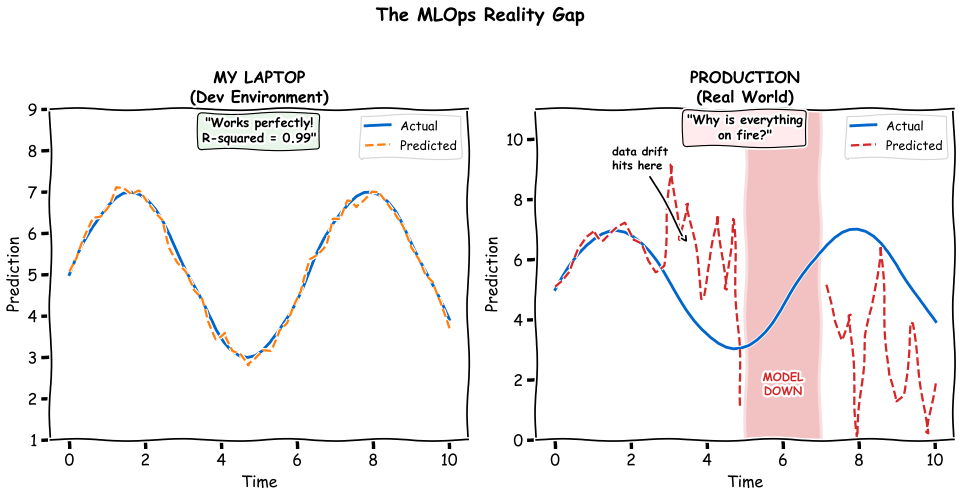
Lesson 5.4: MLOps and Production ML in Finance

Module 5: Automation and Infrastructure

Digital Finance

The MLOps Reality Gap



Building a model is 10% of the work. Running it reliably in production is the other 90%.

Learning Objectives

By the end of this lesson, you will be able to:

1. **Map** the complete ML lifecycle from data ingestion to model retirement [Understand]
2. **Distinguish** concept drift, data drift, and covariate shift with financial examples [Understand]
3. **Design** a model monitoring dashboard with appropriate metrics and alerts [Create]
4. **Explain** SR 11-7 model risk management requirements for regulated institutions [Understand]
5. **Evaluate** champion-challenger testing frameworks for model replacement decisions [Evaluate]

Core theme: Models are not "fire and forget." They are living systems that require continuous care.

These objectives span technical (drift detection), operational (monitoring), and regulatory (governance) dimensions.

From Prediction to Production

Where we are: We understand what models can and cannot predict.
The new question: How do we run them reliably in production?

What Data Scientists Build

- Jupyter notebook with 95% accuracy
- Feature engineering in pandas
- Model saved as pickle file
- "It works on my machine!"

What Production Requires

- Automated pipeline, 99.9% uptime
- Feature store with point-in-time correctness
- Versioned, auditable model registry
- Drift detection, alerting, governance

The gap between these two worlds is what MLOps solves.

Industry surveys consistently report that a substantial share of ML prototypes never reach production; causes include data-pipeline fragility, monitoring gaps, and organisational handoffs (O'Reilly AI Adoption in the Enterprise 2024 (O'Reilly, 2024); IDC MLOps 2024 (IDC, 2024)). Data reviewed: April 2026.

What is MLOps?

Definition: Machine Learning Operations (MLOps) applies DevOps principles—automation, monitoring, versioning, and governance—to the machine learning lifecycle.

Traditional DevOps

- Code version control (Git)
- Continuous Integration (CI)
- Continuous Deployment (CD)
- Automated testing
- Infrastructure monitoring

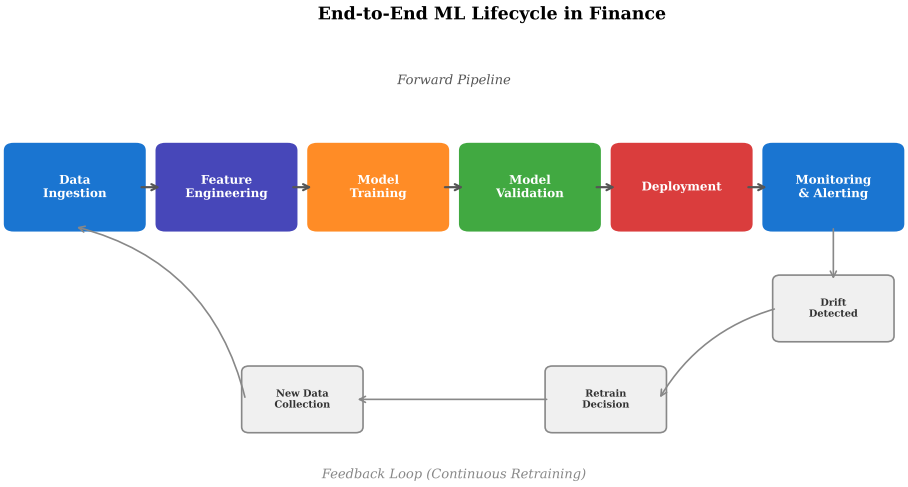
MLOps Adds

- **Data versioning** (Data Version Control (DVC), Delta Lake)
- **Experiment tracking** (MLflow)
- **Feature stores** (Feast, Tecton)
- **Model registry** (staging, production)
- **Drift detection & retraining**

Why it matters in finance: In regulated environments, every model decision must be traceable, reproducible, and auditable. MLOps provides the infrastructure to achieve this.

