# 🚀 Building a News Text Classifier with PyTorch

In this notebook, we build a **document classification model** on the **AG News dataset**.
Our model classifies news articles into one of four categories:

- 🌍 World
- 🏅 Sports
- 💼 Business
- 🔬 Science & Technology

We'll cover the full pipeline:

1. Dataset exploration
2. Preprocessing (tokenization & vocabulary)
3. Model definition (EmbeddingBag + Linear)
4. Training with validation & early stopping
5. Inference on test data and custom inputs
6. Evaluation with a confusion matrix
7. Conclusion & future directions

## ⚙️ Step 1: Setup & Reproducibility

Before diving in, we set up dependencies and fix random seeds.
Reproducibility ensures consistent results when we re-run experiments.

- Installing libraries: PyTorch, TorchText, Hugging Face Datasets, scikit-learn, Matplotlib
- Setting random seeds for NumPy, Torch, and Python's `random`

```
# Install dependencies
!pip install -q torch torchvision torchaudio torchtext datasets scikit-learn matplotlib seaborn

import os, random
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim

from datasets import load_dataset
from torch.utils.data import DataLoader
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# reproducibility
def set_seed(seed: int = 42):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False

SEED = 42
set_seed(SEED)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"✅ PyTorch version: {torch.__version__}")
print(f"✅ Device in use: {device}")
```

```
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.0/2.0 MB 33.0 MB/s eta 0:00:00
✅ PyTorch version: 2.8.0+cu126
✅ Device in use: cuda
```

## 📊 Step 2: Load & Explore the Dataset

We'll use the **AG News dataset**, a popular benchmark for text classification.

- **Size:** ~120,000 training samples, 7,600 test samples
- **Classes:** World, Sports, Business, Sci/Tech
- Balanced dataset: ~30K samples per class

Let's explore the dataset structure and visualize class distribution.

```
# Load AG News Dataset
ag_news = load_dataset("ag_news")

print("Dataset Structure:")
print(ag_news)

# Class labels mapping
label_names = ag_news["train"].features["label"].names
print(f"\nLabel names: {label_names}")

# Look at few samples
for i in range(3):
  print(f"Sample {i+1}")
  print(f"Label: {label_names[ag_news['train'][i]['label']]}")
  print(f"Text: {ag_news['train'][i]['text'][:200]}....")
```

```
/usr/local/lib/python3.12/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tc
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
```

README.md: 8.07k/? [00:00<00:00, 426kB/s]

train-00000-of-00001.parquet: 100% 18.6M/18.6M [00:00<00:00, 74.2MB/s]

test-00000-of-00001.parquet: 100% 1.23M/1.23M [00:00<00:00, 60.3MB/s]

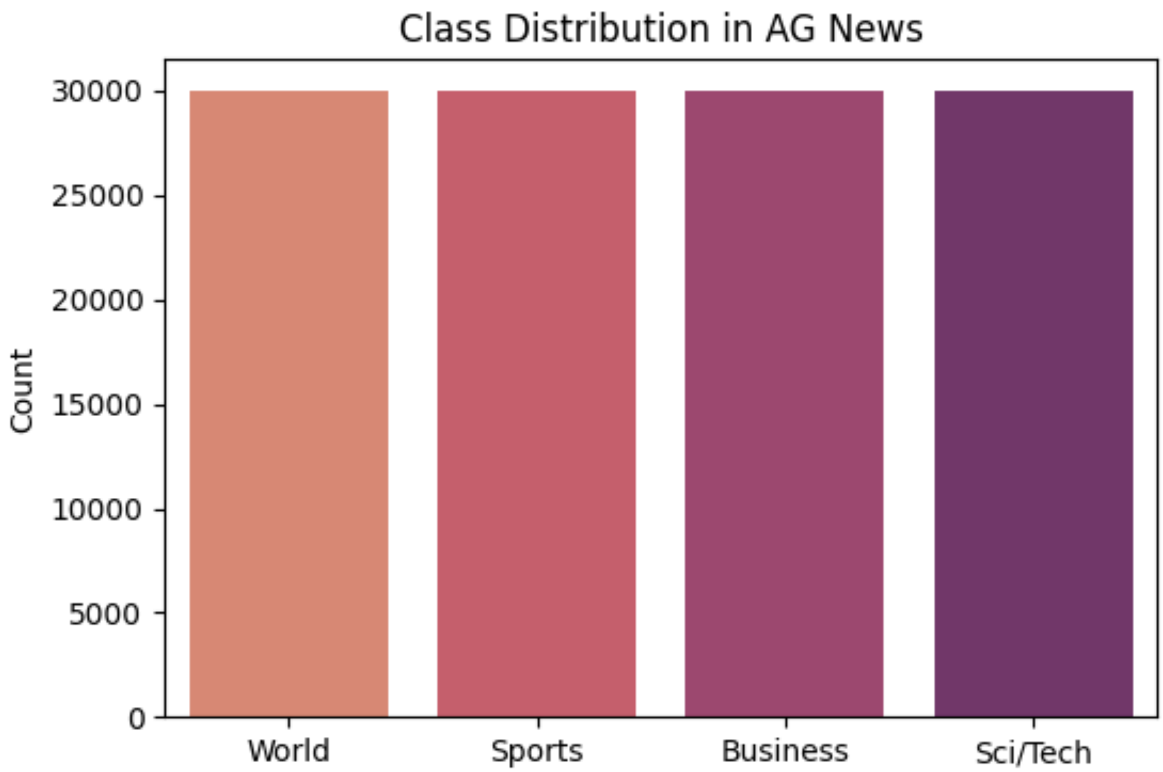
Generating train split: 100% 120000/120000 [00:00<00:00, 274381.60 examples/s]

