Quick Start

Installation

You can specify to install it through `pip`.

```
pip install -U pykt-toolkit
```

We advise to create a new Conda environment with the following command:

```
conda create --name=pykt python=3.7.5
source activate pykt
pip install -U pykt-toolkit
```

Train Your First Model

Prepare a Dataset

1、Obtain a Dataset

Let's start by downloading the dataset from here. Please make sure you have creat the `data/{dataset_name}` folder

2、Data Preprocessing

`python data_preprocess.py [parameter]`

```
Args:
    --dataset_name: dataset name, default="assist2015"
    --min_seq_len: minimum sequence length, default=3
    --maxlen: maximum sequence length, default=200
    --kfold: divided folds, default=5
```

Example:

```
cd examples
python data_preprocess.py --dataset_name=ednet
```

Training a Model

After the data preprocessing, you can use the `python wandb_modelname_train.py [parameter]` to train a model:

```
CUDA_VISIBLE_DEVICES=2 nohup python wandb_sakt_train.py --dataset_name=assist2015 --use_wandb=0 --
add_uuid=0 --num_attn_heads=2 > sakt_train.txt &
```

Evaluating Your Model

Now, let's use `wandb_predict.py` to evaluate the model performance on the testing set.

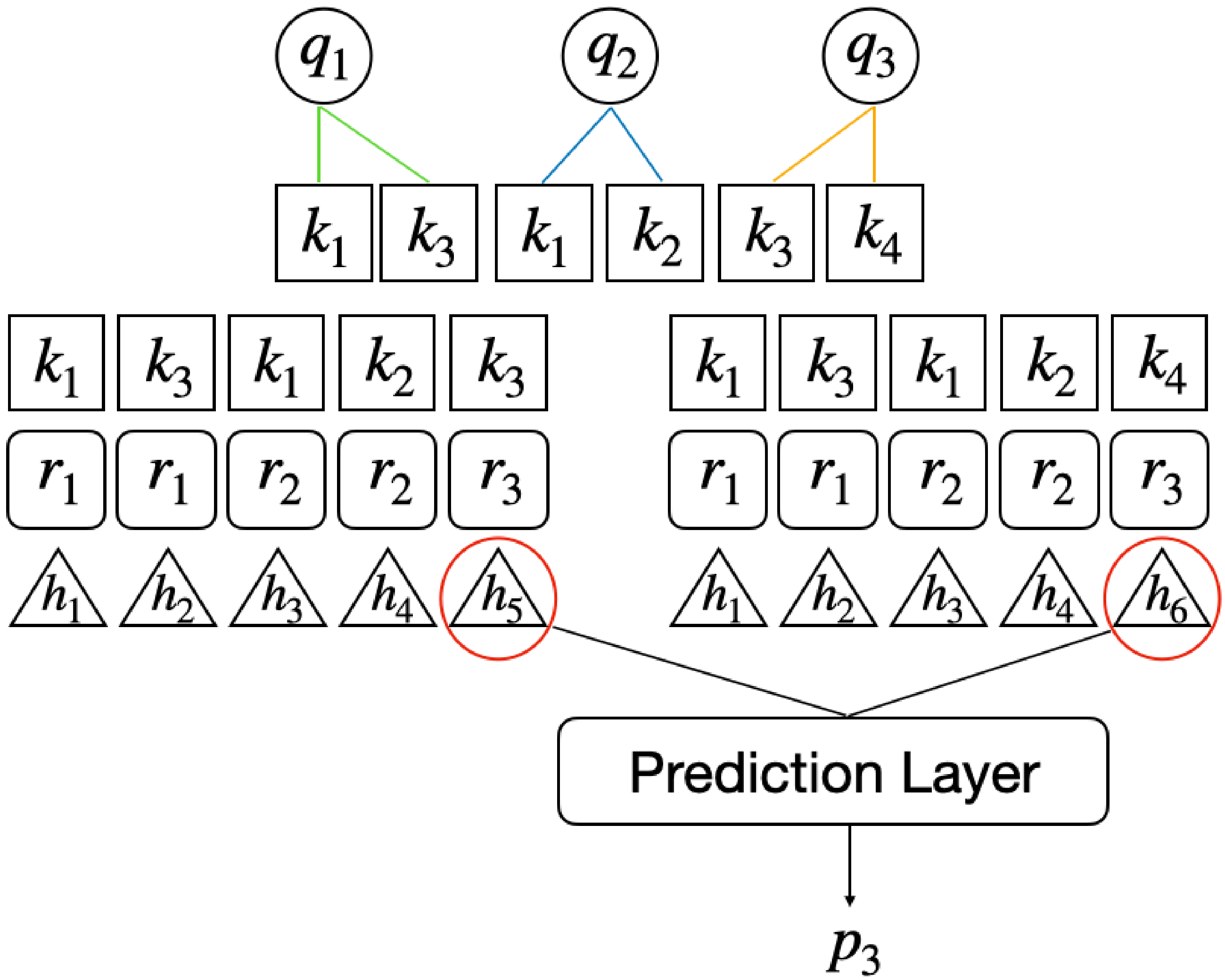
`python wandb_predict.py`

```
Args:
    --bz: batch_size, default is 256
    --save_dir: the dictory of the trained model, default is "saved_model"
    --fusion_type: the fusion mode,default is "late_fusion"
    --use_wandb: use wandb or not, default is 1
```

