Introduction to PyTorch Lightning

SCALABLE AI MODELS WITH PYTORCH LIGHTNING

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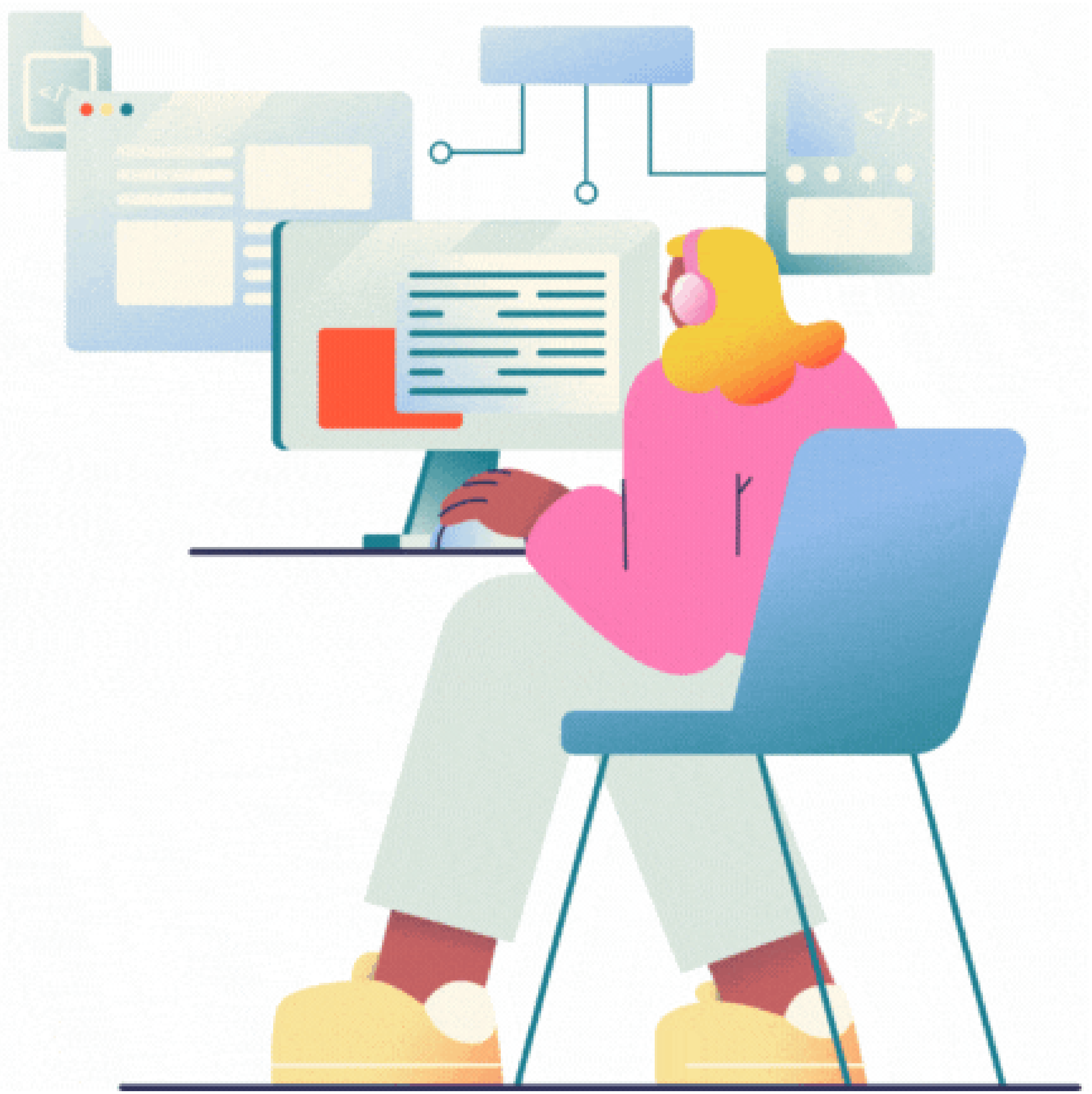
PyTorch & PyTorch Lightning

Standard PyTorch:

- Significant manual effort
- Writing explicit training loops
- GPU/TPU handling, logging, and checkpointing



PyTorch & PyTorch Lightning

PyTorch Lightning:

