UVA CS 6316: Machine Learning : 2019 Fall
Course Project: Deep2Reproduce @
https://github.com/qiyanjun/deep2reproduce/tree/master/2019Fall

AN EMPIRICAL STUDY OF EXAMPLE FORGETTING DURING DEEP NEURAL NETWORK LEARNING

CS6313 - Machine Learning
Fall 2019

Reproduced by
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Original paper: Toneva, M., Alessandro, S., Tachet des Combes, R., Trischler, A., Bengio, Y., & Gordon, G. (2019). *An Empirical Study of Example Forgetting During Deep Neural Network Learning*. ICLR.

Overview

Motivation

Background

Related Work

Claim/Target Task

Why Claim

Proposed Solution

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Experimental Results

Experimental Analysis

Conclusion and Future Work

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Motivation

Inspired by the phenomenon *catastrophic forgetting:*

Phenomenon that neural network forgets previously learned information when trained for the new task

Applied to this current work:

Catastrophic forgetting can cause a problem with mini batch SGD optimization since each batch can be regarded similarly to the new task and SGD optimization is a situation of continuous learning

Hypothesis: shift on input distribution (e.g.: lack of common factors in input lead to different convergent solutions)

Background and Definition

Forgetting event

Example is misclassified after being correctly classified

Learning event

Example is classified correctly for the first time

Unforgettable examples

Learned at some point and never misclassified

Related Work

Curriculum Learning

Learning with increased difficulty helps minimize task loss

Safe to remove *unforgettable* examples

Deep Generalization

Does not depend on complexity of the model

Overparameterized model can reach low test error

Generalization is maintained when removing substantial amount of training examples

Claim/Target Task

Goal 1:

Gain insight into the optimization process and the training examples

Goal 2:

Determine if forgetting statistics can be used to identify important samples and outliers

An Intuitive Figure Showing Why Claim

Unforgettable
Clear features
High contrast with sky

Forgettable
Less visible features
Small contrast with background

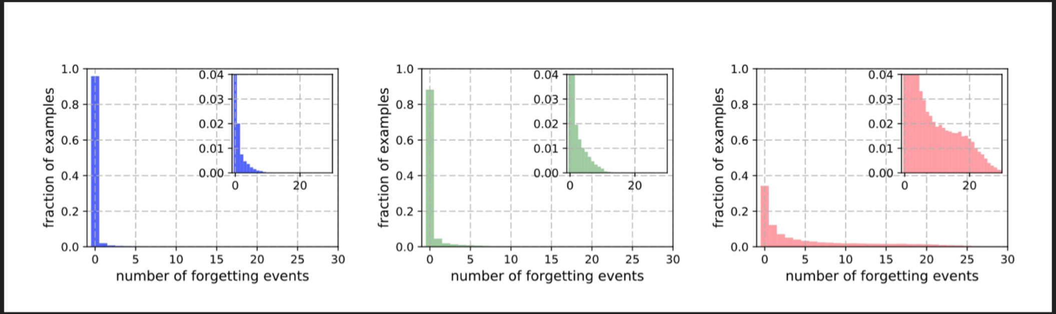
Proposed Solution

Empirical Analysis:

- Train classifier on dataset when sampled in current mini-batch
- Sort dataset examples based on number of forgetting samples
- MNIST, permuted MNIST and CIFAR-10

