

---

# DICE Embeddings

*Release 0.1.3.2*

**Caglar Demir**

**Jun 26, 2024**

## 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>How to cite</b>	<b>9</b>
<b>13</b>	<b>dicee</b>	<b>10</b>
13.1	Subpackages . . . . .	10
13.2	Submodules . . . . .	93
13.3	Attributes . . . . .	133
13.4	Classes . . . . .	134
13.5	Functions . . . . .	135
13.6	Package Contents . . . . .	136
	<b>Python Module Index</b>	<b>174</b>

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

## 1 Dicee Manual

**Version:** dicee 0.1.3.2

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

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

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

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

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, GPU, TPU 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.

<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
```

(continues on next page)

(continued from previous page)

```
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
```

(continues on next page)

(continued from previous page)

```
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
```

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



## 12 How to cite

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

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

# LitCQD
@inproceedings{demir2023litcqd,
  title={LitCQD: Multi-Hop Reasoning in Incomplete Knowledge Graphs with Numeric
  ↪Literals},
  author={Demir, Caglar and Wiebesiek, Michel and Lu, Renzhong and Ngonga Ngomo, Axel-
  ↪Cyrille and Heindorf, Stefan},
  booktitle={Joint European Conference on Machine Learning and Knowledge Discovery in
  ↪Databases},
  pages={617--633},
  year={2023},
  organization={Springer}
}

# DICE Embedding Framework
@article{demir2022hardware,
  title={Hardware-agnostic computation for large-scale knowledge graph embeddings},
  author={Demir, Caglar and Ngomo, Axel-Cyrille Ngonga},
  journal={Software Impacts},
  year={2022},
  publisher={Elsevier}
}

# KronE
@inproceedings{demir2022kronecker,
  title={Kronecker decomposition for knowledge graph embeddings},
  author={Demir, Caglar and Lienen, Julian and Ngonga Ngomo, Axel-Cyrille},
  booktitle={Proceedings of the 33rd ACM Conference on Hypertext and Social Media},
  pages={1--10},
  year={2022}
}

# QMult, OMult, ConvQ, ConvO
@InProceedings{pmlr-v157-demir21a,
  title = {Convolutional Hypercomplex Embeddings for Link Prediction},
  author = {Demir, Caglar and Moussallem, Diego and Heindorf, Stefan and Ngonga
  ↪Ngomo, Axel-Cyrille},
  booktitle = {Proceedings of The 13th Asian Conference on Machine Learning},
  pages = {656--671},
  year = {2021},
  editor = {Balasubramanian, Vineeth N. and Tsang, Ivor},
  volume = {157},
  series = {Proceedings of Machine Learning Research},
  month = {17--19 Nov},
  publisher = {PMLR},
```

(continues on next page)

(continued from previous page)

```
pdf = {https://proceedings.mlr.press/v157/demir21a/demir21a.pdf},
url = {https://proceedings.mlr.press/v157/demir21a.html},
}
# ConEx
@inproceedings{demir2021convolutional,
title={Convolutional Complex Knowledge Graph Embeddings},
author={Caglar Demir and Axel-Cyrille Ngonga Ngomo},
booktitle={Eighteenth Extended Semantic Web Conference - Research Track},
year={2021},
url={https://openreview.net/forum?id=6T45-4TFqaX}}
# Shallom
@inproceedings{demir2021shallow,
title={A shallow neural model for relation prediction},
author={Demir, Caglar and Moussallem, Diego and Ngomo, Axel-Cyrille Ngonga},
booktitle={2021 IEEE 15th International Conference on Semantic Computing (ICSC)},
pages={179--182},
year={2021},
organization={IEEE}
```

For any questions or wishes, please contact: [caglar.demir@upb.de](mailto:caglar.demir@upb.de)

## 13 dicee

### 13.1 Subpackages

**dicee.models**

**Submodules**

**dicee.models.base\_model**

**Classes**

<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.

### Module Contents

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

Bases: `lightning.LightningModule`

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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

---

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

---

### Variables

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

**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 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 to nest them in a tree structure. You can assign the submodules as regular attributes:

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

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

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

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**x** (*B x 2 x T*)

**forward\_byte\_pair\_encoded\_triple** (*x: Tuple[torch.LongTensor, torch.LongTensor]*)

byte pair encoded neural link predictors

### Parameters

-----

**init\_params\_with\_sanity\_checking** ()

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

### Parameters

- **x**
- **y\_idx**
- **ordered\_bpe\_entities**

**forward\_triples** (*x: torch.LongTensor*) → *torch.Tensor*

### Parameters

**x**

**forward\_k\_vs\_all** (*\*args, \*\*kwargs*)

**forward\_k\_vs\_sample** (*\*args, \*\*kwargs*)



`get_triple_representation (idx_hrt)`

`get_head_relation_representation (indexed_triple)`

`get_sentence_representation (x: torch.LongTensor)`

#### Parameters

- `(b (x shape)`
- `3`
- `t)`

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

#### Parameters

`x (B x 2 x T)`

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

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

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

#### Variables

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

`__call__ (x)`

`static forward (x)`

## dicee.models.clifford

### Classes

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

### Module Contents

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

Bases: *dicee.models.base\_model.BaseKGE*

Cl\_(0,0) => Real Numbers

**Cl\_(0,1) =>**

A multivector  $\mathbf{a} = a_0 + a_1 e_1$  A multivector  $\mathbf{b} = b_0 + b_1 e_1$

multiplication is isomorphic to the product of two complex numbers

$$\mathbf{a} \text{ imes } \mathbf{b} = a_0 b_0 + a_0 b_1 e_1 + a_1 b_1 e_1 e_1 \\ = (a_0 b_0 - a_1 b_1) + (a_0 b_1 + a_1 b_0) e_1$$

**Cl\_(2,0) =>**

A multivector  $\mathbf{a} = a_0 + a_1 e_1 + a_2 e_2 + a_{12} e_1 e_2$  A multivector  $\mathbf{b} = b_0 + b_1 e_1 + b_2 e_2 + b_{12} e_1 e_2$

$$\mathbf{a} \text{ imes } \mathbf{b} = a_0 b_0 + a_0 b_1 e_1 + a_0 b_2 e_2 + a_0 b_{12} e_1 e_2 \\ + a_1 b_0 e_1 + a_1 b_1 e_1 e_1 + \dots$$

Cl\_(0,2) => Quaternions

**clifford\_mul** (*x: torch.FloatTensor, y: torch.FloatTensor, p: int, q: int*) → tuple

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

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

$e_j$

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

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

*p*: a non-negative integer  $p \geq 0$  *q*: a non-negative integer  $q \geq 0$

**score** (*head\_ent\_emb, rel\_ent\_emb, tail\_ent\_emb*)

**forward\_triples** (*x: torch.LongTensor*) → torch.FloatTensor

Compute batch triple scores

## Parameter

x: torch.LongTensor with shape n by 3

**rtype**

torch.LongTensor with shape n

**forward\_k\_vs\_all** (x: torch.Tensor) → torch.FloatTensor

Compute batch KvsAll triple scores

## Parameter

x: torch.LongTensor with shape n by 3

**rtype**

torch.LongTensor with shape n

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

## Variables

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

**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., e1e1, e1e2, e1e3,

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

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

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

Compute  $\sigma_{qq} = \sum_{j=1}^{p+q-1} \sum_{k=j+1}^{p+q} (h_{j \ r \ k} - h_{k \ r \ j}) e_j e_k$  captures the interactions between along q bases For instance, let q e\_1, e\_2, e\_3, we compute interactions between e\_1 e\_2, e\_1 e\_3, and e\_2 e\_3 This can be implemented with a nested two for loops

```

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

```

```

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

```

```

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

```

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

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

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

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

```

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

```

```

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

```

```

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

```

```

print(sigma_pq.shape)

```

**apply\_coefficients** (h0, hp, hq, r0, rp, rq)

Multiplying a base vector with its scalar coefficient

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

Compute our CL multiplication

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

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

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

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

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

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

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

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

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

### Parameter

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

#### returns

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

**forward\_k\_vs\_with\_explicit** (*x: torch.Tensor*)

**k\_vs\_all\_score** (*bpe\_head\_ent\_emb, bpe\_rel\_ent\_emb, E*)

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

Kvsall training

- (1) Retrieve real-valued embedding vectors for heads and relations  $\mathbb{R}^d$ .
- (2) Construct head entity and relation embeddings according to  $Cl_{p,q}(\mathbb{R}^d)$ .
- (3) Perform Cl multiplication
- (4) Inner product of (3) and all entity embeddings

forward\_k\_vs\_with\_explicit and this functions are identical Parameter ——— *x*: torch.LongTensor with (n,2) shape :rtype: torch.FloatTensor with (n, **|E|**) shape

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

Kvsall training

- (1) Retrieve real-valued embedding vectors for heads and relations  $\mathbb{R}^d$ .
- (2) Construct head entity and relation embeddings according to  $Cl_{p,q}(\mathbb{R}^d)$ .
- (3) Perform Cl multiplication
- (4) Inner product of (3) and all entity embeddings

### Parameter

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

#### rtype

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

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

**forward\_triples** (*x: torch.Tensor*)  $\rightarrow$  torch.FloatTensor

## Parameter

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

**rtype**

torch.FloatTensor with (n) shape

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

Bases: *Keci*

Without learning dimension scaling

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

## Variables

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

**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:

$$\sigma_0 t = \sigma_0 \cdot t_0 = s0 + s1 - s2s3, s4 \text{ and } s5$$

**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

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

**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  $\text{Cl}_{\{p,q,r\}}(\mathbb{R}^d)$ .
- (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, **IEI**) 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  $\text{Cl}_{\{p,q,r\}}(\mathbb{R}^d)$

## 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

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

sigma\_{q} captures the interactions between along q bases For instance, let q e\_1, e\_2, e\_3, we compute interactions between e\_1 e\_2, e\_1 e\_3, and e\_2 e\_3 This can be implemented with a nested two for loops

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

**for k in range(j + 1, q):**

        results.append(hq[:, :, j] \* rq[:, :, k] - hq[:, :, k] \* rq[:, :, j])

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

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

e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

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

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

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



**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

**residual\_convolution** (*C\_1: Tuple[torch.Tensor, torch.Tensor]*,  
*C\_2: Tuple[torch.Tensor, torch.Tensor]*)  $\rightarrow$  `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*)  $\rightarrow$  `torch.FloatTensor`

**forward\_triples** (*x: torch.Tensor*)  $\rightarrow$  `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

**residual\_convolution** (*C\_1: Tuple[torch.Tensor, torch.Tensor]*,  
*C\_2: Tuple[torch.Tensor, torch.Tensor]*)  $\rightarrow$  `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*)  $\rightarrow$  `torch.FloatTensor`

**forward\_triples** (*x: torch.Tensor*)  $\rightarrow$  `torch.FloatTensor`

Parameters

**x**

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

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

(continues on next page)

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

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

---

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

---

### Variables

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

**static score** (*head\_ent\_emb: torch.FloatTensor, rel\_ent\_emb: torch.FloatTensor, tail\_ent\_emb: torch.FloatTensor*)

**static k\_vs\_all\_score** (*emb\_h: torch.FloatTensor, emb\_r: torch.FloatTensor, emb\_E: torch.FloatTensor*)

### Parameters

- **emb\_h**
- **emb\_r**
- **emb\_E**

**forward\_k\_vs\_all** (*x: torch.LongTensor*) → *torch.FloatTensor*

## dicee.models.dualE

### Classes

*DualE*

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

### Module Contents

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

Bases: `dicee.models.base_model.BaseKGE`

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

**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*)  $\rightarrow$  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*)  $\rightarrow$  torch.tensor

Transpose function

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

## 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

**compute\_func** (*weights: torch.FloatTensor, x*)  $\rightarrow$  `torch.FloatTensor`

**chain\_func** (*weights, x: torch.FloatTensor*)

**forward\_triples** (*idx\_triple: torch.Tensor*)  $\rightarrow$  `torch.Tensor`

**Parameters**

**x**

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

Bases: `dicee.models.base_model.BaseKGE`

Learning Knowledge Neural Graphs

**compute\_func** (*weights: torch.FloatTensor, x*)  $\rightarrow$  `torch.FloatTensor`

**chain\_func** (*weights, x: torch.FloatTensor*)

**forward\_triples** (*idx\_triple: torch.Tensor*)  $\rightarrow$  `torch.Tensor`

**Parameters**

**x**

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

Bases: `dicee.models.base_model.BaseKGE`

Learning Knowledge Neural Graphs

**build\_func** (*Vec*)

**build\_chain\_funcs** (*list\_Vec*)

**compute\_func** (*W, b, x*)  $\rightarrow$  `torch.FloatTensor`

**function** (*list\_W, list\_b*)

**trapezoid** (*list\_W, list\_b*)

**forward\_triples** (*idx\_triple: torch.Tensor*)  $\rightarrow$  `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 different scoring function as in the paper to evaluate the score

**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.

    forward_triples (idx_triple)

        Parameters
        x

    construct_multi_coeff (x)

    poly_NN (x, coeffh, coeffr, coefft)
        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.  $\text{score} = \langle h \circ r, t \rangle$ 

    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,...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** (*coeff*[0][0] + *coeff*[0][1]*x* +...+ *coeff*[0][*d*]*x*^*d*,  
*coeff*[1][0] + *coeff*[1][1]*x* +...+ *coeff*[1][*d*]*x*^*d*)

## dicee.models.octonion

### Classes

<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 Em-beddings

### Functions

```
octonion_mul(*, O_1, O_2)
octonion_mul_norm(*, O_1, O_2)
```

## Module Contents

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

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

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

    def forward(self, x):
```

(continues on next page)

(continued from previous page)

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

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

---

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

---

### Variables

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

**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  $\Rightarrow \text{shape}(\text{size of batch}, |\text{Entities}|)$

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---



### Variables

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

**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

**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:

**forward\_k\_vs\_all** (*x: torch.LongTensor*)

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

# (1) Retrieve embeddings of heads and relations + apply Dropout & Normalization if given. h, r = self.get\_head\_relation\_representation(x) # (2) Reshape (1). if self.last\_dim > 0:

h = h.reshape(len(x), self.embedding\_dim, self.last\_dim) r = r.reshape(len(x), self.embedding\_dim, self.last\_dim)

# (3) Reshape all entities. if self.last\_dim > 0:

t = self.entity\_embeddings.weight.reshape(self.num\_entities, self.embedding\_dim, self.last\_dim)

**else:**

t = self.entity\_embeddings.weight

# (4) Call the score\_t from interactions to generate triple scores. return self.interaction.score\_t(h=h, r=r, all\_entities=t, slice\_size=1)

**forward\_triples** (*x: torch.LongTensor*) → torch.FloatTensor

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

# (1) Retrieve embeddings of heads, relations and tails and apply Dropout & Normalization if given. h, r, t = self.get\_triple\_representation(x) # (2) Reshape (1). if self.last\_dim > 0:

h = h.reshape(len(x), self.embedding\_dim, self.last\_dim) r = r.reshape(len(x), self.embedding\_dim, self.last\_dim) t = t.reshape(len(x), self.embedding\_dim, self.last\_dim)

# (3) Compute the triple score return self.interaction.score(h=h, r=r, t=t, slice\_size=None, slice\_dim=0)

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

## `dicee.models.quaternion`

### Classes

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

## Functions

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

## Module Contents

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

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**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

**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

**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>

**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>

**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>)

**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

**forward\_triples** (*x*: torch.LongTensor)

**Parameters**

**x**

## **dicee.models.static\_funcs**

### **Functions**

<i>quaternion_mul</i> (→ torch.Tensor, ...)	Tuple[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:

## **dicee.models.transformers**

## Classes

<i>Byte</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** `dictee.models.transformers.ByteE(*args, **kwargs)`

Bases: `dictee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**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`

**forward** (*input*)

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

Bases: `torch.nn.Module`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

## Variables

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

**forward** (*x*)

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

Bases: `torch.nn.Module`

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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

---

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

---

### Variables

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

**forward** (*x*)

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

Bases: `torch.nn.Module`

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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

---

**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.

**forward** (*x*)

```
class dicee.models.transformers.GPTConfig
```

```
    block_size: int = 1024
```

```
    vocab_size: int = 50304
```

```
    n_layer: int = 12
```

```
    n_head: int = 12
```

```
    n_embd: int = 768
```

```
    dropout: float = 0.0
```

```
    bias: bool = False
```

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

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**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** (*fwd\_bwd\_per\_iter, dt*)  
 estimate model flops utilization (MFU) in units of A100 bfloat16 peak FLOPS

## Classes

<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.
<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>KeciBase</i>	Without learning dimension scaling
<i>CMult</i>	Cl <sub>1</sub> (0,0) => Real Numbers
<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

continues on next page

Table 1 – continued from previous page

<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

<code>quaternion_mul(→ torch.Tensor, ...)</code>	Tuple[torch.Tensor, ...]	Perform quaternion multiplication
<code>quaternion_mul_with_unit_norm(*, Q_1, Q_2)</code>		
<code>octonion_mul(*, O_1, O_2)</code>		
<code>octonion_mul_norm(*, O_1, O_2)</code>		

## Package Contents

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

Bases: `lightning.LightningModule`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

**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.

**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.
```

(continues on next page)

(continued from previous page)

```
"interval": "epoch",
# How many epochs/steps should pass between calls to
# `scheduler.step()`. 1 corresponds to updating the learning
# rate after every epoch/step.
"frequency": 1,
# Metric to to monitor for schedulers like `ReduceLROnPlateau`
"monitor": "val_loss",
# If set to `True`, will enforce that the value specified 'monitor'
# is available when the scheduler is updated, thus stopping
# training if not found. If set to `False`, it will only produce a warning
"strict": True,
# If using the `LearningRateMonitor` callback to monitor the
# learning rate progress, this keyword can be used to specify
# a custom logged name
"name": None,
}
```

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

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

---

**Note:** Some things to know:

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

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

Bases: `BaseKGELightning`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

(continues on next page)

(continued from previous page)

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

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

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**x** (*B x 2 x T*)

**forward\_byte\_pair\_encoded\_triple** (*x: Tuple[torch.LongTensor, torch.LongTensor]*)

byte pair encoded neural link predictors

### Parameters

-----

**init\_params\_with\_sanity\_checking** ()

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

### Parameters

- **x**
- **y\_idx**
- **ordered\_bpe\_entities**

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

#### Parameters

**x** (*B x 2 x T*)

**get\_embeddings** () → Tuple[numpy.ndarray, numpy.ndarray]

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

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

#### Variables

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

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

**static forward** (*x*)

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

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**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*)  $\rightarrow$  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**

- ( $\mathbf{b}$  ( $x$  *shape*))
- 3
- $\mathbf{t}$ )

**get\_bpe\_head\_and\_relation\_representation** ( $x$ : *torch.LongTensor*)  
 $\rightarrow$  Tuple[*torch.FloatTensor*, *torch.FloatTensor*]

**Parameters**

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

**get\_embeddings** ()  $\rightarrow$  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>

**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>

**score** (*head\_ent\_emb*, *rel\_ent\_emb*, *tail\_ent\_emb*)

**forward\_k\_vs\_all** ( $x$ : *torch.Tensor*)  $\rightarrow$  *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>)

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

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

**forward\_triples** ( $x$ )  $\rightarrow$  *torch.FloatTensor*

**Parameters**

$\mathbf{x}$

### Returns

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

Bases: *dicee.models.base\_model.BaseKGE*

A Physical Embedding Model for Knowledge Graphs

**forward\_triples** (*x: torch.LongTensor*)

### Parameters

**x**

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

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**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.ConEx (args)
    Bases: dicee.models.base_model.BaseKGE
    Convolutional ComplEx Knowledge Graph Embeddings

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

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

Compute residual score of two complex-valued embeddings. :param C\_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C\_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

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

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

**Parameters**

**x**

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

```
class dicee.models.Complex(args)
```

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

**Variables**

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

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

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

#### Parameters

- `emb_h`
- `emb_r`
- `emb_E`

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

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

Perform quaternion multiplication :param Q\_1: :param Q\_2: :return:

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

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

#### Variables

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

```
forward_byte_pair_encoded_k_vs_all (x: torch.LongTensor)
```

#### Parameters

**x** (*B x 2 x T*)

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

byte pair encoded neural link predictors

#### Parameters

-----

```
init_params_with_sanity_checking()
```

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

#### Parameters

- **x**
- **y\_idx**
- **ordered\_bpe\_entities**

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

#### Parameters

**x**

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

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

```
get_triple_representation(idx_hrt)
```

```
get_head_relation_representation(indexed_triple)
```

```
get_sentence_representation(x: torch.LongTensor)
```

#### Parameters

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

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

#### Parameters

**x** ( $B \times 2 \times T$ )

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

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

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

(continues on next page)

(continued from previous page)

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

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

---

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

---

### Variables

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

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

**static forward** (*x*)

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

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**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

**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

**residual\_convolution** (*Q\_1, Q\_2*)

**forward\_triples** (*indexed\_triple: torch.Tensor*) → torch.Tensor

#### Parameters

**x**

**forward\_k\_vs\_all** (*x: torch.Tensor*)

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

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

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

#### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

**Parameters**

**x** (*B x 2 x T*)

**forward\_byte\_pair\_encoded\_triple** (*x: Tuple[torch.LongTensor, torch.LongTensor]*)

byte pair encoded neural link predictors

**Parameters**

-----

**init\_params\_with\_sanity\_checking** ()

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

**Parameters**

- **x**
- **y\_idx**
- **ordered\_bpe\_entities**

**forward\_triples** (*x: torch.LongTensor*) → torch.Tensor

**Parameters**

**x**

**forward\_k\_vs\_all** (\*args, \*\*kwargs)

**forward\_k\_vs\_sample** (\*args, \*\*kwargs)

**get\_triple\_representation** (*idx\_hrt*)

**get\_head\_relation\_representation** (*indexed\_triple*)

**get\_sentence\_representation** (*x: torch.LongTensor*)

**Parameters**

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

**get\_bpe\_head\_and\_relation\_representation** (*x: torch.LongTensor*)  
→ Tuple[torch.FloatTensor, torch.FloatTensor]

**Parameters**

**x** (*B x 2 x T*)

**get\_embeddings** () → Tuple[numpy.ndarray, numpy.ndarray]

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

Bases: torch.nn.Module

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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

---

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

---

### Variables

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

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

**static forward** (*x*)

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

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

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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



---

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

---

### Variables

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

**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  $\Rightarrow \text{shape}(\text{size of batch}, |\text{Entities}|)$

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

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**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)  $\rightarrow$  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]  $\Rightarrow$  [0.0,0.1,...,0.8], shape= $\Rightarrow$  (1, **Entities**) Given a batch of head entities and relations  $\Rightarrow$  shape (size of batch,| Entities)

**class** dicee.models.**AConvo** ( $args$ : dict)

Bases: *dicee.models.base\_model.BaseKGE*

Additive Convolutional Octonion Knowledge Graph Embeddings

**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)  $\rightarrow$  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]  $\Rightarrow$  [0.0,0.1,...,0.8], shape= $\Rightarrow$  (1, **Entities**) Given a batch of head entities and relations  $\Rightarrow$  shape (size of batch,| Entities)

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

### **compute\_sigma\_pp** (*hp, rp*)

Compute  $\text{sigma\_pp} = \sum_{i=1}^{p-1} \sum_{k=i+1}^p (h_{i \ r_k} - h_{k \ r_i}) e_i e_k$

$\text{sigma\_pp}$  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  $\text{sigma\_qq} = \sum_{j=1}^{p+q-1} \sum_{k=j+1}^{p+q} (h_{j \ r_k} - h_{k \ r_j}) e_j e_k$   $\text{sigma\_qq}$  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** (*h0, hp, hq, r0, rp, rq*)

Multiplying a base vector with its scalar coefficient

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

Compute our CL multiplication

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

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

$e_j$

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

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

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

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

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

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

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

**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

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

→ torch.FloatTensor

Kvsall training

- (1) Retrieve real-valued embedding vectors for heads and relations  $\mathbb{R}^d$ .
- (2) Construct head entity and relation embeddings according to  $Cl_{\{p,q\}}(\mathbb{R}^d)$ .

