Managing data with LightningDataModule

SCALABLE AI MODELS WITH PYTORCH LIGHTNING

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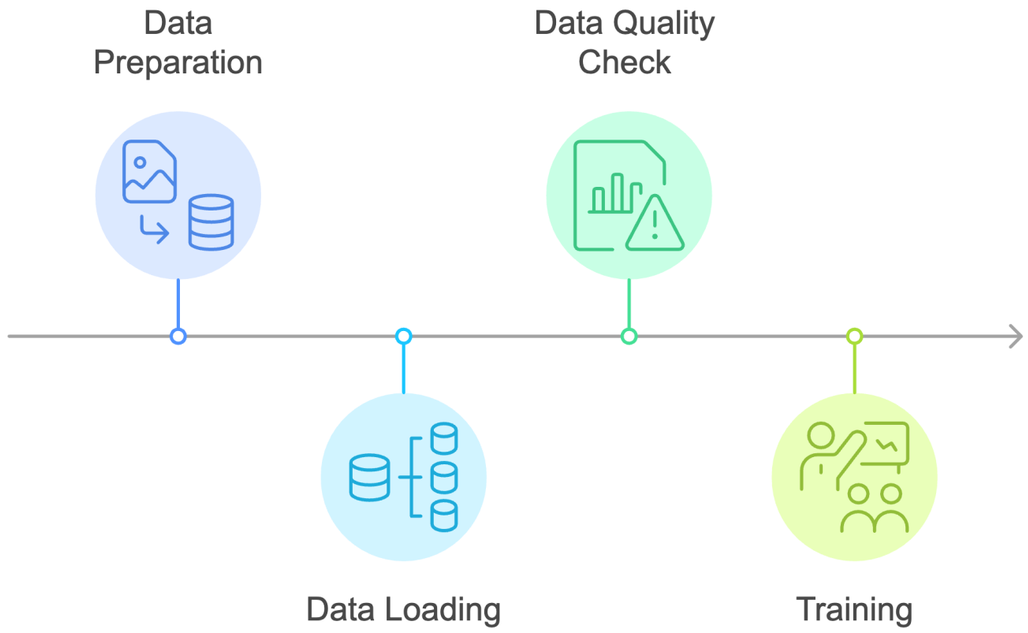
Data preparation for model training

- Poorly prepared data results in training issues
  - Slow training speeds
  - Frequent interruptions
  - Convergence failure



Why use LightningDataModule?

- □ Centralizes dataset handling
- □ Standardizes data preparation workflows
- □ Simplifies training and evaluation phases

Managing data with LightningDataModule

Key methods:

- `prepare_data` : Download and set up data
- `setup` : Split data into train, validation, and test sets

```
class ImageDataModule(pl.LightningDataModule):
    def __init__(self, data_dir="./data", batch_size=32):
        super().__init__()
        ...
    def prepare_data(self):
        datasets.MNIST(self.data_dir, train=True, download=True)
    def setup(self, stage=None):
        dataset = datasets.MNIST(self.data_dir, train=True, transform=self.transform)
        self.train_data, self.val_data = random_split(dataset, [55000, 5000])
        self.test_data = datasets.MNIST(self.data_dir, train=False, transform=self.transform)
```

Creating the train DataLoader

- Supplies batches of training data
- Helps optimize GPU utilization
- Enables efficient iteration over large datasets

```
def train_dataloader(self):
    return DataLoader(self.train_data, batch_size=self.batch_size, shuffle=True)
```

Creating the validation DataLoader

- Supplies data for model validation
- Helps monitor generalization performance
- Ensures consistency across evaluation runs through shuffling

```
def val_dataloader(self):
    return DataLoader(self.val_data, batch_size=self.batch_size)
```

