MATCHING NETWORKS FOR ONE SHOT LEARNING

CONTENTS

- Overview of Few shot learning
- Techniques
- Difference between supervised and one shot learning
- N-way K-shot learning
- Contributions
- Matching nets
- Differentiable Nearest neighbour
  - FCE
  - Attention Kernel
- Training strategy

OVERVIEW OF FEW SHOT LEARNING

Recognize a person/object given just few images of it.

Inspired from how a child able to distinguish a zebra and elephant by just looking at few images.

TECHNIQUES(IN PAPER)

- One shot Learning with attention and memory.
- Uniform training and testing strategy.(training goals and testing goals are same)

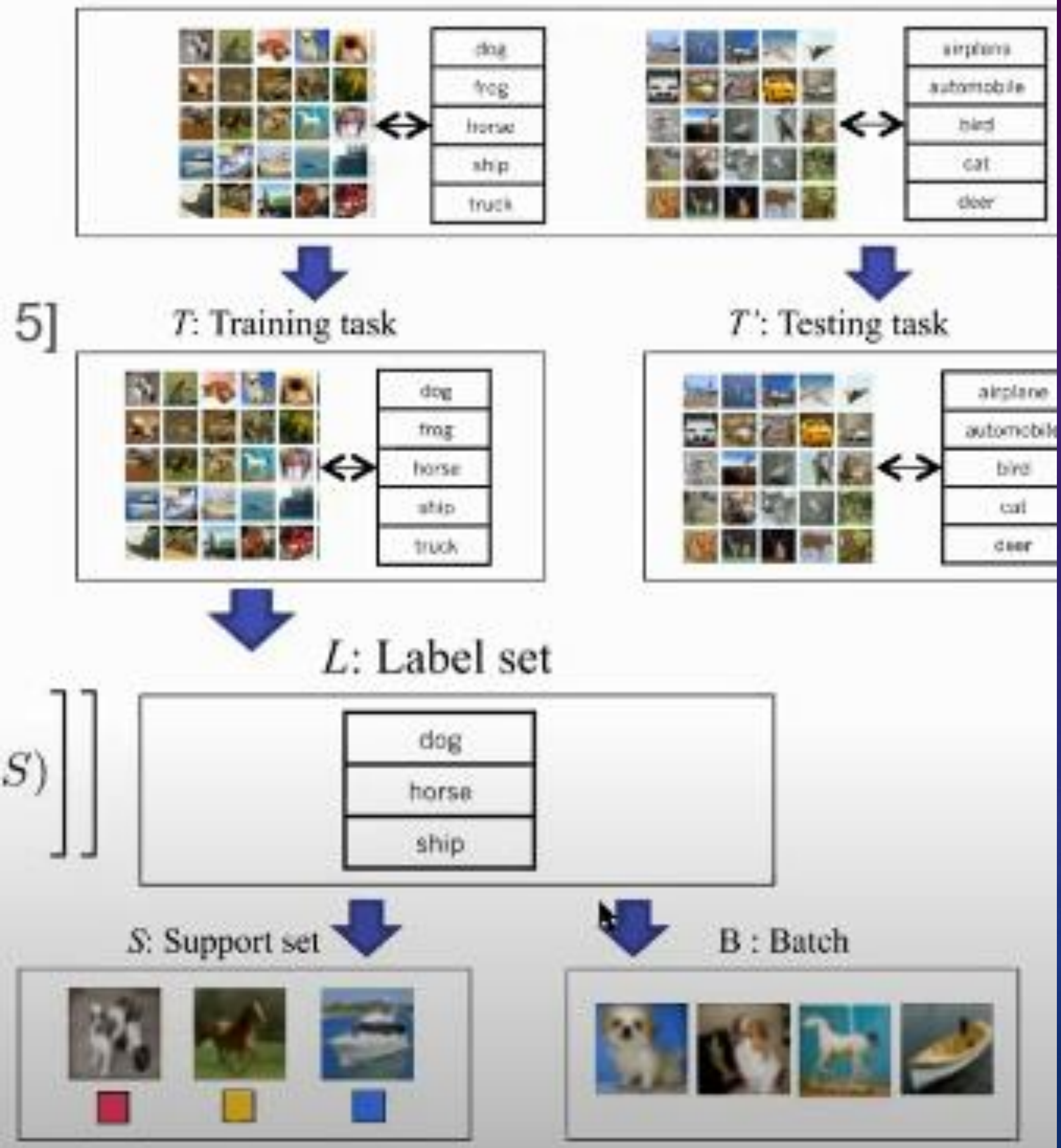
DIFFERENCE BETWEEN SUPERVISED AND ONE-SHOT LEARNING

Supervised learning

- Train image in 'S' label space and try to match a new image to the same 'S' label space.

