Wir haben die falsche Loss function verwendet?

Aus der Pytorch Dokumentation:

The input is expected to contain the unnormalized logits for each class

der unreduzierte Cross Entropy Loss:

$$\ell(x, y) = L = \{l_1, \ldots, l_N\}^\top, \quad l_n = -w_{y_n} \log \frac{\exp(x_{n,y_n})}{\sum_{c=1}^{C} \exp(x_{n,c})} \cdot 1\{y_n \neq \text{ignore\_index}\}$$

Default ist reduction = mean:

$$\ell(x, y) = \begin{cases} \sum_{n=1}^{N} \frac{1}{\sum_{n=1}^{N} w_{y_n} \cdot 1\{y_n \neq \text{ignore\_index}\}} l_n, & \text{if reduction} = \text{'mean';} \\ \sum_{n=1}^{N} l_n, & \text{if reduction} = \text{'sum'.} \end{cases}$$

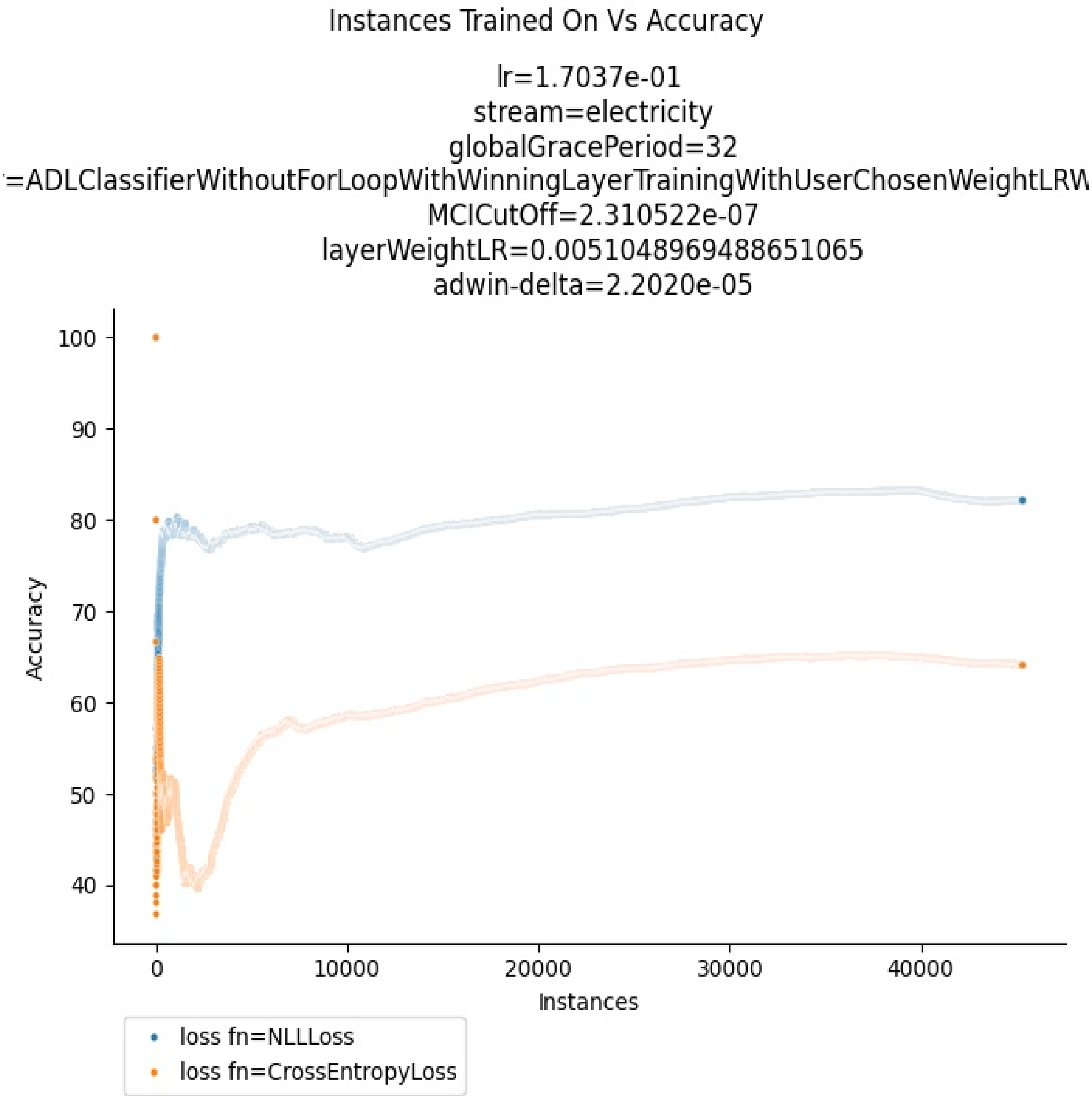
Note that this case is equivalent to applying LogSoftmax on an input, followed by NLLLoss

ADL wendet einen Softmax bereits im Forward Pass an, daher ist CrossEntropy vielleicht nicht die geeigneteste Loss Funktion.

