TextBrewer: An Open-Source Knowledge Distillation Toolkit for Natural Language Processing

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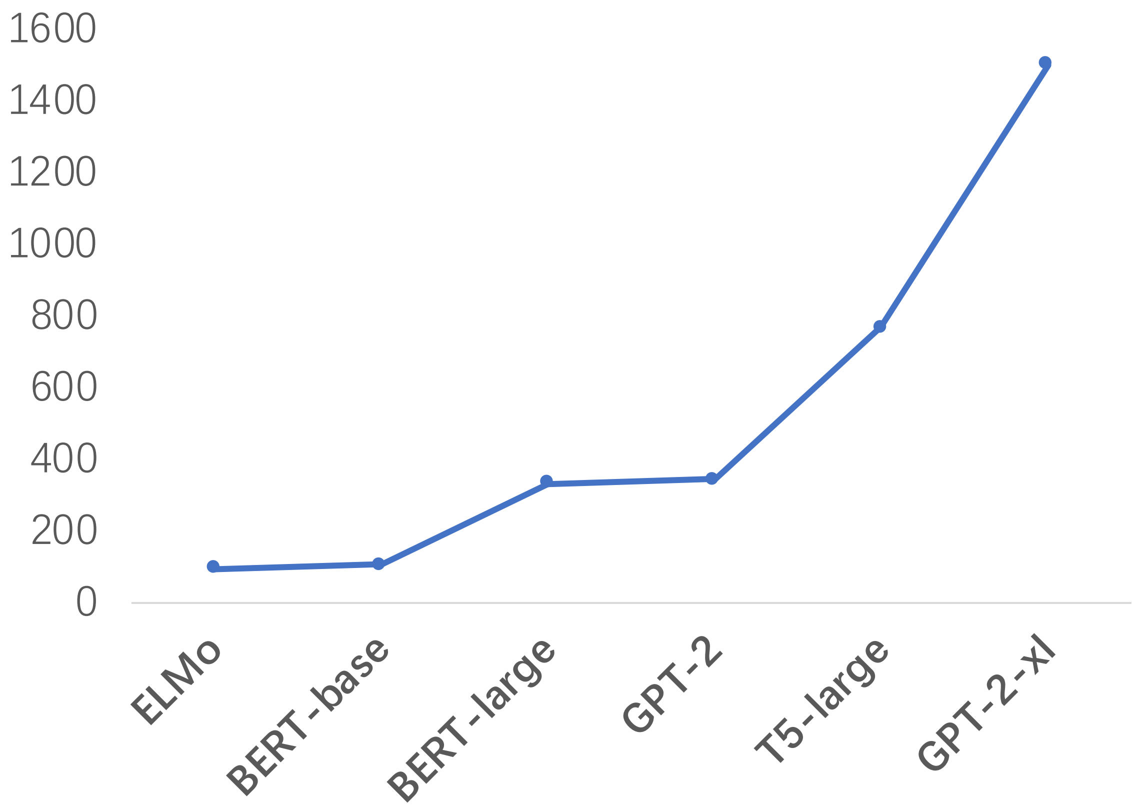
Pretrained Models in NLP

- Size of large pretrained models
  - **ELMo** – 94M parameters
  - **BERT$_{\text{base}}$** – 108M parameters
  - **BERT$_{\text{large}}$** – 334M parameters
  - **GPT2** – 1.5B parameters
  - **T5-11B** – 11B parameters
  - **GPT3** – 170B parameters



