消融实验

本notebook是 `任庆桦` 老师在 `24fall` 江苏大学人工智能专业实践的小组作业。基于 `cifar10` 数据集的模型消融实验，主要是通过有目的地移除或替换模型中的某些组件或功能，研究这些组件对模型性能的影响，从而理解模型的关键特性和有效性。

本次实验探究了以下五种因素对模型的影响：

1. convolution-subsambling pairs
2. feature map nums
3. dense layers
4. dropout
5. Augmentation

导入本次实验的库

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
```

In [2]:
```python
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

Out[2]:
```
device(type='cuda')
```

导入数据集

In [3]:
```python
# Load CIFAR-10
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])

train_dataset = datasets.CIFAR10(root="./data", train=True, download=True, transform=transform)
test_dataset = datasets.CIFAR10(root="./data", train=False, download=True, transform=transform)

train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/cifar-10-python.tar.g
z
100%|██████████| 170498071/170498071 [00:03<00:00, 49038513.09it/s]
Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

创建绘图函数

`plot_model_losses` 函数可以将多个模型的loss训练过程绘画在一张图，便于展示结果。

In [4]:
```python
def plot_model_losses(train_losses, val_losses, names):
    nets = len(names)
    cols = 3

    rows = (nets + cols - 1) // cols  # 计算行数，确保布局合理

    # 创建一个符合网格布局的图形
    fig, axes = plt.subplots(rows, cols, figsize=(cols * 6, rows * 5))

    # if rows == 1:
    #     axes = [axes]  # 如果只有一行，确保 axes 是一个列表

    for i in range(nets):
        row = i // cols
        col = i % cols
        ax = axes[row][col] if rows > 1 else axes[col]

        # 确保 train_losses[i] 和 val_losses[i] 是一维数组或列表
        ax.plot(train_losses[i], label='Train Loss')
        ax.plot(val_losses[i], label='Test Loss')
        ax.set_title(f'Model {names[i]} Losses')
        ax.set_xlabel('Epoch')
        ax.set_ylabel('Loss')
        ax.legend()

    plt.tight_layout()

    # 关闭空的子图
    for j in range(i + 1, rows * cols):
        row = j // cols
        col = j % cols
        ax = axes[row][col] if rows > 1 else axes[col]
        ax.axis('off')

    plt.show()
```

`plot_val_acc` 函数可以接受模型的验证准确率、模型名称、绘图样式，然后将所有模型的验证集准确率进行对比

In [5]:
```python
def plot_val_acc(val_acc_list, model_names, styles=None, figsize=(15, 5), title='Model Accuracy', y

    if styles is None:
        styles = [':', '-.', '--', '-', ':', '-.', '--', '-'] * (len(val_acc_list) // 4 + 1)

    plt.figure(figsize=figsize)
    for i, val_acc in enumerate(val_acc_list):
        plt.plot(val_acc, linestyle=styles[i % len(styles)], label=model_names[i])

    plt.title(title)
    plt.ylabel(ylabel)
    plt.xlabel(xlabel)
    plt.legend(loc='upper left')
    axes = plt.gca()
    axes.set_ylim(ylim)
    plt.show()
```

模型训练函数定义

定义模型训练的函数，返回 `train_loss`，`train_acc`，`val_loss`，`val_acc`
模型的 `Optimizer` 使用 `Adam`，`criterion` 使用交叉熵损失

In [6]:
```python
def train_model(model, train_loader, test_loader, epochs=20, device="cpu"):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=0.001)

    train_acc = []
    val_acc = []
    train_loss = []
    val_loss = []

    for epoch in range(epochs):
        # Training phase
        model.train()
        correct = 0
        total = 0
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

        train_loss.append(running_loss / len(train_loader))
        train_acc.append(correct / total)

        # Validation phase
        model.eval()
        correct = 0
        total = 0
        running_loss = 0.0
        with torch.no_grad():
            for images, labels in test_loader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                loss = criterion(outputs, labels)

                running_loss += loss.item()
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        val_loss.append(running_loss / len(test_loader))
        val_acc.append(correct / total)

        if epoch % 2 == 0 or epoch + 1 == epochs:
            print(f"Epoch {epoch+1}/{epochs}, Train Loss: {train_loss[-1]:.4f}, Train Accuracy: {tr

    return train_loss, train_acc, val_loss, val_acc
```

比较试验

1. 探究 `convolution-subsambling pairs` 对模型影响

建立一个简单的模型，探究不同的 `convolution-subsambling pairs` 对数对模型的影响。我们比较了四种参数的组合，通过堆叠（32x32的卷基层+2x2的池化层）：

1. 32CP2
2. 32CP2-32CP2
3. 32CP2-32CP2-32CP2
4. 32CP2-32CP2-32CP2-32CP2

模型定义

In [7]:
```python
class SimpleCNN(nn.Module):
    def __init__(self, conv_subsample_pairs):
        super(SimpleCNN, self).__init__()
        layers = []
        in_channels = 3
        out_channels = 32

        for i in range(conv_subsample_pairs):
            layers.append(nn.Conv2d(in_channels, out_channels, kernel_size=5, stride=1, padding=2))
            layers.append(nn.ReLU())
            layers.append(nn.MaxPool2d(kernel_size=2, stride=2))
            in_channels = out_channels
            out_channels += 16

        out_channels -= 16
        layers.append(nn.Flatten())
        # Compute the size of the input to the linear layer (taking into account the pooling)
        linear_input_size = out_channels * (32 // (2 ** conv_subsample_pairs)) ** 2
        layers.append(nn.Linear(linear_input_size, 10))

        self.model = nn.Sequential(*layers)

