neural_final

January 3, 2026

1 Modèle de langue neuronal

15 décembre 2025

Adapté du tutoriel d'A. Karphathy "Makemore", deuxième partie: https://www.youtube.com/watch?v=PaCmpygFfXo

1.1 Jeu de données: les mots du code civil

[2]:
```
words = open('civil_mots.txt', 'r').read().splitlines()
chars = sorted(list(set(''.join(words))))
nb_chars = len(chars) + 1  # On ajoute 1 pour EOS
ctoi = {c:i+1 for i,c in enumerate(chars)}
ctoi['.'] = 0
print("CTOI =", ctoi)
# Dictionnaire permettant permettant de passer d'un entier à son caractère
itoc = {i:s for s,i in ctoi.items()}
print("ITOC =", itoc)
```

```
CTOI = {"'": 1, '-': 2, 'a': 3, 'b': 4, 'c': 5, 'd': 6, 'e': 7, 'f': 8, 'g': 9,
'h': 10, 'i': 11, 'j': 12, 'l': 13, 'm': 14, 'n': 15, 'o': 16, 'p': 17, 'q': 18,
'r': 19, 's': 20, 't': 21, 'u': 22, 'v': 23, 'w': 24, 'x': 25, 'y': 26, 'z': 27,
'à': 28, 'â': 29, 'ç': 30, 'è': 31, 'é': 32, 'ê': 33, 'ë': 34, 'î': 35, 'ï': 36,
'ô': 37, 'ù': 38, 'û': 39, 'œ': 40, '.': 0}
ITOC = {1: "'", 2: '-', 3: 'a', 4: 'b', 5: 'c', 6: 'd', 7: 'e', 8: 'f', 9: 'g',
10: 'h', 11: 'i', 12: 'j', 13: 'l', 14: 'm', 15: 'n', 16: 'o', 17: 'p', 18: 'q',
19: 'r', 20: 's', 21: 't', 22: 'u', 23: 'v', 24: 'w', 25: 'x', 26: 'y', 27: 'z',
28: 'à', 29: 'â', 30: 'ç', 31: 'è', 32: 'é', 33: 'ê', 34: 'ë', 35: 'î', 36: 'ï',
37: 'ô', 38: 'ù', 39: 'û', 40: 'œ', 0: '.'}
```

1.2 Approche par réseau de neurones reproduisant l'approche par comptage

1.2.1 Représentation des mots avec des vecteurs "one-hot": exemple avec un seul mot

[3]:
```
import torch

# Création d'un jeu d'entrainement de bigrams (x,y)
xs, ys = [], []
```

```
for w in [words[40]]:
  chs = ['.'] + list(w) + ['.']
  for ch1, ch2 in zip(chs, chs[1:]):
    ix1 = ctoi[ch1]
    ix2 = ctoi[ch2]
    print(ch1, ch2, '->', ix1, ix2)
    xs.append(ix1)
    ys.append(ix2)

xs = torch.tensor(xs)
ys = torch.tensor(ys)
print(words[40])
tensor_dims = len(words[40]) + 1
print("tensor_dims =", tensor_dims)
```

```
. a -> 0 3
a c -> 3 5
c c -> 5 5
c e -> 5 7
e p -> 7 17
p t -> 17 21
t é -> 21 32
é e -> 32 7
e . -> 7 0
acceptée
tensor_dims = 9
```

[4]:
```
xs
```

[4]:
```
tensor([ 0,  3,  5,  5,  7, 17, 21, 32,  7])
```

[5]:
```
ys
```

[5]:
```
tensor([ 3,  5,  5,  7, 17, 21, 32,  7,  0])
```

[6]:
```
# Représentation de chaque caractère par un vecteur one-hot
# seul une composante est à 1.0, correspondant à l'indice du numéro du caractère
import torch.nn.functional as F
xenc = F.one_hot(xs, num_classes=nb_chars).float()
xenc
```

[6]:
```
tensor([[1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0.],
        [0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0.],
```