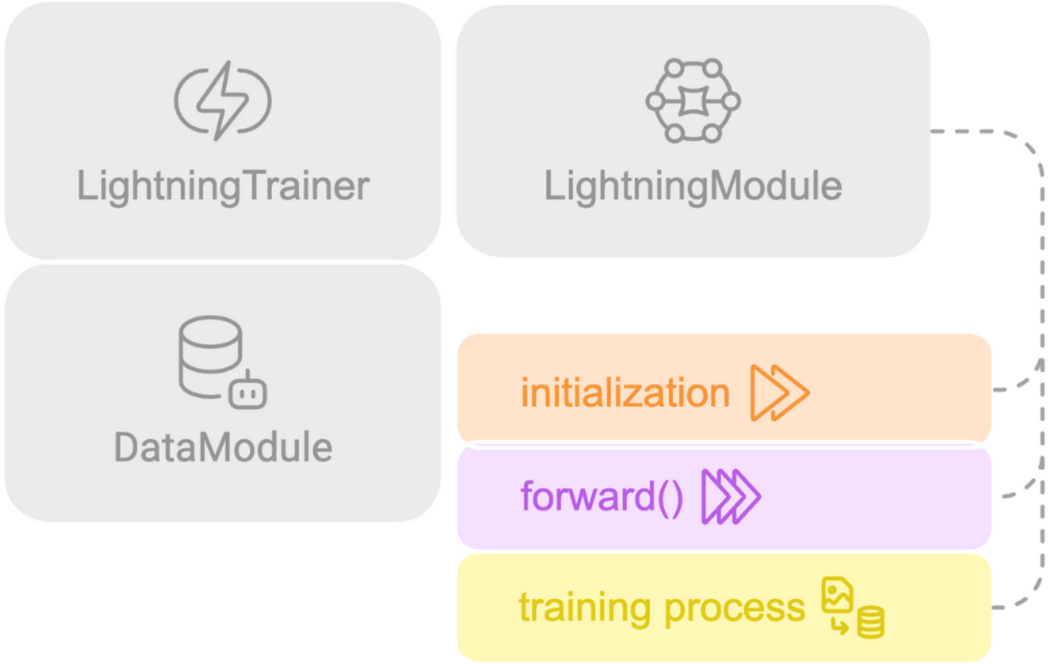
Creating the test DataLoader

- Supplies data for final model evaluation after training is completed
- Simulates real-world performance assessment
- Ensures unbiased performance measurement

```
def test_dataloader(self):
    return DataLoader(self.test_data, batch_size=self.batch_size)
```

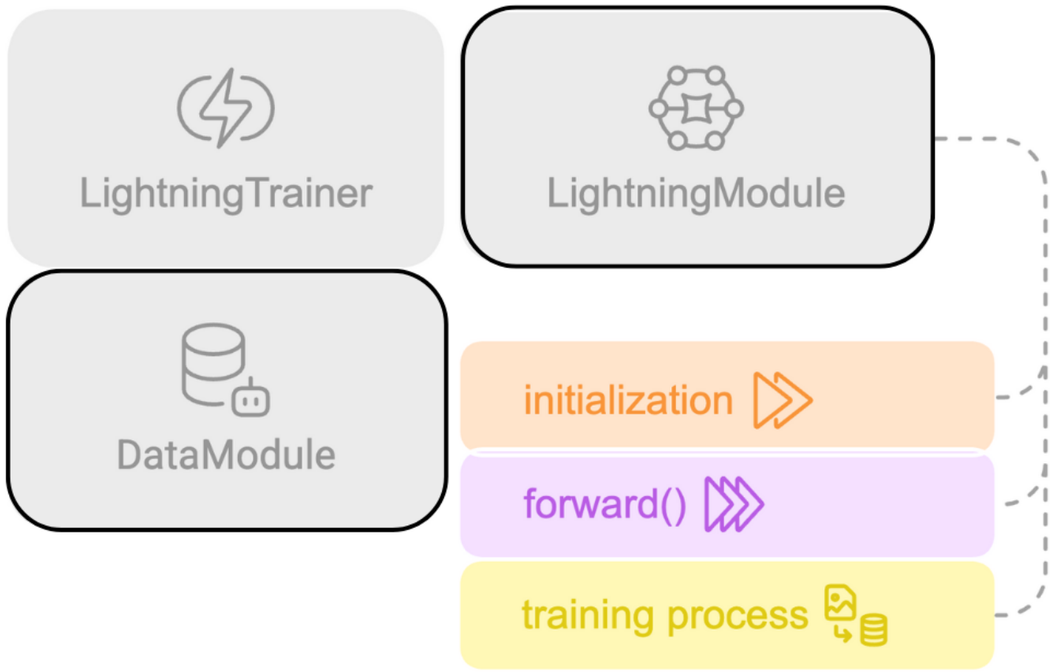
Connecting DataModule to LightningModule

