

- Contents:

1. Packages

2. Dataset

- cat vs non-cat

- train set of m train images labelled as cat (1)/non-cat(0)

- test set of m test images

- image shape: $(\text{num_px}, \text{num_py}, 3) \rightarrow 3$ channels

- Reshape & standardise images

• into vector & ~~flatten~~ make values 0 & 1

3. Model architecture

- 2 models: 2-layer NN, L-layer NN

3.1. 2-layer NN

- Input: $(64, 64, 3)$ image, flattened to a $(12288, 1)$ vector

- $[x_0, x_1, \dots, x_{12287}]^T$ multiplied by W^{E1} of size $(n^{E1}, 12288)$

- Add bias term & take its relu to get $[a_0^{E1}, a_1^{E1}, \dots, a_{n^{E1}-1}^{E1}]^T$

- Repeat

- Multiply resulting vector by W^{E2} and add bias

- Take sigmoid of result; if > 0.5 , then cat

3.2. L-layer NN

- Same input

- Same vector multiplied by W^{E1} & add b^{E1} ; result is the linear unit

- Take ReLU of LU; repeat many times for each W^{E1}, b^{E1} , depending on model architecture

- Take sigmoid of final LU; if > 0.5 , then cat

3.3. General methodology

- DL methodology:

1. Initialise params. / define hyperparameters.

2. Loop for num_iterations:

a. For. prop.

b. Compute CF

c. Backprop.

d. Update params. Using parameters & grads from backprop

3. Use trained params. to predict label