- (3) Perform CI multiplication
- (4) Inner product of (3) and all entity embeddings

### Parameter

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

**rtype**

torch.FloatTensor with (n, **IEI**) 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.**KeciBase** (*args*)

Bases: *Keci*

Without learning dimension scaling

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

Bases: *dicee.models.base\_model.BaseKGE*

Cl\_(0,0) => Real Numbers

**Cl\_(0,1) =>**

A multivector  $\mathbf{a} = a_0 + a_1 e_1$  A multivector  $\mathbf{b} = b_0 + b_1 e_1$

multiplication is isomorphic to the product of two complex numbers

$$\mathbf{a} \text{ imes } \mathbf{b} = a_0 b_0 + a_0 b_1 e_1 + a_1 b_1 e_1 e_1 \\ = (a_0 b_0 - a_1 b_1) + (a_0 b_1 + a_1 b_0) e_1$$

**Cl\_(2,0) =>**

A multivector  $\mathbf{a} = a_0 + a_1 e_1 + a_2 e_2 + a_{12} e_1 e_2$  A multivector  $\mathbf{b} = b_0 + b_1 e_1 + b_2 e_2 + b_{12} e_1 e_2$

$$\mathbf{a} \text{ imes } \mathbf{b} = a_0 b_0 + a_0 b_1 e_1 + a_0 b_2 e_2 + a_0 b_{12} e_1 e_2 \\ + a_1 b_0 e_1 + a_1 b_1 e_1 e_1 + \dots$$

Cl\_(0,2) => Quaternions

**clifford\_mul** (*x: torch.FloatTensor, y: torch.FloatTensor, p: int, q: int*) → tuple

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

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

$e_j$

x: torch.FloatTensor with (n,d) shape  
 y: torch.FloatTensor with (n,d) shape  
 p: a non-negative integer  $p \geq 0$  q: a non-negative integer  $q \geq 0$

**score** (*head\_ent\_emb, rel\_ent\_emb, tail\_ent\_emb*)

**forward\_triples** (*x: torch.LongTensor*) → torch.FloatTensor  
 Compute batch triple scores

### Parameter

x: torch.LongTensor with shape n by 3

**rtype**  
 torch.LongTensor with shape n

**forward\_k\_vs\_all** (*x: torch.Tensor*) → torch.FloatTensor  
 Compute batch KvsAll triple scores

### Parameter

x: torch.LongTensor with shape n by 3

**rtype**  
 torch.LongTensor with shape n

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

## Variables

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

**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

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

**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  $\text{Cl}_{\{p,q,r\}}(\mathbb{R}^d)$ .
- (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

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

$\sigma_{q\{q\}}$  captures the interactions between along q bases For instance, let q e\_1, e\_2, e\_3, we compute interactions between e\_1 e\_2, e\_1 e\_3, and e\_2 e\_3 This can be implemented with a nested two for loops

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

**for k in range(j + 1, q):**

        results.append(hq[:, :, j] \* rq[:, :, k] - hq[:, :, k] \* rq[:, :, j])

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

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



e2e1, e2e2, e2e3, e3e1, e3e2, e3e3

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

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

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

**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 to nest them in a tree structure. You can assign the submodules as regular attributes:

```

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

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

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

```

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**x** (*B x 2 x T*)

**forward\_byte\_pair\_encoded\_triple** (*x: Tuple[torch.LongTensor, torch.LongTensor]*)

byte pair encoded neural link predictors

### Parameters

-----

**init\_params\_with\_sanity\_checking** ()

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

### Parameters

- **x**
- **y\_idx**
- **ordered\_bpe\_entities**

**forward\_triples** (*x: torch.LongTensor*) → *torch.Tensor*

### Parameters

**x**

**forward\_k\_vs\_all** (*\*args, \*\*kwargs*)

**forward\_k\_vs\_sample** (*\*args, \*\*kwargs*)

**get\_triple\_representation** (*idx\_hrt*)

**get\_head\_relation\_representation** (*indexed\_triple*)

**get\_sentence\_representation** (*x: torch.LongTensor*)

**Parameters**

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

**get\_bpe\_head\_and\_relation\_representation** (*x: torch.LongTensor*)

→ Tuple[torch.FloatTensor, torch.FloatTensor]

**Parameters**

**x** (*B x 2 x T*)

**get\_embeddings** () → Tuple[numpy.ndarray, numpy.ndarray]

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

Bases: *dicee.models.base\_model.BaseKGE*

A class for using knowledge graph embedding models implemented in Pykeen

Notes: Pykeen\_DistMult: C Pykeen\_ComplEx: Pykeen\_QuatE: Pykeen\_MuRE: Pykeen\_CP: Pykeen\_HolE: Pykeen\_HolE:

**forward\_k\_vs\_all** (*x: torch.LongTensor*)

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

# (1) Retrieve embeddings of heads and relations + apply Dropout & Normalization if given. h, r = self.get\_head\_relation\_representation(x) # (2) Reshape (1). if self.last\_dim > 0:

h = h.reshape(len(x), self.embedding\_dim, self.last\_dim) r = r.reshape(len(x), self.embedding\_dim, self.last\_dim)

# (3) Reshape all entities. if self.last\_dim > 0:

t = self.entity\_embeddings.weight.reshape(self.num\_entities, self.embedding\_dim, self.last\_dim)

**else:**

t = self.entity\_embeddings.weight

# (4) Call the score\_t from interactions to generate triple scores. return self.interaction.score\_t(h=h, r=r, all\_entities=t, slice\_size=1)

**forward\_triples** (*x: torch.LongTensor*) → torch.FloatTensor

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

# (1) Retrieve embeddings of heads, relations and tails and apply Dropout & Normalization if given. h, r, t = self.get\_triple\_representation(x) # (2) Reshape (1). if self.last\_dim > 0:

h = h.reshape(len(x), self.embedding\_dim, self.last\_dim) r = r.reshape(len(x), self.embedding\_dim, self.last\_dim) t = t.reshape(len(x), self.embedding\_dim, self.last\_dim)

# (3) Compute the triple score return self.interaction.score(h=h, r=r, t=t, slice\_size=None, slice\_dim=0)

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

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

Bases: *BaseKGELightning*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**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*)  $\rightarrow$  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)
    → Tuple[torch.FloatTensor, torch.FloatTensor]

    Parameters
    x ( $B \times 2 \times T$ )

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

class dicee.models.FMult (args)
    Bases: dicee.models.base_model.BaseKGE
    Learning Knowledge Neural Graphs
    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
    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
    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*)  $\rightarrow$  *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

**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:  $f(x) = \sum_{i=0}^{d-1} a_i x^{i\%d}$  and use the three differents scoring function as in the paper to evaluate the score. We also consider combining with Neural Networks.

**forward\_triples** (*idx\_triple*)

**Parameters**

**x**

**construct\_multi\_coeff** (*x*)

**poly\_NN** (*x*, *coefh*, *coefr*, *coeft*)

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

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

**scalar\_batch\_NN** (*a*, *b*, *c*)

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

**tri\_score** (*coeff\_h*, *coeff\_r*, *coeff\_t*)

this part implement the trilinear scoring techniques:

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

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

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

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]

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

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

**class** `dicee.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>)

**kvsall\_score** (*e\_1\_h, e\_2\_h, e\_3\_h, e\_4\_h, e\_5\_h, e\_6\_h, e\_7\_h, e\_8\_h, e\_1\_t, e\_2\_t, e\_3\_t, e\_4\_t, e\_5\_t, e\_6\_t, e\_7\_t, e\_8\_t, r\_1, r\_2, r\_3, r\_4, r\_5, r\_6, r\_7, r\_8*) → torch.tensor

KvsAll scoring function

## Input

x: torch.LongTensor with (n, ) shape

## Output

torch.FloatTensor with (n) shape

**forward\_triples** (*idx\_triple: torch.tensor*) → torch.tensor

Negative Sampling forward pass:

### Input

x: torch.LongTensor with (n, ) shape

### Output

torch.FloatTensor with (n) shape

**forward\_k\_vs\_all** (x)

KvsAll forward pass

### Input

x: torch.LongTensor with (n, ) shape

### Output

torch.FloatTensor with (n) shape

**T** (x: *torch.tensor*) → torch.tensor

Transpose function

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

## dicee.read\_preprocess\_save\_load\_kg

### Submodules

## dicee.read\_preprocess\_save\_load\_kg.preprocess

### Classes

---

*PreprocessKG*

Preprocess the data in memory

---

### Module Contents

**class** dicee.read\_preprocess\_save\_load\_kg.preprocess.**PreprocessKG** (*kg*)

Preprocess the data in memory

**start** () → None

Preprocess train, valid and test datasets stored in knowledge graph instance



## Parameter

**rtype**  
None

**preprocess\_with\_byte\_pair\_encoding()**

**preprocess\_with\_byte\_pair\_encoding\_with\_padding()** → None

**preprocess\_with\_pandas()** → None

Preprocess train, valid and test datasets stored in knowledge graph instance with pandas

- (1) Add recipriocal or noisy triples
- (2) Construct vocabulary
- (3) Index datasets

## Parameter

**rtype**  
None

**preprocess\_with\_polars()** → None

**sequential\_vocabulary\_construction()** → None

- (1) Read input data into memory
- (2) Remove triples with a condition
- (3) **Serialize vocabularies in a pandas dataframe where**  
=> the index is integer and => a single column is string (e.g. URI)

**remove\_triples\_from\_train\_with\_condition()**

**dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk**

## Classes

*ReadFromDisk*

Read the data from disk into memory

## Module Contents

**class** dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk.**ReadFromDisk**(kg)

Read the data from disk into memory

**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*)

**save()**

**load()**

**dicee.read\_preprocess\_save\_load\_kg.util**

## Functions

<code>apply_reciprical_or_noise(add_reciprical, eval_model)</code>	(1) Add reciprocal triples (2) Add noisy triples
<code>timeit(func)</code>	
<code>read_with_polars(→ polars.DataFrame)</code> <code>read_with_pandas(data_path[, read_only_few, ...])</code>	Load and Preprocess via Polars
<code>read_from_disk(data_path[, read_only_few, ...])</code>	
<code>read_from_triple_store(endpoint)</code> <code>get_er_vocab(data[, file_path])</code>	Read triples from triple store into pandas dataframe
<code>get_re_vocab(data[, file_path])</code>	
<code>get_ee_vocab(data[, file_path])</code>	
<code>create_constraints(triples[, file_path])</code>	(1) Extract domains and ranges of relations
<code>load_with_pandas(→ None)</code> <code>save_numpy_ndarray(*, data, file_path)</code>	Deserialize data
<code>load_numpy_ndarray(*, file_path)</code>	
<code>save_pickle(*, data[, file_path])</code>	
<code>load_pickle(*[, file_path])</code>	
<code>create_recipriocal_triples(x)</code> <code>index_triples_with_pandas(→ pan- das.core.frame.DataFrame)</code>	Add inverse triples into dask dataframe <b>param train_set</b> pandas dataframe
<code>dataset_sanity_checking(→ None)</code>	<b>param train_set</b>

## Module Contents

`dicee.read_preprocess_save_load_kg.util.apply_reciprical_or_noise (`  
`add_reciprical: bool, eval_model: str, df: object = None, info: str = None)`

(1) Add reciprocal triples (2) Add noisy triples

`dicee.read_preprocess_save_load_kg.util.timeit (func)`

`dicee.read_preprocess_save_load_kg.util.read_with_polars (data_path,`  
`read_only_few: int = None, sample_triples_ratio: float = None) → polars.DataFrame`

Load and Preprocess via Polars

```
dicee.read_preprocess_save_load_kg.util.read_with_pandas(data_path,  
    read_only_few: int = None, sample_triples_ratio: float = None)
```

```
dicee.read_preprocess_save_load_kg.util.read_from_disk(data_path: str,  
    read_only_few: int = None, sample_triples_ratio: float = None, backend=None)
```

```
dicee.read_preprocess_save_load_kg.util.read_from_triple_store(  
    endpoint: str = None)
```

Read triples from triple store into pandas dataframe

```
dicee.read_preprocess_save_load_kg.util.get_er_vocab(data, file_path: str = None)
```

```
dicee.read_preprocess_save_load_kg.util.get_re_vocab(data, file_path: str = None)
```

```
dicee.read_preprocess_save_load_kg.util.get_ee_vocab(data, file_path: str = None)
```

```
dicee.read_preprocess_save_load_kg.util.create_constraints(triples,  
    file_path: str = None)
```

(1) Extract domains and ranges of relations

(2) Store a mapping from relations to entities that are outside of the domain and range. 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.index_triples_with_pandas(train_set,  
    entity_to_idx: dict, relation_to_idx: dict) → pandas.core.frame.DataFrame
```

#### Parameters

- **train\_set** – pandas dataframe
- **entity\_to\_idx** – a mapping from str to integer index
- **relation\_to\_idx** – a mapping from str to integer index
- **num\_core** – number of cores to be used

#### Returns

indexed triples, i.e., pandas dataframe

```
dicee.read_preprocess_save_load_kg.util.dataset_sanity_checking(  
    train_set: numpy.ndarray, num_entities: int, num_relations: int) → None
```

#### Parameters

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

- **num\_relations**

## Returns

## Classes

<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

**start** () → None

Preprocess train, valid and test datasets stored in knowledge graph instance

### Parameter

**rtype**

None

**preprocess\_with\_byte\_pair\_encoding** ()

**preprocess\_with\_byte\_pair\_encoding\_with\_padding** () → None

**preprocess\_with\_pandas** () → None

Preprocess train, valid and test datasets stored in knowledge graph instance with pandas

(1) Add recipriocal or noisy triples

(2) Construct vocabulary

(3) Index datasets

### Parameter

**rtype**

None

**preprocess\_with\_polars** () → None

**sequential\_vocabulary\_construction** () → None

(1) Read input data into memory

(2) Remove triples with a condition

(3) **Serialize vocabularies in a pandas dataframe where**

=> the index is integer and => a single column is string (e.g. URI)

```

    remove_triples_from_train_with_condition()
class dicee.read_preprocess_save_load_kg.LoadSaveToDisk(kg)
    save()
    load()
class dicee.read_preprocess_save_load_kg.ReadFromDisk(kg)
    Read the data from disk into memory
    start() → None
        Read a knowledge graph from disk into memory
        Data will be available at the train_set, test_set, valid_set attributes.

```

### Parameter

None

**rtype**

None

```

add_noisy_triples_into_training()

```

## dicee.scripts

### Submodules

#### dicee.scripts.index

### Functions

---

```

get_default_arguments()

```

```

main()

```

---

### Module Contents

```

dicee.scripts.index.get_default_arguments()

```

```

dicee.scripts.index.main()

```

## dicee.scripts.run

### Functions

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

### Module Contents

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

Extends pytorch\_lightning Trainer's arguments with ours

`dicee.scripts.run.main()`

## dicee.scripts.serve

### Attributes

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

### Classes

<code>NeuralSearcher</code>
-----------------------------

### Functions

<code>get_default_arguments()</code>
<code>root()</code>
<code>search_embeddings(q)</code>
<code>retrieve_embeddings(q)</code>
<code>main()</code>

## Module Contents

```
dicee.scripts.serve.app
dicee.scripts.serve.neural_searcher = None
dicee.scripts.serve.get_default_arguments()
async dicee.scripts.serve.root()
async dicee.scripts.serve.search_embeddings(q: str)
async dicee.scripts.serve.retrieve_embeddings(q: str)
class dicee.scripts.serve.NeuralSearcher(args)
    get(entity: str)
    search(entity: str)
dicee.scripts.serve.main()
```

## **dicee.trainer**

### Submodules

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

### Classes

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

### Functions

<i>initialize_trainer</i> (args, callbacks)
<i>get_callbacks</i> (args)

## Module Contents

```
dicee.trainer.dice_trainer.initialize_trainer(args, callbacks)
dicee.trainer.dice_trainer.get_callbacks(args)
```



```
class dicee.trainer.dice_trainer.DICE_Trainer (args, is_continual_training, storage_path,  

evaluator=None)
```

#### DICE\_Trainer implement

- 1- Pytorch Lightning trainer (<https://pytorch-lightning.readthedocs.io/en/stable/common/trainer.html>)
- 2- Multi-GPU Trainer(<https://pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.html>)
- 3- CPU Trainer

*args*

*is\_continual\_training:bool*

*storage\_path:str*

*evaluator:*

*report:dict*

```
continual_start ()
```

- (1) Initialize training.
- (2) Load model
- (3) Load trainer (3) Fit model

#### Parameter

##### returns

- *model*
- **form\_of\_labelling** (*str*)

```
initialize_trainer (callbacks: List) → lightning.Trainer
```

Initialize Trainer from input arguments

```
initialize_or_load_model ()
```

```
initialize_dataloader (dataset: torch.utils.data.Dataset) → torch.utils.data.DataLoader
```

```
initialize_dataset (dataset: dicee.knowledge_graph.KG, form_of_labelling)  

→ torch.utils.data.Dataset
```

```
start (knowledge_graph: dicee.knowledge_graph.KG) → Tuple[dicee.models.base_model.BaseKGE, str]
```

Train selected model via the selected training strategy

```
k_fold_cross_validation (dataset) → Tuple[dicee.models.base_model.BaseKGE, str]
```

Perform K-fold Cross-Validation

1. Obtain K train and test splits.
2. **For each split,**
  - 2.1 initialize trainer and model
  - 2.2. Train model with configuration provided in args.
  - 2.3. Compute the mean reciprocal rank (MRR) score of the model on the test respective split.
3. Report the mean and average MRR .

#### Parameters

- **self**

- **dataset**

**Returns**  
model

## **dicee.trainer.torch\_trainer**

### **Classes**

*TorchTrainer*

TorchTrainer for using single GPU or multi CPUs on a single node

### **Module Contents**

**class** `dicee.trainer.torch_trainer.TorchTrainer` (*args, callbacks*)

Bases: *dicee.abstracts.AbstractTrainer*

TorchTrainer for using single GPU or multi CPUs on a single node

Arguments

*callbacks*: list of Abstract callback instances

**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

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

### Functions

<i>print_peak_memory</i> (prefix, device)
---

### Module Contents

dicee.trainer.torch\_trainer\_ddp.**print\_peak\_memory** (*prefix, device*)

**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, optimizer: torch.optim.Optimizer, callbacks, num\_epochs: int*)

```

extract_input_outputs (z: list)

train ()
    Training loop for DDP

class dicee.trainer.torch_trainer_ddp.DDPTrainer (model: torch.nn.Module,
    train_dataset_loader: torch.utils.data.DataLoader, optimizer: torch.optim.Optimizer, gpu_id: int,
    callbacks, num_epochs)

extract_input_outputs (z: list)

train ()

```

## Classes

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

## Package Contents

```

class dicee.trainer.DICE_Trainer (args, is_continual_training, storage_path, evaluator=None)

```

### DICE\_Trainer implement

- 1- Pytorch Lightning trainer (<https://pytorch-lightning.readthedocs.io/en/stable/common/trainer.html>)
- 2- Multi-GPU Trainer(<https://pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.html>)
- 3- CPU Trainer

args

is\_continual\_training:bool

storage\_path:str

evaluator:

report:dict

```

continual_start ()

```

- (1) Initialize training.
- (2) Load model
- (3) Load trainer (3) Fit model

### Parameter

#### returns

- *model*
- **form\_of\_labelling** (*str*)

