Consider exploring more advanced architectures like PixelSNAIL, which integrates both autoregressive modeling and attention in a more sophisticated manner.
    - Hyperparameter Tuning: More extensive tuning of learning rates, batch sizes, and regularization techniques could help stabilize training and improve performance.
    - Longer Training: Extending the training duration or using more sophisticated training techniques could lead to better convergence and improved image quality.

3. Conclusion

    - The project examined different ways to improve the PixelCNN model for producing images.Although, the resulting photos with pixelCNN were noisy and unstructured,performance measurements for enchanced model showed improvements. The findings demonstrate the difficulties in using PixelCNN to complicated image creation tasks and imply that additional improvements and different strategies would be required to produce generative models of a high caliber.
    - An comprehensive summary of the procedures, outcomes, and conclusions from the PixelCNN model is provided in this report. Even though there was progress, the

difficulties faced point the way for additional attempts to improve the caliber of the images that are produced.

Thanks!

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