Vorschlag einer neuen Loss Funktion:

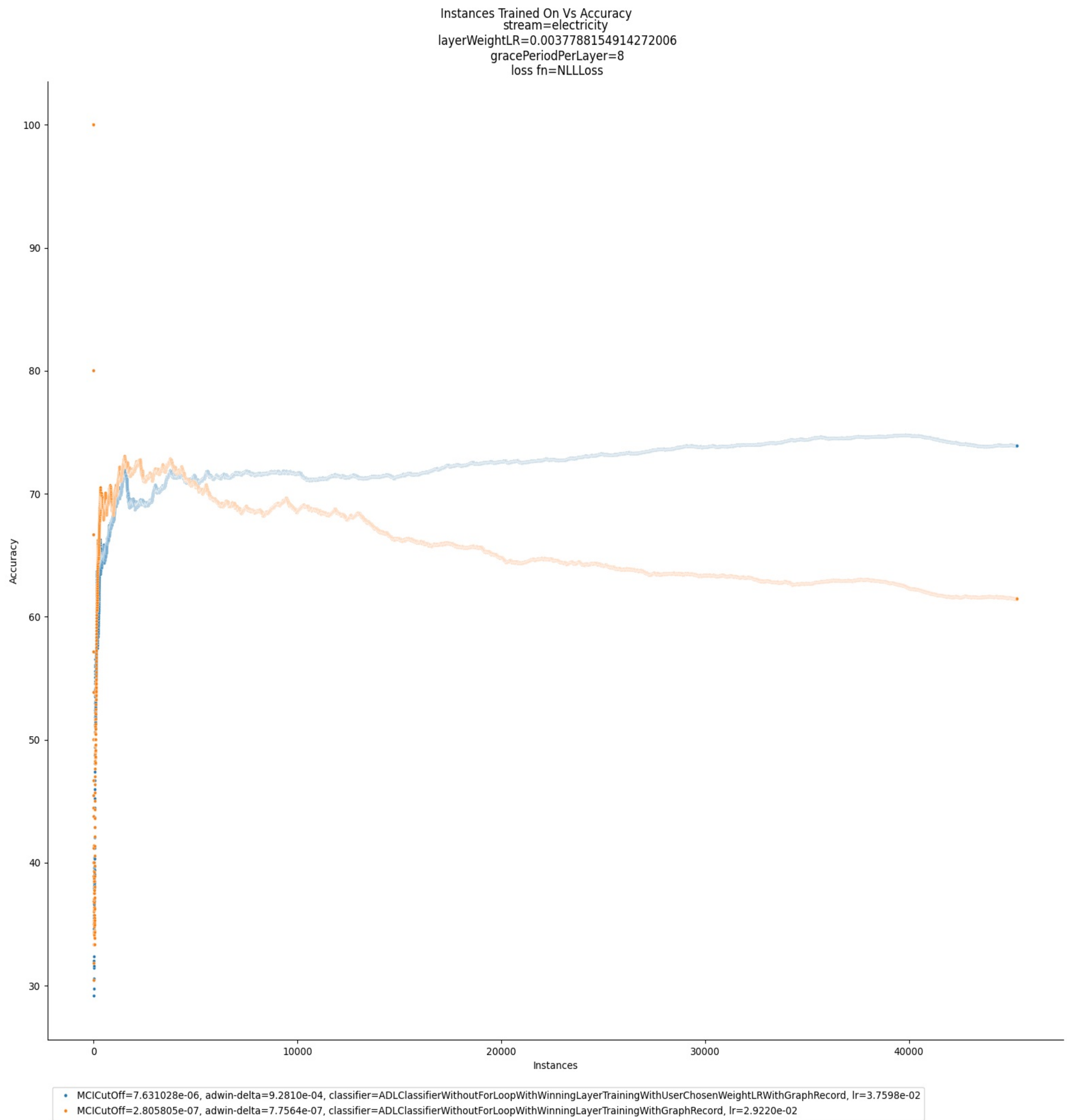
```
import torch
from torch import nn
nr_of_classes, idx_of_true_class = 4, 1

y_pred: torch.Tensor = torch.rand(nr_of_classes)
y_true: torch.Tensor = torch.tensor(idx_of_true_class, dtype=torch.int)
nn.NLLLoss()(torch.log(y_pred), y_true)
```

Vergleich der alten gegen die neue Loss Funktion für ein Set an Hyperparametern:



Decoupeling von Learning Rate und Weight Correction Factor um LR zu senken?