```

initialize_trainer (callbacks: List) → lightning.Trainer

```

Initialize Trainer from input arguments

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

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

**initialize\_dataset** (dataset: *dicee.knowledge\_graph.KG*, form\_of\_labelling)  
→ *torch.utils.data.Dataset*

**start** (knowledge\_graph: *dicee.knowledge\_graph.KG*) → *Tuple[dicee.models.base\_model.BaseKGE, str]*  
Train selected model via the selected training strategy

**k\_fold\_cross\_validation** (dataset) → *Tuple[dicee.models.base\_model.BaseKGE, str]*  
Perform K-fold Cross-Validation

1. Obtain K train and test splits.
2. **For each split,**
  - 2.1 initialize trainer and model
  - 2.2. Train model with configuration provided in args.
  - 2.3. Compute the mean reciprocal rank (MRR) score of the model on the test respective split.
3. Report the mean and average MRR .

**Parameters**

- **self**
- **dataset**

**Returns**  
model

## 13.2 Submodules

### *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>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

## Module Contents

**class** dicee.abstracts.**AbstractTrainer** (*args, callbacks*)

Abstract class for Trainer class for knowledge graph embedding models

### Parameter

**args**

[str] ?

**callbacks:** list

?

**on\_fit\_start** (*\*args, \*\*kwargs*)

A function to call callbacks before the training starts.

### Parameter

args

kwargs

**rtype**

None

**on\_fit\_end** (*\*args, \*\*kwargs*)

A function to call callbacks at the ned of the training.

### Parameter

args

kwargs

**rtype**

None

**on\_train\_epoch\_end** (*\*args, \*\*kwargs*)

A function to call callbacks at the end of an epoch.

### Parameter

args

kwargs

**rtype**

None

**on\_train\_batch\_end** (*\*args, \*\*kwargs*)

A function to call callbacks at the end of each mini-batch during training.

## Parameter

args

kwargs

**rtype**

None

**static save\_checkpoint** (*full\_path: str, model*) → None

A static function to save a model into disk

## Parameter

full\_path : str

model:

**rtype**

None

**class** dicee.abstracts.**BaseInteractiveKGE** (*path: str = None, url: str = None,*  
*construct\_ensemble: bool = False, model\_name: str = None,*  
*apply\_semantic\_constraint: bool = False*)

Abstract/base class for using knowledge graph embedding models interactively.

## Parameter

**path\_of\_pretrained\_model\_dir**

[str] ?

**construct\_ensemble: boolean**

?

model\_name: str apply\_semantic\_constraint : boolean

**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**

**get\_domain\_of\_relation** (*rel: str*) → List[str]

**get\_range\_of\_relation** (*rel: str*) → List[str]

**set\_model\_train\_mode** () → None  
Setting the model into training mode

### Parameter

**set\_model\_eval\_mode** () → None  
Setting the model into eval mode

### Parameter

**property name**

**sample\_entity** (*n: int*) → List[str]

**sample\_relation** (*n: int*) → List[str]

**is\_seen** (*entity: str = None, relation: str = None*) → bool

**save** () → None

**get\_entity\_index** (*x: str*)

**get\_relation\_index** (*x: str*)

**index\_triple** (*head\_entity: List[str], relation: List[str], tail\_entity: List[str]*)  
→ Tuple[torch.LongTensor, torch.LongTensor, torch.LongTensor]  
Index Triple

### Parameter

head\_entity: List[str]

String representation of selected entities.

relation: List[str]

String representation of selected relations.

tail\_entity: List[str]

String representation of selected entities.

### Returns: Tuple

pytorch tensor of triple score

**add\_new\_entity\_embeddings** (*entity\_name: str = None, embeddings: torch.FloatTensor = None*)

**get\_entity\_embeddings** (*items: List[str]*)

Return embedding of an entity given its string representation



## Parameter

**items:**  
entities

**get\_relation\_embeddings** (*items: List[str]*)  
Return embedding of a relation given its string representation

## Parameter

**items:**  
relations

**construct\_input\_and\_output** (*head\_entity: List[str], relation: List[str], tail\_entity: List[str], labels*)  
Construct a data point :param head\_entity: :param relation: :param tail\_entity: :param labels: :return:  
**parameters** ()

**class** dicee.abstracts.**AbstractCallback**  
Bases: abc.ABC, lightning.pytorch.callbacks.Callback  
Abstract class for Callback class for knowledge graph embedding models

## Parameter

**on\_init\_start** (*\*args, \*\*kwargs*)

## Parameter

trainer:  
model:  
**rtype**  
None

**on\_init\_end** (*\*args, \*\*kwargs*)  
Call at the beginning of the training.

## Parameter

trainer:  
model:  
**rtype**  
None

**on\_fit\_start** (*trainer, model*)  
Call at the beginning of the training.

### Parameter

trainer:

model:

**rtype**

None

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

Call at the end of each epoch during training.

### Parameter

trainer:

model:

**rtype**

None

**on\_train\_batch\_end** (*\*args, \*\*kwargs*)

Call at the end of each mini-batch during the training.

### Parameter

trainer:

model:

**rtype**

None

**on\_fit\_end** (*\*args, \*\*kwargs*)

Call at the end of the training.

### 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

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

Call at the beginning of the training.

## Parameter

trainer:

model:

**rtype**

None

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

Call at the end of the training.

## Parameter

trainer:

model:

**rtype**

None

**store\_ensemble** (*param\_ensemble*) → None

## dicee.analyse\_experiments

This script should be moved to dicee/scripts

## Classes

---

*Experiment*

---

## Functions

---

*get\_default\_arguments()*

*analyse(args)*

---

## Module Contents

`dicee.analyse_experiments.get_default_arguments()`

**class** `dicee.analyse_experiments.Experiment`

`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

### Functions

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

## Module Contents

**class** `dicee.callbacks.AccumulateEpochLossCallback` (*path: str*)

Bases: `dicee.abstracts.AbstractCallback`

Abstract class for Callback class for knowledge graph embedding models

## Parameter

**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

**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

**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

**create\_random\_data** ()

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

`dicee.callbacks.estimate_q` (eps)

estimate rate of convergence q from sequence esp

`dicee.callbacks.compute_convergence` (seq, i)

**class** dicee.callbacks.**ASWA** (num\_epochs, path)

Bases: *dicee.abstracts.AbstractCallback*

Adaptive stochastic weight averaging ASWE keeps track of the validation performance and update s the ensemble model accordingly.

**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

**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

**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 :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:

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

Called when the train batch begins.

## dicee.config

## Classes

---

*Namespace*

Simple object for storing attributes.

---

## Module Contents

**class** dicee.config.Namespace (\*\*kwargs)

Bases: argparse.Namespace

Simple object for storing attributes.

Implements equality by attribute names and values, and provides a simple string representation.

**dataset\_dir: str = None**

The path of a folder containing train.txt, and/or valid.txt and/or test.txt

**save\_embeddings\_as\_csv: bool = False**

Embeddings of entities and relations are stored into CSV files to facilitate easy usage.

**storage\_path: str = 'Experiments'**

A directory named with time of execution under `storage_path` that contains related data about embeddings.

**path\_to\_store\_single\_run: str = None**

A single directory created that contains related data about embeddings.

**path\_single\_kg = None**

Path of a file corresponding to the input knowledge graph

**sparql\_endpoint = None**

An endpoint of a triple store.

**model: str = 'Keci'**

KGE model

**optim: str = 'Adam'**

Optimizer

**embedding\_dim: int = 64**

Size of continuous vector representation of an entity/relation

**num\_epochs: int = 150**

Number of pass over the training data

**batch\_size: int = 1024**

Mini-batch size if it is None, an automatic batch finder technique applied

**lr: float = 0.1**

Learning rate

**add\_noise\_rate: float = None**

The ratio of added random triples into training dataset

**gpus = None**

Number GPUs to be used during training

**callbacks**

10}}

**Type**

Callbacks, e.g., {"PPE"}

**Type**

{ "last\_percent\_to\_consider"

**backend: str = 'pandas'**

Backend to read, process, and index input knowledge graph. pandas, polars and rdflib available

**trainer: str = 'torchCPUTrainer'**

Trainer for knowledge graph embedding model

**scoring\_technique: str = 'KvsAll'**

Scoring technique for knowledge graph embedding models

**neg\_ratio: int = 0**

Negative ratio for a true triple in NegSample training\_technique

**weight\_decay: float = 0.0**

Weight decay for all trainable params

**normalization: str = 'None'**

LayerNorm, BatchNorm1d, or None

**init\_param: str = None**

xavier\_normal or None

**gradient\_accumulation\_steps: int = 0**

Not tested e

**num\_folds\_for\_cv: int = 0**

Number of folds for CV

**eval\_model: str = 'train\_val\_test'**

["None", "train", "train\_val", "train\_val\_test", "test"]

#### **Type**

Evaluate trained model choices

**save\_model\_at\_every\_epoch: int = None**

Not tested

**num\_core: int = 0**

Number of CPUs to be used in the mini-batch loading process

**random\_seed: int = 0**

Random Seed

**sample\_triples\_ratio: float = None**

Read some triples that are uniformly at random sampled. Ratio being between 0 and 1

**read\_only\_few: int = None**

Read only first few triples

**pykeen\_model\_kwargs**

Additional keyword arguments for pykeen models

**kernel\_size: int = 3**

Size of a square kernel in a convolution operation

**num\_of\_output\_channels: int = 32**

Number of slices in the generated feature map by convolution.

**p: int = 0**

P parameter of Clifford Embeddings

**q: int = 1**  
 Q parameter of Clifford Embeddings

**input\_dropout\_rate: float = 0.0**  
 Dropout rate on embeddings of input triples

**hidden\_dropout\_rate: float = 0.0**  
 Dropout rate on hidden representations of input triples

**feature\_map\_dropout\_rate: float = 0.0**  
 Dropout rate on a feature map generated by a convolution operation

**byte\_pair\_encoding: bool = False**  
 Byte pair encoding

**Type**  
 WIP

**adaptive\_swa: bool = False**  
 Adaptive stochastic weight averaging

**swa: bool = False**  
 Stochastic weight averaging

**block\_size: int = None**  
 block size of LLM

**continual\_learning = None**  
 Path of a pretrained model size of LLM

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

## dicee.dataset\_classes

### Classes

<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>KvsSampleDataset</i>	KvsSample a Dataset:
<i>NegSampleDataset</i>	An abstract class representing a Dataset.
<i>TriplePredictionDataset</i>	Triple Dataset
<i>CVDDataModule</i>	Create a Dataset for cross validation

## 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.

---

`__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.

---

`__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\_idxes** – mapping.
- **relation\_idxes** – mapping.
- **form** – ?
- **num\_workers** – int for <https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader>

#### Return type

`torch.utils.data.Dataset`

`__len__()`

`__getitem__(idx)`

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

Bases: `torch.utils.data.Dataset`

Dataset for the 1vsALL training strategy

#### Parameters

- **train\_set\_idx** – Indexed triples for the training.
- **entity\_idxes** – mapping.
- **relation\_idxes** – mapping.
- **form** – ?
- **num\_workers** – int for <https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader>

#### Return type

`torch.utils.data.Dataset`

`__len__()`

`__getitem__(idx)`

```
class dicee.dataset_classes.KvsAll(train_set_idx: numpy.ndarray, entity_idxes, relation_idxes,  
    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  $[0, 1]^{|E|}$  **|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\_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 = KvsAll()
>>> a
? array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

**\_\_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  $N = |E| \times |R|$   $y$ : denotes a multi-label vector in  $[0, 1]^{|E|}$  **|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])
```

`__len__()`

`__getitem__(idx)`

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

Bases: torch.utils.data.Dataset

**KvsSample a Dataset:**

**D:= {(x,y)\_i}\_i ^N, where**

. x:(h,r) is a unique h in E and a relation r in R and . y in [0,1]^{**|E|**} is a binary label.

orall y\_i =1 s.t. (h r E\_i) in KG

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

**new\_y| << |E|** new\_y contains all 1's if sum(y)< neg\_sample ratio new\_y contains

**train\_set\_idx**

Indexed triples for the training.

**entity\_idx**

mapping.

**relation\_idx**

mapping.

**form**

?

**store**

?

**label\_smoothing\_rate**

?

torch.utils.data.Dataset

`__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.

---

`__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

`__len__()`

`__getitem__(idx)`

**collate\_fn** (*batch: List[torch.Tensor]*)

**class** dicee.dataset\_classes.**CVDataModule** (*train\_set\_idx: numpy.ndarray, num\_entities,*  
*num\_relations, neg\_sample\_ratio, batch\_size, num\_workers*)

Bases: pytorch\_lightning.LightningDataModule

Create a Dataset for cross validation

**Parameters**

- **train\_set\_idx** – Indexed triples for the training.
- **num\_entities** – entity to index mapping.
- **num\_relations** – relation to index mapping.

- **batch\_size** – int
- **form** – ?
- **num\_workers** – int for <https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader>

### Return type

?

**train\_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.ll = None

    def prepare_data(self):
        download_data()
        tokenize()

        # don't do this
```

(continues on next page)

(continued from previous page)

```
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()
```

## dicee.eval\_static\_funcs

### Functions

<code>evaluate_link_prediction_performance(→ Dict)</code>	<b>param model</b>
<code>evaluate_link_prediction_performance_w</code>	
<code>evaluate_link_prediction_performance_w</code>	
<code>evaluate_link_prediction_performance_w ...)</code>	<b>param model</b>
<code>evaluate_lp_bpe_k_vs_all(model, triples[, er_vocab, ...])</code>	

### Module Contents

```
dicee.eval_static_funcs.evaluate_link_prediction_performance(  
    model: dicee.knowledge_graph_embeddings.KGE, triples, er_vocab: Dict[Tuple, List],  
    re_vocab: Dict[Tuple, List]) → Dict
```

#### Parameters

- **model**
- **triples**
- **er\_vocab**
- **re\_vocab**

```
dicee.eval_static_funcs.  
    evaluate_link_prediction_performance_with_reciprocals(  
        model: dicee.knowledge_graph_embeddings.KGE, triples, er_vocab: Dict[Tuple, List])
```

```
dicee.eval_static_funcs.  
    evaluate_link_prediction_performance_with_bpe_reciprocals(  
        model: dicee.knowledge_graph_embeddings.KGE, within_entities: List[str], triples: List[List[str]],  
        er_vocab: Dict[Tuple, List])
```

```
dicee.eval_static_funcs.evaluate_link_prediction_performance_with_bpe(  
    model: dicee.knowledge_graph_embeddings.KGE, within_entities: List[str], triples: List[Tuple[str]],  
    er_vocab: Dict[Tuple, List], re_vocab: Dict[Tuple, List])
```

#### Parameters

- **model**
- **triples**
- **within\_entities**
- **er\_vocab**
- **re\_vocab**

```
dicee.eval_static_funcs.evaluate_lp_bpe_k_vs_all (model, triples: List[List[str]],
er_vocab=None, batch_size=None, func_triple_to_bpe_representation: Callable = None,
str_to_bpe_entity_to_idx=None)
```

## **dicee.evaluator**

### **Classes**

<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

**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

**read\_or\_load\_kg** ()

**read\_preprocess\_index\_serialize\_data** () → None

Read & Preprocess & Index & Serialize Input Data

- (1) Read or load the data from disk into memory.
- (2) Store the statistics of the data.

#### Parameter

**rtype**

None

**load\_indexed\_data** () → None

Load the indexed data from disk into memory



## Parameter

**rtype**  
None

**save\_trained\_model** () → None

Save a knowledge graph embedding model

- (1) Send model to eval mode and cpu.
- (2) Store the memory footprint of the model.
- (3) Save the model into disk.
- (4) Update the stats of KG again ?

## Parameter

**rtype**  
None

**end** (*form\_of\_labelling: str*) → dict

End training

- (1) Store trained model.
- (2) Report runtimes.
- (3) Eval model if required.

## Parameter

**rtype**  
A dict containing information about the training and/or evaluation

**write\_report** () → None

Report training related information in a report.json file

**start** () → dict

Start training

# (1) Loading the Data # (2) Create an evaluator object. # (3) Create a trainer object. # (4) Start the training

## Parameter

**rtype**  
A dict containing information about the training and/or evaluation

**class** dicee.executer.**ContinuousExecute** (*args*)

Bases: *Execute*

A subclass of Execute Class for retraining

- (1) Loading & Preprocessing & Serializing input data.

- (2) Training & Validation & Testing
- (3) Storing all necessary info

During the continual learning we can only modify \* **num\_epochs** \* parameter. Trained model stored in the same folder as the seed model for the training. Trained model is noted with the current time.

**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_reciprical: bool = None,
eval_model: str = None, read_only_few: int = None, sample_triples_ratio: float = None,
path_for_serialization: str = None, entity_to_idx=None, relation_to_idx=None, backend=None,
training_technique: str = None)
```

Knowledge Graph

**property** entities\_str: List

**property** relations\_str: List

**func** triple\_to\_bpe\_representation (triple: List[str])

## dicee.knowledge\_graph\_embeddings

### Classes

<i>KGE</i>	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, apply_semantic_constraint=False)  
    Bases: dicee.abstracts.BaseInteractiveKGE  
    Knowledge Graph Embedding Class for interactive usage of pre-trained models  
  
    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="")  
  
    __str__ ()  
      Return str(self).  
  
    eval_lp_performance (dataset=List[Tuple[str, str, str]], filtered=True)  
  
    predict_missing_head_entity (relation: List[str] | str, tail_entity: List[str] | str, within=None)  
      → Tuple  
      Given a relation and a tail entity, return top k ranked head entity.  
       $\text{argmax}_{\{e \in E\}} f(e, r, t)$ , 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*)  
→ 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*) → 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: List[str] = None, r: List[str] = None, t: List[str] = None, topk: int = 10, within: List[str] = None)

Predict missing item in a given 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.

k: int

Highest ranked k item.

### Returns: Tuple

Highest K scores and items

**triple\_score** (h: List[str] | str = None, r: List[str] | str = None, t: List[str] | str = None, logits=False)  
→ torch.FloatTensor

Predict triple score

### Parameter

head\_entity: List[str]

String representation of selected entities.

relation: List[str]

String representation of selected relations.

tail\_entity: List[str]

String representation of selected entities.

logits: bool

If logits is True, unnormalized score returned

## Returns: Tuple

pytorch tensor of triple score

**t\_norm** (*tens\_1*: torch.Tensor, *tens\_2*: torch.Tensor, *tnorm*: str = 'min') → torch.Tensor

**tensor\_t\_norm** (*subquery\_scores*: torch.FloatTensor, *tnorm*: str = 'min') → torch.FloatTensor

Compute T-norm over  $[0,1]^{n \times d}$  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

**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 :

forall e in E and forall r in R f(e,r,x)

Return (e,r,x)

notin 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

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

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

**train\_triples** (*h: List[str], r: List[str], t: List[str], labels: List[float], iteration=2, optimizer=None*)

**train\_k\_vs\_all** (*h, r, iteration=1, lr=0.001*)  
Train k vs all :param head\_entity: :param relation: :param iteration: :param lr: :return:

**train** (*kg, lr=0.1, epoch=10, batch\_size=32, neg\_sample\_ratio=10, num\_workers=1*) → None  
Retrained a pretrain model on an input KG via negative sampling.

## dicee.query\_generator

### Classes

---

*QueryGenerator*

---

### Module Contents

**class** `dicee.query_generator.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*)

**list2tuple** (*list\_data*)

**tuple2list** (*x: List | Tuple*) → List | Tuple  
Convert a nested tuple to a nested list.

**set\_global\_seed** (*seed: int*)  
Set seed

**construct\_graph** (*paths: List[str]*) → Tuple[Dict, Dict]  
Construct graph from triples Returns dicts with incoming and outgoing edges

**fill\_query** (*query\_structure: List[str | List], ent\_in: Dict, ent\_out: Dict, answer: int*) → bool  
Private method for fill\_query logic.

**achieve\_answer** (*query: List[str | List], ent\_in: Dict, ent\_out: Dict*) → set  
Private method for achieve\_answer logic. @TODO: Document the code

```

write_links (ent_out, small_ent_out)

ground_queries (query_structure: List[str \ List], ent_in: Dict, ent_out: Dict, small_ent_in: Dict,
                  small_ent_out: Dict, gen_num: int, query_name: str)
    Generating queries and achieving answers

unmap (query_type, queries, tp_answers, fp_answers, fn_answers)

unmap_query (query_structure, query, id2ent, id2rel)

generate_queries (query_struct: List, gen_num: int, query_type: str)
    Passing incoming and outgoing edges to ground queries depending on mode [train valid or text] and getting
    queries and answers in return @ TODO: create a class for each single query struct

save_queries (query_type: str, gen_num: int, save_path: str)

abstract load_queries (path)

get_queries (query_type: str, gen_num: int)

static save_queries_and_answers (path: str,
                                  data: List[Tuple[str, Tuple[collections.defaultdict]]]) → None
    Save Queries into Disk

static load_queries_and_answers (path: str)
    → List[Tuple[str, Tuple[collections.defaultdict]]]
    Load Queries from Disk to Memory

```

## dicee.sanity\_checkers

### Functions

<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.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>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
<code>save_checkpoint_model(→ None)</code>	Store Pytorch model into disk
<code>store(→ None)</code>	Store trained_model model and save embeddings into csv file.
<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_]</code>	
<code>...)</code>	
<code>deploy_head_entity_prediction(pre_trained_]</code>	
<code>...)</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>	

continues on next page

Table 2 – continued from previous page

<code>continual_training_setup_executor(→ None)</code>	storage_path:str A path leading to a parent directory, where a subdirectory containing KGE related data
<code>exponential_function(→ torch.FloatTensor)</code>	
<code>load_numpy(→ numpy.ndarray)</code>	
<code>evaluate(entity_to_idx, scores, easy_answers, hard_answers)</code>	# @TODO: CD: Renamed this function
<code>download_file(url[, destination_folder])</code>	
<code>download_files_from_url(→ None)</code>	param base_url
<code>download_pretrained_model(→ str)</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.select_model(args: dict, is_continual_training: bool = None,
    storage_path: str = None)
dicee.static_funcs.load_model(path_of_experiment_folder: str, model_name='model.pt',
    verbose=0) → Tuple[object, Tuple[dict, dict]]
    Load weights and initialize pytorch module from namespace arguments
dicee.static_funcs.load_model_ensemble(path_of_experiment_folder: str)
    → Tuple[dicee.models.base_model.BaseKGE, Tuple[pandas.DataFrame, pandas.DataFrame]]
    Construct Ensemble Of weights and initialize pytorch module from namespace arguments
    (1) Detect models under given path
    (2) Accumulate parameters of detected models
    (3) Normalize parameters
    (4) Insert (3) into model.
dicee.static_funcs.save_numpy_ndarray(*, data: numpy.ndarray, file_path: str)
```

`dicee.static_funcs.numpy_data_type_changer (train_set: numpy.ndarray, num: int)`  
→ `numpy.ndarray`  
Detect most efficient data type for a given triples :param train\_set: :param num: :return:

