DICE Embeddings

Release 0.1.3.2

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DICE Embeddings[1]: Hardware-agnostic Framework for Large-scale Knowledge Graph Embeddings:

1 Dicee Manual

Version: dicee 0.1.3.2

GitHub repository: https://github.com/dice-group/dice-embeddings

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Dicee is a hardware-agnostic framework for large-scale knowledge graph embeddings.

Knowledge graph embedding research has mainly focused on learning continuous representations of knowledge graphs towards the link prediction problem. Recently developed frameworks can be effectively applied in a wide range of research-related applications. Yet, using these frameworks in real-world applications becomes more challenging as the size of the knowledge graph grows

We developed the DICE Embeddings framework (dicee) to compute embeddings for large-scale knowledge graphs in a hardware-agnostic manner. To achieve this goal, we rely on

1. **Pandas**[3] **& Co.** to use parallelism at preprocessing a large knowledge graph,

2. **PyTorch**[4] **& Co.** to learn knowledge graph embeddings via multi-CPUs, GPUs, TPUs or computing cluster, and

3. **Huggingface**[5] to ease the deployment of pre-trained models.

Why Pandas[6] **& Co. ?** A large knowledge graph can be read and preprocessed (e.g. removing literals) by pandas, modin, or polars in parallel. Through polars, a knowledge graph having more than 1 billion triples can be read in parallel fashion. Importantly, using these frameworks allow us to perform all necessary computations on a single CPU as well as a cluster of computers.

Why PyTorch[7] **& Co. ?** PyTorch is one of the most popular machine learning frameworks available at the time of writing. PytorchLightning facilitates scaling the training procedure of PyTorch without boilerplate. In our framework, we combine PyTorch[8] & PytorchLightning[9]. Users can choose the trainer class (e.g., DDP by Pytorch) to train large knowledge graph embedding models with billions of parameters. PytorchLightning allows us to use state-of-the-art model parallelism techniques (e.g. Fully Sharded Training, FairScale, or DeepSpeed) without extra effort. With our framework, practitioners can directly use PytorchLightning for model parallelism to train gigantic embedding models.

Why Hugging-face Gradio[10]**?** Deploy a pre-trained embedding model without writing a single line of code.

---

[1] https://github.com/dice-group/dice-embeddings

[2] https://github.com/Demirrr

[3] https://pandas.pydata.org/

[4] https://pytorch.org/

[5] https://huggingface.co/

[6] https://pandas.pydata.org/

[7] https://pytorch.org/

[8] https://pytorch.org/

[9] https://www.pytorchlightning.ai/

[10] https://huggingface.co/gradio

2 Installation

2.1 Installation from Source

```
git clone https://github.com/dice-group/dice-embeddings.git
conda create -n dice python=3.10.13 --no-default-packages && conda activate dice &&␣
→cd dice-embeddings &&
pip3 install -e .
```

or

```
pip install dicee
```

3 Download Knowledge Graphs

```
wget https://files.dice-research.org/datasets/dice-embeddings/KGs.zip --no-check-
→certificate && unzip KGs.zip
```

To test the Installation

```
python -m pytest -p no:warnings -x # Runs >114 tests leading to > 15 mins
python -m pytest -p no:warnings --lf # run only the last failed test
python -m pytest -p no:warnings --ff # to run the failures first and then the rest of␣
→the tests.
```

4 Knowledge Graph Embedding Models

1. TransE, DistMult, ComplEx, ConEx, QMult, OMult, ConvO, ConvQ, Keci

2. All 44 models available in https://github.com/pykeen/pykeen#models

   For more, please refer to `examples`.

5 How to Train

To Train a KGE model (KECI) and evaluate it on the train, validation, and test sets of the UMLS benchmark dataset.

```python
from dicee.executer import Execute
from dicee.config import Namespace
args = Namespace()
args.model = 'Keci'
args.scoring_technique = "KvsAll"  # 1vsAll, or AllvsAll, or NegSample
args.dataset_dir = "KGs/UMLS"
args.path_to_store_single_run = "Keci_UMLS"
args.num_epochs = 100
args.embedding_dim = 32
args.batch_size = 1024
reports = Execute(args).start()
print(reports["Train"]["MRR"]) # => 0.9912
```

```python
print(reports["Test"]["MRR"]) # => 0.8155
# See the Keci_UMLS folder embeddings and all other files
```

where the data is in the following form

```
$ head -3 KGs/UMLS/train.txt
acquired_abnormality    location_of     experimental_model_of_disease
anatomical_abnormality  manifestation_of        physiologic_function
alga    isa     entity
```

A KGE model can also be trained from the command line

```
dicee --dataset_dir "KGs/UMLS" --model Keci --eval_model "train_val_test"
```

dicee automaticaly detects available GPUs and trains a model with distributed data parallels technique. Under the hood, dicee uses lighning as a default trainer.

```
# Train a model by only using the GPU-0
CUDA_VISIBLE_DEVICES=0 dicee --dataset_dir "KGs/UMLS" --model Keci --eval_model
→"train_val_test"
# Train a model by only using GPU-1
CUDA_VISIBLE_DEVICES=1 dicee --dataset_dir "KGs/UMLS" --model Keci --eval_model
→"train_val_test"
NCCL_P2P_DISABLE=1 CUDA_VISIBLE_DEVICES=0,1 python dicee/scripts/run.py --trainer PL -
→-dataset_dir "KGs/UMLS" --model Keci --eval_model "train_val_test"
```

Under the hood, dicee executes run.py script and uses lighning as a default trainer

```
# Two equivalent executions
# (1)
dicee --dataset_dir "KGs/UMLS" --model Keci --eval_model "train_val_test"
# Evaluate Keci on Train set: Evaluate Keci on Train set
# {'H@1': 0.9518788343558282, 'H@3': 0.9988496932515337, 'H@10': 1.0, 'MRR': 0.
→9753123402351737}
# Evaluate Keci on Validation set: Evaluate Keci on Validation set
# {'H@1': 0.6932515337423313, 'H@3': 0.9041411042944786, 'H@10': 0.9754601226993865,
→'MRR': 0.8072362996241839}
# Evaluate Keci on Test set: Evaluate Keci on Test set
# {'H@1': 0.6951588502269289, 'H@3': 0.9039334341906202, 'H@10': 0.9750378214826021,
→'MRR': 0.806403229327861}

# (2)
CUDA_VISIBLE_DEVICES=0,1 python dicee/scripts/run.py --trainer PL --dataset_dir "KGs/
→UMLS" --model Keci --eval_model "train_val_test"
# Evaluate Keci on Train set: Evaluate Keci on Train set
# {'H@1': 0.9518788343558282, 'H@3': 0.9988496932515337, 'H@10': 1.0, 'MRR': 0.
→9753123402351737}
# Evaluate Keci on Train set: Evaluate Keci on Train set
# Evaluate Keci on Validation set: Evaluate Keci on Validation set
# {'H@1': 0.6932515337423313, 'H@3': 0.9041411042944786, 'H@10': 0.9754601226993865,
→'MRR': 0.8072362996241839}
# Evaluate Keci on Test set: Evaluate Keci on Test set
# {'H@1': 0.6951588502269289, 'H@3': 0.9039334341906202, 'H@10': 0.9750378214826021,
→'MRR': 0.806403229327861}
```

Similarly, models can be easily trained with torchrun

```
torchrun --standalone --nnodes=1 --nproc_per_node=gpu dicee/scripts/run.py --trainer␣
↪torchDDP --dataset_dir "KGs/UMLS" --model Keci --eval_model "train_val_test"
# Evaluate Keci on Train set: Evaluate Keci on Train set: Evaluate Keci on Train set
# {'H@1': 0.9518788343558282, 'H@3': 0.9988496932515337, 'H@10': 1.0, 'MRR': 0.
↪9753123402351737}
# Evaluate Keci on Validation set: Evaluate Keci on Validation set
# {'H@1': 0.6932515337423313, 'H@3': 0.9041411042944786, 'H@10': 0.9754601226993865,
↪'MRR': 0.8072499937521418}
# Evaluate Keci on Test set: Evaluate Keci on Test set
{'H@1': 0.6951588502269289, 'H@3': 0.9039334341906202, 'H@10': 0.9750378214826021,
↪'MRR': 0.8064032293278861}
```

You can also train a model in multi-node multi-gpu setting.

```
torchrun --nnodes 2 --nproc_per_node=gpu  --node_rank 0 --rdzv_id 455 --rdzv_backend␣
↪c10d --rdzv_endpoint=nebula  dicee/scripts/run.py --trainer torchDDP --dataset_dir␣
↪KGs/UMLS
torchrun --nnodes 2 --nproc_per_node=gpu  --node_rank 1 --rdzv_id 455 --rdzv_backend␣
↪c10d --rdzv_endpoint=nebula dicee/scripts/run.py --trainer torchDDP --dataset_dir␣
↪KGs/UMLS
```

Train a KGE model by providing the path of a single file and store all parameters under newly created directory called
`KeciFamilyRun`.

```
dicee --path_single_kg "KGs/Family/family-benchmark_rich_background.owl" --model Keci␣
↪--path_to_store_single_run KeciFamilyRun --backend rdflib
```

where the data is in the following form

```
$ head -3 KGs/Family/train.txt
_:1 <http://www.w3.org/1999/02/22-rdf-syntax-ns#type> <http://www.w3.org/2002/07/owl
↪#Ontology> .
<http://www.benchmark.org/family#hasChild> <http://www.w3.org/1999/02/22-rdf-syntax-ns
↪#type> <http://www.w3.org/2002/07/owl#ObjectProperty> .
<http://www.benchmark.org/family#hasParent> <http://www.w3.org/1999/02/22-rdf-syntax-
↪ns#type> <http://www.w3.org/2002/07/owl#ObjectProperty> .
```

**Apart from n-triples or standard link prediction dataset formats, we support ["owl", "nt", "turtle", "rdf/xml",
"n3"]***. Moreover, a KGE model can be also trained by providing **an endpoint of a triple store**.

```
dicee --sparql_endpoint "http://localhost:3030/mutagenesis/" --model Keci
```

For more, please refer to `examples`.

6 Creating an Embedding Vector Database

6.1 Learning Embeddings

```
# Train an embedding model
dicee --dataset_dir KGs/Countries-S1 --path_to_store_single_run CountryEmbeddings --
↪model Keci --p 0 --q 1 --embedding_dim 32 --adaptive_swa
```

6.2 Loading Embeddings into Qdrant Vector Database

```
# Ensure that Qdrant available
# docker pull qdrant/qdrant && docker run -p 6333:6333 -p 6334:6334    -v $(pwd)/
→qdrant_storage:/qdrant/storage:z    qdrant/qdrant
diceeindex --path_model "CountryEmbeddings" --collection_name "dummy" --location
→"localhost"
```

6.3 Launching Webservice

```
diceeserve --path_model "CountryEmbeddings" --collection_name "dummy" --collection_
→location "localhost"
```

Retrieve and Search

Get embedding of germany

```
curl -X 'GET' 'http://0.0.0.0:8000/api/get?q=germany' -H 'accept: application/json'
```

Get most similar things to europe

```
curl -X 'GET' 'http://0.0.0.0:8000/api/search?q=europe' -H 'accept: application/json'
{"result":[{"hit":"europe","score":1.0},
{"hit":"northern_europe","score":0.67126536},
{"hit":"western_europe","score":0.6010134},
{"hit":"puerto_rico","score":0.5051694},
{"hit":"southern_europe","score":0.4829831}]}
```

7 Answering Complex Queries

```
# pip install dicee
# wget https://files.dice-research.org/datasets/dice-embeddings/KGs.zip --no-check-
→certificate & unzip KGs.zip
from dicee.executer import Execute
from dicee.config import Namespace
from dicee.knowledge_graph_embeddings import KGE
# (1) Train a KGE model
args = Namespace()
args.model = 'Keci'
args.p=0
args.q=1
args.optim = 'Adam'
args.scoring_technique = "AllvsAll"
args.path_single_kg = "KGs/Family/family-benchmark_rich_background.owl"
args.backend = "rdflib"
args.num_epochs = 200
args.batch_size = 1024
args.lr = 0.1
args.embedding_dim = 512
result = Execute(args).start()
# (2) Load the pre-trained model
```

```python
pre_trained_kge = KGE(path=result['path_experiment_folder'])
# (3) Single-hop query answering
# Query: ?E : \exist E.hasSibling(E, F9M167)
# Question: Who are the siblings of F9M167?
# Answer: [F9M157, F9F141], as (F9M167, hasSibling, F9M157) and (F9M167, hasSibling,␣
→F9F141)
predictions = pre_trained_kge.answer_multi_hop_query(query_type="1p",
                                                     query=('http://www.benchmark.org/
→family#F9M167',
                                                            ('http://www.benchmark.
→org/family#hasSibling',)),
                                                     tnorm="min", k=3)
top_entities = [topk_entity for topk_entity, query_score in predictions]
assert "http://www.benchmark.org/family#F9F141" in top_entities
assert "http://www.benchmark.org/family#F9M157" in top_entities
# (2) Two-hop query answering
# Query: ?D : \exist E.Married(D, E) \land hasSibling(E, F9M167)
# Question: To whom a sibling of F9M167 is married to?
# Answer: [F9F158, F9M142] as (F9M157 #married F9F158) and (F9F141 #married F9M142)
predictions = pre_trained_kge.answer_multi_hop_query(query_type="2p",
                                                     query=("http://www.benchmark.org/
→family#F9M167",
                                                            ("http://www.benchmark.
→org/family#hasSibling",
                                                             "http://www.benchmark.
→org/family#married")),
                                                     tnorm="min", k=3)
top_entities = [topk_entity for topk_entity, query_score in predictions]
assert "http://www.benchmark.org/family#F9M142" in top_entities
assert "http://www.benchmark.org/family#F9F158" in top_entities
# (3) Three-hop query answering
# Query: ?T : \exist D.type(D,T) \land Married(D,E) \land hasSibling(E, F9M167)
# Question: What are the type of people who are married to a sibling of F9M167?
# (3) Answer: [Person, Male, Father] since  F9M157 is [Brother Father Grandfather␣
→Male] and F9M142 is [Male Grandfather Father]

predictions = pre_trained_kge.answer_multi_hop_query(query_type="3p", query=("http://
→www.benchmark.org/family#F9M167",
                                                                            ("http://
→www.benchmark.org/family#hasSibling",
                                                                             "http://
→www.benchmark.org/family#married",
                                                                             "http://
→www.w3.org/1999/02/22-rdf-syntax-ns#type")),
                                                     tnorm="min", k=5)
top_entities = [topk_entity for topk_entity, query_score in predictions]
print(top_entities)
assert "http://www.benchmark.org/family#Person" in top_entities
assert "http://www.benchmark.org/family#Father" in top_entities
assert "http://www.benchmark.org/family#Male" in top_entities
```

For more, please refer to examples/multi_hop_query_answering.

8 Predicting Missing Links

```python
from dicee import KGE
# (1) Train a knowledge graph embedding model..
# (2) Load a pretrained model
pre_trained_kge = KGE(path='..')
# (3) Predict missing links through head entity rankings
pre_trained_kge.predict_topk(h=[".."],r=[".."],topk=10)
# (4) Predict missing links through relation rankings
pre_trained_kge.predict_topk(h=[".."],t=[".."],topk=10)
# (5) Predict missing links through tail entity rankings
pre_trained_kge.predict_topk(r=[".."],t=[".."],topk=10)
```

9 Downloading Pretrained Models

```python
from dicee import KGE
# (1) Load a pretrained ConEx on DBpedia
model = KGE(url="https://files.dice-research.org/projects/DiceEmbeddings/KINSHIP-Keci-
→dim128-epoch256-KvsAll")
```

- For more please look at dice-research.org/projects/DiceEmbeddings/[11]

10 How to Deploy

```python
from dicee import KGE
KGE(path='...').deploy(share=True,top_k=10)
```

11 Docker

To build the Docker image:

```
docker build -t dice-embeddings .
```

To test the Docker image:

```
docker run --rm -v ~/.local/share/dicee/KGs:/dicee/KGs dice-embeddings ./main.py --
→model AConEx --embedding_dim 16
```

---

[11] https://files.dice-research.org/projects/DiceEmbeddings/

12 Coverage Report

The coverage report is generated using coverage.py[12]:

```
Name                                          Stmts   Miss  Cover   Missing
---------------------------------------------------------------------------
dicee/__init__.py                                 7      0   100%
dicee/abstracts.py                              201     82    59%   104-105,␣
→123, 146-147, 152, 165, 197, 240-254, 257-260, 263-266, 301, 314-317, 320-324, 364-
→375, 390-398, 413, 424-428, 555-575, 581-585, 589-591
dicee/callbacks.py                              245    102    58%   50-55,␣
→67-73, 76, 88-93, 98-103, 106-109, 116-133, 138-142, 146-147, 276-280, 286-287, 305-
→311, 314, 319-320, 332-338, 344-353, 358-360, 405, 416-429, 433-468, 480-486
dicee/config.py                                  93      2    98%   141-142
dicee/dataset_classes.py                        299     74    75%   41, 54,␣
→87, 93, 99-106, 109, 112, 115-139, 195-201, 204, 207-209, 314, 325-328, 344, 410-
→411, 429, 528-536, 539, 543-557, 700-707, 710-714
dicee/eval_static_funcs.py                      227     95    58%   101, 106,␣
→ 111, 258-353, 360-411
dicee/evaluator.py                              262     51    81%   46, 51,␣
→56, 84, 89-90, 93, 109, 126, 137, 141, 146, 177-188, 195-206, 314, 344-367, 455,␣
→465, 482-487
dicee/executer.py                               113      4    96%   116, 258-
→259, 291
dicee/knowledge_graph.py                         65      3    95%   79, 110,␣
→114
dicee/knowledge_graph_embeddings.py             636    443    30%   27, 30-
→31, 39-52, 57-90, 93-127, 131-139, 170-184, 215-228, 254-274, 324-327, 330-333, 346,
→ 381-426, 484-486, 502-503, 509-517, 522-525, 528-533, 538, 547, 592-598, 630, 688-
→1053, 1084-1145, 1149-1177, 1200, 1227-1265
dicee/models/__init__.py                          9      0   100%
dicee/models/base_model.py                      234     31    87%   54, 56,␣
→82, 88-103, 157, 190, 230, 236, 245, 248, 252, 259, 263, 265, 280, 288-289, 296-297,
→ 351, 354, 427, 439
dicee/models/clifford.py                        556    357    36%   31-42,␣
→68-117, 122-133, 156-168, 190-220, 235, 237, 241, 248-249, 276-280, 303-311, 325-
→327, 332-333, 364-384, 406, 413, 417-478, 495-499, 511, 514, 519, 524, 571-607, 625-
→631, 644, 647, 652, 657, 686-692, 705, 708, 713, 718, 728-737, 753-754, 774-845,␣
→856-859, 884-909, 933-966, 1002-1006, 1019, 1029, 1032, 1037, 1042, 1047, 1051,␣
→1055, 1064-1065, 1095, 1102, 1107, 1135-1139, 1167-1176, 1186-1194, 1212-1214, 1232-
→1234, 1250-1252
dicee/models/complex.py                         151     15    90%   86-109
dicee/models/dualE.py                            59     10    83%   93-102,␣
→142-156
dicee/models/function_space.py                  262    221    16%   10-24,␣
→28-37, 40-49, 53-70, 77-86, 89-98, 101-110, 114-126, 134-156, 159-165, 168-185, 188-
→194, 197-205, 208, 213-234, 243-246, 250-254, 258-267, 271-292, 301-307, 311-328,␣
→332-335, 344-352, 355, 366-372, 392-406, 424-438, 443-453, 461-465, 474-478
dicee/models/octonion.py                        227     83    63%   21-44,␣
→320-329, 334-345, 348-370, 374-416, 426-474
dicee/models/pykeen_models.py                    50      5    90%   60-63,␣
→118
dicee/models/quaternion.py                      192     69    64%   7-21, 30-
→55, 68-72, 107, 185, 328-342, 345-364, 368-389, 399-426
dicee/models/real.py                             61     12    80%   36-39,␣
```

---

[12] https://coverage.readthedocs.io/en/7.6.0/

```
↪66-69, 87, 103-106
dicee/models/static_funcs.py                          10      0   100%
dicee/models/transformers.py                         236    189    20%    24-43,␣
↪46, 60-75, 84-102, 105-116, 123-125, 128, 134-151, 155-180, 186-190, 193-197, 203-
↪207, 210-212, 229-256, 265-268, 271-276, 279-304, 310-315, 319-372, 376-398, 404-414
dicee/query_generator.py                             374    346     7%    18-52,␣
↪56, 62-65, 69-70, 78-92, 100-147, 155-188, 192-206, 212-269, 274-303, 307-443, 453-
↪472, 480-501, 508-512, 517, 522-528
dicee/read_preprocess_save_load_kg/__init__.py         3      0   100%
dicee/read_preprocess_save_load_kg/preprocess.py     256     41    84%    34, 40,␣
↪78, 102-127, 133, 138-151, 184, 214, 388-389, 444
dicee/read_preprocess_save_load_kg/read_from_disk.py  36     11    69%    33, 38-
↪40, 47, 55, 58-72
dicee/read_preprocess_save_load_kg/save_load_disk.py  45     18    60%    39-60
dicee/read_preprocess_save_load_kg/util.py           219    126    42%    65-67,␣
↪72-73, 91-97, 100-102, 107-109, 121, 134, 140-143, 148-156, 161-167, 172-177, 182-
↪187, 199-220, 226-282, 286-290, 294-295, 299, 303-304, 334, 351, 356, 363-364
dicee/sanity_checkers.py                              54     23    57%    8-12, 21-
↪31, 46, 51, 58, 64-79, 85, 89, 96
dicee/static_funcs.py                                418    163    61%    40, 50,␣
↪56-61, 83, 105-106, 115, 138, 152, 157-159, 163-165, 167, 194-198, 246, 254, 263-
↪268, 290-304, 316-336, 340-357, 362, 386-387, 392-393, 410-411, 413-414, 416-417,␣
↪419-420, 428, 446-450, 467-470, 474-479, 483-487, 491-492, 498-500, 526-527, 539-
↪542, 547-550, 559-610, 615-627, 644-658, 661-669
dicee/static_funcs_training.py                       123     63    49%    118-215,␣
↪223-224
dicee/static_preprocess_funcs.py                     100     44    56%    17-25,␣
↪52, 56, 64, 67, 78, 91-115, 120-123, 128-131, 136-139
dicee/trainer/__init__.py                              1      0   100%
dicee/trainer/dice_trainer.py                        126     13    90%    27-32,␣
↪91, 98, 103-108, 147
dicee/trainer/torch_trainer.py                        79      4    95%    31, 196,␣
↪207-208
dicee/trainer/torch_trainer_ddp.py                   152    128    16%    13-14,␣
↪43, 47-72, 83-112, 131-137, 140-149, 164-194, 204-217, 226-246, 251-260, 263-272,␣
↪275-299, 302-309
-----------------------------------------------------------------------------
TOTAL                                               6181   2828    54%
```

13 How to cite

Currently, we are working on our manuscript describing our framework. If you really like our work and want to cite it now, feel free to chose one :)

```
# Keci
@inproceedings{demir2023clifford,
  title={Clifford Embeddings--A Generalized Approach for Embedding in Normed Algebras}
↪,
  author={Demir, Caglar and Ngonga Ngomo, Axel-Cyrille},
  booktitle={Joint European Conference on Machine Learning and Knowledge Discovery in␣
↪Databases},
  pages={567--582},
  year={2023},
  organization={Springer}
```

```
}
# LitCQD
@inproceedings{demir2023litcqd,
  title={LitCQD: Multi-Hop Reasoning in Incomplete Knowledge Graphs with Numeric␣
→Literals},
  author={Demir, Caglar and Wiebesiek, Michel and Lu, Renzhong and Ngonga Ngomo, Axel-
→Cyrille and Heindorf, Stefan},
  booktitle={Joint European Conference on Machine Learning and Knowledge Discovery in␣
→Databases},
  pages={617--633},
  year={2023},
  organization={Springer}
}
# DICE Embedding Framework
@article{demir2022hardware,
  title={Hardware-agnostic computation for large-scale knowledge graph embeddings},
  author={Demir, Caglar and Ngomo, Axel-Cyrille Ngonga},
  journal={Software Impacts},
  year={2022},
  publisher={Elsevier}
}
# KronE
@inproceedings{demir2022kronecker,
  title={Kronecker decomposition for knowledge graph embeddings},
  author={Demir, Caglar and Lienen, Julian and Ngonga Ngomo, Axel-Cyrille},
  booktitle={Proceedings of the 33rd ACM Conference on Hypertext and Social Media},
  pages={1--10},
  year={2022}
}
# QMult, OMult, ConvQ, ConvO
@InProceedings{pmlr-v157-demir21a,
  title =         {Convolutional Hypercomplex Embeddings for Link Prediction},
  author =        {Demir, Caglar and Moussallem, Diego and Heindorf, Stefan and Ngonga␣
→Ngomo, Axel-Cyrille},
  booktitle =        {Proceedings of The 13th Asian Conference on Machine Learning},
  pages =          {656--671},
  year =          {2021},
  editor =         {Balasubramanian, Vineeth N. and Tsang, Ivor},
  volume =          {157},
  series =          {Proceedings of Machine Learning Research},
  month =         {17--19 Nov},
  publisher =     {PMLR},
  pdf =          {https://proceedings.mlr.press/v157/demir21a/demir21a.pdf},
  url =          {https://proceedings.mlr.press/v157/demir21a.html},
}
# ConEx
@inproceedings{demir2021convolutional,
title={Convolutional Complex Knowledge Graph Embeddings},
author={Caglar Demir and Axel-Cyrille Ngonga Ngomo},
booktitle={Eighteenth Extended Semantic Web Conference – Research Track},
year={2021},
url={https://openreview.net/forum?id=6T45-4TFqaX}}
# Shallom
@inproceedings{demir2021shallow,
  title={A shallow neural model for relation prediction},
  author={Demir, Caglar and Moussallem, Diego and Ngomo, Axel-Cyrille Ngonga},
  booktitle={2021 IEEE 15th International Conference on Semantic Computing (ICSC)},
```

```
pages={179--182},
year={2021},
organization={IEEE}
```

For any questions or wishes, please contact: caglar.demir@upb.de

14 dicee

14.1 Subpackages

dicee.models

Submodules

dicee.models.base_model

Classes

BaseKGELightning	Base class for all neural network modules.
BaseKGE	Base class for all neural network modules.
IdentityClass	Base class for all neural network modules.

Module Contents

class dicee.models.base_model.**BaseKGELightning**(**args*, ***kwargs*)

Bases: lightning.LightningModule

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

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> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
> > **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

training_step_outputs = []

mem_of_model() → Dict

> Size of model in MB and number of params

training_step(*batch*, *batch_idx=None*)

> Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.

> > **Parameters**
> >
> > - **batch** – The output of your data iterable, normally a `DataLoader`.
> >
> > - **batch_idx** – The index of this batch.
> >
> > - **dataloader_idx** – The index of the dataloader that produced this batch. (only if multiple dataloaders used)
> >
> > **Returns**
> >
> > - `Tensor` - The loss tensor
> >
> > - `dict` - A dictionary which can include any keys, but must include the key `'loss'` in the case of automatic optimization.
> >
> > - `None` - In automatic optimization, this will skip to the next batch (but is not supported for multi-GPU, TPU, or DeepSpeed). For manual optimization, this has no special meaning, as returning the loss is not required.

> In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

> Example:

```python
def training_step(self, batch, batch_idx):
    x, y, z = batch
    out = self.encoder(x)
    loss = self.loss(out, x)
    return loss
```

> To use multiple optimizers, you can switch to 'manual optimization' and control their stepping:

```python
def __init__(self):
    super().__init__()
    self.automatic_optimization = False


# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx):
    opt1, opt2 = self.optimizers()

    # do training_step with encoder
```

```
...
opt1.step()
# do training_step with decoder
...
opt2.step()
```

> **ⓘ Note**
>
> When `accumulate_grad_batches` > 1, the loss returned here will be automatically normalized by `accumulate_grad_batches` internally.

loss_function(*yhat_batch: torch.FloatTensor*, *y_batch: torch.FloatTensor*)

> **Parameters**
>
> - **yhat_batch**
>
> - **y_batch**

on_train_epoch_end(**args*, ***kwargs*)

Called in the training loop at the very end of the epoch.

To access all batch outputs at the end of the epoch, you can cache step outputs as an attribute of the `LightningModule` and access them in this hook:

```python
class MyLightningModule(L.LightningModule):
    def __init__(self):
        super().__init__()
        self.training_step_outputs = []

    def training_step(self):
        loss = ...
        self.training_step_outputs.append(loss)
        return loss

    def on_train_epoch_end(self):
        # do something with all training_step outputs, for example:
        epoch_mean = torch.stack(self.training_step_outputs).mean()
        self.log("training_epoch_mean", epoch_mean)
        # free up the memory
        self.training_step_outputs.clear()
```

test_epoch_end(*outputs: List[Any]*)

test_dataloader() → None

An iterable or collection of iterables specifying test samples.

For more information about multiple dataloaders, see this section.

For data processing use the following pattern:

- download in `prepare_data()`

- process and split in `setup()`

However, the above are only necessary for distributed processing.

> ⚠️ **Warning**
>
> do not assign state in prepare_data

- `test()`
- `prepare_data()`
- `setup()`

> ℹ️ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

> ℹ️ **Note**
>
> If you don't need a test dataset and a `test_step()`, you don't need to implement this method.

val_dataloader() → None

    An iterable or collection of iterables specifying validation samples.

    For more information about multiple dataloaders, see this section.

    The dataloader you return will not be reloaded unless you set **:param-ref:`~lightning.pytorch.trainer.trainer.Trainer.reload_dataloaders_every_n_epochs`** to a positive integer.

    It's recommended that all data downloads and preparation happen in `prepare_data()`.

- `fit()`
- `validate()`
- `prepare_data()`
- `setup()`

> ℹ️ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

> ℹ️ **Note**
>
> If you don't need a validation dataset and a `validation_step()`, you don't need to implement this method.

predict_dataloader() → None

    An iterable or collection of iterables specifying prediction samples.

    For more information about multiple dataloaders, see this section.

It's recommended that all data downloads and preparation happen in `prepare_data()`.

- `predict()`
- `prepare_data()`
- `setup()`

> ℹ️ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

Returns

A `torch.utils.data.DataLoader` or a sequence of them specifying prediction samples.

train_dataloader() → None

An iterable or collection of iterables specifying training samples.

For more information about multiple dataloaders, see this section.

The dataloader you return will not be reloaded unless you set **:param-ref:`~lightning.pytorch.trainer.trainer.Trainer.reload_dataloaders_every_n_epochs`** to a positive integer.

For data processing use the following pattern:

- download in `prepare_data()`
- process and split in `setup()`

However, the above are only necessary for distributed processing.

> ⚠️ **Warning**
>
> do not assign state in prepare_data

- `fit()`
- `prepare_data()`
- `setup()`

> ℹ️ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

configure_optimizers(*parameters=None*)

Choose what optimizers and learning-rate schedulers to use in your optimization. Normally you'd need one. But in the case of GANs or similar you might have multiple. Optimization with multiple optimizers only works in the manual optimization mode.

Returns

> Any of these 6 options.
>
> - **Single optimizer**.
>
> - **List or Tuple** of optimizers.
>
> - **Two lists** - The first list has multiple optimizers, and the second has multiple LR schedulers (or multiple `lr_scheduler_config`).
>
> - **Dictionary**, with an `"optimizer"` key, and (optionally) a `"lr_scheduler"` key whose value is a single LR scheduler or `lr_scheduler_config`.
>
> - **None** - Fit will run without any optimizer.

