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BOOK DETAILS

- **Title:** Deep Learning Essentials - Neural Networks Made Practical
- **Edition:** 1st Edition
- **Publisher:** Alkademy Books
- **Chapters in full book:** 10

CHAPTERS IN THIS PREVIEW

- Chapter 1: The Deep Learning Mindset: From Rules to Representations

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Deep Learning Essentials - Neural Networks Made Practical

Alkademy Content Team

1st Edition

Alkademy Books

June 2026

PREFACE

When I first encountered deep learning, I did what most people do: I searched for tutorials, skimmed research papers, and copied code from GitHub repositories I barely understood. Things ran. Loss values decreased. Models produced outputs. But I had no real sense of *why* any of it was working — or, more frustratingly, why it sometimes wasn't. I could follow the steps, but I couldn't think through the problem. That gap between running code and genuine understanding is what eventually motivated this book. I wrote it because I needed it to exist years ago, and I suspect you might need it now.

Deep learning has an unusual reputation. On one hand, it looks approachable — there are libraries that reduce entire architectures to a handful of lines, and tutorials that promise results in minutes. On the other hand, once something breaks, or once you try to build something from your own requirements rather than a borrowed example, the field can feel vast and opaque. The mathematics gets heavy, the terminology multiplies, and the sheer volume of techniques, architectures, and research directions can make it hard to know where to focus. This book is my attempt to cut through that noise and give you something more durable than a collection of code snippets: a practical mental model for how deep learning actually works.

This book is written for ML learners and practitioners who already have some grounding in the fundamentals of machine learning — you understand what training and testing mean, you have a sense of what a loss function is trying to do, and you're comfortable with the idea that models learn from data. What I'm not assuming is that you've worked extensively with neural networks,

that you're fluent in the underlying mathematics, or that you've navigated the full training pipeline on your own. You don't need a PhD to get real value here. You need curiosity, some prior context, and a willingness to think carefully rather than just execute quickly.

The philosophy behind this book is simple: intuition first, mechanics second. Before you can use a technique well, you need to understand what problem it's solving. Before you can debug a training run, you need a clear picture of what's happening inside the process. So rather than marching through every method with equal weight, I've tried to build understanding layer by layer — starting with how neural networks learn at all, moving through the practical realities of training, and then expanding into the major architectural families that dominate modern deep learning. Each chapter tries to answer the question a thoughtful practitioner would actually ask, not just explain what a thing is, but why it exists and when it matters.

Structurally, the book moves from foundations to application. We begin with the core mechanics of neural networks — how information flows forward through a network, how gradients flow backward, and what optimization is actually doing when a model trains. From there, we move into the practical side of building training pipelines: how you think about datasets, batching, loss functions, and the evaluation loop that tells you whether progress is real. The middle sections introduce the major architectural patterns — MLPs, convolutional networks, recurrent networks, and Transformers — not as exhaustive technical deep dives, but as conceptual frameworks. The goal is for you to understand what each architecture is designed to handle and how to reason about which approach fits a given problem. The later chapters focus on training in practice: regularization, common failure modes, and the habits that separate practitioners who iterate confidently from those who feel stuck.

By the time you finish this book, my hope is that you can do several things you couldn't do before. You should be able to look at a training run and have genuine hypotheses about what's going wrong. You should be able to read about an architecture and understand the design decisions behind it, not just the structure. You should feel equipped to build and evaluate models on your own data, with a clear sense of the workflow and the choices it requires. Most importantly, I want you to feel like deep learning is something you can think through — not just something you execute by following instructions.

I want to be honest about what this book is not. It is not a comprehensive survey of deep learning research. It does not cover every architecture, every training trick, or every specialized

domain. Generative models, reinforcement learning, and many advanced topics are either touched on lightly or left out entirely — not because they aren't important, but because depth matters more than breadth here. This book is designed to give you a strong, stable foundation. Once you have it, the more specialized literature becomes far more accessible. I'd rather you finish this book with ten ideas you truly understand than fifty you've merely encountered.

I've tried to write the book I wish someone had handed me early on — one that takes your time seriously, respects your intelligence, and stays focused on what actually moves the needle. Deep learning rewards people who think carefully, and I believe you're capable of that. Let's get started.

To all the lifelong learners, who never stop exploring, questioning, and growing.

To those who dare to teach themselves, and then teach others.

This book is for you.

