Optimization

In [1]:

```
import os
import sys
import math
import time
import numpy as np
import torch
from torch import nn, optim
from torch.autograd import Variable
from torch.utils import data
from torch.utils.data import Dataset,DataLoader
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
from PIL import Image
from IPython import display
from mpl_toolkits import mplot3d
from matplotlib import pyplot as plt
%matplotlib inline

torch.manual_seed(1)
```

Out[1]:

```
<torch._C.Generator at 0x7fedbc130850>
```

In [2]:

```
print(torch.__version__)
os.environ["CUDA_VISIBLE_DEVICES"] = "0"
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
1.0.1
cuda
```

In [3]:

```
def use_svg_display():
    """Use svg format to display plot in jupyter"""
    display.set_matplotlib_formats('svg')
```

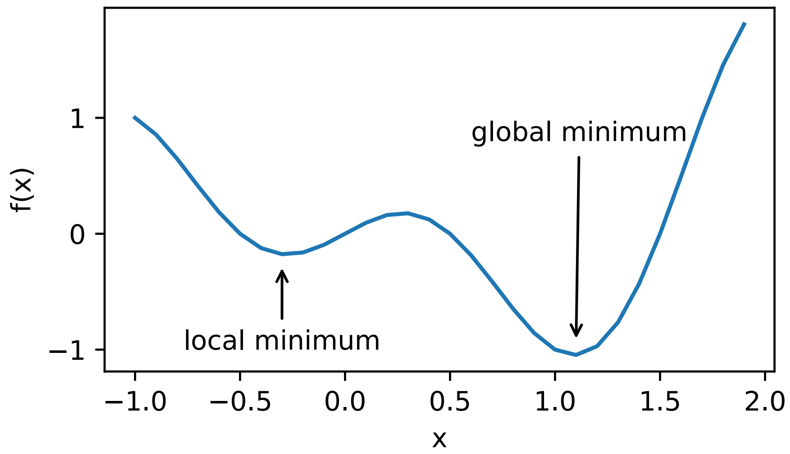
In [4]:

```
def set_figsize(figsize=(3.5, 2.5)):
    use_svg_display()
    plt.rcParams['figure.figsize'] = figsize
```

1. Local and Global Minimum

In [5]:

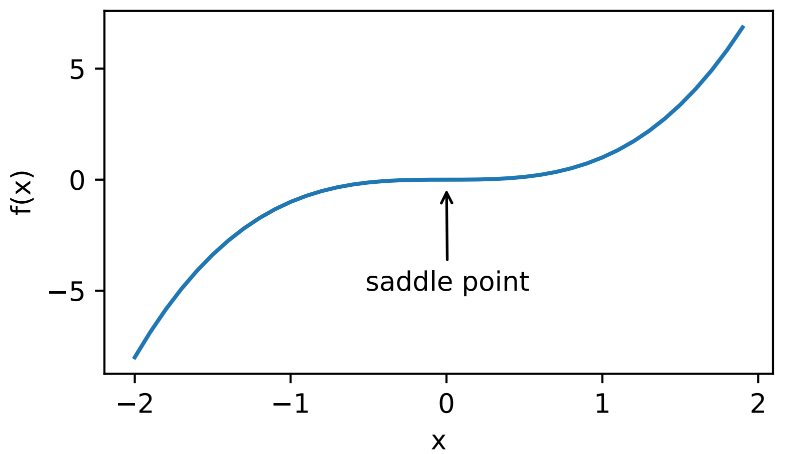
```
def f(x):
    return x * np.cos(np.pi * x)

set_figsize((4.5, 2.5))
x = np.arange(-1.0, 2.0, 0.1)
fig,  = plt.plot(x, f(x))
fig.axes.annotate('local minimum', xy=(-0.3, -0.25), xytext=(-0.77, -1.0),
                  arrowprops=dict(arrowstyle='->'))
fig.axes.annotate('global minimum', xy=(1.1, -0.95), xytext=(0.6, 0.8),
                  arrowprops=dict(arrowstyle='->'))
plt.xlabel('x')
plt.ylabel('f(x)');
```



2. Saddle Point

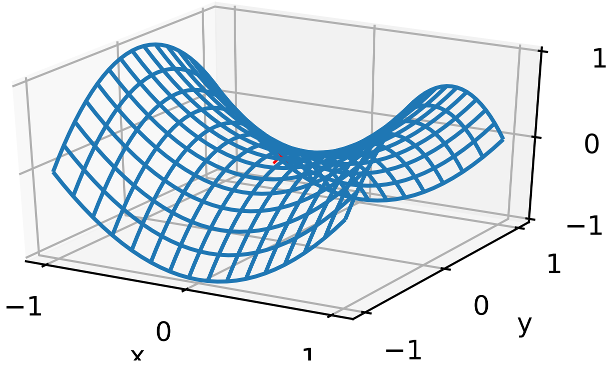
In [6]:

```
x = np.arange(-2.0, 2.0, 0.1)
fig, = plt.plot(x, x**3)
fig.axes.annotate('saddle point', xy=(0, -0.2), xytext=(-0.52, -5.0),
                  arrowprops=dict(arrowstyle='->'))
plt.xlabel('x')
plt.ylabel('f(x)');
```



In [7]:

```
x, y = np.mgrid[-1: 1: 31j, -1: 1: 31j]
z = x**2 - y**2

ax = plt.figure().add_subplot(111, projection='3d')
ax.plot_wireframe(x, y, z, **{'rstride': 2, 'cstride': 2})
ax.plot([0], [0], [0], 'rx')
ticks = [-1,  0, 1]
plt.xticks(ticks)
plt.yticks(ticks)
ax.set_zticks(ticks)
plt.xlabel('x')
plt.ylabel('y');
```



Gradient Descent (GD)

1. One-dimensional Gradient Descent

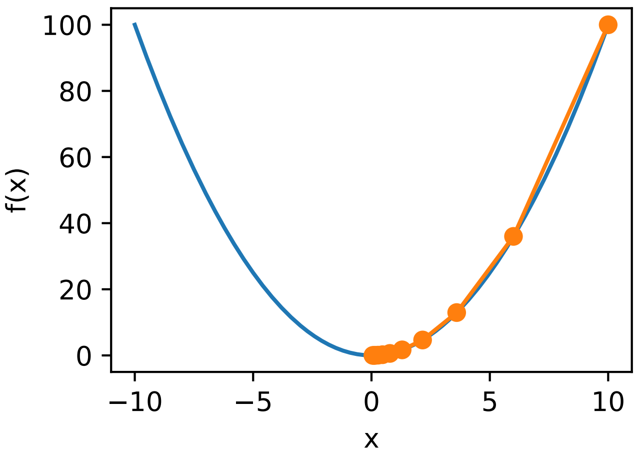
In [8]:

```
def gd(lr):
    x = 10
    results = [x]
    for i in range(10):
        x -= lr * 2 * x
        results.append(x)
    print('epoch 10, x:', x)
    return results

res = gd(0.2)
```

```
epoch 10, x: 0.06046617599999997
```

In [9]:

```
def show_trace(res):
    n = max(abs(min(res)), abs(max(res)), 10)
    f_line = np.arange(-n, n, 0.1)
    set_figsize()
    plt.plot(f_line, [x * x for x in f_line])
    plt.plot(res, [x * x for x in res], '-o')
    plt.xlabel('x')
    plt.ylabel('f(x)')

show_trace(res)
```



Here lr means learning rate This is a super parameter, which needs to be manually set. If a small learning rate is used, it will lead to slow update of x, which requires more iterations to get a better solution.

2. Multidimensional Gradient Descent

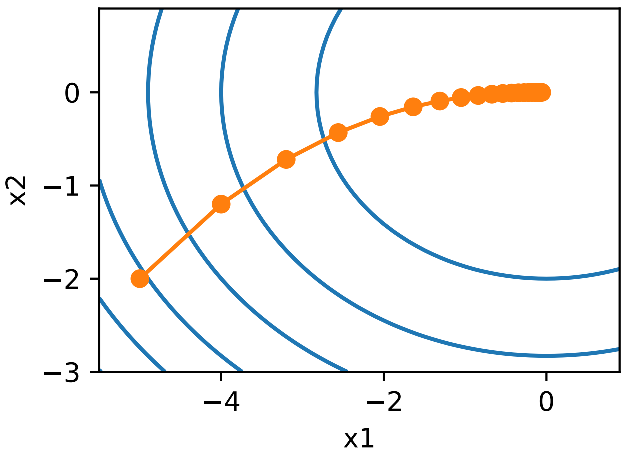
In [10]:

```
def train_2d(trainer):
    x1, x2, s1, s2 = -5, -2, 0, 0
    results = [(x1, x2)]
    for i in range(20):
        x1, x2, s1, s2 = trainer(x1, x2, s1, s2)
        results.append((x1, x2))
    print('epoch %d, x1 %f, x2 %f' % (i + 1, x1, x2))
    return results

def show_trace_2d(f, results):
    plt.plot(*zip(*results), '-o', color='#ff7f0e')
    x1, x2 = np.meshgrid(np.arange(-5.5, 1.0, 0.1), np.arange(-3.0, 1.0, 0.1))
    plt.contour(x1, x2, f(x1, x2), colors='#1f77b4')
    plt.xlabel('x1')
    plt.ylabel('x2')
```

In [11]:

```
lr = 0.1

def f_2d(x1, x2):
    return x1 ** 2 + 2 * x2 ** 2

def gd_2d(x1, x2, s1, s2):
    return (x1 - lr * 2 * x1, x2 - lr * 4 * x2, 0, 0)

show_trace_2d(f_2d, train_2d(gd_2d))
```

```
epoch 20, x1 -0.057646, x2 -0.000073
```

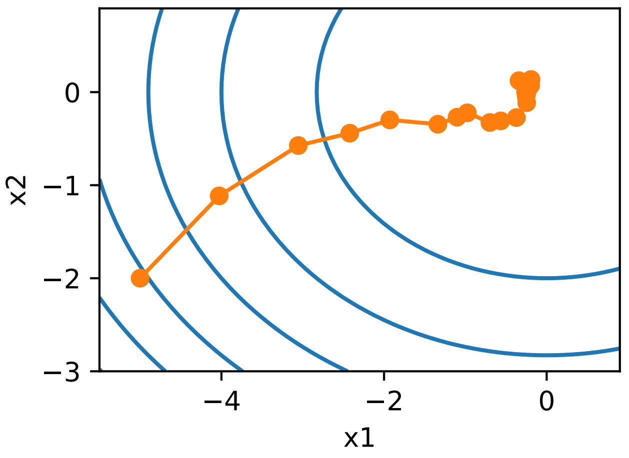


3. Stochastic Gradient Descent (SGD)

In [12]:

```
def sgd_2d(x1, x2, s1, s2):
    return (x1 - lr * (2 * x1 + np.random.normal(0.1)),
            x2 - lr * (4 * x2 + np.random.normal(0.1)), 0, 0)

show_trace_2d(f_2d, train_2d(sgd_2d))
```

```
epoch 20, x1 -0.218127, x2 0.116971
```



4. Batch Gradient Descent

In [13]:

```
def get_noise_data():
    data = np.genfromtxt('airfoil_self_noise.dat', delimiter='\t')
    data = (data - data.mean(axis=0)) / data.std(axis=0)
    return torch.tensor(data[:1500, :-1], dtype=torch.float32), \
           torch.tensor(data[:1500, -1], dtype=torch.float32)

features, labels = get_noise_data()
features.shape
```