`dicee.static_funcs.save_checkpoint_model (model, path: str) → None`  
Store Pytorch model into disk

`dicee.static_funcs.store (trainer, trained_model, model_name: str = 'model',  
full_storage_path: str = None, save_embeddings_as_csv=False) → None`  
Store trained\_model model and save embeddings into csv file. :param trainer: an instance of trainer class :param  
full\_storage\_path: path to save parameters. :param model\_name: string representation of the name of the model.  
:param trained\_model: an instance of BaseKGE see core.models.base\_model . :param save\_embeddings\_as\_csv:  
for easy access of embeddings. :return:

`dicee.static_funcs.add_noisy_triples (train_set: pandas.DataFrame, add_noise_rate: float)`  
→ `pandas.DataFrame`  
Add randomly constructed triples :param train\_set: :param add\_noise\_rate: :return:

`dicee.static_funcs.read_or_load_kg (args, cls)`

`dicee.static_funcs.intialize_model (args: dict, verbose=0) → Tuple[object, str]`

`dicee.static_funcs.load_json (p: str) → dict`

`dicee.static_funcs.save_embeddings (embeddings: numpy.ndarray, indexes, path: str) → None`  
Save it as CSV if memory allows. :param embeddings: :param indexes: :param path: :return:

`dicee.static_funcs.random_prediction (pre_trained_kge)`

`dicee.static_funcs.deploy_triple_prediction (pre_trained_kge, str_subject, str_predicate,  
str_object)`

`dicee.static_funcs.deploy_tail_entity_prediction (pre_trained_kge, str_subject,  
str_predicate, top_k)`

`dicee.static_funcs.deploy_head_entity_prediction (pre_trained_kge, str_object,  
str_predicate, top_k)`

`dicee.static_funcs.deploy_relation_prediction (pre_trained_kge, str_subject, str_object,  
top_k)`

`dicee.static_funcs.vocab_to_parquet (vocab_to_idx, name, path_for_serialization, print_into)`

`dicee.static_funcs.create_experiment_folder (folder_name='Experiments')`

`dicee.static_funcs.continual_training_setup_executor (executor) → None`  
storage\_path:str A path leading to a parent directory, where a subdirectory containing KGE related data  
full\_storage\_path:str A path leading to a subdirectory containing KGE related data

`dicee.static_funcs.exponential_function (x: numpy.ndarray, lam: float,  
ascending_order=True) → torch.FloatTensor`

`dicee.static_funcs.load_numpy (path) → numpy.ndarray`

`dicee.static_funcs.evaluate (entity_to_idx, scores, easy_answers, hard_answers)`  
# @TODO: CD: Renamed this function Evaluate multi hop query answering on different query types

`dicee.static_funcs.download_file (url, destination_folder='.')`

`dicee.static_funcs.download_files_from_url (base_url: str, destination_folder='.') → None`

#### Parameters

- **base\_url** (e.g. `"https://files.dice-research.org/projects/DiceEmbeddings/KINSHIP-Keci-dim128-epoch256-KvsAll"`)
- **destination\_folder** (e.g. `"KINSHIP-Keci-dim128-epoch256-KvsAll"`)

`dicee.static_funcs.download_pretrained_model (url: str) → str`

## `dicee.static_funcs_training`

### Functions

```
evaluate_lp(model, triple_idx, num_entities, Evaluate model in a standard link prediction task  
er_vocab, ...)
```

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

```
efficient_zero_grad(model)
```

### Module Contents

`dicee.static_funcs_training.evaluate_lp (model, triple_idx, num_entities,  
er_vocab: Dict[Tuple, List], re_vocab: Dict[Tuple, List], info='Eval Starts')`

Evaluate model in a standard link prediction task

for each triple the rank is computed by taking the mean of the filtered missing head entity rank and the filtered missing tail entity rank :param model: :param triple\_idx: :param info: :return:

`dicee.static_funcs_training.evaluate_bpe_lp (model, triple_idx: List[Tuple],  
all_bpe_shaped_entities, er_vocab: Dict[Tuple, List], re_vocab: Dict[Tuple, List],  
info='Eval Starts')`

`dicee.static_funcs_training.efficient_zero_grad (model)`

## `dicee.static_preprocess_funcs`

### Attributes

```
enable_log
```

## Functions

```
timeit(func)
```

```
preprocesses_input_args(args)
```

Sanity Checking in input arguments

```
create_constraints(→ Tuple[dict, dict, dict,  
dict])
```

(1) Extract domains and ranges of relations

```
get_er_vocab(data)
```

```
get_re_vocab(data)
```

```
get_ee_vocab(data)
```

```
mapping_from_first_two_cols_to_third(tr
```

## 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)
```

## 13.3 Attributes

```
__version__
```

## 13.4 Classes

<i>CMult</i>	Cl_(0,0) => Real Numbers
<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>KeciBase</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>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>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

continues on next page

Table 3 – continued from previous page

*QueryGenerator*

## 13.5 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>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)	Store trained_model model and save embeddings into csv file.
<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, ...)	
<i>deploy_head_entity_prediction</i> (pre_trained_kge, ...)	
<i>deploy_relation_prediction</i> (pre_trained_kge, ...)	

continues on next page

Table 4 – continued from previous page

<code>vocab_to_parquet(vocab_to_idx, name, ...)</code>	
<code>create_experiment_folder([folder_name])</code>	
<code>continual_training_setup_executor(→ None)</code>	storage_path:str A path leading to a parent directory, where a subdirectory containing KGE related data
<code>exponential_function(→ torch.FloatTensor)</code>	
<code>load_numpy(→ numpy.ndarray)</code>	
<code>evaluate(entity_to_idx, scores, easy_answers, hard_answers)</code>	# @TODO: CD: Renamed this function
<code>download_file(url[, destination_folder])</code>	
<code>download_files_from_url(→ None)</code>	param base_url
<code>download_pretrained_model(→ str)</code>	
<code>mapping_from_first_two_cols_to_third(tr</code>	
<code>timeit(func)</code>	
<code>load_pickle([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>	

## 13.6 Package Contents

**class** `dicee.CMult` (*args*)

Bases: `dicee.models.base_model.BaseKGE`

`CI_(0,0)` => Real Numbers

`CI_(0,1)` =>

A multivector  $\mathbf{a} = a_0 + a_1 e_1$  A multivector  $\mathbf{b} = b_0 + b_1 e_1$

multiplication is isomorphic to the product of two complex numbers

$$\mathbf{a} \mathbf{b} = (a_0 b_0 - a_1 b_1) + (a_0 b_1 + a_1 b_0) e_1$$

`CI_(2,0)` =>

A multivector  $\mathbf{a} = a_0 + a_1 e_1 + a_2 e_2 + a_{12} e_1 e_2$  A multivector  $\mathbf{b} = b_0 + b_1 e_1 + b_2 e_2 + b_{12} e_1 e_2$

$$\mathbf{a} \mathbf{b} = (a_0 b_0 + a_0 b_1 e_1 + a_0 b_2 e_2 + a_0 b_{12} e_1 e_2 + a_1 b_0 e_1 + a_1 b_1 e_1 e_1 + a_1 b_2 e_1 e_2 + a_1 b_{12} e_1 e_1 e_1 + a_2 b_0 e_2 + a_2 b_1 e_2 e_1 + a_2 b_2 e_2 e_2 + a_2 b_{12} e_2 e_1 e_2 + a_{12} b_0 e_1 e_2 + a_{12} b_1 e_1 e_2 e_1 + a_{12} b_2 e_1 e_2 e_2 + a_{12} b_{12} e_1 e_2 e_1 e_2)$$

`CI_(0,2)` => Quaternions



**clifford\_mul** (*x: torch.FloatTensor, y: torch.FloatTensor, p: int, q: int*) → tuple

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

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

$e_j$

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

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

*p*: a non-negative integer  $p \geq 0$  *q*: a non-negative integer  $q \geq 0$

**score** (*head\_ent\_emb, rel\_ent\_emb, tail\_ent\_emb*)

**forward\_triples** (*x: torch.LongTensor*) → torch.FloatTensor

Compute batch triple scores

### Parameter

*x*: torch.LongTensor with shape n by 3

**rtype**

torch.LongTensor with shape n

**forward\_k\_vs\_all** (*x: torch.Tensor*) → torch.FloatTensor

Compute batch KvsAll triple scores

### Parameter

*x*: torch.LongTensor with shape n by 3

**rtype**

torch.LongTensor with shape n

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

Bases: `dicee.models.base_model.BaseKGE`

A Physical Embedding Model for Knowledge Graphs

**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>

**k\_vs\_all\_score** (*emb\_h: torch.FloatTensor, emb\_r: torch.FloatTensor, emb\_E: torch.FloatTensor*)

**Parameters**

• **emb\_h**

• **emb\_r**

• **emb\_E**

**forward\_k\_vs\_all** (*x: torch.LongTensor*)

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

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

**class** `dicee.KeciBase` (*args*)

Bases: `Keci`

Without learning dimension scaling

**class** `dicee.Keci` (*args*)

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

## Variables

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

**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.,  $e_1 e_1, e_1 e_2, e_1 e_3$ ,

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

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

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

Compute  $\sigma_{qq} = \sum_{j=1}^{p+q-1} \sum_{k=j+1}^{p+q} (h_{j,r_k} - h_{k,r_j}) e_j e_k \sigma_{qj}$  captures the interactions between along  $q$  bases For instance, let  $q = e_1, e_2, e_3$ , we compute interactions between  $e_1e_2, e_1e_3$ , and  $e_2e_3$  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** ( $h_0, hp, hq, r_0, rp, rq$ )

Multiplying a base vector with its scalar coefficient

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

Compute our CL multiplication

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

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

$e_j$

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

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

Kvsall training

- (1) Retrieve real-valued embedding vectors for heads and relations  $\mathbb{R}^d$ .
- (2) Construct head entity and relation embeddings according to  $Cl_{\{p,q\}}(\mathbb{R}^d)$ .
- (3) Perform Cl multiplication
- (4) Inner product of (3) and all entity embeddings

## Parameter

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

**rtype**

torch.FloatTensor with (n, **IEI**) 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>

**score**(head\_ent\_emb, rel\_ent\_emb, tail\_ent\_emb)

**forward\_k\_vs\_all**(x: torch.Tensor) → torch.FloatTensor

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

## Variables

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

**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

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

**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  $\text{Cl}_{\{p,q,r\}}(\mathbb{R}^d)$ .
- (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, **IEI**) 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  $\text{Cl}_{\{p,q,r\}}(\mathbb{R}^d)$

## 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

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

$\sigma_{qq}$  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>)

**kvsall\_score** (e\_1\_h, e\_2\_h, e\_3\_h, e\_4\_h, e\_5\_h, e\_6\_h, e\_7\_h, e\_8\_h, e\_1\_t, e\_2\_t, e\_3\_t, e\_4\_t, e\_5\_t, e\_6\_t, e\_7\_t, e\_8\_t, r\_1, r\_2, r\_3, r\_4, r\_5, r\_6, r\_7, r\_8) → torch.tensor

KvsAll scoring function

## Input

x: torch.LongTensor with (n, ) shape



## Output

torch.FloatTensor with (n) shape

**forward\_triples** (*idx\_triple: torch.tensor*) → torch.tensor

Negative Sampling forward pass:

## Input

x: torch.LongTensor with (n, ) shape

## Output

torch.FloatTensor with (n) shape

**forward\_k\_vs\_all** (*x*)

KvsAll forward pass

## Input

x: torch.LongTensor with (n, ) shape

## Output

torch.FloatTensor with (n) shape

**T** (*x: torch.tensor*) → torch.tensor

Transpose function

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

**class** dicee.**Complex** (*args*)

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

#### Variables

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

**static score** (*head\_ent\_emb: torch.FloatTensor, rel\_ent\_emb: torch.FloatTensor, tail\_ent\_emb: torch.FloatTensor*)

**static k\_vs\_all\_score** (*emb\_h: torch.FloatTensor, emb\_r: torch.FloatTensor, emb\_E: torch.FloatTensor*)

#### Parameters

- **emb\_h**
- **emb\_r**
- **emb\_E**

**forward\_k\_vs\_all** (*x: torch.LongTensor*) → *torch.FloatTensor*

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

Bases: `dicee.models.base_model.BaseKGE`

Additive Convolutional ComplEx Knowledge Graph Embeddings

**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

**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

**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

**residual\_convolution** (*Q\_1, Q\_2*)

**forward\_triples** (*indexed\_triple: torch.Tensor*) → torch.Tensor

**Parameters**

**x**

**forward\_k\_vs\_all** (*x: torch.Tensor*)

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

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

### Variables

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

**static octonion\_normalizer** (*emb\_rel\_e0, emb\_rel\_e1, emb\_rel\_e2, emb\_rel\_e3, emb\_rel\_e4, emb\_rel\_e5, emb\_rel\_e6, emb\_rel\_e7*)

**residual\_convolution** (*O\_1, O\_2*)

**forward\_triples** (*x: torch.Tensor*) → torch.Tensor

### Parameters

**x**

**forward\_k\_vs\_all** (*x: torch.Tensor*)

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

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

Bases: *dicee.models.base\_model.BaseKGE*

Convolutional ComplEx Knowledge Graph Embeddings

**residual\_convolution** (*C\_1: Tuple[torch.Tensor, torch.Tensor], C\_2: Tuple[torch.Tensor, torch.Tensor]*) → torch.FloatTensor

Compute residual score of two complex-valued embeddings. :param C\_1: a tuple of two pytorch tensors that corresponds complex-valued embeddings :param C\_2: a tuple of two pytorch tensors that corresponds complex-valued embeddings :return:

**forward\_k\_vs\_all** (*x: torch.Tensor*) → torch.FloatTensor

**forward\_triples** (*x: torch.Tensor*) → torch.FloatTensor

### Parameters

**x**

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

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

Bases: *dicee.models.base\_model.BaseKGE*

Base class for all neural network modules.

Your models should also subclass this class.

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

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

(continues on next page)

(continued from previous page)

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

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

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

---

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

---

### Variables

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

**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.,  $[\text{score}(h,r,x) | x \text{ in Entities}] \Rightarrow [0.0, 0.1, \dots, 0.8]$ , shape  $\Rightarrow (1, \text{Entities})$  Given a batch of head entities and relations  $\Rightarrow$  shape (size of batch, Entities)

`class dicee.OMult(args)`

Bases: `dicee.models.base_model.BaseKGE`

Base class for all neural network modules.

Your models should also subclass this class.

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

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

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

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

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

---

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

---

#### Variables

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

`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=> (1, **Entities**) Given a batch of head entities and  
relations => shape (size of batch,| Entities|)

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

Bases: *dicee.models.base\_model.BaseKGE*

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

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

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

**forward\_triples** (*x*) → torch.FloatTensor

**Parameters**

**x**

**Returns**

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

Bases: *dicee.models.base\_model.BaseKGE*

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

**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,

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

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

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

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

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

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

Bases: *dicee.models.base\_model.BaseKGE*

A class for using knowledge graph embedding models implemented in Pykeen

Notes: Pykeen\_DistMult: C Pykeen\_ComplEx: Pykeen\_QuatE: Pykeen\_MuRE: Pykeen\_CP: Pykeen\_HolE: Pykeen\_HolE:

**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 to nest them in a tree structure. You can assign the submodules as regular attributes:

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

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

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

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

---

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

---

### Variables

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

**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.BaseKGE` (*args: dict*)

Bases: `BaseKGELightning`

Base class for all neural network modules.

Your models should also subclass this class.

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

```

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

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

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

```

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

---

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

---

### Variables

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

**forward\_byte\_pair\_encoded\_k\_vs\_all** (*x: torch.LongTensor*)

### Parameters

**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*)  $\rightarrow$  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*)  
→ Tuple[torch.FloatTensor, torch.FloatTensor]

**Parameters**

**x** (*B x 2 x T*)

**get\_embeddings** () → Tuple[numpy.ndarray, numpy.ndarray]

**dicee.create\_recipriocal\_triples** (*x*)  
Add inverse triples into dask dataframe :param x: :return:

**dicee.get\_er\_vocab** (*data, file\_path: str = None*)

**dicee.get\_re\_vocab** (*data, file\_path: str = None*)

**dicee.get\_ee\_vocab** (*data, file\_path: str = None*)

**dicee.timeit** (*func*)

**dicee.save\_pickle** (\*, *data: object = None, file\_path=str*)

**dicee.load\_pickle** (*file\_path=str*)

**dicee.select\_model** (*args: dict, is\_continual\_training: bool = None, storage\_path: str = None*)

**dicee.load\_model** (*path\_of\_experiment\_folder: str, model\_name='model.pt', verbose=0*)  
→ Tuple[object, Tuple[dict, dict]]  
Load weights and initialize pytorch module from namespace arguments

**dicee.load\_model\_ensemble** (*path\_of\_experiment\_folder: str*)  
→ Tuple[[dicee.models.base\\_model.BaseKGE](#), Tuple[pandas.DataFrame, pandas.DataFrame]]  
Construct Ensemble Of weights and initialize pytorch module from namespace arguments

- (1) Detect models under given path
- (2) Accumulate parameters of detected models
- (3) Normalize parameters
- (4) Insert (3) into model.

**dicee.save\_numpy\_ndarray** (\*, *data: numpy.ndarray, file\_path: str*)

**dicee.numpy\_data\_type\_changer** (*train\_set: numpy.ndarray, num: int*) → numpy.ndarray  
Detect most efficient data type for a given triples :param train\_set: :param num: :return:

**dicee.save\_checkpoint\_model** (*model, path: str*) → None  
Store Pytorch model into disk

`dicee.store` (*trainer, trained\_model, model\_name: str = 'model', full\_storage\_path: str = None, save\_embeddings\_as\_csv=False*) → None

Store trained\_model model and save embeddings into csv file. :param trainer: an instance of trainer class :param full\_storage\_path: path to save parameters. :param model\_name: string representation of the name of the model. :param trained\_model: an instance of BaseKGE see core.models.base\_model . :param save\_embeddings\_as\_csv: for easy access of embeddings. :return:

`dicee.add_noisy_triples` (*train\_set: pandas.DataFrame, add\_noise\_rate: float*) → pandas.DataFrame

Add randomly constructed triples :param train\_set: :param add\_noise\_rate: :return:

`dicee.read_or_load_kg` (*args, cls*)

`dicee.initialize_model` (*args: dict, verbose=0*) → Tuple[object, str]

`dicee.load_json` (*p: str*) → dict

`dicee.save_embeddings` (*embeddings: numpy.ndarray, indexes, path: str*) → None

Save it as CSV if memory allows. :param embeddings: :param indexes: :param path: :return:

`dicee.random_prediction` (*pre\_trained\_kge*)

`dicee.deploy_triple_prediction` (*pre\_trained\_kge, str\_subject, str\_predicate, str\_object*)

`dicee.deploy_tail_entity_prediction` (*pre\_trained\_kge, str\_subject, str\_predicate, top\_k*)

`dicee.deploy_head_entity_prediction` (*pre\_trained\_kge, str\_object, str\_predicate, top\_k*)

`dicee.deploy_relation_prediction` (*pre\_trained\_kge, str\_subject, str\_object, top\_k*)

`dicee.vocab_to_parquet` (*vocab\_to\_idx, name, path\_for\_serialization, print\_into*)

`dicee.create_experiment_folder` (*folder\_name='Experiments'*)

`dicee.continual_training_setup_executor` (*executor*) → None

storage\_path:str A path leading to a parent directory, where a subdirectory containing KGE related data

full\_storage\_path:str A path leading to a subdirectory containing KGE related data

`dicee.exponential_function` (*x: numpy.ndarray, lam: float, ascending\_order=True*) → torch.FloatTensor

`dicee.load_numpy` (*path*) → numpy.ndarray

`dicee.evaluate` (*entity\_to\_idx, scores, easy\_answers, hard\_answers*)

# @TODO: CD: Renamed this function Evaluate multi hop query answering on different query types

`dicee.download_file` (*url, destination\_folder='.'*)

`dicee.download_files_from_url` (*base\_url: str, destination\_folder='.'*) → None

#### Parameters

- **base\_url** (e.g. `"https://files.dice-research.org/projects/DiceEmbeddings/KINSHIP-Keci-dim128-epoch256-KvsAll"`)
- **destination\_folder** (e.g. `"KINSHIP-Keci-dim128-epoch256-KvsAll"`)

`dicee.download_pretrained_model` (*url: str*) → str

```
class dicee.DICE_Trainer (args, is_continual_training, storage_path, evaluator=None)
```

#### DICE\_Trainer implement

- 1- Pytorch Lightning trainer (<https://pytorch-lightning.readthedocs.io/en/stable/common/trainer.html>)
- 2- Multi-GPU Trainer(<https://pytorch.org/docs/stable/generated/torch.nn.parallel.DistributedDataParallel.html>)
- 3- CPU Trainer

args

is\_continual\_training:bool

storage\_path:str

evaluator:

report:dict

```
continual_start ()
```

- (1) Initialize training.
- (2) Load model
- (3) Load trainer (3) Fit model

#### Parameter

##### returns

- *model*
- **form\_of\_labelling** (*str*)

```
initialize_trainer (callbacks: List) → lightning.Trainer
```

Initialize Trainer from input arguments

```
initialize_or_load_model ()
```

```
initialize_data_loader (dataset: torch.utils.data.Dataset) → torch.utils.data.DataLoader
```

```
initialize_dataset (dataset: dicee.knowledge_graph.KG, form_of_labelling)  
→ torch.utils.data.Dataset
```

```
start (knowledge_graph: dicee.knowledge_graph.KG) → Tuple[dicee.models.base_model.BaseKGE, str]
```

Train selected model via the selected training strategy

```
k_fold_cross_validation (dataset) → Tuple[dicee.models.base_model.BaseKGE, str]
```

Perform K-fold Cross-Validation

1. Obtain K train and test splits.
2. **For each split,**
  - 2.1 initialize trainer and model
  - 2.2. Train model with configuration provided in args.
  - 2.3. Compute the mean reciprocal rank (MRR) score of the model on the test respective split.
3. Report the mean and average MRR .

##### Parameters

- **self**
- **dataset**

## Returns

model

```
class dicee.KGE (path=None, url=None, construct_ensemble=False, model_name=None,  
                apply_semantic_constraint=False)
```

Bases: *[dicee.abstracts.BaseInteractiveKGE](#)*

Knowledge Graph Embedding Class for interactive usage of pre-trained models

```
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="")
```

```
__str__ ()
```

Return str(self).