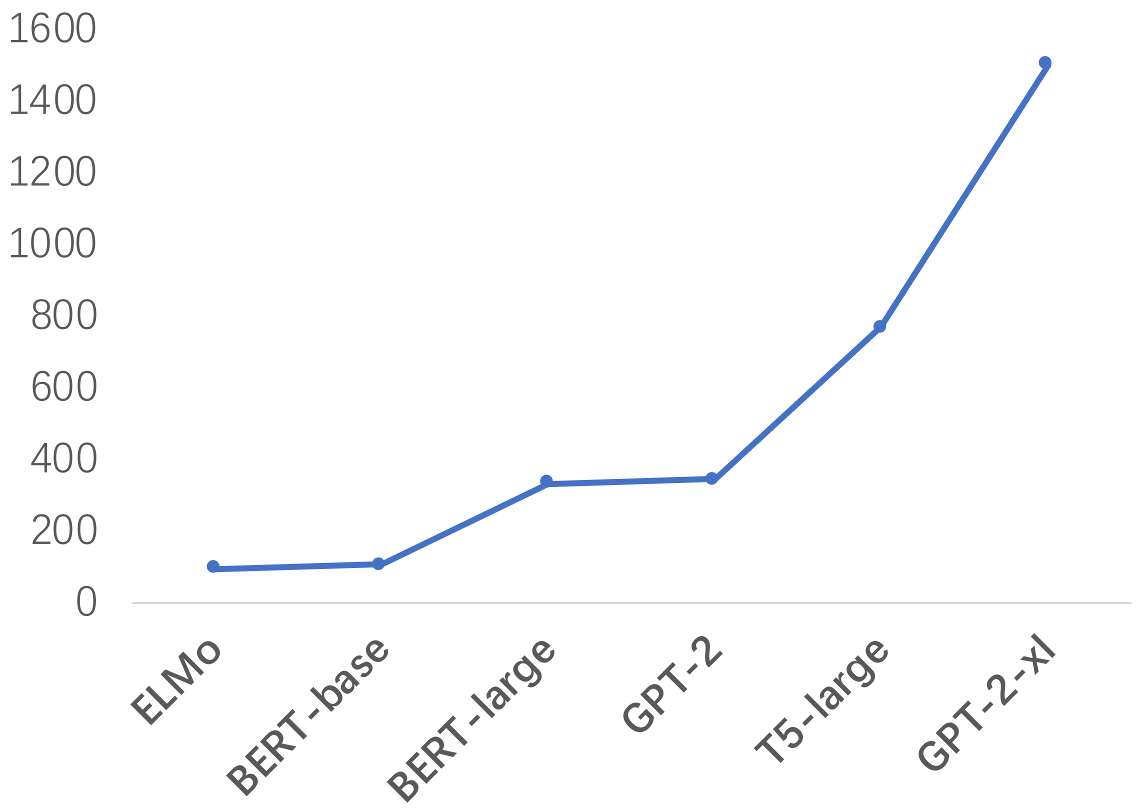
Pretrained Models in NLP

Large models

- Slow inference speed
- State-of-the-art performance
- Resource-demanding

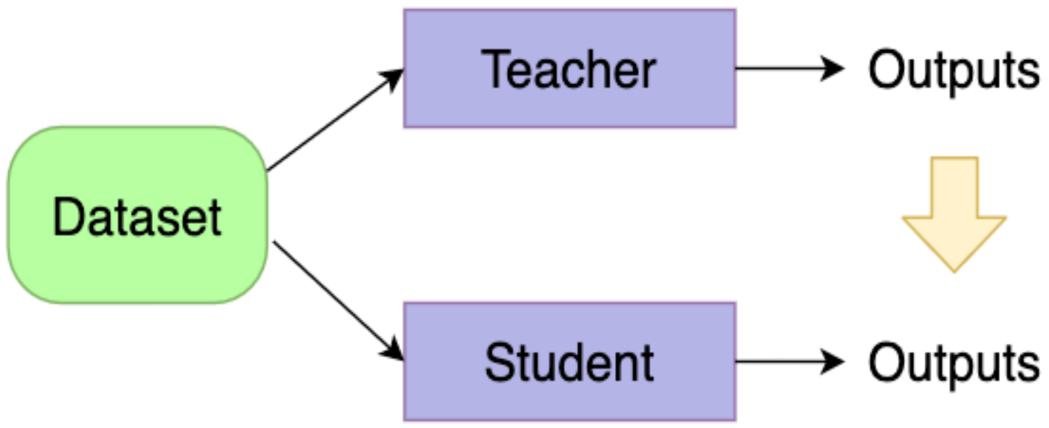
Small models

- Fast inference speed
- Inferior performance
- Resource-friendly



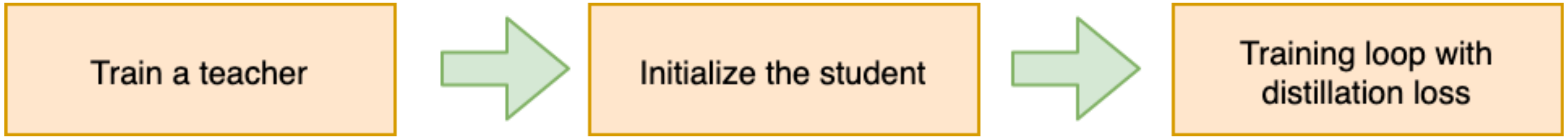
What is knowledge distillation (KD)?

Knowledge distillation is a technique of transferring knowledge from a large (teacher) model to a small (student) model, <u>without significant loss in performance.</u>



Motivation

- Various distillation methods usually share a common workflow:

