Hochschule
Bonn-Rhein-Sieg
University of Applied Sciences

b-it Bonn-Aachen International Center for Information Technology

Master's Thesis

Sonar Patch Matching via Deep Learning

Arka Mallick

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Supervised by

Prof. Dr. Paul G. Plöger
Prof. Dr. Gerhard K. Kraetzschmar
Dr. Matias Valdenegro-torro

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Introduction

1.1 Densenet

In Densenet each layer connects to every layer in a feed-forward fashion. With the basic idea to enhance the feature propagation, each layer of Densenet blocks takes the feature-maps of the previous stages as input.

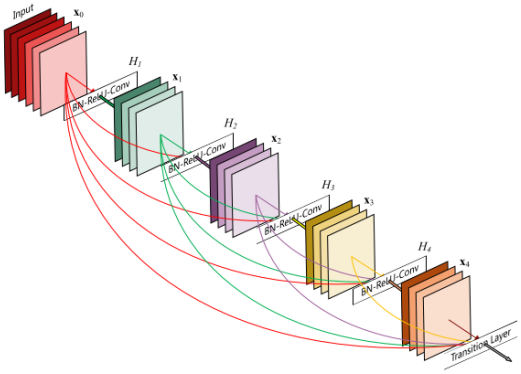


Figure 1.1: Densenet structure.

1.1.1 Siamese Densenet structure

Where the branches of the Siamese network are Densenet.

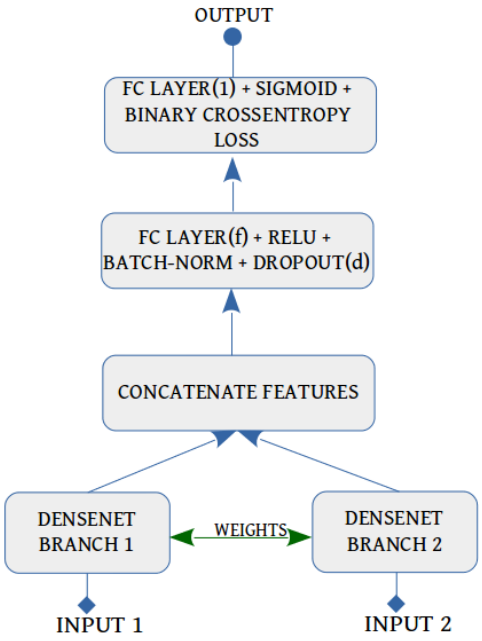


Figure 1.2: Siamese Densenet structure.

1.2 Hyper-parameters

Hyper-parameters are those parameters whose values are set before the training, unlike other parameters whose values are learned during the training. For example learning rate, batch size. [1]

1.2.1 Parameters of Densenet

- **Growth rate**: Number of filters to add per dense block. Growth rate regulates how much information is contributed by each layers to the global state. Global state is the collective knowledge of the network, that is the state of the previous layers are flown into each layer in form of feature-maps, which is considered as global state. Each layer adds k more feature-maps to the current state, when growth rate is k.

- **Nb_filter**: initial number of filters. -1 indicates initial number of filters will default to 2 * growth_rate.
- **Nb_layers_per_block**: number of layers in each dense block. Can be a -1, positive integer or a list. If -1, calculates nb_layer_per_block from the network depth. If positive integer, a set number of layers per dense block. If list, nb_layer is used as provided. Note that list size must be nb_dense_block.
- **Depth**: number or layers in the DenseNet.
- **Nb_dense_block**: number of dense blocks to add to end.
- **Bottleneck Layers**: To improve computation efficiency a bottleneck layer with 1x1 convolution is introduced before each 3x3 convolution layers.
- **Compression**: Reduces the feature maps in transition layers and makes the model more compact and computationally efficient.

Figure 1.3: Hyper parameters word cloud.

1.2.2 Other hyper-parameters

After concatenation of the features from the Densenet branches, the merged features need to pass through a small network figure 1.2 before being connected to the last layer with Sigmoid activation function and single output for binary

classification. Afore mentioned small network from consists of a dense layer, followed by a Batch normalization layer and Relu activation layer respectively. After this a Dropout layer is added to ensure better generalization. So the parameters such as the filter size of the Densenet(f) and Dropout value (d) are the main hyper-parameters related to network barring the Densenet branches. Apart from these, there are other general hyper-parameters such as learning rate, batch size for training, optimizer.

1.3 Grid search method

Currently the search space for the evaluation is hand designed and supplied to the evaluation script externally. Example

epochs	optimizer	reduction	bn	batch_size	fc_dropout	fc_filter	fc_layers
5	adam	0.5	TRUE	64	0	512	1

Figure 1.4: Custom grid search space example.

- Each test cases are evaluated 5 times.
- Dataset is divided into three parts, Train (31K) Validation(7K) Test(7K). Note: Validation data in keras does not contribute to training, but it can affect training indirectly through Earlystop and ReduceLROnPlateau
- Output: ROC AUC score is calculated on the prediction on test data. The mean auc, standard deviation and Maximum auc is presented out of n trials. Also the number of parameters are reported.

1.3.1 Disadvantages

In cutting edge algorithms for hyper parameter tuning like **TPE(Tree-structured parzen estimator)** Sequentially construct models to approximate hyperparameters based on previous measurements. Hence the search time for finding the best parameters are significantly lesser than simple grid search. This was the first choice method. But fails after some trial of evaluation with memory related error, **bad_alloc**. This issue could not be fixed even after decreasing the batch size to 2/4 or clearing the keras backend session.

1.3.2 Advantages

More control over the testing conditions for different networks, for example hand tuning the epochs for different architectures to ensure they train well. Whole search space can be cut into smaller parts and run in parallel.