MLOps bridges the gap between experimental notebooks and enterprise-grade production systems.

The End-to-End ML Lifecycle



- **What you see:** Seven stages in a continuous loop: data ingestion → feature engineering → training → validation → deployment

Stages 1–2: Data Ingestion and Feature Engineering

Data Ingestion

- ETL from databases, APIs, streaming
- Schema validation (types, ranges)
- Data quality checks (missing, outliers)
- Data versioning (snapshots via DVC)

Financial example:

- Transaction data: validate amounts, timestamps
- Market data: check for gaps, split adjustments
- Customer data: PII compliance checks

What is a Feature Store?
A centralized repository that serves features consistently to both training and serving.

Key capabilities:

- Online (low-latency) + offline (batch) storage
- Consistent feature definitions across teams
- Point-in-time correctness for temporal features
- Feature versioning and lineage tracking

Why it matters: Eliminates *training-serving skew*—the silent killer of ML systems.

Training-serving skew occurs when features are computed differently in training vs. production, causing silent accuracy loss.

Stage 3: Model Training and Experiment Tracking

Reproducibility formula:

$$\text{Model}_\text{v} = f\left(\text{Code}_\text{v},\ \text{Data}_\text{v},\ \text{Params}_\text{v},\ \text{Env}_\text{v}\right)$$

What to log for every experiment:

Inputs

- Git commit SHA
- Data version hash
- Hyperparameters
- Random seeds

Outputs

- Performance metrics
- Confusion matrix
- Feature importance
- Model artifact

Context

- Author / team
- Training duration
- Compute cost
- Environment (Docker image)

Financial regulatory requirement: Every production model must be fully reproducible for audit. SR 11-7 mandates "effective challenge" of models, which requires complete lineage.

Tools: MLflow Tracking, Weights & Biases, Neptune.ai, Comet ML.

Stage 4: Model Validation

What is Model Validation? Independent assessment that a model is fit for its intended purpose.

Validation checks before deployment:

- **Performance:** AUC-ROC, precision, recall, F1 vs. baseline
- **Fairness:** Demographic parity, equalized odds across protected groups
- **Robustness:** Performance under adversarial inputs and edge cases
- **Explainability:** SHAP values, feature importance, model cards
- **Business metrics:** Expected revenue impact, operational cost

Financial-specific validation:

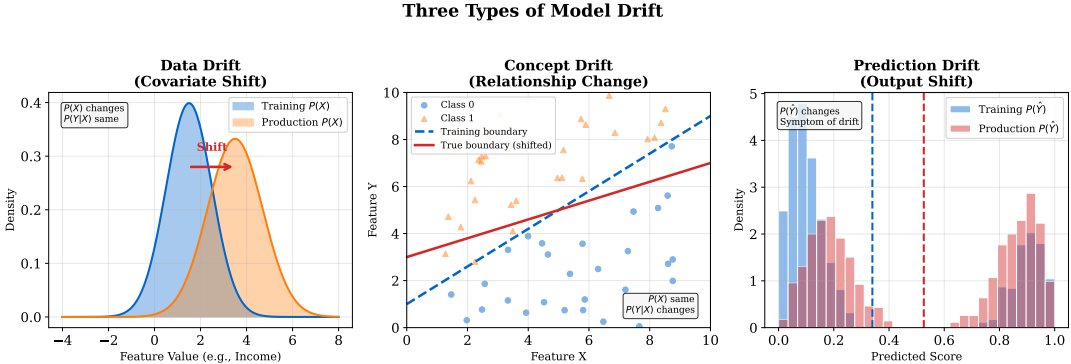
- **Backtesting:** Simulate historical performance (required for VaR models)
- **Stress testing:** Performance during market crises (2008, COVID-19)
- **Sensitivity analysis:** How much do outputs change with small input perturbations?
- **Benchmark comparison:** Must outperform current champion model

Automated gates: Only promote to production if all thresholds pass.

Validation is a regulatory requirement under SR 11-7, not an optional best practice.

What is Model Drift?

Definition: Progressive degradation of model performance due to changes in data or relationships.



- **What you see:** Three drift types—data drift ($P(X)$ changes), concept drift ($P(Y|X)$ changes), prediction drift ($P(\hat{Y})$ changes)
- **Key pattern:** Data drift is common and detectable (PSI); concept drift is rare but catastrophic (model assumptions break)
- **Takeaway:** Monitor all three dimensions—concept drift requires retraining; data drift may only need feature recalibration

All three drift types can occur simultaneously. Concept drift is the most dangerous because the model becomes fundamentally wrong.

Data Drift (Covariate Shift) — What It Is

What is Data Drift? The distribution of input features $P(X)$ changes, while the relationship $P(Y|X)$ stays constant.

Financial examples:

- Average income rises from \$50k to \$65k after inflation
- Transaction amounts shift toward mobile payments
- Customer age distribution skews younger
- Loan sizes increase due to housing prices

Why models struggle:

- Predictions in unfamiliar input regions
- Feature scaling assumptions break
- Decision boundaries may be wrong for new data ranges

Data drift is the most common drift type. The model itself is not wrong—the world has moved to a region the model was not trained on.

