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Homework 2

Image Classification on Small Datasets

Machine Learning course 2021-2022

Recap

- Ensembles of small-scale convolutional networks provide good accuracy in small-data settings (Seminar 1)

- Tuning the hyper-parameters like learning rate and weight decay is a critical factor to ensure the highest performance (Seminar 2)

(Some) open questions

- Do custom/newer architectures work better than popular ResNets?

- Can we do even better choosing hyper-parameters?

- Do heterogeneous ensembles perform better than homogeneous ones?

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Answering these questions with crowd-sourcing

What if each student will train a “small” network to provide an ensemble member?

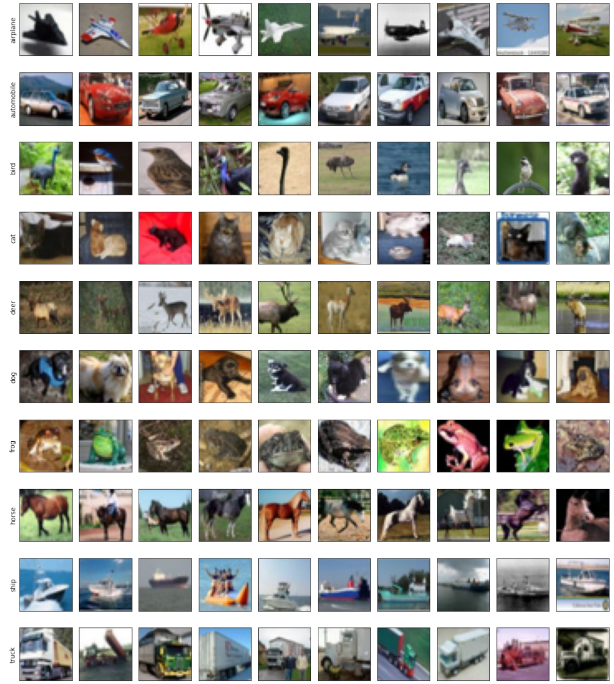
In this way:

- Obtaining a (very!) large and heterogeneous ensemble

- Exploring its own search space is easier for each single member (i.e. hyper-parameters)

Dataset [link]

- The dataset is ciFAIR-10 of the DEIC Benchmark (Seminar 2)
    - 10-class problem
    - 50 training images per class
    - 1000 testing images per class
    - image dimension 32x32x3



- Categories:
    - airplane
    - automobile
    - bird
    - cat
    - deer
    - dog
    - frog
    - horse
    - boat
    - truck

Objectives

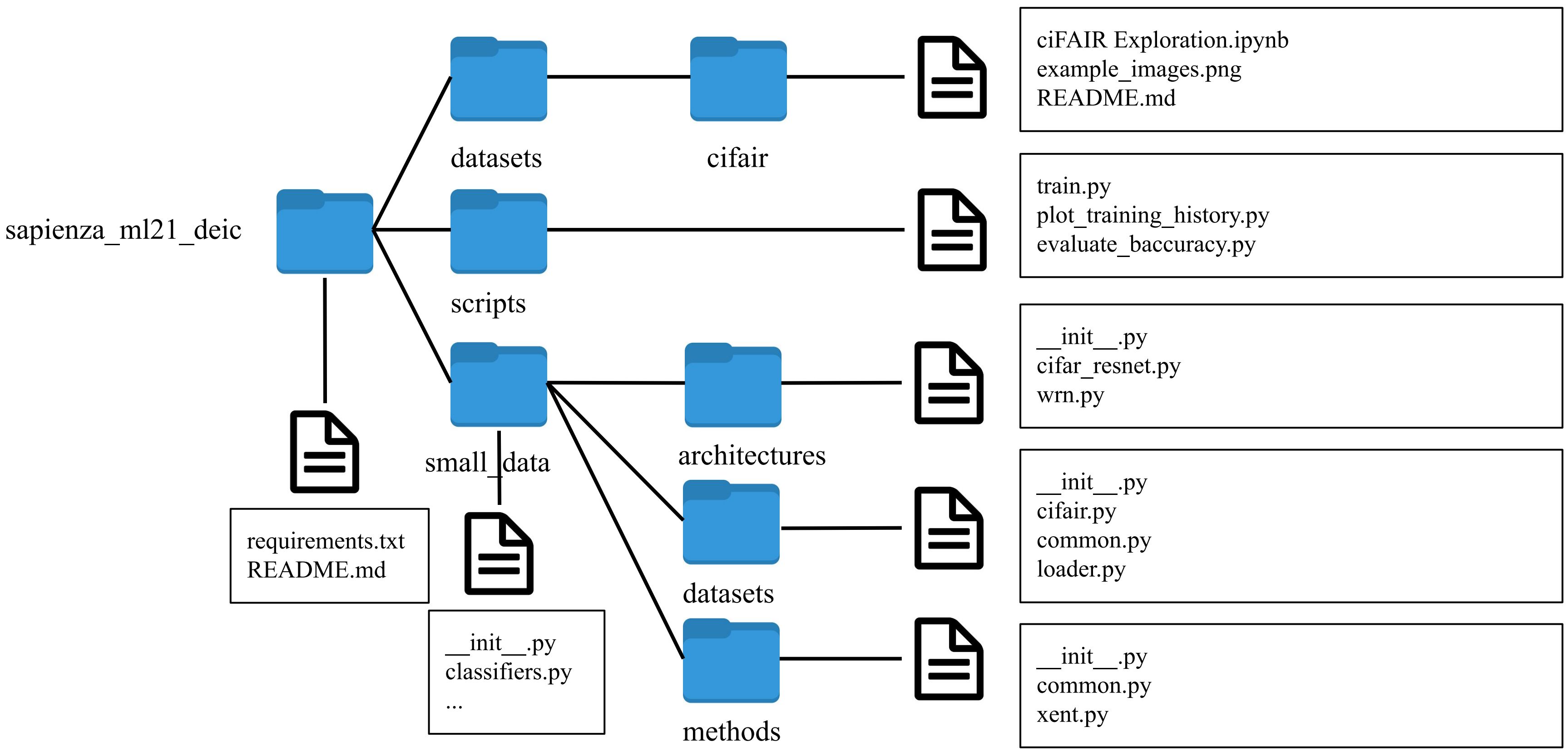
- Train your favorite network architecture:
  - published one (e.g. ResNet, Wide ResNet, EfficientNet…)
  - custom one (note that published ones are a good starting point)

- Analyze results concerning few modifications of chosen architecture:
  - size (e.g., network depth/width)
  - layer configurations (e.g., kernel size, convolution stride)

- Analyze results concerning few modifications of optimization process:
  - optimizer (e.g. SGD, Adam, ...)
  - optimizer parameters (e.g. learning rate, weight decay, momentum)
  - training (e.g. epochs, batch size)

