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White Paper

AI/ML MODELING PATTERNS

ABSTRACT

A whitepaper on reusable ML engineering patterns, their limits, and what they mean for teams maintaining production models

INTRODUCTION: PURPOSE AND AUDIENCE

Teams building AI/ML systems and the stakeholders who fund, govern, or depend on those systems often talk past each other. Engineers reach for established design patterns because they solve problems that have already been encountered and documented. Stakeholders ask a different question: will this model still be trustworthy in a year? Both questions matter, and this paper is written to give both audiences a shared vocabulary for answering them.

This document is intended for three overlapping readers: engineers and data scientists choosing how to structure a model or pipeline; technical leads and architects reviewing design decisions; and non-technical stakeholders — product owners, risk and compliance functions, executive sponsors — who need to know what a model can be trusted to do, and where that trust runs out.

The paper is organized in two halves. The first half surveys the concepts and design patterns engineers reuse across ML projects — proven solutions to recurring, already-encountered problems. The second half addresses what patterns do not cover: the fact that every model is trained on historical data and deployed into a world that keeps changing after training stops. Understanding both halves is necessary for evaluating how dependable an AI/ML system will be over time, not just at launch.

EXECUTIVE SUMMARY

This paper surveys how artificial intelligence and machine learning systems are actually built: the core concepts, the recurring design patterns engineers reuse across projects, and the pipeline that turns raw data into a deployed model. It also covers a problem that gets less attention than it deserves: design patterns are answers to known, already-encountered failures, but every model is trained on historical data and deployed into a world that keeps changing after training stops. Understanding both halves — the established patterns and their limits — is necessary for anyone evaluating how dependable an AI/ML system will be over time, not just at launch.

Who should act on this: engineering leads should use the pattern catalog as a starting checklist, not a finish line; stakeholders should use the "Two Postures" and "What This Means for Your Team" sections to ask better questions during model reviews.

DEFINITIONS

Artificial intelligence (AI): the broad goal of building systems that perform tasks normally requiring human-like reasoning, perception, or decision-making. An AI system is an engineered or machine-based system that, for a given set of objectives, generates outputs such as predictions, recommendations, or decisions that influence real or virtual environments.

Machine learning (ML): the dominant approach to AI today. Rather than hand-coding rules, a system learns patterns directly from data. Deep learning is a subset of ML that uses multi-layered neural networks and underlies most recent advances in vision, speech, and language.

Model: the resulting artifact — a mathematical function with parameters fitted to data, which maps new inputs to outputs. Modelling is the process of choosing that function's structure and fitting its parameters.

DESIGN PATTERNS IN PRACTICE

Patterns are reusable solutions to problems that keep recurring across ML projects — the kind of thing a team learns the hard way once and then writes down so the next team doesn't have to. Thirty such patterns are catalogued in Lakshmanan, Robinson, and Munn's Machine Learning Design Patterns (O'Reilly, 2021), spanning data and problem representation, operationalization, repeatability, reproducibility, flexibility, explainability, and fairness.

Scope of this paper: the eight patterns below are a representative sample, not the full catalog, chosen because they recur most often in the projects this paper draws on. They are grouped here into four families for readability; the source book uses a finer-grained structure. Teams wanting the complete set of thirty should consult the source text directly.

Family	Solves for	Patterns covered in this paper
Data Representation	How raw inputs become model-ready features	Embeddings, Feature Cross
Problem Representation	How the prediction task itself is framed	Reframing, Cascade
Training Resilience	Keeping long training runs safe and reproducible	Checkpoints, Repeatable Splitting
Operationalization	Getting a trained model safely into production	Transform, Keyed Predictions

DATA REPRESENTATION

Embeddings

representing an item (a word, a product, a user) as a dense vector of numbers so that similar items sit near each other mathematically. Recommendation engines use this to find "similar" products without manually defining similarity rules.

Feature cross

combining two features to capture an interaction effect, such as crossing day-of-week with hour of-day in a pricing model, since Friday at 5pm behaves differently than Monday at 5pm.

PROBLEM REPRESENTATION

Reframing

converting a hard regression problem into an easier classification problem — for example, predicting a price bucket instead of an exact price — which is more robust to noise.

Cascade

breaking one prediction into a sequence of smaller models rather than one model handling everything at once.

Repeatable splitting

using a hash of a well-distributed column to assign each record consistently to train, validation, or test sets, preventing data leakage across retraining runs.

OPERATIONALIZATION

Transform

keeping raw inputs, engineered features, and the transformation logic separate, so moving a model to production does not silently break when it receives data formatted differently than during training.

Keyed predictions

exporting a model so client-supplied keys pass through with each prediction — which matters when scoring millions of records in batch and needing to match each output back to the right record.

EXAMPLE: FRAUD DETECTION

A single worked example shows how these patterns combine in a real pipeline:

A rules engine — a set of fixed if-then conditions written by humans rather than learned from data — filters obvious cases first (cascade pattern).

A trained ML model scores the remainder for risk, using features like transaction amount crossed with merchant category (feature cross).

Borderline scores route to human review, and every prediction carries a transaction ID through the pipeline (keyed predictions), so outcomes can be traced and fed back into retraining.

