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# DICE Embeddings

*Release 0.1.3.2*

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Aug 01, 2025

## Contents:

<b>1</b>	<b>Dicee Manual</b>	<b>2</b>
<b>2</b>	<b>Installation</b>	<b>3</b>
2.1	Installation from Source . . . . .	3
<b>3</b>	<b>Download Knowledge Graphs</b>	<b>3</b>
<b>4</b>	<b>Knowledge Graph Embedding Models</b>	<b>3</b>
<b>5</b>	<b>How to Train</b>	<b>3</b>
<b>6</b>	<b>Creating an Embedding Vector Database</b>	<b>5</b>
6.1	Learning Embeddings . . . . .	5
6.2	Loading Embeddings into Qdrant Vector Database . . . . .	6
6.3	Launching Webservice . . . . .	6
<b>7</b>	<b>Answering Complex Queries</b>	<b>6</b>
<b>8</b>	<b>Predicting Missing Links</b>	<b>8</b>
<b>9</b>	<b>Downloading Pretrained Models</b>	<b>8</b>
<b>10</b>	<b>How to Deploy</b>	<b>8</b>
<b>11</b>	<b>Docker</b>	<b>8</b>
<b>12</b>	<b>Coverage Report</b>	<b>8</b>
<b>13</b>	<b>How to cite</b>	<b>10</b>
<b>14</b>	<b>dicee</b>	<b>12</b>
14.1	Submodules . . . . .	12
14.2	Attributes . . . . .	167
14.3	Classes . . . . .	168
14.4	Functions . . . . .	169
14.5	Package Contents . . . . .	170
	<b>Python Module Index</b>	<b>217</b>

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DICE Embeddings<sup>1</sup>: Hardware-agnostic Framework for Large-scale Knowledge Graph Embeddings:

## 1 Dicee Manual

**Version:** dicee 0.2.0

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

**Publisher and maintainer:** Caglar Demir<sup>2</sup>

**Contact:** [caglar.demir@upb.de](mailto:caglar.demir@upb.de)

**License:** OSI Approved :: MIT License

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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**<sup>3</sup> & Co. to use parallelism at preprocessing a large knowledge graph,
2. **PyTorch**<sup>4</sup> & Co. to learn knowledge graph embeddings via multi-CPU, GPUs, TPUs or computing cluster, and
3. **Huggingface**<sup>5</sup> to ease the deployment of pre-trained models.

**Why Pandas<sup>6</sup> & 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<sup>7</sup> & 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**<sup>8</sup> & **PytorchLightning**<sup>9</sup>. 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<sup>10</sup>?** Deploy a pre-trained embedding model without writing a single line of code.

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<sup>1</sup> <https://github.com/dice-group/dice-embeddings>

<sup>2</sup> <https://github.com/Demirrr>

<sup>3</sup> <https://pandas.pydata.org/>

<sup>4</sup> <https://pytorch.org/>

<sup>5</sup> <https://huggingface.co/>

<sup>6</sup> <https://pandas.pydata.org/>

<sup>7</sup> <https://pytorch.org/>

<sup>8</sup> <https://pytorch.org/>

<sup>9</sup> <https://www.pytorchlightning.ai/>

<sup>10</sup> <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.

```
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
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 automatically detects available GPUs and trains a model with distributed data parallels technique. Under the hood, dicee uses lightning 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 lightning 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': 0.8064032293278861}

# (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': 0.8064032293278861}
```

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
```

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```
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

```
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

```
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/](https://dice-research.org/projects/DiceEmbeddings/)<sup>11</sup>

## 10 How to Deploy

```
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
```

## 12 Coverage Report

The coverage report is generated using `coverage.py`<sup>12</sup>:

Name	Stmts	Miss	Cover	Missing
-----	-----	-----	-----	-----
dicee/___init___ .py	7	0	100%	
dicee/abstracts.py	338	115	66%	112-113, 115

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<sup>11</sup> <https://files.dice-research.org/projects/DiceEmbeddings/>

<sup>12</sup> <https://coverage.readthedocs.io/en/7.6.0/>



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```
→131, 154-155, 160, 173, 197, 240-254, 290, 303-306, 309-313, 353-364, 379-387, 402,
→413-417, 427-428, 434-436, 442-445, 448-453, 576-596, 602-606, 610-612, 631, 658-696
dicee/callbacks.py 248 103 58% 50-55,
→67-73, 76, 88-93, 98-103, 106-109, 116-133, 138-142, 146-147, 247, 281-285, 291-292,
→310-316, 319, 324-325, 337-343, 349-358, 363-365, 410, 421-434, 438-473, 485-491
dicee/config.py 97 2 98% 146-147
dicee/dataset_classes.py 430 146 66% 16, 44,
→57, 89-98, 104, 111-118, 121, 124, 127-151, 207-213, 216, 219-221, 324, 335-338,
→354, 420-421, 439, 562-581, 583, 587-599, 606-615, 618, 622-636, 780-787, 790-794,
→845, 866-878, 902-915, 937, 941-954, 964-967, 973, 985, 987, 989, 1012-1022
dicee/eval_static_funcs.py 256 100 61% 104, 109,
→114, 261-356, 363-414, 442, 465-468
dicee/evaluator.py 267 48 82% 48, 53,
→58, 77, 82-83, 86, 102, 119, 130, 134, 139, 173-184, 191-202, 310, 340-358, 452,
→462, 480-485
dicee/executer.py 134 16 88% 53-57,
→166-176, 235-236, 283
dicee/knowledge_graph.py 82 10 88% 84, 94-
→95, 124, 128, 132-134, 137-138, 140
dicee/knowledge_graph_embeddings.py 654 415 37% 25, 28-
→29, 37-50, 55-88, 91-125, 129-137, 171, 173-229, 261, 265, 276-277, 301-303, 311,
→339-362, 493, 497-519, 523-547, 580, 656, 665, 710-716, 748, 806-1171, 1202-1263,
→1267-1295, 1326, 1332
dicee/models/__init__.py 9 0 100%
dicee/models/adopt.py 187 172 8% 50-86,
→99-110, 129-185, 195-242, 266-322, 346-448, 484-517
dicee/models/base_model.py 240 35 85% 30-35,
→64, 66, 92, 99-116, 171, 204, 244, 250, 259, 262, 266, 273, 277, 279, 294, 307-308,
→362, 365, 438, 450
dicee/models/clifford.py 470 278 41% 10, 12,
→16, 24-25, 52-56, 79-87, 101-103, 108-109, 140-160, 184, 191, 195-256, 273-277, 289,
→292, 297, 302, 346-361, 377-444, 464-470, 483, 486, 491, 496, 525-531, 544, 547,
→552, 557, 567-576, 592-593, 613-685, 696-699, 724-749, 773-806, 842-846, 859, 869,
→872, 877, 882, 887, 891, 895, 904-905, 935, 942, 947, 975-979, 1007-1016, 1026-1034,
→1052-1054, 1072-1074, 1090-1092
dicee/models/complex.py 162 25 85% 86-109,
→273-287
dicee/models/dualE.py 59 10 83% 93-102,
→142-156
dicee/models/ensemble.py 89 67 25% 7-29, 31,
→34, 37, 40, 43, 46, 49, 52-54, 56-58, 64-68, 71-90, 93-94, 97-112, 131
dicee/models/function_space.py 262 221 16% 10-23,
→27-36, 39-48, 52-69, 76-87, 90-99, 102-111, 115-127, 135-157, 160-166, 169-186, 189-
→195, 198-206, 209, 214-235, 244-247, 251-255, 259-268, 272-293, 302-308, 312-329,
→333-336, 345-353, 356, 367-373, 393-407, 425-439, 444-454, 462-466, 475-479
dicee/models/literal.py 33 1 97% 82
dicee/models/octonion.py 227 83 63% 21-44,
→320-329, 334-345, 348-370, 374-416, 426-474
dicee/models/pykeen_models.py 55 5 91% 77-80,
→135
dicee/models/quaternion.py 192 69 64% 7-21, 30-
→55, 68-72, 107, 185, 328-342, 345-364, 368-389, 399-426
```

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dicee/models/real.py	61	12	80%	37-42, ↵
↪70-73, 91, 107-110				
dicee/models/static_funcs.py	10	0	100%	
dicee/models/transformers.py	234	189	19%	20-39, ↵
↪42, 56-71, 80-98, 101-112, 119-121, 124, 130-147, 151-176, 182-186, 189-193, 199-				
↪203, 206-208, 225-252, 261-264, 267-272, 275-300, 306-311, 315-368, 372-394, 400-410				
dicee/query_generator.py	374	346	7%	17-51, ↵
↪55, 61-64, 68-69, 77-91, 99-146, 154-187, 191-205, 211-268, 273-302, 306-442, 452-				
↪471, 479-502, 509-513, 518, 523-529				
dicee/read_preprocess_save_load_kg/___init___py	3	0	100%	
dicee/read_preprocess_save_load_kg/preprocess.py	243	40	84%	33, 39, ↵
↪76, 100-125, 131, 136-149, 175, 205, 380-381				
dicee/read_preprocess_save_load_kg/read_from_disk.py	36	11	69%	34, 38-
↪40, 47, 55, 58-72				
dicee/read_preprocess_save_load_kg/save_load_disk.py	53	21	60%	29-30, ↵
↪38, 47-68				
dicee/read_preprocess_save_load_kg/util.py	236	125	47%	159, 173-
↪175, 179-180, 198-204, 207-209, 214-216, 230, 244-247, 252-260, 265-271, 276-281, ↵				
↪286-291, 303-324, 330-386, 390-394, 398-399, 403, 407-408, 436, 441, 448-449				
dicee/sanity_checkers.py	47	19	60%	8-12, 21-
↪31, 46, 51, 58, 69-79				
dicee/static_funcs.py	483	194	60%	42, 52, ↵
↪58-63, 85, 92-96, 109-119, 129-131, 136, 143, 167, 172, 184, 190, 198, 202, 229-233,				
↪295, 303-309, 320-330, 341-361, 389, 413-414, 419-420, 437-438, 440-441, 443-444, ↵				
↪452, 470-474, 491-494, 498-503, 507-511, 515-516, 522-524, 539-553, 558-561, 566-				
↪569, 578-629, 634-646, 663-680, 683-691, 695-713, 724				
dicee/static_funcs_training.py	155	66	57%	7-10, ↵
↪222-319, 327-328				
dicee/static_preprocess_funcs.py	98	43	56%	17-25, ↵
↪50, 57, 59, 70, 83-107, 112-115, 120-123, 128-131				
dicee/trainer/___init___py	1	0	100%	
dicee/trainer/dice_trainer.py	151	18	88%	22, 30-
↪31, 33-35, 97, 104, 109-114, 152, 237, 280-283				
dicee/trainer/model_parallelism.py	99	87	12%	10-25, ↵
↪30-116, 121-132, 136, 141-197				
dicee/trainer/torch_trainer.py	77	6	92%	31, 102, ↵
↪168, 179-181				
dicee/trainer/torch_trainer_ddp.py	89	71	20%	11-14, ↵
↪43, 47-67, 78-94, 113-122, 126-136, 151-158, 168-191				
-----				
TOTAL	6948	3169	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}
  ↪,
```

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```
    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
```

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```
@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](mailto:caglar.demir@upb.de)

## 14 dicee

### 14.1 Submodules

**dicee.\_\_main\_\_**

**dicee.abstracts**

**Classes**

<i>AbstractTrainer</i>	Abstract class for Trainer class for knowledge graph embedding models
<i>BaseInteractiveKGE</i>	Abstract/base class for using knowledge graph embedding models interactively.
<i>InteractiveQueryDecomposition</i>	
<i>AbstractCallback</i>	Abstract class for Callback class for knowledge graph embedding models
<i>AbstractPPECallback</i>	Abstract class for Callback class for knowledge graph embedding models
<i>BaseInteractiveTrainKGE</i>	Abstract/base class for training knowledge graph embedding models interactively.

### 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

**global\_rank** = 0

**local\_rank** = 0

**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 end 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 = False**

**apply\_semantic\_constraint = False**

**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.InteractiveQueryDecomposition

    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  $[0,1]^{n \times d}$  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

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.

### Parameter

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

**class** dicee.abstracts.**BaseInteractiveTrainKGE**

Abstract/base class for training knowledge graph embedding models interactively. This class provides methods for re-training KGE models and also Literal Embedding model.

**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.

**train\_literals** (*train\_file\_path: str = None, num\_epochs: int = 100, lit\_lr: float = 0.001, lit\_normalization\_type: str = 'z-norm', batch\_size: int = 1024, sampling\_ratio: float = None, random\_seed=1, loader\_backend: str = 'pandas', freeze\_entity\_embeddings: bool = True, gate\_residual: bool = True, device: str = None, shuffle\_data: bool = True*)

Trains the Literal Embeddings model using literal data.

## Parameters

- **train\_file\_path** (*str*) – Path to the training data file.
- **num\_epochs** (*int*) – Number of training epochs.
- **lit\_lr** (*float*) – Learning rate for the literal model.
- **norm\_type** (*str*) – Normalization type to use ('z-norm', 'min-max', or None).
- **batch\_size** (*int*) – Batch size for training.
- **sampling\_ratio** (*float*) – Ratio of training triples to use.
- **loader\_backend** (*str*) – Backend for loading the dataset ('pandas' or 'rdflib').
- **freeze\_entity\_embeddings** (*bool*) – If True, freeze the entity embeddings during training.
- **gate\_residual** (*bool*) – If True, use gate residual connections in the model.
- **device** (*str*) – Device to use for training ('cuda' or 'cpu'). If None, will use available GPU or CPU.
- **shuffle\_data** (*bool*) – If True, shuffle the dataset before training.

## dicee.analyse\_experiments

This script should be moved to dicee/scripts Example: `python dicee/analyse_experiments.py --dir Experiments --features "model" "trainMRR" "testMRR"`

## 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**

<i>AccumulateEpochLossCallback</i>	Abstract class for Callback class for knowledge graph embedding models
<i>PrintCallback</i>	Abstract class for Callback class for knowledge graph embedding models
<i>KGESaveCallback</i>	Abstract class for Callback class for knowledge graph embedding models
<i>PseudoLabellingCallback</i>	Abstract class for Callback class for knowledge graph embedding models
<i>ASWA</i>	Adaptive stochastic weight averaging
<i>Eval</i>	Abstract class for Callback class for knowledge graph embedding models
<i>KronE</i>	Abstract class for Callback class for knowledge graph embedding models
<i>Perturb</i>	A callback for a three-Level Perturbation
<i>PeriodicEvalCallback</i>	Callback to periodically evaluate the model and optionally save checkpoints during training.
<i>LRScheduler</i>	Callback for managing learning rate scheduling and model snapshots.

### **Functions**

<i>estimate_q</i> (eps)	estimate rate of convergence q from sequence esp
<i>compute_convergence</i> (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.

### Parameter

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)

**estimate\_q** (eps)

estimate rate of convergence q from sequence esp

**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 = -1

```

**on\_fit\_end** (*trainer*, *model*)  
 Call at the end of the training.

### Parameter

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 = None`

`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 must be the same. :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** = 'input'

**ratio** = 0.0

**method** = None

**scaler** = None

**frequency** = None

**on\_train\_batch\_start** (*trainer, model, batch, batch\_idx*)

Called when the train batch begins.

```
class dicee.callbacks.PeriodicEvalCallback (experiment_path: str, max_epochs: int,  
                                           eval_every_n_epoch: int = 0, eval_at_epochs: list = None,  
                                           save_model_every_n_epoch: bool = True, n_epochs_eval_model: str = 'val_test')
```

Bases: `dicee.abstracts.AbstractCallback`

Callback to periodically evaluate the model and optionally save checkpoints during training.

Evaluates at regular intervals (every N epochs) or at explicitly specified epochs. Stores evaluation reports and model checkpoints.

**experiment\_dir**

**max\_epochs**

**epoch\_counter** = 0

**save\_model\_every\_n\_epoch** = True

**reports**

**n\_epochs\_eval\_model** = 'val\_test'

**default\_eval\_model** = None

**eval\_epochs**

**on\_fit\_end**(*trainer, model*)

Called at the end of training. Saves final evaluation report.

**on\_train\_epoch\_end**(*trainer, model*)

Called at the end of each training epoch. Performs evaluation and checkpointing if scheduled.

#### Parameters

- **trainer** (*object*) – The training controller.
- **model** (*torch.nn.Module*) – The model being trained.

**class** `dicee.callbacks.LRScheduler` (*adaptive\_lr\_config: dict, total\_epochs: int, experiment\_dir: str, eta\_max: float = 0.1, snapshot\_dir: str = 'snapshots'*)

Bases: `dicee.abstracts.AbstractCallback`

Callback for managing learning rate scheduling and model snapshots.

Supports cosine annealing (“cca”), MMCCLR (“mmcclr”), and their deferred (warmup) variants: - “deferred\_cca” - “deferred\_mmcclr”

At the end of each learning rate cycle, the model can optionally be saved as a snapshot.

**total\_epochs**

**experiment\_dir**

**snapshot\_dir**

**batches\_per\_epoch** = None

**total\_steps** = None

**cycle\_length** = None

**warmup\_steps** = None

**lr\_lambda** = None

```

scheduler = None

step_count = 0

snapshot_loss

on_train_start (trainer, model)
    Initialize training parameters and LR scheduler at start of training.

on_train_batch_end (trainer, model, outputs, batch, batch_idx)
    Step the LR scheduler and save model snapshot if needed after each batch.

on_fit_end (trainer, model)
    Call at the end of the training.

```

### Parameter

```

trainer:
model:
    rtype
        None

```

## dicee.config

### Classes

<i>Namespace</i>	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

**separator: str = '\\s+'**  
separator for extracting head, relation and tail from a triple

**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

**auto\_batch\_finding = False**  
A flag for using auto batch finding

**eval\_every\_n\_epochs: int = 0**  
Evaluate model every n epochs. If 0, no evaluation is applied.

**save\_every\_n\_epochs: bool = False**  
Save model every n epochs. If True, save model at every epoch.

**eval\_at\_epochs: list = None**  
List of epoch numbers at which to evaluate the model (e.g., 1 5 10).

**n\_epochs\_eval\_model: str = 'val\_test'**  
Evaluating link prediction performance on data splits while performing periodic evaluation.

**adaptive\_lr**  
0.1}

**Type**  
Adaptive learning rate parameters, e.g., {"lr\_decay"

**swa\_start\_epoch: int = None**  
Epoch at which to start applying stochastic weight averaging.

**\_\_iter\_\_()**

## **dicee.dataset\_classes**

### **Classes**

<i>BPE_NegativeSamplingDataset</i>	An abstract class representing a Dataset.
<i>MultiLabelDataset</i>	An abstract class representing a Dataset.
<i>MultiClassClassificationDataset</i>	Dataset for the 1vsALL training strategy
<i>OnevsAllDataset</i>	Dataset for the 1vsALL training strategy
<i>KvsAll</i>	Creates a dataset for KvsAll training by inheriting from torch.utils.data.Dataset.
<i>AllvsAll</i>	Creates a dataset for AllvsAll training by inheriting from torch.utils.data.Dataset.
<i>OnevsSample</i>	A custom PyTorch Dataset class for knowledge graph embeddings, which includes
<i>KvsSampleDataset</i>	KvsSample a Dataset:
<i>NegSampleDataset</i>	An abstract class representing a Dataset.
<i>TriplePredictionDataset</i>	Triple Dataset
<i>CVDataModule</i>	Create a Dataset for cross validation
<i>LiteralDataset</i>	Dataset for loading and processing literal data for training Literal Embedding model.

## Functions

<code>reload_dataset(path, form_of_labelling, ...)</code>	Reload the files from disk to construct the Pytorch dataset
<code>construct_dataset(→ torch.utils.data.Dataset)</code>	

## 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_idx`s – mapping.
- `relation_idx`s – 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 = 8`

`num_of_data_points`

```
collate_fn = None
```

```
__len__()
```

```
__getitem__(idx)
```

```
class dicee.dataset_classes.OnevsAllDataset (train_set_idx: numpy.ndarray, entity_idx)
```

Bases: torch.utils.data.Dataset

Dataset for the 1vsALL training strategy

#### Parameters

- **train\_set\_idx** – Indexed triples for the training.
- **entity\_idx** – mapping.
- **relation\_idx** – 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.dataset_classes.KvsAll (train_set_idx: numpy.ndarray, entity_idx, relation_idx, 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 a 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.  $(h \in E_i)$  in KG

#### Note

TODO

**train\_set\_idx**

[numpy.ndarray] n by 3 array representing n triples

**entity\_idx**

[dictionary] string representation of an entity to its integer id

**relation\_idx**

[dictionary] 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_idxes, relation_idxes,
    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  $N = |E| \times |R|$   $y_i$  denotes a multi-label vector in  $[0, 1]^{|E|}$  is a binary label.

forall  $y_i = 1$  s.t.  $(h, r, E_i)$  in KG

#### 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\_idxes**

[dictionary] string representation of an entity to its integer id

**relation\_idxes**

[dictionary] 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`

`__len__()`

`__getitem__(idx)`

```
class dicee.dataset_classes.OnevsSample(train_set: numpy.ndarray, num_entities, num_relations,
                                       neg_sample_ratio: int = None, label_smoothing_rate: float = 0.0)
```

Bases: `torch.utils.data.Dataset`

A custom PyTorch Dataset class for knowledge graph embeddings, which includes both positive and negative sampling for a given dataset for multi-class classification problem..

#### Parameters

- **train\_set** (*np.ndarray*) – A numpy array containing triples of knowledge graph data. Each triple consists of (head\_entity, relation, tail\_entity).
- **num\_entities** (*int*) – The number of unique entities in the knowledge graph.
- **num\_relations** (*int*) – The number of unique relations in the knowledge graph.
- **neg\_sample\_ratio** (*int, optional*) – The number of negative samples to be generated per positive sample. Must be a positive integer and less than num\_entities.
- **label\_smoothing\_rate** (*float, optional*) – A label smoothing rate to apply to the positive and negative labels. Defaults to 0.0.

**train\_data**

The input data converted into a PyTorch tensor.

#### Type

`torch.Tensor`

**num\_entities**

Number of entities in the dataset.

#### Type

`int`

**num\_relations**

Number of relations in the dataset.

#### Type

`int`

**neg\_sample\_ratio**

Ratio of negative samples to be drawn for each positive sample.

#### Type

`int`

**label\_smoothing\_rate**

The smoothing factor applied to the labels.

#### Type

`torch.Tensor`

**collate\_fn**

A function that can be used to collate data samples into batches (set to None by default).

**Type**

function, optional

**train\_data**

**num\_entities**

**num\_relations**

**neg\_sample\_ratio = None**

**label\_smoothing\_rate**

**collate\_fn = None**

**\_\_len\_\_()**

Returns the number of samples in the dataset.

**\_\_getitem\_\_(idx)**

Retrieves a single data sample from the dataset at the given index.

**Parameters**

**idx** (*int*) – The index of the sample to retrieve.

**Returns**

**A tuple consisting of:**

- **x** (torch.Tensor): The head and relation part of the triple.
- **y\_idx** (torch.Tensor): The concatenated indices of the true object (tail entity) and the indices of the negative samples.
- **y\_vec** (torch.Tensor): A vector containing the labels for the positive and negative samples, with label smoothing applied.

**Return type**

tuple

```
class dicee.dataset_classes.KvsSampleDataset (train_set_idx: numpy.ndarray, entity_idxes,  
relation_idxes, form, store=None, neg_ratio=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.

**forall 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\_idxes**

mapping.

```

    relation_idx
    mapping.

    form
    ?

    store
    ?

    label_smoothing_rate
    ?

    torch.utils.data.Dataset

```

```

train_data = None

train_target = None

neg_ratio = None

num_entities

label_smoothing_rate

collate_fn = None

max_num_of_classes

__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 . collect_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_idx
                mapping.

            relation_idx
                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.CVDDataModule (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, ...).

### 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:

```
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:

```
# 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.dataset_classes.LiteralDataset (file_path: str, ent_idx: dict = None,
    normalization_type: str = 'z-norm', sampling_ratio: float = None, loader_backend: str = 'pandas')
```

Bases: torch.utils.data.Dataset

Dataset for loading and processing literal data for training Literal Embedding model. This dataset handles the loading, normalization, and preparation of triples for training a literal embedding model.

Extends torch.utils.data.Dataset for supporting PyTorch dataloaders.

**train\_file\_path**

Path to the training data file.

**Type**

str

**normalization**

Type of normalization to apply ('z-norm', 'min-max', or None).

**Type**

str

**normalization\_params**

Parameters used for normalization.

**Type**

dict

**sampling\_ratio**

Fraction of the training set to use for ablations.

**Type**

float

**entity\_to\_idx**

Mapping of entities to their indices.

**Type**

dict

**num\_entities**

Total number of entities.

**Type**

int

**data\_property\_to\_idx**

Mapping of data properties to their indices.

**Type**

dict

**num\_data\_properties**

Total number of data properties.

**Type**

int

**loader\_backend**

Backend to use for loading data ('pandas' or 'rdflib').

**Type**

str

**train\_file\_path**

**loader\_backend** = 'pandas'

**normalization\_type** = 'z-norm'

**normalization\_params**

**sampling\_ratio** = None

**entity\_to\_idx** = None

**num\_entities**

**\_\_getitem\_\_** (*index*)

**\_\_len\_\_** ()

**static load\_and\_validate\_literal\_data** (*file\_path: str = None, loader\_backend: str = 'pandas'*)  
→ pandas.DataFrame

Loads and validates the literal data file. :param file\_path: Path to the literal data file. :type file\_path: str

**Returns**

DataFrame containing the loaded and validated data.

**Return type**

pd.DataFrame

**static denormalize** (*preds\_norm, attributes, normalization\_params*) → numpy.ndarray

Denormalizes the predictions based on the normalization type.

Args: *preds\_norm* (np.ndarray): Normalized predictions to be denormalized. *attributes* (list): List of attributes corresponding to the predictions. *normalization\_params* (dict): Dictionary containing normalization parameters for each attribute.

**Returns**

Denormalized predictions.

**Return type**

np.ndarray

## **dicee.eval\_static\_funcs**

### **Functions**

<code>evaluate_link_prediction_performance(→</code>	
<code>Dict)</code>	
<code>evaluate_link_prediction_performance_with_</code>	
<code>evaluate_link_prediction_performance_with_</code>	
<code>evaluate_link_prediction_performance_with_</code>	
<code>...)</code>	
<code>evaluate_lp_bpe_k_vs_all(model, triples[,</code>	
<code>er_vocab, ...])</code>	
<code>evaluate_literal_prediction(kge_model[, ...])</code>	Evaluates the trained literal prediction model on a test file.
<code>evaluate_ensemble_link_prediction_performai</code>	Evaluates link prediction performance of an ensemble of
<code>Dict)</code>	KGE models.

## **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.eval_static_funcs.evaluate_literal_prediction(  
kge_model: dicee.knowledge_graph_embeddings.KGE, eval_file_path: str = None,  
store_lit_preds: bool = True, eval_literals: bool = True, loader_backend: str = 'pandas',  
return_attr_error_metrics: bool = False)
```

Evaluates the trained literal prediction model on a test file.

### Parameters

- **eval\_file\_path** (*str*) – Path to the evaluation file.
- **store\_lit\_preds** (*bool*) – If True, stores the predictions in a CSV file.
- **eval\_literals** (*bool*) – If True, evaluates the literal predictions and prints error metrics.
- **loader\_backend** (*str*) – Backend for loading the dataset ('pandas' or 'rdflib').

### Returns

DataFrame containing error metrics for each attribute if return\_attr\_error\_metrics is True.

### Return type

pd.DataFrame

### Raises

- **RuntimeError** – If the kGE model does not have a trained literal model.
- **AssertionError** – If the kGE model is not an instance of KGE or if the test set has no valid entities or attributes.

```
dicee.eval_static_funcs.evaluate_ensemble_link_prediction_performance(models, triples,  
er_vocab: Dict[Tuple, List], weights: List[float] = None, batch_size: int = 512,  
weighted_averaging: bool = True) → Dict
```

Evaluates link prediction performance of an ensemble of KGE models. :param models: List of KGE models (snapshots) :param triples: np.ndarray or list of lists, shape (N,3), all integer indices (head, rel, tail) :param er\_vocab: Dict[Tuple, List]

Mapping (head\_idx, rel\_idx) → list of tail\_idx to filter (incl. target).

### Parameters

- **weights** – Optional[List[float]] Weights for model averaging. If None, use uniform (=simple mean).
- **batch\_size** – int

### Returns

dict of link prediction metrics (H@1, H@3, H@10, MRR)

## dicee.evaluator

### Classes

<i>Evaluator</i>	Evaluator class to evaluate KGE models in various downstream 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** = None

**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

<i>Execute</i>	A class for Training, Retraining and Evaluation a model.
<i>ContinuousExecute</i>	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** = **False**

**trainer** = **None**

**trained\_model** = **None**

**knowledge\_graph** = **None**

**report**

**evaluator** = **None**



**start\_time** = None

**setup\_executor**() → 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.

**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

<i>KG</i>	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_reciprocal: 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, separator: str = None)
```

Knowledge Graph

```
dataset_dir = None

sparql_endpoint = None

path_single_kg = None

byte_pair_encoding = False

ordered_shaped_bpe_tokens = None

add_noise_rate = None

num_entities = None

num_relations = None

path_for_deserialization = None

add_reciprocal = None

eval_model = None

read_only_few = None

sample_triples_ratio = None

path_for_serialization = None
```

```

entity_to_idx = None

relation_to_idx = None

backend = 'pandas'

training_technique = None

idx_entity_to_bpe_shaped

enc

num_tokens

num_bpe_entities = None

padding = False

dummy_id

max_length_subword_tokens = None

train_set_target = None

target_dim = None

train_target_indices = None

ordered_bpe_entities = None

separator = None

description_of_input = None

describe() → 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`, `dicee.abstracts.InteractiveQueryDecomposition`, `dicee.abstracts.BaseInteractiveTrainKGE`

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,
      batch_size=2, topk=1, return_indices=False) → Tuple
```

Given a relation and a tail entity, return top k ranked head entity.