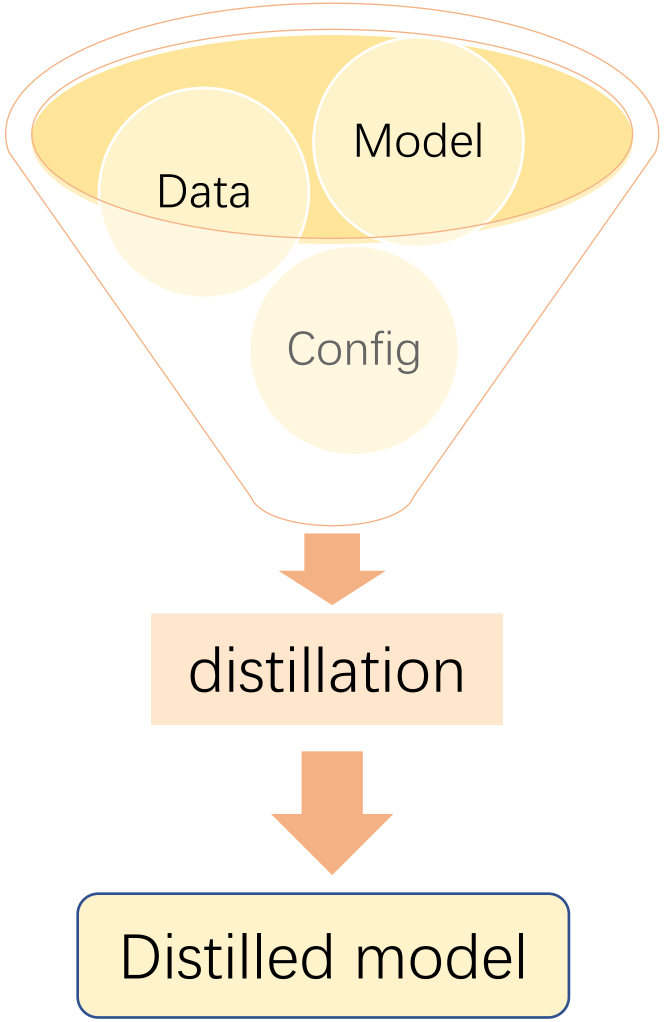


- A reusable distillation workflow framework
    1. Reduce redundant coding
    2. Distillation losses/strategies as plugins
    3. Achieve great flexibility in experimenting with different methods

TextBrewer

- A PyTorch based knowledge distillation toolkit for NLP

- Features
  - Flexibility
    - customizable configurations
  - Easy-to-use
    - re-uses the most parts of their existing training scripts
  - Wide-model-support
    - especially transformer-based models
  - Built for NLP
    - have been test on different tasks

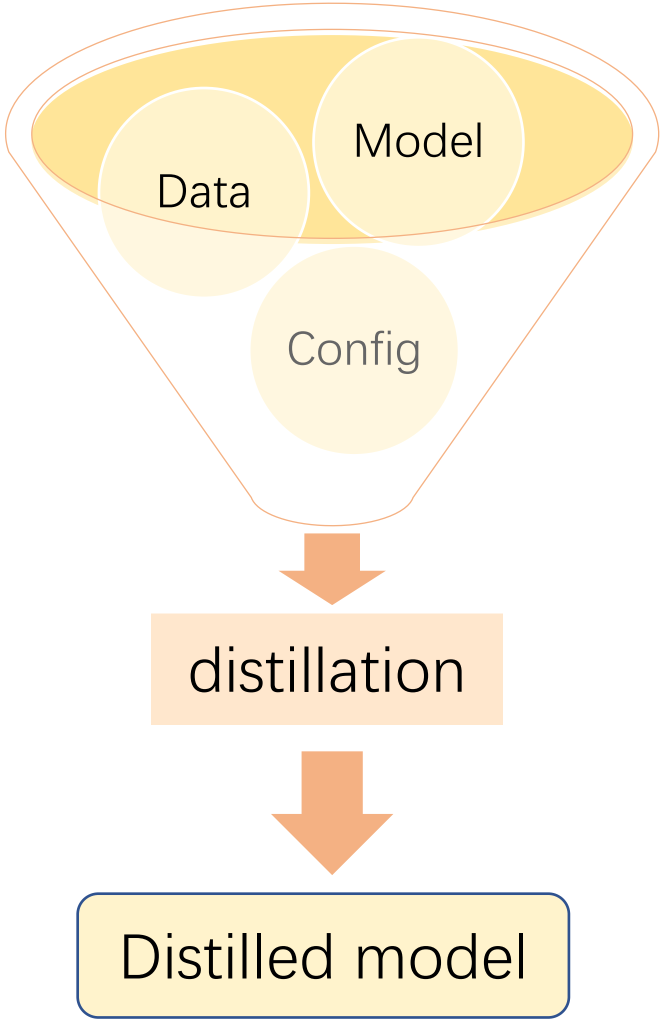


- Available at : http://textbrewer.hfl-rc.com

TextBrewer

- A PyTorch based knowledge distillation toolkit for NLP

Tasks	Models	Distillation modes
Text Classification	BERT/RoBERTa	Traditional
MRC	Electra	Multi-teacher
Sequence Labeling	LSTM/GRU	Multi-task
…	…	normal training