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

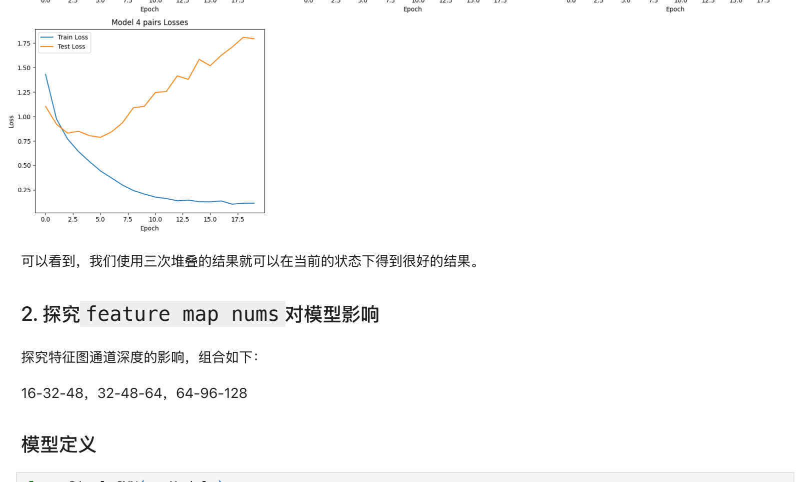
实验过程

In [8]:
```python
pairs_list = [1, 2, 3, 4]
names = [f"{pairs} pairs" for pairs in pairs_list]
styles = [':', '-.', '--', '-']
train_loss_list = []
train_acc_list = []
val_loss_list = []
val_acc_list = []

for pairs in pairs_list:
    print(f"Training with {pairs} convolution-subsampling pairs...")
    model = SimpleCNN(conv_subsample_pairs=pairs).to(device)
    train_loss, train_acc, val_loss, val_acc = train_model(model, train_loader, test_loader, epochs
    train_loss_list.append(train_loss)
    train_acc_list.append(train_acc)
    val_loss_list.append(val_loss)
    val_acc_list.append(val_acc)
```

```
Training with 1 convolution-subsampling pairs...
Epoch 1/20, Train Loss: 1.3810, Train Accuracy: 0.5179, Validation Loss: 1.1692, Validation Accurac
y: 0.5905
Epoch 3/20, Train Loss: 0.9799, Train Accuracy: 0.6658, Validation Loss: 1.0447, Validation Accurac
y: 0.6421
Epoch 5/20, Train Loss: 0.8724, Train Accuracy: 0.7014, Validation Loss: 1.0099, Validation Accurac
y: 0.6563
Epoch 7/20, Train Loss: 0.8006, Train Accuracy: 0.7235, Validation Loss: 1.0607, Validation Accurac
y: 0.6448
Epoch 9/20, Train Loss: 0.7351, Train Accuracy: 0.7486, Validation Loss: 1.0446, Validation Accurac
y: 0.6540
Epoch 11/20, Train Loss: 0.6897, Train Accuracy: 0.7621, Validation Loss: 1.0670, Validation Accura
cy: 0.6510
Epoch 13/20, Train Loss: 0.6447, Train Accuracy: 0.7773, Validation Loss: 1.0926, Validation Accura
cy: 0.6580
Epoch 15/20, Train Loss: 0.6026, Train Accuracy: 0.7918, Validation Loss: 1.1199, Validation Accura
cy: 0.6504
Epoch 17/20, Train Loss: 0.5692, Train Accuracy: 0.8038, Validation Loss: 1.2048, Validation Accura
cy: 0.6400
Epoch 19/20, Train Loss: 0.5367, Train Accuracy: 0.8128, Validation Loss: 1.2488, Validation Accura
cy: 0.6383
Epoch 20/20, Train Loss: 0.5244, Train Accuracy: 0.8178, Validation Loss: 1.2282, Validation Accura
cy: 0.6375
Training with 2 convolution-subsampling pairs...
Epoch 1/20, Train Loss: 1.3429, Train Accuracy: 0.5232, Validation Loss: 1.0762, Validation Accurac
y: 0.6224
Epoch 3/20, Train Loss: 0.8391, Train Accuracy: 0.7084, Validation Loss: 0.8692, Validation Accurac
y: 0.7039
Epoch 5/20, Train Loss: 0.6852, Train Accuracy: 0.7625, Validation Loss: 0.8378, Validation Accurac
y: 0.7229
Epoch 7/20, Train Loss: 0.5915, Train Accuracy: 0.7945, Validation Loss: 0.8225, Validation Accurac
y: 0.7285
Epoch 9/20, Train Loss: 0.5155, Train Accuracy: 0.8207, Validation Loss: 0.8593, Validation Accurac
y: 0.7233
Epoch 11/20, Train Loss: 0.4510, Train Accuracy: 0.8409, Validation Loss: 0.9100, Validation Accura
cy: 0.7219
Epoch 13/20, Train Loss: 0.3986, Train Accuracy: 0.8604, Validation Loss: 0.9556, Validation Accura
cy: 0.7244
Epoch 15/20, Train Loss: 0.3563, Train Accuracy: 0.8747, Validation Loss: 1.0499, Validation Accura
cy: 0.7153
Epoch 17/20, Train Loss: 0.3153, Train Accuracy: 0.8880, Validation Loss: 1.1683, Validation Accura
cy: 0.7088
Epoch 19/20, Train Loss: 0.2778, Train Accuracy: 0.9010, Validation Loss: 1.2234, Validation Accura
cy: 0.7100
Epoch 20/20, Train Loss: 0.2581, Train Accuracy: 0.9088, Validation Loss: 1.2706, Validation Accura
cy: 0.7090
Training with 3 convolution-subsampling pairs...
Epoch 1/20, Train Loss: 1.4008, Train Accuracy: 0.4926, Validation Loss: 1.0932, Validation Accurac
y: 0.6059
Epoch 3/20, Train Loss: 0.8093, Train Accuracy: 0.7189, Validation Loss: 0.8617, Validation Accurac
y: 0.6967
Epoch 5/20, Train Loss: 0.6043, Train Accuracy: 0.7903, Validation Loss: 0.8218, Validation Accurac
y: 0.7283
Epoch 7/20, Train Loss: 0.4654, Train Accuracy: 0.8363, Validation Loss: 0.8296, Validation Accurac
y: 0.7317
Epoch 9/20, Train Loss: 0.3545, Train Accuracy: 0.8761, Validation Loss: 0.9263, Validation Accurac
y: 0.7175
Epoch 11/20, Train Loss: 0.2699, Train Accuracy: 0.9045, Validation Loss: 1.0519, Validation Accura
cy: 0.7263
Epoch 13/20, Train Loss: 0.2131, Train Accuracy: 0.9235, Validation Loss: 1.1838, Validation Accura
cy: 0.7340
Epoch 15/20, Train Loss: 0.1806, Train Accuracy: 0.9352, Validation Loss: 1.3708, Validation Accura
cy: 0.7261
Epoch 17/20, Train Loss: 0.1460, Train Accuracy: 0.9481, Validation Loss: 1.5741, Validation Accura
cy: 0.7170
Epoch 19/20, Train Loss: 0.1352, Train Accuracy: 0.9521, Validation Loss: 1.6596, Validation Accura
cy: 0.7236
Epoch 20/20, Train Loss: 0.1231, Train Accuracy: 0.9559, Validation Loss: 1.8023, Validation Accura
cy: 0.7200
Training with 4 convolution-subsampling pairs...
Epoch 1/20, Train Loss: 1.4315, Train Accuracy: 0.4763, Validation Loss: 1.1034, Validation Accurac
y: 0.6057
Epoch 3/20, Train Loss: 0.7710, Train Accuracy: 0.7303, Validation Loss: 0.8305, Validation Accurac
y: 0.7119
Epoch 5/20, Train Loss: 0.5395, Train Accuracy: 0.8112, Validation Loss: 0.8040, Validation Accurac
y: 0.7349
Epoch 7/20, Train Loss: 0.3727, Train Accuracy: 0.8675, Validation Loss: 0.8422, Validation Accurac
y: 0.7410
Epoch 9/20, Train Loss: 0.2436, Train Accuracy: 0.9137, Validation Loss: 1.0891, Validation Accurac
y: 0.7267
Epoch 11/20, Train Loss: 0.1762, Train Accuracy: 0.9383, Validation Loss: 1.2451, Validation Accura
cy: 0.7348
Epoch 13/20, Train Loss: 0.1387, Train Accuracy: 0.9510, Validation Loss: 1.4151, Validation Accura
cy: 0.7314
Epoch 15/20, Train Loss: 0.1290, Train Accuracy: 0.9556, Validation Loss: 1.5842, Validation Accura
cy: 0.7320
Epoch 17/20, Train Loss: 0.1369, Train Accuracy: 0.9528, Validation Loss: 1.6246, Validation Accura
cy: 0.7317
Epoch 19/20, Train Loss: 0.1137, Train Accuracy: 0.9619, Validation Loss: 1.8086, Validation Accura
cy: 0.7248
Epoch 20/20, Train Loss: 0.1139, Train Accuracy: 0.9618, Validation Loss: 1.7957, Validation Accura
cy: 0.7293
```