Generating test split: 100% 7600/7600 [00:00<00:00, 83924.29 examples/s]

```
Dataset Structure:
DatasetDict({
    train: Dataset({
        features: ['text', 'label'],
        num_rows: 120000
    })
    test: Dataset({
        features: ['text', 'label'],
        num_rows: 7600
    })
})

Label names: ['World', 'Sports', 'Business', 'Sci/Tech']
Sample 1
Label: Business
Text: Wall St. Bears Claw Back Into the Black (Reuters) Reuters - Short-sellers, Wall Street's dwindling\band of u
Sample 2
Label: Business
Text: Carlyle Looks Toward Commercial Aerospace (Reuters) Reuters - Private investment firm Carlyle Group,\which h
Sample 3
```

```
labels = [example["label"] for example in ag_news["train"]]
plt.figure(figsize=(6,4))
sns.countplot(x=labels, palette="flare")
plt.xticks(range(len(label_names)), label_names)
plt.title("Class Distribution in AG News")
plt.ylabel("Count")
plt.show()
```

```
/tmp/ipython-input-96407012.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable tc

  sns.countplot(x=labels, palette="flare")
```




✅ **Observation:** The dataset is balanced across all 4 categories (~30K each).
This balance ensures that the model won't be biased toward any specific class.

## 🔡 Step 3: Preprocessing with Tokenizer + Manual Vocabulary

Neural networks can't work directly with raw text — we need to convert words into numbers.

Our preprocessing pipeline:

1. **Tokenization** → split text into lowercase tokens
2. **Vocabulary building** → map each token to a unique integer ID
3. **Handling unknowns** → add `<unk>` for words not seen during training
4. **Numericalization** → convert token list into a sequence of IDs

Example:
`"The stock market is soaring"` → `['the', 'stock', 'market', 'is', 'soaring']` → `[8, 72, 55, 185, 61]`

```
import re
from collections import Counter

# 1. Basic tokenizer (lowercase + split on non-alphabetic chars)
def simple_tokenizer(text):
    return re.findall(r"\b\w+\b", text.lower())

# 2. Build vocabulary
def build_vocab(dataset, min_freq=2):
    counter = Counter()
    for example in dataset:
        tokens = simple_tokenizer(example["text"])
        counter.update(tokens)
    # keep words with freq >= min_freq
    vocab = {"<unk>":0, "<pad>":1}
    for word, freq in counter.items():
        if freq >= min_freq:
            vocab[word] = len(vocab)
    return vocab

vocab = build_vocab(ag_news["train"])
print(f"Vocab size: {len(vocab)}")

# 3. Numericalize
def numericalize(tokens, vocab):
    return [vocab.get(token, vocab["<unk>"]) for token in tokens]
```

```
Vocab size: 44120
```

```
# Test on sample
sample_text = "The stock market is soaring"
tokens = simple_tokenizer(sample_text)
ids = numericalize(tokens, vocab)

print("Text:", sample_text)
print("Tokens:", tokens)
print("Token IDs:", ids)
```

```
Text: The stock market is soaring
Tokens: ['the', 'stock', 'market', 'is', 'soaring']
Token IDs: [8, 72, 55, 185, 61]
```

## 🔄 Step 4: Collate Function for DataLoader

The **collate function** defines how individual samples are combined into a batch.