- Modular design separates data and model logic



Connecting DataModule to LightningModule

- Modular design separates data and model logic
- `LightningDataModule` pairs with `LightningModule`
- Standardized workflow enhances reproducibility



Let's practice!

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Incorporating validation and testing

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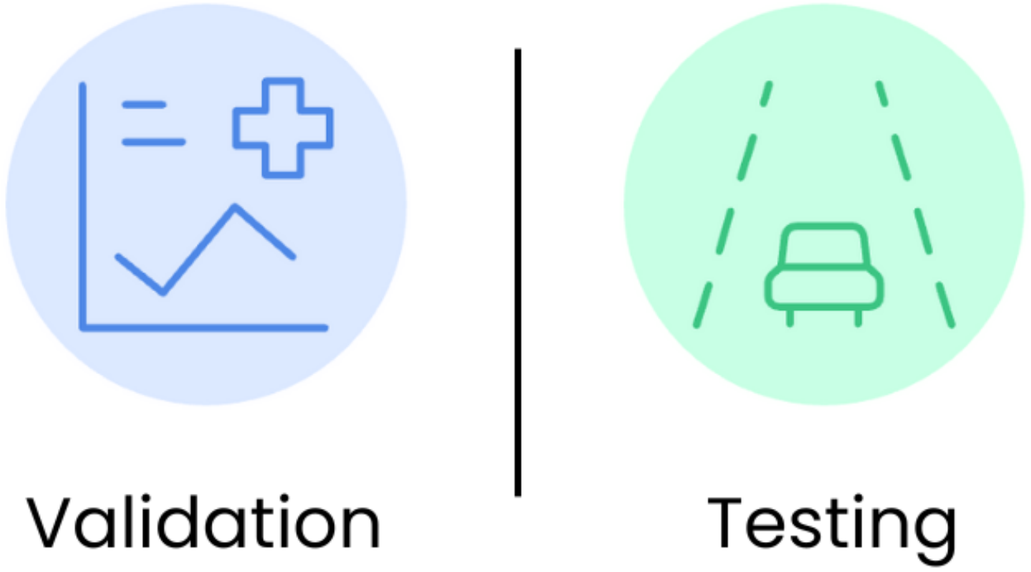
Why incorporate validation and testing?

- Validation
  - Identify model performance issues early
  - Prevent overfitting and underfitting
- Testing
  - Performance on unseen data



Implementing validation

- Evaluate model performance at each epoch
- Aggregate metrics for a more stable view

```
def validation_step(self, batch, batch_idx):
  x, y = batch
  preds = self(x)
  loss = F.cross_entropy(preds, y)
  self.log('val_loss', loss)

def validation_epoch_end(self, outputs):
  avg_loss = torch.stack([x['loss'] for x in outputs]).mean()
  self.log('avg_val_loss', avg_loss)
```

Implementing testing

- Assess final model performance on unseen data
- Benchmark real-world effectiveness
- Provide metrics for model deployment

```
def test_step(self, batch, batch_idx):
  x, y = batch
  y_hat = self(x)
  loss = F.cross_entropy(y_hat, y)
  self.log('test_loss', loss)

def test_epoch_end(self, outputs):
  avg_loss = torch.stack([x['loss'] for x in outputs]).mean()
  self.log('avg_test_loss', avg_loss)
```

