Matrix norms

```
In [1]:
```

```
#keep
import numpy as np
import numpy.linalg as la
import matplotlib.pyplot as pt
%matplotlib inline
```

Here's a matrix of which we're trying to compute the norm:

```
In [2]:
```

```
#keep
n = 2
A = np.random.randn(n, n)
```

Recall:

$$||A|| = \max_{\|x\|=1} \|Ax\|,$$

where the vector norm must be specified, and the value of the matrix norm $\|A\|$ depends on the choice of vector norm.

For instance, for the p-norms, we often write:

$$||A||_2 = \max_{\|x\|=1} \|Ax\|_2,$$

and similarly for different values of p.

We can approximate this by just producing very many random vectors and evaluating the formula:

```
In [3]:
```

```
#keep
xs = np.random.randn(n, 1000)
```

First, we need to bring all those vectors to have norm 1. First, compute the norms:

```
In [4]:
#keep
p = 2
norm_xs = np.sum(np.abs(xs)**p, axis=0)**(1/p)
norm xs.shape
Out[4]:
(1000,)
Then, divide by the norms and assign to normalized_xs:
In [5]:
normalized_xs = xs/norm_xs
la.norm(normalized_xs[:, 316], p)
Out[5]:
1.4190346549699246
Let's take a look:
In [6]:
#keep
pt.plot(normalized_xs[0], normalized_xs[1], "o")
pt.gca().set_aspect("equal")
 3
 2
 1
```

Now apply \boldsymbol{A} to these normalized vectors:

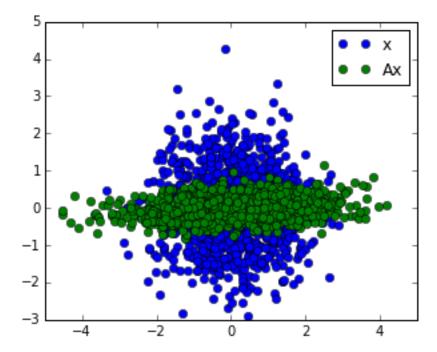
```
In [7]:
```

```
A_nxs = A.dot(normalized_xs)
```

Let's take a look again:

```
In [8]:
```

```
#keep
pt.plot(normalized_xs[0], normalized_xs[1], "o", label="x")
pt.plot(A_nxs[0], A_nxs[1], "o", label="Ax")
pt.legend()
pt.gca().set_aspect("equal")
```



Next, compute norms of the Ax vectors:

```
In [9]:
```

```
norm_Axs = np.sum(np.abs(A_nxs)**p, axis=0)**(1/p)
norm_Axs.shape
```

Out[9]:

(1000,)

What's the biggest one?

```
In [10]:
```

```
np.max(norm_Axs)
```

Out[10]:

1.0

Compare that with what numpy thinks the matrix norm is:

```
In [11]:
la.norm(A, p)
Out[11]:
1.4987148313922474
In [12]:
A = np.arange(9).reshape(3,3)
Out[12]:
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
In [13]:
np.sum(A)
Out[13]:
36
In [ ]:
In [ ]:
```