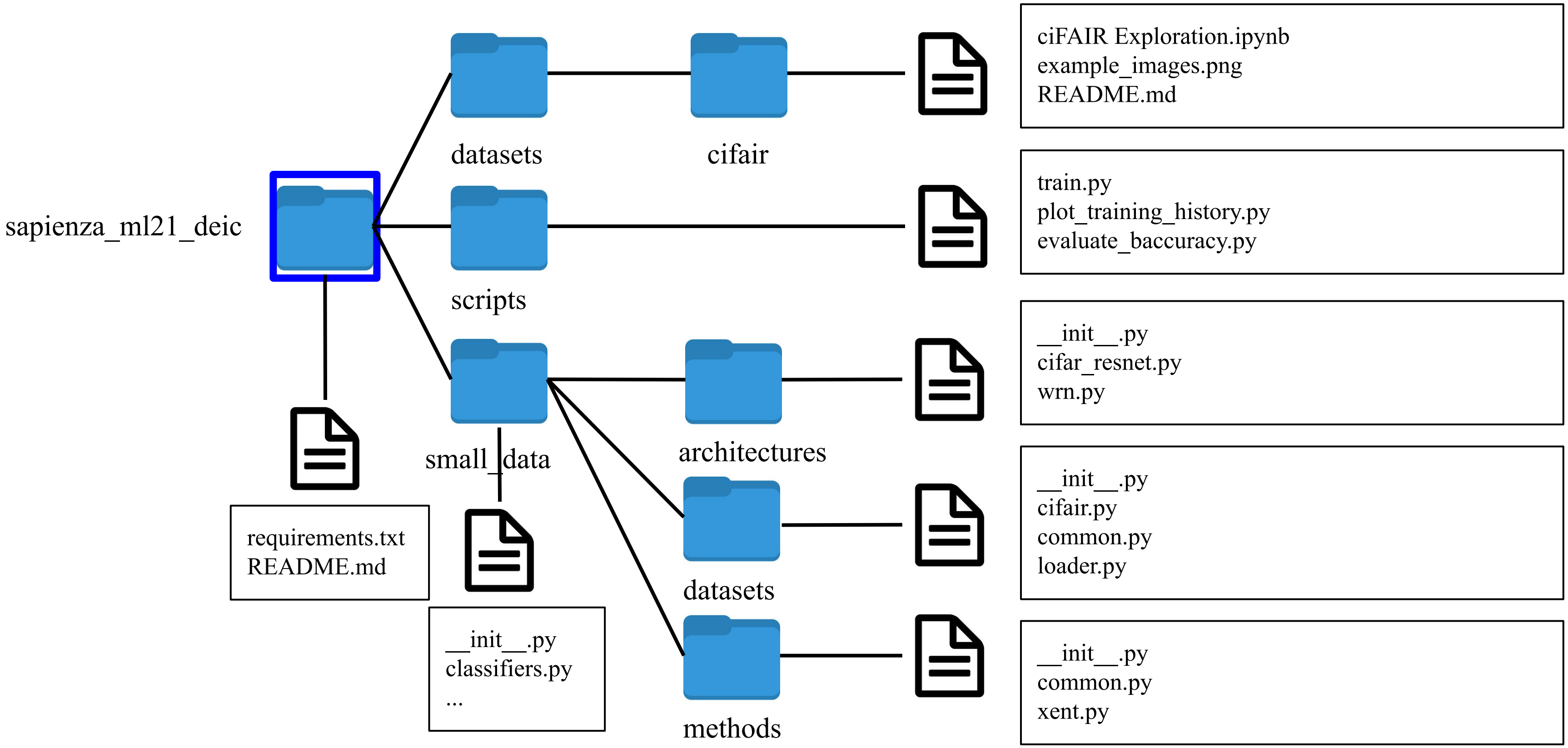
Code Repository [link]

We provide a code repository as starting point for your experiments



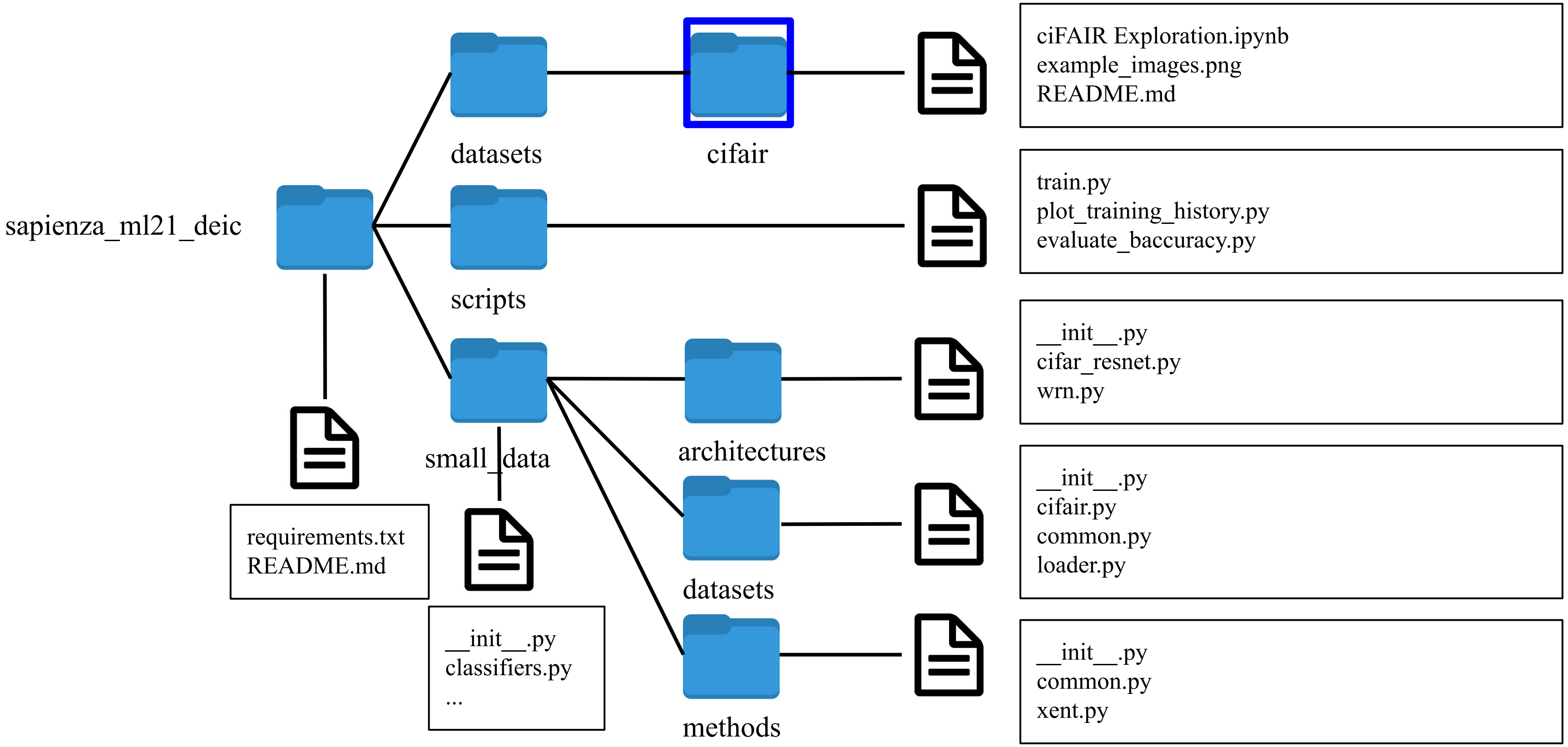
Code Repository

sapienza_ml21_deic is the main directory containing: file with package requirements, readme of the repository and subdirectories.



Code Repository

Put the provided dataset repository (ciFAIR-10 shared on Drive) inside this directory.