1.3.3 Grid search strategy

Since there are lot of parameters, practically, infinite test cases might be designed. To keep the grid search focused and less computationally expensive it makes sense to first search for coarser grid of parameters rather than very fine ones. When and if a bracket of parameters are shortlisted which works better than others, the finer parameter search will be performed only specific to those range of parameters and not the whole grid.

1.4 Results

1.4.1 Coarse grid search on Densenet hyper-parameters

For the estimation of the best performing parameters of Densenet for the branches of the Siamese, first a coarse grid search is been performed with

- Layers per block are chosen among 2,3,4,5,6. For single dense block evaluation goes up-to 12 layers. More than that(14) causes memory to run out as the size gets too big for the cluster gpu memory(16GB).
- Each network has been evaluated for growth rates of 6,12,18,24,30,36.
- Different dense block sizes of 1,2,3,4.
- Not all the possible combinations has been evaluated as quite extensive as possible
- The basic idea here is to narrow down the possible network sizes from the Densenet parameters perspective. There are other parameters but number

of dense block, growth rate and layers per block are three main parameters which controls the architecture/size of the network the most.

- The parameters compression/reduction and bottleneck are set 0.5 and True respectively because both this parameters controls the compactness of the model and help reducing the parameter required, hence in theory enabling us to evaluate much bigger networks. So the network that is being evaluated here are named Densenet-BC by authors, I.e Densenet with bottleneck and compression.
- For more fine grained analysis the compression and bottleneck parameters will also be evaluated.
- nb_filter values are fixed at 16 for this test
- The parameter classes are set to 2, which represents 1 for matching and 0 for not-matching pairs
- 96,96 is the input image dimensions. And its single channel. So depending on local setting of the keras, channel-first or channel-last suitable input_shape is chosen automatically as 1,96,96 or 96,96,1 respectively.
- The learning rate used for the test was 2E-4
- Dropout for Densenet used as 0.2 to handle over-fitting.
- Epochs are different for different architectures to ensure that the networks are able to achieve at least 95% training accuracy.
- From the keras side of the parameters, after concatenating the Densenet branch output feature maps, the combined features then passed through a fully-connected layer of 512 filter size, which is followed by Relu activation and Batchnormalization(BN) and then a dropout(0.5) has been added to ensure better generalization.
- Some of this values needs to be further evaluated as well, how ever current values were obtained using some of manual tuning and assumed to be a decent starting point.

- Flatten is used as pooling at the end of the Densenet, it is introduced by this work which replaces the Globalaveragepooling step with a flatten. This causes increase in parameters overall though.
- Binary_crossentropy loss function with sigmoid activation function used for the binary classification, this final layer acts as the binary classifier.
- In all the cases the networks are being trained from scratch. The weights = None ensures that no previously trained weights are used.

1.4.2 Coarse grid search parameters summary

Fixed hyper-parameters

- Nb_filter: 16
- Subsample initial block: True
- Weights : None
- Dropout rate : 0.2
- Include top : False
- Compression : 0.5
- Bottleneck : True
- Pooling : **Flatten**
- Transition pooling : max

Varying Hyper-parameters

- **Nb_layers_per_block**:
  - **One dense block architecture (nb_dense_block=1):** '2', '3', '4', '6', '8', '10', '12'

  - **Two dense block architecture (nb_dense_block=2):**
    '2-2', '2-3', '2-4', '3-3', '3-4', '3-5', '4-4', '6-6'
  - **Three dense block architecture (nb_dense_block=3):**
    '2-2-2', '2-2-3', '2-3-3', '2-2-4', '2-3-4', '3-3-2', '3-3-3', '3-3-4', '3-4-4', '3-4-5', '3-3-6', '4-4-4', '4-4-2', '4-4-3', '4-4-6', '6-4-2', '6-6-3', '6-6-6'
  - **Four dense block architecture (nb_dense_block=4):**
    '2-2-2-2', '3-3-3-3', '4-4-4-4', '6-6-6-6'

- **Growth rate**:
  - Thin layers: 6, 12, 18
  - Thick layers: 24, 30, 36

1.4.3 AUC analysis

Each network is trained from scratch and evaluated on test data 5 times. The metric for evaluation is Area under curve(AUC).

Displaying below is the top 20 architectures (layers per dense block and growth rates) in terms of highest mean AUC on test data across 5 trials.

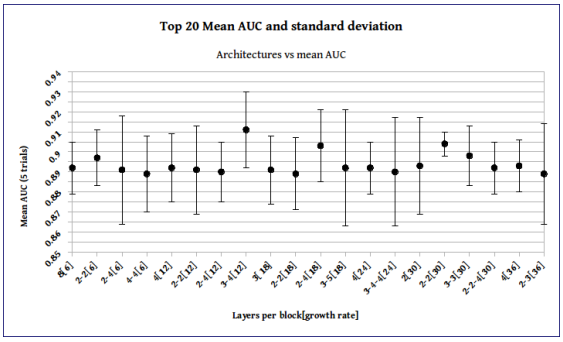


Figure 1.5: AUC analysis sorted by number of growth rate.

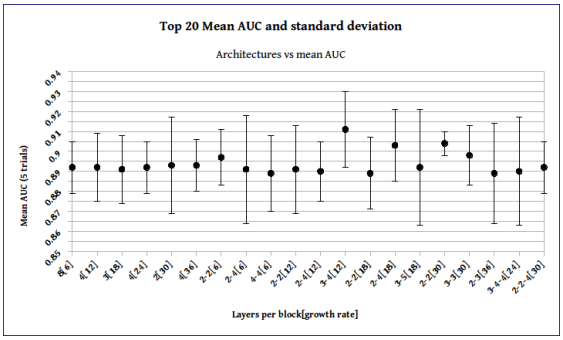


Figure 1.6: AUC analysis sorted by number of dense blocks.