Contents

CHAPTER 1

THE DEEP LEARNING MINDSET: FROM RULES TO REPRESENTATIONS

1.1 The Deep Learning Mindset: From Rules to Representations

Imagine trying to write down every rule a child uses to recognize a cat. You might start with four legs, pointed ears, whiskers, and a tail — but then a Persian cat sitting in shadow breaks your rule about visible whiskers, a Manx cat has no tail, and a kitten barely resembles the adult form you described. Every rule you add spawns three exceptions, and every exception demands a sub-rule. Programmers spent decades attempting exactly this kind of rule-based reasoning in artificial intelligence, and the results were brittle, expensive, and humbling. Deep learning represents a fundamental philosophical break from that tradition. Instead of asking humans to articulate the rules, it asks the data to reveal them.

1.1.1 Why Rules Alone Are Not Enough

For much of computing history, the dominant paradigm in artificial intelligence was *symbolic reasoning*: encode human knowledge as explicit rules, feed those rules to a computer, and let logic do the rest. Expert systems of the 1980s embodied this philosophy. A medical diagnosis system might contain thousands of hand-crafted if-then statements written by physicians: *if the patient has a fever above 38.5°C and reports a sore throat and the throat appears red on examination, then consider streptococcal infection*. These systems worked remarkably well within their narrow domains, and some are still in use today.

The problem is that the real world is not narrow. Language, vision, speech, and complex decision-making involve patterns so subtle and so numerous that no team of human experts can enumerate them completely. Consider the task of spam detection. An early approach was to maintain a list of suspicious words — "free," "winner," "claim your prize" — and block any email containing them. Spammers adapted within weeks, substituting characters, misspelling words deliberately, and embedding text inside images. Every time the rule-writers patched one hole, a new one appeared. The adversarial dynamic exposed a deeper truth: the rules were never capturing the *essence* of spam; they were capturing surface-level symptoms that changed as soon as anyone looked at them.

Example: Google's early spam filters relied heavily on keyword blacklists and sender reputation scores — both hand-engineered features. As the volume of email grew into the billions per day, the maintenance burden became untenable. The transition to machine learning, and eventually to neural network-based classifiers, allowed the system to discover its own indicators of spam from labeled examples, including patterns that no human analyst had thought to look for, such as subtle statistical regularities in header metadata.

The lesson is not that rules are useless. Rules are excellent for well-defined, stable domains: calculating tax, sorting a list, validating a credit card number. The lesson is that rules become inadequate precisely where the problems are most interesting — where the input is high-dimensional, where the patterns are latent rather than obvious, and where the world changes faster than rule-writers can respond.

1.1.2 The Classical Machine Learning Approach

Before deep learning rose to prominence, the field of machine learning had already moved beyond pure rule-writing. Classical machine learning methods — logistic regression, support vector machines, random forests, gradient-boosted trees — offered a compelling middle ground: instead of writing rules by hand, you could *learn* a decision boundary from labeled data. This was a genuine advance, and these methods remain powerful, interpretable, and computationally efficient for many problems.

The catch is that classical methods still required humans to decide *what to measure*. This step is called **feature engineering**, and it is as much an art as a science. A feature is any measurable property of the input that you believe is relevant to the prediction. For image classification, you might compute color histograms, edge orientations using a Sobel filter, or texture descriptors using algorithms like SIFT or HOG. For text classification, you might compute term frequency-inverse document frequency (TF-IDF) scores, sentence length, or the presence of specific n-grams. For fraud detection, you might compute the time since the last transaction, the geographic distance between consecutive purchases, or the ratio of the current transaction amount to the account's historical average.

Feature engineering demands deep domain knowledge. A signal processing expert knows which frequency bands matter for speech recognition. A radiologist knows which image regions are diagnostically significant. Without that expertise, a machine learning pipeline is likely to miss the signal entirely, no matter how sophisticated the downstream classifier. This dependency on human expertise creates a bottleneck: the quality of the model is bounded by the quality of the features, which is bounded by the depth of human understanding of the problem.

Example: The ImageNet Large Scale Visual Recognition Challenge (ILSVRC), run annually from 2010, illustrated this bottleneck vividly. In 2011, the winning system used hand-crafted features combined with classical classifiers and achieved a top-5 error rate of around 26%. In 2012, a deep convolutional neural network called AlexNet — which learned its own features directly from raw pixels — achieved a top-5 error rate of 15.3%, a gap so large it shocked the computer vision community and effectively ended the era of hand-crafted features for image recognition tasks.