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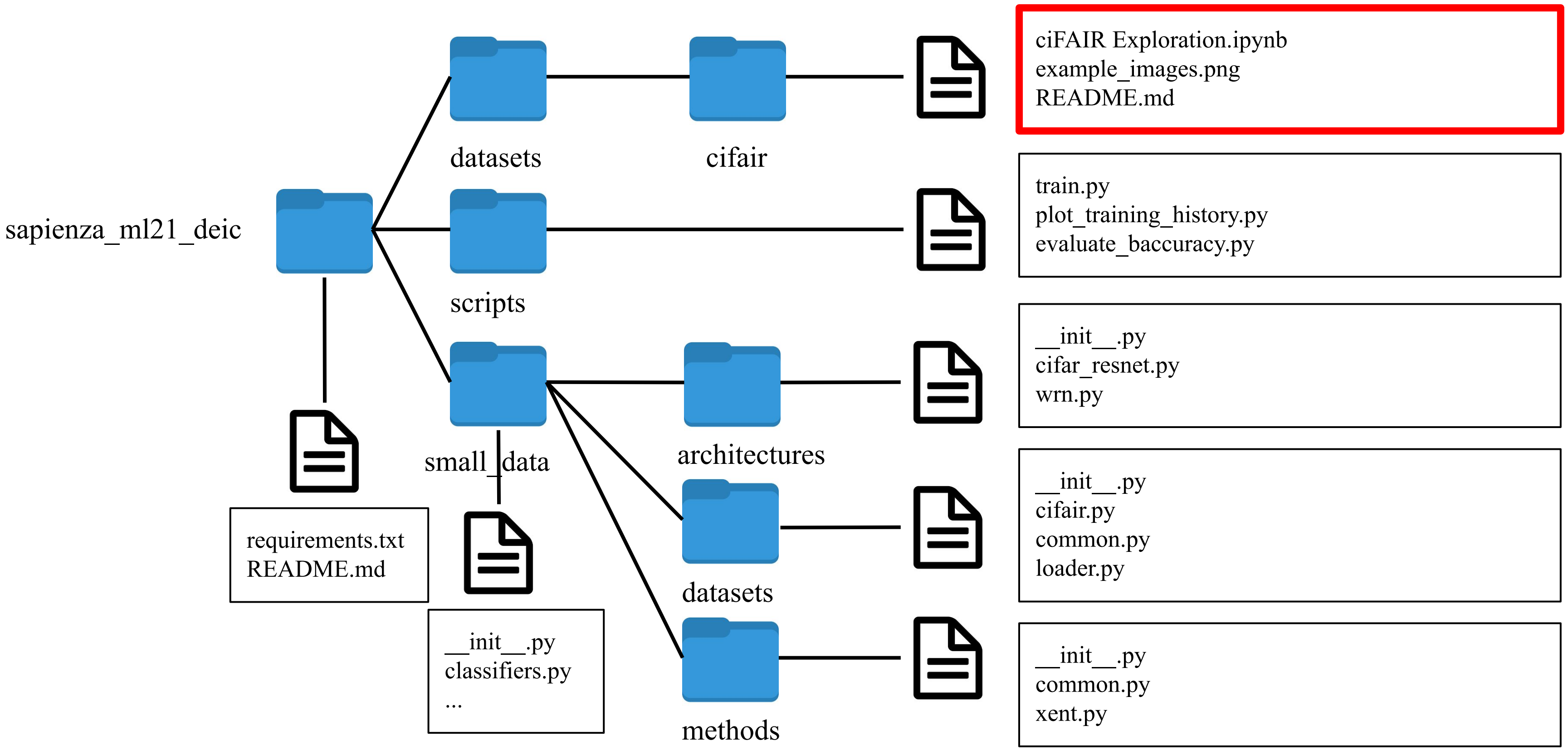
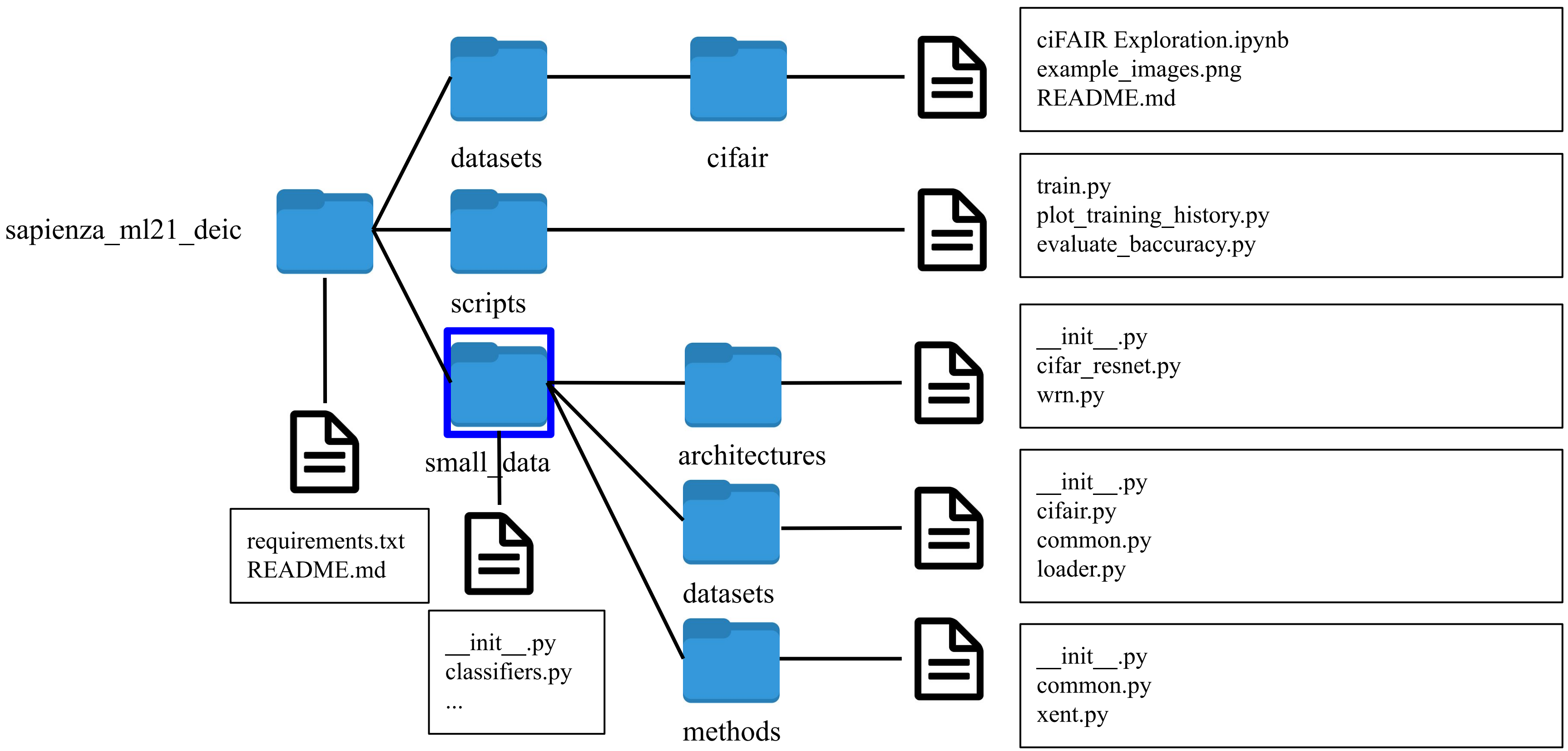
Code Repository

Notebook for dataset visualization and readme file with baseline performance along with terminal command to reproduce the baseline result.



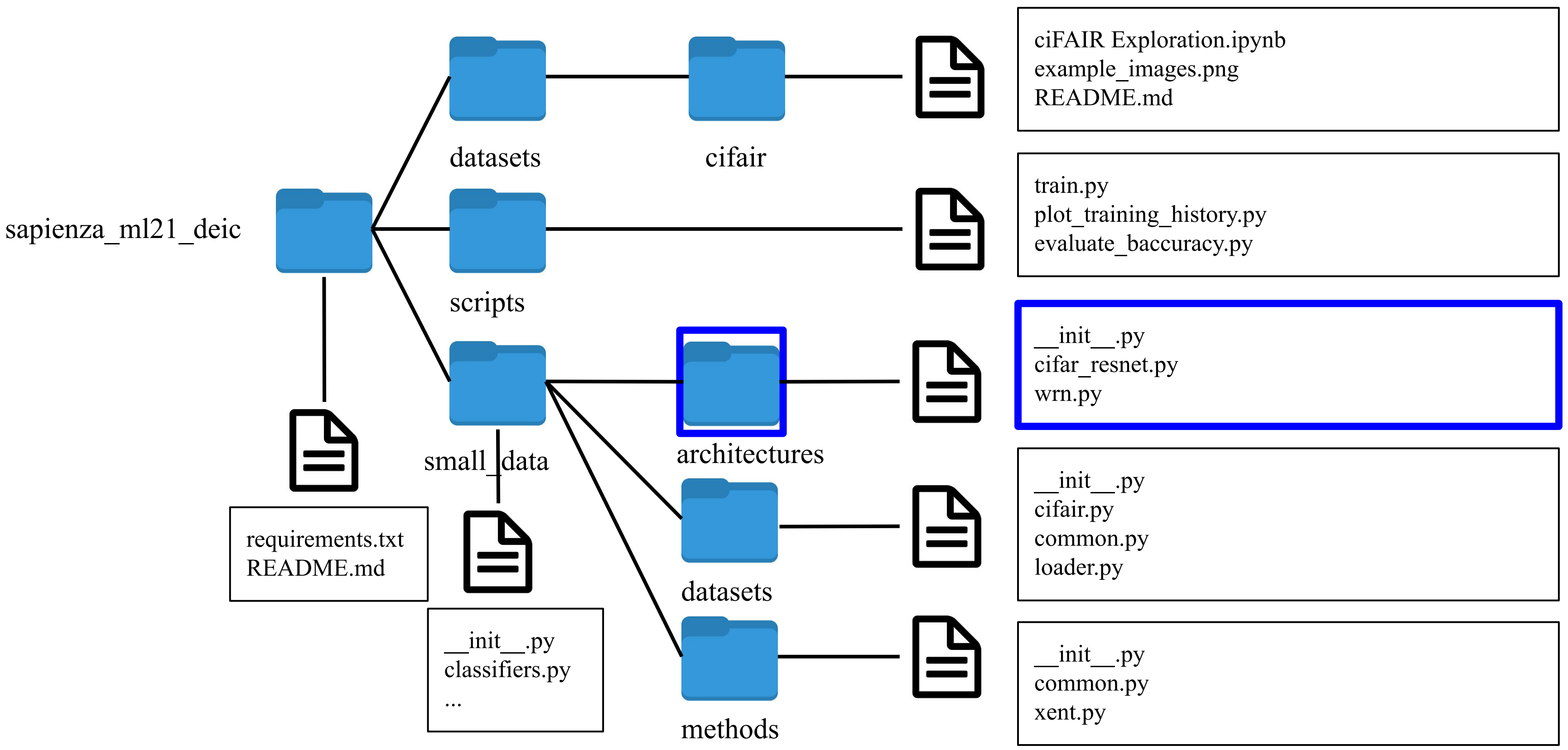
Code Repository

small_data is the directory that you will submit, with all its content.