Data Drift — Detection Methods and Response

Detection methods:

- **Population Stability Index (PSI)**
- **Kolmogorov-Smirnov test (KS test)**
- **Chi-square test** (categorical features)
- **Wasserstein distance**
- **Jensen-Shannon divergence**

Response:

- Monitor performance closely
- Retrain if accuracy degrades
- Update feature preprocessing
- Expand training data range

Data drift is the easiest to detect automatically. PSI is the industry standard; KS test and Wasserstein distance provide additional confirmation.

Concept Drift — What It Is and Financial Examples

What is Concept Drift? The relationship between inputs and target $P(Y|X)$ changes, even if $P(X)$ stays constant.

Financial examples:

- COVID-19 changes default patterns (same income, different risk)
- New fraud techniques emerge (same transaction patterns, different labels)
- Regulatory change alters risk definitions
- Market regime shift (same indicators, opposite signal)

Four subtypes:

- **Sudden:** Regulatory shock, market crash
- **Gradual:** Customer preferences evolve
- **Incremental:** Step-by-step changes
- **Recurring:** Seasonal patterns (holidays)

Concept drift is the most dangerous type—the model's fundamental assumptions become wrong. The same input now has a different correct answer.

Concept Drift — Detection and Response

Detection (harder than data drift):

- Track online accuracy / AUC over time
- Sliding window evaluation
- **Production tooling (2026):** Arize AI, Fiddler, Evidently, WhyLabs dashboards; PSI, Kolmogorov–Smirnov, Jensen–Shannon divergence tests
- **Academic baselines** (ADWIN, DDM, EDDM) remain in textbooks and streaming-ML research but are rarely deployed as-is

Response:

- **Retrain** with recent labeled data
- **New features** to capture new patterns
- **Ensemble** old + new models
- **Online learning** for fast adaptation
- In extreme cases: **rebuild** the model

Data reviewed: April 2026. Production teams prefer commercial observability tools with dashboards and alert integrations; academic drift algorithms (ADWIN/DDM/EDDM) persist as streaming-ML baselines, not production defaults.

Population Stability Index (PSI)

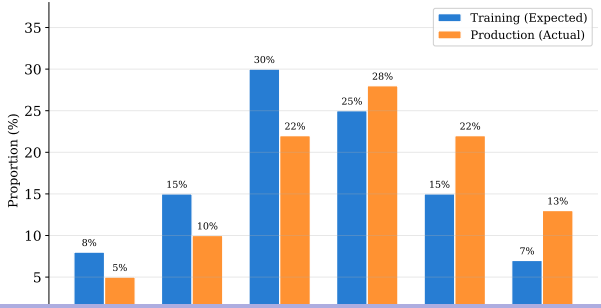
Formula:

$$\text{PSI} = \sum_{i=1}^{n} \left(P_{\text{actual},i} - P_{\text{expected},i}\right) \times \ln\left(\frac{P_{\text{actual},i}}{P_{\text{expected},i}}\right)$$

Example: For bin 1: actual $= 12\%$, expected $= 10\%$. Contribution $= (0.12 - 0.10) \times \ln(0.12/0.10) = 0.02 \times 0.182 = 0.0036$. Summing all bins: if total PSI $= 0.08$, population is stable (< 0.10 threshold).

Population Stability Index (PSI) -- Credit Score Example

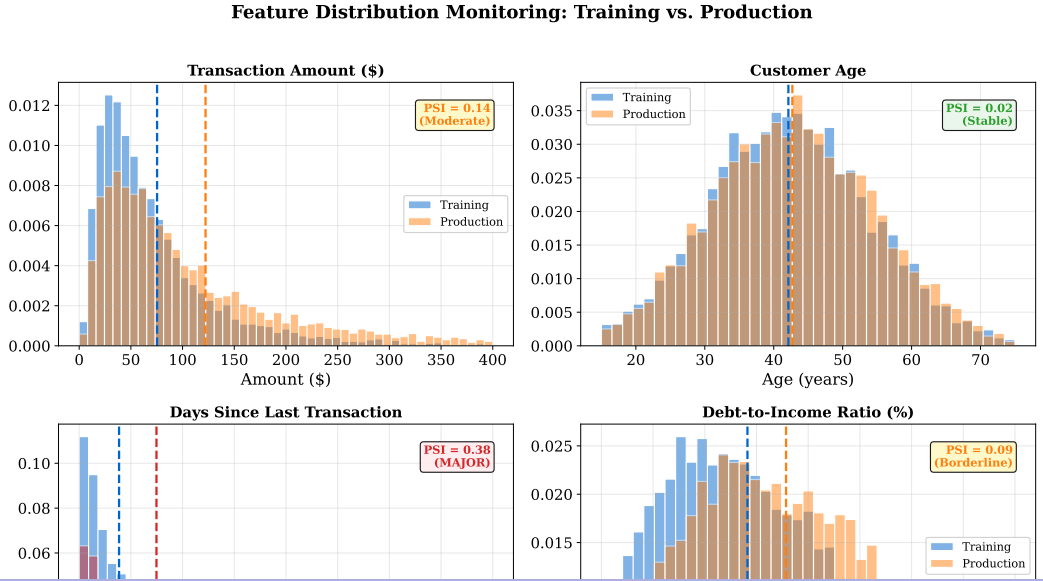
Credit Score Distribution: Training vs. Production