Out[13]:

```
torch.Size([1500, 5])
```

In [14]:

```
def sgd(params, states, hyperparams):
    for p in params:
        p.data -= hyperparams['lr'] * p.grad.data
```

In [15]:

```
def net(X, w, b):
    return torch.mm(X, w) + b

def loss(y_hat, y):
    return ((y_hat - y.view(y_hat.size())) ** 2) / 2
```

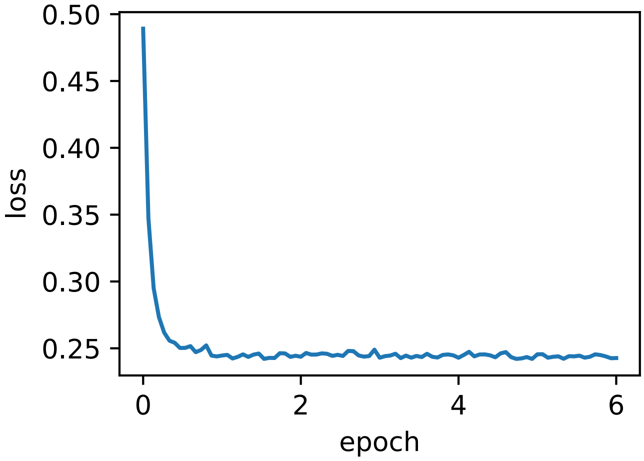
In [16]:

```
def train_op(optimizer_fn, states, hyperparams, features, labels,
              batch_size=10, num_epochs=2):

    w = torch.nn.Parameter(torch.tensor(np.random.normal(0, 0.01, size=(features
.shape[1], 1)), dtype=torch.float32),
                           requires_grad=True)
    b = torch.nn.Parameter(torch.zeros(1, dtype=torch.float32), requires_grad=Tr
ue)

    def eval_loss():
        return loss(net(features, w, b), labels).mean().item()

    ls = [eval_loss()]
    data_iter = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(features, labels), batch_size, shuffle=Tr
ue)

    for _ in range(num_epochs):
        start = time.time()
        for batch_i, (X, y) in enumerate(data_iter):
            l = loss(net(X, w, b), y).mean()

            if w.grad is not None:
                w.grad.data.zero_()
                b.grad.data.zero_()

            l.backward()
            optimizer_fn([w, b], states, hyperparams)
            if (batch_i + 1) * batch_size % 100 == 0:
                ls.append(eval_loss())
    print('loss: %f, %f sec per epoch' % (ls[-1], time.time() - start))
    set_figsize()
    plt.plot(np.linspace(0, num_epochs, len(ls)), ls)
    plt.xlabel('epoch')
    plt.ylabel('loss')
```

In [17]:

```
def train_sgd(lr, batch_size, num_epochs=2):
    train_op(sgd, None, {'lr': lr}, features, labels, batch_size, num_epochs)

train_sgd(0.05,10,6)
```

```
loss: 0.242708, 0.038605 sec per epoch
```

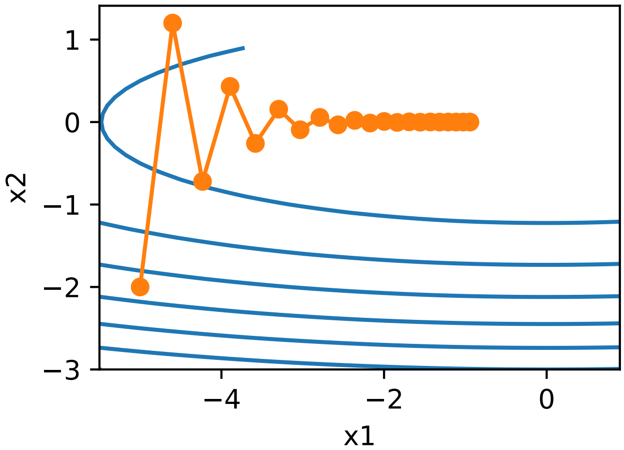


Momentum

In [18]:

```
def f_2d(x1, x2):
    return 0.1 * x1 ** 2 + 2 * x2 ** 2


lr = 0.4
def gd_2d(x1, x2, s1, s2):
    return (x1 - lr * 0.2 * x1, x2 - lr * 4 * x2, 0, 0)

show_trace_2d(f_2d, train_2d(gd_2d))
```

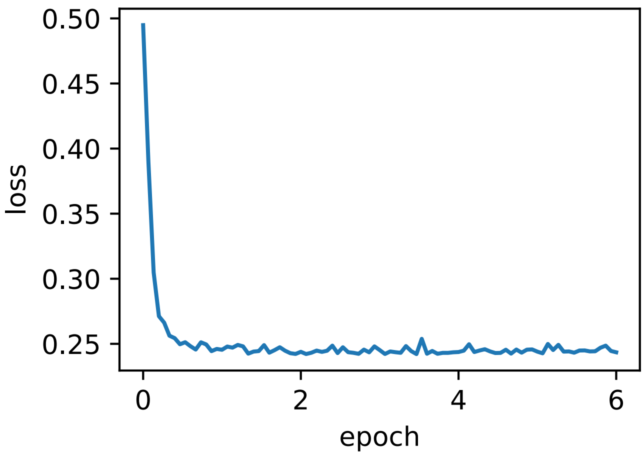
```
epoch 20, x1 -0.943467, x2 -0.000073
```



In [19]:

```
train_sgd(0.005, 1, 6)
```

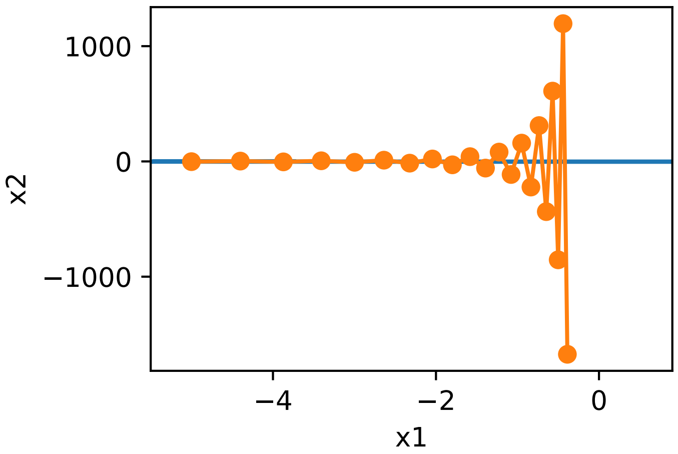
```
loss: 0.243505, 0.326374 sec per epoch
```



In [20]:

```
lr = 0.6
show_trace_2d(f_2d, train_2d(gd_2d))
```

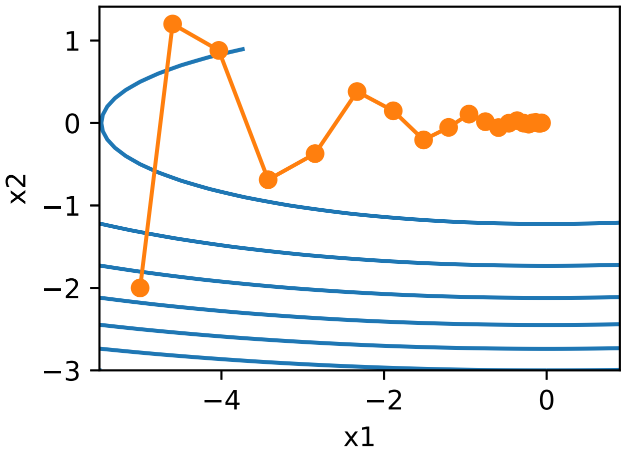
epoch 20, x1 -0.387814, x2 -1673.365109



In [21]:

```
def momentum_2d(x1, x2, v1, v2):
    v1 = gamma * v1 + 0.2 * x1
    v2 = gamma * v2 + 4 * x2
    return x1 - lr * v1, x2 - lr * v2, v1, v2

lr, gamma = 0.4, 0.5
show_trace_2d(f_2d, train_2d(momentum_2d))
```

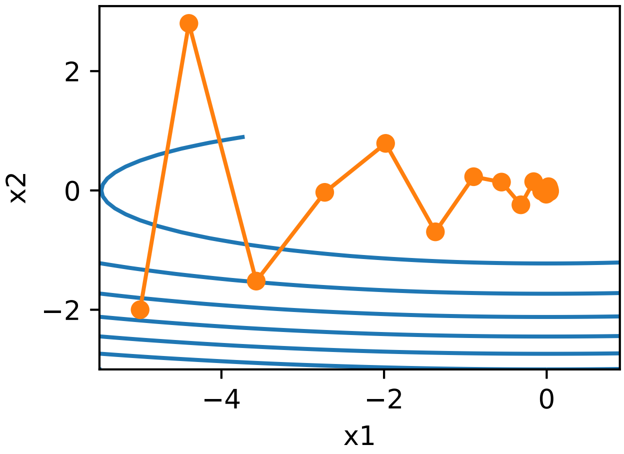
epoch 20, x1 -0.062843, x2 0.001202



In [22]:

```
lr = 0.6
show_trace_2d(f_2d, train_2d(momentum_2d))
```

epoch 20, x1 0.007188, x2 0.002553



In [23]:

```
def get_noise_data():
    data = np.genfromtxt('airfoil_self_noise.dat', delimiter='\t')
    data = (data - data.mean(axis=0)) / data.std(axis=0)
    return torch.tensor(data[:1500, :-1], dtype=torch.float32), \
        torch.tensor(data[:1500, -1], dtype=torch.float32)
```

In [24]:

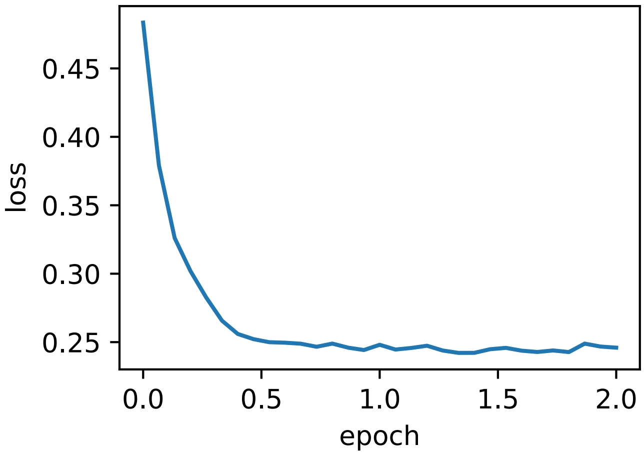
```
features, labels = get_noise_data()

print(features.shape[1])

def init_momentum_states():
    v_w = torch.zeros((features.shape[1], 1), dtype=torch.float32)
    v_b = torch.zeros(1, dtype=torch.float32)
    return (v_w, v_b)

def sgd_momentum(params, states, hyperparams):
    for p, v in zip(params, states):
        v.data = hyperparams['momentum'] * v.data + hyperparams['lr'] * p.grad.d
ata
        p.data -= v.data
```

5

In [25]:

```
train_op(sgd_momentum, init_momentum_states(),
              {'lr': 0.02, 'momentum': 0.5}, features, labels)
```

