

1.5. Broadcasting and the softmax function

$$x_exp = np.exp(x)$$

$$x_sum = np.sum(x_exp, axis=1, keepdims=True)$$

$$s = x_exp / x_sum$$

→ Works due to broadcasting

2. Vectorisation

- Vectorised implementation is cleaner and more efficient

2.1. L1 & L2 loss functions

$$- L_1(\hat{y}, y) = \sum_{i=0}^m |y^{(i)} - \hat{y}^{(i)}|$$

$$loss = np.sum(np.abs(y - y_hat))$$

$$- L_2(\hat{y}, y) = \sum_{i=0}^m (y^{(i)} - \hat{y}^{(i)})^2$$

$$loss = np.sum((y - y_hat)**2)$$

Notebook: Log. Reg. w/ or NN mindset

- Image recognition: cat classifier

- h5py: package to interact w/ a dataset that's stored on an H5 file

- train. set of m_train images ($y=1$ or $y=0$)

- test set of m_test images (cat or non-cat)

- image shape: $(num_px, num_px, 3)$ (square)

- `_orig` (for preprocessing)

- Reshape: $X_flatten = X.reshape(X.shape[0], -1).T$

- Common preprocessing steps:

- Find dimensions and shapes of the problem (m_train, m_test)
- Reshape ~~so~~ that each example is a row of size $(num_px * num_px * 3)$
- "Standardize" the data