Table 1.1: Classical ML vs. Deep Learning Pipeline Comparison

Stage	Classical ML	Deep Learning
Input	Raw data	Raw data
Feature extraction	Manual, domain-expert designed	Automatic, learned from data
Model	Logistic regression, SVM, etc.	Multi-layer neural network
Data requirements	Works with small datasets	Benefits from large datasets
Compute requirements	Low to moderate	Moderate to high
Interpretability	Generally higher	Generally lower
Performance ceiling	Limited by feature quality	Scales with data and compute

1.2 Learning Representations: The Core Idea

At the heart of deep learning is a deceptively simple idea: instead of telling the model what to look for, let the model discover what to look for. This is the concept of **representation learning**. A representation is simply a way of encoding information. Raw pixels are one representation of an image; a description like "orange fur, triangular ears, green eyes" is another. Deep learning systems learn to construct their own internal representations — often called *features* or *activations* — that are useful for the task at hand.

What makes deep learning *deep* is that these representations are organized in a **hierarchy**. The first layer of a neural network might learn to detect simple edges and color gradients. The second layer combines those edges into corners and curves. The third layer assembles curves into object parts — an eye, a snout, a wheel arch. Deeper layers combine parts into whole objects. This hierarchical composition mirrors how humans understand complex concepts: we perceive strokes before letters, letters before words, words before sentences, sentences before arguments. The depth of the network is what allows it to build up this ladder of abstraction automatically.

Example: Visualizations of convolutional neural networks trained on ImageNet have revealed this hierarchy empirically. Researchers at Zeiler and Fergus (2014) used a technique called deconvolution to project the activations of each layer back into pixel space. First-layer filters responded to oriented edges and color blobs — almost identical to the Gabor filters that computer vision researchers had spent years designing by hand. Middle layers responded to textures and object parts. The deepest layers contained neurons that responded maximally to specific object cate-

gories, faces, or even specific individuals, having constructed those high-level concepts entirely from pixel statistics.

The philosophical shift this represents cannot be overstated. In classical machine learning, human intelligence is upstream of the model: humans decide what matters, then the model learns how much each thing matters. In deep learning, human intelligence is still required — to design the architecture, choose the training data, and set the learning objective — but the model itself discovers *what* matters. This is why deep learning has been transformative in domains like speech, vision, and language, where human experts struggle to articulate the features that distinguish one class from another.

1.2.1 Neural Networks as Universal Function Approximators

A neural network is, at its mathematical core, a parameterized function. It takes an input — a vector of numbers representing pixels, words, sensor readings, or anything else you can quantify — and produces an output: a class label, a probability, a translated sentence, a predicted price. The parameters of this function are the **weights** and **biases** stored in the network's layers, and they are adjusted during training to make the function's outputs align with the desired targets.

A foundational theoretical result, known as the **Universal Approximation Theorem**, states that a neural network with at least one hidden layer and a sufficient number of neurons can approximate any continuous function to arbitrary precision, given appropriate weights. This is a remarkable guarantee: whatever mapping you are trying to learn — from MRI scans to cancer diagnoses, from audio waveforms to transcribed text, from board positions to optimal chess moves — a sufficiently large neural network can, in principle, represent it.

The practical caveat is the phrase "given appropriate weights." The theorem guarantees the existence of a solution; it says nothing about whether gradient-based training will find it, how much data is required to find it, or how long the computation will take. These are the hard problems of deep learning, and they occupy most of the research literature. Nevertheless, the theoretical foundation is reassuring: when a deep learning model fails, it is almost never because the architecture is fundamentally incapable of representing the solution. It is because of insufficient data, poor optimization, or mismatched inductive biases.

Key Insight

The Universal Approximation Theorem is often misunderstood as a guarantee of success. It is better understood as a guarantee of *capacity*: a neural network can represent the solution, but training is the process of finding it. More data, better optimization, and thoughtful architecture design are what bridge the gap between theoretical capacity and practical performance.

Neural networks improve with more data and more compute in a way that classical models generally do not. A logistic regression classifier trained on one million examples is not dramatically better than one trained on one hundred thousand examples, because the model's capacity — its ability to represent complex functions — is limited by its linear decision boundary. A deep neural network, by contrast, can exploit additional data to refine increasingly subtle distinctions. This *scaling behavior* is one of the most important empirical facts in modern deep learning, and it underpins the development of large language models, large vision models, and multimodal systems that continue to push the frontier of what machines can do.