- Built on top of PyTorch
- Automates:
  - Training
  - Checkpointing
  - Logging
- Reduces boilerplate
- Improves scalability and reproducibility

Overview of PyTorch Lightning

- Example: global e-commerce streamlining workflows
  - Visual search model development
  - Automated training loops
  - Rapid iteration with minimal boilerplate

- Core components: `LightningModule` and `Trainer`

```
from lightning.pytorch import LightningModule
from lightning.pytorch import Trainer
```

Lightning structure

Key components:

- LightningModule: core model logic

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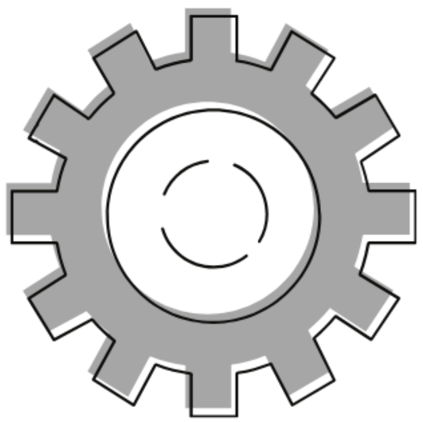
- LightningModule: core model logic
- Lightning Trainer: orchestrates training



Lightning structure

Key components:

- LightningModule: core model logic
- Lightning Trainer: orchestrates training
- DataModule: organizes data pipelines
- Callbacks: automates events
- Logger: tracks experiments

LightningModule in action

Key points:

- `__init__` : Defines model architecture
- `forward()` : Pass data through the model
- `training_step()` : Define training
- Custom hooks available

```
import lightning.pytorch as pl

class LightClassifier(pl.LightningModule):
    def __init__(self, model, criterion, optimizer):
        super().__init__()
        self.model = model
        self.criterion = criterion
        self.optimizer = optimizer
    def forward(self, x):
        return self.model(x)
    def training_step(self, batch, batch_idx):
        x, y = batch
        logits = self(x)
        loss = self.criterion(logits, y)
        return loss
```

Lightning Trainer in action

Key points:

- Manages training loop
- Supports distributed training
- Handles callbacks & logging
- Optimizes resource usage

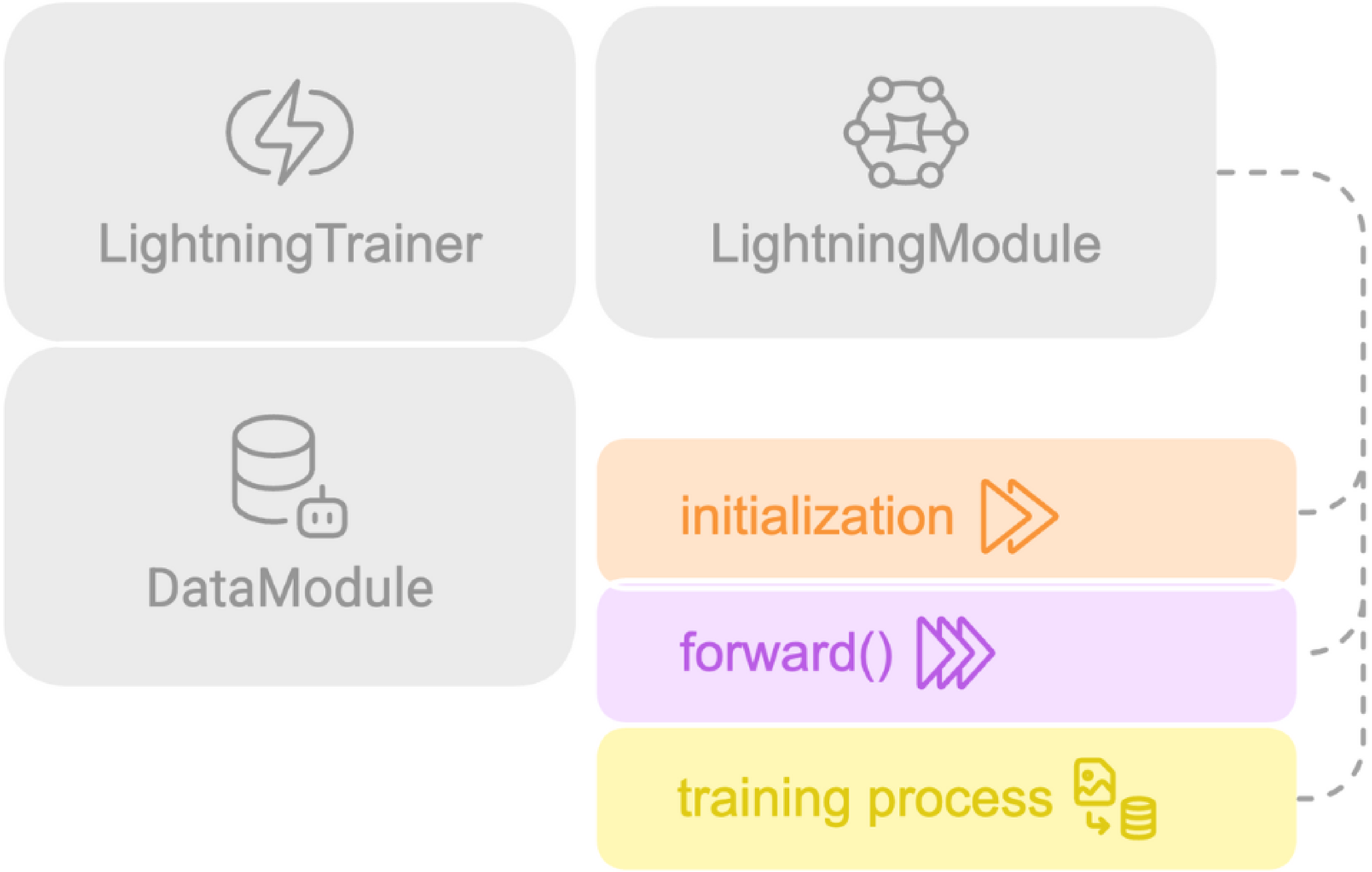
```
model = LightClassifier()



trainer = Trainer(max_epochs=10, accelerator="gpu", devices=1)
trainer.fit(model, train_dataloader, val_dataloader)
```