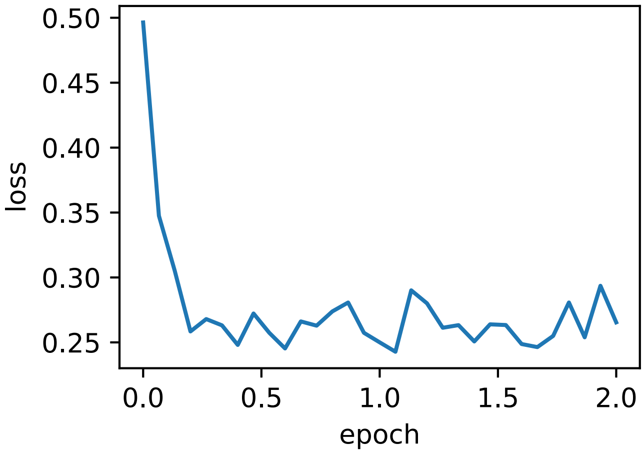
loss: 0.245956, 0.052961 sec per epoch



In [26]:

```
train_op(sgd_momentum, init_momentum_states(),
              {'lr': 0.02, 'momentum': 0.9}, features, labels)
```

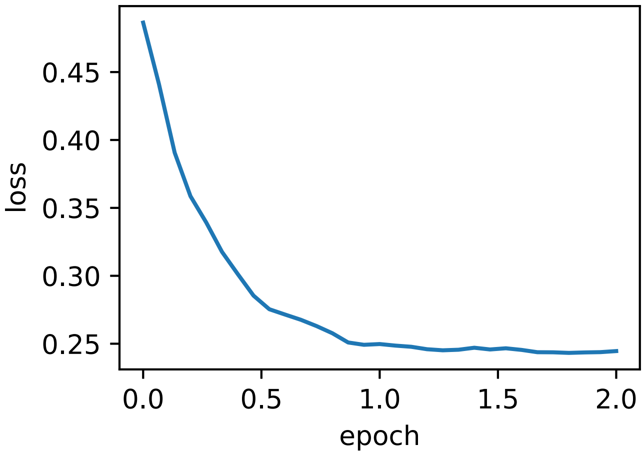
loss: 0.265424, 0.047397 sec per epoch



In [27]:

```
train_op(sgd_momentum, init_momentum_states(),
              {'lr': 0.01, 'momentum': 0.5}, features, labels)
```

loss: 0.244588, 0.054638 sec per epoch



In [28]:

```
data = np.genfromtxt('airfoil_self_noise.dat',delimiter='\t')
data = (data - data.mean(axis=0)) / data.std(axis=0)
print(data)
```

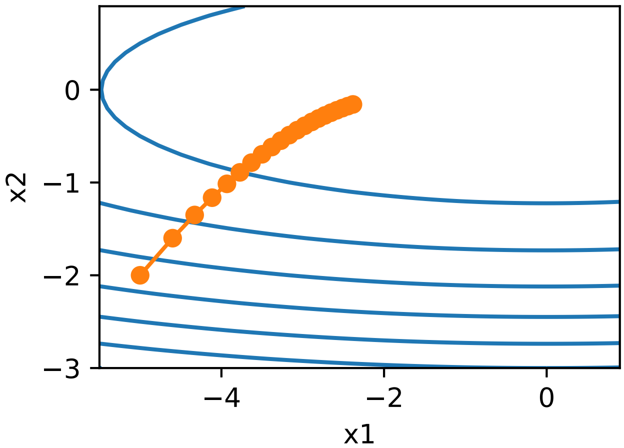
```
[[-0.6620227  -1.14640293  1.79929926  1.31293526 -0.64480461  0.19
793876]
 [-0.59856135 -1.14640293  1.79929926  1.31293526 -0.64480461  0.05
293476]
 [-0.51923465 -1.14640293  1.79929926  1.31293526 -0.64480461  0.16
168776]
 ...
 [ 0.353359    1.49044302 -0.37373954 -0.72334483  3.17277251 -2.64
370471]
 [ 0.67066578  1.49044302 -0.37373954 -0.72334483  3.17277251 -2.69
880623]
 [ 1.08316459  1.49044302 -0.37373954 -0.72334483  3.17277251 -2.99
171432]]
```

AdaGrad

In [29]:

```
def adagrad_2d(x1, x2, s1, s2):
    g1, g2, eps = 0.2 * x1, 4 * x2, 1e-6
    s1 += g1 ** 2
    s2 += g2 ** 2
    x1 -= lr / math.sqrt(s1 + eps) * g1
    x2 -= lr / math.sqrt(s2 + eps) * g2
    return x1, x2, s1, s2

def f_2d(x1, x2):
    return 0.1 * x1 ** 2 + 2 * x2 ** 2

lr = 0.4
show_trace_2d(f_2d, train_2d(adagrad_2d))
```

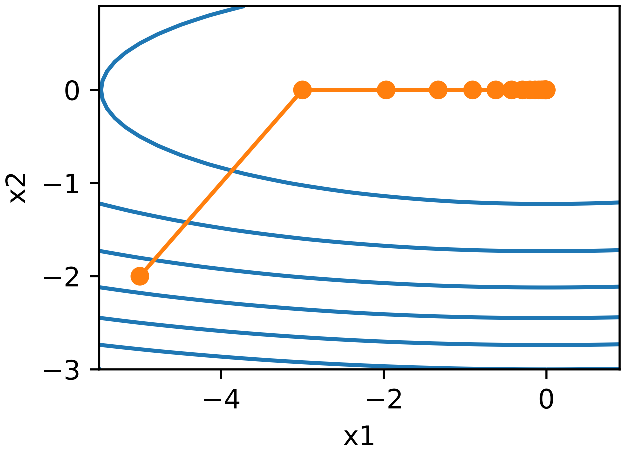
```
epoch 20, x1 -2.382563, x2 -0.158591
```



In [30]:

```
lr = 2
show_trace_2d(f_2d, train_2d(adagrad_2d))
```

```
epoch 20, x1 -0.002295, x2 -0.000000
```



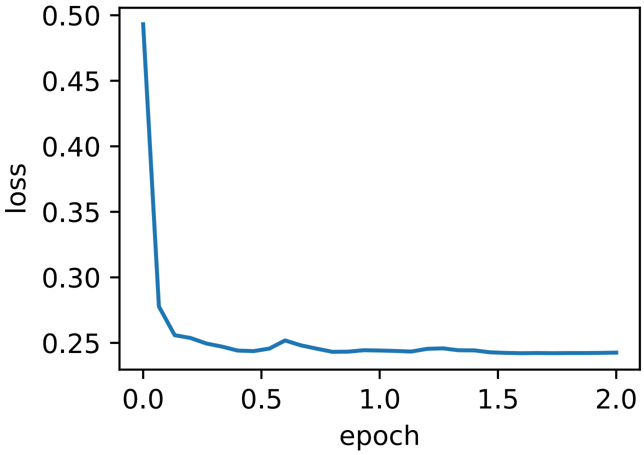
In [31]:

```
features, labels = get_noise_data()

def init_adagrad_states():
    s_w = torch.zeros((features.shape[1], 1), dtype=torch.float32)
    s_b = torch.zeros(1, dtype=torch.float32)
    return (s_w, s_b)

def adagrad(params, states, hyperparams):
    eps = 1e-6
    for p, s in zip(params, states):
        s.data += (p.grad.data**2)
        p.data -= hyperparams['lr'] * p.grad.data / torch.sqrt(s + eps)
```

In [32]:

```
train_op(adagrad, init_adagrad_states(), {'lr': 0.1}, features, labels)
```

```
loss: 0.242567, 0.052091 sec per epoch
```

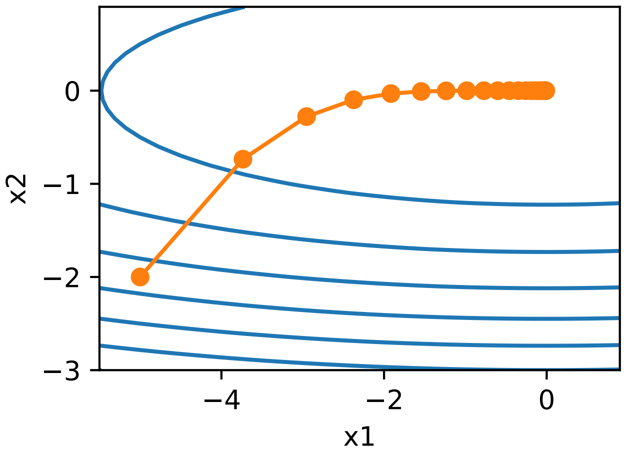


RMSProp

In [33]:

```
def rmsprop_2d(x1, x2, s1, s2):
    g1, g2, eps = 0.2 * x1, 4 * x2, 1e-6
    s1 = gamma * s1 + (1 - gamma) * g1 ** 2
    s2 = gamma * s2 + (1 - gamma) * g2 ** 2
    x1 -= lr / math.sqrt(s1 + eps) * g1
    x2 -= lr / math.sqrt(s2 + eps) * g2
    return x1, x2, s1, s2

def f_2d(x1, x2):
    return 0.1 * x1 ** 2 + 2 * x2 ** 2

lr, gamma = 0.4, 0.9
show_trace_2d(f_2d, train_2d(rmsprop_2d))
```

```
epoch 20, x1 -0.010599, x2 0.000000
```



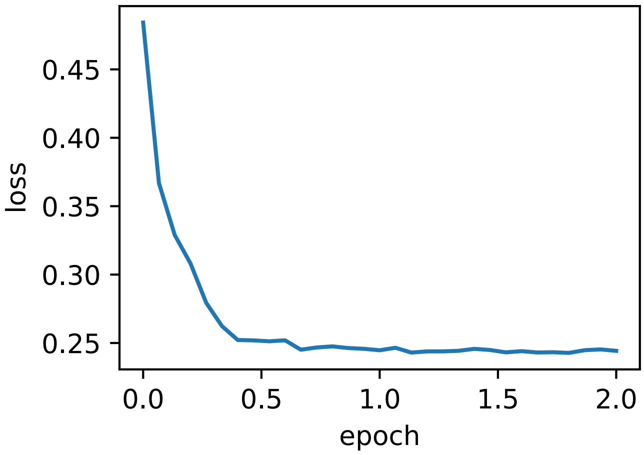
In [34]:

```
features, labels = get_noise_data()

def init_rmsprop_states():
    s_w = torch.zeros((features.shape[1], 1), dtype=torch.float32)
    s_b = torch.zeros(1, dtype=torch.float32)
    return (s_w, s_b)

def rmsprop(params, states, hyperparams):
    gamma, eps = hyperparams['gamma'], 1e-6
    for p, s in zip(params, states):
        s.data = gamma * s.data + (1 - gamma) * (p.grad.data)**2
        p.data -= hyperparams['lr'] * p.grad.data / torch.sqrt(s + eps)
```

In [35]:

```
train_op(rmsprop, init_rmsprop_states(), {'lr': 0.01, 'gamma': 0.9},
              features, labels)
```

```
loss: 0.244262, 0.064748 sec per epoch
```



