Team Raspberry - Image Classification

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Overview

Methods

Data representation

- Treat every image as a 3D-tensor (RGB)
  - Repeat the value of grayscale images three times
  - Colorized are handled as the original tensors
- Original data has 14 labels, we used 15
  - Extra one for the unclassified images
  - One-hot encoded labels

Methods

Data processing

- Read images in batches of size 2000
  - Helps to avoid filling the RAM
- Normalize the pixel values between $[0.0, 1.0]$
- For every batch augmenting the data
  - Provided by Keras
  - Centerify, shear, zoom, rotate and flip
  - To get more variation and samples from classes with few labels

Methods

Class weights 1/2

- Classes are very unbalanced

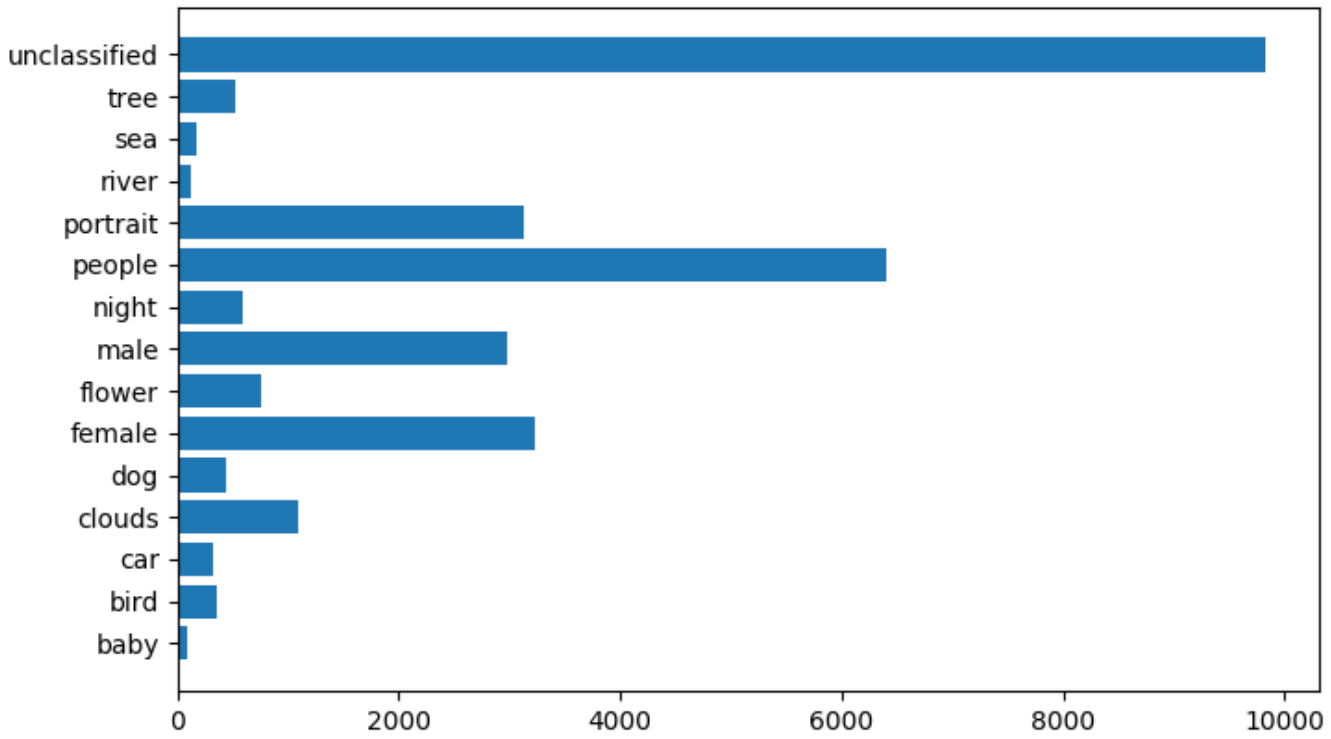


Figure: Class distribution

Methods

Class weights 2/2

- We tackled this problem by custom weights per class
  - Giving them at training phase

Class weight function

$$S(c_i; \lambda) = \ln\left(\lambda \frac{\sum_c |c|}{|c_i|}\right)$$

$$W(c_i; \lambda) = \max(S(c_i; \lambda), 1)$$

Methods

Network topology

- One network that outputs 15 classes
- Four convolution layers all followed by max pooling
  - Filters 16, 32, 32, 64
  - Kernel size $3x3$
  - Max pool size $2x2$
  - ReLU as activation function
- After pooling flattening via dropout to dense layer with sigmoid activation
  - Dropout value: 0.4
- Very simple network

