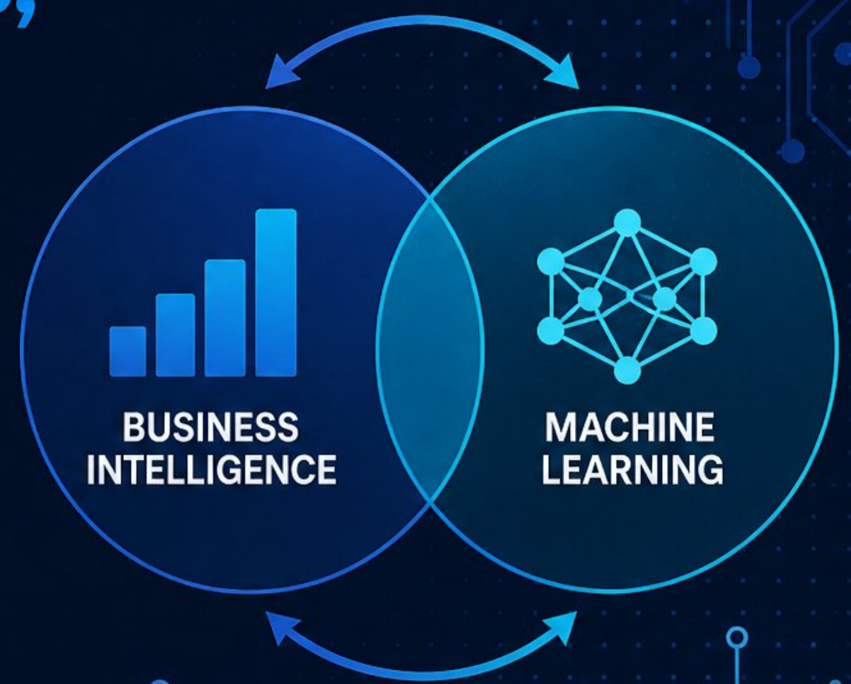
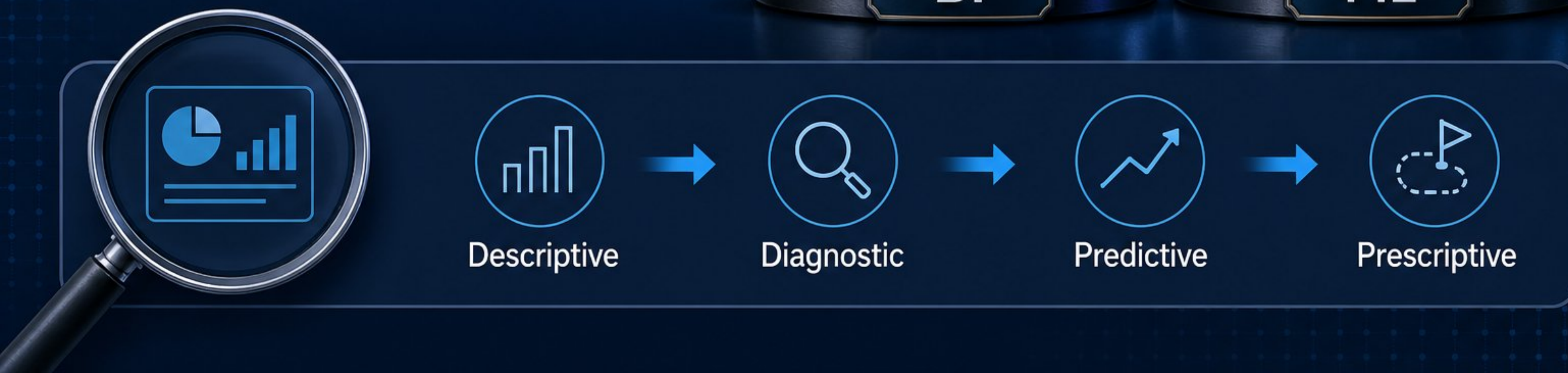
Machine Learning vs Business Intelligence: Differences, Tradeoffs, and Use Cases

- Clarify what BI and ML each are, where they overlap, and where they differ
- For business analysts: framing and requirements; data teams: architecture and delivery; technical managers: staffing, cost, risk, governance
- Common pitfall: choosing dashboards when models are needed, or models when reports suffice
- Agenda: definitions, lifecycles, decision frameworks, use cases, infrastructure, governance, cost and ROI, hybrid approaches, and a capability-action plan



