Deep learning

1.6. Tensor internals

François Fleuret

https://fleuret.org/dlc/
A tensor is a view of a [part of a] storage, which is a low-level 1d vector.

```python
>>> x = torch.zeros(2, 4)
>>> x.storage()
0.0
0.0
0.0
0.0
0.0
0.0
0.0
0.0
0.0
[torch.FloatStorage of size 8]
>>> q = x.storage()
>>> q[4] = 1.0
>>> x
tensor([[ 0., 0., 0., 0.],
        [ 1., 0., 0., 0.]])
```
The first coefficient of a tensor is the one at `storage_offset()` in `storage()`.
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Incrementing index $k$ by 1 move by `stride(k)` elements in the storage.
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Incrementing index \( k \) by 1 move by `stride(k)` elements in the storage.

```python
>>> q = torch.arange(0., 20.).storage()
>>> x = torch.empty(0).set_(q, storage_offset = 5, size = (3, 2), stride = (4, 1))
>>> x
tensor([[ 5.,  6.],
         [ 9., 10.],
         [13., 14.]])
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```

\[ q = \begin{bmatrix}
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19
\end{bmatrix} \]
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```

\( q \):

\[
\begin{array}{cccccccccccccccc}
0 & 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16 & 17 & 18 & 19 \\
\end{array}
\]

\( x \):

\[
\begin{array}{cccc}
x[0,0] & x[0,1] & x[1,0] & x[1,1] & x[2,0] & x[2,1] \\
\end{array}
\]
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```
We can explicitly create different “views” of the same storage

```python
>>> n = torch.linspace(1, 4, 4)
>>> n
    tensor([ 1.,  2.,  3.,  4.])
>>> torch.tensor(0.).set_(n.storage(), 1, (3, 3), (0, 1))
    tensor([[ 2.,  3.,  4.],
            [ 2.,  3.,  4.],
            [ 2.,  3.,  4.]])
>>> torch.tensor(0.).set_(n.storage(), 1, (2, 4), (1, 0))
    tensor([[ 2.,  2.,  2.,  2.],
            [ 3.,  3.,  3.,  3.]])
```
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>>> n
tensor([ 1., 2., 3., 4.])
>>> torch.tensor(0.).set_(n.storage(), 1, (3, 3), (0, 1))
tensor([[ 2., 3., 4.],
        [ 2., 3., 4.],
        [ 2., 3., 4.]])
>>> torch.tensor(0.).set_(n.storage(), 1, (2, 4), (1, 0))
tensor([[ 2., 2., 2., 2.],
        [ 3., 3., 3., 3.]])
```

This is in particular how transpositions and broadcasting are implemented.

```python
>>> x = torch.empty(100, 100)
>>> x.stride()
(100, 1)
>>> y = x.t()
>>> y.stride()
(1, 100)
```
This organization explains the following (maybe surprising) error

```python
>>> x = torch.empty(100, 100)
>>> x.t().view(-1)
Traceback (most recent call last):
  File "<stdin>", line 1, in <module>
RuntimeError: invalid argument 2: view size is not compatible with input tensor's size and stride (at least one dimension spans across two contiguous subspaces). Call .contiguous() before .view()
```

`x.t()` shares `x`'s storage and cannot be “flattened” to 1d.
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This can be fixed with `contiguous()`, which returns a contiguous version of the
tensor, **making a copy if needed.**

The function `reshape()` combines `view()` and `contiguous()`. 
The end