实验结果

In [9]:
```python
plot_val_acc(val_acc_list, names, styles=styles, title="Effect of Convolution-Subsampling Pairs on
```



In [10]:
```python
plot_model_losses(train_loss_list, val_loss_list, names)
```

可以看到，我们使用三次堆叠的结果就可以在当前的状态下得到很好的结果。

2. 探究 `feature map nums` 对模型影响

探究特征图通道深度的影响，组合如下：

16-32-48，32-48-64，64-96-128

模型定义

In [11]:
```python
class SimpleCNN(nn.Module):
    def __init__(self, channels_config=None):
        super(SimpleCNN, self).__init__()
        layers = []
        in_channels = 3

        # 设置默认的通道数递增配置
        if channels_config is None:
            channels_config = [16, 32, 48]  # 默认配置: 16 -> 32 -> 48

        # 根据conv_subsample_pairs和channels_config设置卷积层
        for i in range(3):
            out_channels = channels_config[i]
            layers.append(nn.Conv2d(in_channels, out_channels, kernel_size=5, stride=1, padding=2))
            layers.append(nn.ReLU())
            layers.append(nn.MaxPool2d(kernel_size=2, stride=2))
            in_channels = out_channels

        layers.append(nn.Flatten())

        linear_input_size = in_channels * 16
        layers.append(nn.Linear(linear_input_size, 10))

        self.model = nn.Sequential(*layers)

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

实验过程

In [12]:
```python
# 实验过程
channel_configs = [
    [16, 32, 48],  # 组合1
    [32, 48, 64],  # 组合2
    [64, 96, 128]  # 组合3
]
names = [f"Channels: {cfg}" for cfg in channel_configs]
styles = [':', '-.', '--']

train_loss_list = []
train_acc_list = []
val_loss_list = []
val_acc_list = []
```

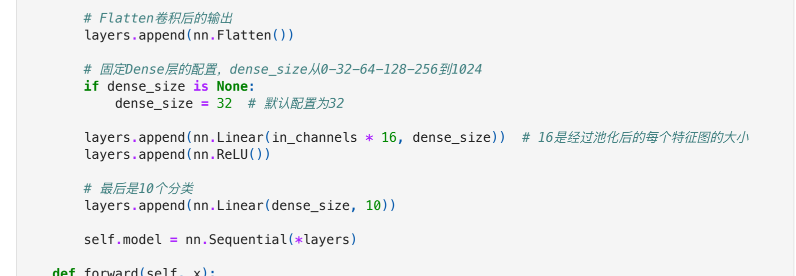
In [13]:
```python
# 进行实验
for channel_config in channel_configs:
    print(f"Training with channel config {channel_config}...")
    model = SimpleCNN(channels_config=channel_config).to(device)  # 假设使用3层卷积
    train_loss, train_acc, val_loss, val_acc = train_model(model, train_loader, test_loader, epochs
    train_loss_list.append(train_loss)
    train_acc_list.append(train_acc)
    val_loss_list.append(val_loss)
    val_acc_list.append(val_acc)
```