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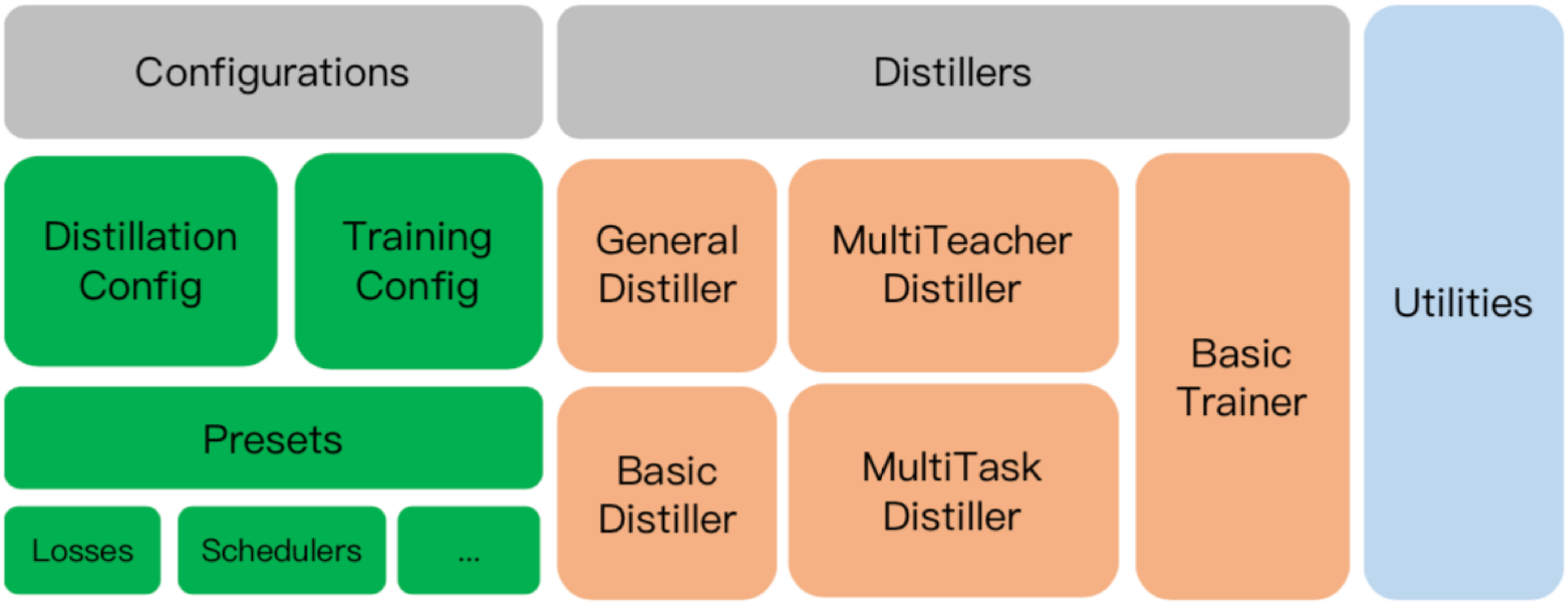
Architecture

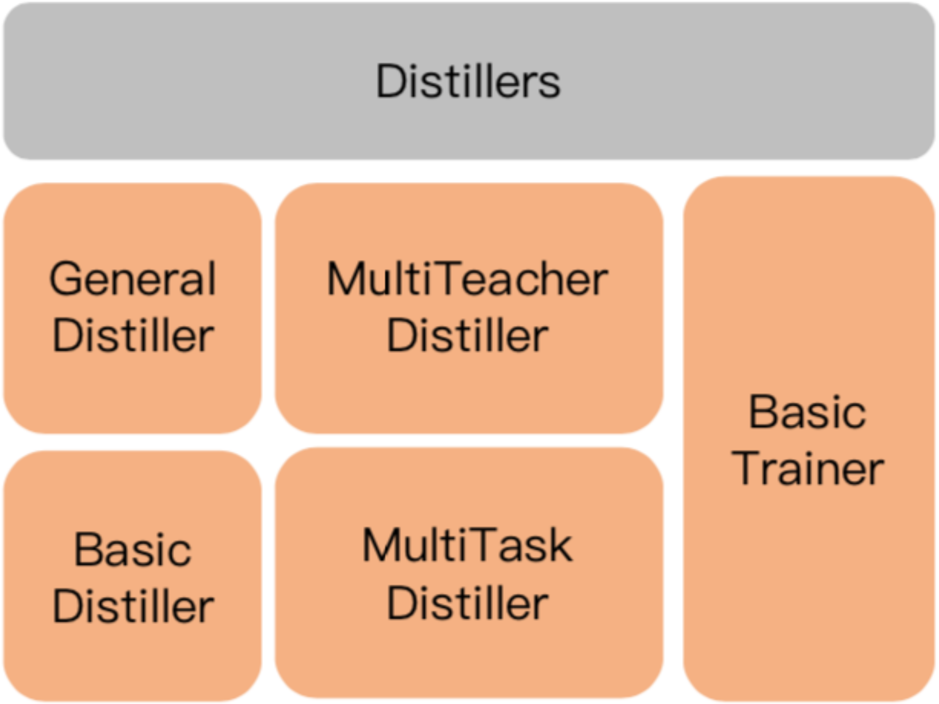
- An overview of the main functionalities of TextBrewer



Distillers

- Automatically train/distill and save models

- Five distillers:
  1. `BasicDistiller`
  2. `GeneralDistiller`
  3. `MultiTeacherDistiller`
  4. `MultiTaskDistiller`
  5. `BasicTrainer`



Configurations

1. `TrainingConfig`
   - gradient accumulation steps
   - checkpoint frequency
   - log directory
   - output directory
   - device

2. `DistillationConfig`
   - temperature
   - KD loss type
   - KD loss weight
   - hard-label loss weight
   - intermediate matches
   - if enable caching logits
   - …