Methods

Loss function 1/2

- Categorical crossentropy wouldn't work as one image can be in many classes
- Binary crossentropy was suggested in many forum posts
  - Still not viable solution when there are many overlapping categories
  - Loss is too forgiving for giving 0 labels

Methods

Loss function 2/2

- Solution: "custom" loss function **BP-MLL***
  - Actually taken directly from the paper [1]†
  - Designed for multi-label problems
  - Implementation for Keras can be found from internet
  - Punishes more from just giving 0 labels

$$E = \sum_{i=1}^{m} \frac{1}{|Y_i||\bar{Y}_i|} \sum_{(k,l)\in Y_i \times \bar{Y}_i} \exp(-(c_k^i - c_l^i))$$

*Backpropagation for Multilabel Learning

†[1] *Multilabel Neural Networks with Applications to Functional Genomics and Text Categorization*, 2006

Methods

Validation

- Per batch, 10% of the data is randomly selected
- This subset is left out from the training phase
- Validated against in the final step
- With F1-score, we also inspected
  - Binary accuracy
  - Categorical accuracy
  - Hamming loss
  - Micro averaged precision score

Parametrization

Tweaks

1. "Default"
2. Increased deeply-connected layers
3. Adagrad optimizer
4. Nadam optimizer
5. More convolutions
6. Even more convolutions
7. Reverse convolution triangle
8. Learning Rate Adjustments
    1. `lr=0.0005`
    2. `lr=0.000333`
    3. `lr=0.002`
    4. `lr=0.005`
9. Activation Functions
    1. Leaky ReLU ($\alpha = 0.3$)
    2. `tanh`

Parametrization

Results

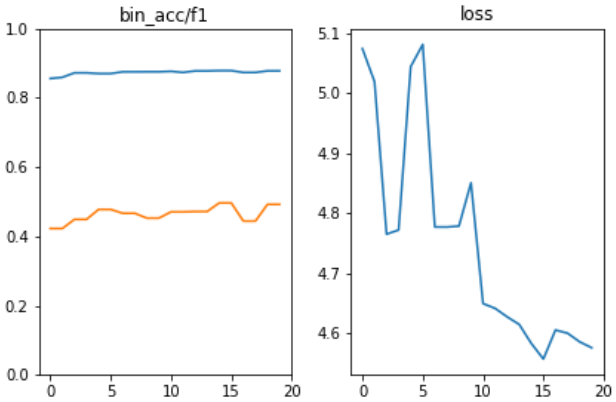
Model n.	F1	HL‡
1	0.462	0.125
2	0.452	0.128
3	0.459	0.125
4	0.469	0.123
5	0.462	0.124
6	0.462	0.126
7	0.463	0.125
8.1	0.464	0.124
8.2	0.457	0.126
8.3	0.465	0.124
8.4	0.457	0.125
9.1	0.083	0.796
9.2	0.378	0.184

‡Hamming Loss

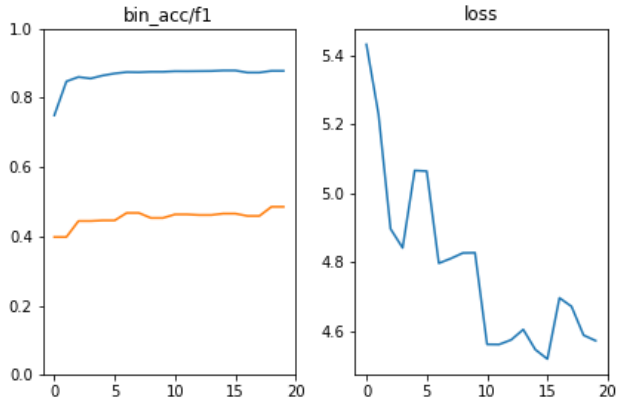
Parametrization

Training

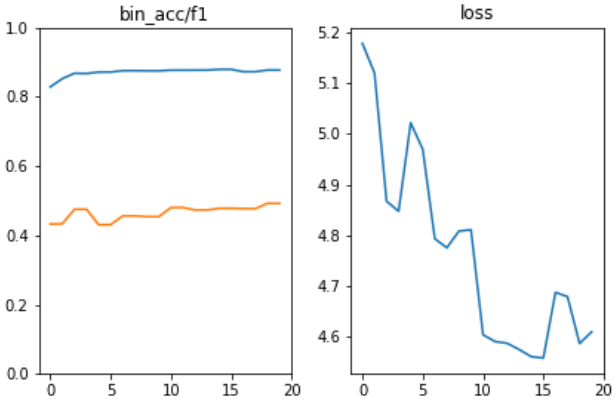
(a) "Default" (1)