Conclusion: Inconclusive!!

Displaying below is the top 20 architectures (layers per dense block and growth rates) in terms of highest max AUC on test data across 5 trials.

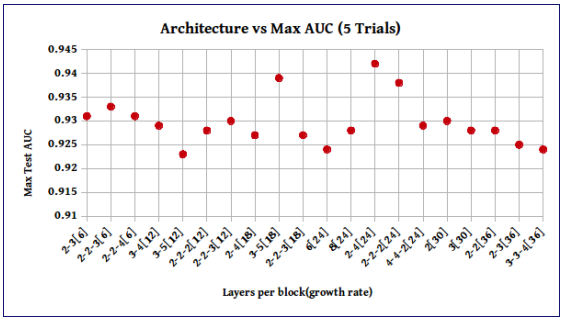


Figure 1.7: AUC analysis Maximum AUC.

Conclusion

- It is clear from the top 20 performer across mean and max AUC analysis that the architectures consisting lesser layers per block outperforms networks with more layers per block in general.

- The four dense block architectures did not make it to the top 20 in any of the case. Their performance on the test data is worse, so under current setup and assumptions they work worse. Even though they are able to train above 95% train accuracy their generalization on the test data seems to be poor in general.

- Two dense block networks in general works best in terms of mean AUC of the 5 evaluations.

- In terms of max AUC score some of the Three block and one block Densenet works very good as well, but may not be that consistent in general and did not make it in the top 20 mean AUC list.

- Some networks though, like 2-2, 2-4, 3-4, 3-5, 3, 8, 2-2-4 etc are of special interest since they have featured in both the list of mean and max top 20 AUC.

1.4.4 Optimal growth rate analysis

It is also important to find out the best growth rate for each of the architectures(layers per block). For this purpose, the growth rate with mean AUC of test data in 5 trials has been selected, the Best growth rates across architectures are displayed in the graph below:

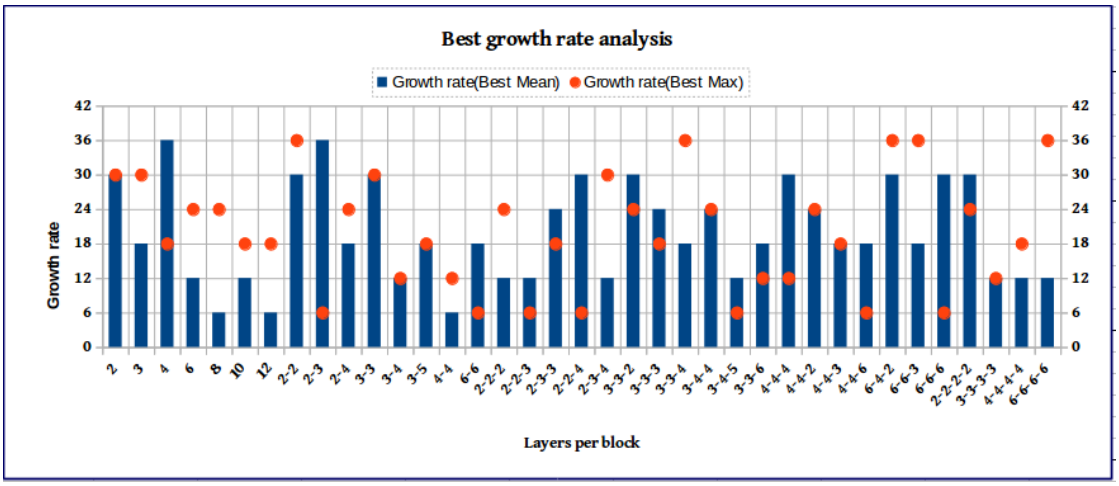
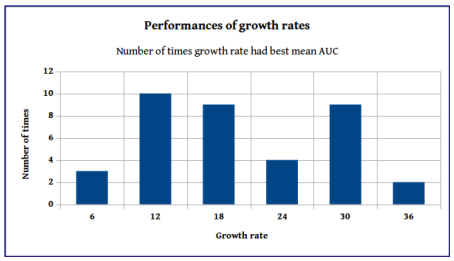


Figure 1.8: Architecture vs growth rate based on mean AUC.

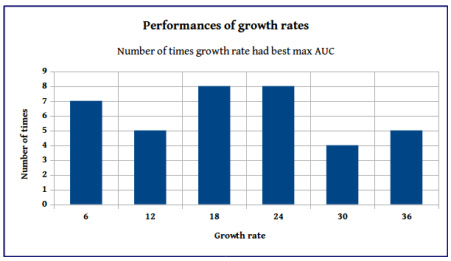
But it is observed that the architectures with max AUC in 5 evaluations on test data. might consist of different growth rates than the one that displays best mean AUC. For this purpose, histogram of best performing growth rates obtained from mean and max AUC analysis is displayed in the figure below:

Conclusion

- It is evident from figure 1.9b, based on the max AUC, there is no strong trend, its very random and inconclusive. Which is not very surprising given its just one run. With so many parameters and initialization and random dropouts involved, the network weights might learn very differently in spite of being trained in a same condition, resulting in a completely different decision boundary.
- In fgiure 1.9a it is visible that the contribution of growth rate 6 and growth



(a) Histogram of growth rates depending on mean AUC



(b) Histogram of growth rates depending on max AUC

Figure 1.9: Cumulative growth rate analysis (histograms)

rate 36 is really less, so probably they are too thin or too thick for the data.