Introducing the Afro-MNIST dataset

A set of synthetic MNIST-style datasets for four orthographies used in Afro-Asiatic and Niger-Congo languages: Ge'ez (Ethiopic), Vai, Osmanya, and N'Ko.

[1] Wu, Daniel J., Andrew C. Yang, and Vinay U. Prabhu. "Afro-MNIST: Synthetic generation of MNIST-style datasets for low-resource languages." arXiv preprint arXiv:2009.13509 (2020).

PyTorch Lightning recap



Let's practice!

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Defining models with LightningModule

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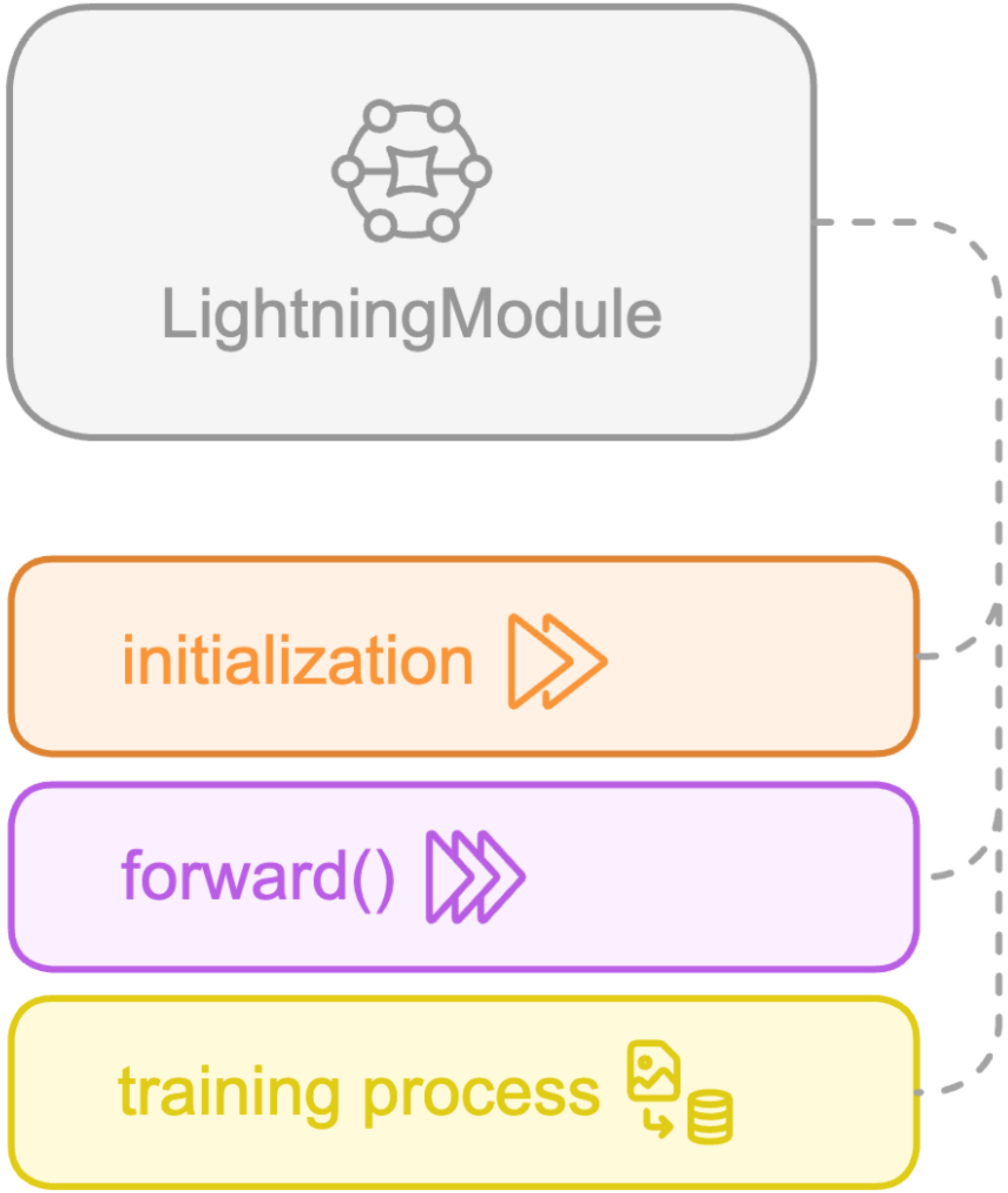
LightningModule in focus

1. Encapsulates your model architecture
2. Organizes training logic into a single, manageable unit
3. Blueprint that brings order and clarity to deep learning projects



Defining the init method

Key tasks:

- Model's initialization
- `super()` :
  - Automated handling of training loops
  - Logging
  - Checkpointing
- Model layers defined after initialization
- Modular and easy to maintain

```python
import lightning.pytorch as pl
import torch.nn as nn

class ClassificationModel(pl.LightningModule):
    def __init__(self, input_dim,
                 hidden_dim, num_class):
          # Initialize parent class
        super().__init__()
        # First layer
        self.layer1 = nn.Linear(input_dim,
                                hidden_dim)
        # Activation function