The `lr_scheduler_config` is a dictionary which contains the scheduler and its associated configuration. The default configuration is shown below.

```python
lr_scheduler_config = {
    # REQUIRED: The scheduler instance
    "scheduler": lr_scheduler,
    # The unit of the scheduler's step size, could also be 'step'.
    # 'epoch' updates the scheduler on epoch end whereas 'step'
    # updates it after a optimizer update.
    "interval": "epoch",
    # How many epochs/steps should pass between calls to
    # `scheduler.step()`. 1 corresponds to updating the learning
    # rate after every epoch/step.
    "frequency": 1,
    # Metric to to monitor for schedulers like `ReduceLROnPlateau`
    "monitor": "val_loss",
    # If set to `True`, will enforce that the value specified 'monitor'
    # is available when the scheduler is updated, thus stopping
    # training if not found. If set to `False`, it will only produce a warning
    "strict": True,
    # If using the `LearningRateMonitor` callback to monitor the
    # learning rate progress, this keyword can be used to specify
    # a custom logged name
    "name": None,
}
```

When there are schedulers in which the `.step()` method is conditioned on a value, such as the `torch.optim.lr_scheduler.ReduceLROnPlateau` scheduler, Lightning requires that the `lr_scheduler_config` contains the keyword `"monitor"` set to the metric name that the scheduler should be conditioned on.

Metrics can be made available to monitor by simply logging it using `self.log('metric_to_track', metric_val)` in your `LightningModule`.

> **ℹ Note**
>
> Some things to know:
>
> - Lightning calls `.backward()` and `.step()` automatically in case of automatic optimization.
>
> - If a learning rate scheduler is specified in `configure_optimizers()` with key `"interval"` (default "epoch") in the scheduler configuration, Lightning will call the scheduler's `.step()` method automatically in case of automatic optimization.
>
> - If you use 16-bit precision (`precision=16`), Lightning will automatically handle the optimizer.

- If you use `torch.optim.LBFGS`, Lightning handles the closure function automatically for you.

- If you use multiple optimizers, you will have to switch to 'manual optimization' mode and step them yourself.

- If you need to control how often the optimizer steps, override the `optimizer_step()` hook.

class `dicee.models.base_model.`**BaseKGE**(*args: dict*)

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
>> **x**(*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)
> byte pair encoded neural link predictors

> **Parameters**
>> ```-------```

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor],*
> *y_idx: torch.LongTensor = None*)

> **Parameters**

>> • **x**

>> • **y_idx**

- **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
> > **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
>
> > - **(b**(*x shape*)
> > - **3**
> > - **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
→ Tuple[torch.FloatTensor, torch.FloatTensor]

> **Parameters**
> > **x**(*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.base_model.**IdentityClass**(*args=None*)

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
>> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

__call__(*x*)

static forward(*x*)

dicee.models.clifford

Classes

CMult	Cl_(0,0) => Real Numbers
Keci	Base class for all neural network modules.
KeciBase	Without learning dimension scaling
DeCaL	Base class for all neural network modules.

Module Contents

class dicee.models.clifford.**CMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Cl_(0,0) => Real Numbers

Cl_(0,1) =>
A multivector mathbf{a} = a_0 + a_1 e_1 A multivector mathbf{b} = b_0 + b_1 e_1

multiplication is isomorphic to the product of two complex numbers

mathbf{a} imes mathbf{b} = a_0 b_0 + a_0b_1 e1 + a_1 b_1 e_1 e_1
= (a_0 b_0 - a_1 b_1) + (a_0 b_1 + a_1 b_0) e_1

Cl_(2,0) =>
A multivector mathbf{a} = a_0 + a_1 e_1 + a_2 e_2 + a_{12} e_1 e_2 A multivector mathbf{b} = b_0 + b_1 e_1 + b_2 e_2 + b_{12} e_1 e_2

mathbf{a} imes mathbf{b} = a_0b_0 + a_0b_1 e_1 + a_0b_2e_2 + a_0 b_12 e_1 e_2

- a_1 b_0 e_1 + a_1b_1 e_1_e1 ..

Cl_(0,2) => Quaternions

name = 'CMult'

entity_embeddings

relation_embeddings

p

q

clifford_mul(*x: torch.FloatTensor*, *y: torch.FloatTensor*, *p: int*, *q: int*) → tuple

Clifford multiplication Cl_{p,q} (mathbb{R})

ei ^2 = +1 for i =< i =< p ej ^2 = -1 for p < j =< p+q ei ej = -eje1 for i

eq j

x: torch.FloatTensor with (n,d) shape

y: torch.FloatTensor with (n,d) shape

p: a non-negative integer p>= 0 q: a non-negative integer q>= 0

score(*head_ent_emb*, *rel_ent_emb*, *tail_ent_emb*)

forward_triples(*x: torch.LongTensor*) → torch.FloatTensor

Compute batch triple scores

Parameter

x: torch.LongTensor with shape n by 3

> **rtype**
> torch.LongTensor with shape n

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

Compute batch KvsAll triple scores

Parameter

x: torch.LongTensor with shape n by 3

> **rtype**
> torch.LongTensor with shape n

class dicee.models.clifford.**Keci**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)
```

```
    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
 training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'Keci'

p

q

r

requires_grad_for_interactions = True

compute_sigma_pp (*hp*, *rp*)

 Compute sigma_{pp} = sum_{i=1}^{p-1} sum_{k=i+1}^p (h_i r_k - h_k r_i) e_i e_k

 sigma_{pp} captures the interactions between along p bases For instance, let p e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

  results = [] for i in range(p - 1):

   for k in range(i + 1, p):
    results.append(hp[:, :, i] * rp[:, :, k] - hp[:, :, k] * rp[:, :, i])

  sigma_pp = torch.stack(results, dim=2) assert sigma_pp.shape == (b, r, int((p * (p - 1)) / 2))

 Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

  e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

 Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_qq (*hq*, *rq*)

 Compute sigma_{qq} = sum_{j=1}^{p+q-1} sum_{k=j+1}^{p+q} (h_j r_k - h_k r_j) e_j e_k sigma_{q} captures the interactions between along q bases For instance, let q e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

  results = [] for j in range(q - 1):

   for k in range(j + 1, q):
    results.append(hq[:, :, j] * rq[:, :, k] - hq[:, :, k] * rq[:, :, j])

  sigma_qq = torch.stack(results, dim=2) assert sigma_qq.shape == (b, r, int((q * (q - 1)) / 2))

 Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

`compute_sigma_pq` (*, *hp*, *hq*, *rp*, *rq*)

sum_{i=1}^{p} sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

for j in range(q):

sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

`apply_coefficients` (*h0*, *hp*, *hq*, *r0*, *rp*, *rq*)

Multiplying a base vector with its scalar coefficient

`clifford_multiplication` (*h0*, *hp*, *hq*, *r0*, *rp*, *rq*)

Compute our CL multiplication

h = h_0 + sum_{i=1}^p h_i e_i + sum_{j=p+1}^{p+q} h_j e_j r = r_0 + sum_{i=1}^p r_i e_i + sum_{j=p+1}^{p+q} r_j e_j

ei ^2 = +1 for i =< i =< p ej ^2 = -1 for p < j =< p+q ei ej = -eje1 for i

eq j

h r = sigma_0 + sigma_p + sigma_q + sigma_{pp} + sigma_{q}+ sigma_{pq} where

(1) sigma_0 = h_0 r_0 + sum_{i=1}^p (h_0 r_i) e_i - sum_{j=p+1}^{p+q} (h_j r_j) e_j

(2) sigma_p = sum_{i=1}^p (h_0 r_i + h_i r_0) e_i

(3) sigma_q = sum_{j=p+1}^{p+q} (h_0 r_j + h_j r_0) e_j

(4) sigma_{pp} = sum_{i=1}^{p-1} sum_{k=i+1}^p (h_i r_k - h_k r_i) e_i e_k

(5) sigma_{qq} = sum_{j=1}^{p+q-1} sum_{k=j+1}^{p+q} (h_j r_k - h_k r_j) e_j e_k

(6) sigma_{pq} = sum_{i=1}^{p} sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j

`construct_cl_multivector` (*x: torch.FloatTensor*, *r: int*, *p: int*, *q: int*)
→ tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]

Construct a batch of multivectors Cl_{p,q}(mathbb{R}^d)

Parameter

x: torch.FloatTensor with (n,d) shape

returns

- **a0** (*torch.FloatTensor with (n,r) shape*)

- **ap** (*torch.FloatTensor with (n,r,p) shape*)

- **aq** (*torch.FloatTensor with (n,r,q) shape*)

`forward_k_vs_with_explicit` (*x: torch.Tensor*)

`k_vs_all_score` (*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

`forward_k_vs_all` (*x: torch.Tensor*) → torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations mathbb{R}^d .

(2) Construct head entity and relation embeddings according to Cl_{p,q}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

forward_k_vs_with_explicit and this funcitons are identical Parameter ——— x: torch.LongTensor with (n,2) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

`forward_k_vs_sample` (*x: torch.LongTensor*, *target_entity_idx: torch.LongTensor*)
→ torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations mathbb{R}^d .

(2) Construct head entity and relation embeddings according to Cl_{p,q}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

Parameter

x: torch.LongTensor with (n,2) shape

> **rtype**
> torch.FloatTensor with (n, **|E|**) shape

`score` (*h*, *r*, *t*)

`forward_triples` (*x: torch.Tensor*) → torch.FloatTensor

Parameter

x: torch.LongTensor with (n,3) shape

> **rtype**
> torch.FloatTensor with (n) shape

class dicee.models.clifford.**KeciBase** (*args*)

Bases: *Keci*

Without learning dimension scaling

name = 'KeciBase'

requires_grad_for_interactions = False

class dicee.models.clifford.**DeCaL** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> ℹ **Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
    training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'DeCaL'

entity_embeddings

relation_embeddings

p

q

r

re

forward_triples (*x: torch.Tensor*) → torch.FloatTensor

Parameter

x: torch.LongTensor with (n,) shape

    rtype
        torch.FloatTensor with (n) shape

cl_pqr (*a: torch.tensor*) → torch.tensor

Input: tensor(batch_size, emb_dim) —> output: tensor with $1+p+q+r$ components with size (batch_size, emb_dim/(1+p+q+r)) each.

1) takes a tensor of size (batch_size, emb_dim), split it into $1 + p + q + r$ components, hence $1+p+q+r$ must be a divisor of the emb_dim. 2) Return a list of the $1+p+q+r$ components vectors, each are tensors of size (batch_size, emb_dim/(1+p+q+r))

`compute_sigmas_single` (*list_h_emb*, *list_r_emb*, *list_t_emb*)

here we compute all the sums with no others vectors interaction taken with the scalar product with t, that is,

$$s0 = h_0 r_0 t_0 \quad s1 = \sum_{i=1}^{p} h_i r_i t_0 \quad s2 = \sum_{j=p+1}^{p+q} h_j r_j t_0 \quad s3 = \sum_{i=1}^{q} (h_0 r_i t_i + h_i r_0 t_i) \quad s4 = \sum_{i=p+1}^{p+q} (h_0 r_i t_i + h_i r_0 t_i) \quad s5 = \sum_{i=p+q+1}^{p+q+r} (h_0 r_i t$$

and return:

$$sigma_0 t = \sigma_0 \cdot t_0 = s0 + s1 - s2 s3, s4 and s5$$

`compute_sigmas_multivect` (*list_h_emb*, *list_r_emb*)

Here we compute and return all the sums with vectors interaction for the same and different bases.

For same bases vectors interaction we have

$$\sigma_p p = \sum_{i=1}^{p-1} \sum_{i'=i+1}^{p} (h_i r_{i'} - h_{i'} r_i)(models the interactions between e_i and e'_i for 1 <= i, i' <= p) \quad \sigma_q q = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q} (h_j r_{j'}$$

For different base vector interactions, we have

$$\sigma_p q = \sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i)(interactions n between e_i and e_j for 1 <= i <= p and p+1 <= j <= p+q) \quad \sigma_p r = \sum_{i=}^{}$$

`forward_k_vs_all` (*x: torch.Tensor*) → torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations

(2) Construct head entity and relation embeddings according to Cl_{p,q, r}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

forward_k_vs_with_explicit and this funcitons are identical Parameter ——— x: torch.LongTensor with (n,) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

`apply_coefficients` (*h0*, *hp*, *hq*, *hk*, *r0*, *rp*, *rq*, *rk*)

Multiplying a base vector with its scalar coefficient

`construct_cl_multivector` (*x: torch.FloatTensor*, *re: int*, *p: int*, *q: int*, *r: int*)
        → tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]
Construct a batch of multivectors Cl_{p,q,r}(mathbb{R}^d)

Parameter

x: torch.FloatTensor with (n,d) shape

returns

- **a0** (*torch.FloatTensor*)

- **ap** (*torch.FloatTensor*)

- **aq** (*torch.FloatTensor*)

- **ar** (*torch.FloatTensor*)

compute_sigma_pp (*hp, rp*)

Compute .. math:

```
\sigma_{p,p}^* = \sum_{i=1}^{p-1}\sum_{i'=i+1}^{p}(x_iy_{i'}-x_{i'}y_i)
```

sigma_{pp} captures the interactions between along p bases For instance, let p e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

results = [] for i in range(p - 1):

for k in range(i + 1, p):
results.append(hp[:, :, i] * rp[:, :, k] - hp[:, :, k] * rp[:, :, i])

sigma_pp = torch.stack(results, dim=2) assert sigma_pp.shape == (b, r, int((p * (p - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_qq (*hq, rq*)

Compute

$$\sigma_{q,q}^* = \sum_{j=p+1}^{p+q-1}\sum_{j'=j+1}^{p+q}(x_jy_{j'} - x_{j'}y_j)Eq.16$$

sigma_{q} captures the interactions between along q bases For instance, let q e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

results = [] for j in range(q - 1):

for k in range(j + 1, q):
results.append(hq[:, :, j] * rq[:, :, k] - hq[:, :, k] * rq[:, :, j])

sigma_qq = torch.stack(results, dim=2) assert sigma_qq.shape == (b, r, int((q * (q - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_rr (*hk, rk*)

$$\sigma_{r,r}^* = \sum_{k=p+q+1}^{p+q+r-1}\sum_{k'=k+1}^{p}(x_ky_{k'} - x_{k'}y_k)$$

compute_sigma_pq (*, *hp, hq, rp, rq*)

Compute

$$\sum_{i=1}^{p}\sum_{j=p+1}^{p+q}(h_ir_j - h_jr_i)e_ie_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

for j in range(q):
sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

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print(sigma_pq.shape)

compute_sigma_pr(*, *hp*, *hk*, *rp*, *rk*)

Compute

$$\sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

    for j in range(q):

        sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

compute_sigma_qr(*, *hq*, *hk*, *rq*, *rk*)

$$\sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

    for j in range(q):

        sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

dicee.models.complex

Classes

ConEx	Convolutional ComplEx Knowledge Graph Embeddings
AConEx	Additive Convolutional ComplEx Knowledge Graph Embeddings
ComplEx	Base class for all neural network modules.

Module Contents

class dicee.models.complex.**ConEx**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Convolutional ComplEx Knowledge Graph Embeddings

name = 'ConEx'

conv2d

fc_num_input

fc1

norm_fc1

bn_conv2d

feature_map_dropout

residual_convolution(*C_1: Tuple[torch.Tensor, torch.Tensor],*
            C_2: Tuple[torch.Tensor, torch.Tensor]) → torch.FloatTensor

> Compute residual score of two complex-valued embeddings. :param C_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

forward_triples(*x: torch.Tensor*) → torch.FloatTensor

> **Parameters**
>   **x**

forward_k_vs_sample(*x: torch.Tensor*, *target_entity_idx: torch.Tensor*)

class dicee.models.complex.**AConEx**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Additive Convolutional ComplEx Knowledge Graph Embeddings

name = 'AConEx'

conv2d

fc_num_input

fc1

norm_fc1

bn_conv2d

feature_map_dropout

residual_convolution(*C_1: Tuple[torch.Tensor, torch.Tensor],*
            C_2: Tuple[torch.Tensor, torch.Tensor]) → torch.FloatTensor

> Compute residual score of two complex-valued embeddings. :param C_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

forward_triples(*x: torch.Tensor*) → torch.FloatTensor

> **Parameters**
>   **x**

forward_k_vs_sample(*x: torch.Tensor*, *target_entity_idx: torch.Tensor*)

class dicee.models.complex.**ComplEx**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Base class for all neural network modules.

> Your models should also subclass this class.

> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
  training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'ComplEx'

static score (*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*, *tail_ent_emb: torch.FloatTensor*)

static k_vs_all_score (*emb_h: torch.FloatTensor*, *emb_r: torch.FloatTensor*, *emb_E: torch.FloatTensor*)

  Parameters
  - **emb_h**
  - **emb_r**
  - **emb_E**

forward_k_vs_all (*x: torch.LongTensor*) → torch.FloatTensor

dicee.models.dualE

Classes

DualE	Dual Quaternion Knowledge Graph Embeddings (https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657)

Module Contents

class dicee.models.dualE.**DualE**(*args*)

   Bases: *dicee.models.base_model.BaseKGE*

   Dual Quaternion Knowledge Graph Embeddings (https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657)

   name = 'DualE'

   entity_embeddings

   relation_embeddings

   num_ent

   kvsall_score(*e_1_h*, *e_2_h*, *e_3_h*, *e_4_h*, *e_5_h*, *e_6_h*, *e_7_h*, *e_8_h*, *e_1_t*, *e_2_t*, *e_3_t*, *e_4_t*, *e_5_t*, *e_6_t*, *e_7_t*, *e_8_t*, *r_1*, *r_2*, *r_3*, *r_4*, *r_5*, *r_6*, *r_7*, *r_8*) → torch.tensor

   KvsAll scoring function

   #### Input

   x: torch.LongTensor with (n,) shape

   #### Output

   torch.FloatTensor with (n) shape

   forward_triples(*idx_triple: torch.tensor*) → torch.tensor

   Negative Sampling forward pass:

   #### Input

   x: torch.LongTensor with (n,) shape

   #### Output

   torch.FloatTensor with (n) shape

   forward_k_vs_all(*x*)

   KvsAll forward pass

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

T (*x: torch.tensor*) → torch.tensor

Transpose function

Input: Tensor with shape (nxm) Output: Tensor with shape (mxn)

dicee.models.function_space

Classes

FMult	Learning Knowledge Neural Graphs
GFMult	Learning Knowledge Neural Graphs
FMult2	Learning Knowledge Neural Graphs
LFMult1	Embedding with trigonometric functions. We represent all entities and relations in the complex number space as:
LFMult	Embedding with polynomial functions. We represent all entities and relations in the polynomial space as:

Module Contents

class dicee.models.function_space.**FMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Learning Knowledge Neural Graphs

name = 'FMult'

entity_embeddings

relation_embeddings

k

num_sample = 50

gamma

roots

weights

compute_func (*weights: torch.FloatTensor*, *x*) → torch.FloatTensor

chain_func (*weights*, *x: torch.FloatTensor*)

forward_triples(*idx_triple: torch.Tensor*) → torch.Tensor

      Parameters
        x

class dicee.models.function_space.**GFMult**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Learning Knowledge Neural Graphs

    name = 'GFMult'

    entity_embeddings

    relation_embeddings

    k

    num_sample = 250

    roots

    weights

    compute_func(*weights: torch.FloatTensor*, *x*) → torch.FloatTensor

    chain_func(*weights*, *x: torch.FloatTensor*)

    forward_triples(*idx_triple: torch.Tensor*) → torch.Tensor

        Parameters
          x

class dicee.models.function_space.**FMult2**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Learning Knowledge Neural Graphs

    name = 'FMult2'

    n_layers = 3

    tuned_embedding_dim = False

    k

    n = 50

    score_func = 'compositional'

    discrete_points

    entity_embeddings

    relation_embeddings

    build_func(*Vec*)

    build_chain_funcs(*list_Vec*)

    compute_func(*W*, *b*, *x*) → torch.FloatTensor

function(*list_W*, *list_b*)

trapezoid(*list_W*, *list_b*)

forward_triples(*idx_triple: torch.Tensor*) → torch.Tensor

> **Parameters**
> > **x**

class dicee.models.function_space.**LFMult1**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

Embedding with trigonometric functions. We represent all entities and relations in the complex number space as: f(x) = sum_{k=0}^{k=d-1}wk e^{kix}. and use the three differents scoring function as in the paper to evaluate the score

name = 'LFMult1'

entity_embeddings

relation_embeddings

forward_triples(*idx_triple*)

> **Parameters**
> > **x**

tri_score(*h*, *r*, *t*)

vtp_score(*h*, *r*, *t*)

class dicee.models.function_space.**LFMult**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

Embedding with polynomial functions. We represent all entities and relations in the polynomial space as: f(x) = sum_{i=0}^{d-1} a_k x^{i%d} and use the three differents scoring function as in the paper to evaluate the score. We also consider combining with Neural Networks.

name = 'LFMult'

entity_embeddings

relation_embeddings

degree

m

x_values

forward_triples(*idx_triple*)

> **Parameters**
> > **x**

construct_multi_coeff(*x*)

poly_NN(*x*, *coefh*, *coefr*, *coeft*)

> Constructing a 2 layers NN to represent the embeddings. h = sigma(wh^T x + bh), r = sigma(wr^T x + br), t = sigma(wt^T x + bt)

linear (*x*, *w*, *b*)

scalar_batch_NN (*a*, *b*, *c*)

   element wise multiplication between a,b and c: Inputs : a, b, c ====> torch.tensor of size batch_size x m x d Output : a tensor of size batch_size x d

tri_score (*coeff_h*, *coeff_r*, *coeff_t*)

   this part implement the trilinear scoring techniques:

   score(h,r,t) = int_{0}{1} h(x)r(x)t(x) dx = sum_{i,j,k = 0}^{d-1} dfrac{a_i*b_j*c_k}{1+(i+j+k)%d}

   1. generate the range for i,j and k from [0 d-1]

   2. perform dfrac{a_i*b_j*c_k}{1+(i+j+k)%d} in parallel for every batch

   3. take the sum over each batch

vtp_score (*h*, *r*, *t*)

   this part implement the vector triple product scoring techniques:

   score(h,r,t) = int_{0}{1} h(x)r(x)t(x) dx = sum_{i,j,k = 0}^{d-1} dfrac{a_i*c_j*b_k - b_i*c_j*a_k}{(1+(i+j)%d)(1+k)}

   1. generate the range for i,j and k from [0 d-1]

   2. Compute the first and second terms of the sum

   3. Multiply with then denominator and take the sum

   4. take the sum over each batch

comp_func (*h*, *r*, *t*)

   this part implement the function composition scoring techniques: i.e. score = <hor, t>

polynomial (*coeff*, *x*, *degree*)

   This function takes a matrix tensor of coefficients (coeff), a tensor vector of points x and range of integer [0,1,…d] and return a vector tensor (coeff[0][0] + coeff[0][1]x +…+ coeff[0][d]x^d,

   coeff[1][0] + coeff[1][1]x +…+ coeff[1][d]x^d)

pop (*coeff*, *x*, *degree*)

   This function allow us to evaluate the composition of two polynomes without for loops :) it takes a matrix tensor of coefficients (coeff), a matrix tensor of points x and range of integer [0,1,…d]

   and return a tensor (coeff[0][0] + coeff[0][1]x +…+ coeff[0][d]x^d,

   coeff[1][0] + coeff[1][1]x +…+ coeff[1][d]x^d)

dicee.models.octonion

Classes

OMult	Base class for all neural network modules.
ConvO	Base class for all neural network modules.
AConvO	Additive Convolutional Octonion Knowledge Graph Embeddings

Functions

---

octonion_mul(*, O_1, O_2)

octonion_mul_norm(*, O_1, O_2)

Module Contents

dicee.models.octonion.**octonion_mul**(*, *O_1*, *O_2*)

dicee.models.octonion.**octonion_mul_norm**(*, *O_1*, *O_2*)

class dicee.models.octonion.**OMult**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Base class for all neural network modules.

> Your models should also subclass this class.

> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> > **ⓘ Note**
> >
> > As per the example above, an __init__() call to the parent class must be made before assignment on the child.

> > **Variables**
> > > **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

> **name = 'OMult'**

> **static octonion_normalizer**(*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

score (*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*,
        tail_ent_emb: torch.FloatTensor)

k_vs_all_score (*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

forward_k_vs_all (*x*)

> Completed. Given a head entity and a relation (h,r), we compute scores for all possible triples,i.e., [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, **|Entities|**) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.octonion.**ConvO** (*args: dict*)

> Bases: *dicee.models.base_model.BaseKGE*
>
> Base class for all neural network modules.
>
> Your models should also subclass this class.
>
> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ℹ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

> **Variables**
> > **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

> **name = 'ConvO'**
>
> **conv2d**
>
> **fc_num_input**
>
> **fc1**
>
> **bn_conv2d**
>
> **norm_fc1**
>
> **feature_map_dropout**

static octonion_normalizer(*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

residual_convolution(*O_1*, *O_2*)

forward_triples(*x: torch.Tensor*) → torch.Tensor

> **Parameters**
> > **x**

forward_k_vs_all(*x: torch.Tensor*)

> Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.octonion.**AConvO**(*args: dict*)

> Bases: *dicee.models.base_model.BaseKGE*

> Additive Convolutional Octonion Knowledge Graph Embeddings

> **name = 'AConvO'**

> **conv2d**

> **fc_num_input**

> **fc1**

> **bn_conv2d**

> **norm_fc1**

> **feature_map_dropout**

> **static octonion_normalizer**(*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

> **residual_convolution**(*O_1*, *O_2*)

> **forward_triples**(*x: torch.Tensor*) → torch.Tensor

> > **Parameters**
> > > **x**

> **forward_k_vs_all**(*x: torch.Tensor*)

> > Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

dicee.models.pykeen_models

Classes

PykeenKGE	A class for using knowledge graph embedding models implemented in Pykeen

Module Contents

class dicee.models.pykeen_models.**PykeenKGE**(*args: dict*)

    Bases: *dicee.models.base_model.BaseKGE*

    A class for using knowledge graph embedding models implemented in Pykeen

    Notes: Pykeen_DistMult: C Pykeen_ComplEx: Pykeen_QuatE: Pykeen_MuRE: Pykeen_CP: Pykeen_HolE: Pykeen_HolE:

    model_kwargs

    name

    model

    loss_history = []

    args

    entity_embeddings = None

    relation_embeddings = None

    forward_k_vs_all(*x: torch.LongTensor*)

        # => Explicit version by this we can apply bn and dropout

        # (1) Retrieve embeddings of heads and relations + apply Dropout & Normalization if given. h, r = self.get_head_relation_representation(x) # (2) Reshape (1). if self.last_dim > 0:

            h = h.reshape(len(x), self.embedding_dim, self.last_dim) r = r.reshape(len(x), self.embedding_dim, self.last_dim)

        # (3) Reshape all entities. if self.last_dim > 0:

            t = self.entity_embeddings.weight.reshape(self.num_entities, self.embedding_dim, self.last_dim)

        else:
            t = self.entity_embeddings.weight

        # (4) Call the score_t from interactions to generate triple scores. return self.interaction.score_t(h=h, r=r, all_entities=t, slice_size=1)

    forward_triples(*x: torch.LongTensor*) → torch.FloatTensor

        # => Explicit version by this we can apply bn and dropout

        # (1) Retrieve embeddings of heads, relations and tails and apply Dropout & Normalization if given. h, r, t = self.get_triple_representation(x) # (2) Reshape (1). if self.last_dim > 0:

            h = h.reshape(len(x), self.embedding_dim, self.last_dim) r = r.reshape(len(x), self.embedding_dim, self.last_dim) t = t.reshape(len(x), self.embedding_dim, self.last_dim)

        # (3) Compute the triple score return self.interaction.score(h=h, r=r, t=t, slice_size=None, slice_dim=0)

    abstract forward_k_vs_sample(*x: torch.LongTensor*, *target_entity_idx*)

dicee.models.quaternion

Classes

QMult	Base class for all neural network modules.
ConvQ	Convolutional Quaternion Knowledge Graph Embeddings
AConvQ	Additive Convolutional Quaternion Knowledge Graph Embeddings

Functions

quaternion_mul_with_unit_norm(*, Q_1, Q_2)

Module Contents

dicee.models.quaternion.**quaternion_mul_with_unit_norm**(*, *Q_1*, *Q_2*)

class dicee.models.quaternion.**QMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> ℹ **Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

Variables

> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'QMult'

explicit = True

quaternion_multiplication_followed_by_inner_product (*h, r, t*)

> **Parameters**
>
> - **h** – shape: (**batch_dims*, dim) The head representations.
>
> - **r** – shape: (**batch_dims*, dim) The head representations.
>
> - **t** – shape: (**batch_dims*, dim) The tail representations.
>
> **Returns**
>
> Triple scores.

static quaternion_normalizer (*x: torch.FloatTensor*) → torch.FloatTensor

Normalize the length of relation vectors, if the forward constraint has not been applied yet.