One-shot learning

- Train image in 'S1' label space and match a new image to different 'S2' label space
- **Idea:** A single image of zebra is enough to distinguish with our objects for humans



N-WAY K-SHOT LEARNING

- Model trained on different label space
- A subset of label set is taken and support set an batch set are created.
- K represents number of examples in support set per each class.
- N represents number of classes in support set.
- In given image it's 3-way 1 shot learning

MATCHING NETS

Combine both embedding and classification to form an end to end differentiable nearset neighbour classifier.

Steps:

- Embed a high dimensional sample into a low dimensional space(FCE)
- Perform a generalised form of nearest neighbours classification(Similarity function)

MATCHING NETS

Parametric models:

- Class props are slowly learnt by models into it's parameters.(Deep learning, traditional ml algo's)

Non Parametric models:

- Doesn't require any training
- Performance depends on the chosen metric.

ARCHITECTURE

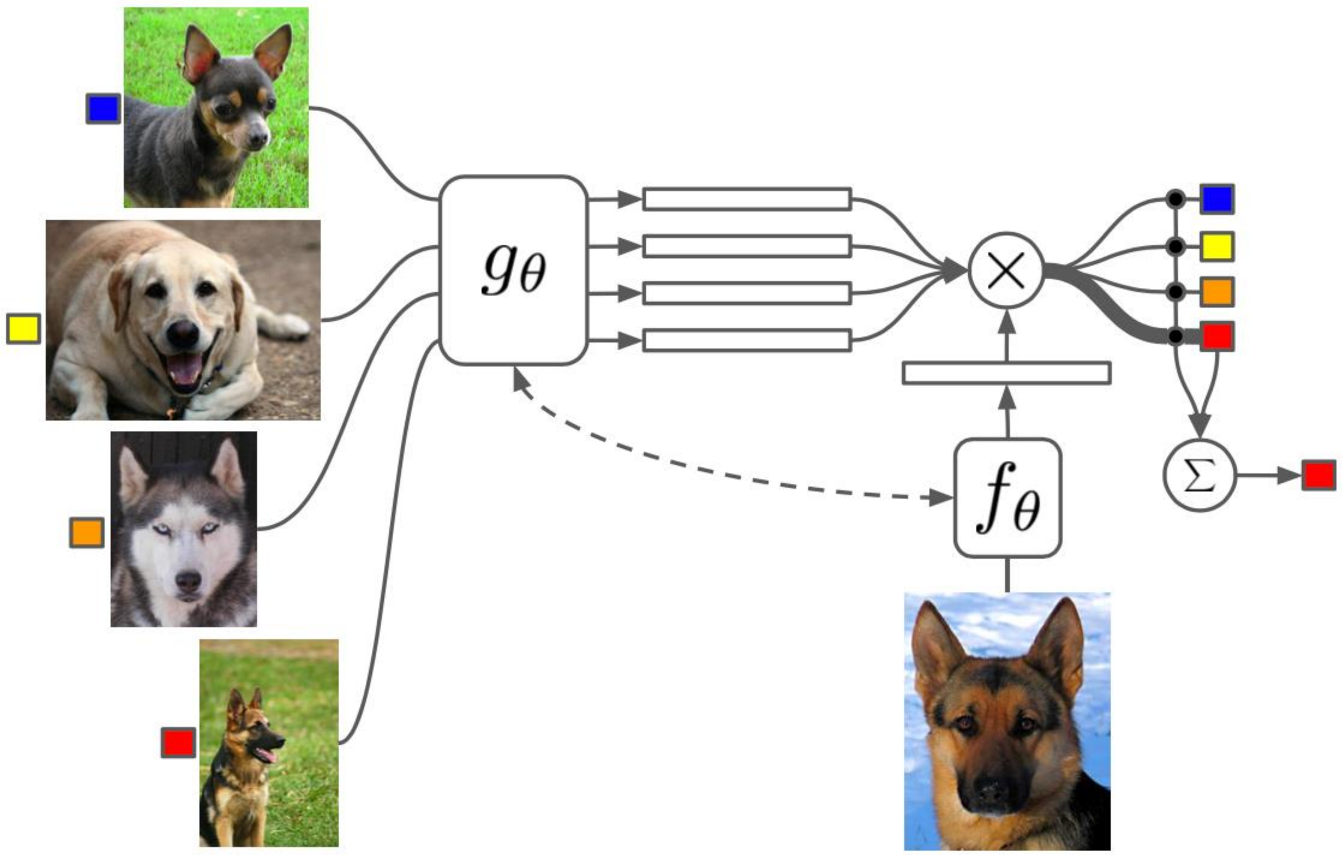


Figure 1: Matching Networks architecture

- All support set embedding are created.
- Query image embedding is formed.
- Calculates distance between them.
- Nearest class is outputed

TERMINOLOGIES

Y^ - Prediction of the model

X^ - Query example

Y_I - support set label - one hot encoded label vectors

X_I – Support set example

A(X^,X_i) - Pairwise similarity function between query example, support set examples – attention function.