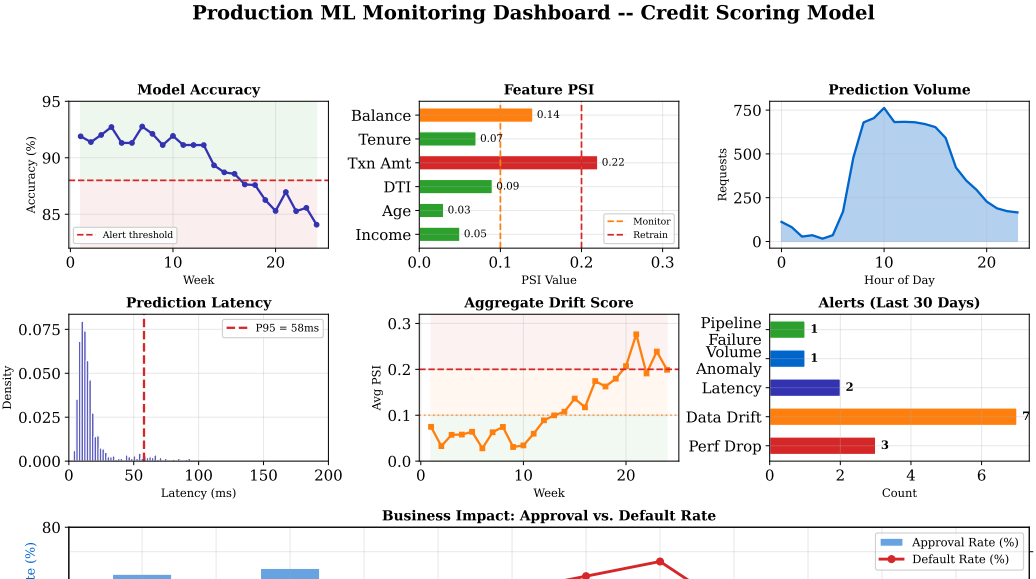


PSI Calculation

Bin	Exp.	Act.	Diff	ln(A/E)	PSI
300-500	0.08	0.05	-0.03	-0.470	0.0141
500-600	0.15	0.10	-0.05	-0.405	0.0203
600-700	0.30	0.22	-0.08	-0.310	0.0248
700-750	0.25	0.28	+0.03	+0.113	0.0034
750-800	0.15	0.22	+0.07	+0.383	0.0268
800+	0.07	0.13	+0.06	+0.619	0.0371
Total					**0.1265**

Feature-Level Distribution Monitoring




Production ML Monitoring Dashboard -- Credit Scoring Model
Model Accuracy
Accuracy (%)
Week
Alert threshold
Feature PSI
Balance
Tenure
Txn Amt
DTI
Age
Income
0.14
0.07
0.22
0.09
0.03
0.05
PSI Value
Monitor
Retrain
Prediction Volume
Requests
Hour of Day
Prediction Latency
Density
Latency (ms)
P95 = 58ms
Aggregate Drift Score
Avg PSI
Week
Alerts (Last 30 Days)
Pipeline Failure
Volume Anomaly
Latency
Data Drift
Perf Drop
Count
Business Impact: Approval vs. Default Rate
Approval Rate (%)
Default Rate (%)

What to Monitor: Model and Data Metrics

1. Model Performance

- Accuracy, AUC-ROC, F1-score
- Compare to baseline SLA
- Track over time with control charts

2. Data Drift

- PSI per feature (weekly)
- KS test, Jensen-Shannon divergence

3. Prediction Drift

- Mean, std, percentiles of $\hat{Y}$
- Prediction rate shift (classifiers)

Why these three come first:

- Performance degradation is the ultimate signal
- Data drift is the earliest warning sign
- Prediction drift bridges the two

Model performance, data drift, and prediction drift are the three core statistical monitors. They detect problems before business impact materializes.

What to Monitor: Quality, Operations, and Business

4. Data Quality

- Missing value rate, schema violations
- Outlier frequency

5. Operational Health

- Latency (P50, P95, P99)
- Error rate, throughput

6. Business Impact

- Approval rate, default rate
- False positive cost
- Revenue per prediction

Alert tiers: CRITICAL (PagerDuty) → WARNING (Slack) → INFO (weekly digest).

Set alert thresholds carefully—alert fatigue is the number-one reason monitoring fails. Data quality bugs cause more "performance drops" than real drift.

SR 11-7: The Three Pillars of Model Risk Management

Definition: Federal Reserve guidance (2011) on model risk management for US banking institutions.

Three pillars:

1. **Model Development:** Sound theory, appropriate methodology, rigorous testing
2. **Model Validation:** Independent review by qualified personnel not involved in development
3. **Model Governance:** Board oversight, model inventory, ongoing monitoring, change management

Scope: SR 11-7 applies to any "quantitative method that processes input data into quantitative estimates"—this explicitly includes machine learning models.

SR 11-7 is the foundational US regulatory framework for model risk. Every bank using ML in decision-making must comply with these three pillars.