Configurations

1. TrainingConfig

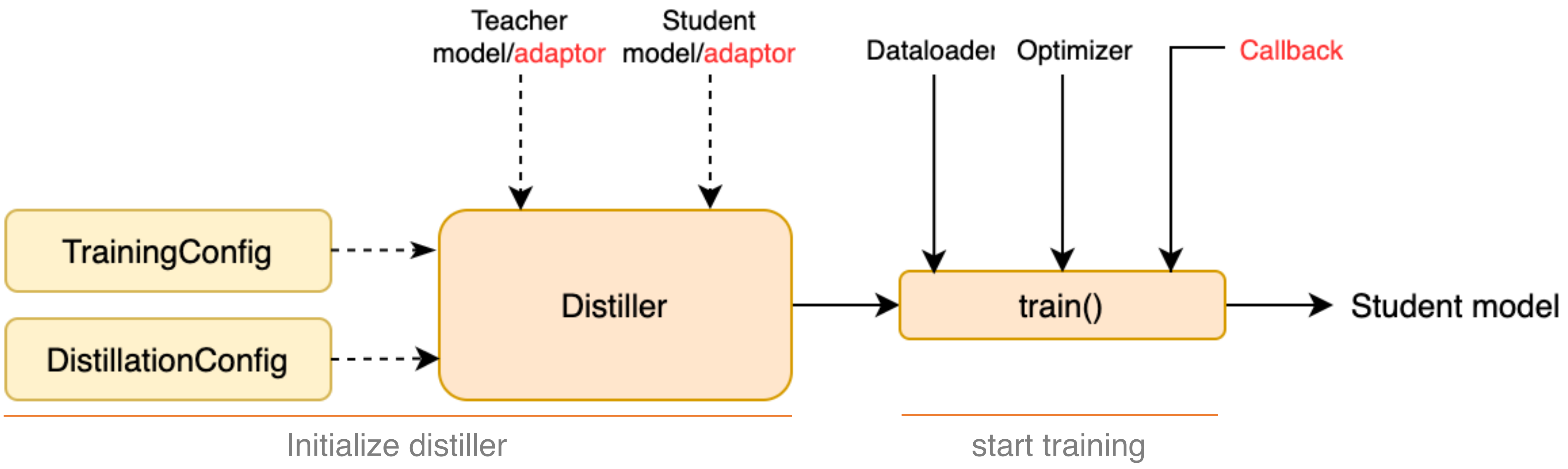
```
{"gradient_accumulation_steps" : 1,
 "ckpt_epoch_frequency" : 1,
 "ckpt_steps" : None,
 "log_dir" : "./logs",
 "output_dir" : "./saved_models",
 "device" : "cuda"}
```

2. DistillationConfig

```
{"temperature" : 8,
 "temperature_scheduler": None,
 "hard_label_weight": 0,
 "hard_label_weight_scheduler": None,
 "kd_loss_type": "ce",
 "kd_loss_weight": 1,
 "kd_loss_weight_scheduler": None,
 "probability_shift": False,
 "intermediate_matches": [
 1  {"layer_T": 0, "layer_S": 0, "feature": "hidden",
     "loss": "hidden_mse", "weight": 1, "proj": ["linear",312,768]},
 2  {"layer_T": 3, "layer_S": 1, "feature": "hidden",
     "loss": "hidden_mse", "weight": 1, "proj": ["linear",312,768]},
 3  {"layer_T": 6, "layer_S": 2, "feature": "hidden",
     "loss": "hidden_mse", "weight": 1, "proj": ["linear",312,768]},
 4  {"layer_T": 9, "layer_S": 3, "feature": "hidden",
     "loss": "hidden_mse", "weight": 1, "proj": ["linear",312,768]},
 5  {"layer_T": 12, "layer_S": 4, "feature": "hidden",
     "loss": "hidden_mse", "weight": 1, "proj": ["linear",312,768]},
 6  {"layer_T": [0,0], "layer_S":[0,0], "feature": "hidden",
     "loss": "nst", "weight": 1},
 7  {"layer_T": [3,3], "layer_S":[1,1], "feature": "hidden",
     "loss": "nst", "weight": 1},
 8  {"layer_T": [6,6], "layer_S":[2,2], "feature": "hidden",
     "loss": "nst", "weight": 1},
 9  {"layer_T": [9,9], "layer_S":[3,3], "feature": "hidden",
     "loss": "nst", "weight": 1},
 10 {"layer_T": [12,12], "layer_S":[4,4], "feature": "hidden",
     "loss": "nst", "weight": 1}]}
```

Workflow

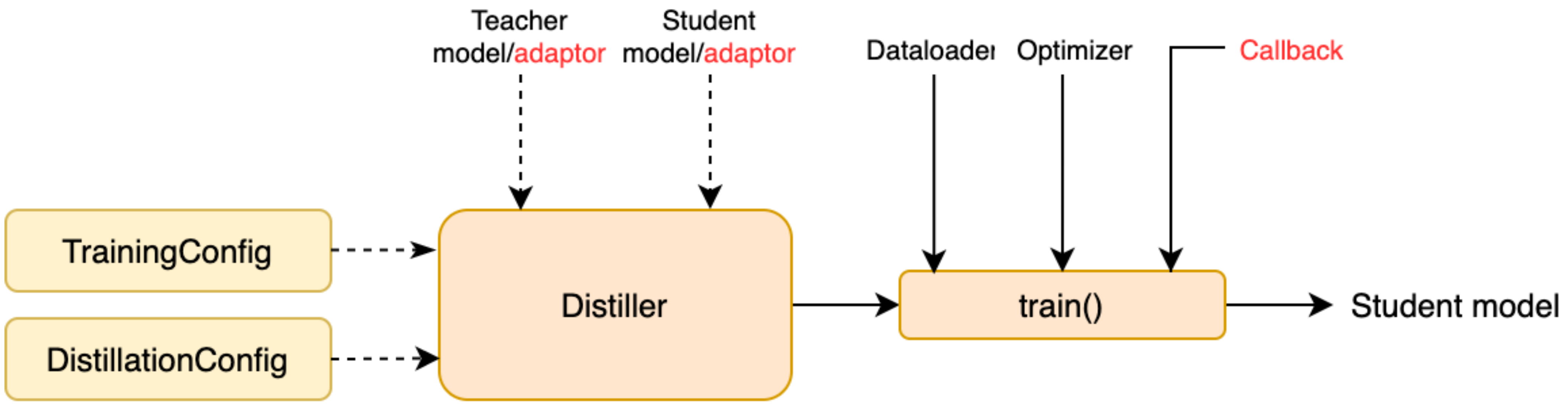
- Distillation with TextBrewer:



