Documentation Assessment Guidelines

Reproducibility Survey Paper

In this document we present criteria guidelines for assigning values for cost for each dimension of reproducibility in AI papers. In this case ‘cost’ in general represents the possibility of documentation being provided in the method to make reproducibility more accessible. The main objective here is to assess for a paper what documentation the authors have shared or could have shared to lower the cost of reproducing their method.

Note that the statements here are **guidelines** and not **rules** as this process is very contextual. Examples are given for each dimension with possible criteria you may run into and how that can increase the cost. Note that sometimes you will have to interpret the situation of the method and how that will fit in with these principles. **We are only interested to evaluate these questions in regards to the presented method: Other presented baselines/comparison methods are not relevant.** Furthermore, we focus on the **main** experiments of a method: Extra experiments in the appendix are less important and only be should be considered **supplemental input to evaluating the main experiments**.

First, the guidelines per dimension are stated. Then, practical examples are given for two papers.

Each dimension’s cost starts off as its minimal value (1) and increases according to the guidelines given below.
Thus the range for each cost is [1,10]

Implementation

Given the documentation given by the authors on the method, how much effort would it be to re-implement the method?

For the implementation we mainly focus on the code given by the authors for their method. In general we look for a link to the implementation of the authors. If this is not provided, we try to find any details that might help to re-implement the method. First check if the authors make their implementation available, if so start with point 1 otherwise with point 2.

1. If the available code is written by the original authors, this is considered part of the documentation. This URL must be stated in the review in the form of “The authors present their implementation online (URL).” The content of the repository must be checked for:

   - Details in the readme regarding installation requirements, how to execute, repository structure, data links(!)/processing. If the readme does not include clear information on how to **run** the code (Installation / examples) this increases the cost by 1.

   - Code regarding the implementation of a paper’s main method (For example: Their algorithm class or functions), data loaders and entry points. It must be skimmed for **comments** in general of how rich in information they are. <u>Discounting comments that are cryptic</u>: If more than 50% of core code is without comments, this increases the cost with 1.

   - If the repository structure is difficult to navigate (e.g. extremely large without index, unclear directory/file names) this increases the cost with 1.

2. If the authors **do not** provide their implementation, or parts are missing, the cost increases by 4. Then, check for other implementation details for other possible criteria to raise cost:

   A. Regarding practical details in which language/framework/libraries their method was developed:

      - If this is not provided, should further increase the cost by 4.

      - If this is provided, but only limited (e.g. “We implemented the method in Python”), increase the cost by 3

      - If this is provided in more detail (e.g. “We implemented using Framework X, version Y, …”), increase the cost by 2.

      - If this is provided in extensive details, with things such as design choices and other practical details, increase the cost by 1.

      - If the authors links other code repositories used for the **core** of their method implementation (e.g. “We used the SciPy implementation of Dijkstra’s Algorithm”), no additional cost is added.

B. Pseudo code definitions and general figures regarding architecture of the method in the paper (If applicable):

   - If none are provided, increase the cost by 2.

   - If either is provided with substantial detail, increase by 1. If both, increase by 0.

C. Any other possible practical information that can be found regarding the implementation that do not apply to any of the above categories can **decrease** the cost by up to 2 points.

Data

Given the data description in the documentation, how much effort would it take to either: Find the same dataset the authors used, or similar datasets and defend the comparability, or acquire one from scratch?

Check what datasets are being used by the authors. Note that usually multiple datasets are used: In general this cost is mostly impacted by the 'most accessible data set' and the 'most used dataset'. At the top it should be stated how many datasets (n) are used and how many of those are public (p) as "(p/n)" including the brackets on a separate line. If it is not clearly stated that the data is public (Either in the text, implementation or the references), assume its private. Environments/Simulators and synthetic data generators are also considered **data sets**. In case the method uses multiple data sets, the cost increase should be **averaged**, taking into account how much it is used. If for example paper X uses 3 different data sets D1, D2 and D3, but the presented results are 50% D1, and 25% D2, 25% D3, the cost should be: (C1 * 0.5 + C2 * 0.25 + C3 *0.25) / 3. Its fine to ballpark this calculation, just write down your reasoning ("The majority of experiments", "the private data set has a public alternative presented, therefore…"). First check below if you are dealing with datasets (First paragraph) or synthetic generators / simulators (Second paragraph).