Adam

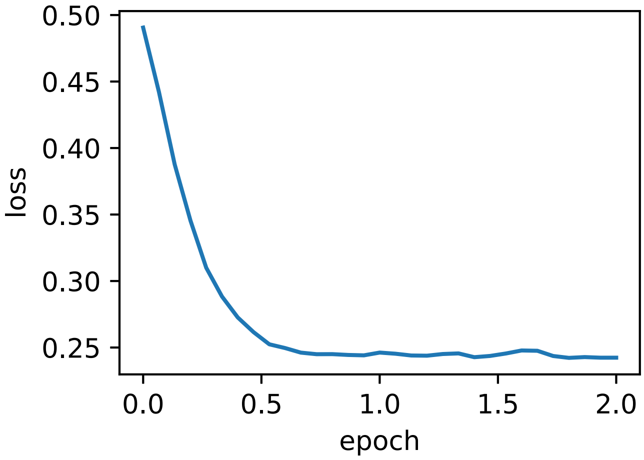
In [36]:

```
def init_adam_states():
    v_w, v_b = torch.zeros((features.shape[1], 1), dtype=torch.float32), torch.z
eros(1, dtype=torch.float32)
    s_w, s_b = torch.zeros((features.shape[1], 1), dtype=torch.float32), torch.z
eros(1, dtype=torch.float32)
    return ((v_w, s_w), (v_b, s_b))

def adam(params, states, hyperparams):
    beta1, beta2, eps = 0.9, 0.999, 1e-6
    for p, (v, s) in zip(params, states):
        v[:] = beta1 * v + (1 - beta1) * p.grad.data
        s[:] = beta2 * s + (1 - beta2) * p.grad.data**2
        v_bias_corr = v / (1 - beta1 ** hyperparams['t'])
        s_bias_corr = s / (1 - beta2 ** hyperparams['t'])
        p.data -= hyperparams['lr'] * v_bias_corr / (torch.sqrt(s_bias_corr) + e
ps)
    hyperparams['t'] += 1
```

In [37]:

```
train_op(adam, init_adam_states(), {'lr': 0.01, 't': 1}, features, labels)
```

loss: 0.242363, 0.082528 sec per epoch



Learning Rate Decay

1. Linear

In [38]:

```
def adjust_learning_rate_linear(lr, epoch, total,decay_rate=.9):
        lr = lr * (1 - epoch/total)
        print("lr: ",lr)
        return lr
```

In [39]:

```
def sgd_lrd(params, states, hyperparams, epoch, total):
    hyperparams['lr'] = adjust_learning_rate_linear(hyperparams['lr'], epoch, to
tal)
    for p in params:
        p.data -= hyperparams['lr'] * p.grad.data
```

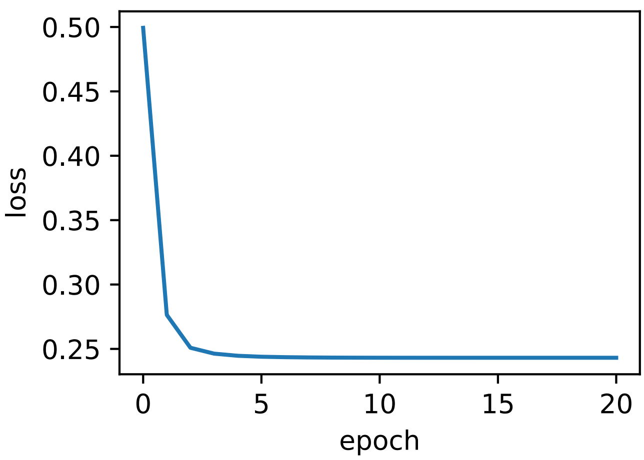
In [40]:

```
def train_op_lrd(optimizer_fn, states, hyperparams, features, labels,
              batch_size=10, num_epochs=2):

    w = torch.nn.Parameter(torch.tensor(np.random.normal(0, 0.01, size=(features
.shape[1], 1)), dtype=torch.float32),
                           requires_grad=True)
    b = torch.nn.Parameter(torch.zeros(1, dtype=torch.float32), requires_grad=Tr
ue)

    def eval_loss():
        return loss(net(features, w, b), labels).mean().item()

    ls = [eval_loss()]
    data_iter = torch.utils.data.DataLoader(
        torch.utils.data.TensorDataset(features, labels), batch_size, shuffle=Tr
ue)

    for e in range(num_epochs):
        print("epoch: ",e)
        start = time.time()
        for batch_i, (X, y) in enumerate(data_iter):
            l = loss(net(X, w, b), y).mean()

            if w.grad is not None:
                w.grad.data.zero_()
                b.grad.data.zero_()

            l.backward()
            optimizer_fn([w, b], states, hyperparams, e, num_epochs)
            if (batch_i + 1) * batch_size % 100 == 0:
                ls.append(eval_loss())
    print('loss: %f, %f sec per epoch' % (ls[-1], time.time() - start))
    set_figsize()
    plt.plot(np.linspace(0, num_epochs, len(ls)), ls)
    plt.xlabel('epoch')
    plt.ylabel('loss')
```

In [41]:

```
def train_sgd_lrd(lr, batch_size, num_epochs=2):
    train_op_lrd(sgd_lrd, None, {'lr': lr}, features, labels, batch_size, num_ep
ochs)

train_sgd_lrd(1, 1500, 20)
```

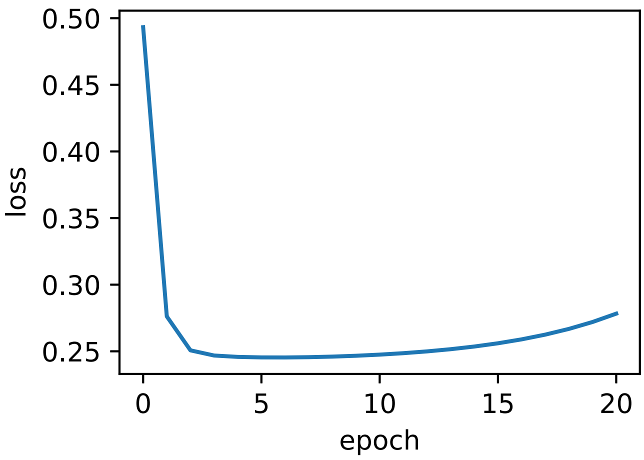
```
epoch:  0
lr:  1.0
epoch:  1
lr:  0.95
epoch:  2
lr:  0.855
epoch:  3
lr:  0.72675
epoch:  4
lr:  0.5814
epoch:  5
lr:  0.43605000000000005
epoch:  6
lr:  0.30523500000000003
epoch:  7
lr:  0.19840275000000002
epoch:  8
lr:  0.11904165
epoch:  9
lr:  0.06547290750000001
epoch:  10
lr:  0.032736453750000005
epoch:  11
lr:  0.014731404187500002
epoch:  12
lr:  0.005892561675000001
epoch:  13
lr:  0.00206239658625
epoch:  14
lr:  0.0006187189758750001
epoch:  15
lr:  0.00015467974396875004
epoch:  16
lr:  3.093594879375e-05
epoch:  17
lr:  4.640392319062501e-06
epoch:  18
lr:  4.6403923190625e-07
epoch:  19
lr:  2.3201961595312522e-08
loss: 0.243114, 0.008923 sec per epoch
```



In [42]:

```
def train_sgd(lr, batch_size, num_epochs=2):
    train_op(sgd, None, {'lr': lr}, features, labels, batch_size, num_epochs)

train_sgd(1, 1500, 20)
```

```
loss: 0.278254, 0.007261 sec per epoch
```



2. Cosine

In [43]:

```
def adjust_learning_rate_cosine(lr, epoch, total,decay_rate=.9):
        lr = 0.5 * lr * (1 + np.cos(np.pi * epoch/total))
        print("lr: ",lr)
        return lr
```

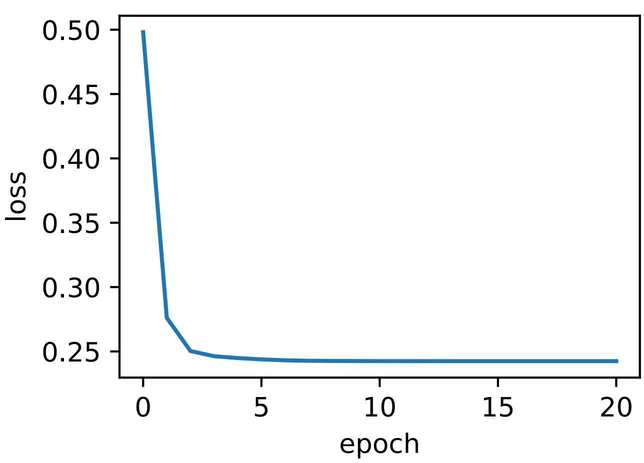
In [44]:

```
def sgd_lrd_cos(params, states, hyperparams, epoch, total):
    hyperparams['lr'] = adjust_learning_rate_cosine(hyperparams['lr'], epoch, to
tal)
    for p in params:
        p.data -= hyperparams['lr'] * p.grad.data
```

In [45]:

```
def train_sgd_lrd_cos(lr, batch_size, num_epochs=2):
    train_op_lrd(sgd_lrd_cos, None, {'lr': lr}, features, labels, batch_size, nu
m_epochs)

train_sgd_lrd_cos(1, 1500, 20)
```

```
epoch:  0
lr:  1.0
epoch:  1
lr:  0.9938441702975689
epoch:  2
lr:  0.969523072320511
epoch:  3
lr:  0.9166872275546185
epoch:  4
lr:  0.8291513865863798
epoch:  5
lr:  0.7077249773359188
epoch:  6
lr:  0.5618576408464984
epoch:  7
lr:  0.40846783599844144
epoch:  8
lr:  0.2673456694887594
epoch:  9
lr:  0.15458387313802793
epoch:  10
lr:  0.07729193656901397
epoch:  11
lr:  0.03260040690995841
epoch:  12
lr:  0.0112631635756214
epoch:  13
lr:  0.00307489715763839
epoch:  14
lr:  0.0006337589780312503
epoch:  15
lr:  9.281185351374852e-05
epoch:  16
lr:  8.862743370843898e-06
epoch:  17
lr:  4.829906026073891e-07
epoch:  18
lr:  1.1819621344154363e-08
epoch:  19
lr:  7.275957614183487e-11
loss: 0.242446, 0.035924 sec per epoch
```



3. Inverse Sqrt

In [46]:

```
def adjust_learning_rate_sqrt(lr, epoch, total, decay_rate=.9):
        lr = lr / np.sqrt(epoch + 1)
        print("lr: ",lr)
        return lr
```

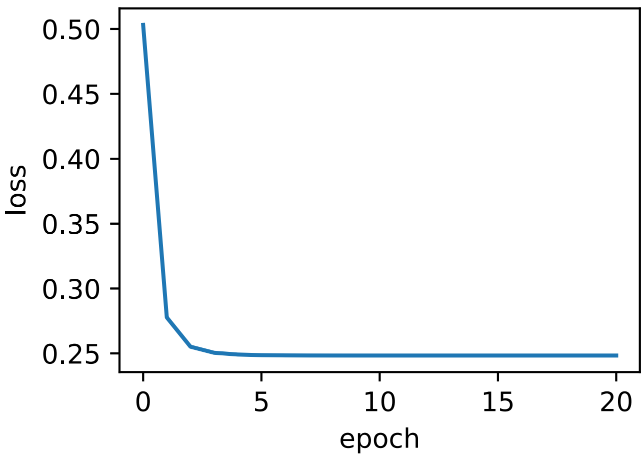
In [47]:

```
def sgd_lrd_sqrt(params, states, hyperparams, epoch, total):
    hyperparams['lr'] = adjust_learning_rate_sqrt(hyperparams['lr'], epoch, tota
l)
    for p in params:
        p.data -= hyperparams['lr'] * p.grad.data
```