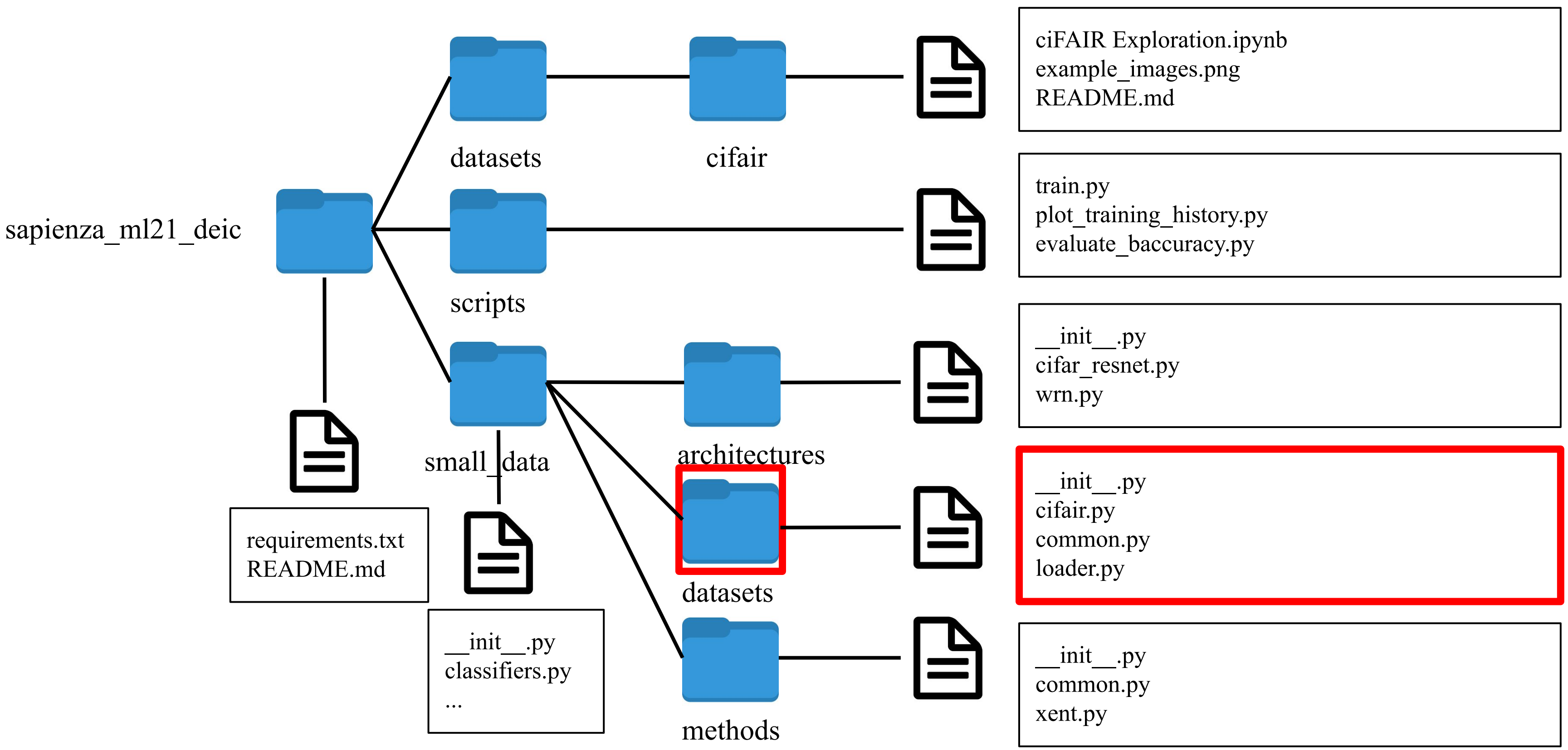
Code Repository

The folder **architectures** is the place to add other architecture files (e.g., densenet.py).



Code Repository

The folder **datasets** contains functions for loading data.