For each dataset that is used, check that it has a description, citation, statistics and a direct link to where it can be found. If you recognise the dataset, feel free to use this information regarding public/private data.

- If there is no direct link present to where the data can be found, increase the cost by 1.

  - If there no direct link **and** no citation, increase by 2.

- If there is no description on the dataset, increase by 1.

- If there are no or limited statistics, increase the cost by 1.

- If the data set is (partially) private, increase the cost by 1-2. If the collection strategy poorly is stated, increase the cost again, by up to another 3.

- If all of the above were true, (e.g. the data set is only **named**) increase the cost by up to an **additional 5** (based on the context).

In case of simulated environments or synthetic data **generators**, check if the environments are publicly available and linked/cited, and the configurations under which they were used.

- If the code on this is not provided, either by link/implementation/citation, increase the cost by 5.

- If the process of the generator or the environment/task of the simulator is not (clearly) described, increase the cost by 2.

- If the simulation/environment has parameters and are not specified, increase by 1.

- If the synthetic generation parameters are not stated **clearly** increase the cost by up to 3.

Configuration

Given the (hyper)parameters, including semantic parameters, of the method: How much effort would it take to acquire the algorithm configurations used for their results, and compare against their budgetary constraints?

Here we are interested in if the authors state what algorithm configurations or hyper parameter values they used for their experiments. Without these values, it can be costly to determine these values to reproduce the method.

1. Regarding the (hyper)parameters, check if the authors summarise their hyperparameters clearly, for example by providing a table, pseudo code or the implementation documents this:

- If this is missing, increase the cost by 3.
- If this informally stated in the text, increase the cost by 2.
- If this is detailed in the text, but an overview is missing, increase by 1.

2. Regarding the (hyper)parameter values:
   - If the values are (almost) not specified, increase by 4.
   - If the authors do not provide all values for each experiment, increase the cost by 1.
   - If large parts of the parameter values per experiment are ambiguous, increase by 2.
3. Regarding the (hyper) parameter acquisition:
   - If the authors do not state a strategy (e.g. ‘empirically’ / ‘we chose’ / ‘based on the values of bla bla et al.’ / ‘grid search’ / ‘SMAC3’), increase the cost by 1.
   - If it is not clarified under what budget the acquisition was done, increase the cost by 1.

Experimental Setup

Given the experimental set-up of the work, how difficult is it to set up a new experiment, similar to those presented in the original work, with the same procedure?

Here we are interested in whether the authors clearly document under which set up the empirical evaluation was done, s.t. we can set up a new experiment under the same conditions. If there are multiple experiments, the result is the (possibly weighted if that is applicable) average.

1. The metrics are being used to evaluate the method:
   - If the authors do not state these/provide citations on them, unless they very standard in AI (‘accuracy’ or ‘F1-score’ needs no explanation) increase the cost by 1 or 2 depending on how many metrics this applies to.
2. The data that is being evaluated on:

- If there is no clear specification of its training/validation/testing data, or its evaluated on the full data set, increase the score by 1.
- If it is not clear how the dataset is split to train / test on, increase the score by 2.

3. The strategy that is used to acquire the evaluations (Can overlap with 2):

- Is the strategy not clearly stated (E.g. multiple folds, k-fold-cross validation, single/multiple runs over seeds,..) but is implied increase by 1, if not specified at all increase by 2.
- If strategy details are missing such as parameters/repetition (E.g. k-fold but no k given), increase by 1.

4. The aggregation of the results:

- Is it clear how the results are aggregated? If not increase by 1.
- If there is a measure of distribution presented over the results, is it clear what type this is (Std. dev, variance, 95% CI,..)? If not increase by 1.

Expertise

How much effort would it take to acquire the expertise required to reproduce the work independently relying on the available documentation?

