AutoEncoder by Forest

Machine Learning 2020 Course

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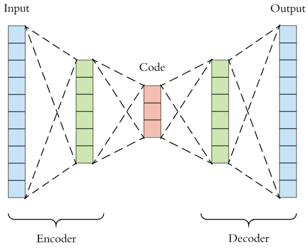
Intro

- AE is a class of models, compressed the input data to a lower-dimensional code and mapped it back to the original space with low reconstruction error as its objective[1].
- Ensemble learning is one of the most powerful techniques of improving the performance of a model, trained and combined various learners to solve a problem.
- eForest is original idea[2] by Feng J. and Zhou Z-H., tree ensemble based AE which can be trained in both supervised or unsupervised fashion.



https://blog.paperspace.com/autoencoder-image-compression-keras/

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Goal and related tasks

The main goal is to **check performance** of eForest AE.

Related tasks:

- Implementation of the eForest algorithm
- Demonstration of its usage in supervised and unsupervised setting
- Comparison with MLP and CNN based AE by the following criteria:
  - Accuracy
  - Efficiency
  - Damage-tolerance (resistance of the model to partial damage)
  - Reusability (application of the model trained from one dataset to the other dataset)

Data description

- **MNIST**[3]: $60,000$ grayscale 28×28 images for training and 10,000 for testing (784 dimensional vector per sample).
- **CIFAR-10**[4]: $50,000$ colored 32×32 images for training and $10,000$ colored images for testing (each image is in R^{1024} per channel).
- **Omniglot**[5]: $19,280$ grayscale 105×105 images (used just for testing).

The test size of each dataset was **reduced** to **1,000** images because of computationally expensive eForest performance evaluation.

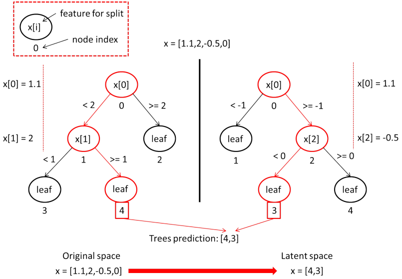
All models were evaluated on this test size.

eForest AE

Algorithm 1 Encoding

Input: trained forest F with T trees, object x
Output: x_{enc}
$x_{enc} = empty(T)$
for i in $range(T)$ **do**
  $x_{enc}[i] = F.tree[i].apply(x)$
  % "$apply$" returns the index of leaf in tree i corresponding to object x
end for
return x_{enc}

Encoding algorithm



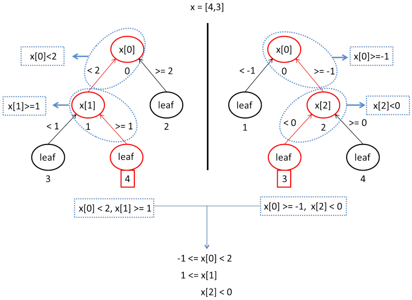
Encoding procedure

eForest AE

Algorithm 2 Calculate set of rules for tree

Input: tree t, n - leaf index of object for tree t
Output: rule set(array of size (N,2); for each feature min and max value)
% N - number of features in original space
$set = [[-infty, infty]\ for\ i\ in\ range(N)]$
$path = t.decision\ path(n)$
% path - array of nodes from root to leaf
for $node\ in\ path$ **do**
  $f = node.feature$
  $thres = node.threshold$
  if $next\ node\ in\ decision\ path\ is\ left$ **then**
    % the threshold for the split is upper bound
    $set[f][1] = min(set[f][1], thres)$
  else
    % the threshold for the split is lower bound
    $set[f][0] = max(set[f][0], thres)$
  end if
end for
return set

Set of rules for one tree



Decoding procedure

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eForest AE

Algorithm 3 MCR

Input: trained forest F with T trees, object x in latent space
Output: final set of rules
$result = [[-infty, infty]\ for\ i\ in\ range(N)]$
for $tree\ in\ F.trees$ **do**
  $set =$ Calculate set of rules for tree$(tree, x[tree])$
  $\%x[tree]$ returns component of x corresponding to $tree$
  $result = intersection(result, set)$
  $\%\ intersection(a, b)$ returns the intersection of rules a and b
end for
return $result$

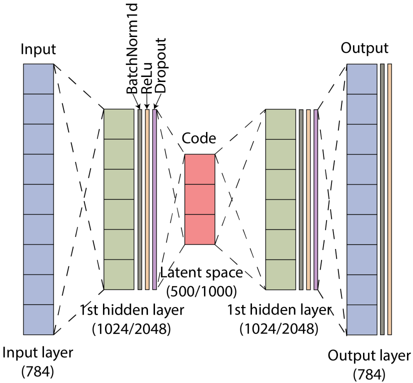
Maximal compatible rule(MCR)