- From fgiure 1.9 above it is safe to assume that growth rate 18 is very good performer in both analysis. Which also makes sense since it is neither too thin nor too thick. Because this conclusion is based on just 5 evaluations of each architectures, we are open to experiment with other growth rates(except 6,36) as well for finer evaluation.

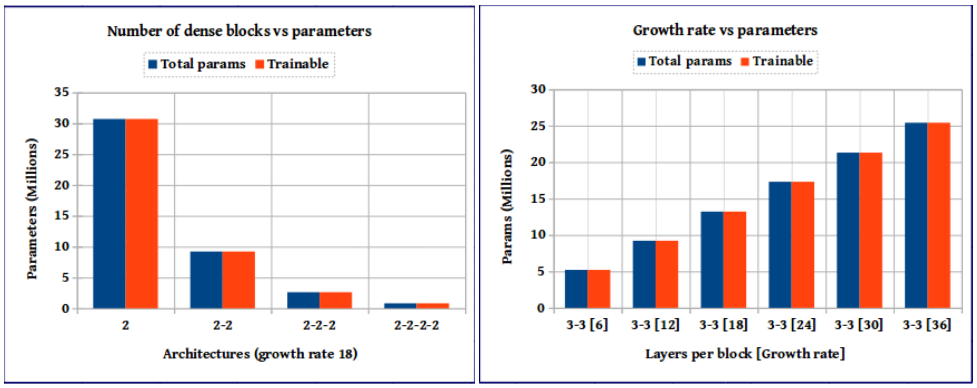
1.4.5 Total parameters analysis

- It might be surprising but the single dense block networks have most parameters. This is also because of the flatten pooling that is used here in this work instead of global average pooling 2D.

- And four block networks have the least total and trainable parameters. This is also supported by the theory in the paper

- How ever as the number of dense blocks keeps getting higher the non-trainable parameters also gets higher. So 4 blocks dense net has most number of non-trainable parameters.

- For the comparison 2, 2-2, 2-2-2, 2-2-2-2 blocks parameter sizes are compared below, all recorded for growth rate 18.



(a) Parameters vs architectures (b) Parameters vs growth rates

Figure 1.10: Total number of parameters analysis

1.4.6 Standard deviation across blocks

Another trend was observed that the standard deviation varies more as the number of dense blocks increases. So the std values for all the readings are collected for 1,2,3,4 number of dense blocks (nb_dense_blocks) separately and their mean values are presented in the table below.

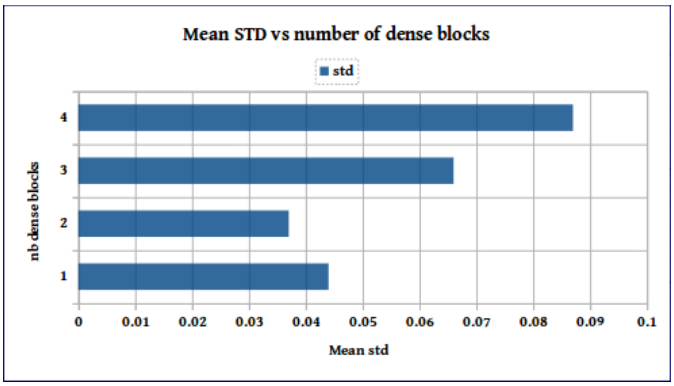


Figure 1.11: Mean Standard deviation vs number of dense blocks.

- Even thought the number of sample size differs a lot [42,48,108,24] respectively for dense blocks 1,2,3,4 it does seem like standard deviation of AUC higher for dense block 3 and 4.

- It is probably because the blocks 3 and 4 networks have much lesser parameters than the 1 and 2 number of dense blocks.

1.4.7 Finer grid search analysis

- From the first analysis the top 5 network based on mean AUC of 5 trials and top 5 network obtaining maximum AUC are further evaluated for 20 evaluations each. Other test conditions remain the same.
- Results after 20 times evaluation are expected to be more dependable than 5 trials.
- In the chart below the mean AUC of 20 evaluations and its standard deviation is displayed in blue dots and black lines.
- In red displayed the maximum AUC obtained in 20 evaluations

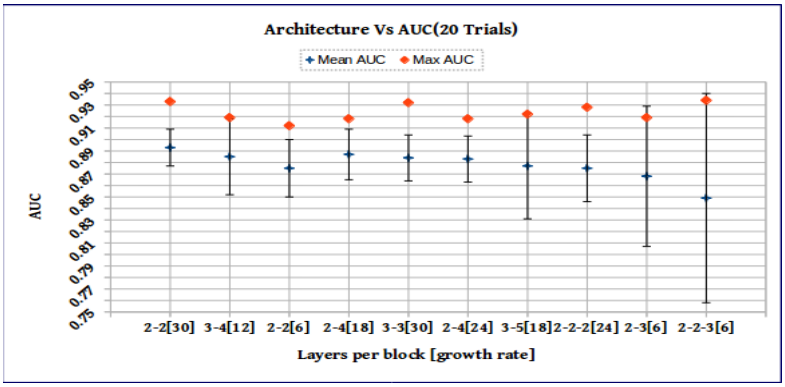


Figure 1.12: Finer search with top 10 architectures

Conclusion

- It seems that in 20 evaluations layers 2-2 with growth rate 30 is the best result both in terms of lowest standard of deviation and highest mean AUC. As it happens its also second highest in terms of the maximum AUC 0.933 just behind 0.934 from 2-2-3.