Here we want to evaluate from a scale from 1-10 (1 being accessible and 10 requiring a lot of expertise). For this question it is the target to assess how much knowledge you have to bring or how much extra reading you have to do **outside** of the documentation given by the authors. General points to consider: How many different fields within AI are being touched upon? How well is the problem introduced, or are we expected to already understand the problem? How much mathematics / logic / proofs are presented, and how well is each introduced? The more we are expected to have previous knowledge before reading the paper, and the more complex the techniques, the higher this cost as we have to rely increasingly on previous experience or external documentation to reproduce the work. This is not by definition a bad thing, rather it means ‘not everybody’ will be able to reproduce the work ‘out of the box’.

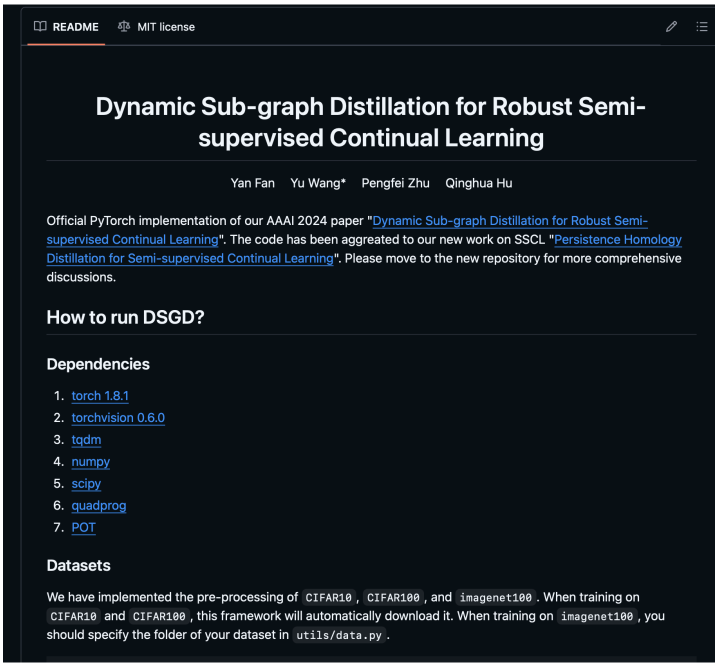
Examples

Dynamic Sub-graph Distillation for Robust Semi-supervised Continual Learning

AAAI 2024, link here

Implementation [4]

The authors provide a GitHub link with their implementation. The readme is a bit short but has a lot of structured information.



Dynamic Sub-graph Distillation for Robust Semi-supervised Continual Learning

Yan Fan Yu Wang* Pengfei Zhu Qinghua Hu

Official PyTorch implementation of our AAAI 2024 paper "Dynamic Sub-graph Distillation for Robust Semi-supervised Continual Learning". The code has been aggregated to our new work on SSCL "Persistence Homology Distillation for Semi-supervised Continual Learning". Please move to the new repository for more comprehensive discussions.

How to run DSGD?

Dependencies

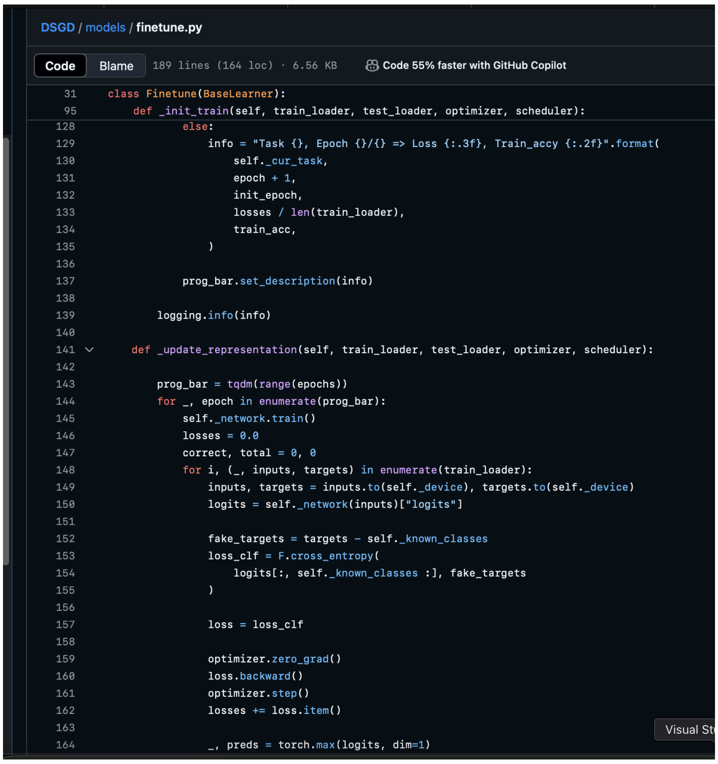
1. torch 1.8.1
2. torchvision 0.6.0
3. tqdm
4. numpy
5. scipy
6. quadprog
7. POT