```
eval_lp_performance (dataset=List[Tuple[str, str, str]], filtered=True)
```

```
predict_missing_head_entity (relation: List[str] | str, tail_entity: List[str] | str, within=None)  
    → Tuple
```

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

$\text{argmax}_{\{e \in E\}} f(e, r, t)$ , 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)  
    → 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*) → torch.FloatTensor

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

argmax\_<sub>{e in E }</sub> 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: List[str] = None, r: List[str] = None, t: List[str] = None, topk: int = 10, within: List[str] = None*)

Predict missing item in a given 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.

k: int

Highest ranked k item.

### Returns: Tuple

Highest K scores and items

**triple\_score** (*h: List[str] | str = None, r: List[str] | str = None, t: List[str] | str = None, logits=False*)  
→ torch.FloatTensor

Predict triple score

### Parameter

head\_entity: List[str]

String representation of selected entities.

relation: List[str]

String representation of selected relations.

tail\_entity: List[str]

String representation of selected entities.

logits: bool

If logits is True, unnormalized score returned

### Returns: Tuple

pytorch tensor of triple score

**t\_norm** (*tens\_1: torch.Tensor, tens\_2: torch.Tensor, tnorm: str = 'min'*) → torch.Tensor

**tensor\_t\_norm** (*subquery\_scores: torch.FloatTensor, tnorm: str = 'min'*) → torch.FloatTensor

Compute T-norm over  $[0,1]^{n \times d}$  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

**return\_multi\_hop\_query\_results** (*aggregated\_query\_for\_all\_entities, k: int, only\_scores*)

**single\_hop\_query\_answering** (*query: tuple, only\_scores: bool = True, k: int = None*)

**answer\_multi\_hop\_query** (*query\_type: str = None,*  
*query: Tuple[str | Tuple[str, str], Ellipsis] = None,*  
*queries: List[Tuple[str | Tuple[str, str], Ellipsis]] = None, tnorm: str = 'prod',*  
*neg\_norm: str = 'standard', lambda\_: float = 0.0, k: int = 10, only\_scores=False*)  
*→ List[Tuple[str, torch.Tensor]]*

# @TODO: Refactoring is needed # @TODO: Score computation for each query type should be done in a static function

Find an answer set for EPFO queries including negation and disjunction

## Parameter

*query\_type: str* The type of the query, e.g., “2p”.

*query: Union[str, Tuple[str, Tuple[str, str]]]* The query itself, either a string or a nested tuple.

*queries: List of Tuple[Union[str, Tuple[str, str]], ...]*

*tnorm: str* The t-norm operator.

*neg\_norm: str* The negation norm.

**lambda\_:** float lambda parameter for sugeno and yager negation norms

*k: int* The top-k substitutions for intermediate variables.

### returns

- *List[Tuple[str, torch.Tensor]]*
- *Entities and corresponding scores sorted in the descening order of scores*

**find\_missing\_triples** (*confidence: float, entities: List[str] = None, relations: List[str] = None,*  
*topk: int = 10, at\_most: int = sys.maxsize*) *→ Set*

Find missing triples

Iterative over a set of entities E and a set of relation R :

orall e in E and orall r in R f(e,r,x)

Return (e,r,x)

otin G and f(e,r,x) > confidence

confidence: float

A threshold for an output of a sigmoid function given a triple.

topk: int

Highest ranked k item to select triples with f(e,r,x) > confidence .

at\_most: int

Stop after finding at\_most missing triples

{(e,r,x) | f(e,r,x) > confidence land (e,r,x)}

otin G

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

**train\_triples** (*h: List[str], r: List[str], t: List[str], labels: List[float], iteration=2, optimizer=None*)

**train\_k\_vs\_all** (*h, r, iteration=1, lr=0.001*)

Train k vs all :param head\_entity: :param relation: :param iteration: :param lr: :return:

**train** (*kg, lr=0.1, epoch=10, batch\_size=32, neg\_sample\_ratio=10, num\_workers=1*) → None

Retrained a pretrain model on an input KG via negative sampling.

**class** dicee.**Execute** (*args, continuous\_training=False*)

A class for Training, Retraining and Evaluation a model.

(1) Loading & Preprocessing & Serializing input data.

(2) Training & Validation & Testing

(3) Storing all necessary info

**read\_or\_load\_kg** ()

**read\_preprocess\_index\_serialize\_data** () → None

Read & Preprocess & Index & Serialize Input Data

(1) Read or load the data from disk into memory.

(2) Store the statistics of the data.

### Parameter

**rtype**

None

**load\_indexed\_data** () → None

Load the indexed data from disk into memory

### Parameter

**rtype**

None

**save\_trained\_model** () → None

Save a knowledge graph embedding model

(1) Send model to eval mode and cpu.

(2) Store the memory footprint of the model.

(3) Save the model into disk.

(4) Update the stats of KG again ?

## Parameter

**rtype**

None

**end** (*form\_of\_labelling: str*) → dict

End training

(1) Store trained model.

(2) Report runtimes.

(3) Eval model if required.

## Parameter

**rtype**

A dict containing information about the training and/or evaluation

**write\_report** () → None

Report training related information in a report.json file

**start** () → dict

Start training

# (1) Loading the Data # (2) Create an evaluator object. # (3) Create a trainer object. # (4) Start the training

## Parameter

**rtype**

A dict containing information about the training and/or evaluation

`dicee.mapping_from_first_two_cols_to_third(train_set_idx)`

`dicee.timeit(func)`

`dicee.load_pickle(file_path=str)`

`dicee.reload_dataset(path: str, form_of_labelling, scoring_technique, neg_ratio, label_smoothing_rate)`

Reload the files from disk to construct the Pytorch dataset

`dicee.construct_dataset(*, train_set: numpy.ndarray | list, valid_set=None, test_set=None, ordered_bpe_entities=None, train_target_indices=None, target_dim: int = None, entity_to_idx: dict, relation_to_idx: dict, form_of_labelling: str, scoring_technique: str, neg_ratio: int, label_smoothing_rate: float, byte_pair_encoding=None, block_size: int = None) → torch.utils.data.Dataset`

`class dicee.BPE_NegativeSamplingDataset(train_set: torch.LongTensor, ordered_shaped_bpe_entities: torch.LongTensor, neg_ratio: int)`

Bases: torch.utils.data.Dataset

An abstract class representing a Dataset.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite `__getitem__()`, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite `__len__()`, which is expected to return the size of the dataset by many `Sampler` implementations and the

default options of `DataLoader`. Subclasses could also optionally implement `__getitems__()`, for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

---

**Note:** `DataLoader` by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

---

`__len__()`

`__getitem__(idx)`

`collate_fn(batch_shaped_bpe_triples: List[Tuple[torch.Tensor, torch.Tensor]])`

```
class dicee.MultiLabelDataset (train_set: torch.LongTensor, train_indices_target: torch.LongTensor,
                               target_dim: int, torch_ordered_shaped_bpe_entities: torch.LongTensor)
```

Bases: `torch.utils.data.Dataset`

An abstract class representing a `Dataset`.

All datasets that represent a map from keys to data samples should subclass it. All subclasses should overwrite `__getitem__()`, supporting fetching a data sample for a given key. Subclasses could also optionally overwrite `__len__()`, which is expected to return the size of the dataset by many `Sampler` implementations and the default options of `DataLoader`. Subclasses could also optionally implement `__getitems__()`, for speedup batched samples loading. This method accepts list of indices of samples of batch and returns list of samples.

---

**Note:** `DataLoader` by default constructs an index sampler that yields integral indices. To make it work with a map-style dataset with non-integral indices/keys, a custom sampler must be provided.

---

`__len__()`

`__getitem__(idx)`

```
class dicee.MultiClassClassificationDataset (subword_units: numpy.ndarray,
                                              block_size: int = 8)
```

Bases: `torch.utils.data.Dataset`

Dataset for the 1vsALL training strategy

#### Parameters

- **train\_set\_idx** – Indexed triples for the training.
- **entity\_idxs** – mapping.
- **relation\_idxs** – mapping.
- **form** – ?
- **num\_workers** – int for <https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader>

#### Return type

`torch.utils.data.Dataset`

`__len__()`

`__getitem__(idx)`

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

Bases: torch.utils.data.Dataset

Dataset for the 1vsALL training strategy

#### Parameters

- **train\_set\_idx** – Indexed triples for the training.
- **entity\_idxxs** – mapping.
- **relation\_idxxs** – mapping.
- **form** – ?
- **num\_workers** – int for <https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader>

#### Return type

torch.utils.data.Dataset

```
__len__ ()
```

```
__getitem__ (idx)
```

```
class dicee.KvsAll (train_set_idx: numpy.ndarray, entity_idxxs, relation_idxxs, 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  $[0, 1]^{|IE|}$  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\_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 = KvsAll ()
>>> a
? array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
__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  $N = |E| \times |R|$   $y$ : denotes a multi-label vector in  $[0, 1]^{|E|}$   $\{ |E| \}$  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\_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])
```

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

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

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

Bases: torch.utils.data.Dataset

**KvsSample a Dataset:**

$D := \{(x, y)_i\}_i^N$ , where

.  $x: (h, r)$  is a unique  $h$  in  $E$  and a relation  $r$  in  $R$  and .  $y$  in  $[0, 1]^{|E|}$   $\{ |E| \}$  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  $\text{sum}(y) < \text{neg\_sample\_ratio}$  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

**\_\_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.

---

**\_\_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\_idx**  
mapping.

**relation\_idx**  
mapping.



```

    form
        ?

    store
        ?

    label_smoothing_rate

    collate_fn: batch:List[torch.IntTensor] Returns —— torch.utils.data.Dataset

__len__ ()

__getitem__ (idx)

collate_fn (batch: List[torch.Tensor])

```

```

class dicee.CVDataModule (train_set_idx: numpy.ndarray, num_entities, num_relations,
                           neg_sample_ratio, batch_size, num_workers)

```

Bases: `pytorch_lightning.LightningDataModule`

Create a Dataset for cross validation

#### Parameters

- **train\_set\_idx** – Indexed triples for the training.
- **num\_entities** – entity to index mapping.
- **num\_relations** – relation to index mapping.
- **batch\_size** – int
- **form** – ?
- **num\_workers** – int for <https://pytorch.org/docs/stable/data.html#torch.utils.data.DataLoader>

#### Return type

?

```

train_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__()
```

(continues on next page)

```

        self.prepare_data_per_node = True

# call on GLOBAL_RANK=0 (great for shared file systems)
class LitDataModule(LightningDataModule):
    def __init__(self):
        super().__init__()
        self.prepare_data_per_node = False

```

This is called before requesting the dataloaders:

```

model.prepare_data()
initialize_distributed()
model.setup(stage)
model.train_dataloader()
model.val_dataloader()
model.test_dataloader()
model.predict_dataloader()

```

```

class dicee.QueryGenerator (train_path: str, val_path: str, test_path: str, ent2id: Dict = None,
                           rel2id: Dict = None, seed: int = 1, gen_valid: bool = False, gen_test: bool = True)

```

**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__ = '0.1.4'

```

## Python Module Index

### d

- `dicee`, 10
- `dicee.abstracts`, 93
- `dicee.analyse_experiments`, 99
- `dicee.callbacks`, 100
- `dicee.config`, 106
- `dicee.dataset_classes`, 109
- `dicee.eval_static_funcs`, 118
- `dicee.evaluator`, 119
- `dicee.executer`, 120
- `dicee.knowledge_graph`, 122
- `dicee.knowledge_graph_embeddings`, 123
- `dicee.models`, 10
  - `dicee.models.base_model`, 10
  - `dicee.models.clifford`, 18
  - `dicee.models.complex`, 25
  - `dicee.models.dualE`, 27
  - `dicee.models.function_space`, 28
  - `dicee.models.octonion`, 31
  - `dicee.models.pykeen_models`, 33
  - `dicee.models.quaternion`, 34
  - `dicee.models.real`, 37
  - `dicee.models.static_funcs`, 38
  - `dicee.models.transformers`, 38
- `dicee.query_generator`, 127
- `dicee.read_preprocess_save_load_kg`, 80
- `dicee.read_preprocess_save_load_kg.preprocess`, 80
- `dicee.read_preprocess_save_load_kg.read_from_disk`, 81
- `dicee.read_preprocess_save_load_kg.save_load_disk`, 82
- `dicee.read_preprocess_save_load_kg.util`, 82
- `dicee.sanity_checkers`, 128
- `dicee.scripts`, 86
  - `dicee.scripts.index`, 86
  - `dicee.scripts.run`, 87
  - `dicee.scripts.serve`, 87
- `dicee.static_funcs`, 129
- `dicee.static_funcs_training`, 132
- `dicee.static_preprocess_funcs`, 132
- `dicee.trainer`, 88
  - `dicee.trainer.dice_trainer`, 88
  - `dicee.trainer.torch_trainer`, 90
  - `dicee.trainer.torch_trainer_ddp`, 91

# Index

## Non-alphabetical

`__call__()` (*dicee.models.base\_model.IdentityClass method*), 17  
`__call__()` (*dicee.models.IdentityClass method*), 52, 60, 64  
`__getitem__()` (*dicee.AllvsAll method*), 167  
`__getitem__()` (*dicee.BPE\_NegativeSamplingDataset method*), 165  
`__getitem__()` (*dicee.dataset\_classes.AllvsAll method*), 113  
`__getitem__()` (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset method*), 110  
`__getitem__()` (*dicee.dataset\_classes.KvsAll method*), 112  
`__getitem__()` (*dicee.dataset\_classes.KvsSampleDataset method*), 113  
`__getitem__()` (*dicee.dataset\_classes.MultiClassClassificationDataset method*), 111  
`__getitem__()` (*dicee.dataset\_classes.MultiLabelDataset method*), 111  
`__getitem__()` (*dicee.dataset\_classes.NegSampleDataset method*), 114  
`__getitem__()` (*dicee.dataset\_classes.OnevsAllDataset method*), 111  
`__getitem__()` (*dicee.dataset\_classes.TriplePredictionDataset method*), 114  
`__getitem__()` (*dicee.KvsAll method*), 166  
`__getitem__()` (*dicee.KvsSampleDataset method*), 168  
`__getitem__()` (*dicee.MultiClassClassificationDataset method*), 165  
`__getitem__()` (*dicee.MultiLabelDataset method*), 165  
`__getitem__()` (*dicee.NegSampleDataset method*), 168  
`__getitem__()` (*dicee.OnevsAllDataset method*), 166  
`__getitem__()` (*dicee.TriplePredictionDataset method*), 169  
`__iter__()` (*dicee.config.Namespace method*), 109  
`__len__()` (*dicee.AllvsAll method*), 167  
`__len__()` (*dicee.BPE\_NegativeSamplingDataset method*), 165  
`__len__()` (*dicee.dataset\_classes.AllvsAll method*), 113  
`__len__()` (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset method*), 110  
`__len__()` (*dicee.dataset\_classes.KvsAll method*), 112  
`__len__()` (*dicee.dataset\_classes.KvsSampleDataset method*), 113  
`__len__()` (*dicee.dataset\_classes.MultiClassClassificationDataset method*), 111  
`__len__()` (*dicee.dataset\_classes.MultiLabelDataset method*), 111  
`__len__()` (*dicee.dataset\_classes.NegSampleDataset method*), 114  
`__len__()` (*dicee.dataset\_classes.OnevsAllDataset method*), 111  
`__len__()` (*dicee.dataset\_classes.TriplePredictionDataset method*), 114  
`__len__()` (*dicee.KvsAll method*), 166  
`__len__()` (*dicee.KvsSampleDataset method*), 168  
`__len__()` (*dicee.MultiClassClassificationDataset method*), 165  
`__len__()` (*dicee.MultiLabelDataset method*), 165  
`__len__()` (*dicee.NegSampleDataset method*), 168  
`__len__()` (*dicee.OnevsAllDataset method*), 166  
`__len__()` (*dicee.TriplePredictionDataset method*), 169  
`__str__()` (*dicee.KGE method*), 159  
`__str__()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 123  
`__version__` (*in module dicee*), 173

## A

`AbstractCallback` (*class in dicee.abstracts*), 97  
`AbstractPPECallback` (*class in dicee.abstracts*), 98  
`AbstractTrainer` (*class in dicee.abstracts*), 94  
`AccumulateEpochLossCallback` (*class in dicee.callbacks*), 100  
`achieve_answer()` (*dicee.query\_generator.QueryGenerator method*), 127  
`achieve_answer()` (*dicee.QueryGenerator method*), 172  
`AConEx` (*class in dicee*), 146  
`AConEx` (*class in dicee.models*), 56  
`AConEx` (*class in dicee.models.complex*), 26  
`AConvO` (*class in dicee*), 146  
`AConvO` (*class in dicee.models*), 66  
`AConvO` (*class in dicee.models.octonion*), 33  
`AConvQ` (*class in dicee*), 147  
`AConvQ` (*class in dicee.models*), 62  
`AConvQ` (*class in dicee.models.quaternion*), 36  
`adaptive_swa` (*dicee.config.Namespace attribute*), 109  
`add_new_entity_embeddings()` (*dicee.abstracts.BaseInteractiveKGE method*), 96  
`add_noise_rate` (*dicee.config.Namespace attribute*), 107  
`add_noisy_triples()` (*in module dicee*), 157

add\_noisy\_triples() (in module *dicee.static\_funcs*), 131  
 add\_noisy\_triples\_into\_training() (*dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk.ReadFromDisk* method), 82  
 add\_noisy\_triples\_into\_training() (*dicee.read\_preprocess\_save\_load\_kg.ReadFromDisk* method), 86  
 AllvsAll (class in *dicee*), 166  
 AllvsAll (class in *dicee.dataset\_classes*), 112  
 analyse() (in module *dicee.analyse\_experiments*), 100  
 answer\_multi\_hop\_query() (*dicee.KGE* method), 162  
 answer\_multi\_hop\_query() (*dicee.knowledge\_graph\_embeddings.KGE* method), 126  
 app (in module *dicee.scripts.serve*), 88  
 apply\_coefficients() (*dicee.DeCaL* method), 142  
 apply\_coefficients() (*dicee.Keci* method), 139  
 apply\_coefficients() (*dicee.models.clifford.DeCaL* method), 23  
 apply\_coefficients() (*dicee.models.clifford.Keci* method), 20  
 apply\_coefficients() (*dicee.models.DeCaL* method), 71  
 apply\_coefficients() (*dicee.models.Keci* method), 67  
 apply\_reciprical\_or\_noise() (in module *dicee.read\_preprocess\_save\_load\_kg.util*), 83  
 ASWA (class in *dicee.callbacks*), 103

## B

backend (*dicee.config.Namespace* attribute), 107  
 BaseInteractiveKGE (class in *dicee.abstracts*), 95  
 BaseKGE (class in *dicee*), 154  
 BaseKGE (class in *dicee.models*), 50, 52, 55, 58, 62, 73, 75  
 BaseKGE (class in *dicee.models.base\_model*), 15  
 BaseKGELightning (class in *dicee.models*), 45  
 BaseKGELightning (class in *dicee.models.base\_model*), 10  
 batch\_kronecker\_product() (*dicee.callbacks.KronE* static method), 106  
 batch\_size (*dicee.config.Namespace* attribute), 107  
 bias (*dicee.models.transformers.GPTConfig* attribute), 43  
 Block (class in *dicee.models.transformers*), 42  
 block\_size (*dicee.config.Namespace* attribute), 109  
 block\_size (*dicee.models.transformers.GPTConfig* attribute), 43  
 BPE\_NegativeSamplingDataset (class in *dicee*), 164  
 BPE\_NegativeSamplingDataset (class in *dicee.dataset\_classes*), 110  
 build\_chain\_funcs() (*dicee.models.FMult2* method), 77  
 build\_chain\_funcs() (*dicee.models.function\_space.FMult2* method), 29  
 build\_func() (*dicee.models.FMult2* method), 77  
 build\_func() (*dicee.models.function\_space.FMult2* method), 29  
 Byte (class in *dicee*), 153  
 Byte (class in *dicee.models.transformers*), 39  
 byte\_pair\_encoding (*dicee.config.Namespace* attribute), 109

## C

callbacks (*dicee.config.Namespace* attribute), 107  
 CausalSelfAttention (class in *dicee.models.transformers*), 41  
 chain\_func() (*dicee.models.FMult* method), 77  
 chain\_func() (*dicee.models.function\_space.FMult* method), 29  
 chain\_func() (*dicee.models.function\_space.GFMult* method), 29  
 chain\_func() (*dicee.models.GFMult* method), 77  
 cl\_pqr() (*dicee.DeCaL* method), 142  
 cl\_pqr() (*dicee.models.clifford.DeCaL* method), 23  
 cl\_pqr() (*dicee.models.DeCaL* method), 71  
 clifford\_mul() (*dicee.CMult* method), 136  
 clifford\_mul() (*dicee.models.clifford.CMult* method), 18  
 clifford\_mul() (*dicee.models.CMult* method), 69  
 clifford\_multiplication() (*dicee.Keci* method), 139  
 clifford\_multiplication() (*dicee.models.clifford.Keci* method), 20  
 clifford\_multiplication() (*dicee.models.Keci* method), 67  
 CMult (class in *dicee*), 136  
 CMult (class in *dicee.models*), 69  
 CMult (class in *dicee.models.clifford*), 18  
 collate\_fn() (*dicee.BPE\_NegativeSamplingDataset* method), 165  
 collate\_fn() (*dicee.dataset\_classes.BPE\_NegativeSamplingDataset* method), 110  
 collate\_fn() (*dicee.dataset\_classes.TriplePredictionDataset* method), 114  
 collate\_fn() (*dicee.TriplePredictionDataset* method), 169  
 comp\_func() (*dicee.LFMult* method), 152  
 comp\_func() (*dicee.models.function\_space.LFMult* method), 30