Layers	Growth rate	Mean AUC	STD	Max AUC
2-2	30	0.893	0.016	0.933
3-4	12	0.885	0.033	0.919
2-2	6	0.875	0.025	0.912
2-4	18	0.887	0.022	0.918
3-3	30	0.884	0.02	0.932
2-4	24	0.883	0.02	0.918
3-5	18	0.877	0.046	0.922
2-2-2	24	0.875	0.029	0.928
2-3	6	0.868	0.061	0.919
2-2-3	6	0.849	0.091	0.934

Figure 1.13: Finer search with 10 architectures

- 3-4, 2-4 networks are also performing well in terms of mean AUC. Their results are very close as well, so just evaluating 3-4 network for the finer analysis.
- 2-2-3 layers is interesting though, it has the highest standard deviation but 2 or 3 very good AUC scores too. So it needs to be further looked into.

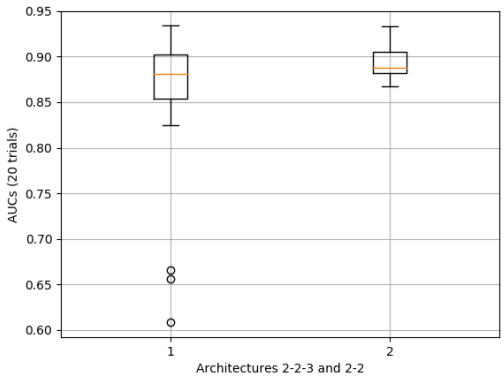


Figure 1.14: Boxplot analysis architectures

in 2-2-3 analysis 3 AUC readings are detected as outliers out of 20 trials at 0.666, 0.608, 0.656

Min	Q1	Median	Q3	Max	No. Outliers
0.608	0.854	0.881	0.902	0.934	3
0.867	0.882	0.887	0.905	0.933	0

The outliers are affecting the overall mean auc for 2-2-3 network, also causing big standard deviation. This outliers are probably caused by training getting stuck

in local minima or similar. 2-2 is found to be more consistant, it has no outliers. It is believed that consistancy is desirable for a network. Hence 2-2-3 network is ruled out of contention for the best network, because of it's lack of consistancy.

1.4.8 Nb_filter analysis

Initial number of filters. 8,16,32,64 are being evaluated here. Also a comparison between mean AUCs obtained from growth rate 18 and 30 is done under this analysis. Ten evaluations of each test cases has been done.

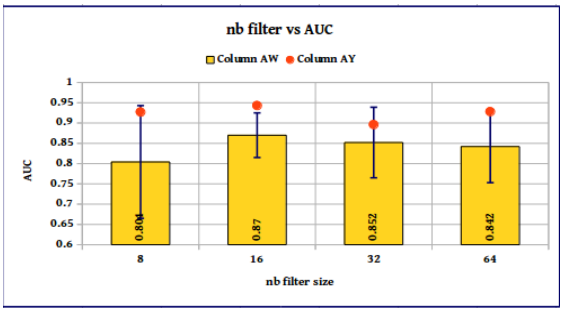


Figure 1.15: Nb_filter vs mean AUC for growth rate 30

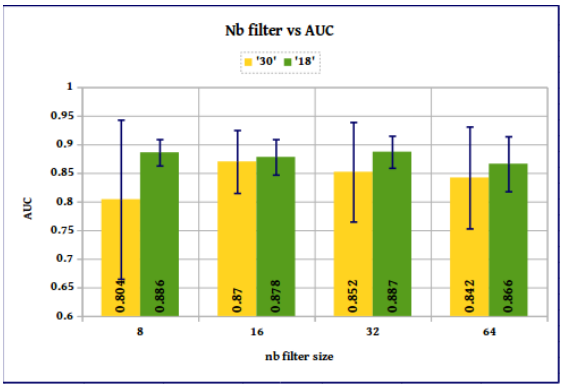


Figure 1.16: Nb_filter (different growth rates)

Conclusion

figure 1.15 shows that the nb_filter 16 works better than others and also happen to have the Maximum AUC recorded and lowest standard deviation as well. Next it

is also curious to know if there is any effect of the growth rate change on the nb filter size. It seems for thinner networks (lower growth rates) it matters lesser than the thicker networks. Since for 18 growth rate the mean AUC for all the values of nb_filter are very close. But there is lot of difference for growth rate 30 for different rates. However both the networks were found to work pretty good with nb_filter value of 16. This could have been further evaluated with more growth rates, but for this work we are settling with 16 as our best nb_filter value.

1.4.9 Dropout analysis

Densenet dropout: 10 evaluations each
Mean AUC is best for dropout 0.4
Max AUC is highest for dropout 0.5
Now it is no surprise that with 0, 0.1 and 0.7 dropouts the results are not the best, because its either too less or too much. But it is bit surprising to have 0.3 and 0.5 performing low. It is out of trend.

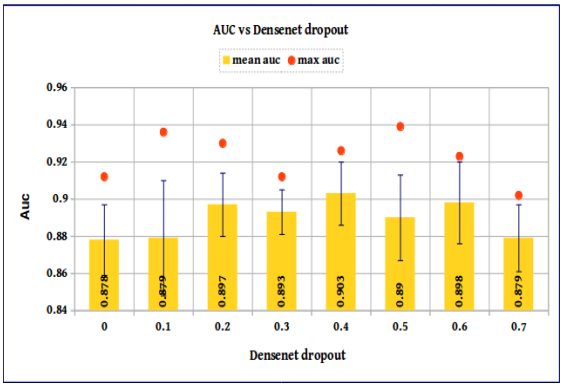


Figure 1.17: Densenet dropout analysis

Choosing 0.4 as the dropout rate value for future evaluations.