Core Concepts: BI, ML, and the Analytics Continuum

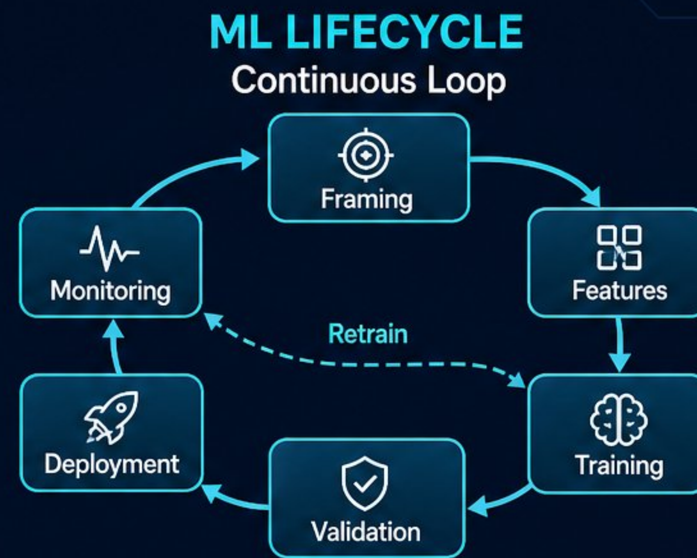
- BI: reporting, dashboards, and descriptive/diagnostic analytics
- ML: predictions and patterns learned from data, not rules
- Analytics levels: descriptive → diagnostic → predictive → prescriptive
- Example: churn dashboard (BI) vs. at-risk account model (ML)



Key Differences in Orientation, Data, and Skills

- BI looks backward, ML looks forward
- BI: structured warehouse data; ML: messy, mixed data
- BI outputs reports; ML outputs predictions and scores
- BI skills: SQL and visualization; ML adds coding and statistics

How the Work and Lifecycle Differ



- BI lifecycle: requirements, modeling, ETL, dashboard design, maintenance
- ML lifecycle: framing, features, training, validation, deployment, monitoring
- BI risk: data quality, metric drift, dashboard sprawl
- ML risk: model drift, deployment failure, silent degradation
- Common failure: wrong tool for the question asked

When to Choose BI, ML, or Both: A Decision Framework

- **BI:** monitoring, root-cause exploration, operational visibility, compliance reporting, historical analysis

- **ML:** future prediction, personalization, automation at scale, pattern discovery, dynamic optimization

- **BI request signals:** what happened, why, how performance compares across segments