`comp_func()` (*dicee.models.LFMult method*), 79  
`Complex` (*class in dicee*), 145  
`Complex` (*class in dicee.models*), 57  
`Complex` (*class in dicee.models.complex*), 26  
`compute_convergence()` (*in module dicee.callbacks*), 103  
`compute_func()` (*dicee.models.FMult method*), 77  
`compute_func()` (*dicee.models.FMult2 method*), 77  
`compute_func()` (*dicee.models.function\_space.FMult method*), 29  
`compute_func()` (*dicee.models.function\_space.FMult2 method*), 29  
`compute_func()` (*dicee.models.function\_space.GFMult method*), 29  
`compute_func()` (*dicee.models.GFMult method*), 77  
`compute_mrr()` (*dicee.callbacks.ASWA static method*), 104  
`compute_sigma_pp()` (*dicee.DeCaL method*), 143  
`compute_sigma_pp()` (*dicee.Keci method*), 138  
`compute_sigma_pp()` (*dicee.models.clifford.DeCaL method*), 24  
`compute_sigma_pp()` (*dicee.models.clifford.Keci method*), 19  
`compute_sigma_pp()` (*dicee.models.DeCaL method*), 72  
`compute_sigma_pp()` (*dicee.models.Keci method*), 67  
`compute_sigma_pq()` (*dicee.DeCaL method*), 144  
`compute_sigma_pq()` (*dicee.Keci method*), 139  
`compute_sigma_pq()` (*dicee.models.clifford.DeCaL method*), 25  
`compute_sigma_pq()` (*dicee.models.clifford.Keci method*), 20  
`compute_sigma_pq()` (*dicee.models.DeCaL method*), 73  
`compute_sigma_pq()` (*dicee.models.Keci method*), 67  
`compute_sigma_pr()` (*dicee.DeCaL method*), 144  
`compute_sigma_pr()` (*dicee.models.clifford.DeCaL method*), 25  
`compute_sigma_pr()` (*dicee.models.DeCaL method*), 73  
`compute_sigma_qq()` (*dicee.DeCaL method*), 143  
`compute_sigma_qq()` (*dicee.Keci method*), 139  
`compute_sigma_qq()` (*dicee.models.clifford.DeCaL method*), 24  
`compute_sigma_qq()` (*dicee.models.clifford.Keci method*), 20  
`compute_sigma_qq()` (*dicee.models.DeCaL method*), 72  
`compute_sigma_qq()` (*dicee.models.Keci method*), 67  
`compute_sigma_qr()` (*dicee.DeCaL method*), 144  
`compute_sigma_qr()` (*dicee.models.clifford.DeCaL method*), 25  
`compute_sigma_qr()` (*dicee.models.DeCaL method*), 73  
`compute_sigma_rr()` (*dicee.DeCaL method*), 143  
`compute_sigma_rr()` (*dicee.models.clifford.DeCaL method*), 24  
`compute_sigma_rr()` (*dicee.models.DeCaL method*), 73  
`compute_sigmas_multivect()` (*dicee.DeCaL method*), 142  
`compute_sigmas_multivect()` (*dicee.models.clifford.DeCaL method*), 23  
`compute_sigmas_multivect()` (*dicee.models.DeCaL method*), 71  
`compute_sigmas_single()` (*dicee.DeCaL method*), 142  
`compute_sigmas_single()` (*dicee.models.clifford.DeCaL method*), 23  
`compute_sigmas_single()` (*dicee.models.DeCaL method*), 71  
`ConEx` (*class in dicee*), 148  
`ConEx` (*class in dicee.models*), 56  
`ConEx` (*class in dicee.models.complex*), 26  
`configure_optimizers()` (*dicee.models.base\_model.BaseKGELightning method*), 14  
`configure_optimizers()` (*dicee.models.BaseKGELightning method*), 49  
`configure_optimizers()` (*dicee.models.transformers.GPT method*), 44  
`construct_cl_multivector()` (*dicee.DeCaL method*), 142  
`construct_cl_multivector()` (*dicee.Keci method*), 139  
`construct_cl_multivector()` (*dicee.models.clifford.DeCaL method*), 23  
`construct_cl_multivector()` (*dicee.models.clifford.Keci method*), 21  
`construct_cl_multivector()` (*dicee.models.DeCaL method*), 72  
`construct_cl_multivector()` (*dicee.models.Keci method*), 68  
`construct_dataset()` (*in module dicee*), 164  
`construct_dataset()` (*in module dicee.dataset\_classes*), 110  
`construct_graph()` (*dicee.query\_generator.QueryGenerator method*), 127  
`construct_graph()` (*dicee.QueryGenerator method*), 172  
`construct_input_and_output()` (*dicee.abstracts.BaseInteractiveKGE method*), 97  
`construct_multi_coeff()` (*dicee.LFMult method*), 151  
`construct_multi_coeff()` (*dicee.models.function\_space.LFMult method*), 30  
`construct_multi_coeff()` (*dicee.models.LFMult method*), 78  
`continual_learning` (*dicee.config.Namespace attribute*), 109  
`continual_start()` (*dicee.DICE\_Trainer method*), 158  
`continual_start()` (*dicee.executer.ContinuousExecute method*), 122

continual\_start() (*dicee.trainer.DICE\_Trainer method*), 92  
 continual\_start() (*dicee.trainer.dice\_trainer.DICE\_Trainer method*), 89  
 continual\_training\_setup\_executor() (*in module dicee*), 157  
 continual\_training\_setup\_executor() (*in module dicee.static\_funcs*), 131  
 ContinuousExecute (*class in dicee.executor*), 121  
 ConvO (*class in dicee*), 147  
 ConvO (*class in dicee.models*), 65  
 ConvO (*class in dicee.models.octonion*), 32  
 ConvQ (*class in dicee*), 147  
 ConvQ (*class in dicee.models*), 61  
 ConvQ (*class in dicee.models.quaternion*), 36  
 create\_constraints() (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 84  
 create\_constraints() (*in module dicee.static\_preprocess\_funcs*), 133  
 create\_experiment\_folder() (*in module dicee*), 157  
 create\_experiment\_folder() (*in module dicee.static\_funcs*), 131  
 create\_random\_data() (*dicee.callbacks.PseudoLabellingCallback method*), 103  
 create\_recipriocal\_triples() (*in module dicee*), 156  
 create\_recipriocal\_triples() (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 84  
 create\_recipriocal\_triples() (*in module dicee.static\_funcs*), 130  
 create\_vector\_database() (*dicee.KGE method*), 159  
 create\_vector\_database() (*dicee.knowledge\_graph\_embeddings.KGE method*), 123  
 crop\_block\_size() (*dicee.models.transformers.GPT method*), 44  
 CVDDataModule (*class in dicee*), 169  
 CVDDataModule (*class in dicee.dataset\_classes*), 114

## D

dataset\_dir (*dicee.config.Namespace attribute*), 107  
 dataset\_sanity\_checking() (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 84  
 DDPTrainer (*class in dicee.trainer.torch\_trainer\_ddp*), 92  
 DeCaL (*class in dicee*), 141  
 DeCaL (*class in dicee.models*), 70  
 DeCaL (*class in dicee.models.clifford*), 22  
 decide() (*dicee.callbacks.ASWA method*), 104  
 deploy() (*dicee.KGE method*), 162  
 deploy() (*dicee.knowledge\_graph\_embeddings.KGE method*), 127  
 deploy\_head\_entity\_prediction() (*in module dicee*), 157  
 deploy\_head\_entity\_prediction() (*in module dicee.static\_funcs*), 131  
 deploy\_relation\_prediction() (*in module dicee*), 157  
 deploy\_relation\_prediction() (*in module dicee.static\_funcs*), 131  
 deploy\_tail\_entity\_prediction() (*in module dicee*), 157  
 deploy\_tail\_entity\_prediction() (*in module dicee.static\_funcs*), 131  
 deploy\_triple\_prediction() (*in module dicee*), 157  
 deploy\_triple\_prediction() (*in module dicee.static\_funcs*), 131  
 DICE\_Trainer (*class in dicee*), 157  
 DICE\_Trainer (*class in dicee.trainer*), 92  
 DICE\_Trainer (*class in dicee.trainer.dice\_trainer*), 88  
 dicee  
     module, 10  
 dicee.abstracts  
     module, 93  
 dicee.analyse\_experiments  
     module, 99  
 dicee.callbacks  
     module, 100  
 dicee.config  
     module, 106  
 dicee.dataset\_classes  
     module, 109  
 dicee.eval\_static\_funcs  
     module, 118  
 dicee.evaluator  
     module, 119  
 dicee.executor  
     module, 120  
 dicee.knowledge\_graph  
     module, 122  
 dicee.knowledge\_graph\_embeddings

- module, 123
- dicee.models
  - module, 10
  - dicee.models.base\_model
    - module, 10
  - dicee.models.clifford
    - module, 18
  - dicee.models.complex
    - module, 25
  - dicee.models.dualE
    - module, 27
  - dicee.models.function\_space
    - module, 28
  - dicee.models.octonion
    - module, 31
  - dicee.models.pykeen\_models
    - module, 33
  - dicee.models.quaternion
    - module, 34
  - dicee.models.real
    - module, 37
  - dicee.models.static\_funcs
    - module, 38
  - dicee.models.transformers
    - module, 38
- dicee.query\_generator
  - module, 127
- dicee.read\_preprocess\_save\_load\_kg
  - module, 80
- dicee.read\_preprocess\_save\_load\_kg.preprocess
  - module, 80
- dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk
  - module, 81
- dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk
  - module, 82
- dicee.read\_preprocess\_save\_load\_kg.util
  - module, 82
- dicee.sanity\_checkers
  - module, 128
- dicee.scripts
  - module, 86
- dicee.scripts.index
  - module, 86
- dicee.scripts.run
  - module, 87
- dicee.scripts.serve
  - module, 87
- dicee.static\_funcs
  - module, 129
- dicee.static\_funcs\_training
  - module, 132
- dicee.static\_preprocess\_funcs
  - module, 132
- dicee.trainer
  - module, 88
- dicee.trainer.dice\_trainer
  - module, 88
- dicee.trainer.torch\_trainer
  - module, 90
- dicee.trainer.torch\_trainer\_ddp
  - module, 91
- DistMult (*class in dicee*), 137
- DistMult (*class in dicee.models*), 54
- DistMult (*class in dicee.models.real*), 37
- download\_file() (*in module dicee*), 157
- download\_file() (*in module dicee.static\_funcs*), 131
- download\_files\_from\_url() (*in module dicee*), 157
- download\_files\_from\_url() (*in module dicee.static\_funcs*), 131

download\_pretrained\_model() (in module dicee), 157  
download\_pretrained\_model() (in module dicee.static\_funcs), 132  
dropout (dicee.models.transformers.GPTConfig attribute), 43  
DualE (class in dicee), 144  
DualE (class in dicee.models), 79  
DualE (class in dicee.models.dualE), 27  
dummy\_eval() (dicee.evaluator.Evaluator method), 120

## E

efficient\_zero\_grad() (in module dicee.static\_funcs\_training), 132  
embedding\_dim (dicee.config.Namespace attribute), 107  
enable\_log (in module dicee.static\_preprocess\_funcs), 133  
end() (dicee.Execute method), 164  
end() (dicee.executer.Execute method), 121  
entities\_str (dicee.knowledge\_graph.KG property), 122  
estimate\_mfu() (dicee.models.transformers.GPT method), 44  
estimate\_q() (in module dicee.callbacks), 103  
Eval (class in dicee.callbacks), 104  
eval() (dicee.evaluator.Evaluator method), 119  
eval\_lp\_performance() (dicee.KGE method), 159  
eval\_lp\_performance() (dicee.knowledge\_graph\_embeddings.KGE method), 123  
eval\_model (dicee.config.Namespace attribute), 108  
eval\_rank\_of\_head\_and\_tail\_byte\_pair\_encoded\_entity() (dicee.evaluator.Evaluator method), 119  
eval\_rank\_of\_head\_and\_tail\_entity() (dicee.evaluator.Evaluator method), 119  
eval\_with\_bpe\_vs\_all() (dicee.evaluator.Evaluator method), 119  
eval\_with\_byte() (dicee.evaluator.Evaluator method), 119  
eval\_with\_data() (dicee.evaluator.Evaluator method), 120  
eval\_with\_vs\_all() (dicee.evaluator.Evaluator method), 119  
evaluate() (in module dicee), 157  
evaluate() (in module dicee.static\_funcs), 131  
evaluate\_bpe\_lp() (in module dicee.static\_funcs\_training), 132  
evaluate\_link\_prediction\_performance() (in module dicee.eval\_static\_funcs), 118  
evaluate\_link\_prediction\_performance\_with\_bpe() (in module dicee.eval\_static\_funcs), 118  
evaluate\_link\_prediction\_performance\_with\_bpe\_reciprocals() (in module dicee.eval\_static\_funcs), 118  
evaluate\_link\_prediction\_performance\_with\_reciprocals() (in module dicee.eval\_static\_funcs), 118  
evaluate\_lp() (dicee.evaluator.Evaluator method), 120  
evaluate\_lp() (in module dicee.static\_funcs\_training), 132  
evaluate\_lp\_bpe\_k\_vs\_all() (dicee.evaluator.Evaluator method), 119  
evaluate\_lp\_bpe\_k\_vs\_all() (in module dicee.eval\_static\_funcs), 118  
evaluate\_lp\_k\_vs\_all() (dicee.evaluator.Evaluator method), 119  
evaluate\_lp\_with\_byte() (dicee.evaluator.Evaluator method), 119  
Evaluator (class in dicee.evaluator), 119  
Execute (class in dicee), 163  
Execute (class in dicee.executer), 120  
Experiment (class in dicee.analyse\_experiments), 100  
exponential\_function() (in module dicee), 157  
exponential\_function() (in module dicee.static\_funcs), 131  
extract\_input\_outputs() (dicee.trainer.torch\_trainer\_ddp.DDPTrainer method), 92  
extract\_input\_outputs() (dicee.trainer.torch\_trainer\_ddp.NodeTrainer method), 91  
extract\_input\_outputs\_set\_device() (dicee.trainer.torch\_trainer.TorchTrainer method), 90

## F

feature\_map\_dropout\_rate (dicee.config.Namespace attribute), 109  
fill\_query() (dicee.query\_generator.QueryGenerator method), 127  
fill\_query() (dicee.QueryGenerator method), 172  
find\_missing\_triples() (dicee.KGE method), 162  
find\_missing\_triples() (dicee.knowledge\_graph\_embeddings.KGE method), 126  
fit() (dicee.trainer.torch\_trainer\_ddp.TorchDDPTrainer method), 91  
fit() (dicee.trainer.torch\_trainer.TorchTrainer method), 90  
FMult (class in dicee.models), 77  
FMult (class in dicee.models.function\_space), 29  
FMult2 (class in dicee.models), 77  
FMult2 (class in dicee.models.function\_space), 29  
forward() (dicee.BaseKGE method), 155  
forward() (dicee.BytE method), 153  
forward() (dicee.models.base\_model.BaseKGE method), 16  
forward() (dicee.models.base\_model.IdentityClass static method), 17

`forward()` (*dicee.models.BaseKGE method*), 51, 53, 55, 59, 63, 74, 76  
`forward()` (*dicee.models.IdentityClass static method*), 52, 60, 64  
`forward()` (*dicee.models.transformers.Block method*), 43  
`forward()` (*dicee.models.transformers.Byte method*), 39  
`forward()` (*dicee.models.transformers.CausalSelfAttention method*), 41  
`forward()` (*dicee.models.transformers.GPT method*), 43  
`forward()` (*dicee.models.transformers.LayerNorm method*), 41  
`forward()` (*dicee.models.transformers.MLP method*), 42  
`forward_backward_update()` (*dicee.trainer.torch\_trainer.TorchTrainer method*), 90  
`forward_byte_pair_encoded_k_vs_all()` (*dicee.BaseKGE method*), 155  
`forward_byte_pair_encoded_k_vs_all()` (*dicee.models.base\_model.BaseKGE method*), 16  
`forward_byte_pair_encoded_k_vs_all()` (*dicee.models.BaseKGE method*), 51, 53, 55, 58, 63, 74, 76  
`forward_byte_pair_encoded_triple()` (*dicee.BaseKGE method*), 155  
`forward_byte_pair_encoded_triple()` (*dicee.models.base\_model.BaseKGE method*), 16  
`forward_byte_pair_encoded_triple()` (*dicee.models.BaseKGE method*), 51, 53, 55, 58, 63, 74, 76  
`forward_k_vs_all()` (*dicee.AConEx method*), 146  
`forward_k_vs_all()` (*dicee.AConvO method*), 146  
`forward_k_vs_all()` (*dicee.AConvQ method*), 147  
`forward_k_vs_all()` (*dicee.BaseKGE method*), 155  
`forward_k_vs_all()` (*dicee.CMult method*), 137  
`forward_k_vs_all()` (*dicee.ComplEx method*), 146  
`forward_k_vs_all()` (*dicee.ConEx method*), 148  
`forward_k_vs_all()` (*dicee.ConvO method*), 148  
`forward_k_vs_all()` (*dicee.ConvQ method*), 147  
`forward_k_vs_all()` (*dicee.DeCaL method*), 142  
`forward_k_vs_all()` (*dicee.DistMult method*), 137  
`forward_k_vs_all()` (*dicee.DualE method*), 145  
`forward_k_vs_all()` (*dicee.Keci method*), 140  
`forward_k_vs_all()` (*dicee.models.AConEx method*), 57  
`forward_k_vs_all()` (*dicee.models.AConvO method*), 66  
`forward_k_vs_all()` (*dicee.models.AConvQ method*), 62  
`forward_k_vs_all()` (*dicee.models.base\_model.BaseKGE method*), 16  
`forward_k_vs_all()` (*dicee.models.BaseKGE method*), 51, 53, 56, 59, 63, 74, 76  
`forward_k_vs_all()` (*dicee.models.clifford.CMult method*), 19  
`forward_k_vs_all()` (*dicee.models.clifford.DeCaL method*), 23  
`forward_k_vs_all()` (*dicee.models.clifford.Keci method*), 21  
`forward_k_vs_all()` (*dicee.models.CMult method*), 70  
`forward_k_vs_all()` (*dicee.models.ComplEx method*), 58  
`forward_k_vs_all()` (*dicee.models.complex.AConEx method*), 26  
`forward_k_vs_all()` (*dicee.models.complex.ComplEx method*), 27  
`forward_k_vs_all()` (*dicee.models.complex.ConEx method*), 26  
`forward_k_vs_all()` (*dicee.models.ConEx method*), 56  
`forward_k_vs_all()` (*dicee.models.ConvO method*), 66  
`forward_k_vs_all()` (*dicee.models.ConvQ method*), 62  
`forward_k_vs_all()` (*dicee.models.DeCaL method*), 71  
`forward_k_vs_all()` (*dicee.models.DistMult method*), 54  
`forward_k_vs_all()` (*dicee.models.DualE method*), 80  
`forward_k_vs_all()` (*dicee.models.dualE.DualE method*), 28  
`forward_k_vs_all()` (*dicee.models.Keci method*), 68  
`forward_k_vs_all()` (*dicee.models.octonion.AConvO method*), 33  
`forward_k_vs_all()` (*dicee.models.octonion.ConvO method*), 33  
`forward_k_vs_all()` (*dicee.models.octonion.OMult method*), 32  
`forward_k_vs_all()` (*dicee.models.OMult method*), 65  
`forward_k_vs_all()` (*dicee.models.pykeen\_models.PykeenKGE method*), 34  
`forward_k_vs_all()` (*dicee.models.PykeenKGE method*), 75  
`forward_k_vs_all()` (*dicee.models.QMult method*), 61  
`forward_k_vs_all()` (*dicee.models.quaternion.AConvQ method*), 37  
`forward_k_vs_all()` (*dicee.models.quaternion.ConvQ method*), 36  
`forward_k_vs_all()` (*dicee.models.quaternion.QMult method*), 36  
`forward_k_vs_all()` (*dicee.models.real.DistMult method*), 37  
`forward_k_vs_all()` (*dicee.models.real.Shallom method*), 38  
`forward_k_vs_all()` (*dicee.models.real.TransE method*), 37  
`forward_k_vs_all()` (*dicee.models.Shallom method*), 54  
`forward_k_vs_all()` (*dicee.models.TransE method*), 54  
`forward_k_vs_all()` (*dicee.OMult method*), 150  
`forward_k_vs_all()` (*dicee.PykeenKGE method*), 152  
`forward_k_vs_all()` (*dicee.QMult method*), 150  
`forward_k_vs_all()` (*dicee.Shallom method*), 151