SR 11-7: Requirements for ML Models

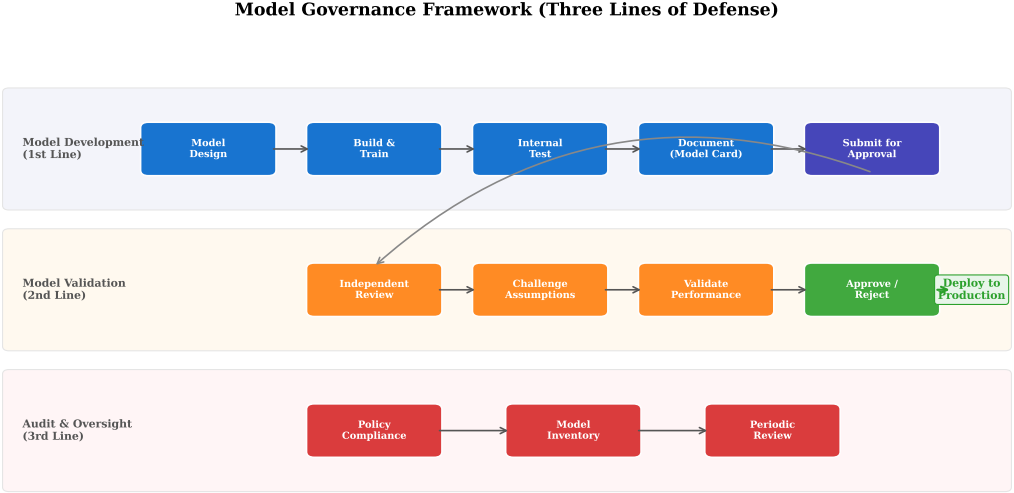
Key requirements that apply specifically to ML models in production:

- **Model inventory:** Centralized catalog of all models with risk tiers
- **Documentation:** Model cards describing purpose, limitations, performance
- **Independent validation:** Second-line review before production deployment
- **Ongoing monitoring:** Continuous performance and drift tracking
- **Audit trail:** Immutable logs of all model changes and decisions
- **Annual review:** Periodic reassessment of all production models

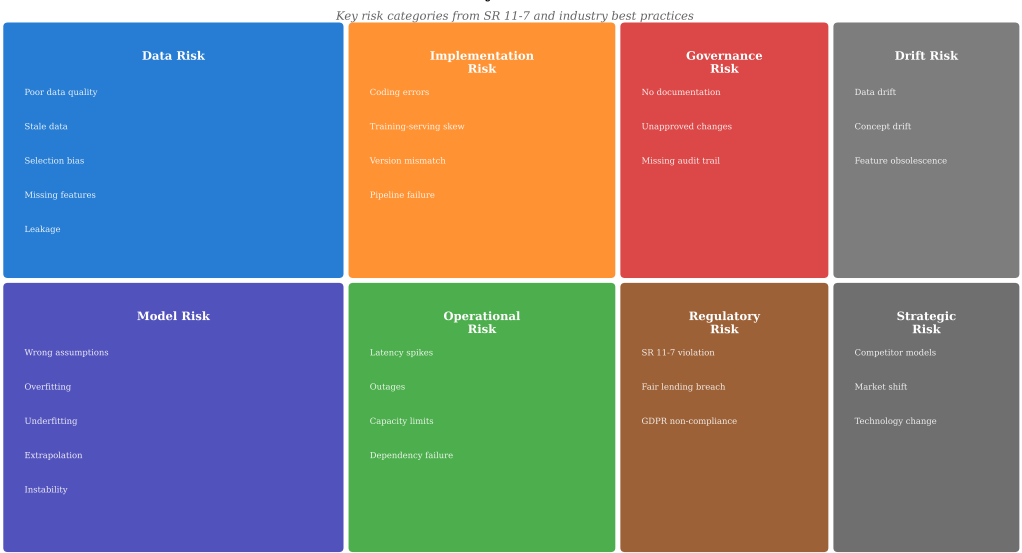
Practical implication: Every production ML model must have a documented owner, a validation report, and a monitoring dashboard before going live.

These six requirements translate the three pillars into actionable obligations for ML engineering teams.

Model Governance: Three Lines of Defense



SR 11-7 / OCC 2011-12: Three Lines of Defense for Model Risk Management


Model Risk Taxonomy for Financial Institutions
Key risk categories from SR 11-7 and industry best practices
Data Risk
Poor data quality
Stale data
Selection bias
Missing features
Leakage
Implementation Risk
Coding errors
Training-serving skew
Version mismatch
Pipeline failure
Governance Risk
No documentation
Unapproved changes
Missing audit trail
Drift Risk
Data drift
Concept drift
Feature obsolescence
Model Risk
Wrong assumptions
Overfitting
Underfitting
Extrapolation
Instability
Operational Risk
Latency spikes
Outages
Capacity limits
Dependency failure
Regulatory Risk
SR 11-7 violation
Fair lending breach
GDPR non-compliance
Strategic Risk
Competitor models
Market shift
Technology change

Model Inventory: Identity and Classification

Definition: A centralized register of every model deployed in the organization.

What to track per model — Identity and status:

- **Identity:** Name, version, owner, team
- **Purpose:** Business use case, decision type
- **Risk tier:** High / Medium / Low
- **Status:** Development / Staging / Production / Retired
- **Training data:** Dataset ID, date range, size

Why it matters: Large banks may have 500+ models in production. Without an inventory, "shadow models" proliferate—unmonitored, undocumented, and uncontrolled.