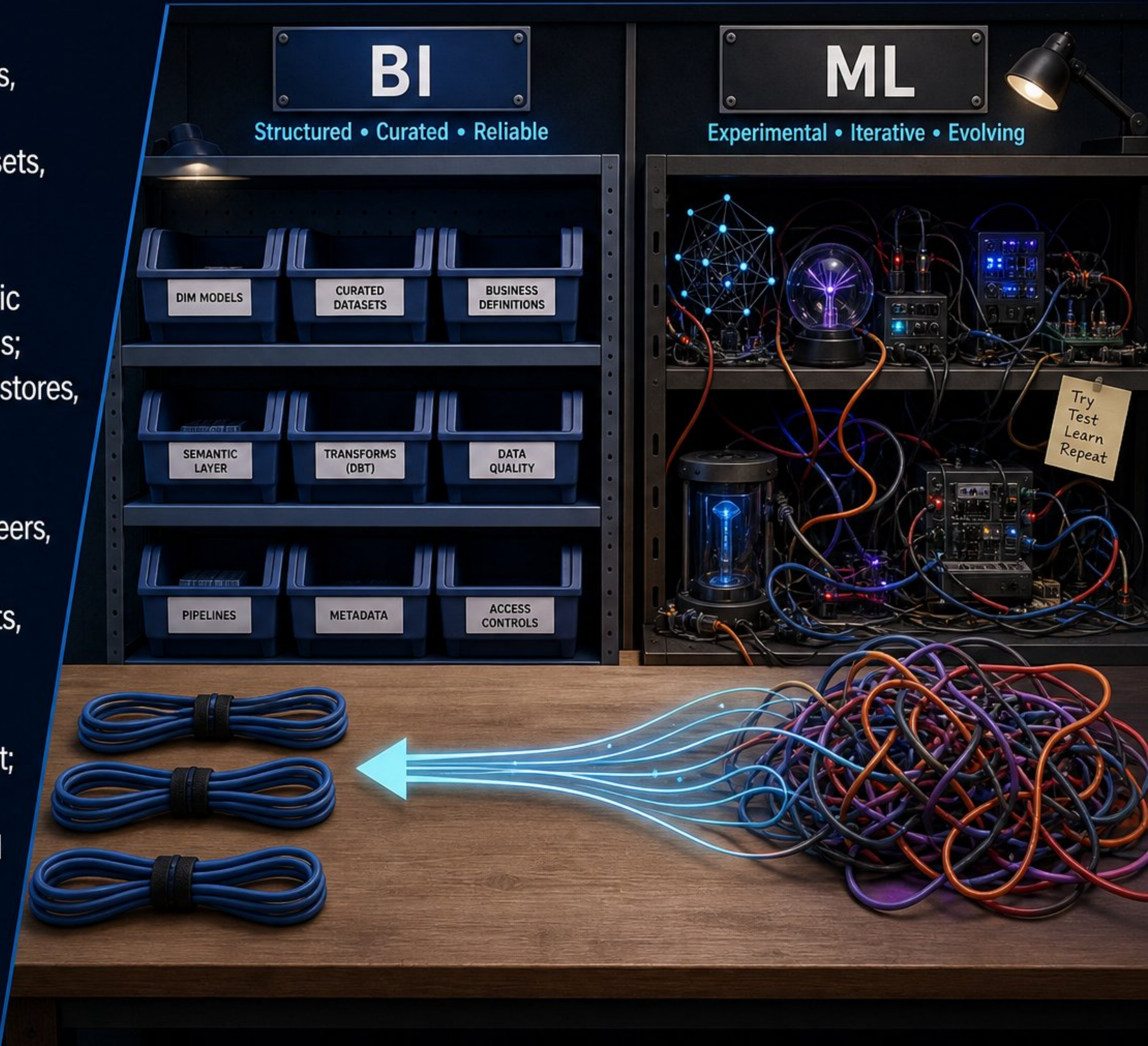
- **ML request signals:** what will happen next, who is at risk, what to recommend?

Use Cases by Business Function

- **Sales & marketing:** BI dashboards for pipeline and ROI; ML for lead scoring and churn propensity
- **Operations & supply chain:** BI for KPI monitoring; ML for demand forecasting and anomaly detection
- **Finance & HR:** BI for variance/SLA reporting; ML for fraud detection and attrition risk
- **Hybrid:** BI surfaces the problem, ML automates the intervention (e.g., retention workflows)

Data, Infrastructure, and Team Requirements

- **BI:** dimensional models, curated datasets; **ML:** features, training sets, versioned data
- **BI tools:** SQL, semantic layers, dbt, BI platforms; **ML:** notebooks, feature stores, model registries
- **Roles:** BI – data engineers, analytics engineers; **ML** adds data scientists, ML engineers
- **Hire** data engineers first; add ML engineers only when models prove demand