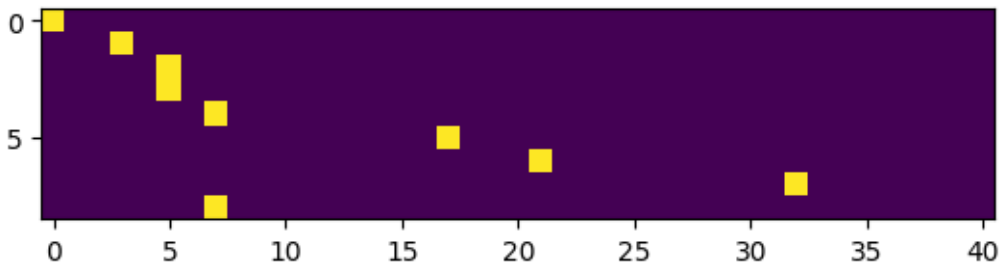
```
[0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.],
[0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.],
[0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.],
[0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.],
[0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.],
[0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.],
[0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
 0., 0., 0., 0., 0.]])
```

[7]:
```
# La première dimension est la dimension du tenseur exemple
xenc.shape
```

[7]:
```
torch.Size([9, 41])
```

[8]:
```
import matplotlib.pyplot as plt
%matplotlib inline
plt.imshow(xenc)
```

[8]:
```
<matplotlib.image.AxesImage at 0x10f450830>
```



[9]:
```
# Pour notre réseau, on va utiliser une matrice W des valeurs normales␣
 ↪aléatoires comme
# point de départ
```

```
W = torch.randn((nb_chars, tensor_dims))  # Quand on aura tous les mots, on␣
 ↪utilisera nb_chars x nb_chars
W
```