`forward_k_vs_all()` (*dicee.TransE method*), 141  
`forward_k_vs_sample()` (*dicee.AConEx method*), 146  
`forward_k_vs_sample()` (*dicee.BaseKGE method*), 155  
`forward_k_vs_sample()` (*dicee.ConEx method*), 148  
`forward_k_vs_sample()` (*dicee.DistMult method*), 138  
`forward_k_vs_sample()` (*dicee.Keci method*), 140  
`forward_k_vs_sample()` (*dicee.models.AConEx method*), 57  
`forward_k_vs_sample()` (*dicee.models.base\_model.BaseKGE method*), 16  
`forward_k_vs_sample()` (*dicee.models.BaseKGE method*), 51, 53, 56, 59, 63, 74, 76  
`forward_k_vs_sample()` (*dicee.models.clifford.Keci method*), 21  
`forward_k_vs_sample()` (*dicee.models.complex.AConEx method*), 26  
`forward_k_vs_sample()` (*dicee.models.complex.ConEx method*), 26  
`forward_k_vs_sample()` (*dicee.models.ConEx method*), 56  
`forward_k_vs_sample()` (*dicee.models.DistMult method*), 54  
`forward_k_vs_sample()` (*dicee.models.Keci method*), 68  
`forward_k_vs_sample()` (*dicee.models.pykeen\_models.PykeenKGE method*), 34  
`forward_k_vs_sample()` (*dicee.models.PykeenKGE method*), 75  
`forward_k_vs_sample()` (*dicee.models.QMult method*), 61  
`forward_k_vs_sample()` (*dicee.models.quaternion.QMult method*), 36  
`forward_k_vs_sample()` (*dicee.models.real.DistMult method*), 37  
`forward_k_vs_sample()` (*dicee.PykeenKGE method*), 152  
`forward_k_vs_sample()` (*dicee.QMult method*), 150  
`forward_k_vs_with_explicit()` (*dicee.Keci method*), 140  
`forward_k_vs_with_explicit()` (*dicee.models.clifford.Keci method*), 21  
`forward_k_vs_with_explicit()` (*dicee.models.Keci method*), 68  
`forward_triples()` (*dicee.AConEx method*), 146  
`forward_triples()` (*dicee.AConvO method*), 146  
`forward_triples()` (*dicee.AConvQ method*), 147  
`forward_triples()` (*dicee.BaseKGE method*), 155  
`forward_triples()` (*dicee.CMult method*), 137  
`forward_triples()` (*dicee.ConEx method*), 148  
`forward_triples()` (*dicee.ConvO method*), 148  
`forward_triples()` (*dicee.ConvQ method*), 147  
`forward_triples()` (*dicee.DeCaL method*), 141  
`forward_triples()` (*dicee.DualE method*), 145  
`forward_triples()` (*dicee.Keci method*), 140  
`forward_triples()` (*dicee.LFMult method*), 151  
`forward_triples()` (*dicee.models.AConEx method*), 57  
`forward_triples()` (*dicee.models.AConvO method*), 66  
`forward_triples()` (*dicee.models.AConvQ method*), 62  
`forward_triples()` (*dicee.models.base\_model.BaseKGE method*), 16  
`forward_triples()` (*dicee.models.BaseKGE method*), 51, 53, 56, 59, 63, 74, 76  
`forward_triples()` (*dicee.models.clifford.CMult method*), 18  
`forward_triples()` (*dicee.models.clifford.DeCaL method*), 22  
`forward_triples()` (*dicee.models.clifford.Keci method*), 21  
`forward_triples()` (*dicee.models.CMult method*), 70  
`forward_triples()` (*dicee.models.complex.AConEx method*), 26  
`forward_triples()` (*dicee.models.complex.ConEx method*), 26  
`forward_triples()` (*dicee.models.ConEx method*), 56  
`forward_triples()` (*dicee.models.ConvO method*), 66  
`forward_triples()` (*dicee.models.ConvQ method*), 61  
`forward_triples()` (*dicee.models.DeCaL method*), 71  
`forward_triples()` (*dicee.models.DualE method*), 79  
`forward_triples()` (*dicee.models.dualE.DualE method*), 28  
`forward_triples()` (*dicee.models.FMult method*), 77  
`forward_triples()` (*dicee.models.FMult2 method*), 78  
`forward_triples()` (*dicee.models.function\_space.FMult method*), 29  
`forward_triples()` (*dicee.models.function\_space.FMult2 method*), 29  
`forward_triples()` (*dicee.models.function\_space.GFMult method*), 29  
`forward_triples()` (*dicee.models.function\_space.LFMult method*), 30  
`forward_triples()` (*dicee.models.function\_space.LFMult1 method*), 29  
`forward_triples()` (*dicee.models.GFMult method*), 77  
`forward_triples()` (*dicee.models.Keci method*), 69  
`forward_triples()` (*dicee.models.LFMult method*), 78  
`forward_triples()` (*dicee.models.LFMult1 method*), 78  
`forward_triples()` (*dicee.models.octonion.AConvO method*), 33  
`forward_triples()` (*dicee.models.octonion.ConvO method*), 33  
`forward_triples()` (*dicee.models.Pyke method*), 55



`forward_triples()` (*dicee.models.pykeen\_models.PykeenKGE method*), 34  
`forward_triples()` (*dicee.models.PykeenKGE method*), 75  
`forward_triples()` (*dicee.models.quaternion.AConvQ method*), 37  
`forward_triples()` (*dicee.models.quaternion.ConvQ method*), 36  
`forward_triples()` (*dicee.models.real.Pyke method*), 38  
`forward_triples()` (*dicee.models.real.Shallom method*), 38  
`forward_triples()` (*dicee.models.Shallom method*), 54  
`forward_triples()` (*dicee.Pyke method*), 137  
`forward_triples()` (*dicee.PykeenKGE method*), 152  
`forward_triples()` (*dicee.Shallom method*), 151  
`from_pretrained()` (*dicee.models.transformers.GPT class method*), 44  
`func_triple_to_bpe_representation()` (*dicee.knowledge\_graph.KG method*), 122  
`function()` (*dicee.models.FMult2 method*), 77  
`function()` (*dicee.models.function\_space.FMult2 method*), 29

## G

`generate()` (*dicee.BytE method*), 153  
`generate()` (*dicee.KGE method*), 159  
`generate()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 123  
`generate()` (*dicee.models.transformers.BytE method*), 40  
`generate_queries()` (*dicee.query\_generator.QueryGenerator method*), 128  
`generate_queries()` (*dicee.QueryGenerator method*), 172  
`get()` (*dicee.scripts.serve.NeuralSearcher method*), 88  
`get_aswa_state_dict()` (*dicee.callbacks.ASWA method*), 104  
`get_bpe_head_and_relation_representation()` (*dicee.BaseKGE method*), 156  
`get_bpe_head_and_relation_representation()` (*dicee.models.base\_model.BaseKGE method*), 17  
`get_bpe_head_and_relation_representation()` (*dicee.models.BaseKGE method*), 52, 54, 56, 59, 63, 75, 77  
`get_bpe_token_representation()` (*dicee.abstracts.BaseInteractiveKGE method*), 95  
`get_callbacks()` (*in module dicee.trainer.dice\_trainer*), 88  
`get_default_arguments()` (*in module dicee.analyse\_experiments*), 100  
`get_default_arguments()` (*in module dicee.scripts.index*), 86  
`get_default_arguments()` (*in module dicee.scripts.run*), 87  
`get_default_arguments()` (*in module dicee.scripts.serve*), 88  
`get_domain_of_relation()` (*dicee.abstracts.BaseInteractiveKGE method*), 95  
`get_ee_vocab()` (*in module dicee*), 156  
`get_ee_vocab()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 84  
`get_ee_vocab()` (*in module dicee.static\_funcs*), 130  
`get_ee_vocab()` (*in module dicee.static\_preprocess\_funcs*), 133  
`get_embeddings()` (*dicee.BaseKGE method*), 156  
`get_embeddings()` (*dicee.models.base\_model.BaseKGE method*), 17  
`get_embeddings()` (*dicee.models.BaseKGE method*), 52, 54, 56, 59, 63, 75, 77  
`get_embeddings()` (*dicee.models.real.Shallom method*), 38  
`get_embeddings()` (*dicee.models.Shallom method*), 54  
`get_embeddings()` (*dicee.Shallom method*), 151  
`get_entity_embeddings()` (*dicee.abstracts.BaseInteractiveKGE method*), 96  
`get_entity_index()` (*dicee.abstracts.BaseInteractiveKGE method*), 96  
`get_er_vocab()` (*in module dicee*), 156  
`get_er_vocab()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 84  
`get_er_vocab()` (*in module dicee.static\_funcs*), 130  
`get_er_vocab()` (*in module dicee.static\_preprocess\_funcs*), 133  
`get_eval_report()` (*dicee.abstracts.BaseInteractiveKGE method*), 95  
`get_head_relation_representation()` (*dicee.BaseKGE method*), 155  
`get_head_relation_representation()` (*dicee.models.base\_model.BaseKGE method*), 17  
`get_head_relation_representation()` (*dicee.models.BaseKGE method*), 51, 53, 56, 59, 63, 74, 77  
`get_kronecker_triple_representation()` (*dicee.callbacks.KronE method*), 106  
`get_num_params()` (*dicee.models.transformers.GPT method*), 43  
`get_padded_bpe_triple_representation()` (*dicee.abstracts.BaseInteractiveKGE method*), 95  
`get_queries()` (*dicee.query\_generator.QueryGenerator method*), 128  
`get_queries()` (*dicee.QueryGenerator method*), 172  
`get_range_of_relation()` (*dicee.abstracts.BaseInteractiveKGE method*), 95  
`get_re_vocab()` (*in module dicee*), 156  
`get_re_vocab()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 84  
`get_re_vocab()` (*in module dicee.static\_funcs*), 130  
`get_re_vocab()` (*in module dicee.static\_preprocess\_funcs*), 133  
`get_relation_embeddings()` (*dicee.abstracts.BaseInteractiveKGE method*), 97  
`get_relation_index()` (*dicee.abstracts.BaseInteractiveKGE method*), 96  
`get_sentence_representation()` (*dicee.BaseKGE method*), 155

`get_sentence_representation()` (*dicее.models.base\_model.BaseKGE method*), 17  
`get_sentence_representation()` (*dicее.models.BaseKGE method*), 51, 53, 56, 59, 63, 74, 77  
`get_transductive_entity_embeddings()` (*dicее.KGE method*), 159  
`get_transductive_entity_embeddings()` (*dicее.knowledge\_graph\_embeddings.KGE method*), 123  
`get_triple_representation()` (*dicее.BaseKGE method*), 155  
`get_triple_representation()` (*dicее.models.base\_model.BaseKGE method*), 16  
`get_triple_representation()` (*dicее.models.BaseKGE method*), 51, 53, 56, 59, 63, 74, 76  
`GFMult` (*class in dicее.models*), 77  
`GFMult` (*class in dicее.models.function\_space*), 29  
`GPT` (*class in dicее.models.transformers*), 43  
`GPTConfig` (*class in dicее.models.transformers*), 43  
`gpus` (*dicее.config.Namespace attribute*), 107  
`gradient_accumulation_steps` (*dicее.config.Namespace attribute*), 108  
`ground_queries()` (*dicее.query\_generator.QueryGenerator method*), 128  
`ground_queries()` (*dicее.QueryGenerator method*), 172

## H

`hidden_dropout_rate` (*dicее.config.Namespace attribute*), 109

## I

`IdentityClass` (*class in dicее.models*), 52, 59, 63  
`IdentityClass` (*class in dicее.models.base\_model*), 17  
`index_triple()` (*dicее.abstracts.BaseInteractiveKGE method*), 96  
`index_triples_with_pandas()` (*in module dicее.read\_preprocess\_save\_load\_kg.util*), 84  
`init_param` (*dicее.config.Namespace attribute*), 108  
`init_params_with_sanity_checking()` (*dicее.BaseKGE method*), 155  
`init_params_with_sanity_checking()` (*dicее.models.base\_model.BaseKGE method*), 16  
`init_params_with_sanity_checking()` (*dicее.models.BaseKGE method*), 51, 53, 55, 58, 63, 74, 76  
`initialize_dataloader()` (*dicее.DICE\_Trainer method*), 158  
`initialize_dataloader()` (*dicее.trainer.DICE\_Trainer method*), 93  
`initialize_dataloader()` (*dicее.trainer.dice\_trainer.DICE\_Trainer method*), 89  
`initialize_dataset()` (*dicее.DICE\_Trainer method*), 158  
`initialize_dataset()` (*dicее.trainer.DICE\_Trainer method*), 93  
`initialize_dataset()` (*dicее.trainer.dice\_trainer.DICE\_Trainer method*), 89  
`initialize_or_load_model()` (*dicее.DICE\_Trainer method*), 158  
`initialize_or_load_model()` (*dicее.trainer.DICE\_Trainer method*), 92  
`initialize_or_load_model()` (*dicее.trainer.dice\_trainer.DICE\_Trainer method*), 89  
`initialize_trainer()` (*dicее.DICE\_Trainer method*), 158  
`initialize_trainer()` (*dicее.trainer.DICE\_Trainer method*), 92  
`initialize_trainer()` (*dicее.trainer.dice\_trainer.DICE\_Trainer method*), 89  
`initialize_trainer()` (*in module dicее.trainer.dice\_trainer*), 88  
`input_dropout_rate` (*dicее.config.Namespace attribute*), 109  
`intialize_model()` (*in module dicее*), 157  
`intialize_model()` (*in module dicее.static\_funcs*), 131  
`is_seen()` (*dicее.abstracts.BaseInteractiveKGE method*), 96  
`is_sparql_endpoint_alive()` (*in module dicее.sanity\_checkers*), 128

## K

`k_fold_cross_validation()` (*dicее.DICE\_Trainer method*), 158  
`k_fold_cross_validation()` (*dicее.trainer.DICE\_Trainer method*), 93  
`k_fold_cross_validation()` (*dicее.trainer.dice\_trainer.DICE\_Trainer method*), 89  
`k_vs_all_score()` (*dicее.ComplEx static method*), 146  
`k_vs_all_score()` (*dicее.DistMult method*), 137  
`k_vs_all_score()` (*dicее.Keci method*), 140  
`k_vs_all_score()` (*dicее.models.clifford.Keci method*), 21  
`k_vs_all_score()` (*dicее.models.ComplEx static method*), 57  
`k_vs_all_score()` (*dicее.models.complex.ComplEx static method*), 27  
`k_vs_all_score()` (*dicее.models.DistMult method*), 54  
`k_vs_all_score()` (*dicее.models.Keci method*), 68  
`k_vs_all_score()` (*dicее.models.octonion.OMult method*), 32  
`k_vs_all_score()` (*dicее.models.OMult method*), 65  
`k_vs_all_score()` (*dicее.models.QMult method*), 61  
`k_vs_all_score()` (*dicее.models.quaternion.QMult method*), 36  
`k_vs_all_score()` (*dicее.models.real.DistMult method*), 37  
`k_vs_all_score()` (*dicее.OMult method*), 150  
`k_vs_all_score()` (*dicее.QMult method*), 149



Keci (class in dicee), 138  
 Keci (class in dicee.models), 66  
 Keci (class in dicee.models.clifford), 19  
 KeciBase (class in dicee), 138  
 KeciBase (class in dicee.models), 69  
 KeciBase (class in dicee.models.clifford), 22  
 kernel\_size (dicee.config.Namespace attribute), 108  
 KG (class in dicee.knowledge\_graph), 122  
 KGE (class in dicee), 159  
 KGE (class in dicee.knowledge\_graph\_embeddings), 123  
 KGSaveCallback (class in dicee.callbacks), 102  
 KronE (class in dicee.callbacks), 105  
 KvsAll (class in dicee), 166  
 KvsAll (class in dicee.dataset\_classes), 111  
 kvsall\_score () (dicee.DualE method), 144  
 kvsall\_score () (dicee.models.DualE method), 79  
 kvsall\_score () (dicee.models.dualE.DualE method), 27  
 KvsSampleDataset (class in dicee), 167  
 KvsSampleDataset (class in dicee.dataset\_classes), 113

## L

LayerNorm (class in dicee.models.transformers), 41  
 LFMult (class in dicee), 151  
 LFMult (class in dicee.models), 78  
 LFMult (class in dicee.models.function\_space), 30  
 LFMult1 (class in dicee.models), 78  
 LFMult1 (class in dicee.models.function\_space), 29  
 linear () (dicee.LFMult method), 151  
 linear () (dicee.models.function\_space.LFMult method), 30  
 linear () (dicee.models.LFMult method), 78  
 list2tuple () (dicee.query\_generator.QueryGenerator method), 127  
 list2tuple () (dicee.QueryGenerator method), 172  
 load () (dicee.read\_preprocess\_save\_load\_kg.LoadSaveToDisk method), 86  
 load () (dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk.LoadSaveToDisk method), 82  
 load\_indexed\_data () (dicee.Execute method), 163  
 load\_indexed\_data () (dicee.executer.Execute method), 120  
 load\_json () (in module dicee), 157  
 load\_json () (in module dicee.static\_funcs), 131  
 load\_model () (in module dicee), 156  
 load\_model () (in module dicee.static\_funcs), 130  
 load\_model\_ensemble () (in module dicee), 156  
 load\_model\_ensemble () (in module dicee.static\_funcs), 130  
 load\_numpy () (in module dicee), 157  
 load\_numpy () (in module dicee.static\_funcs), 131  
 load\_numpy\_ndarray () (in module dicee.read\_preprocess\_save\_load\_kg.util), 84  
 load\_pickle () (in module dicee), 156, 164  
 load\_pickle () (in module dicee.read\_preprocess\_save\_load\_kg.util), 84  
 load\_pickle () (in module dicee.static\_funcs), 130  
 load\_queries () (dicee.query\_generator.QueryGenerator method), 128  
 load\_queries () (dicee.QueryGenerator method), 172  
 load\_queries\_and\_answers () (dicee.query\_generator.QueryGenerator static method), 128  
 load\_queries\_and\_answers () (dicee.QueryGenerator static method), 173  
 load\_with\_pandas () (in module dicee.read\_preprocess\_save\_load\_kg.util), 84  
 LoadSaveToDisk (class in dicee.read\_preprocess\_save\_load\_kg), 86  
 LoadSaveToDisk (class in dicee.read\_preprocess\_save\_load\_kg.save\_load\_disk), 82  
 loss\_function () (dicee.BytE method), 153  
 loss\_function () (dicee.models.base\_model.BaseKGELighting method), 12  
 loss\_function () (dicee.models.BaseKGELighting method), 47  
 loss\_function () (dicee.models.transformers.BytE method), 39  
 lr (dicee.config.Namespace attribute), 107

## M

main () (in module dicee.scripts.index), 86  
 main () (in module dicee.scripts.run), 87  
 main () (in module dicee.scripts.serve), 88  
 mapping\_from\_first\_two\_cols\_to\_third () (in module dicee), 164  
 mapping\_from\_first\_two\_cols\_to\_third () (in module dicee.static\_preprocess\_funcs), 133

- `mem_of_model()` (*dicee.models.base\_model.BaseKGELightning method*), 11
- `mem_of_model()` (*dicee.models.BaseKGELightning method*), 46
- MLP (*class in dicee.models.transformers*), 41
- `model` (*dicee.config.Namespace attribute*), 107
- `module`
  - `dicee`, 10
  - `dicee.abstracts`, 93
  - `dicee.analyse_experiments`, 99
  - `dicee.callbacks`, 100
  - `dicee.config`, 106
  - `dicee.dataset_classes`, 109
  - `dicee.eval_static_funcs`, 118
  - `dicee.evaluator`, 119
  - `dicee.executer`, 120
  - `dicee.knowledge_graph`, 122
  - `dicee.knowledge_graph_embeddings`, 123
  - `dicee.models`, 10
  - `dicee.models.base_model`, 10
  - `dicee.models.clifford`, 18
  - `dicee.models.complex`, 25
  - `dicee.models.dualE`, 27
  - `dicee.models.function_space`, 28
  - `dicee.models.octonion`, 31
  - `dicee.models.pykeen_models`, 33
  - `dicee.models.quaternion`, 34
  - `dicee.models.real`, 37
  - `dicee.models.static_funcs`, 38
  - `dicee.models.transformers`, 38
  - `dicee.query_generator`, 127
  - `dicee.read_preprocess_save_load_kg`, 80
  - `dicee.read_preprocess_save_load_kg.preprocess`, 80
  - `dicee.read_preprocess_save_load_kg.read_from_disk`, 81
  - `dicee.read_preprocess_save_load_kg.save_load_disk`, 82
  - `dicee.read_preprocess_save_load_kg.util`, 82
  - `dicee.sanity_checkers`, 128
  - `dicee.scripts`, 86
  - `dicee.scripts.index`, 86
  - `dicee.scripts.run`, 87
  - `dicee.scripts.serve`, 87
  - `dicee.static_funcs`, 129
  - `dicee.static_funcs_training`, 132
  - `dicee.static_preprocess_funcs`, 132
  - `dicee.trainer`, 88
  - `dicee.trainer.dice_trainer`, 88
  - `dicee.trainer.torch_trainer`, 90
  - `dicee.trainer.torch_trainer_ddp`, 91
- `MultiClassClassificationDataset` (*class in dicee*), 165
- `MultiClassClassificationDataset` (*class in dicee.dataset\_classes*), 111
- `MultiLabelDataset` (*class in dicee*), 165
- `MultiLabelDataset` (*class in dicee.dataset\_classes*), 110

## N

- `n_embd` (*dicee.models.transformers.GPTConfig attribute*), 43
- `n_head` (*dicee.models.transformers.GPTConfig attribute*), 43
- `n_layer` (*dicee.models.transformers.GPTConfig attribute*), 43
- `name` (*dicee.abstracts.BaseInteractiveKGE property*), 96
- `Namespace` (*class in dicee.config*), 107
- `neg_ratio` (*dicee.config.Namespace attribute*), 108
- `negnorm()` (*dicee.KGE method*), 161
- `negnorm()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 126
- `NegSampleDataset` (*class in dicee*), 168
- `NegSampleDataset` (*class in dicee.dataset\_classes*), 113
- `neural_searcher` (*in module dicee.scripts.serve*), 88
- `NeuralSearcher` (*class in dicee.scripts.serve*), 88
- `NodeTrainer` (*class in dicee.trainer.torch\_trainer\_ddp*), 91
- `normalization` (*dicee.config.Namespace attribute*), 108
- `num_core` (*dicee.config.Namespace attribute*), 108

`num_epochs` (*dicee.config.Namespace* attribute), 107  
`num_folds_for_cv` (*dicee.config.Namespace* attribute), 108  
`num_of_output_channels` (*dicee.config.Namespace* attribute), 108  
`numpy_data_type_changer()` (in module *dicee*), 156  
`numpy_data_type_changer()` (in module *dicee.static\_funcs*), 130

