Gigantic MU-MIMO: Toward Channel Statistics Independence in ML Receivers

1. **Introduction**
    1.1. In this project, we explored, extended, and implemented Viterbi-model-based approaches and DNN architectures for learning the underlying statistics of wireless fading channel communication which obeys a Markovian stochastic input-output relationship.
    Based on the main paper **"[ViterbiNet: A Deep Learning Based Viterbi Algorithm for Symbol Detection](#)"** by Nir Shlezinger, Nariman Farsad, Yonina C. Eldar, and Andrea J. Goldsmith
2. **Files Structure and Uses**
    2.1. **Code** folder contains all code subdirectories and files implemented in python
        2.1.1. **channel** folder contains data generation code
            2.1.1.1. **channel.py –** contains ISI AWG transmit function
            2.1.1.2. **channel_dataset.py** – contains the channel data generation class
            2.1.1.3. **channel_estimation.py** – contains the channel method and costs
            2.1.1.4. modulator.py – contains the BPSK modulation function
        2.1.2. **ecc** folder contains the error correction, encoding, decoding files which based on Reed-Solomon algorithm
        https://en.wikiversity.org/wiki/Reed%E2%80%93Solomon_codes_for_coders
        2.1.3. **dir_definitions.py** – includes all project directories and sub-directories
        2.1.4. **detector.py** – contains the Detector class which responsible for the DNN/Statistical models and methods (ModelBased / EndToEnd / Statistical) including the Viterbi algorithm
        2.1.5. **models.py** – contains all the project models ADNN / Sionna / SionnaPlus / Transformer / LSTM' / ViterbiNet / ClassicViterbi additional to experimental models, implemented using PyTorch.
        2.1.6. **trainer.py** – contains the Trainer class which responsible for all training and evaluation flow for a given model including save/load model, configurate loss and optimizer, initialize channel parameters and data, run train loop and backprop, training evaluation, and online evaluation.
        2.1.7. **plotter.py** – contains the plot function which creates graphs based on the models results such as "ser by block index" or "ser by snr'
        2.1.8. **configuration.yaml** – includes configurable project parameters such as channel parameters / train and validation hyper-parameters / loss type and available optimizers.
        2.1.9. **main.py** – responsible for running the project, by looping over SNR list from 7 to 15 cross all models and controls all phases of training, evaluation, and graphs using the "execute_and_plot" function.
        In addition, it contains "HYPERPARAMS_DICT" with configurable parameters and main flags.

2.1.9.1. **Important “HYPERPARAMS_DICT” configurable keys:**

2.1.9.1.1. **HYPERPARAMS_DICT [‘val_frames’]**
HYPERPARAMS_DICT [‘subframes_in_frame’]
Their multiplication result determines the Minibatch size during training.

2.1.9.1.2. **HYPERPARAMS_DICT [‘self_supervised_iterations]**
determine the number of self (online) training iterations on the correctly detected block during online evaluation

2.1.9.1.3. **HYPERPARAMS_DICT [‘train_minibatch_num’]**
determines the number of Minibatches during training

2.1.9.2. **Important main flags:**

2.1.9.2.1. **run_over** – value = 0 load plots from previous runs, else value = 1 load trained weights and start online evaluation, else value = 2 clear all and start training from scratch.

2.1.9.2.2. **plot_by_block** – once set to **True** the project will generate “ser by bock index” plot else set to **False** the project will generate “ser by snr” plot.

2.1.9.2.3. **block_lenght** – determine the transmission length of each block i.e. the number of bits.

2.1.9.2.4. **channel_coefficients** - 'time_decay' / 'cost2100' determine the channel cost type.

2.1.9.2.5. **snr_start, snr_end** – determine the range of SNRs

2.1.9.2.6. **models_list** – contains list of DNN models which will be part of the detector

2.1.9.2.7. **detector_method** – determine the detector methodology ‘ModelBased’ for Viterbi based and llr learning / ‘EndToEnd’ for bit to bit learning without Viterbi / Statistical used only for the ‘ClassicViterbi’ model which is the statistical Viterbi algorithm with perfect CSI.

2.1.9.2.8. **self_supervised** - True/False for online evaluation enable

**** Note -- every parameter configured in the main.py**
**** is the last that counts and overwrites configuration.yaml**
**** file values**

2.2. **Resources** folder contains the channel coefficients vectors for cost2100 (4 taps, each with 300 blocks).

2.3. **Results** folder

2.3.1. **figures** folder – contains all the saved graphs images

2.3.2. **plots** folder – contains all the saved plots data

2.3.3. **weights** folder – contains all the trained models’ weights per channel cost and each by SNR and gamma.