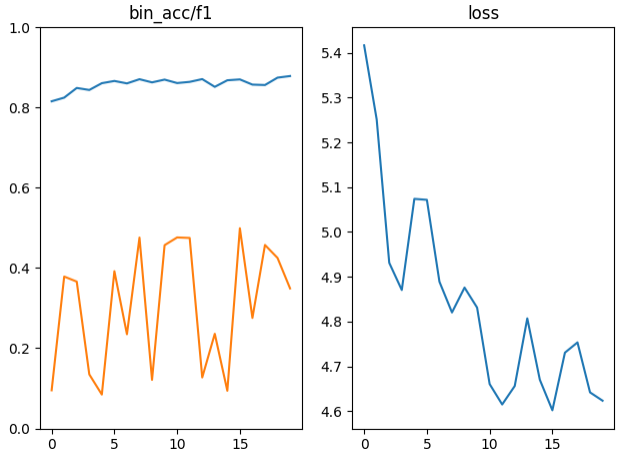
(b) More Dense Layers (2)



(c) More Convolutional Layers (6)



(d) `tanh` (9.2)



Final System

Hyper-parameters of the final system

- Same as described in Methods section
- 1 epoch
- **BP-MLL** Loss
- RMSprop optimizer (learning rate of 0.002 [twice default])

Results

Accuracy and Loss

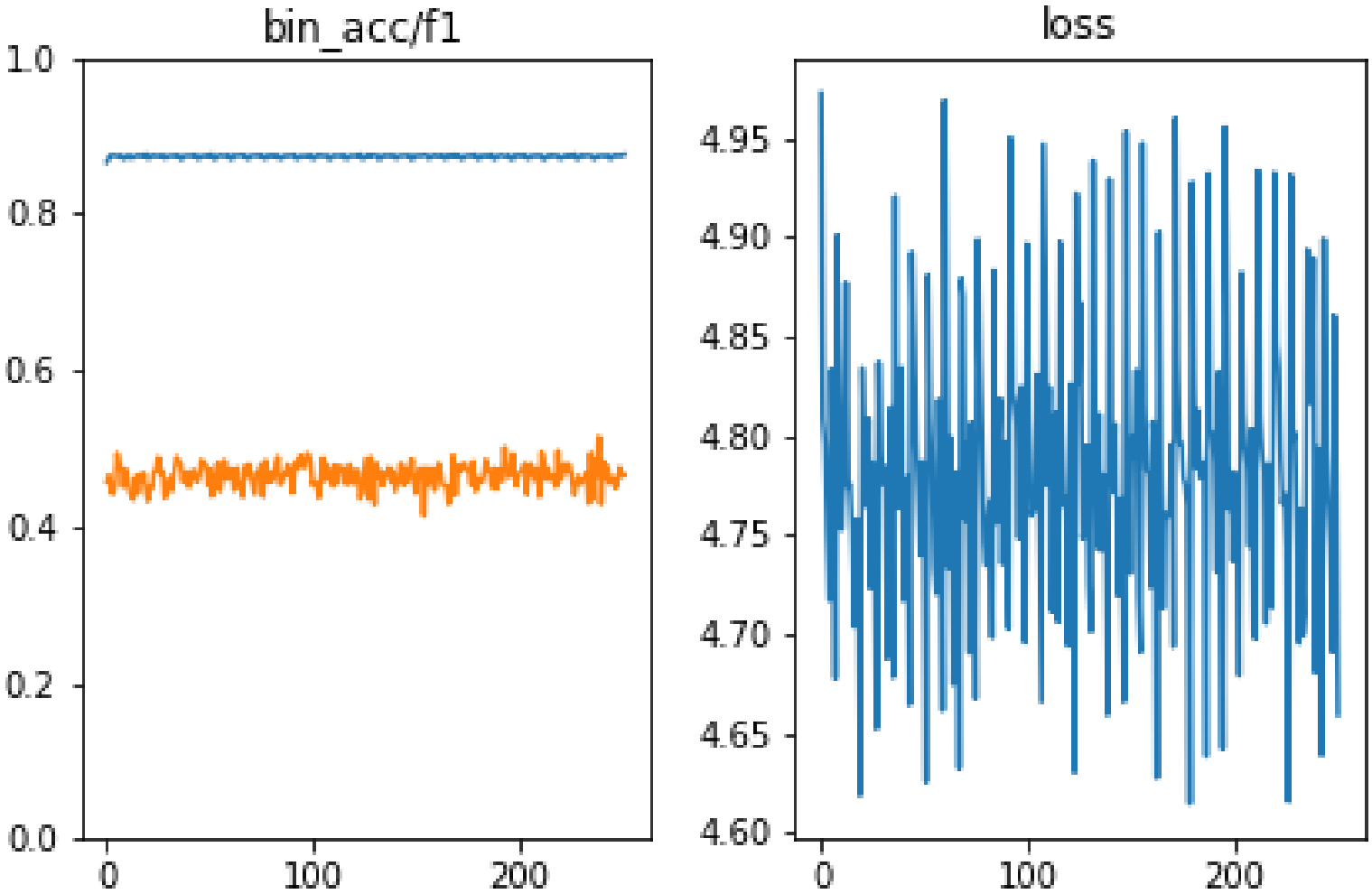


Figure: Final Model (trained over 250 epochs)