Embedding function used - VGG/Inception

Attention function used

- **C :** Cosine similarity
- F,g : embedding functions for the query and support samples.

FCE

G – embedding of support set, Encode each support sample in context of it's neighbours within support set(S).

F - Embedding of tragets, Encode targets in context of it's support

ATTENTION KERNEL

- Softmax over cosine diatnce between f(x,S) and g(X_i) : distance between target embedding and support sample embedding.

MATCHING NETS ON COVIDXCT

```
Epoch 20:  95%|| 95/100 [00:17<00:00,  5.86it/s, loss=0.38, categorical_accuracy=1]

Epoch 20:  96%|| 96/100 [00:17<00:00,  7.69it/s, loss=0.38, categorical_accuracy=1]

Epoch 20:  96%|| 96/100 [00:17<00:00,  7.69it/s, loss=0.376, categorical_accuracy=1]

Epoch 20:  97%|| 97/100 [00:17<00:00,  7.69it/s, loss=0.53, categorical_accuracy=0.867]

Epoch 20:  98%|| 98/100 [00:17<00:00,  7.23it/s, loss=0.53, categorical_accuracy=0.867]

Epoch 20:  98%|| 98/100 [00:17<00:00,  7.23it/s, loss=0.471, categorical_accuracy=0.933]

Epoch 20:  99%|| 99/100 [00:17<00:00,  7.23it/s, loss=0.378, categorical_accuracy=1]

Epoch 20: 100%|| 100/100 [00:33<00:00,  2.76s/it, loss=0.378, categorical_accuracy=1]

Epoch 20: 100%|| 100/100 [00:33<00:00,  2.95it/s, loss=0.424, categorical_accuracy=0.965]
Finished.
```