[9]:
```
tensor([[ 9.1839e-01, -1.1502e+00, -8.3629e-01,  1.5226e+00,  8.4343e-01,
          3.7099e-01,  1.8180e+00, -6.9873e-01,  1.1443e+00],
        [-8.5412e-01,  9.1880e-01,  1.6299e+00, -9.2986e-02,  4.3231e-01,
          3.4169e-01,  6.3554e-01, -2.3884e+00, -1.6909e-01],
        [ 1.1750e+00,  9.7545e-01,  6.1806e-01,  2.2869e-01, -1.2293e+00,
          8.1735e-01, -9.5131e-01,  1.2416e+00,  5.6462e-01],
        [ 2.6404e-01, -1.0920e-01,  5.7622e-01,  1.4399e-01,  7.6392e-01,
          3.0535e-01, -7.3563e-01, -9.6206e-01,  3.5338e-01],
        [ 1.5070e+00,  1.4913e+00,  2.9527e-01, -4.1975e-01, -1.4888e+00,
          6.9776e-01,  8.9753e-01,  1.0222e+00, -1.4788e+00],
        [ 1.2613e-01,  8.5963e-01, -7.1895e-01, -2.6217e+00,  4.3825e-01,
          2.3034e+00, -1.7862e+00,  3.5024e-01,  9.5713e-01],
        [-3.4914e-01,  1.1381e+00, -8.4526e-01,  3.8407e-01, -2.9689e-02,
         -8.9423e-01,  9.8505e-01,  9.0442e-01, -5.1849e-01],
        [ 6.5824e-01, -7.6243e-01, -8.5083e-02, -1.5097e+00,  3.3365e-01,
         -4.7317e-02, -5.2482e-01,  1.1375e+00, -3.8334e-01],
        [-4.3876e-02,  9.8445e-01,  1.6056e-01, -4.3068e-02, -4.3082e-01,
         -2.1318e-01, -4.0735e-01, -8.3677e-01,  3.9790e-01],
        [-1.7768e+00, -9.3988e-01,  1.0934e+00,  8.8543e-01, -1.2180e+00,
         -7.6091e-01,  5.6308e-01, -6.6491e-01, -1.1863e+00],
        [-1.4602e+00,  4.4132e-01, -3.5278e-01, -1.4347e+00, -1.5626e+00,
          6.8525e-01,  4.2568e-01,  8.3430e-01, -1.0295e+00],
        [-1.6114e+00, -5.9811e-01, -6.2155e-01, -2.9091e-03,  5.5972e-01,
         -7.8317e-01, -8.3771e-02,  7.5206e-01, -1.4175e+00],
        [ 8.1634e-01,  4.9134e-01, -2.7166e-01, -6.0395e-01,  7.2573e-01,
          7.1407e-01,  1.7733e-01,  1.7713e-01,  1.4325e-01],
        [ 7.0480e-01, -1.6713e-01,  9.5935e-01, -7.8019e-01,  1.6251e+00,
          1.2835e+00,  4.8042e-02,  5.8192e-01, -3.0040e+00],
        [ 6.3264e-01,  2.4104e-01, -7.3922e-01,  4.7470e-01, -1.7250e+00,
         -7.5146e-01, -9.4407e-01, -8.6993e-01, -2.6355e+00],
        [-1.8073e-01, -1.2490e+00, -8.2327e-01,  1.4730e+00,  5.8836e-01,
          4.1034e-03,  9.9122e-01,  2.5957e-01, -1.8716e-01],
        [ 9.1802e-01, -3.6061e-01, -8.1788e-01,  1.5692e+00, -1.1461e+00,
         -5.7984e-01,  6.7999e-01, -4.1150e-02,  1.0829e+00],
        [ 1.1454e+00, -4.3676e-01,  2.2854e+00,  1.1893e+00,  4.0966e-01,
         -1.1711e-01, -2.1936e-02, -8.4547e-01,  1.2236e-01],
        [ 1.4835e+00, -1.6104e-01,  4.8580e-02, -2.6155e+00, -1.4138e-01,
          1.0443e+00, -2.3830e-01, -1.4911e+00,  3.5307e-01],
        [ 2.0946e+00,  1.9337e+00, -2.6824e-01,  2.3089e-01,  1.1514e-03,
          2.1862e+00,  6.3311e-01, -6.1647e-01, -1.3749e+00],
        [ 1.5384e+00, -7.6717e-01, -7.3752e-01,  1.2570e+00, -5.8681e-01,
          1.3887e+00, -9.6056e-01,  4.8157e-01, -4.1506e-01],
        [ 1.1072e-01,  1.1431e+00,  2.0399e+00, -5.5736e-01,  6.7684e-01,
```

```
 -6.8097e-01, -8.7569e-01, -1.2483e+00,  7.7616e-01],
[-2.6649e-01,  7.9188e-01,  7.2701e-01,  1.7280e+00, -1.1796e+00,
  5.2148e-01, -6.1184e-01,  3.1035e-01,  9.7009e-01],
[-8.3095e-01, -1.6064e+00,  2.3667e+00, -1.2204e+00,  4.1136e-01,
 -1.4684e+00,  6.3564e-02, -1.5051e+00, -2.2001e-01],
[-5.2230e-01,  8.1375e-01,  6.1553e-01, -4.2599e-02,  1.7301e-01,
 -1.2271e-01, -2.0114e+00, -7.8907e-01, -1.2734e+00],
[ 6.8031e-01, -3.0871e-01, -3.0772e-01,  6.3263e-01,  1.5590e+00,
  2.7520e-01, -1.0685e+00,  2.7201e-01,  9.9093e-01],
[ 9.2734e-02, -1.3574e+00,  4.0598e-01,  4.9756e-01,  5.6375e-01,
 -1.1143e+00,  5.2196e-01,  1.4329e-01, -3.9328e-01],
[ 2.9002e-01,  2.9804e-01,  2.2331e+00,  2.1968e+00, -5.0351e-01,
  1.5336e-01,  4.6150e-02,  1.7698e+00, -2.8478e-01],
[ 1.2679e+00, -5.9689e-01, -1.3967e+00,  1.0058e+00,  2.8197e-01,
  1.0780e+00, -5.4874e-01, -5.0334e-01, -2.8814e-01],
[ 2.1569e+00,  6.2626e-01,  1.9641e-01, -1.5439e+00,  5.7199e-01,
 -9.1998e-01, -1.1759e+00, -7.0328e-01,  3.1153e-01],
[-2.3782e-01,  1.5635e+00, -9.9518e-01,  3.7845e-01, -1.5209e+00,
 -7.1817e-01,  3.5974e-01,  1.7197e-01,  3.6362e-01],
[ 2.2835e-01, -1.5459e+00, -9.5902e-01, -1.1907e+00, -3.7331e-01,
  5.8753e-01, -1.4671e+00, -3.0594e-01,  8.4065e-01],
[ 1.1026e+00, -8.7721e-01,  1.5426e+00,  4.4972e-01,  3.1010e-01,
  9.7017e-01,  7.8906e-01,  1.0092e+00,  2.0941e+00],
[-1.7965e+00,  1.8701e-01,  4.3996e-01,  4.6749e-01,  4.0462e-01,
  9.2346e-02, -1.9932e+00,  7.7445e-01,  7.0330e-01],
[ 1.0255e+00,  1.0959e+00,  2.6846e-01, -1.3541e+00, -6.1543e-02,
 -3.2624e-01, -7.2100e-01, -4.0800e-01,  9.1167e-01],
[ 1.0763e+00, -1.4209e+00, -5.9040e-01, -1.2943e+00,  2.4534e-01,
 -9.7199e-01, -1.7028e+00, -1.6392e+00, -1.0653e+00],
[ 2.0118e-01, -2.0262e+00,  1.3364e+00, -1.7834e+00,  6.5608e-01,
 -1.3171e+00,  8.7381e-01, -2.6745e-01,  1.3398e-01],
[ 8.5316e-01,  8.4795e-01, -1.1855e-01, -3.7457e-02,  2.4010e-01,
  2.7003e-01,  1.1791e+00,  1.0496e+00,  1.6055e+00],
[-1.3566e+00, -8.5464e-01,  8.9450e-01,  1.3328e+00,  2.9470e-01,
 -6.0269e-01, -9.7720e-01,  4.0491e-01,  1.5337e+00],
[ 1.5095e+00,  2.3863e-01,  1.1418e+00, -7.8052e-01, -2.4659e-01,
 -8.4775e-01,  3.0722e-01,  6.8697e-01,  8.0159e-02],
[-1.3932e+00, -6.0093e-01, -8.3311e-01,  2.6036e-01, -6.4276e-01,
  3.4897e-01, -1.7955e+00, -7.9129e-01,  1.5356e-01]])
```