Algorithm 4 Decoding

Input: trained forest F with T trees, object x in latent space
Output: x_{dec}
$x_{dec} = empty(N)$
% N - number of features in original space
$set = MCR(F, x)$
for $i\ in\ range(N)$ **do**
  if $set[i][0] == -infty\ and\ set[i][1] == infty$ **then**
    $x_{dec}[i] = median[i]$
    $\%\ median[i]$ - median value for feature i
  else if $set[i][0] \neq -infty\ and\ set[i][1] == infty$ **then**
    $x_{dec}[i] = set[i][0]$
  else if $set[i][0] == -infty\ and\ set[i][1] \neq infty$ **then**
    $x_{dec}[i] = set[i][1]$
  else
    $x_{dec}[i] = mean(set[i][0], set[i][1])$
  end if
end for
return x_{dec}

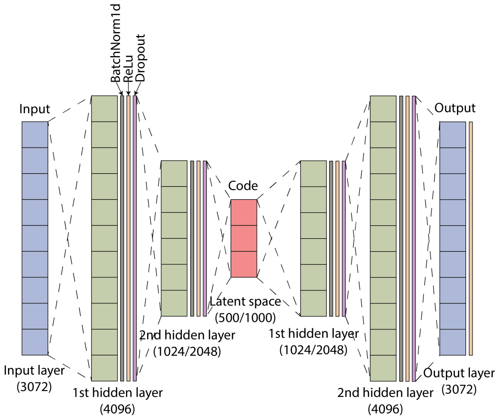
Decoding

MLP based AE



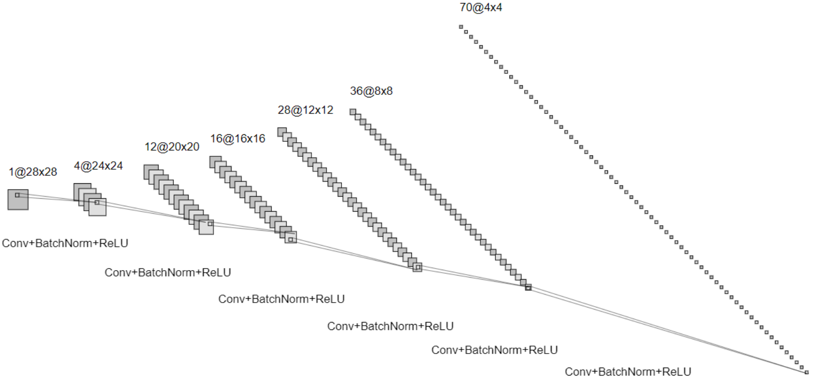
MLP_1/MLP_2 based AE architecture on MNIST

MLP based AE



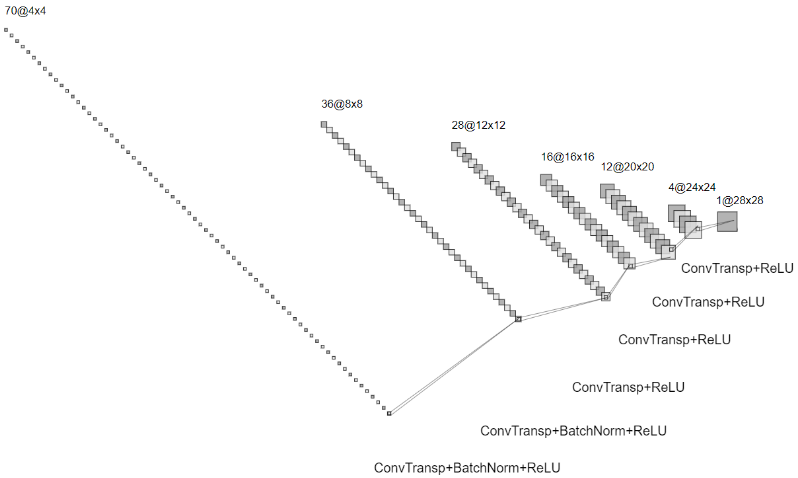
MLP_1/MLP_2 based AE architecture on CIFAR-10

CNN based AE



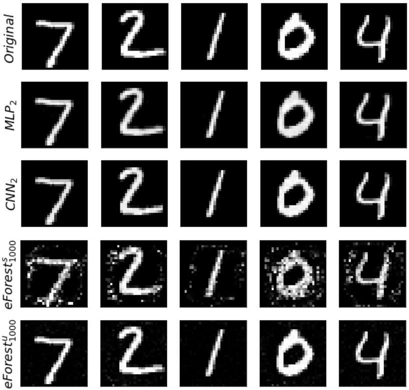
CNN encoder architecture on MNIST

CNN based AE

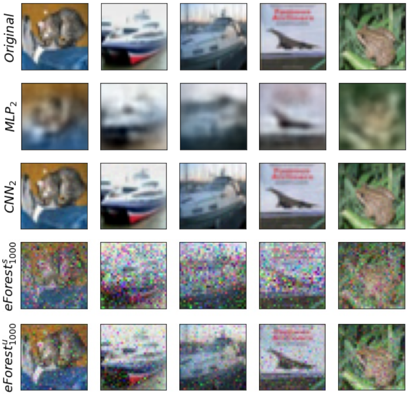


CNN decoder architecture on MNIST

Image Reconstruction



Reconstructed samples on MNIST



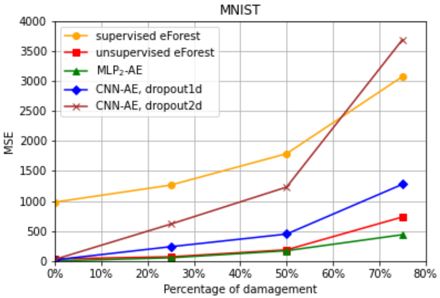
Reconstructed samples on CIFAR-10

Computation Efficiency

Time cost (in seconds). Decoding time is measured in sample per seconds.