Implementation

Number of forgetting events



Histogram of forgetting events of MNIST, permuted MNIST and CIFAR-10

Forgetting by chance

Analyze distribution of forgetting events

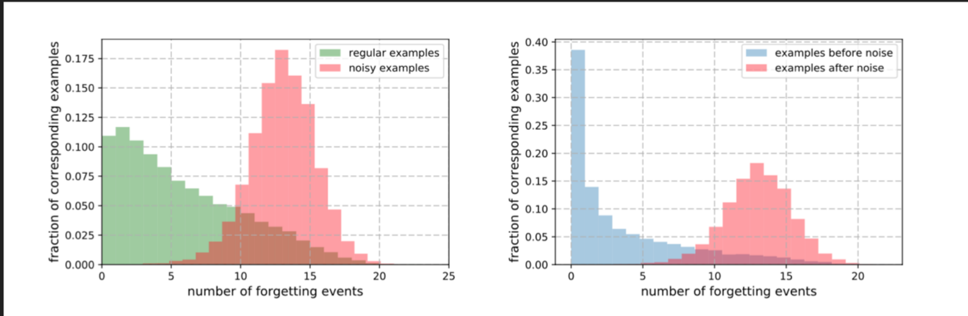
Implementation

First learning events

Order of examples during learning

Detection of noisy examples

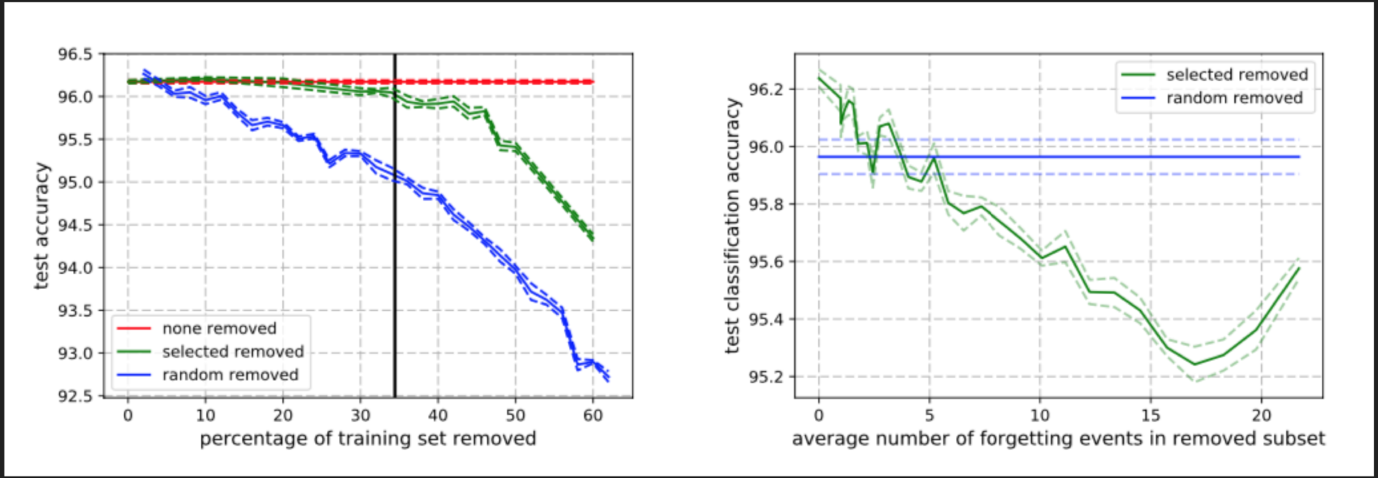
Atypical characteristics



Distribution of forgetting events in CIFAR-10 when labels are changed

Implementation

Removing most forgettable events



Generalization performance of ResNet18 Increasing number of elements are removed from training set

Load and train MNIST data

Step 1: Load MNIST

```
[ ]  ### M: Load data
     trainset = datasets.MNIST(
         root='/tmp/data', train=True, download=True, transform=transform)
     testset = datasets.MNIST(
         root='/tmp/data', train=False, download=True, transform=transform)
```

Step 2: Train MNIST with parameters below

```
args_dict = {'dataset': 'mnist', 'batch_size': 64, 'epochs': 200, 'lr': 0.01,
             'momentum': 0.5, 'no_cuda': True, 'seed': 99, 'sorting_file': 'none',
             'remove_n': 0, 'keep_lowest_n': 0, 'no_dropout': True,
             'input_dir': 'mnist_results/', 'output_dir': 'mnist_results'}
```