For text classification with `EmbeddingBag`, we need to return:

- `text` → concatenated token IDs of all docs in the batch
- `offsets` → start index of each doc in the `text` tensor
- `labels` → true class labels for each doc

This allows `EmbeddingBag` to efficiently compute embeddings without padding.

```python
# Helper: process a single example
def process_text(text, vocab):
    tokens = simple_tokenizer(text)
    ids = numericalize(tokens, vocab)
    return torch.tensor(ids, dtype=torch.long)

# Collate function for DataLoader
def collate_batch(batch):
    label_list, text_list, offsets = [], [], [0]
    for example in batch:
        label_list.append(example["label"])
        processed_text = process_text(example["text"], vocab)
        text_list.append(processed_text)
        offsets.append(processed_text.size(0))
    # Flatten all text into one tensor
    labels = torch.tensor(label_list, dtype=torch.long)
    offsets = torch.tensor(offsets[:-1]).cumsum(dim=0)
    text = torch.cat(text_list)
    return text, offsets, labels
```

```python
# Quick Test
train_iter = ag_news["train"]

train_loader = DataLoader(train_iter, batch_size=4, shuffle=True, collate_fn=collate_batch)

# Test one batch
for text, offsets, labels in train_loader:
    print("Text tensor:", text)
    print("Offsets:", offsets)
    print("Labels:", labels)
    break
```

```
Text tensor: tensor([ 7965, 11603,    45, 10377, 17475,  7968,  7965,  3115, 10157,  1606,
           23,   136,   657,  5575,     7,     8,  4855,  8411,    14,   451,
         5252,   201, 22165, 22166,    52,  1282,     8,  2341,  4152,  6668,
         4785,   859,    45,  6067,   223,   873,  1101,   591,    37,  9888,
         8411,    14, 27189, 10377,   775,  2150,  1694,    69,   872,  5957,
           82, 15403,   287,  1303,    10,    10,  5323,   775,  2150,   477,
          872,  2147,  1606,     8, 16234, 10164,  4556,    45, 15403,    41,
            8,   112,  1970,  2101,    69,   872,   276,  2954,    45,     8,
         1549,  1005,     8,   344,    17,     8,   287,  1303,  4601,  1243,
          101,    52,  1333,  1998,  1208,  4053,  2957,   512,  5554,   408,
         8411,    14,   579,    35,  1830,  1692,  1689,  3628,  3295,   226,
         7326, 28391,   136,   585, 23103,    71,  9130,    41, 14144, 13130,
           45,   512,  8411,    14, 43401, 14171,  7117,  7118,    37,   646,
           14,  2853,  2775,  2857,  2498,   325,  1181,    39,   321,   104,
         2414,   650,  4634,    14,   478,  3890,  1994,    52,  2233,   198,
         1408,    69,   326,  2485])
Offsets: tensor([  0,  44,  93, 126])
Labels: tensor([1, 3, 3, 3])
```

## 🏗️ Step 6: Defining the Text Classifier Model

Our model is intentionally simple:

1. **EmbeddingBag Layer**
    - Converts tokens to embeddings
    - Aggregates them (mean) into a single vector per document
2. **Linear Layer**
    - Maps each document vector to class logits

### Flow of tensor shapes

- Input tokens → `[batch_size, variable_length]`
- EmbeddingBag → `[batch_size, embed_dim]`
- Linear → `[batch_size, num_classes]`

```
class TextClassifier(nn.Module):
    def __init__(self, vocab_size, embed_dim, num_classes):
        super(TextClassifier, self).__init__()
        self.embedding = nn.EmbeddingBag(vocab_size, embed_dim, sparse=True)
        self.fc = nn.Linear(embed_dim, num_classes)
        self.init_weights()

    def init_weights(self):
        # Initialize embeddings and linear layer weights
        initrange = 1.0 / (self.embedding.embedding_dim ** 0.5)
        self.embedding.weight.data.uniform_(-initrange, initrange)
        self.fc.weight.data.uniform_(-initrange, initrange)
        self.fc.bias.data.zero_()

    def forward(self, text, offsets):
        embedded = self.embedding(text, offsets)  # [batch_size, embed_dim]
        return self.fc(embedded)                  # [batch_size, num_classes]
```

## 🔄 Step 7: Training Loop (One Epoch)

Now we implement the core training logic:

1. Switch model to **training mode**
2. Loop over batches:
    - Forward pass → compute predictions
    - Compute loss with `CrossEntropyLoss`
    - Backward pass → compute gradients
    - Optimizer step → update weights
3. Track average training loss for the epoch