Evaluation with Torchmetrics

- Monitor metrics such as accuracy
- Easily integrate into Lightning workflow
- Initialize accuracy
- Calculate accuracy at each validation step

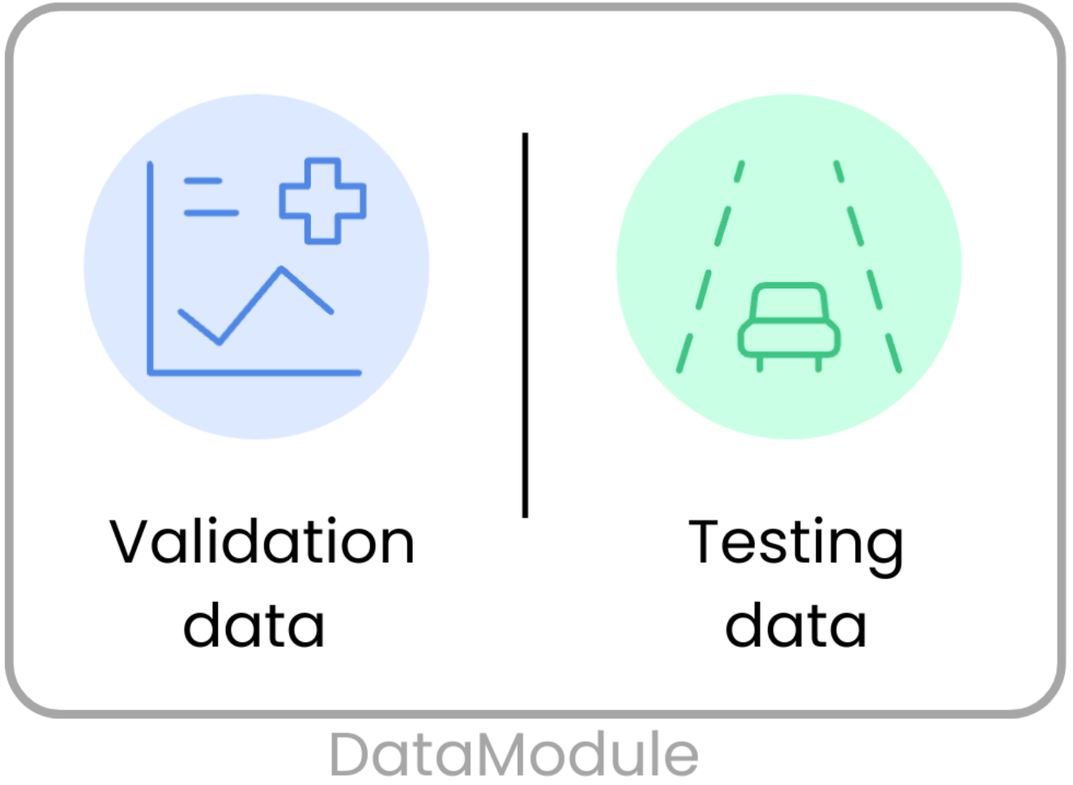
```
from torchmetrics import Accuracy

class BaseModel(pl.LightningModule):
    def __init__(self):
        super().__init__()
        self.accuracy = Accuracy()

    def validation_step(self, batch, batch_idx):
        x, y = batch
        preds = self(x)
        acc = self.accuracy(preds, y)
        self.log('val_acc', acc)
```

Connecting DataModule, validation, and testing

- Data logic centralized in DataModule
- Consistent train/val/test data splits
- Automatic validation metric logging
- Reproducible pipeline from prep to reporting



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Enhancing training with Lightning callbacks