Regulators routinely ask: "How many models do you have in production?" You must be able to answer precisely.

Model Inventory: Performance and Governance Tracking

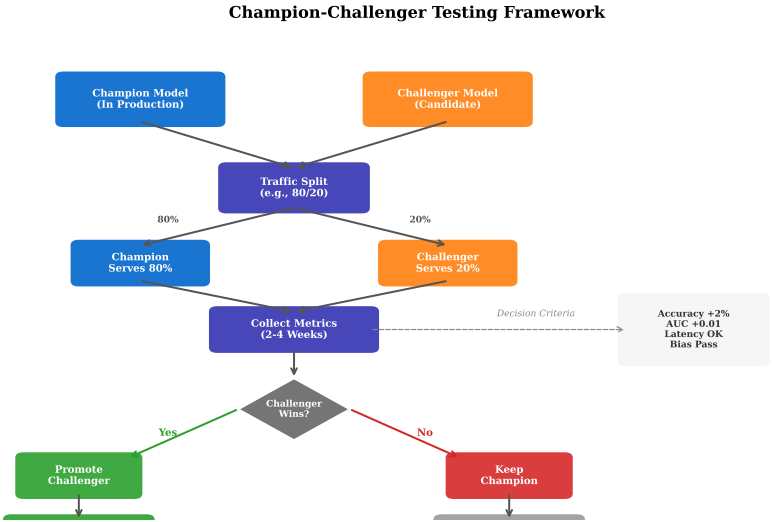
What to track per model — Performance and governance:

- **Performance:** AUC, accuracy, F1 at deployment
- **Validation:** Last review date, reviewer, findings
- **Monitoring:** PSI trend, accuracy trend
- **Dependencies:** Upstream data, downstream consumers
- **Next review:** Scheduled date

Governance workflow: Each model in the inventory should have a clear lifecycle path—from development through validation to production, with documented review gates at each transition.

The model inventory connects all MLOps components: monitoring, validation, governance, and audit. It is the "single source of truth" for model risk management.

Champion-Challenger Testing



What is A/B Testing for Models?

Definition: Randomly splitting live traffic between the current model (champion) and a candidate (challenger) to compare real-world performance.

Typical setup:

- **Control:** 80% traffic to champion
- **Treatment:** 20% traffic to challenger
- **Duration:** 2–4 weeks for statistical significance
- **Randomization:** User-level (consistent assignment)

Promote challenger if:

- Accuracy improvement $> 2\%$ (statistically significant, $p < 0.05$)
- No increase in latency or error rate
- Passes fairness and bias audit
- Positive business metric lift

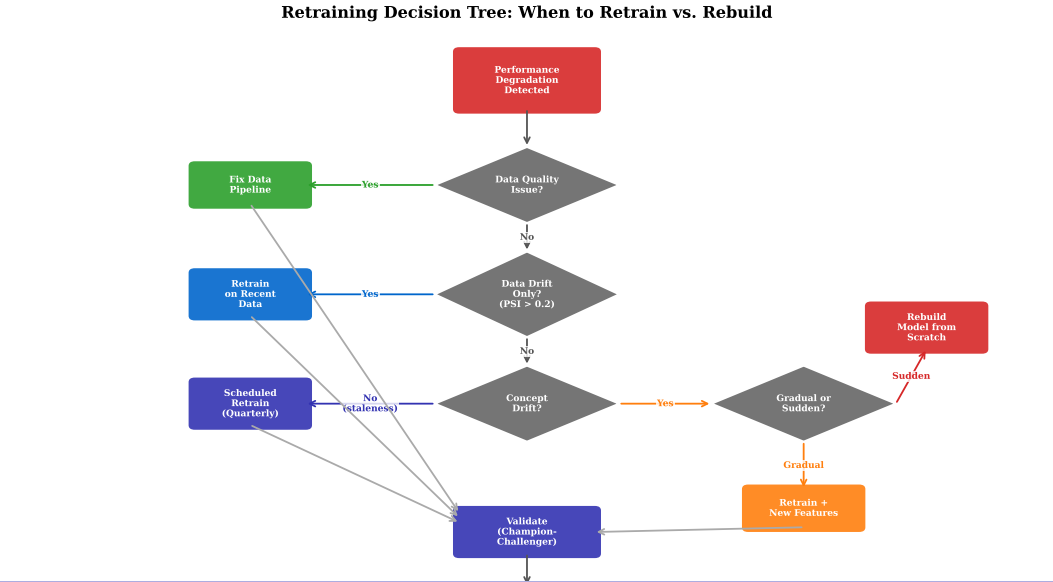
Financial A/B test example (credit scoring):

Metric	Champion	Challenger
AUC-ROC	0.87	0.90
Default rate	3.2%	2.8%
Approval rate	68%	71%
Avg. latency	45ms	52ms

Verdict: Challenger wins on accuracy and business metrics. Latency increase is acceptable. **Promote.**

Offline metrics (cross-validation) and online metrics (A/B test) can disagree—always trust the A/B test.