THE MODELLING PIPELINE

Building a model is a sequence of stages, not a single algorithmic step:

01. Problem Framing

02. Data Collection & Labeling

03. Feature Engineering

04. Model Selection

05. Training & Validation

06. Deployment

07. Monitoring & Retraining

Each stage feeds the next, but the loop back from monitoring to data collection is the one most teams underbuild. A model that performs well at launch can quietly fail months later if the real-world data it sees no longer resembles what it was trained on — a problem called data drift. Overfitting is the inverse risk during training itself: a model that memorizes training data well enough to score perfectly on it, then performs poorly on anything new.

TWO POSTURES TOWARD MODEL MAINTENANCE

Design patterns address known, recurring engineering problems. They do less to address what happens after deployment, when the world the model was trained on keeps moving. The table below contrasts a pattern driven posture with a drift-aware posture; most production systems need elements of both.

	Pattern-driven engineering	Drift-aware monitoring
Optimizes for	Avoiding known, previously-encountered failure modes	Detecting when current data no longer resembles training data
Assumes	The problem space is structurally similar to past projects	The world will change in ways training data cannot anticipate
Typical tooling	Reusable pipelines, checkpointing, feature stores	Statistical drift tests, shadow deployments, retraining triggers
What it misses	Novel failure modes with no precedent in the pattern catalogue	Added cost and complexity not justified for slow-moving domains

WHERE THIS STRUGGLES

Two important limitations should be acknowledged before treating either posture as independently sufficient.

Patterns can import hidden assumptions across domains

Embeddings work well for products and words because similarity there is stable and meaningful: two similar products really do appeal to similar buyers. Applying the same logic to represent people — in hiring or lending models — quietly assumes that two similar-looking profiles should receive similar outcomes.

Amazon's internal recruiting tool, scrapped in 2018, is the clearest documented case: trained on a decade of past hiring decisions that skewed male, the model learned to downgrade resumes containing words like "women's" (as in "women's chess club") and penalized graduates of two all-women's colleges — effectively reproducing the bias in its training data rather than correcting for it (Reuters, 2018).

Drift-aware monitoring is not free

Drift-aware monitoring adds engineering overhead, infrastructure cost, and organizational complexity: statistical drift tests, shadow deployments, alerting, and retraining pipelines all need to be built and maintained by someone. For domains where ground truth is stable and slow-moving — for example, a model estimating physical material properties from lab measurements, where the underlying physics does not change year to year — heavy drift monitoring can be disproportionate to the actual risk. The cost of building it should be weighed against how quickly the domain actually moves, not applied uniformly across every model a team ships.

Together, these two limits point to the same conclusion: neither posture is a checklist a team can complete once. Both require ongoing judgment about which domain a given model sits in.

WHAT THIS MEANS FOR YOUR TEAM

The gap between engineering and stakeholder conversations about AI/ML usually comes down to vocabulary: engineers talk in patterns, stakeholders ask about risk. The table below translates between the two, as a starting checklist for design reviews.

For engineering teams	For stakeholders and reviewers
Document which pattern each design decision maps to, and which assumption it imports (e.g., "similar profile → similar outcome").	Ask which patterns were used to represent people or high-stakes attributes, and what assumption that choice makes.
Size drift monitoring to how fast the domain actually moves — not uniformly across every model.	Ask how fast the underlying domain changes, and whether monitoring investment matches that pace.
Make the monitoring → retraining feedback loop an explicit, owned pipeline stage, not an informal afterthought	Ask who owns the retraining decision, and what threshold triggers it.
Flag when a pattern is being applied outside the domain it was proven in (e.g., embeddings moving from products to people).	Ask for a documented case — like Amazon's recruiting tool — the team has reviewed to understand the failure mode.

CONCLUSION

Design patterns capture the field's accumulated answers to problems that have already occurred. They make ML systems faster to build and less likely to repeat documented mistakes. They do not, on their own, tell a team when the assumptions baked into a model have stopped holding. That is a monitoring and governance problem as much as an engineering one, and it deserves the same deliberate attention that pattern catalogues already receive.

GLOSSARY

	Term	Definition
	AI	The broad goal of building systems that perform tasks normally requiring human-like reasoning, perception, or decision-making.
	Machine learning (ML)	An approach to AI where a system learns patterns directly from data rather than following hand-coded rules.
	Model	A mathematical function with parameters fitted to data, mapping new inputs to outputs.
	Embeddings	Dense numeric vectors representing items so similar items sit near each other mathematically.
	Feature cross	A combined feature capturing the interaction effect between two other features.
	Reframing	Converting a hard regression problem into an easier classification problem.
	Cascade	Breaking one prediction into a sequence of smaller models.
	Checkpoints	Saved intermediate model weights allowing a training run to resume after a crash.
	Repeatable splitting	Using a hash of a well-distributed column to consistently assign records to train/validation/test sets.
	Transform	Keeping raw inputs, engineered features, and transformation logic separate for safe production deployment.
	Keyed predictions	Passing client-supplied keys through with each prediction so batch outputs can be matched back to records.
	Data drift	The tendency for real-world data to diverge from what a model was trained on over time.
	Overfitting	A model memorizing training data well enough to score perfectly on it, then performing poorly on new data.