Datasets

We have implemented the pre-processing of `CIFAR10`, `CIFAR100`, and `imagenet100`. When training on `CIFAR10` and `CIFAR100`, this framework will automatically download it. When training on `imagenet100`, you should specify the folder of your dataset in `utils/data.py`.

However the directory structure is huge and most of the code has no comments see for example: **https://github.com/fanyan0411/DSGD/blob/main/models/finetune.py**

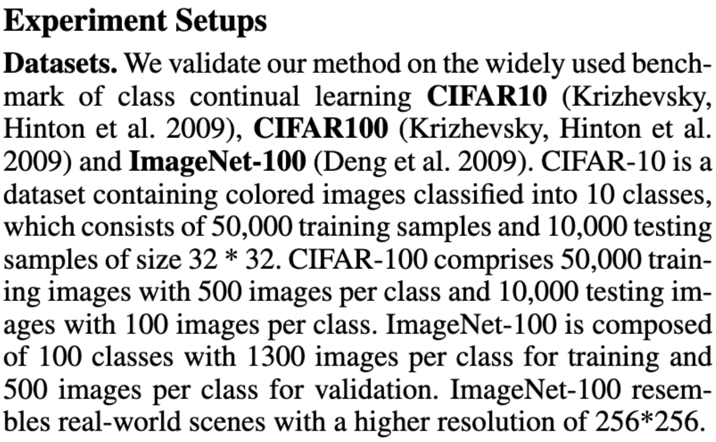
This means understanding the code is costly. Both the structure and the code are very difficult to understand, thus we round up slightly. Therefore its evaluated with a **4**.


DSGD / models / finetune.py
Code
Blame
189 lines (164 loc) · 6.56 KB
Code 55% faster with GitHub Copilot
Visual St

```
class Finetune(BaseLearner):
    def _init_train(self, train_loader, test_loader, optimizer, scheduler):
            else:
                info = "Task {}, Epoch {}/{} => Loss {:.3f}, Train_accy {:.2f}".format(
                    self._cur_task,
                    epoch + 1,
                    init_epoch,
                    losses / len(train_loader),
                    train_acc,
                )

            prog_bar.set_description(info)

        logging.info(info)

    def _update_representation(self, train_loader, test_loader, optimizer, scheduler):

        prog_bar = tqdm(range(epochs))
        for _, epoch in enumerate(prog_bar):
            self._network.train()
            losses = 0.0
            correct, total = 0, 0
            for i, (_, inputs, targets) in enumerate(train_loader):
                inputs, targets = inputs.to(self._device), targets.to(self._device)
                logits = self._network(inputs)["logits"]

                fake_targets = targets - self._known_classes
                loss_clf = F.cross_entropy(
                    logits[:, self._known_classes :], fake_targets
                )

                loss = loss_clf

                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
                losses += loss.item()

                _, preds = torch.max(logits, dim=1)
```

Data [1]

As can be seen in the screen shot of the implementation the authors provide details and automatic downloads in the implementation, thus they are all public. Based on this snippet of the paper (page 5):