$\text{argmax}_{\{e \in E\}} f(e, r, t)$ , 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,
      batch_size=2, topk=1, return_indices=False) → Tuple
```

Given a head entity and a tail entity, return top k ranked relations.

$\text{argmax}_{\{r \in R\}} f(h, r, t)$ , 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, batch\_size=2, topk=1, return\_indices=False*) → torch.FloatTensor

Given a head entity and a relation, return top k ranked entities

$\text{argmax}_{\{e \in E\}} f(h, r, e)$ , 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, batch\_size: int = 1024*)

Predict missing item in a given triple.

#### Returns

- If you query a single (h, r, ?) or (?, r, t) or (h, ?, t), returns List[(item, score)]
- If you query a batch of B, returns List of B such lists.

**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

**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  $f(e,r,x) > \text{confidence}$  .

at\_most: int

Stop after finding at\_most missing triples

$\{(e,r,x) \mid f(e,r,x) > \text{confidence} \text{ and } (e,r,x)$

otin G

**deploy** (*share: bool = False, top\_k: int = 10*)

**predict\_literals** (*entity: List[str] | str = None, attribute: List[str] | str = None, denormalize\_preds: bool = True*)  $\rightarrow$  numpy.ndarray

Predicts literal values for given entities and attributes.

#### Parameters

- **entity** (*Union[List[str], str]*) – Entity or list of entities to predict literals for.
- **attribute** (*Union[List[str], str]*) – Attribute or list of attributes to predict literals for.
- **denormalize\_preds** (*bool*) – If True, denormalizes the predictions.

#### Returns

Predictions for the given entities and attributes.

#### Return type

numpy ndarray

## dicee.models

### Submodules

#### dicee.models.adopt

### Classes

---

*ADOPT*

Base class for all optimizers.

---

### Functions

---

*adopt*(params, grads, exp\_avgs, exp\_avg\_sqs, state\_steps) Functional API that performs ADOPT algorithm computation.

---

### Module Contents

**class** `dicee.models.adopt.ADOPT` (*params: torch.optim.optimizer.ParamsT, lr: float | torch.Tensor = 0.001, betas: Tuple[float, float] = (0.9, 0.9999), eps: float = 1e-06, clip\_lambda: Callable[[int], float] | None = lambda step: ..., weight\_decay: float = 0.0, decouple: bool = False, \*, foreach: bool | None = None, maximize: bool = False, capturable: bool = False, differentiable: bool = False, fused: bool | None = None*)

Bases: `torch.optim.optimizer.Optimizer`

Base class for all optimizers.

### Warning

Parameters need to be specified as collections that have a deterministic ordering that is consistent between runs. Examples of objects that don't satisfy those properties are sets and iterators over values of dictionaries.

### Parameters

- **params** (*iterable*) – an iterable of `torch.Tensor`s or `dict`s. Specifies what Tensors should be optimized.
- **defaults** – (dict): a dict containing default values of optimization options (used when a parameter group doesn't specify them).

**clip\_lambda**

**\_\_setstate\_\_** (*state*)

**step** (*closure=None*)

Perform a single optimization step.

### Parameters

**closure** (*Callable, optional*) – A closure that reevaluates the model and returns the loss.

`dicee.models.adopt.adopt` (*params: List[torch.Tensor], grads: List[torch.Tensor], exp\_avgs: List[torch.Tensor], exp\_avg\_sqs: List[torch.Tensor], state\_steps: List[torch.Tensor], foreach: bool | None = None, capturable: bool = False, differentiable: bool = False, fused: bool | None = None, grad\_scale: torch.Tensor | None = None, found\_inf: torch.Tensor | None = None, has\_complex: bool = False, \*, beta1: float, beta2: float, lr: float | torch.Tensor, clip\_lambda: Callable[[int], float] | None, weight\_decay: float, decouple: bool, eps: float, maximize: bool*)

Functional API that performs ADOPT algorithm computation.

## `dicee.models.base_model`

### Classes

<code>BaseKGELightning</code>	Base class for all neural network modules.
<code>BaseKGE</code>	Base class for all neural network modules.
<code>IdentityClass</code>	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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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.

**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:

```
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:

```
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:

```
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):
```

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```
# 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()`

#### **Note**

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

#### **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()`

#### Note

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

#### 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()`

#### 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()`

#### 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 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.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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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* × 2 × *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* × 2 × *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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:



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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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** = *None*

**\_\_call\_\_** (*x*)

**static forward** (*x*)

## dicee.models.clifford

### Classes

<i>Keci</i>	Base class for all neural network modules.
<i>CKeci</i>	Without learning dimension scaling
<i>DeCaL</i>	Base class for all neural network modules.

### Module Contents

**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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

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```
class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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  $\sigma_{pp} = \sum_{i=1}^{p-1} \sum_{k=i+1}^p (h_{ir_k} - h_{kr_i}) e_i e_k$

$\sigma_{pp}$  captures the interactions between along p bases For instance, let  $p \in \{e_1, e_2, e_3\}$ , 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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

$e_2 e_1, e_2 e_2, e_2 e_3, e_3 e_1, e_3 e_2, e_3 e_3$

Then select the triangular matrix without diagonals:  $e_1 e_2, e_1 e_3, e_2 e_3$ .

**compute\_sigma\_qq** (*hq, rq*)

Compute  $\sigma_{qq} = \sum_{j=1}^{p+q-1} \sum_{k=j+1}^{p+q} (h_{jr_k} - h_{kr_j}) e_j e_k \sigma_q$  captures the interactions between along q bases For instance, let  $q \in \{e_1, e_2, e_3\}$ , 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.,  $e_1e_1$ ,  $e_1e_2$ ,  $e_1e_3$ ,

$e_2e_1$ ,  $e_2e_2$ ,  $e_2e_3$ ,  $e_3e_1$ ,  $e_3e_2$ ,  $e_3e_3$

Then select the triangular matrix without diagonals:  $e_1e_2$ ,  $e_1e_3$ ,  $e_2e_3$ .

```

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

Multiplying a base vector with its scalar coefficient

**clifford\_multiplication** ( $h_0, hp, hq, r_0, rp, rq$ )

Compute our CL multiplication

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

$$e_i^2 = +1 \text{ for } i \leq p, \quad e_j^2 = -1 \text{ for } p < j \leq p+q, \quad e_i e_j = -e_j e_i \text{ for } i \neq j$$

eq j

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

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

(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 functions are identical Parameter ——— *x: torch.LongTensor* with (n,2) shape :rtype: torch.FloatTensor with (n, **IEI**) shape

**construct\_batch\_selected\_cl\_multivector** (*x: torch.FloatTensor, r: int, p: int, q: int*)  
→ tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]

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

### Parameter

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

#### returns

- **a0** (*torch.FloatTensor* with (n,k, m) shape)
- **ap** (*torch.FloatTensor* with (n,k, m, p) shape)
- **aq** (*torch.FloatTensor* with (n,k, m, q) shape)

**forward\_k\_vs\_sample** (*x: torch.LongTensor, target\_entity\_idx: torch.LongTensor*) → torch.FloatTensor

### Parameter

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

*target\_entity\_idx: torch.LongTensor* with (n, k ) shape k denotes the selected number of examples.

#### rtype

*torch.FloatTensor* with (n, k) 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.CKeci` (*args*)

Bases: *Keci*

Without learning dimension scaling

**name** = 'CKeci'

```
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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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*)  $\rightarrow$  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,

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

and return:

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

**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

$$\sigma_p p = \sum_{i=1}^{p-1} \sum_{i'=i+1}^p (h_i r_{i'} - h_{i'} r_i) (\text{model the interactions between } e_i \text{ and } e_{i'} \text{ for } 1 \leq i, i' \leq p) \sigma_q q = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q} (h_j r_{j'} - h_{j'} r_j)$$

For different base vector interactions, we have

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

**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 functions 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:

$$\sigma_{pp} = \sum_{i=1}^{p-1} \sum_{i'=i+1}^p (x_{iy_{i'}} - x_{i'}y_i)$$

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

$$\sigma_{qq}^* = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q} (x_j y_{j'} - x_{j'} y_j) E q.16$$

sigma\_{qq} 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)

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

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

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_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

<i>ConEx</i>	Convolutional ComplEx Knowledge Graph Embeddings
<i>AConEx</i>	Additive Convolutional ComplEx Knowledge Graph Embeddings
<i>Complex</i>	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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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`

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

## dicee.models.dualE

### Classes

<i>DualE</i>	Dual Quaternion Knowledge Graph Embeddings ( <a href="https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657">https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657</a> )
--------------	--

### 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** = None

**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

$\mathbf{T}(x: \text{torch.tensor}) \rightarrow \text{torch.tensor}$

Transpose function

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

## dicee.models.ensemble

### Classes

---

*EnsembleKGE*

---

### Module Contents

```
class dicee.models.ensemble.EnsembleKGE (seed_model=None, pretrained_models: List = None)
```

```
    name
```

```
    train_mode = True
```

```
    named_children()
```

```
    property example_input_array
```

```
    parameters()
```

```
    modules()
```

```
    __iter__()
```

```
    __len__()
```

```
    eval()
```

```
    to (device)
```

```
    mem_of_model()
```

```
    __call__ (x_batch)
```

```
    step()
```

```
    get_embeddings()
```

```
    __str__()
```

## dicee.models.function\_space

### Classes

<i>FMult</i>	Learning Knowledge Neural Graphs
<i>GFMult</i>	Learning Knowledge Neural Graphs
<i>FMult2</i>	Learning Knowledge Neural Graphs
<i>LFMult1</i>	Embedding with trigonometric functions. We represent all entities and relations in the complex number space as:
<i>LFMult</i>	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
    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:
     $f(x) = \sum_{k=0}^{k=d-1} w_k e^{kix}$ . 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:  $f(x) = \sum_{i=0}^{d-1} a_i x^i$  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:

$\text{score}(h,r,t) = \int_0^1 h(x)r(x)t(x) dx = \sum_{i,j,k=0}^{d-1} \text{dfrac}\{a_i*b_j*c_k\}\{1+(i+j+k)\%d\}$

1. generate the range for i,j and k from [0 d-1]
2. perform  $\text{dfrac}\{a_i*b_j*c_k\}\{1+(i+j+k)\%d\}$  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:

$\text{score}(h,r,t) = \int_0^1 h(x)r(x)t(x) dx = \sum_{i,j,k=0}^{d-1} \text{dfrac}\{a_i*c_j*b_k - b_i*c_j*a_k\}\{(1+(i+j)\%d)(1+k)\}$

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 ( $\text{coeff}[0][0] + \text{coeff}[0][1]x + \dots + \text{coeff}[0][d]x^d$ ,

$\text{coeff}[1][0] + \text{coeff}[1][1]x + \dots + \text{coeff}[1][d]x^d$ )

**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 ( $\text{coeff}[0][0] + \text{coeff}[0][1]x + \dots + \text{coeff}[0][d]x^d$ ,

$\text{coeff}[1][0] + \text{coeff}[1][1]x + \dots + \text{coeff}[1][d]x^d$ )

## dicee.models.literal

### Classes

*LiteralEmbeddings*

A model for learning and predicting numerical literals using pre-trained KGE.

### Module Contents

**class** `dicee.models.literal.LiteralEmbeddings` (*num\_of\_data\_properties: int, embedding\_dims: int, entity\_embeddings: torch.tensor, dropout: float = 0.3, gate\_residual=True, freeze\_entity\_embeddings=True*)

Bases: `torch.nn.Module`

A model for learning and predicting numerical literals using pre-trained KGE.

**num\_of\_data\_properties**

Number of data properties (attributes).

**Type**

`int`

**embedding\_dims**

Dimension of the embeddings.

**Type**

`int`

**entity\_embeddings**

Pre-trained entity embeddings.

**Type**

`torch.tensor`



**dropout**

Dropout rate for regularization.

**Type**

float

**gate\_residual**

Whether to use gated residual connections.

**Type**

bool

**freeze\_entity\_embeddings**

Whether to freeze the entity embeddings during training.

**Type**

bool

**embedding\_dim**

**num\_of\_data\_properties**

**hidden\_dim**

**gate\_residual = True**

**freeze\_entity\_embeddings = True**

**entity\_embeddings**

**data\_property\_embeddings**

**fc**

**fc\_out**

**dropout**

**gated\_residual\_proj**

**layer\_norm**

**forward** (*entity\_idx*, *attr\_idx*)

**Parameters**

- **entity\_idx** (*Tensor*) – Entity indices (batch).
- **attr\_idx** (*Tensor*) – Attribute (Data property) indices (batch).

**Returns**

scalar predictions.

**Return type**

Tensor

**property device**

## dicee.models.octonion

### Classes

<i>OMult</i>	Base class for all neural network modules.
<i>ConvO</i>	Base class for all neural network modules.
<i>AConvO</i>	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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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 them to be nested 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) -> None:
        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 also have their parameters converted 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** = '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: Pykeen\_HolE: Pykeen\_TransD: Pykeen\_TransE: Pykeen\_TransF: Pykeen\_TransH: Pykeen\_TransR:

**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)
```

## dicее.models.quaternion

### Classes

<i>QMult</i>	Base class for all neural network modules.
<i>ConvQ</i>	Convolutional Quaternion Knowledge Graph Embeddings
<i>ACConvQ</i>	Additive Convolutional Quaternion Knowledge Graph Embeddings

### Functions

```
quaternion_mul_with_unit_norm(*, Q_1, Q_2)
```

### Module Contents

```
dicее.models.quaternion.quaternion_mul_with_unit_norm(*, Q_1, Q_2)
```

```
class dicее.models.quaternion.QMult (args)
```

Bases: *dicее.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 them to be nested 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) -> None:
        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 also have their parameters converted 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.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

<i>DistMult</i>	Embedding Entities and Relations for Learning and Inference in Knowledge Bases
<i>TransE</i>	Translating Embeddings for Modeling
<i>Shallom</i>	A shallow neural model for relation prediction ( <a href="https://arxiv.org/abs/2101.09090">https://arxiv.org/abs/2101.09090</a> )
<i>Pyke</i>	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

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

---

### Module Contents

```

dicee.models.static_funcs.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:

```

## dicее.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](https://github.com/huggingface/transformers/blob/main/src/transformers/models/gpt2/modeling_gpt2.py)

## Classes

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

## Module Contents

```
class dicее.models.transformers.ByteE(*args, **kwargs)
```

Bases: *dicее.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 them to be nested 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) -> None:
        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 also have their parameters converted 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**

**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:

```
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:

```
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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
```

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```
def __init__(self) -> None:
    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 also have their parameters converted 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.

`c_attn`

`c_proj`

`attn_dropout`

`resid_dropout`

`n_head`

`n_embd`

`dropout`

`flash = True`

`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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
```

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```
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 also have their parameters converted 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 them to be nested 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) -> None:
        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 also have their parameters converted 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.

**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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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**

**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**

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

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Table 1 – continued from previous page

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

## Functions

```

quaternion_mul(→ 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)

```

## Package Contents

```

class dicee.models.ADOPT (params: torch.optim.optimizer.ParamsT, lr: float | torch.Tensor = 0.001,
    betas: Tuple[float, float] = (0.9, 0.9999), eps: float = 1e-06,
    clip_lambda: Callable[[int], float] | None = lambda step: ..., weight_decay: float = 0.0,
    decouple: bool = False, *, foreach: bool | None = None, maximize: bool = False,
    capturable: bool = False, differentiable: bool = False, fused: bool | None = None)

```

Bases: torch.optim.optimizer.Optimizer

Base class for all optimizers.

### Warning

Parameters need to be specified as collections that have a deterministic ordering that is consistent between runs. Examples of objects that don't satisfy those properties are sets and iterators over values of dictionaries.

#### Parameters

- **params** (*iterable*) – an iterable of `torch.Tensor`s or `dict`s. Specifies what Tensors should be optimized.
- **defaults** – (dict): a dict containing default values of optimization options (used when a parameter group doesn't specify them).

`clip_lambda`

`__setstate__` (*state*)

`step` (*closure=None*)

Perform a single optimization step.

#### Parameters

**closure** (*Callable, optional*) – A closure that reevaluates the model and returns the loss.

`class dicee.models.BaseKGE Lightning (*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 them to be nested 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) -> None:
        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 also have their parameters converted 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.

**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:

```
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:

```
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:

```
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()`

#### Note

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

#### 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()`

#### Note

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

#### 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()`

### 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()`

### 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 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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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
         $\mathbf{x}$  ( $B \times 2 \times T$ )

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
        •  $\mathbf{x}$ 
        •  $\mathbf{y\_idx}$ 
        •  $\mathbf{ordered\_bpe\_entities}$ 

```

**forward\_triples** ( $x$ : torch.LongTensor)  $\rightarrow$  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** ( $B \times 2 \times T$ )

**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 them to be nested 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) -> None:
        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 also have their parameters converted 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** = None

**\_\_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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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

$\mathbf{x} (B \times 2 \times T)$

`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* × 2 × *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

    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 them to be nested in a tree structure. You can assign the sub-
    modules as regular attributes:

```

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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
         $\mathbf{x}$  ( $B \times 2 \times T$ )

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

        •  $\mathbf{x}$ 

        •  $\mathbf{y\_idx}$ 

        • ordered_bpe_entities

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

    Parameters
         $\mathbf{x}$ 

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* × 2 × *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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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
```

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

```
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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```
import torch.nn as nn  
import torch.nn.functional as F  
  
class Model(nn.Module):  
    def __init__(self) -> None:  
        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 also have their parameters converted 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

$\mathbf{x} (B \times 2 \times T)$

**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* × 2 × *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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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** = *None*

**\_\_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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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

$\mathbf{x} (B \times 2 \times T)$

**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* × 2 × *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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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** = None

**\_\_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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):

```

(continues on next page)

```
x = F.relu(self.conv1(x))
return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will also have their parameters converted 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.,  $[\text{score}(h,r,x) | x \text{ in Entities}] \Rightarrow [0.0, 0.1, \dots, 0.8]$ , shape  $\Rightarrow (1, \text{Entities})$  Given a batch of head entities and relations  $\Rightarrow$  shape (size of batch, l 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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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** = '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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

$e_2 e_1, e_2 e_2, e_2 e_3, e_3 e_1, e_3 e_2, e_3 e_3$

Then select the triangular matrix without diagonals:  $e_1 e_2, e_1 e_3, e_2 e_3$ .

**compute\_sigma\_qq** (*hq, rq*)

Compute  $\sigma_{qq} = \sum_{j=1}^{p+q-1} \sum_{k=j+1}^{p+q} (h_{j,r_k} - h_{k,r_j}) e_j e_k$   $\sigma_{qq}$  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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

$e_2 e_1, e_2 e_2, e_2 e_3, e_3 e_1, e_3 e_2, e_3 e_3$

Then select the triangular matrix without diagonals:  $e_1 e_2, e_1 e_3, e_2 e_3$ .

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

Multiplying a base vector with its scalar coefficient

**clifford\_multiplication** (*h0, hp, hq, r0, rp, rq*)

Compute our CL multiplication

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

$e_i^2 = +1$  for  $i \leq p$   $e_j^2 = -1$  for  $p < j \leq p+q$   $e_i e_j = -e_j e_i$  for  $i$

$e_j$

$h r = \sigma_0 + \sigma_p + \sigma_q + \sigma_{pp} + \sigma_{qq} + \sigma_{pq}$  where

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

- (2)  $\sigma_p = \sum_{i=1}^p (h_{0r_i} + h_{ir_0}) e_i$
- (3)  $\sigma_q = \sum_{j=p+1}^{p+q} (h_{0r_j} + h_{jr_0}) e_j$
- (4)  $\sigma_{pp} = \sum_{i=1}^{p-1} \sum_{k=i+1}^p (h_{ir_k} - h_{kr_i}) e_i e_k$
- (5)  $\sigma_{qq} = \sum_{j=1}^{p+q-1} \sum_{k=j+1}^{p+q} (h_{jr_k} - h_{kr_j}) e_j e_k$
- (6)  $\sigma_{pq} = \sum_{i=1}^p \sum_{j=p+1}^{p+q} (h_{ir_j} - h_{jr_i}) e_i e_j$

**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 functions are identical Parameter ——— x: torch.LongTensor with (n,2) shape :rtype: torch.FloatTensor with (n, **IEI**) shape

**construct\_batch\_selected\_cl\_multivector** (*x: torch.FloatTensor, r: int, p: int, q: int*)  
 $\rightarrow$  tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]  
Construct a batch of batchs multivectors  $Cl_{\{p,q\}}(\mathbb{R}^d)$

### Parameter

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

#### returns

- **a0** (*torch.FloatTensor with (n,k, m) shape*)
- **ap** (*torch.FloatTensor with (n,k, m, p) shape*)
- **aq** (*torch.FloatTensor with (n,k, m, q) shape*)

**forward\_k\_vs\_sample** (*x: torch.LongTensor, target\_entity\_idx: torch.LongTensor*)  $\rightarrow$  torch.FloatTensor

## Parameter

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

target\_entity\_idx: torch.LongTensor with (n, k ) shape k denotes the selected number of examples.

**rtype**

torch.FloatTensor with (n, k) 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.CKeci (args)
```

Bases: *Keci*

Without learning dimension scaling

**name** = 'CKeci'

**requires\_grad\_for\_interactions** = False

```
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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model (nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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,

$$s_0 = h_0 r_0 t_0 s_1 = \sum_{i=1}^p h_i r_i t_0 s_2 = \sum_{j=p+1}^{p+q} h_j r_j t_0 s_3 = \sum_{i=1}^q (h_0 r_i t_i + h_i r_0 t_i) s_4 = \sum_{i=p+1}^{p+q} (h_0 r_i t_i + h_i r_0 t_i) s_5 = \sum_{i=p+q+1}^{p+q+r} (h_0 r_i t_i + h_i r_0 t_i)$$

and return:

$$\sigma_0 t = \sigma_0 \cdot t_0 = s_0 + s_1 - s_2 s_3, s_4 \text{ and } s_5$$

**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

$$\sigma_p p = \sum_{i=1}^{p-1} \sum_{i'=i+1}^p (h_i r_{i'} - h_{i'} r_i) (\text{model the interactions between } e_i \text{ and } e_{i'} \text{ for } 1 \leq i, i' \leq p) \sigma_q q = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q} (h_j r_{j'} - h_{j'} r_j)$$

For different base vector interactions, we have

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

**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 functions are identical Parameter ——— *x*: torch.LongTensor with (n, ) shape :rtype: torch.FloatTensor with (n, **IE**) 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<sub>1</sub>, e<sub>2</sub>, e<sub>3</sub>, we compute interactions between e<sub>1</sub> e<sub>2</sub>, e<sub>1</sub> e<sub>3</sub>, and e<sub>2</sub> e<sub>3</sub> 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., e<sub>1</sub>e<sub>1</sub>, e<sub>1</sub>e<sub>2</sub>, e<sub>1</sub>e<sub>3</sub>,

e<sub>2</sub>e<sub>1</sub>, e<sub>2</sub>e<sub>2</sub>, e<sub>2</sub>e<sub>3</sub>, e<sub>3</sub>e<sub>1</sub>, e<sub>3</sub>e<sub>2</sub>, e<sub>3</sub>e<sub>3</sub>

Then select the triangular matrix without diagonals: e<sub>1</sub>e<sub>2</sub>, e<sub>1</sub>e<sub>3</sub>, e<sub>2</sub>e<sub>3</sub>.

**compute\_sigma\_qq** (*hq, rq*)

Compute

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

$\sigma_{\{q\}}$  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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

$e_2 e_1, e_2 e_2, e_2 e_3, e_3 e_1, e_3 e_2, e_3 e_3$

Then select the triangular matrix without diagonals:  $e_1 e_2, e_1 e_3, e_2 e_3$ .

**compute\_sigma\_rr** ( $hk, rk$ )

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

**compute\_sigma\_pq** ( $*, hp, hq, rp, rq$ )

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\_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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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
         $\mathbf{x}$  ( $B \times 2 \times T$ )

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
        •  $\mathbf{x}$ 
        •  $\mathbf{y\_idx}$ 
        •  $\mathbf{ordered\_bpe\_entities}$ 

```



**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* × 2 × *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: Pykeen\_HolE: Pykeen\_TransD: Pykeen\_TransE: Pykeen\_TransF: Pykeen\_TransH: Pykeen\_TransR:

**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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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

$\mathbf{x} (B \times 2 \times T)$

```

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
    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:  $f(x) = \sum_{k=0}^{d-1} w_k e^{kix}$ . 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:  $f(x) = \sum_{i=0}^{d-1} a_k x^{i\%d}$  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:

$$\text{score}(h,r,t) = \int_0^1 h(x)r(x)t(x) dx = \sum_{i,j,k=0}^{d-1} \text{dfrac}\{a_i*b_j*c_k\} \{1+(i+j+k)*d\}$$

1. generate the range for i,j and k from [0 d-1]
2. perform  $\text{dfrac}\{a_i*b_j*c_k\} \{1+(i+j+k)*d\}$  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:

$$\text{score}(h,r,t) = \int_0^1 h(x)r(x)t(x) dx = \sum_{i,j,k=0}^{d-1} \text{dfrac}\{a_i*c_j*b_k - b_i*c_j*a_k\} \{(1+(i+j)*d)(1+k)\}$$

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,

$$\text{coeff}[1][0] + \text{coeff}[1][1]x + \dots + \text{coeff}[1][d]x^d)$$

**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,**

$$\text{coeff}[1][0] + \text{coeff}[1][1]x + \dots + \text{coeff}[1][d]x^d)$$

**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 = None

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.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 = False

    gen_test = True

    seed = 1

    max_ans_num = 1000000.0

    mode

    ent2id = None

    rel2id: Dict = None

    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.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)

`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

<code>polars_dataframe_indexer</code> (→ <code>polars.DataFrame</code> )	Replaces 'subject', 'relation', and 'object' columns in the input Polars DataFrame with their corresponding index values
<code>pandas_dataframe_indexer</code> (→ <code>pandas.DataFrame</code> )	Replaces 'subject', 'relation', and 'object' columns in the input Pandas DataFrame with their corresponding index values
<code>apply_reciprical_or_noise</code> ( <code>add_reciprical</code> , <code>eval_model</code> )	
<code>timeit</code> ( <code>func</code> )	
<code>read_with_polars</code> (→ <code>polars.DataFrame</code> )	Load and Preprocess via Polars
<code>read_with_pandas</code> ( <code>data_path</code> [, <code>read_only_few</code> , ...])	
<code>read_from_disk</code> (→ <code>Tuple</code> [ <code>polars.DataFrame</code> , <code>pandas.DataFrame</code> ])	
<code>read_from_triple_store</code> ( <code>[endpoint]</code> )	Read triples from triple store into pandas dataframe
<code>get_er_vocab</code> ( <code>data</code> [, <code>file_path</code> ])	
<code>get_re_vocab</code> ( <code>data</code> [, <code>file_path</code> ])	
<code>get_ee_vocab</code> ( <code>data</code> [, <code>file_path</code> ])	
<code>create_constraints</code> ( <code>triples</code> [, <code>file_path</code> ])	
<code>load_with_pandas</code> (→ <code>None</code> )	Deserialize data
<code>save_numpy_ndarray</code> (*, <code>data</code> , <code>file_path</code> )	
<code>load_numpy_ndarray</code> (*, <code>file_path</code> )	
<code>save_pickle</code> (*, <code>data</code> [, <code>file_path</code> ])	
<code>load_pickle</code> (*, <code>file_path</code> )	
<code>create_recipriocal_triples</code> ( <code>x</code> )	Add inverse triples into dask dataframe
<code>dataset_sanity_checking</code> (→ <code>None</code> )	

## Module Contents

```
dicee.read_preprocess_save_load_kg.util.polars_dataframe_indexer(  
    df_polars: polars.DataFrame, idx_entity: polars.DataFrame, idx_relation: polars.DataFrame)  
    → polars.DataFrame
```

Replaces 'subject', 'relation', and 'object' columns in the input Polars DataFrame with their corresponding index values from the entity and relation index DataFrames.

This function processes the DataFrame in three main steps: 1. Replace the 'relation' values with the corresponding index from *idx\_relation*. 2. Replace the 'subject' values with the corresponding index from *idx\_entity*. 3. Replace the 'object' values with the corresponding index from *idx\_entity*.

### Parameters:

#### **df\_polars**

[polars.DataFrame] The input Polars DataFrame containing columns: 'subject', 'relation', and 'object'.

#### **idx\_entity**

[polars.DataFrame] A Polars DataFrame that contains the mapping between entity names and their corresponding indices. Must have columns: 'entity' and 'index'.

#### **idx\_relation**

[polars.DataFrame] A Polars DataFrame that contains the mapping between relation names and their corresponding indices. Must have columns: 'relation' and 'index'.

### Returns:

#### **polars.DataFrame**

A DataFrame with the 'subject', 'relation', and 'object' columns replaced by their corresponding indices.

### Example Usage:

```
>>> df_polars = pl.DataFrame({  
    "subject": ["Alice", "Bob", "Charlie"],  
    "relation": ["knows", "works_with", "lives_in"],  
    "object": ["Dave", "Eve", "Frank"]  
})  
>>> idx_entity = pl.DataFrame({  
    "entity": ["Alice", "Bob", "Charlie", "Dave", "Eve", "Frank"],  
    "index": [0, 1, 2, 3, 4, 5]  
})  
>>> idx_relation = pl.DataFrame({  
    "relation": ["knows", "works_with", "lives_in"],  
    "index": [0, 1, 2]  
})  
>>> polars_dataframe_indexer(df_polars, idx_entity, idx_relation)
```

### Steps:

1. Join the input DataFrame *df\_polars* on the 'relation' column with *idx\_relation* to replace the relations with their indices.
2. Join on 'subject' to replace it with the corresponding entity index using a left join on *idx\_entity*.
3. Join on 'object' to replace it with the corresponding entity index using a left join on *idx\_entity*.

4. Select only the 'subject', 'relation', and 'object' columns to return the final result.

```
dicee.read_preprocess_save_load_kg.util.pandas_dataframe_indexer(  
    df_pandas: pandas.DataFrame, idx_entity: pandas.DataFrame, idx_relation: pandas.DataFrame)  
    → pandas.DataFrame
```

Replaces 'subject', 'relation', and 'object' columns in the input Pandas DataFrame with their corresponding index values from the entity and relation index DataFrames.

#### Parameters:

##### **df\_pandas**

[pd.DataFrame] The input Pandas DataFrame containing columns: 'subject', 'relation', and 'object'.

##### **idx\_entity**

[pd.DataFrame] A Pandas DataFrame that contains the mapping between entity names and their corresponding indices. Must have columns: 'entity' and 'index'.

##### **idx\_relation**

[pd.DataFrame] A Pandas DataFrame that contains the mapping between relation names and their corresponding indices. Must have columns: 'relation' and 'index'.

#### Returns:

##### **pd.DataFrame**

A DataFrame with the 'subject', 'relation', and 'object' columns replaced by their corresponding indices.

