Minibatch Stochastic Gradient Descent

Outline

- General neural network process
- (Batch) gradient descent
- Stochastic gradient descent (SGD)
- Minibatch stochastic gradient descent (Minibatch SGD)
- Discuss tradeoffs

Recap: Automatic Differentiation

- Take five minutes to draw
  - Whatever will help you remember (no correct or incorrect drawings)
  - You’ll keep a running drawing log the rest of the semester

What do MSE and MAE look like in code?

Mean

Mean

```
def mean(self) -> Matrix:
    """Return the mean of all values across both dimensions."""
    result = Matrix(List2D(1, 1, self.data.mean()), children=(self,))

    def _gradient() -> None:
        info(f"Gradient of mean. Shape: {self.shape}")
        n = self.nrow * self.ncol
        self.grad += List2D(self.nrow, self.ncol, result.grad.vals[0][0] / n)

    result._gradient = _gradient
    return result
```

```
def mean(self) -> float:
    """Compute the mean of all values in the matrix."""
    return self.sum() / (self.nrow * self.ncol)
```

Absolute Value

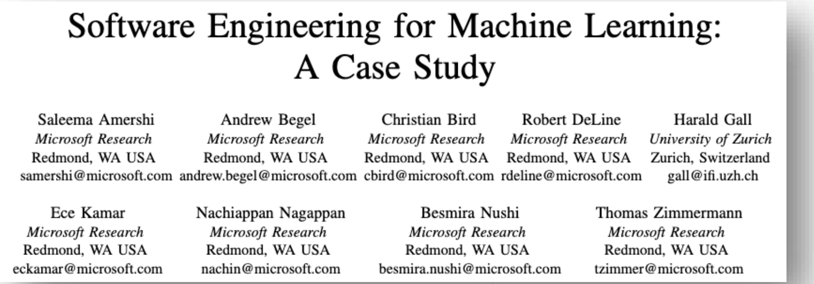
Absolute Value

```python
def abs(self) -> Matrix:
    """Return the element-wise absolute matrix values."""
    result = Matrix(self.data.abs(), children=(self,))

    def _gradient() -> None:
        self.grad += (self.data > 0) * result.grad
        self.grad += -(self.data < 0) * result.grad

    result._gradient = _gradient
    return result

def __abs__(self) -> Matrix:
    """Return the element-wise absolute matrix values."""
    return self.abs()
```

```python
def abs(self) -> List2D:
    data = [
        [abs(self.data[i][j]) for j in range(self.ncol)]
        for i in range(self.nrow)
    ]
    return List2D(*self.shape, data)

def __abs__(self) -> List2D:
    return self.abs()
```

General Neural Network Process

1. Prepare your dataset
   - Normalize inputs
   - Create a proxy (smaller) dataset for debugging and testing workflows
   - Split the dataset into training, validation, and evaluation
2. Design a neural network (architecture)
3. Set initial hyperparameters (learning rate, number of epochs, etc.)
4. Train model parameters (includes validation)
5. Evaluate the trained model
6. Deploy the trained model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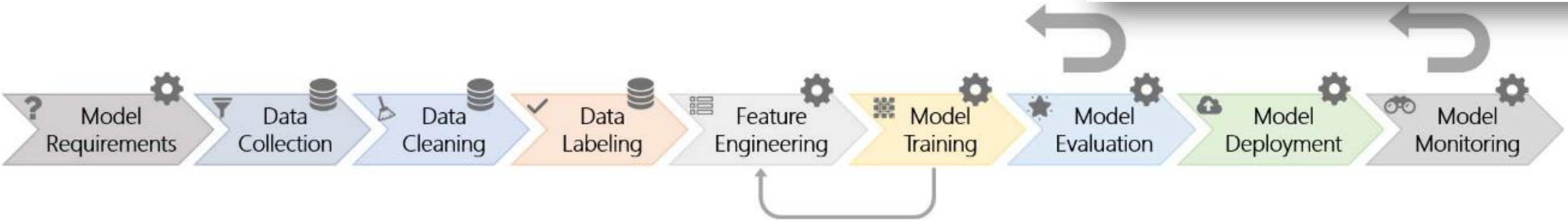