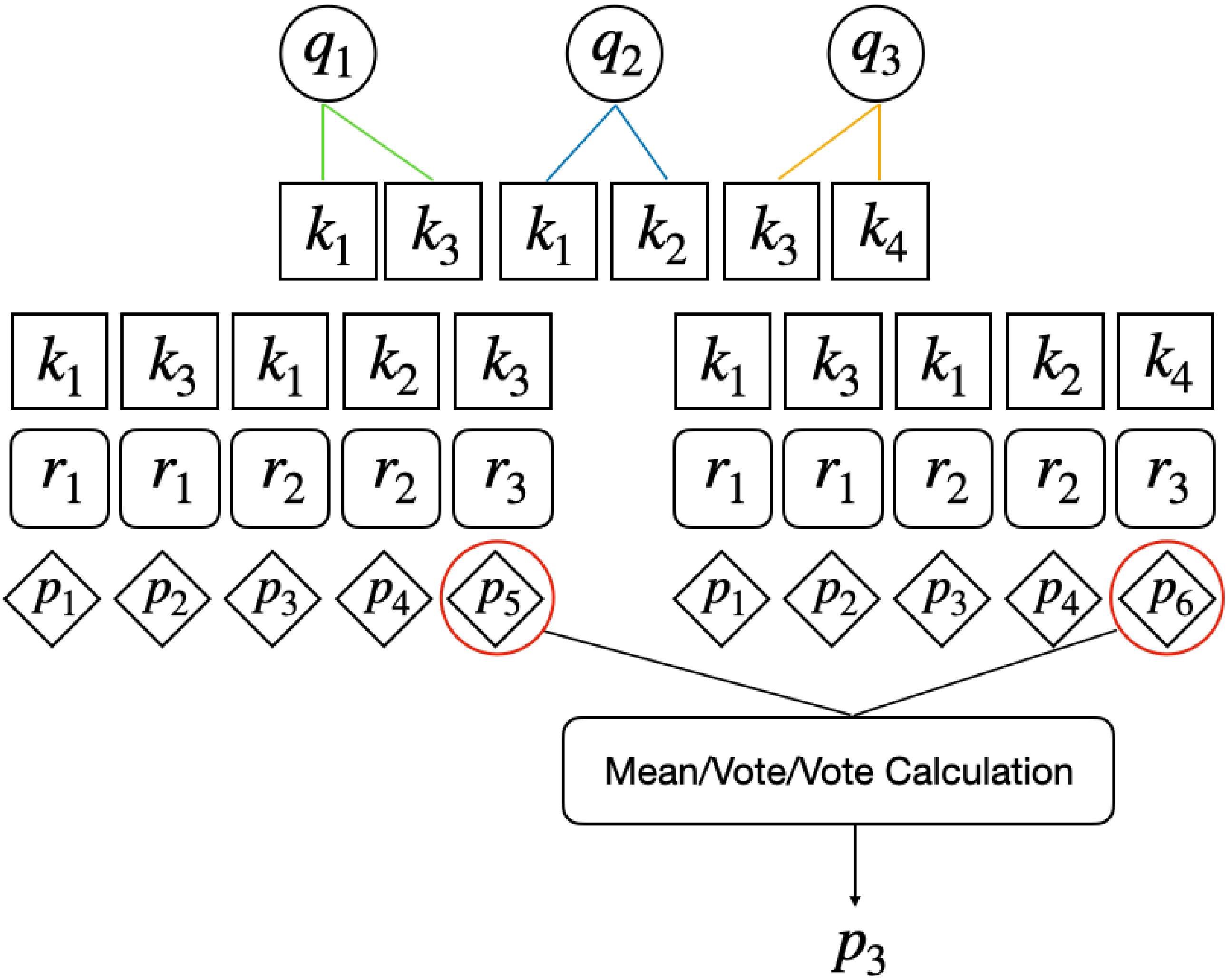
Evaluation Protocol

A question may be related to multiple knowledge concepts (KCs). To make the evaluation of pyKT is consistent with the real-world prediction scenarios, we train DLKT models on KCs but evaluate them on questions level as follows:

- **Early fusion:** Calculate the average of the hidden states on KC levels, and then input the average results into the prediction layer, hence get the prediction results on question level. For example, to obtain the prediction p_3 of q_3, we average the hidden states h_5,h_6 into the prediction layer.