        self.relu = nn.ReLU()
        # Output layer
        self.layer2 = nn.Linear(hidden_dim,
                                num_class)
```

Implementing the forward method

Key steps:

- Define data flow through network
- Process input through layers sequentially
  - Linear transformation
  - Activation
  - Last layer and output

```
import lightning.pytorch as pl
import torch.nn as nn

class ClassificationModel(pl.LightningModule):
    def __init__(self, input_dim,
                 hidden_dim, num_class):
        ...
    def forward(self, x):
        x = self.layer1(x) # Pass input
        x = nn.ReLU(x) # Apply activation
        x = self.layer2(x) # Compute output
        return x # Return result
```

Example: classifying hand written digits

```
import lightning.pytorch as pl
from torch.utils.data import DataLoader
from torchvision.datasets import MNIST
from torchvision import transforms
transform = transforms.ToTensor()
train_ds = MNIST(root='.', train=True,  download=True, transform=transform)
test_ds  = MNIST(root='.', train=False, download=True, transform=transform)

train_loader = DataLoader(train_ds, batch_size=64, shuffle=True)
test_loader  = DataLoader(test_ds,  batch_size=64)

model = ClassificationModel(input_dim=28*28, hidden_dim=128, num_class=10)

trainer = pl.Trainer(max_epochs=3, accelerator='auto')
trainer.fit(model, train_loader, test_loader)
```