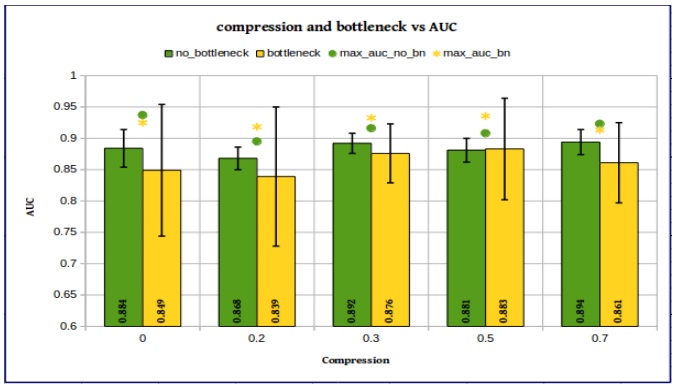


Figure 1.18: Evaluation of compression and bottleneck and mean AUC(across 10 trials). The max AUC obtained by one of the trial is also displayed separately for experiment with bottleneck and without bottleneck.

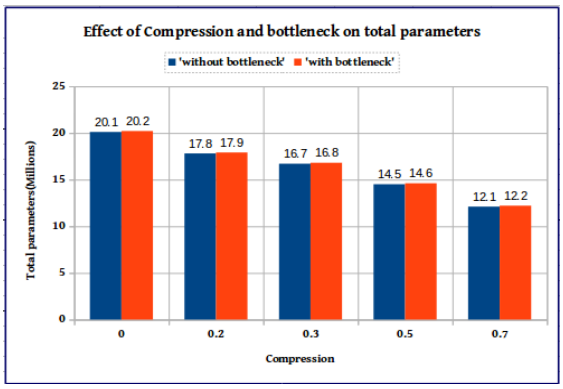


Figure 1.19: The total parameters are varying with reduction. It also gets affected by use of bottleneck or not, how ever that is very minimal.

1.4.10 Bottleneck and Compression(also called reduction) analysis

Conclusion

The use of compression really makes the model much more compact without losing the effectiveness. Without compression the parameter size is 20.1 Millions, after using compression of 0.7 the mean AUC is still as good but the size has become 12.1 millions

Use of bottleneck does in-fact increase the parameters by little more than 0.1

million, but it does not improve the results at all. So this is a strange behavior. Bottleneck also has much higher standard deviation.
Theoretically it is suppose to help making the model more compact. But over all effects on our data is observed to be adverse.VERY STRANGE!
But note: the max auc values still belong to the bottleneck layers 3 out of 5 times. Other two times also its close to highest. That's interesting.

1.4.11 Siamese hyper-parameters analysis

The concatenated feature maps from the two branches are connected to the fully connected layer before feeding it to the decisive fully-connected layer with 1 output and sigmoid activation.

The most interesting hyper-parameters associated to the Siamese side, are the fully-connected(FC) layer filter size (f) and the dropout ratio (d) shown in the figure. Everything else is pretty standard. The fully-connected layers are initialized with He normal initialization as they works great with RELU (TODO: add source).

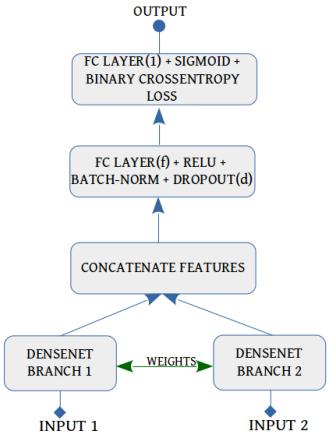


Figure 1.20: Siamese Densenet Structure

Fully-connected dropouts analysis

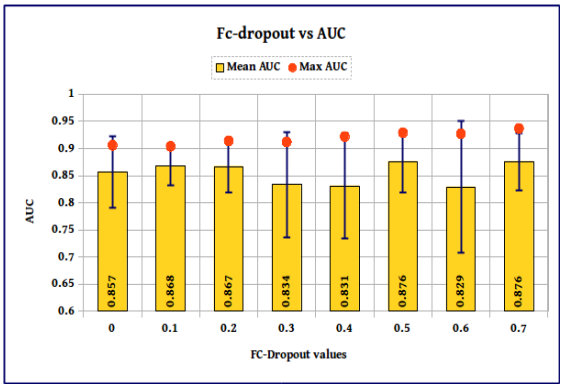


Figure 1.21: Optimal dropout (d) for FC layer analysis

Conclusion

- From figure 1.21 dropouts analysis it seems that the dropout 0.5 has the highest mean AUC along with 0.7.
- The values for 0.3,0.4 is lower than expected and 0.7 is much higher, may be should look for higher dropout values for the analysis.

Fully-connected network filter size analysis

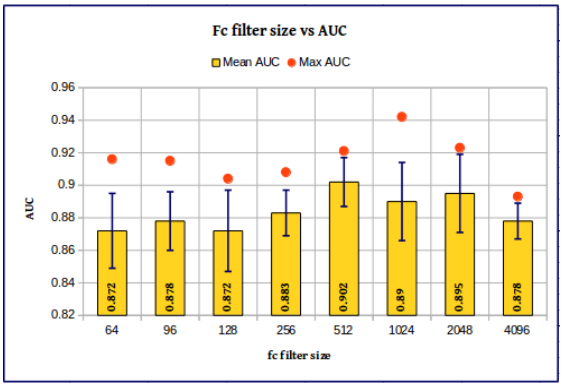


Figure 1.22: optimal FC filter size (f) analysis

Conclusion

- The f=512 works the best in terms of the mean AUC (from the graph above). Though the max AUC obtained by the f=1024 and f=2048 is also scoring very good
- however on this value of f the number of total parameters for the whole network depends as the whole feature map of each Densenet branch are flattened using flatten then concatenated. Hence multiplied by 2 (since 2 branches). This concatenated feature map is then multiplied by the f when they gets connected.
  - One Densenet branch feature map (size=n)
  - Concatenated both branches (size=2n)
  - Concatenated features gets connected to fc network with filter size f (2n*f computations, output size = f)
- In other words the smallest f size which gives good performance, is better since it keeps the computations smaller. So f=512 is chosen.