When to Retrain: Decision Framework



Scheduled vs. Triggered Retraining

Scheduled Retraining

- Retrain on fixed intervals (weekly, monthly, quarterly)
- Predictable resource planning
- Prevents model staleness
- Aligns with regulatory review cycles

Limitations:

- May retrain unnecessarily (wastes compute)
- May miss urgent drift between cycles

Best for: Stable domains, regulatory compliance

Triggered Retraining

- Retrain when monitoring detects drift or performance drop
- Data-driven, resource-efficient
- Responds quickly to urgent issues

Trigger examples:

- PSI > 0.20 on $3+$ features
- AUC drops $> 3\%$ from baseline
- Prediction volume anomaly ($>$2x normal)
- Business KPI breach (default rate spike)

Best for: Dynamic domains (fraud, trading)

Best practice: Hybrid approach—quarterly scheduled **plus** performance-triggered retraining.

Most mature teams use a hybrid strategy: scheduled baselines supplemented by event-driven triggers.

What is CI/CD for ML?

Extension of traditional CI/CD to include data and model artifacts.

CI (Continuous Integration) for ML:

- Automated unit tests for feature engineering code
- Data validation (schema checks, statistical tests)
- Model training smoke tests (does it train without errors?)
- Integration tests (end-to-end pipeline on sample data)

CD (Continuous Delivery) for ML:

- Automated model packaging (Docker containers, ONNX export)
- Shadow deployment for safety validation
- Canary rollout (a deployment pattern where new model serves a small fraction of traffic first): 5% $\rightarrow$ 20% $\rightarrow$ 100%
- Automated rollback if monitoring triggers alert

CT (Continuous Training):

- Automated retraining pipeline triggered by drift detection
- Validation gate: only promote if challenger beats champion
- Full audit trail for regulatory compliance

CI + CD + CT = the full automation stack for production ML.

Feature Store Architecture — Online and Offline Stores

What is a Feature Store? A data management layer that serves pre-computed features to both training and serving.

Online Store (Low Latency)

- Key-value store (Redis, DynamoDB)
- $<$10ms lookup per feature vector
- Latest feature values per entity
- Used for real-time inference

Offline Store (High Throughput)

- Data warehouse (BigQuery, S3)
- Historical feature values
- Point-in-time correctness
- Used for model training

The key innovation: both training and serving use the same feature definitions, eliminating training-serving skew.

Feature Store — Financial Features and Tools

Financial feature examples:

- 30-day rolling average transaction amount
- Count of transactions per hour-of-day
- Days since last address change
- Velocity: transactions per minute
- Debt-to-income ratio (updated monthly)

Tools:

- **Feast:** Open-source, cloud-agnostic
- **Tecton:** Enterprise, real-time focus
- **SageMaker Feature Store:** AWS-native
- **Databricks Feature Store:** Spark-native

Feature stores eliminate training-serving skew and enable feature reuse across teams and models.

Financial MLOps Challenges — Technical and Organizational

Technical Challenges

- **Label delay:** Loan defaults take 6–12 months to materialize
- **Feedback loops:** Model predictions influence future training data
- **Legacy integration:** ML models calling 30-year-old COBOL systems
- **Latency:** Fraud detection needs $<$50ms response

Organizational Challenges

- Siloed teams: data science vs. engineering vs. risk
- Risk aversion: slow approval processes
- Explainability demands: "Why was this loan denied?"

Label delay is the most underestimated challenge in financial ML. You cannot evaluate a credit model until defaults actually occur, months or years later.

Financial MLOps Challenges — Regulatory and Common Pitfalls

Regulatory Challenges

- **SR 11-7:** Model risk management (US)
- **MiFID II:** Algorithmic trading transparency (EU)
- **GDPR Art. 22:** Right to explanation for automated decisions
- **Fair Lending:** Non-discrimination in credit decisions

Common pitfalls:

- Alert fatigue from noisy monitoring
- Retraining too frequently (model churn)
- Confusing data quality bugs with real drift
- "Shadow models" running without governance

Successful financial MLOps requires solving technical, organizational, and regulatory problems simultaneously. Most failures come from ignoring one of these three dimensions.

LLMOps Is Not MLOps: Why 2026 Demands a Second Toolchain

LLM production workloads break the classical MLOps playbook. Drift monitoring, model registries, and A/B testing still matter, but the failure modes differ.

Classical MLOps assumes:

- Model is trained on fixed data
- Output is a number or class label
- "Quality" = accuracy/AUC on a test set
- Latency is deterministic; cost per inference is predictable

LLMOps adds (or replaces):

- **Prompt versioning** (prompts are software)
- **Eval harnesses** (reference, LLM-as-judge, human)
- **Hallucination monitoring** (ungrounded generation)
- **Cost tracking** (tokens $\times$ price; agents can compound)
- **Safety and prompt-injection defences**

Key insight: In MLOps you version data and model weights. In LLMOps you also version *prompts*, *retrieval corpora*, and *evaluation sets* — each of which can silently change model behaviour.

Data reviewed: April 2026. LLMOps is a distinct discipline shaped by API-first consumption, non-deterministic output, and agentic workflows; classical MLOps governance is necessary but not sufficient.

LLMOps Toolchain (April 2026)

Categories and representative tools (vendor-agnostic; toolchain evolves rapidly).