Integrating the model with classification tasks

- Focus on classification use case
- Entire flow within LightningModule
- Output raw outputs for softmax activation
- Integration with Lightning Trainer

```
class ClassificationModel(pl.LightningModule):
  def __init__(self, input_dim,
               hidden_dim, output_dim):
    super().__init__()
    self.hid = nn.Linear(input_dim, hidden_dim)
    self.out = nn.Linear(hidden_dim, output_dim)

  def forward(self, x):
    x = self.hidden(x)
    x = nn.ReLU(x)
    x = self.output(x)
    return x
```

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Implementing training logic

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Defining the training step

- Process input and label batch
- Compute predictions with forward pass
- Calculate cross entropy loss for classification
- Log training loss for monitoring

```
def training_step(self, batch, batch_idx):
    x, y = batch
    y_hat = self(x)
    loss = cross_entropy(y_hat, y)
    self.log("train_loss", loss)
    return loss
```

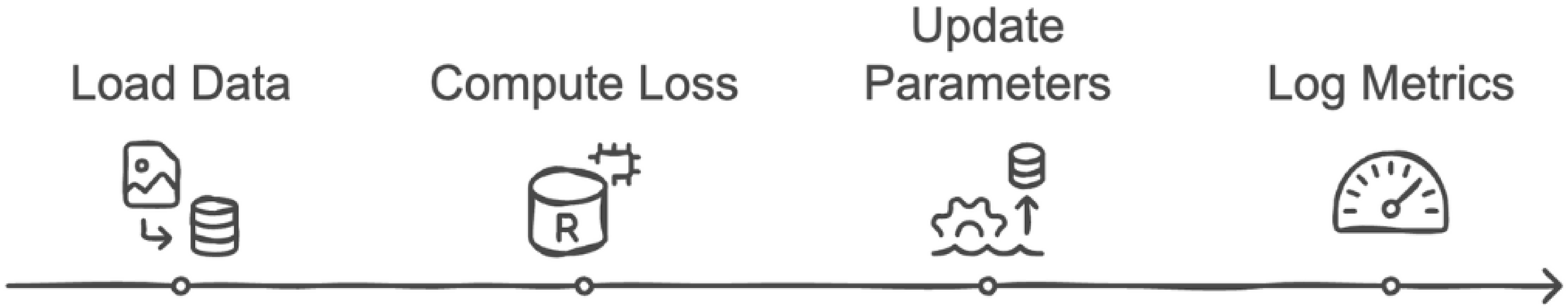
Configuring optimizers

- Select an appropriate optimizer for updates
- Link model parameters for gradient computation
- Set a suitable learning rate for convergence
- Return the optimizer instance for Lightning integration

```
def configure_optimizers(self):
    optimizer = torch.optim.Adam(self.parameters(), lr=1e-3)
    return optimizer
```

Training with Lightning Trainer

- Integrate training logic with Lightning Trainer
- Manage training loops and epochs automatically
- Monitor performance metrics in real time



Using trainer.fit and trainer.validate

- Start training with trainer.fit method
- Validate model with trainer.validate method

```
trainer.fit(model, train_dataloader)
trainer.validate(model, val_dataloader)
```

- Automate training and validation cycles
- Monitor metrics during both phases

Complete training logic example

- Define a custom LightningModule with a classifier
- Implement training_step to compute and log loss
- Configure optimizers to update model parameters
- Train and validate the model

```python
class LightClassifier(pl.LightningModule):
    def __init__(self):
        super().__init__()
        self.layer=torch.nn.Linear(28 * 28, 10)
    def forward(self, x):
        return self.layer(x.view(x.size(0), -1))
    def training_step(self, batch, batch_idx):
        ...
    def configure_optimizers(self):
        params=self.parameters()
        optimizer=torch.optim.Adam(params,lr=1e-3)
        return optimizer
model = LightClassifier() # Define classifier model
trainer = Trainer(max_epochs=5) # Define trainer
trainer.fit(model, train_dataloader)
trainer.validate(model, val_dataloader)
```

Industry applications

Why training logic matters?

- Ensure precise loss tracking for quality control
- Optimize training pipelines for scalable deployment

Real-world examples:

- Enhance image analysis in healthcare diagnostics
- Support fraud detection in financial services

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