Absolute value of a quaternion

$$|a + bi + cj + dk| = \sqrt{a^2 + b^2 + c^2 + d^2}$$

L2 norm of quaternion vector:

$$\|x\|^2 = \sum_{i=1}^{d} |x_i|^2 = \sum_{i=1}^{d}(x_i.re^2 + x_i.im_1^2 + x_i.im_2^2 + x_i.im_3^2)$$

> **Parameters**
>
> **x** – The vector.
>
> **Returns**
>
> The normalized vector.

score (*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*,
tail_ent_emb: torch.FloatTensor)

k_vs_all_score (*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

> **Parameters**
>
> - **bpe_head_ent_emb**
>
> - **bpe_rel_ent_emb**
>
> - **E**

forward_k_vs_all (*x*)

> **Parameters**
>
> **x**

forward_k_vs_sample (*x*, *target_entity_idx*)

Completed. Given a head entity and a relation (h,r), we compute scores for all possible triples,i.e., [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.quaternion.**ConvQ**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Convolutional Quaternion Knowledge Graph Embeddings

    name = 'ConvQ'

    entity_embeddings

    relation_embeddings

    conv2d

    fc_num_input

    fc1

    bn_conv1

    bn_conv2

    feature_map_dropout

    residual_convolution(*Q_1*, *Q_2*)

    forward_triples(*indexed_triple: torch.Tensor*) → torch.Tensor

        Parameters

            x

    forward_k_vs_all(*x: torch.Tensor*)

        Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, **|Entities|**) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.quaternion.**AConvQ**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Additive Convolutional Quaternion Knowledge Graph Embeddings

    name = 'AConvQ'

    entity_embeddings

    relation_embeddings

    conv2d

    fc_num_input

    fc1

    bn_conv1

    bn_conv2

    feature_map_dropout

    residual_convolution(*Q_1*, *Q_2*)

forward_triples (*indexed_triple: torch.Tensor*) → torch.Tensor

> **Parameters**
>> **x**

forward_k_vs_all (*x: torch.Tensor*)

> Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

dicee.models.real

Classes

DistMult	Embedding Entities and Relations for Learning and Inference in Knowledge Bases
TransE	Translating Embeddings for Modeling
Shallom	A shallow neural model for relation prediction (https://arxiv.org/abs/2101.09090)
Pyke	A Physical Embedding Model for Knowledge Graphs

Module Contents

class dicee.models.real.**DistMult** (*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Embedding Entities and Relations for Learning and Inference in Knowledge Bases https://arxiv.org/abs/1412.6575

> **name = 'DistMult'**

> **k_vs_all_score** (*emb_h: torch.FloatTensor*, *emb_r: torch.FloatTensor*, *emb_E: torch.FloatTensor*)

>> **Parameters**
>>> - **emb_h**
>>> - **emb_r**
>>> - **emb_E**

> **forward_k_vs_all** (*x: torch.LongTensor*)

> **forward_k_vs_sample** (*x: torch.LongTensor*, *target_entity_idx: torch.LongTensor*)

> **score** (*h*, *r*, *t*)

class dicee.models.real.**TransE** (*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Translating Embeddings for Modeling Multi-relational Data https://proceedings.neurips.cc/paper/2013/file/1cecc7a77928ca8133fa24680a88d2f9-Paper.pdf

> **name = 'TransE'**

```
margin = 4
```

score(*head_ent_emb*, *rel_ent_emb*, *tail_ent_emb*)

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

class dicee.models.real.**Shallom**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

A shallow neural model for relation prediction (https://arxiv.org/abs/2101.09090)

```
name = 'Shallom'
```

shallom_width

shallom

get_embeddings() → Tuple[numpy.ndarray, None]

forward_k_vs_all(*x*) → torch.FloatTensor

forward_triples(*x*) → torch.FloatTensor

> **Parameters**
>> **x**
> **Returns**

class dicee.models.real.**Pyke**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

A Physical Embedding Model for Knowledge Graphs

```
name = 'Pyke'
```

dist_func

```
margin = 1.0
```

forward_triples(*x: torch.LongTensor*)

> **Parameters**
>> **x**

dicee.models.static_funcs

Functions

quaternion_mul(→ torch.Tensor, ...)	Tuple[torch.Tensor,	Perform quaternion multiplication

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Module Contents

dicee.models.static_funcs.**quaternion_mul**(*, *Q_1*, *Q_2*)
  $\rightarrow$ Tuple[torch.Tensor, torch.Tensor, torch.Tensor, torch.Tensor]

  Perform quaternion multiplication :param Q_1: :param Q_2: :return:

dicee.models.transformers

Full definition of a GPT Language Model, all of it in this single file. References: 1) the official GPT-2 TensorFlow implementation released by OpenAI: https://github.com/openai/gpt-2/blob/master/src/model.py 2) huggingface/transformers PyTorch implementation: https://github.com/huggingface/transformers/blob/main/src/transformers/models/gpt2/modeling_gpt2.py

Classes

BytE	Base class for all neural network modules.
LayerNorm	LayerNorm but with an optional bias. PyTorch doesn't support simply bias=False
CausalSelfAttention	Base class for all neural network modules.
MLP	Base class for all neural network modules.
Block	Base class for all neural network modules.
GPTConfig	
GPT	Base class for all neural network modules.

Module Contents

class dicee.models.transformers.**BytE**(**args*, ***kwargs*)

  Bases: *dicee.models.base_model.BaseKGE*

  Base class for all neural network modules.

  Your models should also subclass this class.

  Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
  training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'BytE'

config

temperature = 0.5

topk = 2

transformer

lm_head

weight

loss_function (*yhat_batch*, *y_batch*)

  Parameters

  - **yhat_batch**

  - **y_batch**

forward (*x: torch.LongTensor*)

  Parameters
    x (*B by T tensor*)

generate (*idx*, *max_new_tokens*, *temperature=1.0*, *top_k=None*)

  Take a conditioning sequence of indices idx (LongTensor of shape (b,t)) and complete the sequence max_new_tokens times, feeding the predictions back into the model each time. Most likely you'll want to make sure to be in model.eval() mode of operation for this.

training_step (*batch*, *batch_idx=None*)

  Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.

  Parameters

  - **batch** – The output of your data iterable, normally a `DataLoader`.

  - **batch_idx** – The index of this batch.

  - **dataloader_idx** – The index of the dataloader that produced this batch. (only if multiple dataloaders used)

  Returns

  - `Tensor` - The loss tensor

  - `dict` - A dictionary which can include any keys, but must include the key `'loss'` in the case of automatic optimization.

- `None` - In automatic optimization, this will skip to the next batch (but is not supported for multi-GPU, TPU, or DeepSpeed). For manual optimization, this has no special meaning, as returning the loss is not required.

In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

Example:

```python
def training_step(self, batch, batch_idx):
    x, y, z = batch
    out = self.encoder(x)
    loss = self.loss(out, x)
    return loss
```

To use multiple optimizers, you can switch to 'manual optimization' and control their stepping:

```python
def __init__(self):
    super().__init__()
    self.automatic_optimization = False


# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx):
    opt1, opt2 = self.optimizers()

    # do training_step with encoder
    ...
    opt1.step()
    # do training_step with decoder
    ...
    opt2.step()
```

> **ⓘ Note**
>
> When `accumulate_grad_batches` > 1, the loss returned here will be automatically normalized by `accumulate_grad_batches` internally.

class dicee.models.transformers.**LayerNorm**(*ndim*, *bias*)

Bases: torch.nn.Module

LayerNorm but with an optional bias. PyTorch doesn't support simply bias=False

weight

bias

forward(*input*)

class dicee.models.transformers.**CausalSelfAttention**(*config*)

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ️ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
    training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

c_attn

c_proj

attn_dropout

resid_dropout

n_head

n_embd

dropout

flash

forward(*x*)

class dicee.models.transformers.**MLP**(*config*)

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
```

```
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
>
> > **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

c_fc

gelu

c_proj

dropout

forward(*x*)

class dicee.models.transformers.**Block**(*config*)

Bases: `torch.nn.Module`

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
>   **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

ln_1

attn

ln_2

mlp

forward(*x*)

class dicee.models.transformers.**GPTConfig**

    block_size: int = 1024

    vocab_size: int = 50304

    n_layer: int = 12

    n_head: int = 12

    n_embd: int = 768

    dropout: float = 0.0

    bias: bool = False

class dicee.models.transformers.**GPT**(*config*)

    Bases: torch.nn.Module

    Base class for all neural network modules.

    Your models should also subclass this class.

    Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
>   **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

config

transformer

lm_head

weight

get_num_params (*non_embedding=True*)

Return the number of parameters in the model. For non-embedding count (default), the position embeddings get subtracted. The token embeddings would too, except due to the parameter sharing these params are actually used as weights in the final layer, so we include them.

forward (*idx*, *targets=None*)

crop_block_size (*block_size*)

classmethod from_pretrained (*model_type*, *override_args=None*)

configure_optimizers (*weight_decay*, *learning_rate*, *betas*, *device_type*)

estimate_mfu (*fwdbwd_per_iter*, *dt*)

estimate model flops utilization (MFU) in units of A100 bfloat16 peak FLOPS

Classes

BaseKGELightning	Base class for all neural network modules.
BaseKGE	Base class for all neural network modules.
IdentityClass	Base class for all neural network modules.
BaseKGE	Base class for all neural network modules.
DistMult	Embedding Entities and Relations for Learning and Inference in Knowledge Bases
TransE	Translating Embeddings for Modeling
Shallom	A shallow neural model for relation prediction (https://arxiv.org/abs/2101.09090)
Pyke	A Physical Embedding Model for Knowledge Graphs
BaseKGE	Base class for all neural network modules.
ConEx	Convolutional ComplEx Knowledge Graph Embeddings
AConEx	Additive Convolutional ComplEx Knowledge Graph Embeddings
ComplEx	Base class for all neural network modules.

Table 1 – continued from previous page

BaseKGE	Base class for all neural network modules.
IdentityClass	Base class for all neural network modules.
QMult	Base class for all neural network modules.
ConvQ	Convolutional Quaternion Knowledge Graph Embeddings
AConvQ	Additive Convolutional Quaternion Knowledge Graph Embeddings
BaseKGE	Base class for all neural network modules.
IdentityClass	Base class for all neural network modules.
OMult	Base class for all neural network modules.
ConvO	Base class for all neural network modules.
AConvO	Additive Convolutional Octonion Knowledge Graph Embeddings
Keci	Base class for all neural network modules.
KeciBase	Without learning dimension scaling
CMult	Cl_(0,0) => Real Numbers
DeCaL	Base class for all neural network modules.
BaseKGE	Base class for all neural network modules.
PykeenKGE	A class for using knowledge graph embedding models implemented in Pykeen
BaseKGE	Base class for all neural network modules.
FMult	Learning Knowledge Neural Graphs
GFMult	Learning Knowledge Neural Graphs
FMult2	Learning Knowledge Neural Graphs
LFMult1	Embedding with trigonometric functions. We represent all entities and relations in the complex number space as:
LFMult	Embedding with polynomial functions. We represent all entities and relations in the polynomial space as:
DualE	Dual Quaternion Knowledge Graph Embeddings (https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657)

Functions

quaternion_mul($\rightarrow$ Tuple[torch.Tensor, torch.Tensor, ...])	Perform quaternion multiplication
quaternion_mul_with_unit_norm(*, Q_1, Q_2)	
octonion_mul(*, O_1, O_2)	
octonion_mul_norm(*, O_1, O_2)	

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Package Contents

class dicee.models.**BaseKGELightning**(**args*, ***kwargs*)

> Bases: lightning.LightningModule
>
> Base class for all neural network modules.
>
> Your models should also subclass this class.
>
> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ℹ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

> > **Variables**
> > > **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.
>
> **training_step_outputs = []**
>
> **mem_of_model**() → Dict
> > Size of model in MB and number of params
>
> **training_step**(*batch*, *batch_idx=None*)
> > Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.
> >
> > > **Parameters**
> > >
> > > - **batch** – The output of your data iterable, normally a DataLoader.
> > >
> > > - **batch_idx** – The index of this batch.
> > >
> > > - **dataloader_idx** – The index of the dataloader that produced this batch. (only if multiple dataloaders used)
> > >
> > > **Returns**
> > >
> > > - Tensor - The loss tensor
> > >
> > > - dict - A dictionary which can include any keys, but must include the key 'loss' in the case of automatic optimization.

- `None` - In automatic optimization, this will skip to the next batch (but is not supported for multi-GPU, TPU, or DeepSpeed). For manual optimization, this has no special meaning, as returning the loss is not required.

In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

Example:

```python
def training_step(self, batch, batch_idx):
    x, y, z = batch
    out = self.encoder(x)
    loss = self.loss(out, x)
    return loss
```

To use multiple optimizers, you can switch to 'manual optimization' and control their stepping:

```python
def __init__(self):
    super().__init__()
    self.automatic_optimization = False


# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx):
    opt1, opt2 = self.optimizers()

    # do training_step with encoder
    ...
    opt1.step()
    # do training_step with decoder
    ...
    opt2.step()
```

> **ⓘ Note**
>
> When `accumulate_grad_batches` > 1, the loss returned here will be automatically normalized by `accumulate_grad_batches` internally.

`loss_function`(*yhat_batch: torch.FloatTensor*, *y_batch: torch.FloatTensor*)

> **Parameters**
>
> - **yhat_batch**
> - **y_batch**

`on_train_epoch_end`(**args*, ***kwargs*)

Called in the training loop at the very end of the epoch.

To access all batch outputs at the end of the epoch, you can cache step outputs as an attribute of the `LightningModule` and access them in this hook:

```python
class MyLightningModule(L.LightningModule):
    def __init__(self):
        super().__init__()
        self.training_step_outputs = []
```

```python
    def training_step(self):
        loss = ...
        self.training_step_outputs.append(loss)
        return loss

    def on_train_epoch_end(self):
        # do something with all training_step outputs, for example:
        epoch_mean = torch.stack(self.training_step_outputs).mean()
        self.log("training_epoch_mean", epoch_mean)
        # free up the memory
        self.training_step_outputs.clear()
```

test_epoch_end(*outputs: List[Any]*)

test_dataloader() → None

> An iterable or collection of iterables specifying test samples.
>
> For more information about multiple dataloaders, see this section.
>
> For data processing use the following pattern:
>
> - download in `prepare_data()`
> - process and split in `setup()`
>
> However, the above are only necessary for distributed processing.

> ⚠️ **Warning**
>
> do not assign state in prepare_data

> - `test()`
> - `prepare_data()`
> - `setup()`

> ℹ️ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

> ℹ️ **Note**
>
> If you don't need a test dataset and a `test_step()`, you don't need to implement this method.

val_dataloader() → None

> An iterable or collection of iterables specifying validation samples.
>
> For more information about multiple dataloaders, see this section.
>
> The dataloader you return will not be reloaded unless you set **:param-ref:`~lightning.pytorch.trainer.trainer.Trainer.reload_dataloaders_every_n_epochs`** to a positive integer.

It's recommended that all data downloads and preparation happen in `prepare_data()`.

- `fit()`
- `validate()`
- `prepare_data()`
- `setup()`

> **ℹ Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

> **ℹ Note**
>
> If you don't need a validation dataset and a `validation_step()`, you don't need to implement this method.

`predict_dataloader`() → None

An iterable or collection of iterables specifying prediction samples.

For more information about multiple dataloaders, see this section.

It's recommended that all data downloads and preparation happen in `prepare_data()`.

- `predict()`
- `prepare_data()`
- `setup()`

> **ℹ Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware There is no need to set it yourself.

> **Returns**
>
> A `torch.utils.data.DataLoader` or a sequence of them specifying prediction samples.

`train_dataloader`() → None

An iterable or collection of iterables specifying training samples.

For more information about multiple dataloaders, see this section.

The dataloader you return will not be reloaded unless you set **:param-ref:`~lightning.pytorch.trainer.trainer.Trainer.reload_dataloaders_every_n_epochs`** to a positive integer.

For data processing use the following pattern:

- download in `prepare_data()`
- process and split in `setup()`

However, the above are only necessary for distributed processing.

> ⚠️ **Warning**
>
> do not assign state in prepare_data

- `fit()`
- `prepare_data()`
- `setup()`

> ℹ️ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

configure_optimizers(*parameters=None*)

Choose what optimizers and learning-rate schedulers to use in your optimization. Normally you'd need one. But in the case of GANs or similar you might have multiple. Optimization with multiple optimizers only works in the manual optimization mode.

> **Returns**
>
> > Any of these 6 options.
> >
> > - **Single optimizer**.
> > - **List or Tuple** of optimizers.
> > - **Two lists** - The first list has multiple optimizers, and the second has multiple LR schedulers (or multiple `lr_scheduler_config`).
> > - **Dictionary**, with an `"optimizer"` key, and (optionally) a `"lr_scheduler"` key whose value is a single LR scheduler or `lr_scheduler_config`.
> > - **None** - Fit will run without any optimizer.

The `lr_scheduler_config` is a dictionary which contains the scheduler and its associated configuration. The default configuration is shown below.

```
lr_scheduler_config = {
    # REQUIRED: The scheduler instance
    "scheduler": lr_scheduler,
    # The unit of the scheduler's step size, could also be 'step'.
    # 'epoch' updates the scheduler on epoch end whereas 'step'
    # updates it after a optimizer update.
    "interval": "epoch",
    # How many epochs/steps should pass between calls to
    # `scheduler.step()`. 1 corresponds to updating the learning
    # rate after every epoch/step.
    "frequency": 1,
    # Metric to to monitor for schedulers like `ReduceLROnPlateau`
    "monitor": "val_loss",
    # If set to `True`, will enforce that the value specified 'monitor'
    # is available when the scheduler is updated, thus stopping
    # training if not found. If set to `False`, it will only produce a warning
```

```
        "strict": True,
        # If using the `LearningRateMonitor` callback to monitor the
        # learning rate progress, this keyword can be used to specify
        # a custom logged name
        "name": None,
}
```

When there are schedulers in which the `.step()` method is conditioned on a value, such as the `torch.optim.lr_scheduler.ReduceLROnPlateau` scheduler, Lightning requires that the `lr_scheduler_config` contains the keyword `"monitor"` set to the metric name that the scheduler should be conditioned on.

Metrics can be made available to monitor by simply logging it using `self.log('metric_to_track', metric_val)` in your `LightningModule`.

> **ⓘ Note**
>
> Some things to know:
>
> - Lightning calls `.backward()` and `.step()` automatically in case of automatic optimization.
>
> - If a learning rate scheduler is specified in `configure_optimizers()` with key `"interval"` (default "epoch") in the scheduler configuration, Lightning will call the scheduler's `.step()` method automatically in case of automatic optimization.
>
> - If you use 16-bit precision (`precision=16`), Lightning will automatically handle the optimizer.
>
> - If you use `torch.optim.LBFGS`, Lightning handles the closure function automatically for you.
>
> - If you use multiple optimizers, you will have to switch to 'manual optimization' mode and step them yourself.
>
> - If you need to control how often the optimizer steps, override the `optimizer_step()` hook.

class dicee.models.**BaseKGE**(*args: dict*)

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call

`to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
>   **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
>> **x**(*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)
> byte pair encoded neural link predictors

> **Parameters**
>> **-------**

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor],*
> *y_idx: torch.LongTensor = None*)

> **Parameters**
>> - **x**
>> - **y_idx**
>> - **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
>> **x**

forward_k_vs_all(**args, **kwargs*)

forward_k_vs_sample(**args, **kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
>> - **(b**(*x shape*)
>> - **3**
>> - **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
> → Tuple[torch.FloatTensor, torch.FloatTensor]

> **Parameters**
>> **x**(*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**IdentityClass**(*args=None*)

Bases: `torch.nn.Module`

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

__call__(*x*)

static forward(*x*)

class dicee.models.**BaseKGE**(*args: dict*)

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
```

```python
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> ℹ **Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
   training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
>   **x** (*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)

> byte pair encoded neural link predictors

> **Parameters**
>   **-------**

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor],*
          y_idx: torch.LongTensor = None)

> **Parameters**
>
> - **x**
>
> - **y_idx**
>
> - **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
>   **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
>
> - **(b** (*x shape*)
>
> - **3**

· **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
→ Tuple[torch.FloatTensor, torch.FloatTensor]

>   **Parameters**
>   **x**(*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**DistMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Embedding Entities and Relations for Learning and Inference in Knowledge Bases https://arxiv.org/abs/1412.6575

name = 'DistMult'

k_vs_all_score(*emb_h: torch.FloatTensor*, *emb_r: torch.FloatTensor*, *emb_E: torch.FloatTensor*)

>   **Parameters**
>   · **emb_h**
>   · **emb_r**
>   · **emb_E**

forward_k_vs_all(*x: torch.LongTensor*)

forward_k_vs_sample(*x: torch.LongTensor*, *target_entity_idx: torch.LongTensor*)

score(*h*, *r*, *t*)

class dicee.models.**TransE**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Translating Embeddings for Modeling Multi-relational Data https://proceedings.neurips.cc/paper/2013/file/1cecc7a77928ca8133fa24680a88d2f9-Paper.pdf

name = 'TransE'

margin = 4

score(*head_ent_emb*, *rel_ent_emb*, *tail_ent_emb*)

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

class dicee.models.**Shallom**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

A shallow neural model for relation prediction (https://arxiv.org/abs/2101.09090)

name = 'Shallom'

shallom_width

shallom

get_embeddings() → Tuple[numpy.ndarray, None]

forward_k_vs_all(*x*) → torch.FloatTensor

forward_triples(*x*) → torch.FloatTensor

> **Parameters**
>> **x**

> **Returns**

class dicee.models.**Pyke**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> A Physical Embedding Model for Knowledge Graphs

> **name = 'Pyke'**

> **dist_func**

> **margin = 1.0**

> **forward_triples**(*x: torch.LongTensor*)

>> **Parameters**
>>> **x**

class dicee.models.**BaseKGE**(*args: dict*)

> Bases: *BaseKGELightning*

> Base class for all neural network modules.

> Your models should also subclass this class.

> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> > **ℹ Note**
> >
> > As per the example above, an __init__() call to the parent class must be made before assignment on the child.

> > **Variables**
> >> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

> **args**

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all *(x: torch.LongTensor)*

> **Parameters**
>> **x** *(B x 2 x T)*

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)

> byte pair encoded neural link predictors

> > **Parameters**
> > -------

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor],*
> *y_idx: torch.LongTensor = None*)

> > **Parameters**

> > > • **x**

> > > • **y_idx**

> > > • **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> > **Parameters**
> > **x**

forward_k_vs_all(**args, **kwargs*)

forward_k_vs_sample(**args, **kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> > **Parameters**

> > > • **(b** (*x shape*)

> > > • **3**

> > > • **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
> → Tuple[torch.FloatTensor, torch.FloatTensor]

> > **Parameters**
> > **x** (*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**ConEx**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Convolutional ComplEx Knowledge Graph Embeddings

> **name = 'ConEx'**

> **conv2d**

> **fc_num_input**

> **fc1**

norm_fc1

bn_conv2d

feature_map_dropout

residual_convolution (*C_1: Tuple[torch.Tensor, torch.Tensor]*,
        C_2: Tuple[torch.Tensor, torch.Tensor]) → torch.FloatTensor

Compute residual score of two complex-valued embeddings. :param C_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

forward_k_vs_all (*x: torch.Tensor*) → torch.FloatTensor

forward_triples (*x: torch.Tensor*) → torch.FloatTensor

> **Parameters**
>   **x**

forward_k_vs_sample (*x: torch.Tensor*, *target_entity_idx: torch.Tensor*)

class dicee.models.**AConEx** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Additive Convolutional ComplEx Knowledge Graph Embeddings

name = 'AConEx'

conv2d

fc_num_input

fc1

norm_fc1

bn_conv2d

feature_map_dropout

residual_convolution (*C_1: Tuple[torch.Tensor, torch.Tensor]*,
        C_2: Tuple[torch.Tensor, torch.Tensor]) → torch.FloatTensor

Compute residual score of two complex-valued embeddings. :param C_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

forward_k_vs_all (*x: torch.Tensor*) → torch.FloatTensor

forward_triples (*x: torch.Tensor*) → torch.FloatTensor

> **Parameters**
>   **x**

forward_k_vs_sample (*x: torch.Tensor*, *target_entity_idx: torch.Tensor*)

class dicee.models.**ComplEx** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables

training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'ComplEx'

static score(*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*, *tail_ent_emb: torch.FloatTensor*)

static k_vs_all_score(*emb_h: torch.FloatTensor*, *emb_r: torch.FloatTensor*, *emb_E: torch.FloatTensor*)

Parameters

- **emb_h**
- **emb_r**
- **emb_E**

forward_k_vs_all(*x: torch.LongTensor*) → torch.FloatTensor

dicee.models.**quaternion_mul**(***, *Q_1*, *Q_2*)
→ Tuple[torch.Tensor, torch.Tensor, torch.Tensor, torch.Tensor]

Perform quaternion multiplication :param Q_1: :param Q_2: :return:

class dicee.models.**BaseKGE**(*args: dict*)

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
      training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

```
normalize_head_entity_embeddings
```

```
normalize_relation_embeddings
```

```
normalize_tail_entity_embeddings
```

```
hidden_normalizer
```

```
param_init
```

```
input_dp_ent_real
```

```
input_dp_rel_real
```

```
hidden_dropout
```

```
loss_history = []
```

```
byte_pair_encoding
```

```
max_length_subword_tokens
```

```
block_size
```

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
> **x** (*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)

byte pair encoded neural link predictors

> **Parameters**
> **-------**

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor]*,
y_idx: torch.LongTensor = None)

> **Parameters**
>
> - **x**
> - **y_idx**
> - **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
> **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
>
> - **(b**(*x shape*)
>
> - **3**
>
> - **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
  → Tuple[torch.FloatTensor, torch.FloatTensor]

> **Parameters**
>   **x**(*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**IdentityClass**(*args=None*)

> Bases: torch.nn.Module
>
> Base class for all neural network modules.
>
> Your models should also subclass this class.
>
> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.
>
> > ℹ️ **Note**
> >
> > As per the example above, an __init__() call to the parent class must be made before assignment on the child.
>
> > **Variables**
> >   **training**(*bool*) – Boolean represents whether this module is in training or evaluation mode.
>
> **args**
>
> **__call__**(*x*)
>
> **static forward**(*x*)

dicee.models.**quaternion_mul_with_unit_norm**(**, Q_1, Q_2*)

class dicee.models.**QMult**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Base class for all neural network modules.

> Your models should also subclass this class.

> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
>> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

> **name = 'QMult'**

> **explicit = True**

> **quaternion_multiplication_followed_by_inner_product**(*h, r, t*)

>> **Parameters**
>>> - **h** – shape: (**batch_dims*, dim) The head representations.
>>>
>>> - **r** – shape: (**batch_dims*, dim) The head representations.
>>>
>>> - **t** – shape: (**batch_dims*, dim) The tail representations.
>>
>> **Returns**
>>> Triple scores.

> **static quaternion_normalizer**(*x: torch.FloatTensor*) → torch.FloatTensor

>> Normalize the length of relation vectors, if the forward constraint has not been applied yet.

>> Absolute value of a quaternion

$$|a + bi + cj + dk| = \sqrt{a^2 + b^2 + c^2 + d^2}$$

L2 norm of quaternion vector:

$$\|x\|^2 = \sum_{i=1}^{d} |x_i|^2 = \sum_{i=1}^{d} (x_i.re^2 + x_i.im_1^2 + x_i.im_2^2 + x_i.im_3^2)$$

Parameters
> **x** – The vector.

Returns
> The normalized vector.

score(*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*, *tail_ent_emb: torch.FloatTensor*)

k_vs_all_score(*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

Parameters

- **bpe_head_ent_emb**

- **bpe_rel_ent_emb**

- **E**

forward_k_vs_all(*x*)

Parameters
> **x**

forward_k_vs_sample(*x*, *target_entity_idx*)

Completed. Given a head entity and a relation (h,r), we compute scores for all possible triples,i.e., [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.**ConvQ**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Convolutional Quaternion Knowledge Graph Embeddings

name = 'ConvQ'

entity_embeddings

relation_embeddings

conv2d

fc_num_input

fc1

bn_conv1

bn_conv2

feature_map_dropout

residual_convolution(*Q_1*, *Q_2*)

forward_triples(*indexed_triple: torch.Tensor*) → torch.Tensor

> **Parameters**
> > **x**

forward_k_vs_all(*x: torch.Tensor*)

> Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.**AConvQ**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*
>
> Additive Convolutional Quaternion Knowledge Graph Embeddings
>
> **name = 'AConvQ'**
>
> **entity_embeddings**
>
> **relation_embeddings**
>
> **conv2d**
>
> **fc_num_input**
>
> **fc1**
>
> **bn_conv1**
>
> **bn_conv2**
>
> **feature_map_dropout**
>
> **residual_convolution**(*Q_1*, *Q_2*)
>
> **forward_triples**(*indexed_triple: torch.Tensor*) → torch.Tensor
>
> > **Parameters**
> > > **x**
>
> **forward_k_vs_all**(*x: torch.Tensor*)
>
> > Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.**BaseKGE**(*args: dict*)

> Bases: *BaseKGELightning*
>
> Base class for all neural network modules.
>
> Your models should also subclass this class.
>
> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
```

```python
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

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normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
> **x** (*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)

> byte pair encoded neural link predictors

> **Parameters**
> **-------**

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor],*
> *y_idx: torch.LongTensor = None*)

> **Parameters**

> - **x**

> - **y_idx**

> - **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
> **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**

> - **(b** (*x shape*)

> - **3**

- **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
$\rightarrow$ Tuple[torch.FloatTensor, torch.FloatTensor]

Parameters
x (*B x 2 x T*)

get_embeddings() $\rightarrow$ Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**IdentityClass**(*args=None*)

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ℹ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

Variables
training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

__call__(*x*)

static forward(*x*)

dicee.models.**octonion_mul**(**, O_1, O_2*)

dicee.models.**octonion_mul_norm**(**, O_1, O_2*)

class dicee.models.**OMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
    training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'OMult'

static octonion_normalizer (*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

score (*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*, *tail_ent_emb: torch.FloatTensor*)

k_vs_all_score (*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

forward_k_vs_all (*x*)

    Completed. Given a head entity and a relation (h,r), we compute scores for all possible triples,i.e., [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.**ConvO** (*args: dict*)

    Bases: *dicee.models.base_model.BaseKGE*

    Base class for all neural network modules.

    Your models should also subclass this class.

    Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F
```

```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables

training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'ConvO'

conv2d

fc_num_input

fc1

bn_conv2d

norm_fc1

feature_map_dropout

static octonion_normalizer(*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

residual_convolution(*O_1*, *O_2*)

forward_triples(*x: torch.Tensor*) → torch.Tensor

Parameters
x

forward_k_vs_all(*x: torch.Tensor*)

Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.**AConvO**(*args: dict*)

Bases: *dicee.models.base_model.BaseKGE*

Additive Convolutional Octonion Knowledge Graph Embeddings

name = 'AConvO'

conv2d

fc_num_input

fc1

bn_conv2d

norm_fc1

feature_map_dropout

static octonion_normalizer(*emb_rel_e0, emb_rel_e1, emb_rel_e2, emb_rel_e3, emb_rel_e4, emb_rel_e5, emb_rel_e6, emb_rel_e7*)

residual_convolution(*O_1, O_2*)

forward_triples(*x: torch.Tensor*) → torch.Tensor

> **Parameters**
> > **x**

forward_k_vs_all(*x: torch.Tensor*)

> Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.models.**Keci**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*
>
> Base class for all neural network modules.
>
> Your models should also subclass this class.
>
> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> > ℹ **Note**
> >
> > As per the example above, an __init__() call to the parent class must be made before assignment on the child.

Variables

    training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'Keci'

p

q

r

requires_grad_for_interactions = True

compute_sigma_pp (*hp*, *rp*)

Compute sigma_{pp} = sum_{i=1}^{p-1} sum_{k=i+1}^p (h_i r_k - h_k r_i) e_i e_k

sigma_{pp} captures the interactions between along p bases For instance, let p e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

    results = [] for i in range(p - 1):

        for k in range(i + 1, p):
            results.append(hp[:, :, i] * rp[:, :, k] - hp[:, :, k] * rp[:, :, i])

    sigma_pp = torch.stack(results, dim=2) assert sigma_pp.shape == (b, r, int((p * (p - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

    e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_qq (*hq*, *rq*)

Compute sigma_{qq} = sum_{j=1}^{p+q-1} sum_{k=j+1}^{p+q} (h_j r_k - h_k r_j) e_j e_k sigma_{q} captures the interactions between along q bases For instance, let q e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

    results = [] for j in range(q - 1):

        for k in range(j + 1, q):
            results.append(hq[:, :, j] * rq[:, :, k] - hq[:, :, k] * rq[:, :, j])

    sigma_qq = torch.stack(results, dim=2) assert sigma_qq.shape == (b, r, int((q * (q - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

    e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_pq (*, *hp*, *hq*, *rp*, *rq*)

sum_{i=1}^{p} sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

    for j in range(q):
        sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

apply_coefficients (*h0*, *hp*, *hq*, *r0*, *rp*, *rq*)

Multiplying a base vector with its scalar coefficient

clifford_multiplication (*h0*, *hp*, *hq*, *r0*, *rp*, *rq*)

Compute our CL multiplication

$h = h\_0 + sum\_\{i=1\}^p h\_i e\_i + sum\_\{j=p+1\}^\{p+q\} h\_j e\_j r = r\_0 + sum\_\{i=1\}^p r\_i e\_i + sum\_\{j=p+1\}^\{p+q\} r\_j e\_j$

ei ^2 = +1 for i =< i =< p ej ^2 = -1 for p < j =< p+q ei ej = -eje1 for i

eq j

h r = sigma_0 + sigma_p + sigma_q + sigma_{pp} + sigma_{q}+ sigma_{pq} where

(1) sigma_0 = h_0 r_0 + sum_{i=1}^p (h_0 r_i) e_i - sum_{j=p+1}^{p+q} (h_j r_j) e_j

(2) sigma_p = sum_{i=1}^p (h_0 r_i + h_i r_0) e_i

(3) sigma_q = sum_{j=p+1}^{p+q} (h_0 r_j + h_j r_0) e_j

(4) sigma_{pp} = sum_{i=1}^{p-1} sum_{k=i+1}^p (h_i r_k - h_k r_i) e_i e_k

(5) sigma_{qq} = sum_{j=1}^{p+q-1} sum_{k=j+1}^{p+q} (h_j r_k - h_k r_j) e_j e_k

(6) sigma_{pq} = sum_{i=1}^{p} sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j

construct_cl_multivector (*x: torch.FloatTensor*, *r: int*, *p: int*, *q: int*)
$\rightarrow$ tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]

Construct a batch of multivectors Cl_{p,q}(mathbb{R}^d)

Parameter

x: torch.FloatTensor with (n,d) shape

returns

- **a0** (*torch.FloatTensor with (n,r) shape*)
- **ap** (*torch.FloatTensor with (n,r,p) shape*)
- **aq** (*torch.FloatTensor with (n,r,q) shape*)

forward_k_vs_with_explicit (*x: torch.Tensor*)

k_vs_all_score (*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

forward_k_vs_all (*x: torch.Tensor*) $\rightarrow$ torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations mathbb{R}^d .