Vergleich best LR Coupled vs Best LR Decoupled



Syntetic Streams Build:

Type of Streams:

Type	Agrawal	SEA	details
no drift	y	y	Function 1
one drift	y	y	Function 1 -> abrupt drift @ 5000 -> Function 3
three drifts	y	y	Function 1 -> abrupt drift @ 5000 -> Function 3 -> abrupt drift @ 10000 -> Function 4 -> abrupt drift @ 15000 -> Function 1
drift back and forth	y	y	Function 1 -> abrupt drift @ 5000 -> Function 3 -> abrupt drift @ 10000 -> Function 1

Results for ADL on Types of Streams

Type	Agrawal	SEA
no drift	53.3%	54.06%
one drift	53.54%	82.00%
three drifts	56.68%	80.95%
drift back and forth	65.71%	81.1%

Suchraum einschränken:

1. Versuch: einfach jeweils die drei Parameter nehmen die am besten auf EletricityTiny performed haben und sie auf Electricity testen:

Lr:

- LinearLearningRateProgression(initial_learning_rate=1, decay_alpha=0.001)
- ExponentialLearningRateProgression(initial_learning_rate=1, decay_alpha=0.001)
- 5e-1
- 5e-2
- 1e-3

    4 Werte weil mir eigentlich alle werte außer den letzen beiden zu hoch sind.

    #### MCI:

- 1e-6
- 1e-7
- 1e-8

    in tiny haben wir damit immer so um die 6-10 activen layer am Ende gehabt

    #### adwin-delta:

- 1e-3
- 1e-5
- 1e-7

grace period per layer

- 4
- 8
- 16?
- None

    finding aus der isolation: je höher die grace period, desto schlechter das ergebnis und per layer out-performed global nach dem ich global auch anwende #-.-
    es kann sein, dass auf mehr instanzen größere grace periods sinn machen bzw positive sind, weil auf den kleinen datastreams haben wir ja anscheinend nur das problem nicht schnell genug lernen zu können Grace Period None: Sieht sehr lange Trainingszeiten, habe ich dann erstmal zu grace period=1 gemacht.

Ray Tunes:

kein Grid Search mehr, sondern Probing:

1. Suchraum:

- maximal 50000
- frühester abbruch nach = 500
- anzahl stichproben = 500
- learner: (vectorized, winning_layer, decoupled_lrs)
- stream: only one stream at a time
- lr: tune.loguniform(1e-4, 5e-1)

- layer_weight_learning_rate: tune.loguniform(1e-4, 5e-1),
- adwin-delta: tune.loguniform(1e-7, 1e-3),
- mci: tune.loguniform(1e-7, 1e-5),
- loss_fn: NLLLoss
- grace_period: choice aus: global/layer/none in 4,8,16,32

Ergebniss des ersten Suchraums:

- lr: 0.17037433308206834,
- layer_weight_learning_rate: 0.0051048969488651065,
- adwin-delta: 2.2019797256079463e-05,
- mci: 2.3105218391180886e-07,
- grace_period": global, 32

=> 82.15% acc bei 6 hidden, 6 active, und 1502 nodes in hidden layern bei 45000 instancen

result_first_ray_tune_search_space.png

These: min_runs=500 zu niedrig, bestraft anfänglich langsame lerner

> Nachteil von hohem min_run: suchen dauern sehr lange
> exemplarisch für Electricity

2. Suchraum:

- maximal 50000
- frühester abbruch nach = 500
- anzahl stichproben = 500
- learner: (vectorized, winning_layer, decoupled_lrs)
- stream: only one stream at a time
- lr: tune.loguniform(1e-4, **5e-2**), (habe die obere grenze extra niedriger gesetzt um lr zu bekommen die gut sind)
- layer_weight_learning_rate: tune.loguniform(1e-4, **5e-2**),
- adwin-delta: tune.loguniform(1e-7, 1e-3),
- mci: tune.loguniform(1e-7, 1e-5),
- loss_fn: NLLLoss
- grace_period: choice aus: global/layer/1 in 4,8,16,32