In [48]:

```
def train_sgd_lrd_sqrt(lr, batch_size, num_epochs=2):
    train_op_lrd(sgd_lrd_sqrt, None, {'lr': lr}, features, labels, batch_size, num_epochs)

train_sgd_lrd_sqrt(1, 1500, 20)
```

```
epoch:  0
lr:  1.0
epoch:  1
lr:  0.7071067811865475
epoch:  2
lr:  0.408248290463863
epoch:  3
lr:  0.2041241452319315
epoch:  4
lr:  0.09128709291752768
epoch:  5
lr:  0.037267799624996496
epoch:  6
lr:  0.014085904245475275
epoch:  7
lr:  0.0049801192055599726
epoch:  8
lr:  0.0016600397351866575
epoch:  9
lr:  0.0005249506569572599
epoch:  10
lr:  0.0001582785784161638
epoch:  11
lr:  4.569108992776173e-05
epoch:  12
lr:  1.2672428274337011e-05
epoch:  13
lr:  3.3868489186454308e-06
epoch:  14
lr:  8.744806305356234e-07
epoch:  15
lr:  2.1862015763390585e-07
epoch:  16
lr:  5.302317657728099e-08
epoch:  17
lr:  1.2497682572615701e-08
epoch:  18
lr:  2.867165019077961e-09
epoch:  19
lr:  6.411175885367802e-10
loss: 0.248344, 0.007719 sec per epoch
```



Regularization

1. Dropout

In [49]:

```
def dropout(X, drop_prob):
    X = X.float()
    assert 0 <= drop_prob <= 1
    keep_prob = 1 - drop_prob
    if keep_prob == 0:
        return torch.zeros_like(X)
    mask = (torch.randn(X.shape) < keep_prob).float()

    return mask * X / keep_prob
```

In [50]:

```
X = torch.arange(16).view(2, 8)
dropout(X, 0)
```

Out[50]:

```
tensor([[ 0.,  1.,  2.,  3.,  4.,  5.,  6.,  7.],
        [ 8.,  9., 10., 11., 12., 13., 14.,  0.]])
```

In [51]:

```
dropout(X, 0.5)
```

Out[51]:

```
tensor([[ 0.,  2.,  0.,  6.,  8., 10., 12.,  0.],
        [ 0., 18.,  0.,  0.,  0., 26., 28.,  0.]])
```

In [52]:

```
dropout(X, 1.0)
```

Out[52]:

```
tensor([[0., 0., 0., 0., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0.]])
```

In [53]:

```
num_inputs, num_outputs, num_hiddens1, num_hiddens2 = 784, 10, 256, 256

W1 = torch.tensor(np.random.normal(0, 0.01, size=(num_inputs, num_hiddens1)), dt
ype=torch.float, requires_grad=True)
b1 = torch.zeros(num_hiddens1, requires_grad=True)
W2 = torch.tensor(np.random.normal(0, 0.01, size=(num_hiddens1, num_hiddens2)),
dtype=torch.float, requires_grad=True)
b2 = torch.zeros(num_hiddens2, requires_grad=True)
W3 = torch.tensor(np.random.normal(0, 0.01, size=(num_hiddens2, num_outputs)), d
type=torch.float, requires_grad=True)
b3 = torch.zeros(num_outputs, requires_grad=True)

params = [W1, b1, W2, b2, W3, b3]
```

In [54]:

```
drop_prob1, drop_prob2 = 0.2, 0.5

def net(X, is_training=True):
    X = X.view(-1, num_inputs)
    H1 = (torch.matmul(X, W1) + b1).relu()
    if is_training:
        H1 = dropout(H1, drop_prob1)
    H2 = (torch.matmul(H1, W2) + b2).relu()
    if is_training:
        H2 = dropout(H2, drop_prob2)
    return torch.matmul(H2, W3) + b3
```

In [55]:

```
def load_data_fashion_mnist(batch_size, resize=None, root='./Datasets/FashionMNI
ST'):
    """Download the fashion mnist dataset and then load into memory."""
    trans = []
    if resize:
        trans.append(torchvision.transforms.Resize(size=resize))
    trans.append(torchvision.transforms.ToTensor())

    transform = torchvision.transforms.Compose(trans)
    mnist_train = torchvision.datasets.FashionMNIST(root=root, train=True, downl
oad=True, transform=transform)
    mnist_test = torchvision.datasets.FashionMNIST(root=root, train=False, downl
oad=True, transform=transform)
    if sys.platform.startswith('win'):
        num_workers = 0
    else:
        num_workers = 4
    train_iter = torch.utils.data.DataLoader(mnist_train, batch_size=batch_size,
shuffle=True, num_workers=num_workers)
    test_iter = torch.utils.data.DataLoader(mnist_test, batch_size=batch_size, s
huffle=False, num_workers=num_workers)

    return train_iter, test_iter
```

In [56]:

```
def SGD(params, lr, batch_size):
    for param in params:
        param.data -= lr * param.grad / batch_size
```

In [57]:

```
def evaluate_accuracy(data_iter, net):
    acc_sum, n = 0.0, 0
    for X, y in data_iter:
        if isinstance(net, torch.nn.Module):
            net.eval()
            acc_sum += (net(X).argmax(dim=1) == y).float().sum().item()
            net.train()
        else:
            if('is_training' in net.__code__.co_varnames):
                acc_sum += (net(X, is_training=False).argmax(dim=1) == y).float
().sum().item()
            else:
                acc_sum += (net(X).argmax(dim=1) == y).float().sum().item()
        n += y.shape[0]
    return acc_sum / n
```

In [58]:

```
def train_drop(net, train_iter, test_iter, loss, num_epochs, batch_size,
              params=None, lr=None, optimizer=None):
    for epoch in range(num_epochs):
        train_l_sum, train_acc_sum, n = 0.0, 0.0, 0
        for X, y in train_iter:
            y_hat = net(X)
            l = loss(y_hat, y).sum()

            if optimizer is not None:
                optimizer.zero_grad()
            elif params is not None and params[0].grad is not None:
                for param in params:
                    param.grad.data.zero_()

            l.backward()
            if optimizer is None:
                SGD(params, lr, batch_size)
            else:
                optimizer.step()


            train_l_sum += l.item()
            train_acc_sum += (y_hat.argmax(dim=1) == y).sum().item()
            n += y.shape[0]
        test_acc = evaluate_accuracy(test_iter, net)
        print('epoch %d, loss %.4f, train acc %.3f, test acc %.3f'
              % (epoch + 1, train_l_sum / n, train_acc_sum / n, test_acc))
```

In [59]:

```
num_epochs, lr, batch_size = 5, 100.0, 256
loss = torch.nn.CrossEntropyLoss()
train_iter, test_iter = load_data_fashion_mnist(batch_size)
train_drop(net, train_iter, test_iter, loss, num_epochs, batch_size, params, lr)
```

```
epoch 1, loss 0.0043, train acc 0.572, test acc 0.702
epoch 2, loss 0.0022, train acc 0.792, test acc 0.792
epoch 3, loss 0.0019, train acc 0.826, test acc 0.810
epoch 4, loss 0.0017, train acc 0.844, test acc 0.830
epoch 5, loss 0.0016, train acc 0.853, test acc 0.812
```

In [60]:

```
class FlattenLayer(torch.nn.Module):
    def __init__(self):
        super(FlattenLayer, self).__init__()
    def forward(self, x):
        return x.view(x.shape[0], -1)
```

In [61]:

```
net = nn.Sequential(
        FlattenLayer(),
        nn.Linear(num_inputs, num_hiddens1),
        nn.ReLU(),
        nn.Dropout(drop_prob1),
        nn.Linear(num_hiddens1, num_hiddens2),
        nn.ReLU(),
        nn.Dropout(drop_prob2),
        nn.Linear(num_hiddens2, 10)
        )

for param in net.parameters():
    nn.init.normal_(param, mean=0, std=0.01)
```

In [62]:

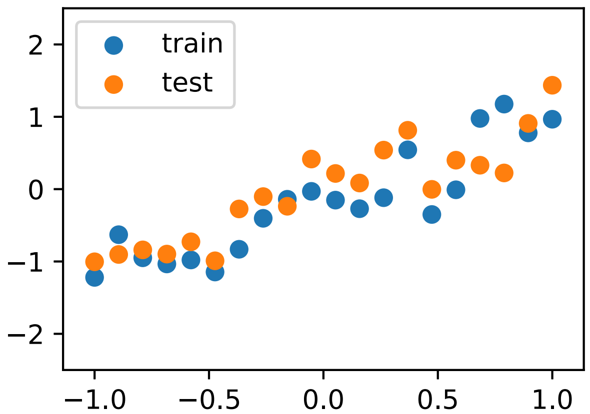
```
optimizer = torch.optim.SGD(net.parameters(), lr=0.5)
train_drop(net, train_iter, test_iter, loss, num_epochs, batch_size, None, None,
optimizer)
```

```
epoch 1, loss 0.0044, train acc 0.561, test acc 0.732
epoch 2, loss 0.0022, train acc 0.789, test acc 0.766
epoch 3, loss 0.0019, train acc 0.819, test acc 0.839
epoch 4, loss 0.0017, train acc 0.840, test acc 0.828
epoch 5, loss 0.0016, train acc 0.848, test acc 0.849
```

2. Dropout Visualization

In [72]:

```
DATA_SIZE = 20

x = torch.unsqueeze(torch.linspace(-1, 1, DATA_SIZE), dim=1) # sieze (20,1)
y = x + 0.3*torch.normal(torch.zeros(DATA_SIZE, 1), torch.ones(DATA_SIZE, 1))
x, y = Variable(x), Variable(y)

test_x = torch.unsqueeze(torch.linspace(-1, 1, DATA_SIZE), dim=1)
test_y = test_x + 0.3*torch.normal(torch.zeros(DATA_SIZE,1), torch.ones(DATA_SIZ
E,1))
test_x, test_y = Variable(test_x), Variable(test_y)

plt.scatter(x.data.numpy(), y.data.numpy(), label='train')
plt.scatter(test_x.data.numpy(), test_y.data.numpy(), label='test')
plt.legend(loc='upper left')
plt.ylim((-2.5, 2.5))
plt.show()
```



In [73]:

```
N_HIDDEN = 100
net_overfitting = torch.nn.Sequential(
    torch.nn.Linear(1, N_HIDDEN),
    torch.nn.ReLU(),
    torch.nn.Linear(N_HIDDEN, N_HIDDEN),
    torch.nn.ReLU(),
    torch.nn.Linear(N_HIDDEN, 1)
)

net_dropout = torch.nn.Sequential(
    torch.nn.Linear(1, N_HIDDEN),
    torch.nn.Dropout(0.5),
    torch.nn.ReLU(),
    torch.nn.Linear(N_HIDDEN, N_HIDDEN),
    torch.nn.Dropout(0.5),
    torch.nn.ReLU(),
    torch.nn.Linear(N_HIDDEN, 1)
)

print('net_overfitting: \n', net_overfitting)
print('\n net_dropout: \n', net_dropout)
```