```
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, separator: str = 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, separator: str = 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: str = None,  
    separator: str = None) → Tuple[polars.DataFrame, pandas.DataFrame]
```

```
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. Create constrained 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.dataset_sanity_checking(train_set: numpy.ndarray, num_entities: int, num_relations: int) → None`

#### Parameters

- **train\_set**
- **num\_entities**
- **num\_relations**

#### Returns

## Classes

<i>PreprocessKG</i>	Preprocess the data in memory
<i>LoadSaveToDisk</i>	
<i>ReadFromDisk</i>	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)

**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.sanity\_checkers**



## Functions

<code>is_sparql_endpoint_alive([sparql_endpoint])</code>	
<code>validate_knowledge_graph(args)</code>	Validating the source of knowledge graph
<code>sanity_checking_with_arguments(args)</code>	

## 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.scripts`

### Submodules

#### `dicee.scripts.index_serve`

```
$ docker pull qdrant/qdrant && docker run -p 6333:6333 -p 6334:6334 -v $(pwd)/qdrant_storage:/qdrant/storage:z  
qdrant/qdrant $ dicee_vector_db -index -serve -path CountryEmbeddings -collection "countries_vdb"
```

## Attributes

<code>app</code>
<code>neural_searcher</code>

## Classes

<code>NeuralSearcher</code>	
<code>StringListRequest</code>	!!! abstract "Usage Documentation"

## Functions

```
get_default_arguments()
```

```
index(args)
```

```
root()
```

```
search_embeddings(q)
```

```
retrieve_embeddings(q)
```

```
search_embeddings_batch(request)
```

```
serve(args)
```

```
main()
```

## Module Contents

```
dicee.scripts.index_serve.get_default_arguments()
```

```
dicee.scripts.index_serve.index(args)
```

```
dicee.scripts.index_serve.app
```

```
dicee.scripts.index_serve.neural_searcher = None
```

```
class dicee.scripts.index_serve.NeuralSearcher(args)
```

```
    collection_name
```

```
    entity_to_idx = None
```

```
    qdrant_client
```

```
    topk = 5
```

```
    retrieve_embedding(entity: str = None, entities: List[str] = None) → List
```

```
    search(entity: str)
```

```
async dicee.scripts.index_serve.root()
```

```
async dicee.scripts.index_serve.search_embeddings(q: str)
```

```
async dicee.scripts.index_serve.retrieve_embeddings(q: str)
```

```
class dicee.scripts.index_serve.StringListRequest(/, **data: Any)
```

```
    Bases: pydantic.BaseModel
```

```
    !!! abstract “Usage Documentation”
```

```
        [Models](../concepts/models.md)
```

```
    A base class for creating Pydantic models.
```

**`__class_vars__`**

The names of the class variables defined on the model.

**`__private_attributes__`**

Metadata about the private attributes of the model.

**`__signature__`**

The synthesized `__init__` [*Signature*][inspect.Signature] of the model.

**`__pydantic_complete__`**

Whether model building is completed, or if there are still undefined fields.

**`__pydantic_core_schema__`**

The core schema of the model.

**`__pydantic_custom_init__`**

Whether the model has a custom `__init__` function.

**`__pydantic_decorators__`**

Metadata containing the decorators defined on the model. This replaces `Model.__validators__` and `Model.__root_validators__` from Pydantic V1.

**`__pydantic_generic_metadata__`**

Metadata for generic models; contains data used for a similar purpose to `__args__`, `__origin__`, `__parameters__` in typing-module generics. May eventually be replaced by these.

**`__pydantic_parent_namespace__`**

Parent namespace of the model, used for automatic rebuilding of models.

**`__pydantic_post_init__`**

The name of the post-init method for the model, if defined.

**`__pydantic_root_model__`**

Whether the model is a [*RootModel*][pydantic.root\_model.RootModel].

**`__pydantic_serializer__`**

The *pydantic-core* *SchemaSerializer* used to dump instances of the model.

**`__pydantic_validator__`**

The *pydantic-core* *SchemaValidator* used to validate instances of the model.

**`__pydantic_fields__`**

A dictionary of field names and their corresponding [*FieldInfo*][pydantic.fields.FieldInfo] objects.

**`__pydantic_computed_fields__`**

A dictionary of computed field names and their corresponding [*ComputedFieldInfo*][pydantic.fields.ComputedFieldInfo] objects.

**`__pydantic_extra__`**

A dictionary containing extra values, if [*extra*][pydantic.config.ConfigDict.extra] is set to 'allow'.

**`__pydantic_fields_set__`**

The names of fields explicitly set during instantiation.

**`__pydantic_private__`**

Values of private attributes set on the model instance.

**`queries: List[str]`**

```
reducer: str | None = None
```

```
async dicee.scripts.index_serve.search_embeddings_batch(request: StringListRequest)
```

```
dicee.scripts.index_serve.serve(args)
```

```
dicee.scripts.index_serve.main()
```

## dicee.scripts.run

### Functions

<code>get_default_arguments([description])</code> <code>main()</code>	Extends pytorch_lightning Trainer's arguments with ours
--	---

## Module Contents

```
dicee.scripts.run.get_default_arguments(description=None)
```

Extends pytorch\_lightning Trainer's arguments with ours

```
dicee.scripts.run.main()
```

## dicee.static\_funcs

### Functions

<code>create_recipriocal_triples(x)</code>	Add inverse triples into dask dataframe
<code>get_er_vocab(data[, file_path])</code>	
<code>get_re_vocab(data[, file_path])</code>	
<code>get_ee_vocab(data[, file_path])</code>	
<code>timeit(func)</code>	
<code>save_pickle(*[, data, file_path])</code>	
<code>load_pickle([file_path])</code>	
<code>load_term_mapping([file_path])</code>	
<code>select_model(args[, is_continual_training, storage_path])</code>	
<code>load_model(→ Tuple[object, Tuple[dict, dict]])</code>	Load weights and initialize pytorch module from namespace arguments
<code>load_model_ensemble(...)</code>	Construct Ensemble Of weights and initialize pytorch module from namespace arguments
<code>save_numpy_ndarray(*, data, file_path)</code>	
<code>numpy_data_type_changer(→ numpy.ndarray)</code>	Detect most efficient data type for a given triples

continues on next page

Table 2 – continued from previous page

<code>save_checkpoint_model(→ None)</code>	Store Pytorch model into disk
<code>store(→ None)</code>	
<code>add_noisy_triples(→ pandas.DataFrame)</code>	Add randomly constructed triples
<code>read_or_load_kg(args, cls)</code>	
<code>intialize_model(→ Tuple[object, str])</code>	
<code>load_json(→ dict)</code>	
<code>save_embeddings(→ None)</code>	Save it as CSV if memory allows.
<code>random_prediction(pre_trained_kge)</code>	
<code>deploy_triple_prediction(pre_trained_kge, str_subject, ...)</code>	
<code>deploy_tail_entity_prediction(pre_trained_kge, ...)</code>	
<code>deploy_head_entity_prediction(pre_trained_kge, ...)</code>	
<code>deploy_relation_prediction(pre_trained_kge, ...)</code>	
<code>vocab_to_parquet(vocab_to_idx, name, ...)</code>	
<code>create_experiment_folder([folder_name])</code>	
<code>continual_training_setup_executor(→ None)</code>	
<code>exponential_function(→ torch.FloatTensor)</code>	
<code>load_numpy(→ numpy.ndarray)</code>	
<code>evaluate(entity_to_idx, scores, easy_answers, # @TODO: CD: Renamed this function hard_answers)</code>	
<code>download_file(url[, destination_folder])</code>	
<code>download_files_from_url(→ None)</code>	
<code>download_pretrained_model(→ str)</code>	
<code>write_csv_from_model_parallel(path)</code>	Create
<code>from_pretrained_model_write_embeddings_int, None)</code>	

## 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.load_term_mapping (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 (trained_model, model_name: str = 'model', full_storage_path: str = None,
                        save_embeddings_as_csv=False) → None

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

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”](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.write_csv_from_model_parallel(path: str)
Create

dicee.static_funcs.from_pretrained_model_write_embeddings_into_csv(path: str) → None

```

### **dicee.static\_funcs\_training**

#### **Functions**

---

```

make_iterable_verbose(→ Iterable)

evaluate_lp([model, triple_idx, num_entities, ...])

evaluate_bpe_lp(model, triple_idx, ..., info])

efficient_zero_grad(model)

```

---

### **Module Contents**

```

dicee.static_funcs_training.make_iterable_verbose(iterable_object, verbose, desc='Default',
position=None, leave=True) → Iterable

```

```
dicee.static_funcs_training.evaluate_lp (model=None, triple_idx=None, num_entities=None,
      er_vocab: Dict[Tuple, List] = None, re_vocab: Dict[Tuple, List] = None, info='Eval Starts',
      batch_size=128, chunk_size=1000)
```

```
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, dict])
```

```
get_er_vocab(data)
```

```
get_re_vocab(data)
```

```
get_ee_vocab(data)
```

```
mapping_from_first_two_cols_to_third(train_se
```

### **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)
```

## **dicee.trainer**

### **Submodules**

#### **dicee.trainer.dice\_trainer**

### **Classes**

<i>DICE_Trainer</i>	DICE_Trainer implement
---------------------	------------------------

### **Functions**

<i>load_term_mapping</i> ([file_path])
<i>initialize_trainer</i> (...)
<i>get_callbacks</i> (args)

### **Module Contents**

```
dicee.trainer.dice_trainer.load_term_mapping(file_path=str)
```

```
dicee.trainer.dice_trainer.initialize_trainer(args, callbacks)  
→ dicee.trainer.torch_trainer.TorchTrainer | dicee.trainer.model_parallelism.TensorParallel | dicee.trainer.torch_trainer_ddp
```

```
dicee.trainer.dice_trainer.get_callbacks(args)
```

```
class dicee.trainer.dice_trainer.DICE_Trainer(args, is_continual_training: bool, 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 = None**

**form\_of\_labelling = None**

**continual\_start** (*knowledge\_graph*)

- (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* | *dicke.trainer.model\_parallelism.TensorParallel* | *dicke.trainer.torch\_trainer.TorchTrainer* | *dicke.*

Initialize Trainer from input arguments

**initialize\_or\_load\_model** ()

**init\_dataloader** (*dataset: torch.utils.data.Dataset*) → *torch.utils.data.DataLoader*

**init\_dataset** () → *torch.utils.data.Dataset*

**start** (*knowledge\_graph: dicke.knowledge\_graph.KG* | *numpy.memmap*)

→ *Tuple[dicke.models.base\_model.BaseKGE, str]*

Start the training

- (1) Initialize Trainer
- (2) Initialize or load a pretrained KGE model

in DDP setup, we need to load the memory map of already read/index KG.

**k\_fold\_cross\_validation** (*dataset*) → *Tuple[dicke.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.model\_parallelism

### Classes

<i>TensorParallel</i>	Abstract class for Trainer class for knowledge graph embedding models
-----------------------	---

### Functions

<i>extract_input_outputs</i> (z[, device])
<i>find_good_batch_size</i> (train_loader, tp_ensemble_model)
<i>forward_backward_update_loss</i> (→ float)

### Module Contents

dicee.trainer.model\_parallelism.**extract\_input\_outputs** (z: list, device=None)

dicee.trainer.model\_parallelism.**find\_good\_batch\_size** (train\_loader, tp\_ensemble\_model)

dicee.trainer.model\_parallelism.**forward\_backward\_update\_loss** (z: Tuple, ensemble\_model)  
→ float

**class** dicee.trainer.model\_parallelism.**TensorParallel** (args, callbacks)

Bases: *dicee.abstracts.AbstractTrainer*

Abstract class for Trainer class for knowledge graph embedding models

#### Parameter

**args**  
[str] ?

**callbacks:** list  
?

**fit** (\*args, \*\*kwargs)  
Train model

## dicee.trainer.torch\_trainer

### Classes

<i>TorchTrainer</i>	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

<code>TorchDDPTrainer</code>	A Trainer based on torch.nn.parallel.DistributedDataParallel
<code>NodeTrainer</code>	

### Functions

<code>make_iterable_verbose</code> ( $\rightarrow$ Iterable)
--

### Module Contents

`dicee.trainer.torch_trainer_ddp.make_iterable_verbose` (*iterable\_object*, *verbose*,  
*desc*='Default', *position*=None, *leave*=True)  $\rightarrow$  Iterable

**class** `dicee.trainer.torch_trainer_ddp.TorchDDPTrainer` (*args*, *callbacks*)

Bases: `dicee.abstracts.AbstractTrainer`

A Trainer based on torch.nn.parallel.DistributedDataParallel

Arguments

**entity\_idx**  
mapping.

**relation\_idx**  
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 = []

ctx

scaler

extract_input_outputs (z: list)

train()
    Training loop for DDP

```

## Classes

<i>DICE_Trainer</i>	DICE_Trainer implement
---------------------	------------------------

## Package Contents

```
class dicee.trainer.DICE_Trainer (args, is_continual_training: bool, 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 = None

form\_of\_labelling = None

**continual\_start** (*knowledge\_graph*)

- (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* | *dicke.trainer.model\_parallelism.TensorParallel* | *dicke.trainer.torch\_trainer.TorchTrainer* | *dicke.t*

Initialize Trainer from input arguments

**initialize\_or\_load\_model** ()

**init\_dataloader** (*dataset: torch.utils.data.Dataset*) → *torch.utils.data.DataLoader*

**init\_dataset** () → *torch.utils.data.Dataset*

**start** (*knowledge\_graph: dicke.knowledge\_graph.KG* | *numpy.memmap*)

→ *Tuple[dicke.models.base\_model.BaseKGE, str]*

Start the training

- (1) Initialize Trainer
- (2) Initialize or load a pretrained KGE model

in DDP setup, we need to load the memory map of already read/index KG.

**k\_fold\_cross\_validation** (*dataset*) → *Tuple[dicke.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 Attributes

`__version__`

## 14.3 Classes

<i>Pyke</i>	A Physical Embedding Model for Knowledge Graphs
<i>DistMult</i>	Embedding Entities and Relations for Learning and Inference in Knowledge Bases
<i>CKeci</i>	Without learning dimension scaling
<i>Keci</i>	Base class for all neural network modules.
<i>TransE</i>	Translating Embeddings for Modeling
<i>DeCaL</i>	Base class for all neural network modules.
<i>DualE</i>	Dual Quaternion Knowledge Graph Embeddings ( <a href="https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657">https://ojs.aaai.org/index.php/AAAI/article/download/16850/16657</a> )
<i>ComplEx</i>	Base class for all neural network modules.
<i>AConEx</i>	Additive Convolutional ComplEx Knowledge Graph Embeddings
<i>AConvO</i>	Additive Convolutional Octonion Knowledge Graph Embeddings
<i>AConvQ</i>	Additive Convolutional Quaternion Knowledge Graph Embeddings
<i>ConvQ</i>	Convolutional Quaternion Knowledge Graph Embeddings
<i>ConvO</i>	Base class for all neural network modules.
<i>ConEx</i>	Convolutional ComplEx Knowledge Graph Embeddings
<i>QMult</i>	Base class for all neural network modules.
<i>OMult</i>	Base class for all neural network modules.
<i>Shallom</i>	A shallow neural model for relation prediction ( <a href="https://arxiv.org/abs/2101.09090">https://arxiv.org/abs/2101.09090</a> )
<i>LFMult</i>	Embedding with polynomial functions. We represent all entities and relations in the polynomial space as:
<i>PykeenKGE</i>	A class for using knowledge graph embedding models implemented in Pykeen
<i>Byte</i>	Base class for all neural network modules.
<i>BaseKGE</i>	Base class for all neural network modules.
<i>EnsembleKGE</i>	
<i>DICE_Trainer</i>	DICE_Trainer implement
<i>KGE</i>	Knowledge Graph Embedding Class for interactive usage of pre-trained models
<i>Execute</i>	A class for Training, Retraining and Evaluation a model.
<i>BPE_NegativeSamplingDataset</i>	An abstract class representing a Dataset.
<i>MultiLabelDataset</i>	An abstract class representing a Dataset.
<i>MultiClassClassificationDataset</i>	Dataset for the 1vsALL training strategy
<i>OnevsAllDataset</i>	Dataset for the 1vsALL training strategy
<i>KvsAll</i>	Creates a dataset for KvsAll training by inheriting from torch.utils.data.Dataset.
<i>AllvsAll</i>	Creates a dataset for AllvsAll training by inheriting from torch.utils.data.Dataset.
<i>OnevsSample</i>	A custom PyTorch Dataset class for knowledge graph embeddings, which includes
<i>KvsSampleDataset</i>	KvsSample a Dataset:
<i>NegSampleDataset</i>	An abstract class representing a Dataset.
<i>TriplePredictionDataset</i>	Triple Dataset

continues on next page



Table 3 – continued from previous page

<i>CVDataModule</i>	Create a Dataset for cross validation
<i>LiteralDataset</i>	Dataset for loading and processing literal data for training Literal Embedding model.
<i>QueryGenerator</i>	

## 14.4 Functions

<i>create_recipriocal_triples</i> (x)	Add inverse triples into dask dataframe
<i>get_er_vocab</i> (data[, file_path])	
<i>get_re_vocab</i> (data[, file_path])	
<i>get_ee_vocab</i> (data[, file_path])	
<i>timeit</i> (func)	
<i>save_pickle</i> (*[, data, file_path])	
<i>load_pickle</i> ([file_path])	
<i>load_term_mapping</i> ([file_path])	
<i>select_model</i> (args[, is_continual_training, storage_path])	
<i>load_model</i> (→ Tuple[object, Tuple[dict, dict]])	Load weights and initialize pytorch module from namespace arguments
<i>load_model_ensemble</i> (...)	Construct Ensemble Of weights and initialize pytorch module from namespace arguments
<i>save_numpy_ndarray</i> (*[, data, file_path])	
<i>numpy_data_type_changer</i> (→ numpy.ndarray)	Detect most efficient data type for a given triples
<i>save_checkpoint_model</i> (→ None)	Store Pytorch model into disk
<i>store</i> (→ None)	
<i>add_noisy_triples</i> (→ pandas.DataFrame)	Add randomly constructed triples
<i>read_or_load_kg</i> (args, cls)	
<i>intialize_model</i> (→ Tuple[object, str])	
<i>load_json</i> (→ dict)	
<i>save_embeddings</i> (→ None)	Save it as CSV if memory allows.
<i>random_prediction</i> (pre_trained_kge)	
<i>deploy_triple_prediction</i> (pre_trained_kge, str_subject, ...)	
<i>deploy_tail_entity_prediction</i> (pre_trained_kge, ...)	

continues on next page

Table 4 – continued from previous page

<code>deploy_head_entity_prediction(pre_trained_kge,</code>	
<code>...)</code>	
<code>deploy_relation_prediction(pre_trained_kge,</code>	
<code>...)</code>	
<code>vocab_to_parquet(vocab_to_idx, name, ...)</code>	
<code>create_experiment_folder([folder_name])</code>	
<code>continual_training_setup_executor(→ None)</code>	
<code>exponential_function(→ torch.FloatTensor)</code>	
<code>load_numpy(→ numpy.ndarray)</code>	
<code>evaluate(entity_to_idx, scores, easy_answers, # @TODO: CD: Renamed this function</code>	
<code>hard_answers)</code>	
<code>download_file(url[, destination_folder])</code>	
<code>download_files_from_url(→ None)</code>	
<code>download_pretrained_model(→ str)</code>	
<code>write_csv_from_model_parallel(path)</code>	Create
<code>from_pretrained_model_write_embeddings_into</code>	
<code>None)</code>	
<code>mapping_from_first_two_cols_to_third(train_se</code>	
<code>timeit(func)</code>	
<code>load_term_mapping([file_path])</code>	
<code>reload_dataset(path, form_of_labelling, ...)</code>	Reload the files from disk to construct the Pytorch dataset
<code>construct_dataset(→ torch.utils.data.Dataset)</code>	

## 14.5 Package Contents

**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.CKeci (args)
    Bases: Keci

    Without learning dimension scaling

    name = 'CKeci'

    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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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  $\sigma_{pp} = \sum_{i=1}^{p-1} \sum_{k=i+1}^p (h_{ir_k} - h_{kr_i}) e_i e_k$

$\sigma_{pp}$  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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

$e_2 e_1, e_2 e_2, e_2 e_3, e_3 e_1, e_3 e_2, e_3 e_3$

Then select the triangular matrix without diagonals:  $e_1 e_2, e_1 e_3, e_2 e_3$ .

`compute_sigma_qq (hq, rq)`

Compute  $\sigma_{qq} = \sum_{j=1}^{q-1} \sum_{k=j+1}^q (h_{jr_k} - h_{kr_j}) e_j e_k$   $\sigma_{qq}$  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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

$e_2 e_1, e_2 e_2, e_2 e_3, e_3 e_1, e_3 e_2, e_3 e_3$

Then select the triangular matrix without diagonals:  $e_1 e_2, e_1 e_3, e_2 e_3$ .

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

$\sum_{i=1}^p \sum_{j=p+1}^{p+q} (h_{ir_j} - h_{jr_i}) e_i e_j$

`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 (hp, hq, rp, rq)
    Multiplying a base vector with its scalar coefficient
clifford_multiplication (h0, hp, hq, r0, rp, rq)
    Compute our CL multiplication
    
$$h = h_0 + \sum_{i=1}^p h_i e_i + \sum_{j=p+1}^{p+q} h_j e_j$$


$$r = r_0 + \sum_{i=1}^p r_i e_i + \sum_{j=p+1}^{p+q} r_j e_j$$


$$e_i^2 = +1 \text{ for } i \leq p, e_j^2 = -1 \text{ for } p < j \leq p+q, e_i e_j = -e_j e_i \text{ for } i \neq j$$

    eq j
    
$$h r = \sigma_0 + \sigma_p + \sigma_q + \sigma_{pp} + \sigma_{qq} + \sigma_{pq}$$

    where
    (1)  $\sigma_0 = h_0 r_0 + \sum_{i=1}^p (h_i r_i) e_i - \sum_{j=p+1}^{p+q} (h_j r_j) e_j$ 
    (2)  $\sigma_p = \sum_{i=1}^p (h_i r_0 + h_0 r_i) e_i$ 
    (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 functions are identical **Parameter** ——— x: torch.LongTensor with (n,2) shape :rtype: torch.FloatTensor with (n, **IEI**) shape

**construct\_batch\_selected\_cl\_multivector** (*x: torch.FloatTensor, r: int, p: int, q: int*)  
→ tuple[torch.FloatTensor, torch.FloatTensor, torch.FloatTensor]

Construct a batch of batchs multivectors  $CL_{\{p,q\}}(\mathbb{R}^d)$

### Parameter

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

#### returns

- **a0** (*torch.FloatTensor with (n,k, m) shape*)
- **ap** (*torch.FloatTensor with (n,k, m, p) shape*)
- **aq** (*torch.FloatTensor with (n,k, m, q) shape*)

**forward\_k\_vs\_sample** (*x: torch.LongTensor, target\_entity\_idx: torch.LongTensor*) → torch.FloatTensor

### Parameter

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

*target\_entity\_idx*: torch.LongTensor with (n, k ) shape k denotes the selected number of examples.

#### rtype

torch.FloatTensor with (n, k) 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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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,

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

and return:

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

**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

$$\sigma_p p = \sum_{i=1}^{p-1} \sum_{i'=i+1}^p (h_i r_{i'} - h_{i'} r_i) (\text{model the interactions between } e_i \text{ and } e_{i'} \text{ for } 1 \leq i, i' \leq p) \sigma_q q = \sum_{j=p+1}^{p+q-1} \sum_{j'=j+1}^{p+q} (h_j r_{j'} - h_{j'} r_j)$$

For different base vector interactions, we have

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

**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 functions are identical Parameter ——— x: torch.LongTensor with (n, ) shape :rtype: torch.FloatTensor with (n, **IE**) 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:

$$\sigma_{p,p}^* = \sum_{i=1}^{p-1} \sum_{i'=i+1}^p (x_i y_{i'} - x_{i'} y_i)$$

$\sigma_{pp}$  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

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

$\sigma_{qq}$  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*)

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

**compute\_sigma\_pq** (\*, *hp, hq, rp, rq*)

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_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 = None

    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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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

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

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, l 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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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** = '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** `dicce.ConEx` (*args*)

Bases: `dicce.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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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.,  $[score(h,r,x) | x \text{ in Entities}] \Rightarrow [0.0, 0.1, \dots, 0.8]$ , shape  $\Rightarrow (1, |\text{Entities}|)$  Given a batch of head entities and relations  $\Rightarrow$  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**

**get\_embeddings** ()  $\rightarrow$  Tuple[numpy.ndarray, None]

**forward\_k\_vs\_all** (*x*)  $\rightarrow$  torch.FloatTensor

**forward\_triples** (*x*)  $\rightarrow$  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:  $f(x) = \sum_{i=0}^{d-1} a_i x^i$  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.  $h = \sigma(w_h^T x + b_h)$ ,  $r = \sigma(w_r^T x + b_r)$ ,  $t = \sigma(w_t^T x + b_t)$

**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:

$\text{score}(h,r,t) = \int_0^1 h(x)r(x)t(x) dx = \sum_{i,j,k=0}^{d-1} \text{dfrac}\{a_i*b_j*c_k\}\{1+(i+j+k)\%d\}$

1. generate the range for i,j and k from [0 d-1]
2. perform  $\text{dfrac}\{a_i*b_j*c_k\}\{1+(i+j+k)\%d\}$  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:

$\text{score}(h,r,t) = \int_0^1 h(x)r(x)t(x) dx = \sum_{i,j,k=0}^{d-1} \text{dfrac}\{a_i*c_j*b_k - b_i*c_j*a_k\}\{(1+(i+j)\%d)(1+k)\}$

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.  $\text{score} = \langle \text{hor}, t \rangle$

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

This function takes a matrix tensor of coefficients (*coeff*), a tensor vector of points *x* and range of integer  $[0, 1, \dots, d]$  and return a vector tensor ( $\text{coeff}[0][0] + \text{coeff}[0][1]x + \dots + \text{coeff}[0][d]x^d$ ,

$\text{coeff}[1][0] + \text{coeff}[1][1]x + \dots + \text{coeff}[1][d]x^d$ )

**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  $[0, 1, \dots, d]$

and return a tensor ( $\text{coeff}[0][0] + \text{coeff}[0][1]x + \dots + \text{coeff}[0][d]x^d$ ,

$\text{coeff}[1][0] + \text{coeff}[1][1]x + \dots + \text{coeff}[1][d]x^d$ )

**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: Pykeen\_HolE: Pykeen\_TransD: Pykeen\_TransE: Pykeen\_TransF: Pykeen\_TransH: Pykeen\_TransR:

**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.ByteE(*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 them to be nested in a tree structure. You can assign the sub-modules as regular attributes:

```

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

class Model(nn.Module):
    def __init__(self) -> None:
        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 also have their parameters converted 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 = 'ByteE'`

`config`

`temperature = 0.5`

`topk = 2`

`transformer`

**lm\_head**

**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:

```
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:

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

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```
# 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 them to be nested 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) -> None:
        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 also have their parameters converted 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

$\mathbf{x} (B \times 2 \times T)$



```

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.EnsembleKGE (seed_model=None, pretrained_models: List = None)

    name

    train_mode = True

    named_children()

    property example_input_array

    parameters()

    modules()

```

```

__iter__()
__len__()
eval()
to(device)
mem_of_model()
__call__(x_batch)
step()
get_embeddings()
__str__()

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.load_term_mapping(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(trained_model, model_name: str = 'model', full_storage_path: str = None,
            save_embeddings_as_csv=False) → None

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

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"](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

dicee.write_csv_from_model_parallel(path: str)
    Create

dicee.from_pretrained_model_write_embeddings_into_csv(path: str) → None

```

```
class dicee.DICE_Trainer(args, is_continual_training: bool, 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 = None**

**form\_of\_labelling = None**

**continual\_start** (*knowledge\_graph*)

- (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 | [dicee.trainer.model\\_parallelism.TensorParallel](#) | [dicee.trainer.torch\\_trainer.TorchTrainer](#) | [dicee.trainer.cpu\\_trainer.CPUTrainer](#)

Initialize Trainer from input arguments

**initialize\_or\_load\_model** ()

**init\_dataloader** (*dataset: torch.utils.data.Dataset*) → torch.utils.data.DataLoader

**init\_dataset** () → torch.utils.data.Dataset

**start** (*knowledge\_graph: dicee.knowledge\_graph.KG | numpy.memmap*)

→ Tuple[[dicee.models.base\\_model.BaseKGE](#), str]

Start the training

- (1) Initialize Trainer

(2) Initialize or load a pretrained KGE model

in DDP setup, we need to load the memory map of already read/index KG.

**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*, *dicee.abstracts.InteractiveQueryDecomposition*, *dicee.abstracts.BaseInteractiveTrainKGE*

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, batch\_size=2, topk=1, return\_indices=False*) → 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, batch\_size=2, topk=1, return\_indices=False*) → Tuple

Given a head entity and a tail entity, return top k ranked relations.

$\text{argmax}_{\{r \in R\}} f(h,r,t)$ , 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, batch\_size=2, topk=1, return\_indices=False*) → torch.FloatTensor

Given a head entity and a relation, return top k ranked entities

$\text{argmax}_{\{e \in E\}} f(h,r,e)$ , 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, batch\_size: int = 1024)

Predict missing item in a given triple.

#### Returns

- If you query a single (h, r, ?) or (?, r, t) or (h, ?, t), returns List[(item, score)]
- If you query a batch of B, returns List of B such lists.

**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

**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*)

**predict\_literals** (*entity: List[str] | str = None, attribute: List[str] | str = None, denormalize\_preds: bool = True*) → numpy.ndarray

Predicts literal values for given entities and attributes.

### Parameters

- **entity** (*Union[List[str], str]*) – Entity or list of entities to predict literals for.
- **attribute** (*Union[List[str], str]*) – Attribute or list of attributes to predict literals for.
- **denormalize\_preds** (*bool*) – If True, denormalizes the predictions.

### Returns

Predictions for the given entities and attributes.