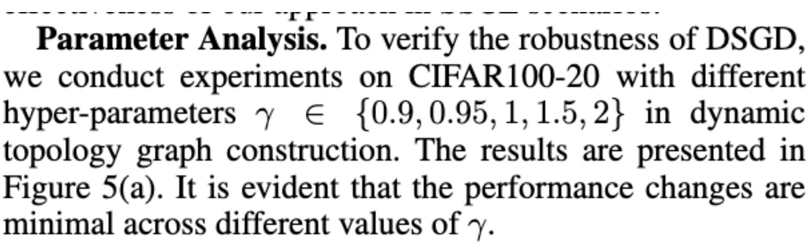
Experiment Setups

Datasets. We validate our method on the widely used benchmark of class continual learning **CIFAR10** (Krizhevsky, Hinton et al. 2009), **CIFAR100** (Krizhevsky, Hinton et al. 2009) and **ImageNet-100** (Deng et al. 2009). CIFAR-10 is a dataset containing colored images classified into 10 classes, which consists of 50,000 training samples and 10,000 testing samples of size 32 * 32. CIFAR-100 comprises 50,000 training images with 500 images per class and 10,000 testing images with 100 images per class. ImageNet-100 is composed of 100 classes with 1300 images per class for training and 500 images per class for validation. ImageNet-100 resembles real-world scenes with a higher resolution of 256*256.

Short descriptions are given, statistics provided, citations presented. Although all brief, since the data is made highly accessible this brings the cost to **1**.

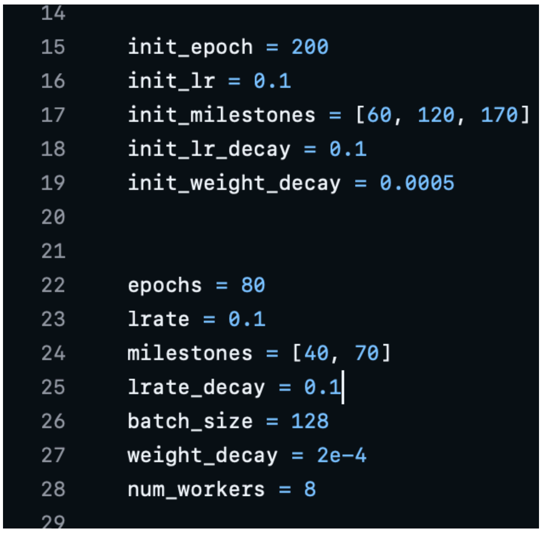
Configuration [3]

The authors present the values of the models hyperparameters hardcoded in the implementation, and conduct a grid search of some of the parameters in figure five.



Parameter Analysis. To verify the robustness of DSGD, we conduct experiments on CIFAR100-20 with different hyper-parameters $\gamma \in \{0.9, 0.95, 1, 1.5, 2\}$ in dynamic topology graph construction. The results are presented in Figure 5(a). It is evident that the performance changes are minimal across different values of γ.

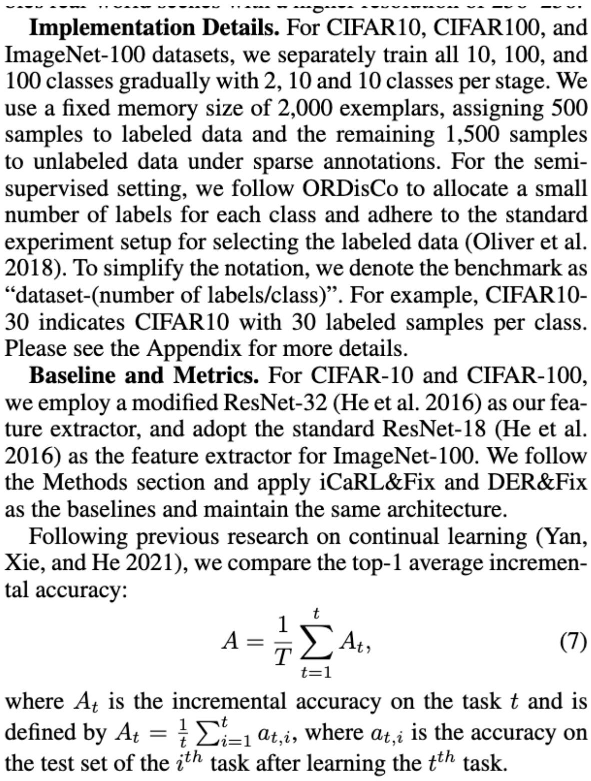
Thus all used values can be determined easily, but as the search strategy/budget is only specified for a small subset of the hyperparameters / datasets the value is still **3**.



```

    init_epoch = 200
    init_lr = 0.1
    init_milestones = [60, 120, 170]
    init_lr_decay = 0.1
    init_weight_decay = 0.0005


    epochs = 80
    lrate = 0.1
    milestones = [40, 70]
    lrate_decay = 0.1
    batch_size = 128
    weight_decay = 2e-4
    num_workers = 8