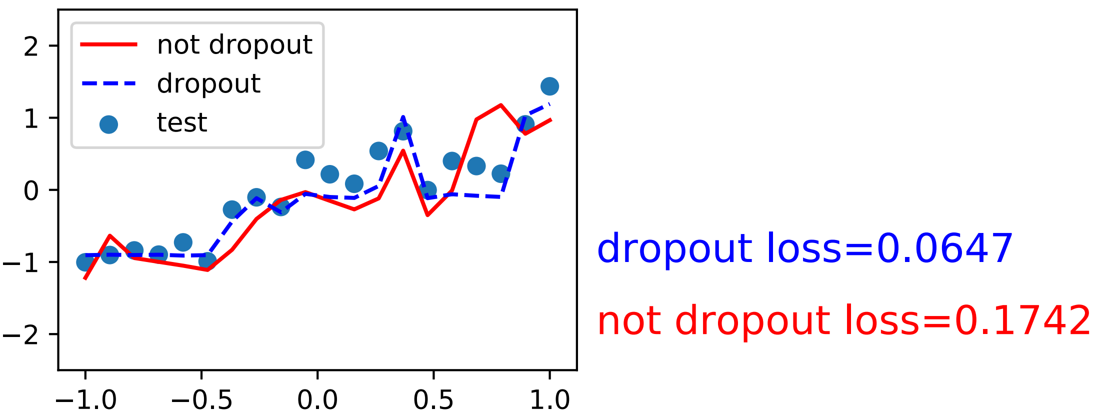
```
net_overfitting:
 Sequential(
  (0): Linear(in_features=1, out_features=100, bias=True)
  (1): ReLU()
  (2): Linear(in_features=100, out_features=100, bias=True)
  (3): ReLU()
  (4): Linear(in_features=100, out_features=1, bias=True)
)

 net_dropout:
 Sequential(
  (0): Linear(in_features=1, out_features=100, bias=True)
  (1): Dropout(p=0.5)
  (2): ReLU()
  (3): Linear(in_features=100, out_features=100, bias=True)
  (4): Dropout(p=0.5)
  (5): ReLU()
  (6): Linear(in_features=100, out_features=1, bias=True)
)
```

In [74]:

```
optimizer_overfitting = torch.optim.Adam(net_overfitting.parameters(), lr=0.01)
optimizer_dropout = torch.optim.Adam(net_dropout.parameters(), lr=0.01)
loss_func = torch.nn.MSELoss()

for t in range(1000):
    prediction_overfitting = net_overfitting(x)
    prediction_dropout = net_dropout(x)
    loss_overfitting = loss_func(prediction_overfitting, y)
    loss_dropout = loss_func(prediction_dropout, y)

    optimizer_overfitting.zero_grad()
    optimizer_dropout.zero_grad()
    loss_overfitting.backward()
    loss_dropout.backward()
    optimizer_overfitting.step()
    optimizer_dropout.step()
```

In [81]:

```
net_dropout.eval()
test_prediction_overfitting = net_overfitting(test_x)
test_prediction_dropout = net_dropout(test_y)

plt.scatter(test_x.data.numpy(), test_y.data.numpy(), label='test')
plt.plot(test_x.data.numpy(), test_prediction_overfitting.data.numpy(),'r-', lab
el='not dropout')
plt.plot(test_x.data.numpy(), test_prediction_dropout.data.numpy(), 'b--', label
='dropout')
plt.text(1.2, -2, 'not dropout loss=%.4f' % loss_func(test_prediction_overfittin
g, test_y).item(), fontdict={'size': 15, 'color':  'red'})
plt.text(1.2, -1, 'dropout loss=%.4f' % loss_func(test_prediction_dropout, test_
y).item(), fontdict={'size': 15, 'color': 'blue'})
plt.legend(loc='upper left')
plt.ylim((-2.5, 2.5))
plt.show()
```



3.Batch Normalization

In [76]:

```
def batch_norm(is_training, X, gamma, beta, moving_mean, moving_var, eps, moment
um):
    if not is_training:
        X_hat = (X - moving_mean) / torch.sqrt(moving_var + eps)
    else:
        assert len(X.shape) in (2, 4)
        if len(X.shape) == 2:
            mean = X.mean(dim=0)
            var = ((X - mean) ** 2).mean(dim=0)
        else:
            mean = X.mean(dim=0, keepdim=True).mean(dim=2, keepdim=True).mean(di
m=3, keepdim=True)
            var = ((X - mean) ** 2).mean(dim=0, keepdim=True).mean(dim=2, keepdi
m=True).mean(dim=3, keepdim=True)
        X_hat = (X - mean) / torch.sqrt(var + eps)
        moving_mean = momentum * moving_mean + (1.0 - momentum) * mean
        moving_var = momentum * moving_var + (1.0 - momentum) * var
    Y = gamma * X_hat + beta
    return Y, moving_mean, moving_var
```

In [77]:

```
class BatchNorm(nn.Module):
    def __init__(self, num_features, num_dims):
        super(BatchNorm, self).__init__()
        if num_dims == 2:
            shape = (1, num_features)
        else:
            shape = (1, num_features, 1, 1)
        self.gamma = nn.Parameter(torch.ones(shape))
        self.beta = nn.Parameter(torch.zeros(shape))
        self.moving_mean = torch.zeros(shape)
        self.moving_var = torch.zeros(shape)

    def forward(self, X):
        if self.moving_mean.device != X.device:
            self.moving_mean = self.moving_mean.to(X.device)
            self.moving_var = self.moving_var.to(X.device)
        Y, self.moving_mean, self.moving_var = batch_norm(self.training,
            X, self.gamma, self.beta, self.moving_mean,
            self.moving_var, eps=1e-5, momentum=0.9)
        return Y
```

In [78]:

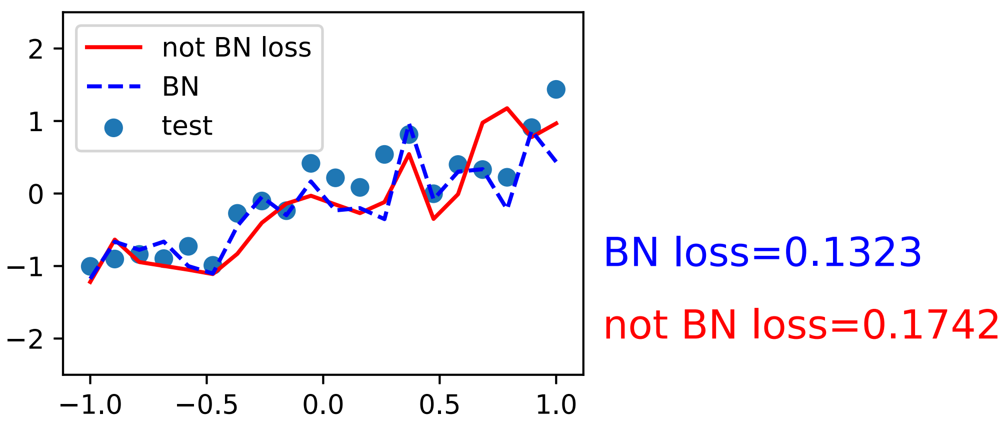
```
net_BN = torch.nn.Sequential(
    torch.nn.Linear(1, N_HIDDEN),
    BatchNorm(N_HIDDEN, num_dims=2),
    torch.nn.ReLU(),
    torch.nn.Linear(N_HIDDEN, N_HIDDEN),
    BatchNorm(N_HIDDEN, num_dims=2),
    torch.nn.ReLU(),
    torch.nn.Linear(N_HIDDEN, 1)
)
```

In [79]:

```
optimizer_overfitting = torch.optim.Adam(net_overfitting.parameters(), lr=0.01)
optimizer_BN = torch.optim.Adam(net_BN.parameters(), lr=0.01)
loss_func = torch.nn.MSELoss()

for t in range(1000):
    # train the NN by training set
    prediction_overfitting = net_overfitting(x)
    prediction_BN = net_BN(x)
    loss_overfitting = loss_func(prediction_overfitting, y)
    loss_BN = loss_func(prediction_BN, y)

    optimizer_overfitting.zero_grad()
    optimizer_BN.zero_grad()
    loss_overfitting.backward()
    loss_BN.backward()
    optimizer_overfitting.step()
    optimizer_BN.step()
```

In [80]:

```
net_BN.eval()
test_prediction_overfitting = net_overfitting(test_x)
test_prediction_BN = net_BN(test_y)

plt.scatter(test_x.data.numpy(), test_y.data.numpy(), label='test')
plt.plot(test_x.data.numpy(), test_prediction_overfitting.data.numpy(),'r-', lab
el='not BN loss')
plt.plot(test_x.data.numpy(), test_prediction_BN.data.numpy(), 'b--', label='BN'
)
plt.text(1.2, -2, 'not BN loss=%.4f' % loss_func(test_prediction_overfitting, te
st_y).item(), fontdict={'size': 15, 'color':  'red'})
plt.text(1.2, -1, 'BN loss=%.4f' % loss_func(test_prediction_BN, test_y).item(),
fontdict={'size': 15, 'color': 'blue'})
plt.legend(loc='upper left')
plt.ylim((-2.5, 2.5))
plt.show()
```



LeNet

In [82]:

```
class LeNet(nn.Module):
    def __init__(self):
        super(LeNet, self).__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(1, 6, 5),
            nn.Sigmoid(),
            nn.MaxPool2d(2, 2),
            nn.Conv2d(6, 16, 5),
            nn.Sigmoid(),
            nn.MaxPool2d(2, 2)
        )
        self.fc = nn.Sequential(
            nn.Linear(16*4*4, 120),
            nn.Sigmoid(),
            nn.Linear(120, 84),
            nn.Sigmoid(),
            nn.Linear(84, 10)
        )

    def forward(self, img):
        feature = self.conv(img)
        output = self.fc(feature.view(img.shape[0], -1))
        return output

net = LeNet()
print(net)
```

```
LeNet(
  (conv): Sequential(
    (0): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1))
    (1): Sigmoid()
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (3): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
    (4): Sigmoid()
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (fc): Sequential(
    (0): Linear(in_features=256, out_features=120, bias=True)
    (1): Sigmoid()
    (2): Linear(in_features=120, out_features=84, bias=True)
    (3): Sigmoid()
    (4): Linear(in_features=84, out_features=10, bias=True)
  )
)
```

In [83]:

```
batch_size = 256
train_iter, test_iter = load_data_fashion_mnist(batch_size=batch_size)
```

In [84]:

```
def evaluate_accuracy(data_iter, net):
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    acc_sum, n = 0.0, 0
    with torch.no_grad():
        for X, y in data_iter:
            if isinstance(net, torch.nn.Module):
                net.eval()
                acc_sum += (net(X.to(device)).argmax(dim=1) == y.to(device)).flo
at().sum().cpu().item()
                net.train()
            else:
                if('is_training' in net.__code__.co_varnames):
                    acc_sum += (net(X, is_training=False).argmax(dim=1) == y).fl
oat().sum().item()
                else:
                    acc_sum += (net(X).argmax(dim=1) == y).float().sum().item()
            n += y.shape[0]
    return acc_sum / n
```

In [85]:

```
def train_BN(net, train_iter, test_iter, batch_size, optimizer, device, num_epoc
hs):
    net = net.to(device)
    print("training on ", device)
    loss = torch.nn.CrossEntropyLoss()
    batch_count = 0
    for epoch in range(num_epochs):
        train_l_sum, train_acc_sum, n, start = 0.0, 0.0, 0, time.time()
        for X, y in train_iter:
            X = X.to(device)
            y = y.to(device)
            y_hat = net(X)
            l = loss(y_hat, y)
            optimizer.zero_grad()
            l.backward()
            optimizer.step()
            train_l_sum += l.cpu().item()
            train_acc_sum += (y_hat.argmax(dim=1) == y).sum().cpu().item()
            n += y.shape[0]
            batch_count += 1
        test_acc = evaluate_accuracy(test_iter, net)
        print('epoch %d, loss %.4f, train acc %.3f, test acc %.3f, time %.1f se
c'
              % (epoch + 1, train_l_sum / batch_count, train_acc_sum / n, test_a
cc, time.time() - start))
```