### Return type

numpy ndarray

**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** = False

**trainer** = None

**trained\_model** = None

**knowledge\_graph** = None

**report**

**evaluator** = None

**start\_time** = None

**setup\_executor**() → 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

```

dicee.mapping_from_first_two_cols_to_third(train_set_idx)

dicee.timeit(func)

dicee.load_term_mapping(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 `__getitem__()`, 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\_idx** – mapping.
- **relation\_idx** – 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 = 8
num_of_data_points
collate_fn = None
__len__()
__getitem__(idx)
```

```
class dicee.OnevsAllDataset (train_set_idx: numpy.ndarray, entity_idx)
```

Bases: torch.utils.data.Dataset

Dataset for the 1vsALL training strategy

#### Parameters

- **train\_set\_idx** – Indexed triples for the training.
- **entity\_idx** – mapping.
- **relation\_idx** – 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_idx, relation_idx, 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 a 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.

forall  $y_i = 1$  s.t.  $(h \ r \ E_i)$  in KG

#### Note

TODO

**train\_set\_idx**

[numpy.ndarray] n by 3 array representing n triples

**entity\_idx**

[dictionary] string representation of an entity to its integer id

**relation\_idx**

[dictionary] 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_idxxs, relation_idxxs, 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  $N = |E| \times |R|$   $y_i$  denotes a multi-label vector in  $[0, 1]^{|E|}$  is a binary label.

orall  $y_i = 1$  s.t.  $(h, r) \in KG$

#### 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_idxxs
    [dictionary] string representation of an entity to its integer id

relation_idxxs
    [dictionary] 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

__len__()

__getitem__(idx)

```

```
class dicee.OnevsSample(train_set: numpy.ndarray, num_entities, num_relations,  
                      neg_sample_ratio: int = None, label_smoothing_rate: float = 0.0)
```

Bases: torch.utils.data.Dataset

A custom PyTorch Dataset class for knowledge graph embeddings, which includes both positive and negative sampling for a given dataset for multi-class classification problem..

#### Parameters

- **train\_set** (*np.ndarray*) – A numpy array containing triples of knowledge graph data. Each triple consists of (head\_entity, relation, tail\_entity).
- **num\_entities** (*int*) – The number of unique entities in the knowledge graph.
- **num\_relations** (*int*) – The number of unique relations in the knowledge graph.
- **neg\_sample\_ratio** (*int, optional*) – The number of negative samples to be generated per positive sample. Must be a positive integer and less than num\_entities.
- **label\_smoothing\_rate** (*float, optional*) – A label smoothing rate to apply to the positive and negative labels. Defaults to 0.0.

#### train\_data

The input data converted into a PyTorch tensor.

##### Type

torch.Tensor

#### num\_entities

Number of entities in the dataset.

##### Type

int

#### num\_relations

Number of relations in the dataset.

##### Type

int

#### neg\_sample\_ratio

Ratio of negative samples to be drawn for each positive sample.

##### Type

int

#### label\_smoothing\_rate

The smoothing factor applied to the labels.

##### Type

torch.Tensor

#### collate\_fn

A function that can be used to collate data samples into batches (set to None by default).

##### Type

function, optional

#### train\_data

#### num\_entities

`num_relations`

`neg_sample_ratio = None`

`label_smoothing_rate`

`collate_fn = None`

`__len__()`

Returns the number of samples in the dataset.

`__getitem__(idx)`

Retrieves a single data sample from the dataset at the given index.

#### Parameters

`idx` (*int*) – The index of the sample to retrieve.

#### Returns

A tuple consisting of:

- `x` (`torch.Tensor`): The head and relation part of the triple.
- `y_idx` (`torch.Tensor`): The concatenated indices of the true object (tail entity) and the indices of the negative samples.
- `y_vec` (`torch.Tensor`): A vector containing the labels for the positive and negative samples, with label smoothing applied.

#### Return type

tuple

```
class dicee.KvsSampleDataset (train_set_idx: numpy.ndarray, entity_idxxs, relation_idxxs, form,
                              store=None, neg_ratio=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.

forall  $y_i = 1$  s.t.  $(h, r, E_i)$  in KG

At each mini-batch construction, we subsample( $y$ ), hence  $n$

$|new\_y| \ll |E|$  new\_y contains all 1's if  $\sum(y) < neg\_sample\_ratio$  new\_y contains

`train_set_idx`

Indexed triples for the training.

`entity_idxxs`

mapping.

`relation_idxxs`

mapping.

`form`

?

`store`

?

`label_smoothing_rate`

?

`torch.utils.data.Dataset`

```
train_data = None

train_target = None

neg_ratio = None

num_entities

label_smoothing_rate

collate_fn = None

max_num_of_classes

__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 . collect\_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\_idxxs**

mapping.

**relation\_idxxs**

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.CVDDataModule (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, ...).

#### 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)
```

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```
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:

```
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:

```
# 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
```

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```
# 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.LiteralDataset (file_path: str, ent_idx: dict = None, normalization_type: str = 'z-norm',
                           sampling_ratio: float = None, loader_backend: str = 'pandas')
```

Bases: torch.utils.data.Dataset

Dataset for loading and processing literal data for training Literal Embedding model. This dataset handles the loading, normalization, and preparation of triples for training a literal embedding model.

Extends torch.utils.data.Dataset for supporting PyTorch dataloaders.

**train\_file\_path**

Path to the training data file.

**Type**

str

**normalization**

Type of normalization to apply ('z-norm', 'min-max', or None).

**Type**

str

**normalization\_params**

Parameters used for normalization.

**Type**

dict

**sampling\_ratio**

Fraction of the training set to use for ablations.

**Type**

float

**entity\_to\_idx**

Mapping of entities to their indices.

**Type**

dict

**num\_entities**

Total number of entities.

**Type**  
int

**data\_property\_to\_idx**  
Mapping of data properties to their indices.

**Type**  
dict

**num\_data\_properties**  
Total number of data properties.

**Type**  
int

**loader\_backend**  
Backend to use for loading data ('pandas' or 'rdflib').

**Type**  
str

**train\_file\_path**

**loader\_backend** = 'pandas'

**normalization\_type** = 'z-norm'

**normalization\_params**

**sampling\_ratio** = None

**entity\_to\_idx** = None

**num\_entities**

**\_\_getitem\_\_** (*index*)

**\_\_len\_\_** ()

**static load\_and\_validate\_literal\_data** (*file\_path: str = None, loader\_backend: str = 'pandas'*)  
→ pandas.DataFrame

Loads and validates the literal data file. :param file\_path: Path to the literal data file. :type file\_path: str

**Returns**  
DataFrame containing the loaded and validated data.

**Return type**  
pd.DataFrame

**static denormalize** (*preds\_norm, attributes, normalization\_params*) → numpy.ndarray

Denormalizes the predictions based on the normalization type.

Args: preds\_norm (np.ndarray): Normalized predictions to be denormalized. attributes (list): List of attributes corresponding to the predictions. normalization\_params (dict): Dictionary containing normalization parameters for each attribute.

**Returns**  
Denormalized predictions.

**Return type**  
np.ndarray

```

class dicee.QueryGenerator (train_path: str, 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 = False

    gen_test = True

    seed = 1

    max_ans_num = 1000000.0

    mode

    ent2id = None

    rel2id: Dict = None

    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'

```



## Python Module Index

### d

- `dicee`, 12
- `dicee.__main__`, 12
- `dicee.abstracts`, 12
- `dicee.analyse_experiments`, 19
- `dicee.callbacks`, 20
- `dicee.config`, 28
- `dicee.dataset_classes`, 31
- `dicee.eval_static_funcs`, 45
- `dicee.evaluator`, 47
- `dicee.executer`, 48
- `dicee.knowledge_graph`, 50
- `dicee.knowledge_graph_embeddings`, 51
- `dicee.models`, 55
  - `adopt`, 55
  - `base_model`, 56
  - `clifford`, 65
  - `complex`, 72
  - `dualE`, 75
  - `ensemble`, 76
  - `function_space`, 77
  - `literal`, 80
  - `octonion`, 82
  - `pykeen_models`, 85
  - `quaternion`, 86
  - `real`, 89
  - `static_funcs`, 90
  - `transformers`, 91
- `dicee.query_generator`, 144
- `dicee.read_preprocess_save_load_kg`, 146
  - `read_preprocess_save_load_kg.preprocess`, 146
  - `read_preprocess_save_load_kg.read_from_disk`, 147
  - `read_preprocess_save_load_kg.save_load_disk`, 147
  - `read_preprocess_save_load_kg.util`, 148
- `dicee.sanity_checkers`, 152
- `dicee.scripts`, 153
  - `index_serve`, 153
  - `run`, 156
- `dicee.static_funcs`, 156
- `dicee.static_funcs_training`, 159
- `dicee.static_preprocess_funcs`, 160
- `dicee.trainer`, 161
  - `dice_trainer`, 161
  - `model_parallelism`, 163
  - `torch_trainer`, 163
  - `torch_trainer_ddp`, 165

# Index

## Non-alphabetical

`__call__()` (*dicee.EnsembleKGE method*), 194  
`__call__()` (*dicee.models.base\_model.IdentityClass method*), 65  
`__call__()` (*dicee.models.ensemble.EnsembleKGE method*), 76  
`__call__()` (*dicee.models.IdentityClass method*), 108, 119, 125  
`__class_vars__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 154  
`__getitem__()` (*dicee.AllvsAll method*), 205  
`__getitem__()` (*dicee.BPE\_NegativeSamplingDataset method*), 202  
`__getitem__()` (*dicee.dataset\_classes.AllvsAll method*), 36  
`__getitem__()` (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset method*), 32  
`__getitem__()` (*dicee.dataset\_classes.KvsAll method*), 35  
`__getitem__()` (*dicee.dataset\_classes.KvsSampleDataset method*), 38  
`__getitem__()` (*dicee.dataset\_classes.LiteralDataset method*), 44  
`__getitem__()` (*dicee.dataset\_classes.MultiClassClassificationDataset method*), 34  
`__getitem__()` (*dicee.dataset\_classes.MultiLabelDataset method*), 33  
`__getitem__()` (*dicee.dataset\_classes.NegSampleDataset method*), 39  
`__getitem__()` (*dicee.dataset\_classes.OnevsAllDataset method*), 34  
`__getitem__()` (*dicee.dataset\_classes.OnevsSample method*), 37  
`__getitem__()` (*dicee.dataset\_classes.TriplePredictionDataset method*), 39  
`__getitem__()` (*dicee.KvsAll method*), 205  
`__getitem__()` (*dicee.KvsSampleDataset method*), 208  
`__getitem__()` (*dicee.LiteralDataset method*), 214  
`__getitem__()` (*dicee.MultiClassClassificationDataset method*), 203  
`__getitem__()` (*dicee.MultiLabelDataset method*), 203  
`__getitem__()` (*dicee.NegSampleDataset method*), 208  
`__getitem__()` (*dicee.OnevsAllDataset method*), 204  
`__getitem__()` (*dicee.OnevsSample method*), 207  
`__getitem__()` (*dicee.TriplePredictionDataset method*), 209  
`__iter__()` (*dicee.config.Namespace method*), 31  
`__iter__()` (*dicee.EnsembleKGE method*), 193  
`__iter__()` (*dicee.knowledge\_graph.KG method*), 51  
`__iter__()` (*dicee.models.ensemble.EnsembleKGE method*), 76  
`__len__()` (*dicee.AllvsAll method*), 205  
`__len__()` (*dicee.BPE\_NegativeSamplingDataset method*), 202  
`__len__()` (*dicee.dataset\_classes.AllvsAll method*), 36  
`__len__()` (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset method*), 32  
`__len__()` (*dicee.dataset\_classes.KvsAll method*), 35  
`__len__()` (*dicee.dataset\_classes.KvsSampleDataset method*), 38  
`__len__()` (*dicee.dataset\_classes.LiteralDataset method*), 44  
`__len__()` (*dicee.dataset\_classes.MultiClassClassificationDataset method*), 34  
`__len__()` (*dicee.dataset\_classes.MultiLabelDataset method*), 33  
`__len__()` (*dicee.dataset\_classes.NegSampleDataset method*), 38  
`__len__()` (*dicee.dataset\_classes.OnevsAllDataset method*), 34  
`__len__()` (*dicee.dataset\_classes.OnevsSample method*), 37  
`__len__()` (*dicee.dataset\_classes.TriplePredictionDataset method*), 39  
`__len__()` (*dicee.EnsembleKGE method*), 194  
`__len__()` (*dicee.knowledge\_graph.KG method*), 51  
`__len__()` (*dicee.KvsAll method*), 205  
`__len__()` (*dicee.KvsSampleDataset method*), 208  
`__len__()` (*dicee.LiteralDataset method*), 214  
`__len__()` (*dicee.models.ensemble.EnsembleKGE method*), 76  
`__len__()` (*dicee.MultiClassClassificationDataset method*), 203  
`__len__()` (*dicee.MultiLabelDataset method*), 203  
`__len__()` (*dicee.NegSampleDataset method*), 208  
`__len__()` (*dicee.OnevsAllDataset method*), 204  
`__len__()` (*dicee.OnevsSample method*), 207  
`__len__()` (*dicee.TriplePredictionDataset method*), 209  
`__private_attributes__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_complete__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_computed_fields__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_core_schema__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_custom_init__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_decorators__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_extra__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155  
`__pydantic_fields__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155

- `__pydantic_fields_set__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_generic_metadata__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_parent_namespace__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_post_init__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_private__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_root_model__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_serializer__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__pydantic_validator__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__setstate__` () (*dicee.models.ADOPT method*), 99
- `__setstate__` () (*dicee.models.adopt.ADOPT method*), 56
- `__signature__` (*dicee.scripts.index\_serve.StringListRequest attribute*), 155
- `__str__` () (*dicee.EnsembleKGE method*), 194
- `__str__` () (*dicee.KGE method*), 197
- `__str__` () (*dicee.knowledge\_graph\_embeddings.KGE method*), 52
- `__str__` () (*dicee.models.ensemble.EnsembleKGE method*), 76
- `__version__` (*in module dicee*), 216

## A

- `AbstractCallback` (*class in dicee.abstracts*), 16
- `AbstractPPECallback` (*class in dicee.abstracts*), 17
- `AbstractTrainer` (*class in dicee.abstracts*), 12
- `AccumulateEpochLossCallback` (*class in dicee.callbacks*), 21
- `achieve_answer` () (*dicee.query\_generator.QueryGenerator method*), 145
- `achieve_answer` () (*dicee.QueryGenerator method*), 215
- `AConEx` (*class in dicee*), 180
- `AConEx` (*class in dicee.models*), 114
- `AConEx` (*class in dicee.models.complex*), 73
- `AConvO` (*class in dicee*), 180
- `AConvO` (*class in dicee.models*), 127
- `AConvO` (*class in dicee.models.octonion*), 84
- `AConvQ` (*class in dicee*), 181
- `AConvQ` (*class in dicee.models*), 121
- `AConvQ` (*class in dicee.models.quaternion*), 88
- `adaptive_lr` (*dicee.config.Namespace attribute*), 31
- `adaptive_swa` (*dicee.config.Namespace attribute*), 30
- `add_new_entity_embeddings` () (*dicee.abstracts.BaseInteractiveKGE method*), 15
- `add_noise_rate` (*dicee.config.Namespace attribute*), 29
- `add_noise_rate` (*dicee.knowledge\_graph.KG attribute*), 50
- `add_noisy_triples` () (*in module dicee*), 195
- `add_noisy_triples` () (*in module dicee.static\_funcs*), 158
- `add_noisy_triples_into_training` () (*dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk.ReadFromDisk method*), 147
- `add_noisy_triples_into_training` () (*dicee.read\_preprocess\_save\_load\_kg.ReadFromDisk method*), 152
- `add_reciprocal` (*dicee.knowledge\_graph.KG attribute*), 50
- `ADOPT` (*class in dicee.models*), 98
- `ADOPT` (*class in dicee.models.adopt*), 55
- `adopt` () (*in module dicee.models.adopt*), 56
- `AllvsAll` (*class in dicee*), 205
- `AllvsAll` (*class in dicee.dataset\_classes*), 35
- `alphas` (*dicee.abstracts.AbstractPPECallback attribute*), 17
- `alphas` (*dicee.callbacks.ASWA attribute*), 24
- `analyse` () (*in module dicee.analyse\_experiments*), 20
- `answer_multi_hop_query` () (*dicee.KGE method*), 199
- `answer_multi_hop_query` () (*dicee.knowledge\_graph\_embeddings.KGE method*), 54
- `app` (*in module dicee.scripts.index\_serve*), 154
- `apply_coefficients` () (*dicee.DeCaL method*), 176
- `apply_coefficients` () (*dicee.Keci method*), 173
- `apply_coefficients` () (*dicee.models.clifford.DeCaL method*), 70
- `apply_coefficients` () (*dicee.models.clifford.Keci method*), 67
- `apply_coefficients` () (*dicee.models.DeCaL method*), 133
- `apply_coefficients` () (*dicee.models.Keci method*), 129
- `apply_reciprical_or_noise` () (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 150
- `apply_semantic_constraint` (*dicee.abstracts.BaseInteractiveKGE attribute*), 14
- `apply_unit_norm` (*dicee.BaseKGE attribute*), 192
- `apply_unit_norm` (*dicee.models.base\_model.BaseKGE attribute*), 63
- `apply_unit_norm` (*dicee.models.BaseKGE attribute*), 105, 109, 112, 117, 123, 135, 139
- `args` (*dicee.BaseKGE attribute*), 191
- `args` (*dicee.DICE\_Trainer attribute*), 196

- args (*dicee.evaluator.Evaluator* attribute), 47
- args (*dicee.Execute* attribute), 200
- args (*dicee.executer.Execute* attribute), 48
- args (*dicee.models.base\_model.BaseKGE* attribute), 63
- args (*dicee.models.base\_model.IdentityClass* attribute), 65
- args (*dicee.models.BaseKGE* attribute), 105, 108, 112, 116, 122, 135, 138
- args (*dicee.models.IdentityClass* attribute), 108, 119, 125
- args (*dicee.models.pykeen\_models.PykeenKGE* attribute), 85
- args (*dicee.models.PykeenKGE* attribute), 137
- args (*dicee.PykeenKGE* attribute), 188
- args (*dicee.trainer.DICE\_Trainer* attribute), 166
- args (*dicee.trainer.dice\_trainer.DICE\_Trainer* attribute), 161
- ASWA (*class in dicee.callbacks*), 23
- aswa (*dicee.analyse\_experiments.Experiment* attribute), 19
- attn (*dicee.models.transformers.Block* attribute), 96
- attn\_dropout (*dicee.models.transformers.CausalSelfAttention* attribute), 94
- attributes (*dicee.abstracts.AbstractTrainer* attribute), 13
- auto\_batch\_finding (*dicee.config.Namespace* attribute), 31

## B

- backend (*dicee.config.Namespace* attribute), 29
- backend (*dicee.knowledge\_graph.KG* attribute), 51
- BaseInteractiveKGE (*class in dicee.abstracts*), 14
- BaseInteractiveTrainKGE (*class in dicee.abstracts*), 18
- BaseKGE (*class in dicee*), 191
- BaseKGE (*class in dicee.models*), 104, 108, 111, 116, 122, 134, 138
- BaseKGE (*class in dicee.models.base\_model*), 62
- BaseKGELightning (*class in dicee.models*), 99
- BaseKGELightning (*class in dicee.models.base\_model*), 56
- batch\_kronecker\_product () (*dicee.callbacks.KronE* static method), 26
- batch\_size (*dicee.analyse\_experiments.Experiment* attribute), 19
- batch\_size (*dicee.callbacks.PseudoLabellingCallback* attribute), 23
- batch\_size (*dicee.config.Namespace* attribute), 29
- batch\_size (*dicee.CVDataModule* attribute), 210
- batch\_size (*dicee.dataset\_classes.CVDataModule* attribute), 40
- batches\_per\_epoch (*dicee.callbacks.LRScheduler* attribute), 27
- bias (*dicee.models.transformers.GPTConfig* attribute), 96
- bias (*dicee.models.transformers.LayerNorm* attribute), 93
- Block (*class in dicee.models.transformers*), 95
- block\_size (*dicee.BaseKGE* attribute), 192
- block\_size (*dicee.config.Namespace* attribute), 31
- block\_size (*dicee.dataset\_classes.MultiClassClassificationDataset* attribute), 33
- block\_size (*dicee.models.base\_model.BaseKGE* attribute), 63
- block\_size (*dicee.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139
- block\_size (*dicee.models.transformers.GPTConfig* attribute), 96
- block\_size (*dicee.MultiClassClassificationDataset* attribute), 203
- bn\_conv1 (*dicee.AConvQ* attribute), 181
- bn\_conv1 (*dicee.ConvQ* attribute), 182
- bn\_conv1 (*dicee.models.AConvQ* attribute), 121
- bn\_conv1 (*dicee.models.ConvQ* attribute), 121
- bn\_conv1 (*dicee.models.quaternion.AConvQ* attribute), 88
- bn\_conv1 (*dicee.models.quaternion.ConvQ* attribute), 88
- bn\_conv2 (*dicee.AConvQ* attribute), 181
- bn\_conv2 (*dicee.ConvQ* attribute), 182
- bn\_conv2 (*dicee.models.AConvQ* attribute), 122
- bn\_conv2 (*dicee.models.ConvQ* attribute), 121
- bn\_conv2 (*dicee.models.quaternion.AConvQ* attribute), 88
- bn\_conv2 (*dicee.models.quaternion.ConvQ* attribute), 88
- bn\_conv2d (*dicee.AConEx* attribute), 180
- bn\_conv2d (*dicee.AConvO* attribute), 181
- bn\_conv2d (*dicee.ConEx* attribute), 183
- bn\_conv2d (*dicee.ConvO* attribute), 183
- bn\_conv2d (*dicee.models.AConEx* attribute), 115
- bn\_conv2d (*dicee.models.AConvO* attribute), 127
- bn\_conv2d (*dicee.models.complex.AConEx* attribute), 73
- bn\_conv2d (*dicee.models.complex.ConEx* attribute), 73
- bn\_conv2d (*dicee.models.ConEx* attribute), 114

bn\_conv2d (*dicee.models.ConvO attribute*), 127  
 bn\_conv2d (*dicee.models.octonion.AConvO attribute*), 84  
 bn\_conv2d (*dicee.models.octonion.ConvO attribute*), 84  
 BPE\_NegativeSamplingDataset (*class in dicee*), 202  
 BPE\_NegativeSamplingDataset (*class in dicee.dataset\_classes*), 32  
 build\_chain\_funcs () (*dicee.models.FMult2 method*), 142  
 build\_chain\_funcs () (*dicee.models.function\_space.FMult2 method*), 78  
 build\_func () (*dicee.models.FMult2 method*), 142  
 build\_func () (*dicee.models.function\_space.FMult2 method*), 78  
 Byte (*class in dicee*), 189  
 Byte (*class in dicee.models.transformers*), 91  
 byte\_pair\_encoding (*dicee.analyse\_experiments.Experiment attribute*), 19  
 byte\_pair\_encoding (*dicee.BaseKGE attribute*), 192  
 byte\_pair\_encoding (*dicee.config.Namespace attribute*), 30  
 byte\_pair\_encoding (*dicee.knowledge\_graph.KG attribute*), 50  
 byte\_pair\_encoding (*dicee.models.base\_model.BaseKGE attribute*), 63  
 byte\_pair\_encoding (*dicee.models.BaseKGE attribute*), 106, 109, 113, 117, 123, 136, 139

## C

c\_attn (*dicee.models.transformers.CausalSelfAttention attribute*), 94  
 c\_fc (*dicee.models.transformers.MLP attribute*), 95  
 c\_proj (*dicee.models.transformers.CausalSelfAttention attribute*), 94  
 c\_proj (*dicee.models.transformers.MLP attribute*), 95  
 callbacks (*dicee.abstracts.AbstractTrainer attribute*), 13  
 callbacks (*dicee.analyse\_experiments.Experiment attribute*), 19  
 callbacks (*dicee.config.Namespace attribute*), 29  
 callbacks (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer attribute*), 166  
 CausalSelfAttention (*class in dicee.models.transformers*), 93  
 chain\_func () (*dicee.models.FMult method*), 141  
 chain\_func () (*dicee.models.function\_space.FMult method*), 77  
 chain\_func () (*dicee.models.function\_space.GFMult method*), 78  
 chain\_func () (*dicee.models.GFMult method*), 141  
 CKeci (*class in dicee*), 171  
 CKeci (*class in dicee.models*), 131  
 CKeci (*class in dicee.models.clifford*), 68  
 cl\_pqr () (*dicee.DeCaL method*), 175  
 cl\_pqr () (*dicee.models.clifford.DeCaL method*), 70  
 cl\_pqr () (*dicee.models.DeCaL method*), 132  
 clifford\_multiplication () (*dicee.Keci method*), 173  
 clifford\_multiplication () (*dicee.models.clifford.Keci method*), 67  
 clifford\_multiplication () (*dicee.models.Keci method*), 129  
 clip\_lambda (*dicee.models.ADOPT attribute*), 99  
 clip\_lambda (*dicee.models.adopt.ADOPT attribute*), 56  
 collate\_fn (*dicee.AllvsAll attribute*), 205  
 collate\_fn (*dicee.dataset\_classes.AllvsAll attribute*), 35  
 collate\_fn (*dicee.dataset\_classes.KvsAll attribute*), 35  
 collate\_fn (*dicee.dataset\_classes.KvsSampleDataset attribute*), 38  
 collate\_fn (*dicee.dataset\_classes.MultiClassClassificationDataset attribute*), 33  
 collate\_fn (*dicee.dataset\_classes.MultiLabelDataset attribute*), 33  
 collate\_fn (*dicee.dataset\_classes.OnevsAllDataset attribute*), 34  
 collate\_fn (*dicee.dataset\_classes.OnevsSample attribute*), 36, 37  
 collate\_fn (*dicee.KvsAll attribute*), 205  
 collate\_fn (*dicee.KvsSampleDataset attribute*), 208  
 collate\_fn (*dicee.MultiClassClassificationDataset attribute*), 203  
 collate\_fn (*dicee.MultiLabelDataset attribute*), 203  
 collate\_fn (*dicee.OnevsAllDataset attribute*), 204  
 collate\_fn (*dicee.OnevsSample attribute*), 206, 207  
 collate\_fn () (*dicee.BPE\_NegativeSamplingDataset method*), 202  
 collate\_fn () (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset method*), 32  
 collate\_fn () (*dicee.dataset\_classes.TriplePredictionDataset method*), 39  
 collate\_fn () (*dicee.TriplePredictionDataset method*), 209  
 collection\_name (*dicee.scripts.index\_serve.NeuralSearcher attribute*), 154  
 comp\_func () (*dicee.LFMult method*), 187  
 comp\_func () (*dicee.models.function\_space.LFMult method*), 80  
 comp\_func () (*dicee.models.LFMult method*), 143  
 ComplEx (*class in dicee*), 179  
 ComplEx (*class in dicee.models*), 115

ComplEx (class in *dicee.models.complex*), 73  
 compute\_convergence () (in module *dicee.callbacks*), 23  
 compute\_func () (*dicee.models.FMult* method), 141  
 compute\_func () (*dicee.models.FMult2* method), 142  
 compute\_func () (*dicee.models.function\_space.FMult* method), 77  
 compute\_func () (*dicee.models.function\_space.FMult2* method), 78  
 compute\_func () (*dicee.models.function\_space.GFMult* method), 78  
 compute\_func () (*dicee.models.GFMult* method), 141  
 compute\_mrr () (*dicee.callbacks.ASWA* static method), 24  
 compute\_sigma\_pp () (*dicee.DeCaL* method), 176  
 compute\_sigma\_pp () (*dicee.Keci* method), 172  
 compute\_sigma\_pp () (*dicee.models.clifford.DeCaL* method), 71  
 compute\_sigma\_pp () (*dicee.models.clifford.Keci* method), 66  
 compute\_sigma\_pp () (*dicee.models.DeCaL* method), 133  
 compute\_sigma\_pp () (*dicee.models.Keci* method), 128  
 compute\_sigma\_pq () (*dicee.DeCaL* method), 177  
 compute\_sigma\_pq () (*dicee.Keci* method), 172  
 compute\_sigma\_pq () (*dicee.models.clifford.DeCaL* method), 72  
 compute\_sigma\_pq () (*dicee.models.clifford.Keci* method), 67  
 compute\_sigma\_pq () (*dicee.models.DeCaL* method), 134  
 compute\_sigma\_pq () (*dicee.models.Keci* method), 129  
 compute\_sigma\_pr () (*dicee.DeCaL* method), 178  
 compute\_sigma\_pr () (*dicee.models.clifford.DeCaL* method), 72  
 compute\_sigma\_pr () (*dicee.models.DeCaL* method), 134  
 compute\_sigma\_qq () (*dicee.DeCaL* method), 177  
 compute\_sigma\_qq () (*dicee.Keci* method), 172  
 compute\_sigma\_qq () (*dicee.models.clifford.DeCaL* method), 71  
 compute\_sigma\_qq () (*dicee.models.clifford.Keci* method), 66  
 compute\_sigma\_qq () (*dicee.models.DeCaL* method), 133  
 compute\_sigma\_qq () (*dicee.models.Keci* method), 129  
 compute\_sigma\_qr () (*dicee.DeCaL* method), 178  
 compute\_sigma\_qr () (*dicee.models.clifford.DeCaL* method), 72  
 compute\_sigma\_qr () (*dicee.models.DeCaL* method), 134  
 compute\_sigma\_rr () (*dicee.DeCaL* method), 177  
 compute\_sigma\_rr () (*dicee.models.clifford.DeCaL* method), 71  
 compute\_sigma\_rr () (*dicee.models.DeCaL* method), 134  
 compute\_sigmas\_multivect () (*dicee.DeCaL* method), 176  
 compute\_sigmas\_multivect () (*dicee.models.clifford.DeCaL* method), 70  
 compute\_sigmas\_multivect () (*dicee.models.DeCaL* method), 132  
 compute\_sigmas\_single () (*dicee.DeCaL* method), 175  
 compute\_sigmas\_single () (*dicee.models.clifford.DeCaL* method), 70  
 compute\_sigmas\_single () (*dicee.models.DeCaL* method), 132  
 ConEx (class in *dicee*), 183  
 ConEx (class in *dicee.models*), 114  
 ConEx (class in *dicee.models.complex*), 72  
 config (*dicee.BytE* attribute), 189  
 config (*dicee.models.transformers.BytE* attribute), 92  
 config (*dicee.models.transformers.GPT* attribute), 97  
 configs (*dicee.abstracts.BaseInteractiveKGE* attribute), 14  
 configure\_optimizers () (*dicee.models.base\_model.BaseKGELightning* method), 61  
 configure\_optimizers () (*dicee.models.BaseKGELightning* method), 103  
 configure\_optimizers () (*dicee.models.transformers.GPT* method), 97  
 construct\_batch\_selected\_cl\_multivector () (*dicee.Keci* method), 173  
 construct\_batch\_selected\_cl\_multivector () (*dicee.models.clifford.Keci* method), 68  
 construct\_batch\_selected\_cl\_multivector () (*dicee.models.Keci* method), 130  
 construct\_cl\_multivector () (*dicee.DeCaL* method), 176  
 construct\_cl\_multivector () (*dicee.Keci* method), 173  
 construct\_cl\_multivector () (*dicee.models.clifford.DeCaL* method), 70  
 construct\_cl\_multivector () (*dicee.models.clifford.Keci* method), 67  
 construct\_cl\_multivector () (*dicee.models.DeCaL* method), 133  
 construct\_cl\_multivector () (*dicee.models.Keci* method), 130  
 construct\_dataset () (in module *dicee*), 202  
 construct\_dataset () (in module *dicee.dataset\_classes*), 32  
 construct\_ensemble (*dicee.abstracts.BaseInteractiveKGE* attribute), 14  
 construct\_graph () (*dicee.query\_generator.QueryGenerator* method), 145  
 construct\_graph () (*dicee.QueryGenerator* method), 215  
 construct\_input\_and\_output () (*dicee.abstracts.BaseInteractiveKGE* method), 15  
 construct\_multi\_coeff () (*dicee.LFMult* method), 187