1.4.12 Batch size analysis

If the batch size is too low then it takes more time and after a certain size it does not train well too.
If the batch size is very big then it may train faster but they generalize lesser as they tend to converge to sharp minimizers of the training function. TODO add source (https://arxiv.org/abs/1609.04836)

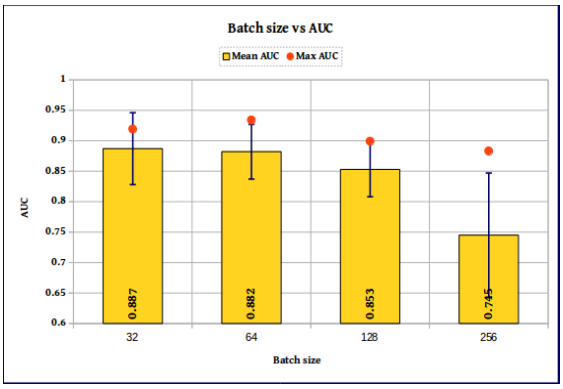


Figure 1.23: Batch size analysis

Conclusion

From the figure 1.23 it is evident that the larger the batch size gets the generalization on the test data gets worse. Batch size 32 or 64 looks very close so may be both can be top picks. The max AUC score for batch size 64 is much higher than others so it is slight favorite though.

1.4.13 Learning rate and optimizer analysis

Optimal learning rate selection is very important for effective learning. However, optimal learning rate varies optimizer to optimizer, hence learning rate and optimizer a very fine grained search is performed here The search space looks as below:

- Learning rate:
  - 0.01, 0.02, 0.03, 0.05, 0.07

Figure 1.24: In order, (a)Adam, (b)Nadam, (c)Adamax, (d)RMSprop, (e)Adadelta learning rate analysis

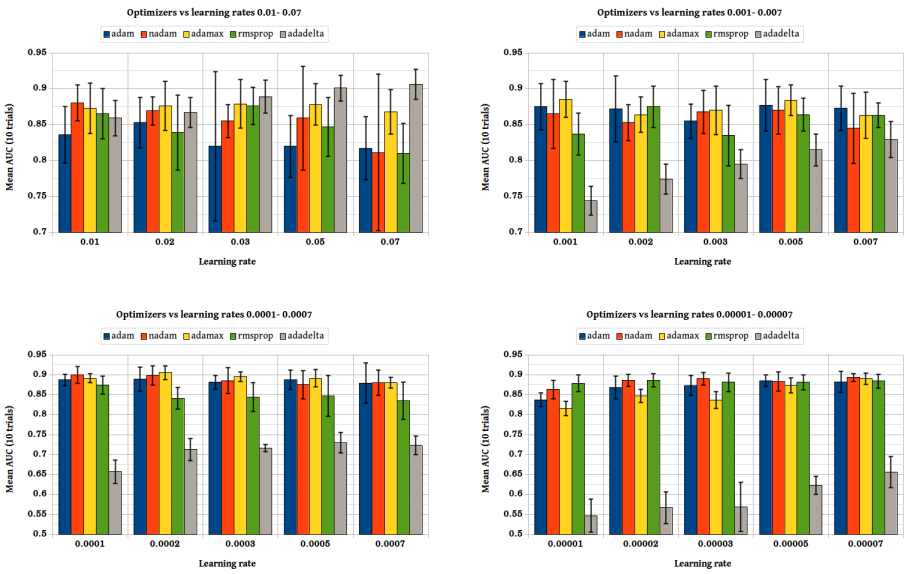


Figure 1.25: comparison of different optimizers across different learning rates

  - 0.001, 0.002, 0.003, 0.005, 0.007
  - 0.0001, 0.0002, 0.0003, 0.0005, 0.0007
  - 0.00001, 0.00002, 0.00003, 0.00005, 0.00007
- Optimizers:
  - Adam
  - Nadam
  - Adamax
  - RMSprop
  - Adadelta

TODO: Justify choice of the particular optimizers

Conclusion

- 10 trials for each test condition
- Overall adadelta (lr 0.07) has the highest mean AUC 0.906

- highest mean AUC for RMSprop(lr 0.00002) is 0.886
- highest mean AUC for Adamax(lr 0.0002) is 0.905
- highest mean AUC for Nadam(lr 0.0001) is 0.9
- highest mean AUC for Adam(lr 0.0002) is 0.889
- So the most effective learning rate varies optimizer to optimizers
- For Adamax,Adam,Nadam, lr 0.0002 works very good, for RMSprop lr 2E-5 works better and for Adadelta as the lr drops the performance also drops significantly.
- For Adadelta the boundary value for the evaluation is the highest so further analysis needs to be done for higher learning rates like 0.1, 0.5, 1.0. The default learning rate for Adadelta in Keras is 1.0 so it is not really surprising.
- From figure 1.26 it is observed that each of the trials with learning rate 0.1, 0.5 and 1.0 somehow had 2 AUCs out of 10, which are far lower than others. Which are displayed in the boxplot as the outliers. Without the outliers the average mean of the trials would drastically improve and look as follows. Though we are chosing the 0.07 as the best lr for Adadelta as it is found to be more dependable and high scoring too.