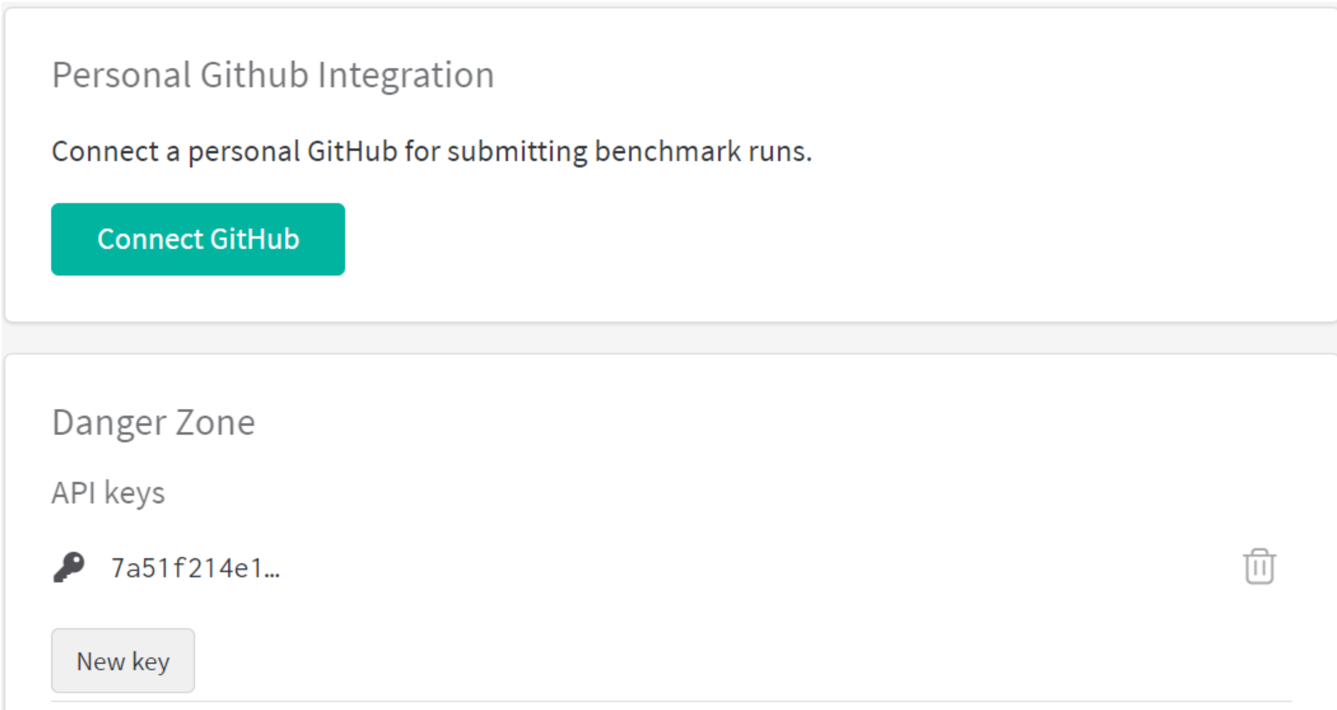
- **Late fusion:** Employ three fusion types to obtain the question-level prediction based on the KC-level prediction results:(1) *Mean*: compute the average of the KC-level prediction results as the final prediction. (2) *Vote*: select half of the values of KC predictions as the final prediction. (3) *All*: only if all KC predictions are correct, the final prediction is correct, otherwise it is wrong.