`construct_multi_coeff()` (*dicee.models.function\_space.LFMMult method*), 79  
`construct_multi_coeff()` (*dicee.models.LFMMult method*), 143  
`continual_learning` (*dicee.config.Namespace attribute*), 31  
`continual_start()` (*dicee.DICE\_Trainer method*), 196  
`continual_start()` (*dicee.executor.ContinuousExecute method*), 49  
`continual_start()` (*dicee.trainer.DICE\_Trainer method*), 166  
`continual_start()` (*dicee.trainer.dice\_trainer.DICE\_Trainer method*), 162  
`continual_training_setup_executor()` (*in module dicee*), 195  
`continual_training_setup_executor()` (*in module dicee.static\_funcs*), 159  
`ContinuousExecute` (*class in dicee.executor*), 49  
`conv2d` (*dicee.AConEx attribute*), 180  
`conv2d` (*dicee.AConvO attribute*), 180  
`conv2d` (*dicee.AConvQ attribute*), 181  
`conv2d` (*dicee.ConEx attribute*), 183  
`conv2d` (*dicee.ConvO attribute*), 183  
`conv2d` (*dicee.ConvQ attribute*), 182  
`conv2d` (*dicee.models.AConEx attribute*), 114  
`conv2d` (*dicee.models.AConvO attribute*), 127  
`conv2d` (*dicee.models.AConvQ attribute*), 121  
`conv2d` (*dicee.models.complex.AConEx attribute*), 73  
`conv2d` (*dicee.models.complex.ConEx attribute*), 72  
`conv2d` (*dicee.models.ConEx attribute*), 114  
`conv2d` (*dicee.models.ConvO attribute*), 127  
`conv2d` (*dicee.models.ConvQ attribute*), 121  
`conv2d` (*dicee.models.octonion.AConvO attribute*), 84  
`conv2d` (*dicee.models.octonion.ConvO attribute*), 83  
`conv2d` (*dicee.models.quaternion.AConvQ attribute*), 88  
`conv2d` (*dicee.models.quaternion.ConvQ attribute*), 88  
`ConvO` (*class in dicee*), 182  
`ConvO` (*class in dicee.models*), 126  
`ConvO` (*class in dicee.models.octonion*), 83  
`ConvQ` (*class in dicee*), 181  
`ConvQ` (*class in dicee.models*), 121  
`ConvQ` (*class in dicee.models.quaternion*), 88  
`create_constraints()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 150  
`create_constraints()` (*in module dicee.static\_preprocess\_funcs*), 160  
`create_experiment_folder()` (*in module dicee*), 195  
`create_experiment_folder()` (*in module dicee.static\_funcs*), 159  
`create_random_data()` (*dicee.callbacks.PseudoLabellingCallback method*), 23  
`create_recipriocal_triples()` (*in module dicee*), 194  
`create_recipriocal_triples()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 151  
`create_recipriocal_triples()` (*in module dicee.static\_funcs*), 157  
`create_vector_database()` (*dicee.KGE method*), 197  
`create_vector_database()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 52  
`crop_block_size()` (*dicee.models.transformers.GPT method*), 97  
`ctx` (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer attribute*), 166  
`CVDDataModule` (*class in dicee*), 209  
`CVDDataModule` (*class in dicee.dataset\_classes*), 39  
`cycle_length` (*dicee.callbacks.LRScheduler attribute*), 27

## D

`data_module` (*dicee.callbacks.PseudoLabellingCallback attribute*), 23  
`data_property_embeddings` (*dicee.models.literal.LiteralEmbeddings attribute*), 81  
`data_property_to_idx` (*dicee.dataset\_classes.LiteralDataset attribute*), 44  
`data_property_to_idx` (*dicee.LiteralDataset attribute*), 214  
`dataset_dir` (*dicee.config.Namespace attribute*), 28  
`dataset_dir` (*dicee.knowledge\_graph.KG attribute*), 50  
`dataset_sanity_checking()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 151  
`DeCaL` (*class in dicee*), 174  
`DeCaL` (*class in dicee.models*), 131  
`DeCaL` (*class in dicee.models.clifford*), 69  
`decide()` (*dicee.callbacks.ASWA method*), 24  
`default_eval_model` (*dicee.callbacks.PeriodicEvalCallback attribute*), 27  
`degree` (*dicee.LFMMult attribute*), 187  
`degree` (*dicee.models.function\_space.LFMMult attribute*), 79  
`degree` (*dicee.models.LFMMult attribute*), 142  
`denormalize()` (*dicee.dataset\_classes.LiteralDataset static method*), 44

- denormalize() (*dicee.LiteralDataset static method*), 214
- deploy() (*dicee.KGE method*), 200
- deploy() (*dicee.knowledge\_graph\_embeddings.KGE method*), 55
- deploy\_head\_entity\_prediction() (*in module dicee*), 195
- deploy\_head\_entity\_prediction() (*in module dicee.static\_funcs*), 158
- deploy\_relation\_prediction() (*in module dicee*), 195
- deploy\_relation\_prediction() (*in module dicee.static\_funcs*), 159
- deploy\_tail\_entity\_prediction() (*in module dicee*), 195
- deploy\_tail\_entity\_prediction() (*in module dicee.static\_funcs*), 158
- deploy\_triple\_prediction() (*in module dicee*), 195
- deploy\_triple\_prediction() (*in module dicee.static\_funcs*), 158
- describe() (*dicee.knowledge\_graph.KG method*), 51
- description\_of\_input (*dicee.knowledge\_graph.KG attribute*), 51
- device (*dicee.models.literal.LiteralEmbeddings property*), 81
- DICE\_Trainer (*class in dicee*), 195
- DICE\_Trainer (*class in dicee.trainer*), 166
- DICE\_Trainer (*class in dicee.trainer.dice\_trainer*), 161
- dicee
  - module, 12
- dicee.\_\_main\_\_
  - module, 12
- dicee.abstracts
  - module, 12
- dicee.analyse\_experiments
  - module, 19
- dicee.callbacks
  - module, 20
- dicee.config
  - module, 28
- dicee.dataset\_classes
  - module, 31
- dicee.eval\_static\_funcs
  - module, 45
- dicee.evaluator
  - module, 47
- dicee.executer
  - module, 48
- dicee.knowledge\_graph
  - module, 50
- dicee.knowledge\_graph\_embeddings
  - module, 51
- dicee.models
  - module, 55
- dicee.models.adopt
  - module, 55
- dicee.models.base\_model
  - module, 56
- dicee.models.clifford
  - module, 65
- dicee.models.complex
  - module, 72
- dicee.models.dualE
  - module, 75
- dicee.models.ensemble
  - module, 76
- dicee.models.function\_space
  - module, 77
- dicee.models.literal
  - module, 80
- dicee.models.octonion
  - module, 82
- dicee.models.pykeen\_models
  - module, 85
- dicee.models.quaternion
  - module, 86
- dicee.models.real
  - module, 89
- dicee.models.static\_funcs



- module, 90
- dicee.models.transformers
  - module, 91
- dicee.query\_generator
  - module, 144
- dicee.read\_preprocess\_save\_load\_kg
  - module, 146
- dicee.read\_preprocess\_save\_load\_kg.preprocess
  - module, 146
- dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk
  - module, 147
- dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk
  - module, 147
- dicee.read\_preprocess\_save\_load\_kg.util
  - module, 148
- dicee.sanity\_checkers
  - module, 152
- dicee.scripts
  - module, 153
- dicee.scripts.index\_serve
  - module, 153
- dicee.scripts.run
  - module, 156
- dicee.static\_funcs
  - module, 156
- dicee.static\_funcs\_training
  - module, 159
- dicee.static\_preprocess\_funcs
  - module, 160
- dicee.trainer
  - module, 161
- dicee.trainer.dice\_trainer
  - module, 161
- dicee.trainer.model\_parallelism
  - module, 163
- dicee.trainer.torch\_trainer
  - module, 163
- dicee.trainer.torch\_trainer\_ddp
  - module, 165
- discrete\_points (*dicee.models.FMult2 attribute*), 141
- discrete\_points (*dicee.models.function\_space.FMult2 attribute*), 78
- dist\_func (*dicee.models.Pyke attribute*), 111
- dist\_func (*dicee.models.real.Pyke attribute*), 90
- dist\_func (*dicee.Pyke attribute*), 170
- DistMult (*class in dicee*), 170
- DistMult (*class in dicee.models*), 110
- DistMult (*class in dicee.models.real*), 89
- download\_file() (*in module dicee*), 195
- download\_file() (*in module dicee.static\_funcs*), 159
- download\_files\_from\_url() (*in module dicee*), 195
- download\_files\_from\_url() (*in module dicee.static\_funcs*), 159
- download\_pretrained\_model() (*in module dicee*), 195
- download\_pretrained\_model() (*in module dicee.static\_funcs*), 159
- dropout (*dicee.models.literal.LiteralEmbeddings attribute*), 80, 81
- dropout (*dicee.models.transformers.CausalSelfAttention attribute*), 94
- dropout (*dicee.models.transformers.GPTConfig attribute*), 96
- dropout (*dicee.models.transformers.MLP attribute*), 95
- DualE (*class in dicee*), 178
- DualE (*class in dicee.models*), 143
- DualE (*class in dicee.models.dualE*), 75
- dummy\_eval() (*dicee.evaluator.Evaluator method*), 48
- dummy\_id (*dicee.knowledge\_graph.KG attribute*), 51
- during\_training (*dicee.evaluator.Evaluator attribute*), 47

## E

- ee\_vocab (*dicee.evaluator.Evaluator attribute*), 47
- efficient\_zero\_grad() (*in module dicee.static\_funcs\_training*), 160

embedding\_dim (*dicee.analyse\_experiments.Experiment* attribute), 19  
 embedding\_dim (*dicee.BaseKGE* attribute), 191  
 embedding\_dim (*dicee.config.Namespace* attribute), 29  
 embedding\_dim (*dicee.models.base\_model.BaseKGE* attribute), 63  
 embedding\_dim (*dicee.models.BaseKGE* attribute), 105, 108, 112, 117, 122, 135, 138  
 embedding\_dim (*dicee.models.literal.LiteralEmbeddings* attribute), 81  
 embedding\_dims (*dicee.models.literal.LiteralEmbeddings* attribute), 80  
 enable\_log (in module *dicee.static\_preprocess\_funcs*), 160  
 enc (*dicee.knowledge\_graph.KG* attribute), 51  
 end () (*dicee.Execute* method), 201  
 end () (*dicee.executer.Execute* method), 49  
 EnsembleKGE (class in *dicee*), 193  
 EnsembleKGE (class in *dicee.models.ensemble*), 76  
 ent2id (*dicee.query\_generator.QueryGenerator* attribute), 145  
 ent2id (*dicee.QueryGenerator* attribute), 215  
 ent\_in (*dicee.query\_generator.QueryGenerator* attribute), 145  
 ent\_in (*dicee.QueryGenerator* attribute), 215  
 ent\_out (*dicee.query\_generator.QueryGenerator* attribute), 145  
 ent\_out (*dicee.QueryGenerator* attribute), 215  
 entities\_str (*dicee.knowledge\_graph.KG* property), 51  
 entity\_embeddings (*dicee.AConvQ* attribute), 181  
 entity\_embeddings (*dicee.ConvQ* attribute), 182  
 entity\_embeddings (*dicee.DeCaL* attribute), 175  
 entity\_embeddings (*dicee.DualE* attribute), 178  
 entity\_embeddings (*dicee.LFMult* attribute), 187  
 entity\_embeddings (*dicee.models.AConvQ* attribute), 121  
 entity\_embeddings (*dicee.models.clifford.DeCaL* attribute), 69  
 entity\_embeddings (*dicee.models.ConvQ* attribute), 121  
 entity\_embeddings (*dicee.models.DeCaL* attribute), 132  
 entity\_embeddings (*dicee.models.DualE* attribute), 144  
 entity\_embeddings (*dicee.models.dualE.DualE* attribute), 75  
 entity\_embeddings (*dicee.models.FMult* attribute), 140  
 entity\_embeddings (*dicee.models.FMult2* attribute), 141  
 entity\_embeddings (*dicee.models.function\_space.FMult* attribute), 77  
 entity\_embeddings (*dicee.models.function\_space.FMult2* attribute), 78  
 entity\_embeddings (*dicee.models.function\_space.GFMult* attribute), 77  
 entity\_embeddings (*dicee.models.function\_space.LFMult* attribute), 79  
 entity\_embeddings (*dicee.models.function\_space.LFMult1* attribute), 78  
 entity\_embeddings (*dicee.models.GFMult* attribute), 141  
 entity\_embeddings (*dicee.models.LFMult* attribute), 142  
 entity\_embeddings (*dicee.models.LFMult1* attribute), 142  
 entity\_embeddings (*dicee.models.literal.LiteralEmbeddings* attribute), 80, 81  
 entity\_embeddings (*dicee.models.pykeen\_models.PykeenKGE* attribute), 85  
 entity\_embeddings (*dicee.models.PykeenKGE* attribute), 137  
 entity\_embeddings (*dicee.models.quaternion.AConvQ* attribute), 88  
 entity\_embeddings (*dicee.models.quaternion.ConvQ* attribute), 88  
 entity\_embeddings (*dicee.PykeenKGE* attribute), 188  
 entity\_to\_idx (*dicee.dataset\_classes.LiteralDataset* attribute), 43, 44  
 entity\_to\_idx (*dicee.knowledge\_graph.KG* attribute), 50  
 entity\_to\_idx (*dicee.LiteralDataset* attribute), 213, 214  
 entity\_to\_idx (*dicee.scripts.index\_serve.NeuralSearcher* attribute), 154  
 epoch\_count (*dicee.abstracts.AbstractPPECallback* attribute), 17  
 epoch\_count (*dicee.callbacks.ASWA* attribute), 24  
 epoch\_counter (*dicee.callbacks.Eval* attribute), 25  
 epoch\_counter (*dicee.callbacks.KGESaveCallback* attribute), 22  
 epoch\_counter (*dicee.callbacks.PeriodicEvalCallback* attribute), 27  
 epoch\_ratio (*dicee.callbacks.Eval* attribute), 25  
 er\_vocab (*dicee.evaluator.Evaluator* attribute), 47  
 estimate\_mfu () (*dicee.models.transformers.GPT* method), 97  
 estimate\_q () (in module *dicee.callbacks*), 23  
 Eval (class in *dicee.callbacks*), 24  
 eval () (*dicee.EnsembleKGE* method), 194  
 eval () (*dicee.evaluator.Evaluator* method), 47  
 eval () (*dicee.models.ensemble.EnsembleKGE* method), 76  
 eval\_at\_epochs (*dicee.config.Namespace* attribute), 31  
 eval\_epochs (*dicee.callbacks.PeriodicEvalCallback* attribute), 27  
 eval\_every\_n\_epochs (*dicee.config.Namespace* attribute), 31  
 eval\_lp\_performance () (*dicee.KGE* method), 197

eval\_lp\_performance() (*dicее.knowledge\_graph\_embeddings.KGE method*), 52  
 eval\_model (*dicее.config.Namespace attribute*), 30  
 eval\_model (*dicее.knowledge\_graph.KG attribute*), 50  
 eval\_rank\_of\_head\_and\_tail\_byte\_pair\_encoded\_entity() (*dicее.evaluator.Evaluator method*), 47  
 eval\_rank\_of\_head\_and\_tail\_entity() (*dicее.evaluator.Evaluator method*), 47  
 eval\_with\_bpe\_vs\_all() (*dicее.evaluator.Evaluator method*), 47  
 eval\_with\_byte() (*dicее.evaluator.Evaluator method*), 47  
 eval\_with\_data() (*dicее.evaluator.Evaluator method*), 48  
 eval\_with\_vs\_all() (*dicее.evaluator.Evaluator method*), 47  
 evaluate() (*in module dicее*), 195  
 evaluate() (*in module dicее.static\_funcs*), 159  
 evaluate\_bpe\_lp() (*in module dicее.static\_funcs\_training*), 160  
 evaluate\_ensemble\_link\_prediction\_performance() (*in module dicее.eval\_static\_funcs*), 46  
 evaluate\_link\_prediction\_performance() (*in module dicее.eval\_static\_funcs*), 45  
 evaluate\_link\_prediction\_performance\_with\_bpe() (*in module dicее.eval\_static\_funcs*), 45  
 evaluate\_link\_prediction\_performance\_with\_bpe\_reciprocals() (*in module dicее.eval\_static\_funcs*), 45  
 evaluate\_link\_prediction\_performance\_with\_reciprocals() (*in module dicее.eval\_static\_funcs*), 45  
 evaluate\_literal\_prediction() (*in module dicее.eval\_static\_funcs*), 46  
 evaluate\_lp() (*dicее.evaluator.Evaluator method*), 48  
 evaluate\_lp() (*in module dicее.static\_funcs\_training*), 159  
 evaluate\_lp\_bpe\_k\_vs\_all() (*dicее.evaluator.Evaluator method*), 48  
 evaluate\_lp\_bpe\_k\_vs\_all() (*in module dicее.eval\_static\_funcs*), 46  
 evaluate\_lp\_k\_vs\_all() (*dicее.evaluator.Evaluator method*), 48  
 evaluate\_lp\_with\_byte() (*dicее.evaluator.Evaluator method*), 48  
 Evaluator (*class in dicее.evaluator*), 47  
 evaluator (*dicее.DICE\_Trainer attribute*), 196  
 evaluator (*dicее.Execute attribute*), 201  
 evaluator (*dicее.executor.Execute attribute*), 48  
 evaluator (*dicее.trainer.DICE\_Trainer attribute*), 166  
 evaluator (*dicее.trainer.dice\_trainer.DICE\_Trainer attribute*), 162  
 every\_x\_epoch (*dicее.callbacks.KGESaveCallback attribute*), 22  
 example\_input\_array (*dicее.EnsembleKGE property*), 193  
 example\_input\_array (*dicее.models.ensemble.EnsembleKGE property*), 76  
 Execute (*class in dicее*), 200  
 Execute (*class in dicее.executor*), 48  
 exists() (*dicее.knowledge\_graph.KG method*), 51  
 Experiment (*class in dicее.analyse\_experiments*), 19  
 experiment\_dir (*dicее.callbacks.LRScheduler attribute*), 27  
 experiment\_dir (*dicее.callbacks.PeriodicEvalCallback attribute*), 27  
 explicit (*dicее.models.QMult attribute*), 120  
 explicit (*dicее.models.quaternion.QMult attribute*), 87  
 explicit (*dicее.QMult attribute*), 184  
 exponential\_function() (*in module dicее*), 195  
 exponential\_function() (*in module dicее.static\_funcs*), 159  
 extract\_input\_outputs() (*dicее.trainer.torch\_trainer\_ddp.NodeTrainer method*), 166  
 extract\_input\_outputs() (*in module dicее.trainer.model\_parallelism*), 163  
 extract\_input\_outputs\_set\_device() (*dicее.trainer.torch\_trainer.TorchTrainer method*), 164

## F

f (*dicее.callbacks.KronE attribute*), 26  
 fc (*dicее.models.literal.LiteralEmbeddings attribute*), 81  
 fc1 (*dicее.AConEx attribute*), 180  
 fc1 (*dicее.AConvO attribute*), 181  
 fc1 (*dicее.AConvQ attribute*), 181  
 fc1 (*dicее.ConEx attribute*), 183  
 fc1 (*dicее.ConvO attribute*), 183  
 fc1 (*dicее.ConvQ attribute*), 182  
 fc1 (*dicее.models.AConEx attribute*), 114  
 fc1 (*dicее.models.AConvO attribute*), 127  
 fc1 (*dicее.models.AConvQ attribute*), 121  
 fc1 (*dicее.models.complex.AConEx attribute*), 73  
 fc1 (*dicее.models.complex.ConEx attribute*), 73  
 fc1 (*dicее.models.ConEx attribute*), 114  
 fc1 (*dicее.models.ConvO attribute*), 127  
 fc1 (*dicее.models.ConvQ attribute*), 121  
 fc1 (*dicее.models.octonion.AConvO attribute*), 84  
 fc1 (*dicее.models.octonion.ConvO attribute*), 84

`fc1` (*dicee.models.quaternion.AConvQ attribute*), 88  
`fc1` (*dicee.models.quaternion.ConvQ attribute*), 88  
`fc_num_input` (*dicee.AConEx attribute*), 180  
`fc_num_input` (*dicee.AConvO attribute*), 180  
`fc_num_input` (*dicee.AConvQ attribute*), 181  
`fc_num_input` (*dicee.ConEx attribute*), 183  
`fc_num_input` (*dicee.ConvO attribute*), 183  
`fc_num_input` (*dicee.ConvQ attribute*), 182  
`fc_num_input` (*dicee.models.AConEx attribute*), 114  
`fc_num_input` (*dicee.models.AConvO attribute*), 127  
`fc_num_input` (*dicee.models.AConvQ attribute*), 121  
`fc_num_input` (*dicee.models.complex.AConEx attribute*), 73  
`fc_num_input` (*dicee.models.complex.ConEx attribute*), 73  
`fc_num_input` (*dicee.models.ConEx attribute*), 114  
`fc_num_input` (*dicee.models.ConvO attribute*), 127  
`fc_num_input` (*dicee.models.ConvQ attribute*), 121  
`fc_num_input` (*dicee.models.octonion.AConvO attribute*), 84  
`fc_num_input` (*dicee.models.octonion.ConvO attribute*), 83  
`fc_num_input` (*dicee.models.quaternion.AConvQ attribute*), 88  
`fc_num_input` (*dicee.models.quaternion.ConvQ attribute*), 88  
`fc_out` (*dicee.models.literal.LiteralEmbeddings attribute*), 81  
`feature_map_dropout` (*dicee.AConEx attribute*), 180  
`feature_map_dropout` (*dicee.AConvO attribute*), 181  
`feature_map_dropout` (*dicee.AConvQ attribute*), 181  
`feature_map_dropout` (*dicee.ConEx attribute*), 183  
`feature_map_dropout` (*dicee.ConvO attribute*), 183  
`feature_map_dropout` (*dicee.ConvQ attribute*), 182  
`feature_map_dropout` (*dicee.models.AConEx attribute*), 115  
`feature_map_dropout` (*dicee.models.AConvO attribute*), 127  
`feature_map_dropout` (*dicee.models.AConvQ attribute*), 122  
`feature_map_dropout` (*dicee.models.complex.AConEx attribute*), 73  
`feature_map_dropout` (*dicee.models.complex.ConEx attribute*), 73  
`feature_map_dropout` (*dicee.models.ConEx attribute*), 114  
`feature_map_dropout` (*dicee.models.ConvO attribute*), 127  
`feature_map_dropout` (*dicee.models.ConvQ attribute*), 121  
`feature_map_dropout` (*dicee.models.octonion.AConvO attribute*), 84  
`feature_map_dropout` (*dicee.models.octonion.ConvO attribute*), 84  
`feature_map_dropout` (*dicee.models.quaternion.AConvQ attribute*), 88  
`feature_map_dropout` (*dicee.models.quaternion.ConvQ attribute*), 88  
`feature_map_dropout_rate` (*dicee.BaseKGE attribute*), 192  
`feature_map_dropout_rate` (*dicee.config.Namespace attribute*), 30  
`feature_map_dropout_rate` (*dicee.models.base\_model.BaseKGE attribute*), 63  
`feature_map_dropout_rate` (*dicee.models.BaseKGE attribute*), 105, 109, 112, 117, 123, 135, 139  
`fill_query()` (*dicee.query\_generator.QueryGenerator method*), 145  
`fill_query()` (*dicee.QueryGenerator method*), 215  
`find_good_batch_size()` (in module *dicee.trainer.model\_parallelism*), 163  
`find_missing_triples()` (*dicee.KGE method*), 200  
`find_missing_triples()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 54  
`fit()` (*dicee.trainer.model\_parallelism.TensorParallel method*), 163  
`fit()` (*dicee.trainer.torch\_trainer\_ddp.TorchDDPTrainer method*), 165  
`fit()` (*dicee.trainer.torch\_trainer.TorchTrainer method*), 164  
`flash` (*dicee.models.transformers.CausalSelfAttention attribute*), 94  
`FMult` (class in *dicee.models*), 140  
`FMult` (class in *dicee.models.function\_space*), 77  
`FMult2` (class in *dicee.models*), 141  
`FMult2` (class in *dicee.models.function\_space*), 78  
`form_of_labelling` (*dicee.DICE\_Trainer attribute*), 196  
`form_of_labelling` (*dicee.trainer.DICE\_Trainer attribute*), 166  
`form_of_labelling` (*dicee.trainer.dice\_trainer.DICE\_Trainer attribute*), 162  
`forward()` (*dicee.BaseKGE method*), 193  
`forward()` (*dicee.BytE method*), 190  
`forward()` (*dicee.models.base\_model.BaseKGE method*), 64  
`forward()` (*dicee.models.base\_model.IdentityClass static method*), 65  
`forward()` (*dicee.models.BaseKGE method*), 106, 110, 113, 118, 124, 136, 140  
`forward()` (*dicee.models.IdentityClass static method*), 108, 119, 125  
`forward()` (*dicee.models.literal.LiteralEmbeddings method*), 81  
`forward()` (*dicee.models.transformers.Block method*), 96  
`forward()` (*dicee.models.transformers.BytE method*), 92

`forward()` (*dicdee.models.transformers.CausalSelfAttention method*), 94  
`forward()` (*dicdee.models.transformers.GPT method*), 97  
`forward()` (*dicdee.models.transformers.LayerNorm method*), 93  
`forward()` (*dicdee.models.transformers.MLP method*), 95  
`forward_backward_update()` (*dicdee.trainer.torch\_trainer.TorchTrainer method*), 164  
`forward_backward_update_loss()` (in module *dicdee.trainer.model\_parallelism*), 163  
`forward_byte_pair_encoded_k_vs_all()` (*dicdee.BaseKGE method*), 192  
`forward_byte_pair_encoded_k_vs_all()` (*dicdee.models.base\_model.BaseKGE method*), 63  
`forward_byte_pair_encoded_k_vs_all()` (*dicdee.models.BaseKGE method*), 106, 109, 113, 117, 123, 136, 139  
`forward_byte_pair_encoded_triple()` (*dicdee.BaseKGE method*), 192  
`forward_byte_pair_encoded_triple()` (*dicdee.models.base\_model.BaseKGE method*), 64  
`forward_byte_pair_encoded_triple()` (*dicdee.models.BaseKGE method*), 106, 109, 113, 117, 123, 136, 139  
`forward_k_vs_all()` (*dicdee.AConEx method*), 180  
`forward_k_vs_all()` (*dicdee.AConvO method*), 181  
`forward_k_vs_all()` (*dicdee.AConvQ method*), 181  
`forward_k_vs_all()` (*dicdee.BaseKGE method*), 193  
`forward_k_vs_all()` (*dicdee.ComplEx method*), 180  
`forward_k_vs_all()` (*dicdee.ConEx method*), 184  
`forward_k_vs_all()` (*dicdee.ConvO method*), 183  
`forward_k_vs_all()` (*dicdee.ConvQ method*), 182  
`forward_k_vs_all()` (*dicdee.DeCaL method*), 176  
`forward_k_vs_all()` (*dicdee.DistMult method*), 171  
`forward_k_vs_all()` (*dicdee.DualE method*), 179  
`forward_k_vs_all()` (*dicdee.Keci method*), 173  
`forward_k_vs_all()` (*dicdee.models.AConEx method*), 115  
`forward_k_vs_all()` (*dicdee.models.AConvO method*), 128  
`forward_k_vs_all()` (*dicdee.models.AConvQ method*), 122  
`forward_k_vs_all()` (*dicdee.models.base\_model.BaseKGE method*), 64  
`forward_k_vs_all()` (*dicdee.models.BaseKGE method*), 107, 110, 113, 118, 124, 137, 140  
`forward_k_vs_all()` (*dicdee.models.clifford.DeCaL method*), 70  
`forward_k_vs_all()` (*dicdee.models.clifford.Keci method*), 68  
`forward_k_vs_all()` (*dicdee.models.ComplEx method*), 116  
`forward_k_vs_all()` (*dicdee.models.complex.AConEx method*), 73  
`forward_k_vs_all()` (*dicdee.models.complex.ComplEx method*), 74  
`forward_k_vs_all()` (*dicdee.models.complex.ConEx method*), 73  
`forward_k_vs_all()` (*dicdee.models.ConEx method*), 114  
`forward_k_vs_all()` (*dicdee.models.ConvO method*), 127  
`forward_k_vs_all()` (*dicdee.models.ConvQ method*), 121  
`forward_k_vs_all()` (*dicdee.models.DeCaL method*), 132  
`forward_k_vs_all()` (*dicdee.models.DistMult method*), 110  
`forward_k_vs_all()` (*dicdee.models.DualE method*), 144  
`forward_k_vs_all()` (*dicdee.models.dualE.DualE method*), 75  
`forward_k_vs_all()` (*dicdee.models.Keci method*), 130  
`forward_k_vs_all()` (*dicdee.models.octonion.AConvO method*), 84  
`forward_k_vs_all()` (*dicdee.models.octonion.ConvO method*), 84  
`forward_k_vs_all()` (*dicdee.models.octonion.OMult method*), 83  
`forward_k_vs_all()` (*dicdee.models.OMult method*), 126  
`forward_k_vs_all()` (*dicdee.models.pykeen\_models.PykeenKGE method*), 85  
`forward_k_vs_all()` (*dicdee.models.PykeenKGE method*), 137  
`forward_k_vs_all()` (*dicdee.models.QMult method*), 120  
`forward_k_vs_all()` (*dicdee.models.quaternion.AConvQ method*), 89  
`forward_k_vs_all()` (*dicdee.models.quaternion.ConvQ method*), 88  
`forward_k_vs_all()` (*dicdee.models.quaternion.QMult method*), 87  
`forward_k_vs_all()` (*dicdee.models.real.DistMult method*), 89  
`forward_k_vs_all()` (*dicdee.models.real.Shallom method*), 90  
`forward_k_vs_all()` (*dicdee.models.real.TransE method*), 90  
`forward_k_vs_all()` (*dicdee.models.Shallom method*), 111  
`forward_k_vs_all()` (*dicdee.models.TransE method*), 111  
`forward_k_vs_all()` (*dicdee.OMult method*), 186  
`forward_k_vs_all()` (*dicdee.PykeenKGE method*), 188  
`forward_k_vs_all()` (*dicdee.QMult method*), 185  
`forward_k_vs_all()` (*dicdee.Shallom method*), 186  
`forward_k_vs_all()` (*dicdee.TransE method*), 174  
`forward_k_vs_sample()` (*dicdee.AConEx method*), 180  
`forward_k_vs_sample()` (*dicdee.BaseKGE method*), 193  
`forward_k_vs_sample()` (*dicdee.ComplEx method*), 180  
`forward_k_vs_sample()` (*dicdee.ConEx method*), 184  
`forward_k_vs_sample()` (*dicdee.DistMult method*), 171