```
Training with channel config [16, 32, 48]...
Epoch 1/10, Train Loss: 1.4488, Train Accuracy: 0.4772, Validation Loss: 1.2008, Validation Accurac
y: 0.5697
Epoch 3/10, Train Loss: 0.9038, Train Accuracy: 0.6826, Validation Loss: 0.8988, Validation Accurac
y: 0.6854
Epoch 5/10, Train Loss: 0.7217, Train Accuracy: 0.7491, Validation Loss: 0.8335, Validation Accurac
y: 0.7096
Epoch 7/10, Train Loss: 0.6109, Train Accuracy: 0.7886, Validation Loss: 0.8067, Validation Accurac
y: 0.7286
Epoch 9/10, Train Loss: 0.5301, Train Accuracy: 0.8143, Validation Loss: 0.8605, Validation Accurac
y: 0.7194
Epoch 10/10, Train Loss: 0.4927, Train Accuracy: 0.8294, Validation Loss: 0.8607, Validation Accura
cy: 0.7263
Training with channel config [32, 48, 64]...
Epoch 1/10, Train Loss: 1.3867, Train Accuracy: 0.4993, Validation Loss: 1.1196, Validation Accurac
y: 0.6078
Epoch 3/10, Train Loss: 0.8048, Train Accuracy: 0.7203, Validation Loss: 0.8600, Validation Accurac
y: 0.7054
Epoch 5/10, Train Loss: 0.6145, Train Accuracy: 0.7860, Validation Loss: 0.7907, Validation Accurac
y: 0.7362
Epoch 7/10, Train Loss: 0.4815, Train Accuracy: 0.8306, Validation Loss: 0.8165, Validation Accurac
y: 0.7400
Epoch 9/10, Train Loss: 0.3714, Train Accuracy: 0.8698, Validation Loss: 0.8755, Validation Accurac
y: 0.7355
Epoch 10/10, Train Loss: 0.3372, Train Accuracy: 0.8820, Validation Loss: 0.9979, Validation Accura
cy: 0.7237
Training with channel config [64, 96, 128]...
Epoch 1/10, Train Loss: 1.2979, Train Accuracy: 0.5336, Validation Loss: 0.9865, Validation Accurac
y: 0.6550
Epoch 3/10, Train Loss: 0.6966, Train Accuracy: 0.7576, Validation Loss: 0.7938, Validation Accurac
y: 0.7297
Epoch 5/10, Train Loss: 0.4601, Train Accuracy: 0.8391, Validation Loss: 0.7734, Validation Accurac
y: 0.7505
Epoch 7/10, Train Loss: 0.2842, Train Accuracy: 0.9015, Validation Loss: 0.8819, Validation Accurac
y: 0.7491
Epoch 9/10, Train Loss: 0.1870, Train Accuracy: 0.9334, Validation Loss: 1.0969, Validation Accurac
y: 0.7298
Epoch 10/10, Train Loss: 0.1584, Train Accuracy: 0.9432, Validation Loss: 1.2290, Validation Accura
cy: 0.7437
```

实验结果

In [14]:
```python
# 绘制验证精度图
plot_val_acc(val_acc_list, names, styles=styles, title="Effect of Different Channel Configurations
```

In [15]:
```python
# 绘制训练和验证损失图
plot_model_losses(train_loss_list, val_loss_list, names)
```



可以看出，feature map nums对模型有一定的影响，我们选择64-96-128，即最大的。

3. 探究 `dense layer` 对模型影响

模型定义

In [16]:
```python
class SimpleCNN(nn.Module):
    def __init__(self, dense_size=None):
        super(SimpleCNN, self).__init__()
        layers = []
        in_channels = 3

        # 固定的通道数配置: [64, 96, 128]
        channels_config = [64, 96, 128]

        # 根据固定的通道配置设置卷积层
        for i in range(3):
            out_channels = channels_config[i]
            layers.append(nn.Conv2d(in_channels, out_channels, kernel_size=5, stride=1, padding=2))
            layers.append(nn.ReLU())
            layers.append(nn.MaxPool2d(kernel_size=2, stride=2))
            in_channels = out_channels

        # Flatten卷积后的输出
        layers.append(nn.Flatten())

        # 固定Dense层的配置，dense_size从0-32-64-128-256到1024
        if dense_size is None:
            dense_size = 32  # 默认配置为32

        layers.append(nn.Linear(in_channels * 16, dense_size))  # 16是经过池化后的每个特征图的大小
        layers.append(nn.ReLU())

        # 最后是10个分类
        layers.append(nn.Linear(dense_size, 10))

        self.model = nn.Sequential(*layers)

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

实验过程

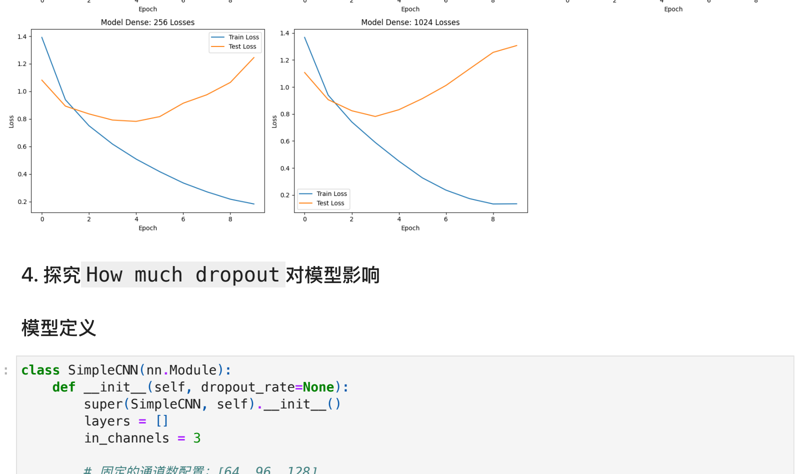
In [17]:
```python
dense_sizes = [32, 64, 128, 256, 1024]  # Dense层的尺寸变化配置
names = [f"Dense: {size}" for size in dense_sizes]
styles = [':','-.','--','-',':','-.','--','-',':','-.','--','-']

train_loss_list = []
train_acc_list = []
val_loss_list = []
val_acc_list = []
```