Load and train MNIST data

Step 3: Call train() on each epoch

```
elapsed_time = 0
for epoch in range(args.epochs):
    start_time = time.time()

    train(args, model, device, trainset, optimizer, epoch, example_stats)
    test(args, model, device, testset, example_stats)
```

Within train():
Permutate samples;
On each minibatch, get indices of each samples (more on next):

```
for batch_idx, batch_start_ind in enumerate(
        range(0, len(trainset.targets), batch_size)):

    # Get trainset indices for batch
    # M: Get indices for minibatch (a subset of the permutted indices)
    batch_inds = trainset_permutation_inds[batch_start_ind:
                                           batch_start_ind + batch_size]
```

Load and train MNIST data

Compute outputs, loss, and get predicted class

```
# Forward propagation, compute loss, get predictions
optimizer.zero_grad()
# M: outputs is the prediction
outputs = model(inputs)
# M: Calculate cross-entropy loss; will only be stored later
loss = criterion(outputs, targets)
# M: The code below get the index of the max in data (a Tensor)
# along 1 dimension
_, predicted = torch.max(outputs.data, 1)
```

Get accuracy and for each sample in mini batch and compute statistics (see next):

```
# Update statistics and loss
# M: Get list of True and False
acc = predicted == targets
# M: iterate over each index in the mini-batch
for j, index in enumerate(batch_inds):

    # Get index in original dataset (not sorted by forgetting)
    index_in_original_dataset = train_indx[index]

    # Compute missclassification margin
    # M: Get the output (log probability) for the correct expected class
    output_correct_class = outputs.data[
        j, targets[j].item()]
```

Load and train MNIST data

Append statistics (loss, accuracy and margin) to example stats and write to pkl file

```
# Add the statistics of the current training example to dictionary
# M: the get below defaults to [[],[],[]]
index_stats = example_stats.get(index_in_original_dataset,
                                [[], [], []])
index_stats[0].append(loss[j].item())
# M: each element will be either 1 or 0
index_stats[1].append(acc[j].sum().item())
index_stats[2].append(margin)
example_stats[index_in_original_dataset] = index_stats
```

Load and train CIFAR10 data

Step 1: CIFAR10 was first trained with no sorting, no sample removal, no data augmentation and no cutout

```
args_dict = {'dataset': 'cifar10', 'data_augmentation': False, 'cutout': False,
             'sorting_file': 'none','input_dir': 'cifar10_results', 'output_dir': 'cifar10_results',
             'seed': 1, 'remove_n': 0, 'keep_lowest_n': 0, 'remove_subsample': 0, 'noise_percent_labels': 0,
             'noise_percent_pixels': 0, 'noise_std_pixels': 0, 'no_cuda': False, 'model': 'resnet18','optimizer':'adam','epochs': 100,
             'batch_size':128}
```

For each event, calculate loss and predict output

```
    model_optimizer.zero_grad()
    inputs = inputs.cuda()
    outputs = model(inputs)
    #print(outputs)
    loss = criterion(outputs, targets)
    #print(loss)
    _, predicted = torch.max(outputs.data, 1)
```

Updata accuracy, loss stats of each event and save it in example_stats

```
    # Add the statistics of the current training example to dictionary
    index_stats = example_stats.get(index_in_original_dataset,
                                    [[], [], []])
    #print(index_stats)
    index_stats[0].append(loss[j].item())
    index_stats[1].append(acc[j].sum().item())
    index_stats[2].append(margin)
    example_stats[index_in_original_dataset] = index_stats
```

Sort dataset based on forgettable events

Step 1: Use accuracy value after training the CIFAR data to compute whether event is learned or unlearned or forgettable