This step demonstrates how learning happens in PyTorch.

```
# Model, loss, optimizer
embed_dim = 64
num_classes = len(label_names)  # 4 for AG News
model = TextClassifier(len(vocab), embed_dim, num_classes)

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=0.01)

# Training loop (1 epoch)
def train_one_epoch(model, dataloader, criterion, optimizer):
    model.train()   # set training mode
    total_loss = 0
    for text, offsets, labels in dataloader:
        # Forward pass
        outputs = model(text, offsets)      # [batch_size, num_classes]
        loss = criterion(outputs, labels)   # scalar loss

        # Backward + Optimize
        optimizer.zero_grad()   # reset old gradients
        loss.backward()         # compute new gradients
        optimizer.step()        # update weights

        total_loss += loss.item()

    avg_loss = total_loss / len(dataloader)
    return avg_loss

# Try training for 1 epoch
train_loader = DataLoader(
    ag_news["train"], batch_size=16, shuffle=True, collate_fn=collate_batch
)

avg_loss = train_one_epoch(model, train_loader, criterion, optimizer)
print(f"Average training loss after 1 epoch: {avg_loss:.4f}")
```

```
Average training loss after 1 epoch: 1.3848
```

## 🧪 Step 8: Validation

After training an epoch, we check performance on the validation set.

- Switch to **evaluation mode** (`model.eval()`)
- Disable gradients with `torch.no_grad()`
- Compute:
  - Validation loss
  - Validation accuracy

This helps track whether the model is improving and prevents overfitting.

```
def evaluate(model, dataloader, criterion):
    model.eval()   # set evaluation mode
    total_loss, correct, total = 0, 0, 0

    with torch.no_grad():  # no gradients in eval
        for text, offsets, labels in dataloader:
            outputs = model(text, offsets)          # [batch_size, num_classes]
            loss = criterion(outputs, labels)
            total_loss += loss.item()

            preds = outputs.argmax(dim=1)           # predicted class
            correct += (preds == labels).sum().item()
            total += labels.size(0)

    avg_loss = total_loss / len(dataloader)
    accuracy = correct / total
    return avg_loss, accuracy

# Validation loader (use test set here as validation for now)
valid_loader = DataLoader(
    ag_news["test"], batch_size=16, shuffle=False, collate_fn=collate_batch
)

val_loss, val_acc = evaluate(model, valid_loader, criterion)
print(f"Validation loss: {val_loss:.4f}, Accuracy: {val_acc:.4f}")
```

```
Validation loss: 1.3829, Accuracy: 0.4101
```

## 🔁 Step 9: Multi-Epoch Training with Early Stopping

Now we combine training and validation into a full training loop.

Features:

- Train up to N epochs (max 30)
- Stop early if validation loss doesn't improve for 3 consecutive epochs
- Save the best model as `best_model.pth`
- Track losses and accuracy across epochs