[10]:
```
# En multipliant ces "poids" par nos vecteurs one-hot organisés en matrice...
# On obtient des valeurs que l'on va "interpréter" comme des logs (log-counts).
# En utilisant l'exponentielle de ces valeurs, on va retrouver quelque chose
# d'équivalent à la matrice N que nous avions définie précédemment dans la␣
 ↪méthode
# par comptage.
xenc @ W
```

[10]:
```
tensor([[ 0.9184, -1.1502, -0.8363,  1.5226,  0.8434,  0.3710,  1.8180, -0.6987,
          1.1443],
        [ 0.2640, -0.1092,  0.5762,  0.1440,  0.7639,  0.3053, -0.7356, -0.9621,
          0.3534],
        [ 0.1261,  0.8596, -0.7190, -2.6217,  0.4382,  2.3034, -1.7862,  0.3502,
          0.9571],
        [ 0.1261,  0.8596, -0.7190, -2.6217,  0.4382,  2.3034, -1.7862,  0.3502,
          0.9571],
        [ 0.6582, -0.7624, -0.0851, -1.5097,  0.3336, -0.0473, -0.5248,  1.1375,
         -0.3833],
        [ 1.1454, -0.4368,  2.2854,  1.1893,  0.4097, -0.1171, -0.0219, -0.8455,
          0.1224],
        [ 0.1107,  1.1431,  2.0399, -0.5574,  0.6768, -0.6810, -0.8757, -1.2483,
          0.7762],
        [ 1.1026, -0.8772,  1.5426,  0.4497,  0.3101,  0.9702,  0.7891,  1.0092,
          2.0941],
        [ 0.6582, -0.7624, -0.0851, -1.5097,  0.3336, -0.0473, -0.5248,  1.1375,
         -0.3833]])
```

[11]:
```
logits = xenc @ W # log-counts
counts = logits.exp() # statut équivalent à N
probs = counts / counts.sum(1, keepdims=True) # distribution de probabilités␣
 ↪(equ. à p)
probs
```