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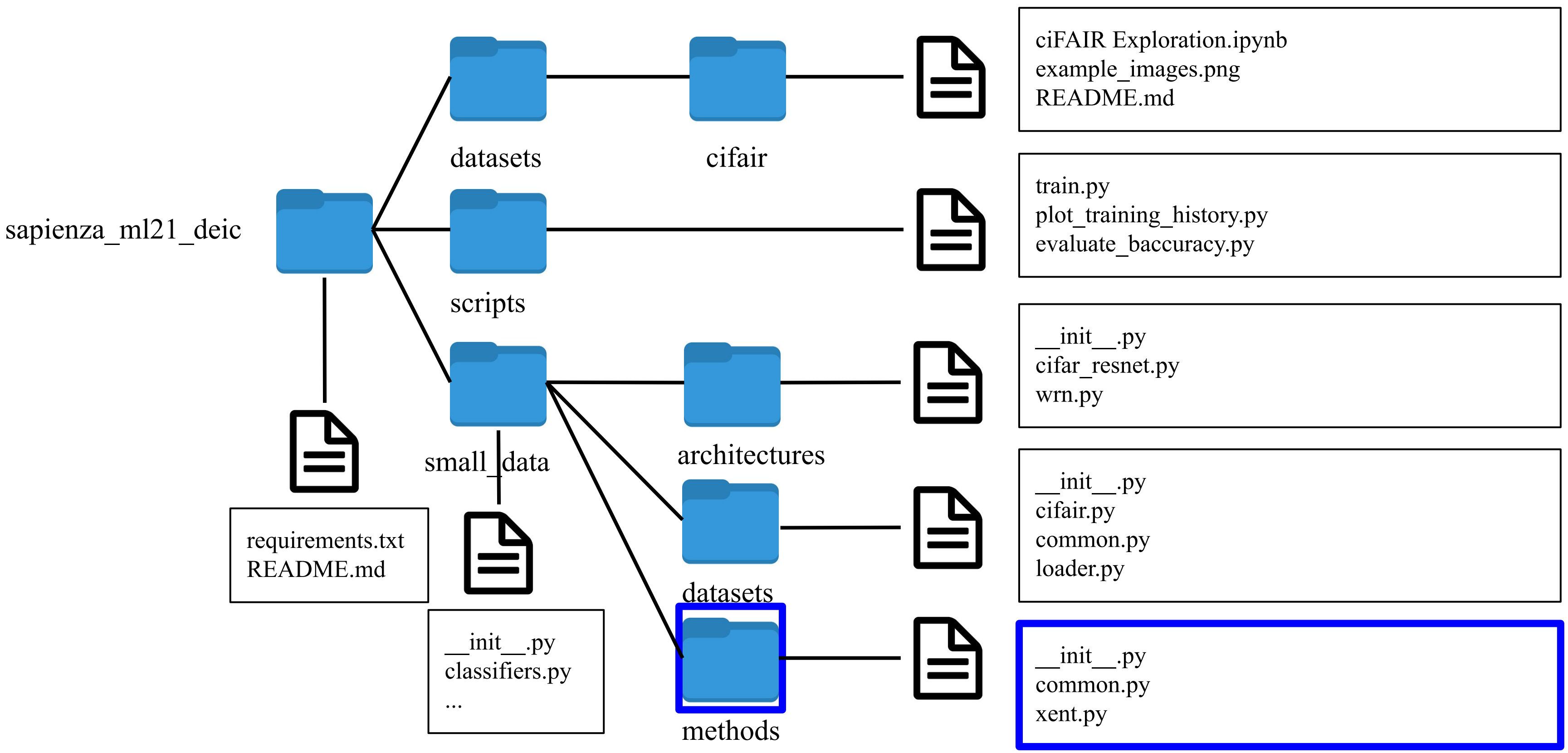
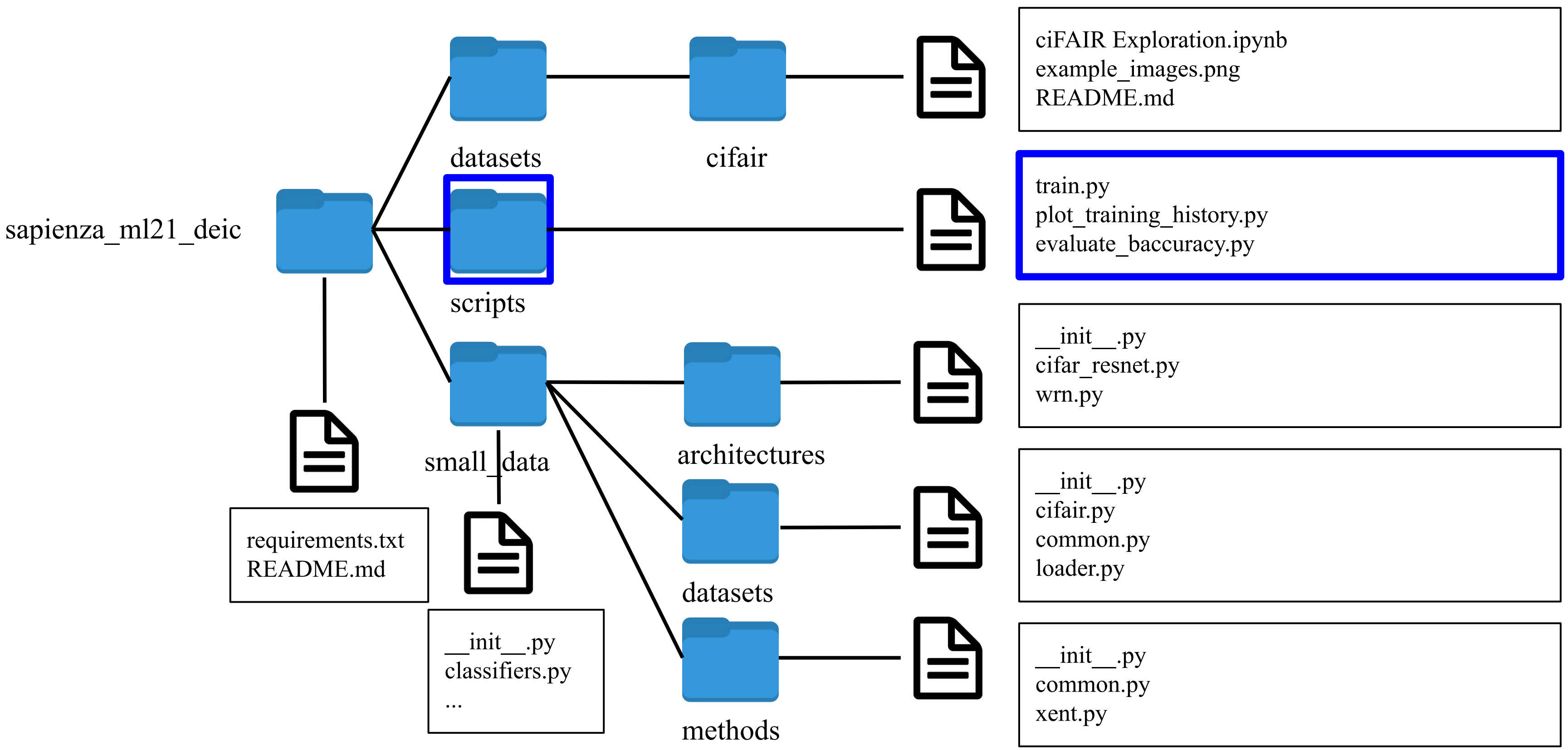
Code Repository

The folder **methods** contains functions for running the training algorithms.



Code Repository

The folder **scripts** contains higher-level scripts to actually run the training or visualize results.



Google Colab Demo

- Setup the code repository on Google Drive with SetupGitRepoOnDrive.ipynb
- Run baseline experiment with ExampleTrain.ipynb

Your Task

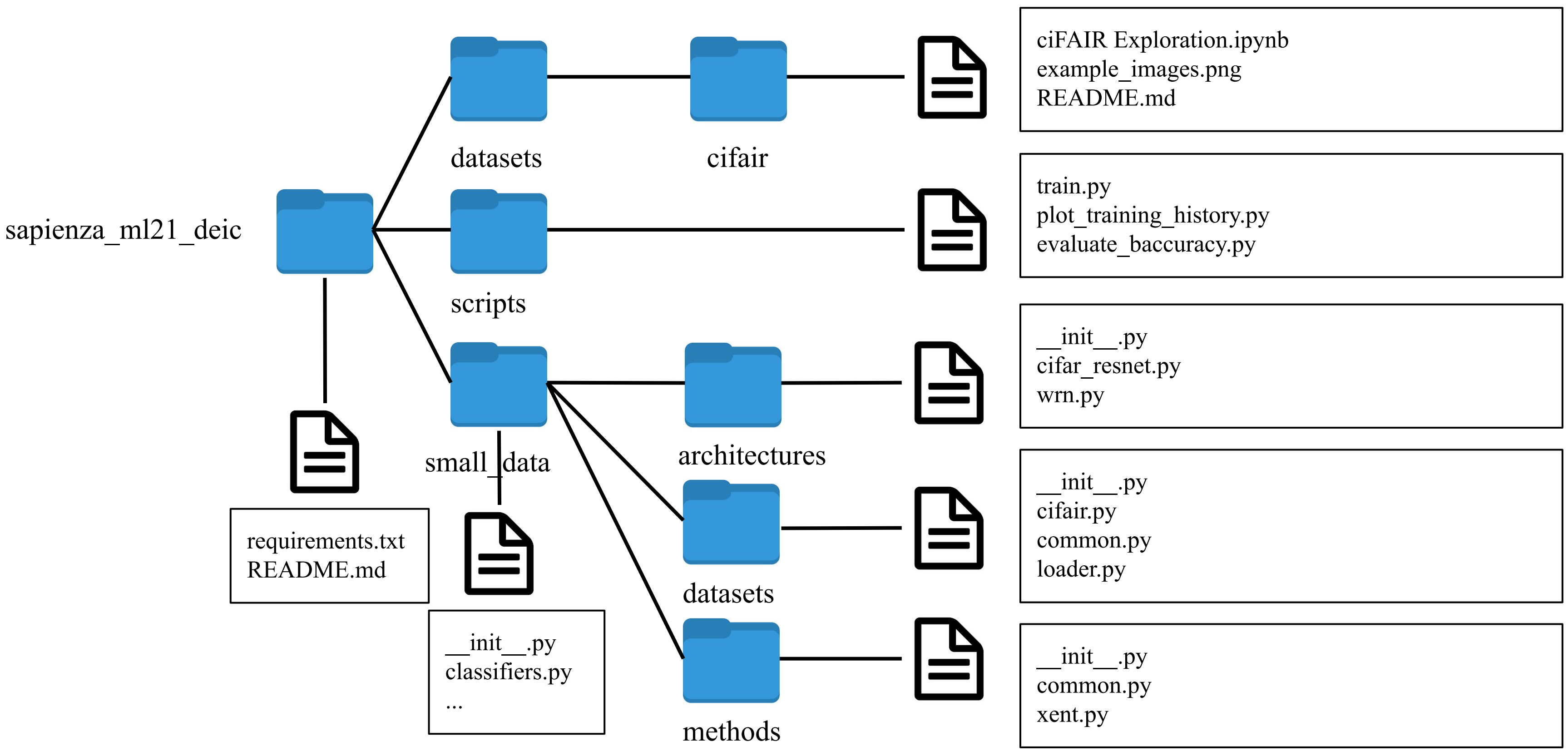
Add something in the code, save the trained model and evaluate it on the test set.

