Linear Regression Implementation from Scratch

In [1]:

```
%matplotlib inline
from IPython import display
from matplotlib import pyplot as plt
from mxnet import autograd, nd
import random
```

Generating Data Sets

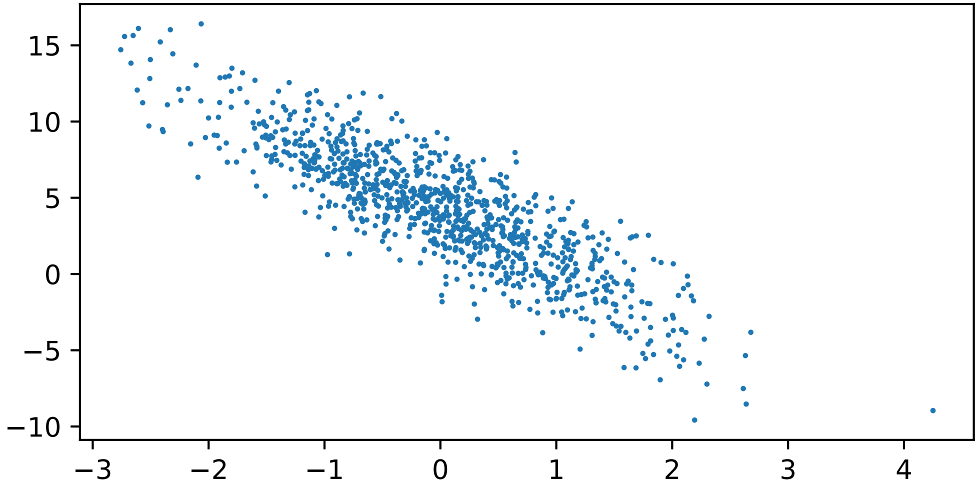
- Randomly generate $\mathbf{X} \in \mathbb{R}^{1000 \times 2}$
- Use ground truth: weight $\mathbf{w} = [2, -3.4]^\top$ and bias $b = 4.2$
- Generate label by $\mathbf{y} = \mathbf{X}\mathbf{w} + b + \epsilon$ with noise ϵ obeying a normal distribution with a mean of 0 and a standard deviation of 0.01.

In [2]:

```
num_inputs = 2
num_examples = 1000
true_w = nd.array([2, -3.4])
true_b = 4.2
features = nd.random.normal(scale=1, shape=(num_examples, num_inputs))
labels = nd.dot(features, true_w) + true_b
labels += nd.random.normal(scale=0.01, shape=labels.shape)
```

Visualize the Second Feature and Label

In [3]:
```
display.set_matplotlib_formats('svg')
plt.figure(figsize=(6, 3))
plt.scatter(features[:, 1].asnumpy(), labels.asnumpy(), 1);
```



Reading Data

Iterate over the data set and return `batch_size` (batch size) random examples every time.

In [4]:
```
def data_iter(batch_size, features, labels):
    num_examples = len(features)
    indices = list(range(num_examples))
    # The examples are read at random, in no particular order
    random.shuffle(indices)
    for i in range(0, num_examples, batch_size):
        j = nd.array(indices[i: min(i + batch_size, num_examples)])
        yield features.take(j), labels.take(j)
        # The “take” function will then return the corresponding element based
        # on the indices
```

Print a Small Data Batch

In [5]:

```
batch_size = 10
for X, y in data_iter(batch_size, features, labels):
    print(X, y)
    break
```

```
[[ 1.7782049   0.17127965]
 [-0.2433725  -0.5560082 ]
 [-0.99795526  0.17728646]
 [-0.41475967 -1.2982413 ]
 [-2.1107438  -1.5111811 ]
 [-1.8830644  -0.4991788 ]
 [ 0.11150214 -0.22487849]
 [ 0.9314184  -0.7470997 ]
 [-0.3884701  -2.0006752 ]
 [-1.0986379   1.691893  ]]
<NDArray 10x2 @cpu(0)>
[ 7.1776037  5.609725   1.5751892  7.7738857  5.1178493  2.1461306
  5.191642   8.586297  10.234753  -3.7403975]
<NDArray 10 @cpu(0)>
```

Initialize Model Parameters

Weights are initialized to normal random numbers using a mean of 0 and a standard deviation of 0.01, with the bias b set to zero.

In [6]:
```
w = nd.random.normal(scale=0.01, shape=(num_inputs, 1))
b = nd.zeros(shape=(1,))
```

Attach Gradients to Parameters

In [7]:
```
w.attach_grad()
b.attach_grad()
```

Define the Linear Model

In [8]:

```
def linreg(X, w, b):
    return nd.dot(X, w) + b
```

Define the Loss Function

In [9]:
```
def squared_loss(y_hat, y):
    return (y_hat - y.reshape(y_hat.shape)) ** 2 / 2
```

Define the Optimization Algorithm

In [10]:

```
def sgd(params, lr, batch_size):
    for param in params:
        param[:] = param - lr * param.grad / batch_size
```

Training

In [11]:

```
lr = 0.1  # Learning rate
num_epochs = 3  # Number of iterations
net = linreg  # Our fancy linear model
loss = squared_loss  # 0.5 (y-y')^2

w = nd.random.normal(scale=0.01, shape=(num_inputs, 1))
b = nd.zeros(shape=(1,))

w.attach_grad()
b.attach_grad()

for epoch in range(num_epochs):
    for X, y in data_iter(batch_size, features, labels):
        with autograd.record():
            l = loss(net(X, w, b), y)  # Minibatch loss in X and y
        l.backward()  # Compute gradient on l with respect to [w,b]
        sgd([w, b], lr, batch_size)  # Update parameters using their gradient
    train_l = loss(net(features, w, b), labels)
    print('epoch %d, loss %f' % (epoch + 1, train_l.mean().asnumpy()))
```

```
epoch 1, loss 0.000049
epoch 2, loss 0.000050
epoch 3, loss 0.000049
```

Evaluate the Trained Model

In [12]:

```
print('Error in estimating w', true_w - w.reshape(true_w.shape))
print('Error in estimating b', true_b - b)
print(w)
print(b)
```

```
Error in estimating w
[-0.00051641  0.00074124]
<NDArray 2 @cpu(0)>
Error in estimating b
[-0.00073719]
<NDArray 1 @cpu(0)>

[[ 2.0005164]
 [-3.4007413]]
<NDArray 2x1 @cpu(0)>

[4.200737]
<NDArray 1 @cpu(0)>
```