Results

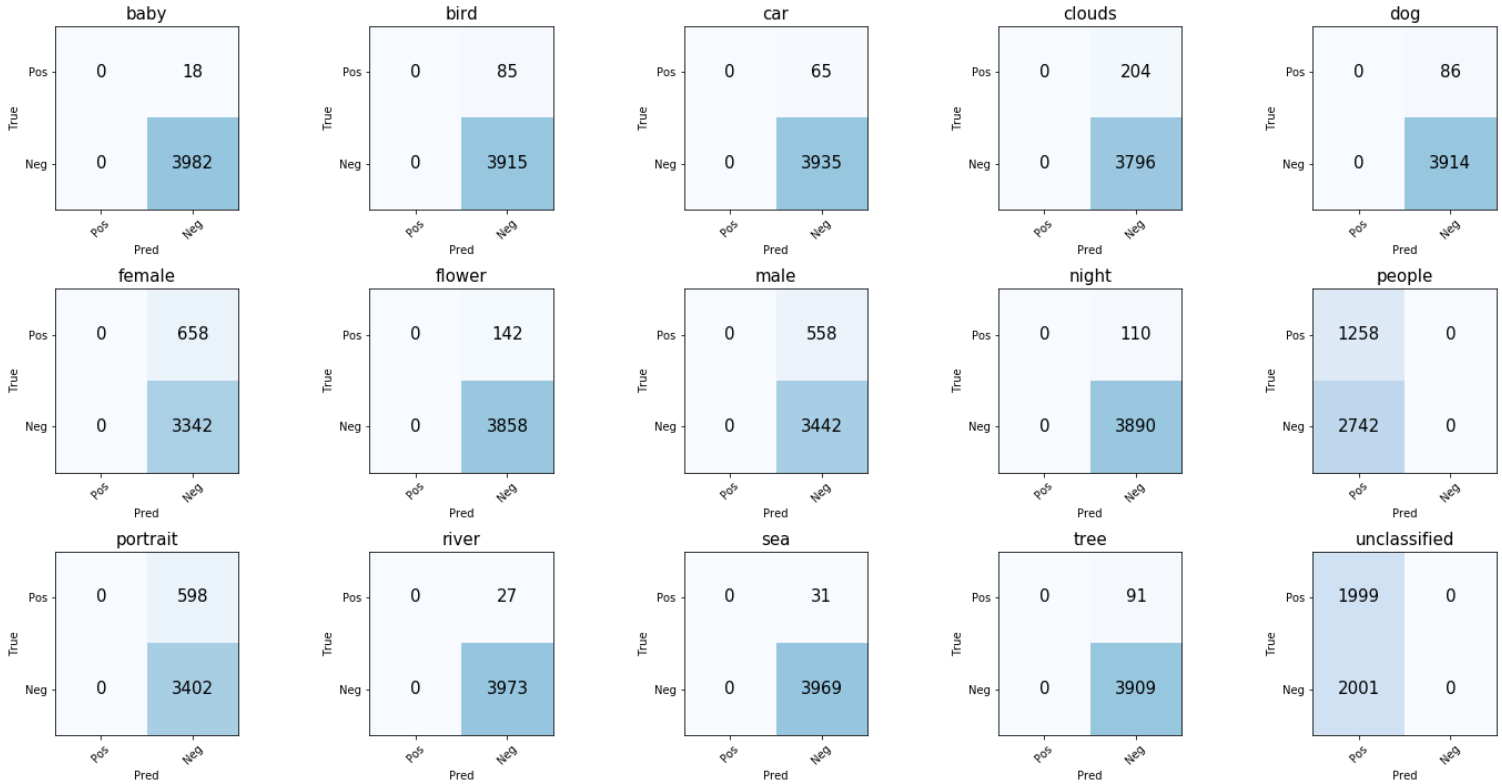
Sample Output

```
0 0 0 0 0 0 0 0 0 1 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 1 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 1 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 1 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 1 0 0 0 0
0 0 0 0 0 0 0 0 0 1 0 0 0 0
```

. . .

Results

Confusion Matrix



- Always predicts same result for each label on every picture