- Learned event: event with accuracy of 1
- Unlearned event: event with accuracy of 0
- Forgettable event: event with accuracy dropping from 1 to 0

```python
def compute_forgetting_statistics(diag_stats, npresentations):

    presentations_needed_to_learn = {} #event that accuracy is still 0
    unlearned_per_presentation = {} #forgettable event
    margins_per_presentation = {} #misclassified margin for each event
    first_learned = {} #event that accuracy = 1 indicating learned event
```

```python
# Find all presentations when forgetting occurs
if len(np.where(transitions == -1)[0]) > 0: #accuracy drops from 1 to 0 indicates forgettable event
    unlearned_per_presentation[example_id] = np.where(
        transitions == -1)[0] + 2
else:
    unlearned_per_presentation[example_id] = []

# Find number of presentations needed to learn example,
# e.g. last presentation when acc is 0
if len(np.where(presentation_acc == 0)[0]) > 0:
    presentations_needed_to_learn[example_id] = np.where(
        presentation_acc == 0)[0][-1] + 1
else:
    presentations_needed_to_learn[example_id] = 0

# Find the misclassication margin for each presentation of the example
margins_per_presentation = np.array(
    example_stats[2][:npresentations])

# Find the presentation at which the example was first learned,
# e.g. first presentation when acc is 1
if len(np.where(presentation_acc == 1)[0]) > 0:
    first_learned[example_id] = np.where(
        presentation_acc == 1)[0][0]
else:
    first_learned[example_id] = np.nan
```

Sort dataset based on forgettable events

Step 2: Sort the example_stats to rank the sample from the highest forgetting count to the lowest forgetting count

```
print('Number of unforgettable examples: {}'.format(
    len(np.where(np.array(example_stats) == 0)[0])))
return np.array(example_original_order)[np.argsort(
    example_stats)], np.sort(example_stats)
```

Step 3: Save the sorted file with a stat of sample ID and sample values

```
# Sort examples by forgetting counts in ascending order, over one or more training runs
ordered_examples, ordered_values = sort_examples_by_forgetting(
    unlearned_per_presentation_all, first_learned_all, args.epochs)
print(ordered_examples)
print(ordered_values)

# Save sorted output
if args.output_name.endswith('.pkl'):
    with open(os.path.join(args.output_dir, args.output_name),
              'wb') as fout:
        pickle.dump({
            'indices': ordered_examples,
            'forgetting counts': ordered_values
        }, fout)
```

Train CIFAR10 with random data removal

```
args_dict = {'dataset': 'cifar10', 'data_augmentation': False, 'cutout': False,
             'sorting_file': 'none','input_dir': 'cifar10_results', 'output_dir': 'cifar10_results',
             'seed': 1, 'remove_n': 20000, 'keep_lowest_n': -1, 'remove_subsample': 0, 'noise_percent_labels': 0,
             'noise_percent_pixels': 0, 'noise_std_pixels': 0, 'no_cuda': False, 'model': 'resnet18','optimizer':'adam','epochs': 50,'batch_size':1
```

Random removal: permute the training data and remove samples

```
if args.keep_lowest_n < 0:
    # Remove remove_n number of examples from the train set at random
    train_indx = npr.permutation(np.arange(len(
        train_dataset.train_labels)))[:len(train_dataset.train_labels) -
                                      args.remove_n]
```

Call the example_stats for accuracy

```
test_acc_remove_20000 = max(example_stats['test'][1])
print(test_acc_remove_20000)
```