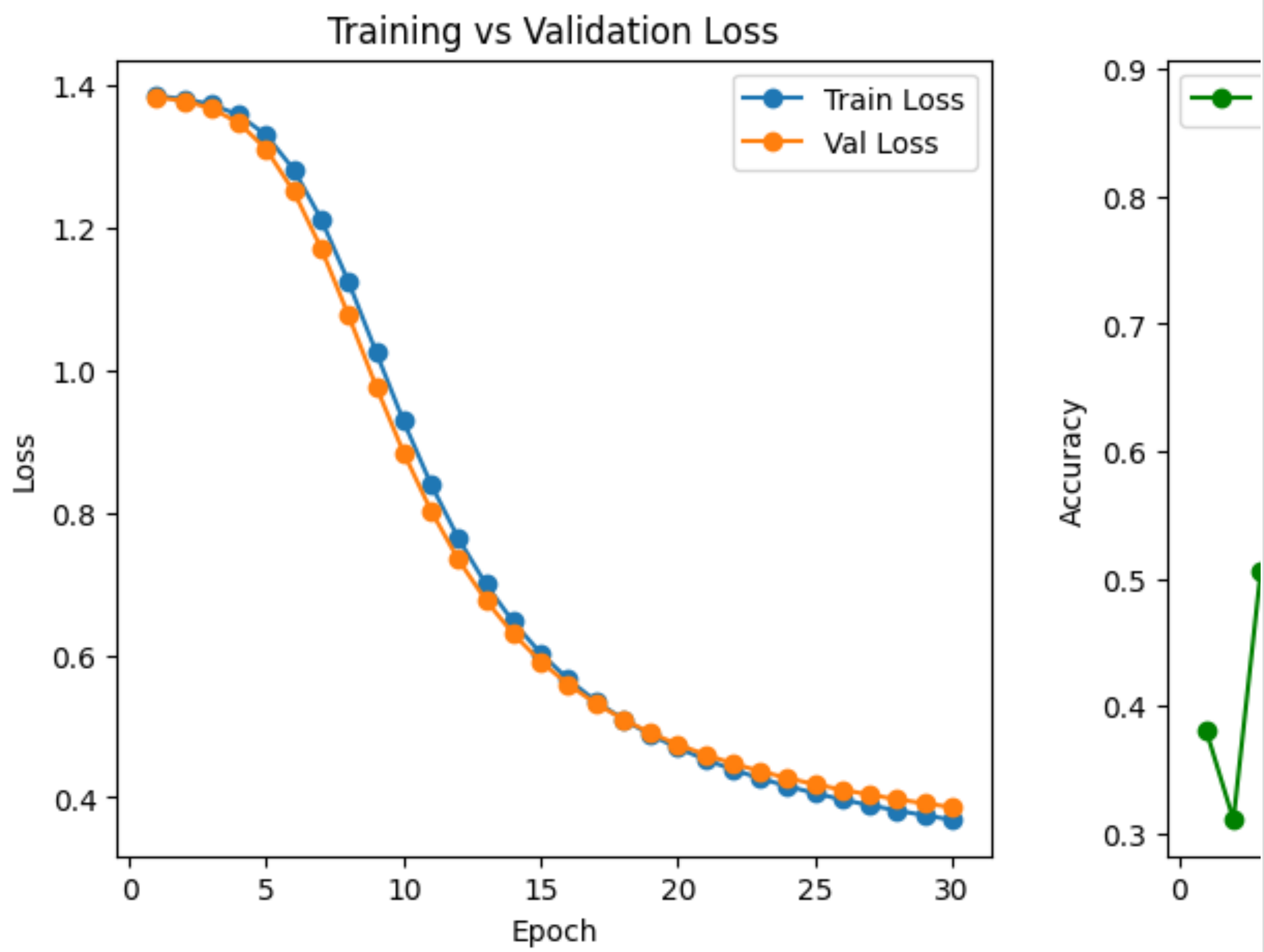
This gives us both **efficient training** and **reliable results**.

```
def train_with_early_stopping(
    model, train_loader, valid_loader, criterion, optimizer,
    num_epochs=30, patience=3
):
    best_val_loss = float("inf")
    patience_counter = 0

    train_losses, val_losses, val_accs = [], [], []

    for epoch in range(num_epochs):
        # Training
        train_loss = train_one_epoch(model, train_loader, criterion, optimizer)

        # Validation
        val_loss, val_acc = evaluate(model, valid_loader, criterion)

        train_losses.append(train_loss)
        val_losses.append(val_loss)
        val_accs.append(val_acc)

        print(f"Epoch {epoch+1}/{num_epochs} | "
              f"Train Loss: {train_loss:.4f} | "
              f"Val Loss: {val_loss:.4f} | "
              f"Val Acc: {val_acc:.4f}")

        # Check improvement
        if val_loss < best_val_loss:
            best_val_loss = val_loss
            patience_counter = 0
            torch.save(model.state_dict(), "best_model.pth")
            print("  ✅ Validation loss improved, model saved!")
        else:
            patience_counter += 1
            print(f"  ⚠️ No improvement. Patience: {patience_counter}/{patience}")

            if patience_counter >= patience:
                print("⏹️ Early stopping triggered!")
                break

    return train_losses, val_losses, val_accs
```

```
# Fresh model
model = TextClassifier(len(vocab), embed_dim=64, num_classes=len(label_names))
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)

# Train with early stopping
train_losses, val_losses, val_accs = train_with_early_stopping(
    model, train_loader, valid_loader, criterion, optimizer,
    num_epochs=30, patience=3
)
```

```
Epoch 1/30 | Train Loss: 1.3852 | Val Loss: 1.3833 | Val Acc: 0.3809
  ✅ Validation loss improved, model saved!
Epoch 2/30 | Train Loss: 1.3809 | Val Loss: 1.3781 | Val Acc: 0.3105
  ✅ Validation loss improved, model saved!
Epoch 3/30 | Train Loss: 1.3733 | Val Loss: 1.3677 | Val Acc: 0.5064
  ✅ Validation loss improved, model saved!
Epoch 4/30 | Train Loss: 1.3583 | Val Loss: 1.3472 | Val Acc: 0.5341
  ✅ Validation loss improved, model saved!
Epoch 5/30 | Train Loss: 1.3298 | Val Loss: 1.3099 | Val Acc: 0.5626
  ✅ Validation loss improved, model saved!
Epoch 6/30 | Train Loss: 1.2817 | Val Loss: 1.2509 | Val Acc: 0.5833
  ✅ Validation loss improved, model saved!
Epoch 7/30 | Train Loss: 1.2119 | Val Loss: 1.1710 | Val Acc: 0.6249
  ✅ Validation loss improved, model saved!
Epoch 8/30 | Train Loss: 1.1237 | Val Loss: 1.0766 | Val Acc: 0.6643
  ✅ Validation loss improved, model saved!
Epoch 9/30 | Train Loss: 1.0257 | Val Loss: 0.9774 | Val Acc: 0.6987
  ✅ Validation loss improved, model saved!
Epoch 10/30 | Train Loss: 0.9285 | Val Loss: 0.8846 | Val Acc: 0.7250