## O

`octonion_mul()` (in module *dicee.models*), 64  
`octonion_mul()` (in module *dicee.models.octonion*), 31  
`octonion_mul_norm()` (in module *dicee.models*), 64  
`octonion_mul_norm()` (in module *dicee.models.octonion*), 31  
`octonion_normalizer()` (*dicee.AConvO* static method), 146  
`octonion_normalizer()` (*dicee.ConvO* static method), 148  
`octonion_normalizer()` (*dicee.models.AConvO* static method), 66  
`octonion_normalizer()` (*dicee.models.ConvO* static method), 65  
`octonion_normalizer()` (*dicee.models.octonion.AConvO* static method), 33  
`octonion_normalizer()` (*dicee.models.octonion.ConvO* static method), 33  
`octonion_normalizer()` (*dicee.models.octonion.OMult* static method), 32  
`octonion_normalizer()` (*dicee.models.OMult* static method), 65  
`octonion_normalizer()` (*dicee.OMult* static method), 150  
`OMult` (class in *dicee*), 150  
`OMult` (class in *dicee.models*), 64  
`OMult` (class in *dicee.models.octonion*), 31  
`on_epoch_end()` (*dicee.callbacks.KGESaveCallback* method), 103  
`on_epoch_end()` (*dicee.callbacks.PseudoLabellingCallback* method), 103  
`on_fit_end()` (*dicee.abstracts.AbstractCallback* method), 98  
`on_fit_end()` (*dicee.abstracts.AbstractPPECallback* method), 99  
`on_fit_end()` (*dicee.abstracts.AbstractTrainer* method), 94  
`on_fit_end()` (*dicee.callbacks.AccumulateEpochLossCallback* method), 101  
`on_fit_end()` (*dicee.callbacks.ASWA* method), 103  
`on_fit_end()` (*dicee.callbacks.Eval* method), 105  
`on_fit_end()` (*dicee.callbacks.KGESaveCallback* method), 103  
`on_fit_end()` (*dicee.callbacks.PrintCallback* method), 101  
`on_fit_start()` (*dicee.abstracts.AbstractCallback* method), 97  
`on_fit_start()` (*dicee.abstracts.AbstractPPECallback* method), 99  
`on_fit_start()` (*dicee.abstracts.AbstractTrainer* method), 94  
`on_fit_start()` (*dicee.callbacks.Eval* method), 104  
`on_fit_start()` (*dicee.callbacks.KGESaveCallback* method), 102  
`on_fit_start()` (*dicee.callbacks.KronE* method), 106  
`on_fit_start()` (*dicee.callbacks.PrintCallback* method), 101  
`on_init_end()` (*dicee.abstracts.AbstractCallback* method), 97  
`on_init_start()` (*dicee.abstracts.AbstractCallback* method), 97  
`on_train_batch_end()` (*dicee.abstracts.AbstractCallback* method), 98  
`on_train_batch_end()` (*dicee.abstracts.AbstractTrainer* method), 94  
`on_train_batch_end()` (*dicee.callbacks.Eval* method), 105  
`on_train_batch_end()` (*dicee.callbacks.KGESaveCallback* method), 102  
`on_train_batch_end()` (*dicee.callbacks.PrintCallback* method), 101  
`on_train_batch_start()` (*dicee.callbacks.Perturb* method), 106  
`on_train_epoch_end()` (*dicee.abstracts.AbstractCallback* method), 98  
`on_train_epoch_end()` (*dicee.abstracts.AbstractTrainer* method), 94  
`on_train_epoch_end()` (*dicee.callbacks.ASWA* method), 104  
`on_train_epoch_end()` (*dicee.callbacks.Eval* method), 105  
`on_train_epoch_end()` (*dicee.callbacks.KGESaveCallback* method), 102  
`on_train_epoch_end()` (*dicee.callbacks.PrintCallback* method), 102  
`on_train_epoch_end()` (*dicee.models.base\_model.BaseKGELightning* method), 12  
`on_train_epoch_end()` (*dicee.models.BaseKGELightning* method), 47  
`OnevsAllDataset` (class in *dicee*), 165  
`OnevsAllDataset` (class in *dicee.dataset\_classes*), 111  
`optim` (*dicee.config.Namespace* attribute), 107

## P

`p` (*dicee.config.Namespace* attribute), 108  
`parameters()` (*dicee.abstracts.BaseInteractiveKGE* method), 97  
`path_single_kg` (*dicee.config.Namespace* attribute), 107  
`path_to_store_single_run` (*dicee.config.Namespace* attribute), 107  
`Perturb` (class in *dicee.callbacks*), 106  
`poly_NN()` (*dicee.LFMult* method), 151

poly\_NN() (*dicee.models.function\_space.LFMult method*), 30  
 poly\_NN() (*dicee.models.LFMult method*), 78  
 polynomial() (*dicee.LFMult method*), 152  
 polynomial() (*dicee.models.function\_space.LFMult method*), 30  
 polynomial() (*dicee.models.LFMult method*), 79  
 pop() (*dicee.LFMult method*), 152  
 pop() (*dicee.models.function\_space.LFMult method*), 30  
 pop() (*dicee.models.LFMult method*), 79  
 predict() (*dicee.KGE method*), 160  
 predict() (*dicee.knowledge\_graph\_embeddings.KGE method*), 124  
 predict\_data\_loader() (*dicee.models.base\_model.BaseKGELightning method*), 13  
 predict\_data\_loader() (*dicee.models.BaseKGELightning method*), 48  
 predict\_missing\_head\_entity() (*dicee.KGE method*), 159  
 predict\_missing\_head\_entity() (*dicee.knowledge\_graph\_embeddings.KGE method*), 123  
 predict\_missing\_relations() (*dicee.KGE method*), 159  
 predict\_missing\_relations() (*dicee.knowledge\_graph\_embeddings.KGE method*), 124  
 predict\_missing\_tail\_entity() (*dicee.KGE method*), 160  
 predict\_missing\_tail\_entity() (*dicee.knowledge\_graph\_embeddings.KGE method*), 124  
 predict\_topk() (*dicee.KGE method*), 160  
 predict\_topk() (*dicee.knowledge\_graph\_embeddings.KGE method*), 125  
 prepare\_data() (*dicee.CVDataModule method*), 171  
 prepare\_data() (*dicee.dataset\_classes.CVDataModule method*), 116  
 preprocess\_with\_byte\_pair\_encoding() (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 85  
 preprocess\_with\_byte\_pair\_encoding() (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 81  
 preprocess\_with\_byte\_pair\_encoding\_with\_padding() (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 85  
 preprocess\_with\_byte\_pair\_encoding\_with\_padding() (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 81  
 preprocess\_with\_pandas() (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 85  
 preprocess\_with\_pandas() (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 81  
 preprocess\_with\_polars() (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 85  
 preprocess\_with\_polars() (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 81  
 preprocesses\_input\_args() (*in module dicee.static\_preprocess\_funcs*), 133  
 PreprocessKG (*class in dicee.read\_preprocess\_save\_load\_kg*), 85  
 PreprocessKG (*class in dicee.read\_preprocess\_save\_load\_kg.preprocess*), 80  
 print\_peak\_memory() (*in module dicee.trainer.torch\_trainer\_ddp*), 91  
 PrintCallback (*class in dicee.callbacks*), 101  
 PseudoLabellingCallback (*class in dicee.callbacks*), 103  
 Pyke (*class in dicee*), 137  
 Pyke (*class in dicee.models*), 55  
 Pyke (*class in dicee.models.real*), 38  
 pykeen\_model\_kwargs (*dicee.config.Namespace attribute*), 108  
 PykeenKGE (*class in dicee*), 152  
 PykeenKGE (*class in dicee.models*), 75  
 PykeenKGE (*class in dicee.models.pykeen\_models*), 34

## Q

q (*dicee.config.Namespace attribute*), 108  
 QMult (*class in dicee*), 148  
 QMult (*class in dicee.models*), 60  
 QMult (*class in dicee.models.quaternion*), 35  
 quaternion\_mul() (*in module dicee.models*), 58  
 quaternion\_mul() (*in module dicee.models.static\_funcs*), 38  
 quaternion\_mul\_with\_unit\_norm() (*in module dicee.models*), 60  
 quaternion\_mul\_with\_unit\_norm() (*in module dicee.models.quaternion*), 35  
 quaternion\_multiplication\_followed\_by\_inner\_product() (*dicee.models.QMult method*), 60  
 quaternion\_multiplication\_followed\_by\_inner\_product() (*dicee.models.quaternion.QMult method*), 35  
 quaternion\_multiplication\_followed\_by\_inner\_product() (*dicee.QMult method*), 149  
 quaternion\_normalizer() (*dicee.models.QMult static method*), 61  
 quaternion\_normalizer() (*dicee.models.quaternion.QMult static method*), 35  
 quaternion\_normalizer() (*dicee.QMult static method*), 149  
 QueryGenerator (*class in dicee*), 172  
 QueryGenerator (*class in dicee.query\_generator*), 127

## R

random\_prediction() (*in module dicee*), 157  
 random\_prediction() (*in module dicee.static\_funcs*), 131  
 random\_seed (*dicee.config.Namespace attribute*), 108

`read_from_disk()` (in module `dicee.read_preprocess_save_load_kg.util`), 84  
`read_from_triple_store()` (in module `dicee.read_preprocess_save_load_kg.util`), 84  
`read_only_few` (`dicee.config.Namespace` attribute), 108  
`read_or_load_kg()` (`dicee.Execute` method), 163  
`read_or_load_kg()` (`dicee.executer.Execute` method), 120  
`read_or_load_kg()` (in module `dicee`), 157  
`read_or_load_kg()` (in module `dicee.static_funcs`), 131  
`read_preprocess_index_serialize_data()` (`dicee.Execute` method), 163  
`read_preprocess_index_serialize_data()` (`dicee.executer.Execute` method), 120  
`read_with_pandas()` (in module `dicee.read_preprocess_save_load_kg.util`), 83  
`read_with_polars()` (in module `dicee.read_preprocess_save_load_kg.util`), 83  
`ReadFromDisk` (class in `dicee.read_preprocess_save_load_kg`), 86  
`ReadFromDisk` (class in `dicee.read_preprocess_save_load_kg.read_from_disk`), 81  
`relations_str` (`dicee.knowledge_graph.KG` property), 122  
`reload_dataset()` (in module `dicee`), 164  
`reload_dataset()` (in module `dicee.dataset_classes`), 110  
`remove_triples_from_train_with_condition()` (`dicee.read_preprocess_save_load_kg.PreprocessKG` method), 85  
`remove_triples_from_train_with_condition()` (`dicee.read_preprocess_save_load_kg.preprocess.PreprocessKG` method), 81  
`residual_convolution()` (`dicee.AConEx` method), 146  
`residual_convolution()` (`dicee.AConvO` method), 146  
`residual_convolution()` (`dicee.AConvQ` method), 147  
`residual_convolution()` (`dicee.ConEx` method), 148  
`residual_convolution()` (`dicee.ConvO` method), 148  
`residual_convolution()` (`dicee.ConvQ` method), 147  
`residual_convolution()` (`dicee.models.AConEx` method), 57  
`residual_convolution()` (`dicee.models.AConvO` method), 66  
`residual_convolution()` (`dicee.models.AConvQ` method), 62  
`residual_convolution()` (`dicee.models.complex.AConEx` method), 26  
`residual_convolution()` (`dicee.models.complex.ConEx` method), 26  
`residual_convolution()` (`dicee.models.ConEx` method), 56  
`residual_convolution()` (`dicee.models.ConvO` method), 65  
`residual_convolution()` (`dicee.models.ConvQ` method), 61  
`residual_convolution()` (`dicee.models.octonion.AConvO` method), 33  
`residual_convolution()` (`dicee.models.octonion.ConvO` method), 33  
`residual_convolution()` (`dicee.models.quaternion.AConvQ` method), 36  
`residual_convolution()` (`dicee.models.quaternion.ConvQ` method), 36  
`retrieve_embeddings()` (in module `dicee.scripts.serve`), 88  
`return_multi_hop_query_results()` (`dicee.KGE` method), 161  
`return_multi_hop_query_results()` (`dicee.knowledge_graph_embeddings.KGE` method), 126  
`root()` (in module `dicee.scripts.serve`), 88

## S

`sample_entity()` (`dicee.abstracts.BaseInteractiveKGE` method), 96  
`sample_relation()` (`dicee.abstracts.BaseInteractiveKGE` method), 96  
`sample_triples_ratio` (`dicee.config.Namespace` attribute), 108  
`sanity_checking_with_arguments()` (in module `dicee.sanity_checkers`), 128  
`save()` (`dicee.abstracts.BaseInteractiveKGE` method), 96  
`save()` (`dicee.read_preprocess_save_load_kg.LoadSaveToDisk` method), 86  
`save()` (`dicee.read_preprocess_save_load_kg.save_load_disk.LoadSaveToDisk` method), 82  
`save_checkpoint()` (`dicee.abstracts.AbstractTrainer` static method), 95  
`save_checkpoint_model()` (in module `dicee`), 156  
`save_checkpoint_model()` (in module `dicee.static_funcs`), 131  
`save_embeddings()` (in module `dicee`), 157  
`save_embeddings()` (in module `dicee.static_funcs`), 131  
`save_embeddings_as_csv` (`dicee.config.Namespace` attribute), 107  
`save_experiment()` (`dicee.analyse_experiments.Experiment` method), 100  
`save_model_at_every_epoch` (`dicee.config.Namespace` attribute), 108  
`save_numpy_ndarray()` (in module `dicee`), 156  
`save_numpy_ndarray()` (in module `dicee.read_preprocess_save_load_kg.util`), 84  
`save_numpy_ndarray()` (in module `dicee.static_funcs`), 130  
`save_pickle()` (in module `dicee`), 156  
`save_pickle()` (in module `dicee.read_preprocess_save_load_kg.util`), 84  
`save_pickle()` (in module `dicee.static_funcs`), 130  
`save_queries()` (`dicee.query_generator.QueryGenerator` method), 128  
`save_queries()` (`dicee.QueryGenerator` method), 172  
`save_queries_and_answers()` (`dicee.query_generator.QueryGenerator` static method), 128  
`save_queries_and_answers()` (`dicee.QueryGenerator` static method), 173

`save_trained_model()` (*dicee.Execute method*), 163  
`save_trained_model()` (*dicee.executer.Execute method*), 121  
`scalar_batch_NN()` (*dicee.LFMMult method*), 151  
`scalar_batch_NN()` (*dicee.models.function\_space.LFMMult method*), 30  
`scalar_batch_NN()` (*dicee.models.LFMMult method*), 78  
`score()` (*dicee.CMMult method*), 137  
`score()` (*dicee.ComplEx static method*), 146  
`score()` (*dicee.DistMult method*), 138  
`score()` (*dicee.Keci method*), 140  
`score()` (*dicee.models.clifford.CMMult method*), 18  
`score()` (*dicee.models.clifford.Keci method*), 21  
`score()` (*dicee.models.CMMult method*), 70  
`score()` (*dicee.models.ComplEx static method*), 57  
`score()` (*dicee.models.complex.ComplEx static method*), 27  
`score()` (*dicee.models.DistMult method*), 54  
`score()` (*dicee.models.Keci method*), 69  
`score()` (*dicee.models.octonion.OMult method*), 32  
`score()` (*dicee.models.OMult method*), 65  
`score()` (*dicee.models.QMMult method*), 61  
`score()` (*dicee.models.quaternion.QMMult method*), 36  
`score()` (*dicee.models.real.DistMult method*), 37  
`score()` (*dicee.models.real.TransE method*), 37  
`score()` (*dicee.models.TransE method*), 54  
`score()` (*dicee.OMult method*), 150  
`score()` (*dicee.QMMult method*), 149  
`score()` (*dicee.TransE method*), 141  
`scoring_technique` (*dicee.config.Namespace attribute*), 108  
`search()` (*dicee.scripts.serve.NeuralSearcher method*), 88  
`search_embeddings()` (*in module dicee.scripts.serve*), 88  
`select_model()` (*in module dicee*), 156  
`select_model()` (*in module dicee.static\_funcs*), 130  
`sequential_vocabulary_construction()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 85  
`sequential_vocabulary_construction()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 81  
`set_global_seed()` (*dicee.query\_generator.QueryGenerator method*), 127  
`set_global_seed()` (*dicee.QueryGenerator method*), 172  
`set_model_eval_mode()` (*dicee.abstracts.BaseInteractiveKGE method*), 96  
`set_model_train_mode()` (*dicee.abstracts.BaseInteractiveKGE method*), 95  
`setup()` (*dicee.CVDDataModule method*), 170  
`setup()` (*dicee.dataset\_classes.CVDDataModule method*), 115  
`Shallom` (*class in dicee*), 151  
`Shallom` (*class in dicee.models*), 54  
`Shallom` (*class in dicee.models.real*), 38  
`single_hop_query_answering()` (*dicee.KGE method*), 161  
`single_hop_query_answering()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 126  
`sparql_endpoint` (*dicee.config.Namespace attribute*), 107  
`start()` (*dicee.DICE\_Trainer method*), 158  
`start()` (*dicee.Execute method*), 164  
`start()` (*dicee.executer.Execute method*), 121  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.PreprocessKG method*), 85  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.preprocess.PreprocessKG method*), 80  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.read\_from\_disk.ReadFromDisk method*), 81  
`start()` (*dicee.read\_preprocess\_save\_load\_kg.ReadFromDisk method*), 86  
`start()` (*dicee.trainer.DICE\_Trainer method*), 93  
`start()` (*dicee.trainer.dice\_trainer.DICE\_Trainer method*), 89  
`storage_path` (*dicee.config.Namespace attribute*), 107  
`store()` (*in module dicee*), 156  
`store()` (*in module dicee.static\_funcs*), 131  
`store_ensemble()` (*dicee.abstracts.AbstractPPECallback method*), 99  
`swa` (*dicee.config.Namespace attribute*), 109

## T

`T()` (*dicee.DualE method*), 145  
`T()` (*dicee.models.DualE method*), 80  
`T()` (*dicee.models.dualE.DualE method*), 28  
`t_conorm()` (*dicee.KGE method*), 161  
`t_conorm()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 126  
`t_norm()` (*dicee.KGE method*), 161



`t_norm()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 126  
`tensor_t_norm()` (*dicee.KGE method*), 161  
`tensor_t_norm()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 126  
`test_data_loader()` (*dicee.models.base\_model.BaseKGELightning method*), 12  
`test_data_loader()` (*dicee.models.BaseKGELightning method*), 47  
`test_epoch_end()` (*dicee.models.base\_model.BaseKGELightning method*), 12  
`test_epoch_end()` (*dicee.models.BaseKGELightning method*), 47  
`timeit()` (*in module dicee*), 156, 164  
`timeit()` (*in module dicee.read\_preprocess\_save\_load\_kg.util*), 83  
`timeit()` (*in module dicee.static\_funcs*), 130  
`timeit()` (*in module dicee.static\_preprocess\_funcs*), 133  
`to_df()` (*dicee.analyse\_experiments.Experiment method*), 100  
`TorchDDPTrainer` (*class in dicee.trainer.torch\_trainer\_ddp*), 91  
`TorchTrainer` (*class in dicee.trainer.torch\_trainer*), 90  
`train()` (*dicee.KGE method*), 163  
`train()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 127  
`train()` (*dicee.trainer.torch\_trainer\_ddp.DDPTrainer method*), 92  
`train()` (*dicee.trainer.torch\_trainer\_ddp.NodeTrainer method*), 92  
`train_data_loader()` (*dicee.CVDataModule method*), 169  
`train_data_loader()` (*dicee.dataset\_classes.CVDataModule method*), 115  
`train_data_loader()` (*dicee.models.base\_model.BaseKGELightning method*), 14  
`train_data_loader()` (*dicee.models.BaseKGELightning method*), 48  
`train_k_vs_all()` (*dicee.KGE method*), 163  
`train_k_vs_all()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 127  
`train_triples()` (*dicee.KGE method*), 162  
`train_triples()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 127  
`trainer` (*dicee.config.Namespace attribute*), 108  
`training_step()` (*dicee.BytE method*), 153  
`training_step()` (*dicee.models.base\_model.BaseKGELightning method*), 11  
`training_step()` (*dicee.models.BaseKGELightning method*), 46  
`training_step()` (*dicee.models.transformers.BytE method*), 40  
`TransE` (*class in dicee*), 141  
`TransE` (*class in dicee.models*), 54  
`TransE` (*class in dicee.models.real*), 37  
`transfer_batch_to_device()` (*dicee.CVDataModule method*), 170  
`transfer_batch_to_device()` (*dicee.dataset\_classes.CVDataModule method*), 116  
`trapezoid()` (*dicee.models.FMult2 method*), 77  
`trapezoid()` (*dicee.models.function\_space.FMult2 method*), 29  
`tri_score()` (*dicee.LFMult method*), 151  
`tri_score()` (*dicee.models.function\_space.LFMult method*), 30  
`tri_score()` (*dicee.models.function\_space.LFMult1 method*), 29  
`tri_score()` (*dicee.models.LFMult method*), 78  
`tri_score()` (*dicee.models.LFMult1 method*), 78  
`triple_score()` (*dicee.KGE method*), 161  
`triple_score()` (*dicee.knowledge\_graph\_embeddings.KGE method*), 125  
`TriplePredictionDataset` (*class in dicee*), 168  
`TriplePredictionDataset` (*class in dicee.dataset\_classes*), 114  
`tuple2list()` (*dicee.query\_generator.QueryGenerator method*), 127  
`tuple2list()` (*dicee.QueryGenerator method*), 172

## U

`unmap()` (*dicee.query\_generator.QueryGenerator method*), 128  
`unmap()` (*dicee.QueryGenerator method*), 172  
`unmap_query()` (*dicee.query\_generator.QueryGenerator method*), 128  
`unmap_query()` (*dicee.QueryGenerator method*), 172

## V

`val_data_loader()` (*dicee.models.base\_model.BaseKGELightning method*), 13  
`val_data_loader()` (*dicee.models.BaseKGELightning method*), 48  
`validate_knowledge_graph()` (*in module dicee.sanity\_checkers*), 128  
`vocab_preparation()` (*dicee.evaluator.Evaluator method*), 119  
`vocab_size` (*dicee.models.transformers.GPTConfig attribute*), 43  
`vocab_to_parquet()` (*in module dicee*), 157  
`vocab_to_parquet()` (*in module dicee.static\_funcs*), 131  
`vtp_score()` (*dicee.LFMult method*), 151  
`vtp_score()` (*dicee.models.function\_space.LFMult method*), 30  
`vtp_score()` (*dicee.models.function\_space.LFMult1 method*), 30

`vtp_score()` (*dicee.models.LFMult method*), 78  
`vtp_score()` (*dicee.models.LFMult1 method*), 78

## W

`weight_decay` (*dicee.config.Namespace attribute*), 108  
`write_links()` (*dicee.query\_generator.QueryGenerator method*), 127  
`write_links()` (*dicee.QueryGenerator method*), 172  
`write_report()` (*dicee.Execute method*), 164  
`write_report()` (*dicee.executer.Execute method*), 121