2.4. **project_env.yml** – conda environment with all related packages and modules run the command "conda env create -f project_env.yml " to create the project env

3. **Execution**

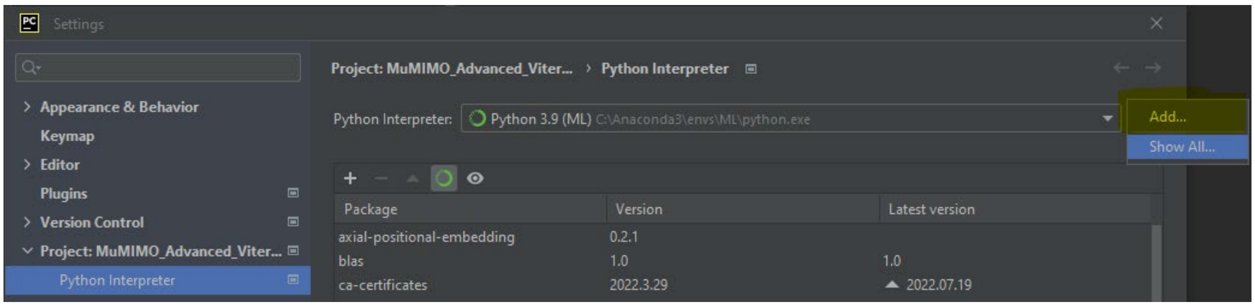
3.1. In order to execute the project first make sure you have Anaconda and PyCharm (IDE) installed, then install the project_env.yml

--- console command "conda env create -f project_env.yml " ---

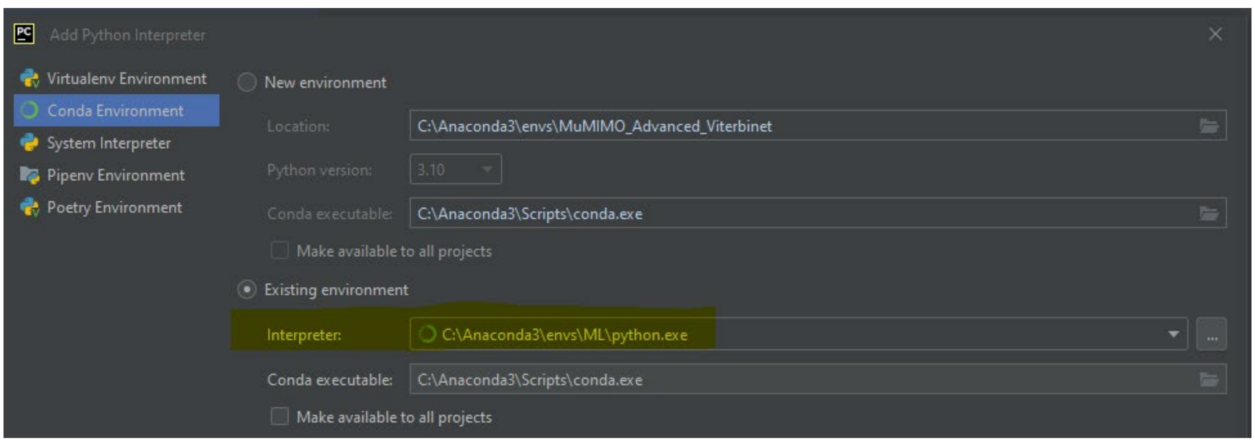
Next follow instructions:

3.1.1. Open **PyCharm** in the project root directory

3.1.2. Go to, File → Settings → Python Interpreter → Add



3.1.3. Select the **Conda Environment** that created from the project_env.yml file



3.1.4. For windows the conda env usually found at C:\Anaconda3\envs\<env_name>\python.exe

4. Now you can run the **Code\main.py** file to execute the project.

5. **Run and Modify Project**

5.1. As described above at the "**Files Structure and Uses**" section, the **Code/main.py** file runs and controls all the project aspects, therefore, most of the running, plotting, training, evaluation and data configuration in it. So please look on the **main.py** sub-section, including all the relevant flags and parameters.
**** All the most important running configuration described there** **

5.2. Use the "**run_over**" flag to:

5.2.1. **run_over** = 0 → **load all plots** from previous results

5.2.2. **run_over** = 1 → **load trained weight** and start **online evaluation**

5.2.3. **run_over** = 2 → **clear all** results and **train** from scratch

```python
HYPERPARAMS_DICT = {
                    'noisy_est_var': 0,
                    'fading_taps_type': 1,  # 1 / 2  for time decay only
                    'fading_in_channel': True,
                    'fading_in_decoder': True,
                    'gamma': 0.2,
                    'channel_type': 'ISI_AWGN',
                    'val_frames': 12,  # up to 12 for cost2100
                    'subframes_in_frame': 25,  # up to 25 for cost2100
                    'self_supervised_iterations': 200,
                    'ser_thresh': 0.02,  # ser threshold for online training
                    'train_minibatch_num': 25,  # 25
                    }


if __name__ == '__main__':
    # main flags
    run_over = 0  # 0 - load plots from previous runs / 1 - load trained weights and start online evaluation / 2 - clear all and start training  from scratch
    plot_by_block = False  # False / True either plot by SNR or by block index
    block_length = 120     # determine the transmission length
    channel_coefficients = 'cost2100'  # 'time_decay' / 'cost2100'
    n_symbol = 2
    snr_start, snr_end = 7, 15

    # deep learning models list 'ADNN', 'Sionna', 'SionnaPlus', 'Transformer', 'LSTM', 'ViterbiNet'
    models_list = ['ADNN', 'Sionna', 'SionnaPlus', 'Transformer', 'LSTM', 'ViterbiNet']
    detector_method = 'ModelBased'  # ModelBased / EndToEnd / Statistical
    self_supervised = True  # True / False for online evaluation enablement
```

Enjoy!