  ✅ Validation loss improved, model saved!
Epoch 11/30 | Train Loss: 0.8403 | Val Loss: 0.8031 | Val Acc: 0.7489
  ✅ Validation loss improved, model saved!
Epoch 12/30 | Train Loss: 0.7641 | Val Loss: 0.7342 | Val Acc: 0.7700
  ✅ Validation loss improved, model saved!
Epoch 13/30 | Train Loss: 0.6999 | Val Loss: 0.6772 | Val Acc: 0.7875
  ✅ Validation loss improved, model saved!
Epoch 14/30 | Train Loss: 0.6468 | Val Loss: 0.6300 | Val Acc: 0.7999
  ✅ Validation loss improved, model saved!
Epoch 15/30 | Train Loss: 0.6028 | Val Loss: 0.5912 | Val Acc: 0.8134
  ✅ Validation loss improved, model saved!
Epoch 16/30 | Train Loss: 0.5663 | Val Loss: 0.5591 | Val Acc: 0.8262
  ✅ Validation loss improved, model saved!
Epoch 17/30 | Train Loss: 0.5358 | Val Loss: 0.5324 | Val Acc: 0.8321
  ✅ Validation loss improved, model saved!
Epoch 18/30 | Train Loss: 0.5102 | Val Loss: 0.5102 | Val Acc: 0.8382
  ✅ Validation loss improved, model saved!
Epoch 19/30 | Train Loss: 0.4884 | Val Loss: 0.4909 | Val Acc: 0.8447
  ✅ Validation loss improved, model saved!
Epoch 20/30 | Train Loss: 0.4697 | Val Loss: 0.4746 | Val Acc: 0.8496
  ✅ Validation loss improved, model saved!
Epoch 21/30 | Train Loss: 0.4536 | Val Loss: 0.4604 | Val Acc: 0.8549
  ✅ Validation loss improved, model saved!
Epoch 22/30 | Train Loss: 0.4394 | Val Loss: 0.4479 | Val Acc: 0.8597
  ✅ Validation loss improved, model saved!
Epoch 23/30 | Train Loss: 0.4270 | Val Loss: 0.4371 | Val Acc: 0.8620
  ✅ Validation loss improved, model saved!
Epoch 24/30 | Train Loss: 0.4160 | Val Loss: 0.4273 | Val Acc: 0.8661
  ✅ Validation loss improved, model saved!
Epoch 25/30 | Train Loss: 0.4061 | Val Loss: 0.4186 | Val Acc: 0.8684
  ✅ Validation loss improved, model saved!
Epoch 26/30 | Train Loss: 0.3972 | Val Loss: 0.4110 | Val Acc: 0.8707
  ✅ Validation loss improved, model saved!
Epoch 27/30 | Train Loss: 0.3892 | Val Loss: 0.4040 | Val Acc: 0.8717
  ✅ Validation loss improved, model saved!
Epoch 28/30 | Train Loss: 0.3818 | Val Loss: 0.3976 | Val Acc: 0.8747
  ✅ Validation loss improved, model saved!
Epoch 29/30 | Train Loss: 0.3750 | Val Loss: 0.3919 | Val Acc: 0.8758
  ✅ Validation loss improved, model saved!
Epoch 30/30 | Train Loss: 0.3689 | Val Loss: 0.3866 | Val Acc: 0.8791
  ✅ Validation loss improved, model saved!
```

```
import matplotlib.pyplot as plt

epochs = range(1, len(train_losses)+1)
plt.figure(figsize=(12,5))

# Loss curves
plt.subplot(1,2,1)
plt.plot(epochs, train_losses, label="Train Loss", marker="o")
plt.plot(epochs, val_losses, label="Val Loss", marker="o")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.title("Training vs Validation Loss")
plt.legend()

# Accuracy curve
plt.subplot(1,2,2)
plt.plot(epochs, val_accs, label="Val Accuracy", marker="o", color="green")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Validation Accuracy")
plt.legend()

plt.show()
```