Ergebnisse aus 2. Suchraum:

> vgl tabelle bei streams beste hyperparameter:

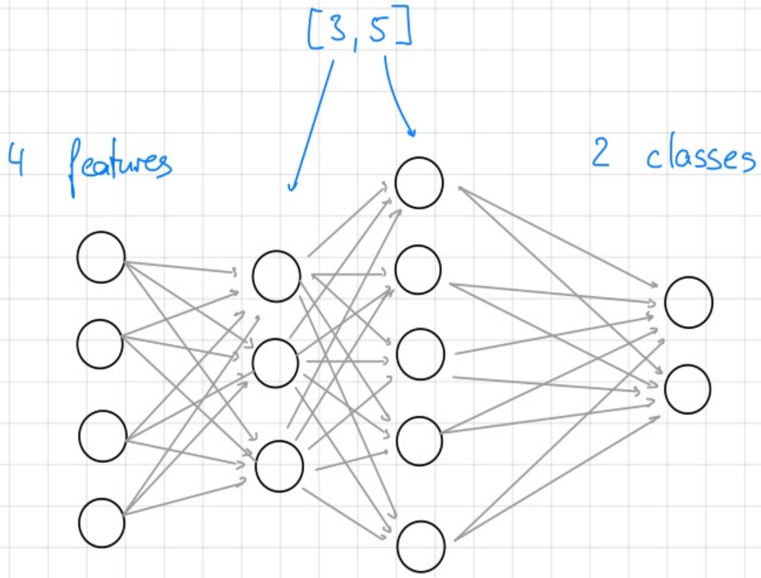
für electricity: python { "learner": ["vectorized", "winning_layer", "decoupled_lrs"], "stream": "electricity", "lr": 0.03759834306496821, "layer_weight_learning_rate": 0.0037788154914272006, "adwin-delta": 0.0009280964263786628, "mci": 7.631027908752775e-06, "grace_period": [8, "layer_grace"], "loss_fn": "NLLLoss" }

Type	Agrawal					SEA				
	lr	Layer Weight Learning Rate	Adwin Delta	MCI	Grace Period	lr	Layer Weight Learning Rate	Adwin Delta	MCI	Grace Period
no drift	0.001	0.013	3.79e-05	6.8e-07	null	0.001	0.02	4.7e-07	1.2e-06	null
one drift	0.0007	0.0008	1.43e-06	2.48e-07	(8, global)	0.039	0.027	4.14e-07	9.6e-06	(8, global)
three drifts	0.04	0.0001	1.77e-06	8.24e-07	(4, layer)	0.039	0.027	4.14e-07	9.6e-06	(8, global)
drift back and forth	0.023	0.002	0.0002	1.13e-07	(4, global)	0.039	0.027	4.14e-07	9.6e-06	(8, global)

Comparision Network

Strukture

input: nr of features (size of input vector)
nr of classes (size of output vector)
model structure how many hidden layers and how big
lr



example
4 features
2 classes
[3, 5]
lr = 0.5

activation function: sigmoid

output function: softmax

Results on Electricity

Suche durch den Suchraum: **alle kombinationen an 2er potenzen an nodes mit genau so vielen layern wie das adl netzwerk (solange die anzahl an layern kleiner als 9 ist, sonst ist space complexität zu groß)** ```python from itertools import product from ray import tune import numpy as np

def SimpleDNNSearchSpace(stream_name: str, nr_of_hidden_layers: int = 5, nr_of_neurons: int = 2**12): “”“ creates a search space for the SimpleDNN model that has no more than nr_of_hidden_layers many linear layers and in total not more than 2*nr_of_neurons many nodes ”“” if nr_of_neurons > 256: list_of_possible_neuron_configs = [list(perm) for h in range(1, nr_of_hidden_layers + 1) for perm in product(list(map(int, 2** np.arange(8, int(np.ceil(np.log2(nr_of_neurons))) + 1))), repeat=h) if np.sum(perm) <= 2**np.ceil(np.log2(nr_of_neurons))] else: list_of_possible_neuron_configs = [list(perm) for h in range(1, nr_of_hidden_layers + 1) for perm in product(list(map(int, 2** np.arange(int(np.ceil(np.log2(nr_of_neurons))) + 1))), repeat=h) if np.sum(perm) <= 2**np.ceil(np.log2(nr_of_neurons))] return { “lr”: tune.loguniform(1e-4, 5e-1), “model_structure”: tune.choice(list_of_possible_neuron_configs), stream: tune.grid_search([stream_name]) }** ``` also nicht jedes mal die gleiche model struktur** lr = 0,005 model 1 layer mit 4096 Nodes Acc: 85.23%