Train CIFAR10 with sorted data removal

```
args_dict = {'dataset': 'cifar10', 'data_augmentation': False, 'cutout': False,
             'sorting_file': 'cifar10_sorted','input_dir': 'cifar10_results', 'output_dir': 'cifar10_results',
             'seed': 1, 'remove_n': 20000, 'keep_lowest_n': 0, 'remove_subsample': 0, 'noise_percent_labels': 0,
             'noise_percent_pixels': 0, 'noise_std_pixels': 0, 'no_cuda': False, 'model': 'resnet18','optimizer':'adam','epochs': 50,
             'batch_size':128}
```

```
if args.sorting_file == 'none':
    #train_indx = np.array(range(len(train_dataset.train_labels)))
    train_indx = np.array(range(len(train_dataset.targets)))
else:
    try:
        with open(
                os.path.join(args.input_dir, args.sorting_file) + '.pkl',
                'rb') as fin:
            ordered_indx = pickle.load(fin)['indices']
    except IOError:
        with open(os.path.join(args.input_dir, args.sorting_file),
                  'rb') as fin:
            ordered_indx = pickle.load(fin)['indices']

    # Get the indices to remove from training
    # O: number of remove_n
    elements_to_remove = np.array(
        ordered_indx)[args.keep_lowest_n:args.keep_lowest_n + args.remove_n]

    # Remove the corresponding elements
    train_indx = np.setdiff1d(
        range(len(train_dataset.train_labels)), elements_to_remove)
```

Sorted removal: Used the sorted file output and remove the samples with the highest forgettable events by using ordered_indx

Load and train CIFAR10 data with noisy labels

Compute number of labels to change

```
# Compute number of labels to change
nlabels = len(train_dataset.targets)
nlabels_to_change = int(args.noise_percent_labels * nlabels / 100)
nclasses = len(np.unique(train_dataset.targets))
print('flipping ' + str(nlabels_to_change) + ' labels')
```

For each label, introduce noise by changing to another label

```
# Flip each of the randomly chosen labels
for l, label_ind_to_change in enumerate(labels_inds_to_change):
    # Possible choices for new label
    label_choices = np.arange(nclasses)
    # Get true label to remove it from the choices
    true_label = train_dataset.targets[label_ind_to_change]
    # Remove true label from choices
    label_choices = np.delete(
        label_choices,
        true_label)  # the label is the same as the index of the label
    # Get new label and relabel the example with it
    noisy_label = npr.choice(label_choices, 1)
    train_dataset.targets[label_ind_to_change] = noisy_label[0]
```

Graph examples with noisy labels

Get indices of examples with noisy labels from file

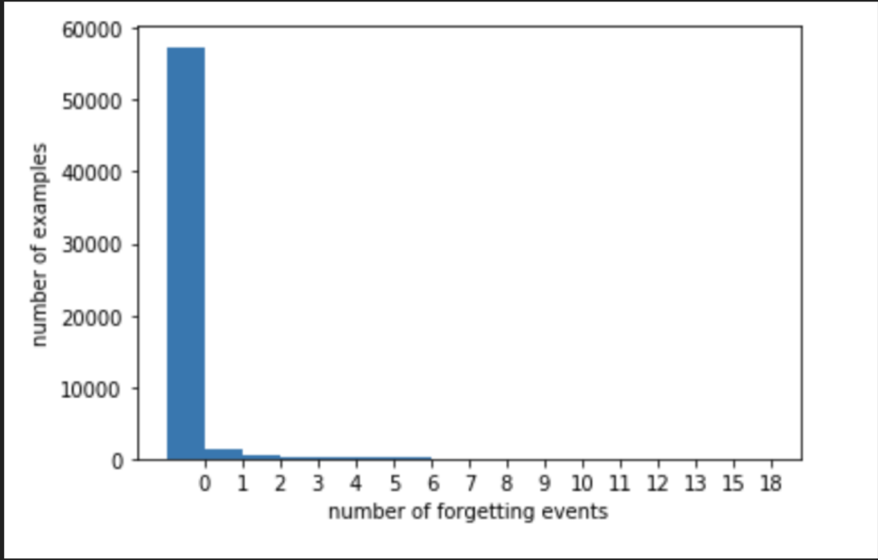
```
noisy_labels = []
with open('/Users/marcoazevedo/Documents/UVa/Fa
          ) as label_file:
    for line in label_file:
        number = int(line.split()[0])
        noisy_labels.append(number)
```