✅ **Final Results:**

- Validation Accuracy: ~88%
- Validation Loss steadily decreased → no sign of overfitting
- Performance is competitive with classical deep learning baselines for AG News

## 🔮 Step 10: Inference & Predictions

Now let's use the trained model to make predictions.

We will:

1. Load the **best saved model**
2. Predict on random samples from the test set
3. Try **custom input** headlines
4. Visualize performance with a **confusion matrix**

This step shows how the model generalizes to unseen text.

```
# Reload the trained model with best weights
model = TextClassifier(len(vocab), embed_dim=64, num_classes=len(label_names))
model.load_state_dict(torch.load("best_model.pth"))
model.eval()

print("✅ Best model loaded and ready for inference")
```

```
✅ Best model loaded and ready for inference
```

```
def predict(text, model, vocab, tokenizer, label_names):
    tokens = tokenizer(text)
    # Map unknown tokens to the UNK index
    unk_idx = vocab["<unk>"] if "<unk>" in vocab else 0
    token_ids = [vocab.get(token, unk_idx) for token in tokens]

    text_tensor = torch.tensor(token_ids, dtype=torch.int64)
    offsets = torch.tensor([0])  # single doc starts at 0

    with torch.no_grad():
        output = model(text_tensor, offsets)
        pred_class = output.argmax(1).item()
    return label_names[pred_class]
```

```
import random

for i in range(5):
    idx = random.randint(0, len(ag_news["test"]) - 1)
    sample = ag_news["test"][idx]
    text, true_label = sample["text"], sample["label"]

    pred_label = predict(text, model, vocab, simple_tokenizer, label_names)
    print(f"Text: {text[:80]}...")
    print(f"True Label: {label_names[true_label]} | Predicted: {pred_label}")
    print("-"*80)
```