MODEL	MNIST		CIFAR-10	
	TRAIN	DECODE	TRAIN	DECODE
MLP_1	1050	0.0003	1237	0.0004
MLP_2	1777	0.0003	1579	0.0005
CNN	2394	0.0006	7988	0.0007
eForest^s_{500}	268	0.9071	1180	1.7208
eForest^s_{1000}	561	1.4393	2333	3.0264
eForest^u_{500}	118	1.0096	90	1.7483
eForest^u_{1000}	223	1.8121	172	3.2822

Damage Tolerable



Performance on MNIST and CIFAR-10 when model is partially damaged

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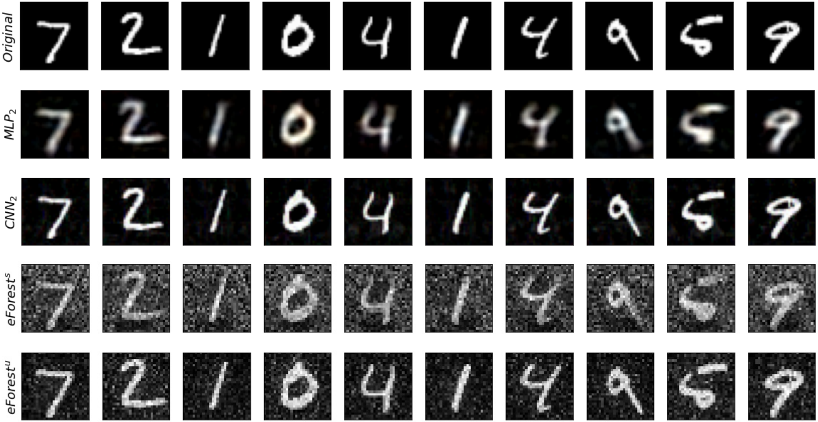
Model Reuse

Performance comparison for model reuse (measured by MSE)

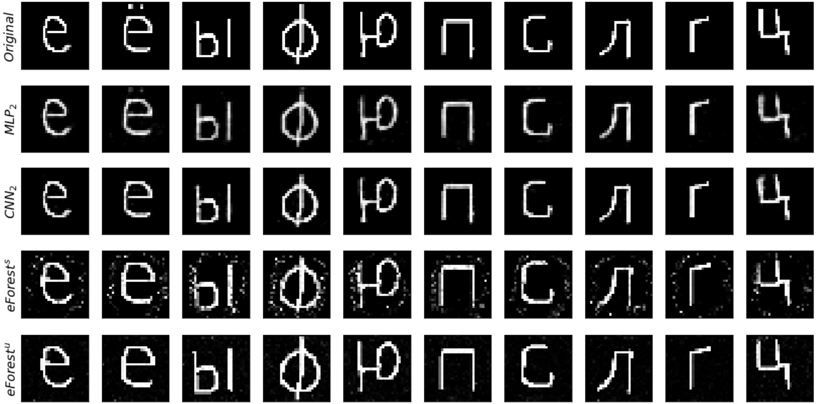
Model	cifar train mnist test	mnist train omniglot test	cifar train omniglot test
MLP_2	931.195	461.723	1855.313
CNN	123.392	210.599	269.476
eForest^s	4132.411	1173.529	4357.183
eForest^u	1438.885	103.896	1671.229

Model Reuse



Model reuse with training on CIFAR-10 and testing on MNIST

Model Reuse



Model reuse with training on MNIST and testing on Omniglot

Conclusion

- **Not accurate**: the eForest approach experimental reconstruction error is much higher than reasonable CNN based autoencoders, but comparable with MLP based autoencoders both on MNIST and CIFAR10 datasets.
- **Efficient**: the eForest on a many-core CPU runs even faster than a CNN autoencoder runs on a Tesla K80 GPU for training.
- **Not damage-tolerable**: the eForest is less resistant to partial damage than MLP and CNNs (to dropout specific neurons and to dropout channels in the layers).
- **Reusable**: In addition to replicating the original experiment, reusability of the eForest model were tested and compared additionally on a new experiment (train on CIFAR10 dataset and perform encoding/decoding task on Omniglot dataset), and the model trained from one dataset can be directly applied on the other dataset in the same domain.

Code and contact info

- https://github.com/Olga013/Skoltech-ML-2020-AutoEncoder-by-Forest/
- kirill.shcherbakov@skoltech.ru

References

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5. Lake, B. M., *et al*. Human-level concept learning through probabilistic program induction. *Science*, 350(6266), 1332-1338, 2015.