1.2.2 What Neural Networks Cannot Do

Intellectual honesty demands that we spend as much time on limitations as on capabilities. Neural networks are not magic, and developing accurate intuitions about their failure modes is as important as understanding their strengths.

Neural networks are, fundamentally, pattern-matching systems. They excel when the test distribution resembles the training distribution — when the patterns they learned during training are the same patterns they encounter during deployment. When the distribution shifts, performance can degrade sharply and in ways that are difficult to predict. A model trained to detect tumors in X-rays from one hospital may perform poorly on X-rays from a different hospital that uses different equipment and imaging protocols. A language model trained on internet text from 2021 will not know about events from 2023. This sensitivity to **distribution shift** is a fundamental limitation, not an engineering bug to be patched.

Neural networks also struggle with **systematic generalization** — the ability to apply learned rules to novel combinations. A human who learns the concept of "blue" and the concept of "cube" can immediately recognize a blue cube they have never seen. Neural networks trained on individual

concepts do not always compose them reliably, particularly in low-data regimes. Researchers have documented cases where image classifiers learn to associate a label with background context rather than the object itself: a model trained to classify wolves versus dogs learned, in part, to associate snowy backgrounds with wolves, because most wolf training images were taken in snowy environments. Remove the snow, and the model's performance collapsed.

Example: In 2018, researchers at MIT published a study showing that several commercial facial recognition systems had dramatically higher error rates for darker-skinned women than for lighter-skinned men — up to 34 percentage points higher in some cases. The root cause was not algorithmic in the narrow sense; it was a representation problem. The training datasets were heavily skewed toward lighter-skinned individuals, so the models learned representations that were simply less informative for darker skin tones. The lesson is that a neural network faithfully learns whatever patterns exist in its training data, including patterns that reflect historical biases and sampling inequities.

1.3 The Training Loop: How Neural Networks Learn

Understanding the training loop is the single most important conceptual step for any practitioner entering the field of deep learning. Everything else — architectures, optimizers, regularization techniques — is either a component of this loop or a modification of it. The loop has four stages, and they repeat thousands or millions of times until the model's performance is satisfactory.

1.3.1 Forward Pass: Making a Prediction

The **forward pass** is the process of feeding an input through the network to produce a prediction. Starting from the input layer, each layer transforms its input by computing a weighted sum of its incoming signals and passing the result through a nonlinear **activation function**. The output of one layer becomes the input of the next, and the chain of transformations continues until the final layer produces the network's prediction.

Consider a simple example: a network trained to classify handwritten digits from the MNIST dataset. The input is a 28×28 grayscale image, which is flattened into a vector of 784 pixel values. The first hidden layer might contain 256 neurons; each neuron computes a weighted sum of all 784 inputs and applies an activation function like ReLU (Rectified Linear Unit). The second

hidden layer might contain 128 neurons, and the output layer contains 10 neurons — one for each digit class — with a softmax activation that converts raw scores into probabilities. During the forward pass, the input image flows through this chain of transformations, and the output is a vector of 10 probabilities representing the network's confidence in each digit class.

1.3.2 Loss Computation: Measuring the Mistake

The **loss function** (also called the cost function or objective function) quantifies how wrong the network's prediction is. It takes the network's output and the true label as inputs and returns a single scalar number — the loss — that measures the discrepancy between them. A perfect prediction yields a loss of zero; larger errors yield larger losses.

For classification tasks, the most common loss function is **cross-entropy loss**, which penalizes confident wrong predictions more harshly than uncertain wrong predictions. If the network assigns a probability of 0.01 to the correct class, the cross-entropy loss is much higher than if it assigns a probability of 0.4. This asymmetry is deliberate: it encourages the network to be not just correct, but confidently correct. For regression tasks — predicting a continuous value like a house price — **mean squared error** is common, penalizing large deviations quadratically.

The choice of loss function is not arbitrary. It encodes the learning objective, and a poorly chosen loss function can produce a model that technically minimizes its training objective while completely failing at the real-world task. Choosing the right loss function requires understanding both the mathematical properties of the optimization and the practical requirements of the deployment context.