In [18]:
```python
# 进行实验
for dense_size in dense_sizes:
    print(f"Training with dense size {dense_size}...")
    model = SimpleCNN(dense_size=dense_size).to(device)
    train_loss, train_acc, val_loss, val_acc = train_model(model, train_loader, test_loader, epochs
    train_loss_list.append(train_loss)
    train_acc_list.append(train_acc)
    val_loss_list.append(val_loss)
    val_acc_list.append(val_acc)
```

```
Training with dense size 32...
Epoch 1/10, Train Loss: 1.4409, Train Accuracy: 0.4744, Validation Loss: 1.1254, Validation Accurac
y: 0.6013
Epoch 3/10, Train Loss: 0.7679, Train Accuracy: 0.7322, Validation Loss: 0.8364, Validation Accurac
y: 0.7098
Epoch 5/10, Train Loss: 0.5414, Train Accuracy: 0.8115, Validation Loss: 0.7561, Validation Accurac
y: 0.7488
Epoch 7/10, Train Loss: 0.3735, Train Accuracy: 0.8684, Validation Loss: 0.8341, Validation Accurac
y: 0.7441
Epoch 9/10, Train Loss: 0.2532, Train Accuracy: 0.9111, Validation Loss: 1.0066, Validation Accurac
y: 0.7395
Epoch 10/10, Train Loss: 0.2144, Train Accuracy: 0.9248, Validation Loss: 1.0987, Validation Accura
cy: 0.7449
Training with dense size 64...
Epoch 1/10, Train Loss: 1.3872, Train Accuracy: 0.4979, Validation Loss: 1.0646, Validation Accurac
y: 0.6220
Epoch 3/10, Train Loss: 0.7280, Train Accuracy: 0.7463, Validation Loss: 0.8746, Validation Accurac
y: 0.7001
Epoch 5/10, Train Loss: 0.4925, Train Accuracy: 0.8269, Validation Loss: 0.7757, Validation Accurac
y: 0.7509
Epoch 7/10, Train Loss: 0.3154, Train Accuracy: 0.8890, Validation Loss: 0.8637, Validation Accurac
y: 0.7513
Epoch 9/10, Train Loss: 0.2039, Train Accuracy: 0.9284, Validation Loss: 1.0075, Validation Accurac
y: 0.7486
Epoch 10/10, Train Loss: 0.1736, Train Accuracy: 0.9386, Validation Loss: 1.1163, Validation Accura
cy: 0.7471
Training with dense size 128...
Epoch 1/10, Train Loss: 1.3708, Train Accuracy: 0.5017, Validation Loss: 1.0513, Validation Accurac
y: 0.6236
Epoch 3/10, Train Loss: 0.7133, Train Accuracy: 0.7493, Validation Loss: 0.7721, Validation Accurac
y: 0.7375
Epoch 5/10, Train Loss: 0.4666, Train Accuracy: 0.8354, Validation Loss: 0.8002, Validation Accurac
y: 0.7356
Epoch 7/10, Train Loss: 0.2932, Train Accuracy: 0.8943, Validation Loss: 0.9680, Validation Accurac
y: 0.7260
Epoch 9/10, Train Loss: 0.1913, Train Accuracy: 0.9317, Validation Loss: 1.0809, Validation Accurac
y: 0.7435
Epoch 10/10, Train Loss: 0.1591, Train Accuracy: 0.9446, Validation Loss: 1.1719, Validation Accura
cy: 0.7470
Training with dense size 256...
Epoch 1/10, Train Loss: 1.3918, Train Accuracy: 0.4919, Validation Loss: 1.0818, Validation Accurac
y: 0.6114
Epoch 3/10, Train Loss: 0.7510, Train Accuracy: 0.7354, Validation Loss: 0.8365, Validation Accurac
y: 0.7169
Epoch 5/10, Train Loss: 0.5091, Train Accuracy: 0.8198, Validation Loss: 0.7824, Validation Accurac
y: 0.7400
Epoch 7/10, Train Loss: 0.3358, Train Accuracy: 0.8816, Validation Loss: 0.9143, Validation Accurac
y: 0.7499
Epoch 9/10, Train Loss: 0.2179, Train Accuracy: 0.9225, Validation Loss: 1.0651, Validation Accurac
y: 0.7484
Epoch 10/10, Train Loss: 0.1834, Train Accuracy: 0.9347, Validation Loss: 1.2453, Validation Accura
cy: 0.7427
Training with dense size 1024...
Epoch 1/10, Train Loss: 1.3677, Train Accuracy: 0.5008, Validation Loss: 1.1076, Validation Accurac
y: 0.6080
Epoch 3/10, Train Loss: 0.7417, Train Accuracy: 0.7396, Validation Loss: 0.8242, Validation Accurac
y: 0.7126
Epoch 5/10, Train Loss: 0.4509, Train Accuracy: 0.8403, Validation Loss: 0.8316, Validation Accurac
y: 0.7344
Epoch 7/10, Train Loss: 0.2359, Train Accuracy: 0.9164, Validation Loss: 1.0117, Validation Accurac
y: 0.7371
Epoch 9/10, Train Loss: 0.1334, Train Accuracy: 0.9533, Validation Loss: 1.2565, Validation Accurac
y: 0.7372
Epoch 10/10, Train Loss: 0.1347, Train Accuracy: 0.9544, Validation Loss: 1.3069, Validation Accura
cy: 0.7342
```

实验结果

In [19]:
```python
# 绘制验证精度图
plot_val_acc(val_acc_list, names, styles=styles, title="Effect of Dense Layer Size on CIFAR-10", yl
```