Learning rate	0.07	0.1	0.5	1.0
Mean AUC	0.906	0.906	0.891	0.887

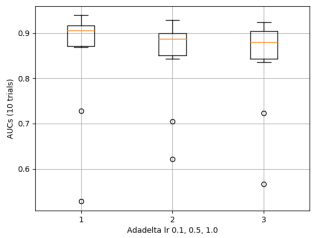


Figure 1.26: Adadelta advance learning rate analysis

1.4.14 Hyper-parameters for final grid search

- Layers per block 2-2, 3-4
- nb_dense_block 2
- Growth rate 12, 18, 30
- Nb_filter 16
- Densenet dropout 0.2, 0.4
- Bottleneck False
- Compression 0.3, 0.7
- FC filter size 512
- FC dropout 0.5, 0.7
- Learning rate 0.0002 and optimizer Adamax, Learning rate 0.07 optimizer Adadelta, Learning rate 0001 optimizer Nadam
- Batch size: 64

1.4.15 Best results in final grid search(as of now)

Top config 1 Adadelta

Epochs 14 batch_size: 64 lr: 0.07 optimizer: adadelta
es_patience: 4 lr_patience: 3
batch_size: 64 fc_dropout: 0.7 fc_filter: 512 fc_layers: 1
Layers: [2, 2] Growth_rate: 30
nb_filter: 16 dropout: 0.4 dense_block 2
reduction_: 0.3 bottleneck: False

Top config 2 Adadelta

Epochs 13 batch_size: 64 lr: 0.07 optimizer: adadelta

es_patience: 4 lr_patience: 3
batch_size: 64 fc_dropout: 0.7 fc_filter: 512 fc_layers: 1
Layers: [2, 2] Growth_rate: 12 nb_filter: 16 dropout: 0.2 dense_block 2 reduction_: 0.7 bottleneck: False

Top config 3 Adamax
Epochs 14 batch_size: 64 lr: 0.0002 optimizer: adamax
es_patience: 4 lr_patience: 3
batch_size: 64 fc_dropout: 0.7 fc_filter: 512 fc_layers: 1
Layers: [3, 4] Growth_rate: 12 nb_filter: 16 dropout: 0.4
dense_block 2 reduction_: 0.7 bottleneck: False

Top config 4 Adamax
Epochs 15 batch_size: 64 lr: 0.0002 optimizer: adamax
es_patience: 4 lr_patience: 3
batch_size: 64 fc_dropout: 0.7 fc_filter: 512 fc_layers: 1
Layers: [2, 2] Growth_rate: 18 nb_filter: 16 dropout: 0.4
dense_block 2 reduction_: 0.7 bottleneck: False

Top config 5 Nadam
Epochs 13 batch_size: 64 lr: 0.0001 optimizer: nadam
es_patience: 4 lr_patience: 3
batch_size: 64 fc_dropout: 0.7 fc_filter: 512 fc_layers: 1
Layers: [3, 4] Growth_rate: 30 nb_filter: 16 dropout: 0.4
dense_block 2 reduction_: 0.3 bottleneck: False

Conclusion

- State of the art highest AUC **0.91**
- Densenet Siamese: Highest mean AUC across 10 trials were for Adadelta with learning rate 0.07. **Mean AUC: 0.921 STD: 0.016 Max AUC: 0.950**
- The mean result for the top configs are very close and it is hard to declare a runaway winner as the highest network has mean AUC of .921 and std of 0.016, second best has mean AUC of 0.918 with std 0.005.

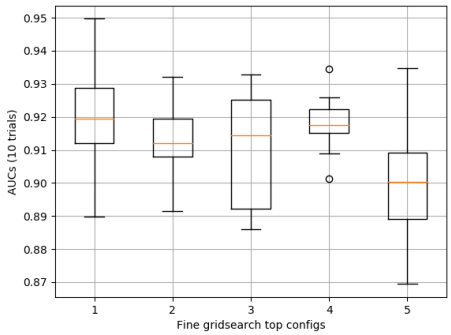


Figure 1.27: Fine grid search top results

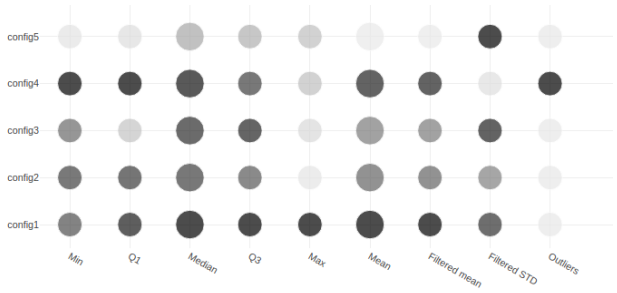


Figure 1.28: Fine grid search top results statistical analysis

- Top Config 4 interestingly has outliers, both high and low.
- It is interesting to note that the dropout values which are giving the best results are high 0.7 for the Siamese side and 0.4 for the densenet side.
- High dropout and Batch normalization is enabling the network to be good in generalization. The training/validation accuracy is could reach 99% still the test AUC score is high enough.
- The statistical comparison of the top 5 performing runs are displayed below in figure 1.27
- In figure 1.28 multiple statistical data is displayed in bubbles whose color indicates the scale of the value. Lower values indicated by lighter shade of grey. The highest value is shown in black. The scale of the shades are normalized between highest and lowest values for each column. But the white

was not visible so for each cases the minimum was lowered little bit so the lowest value is very light grey not white. TODO this needs further finnese.

References

[1] Wikipedia(Hyperparameter). Hyperparameter machine learning, November 2018. URL https://en.wikipedia.org/wiki/Hyperparameter_(machine_learning).