(2) Construct head entity and relation embeddings according to Cl_{p,q}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

forward_k_vs_with_explicit and this funcitons are identical Parameter ——— x: torch.LongTensor with (n,2) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

forward_k_vs_sample (*x: torch.LongTensor*, *target_entity_idx: torch.LongTensor*)
$\rightarrow$ torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations mathbb{R}^d .

(2) Construct head entity and relation embeddings according to Cl_{p,q}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

Parameter

x: torch.LongTensor with (n,2) shape

> **rtype**
> torch.FloatTensor with (n, |E|) shape

score (*h, r, t*)

forward_triples (*x: torch.Tensor*) $\rightarrow$ torch.FloatTensor

Parameter

x: torch.LongTensor with (n,3) shape

> **rtype**
> torch.FloatTensor with (n) shape

class dicee.models.**KeciBase** (*args*)

Bases: *Keci*

Without learning dimension scaling

name = 'KeciBase'

requires_grad_for_interactions = False

class dicee.models.**CMult** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Cl_(0,0) => Real Numbers

Cl_(0,1) =>
A multivector mathbf{a} = a_0 + a_1 e_1 A multivector mathbf{b} = b_0 + b_1 e_1

multiplication is isomorphic to the product of two complex numbers

mathbf{a} imes mathbf{b} = a_0 b_0 + a_0b_1 e1 + a_1 b_1 e_1 e_1
= (a_0 b_0 - a_1 b_1) + (a_0 b_1 + a_1 b_0) e_1

Cl_(2,0) =>
A multivector mathbf{a} = a_0 + a_1 e_1 + a_2 e_2 + a_{12} e_1 e_2 A multivector mathbf{b} = b_0 + b_1 e_1 + b_2 e_2 + b_{12} e_1 e_2

mathbf{a} imes mathbf{b} = a_0b_0 + a_0b_1 e_1 + a_0b_2e_2 + a_0 b_12 e_1 e_2

- a_1 b_0 e_1 + a_1b_1 e_1_e1 ..

Cl_(0,2) => Quaternions

name = 'CMult'

entity_embeddings

relation_embeddings

p

q

clifford_mul (*x: torch.FloatTensor*, *y: torch.FloatTensor*, *p: int*, *q: int*) → tuple

Clifford multiplication Cl_{p,q} (mathbb{R})

ei ^2 = +1 for i =< i =< p ej ^2 = -1 for p < j =< p+q ei ej = -eje1 for i

eq j

x: torch.FloatTensor with (n,d) shape

y: torch.FloatTensor with (n,d) shape

p: a non-negative integer p>= 0 q: a non-negative integer q>= 0

score (*head_ent_emb*, *rel_ent_emb*, *tail_ent_emb*)

forward_triples (*x: torch.LongTensor*) → torch.FloatTensor

Compute batch triple scores

Parameter

x: torch.LongTensor with shape n by 3

> **rtype**
> torch.LongTensor with shape n

forward_k_vs_all (*x: torch.Tensor*) → torch.FloatTensor

Compute batch KvsAll triple scores

Parameter

x: torch.LongTensor with shape n by 3

> **rtype**
> torch.LongTensor with shape n

class dicee.models.**DeCaL**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> ℹ️ **Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'DeCaL'

entity_embeddings

relation_embeddings

p

q

r

re

forward_triples (*x: torch.Tensor*) → torch.FloatTensor

Parameter

x: torch.LongTensor with (n,) shape

> **rtype**
> torch.FloatTensor with (n) shape

cl_pqr (*a: torch.tensor*) → torch.tensor

Input: tensor(batch_size, emb_dim) —> output: tensor with 1+p+q+r components with size (batch_size, emb_dim/(1+p+q+r)) each.

1) takes a tensor of size (batch_size, emb_dim), split it into 1 + p + q +r components, hence 1+p+q+r must be a divisor of the emb_dim. 2) Return a list of the 1+p+q+r components vectors, each are tensors of size (batch_size, emb_dim/(1+p+q+r))

`compute_sigmas_single` (*list_h_emb*, *list_r_emb*, *list_t_emb*)

here we compute all the sums with no others vectors interaction taken with the scalar product with t, that is,

$$s0 = h_0 r_0 t_0 \quad s1 = \sum_{i=1}^{p} h_i r_i t_0 \quad s2 = \sum_{j=p+1}^{p+q} h_j r_j t_0 \quad s3 = \sum_{i=1}^{q}(h_0 r_i t_i + h_i r_0 t_i) \quad s4 = \sum_{i=p+1}^{p+q}(h_0 r_i t_i + h_i r_0 t_i) \quad s5 = \sum_{i=p+q+1}^{p+q+r}(h_0 r_i t$$

and return:

$$sigma_0 t = \sigma_0 \cdot t_0 = s0 + s1 - s2 \, s3, \, s4 \, and \, s5$$

`compute_sigmas_multivect` (*list_h_emb*, *list_r_emb*)

Here we compute and return all the sums with vectors interaction for the same and different bases.

For same bases vectors interaction we have

$$\sigma_p p = \sum_{i=1}^{p-1} \sum_{i'=i+1}^{p}(h_i r_{i'} - h_{i'} r_i)(models\,the\,interactions\,between\,e_i\,and\,e'_i\,for\,1 <= i, i' <= p) \quad \sigma_q q = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q}(h_j r_{j'}$$

For different base vector interactions, we have

$$\sigma_p q = \sum_{i=1}^{p} \sum_{j=p+1}^{p+q}(h_i r_j - h_j r_i)(interactions\,nbetween\,e_i\,and\,e_j\,for\,1 <= i <= p\,and\,p+1 <= j <= p+q) \quad \sigma_p r = \sum_{i=}^{}$$

`forward_k_vs_all` (*x: torch.Tensor*) → torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations

(2) Construct head entity and relation embeddings according to Cl_{p,q, r}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

forward_k_vs_with_explicit and this funcitons are identical Parameter ———— x: torch.LongTensor with (n,) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

`apply_coefficients` (*h0*, *hp*, *hq*, *hk*, *r0*, *rp*, *rq*, *rk*)

Multiplying a base vector with its scalar coefficient

`construct_cl_multivector` (*x: torch.FloatTensor*, *re: int*, *p: int*, *q: int*, *r: int*)
    → tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]
Construct a batch of multivectors Cl_{p,q,r}(mathbb{R}^d)

Parameter

x: torch.FloatTensor with (n,d) shape

returns

- **a0** (*torch.FloatTensor*)
- **ap** (*torch.FloatTensor*)
- **aq** (*torch.FloatTensor*)
- **ar** (*torch.FloatTensor*)

compute_sigma_pp *(hp, rp)*

 Compute .. math:

```
\sigma_{p,p}^* = \sum_{i=1}^{p-1}\sum_{i'=i+1}^{p}(x_iy_{i'}-x_{i'}y_i)
```

sigma_{pp} captures the interactions between along p bases For instance, let p e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

 results = [] for i in range(p - 1):

  for k in range(i + 1, p):
   results.append(hp[:, :, i] * rp[:, :, k] - hp[:, :, k] * rp[:, :, i])

 sigma_pp = torch.stack(results, dim=2) assert sigma_pp.shape == (b, r, int((p * (p - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

 e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_qq *(hq, rq)*

 Compute

$$\sigma_{q,q}^* = \sum_{j=p+1}^{p+q-1}\sum_{j'=j+1}^{p+q}(x_jy_{j'} - x_{j'}y_j) Eq.16$$

sigma_{q} captures the interactions between along q bases For instance, let q e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

 results = [] for j in range(q - 1):

  for k in range(j + 1, q):
   results.append(hq[:, :, j] * rq[:, :, k] - hq[:, :, k] * rq[:, :, j])

 sigma_qq = torch.stack(results, dim=2) assert sigma_qq.shape == (b, r, int((q * (q - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

 e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_rr *(hk, rk)*

$$\sigma_{r,r}^* = \sum_{k=p+q+1}^{p+q+r-1}\sum_{k'=k+1}^{p}(x_ky_{k'} - x_{k'}y_k)$$

compute_sigma_pq *(*, hp, hq, rp, rq)*

 Compute

$$\sum_{i=1}^{p}\sum_{j=p+1}^{p+q}(h_ir_j - h_jr_i)e_ie_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

 for j in range(q):
  sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

compute_sigma_pr(**, hp, hk, rp, rk*)

Compute

$$\sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

for j in range(q):
sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

compute_sigma_qr(**, hq, hk, rq, rk*)

$$\sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

for j in range(q):
sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

class dicee.models.**BaseKGE**(*args: dict*)

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> ℹ️ **Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

Variables

      training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
> > **x** (*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)

> byte pair encoded neural link predictors

> **Parameters**
> > -------

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor]*,
> *y_idx: torch.LongTensor = None*)

> **Parameters**
> > • **x**
> > • **y_idx**
> > • **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
> > **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
> > • **(b** (*x shape*)
> > • **3**
> > • **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
> → Tuple[torch.FloatTensor, torch.FloatTensor]

> **Parameters**
> > **x** (*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**PykeenKGE**(*args: dict*)

Bases: *dicee.models.base_model.BaseKGE*

A class for using knowledge graph embedding models implemented in Pykeen

Notes: Pykeen_DistMult: C Pykeen_ComplEx: Pykeen_QuatE: Pykeen_MuRE: Pykeen_CP: Pykeen_HolE: Pykeen_HolE:

model_kwargs

name

model

loss_history = []

args

entity_embeddings = None

relation_embeddings = None

forward_k_vs_all (*x: torch.LongTensor*)

> \# => Explicit version by this we can apply bn and dropout

> \# (1) Retrieve embeddings of heads and relations + apply Dropout & Normalization if given. h, r = self.get_head_relation_representation(x) # (2) Reshape (1). if self.last_dim > 0:

>> h = h.reshape(len(x), self.embedding_dim, self.last_dim) r = r.reshape(len(x), self.embedding_dim, self.last_dim)

> \# (3) Reshape all entities. if self.last_dim > 0:

>> t = self.entity_embeddings.weight.reshape(self.num_entities, self.embedding_dim, self.last_dim)

> **else:**
>> t = self.entity_embeddings.weight

> \# (4) Call the score_t from interactions to generate triple scores. return self.interaction.score_t(h=h, r=r, all_entities=t, slice_size=1)

forward_triples (*x: torch.LongTensor*) → torch.FloatTensor

> \# => Explicit version by this we can apply bn and dropout

> \# (1) Retrieve embeddings of heads, relations and tails and apply Dropout & Normalization if given. h, r, t = self.get_triple_representation(x) # (2) Reshape (1). if self.last_dim > 0:

>> h = h.reshape(len(x), self.embedding_dim, self.last_dim) r = r.reshape(len(x), self.embedding_dim, self.last_dim) t = t.reshape(len(x), self.embedding_dim, self.last_dim)

> \# (3) Compute the triple score return self.interaction.score(h=h, r=r, t=t, slice_size=None, slice_dim=0)

abstract forward_k_vs_sample (*x: torch.LongTensor*, *target_entity_idx*)

class dicee.models.**BaseKGE** (*args: dict*)

> Bases: *BaseKGELightning*

> Base class for all neural network modules.

> Your models should also subclass this class.

> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
```

(continues on next page)

```
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ⓘ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

Variables

training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

args

embedding_dim = None

num_entities = None

num_relations = None

num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
>> **x** (*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)

> byte pair encoded neural link predictors

> **Parameters**
>> --------

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor]*,
y_idx: torch.LongTensor = None)

> **Parameters**
>> • **x**
>>
>> • **y_idx**
>>
>> • **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
>> **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
>> • **(b** (*x shape*)
>>
>> • **3**

          • **t)**

    get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
        → Tuple[torch.FloatTensor, torch.FloatTensor]

        Parameters
            x(*B x 2 x T*)

    get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

class dicee.models.**FMult**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Learning Knowledge Neural Graphs

    name = 'FMult'

    entity_embeddings

    relation_embeddings

    k

    num_sample = 50

    gamma

    roots

    weights

    compute_func(*weights: torch.FloatTensor*, *x*) → torch.FloatTensor

    chain_func(*weights*, *x: torch.FloatTensor*)

    forward_triples(*idx_triple: torch.Tensor*) → torch.Tensor

        Parameters
            x

class dicee.models.**GFMult**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Learning Knowledge Neural Graphs

    name = 'GFMult'

    entity_embeddings

    relation_embeddings

    k

    num_sample = 250

    roots

    weights

    compute_func(*weights: torch.FloatTensor*, *x*) → torch.FloatTensor

    chain_func(*weights*, *x: torch.FloatTensor*)

forward_triples(*idx_triple: torch.Tensor*) → torch.Tensor

> **Parameters**
>> **x**

class dicee.models.**FMult2**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*
>
> Learning Knowledge Neural Graphs
>
> **name = 'FMult2'**
>
> **n_layers = 3**
>
> **tuned_embedding_dim = False**
>
> **k**
>
> **n = 50**
>
> **score_func = 'compositional'**
>
> **discrete_points**
>
> **entity_embeddings**
>
> **relation_embeddings**
>
> **build_func**(*Vec*)
>
> **build_chain_funcs**(*list_Vec*)
>
> **compute_func**(*W*, *b*, *x*) → torch.FloatTensor
>
> **function**(*list_W*, *list_b*)
>
> **trapezoid**(*list_W*, *list_b*)
>
> **forward_triples**(*idx_triple: torch.Tensor*) → torch.Tensor
>
> > **Parameters**
> >> **x**

class dicee.models.**LFMult1**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*
>
> Embedding with trigonometric functions. We represent all entities and relations in the complex number space as:
> f(x) = sum_{k=0}^{k=d-1}wk e^{kix}. and use the three differents scoring function as in the paper to evaluate
> the score
>
> **name = 'LFMult1'**
>
> **entity_embeddings**
>
> **relation_embeddings**
>
> **forward_triples**(*idx_triple*)
>
> > **Parameters**
> >> **x**

tri_score (*h, r, t*)

vtp_score (*h, r, t*)

class dicee.models.**LFMult** (*args*)

   Bases: *dicee.models.base_model.BaseKGE*

Embedding with polynomial functions. We represent all entities and relations in the polynomial space as: $f(x) = \text{sum}_{\{i=0\}}^{\{d-1\}} a\_k\ x^{\{i\%d\}}$ and use the three differents scoring function as in the paper to evaluate the score. We also consider combining with Neural Networks.

name = 'LFMult'

entity_embeddings

relation_embeddings

degree

m

x_values

forward_triples (*idx_triple*)

   Parameters
   x

construct_multi_coeff (*x*)

poly_NN (*x, coefh, coefr, coeft*)

   Constructing a 2 layers NN to represent the embeddings. $h = \text{sigma}(wh^T x + bh)$, $r = \text{sigma}(wr^T x + br)$, $t = \text{sigma}(wt^T x + bt)$

linear (*x, w, b*)

scalar_batch_NN (*a, b, c*)

   element wise multiplication between a,b and c: Inputs : a, b, c ====> torch.tensor of size batch_size x m x d Output : a tensor of size batch_size x d

tri_score (*coeff_h, coeff_r, coeff_t*)

   this part implement the trilinear scoring techniques:

   score(h,r,t) = int_{0}{1} h(x)r(x)t(x) dx = sum_{i,j,k = 0}^{d-1} dfrac{a_i*b_j*c_k}{1+(i+j+k)%d}

   1. generate the range for i,j and k from [0 d-1]

   2. perform dfrac{a_i*b_j*c_k}{1+(i+j+k)%d} in parallel for every batch

   3. take the sum over each batch

vtp_score (*h, r, t*)

   this part implement the vector triple product scoring techniques:

   score(h,r,t) = int_{0}{1} h(x)r(x)t(x) dx = sum_{i,j,k = 0}^{d-1} dfrac{a_i*c_j*b_k - b_i*c_j*a_k}{(1+(i+j)%d)(1+k)}

   1. generate the range for i,j and k from [0 d-1]

   2. Compute the first and second terms of the sum

   3. Multiply with then denominator and take the sum

4. take the sum over each batch

comp_func (*h*, *r*, *t*)

this part implement the function composition scoring techniques: i.e. score = <hor, t>

polynomial (*coeff*, *x*, *degree*)

This function takes a matrix tensor of coefficients (coeff), a tensor vector of points x and range of integer [0,1,…d] and return a vector tensor (coeff[0][0] + coeff[0][1]x +…+ coeff[0][d]x^d,

coeff[1][0] + coeff[1][1]x +…+ coeff[1][d]x^d)

pop (*coeff*, *x*, *degree*)

This function allow us to evaluate the composition of two polynomes without for loops :) it takes a matrix tensor of coefficients (coeff), a matrix tensor of points x and range of integer [0,1,…d]

and return a tensor (coeff[0][0] + coeff[0][1]x +…+ coeff[0][d]x^d,

coeff[1][0] + coeff[1][1]x +…+ coeff[1][d]x^d)

class dicee.models.**DualE** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Dual Quaternion Knowledge Graph Embeddings (https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657)

name = 'DualE'

entity_embeddings

relation_embeddings

num_ent

kvsall_score (*e_1_h*, *e_2_h*, *e_3_h*, *e_4_h*, *e_5_h*, *e_6_h*, *e_7_h*, *e_8_h*, *e_1_t*, *e_2_t*, *e_3_t*, *e_4_t*, *e_5_t*, *e_6_t*, *e_7_t*, *e_8_t*, *r_1*, *r_2*, *r_3*, *r_4*, *r_5*, *r_6*, *r_7*, *r_8*) → torch.tensor

KvsAll scoring function

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

forward_triples (*idx_triple: torch.tensor*) → torch.tensor

Negative Sampling forward pass:

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

forward_k_vs_all(*x*)

KvsAll forward pass

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

T (*x: torch.tensor*) → torch.tensor

Transpose function

Input: Tensor with shape (nxm) Output: Tensor with shape (mxn)

dicee.read_preprocess_save_load_kg

Submodules

dicee.read_preprocess_save_load_kg.preprocess

Classes

PreprocessKG	Preprocess the data in memory

Module Contents

class dicee.read_preprocess_save_load_kg.preprocess.**PreprocessKG**(*kg*)

Preprocess the data in memory

kg

start() → None

Preprocess train, valid and test datasets stored in knowledge graph instance

Parameter

> **rtype**
>> None

preprocess_with_byte_pair_encoding()

preprocess_with_byte_pair_encoding_with_padding() → None

preprocess_with_pandas() → None

> Preprocess train, valid and test datasets stored in knowledge graph instance with pandas
>
> (1) Add recipriocal or noisy triples
>
> (2) Construct vocabulary
>
> (3) Index datasets

> **Parameter**

>> **rtype**
>>> None

preprocess_with_polars() → None

sequential_vocabulary_construction() → None

> (1) Read input data into memory
>
> (2) Remove triples with a condition
>
> (3) **Serialize vocabularies in a pandas dataframe where**
>> => the index is integer and => a single column is string (e.g. URI)

remove_triples_from_train_with_condition()

dicee.read_preprocess_save_load_kg.read_from_disk

Classes

ReadFromDisk	Read the data from disk into memory

Module Contents

class dicee.read_preprocess_save_load_kg.read_from_disk.**ReadFromDisk**(*kg*)

> Read the data from disk into memory

> **kg**

> **start**() → None

>> Read a knowledge graph from disk into memory

>> Data will be available at the train_set, test_set, valid_set attributes.

Parameter

None

    rtype
      None

add_noisy_triples_into_training()

dicee.read_preprocess_save_load_kg.save_load_disk

Classes

LoadSaveToDisk

Module Contents

class dicee.read_preprocess_save_load_kg.save_load_disk.**LoadSaveToDisk**(*kg*)

    kg

    save()

    load()

dicee.read_preprocess_save_load_kg.util

Functions

apply_reciprical_or_noise(add_reciprical, eval_model)	
timeit(func)	
read_with_polars(→ polars.DataFrame)	Load and Preprocess via Polars
read_with_pandas(data_path[, read_only_few, ...])	
read_from_disk(data_path[, read_only_few, ...])	
read_from_triple_store([endpoint])	Read triples from triple store into pandas dataframe
get_er_vocab(data[, file_path])	
get_re_vocab(data[, file_path])	
get_ee_vocab(data[, file_path])	
create_constraints(triples[, file_path])	
load_with_pandas(→ None)	Deserialize data
save_numpy_ndarray(*, data, file_path)	
load_numpy_ndarray(*, file_path)	
save_pickle(*, data[, file_path])	
load_pickle(*[, file_path])	
create_recipriocal_triples(x)	Add inverse triples into dask dataframe
index_triples_with_pandas(→ pandas.core.frame.DataFrame)	
dataset_sanity_checking(→ None)	

Module Contents

dicee.read_preprocess_save_load_kg.util.**apply_reciprical_or_noise**(
        add_reciprical: bool, *eval_model: str*, *df: object = None*, *info: str = None*)

> (1) Add reciprocal triples (2) Add noisy triples

dicee.read_preprocess_save_load_kg.util.**timeit**(*func*)

dicee.read_preprocess_save_load_kg.util.**read_with_polars**(*data_path*,
        read_only_few: int = None, *sample_triples_ratio: float = None*) → polars.DataFrame

> Load and Preprocess via Polars

dicee.read_preprocess_save_load_kg.util.**read_with_pandas**(*data_path*,
        read_only_few: int = None, *sample_triples_ratio: float = None*)

`dicee.read_preprocess_save_load_kg.util.`**`read_from_disk`**(*data_path: str*, *read_only_few: int = None*, *sample_triples_ratio: float = None*, *backend=None*)

`dicee.read_preprocess_save_load_kg.util.`**`read_from_triple_store`**(*endpoint: str = None*)

> Read triples from triple store into pandas dataframe

`dicee.read_preprocess_save_load_kg.util.`**`get_er_vocab`**(*data*, *file_path: str = None*)

`dicee.read_preprocess_save_load_kg.util.`**`get_re_vocab`**(*data*, *file_path: str = None*)

`dicee.read_preprocess_save_load_kg.util.`**`get_ee_vocab`**(*data*, *file_path: str = None*)

`dicee.read_preprocess_save_load_kg.util.`**`create_constraints`**(*triples*, *file_path: str = None*)

> (1) Extract domains and ranges of relations

> (2) Store a mapping from relations to entities that are outside of the domain and range. Crete constrainted entities based on the range of relations :param triples: :return: Tuple[dict, dict]

`dicee.read_preprocess_save_load_kg.util.`**`load_with_pandas`**(*self*) → None

> Deserialize data

`dicee.read_preprocess_save_load_kg.util.`**`save_numpy_ndarray`**(***, *data: numpy.ndarray*, *file_path: str*)

`dicee.read_preprocess_save_load_kg.util.`**`load_numpy_ndarray`**(***, *file_path: str*)

`dicee.read_preprocess_save_load_kg.util.`**`save_pickle`**(***, *data: object*, *file_path=str*)

`dicee.read_preprocess_save_load_kg.util.`**`load_pickle`**(***, *file_path=str*)

`dicee.read_preprocess_save_load_kg.util.`**`create_recipriocal_triples`**(*x*)

> Add inverse triples into dask dataframe :param x: :return:

`dicee.read_preprocess_save_load_kg.util.`**`index_triples_with_pandas`**(*train_set*, *entity_to_idx: dict*, *relation_to_idx: dict*) → pandas.core.frame.DataFrame

> **Parameters**
>
> - **train_set** – pandas dataframe
> - **entity_to_idx** – a mapping from str to integer index
> - **relation_to_idx** – a mapping from str to integer index
> - **num_core** – number of cores to be used
>
> **Returns**
> indexed triples, i.e., pandas dataframe

`dicee.read_preprocess_save_load_kg.util.`**`dataset_sanity_checking`**(*train_set: numpy.ndarray*, *num_entities: int*, *num_relations: int*) → None

> **Parameters**
>
> - **train_set**
> - **num_entities**
> - **num_relations**
>
> **Returns**

Classes

PreprocessKG *LoadSaveToDisk*	Preprocess the data in memory
ReadFromDisk	Read the data from disk into memory

Package Contents

class dicee.read_preprocess_save_load_kg.**PreprocessKG**(*kg*)

    Preprocess the data in memory

    kg

    start() → None

        Preprocess train, valid and test datasets stored in knowledge graph instance

        Parameter

            rtype
                None

    preprocess_with_byte_pair_encoding()

    preprocess_with_byte_pair_encoding_with_padding() → None

    preprocess_with_pandas() → None

        Preprocess train, valid and test datasets stored in knowledge graph instance with pandas

        (1) Add recipriocal or noisy triples

        (2) Construct vocabulary

        (3) Index datasets

        Parameter

            rtype
                None

    preprocess_with_polars() → None

    sequential_vocabulary_construction() → None

        (1) Read input data into memory

        (2) Remove triples with a condition

        (3) **Serialize vocabularies in a pandas dataframe where**
            => the index is integer and => a single column is string (e.g. URI)

    remove_triples_from_train_with_condition()

class dicee.read_preprocess_save_load_kg.**LoadSaveToDisk**(*kg*)

>   **kg**

>   **save**()

>   **load**()

class dicee.read_preprocess_save_load_kg.**ReadFromDisk**(*kg*)

>   Read the data from disk into memory

>   **kg**

>   **start**() → None

>   Read a knowledge graph from disk into memory

>   Data will be available at the train_set, test_set, valid_set attributes.

>   ### Parameter

>   None

>>   **rtype**
>>   None

>   **add_noisy_triples_into_training**()

dicee.scripts

Submodules

dicee.scripts.index

Functions

get_default_arguments()	
main()	

Module Contents

dicee.scripts.index.**get_default_arguments**()

dicee.scripts.index.**main**()

dicee.scripts.run

Functions

get_default_arguments([description])	Extends pytorch_lightning Trainer's arguments with ours
main()	

Module Contents

dicee.scripts.run.**get_default_arguments**(*description=None*)

Extends pytorch_lightning Trainer's arguments with ours

dicee.scripts.run.**main**()

dicee.scripts.serve

Attributes

app
neural_searcher

Classes

NeuralSearcher

Functions

get_default_arguments()
root()
search_embeddings(q)
retrieve_embeddings(q)
main()

Module Contents

dicee.scripts.serve.**app**

dicee.scripts.serve.**neural_searcher = None**

dicee.scripts.serve.**get_default_arguments**()

async dicee.scripts.serve.**root**()

async dicee.scripts.serve.**search_embeddings**(*q: str*)

async dicee.scripts.serve.**retrieve_embeddings**(*q: str*)

class dicee.scripts.serve.**NeuralSearcher**(*args*)

    collection_name

    model

    qdrant_client

    get(*entity: str*)

    search(*entity: str*)

dicee.scripts.serve.**main**()

dicee.trainer

Submodules

dicee.trainer.dice_trainer

Classes

DICE_Trainer	DICE_Trainer implement

Functions

initialize_trainer(args, callbacks)
get_callbacks(args)

Module Contents

dicee.trainer.dice_trainer.**initialize_trainer**(*args*, *callbacks*)

dicee.trainer.dice_trainer.**get_callbacks**(*args*)

class dicee.trainer.dice_trainer.**DICE_Trainer**(*args*, *is_continual_training*, *storage_path*, *evaluator=None*)

    DICE_Trainer implement
        1- Pytorch Lightning trainer (https://pytorch-lightning.readthedocs.io/en/stable/common/trainer.html)
        2- Multi-GPU Trainer(https://pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.html) 3- CPU Trainer

        args

        is_continual_training:bool

        storage_path:str

        evaluator:

        report:dict

    report

    args

    trainer = None

    is_continual_training

    storage_path

    evaluator

    form_of_labelling = None

    continual_start()

        (1) Initialize training.

        (2) Load model

        (3) Load trainer (3) Fit model

        Parameter

            returns

                • *model*

                • **form_of_labelling** (*str*)

    initialize_trainer(*callbacks: List*) → lightning.Trainer
        Initialize Trainer from input arguments

    initialize_or_load_model()

    initialize_dataloader(*dataset: torch.utils.data.Dataset*) → torch.utils.data.DataLoader

initialize_dataset (*dataset:* *dicee.knowledge_graph.KG*, *form_of_labelling*)
　　　　→ torch.utils.data.Dataset

start (*knowledge_graph:* *dicee.knowledge_graph.KG*) → Tuple[*dicee.models.base_model.BaseKGE*, str]
　　　Train selected model via the selected training strategy

k_fold_cross_validation (*dataset*) → Tuple[*dicee.models.base_model.BaseKGE*, str]
　　　Perform K-fold Cross-Validation

　　　　1. Obtain K train and test splits.

　　　　2. **For each split,**
　　　　　　2.1 initialize trainer and model 2.2. Train model with configuration provided in args. 2.3. Compute the mean reciprocal rank (MRR) score of the model on the test respective split.

　　　　3. Report the mean and average MRR .

　　　　　Parameters
　　　　　　　• **self**

　　　　　　　• **dataset**

　　　　　Returns
　　　　　　model

dicee.trainer.torch_trainer

Classes

[*TorchTrainer*](#)	TorchTrainer for using single GPU or multi CPUs on a single node

Module Contents

class dicee.trainer.torch_trainer.**TorchTrainer** (*args*, *callbacks*)
　　Bases: *dicee.abstracts.AbstractTrainer*

　　　TorchTrainer for using single GPU or multi CPUs on a single node

　　　Arguments

　　callbacks: list of Abstract callback instances

　　loss_function = None

　　optimizer = None

　　model = None

　　train_dataloaders = None

　　training_step = None

　　process

fit(**args*, *train_dataloaders*, ***kwargs*) → None

> Training starts

> Arguments

kwargs:Tuple
empty dictionary

> **Return type**
> batch loss (float)

forward_backward_update(*x_batch: torch.Tensor*, *y_batch: torch.Tensor*) → torch.Tensor

> Compute forward, loss, backward, and parameter update

> Arguments

> **Return type**
> batch loss (float)

extract_input_outputs_set_device(*batch: list*) → Tuple

> Construct inputs and outputs from a batch of inputs with outputs From a batch of inputs and put

> Arguments

> **Return type**
> (tuple) mini-batch on select device

dicee.trainer.torch_trainer_ddp

Classes

TorchDDPTrainer	A Trainer based on torch.nn.parallel.DistributedDataParallel
NodeTrainer	

Functions

make_iterable_verbose(→ Iterable)	

Module Contents

dicee.trainer.torch_trainer_ddp.**make_iterable_verbose**(*iterable_object*, *verbose*, *desc='Default'*, *position=None*, *leave=True*) → Iterable

class dicee.trainer.torch_trainer_ddp.**TorchDDPTrainer**(*args*, *callbacks*)

>   Bases: *dicee.abstracts.AbstractTrainer*

>   A Trainer based on torch.nn.parallel.DistributedDataParallel

>   Arguments

>   **entity_idxs**
>   mapping.