In [20]:
```python
# 绘制训练和验证损失图
plot_model_losses(train_loss_list, val_loss_list, names)
```

4. 探究 `How much dropout` 对模型影响

模型定义

In [21]:
```python
class SimpleCNN(nn.Module):
    def __init__(self, dropout_rate=None):
        super(SimpleCNN, self).__init__()
        layers = []
        in_channels = 3

        # 固定的通道数配置: [64, 96, 128]
        channels_config = [64, 96, 128]

        # 根据固定的通道配置设置卷积层
        for i in range(3):
            out_channels = channels_config[i]
            layers.append(nn.Conv2d(in_channels, out_channels, kernel_size=5, stride=1, padding=2))
            layers.append(nn.ReLU())
            layers.append(nn.MaxPool2d(kernel_size=2, stride=2))
            in_channels = out_channels

        # Flatten卷积后的输出
        layers.append(nn.Flatten())

        # 固定Dense层的配置: 256
        layers.append(nn.Linear(in_channels * 16, 256))  # 16是经过池化后的每个特征图的大小
        layers.append(nn.ReLU())

        # 如果指定了Dropout率，则添加Dropout层
        if dropout_rate is not None:
            layers.append(nn.Dropout(dropout_rate))

        # 最后是10个分类
        layers.append(nn.Linear(256, 10))

        self.model = nn.Sequential(*layers)

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

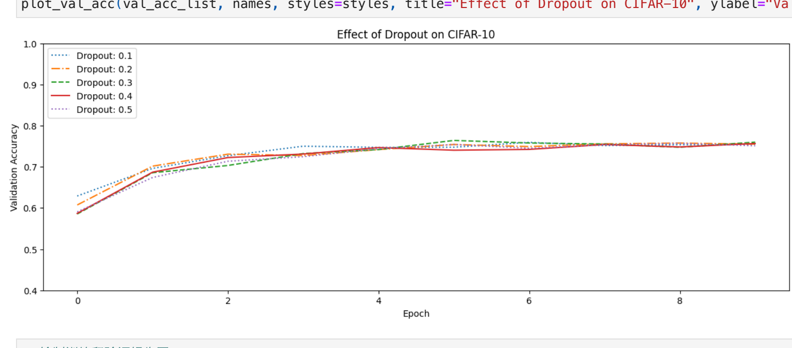
实验过程

In [22]:
```python
# 实验过程
dropout_rates = [0.1, 0.2, 0.3, 0.4, 0.5]  # Dropout层的递增配置
names = [f"Dropout: {rate}" for rate in dropout_rates]
styles = [':', '-.', '--', '-', ':']

train_loss_list = []
train_acc_list = []
val_loss_list = []
val_acc_list = []