1. Initialize configurations and a distiller
2. Define **adaptors** and a **callback function**
3. Call the **train** method of the distiller

Workflow

- Distillation with TextBrewer



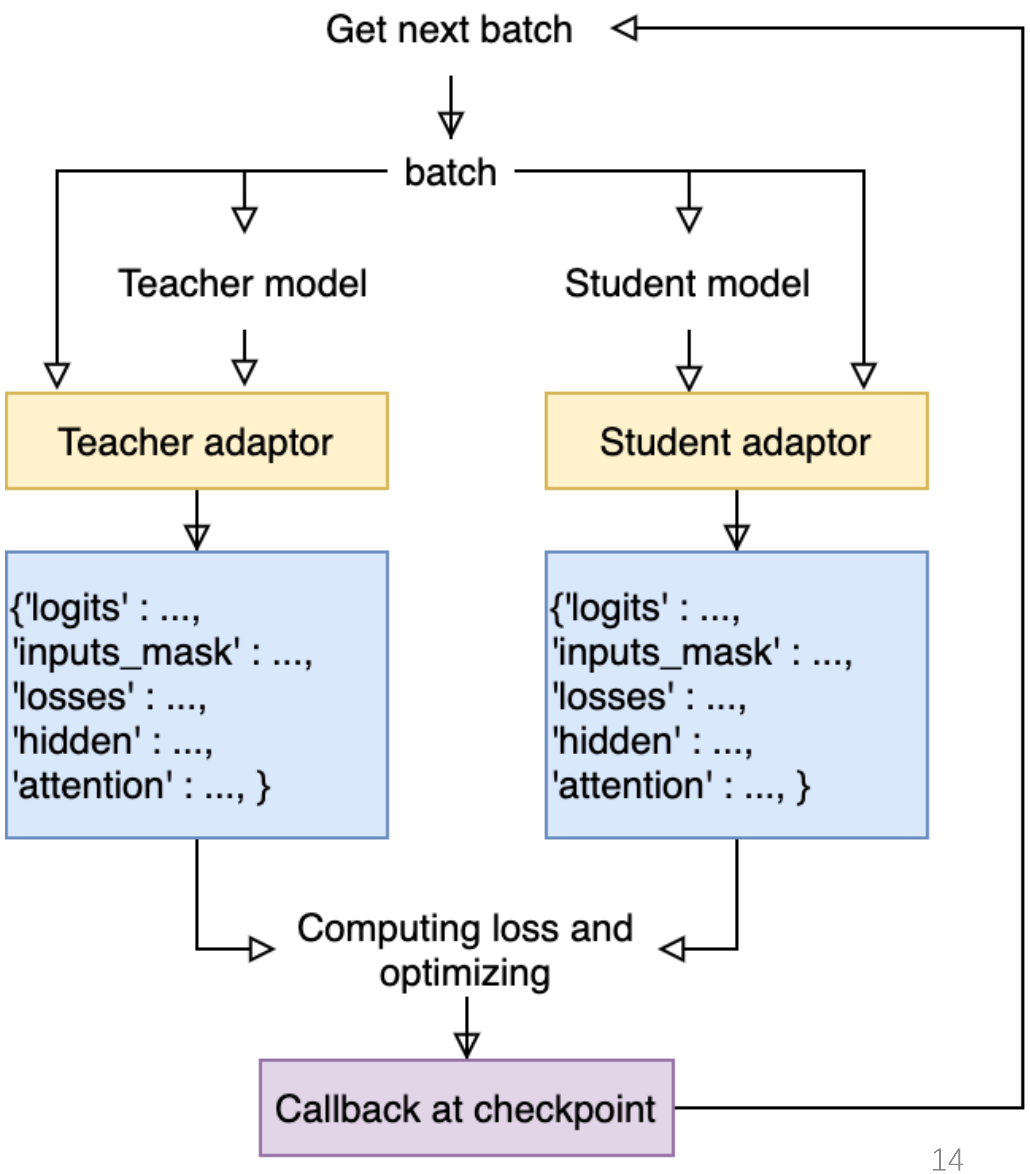

```
train_config = TrainingConfig()
distill_config = DistillationConfig()

distiller = GeneralTrainer(train_config = train_config, distill_config = distill_config,
                           model_T = teacher, model_S = student,
                           adatpor_T = my_adaptor_T, adaptor_S = my_adaptor_S)
with distiller:
    distiller.train(optimizer, dataloader, num_epochs, callback=my_callback)
```