Results for ADL on Types of Streams

Zur Erinnerung:

Type	Agrawal	SEA
no drift	53.3%	54.06%
one drift	53.54%	82.00%
three drifts	56.68%	80.95%
drift back and forth	65.71%	81.1%

Result for Comparision Network

Type	Agrawal	SEA
no drift	58,19%	57.57%
one drift	54.53%	84.25%
three drifts	64.31%	83.94%
drift back and forth	65.584%	83.61%

Hidden layers Disablen:

Einfacher Weg:

```
from torch import nn
nr_of_inputs, nr_of_nodes = 3, 4

nn.Linear(nr_of_inputs, nr_of_nodes).requires_grad_(False)
```

Für alle Hidden layer die gelöscht werden. ohne Gradient keine Berechnung von Backward aber im Forward immer noch anwendung der Matrixmultiplikation und der Sigmoidfunction

implementiert in : ```python from ADLClassifier.BaseClassifier import ADLClassifier

def disabeling_deleted_layers(adl_classifier: type(ADLClassifier)) -> type(ADLClassifier): """ extends an existing ADLClassifier class to disable the gradiant calculation for the corresponding hidden layer if an output layer is deleted :param adl_classifier: the class of ADL Classifier that should be extended :return: the extended ADLClassifier class """

class DisabelingDeletedLayersWrapper(adl_classifier): """ :arg class of ADLClassifier that sets requires_grad to False for hidden layers whose output layer has been deleted """

```
  def __str__(self):
     return f"{super().__str__()}WithDisabledDeletedLayers"

  @classmethod
  def name(cls) -> str:
     return f"{adl_classifier.name()}WithDisabledDeletedLayers"

  def _delete_layer(self, layer_index: int) -> bool:
     if super()._delete_layer(layer_index):
        self.model.layers[layer_index].requires_grad_(False)
        return True
     else:
        return False
```

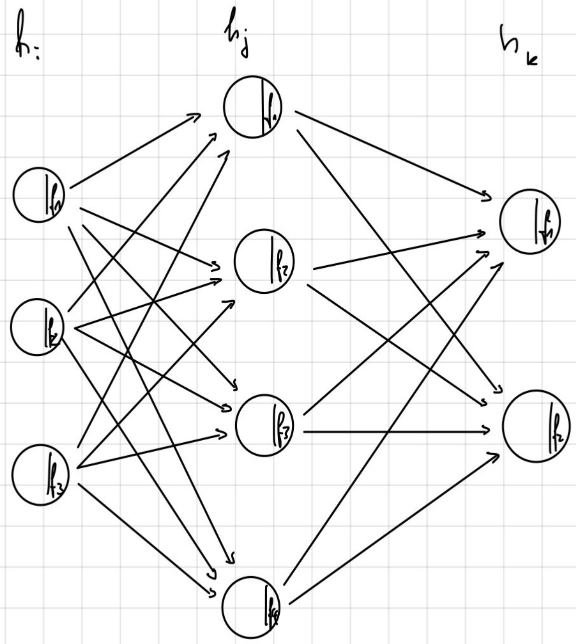
DisabelingDeletedLayersWrapper.**name** = f"{adl_classifier.**name**}WithDisabledDeletedLayers" return DisabelingDeletedLayersWrapper ```

Proposal:

Deletion of Hidden Layer Proposal:

Skizze: Vorher

$$f\left(h_k\left(f\left(h_j\left(f\left(h_i(x)\right)\right)\right)\right)\right)$$



in example: $n = 3$, $m = 4$, $o = 2$

$h_i \in \mathbb{R}^{n \times |x|}$

$h_j \in \mathbb{R}^{m \times n}$

$h_k \in \mathbb{R}^{o \times m}$

$$h_k' = f \circ h_j \circ f \circ h_k$$

Problem: f is non-linear
$\Rightarrow f \circ h_j \circ f \circ h_k$ cannot be reduced to a single layer

