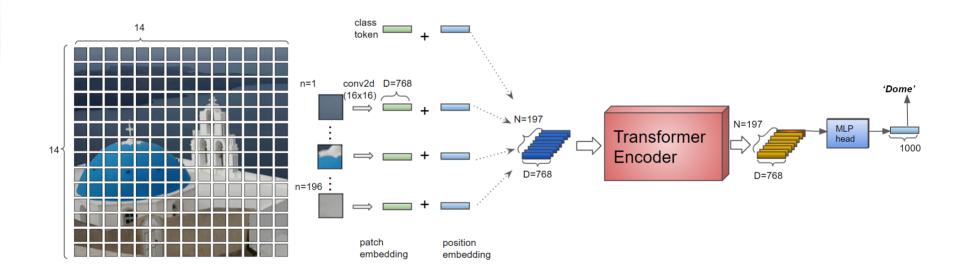


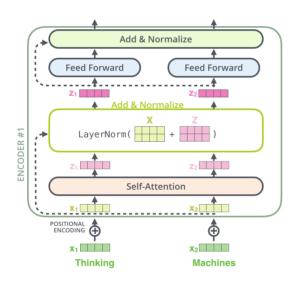
Executive Summary

- → In this project the Vision Transformer(ViT) paper is studied and implemented.
- → A classification task on a new dataset is carried out to test the performance of ViT as backbone.
- → The positional embedding and attention matrix are also studied.

ViT – Vision Transormer



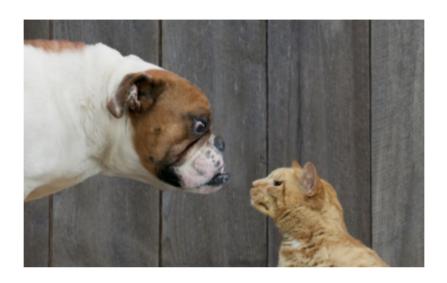
Transformer in ViT



Transformer Encoder L × + MLP Norm Multi-Head Attention Norm Embedded

Patches

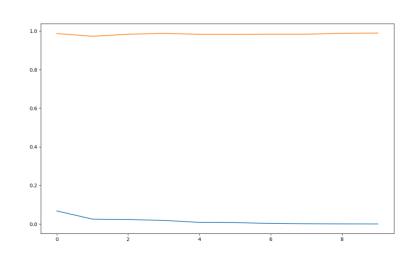
Classification - Dataset



- → A dogs vs. cats competition that still accepts test submissions
- → The dataset is slightly different from the competition on Kaggle
- → Train set: 20k images
- → Validation set: 2k images
- → Test set: 2k images

Classification – Fine Tune

- → Pre-trained model: jx_vit_base_p16_224-80ecf9dd.pth
- → Replace the head with one FC layer, the weight is [2,768] where 768 is the dim of the output of Transformer
- → First experiment: All weights in the model except for the ones in the head is fixed
- → Fine Tune: All weights in the model are trainable
- → Settings
 - → 5 epochs
 - → Batch size: 16
 - → Optimizer: Adam
 - → Learning rate: 0.0001
 - → CosineAnnealingLR decay



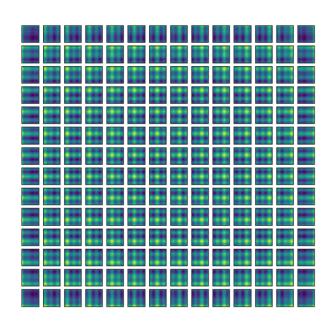
Classification – Results

- → Test Accuracy:
 - → 96.5% before Fine Tune
 - → 98.65% after Fine Tune
- → Obvious that the accuracy becomes better after fine-tune
- → Training with more epochs and bigger learning rates are also explored, but these parameters failed to give better results

16	小白U1635036757	98.75	7	2021-10-24 14:58:16	2021-10-24 14:58:16	暂无
17	小白U1632542321	98.65	3	2021-09-26 20:06:04	2021-09-26 20:06:04	暂无
18	剑飞	98.65	11	2022-06-10 17:41:57	2022-06-10 18:39:39	上传方案
19	独苍	98.6	11	2020-11-03 18:36:12	2020-11-03 18:36:12	暂无
20	花前月下意	98.55	3	2020-07-24 12:39:33	2020-07-24 12:39:33	暂无

Visualization – Positional Embedding





- Several variations of position embedding methods were tried in the original paper
 - → No positional embedding
 - → 1D positional embedding
 - → 2D positional embedding
 - → Relative positional embedding
- → The latter 3 ones give similar performance
- → Visualize the 1D positional embedding for explanation - computing the cosine similarity between the i-th embedding and all the embeddings(except for the class_token one)
- → Each patch of the image has the embedding correctly represents its position in the image. Thus we can say that 1D positional embedding is enough for this model

Visualization – Attention Matrix

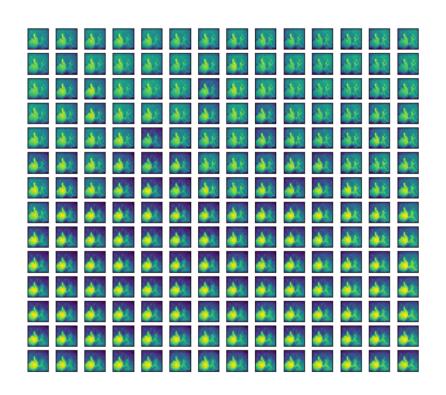
- → The attention matrix, matmul(Q, K^T) / (sqrt(D_K))
- → To see how the attention mechanism works
- → One image from the test set which contains two objects is selected to show the attentions

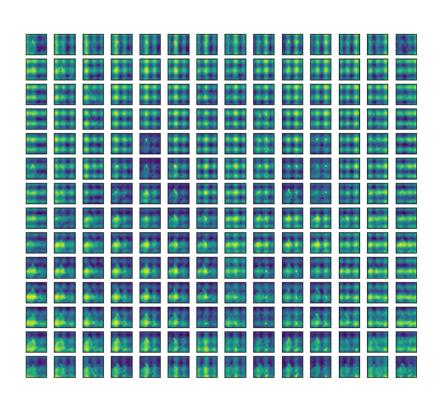


Visualization – Attention Matrix

Visualization of attention

Visualization of attention





Visualization – Attention Matrix

Visualization of attention

Visualization of attention