Adaptor

```
adatpor(batch: Union[Dict,Tuple], model_outputs: Tuple) -> Dict
```

- Translates the inputs and outputs for the distiller

```
'''
class Model(nn.Module):
    def forward(self, input_ids, attention_mask, labels, ...):
        ...
        return logits, hidden_states, loss
'''
def simpleAdaptor(batch, model_outputs):
    return {'logits': (model_outputs[0],),
            'hidden': model_outputs[1],
            'input_mask': batch[1]}
```

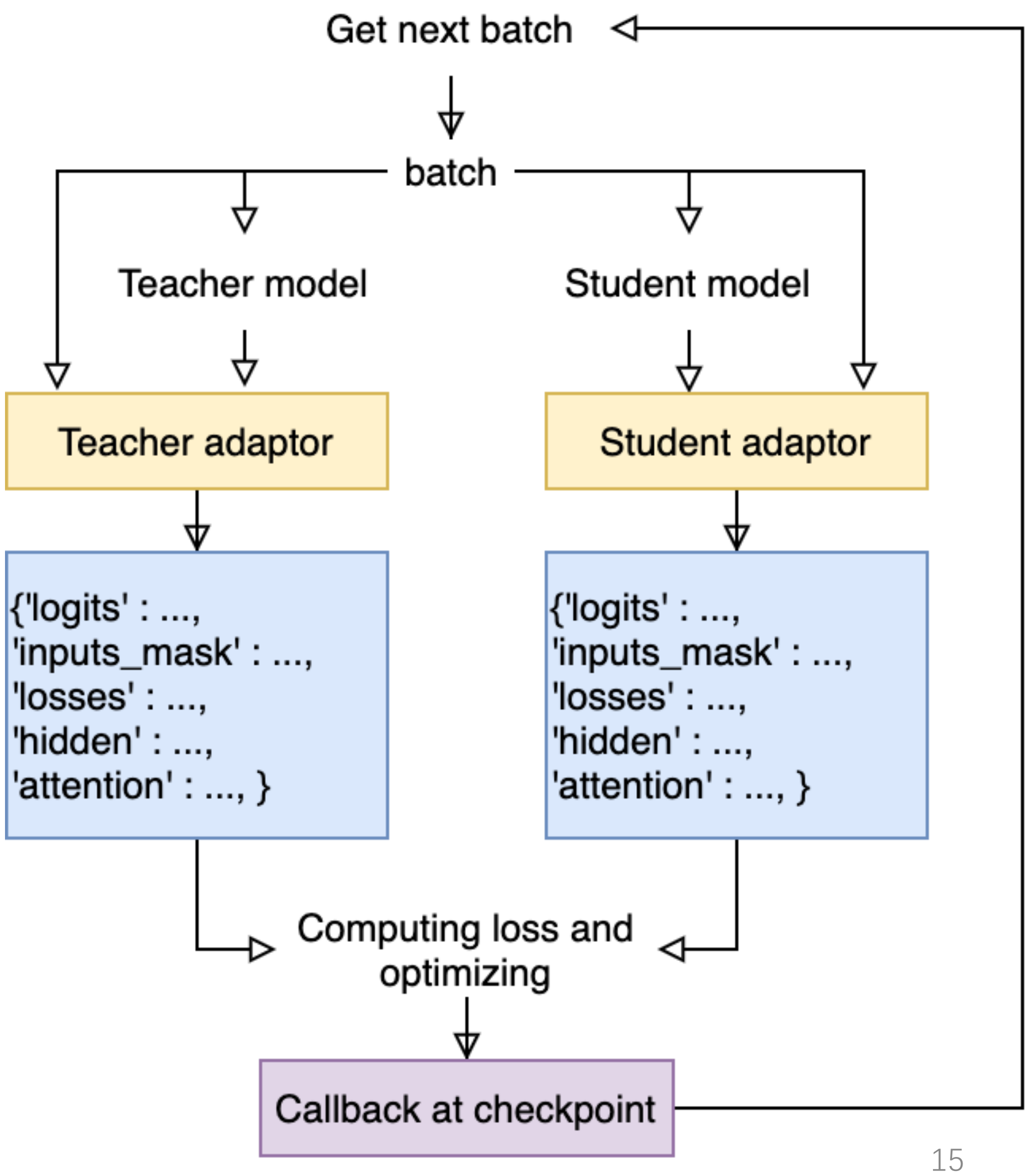


Callback

```
callback(model: torch.nn.Module, step: int) -> Any
```

- For monitoring performance during training

```python
def predict(model, eval_dataset, step, args):
    # your evaluation code here
    ...

my_callback = partial(predict, eval_dataset=my_eval_dataset, args=args)
with distiller:
    distiller.train(..., callback=my_callback)
```



Minimal workflow

```python
from textbrewer import GeneralDistiller
from textbrewer import TrainingConfig, DistillationConfig

# We omit the initialization of models, optimizer, and dataloader.
teacher_model : torch.nn.Module = ...
student_model : torch.nn.Module = ...
dataloader : torch.utils.data.DataLoader = ...
optimizer : torch.optim.Optimizer = ...
scheduler : torch.optim.lr_scheduler = ...

def simple_adaptor(batch, model_outputs):
    # We assume that the first element of model_outputs
    # is the logits before softmax
    return {'logits': model_outputs[0]}

train_config = TrainingConfig()
distill_config = DistillationConfig()
distiller = GeneralDistiller(
    train_config=train_config, distill_config = distill_config,
    model_T = teacher_model, model_S = student_model,
    adaptor_T = simple_adaptor, adaptor_S = simple_adaptor)

distiller.train(optimizer, scheduler,
    dataloader, num_epochs, callback=None)
```

define adaptor

Initialize configurations and distiller

RUN!