>   **relation_idxs**
>   mapping.

>   **form**
>   ?

>   **store**
>   ?

>   **label_smoothing_rate**
>   Using hard targets (0,1) drives weights to infinity. An outlier produces enormous gradients.

>   **Return type**
>   torch.utils.data.Dataset

>   **fit**(**args*, ***kwargs*)
>   Train model

class dicee.trainer.torch_trainer_ddp.**NodeTrainer**(*trainer*, *model: torch.nn.Module*, *train_dataset_loader: torch.utils.data.DataLoader*, *callbacks*, *num_epochs: int*)

>   **trainer**

>   **local_rank**

>   **global_rank**

>   **optimizer**

>   **train_dataset_loader**

>   **loss_func**

>   **callbacks**

>   **model**

>   **num_epochs**

>   **loss_history = []**

>   **extract_input_outputs**(*z: list*)

>   **train**()
>   Training loop for DDP

Classes

DICE_Trainer	DICE_Trainer implement

Package Contents

class dicee.trainer.**DICE_Trainer**(*args*, *is_continual_training*, *storage_path*, *evaluator=None*)

> **DICE_Trainer implement**
> 1- Pytorch Lightning trainer (https://pytorch-lightning.readthedocs.io/en/stable/common/trainer.html)
> 2- Multi-GPU Trainer(https://pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.
> html) 3- CPU Trainer
>
> args
>
> is_continual_training:bool
>
> storage_path:str
>
> evaluator:
>
> report:dict

> **report**

> **args**

> **trainer = None**

> **is_continual_training**

> **storage_path**

> **evaluator**

> **form_of_labelling = None**

> **continual_start**()

> > (1) Initialize training.
> >
> > (2) Load model
> >
> > (3) Load trainer (3) Fit model

> > **Parameter**

> > > **returns**
> > >
> > > > • *model*
> > > >
> > > > • **form_of_labelling** (*str*)

> **initialize_trainer**(*callbacks: List*) → lightning.Trainer
> > Initialize Trainer from input arguments

> **initialize_or_load_model**()

initialize_dataloader (*dataset: torch.utils.data.Dataset*) → torch.utils.data.DataLoader

initialize_dataset (*dataset: dicee.knowledge_graph.KG*, *form_of_labelling*)
    → torch.utils.data.Dataset

start (*knowledge_graph: dicee.knowledge_graph.KG*) → Tuple[*dicee.models.base_model.BaseKGE*, str]
    Train selected model via the selected training strategy

k_fold_cross_validation (*dataset*) → Tuple[*dicee.models.base_model.BaseKGE*, str]
    Perform K-fold Cross-Validation

1. Obtain K train and test splits.

2. **For each split,**
    2.1 initialize trainer and model 2.2. Train model with configuration provided in args. 2.3. Compute the mean reciprocal rank (MRR) score of the model on the test respective split.

3. Report the mean and average MRR .

Parameters
- **self**
- **dataset**

Returns
    model

14.2 Submodules

dicee.__main__

dicee.abstracts

Classes

AbstractTrainer	Abstract class for Trainer class for knowledge graph embedding models
BaseInteractiveKGE	Abstract/base class for using knowledge graph embedding models interactively.
AbstractCallback	Abstract class for Callback class for knowledge graph embedding models
AbstractPPECallback	Abstract class for Callback class for knowledge graph embedding models

Module Contents

class `dicee.abstracts.`**AbstractTrainer**(*args*, *callbacks*)

    Abstract class for Trainer class for knowledge graph embedding models

Parameter

args
    [str] ?

callbacks: list
    ?

attributes

callbacks

is_global_zero = True

strategy = None

on_fit_start(**args*, ***kwargs*)

    A function to call callbacks before the training starts.

Parameter

    args

    kwargs

        rtype
            None

on_fit_end(**args*, ***kwargs*)

    A function to call callbacks at the ned of the training.

Parameter

    args

    kwargs

        rtype
            None

on_train_epoch_end(**args*, ***kwargs*)

    A function to call callbacks at the end of an epoch.

Parameter

args

kwargs

> **rtype**
>   None

on_train_batch_end(**args*, ***kwargs*)

A function to call callbacks at the end of each mini-batch during training.

Parameter

args

kwargs

> **rtype**
>   None

static save_checkpoint(*full_path: str*, *model*) → None

A static function to save a model into disk

Parameter

full_path : str

model:

> **rtype**
>   None

class dicee.abstracts.**BaseInteractiveKGE**(*path: str = None*, *url: str = None*, *construct_ensemble: bool = False*, *model_name: str = None*, *apply_semantic_constraint: bool = False*)

Abstract/base class for using knowledge graph embedding models interactively.

Parameter

path_of_pretrained_model_dir
    [str] ?

construct_ensemble: boolean
    ?

model_name: str apply_semantic_constraint : boolean

construct_ensemble

apply_semantic_constraint

configs

get_eval_report() → dict

get_bpe_token_representation(*str_entity_or_relation: List[str] | str*)
 → List[List[int]] | List[int]

> **Parameters**
> **str_entity_or_relation**(`corresponds to a str or a list of strings to be tokenized via BPE and shaped.`)

> **Return type**
> A list integer(s) or a list of lists containing integer(s)

get_padded_bpe_triple_representation(*triples: List[List[str]]*) → Tuple[List, List, List]

> **Parameters**
> **triples**

set_model_train_mode() → None

Setting the model into training mode

Parameter

set_model_eval_mode() → None

Setting the model into eval mode

Parameter

property name

sample_entity(*n: int*) → List[str]

sample_relation(*n: int*) → List[str]

is_seen(*entity: str = None*, *relation: str = None*) → bool

save() → None

get_entity_index(*x: str*)

get_relation_index(*x: str*)

index_triple(*head_entity: List[str]*, *relation: List[str]*, *tail_entity: List[str]*)
 → Tuple[torch.LongTensor, torch.LongTensor, torch.LongTensor]

Index Triple

Parameter

head_entity: List[str]

String representation of selected entities.

relation: List[str]

String representation of selected relations.

tail_entity: List[str]

String representation of selected entities.

Returns: Tuple

pytorch tensor of triple score

add_new_entity_embeddings(*entity_name: str = None*, *embeddings: torch.FloatTensor = None*)

get_entity_embeddings(*items: List[str]*)

Return embedding of an entity given its string representation

Parameter

items:
entities

get_relation_embeddings(*items: List[str]*)

Return embedding of a relation given its string representation

Parameter

items:
relations

construct_input_and_output(*head_entity: List[str]*, *relation: List[str]*, *tail_entity: List[str]*, *labels*)

Construct a data point :param head_entity: :param relation: :param tail_entity: :param labels: :return:

parameters()

class dicee.abstracts.**AbstractCallback**

Bases: abc.ABC, lightning.pytorch.callbacks.Callback

Abstract class for Callback class for knowledge graph embedding models

Parameter

on_init_start(**args*, ***kwargs*)

Parameter

trainer:

model:

rtype
None

on_init_end(**args*, ***kwargs*)

Call at the beginning of the training.

Parameter

trainer:

model:

> **rtype**
>> None

on_fit_start(*trainer*, *model*)

Call at the beginning of the training.

Parameter

trainer:

model:

> **rtype**
>> None

on_train_epoch_end(*trainer*, *model*)

Call at the end of each epoch during training.

Parameter

trainer:

model:

> **rtype**
>> None

on_train_batch_end(**args*, ***kwargs*)

Call at the end of each mini-batch during the training.

Parameter

trainer:

model:

> **rtype**
>> None

on_fit_end(**args*, ***kwargs*)

Call at the end of the training.

trainer:

model:

> **rtype**
>> None

class dicee.abstracts.**AbstractPPECallback**(*num_epochs*, *path*, *epoch_to_start*, *last_percent_to_consider*)

Bases: *AbstractCallback*

Abstract class for Callback class for knowledge graph embedding models

Parameter

num_epochs

path

sample_counter = 0

epoch_count = 0

alphas = None

on_fit_start(*trainer*, *model*)
> Call at the beginning of the training.

> **Parameter**

> trainer:

> model:

>> **rtype**
>>> None

on_fit_end(*trainer*, *model*)
> Call at the end of the training.

> **Parameter**

> trainer:

> model:

>> **rtype**
>>> None

store_ensemble(*param_ensemble*) → None

dicee.analyse_experiments

This script should be moved to dicee/scripts

Classes

Experiment

Functions

get_default_arguments()
analyse(args)

Module Contents

dicee.analyse_experiments.**get_default_arguments**()

class dicee.analyse_experiments.**Experiment**

    model_name = []

    callbacks = []

    embedding_dim = []

    num_params = []

    num_epochs = []

    batch_size = []

    lr = []

    byte_pair_encoding = []

    aswa = []

    path_dataset_folder = []

    full_storage_path = []

    pq = []

    train_mrr = []

    train_h1 = []

    train_h3 = []

```
train_h10 = []

val_mrr = []

val_h1 = []

val_h3 = []

val_h10 = []

test_mrr = []

test_h1 = []

test_h3 = []

test_h10 = []

runtime = []

normalization = []

scoring_technique = []

save_experiment(x)

to_df()
```

dicee.analyse_experiments.**analyse**(*args*)

dicee.callbacks

Classes

AccumulateEpochLossCallback	Abstract class for Callback class for knowledge graph embedding models
PrintCallback	Abstract class for Callback class for knowledge graph embedding models
KGESaveCallback	Abstract class for Callback class for knowledge graph embedding models
PseudoLabellingCallback	Abstract class for Callback class for knowledge graph embedding models
ASWA	Adaptive stochastic weight averaging
Eval	Abstract class for Callback class for knowledge graph embedding models
KronE	Abstract class for Callback class for knowledge graph embedding models
Perturb	A callback for a three-Level Perturbation

Functions

estimate_q(eps)	estimate rate of convergence q from sequence esp
compute_convergence(seq, i)	

Module Contents

class dicee.callbacks.**AccumulateEpochLossCallback**(*path: str*)

    Bases: *dicee.abstracts.AbstractCallback*

    Abstract class for Callback class for knowledge graph embedding models

    Parameter

    path

    on_fit_end(*trainer*, *model*) → None

        Store epoch loss

        Parameter

        trainer:

        model:

            rtype
                None

class dicee.callbacks.**PrintCallback**

    Bases: *dicee.abstracts.AbstractCallback*

    Abstract class for Callback class for knowledge graph embedding models

    Parameter

    start_time

    on_fit_start(*trainer*, *pl_module*)

        Call at the beginning of the training.

trainer:

model:

> **rtype**
> None

on_fit_end(*trainer*, *pl_module*)
Call at the end of the training.

Parameter

trainer:

model:

> **rtype**
> None

on_train_batch_end(**args*, ***kwargs*)
Call at the end of each mini-batch during the training.

Parameter

trainer:

model:

> **rtype**
> None

on_train_epoch_end(**args*, ***kwargs*)
Call at the end of each epoch during training.

Parameter

trainer:

model:

> **rtype**
> None

class dicee.callbacks.**KGESaveCallback**(*every_x_epoch: int*, *max_epochs: int*, *path: str*)

Bases: *dicee.abstracts.AbstractCallback*

Abstract class for Callback class for knowledge graph embedding models

Parameter

every_x_epoch

max_epochs

epoch_counter = 0

path

on_train_batch_end(**args*, ***kwargs*)

    Call at the end of each mini-batch during the training.

    Parameter

        trainer:

        model:

            rtype
                None

on_fit_start(*trainer*, *pl_module*)

    Call at the beginning of the training.

    Parameter

        trainer:

        model:

            rtype
                None

on_train_epoch_end(**args*, ***kwargs*)

    Call at the end of each epoch during training.

    Parameter

        trainer:

        model:

            rtype
                None

on_fit_end(**args*, ***kwargs*)

    Call at the end of the training.

Parameter

trainer:

model:

> **rtype**
> None

on_epoch_end(*model*, *trainer*, ***kwargs*)

class dicee.callbacks.**PseudoLabellingCallback**(*data_module*, *kg*, *batch_size*)

Bases: *dicee.abstracts.AbstractCallback*

Abstract class for Callback class for knowledge graph embedding models

Parameter

data_module

kg

num_of_epochs = 0

unlabelled_size

batch_size

create_random_data()

on_epoch_end(*trainer*, *model*)

dicee.callbacks.**estimate_q**(*eps*)

estimate rate of convergence q from sequence esp

dicee.callbacks.**compute_convergence**(*seq*, *i*)

class dicee.callbacks.**ASWA**(*num_epochs*, *path*)

Bases: *dicee.abstracts.AbstractCallback*

Adaptive stochastic weight averaging ASWE keeps track of the validation performance and update s the ensemble model accordingly.

path

num_epochs

initial_eval_setting = None

epoch_count = 0

alphas = []

val_aswa

on_fit_end(*trainer*, *model*)

Call at the end of the training.

trainer:

model:

> **rtype**
>> None

static compute_mrr (*trainer*, *model*) → float

get_aswa_state_dict (*model*)

decide (*running_model_state_dict*, *ensemble_state_dict*, *val_running_model*,
        mrr_updated_ensemble_model)
> Perform Hard Update, software or rejection

> **Parameters**
>> - **running_model_state_dict**
>>
>> - **ensemble_state_dict**
>>
>> - **val_running_model**
>>
>> - **mrr_updated_ensemble_model**

on_train_epoch_end (*trainer*, *model*)
> Call at the end of each epoch during training.

Parameter

trainer:

model:

> **rtype**
>> None

class dicee.callbacks.**Eval** (*path*, *epoch_ratio: int = None*)
> Bases: *dicee.abstracts.AbstractCallback*

Abstract class for Callback class for knowledge graph embedding models

Parameter

path

reports = []

epoch_ratio

epoch_counter = 0

on_fit_start (*trainer*, *model*)
> Call at the beginning of the training.

Parameter

trainer:

model:

> **rtype**
> None

on_fit_end(*trainer*, *model*)

Call at the end of the training.

Parameter

trainer:

model:

> **rtype**
> None

on_train_epoch_end(*trainer*, *model*)

Call at the end of each epoch during training.

Parameter

trainer:

model:

> **rtype**
> None

on_train_batch_end(**args*, ***kwargs*)

Call at the end of each mini-batch during the training.

Parameter

trainer:

model:

> **rtype**
> None

class dicee.callbacks.**KronE**

Bases: *dicee.abstracts.AbstractCallback*

Abstract class for Callback class for knowledge graph embedding models

Parameter

f = None

static batch_kronecker_product(*a*, *b*)

>   Kronecker product of matrices a and b with leading batch dimensions. Batch dimensions are broadcast. The number of them mush :type a: torch.Tensor :type b: torch.Tensor :rtype: torch.Tensor

get_kronecker_triple_representation(*indexed_triple: torch.LongTensor*)

>   Get kronecker embeddings

on_fit_start(*trainer*, *model*)

>   Call at the beginning of the training.

>   **Parameter**

>   trainer:

>   model:

>>   **rtype**
>>>   None

class dicee.callbacks.**Perturb**(*level: str = 'input'*, *ratio: float = 0.0*, *method: str = None*, *scaler: float = None*, *frequency=None*)

Bases: *dicee.abstracts.AbstractCallback*

A callback for a three-Level Perturbation

Input Perturbation: During training an input x is perturbed by randomly replacing its element. In the context of knowledge graph embedding models, x can denote a triple, a tuple of an entity and a relation, or a tuple of two entities. A perturbation means that a component of x is randomly replaced by an entity or a relation.

Parameter Perturbation:

Output Perturbation:

level

ratio

method

scaler

frequency

on_train_batch_start(*trainer*, *model*, *batch*, *batch_idx*)

>   Called when the train batch begins.

dicee.config

Classes

Namespace	Simple object for storing attributes.

Module Contents

class dicee.config.**Namespace**(***kwargs*)

Bases: `argparse.Namespace`

Simple object for storing attributes.

Implements equality by attribute names and values, and provides a simple string representation.

dataset_dir: str = None

The path of a folder containing train.txt, and/or valid.txt and/or test.txt

save_embeddings_as_csv: bool = False

Embeddings of entities and relations are stored into CSV files to facilitate easy usage.

storage_path: str = 'Experiments'

A directory named with time of execution under –storage_path that contains related data about embeddings.

path_to_store_single_run: str = None

A single directory created that contains related data about embeddings.

path_single_kg = None

Path of a file corresponding to the input knowledge graph

sparql_endpoint = None

An endpoint of a triple store.

model: str = 'Keci'

KGE model

optim: str = 'Adam'

Optimizer

embedding_dim: int = 64

Size of continuous vector representation of an entity/relation

num_epochs: int = 150

Number of pass over the training data

batch_size: int = 1024

Mini-batch size if it is None, an automatic batch finder technique applied

lr: float = 0.1

Learning rate

add_noise_rate: float = None

The ratio of added random triples into training dataset

gpus = None

    Number GPUs to be used during training

callbacks

    10}}

        Type

            Callbacks, e.g., {"PPE"

        Type

            { "last_percent_to_consider"

backend: str = 'pandas'

    Backend to read, process, and index input knowledge graph. pandas, polars and rdflib available

trainer: str = 'torchCPUTrainer'

    Trainer for knowledge graph embedding model

scoring_technique: str = 'KvsAll'

    Scoring technique for knowledge graph embedding models

neg_ratio: int = 0

    Negative ratio for a true triple in NegSample training_technique

weight_decay: float = 0.0

    Weight decay for all trainable params

normalization: str = 'None'

    LayerNorm, BatchNorm1d, or None

init_param: str = None

    xavier_normal or None

gradient_accumulation_steps: int = 0

    Not tested e

num_folds_for_cv: int = 0

    Number of folds for CV

eval_model: str = 'train_val_test'

    ["None", "train", "train_val", "train_val_test", "test"]

        Type

            Evaluate trained model choices

save_model_at_every_epoch: int = None

    Not tested

label_smoothing_rate: float = 0.0

num_core: int = 0

    Number of CPUs to be used in the mini-batch loading process

random_seed: int = 0

    Random Seed

sample_triples_ratio: float = None

    Read some triples that are uniformly at random sampled. Ratio being between 0 and 1

read_only_few: int = None

    Read only first few triples

pykeen_model_kwargs

    Additional keyword arguments for pykeen models

kernel_size: int = 3

    Size of a square kernel in a convolution operation

num_of_output_channels: int = 32

    Number of slices in the generated feature map by convolution.

p: int = 0

    P parameter of Clifford Embeddings

q: int = 1

    Q parameter of Clifford Embeddings

input_dropout_rate: float = 0.0

    Dropout rate on embeddings of input triples

hidden_dropout_rate: float = 0.0

    Dropout rate on hidden representations of input triples

feature_map_dropout_rate: float = 0.0

    Dropout rate on a feature map generated by a convolution operation

byte_pair_encoding: bool = False

    Byte pair encoding

        Type
          WIP

adaptive_swa: bool = False

    Adaptive stochastic weight averaging

swa: bool = False

    Stochastic weight averaging

block_size: int = None

    block size of LLM

continual_learning = None

    Path of a pretrained model size of LLM

__iter__()

dicee.dataset_classes

Classes

BPE_NegativeSamplingDataset	An abstract class representing a `Dataset`.
MultiLabelDataset	An abstract class representing a `Dataset`.
MultiClassClassificationDataset	Dataset for the 1vsALL training strategy
OnevsAllDataset	Dataset for the 1vsALL training strategy
KvsAll	Creates a dataset for KvsAll training by inheriting from torch.utils.data.Dataset.
AllvsAll	Creates a dataset for AllvsAll training by inheriting from torch.utils.data.Dataset.
KvsSampleDataset	KvsSample a Dataset:
NegSampleDataset	An abstract class representing a `Dataset`.
TriplePredictionDataset	Triple Dataset
CVDataModule	Create a Dataset for cross validation

Functions

reload_dataset(path, form_of_labelling, ...)	Reload the files from disk to construct the Pytorch dataset
construct_dataset(→ torch.utils.data.Dataset)	

Module Contents

dicee.dataset_classes.**reload_dataset**(*path: str*, *form_of_labelling*, *scoring_technique*, *neg_ratio*, *label_smoothing_rate*)

   Reload the files from disk to construct the Pytorch dataset

dicee.dataset_classes.**construct_dataset**(***, *train_set: numpy.ndarray | list*, *valid_set=None*, *test_set=None*, *ordered_bpe_entities=None*, *train_target_indices=None*, *target_dim: int = None*, *entity_to_idx: dict*, *relation_to_idx: dict*, *form_of_labelling: str*, *scoring_technique: str*, *neg_ratio: int*, *label_smoothing_rate: float*, *byte_pair_encoding=None*, *block_size: int = None*) → torch.utils.data.Dataset

class dicee.dataset_classes.**BPE_NegativeSamplingDataset**(*train_set: torch.LongTensor*, *ordered_shaped_bpe_entities: torch.LongTensor*, *neg_ratio: int*)

   Bases: `torch.utils.data.Dataset`

   An abstract class representing a `Dataset`.

   All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite *__getitem__()*, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite *__len__()*, which is expected to return the size of the dataset by many `Sampler` implementations and the default options of `DataLoader`. Subclasses could also optionally implement `__getitems__()`, for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

   > ⓘ **Note**
   >
   > `DataLoader` by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

train_set

ordered_bpe_entities

num_bpe_entities

neg_ratio

num_datapoints

__len__()

__getitem__(*idx*)

collate_fn(*batch_shaped_bpe_triples: List[Tuple[torch.Tensor, torch.Tensor]]*)

class dicee.dataset_classes.**MultiLabelDataset**(*train_set: torch.LongTensor,*
  train_indices_target: torch.LongTensor, target_dim: int,
  torch_ordered_shaped_bpe_entities: torch.LongTensor)

Bases: torch.utils.data.Dataset

An abstract class representing a Dataset.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite *__getitem__()*, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite *__len__()*, which is expected to return the size of the dataset by many Sampler implementations and the default options of DataLoader. Subclasses could also optionally implement __getitems__(), for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

> **ⓘ Note**
>
> DataLoader by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

train_set

train_indices_target

target_dim

num_datapoints

torch_ordered_shaped_bpe_entities

collate_fn = None

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**MultiClassClassificationDataset**(
  subword_units: numpy.ndarray, block_size: int = 8)

Bases: torch.utils.data.Dataset

Dataset for the 1vsALL training strategy

> **Parameters**
>
> • **train_set_idx** – Indexed triples for the training.

- **entity_idxs** – mapping.

- **relation_idxs** – mapping.

- **form** – ?

- **num_workers** – int for [https://pytorch.org/docs/stable/data.html#torch.utils.data.](https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader)
[DataLoader](https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader)

>   **Return type**
>   torch.utils.data.Dataset

train_data

block_size

num_of_data_points

collate_fn = None

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**OnevsAllDataset**(*train_set_idx: numpy.ndarray*, *entity_idxs*)

> Bases: torch.utils.data.Dataset

> Dataset for the 1vsALL training strategy

>   **Parameters**

- **train_set_idx** – Indexed triples for the training.

- **entity_idxs** – mapping.

- **relation_idxs** – mapping.

- **form** – ?

- **num_workers** – int for [https://pytorch.org/docs/stable/data.html#torch.utils.data.](https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader)
[DataLoader](https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader)

>   **Return type**
>   torch.utils.data.Dataset

train_data

target_dim

collate_fn = None

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**KvsAll**(*train_set_idx: numpy.ndarray*, *entity_idxs*, *relation_idxs*, *form*, *store=None*, *label_smoothing_rate: float = 0.0*)

> Bases: torch.utils.data.Dataset

> **Creates a dataset for KvsAll training by inheriting from torch.utils.data.Dataset.**
>   Let D denote a dataset for KvsAll training and be defined as D:= {(x,y)_i}_i ^N, where x: (h,r) is an unique
>   tuple of an entity h in E and a relation r in R that has been seed in the input graph. y: denotes a multi-label
>   vector in [0,1]^{[E]} is a binary label.

orall y_i =1 s.t. (h r E_i) in KG

> **ℹ Note**
>
> TODO

train_set_idx
    [numpy.ndarray] n by 3 array representing n triples

entity_idxs
    [dictonary] string representation of an entity to its integer id

relation_idxs
    [dictonary] string representation of a relation to its integer id

self : torch.utils.data.Dataset

```
>>> a = KvsAll()
>>> a
? array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

train_data = None

train_target = None

label_smoothing_rate

collate_fn = None

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**AllvsAll**(*train_set_idx: numpy.ndarray*, *entity_idxs*, *relation_idxs*, *label_smoothing_rate=0.0*)

    Bases: torch.utils.data.Dataset

Creates a dataset for AllvsAll training by inheriting from torch.utils.data.Dataset.
    Let D denote a dataset for AllvsAll training and be defined as D:= {(x,y)_i}_i ^N, where x: (h,r) is a possible unique tuple of an entity h in E and a relation r in R. Hence N = |E| x |R| y: denotes a multi-label vector in $[0,1]^{\{|E|\}}$ is a binary label.

orall y_i =1 s.t. (h r E_i) in KG

> **ℹ Note**
>
> **AllvsAll extends KvsAll via none existing (h,r). Hence, it adds data points that are labelled without 1s,**
>   only with 0s.

train_set_idx
    [numpy.ndarray] n by 3 array representing n triples

entity_idxs
    [dictonary] string representation of an entity to its integer id

relation_idxs
    [dictonary] string representation of a relation to its integer id

self : torch.utils.data.Dataset

```
>>> a = AllvsAll()
>>> a
? array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

train_data = None

train_target = None

label_smoothing_rate

collate_fn = None

target_dim

store

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**KvsSampleDataset**(*train_set: numpy.ndarray*, *num_entities*, *num_relations*, *neg_sample_ratio: int = None*, *label_smoothing_rate: float = 0.0*)

Bases: torch.utils.data.Dataset

    KvsSample a Dataset:

        D:= {(x,y)_i}_i ^N, where
        . x:(h,r) is a unique h in E and a relation r in R and . y in [0,1]^{|E|} is a binary label.

    orall y_i =1 s.t. (h r E_i) in KG

        At each mini-batch construction, we subsample(y), hence n
        |new_y| << **|E|** new_y contains all 1's if sum(y)< neg_sample ratio new_y contains

    train_set_idx
    Indexed triples for the training.

    entity_idxs
    mapping.

    relation_idxs
    mapping.

    form
        ?

    store
        ?

    label_smoothing_rate
        ?

    torch.utils.data.Dataset

train_data

num_entities

num_relations

neg_sample_ratio

label_smoothing_rate

collate_fn = None

store

train_target

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**NegSampleDataset**(*train_set: numpy.ndarray*, *num_entities: int*, *num_relations: int*, *neg_sample_ratio: int = 1*)

Bases: torch.utils.data.Dataset

An abstract class representing a Dataset.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite *__getitem__()*, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite *__len__()*, which is expected to return the size of the dataset by many Sampler implementations and the default options of DataLoader. Subclasses could also optionally implement __getitems__(), for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

> **ⓘ Note**
>
> DataLoader by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

neg_sample_ratio

train_set

length

num_entities

num_relations

__len__()

__getitem__(*idx*)

class dicee.dataset_classes.**TriplePredictionDataset**(*train_set: numpy.ndarray*, *num_entities: int*, *num_relations: int*, *neg_sample_ratio: int = 1*, *label_smoothing_rate: float = 0.0*)

Bases: torch.utils.data.Dataset

Triple Dataset

D:= {(x)_i}_i ^N, where
. x:(h,r, t) in KG is a unique h in E and a relation r in R and . collact_fn => Generates
negative triples

collect_fn:

orall (h,r,t) in G obtain, create negative triples{(h,r,x),(,r,t),(h,m,t)}

y:labels are represented in torch.float16

train_set_idx
Indexed triples for the training.

entity_idxs
mapping.

relation_idxs
mapping.

form
?

store
?

label_smoothing_rate

collate_fn: batch:List[torch.IntTensor] Returns ——- torch.utils.data.Dataset

`label_smoothing_rate`

`neg_sample_ratio`

`train_set`

`length`

`num_entities`

`num_relations`

`__len__`()

`__getitem__`(*idx*)

`collate_fn`(*batch: List[torch.Tensor]*)

class dicee.dataset_classes.**CVDataModule**(*train_set_idx: numpy.ndarray*, *num_entities*,
num_relations, *neg_sample_ratio*, *batch_size*, *num_workers*)

Bases: pytorch_lightning.LightningDataModule

Create a Dataset for cross validation

Parameters

- **`train_set_idx`** – Indexed triples for the training.

- **`num_entities`** – entity to index mapping.

- **`num_relations`** – relation to index mapping.

- **`batch_size`** – int

- **`form`** – ?

- **num_workers** – int for https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

Return type

?

train_set_idx

num_entities

num_relations

neg_sample_ratio

batch_size

num_workers

train_dataloader() → torch.utils.data.DataLoader

An iterable or collection of iterables specifying training samples.

For more information about multiple dataloaders, see this section.

The dataloader you return will not be reloaded unless you set **:param-ref:`~pytorch_lightning.trainer.trainer.Trainer.reload_dataloaders_every_n_epochs`** to a positive integer.

For data processing use the following pattern:

- download in *prepare_data()*
- process and split in *setup()*

However, the above are only necessary for distributed processing.

> ⚠ **Warning**
>
> do not assign state in prepare_data

- `fit()`
- *prepare_data()*
- *setup()*

> ⓘ **Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

setup(**args*, ***kwargs*)

Called at the beginning of fit (train + validate), validate, test, or predict. This is a good hook when you need to build models dynamically or adjust something about them. This hook is called on every process when using DDP.

Parameters

stage – either `'fit'`, `'validate'`, `'test'`, or `'predict'`

Example:

```
class LitModel(...):
    def __init__(self):
        self.l1 = None

    def prepare_data(self):
        download_data()
        tokenize()

        # don't do this
        self.something = else

    def setup(self, stage):
        data = load_data(...)
        self.l1 = nn.Linear(28, data.num_classes)
```

transfer_batch_to_device(**args*, ***kwargs*)

Override this hook if your `DataLoader` returns tensors wrapped in a custom data structure.

The data types listed below (and any arbitrary nesting of them) are supported out of the box:

- `torch.Tensor` or anything that implements *.to(…)*

- `list`

- `dict`

- `tuple`

For anything else, you need to define how the data is moved to the target device (CPU, GPU, TPU, …).

> **ℹ Note**
>
> This hook should only transfer the data and not modify it, nor should it move the data to any other device than the one passed in as argument (unless you know what you are doing). To check the current state of execution of this hook you can use `self.trainer.training/testing/validating/predicting` so that you can add different logic as per your requirement.

Parameters

- **batch** – A batch of data that needs to be transferred to a new device.

- **device** – The target device as defined in PyTorch.

- **dataloader_idx** – The index of the dataloader to which the batch belongs.

Returns

A reference to the data on the new device.