1.3.3 Backward Pass: Assigning Credit

The **backward pass**, or **backpropagation**, is the mechanism by which the network determines how each weight contributed to the loss. It is an application of the chain rule of calculus, computing the gradient of the loss with respect to every weight in the network. The gradient is a vector that points in the direction of steepest increase in the loss; by moving in the opposite direction, we can reduce the loss.

Backpropagation works by propagating the error signal backward through the network, from the output layer to the input layer. At each layer, it computes how much each weight contributed to

the final error, taking into account all the transformations that followed. This credit assignment — determining which weights are responsible for which part of the error — is conceptually the most subtle part of the training loop, and it was the key algorithmic insight that made training deep networks feasible when it was popularized in the 1980s by Rumelhart, Hinton, and Williams.

Example: Think of backpropagation like a manager reviewing a failed project. The final outcome was bad, but who is responsible? The manager traces the chain of decisions backward: the product shipped late because testing took too long; testing took too long because the test suite was poorly organized; the test suite was poorly organized because the lead engineer made a poor architectural decision early on. Each person in the chain receives a share of the blame proportional to their contribution. Backpropagation does the same thing for weights, assigning each one a gradient that reflects its contribution to the final error.

1.3.4 Weight Update: Adjusting the Parameters

The final stage of the loop is the **weight update**: using the gradients computed during backpropagation to adjust the network's weights in the direction that reduces the loss. The simplest update rule is **stochastic gradient descent** (SGD):

```
# Simplified weight update in pure Python (conceptual)
learning_rate = 0.01

for weight, gradient in zip(weights, gradients):
    weight -= learning_rate * gradient
```

The **learning rate** is a hyperparameter that controls the size of each update step. A learning rate that is too large causes the optimization to overshoot the minimum and diverge; a learning rate that is too small causes training to proceed so slowly that it becomes impractical. Finding a good learning rate — and adapting it over the course of training — is one of the core practical skills in deep learning.

Modern optimizers like Adam, RMSProp, and AdaGrad extend this basic idea with adaptive learning rates, momentum, and other refinements. But the conceptual core remains the same:

compute the gradient, move in the direction that reduces the loss, repeat. Here is what the complete training loop looks like in PyTorch, the dominant deep learning framework for research:

```
import torch
import torch.nn as nn
import torch.optim as optim

# Define a simple two-layer network
model = nn.Sequential(
    nn.Linear(784, 256),
    nn.ReLU(),
    nn.Linear(256, 10)
)

optimizer = optim.Adam(model.parameters(), lr=1e-3)
loss_fn = nn.CrossEntropyLoss()

# One epoch of training
for inputs, labels in dataloader:
    # Stage 1: Forward pass
    predictions = model(inputs)

    # Stage 2: Compute loss
    loss = loss_fn(predictions, labels)

    # Stage 3: Backward pass (compute gradients)
    optimizer.zero_grad()
    loss.backward()

    # Stage 4: Update weights
    optimizer.step()
```

This loop — forward, loss, backward, update — is the heartbeat of every deep learning system

ever built. The architectures change; the loss functions change; the optimizers change. But this four-stage cycle remains constant, whether you are training a two-layer network to classify handwritten digits or a billion-parameter transformer to generate text.

Common Mistake

Forgetting to call `optimizer.zero_grad()` before `loss.backward()` is one of the most common bugs in PyTorch code. PyTorch accumulates gradients by default, so if you skip this step, gradients from previous batches will contaminate the current update, leading to unstable or incorrect training. Always zero the gradients at the start of each training step.

1.4 Developing the Right Intuition

Technical knowledge of architectures and algorithms is necessary but not sufficient for becoming an effective deep learning practitioner. What separates good practitioners from great ones is **intuition** — the ability to look at a problem, a dataset, or a training curve and make sound judgments about what is happening and what to try next.

Intuition in deep learning is built through deliberate practice and reflection, not through memorizing equations. When a model's training loss decreases but its validation loss increases, an experienced practitioner immediately recognizes **overfitting** and reaches for regularization, more data, or a simpler architecture. When a model's loss oscillates wildly instead of decreasing smoothly, the practitioner suspects a learning rate that is too high. When two architectures perform similarly on a benchmark but one is ten times faster to train, the practitioner chooses the faster one and invests the saved compute in better data or more experiments.

One of the most important intuitions to develop early is the relationship between **model capacity** and **dataset size**. A very large, expressive model trained on a small dataset will memorize the training examples rather than learning generalizable patterns — this is overfitting. A very small model trained on a large dataset will fail to capture the complexity of the underlying function — this is underfitting. The art of model selection is finding the sweet spot, and that sweet spot shifts as you collect more data, which is why scaling laws have become such an active area of research.