Hyperparameter Tuning

Create a Wandb Account

We use Weights & Biases (Wandb) for hyperparameter tuning, it is a machine learning platform for developers to build better models faster with experiment tracking. Firstly, let's register an account in Wandb webpage to get the API key from here:



Next, add your `uid` and `api_key` into `configs/wandb.json`.

Sweep Configuration

`[wandb_key] python generate_wandb.py [parameter]`

```
Args:
       --src_dir: The parameter configuration file path of the model
       --project_name: Project name on wandb, default: kt_toolkits
       --dataset_names: Dataset names, you can fill in multiple, separated by commas ",", default:
"assist2015"
       --model_names: Model names, you can fill in multiple, separated by commas ",", default: dkt
       --emb_type: Default:qid
       --folds: Default: "0,1,2,3,4"
       --batch_size: Default: 128
       --save_dir_suffix: Add extra characters to the model storage path name, default: ""
       --all_dir: Generate the configuration file of the model for this dataset, default:
"all_wandbs"
       --launch_file: Generated sweep startup script, default: "all_start.sh"
       --generate_all: The input is "True" or "False", indicating whether to generate the wandb
startup files of all datasets and models in the all_dir directory (True means: generate the
startup files of all data models in the all_dir directory, False means: only the current execution
is generated data model startup file), default: "False"
```

Example:

```
WANDB_API_KEY=xxx python generate_wandb.py --dataset_names "assist2009,assist2015"
hawkes --model_names "dkt,dkt+"
```

Start Sweep

Step1: `sh [launch_file] [parameter]`

```
sh [launch_file] > [Directed log] 2>&1

    - [launch_file]: required, the user submits the script of sweep to wandbs, and directs the execution output to [directed log])
    - [Directed log]: Required, execute the sweep in the log
```

Example:

```
sh all_start.sh > log.all 2>&1
(You need to define the log file. )
```

Step 2: `sh run_all.sh [parameter]`

```
[wandb_key] sh run_all.sh [Directed log] [start_sweep] [end_sweep] [dataset_name] [model_name] [gpu_ids] [project_name]

    - [Directed log]: Required, execute the sweep in the log
    - [start_sweep]: Required, the start id to start a sweep
    - [end_sweep]: Required, start sweep end id
    - [dataset_name]: Required, dataset name
    - [model_name]: Required, model name
    - [gpu_ids]: Required, GPU ID
    - [project_name]: optional, default: kt_toolkits
```

Example:

```
WANDB_API_KEY=xxx sh run_all.sh log.all 0 5 assist2009 dkt 0,1,2,3,4 nips2022-assist2009
```

Start Agents

```
sh start_sweep_0_5.sh
("0", "5" denote the start sweep and end sweep respectively.)
```

Tuning Protocol

We use the Bayes search method to find the best hyperparameter, it is expensive to run all the hyperparameter combinations. Hence, you can run the `pykt-toolkit/examples/check_wandb_status.ipynb` file to check whether to stop the searching. We default to stop the searching if the number of the tuned hyperparameter combinations in each data fold is larger than 200 and there is no AUC improvement on the testing data in the last 100 rounds (output "end!").