Example:

```
def transfer_batch_to_device(self, batch, device, dataloader_idx):
    if isinstance(batch, CustomBatch):
        # move all tensors in your custom data structure to the device
        batch.samples = batch.samples.to(device)
        batch.targets = batch.targets.to(device)
    elif dataloader_idx == 0:
        # skip device transfer for the first dataloader or anything you wish
```

```
        pass
    else:
        batch = super().transfer_batch_to_device(batch, device, dataloader_
→idx)
    return batch
```

> **→ See also**
>
> - move_data_to_device()
>
> - apply_to_collection()

prepare_data(**args*, ***kwargs*)

Use this to download and prepare data. Downloading and saving data with multiple processes (distributed settings) will result in corrupted data. Lightning ensures this method is called only within a single process, so you can safely add your downloading logic within.

> **⚠ Warning**
>
> DO NOT set state to the model (use setup instead) since this is NOT called on every device

Example:

```python
def prepare_data(self):
    # good
    download_data()
    tokenize()
    etc()

    # bad
    self.split = data_split
    self.some_state = some_other_state()
```

In a distributed environment, prepare_data can be called in two ways (using prepare_data_per_node)

1. Once per node. This is the default and is only called on LOCAL_RANK=0.

2. Once in total. Only called on GLOBAL_RANK=0.

Example:

```python
# DEFAULT
# called once per node on LOCAL_RANK=0 of that node
class LitDataModule(LightningDataModule):
    def __init__(self):
        super().__init__()
        self.prepare_data_per_node = True


# call on GLOBAL_RANK=0 (great for shared file systems)
class LitDataModule(LightningDataModule):
    def __init__(self):
        super().__init__()
        self.prepare_data_per_node = False
```

This is called before requesting the dataloaders:

```
model.prepare_data()
initialize_distributed()
model.setup(stage)
model.train_dataloader()
model.val_dataloader()
model.test_dataloader()
model.predict_dataloader()
```

dicee.eval_static_funcs

Functions

evaluate_link_prediction_performance(→ Dict)	
evaluate_link_prediction_performance_w	
evaluate_link_prediction_performance_w	
evaluate_link_prediction_performance_w ...)	
evaluate_lp_bpe_k_vs_all(model, triples[, er_vocab, ...])	

Module Contents

dicee.eval_static_funcs.**evaluate_link_prediction_performance**(
          model: dicee.knowledge_graph_embeddings.KGE, *triples*, *er_vocab: Dict[Tuple, List]*,
          re_vocab: Dict[Tuple, List]) → Dict

> **Parameters**
>
> > - **model**
> >
> > - **triples**
> >
> > - **er_vocab**
> >
> > - **re_vocab**

dicee.eval_static_funcs.
          evaluate_link_prediction_performance_with_reciprocals(
          model: dicee.knowledge_graph_embeddings.KGE, *triples*, *er_vocab: Dict[Tuple, List]*)

dicee.eval_static_funcs.
          evaluate_link_prediction_performance_with_bpe_reciprocals(
          model: dicee.knowledge_graph_embeddings.KGE, *within_entities: List[str]*, *triples: List[List[str]]*,
          er_vocab: Dict[Tuple, List])

dicee.eval_static_funcs.**evaluate_link_prediction_performance_with_bpe**(
          model: dicee.knowledge_graph_embeddings.KGE, *within_entities: List[str]*, *triples: List[Tuple[str]]*,
          er_vocab: Dict[Tuple, List], *re_vocab: Dict[Tuple, List]*)

Parameters

- **model**
- **triples**
- **within_entities**
- **er_vocab**
- **re_vocab**

dicee.eval_static_funcs.**evaluate_lp_bpe_k_vs_all**(*model*, *triples: List[List[str]]*,
    er_vocab=None, *batch_size=None*, *func_triple_to_bpe_representation: Callable = None*,
    str_to_bpe_entity_to_idx=None)

dicee.evaluator

Classes

Evaluator	Evaluator class to evaluate KGE models in various down-stream tasks

Module Contents

class dicee.evaluator.**Evaluator**(*args*, *is_continual_training=None*)

Evaluator class to evaluate KGE models in various downstream tasks

Arguments

re_vocab = None

er_vocab = None

ee_vocab = None

func_triple_to_bpe_representation = None

is_continual_training

num_entities = None

num_relations = None

args

report

during_training = False

vocab_preparation(*dataset*) → None

A function to wait future objects for the attributes of executor

> **Return type**
> None

eval (*dataset: dicee.knowledge_graph.KG, trained_model, form_of_labelling, during_training=False*)
→ None

eval_rank_of_head_and_tail_entity (**, train_set, valid_set=None, test_set=None, trained_model*)

eval_rank_of_head_and_tail_byte_pair_encoded_entity (**, train_set=None, valid_set=None, test_set=None, ordered_bpe_entities, trained_model*)

eval_with_byte (**, raw_train_set, raw_valid_set=None, raw_test_set=None, trained_model, form_of_labelling*) → None

Evaluate model after reciprocal triples are added

eval_with_bpe_vs_all (**, raw_train_set, raw_valid_set=None, raw_test_set=None, trained_model, form_of_labelling*) → None

Evaluate model after reciprocal triples are added

eval_with_vs_all (**, train_set, valid_set=None, test_set=None, trained_model, form_of_labelling*)
→ None

Evaluate model after reciprocal triples are added

evaluate_lp_k_vs_all (*model, triple_idx, info=None, form_of_labelling=None*)

Filtered link prediction evaluation. :param model: :param triple_idx: test triples :param info: :param form_of_labelling: :return:

evaluate_lp_with_byte (*model, triples: List[List[str]], info=None*)

evaluate_lp_bpe_k_vs_all (*model, triples: List[List[str]], info=None, form_of_labelling=None*)

> **Parameters**
>
> - **model**
> - **triples** (*List of lists*)
> - **info**
> - **form_of_labelling**

evaluate_lp (*model, triple_idx, info: str*)

dummy_eval (*trained_model, form_of_labelling: str*)

eval_with_data (*dataset, trained_model, triple_idx: numpy.ndarray, form_of_labelling: str*)

dicee.executer

Classes

Execute	A class for Training, Retraining and Evaluation a model.
ContinuousExecute	A subclass of Execute Class for retraining

Module Contents

class `dicee.executer.`**`Execute`**(*args*, *continuous_training=False*)

    A class for Training, Retraining and Evaluation a model.

      (1) Loading & Preprocessing & Serializing input data.

      (2) Training & Validation & Testing

      (3) Storing all necessary info

    `args`

    `is_continual_training`

    `trainer = None`

    `trained_model = None`

    `knowledge_graph = None`

    `report`

    `evaluator = None`

    `start_time = None`

    `read_or_load_kg`()

    `read_preprocess_index_serialize_data`() → None

        Read & Preprocess & Index & Serialize Input Data

      (1) Read or load the data from disk into memory.

      (2) Store the statistics of the data.

        Parameter

            rtype
                None

    `load_indexed_data`() → None

        Load the indexed data from disk into memory

        Parameter

            rtype
                None

    `save_trained_model`() → None

        Save a knowledge graph embedding model

      (1) Send model to eval mode and cpu.

      (2) Store the memory footprint of the model.

      (3) Save the model into disk.

      (4) Update the stats of KG again ?

Parameter

> **rtype**
> None

end(*form_of_labelling: str*) → dict
> End training

> (1) Store trained model.

> (2) Report runtimes.

> (3) Eval model if required.

Parameter

> **rtype**
> A dict containing information about the training and/or evaluation

write_report() → None
> Report training related information in a report.json file

start() → dict
> Start training

> # (1) Loading the Data # (2) Create an evaluator object. # (3) Create a trainer object. # (4) Start the training

Parameter

> **rtype**
> A dict containing information about the training and/or evaluation

class dicee.executer.**ContinuousExecute**(*args*)
> Bases: *Execute*

> A subclass of Execute Class for retraining

> (1) Loading & Preprocessing & Serializing input data.

> (2) Training & Validation & Testing

> (3) Storing all necessary info

> During the continual learning we can only modify *** num_epochs *** parameter. Trained model stored in the same folder as the seed model for the training. Trained model is noted with the current time.

> **previous_args**

> **args**

> **continual_start**() → dict
> > Start Continual Training

> > (1) Initialize training.

> > (2) Start continual training.

> > (3) Save trained model.

> **Parameter**

> > **rtype**
> >   A dict containing information about the training and/or evaluation

dicee.knowledge_graph

Classes

KG	Knowledge Graph

Module Contents

class dicee.knowledge_graph.**KG**(*dataset_dir: str = None*, *byte_pair_encoding: bool = False*, *padding: bool = False*, *add_noise_rate: float = None*, *sparql_endpoint: str = None*, *path_single_kg: str = None*, *path_for_deserialization: str = None*, *add_reciprical: bool = None*, *eval_model: str = None*, *read_only_few: int = None*, *sample_triples_ratio: float = None*, *path_for_serialization: str = None*, *entity_to_idx=None*, *relation_to_idx=None*, *backend=None*, *training_technique: str = None*)

Knowledge Graph

dataset_dir

byte_pair_encoding

ordered_shaped_bpe_tokens = None

sparql_endpoint

add_noise_rate

num_entities = None

num_relations = None

path_single_kg

path_for_deserialization

add_reciprical

eval_model

read_only_few

sample_triples_ratio

path_for_serialization

entity_to_idx

relation_to_idx

backend

training_technique

idx_entity_to_bpe_shaped

enc

num_tokens

num_bpe_entities = None

padding

dummy_id

max_length_subword_tokens = None

train_set_target = None

target_dim = None

train_target_indices = None

ordered_bpe_entities = None

property entities_str: List

property relations_str: List

exists(*h: str*, *r: str*, *t: str*)

__iter__()

__len__()

func_triple_to_bpe_representation(*triple: List[str]*)

dicee.knowledge_graph_embeddings

Classes

KGE	Knowledge Graph Embedding Class for interactive usage of pre-trained models

Module Contents

class dicee.knowledge_graph_embeddings.**KGE**(*path=None*, *url=None*, *construct_ensemble=False*, *model_name=None*)

Bases: *dicee.abstracts.BaseInteractiveKGE*

Knowledge Graph Embedding Class for interactive usage of pre-trained models

__str__()

to (*device: str*) → None

get_transductive_entity_embeddings (*indices: torch.LongTensor | List[str],*
as_pytorch=False, as_numpy=False, as_list=True)
→ torch.FloatTensor | numpy.ndarray | List[float]

create_vector_database (*collection_name: str*, *distance: str*, *location: str = 'localhost'*,
port: int = 6333)

generate (*h='', r=''*)

eval_lp_performance (*dataset=List[Tuple[str, str, str]]*, *filtered=True*)

predict_missing_head_entity (*relation: List[str] | str*, *tail_entity: List[str] | str*, *within=None*)
→ Tuple

Given a relation and a tail entity, return top k ranked head entity.

argmax_{e in E } f(e,r,t), where r in R, t in E.

Parameter

relation: Union[List[str], str]

String representation of selected relations.

tail_entity: Union[List[str], str]

String representation of selected entities.

k: int

Highest ranked k entities.

Returns: Tuple

Highest K scores and entities

predict_missing_relations (*head_entity: List[str] | str*, *tail_entity: List[str] | str*, *within=None*)
→ Tuple

Given a head entity and a tail entity, return top k ranked relations.

argmax_{r in R } f(h,r,t), where h, t in E.

Parameter

head_entity: List[str]

String representation of selected entities.

tail_entity: List[str]

String representation of selected entities.

k: int

Highest ranked k entities.

Returns: Tuple

Highest K scores and entities

`predict_missing_tail_entity` (*head_entity: List[str] | str*, *relation: List[str] | str*, *within: List[str] = None*) → torch.FloatTensor

Given a head entity and a relation, return top k ranked entities

argmax_{e in E } f(h,r,e), where h in E and r in R.

Parameter

head_entity: List[str]

String representation of selected entities.

tail_entity: List[str]

String representation of selected entities.

Returns: Tuple

scores

`predict` (***, *h: List[str] | str = None*, *r: List[str] | str = None*, *t: List[str] | str = None*, *within=None*, *logits=True*) → torch.FloatTensor

Parameters

- **`logits`**
- **`h`**
- **`r`**
- **`t`**
- **`within`**

`predict_topk` (***, *h: str | List[str] = None*, *r: str | List[str] = None*, *t: str | List[str] = None*, *topk: int = 10*, *within: List[str] = None*)

Predict missing item in a given triple.

Parameter

head_entity: Union[str, List[str]]

String representation of selected entities.

relation: Union[str, List[str]]

String representation of selected relations.

tail_entity: Union[str, List[str]]

String representation of selected entities.

k: int

Highest ranked k item.

Returns: Tuple

Highest K scores and items

triple_score (*h: List[str] | str = None, r: List[str] | str = None, t: List[str] | str = None, logits=False*)
→ torch.FloatTensor
Predict triple score

Parameter

head_entity: List[str]

String representation of selected entities.

relation: List[str]

String representation of selected relations.

tail_entity: List[str]

String representation of selected entities.

logits: bool

If logits is True, unnormalized score returned

Returns: Tuple

pytorch tensor of triple score

t_norm (*tens_1: torch.Tensor, tens_2: torch.Tensor, tnorm: str = 'min'*) → torch.Tensor

tensor_t_norm (*subquery_scores: torch.FloatTensor, tnorm: str = 'min'*) → torch.FloatTensor
Compute T-norm over [0,1] ^{n imes d} where n denotes the number of hops and d denotes number of entities

t_conorm (*tens_1: torch.Tensor, tens_2: torch.Tensor, tconorm: str = 'min'*) → torch.Tensor

negnorm (*tens_1: torch.Tensor, lambda_: float, neg_norm: str = 'standard'*) → torch.Tensor

return_multi_hop_query_results (*aggregated_query_for_all_entities, k: int, only_scores*)

single_hop_query_answering (*query: tuple, only_scores: bool = True, k: int = None*)

answer_multi_hop_query (*query_type: str = None,
query: Tuple[str | Tuple[str, str], Ellipsis] = None,
queries: List[Tuple[str | Tuple[str, str], Ellipsis]] = None, tnorm: str = 'prod',
neg_norm: str = 'standard', lambda_: float = 0.0, k: int = 10, only_scores=False*)
→ List[Tuple[str, torch.Tensor]]
@TODO: Refactoring is needed # @TODO: Score computation for each query type should be done in a static function

Find an answer set for EPFO queries including negation and disjunction

Parameter

query_type: str The type of the query, e.g., "2p".

query: Union[str, Tuple[str, Tuple[str, str]]] The query itself, either a string or a nested tuple.

queries: List of Tuple[Union[str, Tuple[str, str]], …]

tnorm: str The t-norm operator.

neg_norm: str The negation norm.

lambda_: float lambda parameter for sugeno and yager negation norms

k: int The top-k substitutions for intermediate variables.

> **returns**
>> - *List[Tuple[str, torch.Tensor]]*
>> - *Entities and corresponding scores sorted in the descening order of scores*

find_missing_triples (*confidence: float, entities: List[str] = None, relations: List[str] = None, topk: int = 10, at_most: int = sys.maxsize*) $\to$ Set

Find missing triples

Iterative over a set of entities E and a set of relation R :

orall e in E and orall r in R f(e,r,x)

> Return (e,r,x)

otin G and f(e,r,x) > confidence

> confidence: float
>
> A threshold for an output of a sigmoid function given a triple.
>
> topk: int
>
> Highest ranked k item to select triples with f(e,r,x) > confidence .
>
> at_most: int
>
> Stop after finding at_most missing triples
>
> {(e,r,x) | f(e,r,x) > confidence land (e,r,x)}

otin G

deploy (*share: bool = False, top_k: int = 10*)

train_triples (*h: List[str], r: List[str], t: List[str], labels: List[float], iteration=2, optimizer=None*)

train_k_vs_all (*h, r, iteration=1, lr=0.001*)

Train k vs all :param head_entity: :param relation: :param iteration: :param lr: :return:

train (*kg, lr=0.1, epoch=10, batch_size=32, neg_sample_ratio=10, num_workers=1*) $\to$ None

Retrained a pretrain model on an input KG via negative sampling.

dicee.query_generator

Classes

QueryGenerator

Module Contents

class dicee.query_generator.**QueryGenerator**(*train_path*, *val_path: str*, *test_path: str*,
    ent2id: Dict = None, *rel2id: Dict = None*, *seed: int = 1*, *gen_valid: bool = False*,
    gen_test: bool = True)

> **train_path**
>
> **val_path**
>
> **test_path**
>
> **gen_valid**
>
> **gen_test**
>
> **seed**
>
> **max_ans_num = 1000000.0**
>
> **mode**
>
> **ent2id**
>
> **rel2id: Dict**
>
> **ent_in: Dict**
>
> **ent_out: Dict**
>
> **query_name_to_struct**
>
> **list2tuple**(*list_data*)
>
> **tuple2list**(*x: List | Tuple*) → List | Tuple
>> Convert a nested tuple to a nested list.
>
> **set_global_seed**(*seed: int*)
>> Set seed
>
> **construct_graph**(*paths: List[str]*) → Tuple[Dict, Dict]
>> Construct graph from triples Returns dicts with incoming and outgoing edges
>
> **fill_query**(*query_structure: List[str | List]*, *ent_in: Dict*, *ent_out: Dict*, *answer: int*) → bool
>> Private method for fill_query logic.
>
> **achieve_answer**(*query: List[str | List]*, *ent_in: Dict*, *ent_out: Dict*) → set
>> Private method for achieve_answer logic. @TODO: Document the code

write_links(*ent_out*, *small_ent_out*)

ground_queries(*query_structure: List[str | List]*, *ent_in: Dict*, *ent_out: Dict*, *small_ent_in: Dict*, *small_ent_out: Dict*, *gen_num: int*, *query_name: str*)

> Generating queries and achieving answers

unmap(*query_type*, *queries*, *tp_answers*, *fp_answers*, *fn_answers*)

unmap_query(*query_structure*, *query*, *id2ent*, *id2rel*)

generate_queries(*query_struct: List*, *gen_num: int*, *query_type: str*)

> Passing incoming and outgoing edges to ground queries depending on mode [train valid or text] and getting queries and answers in return @ TODO: create a class for each single query struct

save_queries(*query_type: str*, *gen_num: int*, *save_path: str*)

abstract load_queries(*path*)

get_queries(*query_type: str*, *gen_num: int*)

static save_queries_and_answers(*path: str*, *data: List[Tuple[str, Tuple[collections.defaultdict]]]*) → None

> Save Queries into Disk

static load_queries_and_answers(*path: str*) → List[Tuple[str, Tuple[collections.defaultdict]]]

> Load Queries from Disk to Memory

dicee.sanity_checkers

Functions

is_sparql_endpoint_alive([sparql_endpoint])	
validate_knowledge_graph(args)	Validating the source of knowledge graph
sanity_checking_with_arguments(args)	

Module Contents

dicee.sanity_checkers.**is_sparql_endpoint_alive**(*sparql_endpoint: str = None*)

dicee.sanity_checkers.**validate_knowledge_graph**(*args*)

> Validating the source of knowledge graph

dicee.sanity_checkers.**sanity_checking_with_arguments**(*args*)

dicee.static_funcs

Functions

`create_recipriocal_triples`(x)	Add inverse triples into dask dataframe
`get_er_vocab`(data[, file_path])	
`get_re_vocab`(data[, file_path])	
`get_ee_vocab`(data[, file_path])	
`timeit`(func)	
`save_pickle`(*[, data, file_path])	
`load_pickle`([file_path])	
`select_model`(args[, is_continual_training, storage_path])	
`load_model`(→ Tuple[object, Tuple[dict, dict]])	Load weights and initialize pytorch module from namespace arguments
`load_model_ensemble`(...)	Construct Ensemble Of weights and initialize pytorch module from namespace arguments
`save_numpy_ndarray`(*, data, file_path)	
`numpy_data_type_changer`(→ numpy.ndarray)	Detect most efficient data type for a given triples
`save_checkpoint_model`(→ None)	Store Pytorch model into disk
`store`(→ None)	Store trained_model model and save embeddings into csv file.
`add_noisy_triples`(→ pandas.DataFrame)	Add randomly constructed triples
`read_or_load_kg`(args, cls)	
`intialize_model`(→ Tuple[object, str])	
`load_json`(→ dict)	
`save_embeddings`(→ None)	Save it as CSV if memory allows.
`random_prediction`(pre_trained_kge)	
`deploy_triple_prediction`(pre_trained_kge, str_subject, ...)	
`deploy_tail_entity_prediction`(pre_trained_kge, ...)	
`deploy_head_entity_prediction`(pre_trained_kge, ...)	
`deploy_relation_prediction`(pre_trained_kge, ...)	
`vocab_to_parquet`(vocab_to_idx, name, ...)	
`create_experiment_folder`([folder_name])	

Table 2 – continued from previous page

continual_training_setup_executor(→ None)	storage_path:str A path leading to a parent directory, where a subdirectory containing KGE related data
exponential_function(→ torch.FloatTensor)	
load_numpy(→ numpy.ndarray)	
evaluate(entity_to_idx, scores, easy_answers, hard_answers)	# @TODO: CD: Renamed this function
download_file(url[, destination_folder])	
download_files_from_url(→ None)	
download_pretrained_model(→ str)	

Module Contents

dicee.static_funcs.**create_recipriocal_triples**(*x*)

    Add inverse triples into dask dataframe :param x: :return:

dicee.static_funcs.**get_er_vocab**(*data*, *file_path: str = None*)

dicee.static_funcs.**get_re_vocab**(*data*, *file_path: str = None*)

dicee.static_funcs.**get_ee_vocab**(*data*, *file_path: str = None*)

dicee.static_funcs.**timeit**(*func*)

dicee.static_funcs.**save_pickle**(***, *data: object = None*, *file_path=str*)

dicee.static_funcs.**load_pickle**(*file_path=str*)

dicee.static_funcs.**select_model**(*args: dict*, *is_continual_training: bool = None*, *storage_path: str = None*)

dicee.static_funcs.**load_model**(*path_of_experiment_folder: str*, *model_name='model.pt'*, *verbose=0*) → Tuple[object, Tuple[dict, dict]]

    Load weights and initialize pytorch module from namespace arguments

dicee.static_funcs.**load_model_ensemble**(*path_of_experiment_folder: str*)
        → Tuple[*dicee.models.base_model.BaseKGE*, Tuple[pandas.DataFrame, pandas.DataFrame]]

    Construct Ensemble Of weights and initialize pytorch module from namespace arguments

    (1) Detect models under given path

    (2) Accumulate parameters of detected models

    (3) Normalize parameters

    (4) Insert (3) into model.

dicee.static_funcs.**save_numpy_ndarray**(***, *data: numpy.ndarray*, *file_path: str*)

dicee.static_funcs.**numpy_data_type_changer**(*train_set: numpy.ndarray*, *num: int*)
        → numpy.ndarray

    Detect most efficient data type for a given triples :param train_set: :param num: :return:

dicee.static_funcs.**save_checkpoint_model**(*model*, *path: str*) → None

> Store Pytorch model into disk

dicee.static_funcs.**store**(*trainer*, *trained_model*, *model_name: str = 'model'*, *full_storage_path: str = None*, *save_embeddings_as_csv=False*) → None

> Store trained_model model and save embeddings into csv file. :param trainer: an instance of trainer class :param full_storage_path: path to save parameters. :param model_name: string representation of the name of the model. :param trained_model: an instance of BaseKGE see core.models.base_model . :param save_embeddings_as_csv: for easy access of embeddings. :return:

dicee.static_funcs.**add_noisy_triples**(*train_set: pandas.DataFrame*, *add_noise_rate: float*) → pandas.DataFrame

> Add randomly constructed triples :param train_set: :param add_noise_rate: :return:

dicee.static_funcs.**read_or_load_kg**(*args*, *cls*)

dicee.static_funcs.**intialize_model**(*args: dict*, *verbose=0*) → Tuple[object, str]

dicee.static_funcs.**load_json**(*p: str*) → dict

dicee.static_funcs.**save_embeddings**(*embeddings: numpy.ndarray*, *indexes*, *path: str*) → None

> Save it as CSV if memory allows. :param embeddings: :param indexes: :param path: :return:

dicee.static_funcs.**random_prediction**(*pre_trained_kge*)

dicee.static_funcs.**deploy_triple_prediction**(*pre_trained_kge*, *str_subject*, *str_predicate*, *str_object*)

dicee.static_funcs.**deploy_tail_entity_prediction**(*pre_trained_kge*, *str_subject*, *str_predicate*, *top_k*)

dicee.static_funcs.**deploy_head_entity_prediction**(*pre_trained_kge*, *str_object*, *str_predicate*, *top_k*)

dicee.static_funcs.**deploy_relation_prediction**(*pre_trained_kge*, *str_subject*, *str_object*, *top_k*)

dicee.static_funcs.**vocab_to_parquet**(*vocab_to_idx*, *name*, *path_for_serialization*, *print_into*)

dicee.static_funcs.**create_experiment_folder**(*folder_name='Experiments'*)

dicee.static_funcs.**continual_training_setup_executor**(*executor*) → None

> storage_path:str A path leading to a parent directory, where a subdirectory containing KGE related data

> full_storage_path:str A path leading to a subdirectory containing KGE related data

dicee.static_funcs.**exponential_function**(*x: numpy.ndarray*, *lam: float*, *ascending_order=True*) → torch.FloatTensor

dicee.static_funcs.**load_numpy**(*path*) → numpy.ndarray

dicee.static_funcs.**evaluate**(*entity_to_idx*, *scores*, *easy_answers*, *hard_answers*)

> # @TODO: CD: Renamed this function Evaluate multi hop query answering on different query types

dicee.static_funcs.**download_file**(*url*, *destination_folder='.'*)

```
dicee.static_funcs.download_files_from_url(base_url: str, destination_folder='.') → None
```

>   **Parameters**
>
> - **base_url** (e.g. "https://files.dice-research.org/projects/DiceEmbeddings/KINSHIP-Keci-dim128-epoch256-KvsAll")
>
> - **destination_folder**(e.g. "KINSHIP-Keci-dim128-epoch256-KvsAll")

```
dicee.static_funcs.download_pretrained_model(url: str) → str
```

dicee.static_funcs_training

Functions

evaluate_lp(model, triple_idx, num_entities, er_vocab, ...)	Evaluate model in a standard link prediction task
evaluate_bpe_lp(model, triple_idx, ...[, info])	
efficient_zero_grad(model)	

Module Contents

```
dicee.static_funcs_training.evaluate_lp(model, triple_idx, num_entities,
        er_vocab: Dict[Tuple, List], re_vocab: Dict[Tuple, List], info='Eval Starts')
```

Evaluate model in a standard link prediction task

for each triple the rank is computed by taking the mean of the filtered missing head entity rank and the filtered missing tail entity rank :param model: :param triple_idx: :param info: :return:

```
dicee.static_funcs_training.evaluate_bpe_lp(model, triple_idx: List[Tuple],
        all_bpe_shaped_entities, er_vocab: Dict[Tuple, List], re_vocab: Dict[Tuple, List],
        info='Eval Starts')
```

```
dicee.static_funcs_training.efficient_zero_grad(model)
```

dicee.static_preprocess_funcs

Attributes

enable_log	

Functions

timeit(func)	
preprocesses_input_args(args)	Sanity Checking in input arguments
create_constraints(→ Tuple[dict, dict, dict])	
get_er_vocab(data)	
get_re_vocab(data)	
get_ee_vocab(data)	
mapping_from_first_two_cols_to_third(tra	

Module Contents

dicee.static_preprocess_funcs.**enable_log = False**

dicee.static_preprocess_funcs.**timeit**(*func*)

dicee.static_preprocess_funcs.**preprocesses_input_args**(*args*)

    Sanity Checking in input arguments

dicee.static_preprocess_funcs.**create_constraints**(*triples: numpy.ndarray*)
       → Tuple[dict, dict, dict, dict]

   (1) Extract domains and ranges of relations

   (2) Store a mapping from relations to entities that are outside of the domain and range. Create constraints entities based on the range of relations :param triples: :return:

dicee.static_preprocess_funcs.**get_er_vocab**(*data*)

dicee.static_preprocess_funcs.**get_re_vocab**(*data*)

dicee.static_preprocess_funcs.**get_ee_vocab**(*data*)

dicee.static_preprocess_funcs.**mapping_from_first_two_cols_to_third**(
      train_set_idx)

14.3 Attributes

__version__

14.4 Classes

CMult	Cl_(0,0) => Real Numbers
Pyke	A Physical Embedding Model for Knowledge Graphs
DistMult	Embedding Entities and Relations for Learning and Inference in Knowledge Bases
KeciBase	Without learning dimension scaling
Keci	Base class for all neural network modules.
TransE	Translating Embeddings for Modeling
DeCaL	Base class for all neural network modules.
DualE	Dual Quaternion Knowledge Graph Embeddings (https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657)
ComplEx	Base class for all neural network modules.
AConEx	Additive Convolutional ComplEx Knowledge Graph Embeddings
AConvO	Additive Convolutional Octonion Knowledge Graph Embeddings
AConvQ	Additive Convolutional Quaternion Knowledge Graph Embeddings
ConvQ	Convolutional Quaternion Knowledge Graph Embeddings
ConvO	Base class for all neural network modules.
ConEx	Convolutional ComplEx Knowledge Graph Embeddings
QMult	Base class for all neural network modules.
OMult	Base class for all neural network modules.
Shallom	A shallow neural model for relation prediction (https://arxiv.org/abs/2101.09090)
LFMult	Embedding with polynomial functions. We represent all entities and relations in the polynomial space as:
PykeenKGE	A class for using knowledge graph embedding models implemented in Pykeen
BytE	Base class for all neural network modules.
BaseKGE	Base class for all neural network modules.
DICE_Trainer	DICE_Trainer implement
KGE	Knowledge Graph Embedding Class for interactive usage of pre-trained models
Execute	A class for Training, Retraining and Evaluation a model.
BPE_NegativeSamplingDataset	An abstract class representing a `Dataset`.
MultiLabelDataset	An abstract class representing a `Dataset`.
MultiClassClassificationDataset	Dataset for the 1vsALL training strategy
OnevsAllDataset	Dataset for the 1vsALL training strategy
KvsAll	Creates a dataset for KvsAll training by inheriting from torch.utils.data.Dataset.
AllvsAll	Creates a dataset for AllvsAll training by inheriting from torch.utils.data.Dataset.
KvsSampleDataset	KvsSample a Dataset:
NegSampleDataset	An abstract class representing a `Dataset`.
TriplePredictionDataset	Triple Dataset
CVDataModule	Create a Dataset for cross validation

Table 3 – continued from previous page

QueryGenerator	

14.5 Functions

create_recipriocal_triples(x)	Add inverse triples into dask dataframe
get_er_vocab(data[, file_path])	
get_re_vocab(data[, file_path])	
get_ee_vocab(data[, file_path])	
timeit(func)	
save_pickle(*[, data, file_path])	
load_pickle([file_path])	
select_model(args[, is_continual_training, storage_path])	
load_model(→ Tuple[object, Tuple[dict, dict]])	Load weights and initialize pytorch module from namespace arguments
load_model_ensemble(...)	Construct Ensemble Of weights and initialize pytorch module from namespace arguments
save_numpy_ndarray(*, data, file_path)	
numpy_data_type_changer(→ numpy.ndarray)	Detect most efficient data type for a given triples
save_checkpoint_model(→ None)	Store Pytorch model into disk
store(→ None)	Store trained_model model and save embeddings into csv file.
add_noisy_triples(→ pandas.DataFrame)	Add randomly constructed triples
read_or_load_kg(args, cls)	
intialize_model(→ Tuple[object, str])	
load_json(→ dict)	
save_embeddings(→ None)	Save it as CSV if memory allows.
random_prediction(pre_trained_kge)	
deploy_triple_prediction(pre_trained_kge, str_subject, ...)	
deploy_tail_entity_prediction(pre_trained_ ...)	
deploy_head_entity_prediction(pre_trained_ ...)	
deploy_relation_prediction(pre_trained_kge, ...)	