Examples:

- New architecture
- A different optimizer for training
- A choosable hyper-parameter (e.g., momentum parameter of SGD)

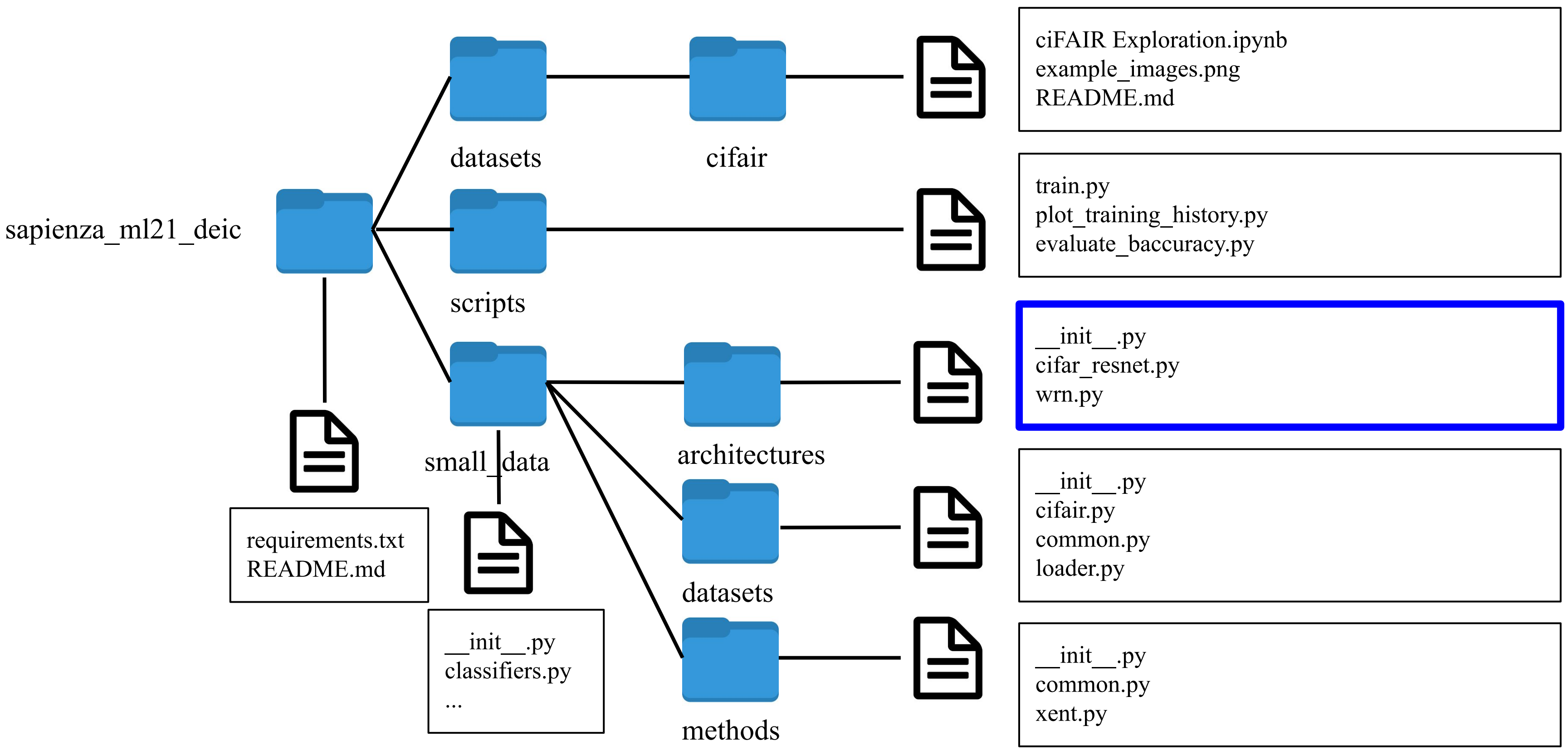
- **At least perform two of these tasks.**
- **Only running the demo would translate in 0 points for your homework.**

Adding a new architecture



Adding a new architecture

You should add a file that define the architecture inside **architectures**.



Adding a new architecture

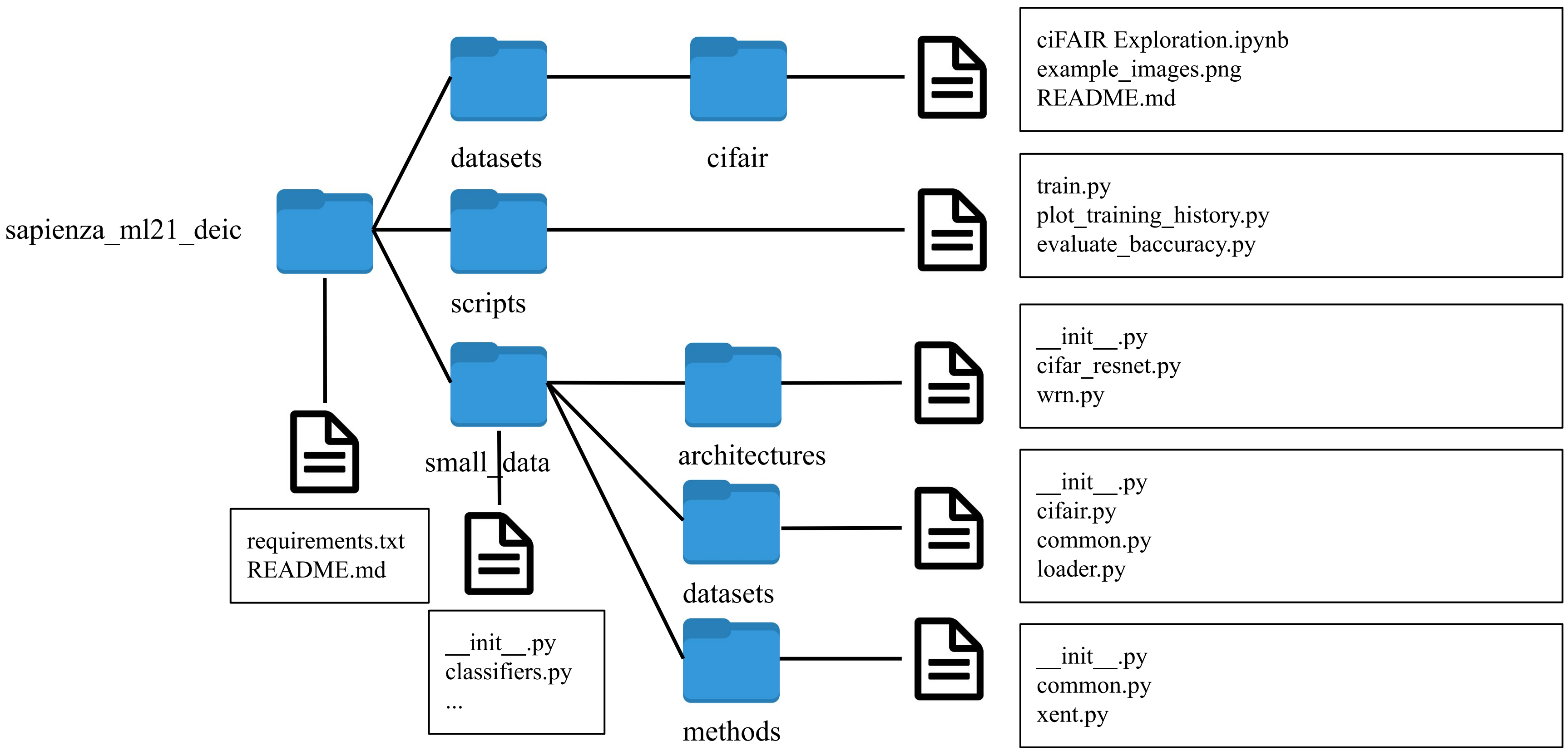
Steps:

- Create a new file inside folder **architectures** (e.g., wrn.py) to contain all the python classes/functions needed by the given architecture.

- The main class must have an `__init__`, `forward`, `get_classifiers`, and `build_classifier` method.