Observability / Eval:

- **LangSmith** (LangChain) — traces + eval harnesses
- **Braintrust** — eval-first workflow
- **Humanloop** — prompt management + human review
- **Langfuse** — open-source tracing
- **Helicone** — proxy-based cost + latency

Guardrails / Safety:

- **Guardrails AI** — output validation
- **Lakera** — prompt-injection detection
- **NeMo Guardrails** (NVIDIA) — dialogue safety
- Built-in provider features (Anthropic system prompt, OpenAI moderation)

RAG / Vector:

- Pinecone, Weaviate, Qdrant, pgvector

Data reviewed: April 2026. Tooling moves quickly; the categories — eval harness, tracing, guardrails, RAG — are stable even as vendors change.

LLMOps Eval Strategies and Production Failure Modes

Four eval strategies (stacked, not exclusive):

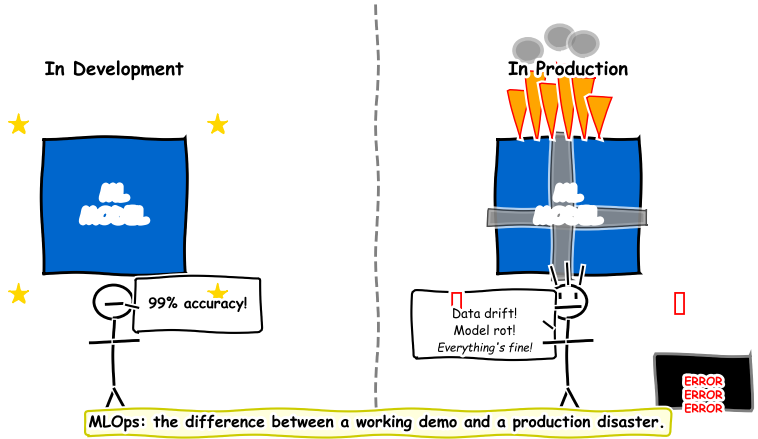
- **Reference-based:** known correct answer; fastest, narrowest.
- **LLM-as-judge:** a frontier model scores outputs against a rubric; scalable but can inherit biases of the judge.
- **Human eval:** gold standard; expensive; required for safety-critical flows.
- **Offline + online A/B:** track task-success metrics and user behaviour in production.

Production failure modes (2026 top five):

1. **Hallucination** — confident but false; mitigate with retrieval grounding + citation requirement.
2. **Prompt injection** — untrusted input overrides system prompt; mitigate with tool-call sandbox + input classifiers.
3. **Data leakage** — training or RAG corpus contains customer PII; mitigate with tokenisation / redaction in the retrieval layer.
4. **Cost runaway** — agentic loops spiralling; mitigate with per-request and per-session budget caps.
5. **Silent regression** — prompt or model upgrade changes behaviour; mitigate with regression test suites on frozen eval sets.

Data reviewed: April 2026. Every production LLM workflow needs: prompt registry, eval harness, cost monitor, guardrail layer, and on-call runbook for injection attacks.

One Last Thought...



Sometimes the best way to remember a concept is to laugh about it.

Key Takeaways

1. **MLOps = DevOps for ML** – automate the lifecycle from data ingestion to model retirement with versioning, monitoring, and governance.
2. **Three drift types** – data drift ($P(X)$ changes), concept drift ($P(Y|X)$ changes), and prediction drift ($P(\hat{Y})$ changes). Each requires different detection and response.
3. **PSI is the industry standard** – Population Stability Index measures distribution shift. Thresholds: <0.10 stable, 0.10–0.20 monitor, >0.20 retrain.
4. **Monitor six dimensions** – model performance, data drift, prediction drift, data quality, operational health, and business impact.
5. **SR 11-7 governs model risk** – three lines of defense (development, validation, audit) with mandatory model inventories and documentation.
6. **Champion-challenger testing** – never deploy without A/B testing against the current production model.
7. **Hybrid retraining** – combine scheduled (quarterly) and triggered (drift-based) retraining for the best coverage.

Building a model is 10% of the work. MLOps is the other 90% that makes it production-ready.

Lesson Summary

What we covered:

- The end-to-end ML lifecycle: ingestion → features → training → validation → deployment → monitoring → retraining
- Three types of model drift and how to detect each
- PSI calculation and interpretation for drift monitoring
- Building a monitoring dashboard with six metric categories
- SR 11-7 model governance and the three lines of defense
- Champion-challenger testing and A/B testing for model replacement
- CI/CD/CT pipelines and feature store architecture

The bottom line:

Without MLOps, models rot in notebooks. With MLOps, models deliver business value continuously—and regulators can sleep at night.

Next lesson: we will explore real-time data pipelines and streaming architectures for financial applications.

Self-Check: MLOps

Attempt these before turning the page.

1. [Understand] Define concept drift, data drift, and covariate shift. Give a financial-services example of each.
2. [Apply] A model's PSI (Population Stability Index) on a credit feature rises from 0.05 (baseline) to 0.35. What does PSI > 0.25 typically indicate? What is your immediate action per SR 11-7?
3. [Evaluate] A bank deploys a new model via "shadow mode" (runs parallel, does not decide). How long should shadow mode run before champion-challenger swap? Argue.

Solutions hidden unless `\solutionstrue` is set before compiling.