# 进行实验
for dropout_rate in dropout_rates:
    print(f"Training with dropout rate {dropout_rate}...")
    model = SimpleCNN(dropout_rate=dropout_rate).to(device)
    train_loss, train_acc, val_loss, val_acc = train_model(model, train_loader, test_loader, epochs
    train_loss_list.append(train_loss)
    train_acc_list.append(train_acc)
    val_loss_list.append(val_loss)
    val_acc_list.append(val_acc)
```

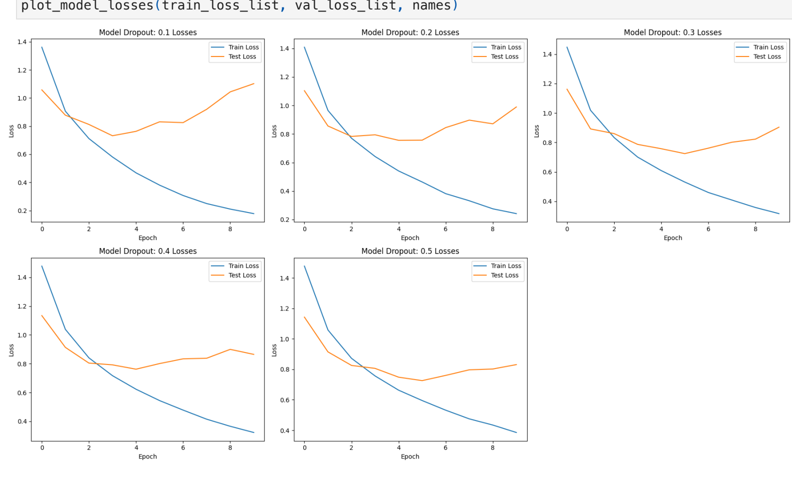
```
Training with dropout rate 0.1...
Epoch 1/10, Train Loss: 1.3614, Train Accuracy: 0.5069, Validation Loss: 1.0579, Validation Accurac
y: 0.6291
Epoch 3/10, Train Loss: 0.7117, Train Accuracy: 0.7520, Validation Loss: 0.8121, Validation Accurac
y: 0.7270
Epoch 5/10, Train Loss: 0.4681, Train Accuracy: 0.8345, Validation Loss: 0.7630, Validation Accurac
y: 0.7473
Epoch 7/10, Train Loss: 0.3068, Train Accuracy: 0.8906, Validation Loss: 0.8251, Validation Accurac
y: 0.7595
Epoch 9/10, Train Loss: 0.2104, Train Accuracy: 0.9247, Validation Loss: 1.0436, Validation Accurac
y: 0.7537
Epoch 10/10, Train Loss: 0.1781, Train Accuracy: 0.9373, Validation Loss: 1.1021, Validation Accura
cy: 0.7547
Training with dropout rate 0.2...
Epoch 1/10, Train Loss: 1.4083, Train Accuracy: 0.4889, Validation Loss: 1.1035, Validation Accurac
y: 0.6073
Epoch 3/10, Train Loss: 0.7703, Train Accuracy: 0.7331, Validation Loss: 0.7829, Validation Accurac
y: 0.7308
Epoch 5/10, Train Loss: 0.5409, Train Accuracy: 0.8111, Validation Loss: 0.7555, Validation Accurac
y: 0.7420
Epoch 7/10, Train Loss: 0.3818, Train Accuracy: 0.8632, Validation Loss: 0.8447, Validation Accurac
y: 0.7492
Epoch 9/10, Train Loss: 0.2757, Train Accuracy: 0.9013, Validation Loss: 0.8712, Validation Accurac
y: 0.7577
Epoch 10/10, Train Loss: 0.2420, Train Accuracy: 0.9132, Validation Loss: 0.9894, Validation Accura
cy: 0.7552
Training with dropout rate 0.3...
Epoch 1/10, Train Loss: 1.4474, Train Accuracy: 0.4699, Validation Loss: 1.1620, Validation Accurac
y: 0.5854
Epoch 3/10, Train Loss: 0.8336, Train Accuracy: 0.7084, Validation Loss: 0.8603, Validation Accurac
y: 0.7033
Epoch 5/10, Train Loss: 0.6090, Train Accuracy: 0.7860, Validation Loss: 0.7576, Validation Accurac
y: 0.7420
Epoch 7/10, Train Loss: 0.4602, Train Accuracy: 0.8365, Validation Loss: 0.7613, Validation Accurac
y: 0.7579
Epoch 9/10, Train Loss: 0.3581, Train Accuracy: 0.8718, Validation Loss: 0.8225, Validation Accurac
y: 0.7476
Epoch 10/10, Train Loss: 0.3166, Train Accuracy: 0.8857, Validation Loss: 0.9037, Validation Accura
cy: 0.7600
Training with dropout rate 0.4...
Epoch 1/10, Train Loss: 1.4778, Train Accuracy: 0.4608, Validation Loss: 1.1343, Validation Accurac
y: 0.5869
Epoch 3/10, Train Loss: 0.8409, Train Accuracy: 0.7065, Validation Loss: 0.8045, Validation Accurac
y: 0.7226
Epoch 5/10, Train Loss: 0.6232, Train Accuracy: 0.7838, Validation Loss: 0.7622, Validation Accurac
y: 0.7469
Epoch 7/10, Train Loss: 0.4783, Train Accuracy: 0.8327, Validation Loss: 0.8340, Validation Accurac
y: 0.7424
Epoch 9/10, Train Loss: 0.3659, Train Accuracy: 0.8709, Validation Loss: 0.8998, Validation Accurac
y: 0.7483
Epoch 10/10, Train Loss: 0.3227, Train Accuracy: 0.8873, Validation Loss: 0.8650, Validation Accura
cy: 0.7567
Training with dropout rate 0.5...
Epoch 1/10, Train Loss: 1.4780, Train Accuracy: 0.4587, Validation Loss: 1.1431, Validation Accurac
y: 0.5906
Epoch 3/10, Train Loss: 0.8725, Train Accuracy: 0.6986, Validation Loss: 0.8259, Validation Accurac
y: 0.7136
Epoch 5/10, Train Loss: 0.6634, Train Accuracy: 0.7690, Validation Loss: 0.7487, Validation Accurac
y: 0.7443
Epoch 7/10, Train Loss: 0.5320, Train Accuracy: 0.8139, Validation Loss: 0.7603, Validation Accurac
y: 0.7451
Epoch 9/10, Train Loss: 0.4345, Train Accuracy: 0.8461, Validation Loss: 0.8024, Validation Accurac
y: 0.7572
Epoch 10/10, Train Loss: 0.3855, Train Accuracy: 0.8626, Validation Loss: 0.8313, Validation Accura
cy: 0.7511
```

实验结果

In [23]:
```python
# 绘制验证精度图
plot_val_acc(val_acc_list, names, styles=styles, title="Effect of Dropout on CIFAR-10", ylabel="Val
```



In [24]:
```python
# 绘制训练和验证损失图
plot_model_losses(train_loss_list, val_loss_list, names)
```



5. 加入 `Augmentation` 对模型影响

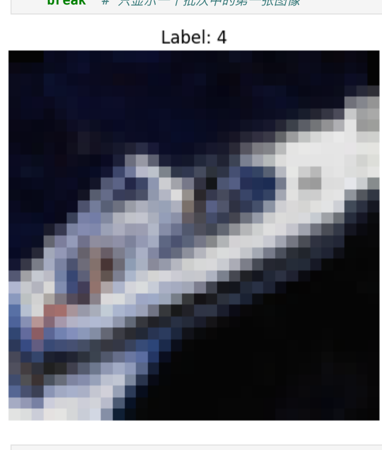
数据增强

In [25]:
```python
# 强力的数据增强组合，只应用于训练集
train_transform = transforms.Compose([
    transforms.RandomHorizontalFlip(),  # 随机水平翻转，保持不变
    transforms.RandomRotation(5),  # 随机旋转角度减小，从15度减少到5度
    transforms.RandomResizedCrop(32, scale=(0.9, 1.0)),  # 随机裁剪，缩放范围减小（不小于90%）
    transforms.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1, hue=0.1),  # 随机调整颜色幅度
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))  # 归一化
])

# 仅进行标准化的转换，应用于测试集
test_transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))  # 归一化
])

# 加载CIFAR-10数据集
train_dataset_aug = datasets.CIFAR10(root="./data", train=True, download=True, transform=train_tran
test_dataset = datasets.CIFAR10(root="./data", train=False, download=True, transform=test_transform

train_loader_aug = DataLoader(train_dataset_aug, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

模型定义

In [26]:
```python
for images, labels in train_loader_aug:
    # 选择第一张图像
    image = images[2]

    # 将图像从Tensor格式转换为NumPy格式
    image = image.numpy().transpose((1, 2, 0))  # 由(3, 32, 32) -> (32, 32, 3)
    image = image * 0.5 + 0.5  # 反标准化，将像素值从[-1, 1]映射回[0, 1]

    # 显示图像
    plt.imshow(image)
    plt.title(f"Label: {labels[0].item()}")
    plt.axis('off')  # 不显示坐标轴
    plt.show()
    break  # 只显示一个批次中的第一张图像
```