Another critical intuition concerns **what the network is actually learning**. It is easy to assume

that a network trained to classify cats has learned a concept of "cat" in a meaningful sense. In reality, it has learned a statistical function that maps pixel patterns to labels, and that function may be exploiting shortcuts that are invisible in the training data but catastrophic in deployment. A model trained to detect pneumonia in chest X-rays might learn to associate the metal tokens placed on X-rays at certain hospitals (used for calibration) with the pneumonia label, because those hospitals happened to take more X-rays of sick patients. The model is not reasoning; it is pattern-matching, and the patterns it finds are not always the ones we intend.

Scenario: Suppose you are building a model to predict customer churn for a subscription service. A classical ML practitioner would spend days engineering features: tenure, usage frequency, support ticket history, payment delays. A deep learning practitioner might feed raw event logs directly into a recurrent network and let the model discover the relevant patterns. Neither approach is universally better. The classical approach is more interpretable and works well with limited data; the deep learning approach may discover subtle temporal patterns that no human analyst thought to engineer, but it requires more data and compute, and its predictions are harder to explain to business stakeholders. Knowing when to use which approach is itself a form of intuition that develops only with experience.

Pro Tip

Before reaching for a deep learning solution, ask whether a simpler model would suffice. Gradient-boosted trees (XGBoost, LightGBM) consistently outperform neural networks on tabular data with fewer than a few hundred thousand rows. Deep learning's advantages are most pronounced with high-dimensional, unstructured data — images, text, audio — and with datasets large enough to support learning rich representations. Starting simple and scaling up is almost always more efficient than starting complex and trying to simplify.

The mindset shift that deep learning demands is ultimately about **trust and verification**. You must trust the optimization process to find useful representations without you specifying them, while simultaneously verifying at every step that the model is learning what you intend. This combination of relinquishing control and maintaining oversight is intellectually demanding, and it is why the best deep learning practitioners are not just engineers — they are curious, skeptical, and comfortable reasoning under uncertainty.

Key Takeaways

- Deep learning differs from classical machine learning by automatically learning feature representations directly from raw data, eliminating the need for hand-crafted features and removing the bottleneck of domain-expert feature engineering.
- Neural networks are universal function approximators: given sufficient capacity, they can represent any continuous function. However, the theorem guarantees capacity, not that training will find the solution — data quality, quantity, and optimization choices determine practical performance.
- The training loop — forward pass, loss computation, backward pass, weight update — is the fundamental cycle of every deep learning system. Mastering this loop conceptually and practically is the foundation upon which all further knowledge is built.
- Developing sound intuition about what neural networks can and cannot do — including their sensitivity to distribution shift, their tendency to exploit spurious correlations, and the relationship between model capacity and dataset size — is more valuable in practice than memorizing specific architectures.
- Deep learning excels with high-dimensional unstructured data and large datasets, but simpler classical methods often outperform it on small tabular datasets. Choosing the right tool requires understanding the strengths and limitations of both paradigms.

Exercises

1. **Explain it simply.** Write a one-paragraph explanation of how a neural network "learns" aimed at a non-technical audience — a family member or a colleague from a non-technical department. Focus on the idea of making a guess, measuring how wrong the guess was, and adjusting internal settings to do better next time. Avoid all mathematical notation. After writing your explanation, reflect: which part was hardest to explain without jargon, and why?
2. **Pipeline comparison.** Choose a toy classification problem — for example, predicting whether a passenger survived the Titanic disaster, using the well-known Kaggle dataset. Design two pipelines in writing: (a) a classical ML pipeline using manual feature engineering

followed by logistic regression, and (b) a deep learning pipeline using an embedding layer and a small feedforward network. For each pipeline, list the steps, the human decisions required at each step, the data requirements, and the expected trade-offs in interpretability and performance. Summarize the key differences in a short table.

3. **Sketch the training loop.** On paper or in a drawing tool, sketch the four stages of the training loop as a cycle: forward pass, loss computation, backward pass, and weight update. For each stage, annotate what information flows into it and what flows out. For example: what enters the forward pass? What does it produce? What does the backward pass receive, and what does it compute? Share your sketch with a peer and discuss any stages where the information flow was unclear to you.

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