`forward_k_vs_sample()` (*dicee.Keci method*), 174  
`forward_k_vs_sample()` (*dicee.models.AConEx method*), 115  
`forward_k_vs_sample()` (*dicee.models.base\_model.BaseKGE method*), 64  
`forward_k_vs_sample()` (*dicee.models.BaseKGE method*), 107, 110, 113, 118, 124, 137, 140  
`forward_k_vs_sample()` (*dicee.models.clifford.Keci method*), 68  
`forward_k_vs_sample()` (*dicee.models.ComplEx method*), 116  
`forward_k_vs_sample()` (*dicee.models.complex.AConEx method*), 73  
`forward_k_vs_sample()` (*dicee.models.complex.ComplEx method*), 74  
`forward_k_vs_sample()` (*dicee.models.complex.ConEx method*), 73  
`forward_k_vs_sample()` (*dicee.models.ConEx method*), 114  
`forward_k_vs_sample()` (*dicee.models.DistMult method*), 110  
`forward_k_vs_sample()` (*dicee.models.Keci method*), 130  
`forward_k_vs_sample()` (*dicee.models.pykeen\_models.PykeenKGE method*), 86  
`forward_k_vs_sample()` (*dicee.models.PykeenKGE method*), 138  
`forward_k_vs_sample()` (*dicee.models.QMult method*), 121  
`forward_k_vs_sample()` (*dicee.models.quaternion.QMult method*), 87  
`forward_k_vs_sample()` (*dicee.models.real.DistMult method*), 89  
`forward_k_vs_sample()` (*dicee.PykeenKGE method*), 189  
`forward_k_vs_sample()` (*dicee.QMult method*), 185  
`forward_k_vs_with_explicit()` (*dicee.Keci method*), 173  
`forward_k_vs_with_explicit()` (*dicee.models.clifford.Keci method*), 67  
`forward_k_vs_with_explicit()` (*dicee.models.Keci method*), 130  
`forward_triples()` (*dicee.AConEx method*), 180  
`forward_triples()` (*dicee.AConvO method*), 181  
`forward_triples()` (*dicee.AConvQ method*), 181  
`forward_triples()` (*dicee.BaseKGE method*), 193  
`forward_triples()` (*dicee.ConEx method*), 184  
`forward_triples()` (*dicee.ConvO method*), 183  
`forward_triples()` (*dicee.ConvQ method*), 182  
`forward_triples()` (*dicee.DeCaL method*), 175  
`forward_triples()` (*dicee.DualE method*), 178  
`forward_triples()` (*dicee.Keci method*), 174  
`forward_triples()` (*dicee.LFMult method*), 187  
`forward_triples()` (*dicee.models.AConEx method*), 115  
`forward_triples()` (*dicee.models.AConvO method*), 128  
`forward_triples()` (*dicee.models.AConvQ method*), 122  
`forward_triples()` (*dicee.models.base\_model.BaseKGE method*), 64  
`forward_triples()` (*dicee.models.BaseKGE method*), 106, 110, 113, 118, 124, 136, 140  
`forward_triples()` (*dicee.models.clifford.DeCaL method*), 69  
`forward_triples()` (*dicee.models.clifford.Keci method*), 68  
`forward_triples()` (*dicee.models.complex.AConEx method*), 73  
`forward_triples()` (*dicee.models.complex.ConEx method*), 73  
`forward_triples()` (*dicee.models.ConEx method*), 114  
`forward_triples()` (*dicee.models.ConvO method*), 127  
`forward_triples()` (*dicee.models.ConvQ method*), 121  
`forward_triples()` (*dicee.models.DeCaL method*), 132  
`forward_triples()` (*dicee.models.DualE method*), 144  
`forward_triples()` (*dicee.models.dualE.DualE method*), 75  
`forward_triples()` (*dicee.models.FMult method*), 141  
`forward_triples()` (*dicee.models.FMult2 method*), 142  
`forward_triples()` (*dicee.models.function\_space.FMult method*), 77  
`forward_triples()` (*dicee.models.function\_space.FMult2 method*), 78  
`forward_triples()` (*dicee.models.function\_space.GFMult method*), 78  
`forward_triples()` (*dicee.models.function\_space.LFMult method*), 79  
`forward_triples()` (*dicee.models.function\_space.LFMult1 method*), 78  
`forward_triples()` (*dicee.models.GFMult method*), 141  
`forward_triples()` (*dicee.models.Keci method*), 131  
`forward_triples()` (*dicee.models.LFMult method*), 142  
`forward_triples()` (*dicee.models.LFMult1 method*), 142  
`forward_triples()` (*dicee.models.octonion.AConvO method*), 84  
`forward_triples()` (*dicee.models.octonion.ConvO method*), 84  
`forward_triples()` (*dicee.models.Pyke method*), 111  
`forward_triples()` (*dicee.models.pykeen\_models.PykeenKGE method*), 85  
`forward_triples()` (*dicee.models.PykeenKGE method*), 138  
`forward_triples()` (*dicee.models.quaternion.AConvQ method*), 89  
`forward_triples()` (*dicee.models.quaternion.ConvQ method*), 88  
`forward_triples()` (*dicee.models.real.Pyke method*), 90  
`forward_triples()` (*dicee.models.real.Shallom method*), 90



`forward_triples()` (*dicee.models.Shallom method*), 111  
`forward_triples()` (*dicee.Pyke method*), 170  
`forward_triples()` (*dicee.PykeenKGE method*), 188  
`forward_triples()` (*dicee.Shallom method*), 186  
`freeze_entity_embeddings` (*dicee.models.literal.LiteralEmbeddings attribute*), 81  
`frequency` (*dicee.callbacks.Perturb attribute*), 26  
`from_pretrained()` (*dicee.models.transformers.GPT class method*), 97  
`from_pretrained_model_write_embeddings_into_csv()` (*in module dicee*), 195  
`from_pretrained_model_write_embeddings_into_csv()` (*in module dicee.static\_funcs*), 159  
`full_storage_path` (*dicee.analyse\_experiments.Experiment attribute*), 19  
`func_triple_to_bpe_representation` (*dicee.evaluator.Evaluator attribute*), 47  
`func_triple_to_bpe_representation()` (*dicee.knowledge\_graph.KG method*), 51  
`function()` (*dicee.models.FMult2 method*), 142  
`function()` (*dicee.models.function\_space.FMult2 method*), 78

## G

`gamma` (*dicee.models.FMult attribute*), 141  
`gamma` (*dicee.models.function\_space.FMult attribute*), 77  
`gate_residual` (*dicee.models.literal.LiteralEmbeddings attribute*), 81  
`gated_residual_proj` (*dicee.models.literal.LiteralEmbeddings attribute*), 81  
`gelu` (*dicee.models.transformers.MLP attribute*), 95  
`gen_test` (*dicee.query\_generator.QueryGenerator attribute*), 145  
`gen_test` (*dicee.QueryGenerator attribute*), 215  
`gen_valid` (*dicee.query\_generator.QueryGenerator attribute*), 145  
`gen_valid` (*dicee.QueryGenerator attribute*), 215  
`generate()` (*dicee.BytE method*), 190  
`generate()` (*dicee.KGE method*), 197  
`generate()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 52  
`generate()` (*dicee.models.transformers.BytE method*), 92  
`generate_queries()` (*dicee.query\_generator.QueryGenerator method*), 145  
`generate_queries()` (*dicee.QueryGenerator method*), 215  
`get_aswa_state_dict()` (*dicee.callbacks.ASWA method*), 24  
`get_bpe_head_and_relation_representation()` (*dicee.BaseKGE method*), 193  
`get_bpe_head_and_relation_representation()` (*dicee.models.base\_model.BaseKGE method*), 64  
`get_bpe_head_and_relation_representation()` (*dicee.models.BaseKGE method*), 107, 110, 114, 118, 124, 137, 140  
`get_bpe_token_representation()` (*dicee.abstracts.BaseInteractiveKGE method*), 14  
`get_callbacks()` (*in module dicee.trainer.dice\_trainer*), 161  
`get_default_arguments()` (*in module dicee.analyse\_experiments*), 19  
`get_default_arguments()` (*in module dicee.scripts.index\_serve*), 154  
`get_default_arguments()` (*in module dicee.scripts.run*), 156  
`get_ee_vocab()` (*in module dicee*), 194  
`get_ee_vocab()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 150  
`get_ee_vocab()` (*in module dicee.static\_funcs*), 157  
`get_ee_vocab()` (*in module dicee.static\_preprocess\_funcs*), 160  
`get_embeddings()` (*dicee.BaseKGE method*), 193  
`get_embeddings()` (*dicee.EnsembleKGE method*), 194  
`get_embeddings()` (*dicee.models.base\_model.BaseKGE method*), 64  
`get_embeddings()` (*dicee.models.BaseKGE method*), 107, 110, 114, 118, 124, 137, 140  
`get_embeddings()` (*dicee.models.ensemble.EnsembleKGE method*), 76  
`get_embeddings()` (*dicee.models.real.Shallom method*), 90  
`get_embeddings()` (*dicee.models.Shallom method*), 111  
`get_embeddings()` (*dicee.Shallom method*), 186  
`get_entity_embeddings()` (*dicee.abstracts.BaseInteractiveKGE method*), 15  
`get_entity_index()` (*dicee.abstracts.BaseInteractiveKGE method*), 15  
`get_er_vocab()` (*in module dicee*), 194  
`get_er_vocab()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 150  
`get_er_vocab()` (*in module dicee.static\_funcs*), 157  
`get_er_vocab()` (*in module dicee.static\_preprocess\_funcs*), 160  
`get_eval_report()` (*dicee.abstracts.BaseInteractiveKGE method*), 14  
`get_head_relation_representation()` (*dicee.BaseKGE method*), 193  
`get_head_relation_representation()` (*dicee.models.base\_model.BaseKGE method*), 64  
`get_head_relation_representation()` (*dicee.models.BaseKGE method*), 107, 110, 113, 118, 124, 137, 140  
`get_kronecker_triple_representation()` (*dicee.callbacks.KronE method*), 26  
`get_num_params()` (*dicee.models.transformers.GPT method*), 97  
`get_padded_bpe_triple_representation()` (*dicee.abstracts.BaseInteractiveKGE method*), 14  
`get_queries()` (*dicee.query\_generator.QueryGenerator method*), 146  
`get_queries()` (*dicee.QueryGenerator method*), 216

`get_re_vocab()` (in module *dicee*), 194  
`get_re_vocab()` (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 150  
`get_re_vocab()` (in module *dicee.static\_funcs*), 157  
`get_re_vocab()` (in module *dicee.static\_preprocess\_funcs*), 160  
`get_relation_embeddings()` (*dicee.abstracts.BaseInteractiveKGE* method), 15  
`get_relation_index()` (*dicee.abstracts.BaseInteractiveKGE* method), 15  
`get_sentence_representation()` (*dicee.BaseKGE* method), 193  
`get_sentence_representation()` (*dicee.models.base\_model.BaseKGE* method), 64  
`get_sentence_representation()` (*dicee.models.BaseKGE* method), 107, 110, 113, 118, 124, 137, 140  
`get_transductive_entity_embeddings()` (*dicee.KGE* method), 197  
`get_transductive_entity_embeddings()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 52  
`get_triple_representation()` (*dicee.BaseKGE* method), 193  
`get_triple_representation()` (*dicee.models.base\_model.BaseKGE* method), 64  
`get_triple_representation()` (*dicee.models.BaseKGE* method), 107, 110, 113, 118, 124, 137, 140  
`GFMult` (class in *dicee.models*), 141  
`GFMult` (class in *dicee.models.function\_space*), 77  
`global_rank` (*dicee.abstracts.AbstractTrainer* attribute), 13  
`global_rank` (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer* attribute), 165  
`GPT` (class in *dicee.models.transformers*), 96  
`GPTConfig` (class in *dicee.models.transformers*), 96  
`gpus` (*dicee.config.Namespace* attribute), 29  
`gradient_accumulation_steps` (*dicee.config.Namespace* attribute), 29  
`ground_queries()` (*dicee.query\_generator.QueryGenerator* method), 145  
`ground_queries()` (*dicee.QueryGenerator* method), 215

## H

`hidden_dim` (*dicee.models.literal.LiteralEmbeddings* attribute), 81  
`hidden_dropout` (*dicee.BaseKGE* attribute), 192  
`hidden_dropout` (*dicee.models.base\_model.BaseKGE* attribute), 63  
`hidden_dropout` (*dicee.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139  
`hidden_dropout_rate` (*dicee.BaseKGE* attribute), 192  
`hidden_dropout_rate` (*dicee.config.Namespace* attribute), 30  
`hidden_dropout_rate` (*dicee.models.base\_model.BaseKGE* attribute), 63  
`hidden_dropout_rate` (*dicee.models.BaseKGE* attribute), 105, 109, 112, 117, 123, 135, 139  
`hidden_normalizer` (*dicee.BaseKGE* attribute), 192  
`hidden_normalizer` (*dicee.models.base\_model.BaseKGE* attribute), 63  
`hidden_normalizer` (*dicee.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139

## I

`IdentityClass` (class in *dicee.models*), 107, 118, 124  
`IdentityClass` (class in *dicee.models.base\_model*), 64  
`idx_entity_to_bpe_shaped` (*dicee.knowledge\_graph.KG* attribute), 51  
`index()` (in module *dicee.scripts.index\_serve*), 154  
`index_triple()` (*dicee.abstracts.BaseInteractiveKGE* method), 15  
`init_dataloader()` (*dicee.DICE\_Trainer* method), 196  
`init_dataloader()` (*dicee.trainer.DICE\_Trainer* method), 167  
`init_dataloader()` (*dicee.trainer.dice\_trainer.DICE\_Trainer* method), 162  
`init_dataset()` (*dicee.DICE\_Trainer* method), 196  
`init_dataset()` (*dicee.trainer.DICE\_Trainer* method), 167  
`init_dataset()` (*dicee.trainer.dice\_trainer.DICE\_Trainer* method), 162  
`init_param` (*dicee.config.Namespace* attribute), 29  
`init_params_with_sanity_checking()` (*dicee.BaseKGE* method), 193  
`init_params_with_sanity_checking()` (*dicee.models.base\_model.BaseKGE* method), 64  
`init_params_with_sanity_checking()` (*dicee.models.BaseKGE* method), 106, 109, 113, 118, 124, 136, 140  
`initial_eval_setting` (*dicee.callbacks.ASWA* attribute), 24  
`initialize_or_load_model()` (*dicee.DICE\_Trainer* method), 196  
`initialize_or_load_model()` (*dicee.trainer.DICE\_Trainer* method), 167  
`initialize_or_load_model()` (*dicee.trainer.dice\_trainer.DICE\_Trainer* method), 162  
`initialize_trainer()` (*dicee.DICE\_Trainer* method), 196  
`initialize_trainer()` (*dicee.trainer.DICE\_Trainer* method), 167  
`initialize_trainer()` (*dicee.trainer.dice\_trainer.DICE\_Trainer* method), 162  
`initialize_trainer()` (in module *dicee.trainer.dice\_trainer*), 161  
`input_dp_ent_real` (*dicee.BaseKGE* attribute), 192  
`input_dp_ent_real` (*dicee.models.base\_model.BaseKGE* attribute), 63  
`input_dp_ent_real` (*dicee.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139  
`input_dp_rel_real` (*dicee.BaseKGE* attribute), 192  
`input_dp_rel_real` (*dicee.models.base\_model.BaseKGE* attribute), 63



dicee.models.BaseKGE attribute), 106, 109, 113, 117, 123, 136, 139  
dicee.BaseKGE attribute), 192  
dicee.config.Namespace attribute), 30  
dicee.models.base\_model.BaseKGE attribute), 63  
dicee.models.BaseKGE attribute), 105, 109, 112, 117, 123, 135, 139  
InteractiveQueryDecomposition (class in *dicee.abstracts*), 16  
intialize\_model() (in module *dicee*), 195  
intialize\_model() (in module *dicee.static\_funcs*), 158  
is\_continual\_training (*dicee.DICE\_Trainer* attribute), 196  
is\_continual\_training (*dicee.evaluator.Evaluator* attribute), 47  
is\_continual\_training (*dicee.Execute* attribute), 200  
is\_continual\_training (*dicee.executer.Execute* attribute), 48  
is\_continual\_training (*dicee.trainer.DICE\_Trainer* attribute), 166  
is\_continual\_training (*dicee.trainer.dice\_trainer.DICE\_Trainer* attribute), 161  
is\_global\_zero (*dicee.abstracts.AbstractTrainer* attribute), 13  
is\_seen() (*dicee.abstracts.BaseInteractiveKGE* method), 15  
is\_sparql\_endpoint\_alive() (in module *dicee.sanity\_checkers*), 153

## K

k (*dicee.models.FMult* attribute), 140  
k (*dicee.models.FMult2* attribute), 141  
k (*dicee.models.function\_space.FMult* attribute), 77  
k (*dicee.models.function\_space.FMult2* attribute), 78  
k (*dicee.models.function\_space.GFMult* attribute), 77  
k (*dicee.models.GFMult* attribute), 141  
k\_fold\_cross\_validation() (*dicee.DICE\_Trainer* method), 197  
k\_fold\_cross\_validation() (*dicee.trainer.DICE\_Trainer* method), 167  
k\_fold\_cross\_validation() (*dicee.trainer.dice\_trainer.DICE\_Trainer* method), 162  
k\_vs\_all\_score() (*dicee.ComplEx* static method), 180  
k\_vs\_all\_score() (*dicee.DistMult* method), 171  
k\_vs\_all\_score() (*dicee.Keci* method), 173  
k\_vs\_all\_score() (*dicee.models.clifford.Keci* method), 68  
k\_vs\_all\_score() (*dicee.models.ComplEx* static method), 116  
k\_vs\_all\_score() (*dicee.models.complex.ComplEx* static method), 74  
k\_vs\_all\_score() (*dicee.models.DistMult* method), 110  
k\_vs\_all\_score() (*dicee.models.Keci* method), 130  
k\_vs\_all\_score() (*dicee.models.octonion.OMult* method), 83  
k\_vs\_all\_score() (*dicee.models.OMult* method), 126  
k\_vs\_all\_score() (*dicee.models.QMult* method), 120  
k\_vs\_all\_score() (*dicee.models.quaternion.QMult* method), 87  
k\_vs\_all\_score() (*dicee.models.real.DistMult* method), 89  
k\_vs\_all\_score() (*dicee.OMult* method), 186  
k\_vs\_all\_score() (*dicee.QMult* method), 185  
Keci (class in *dicee*), 171  
Keci (class in *dicee.models*), 128  
Keci (class in *dicee.models.clifford*), 65  
kernel\_size (*dicee.BaseKGE* attribute), 192  
kernel\_size (*dicee.config.Namespace* attribute), 30  
kernel\_size (*dicee.models.base\_model.BaseKGE* attribute), 63  
kernel\_size (*dicee.models.BaseKGE* attribute), 105, 109, 112, 117, 123, 135, 139  
KG (class in *dicee.knowledge\_graph*), 50  
kg (*dicee.callbacks.PseudoLabellingCallback* attribute), 23  
kg (*dicee.read\_preprocess\_save\_load\_kg.LoadSaveToDisk* attribute), 152  
kg (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG* attribute), 151  
kg (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG* attribute), 146  
kg (*dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk.ReadFromDisk* attribute), 147  
kg (*dicee.read\_preprocess\_save\_load\_kg.ReadFromDisk* attribute), 152  
kg (*dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk.LoadSaveToDisk* attribute), 148  
KGE (class in *dicee*), 197  
KGE (class in *dicee.knowledge\_graph\_embeddings*), 52  
KGESaveCallback (class in *dicee.callbacks*), 22  
knowledge\_graph (*dicee.Execute* attribute), 201  
knowledge\_graph (*dicee.executer.Execute* attribute), 48  
KronE (class in *dicee.callbacks*), 25  
KvsAll (class in *dicee*), 204  
KvsAll (class in *dicee.dataset\_classes*), 34  
kvsall\_score() (*dicee.DualE* method), 178

`kvsall_score()` (*dicee.models.DualE method*), 144  
`kvsall_score()` (*dicee.models.dualE.DualE method*), 75  
`KvsSampleDataset` (*class in dicee*), 207  
`KvsSampleDataset` (*class in dicee.dataset\_classes*), 37

## L

`label_smoothing_rate` (*dicee.AllvsAll attribute*), 205  
`label_smoothing_rate` (*dicee.config.Namespace attribute*), 30  
`label_smoothing_rate` (*dicee.dataset\_classes.AllvsAll attribute*), 35  
`label_smoothing_rate` (*dicee.dataset\_classes.KvsAll attribute*), 35  
`label_smoothing_rate` (*dicee.dataset\_classes.KvsSampleDataset attribute*), 38  
`label_smoothing_rate` (*dicee.dataset\_classes.OnevsSample attribute*), 36, 37  
`label_smoothing_rate` (*dicee.dataset\_classes.TriplePredictionDataset attribute*), 39  
`label_smoothing_rate` (*dicee.KvsAll attribute*), 205  
`label_smoothing_rate` (*dicee.KvsSampleDataset attribute*), 208  
`label_smoothing_rate` (*dicee.OnevsSample attribute*), 206, 207  
`label_smoothing_rate` (*dicee.TriplePredictionDataset attribute*), 209  
`layer_norm` (*dicee.models.literal.LiteralEmbeddings attribute*), 81  
`LayerNorm` (*class in dicee.models.transformers*), 93  
`learning_rate` (*dicee.BaseKGE attribute*), 192  
`learning_rate` (*dicee.models.base\_model.BaseKGE attribute*), 63  
`learning_rate` (*dicee.models.BaseKGE attribute*), 105, 109, 112, 117, 123, 135, 139  
`length` (*dicee.dataset\_classes.NegSampleDataset attribute*), 38  
`length` (*dicee.dataset\_classes.TriplePredictionDataset attribute*), 39  
`length` (*dicee.NegSampleDataset attribute*), 208  
`length` (*dicee.TriplePredictionDataset attribute*), 209  
`level` (*dicee.callbacks.Perturb attribute*), 26  
`LFMult` (*class in dicee*), 187  
`LFMult` (*class in dicee.models*), 142  
`LFMult` (*class in dicee.models.function\_space*), 79  
`LFMult1` (*class in dicee.models*), 142  
`LFMult1` (*class in dicee.models.function\_space*), 78  
`linear()` (*dicee.LFMult method*), 187  
`linear()` (*dicee.models.function\_space.LFMult method*), 79  
`linear()` (*dicee.models.LFMult method*), 143  
`list2tuple()` (*dicee.query\_generator.QueryGenerator method*), 145  
`list2tuple()` (*dicee.QueryGenerator method*), 215  
`LiteralDataset` (*class in dicee*), 213  
`LiteralDataset` (*class in dicee.dataset\_classes*), 43  
`LiteralEmbeddings` (*class in dicee.models.literal*), 80  
`lm_head` (*dicee.BytE attribute*), 189  
`lm_head` (*dicee.models.transformers.BytE attribute*), 92  
`lm_head` (*dicee.models.transformers.GPT attribute*), 97  
`ln_1` (*dicee.models.transformers.Block attribute*), 96  
`ln_2` (*dicee.models.transformers.Block attribute*), 96  
`load()` (*dicee.read\_preprocess\_save\_load\_kg.LoadSaveToDisk method*), 152  
`load()` (*dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk.LoadSaveToDisk method*), 148  
`load_and_validate_literal_data()` (*dicee.dataset\_classes.LiteralDataset static method*), 44  
`load_and_validate_literal_data()` (*dicee.LiteralDataset static method*), 214  
`load_json()` (*in module dicee*), 195  
`load_json()` (*in module dicee.static\_funcs*), 158  
`load_model()` (*in module dicee*), 194  
`load_model()` (*in module dicee.static\_funcs*), 158  
`load_model_ensemble()` (*in module dicee*), 194  
`load_model_ensemble()` (*in module dicee.static\_funcs*), 158  
`load_numpy()` (*in module dicee*), 195  
`load_numpy()` (*in module dicee.static\_funcs*), 159  
`load_numpy_ndarray()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 151  
`load_pickle()` (*in module dicee*), 194  
`load_pickle()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 151  
`load_pickle()` (*in module dicee.static\_funcs*), 158  
`load_queries()` (*dicee.query\_generator.QueryGenerator method*), 146  
`load_queries()` (*dicee.QueryGenerator method*), 216  
`load_queries_and_answers()` (*dicee.query\_generator.QueryGenerator static method*), 146  
`load_queries_and_answers()` (*dicee.QueryGenerator static method*), 216  
`load_term_mapping()` (*in module dicee*), 194, 202  
`load_term_mapping()` (*in module dicee.static\_funcs*), 158

`load_term_mapping()` (in module `dictee.trainer.dice_trainer`), 161  
`load_with_pandas()` (in module `dictee.read_preprocess_save_load_kg.util`), 151  
`loader_backend` (`dictee.dataset_classes.LiteralDataset` attribute), 44  
`loader_backend` (`dictee.LiteralDataset` attribute), 214  
`LoadSaveToDisk` (class in `dictee.read_preprocess_save_load_kg`), 152  
`LoadSaveToDisk` (class in `dictee.read_preprocess_save_load_kg.save_load_disk`), 148  
`local_rank` (`dictee.abstracts.AbstractTrainer` attribute), 13  
`local_rank` (`dictee.trainer.torch_trainer_ddp.NodeTrainer` attribute), 165  
`loss` (`dictee.BaseKGE` attribute), 192  
`loss` (`dictee.models.base_model.BaseKGE` attribute), 63  
`loss` (`dictee.models.BaseKGE` attribute), 106, 109, 112, 117, 123, 136, 139  
`loss_func` (`dictee.trainer.torch_trainer_ddp.NodeTrainer` attribute), 166  
`loss_function` (`dictee.trainer.torch_trainer.TorchTrainer` attribute), 164  
`loss_function()` (`dictee.BytE` method), 190  
`loss_function()` (`dictee.models.base_model.BaseKGELightning` method), 58  
`loss_function()` (`dictee.models.BaseKGELightning` method), 101  
`loss_function()` (`dictee.models.transformers.BytE` method), 92  
`loss_history` (`dictee.BaseKGE` attribute), 192  
`loss_history` (`dictee.models.base_model.BaseKGE` attribute), 63  
`loss_history` (`dictee.models.BaseKGE` attribute), 106, 109, 113, 117, 123, 136, 139  
`loss_history` (`dictee.models.pykeen_models.PykeenKGE` attribute), 85  
`loss_history` (`dictee.models.PykeenKGE` attribute), 137  
`loss_history` (`dictee.PykeenKGE` attribute), 188  
`loss_history` (`dictee.trainer.torch_trainer_ddp.NodeTrainer` attribute), 166  
`lr` (`dictee.analyse_experiments.Experiment` attribute), 19  
`lr` (`dictee.config.Namespace` attribute), 29  
`lr_lambda` (`dictee.callbacks.LRScheduler` attribute), 27  
`LRScheduler` (class in `dictee.callbacks`), 27

## M

`m` (`dictee.LFMult` attribute), 187  
`m` (`dictee.models.function_space.LFMult` attribute), 79  
`m` (`dictee.models.LFMult` attribute), 142  
`main()` (in module `dictee.scripts.index_serve`), 156  
`main()` (in module `dictee.scripts.run`), 156  
`make_iterable_verbose()` (in module `dictee.static_funcs_training`), 159  
`make_iterable_verbose()` (in module `dictee.trainer.torch_trainer_ddp`), 165  
`mapping_from_first_two_cols_to_third()` (in module `dictee`), 201  
`mapping_from_first_two_cols_to_third()` (in module `dictee.static_preprocess_funcs`), 161  
`margin` (`dictee.models.Pyke` attribute), 111  
`margin` (`dictee.models.real.Pyke` attribute), 90  
`margin` (`dictee.models.real.TransE` attribute), 90  
`margin` (`dictee.models.TransE` attribute), 111  
`margin` (`dictee.Pyke` attribute), 170  
`margin` (`dictee.TransE` attribute), 174  
`max_ans_num` (`dictee.query_generator.QueryGenerator` attribute), 145  
`max_ans_num` (`dictee.QueryGenerator` attribute), 215  
`max_epochs` (`dictee.callbacks.KGESaveCallback` attribute), 22  
`max_epochs` (`dictee.callbacks.PeriodicEvalCallback` attribute), 27  
`max_length_subword_tokens` (`dictee.BaseKGE` attribute), 192  
`max_length_subword_tokens` (`dictee.knowledge_graph.KG` attribute), 51  
`max_length_subword_tokens` (`dictee.models.base_model.BaseKGE` attribute), 63  
`max_length_subword_tokens` (`dictee.models.BaseKGE` attribute), 106, 109, 113, 117, 123, 136, 139  
`max_num_of_classes` (`dictee.dataset_classes.KvsSampleDataset` attribute), 38  
`max_num_of_classes` (`dictee.KvsSampleDataset` attribute), 208  
`mem_of_model()` (`dictee.EnsembleKGE` method), 194  
`mem_of_model()` (`dictee.models.base_model.BaseKGELightning` method), 57  
`mem_of_model()` (`dictee.models.BaseKGELightning` method), 100  
`mem_of_model()` (`dictee.models.ensemble.EnsembleKGE` method), 76  
`method` (`dictee.callbacks.Perturb` attribute), 26  
`MLP` (class in `dictee.models.transformers`), 94  
`mlp` (`dictee.models.transformers.Block` attribute), 96  
`mode` (`dictee.query_generator.QueryGenerator` attribute), 145  
`mode` (`dictee.QueryGenerator` attribute), 215  
`model` (`dictee.config.Namespace` attribute), 28  
`model` (`dictee.models.pykeen_models.PykeenKGE` attribute), 85  
`model` (`dictee.models.PykeenKGE` attribute), 137