Experiments

- English datasets
  - **MNLI**
    sentence-pair classification
  - **SQuAD**
    machine reading comprehension
  - **CoNLL-2003**
    named entity recognition

- Chinese datasets
  - **XNLI** and **LCQMC**
    sentence-pair classification
  - **CMRC 2018** and **DRCD**
    SQuAD-like machine reading comprehension

Dataset	**Task**	**Metrics**	**#Train**	**#Dev**
MNLI	Classification	Acc	393K	20K
SQuAD	MRC	EM/F1	88K	11K
CoNLL-2003	NER	F1	23K	6K
XNLI	Classification	Acc	393K	2.5K
LCQMC	Classification	Acc	293K	8.8K
CMRC 2018	MRC	EM/F1	10K	3.4K
DRCD	MRC	EM/F1	27K	3.5K

Experiments

- Model configurations

Model	# Layers	Hidden size	Feed-forward size	# Parameters	Relative size
$\text{BERT}_{\text{BASE}}$ (teacher)	12	768	3072	108M	100%
T6	6	768	3072	65M	60%
T3	3	768	3072	44M	41%
T3-small	3	384	1536	17M	16%
T4-tiny	4	312	1200	14M	13%
BiGRU	1	768	-	31M	29%

- English models: initialized with the weight released by Google
- Chinese models: initialized with RoBERTa-wwm-ext

Results on English datasets

- Single-teacher distillation
  - All the T6 models achieve 99% performance of the teachers
  - T4-tiny outperforms TinyBERT
  - T4-tiny outperforms T3-small in most cases
  - Data augmentation (DA) is critical

Model	MNLI		SQuAD		CoNLL-2003
	m	mm	EM	F1	F1
$\text{BERT}_{\text{BASE}}$	83.7	84.0	81.5	88.6	91.1
Public					
DistilBERT	81.6	81.1	79.1	86.9	-
TinyBERT	80.5	81.0	-	-	-
+DA	82.8	82.9	72.7	82.1	-
TextBrewer					
BiGRU	-	-	-	-	85.3
T6	83.6	84.0	80.8	88.1	90.7
T3	81.6	82.5	76.3	84.8	87.5
T3-small	81.3	81.7	72.3	81.4	78.6
T4-tiny	82.0	82.6	73.7	82.5	77.5
+DA	-	-	75.2	84.0	89.1

Results on English datasets

- Multi-teacher distillation
  - All teachers are $\text{BERT}_{\text{base}}$
  - Student model is the same as the teacher
  - The student achieves the best performance, higher than the ensemble result

Model	MNLI		SQuAD		CoNLL-2003
	m	mm	EM	F1	F1
Teacher 1	83.6	84.0	81.1	88.6	91.2
Teacher 2	83.6	84.2	81.2	88.5	90.8
Teacher 3	83.7	83.8	81.2	88.7	91.3
Ensemble	84.3	84.7	82.3	89.4	91.5
Student	**84.8**	**85.3**	**83.5**	**90.0**	**91.6**

Results on Chinese datasets

- Single-teacher distillation
  - T4-tiny still outperforms T3-small on all tasks
  - Consistent with the observations on English tasks
  - CMRC 2018 has a relatively small training set, DA has a much more significant effect

Model	XNLI	LCQMC	CMRC 2018		DRCD	
	Acc	Acc	EM	F1	EM	F1
RoBERTa-wwm	79.9	89.4	68.8	86.4	86.5	92.5
T3	78.4	89.0	63.4	82.4	76.7	85.2
+DA	-	-	66.4	84.2	78.2	86.4
T3-small	76.0	88.1	46.1	71.0	71.4	82.2
+DA	-	-	58.0	79.3	75.8	84.8
T4-tiny	76.2	88.4	54.3	76.8	75.5	84.9
+DA	-	-	61.8	81.8	77.3	86.1

Summary

- Conclusion
  - We present TextBrewer, a flexible PyTorch-based distillation toolkit for NLP research and applications.
  - TextBrewer is easy-to-use, and provides rich customization options.
  - A series of experiments shows that the distilled models can achieve state-of-the-art results with simple settings.

- Future work
  - Expand TextBrewer's scope of application
  - Automatic search for student model structures

Get TextBrewer

TextBrewer

GitHub repo http://textbrewer.hfl-rc.com

Install via pip `pip install textbrewer`

Star If you like this project, you are welcome to give it a star!

Thanks for listening!

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http://textbrewer.hfl-rc.com