Interpretability, Governance, and Organizational Trust

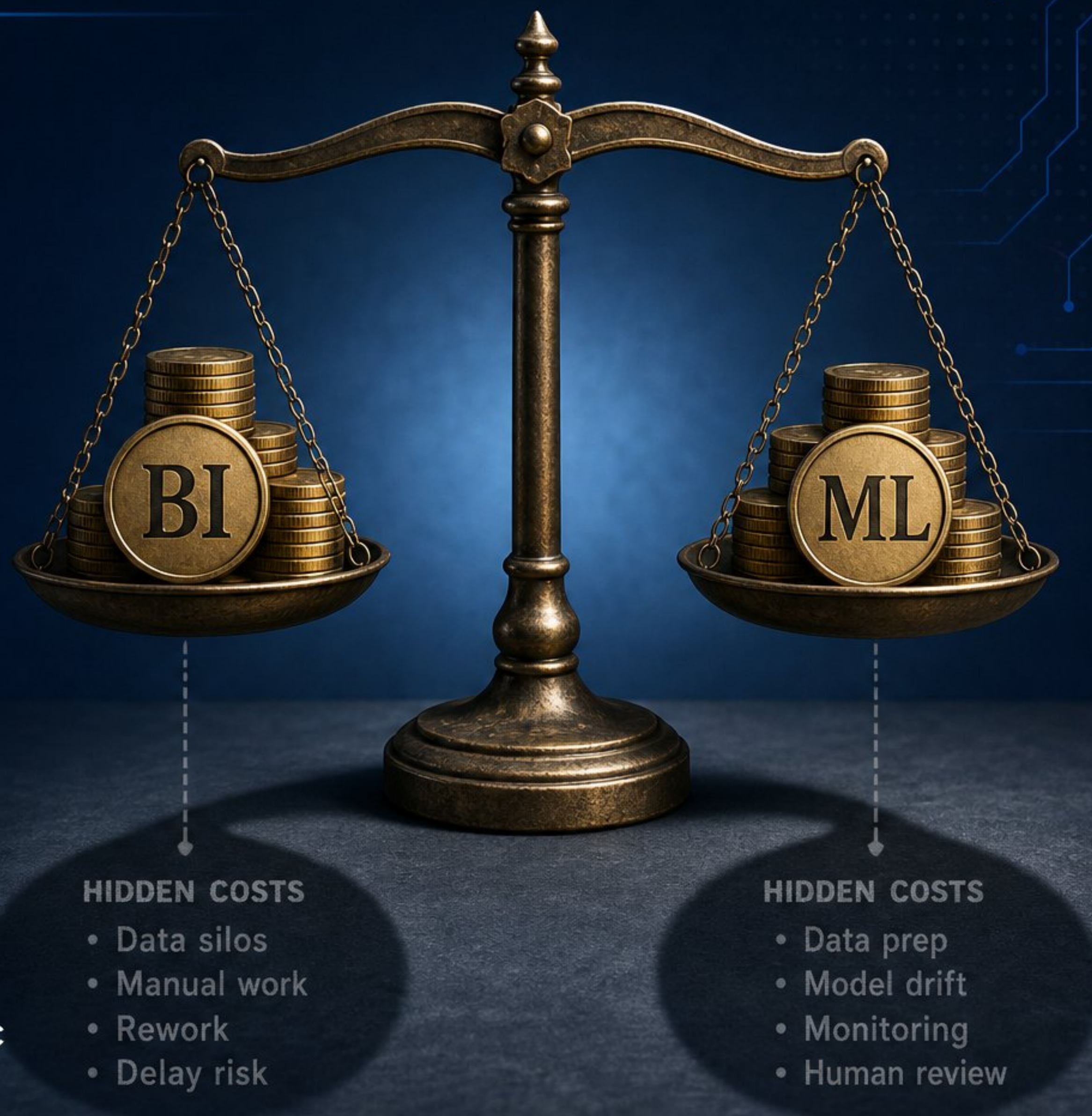
VISIBLE LOGIC
Transparent and auditable

OPAQUE BLACK BOX
Higher accuracy,
lower interpretability

- BI logic explicit in dimensions, measures; transparent and auditable
- ML trades interpretability for accuracy; adds governance, fairness, compliance concerns
- Model governance: validation, monitoring, drift detection, lineage, versioning, rollback
- Technical managers: define model approvers, output reviews, performance monitoring
- Data governance and model governance are distinct but connected

Cost, ROI, and Value Comparison

- **BI costs:** licensing, modeling, data integration, maintenance
- **ML adds:** data prep, training, serving, monitoring, human review
- **BI value:** faster decisions, less manual reporting
- **ML value:** better targeting, reduced losses, automated actions
- **Compare TCO** over 3 years; tie benefits to a business metric