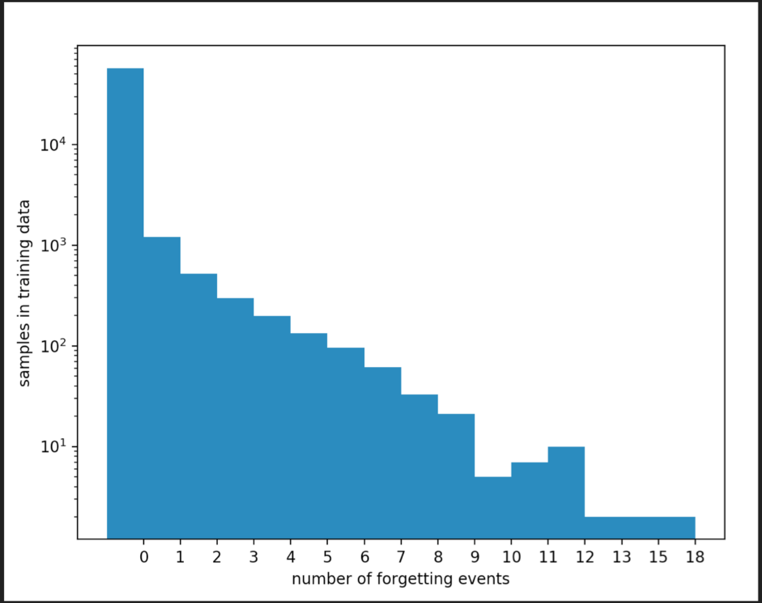
Get index of noisy sample from ordered example

Re-sort elements in from statistics

```
new_indices = np.array([])
for n in noisy_labels: # for each noisy index
    new_index = np.where(ordered_examples == n) # get index of noisy index in ordered_examples
    new_indices = np.append(new_indices, new_index) # append index to list
new_indices = new_indices.astype(int) # cast as int

labels, values = zip(*Counter(ordered_values[new_indices]).items())

width = 1
arr = np.zeros(20)
for i,_ in enumerate(labels):
    arr[labels[i]] = values[i]

indexes = np.arange(len(arr))
# FOR MNIST
#plt.bar(indexes, values, width)
#plt.xticks(indexes + width * 0.5, labels)

#FOR CIFAR
plt.bar(indexes, arr.tolist(), width)
plt.xticks(indexes + width * 0.5, indexes)
plt.xlabel('number of forgetting events')
plt.ylabel('samples in training data')

plt.show()
```

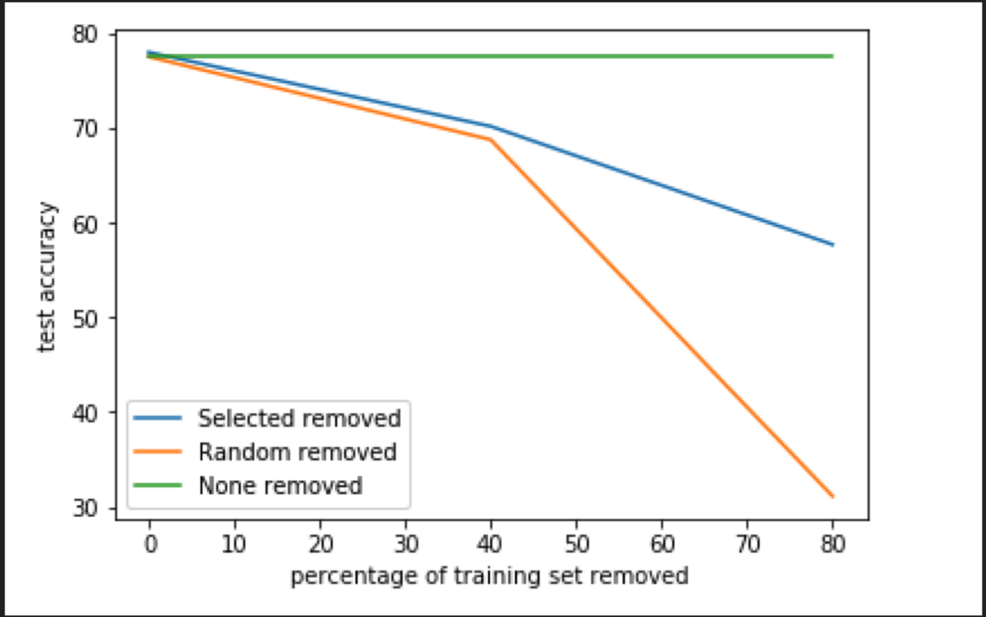
Experimental Results





Number of forgetting events vs. number of samples in MNIST (regular and log respectively)