In [86]:

```
lr, num_epochs = 0.001, 5
optimizer = torch.optim.Adam(net.parameters(), lr=lr)
train_BN(net, train_iter, test_iter, batch_size, optimizer, device, num_epochs)
```

```
training on  cuda
epoch 1, loss 1.9073, train acc 0.291, test acc 0.572, time 2.9 sec
epoch 2, loss 0.4893, train acc 0.614, test acc 0.674, time 2.1 sec
epoch 3, loss 0.2680, train acc 0.702, test acc 0.723, time 2.5 sec
epoch 4, loss 0.1741, train acc 0.738, test acc 0.744, time 2.3 sec
epoch 5, loss 0.1273, train acc 0.755, test acc 0.758, time 1.9 sec
```

In [87]:

```
net_BN = nn.Sequential(
            nn.Conv2d(1, 6, 5), # in_channels, out_channels, kernel_size
            nn.BatchNorm2d(6),
            nn.Sigmoid(),
            nn.MaxPool2d(2, 2), # kernel_size, stride
            nn.Conv2d(6, 16, 5),
            nn.BatchNorm2d(16),
            nn.Sigmoid(),
            nn.MaxPool2d(2, 2),
            FlattenLayer(),
            nn.Linear(16*4*4, 120),
            nn.BatchNorm1d(120),
            nn.Sigmoid(),
            nn.Linear(120, 84),
            nn.BatchNorm1d(84),
            nn.Sigmoid(),
            nn.Linear(84, 10)
        )
```

In [88]:

```
optimizer = torch.optim.Adam(net_BN.parameters(), lr=lr)
train_BN(net_BN, train_iter, test_iter, batch_size, optimizer, device, num_epoch
s)
```

```
training on  cuda
epoch 1, loss 1.3248, train acc 0.762, test acc 0.787, time 2.2 sec
epoch 2, loss 0.2938, train acc 0.852, test acc 0.827, time 2.4 sec
epoch 3, loss 0.1391, train acc 0.872, test acc 0.789, time 2.2 sec
epoch 4, loss 0.0904, train acc 0.880, test acc 0.842, time 2.7 sec
epoch 5, loss 0.0663, train acc 0.888, test acc 0.818, time 2.4 sec
```

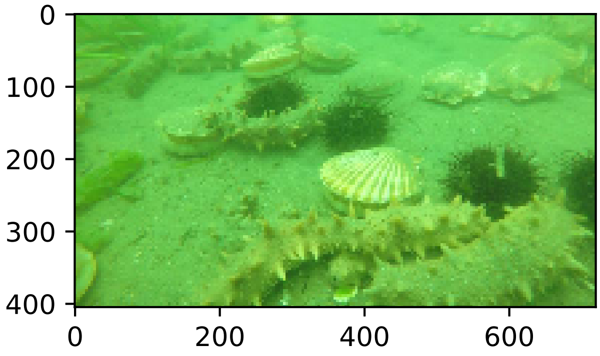
4. Data Augmentation

In [89]:

```
set_figsize()
img = Image.open('Datasets/scallop.jpg')
plt.imshow(img)
```

Out[89]:

```
<matplotlib.image.AxesImage at 0x7fed587279d0>
```



In [90]:

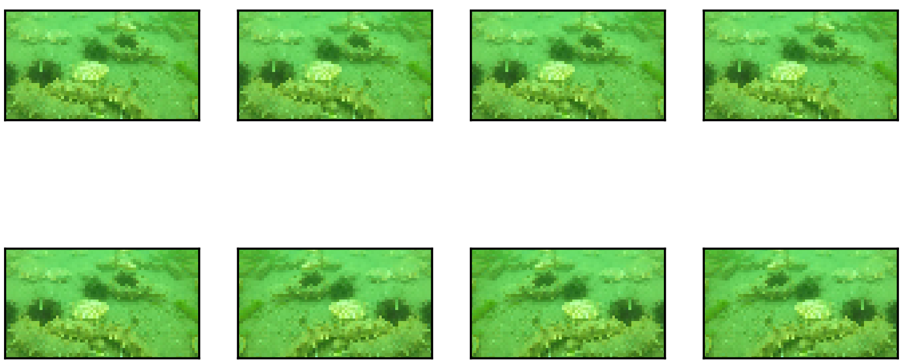
```
def show_images(imgs, num_rows, num_cols, scale=2):
    figsize = (num_cols * scale, num_rows * scale)
    _, axes = plt.subplots(num_rows, num_cols, figsize=figsize)
    for i in range(num_rows):
        for j in range(num_cols):
            axes[i][j].imshow(imgs[i * num_cols + j])
            axes[i][j].axes.get_xaxis().set_visible(False)
            axes[i][j].axes.get_yaxis().set_visible(False)
    return axes
```

In [91]:

```
def apply(img, aug, num_rows=2, num_cols=4, scale=1.5):
    Y = [aug(img) for _ in range(num_rows * num_cols)]
    show_images(Y, num_rows, num_cols, scale)
```

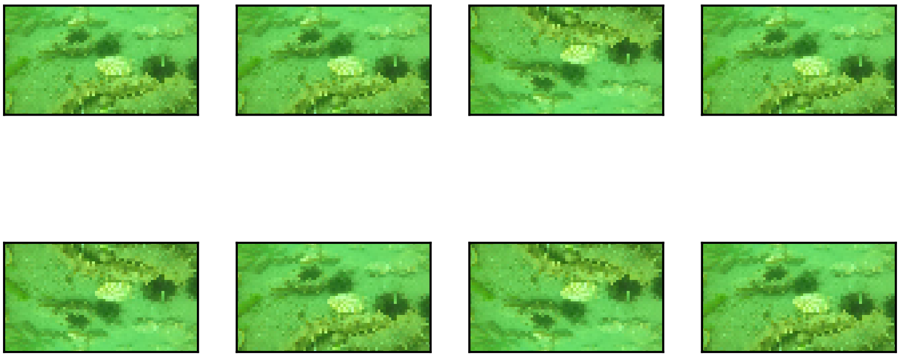
In [92]:

```
apply(img, torchvision.transforms.RandomHorizontalFlip())
```



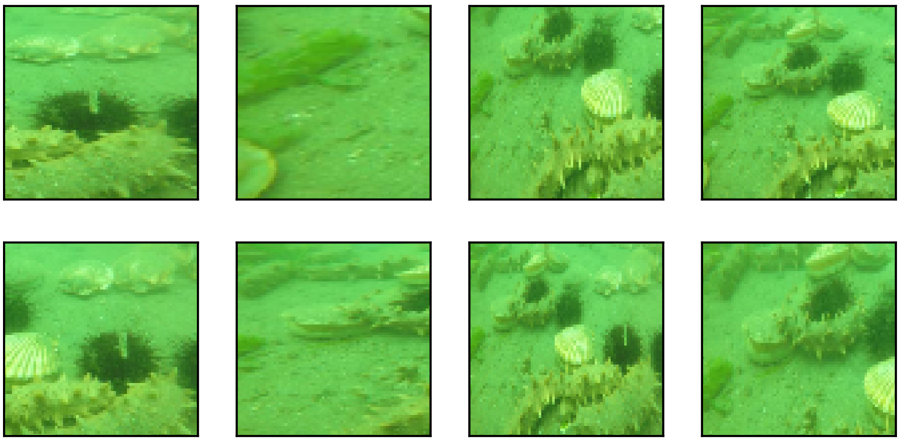
In [93]:

```
apply(img, torchvision.transforms.RandomVerticalFlip())
```



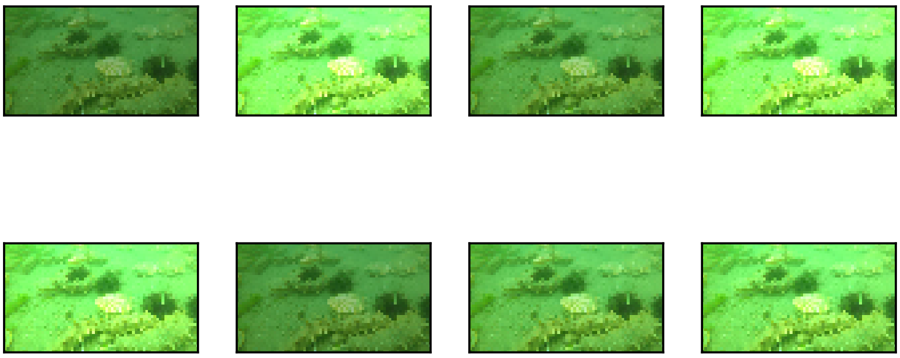
In [94]:

```
shape_aug = torchvision.transforms.RandomResizedCrop(200, scale=(0.1, 1), ratio=(0.5, 2))
apply(img, shape_aug)
```



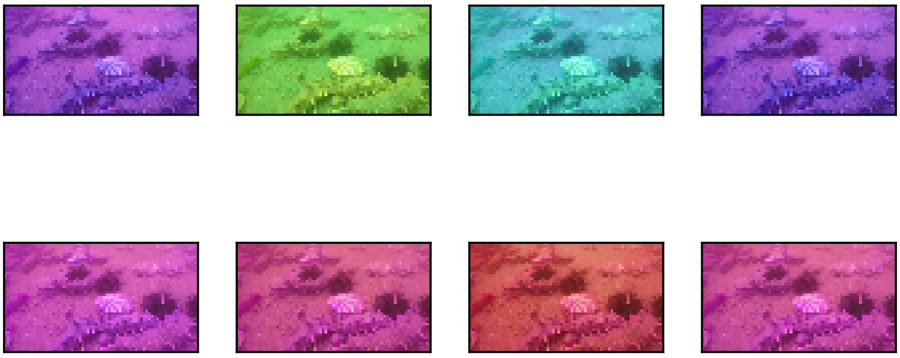
In [95]:

```
apply(img, torchvision.transforms.ColorJitter(brightness=0.5, contrast=0, saturation=0, hue=0))
```



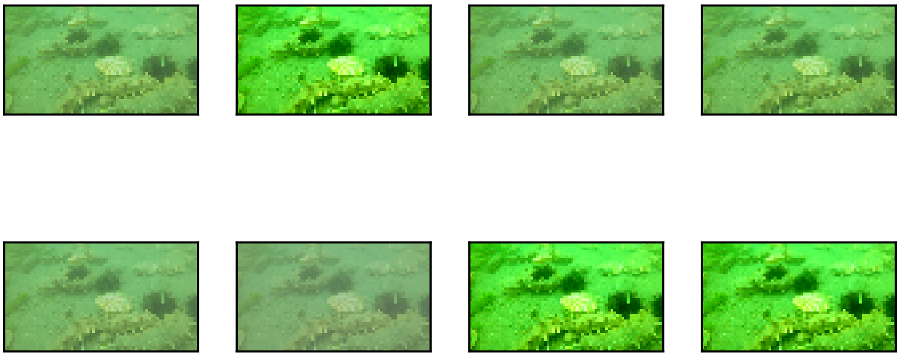
In [96]:

```
apply(img, torchvision.transforms.ColorJitter(brightness=0, contrast=0, saturation=0, hue=0.5))
```