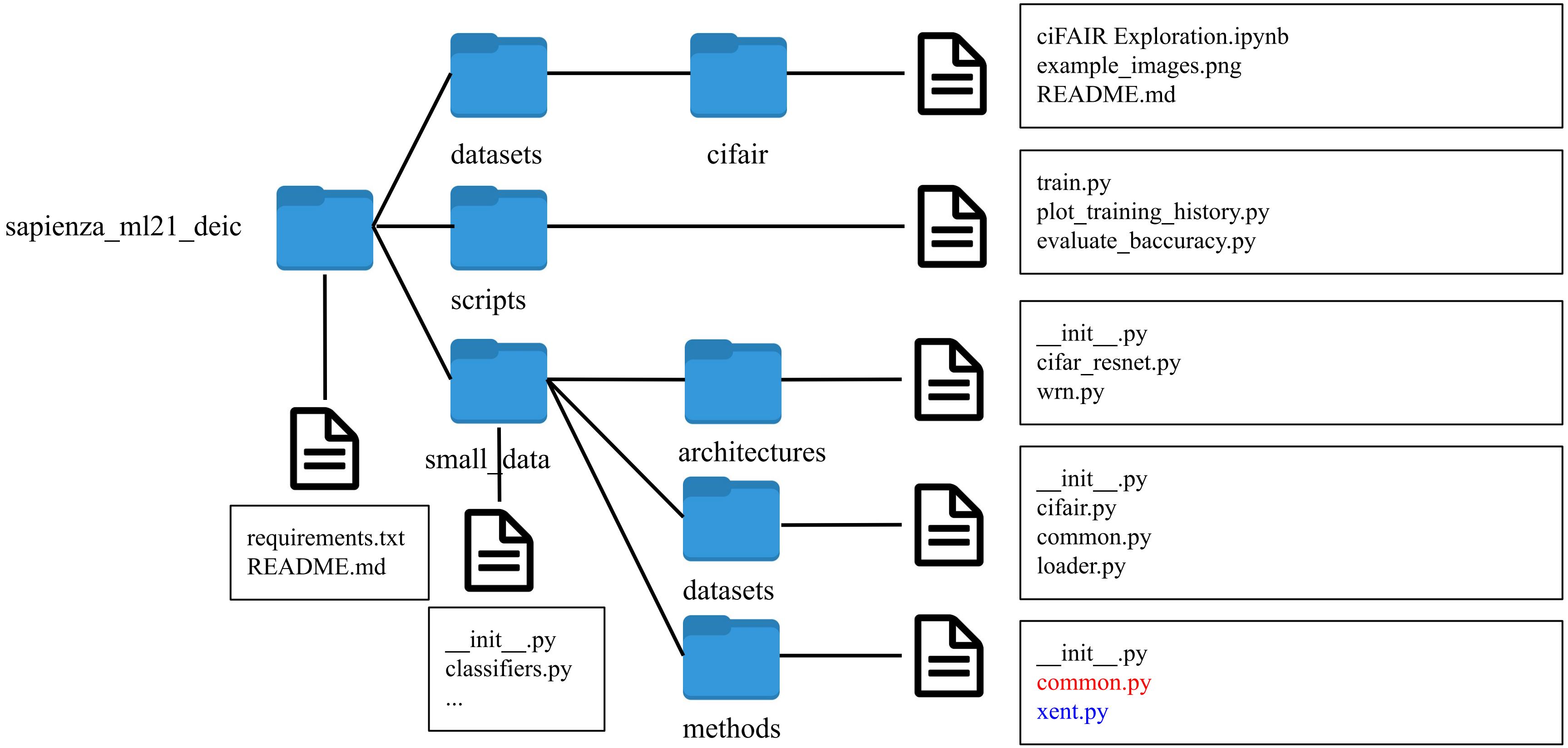
```
class WideResNet(nn.Module):

    def __init__(self, depth, num_classes, input_channels=3, widen_factor=1, ...):
        …

    def forward(self, x):
        …

    @staticmethod
    def get_classifiers():
      return ['wrn-16-8', 'wrn-16-10', ..., 'wrn-28-12']


    @classmethod
    def build_classifier(cls, arch: str, num_classes: int, input_channels: int):

      _, depth, widen_factor = arch.split('-')

      cls_instance = cls(int(depth), num_classes, input_channels=input_channels,
widen_factor=int(widen_factor))

      return cls_instance
```

Using a different optimizer for training



Using a different optimizer for training

You should sub-class the method `get_optimizer` of `LearningMethod` defined in common.py with a different instance inside xent.py.



Using a different optimizer for training

The main training class contains multiple methods that can be sub-classed:

- `LearningMethod` is the general class for a training pipeline of a method defined in common.py.
- An instance of this class is `CrossEntropyClassifier` which is defined in xent.py.
- `CrossEntropyClassifier`, when called will override all methods of `LearningMethod` defined inside its file.
- Any change can be applied by modifying the desired class method (e.g., `get_optimizer`).

Using a different optimizer for training

Original `get_optimizer` function defined inside common.py.

```
def get_optimizer(self, model: nn.Module, max_epochs: int, max_iter: int):

       optimizer = torch.optim.SGD(model.parameters(), lr=self.hparams['lr'], momentum=0.9,
weight_decay=self.hparams['weight_decay'])

       scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=max_iter)

       return optimizer, scheduler
```

Using a different optimizer for training

New `get_optimizer` method (with `Adam` instead of `SGD`) of `CrossEntropyClassifier` defined inside xent.py.

```
def get_optimizer(self, model: nn.Module, max_epochs: int, max_iter: int):

       optimizer = torch.optim.Adam(model.parameters(), lr=self.hparams['lr'],
weight_decay=self.hparams['weight_decay'])

       scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=max_iter)

       return optimizer, scheduler
```

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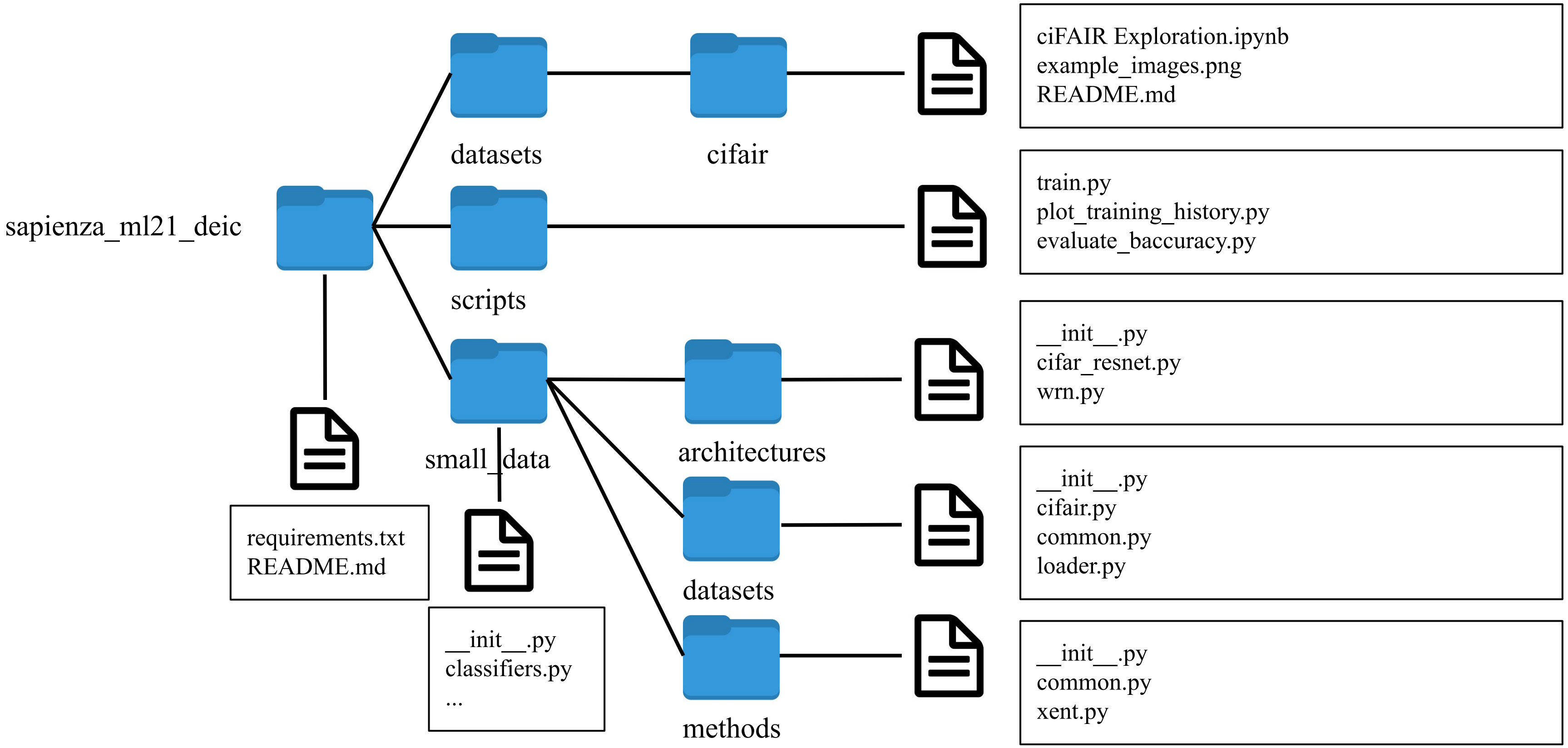
Add choosable hyper-parameter

Making the momentum parameter of SGD as choosable hyper-parameter by the user.