[11]:
```
tensor([[0.1170, 0.0148, 0.0202, 0.2141, 0.1086, 0.0677, 0.2877, 0.0232,
0.1467],
        [0.1192, 0.0821, 0.1629, 0.1057, 0.1965, 0.1243, 0.0439, 0.0350,
0.1304],
        [0.0573, 0.1193, 0.0246, 0.0037, 0.0783, 0.5053, 0.0085, 0.0717,
0.1315],
        [0.0573, 0.1193, 0.0246, 0.0037, 0.0783, 0.5053, 0.0085, 0.0717,
0.1315],
        [0.1879, 0.0454, 0.0893, 0.0215, 0.1358, 0.0928, 0.0576, 0.3034,
0.0663],
        [0.1439, 0.0296, 0.4501, 0.1504, 0.0690, 0.0407, 0.0448, 0.0197,
0.0518],
        [0.0625, 0.1756, 0.4304, 0.0321, 0.1101, 0.0283, 0.0233, 0.0161,
0.1216],
        [0.1126, 0.0156, 0.1749, 0.0586, 0.0510, 0.0987, 0.0823, 0.1026,
0.3036],
        [0.1879, 0.0454, 0.0893, 0.0215, 0.1358, 0.0928, 0.0576, 0.3034,
0.0663]])
```

Réseau de neurones sur cet exemple

[12]:
```
# Initialisation de "nb_chars" poids de neurones
g = torch.Generator().manual_seed(2147483647)
```

```
W = torch.randn((nb_chars, nb_chars), generator=g, requires_grad=True)
```

[13]:
```
# Réseau à une couche (probs)
xenc = F.one_hot(xs, num_classes=nb_chars).float() # input to the network:␣
 ↪one-hot encoding
logits = xenc @ W  # predict log-counts
counts = logits.exp() # counts, equivalent to N
probs = counts / counts.sum(1, keepdims=True)  # probabilities for next␣
 ↪character
# btw: the last 2 lines here are together called a 'softmax'
```