```

Experimental Procedure [2]

The authors state the metrics and data splits for the experiments on page 5. The also state that the metric is averaging by the specified formula 7. However it is not specified if the experiments are (not) repeated under a certain procedure, implying single run results thus a cost of 2 as this must be checked (against the implementation for example).



Implementation Details. For CIFAR10, CIFAR100, and ImageNet-100 datasets, we separately train all 10, 100, and 100 classes gradually with 2, 10 and 10 classes per stage. We use a fixed memory size of 2,000 exemplars, assigning 500 samples to labeled data and the remaining 1,500 samples to unlabeled data under sparse annotations. For the semi-supervised setting, we follow ORDisCo to allocate a small number of labels for each class and adhere to the standard experiment setup for selecting the labeled data (Oliver et al. 2018). To simplify the notation, we denote the benchmark as "dataset-(number of labels/class)". For example, CIFAR10-30 indicates CIFAR10 with 30 labeled samples per class. Please see the Appendix for more details.

Baseline and Metrics. For CIFAR-10 and CIFAR-100, we employ a modified ResNet-32 (He et al. 2016) as our feature extractor, and adopt the standard ResNet-18 (He et al. 2016) as the feature extractor for ImageNet-100. We follow the Methods section and apply iCaRL&Fix and DER&Fix as the baselines and maintain the same architecture.

Following previous research on continual learning (Yan, Xie, and He 2021), we compare the top-1 average incremental accuracy:

$$A = \frac{1}{T}\sum_{t=1}^{t} A_t, \tag{7}$$

where A_t is the incremental accuracy on the task t and is defined by $A_t = \frac{1}{t}\sum_{i=1}^{t} a_{t,i}$, where $a_{t,i}$ is the accuracy on the test set of the i^{th} task after learning the t^{th} task.

pTSE: A Mult-model Ensemble Method for Probabilistic Time Series Forecasting

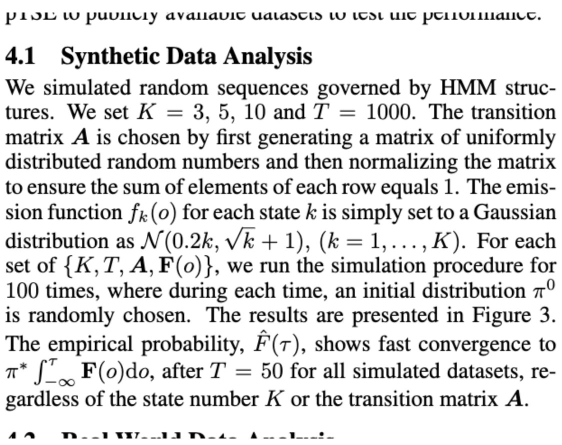
IJCAI 2023, link here

Implementation [10]

There are no implementation details stated in the paper. No links can be found, no practical details whatsoever (Such as libraries/frameworks/programming languages/OS). We can't find any figure overviews nor pseudo code, thus each details while have to be extracted with a lot of effort from the paper for reproduction.

Data [5]

In 4.1 the authors state synthetic data is used and describe how this is generated. Although the code for it is missing, the generation is in general well documented, thus only increasing the cost with 1.



pTSE to publicly available datasets to test the performance.