In [ ]:

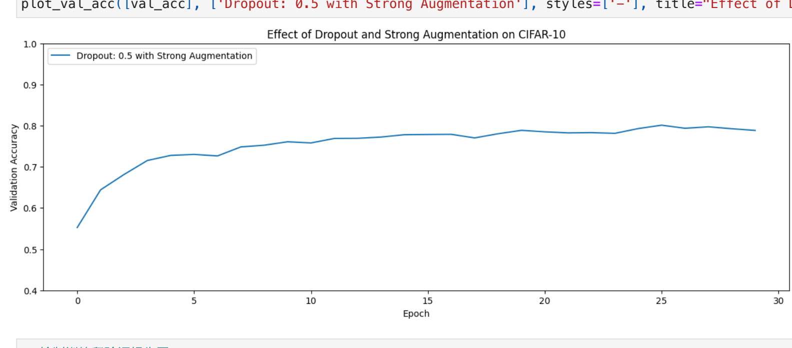
In [27]:
```python
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        layers = []
        in_channels = 3

        # 固定的通道数配置：[64, 96, 128]
        channels_config = [64, 96, 128]

        # 根据固定的通道配置设置卷积层
        for i in range(3):
            out_channels = channels_config[i]
            layers.append(nn.Conv2d(in_channels, out_channels, kernel_size=5, stride=1, padding=2))
            layers.append(nn.ReLU())
            layers.append(nn.MaxPool2d(kernel_size=2, stride=2))
            in_channels = out_channels

        # Flatten卷积后的输出
        layers.append(nn.Flatten())

        # 固定Dense层的配置：256
        layers.append(nn.Linear(in_channels * 16, 256))  # 16是经过池化后的每个特征图的大小
        layers.append(nn.ReLU())


        layers.append(nn.Dropout(0.5))

        # 最后是10个分类
        layers.append(nn.Linear(256, 10))

        self.model = nn.Sequential(*layers)

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

实验过程

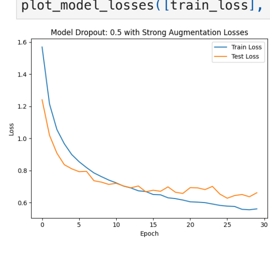
In [28]:
```python
model = SimpleCNN().to(device)
# 进行训练
train_loss, train_acc, val_loss, val_acc = train_model(model, train_loader_aug, test_loader, epochs
```

```
Epoch 1/30, Train Loss: 1.5701, Train Accuracy: 0.4244, Validation Loss: 1.2412, Validation Accurac
y: 0.5524
Epoch 3/30, Train Loss: 1.0553, Train Accuracy: 0.6336, Validation Loss: 0.9081, Validation Accurac
y: 0.6813
Epoch 5/30, Train Loss: 0.8995, Train Accuracy: 0.6918, Validation Loss: 0.8107, Validation Accurac
y: 0.7278
Epoch 7/30, Train Loss: 0.8181, Train Accuracy: 0.7182, Validation Loss: 0.7947, Validation Accurac
y: 0.7265
Epoch 9/30, Train Loss: 0.7621, Train Accuracy: 0.7373, Validation Loss: 0.7275, Validation Accurac
y: 0.7526
Epoch 11/30, Train Loss: 0.7229, Train Accuracy: 0.7518, Validation Loss: 0.7201, Validation Accura
cy: 0.7581
Epoch 13/30, Train Loss: 0.6912, Train Accuracy: 0.7632, Validation Loss: 0.6923, Validation Accura
cy: 0.7693
Epoch 15/30, Train Loss: 0.6690, Train Accuracy: 0.7724, Validation Loss: 0.6676, Validation Accura
cy: 0.7781
Epoch 17/30, Train Loss: 0.6485, Train Accuracy: 0.7784, Validation Loss: 0.6705, Validation Accura
cy: 0.7790
Epoch 19/30, Train Loss: 0.6246, Train Accuracy: 0.7850, Validation Loss: 0.6646, Validation Accura
cy: 0.7804
Epoch 21/30, Train Loss: 0.6048, Train Accuracy: 0.7908, Validation Loss: 0.6932, Validation Accura
cy: 0.7851
Epoch 23/30, Train Loss: 0.5996, Train Accuracy: 0.7942, Validation Loss: 0.6810, Validation Accura
cy: 0.7831
Epoch 25/30, Train Loss: 0.5825, Train Accuracy: 0.8027, Validation Loss: 0.6530, Validation Accura
cy: 0.7930
Epoch 27/30, Train Loss: 0.5758, Train Accuracy: 0.8021, Validation Loss: 0.6441, Validation Accura
cy: 0.7937
Epoch 29/30, Train Loss: 0.5552, Train Accuracy: 0.8091, Validation Loss: 0.6364, Validation Accura
cy: 0.7926
Epoch 30/30, Train Loss: 0.5608, Train Accuracy: 0.8079, Validation Loss: 0.6613, Validation Accura
cy: 0.7885
```

In [29]:
```python
# 绘制验证精度图
plot_val_acc([val_acc], ['Dropout: 0.5 with Strong Augmentation'], styles=['-'], title="Effect of D
```



In [30]:
```python
# 绘制训练和验证损失图
plot_model_losses([train_loss], [val_loss], ['Dropout: 0.5 with Strong Augmentation'])
```



实验结果

我们可以看出，加上数据增强之后模型的泛化能力极大提高，上升了5%左右

实验总结

我们可以看出，数据增强对模型的泛化能力提升最强，约为5%左右。此外，特征图通道数量的深度对模型的提升也非常大。即使我们用了非常小的模型（仅仅三层），用上比较好的调参技巧，也可以在 `cifar10` 上把把模型训练到80%的准确率。通过这次实验，我们组能够很好的理解各种参数对模型的作用。