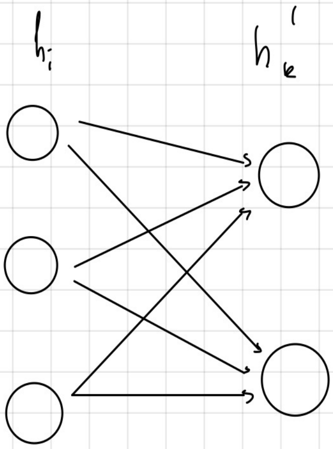
Proposal:

$$h_i'' = f \circ \underbrace{h_j \circ h_k}_{\text{one matrix after multiplication}}$$

$\rightarrow$ one layer + 1 sigmoid

$$f\left(h_k'\left(f\left(h_i(x)\right)\right)\right)$$

Nachher:



With Bias:

$$H_2(H_1 \cdot x + b_1) + b_2$$
$$= H_2 H_1 x + H_2 b_1 + b_2$$

By merging with the layer after the deleted we don't change the output size of newly merged compared to the remaining one
$\Rightarrow$ no need to change the output layer

implementiert in: ```python from ADLClassifier import ADLClassifier

def delete_deleted_layers(adl_classifier: type(ADLClassifier)) -> type(ADLClassifier): “”“ extends an existing ADLClassifier class to disable the gradiant calculation for the corresponding hidden layer if an output layer is deleted :param adl_classifier: the class of ADL Classifier that should be extended :return: the extended ADLClassifier class """

class DeleteDeletedLayersWrapper(adl_classifier): """ :arg class of ADLClassifier that sets requires_grad to False for hidden layers whose output layer has been deleted """

```
  def __str__(self):
     return f"{super().__str__()}WithDeleteDeletedLayers"

  @classmethod
  def name(cls) -> str:
     return f"{adl_classifier.name()}WithDeleteDeletedLayers"

  def _delete_layer(self, layer_index: int) -> bool:
     # not exactly the same output, as we remove a sigmoid function between both layers in the forward s
     if super()._delete_layer(layer_index):
        self.model.delete_hidden_layer(layer_index)
        return True
     else:
        return False
```

DeleteDeletedLayersWrapper.**name** = f"{adl_classifier.**name**}WithDeleteDeletedLayers" return DeleteDeletedLayersWrapper sowie: python from typing import List, Dict, Optional, Tuple

import numpy as np import torch from torch import nn

class AutoDeepLearner(nn.Module):

```
def delete_hidden_layer(self, layer_index: int) -> None:
    """
    deletes a hidden layer whose output layer was deleted beforehand
    :param layer_index: the index of the hidden layer to delete
    """
    # make sure that there is another layer
    assert len(self.layers) > 1, "there needs to be at least another layer to delete a hidden layer"
    assert not self.output_layer_with_index_exists(layer_index), "cannot delete a hidden layer of an act

    layer_to_delete: nn.Module = self.layers[layer_index]
    # merge two layers and take the place of the second layer:
    if layer_index == len(self.layers) - 1:
        # if last layer is deleted just delete the layer, no need to merge anything
        pass

    else:
        # if not first layer is deleted merge with layer in after it
        layer_to_merge_with: nn.Module = self.layers[layer_index + 1]
        new_weight = nn.Parameter(layer_to_merge_with.weight.matmul(layer_to_delete.weight))
        new_bias = nn.Parameter(layer_to_merge_with.bias + layer_to_merge_with.weight.matmul(layer_to_de
        new_layer = nn.Linear(layer_to_delete.in_features, layer_to_merge_with.out_features)
        new_layer.weight = new_weight
        new_layer.bias = new_bias
        self.layers[layer_index + 1] = new_layer

    # remove now merged layer
    self.layers.pop(layer_index)

    # update all keys of all weights, all output keys and all weight_correction_factors
    # for all active layers that follow the deleted layer:
    for active_key in self.active_layer_keys()[self.active_layer_keys() > layer_index].detach().numpy().
        self.__set_output_layer(active_key - 1, self.__pop_output_layer(active_key))
```

```
        self.__set_voting_weight(active_key - 1, self.__pop_voting_weight(active_key))
        self.__set_weight_correction_factor(active_key - 1, self.__pop_weight_correction_factor(active_k
```

Ergebnisse des disablen von hidden layern:

keine zeit mehr für runs gehabt

Accuracy Changes

Emission Changes

Notizen:

1. Wenn Concept Change passiert macht eine Learning Rate Progression nur Sinn wenn sie dann wieder von vorne beginnt
   -> Future Work (nach dem 20.03.)
2. Future Work: Write Capymoa classifier that runs the Matlab Implementation (for benchmarking reasons)