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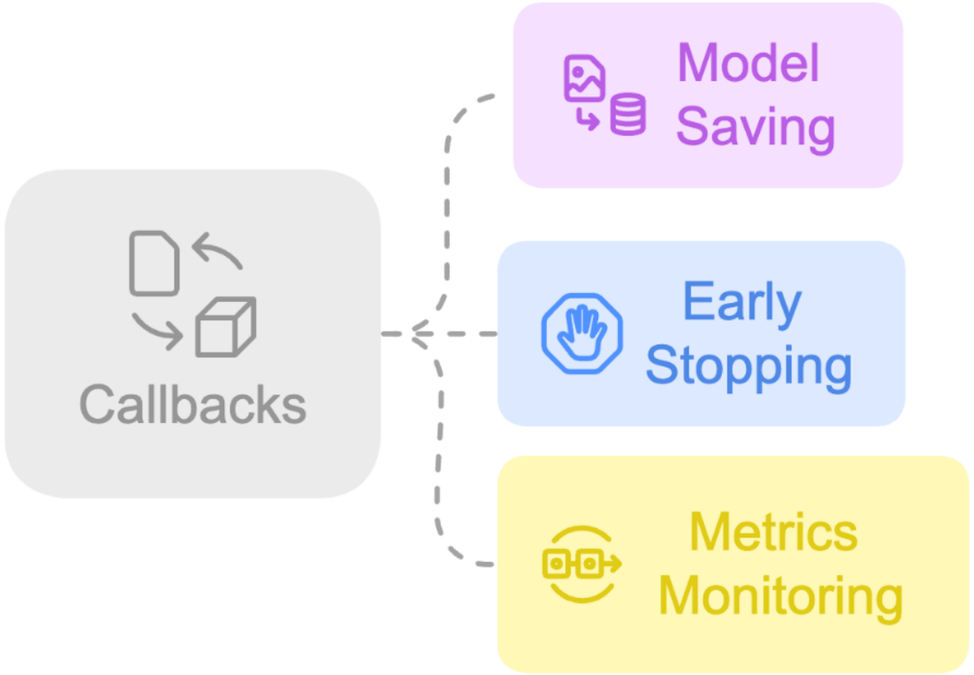
What are callbacks?

- Functions executed at key stages of training
- Add custom actions without cluttering code
- Enhance flexibility and control



What are callbacks?

```
from lightning.pytorch.callbacks import Callback

class MyPrintingCallback(Callback):
    def on_train_start(self, trainer, pl_module):
        print("Training is starting")
    def on_train_end(self, trainer, pl_module):
        print("Training is ending")
```

- Adding custom actions at various stages of training

Lightning ModelCheckpoint callback

- Automatically saves model at specified intervals
- Choose metric to track
- Keep only the best model

```
from lightning.pytorch.callbacks
import ModelCheckpoint
checkpoint_callback = ModelCheckpoint(
    monitor='val_loss',
    dirpath='my/path/',
    filename='{epoch}-{val_loss:.2f}',
    save_top_k=1,
    mode='min'
)
```

[1] https://lightning.ai/docs/pytorch/stable/api/lightning.pytorch.callbacks.ModelCheckpoint.html

Lightning EarlyStopping callback

- Monitor a metric
- Stop training when the metric stops improving

```
from lightning.pytorch.callbacks
import EarlyStopping

early_stopping_callback = EarlyStopping(
    monitor='val_loss',
    patience=3,
    mode='min'
)
```

[1] https://lightning.ai/docs/pytorch/stable/api/lightning.pytorch.callbacks.EarlyStopping.html

Customizing and using lightning callbacks

```
from lightning.pytorch import Trainer
from lightning.pytorch.callbacks import EarlyStopping, ModelCheckpoint
checkpoint = ModelCheckpoint(
    monitor='val_accuracy',
    save_top_k=2,
    mode='max')
early_stopping = EarlyStopping(
    monitor='val_accuracy',
    patience=5,
    mode='max')

trainer = Trainer(max_epochs=50, callbacks=[checkpoint, early_stopping])
```

[1] https://lightning.ai/docs/pytorch/stable/common/trainer.html

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