CROSS VALIDATION ON COVIDXCT

ENSURED BELOW THINGS

01

No Data leakage

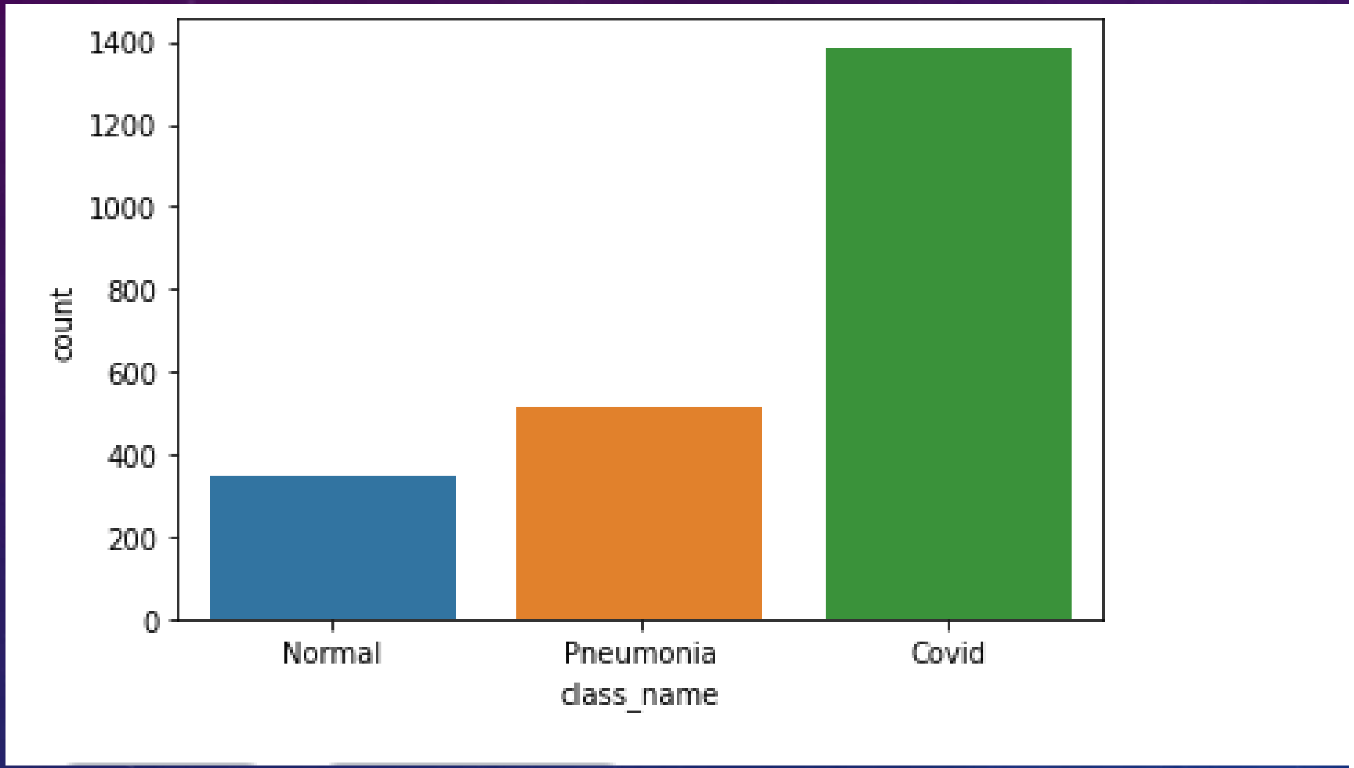
02

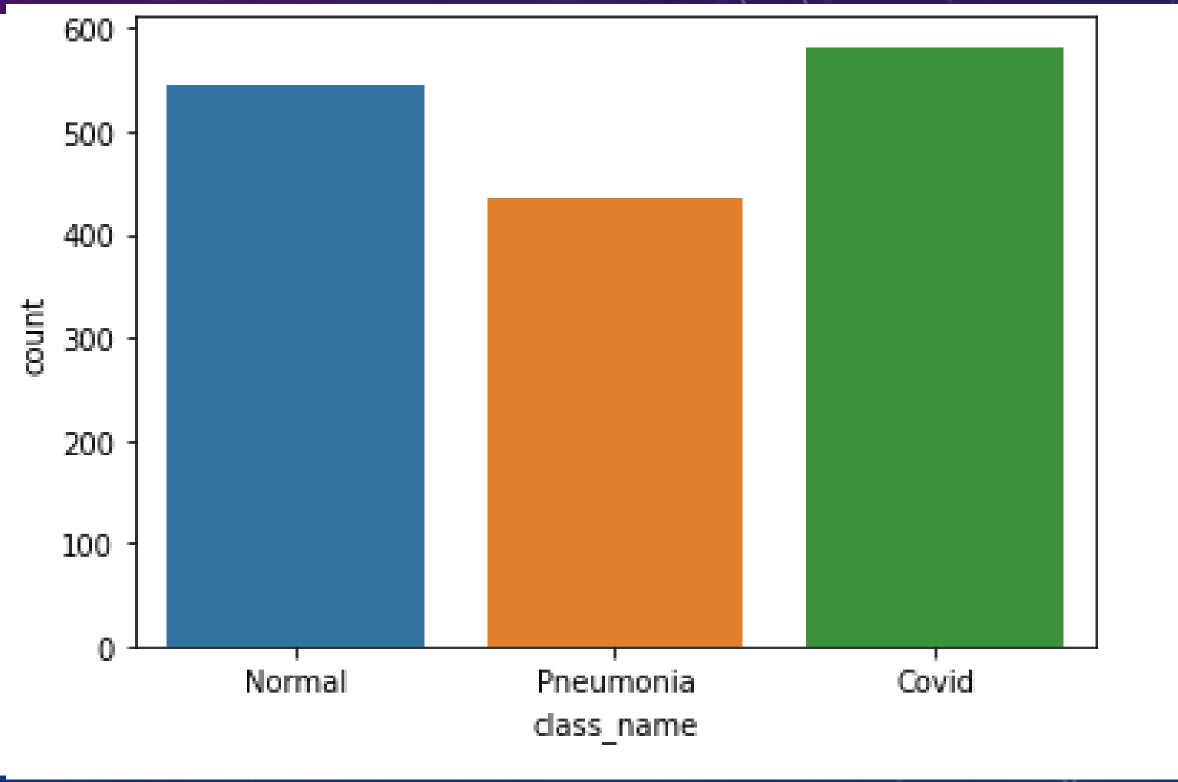
Ensure class ratio while splitting

03

Reduce the class imbalance

A person can't have covid and non coivd images


1400
1200
1000
800
600
400
200
0
count
Normal
Pneumonia
Covid
class_name


600
500
400
300
200
100
0
count
Normal
Pneumonia
Covid
class_name

```
Confusion Matrix

[[5 0 0]
 [0 5 0]
 [4 0 1]]

Accuracy: 0.73

Micro Precision: 0.73
Micro Recall: 0.73
Micro F1-score: 0.73

Macro Precision: 0.85
Macro Recall: 0.73
Macro F1-score: 0.68

Weighted Precision: 0.85
Weighted Recall: 0.73
Weighted F1-score: 0.68

Classification Report

              precision    recall  f1-score   support

     Class 1       0.56      1.00      0.71         5
     Class 2       1.00      1.00      1.00         5
     Class 3       1.00      0.20      0.33         5

    accuracy                           0.73        15
   macro avg       0.85      0.73      0.68        15
```

```
Epoch 20: 100%|██████████| 100/100 [00:12<00:00,  7.73it/s, loss=0.524, categorical_accuracy=0.937]
Finished.
```