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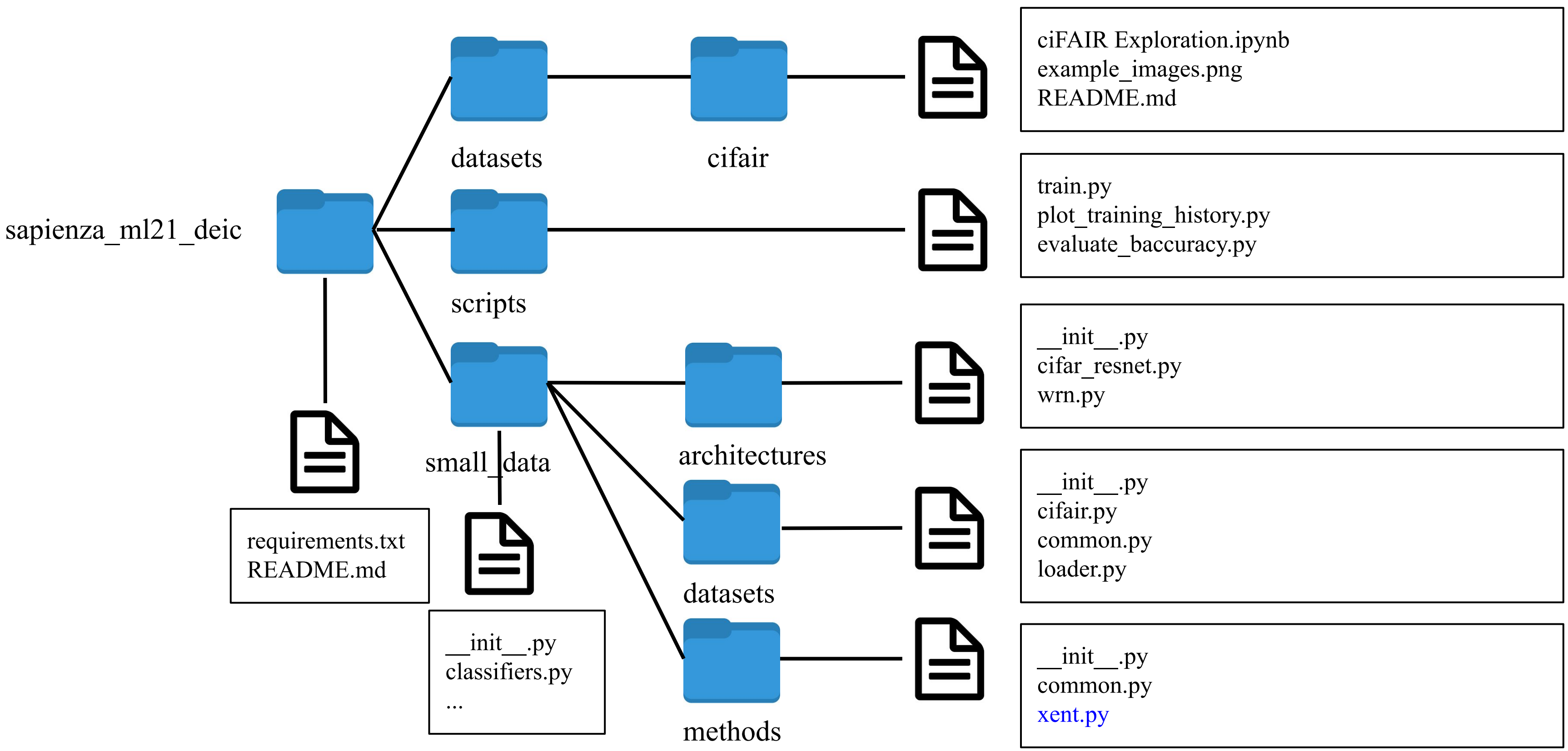
Add choosable hyper-parameter

You should sub-class the static methods `default hparams` and `get_optimizer` of class `CrossEntropyClassifier` in xent.py.



Add choosable hyper-parameter

Sub-class the static `default_hparams` method of `CrossEntropyClassifier` to add `momentum`:

```
@staticmethod
def default_hparams() -> dict:
    return {
        **super(CrossEntropyClassifier, CrossEntropyClassifier).default_hparams(),
        'momentum' : 0.9
    }
```

Update the `get_optimizer` method too:

```
def get_optimizer(self, model: nn.Module, max_epochs: int, max_iter: int):

       optimizer = torch.optim.SGD(model.parameters(), lr=self.hparams['lr'],
momentum=self.hparams['momentum'],     weight_decay=self.hparams['weight_decay'])

       scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=max_iter)

       return optimizer, scheduler
```

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Deep Learning Library

The code is written in PyTorch which is very similar to Tensorflow:

- PyTorch (1.7) documentation [link].

- The modules of `torch.nn` are equivalent to layers in `tf.keras.layers`. Docs [link].

- To use different network architectures I advise looking at the available models at `torchvision.models` [link] and copying, using/modifying their source code (e.g., EfficientNet).

EfficientNet

```
torchvision.models.efficientnet_b0(pretrained: bool = False, progress: bool = True,
**kwargs: Any) → torchvision.models.efficientnet.EfficientNet [SOURCE]
```

```
class EfficientNet(nn.Module):
    def __init__(
            self,
```

Save the trained model

Models in PyTorch are saved similarly to Tensorflow:

- A `torch.nn.Module` has a state dictionary containing all the information concerning the layer weights.

- It is enough to simply call:
  `torch.save(model.state_dict(), “model.pth”)`

- Note that to load back the model, you should first instantiate an instance of the model class and then override the state dictionary.

- Therefore, you should call:
  `model.load_state_dict(torch.load(“model.pth”))`

- Additional documentation is available [link]

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Suggestions

To start from a good baseline take into account these tricks:

- Small batch sizes (e.g., 10 or less) are preferable to improve generalization.
- An high number of epochs (e.g., > 500) allow the network to find better local minima with better generalization.
- Not all lr-wd couples work the same. Choosing a good couple strongly increases the results (Seminar 2) and may change with network width/depth.
- Network width ease the optimization process. With the right hyper-parameters, a wider network (i.e., more conv. filters) may find better solutions than thinner ones.
- Baseline to beat:
  - Wide ResNet-16-8 (wrn-16-8) , epochs = 500, bs = 10, lr = 4.55e-3, wd = 5.29e-3
  - Accuracy on test set: 58.22%
- **Note**: the homework evaluation won't be related to the test set performance obtained (unless for extremely bad results).

Submission

Through Google Classroom:

- **PDF report** with description of the models and results on the test set.
- **ZIP file of small_data folder**, named with your matricola code (e.g, 1771597.zip).
- **Your trained model** saved with your matricola code (e.g, 1771597.pth).

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Expected Outcome

Publish a paper with 100 names!! Or less optimistically:

- Get interesting insights and results about this crowd-sourcing experiment with ensembles on small datasets.

- Not getting the same model from all of you since this would basically ruin the experiment:
  - predictions of average of 100 identical models = predictions of 1 model

- And would give 0 points to your homework!!

- You'll learn important tools and practices to train neural networks.

Summary

To run the code you need a GPU either locally or on the Cloud:

- Use Colab or make sure to have PyTorch locally installed with GPU support
- [For Colab] Use the notebook SetupGitRepoOnDrive.ipynb to clone the repository on your Google Drive.
- [For Colab] Use/take inspiration from ExampleTrain.ipynb to run experiments.
- [For Colab] Note that to change the running code, you should modify the files of the repo that are located in your Google Drive.