[14]:
```
nlls = torch.zeros(5)
for i in range(5):
    # i-th bigram:
    x = xs[i].item() # input character index
    y = ys[i].item() # label character index
    print('--------')
    print(f'bigram example {i+1}: {itoc[x]}{itoc[y]} (indexes {x},{y})')
    print('input to the neural net:', x)
    print('output probabilities from the neural net:', probs[i])
    print('label (actual next character):', y)
    p = probs[i, y]
    print('probability assigned by the net to the the correct character:', p.
 ↪item())
    logp = torch.log(p)
    print('log likelihood:', logp.item())
    nll = -logp
    print('negative log likelihood:', nll.item())
    nlls[i] = nll

print('=========')
print('average negative log likelihood, i.e. loss =', nlls.mean().item())
```

```
--------
bigram example 1: .a (indexes 0,3)
input to the neural net: 0
output probabilities from the neural net: tensor([0.0495, 0.0081, 0.0100,
0.0034, 0.0137, 0.0100, 0.0022, 0.0189, 0.0112,
        0.0255, 0.0064, 0.0227, 0.0074, 0.0067, 0.0407, 0.1939, 0.0492, 0.0020,
        0.0203, 0.0045, 0.0276, 0.0089, 0.0023, 0.0162, 0.0096, 0.1253, 0.1189,
        0.0053, 0.0030, 0.0140, 0.0035, 0.0214, 0.0109, 0.0382, 0.0046, 0.0044,
        0.0017, 0.0361, 0.0030, 0.0348, 0.0039], grad_fn=<SelectBackward0>)
label (actual next character): 3
probability assigned by the net to the the correct character:
0.003431369084864855
log likelihood: -5.674796104431152
negative log likelihood: 5.674796104431152
--------
```

```
bigram example 2: ac (indexes 3,5)
input to the neural net: 3
output probabilities from the neural net: tensor([0.0017, 0.0064, 0.0258,
0.0032, 0.0085, 0.0247, 0.0371, 0.0103, 0.0104,
        0.0024, 0.0027, 0.0207, 0.0226, 0.0620, 0.0193, 0.0406, 0.1549, 0.0225,
        0.0073, 0.0261, 0.0076, 0.0234, 0.0546, 0.0178, 0.0089, 0.0141, 0.0084,
        0.0245, 0.0226, 0.0035, 0.0713, 0.0167, 0.0378, 0.0234, 0.0390, 0.0021,
        0.0092, 0.0017, 0.0368, 0.0490, 0.0181], grad_fn=<SelectBackward0>)
label (actual next character): 5
probability assigned by the net to the the correct character:
0.024747123941779137
log likelihood: -3.6990458965301514
negative log likelihood: 3.6990458965301514
--------
bigram example 3: cc (indexes 5,5)
input to the neural net: 5
output probabilities from the neural net: tensor([0.0355, 0.0383, 0.0081,
0.0299, 0.0039, 0.0132, 0.0410, 0.0156, 0.0065,
        0.0104, 0.0081, 0.0344, 0.0140, 0.0583, 0.0237, 0.0640, 0.0057, 0.0073,
        0.0205, 0.0083, 0.0115, 0.0048, 0.0567, 0.0031, 0.0105, 0.0059, 0.0147,
        0.0128, 0.0543, 0.0087, 0.0325, 0.0304, 0.1164, 0.0116, 0.0171, 0.0283,
        0.0362, 0.0034, 0.0144, 0.0673, 0.0128], grad_fn=<SelectBackward0>)
label (actual next character): 5
probability assigned by the net to the the correct character:
0.013233082368969917
log likelihood: -4.325035572052002
negative log likelihood: 4.325035572052002
--------
bigram example 4: ce (indexes 5,7)
input to the neural net: 5
output probabilities from the neural net: tensor([0.0355, 0.0383, 0.0081,
0.0299, 0.0039, 0.0132, 0.0410, 0.0156, 0.0065,
        0.0104, 0.0081, 0.0344, 0.0140, 0.0583, 0.0237, 0.0640, 0.0057, 0.0073,
        0.0205, 0.0083, 0.0115, 0.0048, 0.0567, 0.0031, 0.0105, 0.0059, 0.0147,
        0.0128, 0.0543, 0.0087, 0.0325, 0.0304, 0.1164, 0.0116, 0.0171, 0.0283,
        0.0362, 0.0034, 0.0144, 0.0673, 0.0128], grad_fn=<SelectBackward0>)
label (actual next character): 7
probability assigned by the net to the the correct character:
0.01563512347638607
log likelihood: -4.158235549926758
negative log likelihood: 4.158235549926758
--------
bigram example 5: ep (indexes 7,17)
input to the neural net: 7
output probabilities from the neural net: tensor([0.0579, 0.0032, 0.0506,
0.0075, 0.0371, 0.0182, 0.0344, 0.0079, 0.0179,
        0.0157, 0.0043, 0.0297, 0.0035, 0.0061, 0.0524, 0.0082, 0.0414, 0.0450,
        0.0362, 0.0097, 0.0044, 0.0414, 0.0829, 0.0135, 0.0096, 0.0334, 0.0228,
```

```
        0.0134, 0.0243, 0.0257, 0.0424, 0.0110, 0.0411, 0.0228, 0.0270, 0.0017,
        0.0121, 0.0113, 0.0182, 0.0468, 0.0071], grad_fn=<SelectBackward0>)
label (actual next character): 17
probability assigned by the net to the the correct character:
0.04502563923597336
log likelihood: -3.1005232334136963
negative log likelihood: 3.1005232334136963
=========
average negative log likelihood, i.e. loss = 4.191527366638184
```

Optimization sur un mot

[36]:
```
# forward pass
xenc = F.one_hot(xs, num_classes=nb_chars).float() # input to the network:␣
 ↪one-hot encoding
logits = xenc @ W # predict log-counts
counts = logits.exp() # counts, equivalent to N
probs = counts / counts.sum(1, keepdims=True) # probabilities for next character
loss = -probs[torch.arange(tensor_dims), ys].log().mean()
```

[37]:
```
print(loss.item())
```

```
3.725316047668457
```

[38]:
```
# backward pass
W.grad = None # set to zero the gradient
loss.backward()
```

[39]:
```
W.data += -0.1 * W.grad
# ^^ loop above from forward pass and see loss decreasing
```