- model (*dicee.PykeenKGE attribute*), 188
- model (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer attribute*), 166
- model (*dicee.trainer.torch\_trainer.TorchTrainer attribute*), 164
- model\_kwargs (*dicee.models.pykeen\_models.PykeenKGE attribute*), 85
- model\_kwargs (*dicee.models.PykeenKGE attribute*), 137
- model\_kwargs (*dicee.PykeenKGE attribute*), 188
- model\_name (*dicee.analyse\_experiments.Experiment attribute*), 19
- module
  - dicee, 12
  - dicee.\_\_main\_\_, 12
  - dicee.abstracts, 12
  - dicee.analyse\_experiments, 19
  - dicee.callbacks, 20
  - dicee.config, 28
  - dicee.dataset\_classes, 31
  - dicee.eval\_static\_funcs, 45
  - dicee.evaluator, 47
  - dicee.executer, 48
  - dicee.knowledge\_graph, 50
  - dicee.knowledge\_graph\_embeddings, 51
  - dicee.models, 55
  - dicee.models.adopt, 55
  - dicee.models.base\_model, 56
  - dicee.models.clifford, 65
  - dicee.models.complex, 72
  - dicee.models.dualE, 75
  - dicee.models.ensemble, 76
  - dicee.models.function\_space, 77
  - dicee.models.literal, 80
  - dicee.models.octonion, 82
  - dicee.models.pykeen\_models, 85
  - dicee.models.quaternion, 86
  - dicee.models.real, 89
  - dicee.models.static\_funcs, 90
  - dicee.models.transformers, 91
  - dicee.query\_generator, 144
  - dicee.read\_preprocess\_save\_load\_kg, 146
  - dicee.read\_preprocess\_save\_load\_kg.preprocess, 146
  - dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk, 147
  - dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk, 147
  - dicee.read\_preprocess\_save\_load\_kg.util, 148
  - dicee.sanity\_checkers, 152
  - dicee.scripts, 153
  - dicee.scripts.index\_serve, 153
  - dicee.scripts.run, 156
  - dicee.static\_funcs, 156
  - dicee.static\_funcs\_training, 159
  - dicee.static\_preprocess\_funcs, 160
  - dicee.trainer, 161
  - dicee.trainer.dice\_trainer, 161
  - dicee.trainer.model\_parallelism, 163
  - dicee.trainer.torch\_trainer, 163
  - dicee.trainer.torch\_trainer\_ddp, 165
- modules() (*dicee.EnsembleKGE method*), 193
- modules() (*dicee.models.ensemble.EnsembleKGE method*), 76
- MultiClassClassificationDataset (*class in dicee*), 203
- MultiClassClassificationDataset (*class in dicee.dataset\_classes*), 33
- MultiLabelDataset (*class in dicee*), 202
- MultiLabelDataset (*class in dicee.dataset\_classes*), 32

## N

- n (*dicee.models.FMult2 attribute*), 141
- n (*dicee.models.function\_space.FMult2 attribute*), 78
- n\_embd (*dicee.models.transformers.CausalSelfAttention attribute*), 94
- n\_embd (*dicee.models.transformers.GPTConfig attribute*), 96
- n\_epochs\_eval\_model (*dicee.callbacks.PeriodicEvalCallback attribute*), 27
- n\_epochs\_eval\_model (*dicee.config.Namespace attribute*), 31

`n_head` (*dicee.models.transformers.CausalSelfAttention* attribute), 94  
`n_head` (*dicee.models.transformers.GPTConfig* attribute), 96  
`n_layer` (*dicee.models.transformers.GPTConfig* attribute), 96  
`n_layers` (*dicee.models.FMult2* attribute), 141  
`n_layers` (*dicee.models.function\_space.FMult2* attribute), 78  
`name` (*dicee.abstracts.BaseInteractiveKGE* property), 15  
`name` (*dicee.AConEx* attribute), 180  
`name` (*dicee.AConvO* attribute), 180  
`name` (*dicee.AConvQ* attribute), 181  
`name` (*dicee.BytE* attribute), 189  
`name` (*dicee.CKeci* attribute), 171  
`name` (*dicee.ComplEx* attribute), 180  
`name` (*dicee.ConEx* attribute), 183  
`name` (*dicee.ConvO* attribute), 183  
`name` (*dicee.ConvQ* attribute), 182  
`name` (*dicee.DeCaL* attribute), 175  
`name` (*dicee.DistMult* attribute), 171  
`name` (*dicee.DualE* attribute), 178  
`name` (*dicee.EnsembleKGE* attribute), 193  
`name` (*dicee.Keci* attribute), 172  
`name` (*dicee.LFMult* attribute), 187  
`name` (*dicee.models.AConEx* attribute), 114  
`name` (*dicee.models.AConvO* attribute), 127  
`name` (*dicee.models.AConvQ* attribute), 121  
`name` (*dicee.models.CKeci* attribute), 131  
`name` (*dicee.models.clifford.CKeci* attribute), 68  
`name` (*dicee.models.clifford.DeCaL* attribute), 69  
`name` (*dicee.models.clifford.Keci* attribute), 66  
`name` (*dicee.models.ComplEx* attribute), 115  
`name` (*dicee.models.complex.AConEx* attribute), 73  
`name` (*dicee.models.complex.ComplEx* attribute), 74  
`name` (*dicee.models.complex.ConEx* attribute), 72  
`name` (*dicee.models.ConEx* attribute), 114  
`name` (*dicee.models.ConvO* attribute), 127  
`name` (*dicee.models.ConvQ* attribute), 121  
`name` (*dicee.models.DeCaL* attribute), 132  
`name` (*dicee.models.DistMult* attribute), 110  
`name` (*dicee.models.DualE* attribute), 143  
`name` (*dicee.models.dualE.DualE* attribute), 75  
`name` (*dicee.models.ensemble.EnsembleKGE* attribute), 76  
`name` (*dicee.models.FMult* attribute), 140  
`name` (*dicee.models.FMult2* attribute), 141  
`name` (*dicee.models.function\_space.FMult* attribute), 77  
`name` (*dicee.models.function\_space.FMult2* attribute), 78  
`name` (*dicee.models.function\_space.GFMult* attribute), 77  
`name` (*dicee.models.function\_space.LFMult* attribute), 79  
`name` (*dicee.models.function\_space.LFMult1* attribute), 78  
`name` (*dicee.models.GFMult* attribute), 141  
`name` (*dicee.models.Keci* attribute), 128  
`name` (*dicee.models.LFMult* attribute), 142  
`name` (*dicee.models.LFMult1* attribute), 142  
`name` (*dicee.models.octonion.AConvO* attribute), 84  
`name` (*dicee.models.octonion.ConvO* attribute), 83  
`name` (*dicee.models.octonion.OMult* attribute), 83  
`name` (*dicee.models.OMult* attribute), 126  
`name` (*dicee.models.Pyke* attribute), 111  
`name` (*dicee.models.pykeen\_models.PykeenKGE* attribute), 85  
`name` (*dicee.models.PykeenKGE* attribute), 137  
`name` (*dicee.models.QMult* attribute), 120  
`name` (*dicee.models.quaternion.AConvQ* attribute), 88  
`name` (*dicee.models.quaternion.ConvQ* attribute), 88  
`name` (*dicee.models.quaternion.QMult* attribute), 87  
`name` (*dicee.models.real.DistMult* attribute), 89  
`name` (*dicee.models.real.Pyke* attribute), 90  
`name` (*dicee.models.real.Shallom* attribute), 90  
`name` (*dicee.models.real.TransE* attribute), 89  
`name` (*dicee.models.Shallom* attribute), 111  
`name` (*dicee.models.TransE* attribute), 111

name (*dicее.models.transformers.BytE* attribute), 92  
 name (*dicее.OMult* attribute), 186  
 name (*dicее.Pyke* attribute), 170  
 name (*dicее.PykeenKGE* attribute), 188  
 name (*dicее.QMult* attribute), 184  
 name (*dicее.Shallom* attribute), 186  
 name (*dicее.TransE* attribute), 174  
 named\_children() (*dicее.EnsembleKGE* method), 193  
 named\_children() (*dicее.models.ensemble.EnsembleKGE* method), 76  
 Namespace (class in *dicее.config*), 28  
 neg\_ratio (*dicее.BPE\_NegativeSamplingDataset* attribute), 202  
 neg\_ratio (*dicее.config.Namespace* attribute), 29  
 neg\_ratio (*dicее.dataset\_classes.BPE\_NegativeSamplingDataset* attribute), 32  
 neg\_ratio (*dicее.dataset\_classes.KvsSampleDataset* attribute), 38  
 neg\_ratio (*dicее.KvsSampleDataset* attribute), 208  
 neg\_sample\_ratio (*dicее.CVDataModule* attribute), 210  
 neg\_sample\_ratio (*dicее.dataset\_classes.CVDataModule* attribute), 40  
 neg\_sample\_ratio (*dicее.dataset\_classes.NegSampleDataset* attribute), 38  
 neg\_sample\_ratio (*dicее.dataset\_classes.OnevsSample* attribute), 36, 37  
 neg\_sample\_ratio (*dicее.dataset\_classes.TriplePredictionDataset* attribute), 39  
 neg\_sample\_ratio (*dicее.NegSampleDataset* attribute), 208  
 neg\_sample\_ratio (*dicее.OnevsSample* attribute), 206, 207  
 neg\_sample\_ratio (*dicее.TriplePredictionDataset* attribute), 209  
 negnorm() (*dicее.abstracts.InteractiveQueryDecomposition* method), 16  
 NegSampleDataset (class in *dicее*), 208  
 NegSampleDataset (class in *dicее.dataset\_classes*), 38  
 neural\_searcher (in module *dicее.scripts.index\_serve*), 154  
 NeuralSearcher (class in *dicее.scripts.index\_serve*), 154  
 NodeTrainer (class in *dicее.trainer.torch\_trainer\_ddp*), 165  
 norm\_fc1 (*dicее.AConEx* attribute), 180  
 norm\_fc1 (*dicее.AConvO* attribute), 181  
 norm\_fc1 (*dicее.ConEx* attribute), 183  
 norm\_fc1 (*dicее.ConvO* attribute), 183  
 norm\_fc1 (*dicее.models.AConEx* attribute), 115  
 norm\_fc1 (*dicее.models.AConvO* attribute), 127  
 norm\_fc1 (*dicее.models.complex.AConEx* attribute), 73  
 norm\_fc1 (*dicее.models.complex.ConEx* attribute), 73  
 norm\_fc1 (*dicее.models.ConEx* attribute), 114  
 norm\_fc1 (*dicее.models.ConvO* attribute), 127  
 norm\_fc1 (*dicее.models.octonion.AConvO* attribute), 84  
 norm\_fc1 (*dicее.models.octonion.ConvO* attribute), 84  
 normalization (*dicее.analyse\_experiments.Experiment* attribute), 20  
 normalization (*dicее.config.Namespace* attribute), 29  
 normalization (*dicее.dataset\_classes.LiteralDataset* attribute), 43  
 normalization (*dicее.LiteralDataset* attribute), 213  
 normalization\_params (*dicее.dataset\_classes.LiteralDataset* attribute), 43, 44  
 normalization\_params (*dicее.LiteralDataset* attribute), 213, 214  
 normalization\_type (*dicее.dataset\_classes.LiteralDataset* attribute), 44  
 normalization\_type (*dicее.LiteralDataset* attribute), 214  
 normalize\_head\_entity\_embeddings (*dicее.BaseKGE* attribute), 192  
 normalize\_head\_entity\_embeddings (*dicее.models.base\_model.BaseKGE* attribute), 63  
 normalize\_head\_entity\_embeddings (*dicее.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139  
 normalize\_relation\_embeddings (*dicее.BaseKGE* attribute), 192  
 normalize\_relation\_embeddings (*dicее.models.base\_model.BaseKGE* attribute), 63  
 normalize\_relation\_embeddings (*dicее.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139  
 normalize\_tail\_entity\_embeddings (*dicее.BaseKGE* attribute), 192  
 normalize\_tail\_entity\_embeddings (*dicее.models.base\_model.BaseKGE* attribute), 63  
 normalize\_tail\_entity\_embeddings (*dicее.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139  
 normalizer\_class (*dicее.BaseKGE* attribute), 192  
 normalizer\_class (*dicее.models.base\_model.BaseKGE* attribute), 63  
 normalizer\_class (*dicее.models.BaseKGE* attribute), 106, 109, 112, 117, 123, 136, 139  
 num\_bpe\_entities (*dicее.BPE\_NegativeSamplingDataset* attribute), 202  
 num\_bpe\_entities (*dicее.dataset\_classes.BPE\_NegativeSamplingDataset* attribute), 32  
 num\_bpe\_entities (*dicее.knowledge\_graph.KG* attribute), 51  
 num\_core (*dicее.config.Namespace* attribute), 30  
 num\_data\_properties (*dicее.dataset\_classes.LiteralDataset* attribute), 44  
 num\_data\_properties (*dicее.LiteralDataset* attribute), 214  
 num\_datapoints (*dicее.BPE\_NegativeSamplingDataset* attribute), 202



num\_datapoints (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset* attribute), 32  
 num\_datapoints (*dicee.dataset\_classes.MultiLabelDataset* attribute), 33  
 num\_datapoints (*dicee.MultiLabelDataset* attribute), 203  
 num\_ent (*dicee.DualE* attribute), 178  
 num\_ent (*dicee.models.DualE* attribute), 144  
 num\_ent (*dicee.models.dualE.DualE* attribute), 75  
 num\_entities (*dicee.BaseKGE* attribute), 192  
 num\_entities (*dicee.CVDDataModule* attribute), 210  
 num\_entities (*dicee.dataset\_classes.CVDDataModule* attribute), 40  
 num\_entities (*dicee.dataset\_classes.KvsSampleDataset* attribute), 38  
 num\_entities (*dicee.dataset\_classes.LiteralDataset* attribute), 44  
 num\_entities (*dicee.dataset\_classes.NegSampleDataset* attribute), 38  
 num\_entities (*dicee.dataset\_classes.OnevsSample* attribute), 36, 37  
 num\_entities (*dicee.dataset\_classes.TriplePredictionDataset* attribute), 39  
 num\_entities (*dicee.evaluator.Evaluator* attribute), 47  
 num\_entities (*dicee.knowledge\_graph.KG* attribute), 50  
 num\_entities (*dicee.KvsSampleDataset* attribute), 208  
 num\_entities (*dicee.LiteralDataset* attribute), 213, 214  
 num\_entities (*dicee.models.base\_model.BaseKGE* attribute), 63  
 num\_entities (*dicee.models.BaseKGE* attribute), 105, 108, 112, 117, 122, 135, 139  
 num\_entities (*dicee.NegSampleDataset* attribute), 208  
 num\_entities (*dicee.OnevsSample* attribute), 206  
 num\_entities (*dicee.TriplePredictionDataset* attribute), 209  
 num\_epochs (*dicee.abstracts.AbstractPPECallback* attribute), 17  
 num\_epochs (*dicee.analyse\_experiments.Experiment* attribute), 19  
 num\_epochs (*dicee.callbacks.ASWA* attribute), 23  
 num\_epochs (*dicee.config.Namespace* attribute), 29  
 num\_epochs (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer* attribute), 166  
 num\_folds\_for\_cv (*dicee.config.Namespace* attribute), 29  
 num\_of\_data\_points (*dicee.dataset\_classes.MultiClassClassificationDataset* attribute), 33  
 num\_of\_data\_points (*dicee.MultiClassClassificationDataset* attribute), 203  
 num\_of\_data\_properties (*dicee.models.literal.LiteralEmbeddings* attribute), 80, 81  
 num\_of\_epochs (*dicee.callbacks.PseudoLabellingCallback* attribute), 23  
 num\_of\_output\_channels (*dicee.BaseKGE* attribute), 192  
 num\_of\_output\_channels (*dicee.config.Namespace* attribute), 30  
 num\_of\_output\_channels (*dicee.models.base\_model.BaseKGE* attribute), 63  
 num\_of\_output\_channels (*dicee.models.BaseKGE* attribute), 106, 109, 112, 117, 123, 136, 139  
 num\_params (*dicee.analyse\_experiments.Experiment* attribute), 19  
 num\_relations (*dicee.BaseKGE* attribute), 192  
 num\_relations (*dicee.CVDDataModule* attribute), 210  
 num\_relations (*dicee.dataset\_classes.CVDDataModule* attribute), 40  
 num\_relations (*dicee.dataset\_classes.NegSampleDataset* attribute), 38  
 num\_relations (*dicee.dataset\_classes.OnevsSample* attribute), 36, 37  
 num\_relations (*dicee.dataset\_classes.TriplePredictionDataset* attribute), 39  
 num\_relations (*dicee.evaluator.Evaluator* attribute), 47  
 num\_relations (*dicee.knowledge\_graph.KG* attribute), 50  
 num\_relations (*dicee.models.base\_model.BaseKGE* attribute), 63  
 num\_relations (*dicee.models.BaseKGE* attribute), 105, 108, 112, 117, 123, 135, 139  
 num\_relations (*dicee.NegSampleDataset* attribute), 208  
 num\_relations (*dicee.OnevsSample* attribute), 206  
 num\_relations (*dicee.TriplePredictionDataset* attribute), 209  
 num\_sample (*dicee.models.FMult* attribute), 140  
 num\_sample (*dicee.models.function\_space.FMult* attribute), 77  
 num\_sample (*dicee.models.function\_space.GFMult* attribute), 77  
 num\_sample (*dicee.models.GFMult* attribute), 141  
 num\_tokens (*dicee.BaseKGE* attribute), 192  
 num\_tokens (*dicee.knowledge\_graph.KG* attribute), 51  
 num\_tokens (*dicee.models.base\_model.BaseKGE* attribute), 63  
 num\_tokens (*dicee.models.BaseKGE* attribute), 105, 109, 112, 117, 123, 135, 139  
 num\_workers (*dicee.CVDDataModule* attribute), 210  
 num\_workers (*dicee.dataset\_classes.CVDDataModule* attribute), 40  
 numpy\_data\_type\_changer () (in module *dicee*), 194  
 numpy\_data\_type\_changer () (in module *dicee.static\_funcs*), 158

## O

octonion\_mul () (in module *dicee.models*), 125  
 octonion\_mul () (in module *dicee.models.octonion*), 82

octonion\_mul\_norm() (in module *dicee.models*), 125  
 octonion\_mul\_norm() (in module *dicee.models.octonion*), 82  
 octonion\_normalizer() (*dicee.AConvO* static method), 181  
 octonion\_normalizer() (*dicee.ConvO* static method), 183  
 octonion\_normalizer() (*dicee.models.AConvO* static method), 127  
 octonion\_normalizer() (*dicee.models.ConvO* static method), 127  
 octonion\_normalizer() (*dicee.models.octonion.AConvO* static method), 84  
 octonion\_normalizer() (*dicee.models.octonion.ConvO* static method), 84  
 octonion\_normalizer() (*dicee.models.octonion.OMult* static method), 83  
 octonion\_normalizer() (*dicee.models.OMult* static method), 126  
 octonion\_normalizer() (*dicee.OMult* static method), 186  
 OMult (class in *dicee*), 185  
 OMult (class in *dicee.models*), 125  
 OMult (class in *dicee.models.octonion*), 82  
 on\_epoch\_end() (*dicee.callbacks.KGESaveCallback* method), 23  
 on\_epoch\_end() (*dicee.callbacks.PseudoLabellingCallback* method), 23  
 on\_fit\_end() (*dicee.abstracts.AbstractCallback* method), 17  
 on\_fit\_end() (*dicee.abstracts.AbstractPPECallback* method), 18  
 on\_fit\_end() (*dicee.abstracts.AbstractTrainer* method), 13  
 on\_fit\_end() (*dicee.callbacks.AccumulateEpochLossCallback* method), 21  
 on\_fit\_end() (*dicee.callbacks.ASWA* method), 24  
 on\_fit\_end() (*dicee.callbacks.Eval* method), 25  
 on\_fit\_end() (*dicee.callbacks.KGESaveCallback* method), 23  
 on\_fit\_end() (*dicee.callbacks.LRScheduler* method), 28  
 on\_fit\_end() (*dicee.callbacks.PeriodicEvalCallback* method), 27  
 on\_fit\_end() (*dicee.callbacks.PrintCallback* method), 21  
 on\_fit\_start() (*dicee.abstracts.AbstractCallback* method), 16  
 on\_fit\_start() (*dicee.abstracts.AbstractPPECallback* method), 17  
 on\_fit\_start() (*dicee.abstracts.AbstractTrainer* method), 13  
 on\_fit\_start() (*dicee.callbacks.Eval* method), 25  
 on\_fit\_start() (*dicee.callbacks.KGESaveCallback* method), 22  
 on\_fit\_start() (*dicee.callbacks.KronE* method), 26  
 on\_fit\_start() (*dicee.callbacks.PrintCallback* method), 21  
 on\_init\_end() (*dicee.abstracts.AbstractCallback* method), 16  
 on\_init\_start() (*dicee.abstracts.AbstractCallback* method), 16  
 on\_train\_batch\_end() (*dicee.abstracts.AbstractCallback* method), 17  
 on\_train\_batch\_end() (*dicee.abstracts.AbstractTrainer* method), 13  
 on\_train\_batch\_end() (*dicee.callbacks.Eval* method), 25  
 on\_train\_batch\_end() (*dicee.callbacks.KGESaveCallback* method), 22  
 on\_train\_batch\_end() (*dicee.callbacks.LRScheduler* method), 28  
 on\_train\_batch\_end() (*dicee.callbacks.PrintCallback* method), 21  
 on\_train\_batch\_start() (*dicee.callbacks.Perturb* method), 26  
 on\_train\_epoch\_end() (*dicee.abstracts.AbstractCallback* method), 16  
 on\_train\_epoch\_end() (*dicee.abstracts.AbstractTrainer* method), 13  
 on\_train\_epoch\_end() (*dicee.callbacks.ASWA* method), 24  
 on\_train\_epoch\_end() (*dicee.callbacks.Eval* method), 25  
 on\_train\_epoch\_end() (*dicee.callbacks.KGESaveCallback* method), 22  
 on\_train\_epoch\_end() (*dicee.callbacks.PeriodicEvalCallback* method), 27  
 on\_train\_epoch\_end() (*dicee.callbacks.PrintCallback* method), 22  
 on\_train\_epoch\_end() (*dicee.models.base\_model.BaseKGELightning* method), 58  
 on\_train\_epoch\_end() (*dicee.models.BaseKGELightning* method), 101  
 on\_train\_start() (*dicee.callbacks.LRScheduler* method), 28  
 OnevsAllDataset (class in *dicee*), 203  
 OnevsAllDataset (class in *dicee.dataset\_classes*), 34  
 OnevsSample (class in *dicee*), 205  
 OnevsSample (class in *dicee.dataset\_classes*), 36  
 optim (*dicee.config.Namespace* attribute), 29  
 optimizer (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer* attribute), 165  
 optimizer (*dicee.trainer.torch\_trainer.TorchTrainer* attribute), 164  
 optimizer\_name (*dicee.BaseKGE* attribute), 192  
 optimizer\_name (*dicee.models.base\_model.BaseKGE* attribute), 63  
 optimizer\_name (*dicee.models.BaseKGE* attribute), 105, 109, 112, 117, 123, 135, 139  
 ordered\_bpe\_entities (*dicee.BPE\_NegativeSamplingDataset* attribute), 202  
 ordered\_bpe\_entities (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset* attribute), 32  
 ordered\_bpe\_entities (*dicee.knowledge\_graph.KG* attribute), 51  
 ordered\_shaped\_bpe\_tokens (*dicee.knowledge\_graph.KG* attribute), 50



## P

- `p` (*dicee.config.Namespace* attribute), 30
- `p` (*dicee.DeCaL* attribute), 175
- `p` (*dicee.Keci* attribute), 172
- `p` (*dicee.models.clifford.DeCaL* attribute), 69
- `p` (*dicee.models.clifford.Keci* attribute), 66
- `p` (*dicee.models.DeCaL* attribute), 132
- `p` (*dicee.models.Keci* attribute), 128
- `padding` (*dicee.knowledge\_graph.KG* attribute), 51
- `pandas_dataframe_indexer()` (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 150
- `param_init` (*dicee.BaseKGE* attribute), 192
- `param_init` (*dicee.models.base\_model.BaseKGE* attribute), 63
- `param_init` (*dicee.models.BaseKGE* attribute), 106, 109, 113, 117, 123, 136, 139
- `parameters()` (*dicee.abstracts.BaseInteractiveKGE* method), 15
- `parameters()` (*dicee.EnsembleKGE* method), 193
- `parameters()` (*dicee.models.ensemble.EnsembleKGE* method), 76
- `path` (*dicee.abstracts.AbstractPPECallback* attribute), 17
- `path` (*dicee.callbacks.AccumulateEpochLossCallback* attribute), 21
- `path` (*dicee.callbacks.ASWA* attribute), 23
- `path` (*dicee.callbacks.Eval* attribute), 25
- `path` (*dicee.callbacks.KGESaveCallback* attribute), 22
- `path_dataset_folder` (*dicee.analyse\_experiments.Experiment* attribute), 19
- `path_for_deserialization` (*dicee.knowledge\_graph.KG* attribute), 50
- `path_for_serialization` (*dicee.knowledge\_graph.KG* attribute), 50
- `path_single_kg` (*dicee.config.Namespace* attribute), 28
- `path_single_kg` (*dicee.knowledge\_graph.KG* attribute), 50
- `path_to_store_single_run` (*dicee.config.Namespace* attribute), 28
- PeriodicEvalCallback* (class in *dicee.callbacks*), 26
- Perturb* (class in *dicee.callbacks*), 26
- `polars_dataframe_indexer()` (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 149
- `poly_NN()` (*dicee.LFMult* method), 187
- `poly_NN()` (*dicee.models.function\_space.LFMult* method), 79
- `poly_NN()` (*dicee.models.LFMult* method), 143
- `polynomial()` (*dicee.LFMult* method), 188
- `polynomial()` (*dicee.models.function\_space.LFMult* method), 80
- `polynomial()` (*dicee.models.LFMult* method), 143
- `pop()` (*dicee.LFMult* method), 188
- `pop()` (*dicee.models.function\_space.LFMult* method), 80
- `pop()` (*dicee.models.LFMult* method), 143
- `pq` (*dicee.analyse\_experiments.Experiment* attribute), 19
- `predict()` (*dicee.KGE* method), 198
- `predict()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 53
- `predict_data_loader()` (*dicee.models.base\_model.BaseKGELightning* method), 60
- `predict_data_loader()` (*dicee.models.BaseKGELightning* method), 102
- `predict_literals()` (*dicee.KGE* method), 200
- `predict_literals()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 55
- `predict_missing_head_entity()` (*dicee.KGE* method), 197
- `predict_missing_head_entity()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 52
- `predict_missing_relations()` (*dicee.KGE* method), 198
- `predict_missing_relations()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 52
- `predict_missing_tail_entity()` (*dicee.KGE* method), 198
- `predict_missing_tail_entity()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 53
- `predict_topk()` (*dicee.KGE* method), 198
- `predict_topk()` (*dicee.knowledge\_graph\_embeddings.KGE* method), 53
- `prepare_data()` (*dicee.CVDataModule* method), 212
- `prepare_data()` (*dicee.dataset\_classes.CVDataModule* method), 42
- `preprocess_with_byte_pair_encoding()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG* method), 151
- `preprocess_with_byte_pair_encoding()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG* method), 146
- `preprocess_with_byte_pair_encoding_with_padding()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG* method), 151
- `preprocess_with_byte_pair_encoding_with_padding()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG* method), 146
- `preprocess_with_pandas()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG* method), 151
- `preprocess_with_pandas()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG* method), 146
- `preprocess_with_polars()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG* method), 152
- `preprocess_with_polars()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG* method), 147
- `preprocesses_input_args()` (in module *dicee.static\_preprocess\_funcs*), 160
- PreprocessKG* (class in *dicee.read\_preprocess\_save\_load\_kg*), 151
- PreprocessKG* (class in *dicee.read\_preprocess\_save\_load\_kg.preprocess*), 146
- PrintCallback* (class in *dicee.callbacks*), 21

process (*dicee.trainer.torch\_trainer.TorchTrainer* attribute), 164  
PseudoLabellingCallback (class in *dicee.callbacks*), 23  
Pyke (class in *dicee*), 170  
Pyke (class in *dicee.models*), 111  
Pyke (class in *dicee.models.real*), 90  
pykeen\_model\_kwargs (*dicee.config.Namespace* attribute), 30  
PykeenKGE (class in *dicee*), 188  
PykeenKGE (class in *dicee.models*), 137  
PykeenKGE (class in *dicee.models.pykeen\_models*), 85