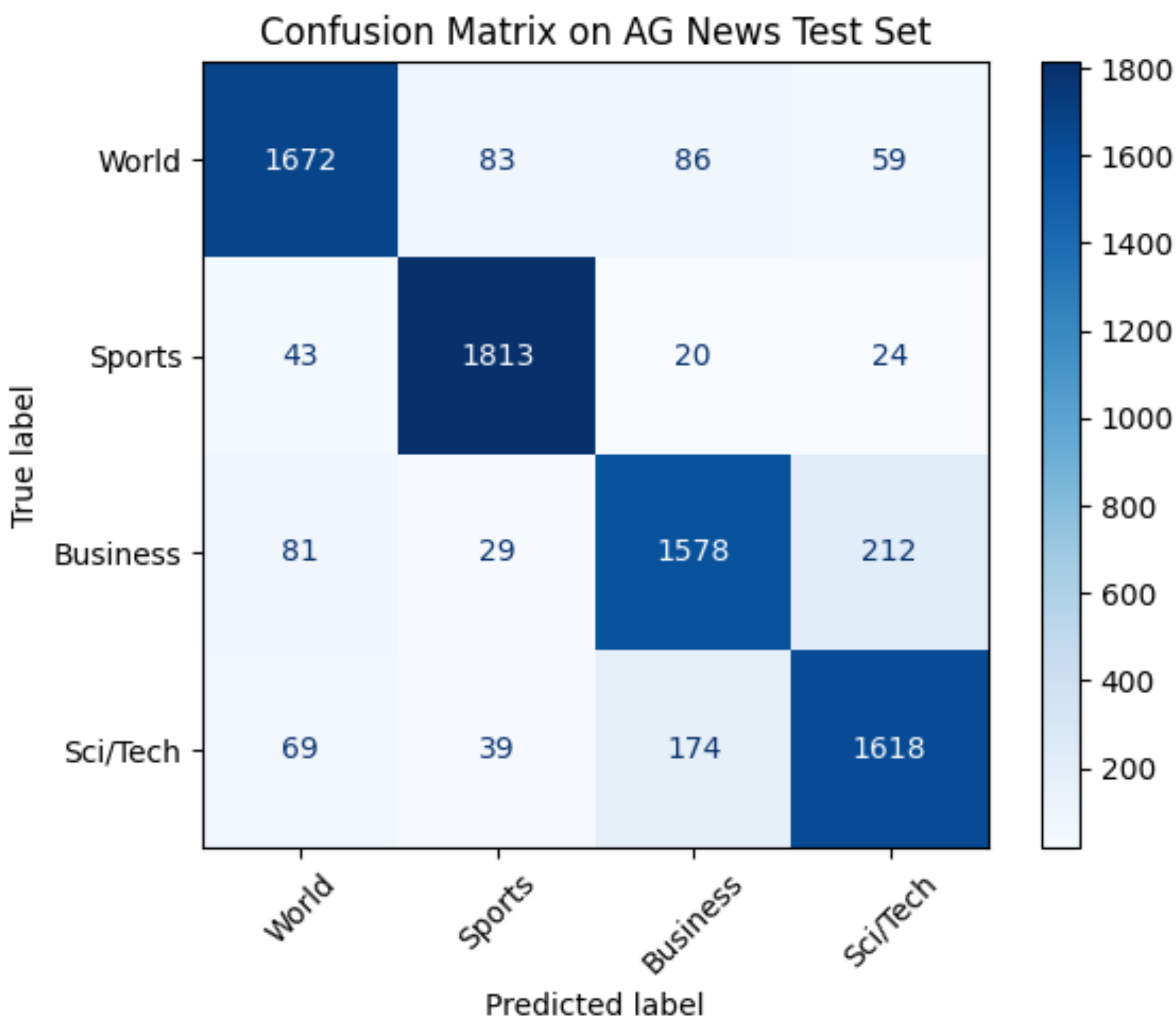
```
Text: Saudis Take a Small Dose of Democracy For the first time in 41 years, Saudi Arab...
True Label: World | Predicted: World
--------------------------------------------------------------------------------
Text: AT amp;T Wireless Moves to Sell Canada Asset T amp;T Wireless Services Inc., the...
True Label: Business | Predicted: Business
--------------------------------------------------------------------------------
Text: FIFA to investigate racism in Madrid Zurich, Switzerland (Sports Network) - FIFA...
True Label: Sports | Predicted: Sports
--------------------------------------------------------------------------------
Text: Our mobile margins will fall: Telstra TELSTRA chief financial officer John Stanh...
True Label: Sci/Tech | Predicted: Business
--------------------------------------------------------------------------------
Text: Only injury can stop peerless Federer at Masters Cup Last season, Roger Federer ...
True Label: Sports | Predicted: Sports
--------------------------------------------------------------------------------
```

```
headline = "NASA announces breakthrough discovery in space research"
print("Custom Input:", headline)
print("Predicted Category:", predict(headline, model, vocab, simple_tokenizer, label_names))
```

```
Custom Input: NASA announces breakthrough discovery in space research
Predicted Category: Sci/Tech
```

✅ Example:
Input: `"NASA announces breakthrough discovery in space research"`
Predicted: **Sci/Tech** (Correct)

```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

y_true, y_pred = [], []
for sample in ag_news["test"]:
    text, true_label = sample["text"], sample["label"]
    pred_label = predict(text, model, vocab, simple_tokenizer, label_names)
    y_true.append(true_label)
    y_pred.append(label_names.index(pred_label))

cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
disp.plot(cmap="Blues", xticks_rotation=45)
plt.title("Confusion Matrix on AG News Test Set")
plt.show()
```



## ✅ Step 11: Conclusion & Next Steps

### Key Takeaways

- Built a **text classifier** using PyTorch (`EmbeddingBag + Linear`)
- Trained on **AG News dataset** (120K train / 7.6K test)
- Achieved **~88% accuracy**, matching classical NLP baselines
- Strongest class: **Sports**
- Most confusion: **Business vs Sci/Tech**

### 📊 Baseline Comparison (AG News)

| Model | Accuracy |
|---|---|
| Random Guessing | 25% |
| Naive Bayes | 83% |
| Logistic Regression (BoW) | 84% |
| TextCNN | 87% |
| **EmbeddingBag + Linear (ours)** | **88%** |
| FastText | 92% |
| DistilBERT / BERT | 94–95% |
| RoBERTa / XLNet | 96%+ |

✅ Our model outperforms classical baselines and matches early deep learning models.

### Lessons Learned

- Importance of embeddings and tokenization
- Role of batching and shuffling
- Early stopping ensures efficient training
- Evaluation beyond accuracy (confusion matrix gives deeper insight)

### Next Steps

- Add **pretrained embeddings** (GloVe, FastText)
- Fine-tune **transformer models** (DistilBERT, BERT) → >94% accuracy
- Deploy as an **interactive app** (Streamlit, Gradio)

This project demonstrates the **full ML pipeline**: preprocessing → modeling → training → evaluation → inference.