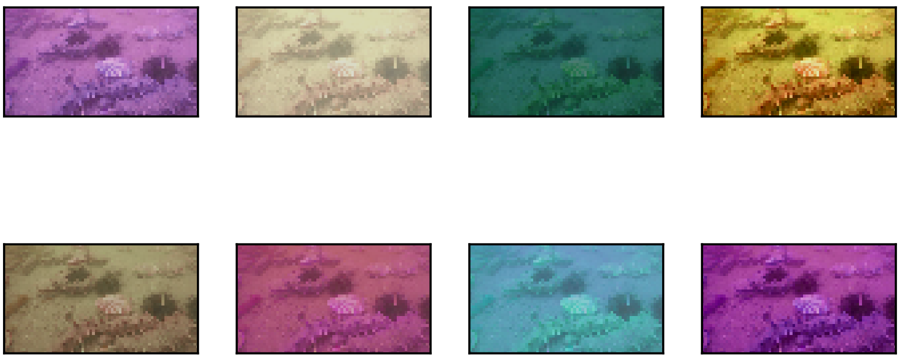
In [97]:

```
apply(img, torchvision.transforms.ColorJitter(brightness=0, contrast=0.5, saturation=0, hue=0))
```



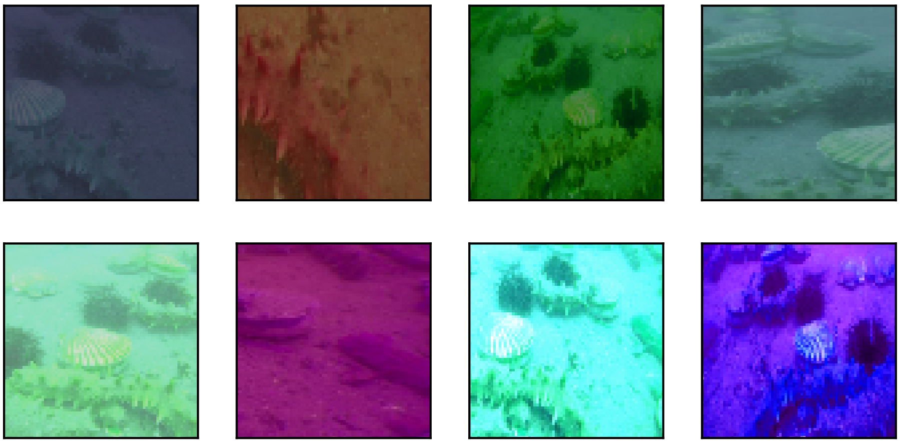
In [98]:

```
color_aug = torchvision.transforms.ColorJitter(brightness=0.5, contrast=0.5, saturation=0.5, hue=0.5)
apply(img, color_aug)
```



In [99]:

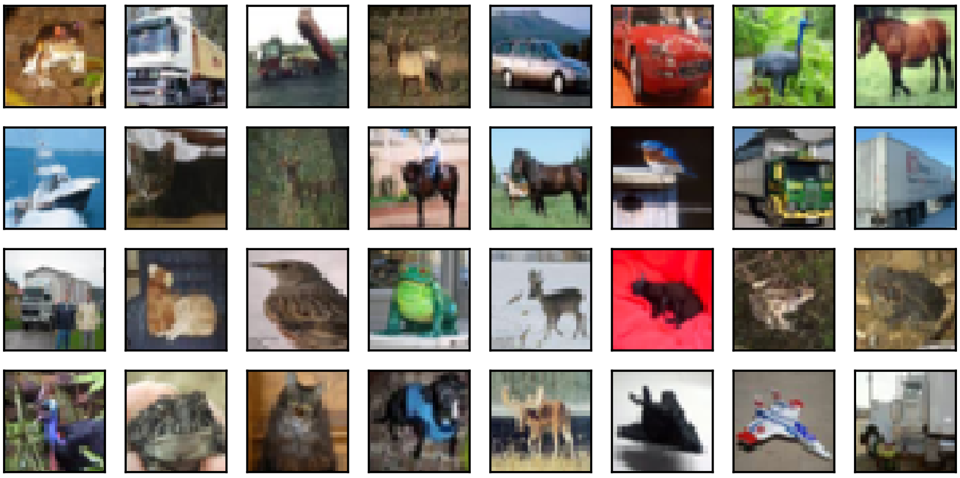
```
augs = torchvision.transforms.Compose([
    torchvision.transforms.RandomHorizontalFlip(), color_aug, shape_aug])
apply(img, augs)
```



Comprehensive Task

In [100]:

```
all_imges = torchvision.datasets.CIFAR10(train=True, root="Datasets/CIFAR", down
load=False)

show_images([all_imges[i][0] for i in range(32)], 4, 8, scale=0.8);
```



In [101]:

```
class GlobalAvgPool2d(nn.Module):

    def __init__(self):
        super(GlobalAvgPool2d, self).__init__()
    def forward(self, x):
        return F.avg_pool2d(x, kernel_size=x.size()[2:])
```

In [102]:

```
class Residual(nn.Module):
    def __init__(self, in_channels, out_channels, use_1x1conv=False, stride=1):
        super(Residual, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, padding
=1, stride=stride)
        self.conv2 = nn.Conv2d(out_channels, out_channels, kernel_size=3, paddin
g=1)
        if use_1x1conv:
            self.conv3 = nn.Conv2d(in_channels, out_channels, kernel_size=1, str
ide=stride)
        else:
            self.conv3 = None
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.bn2 = nn.BatchNorm2d(out_channels)

    def forward(self, X):
        Y = F.relu(self.bn1(self.conv1(X)))
        Y = self.bn2(self.conv2(Y))
        if self.conv3:
            X = self.conv3(X)
        return F.relu(Y + X)

def resnet_block(in_channels, out_channels, num_residuals, first_block=False):
    if first_block:
        assert in_channels == out_channels
    blk = []
    for i in range(num_residuals):
        if i == 0 and not first_block:
            blk.append(Residual(in_channels, out_channels, use_1x1conv=True, str
ide=2))
        else:
            blk.append(Residual(out_channels, out_channels))
    return nn.Sequential(*blk)

def resnet18(output=10, in_channels=3):
    net = nn.Sequential(
        nn.Conv2d(in_channels, 64, kernel_size=7, stride=2, padding=3),
        nn.BatchNorm2d(64),
        nn.ReLU(),
        nn.MaxPool2d(kernel_size=3, stride=2, padding=1))
    net.add_module("resnet_block1", resnet_block(64, 64, 2, first_block=True))
    net.add_module("resnet_block2", resnet_block(64, 128, 2))
    net.add_module("resnet_block3", resnet_block(128, 256, 2))
    net.add_module("resnet_block4", resnet_block(256, 512, 2))
    net.add_module("global_avg_pool", GlobalAvgPool2d()) # GlobalAvgPool2d的输出:
(Batch, 512, 1, 1)
    net.add_module("fc", nn.Sequential(FlattenLayer(), nn.Linear(512, output)))
    return net
```

In [103]:

```
flip_aug = torchvision.transforms.Compose([
     torchvision.transforms.RandomHorizontalFlip(),
     torchvision.transforms.ToTensor()])

no_aug = torchvision.transforms.Compose([
     torchvision.transforms.ToTensor()])
```

In [104]:

```
num_workers = 0 if sys.platform.startswith('win32') else 4
def load_cifar10(is_train, augs, batch_size, root="Datasets/CIFAR"):
    dataset = torchvision.datasets.CIFAR10(root=root, train=is_train, transform=augs, download=False)
    return DataLoader(dataset, batch_size=batch_size, shuffle=is_train, num_workers=num_workers)
```

In [105]:

```
def evaluate_accuracy(data_iter, net,
        device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')):
    acc_sum, n = 0.0, 0
    with torch.no_grad():
        for X, y in data_iter:
            if isinstance(net, torch.nn.Module):
                net.eval() #
                acc_sum += (net(X.to(device)).argmax(dim=1) == y.to(device)).float().sum().cpu().item()
                net.train()
            else:
                if('is_training' in net.__code__.co_varnames):
                    acc_sum += (net(X, is_training=False).argmax(dim=1) == y).float().sum().item()
                else:
                    acc_sum += (net(X).argmax(dim=1) == y).float().sum().item()
            n += y.shape[0]
    return acc_sum / n
```

In [106]:

```
def train(train_iter, test_iter, net, loss, optimizer, device, num_epochs):
    net = net.to(device)
    print("training on ", device)
    batch_count = 0
    for epoch in range(num_epochs):
        train_l_sum, train_acc_sum, n, start = 0.0, 0.0, 0, time.time()
        for X, y in train_iter:
            X = X.to(device)
            y = y.to(device)
            y_hat = net(X)
            l = loss(y_hat, y)
            optimizer.zero_grad()
            l.backward()
            optimizer.step()
            train_l_sum += l.cpu().item()
            train_acc_sum += (y_hat.argmax(dim=1) == y).sum().cpu().item()
            n += y.shape[0]
            batch_count += 1
        test_acc = evaluate_accuracy(test_iter, net)
        print('epoch %d, loss %.4f, train acc %.3f, test acc %.3f, time %.1f sec'
              % (epoch + 1, train_l_sum / batch_count, train_acc_sum / n, test_acc, time.time() - start))
```

In [107]:

```
def train_with_data_aug(train_augs, test_augs, lr=0.001):
    batch_size, net = 256, resnet18(10)
    optimizer = torch.optim.Adam(net.parameters(), lr=lr)
    loss = torch.nn.CrossEntropyLoss()
    train_iter = load_cifar10(True, train_augs, batch_size)
    test_iter = load_cifar10(False, test_augs, batch_size)
    train(train_iter, test_iter, net, loss, optimizer, device, num_epochs=10)
```

In [108]:

```
train_with_data_aug(train_augs=no_aug, test_augs=no_aug)
```

```
training on  cuda
epoch 1, loss 1.3558, train acc 0.508, test acc 0.471, time 32.2 se
c
epoch 2, loss 0.4934, train acc 0.649, test acc 0.549, time 32.6 se
c
epoch 3, loss 0.2729, train acc 0.710, test acc 0.593, time 32.4 se
c
epoch 4, loss 0.1764, train acc 0.751, test acc 0.659, time 32.4 se
c
epoch 5, loss 0.1214, train acc 0.789, test acc 0.709, time 32.5 se
c
epoch 6, loss 0.0861, train acc 0.819, test acc 0.706, time 32.3 se
c
epoch 7, loss 0.0625, train acc 0.848, test acc 0.704, time 32.4 se
c
epoch 8, loss 0.0460, train acc 0.872, test acc 0.667, time 32.4 se
c
epoch 9, loss 0.0341, train acc 0.893, test acc 0.694, time 32.4 se
c
epoch 10, loss 0.0249, train acc 0.914, test acc 0.641, time 32.4 s
ec
```

In [109]:

```
train_with_data_aug(train_augs=flip_aug, test_augs=no_aug)
```

```
training on  cuda
epoch 1, loss 1.3841, train acc 0.499, test acc 0.547, time 32.7 se
c
epoch 2, loss 0.5070, train acc 0.640, test acc 0.629, time 33.3 se
c
epoch 3, loss 0.2844, train acc 0.701, test acc 0.610, time 33.1 se
c
epoch 4, loss 0.1877, train acc 0.737, test acc 0.639, time 33.2 se
c
epoch 5, loss 0.1356, train acc 0.765, test acc 0.658, time 32.6 se
c
epoch 6, loss 0.1015, train acc 0.789, test acc 0.690, time 32.5 se
c
epoch 7, loss 0.0791, train acc 0.806, test acc 0.723, time 32.4 se
c
epoch 8, loss 0.0638, train acc 0.822, test acc 0.676, time 32.8 se
c
epoch 9, loss 0.0515, train acc 0.839, test acc 0.708, time 32.6 se
c
epoch 10, loss 0.0423, train acc 0.853, test acc 0.750, time 32.5 s
ec
```

In [ ]:

```

```