Start Evaluation

- Extract best model

```
def extract_best_models(self, df, dataset_name, model_name, emb_type="qid", eval_test=True,
fpath="./seedwandb/predict.yaml", CONFIG_FILE="../configs/best_model.json", wandb_key="",
pred_dir="pred_wandbs", launch_file="start_predict.sh", generate_all=False):
      """extracting the best models which performance best performance on the validation data for
testing

      Args:
          df: dataframe of best results in each fold
          dataset_name: dataset_name
          model_name: model_name
          emb_type: embedding_type, default:qid
          eval_test: evaluating on testing set, default:True
          fpath: the yaml template for prediction in wandb, default: "./seedwandb/predict.yaml"
          config_file: the config template of generating prediction file, default:
"../configs/best_model.json"
          wandb_key: the key of wandb account
          pred_wandbs: the directory of prediction yaml files, default: "pred_wandbs"
          launch_file: the launch file of starting the wandb prediction, default:
"start_predict.sh"
          generate_all: starting all the files on the pred_wandbs directory or not, default:False

      Returns:
          the launch file (e.g., "start_predict.sh") for wandb prediction of the best models in
each fold
      """
    if not os.path.exists(pred_dir):
        os.makedirs(pred_dir)
    model_path_fold_first = []
    dconfig = dict()
    for i, row in df.iterrows():
        fold, model_path = row["fold"], row["model_save_path"]
        model_path = model_path.rstrip("qid_model.ckpt")
        print(f">>> The best model of {dataset_name}_{model_name}_{fold}:{model_path}")
        model_path_fold_first.append(model_path)
    ftarget = os.path.join(pred_dir, "{}_{}_{}_fold_first_predict.yaml".format(dataset_name,
model_name, emb_type))
    if eval_test:
        self.generate_wandb(fpath, ftarget, model_path_fold_first)
        dconfig["model_path_fold_first"] = model_path_fold_first
        self.write_config(dataset_name, dconfig, CONFIG_FILE)
        self.generate_sweep(wandb_key, pred_dir, launch_file, ftarget, generate_all)
```

Example:

```
df = wandb_api.get_best_run(dataset_name="assist2015",model_name="dkt")
wandb_api.extract_best_models(df, dataset_name, model_name,
                              fpath="../examples/seedwandb/predict.yaml",wandb_key=wandb_key)
```

- `sh [launch_file] [parameter]`

After extracting the best model, we can get the lauch file for evaluation automatically, the default filename is “start_pred.sh”. Then we can start sweep for prediction.

```
sh [launch_file] > [Directed log] 2>&1

    - [launch_file]: required, the user submits the script of sweep to wandbs, and directs the execution output to [directed log])
    - [Directed log]: Required, execute the sweep in the log
```

Example:

```
sh start_predict.sh > pred.log 2>&1
(You need to define the log file. )
```

- `sh run_all.sh [parameter]`

Example:

```
WANDB_API_KEY=xxx sh run_all.sh pred.log 0 1 assist2009 dkt 0 nips2022-assist2009
```

- Start Agents

```
sh start_sweep_0_1.sh
```

There are only 5 sweeps to be run without any parameter tuning in this stage, with each sweep corresponding to the evaluation of each fold of the training data. Finally, you can export the evaluation results externally or call the wandb API for statistical 5- folds results, and calculate the mean and standard deviation of each metric, i.e., ***mean ± standard deviation***

If you want to add new models or datasets into pyKT, you can follow Contribute.