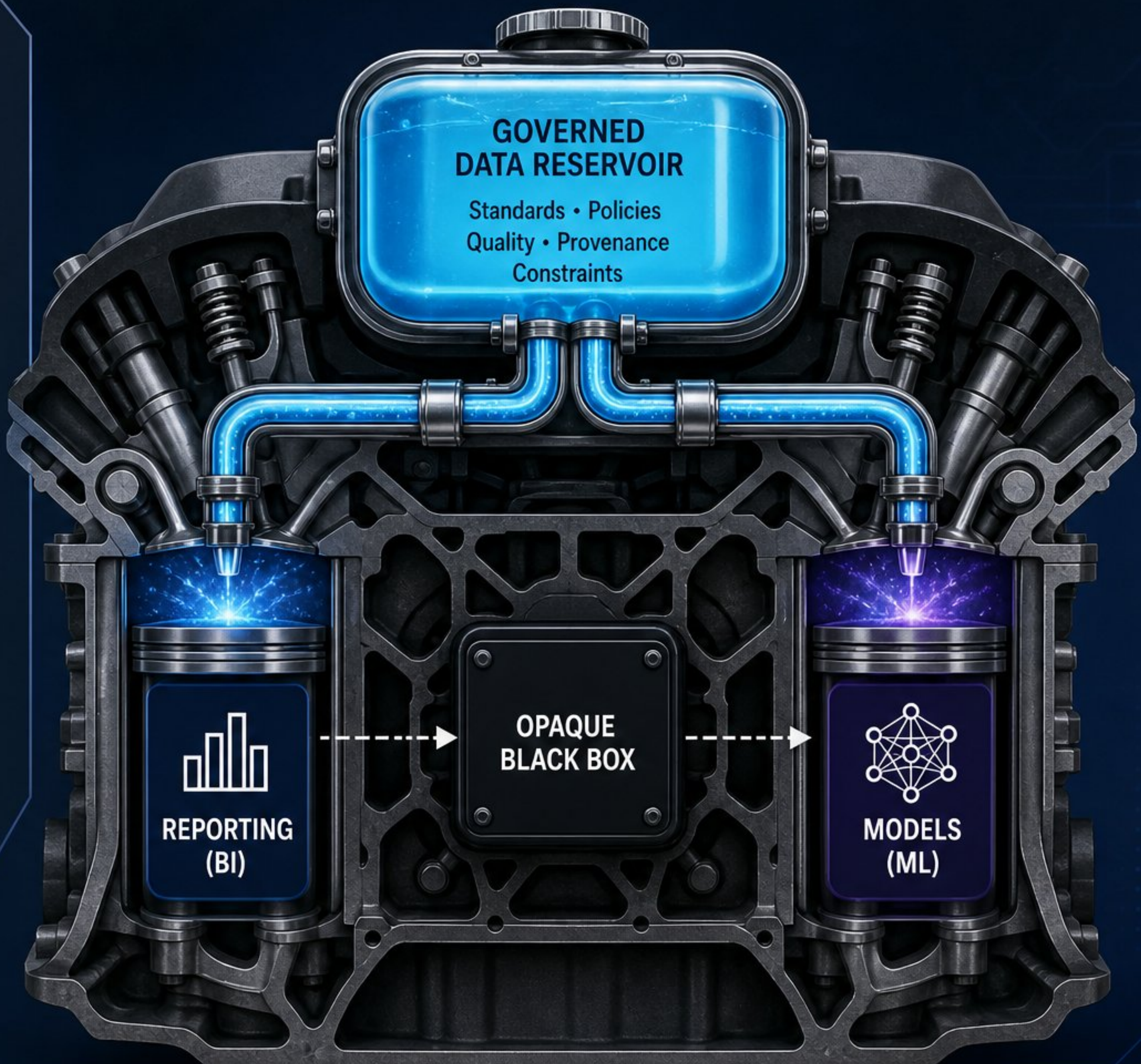


Hybrid Approach: BI-Led Discovery and ML-Led Action

- Dashboards identify problems; ML automates action at scale
- Embed churn scores, forecasts, alerts into Power BI, Looker, QuickSight
- Use BI to monitor ML drift, accuracy, and business impact
- Build progressively: governed semantics → modeling → action