(Batch) Gradient Descent

(Batch) Gradient Descent

```python
for _ in range(num_epochs):

    # Grab the entire dataset as a single batch
    X, y = next(iter(train_loader))

    yhat = model(X)
    loss = criterion(yhat, y)
    train_losses.append(loss.detach().item())

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    # Compare results with validation data
    X, y = next(iter(valid_loader))
    yhat = model(X)
    loss = criterion(yhat, y)
    valid_losses.append(loss.detach().item())
```

Stochastic Gradient Descent

Stochastic Gradient Descent

```
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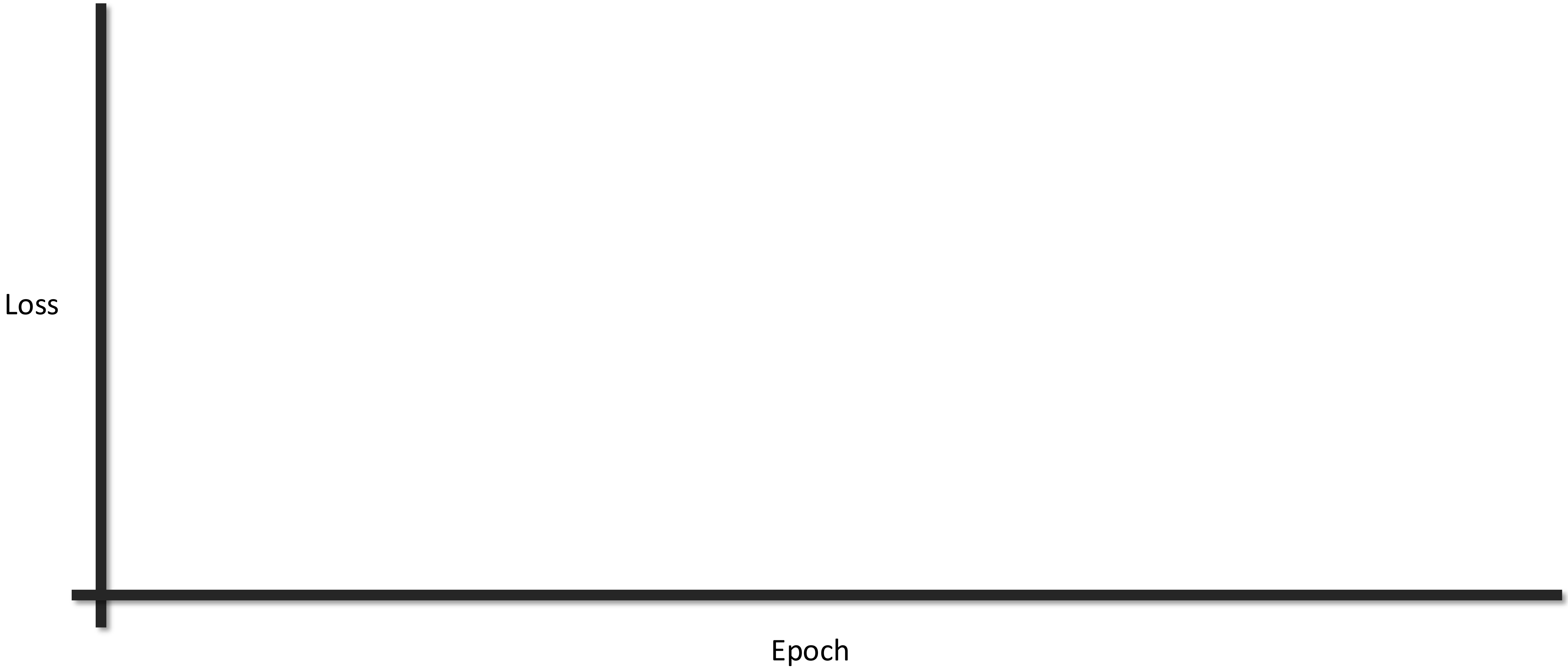
Typical Behavior



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- Minibatch stochastic gradient descent
  - Noisy but less than SGD
  - Pretty fast but slower than batch gradient descent
  - Should always be your default choice
  - Add another hyperparameter called `batch_size`

Code Demo

https://github.com/anthonyjclark/cs152spring25/blob/main/Lectures/06-MinibatchSgd/SgdDemo.ipynb