Table 4 – continued from previous page

vocab_to_parquet(vocab_to_idx, name, ...)	
create_experiment_folder([folder_name])	
continual_training_setup_executor(→ None)	storage_path:str A path leading to a parent directory, where a subdirectory containing KGE related data
exponential_function(→ torch.FloatTensor)	
load_numpy(→ numpy.ndarray)	
evaluate(entity_to_idx, scores, easy_answers, hard_answers)	# @TODO: CD: Renamed this function
download_file(url[, destination_folder])	
download_files_from_url(→ None)	
download_pretrained_model(→ str)	
mapping_from_first_two_cols_to_third(tra	
timeit(func)	
load_pickle([file_path])	
reload_dataset(path, form_of_labelling, ...)	Reload the files from disk to construct the Pytorch dataset
construct_dataset(→ torch.utils.data.Dataset)	

14.6 Package Contents

class dicee.**CMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Cl_(0,0) => Real Numbers

Cl_(0,1) =>
A multivector mathbf{a} = a_0 + a_1 e_1 A multivector mathbf{b} = b_0 + b_1 e_1

multiplication is isomorphic to the product of two complex numbers

mathbf{a} imes mathbf{b} = a_0 b_0 + a_0b_1 e1 + a_1 b_1 e_1 e_1
= (a_0 b_0 - a_1 b_1) + (a_0 b_1 + a_1 b_0) e_1

Cl_(2,0) =>
A multivector mathbf{a} = a_0 + a_1 e_1 + a_2 e_2 + a_{12} e_1 e_2 A multivector mathbf{b} = b_0 + b_1 e_1 + b_2 e_2 + b_{12} e_1 e_2

mathbf{a} imes mathbf{b} = a_0b_0 + a_0b_1 e_1 + a_0b_2e_2 + a_0 b_12 e_1 e_2

• a_1 b_0 e_1 + a_1b_1 e_1_e1 ..

Cl_(0,2) => Quaternions

name = 'CMult'

entity_embeddings

relation_embeddings

p

q

clifford_mul (*x: torch.FloatTensor*, *y: torch.FloatTensor*, *p: int*, *q: int*) $\rightarrow$ tuple

Clifford multiplication Cl_{p,q} (mathbb{R})

ei ^2 = +1 for i =< i =< p ej ^2 = -1 for p < j =< p+q ei ej = -eje1 for i

eq j

x: torch.FloatTensor with (n,d) shape

y: torch.FloatTensor with (n,d) shape

p: a non-negative integer p>= 0 q: a non-negative integer q>= 0

score (*head_ent_emb*, *rel_ent_emb*, *tail_ent_emb*)

forward_triples (*x: torch.LongTensor*) $\rightarrow$ torch.FloatTensor

Compute batch triple scores

Parameter

x: torch.LongTensor with shape n by 3

> **rtype**
> torch.LongTensor with shape n

forward_k_vs_all (*x: torch.Tensor*) $\rightarrow$ torch.FloatTensor

Compute batch KvsAll triple scores

Parameter

x: torch.LongTensor with shape n by 3

> **rtype**
> torch.LongTensor with shape n

class dicee.**Pyke**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

A Physical Embedding Model for Knowledge Graphs

name = 'Pyke'

dist_func

margin = 1.0

forward_triples (*x: torch.LongTensor*)

> **Parameters**
> **x**

class dicee.**DistMult**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Embedding Entities and Relations for Learning and Inference in Knowledge Bases https://arxiv.org/abs/1412.6575

    name = 'DistMult'

    k_vs_all_score(*emb_h: torch.FloatTensor*, *emb_r: torch.FloatTensor*, *emb_E: torch.FloatTensor*)

        Parameters

            • **emb_h**

            • **emb_r**

            • **emb_E**

    forward_k_vs_all(*x: torch.LongTensor*)

    forward_k_vs_sample(*x: torch.LongTensor*, *target_entity_idx: torch.LongTensor*)

    score(*h*, *r*, *t*)

class dicee.**KeciBase**(*args*)

    Bases: *Keci*

    Without learning dimension scaling

    name = 'KeciBase'

    requires_grad_for_interactions = False

class dicee.**Keci**(*args*)

    Bases: *dicee.models.base_model.BaseKGE*

    Base class for all neural network modules.

    Your models should also subclass this class.

    Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

    Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

    Variables

        training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'Keci'

p

q

r

requires_grad_for_interactions = True

compute_sigma_pp(*hp*, *rp*)

Compute sigma_{pp} = sum_{i=1}^{p-1} sum_{k=i+1}^p (h_i r_k - h_k r_i) e_i e_k

sigma_{pp} captures the interactions between along p bases For instance, let p e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

    results = [] for i in range(p - 1):

        for k in range(i + 1, p):
            results.append(hp[:, :, i] * rp[:, :, k] - hp[:, :, k] * rp[:, :, i])

    sigma_pp = torch.stack(results, dim=2) assert sigma_pp.shape == (b, r, int((p * (p - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

    e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_qq(*hq*, *rq*)

Compute sigma_{qq} = sum_{j=1}^{p+q-1} sum_{k=j+1}^{p+q} (h_j r_k - h_k r_j) e_j e_k sigma_{q} captures the interactions between along q bases For instance, let q e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

    results = [] for j in range(q - 1):

        for k in range(j + 1, q):
            results.append(hq[:, :, j] * rq[:, :, k] - hq[:, :, k] * rq[:, :, j])

    sigma_qq = torch.stack(results, dim=2) assert sigma_qq.shape == (b, r, int((q * (q - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

    e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_pq(***, *hp*, *hq*, *rp*, *rq*)

sum_{i=1}^{p} sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

```
        for j in range(q):
            sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

    print(sigma_pq.shape)
```

apply_coefficients(*h0*, *hp*, *hq*, *r0*, *rp*, *rq*)

　　Multiplying a base vector with its scalar coefficient

clifford_multiplication(*h0*, *hp*, *hq*, *r0*, *rp*, *rq*)

　　Compute our CL multiplication

　　　　$h = h\_0 + sum\_\{i=1\}^p h\_i e\_i + sum\_\{j=p+1\}^\{p+q\} h\_j e\_j \; r = r\_0 + sum\_\{i=1\}^p r\_i e\_i + sum\_\{j=p+1\}^\{p+q\} r\_j e\_j$

　　　　$ei \; ^2 = +1 \; for \; i =< i =< p \; ej \; ^2 = -1 \; for \; p < j =< p+q \; ei \; ej = -eje1 \; for \; i$

　　eq j

　　　　h r = sigma_0 + sigma_p + sigma_q + sigma_{pp} + sigma_{q}+ sigma_{pq} where

　　　　(1)　sigma_0 = h_0 r_0 + sum_{i=1}^p (h_0 r_i) e_i - sum_{j=p+1}^{p+q} (h_j r_j) e_j

　　　　(2)　sigma_p = sum_{i=1}^p (h_0 r_i + h_i r_0) e_i

　　　　(3)　sigma_q = sum_{j=p+1}^{p+q} (h_0 r_j + h_j r_0) e_j

　　　　(4)　sigma_{pp} = sum_{i=1}^{p-1} sum_{k=i+1}^p (h_i r_k - h_k r_i) e_i e_k

　　　　(5)　sigma_{qq} = sum_{j=1}^{p+q-1} sum_{k=j+1}^{p+q} (h_j r_k - h_k r_j) e_j e_k

　　　　(6)　sigma_{pq} = sum_{i=1}^{p} sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j

construct_cl_multivector(*x: torch.FloatTensor*, *r: int*, *p: int*, *q: int*)
　　　　→ tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]

　　Construct a batch of multivectors Cl_{p,q}(mathbb{R}^d)

Parameter

　　x: torch.FloatTensor with (n,d) shape

　　　　returns

　　　　　　• **a0** (*torch.FloatTensor with (n,r) shape*)

　　　　　　• **ap** (*torch.FloatTensor with (n,r,p) shape*)

　　　　　　• **aq** (*torch.FloatTensor with (n,r,q) shape*)

forward_k_vs_with_explicit(*x: torch.Tensor*)

k_vs_all_score(*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

　　Kvsall training

　　(1)　Retrieve real-valued embedding vectors for heads and relations mathbb{R}^d .

　　(2)　Construct head entity and relation embeddings according to Cl_{p,q}(mathbb{R}^d) .

　　(3)　Perform Cl multiplication

　　(4)　Inner product of (3) and all entity embeddings

　　forward_k_vs_with_explicit and this funcitons are identical Parameter ——— x: torch.LongTensor with (n,2) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

forward_k_vs_sample(*x: torch.LongTensor*, *target_entity_idx: torch.LongTensor*)
→ torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations mathbb{R}^d .

(2) Construct head entity and relation embeddings according to Cl_{p,q}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

Parameter

x: torch.LongTensor with (n,2) shape

> **rtype**
> torch.FloatTensor with (n, |E|) shape

score(*h*, *r*, *t*)

forward_triples(*x: torch.Tensor*) → torch.FloatTensor

Parameter

x: torch.LongTensor with (n,3) shape

> **rtype**
> torch.FloatTensor with (n) shape

class dicee.**TransE**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Translating Embeddings for Modeling Multi-relational Data https://proceedings.neurips.cc/paper/2013/file/1cecc7a77928ca8133fa24680a88d2f9-Paper.pdf

name = 'TransE'

margin = 4

score(*head_ent_emb*, *rel_ent_emb*, *tail_ent_emb*)

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

class dicee.**DeCaL**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
```

(continues on next page)

```
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
    training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'DeCaL'

entity_embeddings

relation_embeddings

p

q

r

re

forward_triples (*x: torch.Tensor*) → torch.FloatTensor

Parameter

x: torch.LongTensor with (n,) shape

> **rtype**
> torch.FloatTensor with (n) shape

cl_pqr (*a: torch.tensor*) → torch.tensor

Input: tensor(batch_size, emb_dim) —> output: tensor with 1+p+q+r components with size (batch_size, emb_dim/(1+p+q+r)) each.

1) takes a tensor of size (batch_size, emb_dim), split it into 1 + p + q +r components, hence 1+p+q+r must be a divisor of the emb_dim. 2) Return a list of the 1+p+q+r components vectors, each are tensors of size (batch_size, emb_dim/(1+p+q+r))

compute_sigmas_single (*list_h_emb*, *list_r_emb*, *list_t_emb*)

here we compute all the sums with no others vectors interaction taken with the scalar product with t, that is,

$$s0 = h_0 r_0 t_0 \quad s1 = \sum_{i=1}^{p} h_i r_i t_0 \quad s2 = \sum_{j=p+1}^{p+q} h_j r_j t_0 \quad s3 = \sum_{i=1}^{q}(h_0 r_i t_i + h_i r_0 t_i) \quad s4 = \sum_{i=p+1}^{p+q}(h_0 r_i t_i + h_i r_0 t_i) \quad s5 = \sum_{i=p+q+1}^{p+q+r}(h_0 r_i t$$

and return:

$$sigma_0 t = \sigma_0 \cdot t_0 = s0 + s1 - s2s3, s4 and s5$$

compute_sigmas_multivect (*list_h_emb*, *list_r_emb*)

Here we compute and return all the sums with vectors interaction for the same and different bases.

For same bases vectors interaction we have

$$\sigma_p p = \sum_{i=1}^{p-1} \sum_{i'=i+1}^{p} (h_i r_{i'} - h_{i'} r_i)(models the interactions betweene_i and e'_i for 1 <= i, i' <= p)\sigma_q q = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q} (h_j r_{j'}$$

For different base vector interactions, we have

$$\sigma_p q = \sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i)(interactions n betweene_i and e_j for 1 <= i <= p and p+1 <= j <= p+q)\sigma_p r = \sum_{i=}$$

forward_k_vs_all (*x: torch.Tensor*) → torch.FloatTensor

Kvsall training

(1) Retrieve real-valued embedding vectors for heads and relations

(2) Construct head entity and relation embeddings according to Cl_{p,q, r}(mathbb{R}^d) .

(3) Perform Cl multiplication

(4) Inner product of (3) and all entity embeddings

forward_k_vs_with_explicit and this funcitons are identical Parameter ——— x: torch.LongTensor with (n,) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

apply_coefficients (*h0*, *hp*, *hq*, *hk*, *r0*, *rp*, *rq*, *rk*)

Multiplying a base vector with its scalar coefficient

construct_cl_multivector (*x: torch.FloatTensor*, *re: int*, *p: int*, *q: int*, *r: int*)
    → tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]

Construct a batch of multivectors Cl_{p,q,r}(mathbb{R}^d)

Parameter

x: torch.FloatTensor with (n,d) shape

returns

- **a0** (*torch.FloatTensor*)
- **ap** (*torch.FloatTensor*)
- **aq** (*torch.FloatTensor*)
- **ar** (*torch.FloatTensor*)

compute_sigma_pp (*hp*, *rp*)

Compute .. math:

```
\sigma_{p,p}^* = \sum_{i=1}^{p-1}\sum_{i'=i+1}^{p}(x_iy_{i'}-x_{i'}y_i)
```

sigma_{pp} captures the interactions between along p bases For instance, let p e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

results = [] for i in range(p - 1):

for k in range(i + 1, p):
    results.append(hp[:, :, i] * rp[:, :, k] - hp[:, :, k] * rp[:, :, i])

sigma_pp = torch.stack(results, dim=2) assert sigma_pp.shape == (b, r, int((p * (p - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_qq (hq, rq)

Compute

$$\sigma_{q,q}^* = \sum_{j=p+1}^{p+q-1}\sum_{j'=j+1}^{p+q}(x_jy_{j'}-x_{j'}y_j)\,Eq.16$$

sigma_{q} captures the interactions between along q bases For instance, let q e_1, e_2, e_3, we compute interactions between e_1 e_2, e_1 e_3 , and e_2 e_3 This can be implemented with a nested two for loops

results = [] for j in range(q - 1):

for k in range(j + 1, q):
    results.append(hq[:, :, j] * rq[:, :, k] - hq[:, :, k] * rq[:, :, j])

sigma_qq = torch.stack(results, dim=2) assert sigma_qq.shape == (b, r, int((q * (q - 1)) / 2))

Yet, this computation would be quite inefficient. Instead, we compute interactions along all p, e.g., e1e1, e1e2, e1e3,

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

Then select the triangular matrix without diagonals: e1e2, e1e3, e2e3.

compute_sigma_rr (hk, rk)

$$\sigma_{r,r}^* = \sum_{k=p+q+1}^{p+q+r-1}\sum_{k'=k+1}^{p}(x_ky_{k'}-x_{k'}y_k)$$

compute_sigma_pq $(*, hp, hq, rp, rq)$

Compute

$$\sum_{i=1}^{p}\sum_{j=p+1}^{p+q}(h_ir_j-h_jr_i)e_ie_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

for j in range(q):
    sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

compute_sigma_pr(*, *hp*, *hk*, *rp*, *rk*)

Compute

$$\sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

> **for j in range(q):**
>> sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

compute_sigma_qr(*, *hq*, *hk*, *rq*, *rk*)

$$\sum_{i=1}^{p} \sum_{j=p+1}^{p+q} (h_i r_j - h_j r_i) e_i e_j$$

results = [] sigma_pq = torch.zeros(b, r, p, q) for i in range(p):

> **for j in range(q):**
>> sigma_pq[:, :, i, j] = hp[:, :, i] * rq[:, :, j] - hq[:, :, j] * rp[:, :, i]

print(sigma_pq.shape)

class dicee.**DualE**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Dual Quaternion Knowledge Graph Embeddings (https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657)

name = 'DualE'

entity_embeddings

relation_embeddings

num_ent

kvsall_score(*e_1_h*, *e_2_h*, *e_3_h*, *e_4_h*, *e_5_h*, *e_6_h*, *e_7_h*, *e_8_h*, *e_1_t*, *e_2_t*, *e_3_t*, *e_4_t*, *e_5_t*, *e_6_t*, *e_7_t*, *e_8_t*, *r_1*, *r_2*, *r_3*, *r_4*, *r_5*, *r_6*, *r_7*, *r_8*) → torch.tensor

KvsAll scoring function

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

forward_triples(*idx_triple: torch.tensor*) → torch.tensor

Negative Sampling forward pass:

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

forward_k_vs_all(*x*)

KvsAll forward pass

Input

x: torch.LongTensor with (n,) shape

Output

torch.FloatTensor with (n) shape

T (*x: torch.tensor*) → torch.tensor

Transpose function

Input: Tensor with shape (nxm) Output: Tensor with shape (mxn)

class dicee.**ComplEx**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ⓘ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

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> **Variables**
>> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'ComplEx'

static score (*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*,
tail_ent_emb: torch.FloatTensor)

static k_vs_all_score (*emb_h: torch.FloatTensor*, *emb_r: torch.FloatTensor*,
emb_E: torch.FloatTensor)

> **Parameters**
> - **emb_h**
> - **emb_r**
> - **emb_E**

forward_k_vs_all (*x: torch.LongTensor*) → torch.FloatTensor

class dicee.**AConEx** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Additive Convolutional ComplEx Knowledge Graph Embeddings

name = 'AConEx'

conv2d

fc_num_input

fc1

norm_fc1

bn_conv2d

feature_map_dropout

residual_convolution (*C_1: Tuple[torch.Tensor, torch.Tensor]*,
C_2: Tuple[torch.Tensor, torch.Tensor]) → torch.FloatTensor

Compute residual score of two complex-valued embeddings. :param C_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

forward_k_vs_all (*x: torch.Tensor*) → torch.FloatTensor

forward_triples (*x: torch.Tensor*) → torch.FloatTensor

> **Parameters**
>> **x**

forward_k_vs_sample (*x: torch.Tensor*, *target_entity_idx: torch.Tensor*)

class dicee.**AConvO** (*args: dict*)

Bases: *dicee.models.base_model.BaseKGE*

Additive Convolutional Octonion Knowledge Graph Embeddings

name = 'AConvO'

conv2d

fc_num_input

fc1

bn_conv2d

norm_fc1

feature_map_dropout

static octonion_normalizer(*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

residual_convolution(*O_1*, *O_2*)

forward_triples(*x: torch.Tensor*) → torch.Tensor

> **Parameters**
> > **x**

forward_k_vs_all(*x: torch.Tensor*)

> Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, **|Entities|**) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.**AConvQ**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Additive Convolutional Quaternion Knowledge Graph Embeddings

> **name = 'AConvQ'**

> **entity_embeddings**

> **relation_embeddings**

> **conv2d**

> **fc_num_input**

> **fc1**

> **bn_conv1**

> **bn_conv2**

> **feature_map_dropout**

> **residual_convolution**(*Q_1*, *Q_2*)

> **forward_triples**(*indexed_triple: torch.Tensor*) → torch.Tensor

> > **Parameters**
> > > **x**

> **forward_k_vs_all**(*x: torch.Tensor*)

> > Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, **|Entities|**) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.**ConvQ**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Convolutional Quaternion Knowledge Graph Embeddings

name = 'ConvQ'

entity_embeddings

relation_embeddings

conv2d

fc_num_input

fc1

bn_conv1

bn_conv2

feature_map_dropout

residual_convolution(*Q_1*, *Q_2*)

forward_triples(*indexed_triple: torch.Tensor*) → torch.Tensor

> **Parameters**
>> **x**

forward_k_vs_all(*x: torch.Tensor*)

> Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, **|Entities|**) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.**ConvO**(*args: dict*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ℹ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

Variables
    training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'ConvO'

conv2d

fc_num_input

fc1

bn_conv2d

norm_fc1

feature_map_dropout

static octonion_normalizer (*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

residual_convolution (*O_1*, *O_2*)

forward_triples (*x: torch.Tensor*) → torch.Tensor

Parameters
    x

forward_k_vs_all (*x: torch.Tensor*)

Given a head entity and a relation (h,r), we compute scores for all entities. [score(h,r,x)|x in Entities] => [0.0,0.1,…,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.**ConEx** (*args*)

Bases: *dicee.models.base_model.BaseKGE*

Convolutional ComplEx Knowledge Graph Embeddings

name = 'ConEx'

conv2d

fc_num_input

fc1

norm_fc1

bn_conv2d

feature_map_dropout

residual_convolution(*C_1: Tuple[torch.Tensor, torch.Tensor],*
  C_2: Tuple[torch.Tensor, torch.Tensor]) → torch.FloatTensor

> Compute residual score of two complex-valued embeddings. :param C_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

forward_k_vs_all(*x: torch.Tensor*) → torch.FloatTensor

forward_triples(*x: torch.Tensor*) → torch.FloatTensor

> **Parameters**
> **x**

forward_k_vs_sample(*x: torch.Tensor*, *target_entity_idx: torch.Tensor*)

class dicee.**QMult**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*
>
> Base class for all neural network modules.
>
> Your models should also subclass this class.
>
> Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

> Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ⓘ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

> **Variables**
> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'QMult'

explicit = True

quaternion_multiplication_followed_by_inner_product(*h, r, t*)

> **Parameters**
>
> • **h** – shape: (**batch_dims*, dim) The head representations.

- **r** – shape: (**batch_dims*, dim) The head representations.

- **t** – shape: (**batch_dims*, dim) The tail representations.

  Returns

  Triple scores.

static quaternion_normalizer(*x: torch.FloatTensor*) → torch.FloatTensor

Normalize the length of relation vectors, if the forward constraint has not been applied yet.

Absolute value of a quaternion

$$|a + bi + cj + dk| = \sqrt{a^2 + b^2 + c^2 + d^2}$$

L2 norm of quaternion vector:

$$\|x\|^2 = \sum_{i=1}^{d} |x_i|^2 = \sum_{i=1}^{d} (x_i.re^2 + x_i.im_1^2 + x_i.im_2^2 + x_i.im_3^2)$$

  Parameters

  x – The vector.

  Returns

  The normalized vector.

score(*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*,
tail_ent_emb: torch.FloatTensor)

k_vs_all_score(*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

  Parameters

  - **bpe_head_ent_emb**

  - **bpe_rel_ent_emb**

  - **E**

forward_k_vs_all(*x*)

  Parameters

  x

forward_k_vs_sample(*x*, *target_entity_idx*)

Completed. Given a head entity and a relation (h,r), we compute scores for all possible triples,i.e., [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.**OMult**(*args*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```
import torch.nn as nn
import torch.nn.functional as F
```

```python
class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

> **Variables**
> > **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'OMult'

static octonion_normalizer (*emb_rel_e0*, *emb_rel_e1*, *emb_rel_e2*, *emb_rel_e3*, *emb_rel_e4*, *emb_rel_e5*, *emb_rel_e6*, *emb_rel_e7*)

score (*head_ent_emb: torch.FloatTensor*, *rel_ent_emb: torch.FloatTensor*, *tail_ent_emb: torch.FloatTensor*)

k_vs_all_score (*bpe_head_ent_emb*, *bpe_rel_ent_emb*, *E*)

forward_k_vs_all (*x*)

> Completed. Given a head entity and a relation (h,r), we compute scores for all possible triples,i.e., [score(h,r,x)|x in Entities] => [0.0,0.1,...,0.8], shape=> (1, |**Entities**|) Given a batch of head entities and relations => shape (size of batch,| Entities|)

class dicee.**Shallom** (*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> A shallow neural model for relation prediction (https://arxiv.org/abs/2101.09090)

name = 'Shallom'

shallom_width

shallom

get_embeddings () → Tuple[numpy.ndarray, None]

forward_k_vs_all (*x*) → torch.FloatTensor

forward_triples (*x*) → torch.FloatTensor

> > **Parameters**
> > > **x**
> > **Returns**

class dicee.**LFMult**(*args*)

> Bases: *dicee.models.base_model.BaseKGE*

> Embedding with polynomial functions. We represent all entities and relations in the polynomial space as: $f(x) = \sum_{i=0}^{d-1} a_k x^{i\%d}$ and use the three differents scoring function as in the paper to evaluate the score. We also consider combining with Neural Networks.

> **name = 'LFMult'**

> **entity_embeddings**

> **relation_embeddings**

> **degree**

> **m**

> **x_values**

> **forward_triples**(*idx_triple*)

>> **Parameters**
>>> **x**

> **construct_multi_coeff**(*x*)

> **poly_NN**(*x*, *coefh*, *coefr*, *coeft*)

>> Constructing a 2 layers NN to represent the embeddings. $h = sigma(wh^T x + bh)$, $r = sigma(wr^T x + br)$, $t = sigma(wt^T x + bt)$

> **linear**(*x*, *w*, *b*)

> **scalar_batch_NN**(*a*, *b*, *c*)

>> element wise multiplication between a,b and c: Inputs : a, b, c ====> torch.tensor of size batch_size x m x d Output : a tensor of size batch_size x d

> **tri_score**(*coeff_h*, *coeff_r*, *coeff_t*)

>> this part implement the trilinear scoring techniques:

>> $score(h,r,t) = \int_{0}^{1} h(x)r(x)t(x)\, dx = \sum_{i,j,k=0}^{d-1} \dfrac{a_i * b_j * c_k}{1+(i+j+k)\%d}$

>> 1. generate the range for i,j and k from [0 d-1]

>> 2. perform $\dfrac{a_i * b_j * c_k}{1+(i+j+k)\%d}$ in parallel for every batch

>> 3. take the sum over each batch

> **vtp_score**(*h*, *r*, *t*)

>> this part implement the vector triple product scoring techniques:

>> $score(h,r,t) = \int_{0}^{1} h(x)r(x)t(x)\, dx = \sum_{i,j,k=0}^{d-1} \dfrac{a_i * c_j * b_k - b_i * c_j * a_k}{(1+(i+j)\%d)(1+k)}$

>> 1. generate the range for i,j and k from [0 d-1]

>> 2. Compute the first and second terms of the sum

>> 3. Multiply with then denominator and take the sum

>> 4. take the sum over each batch

> **comp_func**(*h*, *r*, *t*)

>> this part implement the function composition scoring techniques: i.e. score = <hor, t>

polynomial (*coeff*, *x*, *degree*)

    This function takes a matrix tensor of coefficients (coeff), a tensor vector of points x and range of integer [0,1,…d] and return a vector tensor (coeff[0][0] + coeff[0][1]x +…+ coeff[0][d]x^d,

        coeff[1][0] + coeff[1][1]x +…+ coeff[1][d]x^d)

pop (*coeff*, *x*, *degree*)

    This function allow us to evaluate the composition of two polynomes without for loops :) it takes a matrix tensor of coefficients (coeff), a matrix tensor of points x and range of integer [0,1,…d]

        and return a tensor (coeff[0][0] + coeff[0][1]x +…+ coeff[0][d]x^d,

        coeff[1][0] + coeff[1][1]x +…+ coeff[1][d]x^d)

class dicee.**PykeenKGE** (*args: dict*)

    Bases: *dicee.models.base_model.BaseKGE*

    A class for using knowledge graph embedding models implemented in Pykeen

    Notes: Pykeen_DistMult: C Pykeen_ComplEx: Pykeen_QuatE: Pykeen_MuRE: Pykeen_CP: Pykeen_HolE: Pykeen_HolE:

    model_kwargs

    name

    model

    loss_history = []

    args

    entity_embeddings = None

    relation_embeddings = None

    forward_k_vs_all (*x: torch.LongTensor*)

        # => Explicit version by this we can apply bn and dropout

        # (1) Retrieve embeddings of heads and relations + apply Dropout & Normalization if given. h, r = self.get_head_relation_representation(x) # (2) Reshape (1). if self.last_dim > 0:

            h = h.reshape(len(x), self.embedding_dim, self.last_dim) r = r.reshape(len(x), self.embedding_dim, self.last_dim)

        # (3) Reshape all entities. if self.last_dim > 0:

            t = self.entity_embeddings.weight.reshape(self.num_entities, self.embedding_dim, self.last_dim)

        else:
            t = self.entity_embeddings.weight

        # (4) Call the score_t from interactions to generate triple scores. return self.interaction.score_t(h=h, r=r, all_entities=t, slice_size=1)

    forward_triples (*x: torch.LongTensor*) → torch.FloatTensor

        # => Explicit version by this we can apply bn and dropout

        # (1) Retrieve embeddings of heads, relations and tails and apply Dropout & Normalization if given. h, r, t = self.get_triple_representation(x) # (2) Reshape (1). if self.last_dim > 0:

h = h.reshape(len(x), self.embedding_dim, self.last_dim) r = r.reshape(len(x), self.embedding_dim, self.last_dim) t = t.reshape(len(x), self.embedding_dim, self.last_dim)

(3) Compute the triple score return self.interaction.score(h=h, r=r, t=t, slice_size=None, slice_dim=0)

abstract **forward_k_vs_sample**(*x: torch.LongTensor*, *target_entity_idx*)

class dicee.**BytE**(**args*, ***kwargs*)

Bases: *dicee.models.base_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call to(), etc.

> **ⓘ Note**
>
> As per the example above, an __init__() call to the parent class must be made before assignment on the child.

> **Variables**
> **training** (*bool*) – Boolean represents whether this module is in training or evaluation mode.

name = 'BytE'

config

temperature = 0.5

topk = 2

transformer

lm_head

weight

loss_function(*yhat_batch*, *y_batch*)

> **Parameters**

- **yhat_batch**

- **y_batch**

forward(*x: torch.LongTensor*)

> **Parameters**
> > **x**(*B by T tensor*)

generate(*idx*, *max_new_tokens*, *temperature=1.0*, *top_k=None*)

Take a conditioning sequence of indices idx (LongTensor of shape (b,t)) and complete the sequence max_new_tokens times, feeding the predictions back into the model each time. Most likely you'll want to make sure to be in model.eval() mode of operation for this.

training_step(*batch*, *batch_idx=None*)

Here you compute and return the training loss and some additional metrics for e.g. the progress bar or logger.

> **Parameters**
>
> - **batch** – The output of your data iterable, normally a `DataLoader`.
>
> - **batch_idx** – The index of this batch.
>
> - **dataloader_idx** – The index of the dataloader that produced this batch. (only if multiple dataloaders used)
>
> **Returns**
>
> - `Tensor` - The loss tensor
>
> - `dict` - A dictionary which can include any keys, but must include the key `'loss'` in the case of automatic optimization.
>
> - `None` - In automatic optimization, this will skip to the next batch (but is not supported for multi-GPU, TPU, or DeepSpeed). For manual optimization, this has no special meaning, as returning the loss is not required.

In this step you'd normally do the forward pass and calculate the loss for a batch. You can also do fancier things like multiple forward passes or something model specific.

Example:

```python
def training_step(self, batch, batch_idx):
    x, y, z = batch
    out = self.encoder(x)
    loss = self.loss(out, x)
    return loss
```

To use multiple optimizers, you can switch to 'manual optimization' and control their stepping:

```python
def __init__(self):
    super().__init__()
    self.automatic_optimization = False


# Multiple optimizers (e.g.: GANs)
def training_step(self, batch, batch_idx):
    opt1, opt2 = self.optimizers()

    # do training_step with encoder
    ...
    opt1.step()
```

```
        # do training_step with decoder
        ...
        opt2.step()
```

> **ⓘ Note**
>
> When `accumulate_grad_batches` > 1, the loss returned here will be automatically normalized by `accumulate_grad_batches` internally.

class dicee.**BaseKGE**(*args: dict*)

    Bases: `BaseKGELightning`

    Base class for all neural network modules.

    Your models should also subclass this class.

    Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

```python
import torch.nn as nn
import torch.nn.functional as F

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

    Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

> **ⓘ Note**
>
> As per the example above, an `__init__()` call to the parent class must be made before assignment on the child.

    Variables

        training (*bool*) – Boolean represents whether this module is in training or evaluation mode.

    args

    embedding_dim = None

    num_entities = None

    num_relations = None

    num_tokens = None

learning_rate = None

apply_unit_norm = None

input_dropout_rate = None

hidden_dropout_rate = None

optimizer_name = None

feature_map_dropout_rate = None

kernel_size = None

num_of_output_channels = None

weight_decay = None

loss

selected_optimizer = None

normalizer_class = None

normalize_head_entity_embeddings

normalize_relation_embeddings

normalize_tail_entity_embeddings

hidden_normalizer

param_init

input_dp_ent_real

input_dp_rel_real

hidden_dropout

loss_history = []

byte_pair_encoding

max_length_subword_tokens

block_size

forward_byte_pair_encoded_k_vs_all(*x: torch.LongTensor*)

> **Parameters**
> **x**(*B x 2 x T*)

forward_byte_pair_encoded_triple(*x: Tuple[torch.LongTensor, torch.LongTensor]*)
> byte pair encoded neural link predictors

> **Parameters**
> -------

init_params_with_sanity_checking()

forward(*x: torch.LongTensor | Tuple[torch.LongTensor, torch.LongTensor]*,
y_idx: torch.LongTensor = None)

> **Parameters**
>
> - **x**
> - **y_idx**
> - **ordered_bpe_entities**

forward_triples(*x: torch.LongTensor*) → torch.Tensor

> **Parameters**
> **x**

forward_k_vs_all(**args*, ***kwargs*)

forward_k_vs_sample(**args*, ***kwargs*)

get_triple_representation(*idx_hrt*)

get_head_relation_representation(*indexed_triple*)

get_sentence_representation(*x: torch.LongTensor*)

> **Parameters**
>
> - **(b**(*x shape*)
> - **3**
> - **t)**

get_bpe_head_and_relation_representation(*x: torch.LongTensor*)
→ Tuple[torch.FloatTensor, torch.FloatTensor]

> **Parameters**
> **x**(*B x 2 x T*)

get_embeddings() → Tuple[numpy.ndarray, numpy.ndarray]

dicee.**create_recipriocal_triples**(*x*)

> Add inverse triples into dask dataframe :param x: :return:

dicee.**get_er_vocab**(*data*, *file_path: str = None*)

dicee.**get_re_vocab**(*data*, *file_path: str = None*)

dicee.**get_ee_vocab**(*data*, *file_path: str = None*)

dicee.**timeit**(*func*)

dicee.**save_pickle**(***, *data: object = None*, *file_path=str*)

dicee.**load_pickle**(*file_path=str*)

dicee.**select_model**(*args: dict*, *is_continual_training: bool = None*, *storage_path: str = None*)

dicee.**load_model**(*path_of_experiment_folder: str*, *model_name='model.pt'*, *verbose=0*)
→ Tuple[object, Tuple[dict, dict]]

> Load weights and initialize pytorch module from namespace arguments

dicee.**load_model_ensemble**(*path_of_experiment_folder: str*)
   → Tuple[*dicee.models.base_model.BaseKGE*, Tuple[pandas.DataFrame, pandas.DataFrame]]

 Construct Ensemble Of weights and initialize pytorch module from namespace arguments

  (1) Detect models under given path

  (2) Accumulate parameters of detected models

  (3) Normalize parameters

  (4) Insert (3) into model.

dicee.**save_numpy_ndarray**(***, *data: numpy.ndarray*, *file_path: str*)

dicee.**numpy_data_type_changer**(*train_set: numpy.ndarray*, *num: int*) → numpy.ndarray

 Detect most efficient data type for a given triples :param train_set: :param num: :return:

dicee.**save_checkpoint_model**(*model*, *path: str*) → None

 Store Pytorch model into disk

dicee.**store**(*trainer*, *trained_model*, *model_name: str = 'model'*, *full_storage_path: str = None*,
   save_embeddings_as_csv=False) → None

 Store trained_model model and save embeddings into csv file. :param trainer: an instance of trainer class :param full_storage_path: path to save parameters. :param model_name: string representation of the name of the model. :param trained_model: an instance of BaseKGE see core.models.base_model . :param save_embeddings_as_csv: for easy access of embeddings. :return:

dicee.**add_noisy_triples**(*train_set: pandas.DataFrame*, *add_noise_rate: float*) → pandas.DataFrame

 Add randomly constructed triples :param train_set: :param add_noise_rate: :return:

dicee.**read_or_load_kg**(*args*, *cls*)

dicee.**intialize_model**(*args: dict*, *verbose=0*) → Tuple[object, str]

dicee.**load_json**(*p: str*) → dict

dicee.**save_embeddings**(*embeddings: numpy.ndarray*, *indexes*, *path: str*) → None

 Save it as CSV if memory allows. :param embeddings: :param indexes: :param path: :return:

dicee.**random_prediction**(*pre_trained_kge*)

dicee.**deploy_triple_prediction**(*pre_trained_kge*, *str_subject*, *str_predicate*, *str_object*)

dicee.**deploy_tail_entity_prediction**(*pre_trained_kge*, *str_subject*, *str_predicate*, *top_k*)

dicee.**deploy_head_entity_prediction**(*pre_trained_kge*, *str_object*, *str_predicate*, *top_k*)

dicee.**deploy_relation_prediction**(*pre_trained_kge*, *str_subject*, *str_object*, *top_k*)

dicee.**vocab_to_parquet**(*vocab_to_idx*, *name*, *path_for_serialization*, *print_into*)

dicee.**create_experiment_folder**(*folder_name='Experiments'*)

dicee.**continual_training_setup_executor**(*executor*) → None

 storage_path:str A path leading to a parent directory, where a subdirectory containing KGE related data

 full_storage_path:str A path leading to a subdirectory containing KGE related data

dicee.**exponential_function**(*x: numpy.ndarray*, *lam: float*, *ascending_order=True*)
   → torch.FloatTensor

dicee.**load_numpy**(*path*) → numpy.ndarray

dicee.**evaluate**(*entity_to_idx*, *scores*, *easy_answers*, *hard_answers*)
> # @TODO: CD: Renamed this function Evaluate multi hop query answering on different query types

dicee.**download_file**(*url*, *destination_folder='.'*)

dicee.**download_files_from_url**(*base_url: str*, *destination_folder='.'*) → None

> **Parameters**
>
> - **base_url** (e.g. "https://files.dice-research.org/projects/DiceEmbeddings/KINSHIP-Keci-dim128-epoch256-KvsAll")
>
> - **destination_folder**(*e.g. "KINSHIP-Keci-dim128-epoch256-KvsAll"*)

dicee.**download_pretrained_model**(*url: str*) → str

class dicee.**DICE_Trainer**(*args*, *is_continual_training*, *storage_path*, *evaluator=None*)

> **DICE_Trainer implement**
> 1- Pytorch Lightning trainer (https://pytorch-lightning.readthedocs.io/en/stable/common/trainer.html)
> 2- Multi-GPU Trainer(https://pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.html) 3- CPU Trainer
>
> args
>
> is_continual_training:bool
>
> storage_path:str
>
> evaluator:
>
> report:dict

> **report**

> **args**

> **trainer = None**

> **is_continual_training**

> **storage_path**

> **evaluator**

> **form_of_labelling = None**

> **continual_start**()
>
> > (1) Initialize training.
> >
> > (2) Load model
> >
> > (3) Load trainer (3) Fit model

Parameter

> **returns**
> - *model*
> - **form_of_labelling** (*str*)

initialize_trainer (*callbacks: List*) → lightning.Trainer
> Initialize Trainer from input arguments

initialize_or_load_model ()

initialize_dataloader (*dataset: torch.utils.data.Dataset*) → torch.utils.data.DataLoader

initialize_dataset (*dataset: dicee.knowledge_graph.KG*, *form_of_labelling*)
> → torch.utils.data.Dataset

start (*knowledge_graph: dicee.knowledge_graph.KG*) → Tuple[*dicee.models.base_model.BaseKGE*, str]
> Train selected model via the selected training strategy

k_fold_cross_validation (*dataset*) → Tuple[*dicee.models.base_model.BaseKGE*, str]
> Perform K-fold Cross-Validation

> 1. Obtain K train and test splits.
>
> 2. **For each split,**
>   2.1 initialize trainer and model 2.2. Train model with configuration provided in args. 2.3. Compute the mean reciprocal rank (MRR) score of the model on the test respective split.
>
> 3. Report the mean and average MRR .

> **Parameters**
> - **self**
> - **dataset**

> **Returns**
> model

class dicee.**KGE** (*path=None*, *url=None*, *construct_ensemble=False*, *model_name=None*)
> Bases: *dicee.abstracts.BaseInteractiveKGE*

> Knowledge Graph Embedding Class for interactive usage of pre-trained models

> **__str__** ()

to (*device: str*) → None

get_transductive_entity_embeddings (*indices: torch.LongTensor | List[str]*,
> *as_pytorch=False*, *as_numpy=False*, *as_list=True*)
> → torch.FloatTensor | numpy.ndarray | List[float]

create_vector_database (*collection_name: str*, *distance: str*, *location: str = 'localhost'*,
> *port: int = 6333*)

generate (*h=''*, *r=''*)

eval_lp_performance (*dataset=List[Tuple[str, str, str]]*, *filtered=True*)

predict_missing_head_entity (*relation: List[str] | str*, *tail_entity: List[str] | str*, *within=None*)
   $\rightarrow$ Tuple

Given a relation and a tail entity, return top k ranked head entity.

argmax_{e in E } f(e,r,t), where r in R, t in E.

Parameter

relation: Union[List[str], str]

String representation of selected relations.

tail_entity: Union[List[str], str]

String representation of selected entities.

k: int

Highest ranked k entities.

Returns: Tuple

Highest K scores and entities

predict_missing_relations (*head_entity: List[str] | str*, *tail_entity: List[str] | str*, *within=None*)
   $\rightarrow$ Tuple

Given a head entity and a tail entity, return top k ranked relations.

argmax_{r in R } f(h,r,t), where h, t in E.

Parameter

head_entity: List[str]

String representation of selected entities.

tail_entity: List[str]

String representation of selected entities.

k: int

Highest ranked k entities.

Returns: Tuple

Highest K scores and entities

predict_missing_tail_entity (*head_entity: List[str] | str*, *relation: List[str] | str*,
   within: List[str] = None) $\rightarrow$ torch.FloatTensor

Given a head entity and a relation, return top k ranked entities

argmax_{e in E } f(h,r,e), where h in E and r in R.

Parameter

head_entity: List[str]

String representation of selected entities.

tail_entity: List[str]

String representation of selected entities.

Returns: Tuple

scores

predict (*, *h: List[str] | str = None*, *r: List[str] | str = None*, *t: List[str] | str = None*, *within=None*, *logits=True*) → torch.FloatTensor

Parameters

- **logits**
- **h**
- **r**
- **t**
- **within**

predict_topk (*, *h: str | List[str] = None*, *r: str | List[str] = None*, *t: str | List[str] = None*, *topk: int = 10*, *within: List[str] = None*)

Predict missing item in a given triple.

Parameter

head_entity: Union[str, List[str]]

String representation of selected entities.

relation: Union[str, List[str]]

String representation of selected relations.

tail_entity: Union[str, List[str]]

String representation of selected entities.

k: int

Highest ranked k item.

Returns: Tuple

Highest K scores and items

triple_score (*h: List[str] | str = None*, *r: List[str] | str = None*, *t: List[str] | str = None*, *logits=False*) → torch.FloatTensor

Predict triple score

Parameter

head_entity: List[str]

String representation of selected entities.

relation: List[str]

String representation of selected relations.

tail_entity: List[str]

String representation of selected entities.

logits: bool

If logits is True, unnormalized score returned

Returns: Tuple

pytorch tensor of triple score

t_norm (*tens_1: torch.Tensor*, *tens_2: torch.Tensor*, *tnorm: str = 'min'*) → torch.Tensor

tensor_t_norm (*subquery_scores: torch.FloatTensor*, *tnorm: str = 'min'*) → torch.FloatTensor

Compute T-norm over $[0,1]$ ^{n imes d} where n denotes the number of hops and d denotes number of entities

t_conorm (*tens_1: torch.Tensor*, *tens_2: torch.Tensor*, *tconorm: str = 'min'*) → torch.Tensor

negnorm (*tens_1: torch.Tensor*, *lambda_: float*, *neg_norm: str = 'standard'*) → torch.Tensor

return_multi_hop_query_results (*aggregated_query_for_all_entities*, *k: int*, *only_scores*)

single_hop_query_answering (*query: tuple*, *only_scores: bool = True*, *k: int = None*)

answer_multi_hop_query (*query_type: str = None*,
query: Tuple[str | Tuple[str, str], Ellipsis] = None,
queries: List[Tuple[str | Tuple[str, str], Ellipsis]] = None, *tnorm: str = 'prod'*,
neg_norm: str = 'standard', *lambda_: float = 0.0*, *k: int = 10*, *only_scores=False*)
→ List[Tuple[str, torch.Tensor]]

@TODO: Refactoring is needed # @TODO: Score computation for each query type should be done in a static function

Find an answer set for EPFO queries including negation and disjunction

Parameter

query_type: str The type of the query, e.g., "2p".

query: Union[str, Tuple[str, Tuple[str, str]]] The query itself, either a string or a nested tuple.

queries: List of Tuple[Union[str, Tuple[str, str]], …]

tnorm: str The t-norm operator.

neg_norm: str The negation norm.

lambda_: float lambda parameter for sugeno and yager negation norms

k: int The top-k substitutions for intermediate variables.

> **returns**
>
> - *List[Tuple[str, torch.Tensor]]*
>
> - *Entities and corresponding scores sorted in the descening order of scores*

find_missing_triples (*confidence: float, entities: List[str] = None, relations: List[str] = None, topk: int = 10, at_most: int = sys.maxsize*) → Set

> Find missing triples
>
> Iterative over a set of entities E and a set of relation R :

orall e in E and orall r in R f(e,r,x)

> Return (e,r,x)

otin G and f(e,r,x) > confidence

> confidence: float
>
> A threshold for an output of a sigmoid function given a triple.
>
> topk: int
>
> Highest ranked k item to select triples with f(e,r,x) > confidence .
>
> at_most: int
>
> Stop after finding at_most missing triples
>
> {(e,r,x) | f(e,r,x) > confidence land (e,r,x)}

> otin G

deploy (*share: bool = False, top_k: int = 10*)

train_triples (*h: List[str], r: List[str], t: List[str], labels: List[float], iteration=2, optimizer=None*)

train_k_vs_all (*h, r, iteration=1, lr=0.001*)
> Train k vs all :param head_entity: :param relation: :param iteration: :param lr: :return:

train (*kg, lr=0.1, epoch=10, batch_size=32, neg_sample_ratio=10, num_workers=1*) → None
> Retrained a pretrain model on an input KG via negative sampling.

class dicee.**Execute** (*args, continuous_training=False*)

A class for Training, Retraining and Evaluation a model.

(1) Loading & Preprocessing & Serializing input data.

(2) Training & Validation & Testing

(3) Storing all necessary info

args

is_continual_training

trainer = None

trained_model = None

knowledge_graph = None

report

evaluator = None

start_time = None

read_or_load_kg()

read_preprocess_index_serialize_data() → None

Read & Preprocess & Index & Serialize Input Data

(1) Read or load the data from disk into memory.

(2) Store the statistics of the data.

Parameter

rtype

None

load_indexed_data() → None

Load the indexed data from disk into memory

Parameter

rtype

None

save_trained_model() → None

Save a knowledge graph embedding model

(1) Send model to eval mode and cpu.

(2) Store the memory footprint of the model.

(3) Save the model into disk.

(4) Update the stats of KG again ?

> **rtype**
> None

end (*form_of_labelling: str*) → dict

> End training
>
> (1) Store trained model.
>
> (2) Report runtimes.
>
> (3) Eval model if required.

> **Parameter**
>
> > **rtype**
> > A dict containing information about the training and/or evaluation

write_report () → None

> Report training related information in a report.json file

start () → dict

> Start training
>
> # (1) Loading the Data # (2) Create an evaluator object. # (3) Create a trainer object. # (4) Start the training

> **Parameter**
>
> > **rtype**
> > A dict containing information about the training and/or evaluation

dicee.**mapping_from_first_two_cols_to_third** (*train_set_idx*)

dicee.**timeit** (*func*)

dicee.**load_pickle** (*file_path=str*)

dicee.**reload_dataset** (*path: str*, *form_of_labelling*, *scoring_technique*, *neg_ratio*, *label_smoothing_rate*)

> Reload the files from disk to construct the Pytorch dataset

dicee.**construct_dataset** (***, *train_set: numpy.ndarray | list*, *valid_set=None*, *test_set=None*, *ordered_bpe_entities=None*, *train_target_indices=None*, *target_dim: int = None*, *entity_to_idx: dict*, *relation_to_idx: dict*, *form_of_labelling: str*, *scoring_technique: str*, *neg_ratio: int*, *label_smoothing_rate: float*, *byte_pair_encoding=None*, *block_size: int = None*) → torch.utils.data.Dataset

class dicee.**BPE_NegativeSamplingDataset** (*train_set: torch.LongTensor*, *ordered_shaped_bpe_entities: torch.LongTensor*, *neg_ratio: int*)

Bases: torch.utils.data.Dataset

An abstract class representing a Dataset.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite __getitem__(), supporting fetching a data sample for a given key. Subclasses could also optionally overwrite __len__(), which is expected to return the size of the dataset by many Sampler implementations and the

default options of `DataLoader`. Subclasses could also optionally implement `__getitems__()`, for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

> **ⓘ Note**
>
> `DataLoader` by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

train_set

ordered_bpe_entities

num_bpe_entities

neg_ratio

num_datapoints

__len__()

__getitem__(*idx*)

collate_fn(*batch_shaped_bpe_triples: List[Tuple[torch.Tensor, torch.Tensor]]*)

class dicee.**MultiLabelDataset**(*train_set: torch.LongTensor*, *train_indices_target: torch.LongTensor*, *target_dim: int*, *torch_ordered_shaped_bpe_entities: torch.LongTensor*)

Bases: `torch.utils.data.Dataset`

An abstract class representing a `Dataset`.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite *__getitem__()*, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite *__len__()*, which is expected to return the size of the dataset by many `Sampler` implementations and the default options of `DataLoader`. Subclasses could also optionally implement `__getitems__()`, for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

> **ⓘ Note**
>
> `DataLoader` by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

train_set

train_indices_target

target_dim

num_datapoints

torch_ordered_shaped_bpe_entities

collate_fn = None

__len__()

__getitem__(*idx*)

class dicee.**MultiClassClassificationDataset**(*subword_units: numpy.ndarray*,
          block_size: int = 8)

    Bases: `torch.utils.data.Dataset`

    Dataset for the 1vsALL training strategy

        Parameters

- **train_set_idx** – Indexed triples for the training.

- **entity_idxs** – mapping.

- **relation_idxs** – mapping.

- **form** – ?

- **num_workers** – int for https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

        Return type

           torch.utils.data.Dataset

    train_data

    block_size

    num_of_data_points

    collate_fn = None

    __len__()

    __getitem__(*idx*)

class dicee.**OnevsAllDataset**(*train_set_idx: numpy.ndarray*, *entity_idxs*)

    Bases: `torch.utils.data.Dataset`

    Dataset for the 1vsALL training strategy

        Parameters

- **train_set_idx** – Indexed triples for the training.

- **entity_idxs** – mapping.

- **relation_idxs** – mapping.

- **form** – ?

- **num_workers** – int for https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

        Return type

           torch.utils.data.Dataset

    train_data

    target_dim

    collate_fn = None

    __len__()

    __getitem__(*idx*)

class dicee.**KvsAll**(*train_set_idx: numpy.ndarray*, *entity_idxs*, *relation_idxs*, *form*, *store=None*,
        label_smoothing_rate: float = 0.0)

   Bases: `torch.utils.data.Dataset`

   Creates a dataset for KvsAll training by inheriting from torch.utils.data.Dataset.
       Let D denote a dataset for KvsAll training and be defined as D:= {(x,y)_i}_i ^N, where x: (h,r) is an unique
       tuple of an entity h in E and a relation r in R that has been seed in the input graph. y: denotes a multi-label
       vector in [0,1]^{|**E**|} is a binary label.

   orall y_i =1 s.t. (h r E_i) in KG

   > ℹ️ **Note**
   >
   > TODO

   train_set_idx
       [numpy.ndarray] n by 3 array representing n triples

   entity_idxs
       [dictonary] string representation of an entity to its integer id

   relation_idxs
       [dictonary] string representation of a relation to its integer id

   self : torch.utils.data.Dataset

   ```
   >>> a = KvsAll()
   >>> a
   ? array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
   ```

   train_data = None

   train_target = None

   label_smoothing_rate

   collate_fn = None

   __len__()

   __getitem__(*idx*)

class dicee.**AllvsAll**(*train_set_idx: numpy.ndarray*, *entity_idxs*, *relation_idxs*,
        label_smoothing_rate=0.0)

   Bases: `torch.utils.data.Dataset`

   Creates a dataset for AllvsAll training by inheriting from torch.utils.data.Dataset.
       Let D denote a dataset for AllvsAll training and be defined as D:= {(x,y)_i}_i ^N, where x: (h,r) is a possible
       unique tuple of an entity h in E and a relation r in R. Hence N = |**E**| x |**R**| y: denotes a multi-label vector in
       [0,1]^{|**E**|} is a binary label.

   orall y_i =1 s.t. (h r E_i) in KG

   > ℹ️ **Note**

> **AllvsAll extends KvsAll via none existing (h,r). Hence, it adds data points that are labelled without 1s,**
>> only with 0s.

train_set_idx
> [numpy.ndarray] n by 3 array representing n triples

entity_idxs
> [dictonary] string representation of an entity to its integer id

relation_idxs
> [dictonary] string representation of a relation to its integer id

self : torch.utils.data.Dataset

```
>>> a = AllvsAll()
>>> a
? array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

train_data = None

train_target = None

label_smoothing_rate

collate_fn = None

target_dim

store

__len__()

__getitem__(*idx*)

class dicee.**KvsSampleDataset**(*train_set: numpy.ndarray*, *num_entities*, *num_relations*, *neg_sample_ratio: int = None*, *label_smoothing_rate: float = 0.0*)

Bases: torch.utils.data.Dataset

> **KvsSample a Dataset:**
>
>> **D:= {(x,y)_i}_i ^N, where**
>>> . x:(h,r) is a unique h in E and a relation r in R and . y in [0,1]^{$|E|$} is a binary label.

orall y_i =1 s.t. (h r E_i) in KG

> **At each mini-batch construction, we subsample(y), hence n**
>> $|new\_y|$ << $|E|$ new_y contains all 1's if sum(y)< neg_sample ratio new_y contains

train_set_idx
> Indexed triples for the training.

entity_idxs
> mapping.

relation_idxs
> mapping.

form
> ?

store
> ?

label_smoothing_rate
> ?

torch.utils.data.Dataset

train_data

num_entities

num_relations

neg_sample_ratio

label_smoothing_rate

collate_fn = None

store

train_target

__len__()

__getitem__(*idx*)

class dicee.**NegSampleDataset**(*train_set: numpy.ndarray*, *num_entities: int*, *num_relations: int*, *neg_sample_ratio: int = 1*)

Bases: torch.utils.data.Dataset

An abstract class representing a Dataset.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite *__getitem__()*, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite *__len__()*, which is expected to return the size of the dataset by many Sampler implementations and the default options of DataLoader. Subclasses could also optionally implement __getitems__(), for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

> **ⓘ Note**
>
> DataLoader by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

neg_sample_ratio

train_set

length

num_entities

num_relations

__len__()

__getitem__(*idx*)

class dicee.**TriplePredictionDataset**(*train_set: numpy.ndarray*, *num_entities: int*,
    num_relations: int, *neg_sample_ratio: int = 1*, *label_smoothing_rate: float = 0.0*)

Bases: `torch.utils.data.Dataset`

Triple Dataset

> **D:= {(x)_i}_i ^N, where**
> . x:(h,r, t) in KG is a unique h in E and a relation r in R and . collact_fn => Generates
> negative triples

collect_fn:

orall (h,r,t) in G obtain, create negative triples{(h,r,x),(,r,t),(h,m,t)}

> y:labels are represented in torch.float16

train_set_idx
  Indexed triples for the training.

entity_idxs
  mapping.

relation_idxs
  mapping.

form
  ?

store
  ?

label_smoothing_rate

collate_fn: batch:List[torch.IntTensor] Returns ——- torch.utils.data.Dataset

label_smoothing_rate

neg_sample_ratio

train_set

length

num_entities

num_relations

__len__()

__getitem__(*idx*)

collate_fn(*batch: List[torch.Tensor]*)

class dicee.**CVDataModule**(*train_set_idx: numpy.ndarray*, *num_entities*, *num_relations*,
    neg_sample_ratio, *batch_size*, *num_workers*)

Bases: `pytorch_lightning.LightningDataModule`

Create a Dataset for cross validation

Parameters

- **train_set_idx** – Indexed triples for the training.

- **num_entities** – entity to index mapping.

- **num_relations** – relation to index mapping.

- **batch_size** – int

- **form** – ?

- **num_workers** – int for https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader

Return type

?

train_set_idx

num_entities

num_relations

neg_sample_ratio

batch_size

num_workers

train_dataloader() → torch.utils.data.DataLoader

An iterable or collection of iterables specifying training samples.

For more information about multiple dataloaders, see this section.

The dataloader you return will not be reloaded unless you set **:param-ref:`~pytorch_lightning.trainer.trainer.Trainer.reload_dataloaders_every_n_epochs`** to a positive integer.

For data processing use the following pattern:

- download in *prepare_data()*

- process and split in *setup()*

However, the above are only necessary for distributed processing.

> ⚠️ **Warning**
>
> do not assign state in prepare_data

- fit()
- *prepare_data()*
- *setup()*

> **ⓘ Note**
>
> Lightning tries to add the correct sampler for distributed and arbitrary hardware. There is no need to set it yourself.

setup(**args*, ***kwargs*)

Called at the beginning of fit (train + validate), validate, test, or predict. This is a good hook when you need to build models dynamically or adjust something about them. This hook is called on every process when using DDP.

> **Parameters**
>
> **stage** – either `'fit'`, `'validate'`, `'test'`, or `'predict'`

Example:

```python
class LitModel(...):
    def __init__(self):
        self.l1 = None

    def prepare_data(self):
        download_data()
        tokenize()

        # don't do this
        self.something = else

    def setup(self, stage):
        data = load_data(...)
        self.l1 = nn.Linear(28, data.num_classes)
```

transfer_batch_to_device(**args*, ***kwargs*)

Override this hook if your `DataLoader` returns tensors wrapped in a custom data structure.

The data types listed below (and any arbitrary nesting of them) are supported out of the box:

- `torch.Tensor` or anything that implements *.to(…)*
- `list`
- `dict`
- `tuple`

For anything else, you need to define how the data is moved to the target device (CPU, GPU, TPU, …).

> **ⓘ Note**
>
> This hook should only transfer the data and not modify it, nor should it move the data to any other device than the one passed in as argument (unless you know what you are doing). To check the current state of execution of this hook you can use `self.trainer.training/testing/validating/predicting` so that you can add different logic as per your requirement.

> **Parameters**
>
> - **batch** – A batch of data that needs to be transferred to a new device.
> - **device** – The target device as defined in PyTorch.

- **dataloader_idx** – The index of the dataloader to which the batch belongs.

Returns

A reference to the data on the new device.

Example:

```python
def transfer_batch_to_device(self, batch, device, dataloader_idx):
    if isinstance(batch, CustomBatch):
        # move all tensors in your custom data structure to the device
        batch.samples = batch.samples.to(device)
        batch.targets = batch.targets.to(device)
    elif dataloader_idx == 0:
        # skip device transfer for the first dataloader or anything you wish
        pass
    else:
        batch = super().transfer_batch_to_device(batch, device, dataloader_
        ↪idx)
    return batch
```

↪ **See also**

- move_data_to_device()

- apply_to_collection()

prepare_data(**args*, ***kwargs*)

Use this to download and prepare data. Downloading and saving data with multiple processes (distributed settings) will result in corrupted data. Lightning ensures this method is called only within a single process, so you can safely add your downloading logic within.

⚠ **Warning**

DO NOT set state to the model (use `setup` instead) since this is NOT called on every device

Example:

```python
def prepare_data(self):
    # good
    download_data()
    tokenize()
    etc()

    # bad
    self.split = data_split
    self.some_state = some_other_state()
```

In a distributed environment, `prepare_data` can be called in two ways (using prepare_data_per_node)

1. Once per node. This is the default and is only called on LOCAL_RANK=0.

2. Once in total. Only called on GLOBAL_RANK=0.

Example:

```python
# DEFAULT
# called once per node on LOCAL_RANK=0 of that node
class LitDataModule(LightningDataModule):
    def __init__(self):
        super().__init__()
        self.prepare_data_per_node = True


# call on GLOBAL_RANK=0 (great for shared file systems)
class LitDataModule(LightningDataModule):
    def __init__(self):
        super().__init__()
        self.prepare_data_per_node = False
```

This is called before requesting the dataloaders:

```
model.prepare_data()
initialize_distributed()
model.setup(stage)
model.train_dataloader()
model.val_dataloader()
model.test_dataloader()
model.predict_dataloader()
```

class dicee.**QueryGenerator** (*train_path*, *val_path: str*, *test_path: str*, *ent2id: Dict = None*,
    rel2id: Dict = None, *seed: int = 1*, *gen_valid: bool = False*, *gen_test: bool = True*)

train_path

val_path

test_path

gen_valid

gen_test

seed

max_ans_num = 1000000.0

mode

ent2id

rel2id: Dict

ent_in: Dict

ent_out: Dict

query_name_to_struct

list2tuple (*list_data*)

tuple2list (*x: List | Tuple*) → List | Tuple

Convert a nested tuple to a nested list.

set_global_seed(*seed: int*)

    Set seed

construct_graph(*paths: List[str]*) → Tuple[Dict, Dict]

    Construct graph from triples Returns dicts with incoming and outgoing edges

fill_query(*query_structure: List[str | List], ent_in: Dict, ent_out: Dict, answer: int*) → bool

    Private method for fill_query logic.

achieve_answer(*query: List[str | List], ent_in: Dict, ent_out: Dict*) → set

    Private method for achieve_answer logic. @TODO: Document the code

write_links(*ent_out*, *small_ent_out*)

ground_queries(*query_structure: List[str | List], ent_in: Dict, ent_out: Dict, small_ent_in: Dict,*
        small_ent_out: Dict, gen_num: int, query_name: str)

    Generating queries and achieving answers

unmap(*query_type*, *queries*, *tp_answers*, *fp_answers*, *fn_answers*)

unmap_query(*query_structure*, *query*, *id2ent*, *id2rel*)

generate_queries(*query_struct: List, gen_num: int, query_type: str*)

    Passing incoming and outgoing edges to ground queries depending on mode [train valid or text] and getting
    queries and answers in return @ TODO: create a class for each single query struct

save_queries(*query_type: str, gen_num: int, save_path: str*)

abstract load_queries(*path*)

get_queries(*query_type: str, gen_num: int*)

static save_queries_and_answers(*path: str,*
        data: List[Tuple[str, Tuple[collections.defaultdict]]]) → None

    Save Queries into Disk

static load_queries_and_answers(*path: str*)
          → List[Tuple[str, Tuple[collections.defaultdict]]]

    Load Queries from Disk to Memory

dicee.**__version__ = '0.1.5'**

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