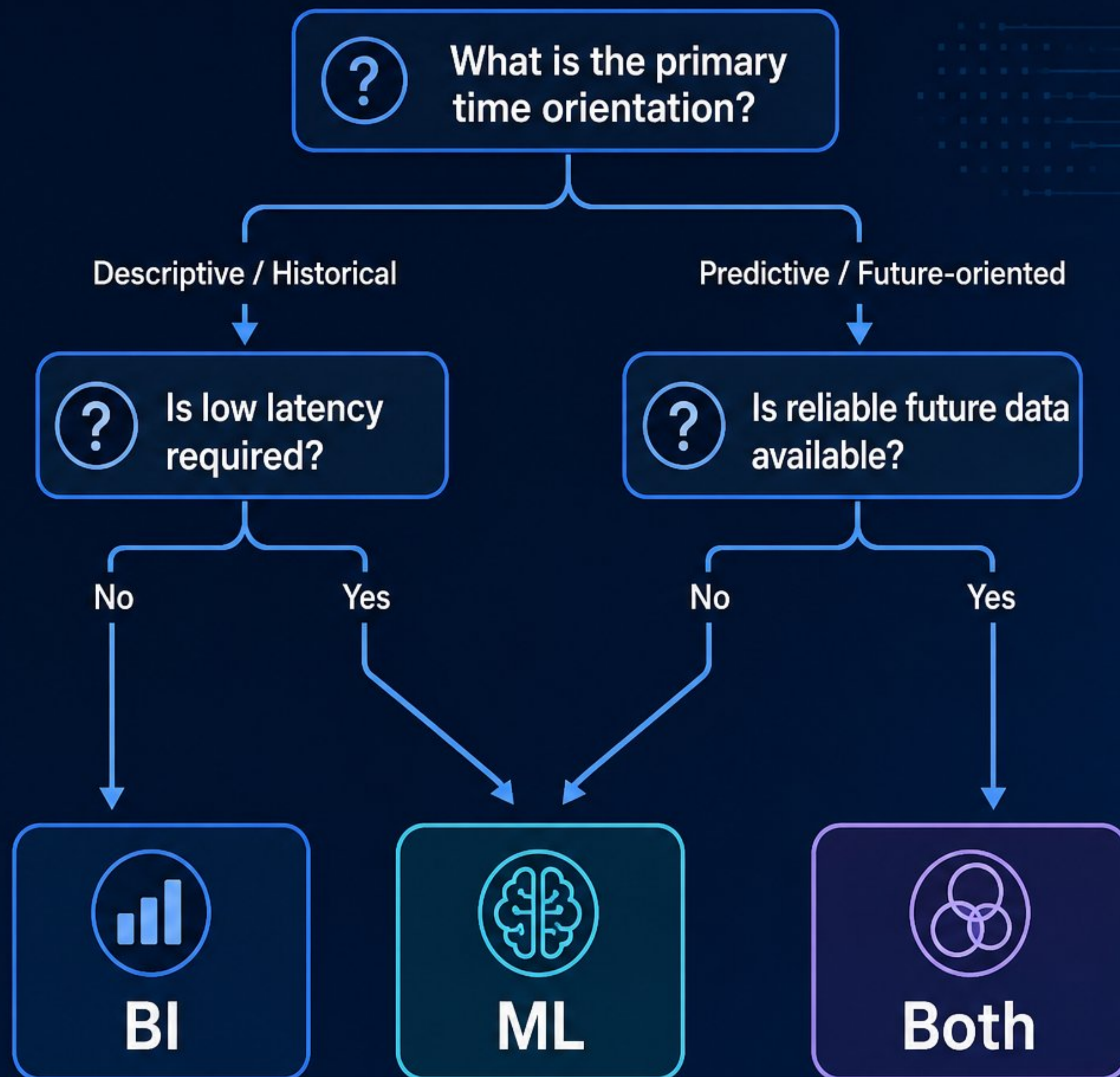
Governance as the Bridge Between BI and ML

- Data governance and model governance are distinct but connected
- ML amplifies data quality problems at machine speed
- Semantic layer ensures consistent definitions and join paths
- Monitor inputs, transformations, policy, and consumer impact
- Explainability begins in the data layer: labels, provenance, constraints



Capability Assessment and Decision Checklist

- Assess data maturity, pipeline reliability, metric alignment, and governance readiness
- Decision checklist: question type, frequency, latency, data availability, interpretability
- Sequence: fix data foundations before hiring data scientists
- Add ML engineers only when models are production-ready
- Roadmap: start with high-value BI, pilot one ML use case, embed predictions



Key Takeaways and Next Steps for Your Organization

- BI explains what happened; ML predicts what will happen and recommends actions
- Choose by question type: prediction vs. reporting, automation vs. interpretation
- Clean data, governed metrics, and reliable pipelines strengthen both BI and ML
- Analysts sharpen requirements; data teams map tooling; managers lead governance