Experimental Results



TRAINING DETAILS

CIFAR10 dataset trained with ResNet18

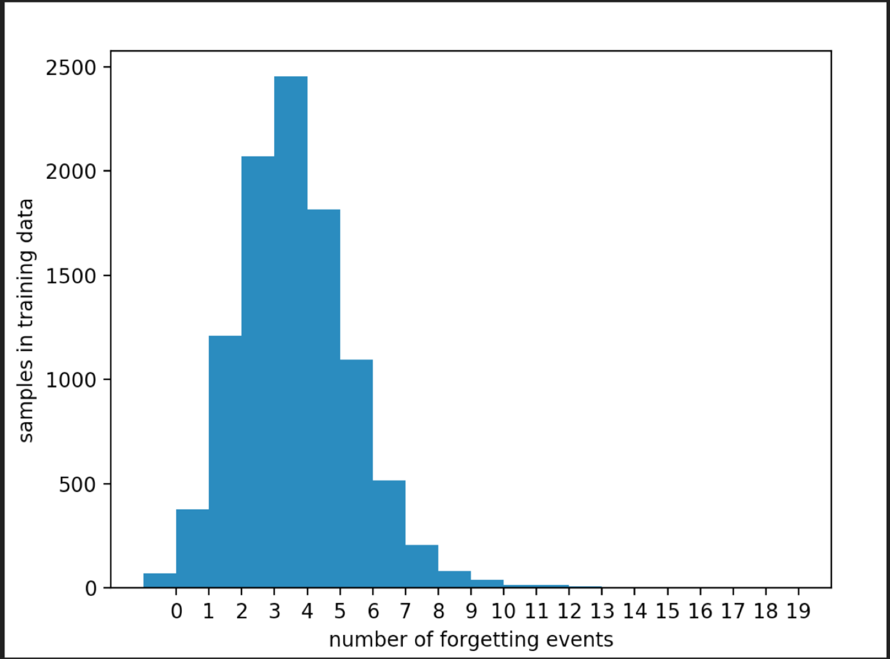
Training iteration was reduced from 200 epochs in the paper to 50 epochs due to computational cost.

After 50 iterations, highest test accuracy was 77.45%

Selected removed: samples were sorted based on forgettable events and most forgettable events were removed first
Random removed: randomly selected samples to be removed

Note: removing most forgettable examples first does not hurt performance as much as randomly removed samples

Experimental Results



Examples with noisy labels are more likely to be forgotten

TRAINING DETAILS

CIFAR10 dataset trained with ResNet18

Training with 100 epochs (~1 hour on Colab)

Randomly selected 20% of examples to change labels

Experimental Analysis and Conclusion and Future Work

There exists a large set of unforgettable examples

Examples with noisy labels and uncommon features are the most forgettable

Removing a large fraction of forgettable examples does not compromise performance of the neural network

Future work:

The theory behind forgetting is needed to be further investigated

Understand forgetting phenomena within other forms of learning (e.g speech or text)

Work Split

Marco

Loaded MNIST data

Trained CIFAR10 data to generate figure that compare forgettable events between normal CIFAR10 and noisy CIFAR10

Made slides for paper review

Oom

Used the loaded MNIST data to generate figure showing forgettable events of each sample in the data

Loaded and trained CIFAR10 dataset

Generated the figure showing test accuracy with and without forgettable samples removed

Made slides for the result section

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