## Q

q (*dicee.config.Namespace* attribute), 30  
q (*dicee.DeCaL* attribute), 175  
q (*dicee.Keci* attribute), 172  
q (*dicee.models.clifford.DeCaL* attribute), 69  
q (*dicee.models.clifford.Keci* attribute), 66  
q (*dicee.models.DeCaL* attribute), 132  
q (*dicee.models.Keci* attribute), 128  
qdrant\_client (*dicee.scripts.index\_serve.NeuralSearcher* attribute), 154  
QMult (class in *dicee*), 184  
QMult (class in *dicee.models*), 119  
QMult (class in *dicee.models.quaternion*), 86  
quaternion\_mul () (in module *dicee.models*), 116  
quaternion\_mul () (in module *dicee.models.static\_funcs*), 90  
quaternion\_mul\_with\_unit\_norm () (in module *dicee.models*), 119  
quaternion\_mul\_with\_unit\_norm () (in module *dicee.models.quaternion*), 86  
quaternion\_multiplication\_followed\_by\_inner\_product () (*dicee.models.QMult* method), 120  
quaternion\_multiplication\_followed\_by\_inner\_product () (*dicee.models.quaternion.QMult* method), 87  
quaternion\_multiplication\_followed\_by\_inner\_product () (*dicee.QMult* method), 184  
quaternion\_normalizer () (*dicee.models.QMult* static method), 120  
quaternion\_normalizer () (*dicee.models.quaternion.QMult* static method), 87  
quaternion\_normalizer () (*dicee.QMult* static method), 185  
queries (*dicee.scripts.index\_serve.StringListRequest* attribute), 155  
query\_name\_to\_struct (*dicee.query\_generator.QueryGenerator* attribute), 145  
query\_name\_to\_struct (*dicee.QueryGenerator* attribute), 215  
QueryGenerator (class in *dicee*), 214  
QueryGenerator (class in *dicee.query\_generator*), 145

## R

r (*dicee.DeCaL* attribute), 175  
r (*dicee.Keci* attribute), 172  
r (*dicee.models.clifford.DeCaL* attribute), 69  
r (*dicee.models.clifford.Keci* attribute), 66  
r (*dicee.models.DeCaL* attribute), 132  
r (*dicee.models.Keci* attribute), 128  
random\_prediction () (in module *dicee*), 195  
random\_prediction () (in module *dicee.static\_funcs*), 158  
random\_seed (*dicee.config.Namespace* attribute), 30  
ratio (*dicee.callbacks.Perturb* attribute), 26  
re (*dicee.DeCaL* attribute), 175  
re (*dicee.models.clifford.DeCaL* attribute), 69  
re (*dicee.models.DeCaL* attribute), 132  
re\_vocab (*dicee.evaluator.Evaluator* attribute), 47  
read\_from\_disk () (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 150  
read\_from\_triple\_store () (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 150  
read\_only\_few (*dicee.config.Namespace* attribute), 30  
read\_only\_few (*dicee.knowledge\_graph.KG* attribute), 50  
read\_or\_load\_kg () (in module *dicee*), 195  
read\_or\_load\_kg () (in module *dicee.static\_funcs*), 158  
read\_with\_pandas () (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 150  
read\_with\_polars () (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 150  
ReadFromDisk (class in *dicee.read\_preprocess\_save\_load\_kg*), 152  
ReadFromDisk (class in *dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk*), 147  
reducer (*dicee.scripts.index\_serve.StringListRequest* attribute), 155  
rel2id (*dicee.query\_generator.QueryGenerator* attribute), 145  
rel2id (*dicee.QueryGenerator* attribute), 215  
relation\_embeddings (*dicee.AConvQ* attribute), 181

- relation\_embeddings (*dicee.ConvQ attribute*), 182
- relation\_embeddings (*dicee.DeCaL attribute*), 175
- relation\_embeddings (*dicee.DualE attribute*), 178
- relation\_embeddings (*dicee.LFMult attribute*), 187
- relation\_embeddings (*dicee.models.AConvQ attribute*), 121
- relation\_embeddings (*dicee.models.clifford.DeCaL attribute*), 69
- relation\_embeddings (*dicee.models.ConvQ attribute*), 121
- relation\_embeddings (*dicee.models.DeCaL attribute*), 132
- relation\_embeddings (*dicee.models.DualE attribute*), 144
- relation\_embeddings (*dicee.models.dualE.DualE attribute*), 75
- relation\_embeddings (*dicee.models.FMult attribute*), 140
- relation\_embeddings (*dicee.models.FMult2 attribute*), 142
- relation\_embeddings (*dicee.models.function\_space.FMult attribute*), 77
- relation\_embeddings (*dicee.models.function\_space.FMult2 attribute*), 78
- relation\_embeddings (*dicee.models.function\_space.GFMult attribute*), 77
- relation\_embeddings (*dicee.models.function\_space.LFMult attribute*), 79
- relation\_embeddings (*dicee.models.function\_space.LFMult1 attribute*), 78
- relation\_embeddings (*dicee.models.GFMult attribute*), 141
- relation\_embeddings (*dicee.models.LFMult attribute*), 142
- relation\_embeddings (*dicee.models.LFMult1 attribute*), 142
- relation\_embeddings (*dicee.models.pykeen\_models.PykeenKGE attribute*), 85
- relation\_embeddings (*dicee.models.PykeenKGE attribute*), 137
- relation\_embeddings (*dicee.models.quaternion.AConvQ attribute*), 88
- relation\_embeddings (*dicee.models.quaternion.ConvQ attribute*), 88
- relation\_embeddings (*dicee.PykeenKGE attribute*), 188
- relation\_to\_idx (*dicee.knowledge\_graph.KG attribute*), 51
- relations\_str (*dicee.knowledge\_graph.KG property*), 51
- reload\_dataset () (*in module dicee*), 202
- reload\_dataset () (*in module dicee.dataset\_classes*), 32
- report (*dicee.DICE\_Trainer attribute*), 196
- report (*dicee.evaluator.Evaluator attribute*), 47
- report (*dicee.Execute attribute*), 201
- report (*dicee.executer.Execute attribute*), 48
- report (*dicee.trainer.DICE\_Trainer attribute*), 166
- report (*dicee.trainer.dice\_trainer.DICE\_Trainer attribute*), 161
- reports (*dicee.callbacks.Eval attribute*), 25
- reports (*dicee.callbacks.PeriodicEvalCallback attribute*), 27
- requires\_grad\_for\_interactions (*dicee.CKeci attribute*), 171
- requires\_grad\_for\_interactions (*dicee.Keci attribute*), 172
- requires\_grad\_for\_interactions (*dicee.models.CKeci attribute*), 131
- requires\_grad\_for\_interactions (*dicee.models.clifford.CKeci attribute*), 68
- requires\_grad\_for\_interactions (*dicee.models.clifford.Keci attribute*), 66
- requires\_grad\_for\_interactions (*dicee.models.Keci attribute*), 128
- resid\_dropout (*dicee.models.transformers.CausalSelfAttention attribute*), 94
- residual\_convolution () (*dicee.AConEx method*), 180
- residual\_convolution () (*dicee.AConvO method*), 181
- residual\_convolution () (*dicee.AConvQ method*), 181
- residual\_convolution () (*dicee.ConEx method*), 183
- residual\_convolution () (*dicee.ConvO method*), 183
- residual\_convolution () (*dicee.ConvQ method*), 182
- residual\_convolution () (*dicee.models.AConEx method*), 115
- residual\_convolution () (*dicee.models.AConvO method*), 127
- residual\_convolution () (*dicee.models.AConvQ method*), 122
- residual\_convolution () (*dicee.models.complex.AConEx method*), 73
- residual\_convolution () (*dicee.models.complex.ConEx method*), 73
- residual\_convolution () (*dicee.models.ConEx method*), 114
- residual\_convolution () (*dicee.models.ConvO method*), 127
- residual\_convolution () (*dicee.models.ConvQ method*), 121
- residual\_convolution () (*dicee.models.octonion.AConvO method*), 84
- residual\_convolution () (*dicee.models.octonion.ConvO method*), 84
- residual\_convolution () (*dicee.models.quaternion.AConvQ method*), 89
- residual\_convolution () (*dicee.models.quaternion.ConvQ method*), 88
- retrieve\_embedding () (*dicee.scripts.index\_serve.NeuralSearcher method*), 154
- retrieve\_embeddings () (*in module dicee.scripts.index\_serve*), 154
- return\_multi\_hop\_query\_results () (*dicee.KGE method*), 199
- return\_multi\_hop\_query\_results () (*dicee.knowledge\_graph\_embeddings.KGE method*), 54
- root () (*in module dicee.scripts.index\_serve*), 154
- roots (*dicee.models.FMult attribute*), 141

roots (*dicее.models.function\_space.FMult* attribute), 77  
 roots (*dicее.models.function\_space.GFMult* attribute), 77  
 roots (*dicее.models.GFMult* attribute), 141  
 runtime (*dicее.analyse\_experiments.Experiment* attribute), 20

## S

sample\_counter (*dicее.abstracts.AbstractPPECallback* attribute), 17  
 sample\_entity() (*dicее.abstracts.BaseInteractiveKGE* method), 15  
 sample\_relation() (*dicее.abstracts.BaseInteractiveKGE* method), 15  
 sample\_triples\_ratio (*dicее.config.Namespace* attribute), 30  
 sample\_triples\_ratio (*dicее.knowledge\_graph.KG* attribute), 50  
 sampling\_ratio (*dicее.dataset\_classes.LiteralDataset* attribute), 43, 44  
 sampling\_ratio (*dicее.LiteralDataset* attribute), 213, 214  
 sanity\_checking\_with\_arguments() (in module *dicее.sanity\_checkers*), 153  
 save() (*dicее.abstracts.BaseInteractiveKGE* method), 15  
 save() (*dicее.read\_preprocess\_save\_load\_kg.LoadSaveToDisk* method), 152  
 save() (*dicее.read\_preprocess\_save\_load\_kg.save\_load\_disk.LoadSaveToDisk* method), 148  
 save\_checkpoint() (*dicее.abstracts.AbstractTrainer* static method), 13  
 save\_checkpoint\_model() (in module *dicее*), 194  
 save\_checkpoint\_model() (in module *dicее.static\_funcs*), 158  
 save\_embeddings() (in module *dicее*), 195  
 save\_embeddings() (in module *dicее.static\_funcs*), 158  
 save\_embeddings\_as\_csv (*dicее.config.Namespace* attribute), 28  
 save\_every\_n\_epochs (*dicее.config.Namespace* attribute), 31  
 save\_experiment() (*dicее.analyse\_experiments.Experiment* method), 20  
 save\_model\_at\_every\_epoch (*dicее.config.Namespace* attribute), 30  
 save\_model\_every\_n\_epoch (*dicее.callbacks.PeriodicEvalCallback* attribute), 27  
 save\_numpy\_ndarray() (in module *dicее*), 194  
 save\_numpy\_ndarray() (in module *dicее.read\_preprocess\_save\_load\_kg.util*), 151  
 save\_numpy\_ndarray() (in module *dicее.static\_funcs*), 158  
 save\_pickle() (in module *dicее*), 194  
 save\_pickle() (in module *dicее.read\_preprocess\_save\_load\_kg.util*), 151  
 save\_pickle() (in module *dicее.static\_funcs*), 158  
 save\_queries() (*dicее.query\_generator.QueryGenerator* method), 146  
 save\_queries() (*dicее.QueryGenerator* method), 215  
 save\_queries\_and\_answers() (*dicее.query\_generator.QueryGenerator* static method), 146  
 save\_queries\_and\_answers() (*dicее.QueryGenerator* static method), 216  
 save\_trained\_model() (*dicее.Execute* method), 201  
 save\_trained\_model() (*dicее.executer.Execute* method), 49  
 scalar\_batch\_NN() (*dicее.LFMult* method), 187  
 scalar\_batch\_NN() (*dicее.models.function\_space.LFMult* method), 79  
 scalar\_batch\_NN() (*dicее.models.LFMult* method), 143  
 scaler (*dicее.callbacks.Perturb* attribute), 26  
 scaler (*dicее.trainer.torch\_trainer\_ddp.NodeTrainer* attribute), 166  
 scheduler (*dicее.callbacks.LRScheduler* attribute), 27  
 score() (*dicее.ComplEx* static method), 180  
 score() (*dicее.DistMult* method), 171  
 score() (*dicее.Keci* method), 174  
 score() (*dicее.models.clifford.Keci* method), 68  
 score() (*dicее.models.ComplEx* static method), 116  
 score() (*dicее.models.complex.ComplEx* static method), 74  
 score() (*dicее.models.DistMult* method), 111  
 score() (*dicее.models.Keci* method), 131  
 score() (*dicее.models.octonion.OMult* method), 83  
 score() (*dicее.models.OMult* method), 126  
 score() (*dicее.models.QMult* method), 120  
 score() (*dicее.models.quaternion.QMult* method), 87  
 score() (*dicее.models.real.DistMult* method), 89  
 score() (*dicее.models.real.TransE* method), 90  
 score() (*dicее.models.TransE* method), 111  
 score() (*dicее.OMult* method), 186  
 score() (*dicее.QMult* method), 185  
 score() (*dicее.TransE* method), 174  
 score\_func (*dicее.models.FMult2* attribute), 141  
 score\_func (*dicее.models.function\_space.FMult2* attribute), 78  
 scoring\_technique (*dicее.analyse\_experiments.Experiment* attribute), 20  
 scoring\_technique (*dicее.config.Namespace* attribute), 29

`search()` (*dicee.scripts.index\_serve.NeuralSearcher method*), 154  
`search_embeddings()` (*in module dicee.scripts.index\_serve*), 154  
`search_embeddings_batch()` (*in module dicee.scripts.index\_serve*), 156  
`seed` (*dicee.query\_generator.QueryGenerator attribute*), 145  
`seed` (*dicee.QueryGenerator attribute*), 215  
`select_model()` (*in module dicee*), 194  
`select_model()` (*in module dicee.static\_funcs*), 158  
`selected_optimizer` (*dicee.BaseKGE attribute*), 192  
`selected_optimizer` (*dicee.models.base\_model.BaseKGE attribute*), 63  
`selected_optimizer` (*dicee.models.BaseKGE attribute*), 106, 109, 112, 117, 123, 136, 139  
`separator` (*dicee.config.Namespace attribute*), 29  
`separator` (*dicee.knowledge\_graph.KG attribute*), 51  
`sequential_vocabulary_construction()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 152  
`sequential_vocabulary_construction()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 147  
`serve()` (*in module dicee.scripts.index\_serve*), 156  
`set_global_seed()` (*dicee.query\_generator.QueryGenerator method*), 145  
`set_global_seed()` (*dicee.QueryGenerator method*), 215  
`set_model_eval_mode()` (*dicee.abstracts.BaseInteractiveKGE method*), 14  
`set_model_train_mode()` (*dicee.abstracts.BaseInteractiveKGE method*), 14  
`setup()` (*dicee.CVDataModule method*), 210  
`setup()` (*dicee.dataset\_classes.CVDataModule method*), 41  
`setup_executor()` (*dicee.Execute method*), 201  
`setup_executor()` (*dicee.executer.Execute method*), 49  
`Shallom` (*class in dicee*), 186  
`Shallom` (*class in dicee.models*), 111  
`Shallom` (*class in dicee.models.real*), 90  
`shallom` (*dicee.models.real.Shallom attribute*), 90  
`shallom` (*dicee.models.Shallom attribute*), 111  
`shallom` (*dicee.Shallom attribute*), 186  
`single_hop_query_answering()` (*dicee.KGE method*), 199  
`single_hop_query_answering()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 54  
`snapshot_dir` (*dicee.callbacks.LRScheduler attribute*), 27  
`snapshot_loss` (*dicee.callbacks.LRScheduler attribute*), 28  
`sparql_endpoint` (*dicee.config.Namespace attribute*), 28  
`sparql_endpoint` (*dicee.knowledge\_graph.KG attribute*), 50  
`start()` (*dicee.DICE\_Trainer method*), 196  
`start()` (*dicee.Execute method*), 201  
`start()` (*dicee.executer.Execute method*), 49  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 151  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 146  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk.ReadFromDisk method*), 147  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.ReadFromDisk method*), 152  
`start()` (*dicee.trainer.DICE\_Trainer method*), 167  
`start()` (*dicee.trainer.dice\_trainer.DICE\_Trainer method*), 162  
`start_time` (*dicee.callbacks.PrintCallback attribute*), 21  
`start_time` (*dicee.Execute attribute*), 201  
`start_time` (*dicee.executer.Execute attribute*), 48  
`step()` (*dicee.EnsembleKGE method*), 194  
`step()` (*dicee.models.ADOPT method*), 99  
`step()` (*dicee.models.adopt.ADOPT method*), 56  
`step()` (*dicee.models.ensemble.EnsembleKGE method*), 76  
`step_count` (*dicee.callbacks.LRScheduler attribute*), 28  
`storage_path` (*dicee.config.Namespace attribute*), 28  
`storage_path` (*dicee.DICE\_Trainer attribute*), 196  
`storage_path` (*dicee.trainer.DICE\_Trainer attribute*), 166  
`storage_path` (*dicee.trainer.dice\_trainer.DICE\_Trainer attribute*), 162  
`store()` (*in module dicee*), 194  
`store()` (*in module dicee.static\_funcs*), 158  
`store_ensemble()` (*dicee.abstracts.AbstractPPECallback method*), 18  
`strategy` (*dicee.abstracts.AbstractTrainer attribute*), 13  
`StringListRequest` (*class in dicee.scripts.index\_serve*), 154  
`swa` (*dicee.config.Namespace attribute*), 30  
`swa_start_epoch` (*dicee.config.Namespace attribute*), 31

## T

`T()` (*dicee.DualE method*), 179  
`T()` (*dicee.models.DualE method*), 144



`T()` (*dicее.models.dualE.DualE method*), 76  
`t_conorm()` (*dicее.abstracts.InteractiveQueryDecomposition method*), 16  
`t_norm()` (*dicее.abstracts.InteractiveQueryDecomposition method*), 16  
`target_dim` (*dicее.AllvsAll attribute*), 205  
`target_dim` (*dicее.dataset\_classes.AllvsAll attribute*), 36  
`target_dim` (*dicее.dataset\_classes.MultiLabelDataset attribute*), 33  
`target_dim` (*dicее.dataset\_classes.OnevsAllDataset attribute*), 34  
`target_dim` (*dicее.knowledge\_graph.KG attribute*), 51  
`target_dim` (*dicее.MultiLabelDataset attribute*), 203  
`target_dim` (*dicее.OnevsAllDataset attribute*), 204  
`temperature` (*dicее.BytE attribute*), 189  
`temperature` (*dicее.models.transformers.BytE attribute*), 92  
`tensor_t_norm()` (*dicее.abstracts.InteractiveQueryDecomposition method*), 16  
`TensorParallel` (class in *dicее.trainer.model\_parallelism*), 163  
`test_data_loader()` (*dicее.models.base\_model.BaseKGELightning method*), 59  
`test_data_loader()` (*dicее.models.BaseKGELightning method*), 101  
`test_epoch_end()` (*dicее.models.base\_model.BaseKGELightning method*), 59  
`test_epoch_end()` (*dicее.models.BaseKGELightning method*), 101  
`test_h1` (*dicее.analyse\_experiments.Experiment attribute*), 20  
`test_h3` (*dicее.analyse\_experiments.Experiment attribute*), 20  
`test_h10` (*dicее.analyse\_experiments.Experiment attribute*), 20  
`test_mrr` (*dicее.analyse\_experiments.Experiment attribute*), 20  
`test_path` (*dicее.query\_generator.QueryGenerator attribute*), 145  
`test_path` (*dicее.QueryGenerator attribute*), 215  
`timeit()` (in module *dicее*), 194, 202  
`timeit()` (in module *dicее.read\_preprocess\_save\_load\_kg.util*), 150  
`timeit()` (in module *dicее.static\_funcs*), 158  
`timeit()` (in module *dicее.static\_preprocess\_funcs*), 160  
`to()` (*dicее.EnsembleKGE method*), 194  
`to()` (*dicее.KGE method*), 197  
`to()` (*dicее.knowledge\_graph\_embeddings.KGE method*), 52  
`to()` (*dicее.models.ensemble.EnsembleKGE method*), 76  
`to_df()` (*dicее.analyse\_experiments.Experiment method*), 20  
`topk` (*dicее.BytE attribute*), 189  
`topk` (*dicее.models.transformers.BytE attribute*), 92  
`topk` (*dicее.scripts.index\_serve.NeuralSearcher attribute*), 154  
`torch_ordered_shaped_bpe_entities` (*dicее.dataset\_classes.MultiLabelDataset attribute*), 33  
`torch_ordered_shaped_bpe_entities` (*dicее.MultiLabelDataset attribute*), 203  
`TorchDDPTrainer` (class in *dicее.trainer.torch\_trainer\_ddp*), 165  
`TorchTrainer` (class in *dicее.trainer.torch\_trainer*), 164  
`total_epochs` (*dicее.callbacks.LRScheduler attribute*), 27  
`total_steps` (*dicее.callbacks.LRScheduler attribute*), 27  
`train()` (*dicее.abstracts.BaseInteractiveTrainKGE method*), 18  
`train()` (*dicее.trainer.torch\_trainer\_ddp.NodeTrainer method*), 166  
`train_data` (*dicее.AllvsAll attribute*), 205  
`train_data` (*dicее.dataset\_classes.AllvsAll attribute*), 35  
`train_data` (*dicее.dataset\_classes.KvsAll attribute*), 35  
`train_data` (*dicее.dataset\_classes.KvsSampleDataset attribute*), 38  
`train_data` (*dicее.dataset\_classes.MultiClassClassificationDataset attribute*), 33  
`train_data` (*dicее.dataset\_classes.OnevsAllDataset attribute*), 34  
`train_data` (*dicее.dataset\_classes.OnevsSample attribute*), 36, 37  
`train_data` (*dicее.KvsAll attribute*), 204  
`train_data` (*dicее.KvsSampleDataset attribute*), 208  
`train_data` (*dicее.MultiClassClassificationDataset attribute*), 203  
`train_data` (*dicее.OnevsAllDataset attribute*), 204  
`train_data` (*dicее.OnevsSample attribute*), 206  
`train_data_loader()` (*dicее.CVDataModule method*), 210  
`train_data_loader()` (*dicее.dataset\_classes.CVDataModule method*), 40  
`train_data_loader()` (*dicее.models.base\_model.BaseKGELightning method*), 60  
`train_data_loader()` (*dicее.models.BaseKGELightning method*), 103  
`train_data_loaders` (*dicее.trainer.torch\_trainer.TorchTrainer attribute*), 164  
`train_dataset_loader` (*dicее.trainer.torch\_trainer\_ddp.NodeTrainer attribute*), 166  
`train_file_path` (*dicее.dataset\_classes.LiteralDataset attribute*), 43, 44  
`train_file_path` (*dicее.LiteralDataset attribute*), 213, 214  
`train_h1` (*dicее.analyse\_experiments.Experiment attribute*), 19  
`train_h3` (*dicее.analyse\_experiments.Experiment attribute*), 19  
`train_h10` (*dicее.analyse\_experiments.Experiment attribute*), 19  
`train_indices_target` (*dicее.dataset\_classes.MultiLabelDataset attribute*), 33

train\_indices\_target (*dicee.MultiLabelDataset* attribute), 203  
 train\_k\_vs\_all () (*dicee.abstracts.BaseInteractiveTrainKGE* method), 18  
 train\_literals () (*dicee.abstracts.BaseInteractiveTrainKGE* method), 18  
 train\_mode (*dicee.EnsembleKGE* attribute), 193  
 train\_mode (*dicee.models.ensemble.EnsembleKGE* attribute), 76  
 train\_mrr (*dicee.analyse\_experiments.Experiment* attribute), 19  
 train\_path (*dicee.query\_generator.QueryGenerator* attribute), 145  
 train\_path (*dicee.QueryGenerator* attribute), 215  
 train\_set (*dicee.BPE\_NegativeSamplingDataset* attribute), 202  
 train\_set (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset* attribute), 32  
 train\_set (*dicee.dataset\_classes.MultiLabelDataset* attribute), 33  
 train\_set (*dicee.dataset\_classes.NegSampleDataset* attribute), 38  
 train\_set (*dicee.dataset\_classes.TriplePredictionDataset* attribute), 39  
 train\_set (*dicee.MultiLabelDataset* attribute), 203  
 train\_set (*dicee.NegSampleDataset* attribute), 208  
 train\_set (*dicee.TriplePredictionDataset* attribute), 209  
 train\_set\_idx (*dicee.CVDataModule* attribute), 210  
 train\_set\_idx (*dicee.dataset\_classes.CVDataModule* attribute), 40  
 train\_set\_target (*dicee.knowledge\_graph.KG* attribute), 51  
 train\_target (*dicee.AllvsAll* attribute), 205  
 train\_target (*dicee.dataset\_classes.AllvsAll* attribute), 35  
 train\_target (*dicee.dataset\_classes.KvsAll* attribute), 35  
 train\_target (*dicee.dataset\_classes.KvsSampleDataset* attribute), 38  
 train\_target (*dicee.KvsAll* attribute), 205  
 train\_target (*dicee.KvsSampleDataset* attribute), 208  
 train\_target\_indices (*dicee.knowledge\_graph.KG* attribute), 51  
 train\_triples () (*dicee.abstracts.BaseInteractiveTrainKGE* method), 18  
 trained\_model (*dicee.Execute* attribute), 201  
 trained\_model (*dicee.executer.Execute* attribute), 48  
 trainer (*dicee.config.Namespace* attribute), 29  
 trainer (*dicee.DICE\_Trainer* attribute), 196  
 trainer (*dicee.Execute* attribute), 201  
 trainer (*dicee.executer.Execute* attribute), 48  
 trainer (*dicee.trainer.DICE\_Trainer* attribute), 166  
 trainer (*dicee.trainer.dice\_trainer.DICE\_Trainer* attribute), 161  
 trainer (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer* attribute), 165  
 training\_step (*dicee.trainer.torch\_trainer.TorchTrainer* attribute), 164  
 training\_step () (*dicee.BytE* method), 190  
 training\_step () (*dicee.models.base\_model.BaseKGELightning* method), 57  
 training\_step () (*dicee.models.BaseKGELightning* method), 100  
 training\_step () (*dicee.models.transformers.BytE* method), 92  
 training\_step\_outputs (*dicee.models.base\_model.BaseKGELightning* attribute), 57  
 training\_step\_outputs (*dicee.models.BaseKGELightning* attribute), 100  
 training\_technique (*dicee.knowledge\_graph.KG* attribute), 51  
 TransE (*class in dicee*), 174  
 TransE (*class in dicee.models*), 111  
 TransE (*class in dicee.models.real*), 89  
 transfer\_batch\_to\_device () (*dicee.CVDataModule* method), 211  
 transfer\_batch\_to\_device () (*dicee.dataset\_classes.CVDataModule* method), 41  
 transformer (*dicee.BytE* attribute), 189  
 transformer (*dicee.models.transformers.BytE* attribute), 92  
 transformer (*dicee.models.transformers.GPT* attribute), 97  
 trapezoid () (*dicee.models.FMult2* method), 142  
 trapezoid () (*dicee.models.function\_space.FMult2* method), 78  
 tri\_score () (*dicee.LFMult* method), 187  
 tri\_score () (*dicee.models.function\_space.LFMult* method), 79  
 tri\_score () (*dicee.models.function\_space.LFMult1* method), 79  
 tri\_score () (*dicee.models.LFMult* method), 143  
 tri\_score () (*dicee.models.LFMult1* method), 142  
 triple\_score () (*dicee.KGE* method), 199  
 triple\_score () (*dicee.knowledge\_graph\_embeddings.KGE* method), 53  
 TriplePredictionDataset (*class in dicee*), 208  
 TriplePredictionDataset (*class in dicee.dataset\_classes*), 39  
 tuple2list () (*dicee.query\_generator.QueryGenerator* method), 145  
 tuple2list () (*dicee.QueryGenerator* method), 215

## U

`unlabelled_size` (*dicee.callbacks.PseudoLabellingCallback attribute*), 23  
`unmap()` (*dicee.query\_generator.QueryGenerator method*), 145  
`unmap()` (*dicee.QueryGenerator method*), 215  
`unmap_query()` (*dicee.query\_generator.QueryGenerator method*), 145  
`unmap_query()` (*dicee.QueryGenerator method*), 215

## V

`val_aswa` (*dicee.callbacks.ASWA attribute*), 24  
`val_dataloader()` (*dicee.models.base\_model.BaseKGELighting method*), 59  
`val_dataloader()` (*dicee.models.BaseKGELighting method*), 102  
`val_h1` (*dicee.analyse\_experiments.Experiment attribute*), 20  
`val_h3` (*dicee.analyse\_experiments.Experiment attribute*), 20  
`val_h10` (*dicee.analyse\_experiments.Experiment attribute*), 20  
`val_mrr` (*dicee.analyse\_experiments.Experiment attribute*), 19  
`val_path` (*dicee.query\_generator.QueryGenerator attribute*), 145  
`val_path` (*dicee.QueryGenerator attribute*), 215  
`validate_knowledge_graph()` (in module *dicee.sanity\_checkers*), 153  
`vocab_preparation()` (*dicee.evaluator.Evaluator method*), 47  
`vocab_size` (*dicee.models.transformers.GPTConfig attribute*), 96  
`vocab_to_parquet()` (in module *dicee*), 195  
`vocab_to_parquet()` (in module *dicee.static\_funcs*), 159  
`vtp_score()` (*dicee.LFMult method*), 187  
`vtp_score()` (*dicee.models.function\_space.LFMult method*), 79  
`vtp_score()` (*dicee.models.function\_space.LFMultI method*), 79  
`vtp_score()` (*dicee.models.LFMult method*), 143  
`vtp_score()` (*dicee.models.LFMultI method*), 142

## W

`warmup_steps` (*dicee.callbacks.LRScheduler attribute*), 27  
`weight` (*dicee.models.transformers.LayerNorm attribute*), 93  
`weight_decay` (*dicee.BaseKGE attribute*), 192  
`weight_decay` (*dicee.config.Namespace attribute*), 29  
`weight_decay` (*dicee.models.base\_model.BaseKGE attribute*), 63  
`weight_decay` (*dicee.models.BaseKGE attribute*), 106, 109, 112, 117, 123, 136, 139  
`weights` (*dicee.models.FMult attribute*), 141  
`weights` (*dicee.models.function\_space.FMult attribute*), 77  
`weights` (*dicee.models.function\_space.GFMult attribute*), 78  
`weights` (*dicee.models.GFMult attribute*), 141  
`write_csv_from_model_parallel()` (in module *dicee*), 195  
`write_csv_from_model_parallel()` (in module *dicee.static\_funcs*), 159  
`write_links()` (*dicee.query\_generator.QueryGenerator method*), 145  
`write_links()` (*dicee.QueryGenerator method*), 215  
`write_report()` (*dicee.Execute method*), 201  
`write_report()` (*dicee.executer.Execute method*), 49

## X

`x_values` (*dicee.LFMult attribute*), 187  
`x_values` (*dicee.models.function\_space.LFMult attribute*), 79  
`x_values` (*dicee.models.LFMult attribute*), 142