1.2.2 Synthèse: apprentissage complet

[40]:
```
#
# Générateur des mots selon notre modèle de langue génératif bigrams par réseau␣
 ↪de neurones
#
import torch

# Lecture des données
EOS='.'
words = open('civil_mots.txt', 'r').read().splitlines()
chars = sorted(list(set(''.join(words))))
nb_chars = len(chars) + 1  # On ajoute 1 pour EOS

# Dictionnaires caractère <-> entier
ctoi = {c:i+1 for i,c in enumerate(chars)}
ctoi['.'] = 0
itoc = {i:c for c,i in ctoi.items()}# Création du dataset avec tous les mots
```

```
# Génération du jeu d'entraînement
xs, ys = [], []
for w in words:
    chs = ['.'] + list(w) + ['.']
    for ch1, ch2 in zip(chs, chs[1:]):
        ix1 = ctoi[ch1]
        ix2 = ctoi[ch2]
        xs.append(ix1)
        ys.append(ix2)
xs = torch.tensor(xs)
ys = torch.tensor(ys)
num = xs.nelement()
print('NB exemples:', num)

# Initialisation du réseau (une seule couche de neurones sans biais)
g = torch.Generator().manual_seed(2147483647)
W = torch.randn((nb_chars, nb_chars), generator=g, requires_grad=True)
```

```
NB exemples: 67652
```

[41]:
```
# Apprentissage: descente du gradient
for k in range(600):

  # Forward pass
  xenc = F.one_hot(xs, num_classes=nb_chars).float() # input to the network: one-hot encoding
  logits = xenc @ W # predict log-counts (logits)
  counts = logits.exp() # counts, equivalent to N
  probs = counts / counts.sum(1, keepdims=True) # probabilities for next character
  loss = -probs[torch.arange(num), ys].log().mean() + 0.01*(W**2).mean()  # + 0.01... for smoothing the model
  print(loss.item())

  # backward pass
  W.grad = None # set to zero the gradient
  loss.backward()

  # update
  W.data += -50 * W.grad
```

```
4.268752574920654
3.8354008197784424
3.5137295722961426
3.2882258892059326
3.136672258377075
3.0282742977142334
```

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2.3835878372192383
2.383578300476074
2.38356876373291
2.383559465408325
2.383549928665161
2.383540630340576
2.383531332015991
2.3835220336914062
2.3835127353668213
2.3835034370422363
2.3834943771362305
2.3834853172302246
2.3834760189056396
2.383467197418213
2.383457899093628
2.383448600769043
2.3834400177001953
2.3834309577941895
2.383422374725342
2.383413553237915
2.383404493331909
2.3833956718444824
2.3833870887756348
2.383378505706787
2.3833696842193604
2.3833611011505127
2.383352279663086

```
2.3833439350128174
2.3833351135253906
2.383326768875122
2.3833186626434326
2.3833096027374268
2.3833014965057373
2.3832931518554688
2.3832848072052
2.3832764625549316
2.383268117904663
2.3832600116729736
2.383251667022705
2.3832435607910156
2.383235454559326
2.3832273483276367
2.3832192420959473
2.383211135864258
2.3832032680511475
```

[42]:
```python
# finally, sample from the 'neural net' model
g = torch.Generator().manual_seed(2147483647)

for i in range(5):

  out = []
  ix = 0
  while True:

    # ----------
    # Avec l'approche par comptage on utilisait:
    #p = P[ix]
    # ----------
    # NOW:
    xenc = F.one_hot(torch.tensor([ix]), num_classes=nb_chars).float()
    logits = xenc @ W # predict log-counts
    counts = logits.exp() # counts, equivalent to N
    p = counts / counts.sum(1, keepdims=True) # probabilities for next character
    # ----------

    ix = torch.multinomial(p, num_samples=1, replacement=True, generator=g).
 ↪item()
    out.append(itoc[ix])
    if ix == 0:
      break
  print(''.join(out))
```

```
éssanée.
mexcororér.
```

```
monts.
ex.
moût.
```

On voit qu'on a les mêmes mots que ceux générés par comptage, nous avons donc bâti une méthode neuronale équivalente à ce qu'on obtient par la méthode par comptage.