4.1 Synthetic Data Analysis

We simulated random sequences governed by HMM structures. We set $K = 3, 5, 10$ and $T = 1000$. The transition matrix $\boldsymbol{A}$ is chosen by first generating a matrix of uniformly distributed random numbers and then normalizing the matrix to ensure the sum of elements of each row equals 1. The emission function $f_k(o)$ for each state k is simply set to a Gaussian distribution as $\mathcal{N}(0.2k, \sqrt{k} + 1)$, $(k = 1, \ldots, K)$. For each set of $\{K, T, \boldsymbol{A}, \mathbf{F}(o)\}$, we run the simulation procedure for 100 times, where during each time, an initial distribution π^0 is randomly chosen. The results are presented in Figure 3. The empirical probability, $\hat{F}(\tau)$, shows fast convergence to $\pi^* \int_{-\infty}^{\tau} \mathbf{F}(o)\mathrm{d}o$, after $T = 50$ for all simulated datasets, regardless of the state number K or the transition matrix $\boldsymbol{A}$.

4.2 Real World Data Analysis

In 4.2 they discuss real world data analysis, and state they use three benchmark datasets (benchmark here indicates publicly available). For solar energy they provide a direct link in the footnote. For traffic they provide a citation. For electricity not link nor citation is provided, making it very difficult to find this dataset. A brief description on the data is given, but more information would be useful to understand the tasks in the data sets. Thus since one is easily accessible (direct link) one only semi (citations but very few details) and one not at all, but the results presented are evenly distributed across the datasets (table 1), we average the increase of 3. Thus 1 + 1 + 3 = **5**.

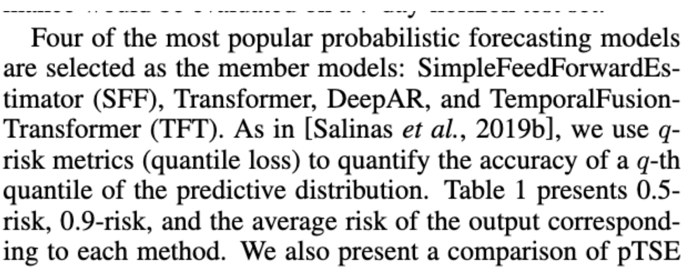
Configuration [2]

The authors do not give an implementation nor pseudo code, so we will have to extract the parameter/hyperparameters with some effort. It is stated in 4.2 that the two ensemble methods are set to the recommended values of the original baselines, but we only care about the parameters of the presented method so this is irrelevant.

The authors discuss a bandwidth parameter sigma in 2.4, but this is 'optimally set' by bootstrapping, thus not a user input value. They state they incorporate a non-parametric method in 2.4, suggesting their method could also be parameter free. In section 2.1, they state what an HMM needs as input, but no configurable parameters seem to be introduced here either. However in the introduction (and the conclusions) they state their method is ‘a semi-parametric method’, thus leaving some ambiguity (Are these configurable parameters or learned parameters?). Thus as the implementation is missing, some effort will have to be made by the independent investigators to verify that indeed no parameters are needed for the method, increasing the cost by 1 to a total of **2**.

Experimental Procedure [3]

The authors state the metrics used briefly in 4.2, and cite a previous work for it (Salinas et al). In table 1 we see single values on each data set, but the last value is ‘Average risk’. It is a bit unclear what this average is calculated over, but perhaps with domain specific expertise this would be more clear. This would have to be looked up, increasing the cost by 1. At the end of the first paragraph of section 4.2 the authors state ‘The model performance would be evaluated on a 7-day-horizon test set’, but its unclear what this test actually is. It could be that these are provided statically by the benchmarks, but this is not stated and would have to be looked up increasing the cost by 1. Thus the total cost is **3**.



Four of the most popular probabilistic forecasting models are selected as the member models: SimpleFeedForwardEstimator (SFF), Transformer, DeepAR, and TemporalFusion-Transformer (TFT). As in [Salinas *et al.*, 2019b], we use q-risk metrics (quantile loss) to quantify the accuracy of a q-th quantile of the predictive distribution. Table 1 presents 0.5-risk, 0.9-risk, and the average risk of the output corresponding to each method. We also present a comparison of pTSE